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# THE PROGRAMMING INTERCONNECTIONS WITH MACHINE LEARNING RESEARCH

Omondullaev Bekhzod Farkhodovich
Teacher, Presidential School in Bukhara, Republic of Uzbekistan
bekbro1995@gmail.com, +998 91 4092905

**Annotation**
Big data and Machine Learning is a particular topic that focuses on the key optimization challenges that underpin machine learning algorithms. We want to look at how state-of-the-art machine learning and mathematical programming interact, and we're looking for articles that either improve the scalability and efficiency of existing machine learning models or encourage new mathematical programming applications in machine learning. The majority of machine learning issues can be reduced to optimization issues. Consider a machine learning analyst who is attempting to solve an issue using a set of data. The modeler formulates the problem by choosing an acceptable model family and manipulating the data into a modeling-friendly format. The model is then usually trained by solving a core optimization problem that optimizes the model's variables or parameters in relation to the chosen loss function and perhaps a regularization function. The fundamental optimization problem may be solved several times during the model selection and validation process. Through these essential optimization challenges, the research topic of mathematical programming connects with machine learning.

**Keywords**: machine learning, mathematical programming, convex optimization

## Introduction

While there's lots of exciting experimentation happening with deep learning, most practical applications you're familiar with are based on image analysis. With image analysis, a computer learns to classify random images by analyzing thousands or millions of other images and their data points. For example, consumer apps like Google Photos and Facebook use deep learning to power face recognition in photos. With machine learning, computer systems can take all the customer data and utilize it. It operates on what's been programmed while also adjusting to new conditions or changes. Algorithms adapt to data, developing behaviors that were not programmed in advance. Learning to read and recognize context means a digital assistant could scan emails and extract the essential information. Inherent in this learning is the ability to make predictions about future customer behaviors. This helps you understand your customers more intimately and not just be responsive, but proactive. Machine learning is relevant in many fields, industries, and has the capability to grow over time. The extra gradient approach produces a simple algorithm consisting of a gradient and projection step. For the class of models considered, the projection requires solution of dynamic program or network flow models for which very efficient algorithms exist. The method is regularized by early stopping. Interestingly the path of the extra gradient algorithm corresponds closely to the parametric solution path of the regularized margin methods in their experiments. This demonstrates the interplay of the optimization algorithm and regularization: the path of the optimization algorithm is part of the regularization and there is no need to accurately solve the model. Machine learning is presently a built up approach to generalize conclusions from a (huge) dataset, where numerous characteristics (highlights) of the populace of intrigued are considered at the same time. The basic suspicion is that the dataset could be a careful representation of that populace so that the space of highlights is broadly and decently investigated. In spite of the fact that the approach and the very term “Machine learning” were coined within the computer science community, the field offers more than a common property with Measurements. In a few cases, the two disciplines conversation approximately the same thing, fair with a bend of words: what machine learning individuals call a dataset would be called a test by most analysts. Additionally, the point of machine learning is basically the same as Insights: pick up data around the populace through the accessible information. Therefore, in spite of the fact that numerous center concepts and strategies of Insights are routinely utilized in machine learning, the two communities have generally created them investigate independently, to the degree that the title of a well-known book by three unmistakable analysts utilized the term “Statistical learning” to cover (more or less) the same points we would discover in a machine learning book. At the same time, the progresses in computational control make it conceivable to plan measurable strategies that would have required a restrictive computational stack something else. We emphatically accept that Machine Learning as a field can intensely advantage from the logical back given by the set up cluster of factual strategies [1].

**Methods**

2.1. Problem statement and solution methods

Machine learning models based on current predominantly convex programs such as linear, second order cone, and semi-definite programming are included in the special topic papers. The definitions of the fundamental convex programs can be found in the Appendix for those who are unfamiliar with them. The authors develop unique modeling techniques to uncertainty, hypothesis selection, domain constraints, and graph clustering in these publications, and they solve the models using off-the-shelf optimization programs. SVM and Bayesian networks, for example, are widely used approaches with well-accepted basic optimization problems and algorithms [2]. The ability to learn with large volumes of data is becoming increasingly popular. The immediate response to this demand from the optimization and machine learning groups is to work on more efficient implementations of these proven and reliable optimization methods. Image recognition is a well-known and widespread example of machine learning in the real world. It can identify an object as a digital image, based on the intensity of the pixels in black and white images or color images.

**Real-World Examples of Image Recognition**

- Label an x-ray as cancerous or not
- Assign a name to a photographed face (aka “tagging” on social media)
- Recognize handwriting by segmenting a single letter into smaller images

Machine learning is also frequently used for facial recognition within an image. Using a database of people, the system can identify commonalities and match them to faces. This is often used in law enforcement. Machine learning is a buzzword for today's technology, and it is growing very rapidly day by day [3].

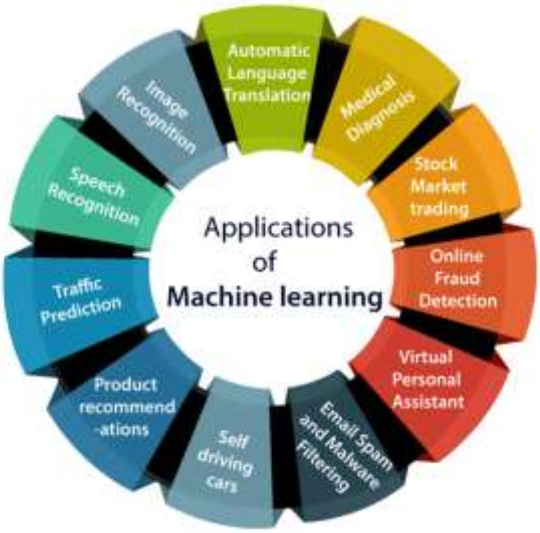


Figure 1. Real-world applications of Machine Learning

These Machine Learning algorithms help to solve different business problems like Regression, Classification, Forecasting, Clustering, and Associations. Based on the methods and way of learning, machine learning is divided into mainly four types, which are:

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- Supervised Machine Learning
- Unsupervised Machine Learning
- Semi-Supervised Machine Learning
- Reinforcement Learning

Along with, for the class of models considered, the projection requires solution of dynamic program or network flow models for which very efficient algorithms exist. The method is regularized by early stopping. Interestingly the path of the extra gradient algorithm corresponds closely to the parametric solution path of the regularized margin methods in their experiments. This demonstrates the interplay of the optimization algorithm and regularization: the path of the optimization algorithm is part of the regularization and there is no need to accurately solve the model. To summarize, in this special issue we see novel approaches to machine learning models that require solution of continuous optimization problems including: unconstrained, quadratic, linear, second-order cone, semi-definite, and semi-infinite convex programs [4]. We first examine the interplay of machine learning and mathematical programming to understand the desirable properties of optimization methods used for training a machine learning model. We observe that the desirable properties of an optimization algorithm from a machine learning perspective can differ quite markedly from those typically seen in mathematical programming papers. Then we will examine the papers within and across the two themes and discuss how they contribute to the state of the art. Many of the papers cross boundaries of both themes. They make small changes in the underlying models that enable the development of powerful new algorithms. Novel methods are developed for multi-kernel, ranking, graph-based clustering, and structured learning. The resulting algorithms decompose the problem into convex sub problems that can be more readily solved.

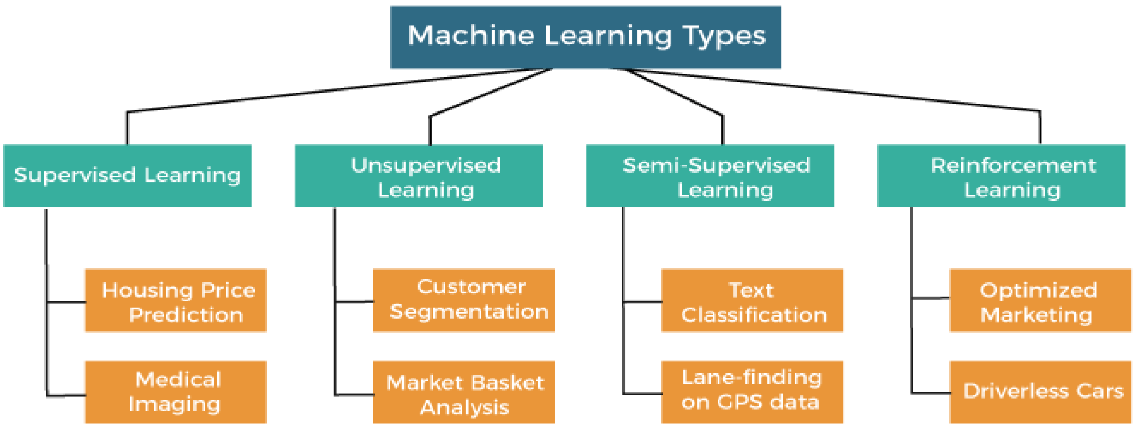


Figure 2. A variety of Machine Learning Types

Supervised Machine Learning, it means in the supervised learning technique, we train the machines using the "labeled" dataset, and based on the training, the machine predicts the output. Here, the labeled data specifies that some of the inputs are already mapped to the output. More preciously, we can say; first, we train the machine with the input and corresponding output, and then we ask the machine to predict the output using the test dataset. Regression algorithms are used to solve regression problems in which there is a linear relationship between input and output variables. These are used to predict continuous output variables, such as market trends, weather prediction [5].

Advantages: Since supervised learning work with the labeled dataset so we can have an exact idea about the classes of objects. These algorithms are helpful in predicting the output on the basis of prior experience.

Disadvantages: These algorithms are not able to solve complex tasks. It may predict the wrong output if the test data is different from the training data. It requires lots of computational time to train the algorithm.

Unsupervised learning is different from the supervised learning technique; as its name suggests, there is no need for supervision. It means, in unsupervised machine learning, the machine is trained using the unlabeled dataset, and the machine predicts the output without any supervision. In unsupervised learning, the models are trained with the data that is neither classified nor labeled, and the model acts on that data without any supervision. The main aim of the unsupervised learning algorithm is to group or categories the unsorted dataset according to the similarities, patterns, and differences. Machines are instructed to find the hidden patterns from the input dataset [6].

Advantages: These algorithms can be used for complicated tasks compared to the supervised ones because these algorithms work on the unlabeled dataset. Unsupervised algorithms are preferable for various tasks as getting the unlabeled dataset is easier as compared to the labeled dataset.

Disadvantages: The output of an unsupervised algorithm can be less accurate as the dataset is not labeled, and algorithms are not trained with the exact output in prior. Working with Unsupervised learning is more difficult as it works with the unlabeled dataset that does not map with the output.

Semi-Supervised learning is a type of Machine Learning algorithm that lies between Supervised and Unsupervised machine learning.

It represents the intermediate ground between Supervised (With Labeled training data) and Unsupervised learning (with no labeled training data) algorithms and uses the combination of labeled and unlabeled datasets during the training period. Although Semi-supervised learning is the middle ground between supervised and unsupervised learning and operates on the data that consists of a few labels, it mostly consists of unlabeled data. As labels are costly, but for corporate purposes, they may have few labels. It is completely different from supervised and unsupervised learning as they are based on the presence & absence of labels. To overcome the drawbacks of supervised learning and unsupervised learning algorithms, the concept of Semi-supervised learning is introduced. The main aim of semi-supervised learning is to effectively use all the available data, rather than only labeled data like in supervised learning. Initially, similar data is clustered along with an unsupervised learning algorithm, and further, it helps to label the unlabeled data into labeled data. It is because labeled data is a comparatively more expensive acquisition than unlabeled data. We can imagine these algorithms with an example. Supervised learning is where a student is under the supervision of an instructor at home and college. Further, if that student is self-analyzing the same concept without any help from the instructor, it comes under unsupervised learning. Under semi-supervised learning, the student has to revise himself after analyzing the same concept under the guidance of an instructor at college [7].

Advantages: It is simple and easy to understand the algorithm. It is highly efficient. It is used to solve drawbacks of Supervised and Unsupervised Learning algorithms.

Disadvantages: Iterations results may not be stable. We cannot apply these algorithms to network-level data. Accuracy is low. Feature engineering is the pre-processing step of machine learning, which is used to transform raw data into features that can be used for creating a predictive model using Machine learning or statistical Modeling. Feature engineering in machine learning aims to improve the performance of models. Feature engineering is the pre-processing step of machine learning; which extracts features from raw data. It helps to represent an underlying problem to predictive models in a better way, which as a result, improves the accuracy of the model for unseen data. The predictive model contains predictor variables and an outcome variable, and while the feature engineering process selects the most useful predictor variables for the model [8].

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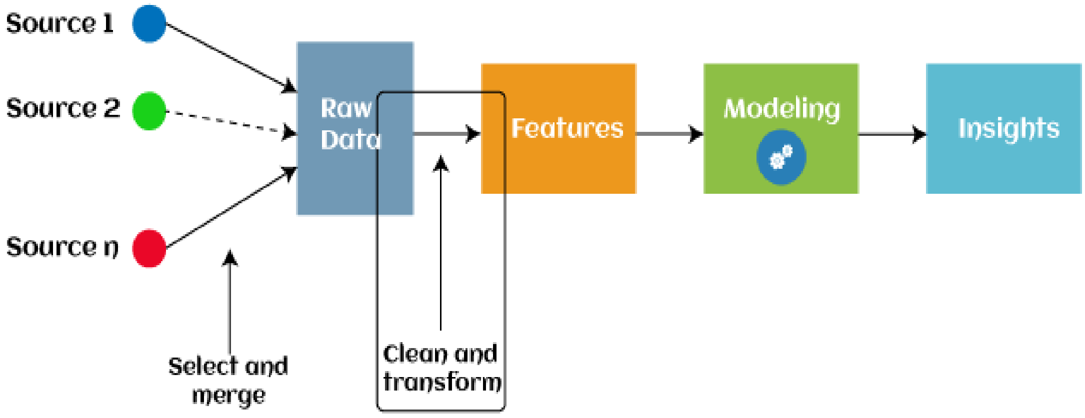


Figure 3. The most useful predictor variables for the model

In Machine Learning, whenever you want to train a model with some data, then Epoch refers to one complete pass of the training dataset through the algorithm. Moreover, it takes a few epochs while training a machine learning model, but, in this scenario, you will face an issue while feeding a bunch of training data in the model. This issue happens due to limitations of computer storage. To overcome this issue, we have to break the training data into small batches according to the computer memory or storage capacity. Then only we can train a machine learning model by feeding these batches without any hassle. This process is called batch in machine learning, and further, when all batches are fed exactly once to train the model, then this entire procedure is known as Epoch in Machine Learning. In this article, "Epoch in Machine Learning" we will briefly discuss the Epoch, batch, and sample, etc. So let's start with the definition of the Epoch in Machine Learning. Deciding you want to pursue a career in Machine Learning means you've got to decide upon which language you would want to use for your implementations [9].

The popular languages among Machine Learning practitioners are Python and R, although there are cases where people have decided to use C, C++, JavaScript, and others. We should choose Python because it was the first language I came across when we decided to start doing machine learning. It ended up working out for me, but in case you're a little more diligent than it was in the beginning, here are some reasons you may want to learn Python for Machine Learning. In recent days, Machine Learning by Python is one of the great courses for beginners that mainly focus on the Fundamentals of Machine Learning algorithms. The lectures are represented in a very interesting way that includes slide animations and a great explanation of algorithms. Python programming language to do the practical implementation of algorithms. With each topic, you will get a chance to practice the topics that you just learner on your own on Jupiter notebook. Each notebook will enhance your knowledge and provide you with an understanding that how to use these algorithms with real-world data. The first part of the course is a Python crash course that covers data structures and Python syntax. Once that's out of the way then we will learn popular libraries used in Data Science and Machine Learning such as NumPy, Pandas, Matplotlib. Many people are using Python for Machine Learning so there's lots of support available online and Python is a high-level programming language with a wide range of Machine Learning frameworks available and additionally there is a low barrier to entry since Python reads like English [10].

Conclusion. In this research, we have explained depiction of include systems in machine learning, working of include designing, strategies. In spite of the fact that include building makes a difference in expanding the exactness and execution of the show, there are too other strategies that can increment expectation precision. In addition, from the above-given strategies, there are numerous more accessible procedures of include building, but we have said the foremost commonly utilized procedures. The coming about Machine Learning models challenge the capacity of common reason solvers coming about within the improvement of novel extraordinary reason calculations that abuse issue structure. These extraordinary reason solvers do not essentially have the characteristics related with great optimization calculations. Regularly, Machine learning requests that calculations find high precision arrangements which they be strength over wide classes of problems. In differentiate, Machine Learning calculation ought to discover great arrangements to contract classes of issues with uncommon structure. Models may be reformulated to permit superior calculations provided that generalization is made strides or at slightest not compromised. Tall precision isn't required since of the inborn mistakes within the machine learning models and the reality that wrong arrangements are intentionally looked for as a shape of regularization, for illustration as in early stopping. Moreover, Machine learning puts more of a premium on calculations that are effectively actualized and caught on at the cost of execution or complexity changes that are ordinarily considered in numerical programming. In this extraordinary theme huge scale issues were effectively handled by strategies that misused both the novel Machine Programming models and the extraordinary issue outlines the numerous shapes of curved programs that can be utilized in Machine Learning.

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