Projekt końcowy Data Science

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źródło: https://www.lendingclub.com

Projekt końcowy - temat projektu

Lending Club

to firma pożyczkowa typu peer-to-peer, która łączy pożyczkobiorców z inwestorami za pośrednictwem platformy internetowej. Obsługuje osoby, które potrzebują pożyczek osobistych w wysokości od 1000 do 40 000 USD. Pożyczkobiorcy otrzymują pełną kwotę udzielonej pożyczki pomniejszoną o opłatę początkową, która jest uiszczana firmie. Inwestorzy kupują weksle zabezpieczone osobistymi pożyczkami i płacą Lending Club opłatę za usługę. Firma Lending Club udostępnia dane o wszystkich pożyczkach udzielonych za pośrednictwem swojej platformy w określonych okresach. Na potrzeby tego projektu zostały użyte dane dotyczące pożyczek udzielonych za pośrednictwem Lending Club na przestrzeni lat 2007 -2011. Każda pożyczka jest opatrzona informacją o tym, czy ostatecznie została spłacona (Fully Paid lub Charged off w kolumnie loan_status).

Cel projektu

Polecenie

Twoim zadaniem jest zbudowanie modelu klasyfikacyjnego, który na podstawie tych danych będzie przewidywał z określoną dokładnością, czy potencjalny pożyczkobiorca spłaci swój dług z tytułu zaciągniętej pożyczki. Do zbioru danych dołączony jest plik z opisem wszystkich zmiennych oraz plik „FICO Score ranged.pdf”, w którym dokładnie opisano znaczenie jednej z kolumn.

Poniżej zaprezentowane są poszczególne etapy analizy, których wykonanie jest konieczne do zaliczenia projektu oraz ich punktacja:

1. Obróbka danych (Data Processing) (70pkt)

Jako doświadczony Data Scientist zapewne znasz poszczególne kroki, które należy wykonać na tym etapie, więc nie będziemy ich tutaj wyszczególniać.

2. EDA, czyli obszerna eksploracja danych (100pkt)

Opisz wnioski płynące z każdego wykresu, swoje hipotezy poprzyj testami statystycznymi takimi jak np. t-test lub Chi-square. Dodatkowo odpowiedz na poniższe pytania:
    1. W jaki sposób wynik FICO wiąże się z prawdopodobieństwem spłacenia pożyczki przez pożyczkobiorcę?
    2. W jaki sposób wiek kredytowy wiąże się z prawdopodobieństwem niewykonania zobowiązania i czy ryzyko to jest niezależne lub związane z wynikiem FICO
    3. W jaki sposób status kredytu hipotecznego na dom wiąże się z prawdopodobieństwem niewypłacalności?
    4. W jaki sposób roczny dochód wiąże się z prawdopodobieństwem niewykonania zobowiązania?
    5. W jaki sposób historia zatrudnienia wiąże się z prawdopodobieństwem niewykonania zobowiązania?
    6. Jak wielkość żądanej pożyczki jest powiązana z prawdopodobieństwem niewykonania zobowiązania?

3. Feature Engineering (60 pkt)

Utwórz 20 nowych zmiennych.

4. Modelowanie (150 pkt)

1. Wykonaj klasteryzację danych (wypróbuj do tego celu kilka metod, min. 3) i sprawdź, czy występują jakieś segmenty pożyczkobiorców, wykorzystaj odpowiednie metody do określenia optymalnej liczby klastrów (40pkt)
2. Wytrenuj 5 różnych modeli, wykorzystując do każdego inny algorytm, a następnie porównaj ich działanie, za metrykę oceny jakości modelu przyjmij AUROC score (50pkt)
3. Sprawdź działanie wcześniej użytych metod na skompresowanych danych za pomocą PCA, porównaj wyniki (AUROC score) z modelami wytrenowanymi w poprzednim podpunkcie (20pkt)
4. Zbuduj finalny model, którego AUROC score będzie >= 80%, pamiętaj o doborze istotnych zmiennych, kroswalidacji oraz dostrojeniu parametrów modelu, pomyśl również o zbalansowaniu klas (40pkt)

Za całość do zdobycia jest 380 punktów. Do zaliczenia projektu potrzeba minimum 300 pkt.

Importing packages / Import bibliotek

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.model_selection import KFold
from sklearn.model_selection import learning_curve
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import ShuffleSplit
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
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.svm import SVC

from sklearn.cluster import KMeans

from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import average_precision_score
from sklearn.metrics import precision_recall_curve


from sklearn.metrics import silhouette_score
from scipy.cluster.hierarchy import linkage
from scipy.cluster.hierarchy import dendrogram

from sklearn.decomposition import IncrementalPCA
from sklearn.decomposition import PCA
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import DBSCAN
from scipy.cluster.hierarchy import fcluster

from scipy import stats

from scipy.stats import ttest_1samp
from scipy.stats import ttest_ind
from scipy.stats import f_oneway
from scipy.stats import chi2_contingency

import xgboost as xgb
import pickle
from collections import Counter
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import GridSearchCV
```

```
from numpy import where
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline
```

Część 1 - Obróbka danych / Data processing

- Poprawne wczytanie danych z pliku
- Usunięcie kolumn które zawierają informacje z przyszłości, niedostępne w momencie udzielania pożyczki
- Usunięcie kolumn ze zbędnymi informacjami
- Usunięcie kolumn z tylko jedną unikalną wartością
- Rzut okiem na wartości w kolumnie ze statusem pożyczki
- Przekształcenie wartości w kolumnach - usunięcie procentów, dodatkowych znaków, itd
- Analiza brakujących wartości wraz z ich uzupełnieniem/usunięciem przy wzięciu pod uwagę pewnych ustalonych kryteriów

Poprawne wczytanie danych z pliku. Otwarcie i analiza obu plików .csv

Pobranie danych z pliku LCDataDictionary.csv.

Usuwam ostatnie dwa wiersze `NaN`. Usuwam puste kolumn z pliku LCDataDictionary.csv.

In [2]:
```
# load our dataset
lc_dict = pd.read_csv("LCDataDictionary.csv")
lc_dict.drop(lc_dict.columns[2:], inplace = True, axis = 1)
lc_dict.drop(lc_dict.tail(2).index, inplace = True)
lc_dict
```

Out[2]:

	LoanStatNew	Description
0	acc_now_delinq	The number of accounts on which the borrower i...
1	acc_open_past_24mths	Number of trades opened in past 24 months.
2	addr_state	The state provided by the borrower in the loan...
3	all_util	Balance to credit limit on all trades
4	annual_inc	The self-reported annual income provided by th...
...	...	...
146	settlement_status	The status of the borrower’s settlement plan. ...
147	settlement_date	The date that the borrower agrees to the settl...
148	settlement_amount	The loan amount that the borrower has agreed t...
149	settlement_percentage	The settlement amount as a percentage of the p...
150	settlement_term	The number of months that the borrower will be...

151 rows × 2 columns

Linki do opisu wszytskich kolumn

Link to LCDataDictionary_str1

Link to LCDataDictionary_str2

Link to LCDataDictionary_str3

Dane zasadnicze (pobrane z pliku Loan_data.csv)

Rzut oka na 3 pierwsze wiersze

In [3]:
```
# load our dataset
data_loan = pd.read_csv("Loan_data.csv")
data_loan.head(3)
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/IPython/core/interactiveshell.py:3457: DtypeWarning: Columns (0,49) have mixed types.Specify dtype option on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

Out[3]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installme
0	1077501	NaN	5000.0	5000.0	4975.0	36 months	10.65%	162.8
1	1077430	NaN	2500.0	2500.0	2500.0	60 months	15.27%	59.8
2	1077175	NaN	2400.0	2400.0	2400.0	36 months	15.96%	84.3

3 rows × 151 columns

Rzut oka na wiersze w środku tabeli, można zauważyć, że wiersz 39786, jest pusty. Dlatego go usuwam

In [4]:
```
data_loan.iloc[39784:39789]
```

Out[4]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	instal
39784	90376	NaN	5000.0	5000.0	650.000000	36 months	7.43%	1
39785	87023	NaN	7500.0	7500.0	800.000000	36 months	13.75%	2
39786	Loans that do not meet the credit policy	NaN	NaN	NaN	NaN	NaN	NaN	
39787	642818	NaN	2950.0	2950.0	2950.000000	60 months	15.95%	
39788	641659	NaN	20000.0	20000.0	16466.109187	60 months	19.66%	5

5 rows × 151 columns

In [5]:
```
data_loan.drop(index = 39786, axis = 0, inplace=True)
```

In [6]:
```
data_loan.iloc[39784:39789]
```

Out[6]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	instal
39784	90376	NaN	5000.0	5000.0	650.000000	36 months	7.43%	1
39785	87023	NaN	7500.0	7500.0	800.000000	36 months	13.75%	2
39787	642818	NaN	2950.0	2950.0	2950.000000	60 months	15.95%	
39788	641659	NaN	20000.0	20000.0	16466.109187	60 months	19.66%	5
39789	641638	NaN	3500.0	3500.0	3500.000000	60 months	15.57%	

5 rows × 151 columns

Rzut oka na trzy ostatnie wiersze, porównanie liczby wierszy z wartością data_loan.info()

In [7]:
```
data_loan.tail(3)
```

Out[7]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installr
42533	72176	NaN	2525.0	2525.0	225.0	36 months	9.33%	8
42534	71623	NaN	6500.0	6500.0	0.0	36 months	8.38%	20
42535	70686	NaN	5000.0	5000.0	0.0	36 months	7.75%	15

3 rows × 151 columns

Zwięzłe podsumowanie DataFrame - inf. o DataFrame, w tym indeksy dtype i kolumny, wartości inne niż null i użycie pamięci.

In [8]:
```
data_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 42535 entries, 0 to 42535
Columns: 151 entries, id to settlement_term
dtypes: float64(120), object(31)
memory usage: 49.3+ MB
```

Problem Charged Off

Charged OFF to odpis, jest to dług, na przykład na karcie kredytowej, którego odzyskanie przez kredytodawcę jest uważane za mało prawdopodobne, ponieważ po pewnym czasie pożyczkobiorca znacznie opóźnił spłatę należności. Jednak odpisanie nie oznacza całkowitego umorzenia długu. Spłata może oznaczać poważne konsekwencje dla historii kredytowej pożyczkobiorcy i przyszłej zdolności kredytowej.

Najważniejsze informacje

Odpis dotyczy długu, który według firmy nie będzie już ściągany, ponieważ pożyczkobiorca zalega z płatnościami. Umorzenie długu nie oznacza, że konsument nie musi już go spłacać. Po spłaceniu długu przez pożyczkodawcę może on sprzedać go zewnętrznej agencji windykacyjnej, która spróbuje pobrać go na koncie zaległych z płatnościami. Konsument jest winien dług do czasu jego spłaty, uregulowania, umorzenia w postępowaniu upadłościowym lub w przypadku postępowania sądowego, przedawnienia.

Jak działa odpis?

Odpisanie ma miejsce zwykle wtedy, gdy wierzyciel uznał, że niespłacony dług jest nieściągalny; zwykle następuje to po 180 dniach lub sześciu miesiącach braku płatności. Ponadto spłaty zadłużenia, które spadną poniżej wymaganej minimalnej spłaty za dany okres, zostaną również odpisane, jeżeli dłużnik nie uzupełni niedoboru. Kredytodawca wykreśla dług konsumenta jako nieściągalny i zaznacza go w raporcie kredytowym konsumenta jako umorzenie.

Skutkiem odpisu w raporcie kredytowym jest spadek zdolności kredytowej i trudności w uzyskaniu zgody na kredyt lub uzyskanie kredytu po przyzwoitym oprocentowaniu w przyszłości.

Spłata lub uregulowanie zaległego zadłużenia nie spowoduje usunięcia statusu odpisu z raportu kredytowego konsumenta. Zamiast tego status zostanie zmieniony na „odpis opłacony” lub „odpis rozliczony”. Tak czy inaczej, odpisy pozostają w raporcie kredytowym przez siedem lat, a strona poszkodowana będzie musiała albo poczekać siedem lat, albo negocjować z wierzycielem w celu usunięcia go po spłacie całego długu.

Zródło https://www.investopedia.com/terms/c/chargeoff.asp

Charged Off podsumowanie

Mówiąc w skrócie Charged Off nie jest jednoznaczne ze spłatą zadłużenia. Jest to niewykonanie zobowiązania w terminie + jakiś termin (180 dni lub 6 miesięcy), co wiąże się z tym, że pożyczkobiorca ma status pożyczki Charged Off, nawet jak po terminie zostanie uregulowana.

W danych jest kilkudziesięciu takich pożyczkobiorców, którzy ostatecznie spłacili pożyczkę, a mimo to mają ten status. Co pokazuję poniżej.

TARGET loan_status

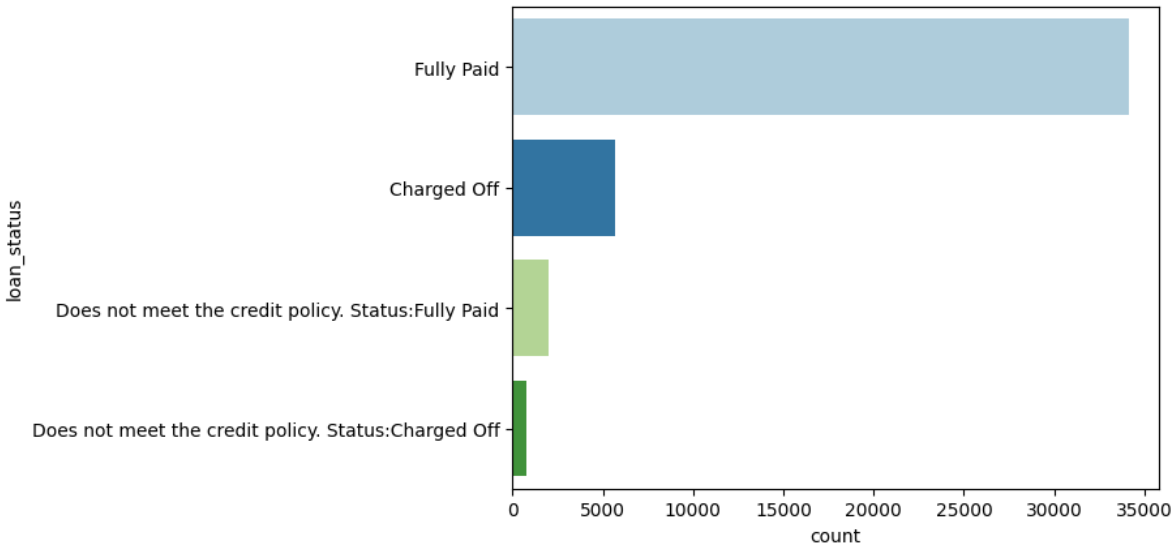
- Rzut okiem na wartości w kolumnie ze statusem pożyczki

In [9]:
```
data_loan['loan_status'].value_counts()
```

Out[9]:
```
Fully Paid                                            34116
Charged Off                                            5670
Does not meet the credit policy. Status:Fully Paid     1988
Does not meet the credit policy. Status:Charged Off     761
Name: loan_status, dtype: int64
```

In [10]:
```
sns.countplot(y=data_loan['loan_status'], palette="Paired")
```

Out[10]:
```
<AxesSubplot:xlabel='count', ylabel='loan_status'>
```



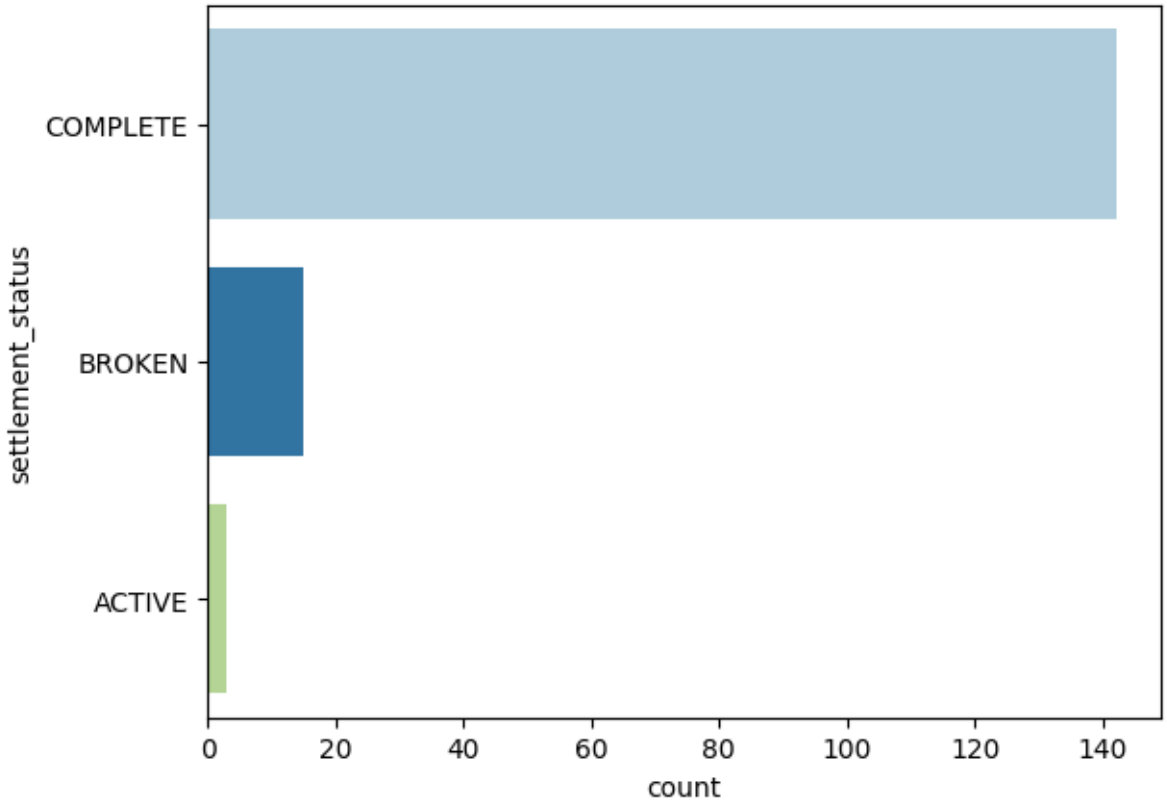
Po tym jak pożyczkobiorca nie spłacił z terminie kredytu, doszło w niektórych przypadkach do podpisania ugody. Tu mamy cechy: zakończona, przerwana i aktywna.

In [11]:
```
data_loan['loan_status'] = data_loan['loan_status'].replace({'Does not meet
data_loan['loan_status'] = data_loan['loan_status'].replace({'Does not meet
data_loan['loan_status'].value_counts()
```

Out[11]:
```
Fully Paid     36104
Charged Off     6431
Name: loan_status, dtype: int64
```

In [12]:
```
sns.countplot(y=data_loan['settlement_status'], palette="Paired")
```

Out[12]:
```
<AxesSubplot:xlabel='count', ylabel='settlement_status'>
```



Chcemy pokazać czy istnieją osoby, które mają utrzymany statut Charged Off mimo spłaty zadłużenia.

In [13]:
```
data_loan[(data_loan.loan_status == 'Charged Off') & (data_loan.settlement_
```

Out[13]:

	loan_status	settlement_status
105	Charged Off	COMPLETE
188	Charged Off	COMPLETE
255	Charged Off	COMPLETE
362	Charged Off	COMPLETE
430	Charged Off	COMPLETE
...	...	...
41344	Charged Off	COMPLETE
41578	Charged Off	COMPLETE
41622	Charged Off	COMPLETE
41927	Charged Off	COMPLETE
42500	Charged Off	COMPLETE

142 rows × 2 columns

Okazuje się, że w danych są 142 osoby, które mają status Charged Off i spłacone zobowiązanie.

Charged Off i Fully Paid

Na potrzeby tego projektu zakładam już do końca, że mamy dwa statusy kredytu:

- Fully Paid - spłata pożyczki
- Charged Off - brak spłaty pożyczki

Informacje o rzeczywistym statusie omówionym powyżej, o ugodach i zawiłościach tej procedury, pomijam w dalszej części mojej analizy.

Wnioski:

Zmienna jest zdrowa. W późniejszej części połączę statusy w dwie kategorie i wykonam encoding, aby użyć ją do modelowania.

Uzupełnianie pustych wartości, usuwanie niepotrzebnych kolumn...

W następnych krokach analizuję wszystkie kolumny (cechy). Dla wygody podglądam je kawałkami tabeli.

In [14]:
```
data_loan.iloc[:5,:11]
```

Out[14]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installme
0	1077501	NaN	5000.0	5000.0	4975.0	36 months	10.65%	162.8
1	1077430	NaN	2500.0	2500.0	2500.0	60 months	15.27%	59.8
2	1077175	NaN	2400.0	2400.0	2400.0	36 months	15.96%	84.3
3	1076863	NaN	10000.0	10000.0	10000.0	36 months	13.49%	339.3
4	1075358	NaN	3000.0	3000.0	3000.0	60 months	12.69%	67.7

In [15]:
```
data_loan.isna().sum()
```

Out[15]:
```
id                          0
member_id               42535
loan_amnt                   0
funded_amnt                 0
funded_amnt_inv             0
                        ...
settlement_status       42375
settlement_date         42375
settlement_amount       42375
settlement_percentage   42375
settlement_term         42375
Length: 151, dtype: int64
```

Usunięcie kolumn: id, member_id,

In [16]:
```
data_loan.drop(['member_id', 'id'], axis=1, inplace=True)
```

Usunięcie brakujących wartości.

In [17]:
```
data_loan.dropna(axis=1, how='all', inplace=True)
```

In [18]:
```
data_loan.dropna(axis=0, how='all', inplace=True)
```

In [19]:
```
total = data_loan.isnull().sum().sort_values(ascending=False)
percent = (data_loan.isnull().sum()/data_loan.isnull().count()).sort_values

missing_data = pd.concat([total, percent], axis=1, keys=["Total", "Percent 
missing_data.head(25)
```

Out[19]:

	Total	Percent %
settlement_term	42375	99.623839
settlement_percentage	42375	99.623839
settlement_amount	42375	99.623839
settlement_date	42375	99.623839
settlement_status	42375	99.623839
debt_settlement_flag_date	42375	99.623839
next_pymnt_d	39786	93.537087
mths_since_last_record	38884	91.416481
mths_since_last_delinq	26926	63.303162
desc	13293	31.251910
emp_title	2626	6.173739
pub_rec_bankruptcies	1365	3.209122
emp_length	1112	2.614318
collections_12_mths_ex_med	145	0.340896
chargeoff_within_12_mths	145	0.340896
tax_liens	105	0.246856
revol_util	90	0.211590
last_pymnt_d	83	0.195133
acc_now_delinq	29	0.068179
earliest_cr_line	29	0.068179
pub_rec	29	0.068179
open_acc	29	0.068179
delinq_amnt	29	0.068179
inq_last_6mths	29	0.068179
total_acc	29	0.068179

Odsetek brakujących danych w niektórych kolumnach i liczba tych kolumn są tak duże, że trudno je wszystkie przeanalizować. Będzie trzeba usunąć pewien procent kolumn, gdzie nulli jest powyżej jakiegoś procentu. Na początek usuwam kolumny, gdzie danych brakujących jest powyżej 90%.

In [20]:
```
data_loan.drop(['settlement_term', 'settlement_percentage', 'settlement_amo
                'debt_settlement_flag_date', 'next_pymnt_d', 'mths_since_la
```

int_rate

Przekształcenie wartości w kolumnach - usunięcie procentów

In [21]:
```
data_loan.int_rate = pd.Series(data_loan.int_rate).str.replace('%', '').ast
data_loan.int_rate
```

Out[21]:
```
0        10.65
1        15.27
2        15.96
3        13.49
4        12.69
         ...
42531    10.28
42532     9.64
42533     9.33
42534     8.38
42535     7.75
Name: int_rate, Length: 42535, dtype: float64
```

Zmiennymi kategorycznymi: grade i sub_grade, home_ownership, verification_status oraz targetem loan_status:

- zajmę się w późniejszej części

Wyświetlenie DF poprzez indeksowanie oparte wyłącznie na liczbach całkowitych do wyboru według pozycji.

In [22]:
```
data_loan.iloc[:5, 0:15]
```

Out[22]:

	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade
0	5000.0	5000.0	4975.0	36 months	10.65	162.87	B	B2
1	2500.0	2500.0	2500.0	60 months	15.27	59.83	C	C4
2	2400.0	2400.0	2400.0	36 months	15.96	84.33	C	C5
3	10000.0	10000.0	10000.0	36 months	13.49	339.31	C	C1
4	3000.0	3000.0	3000.0	60 months	12.69	67.79	B	B5

In [23]:
```
data_loan.isna().sum()
```

Out[23]:

loan_amnt	0
funded_amnt	0
funded_amnt_inv	0
term	0
int_rate	0
installment	0
grade	0
sub_grade	0
emp_title	2626
emp_length	1112
home_ownership	0
annual_inc	4
verification_status	0
issue_d	0
loan_status	0
pymnt_plan	0
url	0
desc	13293
purpose	0
title	13
zip_code	0
addr_state	0
dti	0
delinq_2yrs	29
earliest_cr_line	29
fico_range_low	0
fico_range_high	0
inq_last_6mths	29
mths_since_last_delinq	26926
open_acc	29
pub_rec	29
revol_bal	0
revol_util	90
total_acc	29
initial_list_status	0
out_prncp	0
out_prncp_inv	0
total_pymnt	0
total_pymnt_inv	0
total_rec_prncp	0
total_rec_int	0
total_rec_late_fee	0
recoveries	0
collection_recovery_fee	0
last_pymnt_d	83
last_pymnt_amnt	0
last_credit_pull_d	4
last_fico_range_high	0
last_fico_range_low	0
collections_12_mths_ex_med	145
policy_code	0
application_type	0
acc_now_delinq	29
chargeoff_within_12_mths	145
delinq_amnt	29
pub_rec_bankruptcies	1365
tax_liens	105
hardship_flag	0
disbursement_method	0
debt_settlement_flag	0

dtype: int64

emp_title

Opisy zawodów mają 2626 wartości pustych, dodatkowo są tak zróżnicowane, to są opisy wpisywane przez pożyczkobiorców, także wszelkie relacje miedzy słowami czy frazami mogą dawać mylne wartości. Osoby mogły podawać swoje nazwy zawodów w sposób przekoloryzowany. Ta kolumna jest do usunięcia.

In [24]:
```
data_loan.drop(['emp_title'], axis=1, inplace=True)
```

emp_length

Można zakładać, że ktoś kto nie ma wpisanej długości zatrudnienia, czy historii kredytowej jest młody, nie ma pracy, majątku, np. student, ale czy tak jest na pewno? Może 'purpose' pokaże czy to jest grupa studentów, czy niekoniecznie? Dla studenta pierwszym kredytem byłaby prawdopodobnie edukacja, np. kredyt na studia. W takiej sytuacji zmieniłbym nulle w tej zmiennej na 0 w przeciwym wypadku zamienię na modę (dominantę). Dominantą, w sensie szkolnym, nazywamy wartość występującą w danym zbiorze najczęściej.

In [25]:
```
data_loan.emp_length.isnull().sum()
```

Out[25]:
```
1112
```

In [26]:
```
data_loan['emp_length'].value_counts()
```

Out[26]:
```
10+ years    9369
< 1 year     5062
2 years      4743
3 years      4364
4 years      3649
1 year       3595
5 years      3458
6 years      2375
7 years      1875
8 years      1592
9 years      1341
Name: emp_length, dtype: int64
```

In [27]:
```
data_loan[data_loan.emp_length.isna()].purpose
```

Out[27]:
```
168      debt_consolidation
323      debt_consolidation
394        home_improvement
422           major_purchase
439      debt_consolidation
                ...
40583              medical
40667                other
40672                other
40697    debt_consolidation
40731           educational
Name: purpose, Length: 1112, dtype: object
```

Celem kredytu nie jest edukacja, czyli niekoniecznie jest to student dlatego uzupełniam puste wartości dominantą, aby zróżnicować dane:

- Zamieniam `str` na `int`.

In [28]:
```
data_loan.replace('n/a', np.nan, inplace=True)
data_loan["emp_length"]= data_loan["emp_length"].fillna(data_loan["emp_leng
```

```
data_loan['emp_length'].replace(to_replace='[^0-9]+', value='', inplace=Tru
data_loan['emp_length'] = data_loan['emp_length'].astype(int)
```

In [29]:
```
data_loan['emp_length'].value_counts()
```

Out[29]:
```
10    10481
1      8657
2      4743
3      4364
4      3649
5      3458
6      2375
7      1875
8      1592
9      1341
Name: emp_length, dtype: int64
```

annual_inc

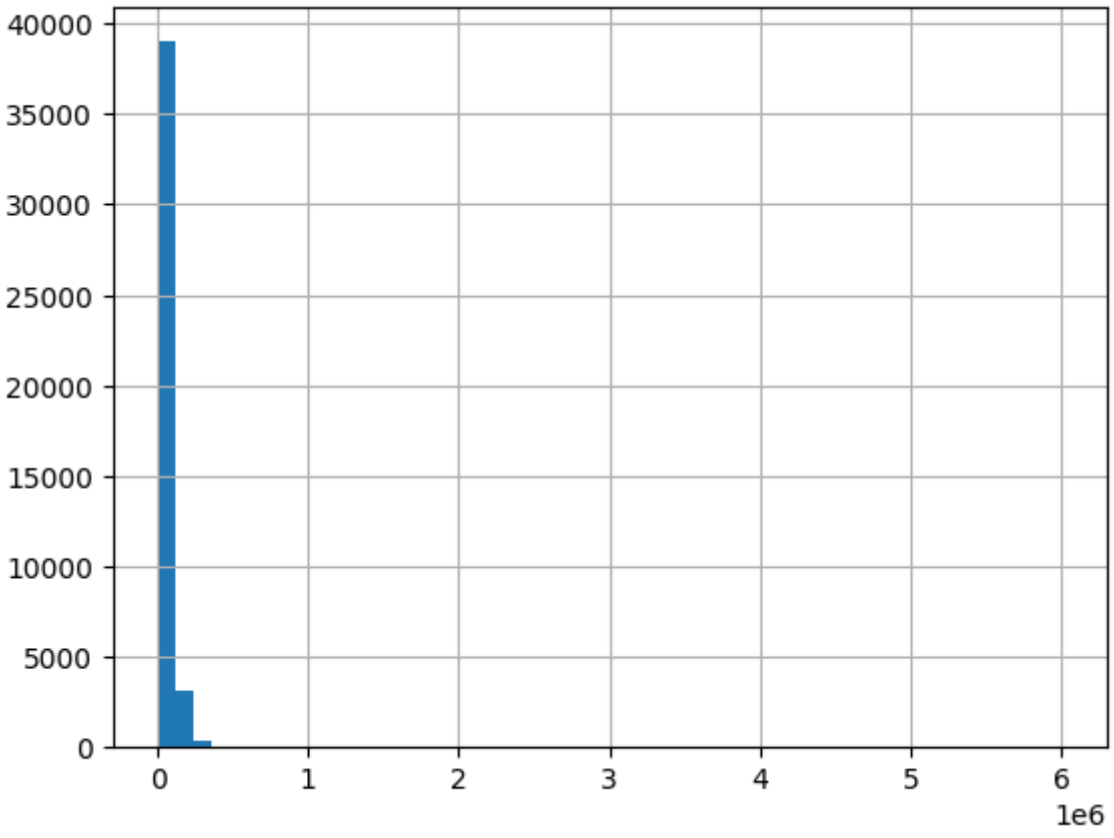
Mamy 4 pozycje, które nie są wypełnione wysokością dochodu rocznego, zakładam, że dochód w annual_inc w pustych wartościach wynika z tego, że jest pomyłkowo niewpisany, uzupełniam wartością najczęściej występującą, czyli dominantą

In [30]:
```
data_loan.annual_inc.isnull().sum()
```

Out[30]:
```
4
```

In [31]:
```
data_loan.annual_inc.hist(bins=50)
```

Out[31]:
```
<AxesSubplot:>
```



In [32]:
```
data_loan[data_loan.annual_inc.isna()].purpose
```

Out[32]:
```
42450    other
42451    other
42481    other
42534    other
Name: purpose, dtype: object
```

In [33]:
```
data_loan.annual_inc.fillna(data_loan.annual_inc.mode()[0], inplace=True)
data_loan.annual_inc
```

Out[33]:
```
0         24000.0
1         30000.0
2         12252.0
3         49200.0
4         80000.0
           ...
42531    180000.0
42532     12000.0
42533    110000.0
42534     60000.0
42535     70000.0
Name: annual_inc, Length: 42535, dtype: float64
```

In [34]:
```
data_loan.iloc[:5, 13:23]
```

Out[34]:

	loan_status	pymnt_plan	url	desc	purpose
0	Fully Paid	n	https://lendingclub.com/browse/loanDetail.acti...	Borrower added on 12/22/11 > I need to upgra...	credit_card
1	Charged Off	n	https://lendingclub.com/browse/loanDetail.acti...	Borrower added on 12/22/11 > I plan to use t...	car
2	Fully Paid	n	https://lendingclub.com/browse/loanDetail.acti...	NaN	small_business
3	Fully Paid	n	https://lendingclub.com/browse/loanDetail.acti...	Borrower added on 12/21/11 > to pay for prop...	other
4	Fully Paid	n	https://lendingclub.com/browse/loanDetail.acti...	Borrower added on 12/21/11 > I plan on combi...	other

pymnt_plan, url, desc

Zmienne url, desc są tekstowe, bardzo róznorodne, nie dające bezpośredniej relacji z targetem. Zmienna pymnt_plan ma wszystkie jednakowe == n (no). Dlatego je usuwam

In [35]:
```
data_loan[data_loan['pymnt_plan'] != 'n']
```

Out[35]:

loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	em

0 rows × 59 columns

In [36]:
```
# Drop unneccesary column
data_loan.drop(['pymnt_plan','url','desc', 'funded_amnt_inv'], axis=1, inpl
```

purpose, title, zip_code

In [37]:
```
print (data_loan.purpose.value_counts())
```

```
debt_consolidation    19776
credit_card            5477
other                  4425
home_improvement       3199
major_purchase         2311
small_business         1992
car                    1615
wedding                1004
medical                 753
moving                  629
house                   426
educational             422
vacation                400
renewable_energy        106
Name: purpose, dtype: int64
```

In [38]:
```
print (data_loan.title.value_counts())
```

```
Debt Consolidation                  2259
Debt Consolidation Loan             1760
Personal Loan                        708
Consolidation                        547
debt consolidation                   532
                                    ...
CitiCard PayOff                        1
Taxes Loan                             1
Blazing in 5 years                     1
I was scammed and now recovering       1
Aroundthehouse                         1
Name: title, Length: 21264, dtype: int64
```

Purpose jest prawdopodobnie wybierane z listy rozwijanej przy składaniu wniosku, natomiast title jest opisem wnioskodawcy i podobnie jak desc nie daje wiążących relacji, bo często jest to 'radosna twórczość' wnioskodawcy. Usuniecie kolumny 'title' zrobię później

In [39]:
```
# usuniecie kolumny 'title' zrobię później
data_loan.drop(['zip_code'], axis=1, inplace=True)
```

deling_2yrs

Jest grupa recordów (29 pozycji), które są puste w kilku poniższych kolumnach. Ten wskaźnik (deling_2yrs) to liczba przypadków przeterminowania o ponad 30 dni wpisanych w aktach kredytowych pożyczkobiorcy z ostatnich 2 lat. Można domniemywać, że skoro w 29 przypadkach to pole jest puste, to wartość powinna być zero, tu ta najczęściej występująca.

Tym bardziej, że może to być grupa osób, które w większości wcześniej nie miały historii kredytowej. Trzy z tych osób nie spłaciły kredytu. Jedna z nich brała pożyczkę w celu konsolidacji, czyli musiała mieć jakąś historię kredytową.

In [40]:
```
data_loan.delinq_2yrs.isnull().sum()
```

Out[40]:
```
29
```

Najczęściej występujące wartości w danej kolumnie

In [41]:
```
data_loan.delinq_2yrs.value_counts()
```

Out[41]:
```
0.0     37771
1.0      3595
2.0       771
3.0       244
4.0        72
5.0        27
6.0        13
7.0         6
8.0         3
11.0        2
9.0         1
13.0        1
Name: delinq_2yrs, dtype: int64
```

Rzut oka na daną kolumnę. sprawdzenie gdzie są puste wartości i sprawdzenie: 'purpose' i 'title' dla tej kolumny

In [42]:
```
data_loan[data_loan.delinq_2yrs.isnull()][['purpose', 'title']]
```

Out[42]:

	purpose	title
42450	other	Moving expenses
42451	other	Education
42460	other	Paying medical bill
42473	other	Moving to Florida
42481	other	Moving expenses and security deposit
42484	other	New Bathroom
42495	other	Consolidate 2 high-interest rate loans
42510	debt_consolidation	Consolidate credit cards
42515	other	College Debt Consolidation
42516	other	Credit Card
42517	other	Starting a new job in a new city
42518	other	Paying down high interest credit cards
42519	other	Indonesia Underwater Photography
42520	other	vacation loan
42521	other	Moving Expenses for relocation
42522	other	Credit card refinancing
42523	other	Lowering My Interest Costs
42524	other	Credit Card Payments
42525	other	Credit card debt
42526	other	roof
42527	other	Dep4774
42528	other	Home improvement
42529	other	Summer stuff
42530	other	One-Debt Loan
42531	other	Wedding coming up
42532	other	delight
42533	other	Car repair bill
42534	other	Buying a car
42535	other	Aroundthehouse

Rzut oka na dane z pustymi wartościami dla kolumn: 'loan_status' i sprawdzenie czy zawiera ta kolumna wartość 'Charged Off'

In [43]:
```
df = data_loan[data_loan.delinq_2yrs.isnull()]['loan_status']
df.str.contains('Charged Off')
```

Out[43]:
```
42450    False
42451    False
42460    False
42473    False
42481    False
42484    False
42495    False
42510    False
42515    False
42516    False
42517    False
42518    False
42519    False
42520    False
42521    False
42522     True
42523    False
42524    False
42525     True
42526    False
42527    False
42528    False
42529    False
42530     True
42531    False
42532    False
42533    False
42534    False
42535    False
Name: loan_status, dtype: bool
```

Rzut oka na dane z pustymi wartościami dla kolumn: 'purpose' i sprawdzenie czy ta kolumna równa się wartość 'debt_consolidation'

In [44]:
```
data_loan[data_loan.delinq_2yrs.isnull()].purpose == 'debt_consolidation'
```

Out[44]:
```
42450    False
42451    False
42460    False
42473    False
42481    False
42484    False
42495    False
42510     True
42515    False
42516    False
42517    False
42518    False
42519    False
42520    False
42521    False
42522    False
42523    False
42524    False
42525    False
42526    False
42527    False
42528    False
42529    False
42530    False
42531    False
42532    False
42533    False
42534    False
42535    False
Name: purpose, dtype: bool
```

Uzupełnienie pustych warotści dominantą, czyli najczęściej występującą wartością w kolumnie

In [45]:
```
data_loan.delinq_2yrs.fillna(data_loan.delinq_2yrs.mode()[0], inplace=True)
```

earliest_cr_line, issue_d

Poniżej widać, że to są te same rekordy. To kolejna kolumna, która ma 29 nulli. Wśród nich trzy niespłacone kredyty. 3/29 to daje 1% niespłaconych. Ogólnie jest 42535 wszystkich pożyczek w tym 6431 niespłaconych, co daje podobny procent 0.015. Z jednej strony im dłużej spłacasz kredyty, tym jesteś wiarygodmiejszy. Ale im jesteś starszy, tym możesz szybciej stracić pracę lub być chory czy nawet umrzeć. Wzrasta prawdopodobieństwo Twojej niewypłacalności. Podobnie jak wyżej wydawałoby się, że to jest grupa młodych, studentów, bez kredytów i historii. Tymczasem są to ludzie, którzy mają hipoteki, biorą kredyt na nową łazienkę, wynajmują mieszkania, chcą skonsolidować kredyty. Uzupełnienie pustych wartości zrobię przez wartość mediany.

In [46]:
```
data_loan.groupby('loan_status')['loan_amnt'].count()
```

Out[46]:
```
loan_status
Charged Off     6431
Fully Paid     36104
Name: loan_amnt, dtype: int64
```

In [47]:
```
data_loan.earliest_cr_line.isnull().sum()
```

Out[47]:
```
29
```

In [48]:
```
data_loan[data_loan.earliest_cr_line.isnull()][['home_ownership', 'purpose'
```

Out[48]:

	home_ownership	purpose	title
42450	NONE	other	Moving expenses
42451	NONE	other	Education
42460	RENT	other	Paying medical bill
42473	RENT	other	Moving to Florida
42481	NONE	other	Moving expenses and security deposit
42484	MORTGAGE	other	New Bathroom
42495	RENT	other	Consolidate 2 high-interest rate loans
42510	MORTGAGE	debt_consolidation	Consolidate credit cards
42515	RENT	other	College Debt Consolidation
42516	RENT	other	Credit Card
42517	RENT	other	Starting a new job in a new city
42518	RENT	other	Paying down high interest credit cards
42519	MORTGAGE	other	Indonesia Underwater Photography
42520	MORTGAGE	other	vacation loan
42521	MORTGAGE	other	Moving Expenses for relocation
42522	MORTGAGE	other	Credit card refinancing
42523	RENT	other	Lowering My Interest Costs
42524	RENT	other	Credit Card Payments
42525	RENT	other	Credit card debt
42526	RENT	other	roof
42527	RENT	other	Dep4774
42528	OWN	other	Home improvement
42529	RENT	other	Summer stuff
42530	RENT	other	One-Debt Loan
42531	RENT	other	Wedding coming up
42532	RENT	other	delight
42533	RENT	other	Car repair bill
42534	NONE	other	Buying a car
42535	MORTGAGE	other	Aroundthehouse

In [49]:
```
data_loan[data_loan.earliest_cr_line.isna()].loan_status.value_counts()
```

Out[49]:
```
Fully Paid     26
Charged Off     3
Name: loan_status, dtype: int64
```

Przekształcenie wartości (str na datę i godzinę) w kolumnach 'issue_d' i 'earliest_cr_line' - usunięcie procentów, dodatkowych znaków, itd

In [50]:
```
data_loan['earliest_cr_line'].sample(5)
```

Out[50]:
```
26379    Mar-2000
31769    Feb-1991
12735    Mar-1999
20923    Apr-1987
2325     Jan-1998
Name: earliest_cr_line, dtype: object
```

Konwertowanie argumentów na datę i godzinę.

In [51]:
```
# Convert to date time
data_loan['earliest_cr_line'] = pd.to_datetime(data_loan['earliest_cr_line'
data_loan['earliest_cr_line'].value_counts(ascending=False).head()
```

Out[51]:
```
1999-10-01    393
1998-11-01    390
2000-10-01    370
1998-12-01    366
1997-12-01    348
Name: earliest_cr_line, dtype: int64
```

Konwertowanie argumentów na datę i godzinę.

In [52]:
```
data_loan['issue_d'] = pd.to_datetime(data_loan['issue_d'])
data_loan['issue_d'].value_counts(ascending=False).head()
```

Out[52]:
```
2011-12-01    2267
2011-11-01    2232
2011-10-01    2118
2011-09-01    2067
2011-08-01    1934
Name: issue_d, dtype: int64
```

In [53]:
```
data_loan['issue_d']= pd.to_datetime(data_loan['issue_d'])
```

Wypełniam wartości NA/NaN przy użyciu określonej metody `fillna`. Puste wartości wypełniam metodą `fillna` wartościami z kolumny `issue_d`.

In [54]:
```
data_loan['earliest_cr_line']= data_loan['earliest_cr_line'].fillna(data_lo
```

In [55]:
```
data_loan.iloc[:5, 11:19]
```

Out[55]:

	issue_d	loan_status	purpose	title	addr_state	dti	delinq_2yrs	earliest_cr_lin
0	2011-12-01	Fully Paid	credit_card	Computer	AZ	27.65	0.0	1985-01-0
1	2011-12-01	Charged Off	car	bike	GA	1.00	0.0	1999-04-0
2	2011-12-01	Fully Paid	small_business	real estate business	IL	8.72	0.0	2001-11-0
3	2011-12-01	Fully Paid	other	personel	CA	20.00	0.0	1996-02-0
4	2011-12-01	Fully Paid	other	Personal	OR	17.94	0.0	1996-01-0

fico_range_low i fico_range_high

Oddzielne zakresy fico nie są przydatne, są skorelowane na 1, stworzyłem nową kolumnę

ze średnią z fico i usuwam kolumny zakresów dolnego i górnego.

In [56]:
```
data_loan[['fico_range_low', 'fico_range_high']].describe()
```

Out[56]:

	fico_range_low	fico_range_high
count	42535.000000	42535.000000
mean	713.052545	717.052545
std	36.188439	36.188439
min	610.000000	614.000000
25%	685.000000	689.000000
50%	710.000000	714.000000
75%	740.000000	744.000000
max	825.000000	829.000000

In [57]:
```
data_loan[['fico_range_low','fico_range_high']].corr()
```

Out[57]:

	fico_range_low	fico_range_high
fico_range_low	1.0	1.0
fico_range_high	1.0	1.0

In [58]:
```
data_loan['fico_mean'] = (data_loan.fico_range_low + data_loan.fico_range_h
```

In [59]:
```
data_loan.drop(['fico_range_low','fico_range_high'],1, inplace=True)
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1:
FutureWarning: In a future version of pandas all arguments of DataFrame.dro
p except for the argument 'labels' will be keyword-only
  """Entry point for launching an IPython kernel.
```

inq_last_6mths

Ta sama grupa 29 rekordów, o których jednoznacznie nie można powiedzieć, czy mają dochody, czy mieli wcześniej kredyty, czy zwlekali z płaceniem rat. Uzupełniam jak poprzednio mode. Ten wskaźnik to liczba zapytań.

In [60]:
```
data_loan.inq_last_6mths.isnull().sum()
```

Out[60]:
```
29
```

In [61]:
```
data_loan['inq_last_6mths'].value_counts()
```

Out[61]:
```
0.0     19657
1.0     11247
2.0      5987
3.0      3182
4.0      1056
5.0       596
6.0       339
7.0       182
8.0       115
9.0        50
10.0       24
11.0       15
12.0       15
15.0        9
13.0        6
14.0        6
18.0        4
16.0        3
17.0        2
24.0        2
19.0        2
32.0        1
33.0        1
31.0        1
28.0        1
25.0        1
27.0        1
20.0        1
Name: inq_last_6mths, dtype: int64
```

In [62]:
```
data_loan['inq_last_6mths'].median()
```

Out[62]:
```
1.0
```

In [63]:
```
data_loan['inq_last_6mths'].mode()[0]
```

Out[63]:
```
0.0
```

In [64]:
```
data_loan['inq_last_6mths'].mean()
```

Out[64]:
```
1.0814237989930833
```

In [65]:
```
data_loan['inq_last_6mths'] = data_loan['inq_last_6mths'].fillna(data_loan[
```

mths_since_last_delinq

Wskaźnik, który mówi o liczbie m-cy od ostatniej zaległości. Wartości brakujących jest ponad 26 tys, czyli ponad połowa 63%. Uzupełniam medianą - wartością środkową. Tymczasem zostawiam tę kolumnę, ale liczba pustych wartości wskazuje na jej usunięcie.

In [66]:
```
data_loan.mths_since_last_delinq.isnull().sum()
```

Out[66]:
```
26926
```

In [67]:
```
data_loan['mths_since_last_delinq'].value_counts()
```

Out[67]:
```
0.0      821
30.0     270
19.0     266
23.0     266
15.0     263
        ...
89.0       1
107.0      1
85.0       1
97.0       1
95.0       1
Name: mths_since_last_delinq, Length: 95, dtype: int64
```

In [68]:
```
data_loan['mths_since_last_delinq'].unique()
```

Out[68]:
```
array([ nan,  35.,  38.,  61.,   8.,  20.,  18.,  68.,  45.,  48.,  41.,
        40.,  74.,  25.,  53.,  39.,  10.,  26.,  56.,  77.,  28.,  52.,
        24.,  16.,  60.,  54.,  23.,   9.,  11.,  13.,  65.,  19.,  80.,
        22.,  59.,  79.,  44.,  64.,  57.,  14.,  63.,  49.,  15.,  73.,
        70.,  29.,  51.,   5.,  75.,  55.,   2.,  30.,  47.,  33.,  69.,
         4.,  43.,  21.,  27.,  46.,  81.,  78.,  82.,  31.,  76.,  62.,
        72.,  42.,  50.,   3.,  12.,  67.,  36.,  34.,  58.,  17.,  71.,
        66.,  32.,   6.,  37.,   7.,   1.,  83.,  86., 115.,  96., 103.,
       120., 106.,  89., 107.,  85.,  97.,  95.,   0.])
```

In [69]:
```
data_loan['mths_since_last_delinq'].median()
```

Out[69]:
```
33.0
```

In [70]:
```
data_loan['mths_since_last_delinq'].mode()[0]
```

Out[70]:
```
0.0
```

In [71]:
```
data_loan['mths_since_last_delinq'] = data_loan['mths_since_last_delinq'].f
```

open_acc

Ta sama grupa 29 rekordow, tu liczba otwartych lini (rachunków) kredytowych. Podobnie jak wcześniej, można przypuszczać, że ich nie ma, czyli powinienem uzupełnić zerami, ale jednak są wśród klienci, którzy konsolidują kredyty. Czyli musieli mieć otwarte inne rachunki kredytowe.

In [72]:
```
data_loan.open_acc.isnull().sum()
```

Out[72]:
```
29
```

In [73]:
```
data_loan['open_acc'].mode()[0]
```

Out[73]:
```
7.0
```

In [74]:
```
data_loan['open_acc'].median()
```

Out[74]:
```
9.0
```

In [75]:
```
data_loan['open_acc'].mean()
```

Out[75]:
```
9.343951442149343
```

In [76]:
```
data_loan['open_acc'].value_counts()
```

Out[76]:
```
7.0     4252
8.0     4176
6.0     4172
9.0     3922
10.0    3386
5.0     3368
11.0    2944
4.0     2508
12.0    2398
13.0    2060
3.0     1608
14.0    1597
15.0    1290
16.0    1022
17.0     812
2.0      692
18.0     588
19.0     442
20.0     335
21.0     276
22.0     170
23.0     121
24.0      87
25.0      63
26.0      40
1.0       39
27.0      29
28.0      29
30.0      17
29.0      16
31.0      13
34.0       8
32.0       6
33.0       5
35.0       4
36.0       2
38.0       2
37.0       1
46.0       1
39.0       1
42.0       1
41.0       1
44.0       1
47.0       1
Name: open_acc, dtype: int64
```

In [77]:
```
data_loan['open_acc']= data_loan['open_acc'].fillna(data_loan['open_acc'].m
```

pub_rec

Ta sama grupa rekordów. 29 pustych. Ta cecha mówi o liczbie rejestrów, gdzie zostali wpisani klienci nierzetelni. Podobnie uzupełniam modą.

In [78]:
```
data_loan['pub_rec'].isnull().sum()
```

Out[78]:
```
29
```

In [79]:
```
data_loan['pub_rec'].median()
```

Out[79]:
```
0.0
```

In [80]:
```
data_loan['pub_rec'].mode()[0]
```

Out[80]:
```
0.0
```

In [81]:
```
data_loan['pub_rec']= data_loan['pub_rec'].fillna(data_loan['pub_rec'].mode
```

revol_util / Przekształcenie wartości w kolumnach - usunięcie procentów, dodatkowych znaków, itd

Stopa procentowa wykorzystania lini kredytowej. Im mniej wykorzystane tym mniejsza kwota do spłaty, zatem pewnie im mniejsza tendencja do niespłacania. To jest wartość numeryczna, do uzupełnienia nulli wykorzystam medianę.

In [82]:
```
data_loan.revol_util.isnull().sum()
```

Out[82]:
```
90
```

In [83]:
```
data_loan.revol_util = pd.Series(data_loan.revol_util).str.replace('%', '')
```

In [84]:
```
data_loan['revol_util'].value_counts(ascending=False)
```

Out[84]:
```
0.00      1070
40.70       65
0.20        64
63.00       63
66.60       62
          ...
21.59        1
39.95        1
0.01         1
17.67        1
105.70       1
Name: revol_util, Length: 1119, dtype: int64
```

In [85]:
```
data_loan['revol_util']= data_loan['revol_util'].fillna(data_loan['revol_ut
```

In [86]:
```
data_loan.iloc[:5, 24:34]
```

Out[86]:

	revol_util	total_acc	initial_list_status	out_prncp	out_prncp_inv	total_pymnt	total_pymnt_
0	83.7	9.0	f	0.0	0.0	5863.155187	5833
1	9.4	4.0	f	0.0	0.0	1014.530000	1014
2	98.5	10.0	f	0.0	0.0	3005.666844	3005
3	21.0	37.0	f	0.0	0.0	12231.890000	12231
4	53.9	38.0	f	0.0	0.0	4066.908161	4066

total_acc

Całkowita liczba lini kredytowych. Znów z grupy tych 29 recordów, uzupełniam medianą.

In [87]:
```
data_loan['total_acc'].isnull().sum()
```

Out[87]:
```
29
```

In [88]:
```
data_loan['total_acc']= data_loan['total_acc'].fillna(data_loan['total_acc'
```

Usuwanie innych kolumn / Usunięcie kolumn tylko jedną unikalną wartością

Cechy, które mają jednakowe wartości lub nie mają lub mają mały wpływ na pożyczkobiorcę, czy spłaci czy nie kredyt. initial_list_status - same 'f'; out_prncp - same zera; out_prncp_inv - same zera; total_pymnt, total_pymnt_inv, total_rec_prncp i total_rec_int, recoveries, collection_recovery_fee, collection_recovery_fee. I title. funded_amnt_inv dotyczy sfinansowania kredytu przez inwestorów. Część z tych kolumn ma pojedyncze jednakowe wartości collections_12_mths_ex_med - 0

In [89]:
```
data_loan.drop(['initial_list_status', 'total_pymnt_inv', 'out_prncp', 'out
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1:
FutureWarning: In a future version of pandas all arguments of DataFrame.dro
p except for the argument 'labels' will be keyword-only
  """Entry point for launching an IPython kernel.
```

Nad tymi pozycjami się zastanawiam czy je badać, hipotetycznie można uważać, że jak ktoś już ma spłaconą prawie całą pożyczkę, to ma większą chęć już domknąć ten temat i spłacić całość. Czyli można znaleźć kontekst. Tymczasem je usuwam.

In [90]:
```
data_loan.drop([ 'total_pymnt', 'total_rec_prncp', 'total_rec_int', 'total_
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1:
FutureWarning: In a future version of pandas all arguments of DataFrame.dro
p except for the argument 'labels' will be keyword-only
  """Entry point for launching an IPython kernel.
```

In [91]:
```
data_loan.iloc[:5, 37:44]
```

Out[91]:

	pub_rec_bankruptcies	tax_liens	hardship_flag	disbursement_method	debt_settlement_flag
0	0.0	0.0	N	Cash	N
1	0.0	0.0	N	Cash	N
2	0.0	0.0	N	Cash	N
3	0.0	0.0	N	Cash	N
4	0.0	0.0	N	Cash	N

In [92]:
```
data_loan['collections_12_mths_ex_med'].value_counts()
```

Out[92]:
```
0.0    42390
Name: collections_12_mths_ex_med, dtype: int64
```

In [93]:
```
data_loan.drop(['collection_recovery_fee', 'last_pymnt_d','last_pymnt_amnt'
                'collections_12_mths_ex_med'], 1, inplace=True)
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:2:
FutureWarning: In a future version of pandas all arguments of DataFrame.dro
p except for the argument 'labels' will be keyword-only
```

last fico_range_low i last fico_range_high

Oddzielne zakresy last_fico nie są przydatne, stworzyłem nową kolumnę ze średnią z last_fico i usuwam kolumny zakresów dolnego i górnego. Nie mam wiedzy, kiedy zostają

wyliczane te last_fico, bo jeśli po spłacie kredytu, to nie mają wpływu na nasz target i można je usunąć. Dziwne jest to, że minimalna wartość obu zakresów to 0, czyli są wartości wpisane jako 0.

In [94]:
```
data_loan[['last_fico_range_high','last_fico_range_low' ]].describe()
```

Out[94]:

	last_fico_range_high	last_fico_range_low
count	42535.000000	42535.000000
mean	689.922511	676.952039
std	80.818099	119.647752
min	0.000000	0.000000
25%	644.000000	640.000000
50%	699.000000	695.000000
75%	749.000000	745.000000
max	850.000000	845.000000

In [95]:
```
data_loan[['last_fico_range_high','last_fico_range_low' ]].corr()
```

Out[95]:

	last_fico_range_high	last_fico_range_low
last_fico_range_high	1.000000	0.852463
last_fico_range_low	0.852463	1.000000

In [96]:
```
data_loan['last_fico_mean'] = (data_loan.last_fico_range_low + data_loan.la
```

In [97]:
```
data_loan.drop(['last_fico_range_low','last_fico_range_high'],1, inplace=Tr
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1:
FutureWarning: In a future version of pandas all arguments of DataFrame.dro
p except for the argument 'labels' will be keyword-only
  """Entry point for launching an IPython kernel.
```

Usunięcie kolumn ze zbędnymi informacjami

acc_now_delinq, chargeoff_within_12_mths, delinq_amnt, tax_liens

To jest Liczba rachunków, wartość odpisów bankowych, wartość zadłużenia, liczba zestawów podatkowych, to są wartości, które nie mają wpływu na pożyczkobiorcę i jego wolę spłacania lub nie.
policy_cod - 1, application_type - individual

In [98]:
```
data_loan['policy_code'].value_counts()
```

Out[98]:
```
1.0    42535
Name: policy_code, dtype: int64
```

In [99]:
```
data_loan['application_type'].value_counts()
```

Out[99]:
```
Individual    42535
Name: application_type, dtype: int64
```

In [100…
```
data_loan['tax_liens'].value_counts()
```

Out[100]:
```
0.0    42429
1.0        1
Name: tax_liens, dtype: int64
```

In [101…
```
data_loan['disbursement_method'].value_counts()
```

Out[101]:
```
Cash    42535
Name: disbursement_method, dtype: int64
```

In [102…
```
data_loan['acc_now_delinq'].value_counts()
```

Out[102]:
```
0.0    42502
1.0        4
Name: acc_now_delinq, dtype: int64
```

In [103…
```
data_loan['chargeoff_within_12_mths'].value_counts()
```

Out[103]:
```
0.0    42390
Name: chargeoff_within_12_mths, dtype: int64
```

In [104…
```
data_loan['delinq_amnt'].value_counts()
```

Out[104]:
```
0.0       42504
27.0          1
6053.0        1
Name: delinq_amnt, dtype: int64
```

debt_settlement_flag

To jest oznaczenie, czy pożyczkobiorca współpracuje czy nie z firmą windykacyjną, czy jest ugoda

In [105…
```
data_loan['debt_settlement_flag'].value_counts()
```

Out[105]:
```
N    42375
Y      160
Name: debt_settlement_flag, dtype: int64
```

In [106…
```
data_loan['hardship_flag'].value_counts()
```

Out[106]:
```
N    42535
Name: hardship_flag, dtype: int64
```

In [107…
```
data_loan.drop(['policy_code', 'application_type','acc_now_delinq','chargeo
                'delinq_amnt','tax_liens','disbursement_method','debt_settl
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:2:
FutureWarning: In a future version of pandas all arguments of DataFrame.dro
p except for the argument 'labels' will be keyword-only
```

pub_rec_bankruptcies

liczba upadłości rejestrowych. Uzupełniam modą

In [108…
```
data_loan['pub_rec_bankruptcies'].value_counts().sort_index()
```

Out[108]:
```
0.0    39316
1.0     1846
2.0        8
Name: pub_rec_bankruptcies, dtype: int64
```

In [109…
```
data_loan['pub_rec_bankruptcies'].median()
```

Out[109]: 0.0

Wypełnij wartości `NA/NaN` przy użyciu określonej metody w tym przypadku dominantą

In [110…
```
data_loan['pub_rec_bankruptcies']= data_loan['pub_rec_bankruptcies'].fillna
```

Sprawdzenie całości:

- Zwięzłe podsumowanie DF, sprawdzam typ danych i kształt każdej kolumny

In [111…
```
## Check data type and shape of every column
data_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 42535 entries, 0 to 42535
Data columns (total 28 columns):
 #   Column                  Non-Null Count  Dtype         
---  ------                  --------------  -----         
 0   loan_amnt               42535 non-null  float64       
 1   funded_amnt             42535 non-null  float64       
 2   term                    42535 non-null  object        
 3   int_rate                42535 non-null  float64       
 4   installment             42535 non-null  float64       
 5   grade                   42535 non-null  object        
 6   sub_grade               42535 non-null  object        
 7   emp_length              42535 non-null  int64         
 8   home_ownership          42535 non-null  object        
 9   annual_inc              42535 non-null  float64       
 10  verification_status     42535 non-null  object        
 11  issue_d                 42535 non-null  datetime64[ns]
 12  loan_status             42535 non-null  object        
 13  purpose                 42535 non-null  object        
 14  addr_state              42535 non-null  object        
 15  dti                     42535 non-null  float64       
 16  delinq_2yrs             42535 non-null  float64       
 17  earliest_cr_line        42535 non-null  datetime64[ns]
 18  inq_last_6mths          42535 non-null  float64       
 19  mths_since_last_delinq  42535 non-null  float64       
 20  open_acc                42535 non-null  float64       
 21  pub_rec                 42535 non-null  float64       
 22  revol_bal               42535 non-null  float64       
 23  revol_util              42535 non-null  float64       
 24  total_acc               42535 non-null  float64       
 25  pub_rec_bankruptcies    42535 non-null  float64       
 26  fico_mean               42535 non-null  float64       
 27  last_fico_mean          42535 non-null  float64       
dtypes: datetime64[ns](2), float64(17), int64(1), object(8)
memory usage: 9.4+ MB
```

Wnioski:

- Wykonano obróbkę danych.
- Przeprowadzono wczytanie danych z pliku.
- Usunięto kolumny, które zawierały informacje z przyszłości, niedostępne w momencie udzielania pożyczki.
- Usunięto kolumny ze zbędnymi informacjami.
- Usunięcie kolum z tylko jedną unikalną wartością.
- Wykonano rzuk oka na wartości w kolumnie ze statusem pożyczki.

- Przekształcono wartości w kolumnach - usunięcie procentów, dodatkowych znaków, itd.
- Przeprowadzono analizę brakujących wartości wraz z ich uzupełnieniem/usunięciem przy wzięciu pod uwagę pewnych ustalonych kryteriów

To co wychodzi z pierwszej części, tj. oczyszczony zbiór. Ze 150 kolmn mam 28 kolumn wyczyszczonych i na tym przeprowadzam dalszą analizę EDA

2. EDA eksploracja danych

EDA, czyli obszerna eksploracja danych **(100pkt)** Opisz wnioski płynące z każdego wykresu, swoje hipotezy poprzyj testami statystycznymi takimi jak np. t-test lub Chi-square. Dodatkowo odpowiedz na poniższe pytania:

1. W jaki sposób wynik FICO wiąże się z prawdopodobieństwem spłacenia pożyczki przez pożyczkobiorcę?
2. W jaki sposób wiek kredytowy wiąże się z prawdopodobieństwem niewykonania zobowiązania i czy ryzyko to jest niezależne lub związane z wynikiem FICO
3. W jaki sposób status kredytu hipotecznego na dom wiąże się z prawdopodobieństwem niewypłacalności?
4. W jaki sposób roczny dochód wiąże się z prawdopodobieństwem niewykonania zobowiązania?
5. W jaki sposób historia zatrudnienia wiąże się z prawdopodobieństwem niewykonania zobowiązania?
6. Jak wielkość żądanej pożyczki jest powiązana z prawdopodobieństwem niewykonania zobowiązania?

1. Wysokopoziomowa analiza cech - ogólny rzut okiem który pozwoli lepiej zrozumieć dane
2. Sprawdzenie korelacji zmiennych (z targetem/między sobą) - choć korelacja bada liniową zależność, a ta może przybierać wiele form to wygenerowanie mapki korelacji może podsunąć kolumny którym warto się przyglądnąć
3. Odpowiedź na 6 pytań z treści projektu:
   - dobrze dobrana wizualizacja
   - opisanie własnych obserwacji
   - poparcie testem statystycznym (opcjonalnie)
4. Dalsza, autorska eksploracja - rozbudowanie części projektu o Wasze pomysły, hipotezy i odkryte wcześniej rzeczy

EDA

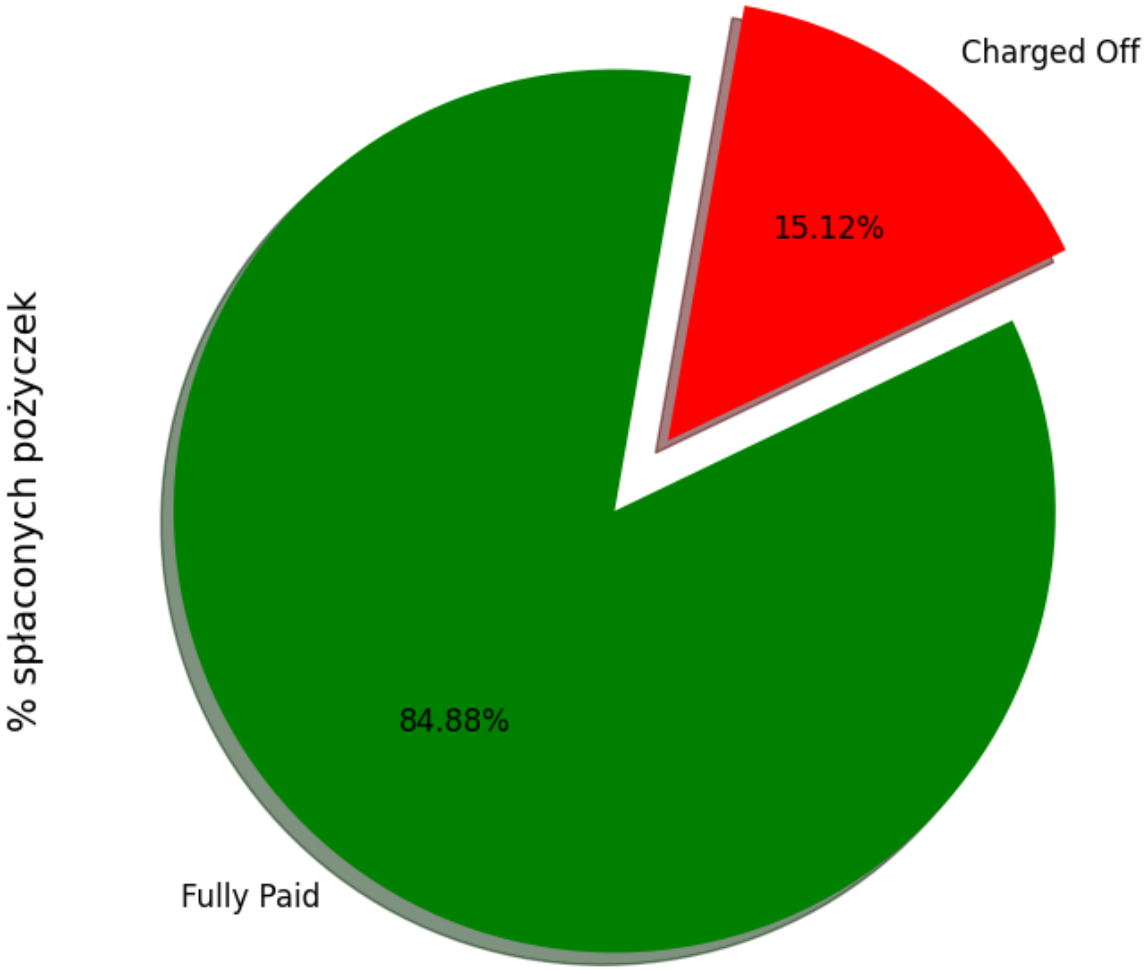
Podzielenie DF na dobry i zły stan pożczyczki

In [112…

```
print(data_loan["loan_status"].value_counts())

# Slice data frame into good and bad loan status
df_good = data_loan.loc[(data_loan.loan_status == 0), :]
df_bad  = data_loan.loc[(data_loan.loan_status == 1), :]
```

```
plt.figure(figsize=(16, 8))
colors = ["g", "r"]
labels = "Fully Paid", "Charged Off"
data_loan["loan_status"].value_counts().plot.pie(explode=[0,0.2], autopct='%
                                                 shadow=True, colors=colors
                                                 fontsize=12, startangle=80
plt.ylabel('% spłaconych pożyczek', fontsize=15)
plt.show()
```

```
Fully Paid     36104
Charged Off     6431
Name: loan_status, dtype: int64
```



Wniosek:

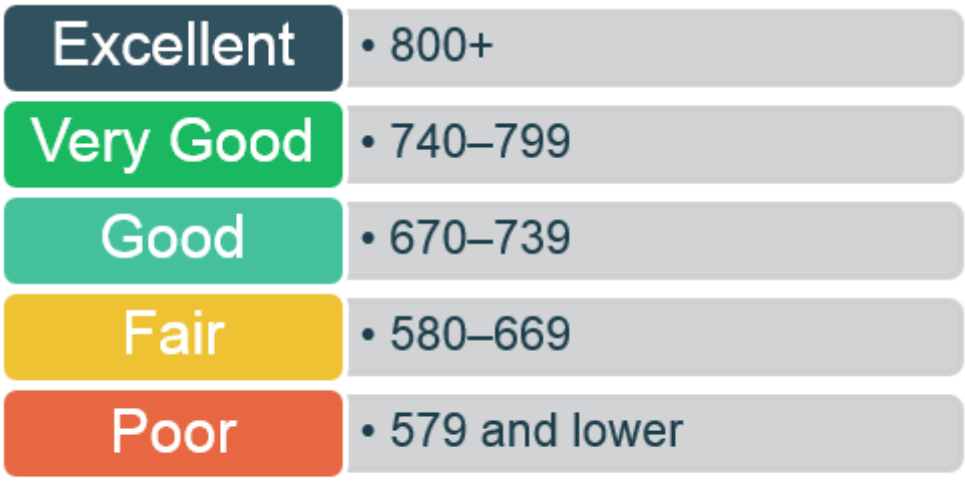
Na podstawie przedstawionego wykresu widać, że mamy 15 % niespłaconych pożyczek, a prawie 85 % spłaconych, co oznacza, że prawie 6 razy więcej osób spłacało pożyczki zgodnie z zasadami Lending Page.

FICO Rating

Jest pięć grup sccoring-owych FICO. Poor: < 580, Fair 580-669, Good 670-739, Very Good 740-799 i Exceptional >= 800. Będę przedstawiać zależności czynników versus FICO sccoring.

In [113…
```
data_loan.fico_mean.head()
```

Out[113]:
```
0    737.0
1    742.0
2    737.0
3    692.0
4    697.0
Name: fico_mean, dtype: float64
```



Source: American Web Loan

Exceptional / **Wyjątkowy**

- Well above the average score of U.S. consumers / - Znacznie powyżej średniego wyniku konsumentów w USA
- Demonstrates to lenders you are an exceptional borrower / - Pokazuje pożyczkodawcom, że jesteś wyjątkowym pożyczkobiorcą

Very Good / **Bardzo dobry**

- Above the average od U.S. consumers / - Powyżej średniej konsumentów w USA
- Demonstrates to lenders you are a very dependable borrower / - Pokazuje pożyczkodawcom, że jesteś bardzo niezawodnym pożyczkobiorcą

Good / **Dobrze**

- Near or slightly above the average od U.S. consumners / - Prawie lub nieco powyżej średniej konsumentów w USA
- Most lenders consider this a good score / - Większość pożyczkodawców uważa to za dobry wynik

Fair / **Sprawiedliwy**

- Belowe tha average score of U.S. consumers / - Poniżej średniego wyniku konsumentów w USA
- Thougth many lenders will approve loans with this score / - Chociaż wielu pożyczkodawców zatwierdzi pożyczki z tym wynikiem

Poor / **Słaby**

- Well below the average score of U.S. consumers / - Znacznie poniżej średniego wyniku konsumentów w USA
- Demonstrates to lenders that you are a risky borrower / - Pokazuje pożyczkodawcom, że jesteś ryzykownym pożyczkobiorcą

In [114…
```
def fico_rating (row):
    if row['fico_mean'] < 580:
        return 'Poor'
    if row['fico_mean'] < 670:
        return 'Fair'
    if row['fico_mean'] < 740:
        return 'Good'
    if row['fico_mean'] < 800:
        return 'Very Good'
    if row['fico_mean']  >= 800:
       return 'Exceptional'
    return 'Other'
data_loan['fico_rating'] = data_loan.apply (lambda row: fico_rating(row), a
data_loan[['loan_amnt','emp_length','annual_inc','fico_mean','int_rate', 'f
```

Out[114]:

	loan_amnt	emp_length	annual_inc	fico_mean	int_rate	fico_rating
0	5000.0	10	24000.0	737.0	10.65	Good
1	2500.0	1	30000.0	742.0	15.27	Very Good
2	2400.0	10	12252.0	737.0	15.96	Good
3	10000.0	10	49200.0	692.0	13.49	Good
4	3000.0	1	80000.0	697.0	12.69	Good
...	...	...	...	...	...	...
42531	3500.0	1	180000.0	687.0	10.28	Good
42532	1000.0	1	12000.0	697.0	9.64	Good
42533	2525.0	1	110000.0	712.0	9.33	Good
42534	6500.0	1	60000.0	742.0	8.38	Very Good
42535	5000.0	10	70000.0	772.0	7.75	Very Good

42535 rows × 6 columns

Pytanie 1. (FICO vs loan_status)

1. W jaki sposób wynik FICO wiąże się z prawdopodobieństwem spłacenia pożyczki przez pożyczkobiorcę?

Obliczam prostą tabelę krzyżową dwóch (lub więcej) czynników. Domyślnie obliczam tabelę częstości współczynników.

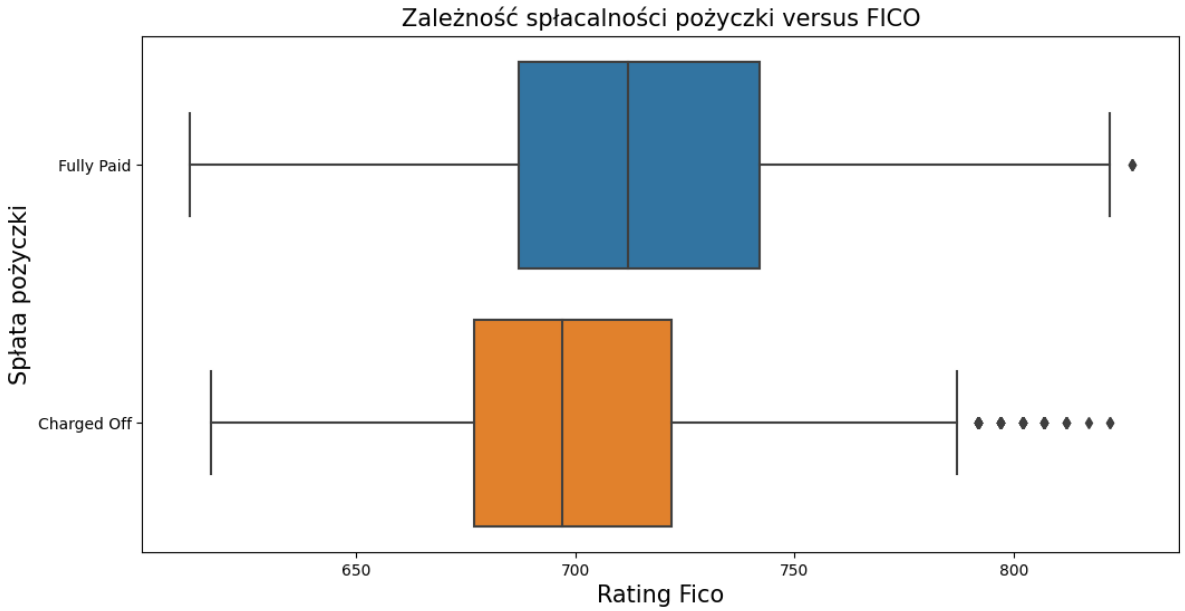
In [115…
```
ficoloan = ['loan_status', 'fico_rating']
cm = sns.light_palette("orange", as_cmap=True)
round(pd.crosstab(data_loan[ficoloan[0]], data_loan[ficoloan[1]],
            normalize='index'),2).fillna(0).style.background_gradient(cmap =
```

Out[115]:

fico_rating	Exceptional	Fair	Good	Very Good
loan_status				
Charged Off	0.010000	0.150000	0.710000	0.140000
Fully Paid	0.020000	0.080000	0.650000	0.260000

In [116…
```
fig = plt.figure(figsize=(12,6))
ax = sns.boxplot(data=data_loan, x="fico_mean", y="loan_status")
plt.xlabel("Rating Fico", fontsize=15)
plt.ylabel("Spłata pożyczki", fontsize=15)
plt.title("Zależność spłacalności pożyczki versus FICO", fontsize=15)
```

Out[116]:
```
Text(0.5, 1.0, 'Zależność spłacalności pożyczki versus FICO')
```



In [117…
```
data_loan[data_loan.loan_status == 'Fully Paid'].describe().fico_mean
```

Out[117]:
```
count    36104.000000
mean       717.220059
std         36.437532
min        612.000000
25%        687.000000
50%        712.000000
75%        742.000000
max        827.000000
Name: fico_mean, dtype: float64
```

In [118…
```
data_loan[data_loan.loan_status == 'Charged Off'].describe().fico_mean
```

Out[118]:
```
count    6431.000000
mean      702.883999
std        32.152072
min       617.000000
25%       677.000000
50%       697.000000
75%       722.000000
max       822.000000
Name: fico_mean, dtype: float64
```

Wniosek:

Na podstawie przedstawionych wykresów i tabel wnioskuję, iż więcej pożyczek jest spłaconych przez pożyczkobiorców z wyższym Fico (exceptional i very good).

Pożyczkobiorcy o dobrym i średnim Fico częściej nie spłacają pożyczek. Fico powyżej 780 to pożyczkobiorcy bardzo dobrze spłacający kredyty. Zdecydowana większość udzielanych pożyczek dla Fico powyżej 670. Pierwszy kwartyl, średnia, mediana i trzeci kwartyl są wyższe dla pożyczkobiorców z lepszym Fico.

Pytanie 2. (earliest_cr_line vs loan_status)

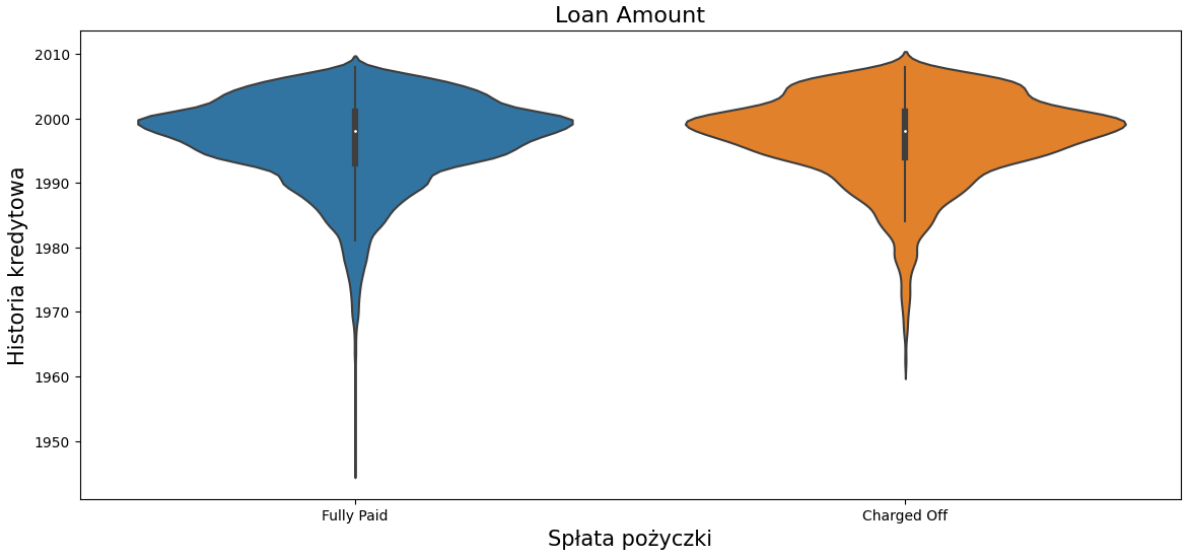
1. W jaki sposób wiek kredytowy wiąże się z prawdopodobieństwem niewykonania zobowiązania i czy ryzyko to jest niezależne lub związane z wynikiem FICO

In [119…
```
data_loan['earliest_cr_line']= pd.to_datetime(data_loan['earliest_cr_line'])
data_loan['earliest_cr_line']
```

Out[119]:
```
0        1985
1        1999
2        2001
3        1996
4        1996
         ...
42531    2007
42532    2007
42533    2007
42534    2007
42535    2007
Name: earliest_cr_line, Length: 42535, dtype: int64
```

In [120…
```
fig = plt.figure(figsize=(14,6))
sns.violinplot(x="loan_status", y="earliest_cr_line", data=data_loan, split
plt.title("Loan Amount", fontsize=16)
plt.xlabel("Spłata pożyczki", fontsize=15)
plt.ylabel("Historia kredytowa", fontsize=15)
```

Out[120]:
```
Text(0, 0.5, 'Historia kredytowa')
```



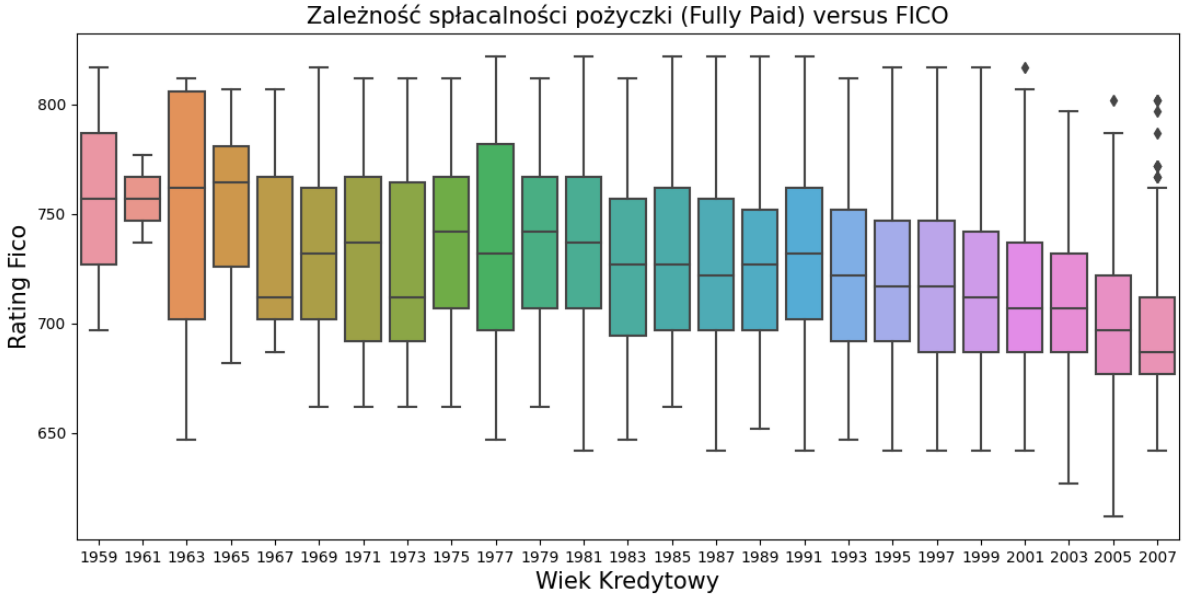
In [121…
```
ECL_loan_status_FP = data_loan[(data_loan.earliest_cr_line) & (data_loan.lo
```

In [122…
```
ECL_loan_status_CO = data_loan[(data_loan.earliest_cr_line) & (data_loan.lo
```

In [123…
```
fig = plt.figure(figsize=(13,6))
ax = sns.boxplot(data=ECL_loan_status_FP, x="earliest_cr_line", y="fico_mea
plt.xlabel("Wiek Kredytowy", fontsize=15)
```

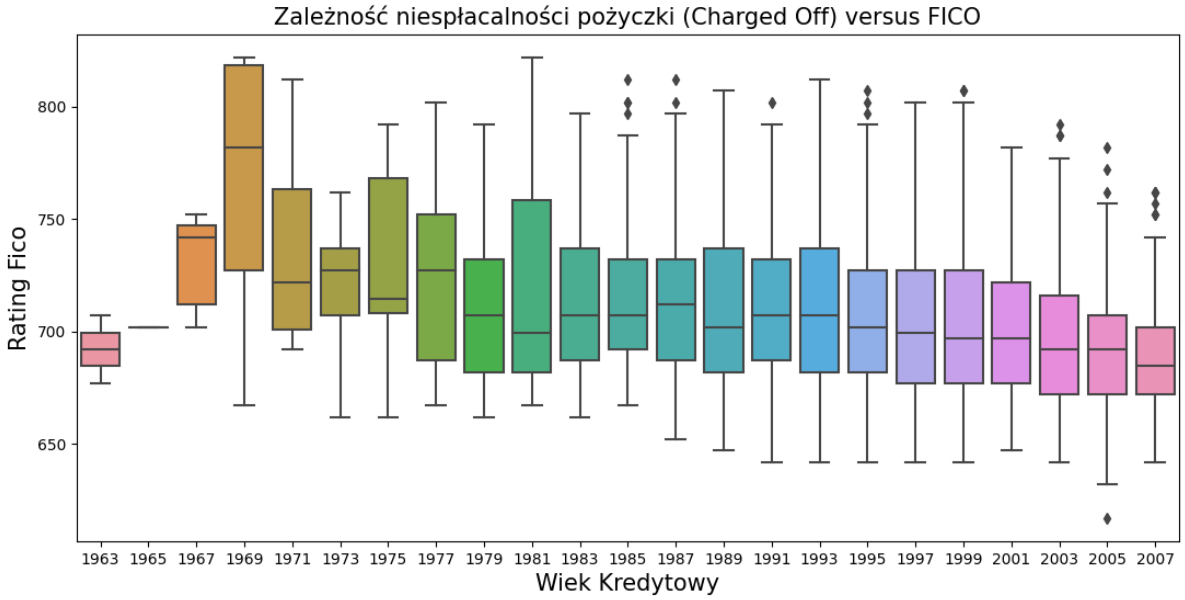
```
plt.ylabel("Rating Fico", fontsize=15)
plt.title("Zależność spłacalności pożyczki (Fully Paid) versus FICO", fonts
```

Out[123]:
```
Text(0.5, 1.0, 'Zależność spłacalności pożyczki (Fully Paid) versus FICO')
```



In [124…
```
fig = plt.figure(figsize=(13,6))
ax = sns.boxplot(data=ECL_loan_status_CO, x="earliest_cr_line", y="fico_mea
plt.xlabel("Wiek Kredytowy", fontsize=15)
plt.ylabel("Rating Fico", fontsize=15)
plt.title("Zależność niespłacalności pożyczki (Charged Off) versus FICO", f
```

Out[124]:
```
Text(0.5, 1.0, 'Zależność niespłacalności pożyczki (Charged Off) versus FI
CO')
```



Wniosek:

Na podstawie przedstawionego wykresu widać, że Ci najstarsi klienci spłacają kredyty częściej, choć jest ich znikoma ilość. W znaczącej wielkości wszystkich pożyczkobiorców, wiek już nie ma specjalnego znaczenia. Ryzyko to jest związane z wynikiem FICO. Im wiek kredytowy jest krótszy, tym ryzyko związane z niewykonaniem zobowiązania rośnie.

Pytanie 3. (home_ownership vs loan_status)

1. W jaki sposób status kredytu hipotecznego na dom wiąże się z prawdopodobieństwem niewypłacalności?

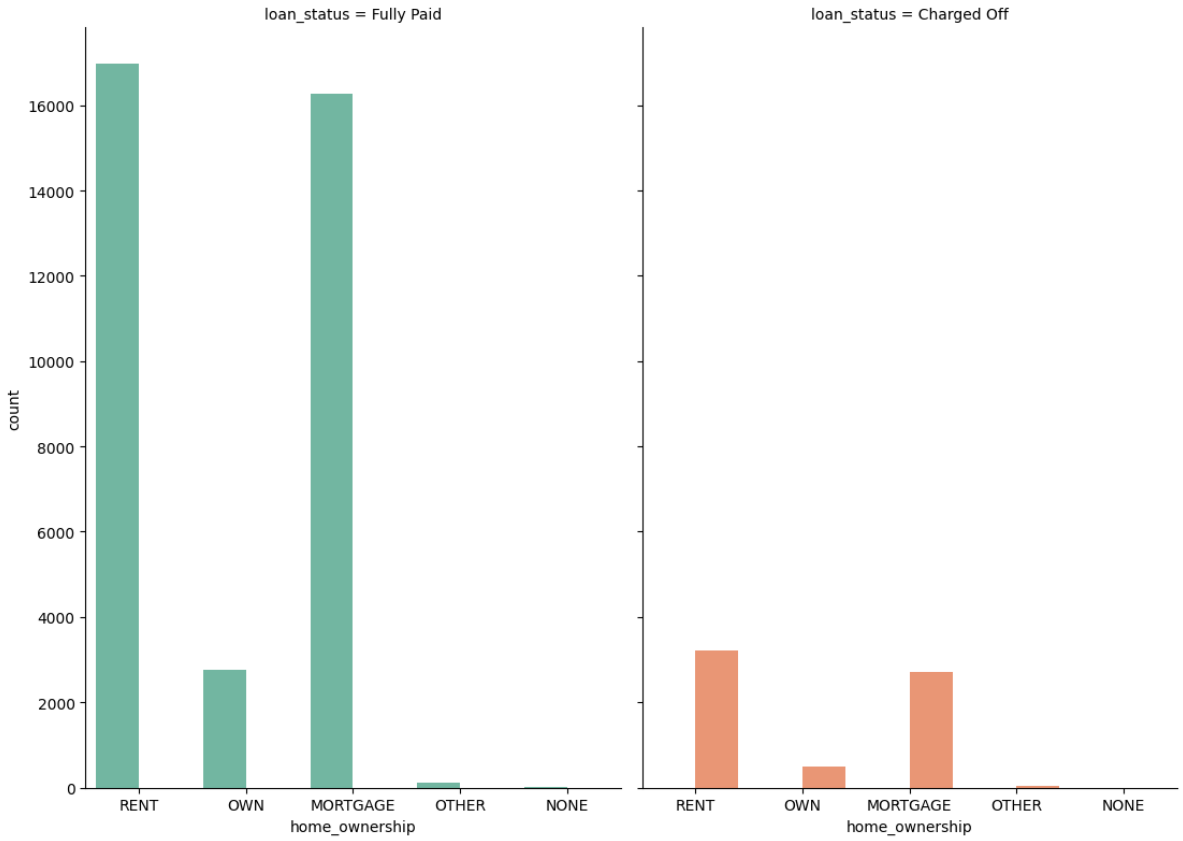
In [125…
```
homeloan = ['loan_status', 'home_ownership']
cm = sns.light_palette( "orange", as_cmap=True)
round(pd.crosstab(data_loan[homeloan[0]], data_loan[homeloan[1]],
            normalize='index'),2).fillna(0).style.background_gradient(cmap =
```

Out[125]:

loan_status \ home_ownership	MORTGAGE	NONE	OTHER	OWN	RENT
Charged Off	0.420000	0.000000	0.000000	0.080000	0.500000
Fully Paid	0.450000	0.000000	0.000000	0.080000	0.470000

In [126…
```
plt.figure(figsize = (8,6))
g = sns.catplot(x="home_ownership", hue="loan_status", col="loan_status", d
                height=8, aspect=.7, palette='Set2')
```

```
<Figure size 800x600 with 0 Axes>
```



Wniosek:

Na podstawie przedstawionych wykresów wnioskuję, iż w każdej grupie pożyczkobiorców (spłacających lub nie) podobnie rozkładają się wyniki. Z tabelki powyżej widać, iż ciut więcej jest osób z kredytem hipotecznym, które spłaciły pożyczkę, a odwrotnie przy mieszkaniu wynajętym. Właściwie brak danych o pożyczkobiorcach w kategoriach 'Other' i 'None'.

Pearson’s Chi-Square Test

Ponieważ mamy dwie zmienne kategoryczne zastosujemy Chi-Square Test. Sprawdzimy czy jest zależność pomiędzy tymi zmiennymi.

- H0 - hipoteza zerowa "Nie ma zależności między statusem mieszkania a spłatą pożyczki"
- H1 - hipoteza alternatywna "Są znaczące relacje między zmiennymi"

In [127…
```
data_cross = pd.crosstab(data_loan['home_ownership'], data_loan['loan_statu
print(data_cross)
```

```
loan_status     Charged Off  Fully Paid
home_ownership
MORTGAGE               2699       16260
NONE                      1           7
OTHER                    29         107
OWN                     495        2756
RENT                   3207       16974
```

In [128…
```
stat, p_value, dof, expected = chi2_contingency(data_cross)
alpha = 0.05
print(p_value)
```

```
4.922904146937375e-05
```

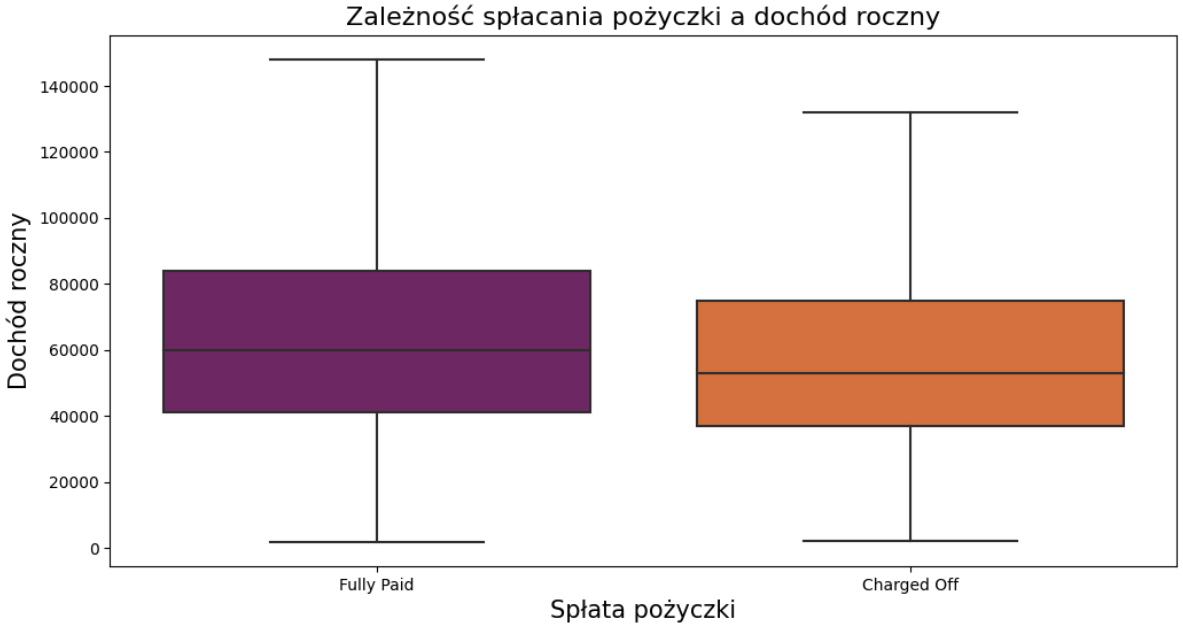
In [129…
```
if p_value <= alpha:
    print('Odrzucamy hipotezę H0 - Są znaczące relacje między zmiennymi')
else:
    print('Akceptujemy hipotezę zerową H0 - Nie ma zależności między status
```

```
Odrzucamy hipotezę H0 - Są znaczące relacje między zmiennymi
```

Pytanie 4. (annual_income vs loan_status)

1. W jaki sposób roczny dochód wiąże się z prawdopodobieństwem niewykonania zobowiązania?

In [130…
```
plt.figure(figsize=(12,6))

ax = sns.boxplot(x="loan_status", y="annual_inc",  data=data_loan, showflie
ax = plt.title('Zależność spłacania pożyczki a dochód roczny', fontsize=16)
ax = plt.xlabel('Spłata pożyczki', fontsize=15)
ax = plt.ylabel('Dochód roczny', fontsize=15)
```



Wniosek:

Na podstawie przedstawionego wykresu widać, że średnia wysokość dochodu rocznego jest wyższa u klientów spłacających swoje pożyczki. Ci z najwyższym dochodem spłacają swoje pożyczki.

Pytanie 5. (emp_length vs loan_status)

1. W jaki sposób historia zatrudnienia wiąże się z prawdopodobieństwem niewykonania zobowiązania?

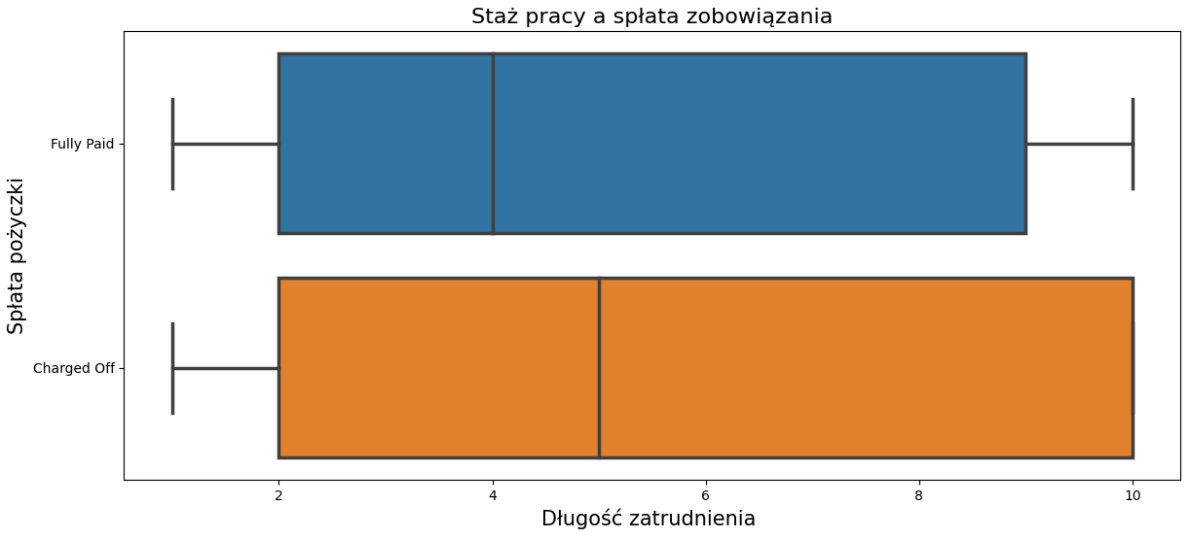
In [131…]
```
emplenght = ['loan_status', 'emp_length']
cm = sns.light_palette("gray", as_cmap=True)
round(pd.crosstab(data_loan[emplenght[0]], data_loan[emplenght[1]],
            normalize='index'),2).fillna(0).style.background_gradient(cmap =
```

Out[131]:

emp_length	1	2	3	4	5	6	7	8
loan_status								
Charged Off	0.200000	0.100000	0.100000	0.080000	0.080000	0.050000	0.050000	0.040000
Fully Paid	0.200000	0.110000	0.100000	0.090000	0.080000	0.060000	0.040000	0.040000

In [132…]
```
plt.figure(figsize = (14,6))
ax = sns.boxplot(x="emp_length" , y= "loan_status", data=data_loan, linewid
plt.title("Staż pracy a spłata zobowiązania", fontsize=16)
plt.xlabel("Długość zatrudnienia ", fontsize=15)
plt.ylabel("Spłata pożyczki", fontsize=15)
```

Out[132]:
```
Text(0, 0.5, 'Spłata pożyczki')
```



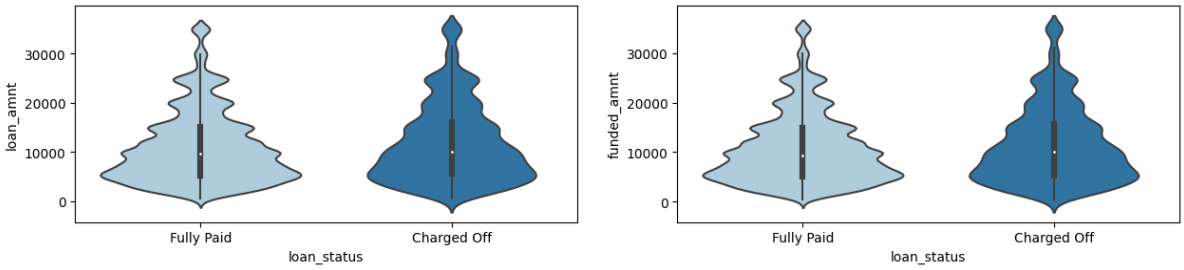
Wniosek:

Na podstawie przedstawionych wykresów wnioskuję, iż jest większa liczba pożyczkobiorców niespłacających kredytu jest od 9 do 10 lat zatrudnienia. Ci spłacający mają krótszy staż pracy. Ci do 4 lat zatrudnienia częściej pozytywnie kończą umowę kredytową.

Pytanie 6. (loan_amnt vs loan_status)

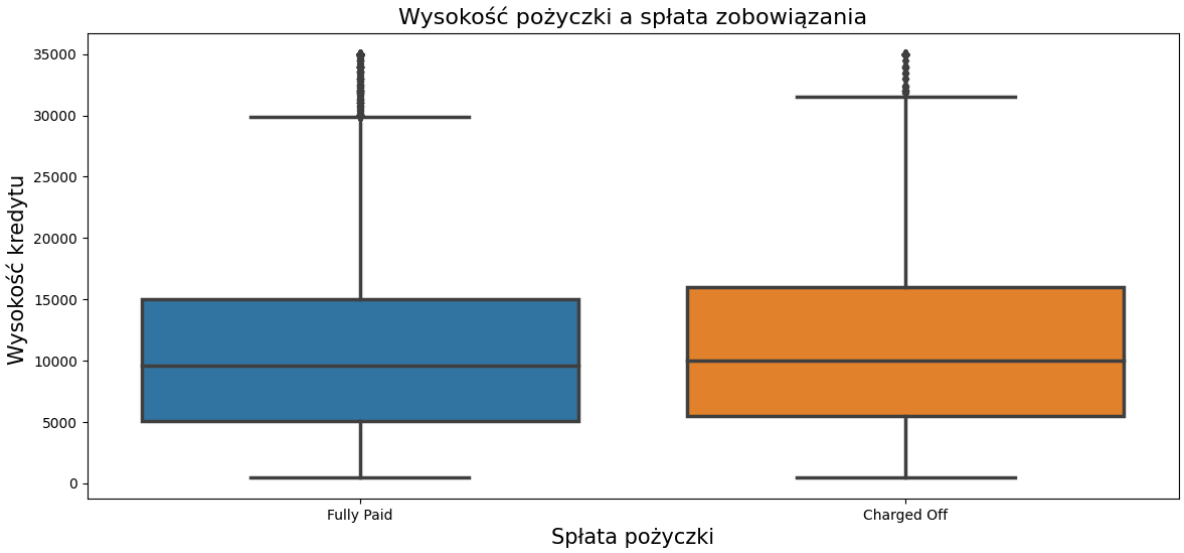
1. Jak wielkość żądanej pożyczki jest powiązana z prawdopodobieństwem niewykonania zobowiązania?

In [133…
```
fig,axes = plt.subplots(3,2, figsize=(15,10))

sns.violinplot(x="loan_status", y="loan_amnt", data=data_loan, ax=axes[0][0
sns.violinplot(x="loan_status", y="funded_amnt", data=data_loan, ax=axes[0]

fig.delaxes(ax = axes[1][0])
fig.delaxes(ax = axes[1][1])
fig.delaxes(ax = axes[2][0])
fig.delaxes(ax = axes[2][1])
```



In [134…
```
plt.figure(figsize = (14,6))
ax = sns.boxplot(y="loan_amnt" , x= "loan_status", data=data_loan, linewidt
plt.title("Wysokość pożyczki a spłata zobowiązania", fontsize=16)
plt.xlabel("Spłata pożyczki", fontsize=15)
plt.ylabel("Wysokość kredytu ", fontsize=15)
```

Out[134]:
```
Text(0, 0.5, 'Wysokość kredytu ')
```

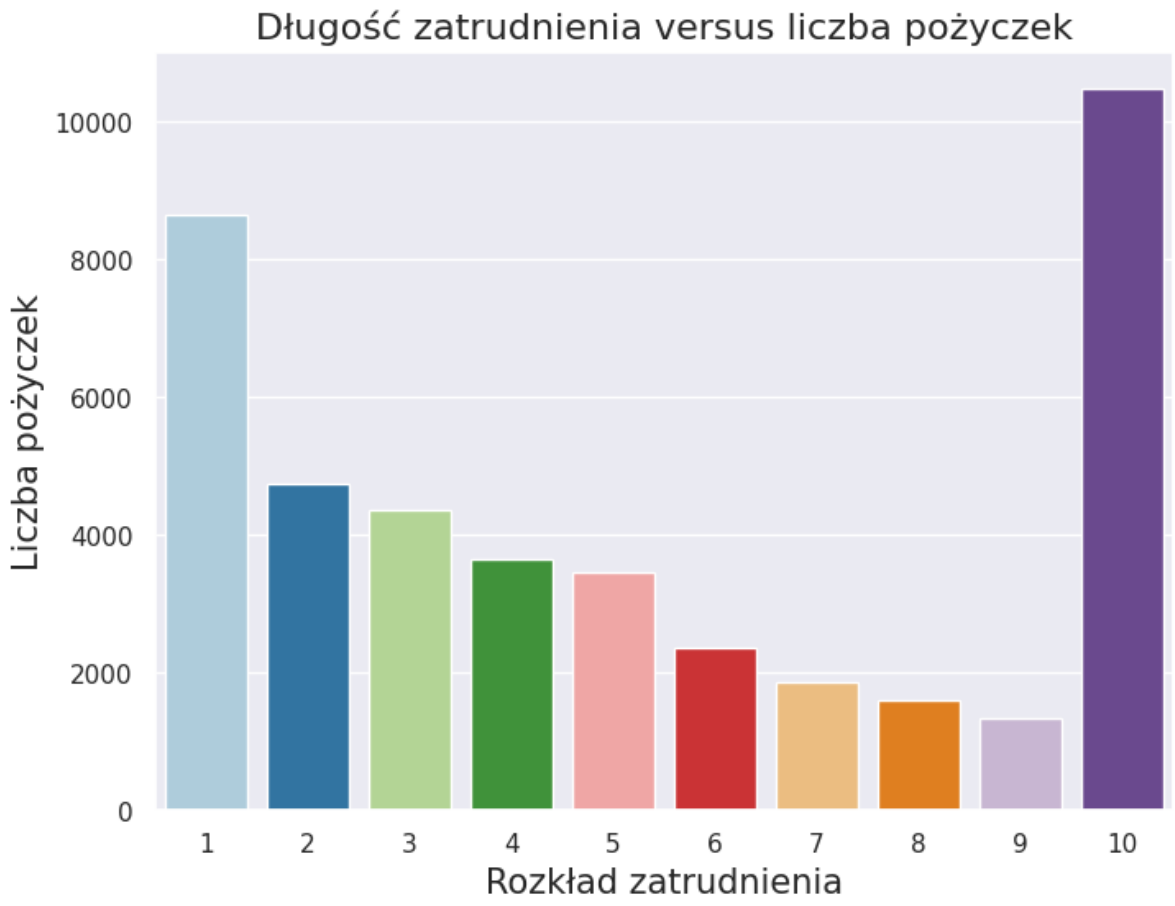


Wniosek:

Na podstawie przedstawionych wykresów widać, że podobnie rozkładają się spłaty pożyczki wnioskowanej i udzielonej. W naszym projekcie loan_amnt to kwota wnioskowana, a nie udzielona. Część pożyczek powyżej 15tys. nie została spłacona częściej.

In [135…
```
sns.set(rc={'figure.figsize':(8,6)})
sns.countplot(x=data_loan['emp_length'], palette='Paired')
plt.xlabel("Rozkład zatrudnienia", fontsize = 15)
plt.ylabel("Liczba pożyczek", fontsize = 15)
```

```
plt.title("Długość zatrudnienia versus liczba pożyczek", fontsize = 16)
plt.show()
```



Wniosek:

W badanym okresie 2007-20011 najwięcej pożyczek zostało udzielonych osobom z długim okresem zatrudnienia, oraz druga grupa osoby zaczynające pracę, czyli pracujące koło roku. W tej kolumnie było ponad 100 nulli, które zostaly uzupełnione wartością dominanty, co zwiększyło jeszcze liczbę udzielonych pożyczek grupie z indeksem 10.

Testowanie Hipotezy One Sample T-test

Ponieważ mamy jedną zmienną numeryczną zastosujemy One Sample T-test na próbce z emp_length. Sprawdzimy czy jest róznica pomiędzy warościami średnich próbki i całej populacji tej zmiennej.

- H0 - hipoteza zerowa "Nie ma różnic między średnią próbki a średnią całości"
- H1 - hipoteza alternatywna "Są różnice w średnich"

In [136…
```
data_loan.emp_length.mean()
```

Out[136]:
```
5.174820735864582
```

In [137…
```
len(data_loan.emp_length)
```

Out[137]:
```
42535
```

In [138…
```
# weźmy próbkę danych emp_length 30%
```

```
sample_size = 14100
emp_length_sample = np.random.choice(data_loan.emp_length, sample_size)
emp_length_sample
```

Out[138]:
```
array([ 6,  5, 10, ...,  3,  6,  2])
```

In [139…
```
ttest, p_value = ttest_1samp(emp_length_sample, data_loan.emp_length.mean())
print(p_value)
```

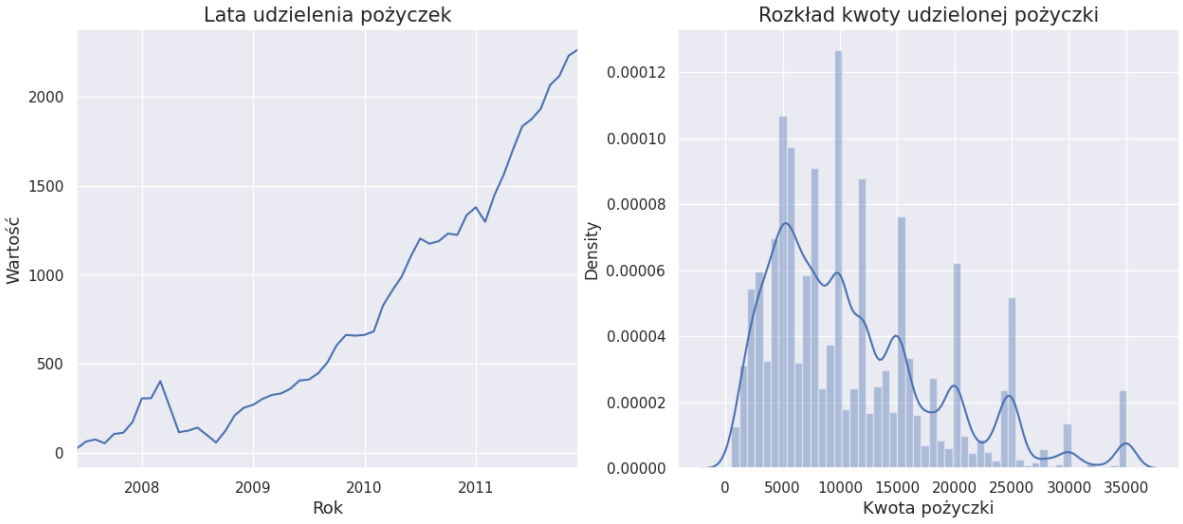
```
0.47582790071912595
```

In [140…
```
if p_value < 0.05:
    print('Odrzucamy hipotezę zerową H0 - Są różnice w średnich')
else:
    print('Akceptujemy hipotezę zerową H0 - Nie ma różnic między średnią pr
```

```
Akceptujemy hipotezę zerową H0 - Nie ma różnic między średnią próbki a śred
nią całości
```

In [141…
```
year_dist = data_loan.groupby(['issue_d']).size()
plt.figure(figsize=(15,6))
sns.set()

ax1 = plt.subplot(1, 2, 1)
ax1 = year_dist.plot()
ax1 = plt.title('Lata udzielenia pożyczek', fontsize = 15)
ax1 = plt.xlabel('Rok', fontsize = 13)
ax1 = plt.ylabel('Wartość', fontsize = 13)

ax2 = plt.subplot(1, 2, 2)
ax2 = sns.distplot(data_loan['loan_amnt'])
ax2 = plt.title('Rozkład kwoty udzielonej pożyczki', fontsize = 15)
ax2 = plt.xlabel('Kwota pożyczki', fontsize = 13)
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:12:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
h
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  if sys.path[0] == "":
```



Wniosek:

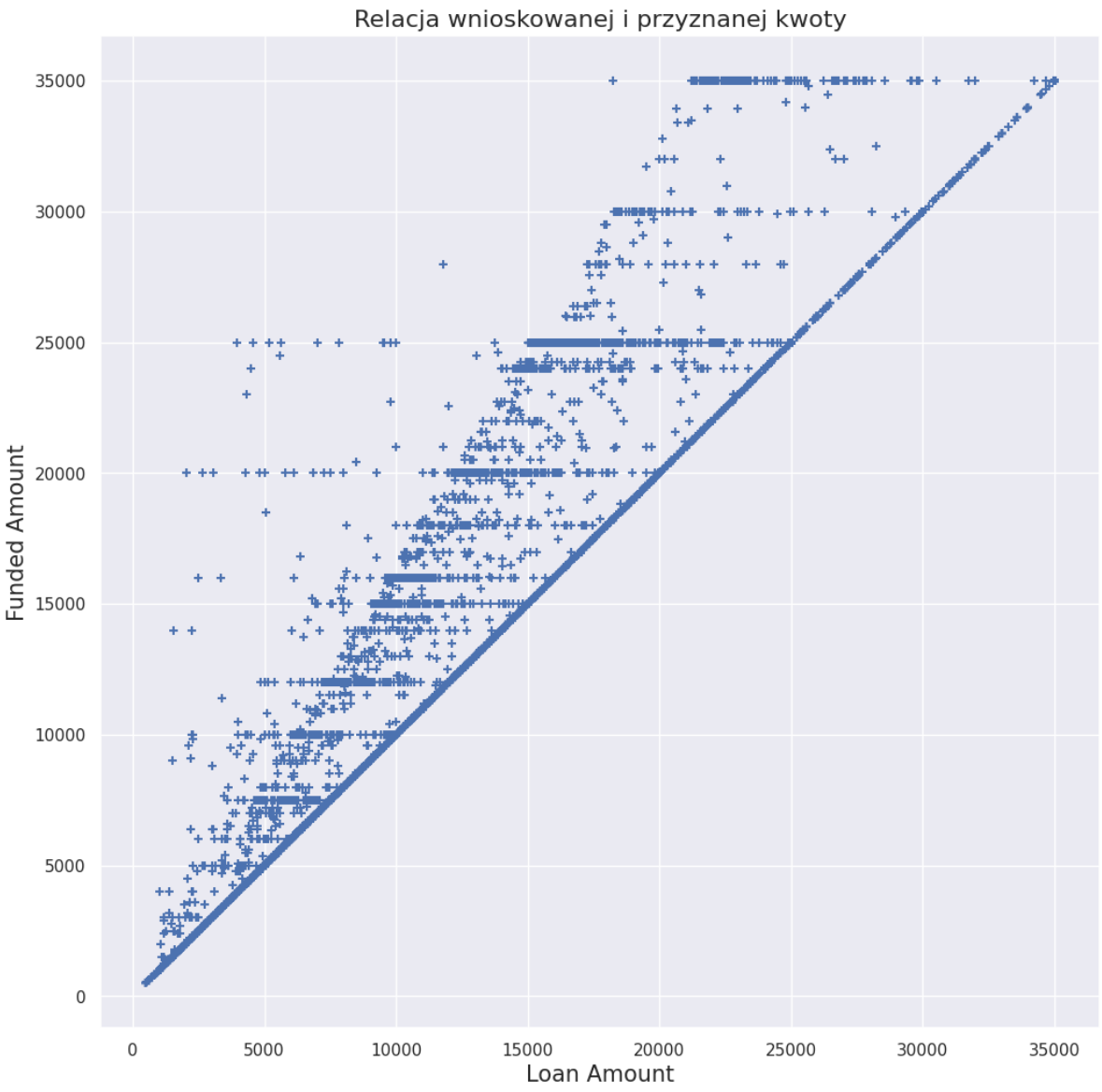
Na podstawie przedstawionych wykresów widać (na pierwszym wykresie) rosnącą popularność kredytów pożyczkowych po 2009 r. w wysokości przekraczającej 5 tys. Do 2008 r. kredyty były udzielane w niskiej wysokości do 2,5 tys. Rozkład kwoty pożyczki jest nieco przesunięty w prawo. Większość pożyczkobiorców ubiegała się o pożyczkę w wysokości około 10 000 USD.

funded czy loan_amnt

W projekcie zajmujemy się wartością loan_amnt, która jest kwotą wnioskowaną, a nie rzeczywiście przyznaną. Funded_amnt to kwota przyznana wynikająca z danych Lending Club. Na potrzeby tego projektu analizujemy loan_amnt.

In [142…

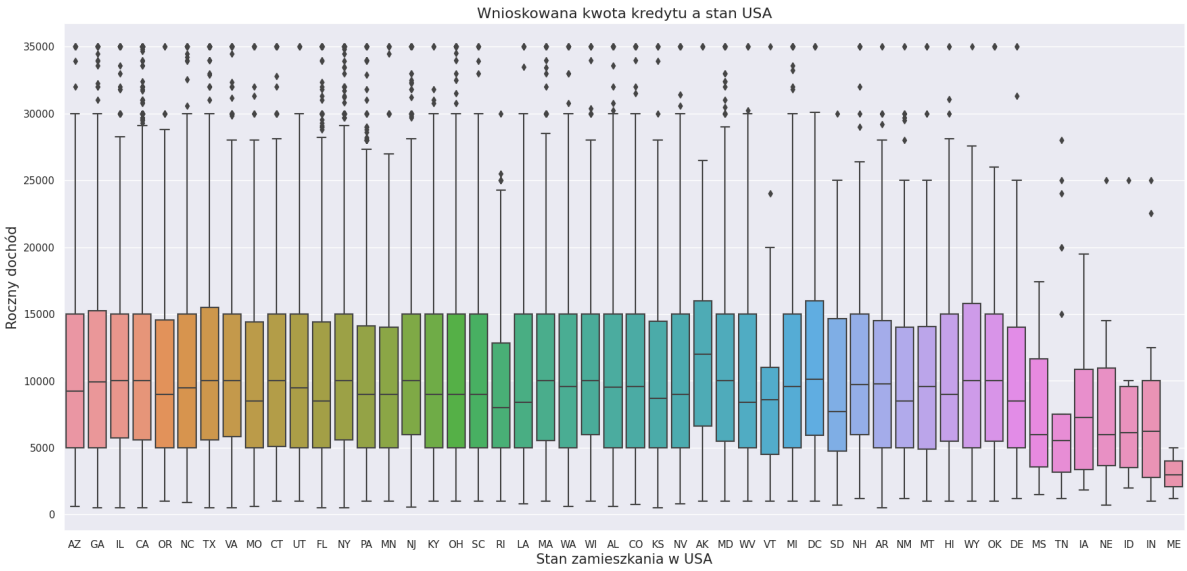
```
plt.figure(figsize=(12,12))
plt.scatter(data_loan['funded_amnt'], data_loan['loan_amnt'], marker="+")
plt.title("Relacja wnioskowanej i przyznanej kwoty", fontsize = 16)
plt.ylabel('Funded Amount', fontsize = 15)
plt.xlabel('Loan Amount', fontsize = 15)
plt.show()
```



Wniosek:

Na podstawie przedstawionego wykresu widać, że w większości wartości wnioskowane są wyższe niż przyznane. Poniżej widać również, że LC nie udziela większej pożyczki niż wnioskowana.

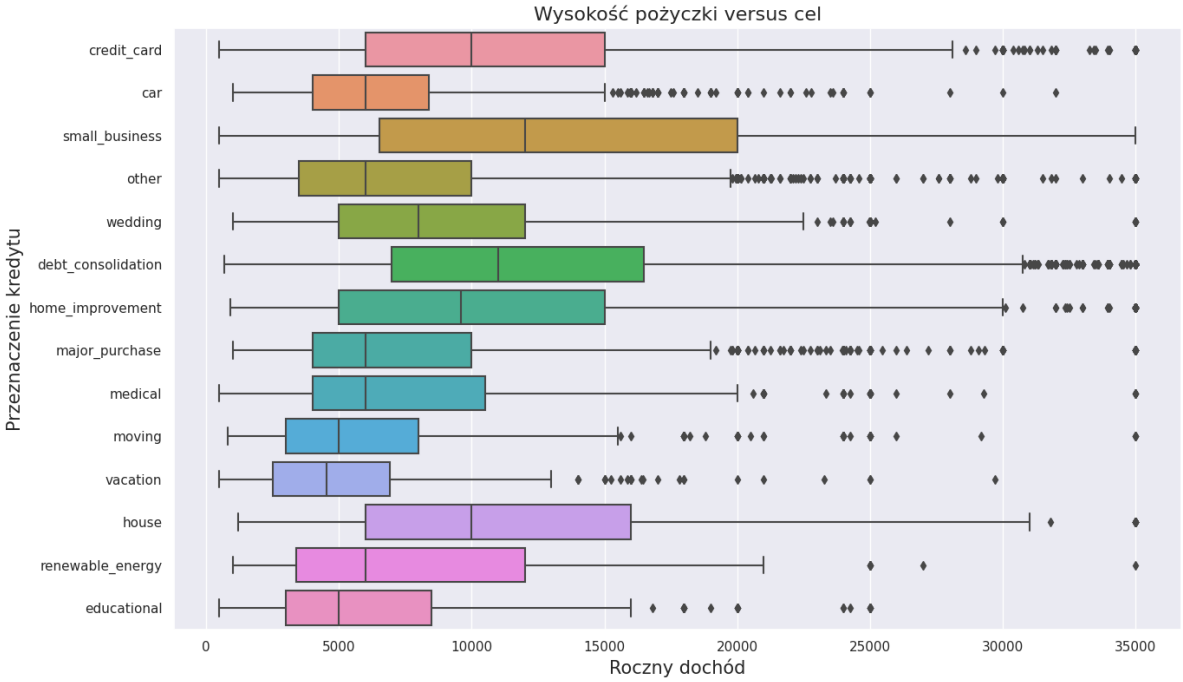
In [143…
```
plt.figure(figsize=(22, 10))
ax = sns.boxplot(x="addr_state", y="loan_amnt", data=data_loan)
ax = plt.xlabel('Stan zamieszkania w USA',fontsize=15)
ax = plt.ylabel('Roczny dochód', fontsize = 15)
ax = plt.title('Wnioskowana kwota kredytu a stan USA', fontsize = 16)
```



Wniosek:

Na podstawie przedstawionego zbioru wykresów boxplots, warto zauważyć, że średni roczny dochód jest najniższy w stanie Maine (ME) i niższy niż minimalny dochów w większości stanów USA. Najwyższa średia zarobków jest w stanie Alaska (AK)

In [144…
```
plt.figure(figsize=(15,9))
ax = sns.boxplot(y="purpose", x="loan_amnt", data=data_loan)
ax = plt.xlabel('Roczny dochód',fontsize=15)
ax = plt.ylabel('Przeznaczenie kredytu',fontsize=15)
ax = plt.title('Wysokość pożyczki versus cel',fontsize=16)
```



Wniosek:

Na podstawie przedstawionego wykresu wyraźnie widać, że najwięcej kredytów jest przyznawanych na rozwój małej przedsiębiorczości. Tu również średnia i największa wartość udzielonych kredytów dotyczy tej grupy. Większość niskich kredytów jest na cel edukacyjny i wakacje.

Pearson’s Chi-Square Test na zależność 'purpose' a 'home_ownership'

Ponieważ mamy dwie zmienne kategoryczne zastosujemy Chi-Square Test. Sprawdzimy czy jest zależność pomiędzy tymi zmiennymi.

- H0 - hipoteza zerowa "Nie ma zależności między statusem mieszkania a celem pożyczki"
- H1 - hipoteza alternatywna "Są znaczące relacje między zmiennymi"

In [145…
```
data_cross1 = pd.crosstab(data_loan['home_ownership'], data_loan['purpose']
print(data_cross1)
```

purpose	car	credit_card	debt_consolidation	educational	\
home_ownership					
MORTGAGE	779	2446	8308	113	
NONE	0	0	1	0	
OTHER	3	16	52	5	
OWN	163	315	1365	34	
RENT	670	2700	10050	270	

purpose	home_improvement	house	major_purchase	medical	moving	\
home_ownership						
MORTGAGE	2540	158	979	333	117	
NONE	0	0	0	0	0	
OTHER	7	3	8	5	3	
OWN	352	34	252	72	28	
RENT	300	231	1072	343	481	

purpose	other	renewable_energy	small_business	vacation	wedding
home_ownership					
MORTGAGE	1644	57	1028	142	315
NONE	7	0	0	0	0
OTHER	19	1	13	0	1
OWN	408	10	128	32	58
RENT	2347	38	823	226	630

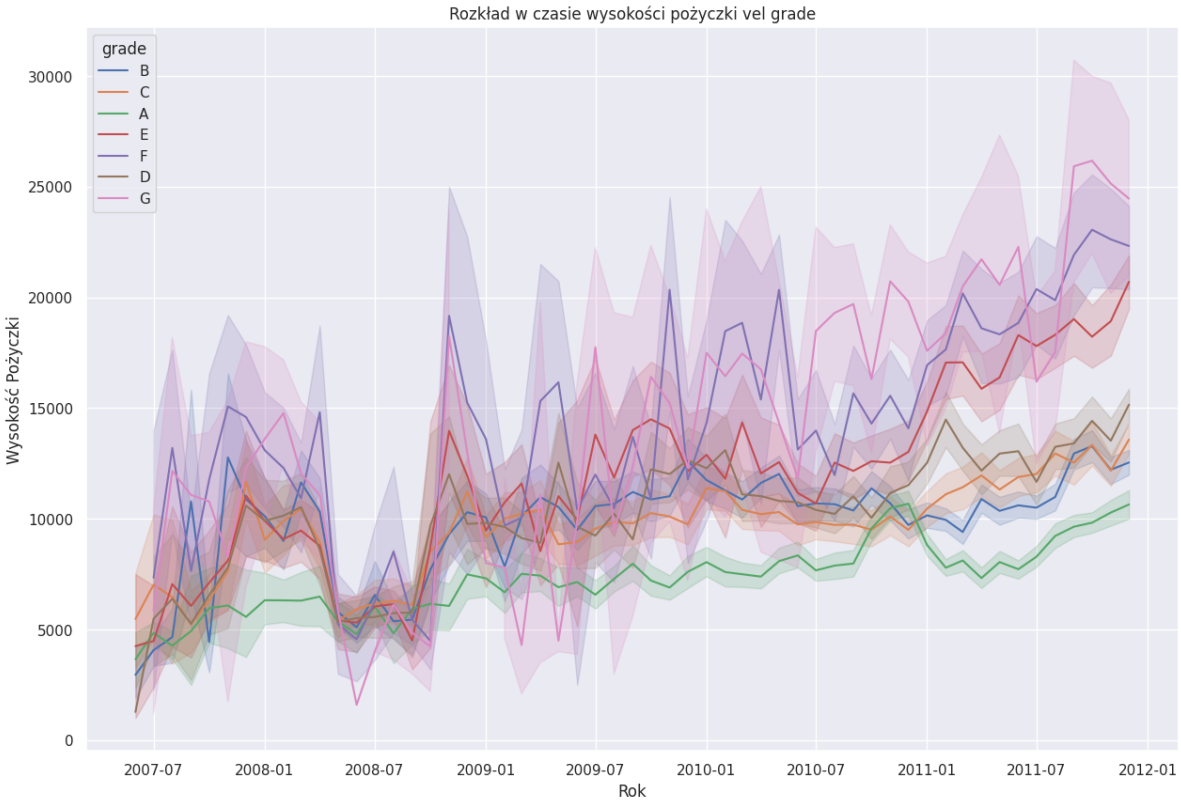
In [146…
```
stat, p_value, dof, expected = chi2_contingency(data_cross1)
alpha = 0.05
print(p_value)
```

```
0.0
```

In [147…
```
if p_value <= alpha:
    print('Odrzucamy hipotezę H0 - Są znaczące relacje między zmiennymi hom
else:
    print('Akceptujemy hipotezę zerową H0 - Nie ma zależności między status
```

```
Odrzucamy hipotezę H0 - Są znaczące relacje między zmiennymi home_ownership
i purpose
```

In [148…
```
plt.figure(figsize=(15,10))

ax = sns.lineplot(x="issue_d", y="loan_amnt", hue="grade", data=data_loan)
ax = plt.title('Rozkład w czasie wysokości pożyczki vel grade')
ax = plt.xlabel('Rok')
ax = plt.ylabel('Wysokość Pożyczki')
```



Wniosek:

Na podstawie przedstawionego wykresu widać, że wartości pożyczek z roku na rok rosły, pomijając spadek między 2008 a 2009. Dla osób z grade A wykres jest dość stabilny, wysokie skoki udzielania pożyczek są dla osób z grade F, D, G.

Dobry czy zły pożyczkobiorca?

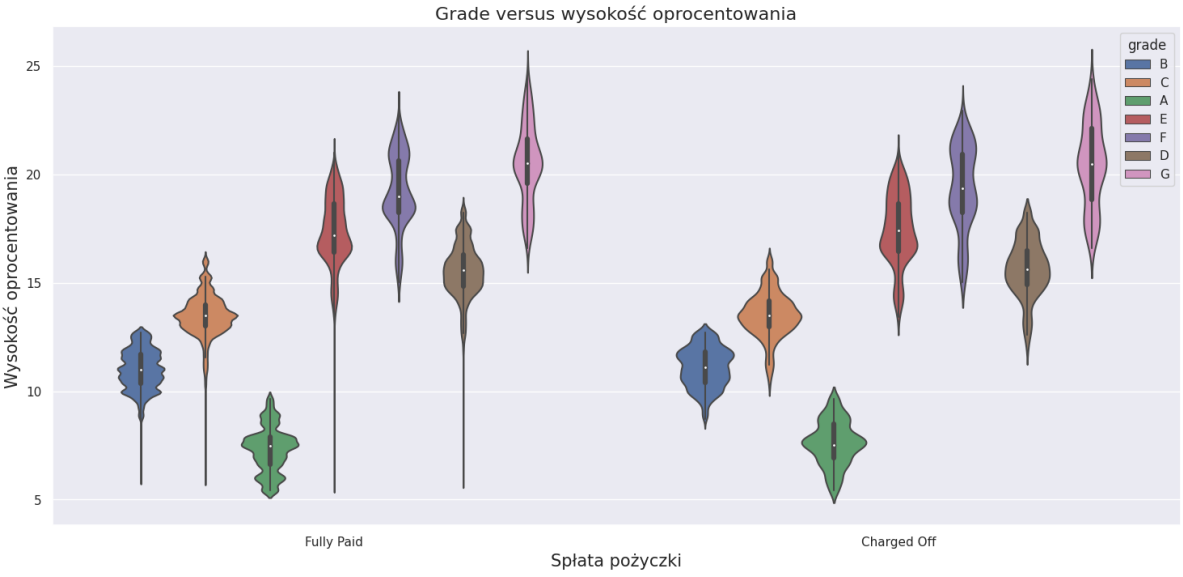
In [149…

```
plt.figure(figsize=(14,6))
plot_data = data_loan.groupby(['grade','loan_status']).size().unstack().T
r = range(7)

ax = plt.bar(r, plot_data.values[0], color='r', edgecolor='white',label='Ch
ax = plt.bar(r, plot_data.values[1], bottom=plot_data.values[0], color='b',
             edgecolor='white',label='Fully Paid')
names = plot_data.columns
ax = plt.xticks(r, names)
ax = plt.legend(loc='upper left')
ax = plt.xlabel('Grade')
ax = plt.ylabel('Wartość')
ax = plt.title('Wysokość kredytu versus grade')
```

Wniosek:

Na podstawie przedstawionego wykresu widać, że większość wyższych pożyczek jest udzielanych osobom z grade A, B, C. Osoby z niższym grade mają niższe zobowiązania.

In [150…
```
fig = plt.figure(figsize=(18,8))
sns.violinplot(x="loan_status",y="int_rate",data=data_loan, hue="grade")
plt.title("Grade versus wysokość oprocentowania", fontsize=16)
plt.xlabel("Spłata pożyczki", fontsize=15)
plt.ylabel("Wysokość oprocentowania", fontsize=15)
plt.show()
```

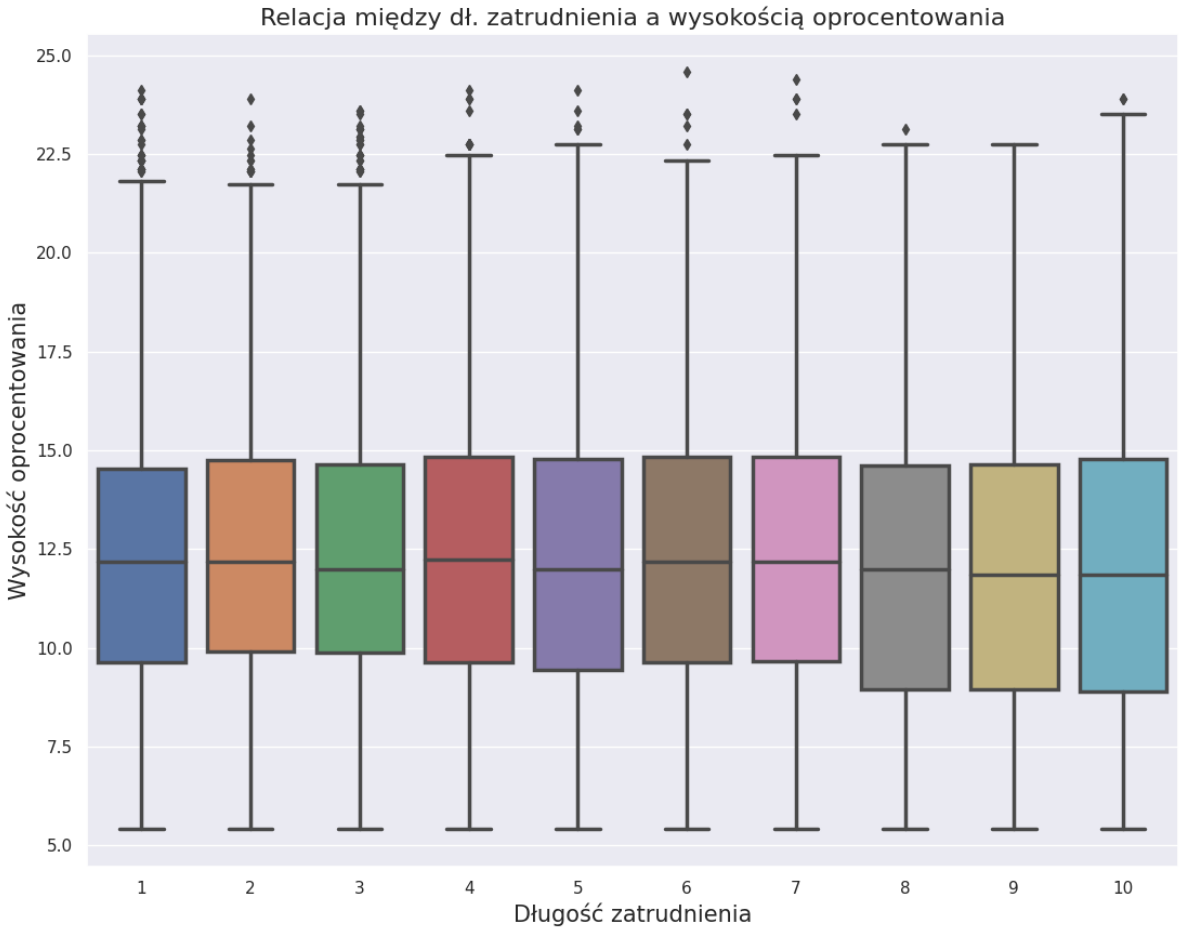


Wniosek:

Na podstawie przedstawionego wykresu widać, że im lepszy grade A czy B tym wysokość oprocentowania kredytu jest niższa. Osoby z grade = A mają oprocentowanie 5%-10%, a pożyczkobiorcy z garde G od 15% do ponad 25%.

In [151…
```
plt.figure(figsize = (13,10))
ax = sns.boxplot(x="emp_length", y= "int_rate", data=data_loan, linewidth=2
plt.xlabel("Długość zatrudnienia",fontsize=15)
plt.ylabel("Wysokość oprocentowania",fontsize=15)
```

```
plt.title("Relacja między dł. zatrudnienia a wysokością oprocentowania", fo
plt.show()
```



Wniosek:

Można podejrzewać, że kredytobiorcy z dłuższym stażem zatrudnienia i ustabilizowaną sytuacją zawodową mają szanse na niższe oprocentowanie kredytu. Część z nich, ze stażem 8,9 czy 10 lat ma najniższe oprocentowanie mniejsze niż 10% a średnia oprocentowania jest dla nich niższa. Spróbuje to sprawdzić na testach. Zastosuję test niezależności, Two Sample T-test

Zastosuję test niezależności, Two Sample T-test

- H0 - Hipoteza zerowa. "Nie ma zależności między długością zatrudnienia w wysokością oprocentowania pożyczki"
- H1 - Hipoteza alternatywna. "Wysokość oprocentowania pożyczki jest związana ze stażem pracy"

In [152…
```
a = data_loan['emp_length']
a.mean()
```

Out[152]:
```
5.174820735864582
```

In [153…
```
b = data_loan['int_rate']
b.mean()
```

Out[153]:
```
12.165015634182389
```

In [154…
```
ttest, p_value = stats.ttest_ind(a, b, equal_var = False)
print(p_value)
```

```
0.0
```

In [155…
```
if p_value < 0.05:
    print('Odrzucamy hipotezę zerową H0 - Wysokość oprocentowania pożyczki
else:
    print('Akceptujemy hipotezę zerową H0 - Nie ma zależności między długoś
```

```
Odrzucamy hipotezę zerową H0 - Wysokość oprocentowania pożyczki jest związa
na ze stażem pracy
```

Two Sample T-test

- H0 - Hipoteza zerowa. "Oprocentowania pożyczki dla pracowników ze stażem 10 i 4 lata są równe"
- H1 - Hipoteza alternatywna. "Wysokość oprocentowania jest inna dla pracowników ze stażem 10 i 4 lata"

In [156…
```
emp_10 = data_loan[data_loan['emp_length'] == 10]['int_rate']
emp_10.mean()
```

Out[156]:
```
12.076703558820464
```

In [157…
```
emp_4 = data_loan[data_loan['emp_length'] == 4]['int_rate']
emp_4.mean()
```

Out[157]:
```
12.30615237051249
```

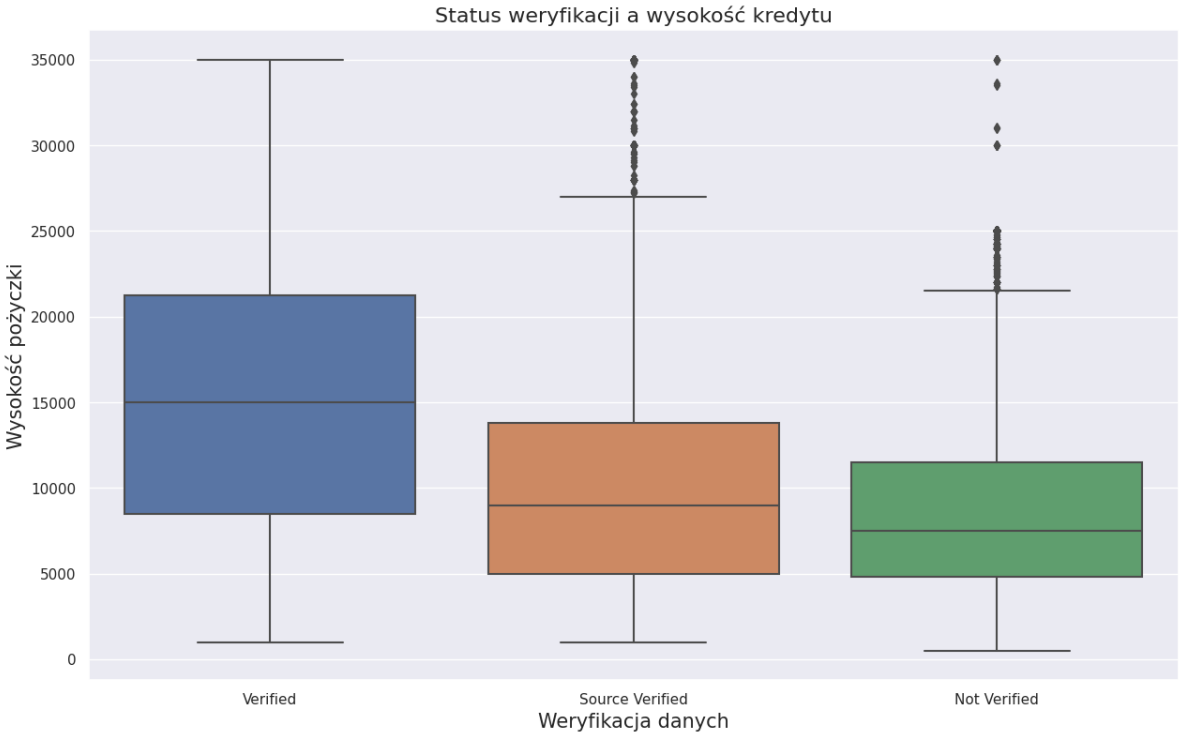
In [158…
```
ttest, p_value = stats.ttest_ind(emp_10, emp_4, equal_var = False)
print(p_value)
```

```
0.0015679055118476121
```

In [159…
```
if p_value < 0.05:
    print('Odrzucamy hipotezę zerową H0 - Wysokość oprocentowania jest inna
else:
    print('Akceptujemy hipotezę zerową H0 - Oprocentowania pożyczki dla pra
```

```
Odrzucamy hipotezę zerową H0 - Wysokość oprocentowania jest inna dla pracow
ników ze stażem 10 i 4 lata
```

In [160…
```
plt.figure(figsize=(15,9))
ax = sns.boxplot(x="verification_status", y="loan_amnt", data=data_loan)
ax = plt.xlabel('Weryfikacja danych',fontsize=15)
ax = plt.ylabel('Wysokość pożyczki',fontsize=15)
ax = plt.title('Status weryfikacji a wysokość kredytu',fontsize=16)
```



Wniosek:

Więcej zweryfikowanych pożyczek jest na pożyczkach między 8500 a 21000. Niższe pożyczki są częściej nieweryfikowane.

Test ANOVA

- H0 hipoteza zerowa - Nie ma różnic w grupach weryfikacji
- H1 hipoteza alternatywna - Średnie w grupach weryfikacyjnych są różne

In [161…
```
a = data_loan[data_loan['verification_status'] == 'Verified']['loan_amnt']
a.mean()
```

Out[161]:
```
15624.330042313117
```

In [162…
```
b = data_loan[data_loan['verification_status'] == 'Source Verified']['loan_
b.mean()
```

Out[162]:
```
10068.780322142442
```

In [163…
```
c = data_loan[data_loan['verification_status'] == 'Not Verified']['loan_amn
c.mean()
```

Out[163]:
```
8394.133169847531
```

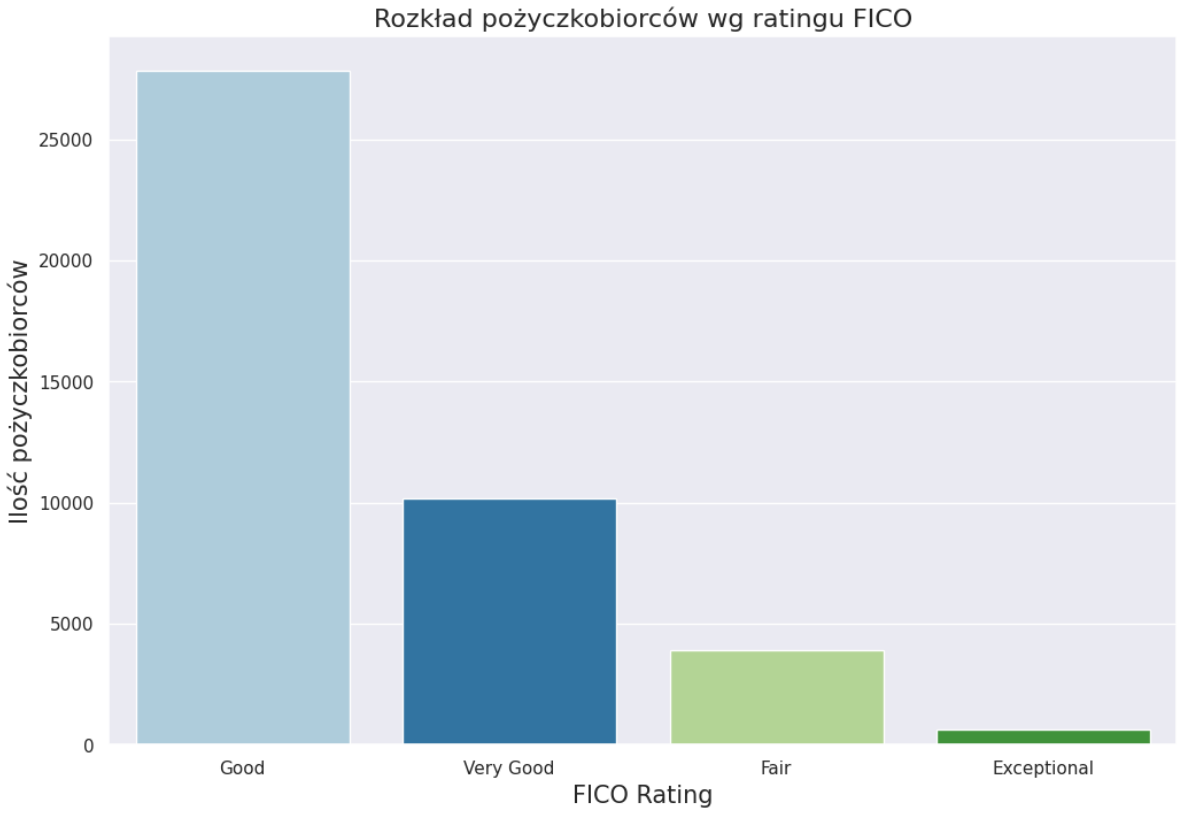
In [164…
```
fvalue, p_value = stats.stats.f_oneway(a, b, c)
print(fvalue, p_value)
```

```
4716.3219777419445 0.0
```

In [165…
```
if p_value < 0.05:
    print('Odrzucamy hipotezę zerową H0 - Średnie w grupach weryfikacyjnych
else:
    print('Akceptujemy hipotezę zerową H0 - Nie ma różnic w grupach weryfik
```

```
Odrzucamy hipotezę zerową H0 - Średnie w grupach weryfikacyjnych są różne
```

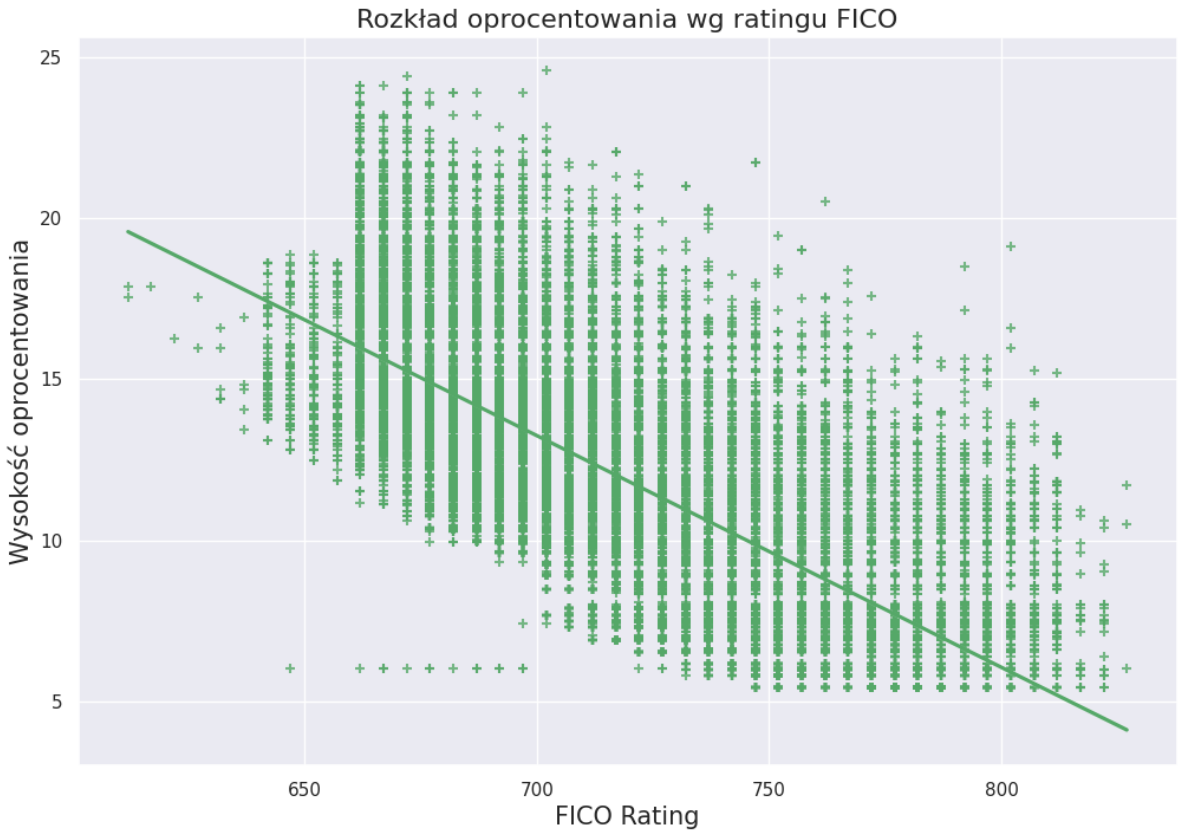
In [166…
```
plt.figure(figsize = (12,8))
sns.set(rc={'figure.figsize':(12,8)})
sns.countplot(x=data_loan['fico_rating'], palette='Paired')
plt.xlabel("FICO Rating",fontsize=15)
plt.ylabel("Ilość pożyczkobiorców",fontsize=15)
plt.title("Rozkład pożyczkobiorców wg ratingu FICO", fontsize=16)
plt.show()
```



Wniosek:

Na podstawie przedstawionego wykresu widać, iż najmniej pożyczkobiorców ma najwyższe Fico.

In [167…
```
sns.regplot(y="int_rate", x="fico_mean", marker="+", data=data_loan, color=
plt.xlabel("FICO Rating",fontsize=15)
plt.ylabel("Wysokość oprocentowania",fontsize=15)
plt.title("Rozkład oprocentowania wg ratingu FICO", fontsize=16)
plt.show()
```

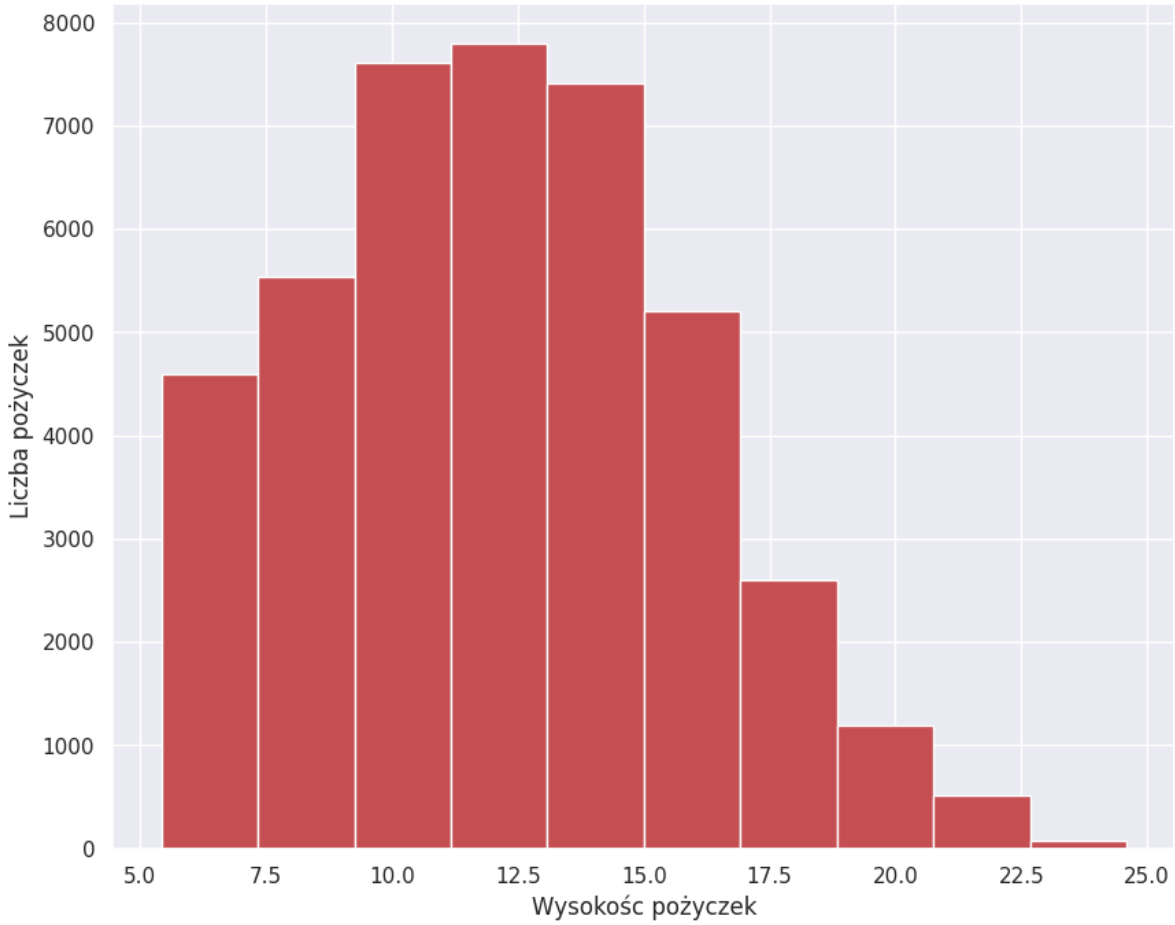


Wniosek:

Na podstawie przedstawionego wykresu "Im wyższe Fico tym niższe oprocentowanie".

In [168…

```
data_loan.int_rate.hist(figsize=(10,8), color='r')
plt.ylabel('Liczba pożyczek')
plt.xlabel('Wysokośc pożyczek')
plt.show()
```



Wniosek:

Na podstawie przedstawionego barplotu widać, że Lending Ckub najchętniej udziela pożyczek do 15 tys.

Feature Engineering

1. Wcześniej stworzyłem 'rating' z FICO (powyżej), który pójdzie do encodowania.
2. Wcześniej było 'grade' do łatwiejszej wizualizacji, teraz jednak 'grade' usuwam i zostawiam analitykę sub_grade.
3. Stworzę przedziały dla 'annual_income' i 'loan_amnt' i pójdzie do encodowania.
4. Stworzę również przedziały dla wysokości pożyczek.

In [169…
```
data_loan.drop([('grade')],axis=1,inplace=True)
```

In [170…
```
def loan_amnt_rate (row):
    if row['loan_amnt'] < 5000:
        return 'Minimal Loan'
    if row['loan_amnt'] < 10000:
        return 'Medium Low Loan'
    if row['loan_amnt'] < 15000:
        return 'Low Loan'
    if row['loan_amnt'] < 20000:
        return 'Medium High Loan'
    if row['loan_amnt'] < 25000:
        return 'High Loan'
```

```
    if row['loan_amnt'] < 30000:
        return 'Very High Loan'
    if row['loan_amnt']  >= 30000:
       return 'Extremely High Loan'
    return 'Other'

data_loan['loan_amnt_rating'] = data_loan.apply (lambda row: loan_amnt_rate
data_loan[['loan_amnt','loan_amnt_rating','emp_length','annual_inc']]
```

Out[170]:

	loan_amnt	loan_amnt_rating	emp_length	annual_inc
0	5000.0	Medium Low Loan	10	24000.0
1	2500.0	Minimal Loan	1	30000.0
2	2400.0	Minimal Loan	10	12252.0
3	10000.0	Low Loan	10	49200.0
4	3000.0	Minimal Loan	1	80000.0
...	...	...	...	...
42531	3500.0	Minimal Loan	1	180000.0
42532	1000.0	Minimal Loan	1	12000.0
42533	2525.0	Minimal Loan	1	110000.0
42534	6500.0	Medium Low Loan	1	60000.0
42535	5000.0	Medium Low Loan	10	70000.0

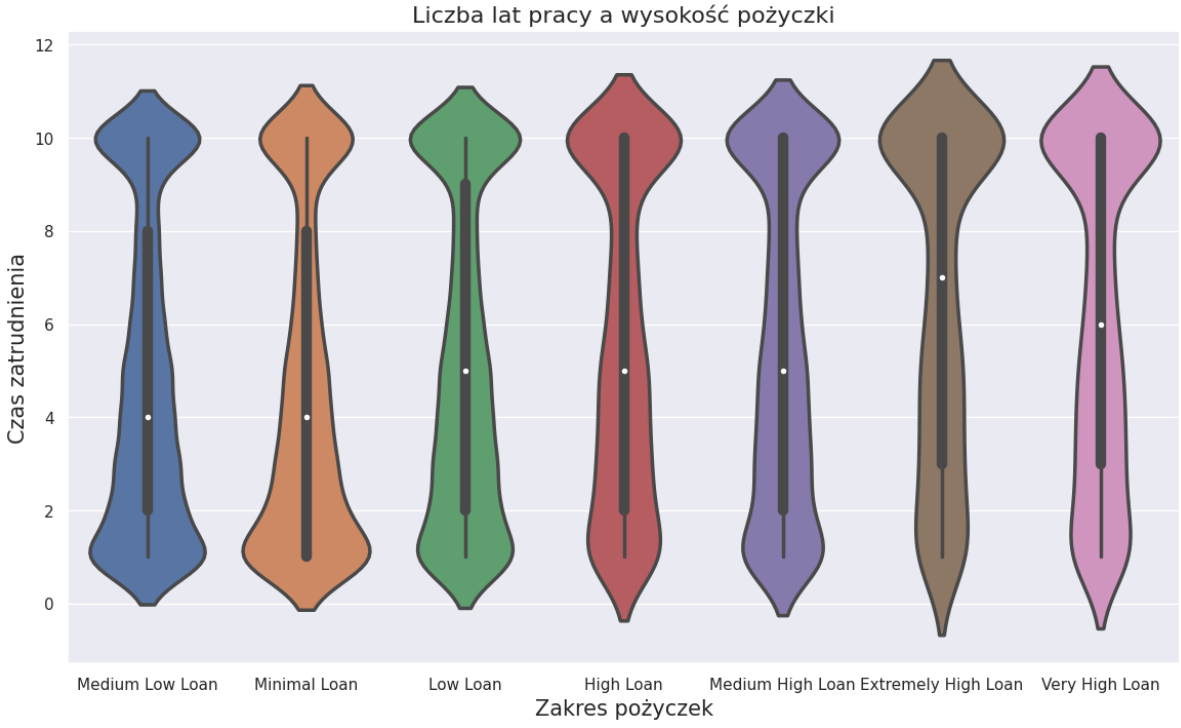
42535 rows × 4 columns

In [171…

```
plt.figure(figsize = (14,8))
ax = sns.violinplot(y="emp_length", x= "loan_amnt_rating", data=data_loan,
plt.title("Liczba lat pracy a wysokość pożyczki", fontsize=16)
plt.xlabel("Zakres pożyczek", fontsize=15)
plt.ylabel("Czas zatrudnienia", fontsize=15)
```

Out[171]:

```
Text(0, 0.5, 'Czas zatrudnienia')
```

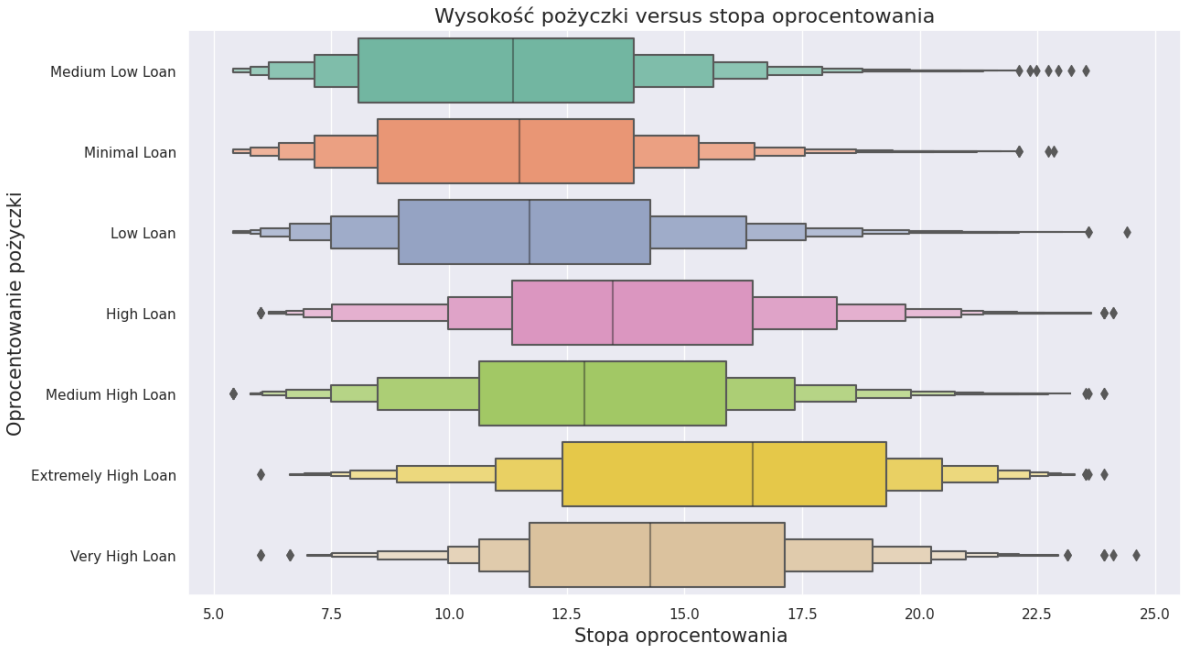


In [172…

```
plt.figure(figsize = (14,8))
```

```
ax = sns.boxenplot(y="loan_amnt_rating", x="int_rate", data=data_loan, pale
plt.title("Wysokość pożyczki versus stopa oprocentowania", fontsize=16)
plt.xlabel("Stopa oprocentowania ", fontsize=15)
plt.ylabel("Oprocentowanie pożyczki", fontsize=15)
```

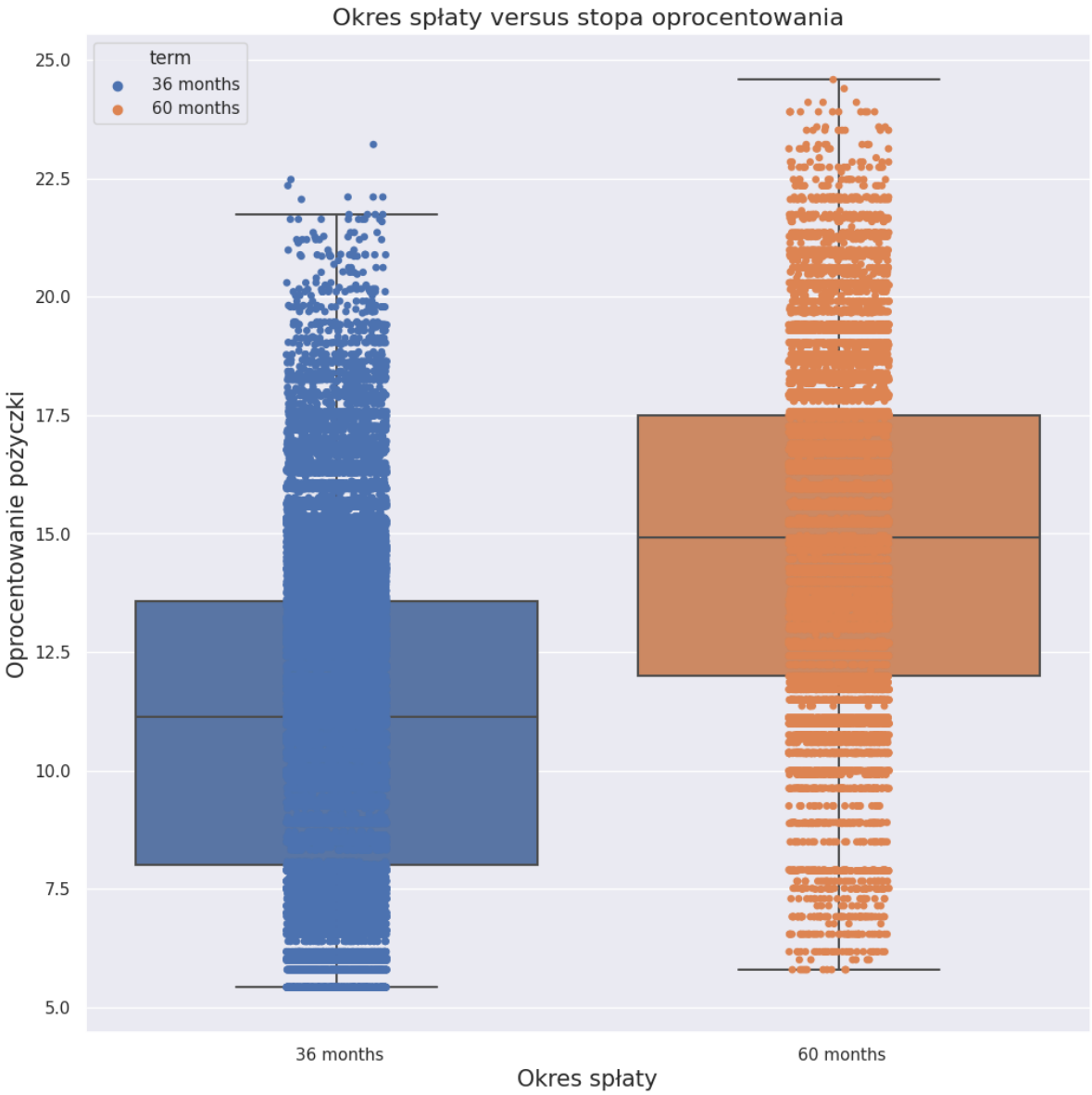
Out[172]: Text(0, 0.5, 'Oprocentowanie pożyczki')



In [173…

```
plt.figure(figsize = (12,12))
sns.boxplot(y='int_rate', x='term', data=data_loan, showfliers = False)
ax = sns.stripplot(y='int_rate', x='term', data=data_loan, hue='term')
plt.title("Okres spłaty versus stopa oprocentowania", fontsize=16)
plt.xlabel("Okres spłaty", fontsize=15)
plt.ylabel("Oprocentowanie pożyczki", fontsize=15)
```

Out[173]: Text(0, 0.5, 'Oprocentowanie pożyczki')



In [174…
```
data_loan.int_rate.describe()
```

Out[174]:
```
count    42535.000000
mean        12.165016
std          3.707936
min          5.420000
25%          9.630000
50%         11.990000
75%         14.720000
max         24.590000
Name: int_rate, dtype: float64
```

In [175…
```
def int_rating (row):
    if row['int_rate'] < data_loan['int_rate'].quantile(0.25):
        return 'Minimal interest rate'
    if row['int_rate'] < data_loan['int_rate'].quantile(0.75):
        return 'Medium interest rate'
    return 'High interest rate'

data_loan['interest_rating'] = data_loan.apply (lambda row: int_rating(row)
```

In [176…
```
data_loan[['int_rate','interest_rating']]
```

Out[176]:

	int_rate	interest_rating
0	10.65	Medium interest rate
1	15.27	High interest rate
2	15.96	High interest rate
3	13.49	Medium interest rate
4	12.69	Medium interest rate
...	...	...
42531	10.28	Medium interest rate
42532	9.64	Medium interest rate
42533	9.33	Minimal interest rate
42534	8.38	Minimal interest rate
42535	7.75	Minimal interest rate

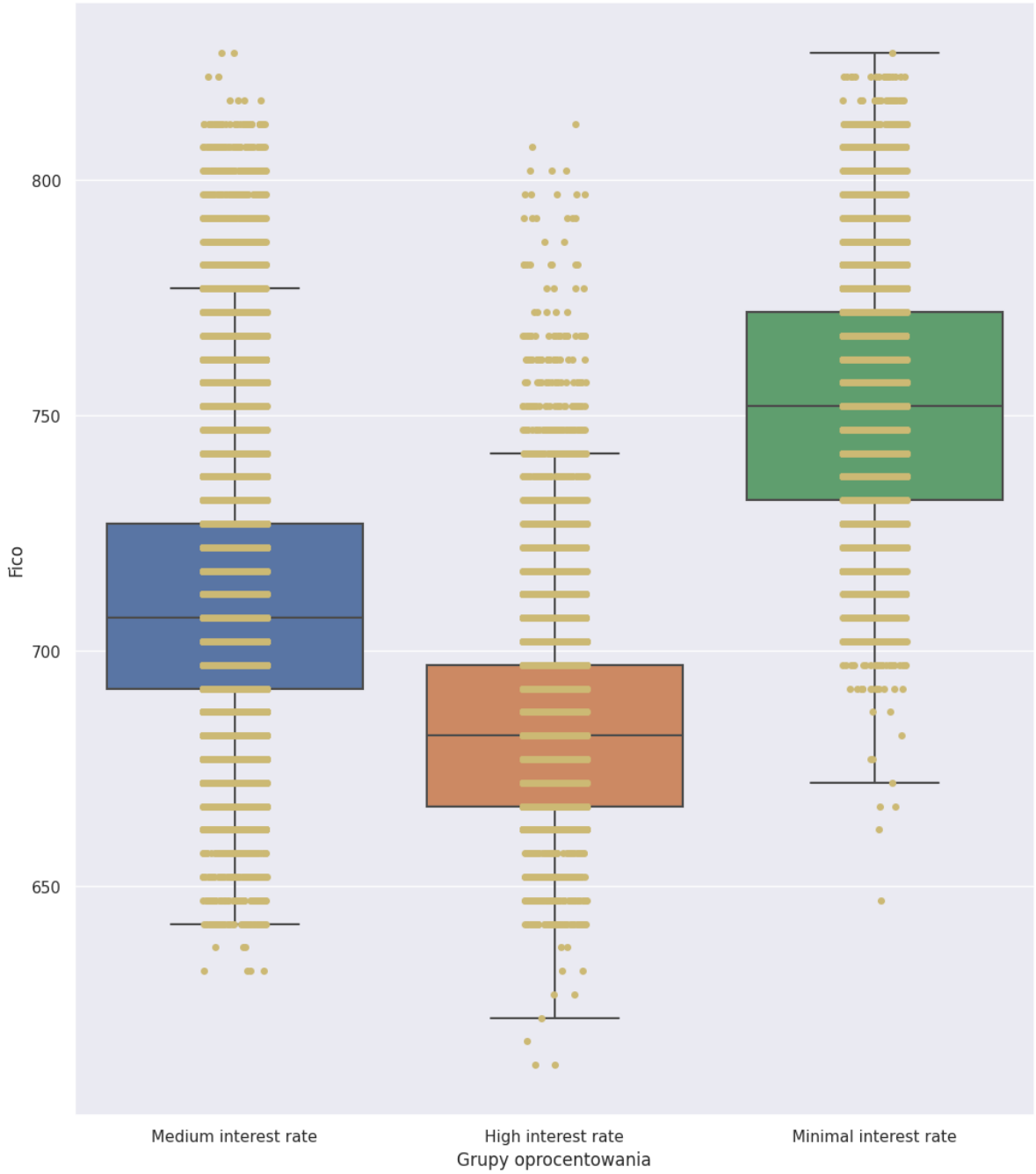
42535 rows × 2 columns

In [177…

```
plt.figure(figsize=(12,14))
sns.boxplot(x = 'interest_rating', y = 'fico_mean', data=data_loan, showfli
ax = sns.stripplot(x = 'interest_rating', y = 'fico_mean', data=data_loan,
plt.ylabel('Fico')
plt.xlabel('Grupy oprocentowania')
```

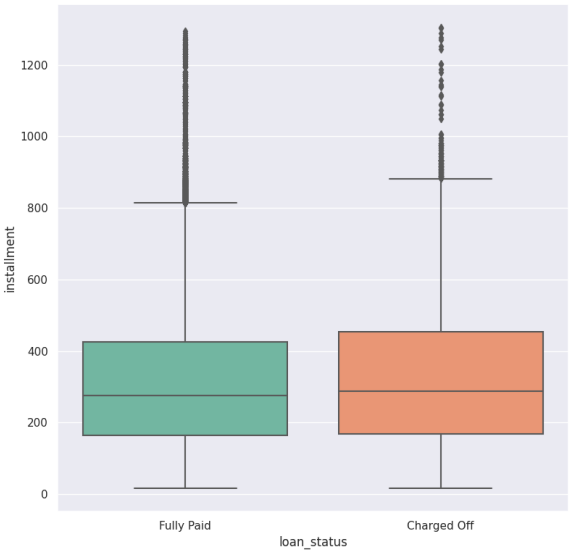
Out[177]:

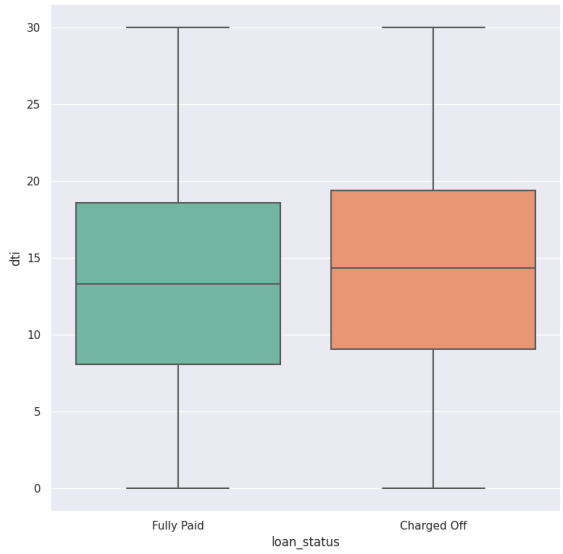
```
Text(0.5, 0, 'Grupy oprocentowania')
```

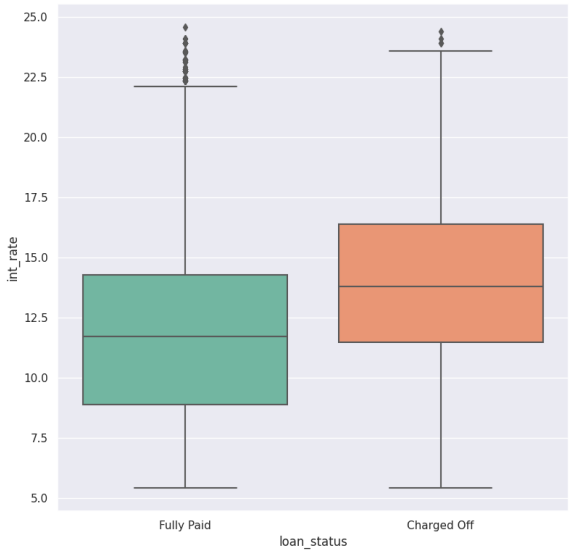


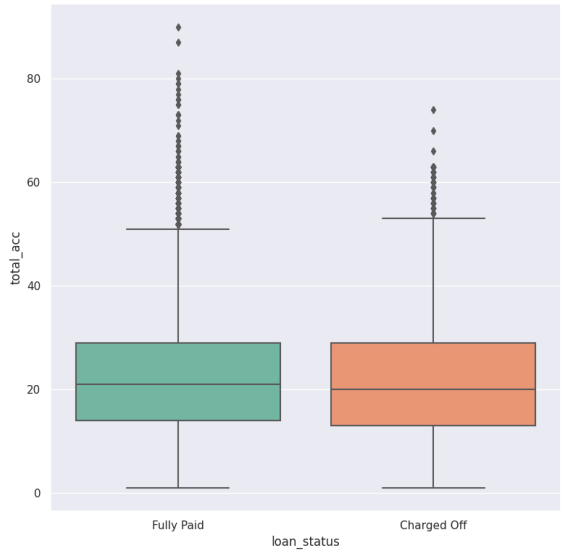
In [178…
```
fig,axes = plt.subplots(2,2, figsize=(20,20))
sns.boxplot(y='installment', x='loan_status', data=data_loan, ax=axes[0][0]
sns.boxplot(y='int_rate', x='loan_status', data=data_loan, ax=axes[1][0], pa
sns.boxplot(y='dti', x='loan_status', data=data_loan, ax=axes[0][1], palett
sns.boxplot(y='total_acc', x='loan_status', data=data_loan, ax=axes[1][1],
```

Out[178]:
```
<AxesSubplot:xlabel='loan_status', ylabel='total_acc'>
```







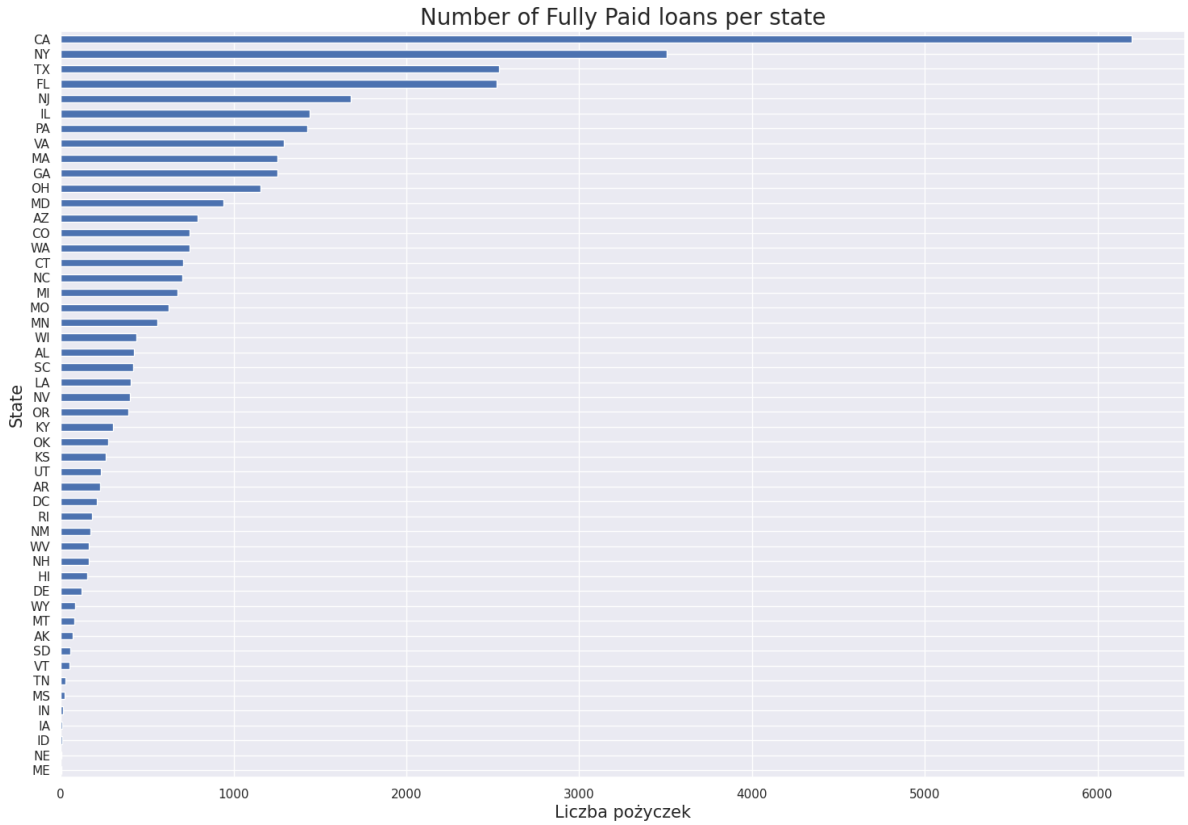


Target - loan_status - encoding

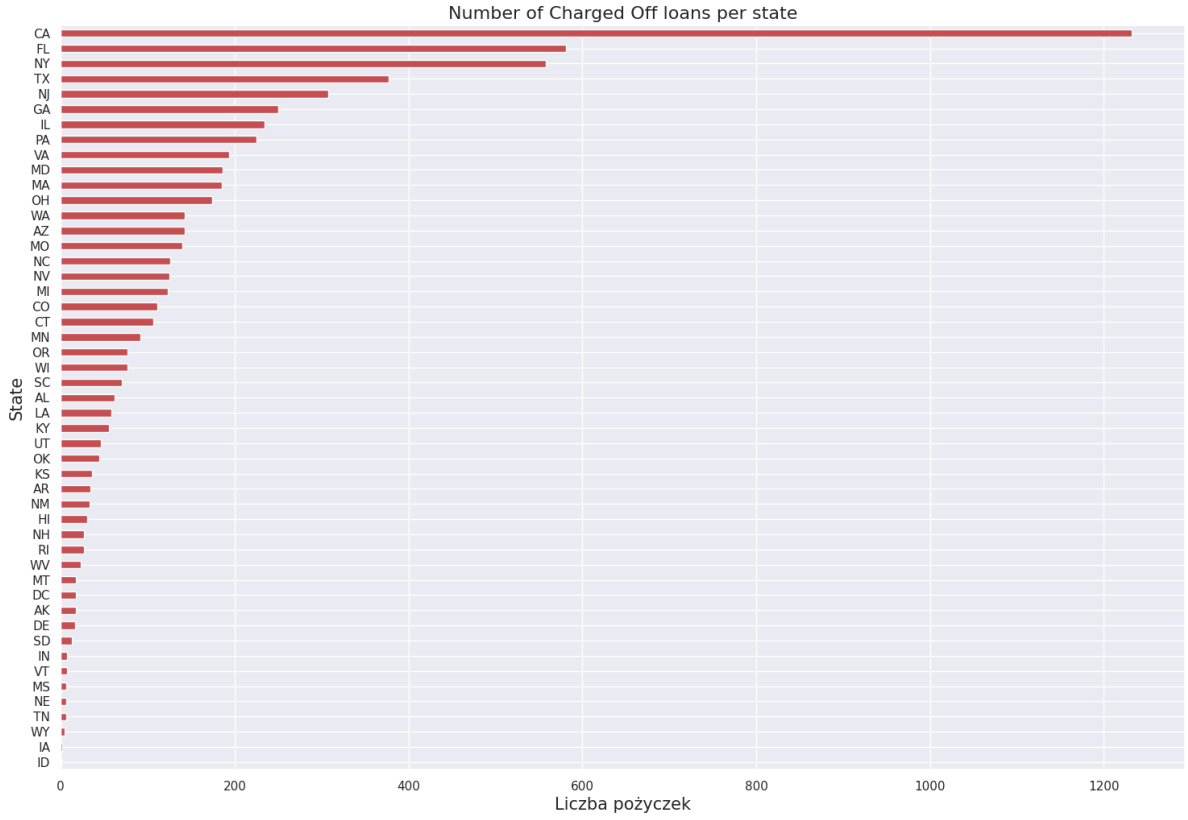
In [179…
```
le = LabelEncoder()
data_loan['loan_status'] = le.fit_transform(data_loan['loan_status'].astype
data_loan['loan_status'].value_counts()
```

Out[179]:
```
1    36104
0     6431
Name: loan_status, dtype: int64
```

In [180…
```
fig = plt.figure(figsize=(18,12))
data_loan[data_loan['loan_status']== 1].groupby('addr_state')['loan_status'
plt.ylabel('State',fontsize=15)
plt.xlabel('Liczba pożyczek',fontsize=15)
plt.title('Number of Fully Paid loans per state',fontsize=20);
```



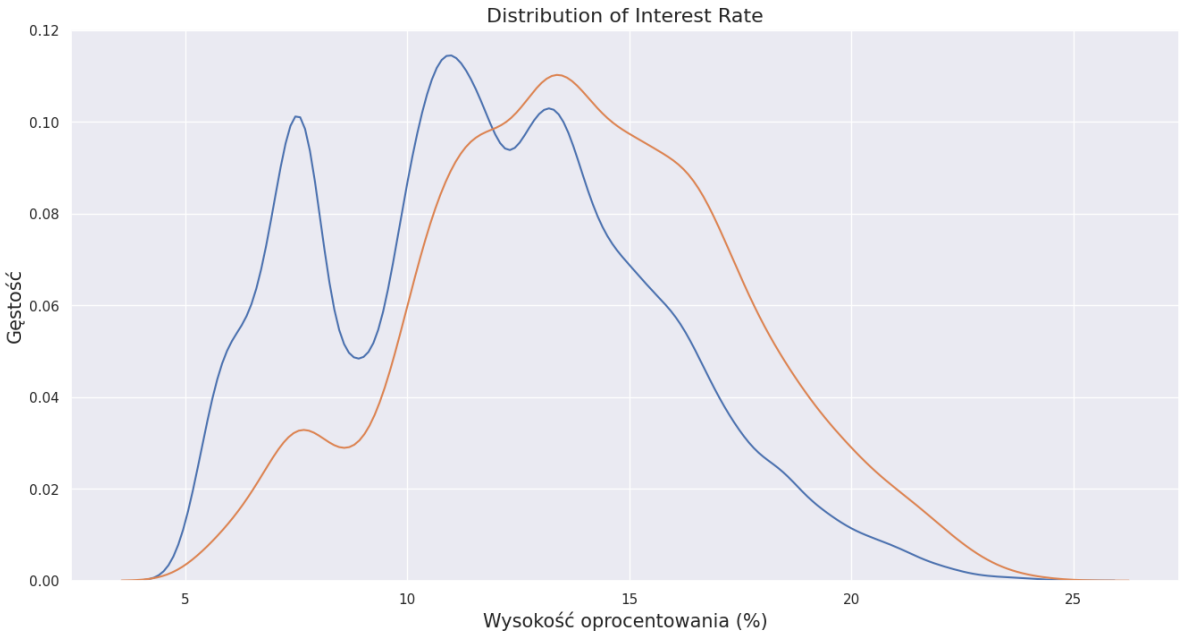
In [181…
```
fig = plt.figure(figsize=(18,12))
data_loan[data_loan['loan_status']== 0].groupby('addr_state')['loan_status'
plt.ylabel('State',fontsize=15)
plt.xlabel('Liczba pożyczek',fontsize=15)
plt.title('Number of Charged Off loans per state',fontsize=16);
```



In [182…
```
fig = plt.figure(figsize=(16,8))
sns.kdeplot(data_loan.loc[data_loan['loan_status'] == 1, 'int_rate'], label
sns.kdeplot(data_loan.loc[data_loan['loan_status'] == 0, 'int_rate'], label
plt.xlabel('Wysokość oprocentowania (%)',fontsize=15)
```

```
plt.ylabel('Gęstość',fontsize=15)
plt.title('Distribution of Interest Rate',fontsize=16)
```

Out[182]:
```
Text(0.5, 1.0, 'Distribution of Interest Rate')
```



In [183…
```
data_loan.dtypes
```

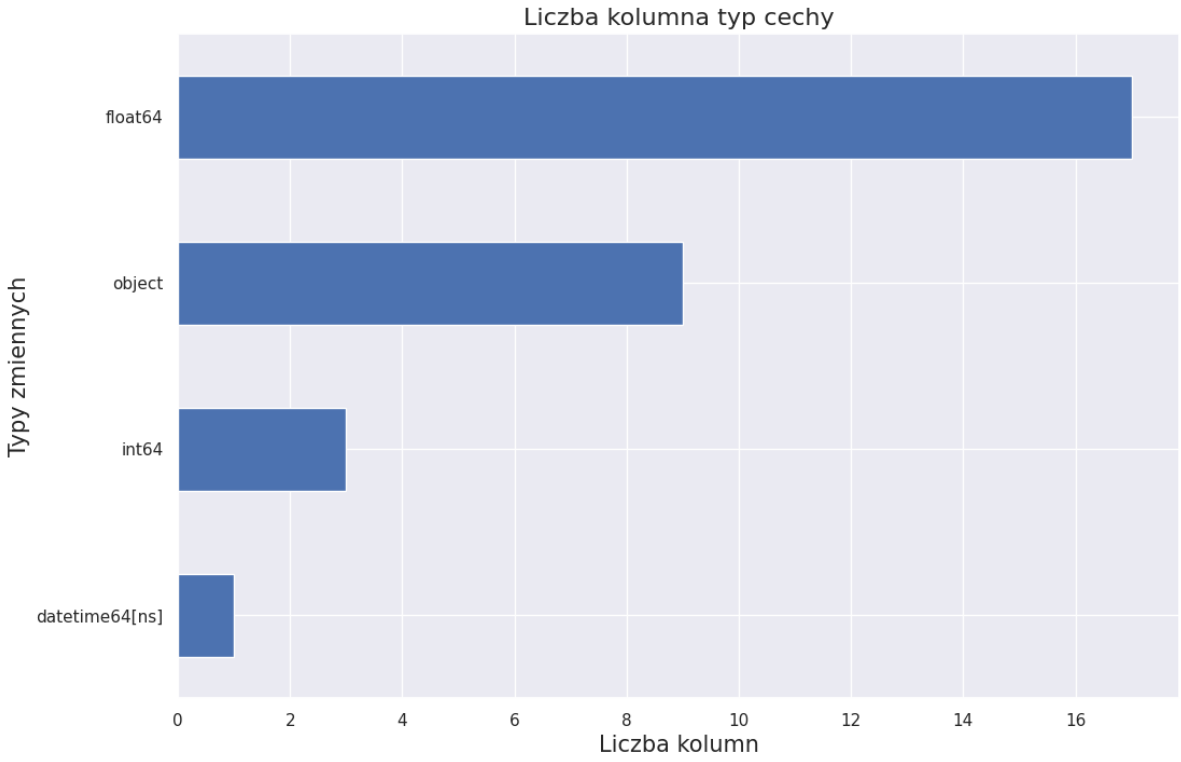
Out[183]:
```
loan_amnt                    float64
funded_amnt                  float64
term                          object
int_rate                     float64
installment                  float64
sub_grade                     object
emp_length                     int64
home_ownership                object
annual_inc                   float64
verification_status           object
issue_d                datetime64[ns]
loan_status                    int64
purpose                       object
addr_state                    object
dti                          float64
delinq_2yrs                  float64
earliest_cr_line               int64
inq_last_6mths               float64
mths_since_last_delinq       float64
open_acc                     float64
pub_rec                      float64
revol_bal                    float64
revol_util                   float64
total_acc                    float64
pub_rec_bankruptcies         float64
fico_mean                    float64
last_fico_mean               float64
fico_rating                   object
loan_amnt_rating              object
interest_rating               object
dtype: object
```

Mamy jeszcze dużą liczbę zmiennych obiektowych, kategrycznych, które będę sukcesywnie enkodował przed modelowaniem.

In [184…
```
data_loan.dtypes.value_counts().sort_values().plot(kind='barh')
```

```
plt.title('Liczba kolumna typ cechy',fontsize=16)
plt.xlabel('Liczba kolumn',fontsize=15)
plt.ylabel('Typy zmiennych',fontsize=15)
```

Out[184]:
```
Text(0, 0.5, 'Typy zmiennych')
```



In [185…
```
data_loan.select_dtypes('object').apply(pd.Series.nunique, axis = 0)
```

Out[185]:
```
term                   2
sub_grade             35
home_ownership         5
verification_status    3
purpose               14
addr_state            50
fico_rating            4
loan_amnt_rating       7
interest_rating        3
dtype: int64
```

In [186…
```
data_loan.shape
```

Out[186]:
```
(42535, 30)
```

Daty

Konwersja dat na integer lata. Najpierw skonwertuję kolumny obiektów daty na całkowitą liczbę lat tylko dlatego, że nie chcę zwiększać liczby kolumn, wykonując na nich one hot encoding.

In [187…
```
data_loan['issue_d']= pd.to_datetime(data_loan['issue_d']).apply(lambda x:
```

In [188…
```
print(data_loan.earliest_cr_line)
```

```
0        1985
1        1999
2        2001
3        1996
4        1996
         ...
42531    2007
42532    2007
42533    2007
42534    2007
42535    2007
Name: earliest_cr_line, Length: 42535, dtype: int64
```

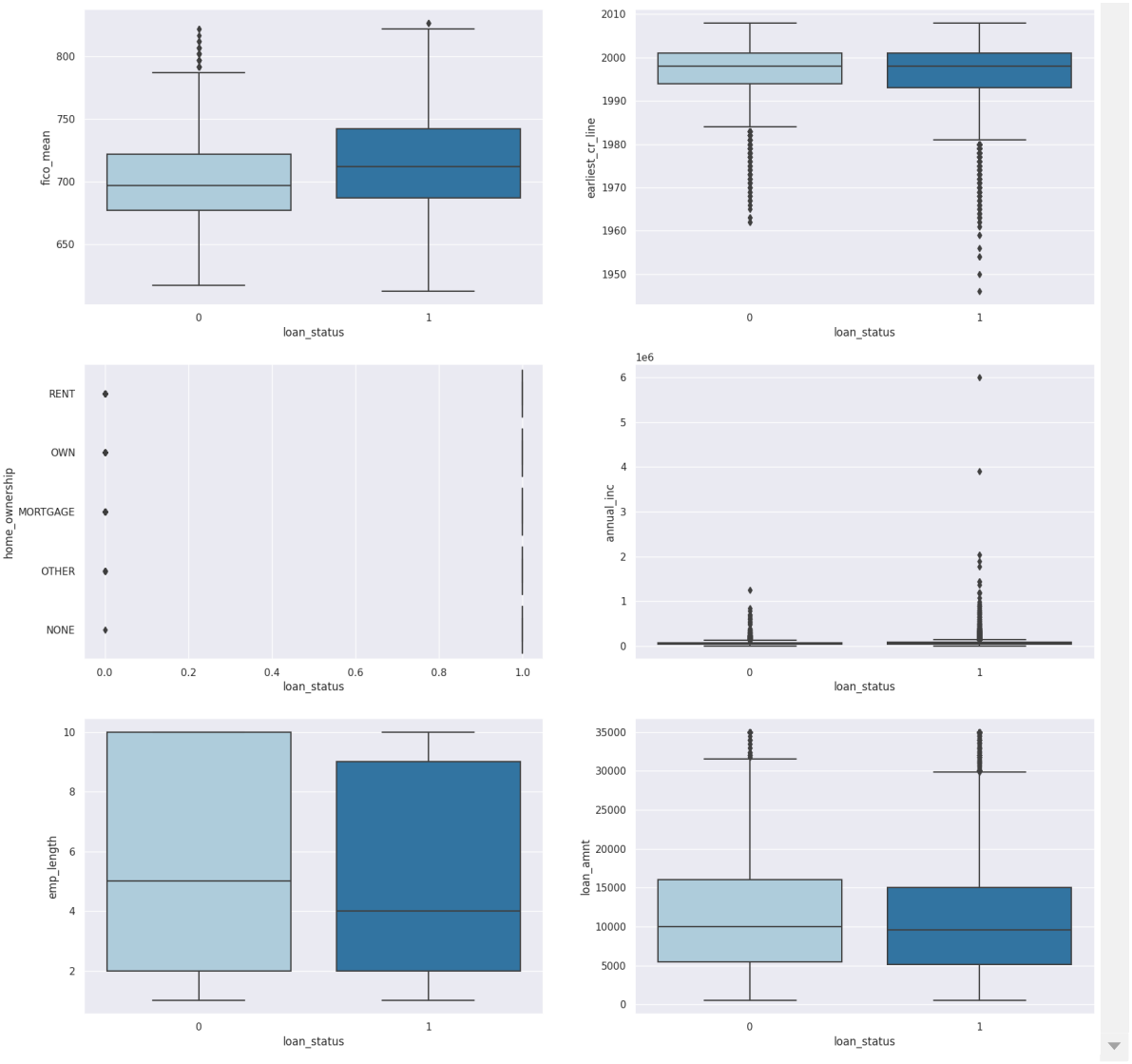
In [189…
```
print(data_loan.issue_d)
```

```
0        2011
1        2011
2        2011
3        2011
4        2011
         ...
42531    2007
42532    2007
42533    2007
42534    2007
42535    2007
Name: issue_d, Length: 42535, dtype: int64
```

Po encodowaniu targetu do pytań z EDA

In [190…
```
fig,axes = plt.subplots(3,2, figsize=(20,20))

sns.boxplot(y='fico_mean', x='loan_status', data=data_loan, ax=axes[0][0],
sns.boxplot(y='earliest_cr_line', x='loan_status', data=data_loan, ax=axes[
sns.boxplot(y='home_ownership', x='loan_status', data=data_loan, ax=axes[1]
sns.boxplot(y='annual_inc', x='loan_status', data=data_loan, ax=axes[1][1],
sns.boxplot(y='emp_length', x='loan_status', data=data_loan, ax=axes[2][0],
sns.boxplot(y='loan_amnt', x='loan_status', data=data_loan, ax=axes[2][1],
```

Out[190]:
```
<AxesSubplot:xlabel='loan_status', ylabel='loan_amnt'>
```



Outliery wartości odstające

In [191…

```
data_loan.describe().T
```

Out[191]:

	count	mean	std	min	25%	50%	
loan_amnt	42535.0	11089.722581	7410.938391	500.00	5200.00	9700.00	150
funded_amnt	42535.0	10821.585753	7146.914675	500.00	5000.00	9600.00	150
int_rate	42535.0	12.165016	3.707936	5.42	9.63	11.99	
installment	42535.0	322.623063	208.927216	15.67	165.52	277.69	4
emp_length	42535.0	5.174821	3.458260	1.00	2.00	4.00	
annual_inc	42535.0	69135.697217	64093.396996	1896.00	40000.00	59000.00	825
issue_d	42535.0	2010.231456	0.966383	2007.00	2010.00	2011.00	20
loan_status	42535.0	0.848807	0.358241	0.00	1.00	1.00	
dti	42535.0	13.373043	6.726315	0.00	8.20	13.47	
delinq_2yrs	42535.0	0.152345	0.512247	0.00	0.00	0.00	
earliest_cr_line	42535.0	1996.589797	6.843186	1946.00	1993.00	1998.00	20
inq_last_6mths	42535.0	1.080686	1.527195	0.00	0.00	1.00	
mths_since_last_delinq	42535.0	33.740402	13.615113	0.00	33.00	33.00	
open_acc	42535.0	9.342353	4.495157	1.00	6.00	9.00	
pub_rec	42535.0	0.058117	0.245634	0.00	0.00	0.00	
revol_bal	42535.0	14297.860915	22018.441010	0.00	3635.00	8821.00	172
revol_util	42535.0	49.118389	28.334260	0.00	25.80	49.70	
total_acc	42535.0	22.122958	11.588991	1.00	13.00	20.00	
pub_rec_bankruptcies	42535.0	0.043776	0.205515	0.00	0.00	0.00	
fico_mean	42535.0	715.052545	36.188439	612.00	687.00	712.00	7
last_fico_mean	42535.0	683.437275	96.609100	0.00	642.00	697.00	7

kopia data_loan i na niej szukam outlierów

In [192…

```
data_outliers = data_loan.select_dtypes(exclude=['object']).copy()

data_outliers
```

Out[192]:

	loan_amnt	funded_amnt	int_rate	installment	emp_length	annual_inc	issue_d	loan_
0	5000.0	5000.0	10.65	162.87	10	24000.0	2011	
1	2500.0	2500.0	15.27	59.83	1	30000.0	2011	
2	2400.0	2400.0	15.96	84.33	10	12252.0	2011	
3	10000.0	10000.0	13.49	339.31	10	49200.0	2011	
4	3000.0	3000.0	12.69	67.79	1	80000.0	2011	
...	...	...	...	...	...	...	...	
42531	3500.0	3500.0	10.28	113.39	1	180000.0	2007	
42532	1000.0	1000.0	9.64	32.11	1	12000.0	2007	
42533	2525.0	2525.0	9.33	80.69	1	110000.0	2007	
42534	6500.0	6500.0	8.38	204.84	1	60000.0	2007	
42535	5000.0	5000.0	7.75	156.11	10	70000.0	2007	

42535 rows × 21 columns

In [193…

```
Q1 = data_outliers.quantile(0.25)
Q3 = data_outliers.quantile(0.75)
IQR = Q3 - Q1

data_outliers_amnt = pd.DataFrame({'Q1':Q1, 'Q3':Q3,'IQR':IQR, 'lower': Q1-
                 'number of Outliers' : ((data_outliers < (Q1 - 1.5 * IQR))
                })

data_outliers_amnt
```

Out[193]:

	Q1	Q3	IQR	lower	upper	number of Outliers
loan_amnt	5200.00	15000.00	9800.00	-9500.000	29700.000	1218
funded_amnt	5000.00	15000.00	10000.00	-10000.000	30000.000	691
int_rate	9.63	14.72	5.09	1.995	22.355	94
installment	165.52	428.18	262.66	-228.470	822.170	1393
emp_length	2.00	9.00	7.00	-8.500	19.500	0
annual_inc	40000.00	82500.00	42500.00	-23750.000	146250.000	2032
issue_d	2010.00	2011.00	1.00	2008.500	2012.500	2996
loan_status	1.00	1.00	0.00	1.000	1.000	6431
dti	8.20	18.68	10.48	-7.520	34.400	0
delinq_2yrs	0.00	0.00	0.00	0.000	0.000	4735
earliest_cr_line	1993.00	2001.00	8.00	1981.000	2013.000	1293
inq_last_6mths	0.00	2.00	2.00	-3.000	5.000	781
mths_since_last_delinq	33.00	33.00	0.00	33.000	33.000	15403
open_acc	6.00	12.00	6.00	-3.000	21.000	619
pub_rec	0.00	0.00	0.00	0.000	0.000	2376
revol_bal	3635.00	17251.00	13616.00	-16789.000	37675.000	2906
revol_util	25.80	72.60	46.80	-44.400	142.800	0
total_acc	13.00	29.00	16.00	-11.000	53.000	604
pub_rec_bankruptcies	0.00	0.00	0.00	0.000	0.000	1854
fico_mean	687.00	742.00	55.00	604.500	824.500	3
last_fico_mean	642.00	747.00	105.00	484.500	904.500	795

data_outliers

Zamieniam outliery na wybranych kolumnach na mediany to będzie drugi zbiór do modelowania

In [194…
```
data_outliers = data_outliers.drop(['loan_status', 'delinq_2yrs', 'pub_rec'
```

In [195…
```
for col_name in data_outliers.columns[:-1]:
    q1 = data_outliers[col_name].quantile(0.25)
    q3 = data_outliers[col_name].quantile(0.75)
    iqr = q3 - q1

    low = q1-1.5*iqr
    high = q3+1.5*iqr
    data_outliers.loc[(data_outliers[col_name] < low) | (data_outliers[col_

data_outliers.describe()
```

Out[195]:

	loan_amnt	funded_amnt	int_rate	installment	emp_length	annual_inc
count	42535.000000	42535.000000	42535.000000	42535.000000	42535.000000	42535.000000
mean	10419.303515	10417.018926	12.140418	301.462641	5.174821	61079.341457
std	6363.021099	6465.777909	3.671836	176.191735	3.458260	27639.749197
min	500.000000	500.000000	5.420000	15.670000	1.000000	1896.000000
25%	5200.000000	5000.000000	9.630000	165.520000	2.000000	40000.000000
50%	9700.000000	9600.000000	11.990000	277.690000	4.000000	59000.000000
75%	14500.000000	14500.000000	14.650000	399.090000	9.000000	76000.000000
max	29700.000000	30000.000000	22.350000	821.590000	10.000000	146000.000000

Korelacja na całym zbiorze data_loan

In [196…

```
corr = data_loan.corr()
corr
```

Out[196]:

	loan_amnt	funded_amnt	int_rate	installment	emp_length	annual_i
loan_amnt	1.000000	0.981746	0.292346	0.930869	0.138589	0.2761
funded_amnt	0.981746	1.000000	0.295154	0.956522	0.138117	0.2720
int_rate	0.292346	0.295154	1.000000	0.271433	-0.012695	0.0543
installment	0.930869	0.956522	0.271433	1.000000	0.108253	0.2783
emp_length	0.138589	0.138117	-0.012695	0.108253	1.000000	0.0987
annual_inc	0.276125	0.272070	0.054377	0.278342	0.098776	1.0000
issue_d	0.142493	0.152112	0.006153	0.072136	0.148266	0.0126
loan_status	-0.042582	-0.039602	-0.200598	-0.021094	-0.019826	0.0379
dti	0.065112	0.064821	0.119607	0.054948	0.052880	-0.1165
delinq_2yrs	-0.032558	-0.033209	0.154807	-0.019894	0.009956	0.0221
earliest_cr_line	-0.191521	-0.185279	0.115051	-0.169694	-0.297036	-0.1889
inq_last_6mths	-0.029830	-0.029560	0.179730	-0.010414	-0.021982	0.0277
mths_since_last_delinq	0.008160	0.008930	-0.011536	-0.000512	0.043536	0.0011
open_acc	0.176791	0.174973	0.024894	0.175611	0.088396	0.1680
pub_rec	-0.051460	-0.052447	0.100456	-0.045678	0.066808	-0.0163
revol_bal	0.254293	0.250313	0.081883	0.264837	0.116641	0.2835
revol_util	0.065231	0.068865	0.456247	0.094486	0.004615	0.0213
total_acc	0.256958	0.251163	-0.031538	0.233939	0.199055	0.2460
pub_rec_bankruptcies	-0.035277	-0.036591	0.084944	-0.032499	0.070377	-0.0146
fico_mean	0.133232	0.125637	-0.702587	0.064362	0.100318	0.0519
last_fico_mean	0.080111	0.080217	-0.282394	0.075866	0.022608	0.0651

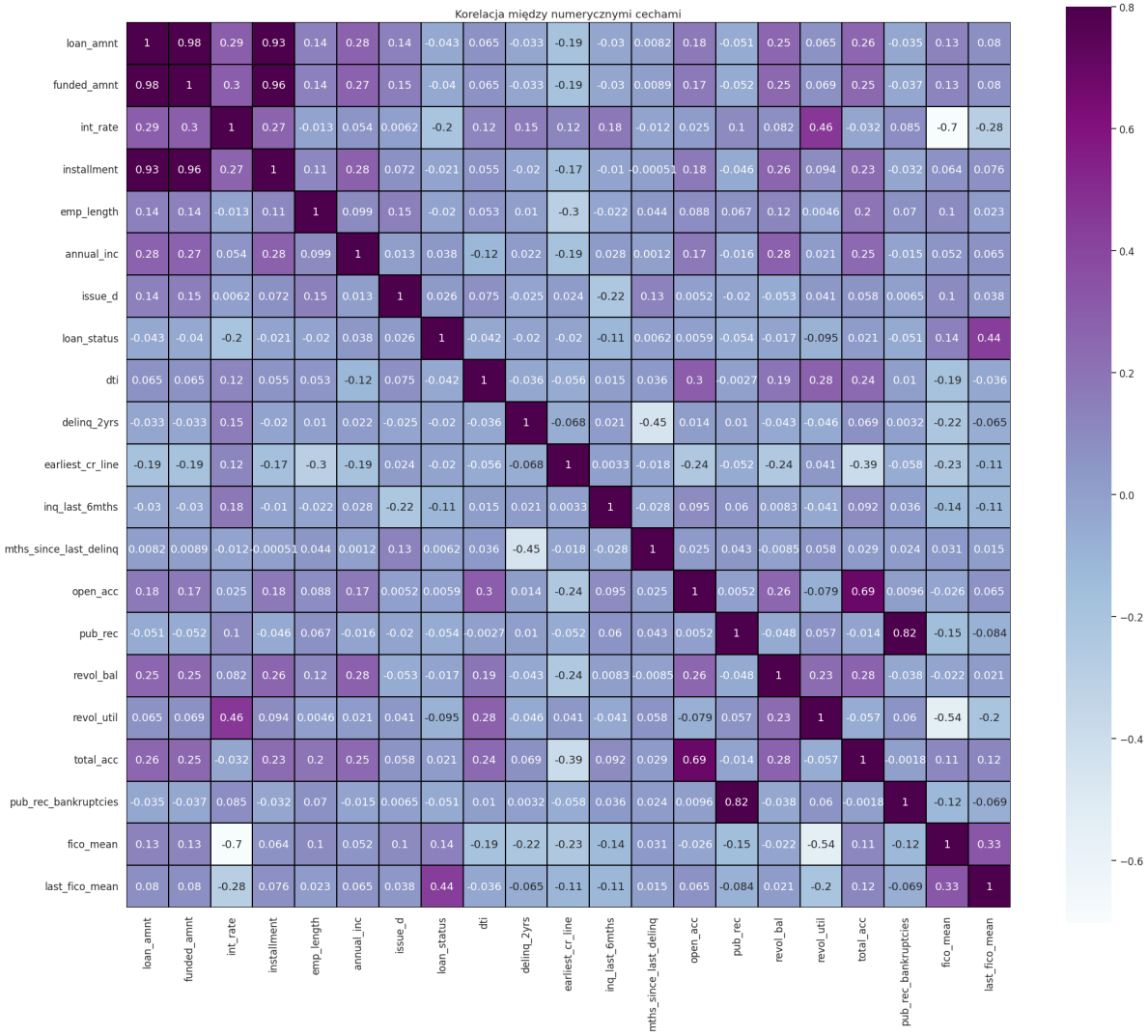
21 rows × 21 columns

In [197…

```
sns.set(font_scale=1.1)
```

```
plt.figure(figsize=(24, 20))

sns.heatmap(corr, vmax=.8, linewidths=0.01,
            square=True, annot=True, cmap="BuPu", linecolor="black")
plt.title('Korelacja między numerycznymi cechami')
```

Out[197]:
```
Text(0.5, 1.0, 'Korelacja między numerycznymi cechami')
```



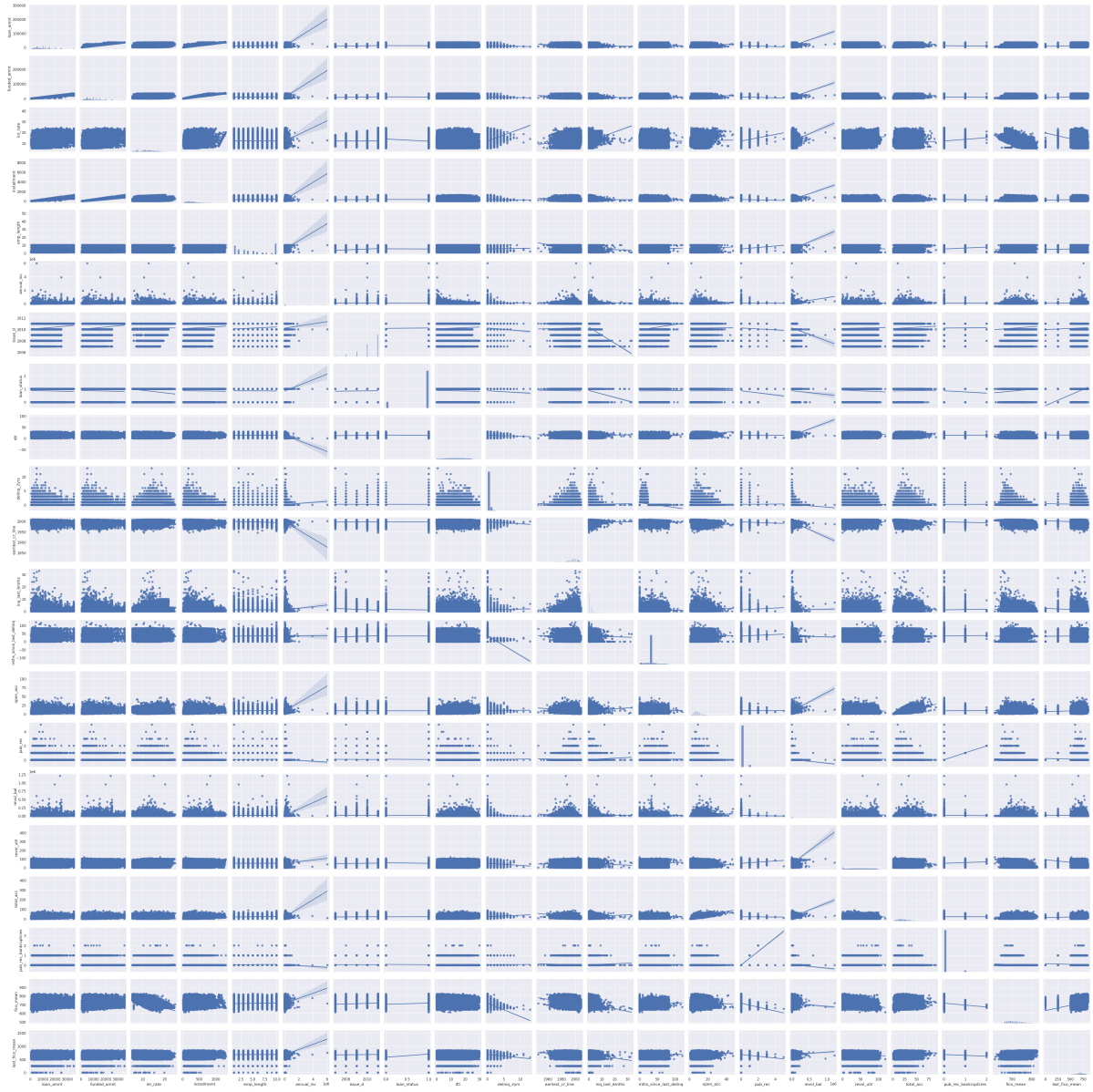
UWAGA!!!

Linia nr 1 poniższego kodu: Tworzenie wykresu `pairplot` zajmuje bardzo dużo czsu. To jest tak ciężkie obliczeniowo, że mi się to w ogóle nie wykonywało i dlatego komętuję tworzenie wykresu `pairplot`. Nie byłem w stanie wyświetlić wyników. Jest za dużo danych, Kernal ma problemy z obliczeniem tego i wyświetleniem wykresu. Zaniecham użycia parametru `palette` (zestaw kolorów do mapowania zmiennej `hue`).

Linia nr 2: Ograniczyłem parametry wykresu `pairplot` tak jak poniżej, aby zwizualizować obliczenia i wyświetlić wykres `pairplot`.

In [198…
```
# sns.pairplot(data_loan, hue='loan_amnt', kind="reg", palette="husl")
sns.pairplot(data_loan, kind="reg")
```

Out[198]:
```
<seaborn.axisgrid.PairGrid at 0x7fb509f28e90>
```



Korelacja wybranych cech - data_loan1

Ograniczam zakres danych, by przyjrzeć się wybranym cechom.

In [199…

```
data_loan1=data_loan[['annual_inc','installment','int_rate','fico_mean',
                      'last_fico_mean','loan_amnt','revol_bal','open_acc','
cor1 = data_loan1.corr()
cor1
```

Out[199]:

	annual_inc	installment	int_rate	fico_mean	last_fico_mean	loan_amnt	rev
annual_inc	1.000000	0.278342	0.054377	0.051989	0.065137	0.276125	0.2
installment	0.278342	1.000000	0.271433	0.064362	0.075866	0.930869	0.2
int_rate	0.054377	0.271433	1.000000	-0.702587	-0.282394	0.292346	0.0
fico_mean	0.051989	0.064362	-0.702587	1.000000	0.328915	0.133232	-0.0
last_fico_mean	0.065137	0.075866	-0.282394	0.328915	1.000000	0.080111	0.0
loan_amnt	0.276125	0.930869	0.292346	0.133232	0.080111	1.000000	0.2
revol_bal	0.283595	0.264837	0.081883	-0.022011	0.021390	0.254293	1.0
open_acc	0.168060	0.175611	0.024894	-0.025763	0.065255	0.176791	0.2
total_acc	0.246085	0.233939	-0.031538	0.110587	0.115398	0.256958	0.2
loan_status	0.037988	-0.021094	-0.200598	0.141917	0.440511	-0.042582	-0.0

In [200…

```
sns.set(font_scale=1.15)
plt.figure(figsize=(24, 14))

sns.heatmap(cor1, vmax=.8, linewidths=0.01,
            square=True, annot=True, cmap="BuPu", linecolor="black")
plt.title('Korelacja między wybranymi cechami')
```

Out[200]: Text(0.5, 1.0, 'Korelacja między wybranymi cechami')

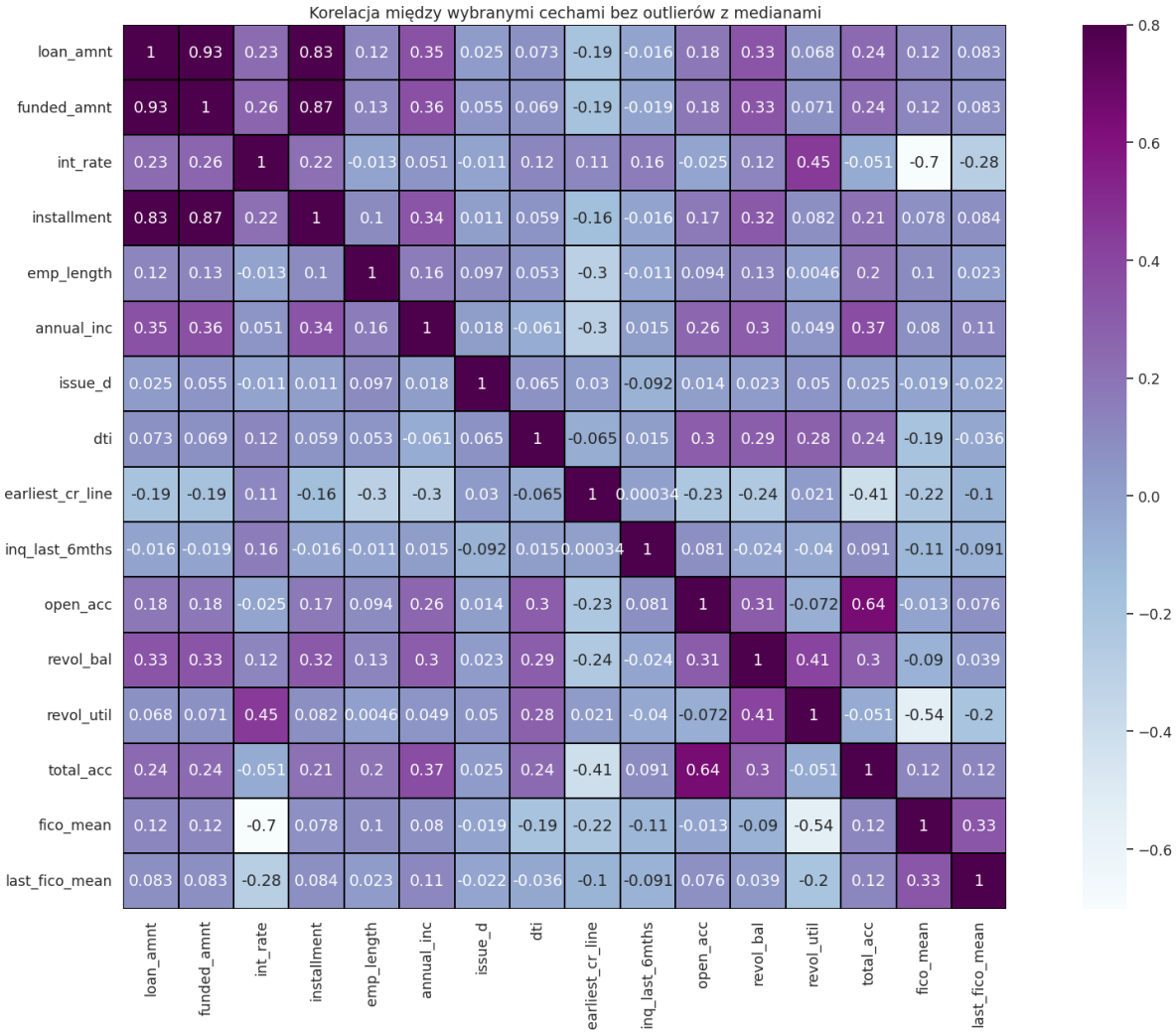
Korelacja X_2 na data_outliers uzupełnione medianą

In [201…
```
cor2 = data_outliers.corr()
cor2
```

Out[201]:

	loan_amnt	funded_amnt	int_rate	installment	emp_length	annual_inc	iss
loan_amnt	1.000000	0.931504	0.233275	0.833385	0.120300	0.346677	0.0
funded_amnt	0.931504	1.000000	0.261402	0.867878	0.127861	0.358465	0.0
int_rate	0.233275	0.261402	1.000000	0.216128	-0.012694	0.050727	-0.0
installment	0.833385	0.867878	0.216128	1.000000	0.100267	0.335973	0.0
emp_length	0.120300	0.127861	-0.012694	0.100267	1.000000	0.157171	0.0
annual_inc	0.346677	0.358465	0.050727	0.335973	0.157171	1.000000	0.0
issue_d	0.025309	0.054919	-0.010814	0.011295	0.096545	0.017886	1.0
dti	0.072677	0.068695	0.119067	0.058989	0.052880	-0.060565	0.0
earliest_cr_line	-0.192102	-0.189354	0.108040	-0.159064	-0.296823	-0.296050	0.0
inq_last_6mths	-0.016351	-0.018798	0.159467	-0.016310	-0.010632	0.015040	-0.0
open_acc	0.181054	0.180008	-0.025289	0.166848	0.094135	0.260163	0.0
revol_bal	0.331274	0.332837	0.124785	0.319037	0.131292	0.296958	0.0
revol_util	0.067966	0.070863	0.453285	0.082023	0.004615	0.049498	0.0
total_acc	0.237972	0.240615	-0.050539	0.210132	0.198047	0.368997	0.0
fico_mean	0.119228	0.115983	-0.701221	0.077789	0.100255	0.079801	-0.0
last_fico_mean	0.083265	0.082703	-0.282352	0.084409	0.022608	0.113134	-0.0

In [202…
```
sns.set(font_scale=1.15)
plt.figure(figsize=(24, 14))

sns.heatmap(cor2, vmax=.8, linewidths=0.01,
            square=True, annot=True, cmap="BuPu", linecolor="black")
plt.title('Korelacja między wybranymi cechami bez outlierów z medianami');
```



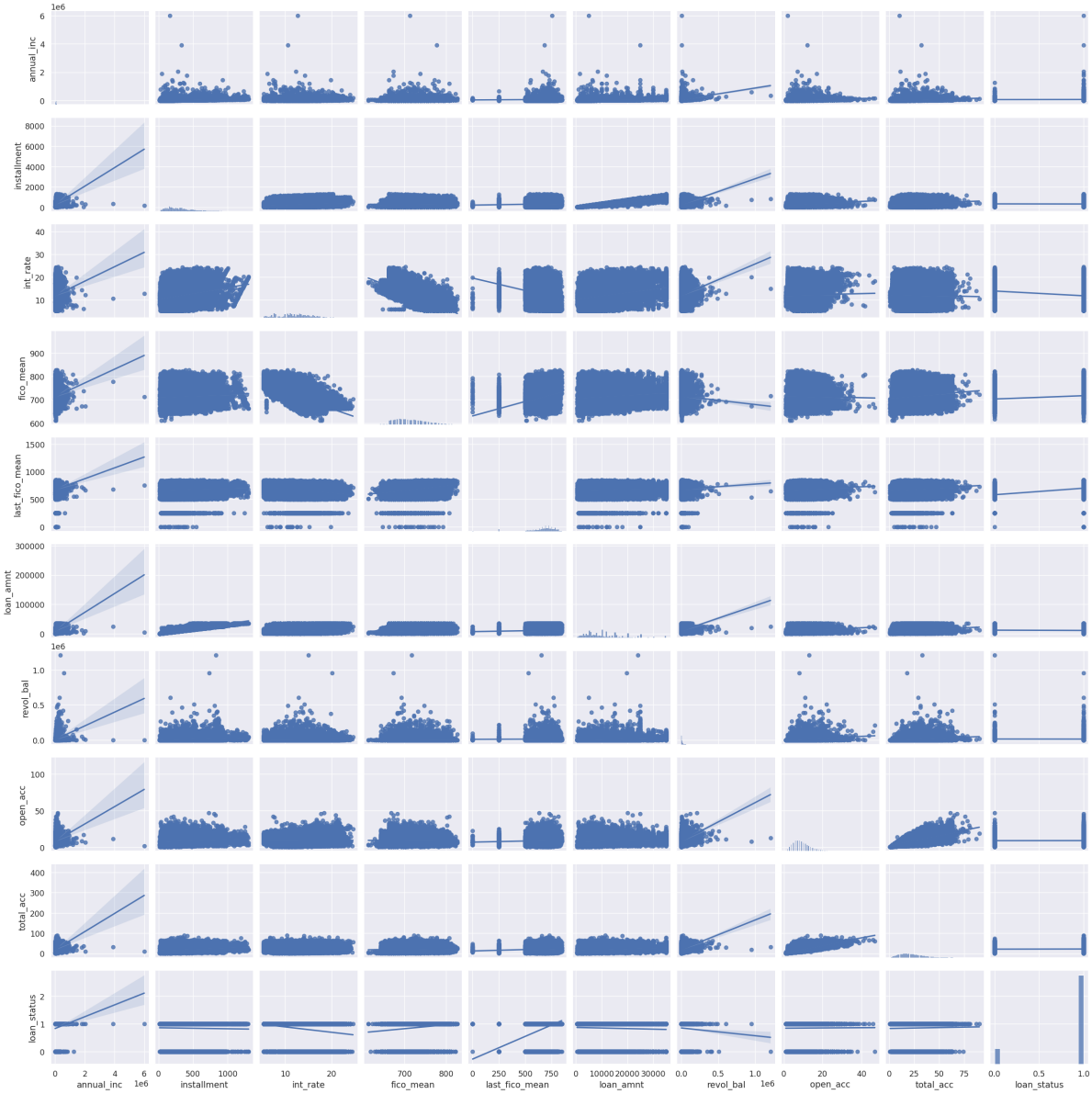
UWAGA!!!

Linia nr 1 poniższego kodu: Tworzenie wykresu `pairplot` zajmuje bardzo dużo czsu. To jest tak ciężkie obliczeniowo, że mi się to w ogóle nie wykonywało i dlatego kometuję tworzenie wykresu `pairplot`. Nie byłem w stanie wyświetlić wyników. Jest za dużo danych, Kernal ma problemy z obliczeniem tego i wyświetleniem wykresu. Zaniecham użycia parametru `palette` (zestaw kolorów do mapowania zmiennej `hue`).

Linia nr 2: Ograniczyłem parametry wykresu `pairplot` tak jak poniżej, aby zwizualizować obliczenia i wyświetlić wykres `pairplot`.

In [203…
```
# sns.pairplot(data_loan1, hue='annual_inc', kind="reg", palette="husl")
sns.pairplot(data_loan1, kind="reg")
```

Out[203]:
```
<seaborn.axisgrid.PairGrid at 0x7fb4eaffc4d0>
```



Encodowanie zmiennych kategorycznych porządkowych:

sub_grade, term i nowych: loan_amnt_rating, interest_rating, fico_rating

In [204…

```
encoder = ce.OrdinalEncoder(cols=['sub_grade', 'term', 'loan_amnt_rating',
data_loan = encoder.fit_transform(data_loan)
data_loan
```

Out[204]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length	home_ov
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	
...	...	...	...	...	...	...	...	
42531	3500.0	3500.0	1	10.28	113.39	4	1	
42532	1000.0	1000.0	1	9.64	32.11	14	1	
42533	2525.0	2525.0	1	9.33	80.69	13	1	
42534	6500.0	6500.0	1	8.38	204.84	18	1	
42535	5000.0	5000.0	1	7.75	156.11	17	10	MOI

42535 rows × 30 columns

Encodowanie pozostałych zmiennych kategorycznych One Hot Encoding

In [205…

```
data_dummies = pd.get_dummies(data_loan)
data_dummies
```

Out[205]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length	annual_i
0	5000.0	5000.0	1	10.65	162.87	1	10	24000
1	2500.0	2500.0	2	15.27	59.83	2	1	30000
2	2400.0	2400.0	1	15.96	84.33	3	10	12252
3	10000.0	10000.0	1	13.49	339.31	4	10	49200
4	3000.0	3000.0	2	12.69	67.79	5	1	80000
...	...	...	...	...	...	...	...	
42531	3500.0	3500.0	1	10.28	113.39	4	1	180000
42532	1000.0	1000.0	1	9.64	32.11	14	1	12000
42533	2525.0	2525.0	1	9.33	80.69	13	1	110000
42534	6500.0	6500.0	1	8.38	204.84	18	1	60000
42535	5000.0	5000.0	1	7.75	156.11	17	10	70000

42535 rows × 98 columns

In [206…

```
data_dummies.columns
```

Out[206]:
```
Index(['loan_amnt', 'funded_amnt', 'term', 'int_rate', 'installment',
       'sub_grade', 'emp_length', 'annual_inc', 'issue_d', 'loan_status',
       '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_mean',
       'last_fico_mean', 'fico_rating', 'loan_amnt_rating', 'interest_rati
ng',
       'home_ownership_MORTGAGE', 'home_ownership_NONE',
       'home_ownership_OTHER', 'home_ownership_OWN', 'home_ownership_REN
T',
       'verification_status_Not Verified',
       'verification_status_Source Verified', 'verification_status_Verifie
d',
       'purpose_car', 'purpose_credit_card', 'purpose_debt_consolidation',
       'purpose_educational', 'purpose_home_improvement', 'purpose_house',
       'purpose_major_purchase', 'purpose_medical', 'purpose_moving',
       'purpose_other', 'purpose_renewable_energy', 'purpose_small_busines
s',
       'purpose_vacation', 'purpose_wedding', 'addr_state_AK', 'addr_state
_AL',
       'addr_state_AR', 'addr_state_AZ', 'addr_state_CA', 'addr_state_CO',
       'addr_state_CT', 'addr_state_DC', 'addr_state_DE', 'addr_state_FL',
       'addr_state_GA', 'addr_state_HI', 'addr_state_IA', 'addr_state_ID',
       'addr_state_IL', 'addr_state_IN', 'addr_state_KS', 'addr_state_KY',
       'addr_state_LA', 'addr_state_MA', 'addr_state_MD', 'addr_state_ME',
       'addr_state_MI', 'addr_state_MN', 'addr_state_MO', 'addr_state_MS',
       'addr_state_MT', 'addr_state_NC', 'addr_state_NE', 'addr_state_NH',
       'addr_state_NJ', 'addr_state_NM', 'addr_state_NV', 'addr_state_NY',
       'addr_state_OH', 'addr_state_OK', 'addr_state_OR', 'addr_state_PA',
       'addr_state_RI', 'addr_state_SC', 'addr_state_SD', 'addr_state_TN',
       'addr_state_TX', 'addr_state_UT', 'addr_state_VA', 'addr_state_VT',
       'addr_state_WA', 'addr_state_WI', 'addr_state_WV', 'addr_state_W
Y'],
      dtype='object')
```

In [207…
```
data_dummies.dtypes
```

Out[207]:
```
loan_amnt        float64
funded_amnt      float64
term               int64
int_rate         float64
installment      float64
                  ...
addr_state_VT      uint8
addr_state_WA      uint8
addr_state_WI      uint8
addr_state_WV      uint8
addr_state_WY      uint8
Length: 98, dtype: object
```

In [208…
```
cor = data_dummies.corr()
cor
```

Out[208]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_le
loan_amnt	1.000000	0.981746	0.355647	0.292346	0.930869	0.119626	0.13
funded_amnt	0.981746	1.000000	0.335137	0.295154	0.956522	0.115749	0.13
term	0.355647	0.335137	1.000000	0.428649	0.097614	0.190461	0.11
int_rate	0.292346	0.295154	0.428649	1.000000	0.271433	0.313232	-0.01
installment	0.930869	0.956522	0.097614	0.271433	1.000000	0.102561	0.10
...	...	...	...	...	...	...	
addr_state_VT	-0.010225	-0.010569	-0.004024	-0.008556	-0.009995	-0.000909	0.00
addr_state_WA	-0.003873	-0.002099	-0.007010	0.006209	0.000584	-0.000473	0.00
addr_state_WI	0.000184	0.000458	0.011548	0.000731	-0.002843	0.000552	0.00
addr_state_WV	-0.003483	-0.002075	0.005385	-0.005369	-0.005191	-0.009206	0.01
addr_state_WY	0.000242	0.000828	-0.006537	0.005543	0.003201	-0.004905	0.00

98 rows × 98 columns

Eksport plików do notebook-ów w celu wielokrotnego przetworzenia danych

In [209…
```
data_loan.to_csv("data_loan.csv")
```

In [210…
```
data_outliers.to_csv("data_outliers.csv")
```

In [211…
```
data_dummies.to_csv("data_dummies.csv")
```

In [212…
```
data_loan1.to_csv("data_loan1.csv")
```

4. Modelowanie

a) PCA i klasteryzacja

Klasteryzacja bedzie robiona na zbiorze data_dummies

In [213…
```
data_dummies.head()
```

Out[213]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length	annual_inc	i
0	5000.0	5000.0	1	10.65	162.87	1	10	24000.0	
1	2500.0	2500.0	2	15.27	59.83	2	1	30000.0	
2	2400.0	2400.0	1	15.96	84.33	3	10	12252.0	
3	10000.0	10000.0	1	13.49	339.31	4	10	49200.0	
4	3000.0	3000.0	2	12.69	67.79	5	1	80000.0	

5 rows × 98 columns

In [214…
```
data_dummies.drop(['loan_status'], axis=1, inplace=True)
```

In [215…
```
data_dummies.shape
```

Out[215]:
```
(42535, 97)
```

In [216…
```
data_dummies.head()
```

Out[216]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length	annual_inc	i
0	5000.0	5000.0	1	10.65	162.87	1	10	24000.0	
1	2500.0	2500.0	2	15.27	59.83	2	1	30000.0	
2	2400.0	2400.0	1	15.96	84.33	3	10	12252.0	
3	10000.0	10000.0	1	13.49	339.31	4	10	49200.0	
4	3000.0	3000.0	2	12.69	67.79	5	1	80000.0	

5 rows × 97 columns

In [217…
```
scaler = StandardScaler()
scaler.fit(data_dummies)
data_dummies_std = scaler.transform(data_dummies)
```

Przygotowanie zbioru do grupowania z PCA

- Zmniejszenie liczby wymiarów.
- Usunięcie wartości ujemnych.
- Usunięcie skośności zmiennych.
- Usuwanie ouliersów.
- Skalowanie danych.

Zmniejszenie liczby wymiarów

In [218…
```
pca = IncrementalPCA(n_components=2)
data_dummies_pca = pca.fit_transform(data_dummies)
data_pca = pd.DataFrame(data_dummies_pca, columns = ['c1', 'c2'], index = d
```

In [219…
```
data_pca
```

Out[219]:

	c1	c2
0	-45282.271425	3158.565432
1	-40786.620453	-9829.325366
2	-58279.298352	-6572.469319
3	-20803.384098	-6458.204225
4	11728.517628	10115.675027
...	...	...
42531	108047.180124	-28463.034380
42532	-58942.348408	-9764.908250
42533	38472.583043	-20656.666720
42534	-10916.473014	-13995.292702
42535	-1084.998316	-15491.374954

42535 rows × 2 columns

In [220…
```
colnames = list(data_dummies.columns)
data_pca1 = pd.DataFrame({'c1':pca.components_[0],'c2':pca.components_[1],
```

In [221…
```
data_pca1
```

Out[221]:

	c1	c2	Feature
0	3.368171e-02	1.186367e-01	loan_amnt
1	3.202302e-02	1.136052e-01	funded_amnt
2	3.275048e-07	1.681826e-06	term
3	3.460200e-06	2.094485e-05	int_rate
4	9.556052e-04	3.336930e-03	installment
...	...	...	...
92	-5.197144e-09	-1.065550e-08	addr_state_VT
93	-1.175526e-08	6.883287e-08	addr_state_WA
94	-1.736147e-08	2.939460e-08	addr_state_WI
95	-1.603709e-08	-1.764391e-08	addr_state_WV
96	-4.312381e-09	6.521946e-09	addr_state_WY

97 rows × 3 columns

In [222…
```
data_pca.agg(['mean','median','std','min','max']).round(2)
```

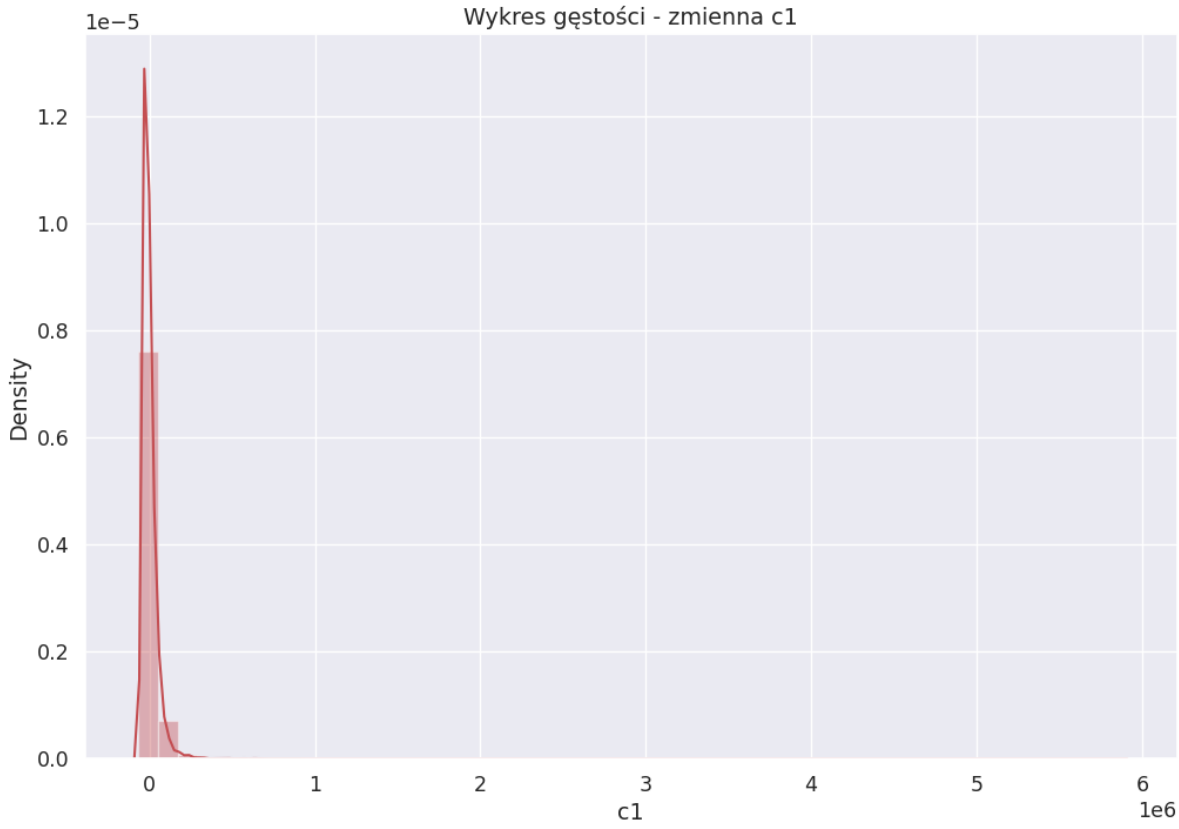
Out[222]:

	c1	c2
mean	0.00	0.00
median	-10743.68	-4325.41
std	64499.50	21068.50
min	-68905.31	-694589.37
max	5887602.48	1139657.99

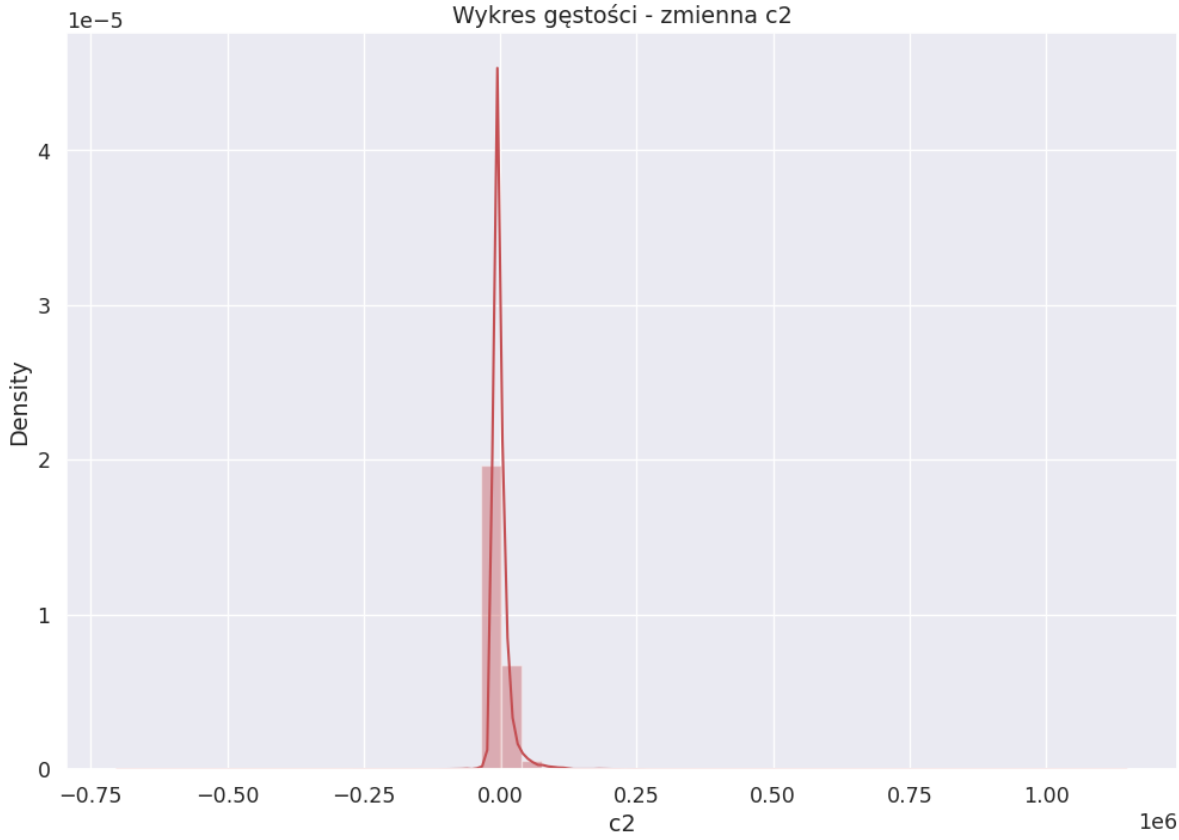
In [223…

```
sns.distplot(data_pca.c1, color = 'r').set(title = 'Wykres gęstości - zmien
plt.show()
sns.distplot(data_pca.c2, color = 'r').set(title = 'Wykres gęstości - zmien
plt.show()
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
h
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  """Entry point for launching an IPython kernel.
```




```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:3:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
h
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  This is separate from the ipykernel package so we can avoid doing imports
until
```



Usuwanie wartości ujemnych, przez dodanie modułu z min najmniejszej wartości i plus 1

In [224…
```
for col in data_pca:
    if data_pca[col].min() <= 0:
        data_pca[col] = data_pca[col] + np.abs(data_pca[col].min())+1
```

Usuwanie skośności

In [225…
```
data_pca = np.log(data_pca)
```

Usuwanie wartości odstających

In [226…
```
q1 = data_pca.quantile(0.25)
q3 = data_pca.quantile(0.75)
iqr = q3 - q1

low_boundary = (q1 - 1.5 * iqr)
upp_boundary = (q3 + 1.5 * iqr)
num_of_outliers_L = (data_pca[iqr.index] < low_boundary).sum()
num_of_outliers_U = (data_pca[iqr.index] > upp_boundary).sum()
outliers = pd.DataFrame({'lower_boundary':low_boundary, 'upper_boundary':up
                         'num_of_outliers__lower_boundary':num_of_outliers_
                         'num_of_outliers__upper_boundary':num_of_outliers_
```

In [227…
```
outliers
```

Out[227]:

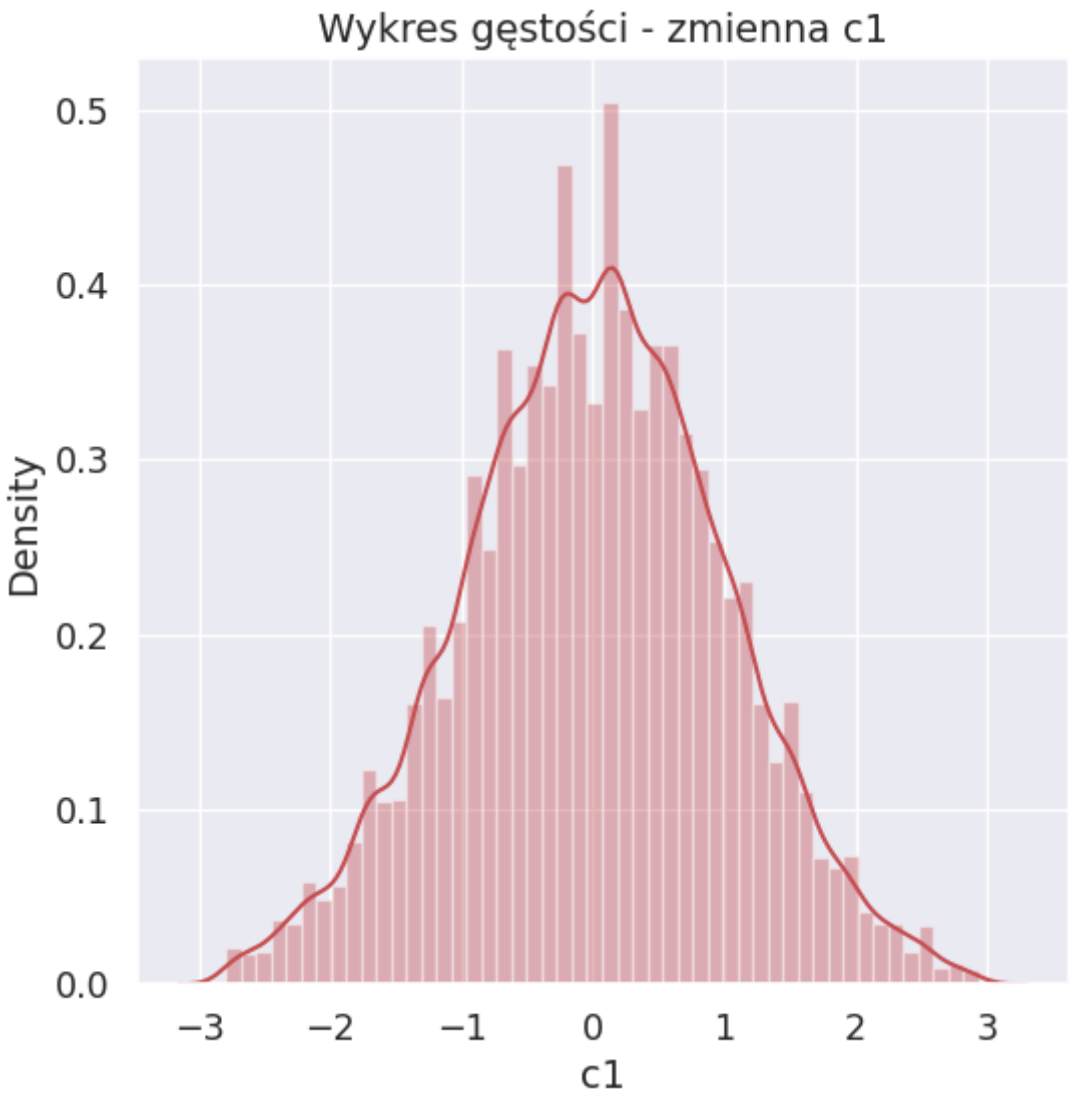
	lower_boundary	upper_boundary	num_of_outliers__lower_boundary	num_of_outliers__uppe
c1	9.492173	12.425370	521	
c2	13.409988	13.483962	188	

In [228…
```
for row in outliers.iterrows():
    data_pca = data_pca[(data_pca[row[0]] >= row[1]['lower_boundary']) & (d
```

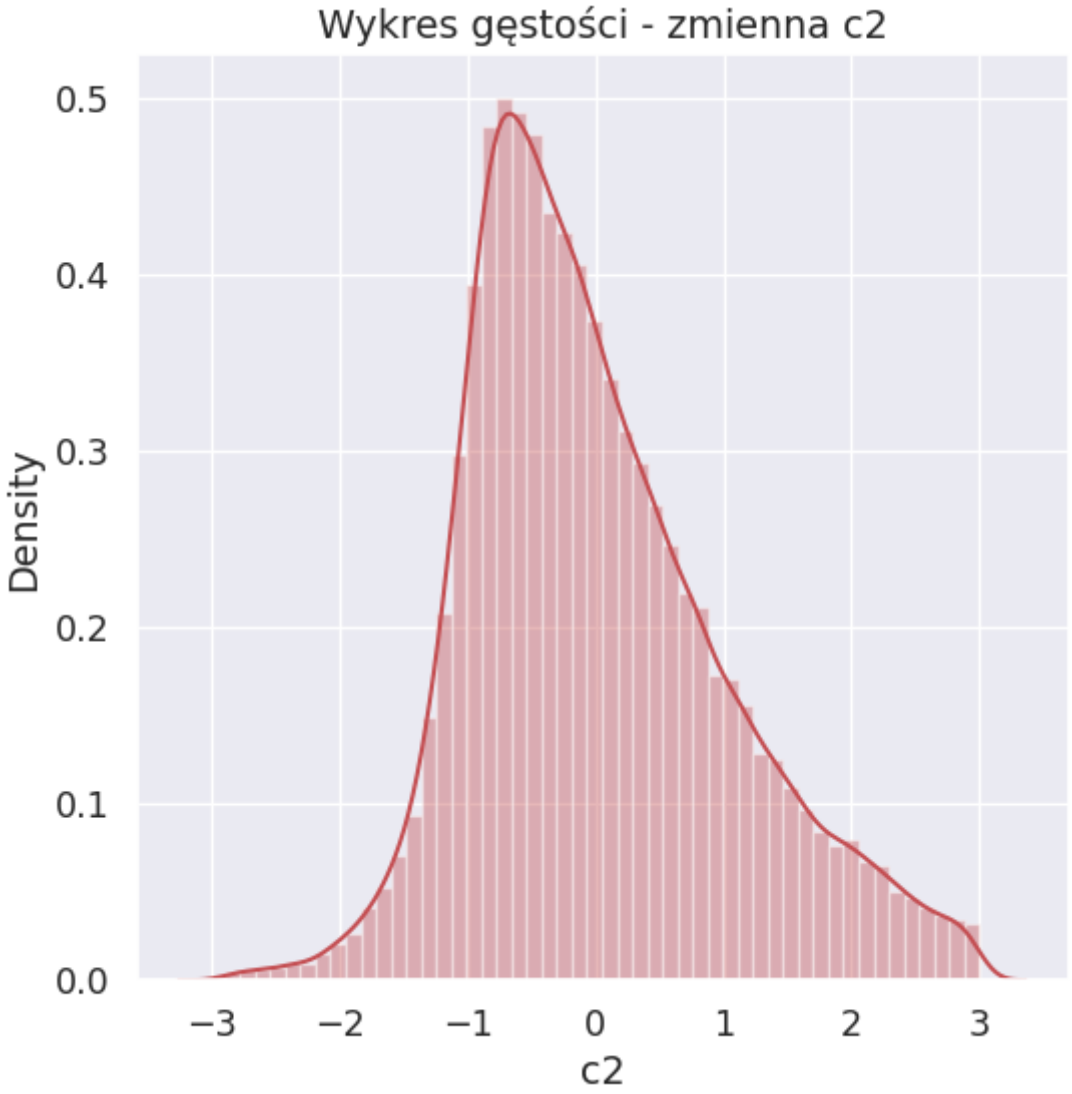
In [229…
```
scaler = StandardScaler()
scaler.fit(data_pca)
data_pca_std = scaler.transform(data_pca)
data_pca = pd.DataFrame(data=data_pca_std, index=data_pca.index, columns=da
```

In [230…
```
plt.figure(figsize = (6,6))
sns.distplot(data_pca.c1, color = 'r').set(title = 'Wykres gęstości - zmien
plt.show()
plt.figure(figsize = (6,6))
sns.distplot(data_pca.c2, color = 'r').set(title = 'Wykres gęstości - zmien
plt.show()
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:2:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
h
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
```



```
/home/marek/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:5:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
h
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  """
```

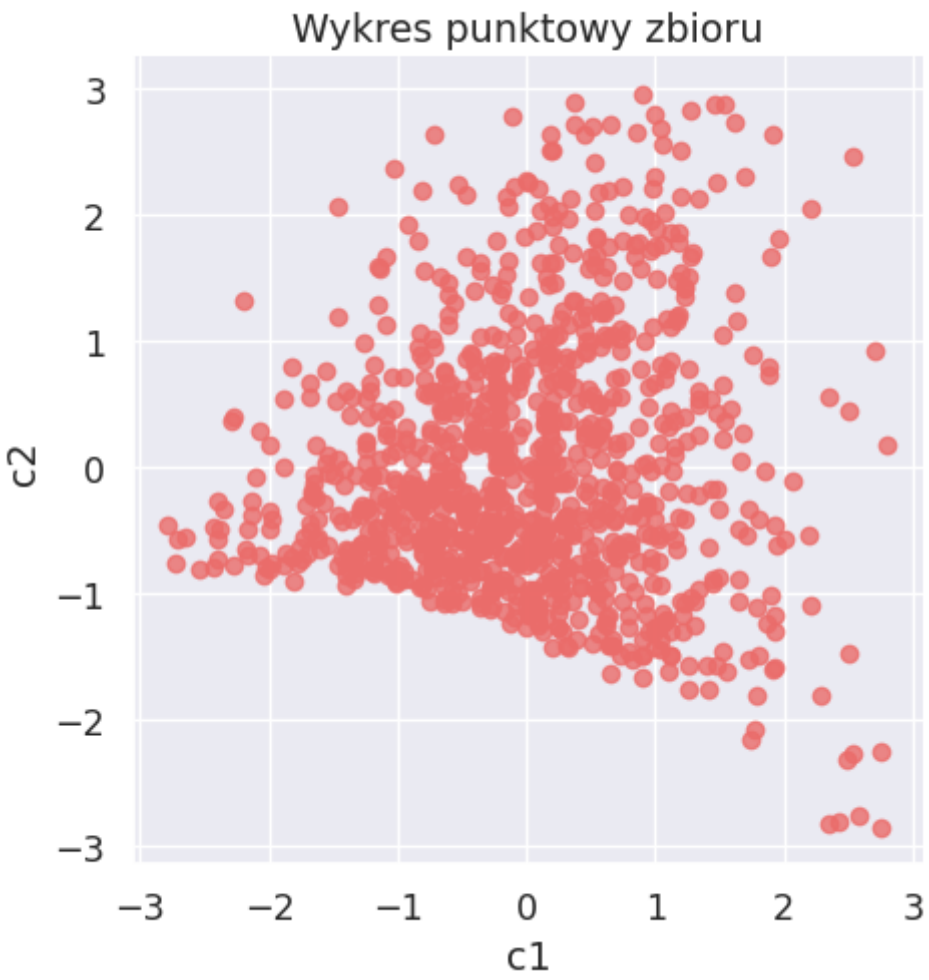


Jako, że hierarchiczna metoda klasteryzacji jest złożona obliczeniowo, ograniczam liczbę obserwacji do 1000. Wcześniej eksportuję plik po PCA do dalszej obróbki w notebooku modelowania.

In [231…
```
# ten plik ma 1000 próbek
data_pca = data_pca.sample(1000, random_state = 67)
```

In [232…
```
plt.figure(figsize = (20,20))
sns.lmplot(x='c1', y='c2', data = data_pca, scatter_kws={"color": "#eb6c6a"
plt.show()
```

```
<Figure size 2000x2000 with 0 Axes>
```



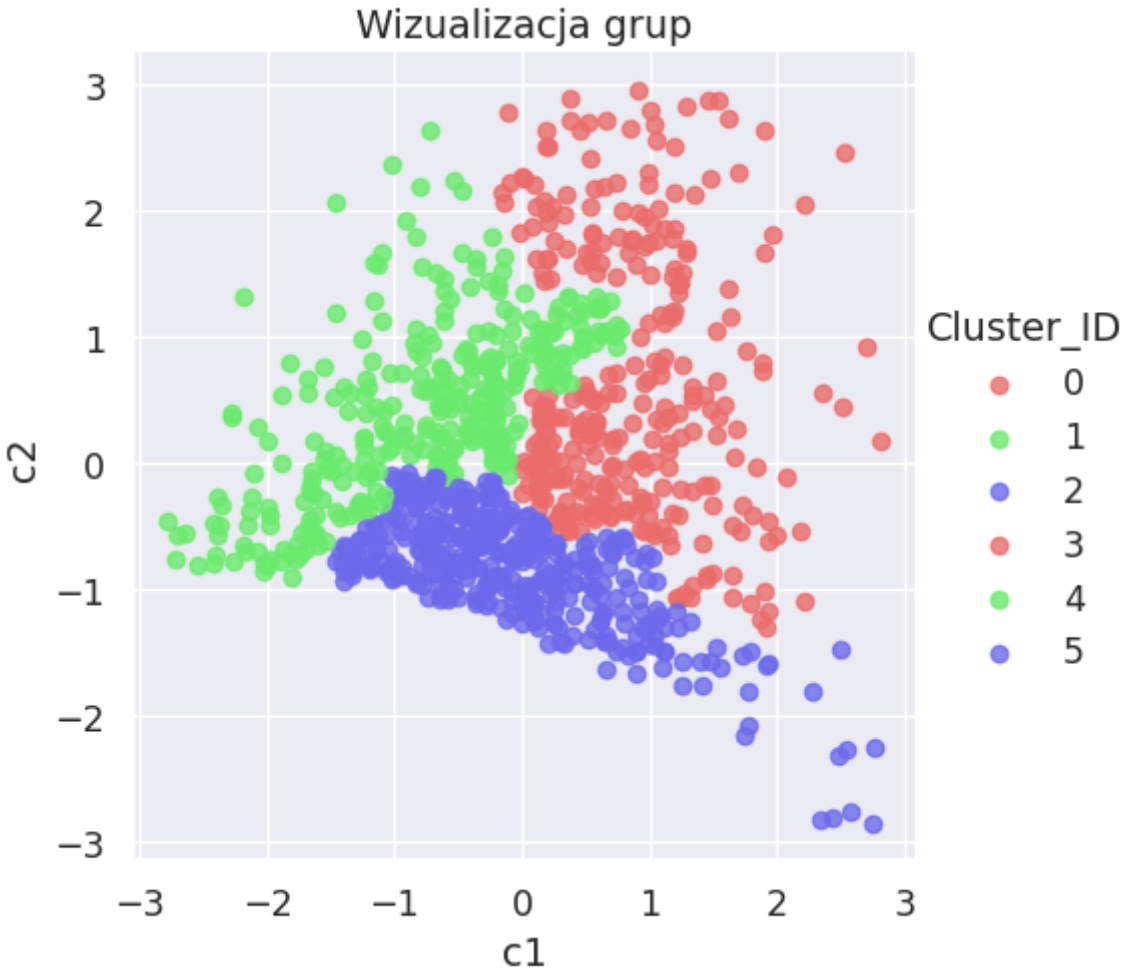
Klastrowanie hierarchiczne metodą Warda

Metoda łączenia grup Warda w bibliotece sklearn.

In [233…
```
model_skl = AgglomerativeClustering(linkage='ward', affinity='euclidean', n
```

In [234…
```
data_pca['Cluster_ID'] = model_skl.labels_
```

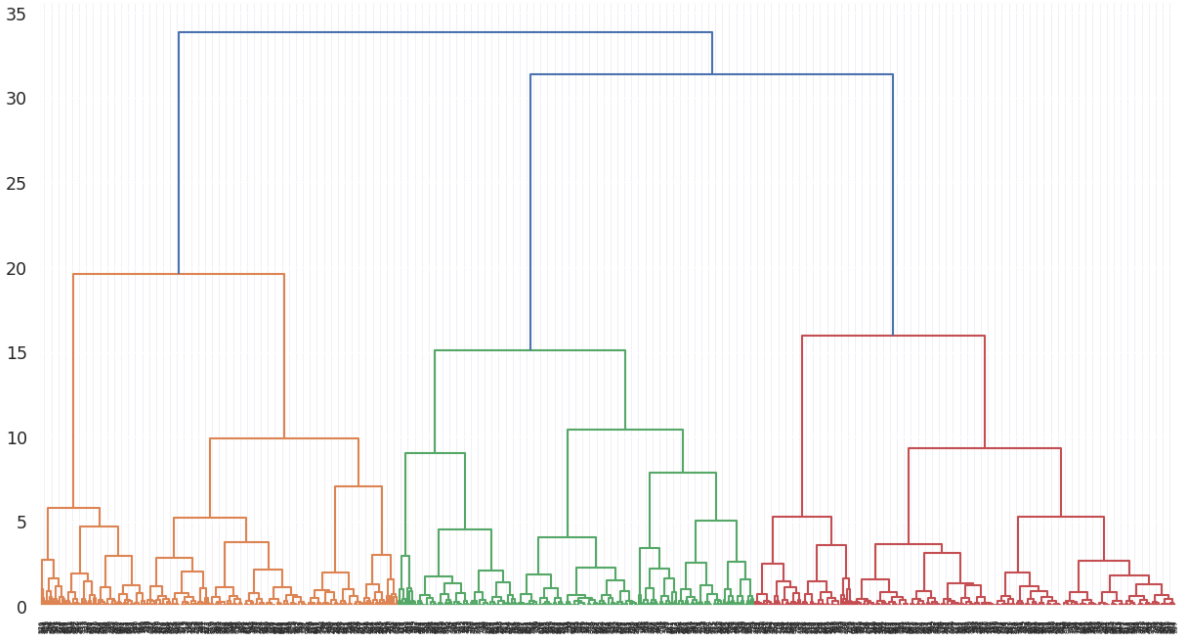
In [235…
```
sns.lmplot(x='c1', y='c2', data = data_pca, hue = 'Cluster_ID', fit_reg=Fal
plt.show()
```



Grupowanie z użyciem biblioteki SciPy

In [236…
```
model_sci = linkage(data_pca.iloc[:,0:2], method = 'ward', metric = 'euclid
```

In [237…
```
fig = plt.figure(figsize=(15, 8))
dn = dendrogram(model_sci)
plt.show()
```



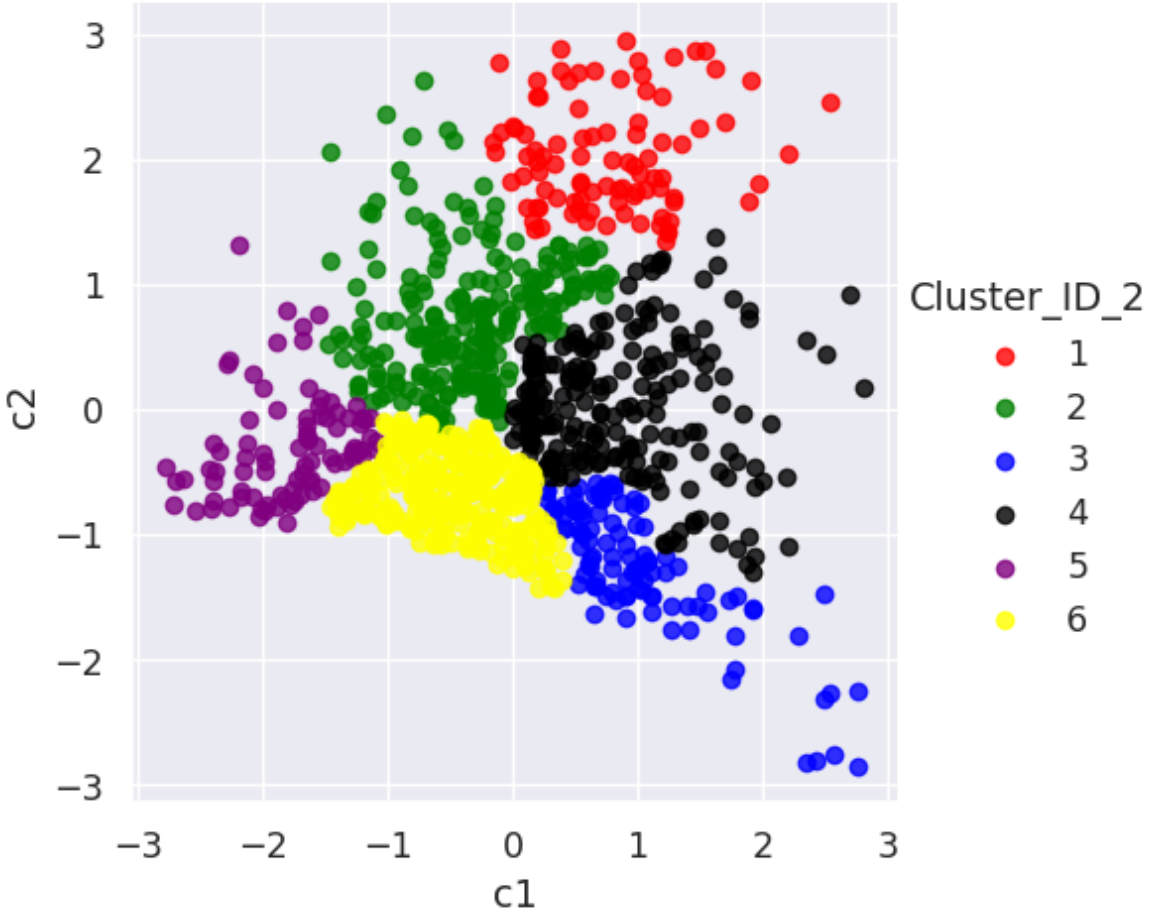
Dzielenie obserwacji na grupy według maksymalnej liczby klastrów.

In [238…
```
clusters = fcluster(model_sci, 6, criterion='maxclust')
data_pca['Cluster_ID_2'] = clusters
clusters
```

Out[238]:
```
array([2, 4, 4, 1, 5, 4, 2, 6, 2, 2, 1, 3, 6, 3, 6, 4, 4, 2, 4, 6, 2, 6,
       4, 5, 4, 6, 6, 1, 2, 6, 5, 2, 5, 4, 4, 6, 3, 5, 4, 2, 6, 3, 3, 5,
       2, 2, 4, 4, 2, 4, 4, 2, 6, 3, 6, 1, 5, 2, 5, 6, 4, 6, 6, 4, 3, 2,
       6, 2, 5, 2, 5, 4, 6, 3, 5, 3, 4, 4, 2, 2, 1, 6, 2, 1, 6, 4, 2, 5,
       2, 2, 3, 3, 6, 4, 5, 6, 6, 4, 6, 6, 2, 2, 2, 6, 4, 6, 2, 3, 6, 6,
       5, 4, 4, 2, 4, 2, 5, 3, 2, 2, 2, 1, 4, 4, 3, 6, 5, 4, 3, 2, 5, 4,
       6, 4, 6, 4, 6, 2, 6, 5, 6, 6, 3, 2, 5, 2, 5, 2, 2, 4, 1, 4, 3, 4,
       3, 6, 1, 5, 5, 3, 1, 2, 4, 6, 2, 6, 4, 4, 3, 6, 4, 2, 1, 4, 5, 6,
       2, 3, 6, 2, 4, 3, 6, 6, 4, 4, 1, 6, 5, 2, 2, 4, 4, 3, 3, 2, 4, 2,
       5, 5, 3, 1, 6, 6, 6, 6, 6, 2, 2, 1, 6, 6, 4, 4, 2, 5, 6, 2, 3, 6,
       5, 6, 4, 4, 2, 2, 2, 5, 1, 2, 6, 6, 1, 6, 3, 6, 4, 4, 5, 4, 2, 1,
       6, 4, 6, 3, 3, 6, 4, 6, 2, 6, 4, 6, 6, 1, 6, 4, 1, 6, 2, 3, 4, 3,
       6, 3, 3, 6, 4, 6, 5, 6, 2, 5, 3, 5, 6, 6, 4, 2, 2, 4, 6, 2, 2, 6,
       5, 4, 2, 5, 3, 5, 3, 6, 1, 4, 2, 6, 3, 4, 4, 4, 2, 6, 5, 6, 6, 1,
       2, 6, 3, 3, 6, 5, 3, 5, 1, 6, 3, 2, 1, 4, 2, 6, 4, 6, 1, 3, 6, 3,
       2, 4, 4, 4, 6, 4, 6, 1, 6, 2, 4, 5, 2, 6, 6, 4, 4, 2, 6, 6, 6, 5,
       5, 3, 6, 6, 4, 6, 4, 6, 6, 6, 4, 6, 6, 6, 4, 6, 6, 4, 4, 1, 2, 2,
       5, 2, 4, 2, 4, 4, 2, 4, 6, 1, 2, 6, 3, 2, 4, 4, 3, 3, 2, 6, 4, 6,
       1, 4, 2, 6, 3, 1, 6, 4, 4, 6, 5, 4, 1, 2, 2, 6, 3, 5, 3, 2, 4, 6,
       2, 4, 1, 3, 1, 6, 4, 1, 2, 1, 2, 2, 4, 3, 3, 1, 4, 6, 6, 2, 2, 4,
       6, 4, 3, 3, 3, 6, 2, 6, 6, 4, 2, 6, 4, 2, 2, 1, 2, 4, 2, 4, 5, 4,
       6, 5, 2, 6, 3, 1, 2, 6, 2, 3, 5, 2, 6, 6, 3, 4, 6, 5, 2, 1, 4, 2,
       2, 6, 6, 6, 6, 6, 4, 6, 2, 3, 1, 2, 6, 4, 2, 6, 1, 4, 2, 2, 4, 6,
       4, 4, 2, 6, 1, 6, 6, 5, 2, 1, 2, 2, 5, 2, 4, 4, 6, 5, 1, 4, 6, 6,
       4, 3, 6, 6, 5, 4, 4, 4, 1, 6, 3, 6, 1, 6, 4, 6, 3, 2, 5, 1, 2, 3,
       6, 1, 2, 1, 4, 6, 1, 3, 4, 4, 3, 1, 6, 5, 1, 4, 4, 1, 2, 4, 6, 1,
       4, 6, 4, 3, 1, 2, 4, 6, 4, 4, 3, 1, 4, 1, 4, 4, 3, 6, 2, 2, 2, 2,
       2, 3, 4, 3, 3, 6, 4, 2, 4, 4, 6, 6, 1, 6, 5, 4, 2, 3, 3, 6, 6, 6,
       4, 6, 6, 4, 1, 3, 5, 1, 5, 5, 2, 2, 2, 2, 2, 2, 5, 6, 6, 2, 2, 6,
       5, 6, 2, 2, 4, 6, 3, 3, 2, 4, 4, 1, 1, 1, 6, 2, 6, 2, 2, 6, 3, 6,
       6, 5, 6, 3, 6, 6, 4, 4, 5, 2, 5, 4, 6, 4, 2, 4, 3, 3, 2, 6, 4, 2,
       6, 6, 6, 2, 5, 6, 6, 2, 4, 2, 2, 6, 4, 5, 6, 6, 6, 6, 5, 6, 6, 1,
       6, 4, 5, 6, 6, 6, 6, 4, 4, 6, 1, 6, 6, 2, 2, 4, 4, 5, 6, 3, 6, 4,
       4, 6, 5, 6, 4, 2, 6, 6, 4, 2, 2, 2, 2, 2, 2, 6, 6, 6, 6, 4, 6, 3,
       1, 4, 1, 2, 3, 2, 6, 1, 5, 4, 4, 3, 2, 2, 3, 1, 3, 2, 4, 2, 2, 4,
       4, 6, 5, 1, 1, 6, 6, 6, 5, 3, 3, 2, 3, 2, 2, 3, 4, 6, 6, 1, 4, 2,
       6, 1, 6, 6, 6, 6, 2, 2, 6, 6, 6, 6, 6, 2, 4, 2, 2, 3, 2, 6, 5, 3,
       3, 2, 1, 2, 6, 3, 2, 3, 6, 4, 6, 2, 6, 6, 6, 3, 5, 6, 4, 2, 6, 2,
       3, 1, 6, 1, 2, 2, 3, 1, 2, 2, 2, 3, 5, 1, 4, 1, 4, 6, 6, 2, 1, 6,
       6, 4, 6, 5, 4, 4, 3, 6, 2, 4, 2, 4, 4, 6, 4, 5, 4, 6, 1, 1, 6, 5,
       6, 6, 6, 1, 4, 4, 6, 1, 6, 3, 4, 6, 6, 2, 4, 2, 4, 1, 6, 4, 6, 2,
       6, 1, 1, 6, 3, 2, 2, 6, 6, 2, 4, 2, 4, 2, 2, 6, 6, 2, 1, 2, 4, 2,
       2, 6, 2, 2, 5, 4, 5, 6, 4, 2, 5, 6, 2, 6, 4, 6, 4, 2, 2, 6, 6, 2,
       6, 6, 1, 1, 3, 6, 2, 6, 4, 6, 4, 6, 5, 6, 4, 2, 2, 1, 4, 6, 6, 4,
       5, 4, 1, 1, 2, 5, 4, 2, 6, 2, 6, 2, 2, 6, 2, 5, 5, 2, 2, 6, 4, 4,
       2, 1, 4, 6, 4, 2, 3, 2, 4, 6], dtype=int32)
```

In [239…
```
plt.figure(figsize = (20,20))
sns.lmplot(x='c1', y='c2', data = data_pca, fit_reg=False, hue = 'Cluster_I
plt.show()
```

```
<Figure size 2000x2000 with 0 Axes>
```



W obu metodach są takie same wyniki.

DBSCAN

Na pliku data_pca po PCA

In [240…
```
clt = DBSCAN(eps=0.5, metric='euclidean', min_samples=5, n_jobs=-1)
model = clt.fit(data_pca)
```

In [241…
```
data_pca['Clasters'] = model.labels_
```

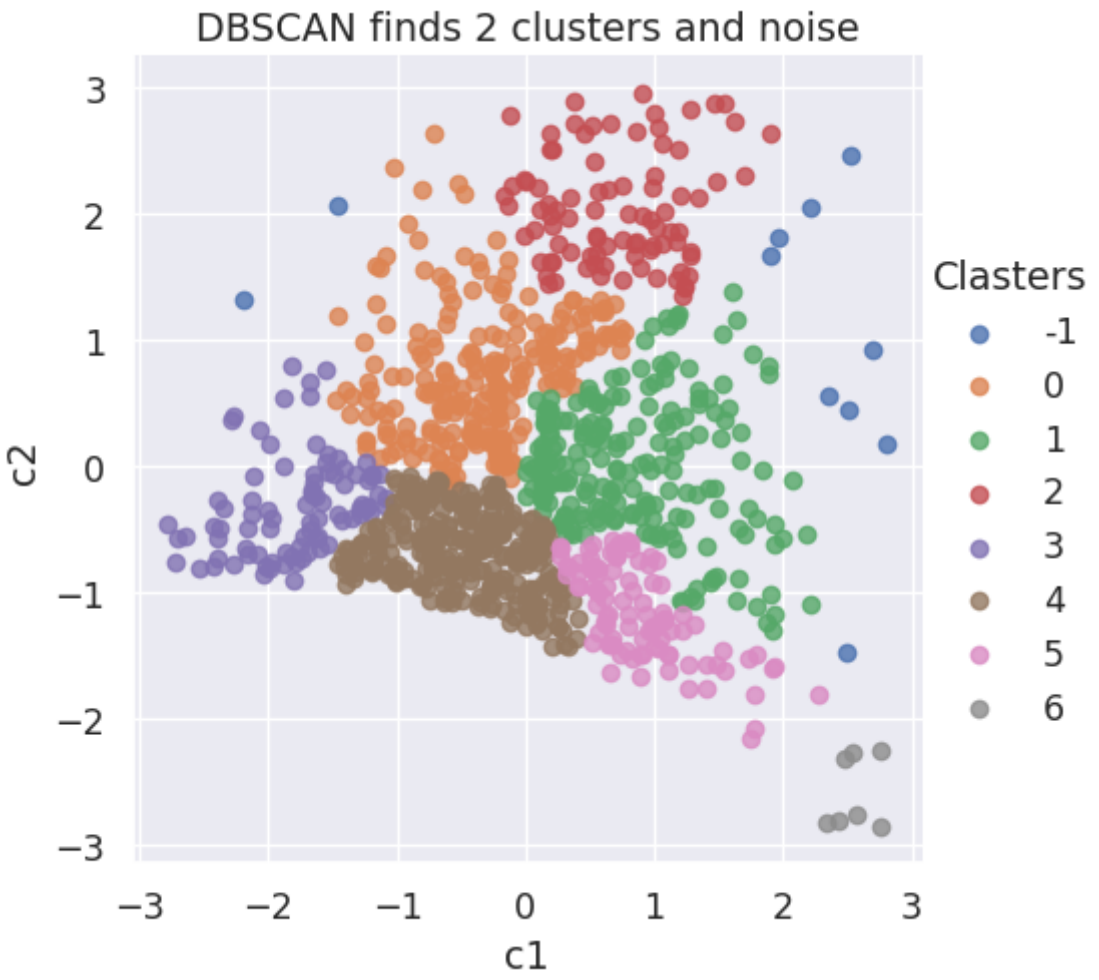
In [242…
```
model.labels_
```

Out[242]:
```
array([ 0,  1,  1,  2,  3,  1,  0,  4,  0,  0,  2,  5,  4,  5,  4,  1,  1,
        0,  1,  4,  0,  4,  1,  3,  1,  4,  4,  2,  0,  4,  3,  0,  3,  1,
        1,  4,  5,  3,  1,  0,  4,  5,  5,  3,  0,  0,  1,  1,  0,  1,  1,
        0,  4,  5,  4,  2,  3,  0,  3,  4,  1,  4,  4,  1,  5,  0,  4,  0,
        3,  0,  3, -1,  4,  5,  3,  6,  1,  1,  0,  0,  2,  4,  0,  2,  4,
       -1,  0,  3,  0,  0,  5,  5,  4,  1,  3,  4,  4,  1,  4,  4,  0,  0,
        0,  4,  1,  4,  0,  5,  4,  4,  3,  1,  1,  0,  1,  0,  3,  5,  0,
        0,  0,  2,  1,  1,  5,  4,  3,  1,  5,  0,  3,  1,  4,  1,  4,  1,
        4,  0,  4,  3,  4,  4,  5,  0,  3,  0,  3,  0,  0,  1,  2,  1,  5,
        1,  5,  4,  2,  3,  3,  6,  2,  0,  1,  4,  0,  4,  1,  1,  5,  4,
        1,  0,  2,  1,  3,  4,  0,  5,  4,  0,  1,  5,  4,  4,  1,  1,  2,
        4,  3,  0,  0,  1,  1,  5,  5,  0,  1,  0,  3,  3,  5,  2,  4,  4,
        4,  4,  4,  0,  0,  2,  4,  4,  1,  1,  0,  3,  4,  0,  5,  4,  3,
        4,  1,  1,  0,  0,  0,  3,  2,  0,  4,  4,  2,  4,  5,  4,  1,  1,
        3,  1,  0,  2,  4,  1,  4,  5,  5,  4, -1,  4,  0,  4,  1,  4,  4,
        2,  4,  1,  2,  4,  0,  5,  1,  6,  4,  5,  5,  4,  1,  4,  3,  4,
        0,  3,  5,  3,  4,  4,  1,  0,  0,  1,  4,  0,  0,  4,  3,  1,  0,
        3,  5,  3,  5,  4,  2,  1,  0,  4,  5,  1,  1,  1,  0,  4,  3,  4,
        4,  2,  0,  4,  6,  5,  4,  3,  5,  3,  2,  4,  5,  0,  2,  1,  0,
        4,  1,  4,  2,  5,  4,  5,  0,  1,  1,  1,  4,  1,  4,  2,  4,  0,
        1,  3,  0,  4,  4,  1,  1,  0,  4,  4,  4,  3,  3,  5,  4,  4,  1,
        4,  1,  4,  4,  4,  1,  4,  4,  4,  1,  4,  4,  1,  1,  2,  0,  0,
        3,  0,  1,  0,  1,  1,  0,  1,  4,  2,  0,  4,  5,  0,  1,  1,  5,
        5,  0,  4,  1,  4,  2,  1,  0,  4,  5,  2,  4,  1,  1,  4,  3, -1,
        2,  0,  0,  4, -1,  3,  5,  0,  1,  4,  0,  1,  2,  5,  2,  4,  1,
        2,  0,  2,  0,  0,  1,  5,  5,  2,  1,  4,  4,  0,  0,  1,  4,  1,
        5,  5,  5,  4,  0,  4,  4,  1,  0,  4,  1,  0,  0,  2,  0,  1,  0,
        1, -1,  1,  4,  3,  0,  4,  5,  2,  0,  4,  0,  5,  3,  0,  4,  4,
        5,  1,  4,  3,  0,  2,  1,  0,  0,  4,  4,  4,  4,  4,  1,  4,  0,
        5,  2,  0,  4,  1,  0,  4,  2,  1,  0,  0,  1,  4,  1,  1,  0,  4,
        2,  4,  4,  3,  0,  2,  0,  0,  3,  0,  1,  1,  4,  3,  2,  1,  4,
        4,  1,  5,  4,  4,  3,  1,  1,  1,  2,  4,  5,  4,  2,  4,  1,  4,
        5,  0,  3,  2,  0,  5,  4,  2,  0,  2,  1,  4,  2,  5,  1,  1,  5,
        2,  4,  3,  2,  1,  1, -1,  0,  1,  4,  2,  1,  4,  1,  5, -1,  0,
        1,  4,  1,  1,  5,  2,  1,  2,  1,  1,  6,  4,  0,  0,  0,  0,  0,
        5,  1,  5,  5,  4,  1,  0,  1,  1,  4,  4,  2,  4,  3,  1,  0,  5,
        5,  4,  4,  4,  1,  4,  4,  1,  2,  5,  3,  2,  3,  3,  0,  0,  0,
        0,  0,  0,  3,  4,  4,  0,  0,  4,  3,  4,  0,  0,  1,  4,  5,  5,
        0,  1,  1,  2,  2,  2,  4,  0,  4,  0,  0,  4,  5,  4,  4,  3,  4,
        5,  4,  4,  1,  1,  3,  0,  3,  1,  4,  1,  0,  1,  5,  5,  0,  4,
        1,  0,  4,  4,  4,  0,  3,  4,  4,  0,  1,  0,  0,  4,  1,  3,  4,
        4,  4,  4,  3,  4,  4,  2,  4,  1,  3,  4,  4,  4,  4,  1,  1,  4,
        2,  4,  4,  0,  0,  1,  1,  3,  4,  5,  4,  1,  1,  4,  3,  4,  1,
        0,  4,  4,  1,  0,  0,  0,  0,  0,  0,  4,  4,  4,  4,  1,  4,  5,
        2,  1,  2,  0,  5,  0,  4,  2,  3,  1,  1,  5,  0,  0,  5,  2,  6,
        0,  1,  0,  0,  1,  1,  4,  3, -1,  2,  4,  4,  4,  3,  6,  5,  0,
        5,  0,  0,  5,  1,  4,  4,  2,  1,  0,  4,  2,  4,  4,  4,  4,  0,
        0,  4,  4,  4,  4,  4,  0,  1,  0,  0,  5,  0,  4,  3,  5,  5,  0,
        2,  0,  4,  5,  0,  5,  4,  1,  4,  0,  4,  4,  4,  5,  3,  4,  1,
        0,  4,  0,  5,  2,  4,  2,  0,  0,  5,  2,  0,  0,  0,  5,  3,  2,
        1,  2,  1,  4,  4,  0,  2,  4,  4,  1,  4,  3,  1,  1,  5,  4,  0,
        1,  0,  1,  1,  4,  1,  3,  1,  4, -1,  2,  4,  3,  4,  4,  4,  2,
        1,  1,  4,  2,  4,  5,  1,  4,  4,  0,  1,  0,  1,  2,  4,  1,  4,
       -1,  4,  2,  2,  4,  5,  0,  0,  4,  4,  0,  1,  0,  1,  0,  0,  4,
        4,  0,  2,  0,  1,  0,  0,  4,  0,  0,  3,  1,  3,  4,  1,  0,  3,
        4,  0,  4,  1,  4,  1,  0,  0,  4,  4,  0,  4,  4,  2,  2,  5,  4,
        0,  4,  1,  4,  1,  4,  3,  4,  1,  0,  0,  2,  1,  4,  4,  1,  3,
        1,  2,  2,  0,  3,  1,  0,  4,  0,  4,  0,  0,  4,  0,  3,  3,  0,
        0,  4,  1,  1,  0,  2,  1,  4,  1,  0,  5,  0,  1,  4])
```

In [243…
```
data_pca.shape
```

Out[243]:
```
(1000, 5)
```

In [244…
```
sns.lmplot(x='c1', y='c2', data=data_pca, fit_reg=False, hue = 'Clasters' )
plt.title('DBSCAN finds 2 clusters and noise')
plt.show()
```



Klasteryzacja KMeans na pliku data_dummies, bez PCA

In [245…
```
data_dummies1 = pd.read_csv('data_dummies.csv')
data_dummies1.drop(['loan_status', 'Unnamed: 0'], axis=1, inplace=True)
data_dummies1
```

Out[245]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length	annual_i
0	5000.0	5000.0	1	10.65	162.87	1	10	24000
1	2500.0	2500.0	2	15.27	59.83	2	1	30000
2	2400.0	2400.0	1	15.96	84.33	3	10	12252
3	10000.0	10000.0	1	13.49	339.31	4	10	49200
4	3000.0	3000.0	2	12.69	67.79	5	1	80000
...	...	...	...	...	...	...	...	
42530	3500.0	3500.0	1	10.28	113.39	4	1	180000
42531	1000.0	1000.0	1	9.64	32.11	14	1	12000
42532	2525.0	2525.0	1	9.33	80.69	13	1	110000
42533	6500.0	6500.0	1	8.38	204.84	18	1	60000
42534	5000.0	5000.0	1	7.75	156.11	17	10	70000

42535 rows × 97 columns

In [246…
```
scaler = StandardScaler()
scaler.fit(data_dummies1)
data_dummies1_std = scaler.transform(data_dummies1)
```

In [247…
```
kmeans = KMeans(n_clusters=5, max_iter=1000)
kmeans.fit(data_dummies1)
```

Out[247]:
```
KMeans(max_iter=1000, n_clusters=5)
```

In [248…
```
kmeans.labels_
```

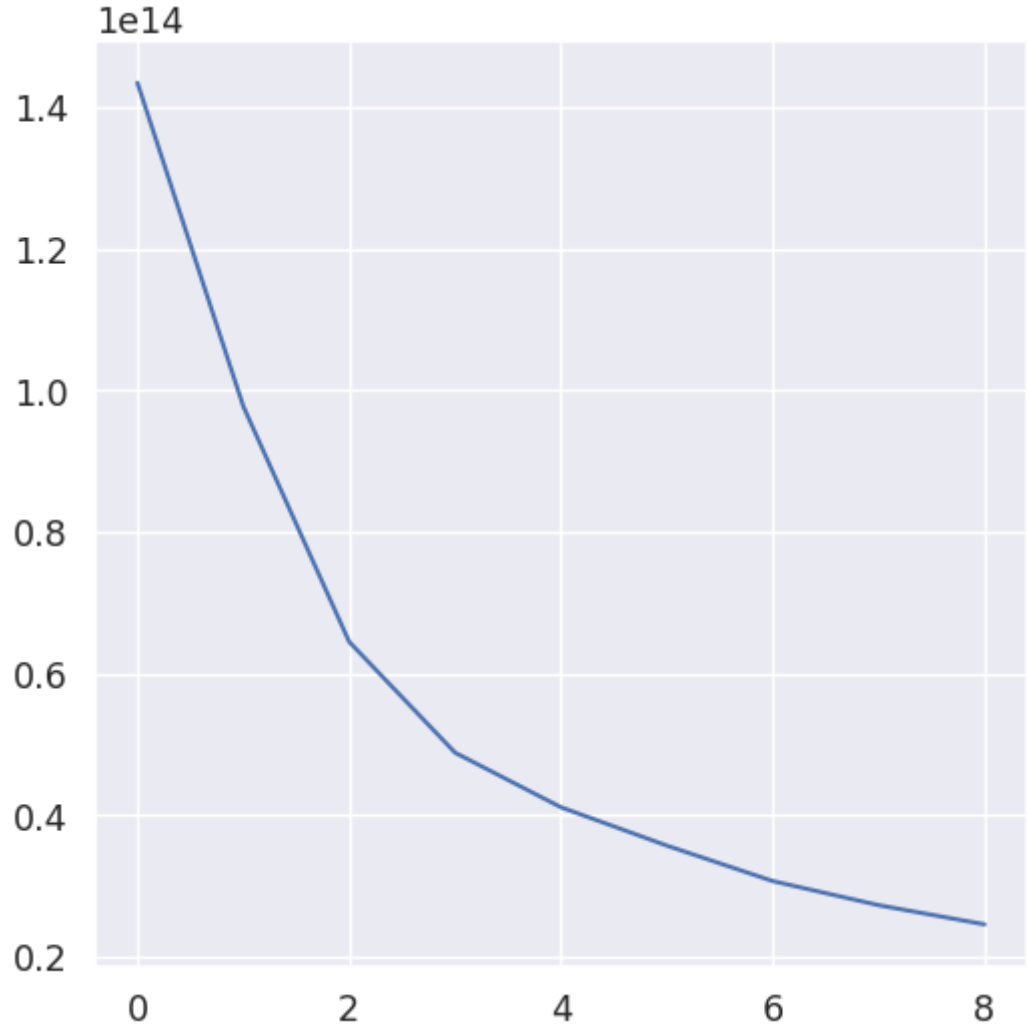
Out[248]:
```
array([2, 2, 2, ..., 0, 2, 2], dtype=int32)
```

Sprawdzamy dwie metody, ile klastrów powinniśmy zastosować

Metoda łokcia

In [249…
```
plt.figure(figsize = (6, 6))
ssd = []
range_n_clusters = [2, 3, 4, 5, 6, 7, 8, 9, 10]
for num_clusters in range_n_clusters:
    kmeans = KMeans(n_clusters=num_clusters, max_iter=1000)
    kmeans.fit(data_dummies1)

    ssd.append(kmeans.inertia_)

plt.plot(ssd)
```

Out[249]:
```
[<matplotlib.lines.Line2D at 0x7fb4dad8ba10>]
```



Miara wewnętrzna - wskaźnik sylwetkowy

In [250…
```
range_n_clusters = [2, 3, 4, 5, 6, 7, 8, 9, 10]

for num_clusters in range_n_clusters:

    kmeans = KMeans(n_clusters=num_clusters, max_iter=1000)
    kmeans.fit(data_dummies1)

    cluster_labels = kmeans.labels_

    silhouette_avg = silhouette_score(data_dummies1, cluster_labels)
    print("For n_clusters={0}, the silhouette score is {1}".format(num_clus
```

```
For n_clusters=2, the silhouette score is 0.6667746635910485
For n_clusters=3, the silhouette score is 0.6425329722711051
For n_clusters=4, the silhouette score is 0.5740388033132029
For n_clusters=5, the silhouette score is 0.47395065385078344
For n_clusters=6, the silhouette score is 0.4067249771604606
For n_clusters=7, the silhouette score is 0.391145726670524
For n_clusters=8, the silhouette score is 0.3917896303690999
For n_clusters=9, the silhouette score is 0.3511350794644952
For n_clusters=10, the silhouette score is 0.3541188396249691
```

W pobliżu k=7 się praktycznie stabilizuje, zaczyna się wypłaszczać przy k=4. Przyjmuję poniżej k=4

In [251…
```
kmeans = KMeans(n_clusters = 4, max_iter=1000, random_state=42)
kmeans.fit(data_dummies1)
```

Out[251]:
```
KMeans(max_iter=1000, n_clusters=4, random_state=42)
```

In [252…
```
kmeans.labels_
```

Out[252]:
```
array([0, 0, 0, ..., 2, 0, 0], dtype=int32)
```

In [253…
```
data_dummies1['K-Means_Cluster_ID'] = kmeans.labels_
```

In [254…
```
data_dummies1.sample(20)
```

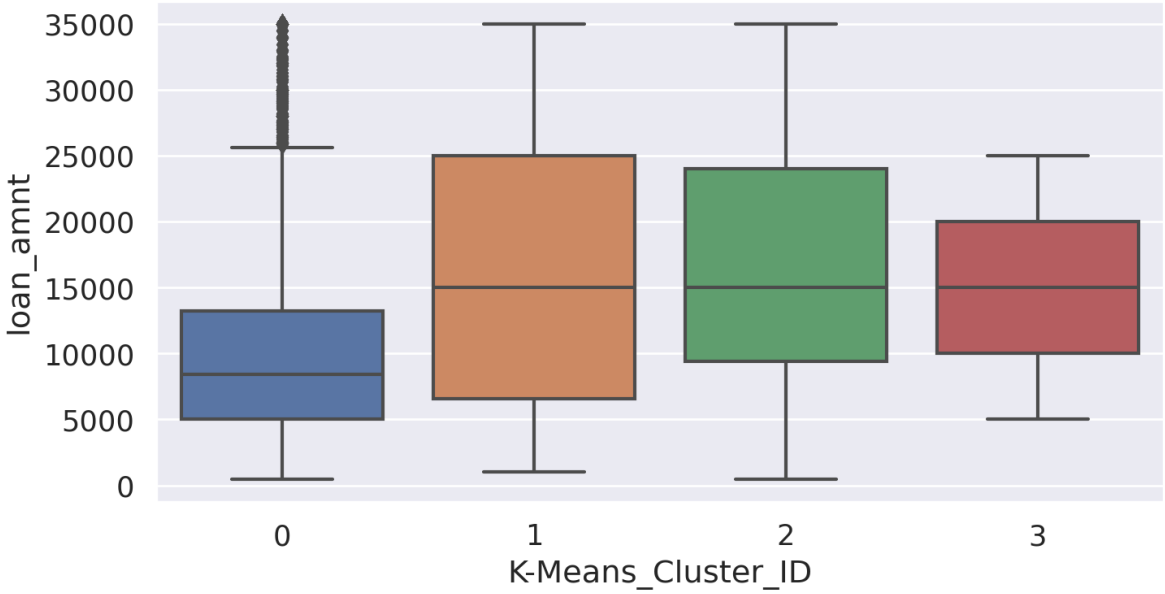
Out[254]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length	annual_i
6466	6500.0	6500.0	1	6.62	199.58	20	10	30000.(
14213	4475.0	4475.0	1	9.99	144.38	10	10	74000.(
8594	4000.0	4000.0	1	11.49	131.89	14	4	31150.(
24307	5000.0	5000.0	2	6.54	97.93	6	1	27096.(
8009	35000.0	35000.0	1	19.29	1288.10	21	3	125000.(
31893	3000.0	3000.0	1	10.62	97.68	13	2	53000.(
3523	35000.0	35000.0	1	10.65	1140.07	1	7	90000.(
6485	3625.0	3625.0	1	6.03	110.33	12	3	65000.(
19693	5000.0	5000.0	2	12.68	112.95	4	1	53000.(
41060	5000.0	5000.0	1	11.26	164.32	1	1	16090.3
7208	5025.0	5025.0	1	8.90	159.56	18	4	70000.(
27784	2000.0	2000.0	1	7.14	61.89	17	10	54000.(
2315	12000.0	12000.0	1	16.77	426.47	16	4	98000.(
23436	6000.0	6000.0	2	15.57	144.55	19	9	50000.(
34662	12000.0	12000.0	1	12.87	403.60	4	8	57720.(
39950	5300.0	5300.0	1	10.36	171.92	5	2	75000.(
15062	10000.0	10000.0	1	10.59	325.45	1	10	72000.(
15632	6600.0	6600.0	1	7.49	205.28	6	1	120000.(
3400	12000.0	12000.0	2	9.91	254.44	10	5	106320.(
35372	6000.0	6000.0	1	8.94	190.63	18	4	40000.(

20 rows × 98 columns

In [255…
```
plt.figure(figsize=(8,4),dpi=200)
sns.boxplot(x='K-Means_Cluster_ID', y='loan_amnt', data=data_dummies1)
```

Out[255]:
```
<AxesSubplot:xlabel='K-Means_Cluster_ID', ylabel='loan_amnt'>
```

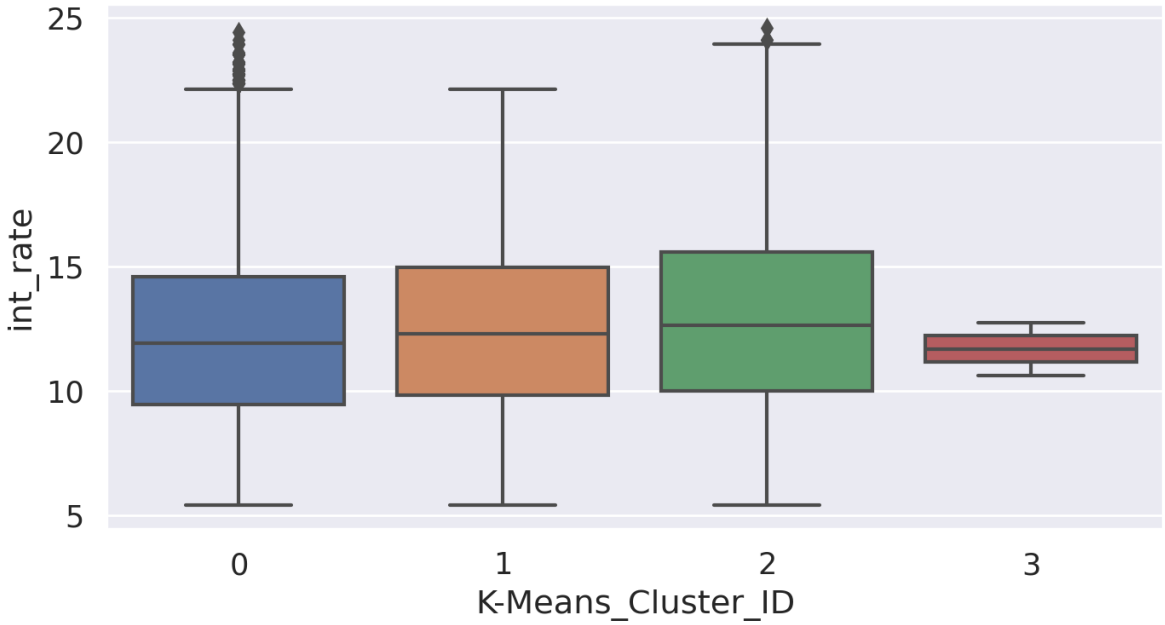


Wniosek:

W klastrze nr 1 jest najwięcej pożyczek od 7 tys do 25 tys. Niższe pozyczki są w klastrze 0.

In [256…
```
plt.figure(figsize=(8,4),dpi=200)
sns.boxplot(x='K-Means_Cluster_ID', y='int_rate', data=data_dummies1)
```

Out[256]:
```
<AxesSubplot:xlabel='K-Means_Cluster_ID', ylabel='int_rate'>
```

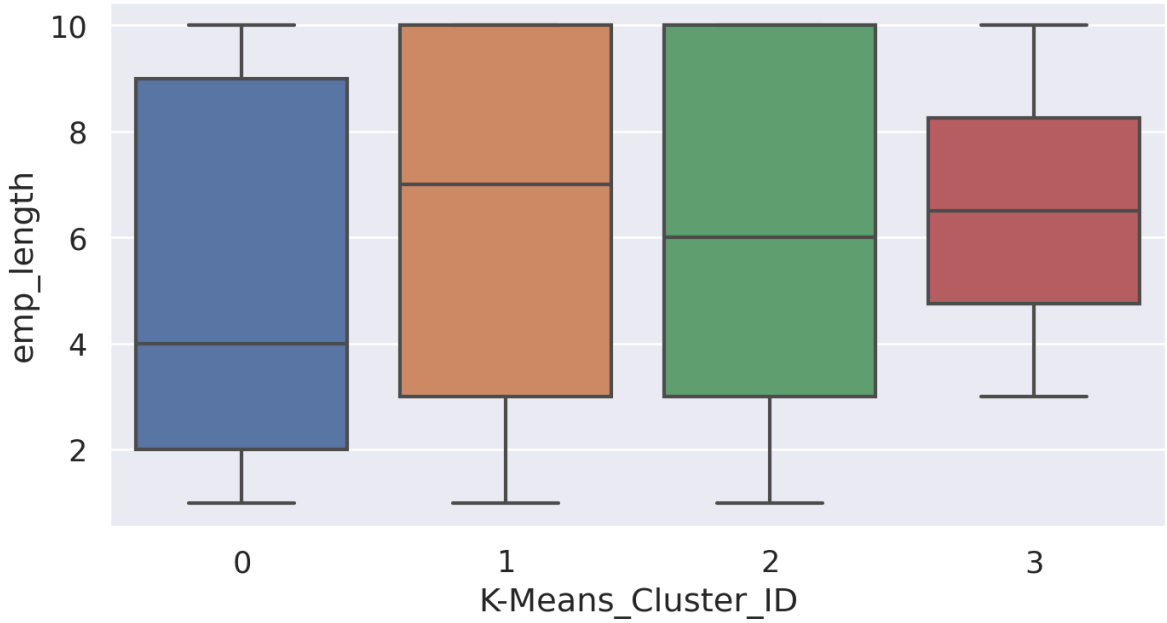


Wnioski:

W tym wypadku właściwie klastry się "zawierają w sobie" co do wysokości oprocentowania.

In [257…
```
plt.figure(figsize=(8,4),dpi=200)
sns.boxplot(x='K-Means_Cluster_ID', y='emp_length', data=data_dummies1)
```

Out[257]:
```
<AxesSubplot:xlabel='K-Means_Cluster_ID', ylabel='emp_length'>
```

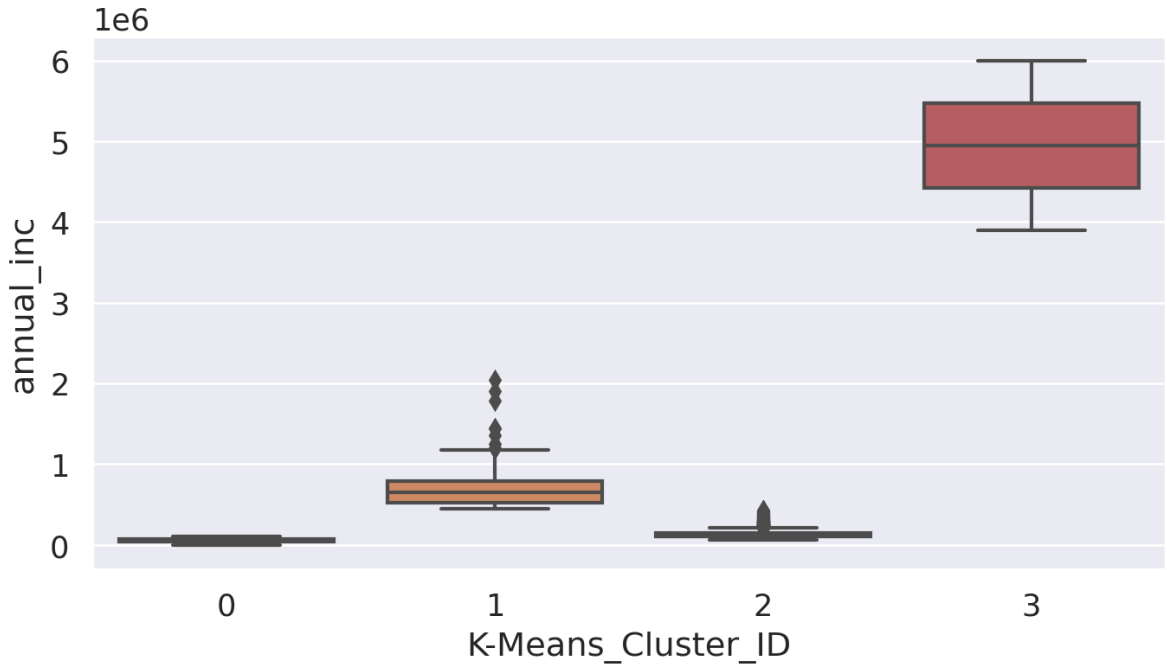


Wnioski:

Grupa pożyzckobiorców 5-9 lat została wrzucona do wszystkich klastrów, ale już ci z najniższym stażem pracy są w klastrze 0.

In [258…
```
plt.figure(figsize=(8,4),dpi=200)
sns.boxplot(x='K-Means_Cluster_ID', y='annual_inc', data=data_dummies1)
```

Out[258]:
```
<AxesSubplot:xlabel='K-Means_Cluster_ID', ylabel='annual_inc'>
```



Wnioski:

Pożyczkobiorcy z najwyższym dochodem zostali wrzuceni do grupy 3.

4. b) Modelowanie dla różnych algorytmów

Model na całym zbiorze - data_dummies

In [259…
```
# 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[259]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length	annual_i
0	5000.0	5000.0	1	10.65	162.87	1	10	24000
1	2500.0	2500.0	2	15.27	59.83	2	1	30000
2	2400.0	2400.0	1	15.96	84.33	3	10	12252
3	10000.0	10000.0	1	13.49	339.31	4	10	49200
4	3000.0	3000.0	2	12.69	67.79	5	1	80000
...	...	...	...	...	...	...	...	
42530	3500.0	3500.0	1	10.28	113.39	4	1	180000
42531	1000.0	1000.0	1	9.64	32.11	14	1	12000
42532	2525.0	2525.0	1	9.33	80.69	13	1	110000
42533	6500.0	6500.0	1	8.38	204.84	18	1	60000
42534	5000.0	5000.0	1	7.75	156.11	17	10	70000

42535 rows × 98 columns

In [260…
```
data_dummies.columns
```

Out[260]:
```
Index(['loan_amnt', 'funded_amnt', 'term', 'int_rate', 'installment',
       'sub_grade', 'emp_length', 'annual_inc', 'issue_d', 'loan_status',
       '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_mean',
       'last_fico_mean', 'fico_rating', 'loan_amnt_rating', 'interest_rati
ng',
       'home_ownership_MORTGAGE', 'home_ownership_NONE',
       'home_ownership_OTHER', 'home_ownership_OWN', 'home_ownership_REN
T',
       'verification_status_Not Verified',
       'verification_status_Source Verified', 'verification_status_Verifie
d',
       'purpose_car', 'purpose_credit_card', 'purpose_debt_consolidation',
       'purpose_educational', 'purpose_home_improvement', 'purpose_house',
       'purpose_major_purchase', 'purpose_medical', 'purpose_moving',
       'purpose_other', 'purpose_renewable_energy', 'purpose_small_busines
s',
       'purpose_vacation', 'purpose_wedding', 'addr_state_AK', 'addr_state
_AL',
       'addr_state_AR', 'addr_state_AZ', 'addr_state_CA', 'addr_state_CO',
       'addr_state_CT', 'addr_state_DC', 'addr_state_DE', 'addr_state_FL',
       'addr_state_GA', 'addr_state_HI', 'addr_state_IA', 'addr_state_ID',
       'addr_state_IL', 'addr_state_IN', 'addr_state_KS', 'addr_state_KY',
       'addr_state_LA', 'addr_state_MA', 'addr_state_MD', 'addr_state_ME',
       'addr_state_MI', 'addr_state_MN', 'addr_state_MO', 'addr_state_MS',
       'addr_state_MT', 'addr_state_NC', 'addr_state_NE', 'addr_state_NH',
       'addr_state_NJ', 'addr_state_NM', 'addr_state_NV', 'addr_state_NY',
       'addr_state_OH', 'addr_state_OK', 'addr_state_OR', 'addr_state_PA',
       'addr_state_RI', 'addr_state_SC', 'addr_state_SD', 'addr_state_TN',
       'addr_state_TX', 'addr_state_UT', 'addr_state_VA', 'addr_state_VT',
       'addr_state_WA', 'addr_state_WI', 'addr_state_WV', 'addr_state_W
Y'],
      dtype='object')
```

Train Test Split

In [261…
```
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=0.3, ra
```

Skalowanie

In [262…
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
X_test
```

Out[262]:
```
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 [263…
```
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 [264…
```
auroc_log = roc_auc_score(y_test, log_pred)
print('AUROC =', auroc_log)
```

```
AUROC = 0.6021051420958372
```

In [265…
```
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 [266…

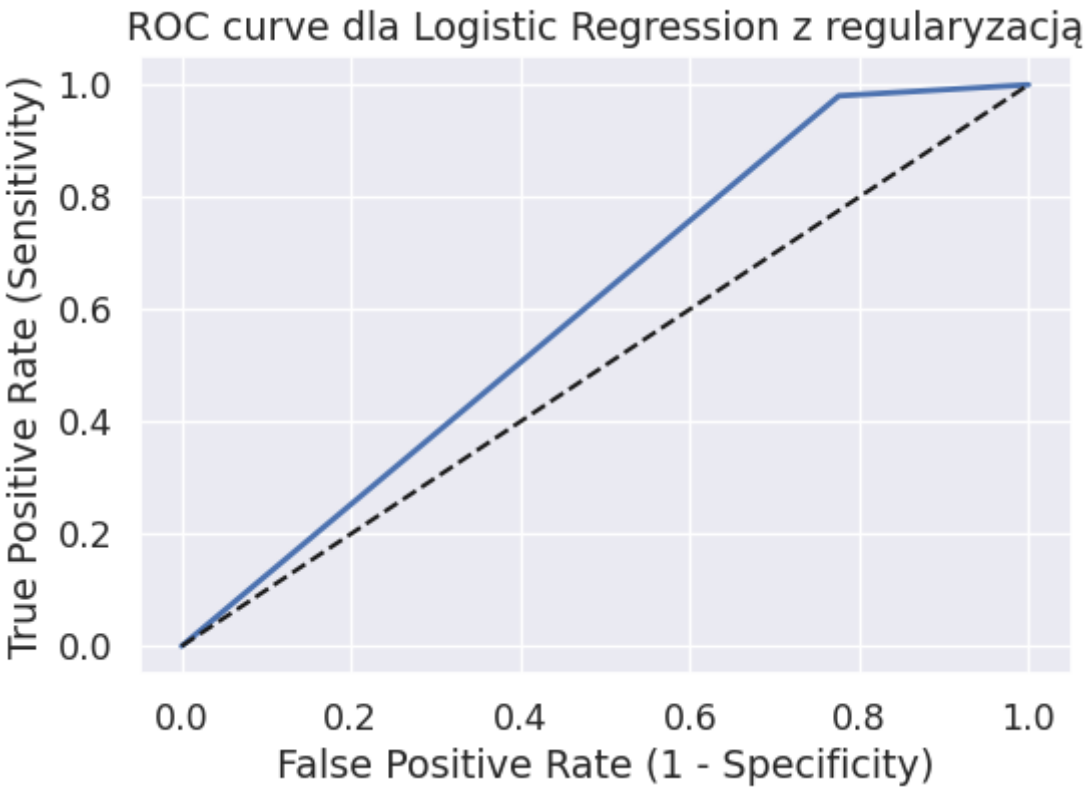
```
C = [.001, .01, 10, 100, 1000]

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(y_test, log1_pred)
    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 = 0.5342539144537797

              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 = 0.5858524498407645

              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 = 0.6021051420958372

              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 = 0.6021051420958372

              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 = 0.6021051420958372
```

In [267…

```
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 37 wyniki:

- max_depth = 37: {'f1-score': 0.89, 'accuracy': 0.81}
- max_depth = 30: {'f1-score': 0.89, 'accuracy': 0.81}
- 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 [268…
```
dtree = DecisionTreeClassifier(max_depth = 2, random_state = 0)
```

In [269…
```
dtree.get_params()
```

Out[269]:
```
{'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_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'random_state': 0,
 'splitter': 'best'}
```

In [270…
```
dtree.fit(X_train,y_train)
```

Out[270]:
```
DecisionTreeClassifier(max_depth=2, random_state=0)
```

In [271…
```
def evaluate(prediction,y_test):
    result = classification_report(y_test,prediction,output_dict=True)
    f1 = result['1']['f1-score']
    accuracy = result['accuracy']
    performance_data= {'f1-score':round(f1, 2),
                       'accuracy':round(accuracy, 2)}
    return performance_data
```

In [272…
```
dt_prediction = dtree.predict(X_test)
```

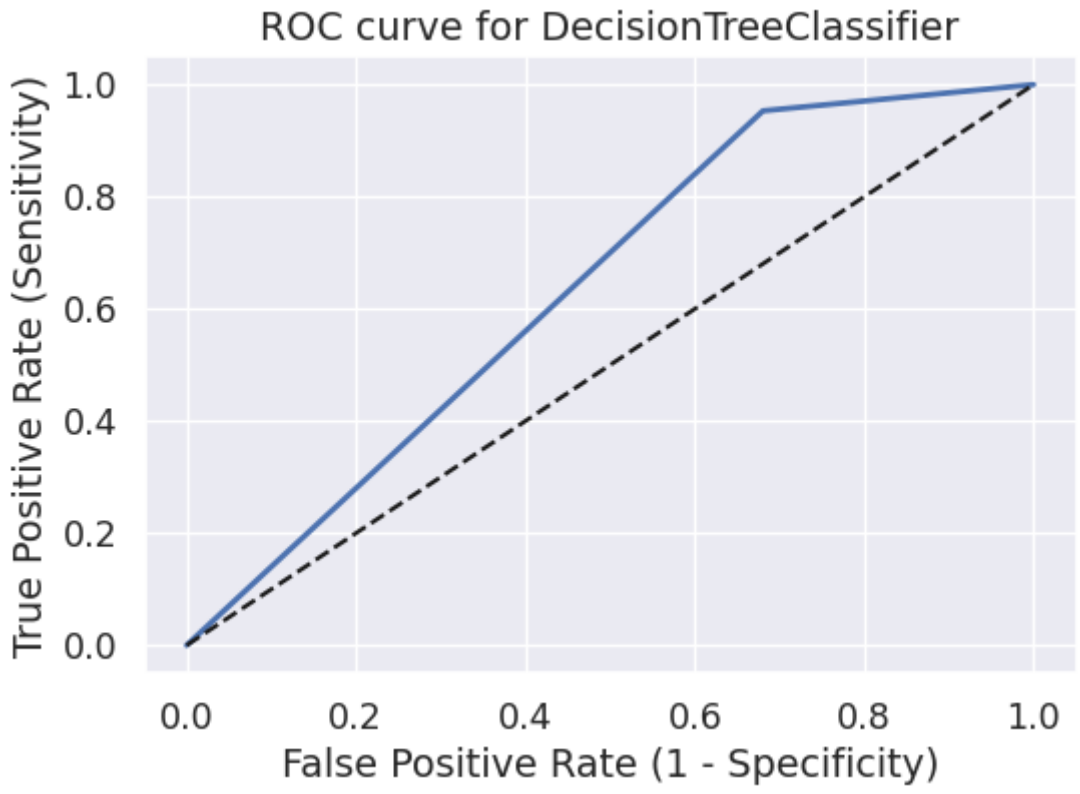
In [273…
```
dtree_pr = evaluate(dt_prediction,y_test)
dtree_pr

# 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 [274…
```
auroc_dtree = roc_auc_score(y_test, dt_prediction)
print('AUROC =', auroc_dtree)
```

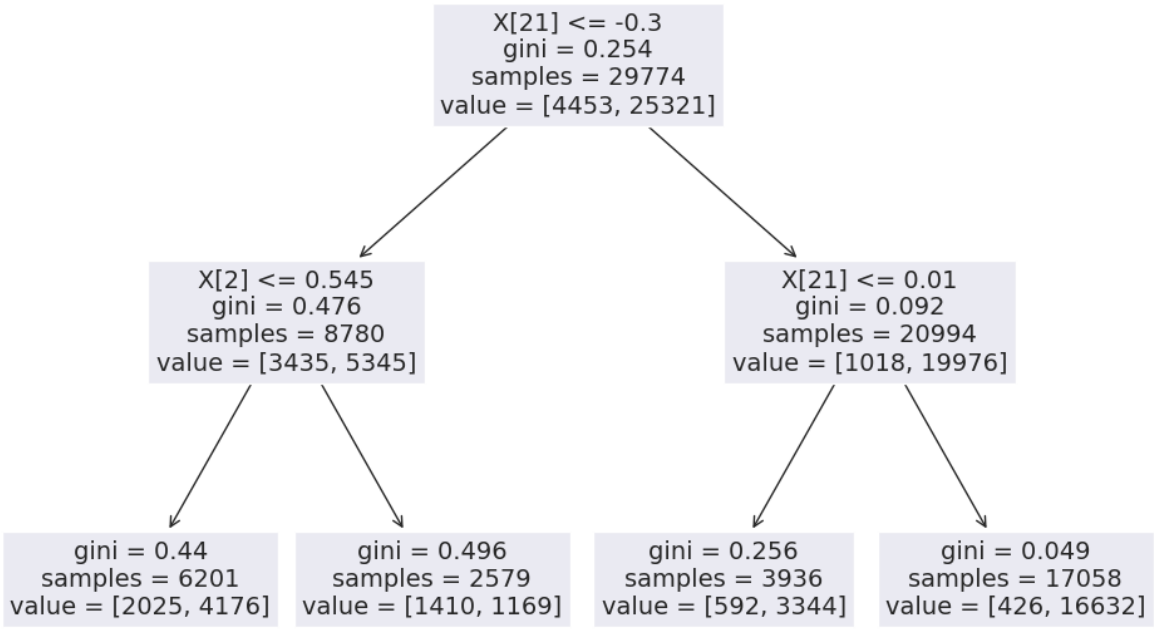
```
AUROC = 0.6363872110042519
```

In [275…
```
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 [276…
```
tree.plot_tree(dtree)
```

Out[276]:
```
[Text(0.5, 0.8333333333333334, 'X[21] <= -0.3\ngini = 0.254\nsamples = 297
74\nvalue = [4453, 25321]'),
 Text(0.25, 0.5, 'X[2] <= 0.545\ngini = 0.476\nsamples = 8780\nvalue = [34
35, 5345]'),
 Text(0.125, 0.16666666666666666, 'gini = 0.44\nsamples = 6201\nvalue = [2
025, 4176]'),
 Text(0.375, 0.16666666666666666, 'gini = 0.496\nsamples = 2579\nvalue =
[1410, 1169]'),
 Text(0.75, 0.5, 'X[21] <= 0.01\ngini = 0.092\nsamples = 20994\nvalue = [1
018, 19976]'),
 Text(0.625, 0.16666666666666666, 'gini = 0.256\nsamples = 3936\nvalue =
[592, 3344]'),
 Text(0.875, 0.16666666666666666, 'gini = 0.049\nsamples = 17058\nvalue =
[426, 16632]')]
```



In [277…
```
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 [278…
```
rf = RandomForestClassifier(n_estimators=100, random_state=0)
```

In [279…
```
rf.fit(X_train, y_train)
```

Out[279]:
```
RandomForestClassifier(random_state=0)
```

In [280…
```
rf_prediction = rf.predict(X_test)
```

In [281…
```
rf_pr = evaluate(rf_prediction,y_test)
rf_pr

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

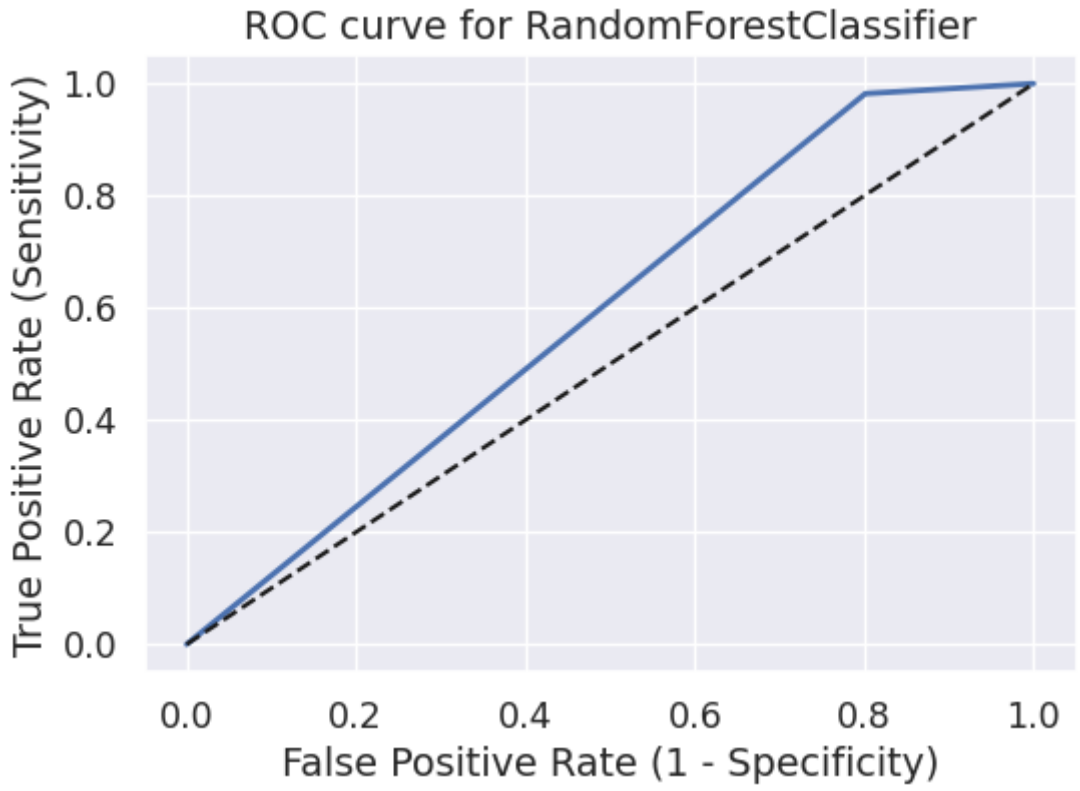
```
print(confusion_matrix(y_test, rf_prediction))
# Accuracy
print('Training accuracy:', rf.score(X_train, y_train))
print('Test accuracy:', rf.score(X_test, y_test))
```

```
              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 [282…
```
auroc_rf = roc_auc_score(y_test, rf_prediction)
print(auroc_rf)
```

```
0.5903934984730017
```

In [283…
```
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 [284…
```
# model = SVC(C=100, random_state = 12)
```

```
supvm = SVC(C=1.0, kernel='linear', random_state = 12)
```

In [285…
```
supvm.fit(X_train,y_train)
```

Out[285]:
```
SVC(kernel='linear', random_state=12)
```

In [286…
```
svm_prediction = supvm.predict(X_test)
```

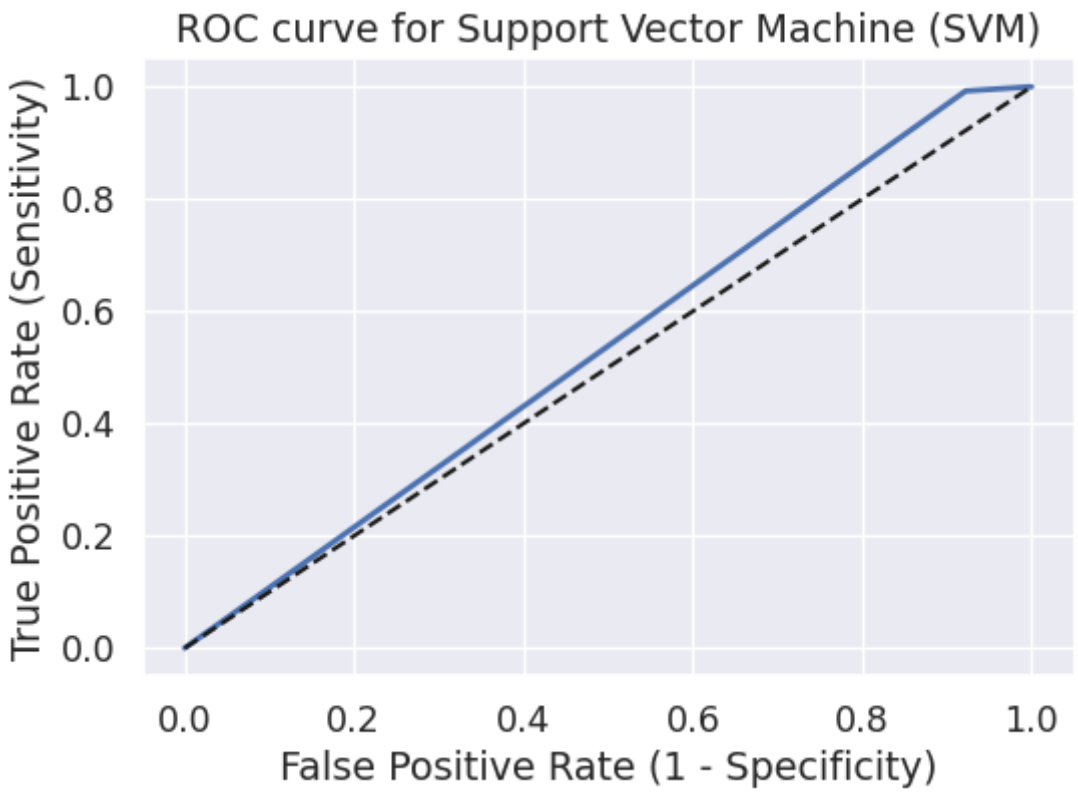
In [287…
```
svm_pr = evaluate(svm_prediction,y_test)
svm_pr
# Summary of the prediction
print(classification_report(y_test, svm_prediction))
print(confusion_matrix(y_test, svm_prediction))

# 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 [288…
```
auroc_svm = roc_auc_score(y_test, svm_prediction)
print('AUROC =', auroc_svm)
```

```
AUROC = 0.5351722982296122
```

In [289…
```
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 [290…
```
knn = KNeighborsClassifier(n_neighbors=2)
```

In [291…
```
knn.get_params()
```

Out[291]:
```
{'algorithm': 'auto',
 'leaf_size': 30,
 'metric': 'minkowski',
 'metric_params': None,
 'n_jobs': None,
 'n_neighbors': 2,
 'p': 2,
 'weights': 'uniform'}
```

In [292…
```
knn.fit(X_train,y_train)
```

Out[292]:
```
KNeighborsClassifier(n_neighbors=2)
```

In [293…
```
knn_prediction = knn.predict(X_test)
```

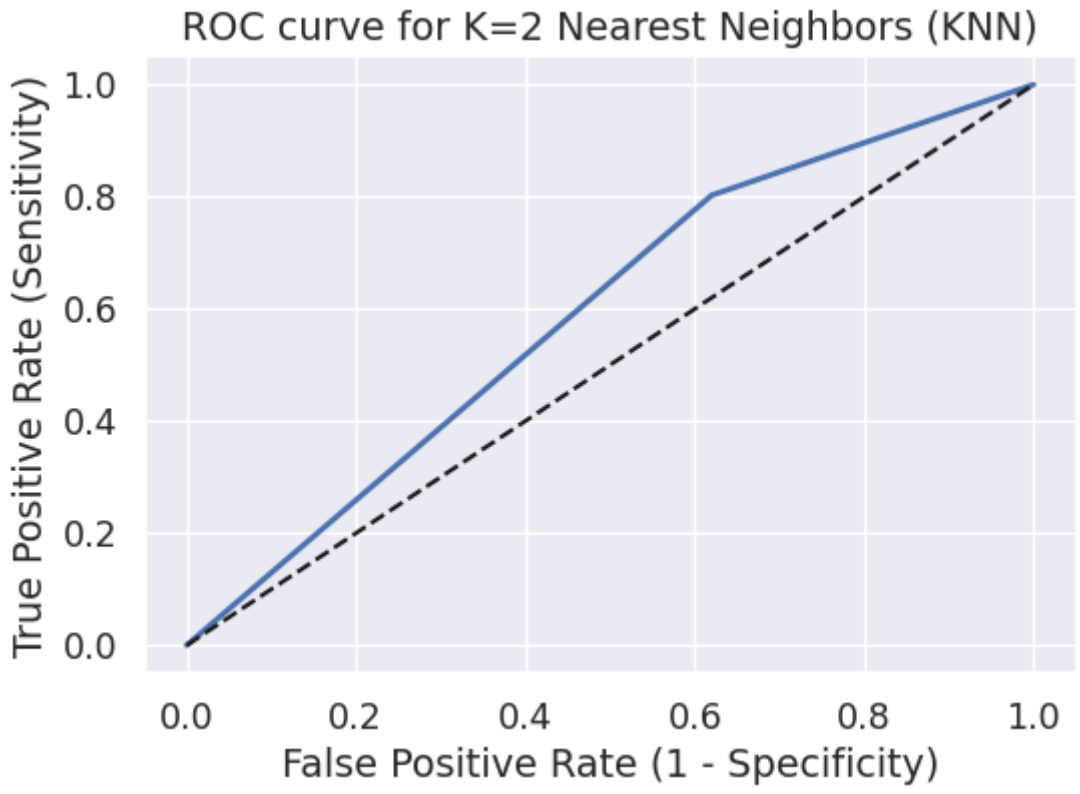
In [294…
```
knn_pr = evaluate(knn_prediction,y_test)
knn_pr
# Summary of the prediction
print(classification_report(y_test, knn_prediction))
print(confusion_matrix(y_test, knn_prediction))
# Accuracy
print('Training accuracy:', knn.score(X_train, y_train))
print('Test accuracy:', knn.score(X_test, y_test))
```

```
                   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 [295…
```
auroc_knn = roc_auc_score(y_test, knn_prediction)
print('AUROC =', auroc_knn)
```

```
AUROC = 0.5913707932767256
```

In [296…
```
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 [297…
```
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, 0.814042786615469]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.814042786615469, 0.
8405297390486639]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.814042786615469, 0.
8405297390486639, 0.8352010030561868]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.814042786615469, 0.
8405297390486639, 0.8352010030561868, 0.8442911997492359]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.814042786615469, 0.
8405297390486639, 0.8352010030561868, 0.8442911997492359, 0.842332105634354
7]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.814042786615469, 0.
8405297390486639, 0.8352010030561868, 0.8442911997492359, 0.842332105634354
7, 0.8460935663349267]
n_neighbors= [0.7370895697829324, 0.8308126322388527, 0.814042786615469, 0.
8405297390486639, 0.8352010030561868, 0.8442911997492359, 0.842332105634354
7, 0.8460935663349267, 0.8441344722200455]
```

In [298…

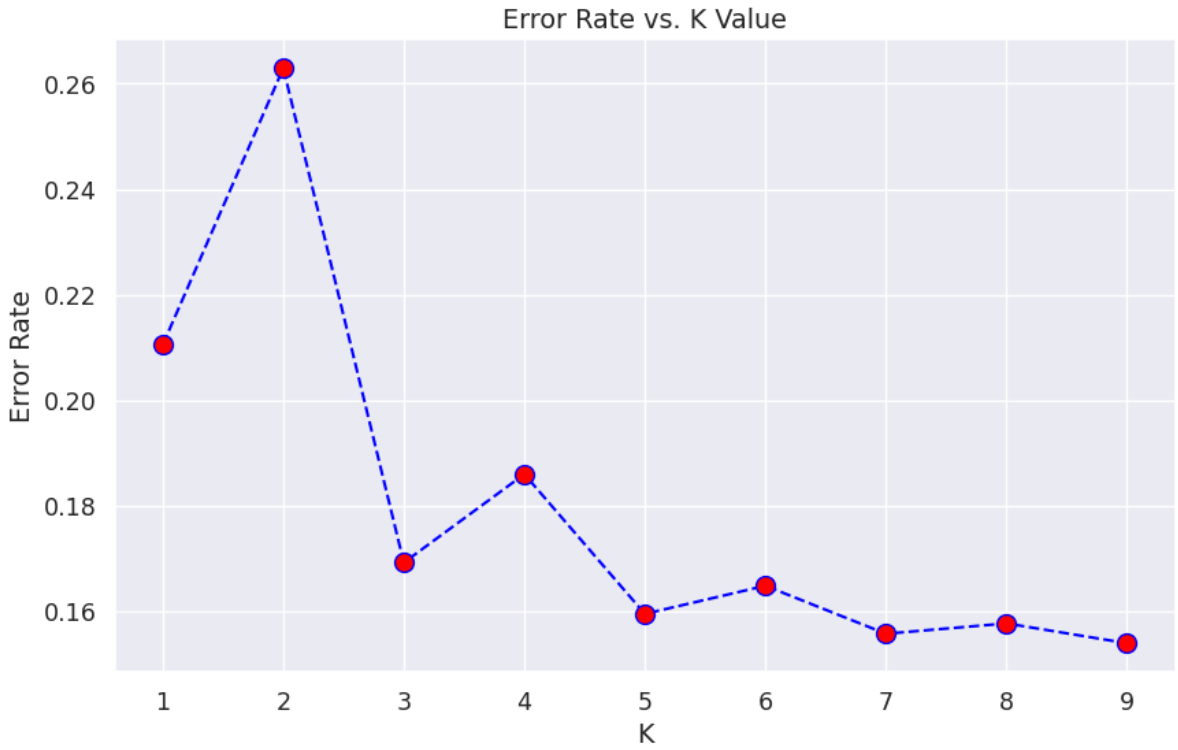
```
error_rate = []

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, 0.18595721338
4531, 0.1594702609513361, 0.16479899694381317, 0.15570880025076406, 0.15766
789436564532, 0.15390643366507328]
```

In [299…

```
plt.figure(figsize=(10,6))
plt.plot(range(1, max_k), error_rate, color = 'blue', linestyle='dashed', m
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

Out[299]: Text(0, 0.5, 'Error Rate')



sprawdź knn dla innej wartości k

In [300…
```
knn1 = KNeighborsClassifier()
```

In [301…
```
knn1.fit(X_train,y_train)
```

Out[301]:
```
KNeighborsClassifier()
```

In [302…
```
knn1_prediction = knn.predict(X_test)
```

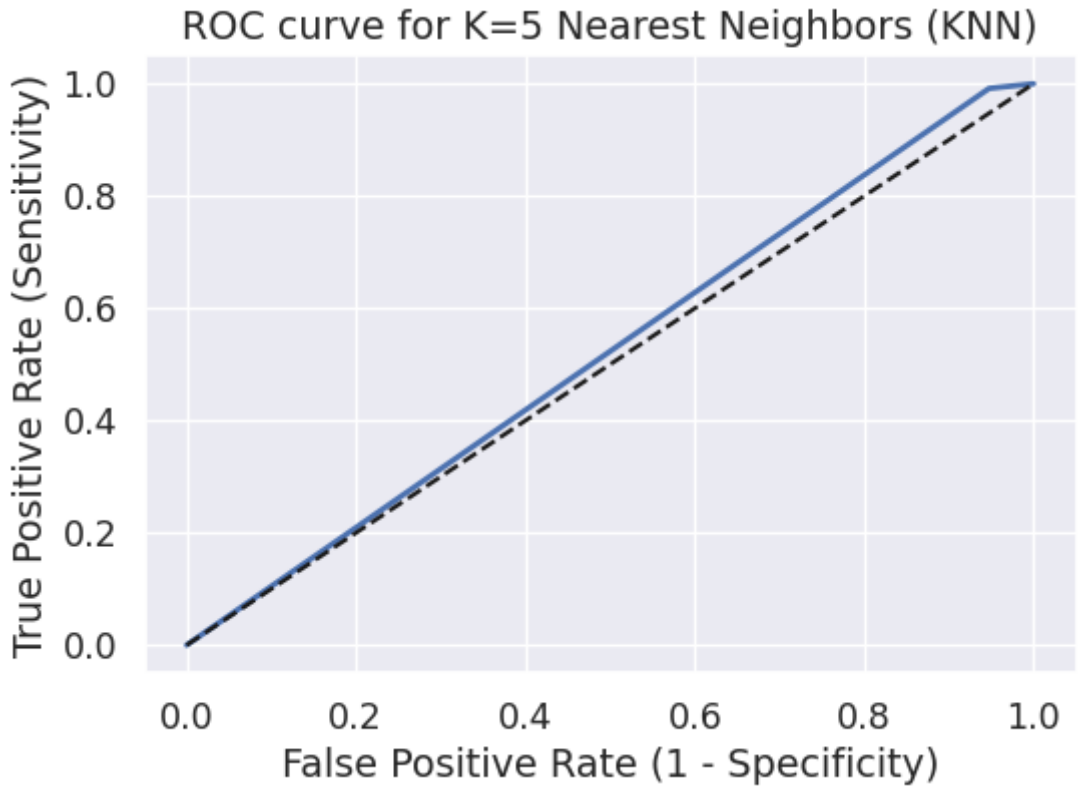
In [303…
```
knn1_pr = evaluate(knn1_prediction,y_test)
knn1_pr
# Summary of the prediction
print(classification_report(y_test, knn1_prediction))
print(confusion_matrix(y_test, knn1_prediction))
# Accuracy
print('Training accuracy:', knn1.score(X_train, y_train))
print('Test accuracy:', knn1.score(X_test, 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 [304…
```
auroc_knn1 = roc_auc_score(y_test, knn1_prediction)
print('AUROC =', auroc_knn1)
```

```
AUROC = 0.5221159453421935
```

In [305…
```
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 [306…
```
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))
```

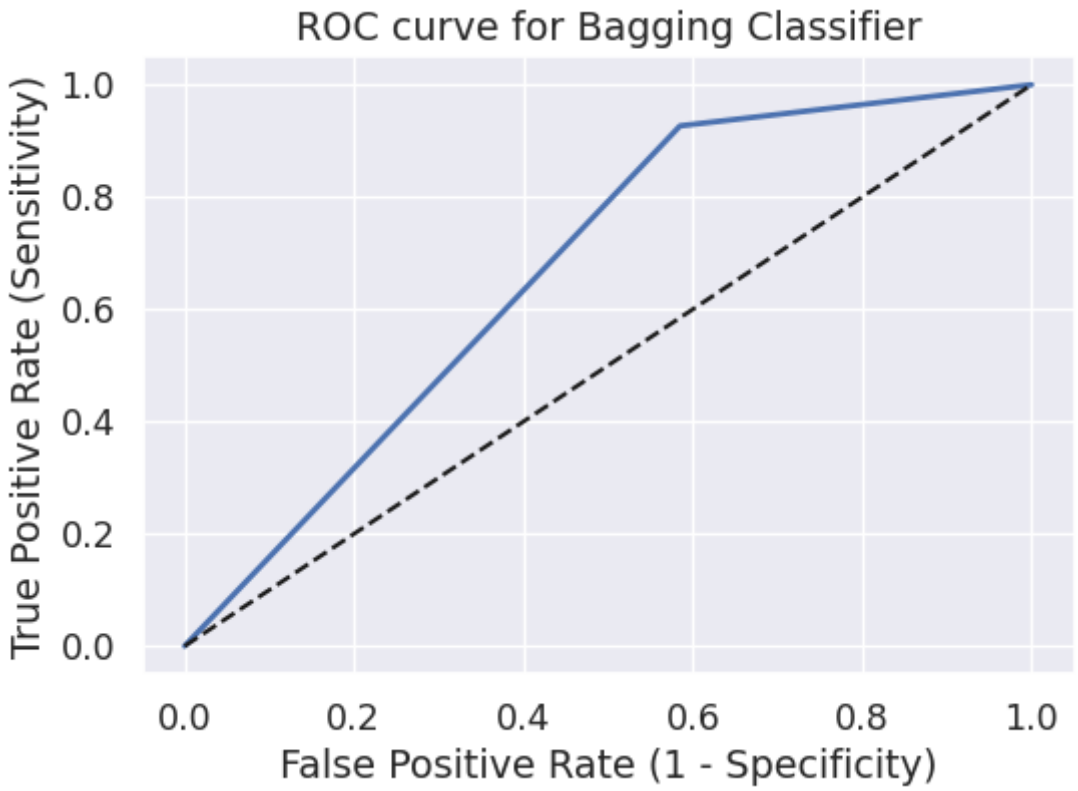
```
              precision    recall  f1-score   support

           0       0.51      0.42      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

[[ 821 1157]
 [ 790 9993]]
```

In [307…
```
auroc_xgbc = roc_auc_score(y_test, xgbc_prediction)
print('AUROC =', auroc_xgbc)
```

```
AUROC = 0.6709011263375945
```

In [308…

```
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 [309…

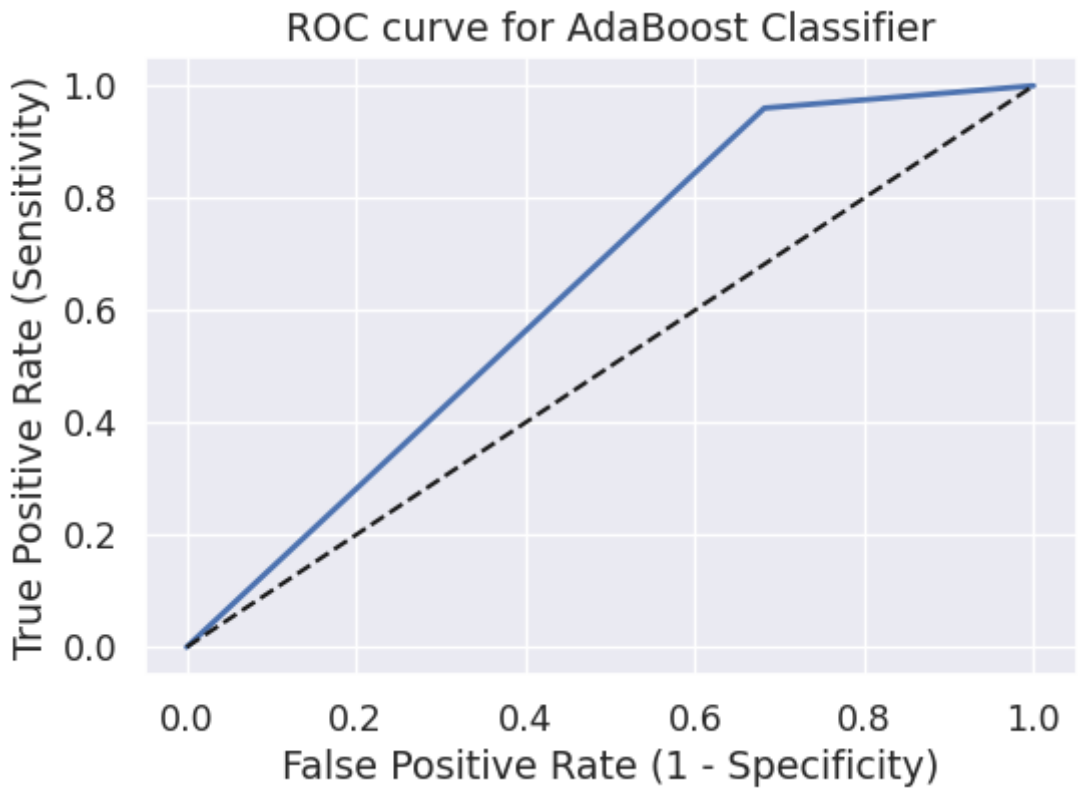
```
ada = AdaBoostClassifier(random_state=1)
ada.fit(X_train, y_train)
ada_prediction = ada.predict(X_test)
print(classification_report(y_test, ada_prediction))
ada = evaluate(ada_prediction,y_test)
ada

# 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 [310…
```
auroc_ada = roc_auc_score(y_test, ada_prediction)
print('AUROC =', auroc_ada)
```

```
AUROC = 0.6390601963338352
```

In [311…
```
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

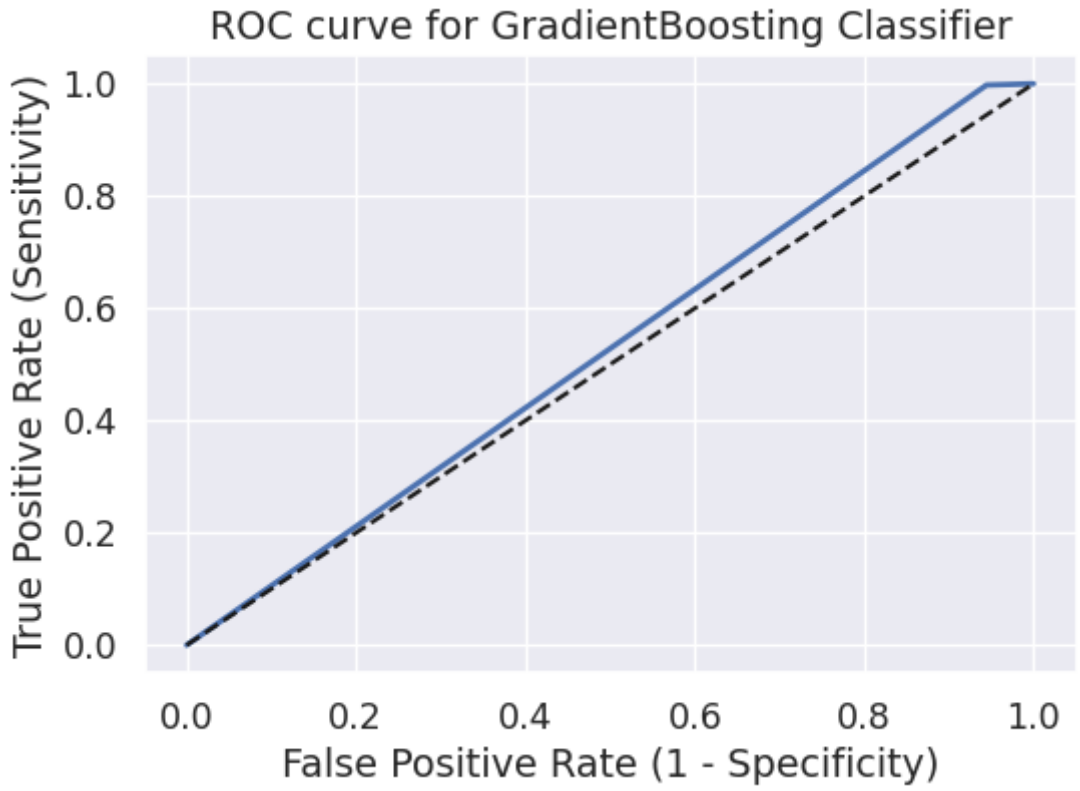
In [312…
```
gbc= GradientBoostingClassifier(learning_rate=0.01, random_state=1)
gbc.fit(X_train, y_train)
gbc_prediction = gbc.predict(X_test)
gbc = evaluate(gbc_prediction,y_test)
gbc

# 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 [313…
```
auroc_gbc = roc_auc_score(y_test, gbc_prediction)
print('AUROC =', auroc_gbc)
```

```
AUROC = 0.5266002630999793
```

In [314…
```
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

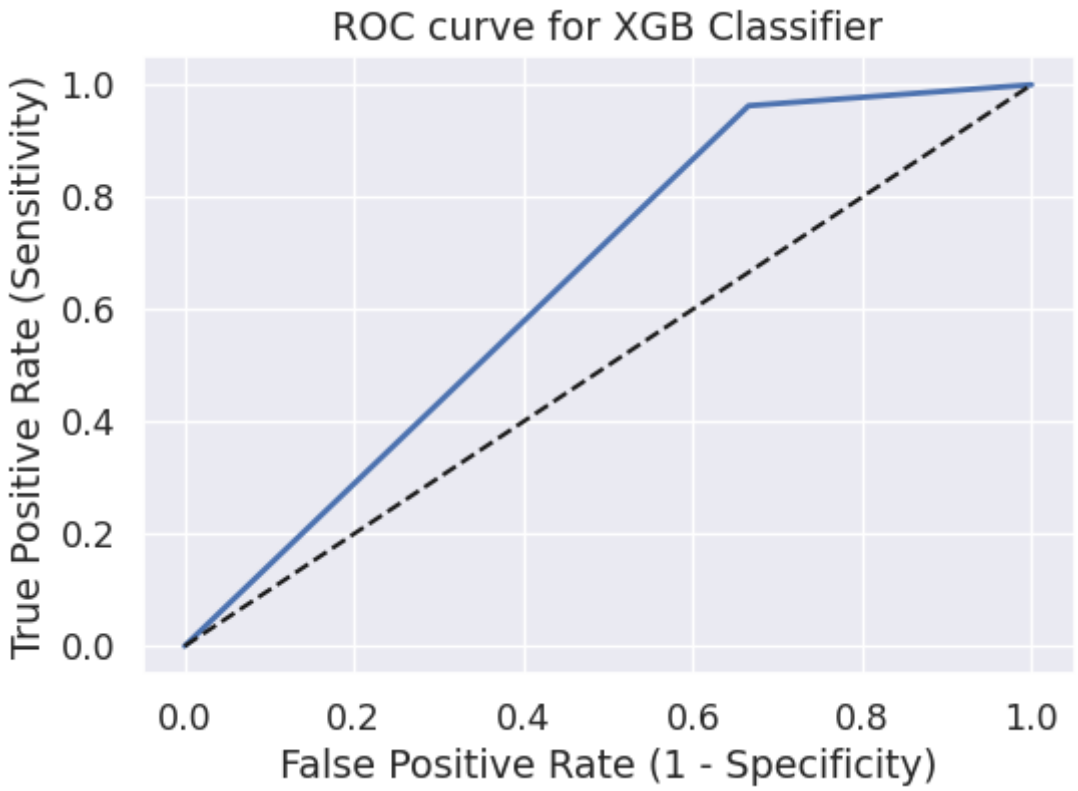
In [315…
```
import xgboost as xgb
xgb_clas=xgb.XGBClassifier(random_state=1,learning_rate=0.01)
xgb_clas.fit(X_train, y_train)
xgb_clas_prediction = xgb_clas.predict(X_test)
xgb_clas = evaluate(xgb_clas_prediction,y_test)
xgb_clas

# 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       0.62      0.33      0.43      1978
           1       0.89      0.96      0.92     10783

    accuracy                           0.87     12761
   macro avg       0.75      0.65      0.68     12761
weighted avg       0.85      0.87      0.85     12761

[[  661  1317]
 [  403 10380]]
```

In [316…
```
auroc_xgb_clas = roc_auc_score(y_test, xgb_clas_prediction)
print('AUROC =', auroc_xgb_clas)
```

```
AUROC = 0.648401145794878
```

In [317…
```
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 [318…
```
results = 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
results.sort_values(by = 'AUROC', ascending = False)
```

Out[318]:

	Method	AUROC
6	Bagging Classifier	0.670901
9	XGB Classifier	0.648401
7	ADA Boost Classifier	0.639060
2	Decision Tree	0.636387
0	Logistic Regression	0.602105
1	Logistic Regression parameters	0.602105
5	KNN	0.591371
3	Random Forest	0.590393
4	Support Vector Machine (SVM)	0.535172
8	Gradient Boosting Classifier	0.526600

Modele na całym zbiorze - data_loan1 - cechy numeryczne

Logistic Regression

In [319…
```
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, test_size=0

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

In [320…
```
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 [321…
```
auroc_log_num = roc_auc_score(y_test, xgb_clas_prediction)
print('AUROC =', auroc_log_num)
```

```
AUROC = 0.648401145794878
```

Bagging Classifier

In [322…
```
xgbc = BaggingClassifier(tree.DecisionTreeClassifier(random_state=1))
xgbc.fit(X1_train, y1_train)
xgbc_prediction = xgbc.predict(X1_test)
xgbc = evaluate(xgbc_prediction,y1_test)
xgbc

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

```
              precision    recall  f1-score   support

           0       0.50      0.41      0.45      1978
           1       0.90      0.92      0.91     10783

    accuracy                           0.84     12761
   macro avg       0.70      0.67      0.68     12761
weighted avg       0.83      0.84      0.84     12761

[[ 813 1165]
 [ 815 9968]]
```

In [323…
```
auroc_gbc_num = roc_auc_score(y1_test, xgbc_prediction)
print('AUROC =', auroc_gbc_num)
```

```
AUROC = 0.6677196495213462
```

Modele na całym zbiorze - data_outliers - z uzupełnionymi medianami

Logistic Regression

In [324…
```
X2 = data_outliers
#target
y2 = data_loan['loan_status']

X2_train, X2_test, y2_train, y2_test = train_test_split(X2, y2, test_size=0

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

In [325…
```
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 [326…

```
auroc_log_med = roc_auc_score(y2_test, y2_pred)
print('AUROC =', auroc_log_med)
```

```
AUROC = 0.5915556609114054
```

Bagging Classifier

In [327…

```
xgbc = BaggingClassifier(tree.DecisionTreeClassifier(random_state=1))
xgbc.fit(X2_train, y2_train)
xgbc_prediction = xgbc.predict(X2_test)
xgbc = evaluate(xgbc_prediction,y2_test)
xgbc

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

```
              precision    recall  f1-score   support

           0       0.49      0.39      0.44      1978
           1       0.89      0.93      0.91     10783

    accuracy                           0.84     12761
   macro avg       0.69      0.66      0.67     12761
weighted avg       0.83      0.84      0.84     12761

[[ 772 1206]
 [ 793 9990]]
```

In [328…

```
auroc_gbc_med = roc_auc_score(y2_test, xgbc_prediction)
print('AUROC =', auroc_gbc_med)
```

```
AUROC = 0.6583757697465404
```

Podsumowanie

Najlepsze wyniki AUROC uzyskałem na modelu Bagging Classifier, na wszystkich danych. Poniżej podsumowanie w zależności od rodzaju danych.

In [329…

```
results = pd.DataFrame({'Method':['Bagging Classifier','Bagging Classifier'
                        'AUROC': [auroc_xgbc, auroc_gbc_num, auroc_gbc_med]
                       'Zbiór danych': ['data_dummies', 'data_loan numerycz
results.sort_values(by = 'AUROC', ascending = False)
```

Out[329]:

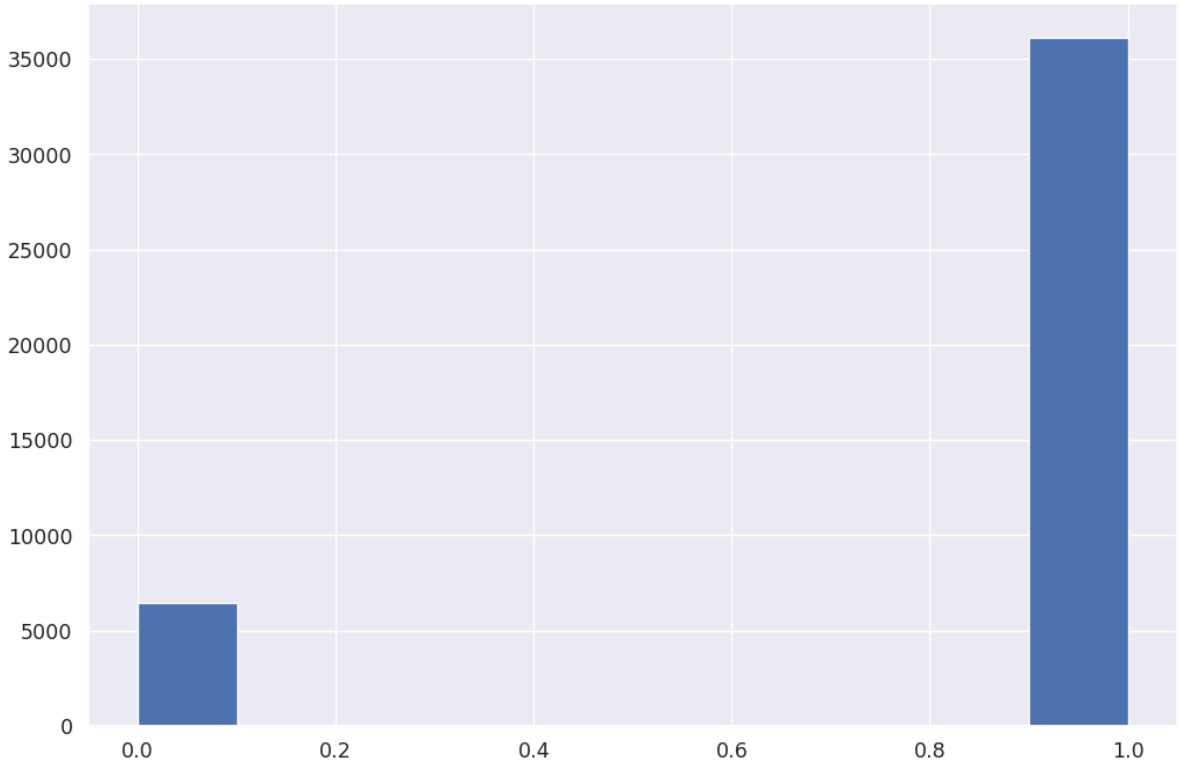
	Method	AUROC	Zbiór danych
0	Bagging Classifier	0.670901	data_dummies
1	Bagging Classifier	0.667720	data_loan numeryczne
2	Bagging Classifier	0.658376	data_loan z medianami

5. Skompresowanie danych metodą PCA

In [330…
```
X = data_dummies.drop('loan_status',axis=1)
#target
y = data_dummies['loan_status']
```

In [331…
```
y.hist()
```

Out[331]:
```
<AxesSubplot:>
```



In [332…
```
X.shape
```

Out[332]:
```
(42535, 97)
```

In [333…
```
y.shape
```

Out[333]:
```
(42535,)
```

In [334…
```
y
```

Out[334]:
```
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 [335…
```
sc = StandardScaler()
X_scaled = sc.fit_transform(X)
X_scaled[:5, :5]
```

Out[335]:
```
array([[-0.82173051, -0.81456887, -0.59064503, -0.40859218, -0.76464399],
       [-1.15907367, -1.16437427,  1.69306429,  0.83739883, -1.25783589],
       [-1.1725674 , -1.17836649, -0.59064503,  1.0234884 , -1.1405688 ],
       [-0.14704418, -0.11495806, -0.59064503,  0.35734169,  0.07987056],
       [-1.09160504, -1.09441319,  1.69306429,  0.14158567, -1.21973605]])
```

In [336…
```
X.columns
```

Out[336]:
```
Index(['loan_amnt', 'funded_amnt', 'term', 'int_rate', 'installment',
       'sub_grade', 'emp_length', 'annual_inc', 'issue_d', '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_mean',
       'last_fico_mean', 'fico_rating', 'loan_amnt_rating', 'interest_rati
ng',
       'home_ownership_MORTGAGE', 'home_ownership_NONE',
       'home_ownership_OTHER', 'home_ownership_OWN', 'home_ownership_REN
T',
       'verification_status_Not Verified',
       'verification_status_Source Verified', 'verification_status_Verifie
d',
       'purpose_car', 'purpose_credit_card', 'purpose_debt_consolidation',
       'purpose_educational', 'purpose_home_improvement', 'purpose_house',
       'purpose_major_purchase', 'purpose_medical', 'purpose_moving',
       'purpose_other', 'purpose_renewable_energy', 'purpose_small_busines
s',
       'purpose_vacation', 'purpose_wedding', 'addr_state_AK', 'addr_state
_AL',
       'addr_state_AR', 'addr_state_AZ', 'addr_state_CA', 'addr_state_CO',
       'addr_state_CT', 'addr_state_DC', 'addr_state_DE', 'addr_state_FL',
       'addr_state_GA', 'addr_state_HI', 'addr_state_IA', 'addr_state_ID',
       'addr_state_IL', 'addr_state_IN', 'addr_state_KS', 'addr_state_KY',
       'addr_state_LA', 'addr_state_MA', 'addr_state_MD', 'addr_state_ME',
       'addr_state_MI', 'addr_state_MN', 'addr_state_MO', 'addr_state_MS',
       'addr_state_MT', 'addr_state_NC', 'addr_state_NE', 'addr_state_NH',
       'addr_state_NJ', 'addr_state_NM', 'addr_state_NV', 'addr_state_NY',
       'addr_state_OH', 'addr_state_OK', 'addr_state_OR', 'addr_state_PA',
       'addr_state_RI', 'addr_state_SC', 'addr_state_SD', 'addr_state_TN',
       'addr_state_TX', 'addr_state_UT', 'addr_state_VA', 'addr_state_VT',
       'addr_state_WA', 'addr_state_WI', 'addr_state_WV', 'addr_state_W
Y'],
      dtype='object')
```

In [337…
```
X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)
```

```
X_scaled_df
```

Out[337]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_length	an
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 [338…

```
plt.figure(figsize = (20,10))
X_scaled_df.corr()
```

Out[338]:

	loan_amnt	funded_amnt	term	int_rate	installment	sub_grade	emp_le
loan_amnt	1.000000	0.981746	0.355647	0.292346	0.930869	0.119626	0.13
funded_amnt	0.981746	1.000000	0.335137	0.295154	0.956522	0.115749	0.13
term	0.355647	0.335137	1.000000	0.428649	0.097614	0.190461	0.1
int_rate	0.292346	0.295154	0.428649	1.000000	0.271433	0.313232	-0.01
installment	0.930869	0.956522	0.097614	0.271433	1.000000	0.102561	0.10
...	...	...	...	...	...	...	
addr_state_VT	-0.010225	-0.010569	-0.004024	-0.008556	-0.009995	-0.000909	0.00
addr_state_WA	-0.003873	-0.002099	-0.007010	0.006209	0.000584	-0.000473	0.00
addr_state_WI	0.000184	0.000458	0.011548	0.000731	-0.002843	0.000552	0.00
addr_state_WV	-0.003483	-0.002075	0.005385	-0.005369	-0.005191	-0.009206	0.01
addr_state_WY	0.000242	0.000828	-0.006537	0.005543	0.003201	-0.004905	0.00

97 rows × 97 columns

```
<Figure size 2000x1000 with 0 Axes>
```

PCA redukcja wymiarów

In [339…

```
pca = PCA(random_state=42)
pca.fit(X_scaled)
```

Out[339]:

```
PCA(random_state=42)
```

Sprawdzam liczbę komponentów

In [340…
```
pca.components_[0]
```

Out[340]:
```
array([ 3.98663613e-01,  3.97415860e-01,  1.75253811e-01,  1.49808078e-01,
        3.73623051e-01,  7.26308430e-02,  1.17359348e-01,  1.68026467e-01,
        9.01326971e-02,  7.89990740e-02, -3.45799486e-03, -1.47489234e-01,
        1.22166090e-03,  1.76536828e-02,  1.60700550e-01, -1.27456455e-02,
        1.76637691e-01,  6.06719717e-02,  2.05562709e-01, -5.02451223e-03,
        2.92654586e-02,  3.51002763e-02, -1.29941452e-02,  3.57000230e-01,
       -3.56261233e-02,  1.63683343e-01, -7.86086491e-03, -7.53057314e-03,
       -2.19799777e-02, -1.50166856e-01, -1.87402351e-01, -3.67182189e-02,
        2.33837977e-01, -5.60760418e-02,  1.36321709e-02,  9.87598382e-02,
       -3.97916297e-02,  2.40204415e-02,  3.01376786e-03, -5.63334818e-02,
       -2.37687289e-02, -4.33795388e-02, -7.96720393e-02, -3.64677788e-03,
        3.17435180e-02, -3.37189468e-02, -2.37466492e-02,  7.47535356e-03,
        5.00539201e-03,  7.64054869e-04,  1.22576842e-03, -6.36342295e-03,
       -4.73190966e-04,  4.18245767e-03,  3.21364884e-03,  1.02145253e-04,
       -1.06614185e-02,  7.63250010e-03, -3.36724690e-03, -4.87892843e-03,
       -5.72070206e-03,  6.66503855e-03, -9.57389476e-03, -1.23677513e-03,
        3.37825240e-03, -2.13857056e-03, -1.67452747e-03,  6.32479087e-03,
       -7.63750339e-03,  5.25425681e-03, -5.07180038e-03, -1.06520751e-03,
       -6.94373179e-03, -6.78989188e-04,  4.50604605e-03, -4.10559373e-03,
        3.69702505e-03,  4.00292628e-03, -9.11197612e-04, -9.67103238e-05,
       -1.24336204e-02,  5.68848655e-04,  3.10858746e-03, -5.00049706e-03,
       -6.46749268e-03, -4.96198826e-03, -3.33212517e-04, -1.86794312e-03,
       -1.03205283e-02,  1.38524425e-02,  2.89482895e-03,  7.81117359e-03,
       -6.46775018e-03, -1.01981039e-03,  1.99175802e-03,  4.08706332e-04,
        8.44971693e-04])
```

In [341…
```
pca.explained_variance_ratio_
```

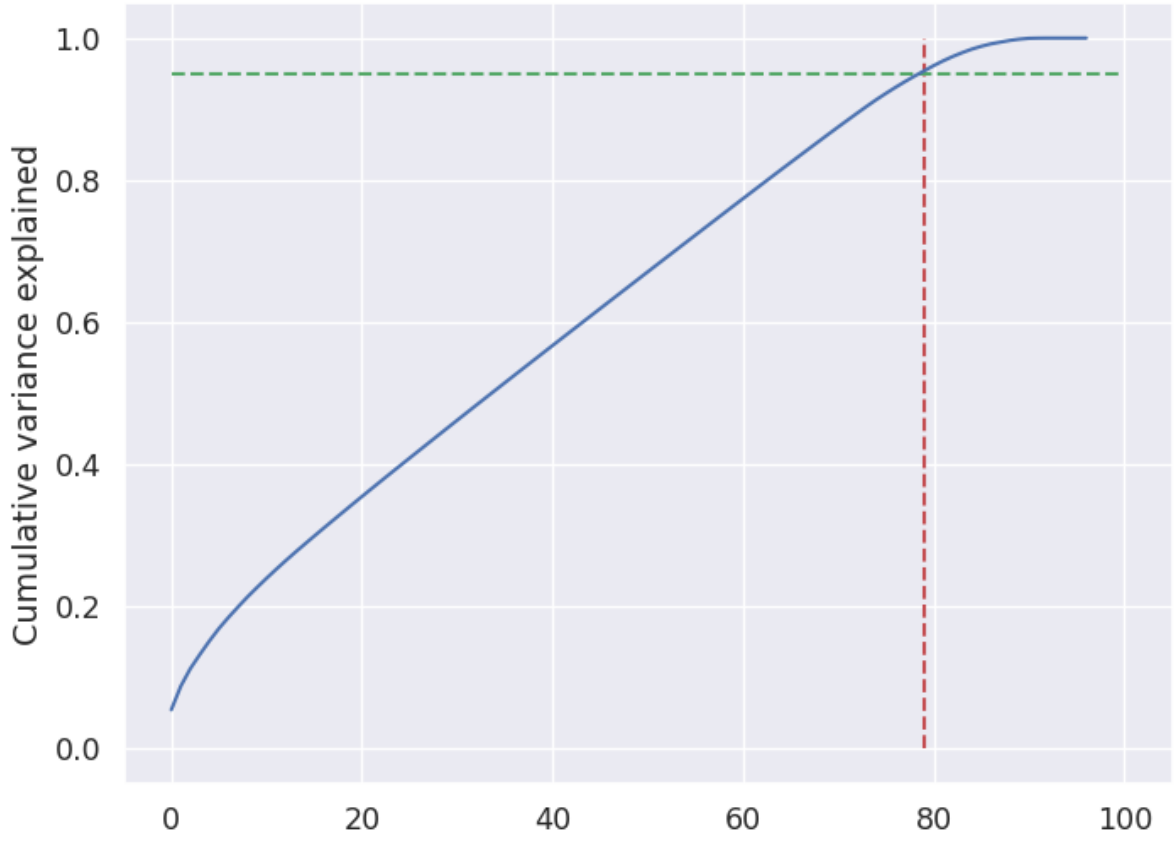
Out[341]:
```
array([5.36600393e-02, 3.33538833e-02, 2.46932832e-02, 1.99650149e-02,
       1.89639579e-02, 1.76088981e-02, 1.55906721e-02, 1.46576546e-02,
       1.42656015e-02, 1.32954042e-02, 1.29603083e-02, 1.25189207e-02,
       1.21724170e-02, 1.17997133e-02, 1.15013606e-02, 1.13861075e-02,
       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-02,
       1.03482132e-02, 1.03388644e-02, 1.03295674e-02, 1.03261227e-02,
       1.03166074e-02, 1.03109621e-02, 1.03041759e-02, 1.02739394e-02,
       1.02638803e-02, 1.02589126e-02, 1.02342300e-02, 1.02031817e-02,
       1.01654416e-02, 1.01006843e-02, 1.00692783e-02, 1.00564559e-02,
       1.00376447e-02, 1.00026466e-02, 9.92638859e-03, 9.79511419e-03,
       9.73167852e-03, 9.62580878e-03, 9.30353684e-03, 8.75380036e-03,
       8.46124635e-03, 8.12309707e-03, 7.71579792e-03, 7.37559815e-03,
       7.34657157e-03, 6.74812327e-03, 6.09740546e-03, 5.44223969e-03,
       4.91044264e-03, 4.05097897e-03, 3.37795579e-03, 2.47588194e-03,
       2.39867183e-03, 1.77979691e-03, 1.17939184e-03, 2.82698123e-04,
       8.30302496e-05, 1.68474721e-32, 9.92170819e-33, 3.26689875e-33,
       1.60728534e-33])
```

Skumulowana suma wariancji

In [342…
```
var_cumu = np.cumsum(pca.explained_variance_ratio_)
var_cumu
```

Out[342]:
```
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 [343…
```
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. Przyjęłem do obliczeń różne wartości komponentów:

- n_components=2 => AUROC LR = 0.500711

- n_components=20 => AUROC LR = 0.522495
- n_components=30 => AUROC LR = 0.531633
- n_components=50 => AUROC LR = 0.542025
- n_components=79 => AUROC LR = 0.586045

Najwyższa wartoś jest dla najwyższej liczby komponentów n=79, a najniższa wartość jest dla najniższej liczny komponentów n=2. Sprawdzam dla różnych n i ostatecznie wybieram na po analizie `n_components=60`.

In [344…
```
pca_final = PCA(n_components=60, random_state=67)
X_pca_final = pca_final.fit_transform(X_scaled)
```

In [345…
```
print(X.shape)
print(X_pca_final.shape)
```

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

In [346…
```
X = X_pca_final
y = data_dummies['loan_status']
```

In [347…
```
X
```

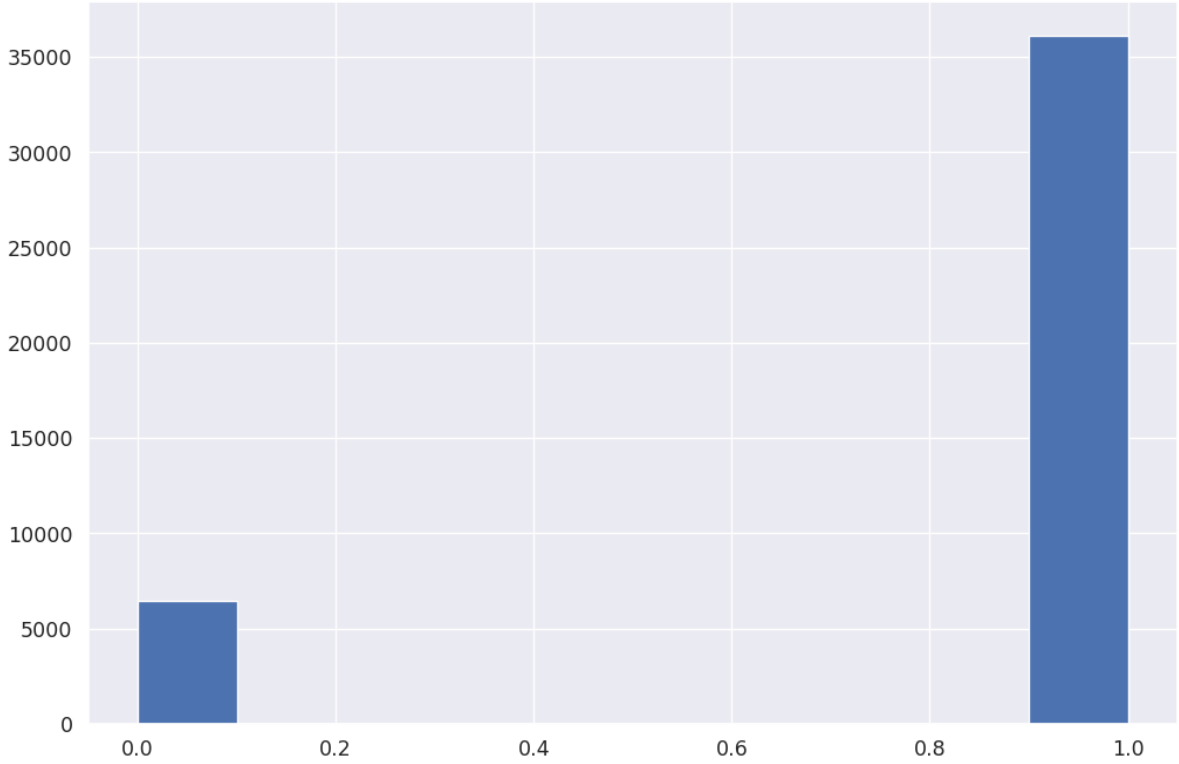
Out[347]:
```
array([[-1.11655169e+00, -5.31510228e-01, -8.03412804e-02, ...,
        -3.38595676e-01,  1.10306479e+00,  3.37215083e-01],
       [-3.13787644e+00, -9.32863225e-01, -1.19380233e+00, ...,
         1.10772959e-01,  4.71776340e-01,  1.21173952e+00],
       [-2.55460322e+00, -9.19670093e-01, -4.98856757e-01, ...,
         4.24293010e-03,  9.11734258e-01, -3.83019902e-01],
       ...,
       [-3.59091585e+00, -2.90853096e-02, -6.89520038e-01, ...,
        -1.17583952e-01, -1.01759569e+00, -1.39844847e-01],
       [-3.60237684e+00,  1.90770322e+00, -1.11990496e+00, ...,
         1.30759504e+01,  2.55313983e+01, -6.84778061e+00],
       [-2.47022223e+00,  2.81377607e+00,  3.96229291e-01, ...,
         2.99656018e-02, -8.69947244e-01, -6.95052633e-01]])
```

In [348…
```
y
```

Out[348]:
```
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
```

In [349…
```
y.hist()
```

Out[349]:
```
<AxesSubplot:>
```



In [350…
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
```

In [351…
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
X_test
```

Out[351]:
```
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 [352…
```
y_test.sample()
```

Out[352]:
```
37424    1
Name: loan_status, dtype: int64
```

Logistic Regression

In [353…
```
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 [354…
```
auroc_log = roc_auc_score(y_test, log_pred)
print('AUROC =', auroc_log)
```

```
AUROC = 0.5420811107098795
```

In [355…
```
X_train
```

Out[355]:
```
array([[ 0.54267509,  0.04836883,  1.72196336, ..., -0.29565733,
         0.07005553,  0.35182011],
       [ 0.57070957, -0.40457212, -1.41525093, ..., -0.18851814,
         0.12186189,  0.71261701],
       [-0.07684331, -1.08951332, -1.18606236, ..., -0.72997119,
        -0.10937829,  0.00560627],
       ...,
       [ 0.91491645, -1.13264268, -0.76790037, ..., -0.02600221,
         1.06980682,  0.52308861],
       [-0.7572509 ,  0.0069002 , -0.807693  , ..., -1.19127997,
         0.72103443, -0.85122503],
       [ 0.19587693, -0.70983357, -1.09921244, ..., -0.19618324,
         0.20209008, -0.0686523 ]])
```

Logistic Regression z regularyzacją

In [356…
```
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 [357…
```
X_train.shape
```

Out[357]:
```
(29774, 60)
```

In [358…
```
auroc_log1 = roc_auc_score(y_test, log1_pred)
print('AUROC =', auroc_log1)
```

```
AUROC = 0.5260857000031975
```

Uwaga

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

In [359…
```
def evaluate(prediction,y_test):
    result = classification_report(y_test,prediction,output_dict=True)
    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 [360…
```
rf = RandomForestClassifier(n_estimators=100, random_state=0)
```

In [361…
```
rf.fit(X_train, y_train)
```

Out[361]:
```
RandomForestClassifier(random_state=0)
```

In [362…
```
rf_prediction = rf.predict(X_test)
```

In [363…
```
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 [364…
```
auroc_rf = roc_auc_score(y_test, rf_prediction)
print(auroc_rf)
```

```
0.5217629949100684
```

K Nearest Neighbors (KNN)

In [365…
```
knn = KNeighborsClassifier(n_neighbors=5)
```

In [366…
```
knn.get_params()
```

Out[366]:
```
{'algorithm': 'auto',
 'leaf_size': 30,
 'metric': 'minkowski',
 'metric_params': None,
 'n_jobs': None,
 'n_neighbors': 5,
 'p': 2,
 'weights': 'uniform'}
```

In [367…
```
knn.fit(X_train,y_train)
```

Out[367]:
```
KNeighborsClassifier()
```

In [368…
```
knn_prediction = knn.predict(X_test)
```

In [369…
```
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 [370…
```
auroc_knn = roc_auc_score(y_test, knn_prediction)
print('AUROC =', auroc_knn)
```

```
AUROC = 0.5209938695960677
```

Bagging Classifier

In [371…
```
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       0.38      0.17      0.24      1978
           1       0.86      0.95      0.90     10783

    accuracy                           0.83     12761
   macro avg       0.62      0.56      0.57     12761
weighted avg       0.79      0.83      0.80     12761

[[  343  1635]
 [  561 10222]]
```

In [372…
```
auroc_xgbc = roc_auc_score(y_test, xgbc_prediction)
print('AUROC =', auroc_xgbc)
```

```
AUROC = 0.5606905722757435
```

ADA Boost Classifier

In [373…
```
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 [374…
```
auroc_ada = roc_auc_score(y_test, ada_prediction)
print('AUROC =', auroc_ada)
```

```
AUROC = 0.5495312810759775
```

XGB Classifier

In [375…
```
xgb_clas=xgb.XGBClassifier(random_state=1,learning_rate=0.1)
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      0.06      0.10      1978
           1       0.85      0.99      0.92     10783

    accuracy                           0.85     12761
   macro avg       0.74      0.53      0.51     12761
weighted avg       0.82      0.85      0.79     12761

[[  112  1866]
 [   67 10716]]
```

In [376…
```
auroc_xgb_clas = roc_auc_score(y_test, xgb_clas_prediction)
print('AUROC =', auroc_xgb_clas)
```

```
AUROC = 0.5252046835884707
```

Support Vector Machine (SVM)

In [377…
```
supvm = SVC(C=1.0, kernel='linear', random_state = 12)
```

In [378…
```
supvm.fit(X_train,y_train)
```

Out[378]:
```
SVC(kernel='linear', random_state=12)
```

In [379…
```
svm_prediction = supvm.predict(X_test)
```

In [380…
```
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))
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
              precision    recall  f1-score   support

           0       0.00      0.00      0.00      1978
           1       0.84      1.00      0.92     10783

    accuracy                           0.84     12761
   macro avg       0.42      0.50      0.46     12761
weighted avg       0.71      0.84      0.77     12761

[[    0  1978]
 [    0 10783]]
Training accuracy: 0.8504399811916438
Test accuracy: 0.8449964736305932
```

In [381…
```
auroc_svm = roc_auc_score(y_test, svm_prediction)
print('AUROC =', auroc_svm)
```

```
AUROC = 0.5
```

Decision Tree

In [382…
```
dtree = DecisionTreeClassifier(max_depth = 2, random_state = 0)
```

In [383…
```
dtree.fit(X_train,y_train)
```

Out[383]:
```
DecisionTreeClassifier(max_depth=2, random_state=0)
```

In [384…
```
def evaluate(prediction,y_test):
    result = classification_report(y_test,prediction,output_dict=True)
    f1 = result['1']['f1-score']
    accuracy = result['accuracy']
    performance_data= {'f1-score':round(f1, 2),
                       'accuracy':round(accuracy, 2)}
    return performance_data
```

In [385…
```
dt_prediction = dtree.predict(X_test)
```

In [386…
```
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))
# metrics.f1_score(y_test, dt_pred, average='weighted', labels=np.unique(dt

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

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00      1978
           1       0.84      1.00      0.92     10783

    accuracy                           0.84     12761
   macro avg       0.42      0.50      0.46     12761
weighted avg       0.71      0.84      0.77     12761

[[    0  1978]
 [    0 10783]]
Training accuracy: 0.8504399811916438
Test accuracy: 0.8449964736305932
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [387…

```
auroc_dtree = roc_auc_score(y_test, dt_prediction)
print('AUROC =', auroc_dtree)
# metrics.f1_score(y_test, dt_prediction, average='weighted', labels=np.uni
```

```
AUROC = 0.5
```

Gradient Boosting Classifier

In [388…

```
gbc = GradientBoostingClassifier(learning_rate=0.01, random_state=0)
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))
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00      1978
           1       0.84      1.00      0.92     10783

    accuracy                           0.84     12761
   macro avg       0.42      0.50      0.46     12761
weighted avg       0.71      0.84      0.77     12761

[[    0  1978]
 [    0 10783]]
```

```
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/marek/anaconda3/lib/python3.7/site-packages/sklearn/metrics/_classifi
cation.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples. Use `zero_divi
sion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [389…

```
auroc_gbc = roc_auc_score(y_test, gbc_predpca)
print('AUROC =', auroc_gbc)
```

```
AUROC = 0.5
```

Analiza

Po wykonaniu PCA i skalowaniu danych wyniki AUROC dla modeli były niższe niż przed wykonaniem PCA.

Sprawdzam 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 LR = 0.500252
- n_components=30 => AUROC LR = 0.519425
- n_components=60 => AUROC LR = 0.526085
- n_components=79 => AUROC LR = 0.566283

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

- AUROC XGBC = 0.675628

4. d) Finalny model

Gradient Boosting Classifier

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

In [390…

```
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, test_size=0
```

Dopasowanie parametrów modelu -> Hyperparameter tuning / GradientBoostingClassifier with GridSearchCV

- Po głębszej analizie zostawiam parametr learning_rate = default, czyli 0.1.

In [391…
```
## Grid Search
grid_search = GridSearchCV(GradientBoostingClassifier(
    random_state=0,
),
                           {
                               "max_depth":[3,5,8],
                               "subsample":[0.5, 0.618, 0.8, 0.85, 0.9, 0.9

                           },cv=5, scoring="r2",verbose=1,n_jobs=-1
                           )
grid_search.fit(X1_train,y1_train)
```

Out[391]:
```
Fitting 5 folds for each of 21 candidates, totalling 105 fits
 GridSearchCV(cv=5, estimator=GradientBoostingClassifier(random_state=0),
              n_jobs=-1,
              param_grid={'max_depth': [3, 5, 8],
                          'subsample': [0.5, 0.618, 0.8, 0.85, 0.9, 0.95,
 1.0]},
              scoring='r2', verbose=1)
```

In [392…
```
# Najlepszy wynik osiagniety podczas grid search
print('GridSearch CV best score : {:.4f}\n\n'.format(grid_search.best_score_
# Parametry, które miał model z najlepszym wynikiem
print('Parameters that give the best results :','\n\n', (grid_search.best_p
# Model, który został wytypowany przez grid search
print('\n\nEstimator that was chosen by the search :','\n\n', (grid_search.
```

```
GridSearch CV best score : -0.0246


Parameters that give the best results :

 {'max_depth': 3, 'subsample': 0.5}


Estimator that was chosen by the search :

 GradientBoostingClassifier(random_state=0, subsample=0.5)
```

Wnioski:

Model, który został wytypowany przez grid search. Posiada następujące parametry: `random_state=0`, `subsample=0.5`.

In [393…
```
gbc= GradientBoostingClassifier(
    random_state=0,
    subsample=0.5
)
```

K-krotna walidacja krzyżowa – k-fold cross-validation

In [394…
```
num_folds = 18
seed = 77
kfold = KFold(n_splits=num_folds, shuffle=True, 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())
```

```
Average accuracy:  0.8692841188381036
Standard Deviation:  0.004308523650902766
```

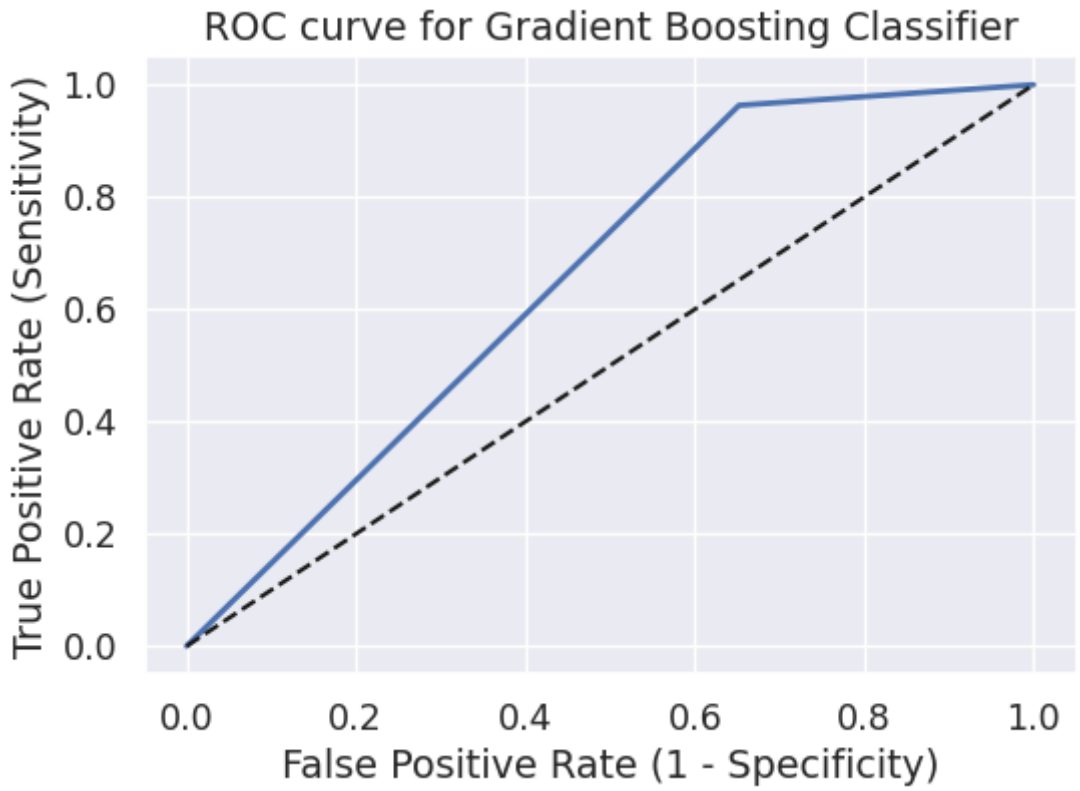
Wygenerowanie krzywej ROC, obliczenie AUROC score i być może innych, dodatkowych metryk

In [395…
```
gbc.fit(X1_train, y1_train)
gbc_prediction = gbc.predict(X1_test)

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

```
              precision    recall  f1-score   support

           0       0.63      0.35      0.45      1978
           1       0.89      0.96      0.92     10783

    accuracy                           0.87     12761
   macro avg       0.76      0.66      0.69     12761
weighted avg       0.85      0.87      0.85     12761

[[  688  1290]
 [  396 10387]]
```

Generowanie krzywej ROC

In [396…
```
fpr, tpr, thresholds = roc_curve(y1_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 Gradient Boosting Classifier')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.show()
```



In [397…
```
auroc_gbc = roc_auc_score(y1_test, gbc_prediction)
print('AUROC =', auroc_gbc)
```

```
AUROC = 0.6555508066239532
```

Sprawdzenie bias-variance tradeoff - czyli czy model jest zbyt słabo a może nadmiernie dopasowany?

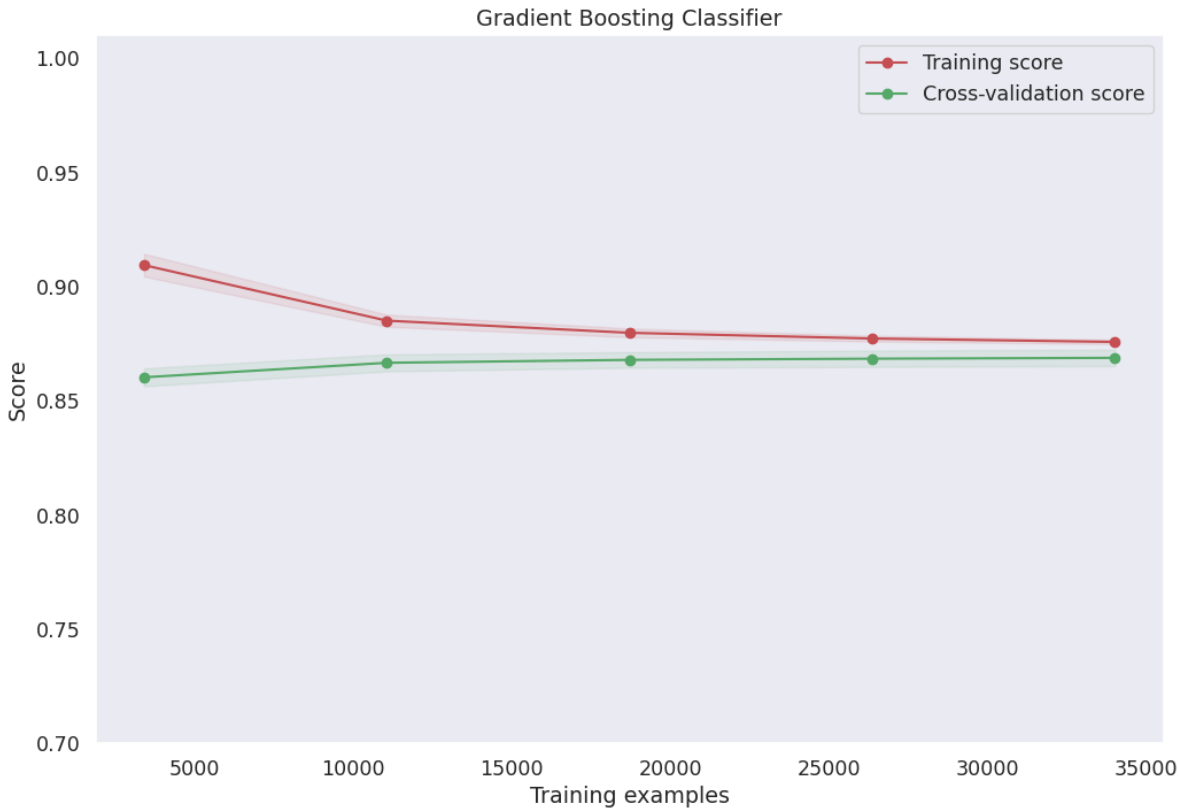
- Pomocny może być kod z zajęć do generowania "learning_curves"

In [398…
```
## źródło: http://scikit-learn.org/stable/auto_examples/model_selection/plo
def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=1, train_sizes=np.linspace(.1, 1.0, 5)):

    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_sizes)
    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_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="
    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 [399…
```
# Shuffle for learning curves
cv = ShuffleSplit(n_splits=100, test_size=0.2, random_state=0)
```

In [400…
```
gbc= GradientBoostingClassifier(random_state=0, subsample=0.5)
plt.figure(figsize=(20,14))
plot_learning_curve(gbc, 'Gradient Boosting Classifier', X1, y1, (0.7, 1.01
plt.show()
```

```
<Figure size 2000x1400 with 0 Axes>
```



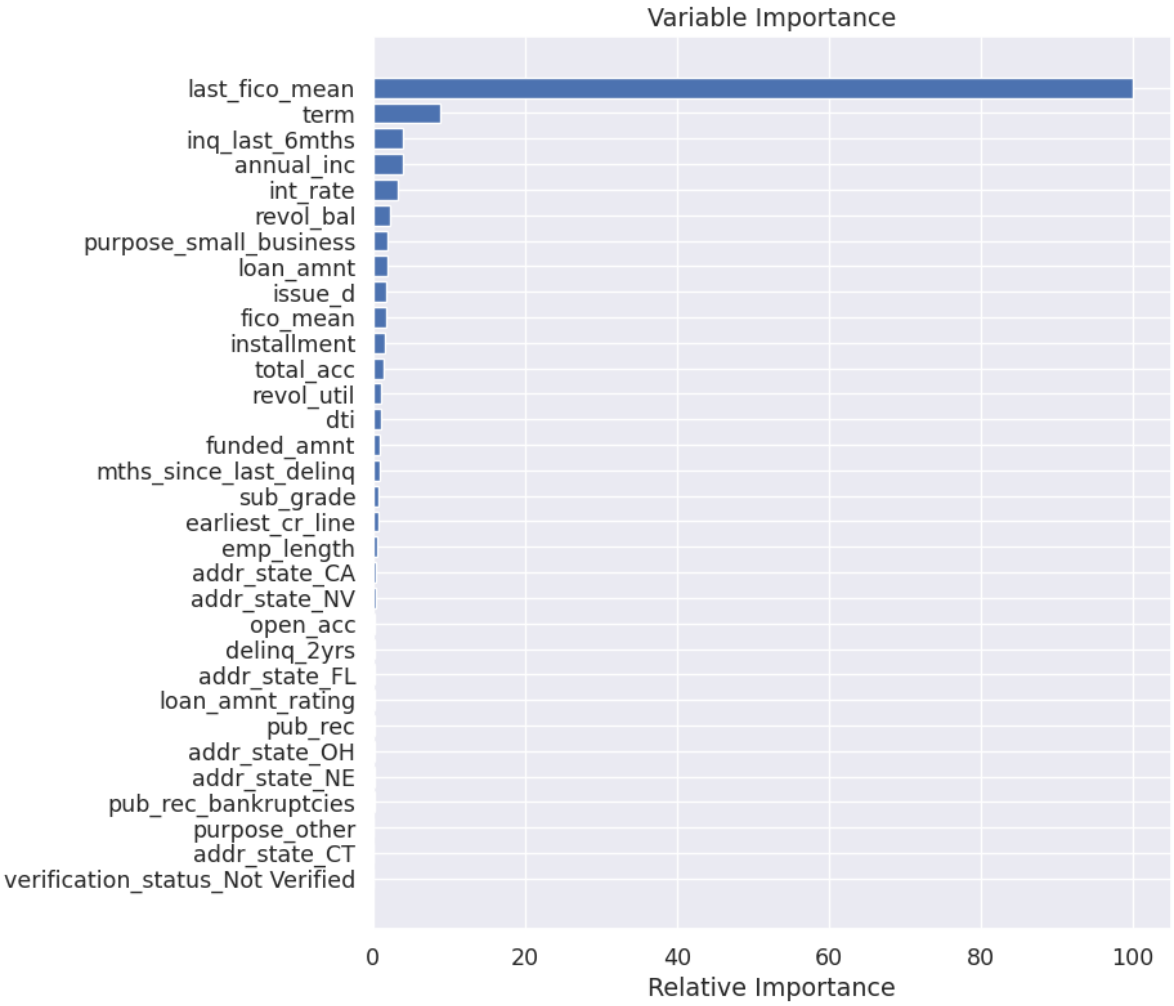
Krzywa `Training score` i krzywa `Cross-validation score`, nie są rozbieżne od siebie. To znaczy że mój model jest w dobrej kondycji. Taki błąd jest akceptowalny.

Feature Importance -> property feature*importances*

Sprawdzenie istotnych cech - to znaczy na podstawie jakich cech model podejmuje decyzję i czy waszym zdaniem ma to sens?

In [401…

```
gbc= GradientBoostingClassifier(random_state=0, subsample=0.5)
gbc.fit(X1_train, y1_train)
# Plot feature importance https://scikit-learn.org/stable/modules/generated
feature_importance = gbc.feature_importances_
# make importances relative to max importance
feature_importance = 100.0 * (feature_importance / feature_importance.max()
sorted_idx = np.argsort(feature_importance)
sorted_idx_last_12 = sorted_idx[65:97]
pos = np.arange(sorted_idx_last_12.shape[0]) + .5
# plt.subplot(1, 2, 2)
plt.figure(figsize=(8, 9))
plt.barh(pos, feature_importance[sorted_idx_last_12], align='center')
plt.yticks(pos, X1_train.keys()[sorted_idx_last_12])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```



In [402…

```
# summarize feature importance
for i, v in enumerate(feature_importance):
    print(X1_train.keys()[i] + ': %0d, Score: %.5f' % (i,v))
```

```
loan_amnt: 0, Score: 1.99685
funded_amnt: 1, Score: 0.99951
term: 2, Score: 8.82353
int_rate: 3, Score: 3.20814
installment: 4, Score: 1.67137
sub_grade: 5, Score: 0.78682
emp_length: 6, Score: 0.51963
annual_inc: 7, Score: 3.95359
issue_d: 8, Score: 1.75050
dti: 9, Score: 1.01448
delinq_2yrs: 10, Score: 0.27403
earliest_cr_line: 11, Score: 0.69020
inq_last_6mths: 12, Score: 3.97414
mths_since_last_delinq: 13, Score: 0.94349
open_acc: 14, Score: 0.29565
pub_rec: 15, Score: 0.18546
revol_bal: 16, Score: 2.20917
revol_util: 17, Score: 1.07551
total_acc: 18, Score: 1.37782
pub_rec_bankruptcies: 19, Score: 0.16017
fico_mean: 20, Score: 1.70320
last_fico_mean: 21, Score: 100.00000
fico_rating: 22, Score: 0.05366
loan_amnt_rating: 23, Score: 0.19744
interest_rating: 24, Score: 0.00000
home_ownership_MORTGAGE: 25, Score: 0.08826
home_ownership_NONE: 26, Score: 0.00000
home_ownership_OTHER: 27, Score: 0.05902
home_ownership_OWN: 28, Score: 0.00000
home_ownership_RENT: 29, Score: 0.00001
verification_status_Not Verified: 30, Score: 0.12426
verification_status_Source Verified: 31, Score: 0.00000
verification_status_Verified: 32, Score: 0.03269
purpose_car: 33, Score: 0.04870
purpose_credit_card: 34, Score: 0.09080
purpose_debt_consolidation: 35, Score: 0.12285
purpose_educational: 36, Score: 0.12105
purpose_home_improvement: 37, Score: 0.00000
purpose_house: 38, Score: 0.00000
purpose_major_purchase: 39, Score: 0.06009
purpose_medical: 40, Score: 0.03376
purpose_moving: 41, Score: 0.00000
purpose_other: 42, Score: 0.14724
purpose_renewable_energy: 43, Score: 0.06039
purpose_small_business: 44, Score: 2.00762
purpose_vacation: 45, Score: 0.00000
purpose_wedding: 46, Score: 0.00000
addr_state_AK: 47, Score: 0.00000
addr_state_AL: 48, Score: 0.00000
addr_state_AR: 49, Score: 0.00000
addr_state_AZ: 50, Score: 0.00000
addr_state_CA: 51, Score: 0.44539
addr_state_CO: 52, Score: 0.00000
addr_state_CT: 53, Score: 0.12834
addr_state_DC: 54, Score: 0.01867
addr_state_DE: 55, Score: 0.00000
addr_state_FL: 56, Score: 0.22465
addr_state_GA: 57, Score: 0.00000
addr_state_HI: 58, Score: 0.00000
addr_state_IA: 59, Score: 0.00000
addr_state_ID: 60, Score: 0.00000
addr_state_IL: 61, Score: 0.00000
addr_state_IN: 62, Score: 0.04481
addr_state_KS: 63, Score: 0.03279
```

```
addr_state_KY: 64, Score: 0.00000
addr_state_LA: 65, Score: 0.03903
addr_state_MA: 66, Score: 0.00000
addr_state_MD: 67, Score: 0.03774
addr_state_ME: 68, Score: 0.00000
addr_state_MI: 69, Score: 0.00000
addr_state_MN: 70, Score: 0.00000
addr_state_MO: 71, Score: 0.02759
addr_state_MS: 72, Score: 0.00000
addr_state_MT: 73, Score: 0.00000
addr_state_NC: 74, Score: 0.00000
addr_state_NE: 75, Score: 0.16801
addr_state_NH: 76, Score: 0.00000
addr_state_NJ: 77, Score: 0.00011
addr_state_NM: 78, Score: 0.00000
addr_state_NV: 79, Score: 0.32798
addr_state_NY: 80, Score: 0.09282
addr_state_OH: 81, Score: 0.18263
addr_state_OK: 82, Score: 0.00000
addr_state_OR: 83, Score: 0.11244
addr_state_PA: 84, Score: 0.07738
addr_state_RI: 85, Score: 0.00000
addr_state_SC: 86, Score: 0.00000
addr_state_SD: 87, Score: 0.00000
addr_state_TN: 88, Score: 0.00000
addr_state_TX: 89, Score: 0.00000
addr_state_UT: 90, Score: 0.00000
addr_state_VA: 91, Score: 0.00000
addr_state_VT: 92, Score: 0.00000
addr_state_WA: 93, Score: 0.00000
addr_state_WI: 94, Score: 0.08650
addr_state_WV: 95, Score: 0.02585
addr_state_WY: 96, Score: 0.00000
```

Wnioski:

Wyniki sugerują, że być może 21 cech z 97 cech jest ważna dla przewidywania. Z czego 5 pierwszych cech ma największe znaczenie. Można zauważyć że jedna cecha z tych 97 cech, wyróżnia się najbardziej tj.: średni zakres graniczny `last_fico_mean`, do którego należy ostatni wyciągnięty FICO kredytobiorcy. Inne cechy, takie, jak: liczba spłat pożyczki `term` (wartości są w miesiącach i mogą wynosić 36 lub 60), czy liczba zapytań `inq_last_6mths` w ciągu ostatnich 6 miesięcy (w tym zapytania dotyczące samochodów i kredytów hipotecznych). Mają conajmniej dziesięciokrotnie mniejszy wpływ przy podejmowaniu decyzji przez model. Co moim zdaniem znacznie upraszcza nam analizę i nie ma sensu. Ponieważ z 97 cech ograniczamy nasz wybór do jednej, dwóch bądź pięciu najstotniejszych cech. Co może powodować błędy w przewidywaniu, czy udzielić pożyczki, czy nie, kredytobiorcy.

SMOTE for Balancing Data

In [403…

```
df_result = pd.DataFrame(columns=['model', 'tp', 'tn', 'fp', 'fn', 'correct
                                  'accuracy', 'precision', 'recall', 'f1',

tn, fp, fn, tp = confusion_matrix(y1_test, gbc_prediction).ravel()
accuracy = accuracy_score(y1_test, gbc_prediction)
precision = precision_score(y1_test, gbc_prediction)
recall = recall_score(y1_test, gbc_prediction)
f1 = f1_score(y1_test, gbc_prediction)
roc_auc = roc_auc_score(y1_test, gbc_prediction)
```

```
avg_precision = average_precision_score(y1_test, gbc_prediction)

row = {'model': 'GradientBoostingClassifier without SMOTE',
        'tp': tp,
        'tn': tn,
        'fp': fp,
        'fn': fn,
        'correct': tp+tn,
        'incorrect': fp+fn,
        'accuracy': round(accuracy,3),
        'precision': round(precision,3),
        'recall': round(recall,3),
        'f1': round(f1,3),
        'roc_auc': round(roc_auc,3),
        'avg_pre': round(avg_precision,3),
    }

df_result = df_result.append(row, ignore_index=True)
df_result.head()
```

Out[403]:

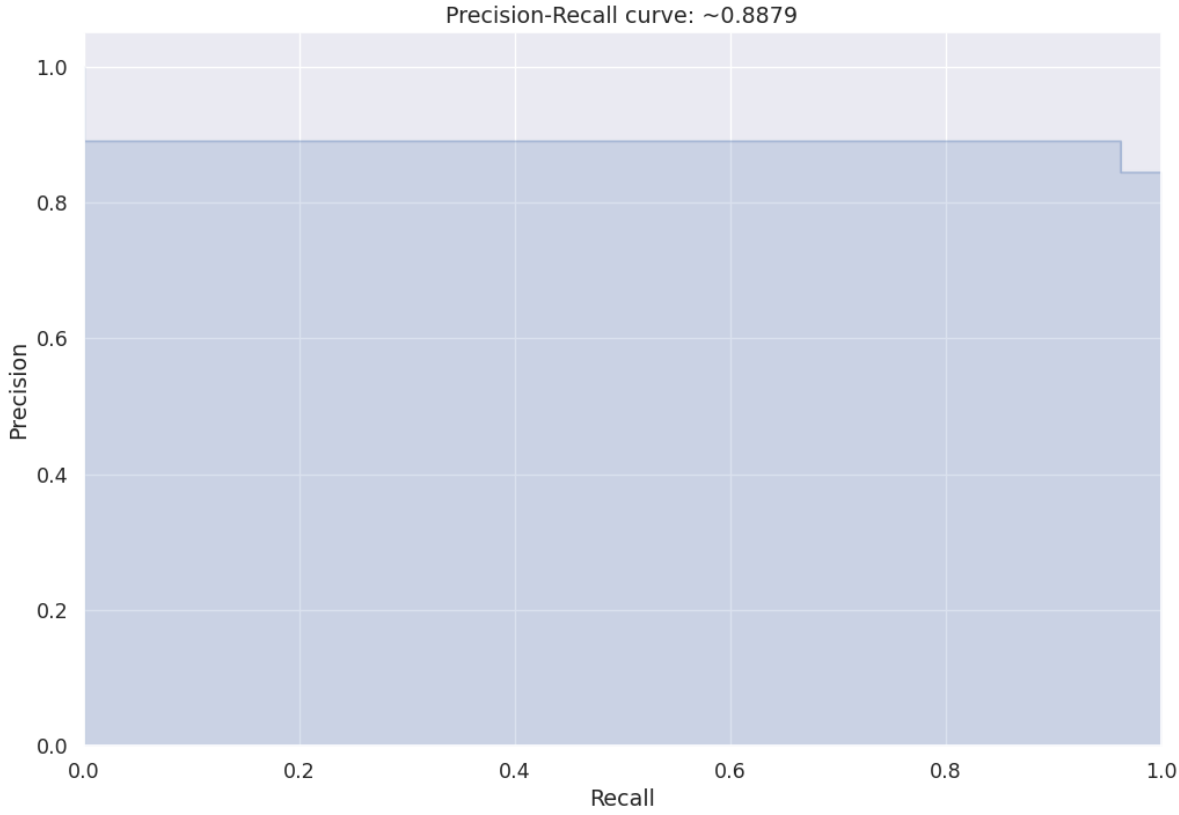
	model	tp	tn	fp	fn	correct	incorrect	accuracy	precision	re
0	GradientBoostingClassifier without SMOTE	10387	688	1290	396	11075	1686	0.868	0.89	0

In [404…

```
avg_precision = average_precision_score(y1_test, gbc_prediction)
precision, recall, _ = precision_recall_curve(y1_test, gbc_prediction)

plt.step(recall, precision, color='b', alpha=0.2, where='post')
plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')

plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Precision-Recall curve: ~{0:0.4f}'.format(avg_precision))
```

Out[404]:

```
Text(0.5, 1.0, 'Precision-Recall curve: ~0.8879')
```



Fit a model using SMOTE

In [405…
```
X1_train, X1_test, y1_train, y1_test = train_test_split(X1, y1, test_size=0
                                                        stratify=y1)
```

In [406…
```
oversampled = SMOTE(random_state=0)
X1_train_smote, y1_train_smote = oversampled.fit_resample(X1_train, y1_trai
```

In [407…
```
y1_train_smote.value_counts()
```

Out[407]:
```
1    25272
0    25272
Name: loan_status, dtype: int64
```

In [408…
```
classifier = GradientBoostingClassifier(random_state=0, subsample=0.5)
model = classifier.fit(X1_train_smote, y1_train_smote)
```

In [409…
```
y1_pred_smote = model.predict(X1_test)
```

In [410…
```
y1_pred_smote.mean()
```

Out[410]:
```
0.848366115508189
```

In [411…
```
y1_test.mean()
```

Out[411]:
```
0.8488362980957606
```

In [412…
```
tn, fp, fn, tp = confusion_matrix(y1_test, y1_pred_smote).ravel()
accuracy = accuracy_score(y1_test, y1_pred_smote)
precision = precision_score(y1_test, y1_pred_smote)
recall = recall_score(y1_test, y1_pred_smote)
f1 = f1_score(y1_test, y1_pred_smote)
roc_auc = roc_auc_score(y1_test, y1_pred_smote)
avg_precision = average_precision_score(y1_test, y1_pred_smote)
```

```
row = {'model': 'GradientBoostingClassifier with SMOTE',
        'tp': tp,
        'tn': tn,
        'fp': fp,
        'fn': fn,
        'correct': tp+tn,
        'incorrect': fp+fn,
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1': f1,
        'roc_auc': roc_auc,
        'avg_pre': round(avg_precision,3),
    }
```

In [413…

```
df_result = df_result.append(row, ignore_index=True)
df_result.head()
```

Out[413]:

	model	tp	tn	fp	fn	correct	incorrect	accuracy	precision
0	GradientBoostingClassifier without SMOTE	10387	688	1290	396	11075	1686	0.868000	0.890000
1	GradientBoostingClassifier with SMOTE	9828	931	998	1004	10759	2002	0.843116	0.907815

In [414…

```
counter = Counter(y1_train_smote)
print(counter)
```

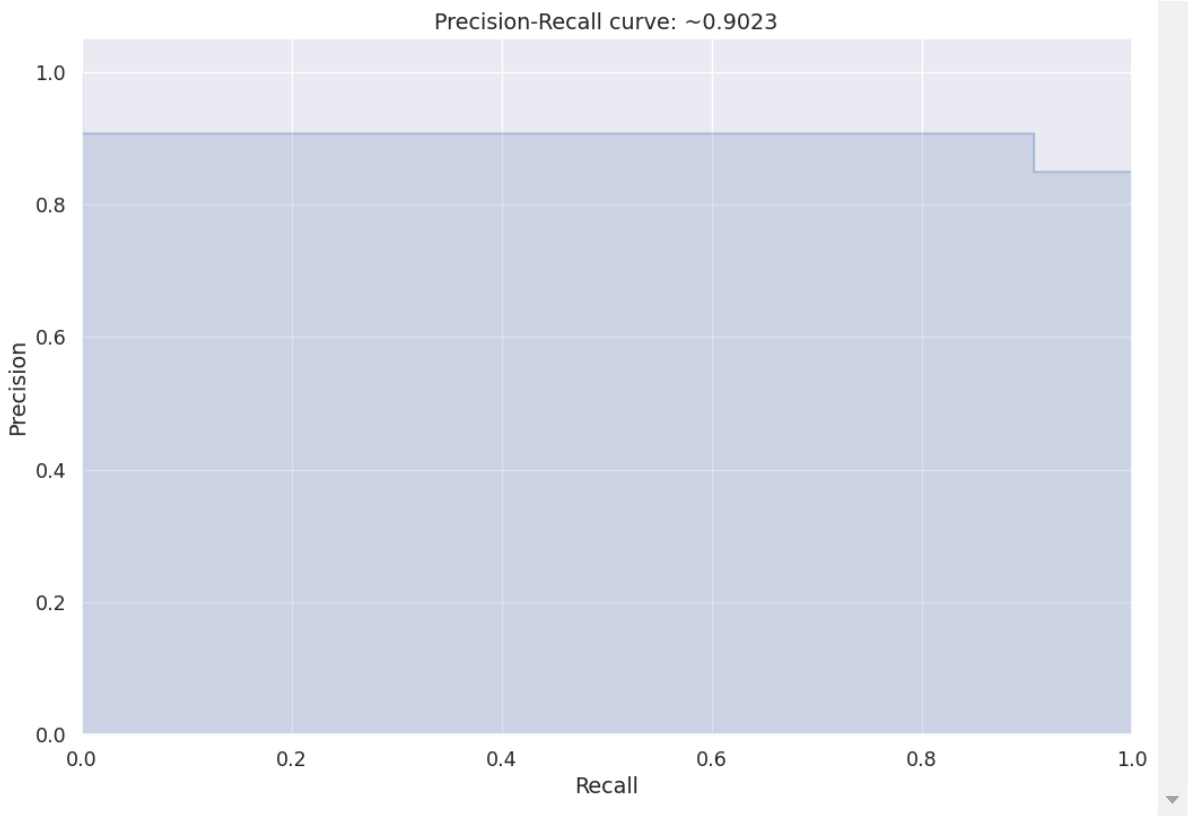
```
Counter({1: 25272, 0: 25272})
```

In [415…

```
avg_precision = average_precision_score(y1_test, y1_pred_smote)
precision, recall, _ = precision_recall_curve(y1_test, y1_pred_smote)

plt.step(recall, precision, color='b', alpha=0.2, where='post')
plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')

plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Precision-Recall curve: ~{0:0.4f}'.format(avg_precision))
```

Out[415]:

```
Text(0.5, 1.0, 'Precision-Recall curve: ~0.9023')
```



In [421…
```
learning_rate = np.arange(.001, .1, .01)
# [0.001, 0.01, 0.02, 0.03]

for c in learning_rate:
    classifier = GradientBoostingClassifier(learning_rate=c, random_state=0
    model = classifier.fit(X1_train_smote, y1_train_smote)
    y1_pred_smote = model.predict(X1_test)
    roc_auc = roc_auc_score(y1_test, y1_pred_smote)
    print('dla c = {0:0.3f};'.format(c), 'roc_auc = {0:0.0f}%'.format(roc_a
```

```
dla c = 0.001; roc_auc = 79%
dla c = 0.011; roc_auc = 78%
dla c = 0.021; roc_auc = 77%
dla c = 0.031; roc_auc = 76%
dla c = 0.041; roc_auc = 74%
dla c = 0.051; roc_auc = 73%
dla c = 0.061; roc_auc = 73%
dla c = 0.071; roc_auc = 71%
dla c = 0.081; roc_auc = 71%
dla c = 0.091; roc_auc = 70%
```

Zapisywanie modelu na dysku

In [422…
```
# save the model to disk
gbc_final_model = 'finalized_model.sav'
pickle.dump(gbc, open(gbc_final_model, 'wb'))
```

Podsumowanie

Przed SMOTE, AUROC wynosił ok.: 66%. Natomiast po SMOTE, AUROC wynosi ok. 70%. Co spowodowało niewielki jego wzrost i jest na dobrym poziomie dlatego, że taki mam model i tak są ustawione parametry. Inne metryki są zdecydowanie na wyższym poziomie od ok. 84% do ok. 91%. Powyższa wartość AUROC i innych parametrów są dla

domyślnego `learning_rate`. Na podstawie tych danych osiągam AUROC score na poziomie ok. 70%.

Następnie na tym modelu po wykonaniu SMOTE, liczę wartość AUROC dla zmiennego `learning_rate` od 0.001 do 0.1, co krok równy = 0.01. Zauważam, że dla PARAMETRU `learning_rate` = 0.001 powoduje to wzrost AUROC do 79%, co daje przewidywalność modelu prawie na poziomie ok. 80%. Im wyższy parametr `learning_rate`, tym niższy AUROC.

UWAGA!!!

Do finalnej analizy wybrałem model `Gradient Boosting Classifier`. Był to model o najniższym AUROC = 0.526600. Prawdopodobnie, gdybym wybrał model `Bagging Classifier`, którego AUROC = 0.674916. Bez problemu osiągnął bym AUROC >= 80%. Należało by to przeanalizować. Niestety z braku czasu, nie mam takiej możliwości.

FINALNY MODEL TO: `Gradient Boosting Classifier`, KTÓREGO AUROC = ~80%.

No. | Method | AUROC

- 6 | Bagging Classifier | 0.674916
- 9 | XGB Classifier | 0.648401
- 7 | ADA Boost Classifier | 0.639060
- 2 | Decision Tree | 0.636387
- 0 | Logistic Regression | 0.602105
- 1 | Logistic Regression parameters | 0.602105
- 5 | KNN | 0.591371
- 3 | Random Forest | 0.590393
- 4 | Support Vector Machine (SVM) | 0.535172
- 8 | Gradient Boosting Classifier | 0.526600

Kraków dnia: 27.10.2022