

Heterogeneous Model Reuse via Optimizing Multiparty Multiclass Margin



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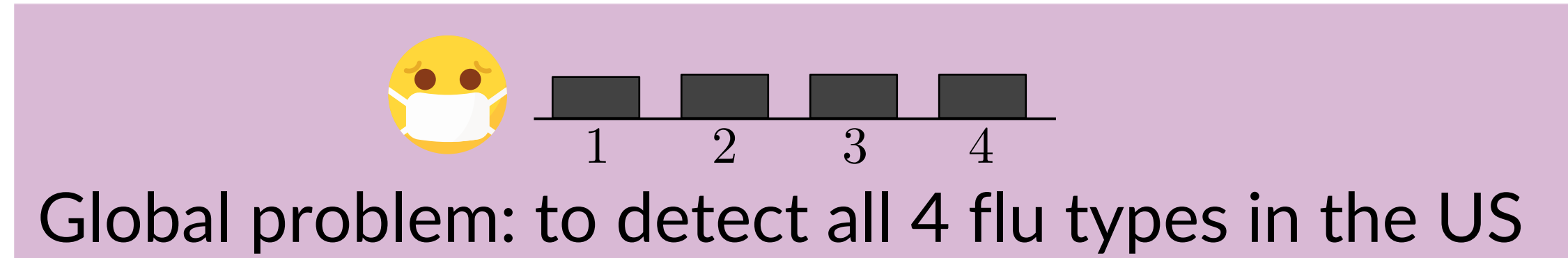
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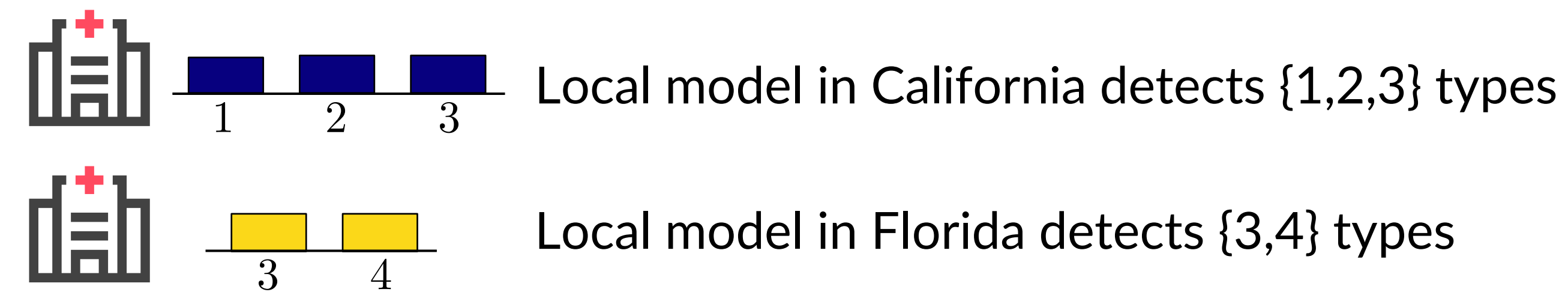


Problem setting

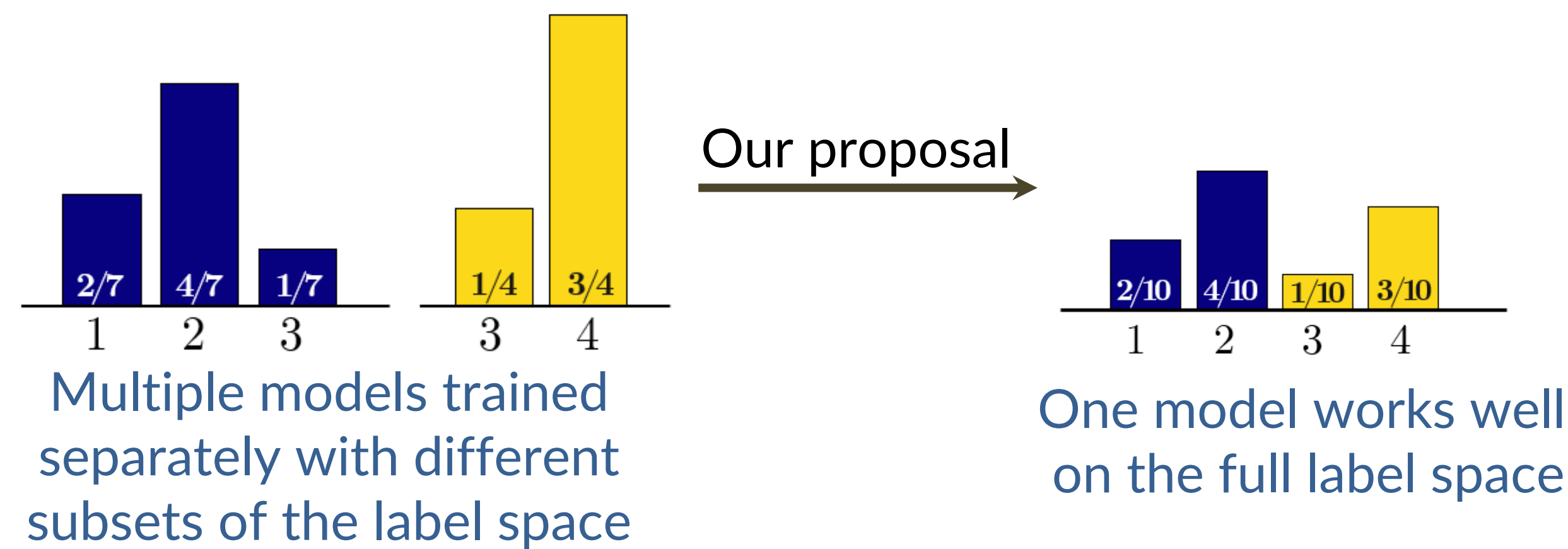
- Problem: **Multiparty multiclass classification**
- Example: Flu detection



But, the types of flu diverse geographically, the distribution of patients records collected by a hospital in California is different from Florida. Good local models are built:



The patients' records are confidential. Can we smartly reuse the local models to learn the global problem, instead of building a model on merged local datasets?



Notations

Parties each with local datasets but different label spaces:

$$S_i = (X_i, Y_i) = \{(x, y) \in \mathcal{X} \times \mathcal{Y}_i\} \subseteq S$$

$$\mathcal{Y}_i \subseteq \mathcal{Y} = \{1, 2, \dots, k\}$$

Local predictor trained by local algorithm on local dataset:

$$h_i : \mathcal{X} \times \mathcal{Y}_i \rightarrow \mathbb{R} \quad h_i = \mathcal{A}_i(S_i)$$

Example	$h_1(x,1)=2/7$	$h_1(x,2)=4/7$	$h_1(x,3)=1/7$	$h_2(x,3)=1/4$	$h_2(x,4)=3/4$
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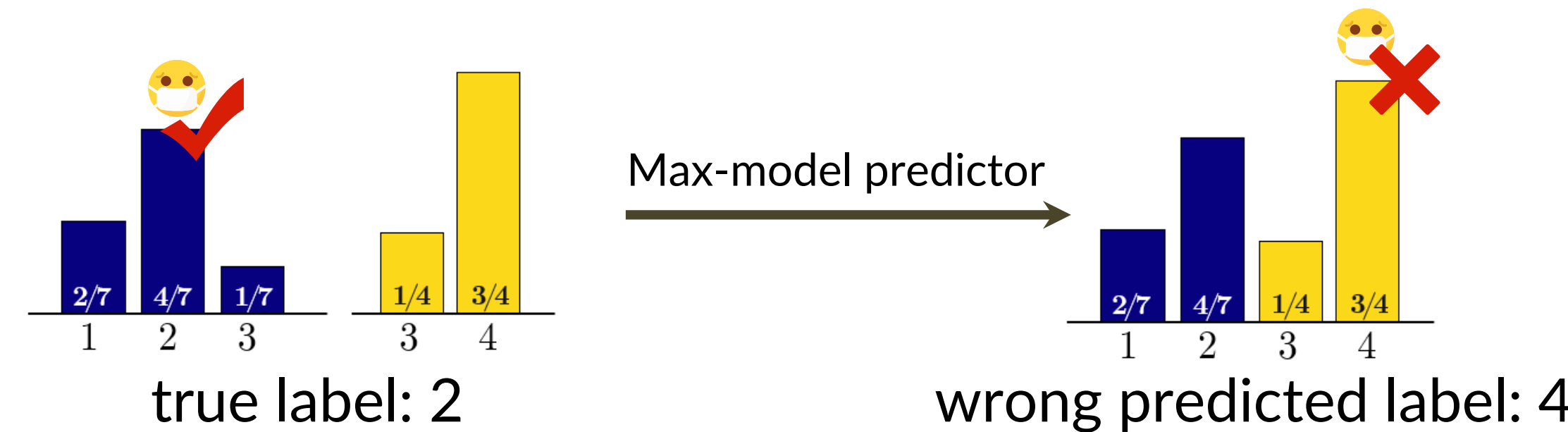
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 Code: <https://github.com/YuriWu/HMR>

Behavior of an ensemble of local models

- The intuitive ensemble of local models is to use **max-model predictor**: Given a set of multi-class predictors $H=\{h_1, \dots, h_n\}$, the max-model predictor h_H is defined as:

$$h_H(x, y) = \max_{y \in \mathcal{Y}_i, h_i \in H} h_i(x, y)$$

- However, max-model predictor may **fail** even if each local model is **perfect** (see Claim 1 in our paper for the formal statement).
- Intuition: another local model which is unaware of the true class may mislead the final prediction.



Contribution

Q: How to measure the global behavior of multiple models?

A: **Multiparty multiclass margin. (MPMC-margin)**

Q: How to optimize the global behavior?

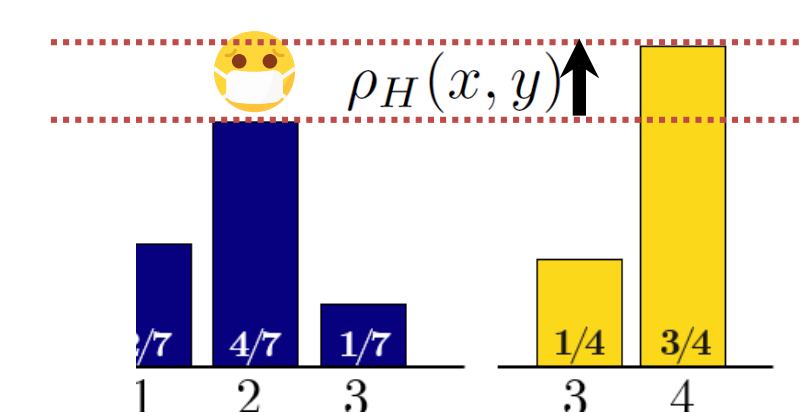
A: **The HMR method, which maximizes MPMC-margin.**
 by modifying local models, without merging local datasets.

MPMC-margin

- The multiparty multiclass margin (MPMC-margin) on the local predictors set $H=\{h_1, \dots, h_n\}$ at a labeled example (x, y) is defined as:

$$\rho_H(x, y) = \max_i h_i(x, y) - \max_{j, y'} h_j(x, y')$$

where $y \in \mathcal{Y}_i, y' \in \mathcal{Y}_j \setminus \{y\}$.



- Non-positive MPMC-margin causes wrong prediction, so we want to maximize it.

Heterogeneous model reuse method

Algorithm 1 HMR

input:

Parties $1, 2, \dots, n$, each owns a local dataset S_i and a local model h_i . Example communication budget N .

output:

Calibrated local models h_1, \dots, h_n .

procedure:

- 1: Each party broadcasts its local model to others.
- 2: Inner iteration counter $T = 0$
- 3: **while** $T < N$ **do**
- 4: Sample a party i according to $|S_i| / \sum_{i=1}^n |S_i|$.
- 5: Party i randomly selects an example $(x, y) \in S_i$.
- 6: Party i computes MPMC-margin $\rho_H(x, y)$ and records the party i^+, i^- and maximum incorrect class y^- as in (8).
- 7: **if** $\rho_H(x, y) \leq 0$ **then**
- 8: Party i sends (x, y, y^-) to i^+ and i^- .
- 9: Party i^+ calibrates h_{i^+} with (x, y, y^-) .
- 10: Party i^- calibrates h_{i^-} with (x, y, y^-) .
- 11: Party i^+ and i^- broadcast their updated model.
- 12: **if** $i^+ \neq i$ or $i^- \neq i$ **then**
- 13: $T = T + 1$.
- 14: **end if**
- 15: **end if**
- 16: **end while**

An iterative method exchanges T examples and maximizes MPMC-margin on "unobserved" merged global dataset.

$$\rho_H(x, y) = h_{i^+}(x, y) - h_{i^-}(x, y^-)$$

$$i^+ = \arg \max_i h_i(x, y), \text{ where } y \in \mathcal{Y}_i, \quad (8)$$

$$(i^-, y^-) = \arg \max_{j, y'} h_j(x, y'), \text{ where } y' \in \mathcal{Y}_j \setminus \{y\}.$$

check MPMC-margin

send out one example if non-positive

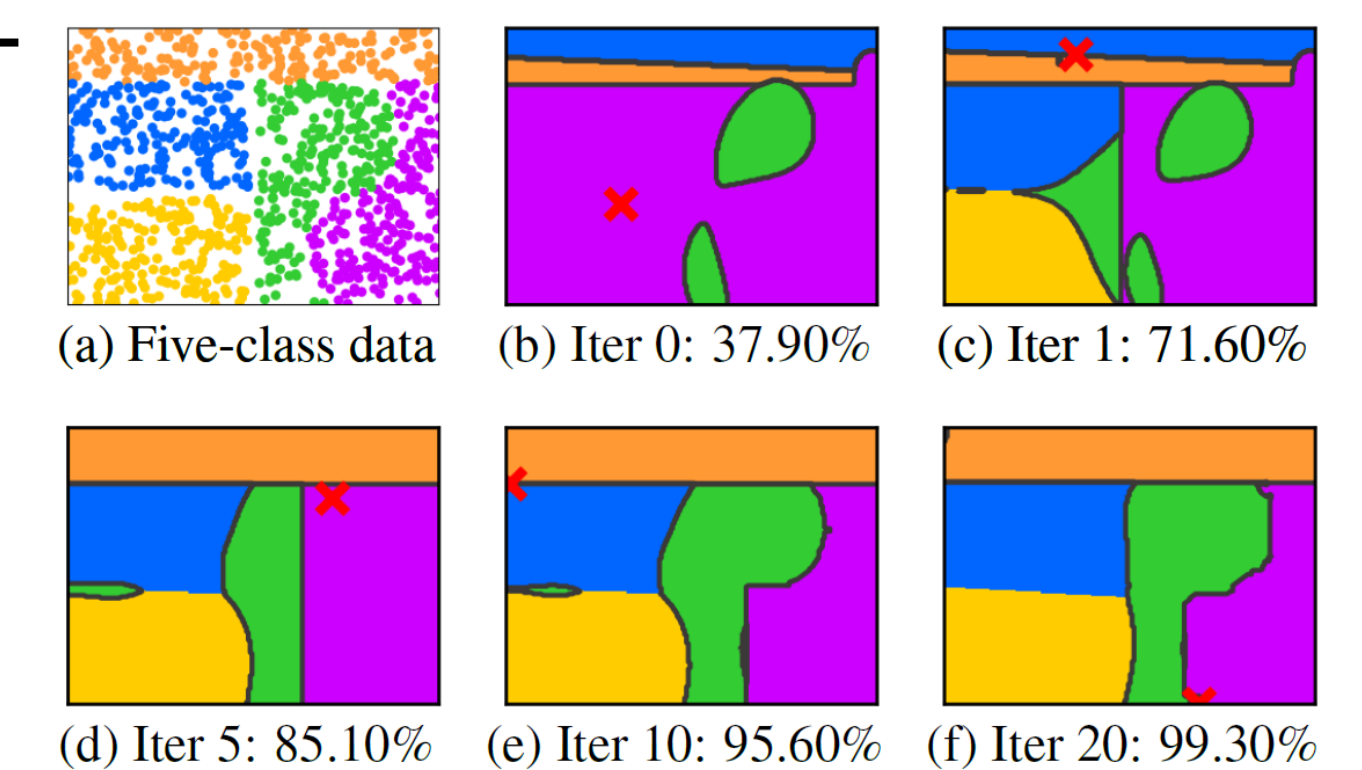
update local models

Privacy issue: If T is small enough, most of the private local data will be protected. Less than 1% of global data are shared in experiments.

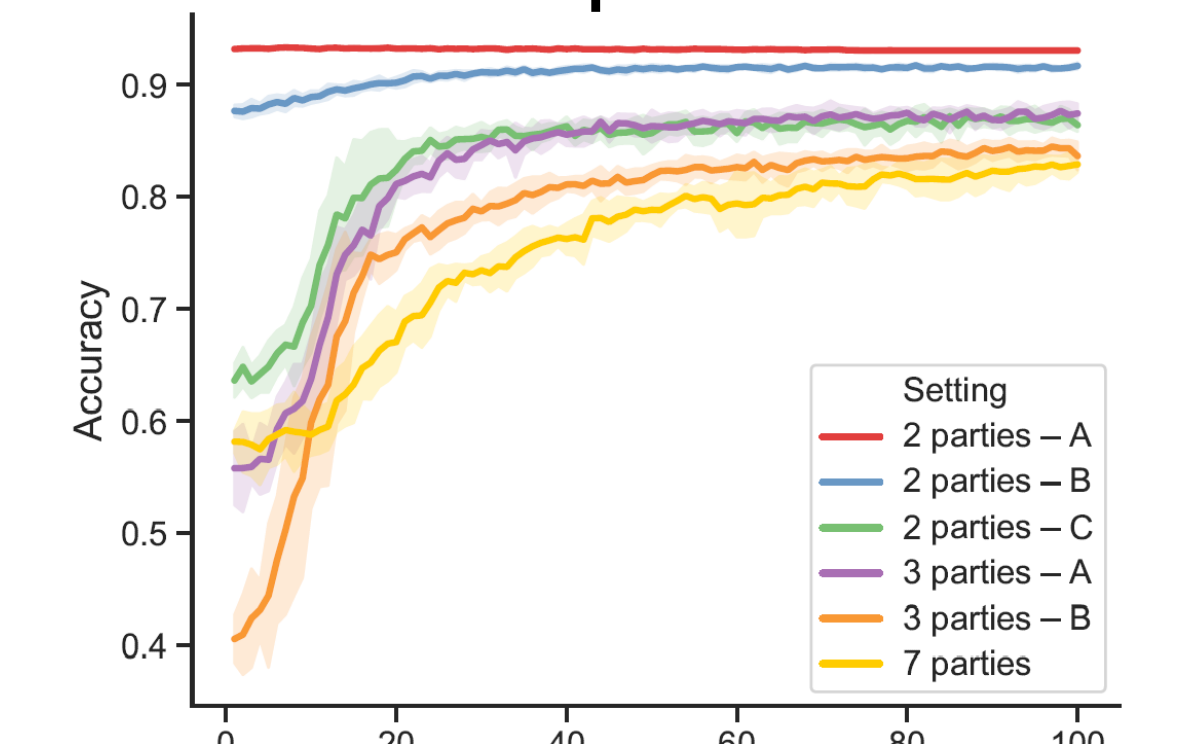
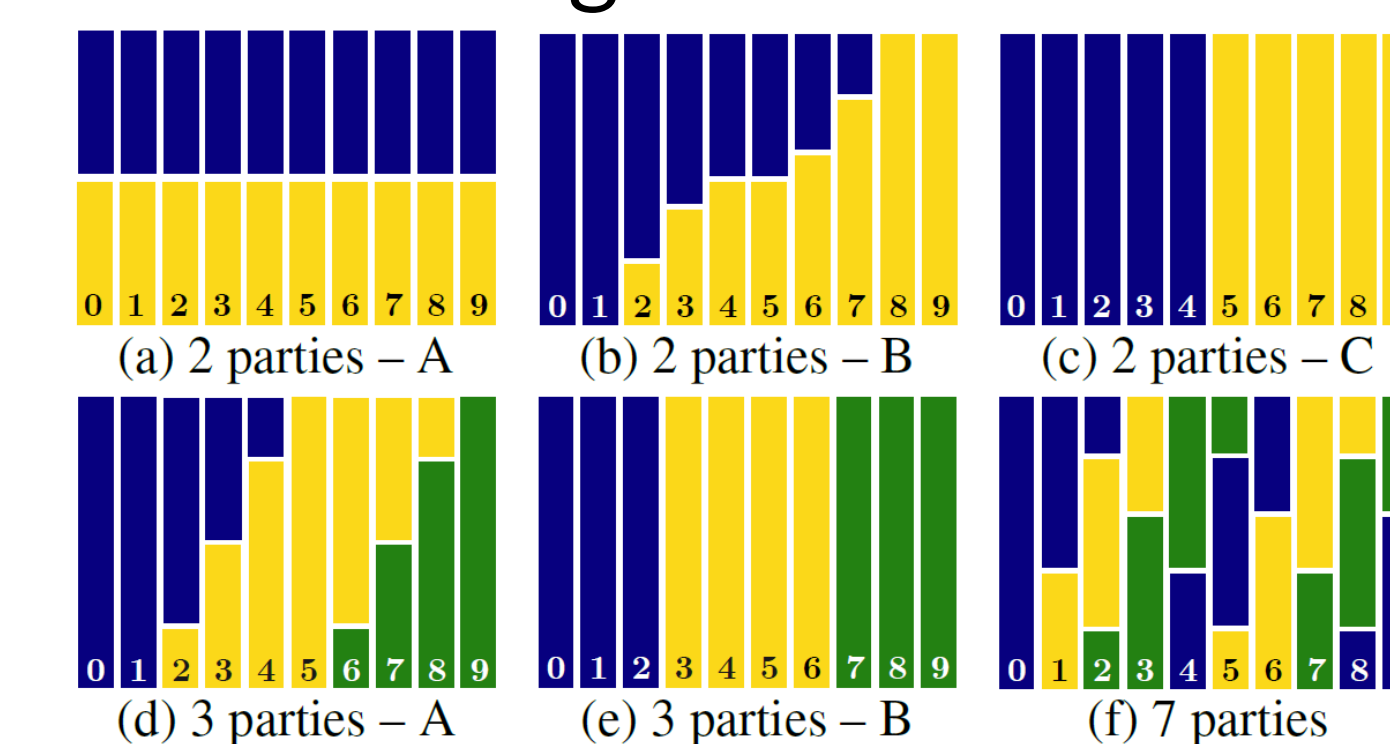
Experiments

- Toy example on LR/SVM/GBDT

- Heterogeneous learning models
 - LR: green, yellow
 - SVM: green, magenta
 - GBDT: magenta, orange
- Exchanged 20 examples
- Nearly perfect performance



- Benchmarking on fashion-MNIST on various data partitions



- Multi-lingual handwriting recognition

- 6 different structured CNNs trained locally on hiragana, katakana, kanji, devanagari, hangul and English letters
- 1600+ classes, 94.32% global accuracy
- Only exchanged 300 out of 420k examples

