Prediction Markets for Machine Learning

Master thesis in COMPUTER SCIENCE

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Abstract

The main topic of the thesis is prediction markets as a machine learning tool. The thesis gives an overview of current state of the art in this research area, relates artificial prediction markets to existing well-known model combination techniques and shows how they extend them. It also develops techniques introduced in one of previously known frameworks, contains a description of a first practical implementation of this framework and evaluates its performance on both synthetic and real data sets from UCI machine learning repository. Finally, results of this evaluation are utilised to understand strengths and weaknesses of this approach and to suggest future directions in this research area.

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Chapter 1

Background

1.1 Supervised and unsupervised learning

If an algorithm is given a set of inputs (also called features vectors) x1, x2, . . . , xn and a set of corresponding outputs (also called labels) y1, y2, . . . , xn and the goal of the algorithm is to learn to produce the correct output given a new input, this is a supervised learning task. A supervised learning task is called classification if the outputs are discrete or regression if the outputs are continuous. If an algorithm is only given a set of inputs x1, x2, . . . , xn and no outputs, this is an unsupervised learning task. Unsupervised learning can be thought of as finding patterns in the data above and beyond what would be considered pure unstructured noise. Two most common examples of unsupervised learning are clustering and dimensionality reduction. Inputs can be vectors of different types of objects, integer numbers, real numbers, strings or more complex objects. Outputs take values each representing a unique state. For example, an algorithm may be given a number of vectors representing numerically external features of a person, such as height, weight, shoe size etc., and corresponding outputs that take one value from the set male, female.

1.2 Classification

Classification is a particular supervised learning task. The objective of a classification algorithm is, given a set of inputs X, that come from a space F L, and corresponding outputs Y, that belong to one of K classes, to learn a function that can predict an output for unseen input. Usually a good measure of performance of a classifier is misclassification rate. Sometimes it's more convenient to use accuracy, which is equal to 1 - M. If an algorithm outputs a probability distribution over classes and not just predicted class, then it learns a function. In

that case, a good complementary measure can be log-likelihood. This may be a good measure in some circumstances as it does not asses how often the classifier was right, instead assessing how much probability mass it put on the correct class. Practical classification algorithms include: support vector machines, logistic regression, neural networks, k nearest neighbours, decision trees and Naive Bayes. Ensemble methods (section 1.4) build more complex models using these. Please see [HasTibFri09] for a comprehensive overview. It is important to understand that function h not only has to describe the training data (X, Y) but also has to be able to generalize to unseen instances. If a classifier has a very low misclassification rate on training data but high misclassification rate on test data, it is said to overfit to the training data. That means that the classifier models the noise in the training data and not the true underlying pattern that is of our interest. Overfitting occurs primarily when the model has too many parameters given the amount of training data available. Therefore, it is very often reasonable to favour simpler models to more complex ones. Figure 1.1 shows an example of this phenomenon. Predicting classifier's performance on unseen data, should never be done on the training data, overfitting is one the reasons. It is typically the best approach, to partition the data into three sets: training set - to train the classifier, validation set - to tune classifier's parameters and test set - to predict performance on new instances.

1.3 Clustering

Clustering is an unsupervised learning task. The objective is to divide a set of objects, represented by inputs x1, x2, ..., xn, into a set of disjoint clusters x1,1, x1,2, ..., x1,n1 ,x2,1, x2,2, ..., x2,n2, ..., x3,1, x3,2, ..., x3,n3, that contain objects similar to each other in some sense. Typically, similarity between two objects is defined by Euclidean distance or Manhattan distance. For a comprehensive overview on clustering algorithms please refer to [Fun01].

1.4 Ensemble methods

Ensemble methods use multiple models to combine them into one stronger model. Experience shows that it is common for individual algorithms to be outperformed by combinations of models and heterogeneous combinations are of special interest ([BelKor07]). As mentioned by [Die00] there are essentially three reasons why ensembles of models perform better than individual models: statistical, computational and representational.

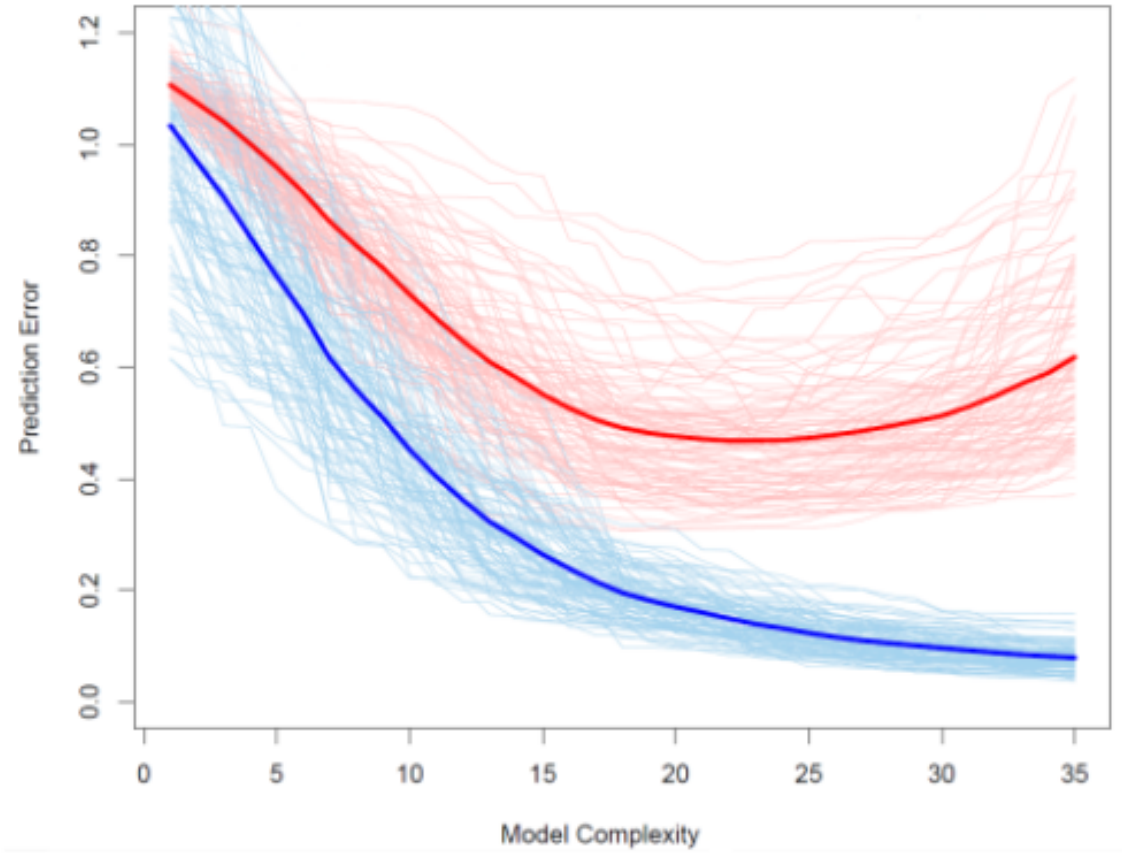
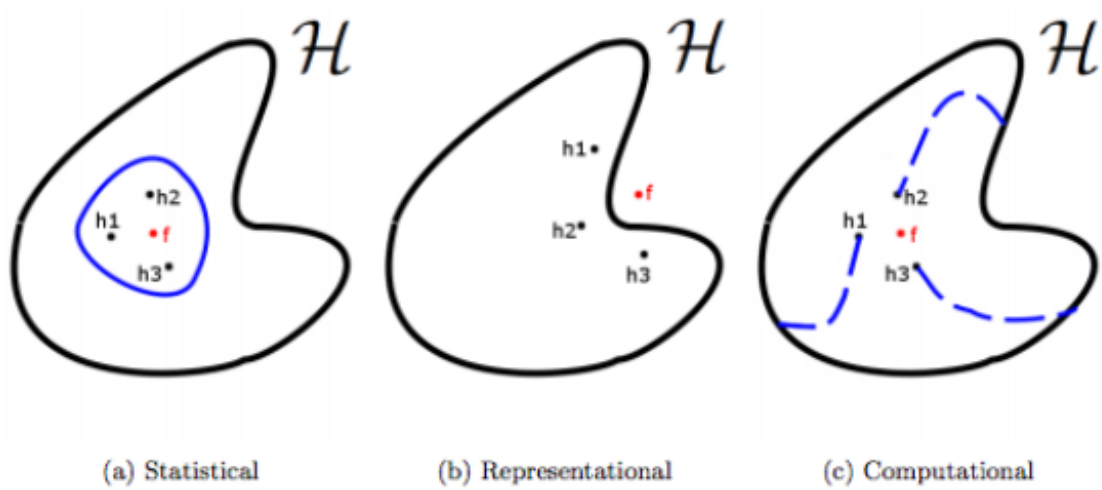


Fig. 1.1 First figure



(a) Statistical (b) Representational (c) Computational

Fig. 1.2 Second figure

1. Statistical. One way to look at a learning algorithm is to view it as searching a hypothesis space H to find the best one. Without enough data the algorithm may find a few different hypotheses in H that give the same accuracy on the training (or validation) data. By constructing an ensemble, the algorithm can find a point that is, in a certain sense, an average of the members of the ensemble and thus reduces a risk of choosing the wrong classifier.

2. Representational. In many cases the true function f cannot be represented within hypothesis space H. By combining classifiers into an ensemble it may be possible to expand a set of representable functions. Even though some algorithms, like neural networks (that actually are universal approximators as shown in [Hor91]), can, in theory, express a lot of functions, it is important to bear in mind that due to the finite amount of training data, they will effectively explore a finite number of hypotheses and will stop when the model fits the training data well enough.

3. Computational. Even when there is enough data, an algorithm performing local search for the best hypothesis may get stuck in local optima. That is the case for neural networks for example. Therefore, starting from different points and combining obtained models in an ensemble may lead to a model that is closer to the true hypothesis. The most widely used ensemble methods are Random Forest ([Bre01]) and AdaBoost ([Sch03]).

1.4.1 Random Forest

Decision trees A decision tree partitions the feature space into rectangular regions and assigns a class to every region. The process of partitioning the space is performed in such a way that the choice of the variable that will be responsible for current split is done by greedily picking a variable that gives the highest information gain. Decision trees are conceptually very simple yet accurate. Algorithm 1 gives a precise description on how to build a decision tree.

1.4.2 AdaBoost

Boosting, and also more specifically the AdaBoost algorithm, is based on the observation that finding a single, very accurate prediction rule is much harder than finding many rough rules. AdaBoost builds multiple weak classifiers, feeding a classification algorithm with a different distribution of training examples each round. At the end of that process, the algorithm combines those weak learners, that have to be only slightly better than random,

into one strong classifier. The two important questions in this approach are how to change the distribution of training examples and how to combine classifiers. AdaBoost answers the first question by putting more weight on those examples that are harder to learn and combines classifiers by plain weighted majority voting, where the weights are chosen according to equations (1.6) and (1.7).