Introduction to the project:

- Sepsis is caused by the dysregulated reduction to infection
- The bacteria enters the blood upon infection and then slowly all the vital organs malfunction and it leads to the death of the patient. So identifying the possibility of a septic shock upto 8 hours or so before it actually occurs helps in a better survival of the patient (increase in survival rate by 14 to 20%)
- Sepsis is an organ failure and it is described as a serious condition in which the body responds improperly to an infection. the fight of the body against the infection turns against it in sepsis.
- Sepsis may progress to a septic shock which can lead to a dramatic drop in BP that can lead to damage of lungs, kidneys and other vital organs.
- We can save the patient if we can identify the occurence of sepsis by 6 to 8 hrs before it occurs.

In [187]:
```
import pandas as pd
import numpy as np

import seaborn as sns
sns.set()

import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

# to see large number of columns and rows
pd.set_option('display.max_columns', 200)
pd.set_option('display.max_rows', 200)


# Evaluation

from sklearn.metrics import confusion_matrix, classification_report, accura
from sklearn.model_selection import cross_val_score
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.metrics import precision_score, recall_score, f1_score
```

read dataset

In [188]:
```
df=pd.read_csv("sepsis_status.csv")
```

In [189]:
```
dictionary=pd.read_csv("Parameter _detail_Dictionary.csv")
```

In [190]:
```
icu_df=df.copy()
icu_df.head()
```

Out[190]:

	encounter_id	patient_id	hospital_id	septic_shock	age	bmi	elective_surgery	ethnicity
0	66154	25312	118	0	68.0	22.73	0	Caucasian
1	114252	59342	81	0	77.0	27.42	0	Caucasian
2	119783	50777	118	0	25.0	31.95	0	Caucasian
3	79267	46918	118	0	81.0	22.64	1	Caucasian
4	92056	34377	33	0	19.0	NaN	0	Caucasian

In [191]:
```
icu_df.shape
```

Out[191]:
```
(91713, 186)
```

information about the features

In [192]:
```
df.columns
```

Out[192]:
```
Index(['encounter_id', 'patient_id', 'hospital_id', 'septic_shock', 'age',
       'bmi', 'elective_surgery', 'ethnicity', 'gender', 'height',
       ...
       'aids', 'cirrhosis', 'diabetes_mellitus', 'hepatic_failure',
       'immunosuppression', 'leukemia', 'lymphoma',
       'solid_tumor_with_metastasis', 'apache_3j_bodysystem',
       'apache_2_bodysystem'],
      dtype='object', length=186)
```

In [193]:
```
icu_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 91713 entries, 0 to 91712
Columns: 186 entries, encounter_id to apache_2_bodysystem
dtypes: float64(170), int64(8), object(8)
memory usage: 130.1+ MB
```

target variable

In [194]:
```
icu_df['septic_shock'].value_counts()
```

Out[194]:
```
septic_shock
0    83798
1     7915
Name: count, dtype: int64
```

In [195]:
```
icu_df['septic_shock'].value_counts(normalize=True)# highly imbalanced data;
```

Out[195]:
```
septic_shock
0    0.913698
1    0.086302
Name: proportion, dtype: float64
```

looking at the dictionary to understand the meaning of the column variables

In [196]:
```
dictionary.head(50)
```

Out[196]:

	Category	Variable Name	Unit of Measure	Data Type	Description	Exa
0	identifier	encounter_id	NaN	integer	Unique identifier associated with a patient un...	
1	identifier	hospital_id	NaN	integer	Unique identifier associated with a hospital	
2	identifier	patient_id	NaN	integer	Unique identifier associated with a patient	
3	demographic	Sepsis_status	NaN	binary	Whether the patient having	

In [197]:
```
for i in range(134,187):
    print(i, dictionary['Variable Name'][i], dictionary['Description'][i])
```

```
134 h1_bun_min The lowest blood urea nitrogen concentration of the patie
nt in their serum or plasma during the first hour of their unit stay
135 h1_calcium_max The highest calcium concentration of the patient in t
heir serum during the first hour of their unit stay
136 h1_calcium_min The lowest calcium concentration of the patient in th
eir serum during the first hour of their unit stay
137 h1_creatinine_max The highest creatinine concentration of the patien
t in their serum or plasma during the first hour of their unit stay
138 h1_creatinine_min The lowest creatinine concentration of the patient
in their serum or plasma during the first hour of their unit stay
139 h1_glucose_max The highest glucose concentration of the patient in t
heir serum or plasma during the first hour of their unit stay
140 h1_glucose_min The lowest glucose concentration of the patient in th
eir serum or plasma during the first hour of their unit stay
141 h1_hco3_max The highest bicarbonate concentration for the patient in
their serum or plasma during the first hour of their unit stay
142 h1_hco3_min The lowest bicarbonate concentration for the patient in
their serum or plasma during the first hour of their unit stay
143 h1_hemaglobin_max The highest hemoglobin concentration for the patie
nt during the first hour of their unit stay
```

In [198]:
```python
# to see the detail of a particular group:

def select_category(data, category):
    return data[data.Category==category]
```

In [199]:
```python
cols=select_category(dictionary, 'APACHE comorbidity')
cols
```

Out[199]:

	Category	Variable Name	Unit of Measure	Data Type	Description	Example
177	APACHE comorbidity	aids	NaN	binary	Whether the patient has a definitive diagnosis...	1
178	APACHE comorbidity	cirrhosis	NaN	binary	Whether the patient has a history of heavy alc...	1
179	APACHE comorbidity	diabetes_mellitus	NaN	binary	Whether the patient has been diagnosed with di...	1
180	APACHE comorbidity	hepatic_failure	NaN	binary	Whether the patient has cirrhosis and addition...	1
181	APACHE comorbidity	immunosuppression	NaN	binary	Whether the patient has their immune system su...	1
182	APACHE comorbidity	leukemia	NaN	binary	Whether the patient has been diagnosed with ac...	1
183	APACHE comorbidity	lymphoma	NaN	binary	Whether the patient has been diagnosed with no...	1
184	APACHE comorbidity	solid_tumor_with_metastasis	NaN	binary	Whether the patient has been diagnosed with an...	1

Preprocessing of the data:

missing value check

In [201]:
```
null=icu_df.isnull().sum()/len(icu_df)
null
```

Out[201]:
```
encounter_id                 0.000000
patient_id                   0.000000
hospital_id                  0.000000
septic_shock                 0.000000
age                          0.046100
bmi                          0.037388
elective_surgery             0.000000
ethnicity                    0.015210
gender                       0.000273
height                       0.014545
hospital_admit_source        0.233435
icu_admit_source             0.001221
icu_id                       0.000000
icu_stay_type                0.000000
icu_type                     0.000000
pre_icu_los_days             0.000000
readmission_status           0.000000
weight                       0.029658
albumin_apache               0.592926
```

- ideally we drop the cols with missing value > 25% but here we cannot drop those columns as it will lead to a huge data loss

approach:

- we will drop the columns where the missing value is greater than 50%, for the rest we will not drop the columns but will drop the rows
- we will not apply missing value imputation for such healthacre or critical care dataset

In [204]:
```
# evaluation of the missing value

high_null=(null[null>0.50]).sort_values(ascending=False)
```

In [205]:
```
high_null
```

Out[205]:
```
h1_bilirubin_max          0.922650
h1_bilirubin_min          0.922650
h1_lactate_max            0.919924
h1_lactate_min            0.919924
h1_albumin_min            0.913982
h1_albumin_max            0.913982
h1_pao2fio2ratio_min      0.874413
h1_pao2fio2ratio_max      0.874413
h1_arterial_ph_min        0.833295
h1_arterial_ph_max        0.833295
h1_hco3_max               0.829697
h1_hco3_min               0.829697
h1_arterial_pco2_max      0.828225
h1_arterial_pco2_min      0.828225
h1_wbc_max                0.828160
h1_wbc_min                0.828160
h1_arterial_po2_max       0.828072
h1_arterial_po2_min       0.828072
h1_calcium_min            0.827178
```

In [206]:
```
high_null.index
```

Out[206]:
```
Index(['h1_bilirubin_max', 'h1_bilirubin_min', 'h1_lactate_max',
       'h1_lactate_min', 'h1_albumin_min', 'h1_albumin_max',
       'h1_pao2fio2ratio_min', 'h1_pao2fio2ratio_max', 'h1_arterial_ph_mi
n',
       'h1_arterial_ph_max', 'h1_hco3_max', 'h1_hco3_min',
       'h1_arterial_pco2_max', 'h1_arterial_pco2_min', 'h1_wbc_max',
       'h1_wbc_min', 'h1_arterial_po2_max', 'h1_arterial_po2_min',
       'h1_calcium_min', 'h1_calcium_max', 'h1_platelets_min',
       'h1_platelets_max', 'h1_bun_min', 'h1_bun_max', 'h1_creatinine_ma
x',
       'h1_creatinine_min', 'h1_diasbp_invasive_max', 'h1_diasbp_invasive_
min',
       'h1_sysbp_invasive_min', 'h1_sysbp_invasive_max', 'h1_mbp_invasive_
min',
       'h1_mbp_invasive_max', 'h1_hematocrit_min', 'h1_hematocrit_max',
       'h1_hemaglobin_max', 'h1_hemaglobin_min', 'h1_sodium_min',
       'h1_sodium_max', 'h1_potassium_max', 'h1_potassium_min',
       'paco2_for_ph_apache', 'pao2_apache', 'ph_apache', 'paco2_apache',
       'fio2_apache', 'd1_lactate_max', 'd1_lactate_min',
       'd1_diasbp_invasive_max', 'd1_diasbp_invasive_min',
       'd1_sysbp_invasive_max', 'd1_sysbp_invasive_min', 'd1_mbp_invasive_
min',
       'd1_mbp_invasive_max', 'd1_pao2fio2ratio_min', 'd1_pao2fio2ratio_ma
x',
       'd1_arterial_ph_max', 'd1_arterial_ph_min', 'd1_arterial_pco2_max',
       'd1_arterial_pco2_min', 'd1_arterial_po2_min', 'd1_arterial_po2_ma
x',
       'bilirubin_apache', 'h1_inr_max', 'h1_inr_min', 'd1_inr_max',
       'd1_inr_min', 'albumin_apache', 'd1_bilirubin_max', 'd1_bilirubin_m
in',
       'h1_glucose_max', 'h1_glucose_min', 'd1_albumin_max', 'd1_albumin_m
in',
       'urineoutput_apache'],
      dtype='object')
```

In [207]:
```python
len(high_null)
```

Out[207]:
```
74
```

In [208]:
```python
icu=icu_df.drop(columns=high_null.index, axis=1)
```

In [209]:
```python
icu.shape
```

Out[209]:
```
(91713, 112)
```

In [210]:
```python
icu.isnull().sum()/len(icu)
```

Out[210]:
```
encounter_id                  0.000000
patient_id                    0.000000
hospital_id                   0.000000
septic_shock                  0.000000
age                           0.046100
bmi                           0.037388
elective_surgery              0.000000
ethnicity                     0.015210
gender                        0.000273
height                        0.014545
hospital_admit_source         0.233435
icu_admit_source              0.001221
icu_id                        0.000000
icu_stay_type                 0.000000
icu_type                      0.000000
pre_icu_los_days              0.000000
readmission_status            0.000000
weight                        0.029658
apache_2_diagnosis            0.018122
```

In [211]:
```python
# the rest of the missing values are less than 25%, we will drop the rows


df1=icu.dropna()
df1.shape
```

Out[211]:
```
(27795, 112)
```

In [212]:
```
df1.isnull().sum()/len(df1)#---> null values removed
```

Out[212]:
```
encounter_id               0.0
patient_id                 0.0
hospital_id                0.0
septic_shock               0.0
age                        0.0
bmi                        0.0
elective_surgery           0.0
ethnicity                  0.0
gender                     0.0
height                     0.0
hospital_admit_source      0.0
icu_admit_source           0.0
icu_id                     0.0
icu_stay_type              0.0
icu_type                   0.0
pre_icu_los_days           0.0
readmission_status         0.0
weight                     0.0
apache_2_diagnosis         0.0
```

dropping unnecessary columns

- In most of the cases the ID columns have no impact on the prediction.
- However, we will keep the hospital id as it indicates the facilities available in the associated hospital

In [214]:
```
columns_to_drop=['encounter_id', 'patient_id', 'hospital_admit_source', 'ic
```

In [215]:
```
columns_to_drop
```

Out[215]:
```
['encounter_id',
 'patient_id',
 'hospital_admit_source',
 'icu_admit_source',
 'icu_id',
 'icu_stay_type']
```

In [216]:
```
df1=df1.drop(columns_to_drop, axis=1)
df1.shape
```

Out[216]:
```
(27795, 106)
```

Encoding the Categorical columns

In [217]:
```
# lets find the object columns

object_columns=df1.select_dtypes(include='object').columns
object_columns
```

Out[217]:
```
Index(['ethnicity', 'gender', 'icu_type', 'apache_3j_bodysystem',
       'apache_2_bodysystem'],
      dtype='object')
```

In [218]:
```
list(object_columns)
```

Out[218]:
```
['ethnicity',
 'gender',
 'icu_type',
 'apache_3j_bodysystem',
 'apache_2_bodysystem']
```

In [219]:
```
# categorical:3,6,7,8,10,11,12,15,17,22, 177-186: the numbers for the variab
#3(target),6(label-encoded), 7(ohe),8(ohe),10(deleted),11(deleted),12(not fo
```

In [220]:
```
df2=pd.get_dummies(df1, columns=list(object_columns), drop_first=True, dtype
```

In [221]:
```
df2.shape
```

Out[221]:
```
(27795, 133)
```

In [222]:
```
df2.head(2)
```

Out[222]:

	hospital_id	septic_shock	age	bmi	elective_surgery	height	pre_icu_los_days	readmis
0	118	0	68.0	22.73	0	180.3	0.541667	
1	81	0	77.0	27.42	0	160.0	0.927778	

In [ ]:

No outlier treatment for healthcare data

In [ ]:

Model building process:

split the data into dep and independent variable

In [224]:
```
X=df2.drop('septic_shock', axis=1)
y=df2['septic_shock'] # target variable
```

In [225]:
```
# any columns having just one unique value: since there is one unique value

one_unique=X.apply(pd.Series.nunique)
one_unique
```

Out[225]:
```
hospital_id                    119
age                             74
bmi                          16993
elective_surgery                 2
height                         271
pre_icu_los_days              4637
readmission_status               1
weight                        2447
apache_2_diagnosis              44
apache_3j_diagnosis            363
apache_post_operative            2
arf_apache                       2
bun_apache                     195
creatinine_apache              938
gcs_eyes_apache                  4
gcs_motor_apache                 6
gcs_unable_apache                1
gcs_verbal_apache                5
glucose_apache                 534
```

In [226]:
```
one_unique_cols=one_unique[one_unique==1].index
```

In [227]:
```
one_unique_cols
```

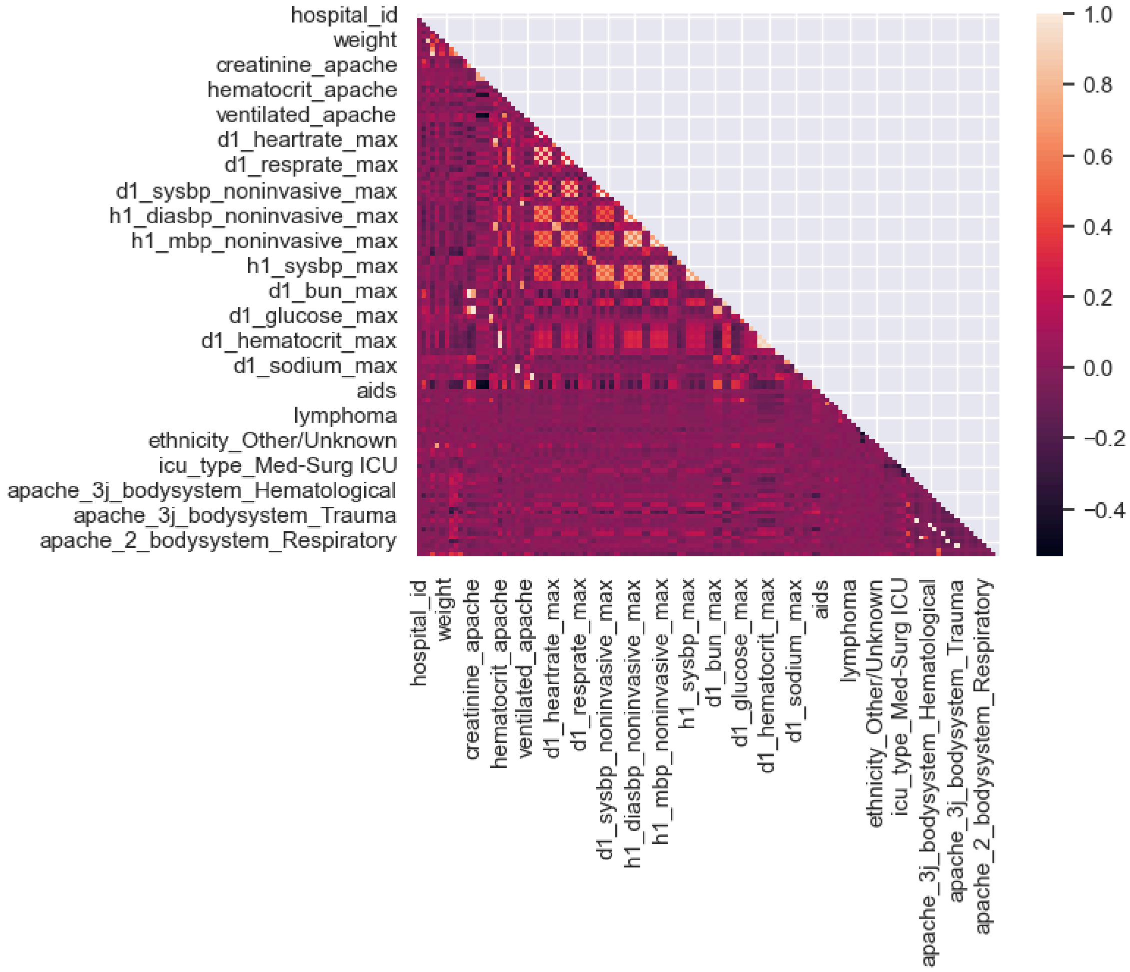
Out[227]:
```
Index(['readmission_status', 'gcs_unable_apache'], dtype='object')
```

In [228]:
```
X=X.drop(one_unique_cols, axis=1)
```

In [229]:
```
X.shape
```

Out[229]:
```
(27795, 130)
```

In [230]:
```python
mask = np.triu(np.ones_like(X.corr(method='spearman'))) # have chosen Spearm
sns.heatmap(X.corr(method='spearman'), mask=mask)
plt.show()
```



In [231]:
```python
corr_matrix=X.corr(method='spearman')
upper=corr_matrix.where(np.triu(np.ones(corr_matrix.shape),k=1).astype(bool
upper
```

Out[231]:

	hospital_id	age	bmi	elective_surg
hospital_id	NaN	-0.023046	0.014703	0.049
age	NaN	NaN	-0.102192	0.054
bmi	NaN	NaN	NaN	0.028
elective_surgery	NaN	NaN	NaN	N
height	NaN	NaN	NaN	N
pre_icu_los_days	NaN	NaN	NaN	N
weight	NaN	NaN	NaN	N
apache_2_diagnosis	NaN	NaN	NaN	N
apache_3j_diagnosis	NaN	NaN	NaN	N
apache_post_operative	NaN	NaN	NaN	N

In [232]:
```
upper.shape
```

Out[232]:
```
(130, 130)
```

In [233]:
```
# for identifying the cols with high correlation


list_c_high, list_c_low=[],[]
list_i_high, list_i_low=[],[]
list_corr_high, list_corr_low=[],[]
for i in upper.columns:
    for j in upper.index:
        p=upper.loc[i,j]
        if (p>0.85 and p<1) or (p<-0.85):
            list_c_high.append(i)
            list_i_high.append(j)
            list_corr_high.append(p)
#             list_corr=set(list_corr)


df_corr_high=pd.DataFrame(data={"var1":list_c_high, "var2": list_i_high, "c
```

In [234]:
```
df_corr_high  # col pairs with high multicollinearity
```

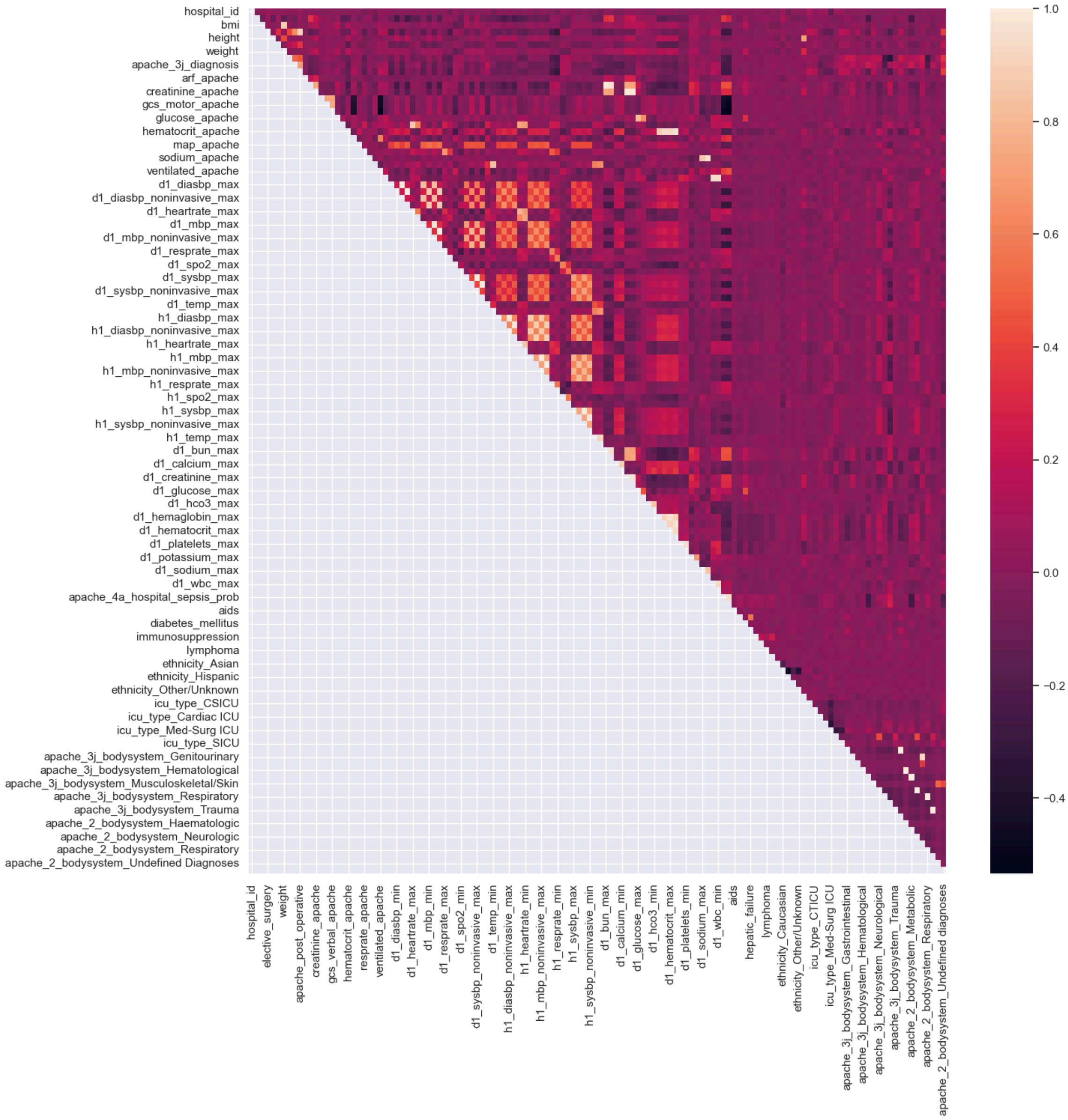
Out[234]:

	var1	var2	correlation
0	bmi	weight	0.880394
1	elective_surgery	apache_post_operative	0.920698
2	bun_apache	d1_bun_max	0.989927
3	bun_apache	d1_bun_min	0.969964
4	creatinine_apache	d1_creatinine_max	0.978576
5	creatinine_apache	d1_creatinine_min	0.981458
6	heart_rate_apache	d1_heartrate_max	0.871626
7	hematocrit_apache	d1_hemaglobin_max	0.891106
8	hematocrit_apache	d1_hemaglobin_min	0.951040
9	hematocrit_apache	d1_hematocrit_max	0.924423
10	hematocrit_apache	d1_hematocrit_min	0.974755
11	sodium_apache	d1_sodium_max	0.870348
12	sodium_apache	d1_sodium_min	0.959834
13	temp_apache	d1_temp_min	0.853881
14	wbc_apache	d1_wbc_max	0.953213
15	wbc_apache	d1_wbc_min	0.951503
16	d1_diasbp_max	d1_diasbp_noninvasive_max	0.998918
17	d1_diasbp_min	d1_diasbp_noninvasive_min	0.998826
18	d1_diasbp_min	d1_mbp_min	0.871799
19	d1_diasbp_min	d1_mbp_noninvasive_min	0.871929
20	d1_diasbp_noninvasive_min	d1_mbp_min	0.871259
21	d1_diasbp_noninvasive_min	d1_mbp_noninvasive_min	0.873157
22	d1_mbp_max	d1_mbp_noninvasive_max	0.991703
23	d1_mbp_min	d1_mbp_noninvasive_min	0.997211
24	d1_sysbp_max	d1_sysbp_noninvasive_max	0.998133
25	d1_sysbp_min	d1_sysbp_noninvasive_min	0.998947
26	h1_diasbp_max	h1_diasbp_noninvasive_max	0.991320
27	h1_diasbp_max	h1_mbp_max	0.866211
28	h1_diasbp_max	h1_mbp_noninvasive_max	0.865098
29	h1_diasbp_min	h1_diasbp_noninvasive_min	0.990628
30	h1_diasbp_min	h1_mbp_min	0.881064
31	h1_diasbp_min	h1_mbp_noninvasive_min	0.878017
32	h1_diasbp_noninvasive_max	h1_mbp_max	0.862321
33	h1_diasbp_noninvasive_max	h1_mbp_noninvasive_max	0.866966
34	h1_diasbp_noninvasive_min	h1_mbp_min	0.878719
35	h1_diasbp_noninvasive_min	h1_mbp_noninvasive_min	0.882484
36	h1_heartrate_max	h1_heartrate_min	0.867243
37	h1_mbp_max	h1_mbp_noninvasive_max	0.991751
38	h1_mbp_min	h1_mbp_noninvasive_min	0.994981

	var1	var2	correlation
39	h1_sysbp_max	h1_sysbp_noninvasive_max	0.994481
40	h1_sysbp_min	h1_sysbp_noninvasive_min	0.993458
41	h1_temp_max	h1_temp_min	0.899770
42	d1_bun_max	d1_bun_min	0.968756
43	d1_calcium_max	d1_calcium_min	0.880314
44	d1_creatinine_max	d1_creatinine_min	0.966421
45	d1_hco3_max	d1_hco3_min	0.865302
46	d1_hemaglobin_max	d1_hemaglobin_min	0.907100
47	d1_hemaglobin_max	d1_hematocrit_max	0.962128
48	d1_hemaglobin_max	d1_hematocrit_min	0.882571
49	d1_hemaglobin_min	d1_hematocrit_max	0.898161
50	d1_hemaglobin_min	d1_hematocrit_min	0.968544
51	d1_hematocrit_max	d1_hematocrit_min	0.916426
52	d1_platelets_max	d1_platelets_min	0.956944
53	d1_wbc_max	d1_wbc_min	0.922230
54	apache_4a_hospital_sepsis_prob	apache_4a_icu_sepsis_prob	0.945028
55	apache_3j_bodysystem_Genitourinary	apache_2_bodysystem_Renal/Genitourinary	0.924330

In [235]:
```python
# to see upper matrix
plt.figure(figsize=(15,15))
sns.heatmap(upper)
plt.show
```

Out[235]: `<function matplotlib.pyplot.show(close=None, block=None)>`



scaling

In [238]:
```python
X.head(2)
```

Out[238]:

	hospital_id	age	bmi	elective_surgery	height	pre_icu_los_days	weight	apache_2_diag
0	118	68.0	22.73	0	180.3	0.541667	73.9	
1	81	77.0	27.42	0	160.0	0.927778	70.2	

In [239]:
```
#Scaling on whole data
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
X_sc=scaler.fit_transform(X)
X_sc=pd.DataFrame(X_sc, columns=X.columns)
X_sc.head()
```

Out[239]:

	hospital_id	age	bmi	elective_surgery	height	pre_icu_los_days	weight	ap
0	0.574257	0.712329	0.148859	0.0	0.738140	0.011390	0.239484	
1	0.391089	0.835616	0.237400	0.0	0.390478	0.017132	0.214383	
2	0.400990	0.698630	0.240043	0.0	0.912828	0.003346	0.416554	
3	0.574257	0.410959	0.207679	0.0	0.520637	0.003336	0.230665	
4	0.574257	0.972603	0.134394	0.0	0.738140	0.078379	0.222524	

In [240]:
```
# Scaling after splitting into train and test

from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test = train_test_split(X,y, random_state=101, str
```

In [241]:
```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
X_train_sc=scaler.fit_transform(X_train)
X_train_sc
```

Out[241]:
```
array([[0.62376238, 0.98630137, 0.13673073, ..., 0.        , 0.        ,
        0.        ],
       [0.92079208, 0.56164384, 0.2210466 , ..., 0.        , 0.        ,
        0.        ],
       [0.92079208, 0.50684932, 0.71984528, ..., 0.        , 0.        ,
        0.        ],
       ...,
       [0.12376238, 0.94520548, 0.06368924, ..., 0.        , 0.        ,
        0.        ],
       [0.92079208, 0.69863014, 0.18025154, ..., 1.        , 0.        ,
        0.        ],
       [0.48514851, 0.5890411 , 0.24944103, ..., 0.        , 0.        ,
        0.        ]])
```

In [242]:
```
X_test_sc=scaler.transform(X_test)  # no need to convert to dataframe. we co
X_test_sc
```

Out[242]:
```
array([[0.22277228, 0.80821918, 0.15091345, ..., 0.        , 0.        ,
        0.        ],
       [0.2970297 , 0.26027397, 0.22612675, ..., 0.        , 0.        ,
        0.        ],
       [0.96039604, 0.53424658, 0.14194316, ..., 1.        , 0.        ,
        0.        ],
       ...,
       [0.57425743, 0.65753425, 0.56304142, ..., 0.        , 0.        ,
        0.        ],
       [0.86138614, 0.12328767, 0.15088858, ..., 0.        , 0.        ,
        0.        ],
       [0.94059406, 0.71232877, 0.24124885, ..., 0.        , 0.        ,
        0.        ]])
```

- we don't do any imbalance treatment generally for such critical healthcare data as that will be creating false data for such a sensitive data.

Model building

In [243]:
```
# import algorithms
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
```

Base classifiers

In [244]:
```
logistic=LogisticRegression(random_state=101)
dt=DecisionTreeClassifier(random_state=101)
rf=RandomForestClassifier(random_state=101)
bgg=BaggingClassifier(random_state=101)
svc=SVC(random_state=101)
knn=KNeighborsClassifier()
```

In [245]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, classificatio
```

In [246]:
```
p=[]
r=[]
model_list=[]


for model in [dt, rf, bgg, svc, knn, logistic]:
    print('########'*3)
    print("Performance of model", model)
    print("##########"*3)

    xyz=model.fit(X_train_sc, Y_train)
    Y_pred_test=xyz.predict(X_test_sc)
    cm=confusion_matrix(Y_test, Y_pred_test)
    cr=classification_report(Y_test, Y_pred_test)

    print("confusion_matrix \n", cm)
    print("classification_report \n", cr)

    p.append(precision_score(Y_test, Y_pred_test))
    r.append(recall_score(Y_test, Y_pred_test))
    model_list.append(model)
```

```
########################
Performance of model DecisionTreeClassifier(random_state=101)
##############################
confusion_matrix
 [[5842  473]
 [ 404  230]]
classification_report
               precision    recall  f1-score   support

           0       0.94      0.93      0.93      6315
           1       0.33      0.36      0.34       634

    accuracy                           0.87      6949
   macro avg       0.63      0.64      0.64      6949
weighted avg       0.88      0.87      0.88      6949

########################
Performance of model RandomForestClassifier(random_state=101)
##############################
confusion_matrix
 [[6255   60]
 [ 464  170]]
classification_report
               precision    recall  f1-score   support

           0       0.93      0.99      0.96      6315
           1       0.74      0.27      0.39       634

    accuracy                           0.92      6949
   macro avg       0.84      0.63      0.68      6949
weighted avg       0.91      0.92      0.91      6949

########################
Performance of model BaggingClassifier(random_state=101)
##############################
confusion_matrix
 [[6199  116]
 [ 471  163]]
classification_report
               precision    recall  f1-score   support

           0       0.93      0.98      0.95      6315
           1       0.58      0.26      0.36       634

    accuracy                           0.92      6949
   macro avg       0.76      0.62      0.66      6949
weighted avg       0.90      0.92      0.90      6949

########################
Performance of model SVC(random_state=101)
##############################
confusion_matrix
 [[6284   31]
 [ 508  126]]
classification_report
               precision    recall  f1-score   support

           0       0.93      1.00      0.96      6315
           1       0.80      0.20      0.32       634

    accuracy                           0.92      6949
```

```
   macro avg       0.86      0.60      0.64      6949
weighted avg       0.91      0.92      0.90      6949

########################
Performance of model KNeighborsClassifier()
##############################
confusion_matrix
 [[6245   70]
 [ 538   96]]
classification_report
               precision    recall  f1-score   support

           0       0.92      0.99      0.95      6315
           1       0.58      0.15      0.24       634

    accuracy                           0.91      6949
   macro avg       0.75      0.57      0.60      6949
weighted avg       0.89      0.91      0.89      6949

########################
Performance of model LogisticRegression(random_state=101)
##############################
confusion_matrix
 [[6215  100]
 [ 447  187]]
classification_report
               precision    recall  f1-score   support

           0       0.93      0.98      0.96      6315
           1       0.65      0.29      0.41       634

    accuracy                           0.92      6949
   macro avg       0.79      0.64      0.68      6949
weighted avg       0.91      0.92      0.91      6949
```

In [247]:

```
# metrics of base classifier


metric_base=pd.DataFrame({'precision': p, 'recall': r, 'model': ['dt', 'rf'
metric_base
```

Out[247]:

	precision	recall	model
0	0.327169	0.362776	dt
5	0.651568	0.294953	logistic
1	0.739130	0.268139	rf
2	0.584229	0.257098	bgg
3	0.802548	0.198738	svc
4	0.578313	0.151420	knn

In [248]:
```python
# Cross validation of the DT model (highest recall seen above):

from sklearn.model_selection import cross_val_score

dt=DecisionTreeClassifier(random_state=101)

cv= cross_val_score(dt, X_train_sc, Y_train, cv=5, scoring='recall')
print(cv)
print(cv.mean())
```

```
[0.36745407 0.34210526 0.38157895 0.42368421 0.37007874]
0.3769802458903163
```

Lets try Boosting classifiers:

In [249]:
```python
from sklearn.ensemble import GradientBoostingClassifier, AdaBoostClassifier
```

In [250]:
```python
from xgboost import XGBClassifier
```

In [251]:
```python
gbc=GradientBoostingClassifier(random_state=101)
abc=AdaBoostClassifier(random_state=101)
xgbc=XGBClassifier(random_state=101)
```

In [252]:

```
p=[]
r=[]
model_list=[]


for model in [gbc, abc, xgbc]:

    print('########'*3)
    print("Performance of model", model)
    print("##########"*3)

    xyz=model.fit(X_train_sc, Y_train)
    Y_pred_test=xyz.predict(X_test_sc)
    cm=confusion_matrix(Y_test, Y_pred_test)
    cr=classification_report(Y_test, Y_pred_test)

    print("confusion_matrix \n", cm)
    print("classification_report \n", cr)

    p.append(precision_score(Y_test, Y_pred_test))
    r.append(recall_score(Y_test, Y_pred_test))
    model_list.append(model)
```

```
########################
Performance of model GradientBoostingClassifier(random_state=101)
##############################
confusion_matrix
 [[6218   97]
 [ 418  216]]
classification_report
               precision    recall  f1-score   support

           0       0.94      0.98      0.96      6315
           1       0.69      0.34      0.46       634

    accuracy                           0.93      6949
   macro avg       0.81      0.66      0.71      6949
weighted avg       0.91      0.93      0.91      6949

########################
Performance of model AdaBoostClassifier(random_state=101)
##############################
confusion_matrix
 [[6185  130]
 [ 416  218]]
classification_report
               precision    recall  f1-score   support

           0       0.94      0.98      0.96      6315
           1       0.63      0.34      0.44       634

    accuracy                           0.92      6949
   macro avg       0.78      0.66      0.70      6949
weighted avg       0.91      0.92      0.91      6949

########################
Performance of model XGBClassifier(base_score=None, booster=None, callback
s=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=No
ne,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=N
one,
              interaction_constraints=None, learning_rate=None, max_bin=No
ne,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=Non
e,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=101, ...)
##############################
confusion_matrix
 [[6186  129]
 [ 405  229]]
classification_report
               precision    recall  f1-score   support

           0       0.94      0.98      0.96      6315
           1       0.64      0.36      0.46       634

    accuracy                           0.92      6949
   macro avg       0.79      0.67      0.71      6949
```

```
weighted avg       0.91      0.92      0.91      6949
```

In [253]:
```
# metrics of boosting classifiers


metric_base=pd.DataFrame({'precision': p, 'recall': r, 'model': ['gbc', 'ab
metric_base
```

Out[253]:

	precision	recall	model
2	0.639665	0.361199	xgbc
1	0.626437	0.343849	abc
0	0.690096	0.340694	gbc

- Insights: XGBoost gives us the best recall and also a high precision amongst all the base models

In [2]:
```
# Cross validation of the XGBoost:

from sklearn.model_selection import cross_val_score

xgbc=XGBClassifier(random_state=101)

cv= cross_val_score(xgbc, X_train_sc, Y_train, cv=5, scoring='recall')
print(cv)
print(cv.mean())
```

In [ ]:
```
[0.30971129 0.32631579 0.33157895 0.29210526 0.27296588]
0.30653543307086617
```

In [ ]:

Weighted algorithms

Class weights in the models:

Most of the machine learning models provide a parameter called class_weights. For example, in a random forest classifier, using class_weights we can specify a higher weight for the minority class using a dictionary.

Without weights set, the model treats each point as equally important. Weights scale the loss function. As the model trains on each point, the error will be multiplied by the weight of the point. The estimator will try to minimize error on the more heavily weighted classes, because they will have a greater effect on error, sending a stronger signal.

In [256]:

```
dt=DecisionTreeClassifier(random_state=101, class_weight='balanced')
rf=RandomForestClassifier(random_state=101, class_weight='balanced')
bgg=BaggingClassifier(random_state=101)
svc=SVC(random_state=101, class_weight='balanced')
knn=KNeighborsClassifier()
gbc=GradientBoostingClassifier(random_state=101)
abc=AdaBoostClassifier(random_state=101)
xgbc=XGBClassifier(random_state=101, class_weight='balanced')
```

In [257]:

```
for model in [dt, rf, bgg, svc, knn, gbc, abc, xgbc]:
    print('########'*3)
    print("Performance of model", model)
    print("##########"*3)

    xyz=model.fit(X_train_sc, Y_train)
    y_pred_test=xyz.predict(X_test_sc)
    cm=confusion_matrix(Y_test, y_pred_test)
    cr=classification_report(Y_test, y_pred_test)

    print("confusion_matrix \n", cm)
    print("classification_report \n", cr)
```

```
########################
Performance of model DecisionTreeClassifier(class_weight='balanced', rando
m_state=101)
##############################
confusion_matrix
 [[5873  442]
 [ 434  200]]
classification_report
               precision    recall  f1-score   support

           0       0.93      0.93      0.93      6315
           1       0.31      0.32      0.31       634

    accuracy                           0.87      6949
   macro avg       0.62      0.62      0.62      6949
weighted avg       0.87      0.87      0.87      6949

########################
Performance of model RandomForestClassifier(class_weight='balanced', rando
m_state=101)
##############################
confusion_matrix
 [[6284   31]
 [ 528  106]]
classification_report
               precision    recall  f1-score   support

           0       0.92      1.00      0.96      6315
           1       0.77      0.17      0.27       634

    accuracy                           0.92      6949
   macro avg       0.85      0.58      0.62      6949
weighted avg       0.91      0.92      0.90      6949

########################
Performance of model BaggingClassifier(random_state=101)
##############################
confusion_matrix
 [[6199  116]
 [ 471  163]]
classification_report
               precision    recall  f1-score   support

           0       0.93      0.98      0.95      6315
           1       0.58      0.26      0.36       634

    accuracy                           0.92      6949
   macro avg       0.76      0.62      0.66      6949
weighted avg       0.90      0.92      0.90      6949

########################
Performance of model SVC(class_weight='balanced', random_state=101)
##############################
confusion_matrix
 [[5206 1109]
 [ 155  479]]
classification_report
               precision    recall  f1-score   support

           0       0.97      0.82      0.89      6315
           1       0.30      0.76      0.43       634
```

```
    accuracy                           0.82      6949
   macro avg       0.64      0.79      0.66      6949
weighted avg       0.91      0.82      0.85      6949

########################
Performance of model KNeighborsClassifier()
##############################
confusion_matrix
 [[6245   70]
 [ 538   96]]
classification_report
               precision    recall  f1-score   support

           0       0.92      0.99      0.95      6315
           1       0.58      0.15      0.24       634

    accuracy                           0.91      6949
   macro avg       0.75      0.57      0.60      6949
weighted avg       0.89      0.91      0.89      6949

########################
Performance of model GradientBoostingClassifier(random_state=101)
##############################
confusion_matrix
 [[6218   97]
 [ 418  216]]
classification_report
               precision    recall  f1-score   support

           0       0.94      0.98      0.96      6315
           1       0.69      0.34      0.46       634

    accuracy                           0.93      6949
   macro avg       0.81      0.66      0.71      6949
weighted avg       0.91      0.93      0.91      6949

########################
Performance of model AdaBoostClassifier(random_state=101)
##############################
confusion_matrix
 [[6185  130]
 [ 416  218]]
classification_report
               precision    recall  f1-score   support

           0       0.94      0.98      0.96      6315
           1       0.63      0.34      0.44       634

    accuracy                           0.92      6949
   macro avg       0.78      0.66      0.70      6949
weighted avg       0.91      0.92      0.91      6949

########################
Performance of model XGBClassifier(base_score=None, booster=None, callback
s=None,
              class_weight='balanced', colsample_bylevel=None,
              colsample_bynode=None, colsample_bytree=None,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, feature_types=None, gamma=None, gpu_id=Non
e,
```

```
                 grow_policy=None, importance_type=None,
                 interaction_constraints=None, learning_rate=None, max_bin=No
ne,
                 max_cat_threshold=None, max_cat_to_onehot=None,
                 max_delta_step=None, max_depth=None, max_leaves=None,
                 min_child_weight=None, missing=nan, monotone_constraints=Non
e,
                 n_estimators=100, n_jobs=None, num_parallel_tree=None,
                 predictor=None, ...)
##############################
[12:33:05] WARNING: C:\buildkite-agent\builds\buildkite-windows-cpu-autosc
aling-group-i-0fdc6d574b9c0d168-1\xgboost\xgboost-ci-windows\src\learner.c
c:767:
Parameters: { "class_weight" } are not used.

confusion_matrix
 [[6186  129]
 [ 405  229]]
classification_report
               precision    recall  f1-score   support

           0       0.94      0.98      0.96      6315
           1       0.64      0.36      0.46       634

    accuracy                           0.92      6949
   macro avg       0.79      0.67      0.71      6949
weighted avg       0.91      0.92      0.91      6949
```

In [258]:

```python
# Cross validation of the SVC weighted (good recall):

from sklearn.model_selection import cross_val_score

svc=SVC(random_state=101, class_weight='balanced')

cv= cross_val_score(svc, X_train_sc, Y_train, cv=5, scoring='recall')
print(cv)
print(cv.mean())
```

```
[0.72703412 0.69736842 0.73421053 0.76578947 0.72440945]
0.7297623981212875
```

In [ ]:

In [ ]:

Hyperparameter Tuning of DT classifier

In [259]:

```python
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

roc_auc

In [260]:
```
param_dt={'criterion':['gini', 'entropy'],
         'max_depth':np.arange(10,150,10),
         'splitter':['best', 'random'],
         'max_features':['sqrt', 'log2'],
          'min_samples_split':[2,5,10]
         }

dt_tuned=DecisionTreeClassifier(class_weight='balanced', random_state=101)

random_cv_dt=RandomizedSearchCV(dt_tuned, param_distributions=param_dt,n_it
random_cv_dt.fit(X_train_sc, Y_train)
```

Out[260]:
```
RandomizedSearchCV(cv=5,
                   estimator=DecisionTreeClassifier(class_weight='balance
d',
                                                    random_state=101),
                   n_iter=100,
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': array([ 10,  20,  30,
40,  50,  60,  70,  80,  90, 100, 110, 120, 130,
       140]),
                                        'max_features': ['sqrt', 'log2'],
                                        'min_samples_split': [2, 5, 10],
                                        'splitter': ['best', 'random']},
                   random_state=101, scoring='roc_auc')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [261]:
```
random_cv_dt.best_estimator_
```

Out[261]:
```
DecisionTreeClassifier(class_weight='balanced', max_depth=10,
                       max_features='log2', min_samples_split=5,
                       random_state=101, splitter='random')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [262]:
```
random_cv_dt.best_score_
```

Out[262]:
```
0.7589549452310805
```

In [263]:
```python
for model in [random_cv_dt]:
    Y_pred_test=model.predict(X_test_sc)
    cm=confusion_matrix(Y_test, Y_pred_test)
    cr=classification_report(Y_test, Y_pred_test)

    print("confusion_matrix \n", cm)
    print("classification_report \n", cr)
```

```
confusion_matrix
 [[4650 1665]
 [ 177  457]]
classification_report
               precision    recall  f1-score   support

           0       0.96      0.74      0.83      6315
           1       0.22      0.72      0.33       634

    accuracy                           0.73      6949
   macro avg       0.59      0.73      0.58      6949
weighted avg       0.90      0.73      0.79      6949
```

In [ ]:
```python

```

Changing the scoring metric to: f1_macro

In [266]:
```
param_dt={'criterion':['gini', 'entropy'],
          'max_depth':np.arange(10,150,10),
          'splitter':['best', 'random'],
          'max_features':['sqrt', 'log2'],
           'min_samples_split':[2,5,10]
          }

dt_tuned=DecisionTreeClassifier(class_weight='balanced', random_state=101)
random_cv_dt2=RandomizedSearchCV(dt_tuned, param_distributions=param_dt,n_i
random_cv_dt2.fit(X_train_sc, Y_train)
```

Out[266]:
```
RandomizedSearchCV(cv=5,
                   estimator=DecisionTreeClassifier(class_weight='balance
d',
                                                    random_state=101),
                   n_iter=100,
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': array([ 10,  20,  30,
40,  50,  60,  70,  80,  90, 100, 110, 120, 130,
       140]),
                                        'max_features': ['sqrt', 'log2'],
                                        'min_samples_split': [2, 5, 10],
                                        'splitter': ['best', 'random']},
                   random_state=101, scoring='f1_macro')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [267]:
```
random_cv_dt2.best_estimator_
```

Out[267]:
```
DecisionTreeClassifier(class_weight='balanced', criterion='entropy',
                       max_depth=20, max_features='sqrt', min_samples_spli
t=5,
                       random_state=101)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [268]:
```
random_cv_dt2.best_score_
```

Out[268]:
```
0.6256322675276955
```

In [269]:
```
for model in [random_cv_dt2]:
    Y_pred_test=model.predict(X_test_sc)
    cm=confusion_matrix(Y_test, Y_pred_test)
    cr=classification_report(Y_test, Y_pred_test)

    print("confusion_matrix \n", cm)
    print("classification_report \n", cr)
```

```
confusion_matrix
 [[5783  532]
 [ 409  225]]
classification_report
               precision    recall  f1-score   support

           0       0.93      0.92      0.92      6315
           1       0.30      0.35      0.32       634

    accuracy                           0.86      6949
   macro avg       0.62      0.64      0.62      6949
weighted avg       0.88      0.86      0.87      6949
```

In [ ]:

In [ ]:

scoring metric= f1_score

In [270]:
```
param_dt={'criterion':['gini', 'entropy'],
          'max_depth':np.arange(10,150,10),
          'splitter':['best', 'random'],
          'max_features':['sqrt', 'log2'],
           'min_samples_split':[2,5,10]
          }

dt_tuned=DecisionTreeClassifier(class_weight='balanced', random_state=101)
random_cv_dt3=RandomizedSearchCV(dt_tuned, param_distributions=param_dt,n_i
random_cv_dt3.fit(X_train_sc, Y_train)
```

Out[270]:
```
RandomizedSearchCV(cv=5,
                   estimator=DecisionTreeClassifier(class_weight='balance
d',
                                                    random_state=101),
                   n_iter=100,
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': array([ 10,  20,  30,
40,  50,  60,  70,  80,  90, 100, 110, 120, 130,
       140]),
                                        'max_features': ['sqrt', 'log2'],
                                        'min_samples_split': [2, 5, 10],
                                        'splitter': ['best', 'random']},
                   random_state=101, scoring='f1')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [271]:
```
random_cv_dt3.best_estimator_
```

Out[271]:
```
DecisionTreeClassifier(class_weight='balanced', max_depth=10,
                       max_features='sqrt', min_samples_split=10,
                       random_state=101)
```

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In [272]:
```
random_cv_dt3.best_score_
```

Out[272]:
```
0.35950225875667213
```

In [273]:
```
for model in [random_cv_dt3]:
    Y_pred_test=model.predict(X_test_sc)
    cm=confusion_matrix(Y_test, Y_pred_test)
    cr=classification_report(Y_test, Y_pred_test)

    print("confusion_matrix \n", cm)
    print("classification_report \n", cr)
```

```
confusion_matrix
 [[5178 1137]
 [ 207  427]]
classification_report
               precision    recall  f1-score   support

           0       0.96      0.82      0.89      6315
           1       0.27      0.67      0.39       634

    accuracy                           0.81      6949
   macro avg       0.62      0.75      0.64      6949
weighted avg       0.90      0.81      0.84      6949
```

In [274]:
```
# Cross validation of the DT tuned-f1 score:

from sklearn.model_selection import cross_val_score

cv= cross_val_score(random_cv_dt3, X_train_sc, Y_train, cv=5, scoring='reca
print(cv)
print(cv.mean())
```

```
[0.61417323 0.62368421 0.63684211 0.62368421 0.60104987]
0.61988672468573
```

In [ ]:

scoring metric: recall

In [275]:
```
param_dt={'criterion':['gini', 'entropy'],
          'max_depth':np.arange(10,150,10),
          'splitter':['best', 'random'],
          'max_features':['sqrt', 'log2'],
           'min_samples_split':[2,5,10]
          }

dt_tuned=DecisionTreeClassifier(class_weight='balanced', random_state=101)
random_cv_dt4=RandomizedSearchCV(dt_tuned, param_distributions=param_dt,n_i
random_cv_dt4.fit(X_train_sc, Y_train)
```

Out[275]:
```
RandomizedSearchCV(cv=5,
                   estimator=DecisionTreeClassifier(class_weight='balance
d',
                                                    random_state=101),
                   n_iter=100,
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': array([ 10,  20,  30,
40,  50,  60,  70,  80,  90, 100, 110, 120, 130,
       140]),
                                        'max_features': ['sqrt', 'log2'],
                                        'min_samples_split': [2, 5, 10],
                                        'splitter': ['best', 'random']},
                   random_state=101, scoring='recall')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [276]:
```
random_cv_dt4.best_estimator_
```

Out[276]:
```
DecisionTreeClassifier(class_weight='balanced', max_depth=10,
                       max_features='log2', min_samples_split=5,
                       random_state=101, splitter='random')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [277]:
```
random_cv_dt4.best_score_
```

Out[277]:
```
0.6677041027766265
```

In [278]:
```
for model in [random_cv_dt4]:
    y_pred_test=model.predict(X_test_sc)
    cm=confusion_matrix(Y_test, y_pred_test)
    cr=classification_report(Y_test, y_pred_test)

    print("confusion_matrix \n", cm)
    print("classification_report \n", cr)
```

```
confusion_matrix
 [[4650 1665]
 [ 177  457]]
classification_report
               precision    recall  f1-score   support

           0       0.96      0.74      0.83      6315
           1       0.22      0.72      0.33       634

    accuracy                           0.73      6949
   macro avg       0.59      0.73      0.58      6949
weighted avg       0.90      0.73      0.79      6949
```

In [279]:
```
# y_pred_test=random_cv_dt4.predict(X_test)
# accuracy_score(Y_test, y_pred_test)
```

- insights: optimizing for recall gives the same result as optimizing for roc_auc above

In [281]:
```
# Cross validation of the DT tuned-recall:

from sklearn.model_selection import cross_val_score

cv= cross_val_score(random_cv_dt4, X_train_sc, Y_train, cv=5, scoring='reca
print(cv)
print(cv.mean())
```

```
[0.67454068 0.63684211 0.69736842 0.64210526 0.68766404]
0.6677041027766265
```

In [ ]:
```

```

scoring: f1_score of minority class

In [282]:
```
from sklearn.metrics import make_scorer, f1_score
```

In [283]:
```
param_dt={'criterion':['gini', 'entropy'],
         'max_depth':np.arange(10,150,10),
         'splitter':['best', 'random'],
         'max_features':['sqrt', 'log2'],
          'min_samples_split':[2,5,10]
         }

dt_tuned=DecisionTreeClassifier(class_weight='balanced', random_state=101)
scoring = {'f1_minority': make_scorer(f1_score, average=None, labels=[1])}

random_cv_dt5=RandomizedSearchCV(dt_tuned, param_distributions=param_dt,n_i
random_cv_dt5.fit(X_train_sc, Y_train)
```

Out[283]:
```
RandomizedSearchCV(cv=5,
                   estimator=DecisionTreeClassifier(class_weight='balance
d',
                                                    random_state=101),
                   n_iter=100,
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': array([ 10,  20,  30,
40,  50,  60,  70,  80,  90, 100, 110, 120, 130,
       140]),
                                        'max_features': ['sqrt', 'log2'],
                                        'min_samples_split': [2, 5, 10],
                                        'splitter': ['best', 'random']},
                   random_state=101, refit='f1_minority',
                   scoring={'f1_minority': make_scorer(f1_score, average=N
one, labels=[1])})
```

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In [284]:
```
random_cv_dt5.best_estimator_
```

Out[284]:
```
DecisionTreeClassifier(class_weight='balanced', max_depth=10,
                       max_features='sqrt', min_samples_split=10,
                       random_state=101)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [285]:
```
random_cv_dt5.best_score_ #best_score_ : Mean cross-validated score of the l
```

Out[285]:
```
0.35950225875667213
```

In [286]:
```
for model in [random_cv_dt5]:
    y_pred_test=model.predict(X_test_sc)
    cm=confusion_matrix(Y_test, y_pred_test)
    cr=classification_report(Y_test, y_pred_test)

    print("confusion_matrix \n", cm)
    print("classification_report \n", cr)
```

```
confusion_matrix
 [[5178 1137]
 [ 207  427]]
classification_report
               precision    recall  f1-score   support

           0       0.96      0.82      0.89      6315
           1       0.27      0.67      0.39       634

    accuracy                           0.81      6949
   macro avg       0.62      0.75      0.64      6949
weighted avg       0.90      0.81      0.84      6949
```

In [287]:
```
precision_score(Y_test, y_pred_test)
```

Out[287]:
```
0.27301790281329924
```

In [288]:
```
recall_score(Y_test, y_pred_test)
```

Out[288]:
```
0.6735015772870663
```

In [289]:
```
# f1 score of minority optimization gives same results as optimizing for f1
```

In [290]:
```
# Cross validation of the DT tuned-f1 minority:

from sklearn.model_selection import cross_val_score

cv= cross_val_score(random_cv_dt4, X_train_sc, Y_train, cv=5, scoring='reca
print(cv)
print(cv.mean())
```

```
[0.67454068 0.63684211 0.69736842 0.64210526 0.68766404]
0.6677041027766265
```

In [ ]:

f_1 score of majority class

```
In [291]: param_dt={'criterion':['gini', 'entropy'],
                   'max_depth':np.arange(10,150,10),
                   'splitter':['best', 'random'],
                   'max_features':['sqrt', 'log2'],
                    'min_samples_split':[2,5,10]
                   }

          dt_tuned=DecisionTreeClassifier(class_weight='balanced', random_state=101)
          scoring = {'f1_majority': make_scorer(f1_score, average=None, labels=[0])}

          random_cv_dt6=RandomizedSearchCV(dt_tuned, param_distributions=param_dt,n_i
          random_cv_dt6.fit(X_train_sc, Y_train)
```

```
Out[291]: RandomizedSearchCV(cv=5,
                             estimator=DecisionTreeClassifier(class_weight='balance
          d',
                                                              random_state=101),
                             n_iter=100,
                             param_distributions={'criterion': ['gini', 'entropy'],
                                                  'max_depth': array([ 10,  20,  30,
          40,  50,  60,  70,  80,  90, 100, 110, 120, 130,
                 140]),
                                                  'max_features': ['sqrt', 'log2'],
                                                  'min_samples_split': [2, 5, 10],
                                                  'splitter': ['best', 'random']},
                             random_state=101, refit='f1_majority',
                             scoring={'f1_majority': make_scorer(f1_score, average=N
          one, labels=[0])})
```

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```
In [292]: random_cv_dt6.best_estimator_
```

```
Out[292]: DecisionTreeClassifier(class_weight='balanced', criterion='entropy',
                                 max_depth=70, max_features='sqrt', random_state=10
          1)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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```
In [293]: random_cv_dt6.best_score_
```

```
Out[293]: 0.9326502291957182
```

In [294]:
```
for model in [random_cv_dt6]:
    y_pred_test=model.predict(X_test_sc)
    cm=confusion_matrix(Y_test, y_pred_test)
    cr=classification_report(Y_test, y_pred_test)

    print("confusion_matrix \n", cm)
    print("classification_report \n", cr)
```

```
confusion_matrix
 [[5896  419]
 [ 430  204]]
classification_report
               precision    recall  f1-score   support

           0       0.93      0.93      0.93      6315
           1       0.33      0.32      0.32       634

    accuracy                           0.88      6949
   macro avg       0.63      0.63      0.63      6949
weighted avg       0.88      0.88      0.88      6949
```

In [295]:
```
# yes, the scorer is correct as here the best hyperparameters are shown for
```

In [ ]:

In [ ]:

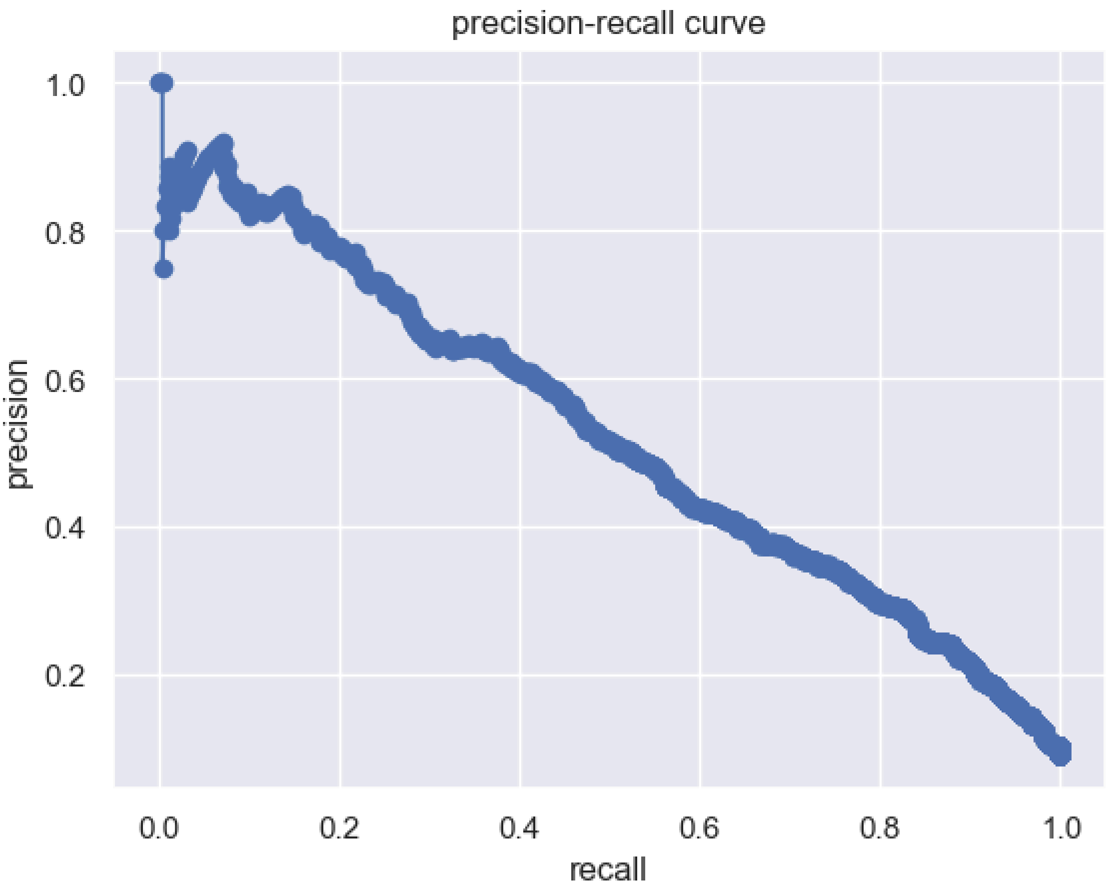
Changing the threshold: to optimize for recall and precision

In [296]:

```
def threshold_change(model):

    # fitting the model
    xyz=model.fit(X_train_sc, Y_train)


    # probabilities
    y_proba=model.predict_proba(X_test_sc)[:,1]



    # defininf a func to generate new new-class labels based on new thresho
    def new_class(y_proba, thresh):
        y_pred_new=[1 if y>thresh else 0 for y in y_proba]
        return y_pred_new



    #calculating new precision and recall for new threshold
    p=[]
    r=[]
    t=[]
    for i in np.arange(0,1,0.05):
        y_pred_new_class=new_class(y_proba, i) #generating new new-class la
        precision=precision_score(Y_test, y_pred_new_class)
        recall=recall_score(Y_test, y_pred_new_class)
        p.append(precision)
        r.append(recall)
        t.append(i)
        if precision>0.60 and recall>0.65:
            print(thresh)



    # precision and recall mterics
    metrics=pd.DataFrame({'precision':p,'recall':r,'threshold':t})
    print(metrics)


    # plot precision-recall curve
    from sklearn.metrics import precision_recall_curve
    pre, re, th=precision_recall_curve(Y_test,y_proba)
    plt.plot(re, pre, marker='o')
    plt.xlabel('recall')
    plt.ylabel('precision')
    plt.title('precision-recall curve')
    plt.show()
```

In [297]:
```
# XGBoost classifier

xgbc=XGBClassifier(random_state=101)
threshold_change(xgbc)
```

	precision	recall	threshold
0	0.091236	1.000000	0.00
1	0.311362	0.782334	0.05
2	0.376991	0.671924	0.10
3	0.424412	0.597792	0.15
4	0.470199	0.559937	0.20
5	0.502283	0.520505	0.25
6	0.529412	0.482650	0.30
7	0.564797	0.460568	0.35
8	0.595133	0.424290	0.40
9	0.615385	0.391167	0.45
10	0.639665	0.361199	0.50
11	0.649351	0.315457	0.55
12	0.670330	0.288644	0.60
13	0.704167	0.266562	0.65
14	0.717489	0.252366	0.70
15	0.752688	0.220820	0.75
16	0.776398	0.197161	0.80
17	0.796875	0.160883	0.85
18	0.826087	0.119874	0.90
19	0.875000	0.077287	0.95

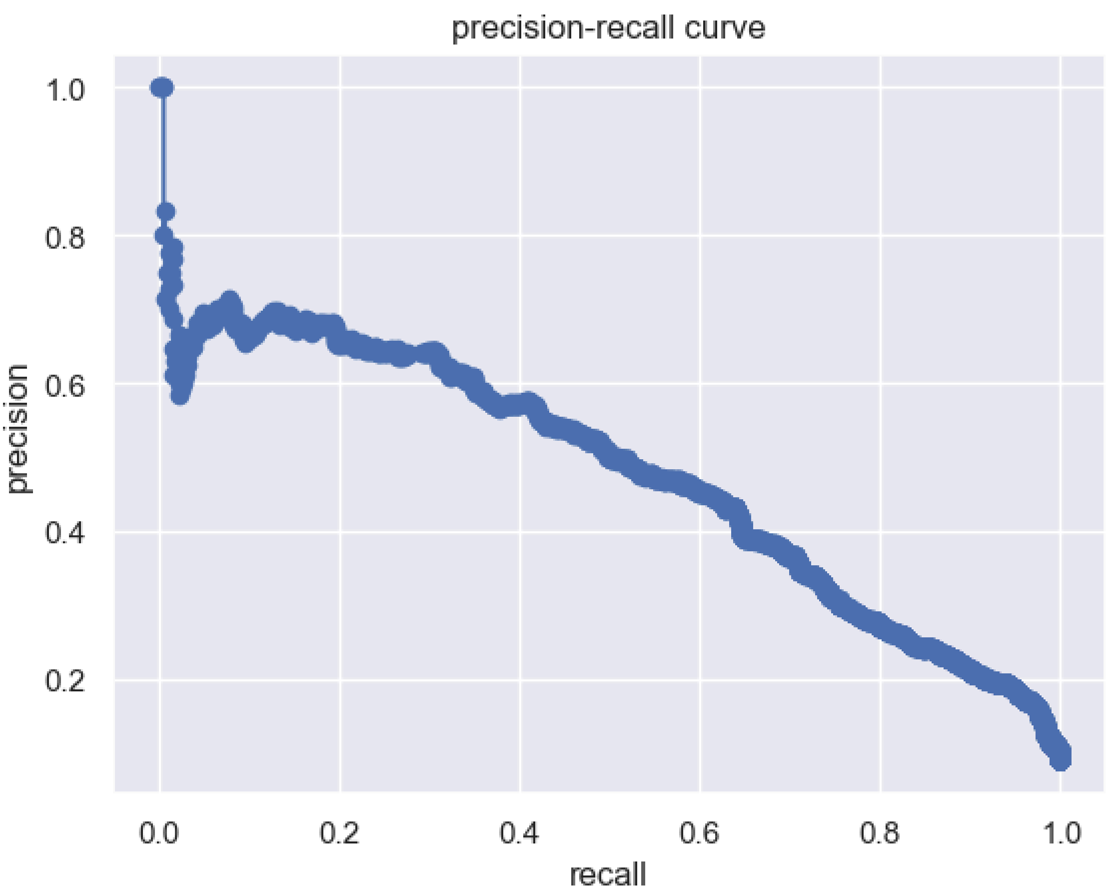


- insight: this is also a good algorithm to consider, where for 0.6 recall there is still fair enough precision 0f nearly 0.4.

In [299]:

```
# SVC weighted

svc=SVC(random_state=101, class_weight='balanced', probability=True)
threshold_change(svc)
```

	precision	recall	threshold
0	0.091236	1.000000	0.00
1	0.209677	0.902208	0.05
2	0.281515	0.785489	0.10
3	0.350195	0.709779	0.15
4	0.406746	0.646688	0.20
5	0.459926	0.588328	0.25
6	0.496951	0.514196	0.30
7	0.531876	0.460568	0.35
8	0.574944	0.405363	0.40
9	0.608815	0.348580	0.45
10	0.638686	0.276025	0.50
11	0.647321	0.228707	0.55
12	0.682635	0.179811	0.60
13	0.680000	0.134069	0.65
14	0.688312	0.083596	0.70
15	0.674419	0.045741	0.75
16	0.611111	0.017350	0.80
17	0.785714	0.017350	0.85
18	1.000000	0.004732	0.90
19	1.000000	0.001577	0.95



- insight: overall, SVC weighted gives the best performance when recall and precision both are important. It gives a recall of about 0.60 and precision of about 0.42.

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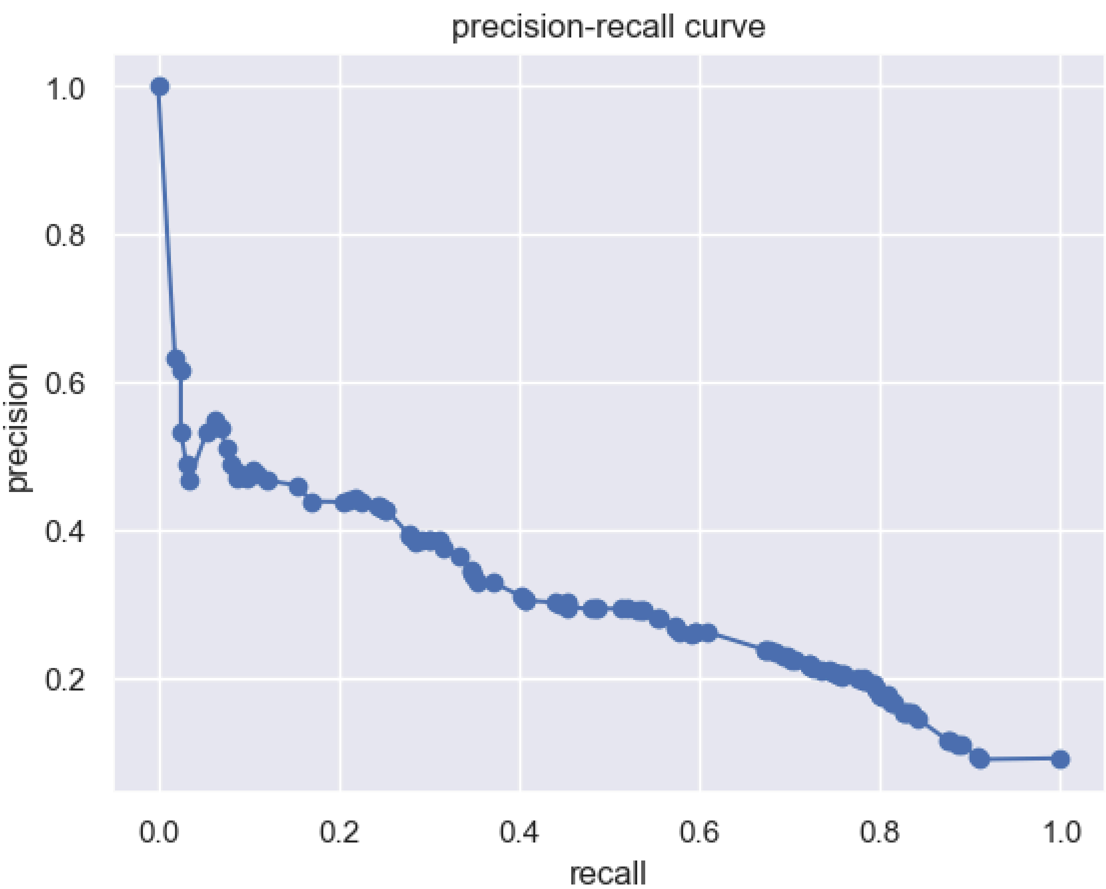
In [302]:
```python
# DT with roc-auc

dt_roc_tuned=DecisionTreeClassifier(class_weight='balanced', max_depth=10,
                             max_features='log2', min_samples_split=5,
                             random_state=101, splitter='random')# --->roc

threshold_change(dt_roc_tuned)
```

	precision	recall	threshold
0	0.089555	0.910095	0.00
1	0.092486	0.908517	0.05
2	0.110458	0.889590	0.10
3	0.114663	0.876972	0.15
4	0.153130	0.829653	0.20
5	0.166883	0.812303	0.25
6	0.176083	0.801262	0.30
7	0.177149	0.799685	0.35
8	0.190657	0.791798	0.40
9	0.203046	0.757098	0.45
10	0.215363	0.720820	0.50
11	0.229047	0.694006	0.55
12	0.260083	0.589905	0.60
13	0.291345	0.536278	0.65
14	0.295082	0.454259	0.70
15	0.300319	0.444795	0.75
16	0.386965	0.299685	0.80
17	0.428962	0.247634	0.85
18	0.466667	0.121451	0.90
19	0.510638	0.075710	0.95

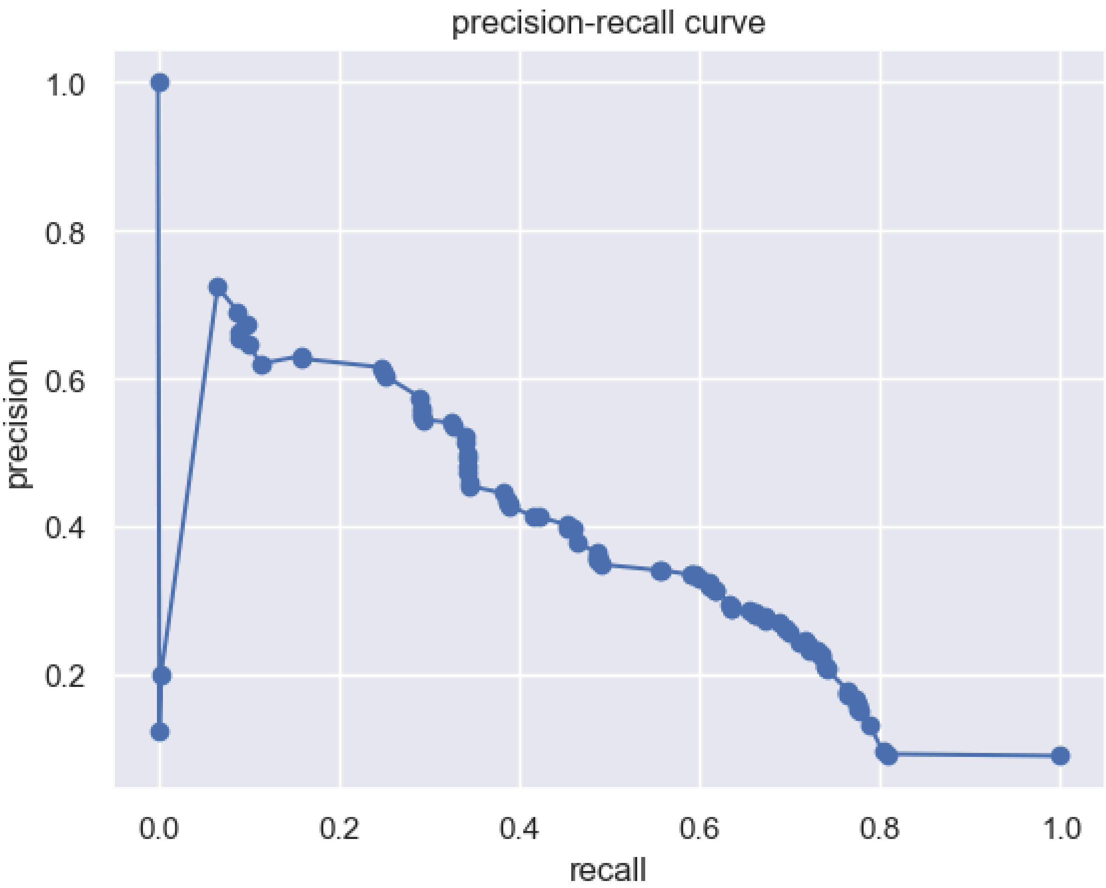


In [303]:
```python
# DT with f1 score

dt_f1_tuned=DecisionTreeClassifier(class_weight='balanced', max_depth=10,
                              max_features='sqrt', min_samples_split=10,
                              random_state=101) #---> f1 score

threshold_change(dt_f1_tuned)
```

	precision	recall	threshold
0	0.093773	0.807571	0.00
1	0.132802	0.788644	0.05
2	0.160615	0.774448	0.10
3	0.179792	0.763407	0.15
4	0.211738	0.739748	0.20
5	0.226214	0.735016	0.25
6	0.233978	0.725552	0.30
7	0.241653	0.719243	0.35
8	0.244698	0.709779	0.40
9	0.270976	0.687697	0.45
10	0.273018	0.673502	0.50
11	0.281501	0.662461	0.55
12	0.285034	0.660883	0.60
13	0.290137	0.635647	0.65
14	0.324121	0.610410	0.70
15	0.334825	0.589905	0.75
16	0.355172	0.487382	0.80
17	0.413580	0.422713	0.85
18	0.498851	0.342271	0.90
19	0.655172	0.089905	0.95

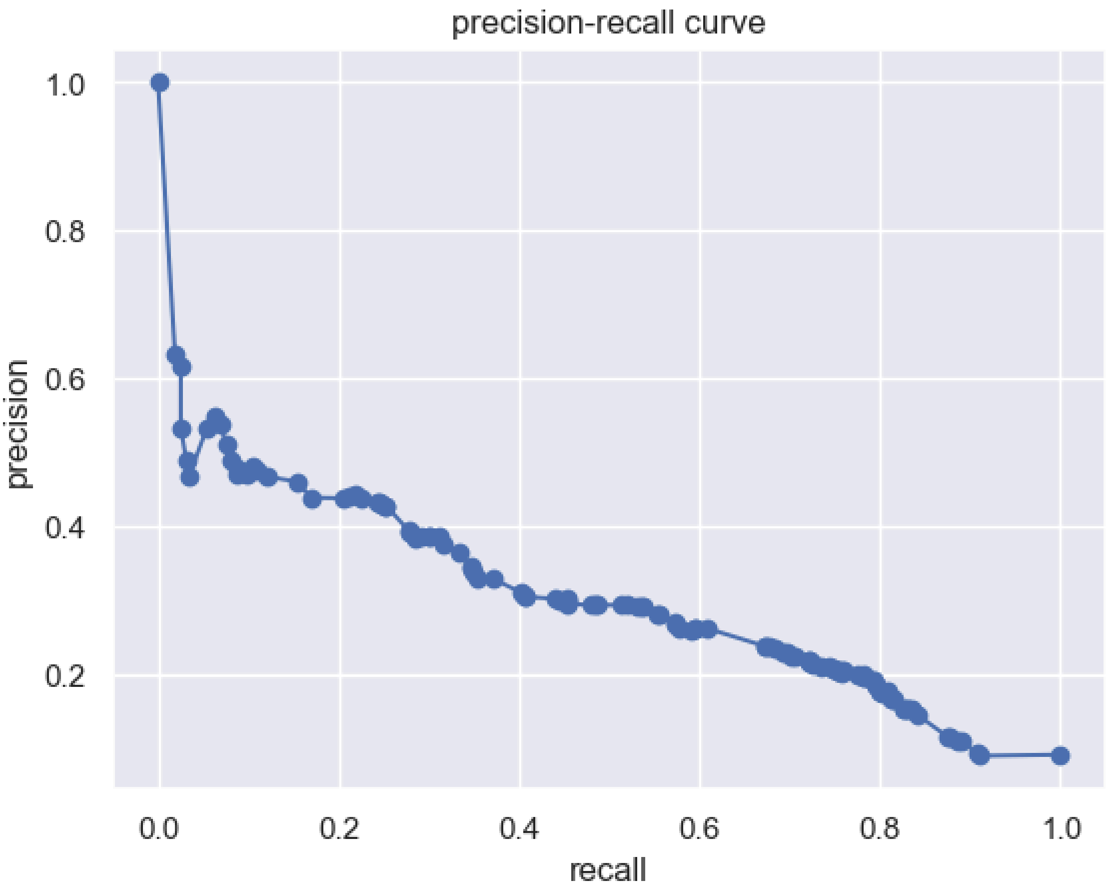


In [304]:
```python
# DT with recall

dt_recall_tuned=DecisionTreeClassifier(class_weight='balanced', max_depth=1(
                        max_features='log2', min_samples_split=5,
                        random_state=101, splitter='random') #---> recall

threshold_change(dt_recall_tuned)
```

	precision	recall	threshold
0	0.089555	0.910095	0.00
1	0.092486	0.908517	0.05
2	0.110458	0.889590	0.10
3	0.114663	0.876972	0.15
4	0.153130	0.829653	0.20
5	0.166883	0.812303	0.25
6	0.176083	0.801262	0.30
7	0.177149	0.799685	0.35
8	0.190657	0.791798	0.40
9	0.203046	0.757098	0.45
10	0.215363	0.720820	0.50
11	0.229047	0.694006	0.55
12	0.260083	0.589905	0.60
13	0.291345	0.536278	0.65
14	0.295082	0.454259	0.70
15	0.300319	0.444795	0.75
16	0.386965	0.299685	0.80
17	0.428962	0.247634	0.85
18	0.466667	0.121451	0.90
19	0.510638	0.075710	0.95



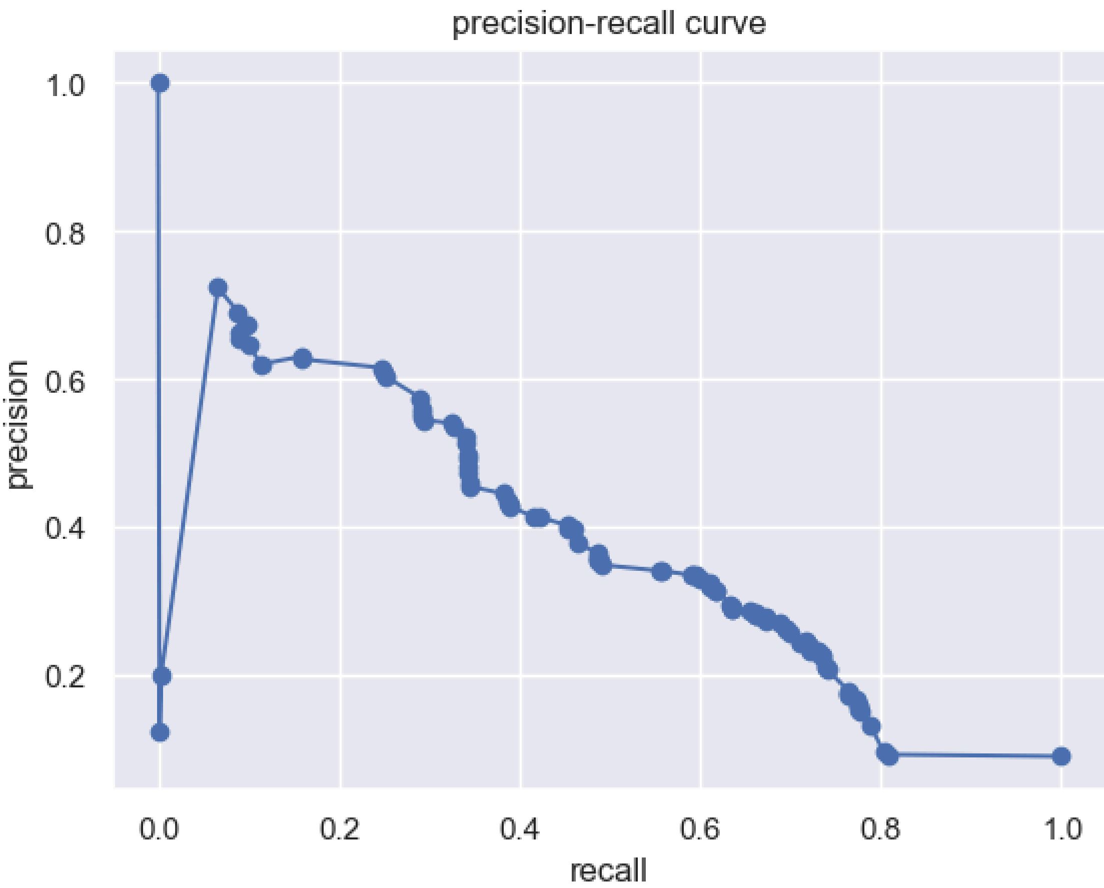
In [305]:

```
# DT with f1_minority

dt_f1_minority_tuned=DecisionTreeClassifier(class_weight='balanced', max_de
                       max_features='sqrt', min_samples_split=10,
                       random_state=101) #---> f1 minority

threshold_change(dt_f1_minority_tuned)
```

	precision	recall	threshold
0	0.093773	0.807571	0.00
1	0.132802	0.788644	0.05
2	0.160615	0.774448	0.10
3	0.179792	0.763407	0.15
4	0.211738	0.739748	0.20
5	0.226214	0.735016	0.25
6	0.233978	0.725552	0.30
7	0.241653	0.719243	0.35
8	0.244698	0.709779	0.40
9	0.270976	0.687697	0.45
10	0.273018	0.673502	0.50
11	0.281501	0.662461	0.55
12	0.285034	0.660883	0.60
13	0.290137	0.635647	0.65
14	0.324121	0.610410	0.70
15	0.334825	0.589905	0.75
16	0.355172	0.487382	0.80
17	0.413580	0.422713	0.85
18	0.498851	0.342271	0.90
19	0.655172	0.089905	0.95



In [ ]:

In [ ]:

In [ ]:

Voting method: on XGboost (Base) + SVC weighted

In [307]:
```
from sklearn.ensemble import VotingClassifier
```

In [308]:
```
# I am choosing XGBoost and SVC as they both show a good possibility of reco
```

In [309]:
```
svc=SVC(random_state=101, class_weight='balanced', probability=True)
xgbc=XGBClassifier(random_state=101)


estimators1=[('svc_weighted', svc), ('XGBoost', xgbc)]
```

In [310]:
```
vc=VotingClassifier(estimators=estimators1, voting='soft')
vc.fit(X_train_sc, Y_train)
y_pred_test=vc.predict(X_test_sc)
cm=confusion_matrix(Y_test, y_pred_test)
cr=classification_report(Y_test, y_pred_test)

print("confusion_matrix \n", cm)
print("classification_report \n", cr)
```

```
confusion_matrix
 [[6211  104]
 [ 422  212]]
classification_report
               precision    recall  f1-score   support

           0       0.94      0.98      0.96      6315
           1       0.67      0.33      0.45       634

    accuracy                           0.92      6949
   macro avg       0.80      0.66      0.70      6949
weighted avg       0.91      0.92      0.91      6949
```

- this is not a very good model as compared to the individual model performance

In [ ]:

In [ ]:

In [312]:
```
# to consider: xgbc,ada,gbc, svc weighted, dt-tuned-roc, dt-tuned-f1-macro,
```

Voting method: choosing the top best classifiers (i.e. models with high recall plus XGBC which also has high precision so as to get better recall and precision as output of Voting classifier)

In [313]:
```
svc=SVC(random_state=101, class_weight='balanced', probability=True)
xgbc=XGBClassifier(random_state=101)

# using the best tuned models fit with the best hyperparameters

dt_roc_tuned=DecisionTreeClassifier(class_weight='balanced', max_depth=10,
                       max_features='log2', min_samples_split=5,
                       random_state=101, splitter='random')# --->roc


dt_f1_tuned=DecisionTreeClassifier(class_weight='balanced', max_depth=10,
                       max_features='sqrt', min_samples_split=10,
                       random_state=101) #---> f1 score


dt_recall_tuned=DecisionTreeClassifier(class_weight='balanced', max_depth=1
                       max_features='log2', min_samples_split=5,
                       random_state=101, splitter='random') #---> recall


dt_f1_minority_tuned=DecisionTreeClassifier(class_weight='balanced', max_de
                       max_features='sqrt', min_samples_split=10,
                       random_state=101) #---> f1 minority




estimators2=[('svc_weighted', svc), ('XGBoost', xgbc), ('dt_roc_tuned', dt_
            ('dt_f1_tuned', dt_f1_tuned), ('dt_recall_tuned', dt_recall_tun
            ('dt_f1_minority_tuned', dt_f1_minority_tuned)]
```

In [314]:
```
vc_soft=VotingClassifier(estimators=estimators2, voting='soft')
vc_soft.fit(X_train_sc, Y_train)
Y_pred_test=vc_soft.predict(X_test_sc)
cm=confusion_matrix(Y_test, Y_pred_test)
cr=classification_report(Y_test, Y_pred_test)

print("confusion_matrix \n", cm)
print("classification_report \n", cr)
```

```
confusion_matrix
 [[5750  565]
 [ 262  372]]
classification_report
               precision    recall  f1-score   support

           0       0.96      0.91      0.93      6315
           1       0.40      0.59      0.47       634

    accuracy                           0.88      6949
   macro avg       0.68      0.75      0.70      6949
weighted avg       0.91      0.88      0.89      6949
```

insights:

- the precision has improved while recall is still high at 60.
- but still this is not higher than the results obtained on changing the threshold where the recall is near 60 and precision is about 42 for the SVC weighted classifier.

In [ ]:
```
- By Jeel Raval
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```