Projekt końcowy Data Science

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4. Modelowanie

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
#import category_encoders as ce

import matplotlib.pyplot as plt

%matplotlib inline

from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OrdinalEncoder

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import DecisionTreeRegressor
from sklearn import tree

from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import (RandomForestRegressor, GradientBoosti
from sklearn.svm import SVR
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier

from sklearn import metrics
from sklearn.ensemble import VotingRegressor

from scipy import stats
from scipy.stats import zscore
from sklearn.metrics import mean_squared_error,mean_absolute_error,
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn import preprocessing
from sklearn preprocessing import PolynomialFeatures
```

```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.cluster import KMeans
from sklearn.utils import resample


from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve

from sklearn.metrics import precision_recall_curve, auc, roc_auc_sc

from sklearn.decomposition import PCA
from sklearn.decomposition import IncrementalPCA
```

In [2]:

```
# wczytuje dane z poprzedniej części
data_loan = pd.read_csv('data_loan.csv')
data_loan.drop('Unnamed: 0', axis=1, inplace=True)
data_loan
```

Out[2]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length	home_
0	5000.0	5000.0	1	10.65	162.87	1	10	
1	2500.0	2500.0	2	15.27	59.83	2	1	
2	2400.0	2400.0	1	15.96	84.33	3	10	
3	10000.0	10000.0	1	13.49	339.31	4	10	
4	3000.0	3000.0	2	12.69	67.79	5	1	
...	...	...	...	...	...	...	...	
42530	3500.0	3500.0	1	10.28	113.39	4	1	
42531	1000.0	1000.0	1	9.64	32.11	14	1	
42532	2525.0	2525.0	1	9.33	80.69	13	1	
42533	6500.0	6500.0	1	8.38	204.84	18	1	
42534	5000.0	5000.0	1	7.75	156.11	17	10	M

42535 rows × 30 columns

In [3]:
```
# wczytuje dane z poprzedniej części
data_loan1 = pd.read_csv('data_loan1.csv')
data_loan1.drop('Unnamed: 0', axis=1, inplace=True)
data_loan1
```

Out[3]:

	annual_inc	installment	int_rate	fico_mean	last_fico_mean	loan_amnt	revol_bal	o
0	24000.0	162.87	10.65	737.0	737.0	5000.0	13648.0	
1	30000.0	59.83	15.27	742.0	249.5	2500.0	1687.0	
2	12252.0	84.33	15.96	737.0	737.0	2400.0	2956.0	
3	49200.0	339.31	13.49	692.0	602.0	10000.0	5598.0	
4	80000.0	67.79	12.69	697.0	682.0	3000.0	27783.0	
...	...	...	...	...	...	...	...	
42530	180000.0	113.39	10.28	687.0	817.0	3500.0	0.0	
42531	12000.0	32.11	9.64	697.0	782.0	1000.0	0.0	
42532	110000.0	80.69	9.33	712.0	712.0	2525.0	0.0	
42533	60000.0	204.84	8.38	742.0	722.0	6500.0	0.0	
42534	70000.0	156.11	7.75	772.0	792.0	5000.0	0.0	

42535 rows × 10 columns

In [4]:
```
# wczytuje dane z poprzedniej części
data_dummies = pd.read_csv('data_dummies.csv')
data_dummies.drop('Unnamed: 0', axis=1, inplace=True)
data_dummies
```

Out[4]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length	annual
0	5000.0	5000.0	1	10.65	162.87	1	10	240
1	2500.0	2500.0	2	15.27	59.83	2	1	300
2	2400.0	2400.0	1	15.96	84.33	3	10	122
3	10000.0	10000.0	1	13.49	339.31	4	10	492
4	3000.0	3000.0	2	12.69	67.79	5	1	800
...	...	...	...	...	...	...	...	
42530	3500.0	3500.0	1	10.28	113.39	4	1	1800
42531	1000.0	1000.0	1	9.64	32.11	14	1	120
42532	2525.0	2525.0	1	9.33	80.69	13	1	1100
42533	6500.0	6500.0	1	8.38	204.84	18	1	600
42534	5000.0	5000.0	1	7.75	156.11	17	10	700

42535 rows × 98 columns

In [5]:
```
data_dummies.columns
```

Out[5]:
```
Index(['loan_amnt', 'funded_amnt', 'term', 'int_rate', 'installmen
t',
       'sub_grade', 'emp_length', 'annual_inc', 'issue_d', 'loan_s
tatus',
       'dti', 'delinq_2yrs', 'earliest_cr_line', 'inq_last_6mths',
       'mths_since_last_delinq', 'open_acc', 'pub_rec', 'revol_bal
',
       'revol_util', 'total_acc', 'pub_rec_bankruptcies', 'fico_me
an',
       'last_fico_mean', 'fico_rating', 'loan_amnt_rating', 'inter
est_rating',
       'home_ownership_MORTGAGE', 'home_ownership_NONE',
       'home_ownership_OTHER', 'home_ownership_OWN', 'home_ownersh
ip_RENT',
       'verification_status_Not Verified',
       'verification_status_Source Verified', 'verification_status
_Verified',
       'purpose_car', 'purpose_credit_card', 'purpose_debt_consoli
dation',
       'purpose_educational', 'purpose_home_improvement', 'purpose
_house',
       'purpose_major_purchase', 'purpose_medical', 'purpose_movin
g',
       'purpose_other', 'purpose_renewable_energy', 'purpose_small
```

```
       'purpose_other', 'purpose_renewable_energy', 'purpose_small
_business',
       'purpose_vacation', 'purpose_wedding', 'addr_state_AK', 'ad
dr_state_AL',
       'addr_state_AR', 'addr_state_AZ', 'addr_state_CA', 'addr_st
ate_CO',
       'addr_state_CT', 'addr_state_DC', 'addr_state_DE', 'addr_st
ate_FL',
       'addr_state_GA', 'addr_state_HI', 'addr_state_IA', 'addr_st
ate_ID',
       'addr_state_IL', 'addr_state_IN', 'addr_state_KS', 'addr_st
ate_KY',
       'addr_state_LA', 'addr_state_MA', 'addr_state_MD', 'addr_st
ate_ME',
       'addr_state_MI', 'addr_state_MN', 'addr_state_MO', 'addr_st
ate_MS',
       'addr_state_MT', 'addr_state_NC', 'addr_state_NE', 'addr_st
ate_NH',
       'addr_state_NJ', 'addr_state_NM', 'addr_state_NV', 'addr_st
ate_NY',
       'addr_state_OH', 'addr_state_OK', 'addr_state_OR', 'addr_st
ate_PA',
       'addr_state_RI', 'addr_state_SC', 'addr_state_SD', 'addr_st
ate_TN',
       'addr_state_TX', 'addr_state_UT', 'addr_state_VA', 'addr_st
ate_VT',
       'addr_state_WA', 'addr_state_WI', 'addr_state_WV', 'addr_st
ate_WY'],
      dtype='object')
```

In [6]:
```
# wczytuje dane z poprzedniej części
data_outliers = pd.read_csv('data_outliers.csv')
data_outliers.drop('Unnamed: 0', axis=1, inplace=True)
data_outliers
```

0	5000.0	5000.0	10.65	162.87	10.0	24000.0	2011.0	27.6
1	2500.0	2500.0	15.27	59.83	1.0	30000.0	2011.0	1.0
2	2400.0	2400.0	15.96	84.33	10.0	12252.0	2011.0	8.7
3	10000.0	10000.0	13.49	339.31	10.0	49200.0	2011.0	20.0
4	3000.0	3000.0	12.69	67.79	1.0	80000.0	2011.0	17.9
...	...	...	...	...	...	...	...	
42530	3500.0	3500.0	10.28	113.39	1.0	59000.0	2011.0	10.0
42531	1000.0	1000.0	9.64	32.11	1.0	12000.0	2011.0	10.0
42532	2525.0	2525.0	9.33	80.69	1.0	110000.0	2011.0	10.0
42533	6500.0	6500.0	8.38	204.84	1.0	60000.0	2011.0	4.0
42534	5000.0	5000.0	7.75	156.11	10.0	70000.0	2011.0	8.8

42535 rows × 16 columns

4. b) Modelowanie dla różnych algorytmów

Model na całym zbiorze - data_dummies

Train Test Split

In [7]:
```
X = data_dummies.drop('loan_status',axis=1)
#target
Y = data_dummies['loan_status']

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size
```

Skalowanie

In [8]:
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
X_test
```

Out[8]:
```
array([[-0.95313026, -0.95140853, -0.59377133, ..., -0.10937932,
        -0.06622215, -0.0456804 ],
       [-1.22287358, -1.23096153, -0.59377133, ..., -0.10937932,
        -0.06622215, -0.0456804 ],
       [ 0.12584299, -0.31891988, -0.59377133, ..., -0.10937932,
        -0.06622215, -0.0456804 ],
       ...,
       [ 0.28768898,  0.33453524, -0.59377133, ..., -0.10937932,
        -0.06622215, -0.0456804 ],
       [ 0.66532962,  0.72590943,  1.68415002, ..., -0.10937932,
        -0.06622215, -0.0456804 ],
       [ 0.12584299,  0.16680344, -0.59377133, ..., -0.10937932,
        -0.06622215, -0.0456804 ]])
```

Logistic Regression

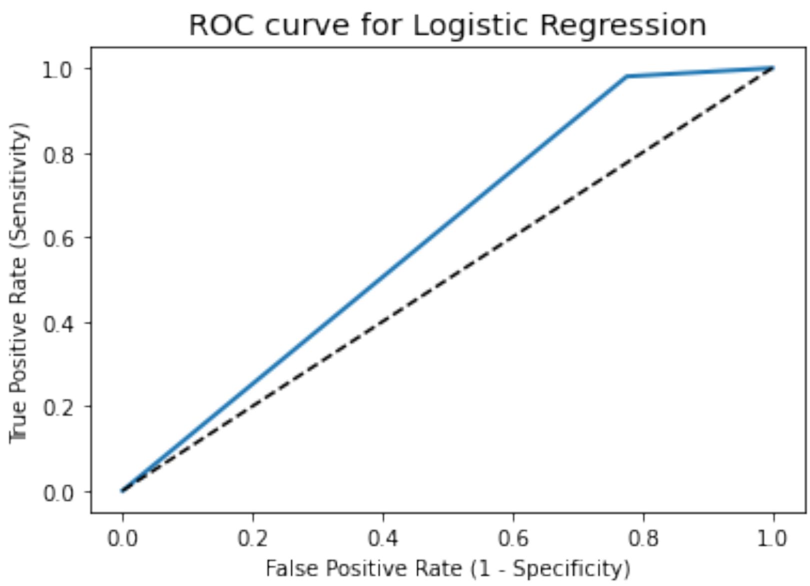
In [9]:
```
log = LogisticRegression()
log.fit(X_train, y_train)

log_pred = log.predict(X_test)

# Summary of the prediction
print(classification_report(y_test, log_pred))
print(confusion_matrix(y_test, log_pred))

# Accuracy
print('Training accuracy:', log.score(X_train, y_train))
print('Test accuracy:', log.score(X_test, y_test))
```

```
              precision    recall  f1-score   support

           0       0.68      0.22      0.34      1978
           1       0.87      0.98      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.77      0.60      0.63     12761
weighted avg       0.84      0.86      0.83     12761

[[  443  1535]
 [  213 10570]]
Training accuracy: 0.8655874252703701
Test accuracy: 0.863020139487501
```

In [10]:
```
auroc_log = roc_auc_score(log_pred,y_test)
print('AUROC =', auroc_log)
```

```
AUROC = 0.7742488867732543
```

In [11]:
```
fpr, tpr, thresholds = roc_curve(y_test, log_pred)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for Logistic Regression')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



Logistic Regression z regularyzacją - 5 parametrów

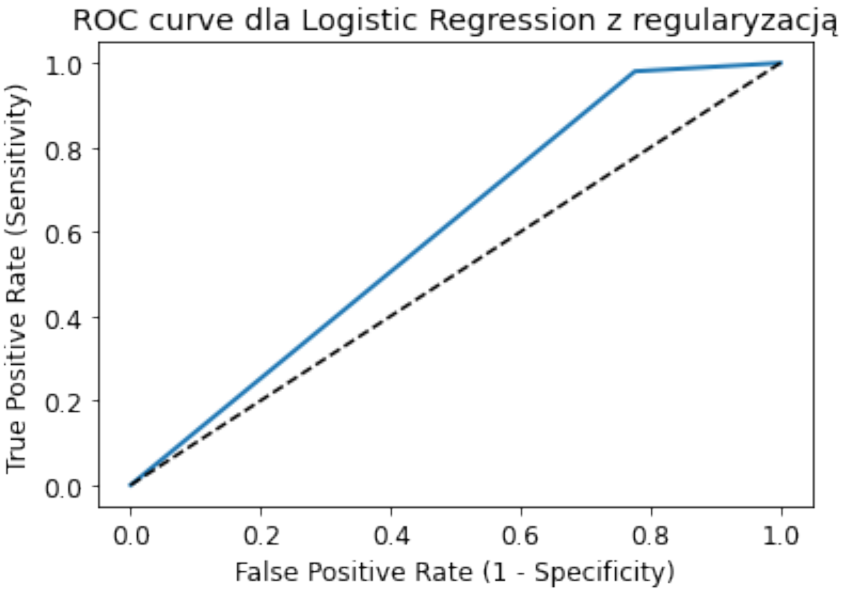
In [12]:
```
C = [.001, .01, 10, 100, 1000]

for c in C:
    log1 = LogisticRegression(penalty='l1', C=c, solver='liblinear'
    log1.fit(X_train, y_train)

    log1_pred = log1.predict(X_test)

    # Summary of the prediction
    print(classification_report(y_test, log1_pred))
    print(confusion_matrix(y_test, log1_pred))
    print('')
    print('C:', c)
    # Accuracy
    # print('Coefficient of each feature:', log1.coef_)
    print('Training accuracy:', log1.score(X_train, y_train))
    print('Test accuracy:', log1.score(X_test, y_test))
```

```
    print('')
    auroc_lrc = roc_auc_score(log1_pred,y_test)
    print('AUROC =', auroc_lrc)
    print('')
```

```
              precision    recall  f1-score   support

           0       0.66      0.08      0.14      1978
           1       0.85      0.99      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.75      0.53      0.53     12761
weighted avg       0.82      0.85      0.80     12761

[[  150  1828]
 [   79 10704]]

C: 0.001
Training accuracy: 0.8552764156646738
Test accuracy: 0.8505603009168561

AUROC = 0.7545776262549533

              precision    recall  f1-score   support

           0       0.68      0.19      0.29      1978
           1       0.87      0.98      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.78      0.59      0.61     12761
weighted avg       0.84      0.86      0.83     12761

[[  371  1607]
 [  171 10612]]

C: 0.01
Training accuracy: 0.8638745213945053
Test accuracy: 0.8606692265496434

AUROC = 0.7764926771536311

              precision    recall  f1-score   support

           0       0.68      0.22      0.34      1978
           1       0.87      0.98      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.77      0.60      0.63     12761
weighted avg       0.84      0.86      0.83     12761

[[  443  1535]
 [  213 10570]]

C: 10
```

```
Training accuracy: 0.8655538389198629
Test accuracy: 0.863020139487501

AUROC = 0.7742488867732543

              precision    recall  f1-score   support

           0       0.68      0.22      0.34      1978
           1       0.87      0.98      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.77      0.60      0.63     12761
weighted avg       0.84      0.86      0.83     12761

[[  443  1535]
 [  213 10570]]

C: 100
Training accuracy: 0.8655538389198629
Test accuracy: 0.863020139487501

AUROC = 0.7742488867732543

              precision    recall  f1-score   support

           0       0.68      0.22      0.34      1978
           1       0.87      0.98      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.77      0.60      0.63     12761
weighted avg       0.84      0.86      0.83     12761

[[  443  1535]
 [  213 10570]]

C: 1000
Training accuracy: 0.8655538389198629
Test accuracy: 0.863020139487501

AUROC = 0.7742488867732543
```

In [13]:
```
fpr, tpr, thresholds = roc_curve(y_test, log1_pred)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve dla Logistic Regression z regularyzacją')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



Decision Tree

Pierwotnie dla max_depth = None głębokość wyszła 41 wyniki:

- max_depth = 41: {'f1-score': 0.89, 'accuracy': 0.81}
- max_depth = 30: {'f1-score': 0.89, 'accuracy': 0.82}
- max_depth = 10: {'f1-score': 0.91, 'accuracy': 0.85}
- max_depth = 6: {'f1-score': 0.92, 'accuracy': 0.86}
- max_depth = 2: {'f1-score': 0.92, 'accuracy': 0.86} zostawiam na wartości 2.

In [14]:
```
dtree = DecisionTreeClassifier(max_depth = 2, random_state = 0)
```

In [15]:
```
dtree.get_params()
```

Out[15]:
```
{'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': 2,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'presort': 'deprecated',
 'random_state': 0,
 'splitter': 'best'}
```

In [16]:
```
dtree.fit(X_train,y_train)
```

Out[16]:
```
DecisionTreeClassifier(max_depth=2, random_state=0)
```

In [17]:
```
def evaluate(prediction,y_test):
    result = classification_report(y_test,prediction,output_dict=Tr
    f1 = result['1']['f1-score']
    accuracy = result['accuracy']
    performance_data= {'f1-score':round(f1, 2),
                       'accuracy':round(accuracy, 2)}
    return performance_data
```

In [18]:
```
dt_prediction = dtree.predict(X_test)
```

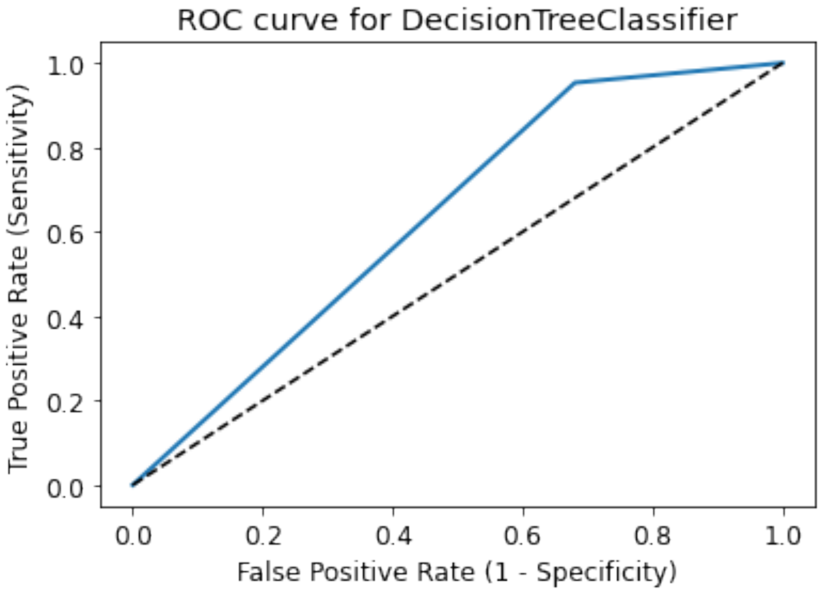
In [19]:
```
dtree_pr = evaluate(dt_prediction,y_test)
dtree_pr

# Summary of the prediction
print(classification_report(y_test, dt_prediction))
print(confusion_matrix(y_test, dt_prediction))
# Accuracy
print('Training accuracy:', dtree.score(X_train, y_train))
print('Test accuracy:', dtree.score(X_test, y_test))
```

```
              precision    recall  f1-score   support

           0       0.56      0.32      0.41      1978
           1       0.88      0.95      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.72      0.64      0.66     12761
weighted avg       0.83      0.86      0.84     12761

[[  632  1346]
 [  504 10279]]
Training accuracy: 0.8585342916638679
Test accuracy: 0.8550270354987853
```

In [20]:
```
auroc_dtree = roc_auc_score(dt_prediction,y_test)
print('AUROC =', auroc_dtree)
```

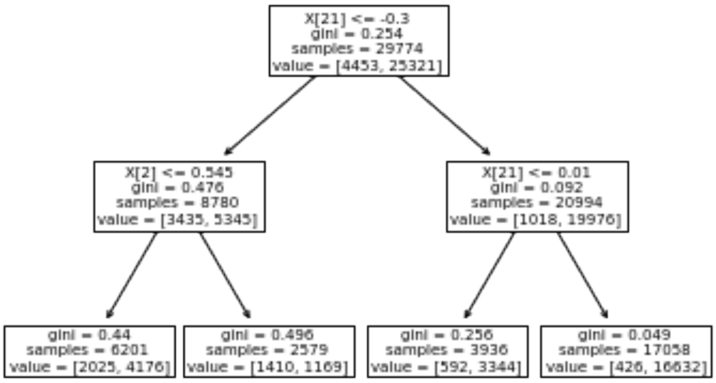
```
AUROC = 0.7202765409662275
```

In [21]:
```
fpr, tpr, thresholds = roc_curve(y_test, dt_prediction)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for DecisionTreeClassifier')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



In [22]:
```
tree.plot_tree(dtree)
```

Out[22]:
```
[Text(167.4, 181.2, 'X[21] <= -0.3\ngini = 0.254\nsamples = 29774\nvalue = [4453, 25321]'),
 Text(83.7, 108.72, 'X[2] <= 0.545\ngini = 0.476\nsamples = 8780\nvalue = [3435, 5345]'),
 Text(41.85, 36.23999999999998, 'gini = 0.44\nsamples = 6201\nvalue = [2025, 4176]'),
 Text(125.55000000000001, 36.23999999999998, 'gini = 0.496\nsamples = 2579\nvalue = [1410, 1169]'),
 Text(251.10000000000002, 108.72, 'X[21] <= 0.01\ngini = 0.092\nsamples = 20994\nvalue = [1018, 19976]'),
 Text(209.25, 36.23999999999998, 'gini = 0.256\nsamples = 3936\nvalue = [592, 3344]'),
 Text(292.95, 36.23999999999998, 'gini = 0.049\nsamples = 17058\nvalue = [426, 16632]')]
```



In [23]:
```
def get_depth(dtree):
    check_is_fitted(self)
    return dtree.tree_.max_depth
print('The maximum depth of the tree', dtree.tree_.max_depth)
```

```
The maximum depth of the tree 2
```

Random Forest Classifier

In [24]:
```
rf = RandomForestClassifier(n_estimators=100, random_state=0)
```

In [25]:
```
rf.fit(X_train, y_train)
```

Out[25]:
```
RandomForestClassifier(random_state=0)
```

In [26]:
```
rf_prediction = rf.predict(X_test)
```

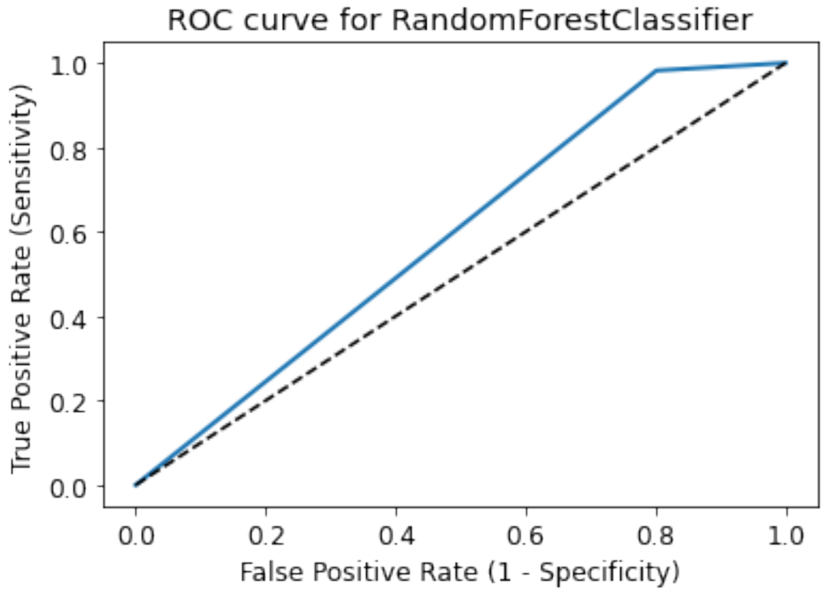
In [27]:
```
rf_pr = evaluate(rf_prediction,y_test)
rf_pr

# Summary of the prediction
print(classification_report(y_test, rf_prediction))
print(confusion_matrix(y_test, rf_prediction))
# Accuracy
print('Training accuracy:', rf.score(X_train, y_train))
print('Test accuracy:', rf.score(X_test, y_test))
```

```
              precision    recall  f1-score   support

           0       0.67      0.20      0.31      1978
           1       0.87      0.98      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.77      0.59      0.61     12761
weighted avg       0.84      0.86      0.83     12761

[[  393  1585]
 [  193 10590]]
Training accuracy: 1.0
Test accuracy: 0.8606692265496434
```

In [28]:
```
auroc_rf = roc_auc_score(rf_prediction,y_test)
print(auroc_rf)
```

```
0.7702318296178455
```

In [29]:
```
fpr, tpr, thresholds = roc_curve(y_test, rf_prediction)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for RandomForestClassifier')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



Support Vector Machine (SVM)

In [30]:
```
# model = SVC(C=100, random_state = 12)
supvm = SVC(C=1.0, kernel='linear', random_state = 12)
```

In [31]:
```
supvm.fit(X_train,y_train)
```

Out[31]:
```
SVC(kernel='linear', random_state=12)
```

In [32]:
```
svm_prediction = supvm.predict(X_test)
```

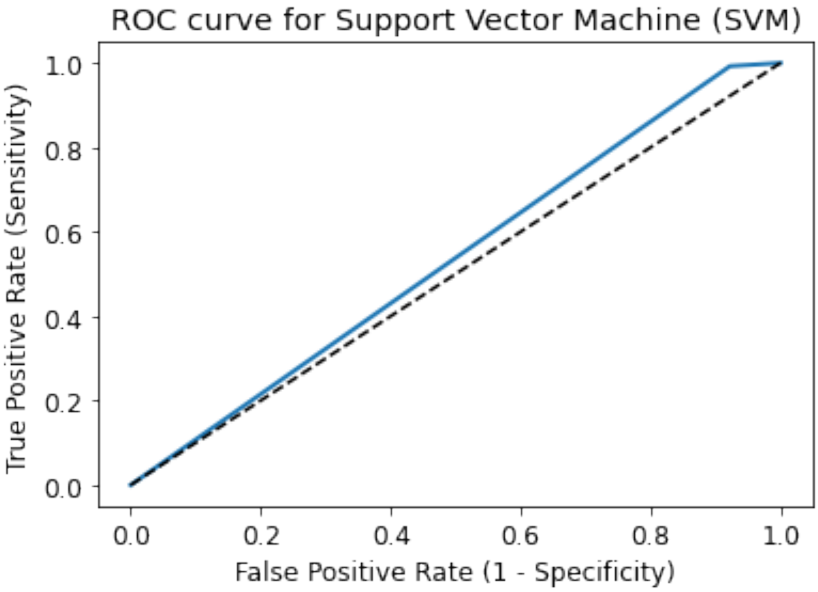
In [33]:
```
svm_pr = evaluate(svm_prediction,y_test)
svm_pr
# Summary of the prediction
print(classification_report(y_test, svm_prediction))
print(confusion_matrix(y_test, svm_prediction))

# Accuracy
print('Training accuracy:', supvm.score(X_train, y_train))
print('Test accuracy:', supvm.score(X_test, y_test))
```

```
              precision    recall  f1-score   support

           0       0.66      0.08      0.14      1978
           1       0.85      0.99      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.75      0.54      0.53     12761
weighted avg       0.82      0.85      0.80     12761

[[  154  1824]
 [   81 10702]]
Training accuracy: 0.8556458655202526
Test accuracy: 0.8507170284460466
```

In [34]:
```
auroc_svm = roc_auc_score(svm_prediction,y_test)
print('AUROC =', auroc_svm)
```

```
AUROC = 0.754851016269139
```

In [35]:
```
fpr, tpr, thresholds = roc_curve(y_test, svm_prediction)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for Support Vector Machine (SVM)')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



K Nearest Neighbors (KNN)

In [36]:
```
knn = KNeighborsClassifier(n_neighbors=2)
```

In [37]:
```
knn.get_params()
```

Out[37]:
```
{'algorithm': 'auto',
 'leaf_size': 30,
 'metric': 'minkowski',
 'metric_params': None,
 'n_jobs': None,
 'n_neighbors': 2,
 'p': 2,
 'weights': 'uniform'}
```

In [38]:
```
knn.fit(X_train,y_train)
```

Out[38]:
```
KNeighborsClassifier(n_neighbors=2)
```

In [39]:
```
knn_prediction = knn.predict(X_test)
```

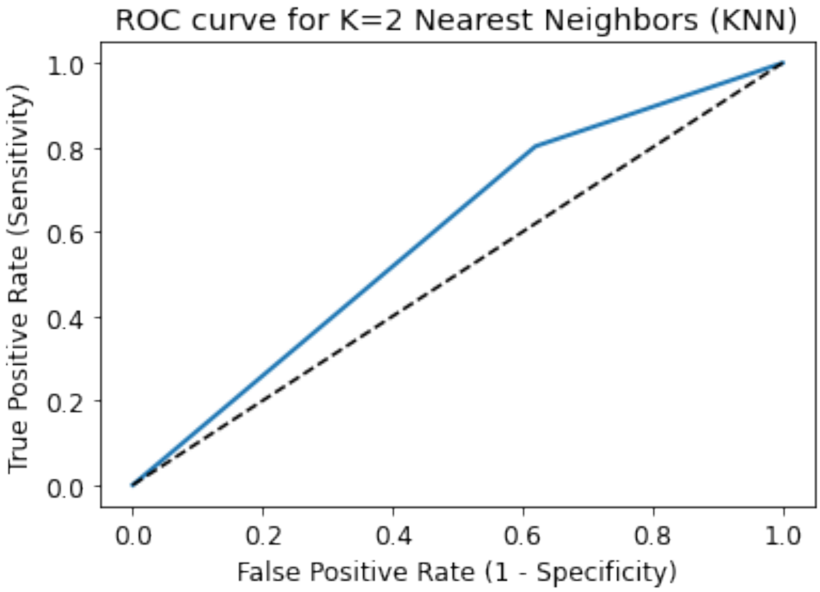
In [40]:
```
knn_pr = evaluate(knn_prediction,y_test)
knn_pr
# Summary of the prediction
print(classification_report(y_test, knn_prediction))
print(confusion_matrix(y_test, knn_prediction))
# Accuracy
print('Training accuracy:', knn.score(X_train, y_train))
print('Test accuracy:', knn.score(X_test, y_test))
```

```
              precision    recall  f1-score   support

           0       0.26      0.38      0.31      1978
           1       0.88      0.80      0.84     10783

    accuracy                           0.74     12761
   macro avg       0.57      0.59      0.57     12761
weighted avg       0.78      0.74      0.76     12761

[[ 752 1226]
 [2129 8654]]
Training accuracy: 0.9072009135487338
Test accuracy: 0.7370895697829324
```

In [41]:
```
auroc_knn = roc_auc_score(knn_prediction,y_test)
print('AUROC =', auroc_knn)
```

```
AUROC = 0.568465705087218
```

In [42]:
```
fpr, tpr, thresholds = roc_curve(y_test, knn_prediction)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for K=2 Nearest Neighbors (KNN)')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



Szukamy optymalnej wartości k

In [43]:
```
scores = []

for k in range(2, 11):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train,y_train)
    knn_prediction = knn.predict(X_test)
    scores.append(accuracy_score(knn_prediction,y_test))
    print('n_neighbors=', scores)
```

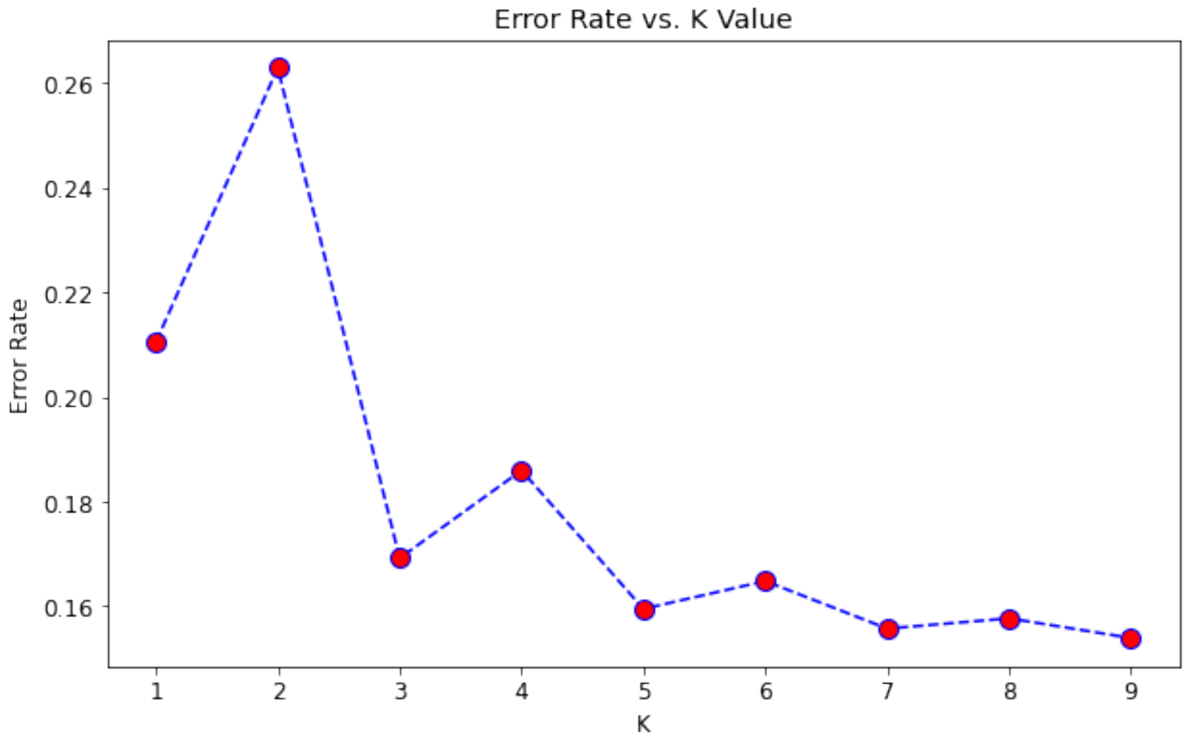
```
n_neighbors= [0.7370895697829324]
n_neighbors= [0.7370895697829324, 0.8308126322388527]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.8140427866
15469]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.8140427866
15469, 0.8405297390486639]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.8140427866
15469, 0.8405297390486639, 0.8352010030561868]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.8140427866
15469, 0.8405297390486639, 0.8352010030561868, 0.8442911997492359]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.8140427866
15469, 0.8405297390486639, 0.8352010030561868, 0.8442911997492359,
0.8423321056343547]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.8140427866
15469, 0.8405297390486639, 0.8352010030561868, 0.8442911997492359,
0.8423321056343547, 0.8460935663349267]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.8140427866
15469, 0.8405297390486639, 0.8352010030561868, 0.8442911997492359,
0.8423321056343547, 0.8460935663349267, 0.8441344722200455]
```

In [44]:
```
error_rate = []

max_k = 10

for k in range(1, max_k):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train,y_train)
    knn_prediction = knn.predict(X_test)
    error_rate.append(np.mean(knn_prediction != y_test))
print(error_rate)
```

```
[0.2104850717028446, 0.2629104302170676, 0.16918736776114723, 0.18
5957213384531, 0.1594702609513361, 0.16479899694381317, 0.15570880
025076406, 0.15766789436564532, 0.15390643366507328]
```

In [45]:
```
plt.figure(figsize=(10,6))
plt.plot(range(1, max_k), error_rate, color = 'blue', linestyle='da
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

Out[45]: Text(0, 0.5, 'Error Rate')



sprawdź knn dla innej wartości k

In [46]:
```
knn1 = KNeighborsClassifier()
```

In [47]:
```
knn1.fit(X_train,y_train)
```

Out[47]: KNeighborsClassifier()

In [48]:
```
knn1_prediction = knn.predict(X_test)
```

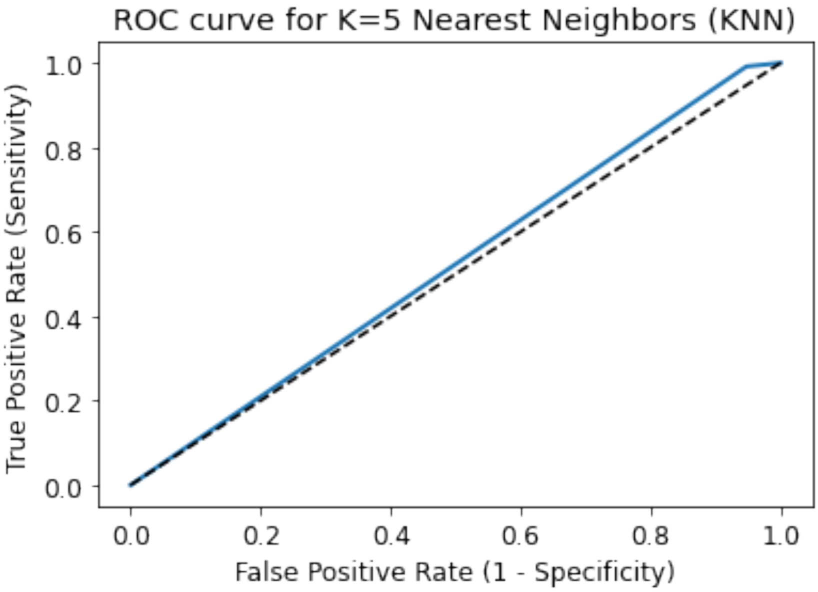
In [49]:
```
knn1_pr = evaluate(knn1_prediction,y_test)
knn1_pr
# Summary of the prediction
print(classification_report(y_test, knn1_prediction))
print(confusion_matrix(y_test, knn1_prediction))
# Accuracy
print('Training accuracy:', knn1.score(X_train, y_train))
print('Test accuracy:', knn1.score(X_test, y_test))
```

```
              precision    recall  f1-score   support

           0       0.54      0.05      0.10      1978
           1       0.85      0.99      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.69      0.52      0.51     12761
weighted avg       0.80      0.85      0.79     12761

[[  104  1874]
 [   90 10693]]
Training accuracy: 0.8720360045677437
Test accuracy: 0.8405297390486639
```

In [50]:
```
auroc_knn1 = roc_auc_score(knn1_prediction,y_test)
print('AUROC =', auroc_knn1)
```

```
AUROC = 0.6934808806241843
```

In [51]:
```
fpr, tpr, thresholds = roc_curve(y_test, knn1_prediction)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for K=5 Nearest Neighbors (KNN)')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



Bagging Classifier

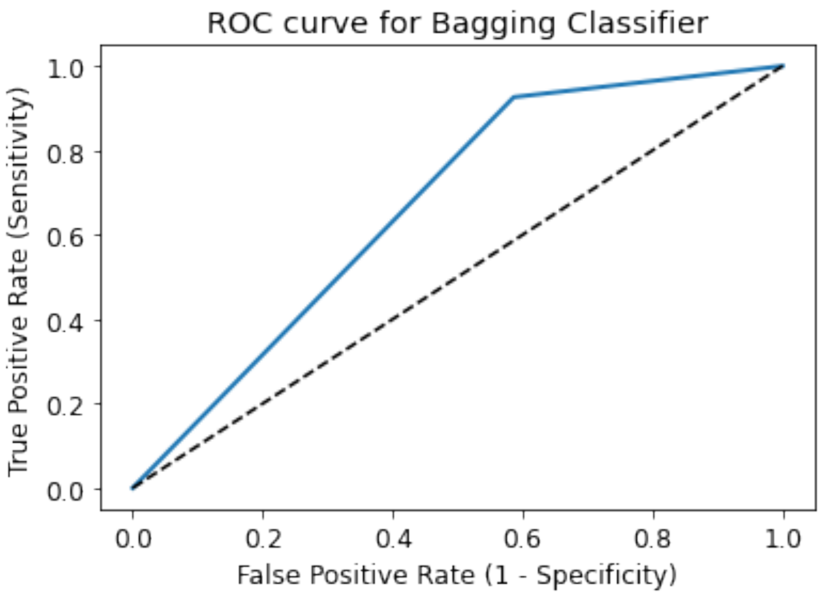
In [52]:
```
xgbc = BaggingClassifier(tree.DecisionTreeClassifier(random_state=1
xgbc.fit(X_train,y_train)
xgbc_prediction = xgbc.predict(X_test)

xgbc = evaluate(xgbc_prediction,y_test)
xgbc

# Summary of the prediction
print(classification_report(y_test, xgbc_prediction))
print(confusion_matrix(y_test, xgbc_prediction))
```

```
              precision    recall  f1-score   support

           0       0.51      0.41      0.46      1978
           1       0.90      0.93      0.91     10783

    accuracy                           0.85     12761
   macro avg       0.70      0.67      0.68     12761
weighted avg       0.84      0.85      0.84     12761

[[ 818 1160]
 [ 796 9987]]
```

In [53]:
```
auroc_xgbc = roc_auc_score(xgbc_prediction,y_test)
print('AUROC =', auroc_xgbc)
```

```
AUROC = 0.7013757459317187
```

In [54]:
```
fpr, tpr, thresholds = roc_curve(y_test, xgbc_prediction)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for Bagging Classifier')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



ADA Boost Classifier

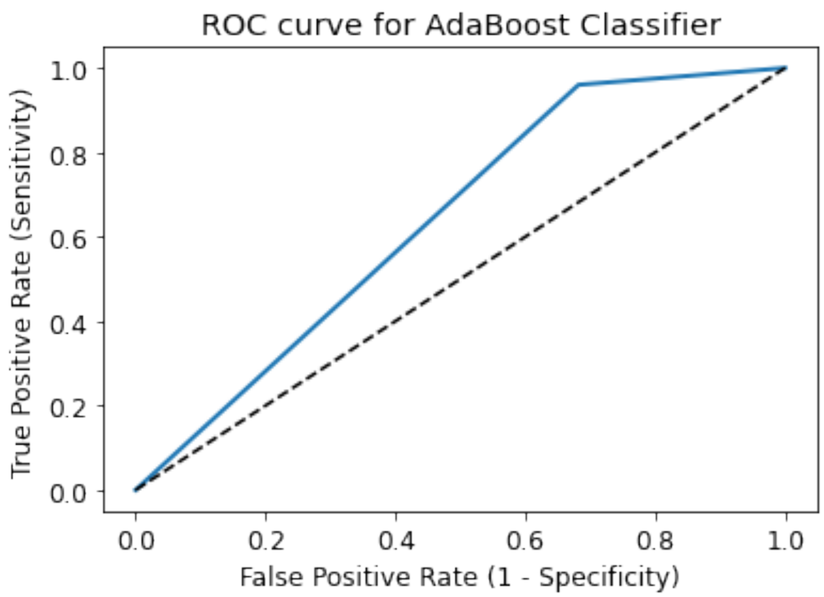
In [55]:
```
ada = AdaBoostClassifier(random_state=1)
ada.fit(X_train, y_train)
ada_prediction = ada.predict(X_test)
print(classification_report(y_test, ada_prediction))
ada = evaluate(ada_prediction,y_test)
ada

# Summary of the prediction
print(classification_report(y_test, ada_prediction))
print(confusion_matrix(y_test, ada_prediction))
```

```
              precision    recall  f1-score   support

           0       0.59      0.32      0.41      1978
           1       0.88      0.96      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.74      0.64      0.67     12761
weighted avg       0.84      0.86      0.84     12761

              precision    recall  f1-score   support

           0       0.59      0.32      0.41      1978
           1       0.88      0.96      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.74      0.64      0.67     12761
weighted avg       0.84      0.86      0.84     12761

[[  629  1349]
 [  430 10353]]
```

In [56]:
```
auroc_ada = roc_auc_score(ada_prediction,y_test)
print('AUROC =', auroc_ada)
```

```
AUROC = 0.7393385616915116
```

In [57]:
```
fpr, tpr, thresholds = roc_curve(y_test, ada_prediction)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for AdaBoost Classifier')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



Gradient Boosting Classifier

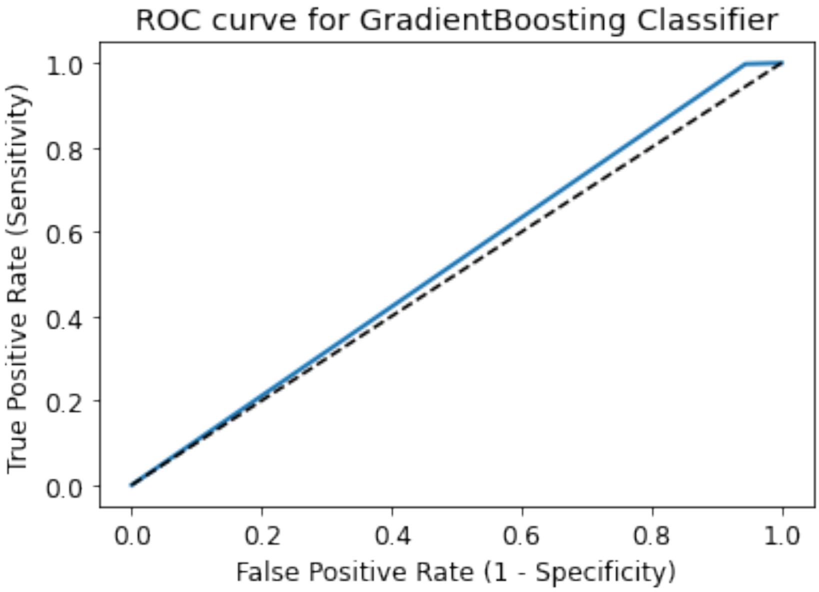
In [58]:
```
gbc= GradientBoostingClassifier(learning_rate=0.01, random_state=1)
gbc.fit(X_train, y_train)
gbc_prediction = gbc.predict(X_test)
gbc = evaluate(gbc_prediction,y_test)
gbc

# Summary of the prediction
print(classification_report(y_test, gbc_prediction))
print(confusion_matrix(y_test, gbc_prediction))
```

```
              precision    recall  f1-score   support

           0       0.81      0.06      0.10      1978
           1       0.85      1.00      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.83      0.53      0.51     12761
weighted avg       0.85      0.85      0.79     12761

[[  110  1868]
 [   26 10757]]
```

In [59]:
```
auroc_gbc = roc_auc_score(gbc_prediction,y_test)
print('AUROC =', auroc_gbc)
```

```
AUROC = 0.8304315666860803
```

In [60]:
```
fpr, tpr, thresholds = roc_curve(y_test, gbc_prediction)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for GradientBoosting Classifier')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



XGB Classifier

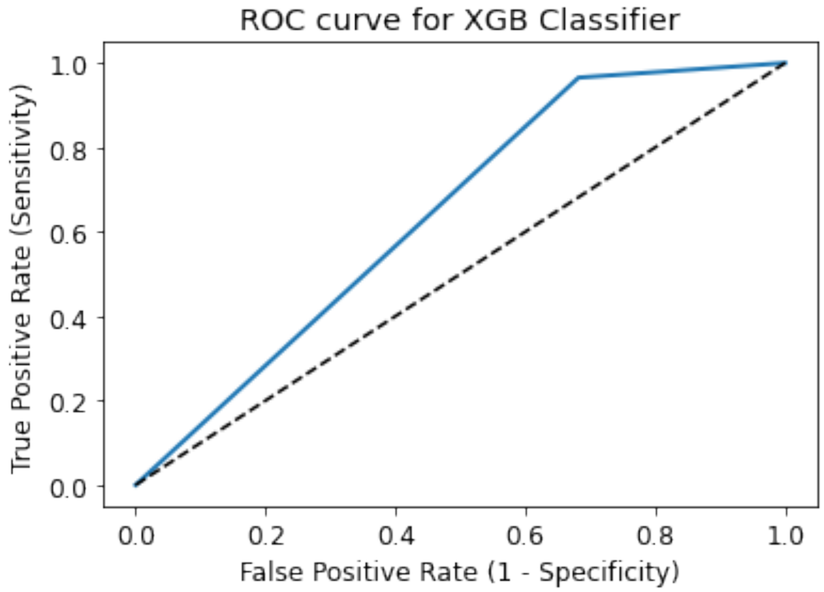
In [61]:
```
import xgboost as xgb
xgb_clas=xgb.XGBClassifier(random_state=1,learning_rate=0.01)
xgb_clas.fit(X_train, y_train)
xgb_clas_prediction = xgb_clas.predict(X_test)
xgb_clas = evaluate(xgb_clas_prediction,y_test)
xgb_clas

# Summary of the prediction
print(classification_report(y_test, xgb_clas_prediction))
print(confusion_matrix(y_test, xgb_clas_prediction))
```

```
              precision    recall  f1-score   support

           0       0.63      0.32      0.42      1978
           1       0.89      0.97      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.76      0.64      0.67     12761
weighted avg       0.85      0.86      0.85     12761

[[  629  1349]
 [  374 10409]]
```

In [62]:
```
auroc_xgb_clas = roc_auc_score(xgb_clas_prediction,y_test)
print('AUROC =', auroc_xgb_clas)
```

```
AUROC = 0.7561941238709455
```

In [63]:
```
fpr, tpr, thresholds = roc_curve(y_test, xgb_clas_prediction)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, linewidth=2)
plt.plot([0,1], [0,1], 'k--' )
plt.rcParams['font.size'] = 12
plt.title('ROC curve for XGB Classifier')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



Porównanie wszystkich modeli na data_dummies

In [64]:
```
= pd.DataFrame({'Method':['Logistic Regression', 'Logistic Regressi
                          ' Support Vector Machine (SVM)', 'KNN', '
                          'Gradient Boosting Classifier', 'XGB Clas
                'AUROC': [auroc_log, auroc_lrc, auroc_dtree, auroc_
                          auroc_knn, auroc_xgbc, auroc_ada, auroc_g
.sort_values(by = 'AUROC', ascending = False)
```

Out[64]:

	Method	AUROC
8	Gradient Boosting Classifier	0.830432
0	Logistic Regression	0.774249
1	Logistic Regression parameters	0.774249
3	Random Forest	0.770232
9	XGB Classifier	0.756194
4	Support Vector Machine (SVM)	0.754851
7	ADA Boost Classifier	0.739339
2	Decision Tree	0.720277
6	Bagging Classifier	0.701376
5	KNN	0.568466

Modele na całym zbiorze - data_loan1 - cechy numeryczne

Logistic Regression

In [65]:
```
X1 = data_loan1.drop('loan_status',axis=1)
#target
y1 = data_loan1['loan_status']

X1_train, X1_test, y1_train, y1_test = train_test_split(X1, y1, tes

sc = StandardScaler()
X1_train = sc.fit_transform(X1_train)
X1_test = sc.transform(X1_test)
```

In [66]:
```
log_num = LogisticRegression()
log_num.fit(X1_train, y1_train)

y1_pred = log_num.predict(X1_test)

# Summary of the prediction
print(classification_report(y1_test, y1_pred))
print(confusion_matrix(y1_test, y1_pred))
```

```
              precision    recall  f1-score   support

           0       0.65      0.19      0.29      1978
           1       0.87      0.98      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.76      0.58      0.61     12761
weighted avg       0.83      0.86      0.82     12761

[[  372  1606]
 [  200 10583]]
```

In [67]:
```
auroc_log_num = roc_auc_score(xgb_clas_prediction,y_test)
print('AUROC =', auroc_log_num)
```

```
AUROC = 0.7561941238709455
```

Gradient Boosting Classifier

In [68]:
```
gbc_num= GradientBoostingClassifier(learning_rate=0.01, random_stat
gbc_num.fit(X1_train, y1_train)
gbc_num_pred = gbc_num.predict(X1_test)
gbc_num = evaluate(gbc_num_pred,y1_test)
gbc_num

# Summary of the prediction
print(classification_report(y1_test, gbc_num_pred))
print(confusion_matrix(y1_test, gbc_num_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.03      0.05      1978
           1       0.85      1.00      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.83      0.51      0.49     12761
weighted avg       0.84      0.85      0.78     12761

[[   54  1924]
 [   12 10771]]
```

In [69]:
```
auroc_gbc_num = roc_auc_score(gbc_num_pred,y_test)
print('AUROC =', auroc_gbc_num)
```

```
AUROC = 0.8333130437896094
```

Modele na całym zbiorze - data_outliers - z uzupełnionymi medianami

Logistic Regression

In [70]:
```
X2 = data_outliers
#target
y2 = data_loan['loan_status']

X2_train, X2_test, y2_train, y2_test = train_test_split(X2, y2, tes

sc = StandardScaler()
X2_train = sc.fit_transform(X2_train)
X2_test = sc.transform(X2_test)
```

In [71]:
```
log_med = LogisticRegression()
log_med.fit(X2_train, y2_train)

y2_pred= log_med.predict(X2_test)

# Summary of the prediction
print(classification_report(y2_test, y2_pred))
print(confusion_matrix(y2_test, y2_pred))
```

```
              precision    recall  f1-score   support

           0       0.65      0.20      0.31      1978
           1       0.87      0.98      0.92     10783

    accuracy                           0.86     12761
   macro avg       0.76      0.59      0.62     12761
weighted avg       0.84      0.86      0.83     12761

[[  402  1576]
 [  217 10566]]
```

In [72]:
```
auroc_log_med = roc_auc_score(y2_pred,y2_test)
print('AUROC =', auroc_log_med)
```

```
AUROC = 0.7598185872133976
```

Gradient Boosting Classifier

In [73]:
```
gbc_med= GradientBoostingClassifier(learning_rate=0.01, random_stat
gbc_med.fit(X2_train, y2_train)
gbc_med_pred = gbc_med.predict(X2_test)
gbc_med = evaluate(gbc_med_pred,y2_test)
gbc_med

# Summary of the prediction
print(classification_report(y2_test, gbc_med_pred))
print(confusion_matrix(y2_test, gbc_med_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.02      0.04      1978
           1       0.85      1.00      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.84      0.51      0.48     12761
weighted avg       0.85      0.85      0.78     12761

[[   44  1934]
 [    9 10774]]
```

In [74]:
```
auroc_gbc_med = roc_auc_score(gbc_med_pred,y_test)
print('AUROC =', auroc_gbc_med)
```

```
AUROC = 0.8390005404410236
```

Podsumowanie

Najlepsze wyniki AUROC uzyskałam na modelach Gradient Boosting Classifier, na wszystkich danych. Poniżej podsumowanie w zależności od rodzaje danych.

In [75]:
```
results = pd.DataFrame({'Method':['Gradient Boosting Classifier','Gı
                        'AUROC': [auroc_xgb_clas, auroc_gbc_num, auı
                       'Zbiór danych': ['data_dummies', 'data_loan ı
results.sort_values(by = 'AUROC', ascending = False)
```

Out[75]:

	Method	AUROC	Zbiór danych
2	Gradient Boosting Classifier	0.839001	data_loan z medianami
1	Gradient Boosting Classifier	0.833313	data_loan numeryczne
0	Gradient Boosting Classifier	0.756194	data_dummies

Kolejna część w pliku "Finalny Model część IV Projekt końcowy Data Science - Dorota Gawrońska-Popa"

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