



EP3260: Machine Learning Over Networks

Lecture 5: Distributed ML

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February 2019

Learning outcomes

- Recap of centralized solution approaches (convex & nonconvex)
- Distributed optimizations in primal domains
- Dual ascent and dual decomposition
- Distributed optimizations in the dual domains
- Topology-dependent convergence rate

Outline

1. Motivating examples
2. Master-worker architecture (single hop networks)
3. Multihop networks

Recap of convex and nonconvex solvers

Our main optimization problem: minimize $\frac{1}{N} \sum_{i \in [N]} f_i(\mathbf{w})$

Convex setting

- Existence of global optimality and efficient solvers

- GD and SGD family for smooth problems

- Subgradient and proximal methods for non-smooth functions

Nonconvex setting

- Importance of structure

- GD, SGD, and perturbed GD for smooth problems

- Successive convex approximation, coordinate descent, and BSUM

- Finding 1oN and 2oN points in non-convex setting

Outline

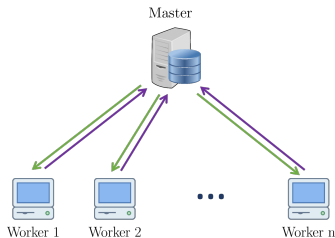
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Motivating examples

- Private dataset \mathcal{D}_i at worker i (or private function f_i)

$$f_i(\mathbf{w}) = \frac{1}{|\mathcal{D}_i|} \sum_{(x,y) \in \mathcal{D}_i} (y - \mathbf{w}^T \mathbf{x})^2$$

$$\text{GD: } \mathbf{w}_{k+1} = \mathbf{w}_k - \frac{\alpha_k}{N} \sum_{i \in [N]} \nabla f_i(\mathbf{w}_k)$$



Algorithm 1: Decentralized gradient descent

Initialize \mathbf{w}_1

for $k = 1, 2, \dots$, **do**

 Master node broadcasts \mathbf{w}_k

 All workers compute in parallel their gradient $\{\nabla f_i(\mathbf{w}_k)\}$

 Master node collects $\{\nabla f_i(\mathbf{w}_k)\}_i$ and computes \mathbf{w}_{k+1}

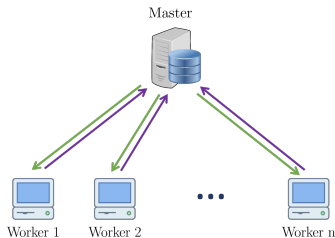
end for

Motivating examples

- Private dataset \mathcal{D}_i at worker i (or private function f_i)

$$f_i(\mathbf{w}) = \frac{1}{|\mathcal{D}_i|} \sum_{(x,y) \in \mathcal{D}_i} (y - \mathbf{w}^T \mathbf{x})^2$$

$$\text{GD: } \mathbf{w}_{k+1} = \mathbf{w}_k - \frac{\alpha_k}{N} \sum_{i \in [N]} \nabla f_i(\mathbf{w}_k)$$



Algorithm 1: Decentralized gradient descent

Initialize \mathbf{w}_1

for $k = 1, 2, \dots$, **do**

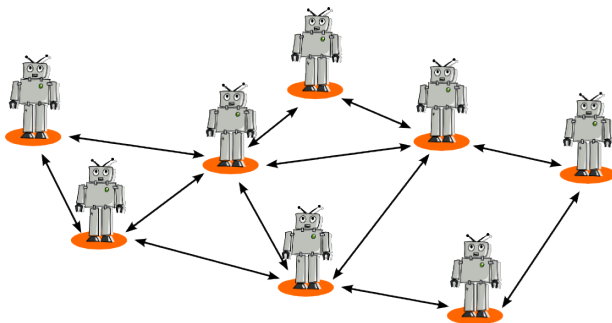
 Master node broadcasts \mathbf{w}_k

 All workers compute in parallel their gradient $\{\nabla f_i(\mathbf{w}_k)\}$

 Master node collects $\{\nabla f_i(\mathbf{w}_k)\}_i$ and computes \mathbf{w}_{k+1}

end for

A more complicated scenario



Lack of a master node to collect global information, e.g., $\{\nabla f_i\}_{i \in [N]}$

How to converge to w^* using only local information exchange (among neighbors)

Warm-up

- **No coupling variables**

$$\underset{\mathbf{w}_1, \mathbf{w}_2}{\text{minimize}} \quad f_1(\mathbf{w}_1) + f_2(\mathbf{w}_2)$$

Well, we can use Algorithm 1

But why not solving in parallel $\underset{\mathbf{w}_1}{\text{minimize}} f_1(\mathbf{w}_1)$ and $\underset{\mathbf{w}_2}{\text{minimize}} f_2(\mathbf{w}_2)$

- **Coupling variables**

$$\underset{\mathbf{w}_1, \mathbf{w}_2, \mathbf{v}}{\text{minimize}} \quad f_1(\mathbf{w}_1, \mathbf{v}) + f_2(\mathbf{w}_2, \mathbf{v})$$

Primal space: Combine ideas from coordinate descent and Algorithm 1

Dual space: replace a local version of coupling variable and add a consensus constraint

See the board!

Warm-up

Algorithm 2: Primal decomposition

Initialize \mathbf{v}_1

for $k = 1, 2, \dots$, **do**

Master node broadcasts \mathbf{v}_k

Solve in parallel

$$\mathbf{w}_{1,k+1} \in \arg \min_{\mathbf{w}_1} f_1(\mathbf{w}_1, \mathbf{v}_k)$$

$$\mathbf{w}_{2,k+1} \in \arg \min_{\mathbf{w}_2} f_2(\mathbf{w}_2, \mathbf{v}_k)$$

Find subgradient $\mathbf{g}_i(\mathbf{v}_k)$ of $\min_{\mathbf{w}_i} f_i(\mathbf{w}_i, \mathbf{v}_k)$ for $i \in \{1, 2\}$

Master node collects $\{\mathbf{g}_i(\mathbf{v}_k)\}_i$ and computes

$$\mathbf{v}_{k+1} = \mathbf{v}_k - \alpha_k (\mathbf{g}_1(\mathbf{v}_k) + \mathbf{g}_2(\mathbf{v}_k))$$

end for

Feasible primal variables (in the case of convex constraint)

Warm-up

Algorithm 3: Dual decomposition

for $k = 1, 2, \dots$, **do**

Master node broadcasts λ_k

Solve in parallel dual subproblems

$$(\mathbf{w}_{1,k+1}, \mathbf{v}_{1,k+1}) \in \operatorname{arginf}_{\mathbf{w}_1, \mathbf{v}_1} f_1(\mathbf{w}_1, \mathbf{v}_1) + \lambda_k^T \mathbf{v}_1$$

$$(\mathbf{w}_{2,k+1}, \mathbf{v}_{2,k+1}) \in \operatorname{arginf}_{\mathbf{w}_2, \mathbf{v}_2} f_2(\mathbf{w}_2, \mathbf{v}_2) - \lambda_k^T \mathbf{v}_2$$

Master node collects $\mathbf{v}_{1,k+1}$ and $\mathbf{v}_{2,k+1}$ and computes

$$\lambda_{k+1} = \lambda_k - \alpha_k (\mathbf{v}_{2,k+1} - \mathbf{v}_{1,k+1})$$

end for

Usually infeasible iterates, i.e., $\mathbf{v}_1 \neq \mathbf{v}_2$

Projection onto feasible set by letting $\bar{\mathbf{v}}_k = (\mathbf{v}_{1,k} + \mathbf{v}_{2,k})/2$

$\mathbf{v}_{1,k+1} - \mathbf{v}_{2,k+1}$ is a subgradient of dual objective

Master node determines prices λ

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Lagrange dual problem and dual ascent

Consider

$$\begin{aligned} &\text{minimize} && f(\mathbf{w}) \\ &\text{s.t.} && \mathbf{A}\mathbf{w} = \mathbf{b} \end{aligned}$$

Lagrange dual function: $g(\boldsymbol{\lambda}) = \inf_{\mathbf{w}} L(\mathbf{w}, \boldsymbol{\lambda}) := f(\mathbf{w}) + \boldsymbol{\lambda}^T (\mathbf{A}\mathbf{w} - \mathbf{b})$

Lagrange dual problem: $\text{maximize}_{\boldsymbol{\lambda}} g(\boldsymbol{\lambda}) = -f^*(-\mathbf{A}^T \boldsymbol{\lambda}) - \boldsymbol{\lambda}^T \mathbf{b}$

HW3(a): Show that for convex and closed f : $\mathbf{A}\mathbf{w} - \mathbf{b} \in \partial g(\boldsymbol{\lambda})$ where ∂ is the set of subgradients

Dual ascent algorithm (gradient ascent for the Lagrange dual problem)

step 1 (primal variable update): $\mathbf{w}_{k+1} \in \arg \min_{\mathbf{w}} L(\mathbf{w}, \boldsymbol{\lambda}_k)$

step 2 (dual variable update): $\boldsymbol{\lambda}_{k+1} = \boldsymbol{\lambda}_k + \alpha_k (\mathbf{A}\mathbf{w}_k - \mathbf{b})$

HW3(b): Analyze the convergence of dual ascent for L -smooth and μ -strongly convex f . Is the solution primal feasible?

Dual decomposition with equality constraints

Consider

$$\begin{aligned} & \text{minimize} && f(\mathbf{w}) = \sum_{i \in [N]} f_i(\mathbf{w}_i) \\ & \text{s.t.} && \sum_{i \in [N]} \mathbf{A}_i \mathbf{w}_i = \mathbf{b} \end{aligned}$$

$$L(\mathbf{w}, \boldsymbol{\lambda}) = \sum_{i \in [N]} L_i(\mathbf{w}_i, \boldsymbol{\lambda}) = \sum_{i \in [N]} f_i(\mathbf{w}_i) + \boldsymbol{\lambda}^T \mathbf{A}_i \mathbf{w}_i - \frac{1}{N} \boldsymbol{\lambda}^T \mathbf{b}$$

Lagrangian is separable in $\mathbf{w} \Rightarrow$ parallel processing in step 1

Master node gathers residual contributions $\mathbf{A}_i \mathbf{w}_{i,k}$ to run step 2

Very useful for large-scale optimization problems, but often **slow**

Dual decomposition

step 1 (primal update): $\mathbf{w}_{i,k+1} \in \arg \min_{\mathbf{w}_i} L_i(\mathbf{w}_i, \boldsymbol{\lambda}_k), \quad i = 1, \dots, N$

step 2 (dual update): $\boldsymbol{\lambda}_{k+1} = \boldsymbol{\lambda}_k + \alpha_k \left(\sum_{i \in [N]} \mathbf{A}_i \mathbf{w}_{i,k+1} - \mathbf{b} \right)$

Dual decomposition with inequality constraints

Consider

$$\begin{aligned} & \text{minimize} && f(\mathbf{w}) = \sum_{i \in [N]} f_i(\mathbf{w}_i) \\ & \text{s.t.} && \sum_{i \in [N]} \mathbf{A}_i \mathbf{w}_i \leq \mathbf{b} \end{aligned}$$

Same as before expect projection of $\boldsymbol{\lambda}$ onto positive orthant ($\boldsymbol{\lambda} \geq 0$)

Price interpretation of $\boldsymbol{\lambda}_{k+1}$

increase the price if resources are over-utilized ($\sum_{i \in [N]} \mathbf{A}_i \mathbf{w}_{i,k} - \mathbf{b} > 0$)

decrease the price if resources are under-utilized ($\sum_{i \in [N]} \mathbf{A}_i \mathbf{w}_{i,k} - \mathbf{b} \leq 0$)

Compatible only with star communication topology (master-worker)

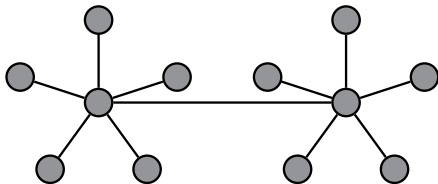
step 1 (primal update): $\mathbf{w}_{i,k+1} \in \arg \min_{\mathbf{w}_i} L_i(\mathbf{w}_i, \boldsymbol{\lambda}_k)$, $i = 1, \dots, N$

step 2 (dual update): $\boldsymbol{\lambda}_{k+1} = \left[\boldsymbol{\lambda}_k + \alpha_k \left(\sum_{i \in [N]} \mathbf{A}_i \mathbf{w}_{i,k} - \mathbf{b} \right) \right]_+$

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Some definitions



(Row)-stochastic matrix $\mathbf{A} \in \mathbb{R}^{d \times d}$: $a_{ij} \geq 0, \forall i, j$ and $\mathbf{A}\mathbf{1} = \mathbf{1}$

Doubly stochastic matrix \mathbf{A} : $a_{ij} \geq 0, \forall i, j$, $\mathbf{A}\mathbf{1} = \mathbf{1}$ and $\mathbf{A}^T\mathbf{1} = \mathbf{1}$

Doubly stochastic matrix \mathbf{A} defines an undirected graph $\mathcal{G}_{\mathbf{A}}(\mathcal{E}, \mathcal{V})$ with vertex set \mathcal{V} and edge set \mathcal{E}

$(i, j) \in \mathcal{E}$ iff $(j, i) \in \mathcal{E}$ and $a_{ij} \geq \eta$ for some small positive η

Set of neighbors of vertex i : $\mathcal{N}_i = \{j \in \mathcal{V} \mid (i, j) \in \mathcal{E}\} \cup \{i\}$

Degree of a vertex $d_i = |\mathcal{N}_i|$

Distributed learning setup

Consider minimize $\frac{1}{N} \sum_{i \in [N]} f_i(\mathbf{w})$

Consensus constraint reformulation

$$\begin{aligned} \text{(P1) : minimize } & \frac{1}{N} \sum_{i \in [N]} f_i(\mathbf{w}_i) \\ \text{s.t. } & \mathbf{w}_i = \mathbf{w}_j, \quad \text{for all } j \in [N] \end{aligned}$$

Now we can run dual decomposition to parallelize computations in (P1)

What if we are restricted to a communication graph \mathcal{G} ?

What about

$$\begin{aligned} \text{(P2) : minimize } & \frac{1}{N} \sum_{i \in [N]} f_i(\mathbf{w}_i) \\ \text{s.t. } & \mathbf{w}_i = \mathbf{w}_j, \quad \text{for all } j \in \mathcal{N}_i \end{aligned}$$

For connected \mathcal{G} , (P1) and (P2) are equivalent

Average consensus problem

$$\begin{aligned} &\text{minimize } 0 \\ &\text{s.t. } \mathbf{w}_i = \mathbf{w}_j, \quad \text{for all } j \in \mathcal{N}_i \end{aligned}$$

Write equivalently as

$$\begin{aligned} &\text{minimize } 0 \\ &\text{s.t. } a_{ij}(\mathbf{w}_i - \mathbf{w}_j) = 0, \quad \text{for all } j \in \mathcal{N}_i \end{aligned}$$

for some doubly stochastic matrix $\mathbf{A} = [a_{ij}]$ compatible with \mathcal{G}

Iterations $\mathbf{w}_{k+1} = \mathbf{A}\mathbf{w}_k$ yield

$$\left\| \mathbf{w}_k - \frac{\sum_{i=1}^N \mathbf{w}_{i,0}}{N} \mathbf{1} \right\|_2 \leq (\sigma_2(\mathbf{A}))^k \left\| \mathbf{w}_0 - \frac{\sum_{i=1}^N \mathbf{w}_{i,0}}{N} \mathbf{1} \right\|_2$$

Linear convergence when $\sigma_2(\mathbf{A}) < 1$

Average consensus problem

minimize 0

s.t. $a_{ij}(\mathbf{w}_i - \mathbf{w}_j) = 0$, for all $j \in \mathcal{N}_i$

Special case of $\mathbf{w}_{k+1} = \mathbf{A}\mathbf{w}_k$: $\mathbf{w}_{i,k+1} = \frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} \mathbf{w}_{j,k} = \frac{1}{d_i} \sum_{j \in \mathcal{N}_i} \mathbf{w}_{j,k}$

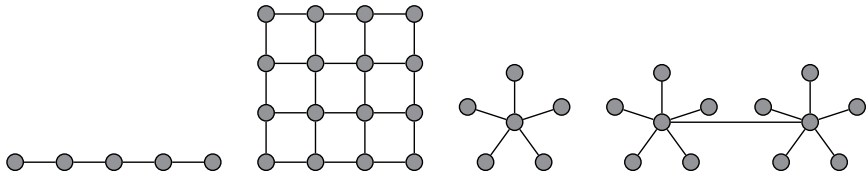
Gossip algorithm: at every iteration pick a random subset of neighbors $\mathcal{S} = \{j \mid j \in \mathcal{N}_i\}$ and update $\mathbf{w}_{i,k+1} = \frac{1}{|\mathcal{S}|} \sum_{j \in \mathcal{S}} \mathbf{w}_{j,k}$

linear convergence (in expectation under some technical conditions)

Lazy Metropolis iteration: $\mathbf{w}_{i,k+1} = \mathbf{w}_{i,k} + \sum_{j \in \mathcal{N}_i} \frac{1}{2 \max(d_i, d_j)} (\mathbf{w}_{j,k} - \mathbf{w}_{i,k})$

linear convergence (under some technical conditions)

Average consensus problem



- Topology-dependent convergence rate

path graph: $\mathcal{O}(N^2 \log \epsilon^{-1})$

2D grid: $\mathcal{O}(N \log N \log \epsilon^{-1})$

star graph: $\mathcal{O}(N^2 \log \epsilon^{-1})$, two-star graph: $\mathcal{O}(N^2 \log \epsilon^{-1})$

geometric random graph: $\mathcal{O}(N \log N \log \epsilon^{-1})$

any connected undirected graph: $\mathcal{O}(N^2 \log \epsilon^{-1})$

complete graph: $\mathcal{O}(1)$

Distributed learning over undirected graph

$$\begin{aligned} \text{(P2)} : \text{ minimize } & \frac{1}{N} \sum_{i \in [N]} f_i(\mathbf{w}_i) \\ \text{s.t. } & \mathbf{w}_i = \mathbf{w}_j, \quad \text{for all } j \in \mathcal{N}_i \end{aligned}$$

Decentralized subgradient method (primal method), v1:

step 1 (consensus): $\bar{\mathbf{w}}_{i,k} = \sum_{j \in \mathcal{N}_i} a_{ij} \mathbf{w}_{j,k}$

step 2 (subgradient descent): $\mathbf{w}_{i,k+1} = \bar{\mathbf{w}}_{i,k} - \alpha_k \mathbf{g}_i(\bar{\mathbf{w}}_{i,k})$

Push toward consensus (blue) vs push toward the minimizer (red)

For static graphs, time-invariant push in blue vs time-dependent push in red

Similar diffusion (mixing) time as of average consensus

Distributed learning over undirected graph

$$\begin{aligned} \text{(P2)} : \text{ minimize } & \frac{1}{N} \sum_{i \in [N]} f_i(\mathbf{w}_i) \\ \text{s.t. } & \mathbf{w}_i = \mathbf{w}_j, \quad \text{for all } j \in \mathcal{N}_i \end{aligned}$$

Decentralized subgradient method (primal method), v2:

$$\begin{aligned} \mathbf{w}_{i,k+1} &= a_{ii}\mathbf{w}_{i,k} - \alpha_k \mathbf{g}_i(\mathbf{w}_{i,k}) + \sum_{j \in \mathcal{N}_i \setminus \{i\}} a_{ij} \mathbf{w}_{j,k} \\ &= \sum_{j \in \mathcal{N}_i} a_{ij} \mathbf{w}_{j,k} - \alpha_k \mathbf{g}_i(\mathbf{w}_{i,k}) \end{aligned}$$

Push toward consensus (blue) vs push toward the minimizer (red)

For static graphs, time-invariant push in blue vs time-dependent push in red

Similar diffusion (mixing) time as of average consensus

Distributed learning over undirected graph

$$\begin{aligned} \text{(P2)} : \quad & \text{minimize} \quad \frac{1}{N} \sum_{i \in [N]} f_i(\mathbf{w}_i) \\ & \text{s.t.} \quad \mathbf{w}_i = \mathbf{w}_j, \quad \text{for all } j \in \mathcal{N}_i \end{aligned}$$

Decentralized dual decomposition (dual method):

HW3(c): extend the dual decomposition of Slide 5-12 to solve (P2).

Compare it to the primal method (analytically or numerically) in terms of total communication cost and convergence rate on a random geometric communication graph.

Further discussions

- Another dual approach: alternating direction method of multipliers (ADMM),
better convergence using augmented Lagrangian (adding $\rho\|\mathbf{Aw} - \mathbf{b}\|^2$)
dual decomposition + augmented Lagrangian + coordinate descent
ADMM over networks
- Directed communication graph
- Latency in communication links
- Faulty communication links
- Nonconvex optimization over network

CA4: Sensitivity to outliers

Split “MNIST” dataset to 10 random disjoint subsets, each for one worker, and consider SVM classifier in the form of $\min_{\mathbf{w}} \frac{1}{N} \sum_{i \in [N]} f_i(\mathbf{w})$ with $N = 10$. Consider the following outlier model: each worker i at every iteration independently and randomly with probability p adds a zero-mean Gaussian noise with a large variance R to the information it shares, i.e., ∇f_i and $\mathbf{w}_{j,k}$ in the cases of Algorithm 1 and decentralized subgradient method respectively.

- Run decentralized gradient descent (Algorithm 1) with 10 workers.

Characterize the convergence against p and R .

Propose an efficient approach to improve the robustness of Algorithm 1 and characterize its convergence against p and R .

- Consider a two-star topology with communication graph $(1,2,3,4)$ -5-6-(7,8,9,10) and run decentralized subgradient method.

Characterize the convergence against p and R .

Propose an efficient approach to improve the robustness to outliers and characterize its convergence against p and R .

- Assume that we can protect only three workers in the sense that they would always send the true information. Which workers you protect in Algorithm 1 and which in the two-star topology, running decentralized subgradient method?

Some references

- S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," FoT in Machine learning, 2011.
- A. Nedic, A. Olshevsky, and M. G. Rabbat, "Network topology and communication-computation tradeoffs in decentralized optimization," Proceedings of the IEEE, 2018.