Libraries and Dataset

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

In [2]:

```
data = pd.read_csv('Paitients_Files_Train.csv')
data_test = pd.read_csv('Paitients_Files_Test.csv')
```

Exploratory Data Analysis

In [3]:

```
data.head()
```

Out[3]:

	ID	PRG	PL	PR	SK	TS	M11	BD2	Age	Insurance	Sepssis
0	ICU200010	6	148	72	35	0	33.6	0.627	50	0	Positive
1	ICU200011	1	85	66	29	0	26.6	0.351	31	0	Negative
2	ICU200012	8	183	64	0	0	23.3	0.672	32	1	Positive
3	ICU200013	1	89	66	23	94	28.1	0.167	21	1	Negative
4	ICU200014	0	137	40	35	168	43.1	2.288	33	1	Positive

In [4]:

```
data.shape
```

Out[4]:

```
(599, 11)
```

In [5]:

```
data.describe()
```

Out[5]:

	PRG	PL	PR	SK	TS	M11	BD2	Age	Insurance
count	599.000000	599.000000	599.000000	599.000000	599.000000	599.000000	599.000000	599.000000	599.000000
mean	3.824708	120.153589	68.732888	20.562604	79.460768	31.920033	0.481187	33.290484	0.686144
std	3.362839	32.682364	19.335675	16.017622	116.576176	8.008227	0.337552	11.828446	0.464447
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	64.000000	0.000000	0.000000	27.100000	0.248000	24.000000	0.000000
50%	3.000000	116.000000	70.000000	23.000000	36.000000	32.000000	0.383000	29.000000	1.000000
75%	6.000000	140.000000	80.000000	32.000000	123.500000	36.550000	0.647000	40.000000	1.000000
max	17.000000	198.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

In [6]:

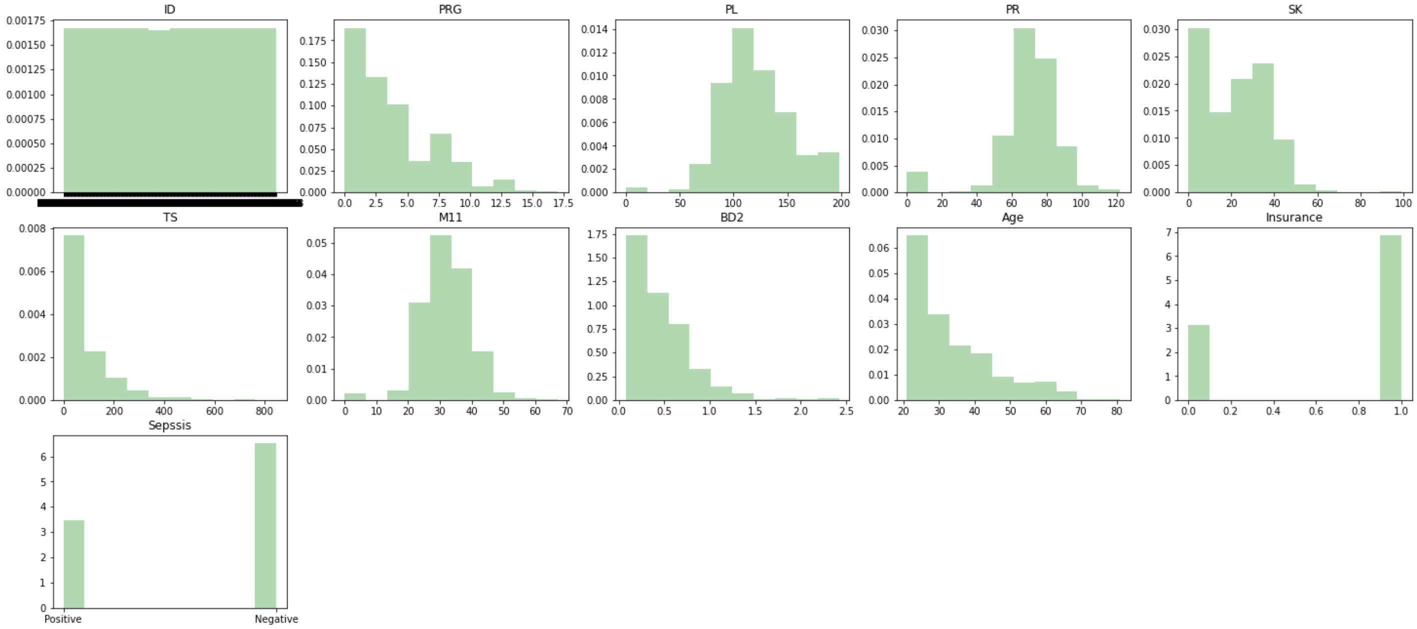
```
#Check for NULL values.

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 599 entries, 0 to 598
```

```
Data columns (total 11 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   ID         599 non-null    object 
 1   PRG        599 non-null    int64  
 2   PL         599 non-null    int64  
 3   PR         599 non-null    int64  
 4   SK         599 non-null    int64  
 5   TS         599 non-null    int64  
 6   M11        599 non-null    float64
 7   BD2        599 non-null    float64
 8   Age        599 non-null    int64  
 9   Insurance  599 non-null    int64  
 10  Sepssis    599 non-null    object 
dtypes: float64(2), int64(7), object(2)
memory usage: 51.6+ KB
```

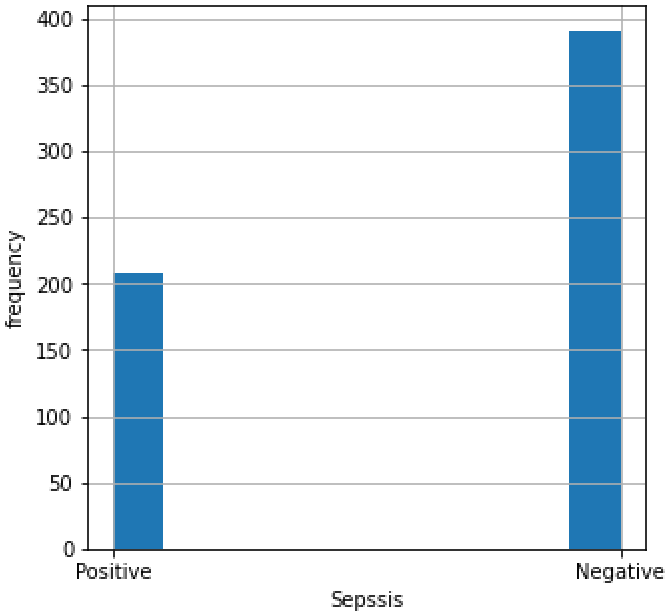
In [7]:

```
#Visualizing the distribution of data.
plt.figure(figsize=(25, 15))
for i, col in enumerate(data.columns):
    plt.subplot(4,5,i+1)
    plt.hist(data[col], alpha=0.3, color='g', density=True)
    plt.title(col)
```



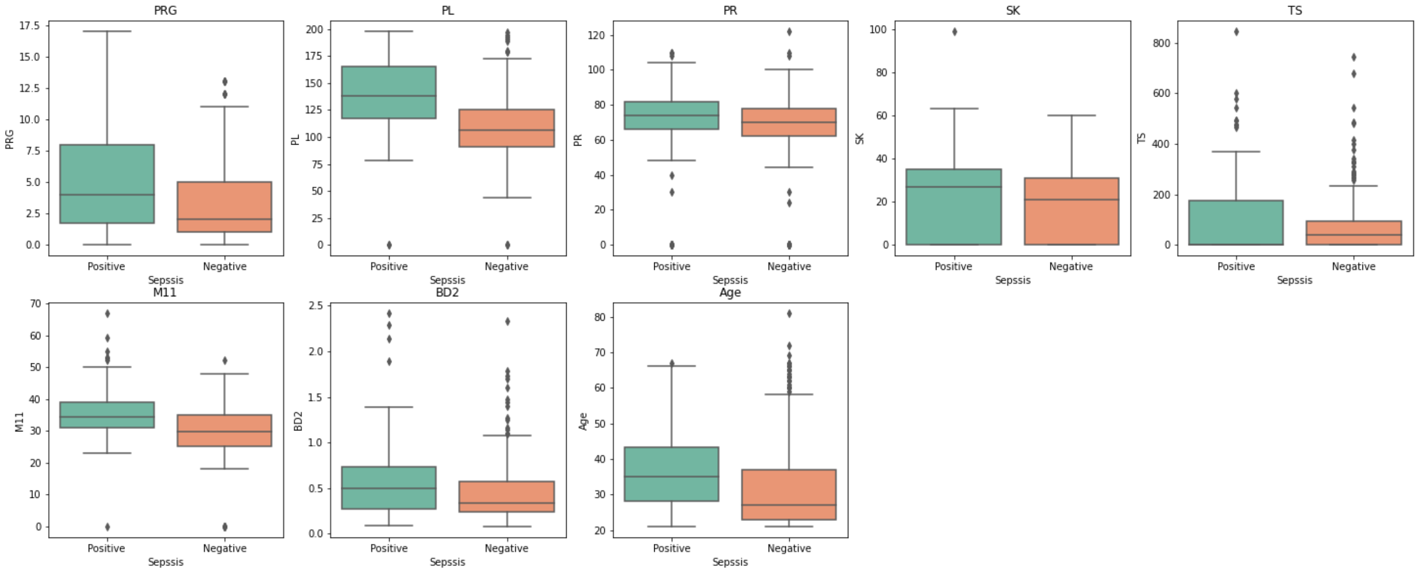
In [8]:

```
#Class Distribution in our Target variable.

data['Sepssis'].hist(figsize=(5,5))
plt.xlabel('Sepssis')
plt.ylabel('frequency')
plt.show()
```



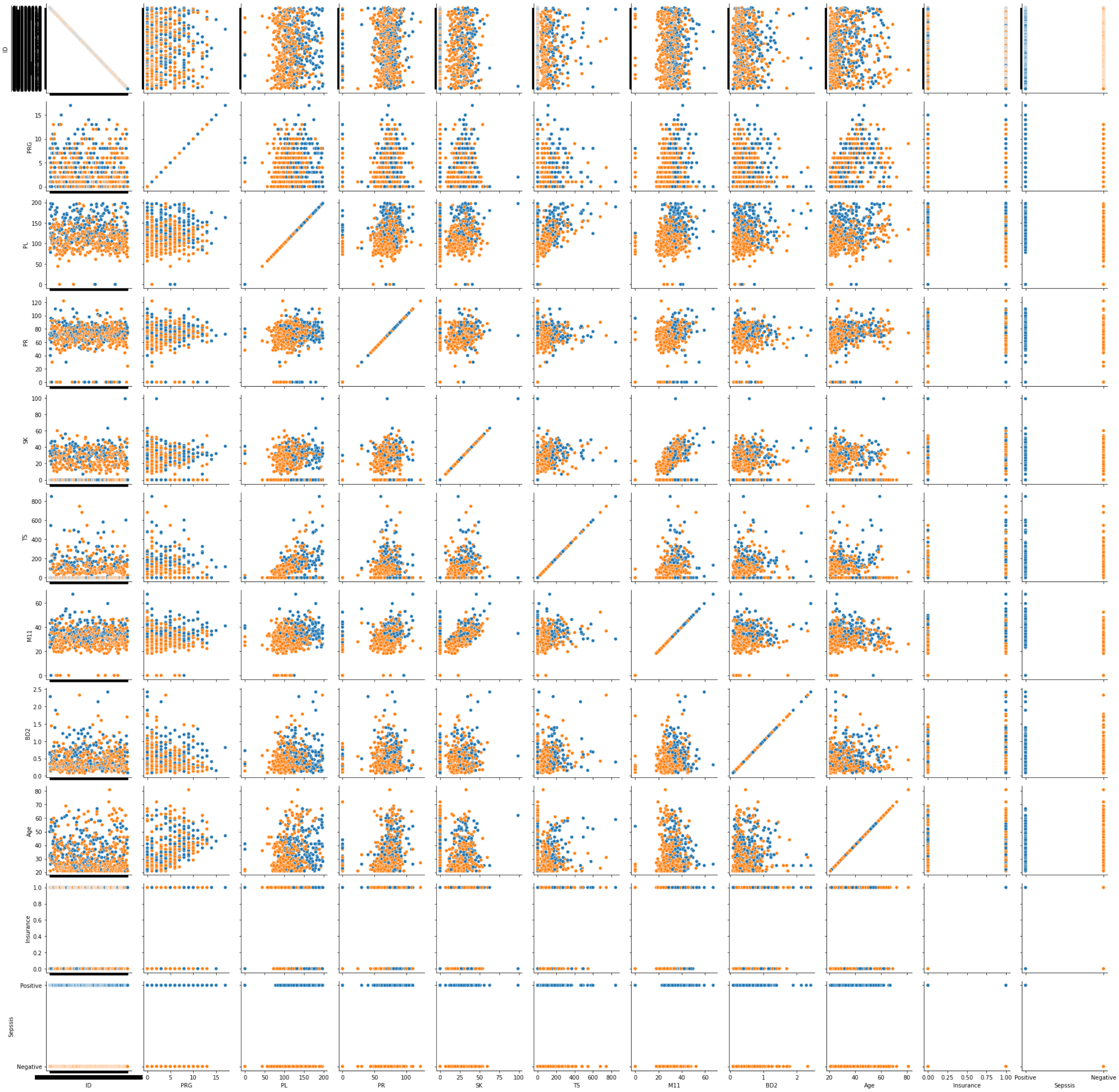
In [9]:

```
#Relationship between Target and other variables.

plt.figure(figsize=(25,15))
i=1
for col in data.columns:

    if col not in ['ID', 'Insurance', 'Sepssis']:

        plt.subplot(3,5,i)
        sns.boxplot(x='Sepssis',y=col,data=data, palette="Set2")
        i = i+1
        plt.title(col)

plt.show()
```



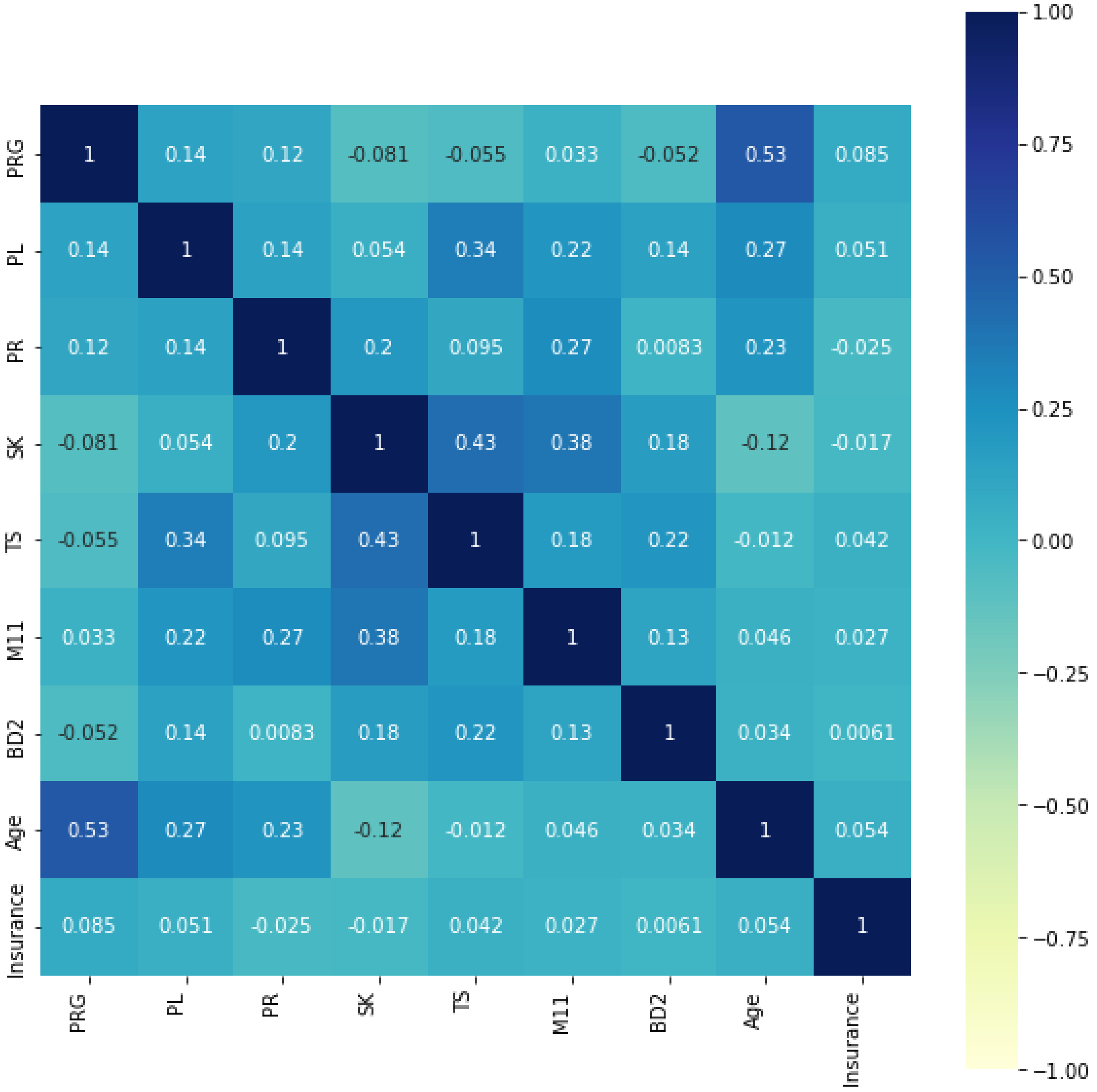
In [10]:

```
#All features w.r.t Sepssis
vis = sns.PairGrid(data, vars=data.columns, hue="Sepssis")
vis.map(sns.scatterplot)
plt.show()
```



In [11]:

```
#Correlation Heatmap

f, ax = plt.subplots(figsize=(10, 10))
corr = data.corr()
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    annot=True,
    cmap='YlGnBu',
    square=True
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=90,
    horizontalalignment='right'
);
```



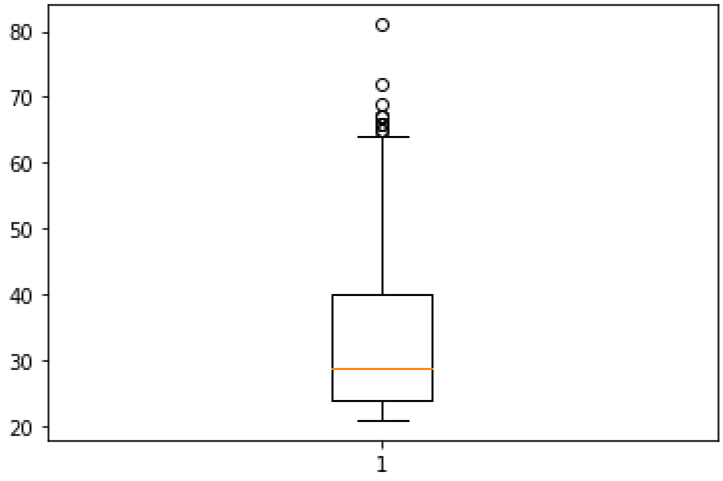
Check for outliers

In [12]:

```
plt.boxplot(x=data['Age'])
```

Out[12]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x1bc6fa2e970>,
  <matplotlib.lines.Line2D at 0x1bc6fa2ec70>],
 'caps': [<matplotlib.lines.Line2D at 0x1bc6fa2ef70>,
  <matplotlib.lines.Line2D at 0x1bc6fa39310>],
 'boxes': [<matplotlib.lines.Line2D at 0x1bc6fa2e640>],
 'medians': [<matplotlib.lines.Line2D at 0x1bc6fa396a0>],
 'fliers': [<matplotlib.lines.Line2D at 0x1bc6fa39a30>],
 'means': []}
```

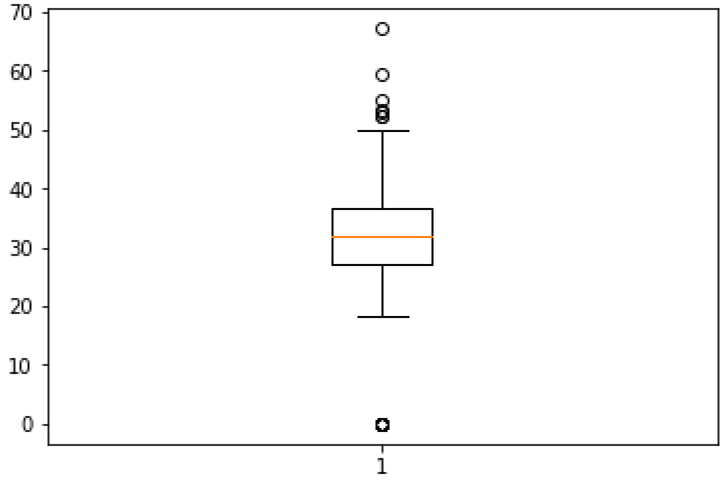


In [13]:

```
plt.boxplot(x=data['M11'])
```

Out[13]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x1bc6fa92af0>,
  <matplotlib.lines.Line2D at 0x1bc6fa92e80>],
 'caps': [<matplotlib.lines.Line2D at 0x1bc6fa9f250>,
  <matplotlib.lines.Line2D at 0x1bc6fa9f5e0>],
 'boxes': [<matplotlib.lines.Line2D at 0x1bc6fa92760>],
 'medians': [<matplotlib.lines.Line2D at 0x1bc6fa9f910>],
 'fliers': [<matplotlib.lines.Line2D at 0x1bc6fa9fbb0>],
 'means': []}
```



In [14]:

```
data.isnull().sum()
```

Out[14]:

```
ID           0
PRG          0
PL           0
PR           0
SK           0
TS           0
M11          0
BD2          0
Age          0
Insurance    0
Sepssis      0
dtype: int64
```

Transforming Target Attribute

In [15]:

```
data['Sepssis'].value_counts()
```

Out[15]:

```
Negative    391
Positive    208
Name: Sepssis, dtype: int64
```

In [16]:

```
data['Sepssis'] = data['Sepssis'].replace('Positive', 1)
data['Sepssis'] = data['Sepssis'].replace('Negative', 0)
```

In [17]:

```
data.head()
```

Out[17]:

	ID	PRG	PL	PR	SK	TS	M11	BD2	Age	Insurance	Sepssis
0	ICU200010	6	148	72	35	0	33.6	0.627	50	0	1
1	ICU200011	1	85	66	29	0	26.6	0.351	31	0	0

	ID	PRG	PL	PR	SK	TS	M11	BD2	Age	Insurance	Sepssis
2	ICU200012	8	183	64	0	0	23.3	0.672	32	1	1
3	ICU200013	1	89	66	23	94	28.1	0.167	21	1	0
4	ICU200014	0	137	40	35	168	43.1	2.288	33	1	1

Training and Modelling

In [18]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score, make_scorer
```

In [19]:

```
with pd.option_context('mode.chained_assignment', None):
    train_data, val_data = train_test_split(data, test_size=0.2, shuffle=True,random_state

print(train_data.shape[0], val_data.shape[0])
```

```
479 120
```

In [20]:

```
train_X = train_data.drop(['ID', 'Insurance', 'Sepssis'], axis=1).to_numpy()
train_y = train_data[['Sepssis']].to_numpy()
val_X = val_data.drop(['ID', 'Insurance', 'Sepssis'], axis=1).to_numpy()
val_y = val_data[['Sepssis']].to_numpy()
```

In [21]:

```
scaler = MinMaxScaler().fit(train_X)
train_X = scaler.transform(train_X)
val_X = scaler.transform(val_X)
```

In [22]:

```
def get_f1_scores(clf, train_X, train_y, val_X, val_y):
    train_pred = clf.predict(train_X)
    val_pred = clf.predict(val_X)

    train_f1 = f1_score(train_y, train_pred, average='macro')
    val_f1 = f1_score(val_y, val_pred, average='macro')

    return train_f1, val_f1
```

Logistic Regression

In [23]:

```
#Without Regularization.

clf = LogisticRegression(random_state=0, solver='liblinear', max_iter=1000, class_weight='

get_f1_scores(clf, train_X, train_y, val_X, val_y)
```

Out[23]:

```
(0.7176123802505527, 0.76)
```

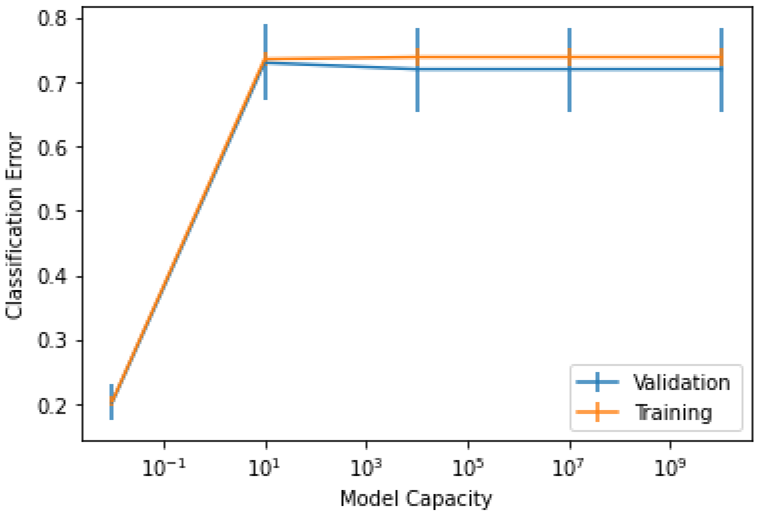
In [24]:

```
#Cross Validation
```

```
f1_scorer = make_scorer(f1_score, average='weighted')
lambda_paras = np.logspace(-10, 2, num=5)

cv_results = dict()

for lambda_para in lambda_paras:
    clf = LogisticRegression(penalty='l2', C = 1.0/lambda_para,
                             solver='liblinear', max_iter=1000,
                             class_weight='balanced')

    scores = cross_validate(clf, train_X, train_y.ravel(),
                            scoring=f1_scorer, return_estimator=True,
                            return_train_score=True, cv=5)

    cv_results[lambda_para] = scores
```

In [25]:

```
#Cross Validation plot

fig, ax = plt.subplots()

val_means = [np.mean(cv_results[lambda_para]['test_score'])
             for lambda_para in lambda_paras]

val_std = [np.std(cv_results[lambda_para]['test_score'])
           for lambda_para in lambda_paras]

train_means = [np.mean(cv_results[lambda_para]['train_score'])
               for lambda_para in lambda_paras]

train_std = [np.std(cv_results[lambda_para]['train_score'])
             for lambda_para in lambda_paras]

ax.errorbar([1.0/lambda_para for lambda_para in lambda_paras],
            val_means,
            yerr=val_std)

ax.errorbar([1.0/lambda_para for lambda_para in lambda_paras],
            train_means,
            yerr=train_std)

plt.xscale("log")
plt.ylabel('Classification Error')
plt.xlabel('Model Capacity')
plt.legend(['Validation','Training',])
plt.show()
```

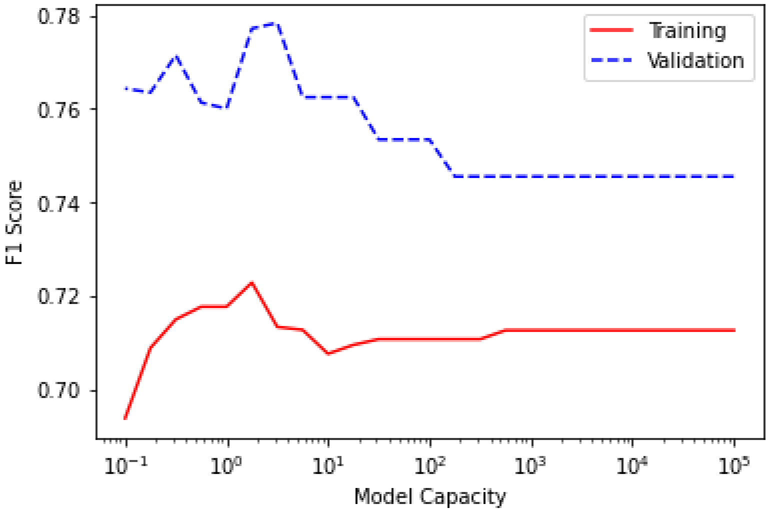


In [26]:

```
#Grid Search to find appropriate Lambda value.
lambda_paras = np.logspace(-5, 1, num=25)

train_performace = list()
valid_performace = list()

for lambda_para in lambda_paras:
    clf = LogisticRegression(penalty='l2', C = 1.0/lambda_para,
                             random_state=0, solver='liblinear', max_iter=100 ,
                             class_weight='balanced').fit(train_X, train_y.ravel())

    train_f1, val_f1 = get_f1_scores(clf, train_X, train_y, val_X, val_y)

    train_performace.append(train_f1)
    valid_performace.append(val_f1)
```

In [27]:

```
plt.plot([1.0/lambda_para for lambda_para in lambda_paras],
         [tp for tp in train_performace], 'r-')
plt.plot([1.0/lambda_para for lambda_para in lambda_paras],
         [vp for vp in valid_performace], 'b--')
plt.xscale("log")
plt.ylabel('F1 Score')
plt.xlabel('Model Capacity')
plt.legend(['Training','Validation'])
plt.show()
```



In [28]:

```
#Regularization

clf_l2 = LogisticRegression(penalty='l2', C = 1, random_state=0, solver='liblinear', max_i

get_f1_scores(clf_l2, train_X, train_y, val_X, val_y)
```

Out[28]:

```
(0.7176123802505527, 0.76)
```

Random Forest

In [29]:

```
from sklearn.metrics import balanced_accuracy_score

def get_acc_scores(clf, train_X, train_y, val_X, val_y):
    train_pred = clf.predict(train_X)
    val_pred = clf.predict(val_X)

    train_acc = balanced_accuracy_score(train_y, train_pred)
    val_acc = balanced_accuracy_score(val_y, val_pred)

    return train_acc, val_acc
```

In [30]:
```
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier(max_depth=8, n_estimators=500, class_weight='balanced_subsamp
clf.fit(train_X, train_y.ravel())
```

Out[30]:
```
RandomForestClassifier(class_weight='balanced_subsample', max_depth=8,
                       n_estimators=500, random_state=0)
```

In [31]:
```
train_acc, val_acc = get_acc_scores(clf, train_X, train_y, val_X, val_y)
print("Train Accuracy score: {:.3f}".format(train_acc))
print("Validation Accuracy score: {:.3f}".format(val_acc))
```

```
Train Accuracy score: 0.972
Validation Accuracy score: 0.709
```

Predictions

In [32]:
```
data_test.head()
```

Out[32]:

	ID	PRG	PL	PR	SK	TS	M11	BD2	Age	Insurance
0	ICU200609	1	109	38	18	120	23.1	0.407	26	1
1	ICU200610	1	108	88	19	0	27.1	0.400	24	1
2	ICU200611	6	96	0	0	0	23.7	0.190	28	1
3	ICU200612	1	124	74	36	0	27.8	0.100	30	1
4	ICU200613	7	150	78	29	126	35.2	0.692	54	0

In [33]:
```
test_X = data_test.drop(['ID', 'Insurance'], axis=1).to_numpy()
```

In [34]:
```
scaler = MinMaxScaler().fit(test_X)
test_X = scaler.transform(test_X)
```

In [35]:
```
pred = clf_l2.predict(test_X)
```

In [36]:
```
pred
```

Out[36]:
```
array([0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0,
       0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1,
       0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0,
       1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0], dtype=int64)
```

In [37]:
```
fin = data_test.copy()
fin.head()
```

```
Out[37]:
          ID  PRG   PL  PR  SK   TS   M11    BD2  Age  Insurance
0  ICU200609    1  109  38  18  120  23.1  0.407   26          1
1  ICU200610    1  108  88  19    0  27.1  0.400   24          1
2  ICU200611    6   96   0   0    0  23.7  0.190   28          1
3  ICU200612    1  124  74  36    0  27.8  0.100   30          1
4  ICU200613    7  150  78  29  126  35.2  0.692   54          0
```

```
In [38]: fin['Sepssis']=pred
```

```
In [39]: fin.head()
```

```
Out[39]:
          ID  PRG   PL  PR  SK   TS   M11    BD2  Age  Insurance  Sepssis
0  ICU200609    1  109  38  18  120  23.1  0.407   26          1        0
1  ICU200610    1  108  88  19    0  27.1  0.400   24          1        0
2  ICU200611    6   96   0   0    0  23.7  0.190   28          1        0
3  ICU200612    1  124  74  36    0  27.8  0.100   30          1        0
4  ICU200613    7  150  78  29  126  35.2  0.692   54          0        1
```

```
In [40]: fin.drop(['PRG', 'PL', 'PR', 'SK', 'TS', 'M11', 'BD2', 'Age', 'Insurance'], axis=1, inplac
```

```
In [41]: fin.to_csv('s3887231_predictions.csv', index=False)
```

Final Judgement

A careful and thorough study was conducted, it was observed through EDA that the dataset was skewed and unbalanced. To overcome this shortcoming, The dataset was scaled using minmax scaler and to overcome the shortcoming of an unbalanced target variable during training the "class-weight" parameter was set to "balanced". After which it is evident that in this paricular experiment the Logistic regression model after regularization performs the best off the 3 models. While the Random forest model gave high accuracy on the train data the validation set accuracy was significantly lower indicating the presence of high variance. The baseline logistic regression model seems to perform well, but after minute parameter tuning and regularization(selecting appropriate Lambda values) it is much more accurate and significantly better and is ready to be used to make predictions.