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Visualizing Processes of Machine Learning frameworks for both Optimization and End Users Understanding

Type B - Literature Review

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Contents

1 Introduction

Machine learning could be said as one of the most popular developing fields in computer science as it plays a vital role in our life nowadays (Michalski et al., 2013). At first, it is easy to build a model for a machine learning system to solve a specific problem. The model is also simple and easy to analyze the result as well as its learning processes. However, as the society is developing day by day, the amount of information also increases rapidly and there are more and more problems in different areas need to be solved. This makes it harder for researchers to analyze a complex model of machine learning.

Albert Einstein stated that "if you cannot explain something simply, that means you dont understand it well enough" (Kesari, 2018), In this context, if we cannot analyze the machine learning model, how can we be sure that the result obtained from the model is correct and how can we rely on these results to make a change in our life. To address this problem, many researchers have proposed different methods for visualizing the processes of machine learning frameworks. This report focuses on reviewing common visualization approaches of a machine learning system for both optimization and end users understanding.

The next section mentions the literature review of this topic, which is divided into two smaller sections to discuss visualization of machine learning for both optimization and understanding of users. The section 3 is about the possible future of visualizing machine learning. The final section is about the conclusion of the report which summarizes the main idea as well as express the authors opinion on this topic.

2 Literature Review

2.1 Visualization of Machine Learning for End Users Understanding

As machine learning is gradually used to help human solve important problems in different fields such as medical area or education, it is a need to understand of how these systems work in order to ensure the reliability of the results. According to Kesari (2018), in order to implement a good humanizing machine learning, there are four key elements that need to be considered, which are information design, adaptive abstraction, model unraveling, and user interactivity.

Information design is the process of visualizing the results of the model. For the purpose of helping end users understand the main content of model results, the process focuses on displaying it in specific formats such as tables or graphical results (Knaflic, 2015).

Adaptive abstraction process aims to design the problem of the machine learn system into different steps and try to solve each step of the problem so as to help users gain a better understanding of the machine learning process by moving the levels step-by-step (Victor, 2011).

Model unraveling is the process of breaking the inside of the model with the aim of understanding how the algorithms learn and are able to process the problem. The visualizer tool for TensorFlow, which is presented in the paper of Wongsuphasawat et al. (2018), analyzes the underlying process of TensorFlow. The tool provides users the ability to analyze the structure of the model as well as understand the process of learning and forming neural networks.

User interactivity involves the activities between users and the machine learning system. The process allows users to be able to perceive the learning and predicting operation of the system by displaying a visual process of machine learning. Users can also interact with the system by modifying, adding, deleting the data during the process of learning (Fails and Olsen, 2003; Holzinger, 2016).

As regards to interactive machine learning system, it is argued that interactivities between users and machine learning systems should not be limited to the only specific stage but should be a process across all stages of machine learning operations including inputting data, learning and predicting process (Amershi et al., 2014) The article of Amershi et al. (2014) supports for the second statement by promoting an approach in interactive machine learning. It shows that their method improves the result of an effective machine learning system as well as user experiences by providing a good understanding of machine learning framework for users.

2.2 Visualization of Machine Learning for Optimization

Optimization in machine learning has been one of the common investigation purposes of researchers. As mentioned in the section **??**, a complex machine learning model with high dimension data is one of the main obstacles that they need to deal with to optimize the system. In order to address the problem of visualization for the complex model, the paper of Lee et al. (2016) proposes a method named transparent boosting tree (TBT) to analyze the internal structure of the model. In each learning step of the interactive machine learning system, the method also visualizes the prediction process and allows the system to receive feedback from users to improve the performance of the boosting tree.

Regarding the medical area, an interactive machine learning system is also promoted in the paper of Holzinger (2016). It is mentioned in the paper that the importance of an interactive system is essential in this area since an automatic machine learning system usually suffers the problem of lacking data for training. In order to address this problem, the group of authors proposes an interactive machine learning system with the aim of achieving an effective machine learning that can solve difficult problems in the medical area. According to the paper, instead of interacting between end users and machine learning system, it is defined as the interactivities between agents and the system. Because of the support from agents, which can also be human, many problems can be solved such as data clustering using k-Mean algorithm (Holzinger, 2016). By manually defining the K value for the K-mean classifier based on the structure of data, the system could effectively classify and label the data.

Also, as there are more and more researchers aiming to interpret machine learning models for optimization, the paper of Liu et al. (2017) focuses on providing an overview of analytic approaches based on their tasks for visualization. For example, EnsembleMatrix, which is also an interactive machine learning system, is proposed to optimize the performance of the system by using combinations of classifiers. Talbot et al. (2009)

3 Possible Future of Visualization

It could be said that an interactive machine learning system not only helps end users to understand the decision process of the system, but it could improve the performance of machine learning models as well. However, it is necessary to consider that in the machine learning system, there is a variety of techniques for automatically handling decision making processes (Settles, 2012; McCallum and Nigam, 1998). It is a good point that developers could combine techniques of handling processes by system and human to optimize the system's performance, but it could lead to conflicts between these two types of techniques. A decision made by a human about the number of clusters in the sampling data could be different from the predictive value of the system. In the future, there should be a better method to address this problem.

In the future, a visual machine learning system could be a combination of 4 key elements as mentioned in section 2.1. The system will be easier to interact with a human. There will be a better visualization of all stages of the machine learning system.

4 Conclusions

On the one hand, Users need to have a good understanding of how a machine learning system works as well as how it could map the inputs to produce the final result. One of the most common methods for interpreting the model is to use an interactive machine learning system. It allows users to interact directly with the machine learning processes in all stages including inputting data, updating variables or sending feedbacks to the system. On the other hand, optimization of a machine learning model is used to achieve a better result and be able to handle hard problems effectively. The optimization process is done by allowing users to manually define values during the learning process or by automatically updating variables in the system from feedbacks of users.

It could be said that there is a relation between the visualization process of machine learning system for optimization and for users understanding. Users could interact with a machine learning system to have a good understanding of the model structure and the machine learning system receives feedback from users to optimize its performance.

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