PRIVACY-PRESERVING ALGORITHMS FOR DECENTRALIZED COLLABORATIVE MACHINE LEARNING

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Joint work with R. Guerraoui, M. Taziki, M. Tommasi and P. Vanhaesebrouck

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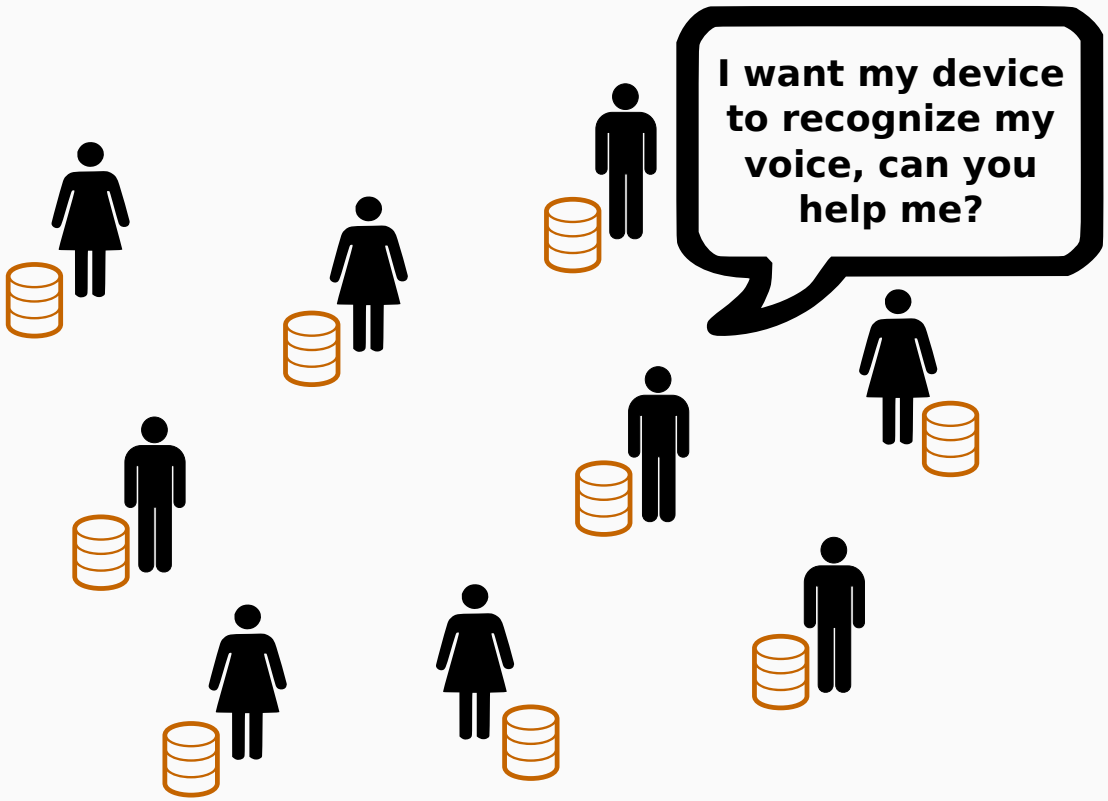
OUTLINE

1. Broad context
2. Problem setting
3. Decentralized algorithms
4. Privacy in decentralized learning
5. Illustrative experiments
6. Future work

BROAD CONTEXT

LEARNING FROM CONNECTED DEVICES DATA



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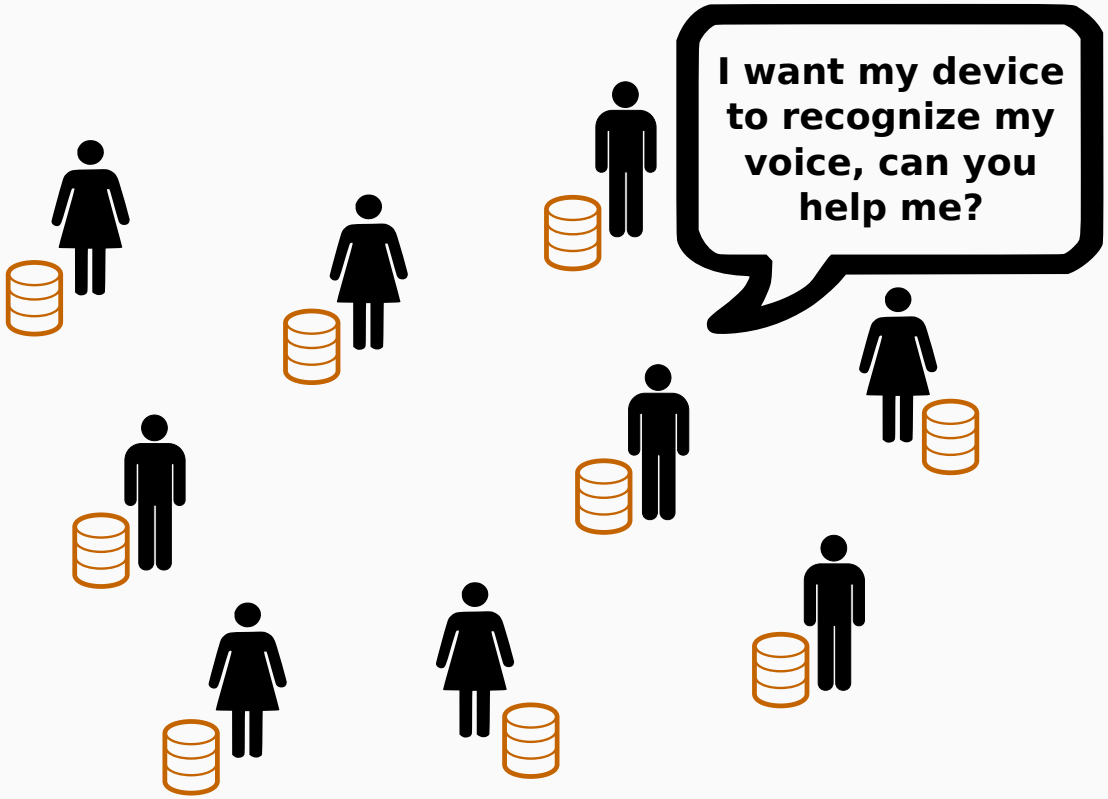
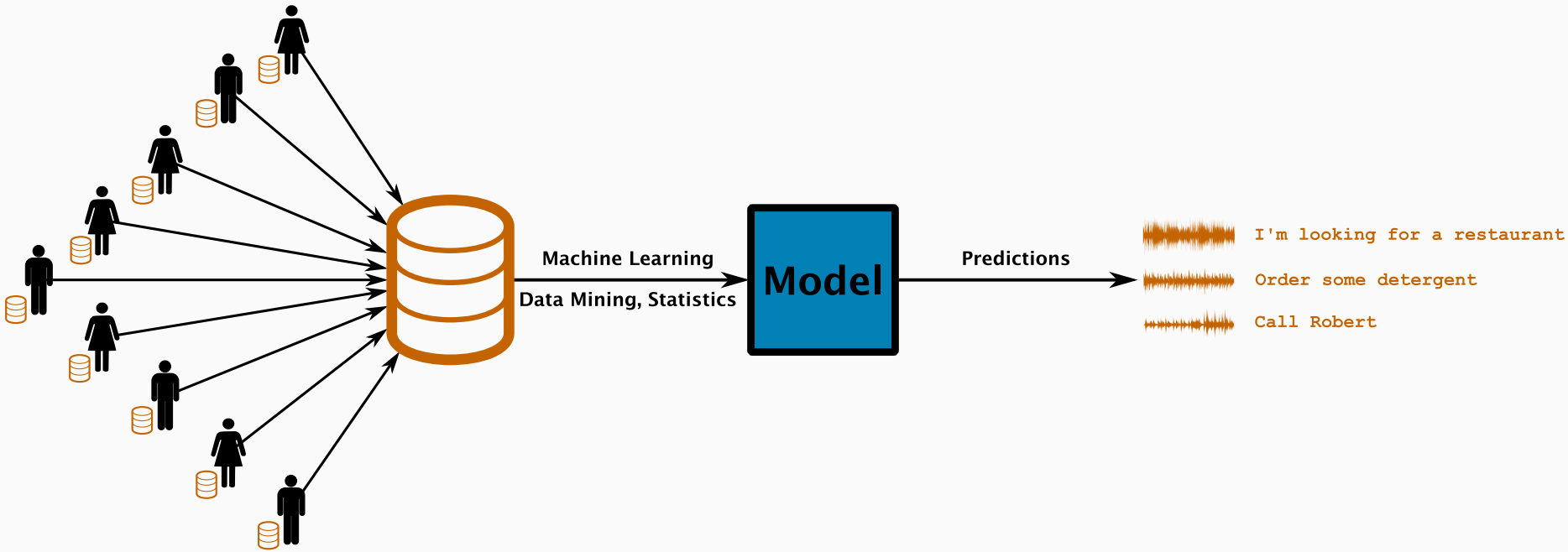


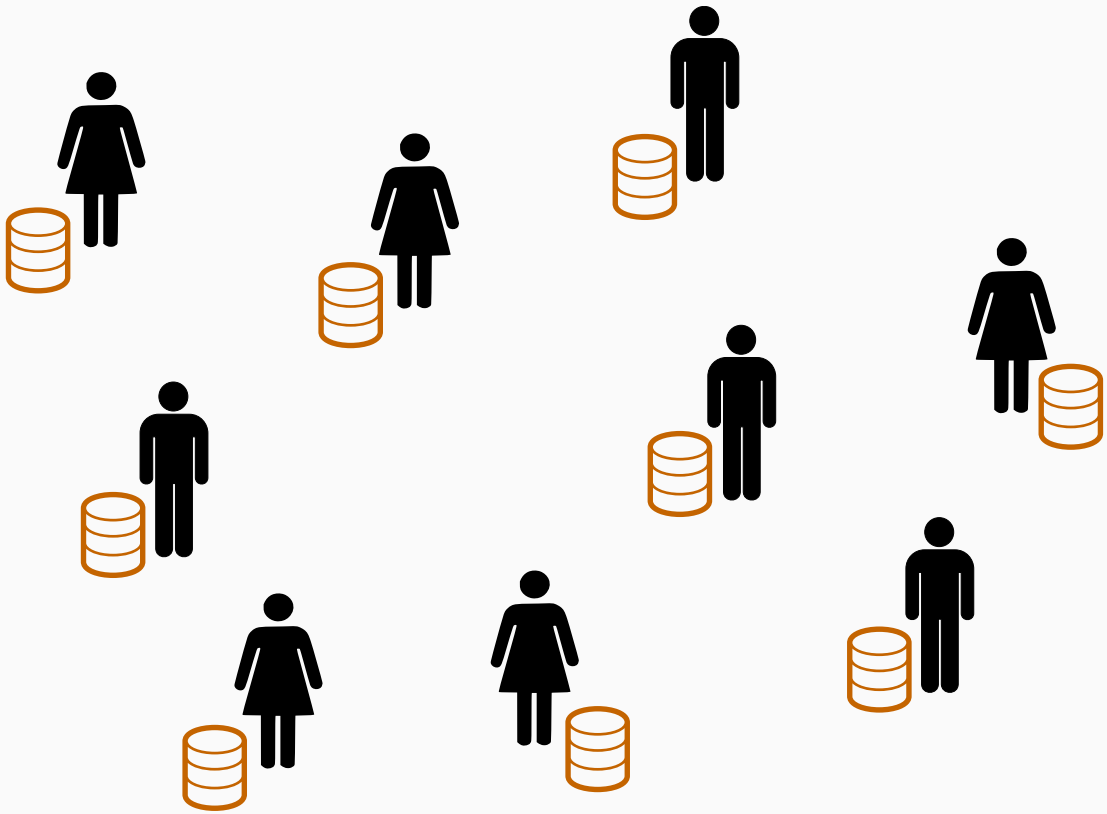
- Other examples of applications
  - Recommend content based on user activity logs
  - Learn personalized treatment from wearable device data

EXTREME APPROACH 1: CENTRALIZED LEARNING



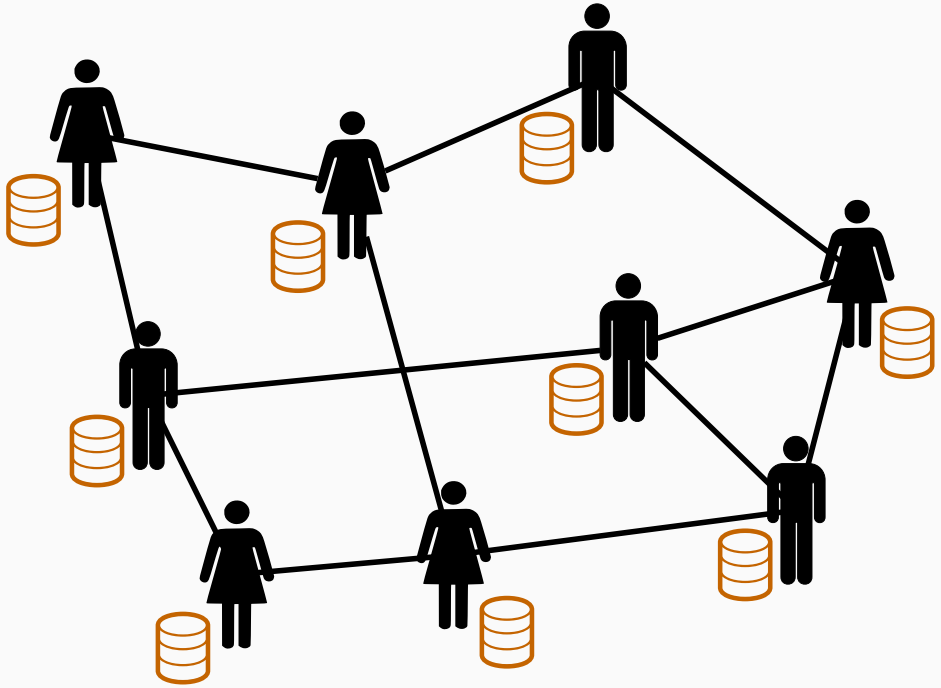
- Best for utility: efficient access and processing
- Lack of user control over its personal data
  - What is collected? Who can access it? How is it used and what for?
- Vulnerability to attacks / subpoenas
  - Yahoo data breach (3B users!), Twitter / Wikileaks court orders
- Costly infrastructure for service provider

EXTREME APPROACH 2: PURELY LOCAL LEARNING



- Best for privacy: no information exchanged between devices
- Bad for utility (especially for users without much data)

OUR APPROACH: FULLY DECENTRALIZED LEARNING



- Personal data stays on user's device
- Peer-to-peer and asynchronous communications
- No single point of failure/entry as in server-client architectures
- Scalability-by-design to many devices through local updates (see e.g., [Lian et al., 2017])

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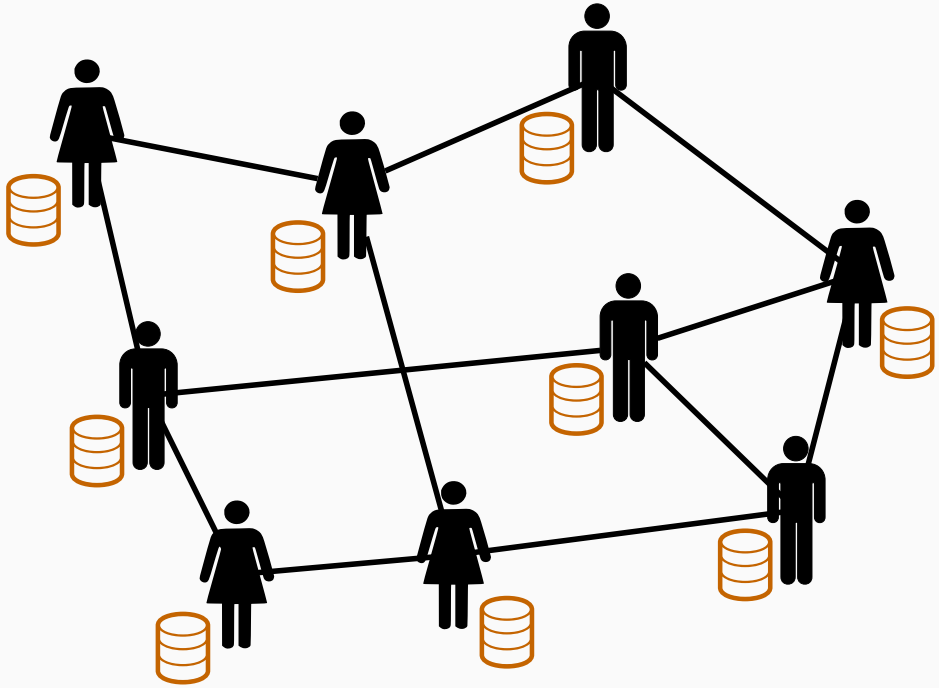
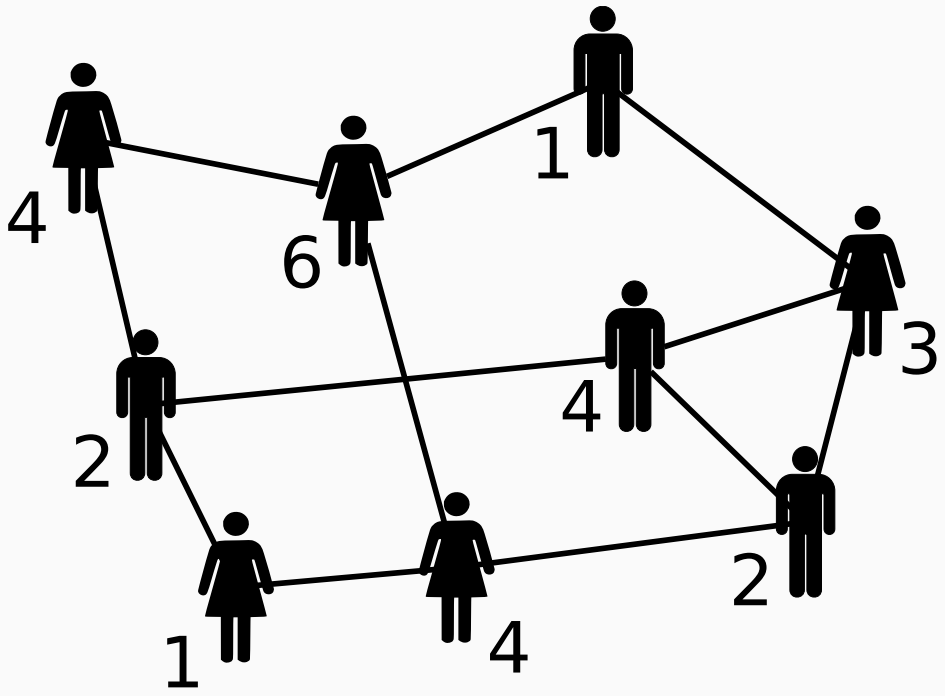


Some scientific challenges

1. How to efficiently learn in a decentralized way under these communication constraints?
2. How to prevent malicious users from inferring sensitive data or manipulating the outcome to their advantage?

KEY PRINCIPLE: GOSSIP ALGORITHM



- Users wake up independently and in parallel, select a random neighbor and exchange information
  - Equivalent view: an iteration is a random edge activation
- Simple and asynchronous $\rightarrow$ well suited to large networks

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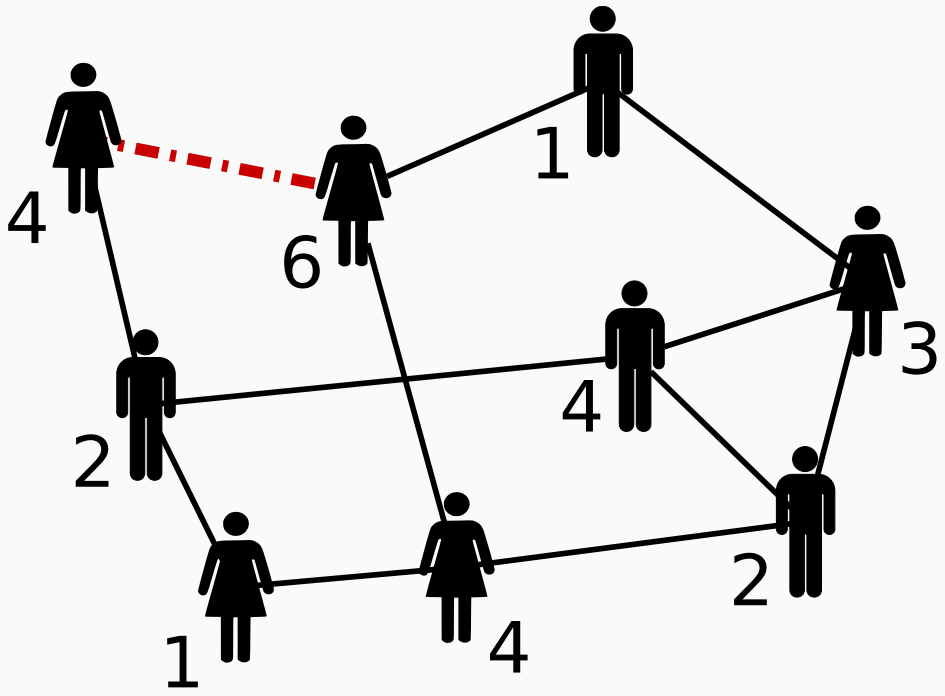

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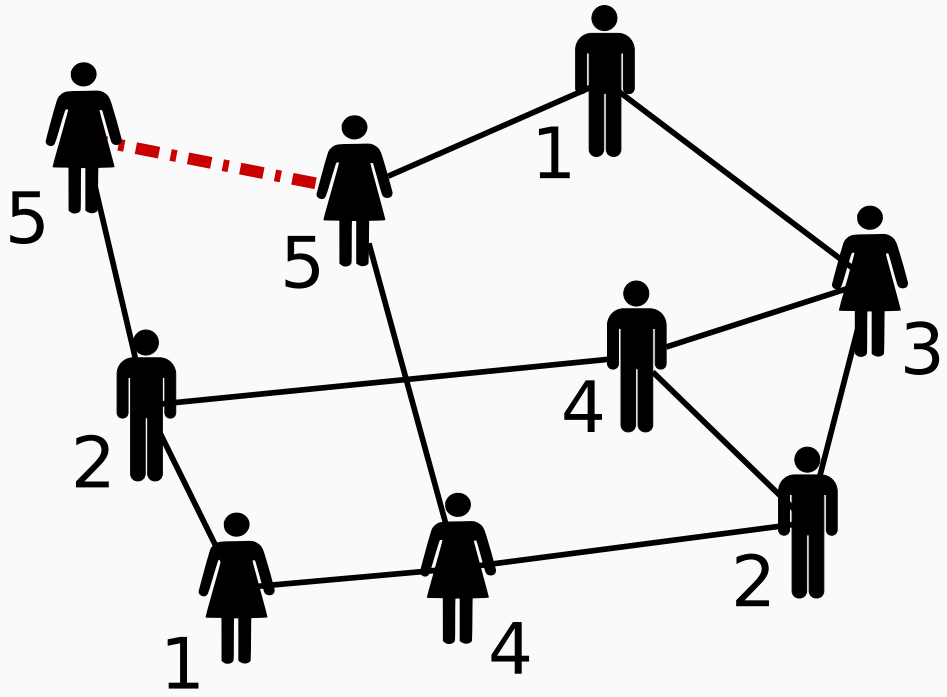

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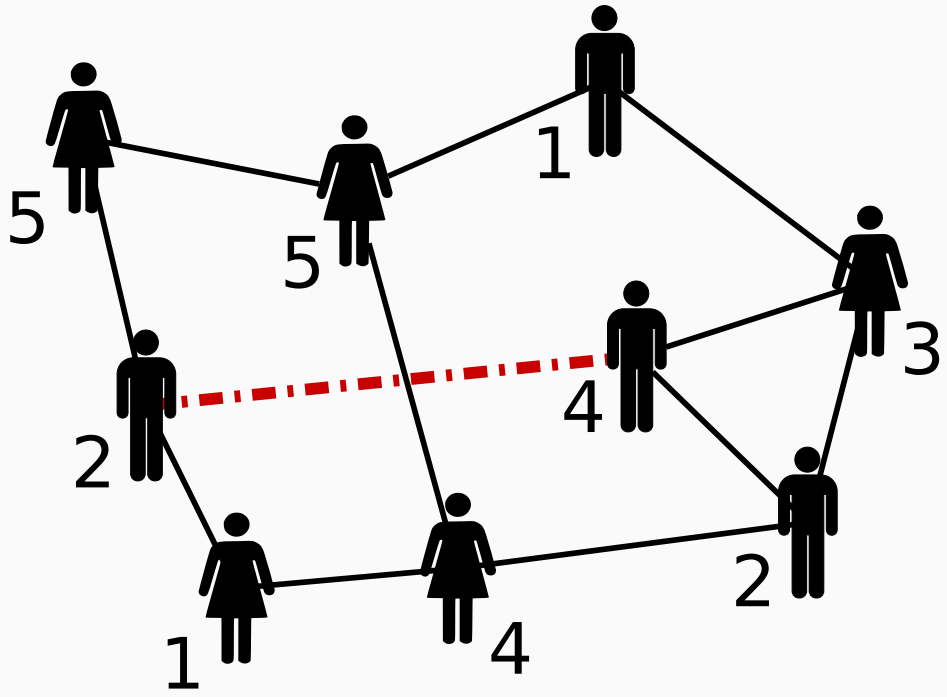

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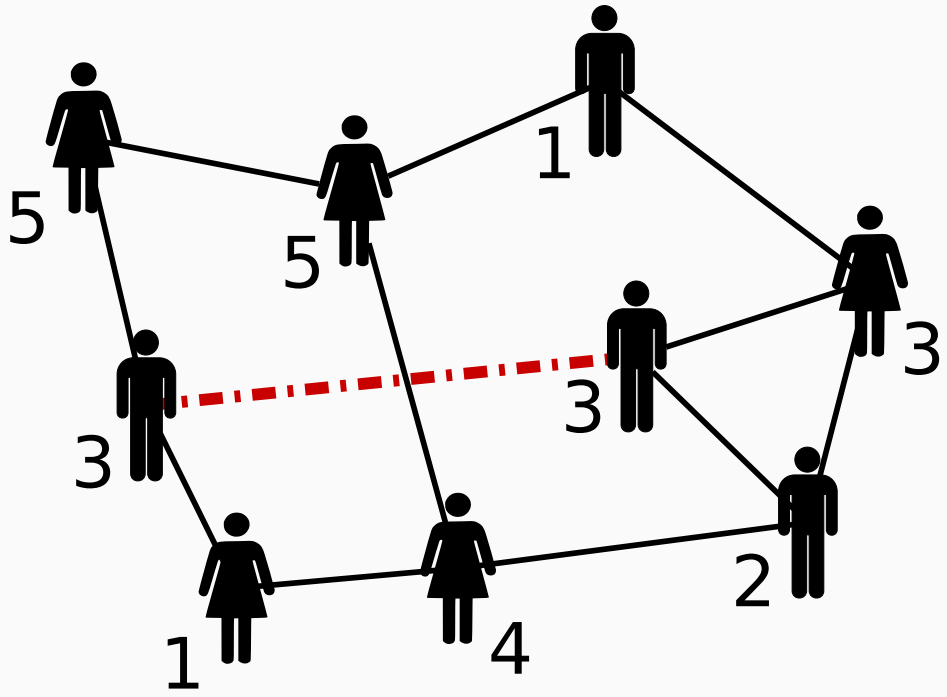

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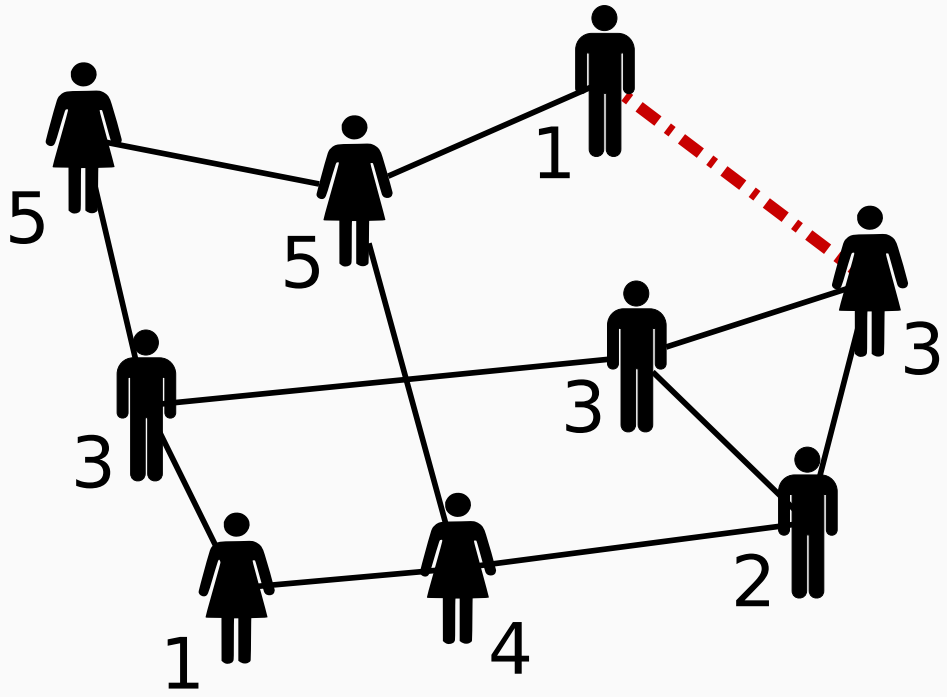

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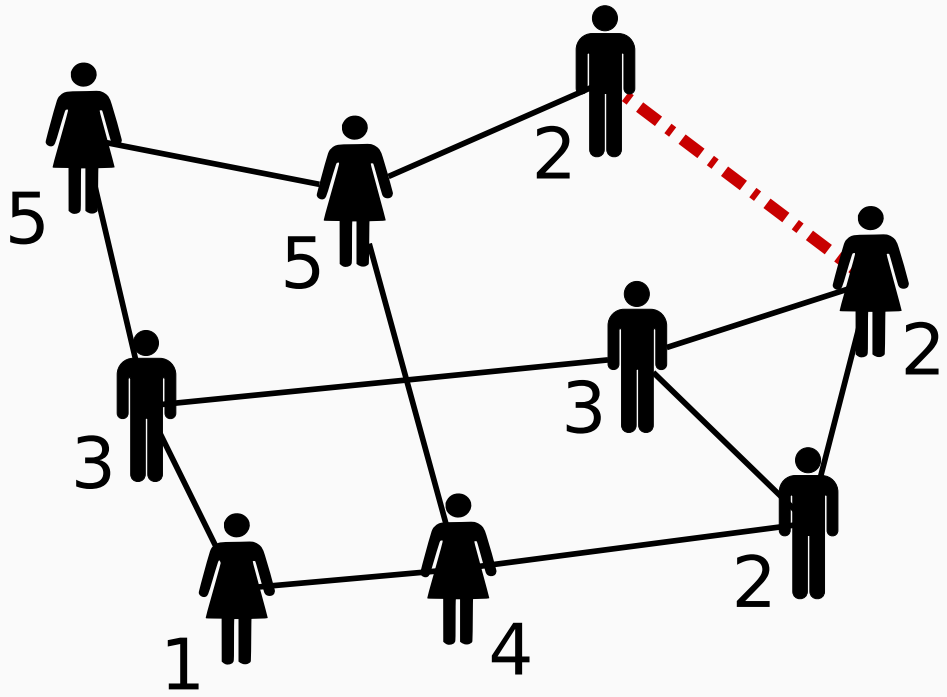

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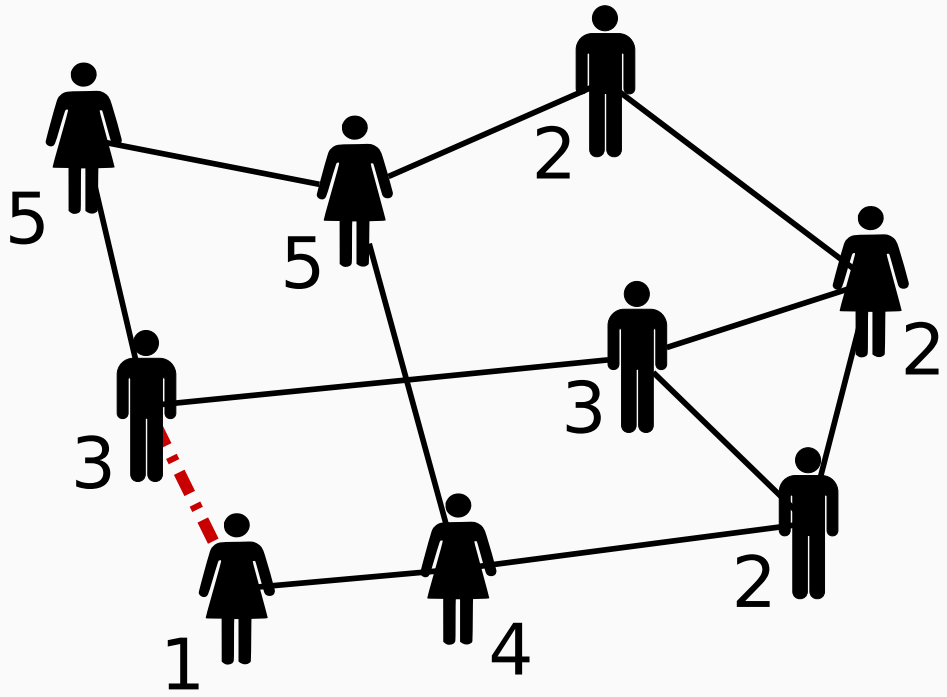

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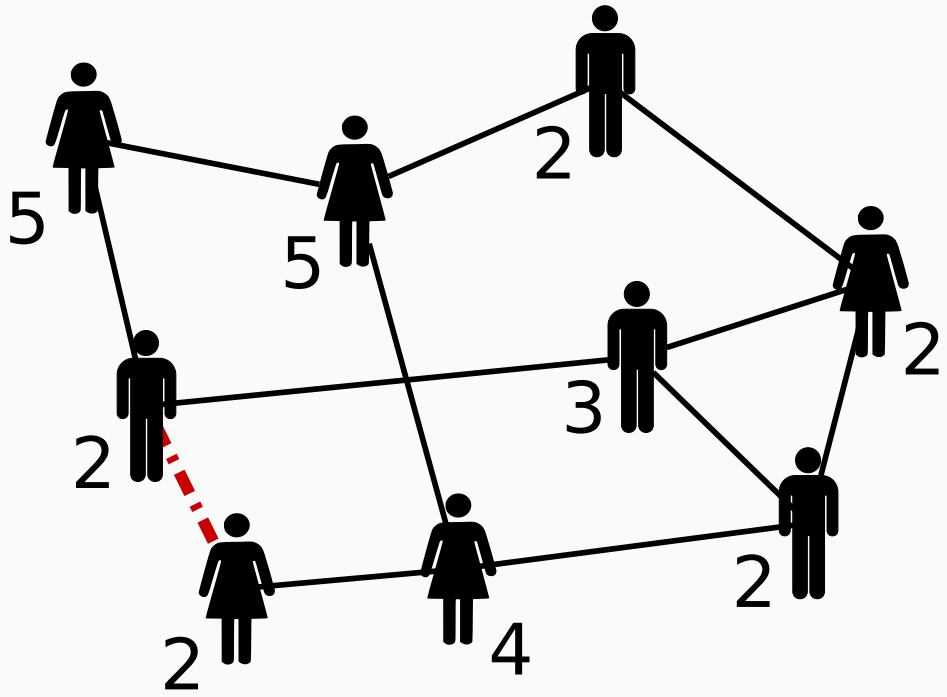

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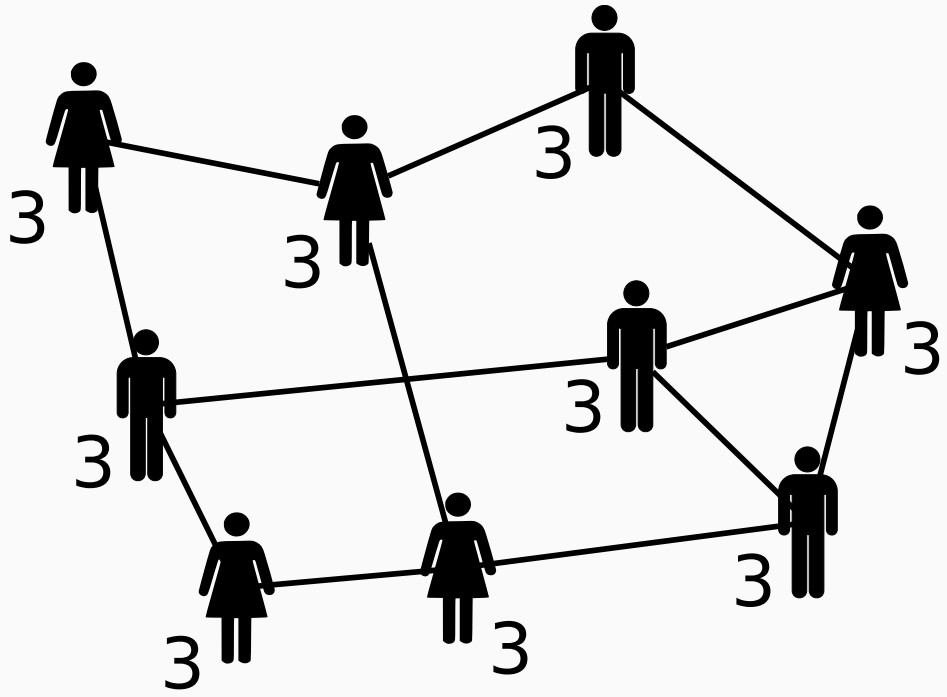

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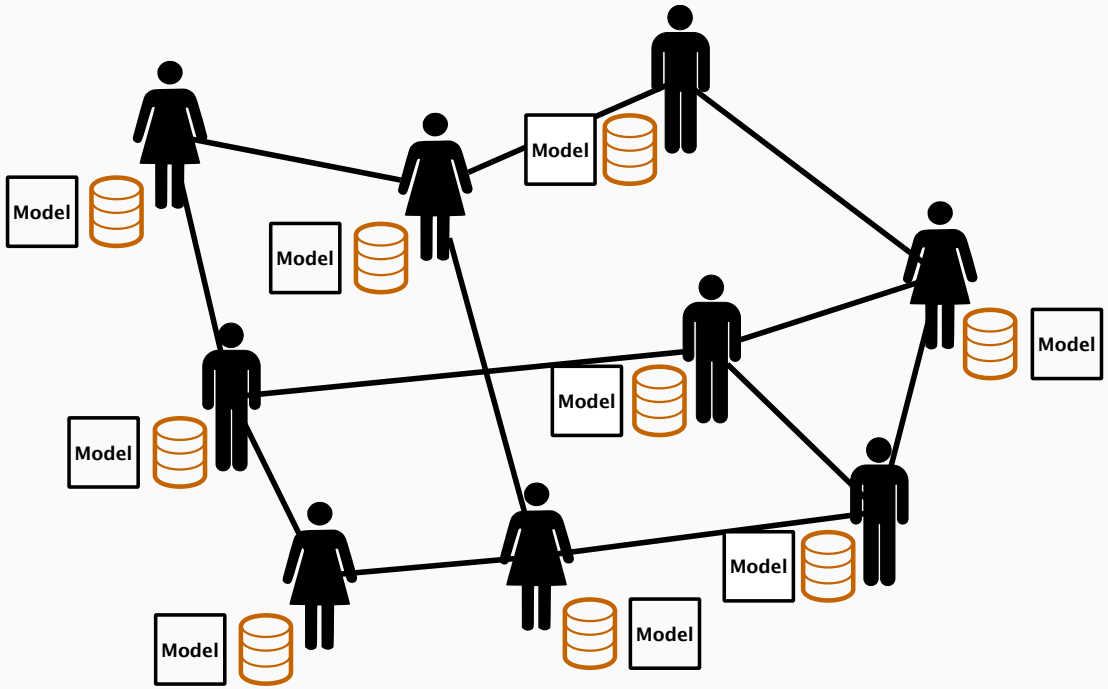

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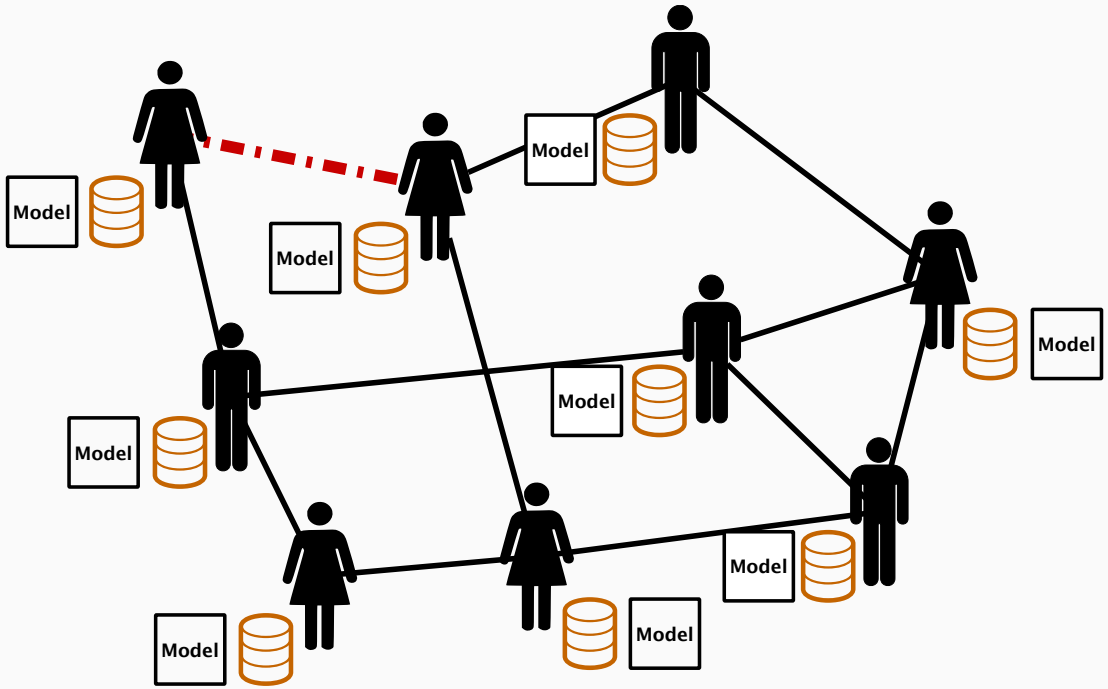

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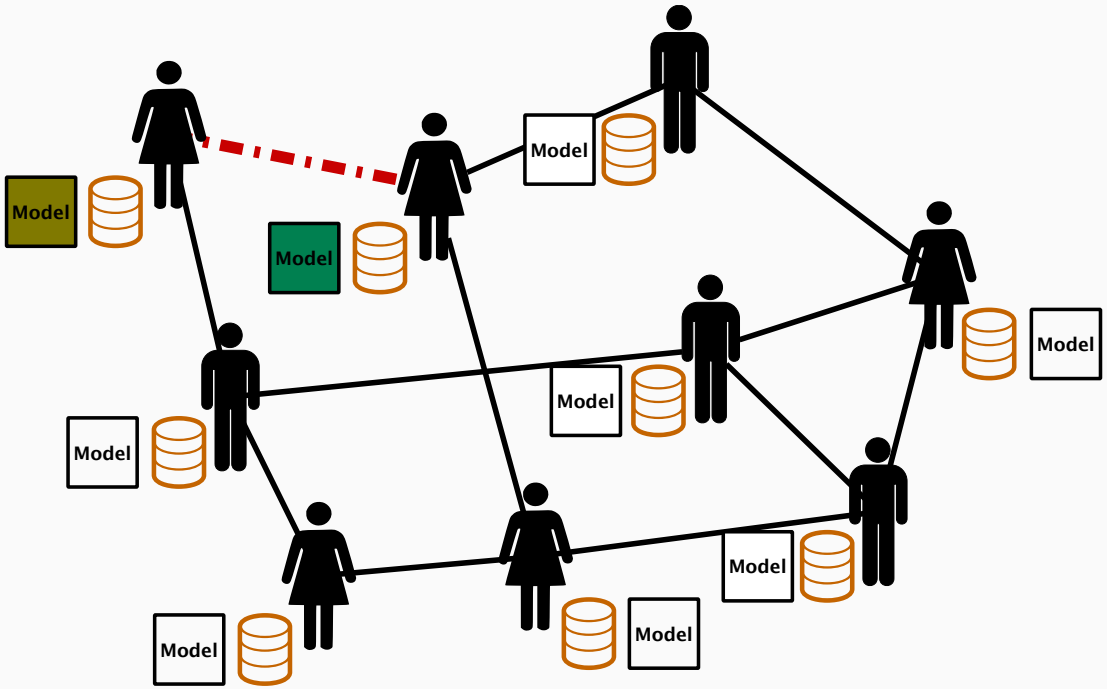

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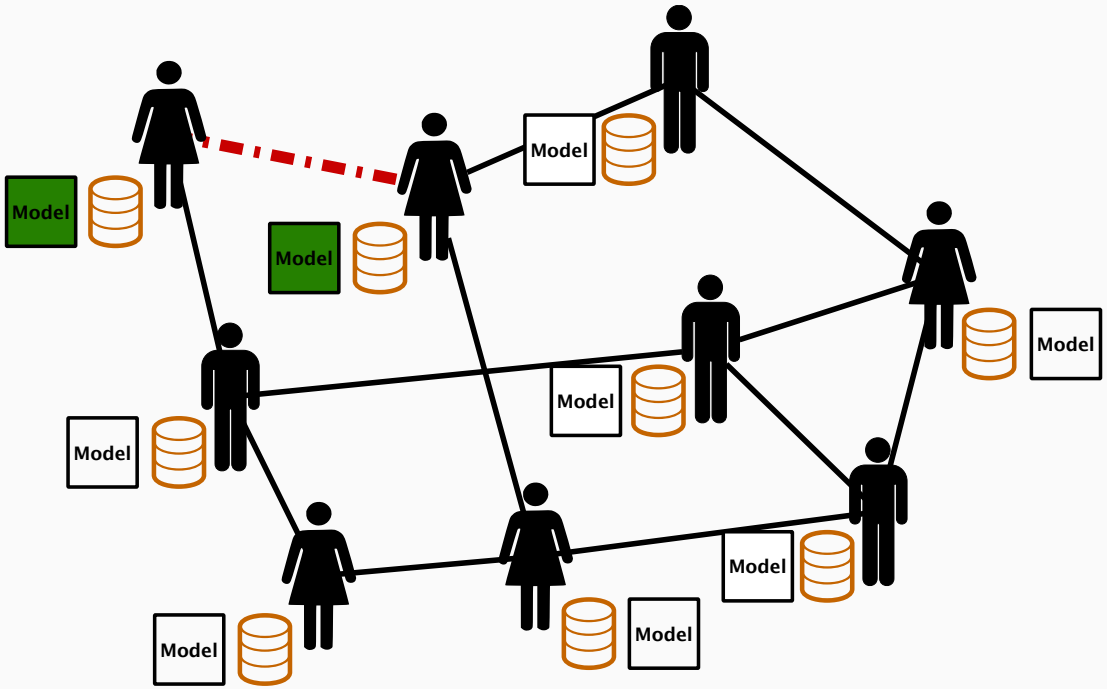

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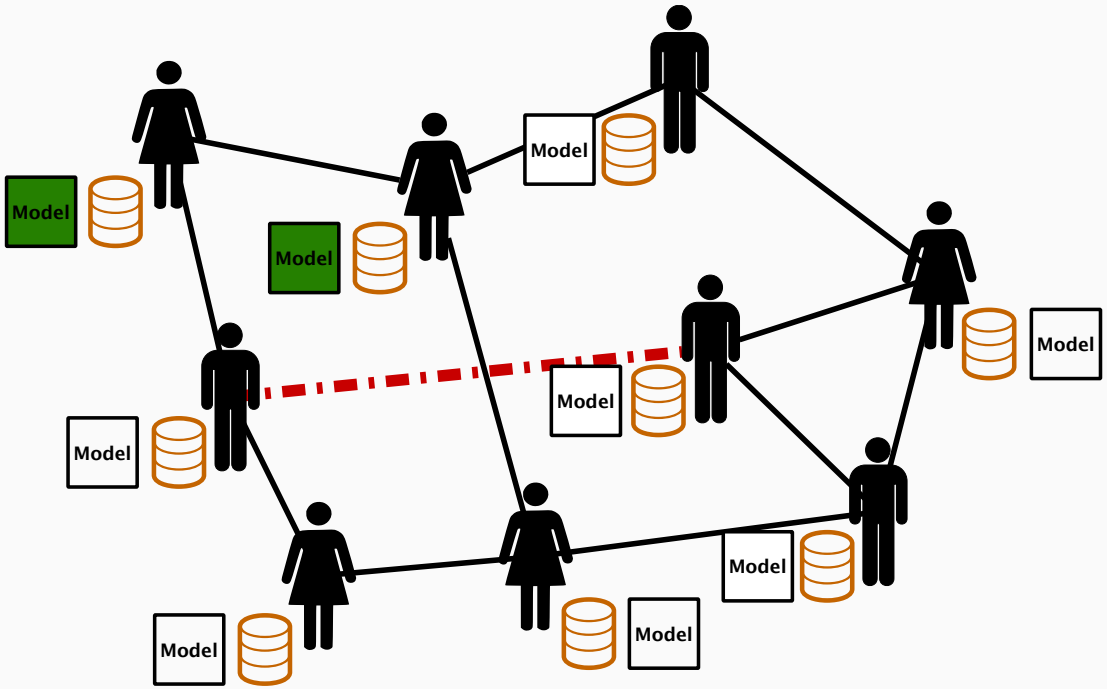

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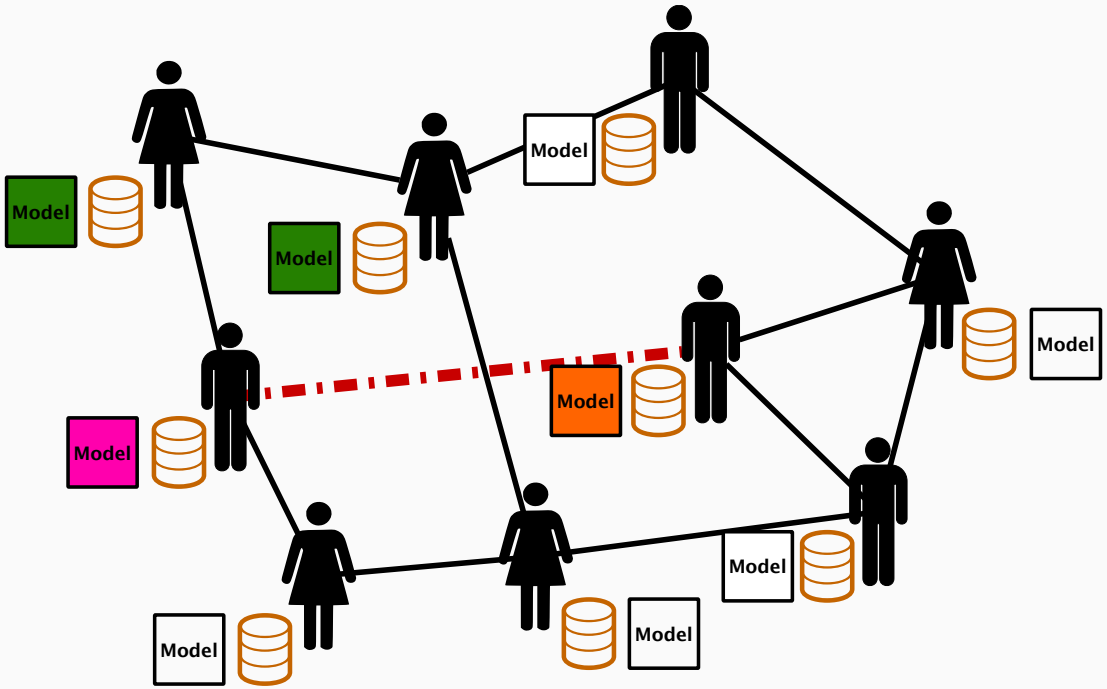

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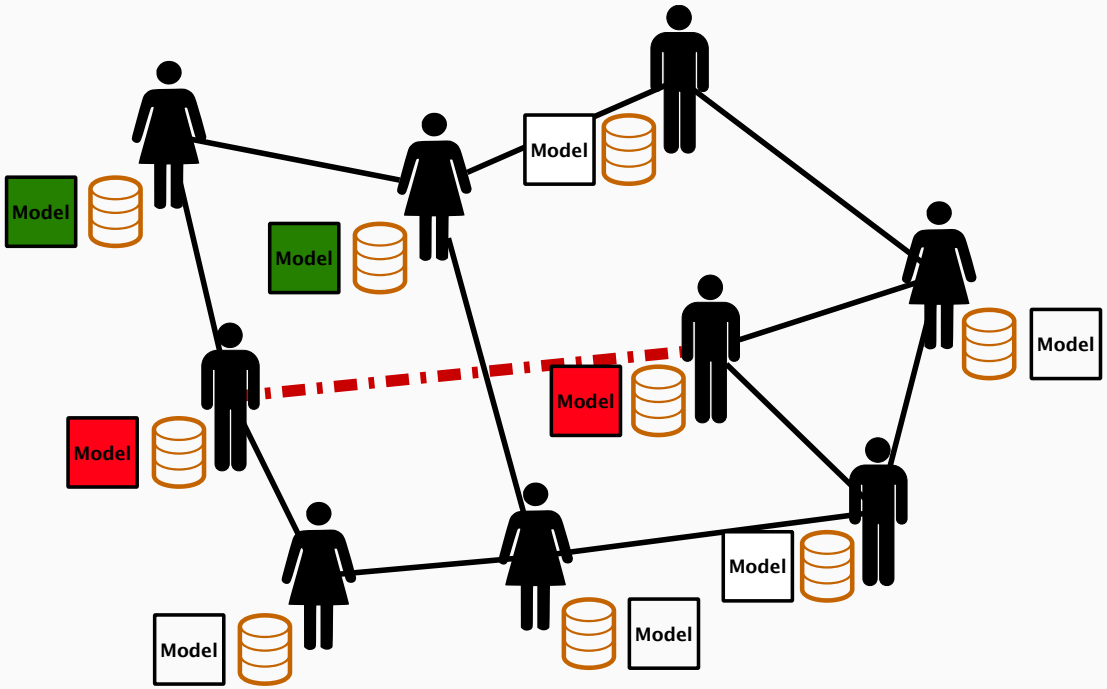

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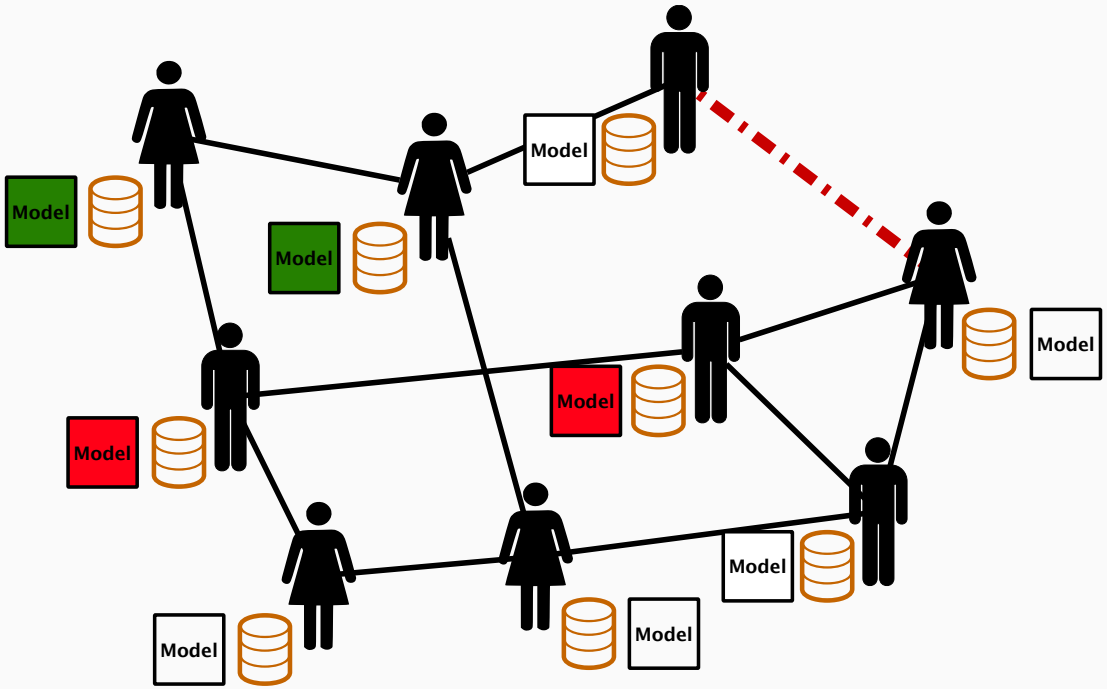

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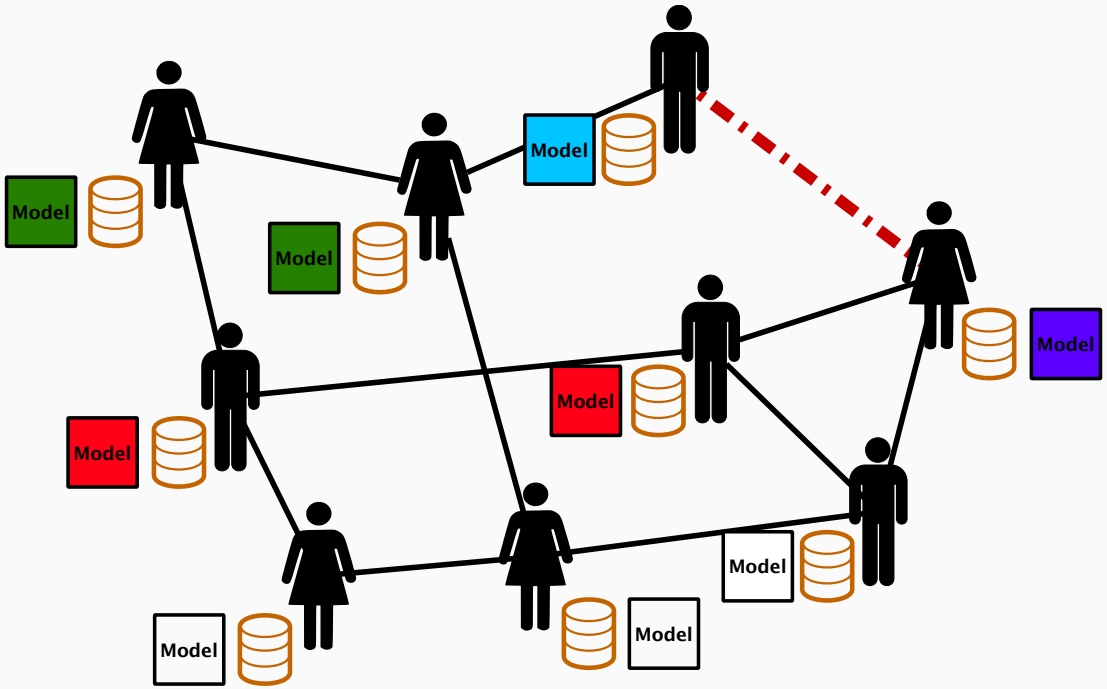

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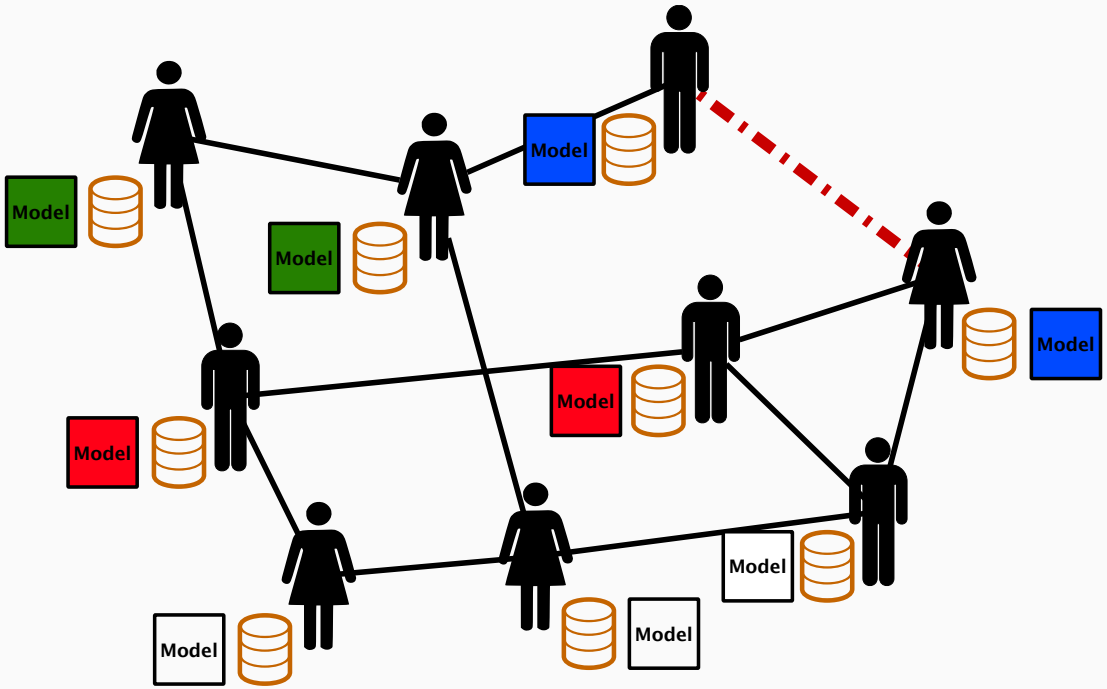

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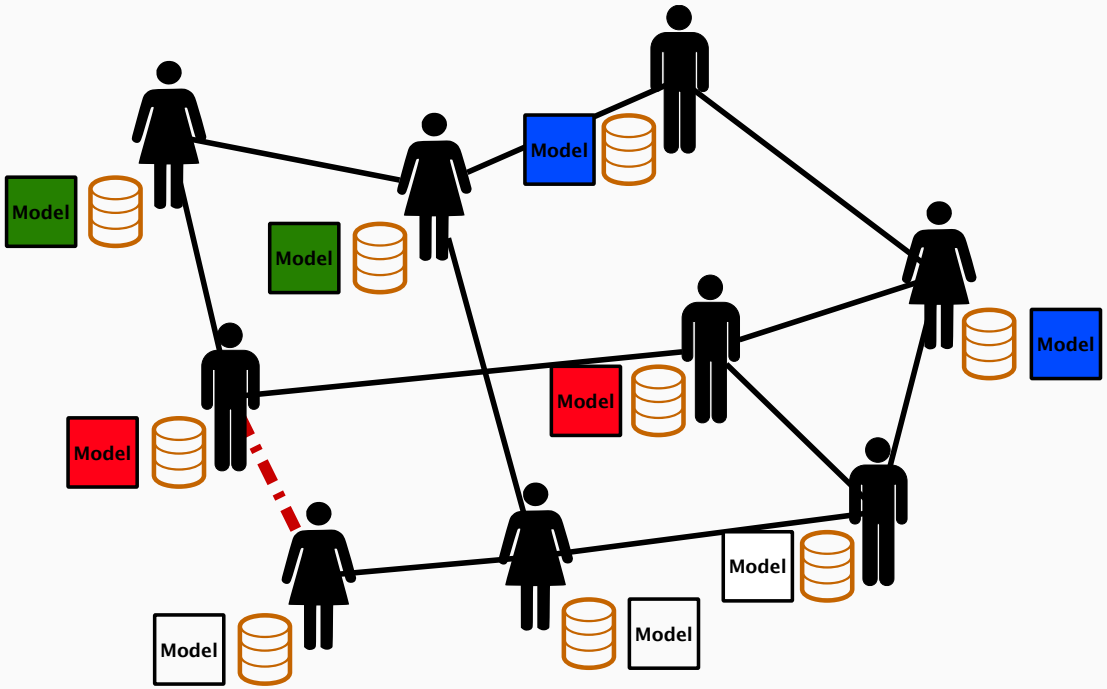

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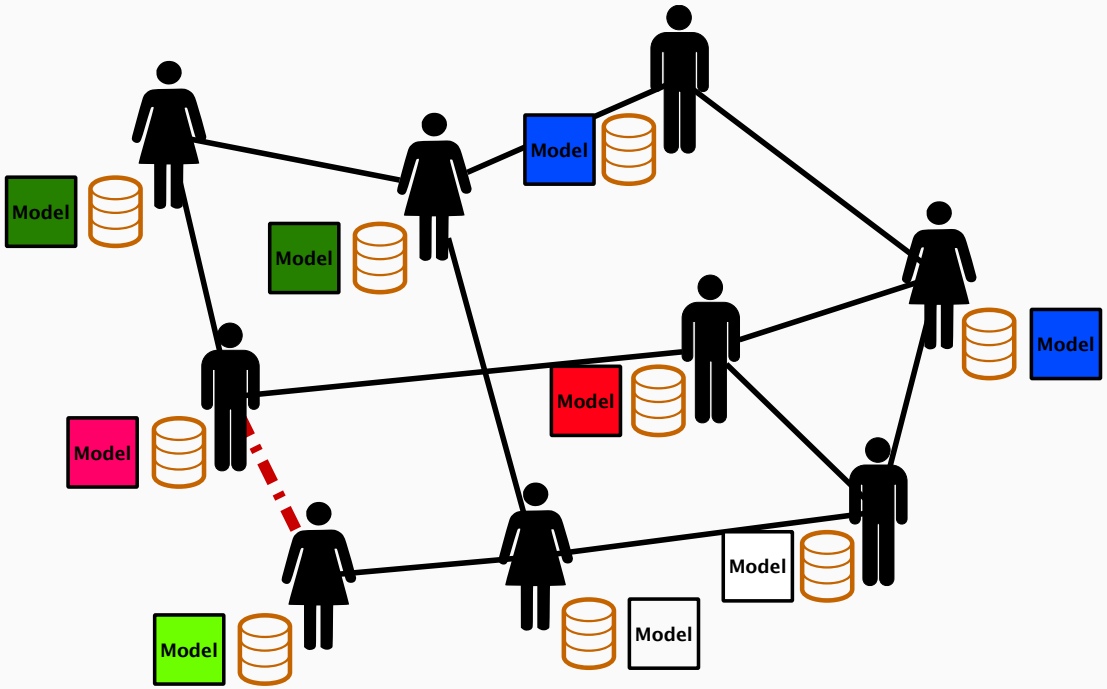

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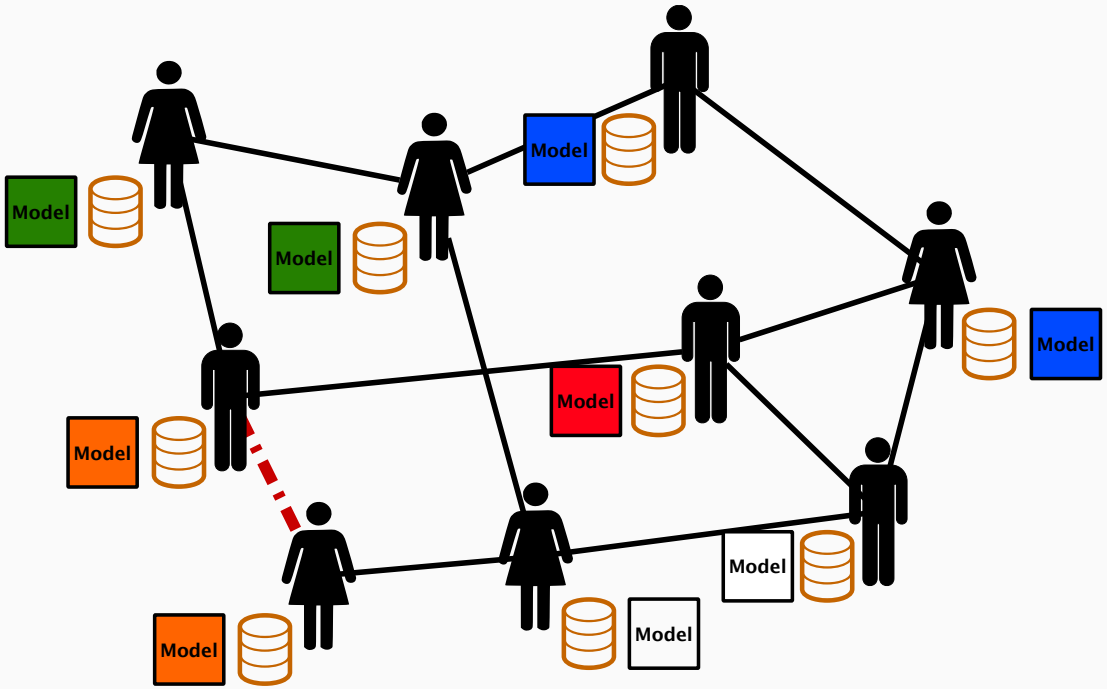

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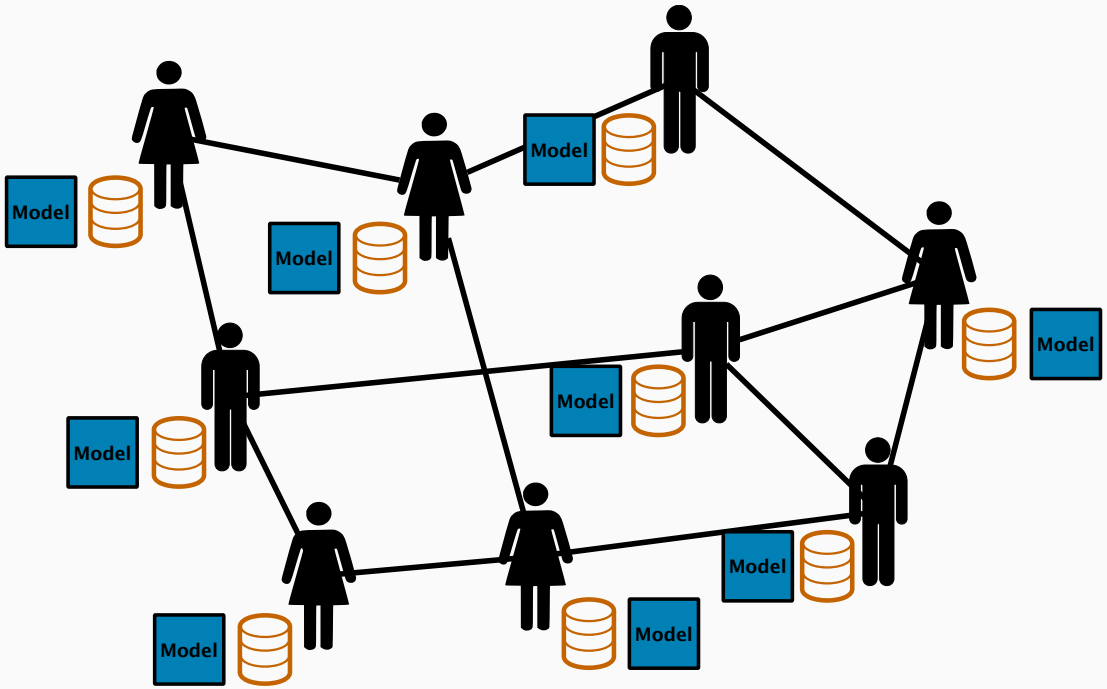

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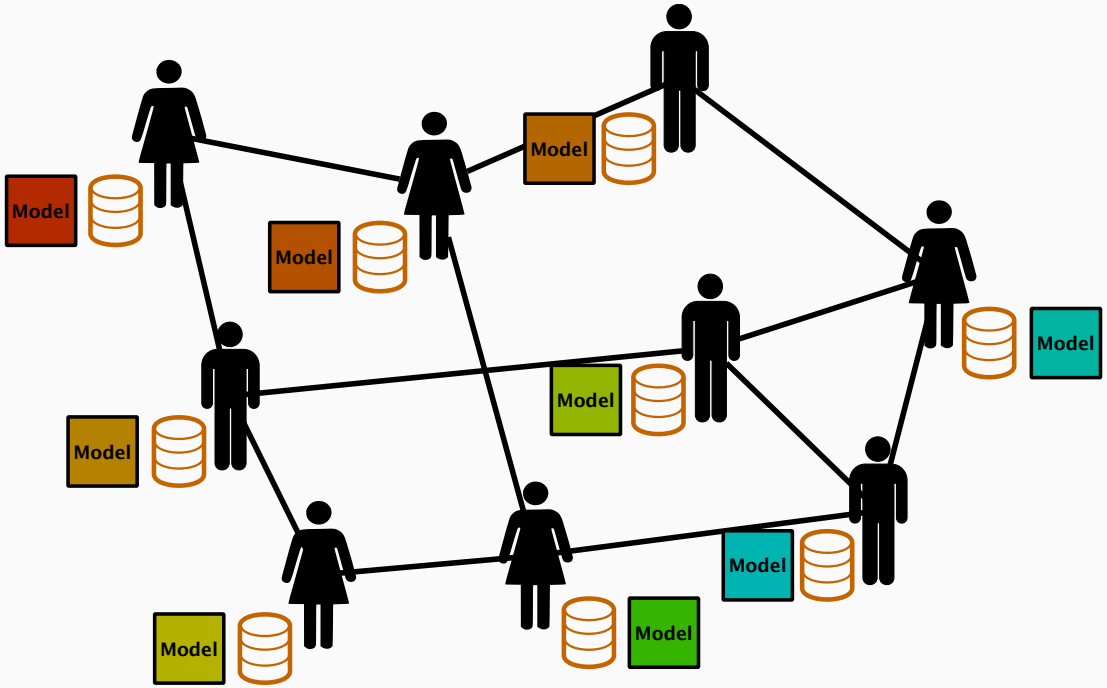
THIS WORK: PERSONALIZED LEARNING

- Gossip algorithms to learn a personalized model for each user according to its own learning objective



- General idea: trade-off between model accuracy on local data and smoothness with respect to similar users

PROBLEM SETTING

PROBLEM SETTING

- We work in the supervised learning setting: predict label $y \in \mathcal{Y}$ from observation $x \in \mathcal{X}$
- The set of possible prediction models will be indexed by parameters $\theta \in \mathbb{R}^p$
- We use a convex loss function $\ell : \mathbb{R}^p \times \mathcal{X} \times \mathcal{Y}$ to measure the error of a model on a labeled observation
- We have a set $V = [\![n]\!] = \{1, \ldots, n\}$ of n learning agents
- Agent i has dataset $\mathcal{S}_i = \{(x_i^j, y_i^j)\}_{j=1}^{m_i}$ of size $m_i \geq 0$ drawn i.i.d. from its own distribution μ_i over $\mathcal{X} \times \mathcal{Y}$

- Goal of agent i: learn a model $\theta_i \in \mathbb{R}^p$ with small expected loss

$$\mathop{\mathbb{E}}_{(x_i,y_i)\sim\mu_i} \ell(\theta_i; x_i, y_i)$$

- In isolation, agent i can learn a "solitary" model

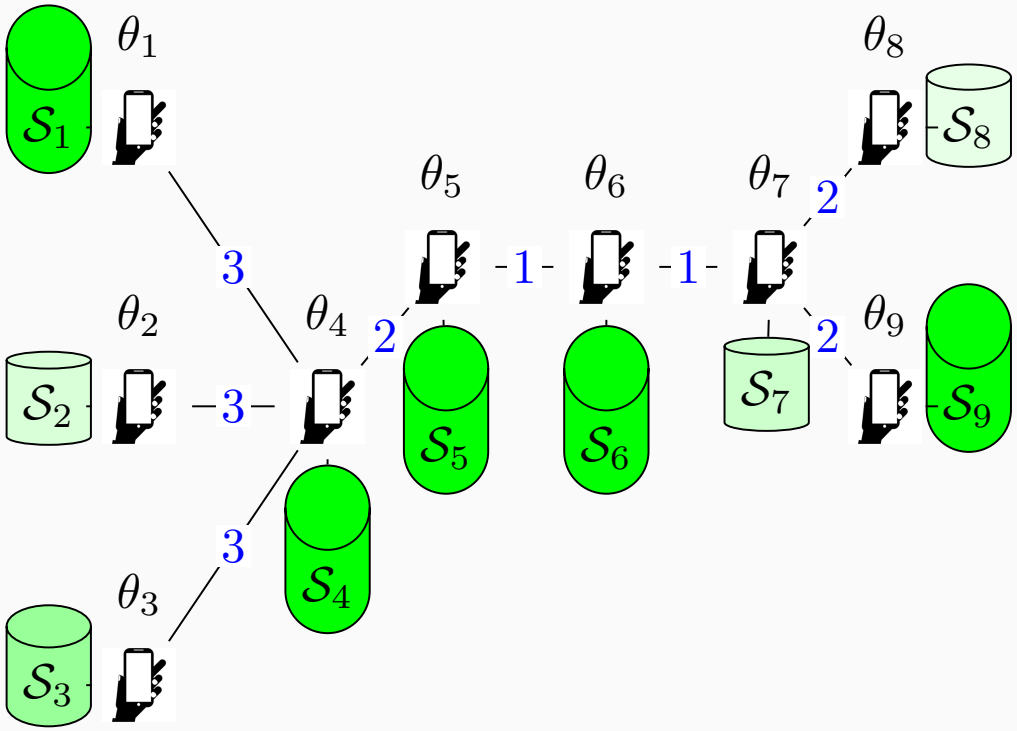
$$\theta_i^{sol} \in \arg\min_{\theta\in\mathbb{R}^p} \mathcal{L}_i(\theta) = \frac{1}{m_i}\sum_{j=1}^{m_i} \ell(\theta; x_i^j, y_i^j) + \lambda_i\|\theta\|^2, \text{ with } \lambda_i \geq 0$$

- **How to improve upon θ_i^{sol} with the help of other users?**

PROBLEM SETTING

- Network: weighted connected graph $G = (V, E)$
- $E \subseteq V \times V$ set of undirected edges
- Weight matrix $W \in \mathbb{R}^{n \times n}$: symmetric, nonnegative, with $W_{ij} = 0$ if $(i, j) \notin E$ or $i = j$
- **Assumption**: network weights are given and represent the underlying similarity between agents
  - Ex: movie recommendation task where the network is set up when users go to the same movie

PROBLEM SETTING



- Agents have only a local view of the network
- They only know their neighborhood $\mathcal{N}_i = \{j \neq i : W_{ij} > 0\}$ and the associated weights

DECENTRALIZED ALGORITHMS

Main idea: smooth the solitary models over the network

- $c_i \in (0, 1]$: confidence in initial model θ_i^{sol}
  - Proportional to the number of training points m_i
- Find new set of models $\Theta \in \mathbb{R}^{n \times p}$ by solving

$$\min_{\Theta \in \mathbb{R}^{n \times p}} \mathcal{Q}_{MP}(\Theta) = \frac{1}{2} \left(\sum_{i<j}^{n} W_{ij} \|\theta_i - \theta_j\|^2 + \mu \sum_{i=1}^{n} D_{ii} c_i \|\theta_i - \theta_i^{sol}\|^2 \right)$$

  - Trade-off between smoothing models within neighborhoods and not diverging too much from confident models
  - Term $D_{ii} = \sum_j W_{ij}$ is just for normalization
- Cannot use closed-form solution (requires global knowledge)

ASYNCHRONOUS GOSSIP ALGORITHM

- Each agent has a local Poisson clock and wakes up when it ticks
- Equivalently: single clock (with counter t) ticking when one of the local clocks ticks
- **Idea of our algorithm**: each agent i maintains a (possibly outdated) knowledge $\widetilde{\Theta}_i(t) \in \mathbb{R}^{n \times p}$ of its neighbors' models
  - $\widetilde{\Theta}_i^i(t) \in \mathbb{R}^p$: agent i's model at time t
  - for $j \neq i$, $\widetilde{\Theta}_i^j(t) \in \mathbb{R}^p$: agent i's *last knowledge* of the model of j
  - For $j \notin \mathcal{N}_i \cup \{i\}$ and any $t > 0$, we maintain $\widetilde{\Theta}_i^j(t) = 0$

ASYNCHRONOUS GOSSIP ALGORITHM

- At step t, some agent i wakes up and two actions are performed
  1. *Communication step*: agent i selects a random neighbor $j \in \mathcal{N}_i$ w.p. π_i^j and both agents update their knowledge of each other:

$$\widetilde{\Theta}_i^j(t+1) = \widetilde{\Theta}_j^j(t) \text{ and } \widetilde{\Theta}_j^i(t+1) = \widetilde{\Theta}_i^i(t),$$

  2. *Update step*: agents i and j update their own models based on current knowledge. For $l \in \{i, j\}$:

$$\widetilde{\Theta}_l^l(t+1) = (\alpha + \bar{\alpha} c_l)^{-1} \Big(\alpha \sum_{k \in \mathcal{N}_l} \frac{W_{lk}}{D_{ll}} \widetilde{\Theta}_l^k(t+1) + \bar{\alpha} c_l \theta_l^{sol} \Big).$$

- All other variables in the network remain unchanged
- For any $i \in [\![n]\!]$, $\pi_i \in [0,1]^n$ must satisfy $\sum_{j=1}^n \pi_i^j = 1$ and $\pi_i^j > 0$ if and only if $j \in \mathcal{N}_i$

Theorem ([Vanhaesebrouck et al., 2017])

Let $\widetilde{\Theta}(0) \in \mathbb{R}^{n^2 \times p}$ be some initial value and $(\widetilde{\Theta}(t))_{t \in \mathbb{N}}$ be the sequence generated by our algorithm. Let $\Theta^\star = \arg\min_{\Theta \in \mathbb{R}^{n \times p}} \mathcal{Q}_{MP}(\Theta)$ be the optimal solution to model propagation. For any $i \in [\![n]\!]$,

$$\lim_{t \to \infty} \mathbb{E}\left[\widetilde{\Theta}_i^j(t)\right] = \Theta_j^\star \text{ for } j \in \mathcal{N}_i \cup \{i\}.$$

Sketch of proof

- Rewrite algorithm as a random iterative process over $\widetilde{\Theta} \in \mathbb{R}^{n^2 \times p}$:

$$\widetilde{\Theta}(t+1) = A(t)\widetilde{\Theta}(t) + b(t)$$

- Show that spectral radius of $\mathbb{E}[A(t)]$ is smaller than 1
- Exhibit convergence to desired quantity

COLLABORATIVE LEARNING: PROBLEM FORMULATION

- Model propagation is very simple but forgets data
- Alternative: learn / propagate models simultaneously by solving

$$\min_{\Theta \in \mathbb{R}^{n \times p}} \mathcal{Q}_{CL}(\Theta) = \sum_{i<j}^{n} W_{ij} \|\theta_i - \theta_j\|^2 + \mu \sum_{i=1}^{n} D_{ii} c_i \mathcal{L}_i(\theta_i)$$

- Trade-off between smoothing models within neighborhoods and good accuracy on local datasets
- More flexibility than model propagation in settings where different parameter values may lead to similar predictions
- Can recover the two extreme cases of learning purely local models ($\mu \to \infty$) and learning a single global model ($\mu \to 0$)

ALGORITHM IN THE BROADCAST SETTING

- For simplicity, consider the broadcast communication model
  - The agent which wakes up sends a message to all its neighbors
  - No reply from neighbors
- Assume that local loss $\mathcal{L}_i$ has L_i^{loc}-Lipschitz continuous gradient
- Then $\nabla \mathcal{Q}_{CL}$ is L_i-Lipschitz w.r.t. block Θ_i with $L_i = D_{ii}(1 + \mu c_i L_i^{loc})$
- Can also assume that $\mathcal{L}_i$ is σ_i^{loc}-strongly convex where $\sigma_i^{loc} > 0$
- Then $\mathcal{Q}_{CL}$ is σ-strongly convex with $\sigma \geq \mu \min_{1 \leq i \leq n} [D_{ii} c_i \sigma_i^{loc}] > 0$

- Randomized block coordinate descent algorithm: assume agent i wakes up at step t:
  1. Agent i updates its model based on information from neighbors:

$$\begin{aligned}\Theta_i(t+1) &= \Theta_i(t) - \frac{1}{L_i}[\nabla \mathcal{Q}_{CL}(\Theta(t))]_i \\ &= (1-\alpha)\Theta_i(t) + \alpha\Big(\sum_{j\in\mathcal{N}_i} \frac{W_{ij}}{D_{ii}}\Theta_j(t) - \mu c_i \nabla \mathcal{L}_i(\Theta_i(t); \mathcal{S}_i)\Big),\end{aligned}$$

     where $\alpha = 1/(1+\mu c_i L_i^{loc}) \in (0, 1]$

  2. Agent i sends its updated model $\Theta_i(t+1)$ to its neighborhood $\mathcal{N}_i$

Proposition ([Bellet et al., 2018])

For any $T > 0$, let $(\Theta(t))_{t=1}^{T}$ be the sequence of iterates generated by the algorithm running for T iterations from an initial point $\Theta(0)$. When $\mathcal{Q}_{CL}$ is σ-strongly convex, we have:

$$\mathbb{E}\left[\mathcal{Q}_{CL}(\Theta(T)) - \mathcal{Q}_{CL}^{\star}\right] \leq \left(1 - \frac{\sigma}{nL_{max}}\right)^{T} \left(\mathcal{Q}_{CL}(\Theta(0)) - \mathcal{Q}_{CL}^{*}\right),$$

where $L_{max} = \max_i L_i$.

- Follows from randomized CD analysis [Wright, 2015]
- Can obtain convergence in $O(1/T)$ in convex case

PRIVACY IN DECENTRALIZED LEARNING

PRIVACY SETTING

- In some applications, data may be sensitive and agents may not want to reveal it to anyone else
- In our algorithms, the agents never communicate their local data but exchange sequences of models computed from data
- Consider an adversary observing all the information sent over the network (but not the internal memory of agents)
- **Goal:** how can we guarantee that no/little information about the local dataset is leaked by the algorithm?

(ϵ, δ)-Differential Privacy

Let $\mathcal{M}$ be a randomized mechanism taking a dataset as input, and let $\epsilon > 0, \delta \geq 0$. We say that $\mathcal{M}$ is (ϵ, δ)-differentially private if for all datasets $\mathcal{S}, \mathcal{S}'$ differing in a single data point and for all sets of possible outputs $\mathcal{O} \subseteq \text{range}(\mathcal{M})$, we have:

$$Pr(\mathcal{M}(\mathcal{S}) \in \mathcal{O}) \leq e^{\epsilon} Pr(\mathcal{M}(\mathcal{S}') \in \mathcal{O}) + \delta.$$

- Guarantees that the output of $\mathcal{M}$ is almost the same regardless of whether a particular data point was used
- Information-theoretic (no computational assumptions)

DIFFERENTIALLY PRIVATE ALGORITHM

1. Replace the update of the algorithm in broadcast setting by

$$\widetilde{\Theta}_i(t+1) = (1-\alpha)\widetilde{\Theta}_i(t) + \alpha\left(\sum_{j\in\mathcal{N}_i} \frac{W_{ij}}{D_{ii}}\widetilde{\Theta}_j(t) - \mu c_i(\nabla\mathcal{L}_i(\widetilde{\Theta}_i(t); \mathcal{S}_i) + \eta_i(t))\right),$$

   where $\eta_i(t) \sim Laplace(0, s_i(t))^p \in \mathbb{R}^p$
2. Agent i then broadcasts noisy iterate $\widetilde{\Theta}_i(t+1)$ to its neighbors

Theorem ([Bellet et al., 2018])

Let $i \in [\![n]\!]$ and assume

- *$\ell(\cdot; x, y)$ L_0-Lipschitz w.r.t. the L_1-norm for all $(x, y) \in \mathcal{X} \times \mathcal{Y}$*
- *Agent i wakes up on iterations $t_i^1, \ldots, t_i^{T_i}$*
- *For some $\epsilon_i(t_i^k) > 0$, the noise scale is $s_i(t_i^k) = \frac{2L_0}{\epsilon_i(t_i^k) m_i}$*

Then for any initial point $\widetilde{\Theta}(0)$ independent of $\mathcal{S}_i$, the mechanism $\mathcal{M}_i(\mathcal{S}_i)$ is $(\bar{\epsilon}_i, 0)$-DP with $\bar{\epsilon}_i = \sum_{k=1}^{T_i} \epsilon_i(t_i^k)$.

- Follows from sensitivity analysis of the update
- Sweet spot in collaborative learning: the less data, the more noise added by the agent, but the least influence in the network
- Can be improved by applying strong composition theorems

Theorem ([Bellet et al., 2018])

For any $T > 0$, let $(\widetilde{\Theta}(t))_{t=1}^{T}$ be the sequence of iterates generated by T iterations. For σ-strongly convex $\mathcal{Q}_{CL}$, we have:

$$\mathbb{E}\left[\mathcal{Q}_{CL}(\widetilde{\Theta}(T)) - \mathcal{Q}_{CL}^{\star}\right] \leq \left(1 - \frac{\sigma}{nL_{max}}\right)^{T} \left(\mathcal{Q}_{CL}(\widetilde{\Theta}(0)) - \mathcal{Q}_{CL}^{\star}\right) + \frac{1}{nL_{min}} \sum_{t=0}^{T-1} \sum_{i=1}^{n} \left(1 - \frac{\sigma}{nL_{max}}\right)^{t} \left(\mu D_{ii} c_i s_i(t)\right)^2,$$

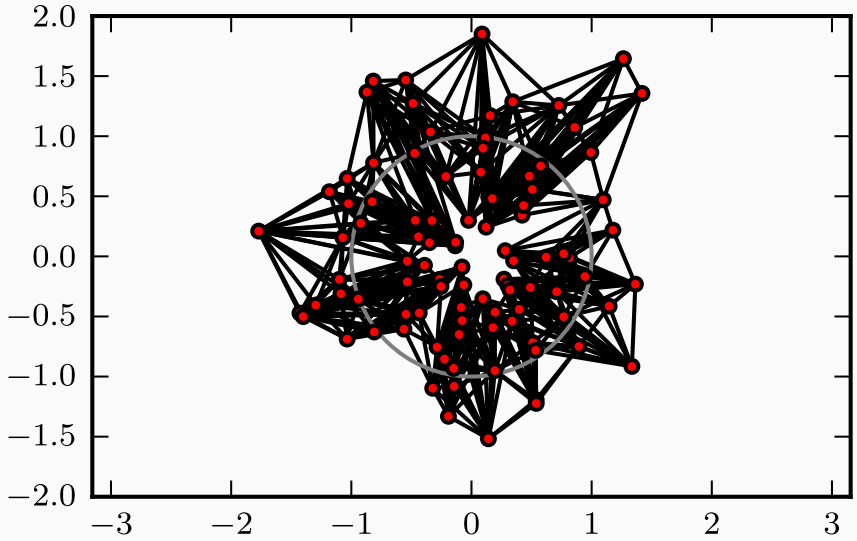
where $L_{min} = \min_{1 \leq i \leq n} L_i$.

- Second term gives additive error due to noise
- When noise scale of each agent constant across iterations, this additive error converges to a finite number as $T \to \infty$
- More results on how to scale noise in the paper

ILLUSTRATIVE EXPERIMENTS

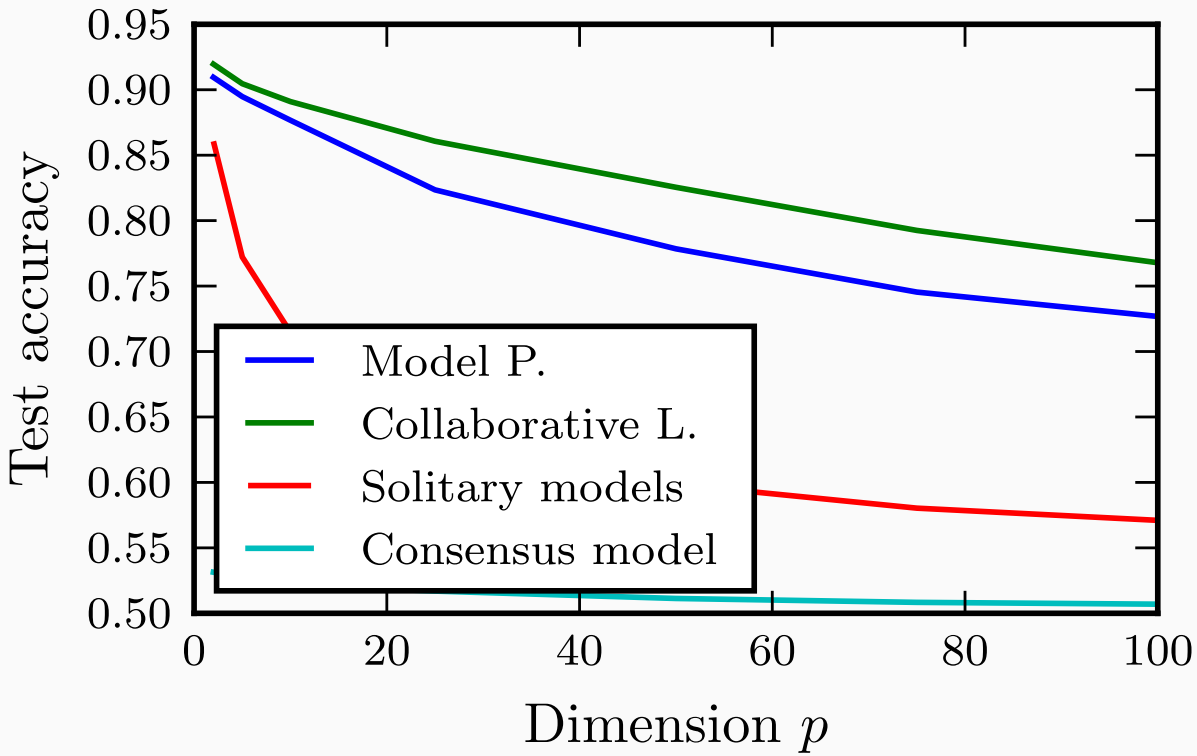
COLLABORATIVE LINEAR CLASSIFICATION

- We consider a set of $n = 100$ agents and a linear classification task in $\mathbb{R}^p$ (with hinge loss)
- Target models lie in a 2D subspace, network weights based on the angle between true models
- Each agent i receives a random number m_i of samples with label given by the prediction of target model (plus noise)



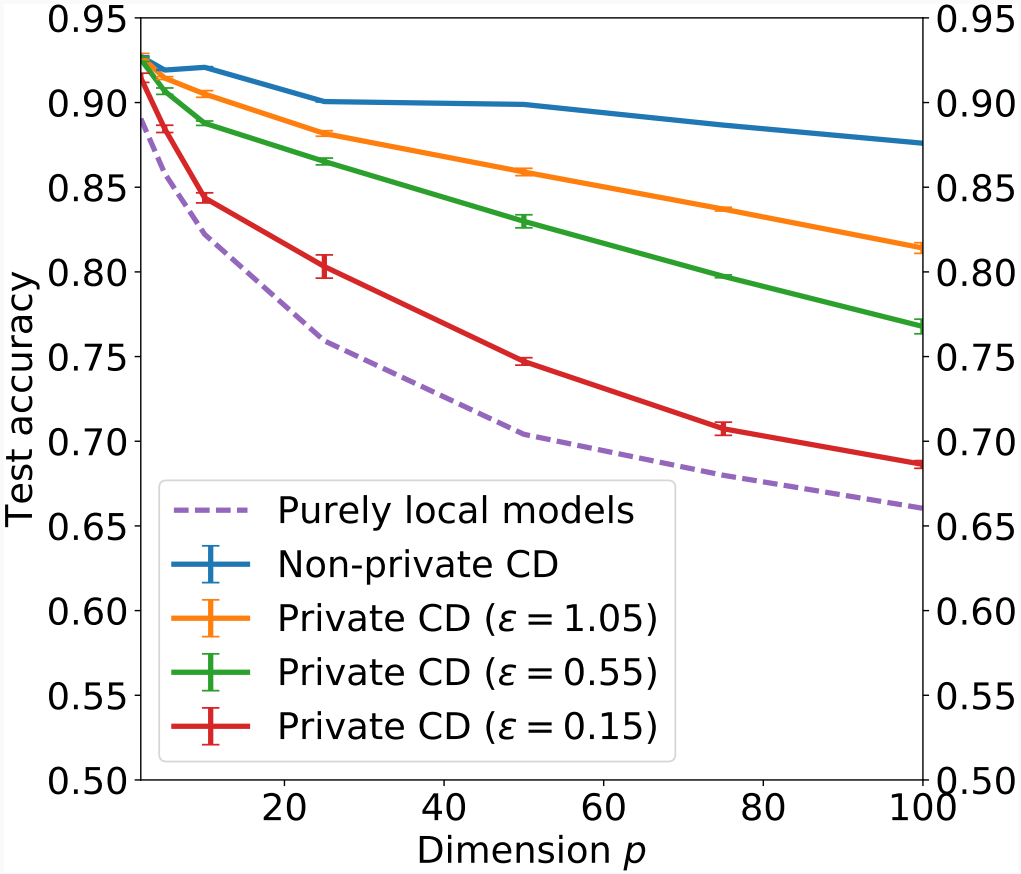
COLLABORATIVE LINEAR CLASSIFICATION: NON-PRIVATE SETTING

- Both CL and MP provide great improvements over local models
- CL consistently outperforms MP by significant margin



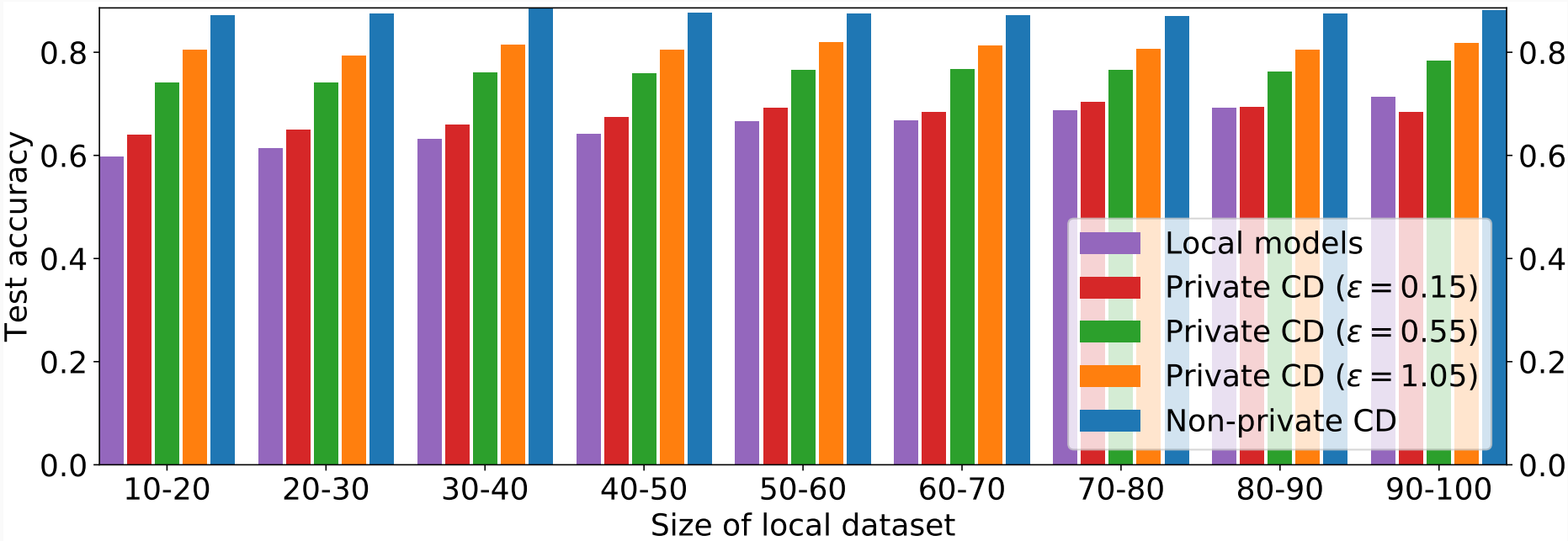
COLLABORATIVE LINEAR CLASSIFICATION: PRIVATE SETTING

- The private variant outperforms the purely local models for "reasonable" values of ϵ



COLLABORATIVE LINEAR CLASSIFICATION: PRIVATE SETTING

- All agents benefit even in private setting
- Agents with small local datasets get a stronger boost



MOVIE RECOMMENDATION

- MovieLens-100K: 100,000 ratings given by $n = 943$ users over $1,682$ movies
- Each user has access only to its own ratings (80% train, 20% test)
- For simplicity, assume known features $\phi_j \in \mathbb{R}^p$ for each movie j
- Quadratic loss: $\ell(\theta; \phi, r) = (\theta^T \phi - r)^2$
- Network: 10-NN graph with cosine similarity on training ratings
- Error: RMSE averaged over users

	Purely local	Non-priv. CD	Priv. $\bar{\epsilon} = 1$	Priv. $\bar{\epsilon} = 0.5$	Priv. $\bar{\epsilon} = 0.1$
Test error	1.2834	0.9502	0.9527	0.9545	0.9855

FUTURE WORK

FUTURE WORK

Theory

- Statistical generalization bounds
- Generic methods to estimate/learn graph weights
- Online learning: data arrive sequentially, agents may join/leave

Applications and practical use

- More real-world experiments (e.g., activity recognition)
- Extend to nonconvex case (e.g., deep nets)
- Decentralized discovery of similar peers
- Cryptographic tools to achieve better accuracy (at the cost of more computation)

Thank you for your attention!

Questions?

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