ALS Algorithm for Robust and Communication-Efficient Federated Learning

Neil Hurley, Erika Duriakova, James Gerraci, Diarmuid O'Reilly-Morgan, Elias Tragos, Barry Smyth and Aonghus Lawlor

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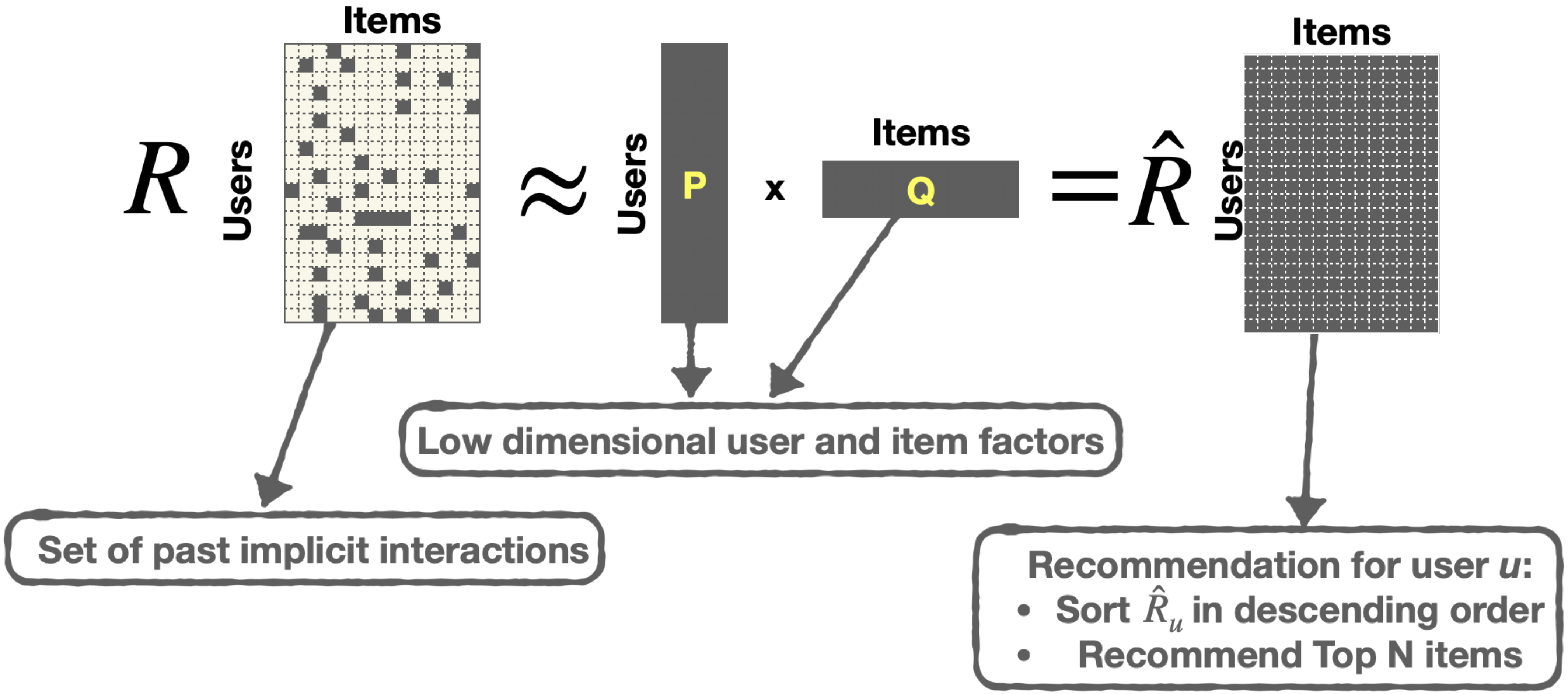
Latent Factor Recommendation Models



Latent Factor Recommendation Models

$$f(\mathrm{P},\mathrm{Q}) = \boxed{\mathcal{L}^{\mathrm{WMF}}(\mathrm{P},\mathrm{Q})} + \boxed{\mathcal{R}(\mathrm{P},\mathrm{Q})},$$

$$\boxed{\textstyle\sum_u \sum_{i\in I} c_{ui}(\mathbf{p}_u^\top \mathbf{q}_i - \tilde{r}_{ui})^2} \qquad \boxed{\lambda_p\|\mathrm{P}\|^2 + \lambda_q\|\mathrm{Q}\|^2}$$

Stochastic Gradient Descent

Uniformly sample S_k adding negative interactions

$$\mathbf{q}_i^{(t)} = \mathbf{q}_i^{(t-1)} - \eta\left(c_{ui}\left(\mathbf{p}_u^{(t-1)\top}\mathbf{q}_i^{(t-1)} - \tilde{r}_{ui}\right)\mathbf{p}_u^{(t-1)} + \lambda_q \mathbf{q}_i^{(t-1)}\right);$$
$$\mathbf{p}_u^{(t)} = \mathbf{p}_u^{(t-1)} - \eta\left(c_{ui}\left(\mathbf{p}_u^{(t-1)\top}\mathbf{q}_i^{(t-1)} - \tilde{r}_{ui}\right)\mathbf{q}_i^{(t-1)} + \lambda_p \mathbf{p}_u^{(t-1)}\right)$$

Alternating Least Squares

$$\forall u \in U \quad \mathbf{p}_u^{(k)} = \mathrm{M}_p^{-1}\Big(\sum_{i\in R_u} c_{ui}\mathbf{q}_u^{(k-1)}\Big) \qquad (P - step)$$

$$\forall i \in I \quad \mathbf{q}_i^{(k)} = \mathrm{M}_q^{-1}\Big(\sum_{\{u|i\in R_u\}} c_{ui}\mathbf{p}_u^{(k)}\Big) \qquad (Q - step)$$

$$\mathrm{M}_q = \lambda_q \mathrm{I} + \mathrm{P}_{\mathrm{all}} + \sum_{i\in R_u}(c_{ui}-1)\mathbf{p}_u^{(k-1)}\mathbf{p}_u^{(k-1)\top};$$

$$\mathrm{M}_p = \lambda_p \mathrm{I} + \mathrm{Q}_{\mathrm{all}} + \sum_{i\in R_u}(c_{ui}-1)\mathbf{q}_i^{(k-1)}\mathbf{q}_i^{(k-1)\top};$$

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Insight

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Latent Factor Recommendation Models

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Stochastic Gradient Descent

Alternating Least Squares

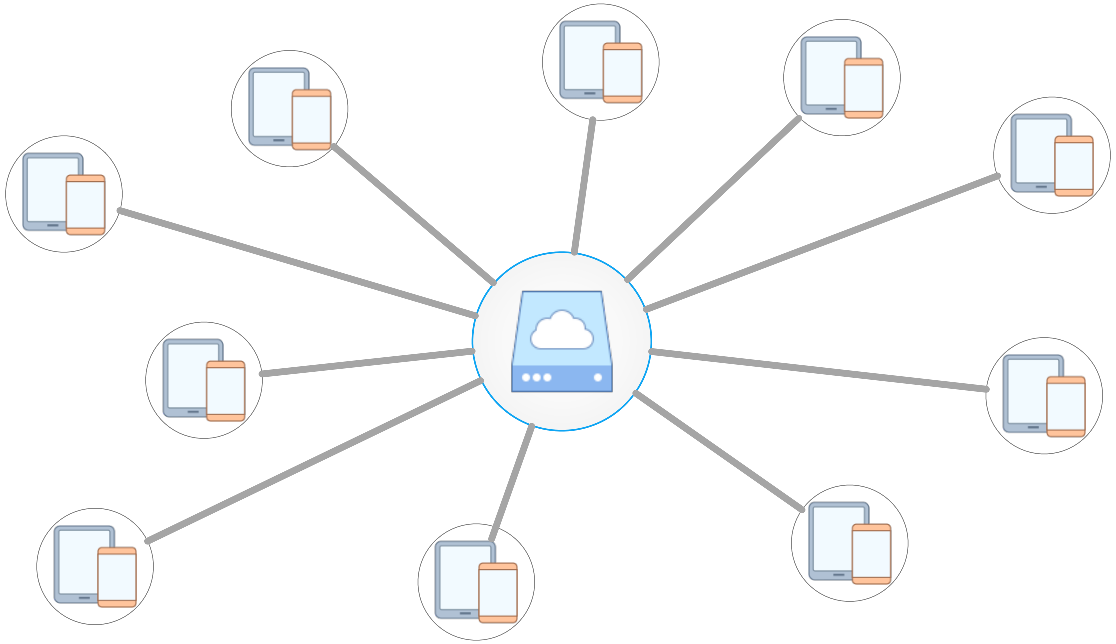
Goal: A communication efficient Federated Learning algorithm for latent factor models that is robust against model poisoning attacks.

$$\mathrm{M}_p = \lambda_p \mathrm{I} + \mathrm{Q}_{\mathrm{all}} + \sum_{i\in R_u} (c_{ui} - 1)\mathrm{q}_i^{(k-1)}\mathrm{q}_i^{(k-1)\top};$$

$$\mathrm{P}_{\mathrm{all}} = \sum_u \mathrm{p}_u^{(k-1)}\mathrm{p}_u^{(k-1)\top}; \quad \mathrm{Q}_{\mathrm{all}} = \sum_i \mathrm{q}_i^{(k-1)}\mathrm{q}_i^{(k-1)\top}.$$

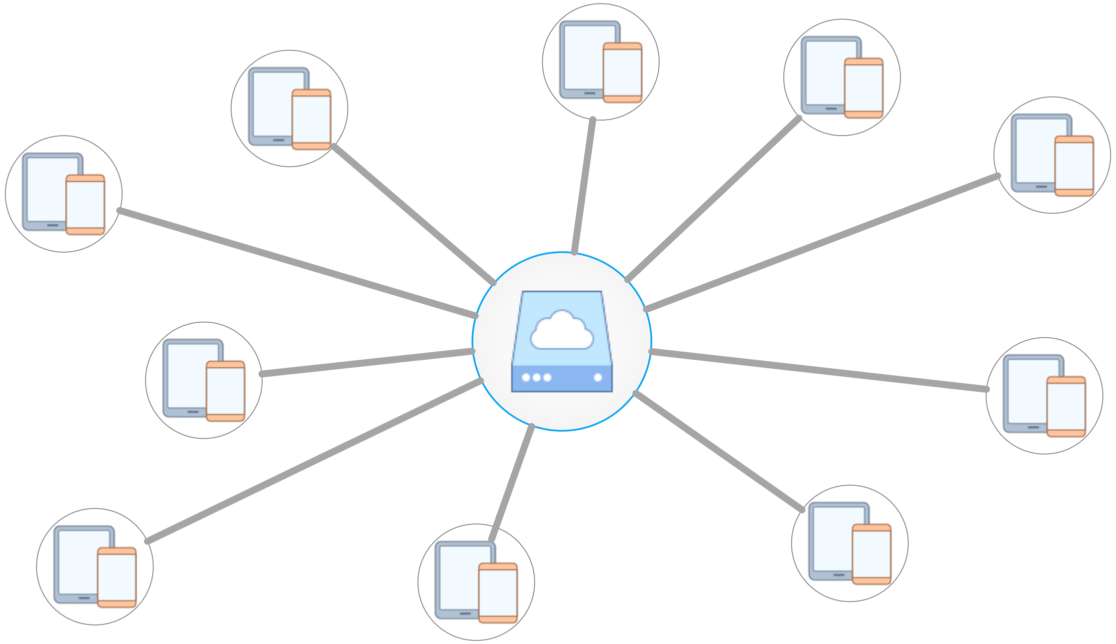
Federated Learning

- Data scattered across devices
- Learning orchestrated by central server
- No sharing of actual data points
- Exchanging model parameters



Contribution

- First Federated ALS Algorithm
- Avoid negative sampling
- Share only item-related parameters
- Reduce communication overhead
- Robustness against model poisoning attacks



Federated ALS Algorithm

$$f(\boldsymbol{P},\boldsymbol{Q}) = \boxed{\mathcal{L}^{WMF}(\boldsymbol{P},\boldsymbol{Q})} + \boxed{\mathcal{R}(\boldsymbol{P},\boldsymbol{Q})}$$

$$\boxed{\sum_{u}\sum_{i\in I} c_{ui}(p_u^T q_i - \tilde{r_{ui}})^2}$$

$$\boxed{\lambda_p||P||^2 + \lambda_q||Q||^2} + \boxed{\mu \sum_{c=1}^{N_c} \sum_{i\in I} ||q_{ci} - q_i^g||^2}$$

Federated ALS Algorithm

$$\boldsymbol{f(P,Q)} = \boxed{\mathcal{L}^{\boldsymbol{WMF}}(\boldsymbol{P},\boldsymbol{Q})} + \boxed{\mathcal{R}(\boldsymbol{P},\boldsymbol{Q})}$$

$$\boxed{\sum_{\boldsymbol{u}}\sum_{\boldsymbol{i}\in\boldsymbol{I}} \boldsymbol{c_{ui}}(\boldsymbol{p_u^T q_i} - \tilde{\boldsymbol{r}}_{\boldsymbol{ui}})^2}$$

$$\boxed{\boldsymbol{\lambda_p}||\boldsymbol{P}||^2 + \boldsymbol{\lambda_q}||\boldsymbol{Q}||^2} + \boldsymbol{\mu}\sum_{\boldsymbol{c=1}}^{\boldsymbol{N_c}}\sum_{\boldsymbol{i\in I}}||\boldsymbol{q_{ci}} - \boldsymbol{q_i^g}||^2$$

Local ALS

Q ← $Q_{all} - \sum_{\{(u,i)\in R_c\}} c_{ui}\, q_i^g q_i^{gT}$
ℓ = 0
while ℓ < E do; ℓ ← ℓ + 1
    for all $u \in U_c$ do *#ALS P-step*
        M ← $\lambda_p I + Q + \sum_{i|(u,i)\in R_c} c_{ui} q_{ci} q_{ci}^T$
        p_u ← $M^{-1}(\sum_{\{i|(u,i)\in R_c\}} c_{ui} q_{ci})$
    end for
    for all $\{i \mid (u, i) \in Rc\}$ do *#ALS Q-step*
        M ← $\mu + \lambda_q I + \sum_{\{u|(u,i)\in R_c\}} c_{ui} p_{ui} p_u^T$
        q_{ci} ← $M^{-1}(\sum_{\{u|(u,i)\in R_c\}} c_{ui} q_{ci} \mu q_i^g)$
    end for
end while

Server Code

k ← 0, $\forall i \in I$, q_i^g ← Initialise()
 # E=number of local epochs
 # θ =algorithm specific client parameters
while $k < T/E$ **do** $k \leftarrow k + 1$
    $Q_{all} = \sum_{i\in I} q_i^g q_i^{gT}$
    Broadcast {Q_{all}, q_i^g, $i \in R_c$, E, θ} to all clients
    $c \leftarrow 0$
    while $c < C$ do $c \leftarrow c + 1$
        Receive {q_{ci}} from participating client c
    end while
    $\forall i \in I$, $q_i^g \leftarrow \sum_{c=1}^{N_c} q_{ci}^{(t_c)}$
end while

Federated ALS Algorithm

Received from server

$q^g_i\ \forall i \in R_c;\quad E \geq 0, \mu \geq 0$

$Q_{all} = \sum_{i \in I} q^g_i q^{gT}_i;$

$$f(P, Q) = \boxed{\mathcal{L}^{WMF}(P, Q)} + \boxed{\mathcal{R}(P, Q)}$$

$$\boxed{\sum_u \sum_{i \in I} c_{ui}(p_u^T q_i - \tilde{r_{ui}})^2}$$

$$\boxed{\lambda_p ||P||^2 + \lambda_q ||Q||^2} + \mu \sum_{c=1}^{N_c} \sum_{i \in I} ||q_{ci} - q_i^g||^2$$

Local ALS

$\boxed{Q} \leftarrow Q_{all} - \sum_{\{(u,i) \in R_c\}} c_{ui}\, q_i^g q_i^{gT}$

$\ell = 0$

while $\ell < E$ do; $\ell \leftarrow \ell + 1$

for all $u \in U_c$ do *#ALS P-step*

$M \leftarrow \lambda_p I + Q + \sum_{i|(u,i) \in R_c} c_{ui} q_{ci} q_{ci}^T$

$p_u \leftarrow M^{-1}(\sum_{\{i|(u,i) \in R_c\}} c_{ui} q_{ci})$

end for

for all $\{i \mid (u, i) \in Rc\}$ do *#ALS Q-step*

$M \leftarrow \mu + \lambda_q I + \sum_{\{u|(u,i) \in R_c\}} c_{ui} p_{ui} p_u^T$

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end for

end while

Send to server

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$k \leftarrow 0$, $\forall i \in I$, $q_i^g \leftarrow$ Initialise()

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$Q_{all} = \sum_{i \in I} q_i^g q_i^{gT}$

Broadcast $\{Q_{all}, q_i^g, i \in R_c, E, \theta\}$ to all clients

$c \leftarrow 0$

while $c < C$ do $c \leftarrow c + 1$

Receive $\{q_{ci}\}$ from participating client c

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$\forall i \in I,\ q_i^g \leftarrow \sum_{c=1}^{N_c} q_{ci}^{(t_c)}$

Aggregation step

end while

Insight

Federated ALS Algorithm

Received from server

$\mathbf{q}^g{}_i\ \forall i \in R_c; \quad E \geq 0, \mu \geq 0$

$\mathrm{Q}_{\mathrm{all}} = \sum_{i \in I} \mathbf{q}^g{}_i \mathbf{q}^{g\top}_i;$

$$f(P,Q) = \boxed{\mathcal{L}^{WMF}(P,Q)} + \boxed{\mathcal{R}(P,Q)}$$

$$\boxed{\sum_u \sum_{i \in I} c_{ui}(p_u^T q_i - \tilde{r_{ui}})^2}$$

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Local ALS

$\boxed{\mathrm{Q}} \leftarrow Q_{all} - \sum_{\{(u,i) \in R_c\}} c_{ui}\, q_i^g q_i^{gT}$

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while $\ell < E$ do; $\ell \leftarrow \ell + 1$

for all $u \in U_c$ do *#ALS P-step*

$\mathrm{M} \leftarrow \lambda_p \mathrm{I} + Q + \sum_{i|(u,i) \in R_c} c_{ui} q_{ci} q_{ci}^T$

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$q^g{}_i \ \forall i \in R_c; \quad E \geq 0, \mu \geq 0$

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Local ALS

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  end while

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  Aggregation step

end while

Empirical Evaluation

Datasets:

- **ML100K** with 943 users, 1,682 items and 100K interactions
- **ML1M** with 6,041 users, 3,953 items and 1M interactions
- Random subset of **Yelp** with 1,358 users, 1,405 items and 17,596 interactions

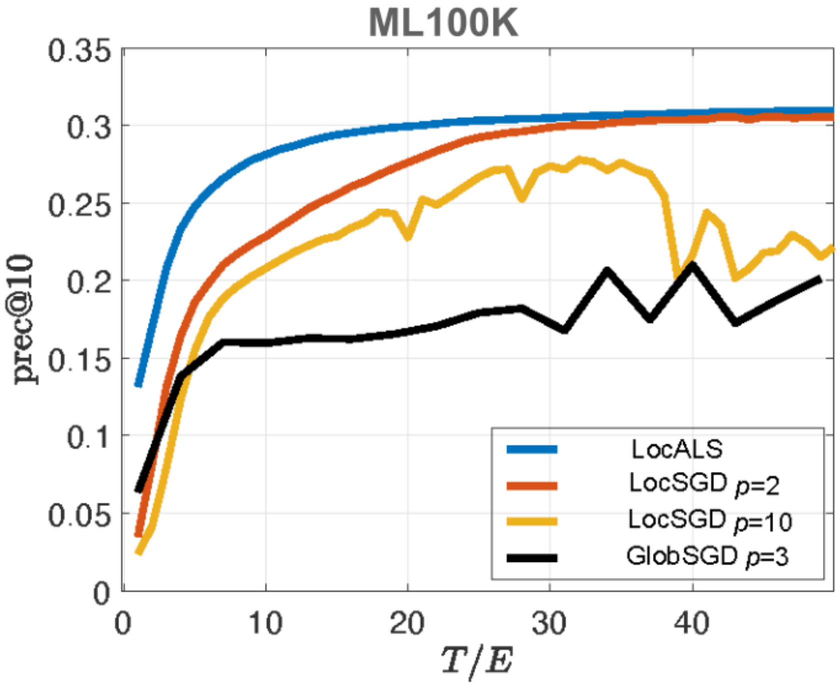
Methods:

- **GlobSGD** using ALS updates for user-factors, local partial derivates are computed on devices and send to server where the global factor is computed
- **LocSGD** using ALS updates for user-factors and several local rounds of SGD updates to compute item-factors
- **LocALS** using ALS updates for both user and item factors

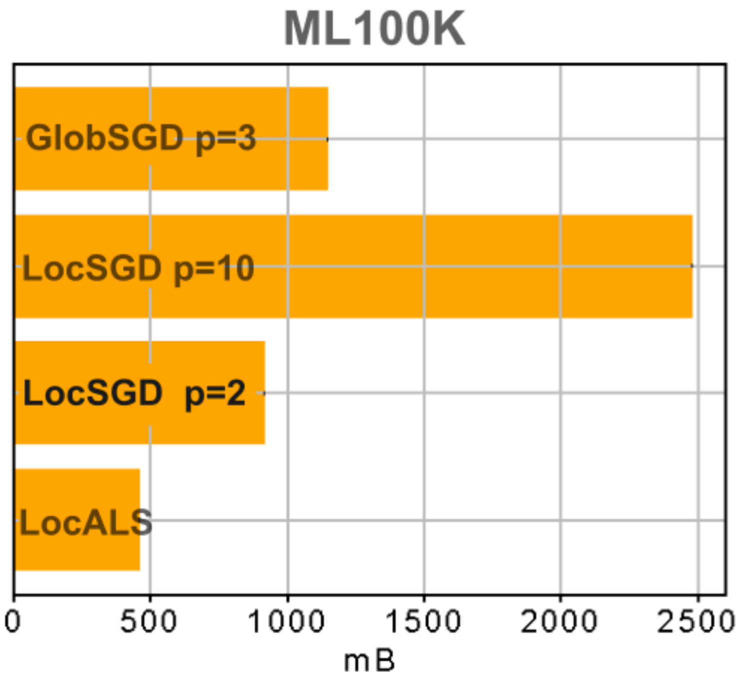
Research Questions:

- Rate of convergence
- Communication overhead
- Robustness against poisoning attack

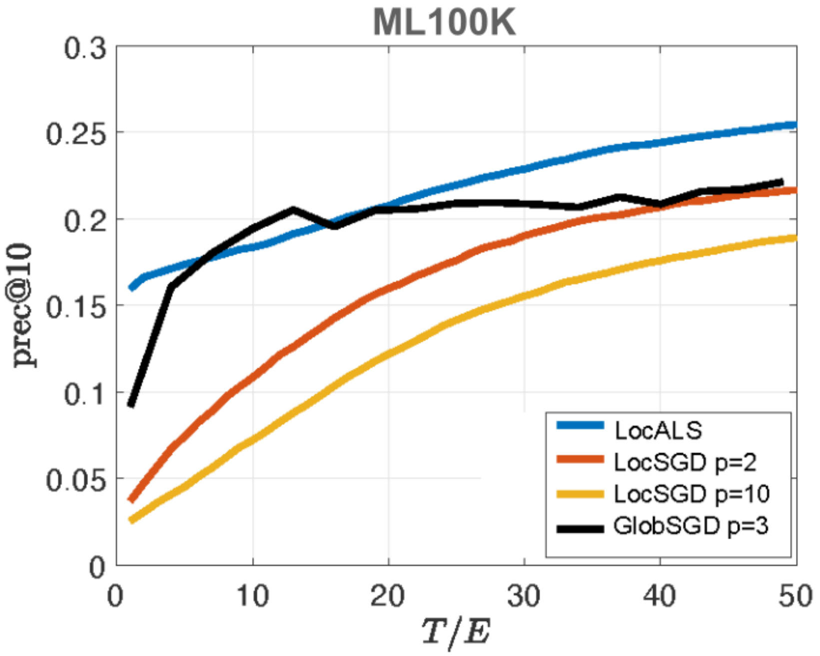
Performance Results



prec@10 vs rounds
(C=n)

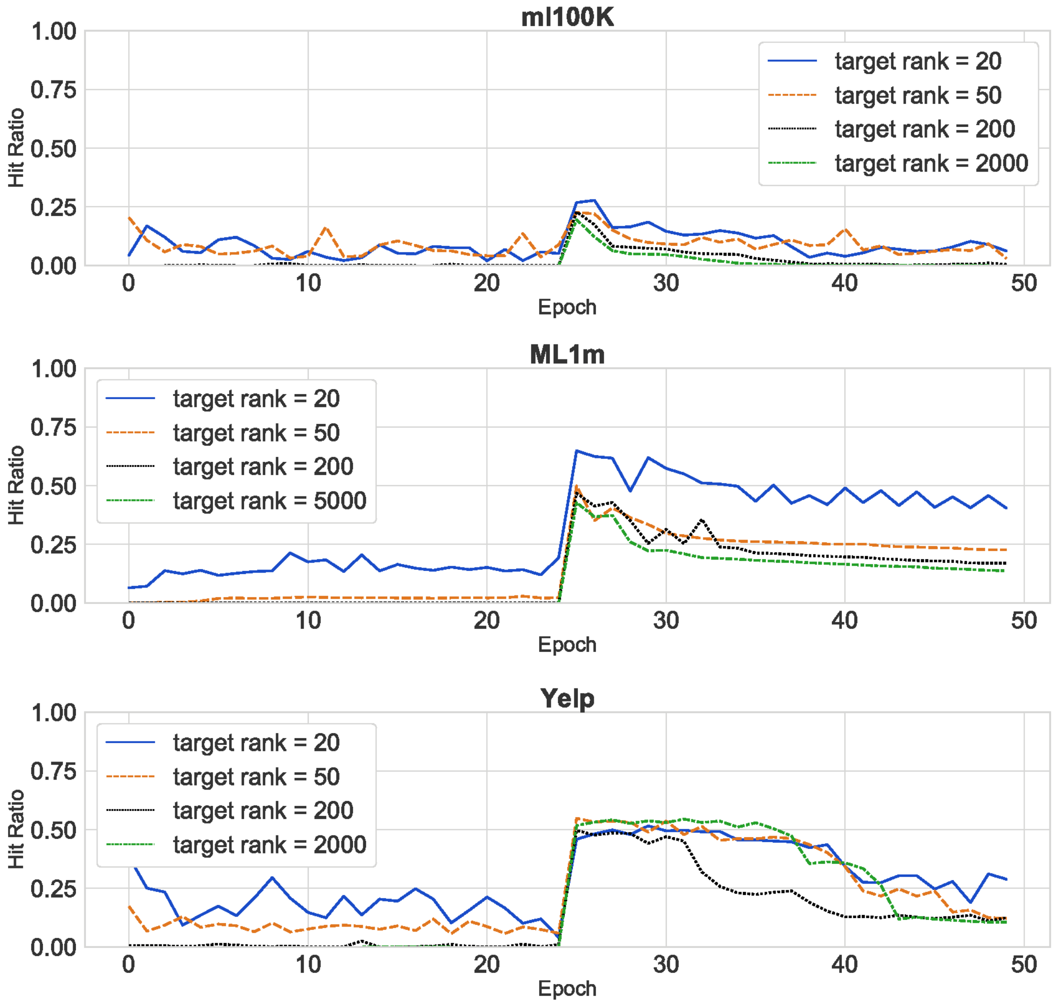


Comm. Vol. @ 30 rounds

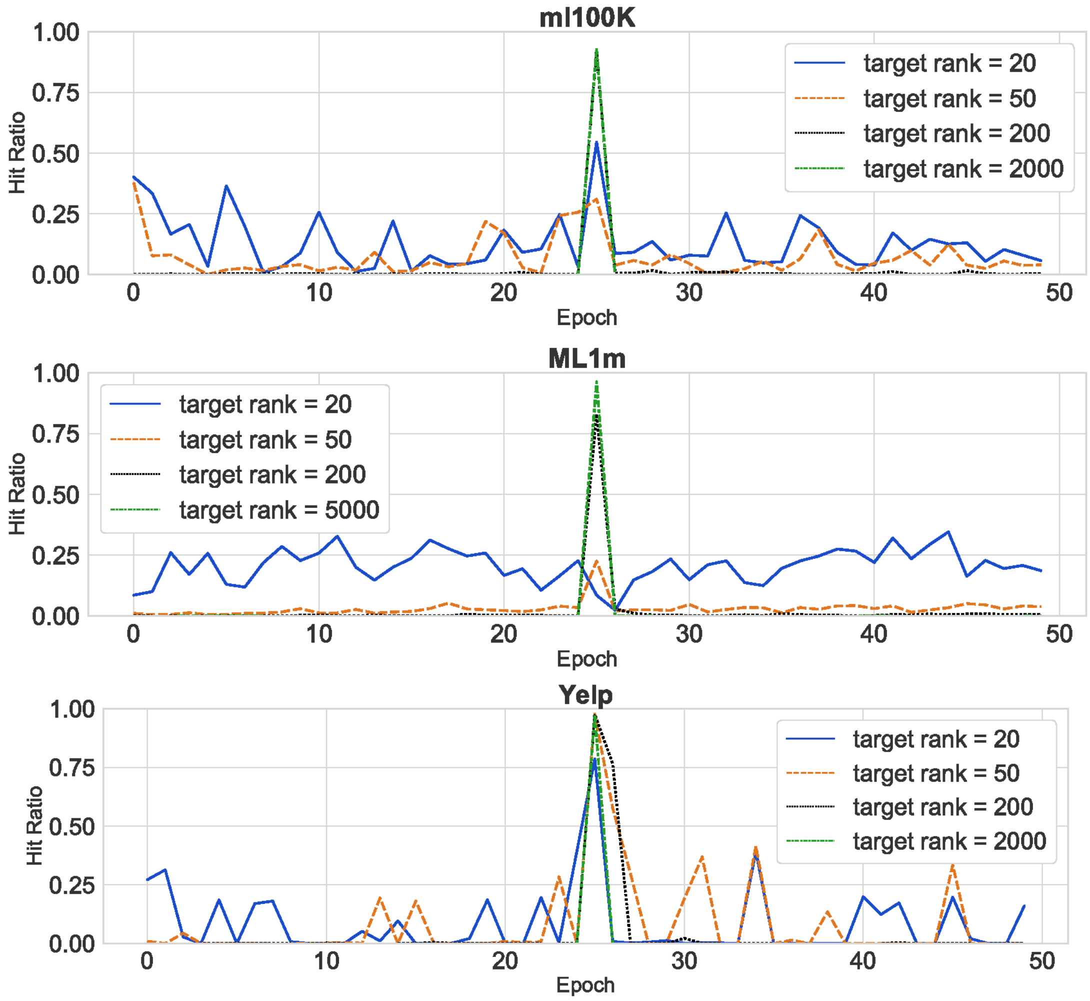


prec@10 vs rounds
(C=0.1n)

Robustness against model poisoning



GlobSGD



LocALS

Insight

Summary

- Novel and efficient federated ALS algorithm for top-N recommendation
- Added new regularisation term to ensure alignment of local and global factors
- Demonstrated superior communication efficiency
- Demonstrated long-term robustness against model poisoning attacks

Open Problems:

- Efficient calculation of inverse matrices for very large data
- Data privacy

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thank you