Detect insider attacks using CNN in Decentralized Optimization

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Gangqiang Li

Shenzhen University

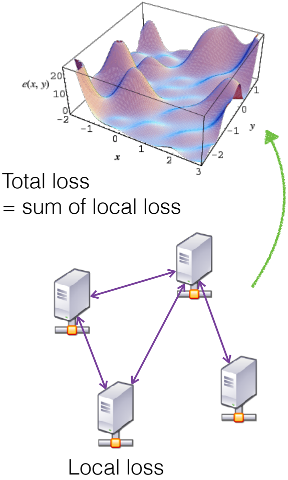
Joint work with:
Xiaoxiao Wu (SZU), Shengli Zhang (SZU), Qiang Li (UESTC)

Big Data Network Challenges

Basic idea: large-scale, massive number of users, computing everywhere...

Context of the Talk: Gossip-based Algorithms

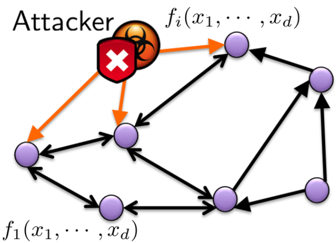
- Data are often measured distributively over large networks
- Gossip-based algorithms: solve multi-agent coordination and optimization problems in a decentralized manner
  - synchronous
  - asynchronous
- Key features:
  - ✓ built-in fault tolerance to intermittent computation/communication.
  - ✓ self reorganization to automatic failure correction.
- Vast literature (see e.g. [NO09, BPC+11, PC06, MBG10, BGPS06, DKM+10, RN04, JXM14])



Problem Statement

The general distributed multi-agent optimization problem has the following syntax:

$$\min_{\boldsymbol{x}} f(\boldsymbol{x}) := \frac{1}{n}\sum_{i=1}^{n} f_i(\boldsymbol{x}) \quad \text{s.t.} \quad \boldsymbol{x} \in X \ . \tag{1}$$

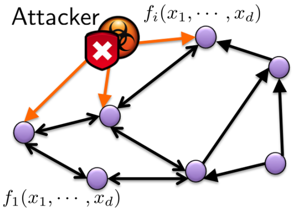


- $f_i : \mathbb{R}^d \to \mathbb{R}$ is a differentiable function over X.
- Each agent i can compute a local estimate $x_i(t) = [\boldsymbol{x}(t)]_i$ of the optimal solution to the problem (at time t), which we refer to as the agent *state*.
- The constraints can be handled either through the use of the Lagrangian or the use of a projection on the constraint set.

The Graph Model

Consider a network of agents described by a connected possibly undirected graph:

- At time t, the network is described by $\mathcal{G}(t) = (\mathcal{V}, \mathcal{E})$. Where $\mathcal{V} = [n] = \{1, ..., n\}$, and $\mathcal{E}(t) \subseteq [n] \times [n]$ is the edge set.
- The weighted adjacency matrix $\boldsymbol{A}(t) \in \mathbb{R}^{n\times n}$ where $[\boldsymbol{A}(t)]_{ij} := A_{ij}(t) = 0$ if $(j, i) \notin \mathcal{E}(t)$. The time varying graph is defined as $\mathcal{G}(t) := (\mathcal{V}, \mathcal{E}(t))$ with $\mathcal{E} := \cup_{t=1}^{\infty} \mathcal{E}(t)$. We have the following assumption:



Assumption 1

There exists a scalar $\eta \in (0, 1)$ such that for all $t \geq 1$ and $i = 1, \cdots, n$:

- $A_{ij}(t) \geq \eta$ if $(i, j) \in \mathcal{E}(t)$, $\boldsymbol{A}(t)\mathbf{1} = \mathbf{1}$, $\boldsymbol{A}^\top(t)\mathbf{1} = \mathbf{1}$;
- The graph $(\mathcal{V}, \cup_{\ell=1}^{B_0} \mathcal{E}(t + \ell))$ is connected for $B_0 < \infty$.

The Protocol for Trustworthy Agents

- At the t^{th} recursion, trustworthy agents follow a typical gossip-based distributed projected gradient (DPG) algorithm:

$$\begin{aligned} \boldsymbol{x}_i(t+1) &= P_X\left(\bar{\boldsymbol{x}}_i(t) - \gamma(t)\nabla f_i\left(\bar{\boldsymbol{x}}_i(t)\right)\right) . \\ \bar{\boldsymbol{x}}_i(t) &= \textstyle\sum_{j=1}^{n} A_{ij}(t)\boldsymbol{x}_j(t) . \end{aligned} \tag{2}$$

  for $t \geq 1$, where $\gamma(t) > 0$ is a diminishing step size. P_X denotes the Euclidean projection onto the set X and $\nabla f_i\left(\bar{\boldsymbol{x}}_i(t)\right)$ is a gradient of the agent i private function $f_i(\boldsymbol{x})$ at $\bar{\boldsymbol{x}}_i(t)$. For convex problems, it was shown in [WWS$^+$18, RNV10] that the DPG method converges to an optimal solution of (1):

Fact 1

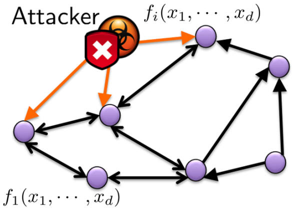
Under Assumption 1. If $\|\nabla f_i(\boldsymbol{x})\| \leq C_1$ for some C_1 and for all $\boldsymbol{x} \in X$, and the step size satisfies $\sum_{t=1}^{\infty} \gamma(t) = \infty$, $\sum_{t=1}^{\infty} \gamma^2(t) < \infty$, then for all $i, j \in \mathcal{V}$ we have

$$\lim_{t\to\infty} f(\boldsymbol{x}_i(t)) = f^\star \quad \text{and} \quad \lim_{t\to\infty} \|\boldsymbol{x}_i(t) - \boldsymbol{x}_j(t)\| = 0 . \tag{3}$$

Without attacker, each node will converge and consensus to the global optimum.

Data Injection Attack from Insiders

- Let $\mathcal{V} = \mathcal{V}_t \cup \mathcal{V}_m, \; n = |\mathcal{V}_t| + |\mathcal{V}_m|$.
- **Coordinated Attack**:
  Disguised consensus injection:
  $$\boldsymbol{x}_j(t) = \underbrace{\boldsymbol{\alpha}}_{\text{attack target value}} + \underbrace{\boldsymbol{r}_j(t)}_{\text{noise to disguise}} \qquad \forall\, j \in \mathcal{V}_m,$$
  where $\lim_{t\to\infty} \|\boldsymbol{z}_j(t)\| \to 0$.



- (Assumption 2). There exists $B_1, B_2 < \infty$ such that for all $t \geq 1$, (a) the composite sub-graph $(\mathcal{V}_t, \cup_{\ell=t+1}^{t+B_1} \mathcal{E}(\mathcal{V}_t; \ell))$ is connected;(b) there exists a pair $i \in \mathcal{V}_t$, $j \in \mathcal{V}_m$ with $(i,j) \in \mathcal{E}(t) \cup \ldots \cup \mathcal{E}(t + B_2 - 1)$.

Fact 2

Under Assumptions 1 and 2. If $\|\nabla f_i(\boldsymbol{x})\| \leq C_2$ for some C_2 and for all $\boldsymbol{x} \in X$, and $\gamma(t) \to 0$, we have:
$$\lim_{t\to\infty} \max_{i\in\mathcal{V}_t} \|\boldsymbol{x}_i(t) - \boldsymbol{\alpha}\| = 0 \,. \tag{4}$$

Attacks succeed: agents will converge and consensus to attackers' desirable value.

Attacker Detection and Localization

We define $\mathcal{H}_0 : \mathcal{V}_m = \emptyset$ and $\mathcal{H}_1 : \mathcal{V}_m \neq \emptyset$ as two scenarios in the network, namely 'no-attacker' and 'attacker is present'. As for the DPG algorithm, we define the following events to execute these two neighborhood tasks:

$$\mathcal{H}_0^i : \mathcal{N}_i \cap \mathcal{V}_m = \emptyset; \quad \mathcal{H}_1^i : \mathcal{N}_i \cap \mathcal{V}_m \neq \emptyset. \tag{5}$$

$$\mathcal{H}_0^{ij} : j \notin \mathcal{V}_m; \quad \mathcal{H}_1^{ij} : j \in \mathcal{V}_m. \tag{6}$$

$\mathcal{H}_0^i$ and $\mathcal{H}_1^i$ as two events of the trustworthy agent i for the neighborhood detection task, i.e., events $\mathcal{H}_0^{ij}$and $\mathcal{H}_1^{ij}$ for neighborhood localization task.

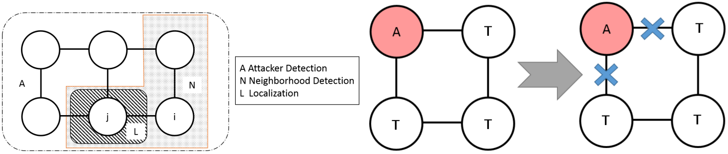


Figure: (Left) Different tasks involved in the attack detection scheme. (Right) Each "trustworthy" agent T performs detection and localization independently, therefore isolating an attacker A from the network.

Neighborhood detection with spatial data

- $\mathcal{H}_0^i$ –there is no attacker in $\mathcal{N}_i$, i.e., $\mathcal{V}_m \cap \mathcal{N}_i = \emptyset$;
- $\mathcal{H}_1^i$ –there exists an attacker in $\mathcal{N}_i$, i.e., $\mathcal{V}_m \cap \mathcal{N}_i \neq \emptyset$.

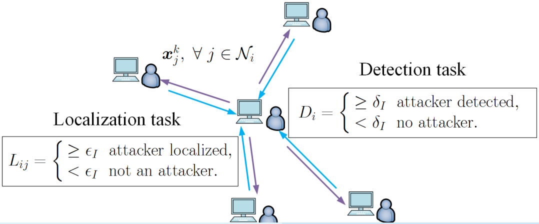
After running the DPG for K different instances, the detection task corresponds to —

Neighborhood Detection Task:

$$\varphi_{ij}^k := \sum_{t=0}^{T} \left(\boldsymbol{x}_j^k(t) - \overline{\boldsymbol{x}}_i^k(t) \right), \tag{7}$$

$$D_i := \frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} \left(\frac{1}{K} \sum_{k=1}^{K} \frac{\mathbf{1}^\top \varphi_{ij}^k}{d} \right)^2 \underset{\mathcal{H}_1^i}{\overset{\mathcal{H}_0^i}{\lessgtr}} \delta_I. \tag{8}$$

where $\overline{\boldsymbol{x}}_i^k(t) = (1/|\mathcal{N}_i|) \sum_{j \in \mathcal{N}_i} \boldsymbol{x}_j^k(t)$. δ_I is a pre-designed threshold, and d is the state dimension of agents.



Neighborhood localization with spatial data

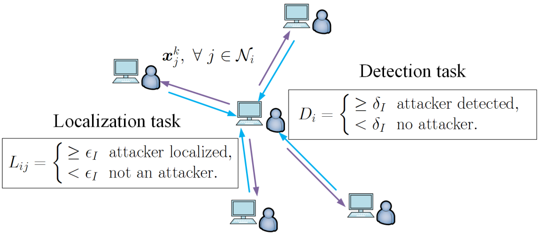
- $\mathcal{H}_0^{ij}$ –agent j is not an attacker, i.e., $j \notin \mathcal{V}_m$;
- $\mathcal{H}_1^{ij}$ –agent j is an attacker, i.e., $j \in \mathcal{V}_m$.

For the localization task, we compare the state of agent j and agent i to check if the neighbor agent is an attacker. We propose checking the metric for localization:

Neighborhood Localization Task:

$$\tilde{\boldsymbol{\varphi}}_{ij}^k := \sum_{t=0}^{T} \left(\boldsymbol{x}_j^k(t) - \boldsymbol{x}_i^k(t) \right) - \boldsymbol{\varphi}_{ii}^k, \tag{9}$$

$$L_{ij} := \left(\frac{1}{K} \sum_{k=1}^{K} \frac{\mathbf{1}^\top \tilde{\boldsymbol{\varphi}}_{ij}^k}{d} \right)^2 \underset{\mathcal{H}_1^{ij}}{\overset{\mathcal{H}_0^{ij}}{\lessgtr}} \epsilon_I. \tag{10}$$



Tackle this Problem using Convolutional Neural Networks

- D_i and L_{ij} are roughly linear functions which fuse the state vector obtained by node i into a scalar score for classification.
- We propose to apply a CNN system to fuse $\{\boldsymbol{x}_i\}_{j \in \mathcal{N}_i}$ for the detection and localization task.
- We consider the detection and localization process as a classification problem.
- The CNN can be trained in an offline manner by using data collected from the neighbors of a trustworthy agent i. We train the CNN in an offline manner and the same CNN can be deployed on each trustworthy agent.

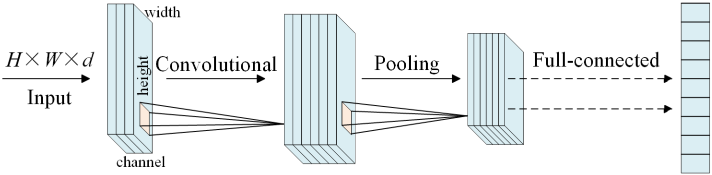


Figure: The structure of CNN.

Detection and localization via CNN

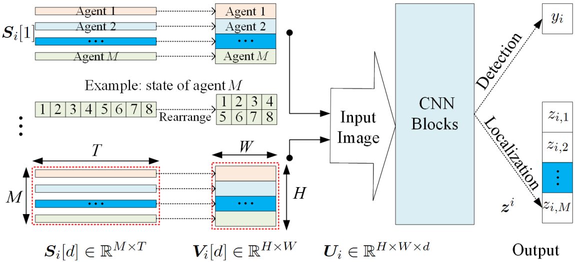
For ease of exposition, we assume $K = 1$ and all the agents have M neighbors. Let T be the number of iterations that the DPG algorithm runs before convergence.

- $\widetilde{x}_i^\ell(t) \in \mathbb{R}$ for $t = 1, \dots, T$ and $\ell = 1, \dots, d$ be the ℓth dimension state vector of agent i at the tth iteration.
- By putting $\{\widetilde{x}_i^\ell(t)\}_{t,\ell}$ together, we get a state matrix $\widetilde{\boldsymbol{X}}_i \in \mathbb{R}^{T\times d}$ of the ith agent,
$$\widetilde{\boldsymbol{X}}_i = \begin{bmatrix} \widetilde{x}_i^1(1), & \dots, & \widetilde{x}_i^d(1) \\ \vdots & \vdots & \vdots \\ \widetilde{x}_i^1(T), & \dots, & \widetilde{x}_i^d(T) \end{bmatrix} \in \mathbb{R}^{T\times d}.$$
Denote $\widetilde{\boldsymbol{x}}_i[\ell] \in \mathbb{R}^{T\times 1}, \ell = 1, \dots, d$ as the ℓth column vector of $\widetilde{\boldsymbol{X}}_i$.
- We then construct the neighborhood state matrix associated with the ℓth dimension of the ith agent,
$$\boldsymbol{S}_i[\ell] = \left[\widetilde{\boldsymbol{x}}_{i(1)}[\ell], \dots, \widetilde{\boldsymbol{x}}_{i(M)}[\ell]\right]^T \in \mathbb{R}^{M\times T}$$
- Next we reshape $\boldsymbol{S}_i[\ell]$ into an image $\boldsymbol{V}_i[\ell] \in \mathbb{R}^{H\times W}$ with height H and width W. We virtually obtain an image with d channels, i.e.,
$$\boldsymbol{U}_i = \{\boldsymbol{V}_i[1], \dots, \boldsymbol{V}_i[d]\} \in \mathbb{R}^{H\times W\times d}, \ i = 1, \dots, n.$$

Detection and localization via CNN

We employ CNNs to detect and localize the malicious agents, as illustrated in the following figure.

- The detection is made according to the following rule in (CNND), wherein $y_i \in \mathbb{R}$.
- The localization is done by using the following rule in (CNNL). We define $\boldsymbol{z}_i = [z_{i,1}, \cdots, z_{i,M}] \in \mathbb{R}^M$ as the output of CNN for localization.
- $\delta_{II} \in [0, 1]$ and $\epsilon_{II} \in [0, 1]$ are some prescribed threshold.



$$\text{(CNND)} \quad y_i \underset{\mathcal{H}_0^i}{\overset{\mathcal{H}_1^i}{\gtrless}} \delta_{II}; \qquad \text{(CNNL)} \quad z_{i,j} \underset{\mathcal{H}_0^{ij}}{\overset{\mathcal{H}_1^{ij}}{\gtrless}} \epsilon_{II}$$

Simulation Settings

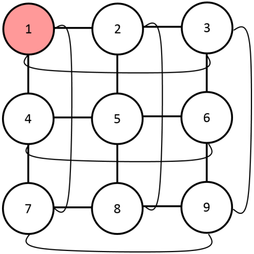


Figure: The Manhattan network topology is considered. We select only node 1 as an attacker, while all other nodes are trustworthy agents.

We take an example of the least square problem; i.e.,

$$f^k(\boldsymbol{x}) = \sum_{i=1}^n f_i^k(\boldsymbol{x}) = \sum_{i=1}^n \left|(\boldsymbol{a}_i^k)^\top \boldsymbol{x}^k - b_i^k\right|^2, k = 1, ..., K.$$

Herein, f_i^k can be seen as a utility function for instance k, $b_i^k = (\boldsymbol{a}_i^k)^T (\boldsymbol{x}^\star)^k$.

Simulation Settings

- We set $\mathbb{E}\left[\boldsymbol{A}(t)\right] = \boldsymbol{I} - \frac{1}{2n}\boldsymbol{\Sigma} + \frac{\boldsymbol{P}+\boldsymbol{P}^\top}{2n}$ with $[\boldsymbol{\Sigma}]_{ii} = \boldsymbol{\Sigma}_{j=1}^{n}(P_{ij} + P_{ji})$, where $\boldsymbol{\Sigma}$ is a diagonal matrix, $P_{ij} = \frac{1}{|\mathcal{N}_i|}$ is the probability between agents i and j at time t.
- A trustworthy agent $i \in \mathcal{V}_t$ is initial by $\boldsymbol{x}_i^k$, $\boldsymbol{x}^k(0) \sim \mathcal{U}[0,1]^d$.
- An attacker agent $j \in \mathcal{V}_m$ follow a update rule (4). We set $\boldsymbol{\alpha}^k \sim \mathcal{U}[-0.5, 0.5]^d$ and $\boldsymbol{r}_j^k(t) \sim \mathcal{U}[-\hat{\lambda}^t, \hat{\lambda}^t]$, where λ is the second largest eigenvalue of $\mathbb{E}[\boldsymbol{A}(t)]$.
- $b_i^k = (\boldsymbol{a}_i^k)^T(\boldsymbol{x}^\star)^k$, where $\boldsymbol{a}_i^k \sim \mathcal{U}[0.5, 2.5]^d$, $(\boldsymbol{x}^\star)^k \sim \mathcal{U}[0,1]^d$.
- $k \in [K] = \{1, 2, \cdots, K\}$, $dim \in [d] = \{1, 2, \cdots, d\}$.
  Among them, K is the numbers of instances and we take $d = 3$; *dim* means that among total d dimensions, how many of which is observed to calculate the metric.

ROC Curves for SD and CNN

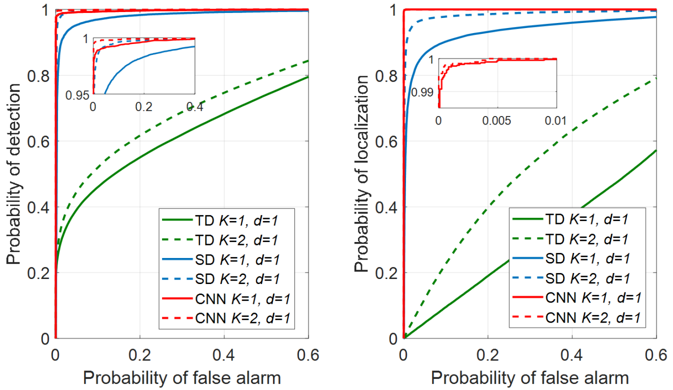


Figure: ROCs performance of TD, SD and CNN methods with $d = 1$.Left: Detection performance at the neighboring nodes of the attacker; Right: Localization performance at the neighboring nodes of the attacker.

Note: This result implies that transient states do provide us more information to identify the malicious agent.

ROC Curves for SD and CNN

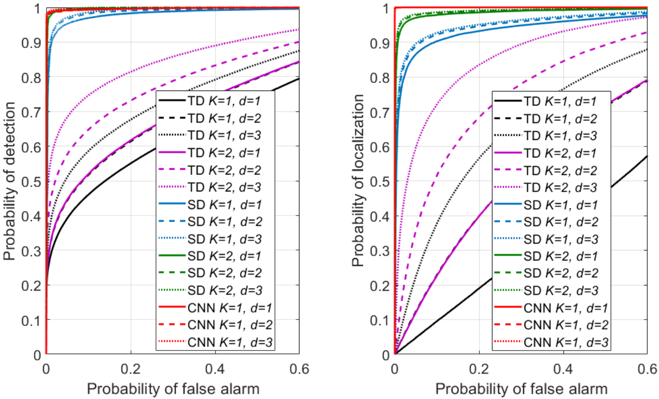


Figure: ROCs of CNN and SD in different dimensions: where d is the state dimension of neighbor agents. Left: Detection performance at the neighboring nodes of the attacker; Right: Localization performance at the neighboring nodes of the attacker.

Note: Increasing K and *dim* can improve the performance.

Summary

- In this work, we proposed two defense strategies for the gossip-based DPG optimization algorithm.
- The first one is a score-based method employing the transient state information from the agents. It can outperform our previous score-based method which only considers initial state and steady state information.
- We further adopt the CNN to secure the DPG algorithm. CNN can automatically learn effective features from original state information without complex calculations.
- We numerically verify the efficiency of the detector for the optimization algorithm based on the least square functions.

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Thank You

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Question Welcomed!