

# 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 recommended 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
```

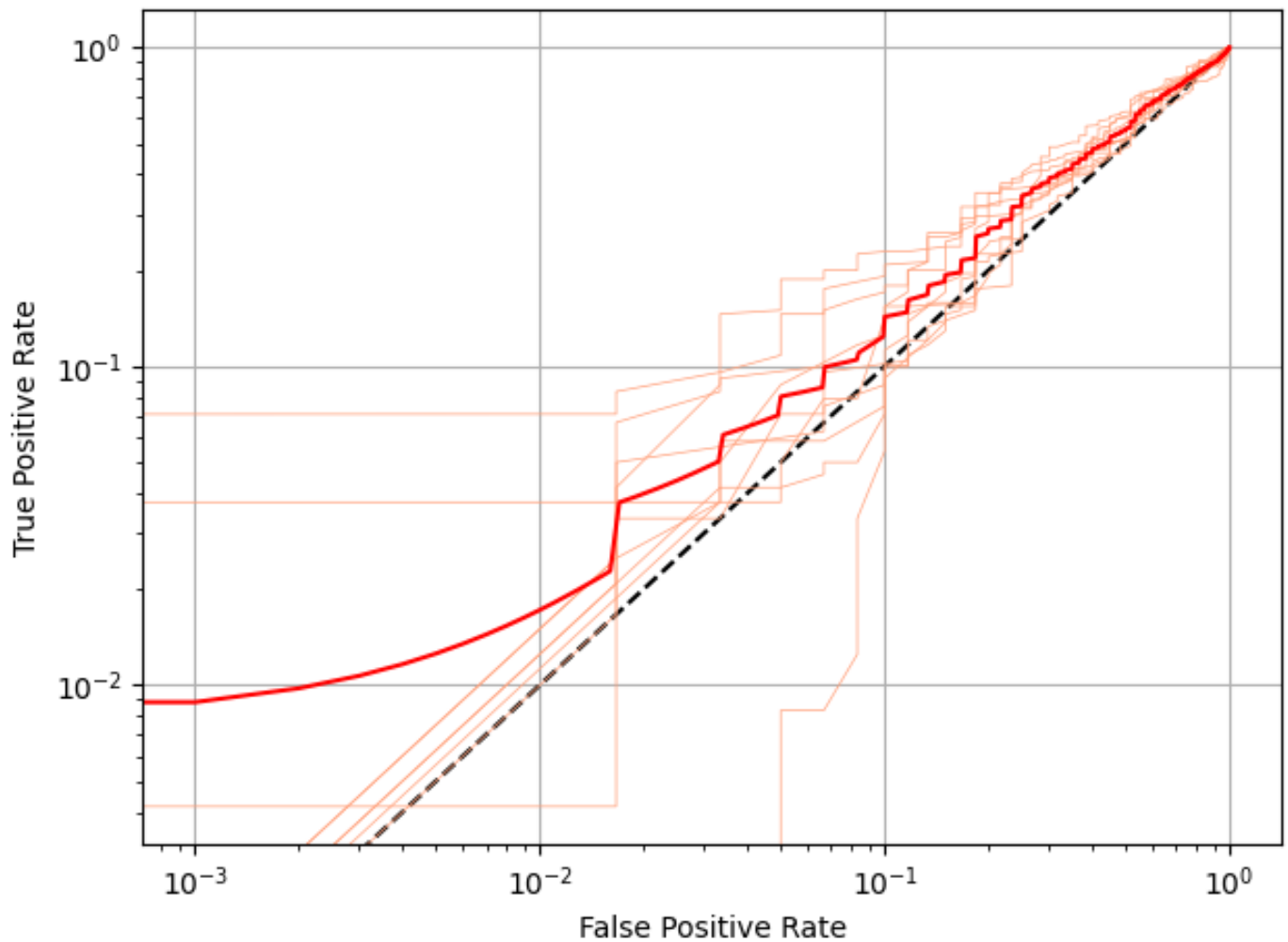
```
n_sig_pdif_vals: 1
n_sig_pdif_vals_corrected: 0
```

## 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)

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ACC

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# Likelihood Ratio Attack Report

## Introduction

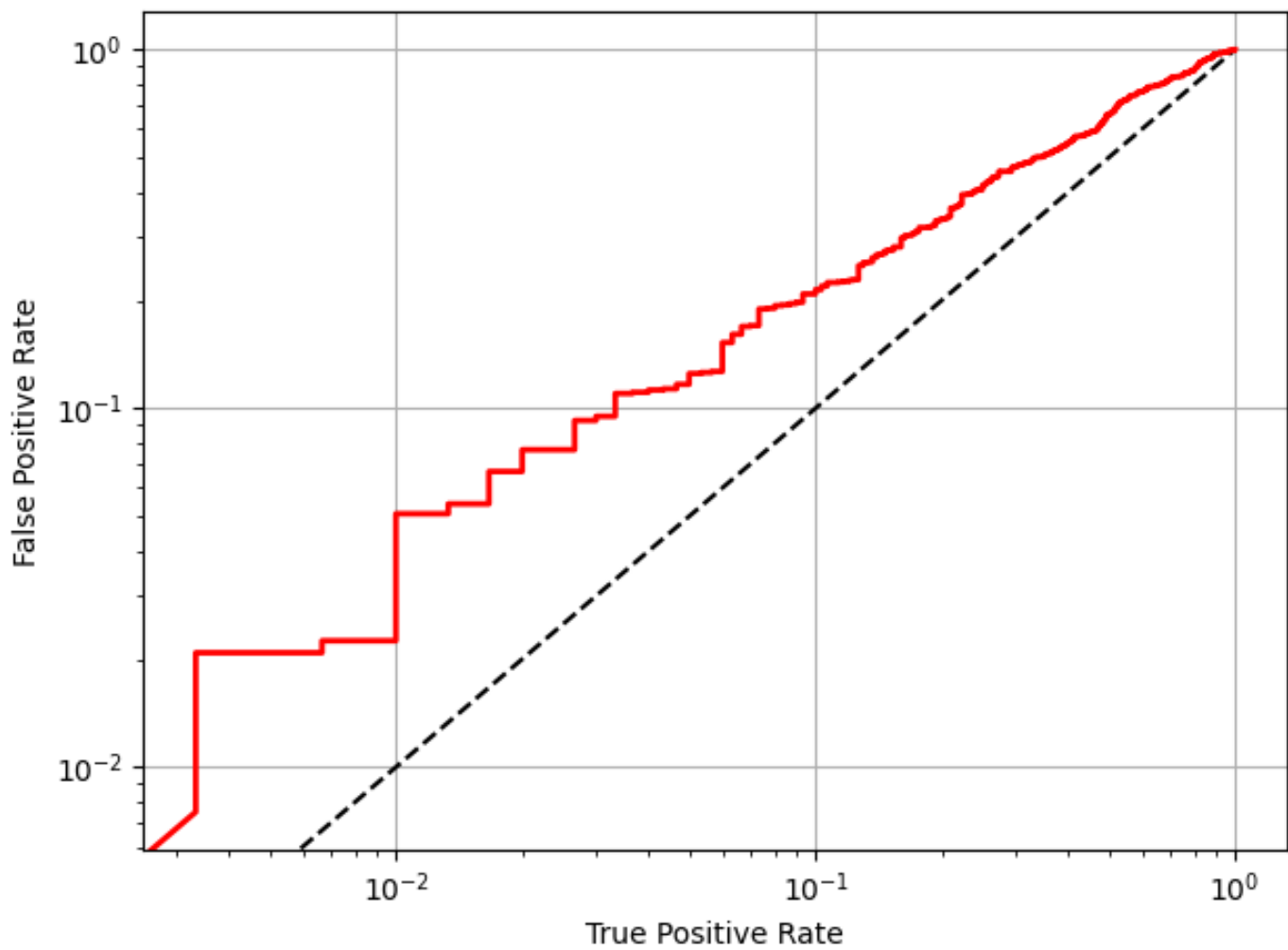
## Metadata

```
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
Flscore: 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



# WorstCase MIA attack result report

## Introduction

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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 recommended 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
```

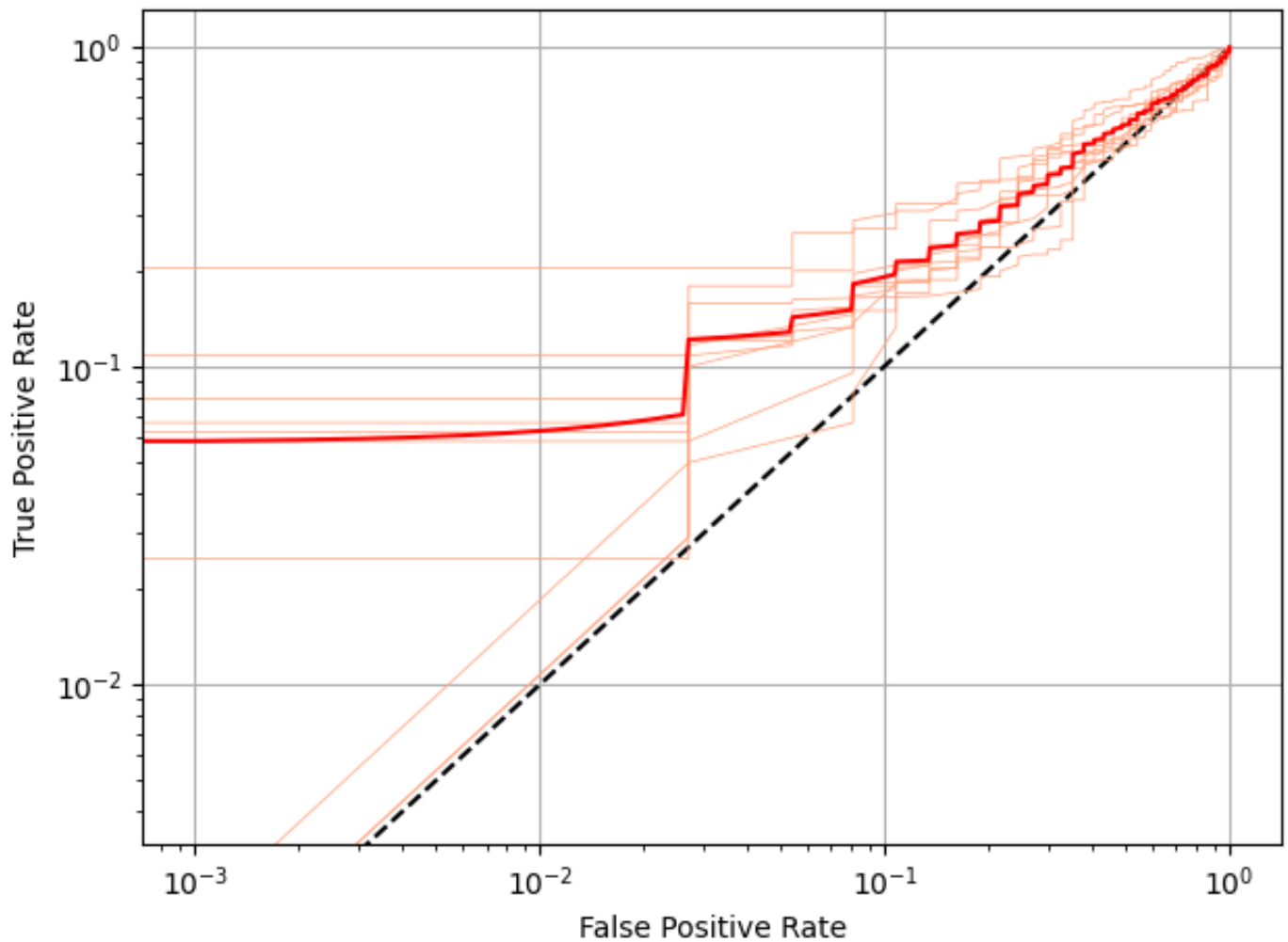
## Metrics

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)**

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**ACC**

The p

# Likelihood Ratio Attack Report

## Introduction

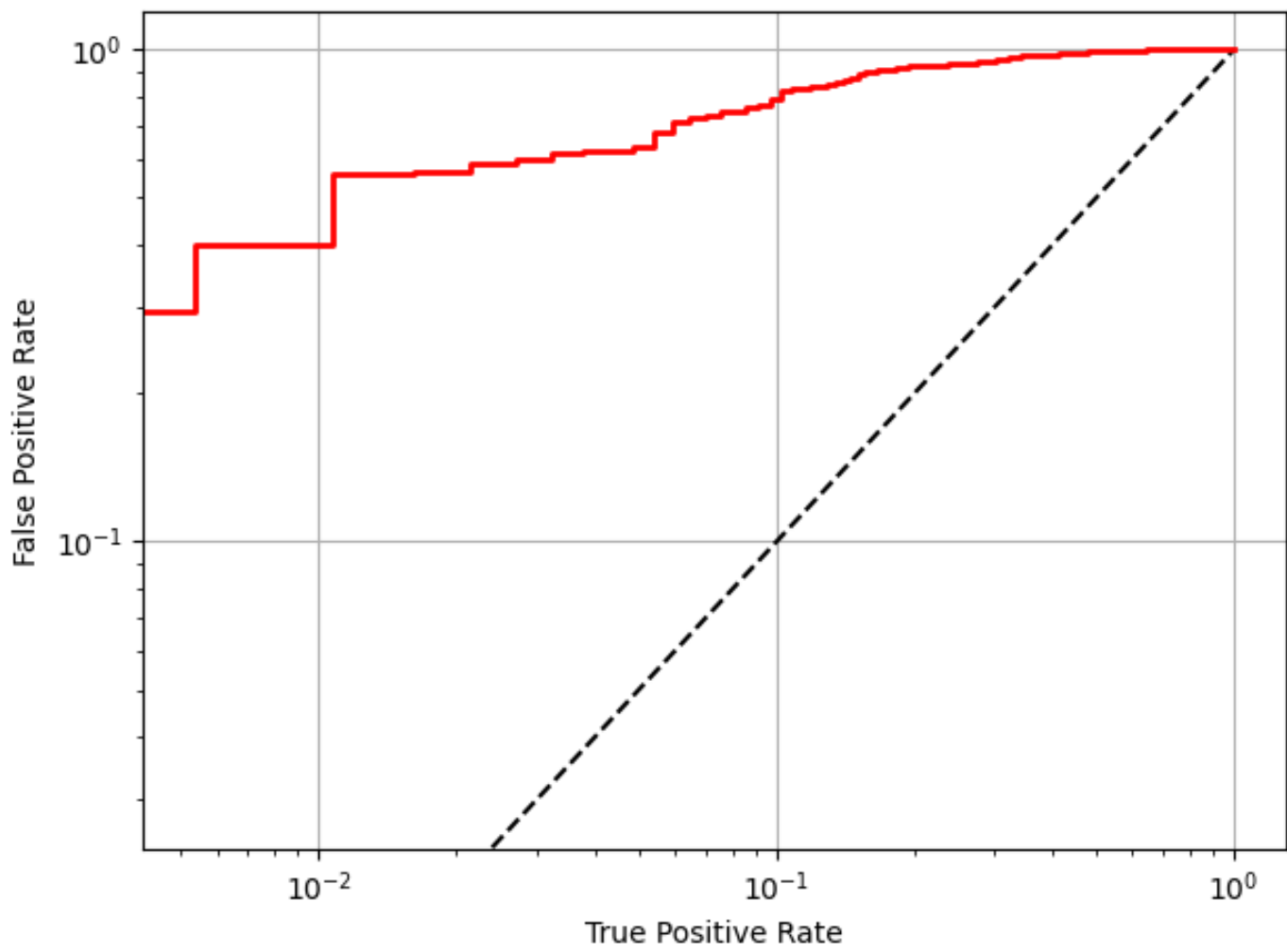
## Metadata

```
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
Flscore: 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



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```
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
```

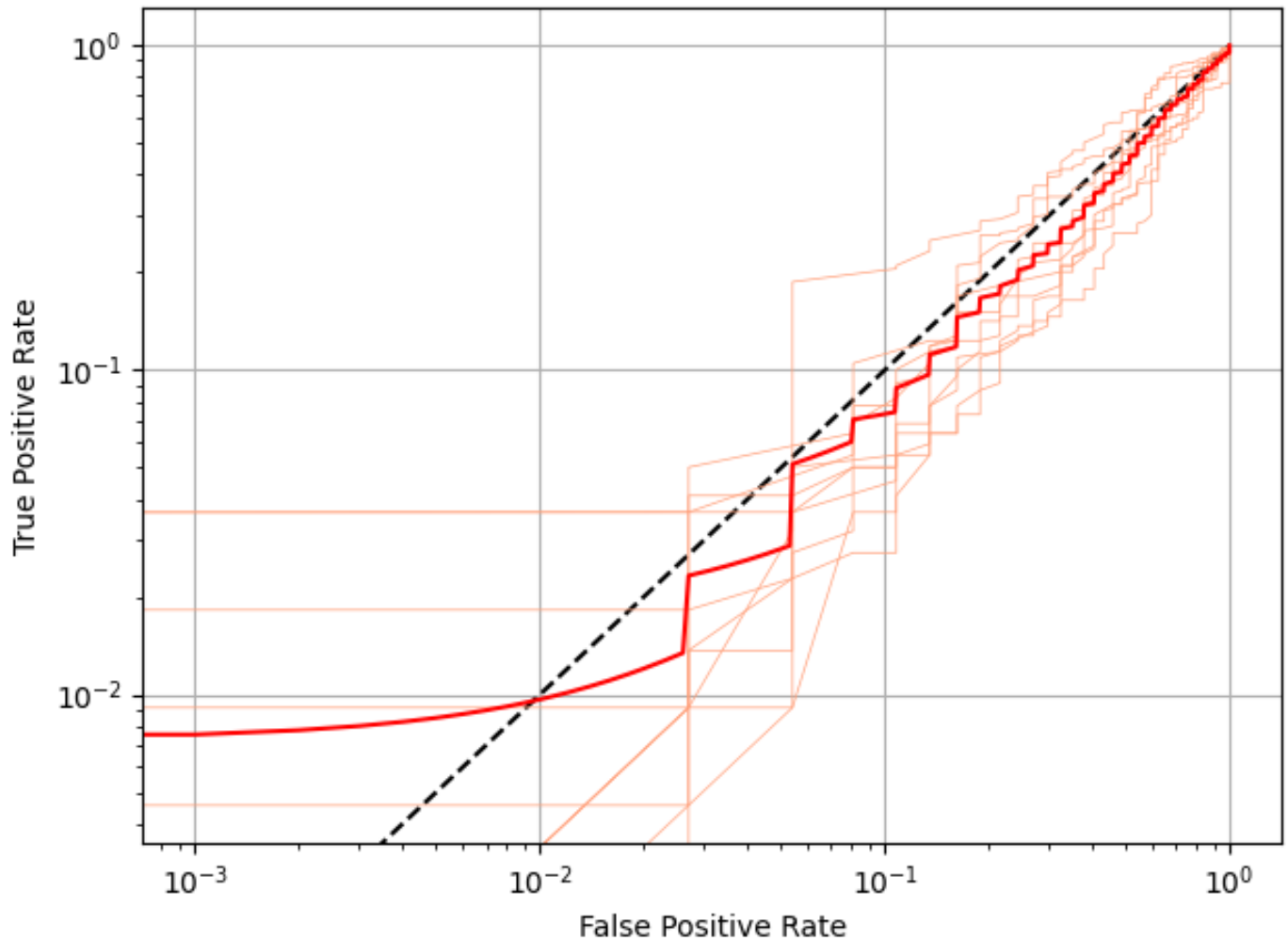
```
n_sig_pdif_vals: 0
n_sig_pdif_vals_corrected: 0
```

## 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

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True Positive Rate (TPR)

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ACC

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# Likelihood Ratio Attack Report

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## Metadata

```
n_shadow_models: 100
  p_thresh: 0.05
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  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
Flscore: 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

