Z5161163 Assignment 3 Report

Variance

Variance calculates the spread between numbers in a dataset. Small variance value for a feature variable indicates that the variable won't have any influence on the prediction since due to lack of spread.

For now, we want to remove variance score of 0 which column "FLAG_MOBIL" scored so we can remove that column for both tasks.

In [2]:

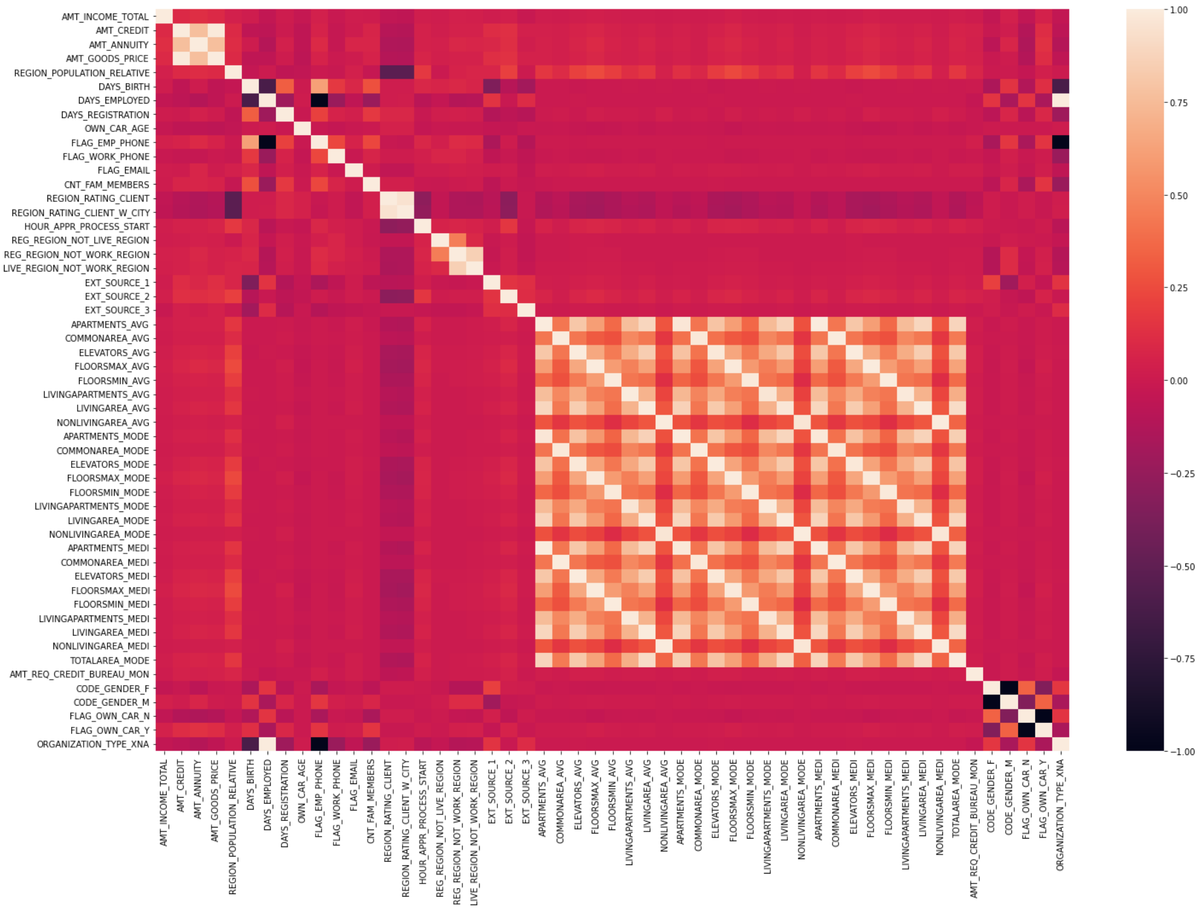
```
from sklearn.feature_selection import VarianceThreshold

df_var = df_train.var(numeric_only=True)
thres = 0

for (name, val) in sorted(list(zip(df_var.index, df_var.values)), key = lambda x:  x[1]):
    if val <= thres and name.isupper():
        print("{}: \t {:f}".format(name, val))
        df_train = df_train.drop(columns=name)
```

```
FLAG_MOBIL:       0.000000
```

Correlation Heatmap



Covariance

Covariance calculates the direction of relationship between 2 variables. We aim to search for high covariance value between feature and target variable which indicates that when a feature is low/high, then the target value will be high/low.

Much like variance, we are only doing numerical variables and not categorical variables.

It's worth to note that all variables "FLAG_DOCUMENT_#" are low in covariance so we can remove it.

In [3]:

```
df_cov = abs(df_train.cov())[target]

for (val, num) in sorted(list(zip(df_cov.index, df_cov.values)), key = lambda x: x[1]):
    if val.isupper():
        print ("{:<40} {}".format(val, round(num,3)))

doc_list = ["FLAG_DOCUMENT_{}".format(x) for x in range(2, 22)]
df_train = df_train.drop(columns=doc_list)
```

```
FLAG_DOCUMENT_10                         0.21
FLAG_DOCUMENT_12                         0.521
FLAG_DOCUMENT_21                         0.711
CODE_GENDER_XNA                          1.084
FLAG_DOCUMENT_2                          2.331
FLAG_DOCUMENT_17                         2.703
FLAG_DOCUMENT_20                         5.262
LANDAREA_AVG                             5.982
FLAG_DOCUMENT_4                          6.029
LANDAREA_MEDI                            8.284
FLAG_DOCUMENT_19                         11.139
FLAG_DOCUMENT_5                          13.502
REG_CITY_NOT_LIVE_CITY                   16.964
FLAG_DOCUMENT_7                          18.698
LANDAREA_MODE                            28.229
AMT_REQ_CREDIT_BUREAU_HOUR               28.827
FLAG_DOCUMENT_11                         31.671
AMT_REQ_CREDIT_BUREAU_WEEK               34.213
NONLIVINGAPARTMENTS_MODE                 45.975
NONLIVINGAPARTMENTS_MEDI                 51.437
YEARS_BEGINEXPLUATATION_AVG              52.959
NONLIVINGAPARTMENTS_AVG                  53.202
YEARS_BEGINEXPLUATATION_MEDI             53.85
YEARS_BEGINEXPLUATATION_MODE             57.308
FLAG_DOCUMENT_18                         57.655
ENTRANCES_MODE                           68.142
FLAG_DOCUMENT_15                         68.963
FLAG_CONT_MOBILE                         78.549
ENTRANCES_MEDI                           103.807
ENTRANCES_AVG                            112.016
YEARS_BUILD_MODE                         114.83
WEEKDAY_APPR_PROCESS_START_FRIDAY        116.153
FLAG_PHONE                               122.39
BASEMENTAREA_MODE                        129.448
```

Correlation

Correlation referes to how much 2 variables have a linear relationship with each other. Think of it as a scaled version of covariance as the value ranges from -1 to 1.

We want to remove feature variables that have correlation value with target variable near 0 which indicates that there is absolute no relation between the feature and target value.

In [108]:

```python
df_corr = abs(df_train.corr())[target]
corr_threshold = 0.01
corr_lst = []

for (val, num) in sorted(list(zip(df_corr.index, df_corr.values)), key = lambda x: x[1]):
    if val.isupper() and num <= corr_threshold:
        print ("{:<40} {}".format(val, round(num,6)))
        corr_lst.append(val)

df_train = df_train.drop(columns=corr_lst)
```

```
FLAG_DOCUMENT_21                          9.4e-05
REG_CITY_NOT_LIVE_CITY                    0.000164
LANDAREA_AVG                              0.000311
LANDAREA_MEDI                             0.000427
AMT_REQ_CREDIT_BUREAU_WEEK                0.000477
CODE_GENDER_XNA                           0.000674
FLAG_PHONE                                0.000732
WEEKDAY_APPR_PROCESS_START_FRIDAY         0.000841
AMT_REQ_CREDIT_BUREAU_HOUR                0.000981
WEEKDAY_APPR_PROCESS_START_THURSDAY       0.001072
TARGET                                    0.001077
WEEKDAY_APPR_PROCESS_START_MONDAY         0.001212
LANDAREA_MODE                             0.001454
WEEKDAY_APPR_PROCESS_START_SATURDAY       0.001763
WEEKDAY_APPR_PROCESS_START_WEDNESDAY      0.002166
WEEKDAY_APPR_PROCESS_START_SUNDAY         0.002303
REG_CITY_NOT_WORK_CITY                    0.002387
ENTRANCES_MODE                            0.002592
DAYS_ID_PUBLISH                           0.002779
AMT_REQ_CREDIT_BUREAU_QRT                 0.002826
YEARS_BEGINEXPLUATATION_MODE              0.003267
YEARS_BEGINEXPLUATATION_AVG               0.003332
YEARS_BEGINEXPLUATATION_MEDI              0.003352
FLAG_OWN_REALTY_N                         0.003512
FLAG_OWN_REALTY_Y                         0.003512
SK_ID_CURR                                0.003519
AMT_REQ_CREDIT_BUREAU_DAY                 0.003531
ENTRANCES_MEDI                            0.003973
ENTRANCES_AVG                             0.004303
FLAG_CONT_MOBILE                          0.004715
LIVE_CITY_NOT_WORK_CITY                   0.004832
YEARS_BUILD_MODE                          0.00489
NONLIVINGAPARTMENTS_MODE                  0.004975
```

P-value

Determine if a variable's change is meaningful to the target variable by checking the null hypothesis. The lower the value is, the better

In [110]:
```
import statsmodels.api as sm

X2 = sm.add_constant(X)
est = sm.OLS(y, X2)
est2 = est.fit()
print(est2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       AMT_INCOME_TOTAL   R-squared:                       0.025
Model:                            OLS   Adj. R-squared:                  0.023
Method:                 Least Squares   F-statistic:                     11.86
Date:                Tue, 19 Apr 2022   Prob (F-statistic):               0.00
Time:                        20:42:12   Log-Likelihood:            -1.5377e+06
No. Observations:              108000   AIC:                         3.076e+06
Df Residuals:                  107767   BIC:                         3.078e+06
Df Model:                         232
Covariance Type:            nonrobust
------------------------------------------------------------------------------------------------------------------------
```

```
==========================================
                                     P>|t|
------------------------------------------
const                                0.261
SK_ID_CURR                           0.165
TARGET                               0.117
CNT_CHILDREN                         0.317
AMT_CREDIT                           0.302
AMT_ANNUITY                          0.000
AMT_GOODS_PRICE                      0.916
REGION_POPULATION_RELATIVE           0.273
DAYS_BIRTH                           0.203
DAYS_EMPLOYED                        0.018
DAYS_REGISTRATION                    0.213
DAYS_ID_PUBLISH                      0.073
OWN_CAR_AGE                          0.000
FLAG_EMP_PHONE                       0.631
FLAG_WORK_PHONE                      0.000
FLAG_CONT_MOBILE                     0.506
FLAG_PHONE                           0.193
FLAG_EMAIL                           0.084
CNT_FAM_MEMBERS                      0.279
REGION_RATING_CLIENT                 0.369
REGION_RATING_CLIENT_W_CITY          0.001
HOUR_APPR_PROCESS_START              0.422
REG_REGION_NOT_LIVE_REGION           0.578
REG_REGION_NOT_WORK_REGION           0.109
LIVE_REGION_NOT_WORK_REGION          0.482
REG_CITY_NOT_LIVE_CITY               0.950
REG_CITY_NOT_WORK_CITY               0.767
LIVE_CITY_NOT_WORK_CITY              0.914
EXT_SOURCE_1                         0.071
EXT_SOURCE_2                         0.633
EXT_SOURCE_3                         0.000
APARTMENTS_AVG                       0.447
```