In [4]: top_features = [] for i in features: if i in train.columns: top_features.append(i) In [5]: #Creating combination of features got from EDA two_way_list = list(combinations(top_features, 2)) three_way_list = list(combinations(top_features, 3)) In [6]: #Creating a dataframe which consists of combinations of features train_numeric_corr = pd.DataFrame() def interaction_features(col): **if** len(col) == 2: train_numeric_corr[str(col[0])+'_add_'+str(col[1])] = train[col[0]]+train[col[1]] train_numeric_corr[str(col[0])+'_add_'+str(col[1])+'_add_'+str(col[2])] = train[col[0]]+train[col[1]]+train[col[2]] In [7]: for i in (two_way_list+three_way_list): interaction_features(i) In [8]: test_numeric_corr = pd.DataFrame() def interaction_features(col): if len(col) == 2: test_numeric_corr[str(col[0])+'_add_'+str(col[1])] = test[col[0]]+test[col[1]] test_numeric_corr[str(col[0])+'_add_'+str(col[1])+'_add_'+str(col[2])] = test[col[0]]]+test[col[1]]+test[col[2]] In [9]: | for i in (two_way_list+three_way_list): interaction_features(i) In [10]: train_numeric_corr['y'] = train['y'] In [11]: | correlation = train_numeric_corr.corr(method = 'pearson') In [12]: | corr_values = list(correlation['y'].sort_values(ascending = False)) corr_cols = list(correlation['y'].sort_values(ascending = False).index) In [13]: #Selecting correlation features which have correlation greater than 0.68 to target variable from above combinations of features top_correlated_features = [] for i in range(len(corr_values)): if corr_values[i] > 0.68: if corr_cols[i] != 'y': top_correlated_features.append(corr_cols[i]) In [14]: len(top_correlated_features) Out[14]: 19 In [15]: | file = 'Corr-features' file_dump = open(file, 'wb') pickle.dump(top_correlated_features, file_dump) file_dump.close() In [16]: train_top_corr_numeric = train_numeric_corr[top_correlated_features] test_top_corr_numeric = test_numeric_corr[top_correlated_features] **PCA and TSVD for Numerical features Creating PCA features** In [17]: | numeric = list(train.select_dtypes(include = 'int64').columns) numeric_train = train[numeric] numeric_test = test[numeric] In [18]: # Using standard scaler to normalize the data scaler = StandardScaler() In [19]: | train_numeric_norm= scaler.fit_transform(numeric_train) In [20]: | train_numeric_norm = pd.DataFrame(train_numeric_norm,columns = numeric_train.columns) In [21]: | test_numeric_norm = scaler.transform(numeric_test) In [22]: | test_numeric_norm = pd.DataFrame(test_numeric_norm, columns = numeric_test.columns) In [164]: file = 'models/pca-scaler.sav' file_dump = open(file, 'wb') pickle.dump(scaler,file_dump) file_dump.close() In [23]: $pca = PCA(n_components = 50)$ train_pca = pca.fit(train_numeric_norm) In [24]: # Plot the explained variances plt.figure(figsize = (10,10)) features = range(train_pca.n_components_) plt.bar(features, train_pca.explained_variance_) plt.xlabel('PCA feature') plt.ylabel('variance') plt.xticks(features) plt.show() 20.0 17.5 15.0 12.5 10.0 7.5 5.0 2.5 0 1 2 3 4 5 6 7 8 9 10111213141516171819202122232425262728293031323334353637383940414243444546474849 PCA feature From above graph we can take number of components as 6 for PCA In [25]: $n_{comp} = 6$ $pca = PCA(n_components = n_comp)$ train_pca = pca.fit_transform(train_numeric_norm) test_pca = pca.transform(test_numeric_norm) In [26]: | train_pca_df = pd.DataFrame() test_pca_df = pd.DataFrame() for i in range(1, n_comp+1): train_pca_df['pca'+str(i)] = train_pca[:,i-1] test_pca_df['pca'+str(i)] = test_pca[:,i-1] In [146]: filename = 'models/pca.sav' pickle.dump(pca,open(filename,'wb')) **Creating TSVD Features Optimal Thresholding of Singular values** In [27]: ## Using Truncated SVD to find the singular values and setting number of components as 100. svd = TruncatedSVD(n_components = 150, random_state = 42) In [28]: train_tsvd = svd.fit_transform(train_numeric_norm) In [29]: | singular_values = svd.singular_values_ In [30]: | var_explained = svd.explained_variance_ratio_.sum() Using 100 as number of components transformed data from tsvd can explain 95% of our data In [31]: | var_explained Out[31]: 0.9562972630843092 Thresholding of singluar values (https://arxiv.org/pdf/1305.5870.pdf) In [32]: def beta_cal(input_matrix): m = min(input_matrix.shape) n = max(input_matrix.shape) return m/n In [33]: def optimal_svht_sigma(beta): **return** (0.56*beta**3)-(0.95*beta**2)+(1.82*beta)+1.43 In [34]: beta = beta_cal(train_numeric_norm) print('Beta value must be in range of (0,1] and beta value is ',beta) Beta value must be in range of (0,1] and beta value is 0.07415355269432522 In [35]: sigma = optimal_svht_sigma(beta) print('w(beta) coefficient according to the paper is ',sigma) w(beta) coefficient according to the paper is 1.55996399500429 In [36]: # Finding median from the singular values generated from the TSVD sv_median = np.median(singular_values) In [37]: # The threshold for the singluar values threshold = sigma*sv_median In [38]: # The number of components we can have in TSVD after thresholding. n_comp = np.max(np.where(singular_values > threshold)) + 1 print('Number of components after thresholding is ',n_comp) Number of components after thresholding is 23 **Creating TSVD features from above n_components** In [39]: | tsvd = TruncatedSVD(n_components = n_comp, random_state = 42) In [40]: | train_tsvd = tsvd.fit_transform(train_numeric_norm) In [41]: | test_tsvd = tsvd.transform(test_numeric_norm) In [42]: train_tsvd_df = pd.DataFrame() test_tsvd_df = pd.DataFrame() for i in range(1, n_comp+1): train_tsvd_df['tsvd'+str(i)] = train_tsvd[:,i-1] test_tsvd_df['tsvd'+str(i)] = test_tsvd[:,i-1] In [147]: | filename = 'models/tsvd.sav' pickle.dump(tsvd,open(filename,'wb')) Datasets-1 (Label Encoding) **Label Encoding of Categorical Features** In [44]: #Loading dataset saved from EDA train_label = pd.read_csv('preprocessed_train_eda.csv') In [45]: test_label = pd.read_csv('preprocessed_test_eda.csv') In [46]: categ = list(train_label.select_dtypes(include = 'object').columns) In [47]: # Label encoding def label_encode(tr,te,col_name): encoder = LabelEncoder() label_encoder = encoder.fit(tr[col_name].values) te[col_name] = te[col_name].map(lambda x: 'nill' if x not in label_encoder.classes_ else label_encoder.classes_ = np.append(label_encoder.classes_, 'nill') tr[col_name] = label_encoder.transform(tr[col_name]) te[col_name] = label_encoder.transform(te[col_name]) In [48]: # Encoding categorical columns using Label Encoder **for** i in categ: label_encode(train_label, test_label, i) In [49]: train_label.head() Out[49]: y X0 X1 X2 X3 X5 X6 X8 X10 X12 ... X373 X374 X375 X376 X377 X378 X379 X380 X383 X384 **0** 130.81 32 23 17 0 24 9 14 0 ... **1** 88.53 32 21 19 4 28 11 14 0 ... 0 0 0 1 0 **2** 76.26 20 24 34 2 27 9 23 0 ... 0 0 ... **3** 80.62 20 21 34 5 27 11 4 0 0 0 0 0 0 0 0 0 0 **4** 78.02 20 23 34 5 12 3 13 0 0 ... 0 0 0 5 rows × 319 columns In [50]: test_label.head() Out[50]: X0 X1 X2 X3 X5 X6 X8 X10 X12 X13 ... X373 X374 X375 X376 X377 X378 X379 X380 X383 X384 **0** 20 23 34 5 29 0 22 0 0 **1** 40 3 7 0 29 0 ... 0 0 6 24 0 0 0 **2** 20 23 16 5 29 9 9 0 0 0 ... **3** 20 13 34 5 29 11 13 0 0 ... 0 0 0 0 0 1 0 0 0 0 0 **4** 43 20 16 2 28 8 12 0 0 0 ... 0 5 rows × 318 columns In [51]: # Using standard scaler to normalize the data scaler = StandardScaler() In [52]: | train_label_norm= scaler.fit_transform(train_label.drop(['y'],axis = 1)) In [53]: train_columns = train_label.drop(['y'],axis = 1).columns In [54]: train_label_norm = pd.DataFrame(train_label_norm, columns = train_columns) In [55]: | train_label_norm.to_csv('label_encoding/preprocessed_train_norm_label.csv',index = False) In [56]: test_label_norm = scaler.transform(test_label) In [57]: test_label_norm = pd.DataFrame(test_label_norm, columns = test_label.columns) In [58]: | test_label_norm.to_csv('label_encoding/preprocessed_test_norm_label.csv',index = False) **Adding Interaction variables** In [59]: | train_label_corr = pd.concat([train_label, train_top_corr_numeric], axis = 1) test_label_corr = pd.concat([test_label,test_top_corr_numeric],axis = 1) In [60]: # Using standard scaler to normalize the data scaler = StandardScaler() In [61]: train_label_interaction = scaler.fit_transform(train_label_corr.drop(['y'],axis = 1)) In [62]: | train_columns = train_label_corr.drop(['y'],axis = 1).columns In [63]: | train_label_interaction = pd.DataFrame(train_label_interaction,columns = train_columns) In [64]: | train_label_interaction.to_csv('label_encoding/preprocessed_train_label_interaction.csv',ind ex = False) In [65]: | test_label_interaction = scaler.transform(test_label_corr) In [66]: | test_label_interaction = pd.DataFrame(test_label_interaction, columns = test_label_corr.column In [67]: | test_label_interaction.to_csv('label_encoding/preprocessed_test_label_interaction.csv', index = False) **Adding PCA and Interaction features** In [68]: train_label_corr_pca = pd.concat([train_label_interaction, train_pca_df], axis = 1) test_label_corr_pca = pd.concat([test_label_interaction, test_pca_df], axis = 1) In [69]: | train_label_corr_pca.to_csv('label_encoding/train_label_interaction_pca.csv', index = False) In [70]: | test_label_corr_pca.to_csv('label_encoding/test_label_interaction_pca.csv',index = False) **Adding TSVD and Interaction features** In [71]: train_label_corr_tsvd = pd.concat([train_label_interaction, train_tsvd_df], axis = 1) test_label_corr_tsvd = pd.concat([test_label_interaction, test_tsvd_df], axis = 1) In [72]: | train_label_corr_tsvd.to_csv('label_encoding/train_label_interaction_tsvd.csv',index = False In [73]: | test_label_corr_tsvd.to_csv('label_encoding/test_label_interaction_tsvd.csv', index = False) **Datasets - 2 (Mean Encoding)** In [77]: #Loading dataset saved from EDA train_mean = pd.read_csv('preprocessed_train_eda.csv') test_mean = pd.read_csv('preprocessed_test_eda.csv') In [78]: # Getting categorical columns from the train categ = list(train_mean.select_dtypes(include = 'object').columns) In [79]: | default_mean = train_mean['y'].mean() In [157]: # Saving class means. def class_means(col_name, train): class_mean = train.groupby(col_name)['y'].mean() filename = 'class-means/mean_'+str(col_name) pickle.dump(class_mean,open(filename,'wb')) pickle.dump(default_mean, open('class-means/default_mean', 'wb')) In [80]: | # Creating a function to implement mean encoding of categorical features #https://www.geeksforgeeks.org/mean-encoding-machine-learning/ def mean_encoding(col_name, tr, te): class_mean = tr.groupby(col_name)['y'].mean() tr[col_name] = [class_mean.loc[i] for i in tr[col_name].values] te[col_name] = [class_mean.loc[i] **if** i **in** class_mean.index **else** default_mean **for** i **in** te [col_name].values] In [81]: # Mean Encoding **for** i **in** categ: mean_encoding(i,train_mean,test_mean) In [82]: train_mean.head() Out[82]: **X1** Х3 **X2** X8 X10 X12 ... X373 X374 X375 X **0** 130.81 99.491818 100.983086 104.218333 102.242763 130.81 101.015569 97.746933 **1** 88.53 99.491818 93.723226 95.510000 100.033190 88.53 98.487815 97.746933 76.26 78.025543 95.764808 83.369927 101.766129 78.44 101.015569 98.078654 80.62 78.025543 93.723226 83.369927 96.111916 78.44 98.487815 104.737232 78.02 78.025543 100.983086 83.369927 96.111916 78.02 101.174141 102.194215 5 rows × 319 columns In [83]: test_mean.head() Out[83]: **X1 X2** Х3 **X5** X6 X8 X10 X12 X13 ... X373 X374 X37! 78.025543 100.983086 83.369927 96.111916 100.439938 97.802524 98.848615 93.722995 102.242763 100.439938 93.538656 99.961284 101.435086 99.550000 78.025543 100.983086 103.575961 96.111916 100.439938 101.015569 100.272428 98.487815 102.194215 78.025543 100.416661 83.369927 96.111916 100.439938 0 **4** 112.151000 101.868462 103.575961 101.766129 88.530000 101.226803 100.051364 5 rows × 318 columns In [84]: # Using standard scaler to normalize the data scaler = StandardScaler() In [85]: | train_mean_norm= scaler.fit_transform(train_mean.drop(['y'],axis = 1)) In [86]: | train_columns = train_mean.drop(['y'],axis = 1).columns In [87]: | train_mean_norm = pd.DataFrame(train_mean_norm, columns = train_columns) In [88]: | test_mean_norm = scaler.transform(test_mean) In [89]: | test_mean_norm = pd.DataFrame(test_mean_norm,columns = test_mean.columns) In [90]: | train_mean_norm.to_csv('mean_encoding/preprocessed_train_norm_mean.csv',index = False) In [91]: | test_mean_norm.to_csv('mean_encoding/preprocessed_test_norm_mean.csv',index = False) **Adding Interaction variables** In [92]: train_mean_corr = pd.concat([train_mean,train_top_corr_numeric],axis = 1) test_mean_corr = pd.concat([test_mean, test_top_corr_numeric], axis = 1) In [93]: # Using standard scaler to normalize the data scaler = StandardScaler() In [94]: train_mean_interaction = scaler.fit_transform(train_mean_corr.drop(['y'],axis = 1)) In [95]: | train_columns = train_mean_corr.drop(['y'],axis = 1).columns In [96]: train_mean_interaction = pd.DataFrame(train_mean_interaction, columns = train_columns) In [97]: | train_mean_interaction.to_csv('mean_encoding/preprocessed_train_mean_interaction.csv',index = False) In [98]: | test_mean_interaction = scaler.transform(test_mean_corr)

In [99]: | test_mean_interaction = pd.DataFrame(test_mean_interaction,columns = test_mean_corr.columns)

In [100]: | test_mean_interaction.to_csv('mean_encoding/preprocessed_test_mean_interaction.csv',index =

In [101]: | train_mean_corr_pca= pd.concat([train_mean_interaction, train_pca_df], axis = 1)

In [104]: | train_mean_corr_tsvd = pd.concat([train_mean_interaction, train_tsvd_df], axis = 1)

categ = np.array(train_glmm.select_dtypes(include = 'object').columns)

In [113]: | train_glmm_categ = glmm_encoder.fit_transform(train_glmm[categ], train_glmm['y'])

test_mean_corr_tsvd = pd.concat([test_mean_interaction, test_tsvd_df], axis = 1)

In [106]: | test_mean_corr_tsvd.to_csv('mean_encoding/test_mean_interaction_tsvd.csv',index = False)

test_mean_corr_pca = pd.concat([test_mean_interaction, test_pca_df], axis = 1)

In [102]: | train_mean_corr_pca.to_csv('mean_encoding/train_mean_interaction_pca.csv', index = False)

test_mean_corr_pca.to_csv('mean_encoding/test_mean_interaction_pca.csv',index = False)

train_mean_corr_tsvd.to_csv('mean_encoding/train_mean_interaction_tsvd.csv',index = False)

c:\Miniconda\lib\site-packages\category_encoders\utils.py:21: FutureWarning: is_categorical i

s deprecated and will be removed in a future version. Use is_categorical_dtype instead

False)

In [105]:

In [163]: | file = 'models/mean-scaler.sav'

file_dump.close()

file_dump = open(file,'wb')
pickle.dump(scaler,file_dump)

Adding PCA and Interaction features

Adding TSVD and Interaction features

Datasets-3 (GLMM Encoding)

In [112]: # Getting categorical columns from the train

Applying GLMM encoding of categorical variables

elif pd.api.types.is_categorical(cols):

train_glmm[i] = train_glmm_categ[i]
test_glmm[i] = test_glmm_categ[i]

In [118]: train_columns = train_glmm.drop(['y'],axis = 1).columns

In [116]: # Using standard scaler to normalize the data

In [120]: test_glmm_norm = scaler.transform(test_glmm)

Adding Interaction variables

scaler = StandardScaler()

In [125]: # Using standard scaler to normalize the data

In [127]: | train_columns = train_glmm_corr.drop(['y'],axis = 1).columns

In [130]: test_glmm_interaction = scaler.transform(test_glmm_corr)

Adding PCA and Interaction features

Adding TSVD and Interaction features

v n f t a w

4 w sascy i m

In [133]:

In [138]:

In []:

In []:

Out[160]:

In [160]: test.head()

2 az v as

5 rows × 318 columns

scaler = StandardScaler()

In [114]: | test_glmm_categ = glmm_encoder.transform(test_glmm[categ])

In [117]: | train_glmm_norm= scaler.fit_transform(train_glmm.drop(['y'],axis = 1))

In [119]: train_glmm_norm = pd.DataFrame(train_glmm_norm,columns = train_columns)

In [121]: | test_glmm_norm = pd.DataFrame(test_glmm_norm, columns = test_glmm.columns)

In [124]: train_glmm_corr = pd.concat([train_glmm, train_top_corr_numeric], axis = 1)

In [122]: | train_glmm_norm.to_csv('glmm_encoding/preprocessed_train_norm_glmm.csv',index = False)

In [123]: | test_glmm_norm.to_csv('glmm_encoding/preprocessed_test_norm_glmm.csv',index = False)

test_glmm_corr = pd.concat([test_glmm,test_top_corr_numeric],axis = 1)

In [126]: | train_glmm_interaction = scaler.fit_transform(train_glmm_corr.drop(['y'],axis = 1))

In [128]: | train_glmm_interaction = pd.DataFrame(train_glmm_interaction, columns = train_columns)

In [129]: | train_glmm_interaction.to_csv('glmm_encoding/preprocessed_train_glmm_interaction.csv',index

In [131]: | test_glmm_interaction = pd.DataFrame(test_glmm_interaction,columns = test_glmm_corr.columns)

In [132]: | test_glmm_interaction.to_csv('glmm_encoding/preprocessed_test_glmm_interaction.csv',index =

train_glmm_corr_pca = pd.concat([train_glmm_interaction,train_pca_df],axis = 1)

test_glmm_corr_pca = pd.concat([test_glmm_interaction, test_pca_df], axis = 1)

In [134]: train_glmm_corr_pca.to_csv('glmm_encoding/train_glmm_interaction_pca.csv',index = False)

In [135]: test_glmm_corr_pca.to_csv('glmm_encoding/test_glmm_interaction_pca.csv',index = False)

test_glmm_corr_tsvd = pd.concat([test_glmm_interaction, test_tsvd_df], axis = 1)

In [137]: train_glmm_corr_tsvd.to_csv('glmm_encoding/train_glmm_interaction_tsvd.csv',index = False)

0 ...

0 ...

0

0

0

test_glmm_corr_tsvd.to_csv('glmm_encoding/test_glmm_interaction_tsvd.csv',index = False)

X0 X1 X2 X3 X5 X6 X8 X10 X12 X13 ... X373 X374 X375 X376 X377 X378 X379 X380 X383 X384

0

0

0

0

0

0

In [136]: train_glmm_corr_tsvd = pd.concat([train_glmm_interaction, train_tsvd_df], axis = 1)

train_glmm = pd.read_csv('preprocessed_train_eda.csv')
test_glmm = pd.read_csv('preprocessed_test_eda.csv')

In [110]: glmm_encoder = GLMMEncoder()

In [115]: **for** i **in** categ:

In [111]: #Loading dataset saved from EDA

Feature Engineering

from itertools import combinations

import matplotlib.pyplot as plt

from sklearn.decomposition import PCA

from sklearn.preprocessing import LabelEncoder

from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import TruncatedSVD

from category_encoders.glmm import GLMMEncoder

train = pd.read_csv('preprocessed_train_eda.csv')
test = pd.read_csv('preprocessed_test_eda.csv')

features = pickle.load(rf_col,encoding = 'latin1')

Interaction Features (Numerical)

In [3]: # Importing top features from the EDA dataset.
rf_col = open('Top-features','rb')

In [1]: # Importing necessary libraries
import pandas as pd

import numpy as np

import numpy as np

Importing dataset

In [2]: #Loading dataset saved from EDA

import pickle

from tqdm import tqdm