Humana Mays Healthcare Analysis Case Competition, 2020

Team Quark

Necessary packages and libraries

Install packages

In [64]:
```
#!pip install <any package that's not loaded already in your system>
```

In [35]:
```
# To ignore any warnings
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

Load the packages/libraries

In [36]:
```
# All packages and libraries that are essential
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from pandas import DataFrame
from sklearn import datasets
from scipy.special import comb
from IPython.display import display
from random import sample
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn import metrics
from xgboost import XGBRegressor
from xgboost import XGBClassifier
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectFromModel
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
import dabl
%matplotlib inline
```

Read the training data

In [72]:

```
# Read the file
df = pd.read_csv('2020_Competition_Training.csv')
```

```
C:\Users\its_t\AppData\Local\Continuum\anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3057: D
typeWarning: Columns (80,193) have mixed types.Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [73]:

```
# File info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 69572 entries, 0 to 69571
Columns: 826 entries, person_id_syn to submcc_rsk_chol_ind
dtypes: float64(443), int64(361), object(22)
memory usage: 438.4+ MB
```

In [74]:

```
# To print top 10 records form the file
df.head(10)
```

Out[74]:

	person_id_syn	transportation_issues	src_platform_cd	sex_cd	est_age	smoker_current_ind	smoker_former_ind	lan
0	0002MOb79ST17bLYAe46elc2	0	EM	F	62	1	0	
1	0004cMOS6bTLf34Y7AIca8f3	0	EM	F	59	1	0	
2	000536M9O3ST98LaYaeA29Ia	1	EM	F	63	0	0	
3	0009bMO9SfTLYe77A51I4ac3	0	EM	M	75	0	0	
4	000M7OeS66bTL8bY89Aa16Ie	0	EM	M	51	1	0	
5	000MOa9ScTdLa4d9f3YAI068	0	EM	F	73	0	0	
6	0013dMOS3TeL28YA12ea5ecI	0	EM	F	57	0	0	
7	001548d79bMeO7S283TLYAI0	0	EM	F	83	0	0	
8	0015M1Ob8S1bT1086LYAf9Ia	1	EM	F	56	0	0	
9	0015M23c489ObSb70TLYcbAI	0	LV	M	69	0	0	

10 rows × 826 columns

In [7]:

```
# Print the features from the file
df.columns
```

Out[7]:

```
Index(['person_id_syn', 'transportation_issues', 'src_platform_cd', 'sex_cd',
       'est_age', 'smoker_current_ind', 'smoker_former_ind', 'lang_spoken_cd',
       'mabh_seg', 'cci_score',
       ...
       'submcc_rar_scl_ind', 'rx_gpi2_74_ind', 'rx_gpi2_89_ind',
       'rx_gpi2_96_ind', 'submcc_rsk_obe_ind', 'rx_gpi2_22_ind',
       'submcc_rsk_synx_ind', 'submcc_rsk_coag_ind', 'submcc_rsk_othr_ind',
       'submcc_rsk_chol_ind'],
      dtype='object', length=826)
```

In [75]:
```
# Records - rows and columns
df.shape
```

Out[75]: (69572, 826)

In [76]:
```
# Summarize the data for each feature
df.describe(include='all')
```

Out[76]:

	person_id_syn	transportation_issues	src_platform_cd	sex_cd	est_age	smoker_current_ind	smoker_forme
count	69572	69572.000000	69572	69572	69572.000000	69572.000000	69572.0
unique	69572	NaN	2	2	NaN	NaN	
top	b39Ma49dO3S09bTL407YA15I	NaN	EM	F	NaN	NaN	
freq	1	NaN	49999	41112	NaN	NaN	
mean	NaN	0.146568	NaN	NaN	70.815673	0.134824	0.1
std	NaN	0.353677	NaN	NaN	10.417384	0.341538	0.3
min	NaN	0.000000	NaN	NaN	18.000000	0.000000	0.0
25%	NaN	0.000000	NaN	NaN	66.000000	0.000000	0.0
50%	NaN	0.000000	NaN	NaN	71.000000	0.000000	0.0
75%	NaN	0.000000	NaN	NaN	77.000000	0.000000	0.0
max	NaN	1.000000	NaN	NaN	101.000000	1.000000	1.0

11 rows × 826 columns

In [10]:

```
# Correlation table
df.corr(method='pearson')
```

Out[10]:

	transportation_issues	est_age	smoker_current_ind	smoker_former_ind	cci_score	dcsi_score	fci_score	hc
transportation_issues	1.000000	-0.182090	0.099859	-0.014584	-0.010039	0.052572	0.103049	
est_age	-0.182090	1.000000	-0.171495	0.064805	0.409230	0.148596	0.004075	
smoker_current_ind	0.099859	-0.171495	1.000000	-0.162033	0.032805	0.079364	0.139417	
smoker_former_ind	-0.014584	0.064805	-0.162033	1.000000	0.143096	0.125453	0.128855	
cci_score	-0.010039	0.409230	0.032805	0.143096	1.000000	0.667714	0.497159	
...	...	...	...	...	...	...	...	
rx_gpi2_22_ind	0.025502	-0.031476	0.067078	0.048260	0.102886	0.091271	0.208342	
submcc_rsk_synx_ind	-0.005258	0.000786	0.001373	0.004569	0.013094	0.014431	0.025156	
submcc_rsk_coag_ind	0.006193	-0.005061	0.000515	0.014516	0.030708	0.030917	0.026798	
submcc_rsk_othr_ind	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
submcc_rsk_chol_ind	-0.026332	0.119659	0.023018	0.061774	0.257820	0.247697	0.251600	

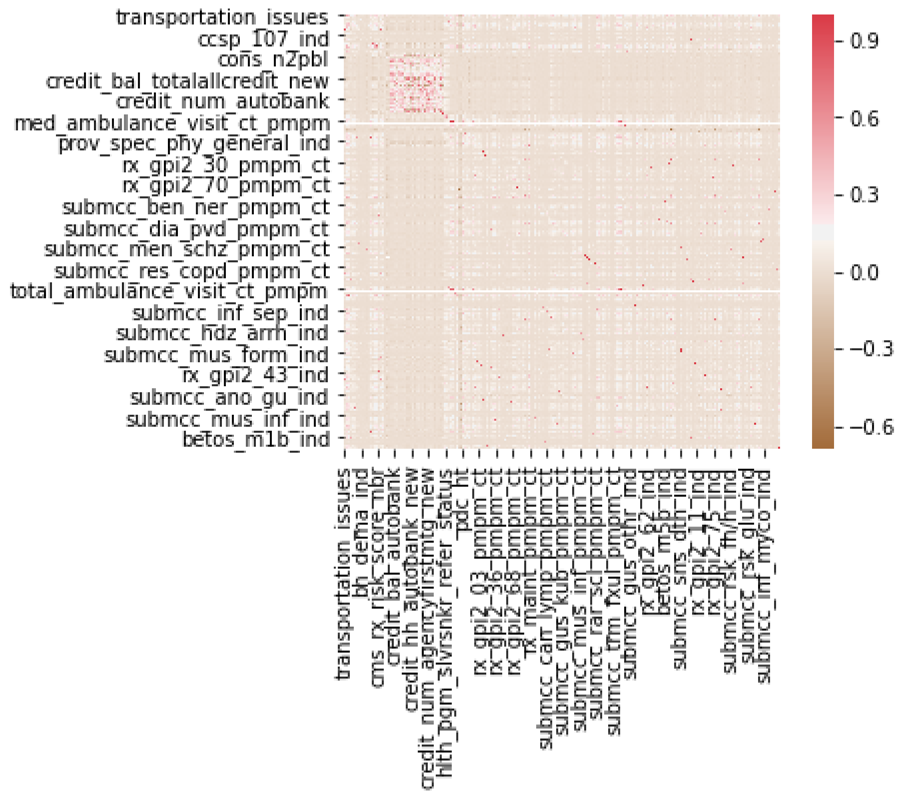
804 rows × 804 columns

In [11]:

```
# Print the correlation matrix

# Put in comments to be removed later - this code takes a long time to generate corr for every feature.
'''
corr = df.corr(method='pearson')
sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool), cmap=sns.diverging_palette(400, 10, as_cmap=Tru
'''
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x214f6db02e8>
```



Data Wrangling

In [11]:
```
# Check for total null values
df.isnull().values.sum()
```

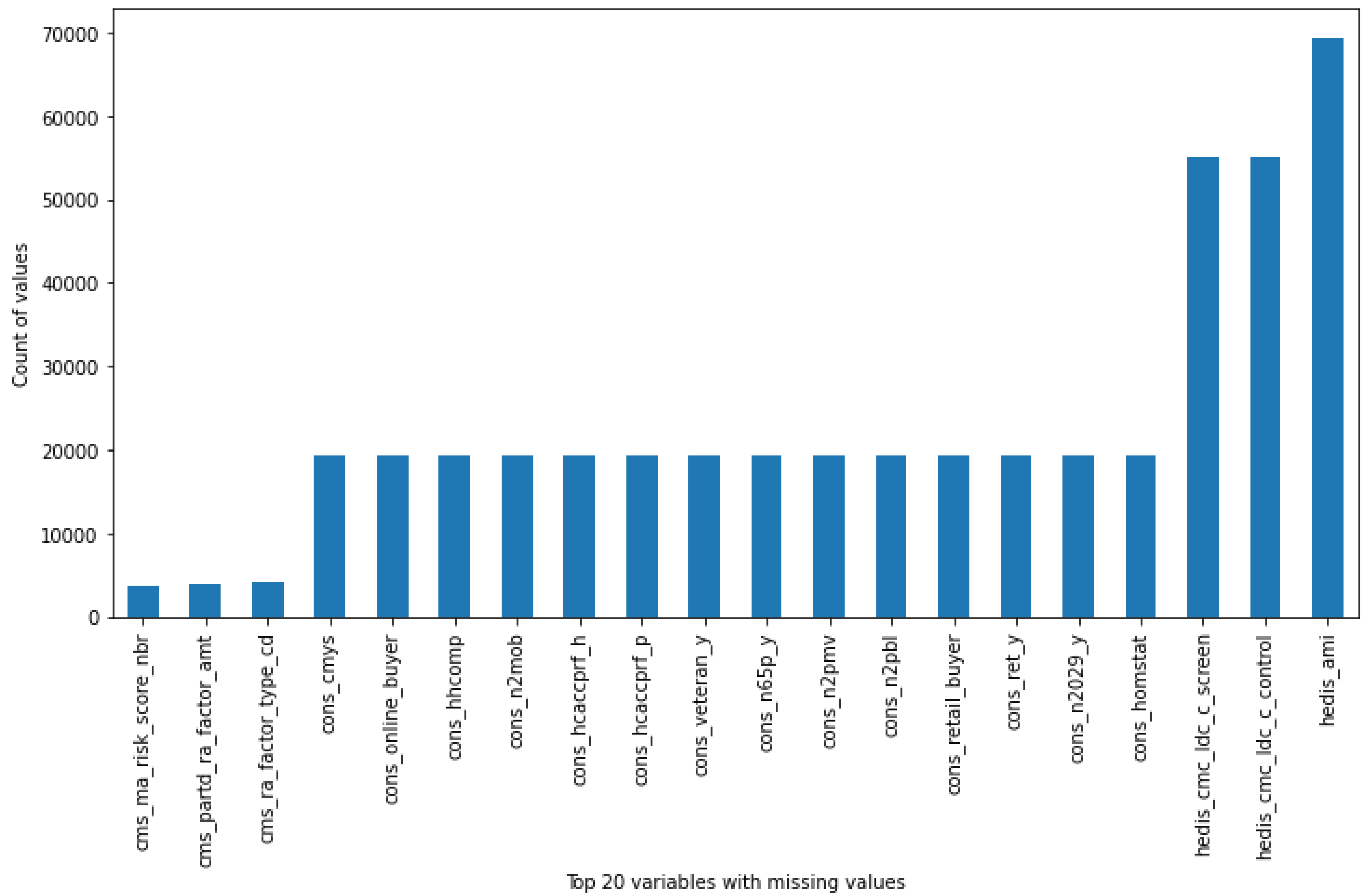
Out[11]: 512802

In [77]:
```
# Null or NAs by column
naColumns = df.isnull().sum()

# naColumns.sort_values()

# Sort for top 20 with Nas
naColumns.sort_values().tail(20)
```

Out[77]:
```
cms_ma_risk_score_nbr       3772
cms_partd_ra_factor_amt     3814
cms_ra_factor_type_cd       4224
cons_cmys                  19267
cons_online_buyer          19275
cons_hhcomp                19277
cons_n2mob                 19278
cons_hcaccprf_h            19278
cons_hcaccprf_p            19278
cons_veteran_y             19278
cons_n65p_y                19278
cons_n2pmv                 19278
cons_n2pbl                 19278
cons_retail_buyer          19279
cons_ret_y                 19279
cons_n2029_y               19279
cons_homstat               19280
hedis_cmc_ldc_c_screen     54930
hedis_cmc_ldc_c_control    54932
hedis_ami                  69339
dtype: int64
```

In [13]:
```
x = naColumns.sort_values().tail(20)

# Print the count of missing NA values
x.plot.bar(figsize=(12,6))
plt.ylabel('Count of values')
plt.xlabel('Top 20 variables with missing values')
```

Out[13]:
```
Text(0.5, 0, 'Top 20 variables with missing values')
```



In [78]:

```
# Number of unique values
df.nunique()

# To check for any one variable:
# df['est_age'].nunique()
```

Out[78]:

```
person_id_syn            69572
transportation_issues        2
src_platform_cd              2
sex_cd                       2
est_age                     83
                         ...
rx_gpi2_22_ind               2
submcc_rsk_synx_ind          2
submcc_rsk_coag_ind          2
submcc_rsk_othr_ind          1
submcc_rsk_chol_ind          2
Length: 826, dtype: int64
```

In [15]:

```
# To plot the distribution of each feature

# the code is commented because there are just too many features but one can check it for one or two rando
# df.hist(bins=30, figsize=(12,12), density=True)
# plt.show()
```

In [79]:

```
# Removing the features which have more than 80% NAs

limit = len(df) * .80
new_df = df.dropna(thresh=limit,axis=1)
new_df
```

Out[79]:

	person_id_syn	transportation_issues	src_platform_cd	sex_cd	est_age	smoker_current_ind	smoker_former_ind
0	0002MOb79ST17bLYAe46elc2	0	EM	F	62	1	0
1	0004cMOS6bTLf34Y7Alca8f3	0	EM	F	59	1	0
2	000536M9O3ST98LaYaeA29la	1	EM	F	63	0	0
3	0009bMO9SfTLYe77A51l4ac3	0	EM	M	75	0	0
4	000M7OeS66bTL8bY89Aa16le	0	EM	M	51	1	0
...	...	...	...	...	...	...	...
69567	ffe33MOS25dTf027LaY7A5l3	0	EM	F	72	1	0
69568	fff1M4O1cfST49LY464A2leb	0	EM	M	75	0	0
69569	fff5MO7e401STLYcAd8e581l	0	EM	M	76	0	0
69570	fffMc37OSfTLfY7853dfA09l	0	LV	M	67	0	1
69571	fffc14bbMOfSTb7eLY5Al14d	1	EM	M	60	0	0

69572 rows × 809 columns

In [80]:

```
new_df.shape
# new df has 809 columns against 822 in the original
```

Out[80]: (69572, 809)

In [81]:

```
# Re-assigning to df the the new df with more clean data will lesser NAs.
df = new_df
```

In [82]:
```
# Fill the missing NAs for rows now

def filling(df):
    for i in df:
        if df[i].dtypes == object:
            fill = df[i].mode().iat[0]
            df.loc[:,i] = df[i].replace(np.nan,fill)
        else:
            the_mean = df[i].mean(skipna=True)
            df.loc[:,i] = df[i].replace(np.nan,the_mean)

filling(df)
```

In [83]:
```
# Should show no more NAs
df.isnull().values.sum()
```

Out[83]:
```
0
```

EDA - Exploratory Data Analysis

In [30]:
```
# Checking for feature type
types = dabl.detect_types(df)
print(types)
```

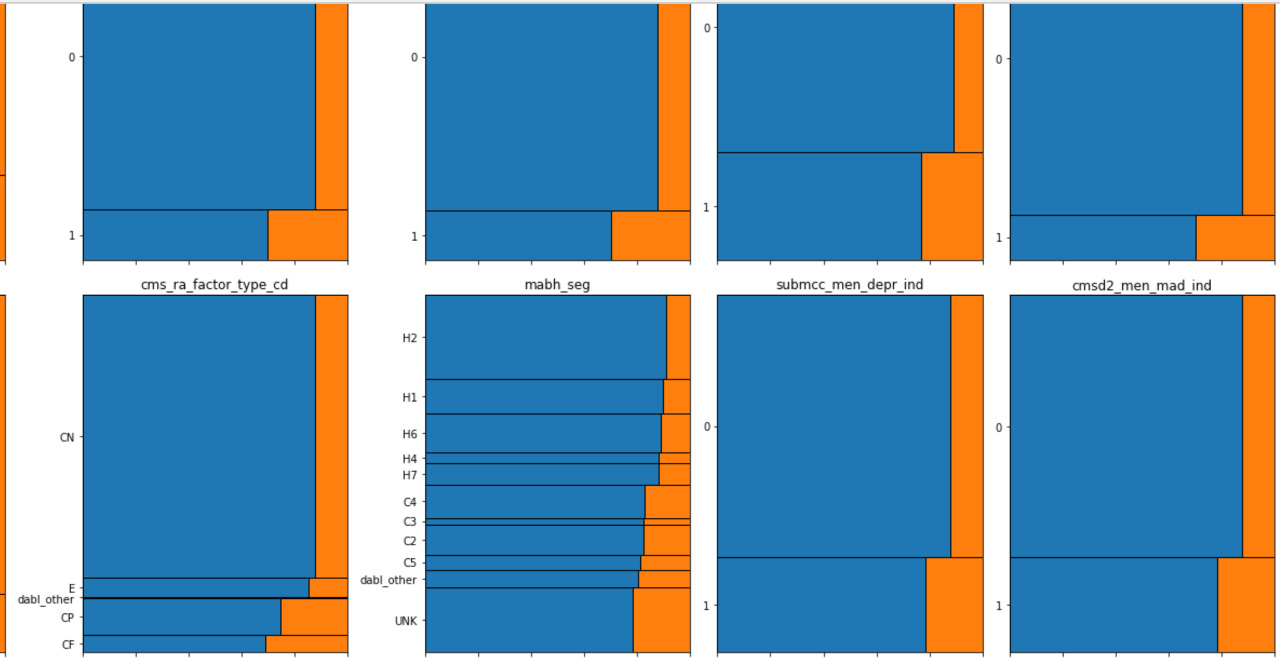
```
                       continuous  dirty_float  low_card_int  categorical  \
person_id_syn               False        False         False        False
transportation_issues       False        False         False         True
src_platform_cd             False        False         False         True
sex_cd                      False        False         False         True
est_age                     False        False          True        False
...                           ...          ...           ...          ...
rx_gpi2_22_ind              False        False         False         True
submcc_rsk_synx_ind         False        False         False        False
submcc_rsk_coag_ind         False        False         False        False
submcc_rsk_othr_ind         False        False         False        False
submcc_rsk_chol_ind         False        False         False         True

                        date  free_string  useless
person_id_syn          False         True    False
transportation_issues  False        False    False
src_platform_cd        False        False    False
sex_cd                 False        False    False
est_age                False        False    False
...                      ...          ...      ...
rx_gpi2_22_ind         False        False    False
submcc_rsk_synx_ind    False        False     True
submcc_rsk_coag_ind    False        False     True
submcc_rsk_othr_ind    False        False     True
submcc_rsk_chol_ind    False        False    False

[809 rows x 7 columns]

C:\Users\its_t\AppData\Local\Continuum\anaconda3\lib\site-packages\dabl\preprocessing.py:318: UserWarning:
Discarding near-constant features: ['betos_d1c_pmpm_ct', 'betos_d1d_pmpm_ct', 'betos_m2c_pmpm_ct', 'betos_o
1b_pmpm_ct', 'bh_adtp_ind', 'bh_bipr_ind', 'bh_cdal_ind', 'ccsp_014_ind', 'ccsp_020_ind', 'ccsp_021_ind',
'ccsp_034_ind', 'ccsp_060_ind', 'ccsp_080_ind', 'ccsp_107_ind', 'ccsp_120_ind', 'ccsp_125_ind', 'ccsp_130_i
nd', 'ccsp_163_ind', 'ccsp_169_ind', 'ccsp_204_ind', 'ccsp_205_ind', 'ccsp_212_ind', 'ccsp_242_ind', 'cms_h
ospice_ind', 'hedis_dia_eye', 'hedis_dia_hba1c_ge9', 'hlth_pgm_slvrsnkr_refer_status', 'lab_bnp_abn_result_
ind', 'lab_hba1_c_abn_result_ind', 'med_ip_ltach_admit_ct_pmpm', 'med_ip_ltach_admit_days_pmpm', 'med_ip_ma
ternity_admit_ct_pmpm', 'med_ip_maternity_admit_days_pmpm', 'med_ip_mhsa_admit_ct_pmpm', 'med_ip_mhsa_admit
_days_pmpm', 'med_ip_rehab_admit_ct_pmpm', 'med_ip_rehab_admit_days_pmpm', 'med_ip_snf_admit_ct_pmpm', 'med
```

```
_ip_snf_admit_days_pmpm', 'pdc_ost', 'phy_em_px_ind', 'prov_spec_chiropractic_ind', 'prov_spec_phy_geriatri
c_ind', 'rev_cms_ambul_ind', 'rev_cms_icu_ind', 'rev_cms_nicu_ind', 'rx_gpi2_07_pmpm_ct', 'rx_gpi2_08_pmpm_
ct', 'rx_gpi2_09_pmpm_ct', 'rx_gpi2_13_pmpm_ct', 'rx_gpi2_14_pmpm_ct', 'rx_gpi2_15_pmpm_ct', 'rx_gpi2_18_pm
pm_ct', 'rx_gpi2_19_pmpm_ct', 'rx_gpi2_20_pmpm_ct', 'rx_gpi2_21_pmpm_ct', 'rx_gpi2_23_pmpm_ct', 'rx_gpi2_24
_pmpm_ct', 'rx_gpi2_25_pmpm_ct', 'rx_gpi2_26_pmpm_ct', 'rx_gpi2_29_pmpm_ct', 'rx_gpi2_31_pmpm_ct', 'rx_gpi2
_35_pmpm_ct', 'rx_gpi2_38_pmpm_ct', 'rx_gpi2_40_pmpm_ct', 'rx_gpi2_41_pmpm_ct', 'rx_gpi2_45_pmpm_ct', 'rx_g
pi2_47_pmpm_ct', 'rx_gpi2_48_pmpm_ct', 'rx_gpi2_51_pmpm_ct', 'rx_gpi2_52_pmpm_ct', 'rx_gpi2_53_pmpm_ct', 'r
x_gpi2_54_pmpm_ct', 'rx_gpi2_55_pmpm_ct', 'rx_gpi2_59_pmpm_ct', 'rx_gpi2_60_pmpm_ct', 'rx_gpi2_61_pmpm_ct',
'rx_gpi2_62_pmpm_ct', 'rx_gpi2_64_pmpm_ct', 'rx_gpi2_67_pmpm_ct', 'rx_gpi2_68_pmpm_ct', 'rx_gpi2_69_pmpm_c
t', 'rx_gpi2_70_pmpm_ct', 'rx_gpi2_73_pmpm_ct', 'rx_gpi2_74_pmpm_ct', 'rx_gpi2_76_pmpm_ct', 'rx_gpi2_77_pmp
m_ct', 'rx_gpi2_78_pmpm_ct', 'rx_gpi2_80_pmpm_ct', 'rx_gpi2_81_pmpm_ct', 'rx_gpi2_82_pmpm_ct', 'rx_gpi2_84_
pmpm_ct', 'rx_gpi2_87_pmpm_ct', 'rx_gpi2_88_pmpm_ct', 'rx_gpi2_89_pmpm_ct', 'rx_gpi2_92_pmpm_ct', 'rx_gpi2_
93_pmpm_ct', 'rx_gpi2_95_pmpm_ct', 'rx_gpi2_96_pmpm_ct', 'rx_gpi2_98_pmpm_ct', 'rx_gpi2_99_pmpm_ct', 'submc
c_ano_cns_pmpm_ct', 'submcc_ano_dig_pmpm_ct', 'submcc_ano_gu_pmpm_ct', 'submcc_ano_hrt_pmpm_ct', 'submcc_an
o_mus_pmpm_ct', 'submcc_ano_othr_pmpm_ct', 'submcc_ben_lymp_pmpm_ct', 'submcc_ben_ner_pmpm_ct', 'submcc_ben
_unk_pmpm_ct', 'submcc_brn_acc_pmpm_ct', 'submcc_brn_othr_pmpm_ct', 'submcc_cad_ang_pmpm_ct', 'submcc_cad_c
abg_pmpm_ct', 'submcc_cad_fh/ho_pmpm_ct', 'submcc_cad_mi_pmpm_ct', 'submcc_cad_ptca_pmpm_ct', 'submcc_can_b
rst_pmpm_ct', 'submcc_can_dig_pmpm_ct', 'submcc_can_end_pmpm_ct', 'submcc_can_gu_pmpm_ct', 'submcc_can_h/n_
pmpm_ct', 'submcc_can_leuk_pmpm_ct', 'submcc_can_lymp_pmpm_ct', 'submcc_can_ner_pmpm_ct', 'submcc_can_res_p
mpm_ct', 'submcc_can_sec_pmpm_ct', 'submcc_can_skn_pmpm_ct', 'submcc_cer_hem_pmpm_ct', 'submcc_cer_seq_pmpm
_ct', 'submcc_cer_tia_pmpm_ct', 'submcc_cir_anur_pmpm_ct', 'submcc_dia_eye_pmpm_ct', 'submcc_dig_p/b_pmpm_c
t', 'submcc_end_gld_pmpm_ct', 'submcc_end_othr_pmpm_ct', 'submcc_gus_brst_pmpm_ct', 'submcc_hdz_it_i_pmpm_c
t', 'submcc_hdz_it_is_pmpm_ct', 'submcc_hdz_myop_pmpm_ct', 'submcc_hdz_surg_pmpm_ct', 'submcc_hiv_kapo_pmpm
_ct', 'submcc_hiv_othr_pmpm_ct', 'submcc_hiv_pcp_pmpm_ct', 'submcc_inf_cand_pmpm_ct', 'submcc_inf_men_pmpm_
ct', 'submcc_inf_myco_pmpm_ct', 'submcc_inf_sep_pmpm_ct', 'submcc_inj_comp_pmpm_ct', 'submcc_men_alco_pmpm_
ct', 'submcc_men_schz_pmpm_ct', 'submcc_mus_atrp_pmpm_ct', 'submcc_mus_inf_pmpm_ct', 'submcc_neo_fh/ho_pmpm
_ct', 'submcc_ner_epil_pmpm_ct', 'submcc_ner_infl_pmpm_ct', 'submcc_ner_migr_pmpm_ct', 'submcc_pre_care_pmp
m_ct', 'submcc_pre_com_pmpm_ct', 'submcc_pre_del_pmpm_ct', 'submcc_pre_ect_pmpm_ct', 'submcc_pre_l/d_pmpm_c
t', 'submcc_pre_mul_pmpm_ct', 'submcc_pre_othr_pmpm_ct', 'submcc_rar_als_pmpm_ct', 'submcc_rar_cf_pmpm_ct',
'submcc_rar_drm_pmpm_ct', 'submcc_rar_hem_pmpm_ct', 'submcc_rar_lup_pmpm_ct', 'submcc_rar_mg_pmpm_ct', 'sub
mcc_rar_ms_pmpm_ct', 'submcc_rar_othr_pmpm_ct', 'submcc_rar_par_pmpm_ct', 'submcc_rar_pol_pmpm_ct', 'submcc
_rar_ra_pmpm_ct', 'submcc_rar_sca_pmpm_ct', 'submcc_rar_scl_pmpm_ct', 'submcc_res_fail_pmpm_ct', 'submcc_rs
k_an_pmpm_ct', 'submcc_rsk_coag_pmpm_ct', 'submcc_rsk_fh/h_pmpm_ct', 'submcc_rsk_othr_pmpm_ct', 'submcc_rsk
_pcos_pmpm_ct', 'submcc_rsk_synx_pmpm_ct', 'submcc_sns_coma_pmpm_ct', 'submcc_sns_dth_pmpm_ct', 'submcc_trm
_brn_pmpm_ct', 'submcc_trm_f/n_pmpm_ct', 'submcc_trm_fxu_pmpm_ct', 'submcc_trm_fxul_pmpm_ct', 'submcc_trm_h
ip_pmpm_ct', 'submcc_trm_prly_pmpm_ct', 'submcc_trm_skul_pmpm_ct', 'submcc_trm_spfx_pmpm_ct', 'submcc_trm_s
pnj_pmpm_ct', 'submcc_vco_end_pmpm_ct', 'total_ip_ltach_admit_ct_pmpm', 'total_ip_ltach_admit_days_pmpm',
'total_ip_maternity_admit_ct_pmpm', 'total_ip_maternity_admit_days_pmpm', 'total_ip_mhsa_admit_ct_pmpm', 't
otal_ip_mhsa_admit_days_pmpm', 'total_ip_rehab_admit_ct_pmpm', 'total_ip_rehab_admit_days_pmpm', 'total_ip_
snf_admit_ct_pmpm', 'total_ip_snf_admit_days_pmpm', 'submcc_cad_ang_ind', 'rx_gpi2_31_ind', 'submcc_trm_spf
x_ind', 'rx_gpi2_18_ind', 'submcc_hdz_it_is_ind', 'rx_gpi2_78_ind', 'rx_gpi2_45_ind', 'rx_gpi2_40_ind', 'su
bmcc_ano_cns_ind', 'rx_gpi2_87_ind', 'submcc_trm_spnj_ind', 'rx_gpi2_84_ind', 'submcc_pre_del_ind', 'submcc
_can_gu_ind', 'submcc_inf_sep_ind', 'submcc_can_ner_ind', 'submcc_ner_migr_ind', 'submcc_can_sec_ind', 'rx_
```

```
gpi2_53_ind', 'submcc_vco_end_ind', 'submcc_rar_drm_ind', 'rx_gpi2_81_ind', 'submcc_dia_eye_ind', 'rx_gpi2_
62_ind', 'submcc_brn_othr_ind', 'rx_gpi2_29_ind', 'submcc_trm_brn_ind', 'submcc_hiv_othr_ind', 'rx_gpi2_14_
ind', 'submcc_ben_ner_ind', 'betos_m2c_ind', 'rx_gpi2_54_ind', 'submcc_ben_lymp_ind', 'rx_gpi2_19_ind', 'su
bmcc_ben_unk_ind', 'submcc_cir_anur_ind', 'submcc_pre_othr_ind', 'submcc_ano_hrt_ind', 'submcc_cer_tia_in
d', 'rx_gpi2_93_ind', 'submcc_rar_ms_ind', 'rx_gpi2_47_ind', 'submcc_ano_mus_ind', 'rx_gpi2_51_ind', 'submc
c_can_leuk_ind', 'submcc_rar_othr_ind', 'rx_gpi2_35_ind', 'submcc_ner_infl_ind', 'submcc_can_end_ind', 'sub
mcc_inj_comp_ind', 'rx_gpi2_92_ind', 'submcc_men_alco_ind', 'rx_gpi2_41_ind', 'rx_gpi2_26_ind', 'submcc_trm
_hip_ind', 'submcc_sns_dth_ind', 'rx_gpi2_60_ind', 'rx_gpi2_95_ind', 'submcc_hdz_surg_ind', 'submcc_ano_oth
r_ind', 'submcc_cad_fh/ho_ind', 'submcc_end_gld_ind', 'rx_gpi2_99_ind', 'submcc_can_res_ind', 'submcc_cer_s
eq_ind', 'submcc_ner_epil_ind', 'submcc_can_skn_ind', 'submcc_neo_fh/ho_ind', 'submcc_inf_cand_ind', 'submc
c_trm_fxul_ind', 'rx_gpi2_64_ind', 'rx_gpi2_08_ind', 'rx_gpi2_23_ind', 'rx_gpi2_69_ind', 'submcc_sns_coma_i
nd', 'submcc_trm_prly_ind', 'submcc_cad_cabg_ind', 'submcc_gus_brst_ind', 'betos_d1c_ind', 'submcc_rar_als_
ind', 'submcc_rar_cf_ind', 'rx_gpi2_25_ind', 'rx_gpi2_59_ind', 'submcc_rar_sca_ind', 'submcc_can_h/n_ind',
'submcc_inf_men_ind', 'rx_gpi2_61_ind', 'submcc_hdz_it_i_ind', 'rx_gpi2_21_ind', 'betos_o1b_ind', 'submcc_r
ar_lup_ind', 'submcc_trm_fxu_ind', 'submcc_pre_com_ind', 'submcc_hiv_pcp_ind', 'submcc_end_othr_ind', 'subm
cc_ano_gu_ind', 'rx_gpi2_24_ind', 'submcc_rar_pol_ind', 'submcc_can_dig_ind', 'submcc_trm_skul_ind', 'betos
_d1d_ind', 'submcc_res_fail_ind', 'submcc_rsk_fh/h_ind', 'rx_gpi2_13_ind', 'rx_gpi2_67_ind', 'submcc_rsk_pc
os_ind', 'submcc_pre_ect_ind', 'rx_gpi2_38_ind', 'submcc_hdz_myop_ind', 'rx_gpi2_76_ind', 'submcc_men_schz_
ind', 'rx_gpi2_82_ind', 'submcc_rar_mg_ind', 'submcc_trm_f/n_ind', 'submcc_pre_l/d_ind', 'submcc_pre_care_i
nd', 'rx_gpi2_77_ind', 'submcc_mus_inf_ind', 'submcc_can_brst_ind', 'submcc_ano_dig_ind', 'submcc_mus_atrp_
ind', 'rx_gpi2_80_ind', 'rx_gpi2_68_ind', 'submcc_pre_mul_ind', 'submcc_cad_ptca_ind', 'submcc_dig_p/b_in
d', 'rx_gpi2_98_ind', 'rx_gpi2_20_ind', 'rx_gpi2_07_ind', 'submcc_rar_ra_ind', 'submcc_brn_acc_ind', 'submc
c_cer_hem_ind', 'rx_gpi2_52_ind', 'submcc_inf_myco_ind', 'submcc_rar_par_ind', 'submcc_rsk_an_ind', 'submcc
_rar_hem_ind', 'rx_gpi2_48_ind', 'rx_gpi2_09_ind', 'rx_gpi2_55_ind', 'submcc_hiv_kapo_ind', 'submcc_cad_mi_
ind', 'rx_gpi2_73_ind', 'rx_gpi2_15_ind', 'rx_gpi2_70_ind', 'rx_gpi2_88_ind', 'submcc_can_lymp_ind', 'submc
c_rar_scl_ind', 'rx_gpi2_74_ind', 'rx_gpi2_89_ind', 'rx_gpi2_96_ind', 'submcc_rsk_synx_ind', 'submcc_rsk_co
ag_ind', 'submcc_rsk_othr_ind']
  near_constant.index[near_constant].tolist()))
```

In [31]:

```
# What do we have for our predictor variable - 'transportation_issues'

import dabl
dabl.plot(df, target_col="transportation_issues")
```



Slicing the data

In [89]:

```
## split the age in groups

def age_group(age):
    # 1 represents young population
    if age >= 18 and age <= 30:
        return 1
    # 2 represents mid life population
    elif age > 30 and age <= 40:
        return 2
    # 3 represents senior population
    elif age > 40 and age <=60:
        return 3
    # 4 represents people above 60 and can be termed as veterans
    else:
        return 4

df['age_group'] = df['est_age'].apply(age_group)
df
```

Out[89]:

	person_id_syn	transportation_issues	src_platform_cd	sex_cd	est_age	smoker_current_ind	smoker_former_ind
0	0002MOb79ST17bLYAe46eIc2	0	EM	F	62	1	0
1	0004cMOS6bTLf34Y7AIca8f3	0	EM	F	59	1	0
2	000536M9O3ST98LaYaeA29Ia	1	EM	F	63	0	0
3	0009bMO9SfTLYe77A51I4ac3	0	EM	M	75	0	0
4	000M7OeS66bTL8bY89Aa16Ie	0	EM	M	51	1	0
...	...	...	...	...	...	...	...
69567	ffe33MOS25dTf027LaY7A5I3	0	EM	F	72	1	0
69568	fff1M4O1cfST49LY464A2Ieb	0	EM	M	75	0	0
69569	fff5MO7e401STLYcAd8e581I	0	EM	M	76	0	0
69570	fffMc37OSfTLfY7853dfA09I	0	LV	M	67	0	1
69571	fffc14bbMOfSTb7eLY5AI14d	1	EM	M	60	0	0

69572 rows × 810 columns

In [90]:
```
df_male = df[df['sex_cd'] == 'M']
```

In [91]:
```
df_male.head(10)
```

Out[91]:

	person_id_syn	transportation_issues	src_platform_cd	sex_cd	est_age	smoker_current_ind	smoker_former_ind	la
3	0009bMO9SfTLYe77A51I4ac3	0	EM	M	75	0	0	
4	000M7OeS66bTL8bY89Aa16Ie	0	EM	M	51	1	0	
9	0015M23c489ObSb70TLYcbAI	0	LV	M	69	0	0	
12	001e35fMOSe8bT8L97Y1AI88	0	EM	M	78	0	0	
13	0021eM3Oa1e11STLYdabAI52	0	EM	M	79	1	0	
14	00252bMOSTaaL16aY3aa7AI6	0	EM	M	61	0	0	
15	002M726OfS94TL475Yc2AI90	0	EM	M	60	0	1	
17	002bMbcOS8TaLaY854b9AI49	1	EM	M	67	0	0	
18	002cMeaf94OSdTL4ad7YdAI9	0	EM	M	72	0	0	
21	0038MOS5TL7Y657A1beI0367	0	LV	M	84	0	0	

10 rows × 810 columns

In [92]:
```
df_female = df[df['sex_cd'] == 'F']
```

In [93]:
```
df_female.head(10)
```

Out[93]:

rx_gpi2_96_ind	submcc_rsk_obe_ind	rx_gpi2_22_ind	submcc_rsk_synx_ind	submcc_rsk_coag_ind	submcc_rsk_othr_ind	submcc_rsk
0	0	0	0	0	0	
0	1	0	0	0	0	
0	0	0	0	0	0	
0	1	0	0	0	0	
0	0	0	0	0	0	
0	1	0	0	0	0	
0	0	0	0	0	0	
0	0	1	0	0	0	
0	1	0	0	0	0	
0	1	0	0	0	0	

In [123]:
```
df_male_age_group = df_male.filter(regex=("age_*"))
df_male_betos = df_male.filter(regex=("betos_*"))
df_male_bh = df_male.filter(regex=("bh_*"))
df_male_bh = df_male.filter(regex=("cssp_*"))
df_male_cms = df_male.filter(regex=("cms_*"))
df_male_cmsd2 = df_male.filter(regex=("cmsd2_*"))
df_male_cons = df_male.filter(regex=("cons_*"))
df_male_credit_bal = df_male.filter(regex=("credit_bal*"))
df_male_credit_hh = df_male.filter(regex=("credit_hh*"))
df_male_credit_minmob = df_male.filter(regex=("credit_minmob*"))
df_male_credit_num = df_male.filter(regex=("credit_num*"))
df_male_credit_num = df_male.filter(regex=("credit_num*"))
df_male_credit_prcnt = df_male.filter(regex=("credit_prcnt*"))
df_male_hedis_ami = df_male.filter(regex=("hedis_ami*"))
df_male_hedis_cmc = df_male.filter(regex=("hedis_cmc*"))
df_male_hedis_dia = df_male.filter(regex=("hedis_dia*"))
df_male_hlth = df_male.filter(regex=("hlth_*"))
df_male_lab = df_male.filter(regex=("lab_*"))
df_male_med = df_male.filter(regex=("med_*"))
df_male_pdc = df_male.filter(regex=("pdc_*"))
df_male_phy = df_male.filter(regex=("phy_*"))
df_male_prov = df_male.filter(regex=("prov_*"))
df_male_prov_spec = df_male.filter(regex=("prov_spec*"))
df_male_rev_cms = df_male.filter(regex=("rev_cms_*"))
df_male_rucc = df_male.filter(regex=("rucc_*"))
df_male_rx_gpi2 = df_male.filter(regex=("rx_gpi2_*"))
df_male_rx_others = df_male.filter(regex=("rx_*"))
df_male_submcc_ano = df_male.filter(regex=("submcc_ano*"))
df_male_submcc_ben = df_male.filter(regex=("submcc_ben*"))
df_male_submcc_bld = df_male.filter(regex=("submcc_bld*"))
df_male_submcc_brn = df_male.filter(regex=("submcc_brn*"))
df_male_submcc_cad = df_male.filter(regex=("submcc_cad*"))
df_male_submcc_can = df_male.filter(regex=("submcc_can*"))
df_male_submcc_cer = df_male.filter(regex=("submcc_cer*"))
df_male_submcc_cir = df_male.filter(regex=("submcc_cir*"))
df_male_submcc_dia = df_male.filter(regex=("submcc_dia*"))
df_male_submcc_end = df_male.filter(regex=("submcc_end*"))
df_male_submcc_gus = df_male.filter(regex=("submcc_gus*"))
df_male_submcc_hdz = df_male.filter(regex=("submcc_hdz*"))
df_male_submcc_hiv = df_male.filter(regex=("submcc_hiv*"))
df_male_submcc_inf = df_male.filter(regex=("submcc_inf*"))
df_male_submcc_inj = df_male.filter(regex=("submcc_inj*"))
```

```
df_male_submcc_men = df_male.filter(regex=("submcc_men*"))
df_male_submcc_mus = df_male.filter(regex=("submcc_mus*"))
df_male_submcc_neo = df_male.filter(regex=("submcc_neo*"))
df_male_submcc_ner = df_male.filter(regex=("submcc_ner*"))
df_male_submcc_pre = df_male.filter(regex=("submcc_pre*"))
df_male_submcc_rar = df_male.filter(regex=("submcc_rar*"))
df_male_submcc_res = df_male.filter(regex=("submcc_res*"))
df_male_submcc_skn = df_male.filter(regex=("submcc_skn*"))
df_male_submcc_rsk = df_male.filter(regex=("submcc_rsk*"))
df_male_submcc_sns = df_male.filter(regex=("submcc_sns*"))
df_male_submcc_sor = df_male.filter(regex=("submcc_sor*"))
df_male_submcc_trm = df_male.filter(regex=("submcc_trm*"))
df_male_submcc_vco = df_male.filter(regex=("submcc_vco*"))
df_male_total_amb = df_male.filter(regex=("total_amb*"))
df_male_total_ip = df_male.filter(regex=("total_ip*"))
```

In [122]:

```
df_female_age_group = df_female.filter(regex=("age_*"))
df_female_betos = df_female.filter(regex=("betos_*"))
df_female_bh = df_female.filter(regex=("bh_*"))
df_female_bh = df_female.filter(regex=("cssp_*"))
df_female_cms = df_female.filter(regex=("cms_*"))
df_female_cmsd2 = df_female.filter(regex=("cmsd2_*"))
df_female_cons = df_female.filter(regex=("cons_*"))
df_female_credit_bal = df_female.filter(regex=("credit_bal*"))
df_female_credit_hh = df_female.filter(regex=("credit_hh*"))
df_female_credit_minmob = df_female.filter(regex=("credit_minmob*"))
df_female_credit_num = df_female.filter(regex=("credit_num*"))
df_female_credit_num = df_female.filter(regex=("credit_num*"))
df_female_credit_prcnt = df_female.filter(regex=("credit_prcnt*"))
df_female_hedis_ami = df_female.filter(regex=("hedis_ami*"))
df_female_hedis_cmc = df_female.filter(regex=("hedis_cmc*"))
df_female_hedis_dia = df_female.filter(regex=("hedis_dia*"))
df_female_hlth = df_female.filter(regex=("hlth_*"))
df_female_lab = df_female.filter(regex=("lab_*"))
df_female_med = df_female.filter(regex=("med_*"))
df_female_pdc = df_female.filter(regex=("pdc_*"))
df_female_phy = df_female.filter(regex=("phy_*"))
df_female_prov = df_female.filter(regex=("prov_*"))
df_female_prov_spec = df_female.filter(regex=("prov_spec*"))
df_female_rev_cms = df_female.filter(regex=("rev_cms_*"))
df_female_rucc = df_female.filter(regex=("rucc_*"))
df_female_rx_gpi2 = df_female.filter(regex=("rx_gpi2_*"))
df_female_rx_others = df_female.filter(regex=("rx_*"))
df_female_submcc_ano = df_female.filter(regex=("submcc_ano*"))
df_female_submcc_ben = df_female.filter(regex=("submcc_ben*"))
df_female_submcc_bld = df_female.filter(regex=("submcc_bld*"))
df_female_submcc_brn = df_female.filter(regex=("submcc_brn*"))
df_female_submcc_cad = df_female.filter(regex=("submcc_cad*"))
df_female_submcc_can = df_female.filter(regex=("submcc_can*"))
df_female_submcc_cer = df_female.filter(regex=("submcc_cer*"))
df_female_submcc_cir = df_female.filter(regex=("submcc_cir*"))
df_female_submcc_dia = df_female.filter(regex=("submcc_dia*"))
df_female_submcc_end = df_female.filter(regex=("submcc_end*"))
df_female_submcc_gus = df_female.filter(regex=("submcc_gus*"))
df_female_submcc_hdz = df_female.filter(regex=("submcc_hdz*"))
df_female_submcc_hiv = df_female.filter(regex=("submcc_hiv*"))
df_female_submcc_inf = df_female.filter(regex=("submcc_inf*"))
df_female_submcc_inj = df_female.filter(regex=("submcc_inj*"))
```

```
df_female_submcc_men = df_female.filter(regex=("submcc_men*"))
df_female_submcc_mus = df_female.filter(regex=("submcc_mus*"))
df_female_submcc_neo = df_female.filter(regex=("submcc_neo*"))
df_female_submcc_ner = df_female.filter(regex=("submcc_ner*"))
df_female_submcc_pre = df_female.filter(regex=("submcc_pre*"))
df_female_submcc_rar = df_female.filter(regex=("submcc_rar*"))
df_female_submcc_res = df_female.filter(regex=("submcc_res*"))
df_female_submcc_skn = df_female.filter(regex=("submcc_skn*"))
df_female_submcc_rsk = df_female.filter(regex=("submcc_rsk*"))
df_female_submcc_sns = df_female.filter(regex=("submcc_sns*"))
df_female_submcc_sor = df_female.filter(regex=("submcc_sor*"))
df_female_submcc_trm = df_female.filter(regex=("submcc_trm*"))
df_female_submcc_vco = df_female.filter(regex=("submcc_vco*"))
df_female_total_amb = df_female.filter(regex=("total_amb*"))
df_female_total_ip = df_female.filter(regex=("total_ip*"))
```

In [ ]:

In [ ]:

Modeling

A. For the whole file with 'transporation issues' as our predicor

Lasso Regression

In [45]:

```
# Remove columns with strings
df = df[df.T[df.dtypes!=np.object].index]
```

In [52]:
```
from sklearn.model_selection import train_test_split
X = df.drop ('transportation_issues', axis=1)
Y = df['transportation_issues']
X_train, X_Valid, y_train, y_test = train_test_split( X, Y, test_size=0.25, random_state=25, stratify= Y)
```

In [48]:
```
predictors
```

Out[48]:
```
Index(['est_age', 'smoker_current_ind', 'smoker_former_ind', 'cci_score',
       'dcsi_score', 'fci_score', 'hcc_weighted_sum', 'betos_d1c_pmpm_ct',
       'betos_d1d_pmpm_ct', 'betos_m1b_pmpm_ct',
       ...
       'submcc_rar_scl_ind', 'rx_gpi2_74_ind', 'rx_gpi2_89_ind',
       'rx_gpi2_96_ind', 'submcc_rsk_obe_ind', 'rx_gpi2_22_ind',
       'submcc_rsk_synx_ind', 'submcc_rsk_coag_ind', 'submcc_rsk_othr_ind',
       'submcc_rsk_chol_ind'],
      dtype='object', length=792)
```

In [49]:
```
from sklearn.linear_model import LassoCV
from sklearn.linear_model import Lasso
from sklearn.model_selection import KFold

n_folds = 10
k_fold = KFold(n_folds)

# Lasso linear model with iterative fitting along a regularization path
lasso_cv = LassoCV(alphas=None, cv=k_fold, max_iter=100000)
lasso_cv.fit(X_train, y_train)
print(lasso_cv.alpha_)

lasso = Lasso(alpha=lasso_cv.alpha_, random_state=50, max_iter=100000)
lasso.fit(X_train, y_train)
pred_test_lasso = lasso.predict(X_test)
```

```
2.586654113331451
```

In [53]:
```
from sklearn.metrics import mean_absolute_error

# Print Mean Absolute Error (MAE)
print('MAE:', mean_absolute_error(y_test, pred_test_lasso))
for i,x in enumerate(list(predictors)):
    print(x, lasso.coef_[i])
```

```
ccsp_239_ind 0.0
ccsp_242_ind -0.0
cms_disabled_ind -0.0
cms_dual_eligible_ind -0.0
cms_hospice_ind -0.0
cms_low_income_ind -0.0
cms_ma_risk_score_nbr 0.0
cms_partd_ra_factor_amt 0.0
cms_risk_adj_payment_rate_a_amt 0.0
cms_risk_adj_payment_rate_b_amt -0.0
cms_risk_adjustment_factor_a_amt 0.0
cms_rx_risk_score_nbr -0.0
cms_tot_ma_payment_amt -0.0
cms_tot_partd_payment_amt -0.0
cmsd2_can_unc_neo/plycyth/myelo_ind -0.0
cmsd2_eye_blindness_ind -0.0
cmsd2_gus_m_genital_ind -0.0
cmsd2_men_mad_ind 0.0
cmsd2_men_men_substance_ind -0.0
cmsd2_mus_polyarthropath_ind 0.0
```

In [54]:
```
lassoWeightsResults = pd.DataFrame(np.vstack((lasso.coef_, predictors)).transpose(), columns=['Weight', 'P
sigWeights = lassoWeightsResults[lassoWeightsResults['Weight']>0].sort_values('Weight',ascending=False)
```

Logistic Regression

In [55]:
```
from sklearn.model_selection import train_test_split
X = df.drop ('transportation_issues', axis=1)
Y = df['transportation_issues']
X_train, X_Valid, y_train, y_Valid = train_test_split( X, Y, test_size=0.25, random_state=25, stratify= Y)
```

In [56]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix

# Fit the logistric regression on the training set
model = LogisticRegression(solver='liblinear', random_state=0)
model.fit(X_train, y_train)
```

Out[56]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=0, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [57]:
```
# Model evaluation:
y_predict = model.predict(X_Valid)
```

In [58]:
```
# Accuracy using confusion matrix
confusion_matrix(y_Valid, model.predict(X_Valid))
```

Out[58]:
```
array([[14735,   109],
       [ 2442,   107]], dtype=int64)
```

In [59]:

```
# Classification for validation set
print(classification_report(y_Valid, y_predict))
```

```
              precision    recall  f1-score   support

           0       0.86      0.99      0.92     14844
           1       0.50      0.04      0.08      2549

    accuracy                           0.85     17393
   macro avg       0.68      0.52      0.50     17393
weighted avg       0.80      0.85      0.80     17393
```

In [ ]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve

logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```

XGBoost

In [149]:

```
from sklearn.model_selection import train_test_split

# Import Linear Regression
from sklearn.linear_model import LinearRegression

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=25, stratify= Y)
```

In [150]:

```
# Initialize LinearRegression model
lin_reg = LinearRegression()

# Fit lin_reg on training data
lin_reg.fit(X_train, y_train)

# Predict X_test using lin_reg
y_pred = lin_reg.predict(X_test)

# Import mean_squared_error
from sklearn.metrics import mean_squared_error

# Import numpy
import numpy as np

# Compute mean_squared_error as mse
mse = mean_squared_error(y_test, y_pred)

# Compute root mean squared error as rmse
rmse = np.sqrt(mse)

# Display root mean squared error
print("RMSE: %0.2f" % (rmse))
```

```
RMSE: 0.34
```

In [151]:

```
# Import XGBRegressor
from xgboost import XGBRegressor

# Instantiate the XGBRegressor, xg_reg
xg_reg = XGBRegressor()

# Fit xg_reg to training set
xg_reg.fit(X_train, y_train)

# Predict labels of test set, y_pred
y_pred = xg_reg.predict(X_test)

# Compute the mean_squared_error, mse
mse = mean_squared_error(y_test, y_pred)

# Compute the root mean squared error, rmse
rmse = np.sqrt(mse)

# Display the root mean squared error
print("RMSE: %0.2f" % (rmse))
```

```
RMSE: 0.34
```

In [152]:

```
from sklearn.model_selection import cross_val_score

# Instantiate Linear Regression
model = LinearRegression()

# Obtain scores of cross-validation using 10 splits and mean squared error
scores = cross_val_score(model, X, y, scoring='neg_mean_squared_error', cv=10)

# Take square root of the scores
rmse = np.sqrt(-scores)

# Display root mean squared error
print('Reg rmse:', np.round(rmse, 2))

# Display mean score
print('RMSE mean: %0.2f' % (rmse.mean()))
```

```
Reg rmse: [0.33 2.87 0.37 0.33 0.34 0.34 0.34 0.34 0.33 0.33]
RMSE mean: 0.59
```

In [153]:

```
# Instantiate XGBRegressor
model = XGBRegressor(objective="reg:squarederror")

# Obtain scores of cross-validation using 10 splits and mean squared error
scores = cross_val_score(model, X, y, scoring='neg_mean_squared_error', cv=10)

# Take square root of the scores
rmse = np.sqrt(-scores)

# Display root mean squared error
print('Reg rmse:', np.round(rmse, 2))

# Display mean score
print('RMSE mean: %0.2f' % (rmse.mean()))
```

```
Reg rmse: [0.34 0.34 0.34 0.33 0.34 0.34 0.34 0.35 0.34 0.34]
RMSE mean: 0.34
```

In [157]:

```
# Import Logistic Regression
from sklearn.linear_model import LogisticRegression
```

In [158]:

```
# Import cross_val_score
from sklearn.model_selection import cross_val_score

# Define cross_val function with classifer and num_splits as input
def cross_val(classifier, num_splits=10):

    # Initialize classifier
    model = classifier

    # Obtain scores of cross-validation
    scores = cross_val_score(model, X, y, cv=num_splits)

    # Display accuracy
    print('Accuracy:', np.round(scores, 2))

    # Display mean accuracy
    print('Accuracy mean: %0.2f' % (scores.mean()))
```

In [159]:

```
# Use cross_val function to score LogisticRegression
cross_val(LogisticRegression())
```

```
C:\Users\its_t\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\svm\base.py:929: ConvergenceWarn
ing: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)

Accuracy: [0.85 0.86 0.86 0.86 0.85 0.85 0.85 0.85 0.85 0.85]
Accuracy mean: 0.85
```

In [160]:

```
from xgboost import XGBClassifier
```

In [161]:

```
# Use cross_val function to score XGBoost
cross_val(XGBClassifier(n_estimators=5))
```

```
Accuracy: [0.86 0.86 0.86 0.86 0.86 0.85 0.86 0.85 0.85 0.86]
Accuracy mean: 0.86
```

Decision Trees

In [162]:

```
# Import Decision Tree classifier
from sklearn.tree import DecisionTreeClassifier

# Import accuracy_score
from sklearn.metrics import accuracy_score

# Initialize classification model
clf = DecisionTreeClassifier(random_state=2)

# Fit model on training data
clf.fit(X_train, y_train)

# Make predictions for test data
y_pred = clf.predict(X_test)

# Calculate accuracy
accuracy_score(y_pred, y_test)
```

Out[162]: 0.7707123555453343

In [163]:

```
# Import Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor

# Import cross_val_score
from sklearn.model_selection import cross_val_score
```

In [165]:

```
# Initialize Decision Tree Regressor
reg = DecisionTreeRegressor(random_state=2)

# Obtain scores of cross-validation using mean squared error
scores = cross_val_score(reg, X_train, y_train, scoring='neg_mean_squared_error', cv=5)

# Take square root of the scores
rmse = np.sqrt(-scores)

# Display mean score
print('RMSE mean: %0.2f' % (rmse.mean()))
```

```
RMSE mean: 0.48
```

In [166]:

```
# Initialize and score DecisionTreeRegressor on training set
reg = DecisionTreeRegressor()
reg.fit(X_train, y_train)
y_pred = reg.predict(X_train)
from sklearn.metrics import mean_squared_error
reg_mse = mean_squared_error(y_train, y_pred)
reg_rmse = np.sqrt(reg_mse)
reg_rmse
```

Out[166]:

```
0.0
```

In [167]:

```
# Import GridSearchCV
from sklearn.model_selection import GridSearchCV

# Choose max_depth hyperparameters
params = {'max_depth':[None,2,3,4,6,8,10,20]}

# Initialize regression model as reg
reg = DecisionTreeRegressor(random_state=2)

# Initialize GridSearchCV as grid_reg
grid_reg = GridSearchCV(reg, params, scoring='neg_mean_squared_error', cv=5, n_jobs=-1)

# Fit grid_reg on X_train and y_train
grid_reg.fit(X_train, y_train)

# Extract best parameters
best_params = grid_reg.best_params_

# Print best hyperparameters
print("Best params:", best_params)
```

```
Best params: {'max_depth': 4}
```

In [168]:

```
# Compute best score
best_score = np.sqrt(-grid_reg.best_score_)

# Print best score
print("Training score: {:.3f}".format(best_score))
```

```
Training score: 0.337
```

In [169]:

```
# Extract best model
best_model = grid_reg.best_estimator_

# Predict test set labels
y_pred = best_model.predict(X_test)

# Import mean_squared_error from sklearn.metrics as MSE
from sklearn.metrics import mean_squared_error

# Compute rmse_test
rmse_test = mean_squared_error(y_test, y_pred)**0.5

# Print rmse_test
print('Test score: {:.3f}'.format(rmse_test))
```

```
Test score: 0.337
```

In [171]:

```
# Create grid_search function
def grid_search(params, reg=DecisionTreeRegressor(random_state=2)):

    # Instantiate GridSearchCV as grid_reg
    grid_reg = GridSearchCV(reg, params, scoring='neg_mean_squared_error', cv=5, n_jobs=-1)

    # Fit grid_reg on X_train and y_train
    grid_reg.fit(X_train, y_train)

    # Extract best params
    best_params = grid_reg.best_params_

    # Print best params
    print("Best params:", best_params)

    # Compute best score
    best_score = np.sqrt(-grid_reg.best_score_)

    # Print best score
    print("Training score: {:.3f}".format(best_score))

    # Predict test set labels
    y_pred = grid_reg.predict(X_test)

    # Compute rmse_test
    rmse_test = mean_squared_error(y_test, y_pred)**0.5

    # Print rmse_test
    print('Test score: {:.3f}'.format(rmse_test))
```

In [172]:

```
grid_search(params={'min_samples_leaf':[1,2,4,6,8,10,20,30]})
```

```
Best params: {'min_samples_leaf': 30}
Training score: 0.366
Test score: 0.366
```

In [173]:

```
grid_search(params={'max_depth':[None,2,3,4,6,8,10,20],'min_samples_leaf':[1,2,4,6,8,10,20,30]})
```

```
Best params: {'max_depth': 4, 'min_samples_leaf': 30}
Training score: 0.337
Test score: 0.337
```

In [174]:

```
grid_search(params={'max_depth':[5,6,7,8,9],'min_samples_leaf':[3,5,7,9]})
```

```
Best params: {'max_depth': 5, 'min_samples_leaf': 3}
Training score: 0.338
Test score: 0.338
```

RandomForest

In [62]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [63]:

```
from sklearn.model_selection import train_test_split
X = df.drop ('transportation_issues', axis=1)
Y = df['transportation_issues']
X_train, X_Valid, y_train, y_Valid = train_test_split( X, Y, test_size=0.25, random_state=25, stratify= Y)
```

In [64]:

```
# Initialize the classifier
rf = RandomForestClassifier(n_estimators=10, random_state=2, n_jobs=-1)

# Obtain scores of cross-validation
scores = cross_val_score(rf, X_train, y_train, cv=5)

# Display accuracy
print('Accuracy:', np.round(scores, 3))

# Display mean accuracy
print('Accuracy mean: %0.3f' % (scores.mean()))
```

```
Accuracy: [0.852 0.851 0.85  0.851 0.848]
Accuracy mean: 0.850
```

B. We now repeat it for each of the variable we created above in slicing section with 'transportation issues' as our predictor

In [138]:

```
# List of all the dataframes created in the environment
for i in dir():
    if type(globals()[i]) == pd.DataFrame:
        print(i)

# Another way:
# x = %who_ls
```

```
df_male_submcc_skn
df_male_submcc_sns
df_male_submcc_sor
df_male_submcc_trm
df_male_submcc_vco
df_male_total_amb
df_male_total_ip
df_med
df_pdc
df_phy
df_prov
df_prov_spec
df_rev_cms
df_rucc
df_rx_gpi2
df_rx_others
df_submcc_ano
df_submcc_ben
df_submcc_bld
```

In [ ]:

```
# Put all those required dfs for modeling evaluation to a list:
df_list = ['df_female_age_group', 'df_female_betos', 'df_female_bh', 'df_female_cms', 'df_female_cmsd2', '
```

In [157]:
```
# Assign each dataframe to a new variable
for n, val in enumerate(df_list):
    globals()["var%d"%n] = val
    n = n+1

print (var1)
print (var2)
print (var3)
print (var4)

# and so on....we can call each variable by number and run the code below
```

```
df_female_betos
df_female_bh
df_female_cms
df_female_cmsd2
```

In [ ]:

```
# We are just printing the accuracy from our logistic regression and xgboost model. The other ones we trie

# X = <all variables for testing>
y = df_male['transportation_issues']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=25, stratify= Y)

# Define cross_val function with classifer and num_splits as input
def cross_val(classifier, num_splits=10):

    # Initialize classifier
    model = classifier

    # Obtain scores of cross-validation
    scores = cross_val_score(model, X, y, cv=num_splits)

    # Display accuracy
    print('Accuracy:', np.round(scores, 2))

    # Display mean accuracy
    print('Accuracy mean: %0.4f' % (scores.mean()))

# Use cross_val function to score LogisticRegression
cross_val(LogisticRegression())
# Use cross_val function to score XGBoost
cross_val(XGBClassifier(n_estimators=5))
```

Validation with the holdout dataset

In [159]:

```
# Read the file
df_ho = pd.read_csv('2020_Competition_Holdout.csv')
```

```
C:\Users\its_t\AppData\Local\Continuum\anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3057: D
typeWarning: Columns (79) have mixed types.Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [161]:

```
df_ho.head(10)
```

Out[161]:

	person_id_syn	src_platform_cd	sex_cd	est_age	smoker_current_ind	smoker_former_ind	lang_spoken_cd	mabh_se
0	000M289dOSbe8dTL75c71YAI	EM	M	68	1	0	ENG	C
1	000b16MOSTLY7A637698c5I3	EM	F	65	0	0	ENG	H
2	0011MOdcfS9188T8aLYA3dIa	LV	M	67	0	0	SPA	UN
3	001MO8SaT6dL8ae755cYA3dI	EM	F	76	0	0	ENG	C
4	001MOS3a40Tc5L1534YAeI40	EM	F	65	0	0	ENG	H
5	001MOS4Tf6LYcb734A09I169	EM	F	56	1	0	ENG	H
6	004M03e7OSe0e42TLYeAIc18	LV	F	79	0	0	ENG	H
7	005dbMdfOSeT507L5YbAad7I	LV	M	81	0	0	ENG	C
8	0067MO997S9TL628f2YAb98I	LV	M	79	0	0	ENG	C
9	0088MfOSbTf7a711LY7AdIab	LV	M	76	0	0	ENG	C

10 rows × 825 columns

In [165]:

```
## split the age in groups

def age_group(age):
    # 1 represents young population
    if age >= 18 and age <= 30:
        return 1
    # 2 represents mid life population
    elif age > 30 and age <= 40:
        return 2
    # 3 represents senior population
    elif age > 40 and age <=60:
        return 3
    # 4 represents people above 60 and can be termed as veterans
    else:
        return 4

df_ho['age_group'] = df_ho['est_age'].apply(age_group)
df_ho_male = df_ho[df_ho['sex_cd'] == 'M']
df_ho_female = df_ho[df_ho['sex_cd'] == 'F']
```

In [166]:

```
# List of all the variable combination from the holdout just as we did for the training set
df_ho_male_age_group = df_ho_male.filter(regex=("age_*"))
df_ho_male_betos = df_ho_male.filter(regex=("betos_*"))
df_ho_male_bh = df_ho_male.filter(regex=("bh_*"))
df_ho_male_bh = df_ho_male.filter(regex=("cssp_*"))
df_ho_male_cms = df_ho_male.filter(regex=("cms_*"))
df_ho_male_cmsd2 = df_ho_male.filter(regex=("cmsd2_*"))
df_ho_male_cons = df_ho_male.filter(regex=("cons_*"))
df_ho_male_credit_bal = df_ho_male.filter(regex=("credit_bal*"))
df_ho_male_credit_hh = df_ho_male.filter(regex=("credit_hh*"))
df_ho_male_credit_minmob = df_ho_male.filter(regex=("credit_minmob*"))
df_ho_male_credit_num = df_ho_male.filter(regex=("credit_num*"))
df_ho_male_credit_num = df_ho_male.filter(regex=("credit_num*"))
df_ho_male_credit_prcnt = df_ho_male.filter(regex=("credit_prcnt*"))
df_ho_male_hedis_ami = df_ho_male.filter(regex=("hedis_ami*"))
df_ho_male_hedis_cmc = df_ho_male.filter(regex=("hedis_cmc*"))
df_ho_male_hedis_dia = df_ho_male.filter(regex=("hedis_dia*"))
df_ho_male_hlth = df_ho_male.filter(regex=("hlth_*"))
df_ho_male_lab = df_ho_male.filter(regex=("lab_*"))
df_ho_male_med = df_ho_male.filter(regex=("med_*"))
df_ho_male_pdc = df_ho_male.filter(regex=("pdc_*"))
df_ho_male_phy = df_ho_male.filter(regex=("phy_*"))
df_ho_male_prov = df_ho_male.filter(regex=("prov_*"))
df_ho_male_prov_spec = df_ho_male.filter(regex=("prov_spec*"))
df_ho_male_rev_cms = df_ho_male.filter(regex=("rev_cms_*"))
df_ho_male_rucc = df_ho_male.filter(regex=("rucc_*"))
df_ho_male_rx_gpi2 = df_ho_male.filter(regex=("rx_gpi2_*"))
df_ho_male_rx_others = df_ho_male.filter(regex=("rx_*"))
df_ho_male_submcc_ano = df_ho_male.filter(regex=("submcc_ano*"))
df_ho_male_submcc_ben = df_ho_male.filter(regex=("submcc_ben*"))
df_ho_male_submcc_bld = df_ho_male.filter(regex=("submcc_bld*"))
df_ho_male_submcc_brn = df_ho_male.filter(regex=("submcc_brn*"))
df_ho_male_submcc_cad = df_ho_male.filter(regex=("submcc_cad*"))
df_ho_male_submcc_can = df_ho_male.filter(regex=("submcc_can*"))
df_ho_male_submcc_cer = df_ho_male.filter(regex=("submcc_cer*"))
df_ho_male_submcc_cir = df_ho_male.filter(regex=("submcc_cir*"))
df_ho_male_submcc_dia = df_ho_male.filter(regex=("submcc_dia*"))
df_ho_male_submcc_end = df_ho_male.filter(regex=("submcc_end*"))
df_ho_male_submcc_gus = df_ho_male.filter(regex=("submcc_gus*"))
df_ho_male_submcc_hdz = df_ho_male.filter(regex=("submcc_hdz*"))
df_ho_male_submcc_hiv = df_ho_male.filter(regex=("submcc_hiv*"))
df_ho_male_submcc_inf = df_ho_male.filter(regex=("submcc_inf*"))
```

```
df_ho_male_submcc_inj = df_ho_male.filter(regex=("submcc_inj*"))
df_ho_male_submcc_men = df_ho_male.filter(regex=("submcc_men*"))
df_ho_male_submcc_mus = df_ho_male.filter(regex=("submcc_mus*"))
df_ho_male_submcc_neo = df_ho_male.filter(regex=("submcc_neo*"))
df_ho_male_submcc_ner = df_ho_male.filter(regex=("submcc_ner*"))
df_ho_male_submcc_pre = df_ho_male.filter(regex=("submcc_pre*"))
df_ho_male_submcc_rar = df_ho_male.filter(regex=("submcc_rar*"))
df_ho_male_submcc_res = df_ho_male.filter(regex=("submcc_res*"))
df_ho_male_submcc_skn = df_ho_male.filter(regex=("submcc_skn*"))
df_ho_male_submcc_rsk = df_ho_male.filter(regex=("submcc_rsk*"))
df_ho_male_submcc_sns = df_ho_male.filter(regex=("submcc_sns*"))
df_ho_male_submcc_sor = df_ho_male.filter(regex=("submcc_sor*"))
df_ho_male_submcc_trm = df_ho_male.filter(regex=("submcc_trm*"))
df_ho_male_submcc_vco = df_ho_male.filter(regex=("submcc_vco*"))
df_ho_male_total_amb = df_ho_male.filter(regex=("total_amb*"))
df_ho_male_total_ip = df_ho_male.filter(regex=("total_ip*"))
df_ho_female_age_group = df_ho_female.filter(regex=("age_*"))
df_ho_female_betos = df_ho_female.filter(regex=("betos_*"))
df_ho_female_bh = df_ho_female.filter(regex=("bh_*"))
df_ho_female_bh = df_ho_female.filter(regex=("cssp_*"))
df_ho_female_cms = df_ho_female.filter(regex=("cms_*"))
df_ho_female_cmsd2 = df_ho_female.filter(regex=("cmsd2_*"))
df_ho_female_cons = df_ho_female.filter(regex=("cons_*"))
df_ho_female_credit_bal = df_ho_female.filter(regex=("credit_bal*"))
df_ho_female_credit_hh = df_ho_female.filter(regex=("credit_hh*"))
df_ho_female_credit_minmob = df_ho_female.filter(regex=("credit_minmob*"))
df_ho_female_credit_num = df_ho_female.filter(regex=("credit_num*"))
df_ho_female_credit_num = df_ho_female.filter(regex=("credit_num*"))
df_ho_female_credit_prcnt = df_ho_female.filter(regex=("credit_prcnt*"))
df_ho_female_hedis_ami = df_ho_female.filter(regex=("hedis_ami*"))
df_ho_female_hedis_cmc = df_ho_female.filter(regex=("hedis_cmc*"))
df_ho_female_hedis_dia = df_ho_female.filter(regex=("hedis_dia*"))
df_ho_female_hlth = df_ho_female.filter(regex=("hlth_*"))
df_ho_female_lab = df_ho_female.filter(regex=("lab_*"))
df_ho_female_med = df_ho_female.filter(regex=("med_*"))
df_ho_female_pdc = df_ho_female.filter(regex=("pdc_*"))
df_ho_female_phy = df_ho_female.filter(regex=("phy_*"))
df_ho_female_prov = df_ho_female.filter(regex=("prov_*"))
df_ho_female_prov_spec = df_ho_female.filter(regex=("prov_spec*"))
df_ho_female_rev_cms = df_ho_female.filter(regex=("rev_cms_*"))
df_ho_female_rucc = df_ho_female.filter(regex=("rucc_*"))
df_ho_female_rx_gpi2 = df_ho_female.filter(regex=("rx_gpi2_*"))
df_ho_female_rx_others = df_ho_female.filter(regex=("rx_*"))
```

```
df_ho_female_submcc_ano = df_ho_female.filter(regex=("submcc_ano*"))
df_ho_female_submcc_ben = df_ho_female.filter(regex=("submcc_ben*"))
df_ho_female_submcc_bld = df_ho_female.filter(regex=("submcc_bld*"))
df_ho_female_submcc_brn = df_ho_female.filter(regex=("submcc_brn*"))
df_ho_female_submcc_cad = df_ho_female.filter(regex=("submcc_cad*"))
df_ho_female_submcc_can = df_ho_female.filter(regex=("submcc_can*"))
df_ho_female_submcc_cer = df_ho_female.filter(regex=("submcc_cer*"))
df_ho_female_submcc_cir = df_ho_female.filter(regex=("submcc_cir*"))
df_ho_female_submcc_dia = df_ho_female.filter(regex=("submcc_dia*"))
df_ho_female_submcc_end = df_ho_female.filter(regex=("submcc_end*"))
df_ho_female_submcc_gus = df_ho_female.filter(regex=("submcc_gus*"))
df_ho_female_submcc_hdz = df_ho_female.filter(regex=("submcc_hdz*"))
df_ho_female_submcc_hiv = df_ho_female.filter(regex=("submcc_hiv*"))
df_ho_female_submcc_inf = df_ho_female.filter(regex=("submcc_inf*"))
df_ho_female_submcc_inj = df_ho_female.filter(regex=("submcc_inj*"))
df_ho_female_submcc_men = df_ho_female.filter(regex=("submcc_men*"))
df_ho_female_submcc_mus = df_ho_female.filter(regex=("submcc_mus*"))
df_ho_female_submcc_neo = df_ho_female.filter(regex=("submcc_neo*"))
df_ho_female_submcc_ner = df_ho_female.filter(regex=("submcc_ner*"))
df_ho_female_submcc_pre = df_ho_female.filter(regex=("submcc_pre*"))
df_ho_female_submcc_rar = df_ho_female.filter(regex=("submcc_rar*"))
df_ho_female_submcc_res = df_ho_female.filter(regex=("submcc_res*"))
df_ho_female_submcc_skn = df_ho_female.filter(regex=("submcc_skn*"))
df_ho_female_submcc_rsk = df_ho_female.filter(regex=("submcc_rsk*"))
df_ho_female_submcc_sns = df_ho_female.filter(regex=("submcc_sns*"))
df_ho_female_submcc_sor = df_ho_female.filter(regex=("submcc_sor*"))
df_ho_female_submcc_trm = df_ho_female.filter(regex=("submcc_trm*"))
df_ho_female_submcc_vco = df_ho_female.filter(regex=("submcc_vco*"))
df_ho_female_total_amb = df_ho_female.filter(regex=("total_amb*"))
df_ho_female_total_ip = df_ho_female.filter(regex=("total_ip*"))
```

In [167]:

```
# List of all the dataframes created in the environment
for i in dir():
    if type(globals()[i]) == pd.DataFrame:
        print(i)

# Another way:
# x = %who_ls
```

```
X
X_Valid
X_test
X_train
_
_10
_102
_103
_105
_106
_16
_160
_161
_39
_40
_6
_70
_71
_74
```

In [168]:

```
# Put all those required dfs for modeling evaluation to a list:
df_ho_list = ['df_ho_female_age_group', 'df_ho_female_betos', 'df_ho_female_bh', 'df_ho_female_cms', 'df_h
```

In [169]:

```
# Assign each dataframe to a new variable
for n, val in enumerate(df_list):
    globals()["var%d"%n] = val
    n = n+1

print (var1)
print (var2)
print (var3)
print (var4)

# and so on....we can call each variable by number and run the code below
```

```
df_female_betos
df_female_bh
df_female_cms
df_female_cmsd2
```

In [ ]:

```
# We are just printing the accuracy from our logistic regression and xgboost model. The other ones we trie

# X = <all variables for testing>
# Example:
X = var8
# y = <precitor variable>

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=25, stratify= Y)

# Define cross_val function with classifier and num_splits as input
def cross_val(classifier, num_splits=10):

    # Initialize classifier
    model = classifier

    # Obtain scores of cross-validation
    scores = cross_val_score(model, X, y, cv=num_splits)

    # Display accuracy
    print('Accuracy:', np.round(scores, 2))

    # Display mean accuracy
    print('Accuracy mean: %0.4f' % (scores.mean()))

# Use cross_val function to score LogisticRegression
cross_val(LogisticRegression())
# Use cross_val function to score XGBoost
cross_val(XGBClassifier(n_estimators=5))
```