INTERACTIVE MACHINE LEARNING

NAME : Azmayen Fayek Sabil
ID : 190042122
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DEFINITION :

Interactive machine learning (iML) is an active machine learning technique in which models are designed and implemented with human- in-the-loop manner. End-users participate in the model building process by iteratively feeding training parameters, inspecting model outputs and providing feedback on intermediate results. However, to the best of our knowledge, there has been a little extensive survey in the field of iML covering the state-of-the-art. Another definition for iML is, we have always searched for a way to increase the prediction accuracy by somehow involving humans in the process. The answer is interactive Machine Learning.

APPROACHES/TYPES OF iML:

We have categorized interactive machine learning based on their merit in the solution space.

- Robust Machine Learning
- Trustworthy Machine Learning
- Low Resources Machine Learning
    - Small Data Machine Learning
    - Pervasive Machine Learning

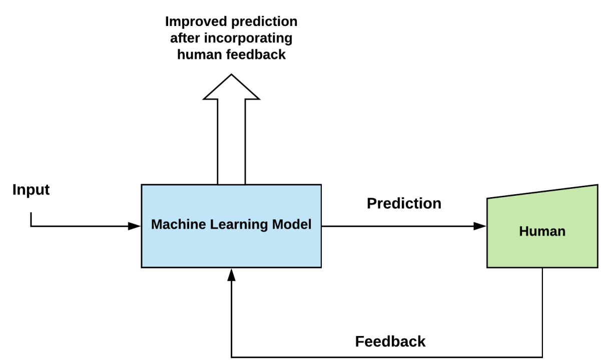
ARCHITECTURE AND OPERATIONS:

The employment of iML has been constrained to only predefined sectors or limited scope of the architecture. To this end, we have thoroughly analyzed the recent iML-inspired research works using merit-oriented taxonomy. After an extensive review of iML-inspired literature and untapped problems, we have categorized contributions into Robust Machine Learning and Low Resource Machine Learning based on their merit in the solution space.

So the behind the scene of interactive machine learning is, first there has to be a dataset, supervised or unsupervised. Then we choose a model and go into the training phase. In the first iterations after the machine learning model has predicted some value, we humans interfere with the decision of the machine and compare our observation against the outcome. This way the model can learn even quicker after every iteration.

Then after the training phase has ended, the model is now in the testing phase. So here we evaluate the score of the model. Even in this case the outcome is sent to the human for comparison. After comparing the result with the actual result, the model is fed with the final data to learn more effectively. So this way the model learns through predicting by itself and with the help of human interaction. So after putting this all together we get that during the whole process of iML; there is

- Probabilistic modeling
- User modeling
- Explainability of model
- Incremental learning
- Interactive system and
- Active learning.



IMPLEMENTATIONS PROCEDURE:

iML has an interesting way of handling machine learning problems. iML based methods propose frameworks that masks the discriminatory biases of black-box classifiers. This plays a vital role to compensate for the effects of perturbated inputs on a given model.

In addition to that it lets the user detect potential adversarial attacks and manage its impacts. iML has also been used to directly engage users in the model building process. This helps to avoid both training phase and test phase adversarial attacks or errors as the user will be there validating inputs and intermediate results. A graph based framework, where user feedback is represented as edges and nodes are the models is a good example of such applications. It proposes a query model based on a robust machine learning framework that interactively learns models like classifiers, orderings/rankings of items or clusterings of data points. In each iteration, the algorithm proposes a model, and the user either accepts it or reveals a specific mistake in the proposal. The feedback is correct only with probability $p > 1/2$ (and adversarially incorrect with probability $1 - p$). For example, The algorithm must be able to learn in the presence of arbitrary noise.

Another implementation is, enhancing the trustworthiness of machine learning algorithms comes with making the model building process interactive. Put succinctly, increasing the explainability and interpretability of machine learning by engaging user-in-the-loop increases its trustworthiness. To this end, various explanatory frameworks that show the implementation details of the model building process have been introduced. The essence of most exploratory algorithms is that intermediate results corresponding to a batch or even tuple are made subject to user-feedback whenever there is a variation between the predicted and the actual label.

Models and feedback from users can also be represented using textual-explanatory systems. An argument based explanatory iML algorithm proposes a framework that exploits the usability of arguments to precisely axiomatize feedback both from the user and system side. It practically shows how to narrow the gap between domain experts and the machine learning model by engaging domain experts. Users provide feedback using a pair of reasons and outputs called arguments. Since arguments are generally presumptive and can’t be untaken for a general set of predictions, the authors introduced prediction-level argument based explanations of decisions made by the learning model. Put succinctly, the training module generates initial features to perform prediction or classification. Whenever the learner notices a major deviation between the desired and actual prediction, it consults the domain expert to provide feedback on the output (both the prediction and explanation). At this stage, the domain expert would be able to see the problem either in the predicted label or the rule yielding the outcome. Then, the user provides a set of arguments for each critical example (predictions with problem) and lets the model to retrain keeping the feedback given from the user.

APPLICATION SCENARIOS OF iML:

iML has not yet been exhaustively applied to areas such as searching and retrieval, pervasive computing and robotics, and clustering and optimization tasks. Moreover, although the importance of iML in decision-sensitive areas such as agriculture, health, education, game and entertainment is evidential, we have seen very few contributions in this regard.

Another application of interactive machine learning is in resource constrained environments, more specifically in pervasive and robotics environments. Sectors like under-developed linguistics, medical science, finance and military may not have sufficient amount of data for the standard machine learning framework to produce accurate outcomes. Consequently, machine learning algorithms have been modified in a way it engages users-in-the-loop.

Besides, it incorporates state-of-the-art visualization techniques to leverage users feedback for data reduction and easing computing resource requirements. To this end, iML plays a vital role. Interactive machine learning has also been applied to tackle adversarial attacks on automatic speech recognition (ASR) models. Another important iML enabled low resource learning is employed for pattern mining research problems.

Interactive machine learning also plays a significant role in image processing and computer vision in general

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