# Progress Report: Towards Safe Machine Learning

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Machine learning algorithms have started influencing every part of our lives, and have moved into safety-critical domains, e.g., machine learning based medical decision support systems, autonomous driving, surgical robots, e.t.c. If the safety of the machine learning component is not guaranteed, it would not be trusted by the users. Therefore, questions about safety must be examined [1] before safety-critical systems with machine learning components can be deployed in real-life successfully.

## I. Challenges and Potential Strategies

During the past few months, we have reviewed the challenges to achieve the safety for systems that contain machine learning components and potential strategies to address these issues. Here we list some challenges as follows.

- Non-transparency: Many machine learning algorithms, e.g., deep neural network, behave mostly as black boxes. Thus, it is difficult to assess the reliability if the reasoning behind machine learning models cannot be understood.
- Unmodeled phenomena: Machine learning algorithms learn from training data and hence they can only be as good as the examples that have learned. For example, a model is trained to recognize dog breeds, and hence can not recognize a cat. Due to the fact that training data is only an incomplete subset of possible scenarios that would be encountered, it is impossible and even not desired to expect that the machine learning has learned everything.
- Instability: A small change in the training process may produce a different result and hence it is difficult to debug models or reuse parts of previous safety assessments.
- Difficulty in verification: Formal verification of machine learning components is a difficult, and somewhat ill-posed, problem due to the complexity of the underlying machine learning algorithms and large feature spaces.

We have reviewed the possible directions to address the above mentioned issues. For example, we can improve interpretablility and transparency of system with machine learning components by insisting on models that can be interpreted by people and by excluding features that are not causally related to the outcome. Even though the models with better interpretablilty cannot solve complex problems, the predictions of more complex machine learning models can still be explained by interpretable models [2]. Since machine learning algorithms are only as good as the examples they have learned, an important technique used in machine learning when predictions cannot be given confidently is the reject option [3].

$$f(x_i) = \text{rejection if } g(f, x_i) \leq \sigma$$

where $g(f, x_i)$ measures the confidence level of function $f$'s prediction for $x_i$, and $\sigma$ is a threshold. However, measuring the uncertainty of a prediction is not a trivial task. To address large feature spaces issue in verifying machine learning algorithm, feature space abstraction technique can be used [6]. An approximate function of the original model is verified based on realistic and meaningful simplifications [6] of the origin high-dimension input space.

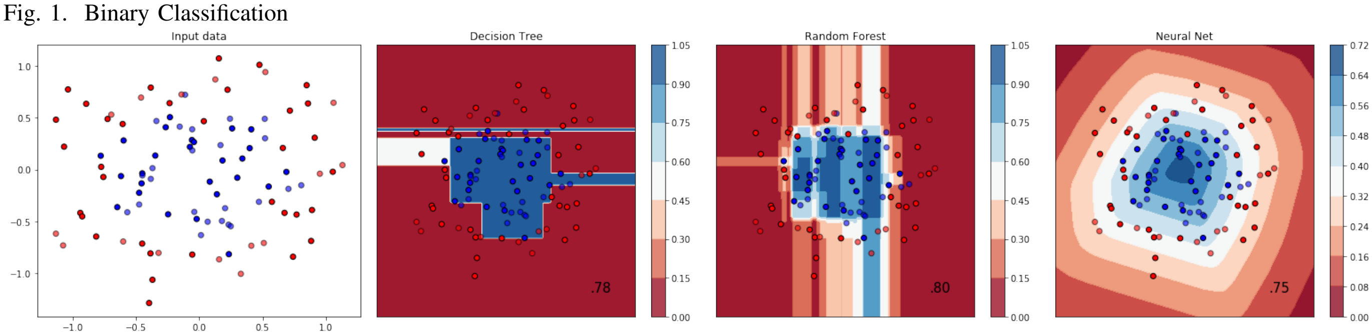
## II. Plan of Future Work

As mentioned, measuring the confidence of a prediction is not a trivial task. In ensemble classification, the overall decision $\hat{y}$ is based on the average classification of the base classifiers $\hat{y}_i(.)$, where $\phi(x) = \frac{1}{m}\sum_{i=1}^{m}\hat{y}_i(x)$. In neural networks, predictive probabilities obtained at the end of the softmax output are often erroneously interpreted as model confidence [5].

$$P(y = j|\mathbf{x}) = \frac{e^{\mathbf{x}^\intercal \mathbf{w}_j}}{\sum_{k=1}^{K} e^{\mathbf{x}^\intercal \mathbf{w}_k}}$$

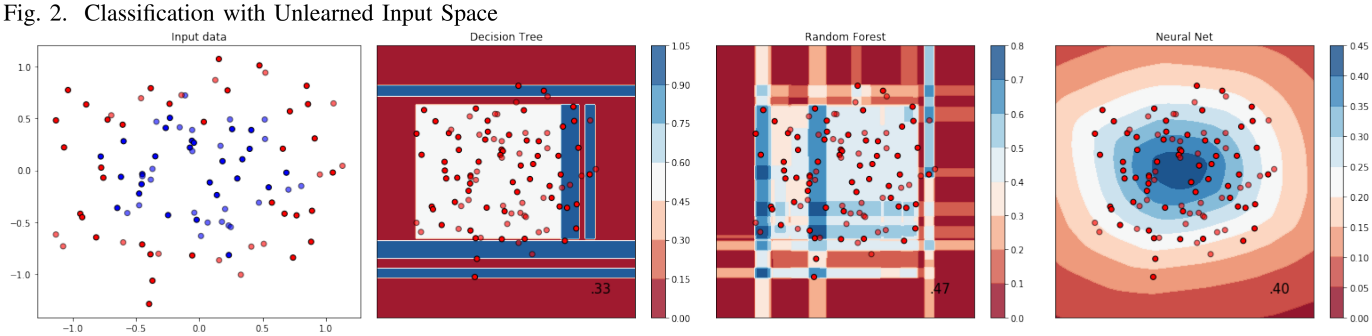
However, a model can be uncertain in its predictions even with a high softmax output [5]. Methods based on Bayesian interference could also measure the confidence level of predictions [7], but a suitable prior distribution has to be chosen. In classification problems, classifier implicitly assumes that distance from the decision boundary is inversely related to confidence [4]. This is reasonable *to some degree* because the decision boundary is located where there is a large overlap in likelihood functions. However, a model could predict with very high confidence for an input space that has never been learned at all. Figure 1 is an contour plot of a binary classification task with label $y \in \{0, 1\}$. If the output $\hat{y}$ is close to $0/1$, it means the classifier has higher confidence that input instance belongs to class $0/1$. If the output is round $0.5$, then it has very low confidence. As we can observe, the classifiers

Fig. 1. Binary Classification




have very high confidence in predictions for input space at the corner even though no training data exists there. Therefore, our next plan is to design a method to identify the confident range of classifier based on the principle that the models are only as good as the examples they have learned. As an toy example, Figure 2 shows a contour plot after we classify the 2-d input space that has trained with the one that has not been trained. When the output is 0, it means the classifier has very low confidence. In the next step, we plan derive an efficient solution to this problem in high dimension space to help machine learning models avoid uncertain predictions that could result in hazard events.

Fig. 2. Classification with Unlearned Input Space

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