Supervised Learning: Building a Student Intervention System

1 Objective

The goal of this project is to identify students who might need early intervention. We want to predict whether a given student will pass or fail based on information about his life and habits. Therefore we approach this task as a classification problem with two classes, pass and fail.

2 Dataset

In what follows we will be working with part of the Student Performance Data Set from the UCI machine learning repository. It is composed of 395 data points with 30 attributes each. The 31'st attribute indicates whether the student passed or failed. Here is a brief description of each feature:

2.1 Attributes for student-data.csv:

- school - student's school (binary: "GP" or "MS")
- sex - student's sex (binary: "F" - female or "M" - male)
- age - student's age (numeric: from 15 to 22)
- address - student's home address type (binary: "U" - urban or "R" - rural)
- famsize - family size (binary: "LE3" - less or equal to 3 or "GT3" - greater than 3)
- Pstatus - parent's cohabitation status (binary: "T" - living together or "A" - apart)
- Medu - mother's education (numeric: 0 - none, 1 - primary education (4th grade), 2 – 5th to 9th grade, 3 – secondary education or 4 – higher education)
- Fedu - father's education (numeric: 0 - none, 1 - primary education (4th grade), 2 – 5th to 9th grade, 3 – secondary education or 4 – higher education)
- Mjob - mother's job (nominal: "teacher", "health" care related, civil "services" (e.g. administrative or police), "at_home" or "other")
- Fjob - father's job (nominal: "teacher", "health" care related, civil "services" (e.g. administrative or police), "at_home" or "other")
- reason - reason to choose this school (nominal: close to "home", school "reputation", "course" preference or "other")
- guardian - student's guardian (nominal: "mother", "father" or "other")
- traveltime - home to school travel time (numeric: 1 - <15 min., 2 - 15 to 30 min., 3 - 30 min. to 1 hour, or 4 - >1 hour)
- studytime - weekly study time (numeric: 1 - <2 hours, 2 - 2 to 5 hours, 3 - 5 to 10 hours, or 4 - >10 hours)
- failures - number of past class failures (numeric: n if 1<=n<3, else 4)
- schoolsup - extra educational support (binary: yes or no)
- famsup - family educational support (binary: yes or no)
- paid - extra paid classes within the course subject (Math or Portuguese) (binary: yes or no)
- activities - extra-curricular activities (binary: yes or no)
- nursery - attended nursery school (binary: yes or no)
- higher - wants to take higher education (binary: yes or no)
- internet - Internet access at home (binary: yes or no)
- romantic - with a romantic relationship (binary: yes or no)
- famrel - quality of family relationships (numeric: from 1 - very bad to 5 - excellent)
- freetime - free time after school (numeric: from 1 - very low to 5 - very high)
- goout - going out with friends (numeric: from 1 - very low to 5 - very high)
- Dalc - workday alcohol consumption (numeric: from 1 - very low to 5 - very high)
- Walc - weekend alcohol consumption (numeric: from 1 - very low to 5 - very high)
- health - current health status (numeric: from 1 - very bad to 5 - very good)
- absences - number of school absences (numeric: from 0 to 93)
- passed - did the student pass the final exam (binary: yes or no)

2.2 Loading the data

2.2.1 Imports

The following python libraries are used in this analysis.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from tabulate import tabulate
import pickle
```

2.2.2 Pre-process

Let us first observe what the graduation rate is for the class;

```
student_data = pd.read_csv("student-data.csv")

n_students = student_data.shape[0]
n_features = student_data.shape[1] - 1
n_passed = sum([1 for y in student_data['passed'] if y == 'yes'])
n_failed = sum([1 for n in student_data['passed'] if n == 'no'])
grad_rate = 100.*n_passed/(n_passed + n_failed)


tabulate( [["Total number of students: ",n_students],
           ["Number of students who passed: ",n_passed],
           ["Number of students who failed: ",n_failed],
```

```
        ["Number of features: ",n_features],
        ["Graduation rate of the class:",  "{:.2f}%".format(grad_rate)]], tablefmt="grid")
```

This gives us the following figures;

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%

Now we will separate the data into the feature columns and our prediction target, i.e., feature “passed”.

```
feature_cols = list(student_data.columns[:-1]) # all columns but last are features
target_col = student_data.columns[-1]          # last column is the target/label

X_all = student_data[feature_cols]             # feature values for all students
y_all = student_data[target_col]               # corresponding targets/labels
```

Additionally, we must transform all categorical features into binary/numeric ones in order to be processed by subsequent algorithms. Pandas’ get_dummies function will come in handy.

```
def preprocess_features(X):
    outX = pd.DataFrame(index=X.index)  # output dataframe, initially empty
    #
    # Check each column
    for col, col_data in X.iteritems():
        #
        # Change the data type for yes/no columns to int
        if col_data.dtype == object:
            col_data = col_data.replace(['yes', 'no'], [1, 0])
        #
        # For other categories convert to one or more dummy variables
        if col_data.dtype == object:
            col_data = pd.get_dummies(col_data, prefix=col)  # e.g. 'school' => 'school_GP', 'school_MS'
        #
        outX = outX.join(col_data)  # collect column(s) in output dataframe
    return outX
```

```
X_all = preprocess_features(X_all)
```

Now we are ready to split the data into training and test sets. Approximately 75% of the data will be used for training. This will leave 300 training samples and 95 test samples. We will employ Sci-kit learn’s train_test_split function to perform the data split.

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X_all, y_all, test_size = .24, random_state = 0)
#
#
"Training set: {} samples".format(X_train.shape[0]), "Test set: {} samples".format(X_test.shape[0])
```

2.3 Data Exploration

To identify whether it is appropriate to treat the data under a single model, that is, to identify whether its a manifold of multiple charts or a single chart, we employ a T-SNE projection. We’ll project to 2-dimensions with red labeling failed and blue labeling passing data points. This may or may not reveal some intrinsic clustering relative to our feature of interest ‘passed’. It is recommended for T-SNE to be fed features scaled to similar ranges, so this is the first pre-process step.

```
from sklearn.preprocessing import MinMaxScaler
#
scaler = MinMaxScaler()
uX_all = scaler.fit_transform(X_all)
```

Since our data set is not large we can indulge in the exact t-sne algorithm instead of the speedier ‘barnes-hut’.

```
from sklearn.manifold import TSNE
#
model = TSNE(n_components=2,
             early_exaggeration=4.0,
             learning_rate=1000,
             n_iter=1000,
             init='pca',
             random_state=0,
             method='exact')
#
clusters = model.fit_transform(uX_all)
```

```
# Painting cluster data according to pass or fail
x_fail, y_fail = zip(*[ tuple(pt) for i, pt in enumerate(clusters) if y_all[i] == 'no'])
x_pass, y_pass = zip(*[ tuple(pt) for i, pt in enumerate(clusters) if y_all[i] == 'yes'])
#
# Build plot
ax = plt.subplot(111)
ax.scatter(x_fail, y_fail, s=50, c='red', alpha=0.5, label="student failed")
ax.scatter(x_pass, y_pass, s=50, c='blue', alpha=0.5, label="student passed")
#
# Saving
plt.savefig("./figures/t-sne_all.png")
```

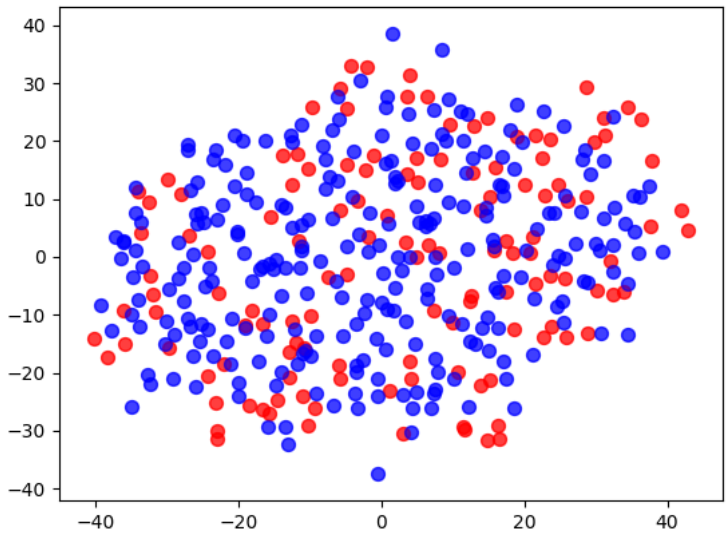


Figure 1: T-SNE 2-d projection all sample points

T-SNE reveals no obvious clustering of the data itself, nor of its pass/fail labeling. We will treat the data under a single model.

3 Training and Evaluating Models

3.1 Baseline Performance

After an analysis of several algorithms, the details of which can be found here, we will proceed with the binary classification using a DecisionTree classifier and a K-neighbors classifier for reference.

Kfold cross validation can be used to get the maximum use of a small data set like the one here. We apply Kfold cross-validation on the training set with 10 folds to have a basic handle on how the models perform out of the box.

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
#
from sklearn.cross_validation import KFold
#
# Setting up KFold cross_validation object
kf = KFold(X_train.shape[0], 10)
#
# Array of classifiers
clfs = [DecisionTreeClassifier(criterion = "entropy"),
        KNeighborsClassifier(n_neighbors = 3)]
#
#Gathering Table column and index labels
classifier_names = [clf.__class__.__name__ for clf in clfs]
benchmarks = ["Training time",  "F1 score training set","Prediction time", "F1 score test set"]
table = pd.DataFrame(columns = classifier_names, index = benchmarks)
#
# Fit Classifiers and average the times and F1 scores resulting from KFold (10 folds)
for clf in clfs:
    classifier   = clf.__class__.__name__
    t_test  = 0.0
    t_train = 0.0
    F1_test = 0.0
    F1_train =0.0
    #
    #Averaging scores and seconds accross the folds
```

```python
    for tr_i ,t_i in kf:
        #Train (k-1 buckets)
        t_train += timeTraining(clf, X_train.iloc[tr_i], y_train.iloc[tr_i])
        pred_train_set = predictAndTime(clf, X_train.iloc[tr_i])[0]
        F1_train += F1(y_train.iloc[tr_i], pred_train_set)
        #Test (kth bucket)
        pred_test_set, t_t = predictAndTime(clf,X_train.iloc[t_i])
        t_test += t_t
        F1_test += F1(y_train.iloc[t_i], pred_test_set)
    #
    #Filling table
    table[classifier]['Training time']         = "{:10.4f} s".format(t_train/10)
    table[classifier]['F1 score training set'] = F1_train/10
    table[classifier]['Prediction time']       = "{:10.4f} s".format(t_test/10)
    table[classifier]['F1 score test set']     = F1_test/10
```

	DecisionTreeClassifier	KNeighborsClassifier
Training time	0.0060 s	0.0008 s
F1 score training set	1.0	0.889300900467
Prediction time	0.0003 s	0.0018 s
F1 score test set	0.708666825808	0.780716646689

The results above show that the tree scores perfectly on the training set and it's outperformed by KNN on the test set, with 0.709 to KNN's .781. The tree is most likely over-fitting. We will tune both models with a grid search.

3.2 Gridsearch Tuning

```python
# Imports
from sklearn import grid_search
from sklearn.metrics import make_scorer
#
scorer = make_scorer(F1)
#
# GridSearch parameters for Tree
tree_param = { 'criterion': ["entropy", "gini"], 'max_features':["sqrt", "log2"], 'random_state': [0],
               'max_depth': range(2,11), 'min_samples_split':range(2,9), 'min_samples_leaf':range(1,9) }
#
# Gridsearch parameters for KNN
neigh_param = {'n_neighbors' : [3,5,10,20,25,30,40], 'weights' : ['uniform', 'distance'], 'p':[1,2,3,5,10],
               'algorithm' : ['ball_tree', 'kd_tree', 'brute']}
#
gs_table = pd.DataFrame(columns=["DecisionTreeClassifier", "KNeighborsClassifier"], index=["Grid search time (s)", "f1_score T
#
final_params = {"DecisionTreeClassifier": None,  "KNeighborsClassifier": None}
#
#Perform grid Search
def gridIt(clf, params):
    #Grid search folds = 10, for consistency with previous computations
    grid_clf = grid_search.GridSearchCV(clf, params,
                                    scorer, n_jobs=4, cv = 10)
    #
    # Grid time
    gs_table[clf.__class__.__name__][0] = timeTraining(grid_clf, X_train, y_train)
    #
    # F1 on Test
    y_pred, predict_t = predictAndTime(grid_clf, X_test)
    gs_table[clf.__class__.__name__][1] = F1(y_test, y_pred)
    #
    # "Parameters of tuned model
    final_params[clf.__class__.__name__] = grid_clf.best_params_
```

```python
gridIt(KNeighborsClassifier(), neigh_param)
```

```python
gridIt(DecisionTreeClassifier(), tree_param)
```

4 Analysis

```python
tabulate(gs_table, headers=["DecisionTreeClassifier", "KNeighborsClassifier"], tablefmt="grid")
```

Here is the F1 performance on the test set for both classifiers after grid search tuning;

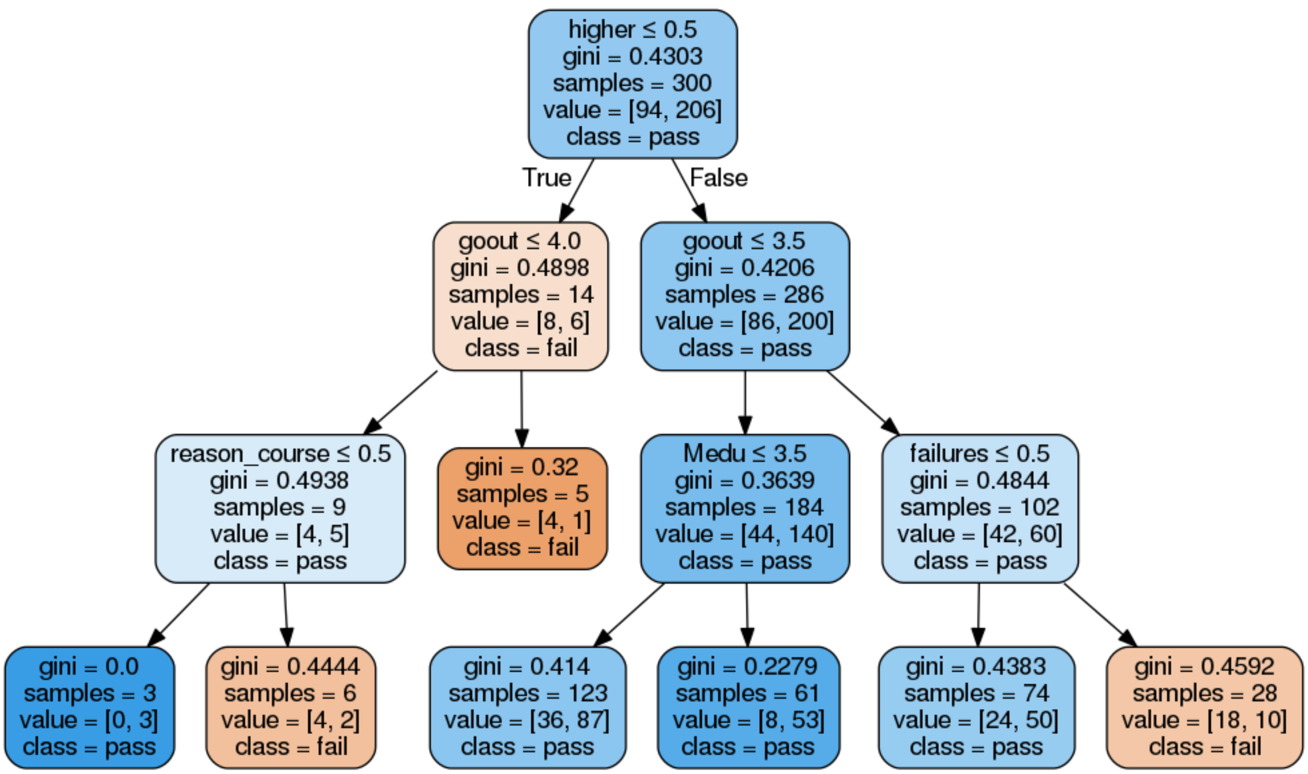
	DecisionTreeClassifier	KNeighborsClassifier
Grid search time (s)	59.2091	12.2915
f1_score Test Set	0.789116	0.786667

So we have a decent 10.2 % percentage increase in performance for the tree classifier and a mere 0.76% percent increase for KNN. Notice also that the decision tree is ~5 times more costly to train, taking a full minute, to KNN's 12 seconds. In the end however, they are virtually on par in terms of F1 score on the test set. We see that KNN will give good out of the box performance without much tuning. But in the present context the Decisiontree has particular advantages. Before we manipulated it, the data was strongly categorical. Even age for example, can basically be thought of as buckets between 15 and 22.

Because of this, the structure of the data is modeled well with a decision tree function, which can literally be visually inspected to glean insights from our model. We proceed to generate this visualization next.

```
from sklearn import tree
import pydotplus

t_p = tuned_m['final_params']["DecisionTreeClassifier"]
tree_clf = tree.DecisionTreeClassifier(min_samples_leaf=3,
                                       max_features='sqrt',
                                       random_state=0,
                                       criterion='gini',
                                       min_samples_split=2,
                                       max_depth=3)
tree_clf.fit(X_train,y_train)
f1_score(tree_clf.predict(X_test), y_test, pos_label='yes')
#
# Make tree graphic
tree_dot_data = tree.export_graphviz(tree_clf, out_file=None,
                                     feature_names=X_train.columns,
                                     class_names=['fail','pass'],
                                     filled=True, rounded=True,
                                     special_characters=True)
graph = pydotplus.graph_from_dot_data(tree_dot_data)
graph.write_png("./figures/student_tree.png")
```



Here we have the model's actual decision function in tree form. It is of depth 3, as we defined it. 3 being the optimal depth we found during the grid search tuning phase. The root displays the binary feature 'higher', that is, whether the student's intention is to move on to higher education or not. Most students in the dataset intend to pursue higher education, 286 to just 14 who don't. But the model strongly predicts failure for those who don't, only 3 of those 14 fall in the 'pass' leaf. For the 286 students who intend to pursue higher education, we see that for the 184 who keep their 'goout' moderate (i.e. <=3.5) the model basically predicts that they will all pass. For the remaining 102 students who's 'goout' > 3.5, the feature that predicts success is number of passed class failures. Basically, only if they have not failed a class in the past, 'failure' < 0.5, does the model predict they'll pass. Even though decision trees provide this convenient visualization for inspecting the relationship between the data and the model's predictions, they tend to be unstable. This means that small variations in the data can result in completely different trees. This must be taken into consideration when using the visualization to interpret the model as we just did, since a decision tree based on completely different feature relationships could perform equally well. This problem however, can be mitigated with ensemble 'averaging' methods.