BanknoteAuthentication

January 18, 2016

0.0.1 Banknote authentication

In this script I will evaluate different predictors for a banknote authentcation system.

The data is taken from the UCI Machine Learning Repository and it contains different features extracted from images that were taken for the evaluation of an authentication procedure for banknotes.

Information about the dataset: It contains four features and the class.
Variance of Wavelet Transformed image (vwti) - continuous
Skewness of Wavelet Transformed image (swti) - continuous
Curtosis of Wavelet Transformed image (cwti) - continuous
Entropy of image (eoi) - continuous
Class - banknote is authenticated (1) ot not (0) - integer

I will first read the data and remove the columns with missing values if this is needed. In the next step I will visually inspect the data to see if there are dangerous outliers that have to be removed and also to see which features to use for the classification part. In the final part I will evaluate multiple classifiers.

```
In [2]: % matplotlib inline
```

```
In [3]: # imports

        import numpy as np
        import matplotlib.pyplot as plt
        import pandas as pd
        from sklearn.cross_validation import train_test_split
        from pandas.tools.plotting import scatter_matrix
        from sklearn.cross_validation import KFold
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import mean_squared_error
        from sklearn.linear_model import LogisticRegression
        from sklearn.grid_search import GridSearchCV
        from sklearn.learning_curve import learning_curve
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.naive_bayes import GaussianNB
        from sklearn.metrics import confusion_matrix
```

```
In [4]: # hide python warnings

        import warnings
        warnings.filterwarnings('ignore')
```

0.0.2 1. Reading the data and removing missing values

```
In [5]: # download and read the data
```

```
header = ["vwti", "swti", "cwti", "eoi", "cls"]
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/00267/data_banknote_authentica
data = pd.read_csv(url, names=header)
```

In [6]:
```
# split data into train 80% and test 20%
train, test = train_test_split(data, test_size = 0.2)
```

In [7]:
```
# a few columns of the dataset
train.head()
```

Out[7]:

	vwti	swti	cwti	eoi	cls
726	0.040498	8.52340	1.4461	-3.93060	0
970	-2.329900	-9.95320	8.4756	-1.87330	1
471	0.395590	6.88660	1.0588	-0.67587	0
870	-1.942300	0.37660	-1.2898	-0.82458	1
1188	-3.020100	-0.67253	2.7056	0.85774	1

In [8]:
```
train.describe()
```

Out[8]:

	vwti	swti	cwti	eoi	cls
count	1097.000000	1097.000000	1097.000000	1097.000000	1097.000000
mean	0.433787	1.989581	1.355283	-1.186164	0.443026
std	2.806766	5.812941	4.242754	2.110082	0.496970
min	-7.042100	-13.773100	-5.286100	-7.871900	0.000000
25%	-1.754900	-1.440200	-1.544300	-2.378900	0.000000
50%	0.487970	2.294800	0.616630	-0.582770	0.000000
75%	2.774400	6.836900	3.114300	0.399980	1.000000
max	6.824800	12.951600	17.927400	2.162500	1.000000

There are no missing values in the dataset.

In [9]:
```
# check the number of features for each class in the training set
pd.value_counts(train['cls'], sort=True)
```

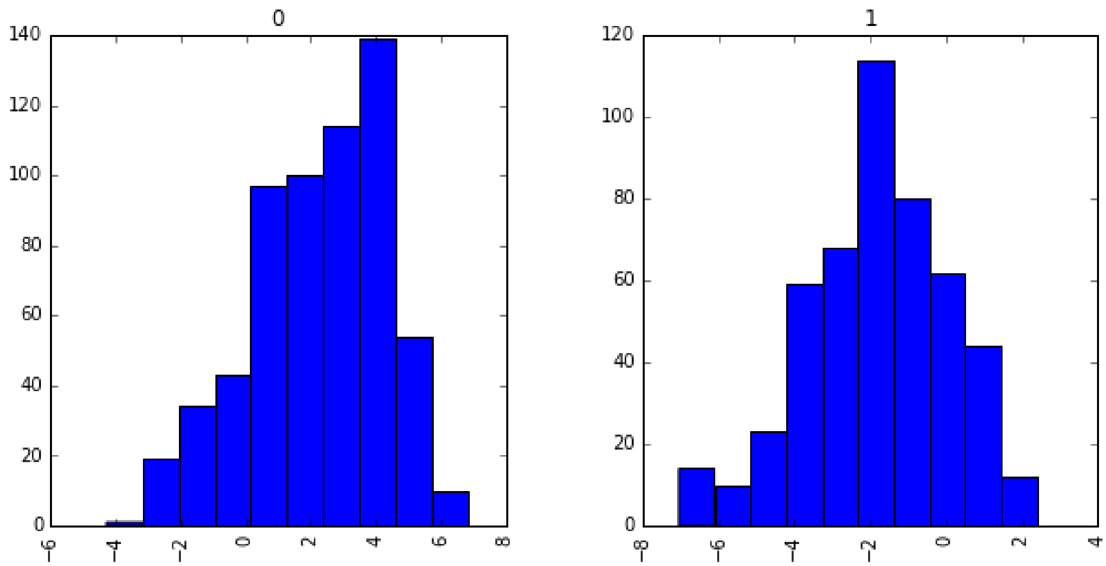
Out[9]:
```
0    611
1    486
Name: cls, dtype: int64
```

We have an almost equal split of the classes in the training set which is ok for the prediction task.

0.0.3 2. Visual data exploration

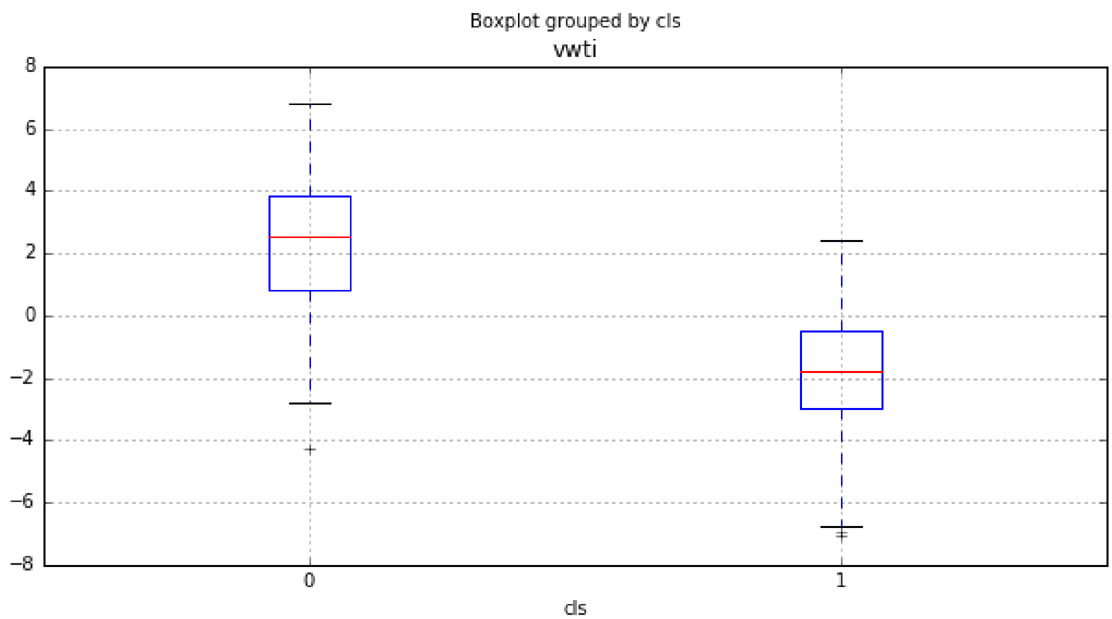
In [10]:
```
train.hist(column='vwti', by='cls', figsize=(10,5))
```

Out[10]:
```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x0000000008B4BBE0>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x0000000008BBCA90>], dtype=object)
```




```
In [11]: train.boxplot(column='vwti', by='cls', figsize=(10,5))
```

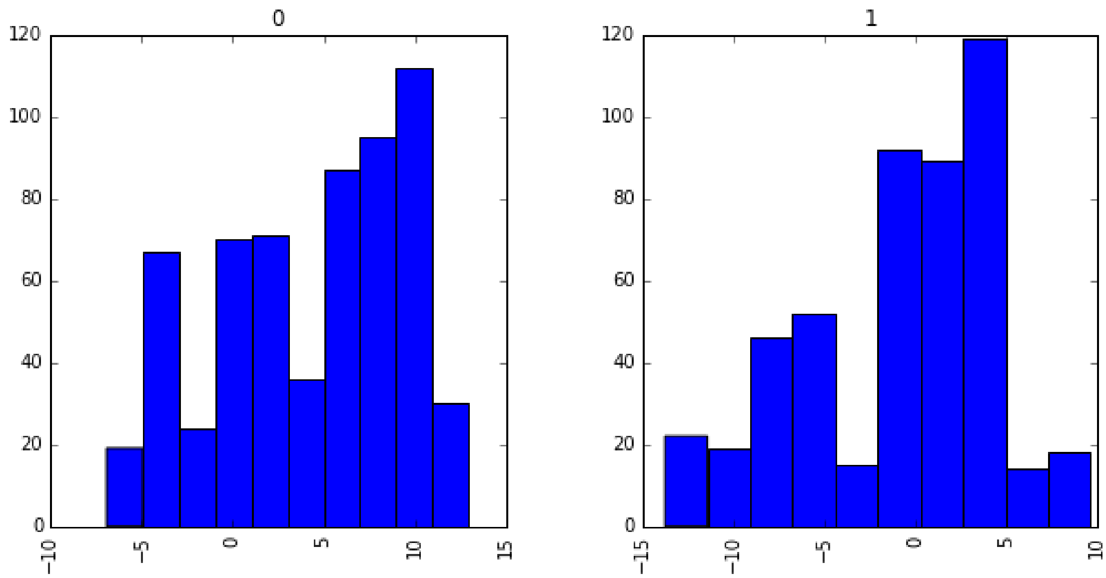
```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x909edd8>
```



The vwti feature has a good variability and the mean and the meadian are quite different for the two classes. This is a good feature for classification.

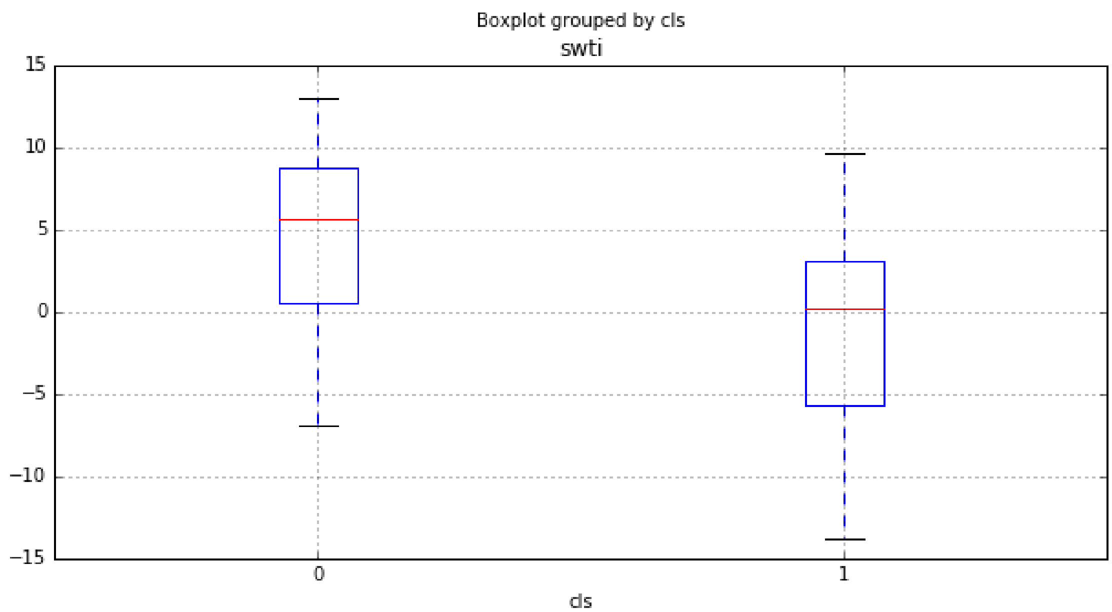
```
In [12]: train.hist(column='swti', by='cls', figsize=(10,5))
```

```
Out[12]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x00000000093EA160>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x000000000943EA58>], dtype=object)
```




```
In [13]: train.boxplot(column='swti', by='cls', figsize=(10,5))
```

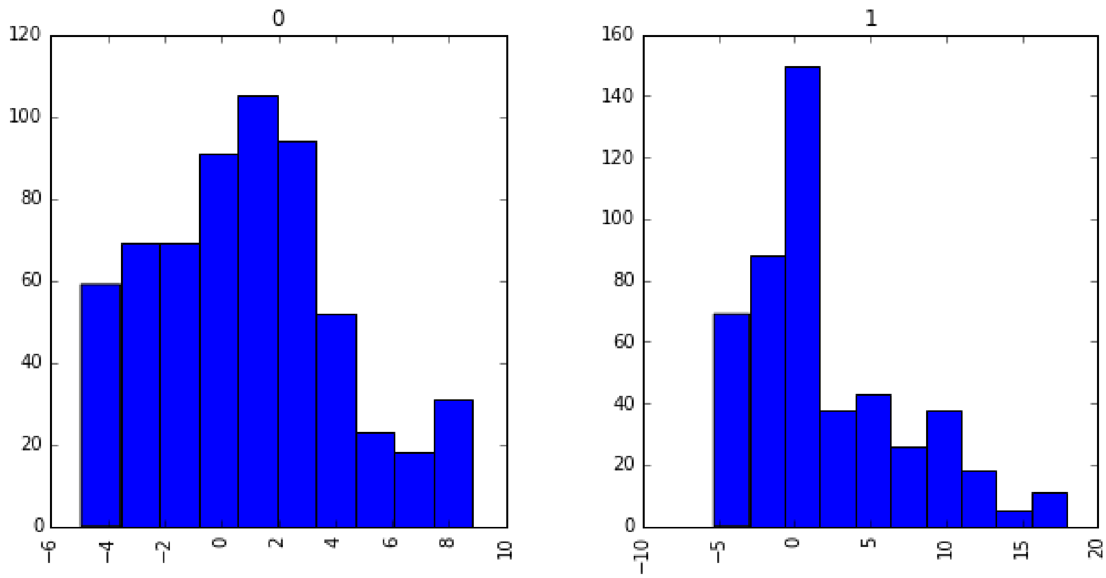
```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x944ee80>
```



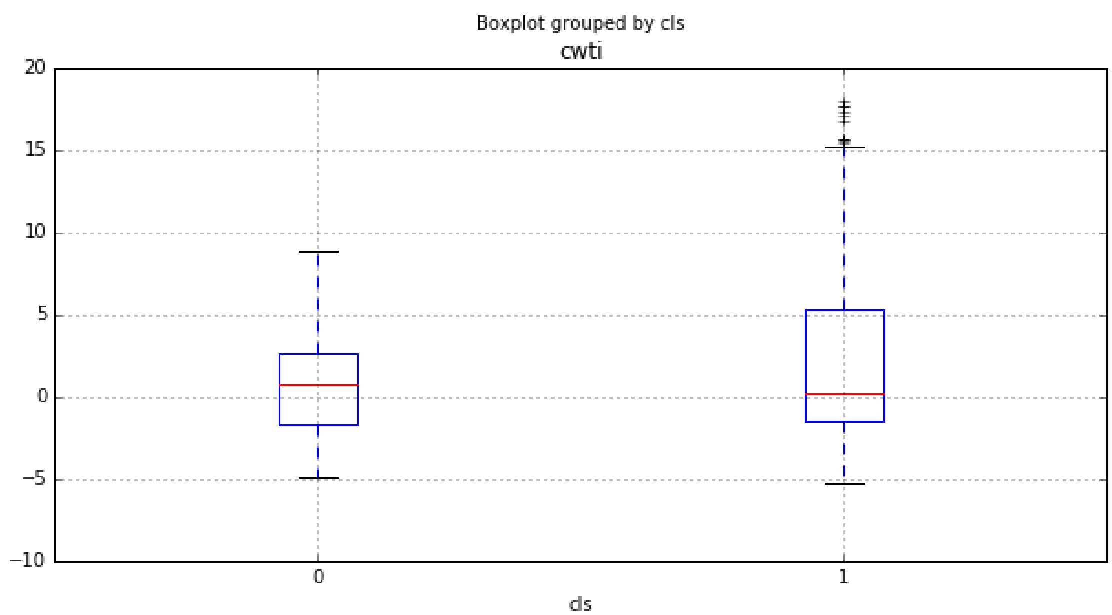
Same for the swti feature.

```
In [14]: train.hist(column='cwti', by='cls', figsize=(10,5))
```

```
Out[14]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x00000000094ADF98>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x000000000A78FDD8>], dtype=object)
```

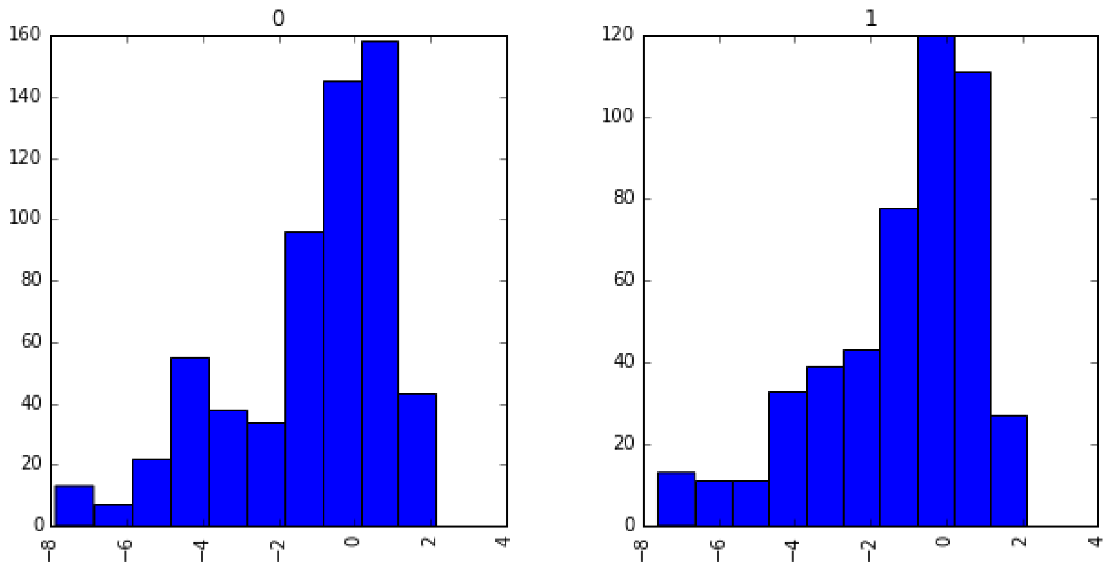



```
In [15]: train.boxplot(column='cwti', by='cls', figsize=(10,5))

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0xa750390>
```

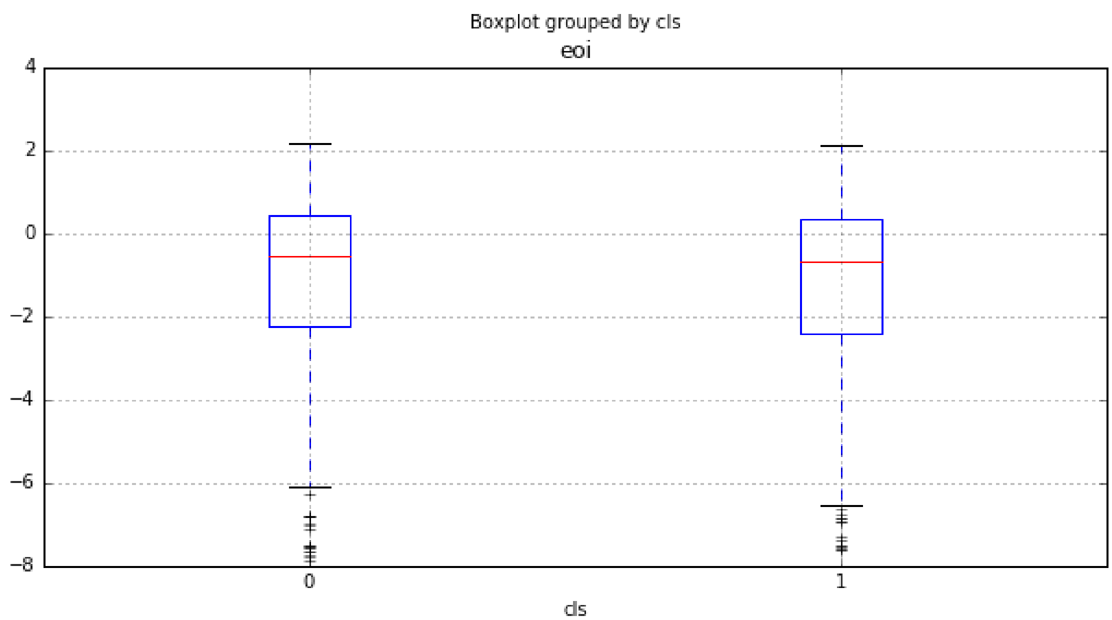


The cwti variable has a good variablity so it's also a good predictor.

```
In [16]: train.hist(column='eoi', by='cls', figsize=(10,5))

Out[16]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x000000000A998390>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x000000000A8D59E8>], dtype=object)
```




```
In [17]: train.boxplot(column='eoi', by='cls', figsize=(10,5))

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0xa9659b0>
```



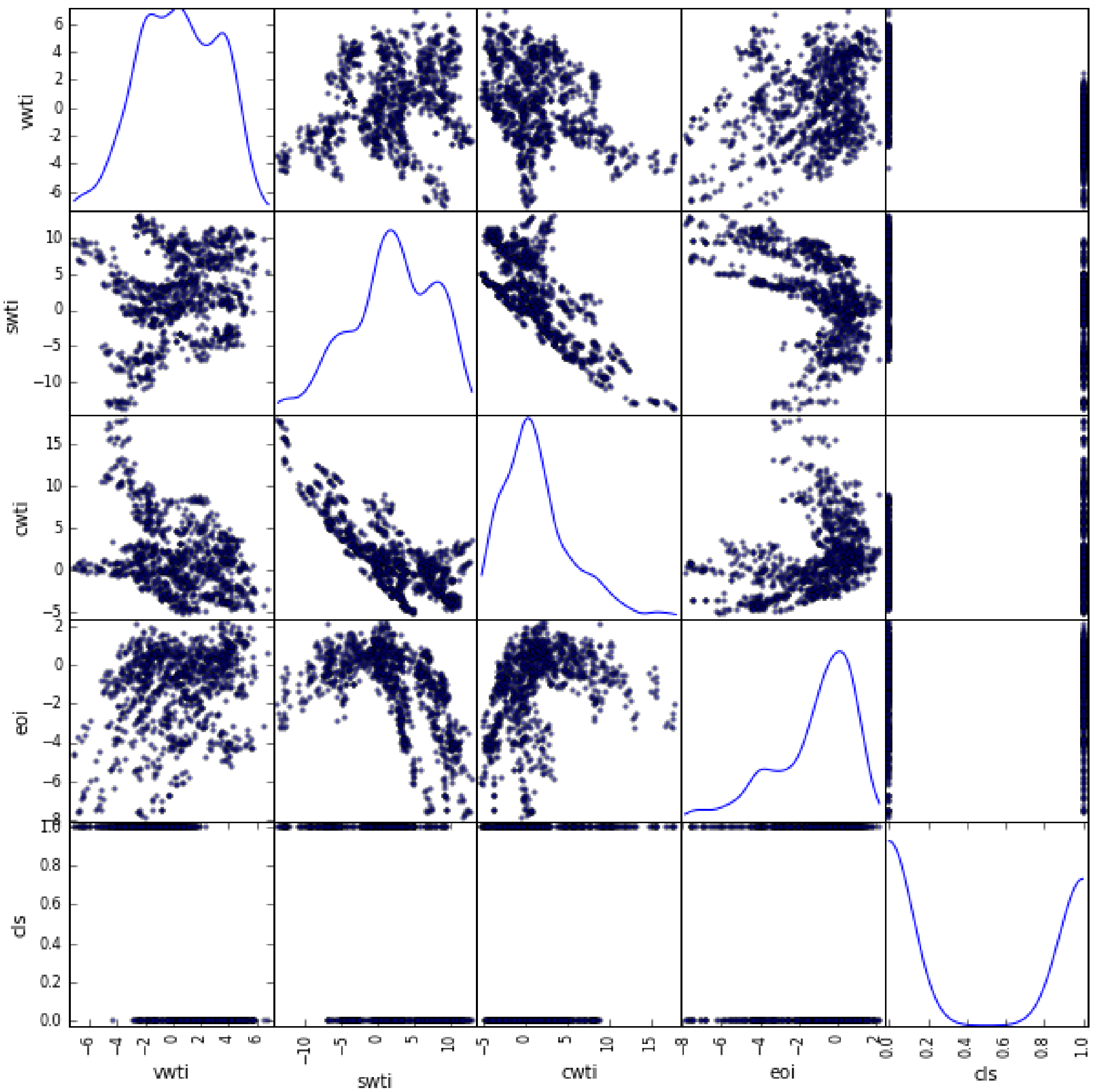
The eoi feature has no differences between then two classes. It has the same mean and median, the same variance and the same distribution. In will not be taken into account for the classification task.

```
In [18]: # check the correlation between the features and the label
         train.corr()
```

```
Out[18]:           vwti      swti      cwti       eoi       cls
         vwti  1.000000  0.250618 -0.365813  0.273184 -0.716075
         swti  0.250618  1.000000 -0.775451 -0.532269 -0.443421
         cwti -0.365813 -0.775451  1.000000  0.322376  0.132679
         eoi   0.273184 -0.532269  0.322376  1.000000 -0.013334
         cls  -0.716075 -0.443421  0.132679 -0.013334  1.000000
```

```
In [21]: scatter_matrix(train, figsize=(10, 10), diagonal='kde')
```

```
Out[21]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000000000A960400>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000AA9AF98>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000AAB9400>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000AD749E8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000ADBDA58>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000ADFCB70>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000AE4B6A0>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000AE82E80>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B0E1128>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B0F7390>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000B1690F0>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B1B4160>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B1F1278>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B23BD68>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000A76B0B8>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000B2AA940>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B2CE080>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B330588>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B37B6D8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B3BC438>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000B403E48>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B440748>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B48F390>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000B458D30>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x000000000C4E3F28>]], dtype=object)
```



From the correlation graph and matrix we can see that eoi can be removed because it's almost independent from the class.

0.0.4 3. Model selection

The model selection phase will contain three steps. First using cross-validation I will select the best parameters for a mode and I will train it. Further I will analyze how the classifier behaves with more data using a learning curve. This is useful in the context of big data. And finally I will evaluate the model with independent data. Three models will be anayled: LogisticRegression, RandomForests and NaiveBayes

```
In [22]: # select only the feature names from the header
         features_columns = header[:3]
```

```
In [23]: # function taken from: http://scikit-learn.org/stable/auto_examples/model_selection/plot_learn

         def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                                 n_jobs=1, train_sizes=np.linspace(.1, 1.0, 5)):
```

```python
"""
Generate a simple plot of the test and traning learning curve.

Parameters
----------
estimator : object type that implements the "fit" and "predict" methods
    An object of that type which is cloned for each validation.

title : string
    Title for the chart.

X : array-like, shape (n_samples, n_features)
    Training vector, where n_samples is the number of samples and
    n_features is the number of features.

y : array-like, shape (n_samples) or (n_samples, n_features), optional
    Target relative to X for classification or regression;
    None for unsupervised learning.

ylim : tuple, shape (ymin, ymax), optional
    Defines minimum and maximum yvalues plotted.

cv : integer, cross-validation generator, optional
    If an integer is passed, it is the number of folds (defaults to 3).
    Specific cross-validation objects can be passed, see
    sklearn.cross_validation module for the list of possible objects

n_jobs : integer, optional
    Number of jobs to run in parallel (default 1).
"""
plt.figure()
plt.title(title)
if ylim is not None:
    plt.ylim(*ylim)
plt.xlabel("Training examples")
plt.ylabel("Score")
train_sizes, train_scores, test_scores = learning_curve(
    estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)
plt.grid()

plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                 train_scores_mean + train_scores_std, alpha=0.1,
                 color="r")
plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                 test_scores_mean + test_scores_std, alpha=0.1, color="g")
plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
         label="Training score")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
         label="Cross-validation score")
```

```
        plt.legend(loc="best")
        return plt
```

In [24]:
```
# prepare the train and test data
train = train.drop("eoi", 1)
x_train = train[features_columns].values
y_train = train.cls.values

test = test.drop("eoi", 1)
x_test = test[features_columns].values
y_test = test.cls.values
```

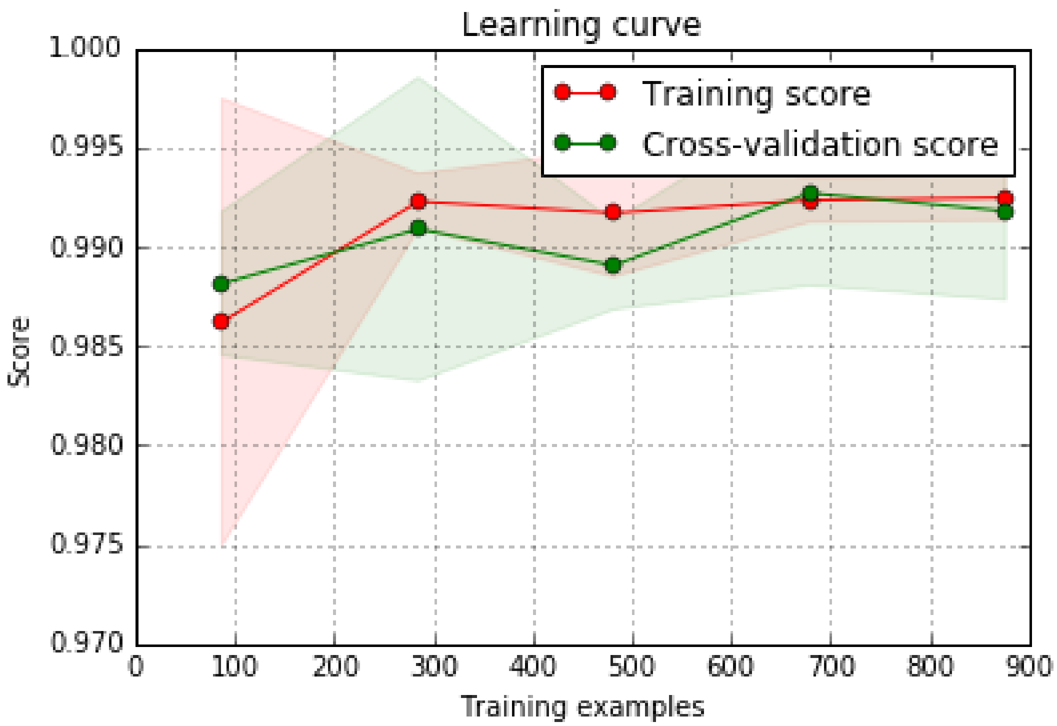
In [25]:
```
cv = KFold(len(x_train), n_folds=5, shuffle=True)
```

In [26]:
```
# first classifier evaluated is LogisticRegression
logReg = LogisticRegression(penalty='l2')

params = {'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000] }
classifier = GridSearchCV(estimator=logReg, cv=cv, param_grid=params)
classifier.fit(x_train, y_train)
```

Out[26]:
```
GridSearchCV(cv=sklearn.cross_validation.KFold(n=1097, n_folds=5, shuffle=True, random_state=No
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000]},
       pre_dispatch='2*n_jobs', refit=True, scoring=None, verbose=0)
```

In [27]:
```
bestLogRegModel = LogisticRegression(penalty='l2',C=classifier.best_estimator_.C)
plot_learning_curve(bestLogRegModel, "Learning curve", x_train, y_train, cv=cv)
```

Out[27]:
```
<module 'matplotlib.pyplot' from 'D:\\Programming\\anaconda3\\envs\\py35\\lib\\site-packages\\m
```

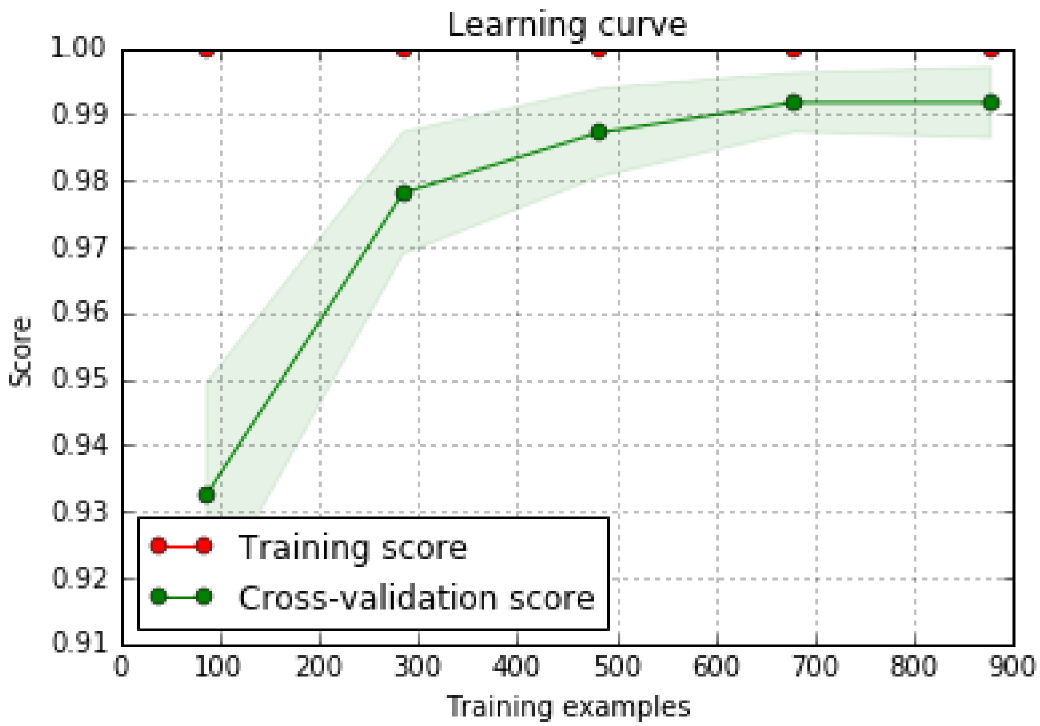



```
In [28]: def evalClassifier(clsf):
             print(clsf.score(x_test, y_test))

             y_pred = clsf.predict(x_test)
             print(confusion_matrix(y_test, y_pred))

In [29]: evalClassifier(classifier)

0.981818181818
[[148   3]
 [  2 122]]

In [35]: # Then we evaluate a RandomForest ensamble
         forest = RandomForestClassifier()

         params = {'n_estimators': [10, 50, 100, 200, 500], 'criterion': ['gini', 'entropy']}
         classifier = GridSearchCV(estimator=forest, cv=cv, param_grid=params)
         classifier.fit(x_train, y_train)

Out[35]: GridSearchCV(cv=sklearn.cross_validation.KFold(n=1097, n_folds=5, shuffle=True, random_state=No
                error_score='raise',
                estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
                     oob_score=False, random_state=None, verbose=0,
                     warm_start=False),
                fit_params={}, iid=True, n_jobs=1,
```

```
             param_grid={'n_estimators': [10, 50, 100, 200, 500], 'criterion': ['gini', 'entropy']},
             pre_dispatch='2*n_jobs', refit=True, scoring=None, verbose=0)
```

In [31]:
```
bestRandForestModel = RandomForestClassifier \
    (n_estimators=classifier.best_estimator_.n_estimators, \
     criterion=classifier.best_estimator_.criterion)
plot_learning_curve(bestRandForestModel, "Learning curve", x_train, y_train, cv=cv)
```

Out[31]:
```
<module 'matplotlib.pyplot' from 'D:\\Programming\\anaconda3\\envs\\py35\\lib\\site-packages\\m
```

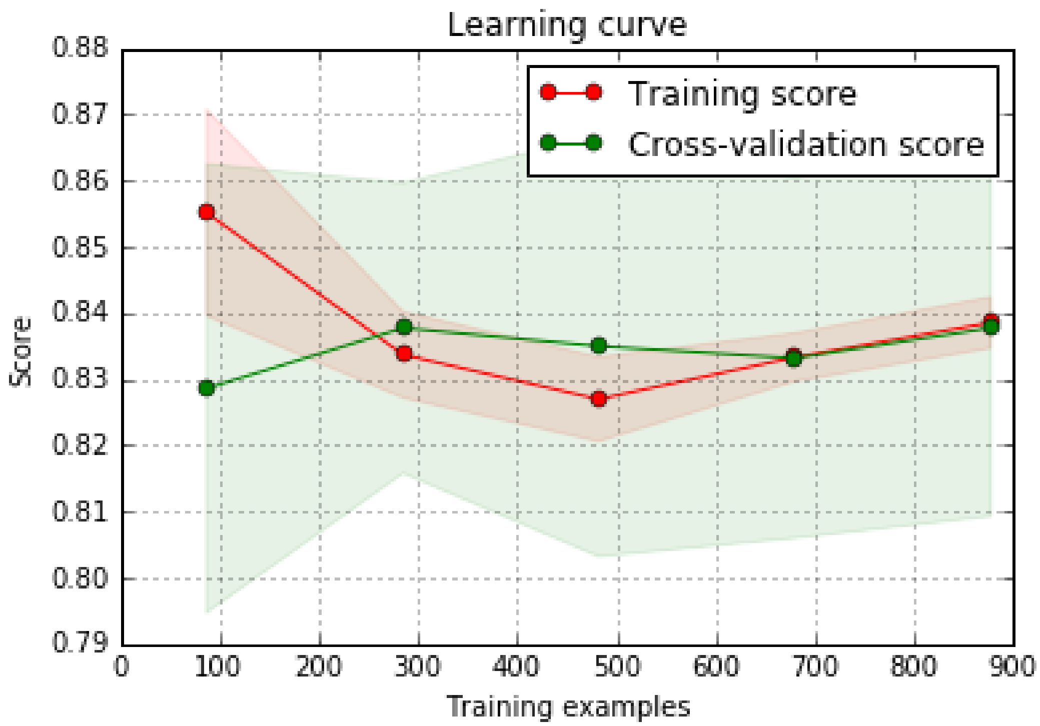


In [32]:
```
evalClassifier(classifier)
```

```
0.996363636364
[[151   0]
 [  1 123]]
```

In [33]:
```
# And finally a naive bayes classifier
nb = GaussianNB()
nb.fit(x_train, y_train)

plot_learning_curve(nb, "Learning curve", x_train, y_train, cv=cv)
```

Out[33]:
```
<module 'matplotlib.pyplot' from 'D:\\Programming\\anaconda3\\envs\\py35\\lib\\site-packages\\m
```




```
In [34]: evalClassifier(nb)
```

```
0.872727272727
[[136  15]
 [ 20 104]]
```

After analyzing the models I've decided to implement further in scala LogisticRegresion and Randome-Forest.