Random Forest Classifier in NPF Data

Creating the dataset

In [2]:
```python
import pandas as pd
import numpy as np

npf = pd.read_csv("npf_train.csv")
npf_test = pd.read_csv("npf_test_hidden.csv")

npf = npf.set_index("date")
npf = npf.drop("id", axis=1)
npf = npf.drop("partlybad", axis=1)

npf_test = npf_test.set_index("date")
npf_test = npf_test.drop("id", axis=1)
npf_test = npf_test.drop("partlybad", axis=1)

class2 = np.array(["nonevent", "event"])
npf["class2"] = class2[(npf["class4"]!="nonevent").astype(int)]
npf_test["class2"] = class2[(npf_test["class4"]!="nonevent").astype(int)]

npf
```

Out[2]:

	class4	CO2168.mean	CO2168.std	CO2336.mean	CO2336.std	CO242.mean	CO242.std
date							
2000-01-17	Ib	368.771711	0.310309	368.665658	0.305127	369.371184	0.333606
2000-02-28	nonevent	378.197295	1.001493	378.083089	1.025472	378.671311	1.017208
2000-03-24	Ib	373.043158	0.749865	372.930066	0.728411	373.569735	0.835240
2000-03-30	II	375.643019	0.558629	375.549430	0.540964	376.045849	0.580730
2000-04-04	nonevent	377.661030	0.408421	377.609576	0.423963	378.117134	0.417243
...	...	...	...	...	...	...	...
2011-08-16	nonevent	381.016623	4.411571	381.030844	4.062115	382.901742	5.061991
2011-08-19	nonevent	383.698146	8.418351	384.052632	8.130389	386.436800	9.901536
2011-08-21	nonevent	379.279128	12.045785	379.363087	11.533353	381.268591	14.043508
2011-08-22	nonevent	384.443758	6.413297	384.364392	5.781036	386.384762	7.663215
2011-08-27	nonevent	382.230839	6.407469	382.448601	6.242533	384.061748	7.748701

464 rows × 102 columns

Splitting train and test data

In [16]:
```
from sklearn.model_selection import train_test_split

X_train = npf.drop(["class4", "class2"], axis=1)
y_train = npf["class2"]

X_test = npf_test.drop(["class4", "class2"], axis=1)
y_test = npf_test["class2"]
```

Using RandomizedSearchCV to find best hyperparameters for RandomForestClassifier

We will be tuning RandomForestClassifier parameters to achieve the highest accuracy model. Let's choose the most common hyperparameters of RandomForestClassifier for tuning:

- n_estimators (amount of trees in the forest)
- max_features (features per split)
- max_depth (max depth of decision trees)
- min_samples_split (The min samples required to split an internal node)
- min_samples_leaf (min samples required to be a leaf)
- bootsrap (if full dataset is used for all trees)

We will be creating a range for all parameters and let RandomizedSearchCV and GridSearchCV pick the best parameters. First we are going to try parameters randomly using RandomizedSearchCV:

In [67]:
```
n_estimators = [int(x) for x in np.linspace(start = 10, stop = 100, num = 10)]
max_features = ['auto', 'sqrt']
max_depth = [int(x) for x in np.linspace(10, 100, num = 10)]
max_depth.append(None)
min_samples_split = [4, 5, 6, 8]
min_samples_leaf = [2, 4, 6]
bootstrap = [True, False]
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
random_grid
```

Out[67]:
```
{'n_estimators': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100],
 'max_features': ['auto', 'sqrt'],
 'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, None],
 'min_samples_split': [4, 5, 6, 8],
 'min_samples_leaf': [2, 4, 6],
 'bootstrap': [True, False]}
```

In [68]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier

rf =  RandomForestClassifier()
```

```
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, 
rf_random.fit(X_train, y_train)

rf_random.best_params_
```

```
Fitting 3 folds for each of 2000 candidates, totalling 6000 fits
```

Out[68]:
```
{'n_estimators': 10,
 'min_samples_split': 8,
 'min_samples_leaf': 6,
 'max_features': 'sqrt',
 'max_depth': 70,
 'bootstrap': True}
```

RandomSearchCV in the first run gave the minimum available features in most features: ´{'n_estimators': 100, 'min_samples_split': 5, 'min_samples_leaf': 4, 'max_features': 'auto', 'max_depth': 70, 'bootstrap': True}´

so I tuned the available features down. Most interesting features turned out to be n_estimators and max_depth. We will be narrowing down these parameters for the next step in hyperparameter optimization: Grid Search with Cross validation:

In [104…
```
from sklearn.model_selection import GridSearchCV
param_grid = {'n_estimators': [100],
 'max_features': ['auto', 'sqrt'],
 'max_depth': [70, 90, 100, 110, 120, 130, 150, None],
 'min_samples_split': [8],
 'min_samples_leaf': [6],
 'bootstrap': [True]}
rf = RandomForestClassifier()
grid_search = GridSearchCV(estimator = rf, param_grid = param_grid,
                          cv = 3, n_jobs = -1, verbose = 2)

grid_search.fit(X_train, y_train)

grid_search.best_params_
```

```
Fitting 3 folds for each of 16 candidates, totalling 48 fits
```

Out[104]:
```
{'bootstrap': True,
 'max_depth': 120,
 'max_features': 'sqrt',
 'min_samples_leaf': 6,
 'min_samples_split': 8,
 'n_estimators': 100}
```

From GridSearchCV we get about:

´{'bootstrap': True, 'max_depth': None, 'max_features': 'auto', 'min_samples_leaf': 6, 'min_samples_split': 8, 'n_estimators': 100}´

Reading the documentation about RandomForestClassifier, we can see that many of these values are close to the default ones:

´{'bootstrap': True (default), 'max_depth': None (default), 'max_features': 'sqrt' (default), 'min_samples_leaf': 6, 'min_samples_split': 8, 'n_estimators': 100 (default)}´

From this we can say that RandomForestClassifier is a very good model with even the default parameters.

Let's test if there is any difference to a default model:

In [111…
```
rf_default = RandomForestClassifier()
rf_modified = RandomForestClassifier(min_samples_leaf=6, min_samples_split=8)

rf_default.fit(X_train, y_train)
rf_modified.fit(X_train, y_train)

print("default", rf_default.score(X_test, y_test))
print("modified", rf_modified.score(X_test, y_test))
```

```
default 0.43626943005181346
modified 0.43523316062176165
```

Now we can say that the difference is close to nothing compared to the default model. From now on we can just use the default model.

Trying feature selection

In order to simplify our model we can cut down the amount of datapoint we use.

Let's try two methods for feature selection SelectKBest and SelectFromModel. SelectKBest selects the k-best amount of features from our model, whereas SelectFromModel selects the best amount of features for us automatically (which is around 25-30 features).

Let's use SelectFromModel.

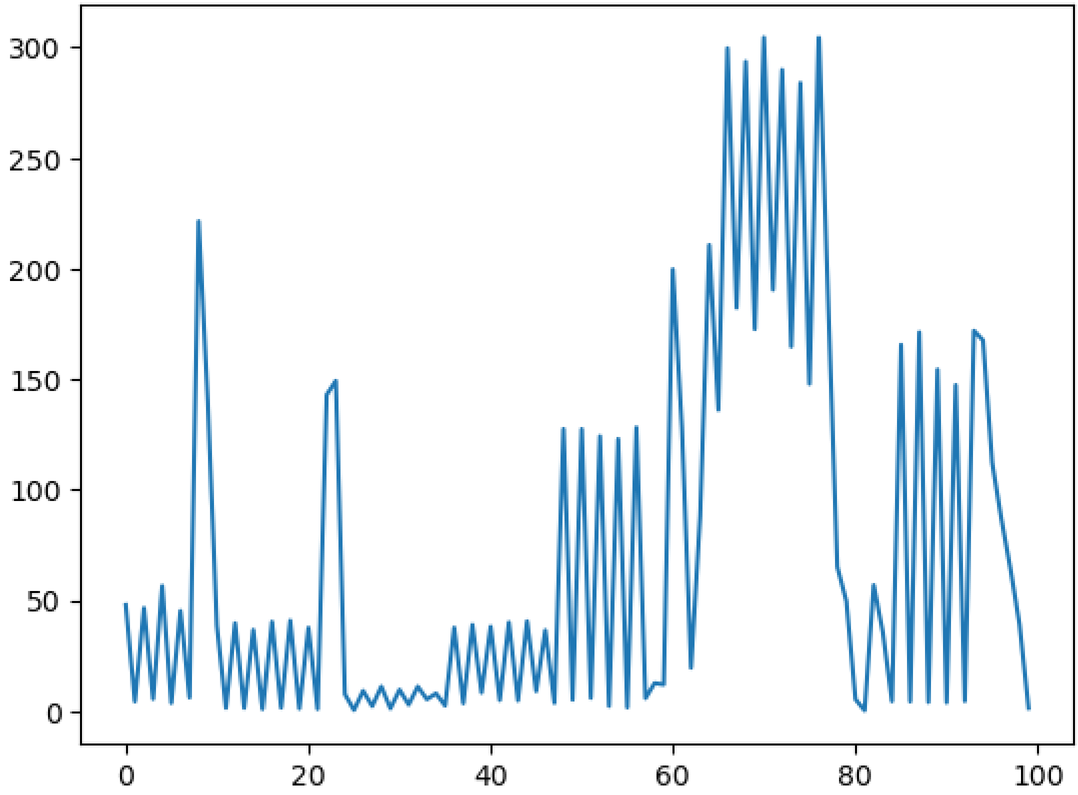
In [136…
```
from sklearn.feature_selection import SelectKBest, f_classif
import matplotlib.pyplot as plt

selector = SelectKBest(f_classif, k="all")
selector.fit_transform(X_train, y_train)
kbestscore = selector.scores_

h=plt.plot(kbestscore)
plt.show()

print(max(kbestscore))

cols = selector.get_support(indices=True)
print(len(cols))
X_new = X_train.iloc[:,cols]
X_new
```



304.5287057946586

In [152…

```
from sklearn.feature_selection import SelectFromModel
from sklearn.ensemble import RandomForestClassifier

m = SelectFromModel(RandomForestClassifier(), max_features=100)
m.fit(X_train, y_train)

columns = m.get_support(indices=True)
X_newtrain = X_train.iloc[:,columns]
X_newtest = X_test.iloc[:,columns]

X_newtrain
```

Out[152]:

	CO2168.std	CO2504.std	Glob.mean	Glob.std	H2O168.mean	H2O336.mean	H2O42.me
date							
2000-01-17	0.310309	0.302364	41.650106	29.942679	4.383158	4.358684	4.448
2000-02-28	1.001493	1.022258	3.478842	2.165706	7.233852	7.172114	7.251
2000-03-24	0.749865	0.692828	297.954063	188.348344	3.575000	3.553026	3.621
2000-03-30	0.558629	0.529970	324.318386	193.207278	6.500566	6.512278	6.515
2000-04-04	0.408421	0.424460	167.479964	135.294894	6.223576	6.213879	6.269
...	...	...	...	...	...	...	
2011-08-16	4.411571	3.840630	121.227780	131.474300	15.121299	15.068442	15.224
2011-08-19	8.418351	7.952936	332.744478	243.722645	10.946556	10.760329	11.328
2011-08-21	12.045785	10.932955	114.298822	99.583613	13.131946	13.056040	13.218
2011-08-22	6.413297	5.506259	180.454576	181.538036	13.616242	13.554527	13.691
2011-08-27	6.407469	6.174042	297.137573	208.858699	15.116923	15.003147	15.321

464 rows × 33 columns

We can test now test the effectivity of this modified dataset by training one model with the default one and the other with the modified one:

In [149…

```
rf_default = RandomForestClassifier()
rf_modified = RandomForestClassifier()

rf_default.fit(X_train, y_train)
rf_modified.fit(X_newtrain, y_train)

print("default", rf_default.score(X_test, y_test))
print("modified", rf_modified.score(X_newtest, y_test))
```

```
default 0.45181347150259066
modified 0.4466321243523316
```

From this we can tell that our modified model is more effective, with better score and less flexibility.

In [161…

```
rf = RandomForestClassifier()
rf.fit(X_newtrain, y_train)

print("Accuracy on train data:", rf.score(X_newtrain, y_train))
print("Accuracy on test data:", rf.score(X_newtest, y_test))
```

```
Accuracy on train data: 1.0
Accuracy on test data: 0.44974093264248705
```

Conclusion week 1

With testing the most influential hyperparameters we can say that none of them really made a big difference. RandomForestClassifier is very effective even with it's default parameters. From modifying the dataset, we can see that it was influential and should be done, since it also makes our model a lot less complicated and easier to iterate with. Accuracy in the training data is 100% and on the test data it is around 44-45%.

Sources:

- RandomForestClassifier - SKLearn
- Hyperparameter Tuning the Random Forest in Python - Towards Data Science
- SelectFromModel - SKLearn
- SelectKBest - SKLearn