Applied Machine Learning
Assignment – Week 1

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Chapter 1: The Roots of Artificial Intelligence

As we know, artificial intelligence (AI) is a result of centuries-old efforts to understand human thought as a mechanical process. The modern field of AI emerged with the invention of computers, which manipulate 0s and 1s. In the early days of computing, pioneers such as Alan Turing and John von Neumann saw strong analogies between computers and the human brain, thinking that the intelligence of machines could be replicated.

John McCarthy coined the term "Artificial Intelligence" during a 1956 workshop at Dartmouth College, which looked at whether intelligence could be precisely described or simulated. Natural language processing, learning, and reasoning were among the topics discussed by participants including Marvin Minsky, Herbert Simon, and Allen Newell. Despite its limited outcomes, the meeting marked the beginning of AI as a distinct discipline and inspired optimism about the accomplishment of intelligence in machines within the next few decades.

It led to ambitious goals and rapid development of symbolic AI, which uses logical symbols and rules to replicate the reasoning of humans. An example of symbolic AI is the General Problem Solver, a program that mimicked human problem-solving by representing tasks symbolically. However, symbolic approaches struggled to handle complex, real-world scenarios requiring common sense or intuitive reasoning.

This chapter also highlights a philosophical divide in AI regarding symbolic and sub-symbolic approaches. Sub-symbolic AI, inspired by neuroscience, attempts to simulate human learning and perception through neural networks, while symbolic AI relies on explicit rules and logical structures. It was this division that laid the foundation for AI's evolving landscape.

Despite early enthusiasm, there were challenges in defining "intelligence" and producing tangible results. The initial AI efforts were marked by overpromises and under deliverance, foreshadowing cycles of optimism and disappointment. Even so, these early experiments laid the foundation for AI research in the present day.

Chapter 2: Neural Networks and the Ascent of Machine Learning

Neural networks, which take inspiration from how our brains work, are at the heart of modern AI. The journey began back in the 1950s with Frank Rosenblatt's perceptron’s. These early models were pretty straightforward, taking numerical inputs and making simple yes-or-no decisions by adding those inputs together with some weights. They could handle basic tasks, like recognizing patterns, but, unfortunately, they had their fair share of limitations. This was laid out in a 1969 book by Marvin Minsky and Seymour Papert called Perceptron’s, and it kind of put a damper on neural network research for quite a while.

In the 1980s, neural networks made a comeback thanks to the creation of back-propagation, which is a cool algorithm that helps these multi-layer networks learn how to tackle tricky tasks. Unlike basic perceptron’s, these networks have "hidden layers" packed with units that help them spot complex patterns. For instance, in image recognition, those hidden layers can pick up on features like edges and shapes, which eventually helps the system recognize different objects, like handwritten numbers. Back-propagation does its magic by tweaking the connections between these layers to reduce mistakes, making the networks much more effective.

The chapter also dives into the idea of connectionism, which suggests that intelligence comes from a web of connected units instead of clear-cut rules. Researchers like David Rumelhart and James McClelland were all about this approach in their game-changing 1986 book, Parallel Distributed Processing. They argued that brain-like systems and learning from data could really help tackle the shortcomings of symbolic AI. Remember the 1980s? Those symbolic expert systems, which were built on strict human-defined rules, were having a tough time with adaptability and generalization. That’s when the spotlight really shifted towards neural networks.

Neural networks, once met with skepticism, achieved significant success in image and speech recognition, paving the way for deep learning. These deep networks, with multiple hidden layers, tackle complex problems by analysing large datasets. This chapter marks a critical transition from rule-based AI to data-driven learning, setting the stage for AI's rapid advancement in the 21st century.

Chapter 3: The Power and Pitfalls of Deep Learning

This chapter dives into the world of deep learning, which is basically a cool branch of machine learning. It uses these fancy multilayered neural networks to nail tasks like recognizing images, understanding language, and even driving cars on their own. The chapter kicks off by breaking down how deep learning builds on older neural network models, and it's really taken off thanks to three big reasons: tons of data available to play with, the boost in processing power especially with those GPUs, and some good training algorithms like stochastic gradient descent.

Deep learning systems, such as convolutional neural networks (CNNs), are particularly adept at visual tasks because they can identify hierarchical features, ranging from edges to complex objects. On the other hand, recurrent neural networks (RNNs) are specifically designed for processing sequential data, such as speech and text. Despite their impressive capabilities, the true power of deep learning lies in its ability to generalize from large amounts of data, rather than in its understanding or reasoning like a human. These systems are often referred to as "black boxes" due to the lack of transparency in their decision-making processes, which raises concerns about trust and interpretability.

While deep learning has led to significant advancements, it also has important limitations. These models require large amounts of labelled data to function effectively, making them quite data-hungry. They are also susceptible to biases inherent in their training datasets, which can result in outputs that are discriminatory or flawed. Moreover, deep learning models struggle with tasks that demand common sense, causal reasoning, or the ability to adapt to new situations, indicating that they are still far from achieving general intelligence.

The chapter also highlights that deep learning is a powerful tool, when used appropriately. While it has driven advancements in AI, its limitations underscore the importance of hybrid models that blend symbolic reasoning with neural networks. It concludes by advocating for a balanced view of deep learning, acknowledging its potential and constraints.