Class Imbalance

My business goal is identifying whether the company will bankrupt or not in next 1-5 years.

I will use Ensemble Method 'XGBoost', eXtreme Gradient Boosting, for classification.

I will focus on the performance of 'recall' metric in order to minimize false negatives. Besides, I will also keep an eye on 'precision', 'f1', 'accuracy, and 'AUC' metrics.

In this botebook, I will work on the class imbalance issue on the dataset.

Load Libraries

In [16]:
```
# Import base libraries
import pandas as pd
import numpy as np
from scipy.io import arff

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

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from xgboost import XGBClassifier

from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import roc_auc_score, roc_curve, auc
from sklearn.metrics import precision_score, recall_score, accuracy_score,
from sklearn.utils import class_weight

from functions import *

from datetime import datetime

import warnings
warnings.filterwarnings('ignore')
```

Load Data

There are five data files:

```
* data1, 1year.arff
* data2, 2year.arff
* data3, 3year.arff
* data4, 4year.arff
* data5, 5year.arff
```

Initially, I will use 'data3' to find the best approcah to handle the class imbalance.

No cleaning applied to data. XGBoost Classifier can handle the missing values.

In [23]:
```
# Load data
data3 = arff.loadarff('data/3year.arff')
df3 = pd.DataFrame(data3[0])

# Change label/class type to binary
df3['class'] = df3['class'].astype('int64')

df3.shape
```

Out[23]:
```
(10503, 65)
```

Pre-process

In [24]:
```
# Assign target and predictor
y = df3['class']
X = df3.drop('class', axis=1)

# Sepearate data into train and test splist
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, r

# Scale/Normalize the predictor variables
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
y_train = y_train.to_numpy()
y_test = y_test.to_numpy()

print('X_train shape = ', X_train.shape)
print('y_train shape = ', y_train.shape)
print('X_test shape = ', X_test.shape)
print('y_test shape = ', y_test.shape)
```

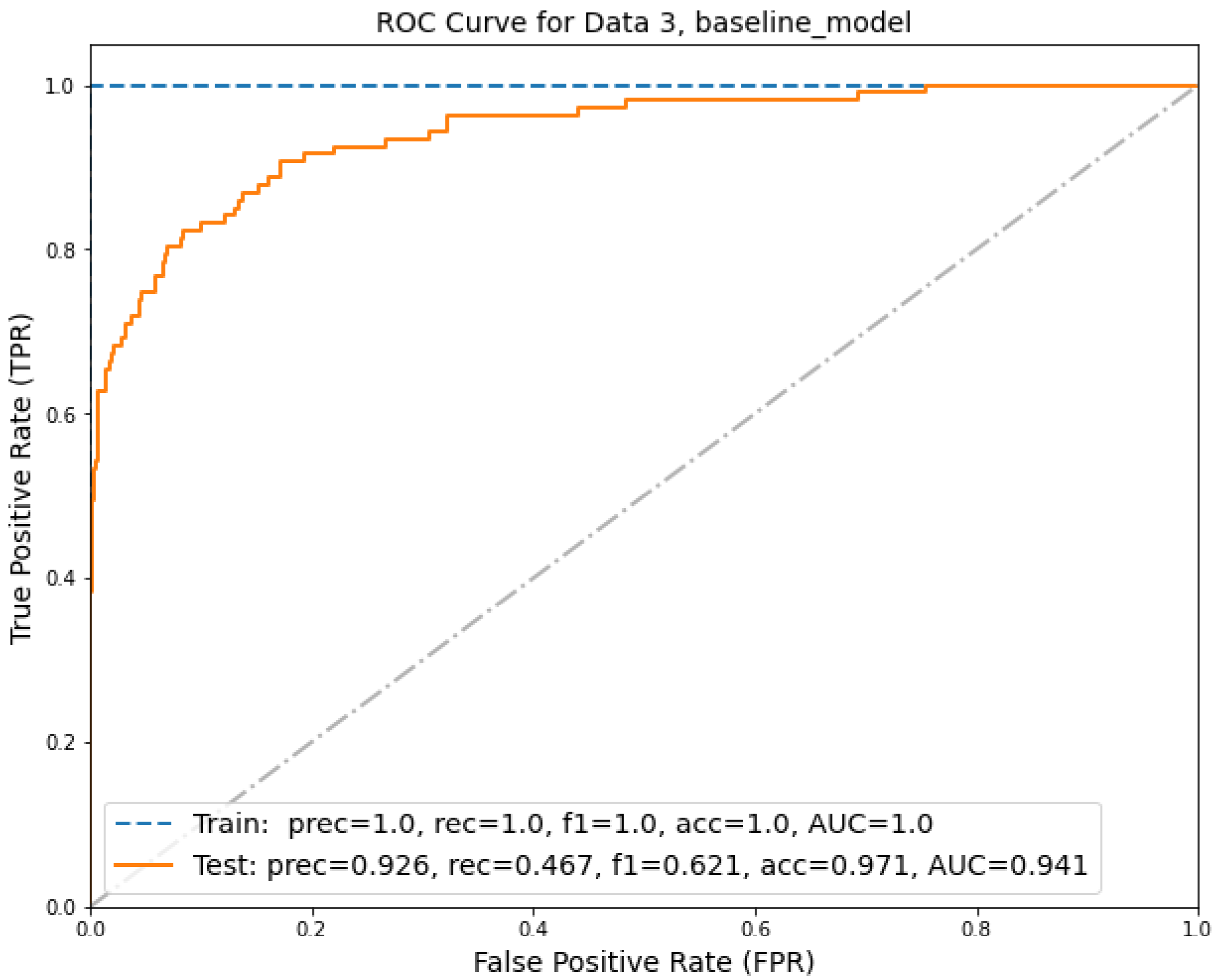
```
X_train shape =  (8402, 64)
y_train shape =  (8402,)
X_test shape =  (2101, 64)
y_test shape =  (2101,)
```

Baseline Model

In [19]:
```python
# Baseline Model

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
}

baseline_model = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbP
```

```
Data 3 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      8014
           1       1.00      1.00      1.00       388

    accuracy                           1.00      8402
   macro avg       1.00      1.00      1.00      8402
weighted avg       1.00      1.00      1.00      8402

Testing Data:
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1994
           1       0.93      0.47      0.62       107

    accuracy                           0.97      2101
   macro avg       0.95      0.73      0.80      2101
weighted avg       0.97      0.97      0.97      2101
```

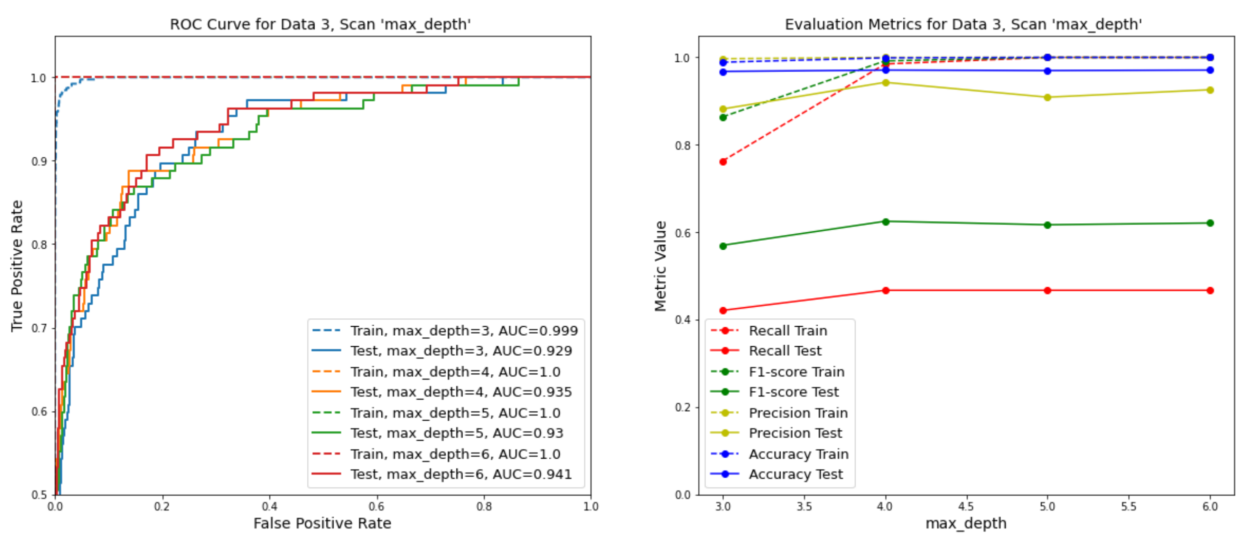
In [6]:
```
#Plot ROC curve

plot_ROC(3, X_train, y_train, X_test, y_test, baseline_model, 'baseline_mod
```



In [7]:
```
model_1.get_params
```

Out[7]:
```
<bound method XGBModel.get_params of XGBClassifier(base_score=0.5, booste
r='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eval_metric='loglos
s',
              gamma=0, gpu_id=-1, importance_type='gain',
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=
nan,
              monotone_constraints='()', n_estimators=100, n_jobs=4,
              num_parallel_tree=1, random_state=42, reg_alpha=0, reg_lamb
da=1,
              scale_pos_weight=1, subsample=1, tree_method='exact',
              validate_parameters=1, verbosity=None)>
```

In [33]:
```
#Scan max_depth

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
}

scanParam = 'max_depth'

scanList = [3, 4, 5, 6]

result_sw_depth = scan_xgb_ROC_metrics(3, X_train, y_train, X_test, y_test,
```



Comments

- According to testing data results, the model performance in identfying the non-bankruptcy companies (class 0) is very good.
- However, the identification of the bankruptcy companies (class 1) is not that good (low recall and f1)
- The class imbalance is probaly the reason for the class 0/1 performance difference.
- There is large overfitting.

Class Imbalance

There are two approaches to deal with the class imbalance:

- 'sample_weight' parameter when training the data
- 'scale_pos_weight' parameter when initiating the classifier

sample_weight

In [24]:
```
# Whole data 3

print('Whole Data3')
d3_class_weights = class_weight.compute_class_weight(class_weight='balanced
print(d3_class_weights)

d3_class_weights_ratio = d3_class_weights[1]/d3_class_weights[0]
print('weights_ratio', d3_class_weights_ratio)
print('Squared Root of weights_ratio', np.sqrt(d3_class_weights_ratio))
```

```
Whole Data3
[ 0.52473022 10.60909091]
weights_ratio 20.218181818182
Squared Root of weights_ratio 4.496463256625347
```

In [28]:
```
#Training sample

print('Training sample, Data3')
d3_class_weights_train = class_weight.compute_class_weight(class_weight='ba

d3_class_weights_train_ratio = d3_class_weights_train[1]/d3_class_weights_t
print('weights_ratio', d3_class_weights_train_ratio)
print('Squared Root of weights_ratio', np.sqrt(d3_class_weights_train_ratio

d3_class_weights_train_array = class_weight.compute_sample_weight(class_wei
print('Class weights per entry:', d3_class_weights_train_array)

# Training weights are used for data training.
```

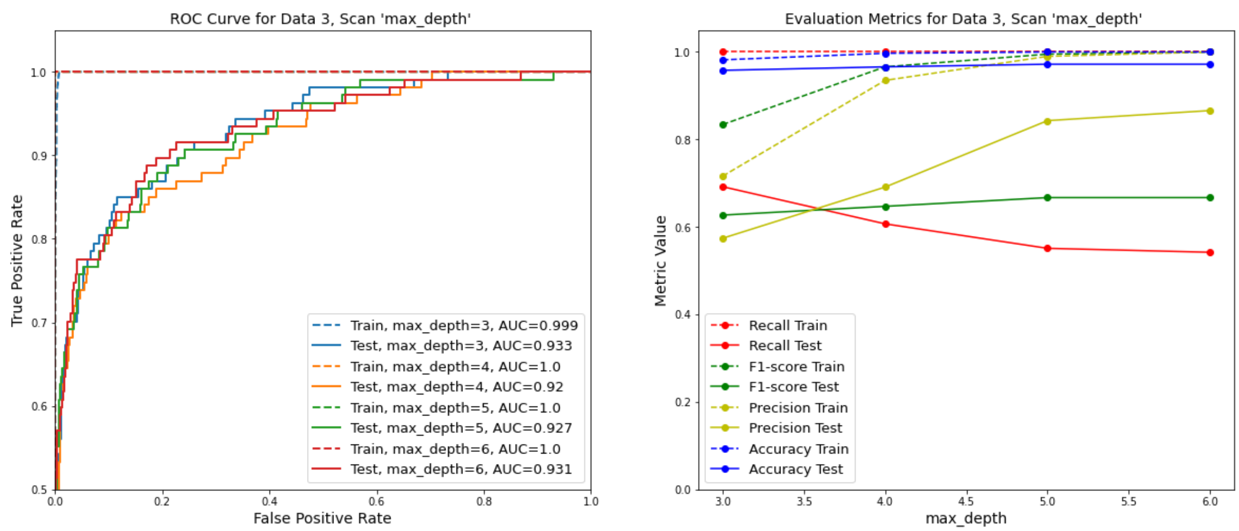
```
Training sample, Data3
weights_ratio 20.65463917525773
Squared Root of weights_ratio 4.544737525452678
Class weights per entry: [0.52420764 0.52420764 0.52420764 ... 0.52420764
0.52420764 0.52420764]
```

In [31]:
```python
# sample_weight applied

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
}

xgb_model_sw = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbPar
```

```
Sample weights are used!
--------

Data 3 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      8014
           1       1.00      1.00      1.00       388

    accuracy                           1.00      8402
   macro avg       1.00      1.00      1.00      8402
weighted avg       1.00      1.00      1.00      8402

Testing Data:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      1994
           1       0.87      0.54      0.67       107

    accuracy                           0.97      2101
   macro avg       0.92      0.77      0.83      2101
weighted avg       0.97      0.97      0.97      2101
```

```
In [35]: #Scan max_depth
         #sample_weight applied

         xgbParams = {
             'eval_metric': 'logloss',
             'random_state': 42,
         }

         scanParam = 'max_depth'

         scanList = [3, 4, 5, 6]

         result_sw_depth = scan_xgb_ROC_metrics(3, X_train, y_train, X_test, y_test,
```

```
Sample weights are used!
--------
```



Comments

- Model performance improved, Recall increased.
- Overfitting continues.
- sample_weight is more effective at lower max_depth (3 or 4)

scale_pos_weight

My goal is find the optimum 'scale_pos_weight' value which creates good recall and f1 value.

The model performance is largely effected by the max_depth. So I will scan the scale_pos_weight at several max_depth.

In [29]:
```
#Check Class Imbalance
df3['class'].value_counts()
```

Out[29]:
```
0    10008
1      495
Name: class, dtype: int64
```

In [30]:
```
#Check Class Imbalance, Normalized
df3['class'].value_counts(normalize=True)
```

Out[30]:
```
0    0.952871
1    0.047129
Name: class, dtype: float64
```

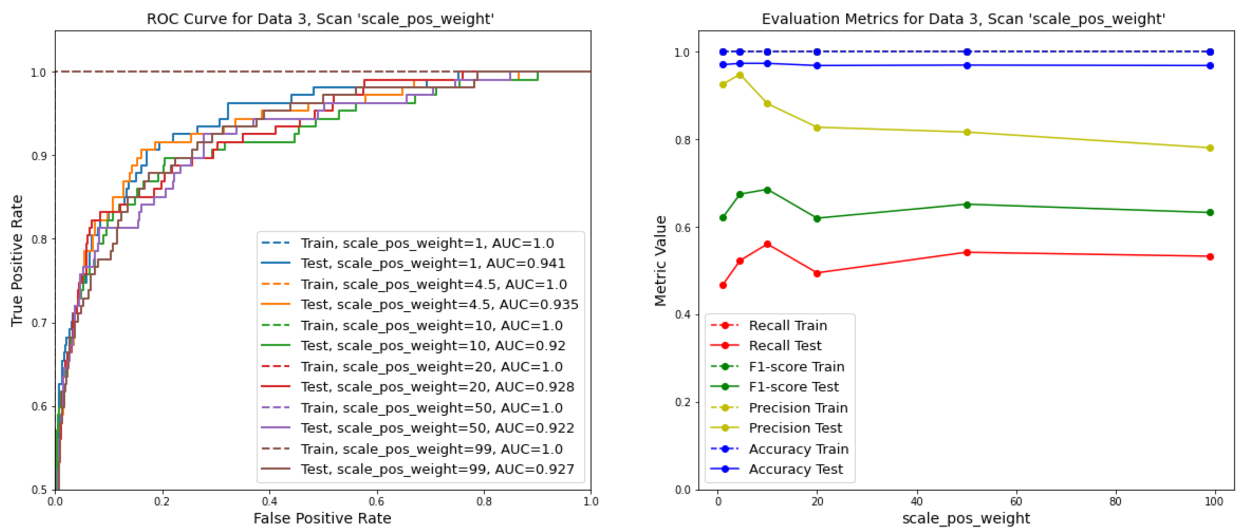
In [15]:
```
# Explore class counts
val_counts = df3['class'].value_counts()
ratio_imbalance = val_counts[0]/val_counts[1]
sqrt_ratio_imbalance = np.sqrt(val_counts[0]/val_counts[1])

print('imbalance ratio:', ratio_imbalance)
print('sqrt of imbalance ratio:', sqrt_ratio_imbalance)

# The values are very similar for train/test/whole datasets.
```

```
imbalance ratio: 20.21818181818182
sqrt of imbalance ratio: 4.496463256625347
```

In [22]:
```
# Explore class counts, Training sample
val_counts = pd.DataFrame(y_train, columns=['class'])['class'].value_counts
ratio_imbalance = val_counts[0]/val_counts[1]
sqrt_ratio_imbalance = np.sqrt(val_counts[0]/val_counts[1])

print('imbalance ratio:', ratio_imbalance)
print('sqrt of imbalance ratio:', sqrt_ratio_imbalance)
```

```
imbalance ratio: 20.65463917525773
sqrt of imbalance ratio: 4.544737525452678
```

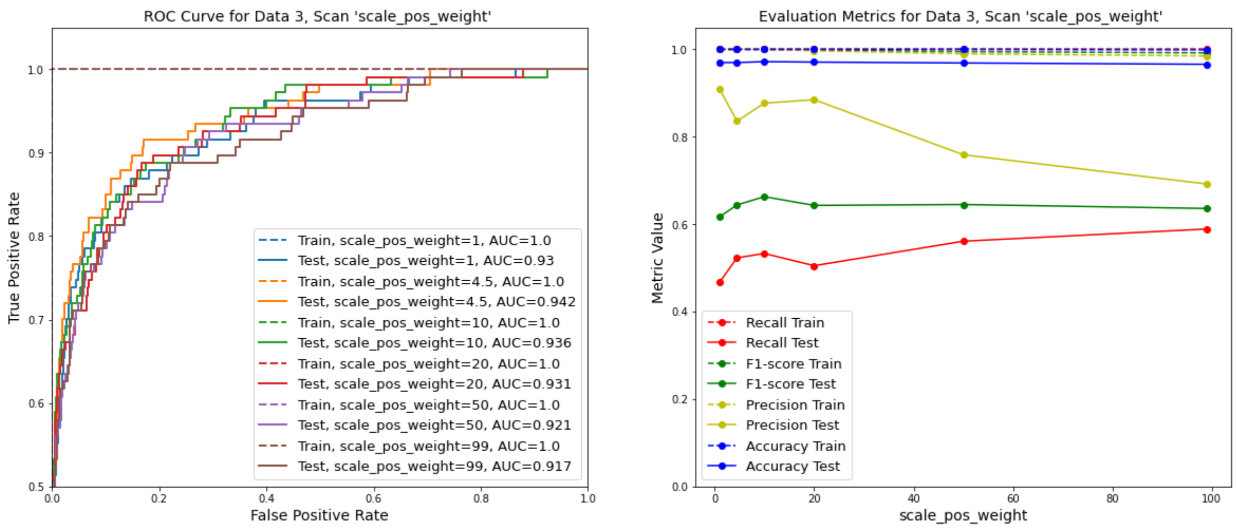
In [37]:
```python
#Scan scale_pos_weight,
# max_depth=6 (default)

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
}

scanParam = 'scale_pos_weight'

scanList = [1, 4.5, 10, 20, 50, 99]
#scanList = [1, 4.5]

result_spw = scan_xgb_ROC_metrics(3, X_train, y_train, X_test, y_test, xgbP
```



In [51]:
```python
# max_depth=6, scale_pos_weight=10

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 6,
    'scale_pos_weight': 10,
}

model_spw10_depth6 = xgb_model_report(3, X_train, y_train, X_test, y_test,
```

```
Data 3 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      8014
           1       1.00      1.00      1.00       388

    accuracy                           1.00      8402
   macro avg       1.00      1.00      1.00      8402
weighted avg       1.00      1.00      1.00      8402

Testing Data:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      1994
           1       0.88      0.56      0.69       107

    accuracy                           0.97      2101
   macro avg       0.93      0.78      0.84      2101
weighted avg       0.97      0.97      0.97      2101
```

In [40]:
```
#Scan scale_pos_weight,
# max_depth=5

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 5
}

scanParam = 'scale_pos_weight'

scanList = [1, 4.5, 10, 20, 50, 99]
#scanList = [1, 4.5]

result_spw_depth5 = scan_xgb_ROC_metrics(3, X_train, y_train, X_test, y_tes
```

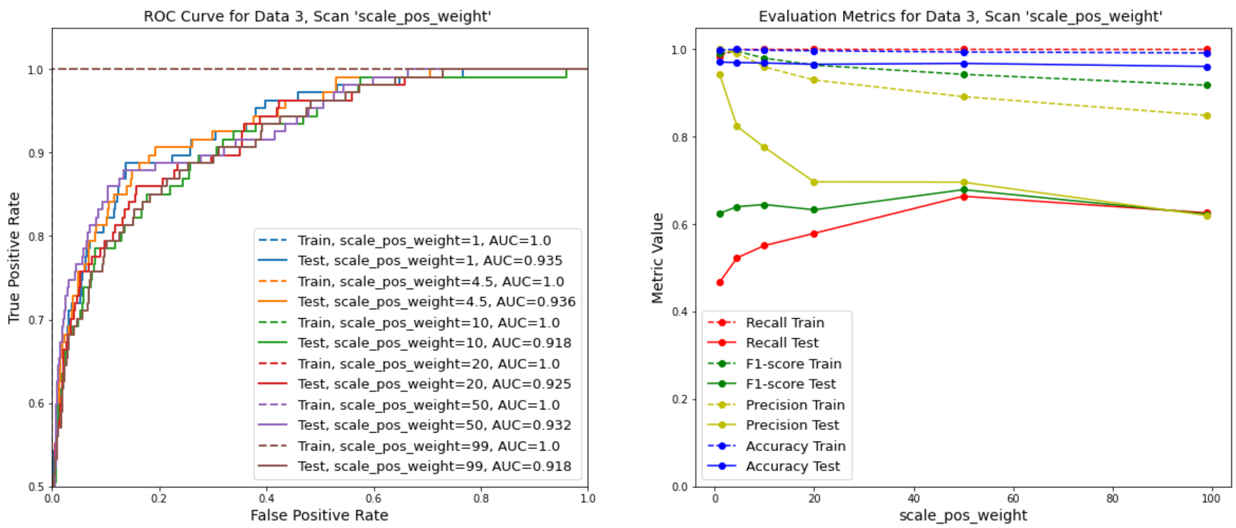


In [52]:
```python
# max_depth=5, scale_pos_weight=50

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 5,
    'scale_pos_weight': 50,
}

model_spw50_depth5 = xgb_model_report(3, X_train, y_train, X_test, y_test,
```

```
Data 3 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      8014
           1       0.99      1.00      0.99       388

    accuracy                           1.00      8402
   macro avg       0.99      1.00      1.00      8402
weighted avg       1.00      1.00      1.00      8402

Testing Data:
              precision    recall  f1-score   support

           0       0.98      0.99      0.98      1994
           1       0.76      0.56      0.65       107

    accuracy                           0.97      2101
   macro avg       0.87      0.78      0.81      2101
weighted avg       0.97      0.97      0.97      2101
```

In [41]:

```
#Scan scale_pos_weight,
# max_depth=4

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 4
}

scanParam = 'scale_pos_weight'

scanList = [1, 4.5, 10, 20, 50, 99]
#scanList = [1, 4.5]

result_spw_depth4= scan_xgb_ROC_metrics(3, X_train, y_train, X_test, y_test
```

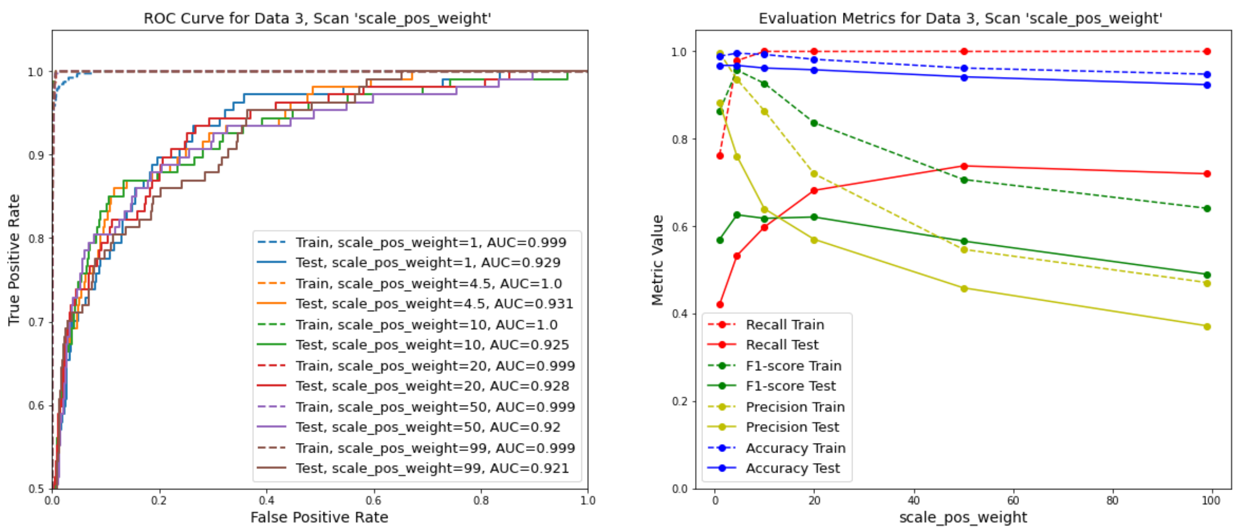


In [53]:
```python
# max_depth=4, scale_pos_weight=50

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 4,
    'scale_pos_weight': 50,
}

model_spw50_depth4 = xgb_model_report(3, X_train, y_train, X_test, y_test,
```

```
Data 3 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      8014
           1       0.89      1.00      0.94       388

    accuracy                           0.99      8402
   macro avg       0.95      1.00      0.97      8402
weighted avg       1.00      0.99      0.99      8402

Testing Data:
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1994
           1       0.70      0.66      0.68       107

    accuracy                           0.97      2101
   macro avg       0.84      0.82      0.83      2101
weighted avg       0.97      0.97      0.97      2101
```

In [42]:

```
#Scan scale_pos_weight,
# max_depth=3

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 3
}

scanParam = 'scale_pos_weight'

scanList = [1, 4.5, 10, 20, 50, 99]
#scanList = [1, 4.5]

result_spw_depth3= scan_xgb_ROC_metrics(3, X_train, y_train, X_test, y_test
```



In [55]:
```python
# max_depth=3, scale_pos_weight=20

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 3,
    'scale_pos_weight': 20,
}

model_spw20_depth3 = xgb_model_report(3, X_train, y_train, X_test, y_test,
```

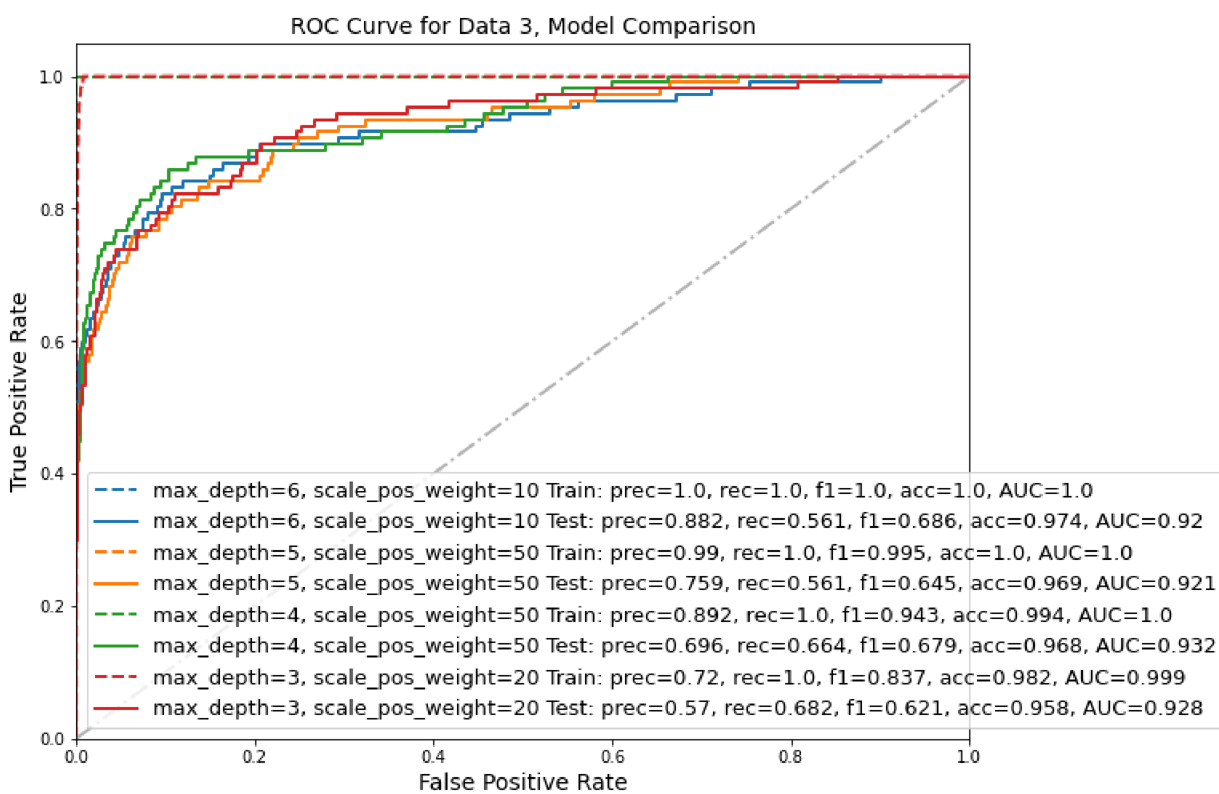
```
Data 3 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99      8014
           1       0.72      1.00      0.84       388

    accuracy                           0.98      8402
   macro avg       0.86      0.99      0.91      8402
weighted avg       0.99      0.98      0.98      8402

Testing Data:
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      1994
           1       0.57      0.68      0.62       107

    accuracy                           0.96      2101
   macro avg       0.78      0.83      0.80      2101
weighted avg       0.96      0.96      0.96      2101
```

In [56]:

```
#Compare models with optimum scale_pos_weight

model_list = [model_spw10_depth6, model_spw50_depth5, model_spw50_depth4, m

model_names_list = ['max_depth=6, scale_pos_weight=10',
                    'max_depth=5, scale_pos_weight=50',
                    'max_depth=4, scale_pos_weight=50',
                    'max_depth=3, scale_pos_weight=20',
                    ]

compare_models(3, X_train, y_train, X_test, y_test, model_list, model_names
```

Out[56]:

Params		precision	recall	f1	accuracy	auc
max_depth=6, scale_pos_weight=10	**Train**	1.000	1.000	1.000	1.000	1.000
	Test	0.882	0.561	0.686	0.974	0.920
max_depth=5, scale_pos_weight=50	**Train**	0.990	1.000	0.995	1.000	1.000
	Test	0.759	0.561	0.645	0.969	0.921
max_depth=4, scale_pos_weight=50	**Train**	0.892	1.000	0.943	0.994	1.000
	Test	0.696	0.664	0.679	0.968	0.932
max_depth=3, scale_pos_weight=20	**Train**	0.720	1.000	0.837	0.982	0.999
	Test	0.570	0.682	0.621	0.958	0.928



Comments

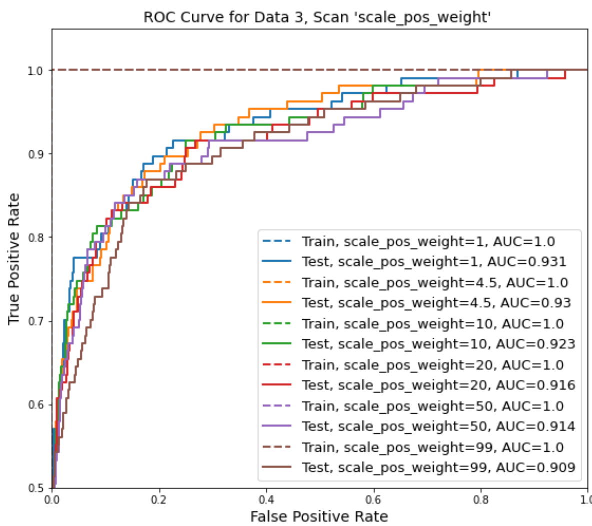
- The model performance improves compared to the baseline model (Model 1) where default scale_pos_weight=1.
- The optimum value may be different when other parameters change, for instance max_depth.
- The optimum scale_pos_weight:
  - scale_pos_weight=10 at max_depth=6
  - scale_pos_weight=50 at max_depth=5
  - scale_pos_weight=50 at max_depth=4
  - scale_pos_weight=20 at max_depth=3
- Overfitting observed.
- The optimum value may be different when another data set is used. It may require additional parameter tuning.

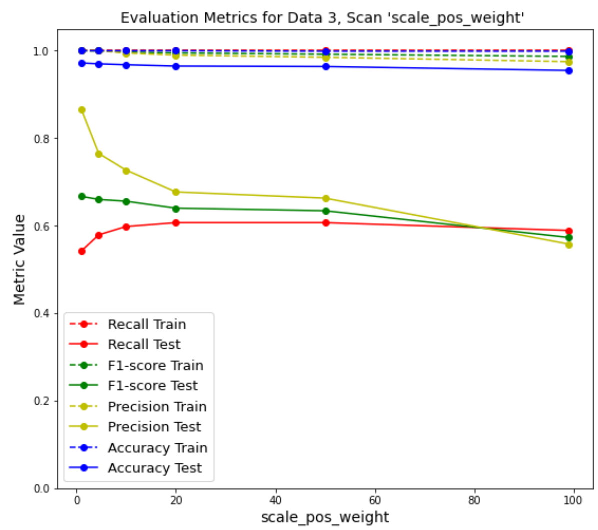
class_weight + scale_pos_weight

In [57]:

```
#Scan scale_pos_weight
# sample_weight applied
#max_depth=6

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
}

scanParam = 'scale_pos_weight'

scanList = [1, 4.5, 10, 20, 50, 99]
#scanList = [1, 4.5]

result_spw_sw_depth6 = scan_xgb_ROC_metrics(3, X_train, y_train, X_test, y_
```

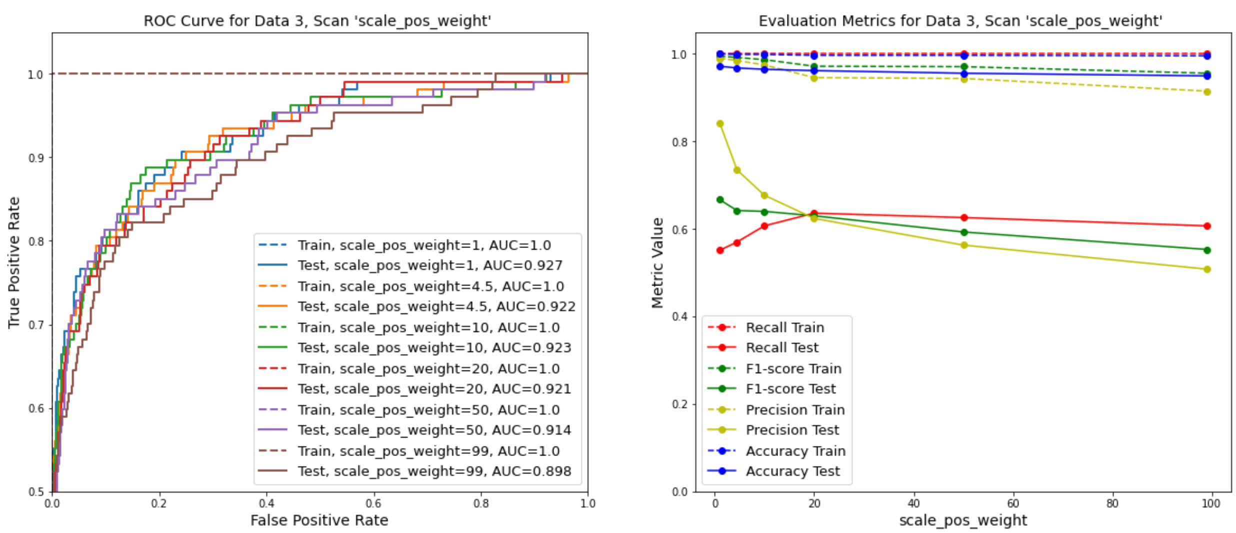
```
Sample weights are used!
--------
```





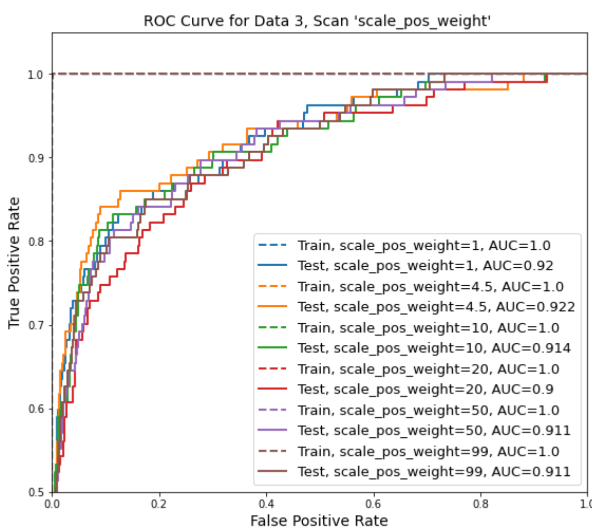
In [58]:
```python
#Scan scale_pos_weight
# sample_weight applied
# max_depth=5

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 5,
}

scanParam = 'scale_pos_weight'

scanList = [1, 4.5, 10, 20, 50, 99]
#scanList = [1, 4.5]

result_spw_sw_depth5 = scan_xgb_ROC_metrics(3, X_train, y_train, X_test, y_
```

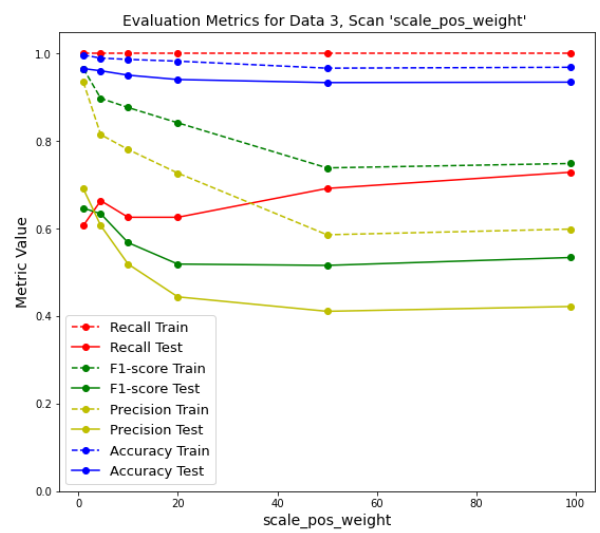
```
Sample weights are used!
--------
```



```
In [60]: #Scan scale_pos_weight
         # sample_weight applied
         # max_depth=4

         xgbParams = {
             'eval_metric': 'logloss',
             'random_state': 42,
             'max_depth': 4,
         }

         scanParam = 'scale_pos_weight'

         scanList = [1, 4.5, 10, 20, 50, 99]
         #scanList = [1, 4.5]

         result_spw_sw_depth4 = scan_xgb_ROC_metrics(3, X_train, y_train, X_test, y_
```

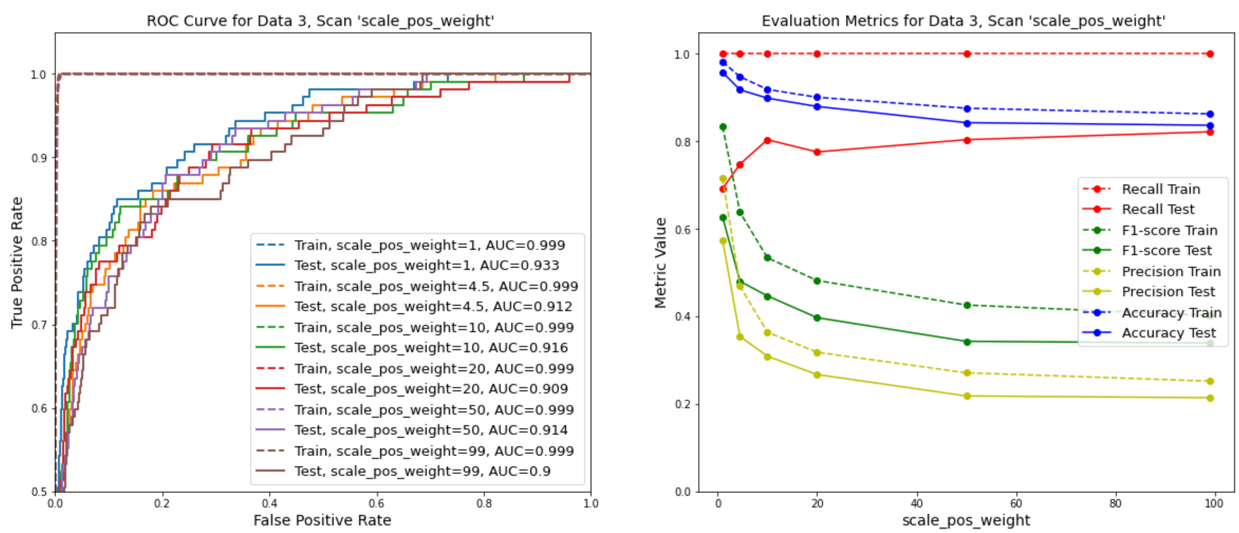
```
Sample weights are used!
--------
```





In [59]:
```python
#Scan scale_pos_weight
# sample_weight applied
# max_depth=3

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 3,
}

scanParam = 'scale_pos_weight'

scanList = [1, 4.5, 10, 20, 50, 99]
#scanList = [1, 4.5]

result_spw_sw_depth3 = scan_xgb_ROC_metrics(3, X_train, y_train, X_test, y_
```

```
Sample weights are used!
--------
```



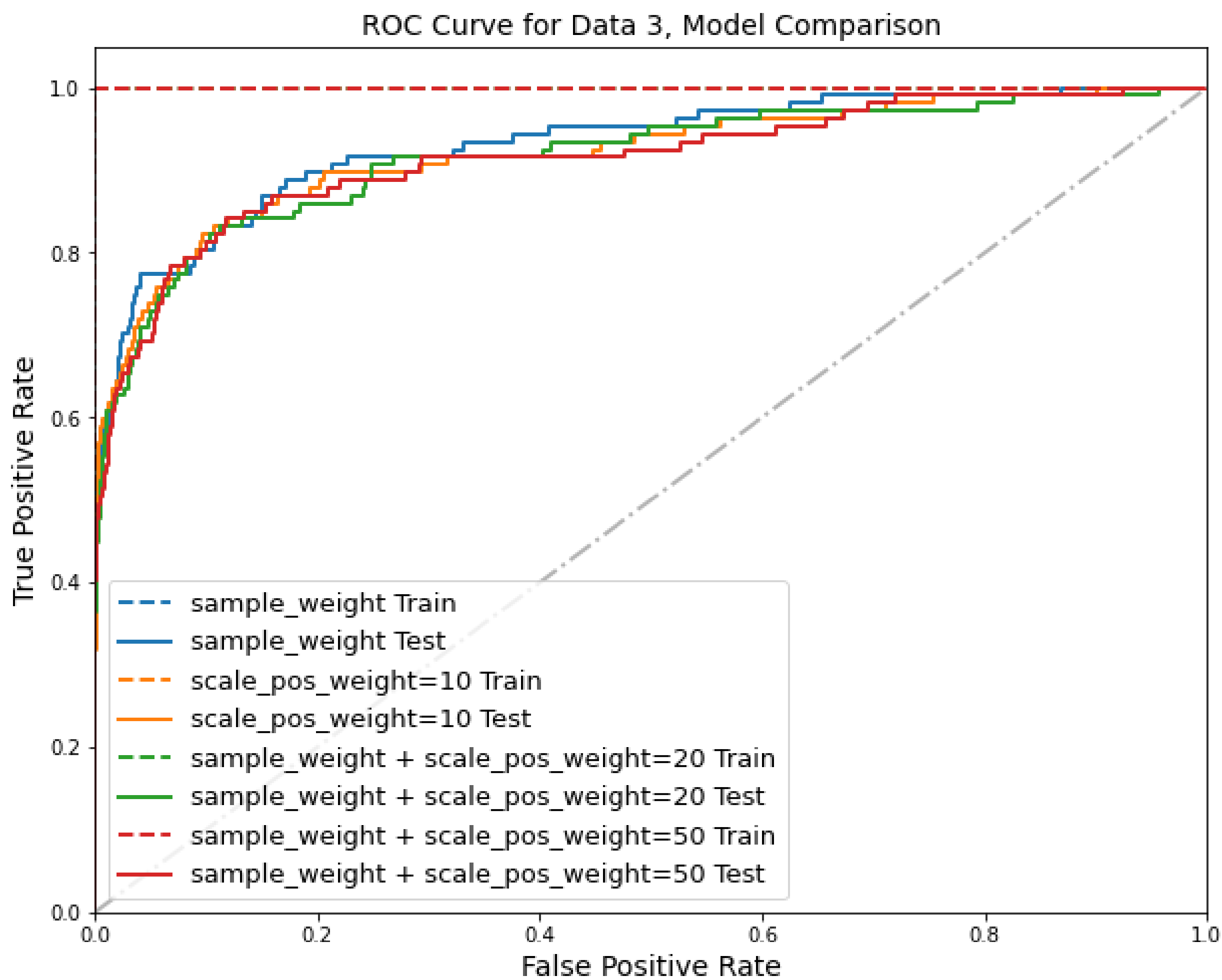
In [14]:
```
#Compare balance methods at max_depth=6

xgbParams1 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 6,
}

mod1 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams1, 'X

xgbParams2 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 6,
    'scale_pos_weight': 10,
}

mod2 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams2, 'X

xgbParams3 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 6,
    'scale_pos_weight': 20,
}

mod3 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams3, 'X

xgbParams4 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 6,
    'scale_pos_weight': 50,
}

mod4 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams4, 'X

model_list = [mod1, mod2, mod3, mod4]

model_names_list = ['sample_weight', 'scale_pos_weight=10', 'sample_weight

compare_models(3, X_train, y_train, X_test, y_test, model_list, model_names
```

```
Sample weights are used!
--------

Sample weights are used!
--------

Sample weights are used!
--------
```

Out[14]:

	precision	recall	f1	accuracy	auc

Params	precision	recall	f1	accuracy	auc
Params					
sample_weight Train	1.000	1.000	1.000	1.000	1.000
Test	0.866	0.542	0.667	0.972	0.931
scale_pos_weight=10 Train	1.000	1.000	1.000	1.000	1.000
Test	0.882	0.561	0.686	0.974	0.920
sample_weight + scale_pos_weight=20 Train	0.990	1.000	0.995	1.000	1.000
Test	0.677	0.607	0.640	0.965	0.916
sample_weight + scale_pos_weight=50 Train	0.985	1.000	0.992	0.999	1.000
Test	0.663	0.607	0.634	0.964	0.914



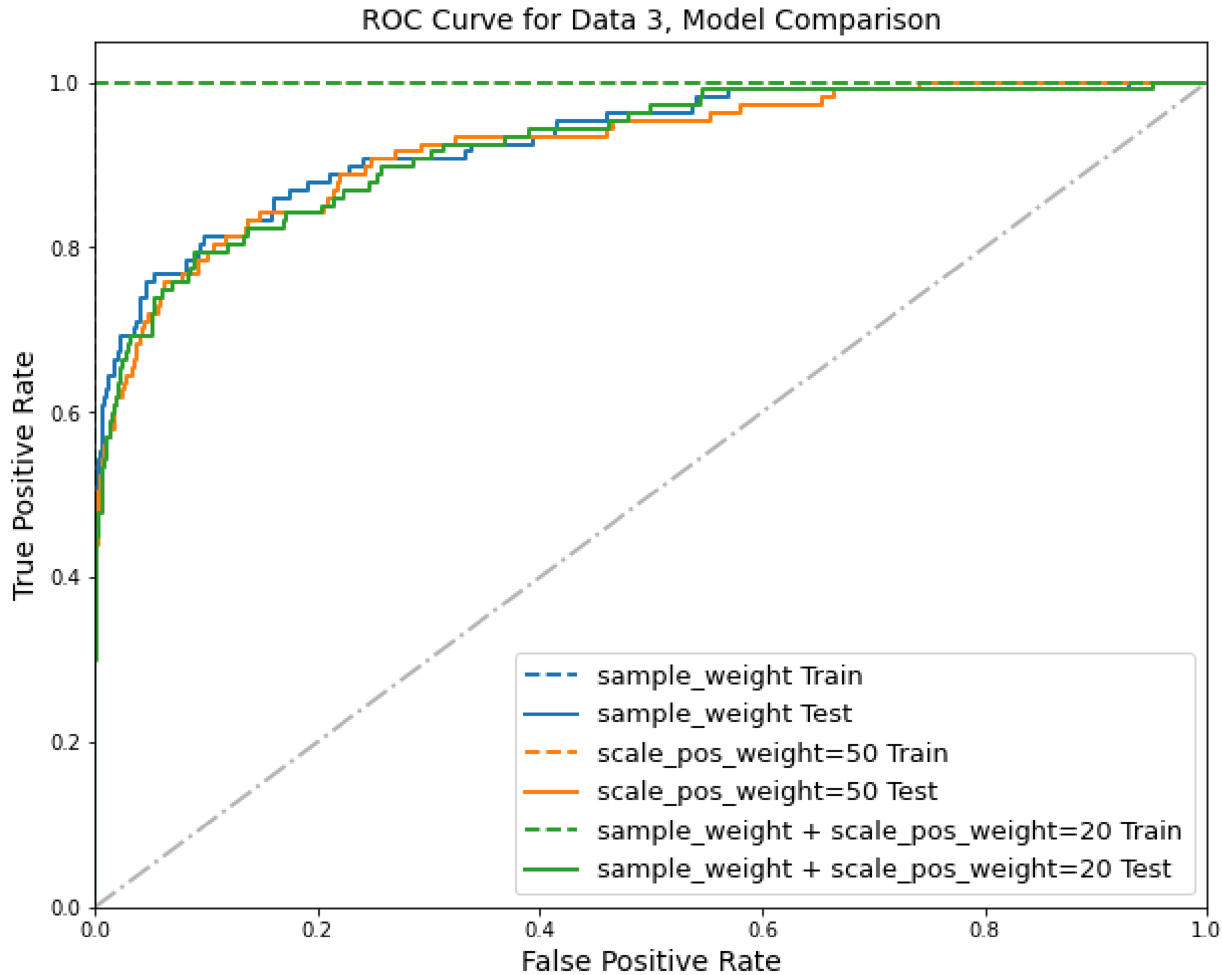
In [8]:

```
#Compare balance methods at max_depth=5

xgbParams1 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 5,
}

mod1 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams1, 'X

xgbParams2 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 5,
    'scale_pos_weight': 50,
}

mod2 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams2, 'X

xgbParams3 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 5,
    'scale_pos_weight': 20,
}

mod3 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams3, 'X

model_list = [mod1, mod2, mod3]

model_names_list = ['sample_weight', 'scale_pos_weight=50', 'sample_weight

compare_models(3, X_train, y_train, X_test, y_test, model_list, model_names
```

```
Sample weights are used!
--------

Sample weights are used!
--------
```

Out[8]:

Params		precision	recall	f1	accuracy	auc
sample_weight	Train	0.990	1.000	0.995	1.000	1.000
	Test	0.843	0.551	0.667	0.972	0.927
scale_pos_weight=50	Train	0.990	1.000	0.995	1.000	1.000
	Test	0.759	0.561	0.645	0.969	0.921
sample_weight + scale_pos_weight=20	Train	0.946	1.000	0.972	0.997	1.000
	Test	0.624	0.636	0.630	0.962	0.921



ROC Curve for Data 3, Model Comparison
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
sample_weight Train
sample_weight Test
scale_pos_weight=50 Train
scale_pos_weight=50 Test
sample_weight + scale_pos_weight=20 Train
sample_weight + scale_pos_weight=20 Test

In [13]:

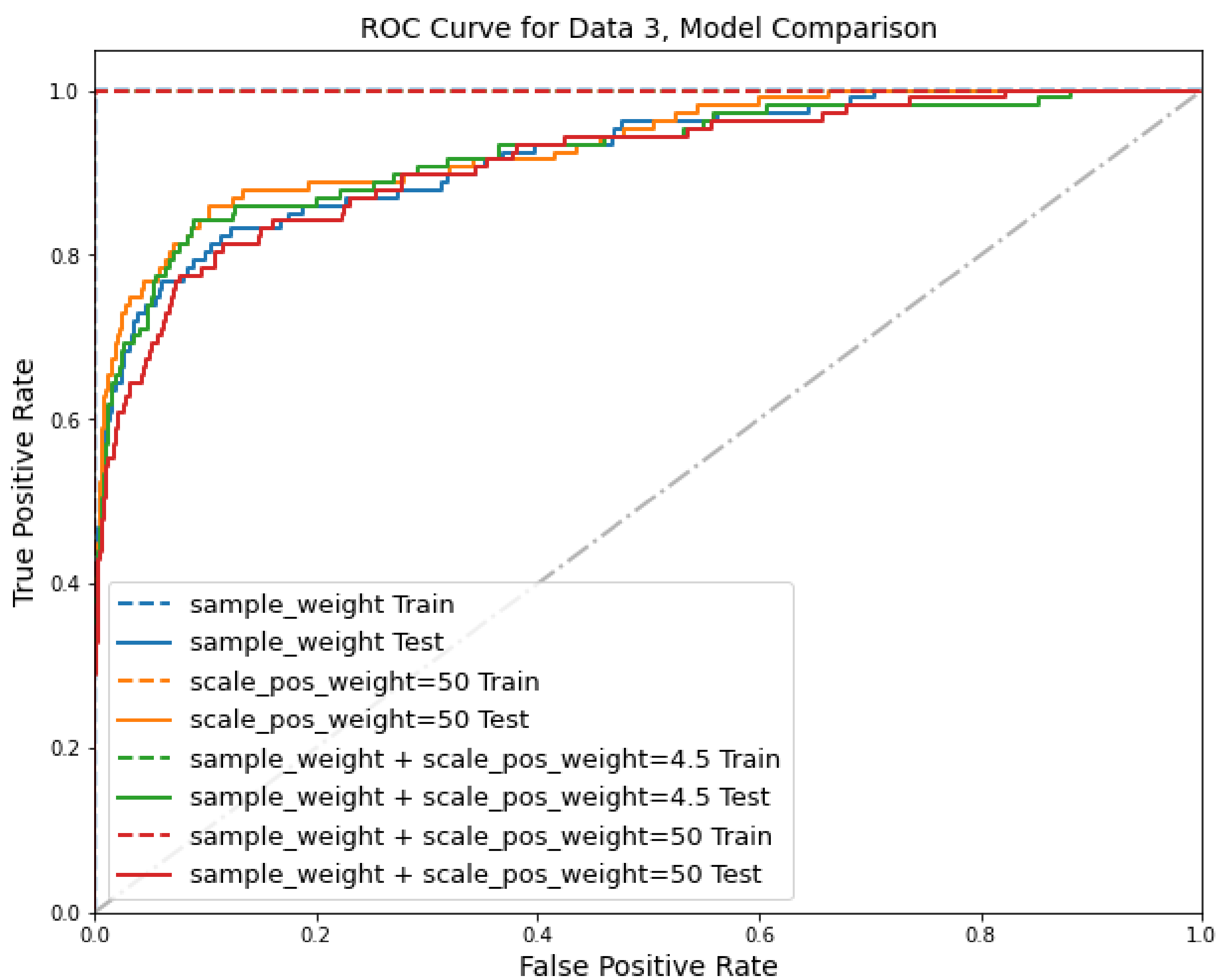
```
#Compare balance methods at max_depth=4

xgbParams1 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 4,
}

mod1 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams1, 'X

xgbParams2 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 4,
    'scale_pos_weight': 50,
}

mod2 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams2, 'X

xgbParams3 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 4,
    'scale_pos_weight': 4.5,
}

mod3 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams3, 'X

xgbParams4 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 4,
    'scale_pos_weight': 50,
}

mod4 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams4, 'X

model_list = [mod1, mod2, mod3, mod4]

model_names_list = ['sample_weight', 'scale_pos_weight=50', 'sample_weight

compare_models(3, X_train, y_train, X_test, y_test, model_list, model_names
```

```
Sample weights are used!
--------

Sample weights are used!
--------

Sample weights are used!
--------
```

Out[13]:

	precision	recall	f1	accuracy	auc

Params	precision	recall	f1	accuracy	auc
Params					
sample_weight Train	0.935	1.000	0.966	0.997	1.000
Test	0.691	0.607	0.647	0.966	0.920
scale_pos_weight=50 Train	0.892	1.000	0.943	0.994	1.000
Test	0.696	0.664	0.679	0.968	0.932
sample_weight + scale_pos_weight=4.5 Train	0.815	1.000	0.898	0.990	1.000
Test	0.607	0.664	0.634	0.961	0.922
sample_weight + scale_pos_weight=50 Train	0.586	1.000	0.739	0.967	1.000
Test	0.411	0.692	0.516	0.934	0.911

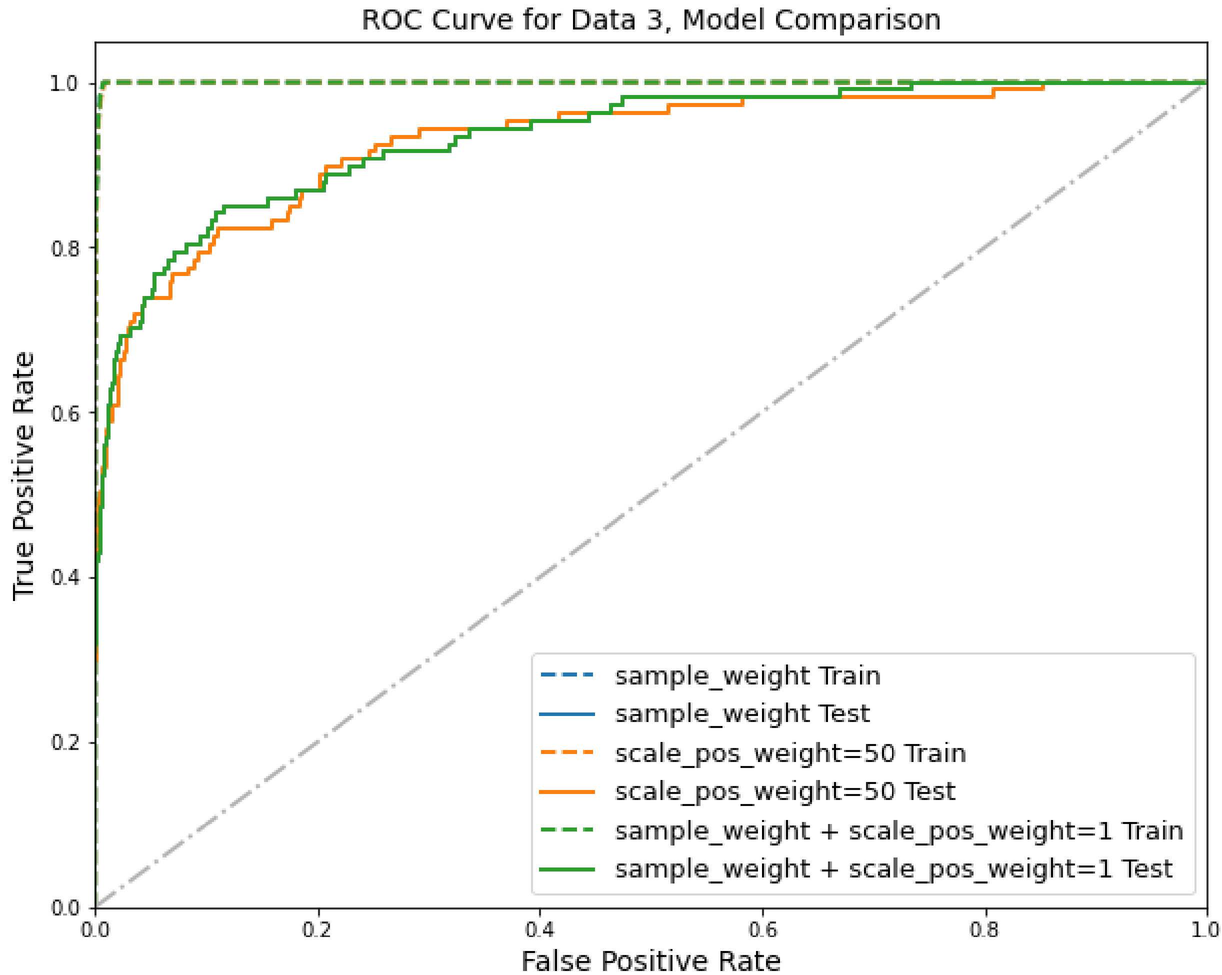


In [12]:
```
#Compare balance methods at max_depth=3

xgbParams1 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 3,
}

mod1 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams1, 'X

xgbParams2 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 3,
    'scale_pos_weight': 20,
}

mod2 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams2, 'X

xgbParams3 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'max_depth': 3,
    'scale_pos_weight': 1,
}

mod3 = xgb_model_report(3, X_train, y_train, X_test, y_test, xgbParams3, 'X

model_list = [mod1, mod2, mod3]

model_names_list = ['sample_weight', 'scale_pos_weight=50', 'sample_weight

compare_models(3, X_train, y_train, X_test, y_test, model_list, model_names
```

```
Sample weights are used!
--------

Sample weights are used!
--------
```

Out[12]:

Params		precision	recall	f1	accuracy	auc
sample_weight	**Train**	0.716	1.000	0.834	0.982	0.999
	Test	0.574	0.692	0.627	0.958	0.933
scale_pos_weight=50	**Train**	0.720	1.000	0.837	0.982	0.999
	Test	0.570	0.682	0.621	0.958	0.928
sample_weight + scale_pos_weight=1	**Train**	0.716	1.000	0.834	0.982	0.999
	Test	0.574	0.692	0.627	0.958	0.933



Comments

- The optimum imbalance depends on the max_depth.
  - max_depth=6: sample_weight + scale_pos_weight=20
  - max_depth=5: sample_weight + scale_pos_weight=20
  - max_depth=4: sample_weight + scale_pos_weight=4.5
  - max_depth=3: sample_weight + scale_pos_weight=1
- The optimum value may be different when another data set is used.

In [ ]:

```
```