Assignment_1

February 22, 2017

1 Foundations of Data Mining: Assignment 1

Please complete all assignments in this notebook. You should submit this notebook, as well as a PDF version (See File > Download as).

```
In [1]: %matplotlib inline
        from preamble import *
        from IPython.display import Image
        plt.rcParams['savefig.dpi'] = 100 # This controls the size of your figures
        # Comment out and restart notebook if you only want the last output of each cell.
        InteractiveShell.ast_node_interactivity = "all"
```

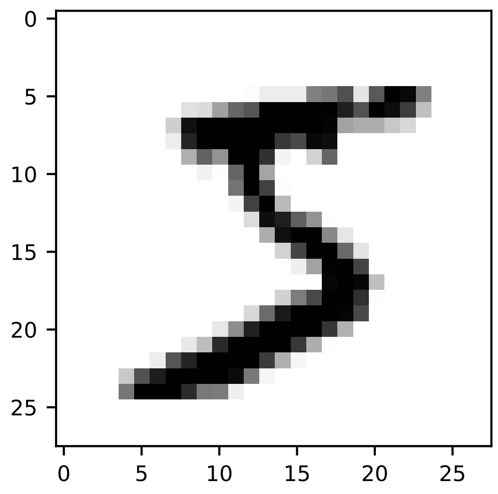
1.1 Handwritten digit recognition (5 points, 1+2+2)

```
In [2]: # This is a temporary read-only OpenML key. Replace with your own key later.
        oml.config.apikey = 'fa31aae3ceb0dba388acb20276cd75d3'
```

```
In [3]: mnist_data = oml.datasets.get_dataset(554) # Download MNIST data
        # Get the predictors X and the labels y
        X, y = mnist_data.get_data(target=mnist_data.default_target_attribute);
        # Take the first example, reshape to a 28x28 image and plot
        plt.imshow(X[0].reshape(28, 28), cmap=plt.cm.gray_r)
        print("Class label:",y[0]) # Print the correct class label
```

```
Out[3]: <matplotlib.image.AxesImage at 0x1dbd1e6fd30>
```

```
Class label: 5
```



- Evaluate a k-Nearest Neighbor classifier with its default settings.
  - Use the first 60,000 examples as the training set and the last 10,000 as the test set
  - What is the predictive accuracy?
  - Find a few misclassifications, and plot them together with the true labels (as above). Are these images really hard to classify?

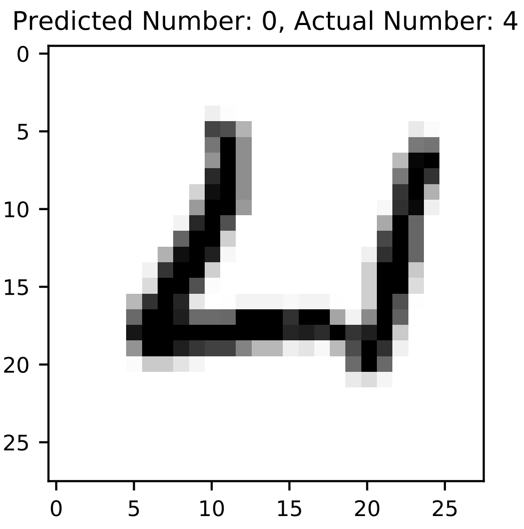
```
In [5]: import openml as oml
        import matplotlib.pyplot as plt
        import numpy as np
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.model_selection import train_test_split

        xTrain, xTest = np.split(X,[60000])
        yTrain, yTest = np.split(y,[60000])

        xReduced, _, yReduced,_ = train_test_split(X,y, stratify=y, train_size=0.1)
        knn = KNeighborsClassifier(n_jobs=-1)
        knn.fit(xTrain, yTrain)

        count = 0
        print("Predictive Score over Test Set: %.2f"%(knn.score(xTest,yTest)) )
        for i in range(0,10000):
            pred = knn.predict(xTest[i].reshape(1,-1))
            if(pred != yTest[i]) and count < 5:
                plt.imshow(xTest[i].reshape(28, 28), cmap=plt.cm.gray_r)
                plt.title("Predicted Number: " + str(pred[0]) + ", Actual Number: " + str(yTes
                count += 1
                plt.show()
            elif count >= 5:
                break
            else:
                continue
```

```
Out[5]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                   metric_params=None, n_jobs=-1, n_neighbors=5, p=2,
                   weights='uniform')
```

```
Predictive Score over Test Set: 0.97
```

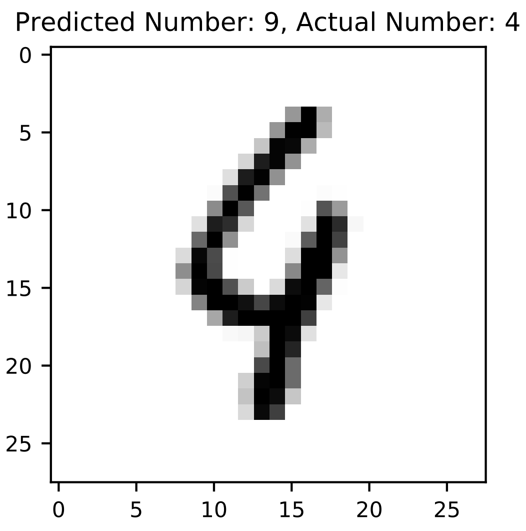
```
Out[5]: <matplotlib.image.AxesImage at 0x1dbd3baaa20>
```

```
Out[5]: <matplotlib.text.Text at 0x1dbd3b636a0>
```

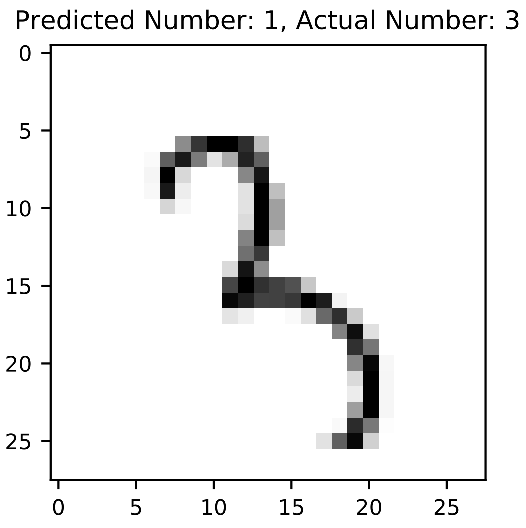


```
Out[5]: <matplotlib.image.AxesImage at 0x1dbd3c41cf8>
```

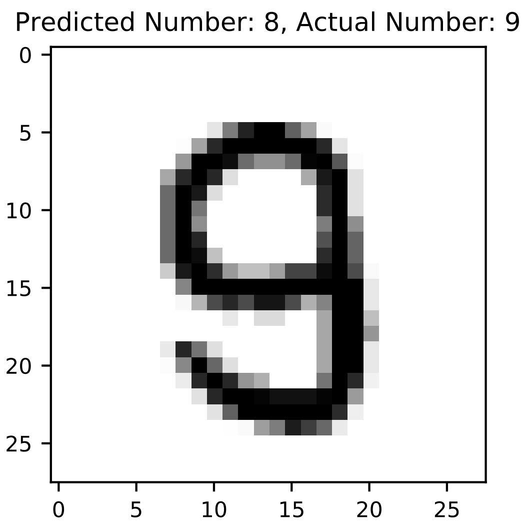
```
Out[5]: <matplotlib.text.Text at 0x1dbd3c04438>
```



```
Out[5]: <matplotlib.image.AxesImage at 0x1dbd3cb4b38>

Out[5]: <matplotlib.text.Text at 0x1dbd3c71240>
```

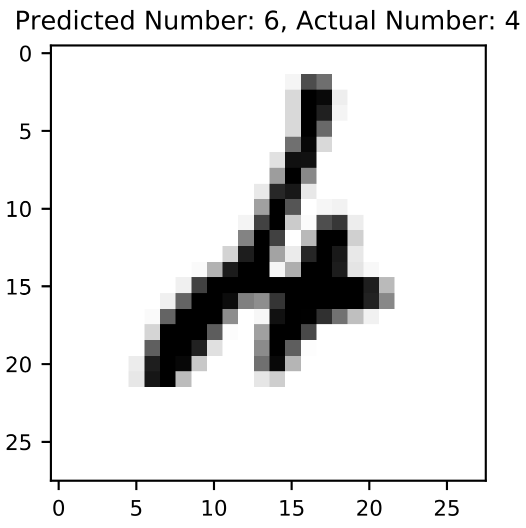


```
Out[5]: <matplotlib.image.AxesImage at 0x1dbd3d50278>

Out[5]: <matplotlib.text.Text at 0x1dbd3d0bbe0>
```



```
Out[5]: <matplotlib.image.AxesImage at 0x1dbd3de26d8>
```

```
Out[5]: <matplotlib.text.Text at 0x1dbd3da0cc0>
```



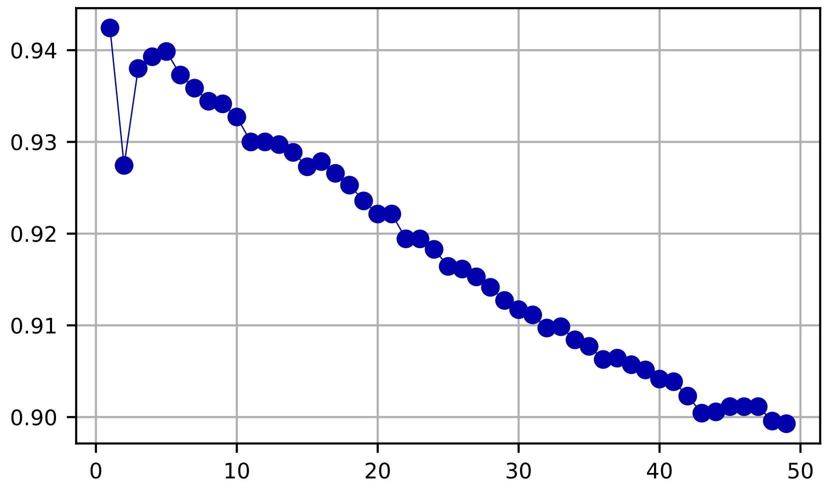
The images that the classifier misclassify are pretty easily confused. Many of the images could be interpreted in both the predicted way and the actual label by humans.

- Optimize the value for the number of neighbors k (keep $k < 50$) on a stratified subsample (e.g. 10%) of the data
  - Use 10-fold crossvalidation and plot k against the misclassification rate. Which value of k should you pick?

```
In [13]: from sklearn.model_selection import cross_val_score


         scores = []
         knn = KNeighborsClassifier(n_jobs=-1)
         for k in range(1,50):
             knn.n_neighbors=k
             print("Calculating with k="+str(k))
             scores.append(np.mean(cross_val_score(knn, xReduced, yReduced, cv=10)))
         x = range(1,50)
         plt.plot(x, scores, marker="o")
         plt.grid()
         plt.show()
```

```
Calculating with k=1
Calculating with k=2
Calculating with k=3
Calculating with k=4
Calculating with k=5
Calculating with k=6
Calculating with k=7
Calculating with k=8
Calculating with k=9
Calculating with k=10
Calculating with k=11
Calculating with k=12
Calculating with k=13
Calculating with k=14
Calculating with k=15
Calculating with k=16
Calculating with k=17
Calculating with k=18
Calculating with k=19
Calculating with k=20
Calculating with k=21
Calculating with k=22
Calculating with k=23
Calculating with k=24
Calculating with k=25
Calculating with k=26
Calculating with k=27
Calculating with k=28
Calculating with k=29
Calculating with k=30
Calculating with k=31
Calculating with k=32
Calculating with k=33
Calculating with k=34
Calculating with k=35
Calculating with k=36
Calculating with k=37
Calculating with k=38
Calculating with k=39
Calculating with k=40
Calculating with k=41
Calculating with k=42
Calculating with k=43
Calculating with k=44
Calculating with k=45
Calculating with k=46
Calculating with k=47
Calculating with k=48
Calculating with k=49
```

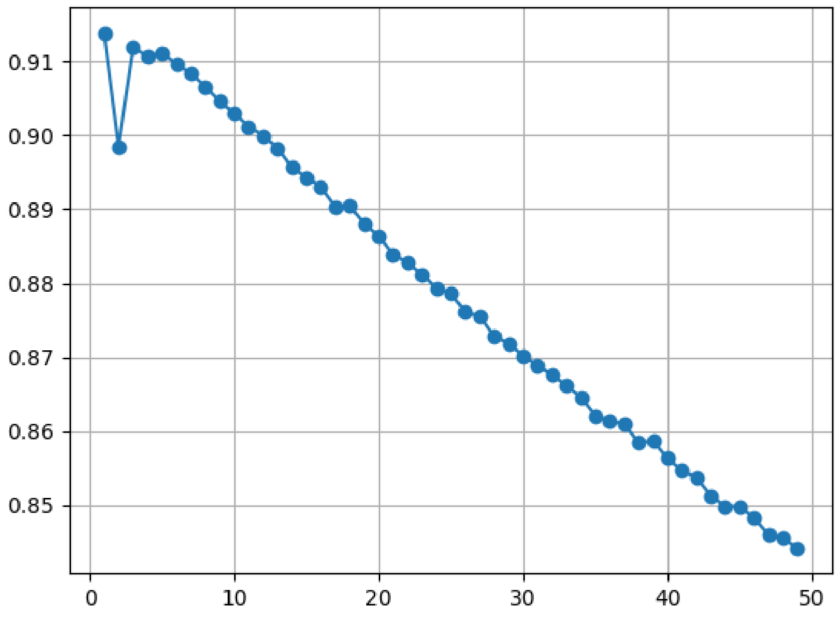
```
Out[13]: [<matplotlib.lines.Line2D at 0x1efe9209898>]
```



From this image, we can clearly see that $k = 1$ delivers the best score.

- Do the same but with 100 bootstrapping repeats. Are the results different? Explain.

```
In [ ]: from sklearn.model_selection import ShuffleSplit

        scores = []
        knn = KNeighborsClassifier(n_jobs=-1)
        for k in range(1,50):
            knn.n_neighbors=k
            print("Calculating with k="+str(k))
            supSplit = ShuffleSplit(train_size=0.66, test_size=0.34, n_splits=100)
```



Bootstrapping Results

```
            mean = np.mean((cross_val_score(knn, xReduced, yReduced, cv=supSplit,n_jobs=4)))
            scores.append(mean)
        x = range(1,50)
        plt.plot(x, scores, marker="o")
        plt.grid()
        plt.show()
```

```
Calculating with k=1
```

Running this code takes quite some time, so an image of the result is included in the deliverable. This image (KNN Bootstrapping) also shows that $k = 1$ offers the best result. However the values of these scores are a lot lower than the cross validation results. This is probably through the fact that we have a smaller training set than in the Cross Validation and this has a significant impact on the performance of the Nearest Neighbor model.

- Compare kNN against the linear classification models that we have covered in the course (logistic regression and linear SVMs).
  - First use the default hyperparameter settings.
  - Next, optimize for the degree of regularization (C) and choice of penalty (L1/L2). Again, plot the accuracy while increasing the degree of regularization for different penalties. Interpret the results.
  - Report is the optimal performance. Can you get better results than kNN?

Report all results clearly and interpret the results.

```
In [ ]: from sklearn.model_selection import cross_val_score

        from sklearn.linear_model import LogisticRegression
        from sklearn.svm import LinearSVC

        logReg = LogisticRegression()
        SVC =  LinearSVC()
        for C, pen in [(x,y) for x in [0.0001, 0.001, 0.01, 0.1, 1] for y in ['l1','l2']]:
            logReg = LogisticRegression(C=C, penalty=pen, n_jobs=-1)
            if(pen=='l1'):
                SVC = LinearSVC(C=C, penalty=pen, dual=False)
            else:
                SVC = LinearSVC(C=C, penalty=pen)
            print("Logistic Regression Score (C: " + str(C) + ", pen: " + pen + "): %.4f"%(np.r
            print("Linear SVC Score(C: " + str(C) + ", pen: " + pen + "): %.4f"%(np.mean(cross_
```

```
Logistic Regression Score (C: 0.0001, pen: l1): 0.8347
Linear SVC Score(C: 0.0001, pen: l1): 0.8708
Logistic Regression Score (C: 0.0001, pen: l2): 0.8783
Linear SVC Score(C: 0.0001, pen: l2): 0.8506
Logistic Regression Score (C: 0.001, pen: l1): 0.8863
Linear SVC Score(C: 0.001, pen: l1): 0.8906
Logistic Regression Score (C: 0.001, pen: l2): 0.8587
Linear SVC Score(C: 0.001, pen: l2): 0.8390
Logistic Regression Score (C: 0.01, pen: l1): 0.8841
Linear SVC Score(C: 0.01, pen: l1): 0.8656
Logistic Regression Score (C: 0.01, pen: l2): 0.8409
Linear SVC Score(C: 0.01, pen: l2): 0.8380
Logistic Regression Score (C: 0.1, pen: l1): 0.8530
Linear SVC Score(C: 0.1, pen: l1): 0.8447
```

The best score is retrieved using a C of 0.001 and a L1 penalty. It seems that the data can be classified best through a relatively simple model, due to the low value of C and the use of an L1 penalty. However it seems that these linear models cannot beat a 1-Nearest Neighbor classifier. The score of 0.89 is significantly lower than the score of 0.94 for the 1-Nearest Neighbor classifier. This seems to imply that this handwriting data works better with a nearest neighbor classifier than through a linear model

1.2 Model selection (4 points (2+2))

Study how RandomForest hyperparameters interact on the Ionosphere dataset (OpenML ID 59).

- Optimize a RandomForest, varying both *n_estimators* and *max_features* at the same time. Use a nested cross-validation and a grid search (or random search) over the possible values, and measure the AUC. Explore how fine-grained this grid/random search can be, given your computational resources. What is the optimal AUC performance you find?
- Again, vary both hyperparameters, but this time use a grid search and visualize the results as a plot (heatmap) $n\_estimators \times max\_features \rightarrow AUC$ with AUC visualized as the color

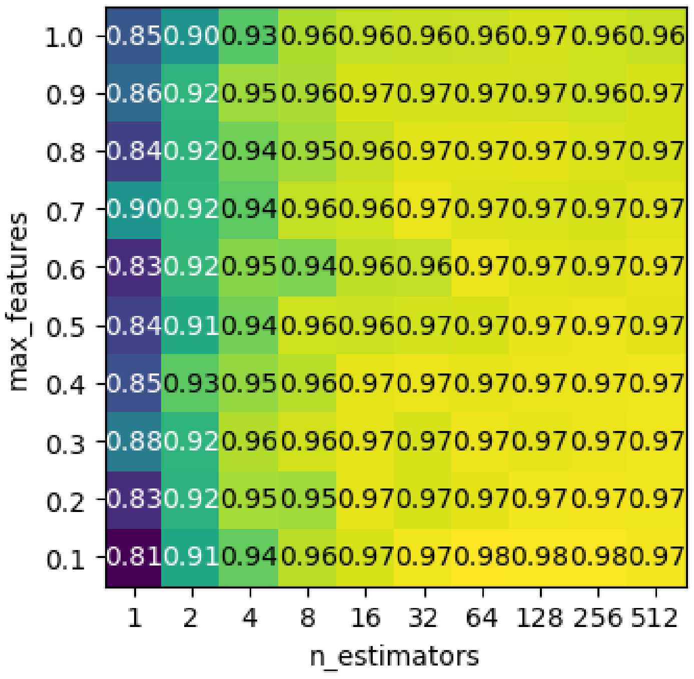
of the data point. Try to make the grid as fine as possible. Interpret the results. Can you explain your observations? What did you learn about tuning RandomForests?

Hint: Running this experiment can take a while, so start early and use a feasible grid/random search. Start with a coarse grid or few random search iterations.
Hint: Use a log scale (1,2,4,8,16,...,512) for *n_estimators*. Vary *max_features* linearly between 1 and the total number of features. Note that, if you give *max_features* a float value, it will use it as the percentage of the total number of features. Hence, you can explore the values [0.1,0.2,0.3,...,0.9]
Hint: We've shown how to do a nested cross-validation in class. You can also pass the evaluation measure to `cross_val_score` using the `scoring` attribute. Hint: Note that in the first question, we are not interested in the actual values of the optimal hyperparameters, only in their AUC performance. Indeed, you will possibly get different optimal hyperparameters in each iteration of the outer CV. In the second question, we do a single grid search, and hence we can retrieve and visualize the hyperparameter values and their performance.

```
In [5]: import openml as oml
        import numpy as np
        from sklearn.model_selection import cross_val_score, GridSearchCV, RandomizedSearchCV,
        from sklearn.ensemble import RandomForestClassifier
        oml.config.apikey = 'fa31aae3ceb0dba388acb20276cd75d3'
        from sklearn.cross_validation import cross_val_score
        from sklearn.metrics.scorer import SCORERS
        import matplotlib as plt
        import pandas as pd
        import IPython
        import mglearn

        import warnings
        warnings.filterwarnings('ignore')

        ionosphere = oml.datasets.get_dataset(59) # Download MNIST data
        X, y = ionosphere.get_data(target=ionosphere.default_target_attribute); # Get the pred

In [6]: #The max features are in percentages of the total, which is 34.
        param_grid = {'n_estimators': [1,2,4,8,16,32,64,128,256,512],
                      'max_features': [0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]}
        print("Parameter grid:\n{}".format(param_grid))

        from sklearn.model_selection import GridSearchCV
        grid_search = GridSearchCV(RandomForestClassifier(), param_grid, cv=5, scoring='roc_auc
        grid_search.fit(X, y)
        print('Non nested CV score:', grid_search.best_score_)
        print("Best parameters: ", grid_search.best_params_)
        nested_scores = cross_val_score(grid_search,X,y, cv=5, scoring='roc_auc', n_jobs=-1)
        print("Nested CV scores: {}".format(nested_scores.mean()))
```

```
Parameter grid:
{'n_estimators': [1, 2, 4, 8, 16, 32, 64, 128, 256, 512], 'max_features': [0.1, 0.2, 0.3, 0.4,
Non nested CV score: 0.977550101054
Best parameters:  {'max_features': 0.1, 'n_estimators': 64}
Nested CV scores: 0.9761675213675213
```

```
In [7]: # convert to Dataframe
        results = pd.DataFrame(grid_search.cv_results_)
        scores = np.array(results.mean_test_score).reshape(10, 10)
        #print("Scores grid:\n{}".format(scores))
        # plot the mean cross-validation scores
        hm = mglearn.tools.heatmap(scores, xlabel='n_estimators', xticklabels=param_grid['n_es
                                   ylabel='max_features', yticklabels=param_grid['max_features'], c
```



1.3 Decision tree heuristics (1 point)

Consider the toy training set created below. It predicts whether your date agrees to go out with you depending on the weather.

Learn a decision tree:

- Implement functions to calculate entropy and information gain

```
In [20]: df = pd.DataFrame({"Sky":['sunny','sunny','rainy','sunny','sunny'],
                            "AirTemp":['warm','warm','warm','cold','warm'],
                            "Humidity":['normal','high','high','high','normal'],
                            "Wind":['strong','strong','strong','strong','weak'],
                           "Water":['warm','warm','cool','warm','warm'],
                           "Forecast":['same','same','change','change','same'],
                           "Date?":['yes','yes','no','yes','no']
                           });
# Fix column ordering
df = df[['Sky', 'AirTemp', 'Humidity', 'Wind', 'Water', 'Forecast', 'Date?']]
df # print
```

```
Out[20]:      Sky AirTemp Humidity    Wind Water Forecast Date?
         0  sunny    warm   normal  strong  warm     same   yes
         1  sunny    warm     high  strong  warm     same   yes
         2  rainy    warm     high  strong  cool   change    no
         3  sunny    cold     high  strong  warm   change   yes
         4  sunny    warm   normal    weak  warm     same    no
```

```
In [18]: # Complete these functions first
         # pos and neg are the number of positive and negative samples in a node
         def entropy(pos, neg):
             if pos == 0 or neg==0:
                 return 0
             p = pos / (pos + neg)
             return -p*np.log2(p) - (1-p)*np.log2(1-p)

         # pos1 and pos2 are the number of positive examples in each branch after the split.
         # Same for neg1 and neg2
         def info_gain(pos1,neg1,pos2,neg2):
             total = pos1 + pos2 + neg1 + neg2
             return entropy(pos1+pos2, neg1+neg2) - entropy(pos1, neg1) * (pos1+neg1)/total - e
```

- What is the class entropy for the entire dataset? What is the information gain when you split the data using the *Water* feature?

```
In [11]: pos1 = df[df['Date?'] == 'yes']
         neg1 = df[df['Date?'] == 'no']
         warm = df[df['Water'] == 'warm']
         cool = df[df['Water'] == 'cool']
         warmP = warm[warm['Date?']=='yes']
         warmN = warm[warm['Date?']=='no']
         coolP = cool[cool['Date?']=='yes']
         coolN = cool[cool['Date?']=='no']
         print('Entropy: ' + str(entropy(len(pos1), len(neg1))))
         print('Info gain on Water split: ' + str(info_gain(len(warmP), len(warmN), len(coolP)
```

```
Entropy: 0.970950594455
Info gain on Water split: 0.321928094887
```

- Implement a basic decision tree:

- Select a feature to split on according to its information gain. If multiple features are equally good, select the leftmost one.
- Split the data and repeat until the tree is complete.
- Print out the results (nodes and splits).

```
In [19]: def determineOccurences(df):
             occ = []
             i=0
             for k in df.columns:
                 occ.append([])
                 res = []
                 n=0
                 for j in df[k].values:
                     occ[i].extend([0,0,0,0])
                     if j in res:
                         if df['Date?'][df.index[n]] == 'yes':
                             occ[i][res.index(j) * 2] +=1
                         else:
                             occ[i][res.index(j) * 2 + 1] +=1
                     else:
                         res.append(j)
                         if df['Date?'][df.index[n]] == 'yes':
                             occ[i][len(res)-1 * 2] +=1
                         else:
                             occ[i][(len(res) - 1) * 2 + 1] += 1
                     n+=1
                 i+=1
             return occ

         def buildTree(df, z):
             occ = determineOccurences(df)
             result = ''
             infGain = []
             for i in occ:
                 infGain.append(info_gain(i[0],i[1],i[2],i[3]))
             infGain[len(infGain)-1] = 0
             if len(df['Date?'].unique()) != 1:
                 toSplit = infGain.index(np.max(infGain))
                 result = "Split on " + df.columns[toSplit]
                 uniq = df[df.columns[toSplit]].unique()
                 for i in uniq:
                     r = buildTree(df[df[df.columns[toSplit]] == i], z+1)
                     result += '\n ' + '\t ' * (z-1) + 'If ' + df.columns[toSplit] + ' is ' +
                     if r:
                         result += ' \n' + ' \t ' * z + r
             else:
                 result = 'Date==' + str(df['Date?'].unique())
             return result
```

```
        print(buildTree(df, 1))

Split on Sky
 If Sky is sunny
         Split on Wind
         If Wind is strong
                  Date==['yes']
         If Wind is weak
                  Date==['no']
 If Sky is rainy
         Date==['no']
```

- Now train a scikit-learn decision tree on the same data. Do you get the same result? Explain.

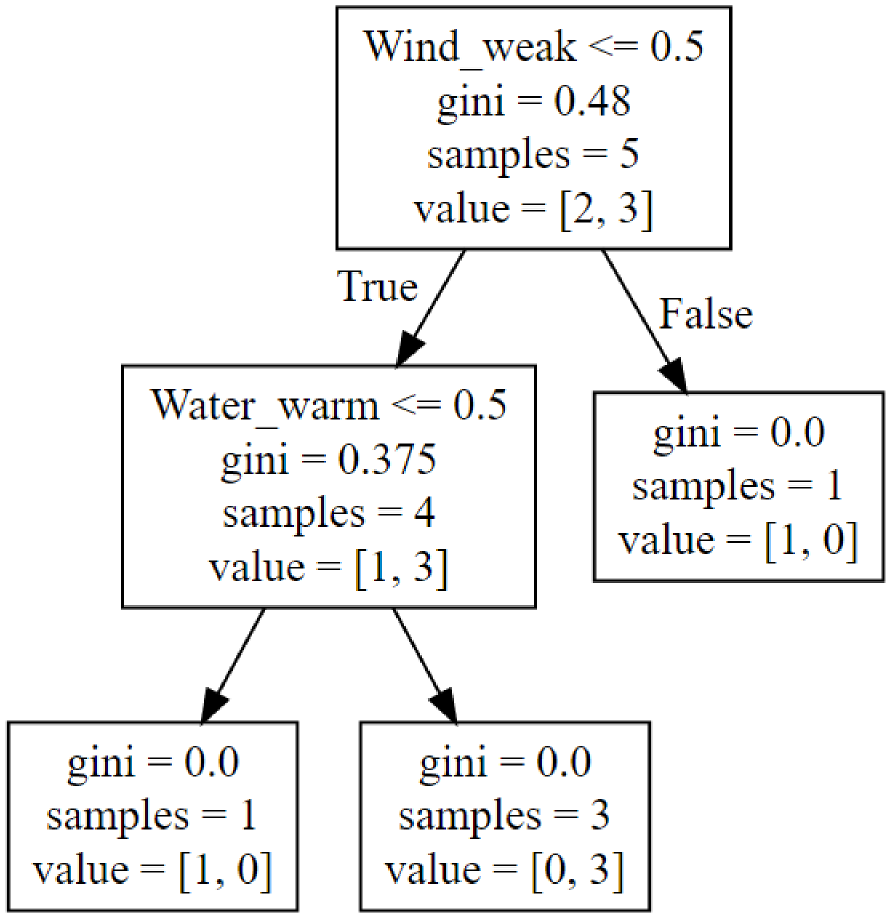
```
In [21]: from sklearn.tree import DecisionTreeClassifier, export_graphviz

         dtc = DecisionTreeClassifier()
         y = df['Date?']
         y = [1 if p == 'yes' else 0 for p in y]

         df = df.drop(['Date?'], axis=1)
         dummies = pd.get_dummies(df)
         dtc.fit(dummies, y)
         export_graphviz(dtc, out_file="tree.dot",feature_names=dummies.keys())

Out[21]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                     max_features=None, max_leaf_nodes=None,
                     min_impurity_split=1e-07, min_samples_leaf=1,
                     min_samples_split=2, min_weight_fraction_leaf=0.0,
                     presort=False, random_state=None, splitter='best')
```

This results in the following tree:
This is the same tree as the one our own method generates. It seems the scikit-learn decision tree classifier uses a similar or the same method to determine what the best split is.

1.4 Random Forests (4 points (1+1+2))

Study the effect of the number of trees in a RandomForest on the EEG-eye-state dataset (http://www.openml.org/d/1471). This dataset measures brain activity using 15 sensors, and you need to predict whether the person's eyes are open or closed.

- Train a RandomForest classifier on this dataset with an increasing number of trees (on a log scale as above). Plot the Out-Of-Bag error against the number of trees.
  - The Out-Of-Bag error is the test error obtained when using bootstrapping, and using the non-drawn data points as the test set. This is what a RandomForest does internally, so you can retrieve it from the classifier. The code below hints on how to do this.



Decision Tree

```
In [ ]: oml.config.apikey = 'fa31aae3ceb0dba388acb20276cd75d3'
        eeg = oml.datasets.get_dataset(1471)
        X, y = eeg.get_data(target=eeg.default_target_attribute)

        # Out of bag errors can be retrieved from the RandomForest classifier.
        # You'll need to loop over the number of trees.
        # http://scikit-learn.org/stable/auto_examples/ensemble/plot_ensemble_oob.html
        from sklearn import ensemble

        xTrain,xTest,yTrain,yTest = train_test_split(X,y, test_size=.1, random_state=0)

        scale = [2 ** i for i in range(0,10)]
        for est in scale:
            clf = ensemble.RandomForestClassifier(n_estimators=int(est), n_jobs=-1, oob_score=
            clf.fit(xTrain, yTrain)
            error = (1-clf.oob_score_)
            errors.append(error)
        plt.plot(scale, errors)
        plt.xscale('log')
        plt.show()
```

- Construct the same plot, but now use 10-fold Cross-validation and error rate instead of the OOB error. Compare the two. What do you learn from this?

```
In [ ]: errors = []
        for est in scale:
            clf = ensemble.RandomForestClassifier(n_estimators=int(est), n_jobs=-1, oob_score=
            errors.append(1-np.mean(cross_val_score(clf,X, y, cv=10)))
        plt.plot(scale, errors)
        plt.xscale('log')
        plt.show()
```

- Compare the performance of the RandomForest ensemble with that of a single full decision tree. Compute the AUC as well as the bias and variance. Does the bias and variance increase/decrease for the ensemble? Does the number of trees affect the result?

```
In [ ]: def calcBiasVariance(clf):
            # Bootstraps
            n_repeat = 100
            shuffle_split = ShuffleSplit(test_size=0.33, n_splits=n_repeat)

            # Store sample predictions
            y_all_pred = [[] for _ in range(len(y))]

            # Train classifier on each bootstrap and score predictions
            for i, (train_index, test_index) in enumerate(shuffle_split.split(X)):
                # Train and predict
                clf.fit(X[train_index], y[train_index])
                y_pred = clf.predict(X[test_index])
                # Store predictions
                for i, index in enumerate(test_index):
                    y_all_pred[index].append(y_pred[i])

            # Compute bias, variance, error
            bias_sq = sum([(1 - x.count(y[i]) / len(x)) ** 2 * len(x) / n_repeat
                           for i, x in enumerate(y_all_pred)])
            var = sum([((1 - ((x.count(0) / len(x)) ** 2 + (x.count(1) / len(x)) ** 2)) / 2) *
                       for i, x in enumerate(y_all_pred)])
            error = sum([(1 - x.count(y[i]) / len(x)) * len(x) / n_repeat
                         for i, x in enumerate(y_all_pred)])
            return bias_sq, var, error

        errors = []
        dtc = DecisionTreeClassifier(random_state=0)
        dtc.fit(xTrain,yTrain)
        tree_auc = roc_auc_score(yTest, dtc.predict(xTest))
        val = calcBiasVariance(dtc)
        print("For Decision Tree, Total Bias Squared: %.2f, Total Variance: %.2f, AUC %.2f"%(va
        for est in scale:
            clf = ensemble.RandomForestClassifier(n_estimators=int(est), n_jobs=4, oob_score=T
            clf.fit(xTrain, yTrain)

            vals = calcBiasVariance(clf)

            for_auc = roc_auc_score(yTest, clf.predict(xTest))

            print("For %.0f estimators and Random Forest, Total Bias Squared: %.2f, Total Varia
```

1.5 A regression benchmark (1 point)

Consider the liver-disorder dataset (http://www.openml.org/d/8). The goal is to predict how much alcohol someone consumed based on blood test values.

- Take a selection of the algorithms that we covered in class that can do regression.
- Based on what you learned in the previous exercises, make educated guesses about good hyperparameter values and set up a grid or random search.
- Evaluate all models with 10-fold cross-validation and root mean squared error (RMSE). Report all results. Which model yields the best results?

Hint: nagmean squared error (MSE) is a standard scoring technique in GridSearchCV and cross_val_score. You'll have to compute the square roots yourself. Of course, during a grid search you can just use MSE, the optimal hyperparameter values will be the same.

```
In [3]: from sklearn.linear_model import LinearRegression, LogisticRegression
        from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
        from sklearn.tree import DecisionTreeRegressor
        from sklearn.svm import LinearSVR
        from sklearn.model_selection import cross_val_score, GridSearchCV, train_test_split
        from sklearn import metrics
        import openml as oml
        import numpy as np
        oml.config.apikey = 'fa31aae3ceb0dba388acb20276cd75d3'

        import warnings
        warnings.filterwarnings('ignore')

        liver = oml.datasets.get_dataset(8) # Download Liver-disorders data
        X, y = liver.get_data(target=liver.default_target_attribute);
        X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

        LogReg = LogisticRegression(n_jobs=-1)
        param_grid_log = {"C": [0.0001,0.001,0.01,0.1,1,10,100,1000], "penalty": ['l1','l2']}
        grid_log = GridSearchCV(LogReg, param_grid=param_grid_log, cv=10, scoring='mean_squared
        grid_log.fit(X_train,y_train)
        rmse = metrics.mean_squared_error(grid_log.predict(X_test), y_test) ** (0.5)
        log_params = grid_log.best_params_
        print("Root mean squared error of Logistic Regression: ", rmse)
        print("Optimal parameters: ", log_params)
```

```
Root mean squared error of Logistic Regression:  3.80864111284
Optimal parameters:  {'C': 10, 'penalty': 'l1'}
```

```
In [4]: RfReg = RandomForestRegressor(n_jobs=-1)
        param_grid_rf = {"n_estimators": [1,4,9,16,25,36,49,64,81,100], "max_features": [0.1,0
        grid_rf = GridSearchCV(RfReg, param_grid=param_grid_rf, cv=10, scoring='mean_squared_e
        grid_rf.fit(X_train,y_train)
        rmse = metrics.mean_squared_error(grid_rf.predict(X_test), y_test) ** (0.5)
        rf_params = grid_rf.best_params_
        print("Root mean squared error of Random Forest Regression Score: ", rmse)
        print("Optimal parameters: ", rf_params)
```

```
Root mean squared error of Random Forest Regression Score:  3.31103578569
Optimal parameters:  {'max_features': 0.3, 'n_estimators': 16}
```

```
In [5]: GbReg = GradientBoostingRegressor()
        param_grid_gb = {"n_estimators": [1,4,9,16,25,36,49,64,81,100], "max_depth": [1,2,4,6,
        grid_gb = GridSearchCV(GbReg, param_grid=param_grid_gb,cv=10, scoring='mean_squared_er
        grid_gb.fit(X_train,y_train)
        rmse = metrics.mean_squared_error(grid_gb.predict(X_test), y_test) ** (0.5)
        gb_params = grid_gb.best_params_
        print("Root mean squared error of Gradient Boosting Regression Score: ", rmse)
        print("Optimal parameters: ", gb_params)
```

```
Root mean squared error of Gradient Boosting Regression Score:  3.15638649032
Optimal parameters:  {'max_depth': 2, 'n_estimators': 64}
```

```
In [6]: DtReg = DecisionTreeRegressor()
        param_grid_dt = {"max_features": [0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]}
        grid_dt = GridSearchCV(DtReg, param_grid=param_grid_dt, cv=10, scoring='mean_squared_e
        grid_dt.fit(X_train,y_train)
        rmse = metrics.mean_squared_error(grid_dt.predict(X_test), y_test) ** (0.5)
        dt_params = grid_dt.best_params_
        print("Root mean squared error of Decision Tree Regression Score: ", rmse)
        print("Optimal parameters: ", dt_params)
```

```
Root mean squared error of Decision Tree Regression Score:  4.35889894354
Optimal parameters:  {'max_features': 0.7}
```

```
In [7]: LSVReg = LinearSVR()
        param_grid_lsv = {"C": [0.0001,0.001,0.01,0.1,1,10,100,1000], "loss": ['l1','l2']}
        print('parameter grid: ', param_grid_lsv)
        grid_lsv = GridSearchCV(LSVReg, param_grid=param_grid_lsv, cv=10, scoring='mean_square
        grid_lsv.fit(X_train,y_train)
        rmse = metrics.mean_squared_error(grid_lsv.predict(X_test), y_test) ** (0.5)
        lsv_params = grid_lsv.best_params_
        print("Root mean squared error of Linear Support Vector Regression Score: ", rmse)
        print("Optimal parameters: ", lsv_params)
```

```
parameter grid:  {'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000], 'loss': ['l1', 'l2']}
Root mean squared error of Linear Support Vector Regression Score:  3.13967466994
Optimal parameters:  {'C': 0.0001, 'loss': 'l2'}
```

We considered the liver-disorder dataset and took a selection of regression algorithms to perform on the data. The regression algorithms we chose were the Logistic Regressor, Random Forest Regressor, Gradient Boosting Regressor, Decision Tree Regressor, Linear Support Vector Regressor. For all regressors the best parameters regarding the mean squared error were searched using grid search and cross validation. The results are below the code blocks. The algorithms performing best were the Linear Support Vector Regressor with parameters {'C': 0.0001, 'loss': 'l2'} and the Gradient Boosting Regressor, with parameters {'max_depth': 2, 'n_estimators': 64}. The root mean squared errors were respectively 3.140 and 3.156, so the difference is minimal and we can not really conclude one is better than the other.

```
In [ ]:
```