

Understanding the Core Processes of Machine Learning Models



A Knowledge-Rich Description for Those
Passionate About Machine Learning

Audience and Scope

This technical document explains how machine learning **models** are fundamental to the underlying processes we see present in recent developments of **artificial intelligence** (AI) and **machine learning** (ML). The algorithms will also be covered in-depth with respect to how they are crucial to recent advancements and groundbreaking strides found in ML models today. Because these models are becoming more integrated within societal functions, the intended audience for this technical document, those who have a profound interest in the topic of the role of machine learning models and their processes, need to understand them properly.

The era of individuals with access to technological devices with Internet access is changing dramatically by the success of machine learning **algorithms**, with each of these individuals' lives becoming more productive and convenient. With that said, this document is intended to give more insight into how machine learning models have changed lives, for better or for worse, by detailing what key role mathematical algorithms hold in ML models and what that might look like.

Introduction

Machine learning models, a key component of today's technological landscape, have a long and rich history that has evolved alongside computing technology. Initially, computer programs were solely reliant on explicit instructions to complete tasks. However, as hardware capabilities improved and datasets became more complicated, the theory shifted (*Figure 1*). Researchers wanted to give computers the ability to learn from data and experiences like how humans learn. The development of machine learning models has imitated the evolution of computing technology itself, with notable achievements such as neural networks, which were inspired by the human brain. **Neural networks** have permitted more complex data processing and analysis. In the late 20th and early 21st centuries, the rapid growth of the Internet provided massive datasets, which fueled the development of a variety of machine learning algorithms adapted to specific problems. Today,

■ **Models**—A representation of something, such as a system or process. Models can be used to predict the thing being modeled.

■ **Artificial Intelligence**—The ability of a computer or machine to mimic the capabilities of a human brain, such as learning, problem-solving, and decision-making.

■ **Machine Learning**—A type of artificial intelligence that allows computers to learn without being explicitly programmed.

■ **Algorithms**—A set of rules or instructions to be followed in a specific order to achieve a desired result.

Figure 1.
Computer Hardware



(Source: LinkedIn. linkedin.com)

■ **Neural Networks**—A machine learning procedure that is modeled after the human brain. It is made up of a series of interconnected nodes, or neurons, that can learn to identify patterns in data.

algorithms are used to form ML models such as recommendation systems or voice recognition.

Machine learning algorithms can be used in neural networks (*Figure 2*). Neural networks are made up of interconnected layers of artificial neurons. The input layer, hidden layers, and output layer are all included in these layers. Each of the layers has a distinct function.

The input layer contains nodes where each of them represent a dataset attribute. The hidden layers lie between the input and output layers, and this is where the network's core processing takes place. Artificial neurons in the layers perform complex mathematical operations, refining data from the previous layer and revealing meaningful patterns. Ultimately, the processed data arrives at the output layer, where the neural network provides its responses. The configuration of the output layer depends on the specific task, such as classification, which signifies the network's prediction based on learned patterns.

Thus, machine learning models are the hidden architects that give neural networks the ability to learn, adapt, and make predictions. Models provide the rules that govern the weight adjustments, activations, and bias calculations within the network. This technical document is centered on how these models work.

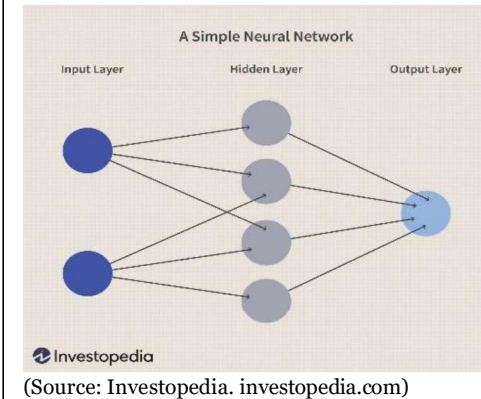
The Components Present in Models

A machine learning model is used to predict an output(s) that it is being modeled after. Models are designed to take advantage of the mathematical complexities that surface from finding patterns in data, which are initially not preprocessed and do not have any meaningful interpretation. As signified in [1], each of the different components, which are almost always addressed when creating a model, undergo preprocessing techniques, feature engineering, and finetuning of model performance through mathematical adjustments.

The iterative nature of the components is present within the creation of machine learning models. Generally, there are five components found in ML models:

- **Input Data.** The input data is the foundation of the machine

Figure 2.
Neural Networks



learning model. It consists of the characteristics, features, or variables that are used to make predictions.

- **Data Preprocessing.** Data preprocessing is the process of cleaning and refining raw data, separating valuable information from **noise** or irrelevant details.
- **Feature Engineering.** Feature engineering is a critical step that involves identifying and extracting the most relevant features from a dataset.
- **Mathematical Operations and Algorithms.** The heart of a machine learning model is made up of mathematical operations and algorithms. Operations, such as **weight adjustments**, **activations**, and **bias** calculations take the processed data and convert it into meaningful patterns and predictions.
- **Output Layer.** The output layer is the final stage of a machine learning model where the model produces its predictions or responses. The structure of the output layer is determined by the task the model is trying to accomplish, and it represents the results of the model's calculations.

The Model Creation Process

Building a machine learning model is a multi-step process, each of which is critical: data gathering, preprocessing, feature engineering, algorithm application, and prediction generation.

Obtaining the Input Data

The input data is used to train the model, which then learns to make predictions based on the data. The quality of the input data is critical to the success of the machine learning model. High-quality input data is the basis of any successful machine learning model. A machine learning model needs meaningful and representative data to function properly.

The input data is the model's instructor, teaching it knowledge and patterns that it will later use for predictions. It is the real-world information that shapes the model's understanding of the problem it is designed to solve.

■ **Noise**—Any contaminated data that interferes with the desired data predictions. Noise can degrade the performance of machine learning models.

■ **Weight Adjustments**—The process of adjusting the weights of the connections between neurons in a neural network to improve the accuracy of its predictions.

■ **Activations**—Applied to the output of a neuron in a neural network. They are used to introduce non-linearity into the network.

■ **Bias**—The difference between the expected value of a model's output and the true value. Bias can lead to a model making incorrect predictions.

However, not just any data will suffice. The input data must reflect the real-world scenarios and conditions that the model will face once it is used. High **accuracy** is desirable because it guarantees that the model understands the problem correctly. Inaccurate or incomplete data leads to unreliable predictions, which can result in costly errors, poor decision-making, and a lack of confidence in the model's output.

■ **Accuracy**—The percentage of correct predictions made by a model on a test set.

Preprocessing the Data

Preprocessing the raw input data (*Figure 3*) is a multi-step process. It helps to guarantee that the data is accurate, and in a format that can be easily analyzed.

The first step involves handling missing values. One must decide how to deal with gaps in the dataset, whether through data removal or other methods. Properly handling missing data is critical to preserving data integrity.

The second step focuses on data scaling. Real-world data often exhibits diversity, featuring a wide range of scales, units, and magnitudes. Scaling techniques, such as **standardization** or **normalization**, play an important role in guaranteeing that the features are within a consistent range, preventing any unintended preference during model training.

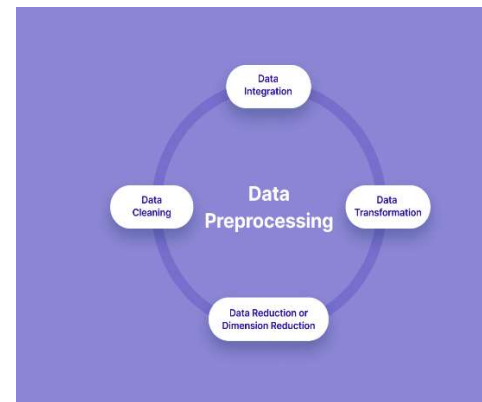
The final step in this process is data transformation. Raw data may not always be in the most appropriate format for machine learning. This step involves converting categorical variables into numerical form and creating new features to capture patterns. Data transformation shapes the data into a format that helps machine learning models effectively understand the underlying structures.

Selecting the Most Relevant Features

This process transforms raw data into meaningful and valuable attributes that can be used to train machine learning models.

The first step in feature selection is to assess the relevance of each feature in the dataset. One must determine the importance of each feature in contributing to the model's predictive capabilities.

Figure 3.
Data Preprocessing Workflow



(Source: V7 Labs. v7labs.com)

■ **Standardization**—A technique that is used to transform data by subtracting the mean from each data point and then dividing it by the standard deviation. It helps to reduce the impact of outliers.

■ **Normalization**—A technique that is used to transform data by dividing each data point by its maximum value. It helps to make the data more consistent.

After assessing the relevance of each attribute, the next step is to remove irrelevant or redundant features (*Figure 4*). They are features that do not provide meaningful information for the model or are highly correlated with other features. Feature selection can also sometimes be extended to dimensionality reduction techniques. Such techniques reduce the number of features while retaining the most important information.

Undergoing Mathematical Operations

The heart of a machine learning model is made up of mathematical operations and algorithms. Consider the three **hyperparameters** to be found in any general machine learning model: weights and biases, learning rate, and activation functions.

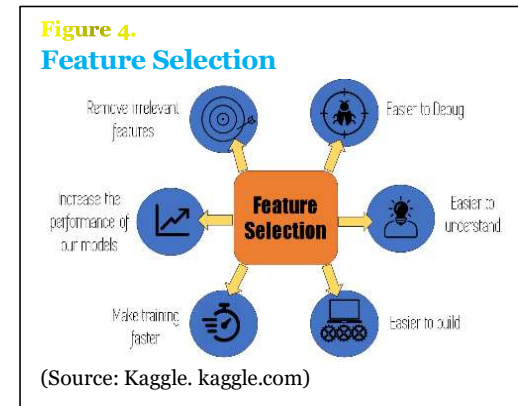
In a model's architecture, weights represent the strength of connections between different features, while biases increase the influence of particular neurons. Parameters change and adjust during the training process, having a significant impact on the model's ability to make accurate predictions.

Another parameter is the learning rate, which controls the size of weight adjustments during training. This parameter has a significant impact on the model's speed of updating its parameters, affecting both the rate of convergence and the final accuracy achieved.

Another parameter is the activation function, which is essential for a model to be able to identify complex, non-linear patterns in the data. The parameters associated with these functions are used to control their behavior, allowing the model to adapt and interpret sophisticated data structures.

Producing Predictions

The output layer is the final stage of a machine learning model where predictions or responses are made (*Figure 5*). This is important because it captures the model's purpose. The output layer of a machine learning model is tailored to the specific task it



■ **Hyperparameter**—A parameter that is used to control the learning algorithm but is not learned by the algorithm itself.

aims to achieve.

The structure of the output layer is modified to confirm that it is consistent with the task's requirements. This allows the model to effectively translate its computations into meaningful results. The correct organization of the output layer is decisive for the model to make predictions that are relevant in the context of the given problem. This makes certain that the model's output is not only accurate, but also interpretable for the intended use case.

Conclusion

As expressed in [2], building a machine learning model is a complex process with several critical steps: gathering data, preprocessing, engineering features, applying algorithms, and generating predictions. Each step is essential for success. High-quality input data, careful preprocessing of data, and feature engineering are essential for accurate, reliable models that provide meaningful insights. The entire process of building a machine learning model is shown (Figure 6).

At the core of the model, mathematical operations and algorithms work together to transform processed data into actionable patterns and predictions. The output layer is the culmination of these efforts, providing task-specific predictions or responses. To utilize the potential of machine learning, one must first comprehend how to build machine learning models. This understanding will enable an individual to utilize models to improve the lives of others, either conveniently or productively.

Figure 5.
Model Prediction

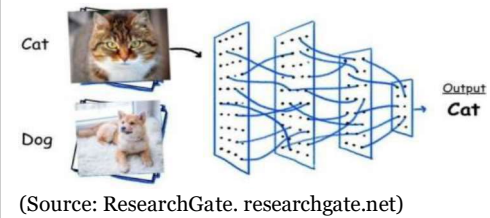


Figure 6.
The Overall Model Creation Process



(Source: AnalyticsVidhya. analyticsvidhya.com)

List of Figures

Figure 1. (cropped): D. Singh, “Let’s talk about AI Hardware - the horsepower behind AI advancements,” [www.linkedin.com](https://www.linkedin.com/pulse/lets-talk-ai-hardware-horsepower-behind-deepak-singh/), Aug. 20, 2020. <https://www.linkedin.com/pulse/lets-talk-ai-hardware-horsepower-behind-deepak-singh/> (accessed Oct. 16, 2023).

Figure 2. (cropped): J. Chen, “What Is a Neural Network?,” Investopedia, Sep. 21, 2022. <https://www.investopedia.com/terms/n/neuralnetwork.asp>.

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Figure 4. (cropped): K. Boke, “Feature Selection-The Most Common Methods to Know,” [kaggle.com](https://www.kaggle.com/code/kaanboke/feature-selection-the-most-common-methods-to-know), Oct. 16, 2021. <https://www.kaggle.com/code/kaanboke/feature-selection-the-most-common-methods-to-know> (accessed Oct. 16, 2023).

Figure 5. (cropped): A. Sharma, “Information Detection Using Image Data Master of Technology in Computer Science and Engineering,” 2021. doi: <https://doi.org/10.13140/RG.2.2.27849.06244>.

Figure 6. (cropped): S. Pandian, “Understand Machine Learning and Its End-to-End Process,” Analytics Vidhya, Dec. 16, 2020. <https://www.analyticsvidhya.com/blog/2020/12/understand-machine-learning-and-its-end-to-end-process/>.

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