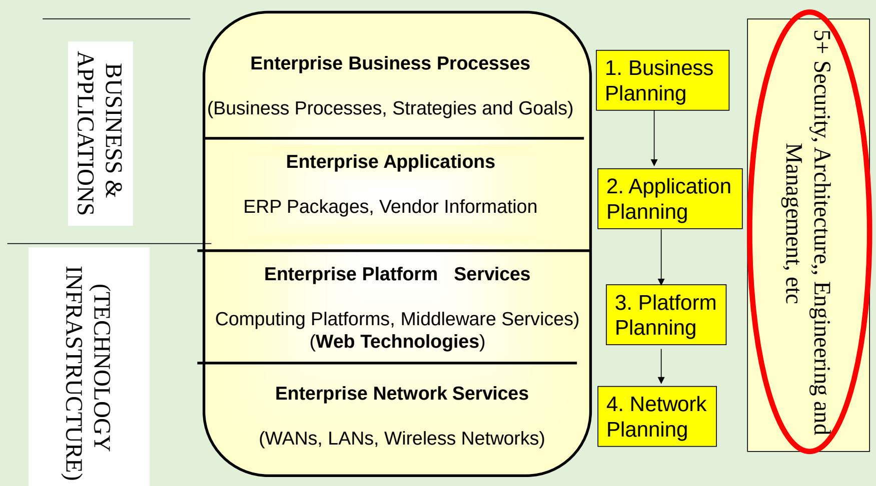
MODULE (Synthesis)

This module consists of the following chapters that attempt to synthesize the concepts, models and the technologies presented so far:

Chapter 10: Artificial Intelligence and Intelligent Systems
Chapter 11: Computer-Aided Planning, Engineering and Management
Chapter 12: Information Security Management
Chapter 13: Systems Management



All layers need to be planned, integrated, secured and administered

10 Artificial Intelligence and Intelligent Systems

Opening Vignette: Driverless Cars

A driverless car, also known as an autonomous car or a self-driving car, is capable of reaching its destination by automatically following directions, sensing its environment and navigating without human input. These cars extensively rely on artificial intelligence (AI) to detect surroundings by using a variety of sensors, adjust quickly based on the situation, and learn to do it better in the next round. For example, an intelligent GPS collaborates with a Vehicle Adhoc Network (VAN) to detect a traffic jam, analyzes a map to determine a different route, and informs other cars so that they do not run into the same problem.

The work on driverless cars began in the 1920s and 30s, but it has become an area of tremendous interest since the early 2000s. Besides auto manufacturers, high tech companies such as Google and Apple are investing heavily in autonomous and driverless cars. The main focus of driverless cars has shifted from providing assistance to the human drivers through automation to completely replacing the human element. The current and future driverless cars are concentrating on machines to negotiate with each other, learn from other cars and the surroundings to reach the destination. The primary human interaction is the initial direction setting for the destination and perhaps the desired time to reach the destination. Of course, a human can interrupt the fun and take over any time.

The long range goal of autonomous/driverless cars is very noble: to completely eliminate car accidents, especially on highways, by developing cars that are intelligent enough to avoid accidents automatically. Naturally, there are many heated debates about the driverless cars with numerous questions about drastic changes in life styles, liability, terrorism, fault tolerance, and hacking. The main question is why these cars are even needed. One of the main advantage of driverless cars is that if any human driver learns to drive, say, in heavy snow then the knowledge just stays with one person. But with driverless cars, the knowledge can be quickly replicated in all cars and also in all cars in the future. Thus the cars can keep learning and improving endlessly.

Naturally, the driverless cars are an evolution of automation to help the driver. The US National Highway Traffic Safety Administration (NHTSA) released in 2013 the following classification system for levels of automation in cars:

- Level 0: The driver completely controls the vehicle at all times.
- Level 1: Individual vehicle controls are automated, such as cruise control.
- Level 2: At least two automated controls collaborate with each other, such as adaptive cruise control in combination with lane keeping.
- Level 3: The driver can fully cede control of all safety-critical functions in certain conditions. The car senses when conditions require the driver to retake control.
- Level 4: The vehicle performs all safety-critical functions for the entire trip, with the driver not expected to control the vehicle at any time. Thus the car can be unoccupied.

Naturally, Level4 cars are one of the best examples of an intelligent system that completely eliminates the human driver. Level4 cars are not needed for all purposes but require extensive use of AI techniques and very sophisticated control systems. It is up to the consumers to weigh the cost versus benefits of such level of sophistication in cars.

Sources:

- www.michiganbusiness.org/CarTech
- Autonomous car, https://en.wikipedia.org/wiki/Autonomous_car
- www.driverless-future.com

Contents

10.1 What is AI – A Practitioner's View

10.1.1 What is Artificial Intelligence (AI)

Simply stated, Artificial Intelligence (AI) is a way of making machines that emulate human experts. An early example of an AI machine is the Turing Test that was introduced by Alan Turing in 1950 while he was working at the University of Manchester [Turing 1950]. In the Turing Test, shown in Figure 10-1, a machine's ability to exhibit intelligent behavior was examined in a simple question and answer session. In the test, a human evaluator would ask questions from two partners who are behind a wall or in different rooms. One of the two partners in conversation is a machine, the other is a human, and all players are physically separated – they cannot see each other. In the Turing Test, the conversation was limited to a text-only keyboard (it was 1950, after all). If the evaluator could not reliably tell the machine from the human, then the machine passed the test and was considered intelligent. The test did not check the ability to give correct answers to questions. It only checked how closely answers resembled those of a human. Based on the results of this test, Turing argued against the idea that the "machines can think".

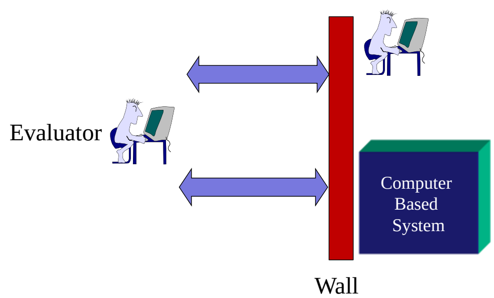


Figure 10-1: Simplified View of Turing Test

A computer and a human, behind a wall, answer questions from an evaluator. If the evaluator cannot tell the difference between the answers, then the computer is intelligent.

Over the years, the Turing Test has been widely analyzed, debated and criticized, and has become an important concept in the overall definition and pursuit of artificial intelligence. With time, questions asked by the evaluator have become more sophisticated, the role of the human player has evolved to a human expert, and the machines have also become more "intelligent". In addition, our own perception of what exactly is intelligent behavior has changed. In fact, a good way to define AI is when machines can do things that *humans think is intelligent*. The idea of computer programs competing against human experts in games such as chess has become a common practice in AI. In fact, the Jeopardy game in 2011 where the IBM Watson system [Jackson 2014] beat the former Jeopardy winners Brad Rutter and Ken Jennings is a recent variation of the Turing Test.

The fundamental question about AI has been the following: C*an a machine think and behave like humans do?* To answer this and other related questions, different definitions and views of AI have evolved over the years. Some of the common views are:

- Cognitive science view that concentrates on human information processing and especially the human brain
- Philosophical view that is centered around the areas of knowledge, wisdom, and consciousness
- Engineering view that focusses on building intelligent systems (also known as Smart Systems)

- Business intelligence and decision support view that is concerned with business aspects of AI

We adopt the engineering and business view in this chapter, i.e., how to build intelligent systems for enterprises. Intelligent systems will be explained later in this chapter. The overall field of AI has gone through several phases since the 1950s resulting in tremendously large number of highly useful AI-based applications and systems in health, education, public safety, public welfare, agriculture, finance, transportation and many other sectors. And many more are currently on the drawing boards. Futurists such as Ray Kurzweil and others have coined the term "Singularity", as a point when AI equals human intel [igence and then surpasses it [Kurzweil 2005]. Some researchers are claiming that the singularity point is as near as 2020 while others contend that it could be as far as 2100. Whatever is the timeline, the fact remains that extremely powerful AI systems are being developed that appear to be surpassing human intelligence already. These developments are being fueled by the combined effect of the following major technologies [Hurwitz 2015]:

- Sophisticated algorithms that mimic different aspects of the human brain
- Very fast machines that can run these sophisticated algorithms much faster than a human being can think
- Very large machine readable data ("the Big Data") that surpasses human memory and vocabulary
- Very fast communication networks that interconnect different machines running different algorithms on different datasets in parallel

For example, the IBM Watson system used more than 100 million books that were accessed by hundreds of parallel algorithms to answer the Jeopardy questions – the algorithm that produced the answer first was used to push the "buzzer" button. Needless to say, humans have difficulty in competing with such a powerful system. Figure 10-2 shows a conceptual view of the key technologies (sophistication of algorithms, computing power, data volume, and network capabilities) that are enabling the AI developments. These technologies are becoming more powerful, yielding more powerful AI applications. The inner circle shows a 1960 view of these technologies and the outer circle shows the current view. In the next few years, more sophisticated technologies will push the outer limits of this view and will fuel greater AI developments.

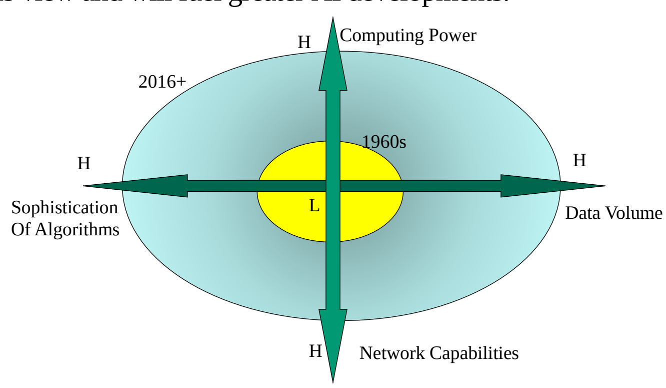


Figure 10-2: Key Technologies that Enable the AI Developments

In other words, the world of AI is evolving rapidly. In the past, knowledge was coded by programmers and then fed into machines (this is known as *Static Knowledge*). But now large number of very fast and interconnected machines can learn from massive amount of data, discover patterns and automatically accumulate new knowledge (known as *Dynamic knowledge*) to make recommendations that humans cannot. But the bad news is that the humans may not be able to understand the recommendations.

For example, suppose that you want to hire the best marketing manager for a company. Instead of using the traditional approach of reviewing resumes and interviewing candidates, suppose that you use an "expert advisor" that uses machine learning and Big Data to find the best candidate. In addition, suppose that the expert advisor can also connect with other advisors on other machines in other countries with their own specialized databases. The answer may be a much better list of potential candidates. That is the good news but the bad news is that we don't really *know why* this is better. It may also be that the recommended candidates are not really interested or available. After all, they never applied for the job. This chapter introduces the basic concept of AI and intelligent systems and attempts to answer the following questions by using numerous examples:

- What is a practioner's view of AI that is important in the planning, engineering and management aspects of modern enterprises (see Section 10.2)
- What are intelligent systems and what are the main categories of such systems in modern enterprises (see Section 10.3)
- What are the examples of intelligent systems and what are the key characteristics of commercially available expert ssystems such as Apple Siri and IBM Watson (see Section 10.4)
- What are the main AI techniques such as machine learning and deep learning that are being used to develop modern intelligent systems (see Section 10.5)
- What are the additional examples of AI in areas such as intelligent robots, gamification and smart enterprises (see Section 10.6)

The Agenda

- AI and Intelligent Systems
- Examples and Case Studies
- AI Tools and Techniques
- More Examples and Case Studies

10.2 A Practitioner's View of AI

10.2.1 The Know-Detect-Adjust-Learn Cycle

We adopt a practical view, i.e., artificial intelligence (AI) is what machines do that human beings feel require intelligence. This view recognizes that we as human beings keep changing our mind about what intelligent behavior is. In the early days of computing, any machine that could quickly add many numbers together was considered intelligent. That is not the case at present. To be intelligent, machines must emulate human behavior which involves knowledge, detecting situations, responding to them and learning from the experience. Figure 10-3 shows our basic approach to AI that captures the four key features of human intelligence (this concept is roughly based on the IBM Smarter Planet Initiative):

- Knowledge (K): familiarity and awareness or understanding of someone or something
- Detection (D): ability to discover, sense or feel a situation such as problem or opportunity
- Adjustment (A): ability to change accordingly, e.g., stop and choose a different strategy
- Learn (L): the capability to gain more knowledge and to use the knowledge to do a better job in the future.

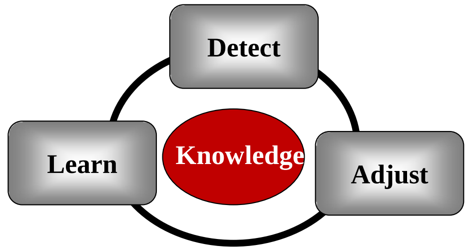


Figure 10-3: Key Features of an Intelligent System

Let us use the example of a driverless car (smart car) to illustrate this concept of AI. We used this example in the opening vignette where a smart car has the *knowledge* about driving and the *intelligence* (i.e., the ability to use the knowledge through the Detect-Adjust and Learn cycle) for a successful journey. Specifically, the smart car must have the following capabilities:

- *Know* about driving, i.e. possess the knowledge and familiarity, awareness and understanding of driving a car at the level of a licensed driver. This static knowledge assures that the smart car knows the concepts of the basic car components (i.e., the steering wheel, the brakes, the windshield wipers, etc), the relationships between these components (i.e., how the brakes are related to the wheels), and the rules (i.e., if the car is going at high speed then the brakes should not be used without an emergency).
- *Detect* a situation, i.e., an event, an opportunity, or a threat. For example, the car must be able to detect rain, snow, a pedestrian, a downhill slope, or a blocked road. Detection involves sensing through hearing, vision, speech recognition, natural language processing and feeling. It also involves fuzzy logic (i.e., similarities) and pattern recognition (i.e., this looks like a pedestrian).
- *Adjust* according to the situation, i.e., stop on a red light and for a crossing pedestrian. Adjustment involves developing plans of action based on alternative analysis and requires reasoning (i.e., inferences) based on rules. For example, if it is raining and the car is on a downhill slope, then slow down. Adjustments also require proper controls and prior knowledge to execute a complicated plan (i.e., if it is snowing heavily and the roads are congested, then it is best to stop and check into a motel).
- *Learn* to do it better in the next round when a similar situation arises. Basically, the smart car should be able to *automatically* acquire knowledge (new things, new relationships between things, and new rules), retain knowledge and remember (through short term memory, long term memory, persistent memory), and update knowledge (revise things, revise relationships between things, and revise rules). For example, a smart car should be able to learn that a particular route is blocked and then remember the alternate route that worked the last time. This is the focus of machine learning and is also known as dynamic knowledge.

Although additional capabilities can be added, we will use this Know-Detect-Adjust-Learn cycle throughout this chapter to characterize AI systems.

10.2.2 A Closer Look at the Know-Detect-Adjust-Learn Cycle

Figure 10-4 displays a more detailed view of the Know-Detect-Learn cycle by identifying different techniques used in AI. The techniques span knowledge acquisition and management, natural language processing, sensors, computer vision, speech recognition, pattern recognition, rule based systems, case based reasoning, business intelligence, machine learning, fuzzy logic, neural networks, and data mining. This figure is not complete – it provides a starting point for further discussion. The distinction between static and dynamic knowledge acquisition is highlighted. We will discuss these techniques in Section 10.5. Table 10-1 shows more specifically how the knowledge, detection, adjustment, and learning capabilities in humans are supported in artificial intelligence systems.

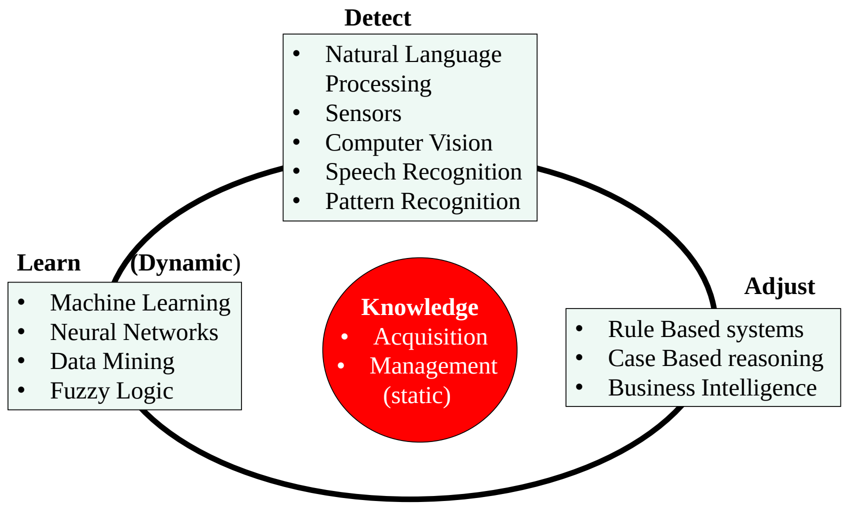


Figure 10-4: The AI Techniques Used in AI Know-Detect-Adjust-Learn Cycle

Intelligent systems such as intelligent robots and driverless cars use many of these capabilities. Similarly, smart enterprises also use many of these capabilities but instead of relying mainly on technologies, smart enterprises use a combination of people, processes and technologies to compete in the marketplace. We will look at these and other intelligent systems in more detail later in this chapter.

Table 10-1: Know-Detect, Adjust, Learn Capabilities in Human and Artificial Intelligence

Human Intelligence	Artificial Intelligence
Know how to get started • Acquire knowledge explicitly to get started (let us say by taking courses or reading) • Manage the initial knowledge, i.e., retain and update our knowledge	Know how to get started • Acquire static knowledge by using knowledge acquisition techniques • Manage the knowledge by using the Knowledge Management (KM) techniques
Detect a situation (an event, opportunity, threat) • Sensing through human hearing, vision, speech recognition, natural language processing, feeling and other natural capabilities • Reasoning through human capabilities of fuzzy things and pattern recognition.	Detect a situation (an event, opportunity, threat) • Sensing through hearing, vision, speech recognition, natural language processing, feeling through an extensive array of sensors connected to wireless sensor networks • Reasoning through computer capabilities of fuzzy logic and pattern recognition.
Adjust according to the situation • Develop plans of action based on alternative analysis by using human capabilities of thinking and reasoning based on rules and guidelines. • Perform human actions and control our actions, as much as possible, based on our	Adjust according to the situation • Develop plans of action based on alternative analysis by using machine capabilities of and reasoning based on rule specifications • Perform machine actions and control the actions, as much as possible, based on learned knowledge

judgement.	
Learn dynamically to handle the situation better in the next round • Acquire knowledge, i.e., learn new things, new relationships between things, and new rules by using our learning capabilities of observations and reasoning • Retain knowledge in our short term memory, long term memory, and persistent memory • Update our knowledge, i.e., revise things, revise relationships between things, and revise rules through observations and human learning	Learn dynamically to handle the situation better in the next round • Acquire knowledge through machine learning, e.g., use data mining to learn new things, new relationships between things, and new rules • Retain knowledge in the computer memory by organizing it into short term memory, long term memory, and persistent memory • Update our knowledge, i.e., revise things, revise relationships between things, and revise rules through machine learning

10.2.3 Knowledge versus Intelligence

Artificial intelligence is based on disciplines such as Computer Science, Biology, Psychology, Linguistics, Mathematics, and Engineering. A major thrust of AI is in the development of computer functions associated with human intelligence, such as reasoning, learning, and problem solving by using knowledge about some topics. While different views and ideas abound, the basic premise of AI practice is that human beings are:

- Knowledgeable, i.e., they have knowledge of concepts, relationships, semantics, and rules about things
- Intelligent , i.e., they have the ability to use knowledge through the Detect-Adjust and Learn cycle

Figure 10-5 shows a two dimensional view of knowledge versus intelligence and displays typical examples of the following types of work: low knowledge and low intelligence, low knowledge but high intelligence, high knowledge and low intelligence, high knowledge and high intelligence. Even if you disagree with the examples, this simple classification allows us to design different types of computer based systems. For example, an expert system must have a great deal of knowledge as well the intelligence to use the knowledge.

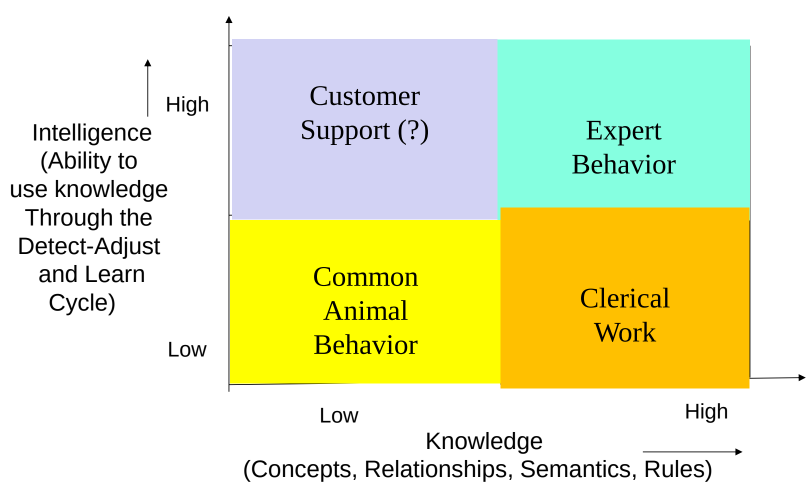


Figure 10-5: Two Dimensional View of Knowledge versus Intelligence

Suggested Review Questions Before Proceeding

- What is AI and how does it differ from human intelligence
- What are the 4 key elements of a Practiooner's View of AI presented in this chapter
- List the AI technologies that are used to support detection and adjustment activities
- List the AI technologies that are used in dynamic learning
- Briefly discuss which of these techniques would be used in a "Smart Building" that concentrates on saving energy

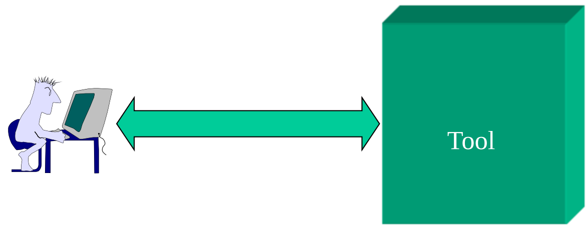
10.3 Intelligent Systems – The Basic Ideas

10.3.1 A Classification of Intelligent Systems

An intelligent system is a computer-based system that has *some* expertise (knowledge plus intelligence) that may range from a clerical tool to a powerful expert system, as shown in Figure 10-6:

- **Clerical Tools**: These tools support the routine clerical tasks in different work environments. The knowledge and the intelligence to use the knowledge resides with the user, i.e., the user is the expert, not the system. Examples of such systems are drawing and description tools such as PowerPoint and Microsoft Word for presentation and communication of the ideas of the users. In fact, the Microsoft Office tools are designed to improve the productivity of the office workers. These tools may provide basic clerical help but in general have no knowledge about the domain and or the problem being addressed. For example, PowerPoint can draw diagram of a network but it cannot tell if the diagram is right or wrong.
- **Knowledge-based (Decision Support) Tools:** These tools have enough of knowledge to help solve a problem and support decisions but do not have the capabilities of detection, adjustment and learning based on the situation. Such tools require that the user has some knowledge about the subject matter. Most decision support tools such as Computer Aided Design tools are good examples because they assist designers to develop better designs. Other examples are flight scheduling systems, financial modeling systems and decision support tools in healthcare.
- **Expert Systems**. These tools emulate the behavior of a human expert and make recommendations. The knowledge and the intelligence to use the knowledge resides with the system but the user can be a novice. A well known example of an expert system is the Turbo Tax system that guides the users in tax preparation – it attempts to simulate a tax expert. The knowledge about the local and federal taxes and appropriate deductions are in the Turbo Tax system so that a novice user can prepare taxes.

In this section, we will take a closer look at the knowledge management, decision support and expert systems by using examples. But first, let us go through a simple example of a travel advisor that can be designed as a simple clerical system and then evolve into an expert system. The actual techniques used to support these systems are discussed in the next section.



	User	Tool
Clerical Tools	Knowledge + Intelligence	Nothing
Knowledge-based Tools	Some Knowledge + Intelligence	Some Knowledge + Intelligence
Expert Systems	Novice	Knowledge + Intelligence

Figure 10-6: Where Does Expertise (Knowledge + Intelligence) Reside

10.3.2 An Example: How to Evolve from a Clerical to an Expert System

Figure 10-7 shows a simple travel advisory system that could help travelers to go from New York to Washington, DC. It shows the main choices (fly, take a train, drive) but not all. For example, taking a boat or riding a bicycle are not mentioned. For some choices, several further choices are provided. For example, the choice of using rental cars is presented.

This *decision tree* where each decision may lead to other decisions represents the choices to be made while planning a trip. The choice at any point (node of the tree) depends on factors such as cost, time, and other considerations. An advisor, human or computer-based, basically walks the user through the various decisions which lead the user to different recommendations.

Figure 10-7: A Simple Travel Advisory System

A decision tree can be automated by using multiple approaches:

- **<u>A clerical tool</u>** that consists of a simple lookup table or database to show different schedules with cost and time information. Examples of such systems are the airline and train reservation systems that show travel expenses between different end-points with departure and arrival times, etc. Additional systems show such as Expedia.com show more than one airline for planning. These systems are very useful but they do not provide help if a traveler cannot decide between, say, flight and train tradeoffs.

- **A knowledge-based system** that represents a more detailed decision tree with different type of choices and the factors that could be used to make the choices. Instead of a table or database lookup that shows flight expenses between different end-points, it asks the users some questions such as cost and time preferences and then guides them to find an acceptable solution. The system consists of rules (written in a programming language or a rule-based system) that guide the users through the tree on multiple factors. Manual choices can be supported through static Web pages in HTML5. Many of these systems, also known as decision support systems, rely on a solid knowledgebase that contains knowledge about different travel scenarios. For example, a traveler from Chicago to London is not shown train and driving options in the decision tree for obvious reasons. In addition, the knowledgebase can be very shallow (just flight and train information) for popular destinations or very deep with flight, train, driving and other options for specific regions.
- **An expert system** emulates the behavior of an expert travel advisor who has comprehensive knowledge about traveling plus has the DAL (detect, adjust, learn) capabilities that represent intelligence. The intelligent expert system could *detect* that certain routes are congested due to some events (e.g., an accident), *adjust* the recommended travel schedules based on the traffic situations, and *learn* how to give a better advice in the next round. The detection capabilities may be simple, based on known holiday seasons or sophisticated based on current newscasts or social media casts. Similarly, the adjustment capabilities may be just telling the users not to travel or find alternate routes and learning may be just a record that an event happened or storing the alternate paths and the rules for invoking different recommendations. An expert system may be a simple advisor that suggests different routes for different situations or a very sophisticated system based on Big Data on travel locations and deep learning that far exceeds the capabilities of any human travel expert.

The needed Travel Advisor can be developed as a game with very basic clerical features to an intelligent advisor with DAL features. Decisions can be made based on rules, previous knowledge and lessons learned and can heavily utilize machine learning.

10.3.3 Knowledge Based Systems and Enterprise Knowledge Management[1]

10.3.3.1 Knowledge Management (KM) Concepts

According to Wikipedia, "Knowledge is a familiarity, awareness or understanding of someone or something, such as facts, information, descriptions, or skills, which is acquired through experience or education by perceiving, discovering, or learning. Knowledge can refer to a theoretical or practical understanding of a subject." See the sidebar on "Difference between Data, Information and Knowledge" for a quick overview of KM concepts. Additional details can be found in [Leondes 2002, Liebowitz 2012]. Our interest is in *Enterprise knowledge* that consists of:

- Knowledge about an enterprise, i.e., its business sector, location, employees, physical layout, business processes, applications, IT infrastructure, security, policies, procedures, etc. This also includes the business strategies that help the company compete and succeed in the marketplace.

[1] This section is based on the textbook, *Management Information Systems, Managing the Digital Firm,* Kenneth C. Laudon and Jane P. Laudon, Prentice-Hall (14th edition), Chapters 11 and 12.

- Knowledge as an asset (i.e., product) of an enterprise that can be offered to its customers. In fact, knowledge is the main asset in many enterprises such as consulting businesses, law firms, educational institutions and research organizations.

This knowledge is spread over several files, databases, documents, slides, reports, presentations, emails, corporate policies, relevant government regulations, and best practices. This knowledge can be categorized as:

- Structured knowledge that exists in the form of databases, reports, and presentations.
- Semi-structured knowledge that exists in e-mails, video clips, voice mails, social media exchanges, digital pictures, brochures, or bulletin board postings.
- Unstructured knowledge that resides in the heads of employees. Much of this knowledge is tacit knowledge that is rarely written down.

Enterprise-wide knowledge management systems deal with all three types of knowledge. At present, most of the knowledge is contained in semi-structured and unstructured sources.

Static Versus Dynamic Knowledge: In the past, knowledge was coded by programmers and then fed into machines (this is known as *Static Knowledge*). But now, machine learning algorithms can learn from massive amount of data, discover patterns and automatically accumulate new knowledge (this is known as *Dynamic knowledge*). Most of the literature in knowledge management is concerned with static knowledge because machine learning and dynamic knowledge are relatively new concepts. In this chapter, we will use the term knowledge to refer to static knowledge unless otherwise specified.

Knowledge Management (KM): KM refers to the set of business processes developed in an organization to create, store, transfer, and apply knowledge. Knowledge management increases the ability of the organization to learn from its environment and to incorporate knowledge into its business processes. In fact, we are all moving towards an information and knowledge economy (more than 55% of the U.S. labor force is classified as knowledge workers). In addition, substantial part of a firm's stock market value is related to intangible assets such as knowledge, reputations, and unique business processes. Knowledge about customer behavior and pricing strategies, for example, are major competitive advantages of retail stores. In this section, we briefly review the key characteristics of knowledge management and knowledge-based systems.

Figure 10-8 shows the knowledge life cycle that illustrates the following basic activities needed in establishing an enterprise knowledge strategy:

- **Knowledge Acquisition**. Organizations acquire knowledge in a number of ways. Some are deliberate corporate knowledge acquisition efforts such as developing corporate repositories of important documents, reports, presentations, emails, and best practices. An interesting example of deliberate knowledge acquisition is by developing online expert networks so that employees can "find the expert" in the company who has the knowledge in his or her head. However, a great deal of knowledge is automatically acquired in modern enterprises in their daily operations through automated logs, audit trails, clickstreams on Web servers, and transaction processing systems that handle customer payments and other critical activities. This automatic knowledge must be mined to discover patterns in corporate data through dash boards and visualizations. A coherent and organized knowledge acquisition strategy is needed in an organization to explicitly acquire new knowledge from all internal systems and also from external sources such as news feeds and industry reports.
- **Knowledge Storage**. The acquired knowledge must be stored somewhere so that it can be used to make decisions. For example, if an organization learns that most of its new customers leave in two months, then it can take appropriate measures. The acquired knowledge must be stored in

such a manner so that it can be easily accessed and used by the stakeholders. The common practice is to create a knowledge database by using a document management system to digitize, index, and tag documents according to a coherent framework. These systems provide different views for different stakeholders. Microsoft SharePoint is used commonly for this purpose because it is integrated with Microsoft Office and email system.

- **Knowledge Dissemination and Application**. The stored knowledge can be disseminated to the decision makers by using a large number of technologies such as instant messaging, emails, portals and the like. In fact, too much information is becoming available to the managers and they cannot decide what to consider and what to ignore. The most relevant knowledge must be shared and applied to the practical problems facing enterprises. This can be done by integrating the knowledge management systems with the company decision-support systems for decision making at the strategic as well as operational levels. Thus knowledge management can create new business practices, new products and services, and new markets for an enterprise.

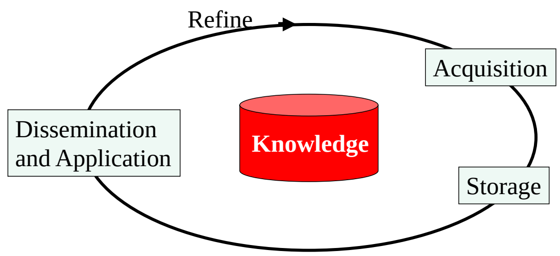


Figure 10-8: Knowledge Life Cycle – Establishing a Knowledge Management Strategy

<u>Difference Between Data, Information and Knowledge</u>

Let us consider a number 55. In its current form, it is just *data*, a number that could be anything (e.g., age of a person, width of a room, or distance between two houses.

Let us now say, 55 miles per hour. Now, this is *information*, it puts the number 55 in context and indicates that it could be speed limit on a road. Information basically converts data into a usable format.

Knowledge is information plus rules. For example, the rule associated with a speed limit is the following: If you go faster than the speed limit, then you will get a ticket. A *knowledgebase* usually has some information plus a set of associated rules.

Wisdom indicates when to use what rules and when to ignore or modify rules. For example, if it is snowing very heavily, then the minimum speed limit can be ignored because it is too dangerous to drive fast when it is snowing.

*Methods and types of knowledg*e :

- Explicit knowledge: explicitly coded, can be automated: facts, trends, unemployment rates, cultural and religious situations
- Tacit knowledge: still in the minds of people, cannot be automated. learned through experiences, hard to describe (e.g., how to ride a bicycle)

10.3.3.2 Knowledge Management Systems Needed to Support the Knowledge Life Cycle

The knowledge life cycle discussed is an extensive investment and needs knowledge management systems to support the knowledge acquisition, knowledge storage and knowledge dissemination/application activities. The key player, discussed below, is the enterprise-wide knowledge management system that supports all the activities. In addition, knowledge workstations, also discussed below, can be employed to discover *useful* knowledge. Both of these systems employ a diverse range of intelligent techniques, such as neural networks, data mining, case based reasoning, fuzzy logic, and genetic algorithms. These techniques, discussed later in this chapter, are used in knowledge management as well as in AI systems.

Enterprise-wide Knowledge Management Systems support the knowledge acquisition, knowledge storage, knowledge dissemination and knowledge application activities described previously. These systems include a combination of the following:

- Directories for locating employee expertise within the company
- Content in the form of structured, unstructured, and semi-structured information
- Portals, search engines, collaboration tools (e-mail, instant messaging, wikis, blogs, and social bookmarking), and learning management systems

Figure 10-9 shows a sample enterprise-wide knowledge management system that houses a large repository of digital content that represents the acquired knowledge. Users also can access external sources of information, such as news feeds and research, and to communicate via e-mail, chat/instant messaging, discussion groups, and videoconferencing. A key problem in managing knowledge is the creation of an appropriate classification scheme, or taxonomy, to organize information into meaningful categories so that it can be easily accessed. Once the categories for classifying knowledge have been created, each knowledge object needs to be "tagged," or classified, so that it can be easily retrieved. Enterprise content management systems have capabilities for tagging, interfacing with corporate databases where the documents are stored, and creating an environment for employees to use when searching for corporate knowledge.

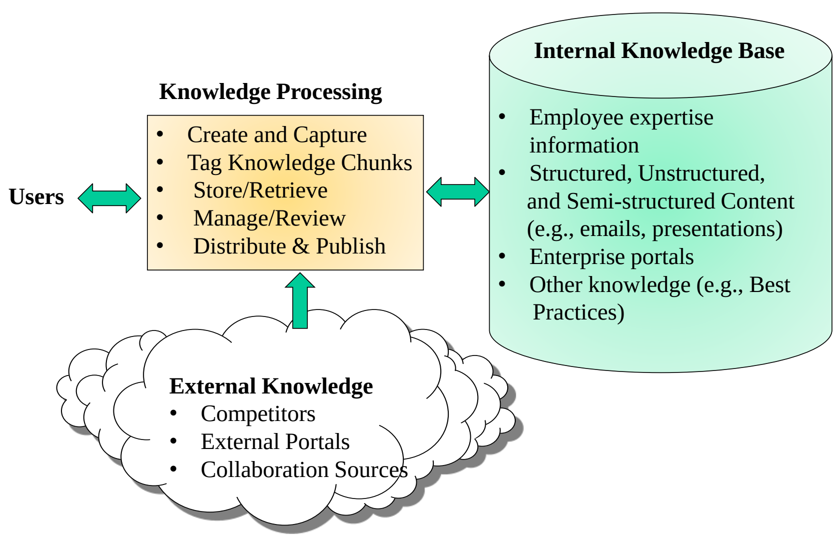


Figure 10-9: A Sample Enterprise-wide Knowledge Management System

An enterprise content management system has capabilities for classifying, organizing, and managing structured and semi-structured knowledge and making it available throughout the enterprise. There are special needs for storing and managing unstructured digital data such as photographs, graphic images, video, and audio content. For example, consulting companies must keep a record of all presentations, reports and meeting minutes on consulting engagements so that this knowledge can be reused in later similar assignments.

Knowledge Workstations (KWS) are specialized systems built for engineers, scientists, and other knowledge workers for discovering and creating new knowledge for a company. Knowledge work systems help knowledge workers to create new knowledge and ensure that the new knowledge is properly integrated into business. Knowledge workers are the researchers, designers, architects, scientists, and engineers who create knowledge and information for the organization. These workers play three roles:

- Keeping organization current in knowledge
- Serving as internal consultants regarding their areas of expertise
- Acting as change agents, evaluating, initiating, and promoting change projects

A typical KWS, shown in Figure 10-10, typically house software tools for assisting engineers and scientists in the utilization of existing and discovery of new knowledge (e.g., data mining and analytics tools). Examples are computer-aided design (CAD), visualization, simulation, and virtual reality systems.

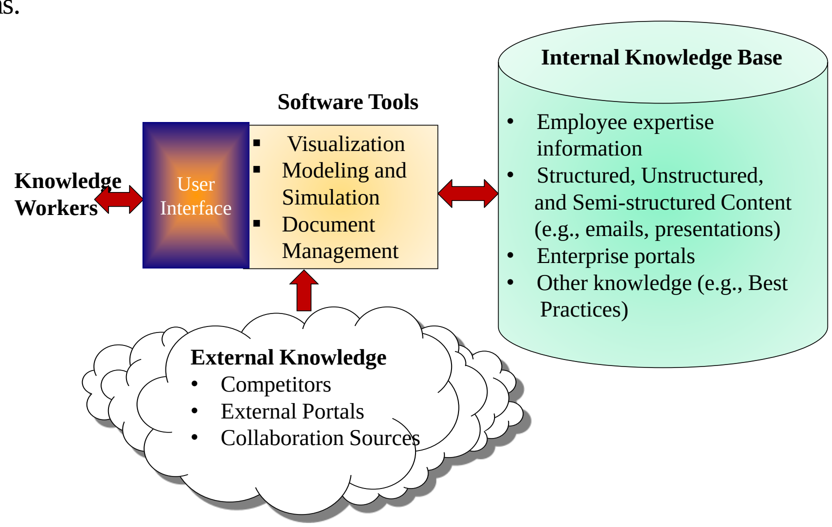


Figure 10-10: A Typical Knowledge Workstation

10.3.4 Decision Support and Business Intelligence (BI) Systems – a Quick Recap

Note: This section is a quick summary and recap of DSS, BI and Data Mining materials covered in Chapter 8 (BI and Databases). It is summarized here for convenience and re-enforcement of the key concepts.

10.3.4.1 Decision Support – Making Decisions based on Data

Figure 10-11 shows a conceptual view of decision support systems (DSSs) that support decisions at various levels in an organization. DSSs use a variety of data sources (e.g., data files, databases, data warehouses and miscellaneous data sources such as satellite and social media data) to produce outputs such as reports, dashboards, charts, graphs and other visualizations. The decision support tools may use from simple to sophisticated AI techniques to help decision makers and maybe called BI tools, data mining tools, analytics tools, visualization tools and the like. In other words, we will use decision support as a general umbrella term to discuss the variety of tools that can be used in a data driven organization. Our main interest is in Business Intelligence (BI), that concentrates on what really happened in the past and how this knowledge can be used to set future business directions. For example, BI tools can predict changes in clothing industries based on changes in weather and BI dashboards can be used to understand which type of storms cause the most damage in what geographical areas.

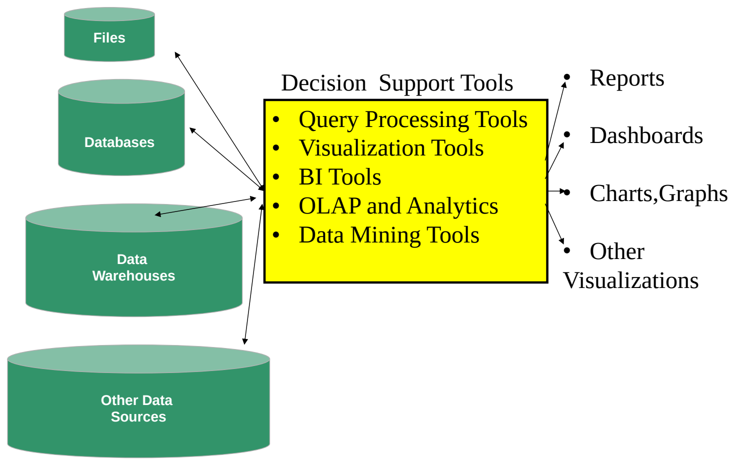


Figure 10-11: Business Intelligence and Decision Support Tools

10.3.4.2 Business Analytics – Using Mathematical Techniques for Business Decisions

Data analytics is the use of *data, information technology, statistical analysis, quantitative methods, and mathematical models* to help managers gain improved insights about their business operations and make better decisions. There are many applications of business analytics (BA) in management of customer relationships, financial and marketing activities, supply chain management, human resource planning, and pricing decisions. BA has evolved from operations research and OLAP (Online Analytical Processing) into a profitable and revenue generation aspect of businesses. Business analytics consists of the following three basic techniques:

- *Descriptive Analytics*: uses data to understand and explore relationships between data items
- *Predictive Analytics*: analyzes past performance and predicts future results based on the past
- *Prescriptive Analytics*: uses optimization techniques to find the best (e.g., least expensive) solution

Data analytics of Big Data is a rapidly evolving area of work especially for business intelligence. For example, descriptive analytics uses Big Data to discover relationships between patient health and medication used, predictive analytics is used to predict the future based on past observations, and prescriptive analytics uses optimization techniques to find, say, the least expensive solutions to a problem. Many data analytics projects at present are based on Big Data repositories in health, education, public safety, public welfare and other vital sectors.

10.3.4.3 Data Mining – Discovering the Knowledge Hidden in Data

Data mining tools exploit a combination of AI and statistical analysis to discover information that is hidden or not apparent through typical query and analysis tools. Traditional database query tools are used to supply answers to simple questions such as "How many VCRs were sold in New York during

December?". Analytics and OLAP (on-line analytical processing) tools go a step beyond the query tools and answer questions such as comparison of sales relative to targets by region for the last three years. Data mining steps go further by *finding patterns* and *inferring rules*. Specifically, the data mining tools use a variety of underlying technologies such as neural networks, decision trees, statistical analysis, and machine learning to detect:

- Associations (e.g., linking purchase of pizzas with beer),
- Sequences (e.g., tying events together such as marriage and purchase of furniture),
- Classifications (e.g., recognize patterns such as the attributes of customers who will discontinue doing business with you), and
- Forecasting (e.g., predicting future buying habits of customers based on past patterns).

Figure 10-12 shows a conceptual view of data mining in modern enterprises. Although some capabilities provided by data mining can be provided by Analytics tools, the *distinguishing feature of data mining is knowledge discovery*, i.e., data mining arrives at insights automatically. For example, suppose that you have noticed a drop in the sales of your product and you want to know what is the cause of this. In most traditional analytical tools, you have to first form a hypothesis (e.g., product sales may be related to price increase), translate your hypothesis into queries, and interpret/understand the results of the queries. A data mining tool, on the other hand, will scan the data repositories and discover the correlations between product sale and other factors that you might have not thought about (sales might have dropped due to a competitor product, assuming this information is in the warehouse). The long range goal of data miners is to behave in a manner similar to "military intelligence" (i.e., gathering useful information from snapshots, notes, maps, observations).

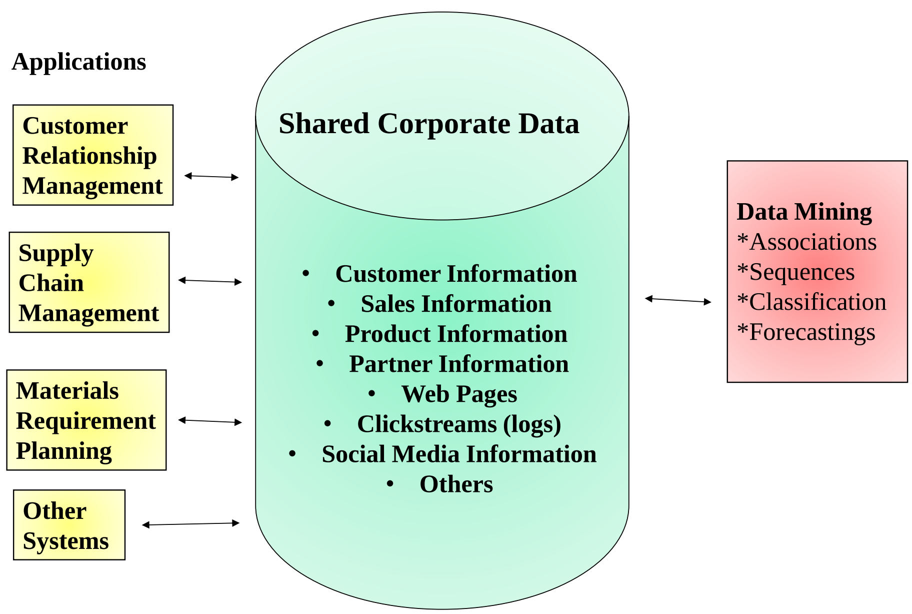


Figure 10-12: Data Mining in Enterprises

10.3.5 Expert Systems

10.3.5.1 What are Expert Systems

Simply stated, an expert system is a computer system that emulates the decision making capabilities of a human expert. It basically captures and uses the knowledge of skilled workers (doctors, lawyers, engineers, designers, etc.) to make decisions [Leondes 2002]. . The expert system consists of a set of rules that represent the main knowledge of a human expert. These rules can be used by others who may not have any knowledge of the subject matter. For example, an expert system may perform tasks such as the following:

- Prepare taxes for individuals and/or small businesses
- Diagnose a malfunctioning machine
- Determine whether to approve or deny a loan
- Suggest design of a home network and or a small office

Expert systems are of a great value in knowledge areas with high demands and tremendous shortage of skills. For example, in many developing countries such as Haiti, there is a high demand but serious shortage of medical professionals. So any expert systems that could even partially perform the tasks of a doctor or a nurse are highly valuable. Although expert systems typically perform limited tasks but by capturing human expertise in limited areas, expert systems can help organizations to make high-quality decisions with fewer people in less time.

The classical expert systems capture the domain knowledge as a set of rules. However, many newer expert systems add other techniques such as case-based reasoning, fuzzy logic, and neural networks. A typical expert system consists of the following two components:

- *Knowledge Base* that consists of facts (e.g., blood pressure of a patient) and rules (e.g., what type of medication to prescribe for low or high blood pressure)
- *Inference Engine* that executes the most appropriate rules to answer questions (e.g., are life style changes needed for patients with medium blood pressure).

The first generation of expert systems were introduced in the 1970s with MYCIN for medical diagnosis for a specific group of diseases. Later, PROSPECTOR was developed for evaluating geological sites for commercial development and XCON was introduced to customize a computer configuration to meet the customer's needs. Development of commercially available expert systems slowed down in the 1990s and early 2000s, but has gained popularity again due to IBM Watson and Apple Siri. We will look at several examples of expert systems later.

10.3.5.2 How Rule-based Expert Systems Work – A Quick Overview

An Expert system may have thousands of rules that model human knowledge and is essentially composed of two sub-systems as stated previously:

- *Knowledge base (KB)* is the set of rules that capture the expert's knowledge. The rules in a KB are typically interconnected with each other, called *nested rules*, because human knowledge can be quite complex where one rule can trigger many other rules, which in turn can trigger more rules depending on different conditions. For example, a home mortgage approval program may have several rules that are related to the income, the debt, the credit rating, the job history, and the age of the applicant.
- *Inference engine* is the strategy used to search through the knowledge base. For example, to answer the question: "will Kim be approved for a home mortgage", the expert system will run through the KB in a certain order to find the answer. However, to answer a different question: "what should Kim do to get a mortgage", the inference engine will search the same KB in a different order. Two strategies, discussed later, are commonly used in expert systems to answer questions: forward chaining and backward chaining.

Figure 10-13 shows a simplified example of an expert system for Home Mortgages. A more detailed discussion of rule-based expert systems with illustration of KB and forward/backward chaining can be found in Section 10.5.1.

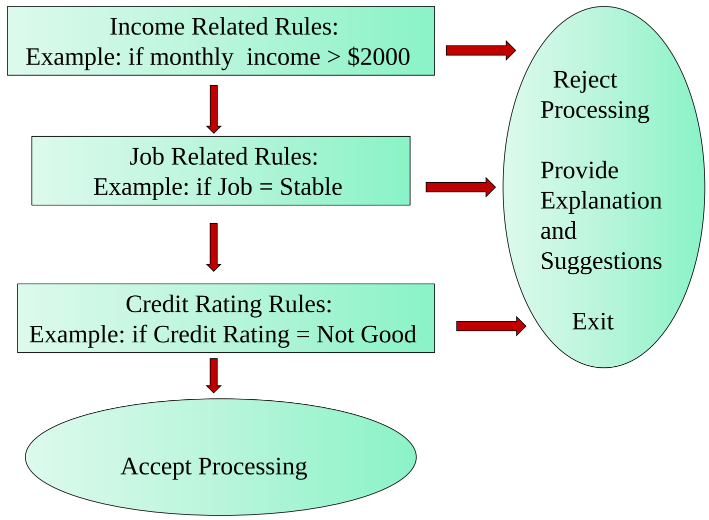


Figure 10-13: Expert System Example: A Mortgage Advisor
The Advisor goes through several sets of rules. The applicant can be rejected in any of the stages.

The popularity of rule-based expert systems in the 1970s led to commercially available Expert System Shells (ESS) that allowed the users to specify the rules in a format that was intuitive and easily understood, reviewed, and even edited by domain experts rather than IT experts. The main benefit of such shells such as Exsys is that expert systems can be developed and maintained by human experts themselves instead of IT experts. However, this does not happen commonly in practice because the human experts are in constant demand and too busy to develop their own tools. For example, it is virtually impossible for a surgeon to find the time to develop an expert system for surgeons. For this and other technical reasons, expert system shells are not commonly used in practice. For example, IBM Watson and Apple Siri do not use any expert system shells. Modern expert systems are commonly developed by IT experts and utilize rules, case-based reasoning and many other techniques written in programming languages such as C, C#, and Java.

References about Expert Systems:

- Jackson, Peter (1998), Introduction To Expert Systems (3 ed.), Addison Wesley, p. 2, ISBN 978-0-201-87686-4
- Hayes-Roth, Frederick; Waterman, Donald; Lenat, Douglas (1983). Building Expert Systems. Addison-Wesley. pp. 6–7. ISBN 0-201-10686-8.
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- Haskin, David (January 16, 2003). "Years After Hype, 'Expert Systems' Paying Off For Some". Datamation.
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10.3.6 Human Brain and AI – A Quick Overview

The study of human brain and how it makes intelligent decisions has been at the heart of AI since the 1950s. In fact, Alan Turing in his classic paper "Computing Machinery and Intelligence" [Turing, 1950], initiated this study by posing a simple question: “can machines think”. To answer this simple question, a great deal of research has been conducted, resulting in a large body of knowledge and several commercially available products with cognitive abilities similar to those of the human brain. We are primarily interested in software and hardware systems that exhibit behavior comparable to that of humans.

While extensive discussion of this topic is strongly beyond the scope of this book, it is informative to take a brief look at the main progress being made in this area. Basically, human brain, shown in Figure 10-14, has the following key properties that are of immediate interest to AI researchers and intelligent systems developers:

- A normal human brain has about 100 billion *neurons*, loosely known as brain cells (more intelligent people have more neurons). This finding is the foundation of neural networks – an active branch of AI and machine learning. Neurons are basically processors that can process instructions. However, human neurons are very slow – they can process only 1 instruction per second. This is why we cannot handle too many instructions quickly. But the neurons are highly interconnected with each other and do very complicated processing in collaboration with each other. Computing machines has have extremely fast processors, each can process more than 100 million instructions per second. The basic premise of *artificial brain* projects is that very large number of interconnected computing processors can exceed the capacity of human brain.
- The human brain consists of 5 lobes, shown in Figure 10-14, that control and support different human functions such as sound, sight, speech, and motion. The idea of the relationship between the lobes and the human functions was established in the 1800s with the discovery that patients who had a speech impediment had part of their brain, roughly the size of a quarter, that was damaged. Several other patients with speech impediments also displayed exactly the same pattern, i.e., part of their brain, size of a quarter, was damaged exactly at the same spot. This established the basic rule of thumb that a lobe in a human brain directly controls the human speech. Since then, medical research has established that lobes of the human brain directly control our ability to speak, see, hear, and make decisions. More brain research is uncovering more functions that are supported by specific lobes in a collaborative fashion. This research has directly led to highly useful brain surgeries to address different disabilities (see below).
- The human brain controls almost all of our body functions by sending electrical signals to different parts of the body. For example, if you want to pick up a glass of water, then the brain sends an electrical signal to the arm and hand to pick up the glass. Hans Berger in 1924 discovered this electrical activity of the human brain that is now known as electroencephalography (EEG). More research has shown that the pulses are further modified to indicate urgency of a function. For example, if you want to pick-up a glass very quickly, then the pulse is modified to indicate the urgency. This research has led to replacing a damaged arm with a robot arm that is sent signals directly from the brain to pick and move objects as desired by the human brain. In other words, if you are thinking of picking up a knife then a remotely located robot can detect your thought, let us say through a Bluetooth connection, and pick up the knife!

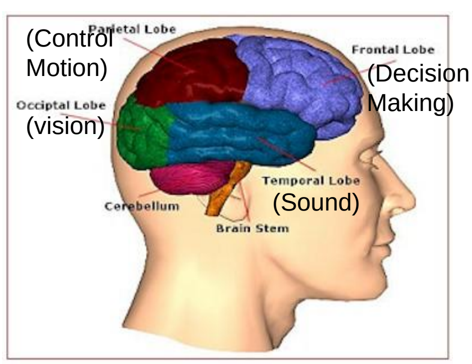

Figure 10-14: The Human Brain

A relatively new area of work, collectively known as *thought computing (or thought controlled computing)*, has emerged based on the aforementioned research on the human brain. Here are some examples of this work:

- If part of a brain is damaged, let us say, due to a head injury or stroke, then no control signals are generated to the appropriate limbs. This leads to paralysis, even though the limbs are not damaged. A brain surgery can replace the damaged part of the brain with a chip that generates the same pulses as the brain. For example, if a head injury paralyses a patient's legs then a chip that produces the same signals for legs can handle this. FDA (Food and Drug Administration) in the US has approved testing of paralyzed people with spinal cord injury by using these techniques.
- If a limb, let us say a hand, gets damaged, then the control signals have no effect. For example, if a soldier's arm has been permanently damaged in the battlefield and the soldier wants to pick up a biscuit, then some probes can capture the brain signals and feed them to a robot arm that picks up the biscuit. In similar scenarios, a person can think of sending an email but a remotely located robot arm can detect this "thought signal" and send the needed email.
- Interesting work in "sixth sense" technologies is going on at present, where machines can go beyond the basic five senses of seeing, hearing, taste, smell and touch. Besides these five sense organs, humans also have awareness of balance, pressure, temperature, pain, and motion -- all of which may involve a coordinated use of multiple sensory organs. The sixth sense technologies are based on a wearable gestural interface that augments the physical world around us with digital information and lets us use natural hand gestures to interact with that information. See the projects at http://www.pranavmistry.com/projects/sixthsense/ for details.

There are many possible applications of thought computing in enterprise settings. For example, some decision support applications which capture brain waves of the decision makers or end users and then adjust the displays accordingly. A closely related area of research is brain-computer interaction (BCI), sometimes called a mind-machine interface (MMI), that provides a direct communication link between a human brain and an external device. The brain–computer interfaces (BCIs) work was initiated in 1924 with Hans Berger's discovery of the electrical activity of the human brain, now known as *electroencephalography* (EEG). Berger identified oscillatory activity, known as Berger's wave or the alpha wave (8–13 Hz), by analyzing EEG traces. Many BCI devices are commercially available at the time of this writing for repairing and/or augmenting brain damage and to handle limb damage by getting brain pulses and sending them to a computer and/or a robot to perform the needed action. A great deal of literature on this topic is available over the Internet.

Major References

- *Turing, Alan (October 1950), "Computing Machinery and Intelligence", Mind, 433–460,*
- *Kurzweil, Ray (2005). The Singularity is Near. New York: Viking Books*
- Charlie Rose – Brain Series:
    - http://www.charlierose.com/view/interview/10694 (Introduction, March 2009)
    - http://www.charlierose.com/view/interview/11437 (Synopsis, Jan 2011)
- Ted Talk on sixth sense

Time To Take a Break

- AI and Intelligent Systems
- Examples and Case Studies
- AI Tools and Techniques
- More Examples and Case Studies

Suggested Review Questions Before Proceeding

- What are the main classifications of Intelligent Systems
- Give an example of a clerical system and an expert system
- What are the key characteristics of a Knowledge Based System
- What is the main difference between a Decision Support and a Business Intelligence (BI) sytem
- What exactly is an Expert System. Please illustrate by using an example

10.4 Selected Examples and Case Studies of Intelligent Systems

A very large number of intelligent systems are currently being used in health, education, public safety, public welfare, agriculture, transportation, entertainment, ecommerce and many other sectors. Even a greater number are on the drawing boards for real life practical situations. Some of these systems are knowledge-based decision support systems, others are expert systems, and many are mixtures. It is not our objective to present a comprehensive survey of the topic in this section. We are presenting a few samples to illustrate different aspects of intelligent systems. Additional examples of intelligent systems can be found on the Net. The following are a few suggested sources of information:

- Expert Systems with Applications, An International Journal, http://www.journals.elsevier.com/expert-systems-with-applications/
- AAAI Innovative Applications of AI Proceedings: http://www.aaai.org/Library/IAAI/iaai15contents.php
- AI & Society Journal: http://link.springer.com/journal/volumesAndIssues/146
- International Knowledge Engineering and Intelligent Systems Conference Proceedings: http://www.sciencedirect.com/science/journal/18770509/60

10.4.1 Computer Aided Consulting – Using a Mixture of Intelligent Systems

Computer aided consulting is an interesting area to illustrate how different types of intelligent systems can be used to succeed.

Figure 10-15 shows a simplified view of how a wide range of intelligent systems, ranging from knowledge-based decision support to expert systems can support an IT consulting practice:

- Body Shop Model in which all of the work is done by the consultants. Virtually no automated assistance is used. This model, typically used in small consulting firms or new divisions of larger consulting firms, is very flexible but is too expensive and does not scale well for remotely located small enterprises in developing countries (it is difficult for a consultant living in Manhattan to offer consulting services to a company in Cambodia).
- Directory Assisted Model in which a directory of consultant expertise (who knows what) is maintained so that the customer questions can be directed to the right consultants. Directories are typically clerical tools that are updated as the consultants gain more experience and training and may also contain FAQs (Frequently Asked Questions). This model, typically used in larger consulting firms is also very flexible but is too expensive and not suitable for the underserved sectors because almost all the work is still done by the consultants.
- Knowledgebase (KB) Assisted Model in which the actual knowledge of the consultants (e.g., presentation slides, analysis reports, proposed solutions, meeting minutes, etc) are maintained in a knowledgebase for reuse among consultants. This model, typically used in large consulting firms, is very flexible and gives the consulting firm a competitive edge due to high reuse of the knowledge. This knowledge-based decision support system can be highly effective. However, it still does not help the underserved sectors because this knowledge is a highly protected intellectual property of the firm that is not freely available to the underserved sectors.
- Integrated Consulting Environment (ICE) Model in which the firm relies primarily on the knowledgebase plus decision support and expert systems tools and games for *directly* delivering consulting services to remotely located users. This model utilizes a mixture of intelligent systems and is an innovative approach to succeed. This is mainly because the users themselves can develop solutions, albeit partially, and the remaining work (if any) is done by the consultants. This is especially of significant value to the developing countries and other underserved sectors for rapid and inexpensive remote delivery of IT consulting services to minimize errors, retries and failures.

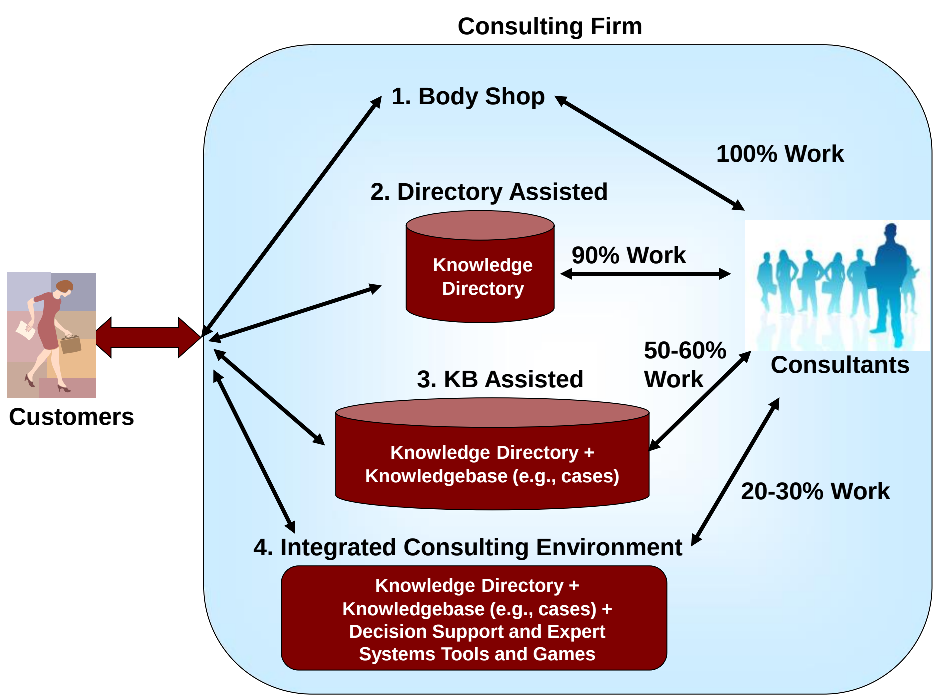

Figure 10-15: Models of Consulting in ICT

These consulting models are not mutually exclusive – a consulting firm may use a mixture of these models based on the expertise of its available consultants, the location and type of customers, and financial considerations. In addition, these models are not restricted to IT – consulting firms in manufacturing, construction, transportation and other sectors also could follow similar models. Additional details about this model can be found in [Umar 2013]

10.4.2 Computer Aided Planning Environment – A Sneak Preview

Planning of modern enterprises is a complex task that involves a large number of decisions and activities such as business strategies adopted by the organization, infrastructure components needed to support the business strategies, Commercial off-the-shelf (COTS) tools to be used for each infrastructure component (e.g., which specific workflow to be used), technical architectures to support the strategies, and project plans to be used. Time to make these decisions and to implement the decisions can be long (according to Gartner, can take up to two staff years and cost more than $1 million for complex sites that provide market differentiator). Any tool that helps in making these crucial decisions quickly can be very valuable.

Figure 10-16 shows the PISA (Planning, Integration, Security & Administration) environment that attempts to automate the planning processes. PISA is not one expert system but in fact a combination of many expert systems (advisors) that collaborate with each other to develop IT plans. In fact, it simulates a team of human consultants who collaborate with each other to solve complex business problems. Each PISA advisor automates a stage of the conceptual model and collaborates with other advisors through an inference engine and an extensive knowledgebase. The advisors provide a combination of expert advice, decision support, and intelligent assistance to support management and planning decisions. PISA advisors, shown in Figure 10-16 are segmented into three modules:

- **PlanIT (Planner for IT)** consists of five advisors that collaborate with each other to quickly create an enterprise model and then develop IT plans that span enterprise applications, computing platforms, and network services.
- **AIM (Architecture and Integration Module)** consists of four advisors that can be used to: a) analyze, architect, and integrate specific applications, b) quickly develop application requirements that can be used to make detailed BRODE decisions, c) examine various architecture and integration configurations and produce a service-oriented architecture, and d) evaluate the impact of selected strategies on computing platforms, network architectures, and security solutions.
- **SAM (Security and Administrative Module)** provides the security and administrative services to produce a complete ad secure IT solution with project plans, extensive documentation and graphic support. Examples of these tools are a Security Planner, Project Planner, a COTS Advisor, a Diagram Generator, and a Document/Report Generator.

The individual PISA advisors concentrate on different tasks by using different techniques. Extensive details about the advisors cannot be provided due to space limitations. Additional details can be found at the PISA Website (www.ngepisa.com). We will take a more detailed look at the computer aided planning, engineering and management environments. Basic information about PISA can be found in [Umar 2012].

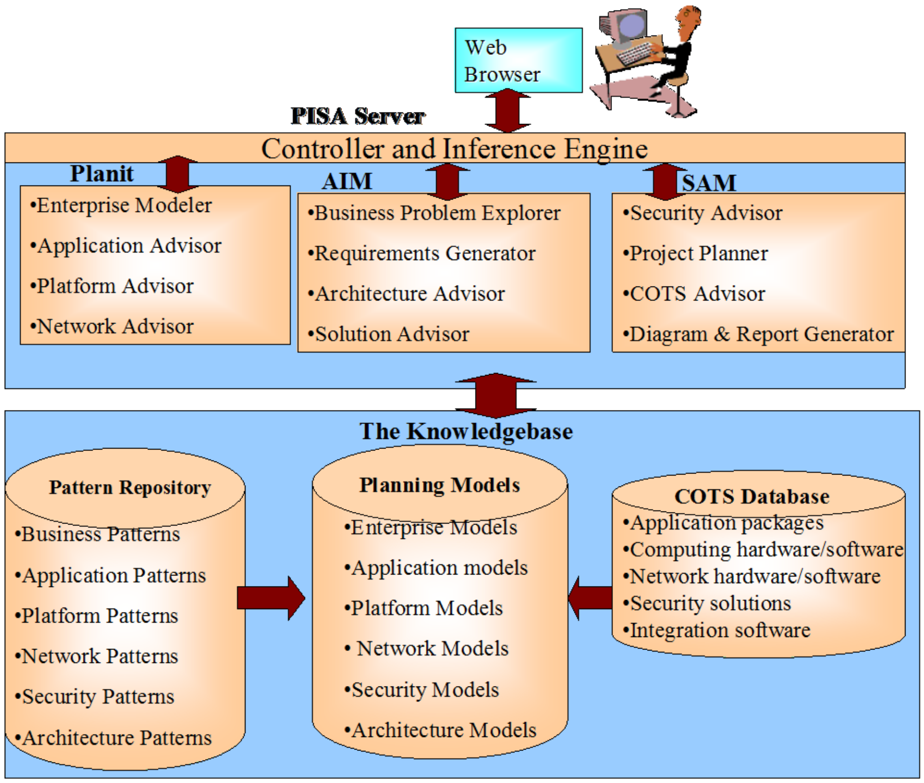

Figure 10-16: High Level Technical View of PISA Environment

10.4.3 GE Uses Machine Learning To Restore Italian Power Plant

Efficiency of power plants to generate urgently needed energy is a major area of work. GE introduced a machine data system for power plants in the Minds + Machines conference in Paris, June 14, 2016. GE claims that its "Digital Power Plant for Steam" suite can increase a facility's efficiency of operation by 1.5%, reduce carbon dioxide emissions by 3%, and reduce coal consumption by 67,000 tons for each megawatt of electricity produced. The features of this application are:

- Boiler Optimization, designed for boiler reliability and efficiency through improved combustion and soot-cleaning processes
- Coal Analyzer, for the ability to plug coal properties, such as its moisture content, into the ongoing operation of the plant
- Plant Optimization, to watch key performance indicators that measure the gap between ideal and actual operational practices

According to GE, the software can collect data from 10,000 sensors in a power plant and interpret it for streamlined operations. In addition to the other gains, doing so will result in a 5% reduction in downtime. The software package uses machine learning and analytics algorithms to produce these results.

Source: *Charles Babcock, Information Week, June 16, 2016, Link:* http://www.informationweek.com/iot/ge-uses-machine-learning-to-restore-italian-power-plant/d/d-id/1325918m

10.4.4 Apple's Siri – A Mobile Expert System

Apple's Siri is a QA (Question Answering) system that uses the latest developments in speech-to-text analysis, grammar analysis and remote service invocations from a large number of service providers. Specifically, it takes a wide range of questions in natural language and provides the best possible answers also in natural language. Apple gives the following list of sample questions:

- Ask to set an alarm.
- Ask for directions.
- Ask to send an email.
- Ask for information (from Yelp, Wolfram|Alpha, or Wikipedia).
- Ask to set a meeting.
- Ask for a phone number.
- Ask for a reminder.
- Ask about stocks.
- Ask to set the timer.
- Ask about the weather.

You can also ask Siri about Siri which simply gets Siri to repeat the aforementioned list.

Figure 10-17 shows a conceptual view of Siri. It basically consists of a user interface, speech to text analyzer, lexical and grammar analyzer, and a remote service invoker that interacts with a wide range of service providers to get the right answers. The service providers at the time of this writing include the calendars, user contacts, text and email providers, Maps app and location services based on GPS, and information providers such as Yahoo! Weather, Yahoo! Finance, Yelp, Wolfram|Alpha, or Wikipedia. These architectural components of Siri are briefly described below.

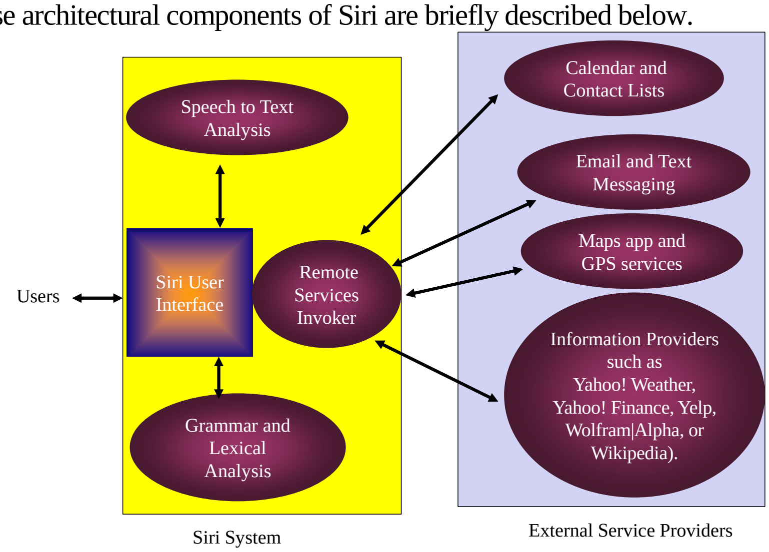

Figure 10-17: Siri Conceptual View

User Interface: Apple has developed several alternative phrases and responses that make Siri seem smarter and human. For example, instead of saying "Loading …", it says "Let me check on that," or "Let me think,". Also, instead of saying yes or no to a question, Siri says "It seems so" or "Doesn't seem like it." These are just nice synonyms and technically not difficult to do. But they do give an impression of an intelligent system.

A Speech-to-Text Analyzer: This is a speech recognition software package that takes audio and turns it into text. Speech recognition is a non-trivial task due to many variations of speech due to accents and other conditions (for example, we sound different when we have a cold or are speaking too fast). However Siri's job is somewhat simplified because it has limited domain knowledge (i.e., appointments, contacts, messages, and maps). This makes it easier for Siri to pick out what the user is saying. In addition, a phone has much better noise control than a typical computer. Thus it is easier to handle speech recognition on a phone than a computer.

Grammar and Lexical analysis: Speech recognition software basically turns a voice into written text. Lexical analysis converts the text into something meaningful, i.e., it converts the text to a semantically meaningful command for the phone. For example, supposing I tell Siri to "send this message to my wife". Then Siri Grammar and Lexical Analyzer will do the following things:

- Recognize that "send this message" means sending a text message
- Recognize that "my wife" is someone in my contact list. Moreover, it will look for a female contact with last name of "Umar". If there are multiple females, then Siri will generate questions such as "Let me be sure, is it Dolorese?". In reality, most contact lists have predefined fields for frequent contacts such as wife, sons, daughters, parents, best friends, etc.
- When I confirm the name of my wife, it will flag Dolorese as my wife for future reference and fetch her phone number from the contact list.

Similarly, if I say "meet me here", Siri lexical analyzer will invoke GPS to find out where I am. Also if I say that "I will leave work at 5 pm", Siri will recognize that my GPS location will change around 5 PM. It can be seen that grammar and lexical analysis is a non-trivial and crucial component of Siri. The basic idea of grammatical and lexical analysis is to search a string for certain key phrases and using those phrases to build up a simple model of what the user wants to do.

Remote Services Invoked: Siri invokes a large number of remote services such as the following:

- A calendar app for viewing and creating appointments.
- A maps app to search and find directions.
- Access to Wikipedia for different sources of information. Siri interface enters the search text on your behalf.
- Access to weather, financial status and other information.

Although we can all can do these things ourselves but Siri provides a consistent, voice-based interface so that we can activate all these services hands-free. The main advantage of Siri is that it integrates a wide range of commonly used services by using natural language processing and speech recognition. The success of Siri depends largely on how well the Siri natural language processing and speech recognition systems work with a diverse range of speech patterns and accents.

References:

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- "How Siri Works" by Jeff Wofford, *www.jeffwofford.com/?p=817*
- Siri - Wikipedia, *https://en.wikipedia.org/wiki/Siri*

10.4.1 IBM Watson – An Expert System that Beat Jeopardy

Watson, named after IBM's first CEO and industrialist Thomas J. Watson, is a question answering computer system capable of answering questions posed in natural language. Watson was specifically developed to answer questions on the quiz show Jeopardy and won against former Jeopardy winners Brad Rutter and Ken Jennings in 2011. Historically, IBM has had interest in developing AI systems. After IBM Deep Blue won a chess game against Garry Kasparov in 1997, IBM was looking for a bigger challenge and embarked on Watson around 2005. The main challenge for Watson was to produce answers, in a few seconds, to extremely difficult questions posed by the game show. The main capabilities of Watson that helped it to win the Jeopardy game in 2011 are the following:

- During the game, Watson had access to 200 million pages of structured and unstructured documents, including the full text of Wikipedia. However, it was not connected to the Internet during the game.
- Watson ran on an extremely fast massively parallel processor computer system that can process the equivalent of a million books per second.
- Watson used IBM's DeepQA technology to generate hypotheses, gather massive evidence, and analyze data. Each question was analyzed by a very large number of algorithms in parallel and the ones that found an answer before the others were selected to produce the final answer.

Naturally, no human being could process that much information so quickly. Despite that, Watson had trouble in a few categories, especially those with short clues containing only a few words.

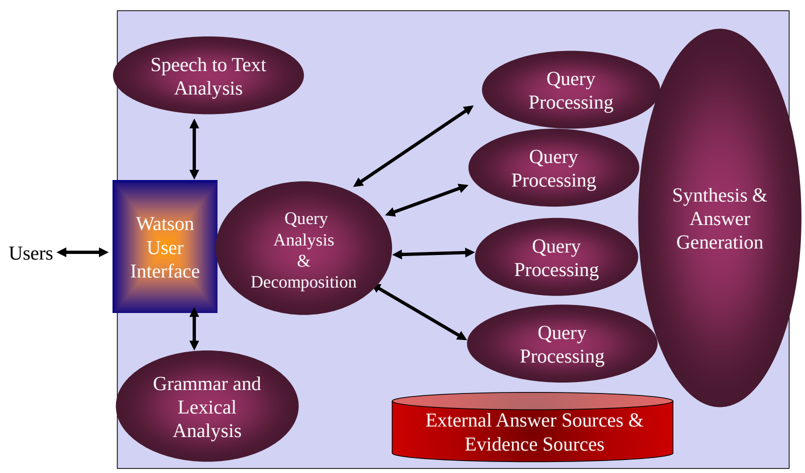

Figure 10-18: Simplified Architecture of Watson System

Figure 10-18 shows an oversimplified architectural view of the Watson System. IBM applied advanced natural language processing, information retrieval, knowledge representation, automated reasoning, and machine learning technologies to build this question answering system. The major challenge in a QA system is that it takes a question, usually expressed in natural language, tries to understand it as much as possible, and generate a precise answer to the question. According to IBM, "more than 100 different techniques are used to analyze natural language, identify sources, find and generate hypotheses, find and score evidence, and merge and rank hypotheses". Instead of any expert system shell, Watson was written in traditional programming languages such as Java, C++, and Prolog, and used Apache Hadoop framework for Big Data. The main architectural parts of Watson are the following:

- The Watson user interface, grammar and lexical analysis, and speech recognition components are, in principle, similar to the Siri system although they both operate in very different domains.
- The external answer and evidence sources for Watson are much larger than Siri. Watson knowledgebase includes encyclopedias, dictionaries, thesauri, newswire articles, literary works, databases, taxonomies, and ontologies.
- The query analysis and decomposition plays a key role in Watson. The core innovation is that it parses questions into different keywords and sentence fragments and then executes hundreds of queries in parallel.
- The parallel queries in Watson use proven language analysis algorithms simultaneously to find the correct answer. The more algorithms that find the same answer independently the more likely it is that the answer is correct.
- The Synthesis and answer generation components check against its database to ascertain whether the solution makes sense. If it does, the answer is generated.

The winning of Jeopardy game in 2011 made Watson a household name and IBM started investigating business opportunities for Watson. In 2013, IBM announced that Watson software system's first commercial application would be for lung cancer treatment at Memorial Sloan Kettering Cancer Center. In healthcare, Watson is being used as a clinical decision support system for use by medical professionals.

- A physician submits a query to the system describing symptoms and other related factors,
- Watson parses the input to identify the most important pieces of information;
- Watson mines patient data to find facts relevant to the patient's medical and hereditary history
- It then examines available data sources to form and test hypotheses
- It finally provides a list of individualized, confidence-scored recommendations.

The external sources of data (the knowledgebase) that Watson uses for analysis can include treatment guidelines, electronic medical record data, notes from physicians and nurses, research materials, clinical studies, journal articles, and patient information. IBM has formed several partnerships and initiated projects in healthcare since 2013. IBM announced in 2014 that it was creating a business unit around Watson with headquarters in New York's Silicon Alley

Main References:

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Time To Take a Break

✓ • AI and Intelligent Systems
✓ • Examples and Case Studies
• AI Tools and Techniques
• More Examples and Case Studies

Suggested Review Questions Before Proceeding

- Surf the Net and give one example of an intelligent system that you feel will be of high value to your enterprise
- Give one example of how thought computing can be used in practice
- Which case study or example discussed in this chapter is of most interest to you and why
- What are the main differences between Apple Siri and IBM Watson

10.5 Overview of AI Techniques – How to Make the Machines Intelligent

A wide range of AI techniques are used to develop intelligent systems. These techniques range from rule-based systems to sophisticated deep learning algorithms. Thorough discussion of the AI techniques is strongly beyond the scope of this chapter. We will instead give a quick overview of the main AI techniques and discuss how they are used in building intelligent systems. Additional details can be found in [Russell 2003, Hurwitz 2015, Leondes 2002] and others.

10.5.1 Rules and Rule-based Expert Systems

Rule-based processing is one of the most commonly used technique in AI. As mentioned previously, expert systems are typically based on a set of rules that are used to make recommendations. The following is a rule in its simplest format:

If *Condition* Then *Action*

The following is an example of a set of rules, written in English, to represent a very simple travel advisor:

R1: If distance < 1 mile then Walk
R2: If distance > 1 mile but < 1000 mile then Drive
R3: If distance > 1000 then R4
R4: If airport < 100 Mile then Fly else Exit

Notice that rule R3 triggers rule R4. Naturally, these rules only represent partial knowledge of a human travel advisor and should be modified to consider other factors such as health and age, financial and time constraints, and the ability and willingness of the traveler to drive and fly. Rules can be very few to very large in a typical intelligent system. They can be written in common programming languages such as C++/Java/C# or in specialized languages such as Prolog, or in expert system shells such as Exsys or JESS. Rules can also be assigned certainty factors (CF) to show probability of an action (0 to 1). For example, R1 can be stated as following:

R1': If distance < 1 mile then Walk (CF =0.3) or Drive (CF =0.7)

Figure 10-19 shows an example of a simple Travel Advisor that is based on the rules R1-R4 specified so far. Rules concerned with same topic area can be clustered into *rulesets* (e.g., a ruleset for flying). For example, the initial rules can invoke additional "rulesets RA-RD, shown in Figure 10-19, that provide suggestions and guidelines for walking, driving and flying. The additional rules may include factors such as expense and time involved for each decision and may also ask the users some questions about cost and time preferences. The objective is to guide the travelers to an acceptable solution. Please note that the Exit Ruleset (RD) has the following rule "R6: If Pleasure Trip then Don't Go (Unpleasant Trip - CF = 0.8)". The Travel Advisor suggests that a long trip with multiple hops will not be a pleasure with certainty of 0.8/1.0.

The rules could be written in a programming language or a rule-based system expert system shell such as Exsys. A more intelligent system emulates the behavior of a highly experienced human travel advisor who has comprehensive knowledge about traveling plus has the DAL (detect, adjust, learn) capabilities mentioned previously. The intelligent expert system would have more rules to *detect* which routes are congested due to some events (e.g., an accident), *adjust* the recommended travel schedules based on the traffic situations, and *learn* how to give a better advice in the next round. Some of these rules may be simple, based on known holiday seasons, or sophisticated based on current newscasts or social media casts.

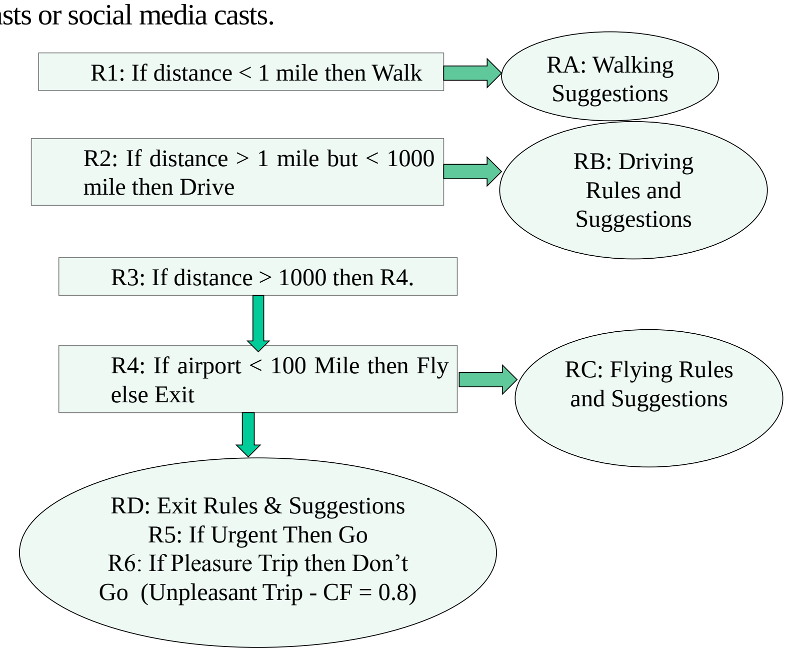


Figure 10-19: Example of a Rule-based Travel Advisor

As stated previously, an expert system, is essentially composed of two sub-systems: the knowledge base and the inference engine. The knowledge base represents facts (for example, the distances between various locations) and the rules that use the facts to make decisions. Let us take a closer look at the inference engine to understand how it controls the processing of various rules and provides explanation capabilities.

Inference Engines. The strategy used to search through the knowledge base is called the Inference Engine. Given a large ruleset, the inference engine decides where to start. Commercially available Expert System Shells like Exsys have powerful inference engines that can execute given rules in a variety of ways. Two strategies are commonly used in the inference engines:

- Forward chaining
- Backward chaining

In *forward chaining*, the inference engine begins with the information entered by the user and searches the rule base to arrive at a recommendation to answer a question such as “what should be my travel plan to attend a conference in Rwanda”. The strategy is to fire, or carry out, the action of the rule when a condition is true. In Figure 10-19, beginning on the left, if the user enters a destination that is more than 100 miles away from starting point, then the engine will fire all rules in sequence from left to right, starting with R2. If the user then enters information indicating the driving preferences in RB, then another pass of the rule base will occur and more rules will fire. Processing continues until no more rules can be fired.

In *backward chaining*, the strategy for searching the rule base starts with a hypothesis and proceeds by asking the user questions about selected facts until the hypothesis is either confirmed or disproved. In our example, in Figure 10-19, let us say that a user asks the question, “Should I go to Hong Kong for a wedding party”. Then then the engine will begin on the conclusion of the diagram and work toward the beginning, asking more questions about the starting point. For a user living in a village in Nigeria that is more than 100 miles away from an airport, the answer will be no but for a person living in Hong Kong, the answer will be yes. The main point is that in backward chaining the answer is always a yes or a no. For example, a user may ask the following questions in a backward chaining system: should I walk to the post office, should I drive to my office, should I fly to this convention. The inference engine will travel backward and keep asking questions to determine a yes or no answer. Then it stops.

Explanation: The use of rules to explicitly represent knowledge also enables explanation capabilities that show why an expert system reached a particular conclusion. This is very important because human experts can also explain why a particular recommendation was made. Explanation is basically a trace of the rules that were “fired” (executed). For example, for the simple advisor, if the recommendation is “Don’t Go” for a 1200 mile trip, then the explanation would simply be that the rules R3 and R4 were fired to reach this conclusion. A significant area for research is the generation of explanations from the knowledge base in simple English rather than simply by showing the more formal but less intuitive rules. Some expert systems such as the Apple Siri produce very natural English explanations.

10.5.2 Case-based Reasoning

Besides rules, case-based reasoning (CBR) is a very powerful technique to represent and process knowledge. The main idea is derived from human specialists who know cases -- descriptions of past experiences – and use these cases to make decisions. For example, lawyers develop legal strategies based on previous cases that are *similar* to the case at hand. Doctors, car mechanics and customer support specialists also use very similar practices. Simply stated, CBR attempts to solve new problems based on the solutions of similar past problems.

Intelligent systems based on CBR search solution databases that could address a similar (analogous) problem. The knowledge is represented as a database of past cases and their solutions. The system uses a multi-step process, shown in Figure 10-20 to generate solutions to new problems encountered by the user. CBR is applicable in the following areas:

- Customer support: Frequently Asked Questions (FAQ) are stored in a database to resolve new problems.
- Medical diagnostic systems: Diagnosis to common medical situations are stored in a database to help with new situations
- ICT in developing countries: ICT solutions to health, education, public safety, public welfare and other vital sectors in different developing countries are stored in a database for future use
- Equipment diagnostic systems: Diagnosis to common machine malfunctions (e.g., cars, computers) are stored in a database to help with new situations

Similarly, knowledge of human specialists in very diverse situations can be represented as cases, and stored in knowledge bases for future problem solving. As shown in Figure 10-20, the commonly used CBR systems use the following process:

- *Problem Description*: The user describes the problem by using given keywords and tags.
- *Retrieval*: Based on the problem, the system searches and retrieves the cases most relevant to solving the problem. A case consists of a problem description, its solution, and some tags that describe the solution.
- *Refinement:* If many possible solutions are retrieved, then the system asks additional questions to find and retrieve the closest fit.
- *Revision:* The retrieved solution is modified and adapted to further fit the solution to the target problem.
- *Retention*: The new solution is tested and if successful, the system stores it to the CBR database as a new case. Thus the CBR database grows with use.

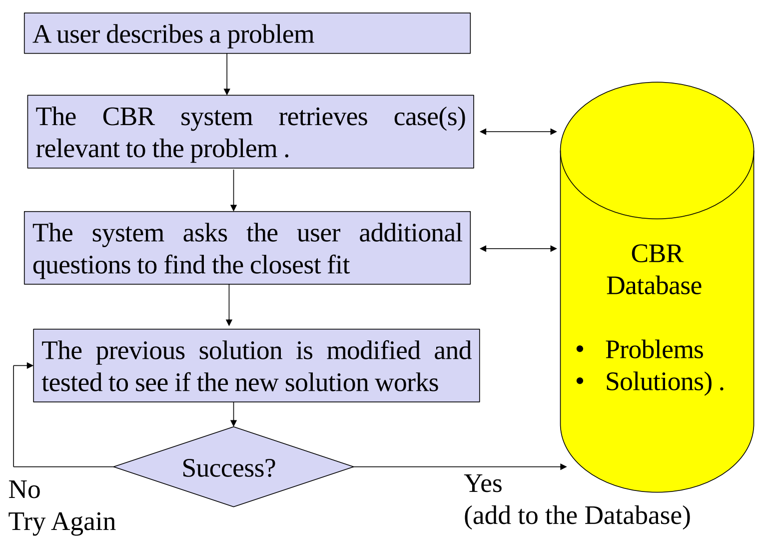


Figure 10-20: How Case Based Reasoning (CBR) Works – A Simplified View

Suppose, for example, that a customer support center has an active CBR system that is based on a FAQ database of cases. Let us assume that a user calls about a network security problem. Then the CBR searches the FAQ database for stored cases for network security, asks more questions (e.g., is it a wireless or wired network) to narrow down the needed solution, finds the closest fit, and modifies the existing solution to further refine the solution. If this case works, then the new solution is added to the CBR database. The CBR knowledge is continuously expanded and refined by users.

Although CBR is used very commonly in several areas. Some critics argue that CBR relies too heavily on past experiences and knowledge. Another challenge is on how to describe the problems and the solutions to find the best fit quickly for the problem. We have done some research in this area where cases are represented by patterns that can be very easily modified. We will discuss this topic in the next chapter.

10.5.1 Decision Trees and Search (Genetic) Algorithms

Decision trees and search algorithms are used in many intelligent systems to find the most suitable solution where many solutions are possible (e.g., the best route to a restaurant). Decision trees are commonly used to graphically display the decision-action scenarios. The main idea is to start with a node and take branches (make decisions) as you move forward. Each decision in the tree leads to more decisions. Different algorithms for following the decision tree have been developed (i.e., when to take a branch and when not to). We have previously described a travel advisor as a decision tree. Figure 10-21 illustrates a decision tree for the blood pressure sample. This tree is first split on age and then on smoking habits. The splits can be based on different factors and domain knowledge.

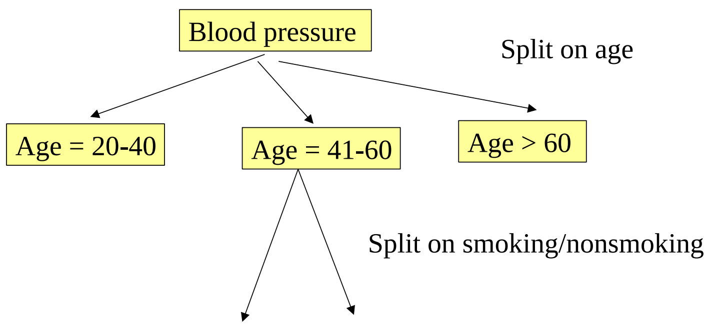


Figure 10-21: Decision Tree

Decision trees can be expanded into genetic algorithms (optimization algorithms) that are useful for finding optimal (best) solutions for specific problems by examining very large number of possible solutions (paths) for that problem. Genetic algorithms are conceptually based on the process of evolution, i.e., search among solutions by changing and reorganizing component parts using inheritance, mutation, selection and other genetic processes. Optimization problems are usually stated as following:

- Minimize (or maximize) an objective function (e.g., minimize cost)
- Subject to a set of constraints (e.g., time constraints)

The following are some examples of common optimization problems:

- Find the cheapest (in terms of fuel consumption) bus route to pick up school kids from various parts of a town and bring them to a school within an hour
- Find the best (in terms of return on investment) stock option for 10 years that does not risk more than $50K.

- Design the cheapest (in terms of component cost) car engine that satisfies all the safety requirements and can be developed within 3 months.

These are complex problems that require extensive search algorithms or mathematical programming techniques such as linear programming, nonlinear programming, integer programming and dynamic programming. Mathematical programming is strongly beyond the scope of this book (see [Winston 2002] for details). However, we will illustrate the concept of search algorithms by using a simple example.

Figure 10-22 shows a simple search algorithm for finding the quickest route from a house to an airport. The algorithm proceeds as follows, starting from home H (we assume that there is no direct route from H to the airport):

- Generate 3 possible routes to locations A1, A2, A3. Let us say that A2 is the closest, so the first destination is A2.
- Test to see if this state (A2) is actually the solution. It is not, so let us now generate 3 more paths (to B2, B3 and Airport).
- Airport is the desired solution, so the algorithm stops and suggests that the desired route is H-A2-Airport.

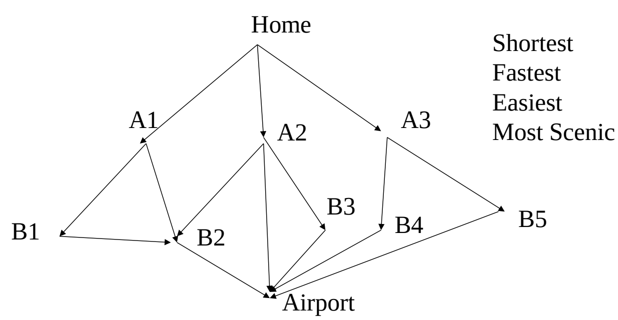


Figure 10-22: Search Algorithm to Find a Route (from Home to Airport)

The search algorithm proceeds from one selected destination (called state) to another. In each step, the quickest solution is found. The search can be for the shortest, quickest, easiest, or most scenic route. Also, the search can be breadth-first or depth-first:

- Depth-First: follow one solution path and descendants
- Breadth-First: Search all siblings before descendants

In general, depth-first search is faster with some human guidance for common sense solutions. The following is a highly simplified version of a search algorithm:

STEP0: Start from an initial state S0 (home) and make Sm=S0
STEP1: Generate several next possible states and select a new "best" solution state Sm
STEP2: Test to see if this state can be the final solution Sf (has optimal objective function)
STEP3: If yes, then Sf = Sm and Exit, else go to step1 and reiterate with a new Sm

10.5.2 Segmentation (Clustering and Classification)

<u>Segmentation</u> is partitioning of a group of records (e.g., customers) into subsets of similar records. This is important for customer support because it helps us to understand who are the customers. It is much easier to analyze twelve segment view vs. million customer view of a customer population.

Segmentation also helps us to identify the common activities among the customers. To make strategic decisions for the business, companies determine product bundling based on segmentations, and then suggest re-pricing strategies. To construct segments, the following approaches are typically used:

- Supervised (hand-built) learning
- Automated (unsupervised) learning

Hand-built (supervised learning), also known as classification. This is a traditional approach to segmentation. You first decide on a classification based on age, income, etc. and create classification “buckets”. Each new record is checked for the attributes and thrown into the appropriate bucket. For example, if buckets were created based on age (i.e., under 30, 30 to 50, and over 50). then a new record with age of 35 will be thrown into the middle bucket. This is shown in Figure 10-23. Basically, the records are split on exactly the fields you define -- and only those fields. This type of clustering shows, for example, how many people in different age groups are buying a certain product.

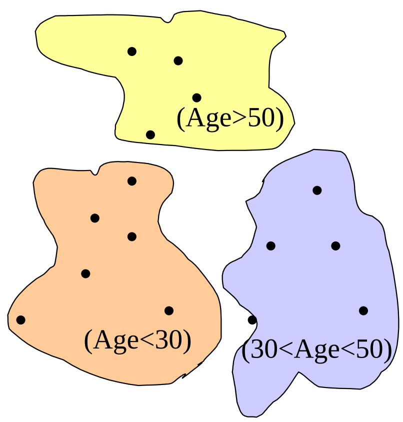


Figure 10-23: Segmentation based on age

Automated clustering (unsupervised learning). In this case, clusters are formed based on discoveries of interdependencies in the population. For example, a study of high blood pressure patients may discover the interrelationships between the high blood pressure and age by simple correlations. Unsupervised learning uses more fields to capture more behavioral data and can discover ways to cluster (generate segments automatically). It can also yield unexpected segments, for better or worse. Due to the importance of this technique in discoveries, this technique is used more often and is discussed in more detail here.

The main idea is to group similar things based on a “distance function” that is discovered, induced, or learned. Consider, for example, a collection of customer records (a "customer data warehouse") with information about age, salary, city, education level, type of job, etc. The clustering is done by the system (unsupervised) based on some “observations” it makes. For example, clustering of customers can be tried based on similar things bought, education level (minimize distance function). It is reasonable to assume that the “distance” between someone with salary of $50K is large with respect to someone with salary over $200K but small with respect to a salary of $60K. Some attributes may have more weight assigned to them based on what is being studied. You can assign a composite distance function (e.g., yuppies, soccer mom).

A large number of clustering techniques have been developed and many are built into existing data mining tools. Here are two examples:

- RFM (Recency, Frequency, Monetary): Segmentation based on when a person became customer, frequency of interactions, and value of customer.

- K-Means Clustering: Pass through customers, assigning each to the closest existing cluster center. Later readjust cluster centers when customers are moved.

There are many other segmentation schemes -- hundreds, if not thousands -- which seek to optimize different objectives. Surveys can be found in [Witten 2011] and KDD (Knowledge Discovery and Data Mining) conferences (www.kdd.org/conferences).

10.5.3 Visualization and Pattern Recognition Using Fuzzy Logic

These approaches can visually identify trends by recognizing dense areas and outliers. This separation is important because the outliers may indicate noise (wandered into a wrong neighborhood) or they may suggest main focus of investigation (i.e., more sales than anyone else). Visualizations use static graphs and charts but animations are much more powerful than static charts.

Pattern recognition heavily uses *fuzzy logic*. Fuzzy logic is based on "degrees of truth" rather than the usual mathematical "true or false" logic. The idea of fuzzy logic was first advanced by Dr. Lotfi Zadeh of the University of California at Berkeley in the 1960s. The following statements show exact versus fuzzy relationships:

- Exact relationship: A > B (A is greater than B)
- Fuzzy relationship: A >> B (A is much greater than B)
- Exact relationship: A = B (A is equal to B)
- Fuzzy relationship: A is similar to B (A is similar to B)

Figure 10-24 shows an example of how character "6" can be recognized in an optical character reader (OCR) by using fuzzy logic. The reader knows that the number is between 0 and 9, so it maps the recognized patterns against the possible characters. The reader recognizes the input character to be 6 because three images point to 6 as compared to two for 3 and two for 8. The recognition will naturally improve as more images are available. So the initial two readings of the images are fuzzy but they become exact after the third readings.

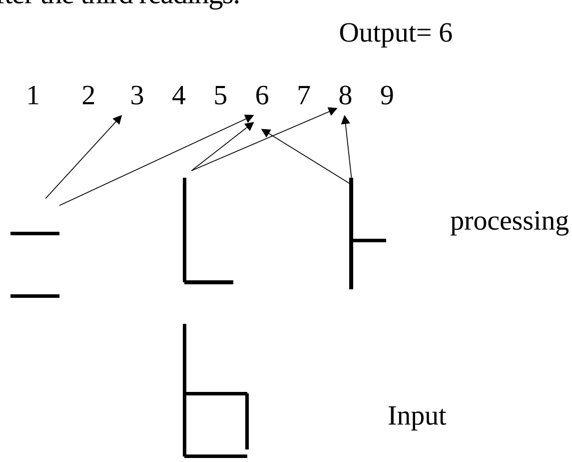


Figure 10-24: Recognizing Character 6 in an Optical Character Reader

This idea of making initial fuzzy observations that are converted to exact logic with more observations is at the core of pattern recognition. Many handwriting analysis systems at present on handset screens use fuzzy logic. Similarly automated heating and cooling systems use fuzzy logic by converting fuzzy terms such as cold, warm, and hot into exact temperatures because different people use different terms to define room temperature. For example, one person may consider may consider

40 degrees Fahrenheit to be cold while someone else may consider it warm. However, no one would consider 120 degrees Fahrenheit to be cold. Many fuzzy logic based temperature control devices are commercially available on the Internet.

10.5.4 Neural Networks and Introduction to Machine Learning

Neural networks attempt to mimic the processes of human brain. As mentioned previously, the human brain consists of neurons (information processors) that are very slow (few instructions per second). However, each brain has a very large number (50 to 150 billion) of neurons that are partitioned into networks where each network has thousands of neurons. In addition, each neural network is highly interconnected thus information is shared across neurons on a regular basis.

ANNs (artificial neural networks) are used to mine data by simulating a limited model of human brain. Basically, software routines represent massively parallel processes that produce results. Routines are typically represented as equations that communicate with each other through messages. More importantly, weights are assigned to inputs/outputs to indicate “importance” and values of weights are adjusted based on learning. The network is exercised (trained) to learn. Some research is also going on in applying massively parallel processors to neural networks (i.e., smart and fast brain).

Consider, for example the equation (customer value = age x 0.7 + income x 1.0) that represents the value of a customer (in terms of his/her ability to pay) to a business. In reality, equations can be very long and complicated Let us determine how the weights (0.7 and 1.0) are assigned in this equation. This is where ANNs come into the picture. Let us consider the following general equation with unknown weights w1 and w2:

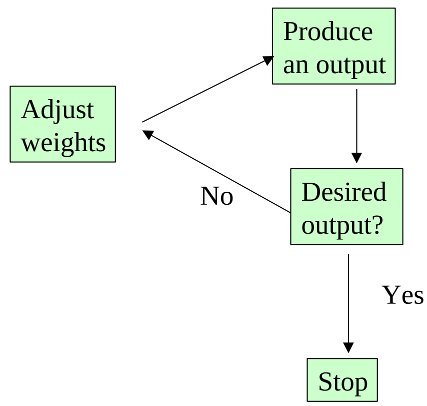
Outcome (ability to pay) = age x w1 + salary x w2

Initial weights are assigned to the links and then the network is trained by exposing it to different data (e.g., samples of customers who have or have not paid loans in the past). For example, w1 is assigned an initial weight of 0 and w2 is assigned a weight of 100. This reflects the thinking that only salary determines the ability to pay. But suppose that actual records from a company show that this is not the case. Learning occurs by adjusting the weights w1 and w2 to match the real outcomes. Once w1 and w2 are adjusted for this company, then they are adjusted for another company records, and so on. This adjustment of weights, called “training the ANN” can be repeated several times. The learning can be supervised (i.e., know the results and adjust accordingly) or unsupervised (discover and determine the weights). See Figure 10-25 for an example of ANN learning. Training/learning is an ongoing process.

10.5.1 Machine Learning and Deep Learning Techniques

10.5.1.1 Machine Learning and Data Mining – Another Look

Machine learning is an active branch of artificial intelligence (AI) that gives “computers the ability to learn without being explicitly programmed", i.e., computer programs can teach themselves to grow and change when exposed to new data. A very simple example is automatic generation of new rules based on observations. Consider that you observe that a crow is black. Then you observe another crow that is also black. After observing a dozen black crows, a new rule is generated “If crow, then color = black”. However, after traveling to different places in the world, you observe that some crows are green. Then this rule is modified to “If crow, then color = black with certainty 0.8”. The basic idea is that we as humans generate and modify rules based on observations, i.e., we learn through observations. Similarly, the machines can automatically learn new rules and modify them based on observations.



•Learning takes place in several “Training sessions”
•In each session, start with a known result and adjust weights to produce the result
•After several sessions, the weights should not change (“trained”)

Supervised Learning: known outputs, adjust weights (e.g., loan applications)
Unsupervised learning: no known results, discover (data mining) based on input/other data (e.g., age with blood pressure)

Figure 10-25: Learning in Artificial Networks

Machine learning is not limited to generating and modifying rules. Machine learning algorithms can generate new code that handles new situations based on observations. Thus the algorithm itself is modified as it encounters more data. Machine learning is used in a wide range of applications such as spam filtering, speech recognition, optical character recognition, and computer vision. Machine learning is also used in predictive models that estimate future results based on past data and adjust themselves as new data is encountered. It is also used in mathematical optimization and search algorithms which modify themselves as they learn new information (e.g., learn to ignore a route if it is too congested). Machine learning is a broad area of work that employs most of the techniques discussed so far (e.g., clustering, segmentation, fuzzy logic, neural networks) and many more.

Machine learning is also used heavily in data mining. In data mining (i.e., discovering knowledge from data), machine learning is used to devise predictive models that future results based on historical relationships and trends found in the data. Data mining tools use artificial intelligence based pattern recognition technologies in their data search algorithms or data visualization techniques to enable human pattern recognition. Data mining tools are more powerful than the traditional query tools that do not recognize hidden relationships within data and cannot handle complex patterns. In most cases, data to be mined is extracted and loaded into a mining file. The main emphasis in data mining is on discovering hidden patterns and relationships in a given data set. This is why data mining is also known as KDD (Knowledge Discovery and Data Mining) to discover and understand the relationships between the dependent and independent variables. Consider the following:

X = f(a,b.c,d)
Where X = dependent variable and a, b, c, d are independent.

Some dependent and independent variables are clearly known, some are not. The main trick is to discover the hidden interdependencies (the function f). For example, buying a gift is dependent on a birthday (i.e., buying a birthday card). Many mining algorithms rely on segmentation (clustering, classification) for discovery. Another key component of data mining algorithms is the use of Artificial Intelligence (AI) to learn and to recognize similar patterns. As stated previously, AI is concerned with machines doing what humans perceive as intelligent behavior. We have already studied the main aspects of AI such as knowledge representation (how do you represent knowledge), inference (making decisions from knowledge), and learning (updating the knowledge). Data mining algorithms use all aspects of AI to discover, learn and remember new patterns.

10.5.1.2 Deep Learning – Learning based on Big Data

Simply stated: Deep Learning = Machine Learning + Big Data. This simple statement has profound implications because machine learning has been given a big boost due to the availability of Big Data – the massive amount of data that is now available. The Big Data (BD) is so large and so diverse that a human being simply cannot understand it, but machines can. In other words, deep learning can surpass human learning because machines can discover and learn hidden patterns from BD but humans cannot.

Deep learning also uses a set of *deep learning algorithms* that attempt to model abstractions in data by using a deep graph with multiple processing layers, composed of multiple transformations. Different aspects of deep learning can be represented in terms of a two dimensional view, shown in Figure 10-26, in terms of type of learning algorithms and type of data being used in learning:

- Traditional machine learning algorithms when applied to regular data reveal knowledge and patterns that can be discovered by human beings. But the machines do it quicker. This is the common practice at present. For example, learning about customer complaints (trouble tickets) based on simple observation of "small datasets" is used commonly in the current situations.
- Traditional machine learning algorithms when applied to Big Data reveal knowledge and patterns that cannot be discovered by human beings. For example, learning about hypertension (i.e., high blood pressure) based on simple observation of "small datasets" (e.g., blood pressure readings in a population of 2,000) is very different than learning from a dataset with readings from a population of 20 million. So, the size of the dataset matters even when the same learning algorithm is used because it can discover statistically significant relationships that do not show up in small datasets. For example, a relationship between blood pressure and patient weight is much more clearer in a 20 million population versus a population of 2,000 .
- Deep learning algorithms can be applied to regular data to reveal knowledge and patterns that require more than just observations. Deep learning algorithms exploit neural networks to discover patterns through different representations. Thus a deep learning algorithm about customer complaints in a dataset of 2,000 complaints could discover interesting patterns of complaints (e.g., customers of products that are heavily marketed tend to complain more because their expectations are higher).
- Deep learning algorithms when applied to Big Data reveal knowledge and patterns that simply cannot be discovered by human beings. This is an area of "advanced deep learning". Deep learning algorithms when applied to huge quantities of data are creating exciting new applications such as driverless cars and intelligent robotics. In particular, deep learning algorithms exploit neural networks in BD to discover innovative patterns through different representations. For example, an image of a face can be represented in many different ways to highlight different features such as eyes, nose, chin, etc. and then compared to determine if two different facial images represent the same person. Use of neural networks in deep learning algorithms to discover patterns in Big Data is an active area of research at present.

Learning Algorithms		Regular Data	Big Data
	Deep	Deep Learning on Regular Data	Advanced Deep Learning
	Simple	Traditional Machine Learning	Simple Learning on Big Data

Figure 10-26: Two Dimensional View of Deep Learning

10.5.1.3 Analytics Tools and Deep Learning -- A Quick Overview

Data analytics is the use of data, information technology, statistical analysis, quantitative methods, and mathematical models to help managers gain improved insights about their business operations and make better decisions. Data analytics of Big Data is a rapidly evolving area of work especially for business intelligence. For example, descriptive analytics uses Big Data to discover relationships between patient health and medication used, predictive analytics is used to predict the future based on past observations, and prescriptive analytics uses optimization techniques to find, say, the least expensive solutions to a problem. Many data analytics projects at present are based on Big Data repositories in health, education, public safety, public welfare and other vital sectors.

The idea is simple: deep learning takes a model of human brain (called neural network) and populates it with Big Data on a subject matter (let us say skin cancer) to develop an expert system that is smarter than any skin cancer doctor. The basic premise of this work is that a human brain cannot store and retain extensive knowledge but a computer brain can. The goal is to develop smart lawyers and smart doctors as expert systems based on deep learning that are far better than human experts. This is the research direction based on IBM Watson.

However, development of super smart systems based on deep learning are raising several issues that range from prediction of massive unemployment to destruction of the human race [*Kurzweil 2005]*. No one knows what the future holds. Nevertheless, the main advantage of super smart systems that are smarter than best human experts is that these systems may discover cure to diseases that human experts cannot. In addition, once built, these systems can exchange information with all others. For example, as stated previously, if you learn about how to drive in heavy snow, then only you know it. But if an intelligent car learns the same lesson, then this knowledge can be replicated to all other cars quickly now and all other cars in the future.

Time To Take a Break

- ✓ AI and Intelligent Systems
- ✓ Examples and Case Studies
- ✓ AI Tools and Techniques
- More Examples and Case Studies

Suggested Review Questions Before Proceeding

- Which AI techniques discussed in this chapter are of most interest to you and why (identify 2)
- How do rule-based systems differ from case-based reasoning
- How is machine learning related to all other AI techniques reviewed in this section
- Suppose you are in the process of developing a marketing plan for an international company. How will the "Two Dimensional View of Deep Learning" presented in Figure 10-26 help you in developing a marketing plan.

10.6 More Examples of AI and Intelligent Systems

As mentioned previously, AI has been used in a very wide range of sectors that span health, education, public safety, public welfare, agriculture, transportation, and other vital fields. The following applications of AI have become routine in business settings:

- Financial institutions have long used artificial neural network systems to detect charges or claims outside of the norm, and then flagging these for human investigation.
- Robots have become common in manufacturing industries. They are often given jobs that are considered dangerous and too repetitive for humans.
- Answering machines of call centers routinely use speech recognition software to allow computers to handle first level of customer support.
- Agent training in marketing is being conducted by automatic mining of best marketing practices from past interactions with customers.
- Agricultural robots are being used for harvesting crops and drones are used for weed control.

However, as our perception of what is considered intelligent behavior has changed, so has been the notion of AI applications. For example, in the in the early 1950s, any machine that could perform basic arithmetic was considered intelligent because only humans can add and subtract. But now the bar for intelligent systems and AI applications has been raised to require more complex operations of reasoning and learning. For the purpose of this chapter, we will stay with our definition of intelligent behavior to having knowledge and then also the ability to use this knowledge to detect, adjust and learn (DAL) repeatedly based on new situations. The following examples display these DAL features.

10.6.1 AI in Healthcare and Medicine

Healthcare and medicine have been a favorite area of work for AI and intelligent systems since the 1970s. For example, MYCIN was one of the first expert system that used artificial intelligence for medical diagnosis. MYCIN was developed in the early 1970s at Stanford University to identify bacteria causing severe infections and to recommend antibiotics, with the dosage adjusted for patient's body weight. In fact, MYCIN is derived from the antibiotics themselves because many antibiotics have the suffix "-mycin" (e.g., LincoMycin). MYCIN was written in Lisp -- a popular programming language in the early days of AI. Although MYCIN was never actually used in practice but research indicated that its proposed therapy was acceptable in about 69% of cases -- better than the performance of infectious disease experts. Fast forward to 2013, when IBM's highly successful expert system that defeated Jeopardy champions was commissioned by the Sloan Kettering Institute for training nurses. In between, there have been dozens of expert systems developed for healthcare and medicine. At present, medical clinics can use artificial intelligence systems to organize bed schedules, make a staff rotation, and provide medical information. In addition, AI is being used as clinical decision support systems for medical diagnosis. Other tasks in medicine that can potentially be performed by AI are:

- Heart sound analysis that listen to heart beats and determine disorders that need to be treated immediately.
- Computer-aided interpretation of medical images. Such systems help scan digital images, e.g. from computed tomography, for typical appearances and to highlight conspicuous sections, such as possible diseases. A typical application is the detection of a tumor.
- Robots being used in telemedicine operations where surgeons in Holland can perform a surgery through a robot on patients who are located in Chicago.

10.6.2 AI in Education and Gamification for Education

A large number of Automated Tutors, also known as **Intelligent Tutoring Systems (ITS)**, have been introduced in the marketplace since the 1970s. These automated systems attempt to provide customized instruction and feedback to learners, usually without any intervention from a human teacher. The overall objective is to provide access to high quality education to each and every student, especially in the underserved populations around the globe. A major advantage of the automated tutors is that they do not get tired or irritated with students who are slower in learning than others. In particular, the intelligent tutoring systems can provide the DAL (Detect, Adjust, Learn) capabilities by *detecting* the limitations of the student, *adjusting* the lessons based on the detected limitations (e.g., repeating some concepts more frequently), and *learning* to improve the lessons based on what really works. A detailed discussion of this topic is beyond the scope of this chapter. An excellent overview of this topic can be found at the Center for Innovative Research in Cyber Learning in an online article "AI Applications in Education" (weblink http://circlcenter.org/ai-applications-education/). In addition, the Wikipedia article on Intelligent Tutorial systems (https://en.wikipedia.org/wiki/Intelligent_tutoring_system) gives a good overview of the topic.

Gamification for Education. Gamification is the use of game design techniques to solve real life problems and engage audiences. It typically involves applying game design thinking to non-game situations and make them more fun and engaging (see Figure 10-27). The basic premise of gamification is that adding game features to regular processes such as studying a procedures manual gets the players involved in the process so that they repeat it over and over again to win. The end result is that the players learn a great deal about the process. Consider, for example, the idea of training a nurse on how to take blood pressure by playing a game where the nurse competes against a machine to take blood pressure. If the nurse defeats the machine by scoring better then the nurse gets a reward that is proportional to how badly the machine was beaten. This exercise is much better than having the nurse read the procedures manual and then taking a test.

Figure 10-27: Gamification = Work + Games (change this picture, from UPenn)

Why Gamification: Gamification is in fact a popular “nudging” tactic to encourage specific behaviors, and increase motivation and engagement. For example, a well known gamification initiatives is the Musical Stairs at the Odenplan sub-way in Stockholm, Sweden [Bates 2009]. Each step of the staircase in the subway was setup to play a musical note when it was stepped on. At the end of the campaign, the results showed that 66% more people used the musical stairs over the escalator. This is a good example of gamification, and is used commonly by companies to illustrate benefits of gamification. Besides being used for marketing, gamification is now being implemented in many educational programs to make learning more fun. The main objective is to narrow the gap between knowledge and actual practice.

Gamification can lead to behavior modification, increased loyalty and increase of knowledge. The common gaming models used in gamification are that they are played between opponents or between an expert and a learner with the goal of winning, scoring points, having fun, and/or learning to do better. AI and psychology are used heavily to keep the players engaged. Specifically, the following approaches are used to engage the users in a learning process by using gamification:

- Scores
- Bonus points
- Competition
- Community Collaboration
- Ownership

The main limitation of gamification is that its *image* is fun and not work. Thus many government agencies do not allow government employees to use gamification because government employees should not have fun at taxpayer’s expense! In addition, some games use too much graphics but the content itself is shallow. For example, some business gamifications use fancy graphics that are built on top of simple Excel spreadsheets.

Platforms for Development of Gamification: Gamification developers need a platform with features such as the following: flow and control, decision making, animation, sound, and others (e.g., collaboration). The following possible approaches can be used:

- Simple games can be developed by using Powerpoint, HTML5, or simple tools such as Twine (http://twinery.org/)
- Serious games can be developed by using C# and Unity3D, and many specialized platforms.

The following is a short list of references on gamification:

- http://gamification.org, Gamification.co and Badgeville.com have good examples of gamifications
- Beyond Business Gamification Thinking, Advanced Research in Scientific Areas 2012 - Mário André Ventura, Daniel Tiago Ribeiro.
- Harnessing the power of game dynamics1 ; Why, how to, and how not to gamify the library experience.

- Serious Games Integration in Companies: A Research and Application Framework
- Advanced Learning Technologies (ICALT), 2012 IEEE 12th International Conference in July 2012

10.6.3 Intelligent Robotics

Simply stated, a robot is a programmable, self-controlled device consisting of electronic, electrical, or mechanical units that perform human functions. Robots are highly suitable for several work functions because, unlike humans, robots never get tired; they can detect and endure physical conditions such as radiation and pollution; they can operate in airless conditions; they do not get bored by repetition; and they cannot be distracted from the task at hand.

Early industrial robots handled radioactive materials in atomic labs and performed heavy lifting jobs in factories (e.g., move tons of metals from one work-station to another in a manufacturing plant). Common industrial robots are heavy and rigid devices that operate in structured manufacturing environments and perform single highly repetitive tasks under pre-programmed controls. These robots were connected together with steel cables and mechanical gadgets. Current robots use sensors, wireless networks and artificial intelligence (AI) techniques to perform unstructured tasks for a variety of scenarios. There are more than a million robots in operation at present that are performing tasks such as the following (see https://www.pc-control.co.uk/robotics.htm) for additional details):

- Industrial robots, as mentioned previously, that perform routine manufacturing tasks for packaging, parts transfer and machine load/unload in factories.
- Security robots patrol the building at night to check for smoke, humidity, and damaging chemicals.
- Robots that can move and work like humans, learn new tasks with little or no training, and react with sensitivity to the changing moods of their mortal masters.
- Domestic robots that perform tasks such as lawn mowing, car washing, vacuuming the home and pouring selected wine. Some of these robots attempt to walk like human beings but are not as even as we are.
- Office assistant and medical assistant robots that get coffee and fetch needed medicine. Some of these tasks are simple but the robots add conversations to augment their effectiveness. For example, to express its understanding of the command, the robot repeats the command as a question: "Get coffee from the kitchen?" "Yes, please," the user answers.

Intelligent Robots are a newer breed of robots that heavily rely on AI techniques, in addition to the mechanical tasks of lifting, moving and walking. Intelligent robotics is also known as *cognitive robotics* where the robots can learn and remember the lessons learned. Specifically, these robots use the following DAL (Detect, Adjust, Learn) capabilities:

- *Detection (D)* through sensors that provide vision, speech recognition, sound, touch and other sensing capabilities. These sensors are connected to other parts of the robot, other robots, mobile apps, and the end users through wireless sensor networks such as Bluetooth and Zigbee.
- *Adjustment (A)* through motion or sound. For example, robots in medical laboratories say “ouch” if the injection is too abrupt -- they detect an abrupt injection and then generate the “ouch” sound. In addition, many robots can quickly detect an obstruction and find a way around it.
- *Learning (L)* by using the machine learning algorithms mentioned previously. For example, a robot can learn that a particular path is obstructed by a wall and automatically adjust its travel plans *before* hitting the wall again, and again. Machine learning techniques such as neural networks are used commonly in the current breed of intelligent robots. A very interesting area of work is using *deep learning* based on Big Data and Deep Algorithms in intelligent robots.

Intelligent/cognitive robotics is an active area of research at present. The basic idea is not to make robots that can do as well as we can (what is the use of that?) but to instead make robots that do *better* than us. Specifically, a highly intelligent robot should be able to do the following:

- Run faster than us
- See what is behind us, in addition to seeing ahead
- Detect dangerous radiations that we cannot detect
- Lift heavier objects and throw them farther than we can
- Operate in extremely hot and cold temperatures
- Learn from Big Data better than we can (i.e., discover patterns and learn lessons that are hidden in the Big Data)

Many of these features are already becoming commercially available in the robots at the time of this writing. This is raising some interesting issues about the *singularity* — the point at which artificial intelligence can match, and then overtake, human smarts. Some futurists think that the singularity might happen by 2020, while others say by 2100. Some feel that it is already happening. Another active area of discussion is the impact of intelligent robots on the society itself – many feel that this research should be suspended because it will cause massive unemployment and destroy humanity. We will just have to see.

Main Sources:

- https://www.pc-control.co.uk/robotics.htm
- www.iros2016.org/. 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems), Deajeon, October, 2016.
- Cognitive robotics - https://en.wikipedia.org/wiki/Cognitive_robotics

10.6.1 IoTs and Smart Devices

A very large number of devices are becoming intelligent ("smart") by utilizing the AI capabilities of DAL (Detect, Adjust, Learn). Most of these devices are IoTs (Internet of Things) that use sensors and wireless networks for detection and can also learn and utilize the knowledge gained for improved future operations. Specifically, these devices use the following DAL capabilities:

- *Detection (D)* through sensors that provide vision, speech recognition, sound, touch and other sensing capabilities. These devices are connected to other devices through wireless sensor networks such as Bluetooth and Zigbee.
- *Adjustment (A)* through sound or other means. For example, a smart radiation detector can detect a dangerous level of radiation and automatically trigger an alarm.
- *Learning (L)* by using the machine learning algorithms of data mining, fuzzy logic and case-based reasoning. For example, a smart university building can detect that there are evening classes on Mondays and adjust the energy controls accordingly.

A very large number of smart devices with DAL capabilities are commercially available at the time of this writing in almost all sectors of our life e.g., health, education, public safety, public welfare, transportation, agriculture, travel, entertainment and many other sectors. For example, smartphones and smart watches have a wide range of sensors with many connectivity options (Cell, WiFi, Bluetooth, Zigbee, etc) and the capacity to learn so that these device in our pockets can automatically monitor our movements, location, and workouts throughout the day and provide suggestions. For example, a smart phone can capture your speech pattern over many years and detect when you are beginning to have dementia. Many interesting applications of smart devices actually are in the WoT (Web of Things) where the IoTs are Web enabled (see http://webofthings.org/). In WoTs, each smart device has an API (Application Programming Interface) that can be invoked by a remote program over a wireless network with links to GPS.

A conceptual view of a smart retail business is shown in Figure 10-28. At the core of this business is a mobile app (RoboApp) that allows the smart phone users to order items through a speech recognition system. The RoboApp then makes selections from a list of ordered items based on the current inventory and also makes suggestions for items that could be added to the inventory. The RoboApp is also linked to a host of vendors that exist on the cloud and to the Big Data about available products on the Internet. The RoboApp also notifies an intelligent robot to receive the items when they arrive in the warehouse and update the inventory database so that it is available for future purchases. Another intelligent robot could, if needed, place the new items on the shelf for the walk-in customers. Many more permutations of automated workflow in a retail store of the future can be envisioned with intelligent apps and intelligent robots performing the tasks that that the humans do at present.

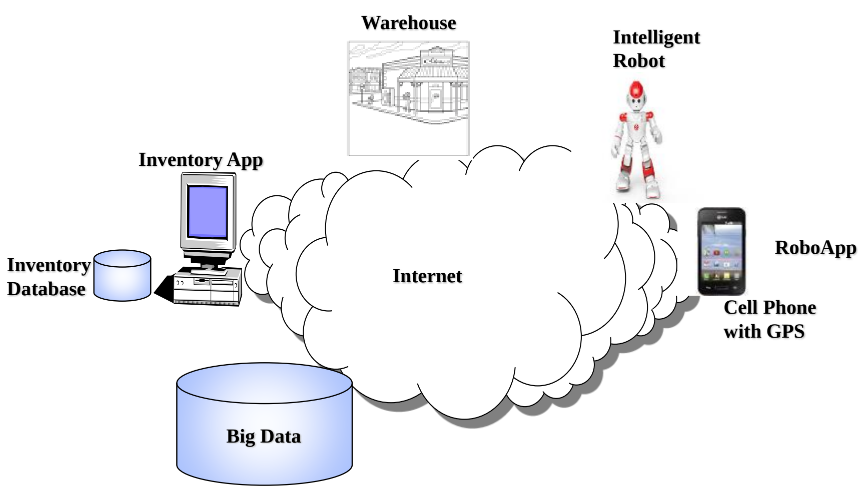


Figure 10-28: Smart Retail with Smart Devices and Apps

10.6.2 Smart Services, Smart Enterprises and Smart Cities

Smart services and enterprises exploit a mixture of agility, detection, and learning capabilities to satisfy the end user needs. For the purpose of this chapter, we have adopted the following definition: A smart system has knowledge plus three basic features, displayed as three axis in Figure 10-29:

- <u>Detect (D)</u> a problem/opportunity
- <u>Adjust (A</u>**)** quickly as needed
- <u>Learn (L)</u> to improve the future operations

In addition, a smart service must also satisfy the functional and non functional requirements imposed by the users – a system that does not provide the basic features needed by the users cannot be considered smart. For example, a smart patient administration system must first register the patient and handle payments, etc and then support intelligent operations. Thus a smart system must provide the DAL (Detect, Adjust, Learn) features and also must satisfy the following:

- Functional requirements (e.g., the features provided by the service must be actually needed by the users and supported completely by the service).
- Non-functional requirements that include security and privacy considerations, usability of the service, interoperability and integration guidelines with other needed services, regulatory and standards compliance, and service continuity in case of disasters and outages.

For example, a smart environmental protection service must be a feature rich service that satisfies the performance and regulatory/security requirements of EPA (environment protection agency) and should *also* be able to:

- Detect pollution concentration in city streets (automatic alarms when the radiation level rises to a certain level)
- Adjust the system to shut down some sources if needed
- Learn what caused the pollution to prevent in the future and predict future pollutions instead of just detecting (predictive versus reactive mode)

The smartness cube shown in Figure 10-29 illustrates how a "dumb" system with almost no capabilities for detection, adjustment or learning (point A) can gradually reach the smartest stage with 100% DAL capabilities (point H). An assessment of existing systems can be represented as different points on the cube and strategies to move towards smarter systems can be represented as different paths on the cube. Thus smartness can be introduced gradually. A wide range of technologies such as sensors, speech recognition, computer vision, pattern recognition, self healing networks, mobile apps, data analytics, and intelligent workflow systems can be used to move existing systems to smarter points in the cube. However, technologies alone cannot make a system smart. In fact, smartness can be achieved through a combination of people, processes and technologies.

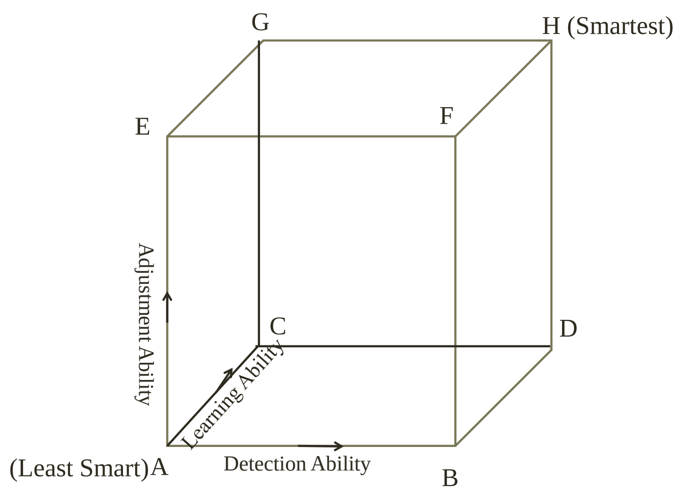


Figure 10-29: The Smartness Cube (Source: [Umar 2014])

Smart enterprises have the knowledge about their enterprise and also have the ability to detect problems as well as opportunities quickly, adjust quickly to handle the detected situation, and learn how to do it better in the next round. The core systems that support enterprises are really a network of interconnected systems. Specifically, inventory shortages impact sales, supply chains directly impact inventory; problems in shipping result in serious customer support issue, etc. We reviewed the main features of smart enterprises in Chapter1 when we introduced the concept of Next Generation Enterprises.

Smart projects face many challenges due to numerous technical as well as business/management decisions that involve

- People, processes and technology tradeoffs (e.g., can well trained people and efficient processes/policies compensate for the lack of technologies especially in developing countries).
- Small versus large projects considerations (e.g., should all components of a large system such as a city be smart and can a smart "bus" between dumb components make it smart).

- Regional factors that differentiate smart systems in the developed versus developing countries (e.g., will a smart city in Nepal be the same as a smart city in Belgium).

Consider, for example, a small city that wants to provide "smart" health and human services. What does that mean? A city supports several sectors that span health, education, public safety and public welfare and each sector provides several services (see Figure 10-30). All the sectors are interconnected through an ICT infrastructure and each sector also has its own internal ICT infrastructure to support its services, shown in Figure 10-30. Specifically:

- Which services in which sectors should be made smart? Large and complex systems (e.g., enterprises) consist of individual components and communication mechanisms between components.
- Small systems have few components, e.g., a small health clinic but large systems consist of many systems (systems of systems), e.g., corporations, cities, healthcare networks
- The components may be technology or human components.
- To build a smart system, individual components are smart (through DAL) or interactions *between* components are smart (e.g., healing networks)
- People, processes, and technology tradeoffs must be evaluated carefully instead of piling up technology bags. In particular, DAL features can be supported by people, processes, or technologies making tradeoff analysis necessary. Low technologies may be compensate through smart people and processes, However, if smart technologies are available, then less smarts are needed in people and processes.
- In developing countries, smart technologies may be available but not be suitable. For example, is it smart to build an automated smart system in Nepal that lays off 200 people (is it better to build smarts in people and processes?).

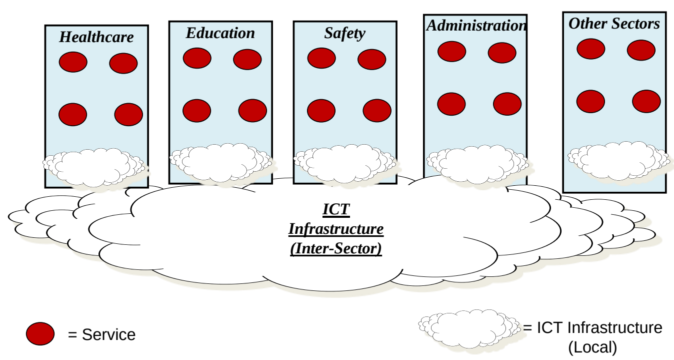


Figure 10-30: Conceptual View of a Smart City

Cities are basically enterprises that concentrate on public service. Thus the core systems that support a city are also a network of interconnected systems. Health and crime issues can reduce tourism. Traffic congestion impacts the environment and wastes energy. Communications problems can affect public safety issues, and water pollution can cause health problems. Modern versions of these interconnected systems have added sensors, monitors, video surveillance, RFID and other devices that enhance their capability and capture volumes and volumes of data. See the sidebar "Sample Features of Smart Cities" for some short examples. Unfortunately, it is very hard to make sense of any of this data. Intelligent analytics and AI technologies help cities understand how their core systems are interconnected and how to make their infrastructures smarter.

IBM introduced its Smarter Planet vision in 2008 that focused on how the next generation of intelligent systems and technologies could be used for smarter power grids, smarter food systems, smarter water, smarter healthcare, and smarter traffic systems (http://www.ibm.com/smarterplanet/us/en/). In addition, sophisticated algorithms and analytics based on Big Data attempt to make sense of it all. In 2015, IBM promoted the concept of cognitive business, with IBM Watson at its center. The Cognitive Era advances the idea of an intelligent, instrumented and interconnected world that relies heavily on analytics, natural language processing and machine learning. The goal is to build the people, processes and technologies systems that can understand, reason and learn from each other. Figure 10-31 shows a broader view of the Smarter Planet vision.

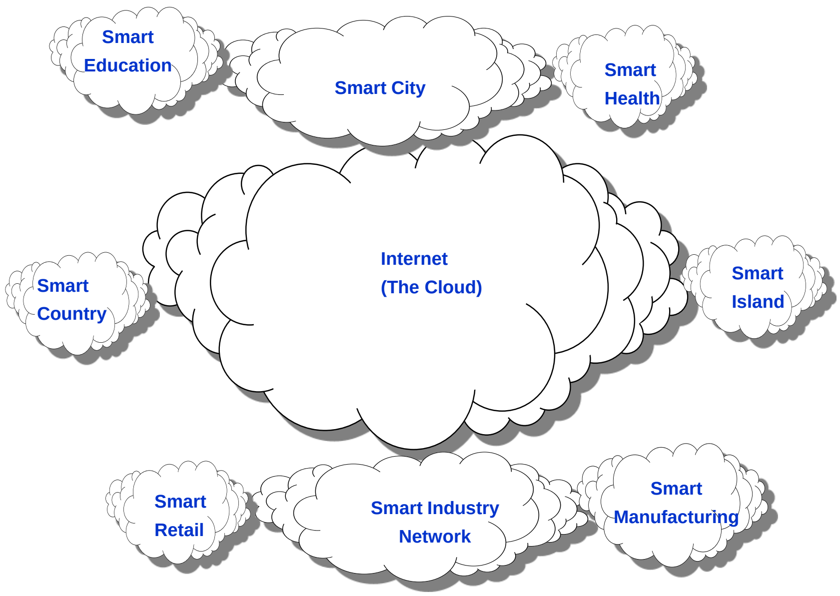


Figure 10-31: Smarter Planet

Sample Features of Smart Cities

- Clean Streets: Sensor enabled trash cans use real-time data collection and alerts to let municipal services know when a bin needs to be emptied. This can reduce the number of pick-ups required and result in fuel and financial savings.
- Improved City Parking: Sensors, mobile apps, and real-time web apps can help drivers to quickly find an open spot for their cars.
- Pollution Warnings: Sensors installed in sewer systems can alert the local residents to avoid flushing their toilets during overflow events.
- Efficient Energy: Sensors measure current on a line and identify general malfunction and meter tampering issues.
- Smart Lights. These systems allow a city to intelligently provide the right level of lighting needed by time of day, season, and weather conditions.
- Smart Traffic Controls: Sensors on busy streets at peak hours detect and broadcast the number of vehicles on these roads and warn the new entrants to use alternate routes.

Time To Take a Break

- ✓ AI and Intelligent Systems
- ✓ Examples and Case Studies
- ✓ AI Tools and Techniques
- ✓ More Examples and Case Studies

Suggested Review Questions Before Proceeding

- Give one example of Machine Learning based on Deep Learning Techniques
- Besides Healthcare, list 5 other application areas of AI
- What is the role of Gamification and AI in Education. Explain through an example.
- Give an example of how Intelligent Robots are being used in practice
- What are the practical implications of Smart Devices, Smart Enterprises and Smart Planet

10.7 Summary

AI has evolved greatly since the 1950s pioneer work by Alan Turing and at present spans disciplines such as biology, computer science, engineering, linguistics, mathematics, medical sciences, and psychology. The main thrust of AI is in the development of computer algorithms associated with human intelligence, such as reasoning, learning, and problem solving based on different situations. One or multiple areas from this list can contribute to build an intelligent system. Figure 10-32 shows our basic approach to AI that captures the four key features of human intelligence: Knowledge (i.e., familiarity and awareness or understanding of someone or something), ability to detect (D) a situation and adjust (A) accordingly, and the capability to learn (L) to do a better job in the future. We have repeatedly used this concept, based on the IBM Smarter Planet Initiative, in this chapter.

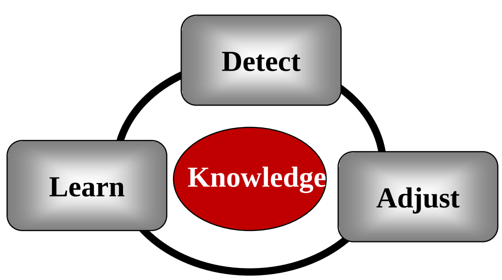


Figure 10-32: Key Features of an Intelligent System

Figure 10-33 shows a more detailed view of AI – it displays different techniques used in the Know-Detect-Learn cycle for AI. The techniques span knowledge acquisition and management, natural language processing, sensors, computer vision, speech recognition, pattern recognition, rule based systems, case based reasoning, business intelligence, fuzzy logic, neural networks, and data mining. This figure is not complete -- it is a starting point. We have briefly discussed these techniques in this chapter. Intelligent systems such as intelligent robots and driverless cars use many of these capabilities. Similarly, smart enterprises also use many of these capabilities but instead of relying mainly on technologies, smart enterprises use a combination of people, processes and technologies to compete in the marketplace. We have used these ideas in this chapter to explain the key concepts and then illustrate them through examples.

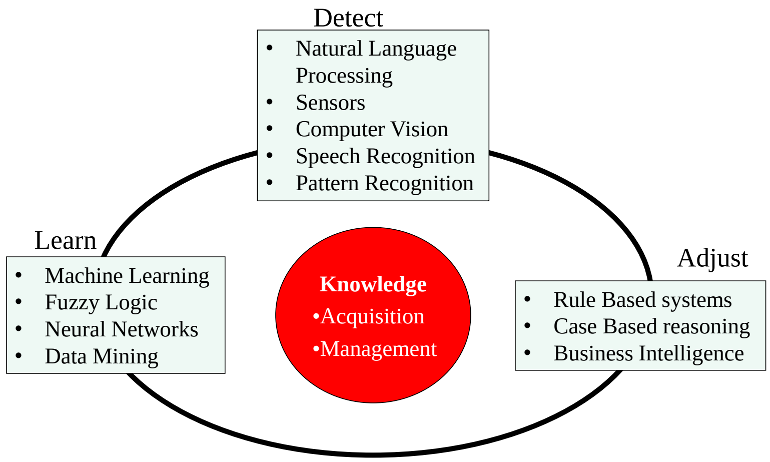


Figure 10-33: Conceptual view of AI

The overall field of AI has gone through several phases since the 1950s. In particular, the world of AI has changed dramatically in the recent years due to the following recent developments:

- Solid research in developing algorithms that mimic different aspects of the human brain and can learn from different situations
- Very fast machine that can run these sophisticated algorithms much faster than a human being can think
- Availability of very large machine readable data ("the Big Data") that surpasses human vocabulary
- Very fast communication networks that interconnect different machines running different algorithms in parallel

The combined effect is that very powerful intelligent systems such as driverless cars have been developed that seem to surpass human intelligence. Some futurists have coined the term "Singularity" as a point when AI equals human intelligence and then surpasses it [Kurzweil 2005]. Some researchers are claiming that the singularity point is as near as 2020 while others contend that it could be as far as 2100. We will just have to see.

Designing a Simple Planner or Advisor – An Exercise

Use the knowledge gained from this chapter to *design* a simple computer aided planning tool that can be used by a small company to plan its IT systems (applications, networks, whatever). Instead of IT planning, you can design any "advisor", e.g., a travel advisor, a loan advisor , or a financial planner. The idea is to use your AI and intelligent systems knowledge to *design* (not implement) a simple expert system for simple situations. The design should show the type of techniques to be used (e.g., rules, case based reasoning, fuzzy logic, neural networks, etc). The deliverable is a gamified design by using PowerPoint, HTML5, Twine or any other suitable tool.

The task is to design only ***one*** out of the following possible advisors:

- Advisor for recommending the right business application software
- Advisor for recommending the right local area network (wired) for a site
- Advisor for recommending the right wireless network for a site
- Advisor for recommending the right computing platforms for a site
- Any other advisor of interest to you (e.g., an office planner, investment planner, loan advisor, whatever)

The Advisor is an expert system that suggests a plan based on a set of factors (questions). The factors may be the company size, type, applications being supported, physical site plan, etc. Potential users of the Advisor are corporate IT planners trying to build a small company. It can be assumed that the users do not know much about technology but know about their business and are literate about general IT principles. The deliverable is a *gamified* design that shows:

- One para on the advisor with a list of key inputs and outputs
- One high level flow chart that describes the overall flow of the advisor
- Show the knowledgebase and the AI techniques used (e.g., the rules, fuzzy logic, case based reasoning, neural networks, etc)

10.8 Major References

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