Analysis on All Data Files

On this notebook, I will apply the best optimized models on all five datasets.

Load Libraries

In [1]:
```
# 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
```

Note: No cleaning applied to data. XGBoost Classifier can handle the missing values and outliers.

In [21]:
```python
# Load all five data files

data1 = arff.loadarff('data/1year.arff')
df1 = pd.DataFrame(data1[0])

data2 = arff.loadarff('data/2year.arff')
df2 = pd.DataFrame(data2[0])

data3 = arff.loadarff('data/3year.arff')
df3 = pd.DataFrame(data3[0])

data4 = arff.loadarff('data/4year.arff')
df4 = pd.DataFrame(data4[0])

data5 = arff.loadarff('data/5year.arff')
df5 = pd.DataFrame(data5[0])
```

In [22]:
```python
# Convert class/label type to binary

df1['class'] = df1['class'].astype('int64')
df2['class'] = df2['class'].astype('int64')
df3['class'] = df3['class'].astype('int64')
df4['class'] = df4['class'].astype('int64')
df5['class'] = df5['class'].astype('int64')
```

In [23]:
```python
# Size of datasets

print('Size of datasets')
print("Data 1 (Year1):", len(df1))
print("Data 2 (Year2):", len(df2))
print("Data 3 (Year3):", len(df3))
print("Data 4 (Year4):", len(df4))
print("Data 5 (Year5):", len(df5))
```

```
Size of datasets
Data 1 (Year1): 7027
Data 2 (Year2): 10173
Data 3 (Year3): 10503
Data 4 (Year4): 9792
Data 5 (Year5): 5910
```

Imbalance Information

I am using both sample_weight and scale_pos_weight parameters to deal with the class imbalance.

- sample_weight: The weights for training sample are calculated for each dataset seperately and used when during training.
- scale_pos_weight: I provide certain values to initiate the classifier. I either use the imbalance ratio or square root of the imbalance ratio. These values are not exactly same for the datasets, but close enough to use a constant about average number.
  - Model 7 (max_depth=5): scale_pos_weight=20 (~imbalance ratio)
  - Model 8 (max_depth=4): scale_pos_weight=4.5 (~square root of imbalance ratio)

- Model 9 (max_depth=6): scale_pos_weight=20 (~imbalance ratio)

In [24]:
```
# Imbalance info using class_weight.compute_class_weight

print('Class Weights:')

df_list = [df1, df2, df3, df4, df5]

for i, df in enumerate(df_list, start=1):
    class_weights = class_weight.compute_class_weight(class_weight='balance
    ratio = class_weights[1]/class_weights[0]
    sqrt_ratio = np.sqrt(class_weights[1]/class_weights[0])
    print(f'Data {i}: Ratio={round(ratio,3)}, sqrt(ratio)={round(sqrt_ratio

# The values are very similar for train/test/whole datasets.
# Training weights are used for data training.
```

```
Class Weights:
Data 1: Ratio=24.93, sqrt(ratio)=4.993, class_weights=[ 0.52005625 12.964
94465]
Data 2: Ratio=24.432, sqrt(ratio)=4.943, class_weights=[ 0.52046455 12.71
625    ]
Data 3: Ratio=20.218, sqrt(ratio)=4.496, class_weights=[ 0.52473022 10.60
909091]
Data 4: Ratio=18.014, sqrt(ratio)=4.244, class_weights=[0.52775682 9.5067
9612]
Data 5: Ratio=13.415, sqrt(ratio)=3.663, class_weights=[0.53727273 7.2073
1707]
```

In [25]:
```
# Imbalance info using class value_counts

print('Imbalance Ratio, based on class value_counts:')

df_list = [df1, df2, df3, df4, df5]

for i, df in enumerate(df_list, start=1):
    val_counts = df['class'].value_counts()
    ratio= val_counts[0]/val_counts[1]
    sqrt_ratio= np.sqrt(val_counts[0]/val_counts[1])
    print(f'Data {i}: Ratio={round(ratio,3)}, sqrt(ratio)={round(sqrt_ratio

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

```
Imbalance Ratio, based on class value_counts:
Data 1: Ratio=24.93, sqrt(ratio)=4.993
Data 2: Ratio=24.432, sqrt(ratio)=4.943
Data 3: Ratio=20.218, sqrt(ratio)=4.496
Data 4: Ratio=18.014, sqrt(ratio)=4.244
Data 5: Ratio=13.415, sqrt(ratio)=3.663
```

Compare Model 7, 9, 10 Performance on All Datasets

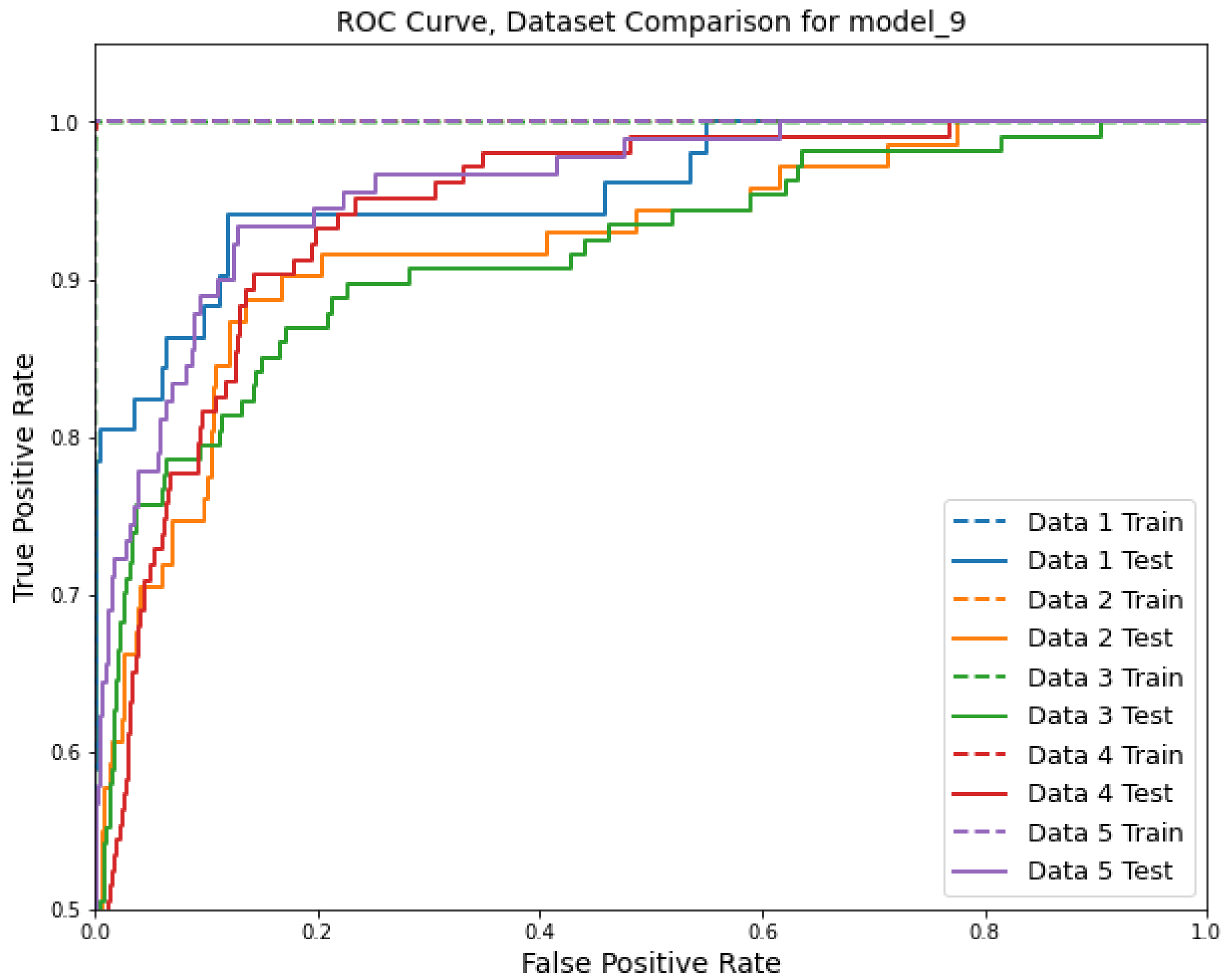
In [26]:

```python
# Model 9: Best Model for Data 3, max_depth=4

xgbParams_m9 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'scale_pos_weight': 4.5,
    'n_estimators': 125,
    'max_depth': 4,
    'min_child_weight': 3,
    'gamma': 0,
    'learning_rate': 0.20,
    'max_delta_step': 0,
    'reg_lambda': 1,
    'reg_alpha': 0,
    'subsample': 1,
    'colsample_bytree': 1
}

df_list = [df1, df2, df3, df4, df5]
#df_list = [df1, df2]

model_9_df = compare_datafiles_perf(df_list, xgbParams_m9, 'model_9', 1, 1,
model_9_df
```

```
------model_9------
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
```

Out[26]:

Data	Sample	precision	recall	f1	accuracy	auc
Data 1	Train	0.9610	1.0000	0.9800	0.998	1.0000
Data 1	Test	0.7190	0.8040	0.7590	0.982	0.9570
Data 2	Train	0.8410	1.0000	0.9140	0.992	1.0000
Data 2	Test	0.4830	0.6060	0.5380	0.964	0.9210
Data 3	Train	0.7190	1.0000	0.8360	0.982	1.0000
Data 3	Test	0.5540	0.7200	0.6260	0.956	0.9160
Data 4	Train	0.7440	1.0000	0.8530	0.982	1.0000
Data 4	Test	0.4960	0.6600	0.5670	0.947	0.9420
Data 5	Train	0.9500	1.0000	0.9740	0.996	1.0000
Data 5	Test	0.6600	0.7330	0.6950	0.951	0.9580
Average	Train	0.8430	1.0000	0.9114	0.990	1.0000
Average	Test	0.5824	0.7046	0.6370	0.960	0.9388



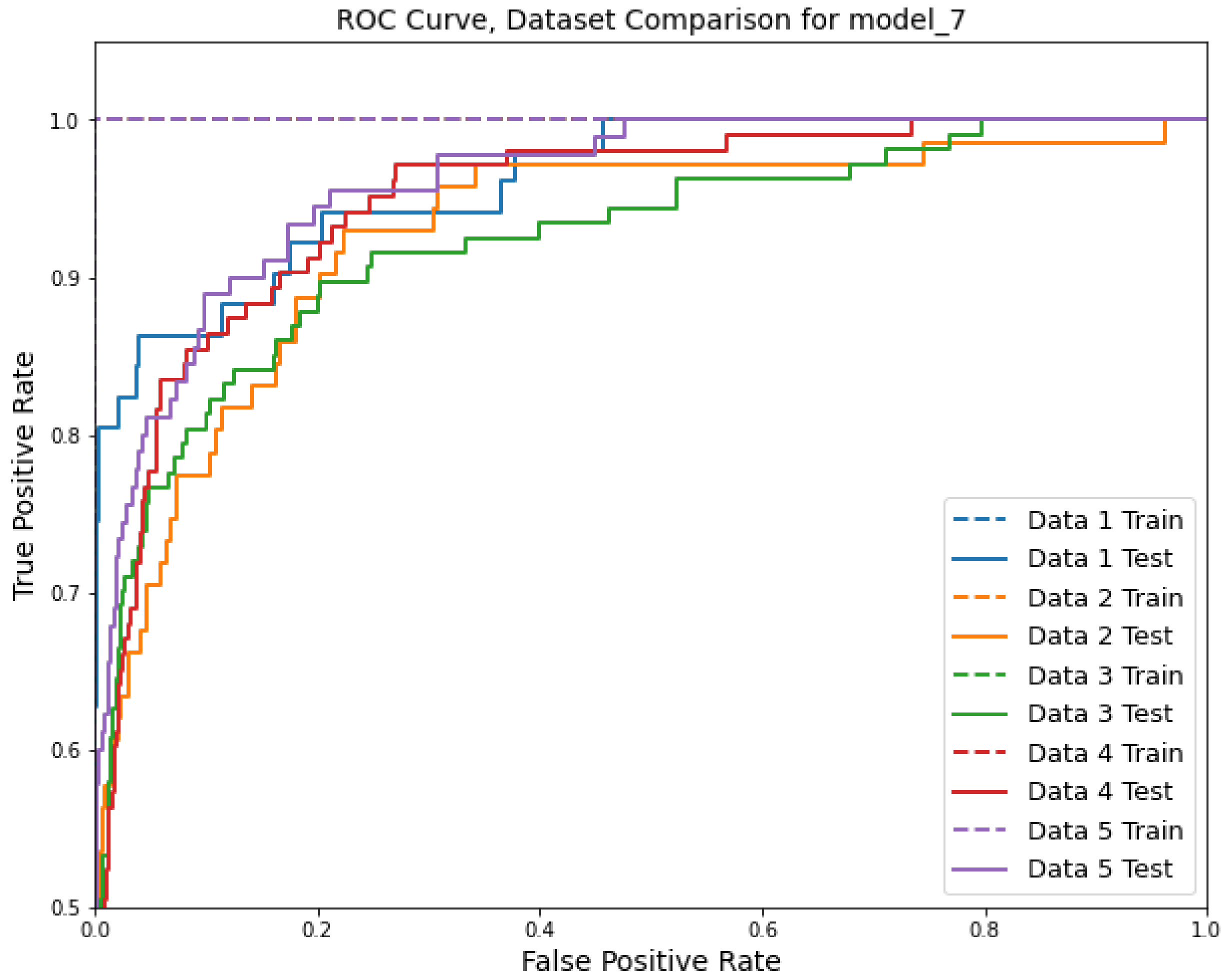
ROC Curve, Dataset Comparison for model_9
True Positive Rate
False Positive Rate
0.5
0.6
0.7
0.8
0.9
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Data 1 Train
Data 1 Test
Data 2 Train
Data 2 Test
Data 3 Train
Data 3 Test
Data 4 Train
Data 4 Test
Data 5 Train
Data 5 Test

In [29]:
```
# Model 7, max_depth=5

xgbParams_m7 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'scale_pos_weight': 20,
    'n_estimators': 125,
    'max_depth': 5,
    'min_child_weight': 3,
    'gamma': 0,
    'learning_rate': 0.20,
    'max_delta_step': 0,
    'reg_lambda': 0,
    'reg_alpha': 5,
    'subsample': 1,
    'colsample_bytree': 0.7
}

df_list = [df1, df2, df3, df4, df5]

model_7_df = compare_datafiles_perf(df_list, xgbParams_m7, 'model_7', 1, 1,
model_7_df
```

```
------model_7------
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
```

Out[29]:

	Sample	precision	recall	f1	accuracy	auc
Data						
Data 1	Train	0.8700	1.0000	0.9300	0.9940	1.0000
Data 1	Test	0.6410	0.8040	0.7130	0.9770	0.9610
Data 2	Train	0.8750	1.0000	0.9330	0.9940	1.0000
Data 2	Test	0.5060	0.6200	0.5570	0.9660	0.9280
Data 3	Train	0.7710	1.0000	0.8710	0.9860	1.0000
Data 3	Test	0.5350	0.7200	0.6140	0.9540	0.9230
Data 4	Train	0.8060	1.0000	0.8930	0.9870	1.0000
Data 4	Test	0.5560	0.6800	0.6110	0.9550	0.9490
Data 5	Train	0.8290	1.0000	0.9070	0.9860	1.0000
Data 5	Test	0.6070	0.7890	0.6860	0.9450	0.9600
Average	Train	0.8302	1.0000	0.9068	0.9894	1.0000
Average	Test	0.5690	0.7226	0.6362	0.9594	0.9442


ROC Curve, Dataset Comparison for model_7
True Positive Rate
False Positive Rate
1.0
0.9
0.8
0.7
0.6
0.5
0.0
0.2
0.4
0.6
0.8
1.0
Data 1 Train
Data 1 Test
Data 2 Train
Data 2 Test
Data 3 Train
Data 3 Test
Data 4 Train
Data 4 Test
Data 5 Train
Data 5 Test

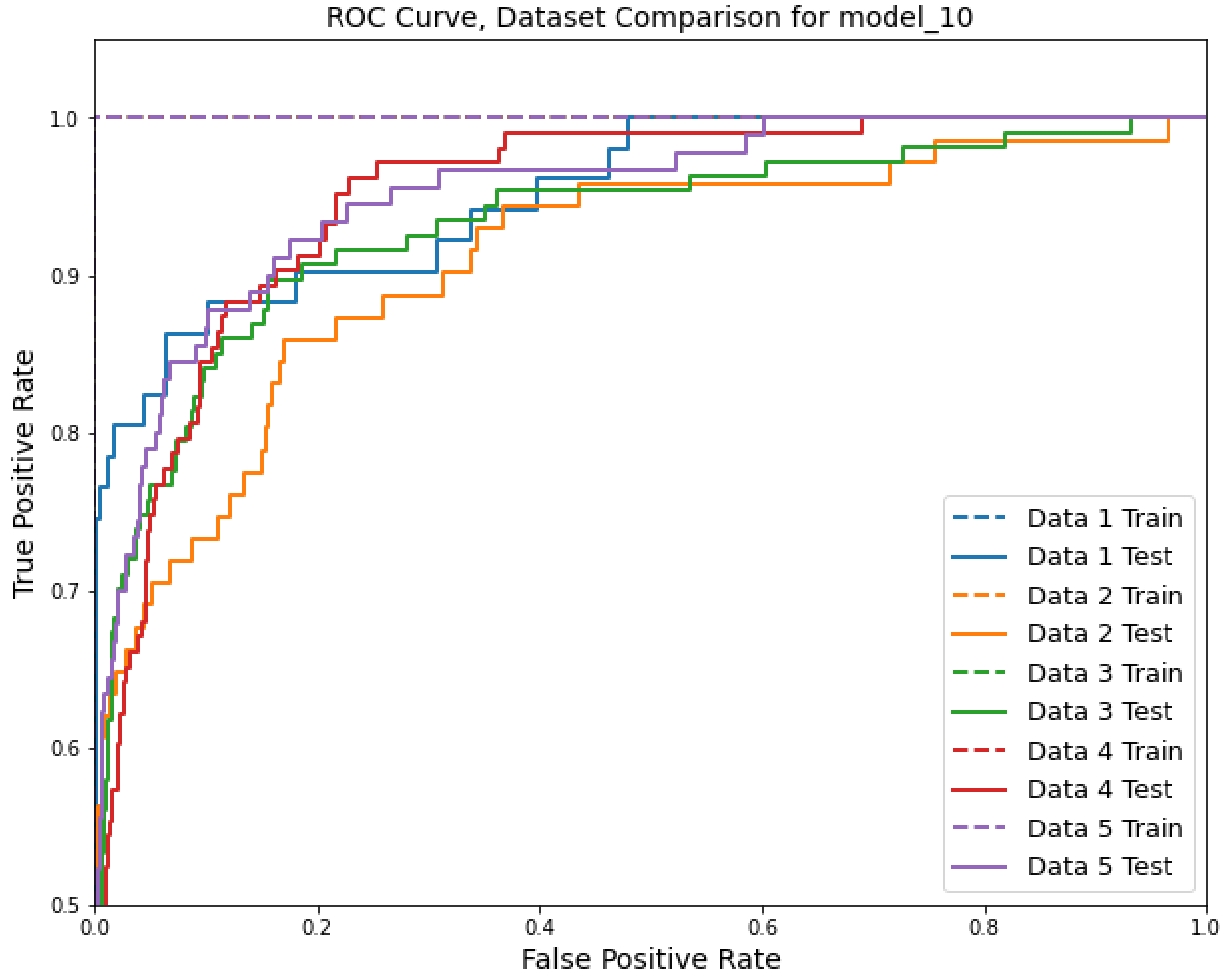
In [27]:

```python
# Model 10, max_depth=6

xgbParams_m10 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'scale_pos_weight': 20,
    'n_estimators': 80,
    'max_depth': 6,
    'min_child_weight': 3,
    'gamma': 0,
    'learning_rate': 0.25,
    'max_delta_step': 4,
    'reg_lambda': 1,
    'reg_alpha': 0,
    'subsample': 1,
    'colsample_bytree': 1,
}

df_list = [df1, df2, df3, df4, df5]

model_10_df = compare_datafiles_perf(df_list, xgbParams_m10, 'model_10', 1,
model_10_df
```

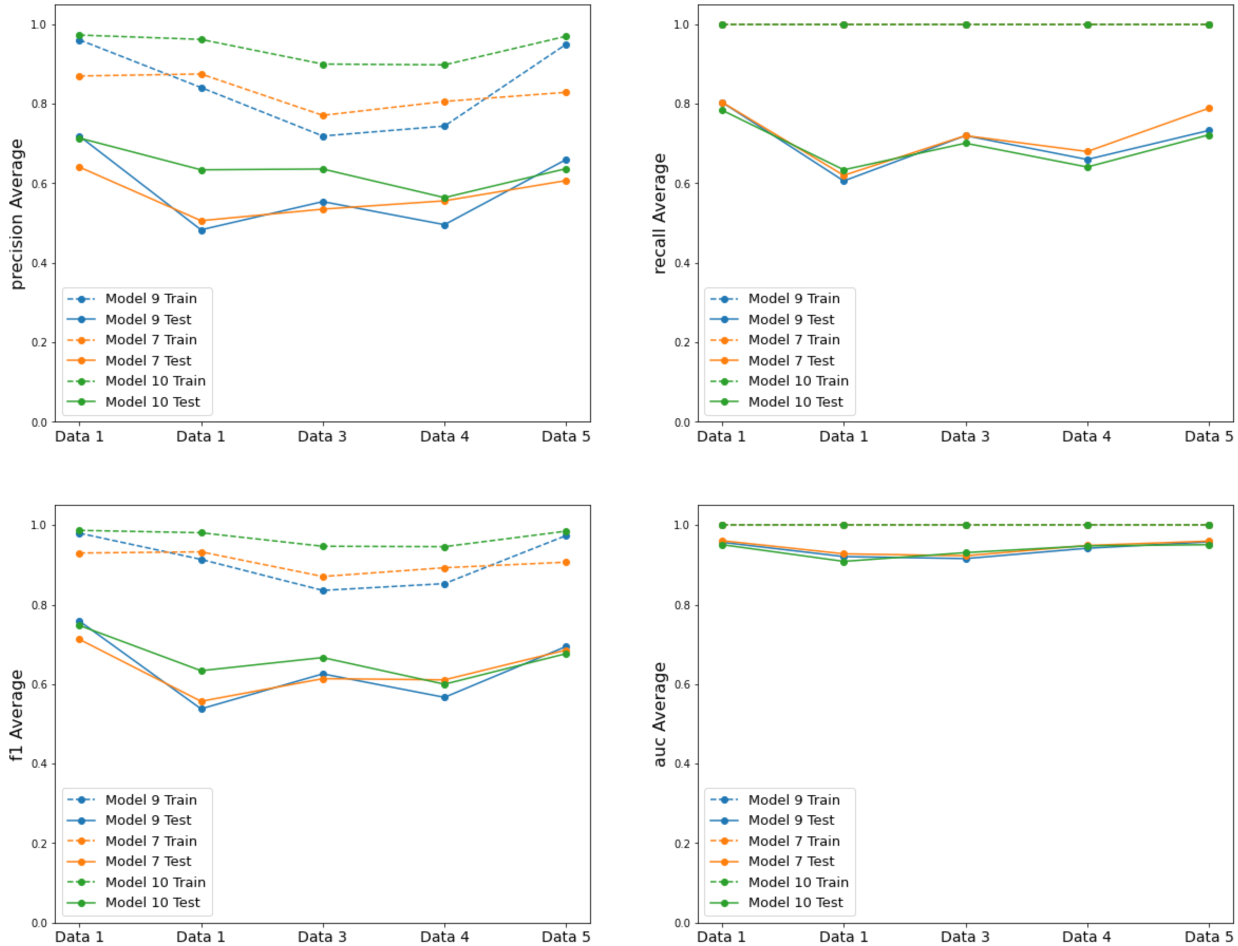
```
------model_10------
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
```

Out[27]:

Data	Sample	precision	recall	f1	accuracy	auc
Data 1	Train	0.9730	1.0000	0.9870	0.9990	1.000
Data 1	Test	0.7140	0.7840	0.7480	0.9810	0.951
Data 2	Train	0.9620	1.0000	0.9810	0.9980	1.000
Data 2	Test	0.6340	0.6340	0.6340	0.9740	0.909
Data 3	Train	0.9000	1.0000	0.9470	0.9950	1.000
Data 3	Test	0.6360	0.7010	0.6670	0.9640	0.931
Data 4	Train	0.8980	1.0000	0.9460	0.9940	1.000
Data 4	Test	0.5640	0.6410	0.6000	0.9550	0.948
Data 5	Train	0.9700	1.0000	0.9850	0.9980	1.000
Data 5	Test	0.6370	0.7220	0.6770	0.9480	0.951
Average	Train	0.9406	1.0000	0.9692	0.9968	1.000
Average	Test	0.6370	0.6964	0.6652	0.9644	0.938


ROC Curve, Dataset Comparison for model_10
True Positive Rate
False Positive Rate
1.0
0.9
0.8
0.7
0.6
0.5
0.0
0.2
0.4
0.6
0.8
1.0
Data 1 Train
Data 1 Test
Data 2 Train
Data 2 Test
Data 3 Train
Data 3 Test
Data 4 Train
Data 4 Test
Data 5 Train
Data 5 Test

In [31]:
```
model_df_list = [model_9_df, model_7_df, model_10_df]

model_names_list = ['Model 9', 'Model 7', 'Model 10']

plot_compare_model_metricsAvg(model_df_list, model_names_list, 1)
```



Comments

```
Model 9 (max_depth=4):
    * Previously Selected performance for data 3
    * Overfitting is least on Data 3

Model 7 (max_depth=5):
    * Performance is similar to Model 9
    * More smooth performance on all datasets

Model 10 (max_depth=6):
    * Highest metrics
    * But overfitting is sligtly larger

Selected model: Model 7
```

Some Tuning and Comparing

In [9]:
```
# sample_weight only, no scale_pos_weight

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    #'scale_pos_weight': 4.5,
    'n_estimators': 125,
    'max_depth': 4,
    'min_child_weight': 3,
    'gamma': 0,
    'learning_rate': 0.20,
    'max_delta_step': 0,
    'reg_lambda': 1,
    'reg_alpha': 0,
    'subsample': 1,
    'colsample_bytree': 1
}

df_list = [df1, df2, df3, df4, df5]

model_noSpw_df = compare_datafiles_perf(df_list, xgbParams, 'noSpw', 1, 0,
model_noSpw_df
```

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

Out[9]:

Data	Sample	precision	recall	f1	accuracy	auc
Data 1	Train	0.9780	1.0000	0.9890	0.9990	1.0000
Data 1	Test	0.8700	0.7840	0.8250	0.9880	0.9680
Data 2	Train	0.9450	1.0000	0.9720	0.9980	1.0000
Data 2	Test	0.6830	0.5770	0.6260	0.9760	0.9360
Data 3	Train	0.8840	1.0000	0.9380	0.9940	1.0000
Data 3	Test	0.7000	0.6540	0.6760	0.9680	0.9310
Data 4	Train	0.9260	1.0000	0.9610	0.9960	1.0000
Data 4	Test	0.6090	0.5150	0.5580	0.9570	0.9450
Data 5	Train	0.9730	1.0000	0.9860	0.9980	1.0000
Data 5	Test	0.7360	0.7110	0.7230	0.9590	0.9580
Average	Train	0.9412	1.0000	0.9692	0.9970	1.0000
Average	Test	0.7196	0.6482	0.6816	0.9696	0.9476

In [10]:

```
#n_estimators=100

xgbParams_11 = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'scale_pos_weight': 4.5,
    'n_estimators': 100,
    'max_depth': 4,
    'min_child_weight': 3,
    'gamma': 0,
    'learning_rate': 0.20,
    'max_delta_step': 0,
    'reg_lambda': 1,
    'reg_alpha': 0,
    'subsample': 1,
    'colsample_bytree': 1
}

df_list = [df1, df2, df3, df4, df5]

model_nEst100_df = compare_datafiles_perf(df_list, xgbParams_11, 'nEst100',
model_nEst100_df
```

```
------nEst100------
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
```

Out[10]:

Data	Sample	precision	recall	f1	accuracy	auc
Data 1	Train	0.8980	1.0000	0.946	0.9960	1.000
Data 1	Test	0.6610	0.8040	0.726	0.9780	0.957
Data 2	Train	0.6730	1.0000	0.804	0.9800	1.000
Data 2	Test	0.4020	0.6620	0.500	0.9540	0.925
Data 3	Train	0.6090	1.0000	0.757	0.9700	1.000
Data 3	Test	0.4910	0.7480	0.593	0.9480	0.916
Data 4	Train	0.6250	1.0000	0.769	0.9680	1.000
Data 4	Test	0.4270	0.6800	0.524	0.9350	0.938
Data 5	Train	0.8420	1.0000	0.914	0.9870	1.000
Data 5	Test	0.6110	0.7330	0.667	0.9440	0.959
Average	Train	0.7294	1.0000	0.838	0.9802	1.000
Average	Test	0.5184	0.7254	0.602	0.9518	0.939

In [11]:

```
# reg_lambda=5

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'scale_pos_weight': 4.5,
    'n_estimators': 125,
    'max_depth': 4,
    'min_child_weight': 3,
    'gamma': 0,
    'learning_rate': 0.20,
    'max_delta_step': 0,
    'reg_lambda': 5,
    'reg_alpha': 0,
    'subsample': 1,
    'colsample_bytree': 1
}

df_list = [df1, df2, df3, df4, df5]

model_lambda5_df = compare_datafiles_perf(df_list, xgbParams, 'lambda5', 1,
model_lambda5_df
```

```
------lambda5------
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
```

Out[11]:

Data	Sample	precision	recall	f1	accuracy	auc
Data 1	Train	0.9170	1.0000	0.9570	0.9960	1.000
Data 1	Test	0.7320	0.8040	0.7660	0.9820	0.968
Data 2	Train	0.7950	1.0000	0.8860	0.9900	1.000
Data 2	Test	0.4730	0.6200	0.5370	0.9630	0.940
Data 3	Train	0.6470	1.0000	0.7850	0.9750	1.000
Data 3	Test	0.5070	0.7200	0.5950	0.9500	0.924
Data 4	Train	0.7330	1.0000	0.8460	0.9810	1.000
Data 4	Test	0.5220	0.6890	0.5940	0.9500	0.952
Data 5	Train	0.8600	1.0000	0.9250	0.9890	1.000
Data 5	Test	0.6190	0.7780	0.6900	0.9470	0.961
Average	Train	0.7904	1.0000	0.8798	0.9862	1.000
Average	Test	0.5706	0.7222	0.6364	0.9584	0.949

In [12]:

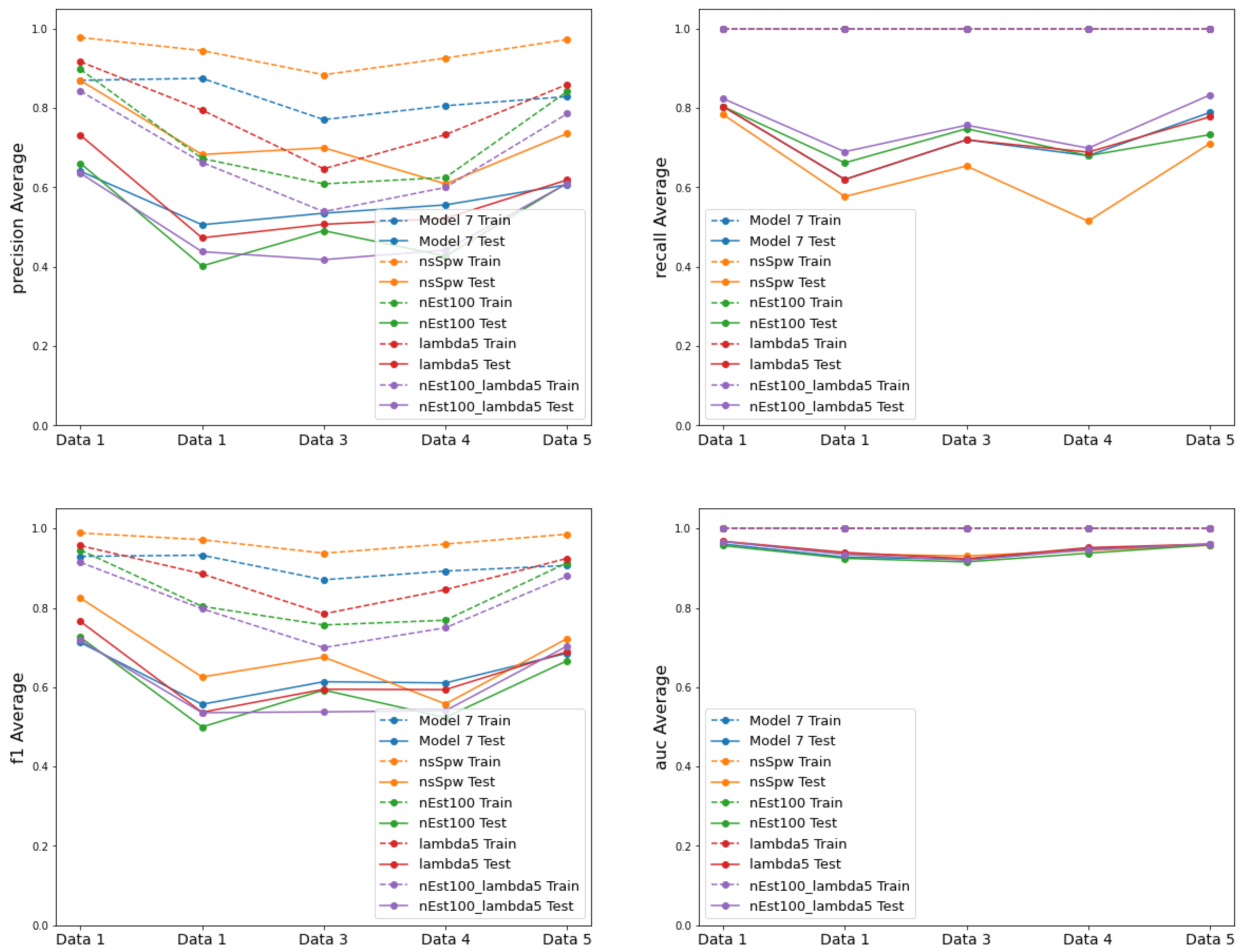
```
#n_estimators=100
# reg_lambda=5

xgbParams = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'scale_pos_weight': 4.5,
    'n_estimators': 100,
    'max_depth': 4,
    'min_child_weight': 3,
    'gamma': 0,
    'learning_rate': 0.20,
    'max_delta_step': 0,
    'reg_lambda': 5,
    'reg_alpha': 0,
    'subsample': 1,
    'colsample_bytree': 1
}

df_list = [df1, df2, df3, df4, df5]

model_nEst100_lambda5_df = compare_datafiles_perf(df_list, xgbParams, 'nEst
model_nEst100_lambda5_df
```

```
------nEst100_lambda5------
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
Sample weights are used!
```

Out[12]:

	Sample	precision	recall	f1	accuracy	auc
Data						
Data 1	Train	0.8430	1.0000	0.9150	0.9930	1.000
Data 1	Test	0.6360	0.8240	0.7180	0.9770	0.967
Data 2	Train	0.6630	1.0000	0.7980	0.9790	1.000
Data 2	Test	0.4380	0.6900	0.5360	0.9580	0.935
Data 3	Train	0.5390	1.0000	0.7000	0.9600	1.000
Data 3	Test	0.4180	0.7570	0.5380	0.9340	0.920
Data 4	Train	0.6000	1.0000	0.7500	0.9650	1.000
Data 4	Test	0.4420	0.6990	0.5410	0.9380	0.947
Data 5	Train	0.7860	1.0000	0.8800	0.9820	1.000
Data 5	Test	0.6100	0.8330	0.7040	0.9470	0.961
Average	Train	0.6862	1.0000	0.8086	0.9758	1.000
Average	Test	0.5088	0.7606	0.6074	0.9508	0.946

```
In [29]: model_df_list2 = [model_7_df, model_noSpw_df, model_nEst100_df, model_lambd

         model_names_list2 = ['Model 7', 'nsSpw', 'nEst100', 'lambda5', 'nEst100_lam

         plot_compare_model_metricsAvg(model_df_list2, model_names_list2)
```



Comments

After some tuning, still best performance is Model 7.

Final Model

Model 7 has the best performance.

In [7]:

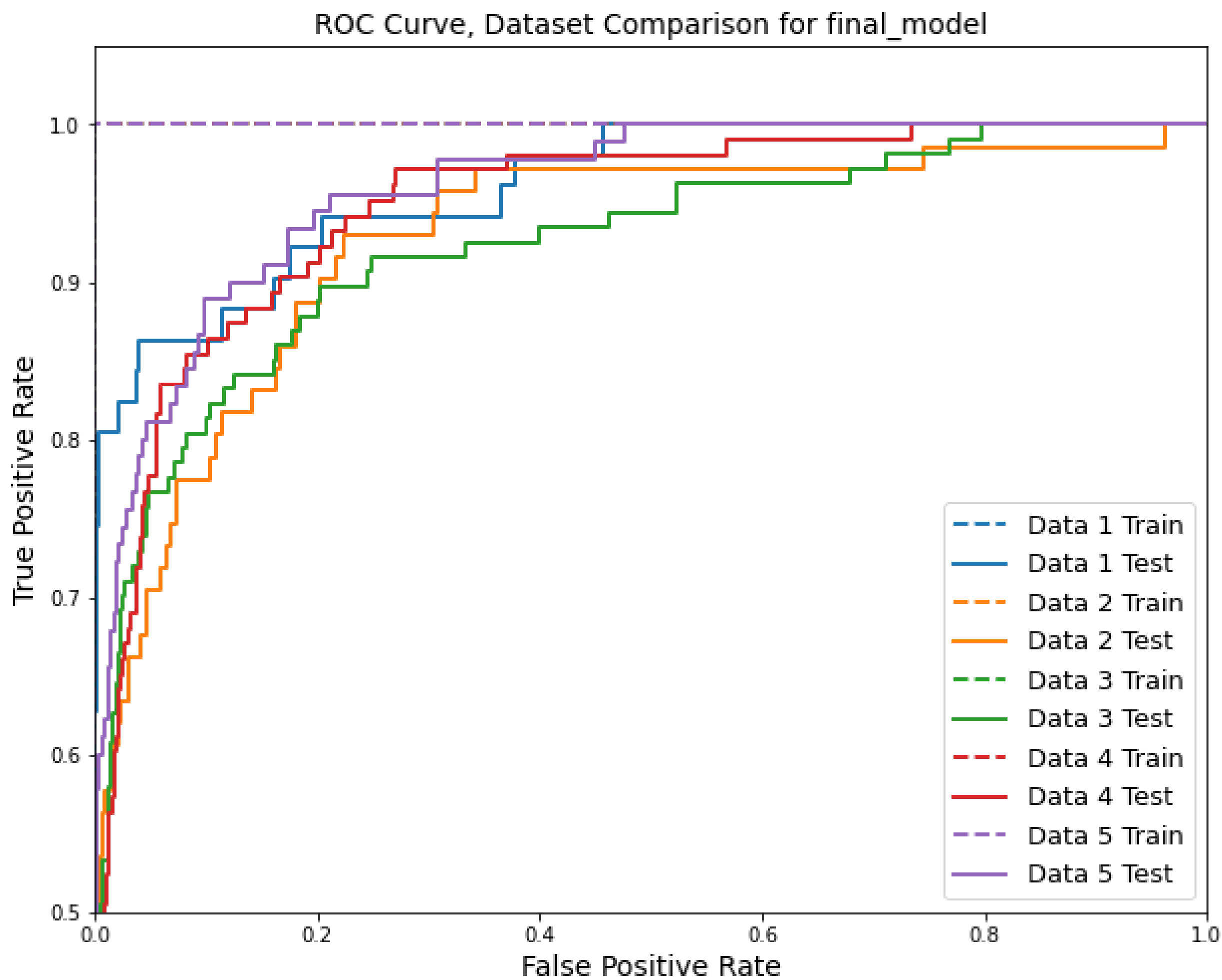
```
# Final Model Parameters
# Model 7, max_depth=5

xgbParams_final = {
    'eval_metric': 'logloss',
    'random_state': 42,
    'scale_pos_weight': 20,
    'n_estimators': 125,
    'max_depth': 5,
    'min_child_weight': 3,
    'gamma': 0,
    'learning_rate': 0.20,
    'max_delta_step': 0,
    'reg_lambda': 0,
    'reg_alpha': 5,
    'subsample': 1,
    'colsample_bytree': 0.7
}
```

In [8]:
```
# Final Model Results for All data files

df_list = [df1, df2, df3, df4, df5]

final_model_df = compare_datafiles_perf(df_list, xgbParams_final, 'final_mo
final_model_df
```

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

Out[8]:

Data	Sample	precision	recall	f1	accuracy	auc
Data 1	Train	0.8700	1.0000	0.9300	0.9940	1.0000
Data 1	Test	0.6410	0.8040	0.7130	0.9770	0.9610
Data 2	Train	0.8750	1.0000	0.9330	0.9940	1.0000
Data 2	Test	0.5060	0.6200	0.5570	0.9660	0.9280
Data 3	Train	0.7710	1.0000	0.8710	0.9860	1.0000
Data 3	Test	0.5350	0.7200	0.6140	0.9540	0.9230
Data 4	Train	0.8060	1.0000	0.8930	0.9870	1.0000
Data 4	Test	0.5560	0.6800	0.6110	0.9550	0.9490
Data 5	Train	0.8290	1.0000	0.9070	0.9860	1.0000
Data 5	Test	0.6070	0.7890	0.6860	0.9450	0.9600
Average	Train	0.8302	1.0000	0.9068	0.9894	1.0000
Average	Test	0.5690	0.7226	0.6362	0.9594	0.9442



In [9]:
```
# Data 1 Final Model
d1_final_model = xgb_model_report2(1, df1, xgbParams_final, 'final_model',
```

```
Sample weights are used!
Data 1 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      5401
           1       0.87      1.00      0.93       220

    accuracy                           0.99      5621
   macro avg       0.93      1.00      0.96      5621
weighted avg       0.99      0.99      0.99      5621

Testing Data:
              precision    recall  f1-score   support

           0       0.99      0.98      0.99      1355
           1       0.64      0.80      0.71        51

    accuracy                           0.98      1406
   macro avg       0.82      0.89      0.85      1406
weighted avg       0.98      0.98      0.98      1406
```

In [10]:
```python
# Data 2 Final Model
d2_final_model = xgb_model_report2(2, df2, xgbParams_final, 'final_model',
```

```
Sample weights are used!
Data 2 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      7809
           1       0.88      1.00      0.93       329

    accuracy                           0.99      8138
   macro avg       0.94      1.00      0.97      8138
weighted avg       0.99      0.99      0.99      8138

Testing Data:
              precision    recall  f1-score   support

           0       0.99      0.98      0.98      1964
           1       0.51      0.62      0.56        71

    accuracy                           0.97      2035
   macro avg       0.75      0.80      0.77      2035
weighted avg       0.97      0.97      0.97      2035
```

In [11]:
```python
# Data 3 Final Model
d3_final_model = xgb_model_report2(3, df3, xgbParams_final, 'final_model',
```

```
Sample weights are used!
Data 3 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      8014
           1       0.77      1.00      0.87       388

    accuracy                           0.99      8402
   macro avg       0.89      0.99      0.93      8402
weighted avg       0.99      0.99      0.99      8402

Testing Data:
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      1994
           1       0.53      0.72      0.61       107

    accuracy                           0.95      2101
   macro avg       0.76      0.84      0.79      2101
weighted avg       0.96      0.95      0.96      2101
```

In [12]:
```python
# Data 4 Final Model
d4_final_model = xgb_model_report2(4, df4, xgbParams_final, 'final_model',
```

```
Sample weights are used!
Data 4 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      7421
           1       0.81      1.00      0.89       412

    accuracy                           0.99      7833
   macro avg       0.90      0.99      0.94      7833
weighted avg       0.99      0.99      0.99      7833

Testing Data:
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      1856
           1       0.56      0.68      0.61       103

    accuracy                           0.95      1959
   macro avg       0.77      0.82      0.79      1959
weighted avg       0.96      0.95      0.96      1959
```

In [13]:
```python
# Data 5 Final Model
d5_final_model = xgb_model_report2(5, df5, xgbParams_final, 'final_model',
```

```
Sample weights are used!
Data 5 Classification Report:

Training Data:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      4408
           1       0.83      1.00      0.91       320

    accuracy                           0.99      4728
   macro avg       0.91      0.99      0.95      4728
weighted avg       0.99      0.99      0.99      4728

Testing Data:
              precision    recall  f1-score   support

           0       0.98      0.96      0.97      1092
           1       0.61      0.79      0.69        90

    accuracy                           0.95      1182
   macro avg       0.79      0.87      0.83      1182
weighted avg       0.95      0.95      0.95      1182
```

Best Predictor Atttributes

Best Predictor Attributes

In [14]:

```
# List important attitudes

final_model_list = [d1_final_model, d2_final_model, d3_final_model, d4_fina

df_important_Attr = pd.DataFrame()
cols = df1.columns

for i,df in enumerate(final_model_list, start=1):
    importance = df.feature_importances_
    attribute_importance = pd.DataFrame([cols, importance], index=['Attribu
    attribute_importance.sort_values(by='Importance', ascending=False, inpl
    df_important_Attr[f'Data{i}'] = attribute_importance['Attribute'][0:20]

df_important_Attr
```

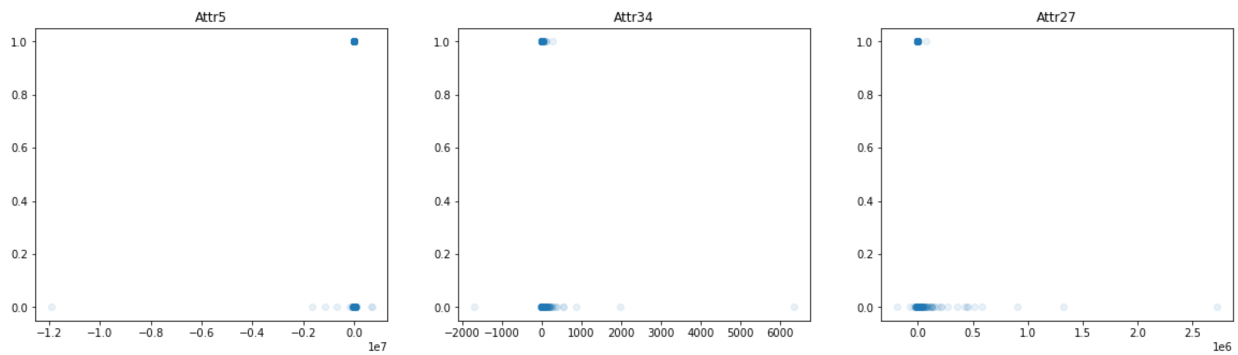
Out[14]:

	Data1	Data2	Data3	Data4	Data5
0	Attr6	Attr34	Attr34	Attr62	Attr62
1	Attr34	Attr59	Attr52	Attr33	Attr34
2	Attr22	Attr10	Attr10	Attr31	Attr64
3	Attr24	Attr5	Attr26	Attr6	Attr7
4	Attr27	Attr7	Attr27	Attr34	Attr27
5	Attr8	Attr26	Attr25	Attr27	Attr6
6	Attr25	Attr27	Attr35	Attr26	Attr42
7	Attr1	Attr11	Attr19	Attr42	Attr16
8	Attr49	Attr15	Attr59	Attr52	Attr49
9	Attr45	Attr25	Attr31	Attr13	Attr5
10	Attr5	Attr16	Attr13	Attr57	Attr48
11	Attr13	Attr24	Attr24	Attr21	Attr25
12	Attr21	Attr41	Attr16	Attr64	Attr51
13	Attr59	Attr23	Attr37	Attr41	Attr43
14	Attr51	Attr58	Attr58	Attr1	Attr31
15	Attr37	Attr20	Attr6	Attr5	Attr23
16	Attr35	Attr42	Attr2	Attr37	Attr2
17	Attr48	Attr17	Attr5	Attr24	Attr50
18	Attr50	Attr13	Attr21	Attr59	Attr21
19	Attr42	Attr22	Attr12	Attr15	Attr14

In [15]:
```python
#Common Best predictors

set1 = set(df_important_Attr['Data1'])
set2 = set(df_important_Attr['Data2'])
set3 = set(df_important_Attr['Data3'])
set4 = set(df_important_Attr['Data4'])
set5 = set(df_important_Attr['Data5'])

important_attr_common = set.intersection(set1, set2, set3, set4, set5)
important_attr_common
```

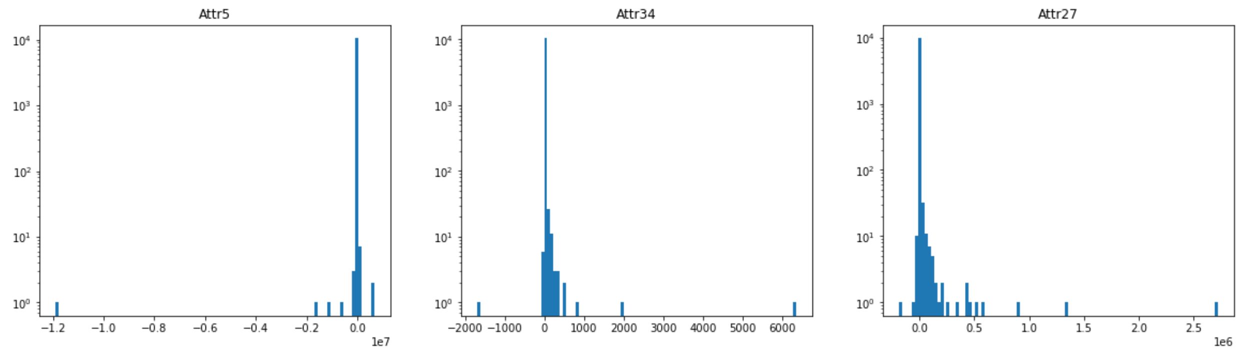
Out[15]:
```
{'Attr27', 'Attr34', 'Attr5'}
```

In [19]:
```python
# Scatter Graphs, Data 3

plt.figure(figsize=(20, 5))

for i, col in enumerate(important_attr_common, start=1):
    plt.subplot(1, 3, i)
    plt.scatter(df3[col], df3['class'], alpha=0.1)
    plt.title(col)

plt.savefig('figures/scatter_d3_importantAttr.png')
```



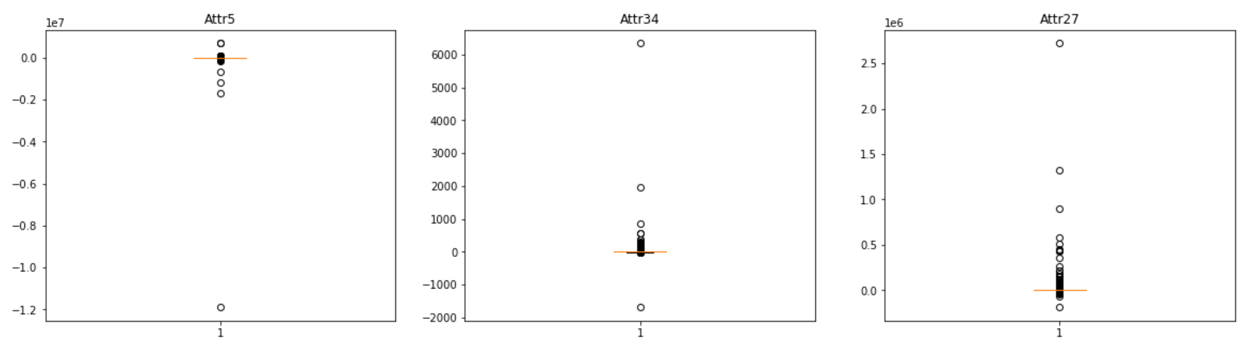
In [20]:

```python
# Histograms

plt.figure(figsize=(20, 5))

for i, col in enumerate(important_attr_common, start=1):
    plt.subplot(1, 3, i)
    plt.hist(df3[col], bins=100, log=True)
    plt.title(col)

plt.savefig('figures/hist_d3_log_importantAttr.png')
```



In [18]:

```python
# Box plots

plt.figure(figsize=(20, 5))

for i, col in enumerate(important_attr_common, start=1):
    plt.subplot(1, 3, i)
    plt.boxplot(df3[col].dropna())
    plt.title(col)

plt.savefig('figures/boxPlot_d3_importantAttr.png')

## Boxplot only draws the attribute only when missing entries removed.
```



Interpretation of Results

5-year Period (Data 1):

- Model correctly identifies the 80.4% of the true bankrupt companies, which will bankrupt 5 years later. (recall)
- Among the model predicted bankruptcy companies, 64.1% of them are true bankrupt companies, which will bankrupt 5 years later. (precision)

- The Harmonic Mean of Precision and Recall (f1-score) is 71.3%.

4-year Period (Data 2):

- Model correctly identifies the 62.0% of the true bankrupt companies, which will bankrupt 4 years later. (recall)
- Among the model predicted bankruptcy companies, 50.6% of them are true bankrupt companies, which will bankrupt 4 years later. (precision)
- The Harmonic Mean of Precision and Recall (f1-score) is 55.7%.

3-year Period (Data 3):

- Model correctly identifies the 72.0% of the true bankrupt companies, which will bankrupt 3 years later. (recall)
- Among the model predicted bankruptcy companies, 53.5% of them are true bankrupt companies, which will bankrupt 3 years later. * The Harmonic Mean of Precision and Recall (f1-score) is 61.4%.

2-year Period (Data 4):

- Model correctly identifies the 68.0% of the true bankrupt companies, which will bankrupt 2 years later. (recall)
- Among the model predicted bankruptcy companies, 55.6% of them are true bankrupt companies, which will bankrupt 2 years later. (precision)
- The Harmonic Mean of Precision and Recall (f1-score) is 61.1%.

1-year Period (Data 5):

- Model correctly identifies the 78.9% of the true bankrupt companies, which will bankrupt 1 years later. (recall)
- Among the model predicted bankruptcy companies, 60.7% of them are true bankrupt companies, which will bankrupt 1 years later. (precision)
- The Harmonic Mean of Precision and Recall (f1-score) is 68.6%.

On Average:

- Model correctly identifies the 72.3% of the true bankrupt companies. (recall)
- Among the model predicted bankruptcy companies, 56.9% of them are true bankrupt companies. (precision)
- The Harmonic Mean of Precision and Recall (f1-score) is 63.6%.

Class 0 predictions:

- Model correctly identifies the ~97% of the true still operating companies. (recall, class 0)
- Among the model predicted still operating companies, ~98% of them are true still operating companies. (precision, class 0)
- The Harmonic Mean of Precision and Recall (f1-score, class 0) is ~98%.

Best common predictors

- X27 profit on operating activities / financial expenses
- X34 operating expenses / total liabilities

- X5 [(cash + short-term securities + receivables - short-term liabilities) / (operating expenses - depreciation)] * 365

Conclusion

I had three main challenges in this project:

1. **Class Imbalance:**

    - Resolved.
    - Balancing the sample increased the recall and so decreased the precision. The balance sample has moderate evaluation scores. See Model 2 for Data 3.
    - However overfitting didn't improve much.
2. **Low recall score:**

    - I managed to improve recall significantly for all datasets. For instance, Data 3 recall score improved from 0.467 to 0.720.
    - I couldn't go for higher recall value, because the precision was decreasing dramatically (below 0.5). The recall and precision are inversely proportional.
3. **Large overfitting:**

    - I did decrease the overfitting, but not on desired level.
    - I tuned parameters which are effecive on overfitting, and find the optimum designs that produces low overfitting, large recall and moderate precision.
    - However, I couldn't enforce larger reduction in overfitting, since it causes the precision go below 0.5. which is the random guess probability.

Overall, my model correctly identifies

```
* 72.3 of the true bankrupt companies
* 97% of the true still operating companies
```

Future Work

- Create seperate final models for each dataset; not just one final model that applies on all.
- Search for alternative Classifier methods/tools.
- Simply/shorten functions that are created during the project. They have repeating codes.