## MScBMI 33200 – Assignment III

### Savita K Gupta¶

```
17 May 2023¶
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```
In [1]:
#Imports
import numpy as np
import pandas as pd
from scipy.stats import sem
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear model import LogisticRegression
from sklearn.linear model import LogisticRegressionCV
from sklearn.linear model import Ridge
from sklearn.linear model import RidgeCV
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import roc auc score
from sklearn.metrics import accuracy score
from sklearn.metrics import precision score
from sklearn.metrics import recall score
from sklearn.metrics import f1 score
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model selection import GridSearchCV
from sklearn.model selection import train test split
from sklearn.model selection import KFold
from sklearn.model selection import cross val score
from sklearn.neural network import MLPClassifier
```

# Section 1: ER Bots 30-Day Readmission Study

## S1 Question 1: Naive Model

In [2]:

```
# Import train and test dataset

rm_train_full = pd.read_csv(r'C:\Users\vitak\Downloads\readmission_train.csv')
rm_test_full = pd.read_csv(r'C:\Users\vitak\Downloads\readmission_test.csv')

In [3]:
# Setup xTrain and yTrain
```

```
rm n = rm train full.drop(rm train full.columns[[2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17]], axis=1)
rm Xtrain n = rm n.drop(["outcome"], axis=1)
rm Ytrain n = rm n['outcome']
In [4]:
#Setup xTest and yTest
rm n test = rm test full.drop(rm train full.columns[[2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17]],
axis=1)
rm Xtest n = rm n test.drop(["outcome"], axis=1)
rm Ytest n = rm n test['outcome']
In [5]:
# Run logistic regression
naive model = LogisticRegression()
naive model.fit(rm Xtrain n, rm Ytrain n)
Out[5]:
LogisticRegression()
In [6]:
#Calculate AUC using predict proba
naive model prediction = naive model.predict proba(rm Xtest n)
print("Naive Model train set AUC score - with predict proba: %f" % roc auc score(rm Ytest n,
naive model prediction[:,1]))
Naive Model train set AUC score - with predict proba: 0.499419
In [7]:
# Calculate Confidence Interval using bootstrap for Naive model
#Y train value for Naive model
y true n = np.array(rm Ytest n)
#Predict proba value for Naive model
y pred n = np.array(naive model prediction[:,1])
n bootstraps = 100
rng seed = 42 # control reproducibility
bootstrapped scores = []
rng = np.random.RandomState(rng seed)
for i in range(n bootstraps):
    indices = rng.randint(0, len(y pred n), len(y pred n))
    if len(np.unique(y true n[indices])) < 2:</pre>
        continue
    score = roc auc score(y true n[indices], y pred n[indices])
```

```
bootstrapped scores.append(score)
sorted scores = np.array(bootstrapped scores)
sorted scores.sort()
con low n = sorted scores[int(0.05 * len(sorted scores))]
con up n = sorted scores[int(0.95 * len(sorted scores))]
print("Confidence interval for the score: [{:0.5f} - {:0.5}]".format(con low n, con up n))
Confidence interval for the score: [0.41708 - 0.56076]
Cross Validation: Naive Model
In [8]:
#Cross Validation with kfold
k = 5
rm kf = KFold(n splits=k, random state=None)
rm model = LogisticRegression(solver= 'liblinear')
result = cross val score(rm model , rm Xtest n, rm Ytest n, cv = rm kf)
print("Avg accuracy: {}".format(result.mean()))
Avg accuracy: 0.9965800273597811
In [9]:
#LogisticRegressionCV (KFold=5)
rm log cv = LogisticRegressionCV(cv=5, random state = 0)
rm log cv.fit(rm Xtrain n, rm Ytrain n)
rm log cv predict = rm log cv.predict proba(rm Xtest n)
rm n auc = roc auc score(rm Ytest n, rm log cv predict[:,1])
print("Naive Model training AUC (with Kfold CV): %f" % rm n auc)
Naive Model training AUC (with Kfold CV): 0.526428
In [10]:
# Calculate Confidence Interval using bootstrap for Naive model (with LogReg Kfold CV)
#Y train value for Naive model
y true n = np.array(rm Ytest n)
#Predict proba value for Naive model
y pred n = np.array(rm log cv predict[:,1])
n bootstraps = 100
rng seed = 42 # control reproducibility
bootstrapped scores = []
rng = np.random.RandomState(rng seed)
for i in range(n bootstraps):
    indices = rng.randint(0, len(y pred n), len(y pred n))
```

```
if len(np.unique(y true n[indices])) < 2:</pre>
        continue
    score = roc auc score(y true n[indices], y pred n[indices])
    bootstrapped scores.append(score)
sorted scores = np.array(bootstrapped scores)
sorted scores.sort()
cv con low n = sorted scores[int(0.05 \star len(sorted scores))]
cv con up n = sorted scores[int(0.95 \star len(sorted scores))]
print("Confidence interval for the score: [{:0.5f} - {:0.5}]".format(cv con low n, cv con up n))
Confidence interval for the score: [0.46040 - 0.58978]
S1 Question 2: GLM Model
In [11]:
# Setup xTrain and yTrain
rm lr train = rm train full.drop duplicates(keep='last')
rm Xtrain lr = rm lr train.drop(["outcome"], axis=1)
rm Ytrain lr = rm lr train['outcome']
In [12]:
#Setup xTest and yTest
rm lr test = rm test full.drop duplicates(keep='last')
rm Xtest lr = rm lr test.drop(["outcome"], axis=1)
rm Ytest lr = rm lr test['outcome']
In [13]:
# Run logistic regression
lr model = LogisticRegression()
lr model.fit(rm Xtrain lr, rm Ytrain lr)
Out[13]:
LogisticRegression()
In [14]:
#Calculate AUC
lr model prediction = lr model.predict proba(rm Xtest lr)
print("Logistic Regression train set AUC score: %f" % roc auc score(rm Ytest lr,
lr model prediction[:,1]))
Logistic Regression train set AUC score: 0.512161
In [15]:
# Calculate Confidence Interval using bootstrap for Logistic Regression model
```

```
#Y train value for Logistic Regression model
y true lr = np.array(rm Ytest lr)
#Predict proba value for Logistic Regression model
y pred lr = np.array(lr model prediction[:,1])
n bootstraps = 100
rng seed = 42 # control reproducibility
bootstrapped scores = []
rng = np.random.RandomState(rng seed)
for i in range(n bootstraps):
    indices = rng.randint(0, len(y pred lr), len(y pred lr))
    if len(np.unique(y true lr[indices])) < 2:</pre>
        continue
    score = roc_auc_score(y_true_lr[indices], y pred lr[indices])
    bootstrapped scores.append(score)
sorted scores = np.array(bootstrapped scores)
sorted scores.sort()
con low lr = sorted scores[int(0.05 * len(sorted scores))]
con up lr = sorted scores[int(0.95 * len(sorted scores))]
print("Confidence interval for the score: [\{:0.5f\} - \{:0.5\}]".format(con low lr, con up lr))
Confidence interval for the score: [0.43869 - 0.57803]
Cross Validation: GLM Model
In [16]:
#Cross Validation with kfold
rm kf lr = KFold(n splits=k, random state=None)
rm model lr = LogisticRegression(solver= 'liblinear')
result lr = cross val score(lr model , rm Xtest lr, rm Ytest lr, cv = rm kf lr)
print("Avg accuracy: {}".format(result lr.mean()))
Avg accuracy: 0.9965800273597811
In [17]:
#LogisticRegressionCV (KFold=5)
lr log cv = LogisticRegressionCV(cv=5, random state = 0)
lr log cv.fit(rm Xtrain lr, rm Ytrain lr)
lr log cv predict = lr log cv.predict proba(rm Xtest lr)
rm lr auc = roc auc score(rm Ytest lr, lr log cv predict[:,1])
print("GLM Model training AUC (with Kfold CV): %f" % rm lr auc)
GLM Model training AUC (with Kfold CV): 0.543278
In [18]:
```

```
# Calculate Confidence Interval using bootstrap for Logistic Regression model (with Kfold CV)
#Y train value for Naive model
y true lr = np.array(rm Ytest lr)
#Predict proba value for Naive model
y pred lr = np.array(lr log cv predict[:,1])
n bootstraps = 100
rng seed = 42 # control reproducibility
bootstrapped scores = []
rng = np.random.RandomState(rng seed)
for i in range(n bootstraps):
    indices = rng.randint(0, len(y_pred_lr), len(y_pred_lr))
    if len(np.unique(y true lr[indices])) < 2:</pre>
    score = roc auc score(y true lr[indices], y pred lr[indices])
    bootstrapped scores.append(score)
sorted scores = np.array(bootstrapped scores)
sorted scores.sort()
cv con low lr = sorted_scores[int(0.05 * len(sorted_scores))]
cv con up lr = sorted scores[int(0.95 * len(sorted scores))]
print("Confidence interval for the score: [{:0.5f} - {:0.5}]".format(cv con low lr, cv con up lr))
Confidence interval for the score: [0.46654 - 0.60726]
S1 Question 3: Neural Net Classifier
In [19]:
mlp = MLPClassifier(
   hidden layer sizes=(100,80,10,1),
    activation='relu',
   \max iter=500,
   alpha=0.10,
    solver="sgd",
    verbose=10,
    random state=1,
    learning rate='adaptive',
    learning rate init=0.001,
)
mlp.fit(rm Xtrain lr, rm Ytrain lr)
mlp predtrain = mlp.predict proba(rm Xtrain lr)
print("Train set AUC score: %f" % roc auc score(rm Ytrain lr, mlp predtrain[:,1]))
mlp predtest = mlp.predict proba(rm Xtest lr)
print("Train set AUC score: %f" % roc auc score(rm Ytest lr, mlp predtest[:,1]))
```

```
Iteration 1, loss = 1.15732308
Iteration 2, loss = 0.77207644
Iteration 3, loss = 0.54423731
Iteration 4, loss = 0.40992959
Iteration 5, loss = 0.32656229
Iteration 6, loss = 0.27162578
Iteration 7, loss = 0.23344792
Iteration 8, loss = 0.20571243
Iteration 9, loss = 0.18481482
Iteration 10, loss = 0.16859700
Iteration 11, loss = 0.15569664
Iteration 12, loss = 0.14521574
Iteration 13, loss = 0.13655940
Iteration 14, loss = 0.12929547
Iteration 15, loss = 0.12313022
Iteration 16, loss = 0.11783121
Iteration 17, loss = 0.11323331
Iteration 18, loss = 0.10921284
Iteration 19, loss = 0.10566712
Iteration 20, loss = 0.10252006
Iteration 21, loss = 0.09970892
Iteration 22, loss = 0.09718369
Iteration 23, loss = 0.09490381
Iteration 24, loss = 0.09283553
Iteration 25, loss = 0.09095184
Iteration 26, loss = 0.08923024
Iteration 27, loss = 0.08764949
Iteration 28, loss = 0.08619258
Iteration 29, loss = 0.08484827
Iteration 30, loss = 0.08360235
Iteration 31, loss = 0.08244613
Iteration 32, loss = 0.08136827
Iteration 33, loss = 0.08036236
Iteration 34, loss = 0.07942191
Iteration 35, loss = 0.07853851
Iteration 36, loss = 0.07770997
Iteration 37, loss = 0.07692921
Iteration 38, loss = 0.07619374
Iteration 39, loss = 0.07549965
Iteration 40, loss = 0.07484266
Iteration 41, loss = 0.07422010
Iteration 42, loss = 0.07363016
Iteration 43, loss = 0.07306858
Iteration 44, loss = 0.07253567
Iteration 45, loss = 0.07202734
Iteration 46, loss = 0.07154264
Iteration 47, loss = 0.07108051
Iteration 48, loss = 0.07063765
Iteration 49, loss = 0.07021467
Iteration 50, loss = 0.06980999
Iteration 51, loss = 0.06942186
Iteration 52, loss = 0.06904900
Iteration 53, loss = 0.06869067
Iteration 54, loss = 0.06834631
Iteration 55, loss = 0.06801406
Iteration 56, loss = 0.06769524
Iteration 57, loss = 0.06738745
Iteration 58, loss = 0.06709080
Iteration 59, loss = 0.06680453
Iteration 60, loss = 0.06652718
```

```
Iteration 61, loss = 0.06626047
Iteration 62, loss = 0.06600186
Iteration 63, loss = 0.06575170
Iteration 64, loss = 0.06550937
Iteration 65, loss = 0.06527459
Iteration 66, loss = 0.06504677
Iteration 67, loss = 0.06482587
Iteration 68, loss = 0.06461141
Iteration 69, loss = 0.06440268
Iteration 70, loss = 0.06419998
Iteration 71, loss = 0.06400305
Iteration 72, loss = 0.06381120
Iteration 73, loss = 0.06362457
Iteration 74, loss = 0.06344306
Iteration 75, loss = 0.06326656
Iteration 76, loss = 0.06309389
Iteration 77, loss = 0.06292556
Iteration 78, loss = 0.06276140
Iteration 79, loss = 0.06260127
Iteration 80, loss = 0.06244486
Iteration 81, loss = 0.06229189
Iteration 82, loss = 0.06214261
Iteration 83, loss = 0.06199634
Iteration 84, loss = 0.06185374
Iteration 85, loss = 0.06171394
Iteration 86, loss = 0.06157731
Iteration 87, loss = 0.06144356
Iteration 88, loss = 0.06131215
Iteration 89, loss = 0.06118358
Iteration 90, loss = 0.06105744
Iteration 91, loss = 0.06093412
Iteration 92, loss = 0.06081282
Iteration 93, loss = 0.06069396
Iteration 94, loss = 0.06057773
Iteration 95, loss = 0.06046359
Iteration 96, loss = 0.06035158
Iteration 97, loss = 0.06024083
Iteration 98, loss = 0.06013240
Iteration 99, loss = 0.06002559
Iteration 100, loss = 0.05992082
Iteration 101, loss = 0.05981778
Iteration 102, loss = 0.05971623
Iteration 103, loss = 0.05961646
Iteration 104, loss = 0.05951869
Iteration 105, loss = 0.05942213
Iteration 106, loss = 0.05932713
Iteration 107, loss = 0.05923352
Iteration 108, loss = 0.05914107
Iteration 109, loss = 0.05905019
Iteration 110, loss = 0.05896059
Iteration 111, loss = 0.05887263
Iteration 112, loss = 0.05878578
Iteration 113, loss = 0.05869997
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning
rate to 0.000200
Iteration 114, loss = 0.05864381
Iteration 115, loss = 0.05862647
Iteration 116, loss = 0.05860972
Iteration 117, loss = 0.05859297
Iteration 118, loss = 0.05857629
```

Iteration 119, loss = 0.05855965

```
Iteration 120, loss = 0.05854299
Iteration 121, loss = 0.05852643
Iteration 122, loss = 0.05850986
Iteration 123, loss = 0.05849337
Iteration 124, loss = 0.05847693
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning
rate to 0.000040
Iteration 125, loss = 0.05846612
Iteration 126, loss = 0.05846273
Iteration 127, loss = 0.05845945
Iteration 128, loss = 0.05845618
Iteration 129, loss = 0.05845291
Iteration 130, loss = 0.05844963
Iteration 131, loss = 0.05844635
Iteration 132, loss = 0.05844309
Iteration 133, loss = 0.05843982
Iteration 134, loss = 0.05843656
Iteration 135, loss = 0.05843330
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning
rate to 0.000008
Iteration 136, loss = 0.05843114
Iteration 137, loss = 0.05843047
Iteration 138, loss = 0.05842982
Iteration 139, loss = 0.05842917
Iteration 140, loss = 0.05842852
Iteration 141, loss = 0.05842786
Iteration 142, loss = 0.05842721
Iteration 143, loss = 0.05842656
Iteration 144, loss = 0.05842591
Iteration 145, loss = 0.05842526
Iteration 146, loss = 0.05842461
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning
rate to 0.000002
Iteration 147, loss = 0.05842418
Iteration 148, loss = 0.05842405
Iteration 149, loss = 0.05842392
Iteration 150, loss = 0.05842379
Iteration 151, loss = 0.05842366
Iteration 152, loss = 0.05842353
Iteration 153, loss = 0.05842340
Iteration 154, loss = 0.05842327
Iteration 155, loss = 0.05842314
Iteration 156, loss = 0.05842300
Iteration 157, loss = 0.05842287
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning
rate to 0.000000
Iteration 158, loss = 0.05842279
Iteration 159, loss = 0.05842276
Iteration 160, loss = 0.05842274
Iteration 161, loss = 0.05842271
Iteration 162, loss = 0.05842268
Iteration 163, loss = 0.05842266
Iteration 164, loss = 0.05842263
Iteration 165, loss = 0.05842261
Iteration 166, loss = 0.05842258
Iteration 167, loss = 0.05842255
Iteration 168, loss = 0.05842253
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Learning rate too
small. Stopping.
Train set AUC score: 0.500000
```

### **Cross Validation: Neural Net Model**

#Calculate AUC after GridSearch

#This section must run overnight - mlp GRIDSEARCH can take up to 8 hours. mlp = MLPClassifier(max\_iter=200) parameter\_space = { 'hidden\_layer\_sizes': [(50,20,10,1),(50,10),(20,10,5),(100,80,10,1)], 'activation': ['relu'], 'solver': ['sgd','adam'], 'batch\_size': [300,500], 'alpha': [0.10,0.40,0.60,0.80,1.0], 'random\_state': [1], 'learning\_rate': ['constant', 'adaptive'], 'learning\_rate\_init': [0.1,0.01,0.001]} clf = GridSearchCV(mlp, parameter\_space, n\_jobs=-1, cv=5) clf.fit(rm\_Xtrain\_lr, rm\_Ytrain\_lr) print('Best parameters found:\n', clf.best\_params\_) In [20]:

```
mlp = MLPClassifier(
    hidden layer sizes=(50, 20, 10, 1),
    activation='relu',
    solver="sgd",
    batch size = 300,
    alpha=0.1,
    random state=1,
    learning rate='constant',
    learning rate init=0.1,
   max iter=500,
   verbose=10,
)
mlp.fit(rm Xtrain lr, rm Ytrain lr)
mlp predtrain = mlp.predict proba(rm Xtrain lr)
print("Train set AUC score: %f" % roc auc score(rm Ytrain lr, mlp predtrain[:,1]))
mlp predtest = mlp.predict proba(rm Xtest lr)
print("Test set AUC score: %f" % roc_auc_score(rm_Ytest_lr, mlp_predtest[:,1]))
Iteration 1, loss = 0.17746690
Iteration 2, loss = 0.03565157
Iteration 3, loss = 0.03495925
Iteration 4, loss = 0.03437503
Iteration 5, loss = 0.03385178
Iteration 6, loss = 0.03336765
Iteration 7, loss = 0.03291337
Iteration 8, loss = 0.03248774
Iteration 9, loss = 0.03208162
Iteration 10, loss = 0.03169665
Iteration 11, loss = 0.03133468
Iteration 12, loss = 0.03098504
Iteration 13, loss = 0.03065611
Iteration 14, loss = 0.03034100
Iteration 15, loss = 0.03004367
Iteration 16, loss = 0.02975651
Iteration 17, loss = 0.02948066
Iteration 18, loss = 0.02922234
Iteration 19, loss = 0.02898125
Iteration 20, loss = 0.02873767
Iteration 21, loss = 0.02851857
Iteration 22, loss = 0.02830582
Iteration 23, loss = 0.02810097
```

```
Iteration 24, loss = 0.02790380
Iteration 25, loss = 0.02772029
Iteration 26, loss = 0.02754282
Iteration 27, loss = 0.02737829
Iteration 28, loss = 0.02721541
Iteration 29, loss = 0.02706395
Iteration 30, loss = 0.02691763
Iteration 31, loss = 0.02678367
Iteration 32, loss = 0.02664662
Iteration 33, loss = 0.02652123
Iteration 34, loss = 0.02640304
Iteration 35, loss = 0.02628797
Iteration 36, loss = 0.02617875
Iteration 37, loss = 0.02607648
Iteration 38, loss = 0.02597706
Iteration 39, loss = 0.02588207
Iteration 40, loss = 0.02579810
Iteration 41, loss = 0.02570791
Iteration 42, loss = 0.02562843
Iteration 43, loss = 0.02555246
Iteration 44, loss = 0.02547759
Iteration 45, loss = 0.02540935
Iteration 46, loss = 0.02533895
Iteration 47, loss = 0.02527500
Iteration 48, loss = 0.02521629
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Stopping.
Train set AUC score: 0.500000
Test set AUC score: 0.500000
In [22]:
#Calculate Confidence Interval After Neural Net GridSearch
y true nn = np.array(rm Ytest lr)
y pred nn = np.array(mlp predtest[:,1])
n bootstraps = 100
rng seed = 42
bootstrapped scores = []
rng = np.random.RandomState(rng seed)
for i in range(n bootstraps):
    indices = rng.randint(0, len(y_pred_nn), len(y_pred_nn))
    if len(np.unique(y true nn[indices])) < 2:</pre>
        continue
    score = roc auc score(y true nn[indices], y pred nn[indices])
    bootstrapped scores.append(score)
sorted scores = np.array(bootstrapped scores)
sorted scores.sort()
confidence lower nn = sorted scores[int(0.05 * len(sorted scores))]
confidence_upper_nn = sorted_scores[int(0.95 * len(sorted_scores))]
print("Confidence interval for the score: [{:0.5f} - {:0.5}]".format(confidence lower nn,
confidence upper nn))
Confidence interval for the score: [0.50000 - 0.5]
```

## **Section 2: Gusto Study**

## S2 Question 1: GLM Model

```
In [23]:
# Import Data
g train = pd.read csv(r'C:\Users\vitak\Downloads\gusto train.csv')
g test = pd.read csv(r'C:\Users\vitak\Downloads\gusto test.csv')
In [24]:
# Setup xTrain and yTrain
g Xtrain = g train.drop(["DAY30"], axis=1)
g Ytrain = g train['DAY30']
In [25]:
# Setup xTest and yTest
g Xtest = g test.drop(["DAY30"], axis=1)
g Ytest = g test['DAY30']
In [26]:
# Run logistic regression
g lr model = LogisticRegression()
g lr model.fit(g Xtrain, g Ytrain)
Out[26]:
LogisticRegression()
In [27]:
#Calculate AUC - GUSTO GLM
g lr model prediction = g lr model.predict proba(g Xtest)
print("GUSTO Logistic Regression AUC score: %f" % roc auc score(g Ytest,
g lr model prediction[:,1]))
GUSTO Logistic Regression AUC score: 0.826736
In [28]:
# Calculate Confidence Interval using bootstrap for GUSTO Logistic Regression model
#Y train value for Logistic Regression model
gy true lr = np.array(g Ytest)
#Predict proba value for Logistic Regression model
gy pred lr = np.array(g lr model prediction[:,1])
n bootstraps = 100
rng seed = 42 # control reproducibility
```

```
bootstrapped scores = []
rng = np.random.RandomState(rng seed)
for i in range(n bootstraps):
    indices = rng.randint(0, len(gy pred lr), len(gy pred lr))
    if len(np.unique(gy true lr[indices])) < 2:</pre>
        continue
    score = roc auc score(gy true lr[indices], gy pred lr[indices])
    bootstrapped scores.append(score)
sorted scores = np.array(bootstrapped scores)
sorted scores.sort()
gcon low lr = sorted scores[int(0.05 * len(sorted scores))]
gcon up lr = sorted scores[int(0.95 * len(sorted scores))]
print("Confidence interval for the score: [{:0.5f} - {:0.5}]".format(gcon low lr, gcon up lr))
Confidence interval for the score: [0.79637 - 0.8585]
Cross Validation: GUSTO GLM
In [29]:
#Cross Validation with kfold
g kf = KFold(n splits=k, random state=None)
g model = LogisticRegression(solver= 'liblinear')
gresult lr = cross val score(g model , g Xtest, g Ytest, cv = g kf)
print("Avg accuracy: {}".format(gresult lr.mean()))
Avg accuracy: 0.9405776203462797
In [30]:
#LogisticRegressionCV (KFold=5)
g log cv = LogisticRegressionCV(cv=5, random state = 0)
g log cv.fit(g Xtrain, g Ytrain)
g log cv predict = g log cv.predict proba(g Xtest)
g lr auc = roc auc score(g Ytest, g log cv predict[:,1])
print("GUSTO GLM AUC (with Kfold CV): %f" % g lr auc)
GUSTO GLM AUC (with Kfold CV): 0.832318
In [31]:
# Calculate Confidence Interval using bootstrap for GUSTO Logistic Regression model (with Kfold CV)
#Y train value for Logistic Regression model
gy true cv = np.array(g Ytest)
#Predict proba value for Logistic Regression model
gy pred cv = np.array(g log cv predict[:,1])
```

```
n bootstraps = 100
rng seed = 42 # control reproducibility
bootstrapped scores = []
rng = np.random.RandomState(rng seed)
for i in range(n bootstraps):
    indices = rng.randint(0, len(gy pred cv), len(gy pred cv))
    if len(np.unique(gy true cv[indices])) < 2:</pre>
    score = roc auc score(gy true cv[indices], gy pred cv[indices])
    bootstrapped scores.append(score)
sorted scores = np.array(bootstrapped scores)
sorted scores.sort()
gcon low cv = sorted scores[int(0.05 * len(sorted scores))]
gcon up cv = sorted scores[int(0.95 * len(sorted scores))]
print("Confidence interval for the score: [{:0.5f} - {:0.5}]".format(gcon low cv, gcon up cv))
Confidence interval for the score: [0.80082 - 0.86391]
S2 Question 2: Ridge Regression Model
In [32]:
#Run Ridge Regression
r = np.logspace(0, 5, 100)
ridge = RidgeCV(alphas = r alphas, scoring = 'r2')
ridge.fit(g Xtrain, g Ytrain)
Out[32]:
RidgeCV(alphas=array([1.00000000e+00, 1.12332403e+00, 1.26185688e+00, 1.41747416e+00,
      1.59228279e+00, 1.78864953e+00, 2.00923300e+00, 2.25701972e+00,
       2.53536449e+00, 2.84803587e+00, 3.19926714e+00, 3.59381366e+00,
      4.03701726e+00, 4.53487851e+00, 5.09413801e+00, 5.72236766e+00,
       6.42807312e+00, 7.22080902e+00, 8.11130831e+00, 9.11162756e+00,
       1.02353102e+01, 1.14975700e+0...
       6.89261210e+03, 7.74263683e+03, 8.69749003e+03, 9.77009957e+03,
       1.09749877e+04, 1.23284674e+04, 1.38488637e+04, 1.55567614e+04,
      1.74752840e+04, 1.96304065e+04, 2.20513074e+04, 2.47707636e+04,
       2.78255940e+04, 3.12571585e+04, 3.51119173e+04, 3.94420606e+04,
       4.43062146e+04, 4.97702356e+04, 5.59081018e+04, 6.28029144e+04,
      7.05480231e+04, 7.92482898e+04, 8.90215085e+04, 1.00000000e+05]),
       scoring='r2')
In [33]:
#Calculate AUC
grr prob = ridge.predict(g Xtest)
grr auc roc = roc auc score(g Ytest, grr prob)
print("Ridge Regression AUC: %f" % grr auc roc)
Ridge Regression AUC: 0.822229
In [34]:
```

```
# Calculate Confidence Interval using bootstrap for GUSTO Ridge Regression model
#Y train value for Logistic Regression model
grr true = np.array(g Ytest)
#Predict proba value for Logistic Regression model
grr pred = np.array(grr prob)
n bootstraps = 100
rng seed = 42 # control reproducibility
bootstrapped scores = []
rng = np.random.RandomState(rng seed)
for i in range(n bootstraps):
    indices = rng.randint(0, len(grr pred), len(grr pred))
    if len(np.unique(grr true[indices])) < 2:</pre>
        continue
    score = roc auc score(grr true[indices], grr pred[indices])
    bootstrapped scores.append(score)
sorted scores = np.array(bootstrapped scores)
sorted scores.sort()
grr low = sorted scores[int(0.05 * len(sorted scores))]
grr up = sorted scores[int(0.95 * len(sorted scores))]
print("Confidence interval for the score: [{:0.5f} - {:0.5}]".format(grr low, grr up))
Confidence interval for the score: [0.79003 - 0.856]
Cross Validation: GUSTO Ridge Regression 
In [35]:
#Cross Validation with kfold
kf = KFold(n splits=k, random state=None)
model1 = RidgeCV(alphas= r alphas, cv = k)
result = cross_val_score(model1 , g_Xtest, g_Ytest, cv = kf)
print("Avg accuracy: {}".format(result.mean()))
Avg accuracy: 0.10941105301450275
In [36]:
#Run RidgeCV with KFold=5
grr cv = RidgeCV(cv=5)
grr cv.fit(g Xtrain,g Ytrain)
grr pred cv = grr cv.predict(g Xtest)
gcv auc roc = roc auc score(g Ytest, grr pred cv)
print("Training AUC: %f" % gcv auc roc)
Training AUC: 0.821861
```

```
In [37]:
# Calculate Confidence Interval using bootstrap for GUSTO Ridge Regression model (with Kfold CV)
#Y train value for Logistic Regression model
grr true cv = np.array(g Ytest)
#Predict value for Ridge Regression model
grr pred cv1 = np.array(grr pred cv)
n bootstraps = 100
rng seed = 42 # control reproducibility
bootstrapped scores = []
rng = np.random.RandomState(rng seed)
for i in range(n bootstraps):
    indices = rng.randint(0, len(grr pred cv1), len(grr pred cv1))
    if len(np.unique(grr true cv[indices])) < 2:</pre>
        continue
    score = roc auc score(grr true cv[indices], grr pred cv1[indices])
    bootstrapped scores.append(score)
sorted scores = np.array(bootstrapped scores)
sorted scores.sort()
grr_low_cv = sorted_scores[int(0.05 * len(sorted_scores))]
grr up cv = sorted scores[int(0.95 * len(sorted scores))]
print("Confidence interval for the score: [{:0.5f} - {:0.5}]".format(grr low cv, grr up cv))
Confidence interval for the score: [0.78978 - 0.85573]
S2 Question 3: GUSTO Neural Net Model
In [38]:
gmlp = MLPClassifier(
   hidden layer sizes=(100,80,10,1),
    activation='relu',
   max iter=500,
   alpha=0.10,
    solver="sgd",
    verbose=10,
    random state=1,
    learning rate='adaptive',
    learning rate init=0.001,
gmlp.fit(g Xtrain, g Ytrain)
gmlp predtrain = gmlp.predict proba(g Xtrain)
print("Train set AUC score: %f" % roc auc score(g Ytrain, gmlp predtrain[:,1]))
```

```
gmlp predtest = gmlp.predict proba(g Xtest)
print("Train set AUC score: %f" % roc auc score(g Ytest, gmlp predtest[:,1]))
Iteration 1, loss = 1.31236731
Iteration 2, loss = 1.29154951
Iteration 3, loss = 1.26254330
Iteration 4, loss = 1.23076716
Iteration 5, loss = 1.19815055
Iteration 6, loss = 1.16601123
Iteration 7, loss = 1.13487002
Iteration 8, loss = 1.10436498
Iteration 9, loss = 1.07494032
Iteration 10, loss = 1.04663807
Iteration 11, loss = 1.01935594
Iteration 12, loss = 0.99310518
Iteration 13, loss = 0.96787853
Iteration 14, loss = 0.94346823
Iteration 15, loss = 0.92007136
Iteration 16, loss = 0.89756764
Iteration 17, loss = 0.87567504
Iteration 18, loss = 0.85489052
Iteration 19, loss = 0.83499409
Iteration 20, loss = 0.81582148
Iteration 21, loss = 0.79724668
Iteration 22, loss = 0.77962692
Iteration 23, loss = 0.76259662
Iteration 24, loss = 0.74632744
Iteration 25, loss = 0.73057282
Iteration 26, loss = 0.71559363
Iteration 27, loss = 0.70111971
Iteration 28, loss = 0.68709223
Iteration 29, loss = 0.67381627
Iteration 30, loss = 0.66087546
Iteration 31, loss = 0.64859847
Iteration 32, loss = 0.63675890
Iteration 33, loss = 0.62544051
Iteration 34, loss = 0.61442427
Iteration 35, loss = 0.60398499
Iteration 36, loss = 0.59390704
Iteration 37, loss = 0.58419201
Iteration 38, loss = 0.57498058
Iteration 39, loss = 0.56597638
Iteration 40, loss = 0.55737579
Iteration 41, loss = 0.54915126
Iteration 42, loss = 0.54124735
Iteration 43, loss = 0.53358895
Iteration 44, loss = 0.52617024
Iteration 45, loss = 0.51911539
Iteration 46, loss = 0.51227741
Iteration 47, loss = 0.50568916
Iteration 48, loss = 0.49931539
Iteration 49, loss = 0.49321829
Iteration 50, loss = 0.48725789
Iteration 51, loss = 0.48152504
Iteration 52, loss = 0.47601297
Iteration 53, loss = 0.47069036
Iteration 54, loss = 0.46558894
Iteration 55, loss = 0.46064778
Iteration 56, loss = 0.45590585
Iteration 57, loss = 0.45128652
Iteration 58, loss = 0.44680325
```

```
Iteration 59, loss = 0.44257387
Iteration 60, loss = 0.43836510
Iteration 61, loss = 0.43433457
Iteration 62, loss = 0.43053706
Iteration 63, loss = 0.42671493
Iteration 64, loss = 0.42307913
Iteration 65, loss = 0.41954710
Iteration 66, loss = 0.41612727
Iteration 67, loss = 0.41288221
Iteration 68, loss = 0.40969204
Iteration 69, loss = 0.40658458
Iteration 70, loss = 0.40359761
Iteration 71, loss = 0.40071412
Iteration 72, loss = 0.39791856
Iteration 73, loss = 0.39522108
Iteration 74, loss = 0.39251946
Iteration 75, loss = 0.38997339
Iteration 76, loss = 0.38747614
Iteration 77, loss = 0.38507367
Iteration 78, loss = 0.38270038
Iteration 79, loss = 0.38036397
Iteration 80, loss = 0.37819214
Iteration 81, loss = 0.37605706
Iteration 82, loss = 0.37397577
Iteration 83, loss = 0.37196239
Iteration 84, loss = 0.36996067
Iteration 85, loss = 0.36803394
Iteration 86, loss = 0.36620572
Iteration 87, loss = 0.36434184
Iteration 88, loss = 0.36253859
Iteration 89, loss = 0.36081063
Iteration 90, loss = 0.35911520
Iteration 91, loss = 0.35745326
Iteration 92, loss = 0.35582475
Iteration 93, loss = 0.35429867
Iteration 94, loss = 0.35277043
Iteration 95, loss = 0.35128044
Iteration 96, loss = 0.34987288
Iteration 97, loss = 0.34841858
Iteration 98, loss = 0.34704019
Iteration 99, loss = 0.34567896
Iteration 100, loss = 0.34437833
Iteration 101, loss = 0.34305819
Iteration 102, loss = 0.34185099
Iteration 103, loss = 0.34059931
Iteration 104, loss = 0.33939864
Iteration 105, loss = 0.33825181
Iteration 106, loss = 0.33713885
Iteration 107, loss = 0.33598902
Iteration 108, loss = 0.33494411
Iteration 109, loss = 0.33387372
Iteration 110, loss = 0.33283972
Iteration 111, loss = 0.33184282
Iteration 112, loss = 0.33087627
Iteration 113, loss = 0.32991800
Iteration 114, loss = 0.32894926
Iteration 115, loss = 0.32806938
Iteration 116, loss = 0.32718674
Iteration 117, loss = 0.32631713
Iteration 118, loss = 0.32549772
```

```
Iteration 119, loss = 0.32467060
Iteration 120, loss = 0.32385318
Iteration 121, loss = 0.32306877
Iteration 122, loss = 0.32228462
Iteration 123, loss = 0.32153596
Iteration 124, loss = 0.32080463
Iteration 125, loss = 0.32008347
Iteration 126, loss = 0.31936026
Iteration 127, loss = 0.31866061
Iteration 128, loss = 0.31802177
Iteration 129, loss = 0.31735204
Iteration 130, loss = 0.31669922
Iteration 131, loss = 0.31606825
Iteration 132, loss = 0.31545674
Iteration 133, loss = 0.31485220
Iteration 134, loss = 0.31425611
Iteration 135, loss = 0.31365778
Iteration 136, loss = 0.31308115
Iteration 137, loss = 0.31253490
Iteration 138, loss = 0.31197677
Iteration 139, loss = 0.31143666
Iteration 140, loss = 0.31090954
Iteration 141, loss = 0.31037585
Iteration 142, loss = 0.30986824
Iteration 143, loss = 0.30934827
Iteration 144, loss = 0.30884997
Iteration 145, loss = 0.30834342
Iteration 146, loss = 0.30787879
Iteration 147, loss = 0.30741721
Iteration 148, loss = 0.30695459
Iteration 149, loss = 0.30652143
Iteration 150, loss = 0.30607240
Iteration 151, loss = 0.30566253
Iteration 152, loss = 0.30523092
Iteration 153, loss = 0.30482504
Iteration 154, loss = 0.30442509
Iteration 155, loss = 0.30403203
Iteration 156, loss = 0.30364422
Iteration 157, loss = 0.30327597
Iteration 158, loss = 0.30289292
Iteration 159, loss = 0.30251654
Iteration 160, loss = 0.30215646
Iteration 161, loss = 0.30179302
Iteration 162, loss = 0.30143485
Iteration 163, loss = 0.30109387
Iteration 164, loss = 0.30076780
Iteration 165, loss = 0.30044541
Iteration 166, loss = 0.30012358
Iteration 167, loss = 0.29980146
Iteration 168, loss = 0.29948587
Iteration 169, loss = 0.29917571
Iteration 170, loss = 0.29886565
Iteration 171, loss = 0.29855540
Iteration 172, loss = 0.29827142
Iteration 173, loss = 0.29796720
Iteration 174, loss = 0.29768917
Iteration 175, loss = 0.29741175
Iteration 176, loss = 0.29714771
Iteration 177, loss = 0.29687901
Iteration 178, loss = 0.29662667
Iteration 179, loss = 0.29637409
```

```
Iteration 180, loss = 0.29613096
Iteration 181, loss = 0.29588563
Iteration 182, loss = 0.29565284
Iteration 183, loss = 0.29539494
Iteration 184, loss = 0.29516439
Iteration 185, loss = 0.29493037
Iteration 186, loss = 0.29470100
Iteration 187, loss = 0.29447903
Iteration 188, loss = 0.29425309
Iteration 189, loss = 0.29403270
Iteration 190, loss = 0.29382014
Iteration 191, loss = 0.29361791
Iteration 192, loss = 0.29341651
Iteration 193, loss = 0.29321232
Iteration 194, loss = 0.29300583
Iteration 195, loss = 0.29279636
Iteration 196, loss = 0.29259894
Iteration 197, loss = 0.29239880
Iteration 198, loss = 0.29219334
Iteration 199, loss = 0.29200993
Iteration 200, loss = 0.29180019
Iteration 201, loss = 0.29163172
Iteration 202, loss = 0.29144895
Iteration 203, loss = 0.29126280
Iteration 204, loss = 0.29109418
Iteration 205, loss = 0.29092701
Iteration 206, loss = 0.29073626
Iteration 207, loss = 0.29057256
Iteration 208, loss = 0.29040317
Iteration 209, loss = 0.29024611
Iteration 210, loss = 0.29008714
Iteration 211, loss = 0.28993761
Iteration 212, loss = 0.28977709
Iteration 213, loss = 0.28963712
Iteration 214, loss = 0.28948684
Iteration 215, loss = 0.28934462
Iteration 216, loss = 0.28920377
Iteration 217, loss = 0.28907014
Iteration 218, loss = 0.28892585
Iteration 219, loss = 0.28879242
Iteration 220, loss = 0.28865970
Iteration 221, loss = 0.28852650
Iteration 222, loss = 0.28840494
Iteration 223, loss = 0.28827708
Iteration 224, loss = 0.28815305
Iteration 225, loss = 0.28803946
Iteration 226, loss = 0.28791331
Iteration 227, loss = 0.28778997
Iteration 228, loss = 0.28767109
Iteration 229, loss = 0.28754482
Iteration 230, loss = 0.28743570
Iteration 231, loss = 0.28731147
Iteration 232, loss = 0.28720531
Iteration 233, loss = 0.28709125
Iteration 234, loss = 0.28699718
Iteration 235, loss = 0.28689029
Iteration 236, loss = 0.28677365
Iteration 237, loss = 0.28666891
Iteration 238, loss = 0.28656443
Iteration 239, loss = 0.28645819
```

```
Iteration 240, loss = 0.28635612
Iteration 241, loss = 0.28624162
Iteration 242, loss = 0.28614694
Iteration 243, loss = 0.28604320
Iteration 244, loss = 0.28594768
Iteration 245, loss = 0.28586022
Iteration 246, loss = 0.28577197
Iteration 247, loss = 0.28568948
Iteration 248, loss = 0.28559410
Iteration 249, loss = 0.28550561
Iteration 250, loss = 0.28541338
Iteration 251, loss = 0.28533350
Iteration 252, loss = 0.28524073
Iteration 253, loss = 0.28515500
Iteration 254, loss = 0.28507186
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning
rate to 0.000200
Iteration 255, loss = 0.28499817
Iteration 256, loss = 0.28495613
Iteration 257, loss = 0.28492560
Iteration 258, loss = 0.28490511
Iteration 259, loss = 0.28488500
Iteration 260, loss = 0.28486790
Iteration 261, loss = 0.28485129
Iteration 262, loss = 0.28483324
Iteration 263, loss = 0.28481692
Iteration 264, loss = 0.28479942
Iteration 265, loss = 0.28478285
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning
rate to 0.000040
Iteration 266, loss = 0.28476977
Iteration 267, loss = 0.28476048
Iteration 268, loss = 0.28475463
Iteration 269, loss = 0.28475018
Iteration 270, loss = 0.28474674
Iteration 271, loss = 0.28474372
Iteration 272, loss = 0.28474029
Iteration 273, loss = 0.28473698
Iteration 274, loss = 0.28473426
Iteration 275, loss = 0.28473073
Iteration 276, loss = 0.28472784
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning
rate to 0.000008
Iteration 277, loss = 0.28472506
Iteration 278, loss = 0.28472333
Iteration 279, loss = 0.28472235
Iteration 280, loss = 0.28472146
Iteration 281, loss = 0.28472082
Iteration 282, loss = 0.28472012
Iteration 283, loss = 0.28471952
Iteration 284, loss = 0.28471889
Iteration 285, loss = 0.28471819
Iteration 286, loss = 0.28471765
Iteration 287, loss = 0.28471700
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning
rate to 0.000002
Iteration 288, loss = 0.28471646
Iteration 289, loss = 0.28471612
Iteration 290, loss = 0.28471591
Iteration 291, loss = 0.28471576
Iteration 292, loss = 0.28471562
```

```
Iteration 293, loss = 0.28471547
Iteration 294, loss = 0.28471535
Iteration 295, loss = 0.28471521
Iteration 296, loss = 0.28471508
Iteration 297, loss = 0.28471497
Iteration 298, loss = 0.28471484
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning
rate to 0.000000
Iteration 299, loss = 0.28471473
Iteration 300, loss = 0.28471468
Iteration 301, loss = 0.28471464
Iteration 302, loss = 0.28471461
Iteration 303, loss = 0.28471458
Iteration 304, loss = 0.28471455
Iteration 305, loss = 0.28471453
Iteration 306, loss = 0.28471450
Iteration 307, loss = 0.28471447
Iteration 308, loss = 0.28471445
Iteration 309, loss = 0.28471442
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. Learning rate too
small. Stopping.
Train set AUC score: 0.500000
Train set AUC score: 0.500000
```

#### Cross Validation: GUSTO Neural Net Model

#This section must run overnight - mlp GRIDSEARCH can take up to 8 hours. gmlp = MLPClassifier(max\_iter=200) parameter\_space = { 'hidden\_layer\_sizes': [(50,20,10,1),(50,10),(20,10,5),(100,80,10,1)], 'activation': ['relu'], 'solver': ['sgd','adam'], 'batch\_size': [300,500], 'alpha': [0.10,0.40,0.60,0.80,1.0], 'random\_state': [1], 'learning\_rate': ['constant', 'adaptive'], 'learning\_rate\_init': [0.1,0.01,0.001] } gclf = GridSearchCV(gmlp, parameter\_space, n\_jobs=-1, cv=5) gclf.fit(g\_Xtrain, g\_Ytrain) print('Best parameters found:\n', gclf.best\_params\_) In [39]:

```
#Calculate AUC after GridSearch
gmlp2 = MLPClassifier(
   hidden layer sizes=(50,10),
    activation='relu',
   max iter=100,
    alpha=0.60,
    solver="sgd",
    verbose=10,
    random state=1,
    learning rate='constant',
   learning rate init=0.01,
   batch size = 500
gmlp2.fit(g Xtrain, g Ytrain)
gmlp predtrain2 = gmlp2.predict_proba(g_Xtrain)
print("Train set AUC score: %f" % roc auc score(g Ytrain, gmlp predtrain2[:,1]))
gmlp predtest2 = gmlp2.predict proba(g Xtest)
print("Test set AUC score: %f" % roc auc score(g Ytest, gmlp predtest2[:,1]))
Iteration 1, loss = 0.63577219
```

```
Iteration 2, loss = 0.52894515
Iteration 3, loss = 0.41730600
Iteration 4, loss = 0.34414531
Iteration 5, loss = 0.31150205
Iteration 6, loss = 0.30537341
Iteration 7, loss = 0.30819080
Iteration 8, loss = 0.31104528
Iteration 9, loss = 0.31084716
Iteration 10, loss = 0.30713292
Iteration 11, loss = 0.30156299
Iteration 12, loss = 0.29602701
Iteration 13, loss = 0.29095907
Iteration 14, loss = 0.28674576
Iteration 15, loss = 0.28419370
Iteration 16, loss = 0.28181150
Iteration 17, loss = 0.27975224
Iteration 18, loss = 0.27803536
Iteration 19, loss = 0.27601248
Iteration 20, loss = 0.27407132
Iteration 21, loss = 0.27211341
Iteration 22, loss = 0.27020226
Iteration 23, loss = 0.26839671
Iteration 24, loss = 0.26666484
Iteration 25, loss = 0.26513046
Iteration 26, loss = 0.26352808
Iteration 27, loss = 0.26209841
Iteration 28, loss = 0.26054231
Iteration 29, loss = 0.25923292
Iteration 30, loss = 0.25790896
Iteration 31, loss = 0.25659911
Iteration 32, loss = 0.25547556
Iteration 33, loss = 0.25434827
Iteration 34, loss = 0.25320586
Iteration 35, loss = 0.25215007
Iteration 36, loss = 0.25099438
Iteration 37, loss = 0.25007309
Iteration 38, loss = 0.24911683
Iteration 39, loss = 0.24815018
Iteration 40, loss = 0.24733306
Iteration 41, loss = 0.24639008
Iteration 42, loss = 0.24558733
Iteration 43, loss = 0.24476332
Iteration 44, loss = 0.24407835
Iteration 45, loss = 0.24329060
Iteration 46, loss = 0.24260020
Iteration 47, loss = 0.24196701
Iteration 48, loss = 0.24125485
Iteration 49, loss = 0.24063624
Iteration 50, loss = 0.24001834
Iteration 51, loss = 0.23942460
Iteration 52, loss = 0.23886063
Iteration 53, loss = 0.23828201
Iteration 54, loss = 0.23779688
Iteration 55, loss = 0.23729721
Iteration 56, loss = 0.23680775
Iteration 57, loss = 0.23631233
Iteration 58, loss = 0.23586576
Iteration 59, loss = 0.23540495
Iteration 60, loss = 0.23505014
Iteration 61, loss = 0.23455160
Iteration 62, loss = 0.23427665
```

```
Iteration 63, loss = 0.23374486
Iteration 64, loss = 0.23340118
Iteration 65, loss = 0.23297374
Iteration 66, loss = 0.23275167
Iteration 67, loss = 0.23232059
Iteration 68, loss = 0.23198671
Iteration 69, loss = 0.23163674
Iteration 70, loss = 0.23133209
Iteration 71, loss = 0.23099957
Iteration 72, loss = 0.23070467
Iteration 73, loss = 0.23041528
Iteration 74, loss = 0.23019043
Iteration 75, loss = 0.22986945
Iteration 76, loss = 0.22959736
Iteration 77, loss = 0.22933801
Iteration 78, loss = 0.22906768
Iteration 79, loss = 0.22885613
Iteration 80, loss = 0.22863951
Iteration 81, loss = 0.22840956
Iteration 82, loss = 0.22817774
Iteration 83, loss = 0.22792960
Iteration 84, loss = 0.22770935
Iteration 85, loss = 0.22749430
Iteration 86, loss = 0.22727542
Iteration 87, loss = 0.22708445
Iteration 88, loss = 0.22688979
Iteration 89, loss = 0.22677113
Iteration 90, loss = 0.22650703
Iteration 91, loss = 0.22632788
Iteration 92, loss = 0.22612026
Iteration 93, loss = 0.22598322
Iteration 94, loss = 0.22577882
Iteration 95, loss = 0.22563013
Iteration 96, loss = 0.22544757
Iteration 97, loss = 0.22528276
Iteration 98, loss = 0.22507226
Iteration 99, loss = 0.22487751
Iteration 100, loss = 0.22477138
Train set AUC score: 0.816600
Test set AUC score: 0.805564
C:\Users\vitak\anaconda3\lib\site-packages\sklearn\neural network\ multilayer perceptron.py:692:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (100) reached and the optimization
hasn't converged yet.
 warnings.warn(
In [41]:
#Calculate Confidence Interval After Neural Net GridSearch GUSTO
y true g = np.array(g Ytest)
y pred g = np.array(gmlp predtest2[:,1])
n bootstraps = 100
rng seed = 42
bootstrapped scores = []
rng = np.random.RandomState(rng seed)
for i in range(n bootstraps):
    indices = rng.randint(0, len(y pred g), len(y pred g))
```

```
if len(np.unique(y_true_g[indices])) < 2:
    continue

score = roc_auc_score(y_true_g[indices], y_pred_g[indices])
bootstrapped_scores.append(score)

sorted_scores = np.array(bootstrapped_scores)
sorted_scores.sort()

confidence_lower_nng = sorted_scores[int(0.05 * len(sorted_scores))]
confidence_upper_nng = sorted_scores[int(0.95 * len(sorted_scores))]
print("Confidence interval for the score: [{:0.5f} - {:0.5}]".format(confidence_lower_nng, confidence_upper_nng))</pre>
Confidence interval for the score: [0.77269 - 0.84376]
```