UNIT - I

1. **CRM** stands for **Customer Relationship Management**. It is a process or methodology used to learn more about customers' needs and behaviors in order to develop stronger relationships with them. There are many technological components to CRM, but thinking about CRM in primarily technological terms is a mistake. The more useful way to think about CRM is as a process that will help bring together lots of pieces of information about customers, sales, marketing effectiveness, responsiveness and market trends.

CRM helps businesses use technology and human resources to gain insight into the behavior of customers and the value of those customers.

We can view CRM as an integrated system of web enabled software tools and databases accomplishing a variety of customer-focused business processes that support the three phases of the relationship between a business and its customer**.**

- **Acquire** new customers by doing superior job of contact management, sales prospecting, selling, direct marketing and fulfilment.
- **Enhance** relations by keeping customers happy by supporting superior service from a responsive networked team of sales and service specialists.
- **Retain** its customers by rewarding loyal and profitable customers, expand their business and reward personalized business relationship.

2. The **benefits** of CRM can help it obtain strategic business value and customer value to its customers

1. Helps identify their best customers
2. It makes possible real time customization of products and services, based on customer needs
3. Helps in providing consistent customer experience and superior service

But many CRM implementations **fail** because of

1. Lack of understanding and preparation
2. Lack of business process changes and change management programs
3. Lack of participation by stakeholders and thus lack of preparedness for new process

There are four **types of CRM implementations** done by organizations.

1. *Operational CRM* systems such as sales force automation and customer service center, help synchronize customer interactions consistently and simplifies the business transactions
2. *Analytical CRM* applications are implemented using several analytical marketing tools, like data mining, to extract vital information about customers and prospective marketing
3. *Collaborative CRM* involves business partners as well as customers in collaborative customer service. It improves efficiency and integration throughout the supply chain.
4. *Portal-based CRM* provides all users with tools and information that fit their individual roles and preferences and provides capabilities to instantly access, link, and use all internal and external customer information

3. Following are five solutions as some of the best CRM applications for small and mid-sized businesses:

Salesforce.com

Salesforce.com was the clear champion in 2006, winning both the mid-market CRM and sales force automation categories, and scoring a position as one of the top five on the small business CRM list.

Kudos went to the company for revolutionizing the on-demand CRM market and delivering a solution with a simple user interface and easy-to-navigate features. Salesforce.com was also applauded for its continued commitment to broadening its customization and integration capabilities.

NetSuite

NetSuite was one of just a few CRM companies to make an appearance on more than one list, being named as an industry leader in both small business CRM and mid-market CRM.

The company scored serious points for delivering a fully-integrated front and back office solution that specifically addresses the needs of smaller businesses. By making CRM, ERP, and e-commerce available via a single hosted platform, NetSuite has achieved considerable recognition within the market for its ability to dramatically reduce the complexity of IT infrastructures.

RightNow Technologies

RightNow Technologies is considered a stand-out among today’s best CRM companies for its solid customer service and support capabilities.

Additionally, its recent acquisition of Salesnet, a provider of on-demand sales workflow automation solutions, is expected to close any product functionality gaps and strengthen the company's sales force automation offering. The CRM Magazine editors also praised RightNow's flexible deployment and payment options.

Maximizer
High scores in both customer satisfaction and depth of functionality earned Maximizer Software the top spot in the small business CRM suite category.
In addition to enhancing its product portfolio with mobile and wireless capabilities, the company has taken a more aggressive approach to marketing and public relations in the past year, making a big play to steal a larger chunk of small business market share away from other CRM companies. Panelists also made note of Maximizer's ability to combine strong capabilities with an intuitive interface, offering smaller businesses some of the best CRM features in an easy-to-use environment.

FrontRange Solutions
Although FrontRange Solutions, the company that designs and develops the GoldMine CRM suite, lost its first place spot among small business CRM companies this year, it still earned a position on the top 5 list – thanks to the continued strength of its contact management/sales force automation product and its contact center utility.
The experts noted that FrontRange has outlined a solid strategy for the near-term future, and will be watching closely as the company begins to execute on it.

In order to manage information,

in order to deliver high quality information to the decision-makers at the right time, in order to automate the process of data collection, collation and refinement, organizations have to make IT an ally, harness its full potential and use it in the best possible way.

For any organization to succeed, all business units or departments should work towards this common goal. At the organizational level, IT should assist in specifying objectives and strategies of the organization. At the departmental level, IT must ensure a smooth flow of information across departments, and should guide organizations to adopt the most viable business practices.

As the departments are large, they remain closed except at the top level, unless a common system is implemented.

An Enterprise is a group of people with a common goal, which has certain resources at its disposal to achieve that goal. Resources included are money, material, man-power and all other things that are required to run the enterprise. Planning is done to ensure that nothing goes wrong. Thus Enterprise Resource planning is a method of effective planning of all the resources in an organization.

ERP is primarily an enterprise-wide system, which encompasses corporate mission, objectives, attitudes, beliefs, values, operating style, and people who make the organization.

ERP covers the techniques and concepts employed for the integrated management of businesses as a whole, from the viewpoint of the effective use of management resources, to improve the efficiency of an enterprise. It is a mirror image of the major business processes of an organization, such as customer order fulfillment and manufacturing. Its set of generic processes, produce the dramatic improvements they are capable of only, when used to connect parts of an organization and integrate its various processes seamlessly.

5. Reasons for the growth of the ERP market

1. To enable improved business performance through reduces cycle time, increased business agility, inventory reduction, order fulfillment improvement
2. To support business growth requirements through new product lines, new customers, meeting global requirements
3. To provide flexibility, integrated, real-time decision support through improved responsiveness across the organization
4. To eliminate limitation in legacy systems of century dating , fragmentation of data, inflexibility to change etc
5. To take advantage of the untapped mid-market by increasing functionality at a reasonable cost, vertical market solutions etc.

The advantages of ERP

1. Business Integration through automatic data updations
2. Flexibility to adapt to global differences
3. Better analysis and Planning capabilities by utilizing many types of support systems
4. Use of latest technology to sustain growth.

Why do many ERP implementations fail?

1. Wrong product
2. Incompetent and hazardous implementation.

3. Lack of training for employees

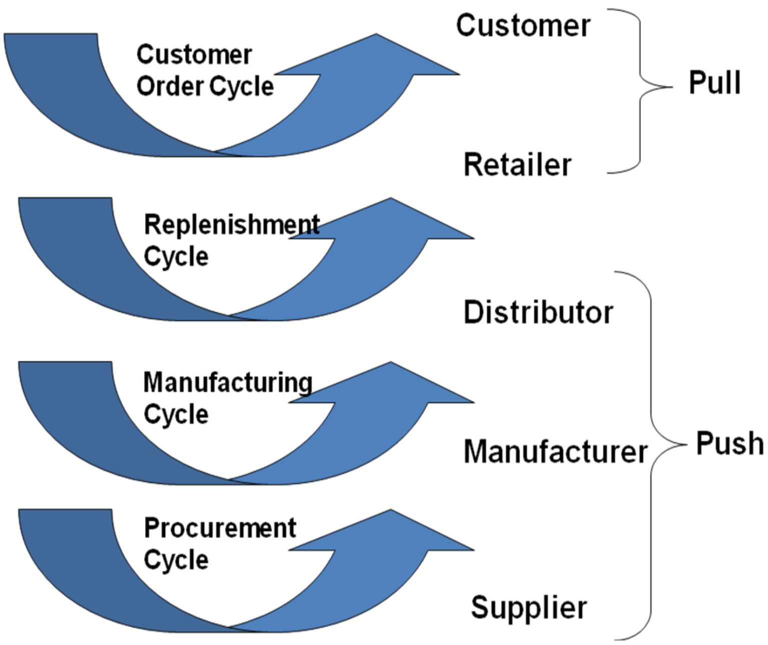
6. ERP Market consists of the big 5 vendors (Sap, Oracle, Peoplesoft, Baan, JD Edwards) and others. The big 5 account for 61% of the market share.

7. Supply Chain Management encompasses every effort involved in producing and delivering a final product or service, from the supplier's supplier to the customer's customer. Supply Chain Management includes managing supply and demand, sourcing raw materials and parts, manufacturing and assembly, warehousing and inventory tracking, order entry and order management, distribution across all channels, and delivery to the customer.

Supply chain objective

- Maximize overall value generated
- Value strongly correlated to **supply chain profitability** – the difference between the revenue generated from the customer and the overall cost across the supply chain

Process View



Customer order cycle

- Customer arrival
- Customer order entry
- Customer order fulfillment
- Customer order receiving

Replenishment cycle

- Retail order trigger
- Retail order entry
- Retail order fulfillment
- Retail order receiving

Manufacturing cycle

- Order arrival from the distributor, retailer, or customer
- Production scheduling
- Manufacturing and shipping
- Receiving at the distributor, retailer, or customer

8. Strategic Advantage – It Can Drive Strategy

* Manufacturing is becoming more efficient

* SCM offers opportunity for differentiation (Dell) or cost reduction (Wal-Mart or Big Bazaar)

- **Globalization – It Covers The World**

* Requires greater coordination of production and distribution

* Increased risk of supply chain interruption

* Increases need for robust and flexible supply chains

- At the company level, supply chain management impacts

  * **COST** – For many products, 20% to 40% of total product costs are controllable logistics costs.

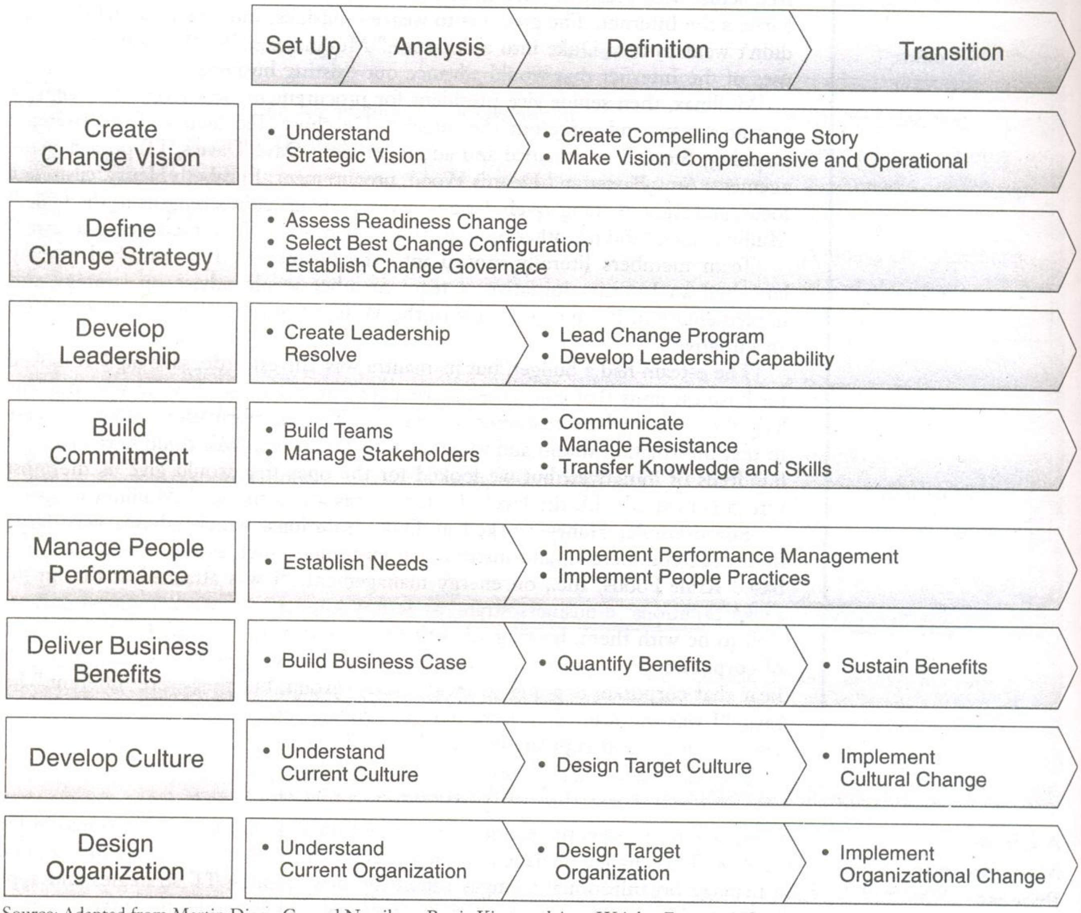
  * **SERVICE** – For many products, performance factors such as inventory availability and speed of delivery are critical to customer satisfaction

9. SCM vendor services from companies such as SAP, **Oracle**, JDA Software, Ariba and Manhattan Associates are the most in demand.

10. Change management involves developing a change action plan, assigning selected managers as change sponsors, developing employee change teams and encouraging open communications and feedback about organizational changes. Change management includes technology, people and process across all levels.

FIGURE 9.18

A process of change management. Examples of the activities involved in successfully managing organizational change caused by the implementation of new business processes.



	Set Up	Analysis	Definition	Transition
Create Change Vision	• Understand Strategic Vision		• Create Compelling Change Story • Make Vision Comprehensive and Operational	
Define Change Strategy	• Assess Readiness Change • Select Best Change Configuration • Establish Change Governace			
Develop Leadership	• Create Leadership Resolve		• Lead Change Program • Develop Leadership Capability	
Build Commitment	• Build Teams • Manage Stakeholders		• Communicate • Manage Resistance • Transfer Knowledge and Skills	
Manage People Performance	• Establish Needs		• Implement Performance Management • Implement People Practices	
Deliver Business Benefits	• Build Business Case		• Quantify Benefits	• Sustain Benefits
Develop Culture	• Understand Current Culture		• Design Target Culture	• Implement Cultural Change
Design Organization	• Understand Current Organization		• Design Target Organization	• Implement Organizational Change

Source: Adapted from Martin Diese, Conrad Nowikow, Patric King, and Amy Wright, *Executive's Guide to E-Business: From Tactics to Strategy*, p. 190. Copyright © 2000 by John Wiley & Sons, Inc. Reprinted by permission.

11. While doing business internationally, a lot of managers face cultural, political and geoeconomic differences. These can be summarized as follows:

Political differences arise because of the regulating rules that differ across border. Tax and import laws vary according to countries.

Geoeconomic challenges refer to the effects of geography on the economic realities of international business activities such as travelling across borders, cost of living in different countries etc.

Cultural challenges include differences in language, interests, customs, social attitudes and political philosophies. The leadership style should suit the cultural environment to coordinate with the workers.

12. Global business IT strategies

- Multinational Strategy: where foreign subsidiaries operate autonomously.

- International strategy : where foreign subsidiaries are autonomous but are dependent on headquarters for new products, processes and ideas
- Global strategies: where a company's worldwide operations are closely managed by corporate headquarters
- **Transnational strategies**: that integrate their global business activities among their international subsidiaries and their corporate headquarters

Transnational strategies are being widely accepted by most of the global companies.

13. Global systems development

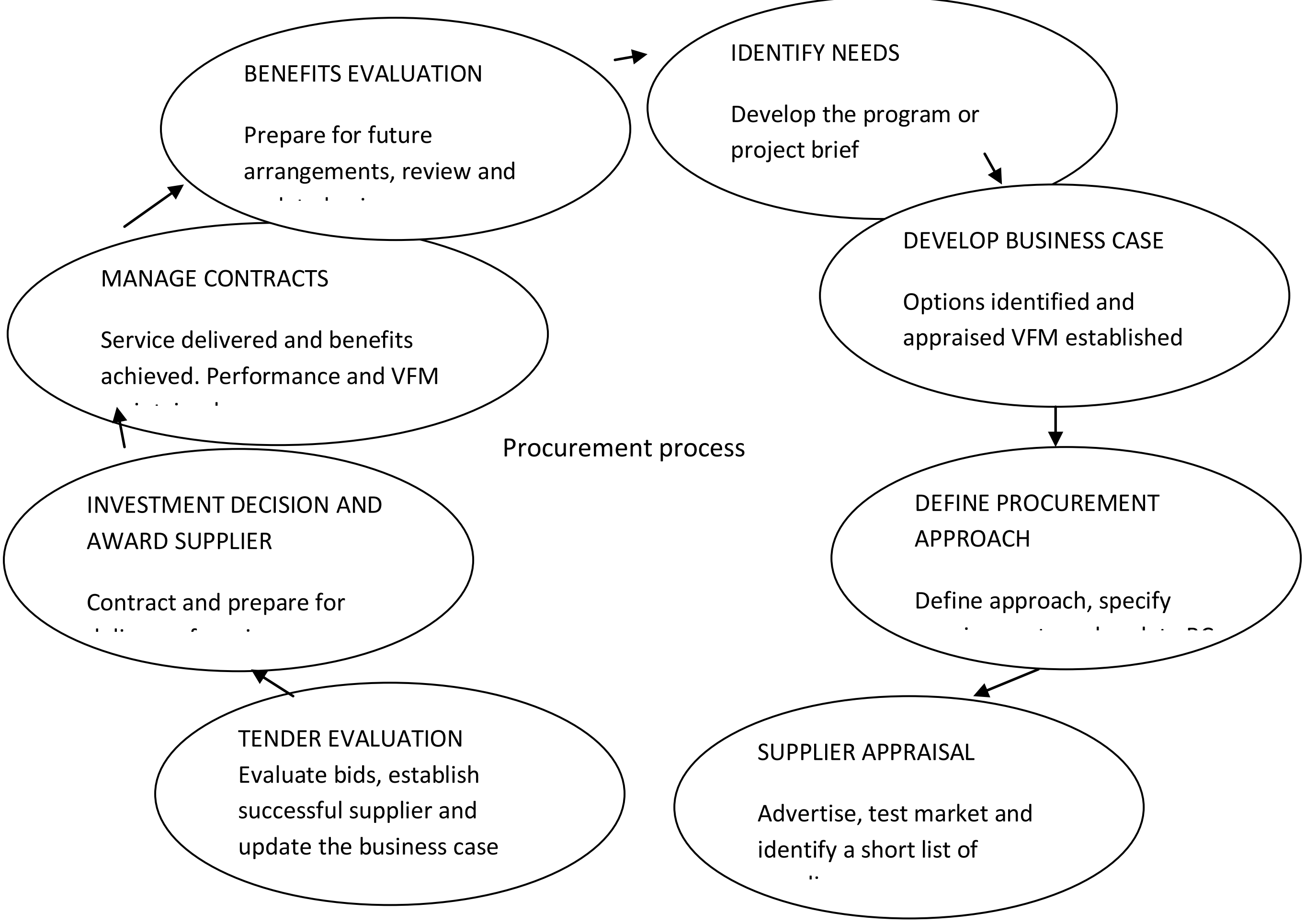
- Transforming an application into a global application
- Multinational development team
- Parallel development
- Center of excellence allows the businesses to develop their applications, allowing their specialization to be used for development.

14. Procurement management system provides a solution to conduct centralized purchase based on the demands individually submitted and approved by competent authorities. It provides a way to businesses that how they purchase their inventories at a reasonable price.

Procurement is often regarded as the narrow process of inviting bids and awarding contracts. The cycle approach to procurement ensures that the early steps in the process and the later steps are given the same emphasis

The following may be involved in the procurement cycle as it depends upon individual implementation

1. Those staff assuming project management roles: project owner, project manager, project board, project team roles.
2. The contract or relationship manager
3. Trained procurement staff
4. Stakeholders such as users, existing suppliers, finance section.
5. Other professional advisors such as accountants, legal advisors, technical advisors


IDENTIFY NEEDS
Develop the program or project brief
DEVELOP BUSINESS CASE
Options identified and appraised VFM established
DEFINE PROCUREMENT APPROACH
Define approach, specify
SUPPLIER APPRAISAL
Advertise, test market and identify a short list of
TENDER EVALUATION
Evaluate bids, establish successful supplier and update the business case
INVESTMENT DECISION AND AWARD SUPPLIER
Contract and prepare for
MANAGE CONTRACTS
Service delivered and benefits achieved. Performance and VFM
BENEFITS EVALUATION
Prepare for future arrangements, review and

Procurement process

UNIT 2

CONSUMER ANALYSIS

INTRODUCTION

The american marketing association: **www.marketingpower.com** defines market research as: "The systematic gathering , recording, and analysis of data about problems relating to the marketing of goods and services". **Consumer analysis** is an important part of this marketing research.

Without marketing research, it is quite impossible today to start any business**. Consumer analysis** is the first step of any marketing research.

In this module, our objective is to develop your skills in **consumer analysis.**

Duration

Lesson: 2 hours

External readings: 3 hours

Do it yourself: 20 hours

Total: About 25 hours

Objectives:

Consumer analysis allows you to identify your prospect and segment market. The objectives of this **consumer analysis** lesson are to give you the fundamental notions about:

-Customer benefit.

-Customer profile.

-Market customer.

By the end , consumer analysis techniques will enable you to establish your market segmentation.

1. Customer benefit 2. Customer profile 3. Market customer 4. Do it yourself 5. Coaching

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1-CUSTOMER BENEFIT

The product must bring a benefit to the customer.

Customer benefit = Sales= Profit.

No customer benefit, no profit.

-Definition: A customer benefit is the value your product or your service gives to the customer.

The customer benefit is not the Unique Selling Advantage (USA). The customer benefit is included in the USA, but it focuses on the point of view of the customer and not of the investor. It implies that you put yourself in the shoes of the customer. It means that the customer benefit is a more precise concept than the USA.

There are two types of customer benefit: **Functional and psychological benefits.**

11-Functional benefit

A functional benefit is measured in money, time, duration, or physical measures:

Examples:

-The product is cheaper than another one: The benefit is measured in **money.**

-This new machine saves the consumer 50% of his time: The benefit can be measured in **hours or minutes.**

-This car has a duration twice another car: The benefit is measured in **years.**

-This chair is lighter than another one (ten kilos instead of twenty). It occupies less space (One square meter instead of two): The benefit is here calculated with **physical measures.**

As time and space can be converted in money, a functional benefit is quite important for a business man. If your corporate sells its products to other corporate's (business to business) you must emphasize the functional benefit.

12-Psychological benefit

A psychological benefit gives to the customer a pleasant feeling such as self esteem, feeling of power, pleasant view and so on.

Examples:

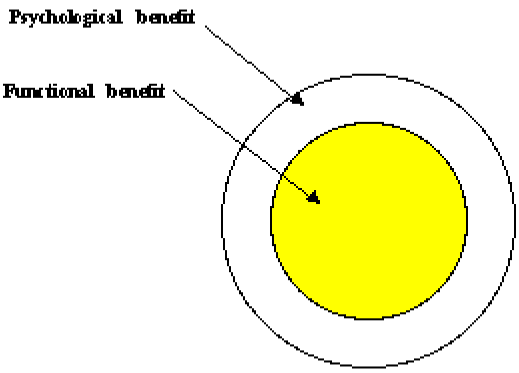
-This product looks attractive and beautiful: Beauty depends on subjective choice.

-This big and expensive car allows you to enjoy speed: As traffic regulations limit speed, the benefit is only a feeling of power.

For starting a business, we recommend to focus on the functional benefit that does not depend on fads. It does not prevent you to add further some psychological benefits.

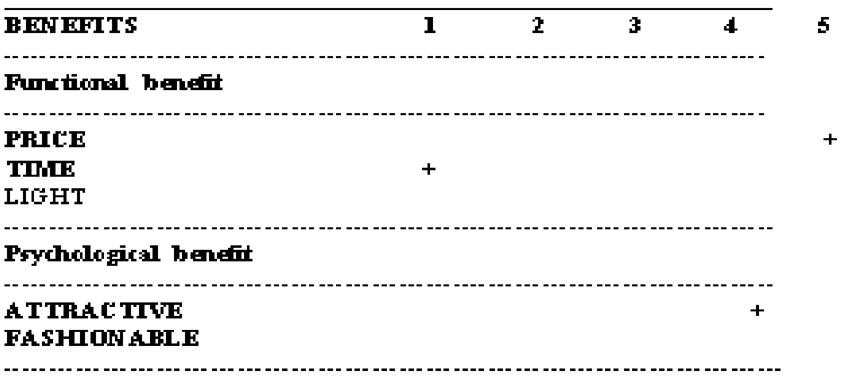
The next drawing shows a product offering both functional and psychological benefits.

DRAWING 1



As a good or a service offers different kinds of benefits. You have to rate them from 1 (low) to 5 (very high) according to their importance for the customer. Of course a low price is rated 5 because it represents a greater benefit to the customer than a high price. In the next drawing the product offers a low price (functional benefit) and is quite attractive (psychological benefit). On the contrary, it does not save any time: It can be a fashionable gadget.

DRAWING 2



BENEFITS	1	2	3	4	5
Functional benefit					
PRICE					+
TIME	+				
LIGHT					
Psychological benefit					
ATTRACTIVE				+	
FASHIONABLE					

Once again, try to forget your own point of view. May be, you think that your low price is an important benefit but in asking around you, you will realize that the customer emphasizes on the time saved, thanks to your product. This analysis is important because it allows you to target your advertisement on the benefits which really matter for the customers.

13-High and low involvement benefits

Now, we have to examine another topic: Are these functional or psychological benefits quite important for the customer. **It means that we have to distinguish low and high involvement products**.

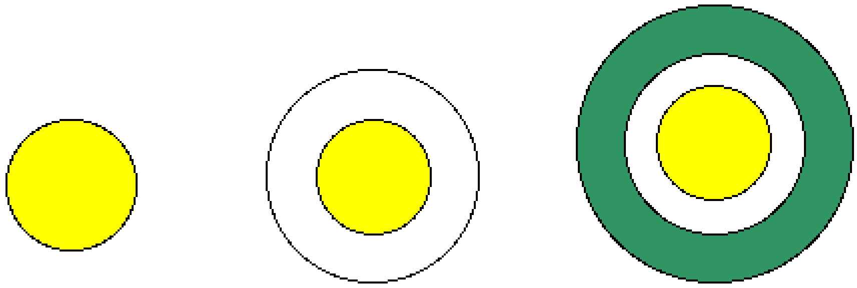
Definition: If a consumer pays attention to buy a product, then it is considered as a high involvement product. If he does not pay too much attention, there is a low involvement product.

Of course, all the **expensive products** are always high involvement products: Flats, cars, antiques and so on. Nevertheless, some inexpensive products can be said high involvement products: For example, **the consumers pay attention in buying cheap drugs because health is an important stake**. What is more, this feature depends also on the customer: For example, a fashionable dress is a psychological benefit but it becomes also a high involvement item for a theater actor who is mainly judged on his appearance.

So, **it is always fruitful to bring some high involvement topics to your product.** For example, if you can assert that your yogurt contains specific vitamins, you bring a high involvement feature to a quite basic product. It enables you to differentiate your product from the competition and to charge a high price.

Finally, the product which gives the greater benefit to the consumer must gather both three characteristics: Functional benefits, psychological benefits, high involvement features.

DRAWING 3



In this drawing, the big circle represents a star because the product combines both functional, psychological and high involvement benefits.

14-User and purchaser benefit

During this analysis, you have to distinguish the **user and the purchaser**

In business to business, You sell a big computer or a software to the heads of the corporate and you are not keeping in touch with the final consumer. Nevertheless, you have to emphasize on **the user benefit** because the head will not buy a product deprived of benefits !

In business to consumer, you sell to a wholesaler or a retailer. Of course you must emphasize on the final customer benefit but you have also to take in account the wholesaler or retailer benefit. These business intermediaries should mainly focus on some functional benefit such as margins or time saving in the delivery of the product.

Real life example:

Times ago, the french chickens were scarcely presented on the German market. Nevertheless, the final consumers were currently saying that they preferred the french chickens because they were gusty.

One asked me to deal with this problem. After a close examination, I realized that the german wholesalers were reluctant to buy french chickens because the product was packaged in box weighting twenty five kilos. As they employed young people in their stores, they had better to buy to the Danes who packaged their chickens by ten kilos only.

When the french producers adopted this packaging, their sales began to shoot up on the german market.

1. Customer benefit 2. Customer profile 3. Market customer 4. Do it yourself 5. Coaching

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2-CUSTOMER PROFILE

The customer profile is deduced from the customer benefit. It includes also the customer buying process.

Definition: The customer profile describes the characteristics of the customer who could really benefit of your product or service.

Clearly, if you intend to sell fun boards, your customer profile is not those of aged persons!

21-Customer characteristics

You can start by defining your ideal customer and list all characteristics you will expect in this profile:

-**Business to consumer:** The main characteristics are quite unlimited: Geographic area, age, sex, income, level of study, employment and so on. So keep close to your benefit analysis and just list the characteristics that correspond to the benefits you offer: If you sell bathing suit, you will not care for people living in north pole. If you sell fur clothes, do not loose your time with the characteristics of people living in Central Africa!

-Business to business: The main characteristics are the company size, the products or services, the level of technology, the turnover, the staff number, the location and so on.

You must describe the required customer profile according to your product or service

Example: What's the customer profile for **fun board**

-Demographic characteristics: 15 to 25 years old, male, healthy

-Economic characteristics: Student or young professional, not less than $30,000 income coming from parents or work.

-Social characteristics: Middle and upper-middle class.

-Geographical area: North America, Australia, Northern Europe.

-Special interests: Sport like and sea like.

You just have to Think in order to define your customer profile: Of course, he is a young man. He has good money because you cannot afford to buy a fun board when you are short for your daily living. So, you can expect that he comes from developed countries. Obviously, he likes sports and sea very much.

Why do you need all these characteristics? The response is that you need the larger information to channel effectively your advertisement: For example, the fact to know where he is located will conduct you to advertise mainly in english and in sportsmen newspapers.

22-Customer buying process

According to your customer profile, you have to focus on the customer buying process. It is not the same thing to buy a candy, a car or a real estate. You have to emphasize on the following aspects. I call it the **DTHP process**:

-Who is the decision making person? In business to business, the purchaser may be a top ranking executive: The more hierarchical levels involved, the more difficult the sale.

In business to consumer, the buying process could imply on person or the entire family. The same observation applies: The more individuals or groups involved, the more difficult the sale.

-At what time or period, does he buy? Consider frequency and regularity of the purchases. Some business follow seasoning periods such as the toys, the bathing suit. This period can be short: For example, the selling of flowers on sunday, or the clothes during the discount periods.

-How does he buy: The buying decision includes the following process:

-The customer becomes aware of a need: The need could originate from an impulse (candy) or from a recognized deficiency (such as a refrigerator)

-The customer begins to explore how meeting the need: He reads newspapers, yellow pages, and so on. It is very important to know how does he explore to target advertisement channels.

-According to the need and his income, the customer refines the buying criteria and defines a budget.

-He narrows the field of his choice in comparing quality/price ratio. He could need physical touch or face to face interaction such as a test drive.

-Finally he closes the sales. In many process, he needs to be helped by a salesman!

How does he pay: Does he use cash, check, or credit card? Does he ask for times payment? Does he need a loan? If you could link some financial services to your product, such as times payments, it should give you a high advantage especially for expensive items.

External readings:

The decision making process is simple for a soda, more complicated for a car: Click on: www.smartcarguide.com . This reading will show you that the buying process for a car implies twenty different steps!

Click also on: ecommerce.vanderbilt.edu then click on "student project", then on "filing the gap in online retailing" and finally on "buying process". This reading compares the buying process in physical world and on line, for books, clothes, flowers, and cars. As you could see, there is a gap in the on line buying process because the customer does not get any physical touch.

The best way to get information about the buying process of your product is to talk with the retailers. You don't need a questionnaire or a customer form. Take it easy: just talk with people in an informal way, have chat about the weather, and ask some short questions to collect right information's.

1. Customer benefit 2. Customer profile 3. Market customer 4. Do it yourself 5. Coaching

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3-MARKET CUSTOMER

You do not intend to sell to only one person. So knowing the customer profile, you have now to group all the persons sharing the same profile: It is your market customer

Definition: A market is a group of customers (or prospects) sharing the characteristics which cope with the benefits offered by your product or service.

Example:

-There is a group of persons eager to travel: there is the tourist market.

-There is a group of persons who use car. There is the car market.

Then we have to separate undifferentiated markets and market segments.

31-Undifferentiated market

If your product brings benefits to everyone, you can treat the market as a whole. For example, anybody whatever his age, sex or revenue drink soda. Nevertheless, you have to take notice of the geographical area. For a retailer, the soda market is around his shop. For Coca cola, that is the entire world.

32-Market segments

In most cases, inside a broad market, you have to differentiate segments. It means that the **market segmentation is one of the most basic concept in marketing.**

-Definition: The market segmentation is the process of splitting customers within a market customer, into different groups sharing some specific characteristics.

Compare with the definition of the market customer. The important word is the adjective **"specific"**. Among the common characteristics of your market customer, you only focus on some **"specific characteristics".**

Examples:

-If your project is to manage an hostel, the tourist market is your customer market but it is not very useful. The tourist market includes cruisers, hostels, tour trip, trekking and so on. Within the tourist market, you have to study the hostel market and inside this broad segment the specific one which corresponds to the benefit your hostel will offer (Is it a five stars or a two stars hostel? is it located on sea shore or in the Rocky Mountains?)

-We have defined above the customer profile for fun board and consequently our customer market. Right now, we will focus on only one geographical characteristic. It means, for example, that we only focus on North America and inside it on USA. In doing so, we isolate a market segment within our broad market.

With a segment you can execute your advertising activities to yield your business targets. Without a segment, you risk wasting money.

Once again, three major variables are used :

- Geographic segmentations divide the market by country, region and city: It is often a good starting point to begin with a single geographical territory. Once you have completed the segmentation for it, you can test the applicability to other and larger areas.

- Demographic segmentations divide the population on measurable variables such as age, sex, income, educational level and so on,

- Psychological segmentation is often quite difficult and needs costly surveys.

External readings:

The next reading shows a list of detailed criteria currently used: Click onwww.businessplans.org . Click on "business planning resources" and then on "segmentation". You will find here many ideas about possible criteria. Some of them could apply to your product. In using them, you will be able to narrow your segment.

Anyway, each segment must be:

-Homogeneous: It's the first quality required for a segment. It means that a segment must be clearly different to others segments in the same broad market. For example, a segment having people income ranking from $20,000 to $200,000 is not homogeneous and worthless for a marketing strategy.

-Consistent: If your segment counts only three prospects, and except you sell nuclear plant, it's not enough to develop sales and profits. A segment must count a large number of prospects.

The factors which can influence the size of the segment are the increase in population, the situation of employment and the changes in income, the supply of resources, the evolution of laws, the consumer tastes and preferences and notably the fads.

-Profitable: A segment must generate profit. It means that the prospects in the segment have a sufficient income with regard of the product price. If you sell luxurious car, it's not very smart to isolate a segment which only contains deprived people!

-Executable: It means that you can reach the segment through advertising, sales force, distribution. It is worthless to isolate a segment if you are unable to join the people who are inside it. For example, there is certainly a consistent segment for fun board in China but If you do not speak chinese, you will never make a dollar with it.

From a practical point of view, **your first task is to evaluate the size of the segment.** Easy to say but it's a real hurdle, because you have to calculate the entire sales volumes of all the suppliers in the segment. It means that you should add all the turnovers of the competitors existing in this segment. **How could you manage that in the specific case of our fun boards?**

Down-earth advice:

With chambers of commerce, producer associations, and so on, you can know how many cars, how many tons of cotton, rice, crude oil and so on, have been produced and imported in the US, and consequently consumed. By the same way, you can know the global amount in $ of the sport sales in the USA by year 2002

Let's suppose that your own segment is in Arizona. First you do the following calculations:

Total sales USA*Arizona population/ US population=Arizona sales

You know the amount of sport stuff sold in Arizona by 2002. Now, you will meet in your area three big retailers selling sport articles and you should just ask them one question: When you are selling $10,000, what is the percentage of fun boards? Suppose they answer one fifth ($2000). Then you have just the calculate:

Sport articles sales in Arizona/5= Estimated fun board sales in Arizona.

You have the total sales of fun board in Arizona. Now, evaluate the average price of a fun board (just visit a lot of shops and quote the prices) and divide the sales volume by the average price:

Fun board sales in Arizona/ average price= number of fun board sold.

You were in the dark at the beginning and now you know the estimated numbers of fun board sold in Arizona by 2002! These calculations look rough but do not worry. By experience, I know that the consulting group which are charging heavy fees just proceed like that!

Be very serious about stats: Too often, people do not like too much the figures and only trust their intuition. In this matter, intuition appears often to be wrong.

Real life example:

In the sixties, an European consulting group decided to study the world milk market. Most of the top executives were convinced that the market was made up with crude milk in bottle and concentrated milk in can. At this time, the European were not familiar with powder milk.

In charge of this study, I scrutinized the import and export stats of about 120 countries. It was not a cool job! In reward, I discovered that the world market was made up of powder milk by 80%!

The executives who had trust their intuition were quite astonished by these results!

When you get a homogeneous, consistent,profitable and executable segment, it means that you have a **marketable product**.

External readings:

For example, the next site shows how these concepts are applied to the agricultural sector:www.gov.mb.ca/agriculture/financial/agribus/agribusiness.html . Go to Manitoba! Click on "new product development" and read "sections 1, 2 and 3".

33-Cluster analysis

To target your customers, you can split the segment into little groups according to a multi-criteria approach:

Example: With our fun board market, we have defined a market segment in Arizona. Now, we shall split this segment in **clusters,** according to new criteria's: People who focus on price, people who had subscribed life insurance, people who only buy from well known brand.

External reading:

To see the methods used, look at: www.sdrnet.com and click on "analytical services" and then on "market segmentation".

As data do not give answers about such characteristics, **you can create a sample**. It's a little group of persons that represent all the characteristics of a larger population. It may be created with friends, relations, chambers of commerce and so on. You must be sure that it is really representative of your whole segment.

When your sample is established, send to each person **a short questionnaire.**Ask questions that produce answers and only focus on the important topics: four or five questions; no more! Test your questionnaire before to field it.

Thanks to the **internet**, some consulting groups suggest to split the cluster into**individuals**. Nevertheless, this ultimate approach raises some problems.

In short, the advanced marketing segmentation looks like the precision guided munitions! I am quite cautious about it**,** because it needs complex computer software, pool opinions, sample analysis and high fees charged by consulting groups**.** It 's good for big corporate's that can afford it.

Anyway, remember that the market segmentation is a compulsory step to define a marketable product. Keep also in mind that only marketable products make money. This point must be underlined

1. Customer benefit 2. Customer profile 3. Market customer 4. Do it yourself 5. Coaching

---

Lesson summary:

A product or a service must bring a benefit to the customer. The customer benefit may be functional and psychological. It may represent a low or a high involvement.

The best benefit gathers both functional, psychological and high involvement features. Any benefit analysis must be conduct both for the user and the purchaser.

The customer profile is deduced of the customer benefit. A market gathers the customers who share the same profile and who could benefit from the product.

A market segment focuses on some specific characteristics of the customer profile. It must be homogeneous, consistent, profitable and executable.

1. Customer benefit 2. Customer profile 3. Market customer 4. Do it yourself 5. Coaching

---

DO IT YOURSELF:

1-You have now to establish for your own business project:

-Your Customer benefit

-Your Customer profile

-Your Market customer

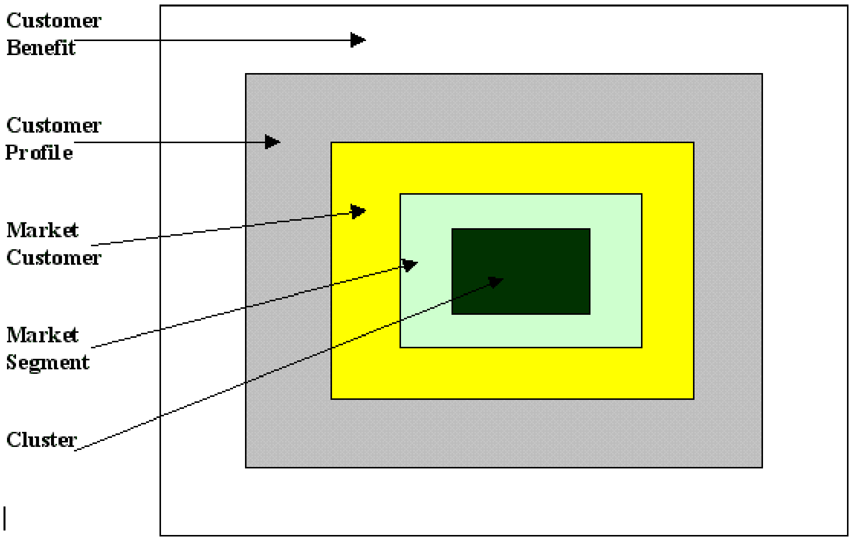
-Your Segment market

Please, follow the logical process you have just learnt: It means that if your customer profile is a young man, your segment can't include a grand mother! Starting with a broad approach, you will more and more focus on your target!

A COTS Acquisition Process: Definition and Application

Experience

DRAWING 4



Useful link:

To perform this job, you will need a lot of data. They are mainly available on the web. So search it by yourself in using keywords. For example, you can use the census web site: www.census.gov

2-Put this analysis in your business plan

Open your plan ware folders and put the analysis under the chapter " Marketing"

Remember that without this analysis you have no hope to succeed in your future business!

1. Customer benefit 2. Customer profile 3. Market customer 4. Do it yourself 5. Coaching

Unit 3

Abstract

The use of Commercial-Off-The-Shelf (COTS) software products in state-of-the-practice software development has shown a substantial increase during the last few years. The benefits of COTS usage are clear: reduced development cost and shorter time-to-market. However, using COTS software in development activities also raises risks such as using software that does not sufficiently satisfy the requirements regarding, e.g., reliability, fault tolerance, functionality. Thus, a sound method that helps to decide which COTS software will be used in a specific development context has become mandatory. This paper introduces and describes a well-defined, systematic, and repeatable COTS acquisition process (CAP) and experience of using a tailored version of the process in a Siemens Business Unit. This includes the definition of the process, a brief description of the activities, and the description of the heuristics for effectiveness and efficiency integrated with the process. Moreover, we present data on cost, benefit, and quality aspects originating from an industrial case study in which the process was applied. From this data collected during the pilot project, conclusions are drawn on the process performance and whether it is worthwhile to apply the CAP.

1. Introduction

The use of Commercial-Off-The-Shelf (COTS) software products in state-of-the-practice software development has shown a substantial increase during the last few years. The benefits of COTS usage are clear: reduced development cost and shorter time-to-market make COTS software an economical choice [13]. Moreover, there are tendencies that many software companies more and more see themselves not as software/system developers but integrators. However, using COTS software in development activities also raises risks, uncertainties and problems [3,11] such as using a software, which does not sufficiently satisfy the requirements regarding, e.g., reliability, fault tolerance, suitability, accuracy, interoperability. Therefore, it is mandatory to have a well-defined, efficient, reliable, and customisable COTS acquisition process (CAP) that soundly interfaces and integrates with other software development processes already in place.

During the past few years a variety of approaches for acquiring COTS software components have been proposed in academia and industry, such as in [4,10,12].

One of these, the OTSO method [4], has similarities with the approach described in this paper. The method proposed in [10] mainly consists of multiple screening steps on the set of alternatives, and reviews and re-/adjustments of the importance weights of the respective criteria. In the OTS component certification process [12] the decision criteria are the compatibility regarding required functionality and the robustness of the COTS software under evaluation. Generally, all these approaches aim at selecting one of the identified alternatives in any case. The option not to buy but to make the required software functionality is not present in the approaches described by other researchers.

The paper is structured as follows: Section 2 defines the CAP model at Siemens. Section 3 describes the setting of the case study, Section 4 presents the results of the case study, and Section 5 gives a summary and an outlook to future work.

2. Description of the CAP Method

The COTS Acquisition Process (CAP) at Siemens consists of three process components: (1) The CAP Initialisation Component (CAP-IC) comprises all activities related to the definition of the decision basis and the measurement plan. (2) The CAP Execution Component (CAP-EC) comprises all activities dealing with the identification of possible COTS software alternatives, and performing measurement and decision-making on the set of available COTS software alternatives. The process components CAP-IC and CAP-EC both end-up in a review activity. (3) The CAP Reuse Component (CAP-RC) comprises all activities referring to packaging information about COTS software for reuse in future CAP enactment. Figure 1 depicts the components of the CAP at Siemens, the inter-component information flow, and the interfaces to external (software) processes.

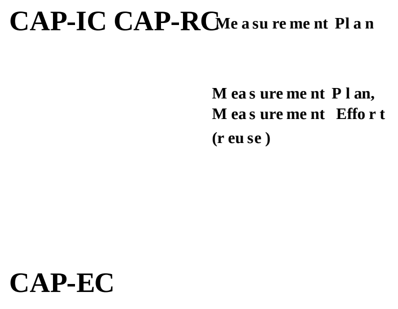


Figure 1: CAP components, internal and external information-flow.

Figure 1 shows the external processes “System Design Process” (SDP) and “Supply Process” (SP), which interface with the CAP. SDP provides input to the CAP in the form of system requirements for the respective system component that shall be implemented through COTS usage. In the case, that there is adequate COTS software available, SP receives the name and supplier of the selected COTS software for negotiation purpose and eventually buy the COTS software. Moreover, SDP can receive input from the CAP in the case that no adequate COTS software was identified and the requirement functionality must be developed in-house or by an external supplier. SDP must then trigger the necessary follow-up processes, e.g. functional specification, coding, etc., in order to get the required functionality built. In the following the components of the CAP will be described.

2.1. CAP-Initialisation Component (IC)

The activities in the CAP-IC are Tailor & Weight Taxonomy, Estimate Measurement Effort, Elaborate Measurement Plan, and IC-Review. The activities are described in Table 1. Optional activities, steps and products are printed in Italics.

Table 1: Description of the CAP-IC activities.

CAP-IC activity	**Steps to be performed**	**Input products**	**Output products**
Tailor & Weight	1. Define and qualify the set of COTS component evaluation criteria (based on the predefined CAP evaluation taxonomy	System Requirements Specification /	Evaluation Taxonomy

CAP-IC activity	Steps to be performed	Input products	Output products
Taxonomy	and specification documents). 2. Establish pair-wise importance rankings on the criteria on all levels of the tailored taxonomy (i.e. assign weights). 3. Calculate overall importance rankings over the various levels of the taxonomy (Eigenvector Method [8]). 4. Iterate steps 2 to 4 until the inconsistencies in importance rankings are sufficiently low. 5. Report the results in product Evaluation Taxonomy.	Functional Specification, Evaluation Taxonomy Template, *IC-Review Report*	
Estimate Measure-ment Effort	*1. Estimate measurement effort based on historical data (for criteria in Evaluation Taxonomy, based on the number of COTS component alternatives in Alternatives_1, and using information on past CAP projects from the CAP Repository).* *2. If step 1 is insufficient, design expert knowledge elicitation questionnaires and acquire expert opinion as an additional input.* *3. Estimate the measurement effort employing quantitative risk analysis methods [15].* 4. *Report estimation results (in product Metric-Effort Mapping).*	Evaluation Taxonomy, *CAP Repository* , Alternatives1, *IC-Review Report*	*MetricEffort Mapping*
Elaborate Measure-ment Plan	*1. Estimate number of remaining COTS component alternatives in activities Screening and Ranking.* *2. Based on information contained in the Project Plan check the feasibility of the Evaluation Taxonomy wrt. budget, resource and time constraints (If taxonomy is feasible, then go to step 4).* 3. *Set up and solve an Integer Linear Program (ILP) [7] to decide which metric will be used for which decision-making procedure in CAP-EC.* 4. Generate Measurement Plan (incl. data collection forms). Whenever possible reuse data from the CAP Repository.	Project Plan, Evaluation Taxonomy, *MetricEffort Mapping* , *CAP Repository* , *IC-Review Report*	Measurement Plan
IC-Review	1. Prepare review meeting. 2. Perform Review. 3. Write and distribute IC-Review Report. 4. If necessary, trigger re-work of CAP-IC-activities.	IC-Review Checklist, Measurement Plan, Evaluation Taxonomy, *MetricEffort Mapping*	IC-Review Report

2.2. CAP-Execution Component (EC)

The activities in the CAP-EC are Exploration, Collect Measures (1), Screening, Collect Measures (2), Ranking, Collect Measures (3), Make-or-Buy Decision, and EC-Review. The activities are described in Table 2.

Table 2: Description of the CAP-EC activities.

CAP-EC activity	Steps to be performed	Input products	Output products
Exploration	1. Analyse System Requirements Specification (SRS) and derive COTS product type and search criteria. 2. Explore the set of COTS software alternatives that match the product type: Search in all available/reachable sources of information. 3. Iterate exploration activities (step 2) until a threshold for the increase of positive search hits over time is reached. 4. Report exploration results in product Alternatives 1.	System Requirements Specification, *CAP Repository* , External Sources (incl. Expert Judgement) *EC-Review Report*	Alternatives 1 (number of alternatives: n_1)
Collect Measures (1)	1. Collect measures (on the COTS software alternatives listed in Alternatives 1; according to the measurement plan). 2. Generate data collection results (product Measures A1).	Alternatives 1, Measurement Plan, *CAP Repository* , *EC-Review Report*	Measures A1
Screening	1. Define filter for screening (using Measures A1). 2. Perform screening, i.e. decide whether to keep or to eliminate a COTS software alternative (listed in Alternatives 1).	Alternatives 1, Measures A1, *EC-Review Report*	Alternatives 2 (number of alternatives: n_2)

CAP-EC activity	Steps to be performed	Input products	Output products
	3. Report screening results (in Alternatives 2: list of remaining COTS software alternatives).		
Collect Measures (2)	1. Collect measures (on the COTS software alternatives listed in Alternatives 1; according to the measurement plan). 2. Generate result of data collection (product Measures A1).	Alternatives 1, Measurement Plan, *CAP Repository*, *EC-Review Report*	Measures A2
Ranking	1. Use Measures A2 to perform an Analytic Hierarchy Process (AHP) [8] analysis on the set Alternatives 2, i.e. a multi-criteria ranking of Alternatives 2 based on Measures A2. 2. Report AHP results (in Alternatives 3: list of ranked COTS software alternatives).	Alternatives 2, Measures A2, *EC-Review Report*	Alternatives 3 (number of alternatives: n_3)
Collect Measures (3)	1. Collect measures (on the top-ranked COTS software alternative in Alternatives 3; according to the measurement plan). 2. Generate result of data collection (Measures A3).	Alternatives 3, Measurement Plan, *CAP Repository*, *EC-Review Report* , *Measures A3*	Measures A3
Make-or-Buy Decision	1. Define filter for Make-or-Buy decision (using Measures A3). 2. Perform Make-or-Buy decision on the top-ranked COTS software alternative. 3. If the top-ranked COTS software alternative passes the Make-or-Buy filter, continue with step 5. 4. Eliminate the top-ranked COTS software alternative from the list Alternatives 3 and continue with Collect Measures (3). 5. Report results in COTS Decision Report. If none of the COTS software alternatives in Alternatives 3 passes Make-or-Buy decision, the COTS Decision Report contains the decision that the specific component of the system must be made in-house or by an external supplier.	Alternatives 3, Measures A3, *EC-Review Report*	COTS Decision, COTS Decision Report
EC-Review	1. Prepare review meeting. 2. Review all decision-making steps that have been performed within CAP-EC. Check them for consistency and validity. If inconsistent decisions are found, re-perform the related decision-making activities. 3. Report review results in in EC-Review Report.	COTS Decision Report, Measures A1/2/3, Alternatives 1/2/3 Project Plan, EC-Review Checklist *EC-Review Report*	EC-Review Report, *System Requirements Feedback Report*, Project Plan

2.3. CAP-Reuse Component (RC)

The only activity in the CAP-RC is Packaging for Reuse. It will be described in more detail in Table 3.

Table 3: Description of CAP-RC activities.

CAP-RC activity	Steps to be performed	Input products	Output products
Packaging for Reuse	1. Package all data that evolved from performing the CAP activities. 2. Store data in the CAP Repository for reuse in current or future projects.	Alternatives 1/2/3, Measures A1/2/3, Measurement Plan, Evaluation Taxonomy	CAP Repository (new or modified)

2.4. Heuristic Underlying the CAP

Since the CAP is concerned with measurement-based decision-making, it is clear that a major effort of the CAP will be allocated for performing measurement activities. Therefore a heuristic for effectiveness and efficiency is underlying the CAP. Since the effort (cost) of a single measurement action and the overall number of alternatives (n) multiply, there would be n? k measures (where k is the overall number of metrics) to be collected when taking a naïve approach to the measurement activities. In order to reduce this effort the measurement plan consists of 3 parts, i.e. one part for screening, ranking, and the make-or-buy decision. The overall number of metrics equals $k = k_1 + k_2 + k_3$. The number of initial COTS alternatives equals $n_1 = n$. n_1 is reduced to $n_2 ? n_1$ after “Screening”. After “Ranking” the $n_3 ? n_2$ top-ranked alternatives are examined in “Make-or-Buy Decision”. The best case is $n_3 = 1$, i.e. the top-ranked alternative already satisfies all make-or-buy criteria. In the straightforward case $n ? k$ equals $n ? (k_1 + k_2 + k_3) = n ? k_1 + n ? k_2 + n ? k_3$. In the heuristic case the number of data collection actions equals $n ? k_1 + n_2 ? k_2 + n_3 ? k_3 ? n ? k_1 + n ? k_2 + n ? k_3$, since $n_3 ? n_2 ? n_1 = n$.

The distribution of the decision criteria across the phases of the CAP-EC is accomplished by applying another heuristic aiming at balancing of the importance of the specified evaluation criteria with the cost of measuring these criteria. This balance is established under the constraints of the project plan, e.g. resources, budget, by solving a linear programme [7] with the objective “maximise the sum of the importance weights of the criteria in the measurement plan”. The measurement plan is the solution of the linear programme.

2.5. The CAP Evaluation Taxonomy

The CAP Evaluation Taxonomy is the core part of the measurement and decision-making procedure within the CAP. It currently comprises a set of more than 100 pre-defined quality metrics. Approximately 60 metrics originate from the ISO9126 standard on product quality [6]; the rest result from expert interviews, literature reviews [4,5] and applied research activities. The evaluation taxonomy is organised in a four-level tree, where the 1st level specifies four high-level categories. Each of these is then refined into 2nd -level categories and further on into the 3rd level, ending up in the 4th level where the evaluation criteria, i.e. the metrics for evaluation, are listed. The categories of the 1st level of the evaluation taxonomy are functional, non-functional, domain/architecture, and strategic criteria. The former two criteria are refined according to ISO9126, whereas the refinement of the latter two criteria was subject of applied research work. Figure 2 depicts the evaluation taxonomy on aggregated level.

Evaluation Goal	Functional (F)	Suitability (Su) Accuracy (Ac) Interoperability (In) Security		ISO9126 + Product Type specific refinements
	Non-Functional (NF)	Reliability (Re) Usability (Us) Efficiency (Ef) Maintainability (Ma) Portability (Po)		ISO9126 + new criteria and metrics
	Domain/Architecture (DA)	Domain Compatibility (DCo) Architecture Compatibility (ACo)		
	Strategic (S)	Cost Factors (CF)	Integration Cost (ICo) Integration Benefit (IBe) Price (P)	New criteria and metrics
		Risk Factors (RF)	Vendor Risk (VR) Product Risk (PR) Market Risk (MR)	

Figure 2: High level structure of the evaluation taxonomy

Some example metrics of the evaluation taxonomy are described in Table 4.

Table 4: Two example evaluation criteria/metrics of the taxonomy.

Taxonomy Path	**Metric**	**Method**	**Formula**	**Interpretation**	**Scale**
[F]-[Su]-	FIC(Feature Implementation Coverage)	Perform functional tests of the system according to the specification. Count number of function the system provides.	FIC=A/B A=#correctly implemented functions B=#required functions	0 ? FIC ? 1 The closer to 1.0 is the better.	interval
[S]-[RF]-	VHA(Vendor	a) Check whether the vendor	a) VHA=0 ? 1	a) 1 is the better	nominal

[P]- Hotline Availability)	provides a support hotline
	b) Ask a specified number of questions and count those questions that could by answered by the hotline.
		b) VHA=A/B
		A=#resolved questions
		B=#questions
			b) 0 ? VHA ?1
			The closer to 1.0 is the better.
				or interval

3. Design of the CAP Case Study at Siemens

The CAP was evaluated in a case study performed within a project at Siemens Health Services (SHS), Picture Archiving and Communication Systems (PACS) development department. The task was to select support software for administrative tasks [1], which was specified by a set of 94 requirements. The case study was performed over a 5 months period, from October '99 until February '00. The goal of the case study was to validate the CAP, gain experience, and, if possible, find opportunities for improvement of the CAP.

In order to characterise the CAP regarding cost, effort, duration, and benefit, a Goal/Question/Metric (GQM) [1,9] measurement plan was developed. The GQM goal specification was *"Analyse the CAP with respect to cost and benefit for the purpose of characterising from the viewpoint of the management in the context of subproject CAP X at SHS"*. For the sake of brevity, not the entire GQM plan but the metrics will be presented in Table 5.

Table 5: Metrics of the GQM plan.

Metric	**Description**	**Definition**	**Scale**	**When/How to measure?**
CDE	COTS-based Development Effort	CDE = $?_{i=1..n}$(Effort of activity I) n: number of activities	CDE > 0 ratio scale	Collect the data for each activity, then sum up
TDE	Traditional Development Effort	TDE = (Ask external suppliers for bids or estimate in-house development effort)	TDE > 0 ratio scale	Use and collect expert knowledge data.
CDD	COTS-based Development Duration	CDD = $?_{i=1..n}$(Duration of activity i) n: number of activities	CDD > 0 ratio scale	Collect this data for each activity, then sum up
TDD	Traditional Development Duration	TDD = Estimate of Traditional Development Time	TDD > 0 ratio scale	Collect and use expert knowledge data.
NCC	Number of COTS Components examined	NCC = #{COTS Components Examined}	NCC ?0 ratio scale	Collect data after "Exploration" and "Screening"
NEC	Number of Evaluation Criteria	NEC = #{4th Level Criteria}	NEC > 0 ratio scale	Collect data after "IC-Review"
NRC	Number of Requirements for Component	NRC = #{Requirements referring to the COTS product type}	NRC > 0 ratio scale	Collect data at any point in time of the CAP-IC
ReC	Requirements Coverage	ReC = (#Fulfilled requirements)/NRC	0 ? ReC ? 1 interval sc.	Collect data after the CAP is finished.

Using the above-defined measures, the case study will be characterised and described. The following economic indicators will be used to characterise the cost and benefit of the CAP compared to building the respective functionality: Return on in Investment (ROI), Cost Effectiveness (CE), and Time Saving Ratio (TSR) of the COTS-based development approach in the sub-project under study, which are shown below [14].

$$ROI ? \frac{TDE ? CDE}{CDE} \qquad CE ? \frac{TDE ? CDE}{TDE} \qquad TSR ? \frac{TDD ? CDD}{TDD}$$

The above measures will also be used to compare the formerly in-place ad-hoc practice for COTS acquisition to the CAP approach. The hypothesis is that the CAP will produce more systematic and reliable decisions for COTS components than the ad-hoc practice by only

[1] Due to reasons of confidentiality the exact product type of the COTS component may not be mentioned in this paper. The COTS component names are labeled with capital letters (A, B, C, …).

marginally increasing the effort. This means that the price for objective, systematic and reliable selections is comparatively low or even at zero.

4. Case Study Results

During the case study a subset of the CAP activities was performed. These activities are Tailor & Weight Taxonomy, Elaborate Measurement Plan, IC-Review, Exploration, Collect Measures 1 and 2, Screening, Ranking, EC-Review. The following activities were not performed during the case study (reasons stated in brackets): Estimate Measurement Effort (there was no budget and resource constraint in the project), Collect Measures 3 and Make-or-Buy Decision (the highest ranked COTS software should automatically be selected), and Packaging for Reuse (the repository will be set up in future).

The exact distribution of the evaluation criteria in classes of functional, non-functional, domain/architecture, and strategic criteria is depicted in the left histogram in Figure 3. In addition, the refinement of the functional and non-functional criteria into sub-criteria is shown.

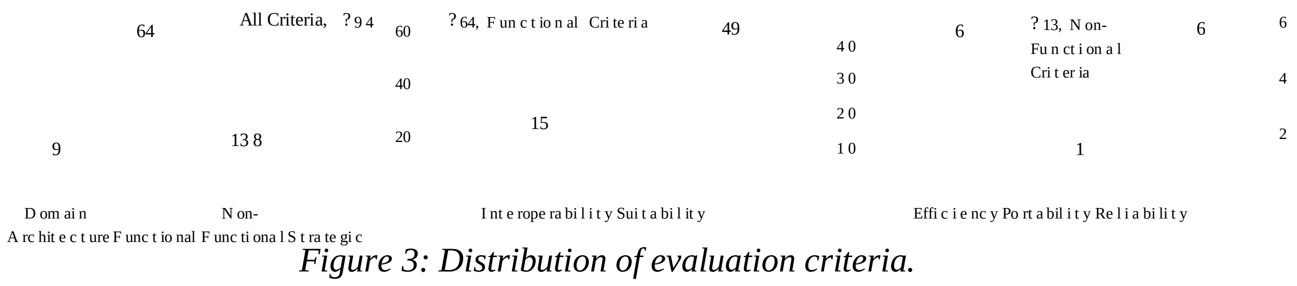


Figure 3: Distribution of evaluation criteria.

In the categories of domain/architecture and strategic criteria there are no specific refinements on the second level of the taxonomy.

The results of measurement during the case study are listed in Table 6.

Table 6: Measurement results of the case study.

Metric	**Value**	**Metric**	**Value**
CDE (COTS selection)	9.5 PM	CDE (COTS integration)	6 PM
CDD (COTS selection)	7 Months	CDD (COTS integration)	6 Months
TDE	~10 PY	NCC	3
TDD	2 Years	NEC	48
ReC	c.f. Table 7	NRC	94

From the data above, the values for ROI, CE, and TSR could be calculated. The results are listed in Table 7. For each indicator the two values are given. One refers to only selecting a COTS software (CAP), the other refers to selecting and integrating a COTS software (CAP+integration). The values for TDE, TDD, CDE, and CDD are based on expert judgement and form the minimum (TDE, TDD) respectively maximum (CDE, CDD) of effort and duration.

Table 7: Economic indicators for the CAP at SHS.

Indicator	**ROI**	**CE**	**TSR**
Value (CAP)	11,63	92,1%	70,83%
Value (CAP+integration)	6,74	87,1%	45,83%

The indicators ROI, CE, and TSR show very high values in both cases. This justifies the use of COTS software at SHS at least at the level of full-size applications. It should be noted that there was an ad-hoc COTS software selection practice in place at SHS before CAP was introduced. One could argue that the ad-hoc practice would be even more beneficial in terms of ROI, CE, and TSR, because it is less formal and does neither imply the definition of a multi-stakeholder weighting scheme and measurement plan, nor the full documentation of the evaluation results. A closer look at the ad-hoc practice indicated, however, that the informal approach is only marginally lower in effort than the new CAP. The main cost driver, i.e. information gathering, has to be performed in either case. The ad-hoc practice mainly differs from the CAP in being less systematic and goal-oriented, possibly resulting in a sub-optimal and less reliable make-or-buy decision. Compared to the ad-hoc practice, the effort increase when performing CAP was 0.5 PM out of a total of 9.5 PMs, which equals an increase of only 5%. But these 5% “buy” a non-negligible increase in process quality due to the systematic, goal-oriented, effectiveness- and efficiency-oriented approach of the CAP. Typically, a higher product quality will result from that.

The evaluation data regarding the selected COTS software is listed in Table 8. This includes the results of the screening activity (pass/no pass), the ranking activity (rank of the respective component), the number of metrics applied in the respective activity of the CAP, and values for the Requirements Coverage (ReC) metric.

Table 8: Requirements Coverage (ReC) of the COTS components and final results.

COTS component	**Screening**	**Ranking**	**Number of applied metrics**	**ReC**
COTS component A	passed screening	2	Screening: 18/Ranking: 30	49 of 94 (52,13%)
COTS component B	passed screening	1 (selected)	Screening: 18/Ranking: 30	67 of 94 (71,28%)
COTS component C	did not pass screening	n/a	Screening: 18/Ranking: 0	47 of 94 (50.00%)
Totals			**Screening: 54/Ranking: 60**	

Table 8 shows that the heuristic described in Section 2.4 came into effect, i.e. the overall number of applied metrics is 3x18+2x30=114 instead of 3x48=144 metrics when performing a brute-force approach to the measurement and decision-making actions. This maps to a reduction of the number of applied metrics by 30, respectively 21%. For example, the OTSO method [4] would have applied 144 metrics. Nevertheless, the OTSO method would have come to exactly the same decision as the CAP.

5. Conclusions and Future Work

The case study demonstrates that the CAP is a systematic, applicable and useful method for the selection of COTS software components. The heuristic integrated into the CAP showed to be effective: a reduction of the number of applied metrics could be accomplished and thus caused an effort reduction. This reduction in effort can compensate the additional cost caused by the higher degree of formality of the CAP, i.e. the systematic, goal-oriented, effectiveness- and efficiency-oriented approach. Moreover, the Return on Investment, Cost Effectiveness, and Time Saving Ratio show that the usage of COTS software is definitely an economical choice compared to pure in-house development. In addition, the reduction in time-to-market has positive effects regarding the acquisition of new customers. If a company throws a product on the market much earlier than competitors, option-pricing models, such as in [2] can be used to quantify the additional profit made by meeting customer demands earlier than competing companies.

Currently there is a second CAP case study performed at SHS, which deals with the selection of a COTS database for a data management system. The preliminary results confirm the results of the case study described in this paper.

Future work directions will focus on refining the evaluation taxonomy regarding strategic criteria, e.g., vendor evaluation. Regarding cost-benefit issues, models for the identification of the critical size point from that on the use of the CAP will be profitable will be defined. Moreover, a COTS acquisition reference model will be developed founding the basis for a new module in process assessment methods focusing on COTS software selection practices.

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Unit 4

CALL CENTRE

Jansankhya Sthirata Kosh, has initiated a first of its kind Call Centre in India on Reproductive, Sexual Health, Family Planning and Infant and Child Health using the services of an international BPO, vCustomer.

OBJECTIVE OF THE CALL CENTRE

Medical experts have found that in India there is a huge gap in information related to reproductive, sexual health especially among the adolescents, about to be married and newly married couples.

The Call Centre initiated by JSK aims to fill this gap by providing easy access and availability of reliable information on reproductive, sexual health, contraception, pregnancy, infant and child health and related issues.

People are initially shy about visiting medical facilities and need guidance to address concerns like contraception, safe abortion, emergency contraception, sexually transmitted diseases and reproductive tract infections. There are also many who are not sure if they need to go to a doctor at all as each visit to a doctor costs money.

The Call Centre service caters mainly to this section of the population, to provide reliable, confidential information. The service however does not substitute for the services of a qualified doctor.

TOPICS INCLUDED UNDER THE CALL CENTRE SERVICE Reproductive system in men and women Puberty Reproductive health concerns in men and women Breast related problems Sexually transmitted infections including HIV/AIDS	Contraception Pregnancy Infertility Sexual Health Abortion Menopause Infant Health (Pre school)

TARGET GROUP

The Call Centre primarily seeks to provide this service to the small towns and in due course villages in the states of Bihar, Jharkhand, Chhattisgarh, Madhya Pradesh, Rajasthan, Uttar Pradesh and Haryana. This is largely because due to various socio - cultural factors people in all age groups, particularly women and young people do not have easy access to authentic information on these issues.

While the publicity of the service is primarily focused in the Hindi speaking northern belt states, it is available to anyone for free across the country. Even without major publicity, calls are being received from states and towns other than those mentioned above.

RESPONSE RECIEVED

More than 50,000 calls have been received from across the country till date. Callers have appreciated the personalized information provided anonymously. The fact there is no commercial interest in promoting any product has also reassured them.

PREPARATION OF THE SPECIALIZED SOFTWARE

A Question Bank of 550 questions on Reproductive, Sexual and Infant & Child Health has been prepared with the help of doctors from leading medical institutes who gave their time pro bono.

They were from:

Maulana Azad Medical College
All India Institute Of Medical Sciences
St. Stephens Medical Hospital
Lady Hardinge Medical College
Kalawati Saran Children Hospital

All details are available on JSK’s website **www.jsk.gov.in** under FAQS on Reproductive and Sexual Health. This material is reviewed periodically.

PROFESSIONAL TRAINING FOR CALL CENTRE EXECUTIVES

The Call Centre Agents have been recruited by the BPO under criteria specified by JSK. While soft skill training has been provided by the BPO, technical training on the topics was given to the Call Centre agents by doctors from St. Stephens Hospital, Delhi followed by Maulana Azad Medical College. Training of the agents is an ongoing process.

TECHNICAL SUPPORT FOR CONCEPT, DESIGN AND SETTING UP OF THE CALL CENTRE

Technical support in identifying the BPO where the service could be hosted and drawing up terms of reference was provided by NIC, NASSCOM and the Central Bureau of Health Intelligence (CBHI).

CRM – Planning

INTRODUCTION

Due to ever-increasing costs and competition, organizations now must sell more products, and provide a higher level of service than at any time in the past. Fast delivery of information and service are now just as important as price. Without current technology, the increasing demands placed on the people in your Customer Facing Departments would make the job almost impossible.

Software now allows sales departments, marketing departments, consultants, support reps and anyone else who interacts with customers and clients to enhance their productivity beyond what many people could have imagined just a few short years ago. Collectively, this technology and the tools associated with it are known as Customer Relationship Management Software, or "CRM".

What is CRM?

CRM is the business strategy, process, culture and technology that enables organizations to optimize revenue and increase value through a more complete understanding and fulfillment of customer needs.

There is a "Revenue Gap" that exists in most companies today. It is the difference in revenue that could be derived if all of a company’s Customer Facing Departments were working with optimum information and at peak efficiency.

Many companies understand that the greatest competitive advantage they have is what they know about their customers and how they use that data. However, most companies have not established the systems and methods necessary to capture customer centric information and leverage it into higher revenues and profits. Once captured, this information may be used to strengthen customer relationships that will then help to differentiate your offering and decrease the necessity to engage in costly price wars. Your ability to capture and leverage this customer information will become the measuring stick for your company’s future success.

Communication is the foundation of any successful relationship and business relationships are no different. Many companies are transitioning from the traditional one-way mass marketing communication model to a two-way communication model that engages their customers in an ongoing dialogue, creating a learning relationship. Every contact with the customer, whether it’s e-mail, phone, Web, or face-to-face, is an opportunity to learn more about the customer’s unique preferences, values and expectations. It is also an opportunity for the customer to gain valuable insight into a company’s product or service offering. Enlightened companies are refining their product or service offerings based on what they learn, and they’re using this greater understanding to create deeper, more profitable long-term customer relationships. The more your customers invest in these learning relationships, the greater their stake in making the relationship work, and the harder it becomes for your competitors to place a wedge between you and your customers.

QIEM starts with the goal of helping companies develop comprehensive Customer Relationship Management strategies and solutions that focus on improving four key areas:

- **Communication** –the exchange of information that, in turn, builds a greater understanding for both parties.
- **Efficiency** – those areas for improving productivity while not in front of the customer.
- **Effectiveness** – those areas for improving productivity while in front of the customer.
- **Decision-Making** – leveraging the information derived to set future direction.

A focus on these four key areas will help your company narrow the Revenue Gap by decreasing expenses and increasing revenue.

Automate Your Best Sales Practices

Standardizing and automating your best sales practices will have many desired effects on your company. A more consistent message creates a greater perception of competence and reduces the negative effect of employee turn over. Automated sales processes also help the company more accurately measure results against activities. In addition, many companies realize that automating best sales practices reduces inefficient time wasting and focuses sales energy on activities historically proven to provide positive results.

Better Training Employees

The most important factor in maintaining positive customer relationships are the people you employ. CRM automation reduces the "trial-by-fire" training methods used at many companies, and leverages the accumulated knowledge of the company. A variety of training benefits can be derived from CRM automation. New employees that start with a systemic standardized set of processes, methodologies and routines, generally come up to speed much more quickly. In addition, they are much less likely to make critical errors during their ramp-up phase. In addition, employees with standardized processes and adequate access to information are happier and more satisfied with their jobs.

Increasing Customer Satisfaction

CRM systems hold at their heart, the customer. Automating key functions such as quick access to critical information and fast turn-around on requests greatly enhances the customers experience while interfacing with your organization. It also gives them greater accuracy in the result.

Increasing Efficiency

Reducing those administrative time wasters will not only increase employee productivity, but will increase their job satisfaction. In return, they will be able to spend more time doing core activities such as interfacing with your customers.

Reducing the Sales Cycle

Improved Communication and rapid delivery of information will reduce the time necessary to close even the largest of deals. Fast delivery of requested information would result in the competitive advantage that may just push those key sales over the top. In addition, the enhanced professionalism and accuracy will enhance your image, shortening the time it takes to earn a prospect's trust.

Improving Communications

Since all corporations have perfect communication pipelines any gain here would be nominal. Just seeing if you were paying attention! Communication is the key element in building greater understanding between internal organizations and between you and your prospects and customers. It is also the hardest element to quantify; but the benefits are tremendous, and for the most part fairly obvious.

Improving Management Decision Making

You need the latest and most accurate information to make sound management decisions. All of your customer and forecast information is consolidated within the CRM solution, so you can receive up-to-date forecasts and generate reports automatically. Also, through consolidation of this data, management can get a more global view of the factors driving real purchase decisions. This greater knowledge will give your management the ability to make decisions based on real data, rather than guesswork.

PLANNING CRM

QIEM offers this guide because we understand the importance of pre-implementation planning and believe it is the foundation of a successful CRM project. The first section will take you through the steps of evaluating, selecting, successfully implementing and maintaining a CRM solution. The second section includes worksheets designed to help you organize your implementation plan.

A well-defined and thought out plan outlines the following:

- The general business goals and objectives
- The necessary people involved
- A date for implementation
- A budget for all phases of the solution
- A Technical Inventory

The General Business Goals and Objectives

The first step in implementing a successful CRM project is to conduct an internal analysis. From this point you can begin to outline your project goals, objectives and requirements.

Current State Analysis

Successful solutions begin with analysis. This usually starts with an assessment of the current state of things. These most usually include the "aches and pains" that hinder your team's productivity and detract from your company's goals, but they might also include certain strengths within the current system. It is important to identify both.

How do you know what the current state is? Begin by asking your sales, marketing and customer service teams a few key questions:

What are the strengths and weaknesses of your company's current processes?

How can the processes be improved?

What administrative activities are detracting from their productivity?

What is the competition doing?

Desired State Analysis

Your desired state will establish and define the ultimate project goals. This analysis will result in a clear direction for the project and be the foundation for measuring the projects success. This analysis will also define the "Gap" between the Current and Desired State. Also, as a result of this phase of the analysis, the areas where the Revenue Gap can be narrowed will become obvious.

Technology is an enabler, not a solution itself. Automating an inefficient process will only speed up the wrong activity. On the other hand, automating very strong processes can be easy and early victories for your system.

Examples:

1. Higher sales per rep
2. Increased customer satisfaction
3. Shorter sales cycle
4. Higher close rate
5. Higher margin per sale
6. More accurate revenue forecasting
7. Improved management information
8. Stronger relationships with partners

Project Goals

Your project will begin to come into focus once you begin to drill down into the measurable, tangible project goals that address your CRM solution's unique requirements and specific needs.

Example Objectives:

1. Reduce the time required to disseminate leads to the sales team
2. Automate quote and proposal generation
3. Create and distribute reports electronically
4. Cut the time required to generate forecasting reports
5. Eliminate duplicate data entry
6. Distribute pricing information, collateral materials or inventory
7. Catalogs more quickly
8. Facilitate group scheduling and activity calendaring

Your project objectives will become your project's critical success factors. You'll use these to evaluate CRM solutions, and in turn, they will become the benchmarks or criteria that the solution must meet in order to be considered successful. If you don't identify the project's objectives, you'll never know if you've achieved them.

Project Deliverables

Your project deliverables drill down further into the specific business needs that your system must address. This detailed list of features and functions will sometimes serve as the body of an RFP used to evaluate and compare CRM applications.

Example Deliverables:

1. Classify contacts by type, such as prospect, customer, reseller, supplier, business partner
2. Automatically notify other team members of important plans, events or customer interactions
3. Run reports automatically and distribute electronically
4. Track customer referrals and lead sources
5. Manage multiple marketing campaigns, projects and activities
6. Create mailing lists and generate targeted direct mailings using fax, e-mail or standard mail
7. Maintain an online encyclopedia of all marketing and sales materials including slide presentations, videos, graphics and audio clips
8. Synchronize data changes, additions, deletions and modifications to records with mobile users

Cost Justification

Your CRM solution plan should also provide a basis for justifying the expense associated with your initiative. Increased revenues and decreased costs are the obvious ROI indicators, but more must be understood. To justify the costs, first determine your ROI expectations. Begin by outlining your project goals and defining your measurable objectives. Convert the measurable objectives into a dollar amount that reflects the operational savings and increased sales that you anticipate. Now you can calculate how quickly you will realize a 100% ROI.

Components:

- Software
- Consulting (analysis and project management)
- Customization, Integration and Data Conversion
- System Implementation
- User and Administrator Training
- Technical and User Support
- Software Maintenance

There are two categories of costs commonly associated with a CRM project:

Implementation Costs: These are the costs associated with the initial system implementation.

Annual Costs: These are the ongoing costs associated with the long-term maintenance and support of the system.

Implementation Costs

To make sure that sufficient resources are available from the outset of the project, it is important to consider the solution's total cost. In addition to the software licenses, other costs associated with the initial implementation of a CRM solution include customization, implementation, training, support, and maintenance. These additional costs over and above the software will generally be 1 to 3 times the cost of the software. A typical middle market CRM solution implementation costs from $1,000 to $4,000 per user.

Annual Costs

Once you've completed your implementation there will be annual expenses required to ensure the long-term success of the solution.

Support – Typical support agreements give you direct access to technical analysts for problem resolution, bug reporting, documentation clarification and technical.

Maintenance – Typical maintenance agreements include software updates, software upgrades and new versions. Without a maintenance agreement, you will have to purchase separately the software upgrades and new versions required to keep your system current.

Industry standards are two to three software updates per year, one software upgrade per nine months to one year, and a new version every 18 months. A support agreement usually costs 10-15% of the software publisher's current suggested price for the software.

Professional Services – In addition to the support and maintenance agreements, you will want to budget annually for the professional services necessary to implement the upgrades, updates, and new versions.

Ongoing Training – When new versions or customizations are planned, you will need to include additional training for your users in the annual budget. New employees will also require user training to ensure they are using the solution successfully.

Unit - V

Building Data Mining Applications for CRM

Introduction

This overview provides a description of some of the most common data mining algorithms in use today. We have broken the discussion into two sections, each with a specific theme:

- Classical Techniques: Statistics, Neighborhoods and Clustering
- Next Generation Techniques: Trees, Networks and Rules

Each section will describe a number of data mining algorithms at a high level, focusing on the "big picture" so that the reader will be able to understand how each algorithm fits into the landscape of data mining techniques. Overall, six broad classes of data mining algorithms are covered. Although there are a number of other algorithms and many variations of the techniques described, one of the algorithms from this group of six is almost always used in real world deployments of data mining systems.

I. Classical Techniques: Statistics, Neighborhoods and Clustering

1.1. The Classics

These two sections have been broken up based on when the data mining technique was developed and when it became technically mature enough to be used for business, especially for aiding in the optimization of customer relationship management systems. Thus this section contains descriptions of techniques that have classically been used for decades the next section represents techniques that have only been widely used since the early 1980s.

This section should help the user to understand the rough differences in the techniques and at least enough information to be dangerous and well armed enough to not be baffled by the vendors of different data mining tools.

The main techniques that we will discuss here are the ones that are used 99.9% of the time on existing business problems. There are certainly many other ones as well as proprietary techniques from particular vendors - but in general the industry is converging to those techniques that work consistently and are understandable and explainable.

1.2. Statistics

By strict definition "statistics" or statistical techniques are not data mining. They were being used long before the term data mining was coined to apply to business applications. However, statistical techniques are driven by the data and are used to discover patterns and build predictive models. And from the users perspective you will be faced with a conscious choice when solving a "data mining" problem as to whether you wish to attack it with statistical methods or other data mining techniques. For this reason it is important to have some idea of how statistical techniques work and how they can be applied.

What is different between statistics and data mining?

I flew the Boston to Newark shuttle recently and sat next to a professor from one the Boston area Universities. He was going to discuss the drosophila (fruit flies) genetic makeup to a pharmaceutical company in New Jersey. He had compiled the world's largest database on the genetic makeup of the fruit fly and had made it available to other researchers on the internet through Java applications accessing a larger relational database.

He explained to me that they not only now were storing the information on the flies but also were doing "data mining" adding as an aside "which seems to be very important these days whatever that is". I mentioned that I had written a book on the subject and he was interested in knowing what the difference was between "data mining" and statistics. There was no easy answer.

The techniques used in data mining, when successful, are successful for precisely the same reasons that statistical techniques are successful (e.g. clean data, a well defined target to predict and good validation to avoid overfitting). And for the most part the techniques are used in the same places for the same types of problems (prediction, classification discovery). In fact some of the techniques that are classical defined as "data mining" such as CART and CHAID arose from statisticians.

So what is the difference? Why aren't we as excited about "statistics" as we are about data mining? There are several reasons. The first is that the classical data mining techniques such as CART neural networks and nearest neighbor techniques tend to be more robust to both messier real world data and also more robust to being used by less expert users. But that is not the only reason. The other reason is that the time is right. Because of the use of computers for closed loop business data storage and generation there now exists large quantities of data that is available to users. IF there were no data - there would be no interest in mining it. Likewise the fact that computer hardware has dramatically upped the ante by several orders of magnitude in storing and processing the data makes some of the most powerful data mining techniques feasible today.

The bottom line though, from an academic standpoint at least, is that there is little practical difference between a statistical technique and a classical data mining technique. Hence we have included a description of some of the most useful in this section.

What is statistics?

Statistics is a branch of mathematics concerning the collection and the description of data. Usually statistics is considered to be one of those scary topics in college right up there with chemistry and physics. However, statistics is probably a much friendlier branch of mathematics because it really can be used every day. Statistics was in fact born from very humble beginnings of real world problems from business, biology, and gambling!

Knowing statistics in your everyday life will help the average business person make better decisions by allowing them to figure out risk and uncertainty when all the facts either aren't known or can't be collected. Even with all the data stored in the largest of data warehouses business decisions still just become more informed guesses. The more and better the data and the better the understanding of statistics the better the decision that can be made.

Statistics has been around for a long time easily a century and arguably many centuries when the ideas of probability began to gel. It could even be argued that the data collected by the ancient Egyptians, Babylonians, and Greeks were all statistics long before the field was officially recognized. Today data mining has been defined independently of statistics though "mining data" for patterns and predictions is really what statistics is all about. Some of the techniques that are classified under data mining such as CHAID and CART really grew out of the statistical profession more than anywhere else, and the basic ideas of probability, independence and causality and overfitting are the foundation on which both data mining and statistics are built.

Data, counting and probability

One thing that is always true about statistics is that there is always data involved, and usually enough data so that the average person cannot keep track of all the data in their heads. This is certainly more true today than it was when the basic ideas of probability and statistics were being formulated and refined early this century. Today people have to deal with up to terabytes of data and have to make sense of it and glean the important patterns from it. Statistics can help greatly in this process by helping to answer several important questions about your data:

- What patterns are there in my database?

- What is the chance that an event will occur?
- Which patterns are significant?
- What is a high level summary of the data that gives me some idea of what is contained in my database?

Certainly statistics can do more than answer these questions but for most people today these are the questions that statistics can help answer. Consider for example that a large part of statistics is concerned with summarizing data, and more often than not, this summarization has to do with counting. One of the great values of statistics is in presenting a high level view of the database that provides some useful information without requiring every record to be understood in detail. This aspect of statistics is the part that people run into every day when they read the daily newspaper and see, for example, a pie chart reporting the number of US citizens of different eye colors, or the average number of annual doctor visits for people of different ages. Statistics at this level is used in the reporting of important information from which people may be able to make useful decisions. There are many different parts of statistics but the idea of collecting data and counting it is often at the base of even these more sophisticated techniques. The first step then in understanding statistics is to understand how the data is collected into a higher level form - one of the most notable ways of doing this is with the histogram.

Histograms

One of the best ways to summarize data is to provide a histogram of the data. In the simple example database shown in Table 1.1 we can create a histogram of eye color by counting the number of occurrences of different colors of eyes in our database. For this example database of 10 records this is fairly easy to do and the results are only slightly more interesting than the database itself. However, for a database of many more records this is a very useful way of getting a high level understanding of the database.

ID	Name	Prediction	Age	Balance	Income	Eyes	Gender
1	Amy	No	62	$0	Medium	Brown	F
2	Al	No	53	$1,800	Medium	Green	M
3	Betty	No	47	$16,543	High	Brown	F
4	Bob	Yes	32	$45	Medium	Green	M
5	Carla	Yes	21	$2,300	High	Blue	F
6	Carl	No	27	$5,400	High	Brown	M
7	Donna	Yes	50	$165	Low	Blue	F
8	Don	Yes	46	$0	High	Blue	M
9	Edna	Yes	27	$500	Low	Blue	F
10	Ed	No	68	$1,200	Low	Blue	M

Table 1.1 *An Example Database of Customers with Different Predictor Types*

This histogram shown in figure 1.1 depicts a simple predictor (eye color) which will have only a few different values no matter if there are 100 customer records in the database or 100 million. There are, however, other predictors that have many more distinct values and can create a much more complex histogram. Consider, for instance, the histogram of ages of the customers in the population. In this case the histogram can be more complex but can also be enlightening. Consider if you found that the histogram of your customer data looked as it does in figure 1.2.

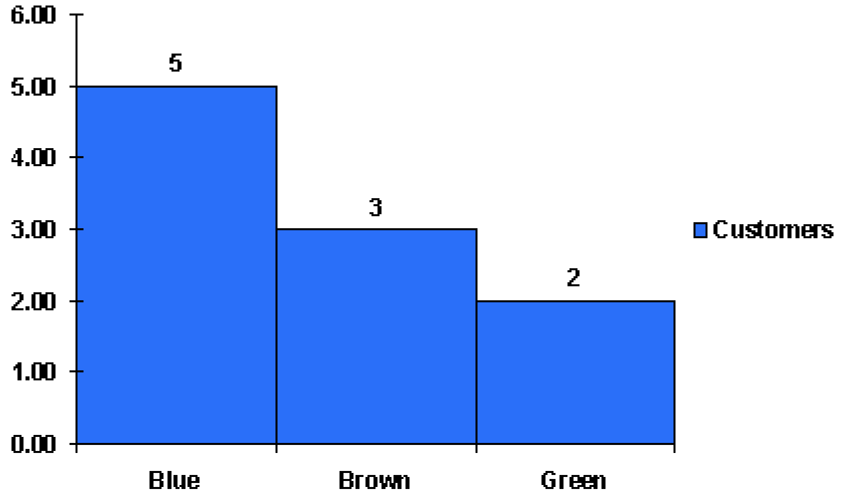

Figure 1.1 *This histogram shows the number of customers with various eye colors. This summary can quickly show important information about the database such as that blue eyes are the most frequent.*

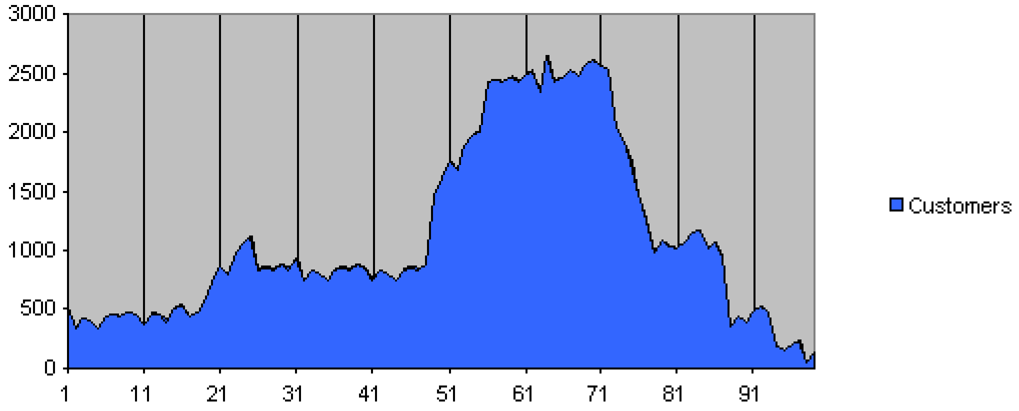

Figure 1.2 *This histogram shows the number of customers of different ages and quickly tells the viewer that the majority of customers are over the age of 50.*

By looking at this second histogram the viewer is in many ways looking at all of the data in the database for a particular predictor or data column. By looking at this histogram it is also possible to build an intuition about other important factors. Such as the average age of the population, the maximum and minimum age. All of which are important. These values are called summary statistics. Some of the most frequently used summary statistics include:

- Max - the maximum value for a given predictor.
- Min - the minimum value for a given predictor.
- Mean - the average value for a given predictor.
- Median - the value for a given predictor that divides the database as nearly as possible into two databases of equal numbers of records.
- Mode - the most common value for the predictor.
- Variance - the measure of how spread out the values are from the average value.

When there are many values for a given predictor the histogram begins to look smoother and smoother (compare the difference between the two histograms above). Sometimes the shape of the distribution of data can be calculated by an equation rather than just represented by the histogram. This is what is called a data distribution. Like a histogram a data distribution can be described by a variety of statistics. In classical statistics the belief is that there is some "true" underlying shape to the data distribution that would be formed if all possible data was collected. The shape of the data distribution can be calculated for some simple examples. The statistician's job then is to take the limited data that may have been collected and from that make their best guess at what the "true" or at least most likely underlying data distribution might be.

Many data distributions are well described by just two numbers, the mean and the variance. The mean is something most people are familiar with, the variance, however, can be problematic. The easiest way to think about it is that it measures the average distance of each predictor value from the mean value over all the records in the database. If the variance is high it implies that the values are all over the place and very different. If the variance is low most of the data values are fairly close to the mean. To be precise the actual definition of the variance uses the square of the distance rather than the actual distance from the mean and the average is taken by dividing the squared sum by one less than the total number of records. In terms of prediction a user could make some guess at the value of a predictor without knowing anything else just by knowing the mean and also gain some basic sense of how variable the guess might be based on the variance.

Statistics for Prediction

In this book the term "prediction" is used for a variety of types of analysis that may elsewhere be more precisely called regression. We have done so in order to simplify some of the concepts and to emphasize the common and most important aspects of predictive modeling. Nonetheless regression is a powerful and commonly used tool in statistics and it will be discussed here.

Linear regression

In statistics prediction is usually synonymous with regression of some form. There are a variety of different types of regression in statistics but the basic idea is that a model is created that maps values from predictors in such a way that the lowest error occurs in making a prediction. The simplest form of regression is simple linear regression that just contains one predictor and a prediction. The relationship between the two can be mapped on a two dimensional space and the records plotted for the prediction values along the Y axis and the predictor values along the X axis. The simple linear regression model then could be viewed as the line that minimized the error rate between the actual prediction value and the point on the line (the prediction from the model). Graphically this would look as it does in Figure 1.3. The simplest form of regression seeks to build a predictive model that is a line that maps between each predictor value to a prediction value. Of the many possible lines that could be drawn through the data the one that minimizes the distance between the line and the data points is the one that is chosen for the predictive model.

On average if you guess the value on the line it should represent an acceptable compromise amongst all the data at that point giving conflicting answers. Likewise if there is no data available for a particular input value the line will provide the best guess at a reasonable answer based on similar data.

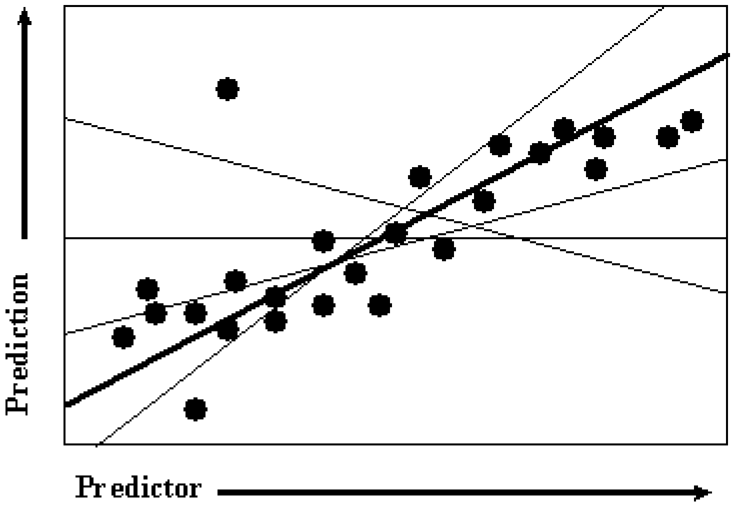

Figure 1.3 *Linear regression is similar to the task of finding the line that minimizes the total distance to a set of data.*

The predictive model is the line shown in Figure 1.3. The line will take a given value for a predictor and map it into a given value for a prediction. The actual equation would look something like: Prediction = a + b * Predictor. Which is just the equation for a line Y = a + bX. As an example for a bank the predicted average consumer bank balance might equal $1,000 + 0.01 * customer's annual income. The trick, as always with predictive modeling, is to find the model that best minimizes the error. The most common way to calculate the error is the square of the difference between the predicted value and the actual value. Calculated this way points that are very far from the line will have a great effect on moving the choice of line towards themselves in order to reduce the error. The values of a and b in the regression equation that minimize this error can be calculated directly from the data relatively quickly.

What if the pattern in my data doesn't look like a straight line?

Regression can become more complicated than the simple linear regression we've introduced so far. It can get more complicated in a variety of different ways in order to better model particular database problems. There are, however, three main modifications that can be made:

1. More predictors than just one can be used.
2. Transformations can be applied to the predictors.
3. Predictors can be multiplied together and used as terms in the equation.
4. Modifications can be made to accommodate response predictions that just have yes/no or 0/1 values.

Adding more predictors to the linear equation can produce more complicated lines that take more information into account and hence make a better prediction. This is called multiple linear regression and might have an equation like the following if 5 predictors were used (X1, X2, X3, X4, X5):

Y = a + b1(X1) + b2(X2) + b3(X3) + b4(X4) + b5(X5)

This equation still describes a line but it is now a line in a6 dimensional space rather than the two dimensional space.

By transforming the predictors by squaring, cubing or taking their square root it is possible to use the same general regression methodology and now create much more complex models that are no longer simple shaped like lines. This is called non-linear regression. A model of just one predictor might look like this: Y = a + b1(X1) + b2 (X12). In many real world cases analysts will perform a wide variety of transformations on their data just to try them out. If they do not contribute to a useful model their coefficients in the equation will tend toward zero and then they can be removed. The other transformation of predictor values that is often performed is multiplying them together. For instance a new predictor created by dividing hourly wage by the minimum wage might be a much more effective predictor than hourly wage by itself.

When trying to predict a customer response that is just yes or no (e.g. they bought the product or they didn't or they defaulted or they didn't) the standard form of a line doesn't work. Since there are only two possible values to be predicted it is relatively easy to fit a line through them. However, that model would be the same no matter what predictors were being used or what particular data was being used. Typically in these situations a transformation of the prediction values is made in order to provide a better predictive model. This type of regression is called logistic regression and because so many business problems are response problems, logistic regression is one of the most widely used statistical techniques for creating predictive models.

1.3. Nearest Neighbor

Clustering and the Nearest Neighbor prediction technique are among the oldest techniques used in data mining. Most people have an intuition that they understand what clustering is - namely that like records are grouped or clustered together. Nearest neighbor is a prediction technique that is quite similar to clustering - its essence is that in order to predict what a prediction value is in one record look for records with similar predictor values in the historical database and use the prediction value from the record that it “nearest” to the unclassified record.

A simple example of clustering

A simple example of clustering would be the clustering that most people perform when they do the laundry - grouping the permanent press, dry cleaning, whites and brightly colored clothes is important because they have similar characteristics. And it turns out they have important attributes in common about the way they behave (and can be ruined) in the wash. To “cluster” your laundry most of your decisions are relatively straightforward. There are of course difficult decisions to be made about which cluster your white shirt with red stripes goes into (since it is mostly white but has some color and is permanent press). When clustering is used in business the clusters are often much more dynamic - even changing weekly to monthly and many more of the decisions concerning which cluster a record falls into can be difficult.

A simple example of nearest neighbor

A simple example of the nearest neighbor prediction algorithm is that if you look at the people in your neighborhood (in this case those people that are in fact geographically near to you). You may notice that, in general, you all have somewhat similar incomes. Thus if your neighbor has an income greater than $100,000 chances are good that you too have a high income. Certainly the chances that you have a high income are greater when all of your neighbors have incomes over $100,000 than if all of your neighbors have incomes of $20,000. Within your neighborhood there may still be a wide variety of incomes possible among even your “closest” neighbors but if you had to predict someone’s income based on only knowing their neighbors you’re best chance of being right would be to predict the incomes of the neighbors who live closest to the unknown person.

The nearest neighbor prediction algorithm works in very much the same way except that “nearness” in a database may consist of a variety of factors not just where the person lives. It may, for instance, be far more important to know which school someone attended and what degree they attained when predicting income. The better definition of “near” might in fact be other people that you graduated from college with rather than the people that you live next to.

Nearest Neighbor techniques are among the easiest to use and understand because they work in a way similar to the way that people think - by detecting closely matching examples. They also perform quite well in terms of automation, as many of the algorithms are robust with respect to dirty data and missing data. Lastly they are particularly adept at performing complex ROI calculations because the predictions are made at a local level where business simulations could be performed in order to optimize ROI. As they enjoy similar levels of accuracy compared to other techniques the measures of accuracy such as lift are as good as from any other.

How to use Nearest Neighbor for Prediction

One of the essential elements underlying the concept of clustering is that one particular object (whether they be cars, food or customers) can be closer to another object than can some third object. It is interesting that most people have an innate sense of ordering placed on a variety of different objects. Most people would agree that an apple is closer to an orange than it is to a tomato and that a Toyota Corolla is closer to a Honda Civic than to a Porsche. This sense of ordering on many different objects helps us place them in time and space and to make sense of the world. It is what allows us to build clusters - both in databases on computers as well as in our daily lives. This definition of nearness that seems to be ubiquitous also allows us to make predictions.

The nearest neighbor prediction algorithm simply stated is:

Objects that are "near" to each other will have similar prediction values as well. Thus if you know the prediction value of one of the objects you can predict it for it's nearest neighbors.

Where has the nearest neighbor technique been used in business?

One of the classical places that nearest neighbor has been used for prediction has been in text retrieval. The problem to be solved in text retrieval is one where the end user defines a document (e.g. Wall Street Journal article, technical conference paper etc.) that is interesting to them and they solicit the system to "find more documents like this one". Effectively defining a target of: "this is the interesting document" or "this is not interesting". The prediction problem is that only a very few of the documents in the database actually have values for this prediction field (namely only the documents that the reader has had a chance to look at so far). The nearest neighbor technique is used to find other documents that share important characteristics with those documents that have been marked as interesting.

Using nearest neighbor for stock market data

As with almost all prediction algorithms, nearest neighbor can be used in a variety of places. Its successful use is mostly dependent on the pre-formatting of the data so that nearness can be calculated and where individual records can be defined. In the text retrieval example this was not too difficult - the objects were documents. This is not always as easy as it is for text retrieval. Consider what it might be like in a time series problem - say for predicting the stock market. In this case the input data is just a long series of stock prices over time without any particular record that could be considered to be an object. The value to be predicted is just the next value of the stock price.

The way that this problem is solved for both nearest neighbor techniques and for some other types of prediction algorithms is to create training records by taking, for instance, 10 consecutive stock prices and using the first 9 as predictor values and the 10th as the prediction value. Doing things this way, if you had 100 data points in your time series you could create 10 different training records.

You could create even more training records than 10 by creating a new record starting at every data point. For instance in the you could take the first 10 data points and create a record. Then you could take the 10 consecutive data points starting at the second data point, then the 10 consecutive data point starting at the third data point. Even though some of the data points would overlap from one record to the next the prediction value would always be different. In our example of 100 initial data points 90 different training records could be created this way as opposed to the 10 training records created via the other method.

Why voting is better - K Nearest Neighbors

One of the improvements that is usually made to the basic nearest neighbor algorithm is to take a vote from the “K” nearest neighbors rather than just relying on the sole nearest neighbor to the unclassified record. In Figure 1.4 we can see that unclassified example C has a nearest neighbor that is a defaulter and yet is surrounded almost exclusively by records that are good credit risks. In this case the nearest neighbor to record C is probably an outlier - which may be incorrect data or some non-repeatable idiosyncrasy. In either case it is more than likely that C is a non-defaulter yet would be predicted to be a defaulter if the sole nearest neighbor were used for the prediction.

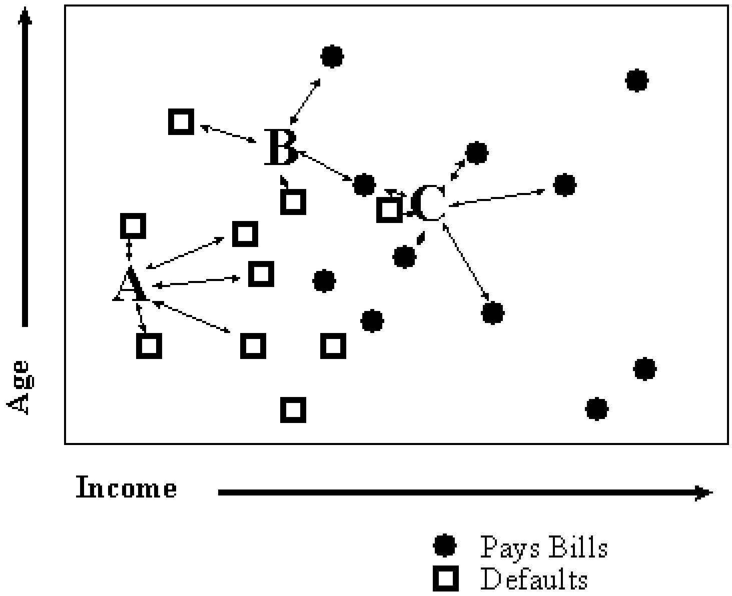

Figure 1.4 *The nearest neighbors are shown graphically for three unclassified records: A, B, and C.*

In cases like these a vote of the 9 or 15 nearest neighbors would provide a better prediction accuracy for the system than would just the single nearest neighbor. Usually this is accomplished by simply taking the majority or plurality of predictions from the K nearest neighbors if the prediction column is a binary or categorical or taking the average value of the prediction column from the K nearest neighbors.

How can the nearest neighbor tell you how confident it is in the prediction?

Another important aspect of any system that is used to make predictions is that the user be provided with, not only the prediction, but also some sense of the confidence in that prediction (e.g. the prediction is defaulter with the chance of being correct 60% of the time). The nearest neighbor algorithm provides this confidence information in a number of ways:

The distance to the nearest neighbor provides a level of confidence. If the neighbor is very close or an exact match then there is much higher confidence in the prediction than if the nearest record is a great distance from the unclassified record.

The degree of homogeneity amongst the predictions within the K nearest neighbors can also be used. If all the nearest neighbors make the same prediction then there is much higher confidence in the prediction than if half the records made one prediction and the other half made another prediction.

1.4. Clustering

Clustering for Clarity

Clustering is the method by which like records are grouped together. Usually this is done to give the end user a high level view of what is going on in the database. Clustering is sometimes used to mean segmentation - which most marketing people will tell you is useful for coming up with a birds eye view of the business. Two of these clustering systems are the PRIZM™ system from Claritas corporation and MicroVision™ from Equifax corporation. These companies have grouped the population by demographic information into segments that they believe are useful for direct marketing and sales. To build these groupings they use information such as income, age, occupation, housing and race collect in the US Census. Then they assign memorable “nicknames” to the clusters. Some examples are shown in Table 1.2.

Name	Income	Age	Education	Vendor
Blue Blood Estates	Wealthy	35-54	College	Claritas Prizm™
Shotguns and Pickups	Middle	35-64	High School	Claritas Prizm™
Southside City	Poor	Mix	Grade School	Claritas Prizm™
Living Off the Land	Middle-Poor	School Age Families	Low	Equifax MicroVision™
University USA	Very low	Young - Mix	Medium to High	Equifax MicroVision™
Sunset Years	Medium	Seniors	Medium	Equifax MicroVision™

Table 1.2 *Some Commercially Available Cluster Tags*

This clustering information is then used by the end user to tag the customers in their database. Once this is done the business user can get a quick high level view of what is happening within the cluster. Once the business user has worked with these codes for some time they also begin to build intuitions about how these different customers clusters will react to the marketing offers particular to their business. For instance some of these clusters may relate to their business and some of them may not. But given that their competition may well be using these same clusters to structure their business and marketing offers it is important to be aware of how you customer base behaves in regard to these clusters.

Finding the ones that don't fit in - Clustering for Outliers

Sometimes clustering is performed not so much to keep records together as to make it easier to see when one record sticks out from the rest. For instance:

Most wine distributors selling inexpensive wine in Missouri and that ship a certain volume of product produce a certain level of profit. There is a cluster of stores that can be formed with these characteristics. One store stands out, however, as producing significantly lower profit. On closer examination it turns out that the distributor was delivering product to but not collecting payment from one of their customers.

A sale on men’s suits is being held in all branches of a department store for southern California . All stores with these characteristics have seen at least a 100% jump in revenue since the start of the sale except one. It turns out that this store had, unlike the others, advertised via radio rather than television.

How is clustering like the nearest neighbor technique?

The nearest neighbor algorithm is basically a refinement of clustering in the sense that they both use distance in some feature space to create either structure in the data or predictions. The nearest neighbor algorithm is a refinement since part of the algorithm usually is a way of automatically determining the weighting of the importance of the predictors and how the distance will be measured within the feature space. Clustering is one special case of this where the importance of each predictor is considered to be equivalent.

How to put clustering and nearest neighbor to work for prediction

To see clustering and nearest neighbor prediction in use let’s go back to our example database and now look at it in two ways. First let’s try to create our own clusters - which if useful we could use internally to help to simplify and clarify large quantities of data (and maybe if we did a very good job sell these new codes to other business users). Secondly let’s try to create predictions based on the nearest neighbor.

First take a look at the data. How would you cluster the data in Table 1.3?

ID	Name	Prediction	Age	Balance	Income	Eyes	Gender
1	Amy	No	62	$0	Medium	Brown	F
2	Al	No	53	$1,800	Medium	Green	M
3	Betty	No	47	$16,543	High	Brown	F
4	Bob	Yes	32	$45	Medium	Green	M
5	Carla	Yes	21	$2,300	High	Blue	F
6	Carl	No	27	$5,400	High	Brown	M
7	Donna	Yes	50	$165	Low	Blue	F
8	Don	Yes	46	$0	High	Blue	M
9	Edna	Yes	27	$500	Low	Blue	F
10	Ed	No	68	$1,200	Low	Blue	M

Table 1.3 *A Simple Example Database*

If these were your friends rather than your customers (hopefully they could be both) and they were single, you might cluster them based on their compatibility with each other. Creating your own mini dating service. If you were a pragmatic person you might cluster your database as follows because you think that marital happiness is mostly dependent on financial compatibility and create three clusters as shown in Table 1.4.

ID	Name	Prediction	Age	Balance	Income	Eyes	Gender

3	Betty	No	47	$16,543	High	Brown	F
5	Carla	Yes	21	$2,300	High	Blue	F
6	Carl	No	27	$5,400	High	Brown	M
8	Don	Yes	46	$0	High	Blue	M

1	Amy	No	62	$0	Medium	Brown	F
2	Al	No	53	$1,800	Medium	Green	M
4	Bob	Yes	32	$45	Medium	Green	M

7	Donna	Yes	50	$165	Low	Blue	F
9	Edna	Yes	27	$500	Low	Blue	F
10	Ed	No	68	$1,200	Low	Blue	M

Table 1.4. *A Simple Clustering of the Example Database*

Is the another "correct" way to cluster?

If on the other hand you are more of a romantic you might note some incompatibilities between 46 year old Don and 21 year old Carla (even though they both make very good incomes). You might instead consider age and some physical characteristics to be most important in creating clusters of friends. Another way you could cluster your friends would be based on their ages and on the color of their eyes. This is shown in Table 1.5. Here three clusters are created where each person in the cluster is about the same age and some attempt has been made to keep people of like eye color together in the same cluster.

ID	Name	Prediction	Age	Balance	Income	Eyes	Gender

5	Carla	Yes	21	$2,300	High	Blue	F
9	Edna	Yes	27	$500	Low	Blue	F
6	Carl	No	27	$5,400	High	Brown	M
4	Bob	Yes	32	$45	Medium	Green	M

8	Don	Yes	46	$0	High	Blue	M
7	Donna	Yes	50	$165	Low	Blue	F
10	Ed	No	68	$1,200	Low	Blue	M

3	Betty	No	47	$16,543	High	Brown	F
2	Al	No	53	$1,800	Medium	Green	M
1	Amy	No	62	$0	Medium	Brown	F

Table 1.5 *A More "Romantic" Clustering of the Example Database to Optimize for Your Dating Service*

There is no best way to cluster.

This example, though simple, points up some important questions about clustering. For instance: Is it possible to say whether the first clustering that was performed above (by financial status) was better or worse than the second clustering (by age and eye color)? Probably not since the clusters were constructed for no particular purpose except to note similarities between some of the records and that the view of the database could be somewhat simplified by using clusters. But even the differences that were created by the two different clusterings were driven by slightly different motivations (financial vs. Romantic). In general the reasons for clustering are just this ill defined because clusters are used more often than not for exploration and summarization as much as they are used for prediction.

How are tradeoffs made when determining which records fall into which clusters?

Notice that for the first clustering example there was a pretty simple rule by which the records could be broken up into clusters - namely by income. In the second clustering example there were less clear dividing lines since two predictors were used to form the clusters (age and eye color). Thus the first cluster is dominated by younger people with somewhat mixed eye colors whereas the latter two clusters have a mix of older people where eye color has been used to separate them out (the second cluster is entirely blue eyed people). In this case these tradeoffs were made arbitrarily but when clustering much larger numbers of records these tradeoffs are explicitly defined by the clustering algorithm.

Clustering is the happy medium between homogeneous clusters and the fewest number of clusters.

In the best possible case clusters would be built where all records within the cluster had identical values for the particular predictors that were being clustered on. This would be the optimum in creating a high level view since knowing the predictor values for any member of the cluster would mean knowing the values for every member of the cluster no matter how large the cluster was. Creating homogeneous clusters where all values for the predictors are the same is difficult to do when there are many predictors and/or the predictors have many different values (high cardinality).

It is possible to guarantee that homogeneous clusters are created by breaking apart any cluster that is inhomogeneous into smaller clusters that are homogeneous. In the extreme, though, this usually means creating clusters with only one record in them which usually defeats the original purpose of the clustering. For instance in our 10 record database above 10 perfectly homogeneous clusters could be formed of 1 record each, but not much progress would have been made in making the original database more understandable.

The second important constraint on clustering is then that a reasonable number of clusters are formed. Where, again, reasonable is defined by the user but is difficult to quantify beyond that except to say that just one cluster is unacceptable (too much generalization) and that as many clusters and original records is also unacceptable Many clustering algorithms either let the user choose the number of clusters that they would like to see created from the database or they provide the user a “knob” by which they can create fewer or greater numbers of clusters interactively after the clustering has been performed.

What is the difference between clustering and nearest neighbor prediction?

The main distinction between clustering and the nearest neighbor technique is that clustering is what is called an unsupervised learning technique and nearest neighbor is generally used for prediction or a supervised learning technique. Unsupervised learning techniques are unsupervised in the sense that when they are run there is not particular reason for the creation of the models the way there is for supervised learning techniques that are trying to perform prediction. In prediction, the patterns that are found in the database and presented in the model are always the most important patterns in the database for performing some particular prediction. In clustering there is no particular sense of why certain records are near to each other or why they all fall into the same cluster. Some of the differences between clustering and nearest neighbor prediction can be summarized in Table 1.6.

Nearest Neighbor	Clustering
Used for prediction as well as consolidation.	Used mostly for consolidating data into a high-level view and general grouping of records into like behaviors.
Space is defined by the problem to be solved (supervised learning).	Space is defined as default n-dimensional space, or is defined by the user, or is a predefined space driven by past experience (unsupervised learning).
Generally only uses distance metrics to determine nearness.	Can use other metrics besides distance to determine nearness of two records - for example linking two points together.

Table 1.6 *Some of the Differences Between the Nearest-Neighbor Data Mining Technique and Clustering*

What is an n-dimensional space? Do I really need to know this?

When people talk about clustering or nearest neighbor prediction they will often talk about a “space” of “N” dimensions. What they mean is that in order to define what is near and what is far away it is helpful to have a “space” defined where distance can be calculated. Generally these spaces behave just like the three dimensional space that we are familiar with where distance between objects is defined by euclidean distance (just like figuring out the length of a side in a triangle).

What goes for three dimensions works pretty well for more dimensions as well. Which is a good thing since most real world problems consists of many more than three dimensions. In fact each predictor (or database column) that is used can be considered to be a new dimension. In the example above the five predictors: age, income, balance, eyes and gender can all be construed to be dimensions in an n dimensional space where n, in this case, equal 5. It is sometimes easier to think about these and other data mining algorithms in terms of n-dimensional spaces because it allows for some intuitions to be used about how the algorithm is working.

Moving from three dimensions to five dimensions is not too large a jump but there are also spaces in real world problems that are far more complex. In the credit card industry credit card issuers typically have over one thousand predictors that could be used to create an n-dimensional space. For text retrieval (e.g. finding useful Wall Street Journal articles from a large database, or finding useful web sites on the internet) the predictors (and hence the dimensions) are typically words or phrases that are found in the document records. In just one year of the Wall Street Journal there are more than 50,000 different words used - which translates to a 50,000 dimensional space in which nearness between records must be calculated.

How is the space for clustering and nearest neighbor defined?

For clustering the n-dimensional space is usually defined by assigning one predictor to each dimension. For the nearest neighbor algorithm predictors are also mapped to dimensions but then those dimensions are literally stretched or compressed based on how important the particular predictor is in making the prediction. The stretching of a dimension effectively makes that dimension (and hence predictor) more important than the others in calculating the distance.

For instance if you are a mountain climber and someone told you that you were 2 miles from your destination the distance is the same whether it's 1 mile north and 1 mile up the face of the mountain or 2 miles north on level ground but clearly the former route is much different from the latter. The distance traveled straight upward is the most important if figuring out how long it will really take to get to the destination and you would probably like to consider this "dimension" to be more important than the others. In fact you, as a mountain climber, could "weight" the importance of the vertical dimension in calculating some new distance by reasoning that every mile upward is equivalent to 10 miles on level ground.

If you used this rule of thumb to weight the importance of one dimension over the other it would be clear that in one case you were much "further away" from your destination ("11 miles") than in the second ("2 miles"). In the next section we'll show how the nearest neighbor algorithm uses distance measure that similarly weight the important dimensions more heavily when calculating a distance measure.

Hierarchical and Non-Hierarchical Clustering

There are two main types of clustering techniques, those that create a hierarchy of clusters and those that do not. The hierarchical clustering techniques create a hierarchy of clusters from small to big. The main reason for this is that, as was already stated, clustering is an unsupervised learning technique, and as such, there is no absolutely correct answer. For this reason and depending on the particular application of the clustering, fewer or greater numbers of clusters may be desired. With a hierarchy of clusters defined it is possible to choose the number of clusters that are desired. At the extreme it is possible to have as many clusters as there are records in the database. In this case the records within the cluster are optimally similar to each other (since there is only one) and certainly different from the other clusters. But of course such a clustering technique misses the point in the sense that the idea of clustering is to find useful patters in the database that summarize it and make it easier to understand. Any clustering algorithm that ends up with as many clusters as there are records has not helped the user understand the data any better. Thus one of the main points about clustering is that there be many fewer clusters than there are original records. Exactly how many clusters should be formed is a matter of interpretation. The advantage of hierarchical clustering methods is that they allow the end user to choose from either many clusters or only a few.

The hierarchy of clusters is usually viewed as a tree where the smallest clusters merge together to create the next highest level of clusters and those at that level merge together to create the next highest level of clusters. Figure 1.5 below shows how several clusters might form a hierarchy. When a hierarchy of clusters like this is created the user can determine what the right number of clusters is that adequately summarizes the data while still providing useful information (at the other extreme a single cluster containing all the records is a great summarization but does not contain enough specific information to be useful).

This hierarchy of clusters is created through the algorithm that builds the clusters. There are two main types of hierarchical clustering algorithms:

- Agglomerative - Agglomerative clustering techniques start with as many clusters as there are records where each cluster contains just one record. The clusters that are nearest each other are merged together to form the next largest cluster. This merging is continued until a hierarchy of clusters is built with just a single cluster containing all the records at the top of the hierarchy.
- Divisive - Divisive clustering techniques take the opposite approach from agglomerative techniques. These techniques start with all the records in one cluster and then try to split that cluster into smaller pieces and then in turn to try to split those smaller pieces.

Of the two the agglomerative techniques are the most commonly used for clustering and have more algorithms developed for them. We'll talk about these in more detail in the next section. The non-hierarchical techniques in general are faster to create from the historical database but require that the user make some decision about the number of clusters desired or the minimum "nearness" required for two records to be within the same cluster. These non-hierarchical techniques often times are run multiple times starting off with some arbitrary or even random clustering and then iteratively improving the clustering by shuffling some records around. Or these techniques some times create clusters that are created with only one pass through the database adding records to existing clusters when they exist and creating new clusters when no existing cluster is a good candidate for the given record. Because the definition of which clusters are formed can depend on these initial choices of which starting clusters should be chosen or even how many clusters these techniques can be less repeatable than the hierarchical techniques and can sometimes create either too many or too few clusters because the number of clusters is predetermined by the user not determined solely by the patterns inherent in the database.

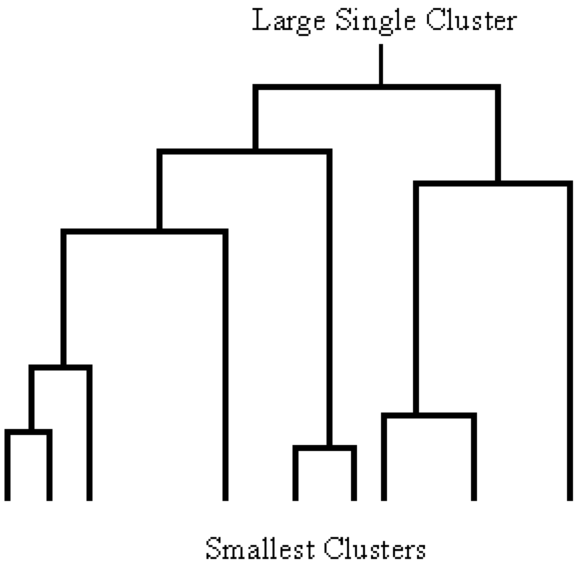

Figure 1.5 *Diagram showing a hierarchy of clusters. Clusters at the lowest level are merged together to form larger clusters at the next level of the hierarchy.*

Non-Hierarchical Clustering

There are two main non-hierarchical clustering techniques. Both of them are very fast to compute on the database but have some drawbacks. The first are the single pass methods. They derive their name from the fact that the database must only be passed through once in order to create the clusters (i.e. each record is only read from the database once). The other class of techniques are called reallocation methods. They get their name from the movement or "reallocation" of records from one cluster to another in order to create better clusters. The reallocation techniques do use multiple passes through the database but are relatively fast in comparison to the hierarchical techniques.

Some techniques allow the user to request the number of clusters that they would like to be pulled out of the data. Predefining the number of clusters rather than having them driven by the data might seem to be a bad idea as there might be some very distinct and observable clustering of the data into a certain number of clusters which the user might not be aware of.

For instance the user may wish to see their data broken up into 10 clusters but the data itself partitions very cleanly into 13 clusters. These non-hierarchical techniques will try to shoe horn these extra three clusters into the existing 10 rather than creating 13 which best fit the data. The saving grace for these methods, however, is that, as we have seen, there is no one right answer for how to cluster so it is rare that by arbitrarily predefining the number of clusters that you would end up with the wrong answer. One of the advantages of these techniques is that often times the user does have some predefined level of summarization that they are interested in (e.g. "25 clusters is too confusing, but 10 will help to give me an insight into my data"). The fact that greater or fewer numbers of clusters would better match the data is actually of secondary importance.

Hierarchical Clustering

Hierarchical clustering has the advantage over non-hierarchical techniques in that the clusters are defined solely by the data (not by the users predetermining the number of clusters) and that the number of clusters can be increased or decreased by simple moving up and down the hierarchy.

The hierarchy is created by starting either at the top (one cluster that includes all records) and subdividing (divisive clustering) or by starting at the bottom with as many clusters as there are records and merging (agglomerative clustering). Usually the merging and subdividing are done two clusters at a time.

The main distinction between the techniques is their ability to favor long, scraggly clusters that are linked together record by record, or to favor the detection of the more classical, compact or spherical cluster that was shown at the beginning of this section. It may seem strange to want to form these long snaking chain like clusters, but in some cases they are the patters that the user would like to have detected in the database. These are the times when the underlying space looks quite different from the spherical clusters and the clusters that should be formed are not based on the distance from the center of the cluster but instead based on the records being “linked” together. Consider the example shown in Figure 1.6 or in Figure 1.7. In these cases there are two clusters that are not very spherical in shape but could be detected by the single link technique.

When looking at the layout of the data in Figure1.6 there appears to be two relatively flat clusters running parallel to each along the income axis. Neither the complete link nor Ward’s method would, however, return these two clusters to the user. These techniques rely on creating a “center” for each cluster and picking these centers so that they average distance of each record from this center is minimized. Points that are very distant from these centers would necessarily fall into a different cluster.

What makes these clusters “visible” in this simple two dimensional space is the fact that each point in a cluster is tightly linked to some other point in the cluster. For the two clusters we see the maximum distance between the nearest two points within a cluster is less than the minimum distance of the nearest two points in different clusters. That is to say that for any point in this space, the nearest point to it is always going to be another point in the same cluster. Now the center of gravity of a cluster could be quite distant from a given point but that every point is linked to every other point by a series of small distances.

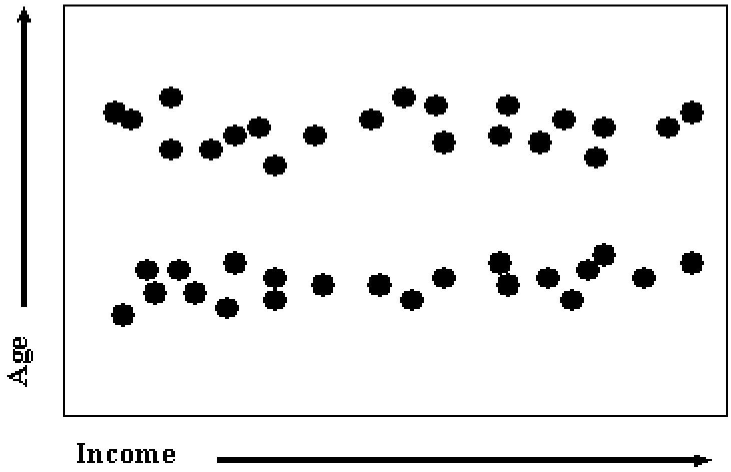

Figure 1.6 *an example of elongated clusters which would not be recovered by the complete link or Ward's methods but would be by the single-link method.*

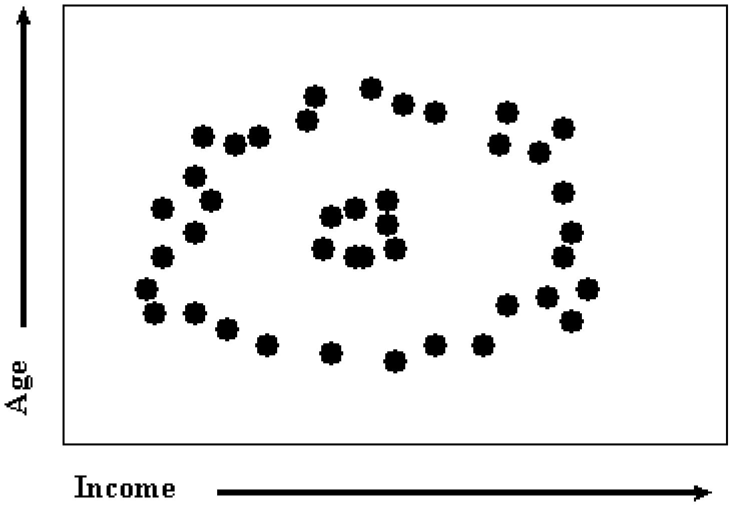

Figure 1.7 *An example of nested clusters which would not be recovered by the complete link or Ward's methods but would be by the single-link method.*

1.5. Choosing the Classics

There is no particular rule that would tell you when to choose a particular technique over another one. Sometimes those decisions are made relatively arbitrarily based on the availability of data mining analysts who are most experienced in one technique over another. And even choosing classical techniques over some of the newer techniques is more dependent on the availability of good tools and good analysts. Whichever techniques are chosen whether classical or next generation all of the techniques presented here have been available and tried for more than two decades. So even the next generation is a solid bet for implementation.

II. Next Generation Techniques: Trees, Networks and Rules

2.1. The Next Generation

The data mining techniques in this section represent the most often used techniques that have been developed over the last two decades of research. They also represent the vast majority of the techniques that are being spoken about when data mining is mentioned in the popular press. These techniques can be used for either discovering new information within large databases or for building predictive models. Though the older decision tree techniques such as CHAID are currently highly used the new techniques such as CART are gaining wider acceptance.

2.2. Decision Trees

What is a Decision Tree?

A decision tree is a predictive model that, as its name implies, can be viewed as a tree. Specifically each branch of the tree is a classification question and the leaves of the tree are partitions of the dataset with their classification. For instance if we were going to classify customers who churn (don't renew their phone contracts) in the Cellular Telephone Industry a decision tree might look something like that found in Figure 2.1.

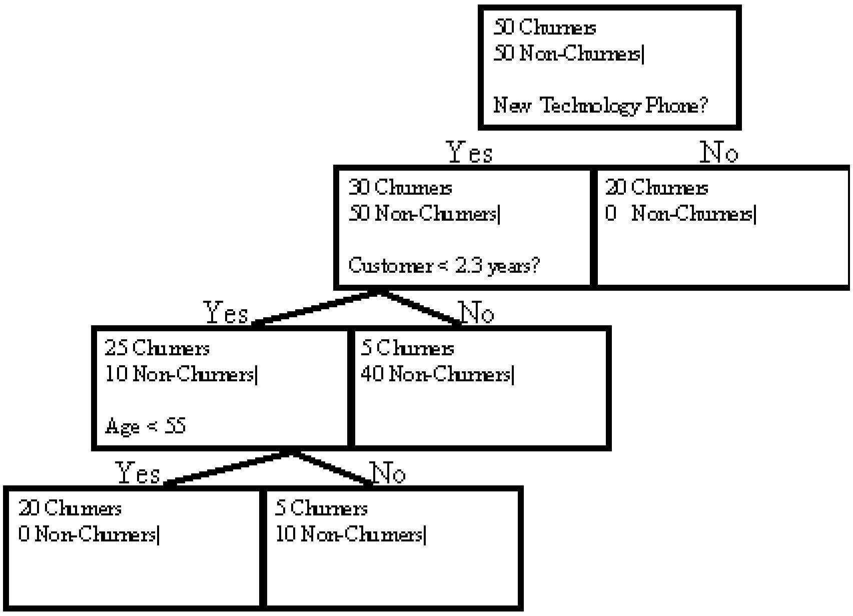

Figure 2.1 *A decision tree is a predictive model that makes a prediction on the basis of a series of decision much like the game of 20 questions.*

You may notice some interesting things about the tree:

- It divides up the data on each branch point without losing any of the data (the number of total records in a given parent node is equal to the sum of the records contained in its two children).
- The number of churners and non-churners is conserved as you move up or down the tree
- It is pretty easy to understand how the model is being built (in contrast to the models from neural networks or from standard statistics).
- It would also be pretty easy to use this model if you actually had to target those customers that are likely to churn with a targeted marketing offer.

You may also build some intuitions about your customer base. E.g. "customers who have been with you for a couple of years and have up to date cellular phones are pretty loyal".

Viewing decision trees as segmentation with a purpose

From a business perspective decision trees can be viewed as creating a segmentation of the original dataset (each segment would be one of the leaves of the tree). Segmentation of customers, products, and sales regions is something that marketing managers have been doing for many years. In the past this segmentation has been performed in order to get a high level view of a large amount of data - with no particular reason for creating the segmentation except that the records within each segmentation were somewhat similar to each other.

In this case the segmentation is done for a particular reason - namely for the prediction of some important piece of information. The records that fall within each segment fall there because they have similarity with respect to the information being predicted - not just that they are similar - without similarity being well defined. These predictive segments that are derived from the decision tree also come with a description of the characteristics that define the predictive segment. Thus the decision trees and the algorithms that create them may be complex, the results can be presented in an easy to understand way that can be quite useful to the business user.

Applying decision trees to Business

Because of their tree structure and ability to easily generate rules decision trees are the favored technique for building understandable models. Because of this clarity they also allow for more complex profit and ROI models to be added easily in on top of the predictive model. For instance once a customer population is found with high predicted likelihood to attrite a variety of cost models can be used to see if an expensive marketing intervention should be used because the customers are highly valuable or a less expensive intervention should be used because the revenue from this sub-population of customers is marginal.

Because of their high level of automation and the ease of translating decision tree models into SQL for deployment in relational databases the technology has also proven to be easy to integrate with existing IT processes, requiring little preprocessing and cleansing of the data, or extraction of a special purpose file specifically for data mining.

Where can decision trees be used?

Decision trees are data mining technology that has been around in a form very similar to the technology of today for almost twenty years now and early versions of the algorithms date back in the 1960s. Often times these techniques were originally developed for statisticians to automate the process of determining which fields in their database were actually useful or correlated with the particular problem that they were trying to understand. Partially because of this history, decision tree algorithms tend to automate the entire process of hypothesis generation and then validation much more completely and in a much more integrated way than any other data mining techniques. They are also particularly adept at handling raw data with little or no pre-processing. Perhaps also because they were originally developed to mimic the way an analyst interactively performs data mining they provide a simple to understand predictive model based on rules (such as “90% of the time credit card customers of less than 3 months who max out their credit limit are going to default on their credit card loan.”).

Because decision trees score so highly on so many of the critical features of data mining they can be used in a wide variety of business problems for both exploration and for prediction. They have been used for problems ranging from credit card attrition prediction to time series prediction of the exchange rate of different international currencies. There are also some problems where decision trees will not do as well. Some very simple problems where the prediction is just a simple multiple of the predictor can be solved much more quickly and easily by linear regression. Usually the models to be built and the interactions to be detected are much more complex in real world problems and this is where decision trees excel.

Using decision trees for Exploration

The decision tree technology can be used for exploration of the dataset and business problem. This is often done by looking at the predictors and values that are chosen for each split of the tree. Often times these predictors provide usable insights or propose questions that need to be answered. For instance if you ran across the following in your database for cellular phone churn you might seriously wonder about the way your telesales operators were making their calls and maybe change the way that they are compensated: “IF customer lifetime < 1.1 years AND sales channel = telesales THEN chance of churn is 65%.

Using decision trees for Data Preprocessing

Another way that the decision tree technology has been used is for preprocessing data for other prediction algorithms. Because the algorithm is fairly robust with respect to a variety of predictor types (e.g. number, categorical etc.) and because it can be run relatively quickly decision trees can be used on the first pass of a data mining run to create a subset of possibly useful predictors that can then be fed into neural networks, nearest neighbor and normal statistical routines - which can take a considerable amount of time to run if there are large numbers of possible predictors to be used in the model.

Decision tress for Prediction

Although some forms of decision trees were initially developed as exploratory tools to refine and preprocess data for more standard statistical techniques like logistic regression. They have also been used and more increasingly often being used for prediction. This is interesting because many statisticians will still use decision trees for exploratory analysis effectively building a predictive model as a by product but then ignore the predictive model in favor of techniques that they are most comfortable with. Sometimes veteran analysts will do this even excluding the predictive model when it is superior to that produced by other techniques. With a host of new products and skilled users now appearing this tendency to use decision trees only for exploration now seems to be changing.

The first step is Growing the Tree

The first step in the process is that of growing the tree. Specifically the algorithm seeks to create a tree that works as perfectly as possible on all the data that is available. Most of the time it is not possible to have the algorithm work perfectly. There is always noise in the database to some degree (there are variables that are not being collected that have an impact on the target you are trying to predict).

The name of the game in growing the tree is in finding the best possible question to ask at each branch point of the tree. At the bottom of the tree you will come up with nodes that you would like to be all of one type or the other. Thus the question: "Are you over 40?" probably does not sufficiently distinguish between those who are churners and those who are not - let's say it is 40%/60%. On the other hand there may be a series of questions that do quite a nice job in distinguishing those cellular phone customers who will churn and those who won't. Maybe the series of questions would be something like: "Have you been a customer for less than a year, do you have a telephone that is more than two years old and were you originally landed as a customer via telesales rather than direct sales?" This series of questions defines a segment of the customer population in which 90% churn. These are then relevant questions to be asking in relation to predicting churn.

The difference between a good question and a bad question

The difference between a good question and a bad question has to do with how much the question can organize the data - or in this case, change the likelihood of a churner appearing in the customer segment. If we started off with our population being half churners and half non-churners then we would expect that a question that didn't organize the data to some degree into one segment that was more likely to churn than the other then it wouldn't be a very useful question to ask. On the other hand if we asked a question that was very good at distinguishing between churners and non-churners - say that split 100 customers into one segment of 50 churners and another segment of 50 non-churners then this would be considered to be a good question. In fact it had decreased the "disorder" of the original segment as much as was possible.

The process in decision tree algorithms is very similar when they build trees. These algorithms look at all possible distinguishing questions that could possibly break up the original training dataset into segments that are nearly homogeneous with respect to the different classes being predicted. Some decision tree algorithms may use heuristics in order to pick the questions or even pick them at random. CART picks the questions in a very unsophisticated way: It tries them all. After it has tried them all CART picks the best one uses it to split the data into two more organized segments and then again asks all possible questions on each of those new segments individually.

When does the tree stop growing?

If the decision tree algorithm just continued growing the tree like this it could conceivably create more and more questions and branches in the tree so that eventually there was only one record in the segment. To let the tree grow to this size is both computationally expensive but also unnecessary. Most decision tree algorithms stop growing the tree when one of three criteria are met:

- The segment contains only one record. (There is no further question that you could ask which could further refine a segment of just one.)
- All the records in the segment have identical characteristics. (There is no reason to continue asking further questions segmentation since all the remaining records are the same.)
- The improvement is not substantial enough to warrant making the split.

Why would a decision tree algorithm stop growing the tree if there wasn't enough data?

Consider the following example shown in Table 2.1 of a segment that we might want to split further which has just two examples. It has been created out of a much larger customer database by selecting only those customers aged 27 with blue eyes and salaries between $80,000 and $81,000.

Name	Age	Eyes	Salary	Churned?
Steve	27	Blue	$80,000	Yes
Alex	27	Blue	$80,000	No

Table 2.1 *Decision tree algorithm segment. This segment cannot be split further except by using the predictor "name".*

In this case all of the possible questions that could be asked about the two customers turn out to have the same value (age, eyes, salary) except for name. It would then be possible to ask a question like: "Is the customer's name Steve?" and create the segments which would be very good at breaking apart those who churned from those who did not:

The problem is that we all have an intuition that the name of the customer is not going to be a very good indicator of whether that customer churns or not. It might work well for this particular 2 record segment but it is unlikely that it will work for other customer databases or even the same customer database at a different time. This particular example has to do with overfitting the model - in this case fitting the model too closely to the idiosyncrasies of the training data. This can be fixed later on but clearly stopping the building of the tree short of either one record segments or very small segments in general is a good idea.

Decision trees aren't necessarily finished after the tree is grown.

After the tree has been grown to a certain size (depending on the particular stopping criteria used in the algorithm) the CART algorithm has still more work to do. The algorithm then checks to see if the model has been overfit to the data. It does this in several ways using a cross validation approach or a test set validation approach. Basically using the same mind numbingly simple approach it used to find the best questions in the first place - namely trying many different simpler versions of the tree on a held aside test set. The tree that does the best on the held aside data is selected by the algorithm as the best model. The nice thing about CART is that this testing and selection is all an integral part of the algorithm as opposed to the after the fact approach that other techniques use.

ID3 and an enhancement - C4.5

In the late 1970s J. Ross Quinlan introduced a decision tree algorithm named ID3. It was one of the first decision tree algorithms yet at the same time built solidly on work that had been done on inference systems and concept learning systems from that decade as well as the preceding decade. Initially ID3 was used for tasks such as learning good game playing strategies for chess end games. Since then ID3 has been applied to a wide variety of problems in both academia and industry and has been modified, improved and borrowed from many times over.

ID3 picks predictors and their splitting values based on the gain in information that the split or splits provide. Gain represents the difference between the amount of information that is needed to correctly make a prediction before a split is made and after the split has been made. If the amount of information required is much lower after the split is made then that split has decreased the disorder of the original single segment. Gain is defined as the difference between the entropy of the original segment and the accumulated entropies of the resulting split segments.

ID3 was later enhanced in the version called C4.5. C4.5 improves on ID3 in several important areas:

- predictors with missing values can still be used
- predictors with continuous values can be used
- pruning is introduced
- rule derivation

Many of these techniques appear in the CART algorithm plus some others so we will go through this introduction in the CART algorithm.

CART - Growing a forest and picking the best tree

CART stands for Classification and Regression Trees and is a data exploration and prediction algorithm developed by Leo Breiman, Jerome Friedman, Richard Olshen and Charles Stone and is nicely detailed in their 1984 book “Classification and Regression Trees” ([Breiman, Friedman, Olshen and Stone 19 84)]. These researchers from Stanford University and the University of California at Berkeley showed how this new algorithm could be used on a variety of different problems from to the detection of Chlorine from the data contained in a mass spectrum.

Predictors are picked as they decrease the disorder of the data.

In building the CART tree each predictor is picked based on how well it teases apart the records with different predictions. For instance one measure that is used to determine whether a given split point for a give predictor is better than another is the entropy metric. The measure originated from the work done by Claude Shannon and Warren Weaver on information theory in 1949. They were concerned with how information could be efficiently communicated over telephone lines. Interestingly, their results also prove useful in creating decision trees.

CART Automatically Validates the Tree

One of the great advantages of CART is that the algorithm has the validation of the model and the discovery of the optimally general model built deeply into the algorithm. CART accomplishes this by building a very complex tree and then pruning it back to the optimally general tree based on the results of cross validation or test set validation. The tree is pruned back based on the performance of the various pruned version of the tree on the test set data. The most complex tree rarely fares the best on the held aside data as it has been overfitted to the training data. By using cross validation the tree that is most likely to do well on new, unseen data can be chosen.

CART Surrogates handle missing data

The CART algorithm is relatively robust with respect to missing data. If the value is missing for a particular predictor in a particular record that record will not be used in making the determination of the optimal split when the tree is being built. In effect CART will utilizes as much information as it has on hand in order to make the decision for picking the best possible split.

When CART is being used to predict on new data, missing values can be handled via surrogates. Surrogates are split values and predictors that mimic the actual split in the tree and can be used when the data for the preferred predictor is missing. For instance though shoe size is not a perfect predictor of height it could be used as a surrogate to try to mimic a split based on height when that information was missing from the particular record being predicted with the CART model.

CHAID

Another equally popular decision tree technology to CART is CHAID or Chi-Square Automatic Interaction Detector. CHAID is similar to CART in that it builds a decision tree but it differs in the way that it chooses its splits. Instead of the entropy or Gini metrics for choosing optimal splits the technique relies on the chi square test used in contingency tables to determine which categorical predictor is furthest from independence with the prediction values.

Because CHAID relies on the contingency tables to form its test of significance for each predictor all predictors must either be categorical or be coerced into a categorical form via binning (e.g. break up possible people ages into 10 bins from 0-9, 10-19, 20-29 etc.). Though this binning can have deleterious consequences the actual accuracy performances of CART and CHAID have been shown to be comparable in real world direct marketing response models.

2.3. Neural Networks

What is a Neural Network?

When data mining algorithms are talked about these days most of the time people are talking about either decision trees or neural networks. Of the two neural networks have probably been of greater interest through the formative stages of data mining technology. As we will see neural networks do have disadvantages that can be limiting in their ease of use and ease of deployment, but they do also have some significant advantages. Foremost among these advantages is their highly accurate predictive models that can be applied across a large number of different types of problems.

To be more precise with the term “neural network” one might better speak of an “artificial neural network”. True neural networks are biological systems (a k a brains) that detect patterns, make predictions and learn. The artificial ones are computer programs implementing sophisticated pattern detection and machine learning algorithms on a computer to build predictive models from large historical databases. Artificial neural networks derive their name from their historical development which started off with the premise that machines could be made to “think” if scientists found ways to mimic the structure and functioning of the human brain on the computer. Thus historically neural networks grew out of the community of Artificial Intelligence rather than from the discipline of statistics. Despite the fact that scientists are still far from understanding the human brain let alone mimicking it, neural networks that run on computers can do some of the things that people can do.

It is difficult to say exactly when the first “neural network” on a computer was built. During World War II a seminal paper was published by McCulloch and Pitts which first outlined the idea that simple processing units (like the individual neurons in the human brain) could be connected together in large networks to create a system that could solve difficult problems and display behavior that was much more complex than the simple pieces that made it up. Since that time much progress has been made in finding ways to apply artificial neural networks to real world prediction problems and in improving the performance of the algorithm in general. In many respects the greatest breakthroughs in neural networks in recent years have been in their application to more mundane real world problems like customer response prediction or fraud detection rather than the loftier goals that were originally set out for the techniques such as overall human learning and computer speech and image understanding.

Don’t Neural Networks Learn to make better predictions?

Because of the origins of the techniques and because of some of their early successes the techniques have enjoyed a great deal of interest. To understand how neural networks can detect patterns in a database an analogy is often made that they “learn” to detect these patterns and make better predictions in a similar way to the way that human beings do. This view is encouraged by the way the historical training data is often supplied to the network - one record (example) at a time. Neural networks do “learn” in a very real sense but under the hood the algorithms and techniques that are being deployed are not truly different from the techniques found in statistics or other data mining algorithms. It is for instance, unfair to assume that neural networks could outperform other techniques because they “learn” and improve over time while the other techniques are static. The other techniques if fact “learn” from historical examples in exactly the same way but often times the examples (historical records) to learn from a processed all at once in a more efficient manner than neural networks which often modify their model one record at a time.

Are Neural Networks easy to use?

A common claim for neural networks is that they are automated to a degree where the user does not need to know that much about how they work, or predictive modeling or even the database in order to use them. The implicit claim is also that most neural networks can be unleashed on your data straight out of the box without having to rearrange or modify the data very much to begin with.

Just the opposite is often true. There are many important design decisions that need to be made in order to effectively use a neural network such as:

- How should the nodes in the network be connected?
- How many neuron like processing units should be used?
- When should “training” be stopped in order to avoid overfitting?

There are also many important steps required for preprocessing the data that goes into a neural network - most often there is a requirement to normalize numeric data between 0.0 and 1.0 and categorical predictors may need to be broken up into virtual predictors that are 0 or 1 for each value of the original categorical predictor. And, as always, understanding what the data in your database means and a clear definition of the business problem to be solved are essential to ensuring eventual success. The bottom line is that neural networks provide no short cuts.

Applying Neural Networks to Business

Neural networks are very powerful predictive modeling techniques but some of the power comes at the expense of ease of use and ease of deployment. As we will see in this section, neural networks, create very complex models that are almost always impossible to fully understand even by experts. The model itself is represented by numeric values in a complex calculation that requires all of the predictor values to be in the form of a number. The output of the neural network is also numeric and needs to be translated if the actual prediction value is categorical (e.g. predicting the demand for blue, white or black jeans for a clothing manufacturer requires that the predictor values blue, black and white for the predictor color to be converted to numbers).

Because of the complexity of these techniques much effort has been expended in trying to increase the clarity with which the model can be understood by the end user. These efforts are still in there infancy but are of tremendous importance since most data mining techniques including neural networks are being deployed against real business problems where significant investments are made based on the predictions from the models (e.g. consider trusting the predictive model from a neural network that dictates which one million customers will receive a $1 mailing).

There are two ways that these shortcomings in understanding the meaning of the neural network model have been successfully addressed:

- The neural network is package up into a complete solution such as fraud prediction. This allows the neural network to be carefully crafted for one particular application and once it has been proven successful it can be used over and over again without requiring a deep understanding of how it works.
- The neural network is package up with expert consulting services. Here the neural network is deployed by trusted experts who have a track record of success. Either the experts are able to explain the models or they are trusted that the models do work.

The first tactic has seemed to work quite well because when the technique is used for a well defined problem many of the difficulties in preprocessing the data can be automated (because the data structures have been seen before) and interpretation of the model is less of an issue since entire industries begin to use the technology successfully and a level of trust is created. There are several vendors who have deployed this strategy (e.g. HNC's Falcon system for credit card fraud prediction and Advanced Software Applications ModelMAX package for direct marketing).

Packaging up neural networks with expert consultants is also a viable strategy that avoids many of the pitfalls of using neural networks, but it can be quite expensive because it is human intensive. One of the great promises of data mining is, after all, the automation of the predictive modeling process. These neural network consulting teams are little different from the analytical departments many companies already have in house. Since there is not a great difference in the overall predictive accuracy of neural networks over standard statistical techniques the main difference becomes the replacement of the statistical expert with the neural network expert. Either with statistics or neural network experts the value of putting easy to use tools into the hands of the business end user is still not achieved.

Where to Use Neural Networks

Neural networks are used in a wide variety of applications. They have been used in all facets of business from detecting the fraudulent use of credit cards and credit risk prediction to increasing the hit rate of targeted mailings. They also have a long history of application in other areas such as the military for the automated driving of an unmanned vehicle at 30 miles per hour on paved roads to biological simulations such as learning the correct pronunciation of English words from written text.

Neural Networks for clustering

Neural networks of various kinds can be used for clustering and prototype creation. The Kohonen network described in this section is probably the most common network used for clustering and segmentation of the database. Typically the networks are used in a unsupervised learning mode to create the clusters. The clusters are created by forcing the system to compress the data by creating prototypes or by algorithms that steer the system toward creating clusters that compete against each other for the records that they contain, thus ensuring that the clusters overlap as little as possible.

Neural Networks for Outlier Analysis

Sometimes clustering is performed not so much to keep records together as to make it easier to see when one record sticks out from the rest. For instance:

Most wine distributors selling inexpensive wine in Missouri and that ship a certain volume of product produce a certain level of profit. There is a cluster of stores that can be formed with these characteristics. One store stands out, however, as producing significantly lower profit. On closer examination it turns out that the distributor was delivering product to but not collecting payment from one of their customers.

A sale on men’s suits is being held in all branches of a department store for southern California . All stores with these characteristics have seen at least a 100% jump in revenue since the start of the sale except one. It turns out that this store had, unlike the others, advertised via radio rather than television.

Neural Networks for feature extraction

One of the important problems in all of data mining is that of determining which predictors are the most relevant and the most important in building models that are most accurate at prediction. These predictors may be used by themselves or they may be used in conjunction with other predictors to form “features”. A simple example of a feature in problems that neural networks are working on is the feature of a vertical line in a computer image. The predictors, or raw input data are just the colored pixels that make up the picture. Recognizing that the predictors (pixels) can be organized in such a way as to create lines, and then using the line as the input predictor can prove to dramatically improve the accuracy of the model and decrease the time to create it.

Some features like lines in computer images are things that humans are already pretty good at detecting, in other problem domains it is more difficult to recognize the features. One novel way that neural networks have been used to detect features is the idea that features are sort of a compression of the training database. For instance you could describe an image to a friend by rattling off the color and intensity of each pixel on every point in the picture or you could describe it at a higher level in terms of lines, circles - or maybe even at a higher level of features such as trees, mountains etc. In either case your friend eventually gets all the information that they need in order to know what the picture looks like, but certainly describing it in terms of high level features requires much less communication of information than the “paint by numbers” approach of describing the color on each square millimeter of the image.

If we think of features in this way, as an efficient way to communicate our data, then neural networks can be used to automatically extract them. The neural network shown in Figure 2.2 is used to extract features by requiring the network to learn to recreate the input data at the output nodes by using just 5 hidden nodes. Consider that if you were allowed 100 hidden nodes, that recreating the data for the network would be rather trivial - simply pass the input node value directly through the corresponding hidden node and on to the output node. But as there are fewer and fewer hidden nodes, that information has to be passed through the hidden layer in a more and more efficient manner since there are less hidden nodes to help pass along the information.

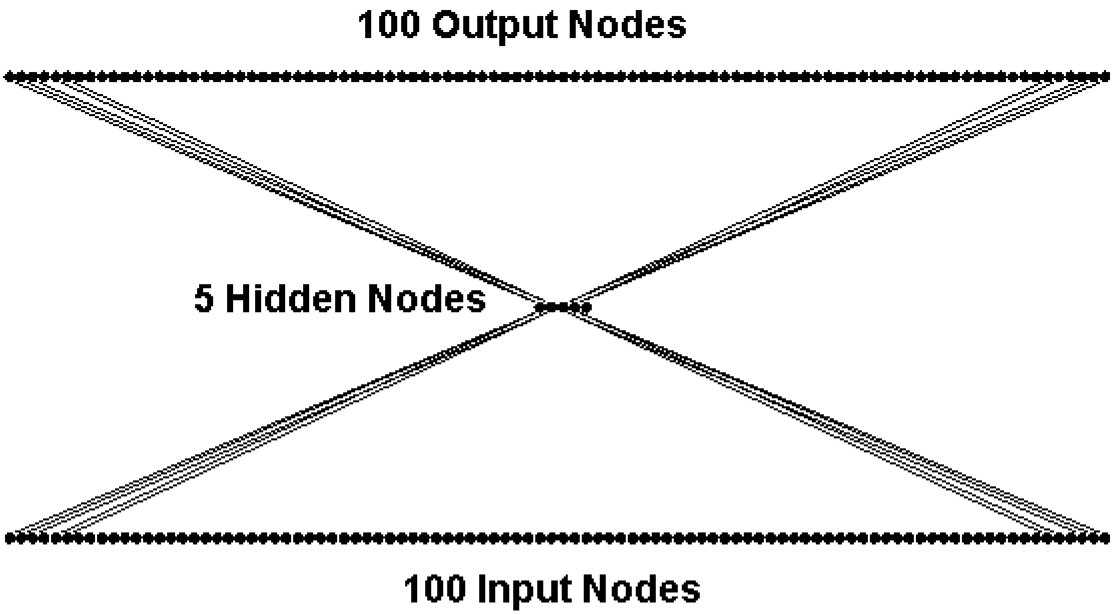

Figure 2.2 *Neural networks can be used for data compression and feature extraction.*

In order to accomplish this the neural network tries to have the hidden nodes extract features from the input nodes that efficiently describe the record represented at the input layer. This forced “squeezing” of the data through the narrow hidden layer forces the neural network to extract only those predictors and combinations of predictors that are best at recreating the input record. The link weights used to create the inputs to the hidden nodes are effectively creating features that are combinations of the input nodes values.

What does a neural net look like?

A neural network is loosely based on how some people believe that the human brain is organized and how it learns. Given that there are two main structures of consequence in the neural network:

The node - which loosely corresponds to the neuron in the human brain.

The link - which loosely corresponds to the connections between neurons (axons, dendrites and synapses) in the human brain.

In Figure 2.3 there is a drawing of a simple neural network. The round circles represent the nodes and the connecting lines represent the links. The neural network functions by accepting predictor values at the left and performing calculations on those values to produce new values in the node at the far right. The value at this node represents the prediction from the neural network model. In this case the network takes in values for predictors for age and income and predicts whether the person will default on a bank loan.

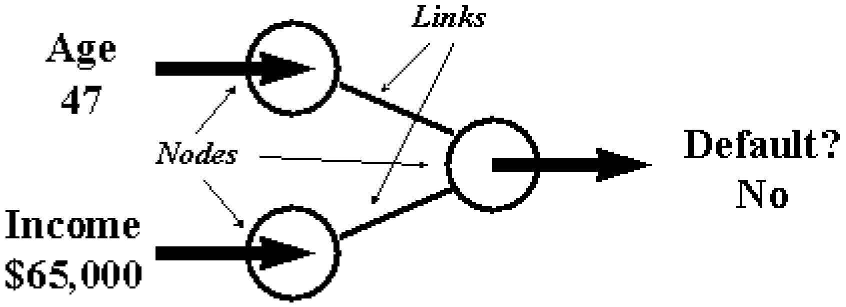

Figure 2.3 *A simplified view of a neural network for prediction of loan default.*

How does a neural net make a prediction?

In order to make a prediction the neural network accepts the values for the predictors on what are called the input nodes. These become the values for those nodes those values are then multiplied by values that are stored in the links (sometimes called links and in some ways similar to the weights that were applied to predictors in the nearest neighbor method). These values are then added together at the node at the far right (the output node) a special thresholding function is applied and the resulting number is the prediction. In this case if the resulting number is 0 the record is considered to be a good credit risk (no default) if the number is 1 the record is considered to be a bad credit risk (likely default).

A simplified version of the calculations made in Figure 2.3 might look like what is shown in Figure 2.4. Here the value age of 47 is normalized to fall between 0.0 and 1.0 and has the value 0.47 and the income is normalized to the value 0.65. This simplified neural network makes the prediction of no default for a 47 year old making $65,000. The links are weighted at 0.7 and 0.1 and the resulting value after multiplying the node values by the link weights is 0.39. The network has been trained to learn that an output value of 1.0 indicates default and that 0.0 indicates non-default. The output value calculated here (0.39) is closer to 0.0 than to 1.0 so the record is assigned a non-default prediction.

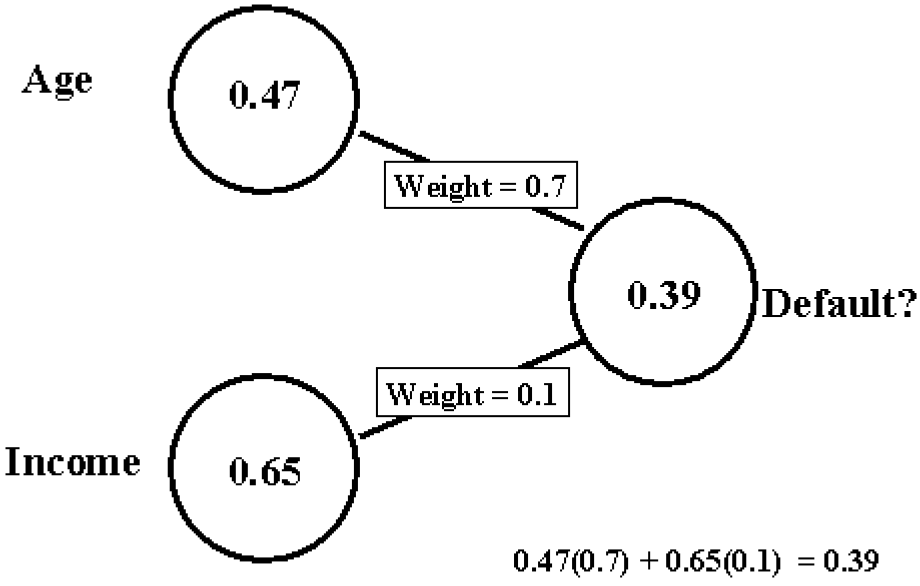

Figure 2.4 *The normalized input values are multiplied by the link weights and added together at the output.*

How is the neural net model created?

The neural network model is created by presenting it with many examples of the predictor values from records in the training set (in this example age and income are used) and the prediction value from those same records. By comparing the correct answer obtained from the training record and the predicted answer from the neural network it is possible to slowly change the behavior of the neural network by changing the values of the link weights. In some ways this is like having a grade school teacher ask questions of her student (a.k.a. the neural network) and if the answer is wrong to verbally correct the student. The greater the error the harsher the verbal correction. So that large errors are given greater attention at correction than are small errors.

For the actual neural network it is the weights of the links that actually control the prediction value for a given record. Thus the particular model that is being found by the neural network is in fact fully determined by the weights and the architectural structure of the network. For this reason it is the link weights that are modified each time an error is made.

How complex can the neural network model become?

The models shown in the figures above have been designed to be as simple as possible in order to make them understandable. In practice no networks are as simple as these. Networks with many more links and many more nodes are possible. This was the case in the architecture of a neural network system called NETtalk that learned how to pronounce written English words. Each node in this network was connected to every node in the level above it and below it resulting in 18,629 link weights that needed to be learned in the network.

In this network there was a row of nodes in between the input nodes and the output nodes. These are called hidden nodes or the hidden layer because the values of these nodes are not visible to the end user the way that the output nodes are (that contain the prediction) and the input nodes (which just contain the predictor values). There are even more complex neural network architectures that have more than one hidden layer. In practice one hidden layer seems to suffice however.

Hidden nodes are like trusted advisors to the output nodes

The meaning of the input nodes and the output nodes are usually pretty well understood - and are usually defined by the end user based on the particular problem to be solved and the nature and structure of the database. The hidden nodes, however, do not have a predefined meaning and are determined by the neural network as it trains. Which poses two problems:

- It is difficult to trust the prediction of the neural network if the meaning of these nodes is not well understood.
- ince the prediction is made at the output layer and the difference between the prediction and the actual value is calculated there, how is this error correction fed back through the hidden layers to modify the link weights that connect them?

The meaning of these hidden nodes is not necessarily well understood but sometimes after the fact they can be looked at to see when they are active and when they are not and derive some meaning from them.

The learning that goes on in the hidden nodes.

The learning procedure for the neural network has been defined to work for the weights in the links connecting the hidden layer. A good metaphor for how this works is to think of a military operation in some war where there are many layers of command with a general ultimately responsible for making the decisions on where to advance and where to retreat. The general probably has several lieutenant generals advising him and each lieutenant general probably has several major generals advising him. This hierarchy continuing downward through colonels and privates at the bottom of the hierarchy.

This is not too far from the structure of a neural network with several hidden layers and one output node. You can think of the inputs coming from the hidden nodes as advice. The link weight corresponds to the trust that the general has in his advisors. Some trusted advisors have very high weights and some advisors may no be trusted and in fact have negative weights. The other part of the advice from the advisors has to do with how competent the particular advisor is for a given situation. The general may have a trusted advisor but if that advisor has no expertise in aerial invasion and the question at hand has to do with a situation involving the air force this advisor may be very well trusted but the advisor himself may not have any strong opinion one way or another.

In this analogy the link weight of a neural network to an output unit is like the trust or confidence that a commander has in his advisors and the actual node value represents how strong an opinion this particular advisor has about this particular situation. To make a decision the general considers how trustworthy and valuable the advice is and how knowledgeable and confident each advisor is in making their suggestion and then taking all of this into account the general makes the decision to advance or retreat.

In the same way the output node will make a decision (a prediction) by taking into account all of the input from its advisors (the nodes connected to it). In the case of the neural network this decision is reach by multiplying the link weight by the output value of the node and summing these values across all nodes. If the prediction is incorrect the nodes that had the most influence on making the decision have their weights modified so that the wrong prediction is less likely to be made the next time.

This learning in the neural network is very similar to what happens when the wrong decision is made by the general. The confidence that the general has in all of those advisors that gave the wrong recommendation is decreased - and all the more so for those advisors who were very confident and vocal in their recommendation. On the other hand any advisors who were making the correct recommendation but whose input was not taken as seriously would be taken more seriously the next time. Likewise any advisor that was reprimanded for giving the wrong advice to the general would then go back to his advisors and determine which of them he had trusted more than he should have in making his recommendation and who he should have listened more closely to.

Sharing the blame and the glory throughout the organization

This feedback can continue in this way down throughout the organization - at each level giving increased emphasis to those advisors who had advised correctly and decreased emphasis to those who had advised incorrectly. In this way the entire organization becomes better and better and supporting the general in making the correct decision more of the time.

A very similar method of training takes place in the neural network. It is called “back propagation” and refers to the propagation of the error backwards from the output nodes (where the error is easy to determine the difference between the actual prediction value from the training database and the prediction from the neural network) through the hidden layers and to the input layers. At each level the link weights between the layers are updated so as to decrease the chance of making the same mistake again.

Different types of neural networks

There are literally hundreds of variations on the back propagation feedforward neural networks that have been briefly described here. Most having to do with changing the architecture of the neural network to include recurrent connections where the output from the output layer is connected back as input into the hidden layer. These recurrent nets are some times used for sequence prediction where the previous outputs from the network need to be stored someplace and then fed back into the network to provide context for the current prediction. Recurrent networks have also been used for decreasing the amount of time that it takes to train the neural network.

Another twist on the neural net theme is to change the way that the network learns. Back propagation is effectively utilizing a search technique called gradient descent to search for the best possible improvement in the link weights to reduce the error. There are, however, many other ways of doing search in a high dimensional space including Newton's methods and conjugate gradient as well as simulating the physics of cooling metals in a process called simulated annealing or in simulating the search process that goes on in biological evolution and using genetic algorithms to optimize the weights of the neural networks. It has even been suggested that creating a large number of neural networks with randomly weighted links and picking the one with the lowest error rate would be the best learning procedure.

Despite all of these choices, the back propagation learning procedure is the most commonly used. It is well understand, relatively simple, and seems to work in a large number of problem domains. There are, however, two other neural network architectures that are used relatively often. Kohonen feature maps are often used for unsupervised learning and clustering and Radial Basis Function networks are used for supervised learning and in some ways represent a hybrid between nearest neighbor and neural network classification.

Kohonen Feature Maps

Kohonen feature maps were developed in the 1970's and as such were created to simulate certain brain function. Today they are used mostly to perform unsupervised learning and clustering.

Kohonen networks are feedforward neural networks generally with no hidden layer. The networks generally contain only an input layer and an output layer but the nodes in the output layer compete amongst themselves to display the strongest activation to a given record. What is sometimes called "winner take all".

The networks originally came about when some of the puzzling yet simple behaviors of the real neurons were taken into effect. Namely that physical locality of the neurons seems to play an important role in the behavior and learning of neurons.

When these networks were run, in order to simulate the real world visual system it became that the organization that was automatically being constructed on the data was also very useful for segmenting and clustering the training database. Each output node represented a cluster and nearby clusters were nearby in the two dimensional output layer. Each record in the database would fall into one and only one cluster (the most active output node) but the other clusters in which it might also fit would be shown and likely to be next to the best matching cluster.

How much like a human brain is the neural network?

Since the inception of the idea of neural networks the ultimate goal for these techniques has been to have them recreate human thought and learning. This has once again proved to be a difficult task - despite the power of these new techniques and the similarities of their architecture to that of the human brain. Many of the things that people take for granted are difficult for neural networks - like avoiding overfitting and working with real world data without a lot of preprocessing required. There have also been some exciting successes.

Combatting overfitting - getting a model you can use somewhere else

As with all predictive modeling techniques some care must be taken to avoid overfitting with a neural network. Neural networks can be quite good at overfitting training data with a predictive model that does not work well on new data. This is particularly problematic for neural networks because it is difficult to understand how the model is working. In the early days of neural networks the predictive accuracy that was often mentioned first was the accuracy on the training set and the vaulted or validation set database was reported as a footnote.

This is in part due to the fact that unlike decision trees or nearest neighbor techniques, which can quickly achieve 100% predictive accuracy on the training database, neural networks can be trained forever and still not be 100% accurate on the training set. While this is an interesting fact it is not terribly relevant since the accuracy on the training set is of little interest and can have little bearing on the validation database accuracy.

Perhaps because overfitting was more obvious for decision trees and nearest neighbor approaches more effort was placed earlier on to add pruning and editing to these techniques. For neural networks generalization of the predictive model is accomplished via rules of thumb and sometimes in a more methodically way by using cross validation as is done with decision trees.

One way to control overfitting in neural networks is to limit the number of links. Since the number of links represents the complexity of the model that can be produced, and since more complex models have the ability to overfit while less complex ones cannot, overfitting can be controlled by simply limiting the number of links in the neural network. Unfortunately there is no god theoretical grounds for picking a certain number of links.

Test set validation can be used to avoid overfitting by building the neural network on one portion of the training database and using the other portion of the training database to detect what the predictive accuracy is on vaulted data. This accuracy will peak at some point in the training and then as training proceeds it will decrease while the accuracy on the training database will continue to increase. The link weights for the network can be saved when the accuracy on the held aside data peaks. The NeuralWare product, and others, provide an automated function that saves out the network when it is best performing on the test set and even continues to search after the minimum is reached.

Explaining the network

One of the indictments against neural networks is that it is difficult to understand the model that they have built and also how the raw data effects the output predictive answer. With nearest neighbor techniques prototypical records are provided to “explain” why the prediction is made, and decision trees provide rules that can be translated in to English to explain why a particular prediction was made for a particular record. The complex models of the neural network are captured solely by the link weights in the network which represent a very complex mathematical equation.

There have been several attempts to alleviate these basic problems of the neural network. The simplest approach is to actually look at the neural network and try to create plausible explanations for the meanings of the hidden nodes. Some times this can be done quite successfully. In the example given at the beginning of this section the hidden nodes of the neural network seemed to have extracted important distinguishing features in predicting the relationship between people by extracting information like country of origin. Features that it would seem that a person would also extract and use for the prediction. But there were also many other hidden nodes, even in this particular example that were hard to explain and didn't seem to have any particular purpose. Except that they aided the neural network in making the correct prediction.

2.4. Rule Induction

Rule induction is one of the major forms of data mining and is perhaps the most common form of knowledge discovery in unsupervised learning systems. It is also perhaps the form of data mining that most closely resembles the process that most people think about when they think about data mining, namely "mining" for gold through a vast database. The gold in this case would be a rule that is interesting - that tells you something about your database that you didn't already know and probably weren't able to explicitly articulate (aside from saying "show me things that are interesting").

Rule induction on a data base can be a massive undertaking where all possible patterns are systematically pulled out of the data and then an accuracy and significance are added to them that tell the user how strong the pattern is and how likely it is to occur again. In general these rules are relatively simple such as for a market basket database of items scanned in a consumer market basket you might find interesting correlations in your database such as:

- If bagels are purchased then cream cheese is purchased 90% of the time and this pattern occurs in 3% of all shopping baskets.
- If live plants are purchased from a hardware store then plant fertilizer is purchased 60% of the time and these two items are bought together in 6% of the shopping baskets.

The rules that are pulled from the database are extracted and ordered to be presented to the user based on the percentage of times that they are correct and how often they apply.

The bane of rule induction systems is also its strength - that it retrieves all possible interesting patterns in the database. This is a strength in the sense that it leaves no stone unturned but it can also be viewed as a weaknes because the user can easily become overwhelmed with such a large number of rules that it is difficult to look through all of them. You almost need a second pass of data mining to go through the list of interesting rules that have been generated by the rule induction system in the first place in order to find the most valuable gold nugget amongst them all. This overabundance of patterns can also be problematic for the simple task of prediction because all possible patterns are culled from the database there may be conflicting predictions made by equally interesting rules. Automating the process of culling the most interesting rules and of combing the recommendations of a variety of rules are well handled by many of the commercially available rule induction systems on the market today and is also an area of active research.

Applying Rule induction to Business

Rule induction systems are highly automated and are probably the best of data mining techniques for exposing all possible predictive patterns in a database. They can be modified to for use in prediction problems but the algorithms for combining evidence from a variety of rules comes more from rules of thumbs and practical experience.

In comparing data mining techniques along an axis of explanation neural networks would be at one extreme of the data mining algorithms and rule induction systems at the other end. Neural networks are extremely proficient and saying exactly what must be done in a prediction task (e.g. who do I give credit to / who do I deny credit to) with little explanation. Rule induction systems when used for prediction on the other hand are like having a committee of trusted advisors each with a slightly different opinion as to what to do but relatively well grounded reasoning and a good explanation for why it should be done.

The business value of rule induction techniques reflects the highly automated way in which the rules are created which makes it easy to use the system but also that this approach can suffer from an overabundance of interesting patterns which can make it complicated in order to make a prediction that is directly tied to return on investment (ROI).

What is a rule?

In rule induction systems the rule itself is of a simple form of “if this and this and this then this”. For example a rule that a supermarket might find in their data collected from scanners would be: “if pickles are purchased then ketchup is purchased’. Or

- If paper plates then plastic forks
- If dip then potato chips
- If salsa then tortilla chips

In order for the rules to be useful there are two pieces of information that must be supplied as well as the actual rule:

- Accuracy - How often is the rule correct?
- Coverage - How often does the rule apply?

Just because the pattern in the data base is expressed as rule does not mean that it is true all the time. Thus just like in other data mining algorithms it is important to recognize and make explicit the uncertainty in the rule. This is what the accuracy of the rule means. The coverage of the rule has to do with how much of the database the rule “covers” or applies to. Examples of these two measure for a variety of rules is shown in Table 2.2.

In some cases accuracy is called the confidence of the rule and coverage is called the support. Accuracy and coverage appear to be the preferred ways of naming these two measurements.

Rule	Accuracy	Coverage
If breakfast cereal purchased then milk purchased.	85%	20%
If bread purchased then swiss cheese purchased.	15%	6%
If 42 years old and purchased pretzels and purchased dry roasted peanuts then beer will be purchased.	95%	0.01%

Table 2.2 *Examples of Rule Accuracy and Coverage*

The rules themselves consist of two halves. The left hand side is called the antecedent and the right hand side is called the consequent. The antecedent can consist of just one condition or multiple conditions which must all be true in order for the consequent to be true at the given accuracy. Generally the consequent is just a single condition (prediction of purchasing just one grocery store item) rather than multiple conditions. Thus rules such as: "if x and y then a and b and c".

What to do with a rule

When the rules are mined out of the database the rules can be used either for understanding better the business problems that the data reflects or for performing actual predictions against some predefined prediction target. Since there is both a left side and a right side to a rule (antecedent and consequent) they can be used in several ways for your business.

Target the antecedent. In this case all rules that have a certain value for the antecedent are gathered and displayed to the user. For instance a grocery store may request all rules that have nails, bolts or screws as the antecedent in order to try to understand whether discontinuing the sale of these low margin items will have any effect on other higher margin. For instance maybe people who buy nails also buy expensive hammers but wouldn't do so at the store if the nails were not available.

Target the consequent. In this case all rules that have a certain value for the consequent can be used to understand what is associated with the consequent and perhaps what affects the consequent. For instance it might be useful to know all of the interesting rules that have "coffee" in their consequent. These may well be the rules that affect the purchases of coffee and that a store owner may want to put close to the coffee in order to increase the sale of both items. Or it might be the rule that the coffee manufacturer uses to determine in which magazine to place their next coupons.

Target based on accuracy. Some times the most important thing for a user is the accuracy of the rules that are being generated. Highly accurate rules of 80% or 90% imply strong relationships that can be exploited even if they have low coverage of the database and only occur a limited number of times. For instance a rule that only has 0.1% coverage but 95% can only be applied one time out of one thousand but it will very likely be correct. If this one time is highly profitable that it can be worthwhile. This, for instance, is how some of the most successful data mining applications work in the financial markets - looking for that limited amount of time where a very confident prediction can be made.

Target based on coverage. Some times user want to know what the most ubiquitous rules are or those rules that are most readily applicable. By looking at rules ranked by coverage they can quickly get a high level view of what is happening within their database most of the time.

Target based on “interestingness”. Rules are interesting when they have high coverage and high accuracy and deviate from the norm. There have been many ways that rules have been ranked by some measure of interestingness so that the trade off between coverage and accuracy can be made.

Since rule induction systems are so often used for pattern discovery and unsupervised learning it is less easy to compare them. For example it is very easy for just about any rule induction system to generate all possible rules, it is, however, much more difficult to devise a way to present those rules (which could easily be in the hundreds of thousands) in a way that is most useful to the end user. When interesting rules are found they usually have been created to find relationships between many different predictor values in the database not just one well defined target of the prediction. For this reason it is often much more difficult to assign a measure of value to the rule aside from its interestingness. For instance it would be difficult to determine the monetary value of knowing that if people buy breakfast sausage they also buy eggs 60% of the time. For data mining systems that are more focused on prediction for things like customer attrition, targeted marketing response or risk it is much easier to measure the value of the system and compare it to other systems and other methods for solving the problem.

Caveat: Rules do not imply causality

It is important to recognize that even though the patterns produced from rule induction systems are delivered as if then rules they do not necessarily mean that the left hand side of the rule (the “if” part) causes the right hand side of the rule (the “then” part) to happen. Purchasing cheese does not cause the purchase of wine even though the rule if cheese then wine may be very strong.

This is particularly important to remember for rule induction systems because the results are presented as if this then that as many causal relationships are presented.

Types of databases used for rule induction

Typically rule induction is used on databases with either fields of high cardinality (many different values) or many columns of binary fields. The classical case of this is the super market basket data from store scanners that contains individual product names and quantities and may contain tens of thousands of different items with different packaging that create hundreds of thousands of SKU identifiers (Stock Keeping Units).

Sometimes in these databases the concept of a record is not easily defined within the database - consider the typical Star Schema for many data warehouses that store the supermarket transactions as separate entries in the fact table. Where the columns in the fact table are some unique identifier of the shopping basket (so all items can be noted as being in the same shopping basket), the quantity, the time of purchase, whether the item was purchased with a special promotion (sale or coupon). Thus each item in the shopping basket has a different row in the fact table. This layout of the data is not typically the best for most data mining algorithms which would prefer to have the data structured as one row per shopping basket and each column to represent the presence or absence of a given item. This can be an expensive way to store the data, however, since the typical grocery store contains 60,000 SKUs or different items that could come across the checkout counter. This structure of the records can also create a very high dimensional space (60,000 binary dimensions) which would be unwieldy for many classical data mining algorithms like neural networks and decision trees. As we'll see several tricks are played to make this computationally feasible for the data mining algorithm while not requiring a massive reorganization of the database.

Discovery

The claim to fame of these ruled induction systems is much more so for knowledge discovers in unsupervised learning systems than it is for prediction. These systems provide both a very detailed view of the data where significant patterns that only occur a small portion of the time and only can be found when looking at the detail data as well as a broad overview of the data where some systems seek to deliver to the user an overall view of the patterns contained n the database. These systems thus display a nice combination of both micro and macro views:

- Macro Level - Patterns that cover many situations are provided to the user that can be used very often and with great confidence and can also be used to summarize the database.
- Micro Level - Strong rules that cover only a very few situations can still be retrieved by the system and proposed to the end user. These may be valuable if the situations that are covered are highly valuable (maybe they only apply to the most profitable customers) or represent a small but growing subpopulation which may indicate a market shift or the emergence of a new competitor (e.g. customers are only being lost in one particular area of the country where a new competitor is emerging).

Prediction

After the rules are created and their interestingness is measured there is also a call for performing prediction with the rules. Each rule by itself can perform prediction - the consequent is the target and the accuracy of the rule is the accuracy of the prediction. But because rule induction systems produce many rules for a given antecedent or consequent there can be conflicting predictions with different accuracies. This is an opportunity for improving the overall performance of the systems by combining the rules. This can be done in a variety of ways by summing the accuracies as if they were weights or just by taking the prediction of the rule with the maximum accuracy.

Table 2.3 shows how a given consequent or antecedent can be part of many rules with different accuracies and coverages. From this example consider the prediction problem of trying to predict whether milk was purchased based solely on the other items that were in the shopping basket. If the shopping basket contained only bread then from the table we would guess that there was a 35% chance that milk was also purchased. If, however, bread and butter and eggs and cheese were purchased what would be the prediction for milk then? 65% chance of milk because the relationship between butter and milk is the greatest at 65%? Or would all of the other items in the basket increase even further the chance of milk being purchased to well beyond 65%? Determining how to combine evidence from multiple rules is a key part of the algorithms for using rules for prediction.

Antecedent	Consequent	Accuracy	Coverage
bagels	cream cheese	80%	5%
bagels	orange juice	40%	3%
bagels	coffee	40%	2%
bagels	eggs	25%	2%
bread	milk	35%	30%
butter	milk	65%	20%
eggs	milk	35%	15%
cheese	milk	40%	8%

Table 2.3 *Accuracy and Coverage in Rule Antecedents and Consequents*

The General Idea

The general idea of a rule classification system is that rules are created that show the relationship between events captured in your database. These rules can be simple with just one element in the antecedent or they might be more complicated with many column value pairs in the antecedent all joined together by a conjunction (item1 and item2 and item3 … must all occur for the antecedent to be true).

The rules are used to find interesting patterns in the database but they are also used at times for prediction. There are two main things that are important to understanding a rule:

Accuracy - Accuracy refers to the probability that if the antecedent is true that the precedent will be true. High accuracy means that this is a rule that is highly dependable.

Coverage - Coverage refers to the number of records in the database that the rule applies to. High coverage means that the rule can be used very often and also that it is less likely to be a spurious artifact of the sampling technique or idiosyncrasies of the database.

The business importance of accuracy and coverage

From a business perspective accurate rules are important because they imply that there is useful predictive information in the database that can be exploited - namely that there is something far from independent between the antecedent and the consequent. The lower the accuracy the closer the rule comes to just random guessing. If the accuracy is significantly below that of what would be expected from random guessing then the negation of the antecedent may well in fact be useful (for instance people who buy denture adhesive are much less likely to buy fresh corn on the cob than normal).

From a business perspective coverage implies how often you can use a useful rule. For instance you may have a rule that is 100% accurate but is only applicable in 1 out of every 100,000 shopping baskets. You can rearrange your shelf space to take advantage of this fact but it will not make you much money since the event is not very likely to happen. Table 2.4. Displays the trade off between coverage and accuracy.

	Accuracy Low	Accuracy High
Coverage High	Rule is rarely correct but can be used often.	Rule is often correct and can be used often.
Coverage Low	Rule is rarely correct and can be only rarely used.	Rule is often correct but can be only rarely used.

Table 2.4 *Rule coverage versus accuracy*.

Trading off accuracy and coverage is like betting at the track

An analogy between coverage and accuracy and making money is the following from betting on horses. Having a high accuracy rule with low coverage would be like owning a race horse that always won when he raced but could only race once a year. In betting, you could probably still make a lot of money on such a horse. In rule induction for retail stores it is unlikely that finding that one rule between mayonnaise, ice cream and sardines that seems to always be true will have much of an impact on your bottom line.

How to evaluate the rule

One way to look at accuracy and coverage is to see how they relate so some simple statistics and how they can be represented graphically. From statistics coverage is simply the a priori probability of the antecedent and the consequent occurring at the same time. The accuracy is just the probability of the consequent conditional on the precedent. So, for instance the if we were looking at the following database of super market basket scanner data we would need the following information in order to calculate the accuracy and coverage for a simple rule (let’s say milk purchase implies eggs purchased).

T = 100 = Total number of shopping baskets in the database.

E = 30 = Number of baskets with eggs in them.

M = 40 = Number of baskets with milk in them.

B = 20 = Number of baskets with both eggs and milk in them.

Accuracy is then just the number of baskets with eggs and milk in them divided by the number of baskets with milk in them. In this case that would be 20/40 = 50%. The coverage would be the number of baskets with milk in them divided by the total number of baskets. This would be 40/100 = 40%. This can be seen graphically in Figure 2.5.

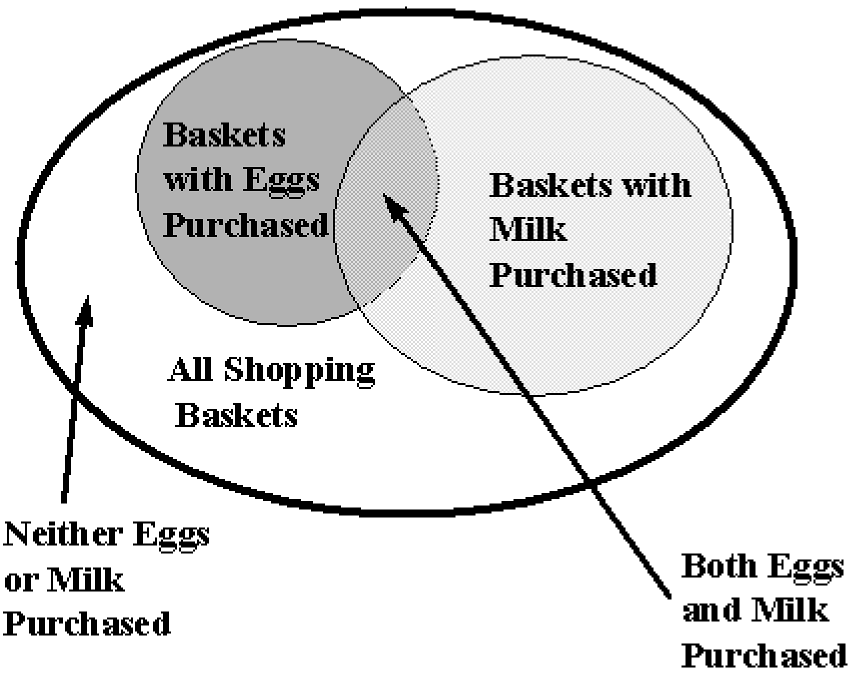
Baskets with Eggs Purchased
Baskets with Milk Purchased
All Shopping Baskets
Neither Eggs or Milk Purchased
Both Eggs and Milk Purchased

Figure 2.5 *Graphically the total number of shopping baskets can be represented in a space and the number of baskets containing eggs or milk can be represented by the area of a circle. The coverage of the rule "If Milk then Eggs" is just the relative size of the circle corresponding to milk. The accuracy is the relative size of the overlap between the two to the circle representing milk purchased.*

Notice that we haven't used E the number of baskets with eggs in these calculations. One way that eggs could be used would be to calculate the expected number of baskets with eggs and milk in them based on the independence of the events. This would give us some sense of how unlikely and how special the event is that 20% of the baskets have both eggs and milk in them. Remember from the statistics section that if two events are independent (have no effect on one another) that the product of their individual probabilities of occurrence should equal the probability of the occurrence of them both together.

If the purchase of eggs and milk were independent of each other one would expect that 0.3 x 0.4 = 0.12 or 12% of the time we would see shopping baskets with both eggs and milk in them. The fact that this combination of products occurs 20% of the time is out of the ordinary if these events were independent. That is to say there is a good chance that the purchase of one effects the other and the degree to which this is the case could be calculated through statistical tests and hypothesis testing.

Defining "interestingness"

One of the biggest problems with rule induction systems is the sometimes overwhelming number of rules that are produced. Most of which have no practical value or interest. Some of the rules are so inaccurate that they cannot be used, some have so little coverage that though they are interesting they have little applicability, and finally many of the rules capture patterns and information that the user is already familiar with. To combat this problem researchers have sought to measure the usefulness or interestingness of rules.

Certainly any measure of interestingness would have something to do with accuracy and coverage. We might also expect it to have at least the following four basic behaviors:

- Interestingness = 0 if the accuracy of the rule is equal to the background accuracy (a priori probability of the consequent). The example in Table 2.5 shows an example of this. Where a rule for attrition is no better than just guessing the overall rate of attrition.
- Interestingness increases as accuracy increases (or decreases with decreasing accuracy) if the coverage is fixed.
- Interestingness increases or decreases with coverage if accuracy stays fixed
- Interestingness decreases with coverage for a fixed number of correct responses (remember accuracy equals the number of correct responses divided by the coverage).

Antecedent	Consequent	Accuracy	Coverage
<no constraints>	then customer will attrite	10%	100%
If customer balance > $3,000	then customer will attrite	10%	60%
If customer eyes = blue	then customer will attrite	10%	30%
If customer social security number = 144 30 8217	then customer will attrite	100%	0.000001%

Table 2.5 *Uninteresting rules*

There are a variety of measures of interestingness that are used that have these general characteristics. They are used for pruning back the total possible number of rules that might be generated and then presented to the user.

Other measures of usefulness

Another important measure is that of simplicity of the rule. This is an important solely for the end user. As complex rules, as powerful and as interesting as they might be, may be difficult to understand or to confirm via intuition. Thus the user has a desire to see simpler rules and consequently this desire can be manifest directly in the rules that are chosen and supplied automatically to the user.

Finally a measure of novelty is also required both during the creation of the rules - so that rules that are redundant but strong are less favored to be searched than rules that may not be as strong but cover important examples that are not covered by other strong rules. For instance there may be few historical records to provide rules on a little sold grocery item (e.g. mint jelly) and they may have low accuracy but since there are so few possible rules even though they are not interesting they will be “novel” and should be retained and presented to the user for that reason alone.

Rules vs. Decision trees

Decision trees also produce rules but in a very different way than rule induction systems. The main difference between the rules that are produced by decision trees and rule induction systems is as follows:

Decision trees produce rules that are mutually exclusive and collectively exhaustive with respect to the training database while rule induction systems produce rules that are not mutually exclusive and might be collectively exhaustive.

In plain English this means that for an given record there will be a rule to cover it and there will only be one rule for rules that come from decision trees. There may be many rules that match a given record from a rule induction system and for many systems it is not guaranteed that a rule will exist for each and every possible record that might be encountered (though most systems do create very general default rules to capture these records).

The reason for this difference is the way in which the two algorithms operate. Rule induction seeks to go from the bottom up and collect all possible patterns that are interesting and then later use those patterns for some prediction target. Decisions trees on the other hand work from a prediction target downward in what is known as a “greedy” search. Looking for the best possible split on the next step (i.e. greedily picking the best one without looking any further than the next step). Though the greedy algorithm can make choices at the higher levels of the tree which are less than optimal at the lower levels of the tree it is very good at effectively squeezing out any correlations between predictors and the prediction. Rule induction systems on the other hand retain all possible patterns even if they are redundant or do not aid in predictive accuracy.

For instance, consider that in a rule induction system that if there were two columns of data that were highly correlated (or in fact just simple transformations of each other) they would result in two rules whereas in a decision tree one predictor would be chosen and then since the second one was redundant it would not be chosen again. An example might be the two predictors annual charges and average monthly charges (average monthly charges being the annual charges divided by 12). If the amount charged was predictive then the decision tree would choose one of the predictors and use it for a split point somewhere in the tree. The decision tree effectively “squeezed” the predictive value out of the predictor and then moved onto the next. A rule induction system would on the other hand create two rules. Perhaps something like:

If annual charges > 12,000 then default = true 90% accuracy

If average monthly charges > 1,000 the default = true 90% accuracy.

In this case we’ve shown an extreme case where two predictors were exactly the same, but there can also be less extreme cases. For instance height might be used rather than shoe size in the decision tree whereas in a rule induction system both would be presented as rules.

Neither one technique or the other is necessarily better though having a variety of rules and predictors helps with the prediction when there are missing values. For instance if the decision tree did choose height as a split point but that predictor was not captured in the record (a null value) but shoe size was the rule induction system would still have a matching rule to capture this record. Decision trees do have ways of overcoming this difficulty by keeping “surrogates” at each split point that work almost as well at splitting the data as does the chosen predictor. In this case shoe size might have been kept as a surrogate for height at this particular branch of the tree.

Another commonality between decision trees and rule induction systems

One other thing that decision trees and rule induction systems have in common is the fact that they both need to find ways to combine and simplify rules. In a decision tree this can be as simple as recognizing that if a lower split on a predictor is more constrained than a split on the same predictor further up in the tree that both don’t need to be provided to the user but only the more restrictive one. For instance if the first split of the tree is age <= 50 years and the lowest split for the given leaf is age <= 30 years then only the latter constraint needs to be captured in the rule for that leaf.

Rules from rule induction systems are generally created by taking a simple high level rule and adding new constraints to it until the coverage gets so small as to not be meaningful. This means that the rules actually have families or what is called “cones of specialization” where one more general rule can be the parent of many more specialized rules. These cones then can be presented to the user as high level views of the families of rules and can be viewed in a hierarchical manner to aid in understanding.

2.5. Which Technique and When?

Clearly one of the hardest things to do when deciding to implement a data mining system is to determine which technique to use when. When are neural networks appropriate and when are decision trees appropriate? When is data mining appropriate at all as opposed to just working with relational databases and reporting? When would just using OLAP and a multidimensional database be appropriate?

Some of the criteria that are important in determining the technique to be used are determined by trial and error. There are definite differences in the types of problems that are most conducive to each technique but the reality of real world data and the dynamic way in which markets, customers and hence the data that represents them is formed means that the data is constantly changing. These dynamics mean that it no longer makes sense to build the "perfect" model on the historical data since whatever was known in the past cannot adequately predict the future because the future is so unlike what has gone before.

In some ways this situation is analogous to the business person who is waiting for all information to come in before they make their decision. They are trying out different scenarios, different formulae and researching new sources of information. But this is a task that will never be accomplished - at least in part because the business the economy and even the world is changing in unpredictable and even chaotic ways that could never be adequately predicted. Better to take a robust model that perhaps is an under-performer compared to what some of the best data mining tools could provide with a great deal of analysis and execute it today rather than to wait until tomorrow when it may be too late.

Balancing exploration and exploitation

There is always the trade off between exploration (learning more and gathering more facts) and exploitation (taking immediate advantage of everything that is currently known). This theme of exploration versus exploitation is echoed also at the level of collecting data in a targeted marketing system: from a limited population of prospects/customers to choose from how many to you sacrifice to exploration (trying out new promotions or messages at random) versus optimizing what you already know.

There was for instance no reasonable way that Barnes and Noble bookstores could in 1995 look at past sales figures and foresee the impact that Amazon books and others would have based on the internet sales model.

Compared to historic sales and marketing data the event of the internet could not be predicted based on the data alone. Instead perhaps data mining could have been used to detect trends of decreased sales to certain customer sub-populations - such as to those involved in the high tech industry that were the first to begin to buy books online at Amazon.

So caveat emptor - use the data mining tools well but strike while the iron is hot. The performance of predictive model provided by data mining tools have a limited half life of decay. Unlike a good bottle of wine they do not increase in value with age.