

**THINK BEFORE STARTING THE WRITING OF A PROOF. THINK OF ALL THE NECESSARY COMPONENTS FIRST. THERE IS ENOUGH TIME.**

| Definitions  |
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| <ul style="list-style-type: none"> <li><b>Differentiable:</b> <math>f : \mathbb{R}^d \rightarrow \mathbb{R}</math> is differentiable if <div> <math display="block">f(\mathbf{y}) = f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + r(\mathbf{y} - \mathbf{x}),</math> <div> where <math>\lim_{\mathbf{v} \rightarrow 0} \frac{ r(\mathbf{v}) }{\ \mathbf{v}\ } = 0</math>. </div> </div> </li> <li><b>Spectral norm:</b> <math>\ A\ _2 = \sup_{\ \mathbf{x}\ =1} \ A\mathbf{x}\ </math> (largest eigenvalue).</li> <li><b>Positive semi-definite:</b> <math>\forall \mathbf{x} \in \mathbb{R}^d: \mathbf{x}^\top A \mathbf{x} \geq 0</math>.</li> <li><b>Directional derivative:</b> If <math>f</math> is diff., <math>\langle \nabla f(\mathbf{x}), \mathbf{v} \rangle = \lim_{h \rightarrow 0} \frac{f(\mathbf{x} + h\mathbf{v}) - f(\mathbf{x})}{h}</math>.</li> <li><b><math>B</math>-Lipschitz:</b> <math>\forall \mathbf{x}, \mathbf{y} \in \text{dom}(f)</math>, <div> [1] <math>\ f(\mathbf{x}) - f(\mathbf{y})\  \leq B\ \mathbf{x} - \mathbf{y}\ </math>. [2] If <math>f</math> differentiable, <math>\ \nabla f(\mathbf{x})\  \leq B</math>. [3] If <math>f</math> convex, <math>\ g\  \leq B, \forall g \in \partial f(\mathbf{x})</math> (proof: subgrad def <math>\Rightarrow</math> Cauchy-Schwarz). </div> </li> <li><b>Convex set:</b> <math>\forall \mathbf{x}, \mathbf{y} \in X, \lambda \in [0, 1]: \lambda \mathbf{x} + (1 - \lambda)\mathbf{y} \in X</math>.</li> <li><b>Cone:</b> <math>X</math> is a cone if <math>\forall \mathbf{x} \in X, \lambda &gt; 0: \lambda \mathbf{x} \in X</math>.</li> <li><b>Convexity:</b> <math>\forall \mathbf{x}, \mathbf{y} \in \text{dom}(f)</math> and <math>\forall \lambda \in [0, 1]</math>, <div> [1] <math>f(\lambda \mathbf{x} + (1 - \lambda)\mathbf{y}) \leq \lambda f(\mathbf{x}) + (1 - \lambda)f(\mathbf{y})</math>. [2] <math>f(\mathbf{y}) \geq f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle</math>. [3] <math>\langle \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq 0</math>. [4] <math>\nabla^2 f(\mathbf{x})</math> is positive semi-definite. </div> </li> <li><b>Convexity preservation:</b> Positive scaling, Sum, Max, and <math>f(A\mathbf{x} + \mathbf{b})</math>.</li> <li><b><math>L</math>-smoothness:</b> <math>\forall \mathbf{x}, \mathbf{y} \in \text{dom}(f)</math>, <div> [1] <math>\ \nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\  \leq L\ \mathbf{x} - \mathbf{y}\ </math>. [2] <math>g(\mathbf{x}) := \frac{L}{2}\ \mathbf{x}\ ^2 - f(\mathbf{x})</math> is convex. [3] <math>f(\mathbf{y}) \leq f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + \frac{L}{2}\ \mathbf{x} - \mathbf{y}\ ^2</math> (canonical). [4] <math>\langle \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \leq L\ \mathbf{x} - \mathbf{y}\ ^2</math>. [5] <math>\ \nabla^2 f(\mathbf{x})\ _2 \leq L</math>. [6] If <math>f</math> is convex and <math>L</math>-smooth, then <math>f</math> is <math>1/L</math>-strongly convex: <math display="block">f(\mathbf{y}) \geq f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + \frac{1}{2L}\ \mathbf{x} - \mathbf{y}\ ^2</math>. [7] Coordinate-wise: <math>f(\mathbf{x} + \lambda \mathbf{e}_i) \leq f(\mathbf{x}) + \lambda \nabla_i f(\mathbf{x}) + \frac{L_i}{2}\lambda^2, \forall \lambda \in \mathbb{R}</math>. <div> Relations: [5] <math>\Leftrightarrow</math> [1] <math>\Rightarrow</math> [2] <math>\Leftrightarrow</math> [3] <math>\Leftrightarrow</math> [4] (If convex, all <math>\Leftrightarrow</math>). </div> </div> </li> <li><b>Smoothness preservation:</b> Pos. scaling scales, Sum sums. <math>f(A\mathbf{x} + \mathbf{b})</math> has <math>L\ A\ _2^2</math>.</li> <li><b><math>\mu</math>-strong convexity:</b> <math>\forall \mathbf{x}, \mathbf{y} \in \text{dom}(f)</math>, <div> [1] <math>f(\mathbf{y}) \geq f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + \frac{\mu}{2}\ \mathbf{x} - \mathbf{y}\ ^2</math> (canonical). [2] <math>g(\mathbf{x}) := f(\mathbf{x}) - \frac{\mu}{2}\ \mathbf{x}\ ^2</math> is convex. [3] <math>\langle \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq \mu\ \mathbf{x} - \mathbf{y}\ ^2</math> (proof: sum [1] for <math>(\mathbf{x}, \mathbf{y})</math> and <math>(\mathbf{y}, \mathbf{x})</math>). [4] <math>\mu</math>-SC <math>\Rightarrow</math> PL inequality: <math>\frac{1}{2}\ \nabla f(\mathbf{x})\ ^2 \geq \mu(f(\mathbf{x}) - f^*)</math>. </div> </li> <li><b>Subgradient:</b> <math>g \in \partial f(\mathbf{x}) \Leftrightarrow f(\mathbf{y}) \geq f(\mathbf{x}) + \langle g, \mathbf{y} - \mathbf{x} \rangle, \forall \mathbf{y} \in \text{dom}(f)</math>.</li> <li><b>Conjugate function:</b> <math>f^*(\mathbf{y}) := \sup_{\mathbf{x} \in \text{dom}(f)} \langle \mathbf{x}, \mathbf{y} \rangle - f(\mathbf{x})</math>.</li> <li><b>Dual norm:</b> <math>\ \mathbf{y}\ _* := \max_{\ \mathbf{x}\  \leq 1} \langle \mathbf{x}, \mathbf{y} \rangle</math>.</li> </ul> |
| Lemmas   |
| <ul style="list-style-type: none"> <li><math>\frac{d}{dx} \frac{f(x)}{g(x)} = \frac{f'(x)g(x) - f(x)g'(x)}{g(x)^2}</math>.</li> <li><b>Cosine theorem:</b> All equivalent formulations, <div> [1] <math>\ \mathbf{x} - \mathbf{y}\ ^2 = \ \mathbf{x}\ ^2 + \ \mathbf{y}\ ^2 - 2\langle \mathbf{x}, \mathbf{y} \rangle</math>. [2] <math>\langle \mathbf{x}, \mathbf{y} \rangle = \frac{1}{2}(\ \mathbf{x}\ ^2 + \ \mathbf{y}\ ^2 - \ \mathbf{x} - \mathbf{y}\ ^2)</math>. [3] <math>\langle \mathbf{x} - \mathbf{y}, \mathbf{x} - \mathbf{z} \rangle = \frac{1}{2}(\ \mathbf{x} - \mathbf{y}\ ^2 + \ \mathbf{x} - \mathbf{z}\ ^2 - \ \mathbf{y} - \mathbf{z}\ ^2)</math>. </div> </li> <li><b>Cauchy-Schwarz:</b> <div> [1] <math> \langle \mathbf{x}, \mathbf{y} \rangle  \leq \ \mathbf{x}\  \ \mathbf{y}\ </math>. [2] <math>(\sum_{i=1}^n a_i b_i)^2 \leq (\sum_{i=1}^n a_i^2)(\sum_{i=1}^n b_i^2)</math>. [3] <b>Titu's lemma</b> (<math>b_i \geq 0</math>): <math>\frac{(\sum_{i=1}^n \frac{a_i}{b_i})^2}{\sum_{i=1}^n \frac{a_i^2}{b_i}} \leq \sum_{i=1}^n \frac{a_i^2}{b_i}</math> (proof: <math>a'_i = \frac{a_i}{\sqrt{b_i}}, b'_i = \sqrt{b_i}</math>). </div> </li> <li><b>Hölder's inequality</b> (special case): <math> \langle \mathbf{x}, \mathbf{y} \rangle  \leq \ \mathbf{x}\ _1 \ \mathbf{y}\ _\infty</math>.</li> <li><b>Parallelogram law:</b> <math>2\ \mathbf{x}\ ^2 + 2\ \mathbf{y}\ ^2 = \ \mathbf{x} + \mathbf{y}\ ^2 + \ \mathbf{x} - \mathbf{y}\ ^2</math>.</li> <li><b>Jensen's inequality</b> (<math>\varphi</math> convex, <math>a_i \geq 0</math>): <math>\varphi\left(\frac{\sum_{i=1}^m a_i \mathbf{x}_i}{\sum_{i=1}^m a_i}\right) \leq \frac{\sum_{i=1}^m a_i \varphi(\mathbf{x}_i)}{\sum_{i=1}^m a_i}</math>.</li> <li><b>Fenchel's inequality:</b> <math>\langle \mathbf{x}, \mathbf{y} \rangle \leq f(\mathbf{x}) + f^*(\mathbf{x}) \Rightarrow \langle \mathbf{x}, \mathbf{y} \rangle \leq \frac{1}{2}(\ \mathbf{x}\ ^2 + \ \mathbf{y}\ _*^2)</math>.</li> <li><b>Young's inequality</b> (<math>a, b \geq 0, \frac{1}{p} + \frac{1}{q} = 1</math>): <math>ab \leq \frac{a^p}{p} + \frac{b^q}{q} \Rightarrow \ \mathbf{x}\  \ \mathbf{y}\  \leq \frac{1}{2}(\ \mathbf{x}\ ^2 + \ \mathbf{y}\ ^2)</math>.</li> <li><math>\frac{1}{\sqrt{d}}\ \mathbf{x}\ _2 \leq \ \mathbf{x}\ _\infty \leq \ \mathbf{x}\ _2 \leq \ \mathbf{x}\ _1 \leq \sqrt{d}\ \mathbf{x}\ _2</math>.</li> <li><math>\ A\mathbf{x}\  \leq \ A\ _2 \ \mathbf{x}\ </math>.</li> <li><math>\ A\ _2 \leq \ A\ _F</math>.</li> </ul>   |

- Mean-value theorem** ( $h$  cont. on  $[a, b]$ , diff. on  $(a, b)$ ):

$$h'(c) = \frac{h(b) - h(a)}{b - a}, \quad \exists c \in (a, b).$$

- Fund. theorem of calculus** ( $h$  diff. on  $[a, b]$ ,  $h'$  cont. on  $[a, b]$ ):

$$h(b) - h(a) = \int_a^b h'(t) dt.$$

- $\left\| \int_0^1 \nabla h(t) dt \right\| \leq \int_0^1 \|\nabla h(t)\| dt$ .

- $\int_0^1 c dt = c, \quad \int_0^1 t dt = \frac{1}{2}$ .

- Subgradient calculus:**

$$[1] \quad h(\mathbf{x}) = \alpha f(\mathbf{x}) + \beta g(\mathbf{x}) \Rightarrow \partial h(\mathbf{x}) = \alpha \cdot \partial f(\mathbf{x}) + \beta \cdot \partial g(\mathbf{x}).$$

$$[2] \quad h(\mathbf{x}) = f(A\mathbf{x} + \mathbf{b}) \Rightarrow \partial h(\mathbf{x}) = A^\top \partial f(A\mathbf{x} + \mathbf{b}).$$

$$[3] \quad h(\mathbf{x}) = \max f_i(\mathbf{x}) \Rightarrow \partial h(\mathbf{x}) = \text{conv}(\{\partial f_i(\mathbf{x}) \mid f_i(\mathbf{x}) = h(\mathbf{x})\}).$$

- If  $f$  is differentiable at  $\mathbf{x}$ , then  $\partial f(\mathbf{x}) \subseteq \{\nabla f(\mathbf{x}_t)\}$ .
- If  $f$  is convex, then  $\partial f(\mathbf{x}) \neq \emptyset$  for all in  $\mathbf{x}$  in the relative interior.
- If  $\text{dom}(f)$  convex and  $\partial f(\mathbf{x}) \neq \emptyset, \forall \mathbf{x} \in \text{dom}(f)$ , then  $f$  is convex.
- If  $f$  is strictly concave, the subgradient exists nowhere.
- For  $p \geq 1, \frac{1}{p} + \frac{1}{q} = 1$ , we have dual norms,  $\|\cdot\|_{p,*} = \|\cdot\|_q$ .

| Optimality lemmas (assume convexity) |
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The constrained and non-diff. cases are useful when update rule contains argmin.

- $\mathbf{x}^*$  is a local minimum:  $\exists \epsilon > 0$  such that  $f(\mathbf{x}^*) \leq f(\mathbf{y}), \forall \mathbf{y} : \|\mathbf{x}^* - \mathbf{y}\| \leq \epsilon$ .
- $\nabla f(\mathbf{x}^*) = \mathbf{0}$ .
- Constrained:  $\langle \nabla f(\mathbf{x}^*), \mathbf{x} - \mathbf{x}^* \rangle \geq 0, \forall \mathbf{x} \in X$ .
- Non-differentiable:  $\mathbf{0} \in \partial f(\mathbf{x}^*)$ .

| Common tricks |
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- Rearrange the update rule** for an equality. E.g.,  $\nabla f(\mathbf{x}_t) = \frac{\mathbf{x}_t - \mathbf{x}_{t+1}}{\gamma_t}$ .

- Define  $h(t) := f(\mathbf{x} + t(\mathbf{y} - \mathbf{x}))$ , where  $h'(t) = \nabla f(\mathbf{x} + t(\mathbf{y} - \mathbf{x}))^\top (\mathbf{y} - \mathbf{x})$  and use with FTOC:  $f(\mathbf{y}) - f(\mathbf{x}) = \int_0^1 \nabla f(\mathbf{x} + t(\mathbf{y} - \mathbf{x}))^\top (\mathbf{y} - \mathbf{x}) dt$ .  
Or, mean-value theorem:  $\exists c \in (0, 1) : \nabla f(\mathbf{x} + c(\mathbf{y} - \mathbf{x}))^\top (\mathbf{y} - \mathbf{x}) = f(\mathbf{y}) - f(\mathbf{x})$ .

- Projection is non-expansive:**  $\|\Pi_X(\mathbf{x}) - \Pi_X(\mathbf{y})\| \leq \|\mathbf{x} - \mathbf{y}\|$ .

- $\min_{1 \leq t \leq T} f(\mathbf{x}_t) - f^* \leq \frac{\sum_{t=1}^T \gamma_t (f(\mathbf{x}_t) - f^*)}{\sum_{t=1}^T \gamma_t}$ .

- Telescoping sum** inequality:  $\sum_{t=1}^T \|\mathbf{x}_t - \mathbf{x}^*\|^2 - \|\mathbf{x}_{t+1} - \mathbf{x}^*\|^2 \leq \|\mathbf{x}_1 - \mathbf{x}^*\|^2$ .

- A monotone and bounded sequence has a limit.

- If a value  $\alpha$  is unknown for an algorithm. Start with a lower bound (or just  $\hat{\alpha}_0 = 1$ ) and run the algorithm, doubling every time  $\hat{\alpha}_{t+1} = 2 \cdot \hat{\alpha}_t$  it is incorrect. This does not increase complexity because, in the end,  $\hat{\alpha}_T \leq 2\alpha$  and all the previous values with their iterations are a constant factor, smaller than the final run.

- To find the optimal  $\gamma^*$  that minimizes bound  $q(\gamma)$ , use 1st-order opt:  $q(\gamma^*) \stackrel{!}{=} 0$ .

- $\max\{a, b\} \leq a + b$  if  $a, b \geq 0$ .

- $\sum_{t=1}^T \frac{1}{\sqrt{t}} = \mathcal{O}(\sqrt{T}), \quad \sum_{t=1}^T \frac{1}{t} = \mathcal{O}(\log T)$ .

- $\|\mathbf{x}\| = \|\mathbf{x} - \mathbf{y} + \mathbf{y}\| \leq \|\mathbf{x} - \mathbf{y}\| + \|\mathbf{y}\|, \quad \|\mathbf{x} - \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\| \Rightarrow \|\mathbf{x} - \mathbf{y}\| - \|\mathbf{y}\| \leq \|\mathbf{x}\| \leq \|\mathbf{x} - \mathbf{y}\| + \|\mathbf{y}\|$ .

- $1 - x \leq \exp(-x), \forall x \geq 0 \Rightarrow (1 - x)^y \leq \exp(-xy), \forall x \geq 0, y \in \mathbb{R}$ .

| IMPORTANT TIPS TO KEEP IN MIND |
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- When showing convexity, make sure to show that the domain is a convex set.
- If  $f$  is convex and want to use the subgradient, state that it exists bc of convexity.
- If something is obviously false, still provide a counterexample.

- Keep in mind divisions by 0 when defining functions. For example, when dividing by norm. Then, the gradient is not defined  $\Rightarrow$  Use subgradient.

- Structure of a proof:

$$[1] \quad \text{State what needs to be shown exactly and mark by } (\star).$$

$$[2] \quad \text{State the assumptions of the question and their implications (think about which implications are relevant to the proof).}$$

$$[3] \quad \text{Proof should follow easily: "Hence, } (\star) \text{ holds and the proof is concluded."}$$

- If need to show that something does not exist, use proof by contradiction.

- If  $\gamma_t$  is timestep-dependent, generally need to use induction.

| Expectation and variance for SGD |
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- $\text{Var}[\mathbf{X}] := \mathbb{E}[\|\mathbf{X} - \mathbb{E}[\mathbf{X}]\|^2] = \mathbb{E}[\|\mathbf{X}\|^2] - \|\mathbb{E}[\mathbf{X}]\|^2$ .  

$$\Rightarrow \quad \mathbb{E}[\|\nabla f(\mathbf{x}_t, \boldsymbol{\xi}_t)\|^2] = \|\nabla F(\mathbf{x}_t)\|^2 + \mathbb{E}[\|\nabla f(\mathbf{x}_t, \boldsymbol{\xi}_t) - \nabla F(\mathbf{x}_t)\|^2]$$

$$\leq \|\nabla F(\mathbf{x}_t)\|^2 + \sigma^2.$$

- Law of total expectation:**  $\mathbb{E}[X] = \mathbb{E}_Y[\mathbb{E}_X[X \mid Y]]$ .
- Law of total variance:**  $\text{Var}[Y] = \mathbb{E}_X[\text{Var}_Y[Y \mid X]] + \text{Var}_Y[\mathbb{E}_X[Y \mid X]]$ .
- $\text{Var}[X - Y] = \text{Var}[X] + \text{Var}[Y] - 2 \cdot \text{Cov}(X, Y)$ .
- $\text{Var}[\alpha X] = \alpha^2 \text{Var}[X], \text{Var}[X + \beta] = \text{Var}[X]$ .

## Risk minimization

- Unknown distribution  $P$ . We only have access to samples  $X_1, \dots, X_n \sim P$ . We want to explain data source  $X$  through these samples by minimizing risk.
- Expected risk:**  $\ell(H) := \mathbb{E}_X[\ell(H, X)]$ .
- Empirical risk:**  $\ell_n(H) := \frac{1}{n} \sum_{i=1}^n \ell(H, X_i)$ .
- Probably approximately correct (PAC):** Let  $\epsilon, \delta > 0$ ,  $\tilde{H} \in \mathcal{H}$  is PAC if, with probability at least  $1 - \delta$ ,  $\ell(\tilde{H}) \leq \inf_{H \in \mathcal{H}} \ell(H) + \epsilon$ .
- Weak law of large numbers (WLLM):** Let  $H \in \mathcal{H}$  be fixed. For any  $\delta, \epsilon > 0$ , there exists  $n_0 \in \mathbb{N}$  such that for  $n \geq n_0$ ,  $|\ell_n(H) - \ell(H)| \leq \epsilon$  with probability at least  $1 - \delta$ .
- Assume that for any  $\delta, \epsilon > 0$ , there exists  $n_0 \in \mathbb{N}$  such that for  $n \geq n_0$ ,  $\sup_{H \in \mathcal{H}} |\ell_n(H) - \ell(H)| \leq \epsilon$  with probability at least  $1 - \delta$ . (WLLM holds uniformly for all hypotheses.) Then, an approximate empirical risk minimizer  $\tilde{H}_n$  ( $\ell_n(\tilde{H}_n) \leq \inf_{H \in \mathcal{H}} \ell_n(H) + \epsilon$ ) is PAC for expected risk minimization, meaning  $\ell(\tilde{H}_n) \leq \inf_{H \in \mathcal{H}} \ell(H) + 3\epsilon$  with probability at least  $1 - \delta$ .

$$\ell(\tilde{H}_n) \stackrel{\text{uniform WLLM}}{\leq} \inf_{H \in \mathcal{H}} \ell(H) + 3\epsilon \leq \ell_n(\tilde{H}_n) + \epsilon \stackrel{\text{emp. risk min.}}{\leq} \inf_{H \in \mathcal{H}} \ell_n(H) + 2\epsilon \stackrel{\text{uniform WLLM}}{\leq} \inf_{H \in \mathcal{H}} \ell(H) + 3\epsilon \quad \square$$

- Empirical risk minimization** ( $\ell_n(H_n)$ : empirical, training;  $\ell(H_n)$ : expected, validation): We want generalization and learning,
  - (Low  $\ell_n(H_n)$ , High  $\ell(H_n)$ ): Overfitting (theory is too complex).
  - (High  $\ell_n(H_n)$ , High  $\ell(H_n)$ ): Underfitting (theory is too simple).
  - (Low  $\ell_n(H_n)$ , Low  $\ell(H_n)$ ): Learning.
  - ( $\ell_n(H_n) \approx \ell(H_n)$ ): Generalization.
  - Regularization: Punish complex hypotheses.
  - W.h.p. we do not have high  $\ell_n(H_n)$ , low  $\ell(H_n)$ , because  $\ell_n(H_n) \leq \inf_{H \in \mathcal{H}} \ell_n(H) + \epsilon \leq \ell_n(\tilde{H}) + \epsilon \leq \ell(\tilde{H}) + 2\epsilon \leq \ell(\tilde{H}_n) + 3\epsilon$ .

## Non-linear programming

- Optimization problem:**
$$\begin{array}{ll} \text{minimize} & f_0(\mathbf{x}) \\ \text{subject to} & f_i(\mathbf{x}) \leq 0, \quad i \in [m] \\ & h_j(\mathbf{x}) = 0, \quad j \in [p]. \end{array}$$
- Problem domain:**  $X = \left(\bigcap_{i=0}^m \text{dom}(f_i)\right) \cap \left(\bigcap_{j=1}^p \text{dom}(h_j)\right)$ .
- Convex program:** All  $f_i$  are convex and all  $h_j$  are affine with domain  $\mathbb{R}^d$ .
- Lagrangian:**  $L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\nu}) := f_0(\mathbf{x}) + \sum_{i=1}^m \lambda_i f_i(\mathbf{x}) + \sum_{j=1}^p \nu_j h_j(\mathbf{x})$ .
- Lagrange dual function:**  $g(\boldsymbol{\lambda}, \boldsymbol{\nu}) := \inf_{\mathbf{x} \in X} L(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\nu})$ .
- Weak Lagrange duality** ( $\lambda \geq 0$ ,  $\mathbf{x}$  is feasible):  $g(\boldsymbol{\lambda}, \boldsymbol{\nu}) \leq f_0(\mathbf{x})$ .
- Lagrange dual problem** (convex program, even if primal is not):
$$\begin{array}{ll} \text{maximize} & g(\boldsymbol{\lambda}, \boldsymbol{\nu}) \\ \text{subject to} & \boldsymbol{\lambda} \geq 0. \end{array}$$
- If a convex program has a feasible solution  $\tilde{\mathbf{x}}$  that is a Slater point ( $f_i(\tilde{\mathbf{x}}) < 0, \forall i \in [m]$ ), then  $\max_{\boldsymbol{\lambda} \geq 0, \boldsymbol{\nu}} g(\boldsymbol{\lambda}, \boldsymbol{\nu}) = \inf_{\mathbf{x} \in X} f_0(\mathbf{x})$ .
- Zero duality gap:** Feasible solutions  $\tilde{\mathbf{x}}$  and  $(\tilde{\boldsymbol{\lambda}}, \tilde{\boldsymbol{\nu}})$  have zero duality gap if  $f_0(\tilde{\mathbf{x}}) = g(\tilde{\boldsymbol{\lambda}}, \tilde{\boldsymbol{\nu}})$  ( $\Rightarrow \tilde{\mathbf{x}}$  is a minimizer of primal).
- KKT necessary:** Zero duality gap  $\Rightarrow \tilde{\lambda}_i f_i(\tilde{\mathbf{x}}) = 0, \forall i \in [m]$  (complementary slackness) and  $\nabla_{\mathbf{x}} L(\tilde{\mathbf{x}}, \tilde{\boldsymbol{\lambda}}, \tilde{\boldsymbol{\nu}}) = \mathbf{0}$  (vanishing Lagrangian gradient).
- KKT sufficient:** Convex program, complementary slackness, and vanishing Lagrangian gradient  $\Rightarrow$  Zero duality gap.

$$\text{Complementary slackness } (f_0(\tilde{\mathbf{x}}) = L(\tilde{\mathbf{x}}, \tilde{\boldsymbol{\lambda}}, \tilde{\boldsymbol{\nu}})) \Rightarrow L \text{ is convex in } \mathbf{x} \text{ and gradient is zero, so } \tilde{\mathbf{x}} \text{ is a global minimizer.} \quad \square$$

- Program maybe not solvable, but if Slater point, then a solution exists  $\Rightarrow$  Only need to show that the KKT conditions are satisfied.

## Gradient descent

- Update rule:**  $\mathbf{x}_{t+1} = \mathbf{x}_t - \gamma \nabla f(\mathbf{x}_t)$ .
- VA:**  $\sum_{t=0}^{T-1} (f(\mathbf{x}_t) - f^*) \leq \frac{\gamma}{2} \sum_{t=0}^{T-1} \|\nabla f(\mathbf{x}_t)\|^2 + \frac{1}{2\gamma} \|\mathbf{x}_0 - \mathbf{x}^*\|^2$ .

$$\text{1st-order convexity on } (\mathbf{x}^*, \mathbf{x}_t) \Rightarrow \nabla f(\mathbf{x}_t) = \frac{\mathbf{x}_t - \mathbf{x}_{t+1}}{\gamma} \Rightarrow \text{Cosine theorem} \Rightarrow \mathbf{x}_t - \mathbf{x}_{t+1} = \gamma \nabla f(\mathbf{x}_t) \Rightarrow \text{Telescoping sum.} \quad \square$$
- Sufficient decrease** ( $L$ -smooth,  $\gamma := \frac{1}{L}$ ):  $f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2$ .

$$\text{Smoothness on } (\mathbf{x}_{t+1}, \mathbf{x}_t) \Rightarrow \mathbf{x}_{t+1} - \mathbf{x}_t = -\frac{1}{L} \nabla f(\mathbf{x}_t). \quad \square$$
- Convergence results:** ( $\|\mathbf{x}_0 - \mathbf{x}^*\| \leq R$ )
  - ( $B$ -Lipschitz, convex,  $\gamma := \frac{R}{B\sqrt{T}}$ )  $\frac{1}{T} \sum_{t=0}^{T-1} (f(\mathbf{x}_t) - f^*) \leq \frac{RB}{\sqrt{T}}$ .

$$\text{Apply bounds to VA and find } \gamma \text{ by 1st-order optimality.} \quad \square$$
  - ( $L$ -smooth, convex,  $\gamma := \frac{1}{L}$ )  $f(\mathbf{x}_T) - f^* \leq \frac{L}{2T} \|\mathbf{x}_0 - \mathbf{x}^*\|^2$ 

$$\text{Sufficient decrease to bound gradients of VA with telescoping sum.} \quad \square$$

$$\circ (L\text{-smooth, } \mu\text{-SC, } \gamma := \frac{1}{L}) f(\mathbf{x}_T) - f^* \leq \frac{L}{2} \left(1 - \frac{\mu}{L}\right)^T \|\mathbf{x}_0 - \mathbf{x}^*\|^2$$

$$\text{Use } \mu\text{-SC to strengthen VA bound for squared norm } \Rightarrow \text{Upper bound "noise" with } f^* \leq f(\mathbf{x}_{t+1}) \text{ and SD } \Rightarrow \text{Smoothness on } (\mathbf{x}^*, \mathbf{x}_T). \quad \square$$

- Accelerated gradient descent:**

$$\begin{aligned} \mathbf{y}_{t+1} &= \mathbf{x}_t - \frac{1}{L} \nabla f(\mathbf{x}_t) \\ \mathbf{z}_{t+1} &= \mathbf{z}_t - \frac{t+1}{2L} \nabla f(\mathbf{x}_t) \\ \mathbf{x}_{t+1} &= \frac{t+1}{t+3} \mathbf{y}_{t+1} + \frac{2}{t+3} \mathbf{z}_{t+1}. \end{aligned}$$

## Projected gradient descent

- Update rule** ( $X \subset \mathbb{R}^d$  is closed and convex):
$$\begin{aligned} \mathbf{y}_{t+1} &= \mathbf{x}_t - \gamma \nabla f(\mathbf{x}_t) \\ \mathbf{x}_{t+1} &= \Pi_X(\mathbf{y}_{t+1}) := \underset{\mathbf{x} \in X}{\operatorname{argmin}} \|\mathbf{x} - \mathbf{y}_{t+1}\|^2. \end{aligned}$$
- Projection onto  $\ell_1$ -ball** can be done in  $\mathcal{O}(d \log d)$ .
- 1.  $(\mathbf{x} \in X, \mathbf{y} \in \mathbb{R}^d)$ :  $\langle \mathbf{x} - \Pi_X(\mathbf{y}), \mathbf{y} - \Pi_X(\mathbf{y}) \rangle \leq 0$ .

$$\text{Constrained 1st-order optimality } \Rightarrow \text{Rearrange.} \quad \square$$
- 2.  $(\mathbf{x} \in X, \mathbf{y} \in \mathbb{R}^d)$ :  $\|\mathbf{x} - \Pi_X(\mathbf{y})\|^2 + \|\mathbf{y} - \Pi_X(\mathbf{y})\|^2 \leq \|\mathbf{x} - \mathbf{y}\|^2$ .

$$\text{Cosine theorem on (1).} \quad \square$$
- If  $\mathbf{x}_{t+1} = \mathbf{x}_t$ , then  $\mathbf{x}_t = \mathbf{x}^*$ .

$$\text{Use (1) and } \mathbf{x}_{t+1} = \mathbf{x}_t \text{ to show that 1st-order optimality holds.} \quad \square$$
- Projected SD:**  $f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2 + \frac{L}{2} \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2$ .

$$\text{Smoothness on } (\mathbf{x}_{t+1}, \mathbf{x}_t) \Rightarrow \nabla f(\mathbf{x}_t) = L(\mathbf{y}_{t+1} - \mathbf{x}_t) \Rightarrow \text{Cosine theorem } \Rightarrow \mathbf{y}_{t+1} - \mathbf{x}_t = -\frac{1}{L} \nabla f(\mathbf{x}_t). \quad \square$$
- ( $L$ -smooth, convex,  $\gamma := \frac{1}{L}$ ):  $f(\mathbf{x}_T) - f^* \leq \frac{L}{2T} \|\mathbf{x}_0 - \mathbf{x}^*\|^2$ .

$$\text{VA with additional term } (\mathbf{y}_{t+1} \text{ instead of } \mathbf{x}_{t+1} \text{ and use (2)) and bound gradients with projected SD. Additional terms cancel.} \quad \square$$

## Coordinate descent

- Update rule:**  $\mathbf{x}_{t+1} = \mathbf{x}_t - \gamma_i \nabla_i f(\mathbf{x}_t) \mathbf{e}_i, \quad i \in [d]$ .
- Coordinate-wise SD:**  $f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \frac{1}{2L_i} |\nabla_i f(\mathbf{x}_t)|^2$ .

$$\text{CW smoothness with } \lambda = \frac{-\nabla_i f(\mathbf{x}_t)}{L_i} \text{ such that } \mathbf{x}_{t+1} = \mathbf{x}_t + \lambda \mathbf{e}_i. \quad \square$$
- Convergence results** ( $\mu$ -PL,  $\mathcal{L}$ -CS,  $\bar{L} = \frac{1}{d} \sum_{i=1}^d L_i, \gamma_i := \frac{1}{L_i}$ ):
  - ( $L$ -smooth,  $\mu$ -PL,  $i \sim \text{Unif}([d])$ )
$$\mathbb{E}[f(\mathbf{x}_T) - f^*] \leq \left(1 - \frac{\mu}{dL}\right)^T (f(\mathbf{x}_0) - f^*).$$

$$\text{CW SD } \Rightarrow \mathbb{E}_i[\cdot | \mathbf{x}_t] \Rightarrow \text{Use sample prob. } \Rightarrow \text{PL } \Rightarrow \mathbb{E}_{\mathbf{x}_t} (\text{LoTE}). \quad \square$$
  - ( $\mu$ -PL,  $i \sim \text{Cat}(L_1/\sum_{j=1}^d L_j, \dots, L_d/\sum_{j=1}^d L_j)$ )
$$\mathbb{E}[f(\mathbf{x}_T) - f^*] \leq \left(1 - \frac{\mu}{dL}\right)^T (f(\mathbf{x}_0) - f^*).$$

$$\text{Same as above with different probabilities. } \bar{L} := \frac{1}{d} \sum_{i=1}^d L_i. \quad \square$$
  - ( $L$ -smooth,  $\mu_1$ -SC w.r.t.  $\ell_1 \Rightarrow \mu_1$ -PL w.r.t.  $\ell_\infty, i \in \operatorname{argmax}_{j \in [d]} |\nabla_j f(\mathbf{x}_t)|$ )
$$\begin{aligned} f(\mathbf{x}_T) - f^* &\leq \left(1 - \frac{\mu}{dL}\right)^T (f(\mathbf{x}_0) - f^*) \\ f(\mathbf{x}_T) - f^* &\leq \left(1 - \frac{\mu_1}{L}\right)^T (f(\mathbf{x}_0) - f^*). \end{aligned}$$

$$\text{CW SD } \Rightarrow \ell_\infty \text{ because of update rule } \Rightarrow \text{PL.} \quad \square$$
- $\frac{1}{\sqrt{d}} \|\mathbf{x} - \mathbf{y}\|_2 \leq \|\mathbf{x} - \mathbf{y}\|_1 \leq \|\mathbf{x} - \mathbf{y}\|_2 \Rightarrow \frac{\mu}{d} \leq \mu_1 \leq \mu$ .

## Nonconvex functions

- ( $L$ -smooth,  $\gamma := \frac{1}{L}, \exists \mathbf{x}^*$ ):  $\frac{1}{T} \sum_{t=0}^{T-1} \|\nabla f(\mathbf{x}_t)\|^2 \leq \frac{2L}{T} (f(\mathbf{x}_0) - f^*)$ .

$$\text{SD does not require convexity. Rewrite with telescoping sum.} \quad \square$$
$$\Rightarrow \lim_{t \rightarrow \infty} \|\nabla f(\mathbf{x}_t)\| = 0.$$
- Trajectory analysis:** Optimize  $f(\mathbf{x}) := \frac{1}{2} \left(\prod_{k=1}^d x_k - 1\right)^2$ .
- $\frac{\partial f(\mathbf{x})}{\partial x_i} = \left(\prod_k x_k - 1\right) \prod_{k \neq i} x_k$  ( $\nabla f(\mathbf{x}) = \mathbf{0}$  if 2 dims are 0 or all 1).
- $\frac{\partial^2 f(\mathbf{x})}{\partial x_i^2} = \left(\prod_{k \neq i} x_k\right)^2$ .
- $\frac{\partial^2 f(\mathbf{x})}{\partial x_i \partial x_j} = 2 \prod_{k \neq i} x_k \prod_{k \neq j} x_k - \prod_{k \neq i, j} x_k$ , if  $i \neq j$ .
- $c$ -**balanced:** Let  $\mathbf{x} > \mathbf{0}, c \geq 1$ .  $\mathbf{x}$  is  $c$ -balanced if  $x_i \leq c \cdot x_j, \forall i, j \in [d]$ .
- If  $\mathbf{x}_t$  is  $c$ -balanced,  $\gamma > 0$ , then  $\mathbf{x}_{t+1}$  is  $c$ -balanced and  $\mathbf{x}_{t+1} \geq \mathbf{x}_t$ .

o If  $\mathbf{x}$  is  $c$ -balanced, then for any  $I \subseteq [d]$ , we have

$$\prod_{k \notin I} x_k \leq c^{|I|} \left( \prod_{k=1}^d x_k \right)^{1-|I|/d} \leq c^{|I|}.$$

o Let  $\mathbf{x}$  be  $c$ -balanced and  $\prod_k x_k \leq 1$ , then

$$\|\nabla^2 f(\mathbf{x})\|_2 \leq \|\nabla^2 f(\mathbf{x})\|_F \leq 3dc^2.$$

Thus,  $f$  is smooth along the whole trajectory of GD with  $L = 3dc^2$ .

o **Convergence** ( $\gamma := \frac{1}{3dc^2}$ ,  $\mathbf{x}_0 > \mathbf{0}$  and  $c$ -balanced,  $\delta \leq \prod_k x_{0,k} < 1$ )

$$f(\mathbf{x}_T) \leq \left(1 - \frac{\delta^2}{3c^4}\right)^T f(\mathbf{x}_0).$$

o  $\delta$  decays polynomially in  $d$ , so we must start  $\mathcal{O}(1/\sqrt{d})$  from  $\mathbf{x}^* = \mathbf{1}$ .

### Frank-Wolfe

o **Linear minimization oracle:**  $\text{LMO}_X(\mathbf{g}) := \arg\min_{\mathbf{z} \in X} \langle \mathbf{g}, \mathbf{z} \rangle$ .

If  $\mathbf{g} = \mathbf{0}$ , any  $\mathbf{z}$  minimizes.

o **Update rule:**  $\mathbf{x}_{t+1} = (1 - \gamma_t)\mathbf{x}_t + \gamma_t \mathbf{s}_t$ ,  $\mathbf{s}_t = \text{LMO}_X(\nabla f(\mathbf{x}_t))$ .

o If  $X = \text{conv}(A)$ , then  $\text{LMO}_X(\mathbf{g}) \in A$ : Easy optimization problem in  $\mathcal{O}(|A|)$ .

o Advantages: (1) Iterates are always feasible if  $X$  is convex, (2) No projections, (3) Iterates  $\mathbf{x}_T$  have simple sparse representations as convex combination of  $\{\mathbf{x}_0, \mathbf{s}_0, \dots, \mathbf{s}_{T-1}\}$ :  $\mathbf{x}_T = \left(\prod_{t=0}^{T-1} 1 - \gamma_t\right) \mathbf{x}_0 + \sum_{t=0}^{T-1} \gamma_t \left(\prod_{\tau=t+1}^{T-1} 1 - \gamma_\tau\right) \mathbf{s}_t$ .

o  $\ell_1$ -ball LMO:  $\text{LMO}(\mathbf{g}) = -\text{sgn}(g_i)\mathbf{e}_i, i \in \arg\max_{j \in [d]} |g_j|$ .

o **Spectahedron LMO:**  $\text{LMO}_X(\mathbf{G}) = \arg\min_{\substack{Z \text{ is PSD} \\ Z \in X}} \text{tr}(Z) = \mathbf{v}_1 \mathbf{v}_1^\top$ , where  $\mathbf{v}_1$  is the eigenvector associated with the smallest eigenvalue of  $G$ .

o **Duality gap:**  $g(\mathbf{x}) := \langle \nabla f(\mathbf{x}), \mathbf{x} - \mathbf{s} \rangle, \mathbf{s} = \text{LMO}_X(\nabla f(\mathbf{x}))$ .

o **Upper bound of optimality gap** (convex):  $g(\mathbf{x}) \geq f(\mathbf{x}) - f^*$ .

$$g(\mathbf{x}) = \langle \nabla f(\mathbf{x}), \mathbf{x} - \mathbf{s} \rangle \geq \langle \nabla f(\mathbf{x}), \mathbf{x} - \mathbf{x}^* \rangle \geq f(\mathbf{x}) - f^*. \quad \square$$

o **Descent lemma:**  $f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \gamma_t g(\mathbf{x}_t) + \gamma_t^2 \frac{L}{2} \|\mathbf{s}_t - \mathbf{x}_t\|^2$ .

o **Convergence** ( $L$ -smooth, convex,  $X$  is compact,  $\gamma_t = \frac{2}{t+2}$ ):

$$f(\mathbf{x}_T) - f^* \leq \frac{4C}{T+1}, \quad C = \frac{L}{2} \text{diam}(X)^2.$$

$$\text{Lemma} - f^* \Rightarrow \text{Use } g(\mathbf{x}) \geq f(\mathbf{x}) - f^* \Rightarrow \text{Rearrange and induction.} \quad \square$$

o **Affine equivalence:**  $(f, X)$  and  $(f', X')$  are affinely equivalent if  $f'(\mathbf{x}) = f(A\mathbf{x} + \mathbf{b})$  and  $X' = \{A^{-1}(\mathbf{x} - \mathbf{b}) \mid \mathbf{x} \in X\}$ . Then,

$$\nabla f'(\mathbf{x}') = A^\top \nabla f(\mathbf{x}), \quad \mathbf{x}' = A^{-1}(\mathbf{x} - \mathbf{b})$$

$$\text{LMO}_{X'}(\nabla f'(\mathbf{x}')) = A^{-1}(\mathbf{s} - \mathbf{b}), \quad \mathbf{s} = \text{LMO}_X(\nabla f(\mathbf{x})).$$

o **Curvature constant:**

$$C_{(f,X)} := \sup_{\substack{\mathbf{x}, \mathbf{s} \in X, \gamma \in (0,1) \\ \mathbf{y} = (1-\gamma)\mathbf{x} + \gamma\mathbf{s}}} \frac{1}{\gamma^2} (f(\mathbf{y}) - f(\mathbf{x}) - \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle).$$

o **Affine invariant convergence** (same ass.):  $f(\mathbf{x}_T) - f^* \leq \frac{4C_{(f,X)}}{T+1}$ .

$$\text{Descent lemma w.r.t. } C_{(f,X)} \text{ by setting } \mathbf{x} = \mathbf{x}_t, \mathbf{s} = \text{LMO}_X(\nabla f(\mathbf{x}_t)), \gamma = \gamma_t, \mathbf{y} = \mathbf{x}_{t+1} \text{ in the supremum. Proof follows in the same way.} \quad \square$$

o **Convergence of  $g(\mathbf{x}_t)$ :**  $\min_{1 \leq t \leq T} g(\mathbf{x}_t) \leq \frac{27/2 \cdot C_{(f,X)}}{T+1}$ .

### Newton's method

o **Update rule:**  $\mathbf{x}_{t+1} = \mathbf{x}_t - \nabla^2 f(\mathbf{x}_t)^{-1} \nabla f(\mathbf{x}_t)$ .

o **Interp:** (1) Adaptive gradient descent, (2) Min. 2nd-order Taylor approx. at  $\mathbf{x}_t$ :

$$\mathbf{x}_{t+1} \in \arg\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}_t) + \nabla f(\mathbf{x}_t)^\top (\mathbf{x} - \mathbf{x}_t) + \frac{1}{2} (\mathbf{x} - \mathbf{x}_t)^\top \nabla^2 f(\mathbf{x}_t) (\mathbf{x} - \mathbf{x}_t).$$

o **Convergence** ( $\|\nabla^2 f(\mathbf{x})^{-1}\| \leq \frac{1}{\mu}$ ,  $\|\nabla^2 f(\mathbf{x}) - \nabla^2 f(\mathbf{y})\| \leq B\|\mathbf{x} - \mathbf{y}\|$ ):

$$\|\mathbf{x}_{t+1} - \mathbf{x}^*\| \leq \frac{B}{2\mu} \|\mathbf{x}_t - \mathbf{x}^*\|^2.$$

$$\mathbf{x}_{t+1} - \mathbf{x}^* \leq \mathbf{x}_t - \mathbf{x}^* + H(\mathbf{x}_t)^{-1} (\nabla f(\mathbf{x}^*) - \nabla f(\mathbf{x}_t)) \Rightarrow h(t) := \nabla f(\mathbf{x} + t(\mathbf{x}^* - \mathbf{x})) \text{ with fundamental theorem of calculus} \Rightarrow \text{Take norm of both sides and simplify using } \|A\mathbf{x}\| = \|A\|_2 \|\mathbf{x}\| \text{ and assumptions.} \quad \square$$

o Ensure bounded inverse Hessians by requiring strong convexity over  $X$ .

o If  $\|\mathbf{x}_0 - \mathbf{x}^*\| \leq \frac{\mu}{B}$ , then  $\|\mathbf{x}_T - \mathbf{x}^*\| \leq \frac{\mu}{B} \left(\frac{1}{2}\right)^{2T-1}$ .

### Quasi-Newton methods

o Time complexity of Hessian is  $\mathcal{O}(d^3) \Rightarrow$  Approximate by  $H_t$ .

o **Secant condition:**  $\nabla f(\mathbf{x}_t) - \nabla f(\mathbf{x}_{t-1}) = H_t(\mathbf{x}_t - \mathbf{x}_{t-1})$ .

o **Idea:** We wanted Hessian to fluctuate little in regions of fast convergence  $\Rightarrow$  Update  $H_t^{-1} = H_{t-1}^{-1} + E_t$  while minimizing  $\|AEA^\top\|_F^2$  for some invertible  $A$ .

o  $H := H_{t-1}^{-1}$ ,  $H' := H_t^{-1}$ ,  $E := E_t$ ,  $\boldsymbol{\sigma} := \mathbf{x}_t - \mathbf{x}_{t-1}$ ,  $\mathbf{y} := \nabla f(\mathbf{x}_t) - \nabla f(\mathbf{x}_{t-1})$ ,  $\mathbf{r} := \boldsymbol{\sigma} - H\mathbf{y}$ . Convex program:

$$\begin{aligned} &\text{minimize} && \frac{1}{2} \|AEA^\top\|_F^2 \\ &\text{subject to} && E\mathbf{y} = \mathbf{r} \quad (\text{secant condition}) \end{aligned}$$

$$E^\top - E = 0. \quad (\text{symmetry})$$

o **Greenstadt method** ( $\mathcal{O}(d^2)$ ): Solving (with Lagrange multipliers) yields

$$E^* = \frac{1}{\mathbf{y}^\top M \mathbf{y}} \left( \boldsymbol{\sigma} \mathbf{y}^\top M + M \mathbf{y} \boldsymbol{\sigma}^\top - H \mathbf{y} \mathbf{y}^\top M - M \mathbf{y} \mathbf{y}^\top H \right. \\ \left. - \frac{1}{\mathbf{y}^\top M \mathbf{y}} \left( \mathbf{y}^\top \boldsymbol{\sigma} - \mathbf{y}^\top H \mathbf{y} \right) M \mathbf{y} \mathbf{y}^\top M \right)$$

for some matrix parameter  $M$  (induced by  $A$ ).

o **BFGS:** Set  $M = H'$ :  $E^* = \frac{1}{\mathbf{y}^\top \boldsymbol{\sigma}} \left( -H \mathbf{y} \boldsymbol{\sigma}^\top - \boldsymbol{\sigma} \mathbf{y}^\top H + \left(1 + \frac{\mathbf{y}^\top H \mathbf{y}}{\mathbf{y}^\top \boldsymbol{\sigma}}\right) \boldsymbol{\sigma} \boldsymbol{\sigma}^\top \right)$ .

$$\text{Equivalent update: } H' = \left( I - \frac{\boldsymbol{\sigma} \mathbf{y}^\top}{\mathbf{y}^\top \boldsymbol{\sigma}} \right) H \left( I - \frac{\mathbf{y} \boldsymbol{\sigma}^\top}{\mathbf{y}^\top \boldsymbol{\sigma}} \right) + \frac{\boldsymbol{\sigma} \boldsymbol{\sigma}^\top}{\mathbf{y}^\top \boldsymbol{\sigma}}.$$

o **L-BFGS** ( $\mathcal{O}(md)$ ): Recursive BFGS and only go down  $m$  steps.

### Subgradient method

o Until now, we have only considered smooth (and hence differentiable) functions  $\Rightarrow$  Generalize notion of gradient.

o **Update rule:**  $\mathbf{x}_{t+1} = \Pi_X(\mathbf{x}_t - \gamma_t \mathbf{g}_t)$ ,  $\mathbf{g}_t \in \partial f(\mathbf{x}_t)$ .

o **Lemma** (convex):  $\|\mathbf{x}_{t+1} - \mathbf{x}^*\|^2 \leq \|\mathbf{x}_t - \mathbf{x}^*\|^2 - 2\gamma_t(f(\mathbf{x}_t) - f^*) + \gamma_t^2 \|\mathbf{g}_t\|^2$ .

$$\text{Norm of update rule} - \mathbf{x}^* \Rightarrow \Pi_X \text{ is non-expansive} \Rightarrow \text{Cosine theorem} \Rightarrow \text{Subgradient definition on } (\mathbf{x}^*, \mathbf{x}_t) \text{ (exists because of convexity).} \quad \square$$

o (convex):  $\min_{1 \leq t \leq T} f(\mathbf{x}_t) - f^* \leq \frac{\|\mathbf{x}_1 - \mathbf{x}^*\|^2 + \sum_{t=1}^T \gamma_t^2 \|\mathbf{g}_t\|^2}{2 \sum_{t=1}^T \gamma_t}$ .

$$\text{Rearrange "descent" lemma} \Rightarrow \text{Sum and divide by } \sum_{t=1}^T \gamma_t. \quad \square$$

o ( $\mu$ -SC,  $B$ -Lipschitz,  $\gamma_t := \frac{2}{\mu(t+1)}$ ):  $\min_{1 \leq t \leq T} f(\mathbf{x}_t) - f^* \leq \frac{2B^2}{\mu(T+1)}$ .

$$\text{Adapt "descent" lemma with } \mu\text{-SC} \Rightarrow \text{Def. of } \gamma_t \text{ and } \|\mathbf{g}_t\| \leq B. \quad \square$$

### Mirror descent

o Exploit non-Euclidean geometry of convex set  $X$ .

o **Bregman divergence:** Let  $\omega : \Omega \rightarrow \mathbb{R}$  be continuously differentiable on  $\Omega$  and 1-SC w.r.t. some norm  $\|\cdot\|$ . Then,

$$V_\omega(\mathbf{x}, \mathbf{y}) := \omega(\mathbf{x}) - \omega(\mathbf{y}) - \langle \nabla \omega(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle.$$

o **Properties:**  $V_\omega(\mathbf{x}, \mathbf{y}) \geq 0$ ;  $V_\omega(\mathbf{x}, \mathbf{y})$  is convex in  $\mathbf{x}$ ;  $V_\omega(\mathbf{x}, \mathbf{y}) = 0$  iff  $\mathbf{x} = \mathbf{y}$ ;  $V_\omega(\mathbf{x}, \mathbf{y}) \geq \frac{1}{2} \|\mathbf{x} - \mathbf{y}\|^2$ ; and  $\nabla_{\mathbf{x}} V_\omega(\mathbf{x}, \mathbf{y}) = \nabla \omega(\mathbf{x}) - \nabla \omega(\mathbf{y})$ .

o **3-point id.:**  $V_\omega(\mathbf{x}, \mathbf{z}) = V_\omega(\mathbf{x}, \mathbf{y}) + V_\omega(\mathbf{y}, \mathbf{z}) - \langle \nabla \omega(\mathbf{z}) - \nabla \omega(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle$ .

o **Update rule:**  $\mathbf{x}_{t+1} \in \arg\min_{\mathbf{x} \in X} V_\omega(\mathbf{x}, \mathbf{x}_t) + \langle \gamma_t \mathbf{g}_t, \mathbf{x} \rangle, \mathbf{g}_t \in \partial f(\mathbf{x}_t)$ . This is a generalization of subgradient descent.

o **Lemma:**  $\gamma_t(f(\mathbf{x}_t) - f^*) \leq V_\omega(\mathbf{x}^*, \mathbf{x}_t) - V_\omega(\mathbf{x}^*, \mathbf{x}_{t+1}) + \frac{\gamma_t^2}{2} \|\mathbf{g}_t\|_*^2$ .

$$\text{Rearrange update rule constrained optimality condition} \Rightarrow 3\text{PI} \Rightarrow \\ -V_\omega(\mathbf{x}_{t+1}, \mathbf{x}_t) \leq -\frac{1}{2} \|\mathbf{x}_t - \mathbf{x}_{t+1}\|^2 \Rightarrow [\text{Subgradient on } (\mathbf{x}^*, \mathbf{x}_t)] \cdot \gamma_t \\ (\pm \mathbf{x}_{t+1} \text{ in inner product) and bound with prev.} \Rightarrow \text{Young's inequality:} \\ \langle \gamma_t \mathbf{g}_t, \mathbf{x}_t - \mathbf{x}_{t+1} \rangle \leq \frac{1}{2} \|\mathbf{x}_t - \mathbf{x}_{t+1}\|^2 + \frac{1}{2} \|\gamma_t \mathbf{g}_t\|_*^2. \quad \square$$

o (Convex):  $\min_{1 \leq t \leq T} f(\mathbf{x}_t) - f^* \leq \frac{V_\omega(\mathbf{x}^*, \mathbf{x}_0) + \frac{1}{2} \sum_{t=1}^T \gamma_t^2 \|\mathbf{g}_t\|_*^2}{\sum_{t=1}^T \gamma_t}$ .

$$\text{Easily follows from above lemma by summing, dividing by summed } \gamma_t, \text{ and telescoping sum.} \quad \square$$

### Smoothing

o **Nesterov smoothing:**  $f_\mu(\mathbf{x}) := \max_{\mathbf{y} \in \text{dom}(f^*)} \langle \mathbf{x}, \mathbf{y} \rangle - f^*(\mathbf{y}) - \mu \cdot d(\mathbf{y})$ , where  $d$  is 1-SC and non-negative (proximity function).

o  $f_\mu$  is  $1/\mu$ -smooth and approximates  $f$  by  $f(\mathbf{x}) - \mu D^2 \leq f_\mu(\mathbf{x}) \leq f(\mathbf{x})$ ,  $D^2 := \max_{\mathbf{y} \in \text{dom}(f^*)} d(\mathbf{y})$ .

o Applying GD to  $f_\mu$  converges faster than subgradient descent.

o **Moreau-Yosida smoothing:**  $f_\mu(\mathbf{x}) := \min_{\mathbf{y} \in \text{dom}(f^*)} f(\mathbf{y}) - \frac{1}{2\mu} \|\mathbf{x} - \mathbf{y}\|_*^2$ .

o  $f_\mu$  is  $1/\mu$ -smooth and minimizes exactly:  $\arg\min_{\mathbf{x} \in X} f(\mathbf{x}) = \arg\min_{\mathbf{x} \in X} f_\mu(\mathbf{x})$ .

o  $\nabla f_\mu(\mathbf{x}) = \frac{1}{\mu}(\mathbf{x} - \text{prox}_{\mu f}(\mathbf{x}))$  (found by Danshkin's theorem).

### Proximal algorithms

o **Proximal operator:**  $\text{prox}_{\mu f}(\mathbf{x}) := \arg\min_{\mathbf{y} \in \text{dom}(f)} f(\mathbf{y}) + \frac{1}{2\mu} \|\mathbf{x} - \mathbf{y}\|^2$ .

o **Minimizer:**  $\mathbf{x}^* = \text{prox}_{\mu f}(\mathbf{x}^*)$ ,  $\forall \mu$ .

o **Non-expansiveness:**  $\|\text{prox}_{\mu f}(\mathbf{x}) - \text{prox}_{\mu f}(\mathbf{y})\| \leq \|\mathbf{x} - \mathbf{y}\|$ ,  $\forall \mathbf{x}, \mathbf{y}$ .

o **Proximal point algorithm:** Apply gradient descent to Moreau-Yosida  $f_\mu$ :  $\mathbf{x}_{t+1} = \text{prox}_{\lambda_t f}(\mathbf{x}_t)$ .

o (Convex):  $f(\mathbf{x}_{T+1}) - f^* \leq \frac{\|\mathbf{x}_1 - \mathbf{x}^*\|^2}{2 \sum_{t=1}^T \lambda_t}$

$$\text{Subgradient optimality: } -\frac{\mathbf{x}_{t+1} - \mathbf{x}_t}{\lambda_t} \in \partial f(\mathbf{x}_{t+1}) \Rightarrow \text{Subgradient exists because of convexity} \Rightarrow \text{Subgradient definition} \Rightarrow \text{Cosine theorem} \Rightarrow \text{Sum over timesteps and use that it is a descent method.} \quad \square$$

o **Proximal gradient method:** Consider  $F(\mathbf{x}) := f(\mathbf{x}) + g(\mathbf{x})$  with differentiable  $f$  (both are convex):  $\mathbf{x}_{t+1} = \text{prox}_{\gamma_t g}(\mathbf{x}_t - \gamma_t \nabla f(\mathbf{x}_t))$ .

o  $(f \text{ is } L\text{-smooth}, \gamma_t := \frac{1}{L}): F(\mathbf{x}_{T+1}) - F^* \leq \frac{L\|\mathbf{x}_1 - \mathbf{x}^*\|^2}{2T}.$

Subgradient optimality:  $\frac{1}{\gamma_t}(\mathbf{x}_t - \mathbf{x}_{t+1} - \gamma_t \nabla f(\mathbf{x}_t)) \in \partial g(\mathbf{x}_{t+1}) \Rightarrow$  Subgradient exists because of convexity  $\Rightarrow$  Subgradient definition  $\Rightarrow$  Cosine theorem  $\Rightarrow -\langle \nabla f(\mathbf{x}_t), \mathbf{x}_{t+1} - \mathbf{x} \rangle = -\langle \nabla f(\mathbf{x}_t), \mathbf{x}_{t+1} - \mathbf{x}_t \rangle - \langle \nabla f(\mathbf{x}_{t+1}), \mathbf{x}_t - \mathbf{x} \rangle \Rightarrow$  Smoothness, convexity, and definition of  $\gamma_t$ .  $\square$

### Stochastic optimization

- o **Optimization problem:**  $\min_{\mathbf{x} \in \mathbb{R}^d} F(\mathbf{x}) := \mathbb{E}_{\xi}[f(\mathbf{x}, \xi)]$ .
- o **Unbiased gradient:**  $\mathbb{E}_{\xi}[\nabla f(\mathbf{x}, \xi) \mid \mathbf{x}] = \nabla F(\mathbf{x})$  (typical assumption).
- o **Update rule:**  $\xi_t \sim P, \mathbf{x}_{t+1} = \mathbf{x}_t - \gamma_t \nabla f(\mathbf{x}_t, \xi_t)$ .
- o **Bounded variance:**  $\mathbb{E}[\|\nabla f(\mathbf{x}_t, \xi_t) - \nabla F(\mathbf{x})\|^2] \leq \sigma^2$ .
- o  $(L\text{-smooth}, \text{bounded variance, random output}, \gamma := \min\{\frac{1}{L}, \frac{\gamma_0}{\sigma\sqrt{T}}\})$ :  

$$\mathbb{E}[\|\nabla F(\hat{\mathbf{x}}_T)\|^2] \leq \frac{\sigma}{\sqrt{T}} \left( \frac{2(F(\mathbf{x}_1) - F^*)}{\gamma_0} + L\gamma_0 \right) + \frac{2L(F(\mathbf{x}_1) - F^*)}{T}, \text{ where } \hat{\mathbf{x}}_T \sim \text{Unif}(\{\mathbf{x}_1, \dots, \mathbf{x}_T\}).$$

Smoothness of  $F$  on  $(\mathbf{x}_{t+1}, \mathbf{x}_t)$  in  $\mathbb{E} \Rightarrow$  Update rule:  $\mathbf{x}_{t+1} - \mathbf{x}_t = -\gamma_t \nabla f(\mathbf{x}_t, \xi_t) \Rightarrow \mathbb{E}[X^2] + \mathbb{E}[X]^2 + \text{Var}[X]: \mathbb{E}[\|\nabla f(\mathbf{x}_t, \xi_t)\|^2] = \|\nabla F(\mathbf{x}_t)\|^2 + \mathbb{E}[\|\nabla f(\mathbf{x}_t, \xi_t) - \nabla F(\mathbf{x}_t)\|^2] \leq \|\nabla F(\mathbf{x}_t)\|^2 + \sigma^2 \Rightarrow \gamma_t \leq \frac{1}{L} \Rightarrow$  Rearrange  $\Rightarrow$  Use definition of  $\hat{\mathbf{x}}_T \Rightarrow$  Telescoping sum  $\Rightarrow$  Definition of  $\gamma_t \Rightarrow \max\{a, b\} \leq a + b$  if  $a, b \geq 0$ .  $\square$

- o  $(L\text{-smooth}, \mathbb{E}[\|\nabla f(\mathbf{x}, \xi)\|^2] \leq B^2)$ :  

$$\mathbb{E}[F(\hat{\mathbf{x}}_T) - F^*] \leq \frac{R^2 + B^2 \sum_{t=1}^T \gamma_t^2}{2 \sum_{t=1}^T \gamma_t}, \text{ where } \hat{\mathbf{x}}_T := \frac{\sum_{t=1}^T \gamma_t \mathbf{x}_t}{\sum_{t=1}^T \gamma_t} \text{ and } \|\mathbf{x}_1 - \mathbf{x}^*\| \leq R.$$

Squared norm of update rule  $-\mathbf{x}^* \Rightarrow$  Cosine theorem  $\Rightarrow$  Law of total exp. to bound inner product  $\Rightarrow$  Convexity of  $F \Rightarrow$  Telescoping sum  $\Rightarrow$  Jensen's ineq.  $\square$

- o  $(\mu\text{-SC}, \mathbb{E}[\|\nabla f(\mathbf{x}, \xi)\|^2] \leq B^2, \gamma_t := \frac{\gamma}{t}, \gamma > \frac{1}{2\mu})$   

$$\mathbb{E}[\|\mathbf{x}_T - \mathbf{x}^*\|^2] \leq \frac{\max\{\frac{\gamma^2 B^2}{2\mu\gamma-1}, \|\mathbf{x}_1 - \mathbf{x}^*\|^2\}}{T}.$$

Squared norm of update rule  $-\mathbf{x}^* \Rightarrow$  Cosine theorem  $\Rightarrow \mu\text{-SC}$  to get  $\mathbb{E}[\langle \nabla f(\mathbf{x}_t, \xi_t), \mathbf{x}_t - \mathbf{x}^* \rangle] \geq \mu \cdot \mathbb{E}[\|\mathbf{x}_t - \mathbf{x}^*\|^2] \Rightarrow$  Recursion.  $\square$

- o **Adaptive method:**  $\mathbf{g}_t = \nabla f(\mathbf{x}_t, \xi_t), \mathbf{m}_t = \phi_t(\mathbf{g}_1, \dots, \mathbf{g}_t), V_t = \psi_t(\mathbf{g}_1, \dots, \mathbf{g}_t), \hat{\mathbf{x}}_t = \mathbf{x}_t - \alpha_t V_t^{-1/2} \mathbf{m}_t, \mathbf{x}_{t+1} = \text{argmin}_{\mathbf{x} \in X} \left\{ (\mathbf{x} - \hat{\mathbf{x}}_t)^\top V_t^{-1/2} (\mathbf{x} - \hat{\mathbf{x}}_t) \right\}$ .
- o **SGD:**  $\mathbf{m}_t = \mathbf{g}_t, V_t = I$ .
- o **AdaGrad:**  $\mathbf{m}_t = \mathbf{g}_t, V_t = \frac{\text{diag}(\sum_{\tau=1}^t \mathbf{g}_\tau^2)}{t}$ .
- o **Adam:**  $\mathbf{m}_t = (1 - \alpha) \sum_{\tau=1}^t \alpha^{t-\tau} \mathbf{g}_\tau, V_t = (1 - \beta) \text{diag}(\sum_{\tau=1}^t \beta^{t-\tau} \mathbf{g}_\tau^2)$ .  
Recursively:  $\mathbf{m}_t = \alpha \mathbf{m}_{t-1} + (1 - \alpha) \mathbf{g}_t, V_t = \beta V_{t-1} + (1 - \beta) \text{diag}(\mathbf{g}_t^2)$ .

### Variance reduction

- o SGD requires more iterations due to high variance  $\Rightarrow$  Reduce variance.
- o **Finite-sum optimization:**  $\min_{\mathbf{x} \in \mathbb{R}^d} F(\mathbf{x}) := \frac{1}{n} \sum_{i=1}^n f_i(\mathbf{x})$ .
- o If we want to estimate  $\theta = \mathbb{E}[X]$ , we can also estimate  $\theta$  as  $\mathbb{E}[X - Y]$  if and only if  $\mathbb{E}[Y] = 0$ . Furthermore,  $\text{Var}[X - Y] \leq \text{Var}[X]$  if  $Y$  is highly positively correlated with  $X$ . Specifically, if  $\text{Cov}(X, Y) > \frac{1}{2} \text{Var}[Y]$ , the variance will be reduced.
- o Let  $\alpha \in [0, 1]$ , we estimate  $\theta$  by  $\hat{\theta}_\alpha = \alpha(X - Y) + \mathbb{E}[Y]$ . We then have  

$$\mathbb{E}[\hat{\theta}_\alpha] = \alpha \mathbb{E}[X] + (1 - \alpha) \mathbb{E}[Y]$$

$$\text{Var}[\hat{\theta}_\alpha] = \alpha^2 (\text{Var}[X] + \text{Var}[Y] - 2 \cdot \text{Cov}(X, Y)).$$
Implication: Trade-off between bias and variance, where  $\alpha = 1$  makes the estimator unbiased, but the variance decreases when  $\alpha$  decreases.
- o SGD estimates  $\nabla F(\mathbf{x}_t)$  by  $\nabla f_{i_t}(\mathbf{x}_t)$ , but VR estimates the full gradient by  

$$\mathbf{g}_t := \alpha (\nabla f_{i_t}(\mathbf{x}_t) - Y) + \mathbb{E}[Y],$$
such that  $\mathbf{g}_t$  satisfies the **VR property**:  $\lim_{t \rightarrow \infty} \mathbb{E}[\|\mathbf{g}_t - \nabla F(\mathbf{x}_t)\|^2] = 0$ .
- o **Key idea:** If  $\mathbf{x}_t$  is not too far away from previous iterates  $\mathbf{x}_{1:t-1}$ , we can leverage previous gradient information to construct positively correlated control variates  $Y$ .
  - o **Stochastic Average Gradient (SAG):** Keep track of the latest gradients  $\mathbf{v}_i^t$  for all points  $i \in [n]: \mathcal{O}(nd)$  storage requirement. Estimate full gradient by average of these:  $\mathbf{g}_t = \frac{1}{n} \sum_{i=1}^n \mathbf{v}_i^t$ . Each iteration we update  $\mathbf{v}_i^t$  by  

$$\mathbf{v}_i^t = \begin{cases} \nabla f_{i_t}(\mathbf{x}_t) & i = i_t \\ \mathbf{v}_{i_t-1}^t & i \neq i_t. \end{cases}$$
Thus, we have  $\alpha = \frac{1}{n}, Y = \mathbf{v}_{i_t}^{t-1}$ , and  $\mathbb{E}[Y] = \mathbf{g}_{t-1}$ ,  

$$\mathbf{g}_t = \frac{1}{n} \left( \nabla f_{i_t}(\mathbf{x}_t) - \mathbf{v}_{i_t}^{t-1} \right) + \mathbf{g}_{t-1}.$$
Problem: (1)  $\mathcal{O}(nd)$  storage, (2) biased  $\alpha \neq 1$ . Advantage:  $\mathcal{O}((n + \kappa_{\max} \log \frac{1}{\epsilon}))$  iteration complexity, where  $\kappa_{\max} = \max_{i \in [n]} \frac{L_i}{\mu}$ .
  - o **SAGA:** Unbiased version of SAG, because it sets  $\alpha = 1$ :  $\mathbf{g}_t = \nabla f_{i_t}(\mathbf{x}_t) - \mathbf{v}_{i_t}^{t-1} + \mathbf{g}_{t-1}$ . But, it still enjoys the same benefits.
  - o **Stochastic variance reduced gradient (SVRG):** Build covariates based on a fixed reference point  $\bar{\mathbf{x}}$  that is periodically updated every  $m$ -th iteration:  

$$\mathbf{g}_t = \nabla f_{i_t}(\mathbf{x}_t) - \nabla f_{i_t}(\bar{\mathbf{x}}) + \nabla F(\bar{\mathbf{x}}).$$
Problems: (1)  $\mathcal{O}(n + 2m)$  gradient evaluations per epoch, (2) More hyperparameters. Advantages: (1) Unbiased, (2)  $\mathcal{O}(d)$  memory cost, (3) Same iteration complexity as SAG(A).

### Min-max optimization

- o **Optimization problem:**  $\min_{\mathbf{x} \in X} \max_{\mathbf{y} \in Y} \phi(\mathbf{x}, \mathbf{y})$ .
- o **Saddle point:**  $(\mathbf{x}^*, \mathbf{y}^*)$  is a saddle point if  

$$\phi(\mathbf{x}^*, \mathbf{y}) \leq \phi(\mathbf{x}^*, \mathbf{y}^*) \leq \phi(\mathbf{x}, \mathbf{y}^*), \quad \forall \mathbf{x} \in X, \mathbf{y} \in Y.$$
Interpretation: No player has the incentive to make a unilateral change, because it can only get worse. Game theory: Nash equilibrium.
- o **Global minimax point:**  $(\mathbf{x}^*, \mathbf{y}^*)$  is a global minimax point if  

$$\phi(\mathbf{x}^*, \mathbf{y}) \leq \phi(\mathbf{x}^*, \mathbf{y}^*) \leq \max_{\mathbf{y}' \in Y} \phi(\mathbf{x}, \mathbf{y}'), \quad \forall \mathbf{x} \in X, \mathbf{y} \in Y.$$
Interpretation:  $\mathbf{x}^*$  is the best response to the best response. Game theory: Stackelberg equilibrium.
- o  $\max_{\mathbf{y} \in Y} \min_{\mathbf{x} \in X} \phi(\mathbf{x}, \mathbf{y}) \leq \min_{\mathbf{x} \in X} \max_{\mathbf{y} \in Y} \phi(\mathbf{x}, \mathbf{y})$ .
- o **Saddle point lemma:**  $(\mathbf{x}^*, \mathbf{y}^*)$  is a saddle point iff  $\max_{\mathbf{y} \in Y} \min_{\mathbf{x} \in X} \phi(\mathbf{x}, \mathbf{y}) = \min_{\mathbf{x} \in X} \max_{\mathbf{y} \in Y} \phi(\mathbf{x}, \mathbf{y})$  and  $(\mathbf{x}^*, \mathbf{y}^*)$  are the arguments.
- o **Minimax theorem:** If  $X$  and  $Y$  are closed convex sets, one of them is bounded, and  $\phi$  is a continuous C-C function, then there exists a saddle point in  $X \times Y$ .
- o **Duality gap:**  $\hat{\epsilon}(\mathbf{x}, \mathbf{y}) := \max_{\mathbf{y}' \in Y} \phi(\mathbf{x}, \mathbf{y}') - \min_{\mathbf{x}' \in X} \phi(\mathbf{x}', \mathbf{y}) \geq 0$ .
- o **Saddle point by duality gap:** If  $\hat{\epsilon}(\mathbf{x}, \mathbf{y}) = 0$ , then  $(\mathbf{x}, \mathbf{y})$  is a saddle point and if  $\hat{\epsilon}(\mathbf{x}, \mathbf{y}) \leq \epsilon$ , then  $(\mathbf{x}, \mathbf{y})$  is an  $\epsilon$ -saddle point.
- o **Gradient descent ascent (GDA):**  
 $\mathbf{x}_{t+1} = \Pi_X(\mathbf{x}_t - \gamma \nabla_{\mathbf{x}} \phi(\mathbf{x}_t, \mathbf{y}_t)), \quad \mathbf{y}_{t+1} = \Pi_Y(\mathbf{y}_t + \gamma \nabla_{\mathbf{y}} \phi(\mathbf{x}_t, \mathbf{y}_t)).$ 
Does not guarantee convergence in C-C setting (consider  $\phi(x, y) = xy$ ).

- o  $(L\text{-smooth}, \mu\text{-SC-SC}, \gamma := \frac{\mu}{4L^2})$ :  

$$\|\mathbf{x}_T - \mathbf{x}^*\|^2 + \|\mathbf{y}_T - \mathbf{y}^*\|^2 \leq \left(1 - \frac{\mu^2}{4L^2}\right)^T (\|\mathbf{x}_1 - \mathbf{x}^*\|^2 + \|\mathbf{y}_1 - \mathbf{y}^*\|^2).$$

Add  $\mu\text{-SC-SC}$  definitions together  $\Rightarrow$  Use  $L\text{-smoothness}$  for a bound  $\Rightarrow$  Use update rule in  $\|\mathbf{x}_{t+1} - \mathbf{x}^*\|^2 + \|\mathbf{y}_{t+1} - \mathbf{y}^*\|^2 \Rightarrow$  Non-expansiveness of projection  $\Rightarrow$  Rearrange  $\Rightarrow$  Cosine theorem  $\Rightarrow$  Bound inner products using SC-SC and smoothness.  $\square$

- o **Extragradient method (EG):**  

$$\mathbf{x}_{t+1/2} = \Pi_X(\mathbf{x}_t - \gamma \nabla_{\mathbf{x}} \phi(\mathbf{x}_t, \mathbf{y}_t))$$

$$\mathbf{y}_{t+1/2} = \Pi_Y(\mathbf{y}_t + \gamma \nabla_{\mathbf{y}} \phi(\mathbf{x}_t, \mathbf{y}_t))$$

$$\mathbf{x}_{t+1} = \Pi_X(\mathbf{x}_t - \gamma \nabla_{\mathbf{x}} \phi(\mathbf{x}_{t+1/2}, \mathbf{y}_{t+1/2}))$$

$$\mathbf{y}_{t+1} = \Pi_Y(\mathbf{y}_t + \gamma \nabla_{\mathbf{y}} \phi(\mathbf{x}_{t+1/2}, \mathbf{y}_{t+1/2})).$$
- o  $(L\text{-smooth}, \text{C-C}, \gamma \leq \frac{1}{2L})$ :  $\hat{\epsilon}(\bar{\mathbf{x}}, \bar{\mathbf{y}}) \leq \frac{D_X^2 + D_Y^2}{2\gamma T}$ , where  $\bar{\mathbf{x}} = \frac{1}{T} \sum_{t=1}^T \mathbf{x}_{t+1/2}, \bar{\mathbf{y}} = \frac{1}{T} \sum_{t=1}^T \mathbf{y}_{t+1/2}$ , and  $D_Z = \max_{\mathbf{z}, \mathbf{z}' \in Z} \|\mathbf{z} - \mathbf{z}'\|$ .
- o  $(L\text{-smooth}, \mu\text{-SC-SC}, \gamma := \frac{1}{8L})$ :  

$$\|\mathbf{x}_{t+1} - \mathbf{x}^*\|^2 + \|\mathbf{y}_{t+1} - \mathbf{y}^*\|^2 \leq \left(1 - \frac{\mu}{4L}\right) (\|\mathbf{x}_t - \mathbf{x}^*\|^2 + \|\mathbf{y}_t - \mathbf{y}^*\|^2).$$
- o **Optimistic gradient descent ascent (OGDA):**  

$$\mathbf{x}_{t+1/2} = \Pi_X(\mathbf{x}_t - \gamma \nabla_{\mathbf{x}} \phi(\mathbf{x}_{t-1/2}, \mathbf{y}_{t-1/2}))$$

$$\mathbf{y}_{t+1/2} = \Pi_Y(\mathbf{y}_t + \gamma \nabla_{\mathbf{y}} \phi(\mathbf{x}_{t-1/2}, \mathbf{y}_{t-1/2}))$$

$$\mathbf{x}_{t+1} = \Pi_X(\mathbf{x}_t - \gamma \nabla_{\mathbf{x}} \phi(\mathbf{x}_{t+1/2}, \mathbf{y}_{t+1/2}))$$

$$\mathbf{y}_{t+1} = \Pi_Y(\mathbf{y}_t + \gamma \nabla_{\mathbf{y}} \phi(\mathbf{x}_{t+1/2}, \mathbf{y}_{t+1/2})).$$
- o In the case  $X = Y = \mathbb{R}^d$ , this can be seen as negative momentum:  

$$\mathbf{x}_{t+1} = \mathbf{x}_t - 2\gamma \nabla_{\mathbf{x}} \phi(\mathbf{x}_t, \mathbf{y}_t) + \gamma \nabla_{\mathbf{x}} \phi(\mathbf{x}_{t-1}, \mathbf{y}_{t-1})$$

$$\mathbf{y}_{t+1} = \mathbf{y}_t + 2\gamma \nabla_{\mathbf{y}} \phi(\mathbf{x}_t, \mathbf{y}_t) - \gamma \nabla_{\mathbf{y}} \phi(\mathbf{x}_{t-1}, \mathbf{y}_{t-1}).$$

- o **Proximal point algorithm:**  

$$(\mathbf{x}_{t+1}, \mathbf{y}_{t+1}) \in \underset{\mathbf{x} \in X}{\text{argmin}} \underset{\mathbf{y} \in Y}{\text{argmax}} \phi(\mathbf{x}, \mathbf{y}) + \frac{1}{2\gamma} \|\mathbf{x} - \mathbf{x}_t\|^2 - \frac{1}{2\gamma} \|\mathbf{y} - \mathbf{y}_t\|^2.$$

### Variational inequalities

- o Generalizes all of the above to mapping  $F: \mathcal{Z} \rightarrow \mathbb{R}^d$ . Goal: Find  $\mathbf{z}^* \in \mathcal{Z}$ , such that  $\langle F(\mathbf{z}^*), \mathbf{z} - \mathbf{z}^* \rangle \geq 0, \forall \mathbf{z} \in \mathcal{Z}$ .
- o **Monotone operator:**  $\langle F(\mathbf{x}) - F(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq 0$ .
- o  $\mu$ -**strongly monotone:**  $\langle F(\mathbf{x}) - F(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq \mu \|\mathbf{x} - \mathbf{y}\|^2$ .
- o **VI strong solution (Stampacchia):**  $\langle F(\mathbf{z}^*), \mathbf{z} - \mathbf{z}^* \rangle \geq 0, \forall \mathbf{z} \in \mathcal{Z}$ .
- o **VI weak solution (Minty):**  $\langle F(\mathbf{z}), \mathbf{z} - \mathbf{z}^* \rangle \geq 0, \forall \mathbf{z} \in \mathcal{Z}$ .
- o If  $F$  is monotone, then strong  $\Rightarrow$  weak. If  $F$  is continuous, then weak  $\Rightarrow$  strong.
- o Convex minimization can be cast as VI problem by defining  $F = \nabla f$  for a convex function. Min-max problems can be cast as VI problem by defining  $F = [\nabla_{\mathbf{x}} \phi, -\nabla_{\mathbf{y}} \phi]$  for a convex-concave  $\phi$ .
- o **Extragradient method:**  

$$\mathbf{z}_{t+1/2} = \Pi_{\mathcal{Z}}(\mathbf{z}_t - \gamma_t F(\mathbf{z}_t))$$

$$\mathbf{z}_{t+1} = \Pi_{\mathcal{Z}}(\mathbf{z}_t - \gamma_t F(\mathbf{z}_{t+1/2})).$$
- o  $(L\text{-smooth}, \text{monotone}, \gamma := \frac{1}{\sqrt{2L}})$ :  

$$\max_{\mathbf{z} \in \mathcal{Z}} \langle F(\mathbf{z}), \bar{\mathbf{z}} - \mathbf{z} \rangle \leq \frac{\sqrt{2L} D_{\mathcal{Z}}^2}{T}, \text{ where } \bar{\mathbf{z}} = \frac{1}{T} \sum_{t=1}^T \mathbf{z}_{t+1/2}.$$

Optimality condition w.r.t.  $\mathbf{z}_{t+1/2} \Rightarrow$  Rewrite using cosine theorem  $\Rightarrow$  Optimality condition w.r.t.  $\mathbf{z}_{t+1}$  (set  $\mathbf{z} = \mathbf{z}_{t+1}$  in the other optimality condition)  $\Rightarrow$  Use previous and Cauchy-Schwarz to bound  $2\gamma \langle F(\mathbf{z}_{t+1/2}), \mathbf{z}_{t+1/2} - \mathbf{z} \rangle = 2\gamma \langle F(\mathbf{z}_{t+1/2}), \mathbf{z}_{t+1/2} - \mathbf{z}_{t+1} \rangle + 2\gamma \langle F(\mathbf{z}_{t+1/2}), \mathbf{z}_{t+1} - \mathbf{z} \rangle \Rightarrow$  Smoothness and  $\gamma = \frac{1}{L} \Rightarrow$  Young's inequality:  $\|\mathbf{x}\| \cdot \|\mathbf{y}\| \leq \frac{1}{2} \|\mathbf{x}\|^2 + \frac{1}{2} \|\mathbf{y}\|^2 \Rightarrow$  Use monotonicity and sum over all timesteps.  $\square$