Week 8: Artificial Intelligence for Business

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# Artificial Intelligence for Business

The most powerful artificial intelligence applications use machines to enhance human capabilities rather than replace them (Heer, 2019; Boire, 2017). For instance, a person can write a more profound business case than a machine; however, the same machine will have fewer misspellings and grammatical errors. This dichotomy exists because humans specialize in contextualizing thought versus automation uses patterns to make predictions (Schleer et al., 2019). Smart vehicles and autonomous driving industries are areas of research that seeks to fuse this symbiotic relationship. As this human and machine partnership flourishes, it will continue creating advancements across safety, convenience, resource utilization, and smart city integrations.

# Technical Characteristics of Systems

When people hear about smart vehicles, their imagination quickly pivots to driver-less cars. However, artificial intelligence applies to a broader set of business use-cases. These features each ingests data, model systems, and simulates interactions to make predictions.

## Objectives of AI

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. Models for realizing these autonomous creatures began in mathematics, biology, and computer science before eventually producing modern artificial intelligence (Lukac et al., 2018). While these different domains have unique perspectives, they collectively divide systems into those that ‘*think* versus *act’* and behave like ‘*humans* or *rationally’* (see Table 1)*.*

Table 1: System Characteristics

|  |  |  |
| --- | --- | --- |
|  | Think | Act |
| Human | Cruise Control | Mimic rolling to the stop sign |
| Rational | Adaptive Cruise Control | Change lanes to avoid a pothole |

## System Requirements

Machine learning can enhance every aspect of the drive, from extending the physical parts’ lifespan to increasing the driver’s overall satisfaction. Figure 1 contains a non-exhaustive taxonomy of use-cases for artificial intelligence in motor vehicles, such as reducing wear and tear and object detection. Many items, such as Voice Assistance (VA), could arguably live under a different pillar (e.g., safety). However, safety systems could exist in the same capacity using more traditional interfaces, making this example fall under conveniences.

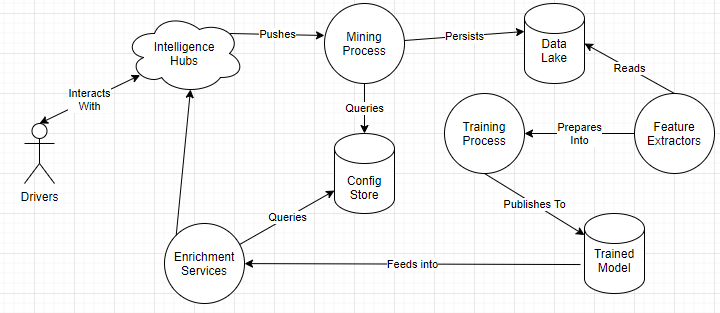
Figure 1: Taxonomy of Example Use-Cases

## Resources Requirements

Since covering each use-case in full detail would fill multiple books, this section reviews these user-scenarios’ commonality. The lifeblood of these systems is data, and only through synthesizing information into knowledge can they be more adaptive. These processes require mechanisms for collecting telemetry, performing data mining, and modeling the interactions (see Figure 2). As simulations run across that model, statistical distributions form, leading to predictive capabilities. When the model’s complexity grows or the required accuracy increases, the learning system also needs more examples to cover each scenario.

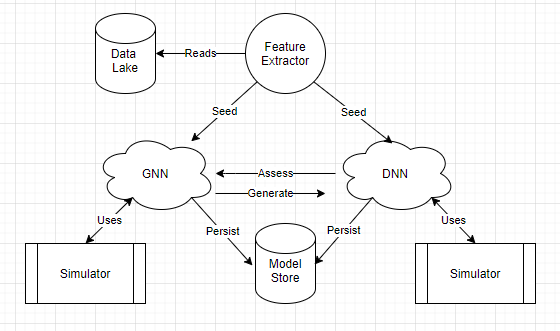
Consider the analogy of building an All-Wheel-Drive (AWD) feature that only knows about Florida’s flat tropical roads. Despite the engineers’ best efforts, the vehicle will encounter challenges on Colorado’s ice-covered mountainous climbs. Similar behaviors exist across the autonomous vehicle supply chain and demand either (a) more data or (b) more erroneous assumptions. This trade-off introduces acceptable feature risks in specific situations (e.g., entertainment modules) and undesirable consequences for others (e.g., safety modules).

Figure 2: System Design



Around 2014, GAN (Generative Adversarial) Networks became the state-of-the-art approach to produce high-quality detection and fabricated content (Fridman, 2020). These systems utilize a feedback loop between a Generative Neural Network (GNN) and Discriminator Neural Network (DNN). Each iteration outputs a ‘Deep-Fake’ asset and an assessment of its validity (see Figure 3). Under this process, both systems learn from one another, continuously improving their expertise.

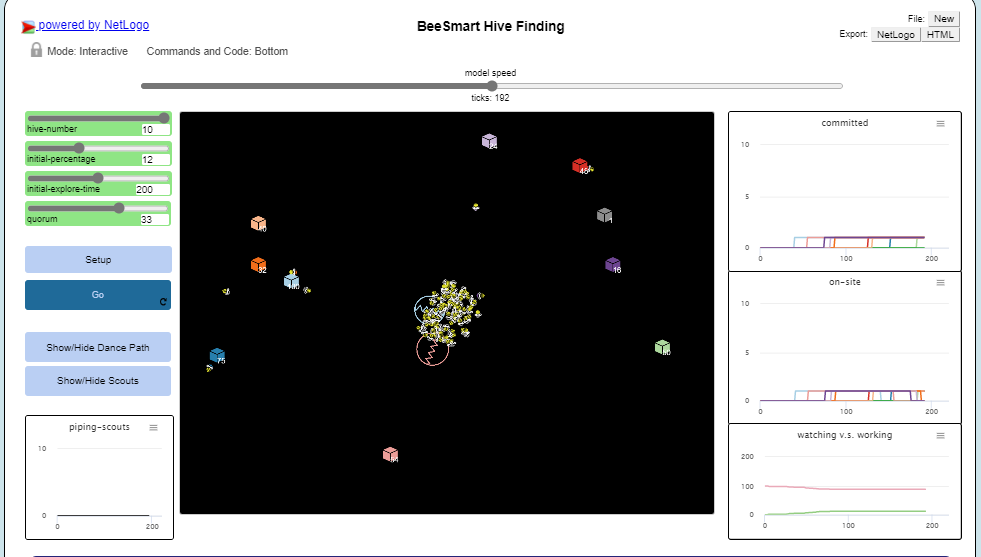
Figure 3: Training Configuration



Automotive companies like Formula-One use this methodology to synthesize more efficient race-cars that can safely operate at high speeds (Smedley, 2019). First, a collection of features load into the GNN and its simulation environment. Next, the output flows into a DNN, which assesses the feasibility of that solution. Then, the GNN modifies the solution’s parameters to search for a higher score. After executing thousands of cycles, both networks converge with optimal solutions to detect problems (DNN) or deliver innovation (GNN).

Within the simulation consists of the environment, participants, and one or more objectives. Each participant, called an agent, attempts to complete its objective under a set of guiding rules and principles. NetLogo’s BeeSmart environment demonstrates these ideas with multiple bees that attempt to maximize food production from various honey pots within a given scene (Wilensky, 2014). Initially, the swarm fumbles around until discovering a couple of locations. After some time, the colony will divide across multiple honey pots and compare site values with neighboring peers. Eventually, the bees converge to the optimal configuration that provides the maximum food for the hive.

Figure 4: BeeSmart Simulation (Wilensky, 2014)



While no individual agent (bee) understands the ideal resource utilization across the environment, the aggregate of independent decisions enables analysts to extract sophisticated observations about the broader objectives. It is also possible to quickly expand upon this simulation by designing expert agents, such as communication specialists, that propagate messages twice as fast. After defining the role and its local rules, the existing simulation can immediately incorporate those customizations.

# Timelines

Building sophisticated systems across automotive manufacturing businesses is a complicated feat that needs an iterative approach. These iterations must bring together industry-standard toolings such as Deep Learning frameworks (e.g., Tensorflow and PyTorch), big data processing networks (e.g., Apache Hadoop), and massively parallel processing (e.g., HPCS (High-Performance Computing Services)).

## Cloud Components

Modern businesses design these workloads to run on ubiquitous cloud computing environments (Harper, 2019). When a business can use Public Cloud Services (PCS), it speeds up their time to market by enabling instantaneous provisioning of elastic resources (Jassy, 2019). For instance, a data scientist team can access hundreds of GPGPU (General Purpose Graphical Processing Units) during a training simulation and then release them afterward. This paradigm shift pivots the acquisition conversation away from technology toward people and processes.

## Edge Components

However, not all workloads can transition into the cloud and need solutions for hybrid and edge computing. For instance, safety systems in the car must work despite Internet connectivity. Another situation comes from fluid dynamic modeling with real vehicles, as insane volumes of data exceeding facility upload bandwidth. These situations require edge processing units that perform the predictions in a partially disconnected state. It can be challenging to support these models due to less frequent updates, less processing power, and longer purchasing cycles.

# User Considerations

## Influence of Task Types

Traditional software follows the model of *.* In contrast, intelligent systems derive . 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 et al., 2019). As the task type moves from left to right (see Table 2), it requires substantially more sophistication to produce quality results.

Table 2: Task Types

|  |  |  |  |
| --- | --- | --- | --- |
|  | Mechanical | Thinking | Feeling |
| Description | Highly repetitive actions that benefit from automation | Operations that require analysis and rationalization | Emulate interpersonal experiences, and express empathy toward the users |
| Examples | * Turning on lights * Assembly line construction | * Image recognition * Grammar validation * Safe to change lanes | * Empathizing with a driver after an accident * Human Resource Systems |

## Interactions

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, NCU 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.

Huang et al. (2019) state that incorporating human emotion into AI systems is a decade away. Perhaps this is true for the general case, but initial wins also exist along the way. For instance, the system could also capture sentiment analysis information about the thread before commenting. Those reactions can then feed into a stylistic decision model that chooses more appropriate tones. This capability would allow the publishing pipeline to emit more impactful content that harnesses the customer’s emotions.

# Performance Metrics

## Measuring Success

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.

## Monitoring Efficiency

Large-scale artificial intelligence solutions have numerous components ranging across Human-Computer Interfaces (HCI), mechanical sensors, computation, and data lake storage. Such an environmental configuration requires administrators from broad specializations to monitor and tune these inter-related technologies. The organization needs to define KPI (Key Performance Indicators) and reporting strategies to monitor the system’s holistic health. It is critical that reporting technologies also exist to compare track changes within the baseline profile. Over time, subtle changes will take place, causing costs to increase and response times to decrease.

# Limitations and Challenges

## Modeling Complexity

It can be challenging to model real-world business scenarios due to the volume of interactions and their inter-relationships. Some organizations approach these issues by building monolithic models that are difficult to scale, operate, and update. Instead, businesses need to decompose the problem into an environment, participants, and objectives. An agent program manages the state of an individual and any behavior policies. When additional scenarios or behaviors are necessary, engineers can create isolated changes, enabling agile experimentation.

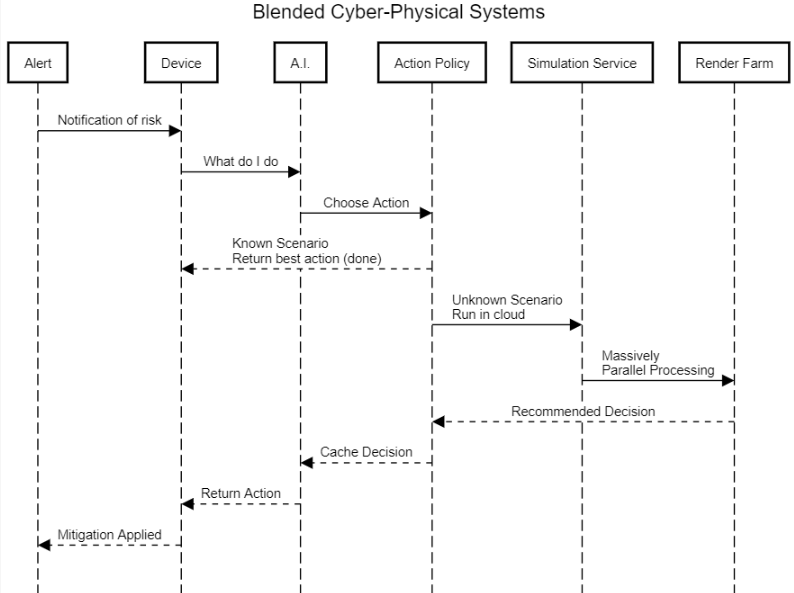
An analyst can study macro-systems by invoking multiple agent program instances and aggregating individual decisions into swarms.

Many simulation environments need to find the best choice from K-states across L-decisions. This setup creates exponential permutations (e.g., KL choices), which is difficult to enumerate even with cloud computing. Using Genetic Algorithms (GA) reduces the search by cross-breeding the fittest specimens. Simulation models can also require different levels of fidelity and precision. Administrators can incorporate these needs into Multi-Level Agent-Based Modeling (ML-ABM) to approximate tedious values and provide supporting evidence for critical data points.

## Catching up to humans

Intelligent agents form decisions from a predefined action space using static rules or Neural Networks (NN). Artificial neural networks (ANN) are inferior to humans because they are greedy, brittle, rigid, and opaque (Hole & Ahmad, 2019). These technologies excel at memorizing patterns, not contextually understanding them, which causes erroneous behavior under novel conditions. While researchers are quick to highlight this issue (Hole & Ahmad, 2019; Wildberger, 1996), does it matter in the world of tomorrow?

Figure 5: Blended Cyber-Physical System



With the availability of Massively Parallel Processing (MPP) and high-speed networking, administrators can further blur the lines between cyber-physical systems. When unknown situations arise, an artificial brain can treat it as a cache miss and fetch the appropriate response from a simulation service (see Figure 5). Next, the simulator will render the calling agent’s state before searching for the best reaction. After confirming the virtual world’s behavior meets administrative policies, the decision can safely execute in the physical world. This mechanism is not appropriate for every situation but could apply to broad types of problems.

## Legal Limitations

Laws cannot keep up with technology’s high-velocity innovation, causing businesses to define and self-regulate their ethical behavior (Upchurch, 2018). Without an official solution for maintaining accountability, this ethical desire must compete against existing business priorities. Those priorities will vary significantly between organizations, as even defining ‘human-centric systems’ is ambiguous. Moving past those challenges are issues with the fundamental integrity of neural network technologies (Lin et al., 2018; Sethi & Kantardzic, 2018). Implementing transparency and explainability are open research problems for all but the most trivial systems (Gilpin et al., 2018). After solving those issues, ensuring the training data is inclusive requires significant investments into unverifiable results.

# Ethical Considerations

## Historical Analogy

Before 1949, digging a ditch would take hours or even days with a crew of manual workers. After the invention of the backhoe, these jobs required less time with fewer employees. From the organization’s perspective, these efficiencies translate into faster time to market at lower costs. Meanwhile, the former diggers became displaced into new roles, repairing, operating, and supervising the machinery. Each of these positions requires entire supply chains of support. For instance, it takes factories to produce the backhoe parts, each staffed with hundreds of blue-collar jobs. Cities must also build universities and technical schools to train team members that will fill these roles, further expanding the job market.

Artificial intelligence is a tool that can automate mechanical tasks, pattern match data, and enhance human capabilities. Organizations can use these means to improve efficiency and reduce wastefulness. These innovations deprecate the need for specific skill sets and lower the entry barrier into other expert systems. While this causes an initial decrease number of jobs necessary, entirely new industries follow shortly afterward. When a society can replace low-paying jobs with high-paying alternatives, this promotion justifies the short term pain.

## Machines and Business-Critical Decisions

Machine learning technology is too immature to delegate business-critical decisions. Instead, professionals should consider these technologies for initial recommendations and to verify their choices are free of unconscious biases. For example, a court judge should assess their sentencing aligns with a regression algorithm’s prediction, not blindly issue that verdict. Humans must remain accountable for maintaining control of our actions and their consequences.

These limitations bring the discussion around full circle to the beginning. Artificial intelligent systems are not ethical, evil, or corruptive. They are tools that automate everyday tasks and lower the barrier to entry. Users of that tool need to be cognizant of what these predictions mean and how they influence decisions. However, that is not the same thing as delegating control with impunity.

# Strategic Implications of the System

Modern businesses are actively seeking methods that reduce costs and improve efficiencies through automation. The most powerful artificial intelligence applications use machines to enhance human capabilities rather than replace them (Heer, 2019; Boire, 2017). Many professions exist as a combination of mechanical tasks, decision-making, and pattern recognition. Expert systems address specific aspects of these job requirements; however, replicating the unified role and soft-skill components is challenging (Huang et al., 2019).

Specific low-skilled jobs, such as bank tellers and office clerical staff, are at risk of being replaced (Hamid et al., 2017). Similarly, expert pattern matching tasks like identifying tumors in MRI (Magnetic Resonance Imaging) becomes commoditized through AI systems. Given the lower entry barrier, some low-skilled workers will transition to better-paying jobs that operate those sophisticated and commoditized systems. For instance, many workers cannot access foreign markets due to language and communication limitations. Artificial intelligence can aid these in those translation scenarios while leaving control with humans.

# Conclusions

Artificial intelligence systems automate mechanical, analytical, and feeling tasks. These capabilities will transform business processes in many areas, such as the smart vehicle industry. While media sources focus on driver-less scenarios, significant investments will improve the driver experience, making it safer and more convenient. Those intelligent systems will need to collect vast quantities of data, extract features to build models, run simulations, and approximate statistical outcome distributions. The state-of-the-art technologies will incorporate multiple neural networks, like Generative Adversarial Network (GAN) and other Actor-Critical configurations. Accompanying neural network technologies are multi-agent systems that promote agile development through micro rule engines.

Automotive businesses need to take an iterative approach that builds out their artificial intelligent platforms. When these organizations leverage industry-standard tooling, they can provide solutions quickly, and hire employees with extensive experience. Not every workload is compatible with the public cloud, such as safety systems in the vehicle. However, aspects of the supply chain do, gain agility and capabilities to deliver innovation faster.

While making investments into smart vehicle services, successful project managers need to focus on end-user interactions and leadership transparency. If the system is cumbersome and clunky, then users will perceive the technology as substandard. Like any other Information Technology and Communication (ITC) project, leadership needs to have insights into the business value delivered and its operational efficiency. Without these data points, the project will become the victim of budget cuts and political struggles.

Ethical debates about machinery date back hundreds of years, and artificial intelligence is merely the latest discussion subject. A familiar argument states that these technologies will take our jobs. However, any job displacement is temporary and soon requires deep supply chains to support those devices similar to previous innovations. Instead, organizations should look at those machines' strategic value to reduce costs, promote value-creation, and reduce entry barriers into expert capabilities.

# References

Boire, R. (2017). Artificial Intelligence, automation, and its impact on data science. *IEEE International Conference on Big Data* (pp., 3571-3574). Boston, MA: Institute of Electrical and Electronics Engineers. doi:10.1109/BigData.2017.8258349

Fridman, L. (2020, January). *Deep Learning State of the Art*. (Massachusetts Institute of Technology (MIT)) Retrieved from YouTube: https://youtu.be/0VH1Lim8gL8

Garbuio, M., & Lin, N. (2019). AI as a growth engine. *California Management Review, 61*(2), 59-83. doi:https://doi-org.proxy1.ncu.edu/10.1177/0008125618811931

Gilpin, L., Bau, D., Yuan, B., Bajwa, A., Specter, M., & Kagal, L. (2018). Explaining Explanations: an overview of interpretability of machine learning. *5th International Conference on Data Science and Advanced Analytics* (pp. 80-89). Turin, Italy: Institute of Electrical and Electronics Engineers. doi:10.1109/DSAA.2018.00018

Hamid, O., Smith, N., & Barzanji, A. (2017). Automation, per se, is not job elimination: How artificial intelligence forwards cooperative human-machine coexistence. *15th International Conference on Industrial Informatics* (pp. 899-904). Emden, Germany: Institute of Electrical and Electronics Engineers. doi:10.1109/INDIN.2017.8104891

Harper, J. (2019, May/June). Business Intelligence Tomorrow and what it means for today. *KM World*, 12-16.

Heer, J. (2019). Agency plus automation. *Proceedings of the National Academy of Sciences of the United States of America, 116*(6), 1844-1850. doi:10.1073/pnas.1807184115

Hole, H., & Ahmad, S. (2019). Biologically driven artificial intelligence. *Computer, 52*(8), 72-75. doi:10.1109/MC.2019.2917455

Huang, M., Rust, R., & Maksimovic, V. (2019). The feeling economy: managing in the next generation of artificial intelligence. *California Management Review, 61*(4), 43-65. doi:https://doi-org.proxy1.ncu.edu/10.1177/0008125619863436

Jain, N. (2018, February 21). *Top 10 reasons for project failure*. Retrieved 28 2020, June, from Whiz Labs: https://www.whizlabs.com/blog/top-10-reasons-for-project-failure/

Jassy, A. (2019, December 3). *AWS re:Invent 2019 - Keynote with Andy Jassy*. Retrieved from YouTube: https://www.youtube.com/watch?v=7-31KgImGgU

Lin, Z., Xiao, F., Sun, Y., Ma, Y., Xing, C., & Huang, J. (2018, April). Secure Encryption-Based Malware. *Transactions on Internet and Information Systems, 12*(4), 1799-1818. doi:10.3837/tiis.2018.04.022

Lukac, D., Milic, M., & Nikolic, J. (2018). From artificial intelligence to augmented age, an overview. *Zooming Innovation in Consumer Technologies Conference* (pp. 100-103). doi:https://doi-org.proxy1.ncu.edu/10.1109/ZINC.2018.8448793

Schleer, P., Drobinsky, S., de la Fuente, M., & Radermacher, K. (2019). Toward versatile cooperative surgical robotics: a review and future challenges. *International Journal of Computer Assisted Radiology and Surgery, 14*(10), 1673-1686. doi:10.1007/s11548-019-01927-z

Sethi, T., & Kantardzic, M. (2018). Data-driven exploratory attacks on black-box classifiers in adversarial. *Neurocomputing, 289*, 129-143. doi:10.1016/j.neucom.2018.02.007

Smedley, R. (2019, December 4). *Rob Smedley From Formula 1 Talks About Using AWS to Improve the Fan Experience*. Retrieved from YouTube: https://youtu.be/eBX7lPk5qmA

Upchurch, M. (2018). Robots and AI at work: the prospects for singularity. *New Technology, 33*(3), 205-218. doi:10.1111/ntwe.12124

Wildberger, A. (1996). Introduction and overview of artificial life evolving intelligent agents for modeling and simulation. *Winter Simulation Conference* (pp. 161-168). doi:10.1109/WSC.1996.873274

Wilensky, U. (2014). *BeeSmart hive finding*. Retrieved from Netlogo: https://ccl.northwestern.edu/netlogo/models/BeeSmartHiveFinding