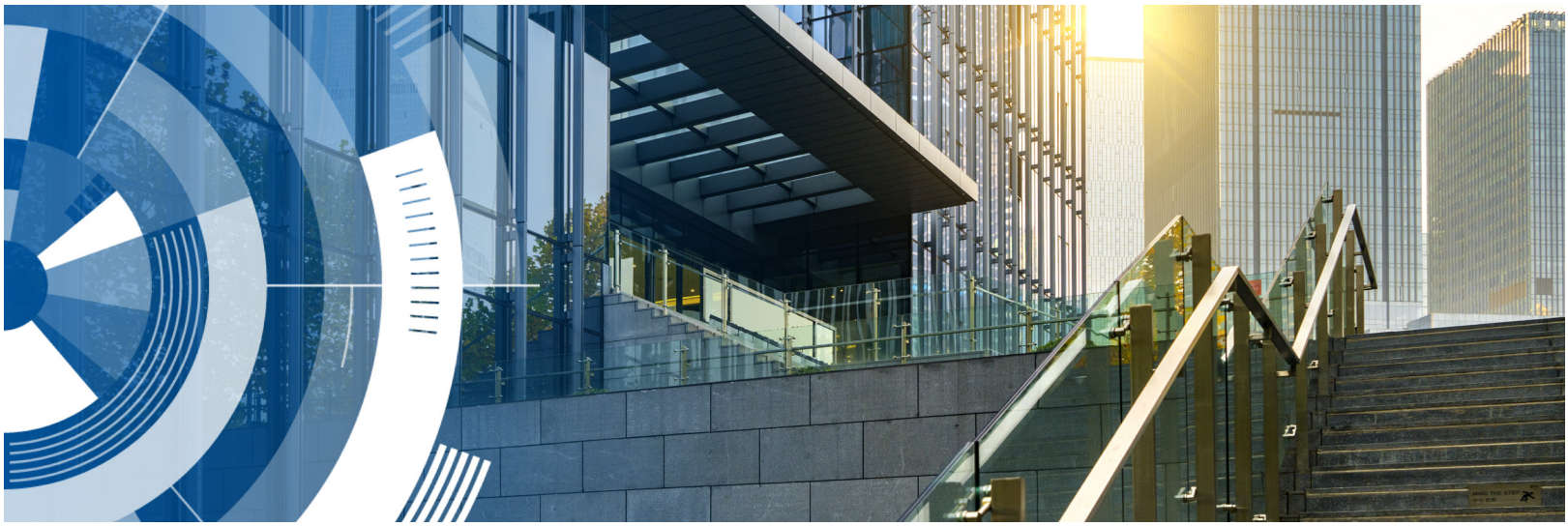

Applying Artificial Intelligence to Built Environments through Machine Learning

MACHINE LEARNING DEFINED

Machine learning (ML) is an application of **artificial intelligence (AI)** that allows systems to automatically learn and improve from exposure to more data without being explicitly programmed. ML focuses on the development of computer programs that can access data and use it to learn for themselves.[1]

While AI represents the broader concept of machines being able to carry out tasks in an intelligent way, machine learning is a current application of AI based on the idea that we can give machines access to data, and they can use that data to learn for themselves.

Many consumers will have their first interaction with AI in the built environment through voice commands given to a smart home device personal assistant made such as those by Amazon, Google or Apple.

HOW IS MACHINE LEARNING USED?

> **"AI makes over 85% of all stock trades, controls operation of power plants, nuclear reactors, electric grid, traffic light coordination and...military nuclear response... Complexity and speed required to meaningfully control those sophisticated processes prevent meaningful human control. We are simply not quick enough to respond to ultrafast events such as those in algorithmic trading and...in military drones."**
>
> *~ Excerpted article from the Future of Life Institute article, by Roman Yampolskiy, AI researcher at the University of Louisville*

Most of the recent progress made by AI has been in the field of ML and today, machine learning is predominantly being used to augment human effort in simple activities rather than replace workers completely. Recent research from McKinsey states: "According to our analysis, fewer than 5 percent of occupations can be entirely automated using current technology. However, about 60 percent of occupations could have 30 percent or more of their constituent activities automated. In other words, automation is likely to change the vast majority of occupations—at least to some degree—which will necessitate significant job redefinition and a transformation of business processes."[2]

[1]From Expert System: https://www.expertsystem.com/machine-learning-definition/

[2]https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/four-fundamentals-of-workplace-automation

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ML takes input data to generate a simple response. In ML, the algorithm "learns from experience" (i.e., from the given data) and is then able to improve at predicting outcomes as new data sets are presented.

THREE GENERAL TYPES OF MACHINE LEARNING INCLUDE:

- **Supervised machine learning where a computer algorithm learns the mapping function between input variables (X) and output variables (Y): Y=f(X).** The mapping function is often called the "model." Supervised machine learning requires training data, or labeled examples, that the machine learning algorithms can use to learn how to map the input variables to the output variables for the model. When using supervised machine learning, the effort is divided into two phases: a "training phase," where the labeled examples are fed to the algorithm to create a model that can make predictions and a "prediction" phase where the model is shown unlabeled data to make a prediction for the label. Examples of common supervised machine learning applications are photo tagging or fault predictions. Supervised machine learning is predominantly used to replace human effort but often requires a significant amount of data for training the algorithm to create the model. The time and compute capacity to create the model during the "training" phase can also be considerable, though the compute and time requirements for each "prediction" after the model is trained is usually dramatically lower.

- **Unsupervised machine learning where only input data (X) is available without corresponding output variables and the goal of the machine learning is to model underlying patterns within the data.** Unsupervised machine learning is typically used to group similar data together, and the groupings can either provide the context (e.g. "a sample of the documents from this group all appear to be about banking, so we can label all the documents in this group as 'banking'") or as a way to search for similar data given an example document based on what group the unsupervised machine learning placed the example document.

Please note that as ML has evolved, a class of semi-supervised learning has also been utilized. Semi-supervised machine learning falls between supervised and unsupervised learning. Semi-supervised learning typically uses a large amount of input data (X) but only small amount of corresponding output data (Y).

- **Reinforcement learning where optimal sequential decision (also called action, a) is made using evaluative feedback (commonly known as reward, r) without supervised labels**. Put another way, in a reinforcement learning problem, it may be easy to explain the rules of a game and how to tell if the AI won the game, but it is very difficult to write a strategy for playing the game. A reinforcement learning AI might play a simulated version of the game following the rules millions of times, each time attempting to learn a better strategy through trial and error. Beyond games, other use cases of reinforcement learning include steering a car or a robot or adjusting the set of controls for a complicated building to find an optimal configuration.

HOW IS SUPERVISED ML USED IN THE BUILT ENVIRONMENT?

In the case of voice control of building functions, ML applications are coming online to help consumers manage their home environments, home security, thermostat settings, lighting and a host of other in-home functions. Consumer uptake in these home settings will depend to a large extent on trust: trust in how well the technology performs its intended use, trust in how easy the technology is to use and understand and trust in how well the technology provider preserves the user's privacy. Voice control is not yet big in commercial settings outside of personal devices like the building occupant's phone, laptop or wearables, but enterprises are beginning to deploy voice controls in more communal spaces, such as conference rooms.

In a more commercial, industrial setting, ML is being applied in energy management and predictive energy optimization. Corporate real estate owners and operators can leverage internal and external data to benchmark building performance, monitor building equipment, ensure occupant comfort and forecast operational budgets. Predictive analytics can be applied for load management (for HVAC, lighting, appliances, devices), as well as fault detection and diagnosis, so potential issues can be addressed before something serious happens. Predictive analytics can also manage upcoming load, either by preemptively shedding load or optimizing processes to prepare for upcoming challenges. For example, intelligently pre-cool or store chilled water in advance of anticipated loads, creating just the right amount of chilled water early in the day before peak utility rates apply.

In the built environment, ML is foundational to many systems that rely on biometric recognition to enable physical access. For example, users present their access control credentials in the form of a card or pin as they traditionally have but then face a camera to further verify their identity. These cameras, or the servers behind the cameras, have used supervised machine learning techniques like neural networks to identify users. Modern AI algorithms can identify users with very high confidence, and the combination of facial recognition and traditional card access provides a higher level of assurance for secure access while minimizing disruption for the users.

SOME CONCERNS ABOUT AI AND ML

While Artificial Intelligence and Machine Learning hold enormous promise, they are still maturing as technologies and anxieties exist across economies and societies.

1. **Considerations about data quality and volume of data required.** As mentioned, ML requires a significant amount of data for training. The data includes both Input (A) and Response (B) to train the algorithm. In addition, the quality of data input into the model is important, as higher quality data should enable better predictive capabilities. Obtaining sufficient quality labeled data can be a costly proposition and often depends on human experts to perform the labeling. Often data labeling is handled by asking the "crowd" to label the data, which is possible for some data sets but other labeling tasks require experts for assistance, such as identifying sensor readings that indicate failure.
2. **Trusting that the machine and data will make the right decision**. As AI and ML become more advanced, they will start to make more sophisticated decisions. While ML may be better and faster than humans at making decisions, some concern exists that automated processes could "learn" patterns that lead to undesired or unintended consequences or biases. If the underlying data set included biases, or is collected from a process that structurally included some form of bias, the ML algorithms will replicate and perpetuate those biases. For example, if ML is being used to assist in loan decisions, if the dataset used to train the model included loans that were denied due to racial discrimination, the model will perpetuate that discrimination. Business leaders will need to pay careful attention to the history and provenance of their datasets. Many ML algorithms and resulting models are created as combinations of thousands of variables and their predictions are not easily explainable, which can make it difficult for observers to trust the output of the algorithm.
3. **Economic disruption: Impact on jobs and ways of working**. As these new technologies become more ubiquitous, economic effects and impacts to the world of work are inevitable. As automation replaces many administrative, predictable physical tasks, data collection and processing, job functions will change. Concerns exist that many jobs as we know them today will be lost altogether or significantly re-shaped, at a minimum. Business leaders and policy makers need to take these concerns seriously and assume some responsibility for enabling and applying "Responsible AI."

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CASE STUDY: JOHNSON CONTROLS

Johnson Controls offers a portfolio of products that provide data-enabled outcomes. The products serve a wide variety of industries and customer priorities. Below are several interesting outcomes for buildings.

- **Energy Prediction:**
  Predicts energy consumption of a whole building, piece of equipment or appliance. It enables peak shaving, avoiding utility penalty, cost-effective energy supply planning and energy demand planning.

- **Fault Detection and Diagnostics (FDD):**
  Model-based (AI) or sensor-based capability that predicts anomalies and faults in equipment operation. The anomaly/FDD can be done for various equipment in buildings such as chillers, boilers, AHU, VRF, RTU, cooling tower, lighting and appliances, as well as for the whole building. FDD detects and eliminates wasted energy.

- **Optimization of HVAC Operation:**
  Computes optimal operational set-points for various components of HVAC systems, including plant-side (chillers, boilers, cooling towers, etc.), air-side (AHU, VAV) and zones (dampers and thermostats) using Reinforcement Learning with feedback of human comfort and energy consumption.

- **Predictive Maintenance Planning and Scheduling:**
  One example is the optimization of a short-term decision (e.g., daily or hourly), which is to optimally assign and route a technician to maintenance tasks and to synchronize a technician with his/her resources (equipment, tools, vehicle, etc.) A second example is the optimization of longer-term decisions (monthly or yearly), which may involve optimally planning Energy Conservation Measure (ECM), retrofits or replacements of equipment considering energy operational cost, maintenance cost, replacement cost, failure cost, maintenance budget and resources. The optimal decision is based on predicted failure risk of equipment or operations and predicted faults and anomalies.

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