

# Project 2: Supervised Learning

## Building a Student Intervention System

### 1. Classification vs Regression

Your goal is to identify students who might need early intervention - which type of supervised machine learning problem is this, classification or regression? Why?

This is classification problem. Here we need to divide our data in pass and failure. Regression is suitable for continuous output type data as dependant variable like score in exams. But here we have outcome as categorical variable i.e pass and failure.

### 2. Exploring the Data

Let's go ahead and read in the student dataset first.

To execute a code cell, click inside it and press **Shift+Enter**.

```
In [27]: # Import Libraries
import numpy as np
import pandas as pd
```

```
In [28]: # Read student data
student_data = pd.read_csv("student-data.csv")
print "Student data read successfully!"
# Note: The last column 'passed' is the target/label, all other are feature columns
```

Student data read successfully!

```
In [29]: #temporary - to delete
student_data.columns
```

```
Out[29]: Index([u'school', u'sex', u'age', u'address', u'famsize', u'Pstatus',
u'Medu',
u'Fedu', u'Mjob', u'Fjob', u'reason', u'guardian', u'traveltime',
u'studytime', u'failures', u'schoolsup', u'famsup', u'paid',
u'activities', u'nursery', u'higher', u'internet', u'romantic',
u'famrel', u'freetime', u'goout', u'Dalc', u'Walc', u'health',
u'absences', u'passed'],
dtype='object')
```

Now, can you find out the following facts about the dataset?

- Total number of students
- Number of students who passed
- Number of students who failed
- Graduation rate of the class (%)
- Number of features

Use the code block below to compute these values. Instructions/steps are marked using **TODOs**.

```
In [30]: # TODO: Compute desired values - replace each '?' with an appropriate expression/function call
n_students = len(student_data.index)
n_features = len(student_data.columns)-1 # 1 column for pass/fail is not a feature
n_passed = len(student_data[student_data['passed'] == 'yes'])
n_failed = len(student_data[student_data['passed'] == 'no'])
grad_rate = (n_passed*100)/float(n_students)
print "Total number of students: {}".format(n_students)
print "Number of students who passed: {}".format(n_passed)
print "Number of students who failed: {}".format(n_failed)
print "Number of features: {}".format(n_features)
print "Graduation rate of the class: {:.2f}%".format(grad_rate)
```

```
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%
```

### 3. Preparing the Data

In this section, we will prepare the data for modeling, training and testing.

#### Identify feature and target columns

It is often the case that the data you obtain contains non-numeric features. This can be a problem, as most machine learning algorithms expect numeric data to perform computations with.

Let's first separate our data into feature and target columns, and see if any features are non-numeric.

```
In [31]: # Extract feature (X) and target (y) columns
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
print "Feature column(s):-\n{}".format(feature_cols)
print "Target column: {}".format(target_col)

X_all = student_data[feature_cols] # feature values for all students
y_all = student_data[target_col] # corresponding targets/labels
print "\nFeature values:-"
print X_all.head() # print the first 5 rows
```

Feature column(s):-

```
['school', 'sex', 'age', 'address', 'famsize', 'Pstatus', 'Medu', 'Fedu', 'Mjob', 'Fjob', 'reason', 'guardian', 'traveltime', 'studytime', 'failures', 'schoolsup', 'famsup', 'paid', 'activities', 'nursery', 'higher', 'internet', 'romantic', 'famrel', 'freetime', 'goout', 'Dalc', 'Walc', 'health', 'absences']
```

Target column: passed

Feature values:-

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob
0	GP	F	18	U	GT3	A	4	4	at_home	teacher
1	GP	F	17	U	GT3	T	1	1	at_home	other
2	GP	F	15	U	LE3	T	1	1	at_home	other
3	GP	F	15	U	GT3	T	4	2	health	services
4	GP	F	16	U	GT3	T	3	3	other	other

	...	higher	internet	romantic	famrel	freetime	goout	Dalc	Walc
0	...	yes	no	no	4	3	4	1	1
1	...	yes	yes	no	5	3	3	1	1
2	...	yes	yes	no	4	3	2	2	3
3	...	yes	yes	yes	3	2	2	1	1
4	...	yes	no	no	4	3	2	1	2

absences

0	6
1	4
2	10
3	2
4	4

[5 rows x 30 columns]

## Preprocess feature columns

As you can see, there are several non-numeric columns that need to be converted! Many of them are simply yes/no, e.g. internet. These can be reasonably converted into 1/0 (binary) values.

Other columns, like Mjob and Fjob, have more than two values, and are known as *categorical variables*. The recommended way to handle such a column is to create as many columns as possible values (e.g. Fjob\_teacher, Fjob\_other, Fjob\_services, etc.), and assign a 1 to one of them and 0 to all others.

These generated columns are sometimes called *dummy variables*, and we will use the `pandas.get_dummies()` ([http://pandas.pydata.org/pandas-docs/stable/generated/pandas.get\\_dummies.html?highlight=get\\_dummies#pandas.get\\_dummies](http://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html?highlight=get_dummies#pandas.get_dummies)) function to perform this transformation.

```
In [32]: # Preprocess feature columns
def preprocess_features(X):
    outX = pd.DataFrame(index=X.index) # output dataframe, initially empty

    # Check each column
    for col, col_data in X.iteritems():
        # If data type is non-numeric, try to replace all yes/no values
        with 1/0
        if col_data.dtype == object:
            col_data = col_data.replace(['yes', 'no'], [1, 0])
        # Note: This should change the data type for yes/no columns to int

        # If still non-numeric, 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)
print "Processed feature columns ({}):-\n{}".format(len(X_all.columns),
list(X_all.columns))
```

Processed feature columns (48):-

```
['school_GP', 'school_MS', 'sex_F', 'sex_M', 'age', 'address_R', 'address_U', 'famsize_GT3', 'famsize_LE3', 'Pstatus_A', 'Pstatus_T', 'Medu', 'Fedu', 'Mjob_at_home', 'Mjob_health', 'Mjob_other', 'Mjob_services', 'Mjob_teacher', 'Fjob_at_home', 'Fjob_health', 'Fjob_other', 'Fjob_services', 'Fjob_teacher', 'reason_course', 'reason_home', 'reason_other', 'reason_reputation', 'guardian_father', 'guardian_mother', 'guardian_other', 'traveltime', 'studytime', 'failures', 'schoolsup', 'famsup', 'paid', 'activities', 'nursery', 'higher', 'internet', 'romantic', 'famrel', 'freetime', 'goout', 'Dalc', 'Walc', 'health', 'absences']
```

## Split data into training and test sets

So far, we have converted all *categorical* features into numeric values. In this next step, we split the data (both features and corresponding labels) into training and test sets.

```
In [33]: # First, decide how many training vs test samples you want
from sklearn import cross_validation
num_all = student_data.shape[0] # same as len(student_data)
num_train = 300 # about 75% of the data
num_test = num_all - num_train

# TODO: Then, select features (X) and corresponding labels (y) for the t
raining and test sets
# Note: Shuffle the data or randomly select samples to avoid any bias du
e to ordering in the dataset
X_train, X_test, y_train, y_test = cross_validation.train_test_split(X_a
ll, y_all, train_size=num_train)
print "Training set: {} samples".format(X_train.shape[0])
print "Test set: {} samples".format(X_test.shape[0])
```

Training set: 300 samples

Test set: 95 samples

## 4. Training and Evaluating Models

Choose 3 supervised learning models that are available in scikit-learn, and appropriate for this problem. For each model:

- What are the general applications of this model? What are its strengths and weaknesses?
- Given what you know about the data so far, why did you choose this model to apply?
- Fit this model to the training data, try to predict labels (for both training and test sets), and measure the  $F_1$  score. Repeat this process with different training set sizes (100, 200, 300), keeping test set constant.

Produce a table showing training time, prediction time,  $F_1$  score on training set and  $F_1$  score on test set, for each training set size.

Note: You need to produce 3 such tables - one for each model.



```

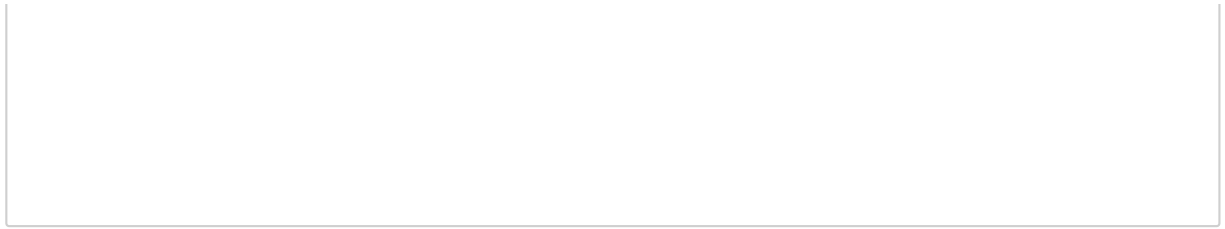
In [34]: import time
# Trains the classifier model and returns training time
def train_classifier(clf, X_train, y_train):
#     print "Training {}...".format(clf.__class__.__name__)
    start = time.time()
    clf.fit(X_train, y_train)
    end = time.time()
    return (end-start)
#     print "Done!\nTraining time (secs): {:.3f}".format(end - start)

# Predict on training set and compute F1 score
# returns [prediction_time, f1_score]
from sklearn.metrics import f1_score
def predict_labels(clf, features, target):
#     print "Predicting labels using {}...".format(clf.__class__.__name__)
    start = time.time()
    y_pred = clf.predict(features)
    end = time.time()
#     print "Done!\nPrediction time (secs): {:.3f}".format(end - start)
    return [end-start, f1_score(target.values, y_pred, pos_label='yes')]

# splits the data in training and testing samples. Trains and predicts o
n training/testing data respectively
# returns [training_time, prediction_time, f1_score_training, f1_score_t
esting_sample]
def splitTrainAndValidatePredictor(clf, _train_size):
    # As test size needs to be kept same and only train size needs to va
ried. X_train is already randomly
    # distributed so continuous data around it can be taken
    _X_train = X_train[:_train_size]
    _y_train = y_train[:_train_size]
    train_time = train_classifier(clf, _X_train, _y_train)
    [time_training_predict, f1_train] = predict_labels(clf, _X_train, _
y_train)
    [time_testing_predict, f1_test] = predict_labels(clf, X_test, y_tes
t)
    return [train_time, time_testing_predict, f1_train, f1_test]

# wrapper to iterate on different sample sizes
# return dataframe with data on performance/scores corresponding to algo
rithm passed.
def createLearningTable(clf):
    sample_sizes = [50, 100, 150, 200, 250, 300]
    rows = []
    for s in sample_sizes:
        rows.append([s] + splitTrainAndValidatePredictor(clf, s))
    df = pd.DataFrame(rows, columns = ['size', 'train_time', 'prediction
_time', 'train_score', 'test_score'])
    return df

```



Now we would try above learning framework on different types of algorithms.

## DECISION TREE

Decision Trees(DTs) are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features.

Generally Decision Tree is used for modelling data with non-linear relationships.

Advantages of Decision Tree are:-

- **Simple** to understand and interpret. Trees can be visualized.
- **Cost** of using the tree is logarithmic in the number of data points used to train the tree.
- Able to handle both numerical and categorical data.
- Able to handle multi-output problems.

Disadvantages of decision trees include:

- **Overfitting** Decision Tree learners can create over-complex trees that do not generalise the data well.
- **NP-complete** Problem of learning an optimal decision tree is NP-complete. so most algorithms are based on heuristic like greedy algorithm.

Reasons for choosing decision tree for this student intervention problem are-

- Advantages of decision tree mentioned above satisfy our requirements. As our resources are limited, so we want efficient algorithm. Also our output data is categorical ('pass' or 'failed').
- As node of decision tree splits the data based on value of particular attribute, it helps building intuition to intervene in a particular feature for better success rate.
- It would be easier to explain to management if we finally chose it.
- We don't know which are relevant columns/feature in our data set. Decision Tree would easily handle it through information gain.
- Also Decision tree doesn't make any assumption about linearity of which we are not sure about given data set.

```
In [35]: from sklearn import tree
         clf = tree.DecisionTreeClassifier()
         df_tree = createLearningTable(clf)
         df_tree
```

Out[35]:

	size	train_time	prediction_time	train_score	test_score
0	50	0.000	0	1	0.676692
1	100	0.016	0	1	0.740741
2	150	0.000	0	1	0.788732
3	200	0.000	0	1	0.762590
4	250	0.016	0	1	0.757143
5	300	0.000	0	1	0.740741

## SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to category based on which side of the gap they fall on.

Support vector machines are generally used on data on which boundaries between different categories is complex and not easy to model through linear models or decision Tree.

Advantages are

- Effective in **high dimensional** spaces
- Still effective in cases where number of dimensions is greater than the number of samples.
- Uses a subset of training points in the decision function(called support vectors), so that it is also **memory efficient**.
- **versatile**: different kernel functions can be specified for the decision function.

Disadvantages are

- If the number of features is much greater than the number of samples, the method is likely to give poor performances.
- SVMs do not directly provide probability estimates, these are calculated using an expensive five-fold cross validation.

We chose SVM to use for this student intervention problem as:

- our number of features are large, which is handled by SVM better.
- Our problems is classification, which is optimized and solved by SVM algorithm.
- We would have number of different parameters, kernels to finetune our model.

```
In [36]: from sklearn import svm
         clf = svm.SVC()
         df_svm = createLearningTable(clf)
         df_svm
```

Out[36]:

	size	train_time	prediction_time	train_score	test_score
0	50	0.016	0.000	0.878788	0.851613
1	100	0.000	0.000	0.876712	0.860759
2	150	0.015	0.000	0.847162	0.860759
3	200	0.022	0.002	0.865772	0.862745
4	250	0.005	0.016	0.858639	0.844156
5	300	0.015	0.016	0.855895	0.855263

## LOGISTIC REGRESSION

Logistic regression is a linear model for classification rather than regression. Here maximum likelihood is used to determine significance of the variables which will be part of the logistic regression equation.

Logistic regression dominates social and biomedical sciences. Some of application of logistic regression would be:-

- predicting whether a patient has given disease based on observed characteristics.
- predicting whom someone is going to vote
- predicting probability of failure or success in a process.

Advantages of Logistic Regression are:

- Parametric analytic tool
- Provides probability outcome
- Controls confounding
- avoids overfit

Disadvantages of Logistic regression are:

- It assumes that there is a single linear decision boundary which can separate data.
- Large sample sizes are required.

We chose logistic regression as this algorithm has high success for binary classification, which corresponds to our predicted data of pass/failure. Logistic regression make a single boundary while separating data irrespective of number of features. So this might be a better generalization in logistic regression than other fast algorithms like decision tree, which would create complex model to fit number of features as in given data number of features(~30) are moderately high given small number of samples.

```
In [37]: from sklearn import linear_model  
clf = linear_model.LogisticRegression()  
df_logistic = createLearningTable(clf)  
df_logistic
```

Out[37]:

	size	train_time	prediction_time	train_score	test_score
0	50	0.016	0.000	0.918033	0.713178
1	100	0.000	0.016	0.874074	0.773723
2	150	0.000	0.000	0.834123	0.814286
3	200	0.018	0.000	0.826087	0.802920
4	250	0.006	0.000	0.828169	0.788321
5	300	0.006	0.000	0.841121	0.779412

## 5. Choosing the Best Model

- Based on the experiments you performed earlier, in 1-2 paragraphs explain to the board of supervisors what single model you chose as the best model. Which model is generally the most appropriate based on the available data, limited resources, cost, and performance?
- In 1-2 paragraphs explain to the board of supervisors in layman's terms how the final model chosen is supposed to work (for example if you chose a Decision Tree or Support Vector Machine, how does it make a prediction).
- Fine-tune the model. Use Gridsearch with at least one important parameter tuned and with at least 3 settings. Use the entire training set for this.
- What is the model's final  $F_1$  score?

We have tried following models on our data and calculated both computational and learning performance on training/testing data.

- Decision Tree
- SVM
- Logistic Regression

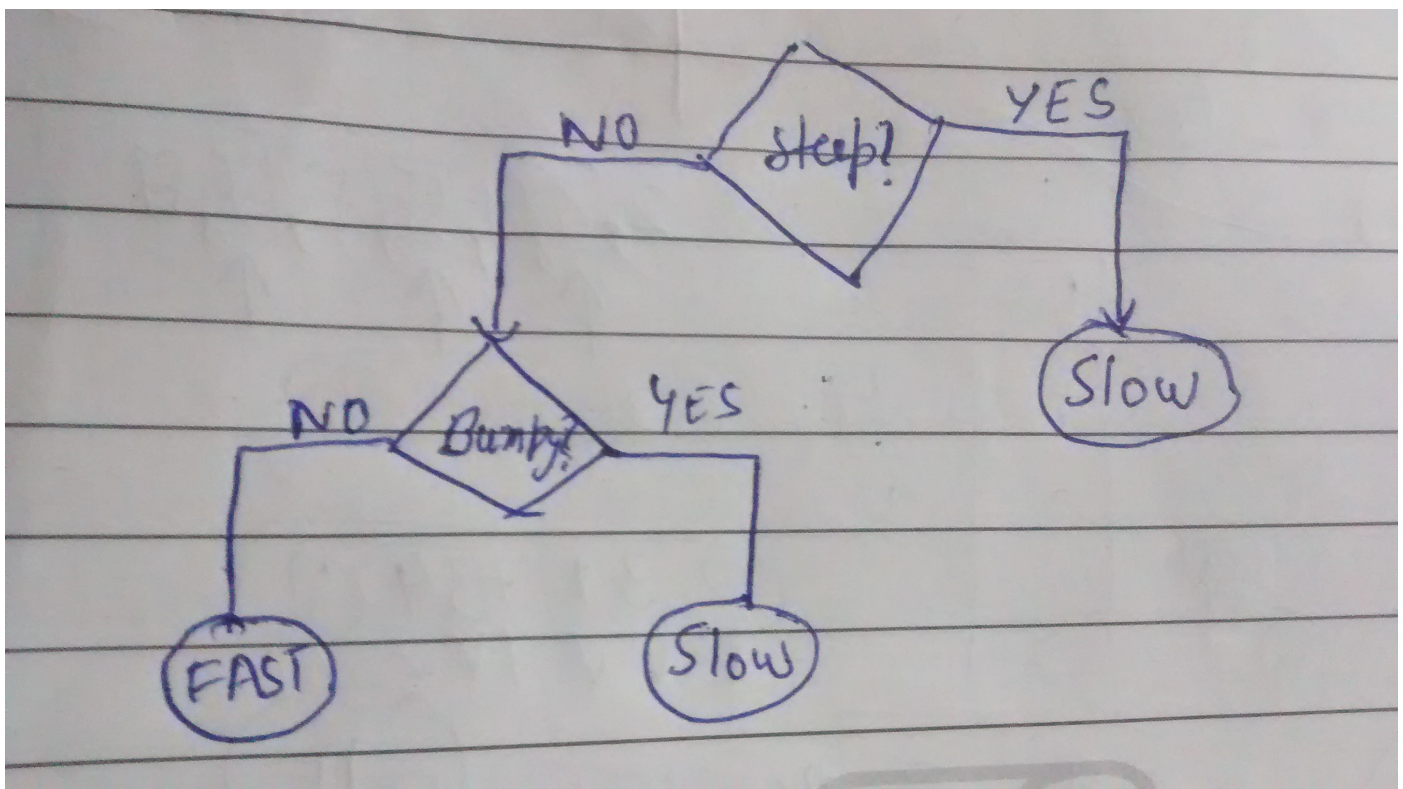
Decision Tree f1 score ( $< 0.8$ ) is nearly same as logistic regression, but less than SVM ( $> .8$ ). We found that training and testing time of Decision Tree and logistic regression algorithm is low when compared to SVM. Although SVM has best generalized the model and has highest testing score, but its performance cost in terms of runtime is not as efficient as compared to decision tree/logistic regression. When we compared decision tree to logistic regression, logistic regression has similar performance or slightly better testing score as that of decision tree. We have chosen decision tree as its training score is high, even though testing scores are similar. This high training score gives us leeway to do pruning in model which would generalize the model and improve testing score. Decision tree would be easier to interpret and explain anyway.

Decision Tree models a series of choices/decisions to get final outcome. Here Consecutive decisions or series of choices taken are based on previous choices. At each choice(node), we are deciding on the basis of value of a feature what decisions or checks(nodes) would be taken later. Thus we are splitting our data in these nodes. There are some special leaf nodes after which no subsequent decisions are made and data is finally categorized in an output category. This model is called tree, because if we visualize our model it would look like tree as different choices are splitting the data just like branches of tree.

For creating a decision tree, nodes are made such that they best segregates the pass and failed data in training set, which in mathematical jargon is measured by entropy. For nodes which have been able to split the data perfectly become leaf nodes and need not be augmented by children nodes for further split of data.

Now for predicting data on test set, we starting from first node(root) of decision tree and as per range of its features and decision expression on node traverse to subsequent decision node made to best split data while training. This process is followed until we reach a leaf node where test data is categorized i.e. pass or failures as per this leaf node category designated while training.

We can understand concept of decision tree through this very simplified example of whether to drive slow or fast as per bumpiness and steepness of road.



```
In [38]: from sklearn import grid_search
from sklearn import metrics
regressor = tree.DecisionTreeClassifier()
parameters = {'max_depth':(1,2,3,4,5,6,7,8,9,10), 'min_samples_leaf':(5,10,50)}
f1_scorer = metrics.make_scorer(f1_score, pos_label="yes")
clf = grid_search.GridSearchCV(regressor, parameters, f1_scorer)
clf.fit(X_train, y_train)
print "F1 score for train set with fine tuned Decision Tree : {}".format(
predict_labels(clf.best_estimator_, X_train, y_train)[1])
print "F1 score for test set with fine tuned Decision Tree: {}".format(p
redict_labels(clf.best_estimator_, X_test, y_test)[1])
```

F1 score for train set with fine tuned Decision Tree : 0.804597701149

F1 score for test set with fine tuned Decision Tree: 0.830985915493