

CaPC Learning: Confidential & Private Collaborative Learning

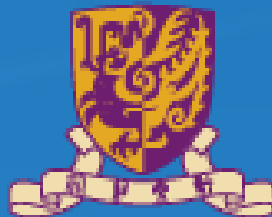
Christopher A. Choquette-Choo, Natalie Dullerud, Adam Dziedzic, Yunxiang Zhang, Somesh Jha, Nicolas Papernot, Xiao Wang



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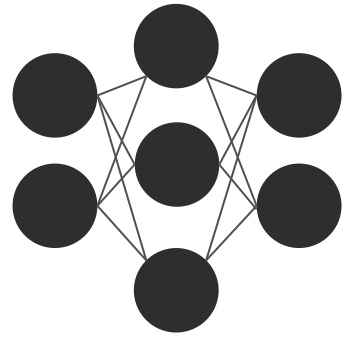
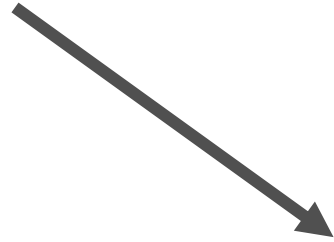
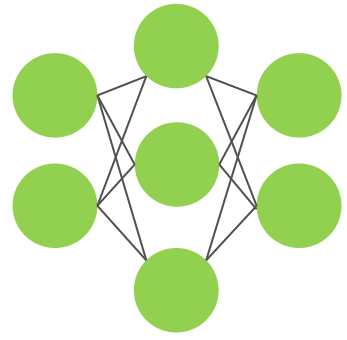
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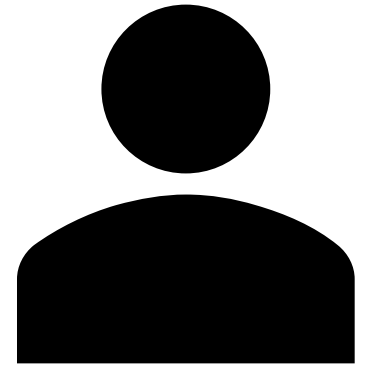
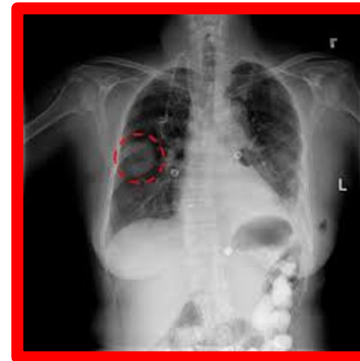
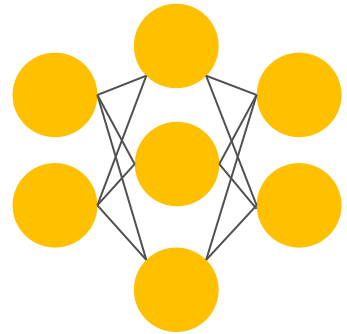
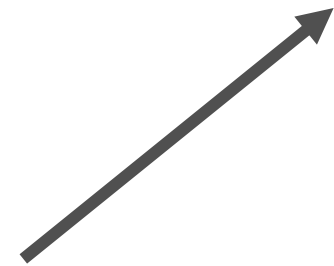
Private Consultation



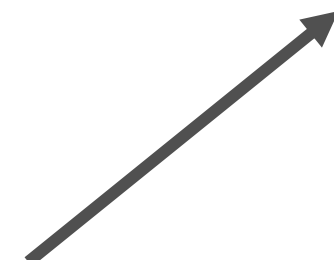
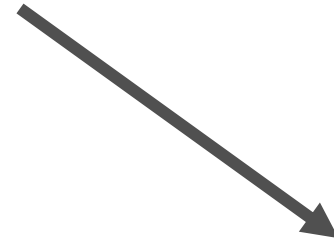
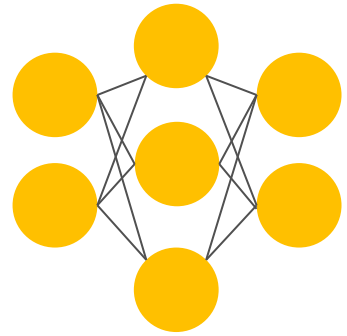
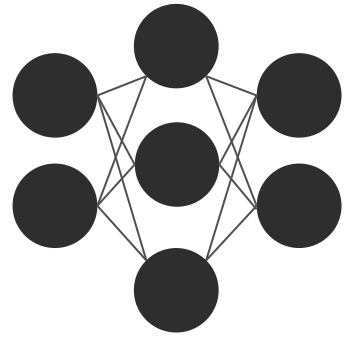
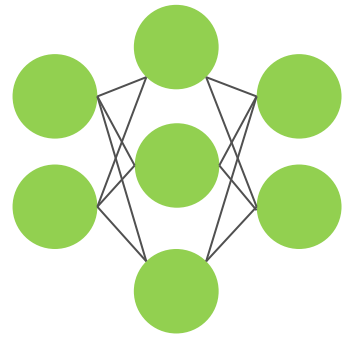
Aggregation



Disease



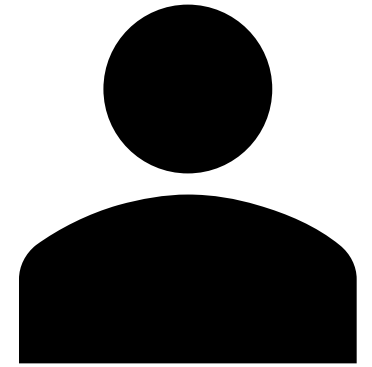
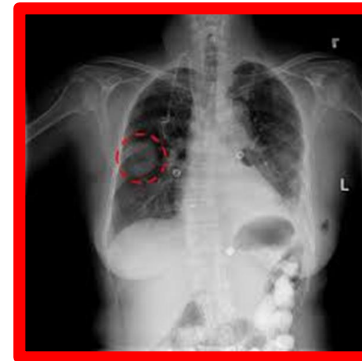
How to Protect Confidentiality and Privacy?



Aggregation



Disease

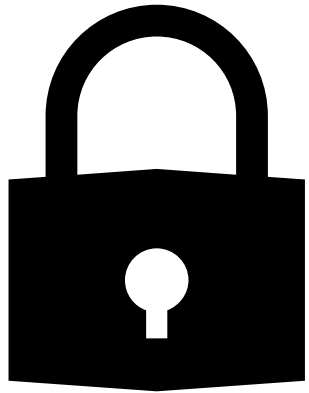


Requirements for CaPC

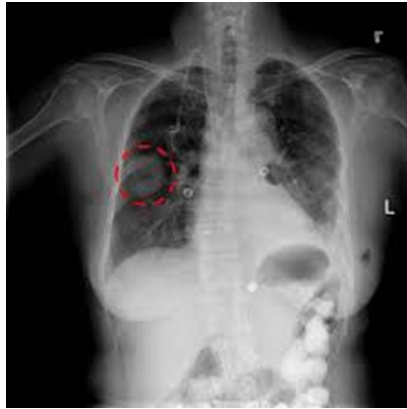
Requirement	What do we do?
Privacy of training data	Guarantee protection of personally identifiable information contained in training data via Differential Privacy.
Query confidentiality	Encrypt input data and do inference on encrypted data using Homomorphic Encryption and Secure Multi-Party Computation.
Model confidentiality	Prevent leakage of the answering parties' models to the querying party.

Use CaPC in Healthcare

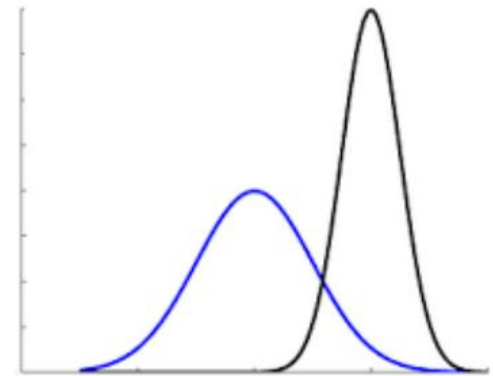
- Hospitals act as collaborating parties.
- Protect privacy & confidentiality of patients' data.
- Using collaborative learning setup to investigate and possibly address some of the issues in healthcare.



Strong Privacy
Guarantees

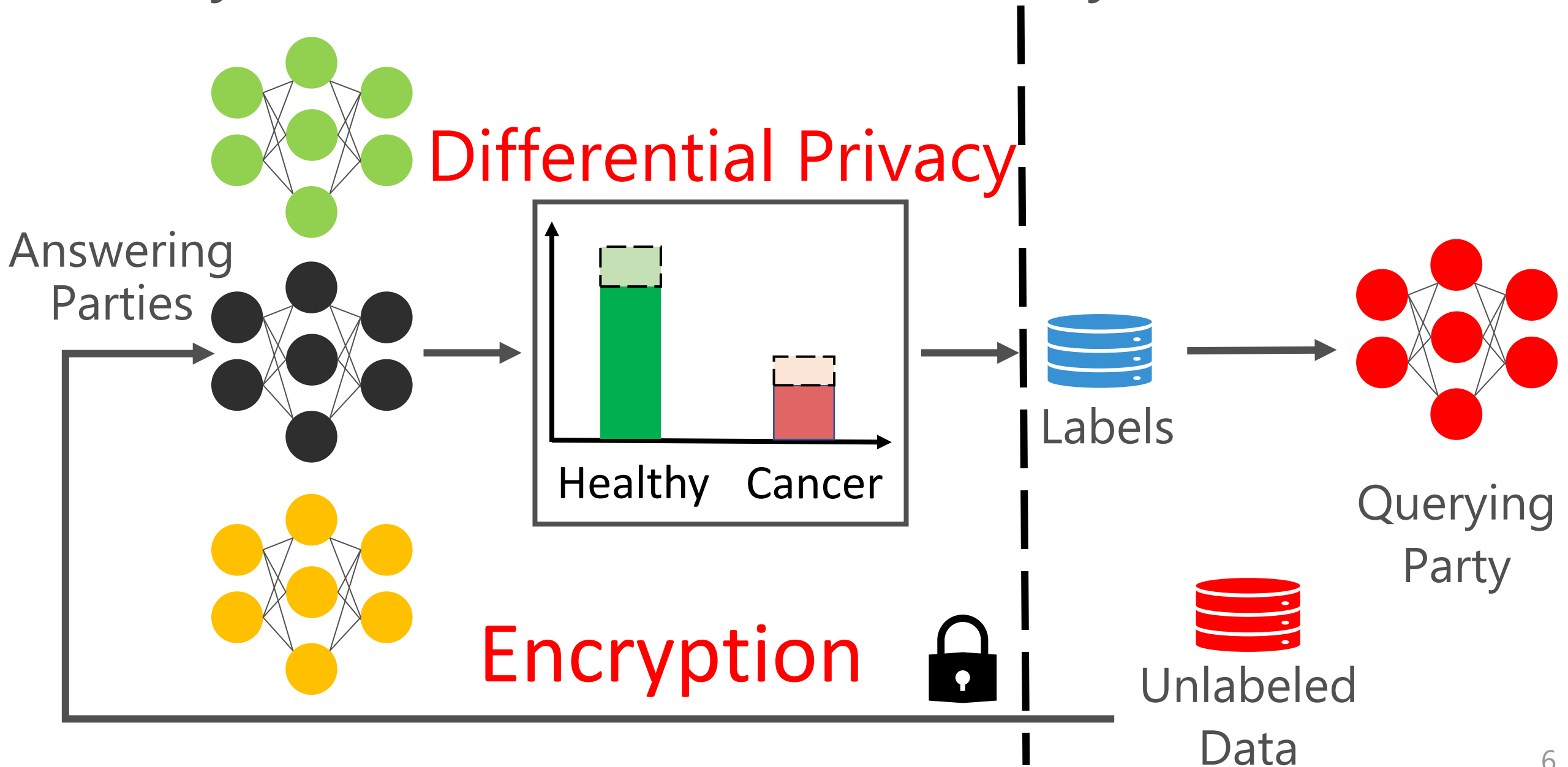


Private
Consultation



Robustness to
Distribution Shift

Privacy of Train & Confidentiality of Test Data



CaPC Workflow

1a Private Inference

1b Blind Outputs

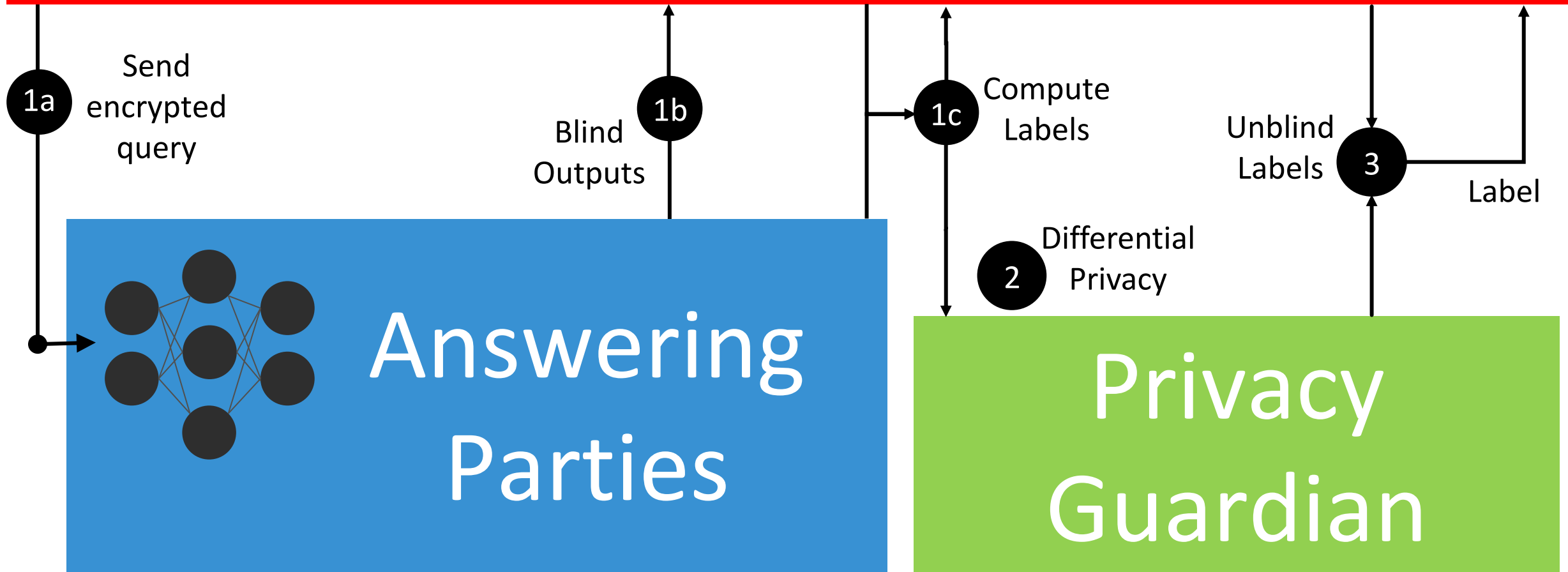
1c Compute Labels

2 Add DP Noise + Aggregate Labels

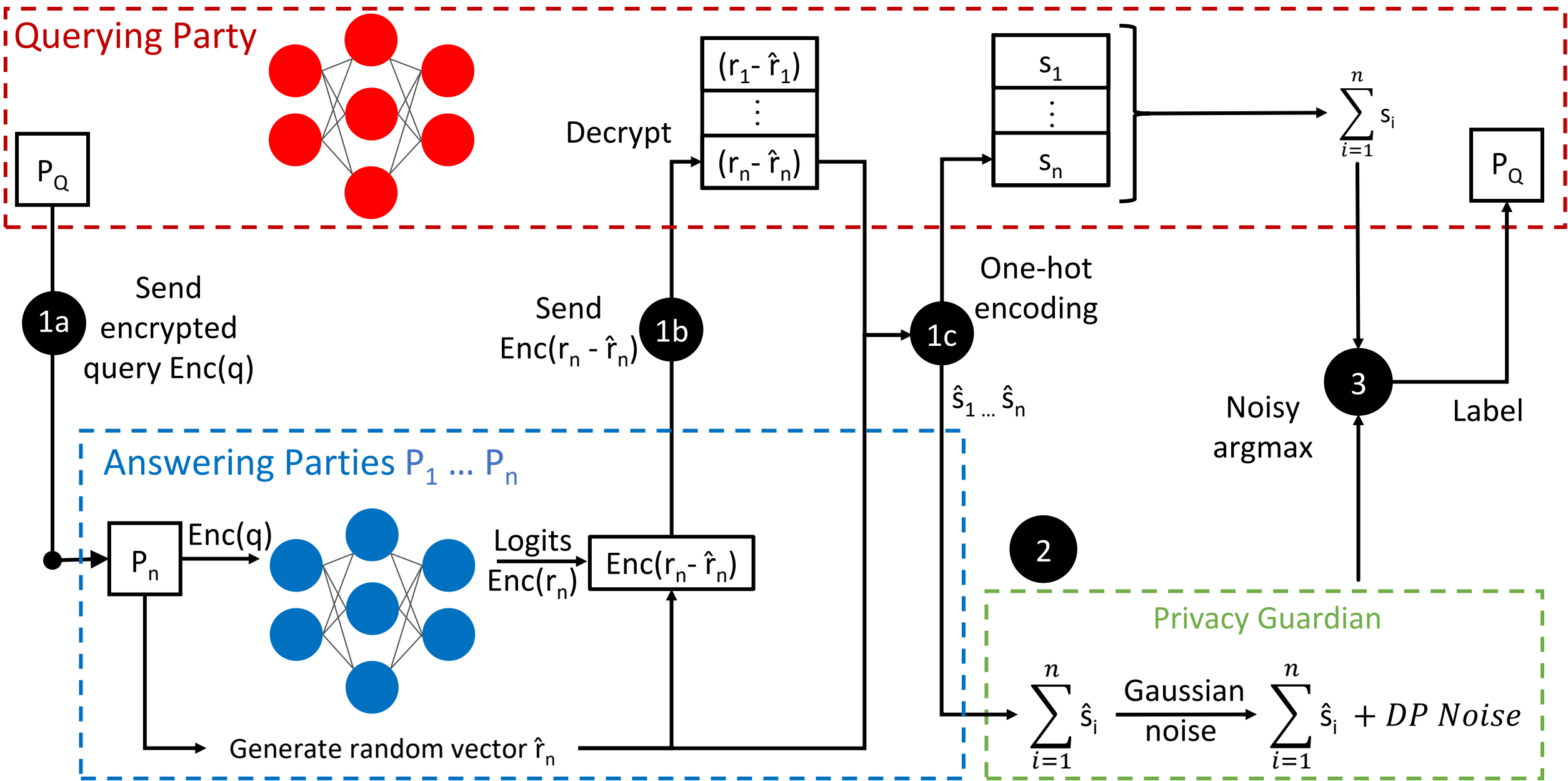
3 Unblind Final Label

Actors in CaPC

Querying Party

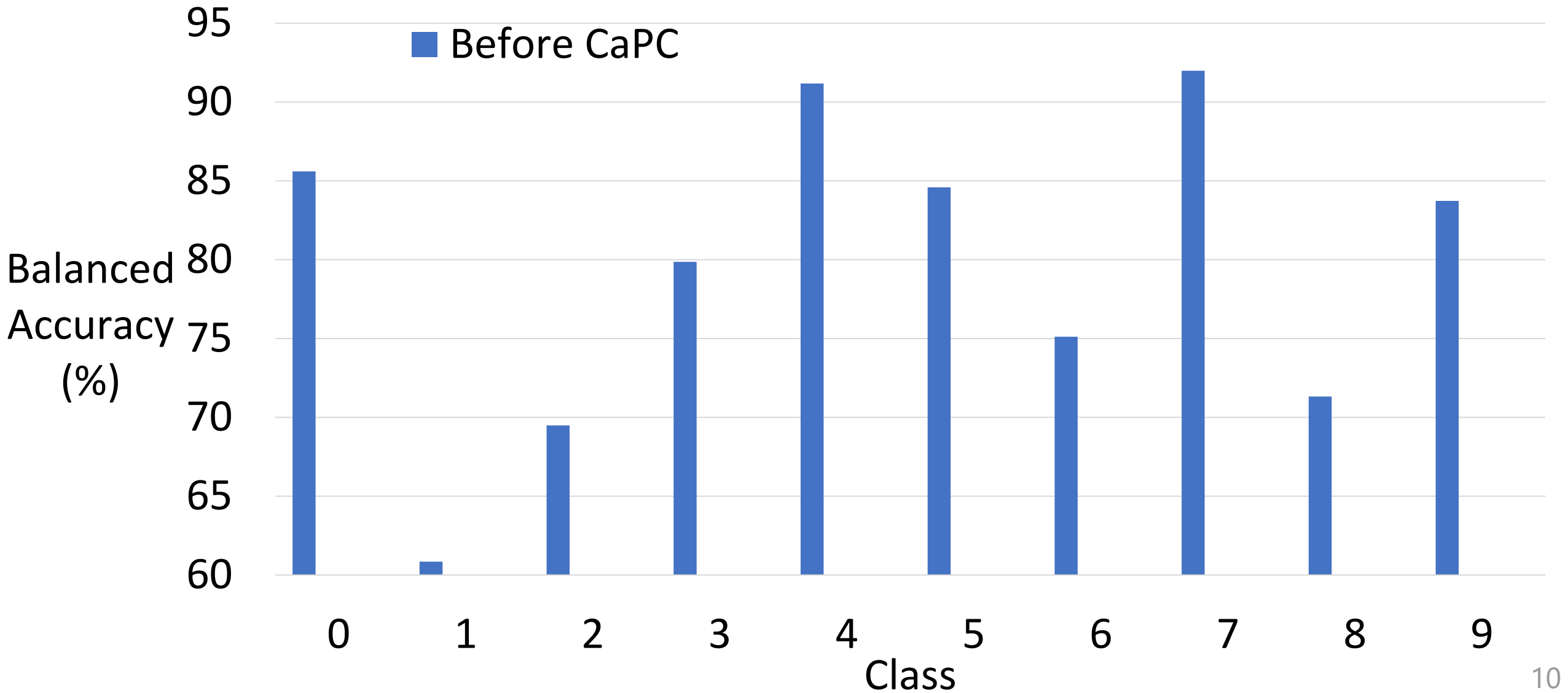


CaPC Protocol



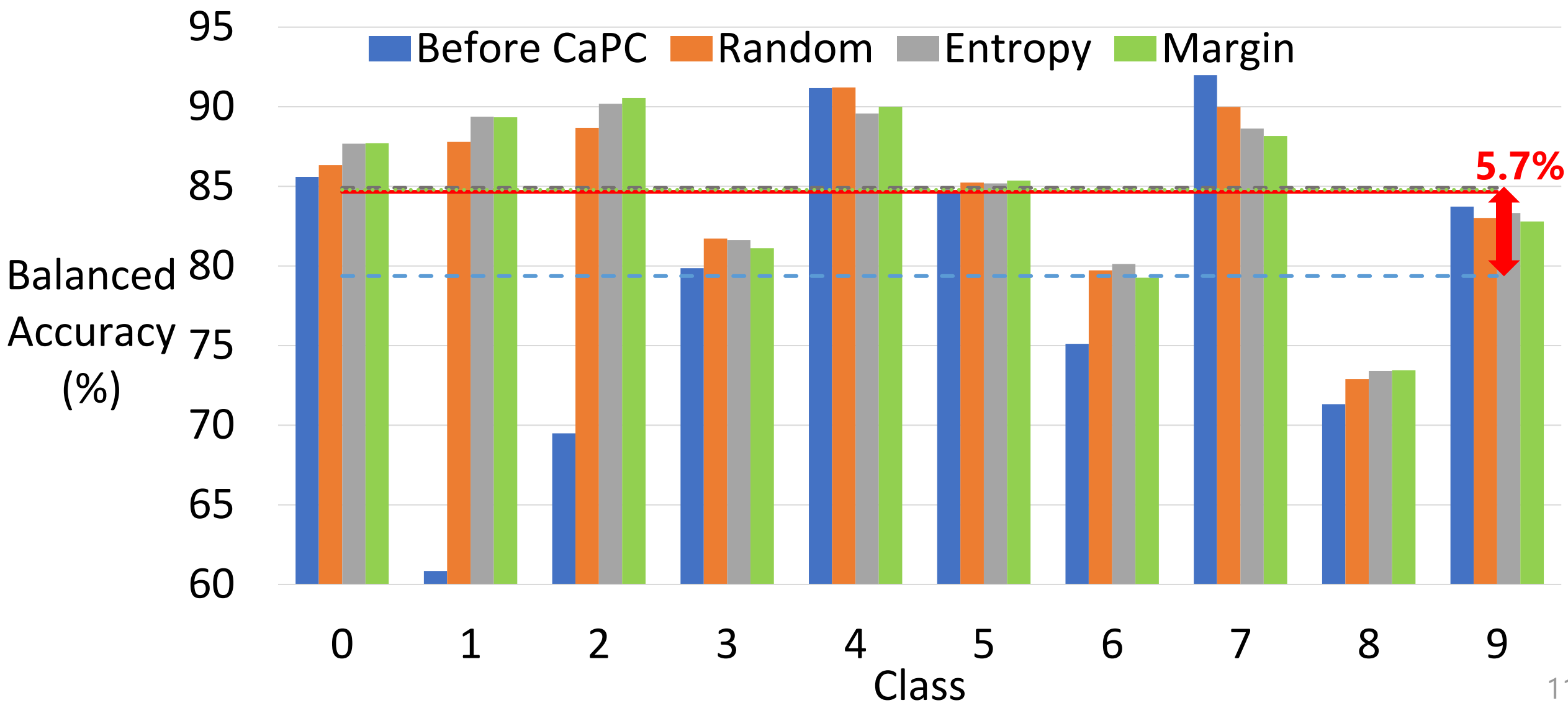
Non-uniform Data Distribution

*SVHN on VGG-7, 250 parties, $\epsilon = 2.0$, $\delta = 10^{-6}$, **classes 1 & 2 are under-represented***



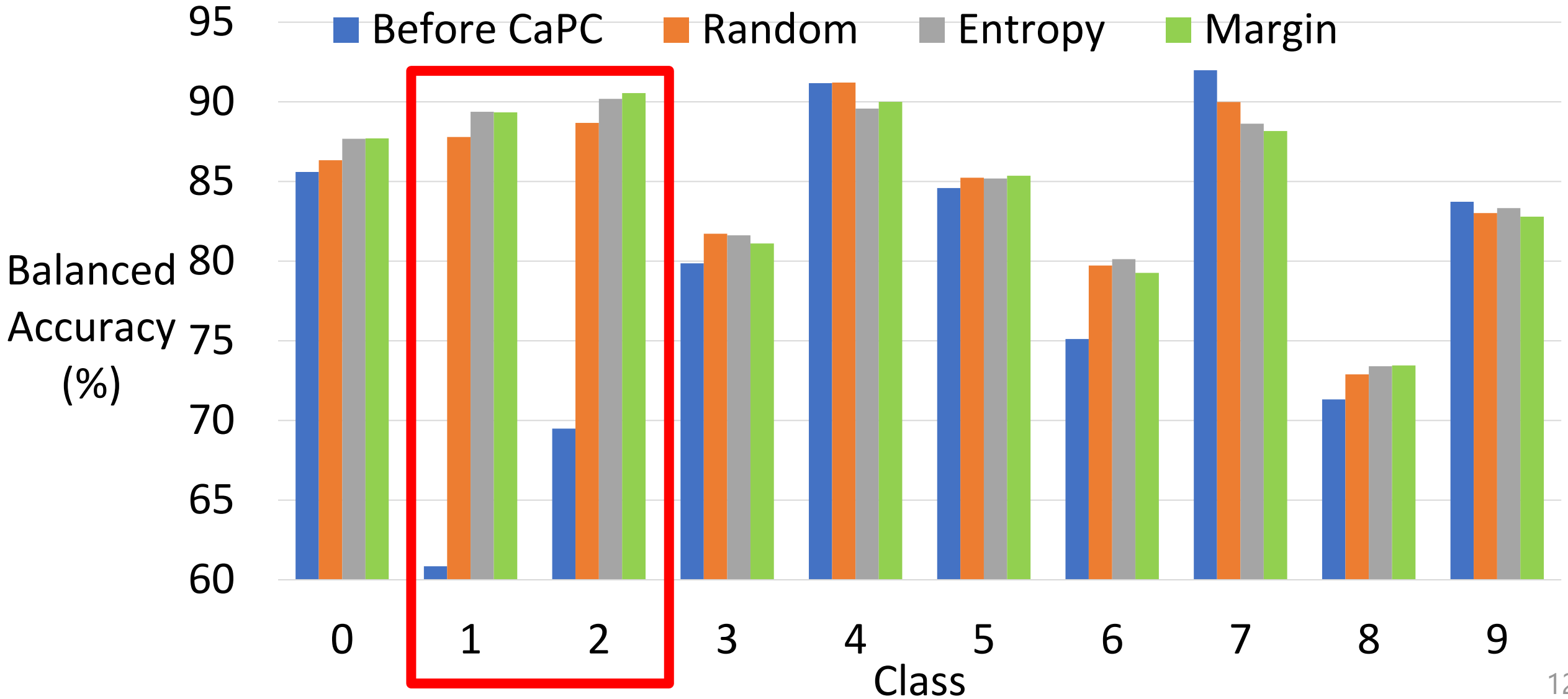
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Conclusions

- CaPC protocol for privacy preserving collaboration and learning.
- Privacy of train data with differential privacy & Pâté.
- Confidentiality of test data via secure multi-party computation and homomorphic encryption.
- Participants label their new data items and use them to improve their own ML models.
- CaPC improves performance of models with heterogenous architectures and when there is skew in data.

Thank you

<https://arxiv.org/abs/2102.05188>