Projekt końcowy Data Science

Dorota Gawrońska-Popa

4. c) Przykłady modeli po PCA

(zmniejszaniu liczby wymiarów)

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 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.cluster import KMeans
```

```
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

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
```

wczytuję dane z poprzedniej części

In [2]:
```
data_dummies = pd.read_csv('data_dummies.csv')
data_dummies.drop('Unnamed: 0', axis=1, inplace=True)
data_dummies
```

Out[2]:

	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 [3]:
```
X = data_dummies.drop('loan_status',axis=1)
#target
y = data_dummies['loan_status']
```

In [4]:
```
X.shape
```
Out[4]:
```
(42535, 97)
```

In [5]:
```
y.shape
```
Out[5]:
```
(42535,)
```

In [6]:
```
y
```
Out[6]:
```
0        1
1        0
2        1
3        1
4        1
        ..
42530    1
42531    1
42532    1
42533    1
42534    1
Name: loan_status, Length: 42535, dtype: int64
```

Standaryzacja, przed wykonaniem PCA

In [7]:
```
sc = StandardScaler()
X_scaled = sc.fit_transform(X)
X_scaled[:5, :5]
```
Out[7]:
```
array([[-0.82173051, -0.81456887, -0.59064503, -0.40859218, -0.764
64399],
       [-1.15907367, -1.16437427,  1.69306429,  0.83739883, -1.257
83589],
       [-1.1725674 , -1.17836649, -0.59064503,  1.0234884 , -1.140
5688 ],
       [-0.14704418, -0.11495806, -0.59064503,  0.35734169,  0.079
87056],
       [-1.09160504, -1.09441319,  1.69306429,  0.14158567, -1.219
73605]])
```

In [8]:
```
X.columns
```

```
       '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
_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'
```

In [9]:
```
X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)
X_scaled_df
```

Out[9]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length
0	-0.821731	-0.814569	-0.590645	-0.408592	-0.764644	-1.532735	1.395279
1	-1.159074	-1.164374	1.693064	0.837399	-1.257836	-1.402702	-1.207217
2	-1.172567	-1.178366	-0.590645	1.023488	-1.140569	-1.272670	1.395279
3	-0.147044	-0.114958	-0.590645	0.357342	0.079871	-1.142637	1.395279
4	-1.091605	-1.094413	1.693064	0.141586	-1.219736	-1.012604	-1.207217
...	...	...	...	...	...	...	...
42530	-1.024136	-1.024452	-0.590645	-0.508379	-1.001476	-1.142637	-1.207217
42531	-1.361480	-1.374258	-0.590645	-0.680984	-1.390515	0.157690	-1.207217
42532	-1.155700	-1.160876	-0.590645	-0.764590	-1.157991	0.027657	-1.207217
42533	-0.619325	-0.604686	-0.590645	-1.020800	-0.563758	0.677821	-1.207217
42534	-0.821731	-0.814569	-0.590645	-1.190708	-0.797000	0.547788	1.395279

42535 rows × 97 columns

Sprawdzamy korelację

In [10]:
```
plt.figure(figsize = (20,10))
X_scaled_df.corr()
```

Out[10]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp
loan_amnt	1.000000	0.981746	0.355647	0.292346	0.930869	0.119626	0
funded_amnt	0.981746	1.000000	0.335137	0.295154	0.956522	0.115749	0
term	0.355647	0.335137	1.000000	0.428649	0.097614	0.190461	0
int_rate	0.292346	0.295154	0.428649	1.000000	0.271433	0.313232	-0
installment	0.930869	0.956522	0.097614	0.271433	1.000000	0.102561	0
...	...	...	...	...	...	...	
addr_state_VT	-0.010225	-0.010569	-0.004024	-0.008556	-0.009995	-0.000909	0
addr_state_WA	-0.003873	-0.002099	-0.007010	0.006209	0.000584	-0.000473	0
addr_state_WI	0.000184	0.000458	0.011548	0.000731	-0.002843	0.000552	0
addr_state_WV	-0.003483	-0.002075	0.005385	-0.005369	-0.005191	-0.009206	0
addr_state_WY	0.000242	0.000828	-0.006537	0.005543	0.003201	-0.004905	0

97 rows × 97 columns

```
<Figure size 1440x720 with 0 Axes>
```

PCA redukcja wymiarów

In [11]:
```
pca = PCA(random_state=42)
pca.fit(X_scaled)
```

Out[11]:
```
PCA(random_state=42)
```

Sprawdzam liczbę komponentów

In [12]:
```
pca.components_[0]
```

```
234e-01,
        1.22166090e-03,  1.76536828e-02,  1.60700550e-01, -1.27456
455e-02,
        1.76637691e-01,  6.06719717e-02,  2.05562709e-01, -5.02451
223e-03,
        2.92654586e-02,  3.51002763e-02, -1.29941452e-02,  3.57000
230e-01,
       -3.56261233e-02,  1.63683343e-01, -7.86086491e-03, -7.53057
314e-03,
       -2.19799777e-02, -1.50166856e-01, -1.87402351e-01, -3.67182
189e-02,
        2.33837977e-01, -5.60760418e-02,  1.36321709e-02,  9.87598
382e-02,
       -3.97916297e-02,  2.40204415e-02,  3.01376786e-03, -5.63334
818e-02,
       -2.37687289e-02, -4.33795388e-02, -7.96720393e-02, -3.64677
788e-03,
        3.17435180e-02, -3.37189468e-02, -2.37466492e-02,  7.47535
356e-03,
        5.00539201e-03,  7.64054869e-04,  1.22576842e-03, -6.36342
```

In [13]:
```
pca.explained_variance_ratio_
```

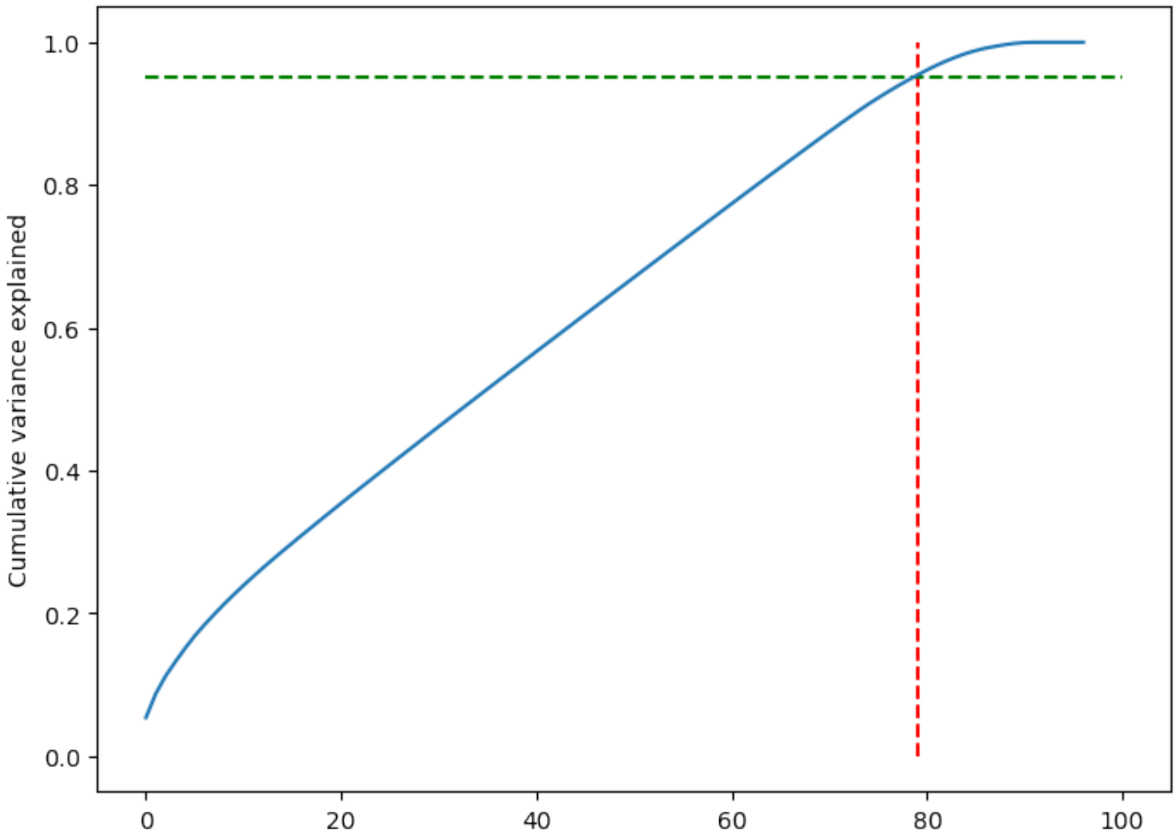
```
-02,
       1.21724170e-02, 1.17997133e-02, 1.15013606e-02, 1.13861075e
-02,
       1.12913340e-02, 1.11791430e-02, 1.11144655e-02, 1.10909198e
-02,
       1.09967637e-02, 1.09566878e-02, 1.08591267e-02, 1.08375646e
-02,
       1.07571345e-02, 1.07411810e-02, 1.06999495e-02, 1.06931807e
-02,
       1.06807625e-02, 1.06634483e-02, 1.06375786e-02, 1.06205350e
-02,
       1.05754055e-02, 1.05522768e-02, 1.05331589e-02, 1.05221234e
-02,
       1.05001026e-02, 1.04931010e-02, 1.04708469e-02, 1.04663513e
-02,
       1.04490882e-02, 1.04345887e-02, 1.04224166e-02, 1.04122505e
-02,
       1.04053309e-02, 1.04007455e-02, 1.03892348e-02, 1.03844509e
-02,
       1.03712557e-02, 1.03644878e-02, 1.03592249e-02, 1.03544839e
```

Skumulowana suma wariancji

In [14]:
```
var_cumu = np.cumsum(pca.explained_variance_ratio_)
var_cumu
```

Out[14]:
```
array([0.05366004, 0.08701392, 0.11170721, 0.13167222, 0.15063618,
       0.16824508, 0.18383575, 0.1984934 , 0.21275901, 0.22605441,
       0.23901472, 0.25153364, 0.26370606, 0.27550577, 0.28700713,
       0.29839324, 0.30968457, 0.32086371, 0.33197818, 0.3430691 ,
       0.35406586, 0.36502255, 0.37588168, 0.38671924, 0.39747638,
       0.40821756, 0.41891751, 0.42961069, 0.44029145, 0.4509549 ,
       0.46159248, 0.47221301, 0.48278842, 0.49334069, 0.50387385,
       0.51439598, 0.52489608, 0.53538918, 0.54586003, 0.55632638,
       0.56677547, 0.57721006, 0.58763247, 0.59804472, 0.60845005,
       0.6188508 , 0.62924003, 0.63962448, 0.64999574, 0.66036023,
       0.67071945, 0.68107394, 0.69142215, 0.70176101, 0.71209058,
       0.7224167 , 0.73273331, 0.74304427, 0.75334845, 0.76362239,
       0.77388627, 0.78414518, 0.79437941, 0.80458259, 0.81474804,
       0.82484872, 0.834918  , 0.84497445, 0.8550121 , 0.86501474,
       0.87494113, 0.88473625, 0.89446793, 0.90409374, 0.91339727,
       0.92215107, 0.93061232, 0.93873542, 0.94645121, 0.95382681,
       0.96117338, 0.96792151, 0.97401891, 0.97946115, 0.98437159,
       0.98842257, 0.99180053, 0.99427641, 0.99667508, 0.99845488,
       0.99963427, 0.99991697, 1.        , 1.        , 1.        ,
       1.        , 1.        ])
```

In [15]:
```
fig = plt.figure(figsize=[8,6],dpi=100)
plt.vlines(x=79, ymax=1, ymin=0, colors="r", linestyles="--")
plt.hlines(y=0.95, xmax=100, xmin=0, colors="g", linestyles="--")
plt.plot(var_cumu)
plt.ylabel("Cumulative variance explained")
plt.show()
```



Mamy 79 komponentów,

przy których zachowujemy 95% pierwotnych danych. Budujemy nowe dane. 79 komponentów to ponad 81% wszystkich, co prawdopodobnie nie da wielkiej zmiany. Przyjęłam do obliczeń różne wartości komponentów:

- n_components=2 => AUROC LG = 0.7975915
- n_components=20 => AUROC LG = 0.737982
- n_components=30 => AUROC LG = 0.743456
- n_components=50 => AUROC LG = 0.730057
- n_components=79 => AUROC LG = 0.758493

Najwyższe wartości są dla skrajnych liczb komponentów n=2 i n=79. Sprawdzam dla różnych n, i ostatecznie wybieram na po analizie.

In [16]:
```
pca_final = PCA(n_components=60, random_state=67)
X_pca_final = pca_final.fit_transform(X_scaled)
```

In [17]:
```
print(X.shape)
print(X_pca_final.shape)
```

```
(42535, 97)
(42535, 60)
```

In [18]:
```
X = X_pca_final
y = data_dummies['loan_status']
```

In [19]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size
```

In [20]:
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
X_test
```

Out[20]:
```
array([[-1.13915721, -0.78008089, -0.549711  , ..., -0.30889461,
        -0.26340202, -2.37898625],
       [-1.30916994,  0.02361284,  0.2034459 , ..., -0.1966055 ,
        -0.40182079,  0.52121232],
       [-0.12324974,  1.13157697,  0.62666237, ...,  0.55362987,
         0.53596514,  0.30089312],
       ...,
       [ 0.3790809 ,  1.47120904, -0.55698086, ..., -0.16396143,
         0.79168164,  0.4471615 ],
       [ 0.87702519, -1.55075332, -1.01377858, ...,  0.31099657,
        -0.42649259, -0.55116541],
       [ 0.28118921, -0.2912634 ,  2.36675704, ..., -0.66702674,
        -0.11695606,  0.7017783 ]])
```

In [21]:
```
y_test.sample()
```

Out[21]:
```
12060    0
Name: loan_status, dtype: int64
```

Logistic Regression

In [22]:
```
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       0.65      0.09      0.16      1978
           1       0.86      0.99      0.92     10783

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

[[  185  1793]
 [  101 10682]]
Training accuracy: 0.8556794518707598
Test accuracy: 0.8515790298565943
```

In [23]:
```
auroc_log = roc_auc_score(log_pred,y_test)
print('AUROC =', auroc_log)
```

```
AUROC = 0.7515628459716636
```

Logistic Regression z regularyzacją

In [24]:
```
log1 = LogisticRegression(penalty='l1', C=.01, 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))

# Accuracy
print('Training accuracy:', log1.score(X_train, y_train))
print('Test accuracy:', log1.score(X_test, y_test))
```

```
              precision    recall  f1-score   support

           0       0.70      0.06      0.10      1978
           1       0.85      1.00      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.78      0.53      0.51     12761
weighted avg       0.83      0.85      0.79     12761

[[  112  1866]
 [   48 10735]]
Training accuracy: 0.8535970981393162
Test accuracy: 0.8500117545646892
```

In [25]:
```
auroc_log1 = roc_auc_score(log1_pred,y_test)
print('AUROC =', auroc_log1)
```

```
AUROC = 0.7759582572811682
```

Uwaga

Wyniki ewaluacji LR z regularyzacją wyszły lepsze po ponownym skalowanie nowych danych.

In [26]:
```
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
```

Random Forest Classifier

In [27]:
```
rf = RandomForestClassifier(n_estimators=100, random_state=0)
```

In [28]:
```
rf.fit(X_train, y_train)
```
Out[28]:
```
RandomForestClassifier(random_state=0)
```

In [29]:
```
rf_prediction = rf.predict(X_test)
```

In [30]:
```
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       0.64      0.05      0.09      1978
           1       0.85      0.99      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.75      0.52      0.50     12761
weighted avg       0.82      0.85      0.79     12761

[[   96  1882]
 [   54 10729]]
Training accuracy: 0.9999664136494928
Test accuracy: 0.8482877517435937
```

In [31]:
```
auroc_rf = roc_auc_score(rf_prediction,y_test)
print(auroc_rf)
```
```
0.7453826024898899
```

K Nearest Neighbors (KNN)

In [32]:
```
knn = KNeighborsClassifier(n_neighbors=5)
```

In [33]:
```
knn.get_params()
```
Out[33]:
```
{'algorithm': 'auto',
 'leaf_size': 30,
 'metric': 'minkowski',
 'metric_params': None,
 'n_jobs': None,
 'n_neighbors': 5,
 'p': 2,
 'weights': 'uniform'}
```

In [34]:
```
knn.fit(X_train,y_train)
```

Out[34]:
```
KNeighborsClassifier()
```

In [35]:
```
knn_prediction = knn.predict(X_test)
```

In [36]:
```
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       0.31      0.07      0.11      1978
           1       0.85      0.97      0.91     10783

    accuracy                           0.83     12761
   macro avg       0.58      0.52      0.51     12761
weighted avg       0.77      0.83      0.78     12761

[[  139  1839]
 [  305 10478]]
Training accuracy: 0.8683750923624639
Test accuracy: 0.8319880887077815
```

In [37]:
```
auroc_knn = roc_auc_score(knn_prediction,y_test)
print('AUROC =', auroc_knn)
```

```
AUROC = 0.5818786128013212
```

Bagging Classifier

In [38]:
```
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       0.39      0.18      0.25      1978
           1       0.86      0.95      0.90     10783

    accuracy                           0.83     12761
   macro avg       0.63      0.57      0.58     12761
weighted avg       0.79      0.83      0.80     12761

[[  364  1614]
 [  577 10206]]
```

In [39]:
```
auroc_xgbc = roc_auc_score(xgbc_prediction,y_test)
print('AUROC =', auroc_xgbc)
```

```
AUROC = 0.6251371529369878
```

ADA Boost Classifier

In [40]:
```
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       0.54      0.12      0.19      1978
           1       0.86      0.98      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.70      0.55      0.55     12761
weighted avg       0.81      0.85      0.80     12761

              precision    recall  f1-score   support

           0       0.54      0.12      0.19      1978
           1       0.86      0.98      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.70      0.55      0.55     12761
weighted avg       0.81      0.85      0.80     12761

[[  233  1745]
 [  202 10581]]
```

In [41]:
```
auroc_ada = roc_auc_score(ada_prediction,y_test)
print('AUROC =', auroc_ada)
```

```
AUROC = 0.6970307601351037
```

XGB Classifier

In [42]:
```
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       0.61      0.03      0.06      1978
           1       0.85      1.00      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.73      0.51      0.49     12761
weighted avg       0.81      0.85      0.78     12761

[[   61  1917]
 [   39 10744]]
```

In [43]:
```
auroc_xgb_clas = roc_auc_score(xgb_clas_prediction,y_test)
print('AUROC =', auroc_xgb_clas)
```

```
AUROC = 0.7292950793776163
```

Nie liczy AUROC po PCA

Support Vector Machine (SVM)

In [44]:
```
#supvm = SVC(C=1.0, kernel='linear', random_state = 12)
```

In [45]:
```
#supvm.fit(X_train,y_train)
```

In [46]:
```
#svm_prediction = supvm.predict(X_test)
```

In [47]:
```
# 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))
```

Nie liczy AUROC po PCA

Decision Tree

In [48]:
```
#dtree = DecisionTreeClassifier(max_depth = 2, random_state = 0)
```

In [49]:
```
#dtree.fit(X_train,y_train)
```

In [50]:
```
#dt_pred = dtree.predict(X_test)
```

In [51]:
```
# dtree_pr = evaluate(dt_prediction,y_test)
# dtree_pr

# # Summary of the prediction
# print(classification_report(y_test, dt_pred))
# print(confusion_matrix(y_test, dt_pred))
# # Accuracy
# print('Training accuracy:', dtree.score(X_train, y_train))
# print('Test accuracy:', dtree.score(X_test, y_test))
# # metrics.f1_score(y_test, dt_pred, average='weighted', labels=np

# # import warnings
# # warnings.filterwarnings('always')  # "error", "ignore", "always'
```

In [52]:
```
# auroc_dtree = roc_auc_score(dt_prediction,y_test)
# print('AUROC =', auroc_dtree)
# metrics.f1_score(y_test, dt_prediction, average='weighted', label.
```

Nie liczy AUROC po PCA

Gradient Boosting Classifier

In [53]:
```
# gbc = GradientBoostingClassifier(learning_rate=0.01, random_state
# gbc.fit(X_train, y_train)
# gbc_predpca = gbc.predict(X_test)
# # gbc = evaluate(gbc_predpca,y_test)
# gbc

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

In [54]:
```
# auroc_gbc = roc_auc_score(gbc_predpca,y_test)
# print('AUROC =', gbc_predpca)
```

4. d) Finalny model

Analiza

Po wykonaniu PCA i skalowaniu danych wyniki AUROC dla większości modeli były niższe niż przed wykonaniem PCA. Ponadto w przypadku kilka modeli, nie dało się ich wdrożyć po kompresji danych za pomocą PCA.

Sprawdzałam działanie wszystkich powyższych modeli na różnych wartościach komponentów n=2, n=30, n=60 i n=79. Najbardziej wrażliwy na zmianę liczby komponentów okazał się algorytm 'Logistic Regression (z regularyzacją)', który miał dla odpowiedniej liczby komponentów następujace wyniki:

- n_components=2 => AUROC LG = 0.922531 (wartość odstająca, przy pewnym random_forest)
- n_components=30 => AUROC LG = 0.766530
- n_components=60 => AUROC LG = 0.775958
- n_components=79 => AUROC LG = 0.763670

Z modeli bez kompresji PCA najlepszy okazał się Gradient Boosting Classifier, który miał

- AUROC GBC = 0.830432

Finalny model

Gradient Boosting Classifier

Ten model wybieram jako finalny, poniżej zrobię krosswalidację i ...!!!!!

In [55]:
```
X1 = data_dummies.drop('loan_status',axis=1)
#target
y1 = data_dummies['loan_status']

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

In [56]:
```
sc = StandardScaler()
X1_train = sc.fit_transform(X1_train)
X1_test = sc.transform(X1_test)
X1_test
```

Out[56]:
```
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 ]])
```

In [57]:
```
gbc= GradientBoostingClassifier(learning_rate=0.01, random_state=1)
gbc.fit(X1_train, y1_train)
gbc_prediction = gbc.predict(X1_test)
gbc = evaluate(gbc_prediction,y1_test)
gbc

# Summary of the prediction
print(classification_report(y1_test, gbc_prediction))
print(confusion_matrix(y1_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 [58]:
```
auroc_gbc = roc_auc_score(gbc_prediction,y1_test)
print('AUROC =', auroc_gbc)
```

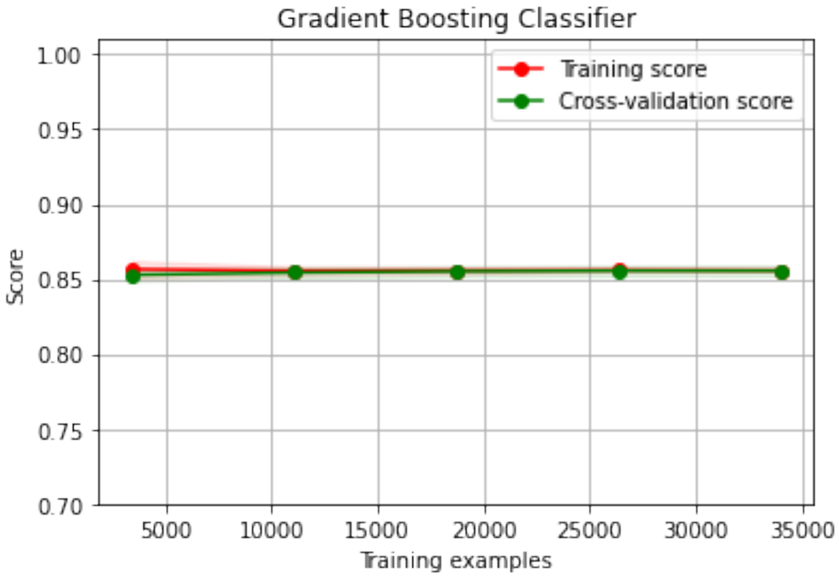
```
AUROC = 0.8304315666860803
```

In [59]:
```
## źródło: http://scikit-learn.org/stable/auto_examples/model_selec
def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=1, train_sizes=np.linspace(.1, 1.0, 

    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_si
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_
                     train_scores_mean + train_scores_std, alpha=0.
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_st
                     test_scores_mean + test_scores_std, alpha=0.1,
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Cross-validation score")

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

In [60]:
```
# Shuffle for learning curves
cv = ShuffleSplit(n_splits=100, test_size=0.2, random_state=0)
```

In [61]:
```
gbc = GradientBoostingClassifier(learning_rate=0.01, random_state=1
plt.figure(figsize=(20,14))
plot_learning_curve(gbc, 'Gradient Boosting Classifier', X1, y1, (0
plt.show()
```

```
<Figure size 1440x1008 with 0 Axes>
```



In [62]:
```
num_folds = 18
seed = 77
kfold = KFold(n_splits=num_folds, random_state=seed)
results1 = cross_val_score(gbc,X1, y1, cv=kfold)
accuracy=np.mean(abs(results1))
print('Average accuracy: ',accuracy)
print('Standard Deviation: ',results1.std())
```

```
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages/sklearn/model_selection/_split.py:293: FutureWarning: Setting a random_state has no effect since shuffle is False. This will raise an error in 0.24. You should leave random_state to its default (None), or set shuffle=True.
  warnings.warn(

Average accuracy:  0.8557662777909454
Standard Deviation:  0.0352216027446583
```

Zapisywanie modelu na dysku

In [63]:
```
import pickle

# save the model to disk
gbc_final_model = 'finalized_model.sav'
pickle.dump(gbc, open(gbc_final_model, 'wb'))
```

Łódź 4.10.2020