L07
Introduction to Min-max Optimization

50.579 Optimization for Machine Learning

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Recap (GANs)

In Generative Adversarial Networks (GANs) one would like to solve

$$\min_{\theta} \max_{w} \mathbb{E}_{x \sim Q}[D_w(x)] - \mathbb{E}_{z \sim F}[D_w(G_\theta(z))]$$

- D_w is the discriminator, G_θ the generator.
- Q is the data distribution, F say Gaussian (noise)
- D_w might (or not) capture the probability to classify data point as true!

- The aforementioned min-max problem is really hard! Many challenges!

GANs (Goodfellow et al.)

In their seminal paper, Goodfellow et al. defined the following min-max problem:

$$\min_{\theta} \max_{w} \mathbb{E}_{x \sim p_{\text{data}}}[\log D_w(x)] + \mathbb{E}_{z \sim p_{\text{noise}}}[\log(1 - D_w(G_\theta(z)))]$$

- D_w is the discriminator, G_θ the generator.
- p_{data} is the data distribution, p_{noise} say Gaussian (noise).
- D_w captures the probability to classify data point as true!
- D is trying to maximize prob to assign correct label to both samples from data and from G.

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Lemma (Optimality). *For G fixed, the optimal discriminator D has density*

$$D_{w^*}(x) = \frac{p_{data}(x)}{p_{data}(x) + p_G(x)},$$

where p_G is the implicit distribution of the Generator over the data.

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where p_G is the implicit distribution of the Generator over the data.

Proof. For fixed G, D is trying to maximize

$$\int_x \log D(x) p_{\text{data}}(x) dx + \int_z \log(1 - D(G(z)) p_{\text{noise}}(z) dz.$$

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$$\int_x \log D(x)p_{\text{data}}(x)dx + \int_x \log(1 - D(x)p_G(x)dx.$$

Finally, observe that function

$$f(y) = a \log y + b \log(1 - y)$$

achieves maximum at $\frac{a}{a+b}$.

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F

Define cost function $C(G)$

$$C(G) := \mathbb{E}_{x \sim p_{\text{data}}} \left[\log \frac{p_{\text{data}}}{p_{\text{data}} + p_G} \right] + \mathbb{E}_{x \sim p_G} \left[\log \frac{p_G}{p_{\text{data}} + p_G} \right].$$

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GANs (Goodfellow et al.)

Theorem (Global solution)**.** *The global minimum of $C(G)$ is achieved if and only if*

$$p_G = p_{data}.$$

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Proof. Observe that for $p_{\text{data}} = p_G$ we get that $C(G) = -\log 4$.

Quick recap $\text{KL}(p||q) = \mathbb{E}_{x\sim p}\left[\log \frac{p(x)}{q(x)}\right]$ is non-negative!

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Quick recap $\mathrm{KL}(p||q) = \mathbb{E}_{x\sim p}\left[\log \frac{p(x)}{q(x)}\right]$ is non-negative!

Finally observe that

$$C(G) = -\log 4 + \mathrm{KL}\left(p_{\text{data}}||\frac{p_{\text{data}} + p_G}{2}\right) + \mathrm{KL}\left(p_G||\frac{p_{\text{data}} + p_G}{2}\right).$$

Min-max Optimization

GANs motivate the study of min-max optimization (in general harder than minimization), i.e., for some continuous function f we want to solve

$$\min_{x \in \mathcal{X}} \max_{y \in \mathcal{Y}} f(x, y)$$

Remarks

- Domains are typically compact.
- In general the above problem might not have a solution.
- There are guarantees when domains are compact and f is convex-concave.

Minimax Theorem

Theorem (Minimax by John von Neumann). *Let $\mathcal{X} \subset \mathbb{R}^n$ and $\mathcal{Y} \subset \mathbb{R}^m$ be compact convex sets. If f is a continuous function that is convex-concave it holds*

$$\min_{x \in \mathcal{X}} \max_{y \in \mathcal{Y}} f(x, y) = \max_{y \in \mathcal{Y}} \min_{x \in \mathcal{X}} f(x, y)$$

Remarks

- Many applications, especially in Game Theory.
- If $f = x^T A y$, and the domains are Δ_n, Δ_m it captures classic zero sum games
- The above is the value of the game.
- Note that It is always true (min-max inequality):

$$\boxed{\inf_{x \in \mathcal{X}} \sup_{y \in \mathcal{Y}} f(x, y) \geq \sup_{y \in \mathcal{Y}} \inf_{x \in \mathcal{X}} f(x, y)}$$

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Define $g(z) \triangleq \inf_{w \in W} f(z, w)$.

$$\forall w, \forall z, g(z) \leq f(z, w)$$

$$\implies \forall w, \sup_z g(z) \leq \sup_z f(z, w)$$

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Proof. Let's use no-regret learning for both "players"!

Online Gradient Descent (Recap)

Definition (Online Gradient Descent)**.** *Let $f : \mathbb{R}^n \to \mathbb{R}$ be convex function, differentiable and L-Lipschitz in some compact convex set $\mathcal{X}$ of diameter D. Online GD is defined:*

Initialize at some x_0.
For t:=1 to T do

1. Choose x_t and observe $\ell_t(x_t)$.
2. $y_t = x_t - \alpha_t \nabla \ell_t(x_t)$.
3. $x_{t+1} = \Pi_{\mathcal{X}}(y_t)$.

Regret: $\frac{1}{T}\left(\sum_{t=1}^{T} \ell_t(x_t) - \min_x \sum_{t=1}^{T} \ell_t(x)\right)$.

Analysis of Online GD for L-Lipschitz (Recap)

Theorem (Online Gradient Descent). *Let $f : \mathbb{R}^n \to \mathbb{R}$ be convex function, differentiable and L-Lipschitz in some compact convex set $\mathcal{X}$ of diameter D. It holds*

$$\left(\frac{1}{T}\sum_{t=1}^{T}\ell_t(x_t) - \min_x \sum_{t=1}^{T}\ell_t(x)\right) \leq \frac{3}{2}\frac{LD}{\sqrt{T}},$$

with appropriately choosing $\alpha = \frac{D}{L\sqrt{t}}$.

Remarks:

- If we want error ϵ, we need $T = \Theta\left(\frac{L^2D^2}{\epsilon^2}\right)$ iterations (same as GD for L-Lipschitz).

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Let $x_1, \ldots, x_T$ and $y_1, \ldots, y_T$ be the iterates as advised by some no-regret algorithm and define $\hat{x} = \frac{1}{T}\sum_{i=1}^T x_i$ and $\hat{y} = \frac{1}{T}\sum_{i=1}^T y_i$ and $T = \Theta(\frac{1}{\epsilon^2})$.

Choose any x, then from the no-regret property for x we get that

$$\frac{1}{T}\sum_t f(x_t, y_t) \leq \frac{1}{T}\sum_t f(x, y_t) + \epsilon$$

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$$\begin{aligned} \tfrac{1}{T}\textstyle\sum_t f(x_t, y_t) &\leq \tfrac{1}{T}\textstyle\sum_t f(x, y_t) + \epsilon \\ &\leq f(x, \hat{y}) + \epsilon \text{ by concavity.} \end{aligned}$$

Minimax Theorem

Proof cont.

Choose any y, then from the no-regret property for y we get that

$$\begin{aligned} \tfrac{1}{T}\textstyle\sum_t f(x_t, y_t) &\geq \tfrac{1}{T}\textstyle\sum_t f(x_t, y) - \epsilon \\ &\geq f(\hat{x}, y) - \epsilon \text{ by convexity.} \end{aligned}$$

Minimax Theorem

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$$\geq f(\hat{x}, y) - \epsilon \text{ by convexity.}$$

We conclude that for all x, y we have

$$\boxed{f(\hat{x}, y) - 2\epsilon \leq f(x, \hat{y}).}$$

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We conclude that for all x, y we have

$$\boxed{\max_y f(\hat{x}, y) - 2\epsilon \leq \min_x f(x, \hat{y}).}$$

Finally we get $\max_y \min_x f(x, y) \geq \min_x f(x, \hat{y})$

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$$\begin{aligned}\text{Finally we get } \max_y \min_x f(x, y) &\geq \min_x f(x, \hat{y}) \\ &\geq \max_y f(\hat{x}, y) - 2\epsilon \\ &\geq \min_x \max_y f(x, y) - 2\epsilon\end{aligned}$$

Minimax Theorem

Proof cont.

Choose an

Set $\epsilon \to 0$ and we are done!

t

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Last iterate convergence?

Convex-concave settings (with compact domains) are easy.
Nevertheless in GANs

- Functions are not necessarily convex-concave.
- Time averaging does not help (Jensen's ineq not applicable).
- Motivation to care about last iterate convergence!

For the rest of the lecture let's focus on

$$\min_{x \in \mathcal{X}} \max_{y \in \mathcal{Y}} x^T A y.$$

Can we guarantee last iterate convergence using GD or MWUA?

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Can we guarantee last iterate convergence using GD or MWUA?

Not really...

Last iterate convergence

Consider Gradient Descent/Ascent that is

$$x_{t+1} = x_t - \eta \nabla_x f(x_t, y_t),$$
$$y_{t+1} = y_t + \eta \nabla_y f(x_t, y_t).$$

Consider the simplest case $f(x, y) = xy$. GDA boils down to:

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Claim (Divergence). *It holds that $x_t^2 + y_t^2$ is increasing in t.*

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Claim (Divergence). *It holds that $x_t^2 + y_t^2$ is increasing in t.*

Proof.

$$x_{t+1}^2 + y_{t+1}^2 = (\eta^2 + 1)(x_t^2 + y_t^2).$$

Last iterate convergence

Consider MWUA that is

$$x_i^{t+1} = \frac{x_i^t e^{-\eta(Ay^t)_i}}{Z_x},$$

$$y_j^{t+1} = \frac{y_j^t e^{\eta(A^T x^t)_j}}{Z_y}.$$

Theorem (Divergence). *Assume there exists a unique fully mixed Nash (x^*, y^*) equilibrium (full support). It holds that the KL divergence between a player strategies the fully mixed Nash goes to infinity, i.e,*

$$\lim_t \mathrm{KL}(x^* || x^t) = \infty \text{ and } \lim_t \mathrm{KL}(y^* || y^t) = \infty.$$

Conclusion

- Introduction to min-max optimization.
  - GANs.
  - Minimax Theorem
  - Last iterate convergence?

- Next lecture we will talk more about min-max optimization and optimism.