Problem Statement:

Home Credit is an organization that serves the unbanked population with access to loans. Such individuals that do not have a built-up credit score have a challenging time securing loans from financial institutions.

Home Credit strives to broaden financial inclusion for the unbanked population by providing a positive and safe borrowing experience. In order to make sure this underserved population has a positive loan experience; Home Credit makes use of a variety of alternative data--including telco and transactional information--to predict their clients' repayment abilities

So, problem statement would be predicting how likely each applicant is of repaying a loan?

Dataset Description:

There are seven data sets that are at the disposal of Home Credit:

Application_train.csv - this is the principal table and presents all the application information. There is a single row per application, which has a unique identifier.

previous_application.csv - this file presents previous applications for people in the sample through Home Credit. There is a row per each application.

installments_payments.csv - this is the repayment history on loans given out through Home Credit for people in the sample. Each row is a made or missed payment.

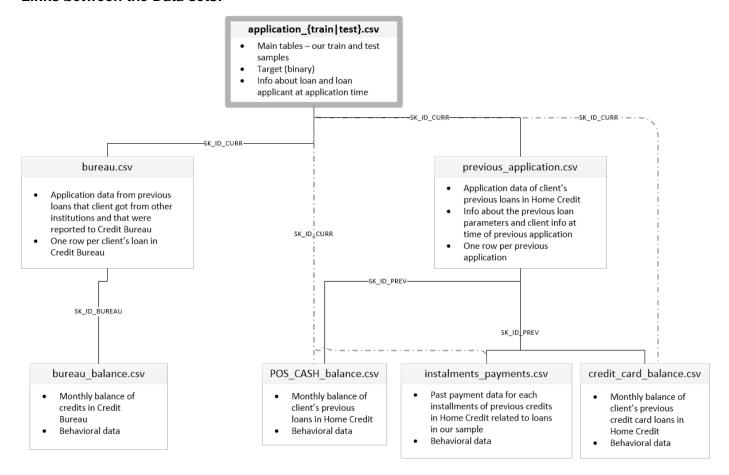
bureau.csv - credit information from other financial institutions that were reported to Home Credit. Each row represents a credit that was given to an individual in the sample.

bureau_balance.csv - monthly information per credit, per loan for users in the sample..

POS_CASH_balance.csv - like bureau_balance.csv, this data set is the internal version of the previous monthly breakdown of balances for consumer credit and cash loans that were taken out through Home Credit.

credit_card_calance.csv - each row in this data set represents a monthly balance of credit cards that were issued to applicants in the sample through Home Credit.

Links between the Data sets:



Data Wrangling and Cleaning:

A) bureau_balance.csv:

- Analyzed dataset with few rows & identified categorical column
- "STATUS" column being used to denote "Status of Credit Bureau loan during the month (active, closed, DPD0-30,... [C means closed, X means status unknown, 0 means no DPD, 1 means maximal did during month between 1-30, 2 means DPD 31-60,... 5 means DPD 120+ or sold or written off])" which typically denotes on which month Paid , Not paid , closed . used ordinal encoder for numeric conversion.
- Then it summing based on 'SK_ID_BUREAU', which will be representing
 'Month_Balance_Count'. Also, we are dropping 'MONTHS_BALANCE' original column
- Grouped Data set is ready for Merge

B) bureau.csv

- Transforming Categorical variables to Numerical
- Merging with bureau_balance dataset based on 'SK_ID_BUREAU'
- Now Merged Data set is ready

C) credit_card_balance.csv

- It has Each month credit record
- Transforming Categorical variables to Numerical variables
- Step 2: Creating new unique DF for 'SK_ID_PREV' & 'SK_ID_CURR'
- Dropping "SK_ID_CURR" from credit_card_balance data frame.
- Grouping DF based on **'SK_ID_PREV'** Summing past Installement payment information and grouping by previous ID.
- Merging with Step 2 DF, based on 'SK_ID_PREV'
- So it has unique 'SK_ID_PREV' & 'SK_ID_CURR' with all data's Merged together

D) previous_application.csv

- Transforming Categorical variables to Numerical variables

E) POS_CASH_BALANCE.csv

- Transforming Categorical variables to Numerical variables

F) installments_payments.csv

- Transforming Categorical variables to Numerical variables
- Dropping "SK_ID_CURR" from installments_payments data frame.
- New Variable Created to know whether Payment Made on date or Late
- Grouping DF based on **'SK_ID_PREV'** Summing past Installment payment information and grouping by previous ID.
- Merging with Step 2 DF, based on 'SK_ID_PREV' from credit_card_balance.csv
- So, it has unique 'SK_ID_PREV' & 'SK_ID_CURR' with all data's Merged together

General Merging Strategy:

- Dropping "SK_ID_CURR" from installments_payments, pos_cash_balance, cc_balance data frame.
- previous application & installments payments Merged based on 'SK ID PREV'
- Above Merged to cc_balance based on 'SK_ID_PREV'
- 1-1 Mapping enabled for 'SK_ID_PREV' & 'SK_ID_CURR'. Then Merged with above 4 data set
- So Right side of above Image is completely Merged.
- All Previous Data is Grouped By **'SK_ID_CURR'** then dropped **'SK_ID_PREV'**, to merge with training data set
- Merged Previous Data sets & bureau grouped datasets with training data set through 'SK_ID_CURR'
- All data sets Merged with Training Data set. Merging Process completed.

Categorical variables encoding Technique:

- OrdinalEncoder from sklearn being used for conversion

Missing Variables Handling:

- There are 283 columns with missing variables out of 339 columns in the data frame.
- Above 35 % Missing variables columns dropped as it is not going to impact predictions.

- np.isfinite() Method being used to drop few rows from the data set which depends on 'late' & 'closed' Which is being referred from Missing variable % table . which shares same % of missing values.
- 'OCCUPATION_TYPE' is important feature though it has 31 % of missing values, so NAN marked as Unemployment
- Rest of below 10 % missing variables being filled with either 0 or Mean, based on feature reference from excel.

After Handling Missing variables, data set stored to CSV as a single Merged data set.

Outlier Handling:

- Have not gone through complete data set columns, so looked at few important columns
- DOB has not any outliers
- Days Employed has outlier, it's been handling after divided by -365 then > 0's will be marked & masked as 0.
- Negative values being identified &removed

Application_train_merged.csv & Application_test_merged.csv – Preparation:

- Identified categorial variables
- Transforming Categorical variables to Numerical variables
- Replaced all negative values to 0

Conclusion:

- After all, above steps dataset stored to new file for EDA process