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Medical Data Privacy Preserving Machine Learning

ppAURORA: Privacy Preserving Area Under Receiver Operating Characteristic and Precision-Recall Curves

Ali Burak Ünal, Nico Pfeifer, Mete Akgün

Motivation

- Data is everywhere!

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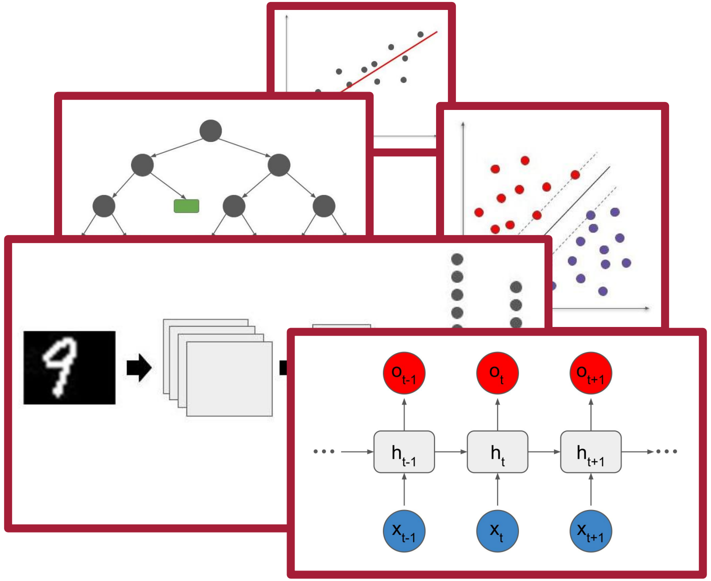
- Machine learning algorithms demand data.



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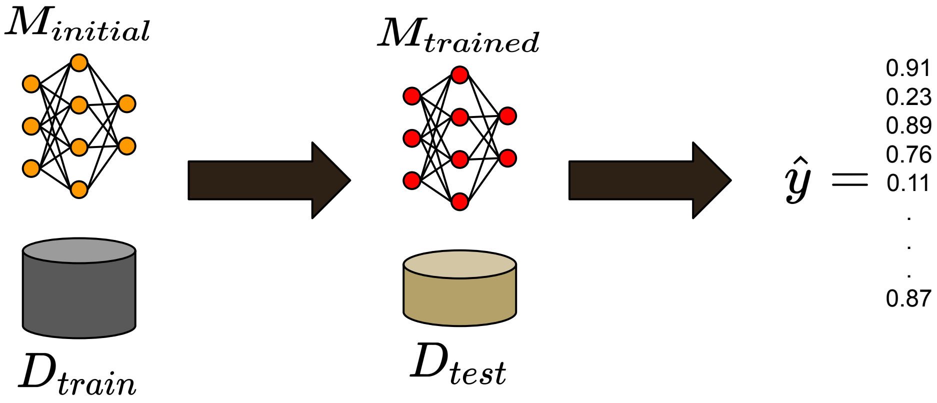

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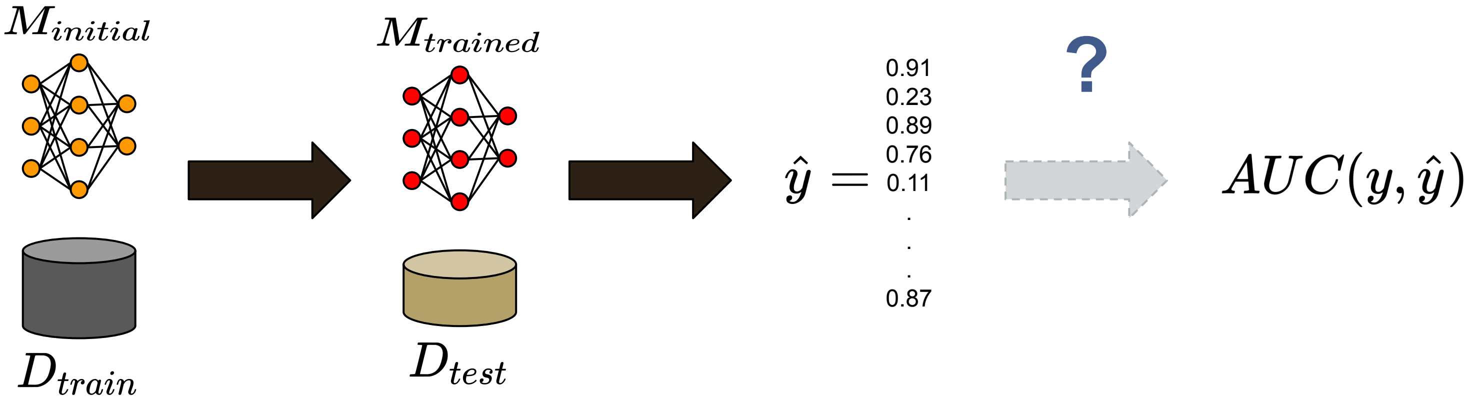
- Data is everywhere!
- Machine learning algorithms demand data.
- Privacy of the sensitive information!
    - Privacy preserving model training and testing
    - How about the privacy preserving model evaluation such as the area under curve?



ppAURORA

- Privacy preserving model evaluation based on 3-party computation (MPC) framework[1]

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Proxies

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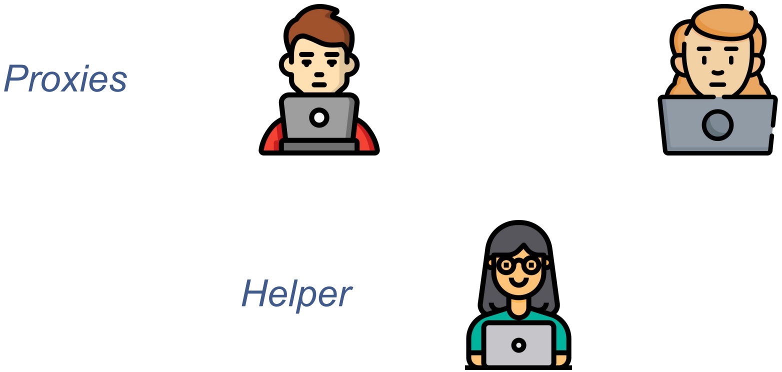

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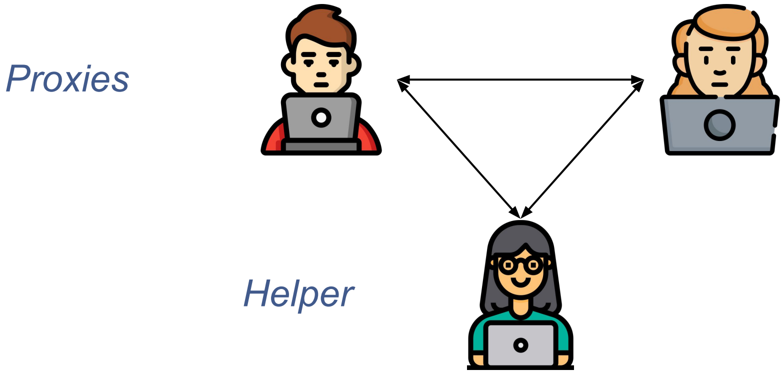

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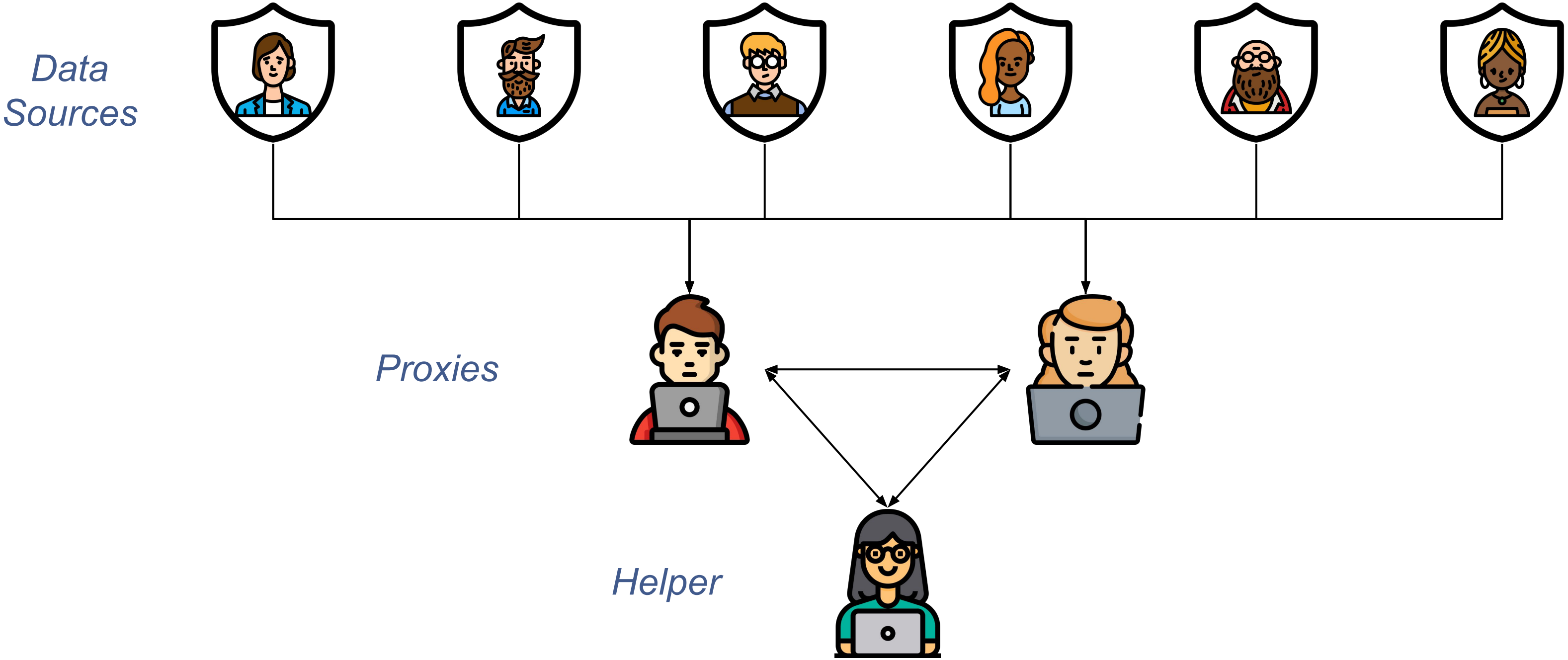

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ppAURORA

- Privacy preserving model evaluation based on 3-party computation (MPC) framework

- Area under the curve (AUC) as the model evaluation metric
    - Summarizes the plot-based model evaluation metrics by measuring the area between the curve and the x-axis
    - Receiver operating characteristic (ROC) curve
    - Precision-Recall (PR) Curve

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- Area under the curve (AUC) as the model evaluation metric
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  - Receiver operating characteristic (ROC) curve
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- Exact AUC computation via the MPC building blocks
  - Especially for the small size test set

Area Under the ROC Curve (AUROC)

- ppAURORA for the area under the ROC curve (AUROC)

Area Under the ROC Curve (AUROC)

- ppAURORA for the area under the ROC curve (AUROC)

- Two versions
  - No tie condition in the prediction scores (AUROC no-tie)
  - With tie condition in the prediction scores (AUROC with-tie)

Area Under the ROC Curve (AUROC)

- For AUROC no-tie

$$AUROC = \frac{\sum_{i=1}^{M}\left(TP[i]\cdot(FP[i]-FP[i-1])\right)}{T\cdot F}$$

Area Under the ROC Curve (AUROC)

- For AUROC no-tie

all samples # true positives # false positives

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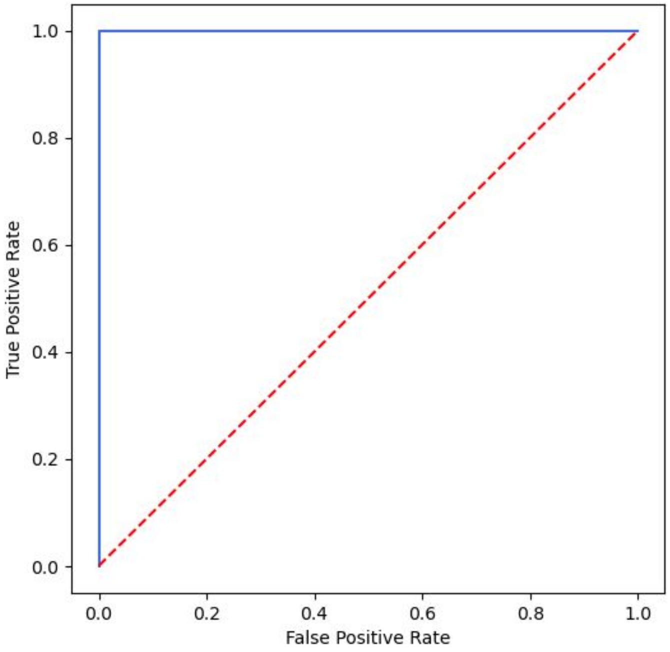
DIV

MUL

Why AUROC *with-tie*?

Prediction Score	Label
0.5	1
0.5	1
0.5	1
0.5	1
0.5	1
0.5	0
0.5	0
0.5	0
0.5	0
0.5	0



Why AUROC *with-tie*?

TPR	FPR
0.2	0
0.4	0
0.6	0
0.8	0
1	0
1	0.2
1	0.4
1	0.6
1	0.8
1	1

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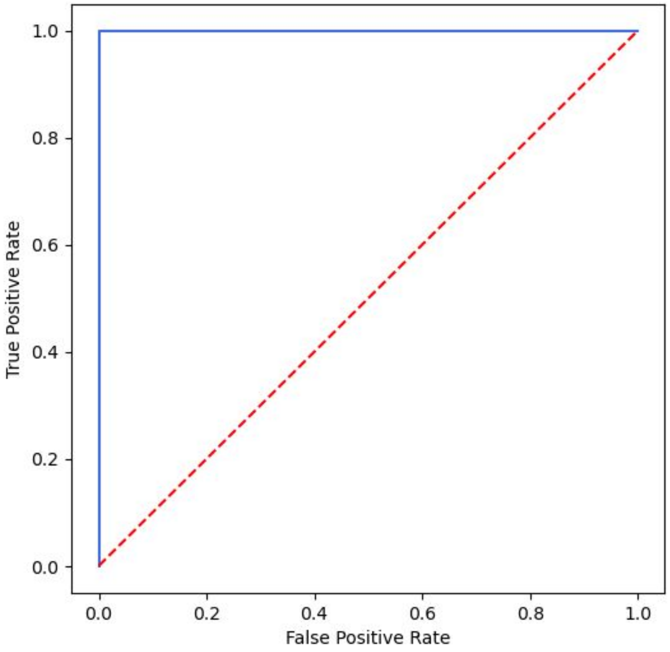

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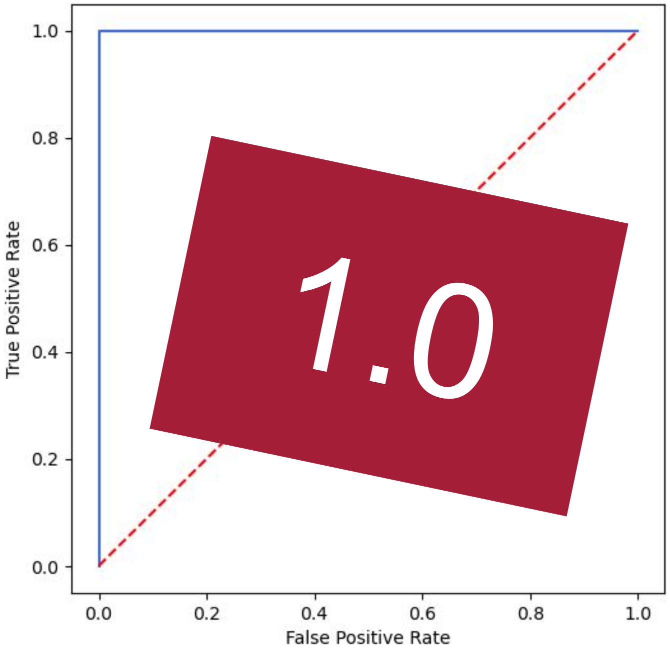

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all samples   # true positives   # false positives

$$AUROC = \frac{\sum_{i=1}^{M}\left(TP[i]\cdot(FP[i]-FP[i-1])\right)}{T\cdot F}$$

true samples   # false samples

- For AUROC with-tie

$$AUROC = \sum_{i=1}^{\Theta}\left(\frac{(TP[i]+TP[i-1])\cdot(FP[i]-FP[i-1])}{2\cdot T\cdot F}\right)$$

Area Under the ROC Curve (AUROC)

- For AUROC no-tie

all samples

true positives

false positives

$$AUROC = \frac{\sum_{i=1}^{M}\left(TP[i]\cdot(FP[i]-FP[i-1])\right)}{T\cdot F}$$

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threshold samples
determined via secure tie detection

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Area Under the Precision-Recall Curve (AUPR)

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  - Precision and recall can change at the same time.
  - No common denominator though

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$$AUROC = \sum_{i=1}^{\Theta} \left(PRE[i-1] \cdot (REC[i] - REC[i-1]) + \frac{(PRE[i]-PRE[i-1]) \cdot (REC[i]-REC[i-1])}{2} \right)$$

Precision

Recall

Area Under the Precision-Recall Curve (AUPR)

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Precision

Recall

MUL

DIV

Sorting

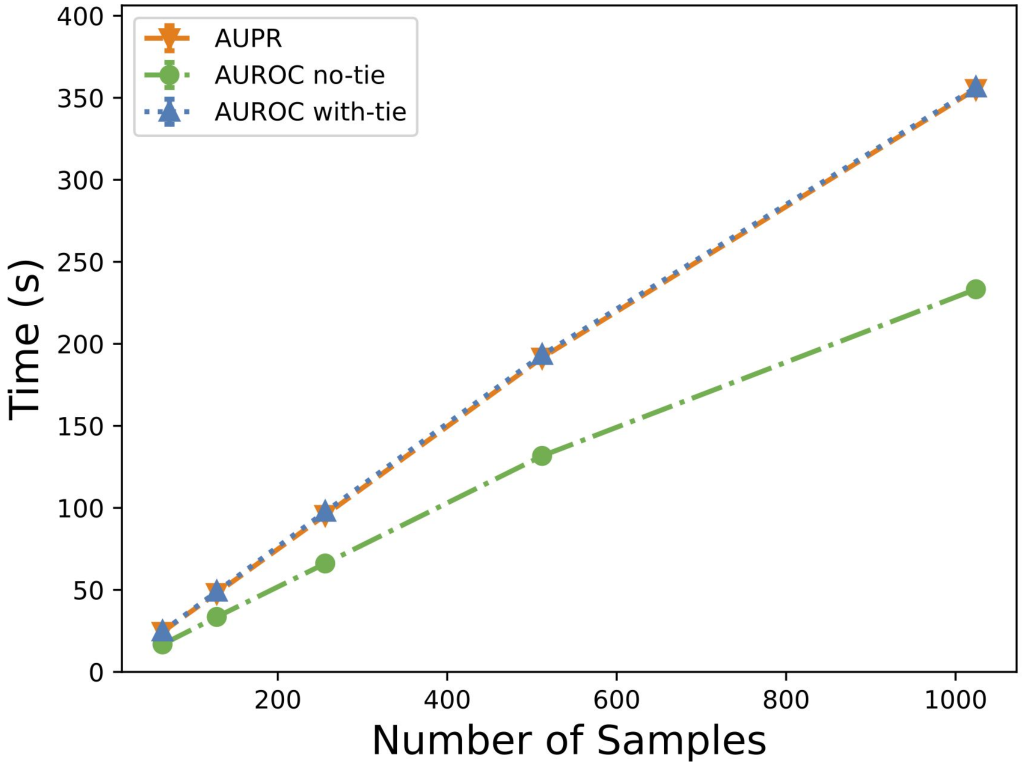
- The first task to perform before both AUROC and AUPR
  - Individually sorted lists from multiple data sources
- Merging individually sorted lists using the MPC building blocks
  - Parametric sorting algorithm adjusting the privacy-performance trade-off
- Skipping due to the time limitation

Results

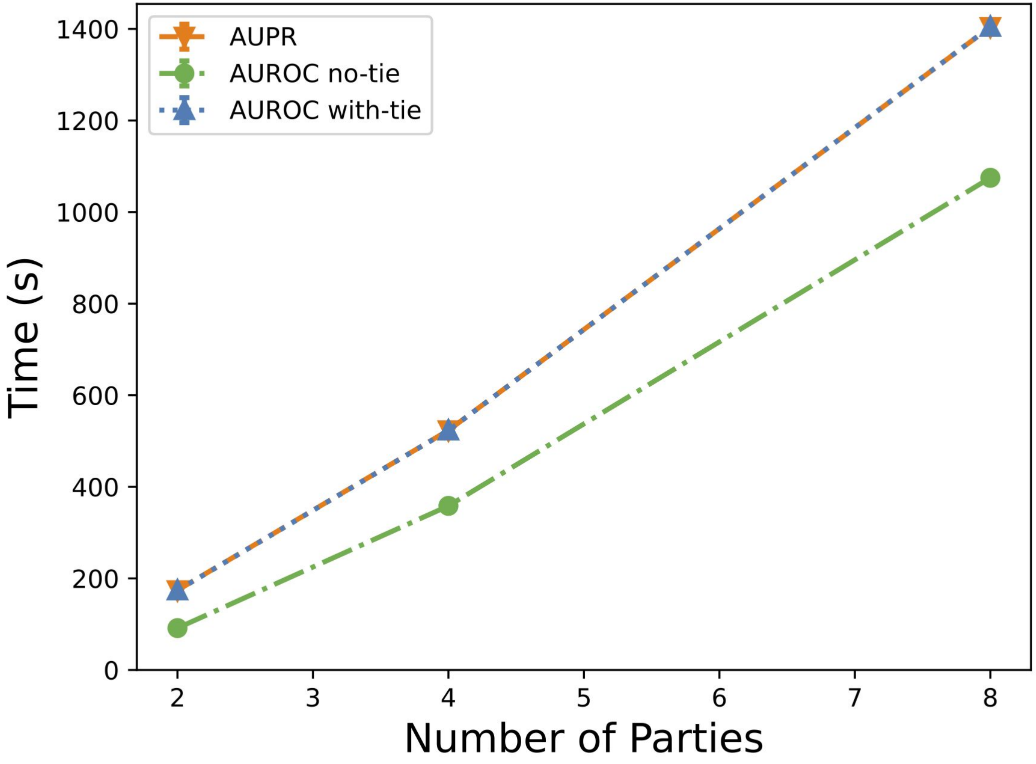
- Correctness analysis on
  - Acute Myeloid Leukemia dataset
  - UCI Heart Disease dataset
  - Same as the result of the plaintext analysis

- Scalability analysis on
  - Synthetic dataset
  - Various scenarios

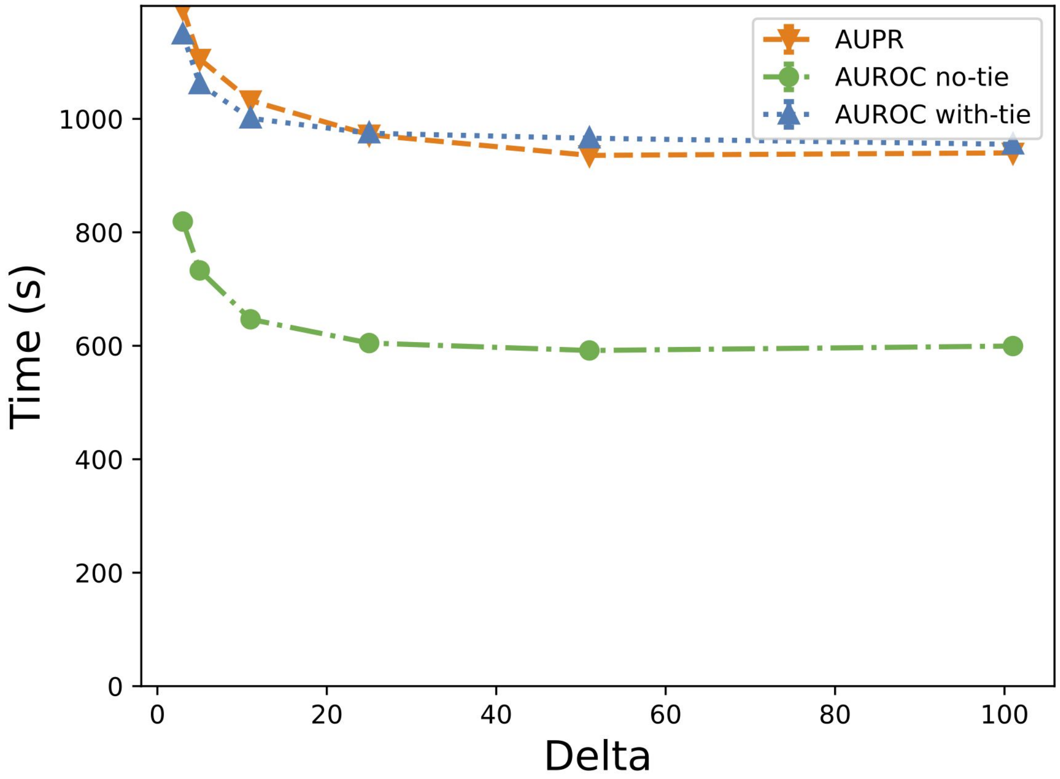
Results: Scalability to the Number of Samples



Results: Scalability to the Number of Parties



Results: Scalability to the Delta



Summary

- Not only the training and testing privately but also evaluation privately
- ppAURORA based on 3-party computation for AUC of ROC and PR curves
- Exact AUC result
- Linearly scalable to the number of samples and the parties
- Logarithmic decrease in the execution time parallel to the increase in delta

Thanks for listening!

Any Questions?

The icons in this presentation are from https://www.flaticon.com/