WorstCase MIA attack result report

Introduction

This report provides a summary of a series of simulated attack experiments performed on the model outputs provided. An attack model is trained to attempt to distinguish between outputs from training (in-sample) and testing (out-of-sample) data. The metrics below describe the success of this classifier. A successful classifier indicates that the original model is unsafe and should not be allowed to be released from the TRE.
In particular, the simulation splits the data provided into test and train sets (each will in- and out-of-sample examples). The classifier is trained on the train set and evaluated on the test set. This is repeated with different train/test splits a user-specified number of times.
To help place the results in context, the code may also have run a series of baseline experiments. In these, random model outputs for hypothetical in- and out-of-sample data are generated with identical statistical properties. In these baseline cases, there is no signal that an attacker could leverage and therefore these values provide a baseline against which the actual values can be compared.
For some metrics (FDIF and AUC), we are able to compute p-values. In each case, shown below (in the Global metrics sections) is the number of repetitions that exceeded the p-value threshold both without, and with correction for multiple testing (Benjamini-Hochberg procedure).
ROC curves for all real (red) and dummy (blue) repetitions are provided. These are shown in log space (as reommended here [ADD URL]) to emphasise the region in which risk is highest -- the bottom left (are high true positive rates possible with low false positive rates).
A description of the metrics and how to interpret them within the context of an attack is given below.

Experiment summary

```
                      n_reps: 10
             reproduce_split: [5, 25, 36, 49, 64, 81, 100, 121, 144, 169]
                    p_thresh: 0.05
                n_dummy_reps: 10
                  train_beta: 1
                   test_beta: 1
                   test_prop: 0.2
                   n_rows_in: 1200
                  n_rows_out: 300
    training_preds_filename: None
        test_preds_filename: None
                 output_dir: ./SVM_unsafe_90synth
                report_name: attack_output
 include_model_correct_feature: False
                 sort_probs: True
           mia_attack_model: <class
'sklearn.ensemble._forest.RandomForestClassifier'>
       mia_attack_model_hyp: {'min_samples_split': 20, 'min_samples_leaf':
10, 'max_depth': 5}
   attack_metric_success_name: P_HIGHER_AUC
 attack_metric_success_thresh: 0.05
attack_metric_success_comp_type: lte
attack_metric_success_count_thresh: 5
          attack_fail_fast: False
  attack_config_json_file_name: None
               target_path: None
```

Global metrics

```
         null_auc_3sd_range: 0.3748 -> 0.6252
           n_sig_auc_p_vals: 1
   n_sig_auc_p_vals_corrected: 1
```

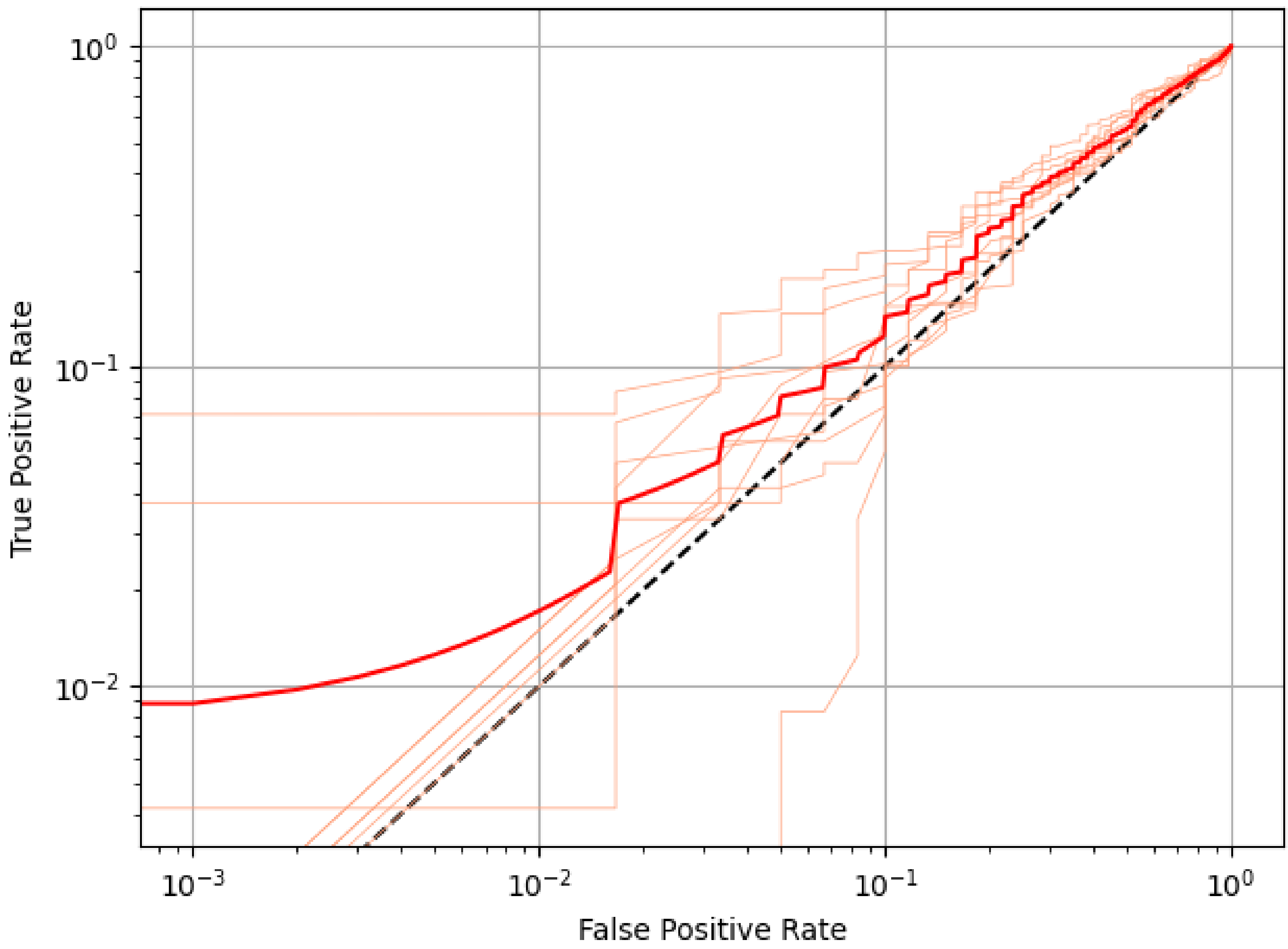
```
           n_sig_pdif_vals: 1
 n_sig_pdif_vals_corrected: 0
```

Metrics

The following show summaries of the attack metrics over the repetitions

```
      AUC mean = 0.55, var = 0.0009, min = 0.50, max = 0.61
      ACC mean = 0.80, var = 0.0000, min = 0.78, max = 0.80
Advantage mean = 0.01, var = 0.0001, min = 0.00, max = 0.03
   FDIF01 mean = 0.03, var = 0.0119, min = -0.17, max = 0.23
   PDIF01 mean = 0.43, var = 0.0822, min = 0.01, max = 0.95
  TPR@0.1 mean = 0.14, var = 0.0022, min = 0.09, max = 0.23
 TPR@0.01 mean = 0.01, var = 0.0004, min = 0.00, max = 0.06
TPR@0.001 mean = 0.01, var = 0.0002, min = 0.00, max = 0.05
TPR@1e-05 mean = 0.01, var = 0.0002, min = 0.00, max = 0.05
```

Log ROC



This plot shows the False Positive Rate (x) versus the True Positive Rate (y). The axes are in log space enabling us to focus on areas where the False Positive Rate is low (left hand area). Curves above the y = x line (black dashes) in this region represent a disclosure risk as an attacker can obtain many more true than false positives. The solid coloured lines show the curves for the attack simulations with the true model outputs. The lighter grey lines show the curves for randomly generated outputs with no structure (i.e. in- and out-of- sample predictions are generated from the same distributions. Solid curves consistently higher than the grey curves in the left hand part of the plot are a sign of concern.

Glossary

AUC

Area

True Positive Rate (TPR)

The t
posit
exam
these

ACC

The p

Likelihood Ratio Attack Report

Introduction

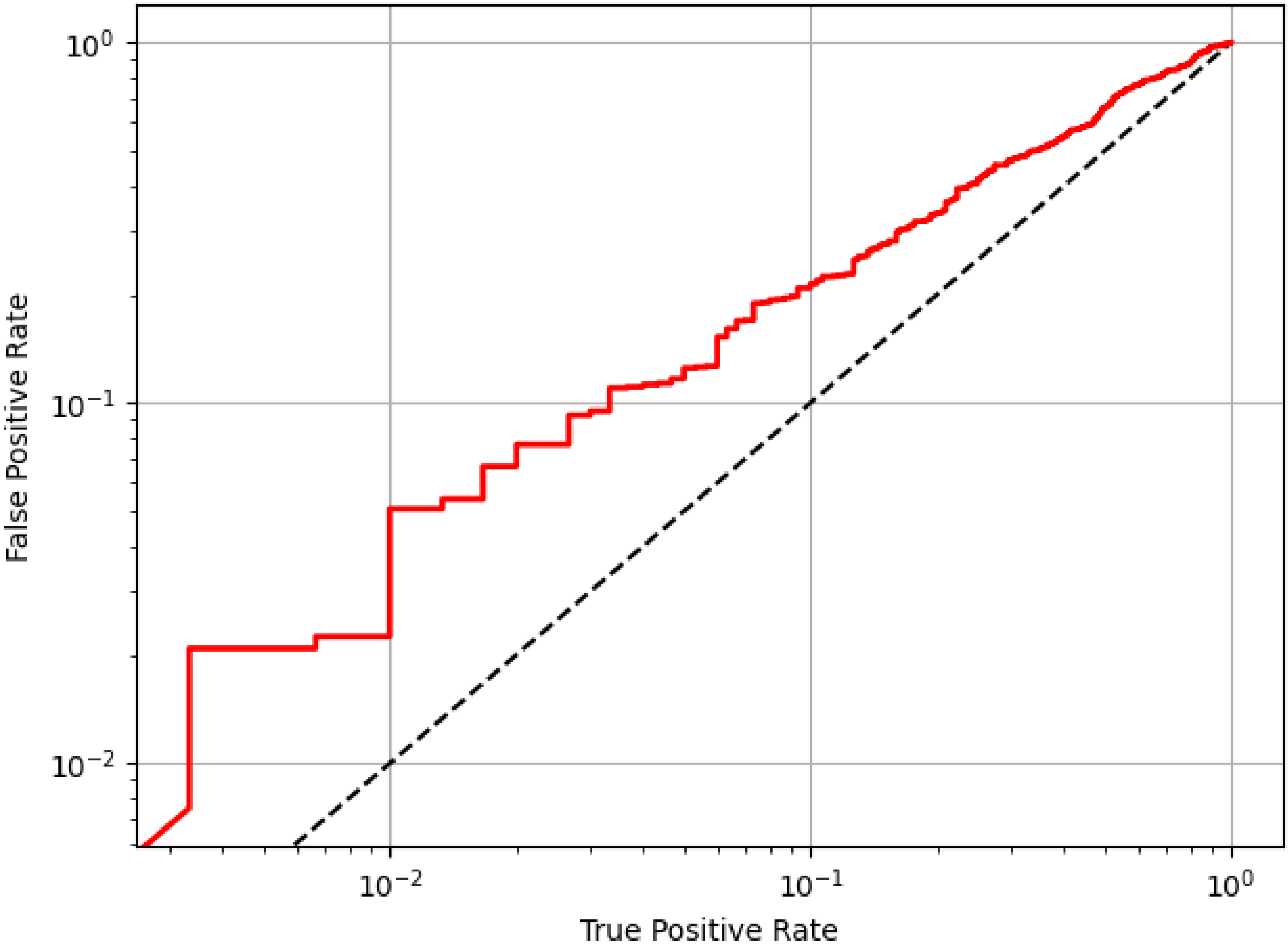
Metadata

```
            n_shadow_models: 100
                   p_thresh: 0.05
                 output_dir: ./SVM_unsafe_90synth
                report_name: attack_output
     training_data_filename: train_data.csv
         test_data_filename: test_data.csv
    training_preds_filename: train_preds.csv
        test_preds_filename: test_preds.csv
               target_model: ['sklearn.svm']
           target_model_hyp: {'C': 10, 'gamma': 'scale'}
attack_config_json_file_name: ./SVM_unsafe_90synth\lira_config.json
n_shadow_rows_confidences_min: 10
   shadow_models_fail_fast: False
                target_path: None
                   PDIF_sig: Significant at p=0.05
                    AUC_sig: Significant at p=0.05
         null_auc_3sd_range: 0.44407966976730795 -> 0.555920330232692
```

Metrics

```
          TPR: 0.6692
          FPR: 0.5067
          FAR: 0.1592
          TNR: 0.4933
          PPV: 0.8408
          NPV: 0.2716
          FNR: 0.3308
          ACC: 0.6340
      F1score: 0.7452
    Advantage: 0.1625
          AUC: 0.6196
 P_HIGHER_AUC: 0.0000
       FMAX01: 0.9067
       FMIN01: 0.6533
       FDIF01: 0.2533
       PDIF01: 0.0000
       FMAX02: 0.8933
       FMIN02: 0.7000
       FDIF02: 0.1933
       PDIF02: 20.2448
      FMAX001: 0.9333
      FMIN001: 0.5333
      FDIF001: 0.4000
      PDIF001: 5.7812
 pred_prob_var: 0.1461
```

ROC Curve



10^0
10^{-1}
10^{-2}
False Positive Rate
10^{-2}
10^{-1}
10^0
True Positive Rate

WorstCase MIA attack result report

Introduction

This report provides a summary of a series of simulated attack experiments performed on the model outputs provided. An attack model is trained to attempt to distinguish between outputs from training (in-sample) and testing (out-of-sample) data. The metrics below describe the success of this classifier. A successful classifier indicates that the original model is unsafe and should not be allowed to be released from the TRE.
In particular, the simulation splits the data provided into test and train sets (each will in- and out-of-sample examples). The classifier is trained on the train set and evaluated on the test set. This is repeated with different train/test splits a user-specified number of times.
To help place the results in context, the code may also have run a series of baseline experiments. In these, random model outputs for hypothetical in- and out-of-sample data are generated with identical statistical properties. In these baseline cases, there is no signal that an attacker could leverage and therefore these values provide a baseline against which the actual values can be compared.
For some metrics (FDIF and AUC), we are able to compute p-values. In each case, shown below (in the Global metrics sections) is the number of repetitions that exceeded the p-value threshold both without, and with correction for multiple testing (Benjamini-Hochberg procedure).
ROC curves for all real (red) and dummy (blue) repetitions are provided. These are shown in log space (as reommended here [ADD URL]) to emphasise the region in which risk is highest -- the bottom left (are high true positive rates possible with low false positive rates).
A description of the metrics and how to interpret them within the context of an attack is given below.

Experiment summary

```
                   n_reps: 10
          reproduce_split: [5, 25, 36, 49, 64, 81, 100, 121, 144, 169]
                 p_thresh: 0.05
             n_dummy_reps: 10
               train_beta: 1
                test_beta: 1
                test_prop: 0.2
                n_rows_in: 1200
               n_rows_out: 186
  training_preds_filename: None
      test_preds_filename: None
               output_dir: ./SVM_unsafe_90synth
              report_name: attack_output
include_model_correct_feature: False
               sort_probs: True
         mia_attack_model: <class
'sklearn.ensemble._forest.RandomForestClassifier'>
     mia_attack_model_hyp: {'min_samples_split': 20, 'min_samples_leaf':
10, 'max_depth': 5}
 attack_metric_success_name: P_HIGHER_AUC
 attack_metric_success_thresh: 0.05
attack_metric_success_comp_type: lte
attack_metric_success_count_thresh: 5
        attack_fail_fast: False
 attack_config_json_file_name: None
              target_path: None
```

Global metrics

```
       null_auc_3sd_range: 0.3468 -> 0.6532
          n_sig_auc_p_vals: 2
  n_sig_auc_p_vals_corrected: 1
```

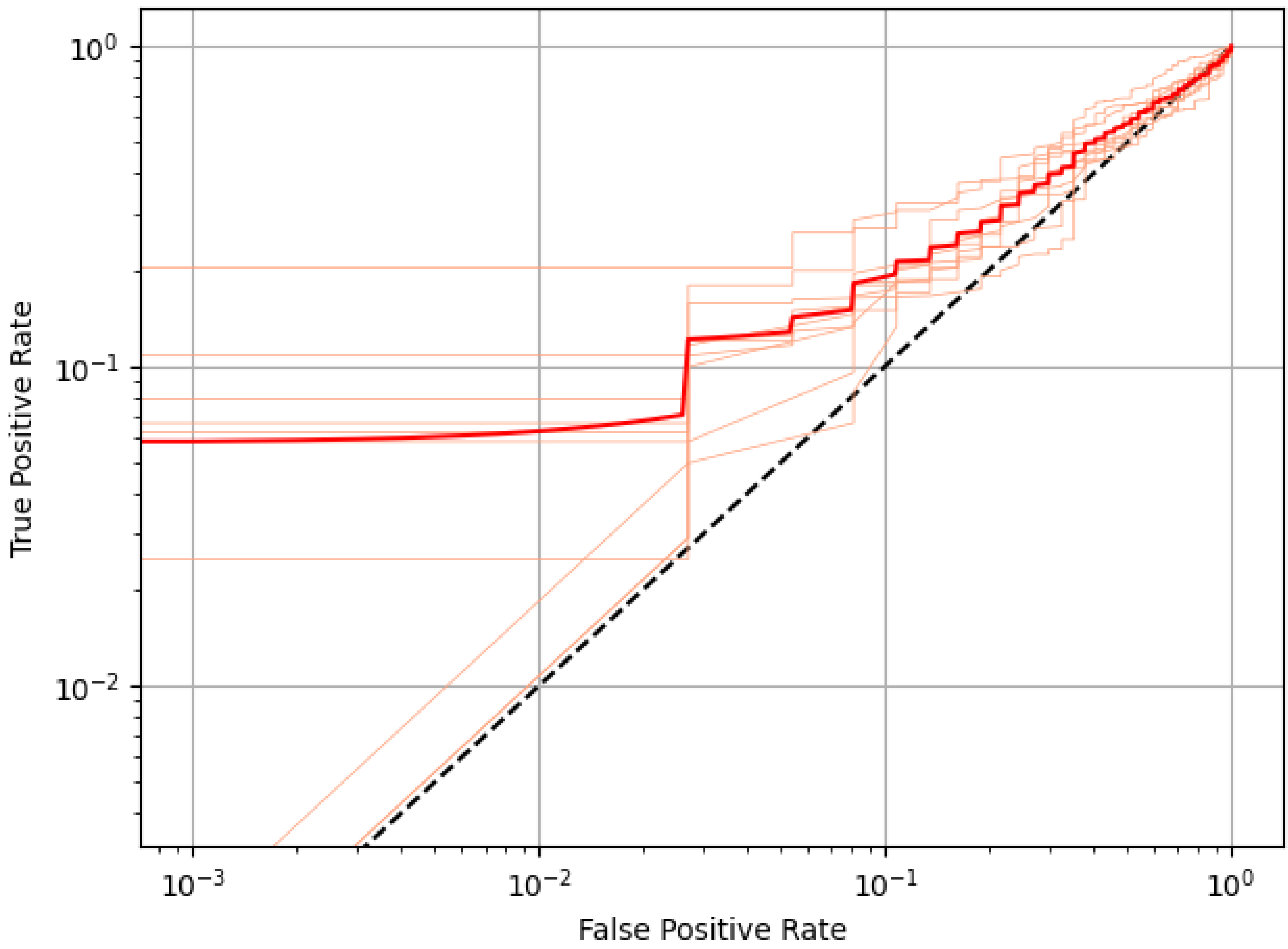
```
              n_sig_pdif_vals: 1
    n_sig_pdif_vals_corrected: 1
```

Metrics

The following show summaries of the attack metrics over the repetitions

```
      AUC mean = 0.55, var = 0.0020, min = 0.50, max = 0.63
      ACC mean = 0.87, var = 0.0000, min = 0.87, max = 0.87
Advantage mean = 0.00, var = 0.0000, min = 0.00, max = 0.00
   FDIF01 mean = 0.07, var = 0.0060, min = 0.00, max = 0.29
   PDIF01 mean = 0.29, var = 0.0182, min = 0.00, max = 0.50
  TPR@0.1 mean = 0.19, var = 0.0027, min = 0.12, max = 0.30
 TPR@0.01 mean = 0.06, var = 0.0036, min = 0.00, max = 0.20
TPR@0.001 mean = 0.06, var = 0.0036, min = 0.00, max = 0.20
TPR@1e-05 mean = 0.06, var = 0.0036, min = 0.00, max = 0.20
```

Log ROC



This plot shows the False Positive Rate (x) versus the True Positive Rate (y). The axes are in log space enabling us to focus on areas where the False Positive Rate is low (left hand area). Curves above the y = x line (black dashes) in this region represent a disclosure risk as an attacker can obtain many more true than false positives. The solid coloured lines show the curves for the attack simulations with the true model outputs. The lighter grey lines show the curves for randomly generated outputs with no structure (i.e. in- and out-of- sample predictions are generated from the same distributions. Solid curves consistently higher than the grey curves in the left hand part of the plot are a sign of concern.

Glossary

AUC

Area

True Positive Rate (TPR)

The t
posit
exam
these

ACC

The p

Likelihood Ratio Attack Report

Introduction

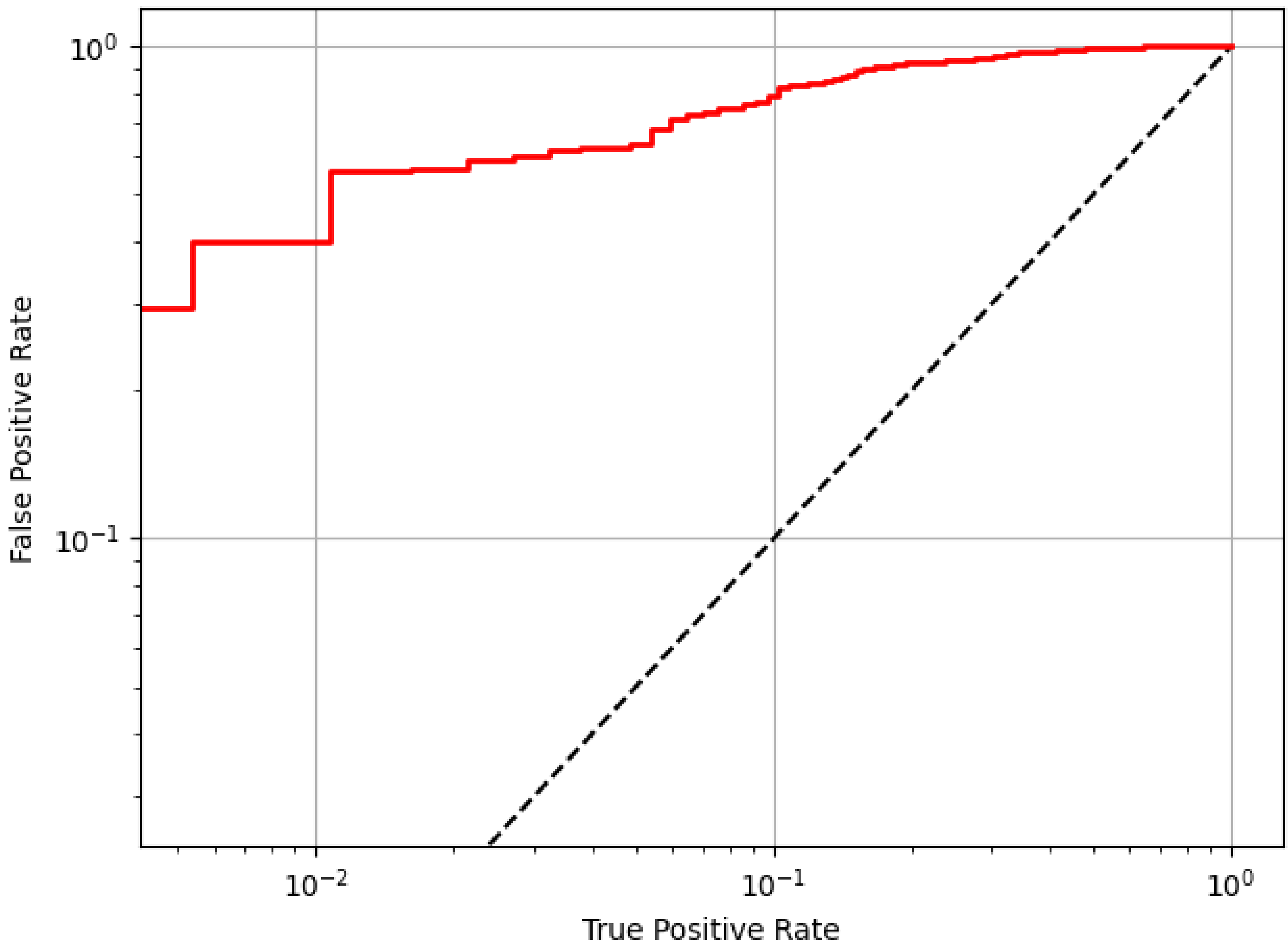
Metadata

n_shadow_models:	100
p_thresh:	0.05
output_dir:	./SVM_unsafe_90synth
report_name:	attack_output
training_data_filename:	train_data.csv
test_data_filename:	test_data.csv
training_preds_filename:	train_preds.csv
test_preds_filename:	test_preds.csv
target_model:	['sklearn.svm']
target_model_hyp:	{'C': 10, 'gamma': 'scale'}
attack_config_json_file_name:	./SVM_unsafe_90synth\lira_config.json
n_shadow_rows_confidences_min:	10
shadow_models_fail_fast:	False
target_path:	None
PDIF_sig:	Significant at p=0.05
AUC_sig:	Significant at p=0.05
null_auc_3sd_range:	0.4317312789077612 -> 0.5682687210922388

Metrics

TPR:	0.6650
FPR:	0.0538
FAR:	0.0124
TNR:	0.9462
PPV:	0.9876
NPV:	0.3045
FNR:	0.3350
ACC:	0.7027
F1score:	0.7948
Advantage:	0.6112
AUC:	0.9391
P_HIGHER_AUC:	0.0000
FMAX01:	1.0000
FMIN01:	0.1942
FDIF01:	0.8058
PDIF01:	0.0000
FMAX02:	1.0000
FMIN02:	0.4353
FDIF02:	0.5647
PDIF02:	115.1300
FMAX001:	1.0000
FMIN001:	0.0000
FDIF001:	1.0000
PDIF001:	33.0992
pred_prob_var:	0.1764

ROC Curve



WorstCase MIA attack result report

Introduction

This report provides a summary of a series of simulated attack experiments performed on the model outputs provided. An attack model is trained to attempt to distinguish between outputs from training (in-sample) and testing (out-of-sample) data. The metrics below describe the success of this classifier. A successful classifier indicates that the original model is unsafe and should not be allowed to be released from the TRE.
In particular, the simulation splits the data provided into test and train sets (each will in- and out-of-sample examples). The classifier is trained on the train set and evaluated on the test set. This is repeated with different train/test splits a user-specified number of times.
To help place the results in context, the code may also have run a series of baseline experiments. In these, random model outputs for hypothetical in- and out-of-sample data are generated with identical statistical properties. In these baseline cases, there is no signal that an attacker could leverage and therefore these values provide a baseline against which the actual values can be compared.
For some metrics (FDIF and AUC), we are able to compute p-values. In each case, shown below (in the Global metrics sections) is the number of repetitions that exceeded the p-value threshold both without, and with correction for multiple testing (Benjamini-Hochberg procedure).
ROC curves for all real (red) and dummy (blue) repetitions are provided. These are shown in log space (as reommended here [ADD URL]) to emphasise the region in which risk is highest -- the bottom left (are high true positive rates possible with low false positive rates).
A description of the metrics and how to interpret them within the context of an attack is given below.

Experiment summary

```
                    n_reps: 10
           reproduce_split: [5, 25, 36, 49, 64, 81, 100, 121, 144, 169]
                  p_thresh: 0.05
              n_dummy_reps: 10
                train_beta: 1
                 test_beta: 1
                 test_prop: 0.2
                 n_rows_in: 1094
                n_rows_out: 186
   training_preds_filename: None
       test_preds_filename: None
                output_dir: ./SVM_unsafe_90synth
               report_name: attack_output
 include_model_correct_feature: False
                sort_probs: True
          mia_attack_model: <class
'sklearn.ensemble._forest.RandomForestClassifier'>
      mia_attack_model_hyp: {'min_samples_split': 20, 'min_samples_leaf':
10, 'max_depth': 5}
  attack_metric_success_name: P_HIGHER_AUC
 attack_metric_success_thresh: 0.05
attack_metric_success_comp_type: lte
attack_metric_success_count_thresh: 5
         attack_fail_fast: False
 attack_config_json_file_name: None
               target_path: None
```

Global metrics

```
        null_auc_3sd_range: 0.3458 -> 0.6542
           n_sig_auc_p_vals: 0
  n_sig_auc_p_vals_corrected: 0
```

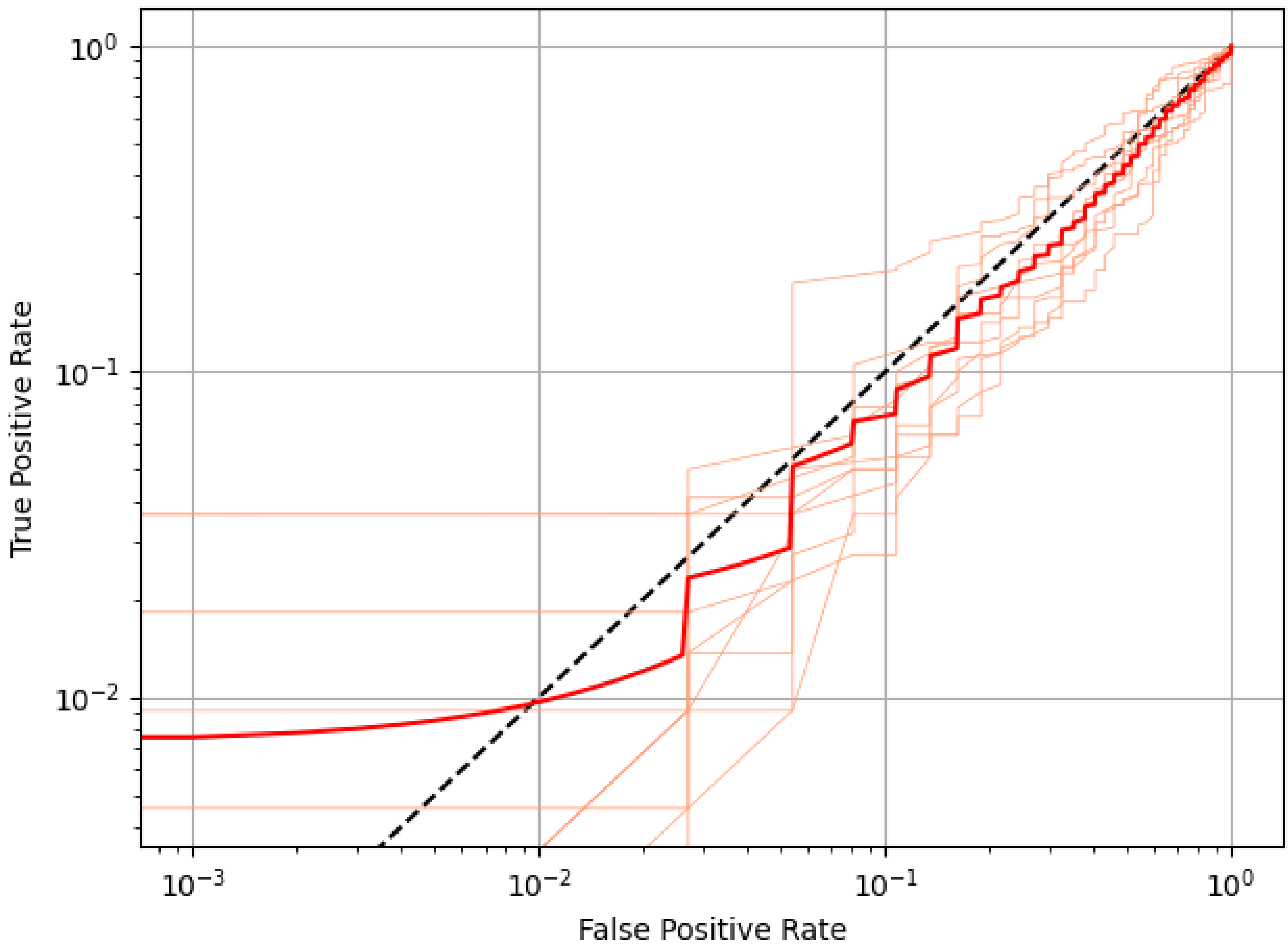
```
             n_sig_pdif_vals: 0
   n_sig_pdif_vals_corrected: 0
```

Metrics

The following show summaries of the attack metrics over the repetitions

```
        AUC mean = 0.46, var = 0.0038, min = 0.38, max = 0.58
        ACC mean = 0.86, var = 0.0000, min = 0.86, max = 0.86
  Advantage mean = 0.00, var = 0.0000, min = 0.00, max = 0.00
     FDIF01 mean = -0.06, var = 0.0095, min = -0.19, max = 0.08
     PDIF01 mean = 0.66, var = 0.0823, min = 0.22, max = 0.98
    TPR@0.1 mean = 0.07, var = 0.0024, min = 0.03, max = 0.20
   TPR@0.01 mean = 0.01, var = 0.0001, min = 0.00, max = 0.03
  TPR@0.001 mean = 0.01, var = 0.0001, min = 0.00, max = 0.02
  TPR@1e-05 mean = 0.01, var = 0.0001, min = 0.00, max = 0.02
```

Log ROC



This plot shows the False Positive Rate (x) versus the True Positive Rate (y). The axes are in log space enabling us to focus on areas where the False Positive Rate is low (left hand area). Curves above the y = x line (black dashes) in this region represent a disclosure risk as an attacker can obtain many more true than false positives. The solid coloured lines show the curves for the attack simulations with the true model outputs. The lighter grey lines show the curves for randomly generated outputs with no structure (i.e. in- and out-of- sample predictions are generated from the same distributions. Solid curves consistently higher than the grey curves in the left hand part of the plot are a sign of concern.

Glossary

AUC

Area

True Positive Rate (TPR)

The t
posit
exam
these

ACC

The p

Likelihood Ratio Attack Report

Introduction

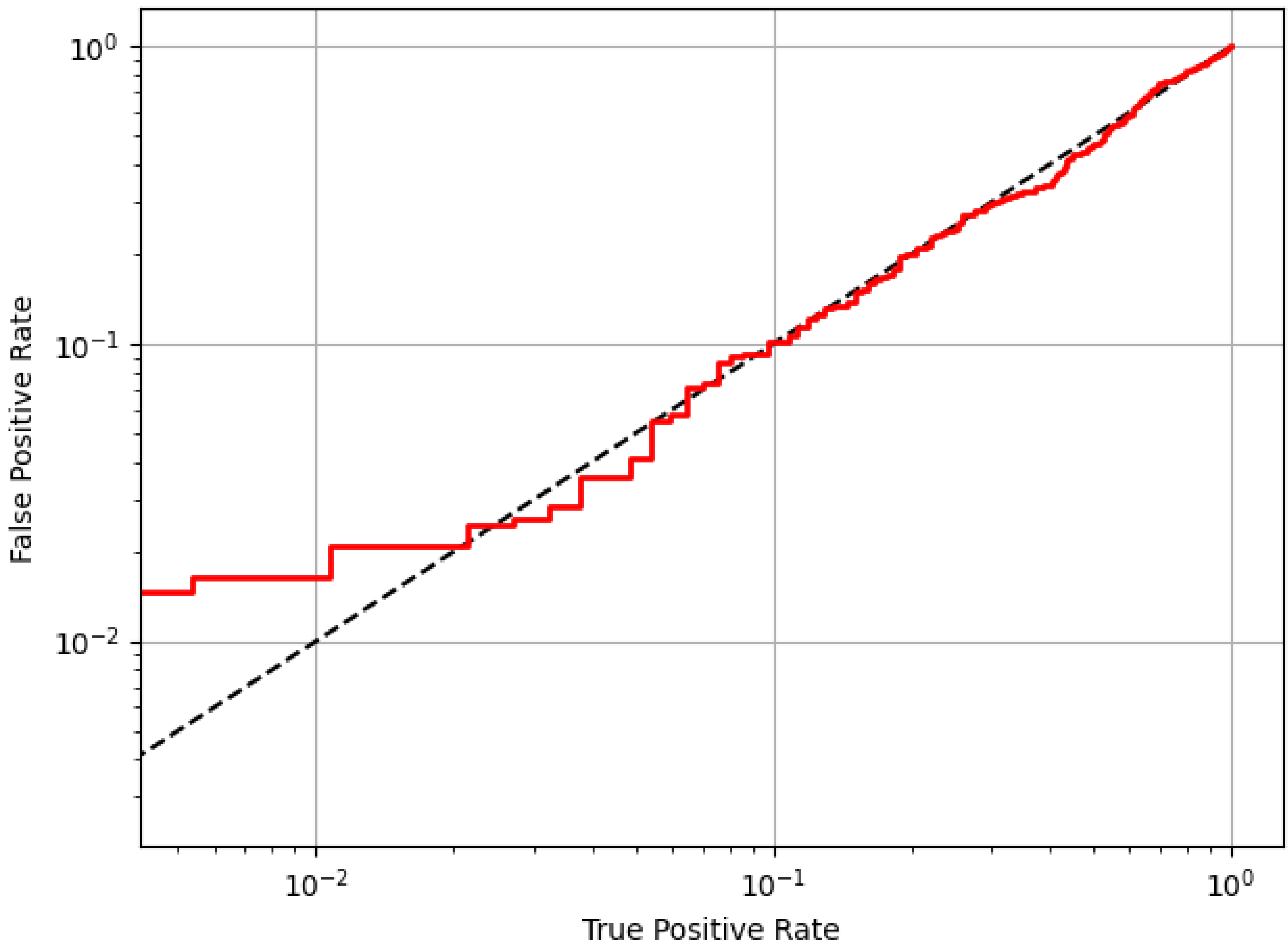
Metadata

```
              n_shadow_models: 100
                     p_thresh: 0.05
                   output_dir: ./SVM_unsafe_90synth
                  report_name: attack_output
       training_data_filename: train_data.csv
           test_data_filename: test_data.csv
      training_preds_filename: train_preds.csv
          test_preds_filename: test_preds.csv
                 target_model: ['sklearn.svm']
             target_model_hyp: {'C': 10, 'gamma': 'scale'}
  attack_config_json_file_name: ./SVM_unsafe_90synth\lira_config.json
n_shadow_rows_confidences_min: 10
      shadow_models_fail_fast: False
                  target_path: None
                     PDIF_sig: Not significant at p=0.05
                      AUC_sig: Not significant at p=0.05
            null_auc_3sd_range: 0.4312868175323611 -> 0.5687131824676389
```

Metrics

```
          TPR: 0.0402
          FPR: 0.0484
          FAR: 0.1698
          TNR: 0.9516
          PPV: 0.8302
          NPV: 0.1443
          FNR: 0.9598
          ACC: 0.1727
      F1score: 0.0767
    Advantage: 0.0082
          AUC: 0.4971
 P_HIGHER_AUC: 0.5507
       FMAX01: 0.8594
       FMIN01: 0.8594
       FDIF01: 0.0000
       PDIF01: 0.5000
       FMAX02: 0.8555
       FMIN02: 0.8477
       FDIF02: 0.0078
       PDIF02: 0.9138
      FMAX001: 1.0000
      FMIN001: 0.7692
      FDIF001: 0.2308
      PDIF001: 3.0468
 pred_prob_var: 0.0316
```

ROC Curve



10^0
10^{-1}
10^{-2}
False Positive Rate
10^{-2}
10^{-1}
10^0
True Positive Rate

WorstCase MIA attack result report

Introduction

This report provides a summary of a series of simulated attack experiments performed on the model outputs provided. An attack model is trained to attempt to distinguish between outputs from training (in-sample) and testing (out-of-sample) data. The metrics below describe the success of this classifier. A successful classifier indicates that the original model is unsafe and should not be allowed to be released from the TRE.
In particular, the simulation splits the data provided into test and train sets (each will in- and out-of-sample examples). The classifier is trained on the train set and evaluated on the test set. This is repeated with different train/test splits a user-specified number of times.
To help place the results in context, the code may also have run a series of baseline experiments. In these, random model outputs for hypothetical in- and out-of-sample data are generated with identical statistical properties. In these baseline cases, there is no signal that an attacker could leverage and therefore these values provide a baseline against which the actual values can be compared.
For some metrics (FDIF and AUC), we are able to compute p-values. In each case, shown below (in the Global metrics sections) is the number of repetitions that exceeded the p-value threshold both without, and with correction for multiple testing (Benjamini-Hochberg procedure).
ROC curves for all real (red) and dummy (blue) repetitions are provided. These are shown in log space (as reommended here [ADD URL]) to emphasise the region in which risk is highest -- the bottom left (are high true positive rates possible with low false positive rates).
A description of the metrics and how to interpret them within the context of an attack is given below.

Experiment summary

```
                          n_reps: 10
                 reproduce_split: [5, 25, 36, 49, 64, 81, 100, 121, 144, 169]
                        p_thresh: 0.05
                    n_dummy_reps: 10
                      train_beta: 1
                       test_beta: 1
                       test_prop: 0.2
                       n_rows_in: 1094
                      n_rows_out: 186
        training_preds_filename: None
            test_preds_filename: None
                      output_dir: ./SVM_unsafe_87synth
                     report_name: attack_output
  include_model_correct_feature: False
                      sort_probs: True
                mia_attack_model: <class
'sklearn.ensemble._forest.RandomForestClassifier'>
            mia_attack_model_hyp: {'min_samples_split': 20, 'min_samples_leaf':
10, 'max_depth': 5}
     attack_metric_success_name: P_HIGHER_AUC
   attack_metric_success_thresh: 0.05
attack_metric_success_comp_type: lte
attack_metric_success_count_thresh: 5
               attack_fail_fast: False
   attack_config_json_file_name: None
                     target_path: None
```

Global metrics

```
              null_auc_3sd_range: 0.3458 -> 0.6542
                 n_sig_auc_p_vals: 0
     n_sig_auc_p_vals_corrected: 0
```

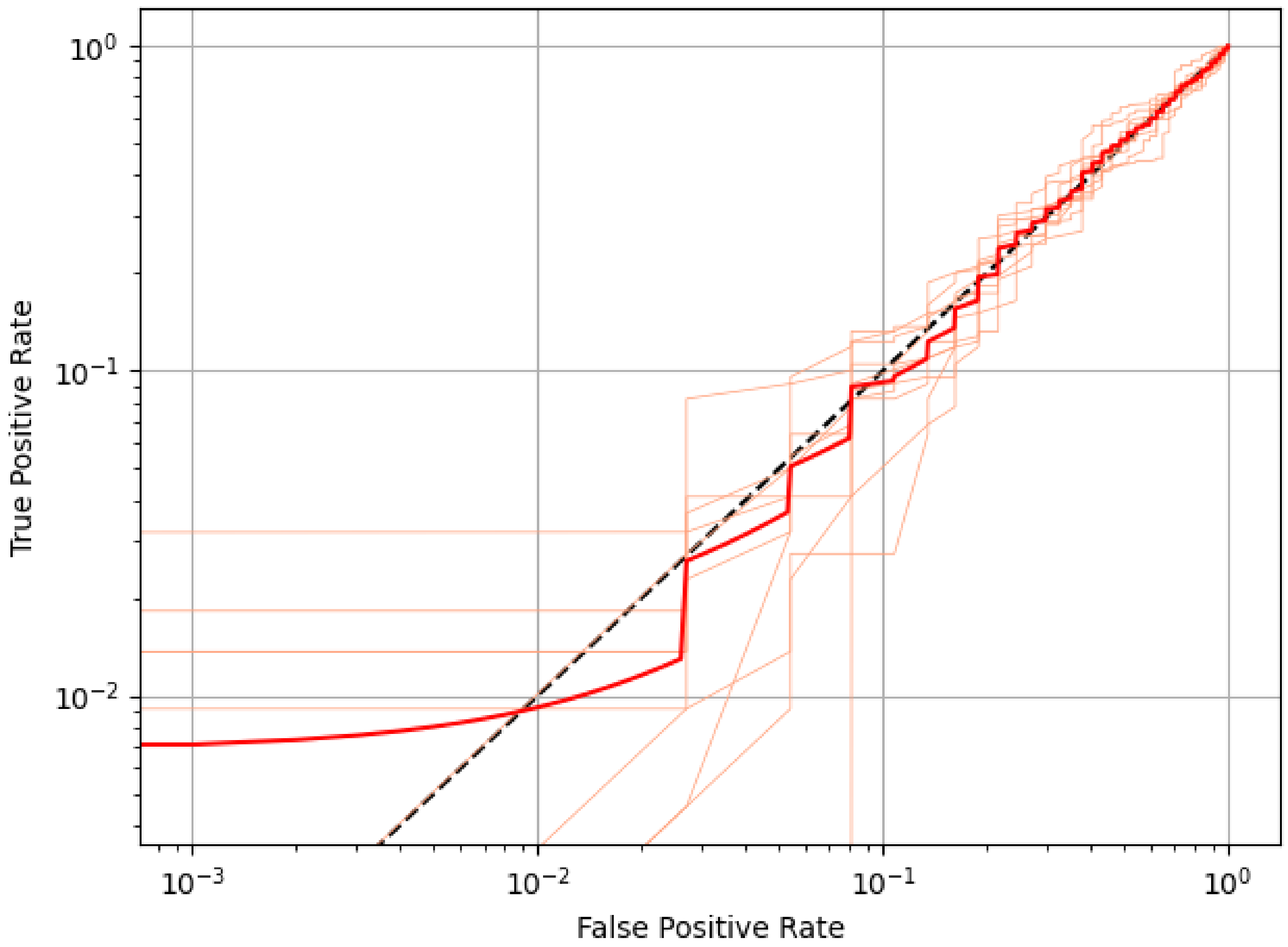
```
            n_sig_pdif_vals: 0
  n_sig_pdif_vals_corrected: 0
```

Metrics

The following show summaries of the attack metrics over the repetitions

```
      AUC mean = 0.50, var = 0.0006, min = 0.47, max = 0.55
      ACC mean = 0.86, var = 0.0000, min = 0.86, max = 0.86
Advantage mean = 0.00, var = 0.0000, min = 0.00, max = 0.00
   FDIF01 mean = -0.03, var = 0.0055, min = -0.15, max = 0.08
   PDIF01 mean = 0.61, var = 0.0632, min = 0.22, max = 0.94
  TPR@0.1 mean = 0.09, var = 0.0010, min = 0.03, max = 0.13
 TPR@0.01 mean = 0.01, var = 0.0001, min = 0.00, max = 0.02
TPR@0.001 mean = 0.01, var = 0.0001, min = 0.00, max = 0.02
TPR@1e-05 mean = 0.01, var = 0.0001, min = 0.00, max = 0.02
```

Log ROC



This plot shows the False Positive Rate (x) versus the True Positive Rate (y). The axes are in log space enabling us to focus on areas where the False Positive Rate is low (left hand area). Curves above the y = x line (black dashes) in this region represent a disclosure risk as an attacker can obtain many more true than false positives. The solid coloured lines show the curves for the attack simulations with the true model outputs. The lighter grey lines show the curves for randomly generated outputs with no structure (i.e. in- and out-of- sample predictions are generated from the same distributions. Solid curves consistently higher than the grey curves in the left hand part of the plot are a sign of concern.

Glossary

AUC

Area

True Positive Rate (TPR)

The t
posit
exam
these

ACC

The p

Likelihood Ratio Attack Report

Introduction

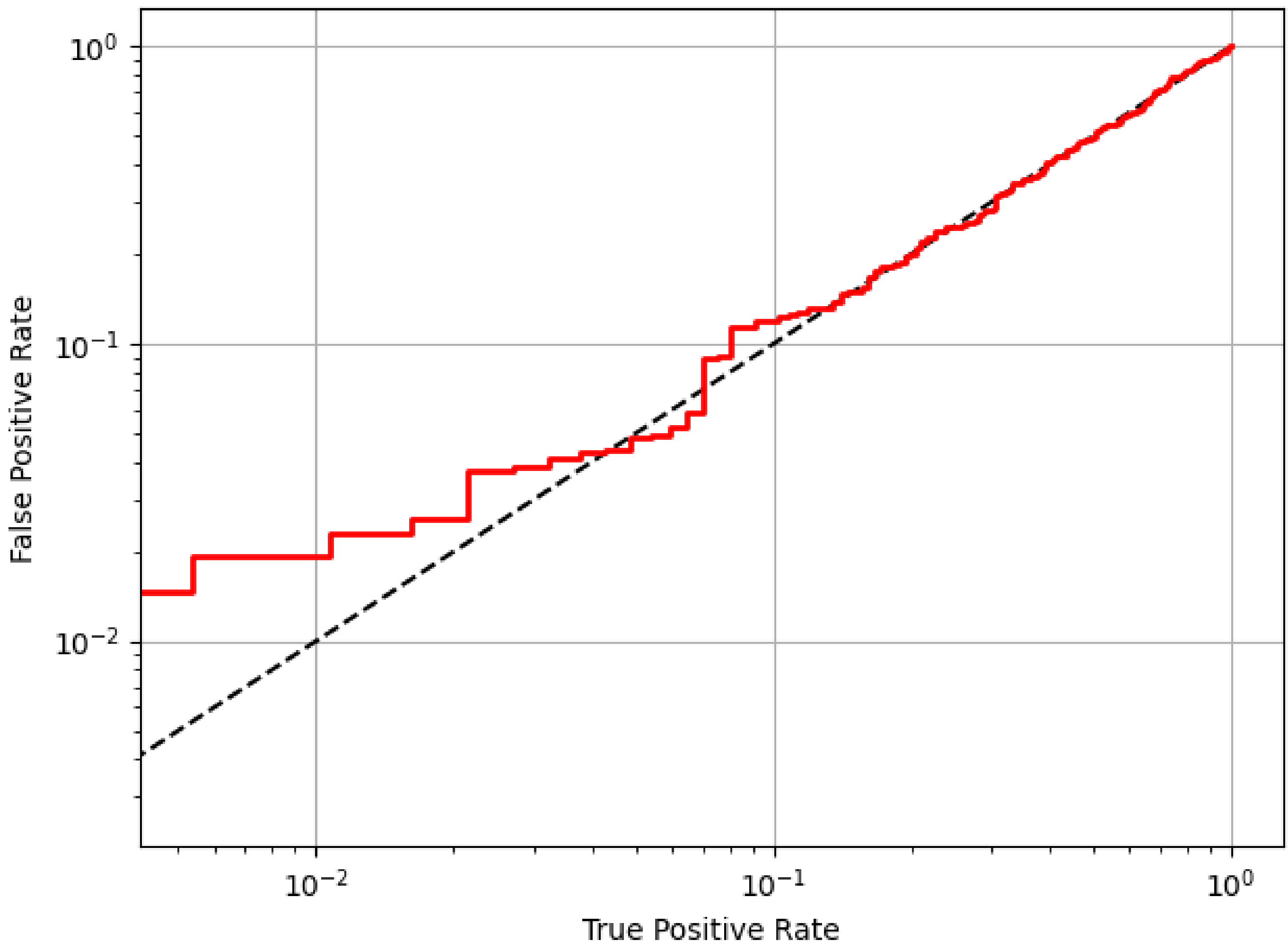
Metadata

```
            n_shadow_models: 100
                   p_thresh: 0.05
                 output_dir: ./SVM_unsafe_87synth
                report_name: attack_output
     training_data_filename: train_data.csv
         test_data_filename: test_data.csv
    training_preds_filename: train_preds.csv
        test_preds_filename: test_preds.csv
               target_model: ['sklearn.svm']
           target_model_hyp: {'C': 10, 'gamma': 'scale'}
attack_config_json_file_name: ./SVM_unsafe_87synth\lira_config.json
n_shadow_rows_confidences_min: 10
     shadow_models_fail_fast: False
                target_path: None
                   PDIF_sig: Not significant at p=0.05
                    AUC_sig: Not significant at p=0.05
          null_auc_3sd_range: 0.4312868175323611 -> 0.5687131824676389
```

Metrics

```
                        TPR: 0.0411
                        FPR: 0.0323
                        FAR: 0.1176
                        TNR: 0.9677
                        PPV: 0.8824
                        NPV: 0.1465
                        FNR: 0.9589
                        ACC: 0.1758
                    F1score: 0.0786
                  Advantage: 0.0089
                        AUC: 0.5052
               P_HIGHER_AUC: 0.4099
                     FMAX01: 0.8828
                     FMIN01: 0.8438
                     FDIF01: 0.0391
                     PDIF01: 0.1876
                     FMAX02: 0.8555
                     FMIN02: 0.8398
                     FDIF02: 0.0156
                     PDIF02: 1.1778
                    FMAX001: 1.0000
                    FMIN001: 0.8462
                    FDIF001: 0.1538
                    PDIF001: 2.0185
               pred_prob_var: 0.0311
```

ROC Curve



10^0
10^{-1}
10^{-2}
False Positive Rate
10^{-2}
10^{-1}
10^0
True Positive Rate