Logistic Regression Baseline Model Development

The purpose of this notebook is to explore preprocessing techniques beyond the simple data cleaning formalized in the [EDA notebook (./EDA.ipynb)](./EDA.ipynb).

My main goal is to discover the best sampling method to address the class imbalance present in the target variable. My plan is to build a series of logistic regression models all with the same settings, the only difference being what sampling strategy will be used.

It is most important to succesfuly classify disloyal customers (label: 1) as much as possible, and it is not necessarily risky to the business to misclassify loyal customers (label: 0), also it is not obvious to me that neither recall nor precision are necessarily more relevant than the other here. So, I will be depending on the F1-score as my primary performance metric through this notebook, and the remaind of the project.

Load and clean data

In [1]:

```
from preprocessor import data_cleaner

import pandas as pd
import numpy as np

from sklearn.linear_model import LogisticRegression,LogisticRegressionCV
from sklearn.metrics import plot_confusion_matrix, classification_report
from sklearn.model_selection import cross_val_score,cross_val_predict

```

In [2]:

```
# import and define training data. See preprocessor.py file for details o
X_train, y_train = data_cleaner("../data/train.csv.zip")
```

In [3]:

```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 103904 entries, 0 to 103903
Data columns (total 27 columns):
 #   Column                             Non-Null Count   Dtype  
---  ------                             --------------   -----  
 0   Age                                103904 non-null  int64  
 1   Flight Distance                    103904 non-null  int64  
 2   Inflight wifi service              103904 non-null  int64  
 3   Departure/Arrival time convenient  103904 non-null  int64  
 4   Ease of Online booking             103904 non-null  int64  
 5   Gate location                      103904 non-null  int64  
 6   Food and drink                     103904 non-null  int64  
 7   Online boarding                    103904 non-null  int64  
 8   Seat comfort                       103904 non-null  int64  
 9   Inflight entertainment             103904 non-null  int64  
 10  On-board service                   103904 non-null  int64  
 11  Leg room service                   103904 non-null  int64  
 12  Baggage handling                   103904 non-null  int64  
 13  Checkin service                    103904 non-null  int64  
 14  Inflight service                   103904 non-null  int64  
 15  Cleanliness                        103904 non-null  int64  
 16  Departure Delay in Minutes         103904 non-null  int64  
 17  Arrival Delay in Minutes           103904 non-null  float64
 18  Female                             103904 non-null  float64
 19  Male                               103904 non-null  float64
 20  Business travel                    103904 non-null  float64
 21  Personal Travel                    103904 non-null  float64
 22  Business                           103904 non-null  float64
 23  Eco                                103904 non-null  float64
 24  Eco Plus                           103904 non-null  float64
 25  neutral or dissatisfied            103904 non-null  float64
 26  satisfied                          103904 non-null  float64
dtypes: float64(10), int64(17)
memory usage: 22.2 MB
```

Develop baseline model

In [4]:

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from sklearn.model_selection import cross_val_predict,cross_val_score
from sklearn.metrics import plot_confusion_matrix,confusion_matrix,class
```

In [5]:
```
def print_weights(y:np.array):
    unique_train, counts_train = np.unique(y_train, return_counts=True)
    loyal_original = round(counts_train[0]/(counts_train[0]+counts_train
    disloyal_original = round(counts_train[1]/(counts_train[0]+counts_tra

    unique_resample, counts_resample = np.unique(y, return_counts=True)
    loyal_resample = round(counts_resample[0]/(counts_resample[0]+counts_
    disloyal_resample = round(counts_resample[1]/(counts_resample[0]+cou

    print('Original dataset weights:', loyal_original,disloyal_original)
    print('Original dataset size:',len(y_train))
    print('\nResample dataset weights', loyal_resample,disloyal_resample
    print('Resample dataset size:', len(y_smote))
```

fit estimator

In [6]:
```
logreg = LogisticRegression(solver='liblinear')
logreg.fit(X_train,y_train)

y_train_pred = cross_val_predict(logreg,X_train,y_train)

train_score = cross_val_score(logreg,X_train,y_train_pred,scoring='f1')
```

In [7]:
```
train_score.mean()
```

Out[7]: 0.9808701035069809

print classification report

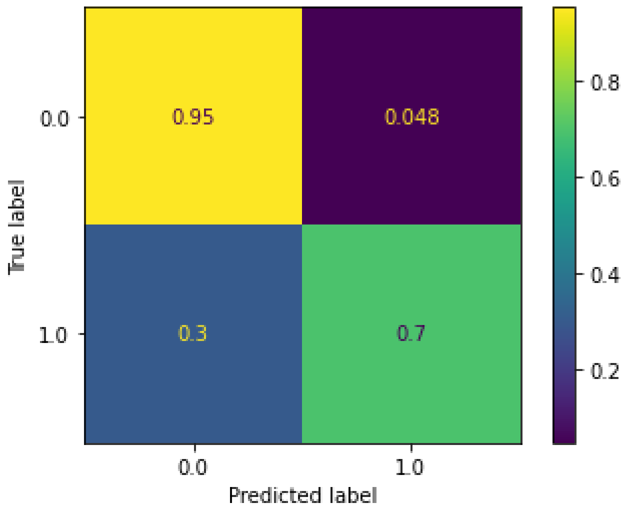
In [8]:
```
baseline_report = classification_report(y_train,y_train_pred,output_dict
baseline_report = pd.DataFrame(baseline_report).iloc[:,0:3]
baseline_report
```

Out[8]:

	0.0	1.0	accuracy
precision	0.933367	0.763805	0.905143
recall	0.951898	0.695959	0.905143
f1-score	0.942541	0.728305	0.905143
support	84923.000000	18981.000000	0.905143

plot confusion matrix

In [9]:
```
plot_confusion_matrix(logreg,X_train,y_train,normalize='true')
plt.show()
```



In [10]:
```
# Calculate the probability scores of each point in the training set
y_train_score = logreg.decision_function(X_train)

# Calculate the fpr, tpr, and thresholds for the training set
train_fpr, train_tpr, thresholds = roc_curve(y_train, y_train_score)
```

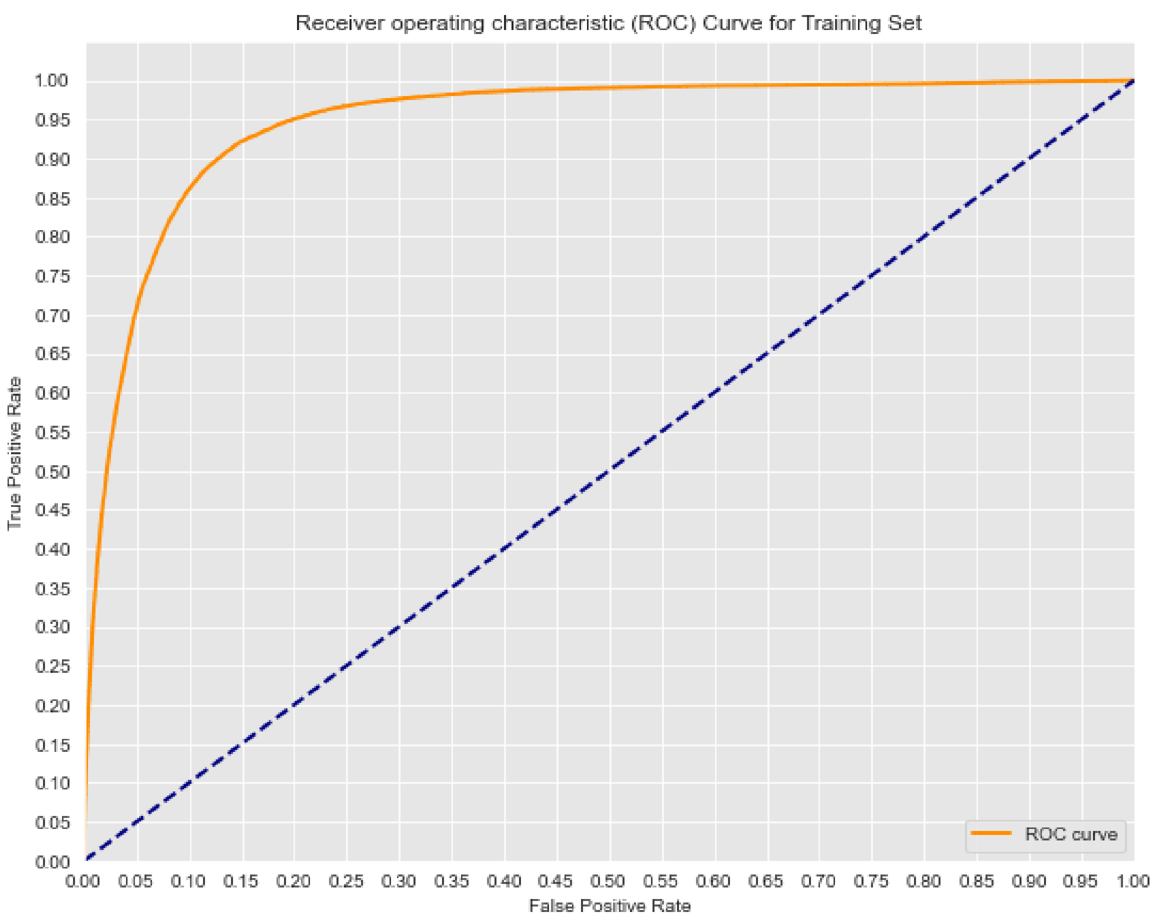
In [11]:
```
baseline_auc = auc(train_fpr, train_tpr)
```

calculate ROC AUC and plot curve

In [12]:

```python
# Seaborn's beautiful styling
sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

# ROC curve for training set
plt.figure(figsize=(10, 8))
lw = 2
plt.plot(train_fpr, train_tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve for Training Se
plt.legend(loc='lower right')
print('Training AUC: {}'.format(auc(train_fpr, train_tpr)))
plt.show()
```

```
Training AUC: 0.9471699866930965
```



Prototype sampling methods

- SMOTE (synthetic over sampling)
- Tomek Links (under sampling against decision boundary)
- Near Miss (distance based under sampling)
- Edited Nearest Neighbors (under samplin against decision boundary)
- SMOTETomek (SMOTE/Tomek Link ensemble)
- SMOETENN (SMOTE/Edited Nearest Neighbors Ensemble)

SMOTE

resample data

In [13]:

```
from imblearn.over_sampling import SMOTE
smote = SMOTE()
X_smote, y_smote = smote.fit_resample(X_train, y_train)


print_weights(y_smote)
```

```
Original dataset weights: 0.817 0.183
Original dataset size: 103904

Resample dataset weights 0.5 0.5
Resample dataset size: 169846
```

In [14]:

```
unique_elements, counts_elements = np.unique(y_train, return_counts=True
print(unique_elements)
print(counts_elements)
```

```
[0. 1.]
[84923 18981]
```

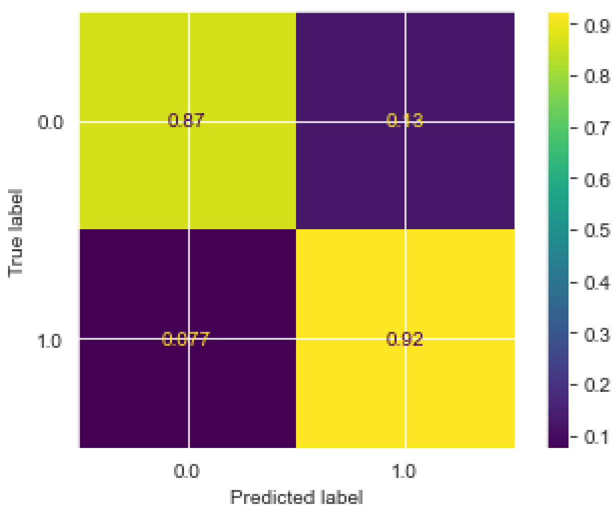
fit estimator

In [15]:
```
logreg_smote = LogisticRegression(solver='liblinear')
logreg_smote.fit(X_smote,y_smote)

smote_train_pred = logreg_smote.predict(X_smote)

smote_train_score = cross_val_score(logreg_smote,X_smote,smote_train_pre
print(smote_train_score.mean())
```

```
0.9944599766095351
```

plot confusion matrix

In [16]:
```
plot_confusion_matrix(logreg_smote,X_smote,y_smote,normalize='true')
plt.show()
```



print classification report

In [17]:
```
smote_report = classification_report(y_smote,smote_train_pred,output_dic
smote_report = pd.DataFrame(smote_report).iloc[:,0:3]
smote_report
```

Out[17]:

	0.0	1.0	accuracy
precision	0.919067	0.875912	0.896318
recall	0.869176	0.923460	0.896318
f1-score	0.893425	0.899058	0.896318
support	84923.000000	84923.000000	0.896318

calculate ROC AUC

In [18]:
```
# Calculate the probability scores of each point in the training set
y_smote_score = logreg_smote.decision_function(X_smote)
# Calculate the fpr, tpr, and thresholds for the training set
smote_fpr, smote_tpr, smote_thresholds = roc_curve(y_smote, y_smote_scor
smote_auc = auc(smote_fpr, smote_tpr)
print('Training AUC: {}'.format(smote_auc))
```

```
Training AUC: 0.9501178971660749
```

Tomek Links

resample data

In [19]:
```
from imblearn.under_sampling import TomekLinks
tl = TomekLinks(sampling_strategy='majority',n_jobs=3)
X_tl, y_tl = tl.fit_resample(X_train, y_train)

print_weights(y_tl)
```

```
Original dataset weights: 0.817 0.183
Original dataset size: 103904

Resample dataset weights 0.809 0.191
Resample dataset size: 169846
```

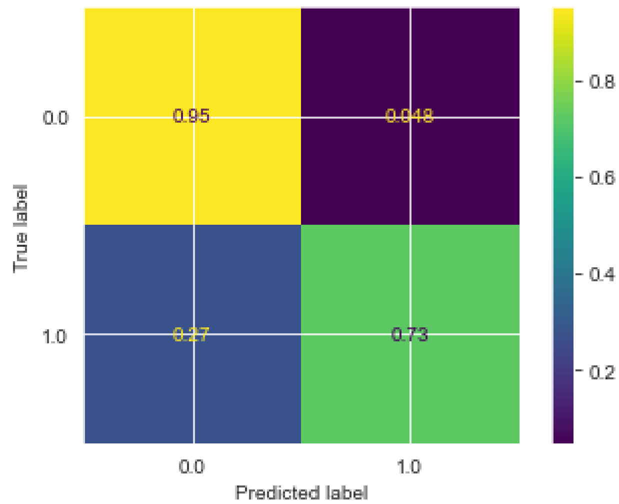
fit estimator

In [20]:
```
logreg_tl = LogisticRegression(solver='liblinear')
logreg_tl.fit(X_tl,y_tl)

tl_train_pred = logreg_tl.predict(X_tl)

tl_train_score = cross_val_score(logreg_tl,X_tl,y_tl,n_jobs=3,scoring='f1
print(tl_train_score.mean())
```

```
0.7508259263452878
```

plot confusion matrix

In [21]:
```
plot_confusion_matrix(logreg_tl,X_tl,y_tl,normalize='true')
plt.show()
```



print classification report

In [22]:
```
tomek_report = classification_report(y_tl,tl_train_pred,output_dict=True
tomek_report = pd.DataFrame(tomek_report).iloc[:,0:3]
tomek_report
```

Out[22]:

	0.0	1.0	accuracy
precision	0.936407	0.781099	0.90891
recall	0.952116	0.725462	0.90891
f1-score	0.944196	0.752253	0.90891
support	80591.000000	18981.000000	0.90891

calculate ROC AUC

In [23]:

```
# Calculate the probability scores of each point in the training set
y_tomek_score = logreg_smote.decision_function(X_tl)
# Calculate the fpr, tpr, and thresholds for the training set
tl_fpr , tl_tpr, tomek_thresholds = roc_curve(y_tl, y_tomek_score)
tl_auc = auc(tl_fpr, tl_tpr)
print('Training AUC: {}'.format(tl_auc))
```

```
Training AUC: 0.9439161672152295
```

Near Miss

resample the data

In [24]:

```
from imblearn.under_sampling import NearMiss
nm = NearMiss(sampling_strategy='all',n_jobs=3)
X_nm, y_nm = nm.fit_resample(X_train,y_train)

print_weights(y_nm)
```

```
Original dataset weights: 0.817 0.183
Original dataset size: 103904

Resample dataset weights 0.5 0.5
Resample dataset size: 169846
```

fit estimator

In [25]:

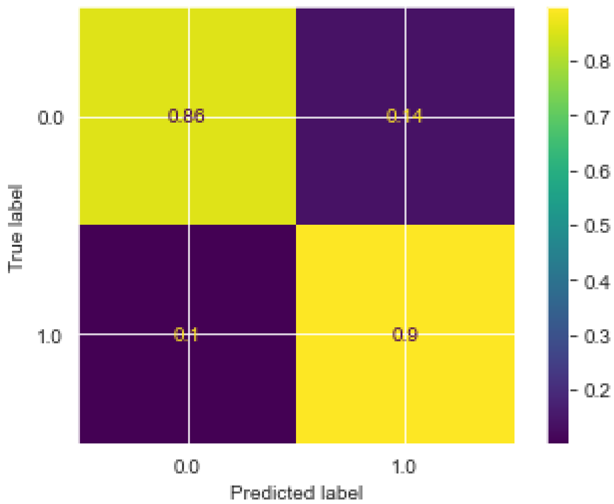
```
logreg_nm = LogisticRegression(solver='liblinear')
logreg_nm.fit(X_nm,y_nm)

nm_train_pred = logreg_nm.predict(X_nm)

nm_train_score = cross_val_score(logreg_nm,X_nm,y_nm,n_jobs=3,scoring='f
print(nm_train_score.mean())
```

```
0.869810080157241
```

plot confusion matrix

In [26]:

```
plot_confusion_matrix(logreg_nm,X_nm,y_nm,normalize='true')
plt.show()
```



print classification report

In [27]:

```
nm_report = classification_report(y_nm,nm_train_pred,output_dict=True)
nm_report = pd.DataFrame(nm_report).iloc[:,0:3]
nm_report
```

Out[27]:

	0.0	1.0	accuracy
precision	0.893693	0.864455	0.87851
recall	0.859228	0.897793	0.87851
f1-score	0.876121	0.880808	0.87851
support	18981.000000	18981.000000	0.87851

calculate ROC AUC

In [28]:

```
# Calculate the probability scores of each point in the training set
y_nm_score  = logreg_nm.decision_function(X_nm)
# Calculate the fpr, tpr, and thresholds for the training set
nm_fpr , nm_tpr, nm_thresholds = roc_curve(y_nm, y_nm_score )
nm_auc = auc(nm_fpr, nm_tpr)
print('Training AUC: {}'.format(nm_auc))
```

```
Training AUC: 0.9492465604949281
```

Edited Nearest Neighbors

resample the data

In [29]:

```
from imblearn.under_sampling import EditedNearestNeighbours
ENN = EditedNearestNeighbours(sampling_strategy='majority')
X_enn, y_enn = ENN.fit_resample(X_train,y_train)

print_weights(y_enn)
```

```
Original dataset weights: 0.817 0.183
Original dataset size: 103904

Resample dataset weights 0.762 0.238
Resample dataset size: 169846
```

fit estimator

In [30]:

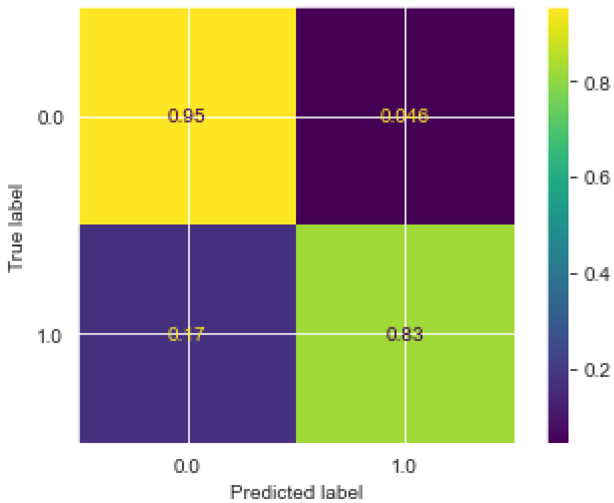
```
logreg_ENN = LogisticRegression(solver='liblinear')
logreg_ENN.fit(X_enn,y_enn)

enn_train_pred = cross_val_predict(logreg_ENN,X_enn,y_enn,n_jobs=3)

enn_train_score = cross_val_score(logreg_ENN,X_enn,y_enn,n_jobs=3,scorin
print(enn_train_score.mean())
```

```
0.8373544378234661
```

plot confusion matrix

In [31]:

```
plot_confusion_matrix(logreg_ENN,X_enn,y_enn,normalize='true')
plt.show()
```



print classification matrix

In [32]:

```
enn_report = classification_report(y_enn,enn_train_pred,output_dict=True
enn_report = pd.DataFrame(enn_report).iloc[:,0:3]
enn_report
```

Out[32]:

	0.0	1.0	accuracy
precision	0.946071	0.848785	0.923498
recall	0.953933	0.826247	0.923498
f1-score	0.949986	0.837365	0.923498
support	60651.000000	18981.000000	0.923498

calculate ROC AUC

In [33]:

```
# Calculate the probability scores of each point in the training set
y_enn_score  = logreg_nm.decision_function(X_enn)
# Calculate the fpr, tpr, and thresholds for the training set
enn_fpr , enn_tpr, enn_thresholds = roc_curve(y_enn, y_enn_score )
enn_auc = auc(enn_fpr, enn_tpr)
print('Training AUC: {}'.format(enn_auc))
```

```
Training AUC: 0.7846937445781219
```

SMOTETomek

resample the data

In [34]:

```
from imblearn.combine import SMOTETomek
SMOTek = SMOTETomek(sampling_strategy='all',smote=smote,tomek=tl,n_jobs=
X_smotek, y_smotek = SMOTek.fit_resample(X_train,y_train)

print_weights(y_smotek)
```

```
Original dataset weights: 0.817 0.183
Original dataset size: 103904

Resample dataset weights 0.499 0.501
Resample dataset size: 169846
```

fit estimator

In [35]:

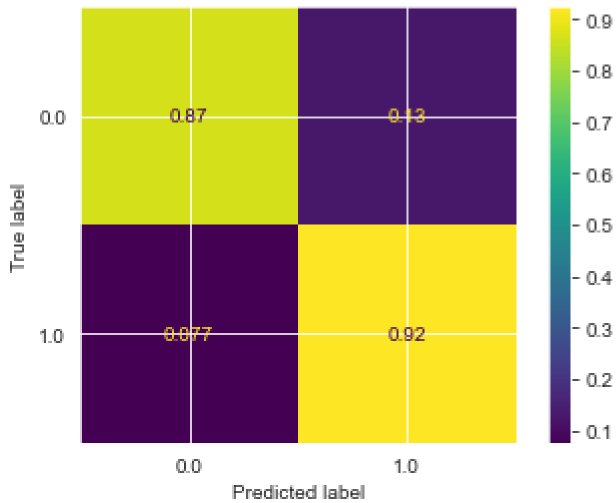
```
logreg_SMOTek = LogisticRegression(solver='liblinear')
logreg_SMOTek.fit(X_smotek,y_smotek)

smotek_train_pred = logreg_SMOTek.predict(X_smotek)

smotek_train_score = cross_val_score(logreg_SMOTek,X_smotek,y_smotek,n_j
print(smotek_train_score.mean())
```

```
0.8972609324005788
```

plot confusion matrix

In [36]:

```
plot_confusion_matrix(logreg_SMOTek,X_smotek,y_smotek,normalize='true')
plt.show()
```



print classification report

In [37]:

```
smotek_report = classification_report(y_nm,nm_train_pred,output_dict=Tru
smotek_report = pd.DataFrame(smotek_report).iloc[:,0:3]
smotek_report
```

Out[37]:

	0.0	1.0	accuracy
precision	0.893693	0.864455	0.87851
recall	0.859228	0.897793	0.87851
f1-score	0.876121	0.880808	0.87851
support	18981.000000	18981.000000	0.87851

calculate ROC AUC

In [38]:

```
# Calculate the probability scores of each point in the training set
y_smotek_score  = logreg_SMOTek.decision_function(X_smotek)
# Calculate the fpr, tpr, and thresholds for the training set
smotek_fpr , smotek_tpr, smotek_thresholds = roc_curve(y_smotek, y_smotel
smotek_auc = auc(smotek_fpr, smotek_tpr)
print('Training AUC: {}'.format(smotek_auc))
```

```
Training AUC: 0.9500785179113276
```

SMOTENN

resmaple the data

In [39]:

```
from imblearn.combine import SMOTEENN
SMN = SMOTEENN(sampling_strategy='all',smote=smote,enn=ENN,n_jobs=3)
X_smn, y_smn = SMN.fit_resample(X_train,y_train)

print_weights(y_smn)
```

```
Original dataset weights: 0.817 0.183
Original dataset size: 103904

Resample dataset weights 0.382 0.618
Resample dataset size: 169846
```

fit estimator

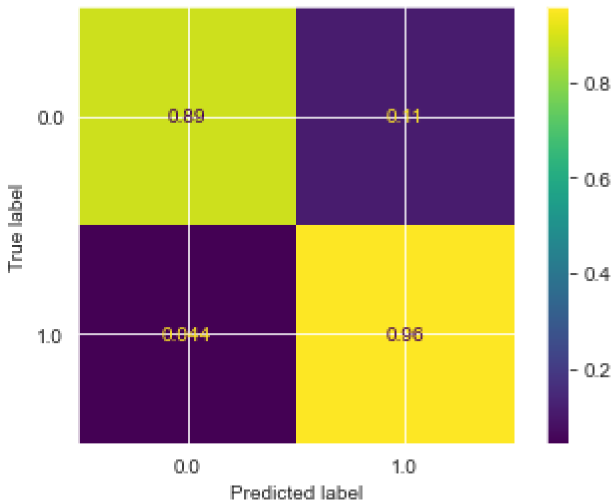
In [40]:

```
logreg_SMOTENN = LogisticRegression(solver='liblinear')
logreg_SMOTENN.fit(X_smn,y_smn)

smn_train_pred = logreg_SMOTENN.predict(X_smn)

smn_train_score = cross_val_score(logreg_SMOTENN,X_smn,y_smn,n_jobs=3,sc
print(smn_train_score.mean())
```

```
0.9425697164915263
```

plot confusion matrix

In [41]:
```
plot_confusion_matrix(logreg_SMOTENN,X_smn,y_smn,normalize='true')
plt.show()
```



print classification report

In [42]:
```
SMOTENN_report = classification_report(y_smn,smn_train_pred,output_dict=
SMOTENN_report = pd.DataFrame(SMOTENN_report).iloc[:,0:3]
SMOTENN_report
```

Out[42]:

	0.0	1.0	accuracy
precision	0.925627	0.931012	0.929044
recall	0.885412	0.956019	0.929044
f1-score	0.905073	0.943350	0.929044
support	52501.000000	84923.000000	0.929044

calculate ROC AUC

In [43]:
```
# Calculate the probability scores of each point in the training set
SMOTENN_score  = logreg_SMOTENN.decision_function(X_smn)
# Calculate the fpr, tpr, and thresholds for the training set
smotenn_fpr , smotenn_tpr, smotenn_thresholds = roc_curve(y_smn, SMOTENN_
smotenn_auc = auc(smotenn_fpr, smotenn_tpr)
print('Training AUC: {}'.format(smotenn_auc))
```

```
Training AUC: 0.9727681543695383
```

Validate sample and select method(s)

- First tried SMOTENN because it had the highest F1, validation however had a ROC AUC of about .06, indicating the model is overfitting the data.
- Next I am trying Near Miss because it only undersamples the majority and had a training F1 score between SMOTE and Edited Nearest Neighbors, the two methods used in SMOTENN. Not synthesizing new data, and only undersampling I expect will reduce overfitting.

In [44]:
```
# Load and clean validation set
X_test, y_test = data_cleaner("../data/train.csv.zip")
```

SMOTENN CV Test

fit cross validated model

In [45]:
```
logreg_SMOTENN_CV = LogisticRegressionCV(solver='liblinear',n_jobs=3)
logreg_SMOTENN_CV.fit(X_smn,y_smn)
```

Out[45]:
```
LogisticRegressionCV(n_jobs=3, solver='liblinear')
```

In [46]:
```
smn_test_pred = logreg_SMOTENN_CV.predict(X_test)
smn_test_report = classification_report(y_test,smn_test_pred,output_dict
SMOTENN_CV_report = pd.DataFrame(smn_test_report).iloc[:,0:3]
SMOTENN_CV_report
```

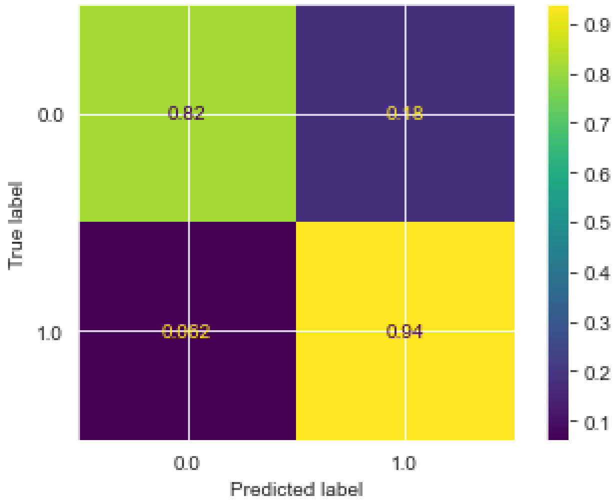
Out[46]:

	0.0	1.0	accuracy
precision	0.983513	0.539741	0.842566
recall	0.821144	0.938412	0.842566
f1-score	0.895024	0.685314	0.842566
support	84923.000000	18981.000000	0.842566

plot confusion matrix

In [47]:

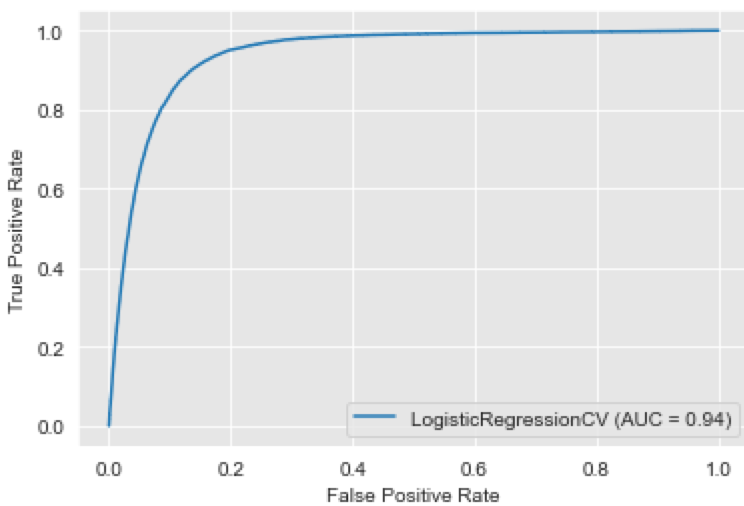
```
# plot confusion matrix
plot_confusion_matrix(logreg_SMOTENN_CV,X_test,y_test,normalize='true')
plt.show()
```



plot ROC AUC

In [48]:

```
from sklearn.metrics import plot_roc_curve
plot_roc_curve(logreg_SMOTENN_CV,X_test,y_test)
plt.show()
```



In [49]:
```
# Calculate the probability scores of each point in the training set
SMOTENN_CV_score  = logreg_SMOTENN_CV.decision_function(X_test)
# Calculate the fpr, tpr, and thresholds for the training set
smotenn_cv_fpr , smotenn_cv_tpr, smotenn_cv_thresholds = roc_curve(y_tes
smotenn_cv_auc = auc(smotenn_cv_fpr, smotenn_cv_tpr)
print('SMOTENN Test AUC: {}'.format(smotenn_cv_auc))
```

```
SMOTENN Test AUC: 0.9395813825932257
```

SMOTE CV Test

In [50]:
```
logreg_SMOTE_CV = LogisticRegressionCV(solver='liblinear',n_jobs=3)
logreg_SMOTE_CV.fit(X_smote,y_smote)
```

Out[50]:
```
LogisticRegressionCV(n_jobs=3, solver='liblinear')
```

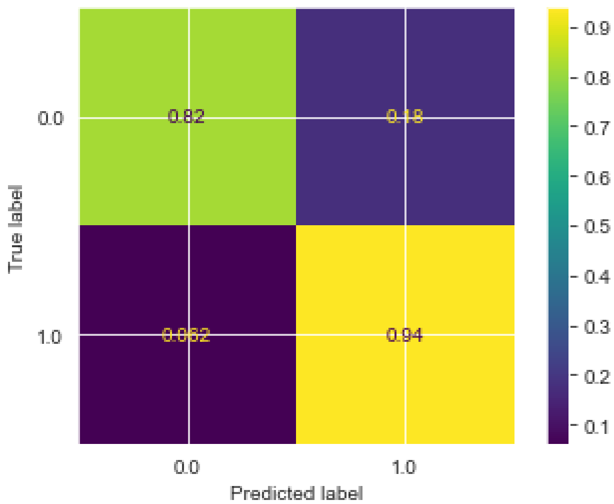
In [51]:
```
smote_test_pred = logreg_SMOTE_CV.predict(X_test)
smote_test_report = classification_report(y_test,smote_test_pred,output_
SMOTE_CV_report = pd.DataFrame(smote_test_report).iloc[:,0:3]
SMOTE_CV_report
```

Out[51]:

	0.0	1.0	accuracy
precision	0.973479	0.603628	0.873402
recall	0.868775	0.894105	0.873402
f1-score	0.918152	0.720698	0.873402
support	84923.000000	18981.000000	0.873402

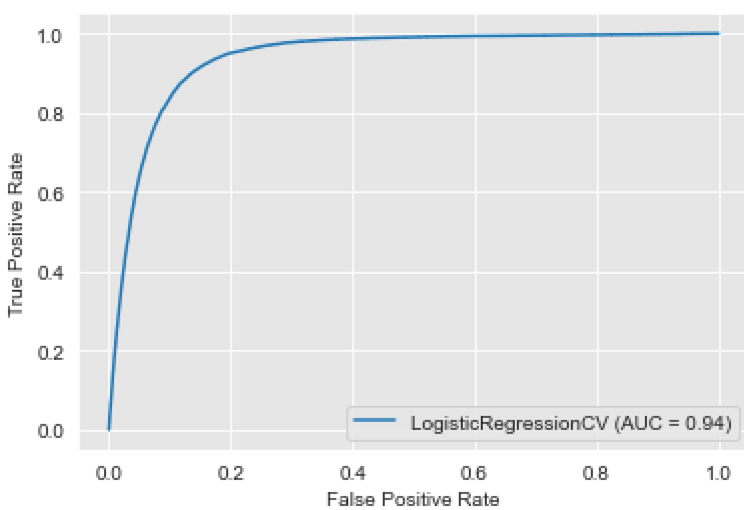
plot confusion matrix

In [52]:
```
# plot confusion matrix
plot_confusion_matrix(logreg_SMOTENN_CV,X_test,y_test,normalize='true')
plt.show()
```



plot ROC AUC

In [53]:
```
plot_roc_curve(logreg_SMOTENN_CV,X_test,y_test)
plt.show()
```



In [60]:
```
# Calculate the probability scores of each point in the training set
SMOTE_CV_score  = logreg_SMOTE_CV.decision_function(X_test)
# Calculate the fpr, tpr, and thresholds for the training set
smote_cv_fpr , smote_cv_tpr, smote_cv_thresholds = roc_curve(y_test, SMO
smote_cv_auc = auc(smote_cv_fpr, smote_cv_tpr)
print('SMOTE Test AUC: {}'.format(smote_cv_auc))
```

```
SMOTE Test AUC: 0.9402851542213703
```

Near Miss CV Test

Near Miss CV Test

fit cross validated model

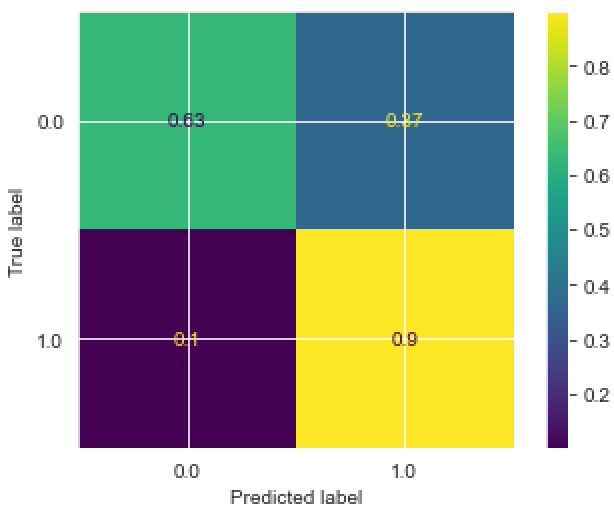
In [54]:
```
logreg_nm_cv = LogisticRegressionCV(solver='liblinear',n_jobs=3)
logreg_nm_cv.fit(X_nm,y_nm)

nm_test_pred = logreg_nm_cv.predict(X_test)
nm_test_report = classification_report(y_test,nm_test_pred,output_dict=Tr
nm_test_report = pd.DataFrame(nm_test_report).iloc[:,0:3]
nm_test_report
```

Out[54]:

	0.0	1.0	accuracy
precision	0.965721	0.354473	0.682428
recall	0.633951	0.899320	0.682428
f1-score	0.765431	0.508512	0.682428
support	84923.000000	18981.000000	0.682428

plot confusion matrix

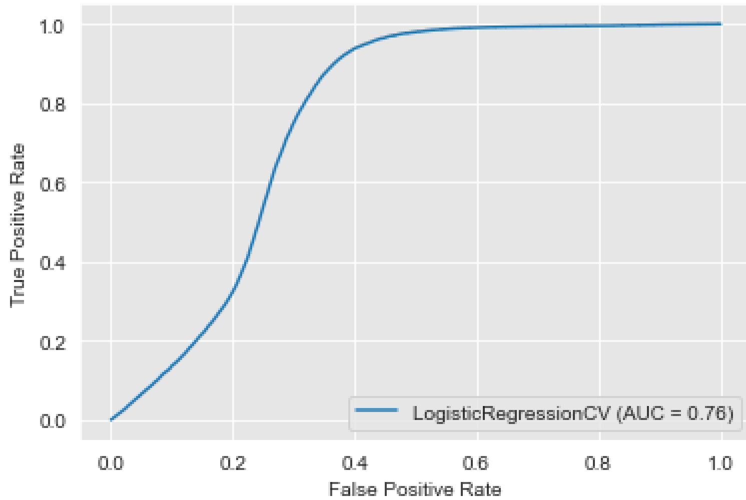
In [55]:
```
plot_confusion_matrix(logreg_nm_cv,X_test,y_test,normalize='true')
plt.show()
```



plot ROC AUC

In [56]:

```
plot_roc_curve(logreg_nm_cv,X_test,y_test)
plt.show()
```



In [57]:

```
# Calculate the probability scores of each point in the training set
nm_cv_score  = logreg_nm_cv.decision_function(X_test)
# Calculate the fpr, tpr, and thresholds for the training set
nm_cv_fpr , nm_cv_tpr, nm_cv_thresholds = roc_curve(y_test, nm_cv_score)
nm_cv_auc = auc(nm_cv_fpr, nm_cv_tpr)
print('Near Miss Test AUC: {}'.format(nm_cv_auc))
```

```
Near Miss Test AUC: 0.7619659221996201
```

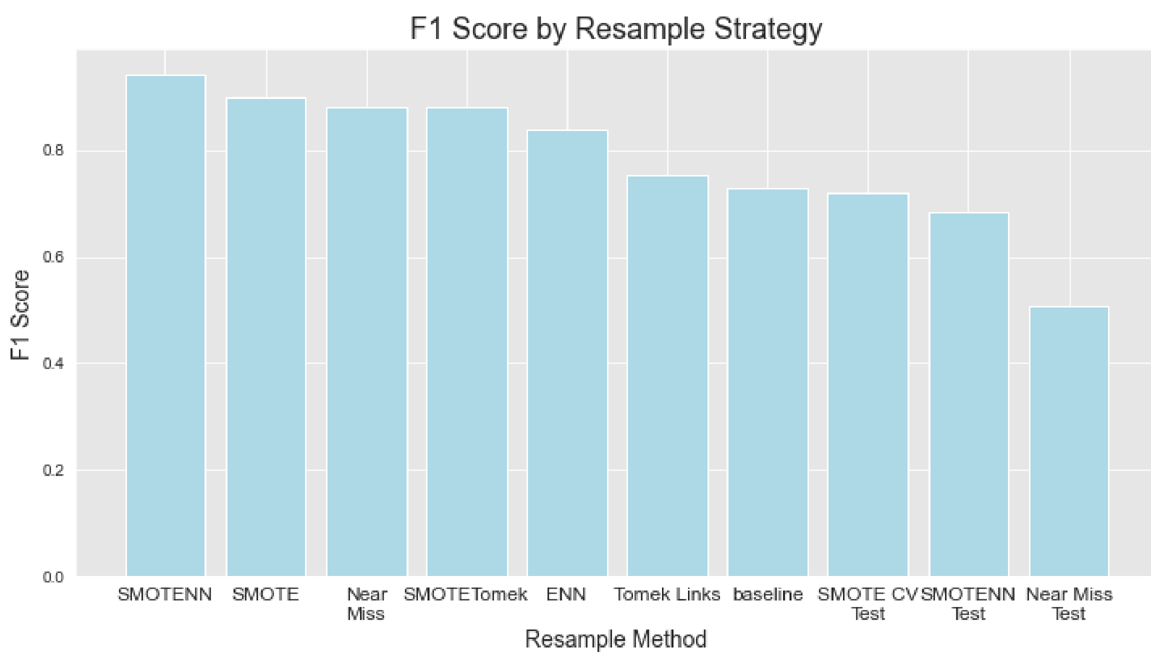
Visualize F1, ROC AUC iterative performance

In [67]:

```
f1_dict = {
    'baseline':baseline_report.iloc[2,1],
    'SMOTE':smote_report.iloc[2,1],
    'Tomek Links':tomek_report.iloc[2,1],
    'Near\nMiss':nm_report.iloc[2,1],
    'ENN':enn_report.iloc[2,1],
    'SMOTETomek':smotek_report.iloc[2,1],
    'SMOTENN':SMOTENN_report.iloc[2,1],
    'SMOTENN\nTest':SMOTENN_CV_report.iloc[2,1],
    'SMOTE CV\nTest':SMOTE_CV_report.iloc[2,1],
    'Near Miss\nTest':nm_test_report.iloc[2,1]
}
f1_dict = dict(sorted(f1_dict.items(), key=lambda item: item[1],reverse=
```

In [68]:

```
plt.figure(figsize=(12,6))
plt.bar(x=f1_dict.keys(),height=f1_dict.values(),color='lightblue')
plt.ylabel('F1 Score',fontsize=14)
plt.xlabel('Resample Method',fontsize=14)
plt.xticks(fontsize=12)
plt.title("F1 Score by Resample Strategy",fontsize=18)
plt.show()
```



SMOTEENN performs the better on training data than SMOTE, however on the test data SMOTE performs slightly better than SMOTEENN. The gap between train and test F1-score is narrower for SMOTE than SMOTEENN. Inidicating that despite performing slightly worse on the training data SMOTE generalizes to unseen data better than SMOTEENN.

In [61]:

```
roc_auc_scores = [
    baseline_auc,
    smote_auc,
    tl_auc,
    nm_auc,
    enn_auc,
    smotek_auc,
    smotenn_auc,
    smotenn_cv_auc,
    smote_cv_auc,
    nm_cv_auc
]
np.mean(roc_auc_scores)
```

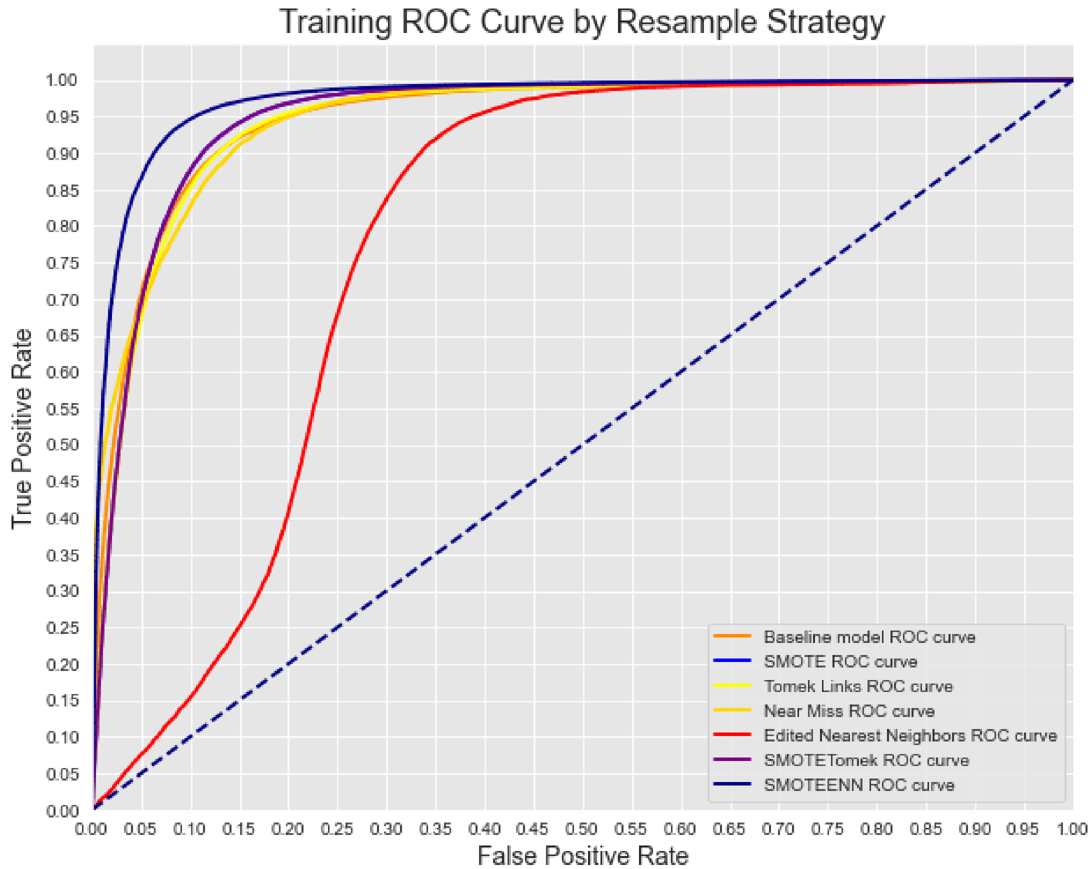
Out[61]: 0.9139823487442532

plot ROC AUC curves

In [62]:

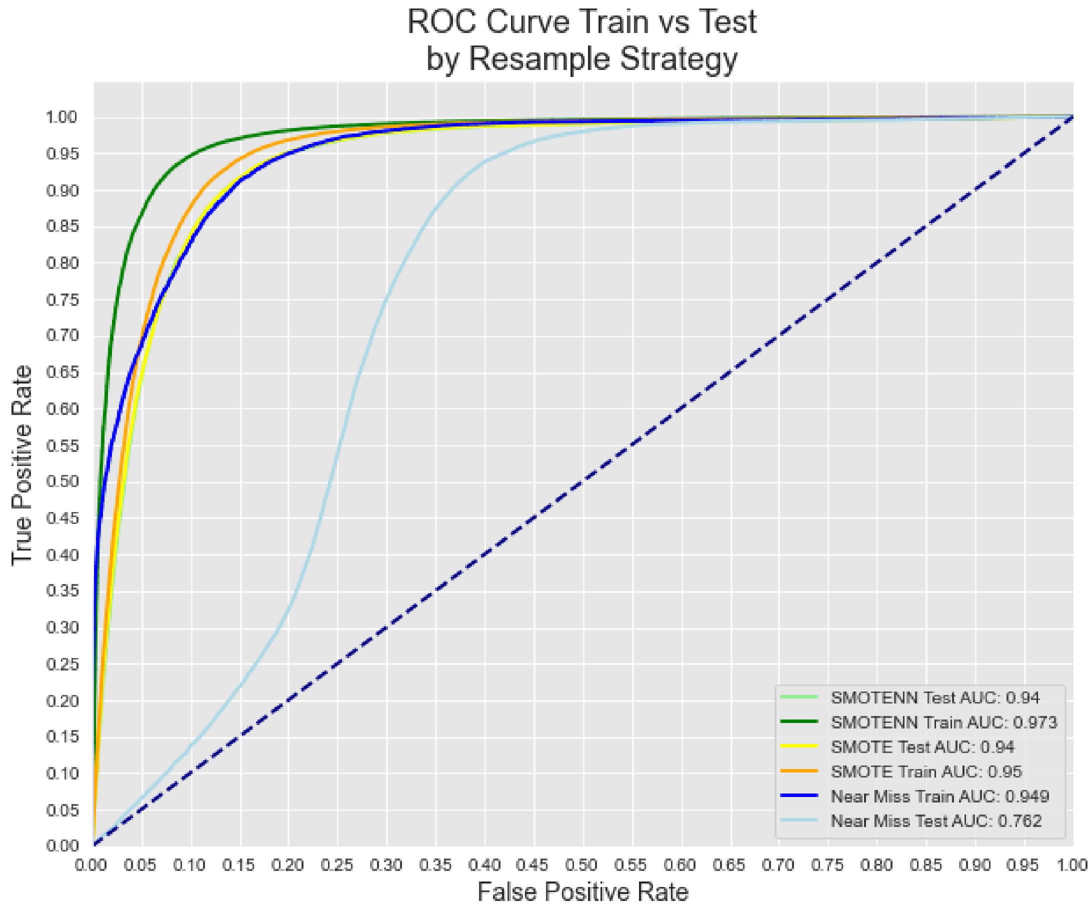
```
plt.figure(figsize=(10,8))
lw = 2

print('Baseline Model AUC: {}'.format(baseline_auc))
print('SMOTE resample AUC: {}'.format(smote_auc))

plt.plot(train_fpr, train_tpr, color='darkorange',
         lw=lw, label='Baseline model ROC curve')
plt.plot(smote_fpr, smote_tpr, color='blue',
         lw=lw, label='SMOTE ROC curve')


print('Tomek Links AUC: {}'.format(tl_auc))
print('Near Miss AUC: {}'.format(nm_auc))

plt.plot(tl_fpr, tl_tpr, color='yellow',
         lw=lw, label='Tomek Links ROC curve')
plt.plot(nm_fpr, nm_tpr, color='gold',
         lw=lw, label='Near Miss ROC curve')


print('Edited Nearest Neighbors AUC: {}'.format(enn_auc))
print('SMOTETomek AUC: {}'.format(smotek_auc))

plt.plot(enn_fpr, enn_tpr, color='red',
         lw=lw, label='Edited Nearest Neighbors ROC curve')
plt.plot(smotek_fpr, smotek_tpr, color='purple',
         lw=lw, label='SMOTETomek ROC curve')


print('SMOTEENN AUC: {}'.format(smotenn_auc))
plt.plot(smotenn_fpr, smotenn_tpr, color='darkblue',
         lw=lw, label='SMOTEENN ROC curve')


# Formatting
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate',fontsize=14)
plt.ylabel('True Positive Rate',fontsize=14)
plt.title('Training ROC Curve by Resample Strategy',fontsize=18)
plt.legend(loc="lower right")
plt.show()
```

```
Baseline Model AUC: 0.9471699866930965
SMOTE resample AUC: 0.9501178971660749
Tomek Links AUC: 0.9439161672152295
Near Miss AUC: 0.9492465604949281
Edited Nearest Neighbors AUC: 0.7846937445781219
SMOTETomek AUC: 0.9500785179113276
SMOTEENN AUC: 0.9727681543695383
```


Training ROC Curve by Resample Strategy
True Positive Rate
False Positive Rate
Baseline model ROC curve
SMOTE ROC curve
Tomek Links ROC curve
Near Miss ROC curve
Edited Nearest Neighbors ROC curve
SMOTETomek ROC curve
SMOTEENN ROC curve

In [70]:

```
plt.figure(figsize=(10,8))
lw = 2

plt.plot(smotenn_cv_fpr, smotenn_cv_tpr, color='lightgreen',
         lw=lw, label=f'SMOTENN Test AUC: {round(smotenn_cv_auc,3)}')
plt.plot(smotenn_fpr,smotenn_tpr,color='green',
         lw=lw, label=f'SMOTENN Train AUC: {round(smotenn_auc,3)}')

plt.plot(smote_cv_fpr, smote_cv_tpr, color='yellow',
         lw=lw, label=f'SMOTE Test AUC: {round(smote_cv_auc,3)}')
plt.plot(smote_fpr,smote_tpr,color='orange',
         lw=lw, label=f'SMOTE Train AUC: {round(smote_auc,3)}')

plt.plot(nm_fpr, nm_tpr, color='blue',
         lw=lw, label=f'Near Miss Train AUC: {round(nm_auc,3)}')
plt.plot(nm_cv_fpr, nm_cv_tpr, color='lightblue',
         lw=lw, label=f'Near Miss Test AUC: {round(nm_cv_auc,3)}')

# Formatting
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate',fontsize=14)
plt.ylabel('True Positive Rate',fontsize=14)
plt.title('ROC Curve Train vs Test\nby Resample Strategy',fontsize=18)
plt.legend(loc="lower right")
plt.show()
```



Final Observations

My initial analysis was that SMOTEENN was the strongest performer of all the resample strategies presented here. That is indeed true on the test data alone. Classic SMOTE the second strongest performer on the training data, and performs on the test data *nearly* as well as SMOTEENN, in fact their ROC AUC scores are exactly the same. The difference in F1-score between SMOTE and SMOTEENN is only about 0.04. However the difference in F1 score between train and test for SMOTEENN is 0.26, while the difference for SMOTE is only about 0.18 (see cells below). In other words, in terms of F1-score, SMOTE performs about 8% better than SMOTEENN. The difference is not massive but enough to reconsider SMOTE in lieu of SMOTEENN as the resample strategy to be used moving forward.

In the next development notebook I will use the preprocessing from EDA, and the SMOTE resampling method found here to train and optimize via gridsearching a decision tree and/or random forest. To use as my final model.

In [78]:

```
# difference in F1 for classic SMOTE and SMOTEENN
SMOTE_CV_report.iloc[2,1] - SMOTENN_CV_report.iloc[2,1]
```

Out[78]: 0.035384001257912745

In [81]:

```
# difference in F1 for classic SMOTE train vs test
SMOTENN_report.iloc[2,1] - SMOTENN_CV_report.iloc[2,1]
```

Out[81]: 0.25803582113253065

In [82]:

```
# difference in F1 for classic SMOTE train vs test
smote_report.iloc[2,1] - SMOTE_CV_report.iloc[2,1]
```

Out[82]: 0.17835949357883185

In [ ]:

```

```