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MACHINE LEARNING: A REVIEW OF LEARNING TYPES

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ABSTRACT

In this paper, various machine learning techniques are discussed. These algorithms are used for many applications which include data classification, prediction, or pattern recognition. The primary goal of machine learning is to automate human assistance by training an algorithm on relevant data. This paper should also serve as a collection of various machine learning terminology for easy reference.

I. INTRODUCTION

Machine learning is the study of computer algorithms that provides systems the ability to automatically learn and improve from experience. It is seen as a sub-field of artificial intelligence. Machine learning algorithms allow the systems to make decisions autonomously without any external support. Such decisions are made by finding valuable underlying patterns within complex data.

II. PRIMARY APPROACHES

2.1. Supervised Learning

Supervised learning is applied when the data is in the form of input variables and output target values. The algorithm learns the mapping function from the input to the output.

The availability of large-scale labelled data samples makes it an expensive approach for tasks where data is scarce. These approaches can be broadly divided into two main categories.

2.1.1. CLASSIFICATION

The output variable is one of some known number of categories. For example," cat" or" dog"," positive" or" negative."

2.1.2. REGRESSION

The output variable is a real or a continuous value. For example," price"," geographical location."

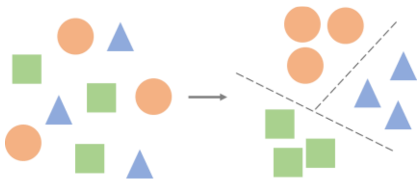

Figure 1. Overview of supervised learning. Input examples are categorized into a known set of classes.

2.2. Unsupervised Learning

Unsupervised learning is applied when the data is available only in the form of an input and there is no corresponding output variable. Such algorithms model the underlying patterns in the data to learn more about its characteristics.

2.3. Reinforcement Learning

Reinforcement learning is applied in making a series of decisions to get the final reward. During the learning process, the artificial agent receives rewards or penalties for the actions it performs. His goal is to maximize the total bonus. Examples include computer learning his game or performing a robotics task with an end goal.

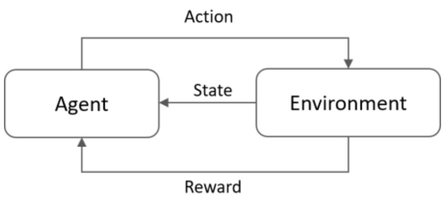

Figure 2. Overview of reinforcement learning. An agent observes the environment state and performs actions to maximize an overall reward.

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III. HYBRID APPROACHES

3.1. Semi-supervised Learning

As the name suggests, this is an intermediate level between supervised and unsupervised learning techniques. These algorithms are trained on a combination of labelled and unlabeled data. A typical environment has a small amount of tagged data and a large amount of untagged data. The basic technique is to first cluster similar data using an unsupervised learning algorithm, then use existing tagged data to tag the remaining untagged data.

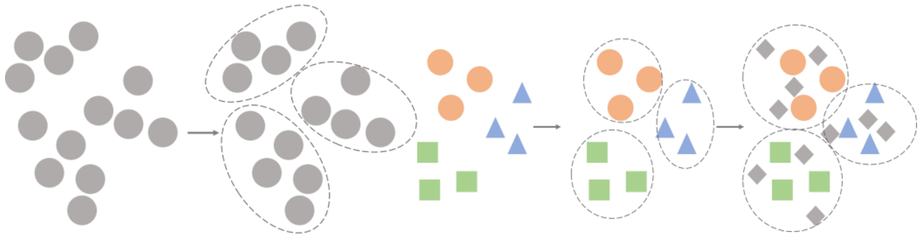

Figure 3. Overview of semi-supervised learning. The clusters formed by a large amount of unlabeled data are used to classify a limited amount of labelled data.

3.2. Self-supervised Learning

Self-supervised learning is a form of unsupervised learning in which the training data is labelled autonomously (or automatically). The data does not have to be labelled manually, but is done by finding and exploiting relationships (or correlations) between the various input features. It does this unattended by forcing the network to learn a semantic representation of the data. Knowledge is then transferred to the model of the main task. Also called a preconcerted.

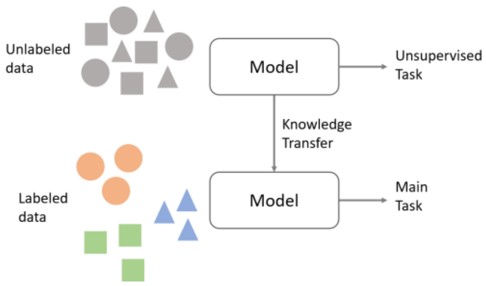

Figure 4. Overview of self-supervised learning. A model is learned on unlabelled data (data is like the labelled data) using a dummy task and then the learned model is used for the main task.

3.3. Self-taught Learning

Self-paced learning can be applied in solving supervised learning tasks given both labelled and unlabeled data. Unlabeled data do not share class labels or generative distributions of labelled data. Simply put, it applies transfer learning from unlabeled data. Once the representation is learned in the first stage, it can be applied many times to different classification tasks.

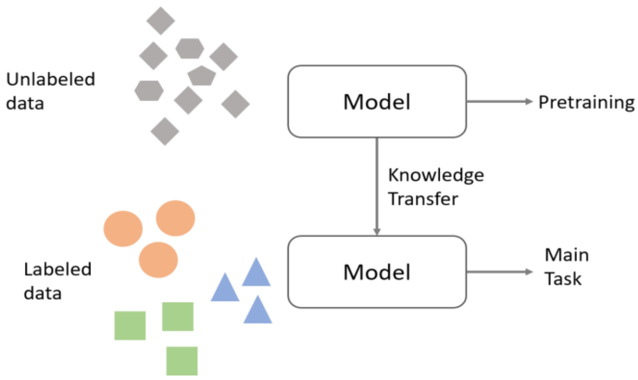

Figure 5. Overview of self-taught learning. A model is learned on unlabelled data (data may be from a dissimilar domain as the data used in main task) and then trained with lesser amounts of labelled data.

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IV. OTHER COMMON APPROACHES

4.1. Multi-task Learning:

Multitask learning refers to a training paradigm that learns multiple tasks simultaneously from a single model. This allows you to use useful relationships contained in related tasks. They improve generalization across all tasks and improve predictive accuracy for specific tasks compared to individually trained models.

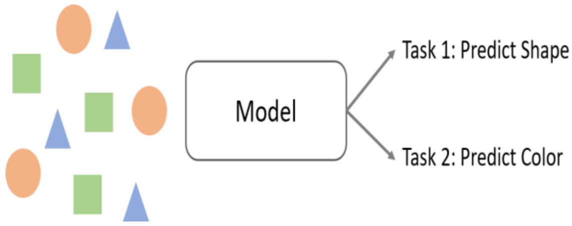

Figure 6. Overview of multi-task learning. Model learning is achieved through multiple tasks that represent properties of the data.

4.2. Active Learning

The algorithm aggressively selects a subset of data samples for learning. Samples are selected from a large pool of unlabeled samples and labelled.

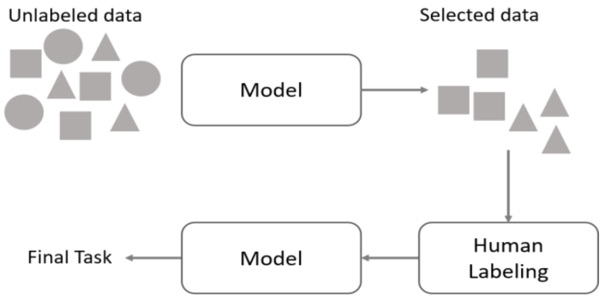

Figure 7. Overview of active learning. From a large pool of unlabeled data, a model selects the samples that it can learn most from for a required task. The selected data is labelled and then used to train the model.

4.3. Online Learning

Online learning involves training with data that becomes available in sequence. This technique contrasts with batch sampling-based learning, where full training data is always available.

4.3.1. INCREMENTAL LEARNING

Incremental learning strategies are similar (or sometimes the same) to online learning. The main difference is that online learning uses the training pattern only once from the incoming data stream. In incremental learning, samples are typically selected from a finite dataset and the same sample can be processed multiple times.

4.3.2. SEQUENTIAL LEARNING

Sequential learning is a commonly used term for learning with temporally ordered data. Under certain conditions, it can also be interpreted as an online learning.

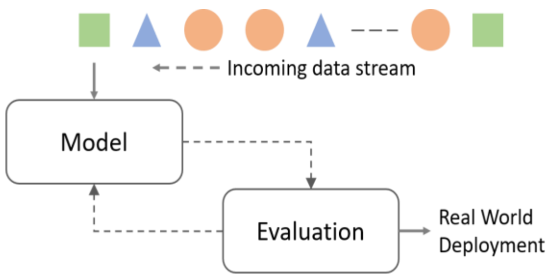

Figure 8. Overview of online learning. The model learns from a continuous incoming stream of data.

4.4. Transfer Learning

Transfer learning refers to the training (or fine-tuning) of algorithms designed for different but related tasks. The main idea is to transfer information from one supervised reading task to another reading task.

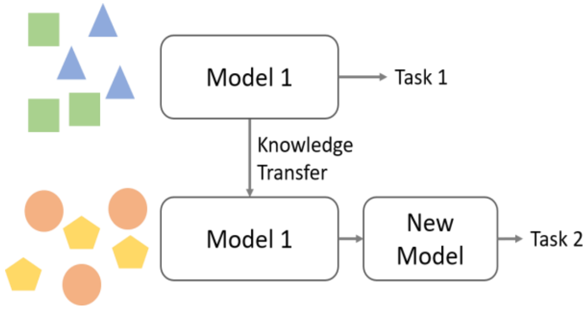

Figure 9. Overview of transfer learning. A model is learned on a dataset and the knowledge is transferred to a new task by retaining a part of the model.

4.5. Federated Learning

Federated learning enables distributed training with large data corpora residing on independent devices. Distribute model training without sharing data samples between individual units. This solves fundamental questions about data privacy, ownership, and locality.

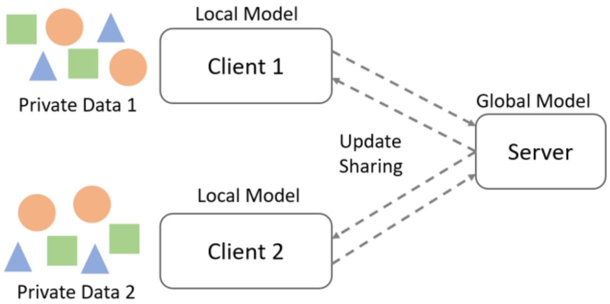

Figure 10. Overview of federated learning. The data resides with individual entities which provides model updates to a centralized server without sharing their data.

4.6. Ensemble Learning

Ensemble learning is a machine learning paradigm in which multiple learners are trained to solve the same problem. They achieve better predictive performance than any constituent learning algorithm. An ensemble consists of several learners, commonly called base learners. The generalization power of the ensemble is typically much stronger than that of the base learners

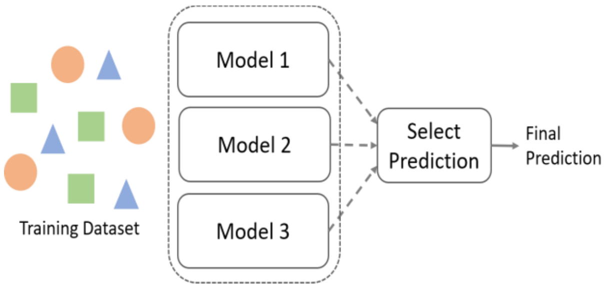

Figure 11. Overview of ensemble learning. Multiple models are learned for the same task and their individual predictions are used to obtain the best result.

4.7. Adversarial Learning

In adversarial machine learning, a model is explicitly trained on a lot of adversarial data such that it is not fooled by those examples. When a standard machine learning model is deployed in the real world, it is susceptible to failures due to presence of intelligent and adaptive adversaries. This is because common machine learning techniques are designed for stationary environments where the training and test data are assumed to be generated from the same statistical distribution.

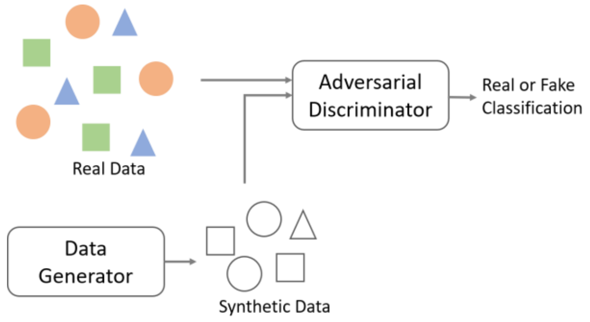

Figure 12. Overview of adversarial learning. The model is trained to discriminate between real and synthetic data samples.

4.8. Meta Learning:

In meta-learning paradigms, machine learning models accumulate experience over multiple learning episodes, often covering a distribution of relevant tasks, and use that experience to improve future learning performance. The aim is to solve a new task with some training examples.

4.8.1. METRIC LEARNING:

Metric learning is a form of machine learning that uses distances between data samples. Learn from similarities or dissimilarities between examples. It is often used for dimensionality reduction, recommender systems, identity verification, etc.

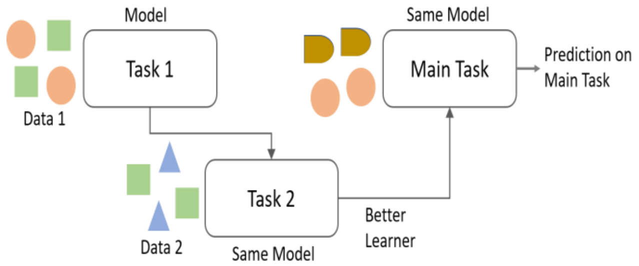

Figure 13. Overview of meta learning. The model gains experience by learning over multiple learning episodes on related tasks before using the knowledge on the main task.

4.9. Targeted Learning

Targeted learning methods build machine learning-based models that estimate features of probability distributions in data. Simply put, we direct learning towards a particular parameter of interest. These methods are also used to obtain impact statistics about model parameters.

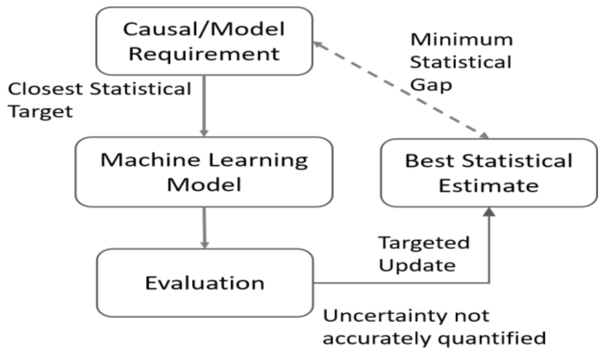

Figure 14. Overview of targeted learning. The model makes targeted updates to specific parameters that minimize the statistical goal.

4.10. Concept Learning

This approach learns from concepts to determine whether a sample belongs to a particular category. This is done by processing the training data to find the best hypotheses (or functions) for the training samples. The

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goal is to classify data points as belonging to a particular concept or idea. In this context, concepts can be viewed as Boolean functions defined over large data sets. A common approach is to use the Find-S algorithm.

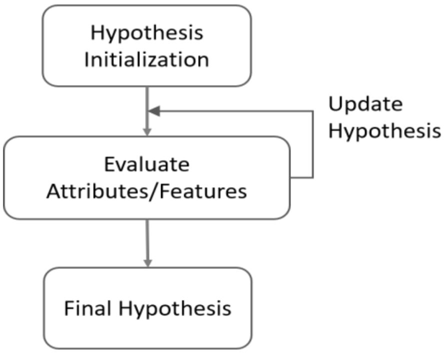

Figure 15. Overview of concept learning. The model finds the best hypothesis that satisfies all the Boolean concepts in the data.

4.11. Bayesian Learning

Bayesian learning uses Bayes' theorem to determine the conditional probability of a hypothesis given some evidence or observation. In contrast to maximum likelihood learning, Bayesian learning explicitly models uncertainty about both input data and model parameters.

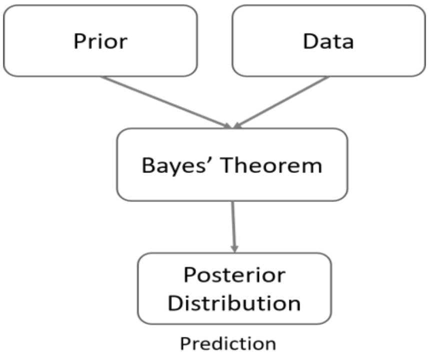

Figure 16. Overview of Bayesian learning. The model used initial knowledge (prior) and the data observations to determine the conditional probability of for data using Bayes' theorem.

4.12. Analytical Learning

The goal is to use logical reasoning to identify features that can distinguish different example inputs. It is a non-statistical approach to learning that allows learners to process information, decompose it into components (characteristics), and use critical and logical thinking skills to generate hypotheses.

4.12.1. INDUCTIVE LEARNING

The goal is to use statistical inference to identify features that empirically distinguish different input examples. Performance is highly dependent on the number of training samples.

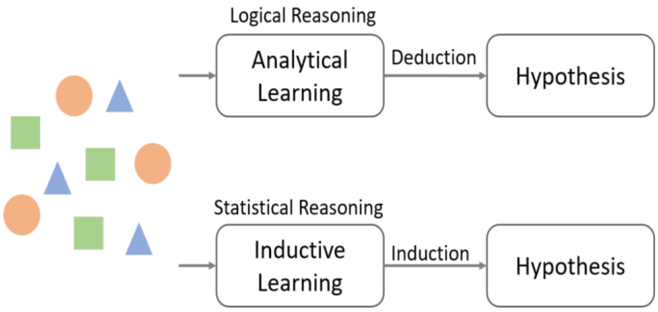

Figure 17. Overview of analytical and inductive learning. This terminology is used to distinguish between models learning using logical or statistical reasoning.

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4.13. Multi-modal Learning

These are types of algorithms that learn features across multiple modalities. Examples of modalities include visual, auditory, kinaesthetic, and other sensory data. Combining such modes allows learners to combine information from various sources for better feature extraction and prediction at scale.

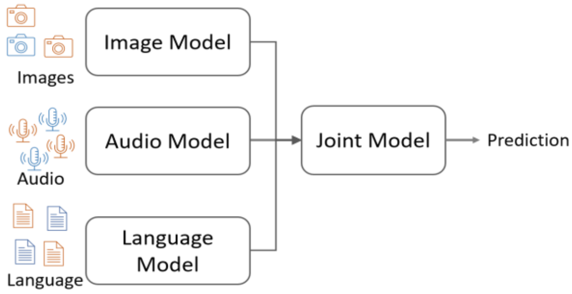

Figure 18. Overview of multi-modal learning. The model is learned using data from multiple modalities to exploit their relationships.

4.14. Deep Learning

Deep learning is a technique for implementing various machine learning algorithms using multilayer neural networks. These multiple processing layers learn representations of the data using multiple levels of abstraction to make sense of the input data.

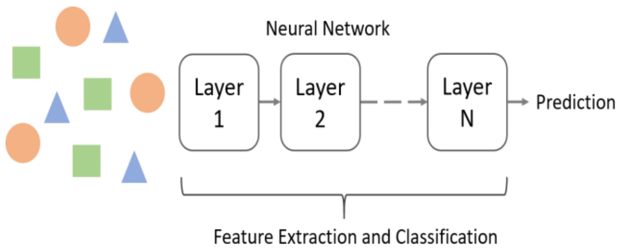

Figure 19. Overview of deep learning. A term used for a multi-layered neural network that learns feature extraction and classification (or other discrimination task) in an end-to-end manner.

4.15. Curriculum Learning

In the curriculum-learning paradigm, training data is organized in meaningful sequences that progressively explain more complex concepts. This idea is like human learning in organized education systems, introducing different concepts at various times. This technique allows you to use previously learned concepts to facilitate learning new abstractions.

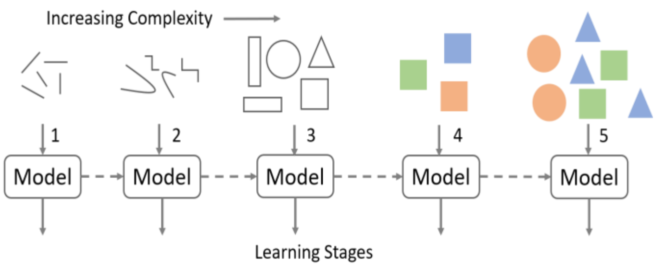

Figure 20. Overview of curriculum learning. The model is learned in stages where data is organized in a meaningful order such that the complexity gradually increases.

V. CONCLUSION

The main contribution of this review is to discuss the various Machine-Learning Techniques employed in effort estimation, cost estimation, size estimation and other field of Software Engineering. The paper also gives a relative comparison of all the techniques based on their applications, advantages, and limitations. After analysis of all the techniques, we cannot state as any one technique being the best. Each technique has different application areas and is useful in different domains based on its advantages.

Our study also encourages that no one technique can be classified as being the perfect machine learning technique. For this reason, there is a strong need for better insight into the validity and generality of many of the discussed techniques.

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