P2: Student Intervention System

Jan 16, 2016

OVERVIEW

Find the most effective model with the least amount of computation costs to model the factors that predict how likely a student is to pass their respective classes.

GOALS

Choose and develop a model that will predict the likelihood that a given student will pass, thus helping diagnose whether or not an intervention is necessary.

SPECIFICATIONS

Develop this model in conformation with this Rubric:
https://docs.google.com/document/d/1eyMT5SkhK4qiiFfTz1TrSnSqkV9gbH8g0Jfh3kW6apl/pub?embedded=true

MILESTONES

Classification OR Regression

Primary objective of this project is to classify if a student needs intervention or not. Hence this is a classification problem. Output hypothesis of chosen model will predict if the features corresponding to a specific student classify her / him in either of the only 2 classes - those needing intervention or not.

Some of the input features, like absences, are continuous. So techniques useful in regression, like outlier identification, can be used to analyze such continuous features, or could be used for feature reduction. But most other features are either categorical or boolean. Further data exploration will be required to better understand feature set.

Exploring the data

Here is statistical summary of data, as generated from program:

Total number of students: 395

Number of students who passed: 265

Number of students who failed: 130

Number of features: 30

Graduation rate of the class: 67.09%

One observation is that feature count is less than amount of data available. Although the amount of data might still not be sufficient to create a perfect model, if there is much general or feature-specific noise in it.

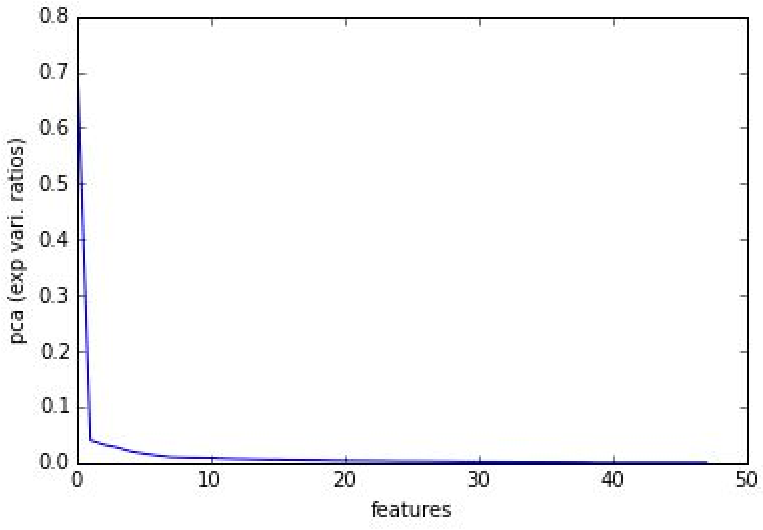
Preparing the Data

Since some of the features are boolean, while some others are categorical, the data has been pre-processed to convert it into numeric data. But this has increased the number of features / columns from 30 to 48, thus making it difficult to create great models with the given amount of data.

As a side project, I did two things to reduce features from this modified data:

1. Visualize relationships between various features.
2. And ran a PCA to reduce features, and plotted variance ratios against feature numbers. This showed that about top 25 features after PCA fitting are main influencers.

But since this was not required for this project, I have not included that version of code in submission.



After pre-processing data, it has been split into Training (count=300) and Test sets (count = 96), using cross_validation.train_test_split method from sklearn.

Training and Evaluation Models

Given the mostly non-continuous nature of feature set, and its relatively small size, we can start with 3 classification models:

1. Support Vector Machines

This is good for a mixture of boolean and continuous data, and can handle non-linear decision boundaries as well, by means of kernel trick. Although it is not good for large data sizes, which is not the case here with only about 400 records. And this is simple to understand, and visualize. We will use **SVC** algorithm for this project.

Ensemble methods can be scaled easily for available computing resources.

So, we are using 1 from each type of ensemble methods - Averaging and Boosting methods.

2. Boosting

Boosting starts with a basic simple model, and then improves upon it by way of weak learners. Since it learns more from difficult / misclassified examples, it concludes quickly on correct model. We will use **AdaBoost** algorithm, as it allows multiple base estimators, and allows scaling as per available computing resources.

But AdaBoost is not suitable if the weak estimator is too complex as it could lead to overfitting. This overfitting can be overcome by setting hyper-parameters like depth, or by pruning trees back. Also AdaBoost is vulnerable to uniform noise in training data.

3. Bagging

Bagging models start with simpler models, and then use randomization to reduce overfitting and variance. We will be using **RandomForestClassifier** implementation for our project. This implementation support parallelization as well, hence is suitable for Big Data sets, and can predict well even when some data is missing.

But RandomForest could be very slow at times, and are hard to interpret. Since they do feature selection implicitly, which if based on information loss, could be biased towards features that have more categories.

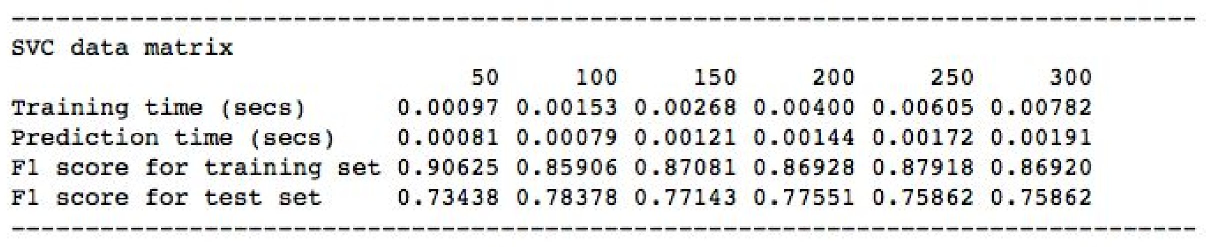
To start with we will use default parameters, to see the starting performance, and then select one model to improve upon it.

Training of 3 models

Here we are training and testing all 3 models on Training Sizes of 50, 100, 150, 200, 250, and 300. This would be helpful in visualizing the patterns.

Here are required data points for the 3 models:

SVC:



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SVC data matrix
                              50     100     150     200     250     300
Training time (secs)      0.00097 0.00153 0.00268 0.00400 0.00605 0.00782
Prediction time (secs)    0.00081 0.00079 0.00121 0.00144 0.00172 0.00191
F1 score for training set 0.90625 0.85906 0.87081 0.86928 0.87918 0.86920
F1 score for test set     0.73438 0.78378 0.77143 0.77551 0.75862 0.75862
--------------------------------------------------------------------------------
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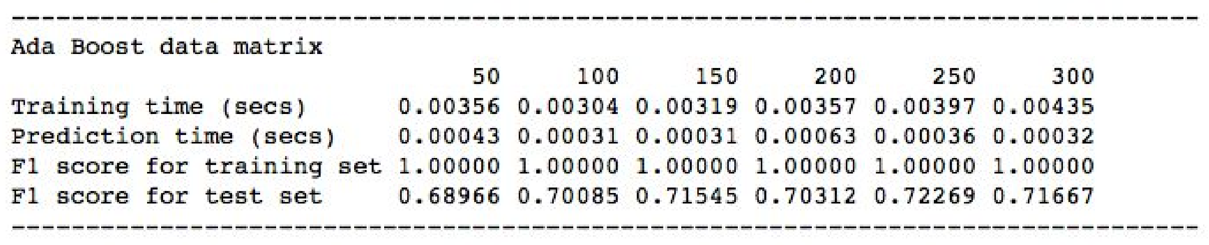
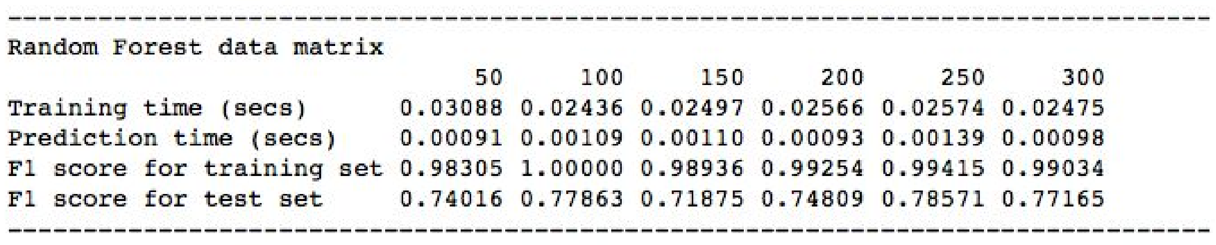
AdaBoost:



```
--------------------------------------------------------------------------------
Ada Boost data matrix
                              50     100     150     200     250     300
Training time (secs)      0.00356 0.00304 0.00319 0.00357 0.00397 0.00435
Prediction time (secs)    0.00043 0.00031 0.00031 0.00063 0.00036 0.00032
F1 score for training set 1.00000 1.00000 1.00000 1.00000 1.00000 1.00000
F1 score for test set     0.68966 0.70085 0.71545 0.70312 0.72269 0.71667
--------------------------------------------------------------------------------
```

Random Forests:



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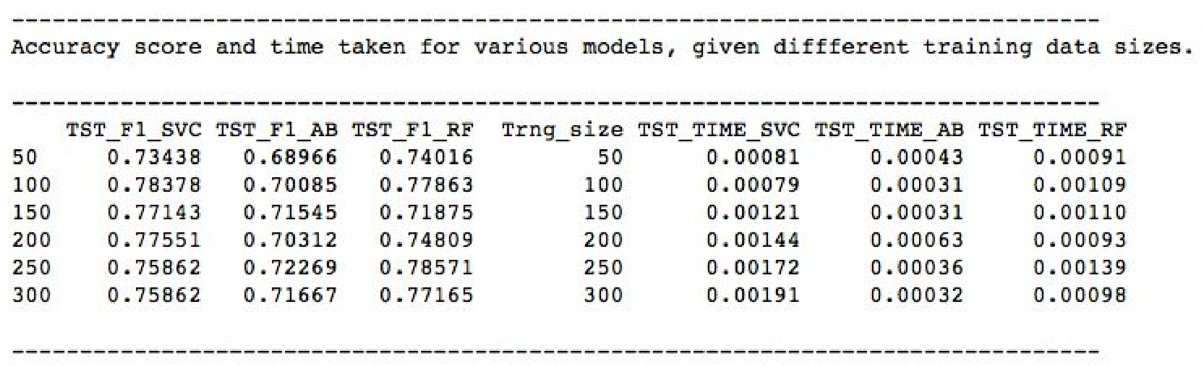
-------------------------------------------------------------------------------
Random Forest data matrix
                               50      100      150      200      250      300
Training time (secs)      0.03088 0.02436 0.02497 0.02566 0.02574 0.02475
Prediction time (secs)    0.00091 0.00109 0.00110 0.00093 0.00139 0.00098
F1 score for training set 0.98305 1.00000 0.98936 0.99254 0.99415 0.99034
F1 score for test set     0.74016 0.77863 0.71875 0.74809 0.78571 0.77165
-------------------------------------------------------------------------------
```

Above results from one of the several runs, which had similar results. Prediction times and F1 scores for Test Features using the 3 selected models varies a little. More specifically, F1 scores varied within +/- 0.07. But what was consistent was that AdaBoost took least amount of time, always.

Choosing the Best Model

To choose most optimal model, we have an additional matrix / plot of accuracies and time taken to predict each model:

Aggregated model performance numbers:



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Accuracy score and time taken for various models, given diffferent training data sizes.

------------------------------------------------------------------------------
    TST_F1_SVC TST_F1_AB TST_F1_RF  Trng_size TST_TIME_SVC TST_TIME_AB TST_TIME_RF
50     0.73438   0.68966   0.74016         50      0.00081     0.00043     0.00091
100    0.78378   0.70085   0.77863        100      0.00079     0.00031     0.00109
150    0.77143   0.71545   0.71875        150      0.00121     0.00031     0.00110
200    0.77551   0.70312   0.74809        200      0.00144     0.00063     0.00093
250    0.75862   0.72269   0.78571        250      0.00172     0.00036     0.00139
300    0.75862   0.71667   0.77165        300      0.00191     0.00032     0.00098

------------------------------------------------------------------------------
```

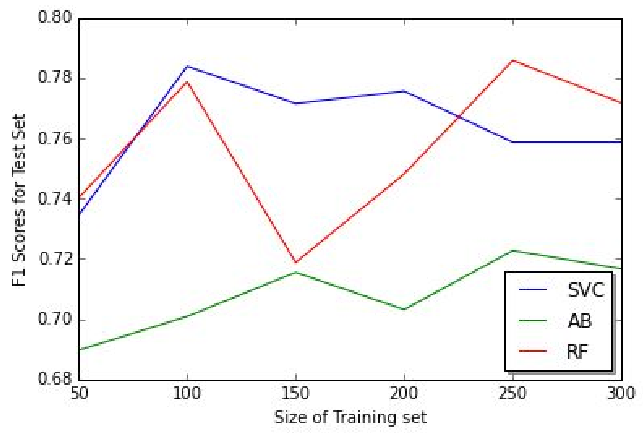

To make a more informed choice of model, I also tried to get memory consumption of the 3 models, in the manner explained below:

1. Clone the main program into 3 different versions, each having common code until train_predict() method, plus a model-specific code.
2. So, student_intervention_SVC.py has common code plus code for SVC model.
3. Similarly, student_intervention_RF.py had common code and code for Random Forest model, and so on student_intervention_AB.py for AdaBoost model.
4. Use program available here: https://github.com/FrancescAlted/ipython_memwatcher for memory usage analysis.
5. Ran following sequence of commands 3 times, one for each model
    a. import numpy as np
    b. from ipython_memwatcher import MemWatcher
    c. mw = MemWatcher()
    d. mw.start_watching_memory()
    e. run student_intervention_SVC.py OR run student_intervention_AB.py OR run student_intervention_RF.py

At the end of program execution, output similar to following was generated on command line:

In [5] used **44.332 MiB RAM** in 1.951s, peaked 0.000 MiB above current, total RAM usage 100.953 MiB

Repeated this on a separate ipython instance, twice for each model.

These memory numbers are reported below. Although there is small difference in memory usage, but still the pattern apparent is that memory utilization of SVM < Adaboost < Random Forest.

But time takes was always least for AdaBoost.

Of-course this was using default features.

Model / Time & Memory	**SVM**	**AdaBoost**	**Random Forest**
Memory Used:	1.) 42.895 2.) 43.152	1.) 43.371 2.) 43.871	1.) 44.227 2.) 44.172
F1 Score on Test Features while using Trng Size=300	0.75862	0.72881	0.76119
Prediction time on Test features while using Trng Size=300	0.00171	0.00031	0.00096

Choosing the Best Model

AdaBoost took least time .3 millisecond, which was the least amount of time taken by other models. It also provides comparable F1-Score of .72. So we choose to tune its hyper-parameters further using Grid Search, in effort to improve its accuracy.

Auto-tuning using GridSearch

Hyper parameters we can use in param grid are learning rate, n_estimators, base estimator tree params, and algorithm.

Using these features, as coded at the end of student_intervention.py, we get following values for params and F1 score.

Best model parameter: Best model parameter: {'base_estimator__min_samples_split': 1, 'base_estimator__max_depth': 3, 'algorithm': 'SAMME', 'learning_rate': 0.6, 'n_estimators': 5, 'base_estimator__min_samples_leaf': 2}

f1 score: 0.83916

Now this F1 score is slightly better than that from previous, non GridSearch, version of all other models..

Conclusions:

1. There is not much difference in F1 scores of SVM, AB, and RF algorithms.
2. GridSearchCV could be used to tune meta-parameters, and can help.
3. Identifying relationships between various features, and using that domain knowledge to manually tune params can also improve accuracy.
4. 0.81 is the ceiling for F1 score, for all the models we tried.
5. Although, F1 scores are best when using all 300 data points, but there is negligible difference in F1 when using 200 data points and 300 data points.
6. Increasing estimator count, and number of jobs takes increasingly more resources with small or no improvement in accuracy. This means the choice of base estimator, and pre-processing (noise-reduction and feature reduction) are very important. Just giving more resources will not help always.

Further analysis recommended on following points:

1. Reason for ceiling of 0.81 for F1 score.
2. Reason for variation in F1 scores with increase in training size.
3. Find bias and variance in each of the models.
4. Further analyze the models, if more data is available from different sources or over time from same institute.

Explanation to board of supervisors

Our goal for this project is to create a model that can predict with fair amount of certainty if a student needs intervention to pass a class.

Over last week, we have analyzed student data, and came across interesting patterns. For example, there is negligible correlation between consuming alcohol during weekdays and absenteeism. Also, students whose both parents are either very less educated or highly educated, have not failed in past.

Based on our analysis, we have found that while some of the attributes of student data have more impact on prediction, other attributes are not of much significance.

We started with 3 models, and planned to choose the best mode that can predict best while using minimal computing resources and time. Time parameter considered here was time required by model to predict whether a student needs intervention or not. Training a model is a less-frequent task when compared to how frequent the chosen model will be used to predict. So training time is of less importance, but cannot be ignored. Training time of SVC, AdaBoost, and Random Forest models using 300 training data points was 8, 4, and 25 milli seconds. This makes AdaBoost the fastest to train. Also the time taken to predict was least for AdaBoost. Prediction time for SVC, AdaBoost, and Random Forest were 1.3 milli-sec, 0.3 milli-sec, and 0.98 milli-sec respectively.

We have found 2 models that are equally good in terms of accuracy of prediction, but differ in terms of required computing resources and time required to predict.

Since AdaBoost took least time, and had comparable accuracy we decided to use AdaBoost model, and tune it further for better accuracy. For tuning, we used Grid Search technique that tests the model on certain provided parameters, and then suggests the best parameters to use. Using Grid Search, we were able to tune AdaBoost to improve F1 score to **0.83916**

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<u>Training and Prediction process - summary explaination</u>

Let me explain how the models are created and how they are able to predict the outcome.

Since the best performing models above are ensemble methods, we will focus on those.

Ensemble methods start with a base model and then use different techniques to improve upon the base model. Base model in this case was Decision Trees. Decision Trees work by finding the features that have most influence on the outcome. For example, in this project 2 such features are - “failures”, and “absences”. Decision Tree model identifies such features, and and creates a hierarchical structure of these features in the manner that best explains importance of various features in determining an outcome. So, Decision Trees are very intuitive and easy to understand and visualize.

But Decision Trees can be susceptible to overfitting. As seen in this project, when using plain DecisionTreeClassfifier, F1 score was 0.7.

To overcome overfitting and allow diversity in models, we use ensemble methods. These methods combine results from these diverse models to create a final model, that is more accurate than any of the candidate models.

For example in this case, AdaBoost model uses random samples to train a model at each stage. First model is only slightly better than random selection. Model at each stage is slightly better better than the previous model by way of learning from data points misclassified in previous iteration / learner. This is achieved by giving more weight to this misclassified sample. Over multiple iterations, the model improves. In this case we achieved an accuracy of 0.83 using tuned hyperparameters for AdaBoost.

We will use this model to predict if there is need for intervention.