ROYAL INSTITUTE
OF TECHNOLOGY

EP3260: Machine Learning Over Networks

Lecture 1: Introduction

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https://sites.google.com/view/mlons2020/home

February 2020

Outline

1. Logistics
2. Course Contents
3. Lectures

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Logistics

- 10 credits advanced Ph.D. course
- 16 lectures:

  Fundamentals (Lectures 1-10), Special Topics (Lectures 11-16)
- Student groups for homework (HW) and computer assignments (CAs)

  2-3 students per group

  Deadline for groups formation: end of Lecture 2
- 3 HW and 6 CAs (for groups)

  HW due in one week, CA due in two weeks

  peer-to-peer review of HW and CAs
- Optional assignments and final research project

Logistics cont.

- Last round of the course:
  `https://sites.google.com/view/mlons2019/home`
- 41 participants (25 outside Sweden)
- Email: hshokri@kth.se, jmbdsj@kth.se, carlofi@kth.se
  (please **use "MLoN-2020:" in the email subject**)
- Course website:
  `https://sites.google.com/view/mlons2020/home`
- YouTube channel: `https://www.youtube.com/channel/UCoFj1tFuK4b_Wh21-KQoU5g?view_as=subscriber`
- GitHub account for HW and CA submissions:
  `https://github.com/hshokrig/EP3260-MLoNs-2020`

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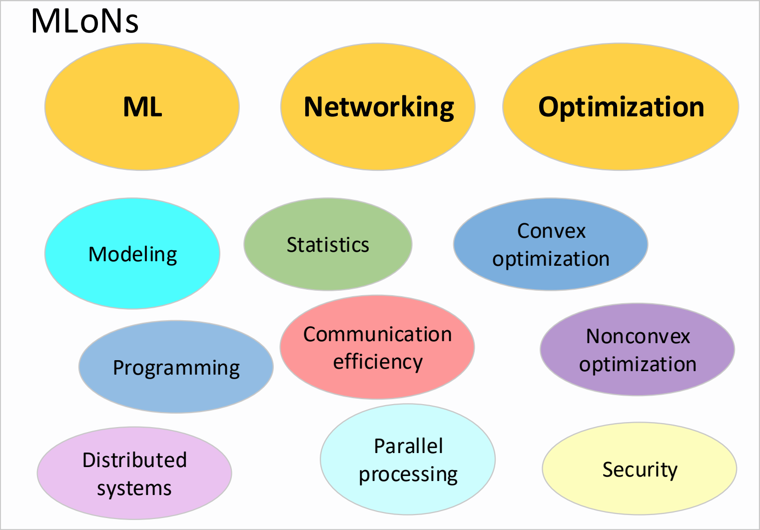
Course contents



Machine learning!

- Unsupervised learning (e.g., k-means)

  learning from unlabeled data: identifies commonalities

- Supervised learning (e.g., deep neural networks)

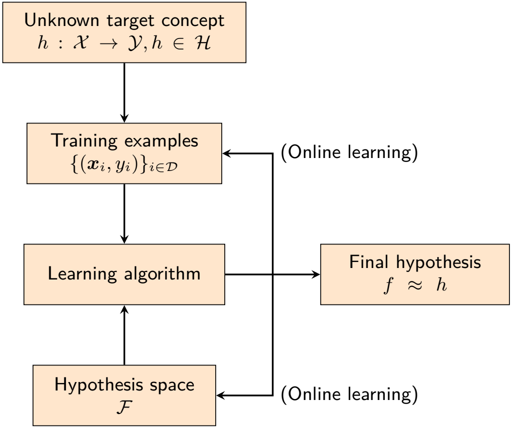
  learning from labeled data: regression and classification

- Reinforcement learning (e.g., Q-learning)

  learning by interacting with an unknown environment (modeled by a Markov decision process)

  sequential decision making, lack of correct dataset a priori, suboptimal actions are allowed in the learning process

Supervised learning



- $\mathcal{F}$ instead of $\mathcal{H}$, e.g., an easier class of mappings like linear regression or neural networks

Supervised learning

- A dataset of N training samples $\mathcal{D} = \{(\boldsymbol{x}_i, y_i = h(\boldsymbol{x}_i))\}_{i=1}^{N}$
- Our prediction: $\hat{y} = f(\boldsymbol{x}), f \in \mathcal{F}$
- Loss on a single observation: $\ell(\boldsymbol{x}, h(\boldsymbol{x}), f(\boldsymbol{x}))$
- **Expected risk (test error):** $L = \mathbb{E}_{(\boldsymbol{x},y)}\left[\ell(\boldsymbol{x}, h(\boldsymbol{x}), f(\boldsymbol{x}))\right]$
- **Empirical risk (training error):** $\hat{L} = \frac{1}{N}\sum_{i\in[N]} \ell(\boldsymbol{x}_i, h(\boldsymbol{x}_i), f(\boldsymbol{x}_i))$

- Assume $\boldsymbol{w}$ parameterizes both h and f, and $\boldsymbol{w}^\star$ is the solution of our algorithm.

$$f(\boldsymbol{w}^\star) - \min_{\boldsymbol{w}\in\mathbb{R}^d} f(\boldsymbol{w}) = \left(f(\boldsymbol{w}^\star) - \min_{\boldsymbol{w}\in\mathcal{W}} f(\boldsymbol{w})\right) + \left(\min_{\boldsymbol{w}\in\mathcal{W}} f(\boldsymbol{w}) - \min_{\boldsymbol{w}\in\mathbb{R}^d} f(\boldsymbol{w})\right)$$

estimation error $+$ approximation error

Some examples

Linear ridge regression:

$$f(\boldsymbol{x};\boldsymbol{w}) = \frac{1}{|\mathcal{D}|}\sum_{i\in\mathcal{D}}\left(y_i - \boldsymbol{w}^T\boldsymbol{x}_i\right)^2 \quad + \quad \lambda\|\boldsymbol{w}\|_2^2$$

data fitting $\quad + \quad$ regularizer

Linear LASSO regression:

$$f(\boldsymbol{x};\boldsymbol{w}) = \frac{1}{|\mathcal{D}|}\sum_{i\in\mathcal{D}}\left(y_i - \boldsymbol{w}^T\boldsymbol{x}_i\right)^2 + \lambda\|\boldsymbol{w}\|_1$$

Support vector machine (binary classification):

$$f(\boldsymbol{x};\boldsymbol{w}) = \frac{1}{|\mathcal{D}|}\sum_{i\in\mathcal{D}}\max\left(0, 1 - y_i\left(\boldsymbol{w}^T\boldsymbol{x}_i - b\right)\right) + \lambda\|\boldsymbol{w}\|_2^2$$

Optimization

- Convexity

convex set: $\mathcal{X} \subseteq \mathbb{R}^d$ is convex if

$$\forall \boldsymbol{x}_1, \boldsymbol{x}_2 \in \mathcal{X}, \theta \in [0,1], \theta \boldsymbol{x}_1 + (1-\theta)\boldsymbol{x}_2 \in \mathcal{X}$$

convex function: $f : \mathcal{X} \to \mathbb{R} \cup \{+\infty\}$ for convex $\mathcal{X}$ is convex if

$$\forall \boldsymbol{x}, \boldsymbol{y} \in \mathbb{R}^d, \lambda \in [0,1], f(\lambda \boldsymbol{x} + (1-\lambda)\boldsymbol{y}) \leq \lambda f(\boldsymbol{x}) + (1-\lambda) f(\boldsymbol{y})$$

convex function: its epigraph $\{(t, \boldsymbol{x}) : f(x) \leq t\}$ is a convex set

strictly convex function: convex f for which $<$ holds

Useful forms of Jensen's inequality: f is convex, $\{x_i\}_i$ are deterministic real numbers, $a_i > 0$, X is random variable (proof?):

$$f\left(\frac{\sum a_i x_i}{\sum a_i}\right) \leq \frac{\sum a_i f(x_i)}{\sum a_i}, \quad f(E[X]) \leq E[f(X)]$$

Optimization

- **Convex optimization**

  f and $\mathcal{W}$ are convex, then: $\underset{\boldsymbol{w}\in\mathcal{W}}{\text{minimize}}\ f(\boldsymbol{w})$

  local optimum $\Rightarrow$ global optimum

  Linear convergence with strongly convex and smooth f

- **Efficient solvers.** Let $f(\boldsymbol{w}) := \frac{1}{N}\sum_{i=1}^{N} f(\boldsymbol{x}_i;\boldsymbol{w})$.

  Gradient descent: $\boldsymbol{w}_{k+1} = \boldsymbol{w}_k - \alpha_k \nabla_w f(\boldsymbol{w}_k)$

  Stochastic gradient descent (SGD): $\boldsymbol{w}_{k+1} = \boldsymbol{w}_k - \alpha_k \nabla_w f(\boldsymbol{x}_\zeta;\boldsymbol{w}_k)$

  SGD with memory, e.g., stochastic average gradient

  Acceleration: $\boldsymbol{v}_{k+1} = \gamma\boldsymbol{v}_k - \alpha_k \nabla_{\boldsymbol{w}} f(\boldsymbol{w}_k), \boldsymbol{w}_k = \boldsymbol{w}_{k-1} - \boldsymbol{v}_k$

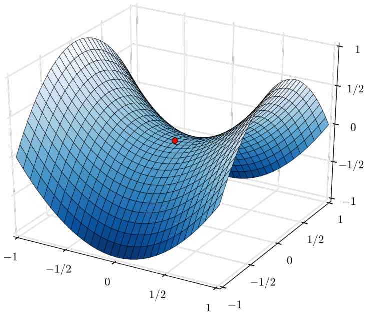
Optimization

- **on-convex optimization**

  local optimum $\nrightarrow$ global optimum

  saddle points: $f(x, y) = y^2 - x^2$

  perturbed gradient descent

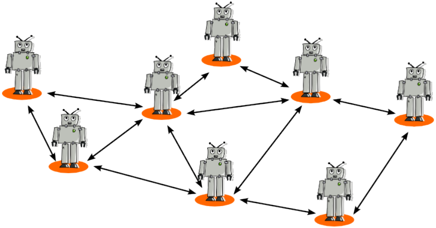


Networked systems

- Graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$

  $\mathcal{V}$: set of vertices

  $\mathcal{E}$: set of edges



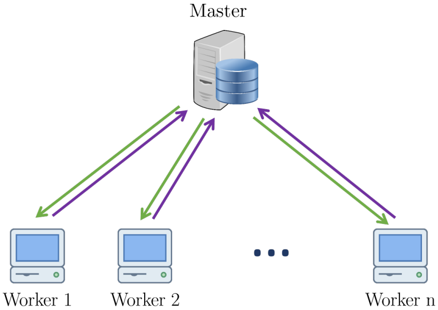
Example	$v_i \in \mathcal{V}$	$e_{ij} \in \mathcal{E}$
Computer networks	worker i	communication link $v_i \to v_j$
Wireless networks	link i	interference from v_i to v_j
Biological networks	sensor i	communication link $v_i \to v_j$

Example 1: Large-scale ML

$$\underset{\boldsymbol{w}\in\mathbb{R}^d}{\text{minimize}} \ \frac{1}{N}\sum_{i=1}^{N} f(\boldsymbol{x}_i;\boldsymbol{w})$$

- Large N
  parallel processing?
  random sampling?

- Large d:
  sparse solutions?
  quantization?



Example 2: Multiagent systems

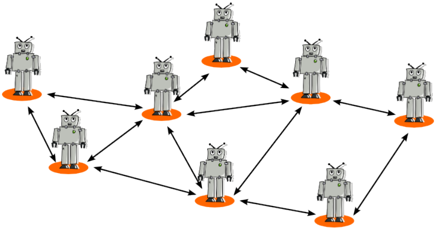
$$\underset{\boldsymbol{w}\in\mathbb{R}^d}{\text{minimize}} \ \frac{1}{N}\sum_{i=1}^{N} f_i(\boldsymbol{w})$$

d combined decision variables

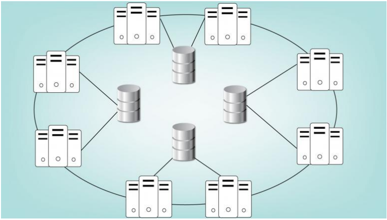
- Local variables: $\boldsymbol{w}_1 \neq \boldsymbol{w}_2$
- Private information: $f_i(\boldsymbol{w}) = \frac{1}{N_i}\sum_{j=1}^{N_i} h(\boldsymbol{w};\boldsymbol{x}_{ij})$
- Consensus form (separable ☺)

$$\underset{\{\boldsymbol{z}_i\}}{\text{minimize}} \ \sum_{i=1}^{N} f_i(\boldsymbol{z}_i)$$

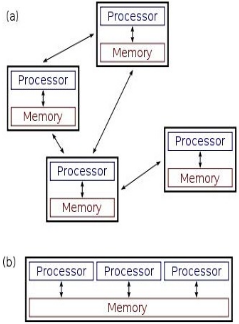
$$\text{s.t.}\, \boldsymbol{z}_i = \boldsymbol{z}_j \in \mathbb{R}^d$$



Example 3: Distributed systems



- Local information
- Privacy constraints
- Security challenges



Example 4: Intra-body sensor networks

- Abstractly, same as before
- Low processing power
- Harsh communication environment
- Higher system dynamics
- Time-sensitive decisions

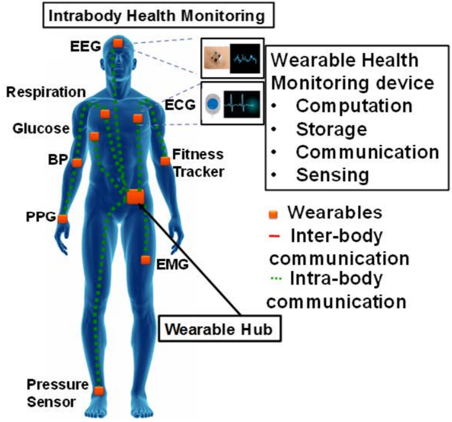


Image source: "Wearable Health Monitoring Using Capacitive Voltage-Mode Human Body Communication," arXiv'17.

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Lectures

- Lecture 1: Introduction, – Today!
- Lecture 2: Centralized Convex ML (deterministic algorithms), Feb. 12, 2020, 10:00-12:00.
- Lecture 3: Centralized Convex ML (stochastic algorithms), Feb. 19, 2020, 10:00-12:00.
- Lecture 4: Computer Assignment Session and Homework (part 1), Feb. 26, 2020, 10:00-12:00.
- Lecture 5: Centralized Nonconvex ML, Mar. 4, 2020, 10:00-12:00.
- Lecture 6: Distributed ML, Mar. 6, 2020, 10:00-12:00.
- Lecture 7: ADMM, Mar. 12, 2020, 10:00-12:00.
- Lecture 8: Communication Efficiency, Mar. 18, 2020, 10:00-12:00.
- Lecture 9: Computer Assignment Session and Homework (part 2), Mar. 25, 2020, 10:00-12:00.
- Lecture 10: Deep Neural Networks, Apr. 1, 2020, 10:00-12:00.
- Lecture 11: Special Topic 1: Large-scale MLoN
- Lecture 12: Special Topic 2: Application areas: Federated learning and privacy-preserving distributed MLoN
- Lecture 13: Special Topic 3: Security in MLoN
- Lecture 14: Special Topic 4: Online MLoNs
- Lecture 15: Special Topic 5: Robust MLoN
- Lecture 16: Application areas and open research problems

Special topics: two-days workshop

- Poster workshop for Lectures 11–16
- Date: April 23 and 24, 2020, 10:00–18:00
- Some invited talks, one 30-min oral presentation per group, integrated into poster sessions
- Panel discussion on recent progresses and the future of machine learning
- Networking!

Some references

- S. Bubeck, "Convex optimization: Algorithms and complexity," Foundations and Trends in Machine Learning, 2015.
- L. Bottou, F. Curtis, and J. Norcedal, "Optimization methods for large-scale machine learning," SIAM Rev., 2018.
- S. Boyd, et al. "Distributed optimization and statistical learning via the alternating direction method of multipliers," Foundations and Trends in Machine Learning, 2011.
- M.I. Jordan, J.D. Lee, and Y. Yang, "Communication-efficient distributed statistical inference," Journal of the American Statistical Association, 2018.
- M. Schmidt, N. Le Roux, and F. Bach, "Minimizing finite sums with the stochastic average gradient," Mathematical Programming, 2017.
- Goodfellow, Y. Bengio, and A. Courville, "Deep Learning," MIT press 2016.
- S. Sra, S. Nowozin, and S.J. Wright (eds), "Optimization for machine learning" Mit Press, 2012.

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