COMS 4771 Kaggle Competition Report from Deus Ex Machina Team

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***Abstract*—The main purpose of this report is to present our team's Kaggle result, document the competition process and explain our approach to achieve the accuracy score of 0.95667 which placed us in the 2nd position in the Public Leader Board.**

We will briefly discuss about feature design in the first section, analysis and experiment of classifiers we used in the competition in 2nd section, our final "recipe" of algorithm in the 3rd section, metric performance in the 4th section and end result of quiz set in the last section.

I. Data Processing and Feature design

In our experiment, we have tried two feature presentation methods: label encoding and one-hot label encoding.

A. Label Encoding

Label encoding assigns an integer to every categorical feature. It's the most simply form of feature representation. However, it assumes that all categories are ordered, which is not always true. For example, in distance-based algorithm such as SVM, it assumes that one feature is farther away from another, which is not always desirable.

B. One-hot Encoding

One-hot encoding is an efficient way to convert represent categorical features. It transforms each categorical feature with m possible values into m binary features, with only the active one as 1 and left the other as 0.

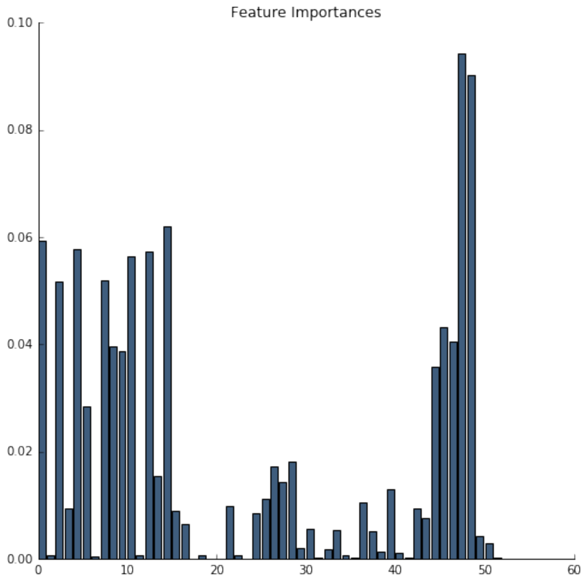
$$\Phi(x) = \begin{bmatrix} 0 & \dots & 0 & 1 & 0 & \dots & 0 \end{bmatrix}^T \tag{1}$$

This will solve the order problem of label encoding described above.

C. Performance

We find that one-hot encoding and label encoder are comparable in term of accuracy score when applying with various standard classifiers such as decision tree, k-NN and SVM. However, we notice signifcant running time performance with label encoder. It makes sense since label encoder maintains only 52 features while one-hot encoder creates more than 1500+ features!

On the other not all the features are equally important. The below is extracted from extra tree classifier internal property. As you observe, features 27-55 are virtually nonessential in this classifier decision. Nevertheless, we notice no performance gain after dropping off these extra features while keeping these features permits us to sustain about 0.1% more accuracy which is more than enough to differentiate ranking in the competition, so we decide to utilize all features.



II. Model Description

We begin our investigation by testing our favorite classifiers, SVM and SGD. However, they did not perform very well in this dataset (80% vs 76%) and the class benchmark is 90%. On the second look at the dataset description and our feature design, we find out why. Firstly, we use label encoder to encode categorical variables, and so we have removed concept of distance from the most important features of the data. Secondly, most of feaures deal with some sorts of syntatic structures which are rule-based by nature. As such, we suspect that non-linear classifier like decision tree or ensemble of trees may perform best.

In the proceeding, we will discuss in length about multiple classifiers we use to achieve great performance. As expected, the ensemble of trees accomplish superior performance($> 94\%$). In order to boost our score further, we take the concept of ensembling to the extreme by employing a variation of ensemble blending popularized in Netflix Grand Prize competition.

A. *K Nearest Neighbors*

The KNN algorithm tries to directly approximate the decision boundaries of f. It computes the k, which is also one of the model parameter, training points that are closest to x based on Euclidean distance, then returns the purality of the labels of these k points as the prediction result for this sample x. KNN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification.

B. *Decision Tree*

A decision tree is a flowchart-like structure in which each internal node represents a decision boundary on a feature, each branch represents the outcome of the test and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represents classification rules. During the learning process, the decision tree algorithm create a decision function $f : \mathcal{X} \rightarrow \mathcal{Y}$ represented by a binary tree, and for each node, it picks the rule h, which splits the node S into two children nodes S_L and S_R, that can obtain the maximally reduces in uncertainty.

$$h = \arg\max_{h}(u(S) - (p_L \cdot u(S_L) + p_R \cdot u(S_R))) \tag{2}$$

The uncertainty is the value to quantify the mismatch between the prediction result for a rule, and all samples within this rule (node). There are many different methods to compute the uncertainly, and in this competition the uncertainty we used are:

1) Classification error:
$$u(S) = 1 - \max_{k \in \mathcal{Y}} p_k^2 \tag{3}$$
2) Gini index:
$$u(S) = 1 - \sum_{k \in \mathcal{Y}} p_k^2 \tag{4}$$

C. *Random Forest*

Random Forest is a kind of boosting algorithm, which combines a lot of weak classifiers(decision tree) and vote/average these trees to get the predication result.

1) it grows each tree with N independently sampled points with replacement from the training data.
2) At each node:
   a) It randomly select S features out of all possible features.
   b) Find the rule that maximally reduces uncertainty on the selected m features.
3) It vote/average the predictions of all the trees to get the final prediction.

D. *Extra tree*

Extra trees algorithm is a variance of random forest. The difference is that random forest choosing the most discriminative thresholds from the random subset of candidate features, while extra trees randomly select some thresholds and choose pick the best one as the splitting rule.

E. *Gradient Tree Boosting*

The algorithm is an additive models with the following form

$$F_m(x) = \sum_{m=1}^{M} \gamma_m h_m(x) \tag{5}$$

where $h_m(x)$ is the weak classifier which is a fixed-size decision tree for the Gradient Tree Boosting algorithm.
At each stage the we choose a decision tree $h_m(x)$that minimize the loos function L given the current model F_{m-1}:

$$F_m(x) = F_{m-1} + \gamma_m \arg\min_{h} \sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) - h(x)) \tag{6}$$

Thus, we can solve the minimization problem by using gradient descent and the steepest descent direction is the negative gradient of the loss function:

$$F_m(x) = F_{m-1} + \gamma_m \sum_{i=1}^{n} \nabla_F L(y_i, F_{m-1}(x_i)) \tag{7}$$

Where the step length γ_m is

$$\gamma_m = \arg\min_{\gamma} \sum_{i=1}^{n} (\nabla_F L(y_i, F_{m-1}(x_i)) - \gamma \frac{\partial L(y_i, F_{m-1}(x_i))}{\partial F_{m-1}(x_i)}) \tag{8}$$

F. *Adaboost*

The core idea of Adaboost algorithm is to learn a lot of weak classifiers aw subset of the data. Then we assign a weight to each classifier and combine the weighted majority vote to produce the final prediction.

For this competition, we choose random forest and extra trees to be the ”weak” classifier of Adaboost.

G. *Bagging method*

bagging method takes several instances of a base estimator and produces random subsets of the training set to train each base estimator. At last, it takes the individual predictions of the base estimators and form a final prediction.

In our implementation, we used random forest, extra trees and decision tree as the base estimators and fed the three models to the next layer.

H. 3-Layer Ensemble Blending

As mentioned in previous subsections, algorithms which employ ensemble mechanism such boosting or bagging perform really well. However, they all seem to hit a plateau around 94.5% accuracy score. Similar to boosting technique, an intuitive idea is to find a way to make these great performers to work together in hope of achieving stellar score.

Inspired by blending algorithms popularized by Netflix competition and Neural Network, we introduce 3-layer blending algorithm.

- **Layer 1: Online training** In this layer, we collect an ensemble of high achievers consisting of 2 random forest classifiers, 2 extra tree classifiers, one gradient boosting machine classifier, one AdaBoost of random forest, one AdaBoost of extra tree classifier, one bagging classifier of random forest, one bagging classifier of extra tree classifier, one bagging classifier of a simple decision tree, 2 decision tree classifiers and 3 kNN classifiers. Each is trained over the dataset multiple times by using 5-fold cross validation and output the average of probablistic predictions. Then, their results are combined together as a new dataset where each column feature representing one particular model mean probabilistic guesses and each row is an data example.
- **Layer 2: Online Logistic Regression** inspired by Neural Network structure, we use logistic regression in the 2nd layer to regress layer 1 probablistic guesses into the final answers. We compute the 3-fold cross validation score and save output to a file.
- **Layer 3: Offline aggregating** Over the course of the competition, we have trained literally dozen of models, some have very high cross validation score. By choosing only one best model, we lose most of our efforts doing extensive model experimentation in last couple of weeks and be unfair to marginally worse models. As such, we come up with offline hard voting scheme where we load all quiz prediction files with high internal cross validation score and aggregate them all together by using majority voting scheme.

III. Model Selection

To select the best parameters, we uses 3-fold cross validation. The k-fold cross validation procedure is as followed:

1) Splited the data into K parts.
2) For each value of $\mathbf{h}$:
   - For each $k \in 1, 2, \dots, K$
     a) Train classifier $\hat{f}_{\mathbf{h},k}$ using all S_i except S_k.
     b) Evaluate classifier $\hat{f}_{\mathbf{h},k}$ using S_k: err($\hat{f}_{\mathbf{h},k}$,S_k)
   - Cross-validation error for $\mathbf{h}$: $\frac{1}{K}\sum_{k=1}^{K}$ err$(\hat{f}_{\mathbf{h},k}, S_k)$
3) Select the value $\hat{\mathbf{h}}$ with lowest cross-validation error.

Cross validation is used to tune the parameters for each algorithms listed above. Then we choose the models with the fair performance and feed them into the blending algorithm to see if they contribute to the final result. At last, we choose a combination of model that produce the best result.

IV. Predictor Evaluation

In the begining, we tend to base our algorithm decision on the Kaggle Public Leaderboard score. However, we quickly realize that it is not a good idea. By doing so, we are exposed ourselves to chance of overfiitng the public leaderboard and spend unproductive time twisting parameters to gain minimal gain.

Gradually, we learn to trust our local cross validation procedure, by using sklearn GridSearchCV to tune paremeters, we are able to combine the task of tuning parameters with the quest of searching for a high cross validation score. We discover that there is a high correlation between hiking local cross validation score and boosting public leaderboard score.

V. Result of evaluation and analysis

By spending many hours exploring and experiment, we are able to come up with the 3-layer algorithm discussed in **Model Description**. The algorithm is able to accomplish 95.667% accuracy in the Kaggle Public Leaderboard and attain around 95.27% local 3-fold cross validation score. As you can see there is a slight disprepancy between local cv score and leaderboard score. This reflects our bias of trying to submit the results that increases the leaderboard ranking. However, the disprepancy is small enough to be negligible.

VI. Individual Contributions

A. Bach Viet Do

Designed the whole architecture of the program and worked on parameters tuning; Contributed to the report writing.

B. Keyu Lai

Tested the performances of different algorithm and worked on parameters tuning; Contributed to the report writing.

C. Qianyuan Chen

Experimented with different features selection and classificiton algorithms; Contributed to the report writing.

Acknowledgment

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References

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