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March 24, 2022

[20]:
```
# !pip install --user lightgbm==2.2.3 -i https://pypi.tuna.tsinghua.edu.cn/
↪simple
```

[21]:
```
# !pip install phik
# !pip install bayesian-optimization
```

[22]:
```
# Importing modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Statistical function packages
from scipy.stats import chi2_contingency
import phik
from bayes_opt import BayesianOptimization

# Machine Learning packages
import lightgbm as lgb
from lightgbm import LGBMClassifier
from lightgbm import LGBMRegressor
from sklearn.preprocessing import MinMaxScaler, StandardScaler, LabelEncoder
from sklearn.model_selection import KFold, StratifiedKFold, train_test_split
from sklearn.model_selection import LeaveOneOut, cross_val_score
from sklearn.metrics import precision_score, recall_score, roc_curve,␣
↪roc_auc_score, confusion_matrix, classification_report

# other packages
import os
import gc
import pickle
from datetime import datetime

# Suppress warnings
import warnings
warnings.filterwarnings('ignore')
```

```
[23]: # Data Folder
data_dir = './home-credit-default-risk'

# Excact Data Directory
app_train_dir = data_dir + '/application_train.csv'
app_test_dir = data_dir + '/application_test.csv'

bureau_dir = data_dir + '/bureau.csv'
bureau_balance_dir = data_dir + '/bureau_balance.csv'
pos_cash_balance_dir = data_dir + '/POS_CASH_balance.csv'
credit_card_balance_dir = data_dir + '/credit_card_balance.csv'
previous_application_dir = data_dir + '/previous_application.csv'
installments_payments_dir = data_dir + '/installments_payments.csv'
```

0.1 Define Utility Wrapped Functions

Missing Values

```
[24]: # check missing values & with missing percentage
def count_missing_value(df, print_info=False):
    miss_value = df.isnull().sum()
    miss_percent = round(miss_value/df.shape[0], 4)
    miss_df = pd.concat([miss_value, miss_percent], axis=1)
    miss_df = miss_df.rename(columns={0:'miss_value', 1:'% miss_percentage'})
    miss_df = miss_df.loc[miss_df.miss_value!=0, :]

    miss_df = miss_df.sort_values(by='% miss_percentage',ascending=False)

    if print_info:
        print('There are {0} columns in total \nThere are {1} columns have miss␣
↪values'.format(df.shape[1],miss_df.shape[0]))
    return miss_df
```

```
[25]: def plot_missing(miss_df, title_name, tight_layout = True, figsize = (20,8),␣
↪grid = False, rotation = 90):

    # checking if there is any column with NaNs or not.
    if miss_df['miss_value'].sum() != 0:
        print(f"Number of columns having NaN values:␣
↪{miss_df[miss_df['miss_value'] != 0].shape[0]} columns")

        # plotting the Bar-Plot for NaN percentages (only for columns with␣
↪Non-Zero percentage of NaN values)
        plt.figure(figsize=figsize, tight_layout=tight_layout)
        temp_df = pd.DataFrame({'column': miss_df.index, 'miss_value':␣
↪miss_df['miss_value'], 'percent': miss_df['% miss_percentage']})
```

```
        sns.barplot(x='column', y='percent', data=temp_df[temp_df['miss_value']␣
↪> 0])
        plt.xticks(rotation=rotation)
        plt.xlabel('Column Name')
        plt.ylabel('Percentage of NaN values')
        plt.title(f'Percentage of NaN values in {title_name}')
        if grid:
            plt.grid()
        plt.show()
    else:
        print(f"The dataframe {title_name} does not contain any NaN values.")
```

Pie chart of TARGET distribution (Defaulter / NonDefaulter)

[26]:
```
def pie_target(df, title_name, my_dpi=96):
    target_distribution = df.TARGET.value_counts()
    labels = ['Non-Defaulter', 'Defaulter']

    plt.figure(figsize=(480/my_dpi,480/my_dpi),dpi=my_dpi)
    plt.pie(target_distribution,
            labels=labels,
    #         colors=["#d5695d", "#5d8ca8", "#65a479"],
            autopct='%.2f%%',
            wedgeprops={'edgecolor':'r',
                        'linestyle':'--',
                        'alpha':0.5,}
           )
    plt.title(f'Distribution of {title_name}\'s Target Variable')
    plt.show()
```

Categorical Features EDA phi-k matrix – judge correlation coefficient among categorical features

[27]:
```
def plot_phik_matrix(data, CATEGORICAL_FEATS, figsize = (20,20), mask_upper =␣
↪True, tight_layout = True, linewidth = 0.1, fontsize = 10, cmap = 'Blues',␣
↪show_target_top_corr = True, target_top_columns = 10):

    #first fetching only the categorical features
    phik_matrix = data[CATEGORICAL_FEATS].astype('object').phik_matrix()

    print('-'*100)

    if mask_upper:
        mask_array = np.ones(phik_matrix.shape)
        mask_array = np.triu(mask_array)
    else:
        mask_array = np.zeros(phik_matrix.shape)
```

```
    plt.figure(figsize = figsize, tight_layout = tight_layout)
    sns.heatmap(phik_matrix, annot = False, mask = mask_array, linewidth =␣
↪linewidth, cmap = cmap)
    plt.xticks(rotation = 90, fontsize = fontsize)
    plt.yticks(rotation = 0, fontsize = fontsize)
    plt.title("Phi-K Correlation Heatmap for Categorical Features", fontsize=20)
    plt.show()
    print("-"*100)

    if show_target_top_corr:
        #Seeing the top columns with highest correlation with the target␣
↪variable in application_train
        print("Categories with highest values of Phi-K Correlation value with␣
↪Target Variable are:")
        phik_df = pd.DataFrame({'Column Name' : phik_matrix.TARGET.index[1:],␣
↪'Phik-Correlation' : phik_matrix.TARGET.values[1:]})
        phik_df = phik_df.sort_values(by = 'Phik-Correlation', ascending =␣
↪False)
        display(phik_df.head(target_top_columns))
        print("-"*100)
```

Numerical Features EDA Pearson Correlation Heatmap

[28]:
```
def plot_numerical_heatmap(data, NUMERICAL_FEATS, figsize=(17,17), linewidth=0.
↪1, cmap='inferno'):
    corr = app_train_feats2target[NUMERICAL_FEATS].corr()
    mask = np.zeros_like(corr)
    mask[np.triu_indices_from(mask)] = True
    with sns.axes_style("white"):
        f, ax = plt.subplots(figsize=figsize)
        ax = sns.heatmap(corr, mask=mask, square=True, cmap=cmap,␣
↪linewidth=linewidth)
        plt.title("Correlation Heatmap for Numerical Features", fontsize=20)
        plt.show()

    return corr
```

Feature Engineering part

[29]:
```
# Categorical Feature Encoding
def feature_class_encoding(df, BI_CLASSES, MULTI_CLASSES):
    df[BI_CLASSES] = df[BI_CLASSES].apply(LabelEncoder().fit_transform)    #␣
↪Label Encoder
    df = pd.get_dummies(df, columns=MULTI_CLASSES)    # One-hot Encoding
    print(df.shape)
```

```
    return df
```

Creating New Variables
['DAYS_EMPLOYED_RATIO','EXTSOURCE_MEAN','EXTSOURCES_GM','ANNUITY_CREDIT_RATIO

[30]:
```
def add_variable(df):
    # 1 DAYS_EMPLOYED_RATIO
    # We believe it is more reasonable to consider one's employment history␣
↪relative to his/her age
    # So we add a variable to calculate the ratio.
    # The more time he/she spend in working in his/her whole life, he/she may␣
↪be more responsible or capable,
    # and thus having more ability to repay
    df['DAYS_EMPLOYED_RATIO'] = df['DAYS_EMPLOYED'] / df['DAYS_BIRTH']

    # The next two transform the credit score from external sources
    # 2 Simple average of EXT_SOURCE_1 to EXT_SOURCE_3
    df["EXTSOURCE_MEAN"] = df[['EXT_SOURCE_1', 'EXT_SOURCE_2', 'EXT_SOURCE_3']].
↪mean(axis=1)

    # 3 Geometric mean of EXT_SOURCE_1 to EXT_SOURCE_3, in case one client␣
↪scores very high in one, but low in the other two
    df['EXTSOURCES_GM'] = pow(df['EXT_SOURCE_1'] * df['EXT_SOURCE_2'] *␣
↪df['EXT_SOURCE_3'], 1/3)

    # The next three calculate ratios of annuity, income and credit amount. We␣
↪postulate that higher income level relative to
    # loan amount should imply better ability to repay

    # 4 Ratio of loan annuity to the credit amount of the loan
    df['ANNUITY_CREDIT_RATIO'] = df['AMT_ANNUITY'] / df['AMT_CREDIT']

    # 5 Ratio of loan annuity to the income level of the loan
    df['ANNUITY_INCOME_RATIO'] = df['AMT_ANNUITY'] / df['AMT_INCOME_TOTAL']

    # 6 Ratio of income level of client to credit amount
    df['INCOME_CREDIT_RATIO'] = df['AMT_INCOME_TOTAL'] / df['AMT_CREDIT']

    # The next two added variable consider the credit amount relative to the␣
↪customer consumption
    # 7 Ratio of credit amount to value of goods purchased
    df["CREDIT_GOODS_RATIO"] = df["AMT_CREDIT"]/df["AMT_GOODS_PRICE"]
    # 8 Diff btw credit amount and value of goods purchased
    df["CREDIT_GOODS_DIFF"] = df["AMT_CREDIT"] - df["AMT_GOODS_PRICE"]
```

Model Training & Evaluation

[31]:
```
def lgbm_evaluation(num_leaves, max_depth, min_split_gain, min_child_weight,
                    min_child_samples, subsample, colsample_bytree, reg_alpha,␣
↪reg_lambda):
    '''
    Objective function for Bayesian Optimization of LightGBM's Hyperparamters.␣
↪Takes the hyperparameters as input, and
    returns the Cross-Validation AUC as output.

    Inputs: Hyperparamters to be tuned.
        num_leaves, max_depth, min_split_gain, min_child_weight,
        min_child_samples, subsample, colsample_bytree, reg_alpha, reg_lambda

    Returns:
        CV ROC-AUC Score
    '''

    params = {
        'objective' : 'binary',
        'boosting_type' : 'gbdt',
        'learning_rate' : 0.005,
        'n_estimators' : 10000,
        'n_jobs' : -1,
        'num_leaves' : int(round(num_leaves)),
        'max_depth' : int(round(max_depth)),
        'min_split_gain' : min_split_gain,
        'min_child_weight' : min_child_weight,
        'min_child_samples' : int(round(min_child_samples)),
        'subsample': subsample,
        'subsample_freq' : 1,
        'colsample_bytree' : colsample_bytree,
        'reg_alpha' : reg_alpha,
        'reg_lambda' : reg_lambda,
        'verbosity' : -1,
        'seed' : 266
    }
    n_folds = 5    # 3
    stratified_cv = StratifiedKFold(n_splits = n_folds, shuffle = True,␣
↪random_state = 33)

    cv_preds = np.zeros(X.shape[0])
    for train_indices, cv_indices in stratified_cv.split(X, y):

        x_tr = X.iloc[train_indices]
        y_tr = y.iloc[train_indices]
        x_cv = X.iloc[cv_indices]
        y_cv = y.iloc[cv_indices]
```

```
        lgbm_clf = lgb.LGBMClassifier(**params)
        lgbm_clf.fit(x_tr, y_tr, eval_set= [(x_cv, y_cv)],
                eval_metric='auc', verbose = False, early_stopping_rounds=200)

        cv_preds[cv_indices] = lgbm_clf.predict_proba(x_cv, num_iteration =␣
↪lgbm_clf.best_iteration_)[:,1]

    return roc_auc_score(y, cv_preds)
```

[32]:
```
class Boosting:
    '''
    Class for Boosting Ensembles and displaying results. Contains 6 methods:

        1. init method
        2. train method
        3. proba_to_class method
        4. tune_threshold method
        5. results method
        6. feat_importance_show
    '''

    def __init__(self, x_train, y_train, x_test, params, num_folds = 5,␣
↪random_state = 33, verbose = True, save_model_to_pickle = False):
        '''
        Function to initialize the class members.

        Inputs:
            self
            x_train: DataFrame
                Training DataFrame
            y_train: DataFrame
                Training Class labels
            x_test: DataFrame
                Test DataFrame
            params: dict
                Parameters for the boosting ensemble
            num_folds: int, default = 3
                Number of folds for k-Fold Cross Validation
            random_state: int, default = 33
                Random State for Splitting the data for K-Fold Cross Validation
            verbose: bool, default = True
                Whether to keep verbosity or not
            save_model_to_pickle: bool, default = False
                Whether to save the model to pickle file or not

        Returns:
            None
```

```
        '''

        self.x_train = x_train
        self.y_train = y_train
        self.x_test = x_test
        self.params = params
        self.num_folds = num_folds
        self.stratified_cv = StratifiedKFold(n_splits = num_folds, shuffle =␣
↪True, random_state = random_state)
        self.verbose = verbose
        self.save_model = save_model_to_pickle

    def train(self, booster, verbose = 400, early_stopping = 200, pickle_name =␣
↪''):
        '''
        Function to train the Classifier on given parameters. It fits the␣
↪classifier for each fold, and for Cross Validation,
        uses Out-of-Fold Predictions. The test predictions are averaged␣
↪predictions over each fold.

        Inputs:
            self
            booster: str
                Whether the booster is 'xgboost' or 'lightgbm'
            verbose: int, default = 400
                Number of boosting rounds for printint boosting results.
            early_stopping: int, default = 200
                Number of boosting rounds to look for early stopping
            pickle_name: str, default = ''
                The string to add to end of pickle file of model, if any

        Returns:
            None
        '''

        self.train_preds_proba_mean = np.zeros(self.x_train.shape[0])
        #out-of-fold cv predictions
        self.cv_preds_proba = np.zeros(self.x_train.shape[0])
        self.test_preds_proba_mean = np.zeros(self.x_test.shape[0])
        #best threshold will be
        self.best_threshold_train = 0
        self.feature_importance = pd.DataFrame()
        self.feature_importance['features'] = self.x_train.columns
        self.feature_importance['gain'] = np.zeros(self.x_train.shape[1])

        if self.verbose:
```

```
            print(f"Fitting the {booster} on Training Data with {self.
↪num_folds} fold cross validation, and using Out-Of-Folds Predictions for␣
↪Cross-Validation")
            start = datetime.now()

        for fold_number, (train_indices, cv_indices) in enumerate(self.
↪stratified_cv.split(self.x_train, self.y_train), 1):
            if self.verbose:
                print(f"\n\tFold Number {fold_number}\n")

            x_tr = self.x_train.iloc[train_indices]
            y_tr = self.y_train.iloc[train_indices]
            x_cv = self.x_train.iloc[cv_indices]
            y_cv = self.y_train.iloc[cv_indices]

            if booster == 'xgboost':
                clf = XGBClassifier(**self.params)
            else:
                clf = LGBMClassifier(**self.params)

            clf.fit(x_tr, y_tr, eval_set = [(x_tr, y_tr), (x_cv, y_cv)],␣
↪eval_metric = 'auc',
                     verbose = verbose, early_stopping_rounds = 200)

            if booster == 'xgboost':
                self.train_preds_proba_mean[train_indices] = clf.
↪predict_proba(x_tr, ntree_limit = clf.get_booster().best_ntree_limit)[:, 1] /
↪ (self.num_folds - 1)
                self.cv_preds_proba[cv_indices] = clf.predict_proba(x_cv,␣
↪ntree_limit = clf.get_booster().best_ntree_limit)[:,1]
                self.test_preds_proba_mean += clf.predict_proba(self.x_test,␣
↪ntree_limit = clf.get_booster().best_ntree_limit)[:,1] / self.num_folds

                #feature importance
                gain_fold = clf.get_booster().get_score(importance_type =␣
↪'gain')
                feat_imp = pd.DataFrame()
                feat_imp['features'] = gain_fold.keys()
                feat_imp['gain'] = gain_fold.values()

            else:
                self.train_preds_proba_mean[train_indices] = clf.
↪predict_proba(x_tr, num_iteration = clf.best_iteration_)[:,1] / (self.
↪num_folds - 1)
                self.cv_preds_proba[cv_indices] = clf.predict_proba(x_cv,␣
↪num_iteration = clf.best_iteration_)[:,1]
```

```
                self.test_preds_proba_mean += clf.predict_proba(self.x_test, num_iteration = clf.best_iteration_)[:,1] / self.num_folds

                #feature importance
                gain_fold = clf.booster_.feature_importance(importance_type='gain')
                feat_imp = pd.DataFrame()
                feat_imp['features'] = self.x_train.columns
                feat_imp['gain'] = gain_fold

            #tuning the threshold for optimal TPR and FPR from ROC Curve
            self.best_threshold_train += self.tune_threshold(self.y_train[train_indices], self.train_preds_proba_mean[train_indices]) / self.num_folds
            #concatenating the feature importance of each fold to original df
            self.feature_importance = pd.concat([self.feature_importance, feat_imp], axis = 0)

            if self.save_model:
                #saving the model into a pickle file
                with open(f'./pickle/clf_{booster}_fold_{fold_number}_model_{pickle_name}.pkl', 'wb') as f:
                    pickle.dump(clf, f)

        #mean feature importance averaged over all folds
        self.feature_importance = self.feature_importance.groupby('features', as_index = False).mean()
        #sorting the feature importance
        self.feature_importance = self.feature_importance.sort_values(by = 'gain', ascending = False)

        if self.verbose:
            print("Done.")
            print(f"Time elapsed = {datetime.now() - start}")
        gc.collect()

    def proba_to_class(self, proba, threshold):
        '''
        Function to convert a given probability to class label based on a threshold value.

        Inputs:
            self
            proba: numpy array
                Probabilities of class label = 1
            threshold: int
```

```
                Threshold probability to be considered as Positive or Negative␣
↪Class Label

        Returns:
            Converted Class Label
        '''

        return np.where(proba >= threshold, 1, 0)

    def tune_threshold(self, true_labels, predicted_probas):
        '''
        Function to find the optimal threshold for maximizing the TPR and␣
↪minimizing the FPR from ROC-AUC Curve.
        This is found out by using the J Statistic, which is J = TPR - FPR.
        Reference: https://machinelearningmastery.com/
↪threshold-moving-for-imbalanced-classification/

        Inputs:
            self
            true_labels: numpy array or pandas series
                True Class Labels
            predicted_probas: numpy array
                Predicted Probability of Positive Class label

        Returns:
            Threshold probability.
        '''

        fpr, tpr, threshold = roc_curve(true_labels, predicted_probas)
        j_stat = tpr - fpr
        index_for_best_threshold = np.argmax(j_stat)

        return threshold[index_for_best_threshold]

    def results(self, roc_auc = True, precision_recall = True, confusion_matrix␣
↪= True, cv_test_distribution = False):
        '''
        Function to display the final results of Train, CV and Test Dataset.

        Inputs:
            self

        Returns:
            None
        '''

        #getting the crisp class labels
```

```
        self.train_preds_class = self.proba_to_class(self.
↪train_preds_proba_mean, self.best_threshold_train)
        self.cv_preds_class = self.proba_to_class(self.cv_preds_proba, self.
↪best_threshold_train)
        self.test_preds_class = self.proba_to_class(self.test_preds_proba_mean,␣
↪self.best_threshold_train)
        print("=" * 100)
        print("Train Results:")
        print(f"\nThe best selected Threshold as per the J-Statistic, which is␣
↪J = TPR - FPR, is = {self.best_threshold_train}\n")
        if roc_auc:
            print(f"\tROC-AUC Score = {roc_auc_score(self.y_train, self.
↪train_preds_proba_mean)}")
        if precision_recall:
            print(f"\tPrecision Score = {precision_score(self.y_train, self.
↪train_preds_class)}")
            print(f"\tRecall Score = {recall_score(self.y_train, self.
↪train_preds_class)}")
        print("CV Results:")
        if roc_auc:
            print(f"\tROC-AUC Score = {roc_auc_score(self.y_train, self.
↪cv_preds_proba)}")
        if precision_recall:
            print(f"\tPrecision Score = {precision_score(self.y_train, self.
↪cv_preds_class)}")
            print(f"\tRecall Score = {recall_score(self.y_train, self.
↪cv_preds_class)}")

#          if confusion_matrix:
#              print('=' * 100)
#              print("Confusion, Precision and Recall Matrix on CV data:")
#              conf_mat = confusion_matrix(self.y_train, self.cv_preds_class)
#              conf_mat = pd.DataFrame(conf_mat, columns =␣
↪['Predicted_0','Predicted_1'], index = ['Actual_0','Actual_1'])
#              plt.figure(figsize = (7,6))
#              plt.title('Confusion Matrix Heatmap')
#              sns.heatmap(conf_mat, annot = True, fmt = 'g', linewidth = 0.5,␣
↪annot_kws = {'size' : 15})
#              plt.show()

        if cv_test_distribution:
            print('=' * 100)
            print("Distribution of Original Class Labels and Predicted CV and␣
↪Test Class Labels")
            plt.figure(figsize = (20,6))
            plt.subplot(1,3,1)
```

```
            plt.title('Class Distribution of Original Dataset')
            sns.countplot(self.y_train)
            plt.subplot(1,3,2)
            plt.title('Class Distribution of predicted Class Labels on CV')
            sns.countplot(self.cv_preds_class)
            plt.subplot(1,3,3)
            plt.title('Class Distribution of predicted Test Dataset')
            sns.countplot(self.test_preds_class)
            plt.show()
        print('=' * 100)

        gc.collect()

    def feat_importances_show(self, num_features, figsize = (10,15)):
        '''
        Function to display the top most important features.

        Inputs:
            self
            num_features: int
                Number of top features importances to display
            figsize: tuple, default = (10,15)
                Size of figure to be displayed

        Returns:
            None
        '''

        plt.figure(figsize = figsize)
        sns.barplot(self.feature_importance['gain'].iloc[:num_features], self.
↪feature_importance['features'].iloc[:num_features], orient = 'h')
        plt.title(f'Top {num_features} features as per classifier')
        plt.xlabel('Feature Importance')
        plt.ylabel('Feature Names')
        plt.grid()
        plt.show()
        print('=' * 100)

        gc.collect()
```

[ ]:

[ ]:

0.2 EDA for each dataset

0.2.1 application_train.csv and application_test.csv

[33]:
```
app_train = pd.read_csv(app_train_dir)
app_test = pd.read_csv(app_test_dir)
```

[34]:
```
add_variable(app_train)
add_variable(app_test)
```

[35]:
```
app_train.head()
```

[35]:
```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      100002       1         Cash loans           M            N
1      100003       0         Cash loans           F            N
2      100004       0    Revolving loans           M            Y
3      100006       0         Cash loans           F            N
4      100007       0         Cash loans           M            N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  \
0               Y             0          202500.0    406597.5      24700.5
1               N             0          270000.0   1293502.5      35698.5
2               Y             0           67500.0    135000.0       6750.0
3               Y             0          135000.0    312682.5      29686.5
4               Y             0          121500.0    513000.0      21865.5

   …  AMT_REQ_CREDIT_BUREAU_QRT AMT_REQ_CREDIT_BUREAU_YEAR  \
0  …                        0.0                        1.0
1  …                        0.0                        0.0
2  …                        0.0                        0.0
3  …                        NaN                        NaN
4  …                        0.0                        0.0

  DAYS_EMPLOYED_RATIO EXTSOURCE_MEAN EXTSOURCES_GM ANNUITY_CREDIT_RATIO  \
0            0.067329       0.161787      0.144914             0.060749
1            0.070862       0.466757           NaN             0.027598
2            0.011814       0.642739           NaN             0.050000
3            0.159905       0.650442           NaN             0.094941
4            0.152418       0.322738           NaN             0.042623

   ANNUITY_INCOME_RATIO  INCOME_CREDIT_RATIO  CREDIT_GOODS_RATIO  \
0              0.121978             0.498036            1.158397
1              0.132217             0.208736            1.145199
2              0.100000             0.500000            1.000000
3              0.219900             0.431748            1.052803
4              0.179963             0.236842            1.000000

   CREDIT_GOODS_DIFF
```

```
0            55597.5
1           164002.5
2                0.0
3            15682.5
4                0.0

[5 rows x 130 columns]
```

[36]:
```
print(f"train size: {app_train.shape}")
print(f"test size: {app_test.shape}")
```

```
train size: (307511, 130)
test size: (48744, 129)
```

========================= ID & Feature & Target split for app_train =========================

[37]:
```
app_train_id = app_train[['SK_ID_CURR']]
app_train_feats = app_train.drop(['SK_ID_CURR', 'TARGET'], axis=1)
app_train_target = app_train[['TARGET']]
```

========================= ID & Feature split for app_test =========================

[38]:
```
app_test_id = app_test[['SK_ID_CURR']]
app_test_feats = app_test.drop(['SK_ID_CURR'], axis=1)
```

Data type exploration Features including: numerical & cateogircal features. Check each distribution for encoding preparation.

[39]:
```
app_train_feats.dtypes.value_counts()
```

[39]:
```
float64    73
int64      39
object     16
dtype: int64
```

[40]:
```
app_test_feats.dtypes.value_counts()
```

[40]:
```
float64    73
int64      39
object     16
dtype: int64
```

There are 16 categorical features.

[41]:
```
app_train_feats.select_dtypes('object').head()
```

[41]:
```
  NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR FLAG_OWN_REALTY NAME_TYPE_SUITE  \
0         Cash loans           M            N               Y   Unaccompanied
1         Cash loans           F            N               N          Family
2    Revolving loans           M            Y               Y   Unaccompanied
3         Cash loans           F            N               Y   Unaccompanied
4         Cash loans           M            N               Y   Unaccompanied

  NAME_INCOME_TYPE            NAME_EDUCATION_TYPE    NAME_FAMILY_STATUS  \
0          Working  Secondary / secondary special  Single / not married
1    State servant               Higher education               Married
2          Working  Secondary / secondary special  Single / not married
3          Working  Secondary / secondary special        Civil marriage
4          Working  Secondary / secondary special  Single / not married

   NAME_HOUSING_TYPE OCCUPATION_TYPE WEEKDAY_APPR_PROCESS_START  \
0  House / apartment        Laborers                  WEDNESDAY
1  House / apartment      Core staff                     MONDAY
2  House / apartment        Laborers                     MONDAY
3  House / apartment        Laborers                  WEDNESDAY
4  House / apartment      Core staff                   THURSDAY

        ORGANIZATION_TYPE FONDKAPREMONT_MODE  HOUSETYPE_MODE  \
0  Business Entity Type 3   reg oper account  block of flats
1                  School   reg oper account  block of flats
2              Government                NaN             NaN
3  Business Entity Type 3                NaN             NaN
4                Religion                NaN             NaN

  WALLSMATERIAL_MODE EMERGENCYSTATE_MODE
0       Stone, brick                  No
1              Block                  No
2                NaN                 NaN
3                NaN                 NaN
4                NaN                 NaN
```

Check missing values

[42]:
```python
# app_train
count_miss_train = count_missing_value(app_train, print_info=True)
count_miss_train
```

```
There are 130 columns in total
There are 73 columns have miss values
```

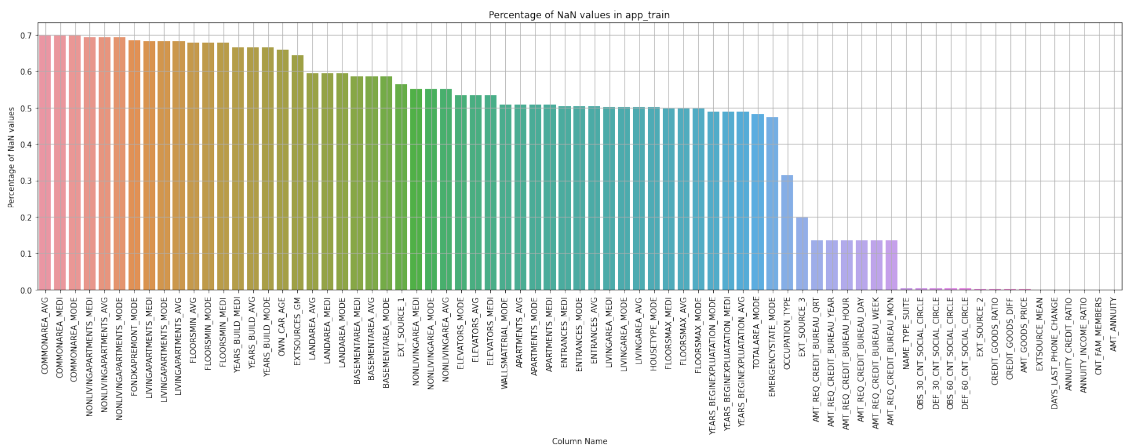
[42]:
```
                          miss_value  % miss_percentage
COMMONAREA_AVG                214865             0.6987
COMMONAREA_MEDI               214865             0.6987
COMMONAREA_MODE               214865             0.6987
```

NONLIVINGAPARTMENTS_MEDI	213514	0.6943
NONLIVINGAPARTMENTS_AVG	213514	0.6943
…	…	…
DAYS_LAST_PHONE_CHANGE	1	0.0000
ANNUITY_CREDIT_RATIO	12	0.0000
ANNUITY_INCOME_RATIO	12	0.0000
CNT_FAM_MEMBERS	2	0.0000
AMT_ANNUITY	12	0.0000

[73 rows x 2 columns]

[43]:
```python
plot_missing(count_miss_train, 'app_train', grid = True)
```

Number of columns having NaN values: 73 columns



[44]:
```python
# app_test
count_miss_test = count_missing_value(app_test, print_info=True)
count_miss_test
```

There are 129 columns in total
There are 68 columns have miss values

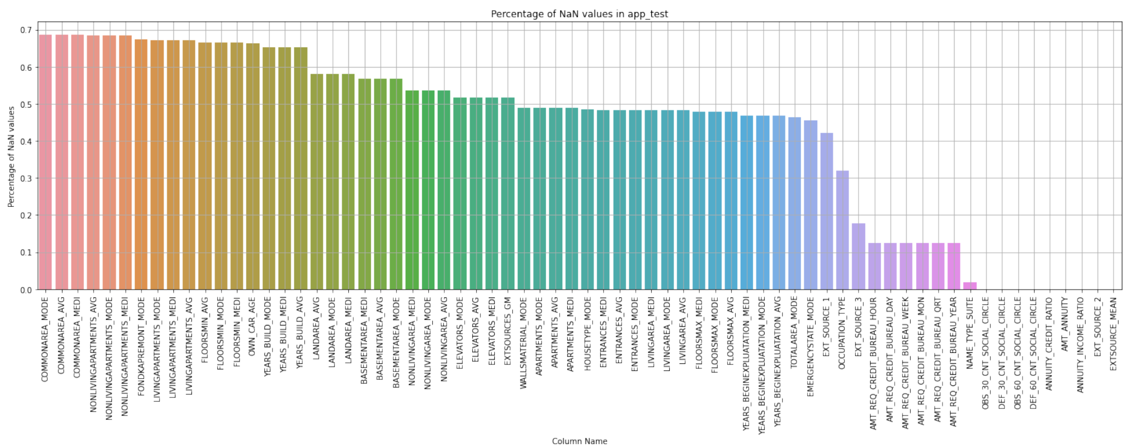
[44]:

	miss_value	% miss_percentage
COMMONAREA_MODE	33495	0.6872
COMMONAREA_AVG	33495	0.6872
COMMONAREA_MEDI	33495	0.6872
NONLIVINGAPARTMENTS_AVG	33347	0.6841
NONLIVINGAPARTMENTS_MODE	33347	0.6841
…	…	…
ANNUITY_CREDIT_RATIO	24	0.0005
AMT_ANNUITY	24	0.0005
ANNUITY_INCOME_RATIO	24	0.0005

```
EXT_SOURCE_2                          8             0.0002
EXTSOURCE_MEAN                        7             0.0001

[68 rows x 2 columns]
```

[45]:
```python
plot_missing(count_miss_test, 'app_test', grid = True)
```

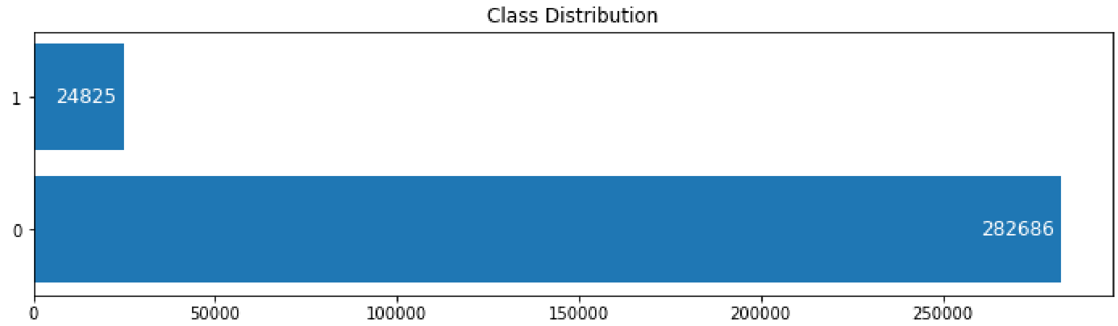
```
Number of columns having NaN values: 68 columns
```



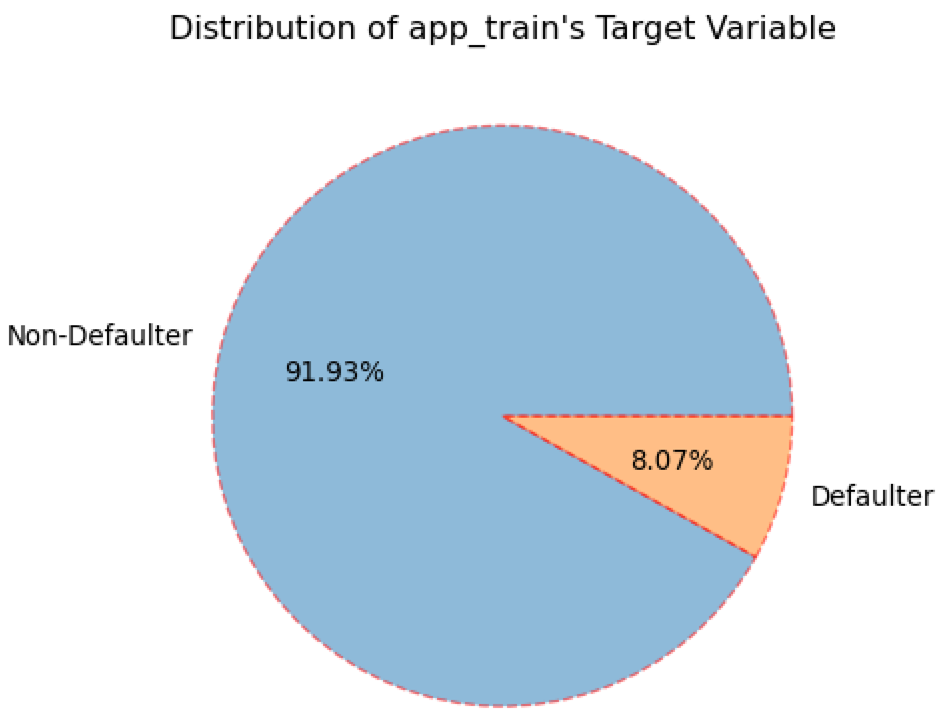
Check distribution of 'Target' column

[46]:
```python
print("0: will repay on time")
print("1: will have difficulty repaying loan")

class_dist = app_train['TARGET'].value_counts()

plt.figure(figsize=(12,3))
plt.title('Class Distribution')
plt.barh(class_dist.index, class_dist.values)
plt.yticks([0, 1])

for i, value in enumerate(class_dist.values):
    plt.text(value-2000, i, str(value), fontsize=12, color='white',
             horizontalalignment='right', verticalalignment='center')

plt.show()
```

```
0: will repay on time
1: will have difficulty repaying loan
```



[47]:
```
pie_target(app_train, 'app_train')
```



Categorical features We can use **p-value of Chi-square test** to judge the importance of each categorical feature.

```
H0: The variables are not correlated with each other. This is the H0 used in the Chi-square tes
This means, if two variables are correlated, then the P-value will come very close to zero.
```

[48]:
```
app_train_feats2target = pd.concat([app_train_feats, app_train_target], axis=1)
```

[49]:
```
# CATEGORICAL_FEATS = list(app_train_feats.select_dtypes('object').columns)
# print(CATEGORICAL_FEATS, f'\n\nTotally {len(CATEGORICAL_FEATS)} categorical␣
↪features.')

# We can directly find categorical features according to␣
↪'HomeCredit_columns_description.csv'
CATEGORICAL_FEATS = ['FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE',␣
↪'FLAG_CONT_MOBILE','FLAG_PHONE',\
                     ␣
↪'FLAG_EMAIL','REGION_RATING_CLIENT','REGION_RATING_CLIENT_W_CITY',␣
↪'REG_REGION_NOT_LIVE_REGION',\
                     'REG_REGION_NOT_WORK_REGION',␣
↪'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY',␣
↪'REG_CITY_NOT_WORK_CITY', \
                     'LIVE_CITY_NOT_WORK_CITY'] + ['FLAG_DOCUMENT_' + str(i)␣
↪for i in range(2,22)] + app_train_feats.dtypes[app_train_feats.dtypes ==␣
↪'object'].index.tolist()
print(CATEGORICAL_FEATS, f'\n\nTotally {len(CATEGORICAL_FEATS)} categorical␣
↪features.')
```

```
['FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE',
'FLAG_PHONE', 'FLAG_EMAIL', 'REGION_RATING_CLIENT',
'REGION_RATING_CLIENT_W_CITY', 'REG_REGION_NOT_LIVE_REGION',
'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGION',
'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY',
'FLAG_DOCUMENT_2', 'FLAG_DOCUMENT_3', 'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_5',
'FLAG_DOCUMENT_6', 'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8', 'FLAG_DOCUMENT_9',
'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11', 'FLAG_DOCUMENT_12', 'FLAG_DOCUMENT_13',
'FLAG_DOCUMENT_14', 'FLAG_DOCUMENT_15', 'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17',
'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20', 'FLAG_DOCUMENT_21',
'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY',
'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',
'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE',
'WEEKDAY_APPR_PROCESS_START', 'ORGANIZATION_TYPE', 'FONDKAPREMONT_MODE',
'HOUSETYPE_MODE', 'WALLSMATERIAL_MODE', 'EMERGENCYSTATE_MODE']

Totally 50 categorical features.
```

[50]:
```
#########################################################
accepted_P_Value_dict = dict()

for each_FEAT in CATEGORICAL_FEATS:

    # Cross tabulation between each_FEAT and TARGET
    print(f'Feature {CATEGORICAL_FEATS.index(each_FEAT)+1}, {each_FEAT}:\n')
    CrosstabResult = pd.crosstab(index=app_train_feats2target[each_FEAT],␣
↪columns=app_train_feats2target['TARGET'])
```

```python
    print(CrosstabResult)

    # Performing Chi-sq test
    ChiSqResult = chi2_contingency(CrosstabResult)

    # P-Value is the Probability of H0 being True
    # If P-Value >= 0.05, then we Accept the assumption(H0)
    # If P-Value < 0.05, then we reject the assumption H0, which indicates␣
↪significant variables.
    p_value = ChiSqResult[1]
    print(f'The P-Value of the ChiSq Test is: {p_value}\n\n')

    if p_value < 0.05:
        accepted_P_Value_dict[each_FEAT] = p_value
```

```
Feature 1, FLAG_MOBIL:

TARGET           0      1
FLAG_MOBIL
0                1      0
1           282685  24825
The P-Value of the ChiSq Test is: 0.12378615154489829


Feature 2, FLAG_EMP_PHONE:

TARGET               0      1
FLAG_EMP_PHONE
0                52395   2991
1               230291  21834
The P-Value of the ChiSq Test is: 2.5306059279614537e-143


Feature 3, FLAG_WORK_PHONE:

TARGET                0      1
FLAG_WORK_PHONE
0                227282  18921
1                 55404   5904
The P-Value of the ChiSq Test is: 2.6758000919452704e-56


Feature 4, FLAG_CONT_MOBILE:

TARGET                 0      1
FLAG_CONT_MOBILE
0                    529     45
```

```
1                 282157  24780
The P-Value of the ChiSq Test is: 0.8976989816319643


Feature 5, FLAG_PHONE:

TARGET           0      1
FLAG_PHONE
0           202336  18744
1            80350   6081
The P-Value of the ChiSq Test is: 9.489418049556951e-40


Feature 6, FLAG_EMAIL:

TARGET           0      1
FLAG_EMAIL
0           266618  23451
1            16068   1374
The P-Value of the ChiSq Test is: 0.3366632895181666


Feature 7, REGION_RATING_CLIENT:

TARGET                     0      1
REGION_RATING_CLIENT
1                      30645   1552
2                     209077  17907
3                      42964   5366
The P-Value of the ChiSq Test is: 1.8283164955910817e-232


Feature 8, REGION_RATING_CLIENT_W_CITY:

TARGET                            0      1
REGION_RATING_CLIENT_W_CITY
1                             32513   1654
2                            211314  18170
3                             38859   5001
The P-Value of the ChiSq Test is: 5.05571529094165e-249


Feature 9, REG_REGION_NOT_LIVE_REGION:

TARGET                           0      1
REG_REGION_NOT_LIVE_REGION
0                           278462  24392
1                             4224    433
```

```
The P-Value of the ChiSq Test is: 0.0021769580022904804
```

```
Feature 10, REG_REGION_NOT_WORK_REGION:

TARGET                          0      1
REG_REGION_NOT_WORK_REGION
0                          268462  23437
1                           14224   1388
The P-Value of the ChiSq Test is: 0.0001258375420219184
```

```
Feature 11, LIVE_REGION_NOT_WORK_REGION:

TARGET                           0      1
LIVE_REGION_NOT_WORK_REGION
0                           271239  23769
1                            11447   1056
The P-Value of the ChiSq Test is: 0.12192447948152679
```

```
Feature 12, REG_CITY_NOT_LIVE_CITY:

TARGET                      0      1
REG_CITY_NOT_LIVE_CITY
0                      261586  21886
1                       21100   2939
The P-Value of the ChiSq Test is: 1.0752352295806783e-133
```

```
Feature 13, REG_CITY_NOT_WORK_CITY:

TARGET                      0      1
REG_CITY_NOT_WORK_CITY
0                      219339  17305
1                       63347   7520
The P-Value of the ChiSq Test is: 7.98127695863221e-176
```

```
Feature 14, LIVE_CITY_NOT_WORK_CITY:

TARGET                       0      1
LIVE_CITY_NOT_WORK_CITY
0                       232974  19322
1                        49712   5503
The P-Value of the ChiSq Test is: 1.2629385266970663e-72
```

```
Feature 15, FLAG_DOCUMENT_2:

TARGET                0      1
FLAG_DOCUMENT_2
0                282677  24821
1                     9      4
The P-Value of the ChiSq Test is: 0.012597746385457218


Feature 16, FLAG_DOCUMENT_3:

TARGET                0      1
FLAG_DOCUMENT_3
0                 83658   5513
1                199028  19312
The P-Value of the ChiSq Test is: 1.8557477135709125e-133


Feature 17, FLAG_DOCUMENT_4:

TARGET                0      1
FLAG_DOCUMENT_4
0                282661  24825
1                    25      0
The P-Value of the ChiSq Test is: 0.2649917939107048


Feature 18, FLAG_DOCUMENT_5:

TARGET                0      1
FLAG_DOCUMENT_5
0                278410  24453
1                  4276    372
The P-Value of the ChiSq Test is: 0.8823563514069667


Feature 19, FLAG_DOCUMENT_6:

TARGET                0      1
FLAG_DOCUMENT_6
0                257115  23318
1                 25571   1507
The P-Value of the ChiSq Test is: 1.425605347566481e-56


Feature 20, FLAG_DOCUMENT_7:

TARGET                0      1
```

```
FLAG_DOCUMENT_7
0                282630  24822
1                    56      3
The P-Value of the ChiSq Test is: 0.5460783940196792


Feature 21, FLAG_DOCUMENT_8:

TARGET                0      1
FLAG_DOCUMENT_8
0                259498  22989
1                 23188   1836
The P-Value of the ChiSq Test is: 8.724696176376265e-06


Feature 22, FLAG_DOCUMENT_9:

TARGET                0      1
FLAG_DOCUMENT_9
0                281562  24751
1                  1124     74
The P-Value of the ChiSq Test is: 0.0182533270011425


Feature 23, FLAG_DOCUMENT_10:

TARGET                 0      1
FLAG_DOCUMENT_10
0                 282679  24825
1                      7      0
The P-Value of the ChiSq Test is: 0.9280282269633106


Feature 24, FLAG_DOCUMENT_11:

TARGET                 0      1
FLAG_DOCUMENT_11
0                 281558  24750
1                   1128     75
The P-Value of the ChiSq Test is: 0.02188786168173307


Feature 25, FLAG_DOCUMENT_12:

TARGET                 0      1
FLAG_DOCUMENT_12
0                 282684  24825
1                      2      0
```

```
The P-Value of the ChiSq Test is: 0.3795390674134992


Feature 26, FLAG_DOCUMENT_13:

TARGET                0      1
FLAG_DOCUMENT_13
0                281632  24795
1                  1054     30
The P-Value of the ChiSq Test is: 1.921626387971088e-10


Feature 27, FLAG_DOCUMENT_14:

TARGET                0      1
FLAG_DOCUMENT_14
0                281813  24795
1                   873     30
The P-Value of the ChiSq Test is: 2.138597509727043e-07


Feature 28, FLAG_DOCUMENT_15:

TARGET                0      1
FLAG_DOCUMENT_15
0                282325  24814
1                   361     11
The P-Value of the ChiSq Test is: 0.00041706549210387414


Feature 29, FLAG_DOCUMENT_16:

TARGET                0      1
FLAG_DOCUMENT_16
0                279783  24675
1                  2903    150
The P-Value of the ChiSq Test is: 1.4804321259373877e-10


Feature 30, FLAG_DOCUMENT_17:

TARGET                0      1
FLAG_DOCUMENT_17
0                282606  24823
1                    80      2
The P-Value of the ChiSq Test is: 0.09486562522282957
```

```
Feature 31, FLAG_DOCUMENT_18:

TARGET                 0      1
FLAG_DOCUMENT_18
0                 280328  24683
1                   2358    142
The P-Value of the ChiSq Test is: 1.2253312611830229e-05


Feature 32, FLAG_DOCUMENT_19:

TARGET                 0      1
FLAG_DOCUMENT_19
0                 282515  24813
1                    171     12
The P-Value of the ChiSq Test is: 0.5371847664073595


Feature 33, FLAG_DOCUMENT_20:

TARGET                 0      1
FLAG_DOCUMENT_20
0                 282543  24812
1                    143     13
The P-Value of the ChiSq Test is: 0.9780255911989449


Feature 34, FLAG_DOCUMENT_21:

TARGET                 0      1
FLAG_DOCUMENT_21
0                 282597  24811
1                     89     14
The P-Value of the ChiSq Test is: 0.06069787317885163


Feature 35, NAME_CONTRACT_TYPE:

TARGET                   0      1
NAME_CONTRACT_TYPE
Cash loans          255011  23221
Revolving loans      27675   1604
The P-Value of the ChiSq Test is: 1.0235150721172847e-65


Feature 36, CODE_GENDER:

TARGET            0      1
```

```
CODE_GENDER
F            188278  14170
M             94404  10655
XNA               4      0
The P-Value of the ChiSq Test is: 1.1290217848908289e-200


Feature 37, FLAG_OWN_CAR:

TARGET            0      1
FLAG_OWN_CAR
N            185675  17249
Y             97011   7576
The P-Value of the ChiSq Test is: 9.330994431109667e-34


Feature 38, FLAG_OWN_REALTY:

TARGET               0      1
FLAG_OWN_REALTY
N                86357   7842
Y               196329  16983
The P-Value of the ChiSq Test is: 0.0006681470317545887


Feature 39, NAME_TYPE_SUITE:

TARGET               0      1
NAME_TYPE_SUITE
Children          3026    241
Family           37140   3009
Group of people    248     23
Other_A            790     76
Other_B           1596    174
Spouse, partner  10475    895
Unaccompanied   228189  20337
The P-Value of the ChiSq Test is: 1.1329313903575907e-05


Feature 40, NAME_INCOME_TYPE:

TARGET                   0      1
NAME_INCOME_TYPE
Businessman             10      0
Commercial associate  66257   5360
Maternity leave          3      2
Pensioner            52380   2982
State servant        20454   1249
```

```
Student                   18      0
Unemployed                14      8
Working               143550  15224
The P-Value of the ChiSq Test is: 1.9281456056861122e-266


Feature 41, NAME_EDUCATION_TYPE:

TARGET                                0      1
NAME_EDUCATION_TYPE
Academic degree                     161      3
Higher education                  70854   4009
Incomplete higher                  9405    872
Lower secondary                    3399    417
Secondary / secondary special    198867  19524
The P-Value of the ChiSq Test is: 2.4476812052198174e-219


Feature 42, NAME_FAMILY_STATUS:

TARGET                     0      1
NAME_FAMILY_STATUS
Civil marriage         26814   2961
Married               181582  14850
Separated              18150   1620
Single / not married   40987   4457
Unknown                    2      0
Widow                  15151    937
The P-Value of the ChiSq Test is: 7.744841561414037e-107


Feature 43, NAME_HOUSING_TYPE:

TARGET                    0      1
NAME_HOUSING_TYPE
Co-op apartment        1033     89
House / apartment    251596  21272
Municipal apartment   10228    955
Office apartment       2445    172
Rented apartment       4280    601
With parents          13104   1736
The P-Value of the ChiSq Test is: 1.0990890032617707e-88


Feature 44, OCCUPATION_TYPE:

TARGET                     0     1
OCCUPATION_TYPE
```

```
Accountants             9339   474
Cleaning staff          4206   447
Cooking staff           5325   621
Core staff             25832  1738
Drivers                16496  2107
HR staff                 527    36
High skill tech staff  10679   701
IT staff                 492    34
Laborers               49348  5838
Low-skill Laborers      1734   359
Managers               20043  1328
Medicine staff          7965   572
Private service staff   2477   175
Realty agents            692    59
Sales staff            29010  3092
Secretaries             1213    92
Security staff          5999   722
Waiters/barmen staff    1196   152
The P-Value of the ChiSq Test is: 3.7844998567642684e-288


Feature 45, WEEKDAY_APPR_PROCESS_START:

TARGET                          0     1
WEEKDAY_APPR_PROCESS_START
FRIDAY                      46237  4101
MONDAY                      46780  3934
SATURDAY                    31182  2670
SUNDAY                      14898  1283
THURSDAY                    46493  4098
TUESDAY                     49400  4501
WEDNESDAY                   47696  4238
The P-Value of the ChiSq Test is: 0.01744736931389504


Feature 46, ORGANIZATION_TYPE:

TARGET                      0     1
ORGANIZATION_TYPE
Advertising               394    35
Agriculture              2197   257
Bank                     2377   130
Business Entity Type 1   5497   487
Business Entity Type 2   9653   900
Business Entity Type 3  61669  6323
Cleaning                  231    29
Construction             5936   785
Culture                   358    21
```

Electricity	887	63
Emergency	520	40
Government	9678	726
Hotel	904	62
Housing	2723	235
Industry: type 1	924	115
Industry: type 10	102	7
Industry: type 11	2470	234
Industry: type 12	355	14
Industry: type 13	58	9
Industry: type 2	425	33
Industry: type 3	2930	348
Industry: type 4	788	89
Industry: type 5	558	41
Industry: type 6	104	8
Industry: type 7	1202	105
Industry: type 8	21	3
Industry: type 9	3143	225
Insurance	563	34
Kindergarten	6396	484
Legal Services	281	24
Medicine	10456	737
Military	2499	135
Mobile	288	29
Other	15408	1275
Police	2224	117
Postal	1975	182
Realtor	354	42
Religion	80	5
Restaurant	1599	212
School	8367	526
Security	2923	324
Security Ministries	1878	96
Self-employed	34504	3908
Services	1471	104
Telecom	533	44
Trade: type 1	317	31
Trade: type 2	1767	133
Trade: type 3	3131	361
Trade: type 4	62	2
Trade: type 5	46	3
Trade: type 6	602	29
Trade: type 7	7091	740
Transport: type 1	192	9
Transport: type 2	2032	172
Transport: type 3	1000	187
Transport: type 4	4897	501
University	1262	65

```
XNA                     52384  2990
The P-Value of the ChiSq Test is: 5.224541090300172e-299
```

```
Feature 47, FONDKAPREMONT_MODE:

TARGET                      0     1
FONDKAPREMONT_MODE
not specified            5258   429
org spec account         5292   327
reg oper account        68678  5152
reg oper spec account   11288   792
The P-Value of the ChiSq Test is: 0.0007732982001133781
```

```
Feature 48, HOUSETYPE_MODE:

TARGET                 0      1
HOUSETYPE_MODE
block of flats    140053  10450
specific housing    1347    152
terraced house      1109    103
The P-Value of the ChiSq Test is: 9.992328040454538e-07
```

```
Feature 49, WALLSMATERIAL_MODE:

TARGET                  0     1
WALLSMATERIAL_MODE
Block                8603   650
Mixed                2123   173
Monolithic           1695    84
Others               1490   135
Panel               61848  4192
Stone, brick        60015  4800
Wooden               4842   520
The P-Value of the ChiSq Test is: 1.4531802848120748e-27
```

```
Feature 50, EMERGENCYSTATE_MODE:

TARGET                     0      1
EMERGENCYSTATE_MODE
No                    148324  11104
Yes                     2105    223
The P-Value of the ChiSq Test is: 1.1386802431747463e-06
```

[51]:
```
P_values_sorted = dict(sorted(accepted_P_Value_dict.items(), key=lambda x:x[1]))
P_values_sorted
```

[51]:
```
{'ORGANIZATION_TYPE': 5.224541090300172e-299,
 'OCCUPATION_TYPE': 3.7844998567642684e-288,
 'NAME_INCOME_TYPE': 1.9281456056861122e-266,
 'REGION_RATING_CLIENT_W_CITY': 5.05571529094165e-249,
 'REGION_RATING_CLIENT': 1.8283164955910817e-232,
 'NAME_EDUCATION_TYPE': 2.4476812052198174e-219,
 'CODE_GENDER': 1.1290217848908289e-200,
 'REG_CITY_NOT_WORK_CITY': 7.98127695863221e-176,
 'FLAG_EMP_PHONE': 2.5306059279614537e-143,
 'REG_CITY_NOT_LIVE_CITY': 1.0752352295806783e-133,
 'FLAG_DOCUMENT_3': 1.8557477135709125e-133,
 'NAME_FAMILY_STATUS': 7.744841561414037e-107,
 'NAME_HOUSING_TYPE': 1.0990890032617707e-88,
 'LIVE_CITY_NOT_WORK_CITY': 1.2629385266970663e-72,
 'NAME_CONTRACT_TYPE': 1.0235150721172847e-65,
 'FLAG_DOCUMENT_6': 1.425605347566481e-56,
 'FLAG_WORK_PHONE': 2.6758000919452704e-56,
 'FLAG_PHONE': 9.489418049556951e-40,
 'FLAG_OWN_CAR': 9.330994431109667e-34,
 'WALLSMATERIAL_MODE': 1.4531802848120748e-27,
 'FLAG_DOCUMENT_16': 1.4804321259373877e-10,
 'FLAG_DOCUMENT_13': 1.921626387971088e-10,
 'FLAG_DOCUMENT_14': 2.138597509727043e-07,
 'HOUSETYPE_MODE': 9.992328040454538e-07,
 'EMERGENCYSTATE_MODE': 1.1386802431747463e-06,
 'FLAG_DOCUMENT_8': 8.724696176376265e-06,
 'NAME_TYPE_SUITE': 1.1329313903575907e-05,
 'FLAG_DOCUMENT_18': 1.2253312611830229e-05,
 'REG_REGION_NOT_WORK_REGION': 0.0001258375420219184,
 'FLAG_DOCUMENT_15': 0.00041706549210387414,
 'FLAG_OWN_REALTY': 0.0006681470317545887,
 'FONDKAPREMONT_MODE': 0.0007732982001133781,
 'REG_REGION_NOT_LIVE_REGION': 0.0021769580022904804,
 'FLAG_DOCUMENT_2': 0.012597746385457218,
 'WEEKDAY_APPR_PROCESS_START': 0.01744736931389504,
 'FLAG_DOCUMENT_9': 0.0182533270011425,
 'FLAG_DOCUMENT_11': 0.02188786168173307}
```

[52]:
```
print(list(P_values_sorted.keys()))
```

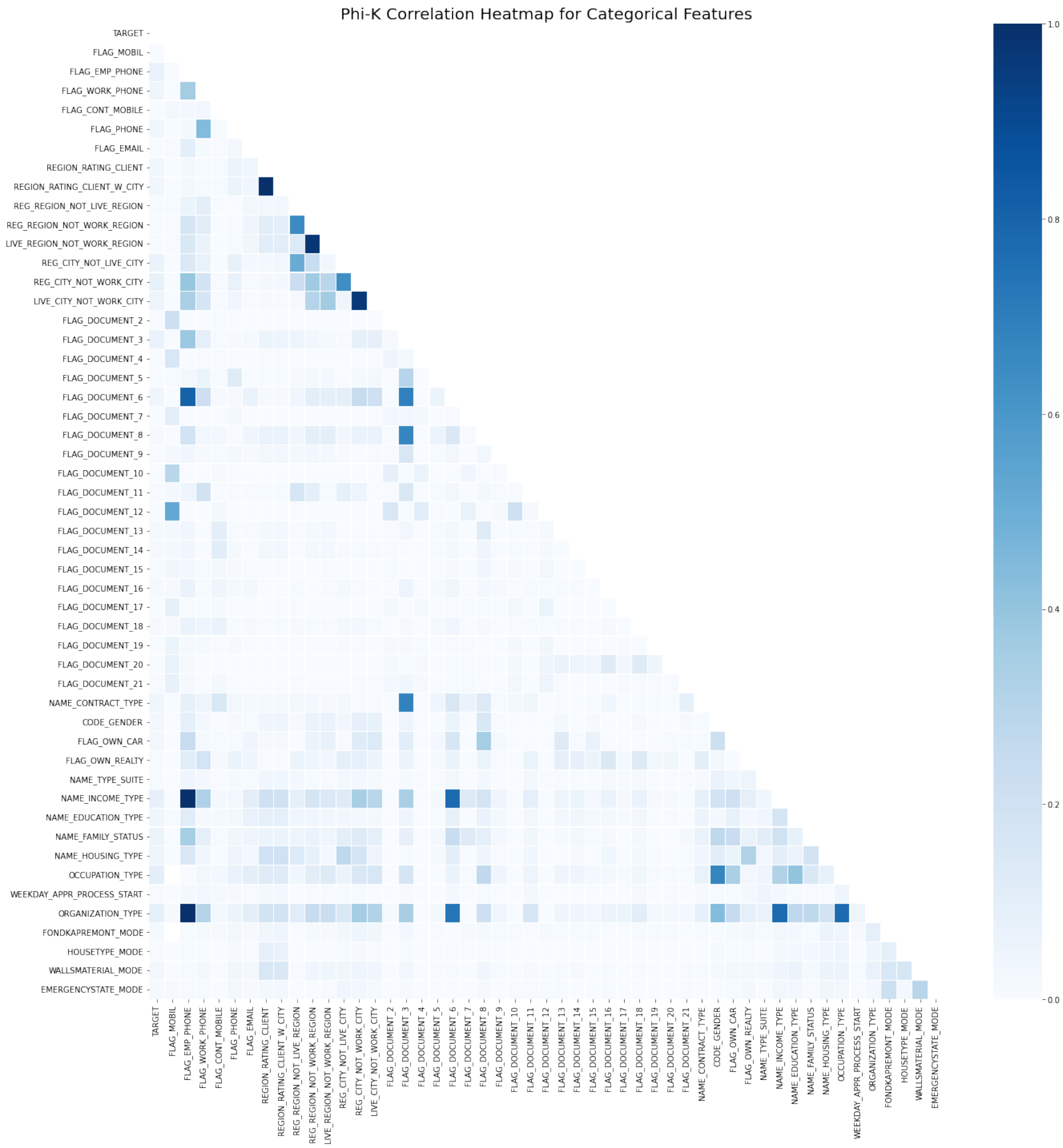
```
['ORGANIZATION_TYPE', 'OCCUPATION_TYPE', 'NAME_INCOME_TYPE',
'REGION_RATING_CLIENT_W_CITY', 'REGION_RATING_CLIENT', 'NAME_EDUCATION_TYPE',
'CODE_GENDER', 'REG_CITY_NOT_WORK_CITY', 'FLAG_EMP_PHONE',
'REG_CITY_NOT_LIVE_CITY', 'FLAG_DOCUMENT_3', 'NAME_FAMILY_STATUS',
```

```
'NAME_HOUSING_TYPE', 'LIVE_CITY_NOT_WORK_CITY', 'NAME_CONTRACT_TYPE',
'FLAG_DOCUMENT_6', 'FLAG_WORK_PHONE', 'FLAG_PHONE', 'FLAG_OWN_CAR',
'WALLSMATERIAL_MODE', 'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_13',
'FLAG_DOCUMENT_14', 'HOUSETYPE_MODE', 'EMERGENCYSTATE_MODE', 'FLAG_DOCUMENT_8',
'NAME_TYPE_SUITE', 'FLAG_DOCUMENT_18', 'REG_REGION_NOT_WORK_REGION',
'FLAG_DOCUMENT_15', 'FLAG_OWN_REALTY', 'FONDKAPREMONT_MODE',
'REG_REGION_NOT_LIVE_REGION', 'FLAG_DOCUMENT_2', 'WEEKDAY_APPR_PROCESS_START',
'FLAG_DOCUMENT_9', 'FLAG_DOCUMENT_11']
```

Combining phi-k correlation for judging the most significant categorical variables.

[53]:
```
plot_phik_matrix(app_train, ['TARGET']+CATEGORICAL_FEATS)
```

```
---------------------------------------------------------------------------------
--------------------
```



Categories with highest values of Phi-K Correlation value with Target Variable are:

	Column Name	Phik-Correlation
43	OCCUPATION_TYPE	0.102846
45	ORGANIZATION_TYPE	0.089164
39	NAME_INCOME_TYPE	0.084831
12	REG_CITY_NOT_WORK_CITY	0.079946
1	FLAG_EMP_PHONE	0.072087

```
11   REG_CITY_NOT_LIVE_CITY          0.069588
15          FLAG_DOCUMENT_3          0.069525
41        NAME_FAMILY_STATUS         0.056043
42         NAME_HOUSING_TYPE         0.051107
13  LIVE_CITY_NOT_WORK_CITY          0.050956

--------------------------------------------------------------------------------
--------------------
```

High-correlated Features: (these features we can just select one of them, due to the high colinearity) 1. REGION_RATING_CLIENT_W_CITY & REGION_RATING_CLIENT (keep **REGION_RATING_CLIENT_W_CITY**, due to lower p-value) 2. LIVE_REGION_NOT_WORK_REGION & REG_REGION_NOT_WORK_REGION (not necessay to keep both) 3. LIVE_CITY_NOT_WORK_CITY & REG_CITY_NOT_WORK_CITY (keep **REG_CITY_NOT_WORK_CITY**, due to lower p-value & higher Phik-correlation) 4. NAME_INCOME_TYPE & FLAG_EMP_PHONE (keep **NAME_INCOME_TYPE**) 5. ORGANIZATION_TYPE & FLAG_EMP_PHONE (keep **ORGANIZATION_TYPE**)

Finally, we can select:

[‘ORGANIZATION_TYPE’, ‘OCCUPATION_TYPE’, ‘NAME_INCOME_TYPE’, ‘REGION_RATING_CLIENT_W_CITY’, ‘NAME_EDUCATION_TYPE’, ‘CODE_GENDER’, ‘REG_CITY_NOT_WORK_CITY’, ‘REG_CITY_NOT_LIVE_CITY’, ‘FLAG_DOCUMENT_3’, ‘NAME_FAMILY_STATUS’, ‘NAME_HOUSING_TYPE’, ‘LIVE_CITY_NOT_WORK_CITY’]

```
12 categorical columns into our selected features.
```

Numerical features correlation heatmap

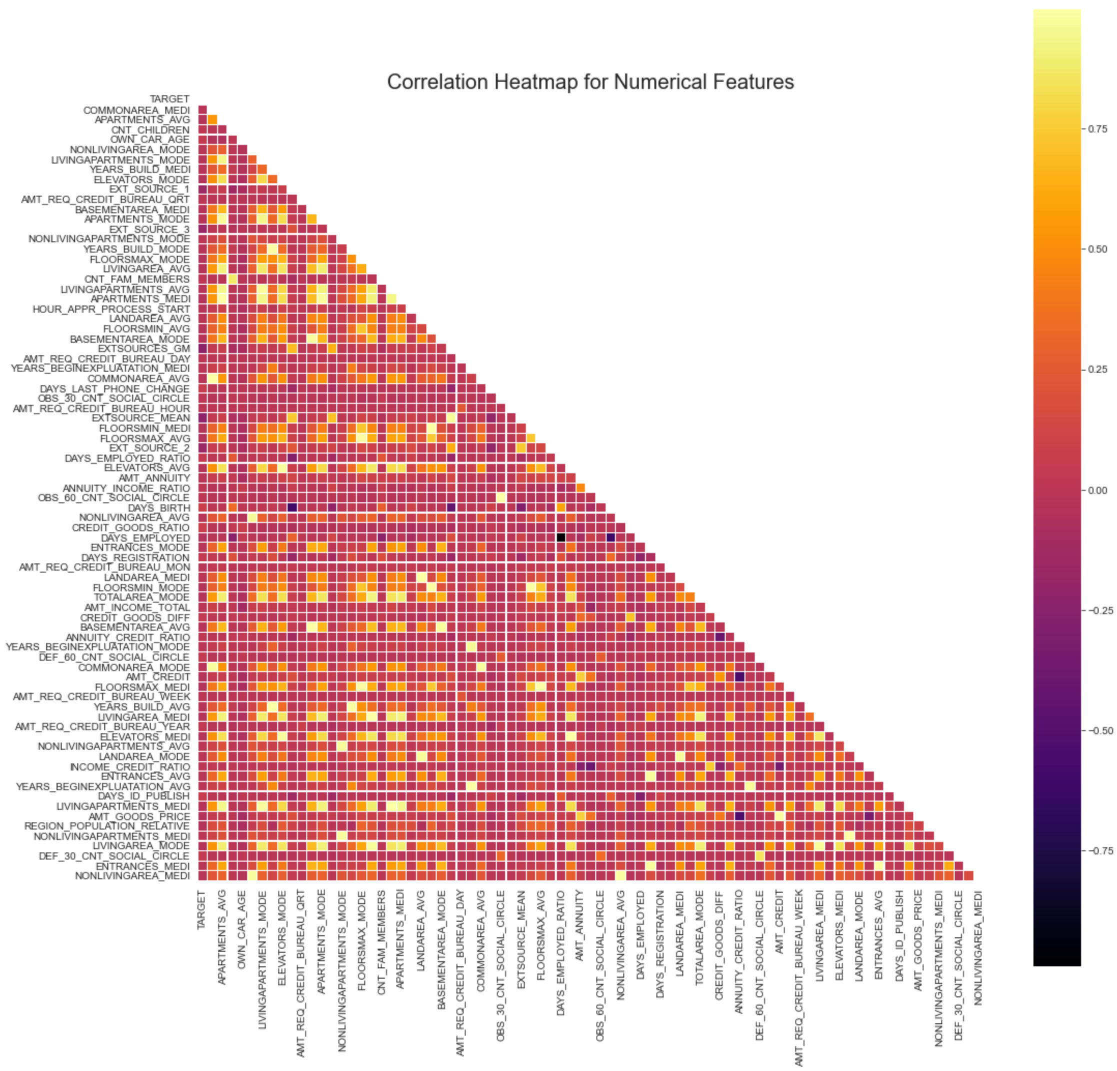
[54]:
```python
# "pure-numerical type"
NUMERICAL_FEATS = list(set(app_train_feats.columns)-set(CATEGORICAL_FEATS))
print(NUMERICAL_FEATS, f'\n\nTotally {len(NUMERICAL_FEATS)} float-type features.
 ↪')
```

```
['COMMONAREA_MEDI', 'APARTMENTS_AVG', 'CNT_CHILDREN', 'OWN_CAR_AGE',
'NONLIVINGAREA_MODE', 'LIVINGAPARTMENTS_MODE', 'YEARS_BUILD_MEDI',
'ELEVATORS_MODE', 'EXT_SOURCE_1', 'AMT_REQ_CREDIT_BUREAU_QRT',
'BASEMENTAREA_MEDI', 'APARTMENTS_MODE', 'EXT_SOURCE_3',
'NONLIVINGAPARTMENTS_MODE', 'YEARS_BUILD_MODE', 'FLOORSMAX_MODE',
'LIVINGAREA_AVG', 'CNT_FAM_MEMBERS', 'LIVINGAPARTMENTS_AVG', 'APARTMENTS_MEDI',
'HOUR_APPR_PROCESS_START', 'LANDAREA_AVG', 'FLOORSMIN_AVG', 'BASEMENTAREA_MODE',
'EXTSOURCES_GM', 'AMT_REQ_CREDIT_BUREAU_DAY', 'YEARS_BEGINEXPLUATATION_MEDI',
'COMMONAREA_AVG', 'DAYS_LAST_PHONE_CHANGE', 'OBS_30_CNT_SOCIAL_CIRCLE',
'AMT_REQ_CREDIT_BUREAU_HOUR', 'EXTSOURCE_MEAN', 'FLOORSMIN_MEDI',
'FLOORSMAX_AVG', 'EXT_SOURCE_2', 'DAYS_EMPLOYED_RATIO', 'ELEVATORS_AVG',
'AMT_ANNUITY', 'ANNUITY_INCOME_RATIO', 'OBS_60_CNT_SOCIAL_CIRCLE', 'DAYS_BIRTH',
'NONLIVINGAREA_AVG', 'CREDIT_GOODS_RATIO', 'DAYS_EMPLOYED', 'ENTRANCES_MODE',
'DAYS_REGISTRATION', 'AMT_REQ_CREDIT_BUREAU_MON', 'LANDAREA_MEDI',
```

```
'FLOORSMIN_MODE', 'TOTALAREA_MODE', 'AMT_INCOME_TOTAL', 'CREDIT_GOODS_DIFF',
'BASEMENTAREA_AVG', 'ANNUITY_CREDIT_RATIO', 'YEARS_BEGINEXPLUATATION_MODE',
'DEF_60_CNT_SOCIAL_CIRCLE', 'COMMONAREA_MODE', 'AMT_CREDIT', 'FLOORSMAX_MEDI',
'AMT_REQ_CREDIT_BUREAU_WEEK', 'YEARS_BUILD_AVG', 'LIVINGAREA_MEDI',
'AMT_REQ_CREDIT_BUREAU_YEAR', 'ELEVATORS_MEDI', 'NONLIVINGAPARTMENTS_AVG',
'LANDAREA_MODE', 'INCOME_CREDIT_RATIO', 'ENTRANCES_AVG',
'YEARS_BEGINEXPLUATATION_AVG', 'DAYS_ID_PUBLISH', 'LIVINGAPARTMENTS_MEDI',
'AMT_GOODS_PRICE', 'REGION_POPULATION_RELATIVE', 'NONLIVINGAPARTMENTS_MEDI',
'LIVINGAREA_MODE', 'DEF_30_CNT_SOCIAL_CIRCLE', 'ENTRANCES_MEDI',
'NONLIVINGAREA_MEDI']

Totally 78 float-type features.
```

[55]:

```python
corr_mat = plot_numerical_heatmap(app_train, ['TARGET']+NUMERICAL_FEATS)
corr_mat
```



[55]:

```
                              TARGET  COMMONAREA_MEDI  APARTMENTS_AVG  \
TARGET                      1.000000        -0.018573       -0.029498
COMMONAREA_MEDI            -0.018573         1.000000        0.539610
APARTMENTS_AVG             -0.029498         0.539610        1.000000
CNT_CHILDREN                0.019187         0.000609       -0.013222
OWN_CAR_AGE                 0.037612        -0.035066       -0.051177
…                                …              …              …
NONLIVINGAPARTMENTS_MEDI -0.002757         0.105944        0.192635
LIVINGAREA_MODE            -0.030685         0.527076        0.893463
DEF_30_CNT_SOCIAL_CIRCLE    0.032248        -0.012343       -0.013608
ENTRANCES_MEDI             -0.019025         0.326372        0.607629
NONLIVINGAREA_MEDI         -0.013337         0.228645        0.297454

                          CNT_CHILDREN  OWN_CAR_AGE  NONLIVINGAREA_MODE  \
TARGET                        0.019187     0.037612           -0.012711
COMMONAREA_MEDI               0.000609    -0.035066            0.218972
APARTMENTS_AVG               -0.013222    -0.051177            0.284942
CNT_CHILDREN                  1.000000     0.008494            0.000231
OWN_CAR_AGE                   0.008494     1.000000           -0.027811
…                                  …           …                  …
NONLIVINGAPARTMENTS_MEDI      0.004133    -0.024251            0.210271
LIVINGAREA_MODE              -0.009517    -0.055302            0.295725
DEF_30_CNT_SOCIAL_CIRCLE     -0.001262     0.008868           -0.009908
ENTRANCES_MEDI               -0.008325    -0.017280            0.170664
NONLIVINGAREA_MEDI            0.000061    -0.030684            0.975839

                          LIVINGAPARTMENTS_MODE  YEARS_BUILD_MEDI  \
TARGET                                -0.023393         -0.022326
COMMONAREA_MEDI                        0.529557          0.232778
APARTMENTS_AVG                         0.930554          0.339670
CNT_CHILDREN                          -0.007955          0.030124
OWN_CAR_AGE                           -0.044226         -0.048787
…                                          …                …
NONLIVINGAPARTMENTS_MEDI               0.142787          0.069126
LIVINGAREA_MODE                        0.878471          0.337614
DEF_30_CNT_SOCIAL_CIRCLE              -0.014732         -0.010672
ENTRANCES_MEDI                         0.574676          0.087491
NONLIVINGAREA_MEDI                     0.287765          0.125151

                          ELEVATORS_MODE  EXT_SOURCE_1  …  \
TARGET                         -0.032131     -0.155317  …
COMMONAREA_MEDI                 0.507060      0.032147  …
APARTMENTS_AVG                  0.822553      0.054034  …
CNT_CHILDREN                   -0.006397     -0.138470  …
OWN_CAR_AGE                    -0.061365     -0.083411  …
…                                   …             …  …
```

```
NONLIVINGAPARTMENTS_MEDI        0.114100      0.015263  …
LIVINGAREA_MODE                 0.855978      0.062046  …
DEF_30_CNT_SOCIAL_CIRCLE       -0.020207     -0.028751  …
ENTRANCES_MEDI                  0.404202      0.021488  …
NONLIVINGAREA_MEDI              0.275252      0.030375  …

                          YEARS_BEGINEXPLUATATION_AVG  DAYS_ID_PUBLISH  \
TARGET                                      -0.009728         0.051457
COMMONAREA_MEDI                              0.091667         0.000372
APARTMENTS_AVG                               0.100098        -0.007322
CNT_CHILDREN                                 0.006902        -0.028019
OWN_CAR_AGE                                  0.000418         0.008633
…                                                   …                …
NONLIVINGAPARTMENTS_MEDI                     0.034079        -0.003288
LIVINGAREA_MODE                              0.089123        -0.012096
DEF_30_CNT_SOCIAL_CIRCLE                    -0.005107         0.002738
ENTRANCES_MEDI                               0.041334        -0.015647
NONLIVINGAREA_MEDI                           0.008453         0.002488

                          LIVINGAPARTMENTS_MEDI  AMT_GOODS_PRICE  \
TARGET                                -0.024621        -0.039645
COMMONAREA_MEDI                        0.536985         0.049519
APARTMENTS_AVG                         0.941907         0.064918
CNT_CHILDREN                          -0.007962        -0.001827
OWN_CAR_AGE                           -0.050121        -0.103733
…                                             …                …
NONLIVINGAPARTMENTS_MEDI               0.157284         0.014381
LIVINGAREA_MODE                        0.857379         0.069324
DEF_30_CNT_SOCIAL_CIRCLE              -0.014474        -0.022244
ENTRANCES_MEDI                         0.567221         0.017585
NONLIVINGAREA_MEDI                     0.292943         0.039874

                          REGION_POPULATION_RELATIVE  \
TARGET                                     -0.037227
COMMONAREA_MEDI                             0.160275
APARTMENTS_AVG                              0.205942
CNT_CHILDREN                               -0.025573
OWN_CAR_AGE                                -0.081429
…                                                  …
NONLIVINGAPARTMENTS_MEDI                    0.021873
LIVINGAREA_MODE                             0.180932
DEF_30_CNT_SOCIAL_CIRCLE                    0.006329
ENTRANCES_MEDI                              0.033628
NONLIVINGAREA_MEDI                          0.066060

                          NONLIVINGAPARTMENTS_MEDI  LIVINGAREA_MODE  \
TARGET                                   -0.002757        -0.030685
```

```
COMMONAREA_MEDI                          0.105944         0.527076
APARTMENTS_AVG                           0.192635         0.893463
CNT_CHILDREN                             0.004133        -0.009517
OWN_CAR_AGE                             -0.024251        -0.055302
…                                             …              …
NONLIVINGAPARTMENTS_MEDI                 1.000000         0.128294
LIVINGAREA_MODE                          0.128294         1.000000
DEF_30_CNT_SOCIAL_CIRCLE                 0.004370        -0.014851
ENTRANCES_MEDI                           0.062346         0.622235
NONLIVINGAREA_MEDI                       0.218105         0.290368

                          DEF_30_CNT_SOCIAL_CIRCLE  ENTRANCES_MEDI  \
TARGET                                    0.032248       -0.019025
COMMONAREA_MEDI                          -0.012343        0.326372
APARTMENTS_AVG                           -0.013608        0.607629
CNT_CHILDREN                             -0.001262       -0.008325
OWN_CAR_AGE                               0.008868       -0.017280
…                                             …              …
NONLIVINGAPARTMENTS_MEDI                  0.004370        0.062346
LIVINGAREA_MODE                          -0.014851        0.622235
DEF_30_CNT_SOCIAL_CIRCLE                  1.000000       -0.002537
ENTRANCES_MEDI                           -0.002537        1.000000
NONLIVINGAREA_MEDI                       -0.011062        0.165916

                          NONLIVINGAREA_MEDI
TARGET                             -0.013337
COMMONAREA_MEDI                     0.228645
APARTMENTS_AVG                      0.297454
CNT_CHILDREN                        0.000061
OWN_CAR_AGE                        -0.030684
…                                       …
NONLIVINGAPARTMENTS_MEDI            0.218105
LIVINGAREA_MODE                     0.290368
DEF_30_CNT_SOCIAL_CIRCLE           -0.011062
ENTRANCES_MEDI                      0.165916
NONLIVINGAREA_MEDI                  1.000000

[79 rows x 79 columns]
```

[56]:

```python
abs_correlation = corr_mat.abs()['TARGET'].sort_values(ascending=False)
print(f'Top-10 related \n{abs_correlation.head(10)}\n')
print('********************************************')

correlation = corr_mat['TARGET'].sort_values(ascending=False)
print(f'Top-10 positive related \n{correlation.head(10)}\n')
print(f'Top-10 negative related \n{correlation.tail(10)}')
```

```
Top-10 related
TARGET                    1.000000
EXTSOURCES_GM             0.232671
EXTSOURCE_MEAN            0.222052
EXT_SOURCE_3              0.178919
EXT_SOURCE_2              0.160472
EXT_SOURCE_1              0.155317
DAYS_BIRTH                0.078239
CREDIT_GOODS_RATIO        0.069427
DAYS_LAST_PHONE_CHANGE    0.055218
DAYS_ID_PUBLISH           0.051457
Name: TARGET, dtype: float64

********************************************
Top-10 positive related
TARGET                      1.000000
DAYS_BIRTH                  0.078239
CREDIT_GOODS_RATIO          0.069427
DAYS_LAST_PHONE_CHANGE      0.055218
DAYS_ID_PUBLISH             0.051457
DAYS_EMPLOYED_RATIO         0.042206
DAYS_REGISTRATION           0.041975
OWN_CAR_AGE                 0.037612
CREDIT_GOODS_DIFF           0.034254
DEF_30_CNT_SOCIAL_CIRCLE    0.032248
Name: TARGET, dtype: float64

Top-10 negative related
AMT_GOODS_PRICE   -0.039645
FLOORSMAX_MODE    -0.043226
FLOORSMAX_MEDI    -0.043768
FLOORSMAX_AVG     -0.044003
DAYS_EMPLOYED     -0.044932
EXT_SOURCE_1      -0.155317
EXT_SOURCE_2      -0.160472
EXT_SOURCE_3      -0.178919
EXTSOURCE_MEAN    -0.222052
EXTSOURCES_GM     -0.232671
Name: TARGET, dtype: float64
```

[57]:
```
abs_correlation.index[:10]
```

[57]:
```
Index(['TARGET', 'EXTSOURCES_GM', 'EXTSOURCE_MEAN', 'EXT_SOURCE_3',
       'EXT_SOURCE_2', 'EXT_SOURCE_1', 'DAYS_BIRTH', 'CREDIT_GOODS_RATIO',
       'DAYS_LAST_PHONE_CHANGE', 'DAYS_ID_PUBLISH'],
      dtype='object')
```

if we choose 0.05 as our correlation threshold, we can select:

['EXT_SOURCE_3', 'EXT_SOURCE_2', 'EXT_SOURCE_1', 'DAYS_BIRTH','DAYS_LAST_PHONE_CHANGE', 'DAYS_ID_PUBLISH']

6 numerical columns into our selected features.

Summarization:

Totally select 18 features for app_train | test data. (120 features reduced to 18 features!!!)

['EXT_SOURCE_3', 'EXT_SOURCE_2', 'EXT_SOURCE_1', 'DAYS_BIRTH','DAYS_LAST_PHONE_CHANGE', 'DAYS_ID_PUBLISH', 'ORGANIZATION_TYPE', 'OCCUPATION_TYPE', 'NAME_INCOME_TYPE', 'REGION_RATING_CLIENT_W_CITY', 'NAME_EDUCATION_TYPE', 'CODE_GENDER', 'REG_CITY_NOT_WORK_CITY', 'REG_CITY_NOT_LIVE_CITY', 'FLAG_DOCUMENT_3', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'LIVE_CITY_NOT_WORK_CITY']

0.2.2 Explore the overlap of other csv

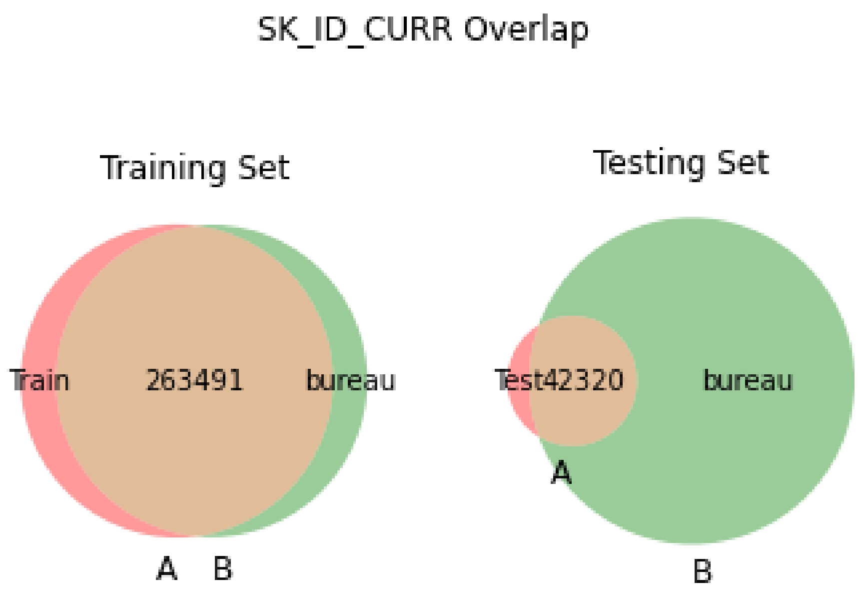
[94]:
```
bureau = pd.read_csv(bureau_dir)
bureau_balance = pd.read_csv(bureau_balance_dir)
pos_cash_balance = pd.read_csv(pos_cash_balance_dir)
credit_card_balance = pd.read_csv(credit_card_balance_dir)
previous_application = pd.read_csv(previous_application_dir)
installments_payments = pd.read_csv(installments_payments_dir)
# !pip install matplotlib_venn


from matplotlib_venn import venn2

def check_SK_ID_CURR_overlap(df,name):
    '''
    Check the number of SK_ID_CURR overlap the supporting table has with the␣
 ↪training and testing set
    '''
    unique_loan_df = len(df.SK_ID_CURR.unique())
    print(f'Number of unique SK_ID_CURR in table are: {unique_loan_df}')
    print('-'*50)
    unique_loan_app_train = len(app_train.SK_ID_CURR.unique())
    unique_loan_overlap1 = len(set(app_train.SK_ID_CURR.unique()).
 ↪intersection(set(df.SK_ID_CURR.unique())))
    print(f'{len(set(app_train.SK_ID_CURR.unique()).intersection(set(df.
 ↪SK_ID_CURR.unique())))} application_train.csv')
    unique_loan_app_test = len(app_test.SK_ID_CURR.unique())
    unique_loan_overlap2 = len(set(app_test.SK_ID_CURR.unique()).
 ↪intersection(set(df.SK_ID_CURR.unique())))
    print(f'{len(set(app_test.SK_ID_CURR.unique()).intersection(set(df.
 ↪SK_ID_CURR.unique())))} SK_ID_CURR overlap with application_test.csv')
```

```
    print('-'*50)

    plt.style.use('seaborn-pastel')

    fig, (ax1, ax2) = plt.subplots(1, 2)
    fig.suptitle('SK_ID_CURR Overlap')

    v =␣
 ↪venn2(subsets=(unique_loan_app_train-unique_loan_overlap1,unique_loan_df-unique_loan_overla
    v.get_label_by_id('100').set_text('Train')
    v.get_label_by_id('010').set_text(name)
    ax1.set_title('Training Set')

    v2 =␣
 ↪venn2(subsets=(unique_loan_app_test-unique_loan_overlap2,unique_loan_df-unique_loan_overlap
    v2.get_label_by_id('100').set_text('Test')
    v2.get_label_by_id('010').set_text(name)

    ax2.set_title('Testing Set')
    fig.show()
```

0.2.3 bureau.csv

[95]:
```
check_SK_ID_CURR_overlap(bureau,'bureau')
```

```
Number of unique SK_ID_CURR in table are: 305811
--------------------------------------------------
263491 application_train.csv
42320 SK_ID_CURR overlap with application_test.csv
--------------------------------------------------
```



0.2.4 bureau_balance.csv

[59]:
```
#bureau_balance
```

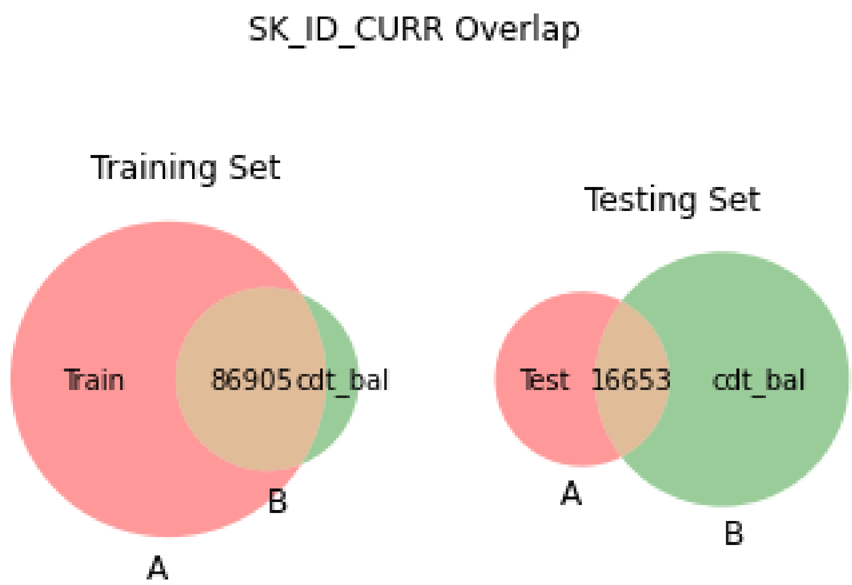
0.2.5 POS_CASH_balance.csv

[60]:
```
#pos_cash_balance
```

0.2.6 credit_card_balance.csv

[96]:
```
#credit_card_balance
check_SK_ID_CURR_overlap(credit_card_balance,'cdt_bal')
```

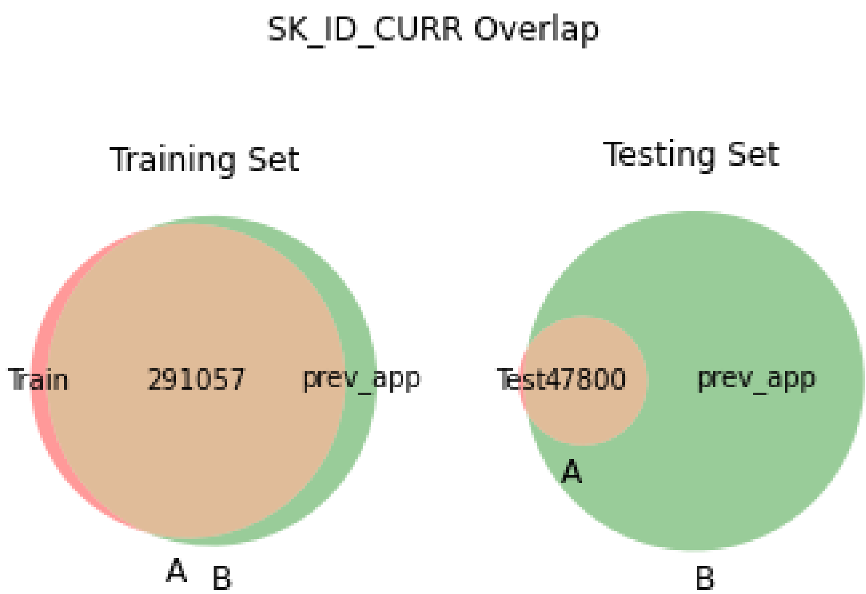
```
Number of unique SK_ID_CURR in table are: 103558
--------------------------------------------------
86905 application_train.csv
16653 SK_ID_CURR overlap with application_test.csv
--------------------------------------------------
```



0.2.7 previous_application.csv

[97]:
```
#previous_application
check_SK_ID_CURR_overlap(previous_application,'prev_app')
```

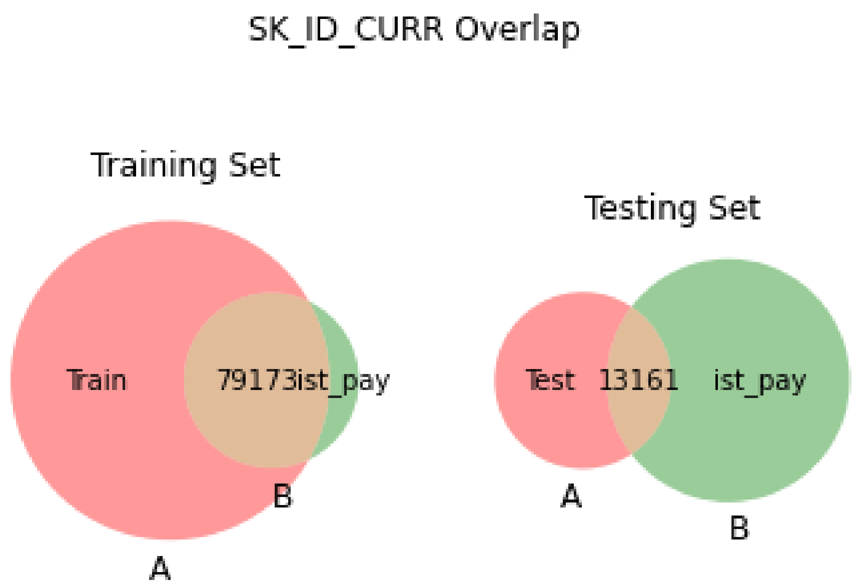
```
Number of unique SK_ID_CURR in table are: 338857
--------------------------------------------------
291057 application_train.csv
47800 SK_ID_CURR overlap with application_test.csv
--------------------------------------------------
```



0.2.8 installments_payments.csv

[98]:
```
#installments_payments
check_SK_ID_CURR_overlap(installments_payments,'ist_pay')
```

```
Number of unique SK_ID_CURR in table are: 92334
--------------------------------------------------
79173 application_train.csv
13161 SK_ID_CURR overlap with application_test.csv
--------------------------------------------------
```



[ ]:

0.3 Data Preprocessing & Feature Engineering

0.3.1 1. app_{train | test} dataset

Missing Value processing

[64]:
```
CATE_FEATS = ['ORGANIZATION_TYPE', 'OCCUPATION_TYPE', 'NAME_INCOME_TYPE',␣
 ↪'REGION_RATING_CLIENT_W_CITY', 'NAME_EDUCATION_TYPE', 'CODE_GENDER',␣
 ↪'REG_CITY_NOT_WORK_CITY', 'REG_CITY_NOT_LIVE_CITY', 'FLAG_DOCUMENT_3',␣
 ↪'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'LIVE_CITY_NOT_WORK_CITY']
NUM_FEATS = ['EXT_SOURCE_3', 'EXT_SOURCE_2', 'EXT_SOURCE_1', 'DAYS_BIRTH',␣
 ↪'DAYS_LAST_PHONE_CHANGE',␣
 ↪'DAYS_ID_PUBLISH','DAYS_EMPLOYED_RATIO','EXTSOURCE_MEAN','EXTSOURCES_GM','ANNUITY_CREDIT_RA

app_features = CATE_FEATS + NUM_FEATS

app_train_cate_df = app_train[CATE_FEATS].astype('object')    # convert␣
 ↪mixed-type to unique "object" type
app_train_num_df = app_train[NUM_FEATS]

app_test_cate_df = app_test[CATE_FEATS].astype('object')
app_test_num_df = app_test[NUM_FEATS]
```

[65]:
```
app_train_feats_reduced = pd.concat([app_train_cate_df, app_train_num_df],␣
 ↪axis=1)    # train features!!!
```

```python
app_train_df = pd.concat([app_train_id, app_train_target,␣
↪app_train_feats_reduced], axis=1)

app_test_feats_reduced = pd.concat([app_test_cate_df, app_test_num_df], axis=1)␣
↪   # test features!!!
app_test_df = pd.concat([app_test_id, app_test_feats_reduced], axis=1)

app_train_df.head()
```

[65]:

```
   SK_ID_CURR  TARGET       ORGANIZATION_TYPE OCCUPATION_TYPE  \
0      100002       1  Business Entity Type 3        Laborers
1      100003       0                  School      Core staff
2      100004       0              Government        Laborers
3      100006       0  Business Entity Type 3        Laborers
4      100007       0                Religion      Core staff

  NAME_INCOME_TYPE REGION_RATING_CLIENT_W_CITY            NAME_EDUCATION_TYPE  \
0          Working                           2  Secondary / secondary special
1    State servant                           1               Higher education
2          Working                           2  Secondary / secondary special
3          Working                           2  Secondary / secondary special
4          Working                           2  Secondary / secondary special

  CODE_GENDER REG_CITY_NOT_WORK_CITY REG_CITY_NOT_LIVE_CITY  …  \
0           M                      0                      0  …
1           F                      0                      0  …
2           M                      0                      0  …
3           F                      0                      0  …
4           M                      1                      0  …

  DAYS_LAST_PHONE_CHANGE DAYS_ID_PUBLISH DAYS_EMPLOYED_RATIO EXTSOURCE_MEAN  \
0                -1134.0           -2120            0.067329       0.161787
1                 -828.0            -291            0.070862       0.466757
2                 -815.0           -2531            0.011814       0.642739
3                 -617.0           -2437            0.159905       0.650442
4                -1106.0           -3458            0.152418       0.322738

   EXTSOURCES_GM  ANNUITY_CREDIT_RATIO  ANNUITY_INCOME_RATIO  \
0       0.144914              0.060749              0.121978
1            NaN              0.027598              0.132217
2            NaN              0.050000              0.100000
3            NaN              0.094941              0.219900
4            NaN              0.042623              0.179963

   INCOME_CREDIT_RATIO  CREDIT_GOODS_RATIO  CREDIT_GOODS_DIFF
0             0.498036            1.158397            55597.5
1             0.208736            1.145199           164002.5
```

```
2            0.500000           1.000000              0.0
3            0.431748           1.052803          15682.5
4            0.236842           1.000000              0.0

[5 rows x 28 columns]
```

[66]:

```python
# app_train_df
count_miss_train1 = count_missing_value(app_train_df, print_info=True)
count_miss_train1
```

```
There are 28 columns in total
There are 11 columns have miss values
```

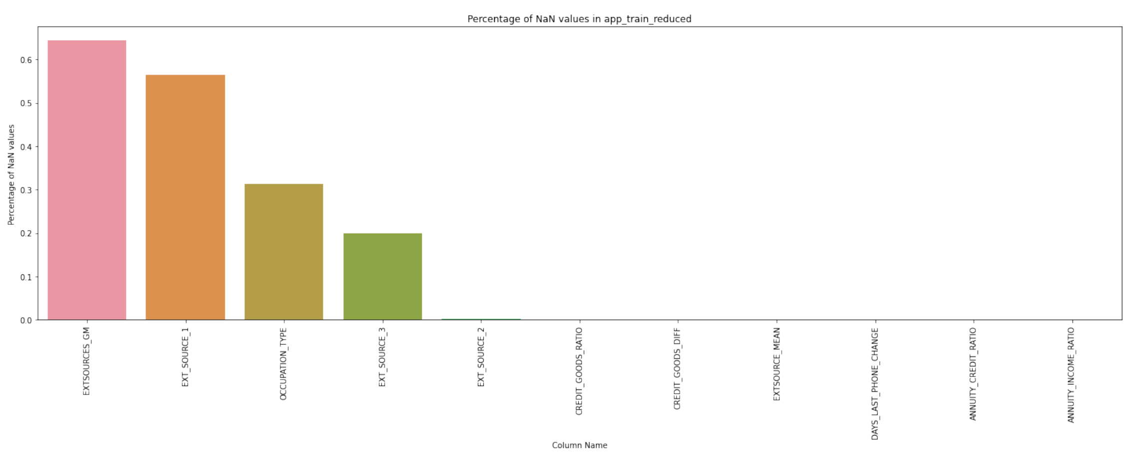
[66]:

	miss_value	% miss_percentage
EXTSOURCES_GM	197922	0.6436
EXT_SOURCE_1	173378	0.5638
OCCUPATION_TYPE	96391	0.3135
EXT_SOURCE_3	60965	0.1983
EXT_SOURCE_2	660	0.0021
CREDIT_GOODS_RATIO	278	0.0009
CREDIT_GOODS_DIFF	278	0.0009
EXTSOURCE_MEAN	172	0.0006
DAYS_LAST_PHONE_CHANGE	1	0.0000
ANNUITY_CREDIT_RATIO	12	0.0000
ANNUITY_INCOME_RATIO	12	0.0000

[67]:

```python
plot_missing(count_miss_train1, 'app_train_reduced')
```

```
Number of columns having NaN values: 11 columns
```



[68]:

```python
# app_test_df
count_miss_test1 = count_missing_value(app_test_df, print_info=True)
```

```
count_miss_test1
```

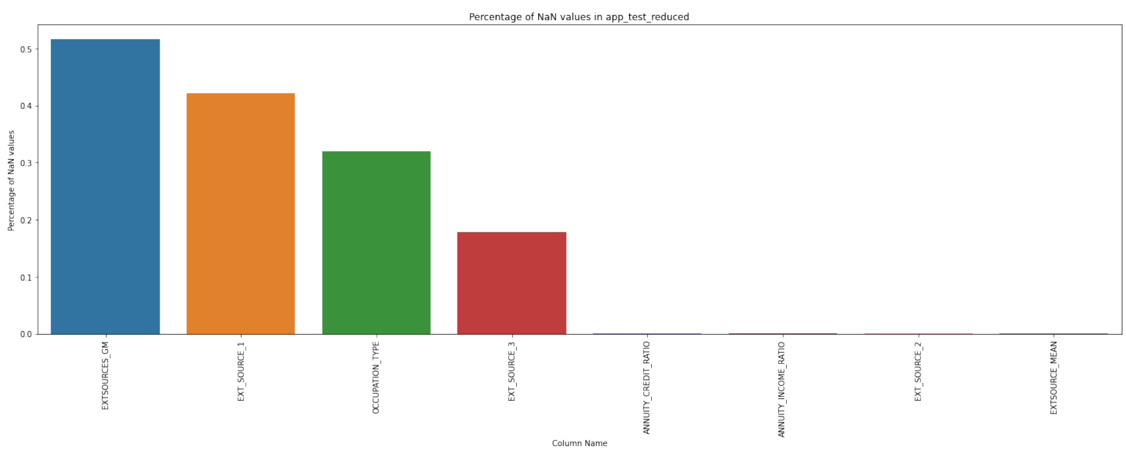
```
There are 27 columns in total
There are 8 columns have miss values
```

[68]:

	miss_value	% miss_percentage
EXTSOURCES_GM	25160	0.5162
EXT_SOURCE_1	20532	0.4212
OCCUPATION_TYPE	15605	0.3201
EXT_SOURCE_3	8668	0.1778
ANNUITY_CREDIT_RATIO	24	0.0005
ANNUITY_INCOME_RATIO	24	0.0005
EXT_SOURCE_2	8	0.0002
EXTSOURCE_MEAN	7	0.0001

[69]:
```
plot_missing(count_miss_test1, 'app_test_reduced')
```

```
Number of columns having NaN values: 8 columns
```



For categorical values, we can use a string ‘Missing’ (as another category for augmentation) to fill NaN values.

For numerical values, we can use mean value to simply fill NaN values.

[70]:
```
# app_train_df
# MISSING_COLS_train =␣
↪['EXT_SOURCE_1','OCCUPATION_TYPE','EXT_SOURCE_3','EXT_SOURCE_2','DAYS_LAST_PHONE_CHANGE',]
MISSING_COLS_train = count_miss_train1.index.to_list()

for each_col in MISSING_COLS_train:
    if each_col in CATE_FEATS:
        app_train_df[each_col] = app_train_df[each_col].fillna('Missing')
    elif each_col in NUM_FEATS:
```

```
        app_train_df[each_col] = app_train_df[each_col].replace(np.NaN,␣
↪app_train_df[each_col].mean())

app_train_df.head()
```

[70]:

```
   SK_ID_CURR  TARGET       ORGANIZATION_TYPE OCCUPATION_TYPE  \
0      100002       1  Business Entity Type 3        Laborers
1      100003       0                  School      Core staff
2      100004       0              Government        Laborers
3      100006       0  Business Entity Type 3        Laborers
4      100007       0                Religion      Core staff

  NAME_INCOME_TYPE REGION_RATING_CLIENT_W_CITY            NAME_EDUCATION_TYPE  \
0          Working                           2  Secondary / secondary special
1    State servant                           1               Higher education
2          Working                           2  Secondary / secondary special
3          Working                           2  Secondary / secondary special
4          Working                           2  Secondary / secondary special

  CODE_GENDER REG_CITY_NOT_WORK_CITY REG_CITY_NOT_LIVE_CITY  …  \
0           M                      0                      0  …
1           F                      0                      0  …
2           M                      0                      0  …
3           F                      0                      0  …
4           M                      1                      0  …

  DAYS_LAST_PHONE_CHANGE DAYS_ID_PUBLISH DAYS_EMPLOYED_RATIO EXTSOURCE_MEAN  \
0                -1134.0           -2120            0.067329       0.161787
1                 -828.0            -291            0.070862       0.466757
2                 -815.0           -2531            0.011814       0.642739
3                 -617.0           -2437            0.159905       0.650442
4                -1106.0           -3458            0.152418       0.322738

   EXTSOURCES_GM  ANNUITY_CREDIT_RATIO  ANNUITY_INCOME_RATIO  \
0       0.144914              0.060749              0.121978
1       0.483200              0.027598              0.132217
2       0.483200              0.050000              0.100000
3       0.483200              0.094941              0.219900
4       0.483200              0.042623              0.179963

   INCOME_CREDIT_RATIO  CREDIT_GOODS_RATIO  CREDIT_GOODS_DIFF
0             0.498036            1.158397            55597.5
1             0.208736            1.145199           164002.5
2             0.500000            1.000000                0.0
3             0.431748            1.052803            15682.5
4             0.236842            1.000000                0.0
```

```
[5 rows x 28 columns]
```

[71]:
```python
# app_test_df
# MISSING_COLS_test =␣
↪['EXT_SOURCE_1','OCCUPATION_TYPE','EXT_SOURCE_3','EXT_SOURCE_2']
MISSING_COLS_test = count_miss_test1.index.to_list()

for each_col in MISSING_COLS_test:
    if each_col in CATE_FEATS:
        app_test_df[each_col] = app_test_df[each_col].fillna('Missing')
    elif each_col in NUM_FEATS:
        app_test_df[each_col] = app_test_df[each_col].replace(np.NaN,␣
↪app_test_df[each_col].mean())

app_test_df.head()
```

[71]:
```
   SK_ID_CURR       ORGANIZATION_TYPE     OCCUPATION_TYPE NAME_INCOME_TYPE  \
0      100001            Kindergarten             Missing          Working
1      100005           Self-employed  Low-skill Laborers          Working
2      100013       Transport: type 3             Drivers          Working
3      100028  Business Entity Type 3         Sales staff          Working
4      100038  Business Entity Type 3             Missing          Working

  REGION_RATING_CLIENT_W_CITY            NAME_EDUCATION_TYPE CODE_GENDER  \
0                           2               Higher education           F
1                           2  Secondary / secondary special           M
2                           2               Higher education           M
3                           2  Secondary / secondary special           F
4                           2  Secondary / secondary special           M

  REG_CITY_NOT_WORK_CITY REG_CITY_NOT_LIVE_CITY FLAG_DOCUMENT_3  …  \
0                      0                      0               1  …
1                      0                      0               1  …
2                      0                      0               0  …
3                      0                      0               1  …
4                      1                      0               1  …

  DAYS_LAST_PHONE_CHANGE DAYS_ID_PUBLISH DAYS_EMPLOYED_RATIO  EXTSOURCE_MEAN  \
0                -1740.0            -812            0.121044        0.567263
1                    0.0           -1623            0.247398        0.429869
2                 -856.0           -3503            0.222477        0.655389
3                -1805.0           -4208            0.133515        0.549372
4                 -821.0           -4262            0.168021        0.313916

   EXTSOURCES_GM  ANNUITY_CREDIT_RATIO  ANNUITY_INCOME_RATIO  \
0       0.455975              0.036147              0.152300
1       0.414750              0.077973              0.175455
```

```
2       0.481913               0.105202               0.344578
3       0.547567               0.031123               0.155614
4       0.481913               0.051266               0.178150

   INCOME_CREDIT_RATIO  CREDIT_GOODS_RATIO  CREDIT_GOODS_DIFF
0             0.237342              1.2640           118800.0
1             0.444409              1.2376            42768.0
2             0.305308              1.0528            33264.0
3             0.200000              1.0000                0.0
4             0.287770              1.0000                0.0

[5 rows x 27 columns]
```

Feature instances encoding

[72]:
```
app_train_df.select_dtypes('object').apply(pd.Series.nunique).
↪sort_values(ascending=False)
```

[72]:
```
ORGANIZATION_TYPE              58
OCCUPATION_TYPE                19
NAME_INCOME_TYPE                8
NAME_HOUSING_TYPE               6
NAME_FAMILY_STATUS              6
NAME_EDUCATION_TYPE             5
CODE_GENDER                     3
REGION_RATING_CLIENT_W_CITY     3
LIVE_CITY_NOT_WORK_CITY         2
FLAG_DOCUMENT_3                 2
REG_CITY_NOT_LIVE_CITY          2
REG_CITY_NOT_WORK_CITY          2
dtype: int64
```

[73]:
```
print(app_train_df.shape)
print(app_test_df.shape)
```

```
(307511, 28)
(48744, 27)
```

[74]:
```
BI_CLASSES = ['REG_CITY_NOT_WORK_CITY', 'REG_CITY_NOT_LIVE_CITY',␣
↪'FLAG_DOCUMENT_3', 'LIVE_CITY_NOT_WORK_CITY']
MULTI_CLASSES = ['ORGANIZATION_TYPE', 'OCCUPATION_TYPE', 'NAME_INCOME_TYPE',␣
↪'REGION_RATING_CLIENT_W_CITY', 'NAME_EDUCATION_TYPE', 'CODE_GENDER',␣
↪'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE']

app_train_df = feature_class_encoding(app_train_df, BI_CLASSES, MULTI_CLASSES)
app_test_df = feature_class_encoding(app_test_df, BI_CLASSES, MULTI_CLASSES)
```

```
(307511, 128)
```

```
(48744, 125)
```

[75]:
```
app_train_df.head()
```

[75]:
```
   SK_ID_CURR  TARGET  REG_CITY_NOT_WORK_CITY  REG_CITY_NOT_LIVE_CITY  \
0      100002       1                       0                       0
1      100003       0                       0                       0
2      100004       0                       0                       0
3      100006       0                       0                       0
4      100007       0                       1                       0

   FLAG_DOCUMENT_3  LIVE_CITY_NOT_WORK_CITY  EXT_SOURCE_3  EXT_SOURCE_2  \
0                1                        0      0.139376      0.262949
1                1                        0      0.510853      0.622246
2                0                        0      0.729567      0.555912
3                1                        0      0.510853      0.650442
4                0                        1      0.510853      0.322738

   EXT_SOURCE_1  DAYS_BIRTH  …  NAME_FAMILY_STATUS_Separated  \
0      0.083037       -9461  …                             0
1      0.311267      -16765  …                             0
2      0.502130      -19046  …                             0
3      0.502130      -19005  …                             0
4      0.502130      -19932  …                             0

   NAME_FAMILY_STATUS_Single / not married  NAME_FAMILY_STATUS_Unknown  \
0                                        1                           0
1                                        0                           0
2                                        1                           0
3                                        0                           0
4                                        1                           0

   NAME_FAMILY_STATUS_Widow  NAME_HOUSING_TYPE_Co-op apartment  \
0                         0                                  0
1                         0                                  0
2                         0                                  0
3                         0                                  0
4                         0                                  0

   NAME_HOUSING_TYPE_House / apartment  NAME_HOUSING_TYPE_Municipal apartment  \
0                                    1                                      0
1                                    1                                      0
2                                    1                                      0
3                                    1                                      0
4                                    1                                      0

   NAME_HOUSING_TYPE_Office apartment  NAME_HOUSING_TYPE_Rented apartment  \
```

```
0                                      0                                      0
1                                      0                                      0
2                                      0                                      0
3                                      0                                      0
4                                      0                                      0

   NAME_HOUSING_TYPE_With parents
0                               0
1                               0
2                               0
3                               0
4                               0

[5 rows x 128 columns]
```

[76]:
```
app_test_df.head()
```

[76]:
```
   SK_ID_CURR  REG_CITY_NOT_WORK_CITY  REG_CITY_NOT_LIVE_CITY  \
0      100001                       0                       0
1      100005                       0                       0
2      100013                       0                       0
3      100028                       0                       0
4      100038                       1                       0

   FLAG_DOCUMENT_3  LIVE_CITY_NOT_WORK_CITY  EXT_SOURCE_3  EXT_SOURCE_2  \
0                1                        0      0.159520      0.789654
1                1                        0      0.432962      0.291656
2                0                        0      0.610991      0.699787
3                1                        0      0.612704      0.509677
4                1                        1      0.500106      0.425687

   EXT_SOURCE_1  DAYS_BIRTH  DAYS_LAST_PHONE_CHANGE  …  \
0      0.752614      -19241                 -1740.0  …
1      0.564990      -18064                     0.0  …
2      0.501180      -20038                  -856.0  …
3      0.525734      -13976                 -1805.0  …
4      0.202145      -13040                  -821.0  …

   NAME_FAMILY_STATUS_Married  NAME_FAMILY_STATUS_Separated  \
0                           1                             0
1                           1                             0
2                           1                             0
3                           1                             0
4                           1                             0

   NAME_FAMILY_STATUS_Single / not married  NAME_FAMILY_STATUS_Widow  \
0                                        0                         0
```

```
1                                        0                          0
2                                        0                          0
3                                        0                          0
4                                        0                          0

   NAME_HOUSING_TYPE_Co-op apartment  NAME_HOUSING_TYPE_House / apartment  \
0                                  0                                    1
1                                  0                                    1
2                                  0                                    1
3                                  0                                    1
4                                  0                                    1

   NAME_HOUSING_TYPE_Municipal apartment  NAME_HOUSING_TYPE_Office apartment  \
0                                      0                                   0
1                                      0                                   0
2                                      0                                   0
3                                      0                                   0
4                                      0                                   0

   NAME_HOUSING_TYPE_Rented apartment  NAME_HOUSING_TYPE_With parents
0                                   0                               0
1                                   0                               0
2                                   0                               0
3                                   0                               0
4                                   0                               0

[5 rows x 125 columns]
```

[77]:
```python
print(app_train_df.shape)
print(app_test_df.shape)
```

```
(307511, 128)
(48744, 125)
```

After encoding, shape: (307511, 120) (48744, 117).

Dimension of training dataset & testing dataset exists differences (since the exact classes in app_train_df & app_test_df for each features may slightly various)

[78]:
```python
app_train_features = app_train_df.drop('TARGET', axis=1)
app_train_target = app_train_df['TARGET']

#  app_train features align    app_train TARGET
app_train_features, app_test_df = app_train_features.
 ↪align(app_test_df,join='inner',axis=1)

app_train_df = pd.concat([app_train_features, app_train_target], axis=1)
```

```python
print(app_train_df.shape)
print(app_test_df.shape)
```

```
(307511, 125)
(48744, 124)
```

[79]:
```python
app_train_df.head()
```

[79]:
```
   SK_ID_CURR  REG_CITY_NOT_WORK_CITY  REG_CITY_NOT_LIVE_CITY  \
0      100002                       0                       0
1      100003                       0                       0
2      100004                       0                       0
3      100006                       0                       0
4      100007                       1                       0

   FLAG_DOCUMENT_3  LIVE_CITY_NOT_WORK_CITY  EXT_SOURCE_3  EXT_SOURCE_2  \
0                1                        0      0.139376      0.262949
1                1                        0      0.510853      0.622246
2                0                        0      0.729567      0.555912
3                1                        0      0.510853      0.650442
4                0                        1      0.510853      0.322738

   EXT_SOURCE_1  DAYS_BIRTH  DAYS_LAST_PHONE_CHANGE  …  \
0      0.083037       -9461                 -1134.0  …
1      0.311267      -16765                  -828.0  …
2      0.502130      -19046                  -815.0  …
3      0.502130      -19005                  -617.0  …
4      0.502130      -19932                 -1106.0  …

   NAME_FAMILY_STATUS_Separated  NAME_FAMILY_STATUS_Single / not married  \
0                             0                                        1
1                             0                                        0
2                             0                                        1
3                             0                                        0
4                             0                                        1

   NAME_FAMILY_STATUS_Widow  NAME_HOUSING_TYPE_Co-op apartment  \
0                         0                                  0
1                         0                                  0
2                         0                                  0
3                         0                                  0
4                         0                                  0

   NAME_HOUSING_TYPE_House / apartment  NAME_HOUSING_TYPE_Municipal apartment  \
0                                    1                                      0
1                                    1                                      0
2                                    1                                      0
```

```
3                                     1                                       0
4                                     1                                       0

   NAME_HOUSING_TYPE_Office apartment  NAME_HOUSING_TYPE_Rented apartment  \
0                                   0                                   0
1                                   0                                   0
2                                   0                                   0
3                                   0                                   0
4                                   0                                   0

   NAME_HOUSING_TYPE_With parents  TARGET
0                               0       1
1                               0       0
2                               0       0
3                               0       0
4                               0       0

[5 rows x 125 columns]
```

[ ]:

```

```

[ ]:

```

```

0.4 Model Training (LightGBM)

Before the model is trained, we need to split the data into train and test in advance. This is going to be useful to find out whether our final model suffers overfitting. To do so, we are going to employ train_test_split() function taken from Sklearn module.

[80]:

```
X = app_train_df.drop(['SK_ID_CURR', 'TARGET'], axis=1)
y = app_train_df['TARGET']

X_test = app_test_df.drop(['SK_ID_CURR'], axis=1)
```

Simple train_test_split

[81]:

```
# X = app_train_df.drop(['SK_ID_CURR', 'TARGET'], axis=1).values
# y = app_train_df['TARGET'].values

# X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=50)
# # cross-validation can also be performed!!!
```

Nomalization

[82]:

```
# Value normalization
scaler = StandardScaler()
```

```
pre_cols = X.columns
X = scaler.fit_transform(X)
X = pd.DataFrame(X, columns=pre_cols)

pre_cols1 = X_test.columns
X_test = scaler.fit_transform(X_test)
X_test = pd.DataFrame(X_test, columns=pre_cols1)
```

Model Training

[83]:
```
# # Initializing LightGBM classifier

# # lgb_clf = lgb.LGBMClassifier(n_estimators=100, class_weight='balanced',␣
↪random_state=22)
# lgb_clf = lgb.LGBMClassifier(n_estimators=1000, objective = 'binary',
#                                     class_weight = 'balanced', learning_rate =␣
↪0.05,
#                                     reg_alpha = 0.1, reg_lambda = 0.1,
#                                     subsample = 0.8, n_jobs = -1, random_state␣
↪= 50)

# # Training the LightGBM model
# lgb_clf.fit(X_train_scaled, y_train, eval_metric='auc',
#             eval_set=[(X_train_scaled, y_train),(X_test_scaled, y_test)])
```

[84]:
```
processed_col = list()
for string in X.columns:
    a = ''.join(char for char in string if char.isalnum())
    processed_col.append(a)

X.columns = processed_col



processed_col1 = list()
for string1 in X_test.columns:
    a = ''.join(char for char in string1 if char.isalnum())
    processed_col1.append(a)

X_test.columns = processed_col1
```

[161]:
```
bopt_lgbm = BayesianOptimization(lgbm_evaluation, {'num_leaves' : (25,50),
                                                   'max_depth' : (6,11),
                                                   'min_split_gain' : (0, 0.1),
                                                   'min_child_weight' : (5,80),
                                                   'min_child_samples' : (5,80),
                                                   'subsample' : (0.5,1),
```

```
                                                    'colsample_bytree' : (0.5,1),
                                                    'reg_alpha' : (0.001, 0.3),
                                                    'reg_lambda' : (0.001, 0.3)},
                                 random_state = 4976)

bayesian_optimization = bopt_lgbm.maximize(n_iter=6, init_points=4)
```

```
|   iter    |  target   | colsam… | max_depth | min_ch… | min_ch… |
min_sp… | num_le… | reg_alpha | reg_la… | subsample |
-------------------------------------------------------------------------------
-----------------------------------------------------
| 1         | 0.7668    | 0.9839    | 9.624
| 65.58     | 60.98     | 0.08223   | 39.55
| 0.1133    | 0.2049    | 0.6677    |
| 2         | 0.7675    | 0.5453    | 10.99

 | 36.09     | 42.7      | 0.02383   |

43.12     | 0.1206    | 0.1951    | 0.8343    |
| 3         | 0.7669    | 0.7313    | 9.478
| 47.08     | 53.08     | 0.0249    | 36.94
| 0.2417    | 0.1072    | 0.5916    |
| 4         | 0.7669    | 0.5671    | 7.674
| 26.69     | 8.717     | 0.004937 | 31.48
| 0.118     | 0.09472   | 0.9706    |
| 5         | 0.767     | 0.843     | 10.6
| 46.36     | 16.37     | 0.0809    | 31.43
| 0.03722   | 0.2425    | 0.8722    |
| 6         | 0.7674    | 0.6623    | 8.873
| 31.68     | 31.9      | 0.01941   | 38.28
| 0.1281    | 0.1982    | 0.7704    |
| 7         | 0.7671    | 0.9918    | 10.51
| 35.37     | 42.2      | 0.0308    | 42.03
| 0.09412   | 0.1678    | 0.8658    |
| 8         | 0.7671    | 0.6562    | 9.801
| 35.71     | 42.55     | 0.007597 | 43.33
| 0.1047    | 0.2237    | 0.6777    |
| 9         | 0.7666    | 0.6654    | 9.813
| 36.67     | 42.41     | 0.09299   | 43.6
| 0.2258    | 0.211     | 0.5138    |
| 10        | 0.767     | 0.6714    | 8.987
| 70.4      | 36.58     | 0.000376 | 36.43
| 0.2342    | 0.1167    | 0.5774    |
===============================================================================
=====================================================
```

[162]:

```
#extracting the best parameters
target_values = []
```

```
for result in bopt_lgbm.res:
    target_values.append(result['target'])
    if result['target'] == max(target_values):
        best_params = result['params']
print("Best Hyperparameters obtained are:\n")
print(best_params)
```

```
Best Hyperparameters obtained are:

{'colsample_bytree': 0.5453481803843285, 'max_depth': 10.994238196555454,
'min_child_samples': 36.094466384848104, 'min_child_weight': 42.69837589745545,
'min_split_gain': 0.023832030441816324, 'num_leaves': 43.12210378807271,
'reg_alpha': 0.12058913831355167, 'reg_lambda': 0.1951050278798116, 'subsample':
0.8343200716558421}
```

Training on Optimized Parameters

[85]:
```
params = {
        'objective' : 'binary',
        'boosting_type' : 'gbdt',
        'learning_rate' : 0.005,
        'n_estimators' : 10000,
        'n_jobs' : -1,
        'num_leaves' : 43,
        #'max_depth' : 9,
        'max_depth' :11,
        'min_split_gain' : 0.023832030441816324,
        'min_child_weight' :  42.69837589745545,
        'min_child_samples' : 36,
        'subsample': 0.8343200716558421,
        'subsample_freq' : 1,
        'colsample_bytree' : 0.5453481803843285,
        'reg_alpha' : 0.12058913831355167,
        'reg_lambda' : 0.1951050278798116,
        'verbosity' : -1,
        'seed' : 266
    }
lgbm_boosting = Boosting(X, y, X_test, params, random_state = 98,␣
 ↪save_model_to_pickle = True)
lgbm_boosting.train(booster = 'lightgbm')
```

```
Fitting the lightgbm on Training Data with 5 fold cross validation, and using
Out-Of-Folds Predictions for Cross-Validation

        Fold Number 1

Training until validation scores don't improve for 200 rounds.
[400]   training's auc: 0.761354        training's binary_logloss: 0.247609
```

```
valid_1's auc: 0.75436  valid_1's binary_logloss: 0.249467
[800]   training's auc: 0.77383 training's binary_logloss: 0.241792
valid_1's auc: 0.761221 valid_1's binary_logloss: 0.245578
[1200]  training's auc: 0.783098        training's binary_logloss: 0.238532
valid_1's auc: 0.765132 valid_1's binary_logloss: 0.244172
[1600]  training's auc: 0.790004        training's binary_logloss: 0.236222
valid_1's auc: 0.766768 valid_1's binary_logloss: 0.243614
[2000]  training's auc: 0.795969        training's binary_logloss: 0.234254
valid_1's auc: 0.767531 valid_1's binary_logloss: 0.243355
[2400]  training's auc: 0.801431        training's binary_logloss: 0.23244
valid_1's auc: 0.767976 valid_1's binary_logloss: 0.243192
[2800]  training's auc: 0.806499        training's binary_logloss: 0.230756
valid_1's auc: 0.768189 valid_1's binary_logloss: 0.2431
[3200]  training's auc: 0.811136        training's binary_logloss: 0.229186
valid_1's auc: 0.768364 valid_1's binary_logloss: 0.24303
Early stopping, best iteration is:
[3272]  training's auc: 0.811937        training's binary_logloss: 0.228907
valid_1's auc: 0.76838  valid_1's binary_logloss: 0.243025

        Fold Number 2

Training until validation scores don't improve for 200 rounds.
[400]   training's auc: 0.762487        training's binary_logloss: 0.247241
valid_1's auc: 0.749849 valid_1's binary_logloss: 0.25066
[800]   training's auc: 0.77505 training's binary_logloss: 0.24138
valid_1's auc: 0.75712  valid_1's binary_logloss: 0.246941
[1200]  training's auc: 0.78415 training's binary_logloss: 0.238141
valid_1's auc: 0.760964 valid_1's binary_logloss: 0.245654
[1600]  training's auc: 0.791084        training's binary_logloss: 0.235816
valid_1's auc: 0.762687 valid_1's binary_logloss: 0.245132
[2000]  training's auc: 0.797036        training's binary_logloss: 0.23383
valid_1's auc: 0.763783 valid_1's binary_logloss: 0.244823
[2400]  training's auc: 0.802356        training's binary_logloss: 0.232053
valid_1's auc: 0.764442 valid_1's binary_logloss: 0.244657
[2800]  training's auc: 0.807193        training's binary_logloss: 0.230403
valid_1's auc: 0.764904 valid_1's binary_logloss: 0.244531
[3200]  training's auc: 0.81176 training's binary_logloss: 0.228833
valid_1's auc: 0.765102 valid_1's binary_logloss: 0.244484
[3600]  training's auc: 0.816149        training's binary_logloss: 0.227319
valid_1's auc: 0.76526  valid_1's binary_logloss: 0.24446
Early stopping, best iteration is:
[3690]  training's auc: 0.817108        training's binary_logloss: 0.226981
valid_1's auc: 0.765332 valid_1's binary_logloss: 0.24445

        Fold Number 3

Training until validation scores don't improve for 200 rounds.
[400]   training's auc: 0.761885        training's binary_logloss: 0.247537
```

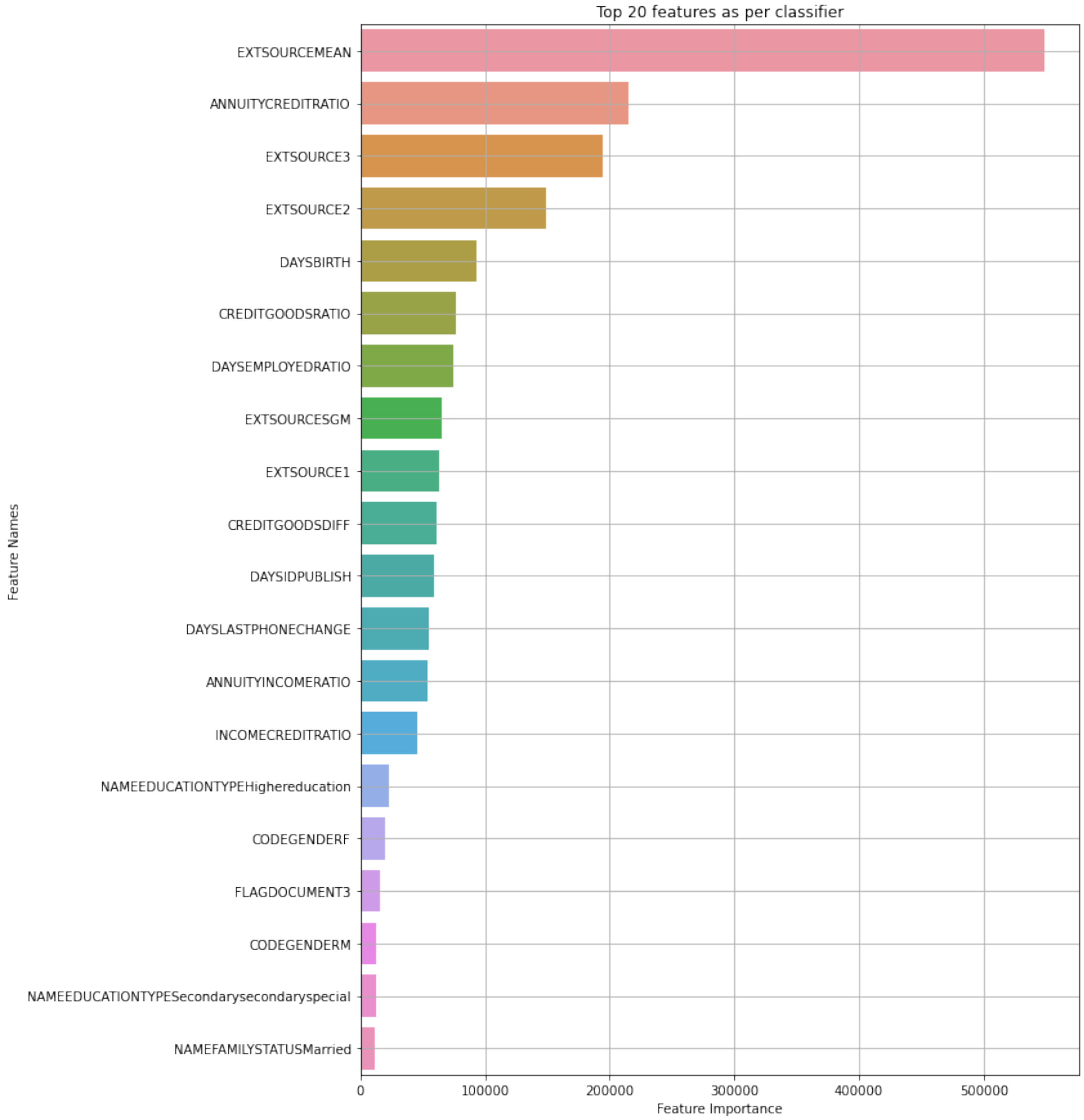
```
valid_1's auc: 0.752691 valid_1's binary_logloss: 0.249713
[800]   training's auc: 0.774188        training's binary_logloss: 0.241743
valid_1's auc: 0.759946 valid_1's binary_logloss: 0.245703
[1200]  training's auc: 0.783098        training's binary_logloss: 0.238578
valid_1's auc: 0.764034 valid_1's binary_logloss: 0.244227
[1600]  training's auc: 0.789985        training's binary_logloss: 0.236244
valid_1's auc: 0.766266 valid_1's binary_logloss: 0.243508
[2000]  training's auc: 0.795823        training's binary_logloss: 0.234304
valid_1's auc: 0.767439 valid_1's binary_logloss: 0.243133
[2400]  training's auc: 0.80118 training's binary_logloss: 0.232525
valid_1's auc: 0.768145 valid_1's binary_logloss: 0.242921
[2800]  training's auc: 0.806068        training's binary_logloss: 0.230884
valid_1's auc: 0.768495 valid_1's binary_logloss: 0.242818
[3200]  training's auc: 0.810534        training's binary_logloss: 0.229354
valid_1's auc: 0.768641 valid_1's binary_logloss: 0.242768
Early stopping, best iteration is:
[3386]  training's auc: 0.812574        training's binary_logloss: 0.228659
valid_1's auc: 0.768703 valid_1's binary_logloss: 0.242755

        Fold Number 4

Training until validation scores don't improve for 200 rounds.
[400]   training's auc: 0.76364 training's binary_logloss: 0.247078
valid_1's auc: 0.744789 valid_1's binary_logloss: 0.251009
[800]   training's auc: 0.776103        training's binary_logloss: 0.241146
valid_1's auc: 0.752196 valid_1's binary_logloss: 0.247554
[1200]  training's auc: 0.785065        training's binary_logloss: 0.237907
valid_1's auc: 0.756318 valid_1's binary_logloss: 0.246325
[1600]  training's auc: 0.79183 training's binary_logloss: 0.235572
valid_1's auc: 0.758372 valid_1's binary_logloss: 0.245803
[2000]  training's auc: 0.797613        training's binary_logloss: 0.233602
valid_1's auc: 0.759619 valid_1's binary_logloss: 0.245509
[2400]  training's auc: 0.802789        training's binary_logloss: 0.231845
valid_1's auc: 0.760371 valid_1's binary_logloss: 0.245349
[2800]  training's auc: 0.807639        training's binary_logloss: 0.230194
valid_1's auc: 0.760806 valid_1's binary_logloss: 0.245263
[3200]  training's auc: 0.812258        training's binary_logloss: 0.228625
valid_1's auc: 0.761058 valid_1's binary_logloss: 0.245221
Early stopping, best iteration is:
[3202]  training's auc: 0.812276        training's binary_logloss: 0.228619
valid_1's auc: 0.761064 valid_1's binary_logloss: 0.24522

        Fold Number 5

Training until validation scores don't improve for 200 rounds.
[400]   training's auc: 0.761213        training's binary_logloss: 0.247651
valid_1's auc: 0.754673 valid_1's binary_logloss: 0.24928
[800]   training's auc: 0.773652        training's binary_logloss: 0.241856
```

```
valid_1's auc: 0.762283 valid_1's binary_logloss: 0.245222
[1200]  training's auc: 0.782751        training's binary_logloss: 0.238632
valid_1's auc: 0.766558 valid_1's binary_logloss: 0.243681
[1600]  training's auc: 0.789655        training's binary_logloss: 0.236307
valid_1's auc: 0.768732 valid_1's binary_logloss: 0.242947
[2000]  training's auc: 0.795513        training's binary_logloss: 0.234365
valid_1's auc: 0.769891 valid_1's binary_logloss: 0.242562
[2400]  training's auc: 0.800743        training's binary_logloss: 0.232636
valid_1's auc: 0.770618 valid_1's binary_logloss: 0.242321
[2800]  training's auc: 0.805655        training's binary_logloss: 0.230994
valid_1's auc: 0.771029 valid_1's binary_logloss: 0.242163
[3200]  training's auc: 0.810178        training's binary_logloss: 0.229466
valid_1's auc: 0.771287 valid_1's binary_logloss: 0.242069
[3600]  training's auc: 0.814444        training's binary_logloss: 0.228001
valid_1's auc: 0.771471 valid_1's binary_logloss: 0.242
[4000]  training's auc: 0.818559        training's binary_logloss: 0.226566
valid_1's auc: 0.771545 valid_1's binary_logloss: 0.241971
[4400]  training's auc: 0.822579        training's binary_logloss: 0.225163
valid_1's auc: 0.771577 valid_1's binary_logloss: 0.241955
Early stopping, best iteration is:
[4484]  training's auc: 0.823392        training's binary_logloss: 0.22487
valid_1's auc: 0.771596 valid_1's binary_logloss: 0.241952
Done.
Time elapsed = 0:21:10.943517
```

[86]:

```
#displaying the results and metrics
lgbm_boosting.results()
#displaying top 20 important features
lgbm_boosting.feat_importances_show(20)
```

```
================================================================================
====================
Train Results:

The best selected Threshold as per the J-Statistic, which is J = TPR - FPR, is =
0.020892953251537207

        ROC-AUC Score = 0.8215516552589436
        Precision Score = 0.19505400619284818
        Recall Score = 0.758710976837865
CV Results:
        ROC-AUC Score = 0.7670148810362889
        Precision Score = 0.0942692861687635
        Recall Score = 0.972809667673716
================================================================================
====================
```




```
================================================================================
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```

[87]:
```
features_with_zero_importances  = lgbm_boosting.
↪feature_importance[lgbm_boosting.feature_importance.gain == 0]

print(f"There are {len(features_with_zero_importances)} features with Zero Gain␣
↪in LGBMClassifier. They are:\n")
print(features_with_zero_importances.features.values)
```

```
There are 30 features with Zero Gain in LGBMClassifier. They are:
```

```
['ORGANIZATIONTYPETradetype5' 'ORGANIZATIONTYPETradetype6'
 'OCCUPATIONTYPERealtyagents' 'ORGANIZATIONTYPETransporttype1'
 'ORGANIZATIONTYPEIndustrytype5' 'OCCUPATIONTYPEITstaff'
 'OCCUPATIONTYPEHRstaff' 'ORGANIZATIONTYPEIndustrytype8'
 'NAMEEDUCATIONTYPEAcademicdegree' 'NAMEINCOMETYPEUnemployed'
 'NAMEINCOMETYPEStudent' 'NAMEINCOMETYPEBusinessman'
 'ORGANIZATIONTYPETradetype4' 'ORGANIZATIONTYPETradetype1'
 'ORGANIZATIONTYPEAdvertising' 'ORGANIZATIONTYPELegalServices'
 'ORGANIZATIONTYPETelecom' 'ORGANIZATIONTYPECleaning'
 'ORGANIZATIONTYPECulture' 'ORGANIZATIONTYPEElectricity'
 'ORGANIZATIONTYPEEmergency' 'ORGANIZATIONTYPEReligion'
 'ORGANIZATIONTYPERealtor' 'ORGANIZATIONTYPEIndustrytype10'
 'ORGANIZATIONTYPEInsurance' 'ORGANIZATIONTYPEIndustrytype12'
 'ORGANIZATIONTYPEMobile' 'ORGANIZATIONTYPEIndustrytype13'
 'ORGANIZATIONTYPEIndustrytype2' 'ORGANIZATIONTYPEIndustrytype6']
```

0.5 Submit Result

[88]:
```
#submitting the result
# pd.DataFrame({'SK_ID_CURR': skid_test, 'TARGET' : lgbm_boosting.
 ↪test_preds_proba_mean}).to_csv('LGBM_3folds.csv',index = False)



# Write final results to submission.csv
app_pred_df = pd.DataFrame(lgbm_boosting.test_preds_proba_mean,␣
 ↪columns=['TARGET'])
app_pred_ids = pd.DataFrame(app_test_df['SK_ID_CURR'], columns=['SK_ID_CURR'])
final_df = pd.concat([app_pred_ids, app_pred_df], axis=1)
final_df.head()
```

[88]:

	SK_ID_CURR	TARGET
0	100001	0.021422
1	100005	0.071864
2	100013	0.034266
3	100028	0.025375
4	100038	0.101609

[90]:
```
submission_dir = './submission/lgbm5folds.csv'
final_df.to_csv(submission_dir, index=False)
```

[ ]:

[ ]: