ps02

March 22, 2020

1 Data Science in Practice 2020

1.1 Problem Set 2

1.1.1 Descriptive report

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1.1.2 1. Initialization

Loading modules :

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns

from operator import itemgetter, attrgetter
from scipy.stats import randint as sp_randint

from sklearn.model_selection import train_test_split, GridSearchCV,␣
 ↪RandomizedSearchCV, cross_val_score
from sklearn.metrics import log_loss, classification_report, confusion_matrix,␣
 ↪roc_curve, accuracy_score, roc_auc_score, precision_recall_fscore_support,␣
 ↪precision_recall_curve, auc
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier,␣
 ↪NeighborhoodComponentsAnalysis
from sklearn.preprocessing import StandardScaler

# import time

from matplotlib import pyplot as plt

import argparse
import logging
import os
import sys
from ipyparallel import Client
from ipyparallel.joblib import IPythonParallelBackend
```

```python
from joblib import Parallel, parallel_backend, register_parallel_backend
```

Defining functions :

[2]:
```python
def df_pp() :

    df_raw = pd.read_csv('customers.csv')

    # clean up lines

    total_length = len(df_raw)
    df_raw = df_raw[df_raw['TotalCharges'] != ' ']
    df_raw.TotalCharges = df_raw.TotalCharges.astype('float')
    cleanup_length = len(df_raw)
    print('%s lines were deleted.' %(total_length - cleanup_length))

    # output into dummies

    churn_dummy_dict = {'Yes': 1, 'No': 0}
    df_raw.Churn.replace(churn_dummy_dict, inplace = True)

    # X y splitting

    y = df_raw.Churn.copy()
    X_raw = df_raw.drop(columns ='Churn').copy()

    # input into dummies

    X_raw_types = dict(X_raw.dtypes)
    features = list(X_raw.columns)
    categorical_features = [feat for feat in features if X_raw_types[feat] ==␣
↪'O']
    categorical_features.remove('customerID')

    X = pd.get_dummies(X_raw, columns = categorical_features,prefix_sep=':')
    X = X.drop(columns = 'customerID').copy()

    return df_raw,categorical_features, X, y, cleanup_length
```

[3]:
```python
def df_preprocessing_knn() :

    df_raw,categorical_features, X, y, _ = df_pp()

    # train val splitting

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20)
```

```
    y_train = y_train.tolist()
    y_test = y_test.tolist()

    return df_raw,categorical_features, X, X_train, X_test, y, y_train, y_test
```

[4]:
```
def df_preprocessing_rf(test_size) :

    df_raw,categorical_features, X, y, cleanup_length = df_pp()

    # train val splitting

    train = np.random.rand(cleanup_length)> test_size

    X_train = X[train]
    X_test = X[~train]

    y_train = y[train].tolist()
    y_test = y[~train].tolist()

    return df_raw,categorical_features, X, X_train, X_test, y, y_train, y_test
```

[5]:
```
def plot_importance(feature_importance_sorted, n, type_of_search):

    plt.figure(figsize=(15,5))
    x = np.arange(n)
    y = [feature_importance_sorted[i][1] for i in range(n)]
    labels = [feature_importance_sorted[i][0] for i in range(n)]
    ax = sns.barplot(y,x,orient="h");
    plt.xlabel("Importance fraction", fontsize = 12)
    ax.set_xticklabels(['{:,.0%}'.format(x) for x in ax.get_xticks()])
    plt.yticks(x,labels, fontsize = 15)
    plt.title('Most important feature: {}'.format(type_of_search), fontsize =␣
 ↪15)
    plt.show()
```

[6]:
```
c = Client()
bview = c.load_balanced_view()
register_parallel_backend('ipyparallel',
                          lambda : IPythonParallelBackend(view=bview))
```

1.1.3 2. K-Nearest Neighbors Classifier

We start by scaling the data.

[7]:
```
df_raw,categorical_features, X, X_train, X_test, y, y_train, y_test =␣
 ↪df_preprocessing_knn()
```

```
11 lines were deleted.
```

[8]:
```
scaler = StandardScaler()
scaler.fit(X_train)

X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

We run simulations for k-values between 1 and 100 to find the best fit parameters.

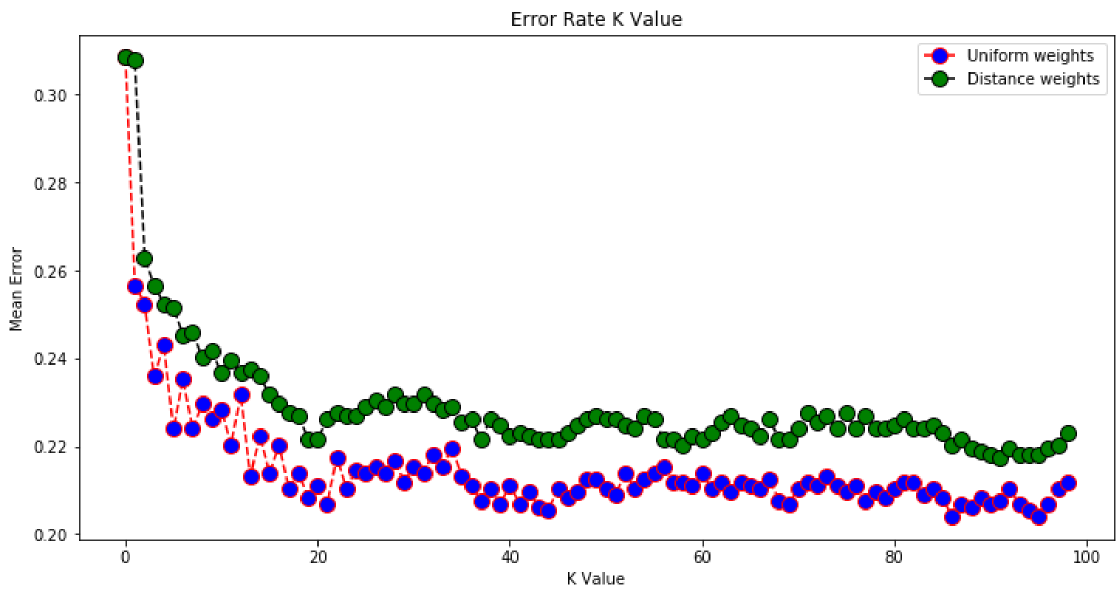
[9]:
```
error_uni = np.array([0])
error_dist = np.array([0])

for i in range(1, 100):
    knn_uni = KNeighborsClassifier(n_neighbors=i, weights='uniform', n_jobs=-1)
    knn_uni.fit(X_train, y_train)
    pred_i_uni = knn_uni.predict(X_test)
    error_uni = np.append(error_uni, np.array(np.mean(pred_i_uni != y_test)))

    knn_dist = KNeighborsClassifier(n_neighbors=i, weights='distance',␣
 ↪n_jobs=-1)
    knn_dist.fit(X_train, y_train)
    pred_i_dist = knn_dist.predict(X_test)
    error_dist = np.append(error_dist, np.array(np.mean(pred_i_dist != y_test)))


plt.figure(figsize=(12, 6))
plt.plot(error_uni[1:], color='red', linestyle='dashed', marker='o',␣
 ↪markerfacecolor='blue', markersize=10, label='Uniform weights')
plt.plot(error_dist[1:], color='black', linestyle='dashed', marker='o',␣
 ↪markerfacecolor='green', markersize=10, label='Distance weights')
plt.title('Error Rate K Value')
plt.xlabel('K Value')
plt.ylabel('Mean Error')
plt.legend(loc='best')
plt.show()

print('Minimum error rate with uniform weights: {:.2%} for k = {}'.
 ↪format(min(error_uni[1:]), np.argmin(error_uni[1:]) + 1))
print('Minimum error rate with distance weights: {:.2%} for k = {}'.
 ↪format(min(error_dist[1:]), np.argmin(error_dist[1:]) + 1))
```




```
Minimum error rate with uniform weights: 20.40% for k = 87
Minimum error rate with distance weights: 21.75% for k = 92
```

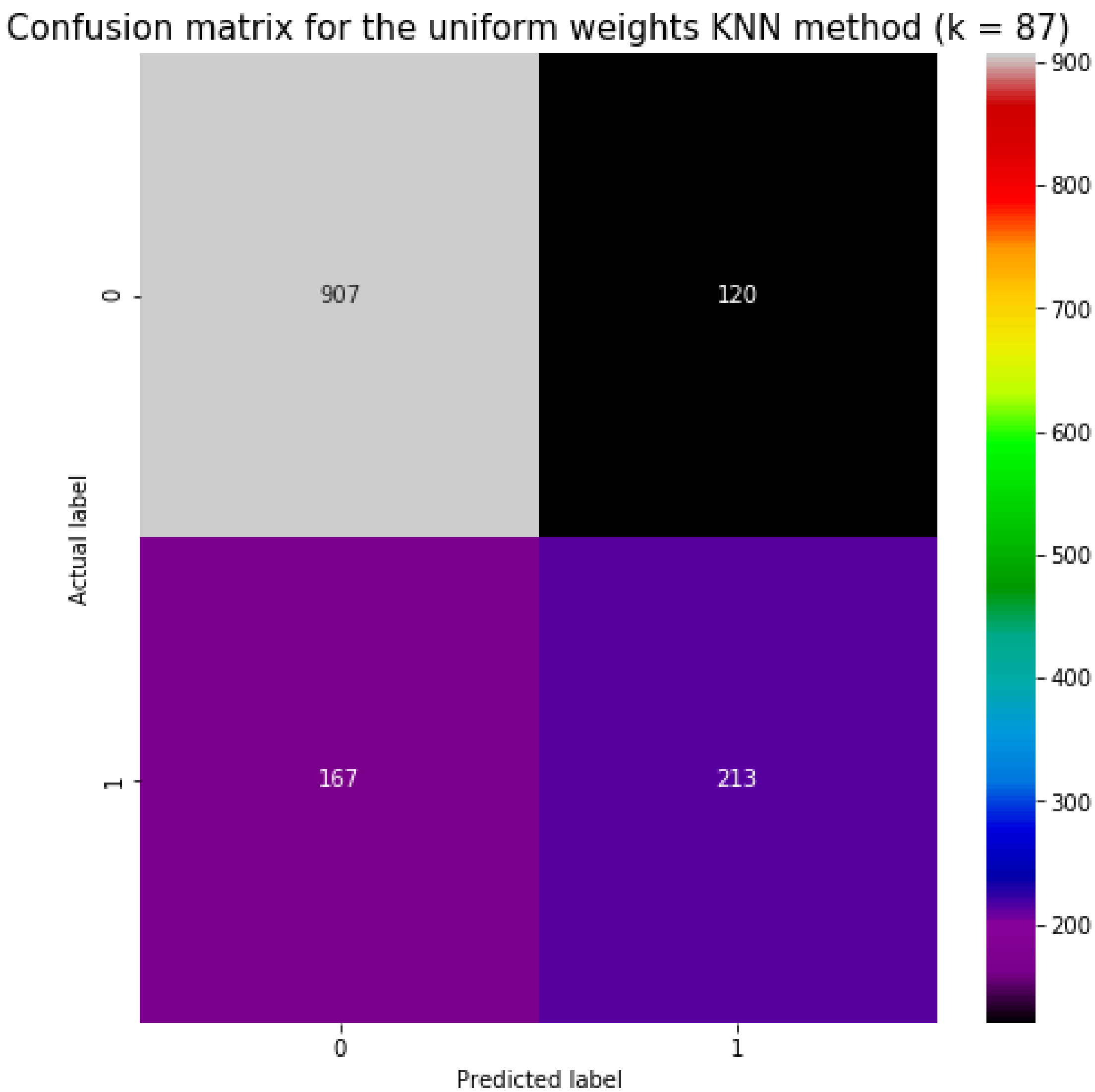
[10]:
```
classifier_uni = KNeighborsClassifier(n_neighbors = (np.argmin(error_uni[1:]) +
 ↪1), weights='uniform')
classifier_uni.fit(X_train, y_train)
classifier_dist = KNeighborsClassifier(n_neighbors = (np.argmin(error_dist[1:])
 ↪+ 1), weights='distance')
classifier_dist.fit(X_train, y_train)

y_pred_uni = classifier_uni.predict(X_test)
y_pred_dist = classifier_dist.predict(X_test)
```

[11]:
```
plt.figure(figsize=(8,8))
sns.heatmap(confusion_matrix(y_test, y_pred_uni), annot=True, fmt="d",
 ↪cmap="nipy_spectral")
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
plt.title('Confusion matrix for the uniform weights KNN method (k = {})'.
 ↪format(np.argmin(error_uni[1:]) + 1), fontsize = 15);
print("UNIFORM WEIGHTS")
print("Accuracy: {:.2%}".format(accuracy_score(y_test, y_pred_uni)))
print(classification_report(y_test, y_pred_uni))
```

```
UNIFORM WEIGHTS
Accuracy: 79.60%
              precision    recall  f1-score   support
```

0	0.84	0.88	0.86	1027
1	0.64	0.56	0.60	380
accuracy			0.80	1407
macro avg	0.74	0.72	0.73	1407
weighted avg	0.79	0.80	0.79	1407



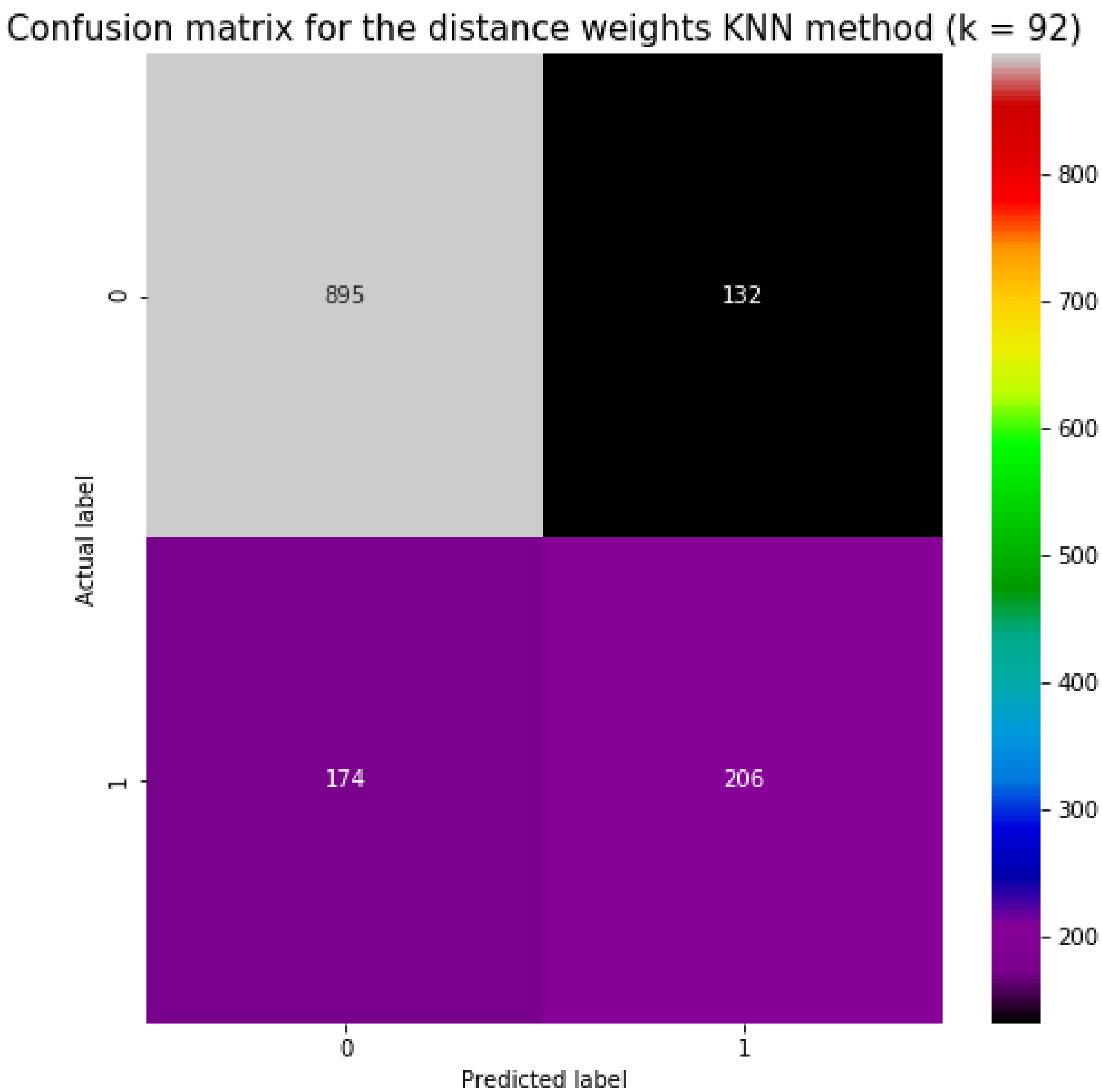
[12]:
```
plt.figure(figsize=(8,8))
sns.heatmap(confusion_matrix(y_test, y_pred_dist), annot=True, fmt="d",␣
↪cmap="nipy_spectral")
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
```

```python
plt.title('Confusion matrix for the distance weights KNN method (k = {})'.
 ↪format(np.argmin(error_dist[1:]) + 1), fontsize = 15);
print("DISTANCE WEIGHTS")
print("Accuracy: {:.2%}".format(accuracy_score(y_test, y_pred_dist)))
print(classification_report(y_test, y_pred_dist))
```

```
DISTANCE WEIGHTS
Accuracy: 78.25%
              precision    recall  f1-score   support

           0       0.84      0.87      0.85      1027
           1       0.61      0.54      0.57       380

    accuracy                           0.78      1407
   macro avg       0.72      0.71      0.71      1407
weighted avg       0.78      0.78      0.78      1407
```



1.1.4 3. Random Forest Classifier

We will compare two methods, which are grid search and random search.

[13]:
```
df_raw,categorical_features, X, X_train, X_test, y, y_train, y_test =␣
↪df_preprocessing_rf(0.3)
```

```
11 lines were deleted.
```

[14]:
```
clf = RandomForestClassifier(n_jobs=-1)
```

3.1 Grid search To avoid having too high a computational time, we will focus on 2 of the mot important parameters that are max depth and the number of estimators.

Max Depth This parameter is the depth of the trees, which is one of the most important. We range it between 4 (anything lower seems too low and imcreases computational time without much results) and 15.

Number of estimators This parameter is the number of trees that are going to be generated. Here the choice of the number of trees will mostly affect the computational time. Let's set the values between 10 and 500 and see the effects.

[15]:
```
max_depth = list(range(4,16))
```

[16]:
```
n_estimators = [10, 15, 20, 50, 100, 200, 500]
```

Let's use the default 5 folds of cross validation.

[17]:
```
grid_parameters = {'max_depth' : max_depth, 'n_estimators' : n_estimators }
```

[18]:
```
grid_clf = GridSearchCV(clf, param_grid = grid_parameters,␣
 ↪return_train_score=True, verbose = 3)
```

[19]:
```
with parallel_backend('ipyparallel'):
    grid_clf.fit(X_train, y_train);
```

```
Fitting 5 folds for each of 84 candidates, totalling 420 fits
```

```
[Parallel(n_jobs=-1)]: Using backend IPythonParallelBackend with 8 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  16 tasks      | elapsed:    5.2s
[Parallel(n_jobs=-1)]: Done 112 tasks      | elapsed:   30.5s
[Parallel(n_jobs=-1)]: Done 272 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 420 out of 420 | elapsed:  2.3min finished
```

Let's check which model is the best.

[20]:
```
grid_best_score = grid_clf.best_score_
grid_best_parameters = grid_clf.best_params_
grid_best_max_depth = grid_best_parameters.get('max_depth')
grid_best_n_estimators = grid_best_parameters.get('n_estimators')

print('Grid search best_score: {:.5}'.format(grid_best_score))
print('best_max_depth: {}'.format(grid_best_max_depth))
print('best_n_estimators: {}'.format(grid_best_n_estimators))
```

```
Grid search best_score: 0.80628
best_max_depth: 7
best_n_estimators: 20
```

[21]:
```
grid_clf_best = RandomForestClassifier(n_jobs = -1,max_depth =␣
 ↪grid_best_max_depth, n_estimators = grid_best_n_estimators )
```

[22]:

```
grid_clf_best.fit(X_train, y_train);
```

Let's apply it to our validation set.

[23]:

```
grid_y_pred = grid_clf_best.predict(X_test)
```

[24]:

```
print("Accuracy: {:.2%}".format(accuracy_score(y_test, grid_y_pred)))
```

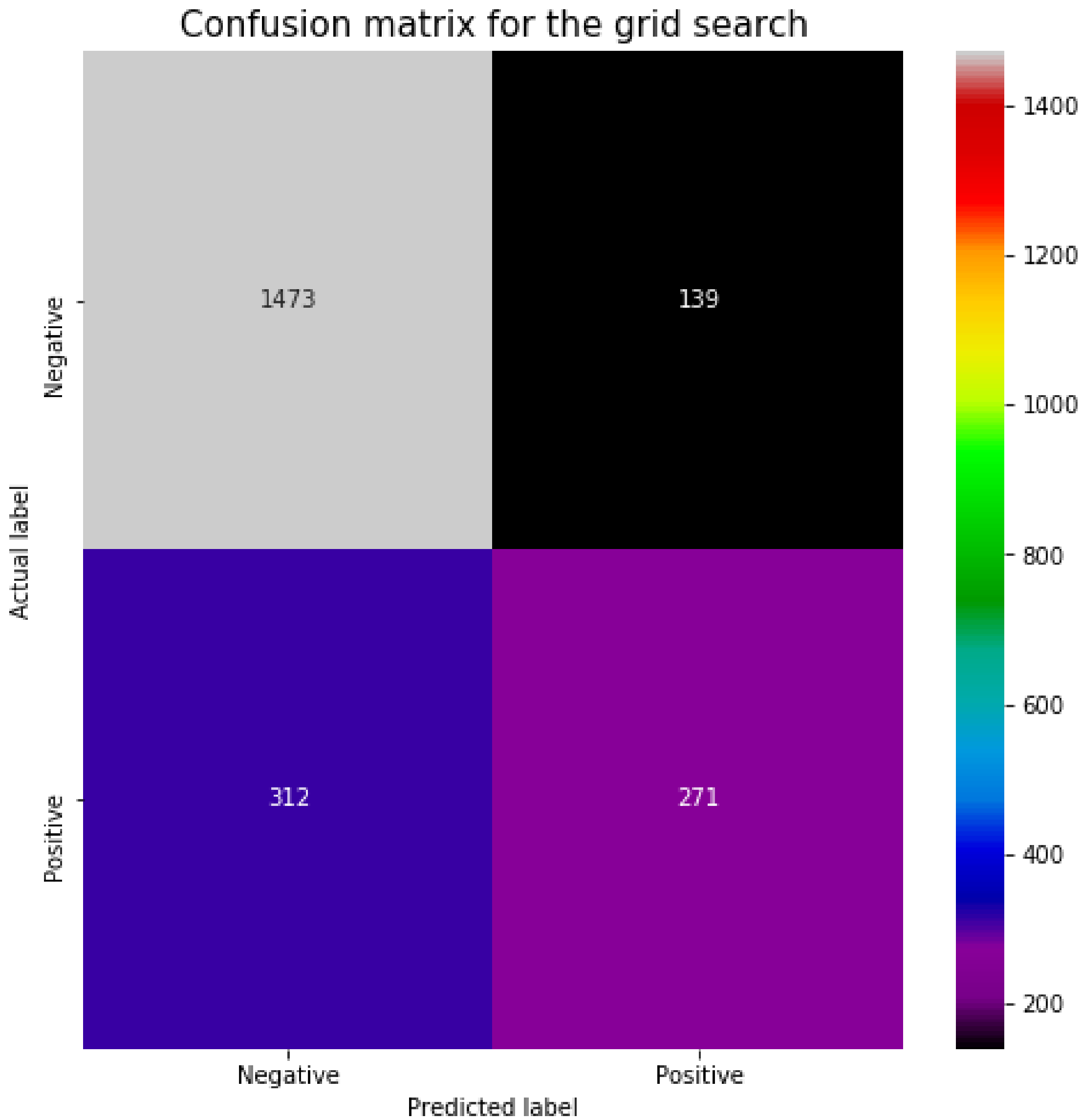
```
Accuracy: 79.45%
```

Given this accuracy, we can take a deeper look into the results.

[25]:

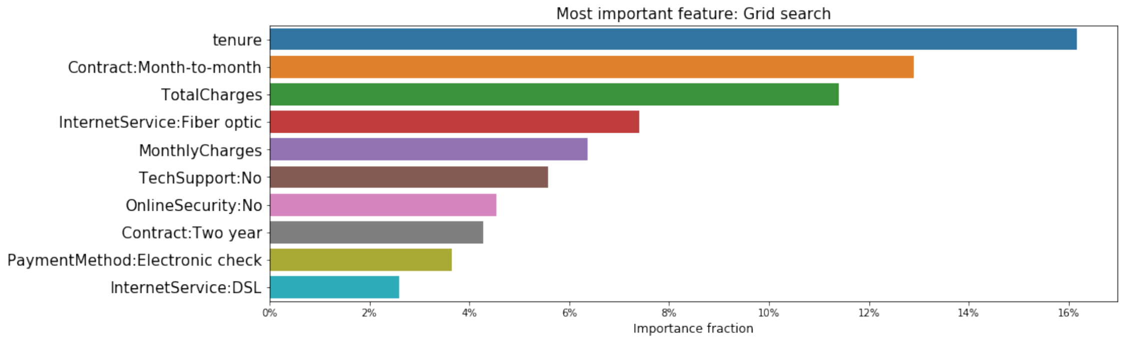
```
grid_cm = confusion_matrix(y_test, grid_y_pred)
index = ['Negative','Positive']
columns = ['Negative','Positive']
cm_df = pd.DataFrame(grid_cm,columns,index)


plt.figure(figsize=(8,8))
sns.heatmap(cm_df, annot=True, fmt="d", cmap="nipy_spectral")
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
plt.title('Confusion matrix for the grid search', fontsize = 15);
```



Feature importance

[26]:
```
grid_feature_importances = [(list(X.columns)[i], grid_clf_best.
 ↪feature_importances_[i]) for i in range(len(list(X.columns)))]
grid_feature_importances.sort(key=itemgetter(1), reverse = True)
plot_importance(grid_feature_importances, 10, 'Grid search')
```



[27]:
```
print(classification_report(y_test,grid_y_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.91      0.87      1612
           1       0.66      0.46      0.55       583

    accuracy                           0.79      2195
   macro avg       0.74      0.69      0.71      2195
weighted avg       0.78      0.79      0.78      2195
```

Feature selection Let's try to run the model again, but this time selecting only the most impacting features to save us some work and let's compare the results.

[28]:
```
grid_selected_features = [grid_feature_importances[i][0] for i in range(15)]
grid_X_train_sel = X_train[grid_selected_features]
grid_X_test_sel = X_test[grid_selected_features]
```

[29]:
```
with parallel_backend('ipyparallel'):
    grid_clf.fit(grid_X_train_sel, y_train);
```

```
Fitting 5 folds for each of 84 candidates, totalling 420 fits
```

```
[Parallel(n_jobs=-1)]: Using backend IPythonParallelBackend with 8 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  16 tasks      | elapsed:    1.5s
[Parallel(n_jobs=-1)]: Done 112 tasks      | elapsed:   25.6s
[Parallel(n_jobs=-1)]: Done 272 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 420 out of 420 | elapsed:  2.2min finished
```

[30]:
```
grid_best_score_sel = grid_clf.best_score_
grid_best_parameters_sel = grid_clf.best_params_
grid_best_max_depth_sel = grid_best_parameters.get('max_depth')
grid_best_n_estimators_sel = grid_best_parameters.get('n_estimators')
```

```
print('Grid search best_score with selected features: {:.5}'.
 ↪format(grid_best_score_sel))
print('Grid search best_max_depth with selected features: {}'.
 ↪format(grid_best_max_depth_sel))
print('Grid search best_n_estimators with selected features: {}'.
 ↪format(grid_best_n_estimators_sel))
```

```
Grid search best_score with selected features: 0.80318
Grid search best_max_depth with selected features: 7
Grid search best_n_estimators with selected features: 20
```

[31]:
```
grid_clf_best_sel = RandomForestClassifier(n_jobs = -1,max_depth =␣
 ↪grid_best_max_depth_sel, n_estimators = grid_best_n_estimators_sel )
```

[32]:
```
grid_clf_best_sel.fit(grid_X_train_sel, y_train);
```

[33]:
```
grid_y_pred_sel = grid_clf_best_sel.predict(grid_X_test_sel)
```

[34]:
```
print("Accuracy: {:.2%}".format(accuracy_score(y_test, grid_y_pred_sel)))
```

```
Accuracy: 79.95%
```

3.2 Random Search After having explored a grid search, we can adopt another approach. Instead of searching for each value, let's give our model more parameters input, but instead let it choose randomly at each iteration one value for each parameter. It will then be evaluated again.

[35]:
```
n_estimators = range(10,1000,50)
criterion = ['gini', 'entropy']
max_features = ['sqrt', 'log2', None]
bootstrap = [True,False]
max_depth = range(5,50,10)
min_samples_leaf = range(2,100, 2)
min_samples_split = range(2,100,2)

random_parameters = {'n_estimators':n_estimators, 'max_features':max_features,␣
 ↪'max_depth':max_depth, 'min_samples_leaf':
              min_samples_leaf}
```

[36]:
```
random_clf = RandomizedSearchCV(clf, param_distributions = random_parameters,␣
 ↪n_iter = 20, verbose = 3)
```

[37]:
```
with parallel_backend('ipyparallel'):
    random_clf.fit(X_train, y_train);
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=-1)]: Using backend IPythonParallelBackend with 8 concurrent
workers.
```

```
[Parallel(n_jobs=-1)]: Done  16 tasks      | elapsed:   39.3s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:  2.7min finished
```

[38]:
```
random_best_score = random_clf.best_score_
print('Random search best_score: {:.4}'.format(random_best_score))
random_best_parameters = random_clf.best_params_
```

```
Random search best_score: 0.8081
```

[39]:
```
random_best_parameters
```

[39]:
```
{'n_estimators': 410,
 'min_samples_leaf': 6,
 'max_features': 'sqrt',
 'max_depth': 45}
```

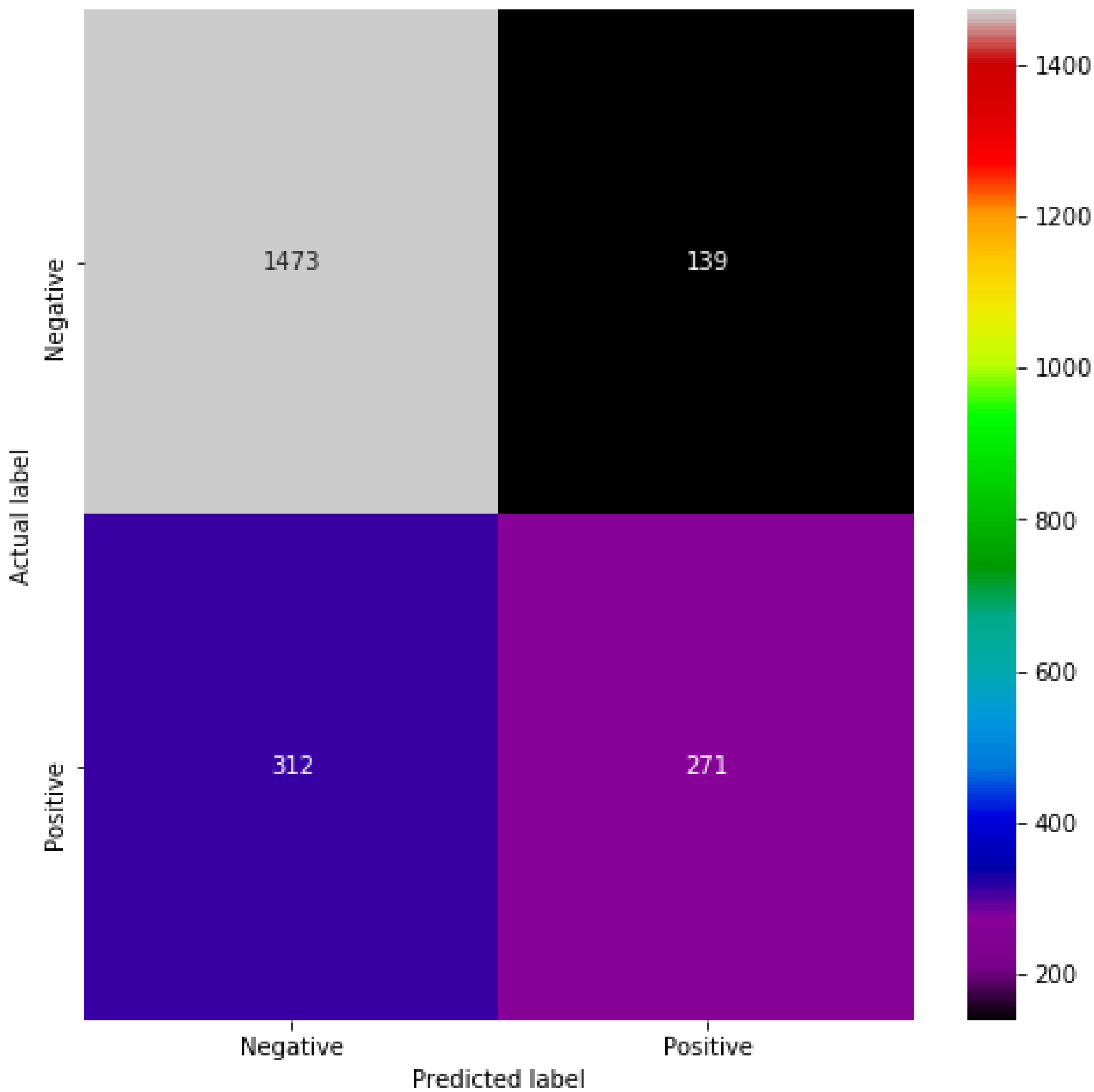
[40]:
```
random_clf_best = RandomForestClassifier(max_depth = 35, max_features = 'sqrt',␣
 ↪min_samples_leaf = 9, n_estimators = 250)
```

[41]:
```
random_clf_best.fit(X_train, y_train);
```

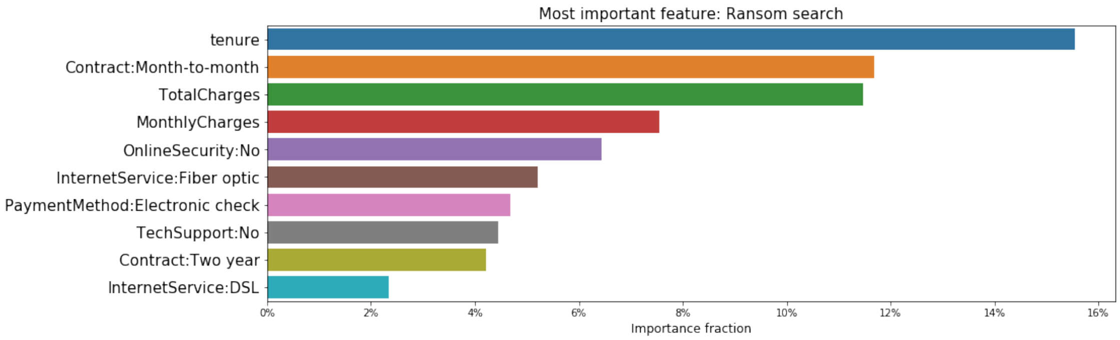
[42]:
```
random_y_pred = random_clf_best.predict(X_test)
```

[43]:
```
random_cm = confusion_matrix(y_test, random_y_pred)
annot_kws = {"ha": 'center',"va": 'center'}


plt.figure(figsize=(8,8))
sns.heatmap(cm_df, annot=True, fmt="d", cmap="nipy_spectral")
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
```



[44]:
```
random_feature_importances = [(list(X.columns)[i], random_clf_best.
 ↪feature_importances_[i]) for i in range(len(list(X.columns)))]
random_feature_importances.sort(key=itemgetter(1), reverse = True)
plot_importance(random_feature_importances, 10, 'Ransom search')
```



[45]:
```
print(classification_report(y_test,random_y_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.90      0.87      1612
           1       0.66      0.52      0.58       583

    accuracy                           0.80      2195
   macro avg       0.75      0.71      0.73      2195
weighted avg       0.79      0.80      0.79      2195
```

[46]:
```
print("Accuracy: {:.2%}".format(accuracy_score(y_test, random_y_pred)))
```

```
Accuracy: 80.14%
```

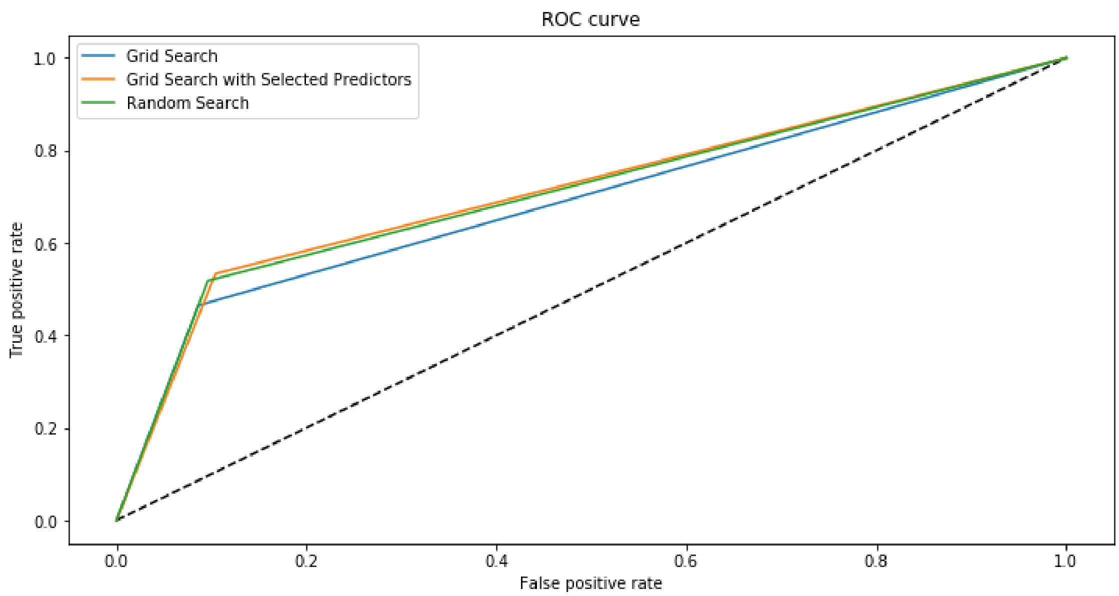
3.3 Comparison

ROC Curve

[47]:
```
fpr_grid, tpr_grid, _ = roc_curve(y_test, grid_y_pred)
fpr_grid_sel, tpr_grid_sel, _ = roc_curve(y_test, grid_y_pred_sel)
fpr_random, tpr_random, _ = roc_curve(y_test, random_y_pred)
```

[48]:
```
plt.figure(figsize=(12, 6))
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr_grid, tpr_grid, label='Grid Search')
plt.plot(fpr_grid_sel, tpr_grid_sel, label='Grid Search with Selected␣
↪Predictors')
plt.plot(fpr_random, tpr_random, label='Random Search')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve')
plt.legend(loc='best')
plt.show()
```

```
roc_auc_grid = roc_auc_score(y_test, grid_y_pred)
print('ROC AUC for Grid Search: %.5f' % roc_auc_grid)
roc_auc_grid_sel = roc_auc_score(y_test, grid_y_pred_sel)
print('ROC AUC for Grid Search with selected predictors: %.5f' %␣
 ↪roc_auc_grid_sel)
roc_auc_random = roc_auc_score(y_test, random_y_pred)
print('ROC AUC for Random Search: %.5f' % roc_auc_random)
```

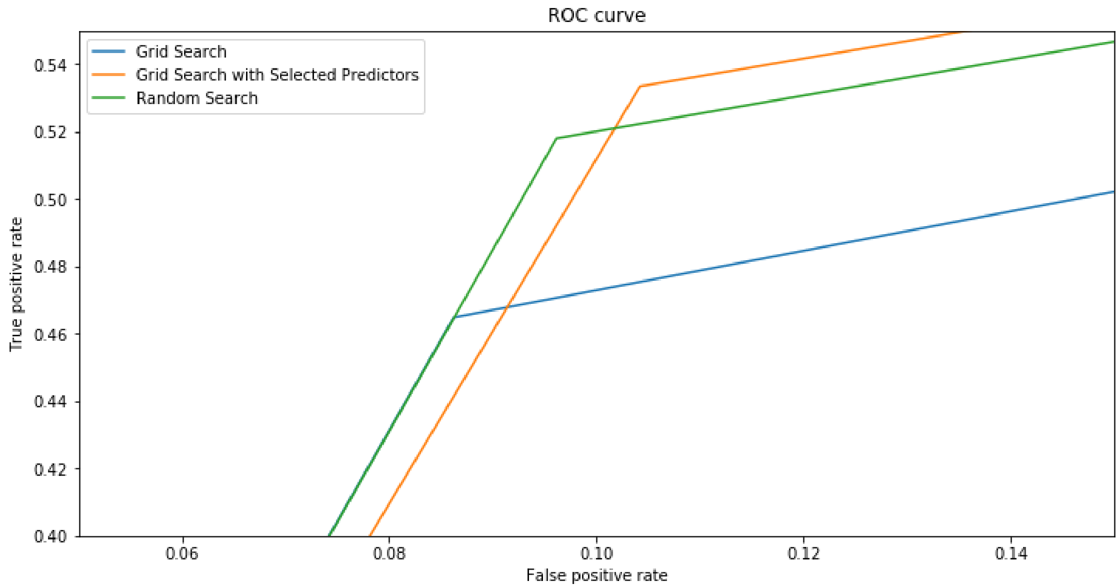



```
ROC AUC for Grid Search: 0.68930
ROC AUC for Grid Search with selected predictors: 0.71461
ROC AUC for Random Search: 0.71093
```

We observe that all three methods are better than a random prediction. The Grid Search with Selected Predictors has slightly better prediction than the Random Search, which has in turn slightly better prediction than the basic Grid Search.

[49]:
```
plt.figure(figsize=(12, 6))
plt.xlim(0.05, 0.15)
plt.ylim(0.4, 0.55)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr_grid, tpr_grid, label='Grid Search')
plt.plot(fpr_grid_sel, tpr_grid_sel, label='Grid Search with Selected␣
 ↪Predictors')
plt.plot(fpr_random, tpr_random, label='Random Search')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve')
```

```
plt.legend(loc='best')
plt.show()
```



Precision - Recall Curve

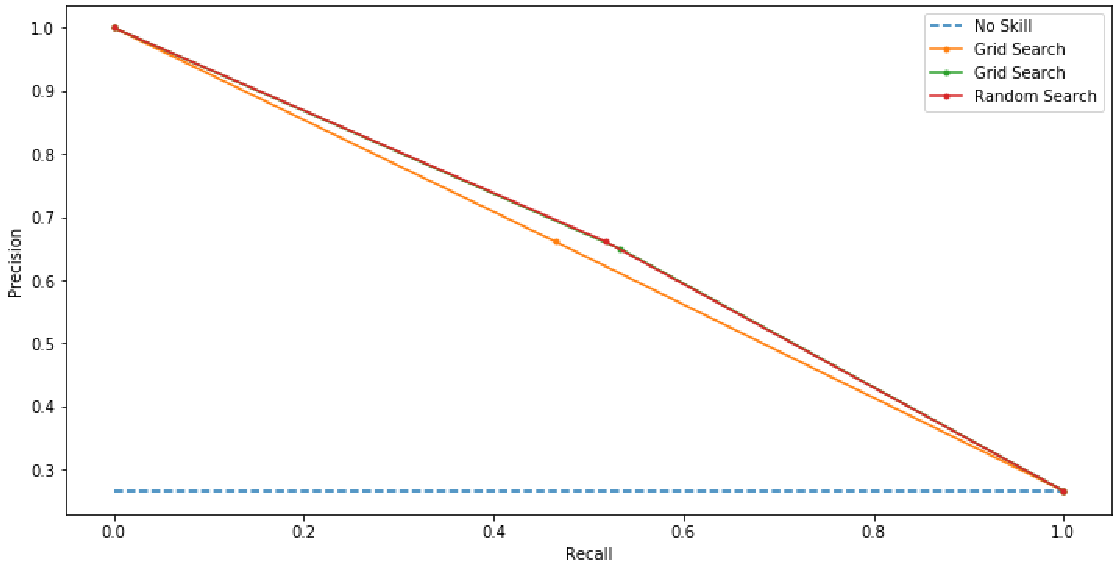
[50]:
```
grid_precision, grid_recall, _ = precision_recall_curve(y_test, grid_y_pred)
grid_precision_sel, grid_recall_sel, _ = precision_recall_curve(y_test,␣
↪grid_y_pred_sel)
random_precision, random_recall, _ = precision_recall_curve(y_test,␣
↪random_y_pred)
```

[51]:
```
y_test = np.array(y_test)
no_skill = len(y_test[y_test == 1]) / len(y_test)

plt.figure(figsize=(12, 6))
plt.plot([0, 1], [no_skill, no_skill], linestyle='--', label='No Skill')
plt.plot(grid_recall, grid_precision, marker='.', label='Grid Search')
plt.plot(grid_recall_sel, grid_precision_sel, marker='.', label='Grid Search')
plt.plot(random_recall, random_precision, marker='.', label='Random Search')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.legend(loc='best')
plt.show()

pr_auc_grid = auc(grid_recall, grid_precision)
print('Precision-Recall AUC for Grid Search: %.5f' % pr_auc_grid)
pr_auc_grid_sel = auc(grid_recall_sel, grid_precision_sel)
```

```python
print('Precision-Recall AUC for Grid Search with selected predictors: %.5f' %␣
 ↪pr_auc_grid_sel)
pr_auc_random = auc(random_recall, random_precision)
print('Precision-Recall AUC for Random Search: %.5f' % pr_auc_random)
```




```
Precision-Recall AUC for Grid Search: 0.63398
Precision-Recall AUC for Grid Search with selected predictors: 0.65332
Precision-Recall AUC for Random Search: 0.65343
```

1.1.5 4. Conclusion

We illustrated two main methods which are K Nearest Neighbors and Random Forest. Each of these methods can be used differently, given the different inputs we give them or the approach we want to have. In the long run, we see that all of them approach a 80% accuracy, with small differences among them.

Analyzing the feature importance can give the company some insights into what is affecting the rate of churn and how it could help them retain a higher number of customers.