data_exploration_&_prep

July 31, 2025

[158]:
```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 20% 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/clean', exist_ok=True)
data.to_parquet('../data/clean/data_chunck.parquet')
```

First step : some data exploration

[ ]:
```python
data = pd.read_parquet('../data/clean/data_chunck.parquet').sample(frac=0.5,␣
↪random_state=0)
data.describe()
```

[ ]:
```
       member_id     loan_amnt   funded_amnt  funded_amnt_inv      int_rate  \
count        0.0  1.130329e+06  1.130329e+06     1.130329e+06  1.130329e+06
mean         NaN  1.505392e+04  1.504873e+04     1.503096e+04  1.309273e+01
std          NaN  9.200472e+03  9.198707e+03     9.202521e+03  4.836388e+00
min          NaN  5.000000e+02  5.000000e+02     0.000000e+00  5.310000e+00
25%          NaN  8.000000e+03  8.000000e+03     8.000000e+03  9.490000e+00
50%          NaN  1.292500e+04  1.290000e+04     1.280000e+04  1.262000e+01
```

75%	NaN	2.000000e+04	2.000000e+04	2.000000e+04	1.599000e+01
max	NaN	4.000000e+04	4.000000e+04	4.000000e+04	3.099000e+01

	installment	annual_inc	dti	delinq_2yrs	fico_range_low \
count	1.130329e+06	1.130327e+06	1.129453e+06	1.130316e+06	1.130329e+06
mean	4.459697e+02	7.796788e+04	1.883210e+01	3.064745e-01	6.986019e+02
std	2.675203e+02	9.340873e+04	1.432857e+01	8.690206e-01	3.299986e+01
min	4.930000e+00	0.000000e+00	0.000000e+00	0.000000e+00	6.100000e+02
25%	2.515800e+02	4.600000e+04	1.189000e+01	0.000000e+00	6.750000e+02
50%	3.782000e+02	6.500000e+04	1.785000e+01	0.000000e+00	6.900000e+02
75%	5.934900e+02	9.300000e+04	2.450000e+01	0.000000e+00	7.150000e+02
max	1.719830e+03	6.100000e+07	9.990000e+02	5.800000e+01	8.450000e+02

	…	deferral_term	hardship_amount	hardship_length	hardship_dpd \
count	…	5567.0	5567.000000	5567.0	5567.000000
mean	…	3.0	154.326677	3.0	13.754985
std	…	0.0	128.651842	0.0	9.697526
min	…	3.0	1.610000	3.0	0.000000
25%	…	3.0	59.090000	3.0	5.000000
50%	…	3.0	118.580000	3.0	15.000000
75%	…	3.0	213.270000	3.0	22.000000
max	…	3.0	943.940000	3.0	37.000000

	orig_projected_additional_accrued_interest \
count	4419.000000
mean	448.132057
std	370.562907
min	11.280000
25%	173.295000
50%	348.150000
75%	612.885000
max	2680.890000

	hardship_payoff_balance_amount	hardship_last_payment_amount \
count	5567.000000	5567.000000
mean	11606.486578	196.187244
std	7622.128024	202.237777
min	193.980000	0.010000
25%	5603.180000	44.435000
50%	9949.480000	134.120000
75%	16210.065000	286.830000
max	40306.410000	1407.860000

	settlement_amount	settlement_percentage	settlement_term
count	17188.000000	17188.000000	17188.000000
mean	4995.950615	47.793343	13.185129
std	3664.122578	7.743815	8.173729

```
min          44.210000               0.200000          0.000000
25%        2208.880000              45.000000          6.000000
50%        4154.935000              45.000000         14.000000
75%        6793.097500              50.000000         18.000000
max       27000.000000             521.350000        181.000000

[8 rows x 113 columns]
```

[ ]:
```
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

[2]:
```
def data_mapping(data):
    mapping = {
        'Fully Paid': 0,
        'Current': 0,
        'In Grace Period': 1,
        'Late (16-30 days)': 2,
        'Late (31-120 days)': 3,
        'Does not meet the credit policy. Status:Fully Paid': 0,
        'Does not meet the credit policy. Status:Charged Off': 4,
        'Charged Off': 4,
        'Default': 5
    }

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

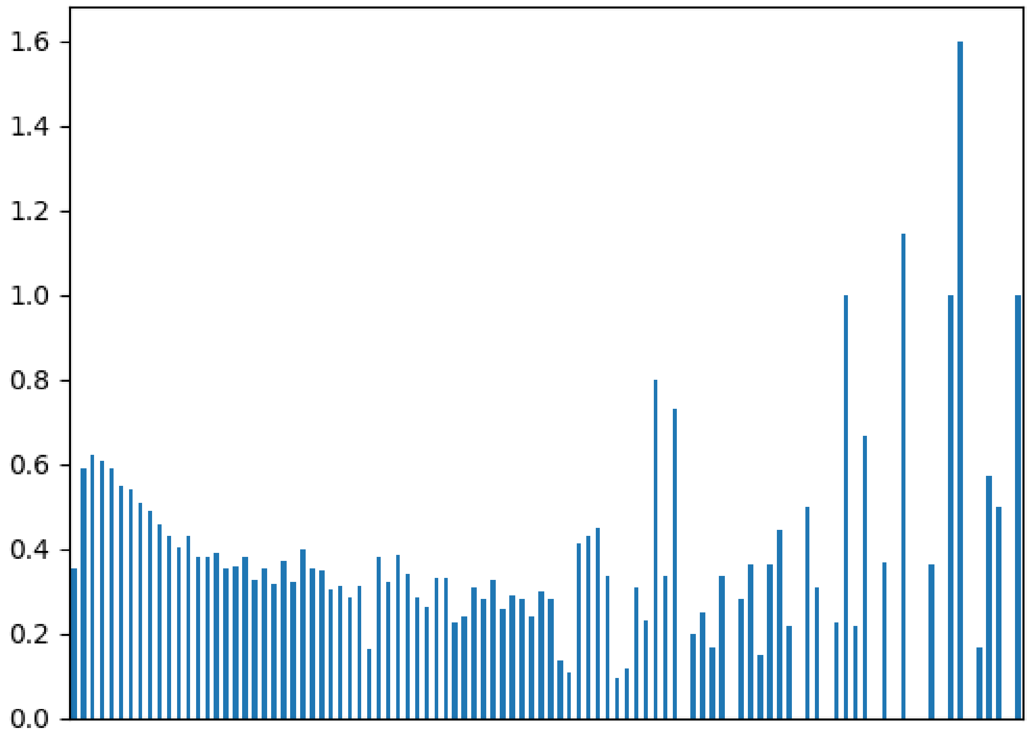
Now what we wanna look for is maybe a correlation in the data, let's check with annual income

[ ]:
```
sample_data = data[['risk_score','annual_inc']].copy()
sample_data = sample_data[sample_data['annual_inc'] < 1_000_000]

sample_data['income_bin'] = pd.cut(sample_data['annual_inc'], bins=100)
sample_data = (sample_data.drop(labels='annual_inc', axis=1)
               .groupby(by='income_bin')
               .mean()
               )
sample_data.plot(kind='bar', legend=False, xticks=[])
plt.xlabel("")
```

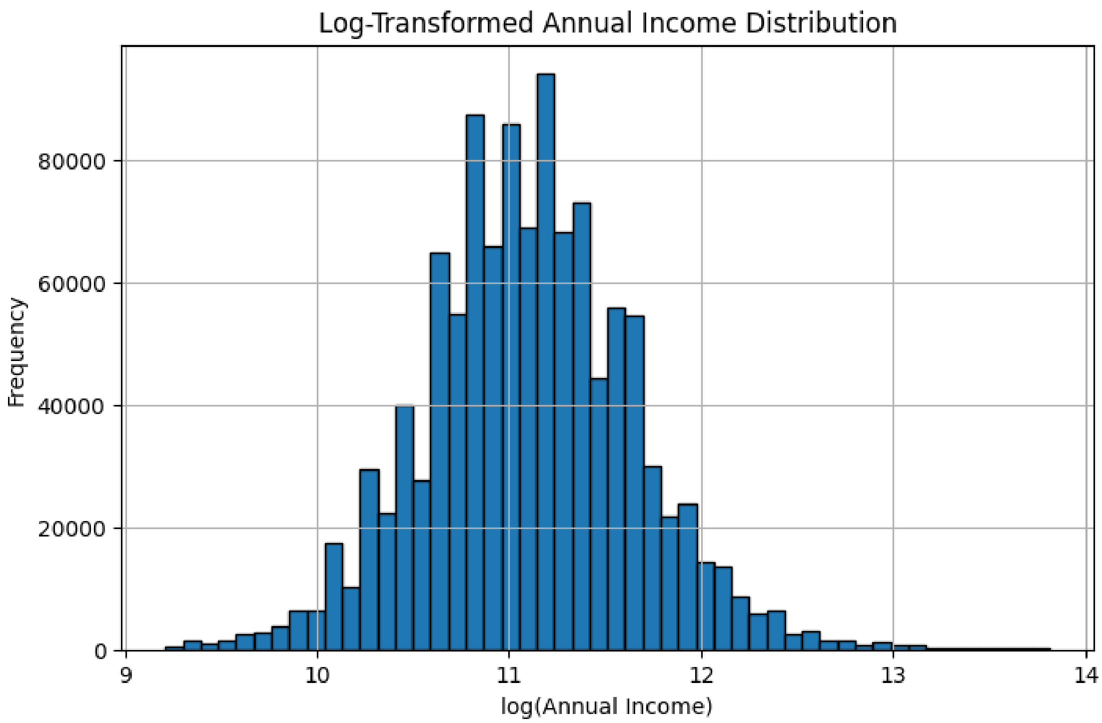
```
C:\Users\PC\AppData\Local\Temp\ipykernel_18324\871108651.py:6: FutureWarning:
The default of observed=False is deprecated and will be changed to True in a
future version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
  .groupby(by='income_bin')
```

[ ]: Text(0.5, 0, '')



We see no clear relation between risk and income, maybe due to the fact that people with more money tend to borrow more To make sure the data is good,we should also look at the distribution of income We apply a log transform and we filter outliers (>1M a year and <10k)

[ ]:
```
sample_data = data.loc[(data['annual_inc'] < 1_000_000) & (data['annual_inc'] >␣
  ↪10_000), 'annual_inc']
log_income = np.log(sample_data)
plt.figure(figsize=(8, 5))
plt.hist(log_income, bins=50, edgecolor='black')
plt.title('Log-Transformed Annual Income Distribution')
plt.xlabel('log(Annual Income)')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```

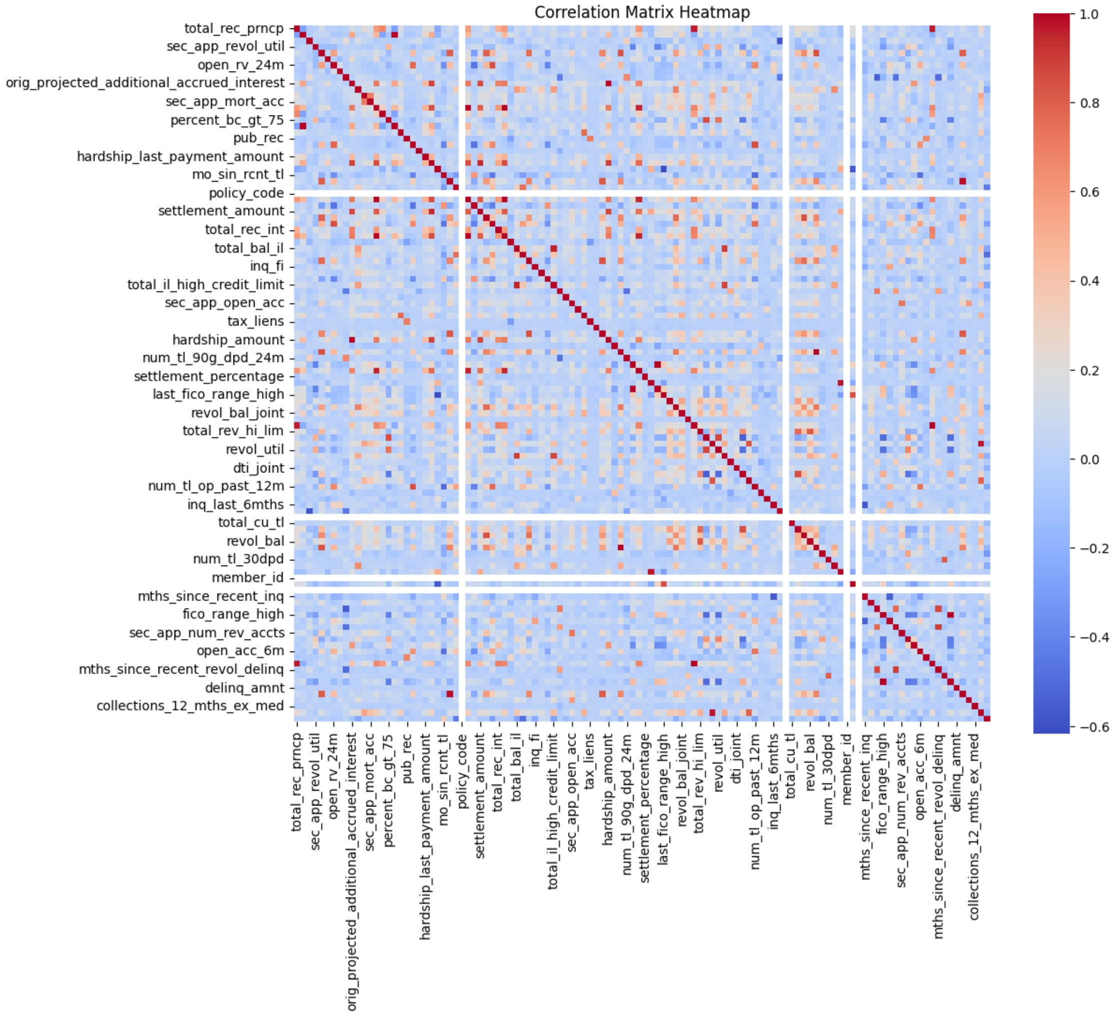


The distribution looks good, we may look for correlation in other variables, but some cleaning before

[3]:
```
def correlation_matrix(data):
    cat_columns = [col for col in data.columns if data[col].dtype=='object']
    num_columns = [col for col in set(data.columns) if col not in␣
 ↪set(cat_columns)]

    numeric_data = data[num_columns].copy()
    corr_matrix = numeric_data.corr()
    return (cat_columns,num_columns, corr_matrix)
```

[ ]:
```
_,_,corr_matrix=correlation_matrix(data)
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=False, fmt=".2f", cmap='coolwarm', square=True)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



We're looking for columns to drop, because this data is too high dimentional, so to not affect future model performance, we'll look for every 2 columns that have a correlation c where $|c| > .9$

[4]:
```
def filter_matrix(corr_matrix):
    coef_dict = {}
    #we'll get correlated columns in a dict
    for i,col1 in enumerate(corr_matrix.columns):
        for j,col2 in enumerate(corr_matrix.columns):
            if j<i: #we do this to go throught only the triangular half so we filter the diagonal and avoid dupes (a,b)(b,a)
                correlation = corr_matrix.loc[col1,col2]
                if np.abs(correlation) >= 0.9:
                    coef_dict[(col1,col2)] = correlation
    return coef_dict
```

[ ]:
```python
_,num_columns,_ = correlation_matrix(data)
numeric_data = data[num_columns].copy()
coef_dict= filter_matrix(corr_matrix)
temp_set = set()
for a,b in coef_dict.keys():
    if a not in temp_set:
        temp_set.add(a)
        numeric_data = numeric_data.drop(labels=a, axis=1)

print(temp_set)
```

```
{'num_rev_tl_bal_gt_0', 'total_pymnt', 'sec_app_fico_range_high',
'total_il_high_credit_limit', 'loan_amnt', 'settlement_amount',
'total_pymnt_inv', 'fico_range_low', 'tot_hi_cred_lim', 'installment',
'open_acc', 'funded_amnt', 'hardship_amount', 'recoveries', 'out_prncp'}
```

[ ]:
```python
new_corr_mat = numeric_data.corr()
new_dict = filter_matrix(new_corr_mat)
print(new_dict)
numeric_data.shape
```

```
{}
```

[ ]:
```
(1130329, 99)
```

Perfect ! we rules out the correlated data and are left with 99 numerical columns

[ ]:
```python
#we now look for missing values
row_nan_counts = numeric_data.isna().sum(axis=1)
print(row_nan_counts.value_counts().sort_index())
```

```
3      2
4     12
5     27
6     32
7     21
      ..
74    33
75     3
76     5
83    11
84     2
Name: count, Length: 69, dtype: int64
```

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

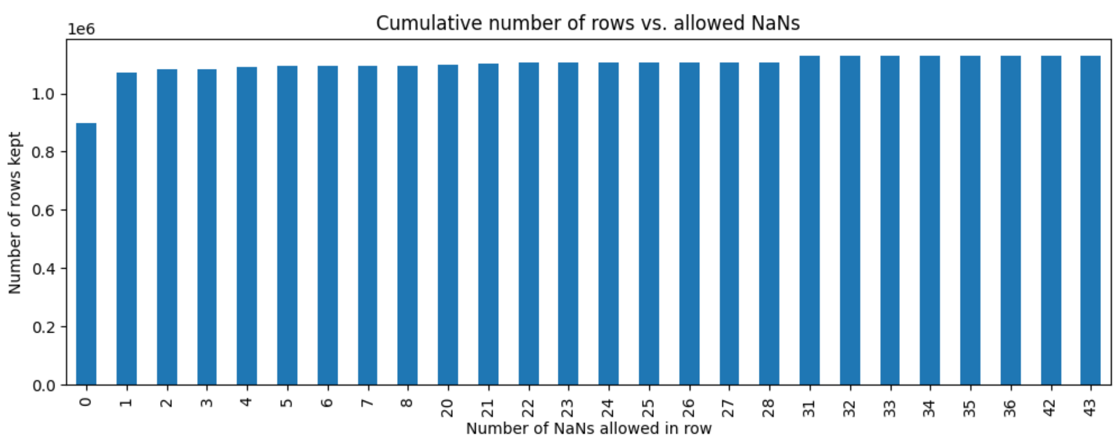
[ ]:
```python
cols_over_30pct_nan = numeric_data.columns[numeric_data.isna().mean() > 0.3].
 ↪tolist()
print(cols_over_30pct_nan)
```

```
#we directly drop them, too shallow for any realistic use
numeric_data = numeric_data.drop(labels=cols_over_30pct_nan, axis=1)
numeric_data.shape
```

```
['sec_app_revol_util', 'settlement_term', 'open_rv_24m',
'sec_app_inq_last_6mths', 'orig_projected_additional_accrued_interest',
'sec_app_mort_acc', 'open_rv_12m', 'hardship_last_payment_amount',
'hardship_payoff_balance_amount', 'open_il_12m', 'mths_since_last_record',
'total_bal_il', 'open_il_24m', 'inq_fi', 'mths_since_last_major_derog',
'sec_app_open_acc', 'annual_inc_joint', 'sec_app_collections_12_mths_ex_med',
'sec_app_fico_range_low', 'settlement_percentage', 'max_bal_bc',
'revol_bal_joint', 'sec_app_mths_since_last_major_derog', 'dti_joint',
'sec_app_chargeoff_within_12_mths', 'hardship_dpd', 'deferral_term',
'total_cu_tl', 'il_util', 'open_act_il', 'member_id', 'hardship_length',
'mths_since_last_delinq', 'inq_last_12m', 'mths_since_recent_bc_dlq',
'sec_app_num_rev_accts', 'all_util', 'open_acc_6m',
'mths_since_recent_revol_delinq', 'sec_app_open_act_il', 'mths_since_rcnt_il']
```

[ ]: (1130329, 58)

[ ]:
```
#we do a plot to decide from where to limit the number of nans in the rows
row_nan_counts = numeric_data.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 900k rows to use

[133]:
```python
#we condense all our precedent code in a single function for easier future use
def num_data_prep(data):

    num_cols = [col for col in data.columns if data[col].dtype != 'object']
    mat = data[num_cols].corr()

    coef_dict= filter_matrix(mat)
    temp_set = set()
    for a,b in coef_dict.keys():
        if a not in temp_set:
            temp_set.add(a)
            data = data.drop(labels=a, axis=1)

    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
cat,_,_ = correlation_matrix(data)
categoric_data = data[cat].copy()
categoric_data.head()
```

[ ]:
```
                term grade sub_grade           emp_title emp_length  \
1010636   36 months     B        B1                None       None
2083227   36 months     C        C3  Mechanic Supervisor   < 1 year
1975179   36 months     D        D3          Supervisor    5 years
858623    36 months     A        A3          Tour Guide    5 years
779019    36 months     D        D1   Assistant Manager    3 years

        home_ownership verification_status   issue_d loan_status pymnt_plan  \
1010636            OWN        Not Verified  Mar-2016     Current          n
2083227       MORTGAGE        Not Verified  Nov-2017  Fully Paid          n
1975179           RENT            Verified  Aug-2016  Fully Paid          n
858623            RENT        Not Verified  Jul-2018     Current          n
779019            RENT            Verified  Sep-2018     Current          n

         … hardship_status hardship_start_date hardship_end_date  \
1010636  …            None                None              None
2083227  …            None                None              None
1975179  …            None                None              None
858623   …            None                None              None
779019   …            None                None              None

        payment_plan_start_date hardship_loan_status disbursement_method  \
1010636                    None                 None                Cash
```

```
2083227                     None                 None                Cash
1975179                     None                 None                Cash
858623                      None                 None           DirectPay
779019                      None                 None                Cash

        debt_settlement_flag debt_settlement_flag_date settlement_status  \
1010636                    N                      None              None
2083227                    N                      None              None
1975179                    N                      None              None
858623                     N                      None              None
779019                     N                      None              None

        settlement_date
1010636            None
2083227            None
1975179            None
858623             None
779019             None

[5 rows x 35 columns]
```

[ ]:
```
print(categoric_data.columns.to_list())
```

```
['term', 'grade', 'sub_grade', 'emp_title', 'emp_length', 'home_ownership',
'verification_status', 'issue_d', 'pymnt_plan', 'url', 'purpose', 'zip_code',
'addr_state', 'earliest_cr_line', 'initial_list_status', 'last_pymnt_d',
'next_pymnt_d', 'last_credit_pull_d', 'application_type',
'verification_status_joint', 'sec_app_earliest_cr_line', 'hardship_flag',
'hardship_type', 'hardship_reason', 'hardship_status', 'hardship_start_date',
'hardship_end_date', 'payment_plan_start_date', 'hardship_loan_status',
'disbursement_method', 'debt_settlement_flag', 'debt_settlement_flag_date',
'settlement_status', 'settlement_date']
```

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

[141]:
```
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
```

[ ]:
```python
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])
```

[ ]:
```
[('term', 2),
 ('debt_settlement_flag', 2),
 ('initial_list_status', 2),
 ('verification_status', 3),
 ('home_ownership', 6),
 ('loan_status', 9),
 ('emp_length', 11),
 ('purpose', 14),
 ('addr_state', 51),
 ('earliest_cr_line', 734)]
```

[38]:
```python
#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
```

[93]:
```python
#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
```

[36]:

```
#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

[152]:

```
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
    ]
cat_columns = [col for col in X_train.columns if X_train[col].dtype=='object']
num_columns = [col for col in set(X_train.columns) if col not in␣
 ↪set(cat_columns)]
```

[159]:

```
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([

    ('num_auto_clean', FunctionTransformer(num_data_prep)),
    ('drop', FunctionTransformer(drop_useless)),
    ('features', preprocessor),
    ('model', DummyRegressor())
], verbose=True)
```

[11]:
```
df = pd.read_parquet('../data/clean/data_chunck.parquet').sample(frac=0.5,␣
 ↪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)
```

[165]:
```
X_trans = pipe[:-1].transform(X_train)
```

```
number of cols to drop: 26
data shape before dropping: (167178, 78)
26 columns dropped successfuly
data shape after dropping: (167178, 66)
frequency data encoded successfuly
employement lenght encoded successfuly
Rows with invalid 'earliest_cr_line': 0
Remaining rows: 167178, earliest cr data encoded successfuly
```

[164]:
```
pd.DataFrame(X_trans).describe()
```

[164]:
```
                   0              1              2              3   \
count  167178.000000  167178.000000  167178.000000  167178.000000
mean        0.147923       0.083326       0.268988       0.071157
std         0.768043       0.774978       1.749972       0.952020
min        -1.050000      -1.177033      -1.498478      -1.477697
25%        -0.466667      -0.468900      -0.413043      -0.468775
50%         0.000000       0.000000       0.000000       0.000000
75%         0.533333       0.531100       0.586957       0.531225
max         2.200000       2.918660     183.282609      79.544201

                   4              5              6              7   \
```

```
count  167178.000000  167178.000000  167178.000000  167178.000000
mean        0.316872       0.193785       0.608746       0.170252
std         0.879321       0.810434       0.864320       0.814643
min         0.000000      -0.750000       0.000000      -1.428571
25%         0.000000      -0.375000       0.000000      -0.428571
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.625000       1.000000       0.571429
max        35.000000       3.875000       6.000000      11.428571

                   8              9  …             66             67  \
count  167178.000000  167178.000000  …  167178.000000  167178.000000
mean        0.204788       0.354139  …       0.699793       0.324863
std         0.619440       1.494038  …       0.458349       0.468325
min         0.000000      -0.808309  …       0.000000       0.000000
25%         0.000000      -0.376634  …       0.000000       0.000000
50%         0.000000       0.000000  …       1.000000       0.000000
75%         0.000000       0.623366  …       1.000000       1.000000
max        86.000000      62.006116  …       1.000000       1.000000

                  68             69             70             71  \
count  167178.000000  167178.000000  167178.000000  167178.000000
mean        0.420444       0.254693       0.000371       0.514398
std         0.493632       0.435690       0.019254       0.499794
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       1.000000
75%         1.000000       1.000000       0.000000       1.000000
max         1.000000       1.000000       1.000000       1.000000

                  72             73             74             75
count  167178.000000  167178.000000  167178.000000  167178.000000
mean        0.000012       0.000024       0.103823       0.381372
std         0.003459       0.004891       0.305032       0.485725
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       0.000000       0.000000       1.000000
max         1.000000       1.000000       1.000000       1.000000

[8 rows x 76 columns]
```