DECENTRALIZED COLLABORATIVE LEARNING OF PERSONALIZED MODELS OVER NETWORKS

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Joint work with Paul Vanhaesebrouck and Marc Tommasi

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1. Broad context

2. Problem setting

3. Model propagation

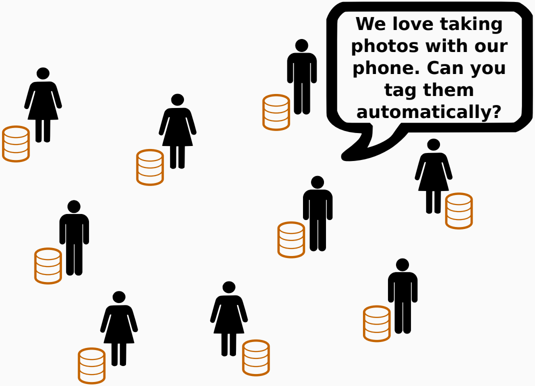
4. Collaborative learning

5. Experiments

6. Future work

BROAD CONTEXT

LEARNING FROM PERSONAL DATA



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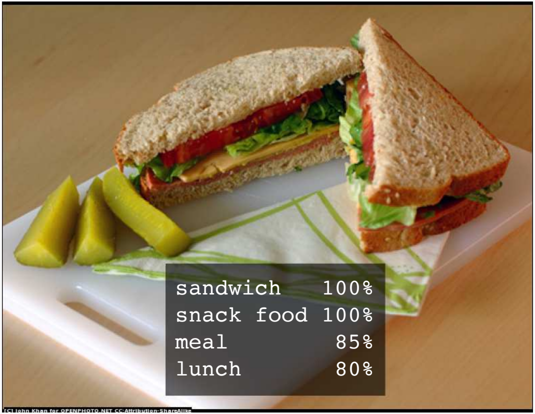
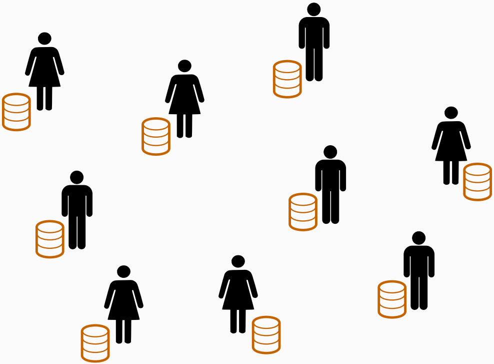
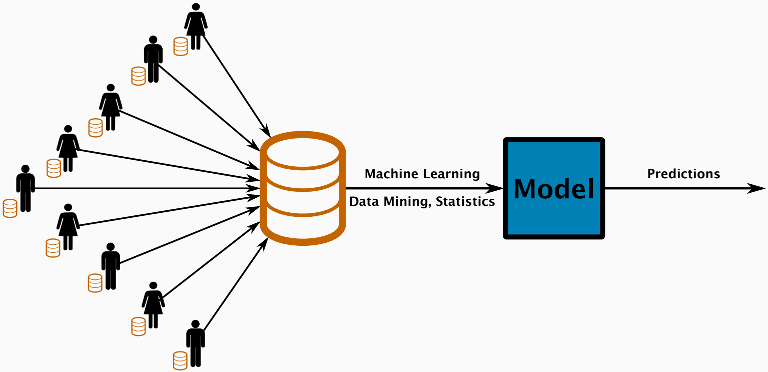




- Other examples of applications
    - Recommend content based on user activity logs
    - Predict health risks based on medical history

CURRENTLY DOMINANT APPROACH



- Centralized data can be processed efficiently in a data center

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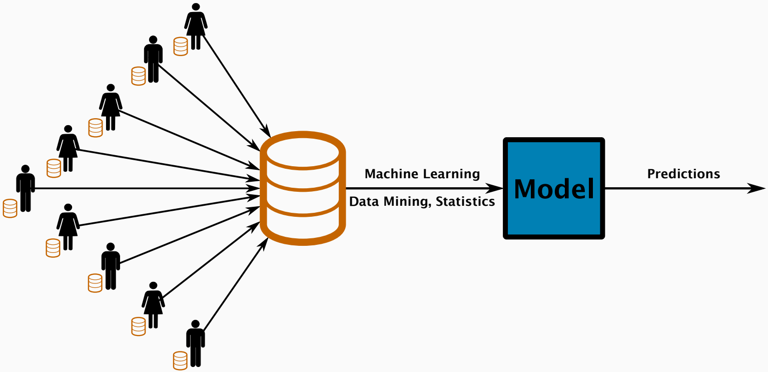
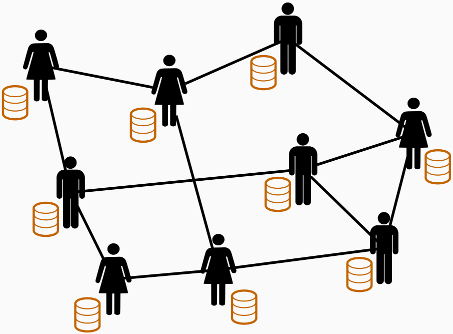
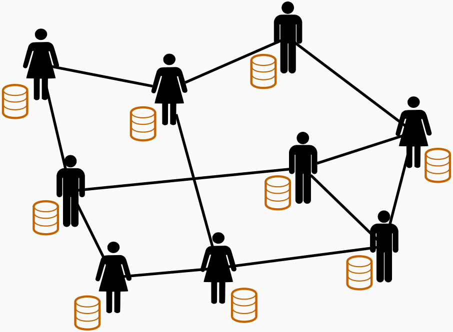


- Lack of user control over its personal data
  - What is collected? Who can access it? How is it used and what for?
- Vulnerability to attacks / subpoenas
  - Yahoo data breach (500M users), Twitter / Wikileaks court orders
- Costly infrastructure for service provider

ALTERNATIVE : DECENTRALIZED ARCHITECTURE

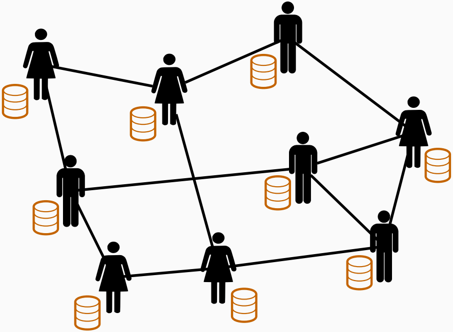


- Personal data stays on user's device → better control
- Peer-to-peer communications without a central server → harder to collect data systematically (no single point of entry)



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?



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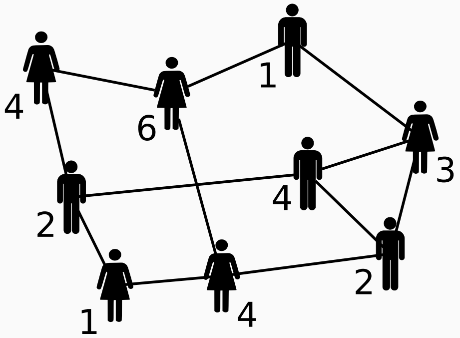

- Users wake up independently and asynchronously, select a random neighbor and exchange information
    - Equivalent view: at each step, activate a random network edge
- Simple and asynchronous $\rightarrow$ well suited to large networks

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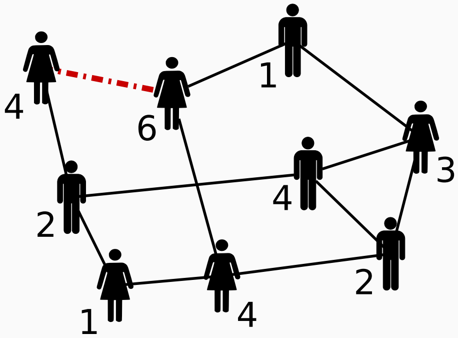

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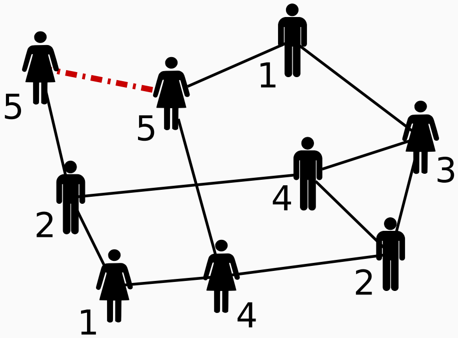

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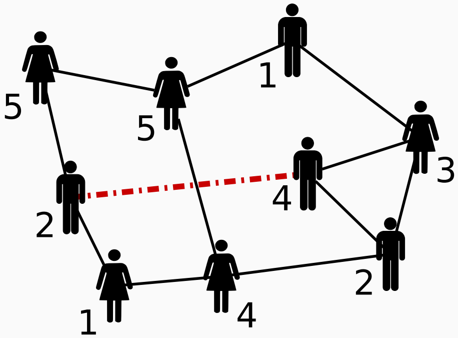

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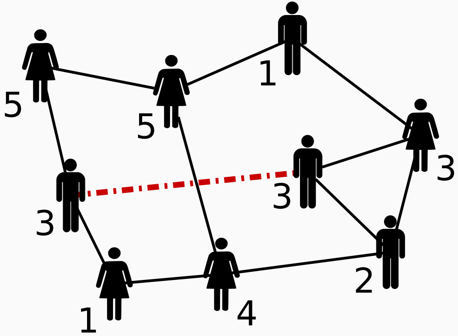

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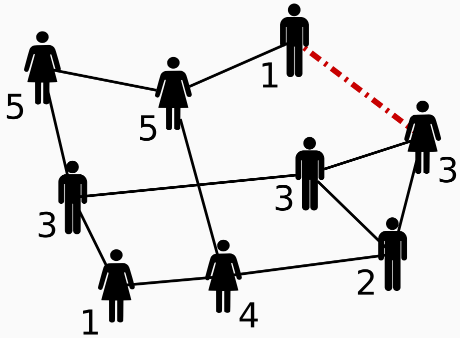

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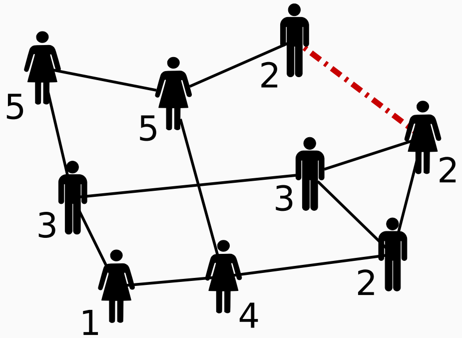

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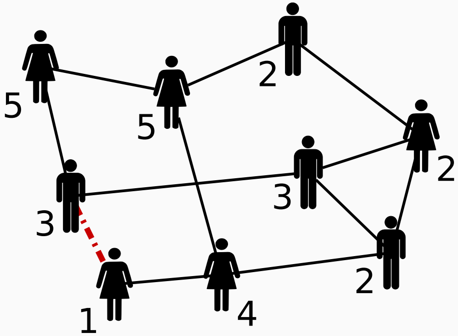

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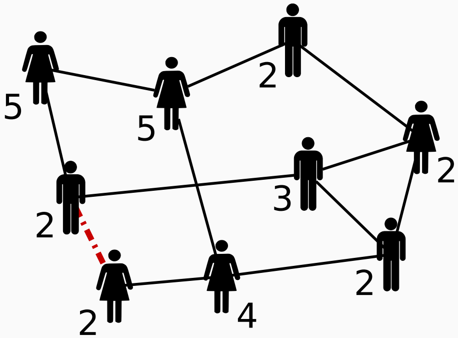

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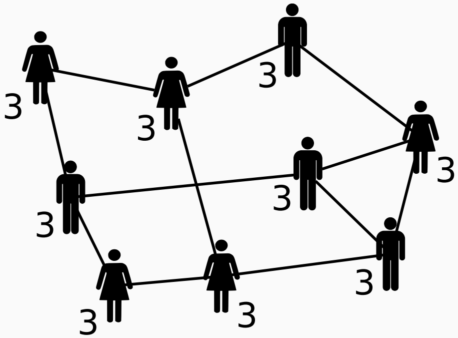

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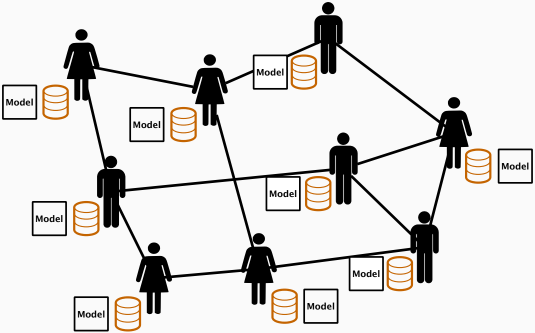
EXISTING WORK: CONSENSUS LEARNING

- Gossip algorithms to optimize a loss function over the union of personal datasets [Nedic and Ozdaglar, 2009, Duchi et al., 2012, Wei and Ozdaglar, 2012, Colin et al., 2016]



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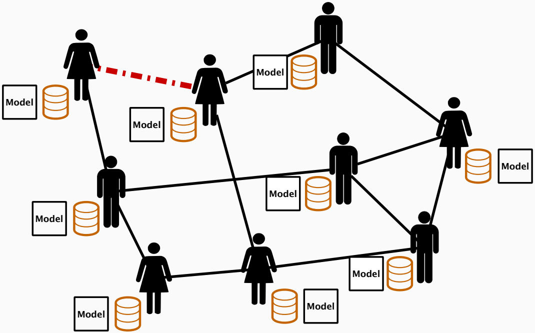

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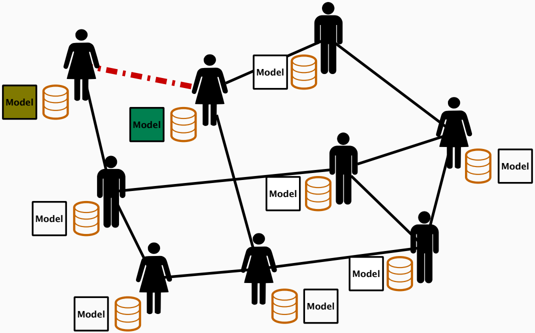

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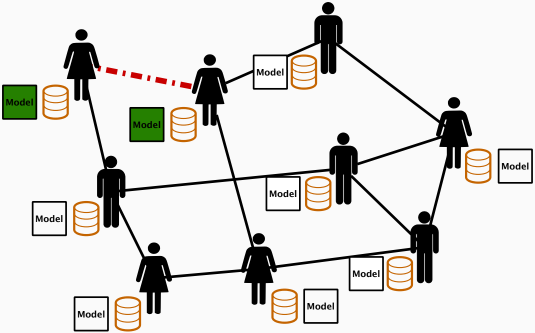

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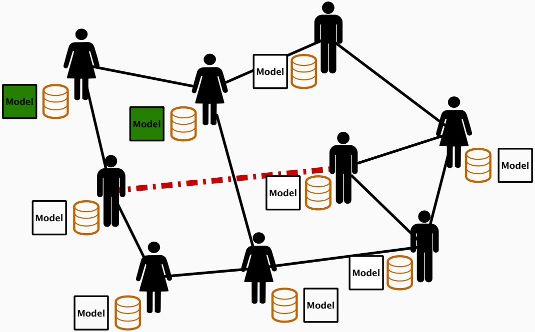

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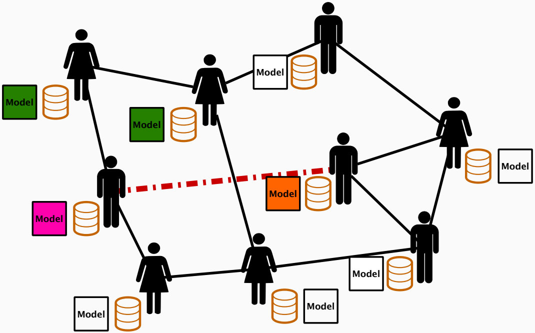

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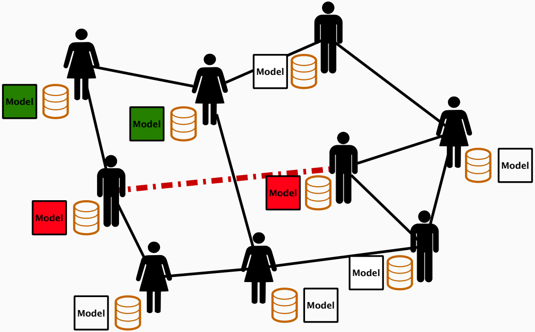

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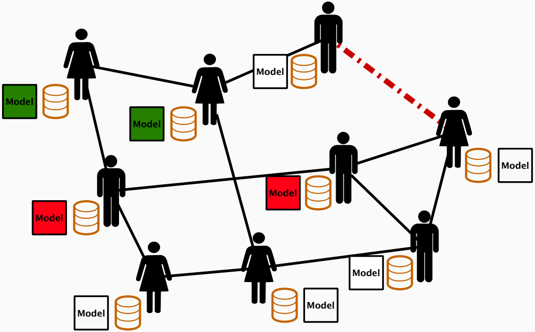

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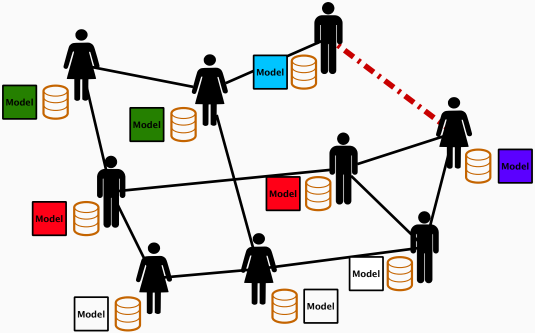

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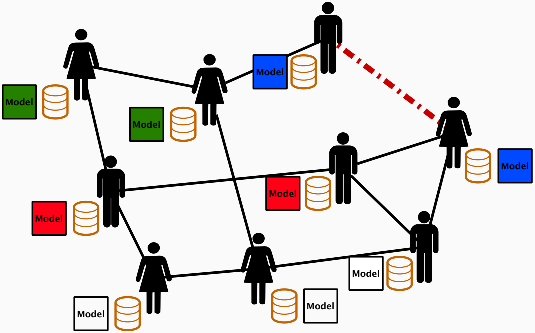

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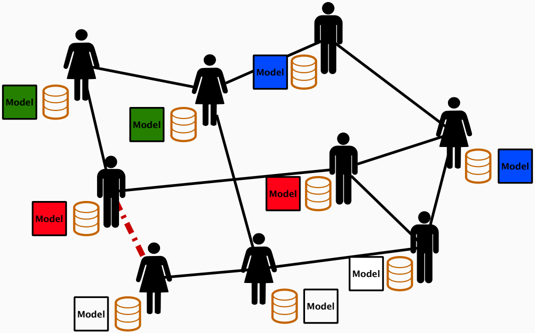

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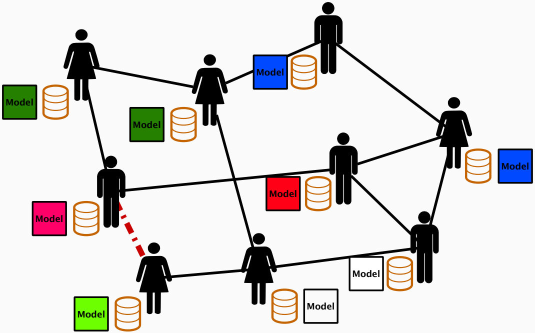

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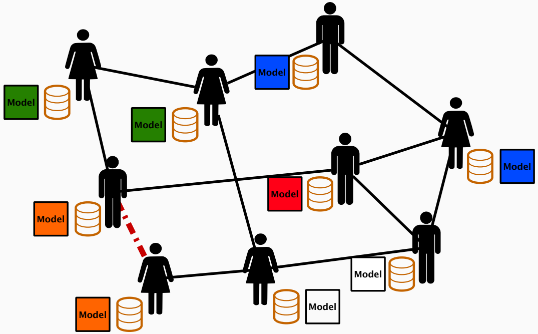

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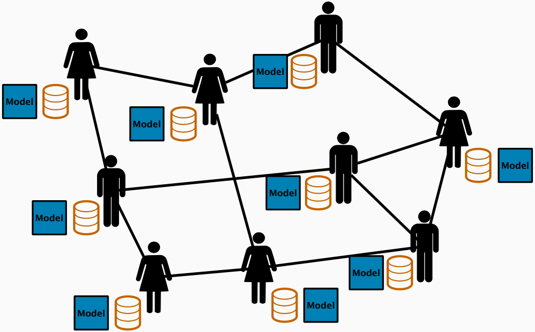

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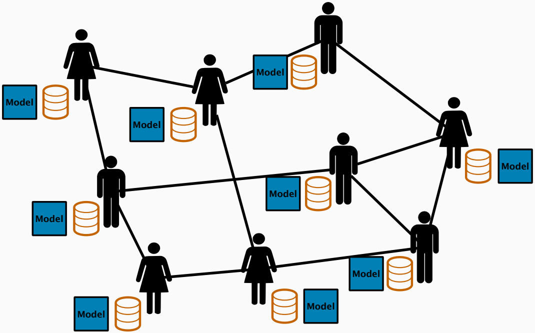

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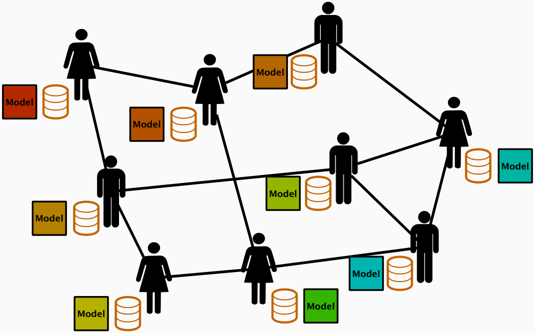
THIS WORK: PERSONALIZED LEARNING

- 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

- A set $V = [\![n]\!] = \{1, \dots, n\}$ of n learning agents
- A convex loss function $\ell : \mathbb{R}^p \times \mathcal{X} \times \mathcal{Y}$
- 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

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

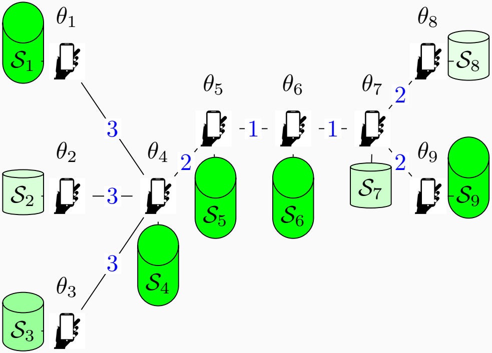
- In isolation, agent i can learn a "solitary" model

$$\theta_i^{sol} \in \mathop{\arg\min}_{\theta \in \mathbb{R}^p} \mathcal{L}_i(\theta) = \sum_{j=1}^{m_i} \ell(\theta; x_i^j, y_i^j)$$

- **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 $i = j$
- **Simplifying 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
- In a more general setup one would need to
  - estimate weights based on auxiliary observation or local data
  - construct a k-NN overlay on top of the physical communication network [Jelasity et al., 2009]



- 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

MODEL PROPAGATION

MODEL PROPAGATION: PROBLEM FORMULATION

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
- Strict generalization of Label Propagation (LP) [Zhou et al., 2004]
  - Constant c_i's $\rightarrow$ recover LP
  - Variable c_i's $\rightarrow$ cannot be expressed as LP
  - Our gossip algorithm will readily apply to LP!

SYNCHRONOUS DECENTRALIZED ALGORITHM

- Cannot use closed-form solution (requires global knowledge)
- The following iteration converges to the same quantity

$$\Theta(t+1) = (\alpha I + \bar{\alpha} C)^{-1} \left(\alpha P \Theta(t) + \bar{\alpha} C \Theta^{sol} \right)$$

  - $P = D^{-1}W$ (stochastic similarity matrix)
  - $\alpha \in (0,1)$ such that $\mu = (1-\alpha)/\alpha$, $\bar{\alpha} = 1 - \alpha$
- Decomposes into

$$\theta_i(t+1) = \frac{1}{\alpha + \bar{\alpha} c_i} \left(\alpha \sum_{j \in \mathcal{N}_i} \frac{W_{ij}}{D_{ii}} \theta_j(t) + \bar{\alpha} c_i \theta_i^{sol} \right)$$

- This is a decentralized but synchronous process
  - Assumes availability of global clock
  - Synchronization incurs delays (must wait for everyone to finish)
  - All neighbors must be contacted at each step

- Each agent has a local Poisson clock and wakes up when it ticks $\rightarrow$ equivalent to activating a random node at each step t
- **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., 2016])

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 $i \in [\![n]\!]$,

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

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

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

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

  - Trade-off between smoothing models within neighborhoods and good accuracy on local datasets
  - Note: confidence is built in second term
- More flexibility in settings where different parameter values may lead to similar predictions

- We will rely on ADMM [Boyd et al., 2011, Wei and Ozdaglar, 2012], which is popular for solving decentralized consensus problems

$$\min_{\theta \in \mathbb{R}^p} \sum_{i=1}^{n} \mathcal{L}_i(\theta)$$

- **Main idea:** reformulate our problem as a partial consensus and decouple the objectives
- Let Θ_i be the set of $|\mathcal{N}_i| + 1$ variables $\theta_j \in \mathbb{R}^p$ for $j \in \mathcal{N}_i \cup \{i\}$, denote θ_j by Θ_i^j and define

$$\mathcal{Q}_{CL}^i(\Theta_i) = \frac{1}{2} \sum_{j \in \mathcal{N}_i} W_{ij} \|\Theta_i^i - \Theta_i^j\|^2 + \mu D_{ii} \mathcal{L}_i(\Theta_i^i),$$

- We can rewrite our problem as $\min_{\Theta \in \mathbb{R}^{n \times p}} \sum_{i=1}^{n} \mathcal{Q}_{CL}^i(\Theta_i)$

- *Decoupling*: introduce a local copy $\widetilde{\Theta}_i \in \mathbb{R}^{(|\mathcal{N}_i|+1)\times p}$ of the decision variables Θ_i for each agent i
- *Partial consensus*: impose equality constraints on the variables $\widetilde{\Theta}_i^i = \widetilde{\Theta}_j^i$ for all $i \in [\![n]\!], j \in \mathcal{N}_i$
  - two neighboring agents agree on each other's personalized model
- Further introduce 4 secondary variables Z_{ei}^i, Z_{ej}^i, Z_{ei}^j and Z_{ej}^j for each edge $e = (i, j)$
  - can be viewed as estimates of the models $\widetilde{\Theta}_i$ and $\widetilde{\Theta}_j$ known by each end of e
  - will allow efficient decomposition of ADMM updates

- **Final reformulation:** denoting $\widetilde{\Theta} = [\widetilde{\Theta}_1^\top, \dots, \widetilde{\Theta}_n^\top]^\top \in \mathbb{R}^{(2|E|+n)\times p}$ and $Z \in \mathbb{R}^{4|E|\times p}$

$$\min_{\substack{\widetilde{\Theta}\in\mathbb{R}^{(2|E|+n)\times p}\\ Z\in\mathcal{C}_E}} \quad \sum_{i=1}^n \mathcal{Q}_{CL}^i(\widetilde{\Theta}_i)$$

$$\text{s.t. } \forall e=(i,j)\in E, \quad \begin{cases} Z_{ei}^i = \widetilde{\Theta}_i^i,\ Z_{ei}^j = \widetilde{\Theta}_i^j \\ Z_{ej}^j = \widetilde{\Theta}_j^j,\ Z_{ej}^i = \widetilde{\Theta}_j^i, \end{cases}$$

where $\mathcal{C}_E = \{Z \in \mathbb{R}^{4|E|\times p} \mid Z_{ei}^i = Z_{ej}^i, Z_{ej}^j = Z_{ei}^j \text{ for all } e=(i,j)\in E\}$

- Constraints involving $\widetilde{\Theta}$ can be written $D\widetilde{\Theta} + HZ = 0$ where
  - $H = -I$ of dimension $4|E| \times 4|E|$ is diagonal invertible
  - $D \in \mathbb{R}^{4|E|\times(2|E|+n)}$ contains exactly one entry of 1 in each row
- Assumptions of [Wei and Ozdaglar, 2013] satisfied

- The augmented Lagrangian of the problem is

$$L_\rho(\widetilde{\Theta}, Z, \Lambda) = \sum_{i=1}^{n} L_\rho^i(\widetilde{\Theta}_i, Z_i, \Lambda_i),$$

  where $\rho > 0$ is a penalty parameter, $Z \in \mathcal{C}_E$ and

$$\begin{aligned} L_\rho^i(\widetilde{\Theta}_i, Z_i, \Lambda_i) = \mathcal{Q}_{CL}^i(\widetilde{\Theta}_i) + \sum_{j:e=(i,j)\in E} \Big[& \Lambda_{ei}^i(\widetilde{\Theta}_i^i - Z_{ei}^i) \\ & + \Lambda_{ei}^j(\widetilde{\Theta}_i^j - Z_{ei}^j) + \frac{\rho}{2}\left(\|\widetilde{\Theta}_i^i - Z_{ei}^i\|^2 + \|\widetilde{\Theta}_i^j - Z_{ei}^j\|^2 \right) \Big]. \end{aligned}$$

- ADMM iteratively minimize the augmented Lagrangian by alternating
  1. minimization w.r.t. primal variable $\widetilde{\Theta}$
  2. minimization w.r.t. secondary variable Z
  3. update of the dual variable Λ

- Assume that agent i wakes up at step t and selects $j \in \mathcal{N}_i$. Denoting $e = (i, j)$
    1. Agent i updates its primal variables:

    $$\widetilde{\Theta}_i(t+1) = \arg\min_{\Theta \in \mathbb{R}^{(|\mathcal{N}_i|+1)\times p}} L^i_\rho(\Theta, Z_i(t), \Lambda_i(t)),$$

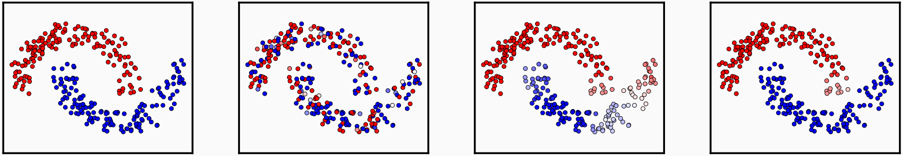
    and sends $\widetilde{\Theta}^i_i(t+1), \widetilde{\Theta}^j_i(t+1), \Lambda^i_{ei}(t), \Lambda^j_{ei}(t)$ to agent j. Agent j executes the same steps w.r.t. i.
    2. Using $\widetilde{\Theta}^j_j(t+1), \widetilde{\Theta}^i_j(t+1), \Lambda^j_{ej}(t), \Lambda^i_{ej}(t)$ received from j, agent i updates its secondary variables $Z^i_{ei}(t+1)$ and $Z^j_{ei}(t+1)$ (closed form). Agent j updates its secondary variables symmetrically
    3. Agent i updates its dual variables $\Lambda^i_{ei}(t+1)$ and $\Lambda^j_{ei}(t+1)$ (closed-form). Agent j updates its dual variables symmetrically.
- Convergence in $O(1/t)$ [Wei and Ozdaglar, 2013]

EXPERIMENTS

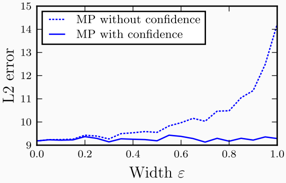
- We consider $n = 300$ agents and a 1D mean estimation task (loss $f(\theta; x_i) = \|\theta - x_i\|^2$)
    - Network topology derived from the two moons dataset
    - Each agent i has a true 1D Gaussian distribution μ_i centered at -1 or +1 depending on the moon it belongs to
    - Each agent i receives a random number m_i of samples from μ_i

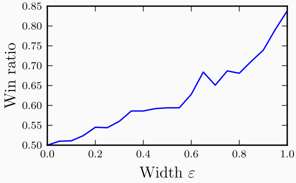
COLLABORATIVE MEAN ESTIMATION

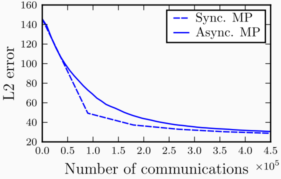
- Confidence values help a lot for imbalanced datasets
- Our MP algorithm has fast convergence without synchronization



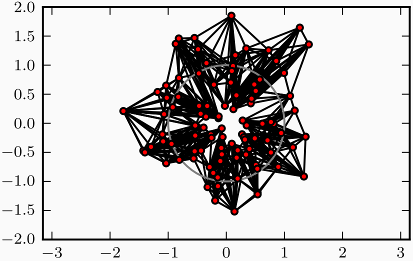
(a) Ground models (b) Solitary models (c) MP without confidence (d) MP with confidence



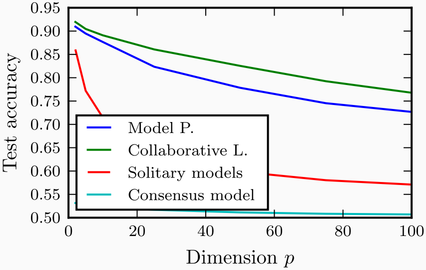


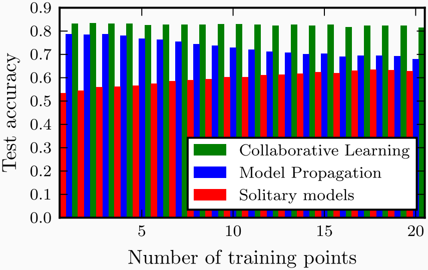


- We consider a set of $n = 100$ agents and a linear classification task in $\mathbb{R}^p$ (with hinge loss)
  - Target models lie in a 2D subspace, network weights based on the angle between true models
  - Each agent i receives a random number m_i of samples with label given by the prediction of target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

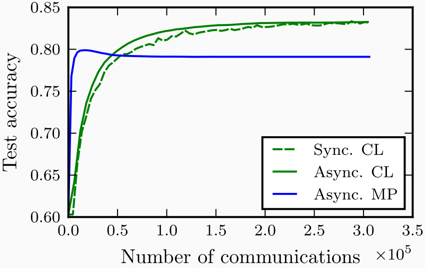


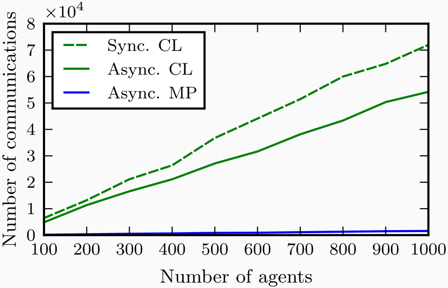
- Both CL and MP provide great improvements over local models
- CL consistently outperforms MP by significant margin
- Effectively compensating for training size imbalance





- CL algorithm converges as fast as a synchronous approach
- MP much faster to converge and can be used as warm-start to speed up CL
- Number of iterations to converge to near-optimal accuracy scales linearly with network size





FUTURE WORK

FUTURE WORK (AND ADS)

- Study link between similarity graph and generalization performance
- Generic methods to estimate/learn graph weights
- Decentralized discovery of similar peers
- Privacy-preserving mechanisms

Quick ads

- Make sure you attend the NIPS 2016 workshop on **Private Multi-Party Machine Learning**!
- We have **many open positions** in our Inria team (tenured, postdocs, PhDs, Master internships) with exciting projects!

Thank you for your attention!
Questions?

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