data_exploration

August 9, 2025

[1]:
```python
#imports
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime
import numpy as np
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder, FunctionTransformer,␣
↪RobustScaler
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer, make_column_selector
from sklearn.dummy import DummyRegressor
from sklearn.model_selection import train_test_split
import os
```

[ ]:
```python
path = '../data/raw/archive'
#after this we'll load a portion of the data 50% should be enough

data = (pd.read_csv(os.path.join(path, 'accepted_2007_to_2018Q4.csv'))
        .sample(frac=1, random_state=1)
        .drop(labels=['id','desc','title'], axis=1)
        )
#we save it as a parquet file for faster future sessions loading
os.makedirs('../data/raw', exist_ok=True)
data.to_parquet('../data/raw/data_chunck.parquet')
```

First step : some data exploration

[58]:
```python
data = pd.read_parquet('../data/raw/data_chunck.parquet').sample(frac=0.1,␣
↪random_state=0)
data.describe()
```

[58]:
```
       member_id      loan_amnt    funded_amnt  funded_amnt_inv  \
count        0.0  226068.000000  226068.000000    226068.000000
mean         NaN   15104.096334   15098.682476     15079.811532
std          NaN    9231.578787    9229.514882      9233.551621
min          NaN     500.000000     500.000000         0.000000
25%          NaN    8000.000000    8000.000000      8000.000000
50%          NaN   13000.000000   13000.000000     13000.000000
```

```
75%          NaN   20000.000000   20000.000000     20000.000000
max          NaN   40000.000000   40000.000000     40000.000000

            int_rate    installment    annual_inc            dti  \
count  226068.000000  226068.000000  2.260660e+05  225869.000000
mean       13.105345     447.434478  7.791767e+04      18.853259
std         4.839268     268.687634  7.156721e+04      14.141657
min         5.310000      15.910000  0.000000e+00       0.000000
25%         9.490000     251.610000  4.600000e+04      11.920000
50%        12.620000     378.965000  6.500000e+04      17.880000
75%        15.990000     596.125000  9.300000e+04      24.530000
max        30.990000    1717.630000  8.500000e+06     999.000000

         delinq_2yrs  fico_range_low  …  deferral_term  hardship_amount  \
count  226064.000000   226068.000000  …         1124.0      1124.000000
mean        0.305829      698.531924  …            3.0       155.094048
std         0.864322       32.887299  …            0.0       125.758586
min         0.000000      630.000000  …            3.0         3.760000
25%         0.000000      675.000000  …            3.0        58.500000
50%         0.000000      690.000000  …            3.0       125.440000
75%         0.000000      715.000000  …            3.0       215.890000
max        30.000000      845.000000  …            3.0       893.630000

       hardship_length  hardship_dpd  \
count           1124.0   1124.000000
mean               3.0     13.675267
std                0.0      9.617274
min                3.0      0.000000
25%                3.0      5.000000
50%                3.0     15.000000
75%                3.0     22.000000
max                3.0     37.000000

       orig_projected_additional_accrued_interest  \
count                                  902.000000
mean                                   447.967749
std                                    362.026073
min                                     11.280000
25%                                    167.602500
50%                                    362.640000
75%                                    633.855000
max                                   2680.890000

       hardship_payoff_balance_amount  hardship_last_payment_amount  \
count                     1124.000000                   1124.000000
mean                     11707.864484                    197.183932
std                       7442.094210                    199.038661
```

```
min                         414.300000                         0.010000
25%                        5573.837500                        42.800000
50%                       10484.515000                       134.820000
75%                       16670.330000                       295.320000
max                       36382.690000                      1187.560000

       settlement_amount  settlement_percentage  settlement_term
count        3457.000000            3457.000000      3457.000000
mean         5000.848635              47.832337        13.229100
std          3725.823810               6.944765         8.088854
min           133.000000               0.200000         0.000000
25%          2183.510000              45.000000         6.000000
50%          4071.000000              45.000000        14.000000
75%          6859.190000              50.000000        18.000000
max         25000.000000              98.570000        28.000000

[8 rows x 113 columns]
```

[5]:
```
print(data['loan_status'].unique())
```

```
['Current' 'Fully Paid' 'Charged Off' 'In Grace Period'
 'Late (31-120 days)'
 'Does not meet the credit policy. Status:Charged Off' 'Late (16-30 days)'
 'Does not meet the credit policy. Status:Fully Paid' 'Default' None]
```

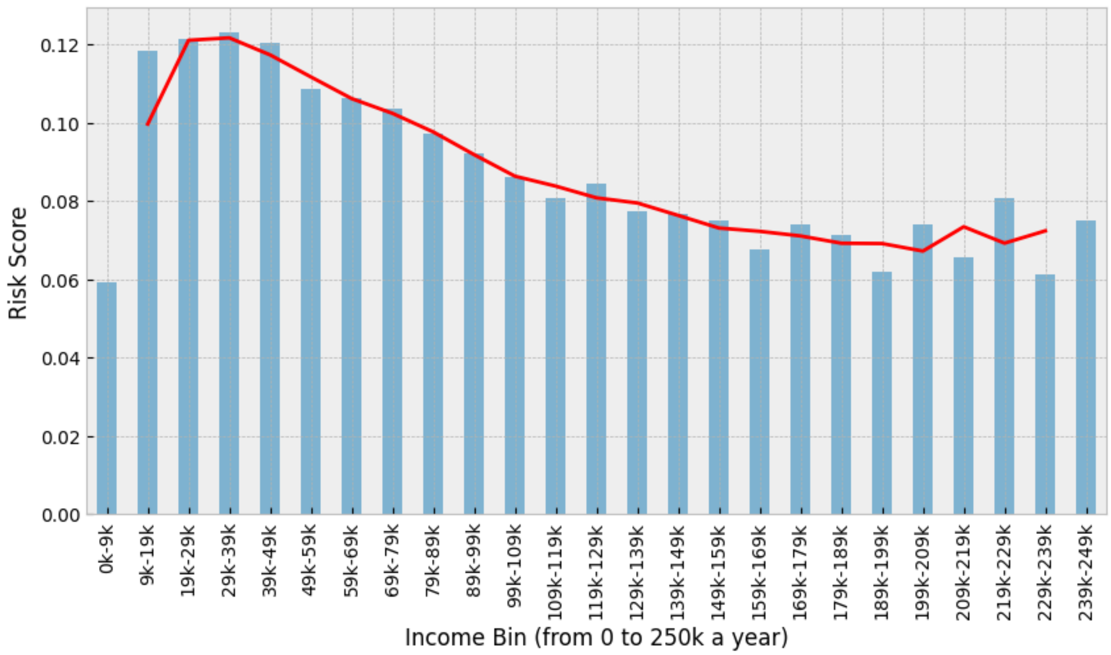
As the loan status is not binary and some situations are worse than other, instead of classifying good vs bad, we will do a mapping of the risk score in the interval $[0, 1]$, 0 being fully paid and 1 being default.

[59]:
```
def data_mapping(data):
    mapping = {
        'Fully Paid': 0,
        'Current': 0,
        'In Grace Period': 0.2,
        'Late (16-30 days)': 0.4,
        'Late (31-120 days)': 0.6,
        'Does not meet the credit policy. Status:Fully Paid': 0,
        'Does not meet the credit policy. Status:Charged Off': 0.8,
        'Charged Off': 0.8,
        'Default': 1
    }

    data['risk_score']= data['loan_status'].map(mapping)
    data = (data.dropna(subset=['risk_score'])
            .drop(labels='loan_status', axis=1)
            )
    return data
```

Now what we wanna look for is maybe a correlation in the data, let's check with annual income, we don't forget to take out outliers, as the mean is ~$77k$ and the standard deviation is ~$70k$ we take everything above $Mean + 2 * Standard\ Deviation$ as outlier (we round up to $250k$)

[61]:
```python
data = data_mapping(data)
sample_data = data[['risk_score','annual_inc']].copy()
sample_data = sample_data[sample_data['annual_inc'] < 250_000]

sample_data['income_bin'] = pd.cut(sample_data['annual_inc'], bins=25)
sample_data = (sample_data.drop(labels='annual_inc', axis=1)
               .groupby(by='income_bin')
               .mean()
               )

#rolling window for trend line
sample_data['rolling_avg'] = sample_data['risk_score'].rolling(window=3,␣
 ↪center=True).mean()

#for cleaner labels on x axis
sample_data.index = [f"{int(bin.left/1000)}k-{int(bin.right/1000)}k"
                     for bin in sample_data.index]
#plot
plt.style.use('bmh')
fig, ax = plt.subplots(figsize=(10,5))

sample_data['risk_score'].plot(kind='bar', alpha=0.6)
sample_data['rolling_avg'].plot(color='red', linewidth=2)

plt.xticks(rotation=90)
ax.set_ylabel('Risk Score')
ax.set_xlabel('Income Bin (from 0 to 250k a year)')
plt.show()
```

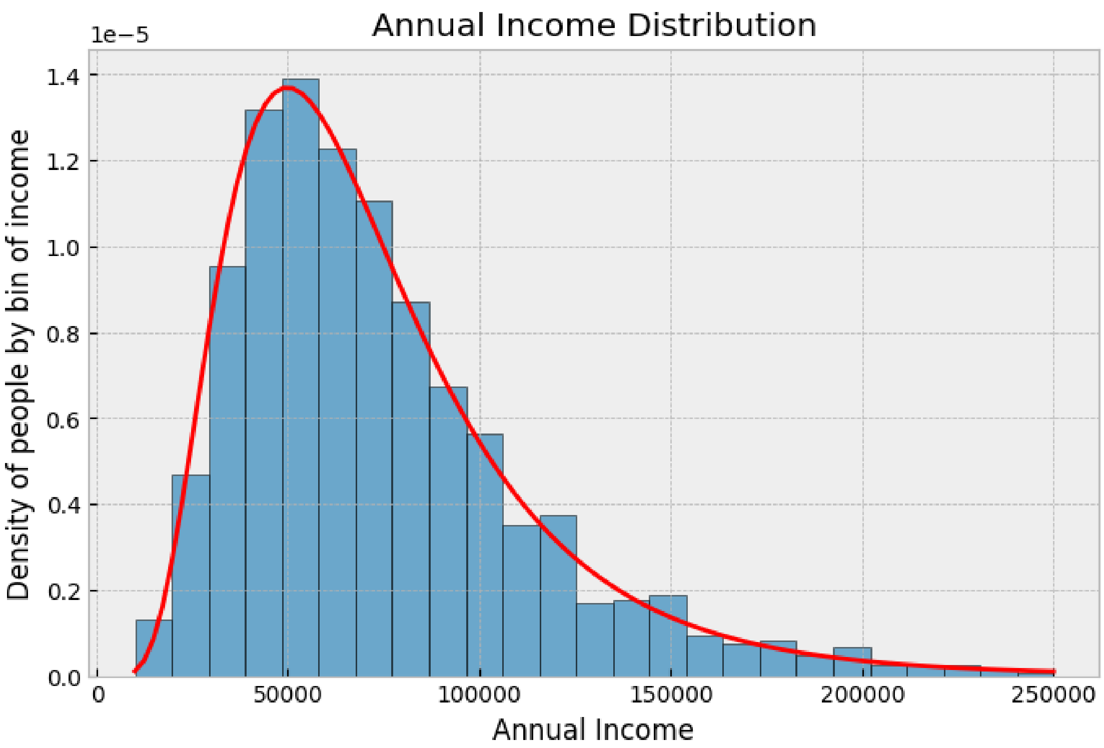
```
C:\Users\PC\AppData\Local\Temp\ipykernel_11140\2044984029.py:7: FutureWarning:
The default of observed=False is deprecated and will be changed to True in a
future version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
  .groupby(by='income_bin')
```



We see a reasonable downward trend between the anual income and the loan risk score, but not a linear relationship, this means there are many other factors influencing the final score.

we may take a look at the income distribution to verify it follow a Log-Normal distribution (what we usually see in income).

[62]:
```python
from scipy.stats import lognorm

sample_data = data.loc[(data['annual_inc'] < 250_000) & (data['annual_inc'] >␣
↪10_000), 'annual_inc']
shape, loc, scale = lognorm.fit(sample_data, floc=0)


plt.figure(figsize=(8, 5))
plt.hist(sample_data, bins=25, edgecolor='black', density=True, alpha=0.7)

x = np.linspace(sample_data.min(), sample_data.max(), 100)
pdf = lognorm.pdf(x, shape, loc, scale)
plt.plot(x, pdf, 'r', linewidth=2)

plt.title('Annual Income Distribution')
plt.xlabel('Annual Income')
plt.ylabel('Density of people by bin of income')
plt.grid(True)
plt.show()
```



The distribution looks good, we may look for correlation in other variables, we will list the variables most correlated with the target value, for categorical data we use label encoding.

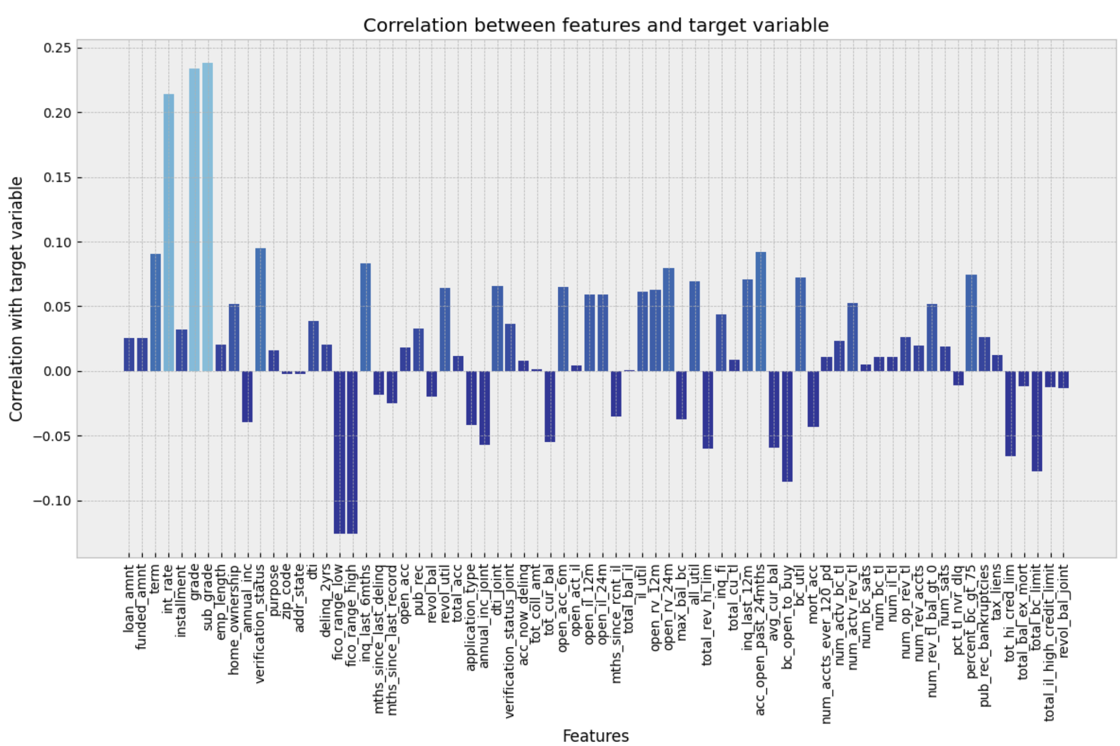
Some variables are directly correlated with the target value because they are a result of the event of a loan applicant repaying or defaulting, so we will not be using these in our final model.

We drop all the columns that weren't available at origination the list of columns to keep and to drop are in the 'config.py' file to not disturb user readability.

[64]:
```
from config import features_to_drop

data = data.drop(columns=features_to_drop, errors='ignore')
```

[65]:
```
from sklearn.preprocessing import LabelEncoder

cat_cols = [col for col in data.columns if data[col].dtype == 'object']
num_cols = [col for col in data.columns if col not in cat_cols]

data_encoded = data.copy()
le = LabelEncoder()

for col in cat_cols:
    data_encoded[col] = le.fit_transform(data[col])
```

```python
x = [col for col in data_encoded.columns if (col != 'risk_score')]
y = [data_encoded[col].corr(data_encoded['risk_score']) for col in x]

abs_y = np.abs(y)
colors = plt.cm.RdYlBu_r(y)

plt.figure(figsize=(12,8))

plt.bar(x=x, height=y, color=colors)
"""
plt.hlines(
    y=0,
    xmin=0,
    xmax=123,
    colors='black',
    linestyles='-'
)
"""
plt.ylabel('Correlation with target variable')
plt.xlabel('Features')
plt.xticks(rotation=90)
plt.title('Correlation between features and target variable')

plt.tight_layout()
plt.show()
```



We see that some variables are fairly correlated to the target, but the majority have a correlation $|\rho| < 0.1$.

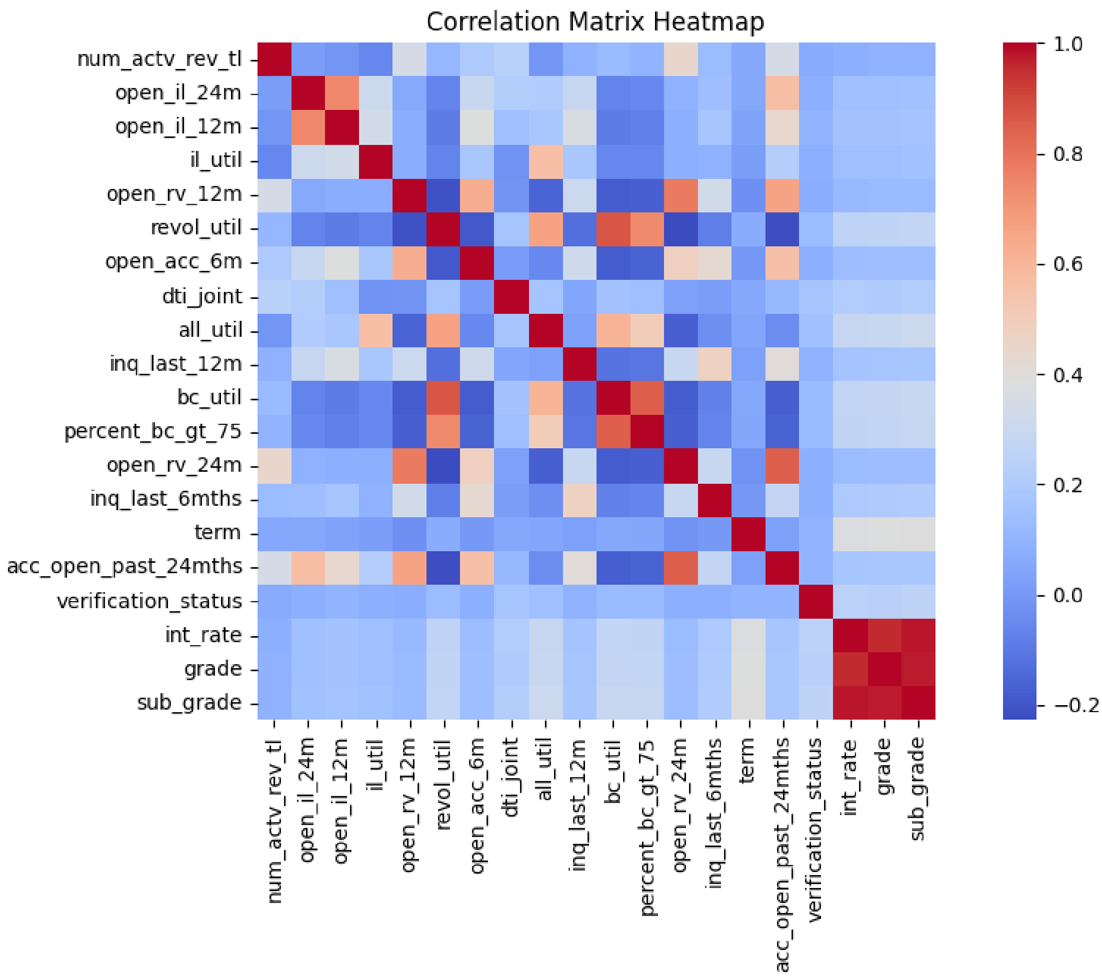
Some others stand out like, 'int_rate', 'grade' and 'sub-grade', we'll need to decide if these are available at the moment the loan is given or not.

What we can do now is take the ones with the highest correlation coefficient and see how they interact between them.

[17]:
```
#we select the 20 most correlated with the target variable
tmp = list(y)
tmp.sort()

#we suppose there are no duplicates
heavy_corr_values = tmp[-20:]
indexes = [y.index(val) for val in heavy_corr_values]
heavy_corr_cols = [x[i] for i in indexes]

print(heavy_corr_cols)
```

```
['num_actv_rev_tl', 'open_il_24m', 'open_il_12m', 'il_util', 'open_rv_12m',
'revol_util', 'open_acc_6m', 'dti_joint', 'all_util', 'inq_last_12m', 'bc_util',
'percent_bc_gt_75', 'open_rv_24m', 'inq_last_6mths', 'term',
'acc_open_past_24mths', 'verification_status', 'int_rate', 'grade', 'sub_grade']
```

[21]:
```
corr_matrix = data_encoded[heavy_corr_cols].corr()

plt.figure(figsize=(12, 6))
sns.heatmap(corr_matrix, annot=False, fmt=".2f", cmap='coolwarm', square=True)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



We have some clusters of heavy correlated data, int_rate,grade and sub-grade are all perfectly correlated because they are all a measure of the quality of the client, in fact, these features are decided by the bank analysing the profile of the client then giving what is basically our risk score we are trying to predict, that explains the high linear correlation with the target variable so we add these to our list of leaky columns.

To address multicolinearity we now want to check for the variance inflation factor of each column, which is a mesure of how much variables are correlated.

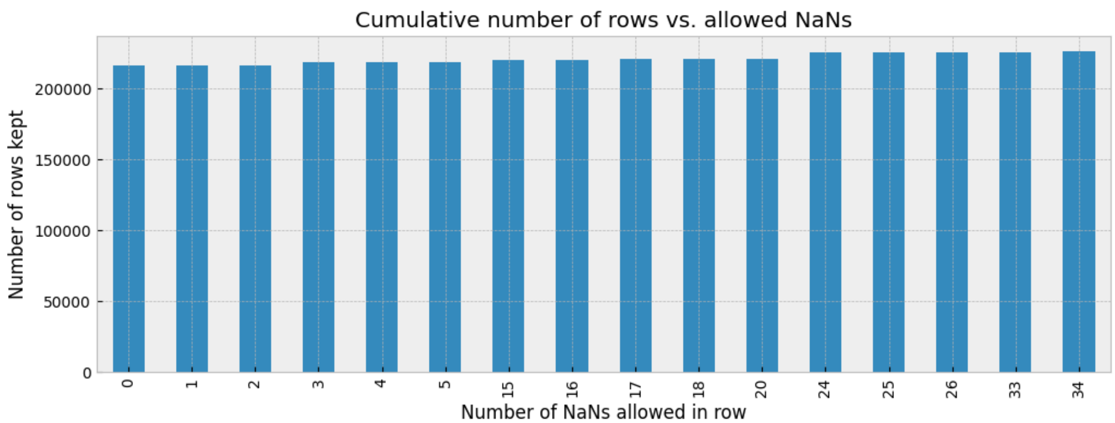
Before that we also check for columns that may have a lot of missing values, more than 30% missing values is not reasonable to keep and breaks

[66]:
```
cols_over_30pct_nan = data_encoded.columns[data_encoded.isna().mean() > 0.3].
 ↪tolist()
print(cols_over_30pct_nan)
#we directly drop them, too shallow for any realistic use
data_encoded = data_encoded.drop(labels=cols_over_30pct_nan, axis=1)
data_encoded.shape
```

```
['mths_since_last_delinq', 'mths_since_last_record', 'annual_inc_joint',
'dti_joint', 'open_acc_6m', 'open_act_il', 'open_il_12m', 'open_il_24m',
'mths_since_rcnt_il', 'total_bal_il', 'il_util', 'open_rv_12m', 'open_rv_24m',
'max_bal_bc', 'all_util', 'inq_fi', 'total_cu_tl', 'inq_last_12m',
'revol_bal_joint']
```

[66]: (226068, 54)

[67]:
```
#we do a plot to decide from where to limit the number of nans in the rows
row_nan_counts = data_encoded.isna().sum(axis=1)
row_nan_counts.value_counts().sort_index().cumsum().plot(kind='bar',␣
↪figsize=(12,4))
plt.title('Cumulative number of rows vs. allowed NaNs')
plt.xlabel('Number of NaNs allowed in row')
plt.ylabel('Number of rows kept')
plt.show()
```



Good News ! we can drop all missing value columns and be left with practically all the rows

[68]:
```
data_encoded = data_encoded.dropna()
print(data_encoded.shape)
print(f'number of NaN values in the data: {data_encoded.isna().sum().sum()}')
```

```
(216195, 54)
number of NaN values in the data: 0
```

[69]:
```
#now for the VIF values between columns
from statsmodels.stats.outliers_influence import variance_inflation_factor
def vif_compute(data_encoded):
    vif_data = pd.DataFrame()
    vif_data["Feature"] = data_encoded.columns
    vif_data["VIF"] = [variance_inflation_factor(data_encoded.values, i) for i␣
↪in range(len(data_encoded.columns))]
```

```
    return vif_data
```

[70]:
```
vif_data = vif_compute(data_encoded)

def vif_interpret(vif_data):
    no_multico = vif_data[vif_data['VIF'] == 1]
    acceptable = vif_data[(vif_data['VIF'] > 1) & (vif_data['VIF'] < 5)]
    concerning = vif_data[(vif_data['VIF'] > 5) & (vif_data['VIF'] < 10)]
    severe = vif_data[vif_data['VIF'] > 10]

    return (no_multico,acceptable,concerning,severe)

vif_cols = vif_interpret(vif_data)
print(f'columns with no multicolinearity: {len(vif_cols[0])}')
print(f'columns with acceptable multicolinearity: {len(vif_cols[1])}')
print(f'columns with concerning multicolinearity: {len(vif_cols[2])}')
print(f'columns with severe multicolinearity: {len(vif_cols[3])}')
```

```
C:\Users\PC\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.12_qbz5n2kf
ra8p0\LocalCache\local-packages\Python312\site-
packages\statsmodels\stats\outliers_influence.py:197: RuntimeWarning: divide by
zero encountered in scalar divide
  vif = 1. / (1. - r_squared_i)
```

```
columns with no multicolinearity: 0
columns with acceptable multicolinearity: 13
columns with concerning multicolinearity: 8
columns with severe multicolinearity: 33
```

This is very concerning as a VIF $>$ 10 indicates that $>$90% of the variance in the feature is explained by other features, meaning all these columns are likely close to perfect linear combination of each other, we need to use some domain knowledge to determine how to organise them and select the most important from them.

[ ]:
```
print(list(vif_cols[3]['Feature']))
#we direcrly drop 'fico_range_*','int_rate' because they leak the target␣
↪variable
#'funded_ammnt' and keep 'loan_amnt' because they are 100% correlated
#'grade' and keep 'sub_grade' for the same reason
data_encoded = data_encoded.
↪drop(columns=['fico_range_high','fico_range_low','int_rate','funded_amnt','grade'],␣
↪errors='ignore')
```

```
['loan_amnt', 'funded_amnt', 'int_rate', 'installment', 'grade', 'sub_grade',
'fico_range_low', 'fico_range_high', 'open_acc', 'pub_rec', 'revol_bal',
'revol_util', 'total_acc', 'verification_status_joint', 'tot_cur_bal',
'total_rev_hi_lim', 'bc_open_to_buy', 'bc_util', 'mort_acc', 'num_actv_bc_tl',
'num_actv_rev_tl', 'num_bc_sats', 'num_bc_tl', 'num_il_tl', 'num_op_rev_tl',
'num_rev_accts', 'num_rev_tl_bal_gt_0', 'num_sats', 'pct_tl_nvr_dlq',
```

'tot_hi_cred_lim', 'total_bal_ex_mort', 'total_bc_limit',
'total_il_high_credit_limit']

Now we design a quick algorithm to take aways columns with the highest VIF and recalculate VIF values until we reach all values bellow a decided theshold.

[ ]:
```python
def feature_selection_algorithm(data, thershold=15):
    highest_vif = np.inf

    while(highest_vif > thershold):
        vif_data = vif_compute(data)
        highest_vif = np.max(vif_data['VIF'])
        print(f'highest actual VIF is: {highest_vif}')

        highest_vif_col = vif_data.sort_values(by='VIF', ascending=False).
↪iloc[0]['Feature']
        data = data.drop(columns=highest_vif_col)
    return data, vif_data
```

[ ]:
```python
data_test = data_encoded.copy()

data_test, vif_test = feature_selection_algorithm(data_test)
vif_eval = vif_interpret(vif_test)

for i in range(0,4):
    print(vif_eval[i])
```

```
C:\Users\PC\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.12_qbz5n2kf
ra8p0\LocalCache\local-packages\Python312\site-
packages\statsmodels\stats\outliers_influence.py:197: RuntimeWarning: divide by
zero encountered in scalar divide
  vif = 1. / (1. - r_squared_i)
```

```
highest actual VIF is: inf
```

[ ]:
```python
#we condense all our precedent code in a single function for easier future use␣
↪and code mudularization
def num_data_prep(data):

    cols_over_30pct_nan = data.columns[data.isna().mean() > 0.3].tolist()
    data = data.drop(labels=cols_over_30pct_nan, axis=1)
    data = data.dropna(axis=0)

    return data
```

We now have to deal with the categorical variables

[ ]:
```python
categoric_data = data[cat_cols]
print(categoric_data.columns.to_list())
```

We'll do some cleaning on features already encoded in others, with no useful information or with very high cardinality

[19]:
```
def drop_useless(data):
    print(f'number of cols to drop: {len(cols_to_drop)}')
    print(f'data shape before dropping: {data.shape}')

    data = data.drop(labels=cols_to_drop, axis=1, errors='ignore')
    data = data.dropna()

    print(f'{len(cols_to_drop)} columns dropped successfuly')
    print(f'data shape after dropping: {data.shape}')

    return data
```

[18]:
```
data = drop_useless(data)
#we get number of unique entries in each column with categorical data
object_nunique = list(map(lambda col: data[col].nunique(), cat))
d = dict(zip(cat, object_nunique))

sorted(d.items(), key=lambda x: x[1])
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[18], line 1
----> 1 data = drop_useless(data)
      2 #we get number of unique entries in each column with categorical data
      3 object_nunique = list(map(lambda col: data[col].nunique(), cat))

NameError: name 'drop_useless' is not defined
```

[16]:
```
#we encode employement lenght and map it to integer values
def emp_lenght_map(categoric_data):
    map_emp_lenght = {
        None: -1,'< 1 year': 0,'1 year':1,'2 years':2,'3 years':3,
        '4 years':4,'5 years':5,'6 years':6,'7 years':7,'8 years':8,
        '9 years':9,'10+ years':10
    }
    categoric_data['length'] = categoric_data['emp_length'].map(map_emp_lenght)
    categoric_data = categoric_data.drop(labels='emp_length',axis=1)
    print('employement lenght encoded successfuly')
    return categoric_data
```

[15]:
```
#we convert to datetime and compute how long it was
def earliest_to_date(categoric_data):
```

```
    categoric_data = categoric_data.copy()
    categoric_data['earliest_cr_line'] = pd.to_datetime(
        categoric_data['earliest_cr_line'], format='%b-%Y', errors='coerce'
    )
    print(f"Rows with invalid 'earliest_cr_line':␣
  ↪{categoric_data['earliest_cr_line'].isna().sum()}")

    #took this part out because we'll need all the columns transformers to␣
  ↪output the same number of rows, we'll drop them later
    #categoric_data = categoric_data[categoric_data['earliest_cr_line'].
  ↪notna()]
    #print(f"Rows with invalid 'earliest_cr_line' after droping:␣
  ↪{categoric_data['earliest_cr_line'].isna().sum()}")

    today = pd.to_datetime('today')
    categoric_data['credit_history_length'] = (today -␣
  ↪categoric_data['earliest_cr_line']).dt.days

    categoric_data = pd.DataFrame(categoric_data).
  ↪drop(columns=['earliest_cr_line'], axis=1)

    print(f"Remaining rows: {len(categoric_data)}, earliest cr data encoded␣
  ↪successfuly")
    return categoric_data
```

[14]:
```
#frequency encoding the last two with high cardinality
def freq_encoding(categoric_data):
    for col in ['purpose', 'addr_state']:
        freq_encoding = categoric_data[col].value_counts(normalize=True)
        categoric_data[col + '_freq'] = categoric_data[col].map(freq_encoding)

    categoric_data.drop(columns=['purpose', 'addr_state'], inplace=True)
    print(f'frequency data encoded successfuly')
    return categoric_data
```

We are finally ready to build a full preprocessing Pipeline, the categorical columns left all are of cardinality <10 we can one hot encode them without exploding the data size

[13]:
```
ohe_cols =␣
  ↪['term','debt_settlement_flag','initial_list_status','verification_status','home_ownership'
freq_cols = ['purpose','addr_state']
cols_to_drop=['sub_grade','issue_d','url','emp_title','settlement_date','verification_status_j
                  ␣
  ↪'sec_app_earliest_cr_line','zip_code','pymnt_plan','application_type','disbursement_method'
                  ␣
  ↪'debt_settlement_flag_date','settlement_status','hardship_start_date','hardship_end_date',
```

```
                ␣
↪'payment_plan_start_date','next_pymnt_d','issue_d','grade','hardship_type','last_pymnt_d',
                ␣
↪'last_credit_pull_d','hardship_loan_status','hardship_flag','hardship_status','hardship_rea
    ]
#some other columns will be dropped because they represent a leakage, i.e. they␣
↪are unknown at the moment of the prediction
```

[32]:
```
preprocessor = ColumnTransformer([

    ('scale', RobustScaler(), make_column_selector(dtype_include='number')),
    ('frequency_cols', FunctionTransformer(freq_encoding), freq_cols),
    ('employement_lenght', FunctionTransformer(emp_lenght_map), ['emp_length']),
    ('account_age', FunctionTransformer(earliest_to_date),␣
↪['earliest_cr_line']),
    ('cat_left', OneHotEncoder(), ohe_cols)

], verbose=True)

pipe = Pipeline([

    ('features', preprocessor),
    ('model', DummyRegressor())
], verbose=True)
```

[ ]:
```
df = pd.read_parquet('../data/raw/data_chunck.parquet').sample(frac=1,␣
↪random_state=19)

df = data_mapping(df)
df_y = df['risk_score']
df = df.drop(labels='risk_score',axis=1)

X_train, X_val, y_train, y_val = train_test_split(df,df_y, test_size=0.8,␣
↪random_state=19)
```

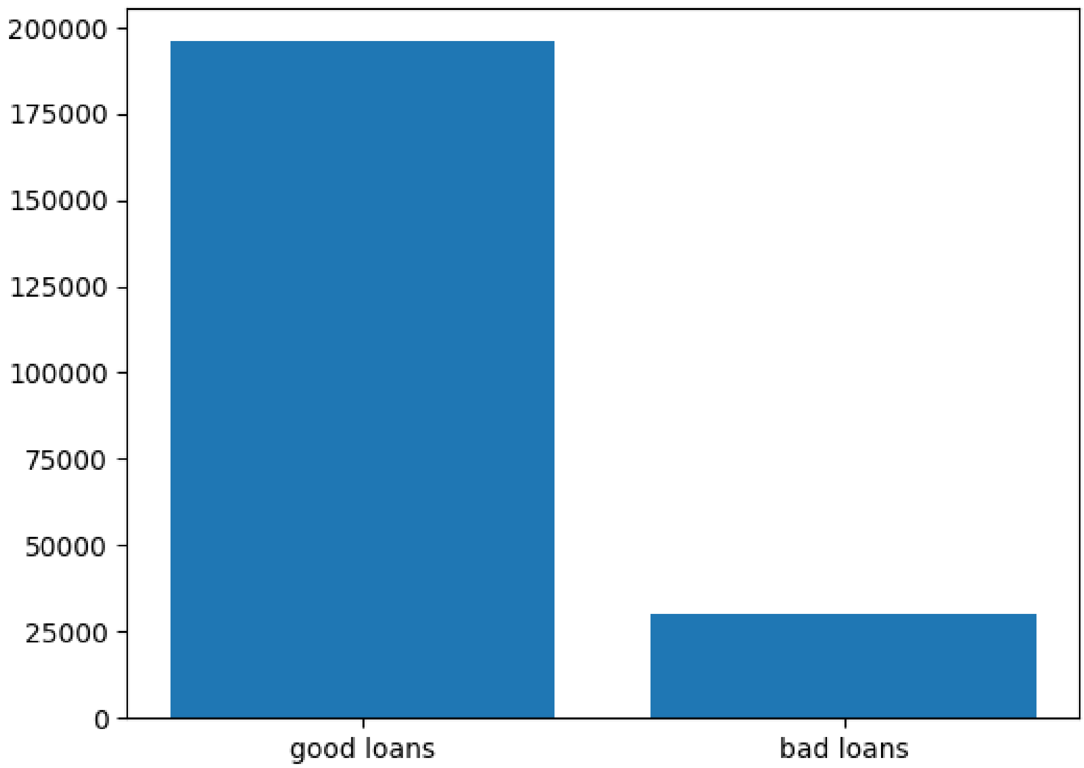
[ ]:
```
X_trans = pipe[:-1].transform(X_train)
```

[ ]:
```
pd.DataFrame(X_trans).describe()
```

We now need to check data distribution, an unbalanced dataset can make even the best model behave poorly

[33]:
```
df = pd.read_parquet('../data/raw/data_chunck.parquet').sample(frac=0.1,␣
↪random_state=1)
df = data_mapping(df)
```

[8]:
```
def check_proportion(df):
    good_loans = len(df[df['risk_score'] == 0])
    bad_loans = len(df[df['risk_score'] != 0])

    plt.bar(x=['good loans','bad loans'], height=[good_loans,bad_loans])

    desc = pd.DataFrame({'good_loans': [float(good_loans/
 ↪(good_loans+bad_loans))*100],
                         'bad_loans': [float(bad_loans/
 ↪(good_loans+bad_loans))*100]})
    return desc
ratio = check_proportion(df)
```



[9]:
```
#The proportions
ratio.round(2).head()
```

[9]:
```
   good_loans  bad_loans
0       86.61      13.39
```

We see that we have way more good loans than bad loans, we have two approaches we can consider, upsampling the bad loans by dumplicating some of them or downsampling the good loan by dropping some good rows randomly, as we have many types.

As the class imbalance is very big 87/13 we will use a mix of downsampling and upsampling using SMOTE that creates synthetic data from the minority class (better for generalization than simply duplicationg) and Tomek links to downsample the good loans.

The library imbalanced-learn gives us a function to do exactly that in a few lines of code.

[34]:
```
from imblearn.combine import SMOTETomek

df = num_data_prep(df)
df = drop_useless(df)

df_y = df['risk_score']
df = df.drop(columns='risk_score')
df = pipe[:-1].fit_transform(df)

smote_tomek = SMOTETomek(random_state=42)
X_resampled, y_resampled = smote_tomek.fit_resample(df, df_y)

df = pd.concat([X_resampled, y_resampled], axis=1)
check_proportion(df)
```

```
number of cols to drop: 26
data shape before dropping: (167101, 78)
26 columns dropped successfuly
data shape after dropping: (167101, 66)
[ColumnTransformer] … (1 of 5) Processing scale, total=   0.3s
frequency data encoded successfuly
[ColumnTransformer]  (2 of 5) Processing frequency_cols, total=   0.0s
employement lenght encoded successfuly
[ColumnTransformer]  (3 of 5) Processing employement_lenght, total=   0.0s
Rows with invalid 'earliest_cr_line': 0
Remaining rows: 167101, earliest cr data encoded successfuly
[ColumnTransformer] … (4 of 5) Processing account_age, total=   0.0s
[ColumnTransformer] … (5 of 5) Processing cat_left, total=   0.1s
[Pipeline] … (step 1 of 1) Processing features, total=   0.6s
```

```
Cannot execute code, session has been disposed. Please try restarting the Kernel.
```

```
Cannot execute code, session has been disposed. Please try restarting the Kernel.


View Jupyter <a href='command:jupyter.viewOutput'>log</a> for further details.
```

[ ]:
```
```