Week 1: Core A.I. Technologies

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# Core A.I. Technologies

## What exactly is “artificial intelligence”

Dreams of artificial intelligence trace back to philosophical debates in ancient Greece. Prometheus would mold handfuls of clay into images of the gods, and later these creatures were given life. The sprouting of ideas came from mathematics, biology, and computer science before eventually producing modern artificial intelligence. While these different domains have unique perspectives, they collectively land at four categories of intelligent systems (Lukac, Milic, & Nikolic, 2018). The first divide asks if the system *thinks* or *acts*, or more precisely, can reason about the problem. Each of these top-level categories contains subcategories of applications that mimic *humans* versus *rational* actors.

Within a smart car are multiple features that fit into these various areas. For instance, traditional cruise controls attempt to *act human* by following a fixed speed. Meanwhile, a vehicle with an adaptive cruise will *act rationally* through avoid an accident by compensating to slow traffic. The design of some autonomous cars includes capabilities to *think human*, like crawling toward a stop sign, giving the appearance of a human driver.

## Description of Technology

There are three high-level categories of artificial intelligence, specifically rules and heuristics, machine learning, and deep learning (Buchanan, 2005).

1. Before 1962, applications would rely on practical techniques for reducing the trial-and-error search space. This heuristic-centric approach is useful for chess and other video game engines. Despite criticism for being naïve, many LOB (Line of Business) applications continue to leverage this technique successfully.
2. In 1963, Edward Feigenbaum and Julian Feldman’s *Computers and Thought* centralized many ideas across the computing industry. Their literature and new programming paradigms, such as McCarthy’s LISP, lay the foundation that became machine learning. Researches use these tools to build statistical models that represent a situation. For instance, if a customer purchases bread, what else could you recommend? Perhaps butter, jam, and deli meat.
3. In 1949, neural scientists found that the human brain transmits signals between a weighted graph of neurons (Lukac, Milic, & Nikolic, 2018). Despite unlocking the biological key to mimicking cognitive learning, the processing power was unavailable until the early 2000s. Today, researchers use neural networks to extract patterns to nebulous problems that met or exceed human capacities.

## Purpose and Function

Traditional software follows the model of *data* plus *rules* equals *outcomes.* In contrast, intelligent systems use data and outcomes to derive rules. This distinction can be valuable when the *rules* are fuzzy or not entirely understood. After extracting those rules into a model, researchers and engineering teams can predict actions across mechanical, thinking, and feeling tasks (Huang, Rust, & Maksimovic, 2019).

* Mechanical tasks are actions that are highly repetitive and benefit from automation. These are operations like turning on lights or assembly-line construction.
* Thinking tasks are operations that require analysis and rationalization. For instance, “does this picture contain a hotdog,” or “is this sentence grammatically correct?”
* Feeling tasks, emulate interpersonal experiences, and express empathy toward the users. These autonomous systems might replace a call center or control support chatbots.

## Example Use Cases

Numerous business scenarios can leverage artificial intelligence through heuristics, machine learning, or deep neural networks. Under each type are several subcategories, like natural language processing. These technologies allow the software to reason about a textual source, then project capabilities such as translation or autocomplete predictions. Another use case is fraud detection, which attempts to stop criminals from exploiting payment processing systems. Researchers create evolutionary intelligence, like Google’s AlpaGo, to learn new strategies for playing complicated games, far superior to humans (Silver, Huang, & Maddison, 2016). Many times, the concepts that flow into these intelligent systems are adaptable to other scenarios.

## Levels of Success versus Alternatives

Artificial intelligence comes in many forms and applies to a wide array of scenarios, making it challenging to define success arbitrarily. Instead, organizations should identify both the value and resource constraints involved with the project, similar to any other Information Communication and Technology (ICT) system (Jain, 2018). For instance, Contoso Motors wants to implement a smarter cruise control with 3% better fuel mileage for its SUV (Sport Utility Vehicles). According to the data, the vehicle expends significant fuel on inclines, so the engineering team chooses to optimize this aspect with a terrain classification system. Now that the researchers have a problem definition, performance metrics, and potential solution, they can report what level of success is delivered.

However, alternative solutions might also exist that do not require artificial intelligence. Instead, the engineering team might implement business policies as static firmware code. Perhaps upgrading the hardware of the onboard also results in a three percent improvement.

## Advantages and Disadvantages

There are many strengths to introducing artificial intelligence across products and features. For instance, those services can adapt at greater precision with higher accuracy. That leads to cost reductions and the ability to automate more complicated tasks. Decision processes can also remove humans from the workflow, enabling faster and safer reactions to stressful situations. Perhaps our SUV is about to crash, and while the driver freezes, technology takes the wheel, minimizing the impact. A.I. can also exist in less dire scenarios, such as recommending the next song in the playlist.

However, not every problem requires a hammer, and sometimes a screwdriver works better. Many business domains have well-established rules, minimizing the value from reverse- engineering them from outcomes. Other domains, such as insurance, have enormous models full of ambiguity or encounter concept drift (Krishna, Rohit, & Mohana, 2018). These situations cause artificial learning systems to produce incorrect or incomplete results.

## Challenges and Barriers

Brock et al. (2019) provide the acronym ‘DIGITAL’ to enumerate why some artificial intelligence systems fail. A critical concept to remember is that machine learnings solutions produce answers to specific questions. When questions lack a precise definition, it can be nearly impossible to find enough of the right data to churn into facts. Next, grounding questions within the constraints of the organization’s resources and competencies is necessary, or the project will not be obtainable. When A.I. systems lack integration into existing processes, it results in pie-in-the-sky thinking that does not center on business value. Similarly, projects that do not have strong cohesiveness are likely to encounter political pressure from leadership.

## Supporting Operations and Innovation

Artificial intelligent systems that augment existing business processes are more likely to succeed (Garbuio & Lin, 2019). Accomplishing this goal begins with identifying what problem exists, its impact, and potential value.

Today, Contoso Motors employs several staff members to read and monitor social media. The business can use sentiment analysis to classify and prioritize only the messages that require human intervention. Since the team does not need to review every tweet, this automation change frees them to perform additional customer relationship tasks. In addition to providing immediate value to the organization, its statement of work and purpose is explainable to senior leadership.

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