

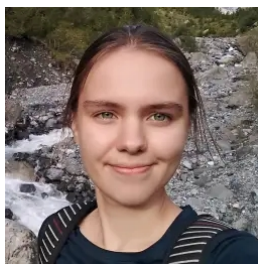
Decentralized Local Stochastic Extra-Gradient for Variational Inequalities



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NeurIPS 2022

Variational Inequality Problem

Find $z^* \in \mathbb{R}^d$ such that $\langle F(z), z - z^* \rangle \geq 0, \quad \forall z \in \mathbb{R}^d$

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Variational Inequality Problem

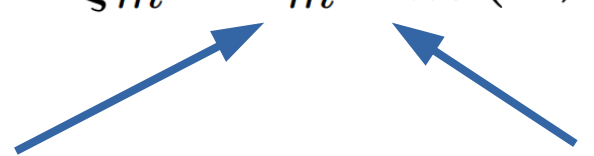
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- Find $z^* \in \mathbb{R}^d$ such that $T(z^*) = z^*$
 \downarrow
 $F(z) := z - T(z)$

Distributed Stochastic Setting

$$F(z) := \frac{1}{M} \sum_{m=1}^M \mathbb{E}_{\xi_m \sim \mathcal{D}_m} F_m(z, \xi_m)$$

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(unknown) distribution on local devices

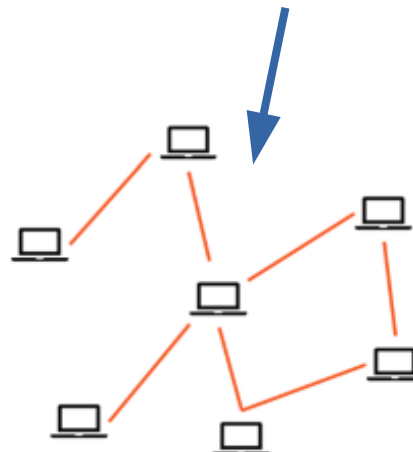
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on local devices

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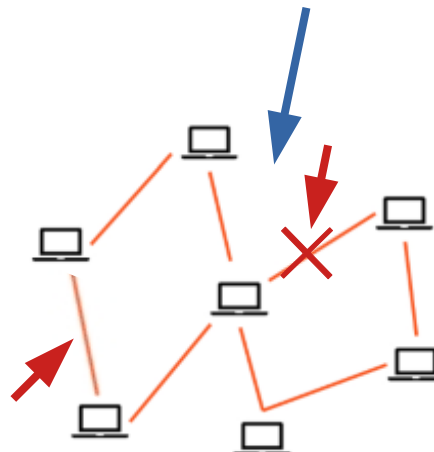
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- Time-varying network



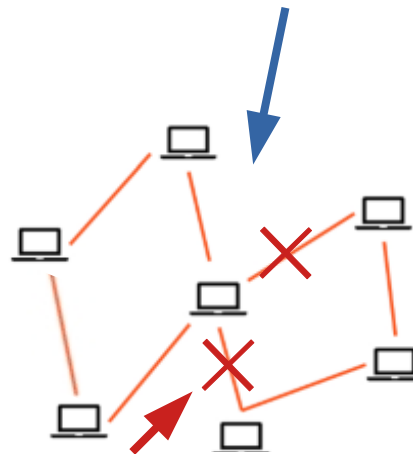
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- Arbitrary network
- Time-varying network
- Disconnected network



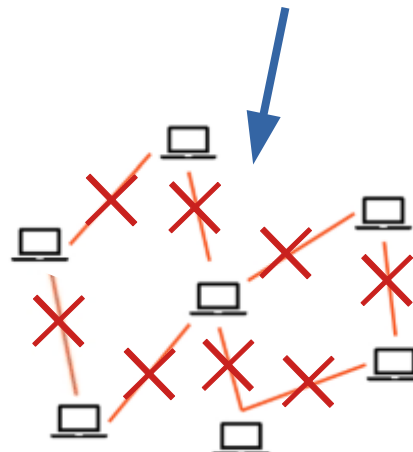
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on local devices

- Arbitrary network
- Time-varying network
- Disconnected network
- Local updates



Algorithms

Algorithm 1 Extra Step Time-Varying Gossip Method

parameters: stepsize $\gamma > 0$, $\{\mathcal{W}^k\}_{k \geq 0}$ – rules or distributions for mixing matrix in iteration k .

initialize: $z^0 \in \mathcal{Z}, \forall m : z_m^0 = z^0$

- 1: **for** $k = 0, 1, 2, \dots$ **do**
 - 2: Sample matrix W^k from \mathcal{W}^k
 - 3: **for** each node m **do**
 - 4: Generate independently $\xi_m^k \sim \mathcal{D}_k, \xi_m^{k+1/3} \sim \mathcal{D}_k$
 - 5: $z_m^{k+1/3} = z_m^k - \gamma F_m(z_m^k, \xi_m^k)$
 - 6: $z_m^{k+2/3} = z_m^k - \gamma F_m(z_m^{k+1/3}, \xi_m^{k+1/3})$
 - 7: $z_m^{k+1} = \sum_{i \in \mathcal{N}_m^k} w_{m,i}^k z_i^{k+2/3}$
 - 8: **end for**
 - 9: **end for**
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Ideas:

- Extragradient

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Ideas:

- Extragradient
- Gossip step = weighted averaging with network neighbors

Thank you!