# The Ubiquity of AI in Networking

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## Abstract

This paper provides a high-level overview of the different ways AI can be implemented into networking. It highlights a few of the reasons AI is being incorporated into networking at this current moment while briefly touching on basic AI concepts. Areas of networking explored include traffic classification, rate adaptation, and network and channel modeling. As with any advancement in technology, there are two sides to a coin and ethical concerns are evaluated as AI looks to revolutionize networking.

## Keywords

Networking, Artificial Intelligence, Machine Learning, Neural Network

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# 1. Introduction

AI has captured the minds of engineers by the ways it can see things the human mind cannot. Mastering these once hidden insights is a tantalizing challenge for the inspiring engineer. These new ideas can breathe life into systems constrained by ridged mathematical models, one of which is networking. Networks have been continuously evolving since their conception and these advancements have led us to modern networks that have become more specialized and complex than ever. AI can more easily find solutions for specific networks as well as find solutions that adapt better over a variety of distinct networks. There are few examples of AI currently employed in real-world networks, but many studies have identified capacities AI can shine. As AI is a broad field, to help narrow the focus, this paper will explore solutions utilizing machine learning (ML), a subfield in AI. Current work has proven that ML has the potential to enhance nearly every aspect of modern networking.

## 1.1 A Quick Introduction to AI

AI can be a confusing topic because many of its terms are used interchangeably. This section will strive to provide clarity by introducing common terms of AI that are important in understanding how models differ from each other. First, it will cover the relationship between AI, ML, and DL, which is displayed visually in Figure 1, then go over terms commonly used in AI, and finally definitions of the models mentioned in this paper. It is important to realize that AI is an expansive field and while this section covers concepts that are essential to this paper, it is in no way a comprehensive overview of the topic.

Artificial Intelligence (AI): The practice of using machines mimicking human behaviors such as problem solving or learning.

Machine Learning (ML): A subset of AI. ML can utilize neural networks, but not all ML algorithms do. Inputs to ML models need to be structured and humans need to identify which features the model should use.

Deep Learning (DL): A sub-set of ML. DL utilizes neural networks with three or more layers. Inputs to DL models are unstructured and the models themselves identify which features to use.
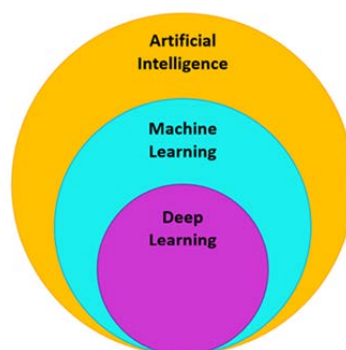


**Figure 1: AI Hierarchy**

Supervised Learning: training data is provided with labels and a desired output

Unsupervised Learning: training data is provided without labels; the model makes its own inferences on the data

Reinforcement Learning: training data is provided without labels; the model improves by taking into account an award function that provides feedback on the last action

Classification Model: the output of a supervised model is categorical

Regression Model: the output of a supervised model is continuous

Artificial Neural Networks (ANN) | supervised/unsupervised/reinforcement | classification/regression A network of perceptrons, arranged in at least three layers, as shown in Figure 2. The first layer, the input layer, forwards data to the hidden layer(s) which is where the learning happens and perceptrons reside. Each perceptron performs Equation 1, where m is the number of inputs, is the weight assigned to an edge and b is the bias assigned to the whole layer. If the result of this equation passes a threshold, the resulting value is passed on to the next layer. After the data is processed through the hidden layer(s) it is passed to the output layer [Wiki1]. ANNs are the base for all other types of neural networks.
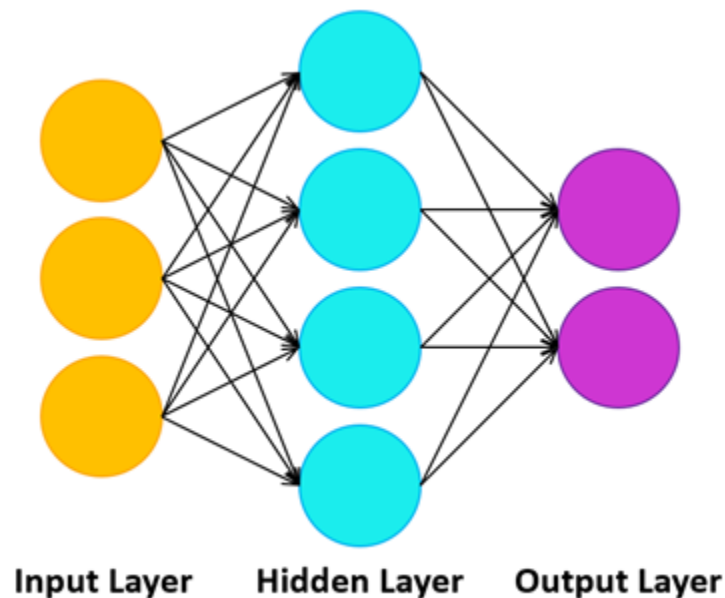


**Figure 2: Example of an Artificial Neural Network**

$$f(x) = \sum_{i}^{m} x_i w_i + b$$

**Equation 1**

Deep Neural Network (DNN) | supervised/unsupervised/reinforcement | classification/regression
A variant of an AAN. DNNs use multiple (at least 3) hidden layers. DNNs use each layer to progressively extract higher-level features.

Graph Neural Networks (GNN) | supervised? | classification/regression?? A variant of an ANN. GNNs are particularly suited to learn from graph-based input. Due to the complexity of graphs, GNNs are required to be shallower than other neural networks.

### 1.2 Why AI and Networking Now?

Recent trends in networking see many components of a network going through virtualization. Virtualization can help split a physical resource into multiple virtual resources, or it can also aggregate multiple physical resources to act as one physical resource. Virtualization enables a physical network to be efficiently split between different customers. The resulting virtual networks can be tailored to meet customers' different services. The complexity of managing the resources and functionality of these virtual networks can prove to be too much for traditional models. Virtual networks need AI to help harness the full functionality they have to offer [Zappone19].

As more devices join networks, the traffic, and therefore data, created by the networks increases. To effectively design and optimize these networks the whole of the dataset needs to be considered. ML is especially aligned for this task since it can process large amounts of unstructured data [C.X.Wang20, X.Wang20]. Learning from unstructured data is critical because it removes the need for preprocessing of the data and therefore can be learned from in real-time. None of this would be viable without recent gains in more powerful and cheaper processing [Vulpe21]. The current path of networking has naturally opened a spot for AI to collaborate. The rest of this paper is organized as follows: Section 2 highlights a few aspects of networking where ML has been exercised. Section 3 discusses what ethical AI looks like and how it applies to the models talked about in this paper. Section 4 provides a summary of the main points; section 5 is the list of acronyms and section 6 is the references.

# 2. AI Applications in Networking

Network optimization provides benefits to both carriers and customers. An optimized network can save capital for the providers and deliver a higher quality of service to customers. While there are already many protocols that safely and effectively manage networks today, AI models can provide solutions that are more adaptable and reliable. As will become evident below, there is no one way to implement an ML model into a network.

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## 2.1 Traffic Classification

One way traffic classification has traditionally been performed was through port-number identification. As networks move towards virtualization, ports can be reallocated on the fly, making this technique impossible [Vulpe21, Malik20]. Another way to classify traffic is to look at flow characteristics, which in some networks can grow to over 200. Examples of flow features can be the source, destination, number of packets, and duration time. ANNs and DL are particularly attractive in this situation because they can ingest large feature sets and learn hidden patterns of flow classification that are unnoticeable to humans [Malik20].

Traffic classification is intuitively an ML classification problem. Using a supervised ANN model is highly customizable as layers and perceptrons can easily be added to accommodate larger and more varied data sets. The drawback to a supervised ANN is that it requires the data to be preprocessed and can show particularly poor performance when the data is not normalized [Vulpe23]. An unsupervised DL model, while can benefit from dataset normalization, does not require that the traffic flow dataset be preprocessed. A DL technique called dropout can be used to remove perceptrons at random throughout the layers of the neural network which helps prevent overfitting on training datasets. Applying this to network classification can help the efficiency of DL models because it helps to generalize types of traffic, as types of traffic can evolve throughout a network's existence [Malik20].

## 2.2 Rate Adaption

The dynamic environment that most networks operate in requires them to implement congestion control to maintain throughput. Maintaining data rates is a deciding factor in the QoS of a network and many schemas for rate control have been developed. Rate control is driven by the history of a network's performance based on the packets lost, which is used to predict the next rate to choose. There exist many schemas that follow a rules-based adaptation rate that do a sufficient job of congestion control. They begin to run into issues when traffic begins to change more dynamically. Their penalties may be too high, and they may be reacting to pack loss not caused by congestion [Jay19].

RL is particularly suited for rate adaptation because it considers feedback from its last action. Where older schemas don't adjust for over-correcting, RL models can make throughput transitions gentler. Combining RL with deep learning allows the algorithm to learn intricate relationships between network and traffic behavior with the rate it selected [Pratama23]. Based on these insights and the history it maintains, a deep RL model can eventually learn when a packet loss is due to throughput or other reasons. This ability helps the algorithm avoid unnecessary changes to the rate when loss is not due to throughput [Jay19]

## 2.3 Network Modeling

Network modeling is a technique used to predict the mean packet delay based on a network's topology, traffic matrix, and routing. Optimizing a network model before deployment is a cost-saving method for providers but also ensures QoS for customers. Packet simulation is a practice deployed in networking modeling, used to stress network models but has proven to be

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computationally expensive. On the other hand, analytical models are cheaper and more efficient but suffer on network models that implement multi-hop routing and multi-queue scheduling [Suarez-Varela21]. ML models can learn correlations between network setups and performances, where traditional modeling cannot, and reduce the necessity of dataset set generation [Zappone19].

Predicting packet delay is a regression-based problem where ANNs can be trained supervised or unsupervised. ANN would typically be trained on data generated from synthetic network models like the target model so it can learn relationships between the interconnections. One possible ML framework could use the combination of two ANNs to create a reinforcement model where the first ANN sets the baseline and the second ANN is used in the live network, analyzing a small amount of live data to improve on the original design and adapt to changes in network flows [Zappone19]. The network modeling problem is a particular area where ANNs can show off their flexibility.

GNNs have shown promise in network modeling since most network information such as topologies and routing configurations are naturally represented as graphs. Figure 3 demonstrates this with a simple example topology. Each user (computer icon), router, and the internet represent nodes of different types. The edges are represented by the communication connections between each network component. Nodes could be encoded with their capacity, drop rate, and/or scheduling policy. Edges can be combined to represent paths defined within the network. A GNN model can ingest this graphically encoded information to predict source-destination delays [Suarez-Varela21].
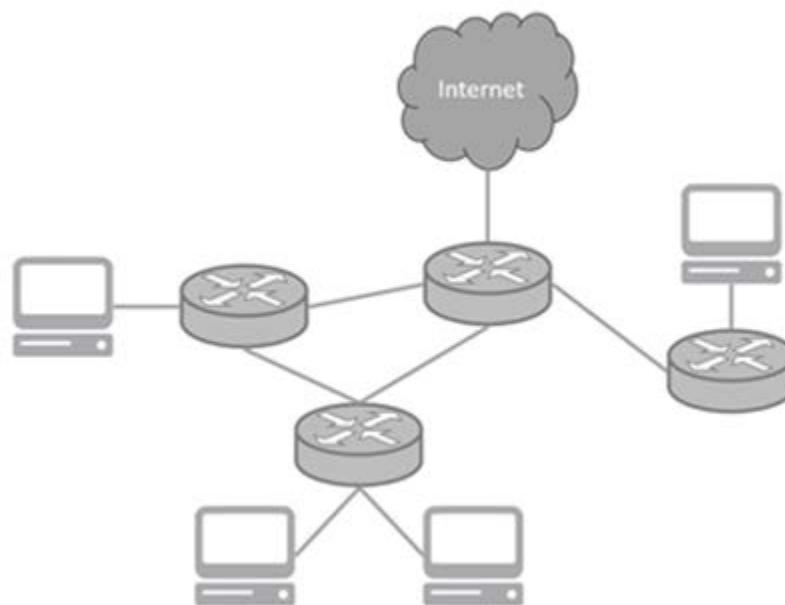


**Figure 3: Example Topology**

## 2.4 Channel Modeling

A feature of evolving wireless networks is that channels will be expanded to use frequencies not used in networking currently. 6G is expected to use bands above 52.6 GHz, and networks beyond 6G have the potential to use sub-6 GHz, millimeter-wave, terahertz, and optical bands [C.X.Wang20]. As channels move through the frequency bands their characteristics fluctuate, such as phase noise, interference with the atmosphere, and lower power amplifier efficiency to name a few [Song22]. Modeling channel interactions becomes more complex as the range of bands grows and therefore the range of feature space grows. When introducing a new channel, traditionally to gather data on it, a manual process of collecting measurements is performed.

ML can help fill in the knowledge gaps of new bands by using channel and environment measurements to predict the behavior of new channels. There have been studies that have shown promising prediction results for using neural networks for singular channel properties, but no work has been completed compromising a full channel model. Harnessing ML in channel modeling can reduce costs from traditional data-based methodology with supposedly higher accuracy. These gains can help bring new channels online faster [C.X.Wang20].

# 3. Ethical Concerns

Understanding why ethics is important to networking can be a little abstract. It usually works silently in the background of everyday tasks. It does not create content, only relays it. From the average user's perspective, if the network they use is connected, it has little effect on how they live. In the background though, there are standards that uphold the quality and distribution of a network that help to ensure fairness of service. While AI can help ensure that these standards are met, it could also be a tool to tilt the scale. Areas, where ethics is particularly concerned in networking, are algorithm interpretability and access to research resources.

## 3.1 Interpretability

Interpretability in AI means being able to understand how and why a model decides. Explainable AI (XAI) is the concept of models and methods in AI that allow an operator to provide oversight on an AI's decision-making process. It attempts to remove the "black box" characteristics of AI models where a user has little idea of how a model draws a conclusion [Wiki2]. There are a couple of core methods that XAI employs to achieve these goals: visualization, model simplification, and feature relevance.

In terms of interpretability models can be grouped into two different categories: transparent and opaque. Transparent models are simple in the way that it is easy for a human to follow along with the model's decision-making process. These models are usually linear in nature. Opaque models are more confusing and less interpretable to humans. Their value usually comes from their ability to handle large amounts of data in a complex way that is beyond human-level computation [Zhang22]. Most all the models discussed in the above solutions utilized neural networks, which fall into the opaque category. Their ability to solve complex problems is also the reason they are not understandable to humans.

The reality is that XAI and the legal framework for AI are both still in their infancy [Guo20, Zhang22]. The GDPR in the EU requires algorithms to explain their decisions while France has the French Digital Republic Act that requires transparency at the model, data, and decision level. An example of unethical AI employment in networking could be an RL congestion control model deployed on the internet alongside older congestion control schemas. The RL model could learn to provoke packet loss to cause the other schemas to back off providing more bandwidth for the RL model. This could disproportionately affect the QoS for users on networks with legacy schemas with no fast fix if network operators cannot identify the behavior [Jay19].

### 3.2 Research Resources

Data sets from applied networks are hard to access in the academic world. In many experiments employing AI models, the authors must use a simulated network to create data for their experiments. Many of the studies in this paper had to simulate their network datasets [Jay19, Pratama23, Suarez-Varela21, Vulpe21, Vulpe23]. While this can usually serve the purpose of the experiment it also creates a limitation of the relatability of the results to a real network environment.

The issue is data to real-world networks is usually only available to the companies that facilitate the networks. The industry owners of these datasets usually do not share with academia. The issue is that researchers in industry and academia have different motivations driving their research, the most concerning being that industry is profit-driven. A provider may be more incentivized to implement a congestion control model like the one described above, without thoroughly testing it or not disclosing the issue though it was known. It could provide a competitive advantage over other providers and without regulation on AI, they may never be reprimanded.

One proposition to level the research field between industry and academia is utilizing university networks to create datasets. Campus networks provide realism in the sense of scale, complexity, and diversity and are more accessible to researchers. Researchers can work directly with IT on their campuses, essentially getting more value out of an already existing service [Gupta19]. New AI networking advancements from academia may arguably have less of a chance of providing malicious results, but at the very least they provide solutions derived from different motivations.

# 4. Summary

While it seems like AI is expanding to many aspects of daily life, it is certainly ubiquitous in the development of networking technologies. AI's advantages are that it can adapt to a changing network environment more gracefully than traditional models, even learning how its actions have affected performance. It is also more equipped to handle the intricacies providers face as they divide their infrastructure into specialized networks. Just as fast as AI can bring improvements to networking, it can also bring inequality to how networks perform. Judicious effort must be put forth to govern AI because it is hard to imagine the future of networking without AI.

# 5. List of Acronyms

AI    Artificial Intelligence
ANN Artificial Neural Network
DL    Deep Learning
DNN Deep Neural Network
GNN Graph Neural Network
ML   Machine Learning
QoS  Quality of service
RL    Reinforcement Learning
XAI  Explainable AI

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