

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

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

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

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

• 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 $f(\mathbf{x}^*) \leq f(\mathbf{y}), \forall \mathbf{y} : \|\mathbf{x}^* - \mathbf{y}\| \leq \epsilon$.

• $\nabla f(\mathbf{x}^*) = 0$.

• 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 α 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 γ^* that minimizes bound $q(\gamma)$, use 1st-order opt: $q(\gamma^*) \stackrel{!}{=} 0$.

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

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

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

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

| 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] State what needs to be shown exactly and mark by (\star) .

[2] State the assumptions of the question and their implications (think about which implications are relevant to the proof).

[3] Proof should follow easily: “Hence, (\star) holds and the proof is concluded.”.

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

• If γ_t is timestep-dependent, generally need to use induction.

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

$$\begin{aligned} \Rightarrow \mathbb{E}[\|\nabla f(\mathbf{x}_t, \boldsymbol{\xi}_t)\|^2] &= \|\nabla F(\mathbf{x}_t)\|^2 + \mathbb{E}[\|\nabla f(\mathbf{x}_t, \boldsymbol{\xi}_t) - \nabla F(\mathbf{x}_t)\|^2] \\ &\leq \|\nabla F(\mathbf{x}_t)\|^2 + \sigma^2. \end{aligned}$$

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

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

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

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

Sufficient decrease to bound gradients of VA with telescoping sum. \square

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

Use μ -SC to strengthen VA bound for squared norm \Rightarrow Upper bound “noise” with $f^* \leq f(\mathbf{x}_{t+1})$ and SD \Rightarrow Smoothness on $(\mathbf{x}^*, \mathbf{x}_T)$. \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 ℓ_1 -ball** can be done in $\mathcal{O}(d \log d)$.
- 1. $(\mathbf{x} \in X, \mathbf{y} \in \mathbb{R}^d)$: $\langle \mathbf{x} - \Pi_X(\mathbf{y}), \mathbf{y} - \Pi_X(\mathbf{y}) \rangle \leq 0$.

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

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

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

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

VA with additional term (\mathbf{y}_{t+1} instead of \mathbf{x}_{t+1} and use (2)) and bound gradients with projected SD. Additional terms cancel. \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:** $f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \frac{1}{2L_i} |\nabla_i f(\mathbf{x}_t)|^2$.

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

$$\mathbb{E}[f(\mathbf{x}_T) - f^*] \leq \left(1 - \frac{\mu}{dL}\right)^T (f(\mathbf{x}_0) - f^*).$$

CW SD $\Rightarrow \mathbb{E}_i[\cdot | \mathbf{x}_t] \Rightarrow$ Use sample prob. \Rightarrow PL $\Rightarrow \mathbb{E}_{\mathbf{x}_t}$ (LoTE). \square
 - (μ -PL, $i \sim \text{Cat}(L_1/\sum_{j=1}^d L_j, \dots, L_d/\sum_{j=1}^d L_j)$)

$$\mathbb{E}[f(\mathbf{x}_T) - f^*] \leq \left(1 - \frac{\mu}{dL}\right)^T (f(\mathbf{x}_0) - f^*).$$

Same as above with different probabilities. $\bar{L} := \frac{1}{d} \sum_{i=1}^d L_i$. \square
 - (L -smooth, μ_1 -SC w.r.t. $\ell_1 \Rightarrow \mu_1$ -PL w.r.t. $\ell_\infty, i \in \operatorname{argmax}_{j \in [d]} |\nabla_j f(\mathbf{x}_t)|$)

$$\begin{aligned} f(\mathbf{x}_T) - f^* &\leq \left(1 - \frac{\mu}{dL}\right)^T (f(\mathbf{x}_0) - f^*) \\ f(\mathbf{x}_T) - f^* &\leq \left(1 - \frac{\mu_1}{L}\right)^T (f(\mathbf{x}_0) - f^*). \end{aligned}$$

CW SD $\Rightarrow \ell_\infty$ because of update rule \Rightarrow PL. \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, $\gamma := \frac{1}{L}, \exists \mathbf{x}^*$): $\frac{1}{T} \sum_{t=0}^{T-1} \|\nabla f(\mathbf{x}_t)\|^2 \leq \frac{2L}{T} (f(\mathbf{x}_0) - f^*)$.

SD does not require convexity. Rewrite with telescoping sum. \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 δ 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 ℓ_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:** $\text{LMO}_X(\mathbf{G}) = \arg\min_{\substack{Z \text{ is PSD} \\ Z \in X}} \text{tr}(\mathbf{G}Z) = \mathbf{v}_1 \mathbf{v}_1^\top$, where \mathbf{v}_1 is the eigenvector associated with the smallest eigenvalue of \mathbf{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 (μ -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 Ω 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:** $\gamma_t(f(\mathbf{x}_t) - f^*) \leq V_\omega(\mathbf{x}^*, \mathbf{x}_t) - V_\omega(\mathbf{x}^*, \mathbf{x}_{t+1}) + \frac{\gamma_t^2}{2} \|\mathbf{g}_t\|_*^2$.

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

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_μ 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_μ converges faster than subgradient descent.

o **Moreau-Yosida smoothing:** $f_\mu(\mathbf{x}) := \min_{\mathbf{y} \in \text{dom}(f^*)} f(\mathbf{y}) - \frac{1}{2\mu} \|\mathbf{x} - \mathbf{y}\|_2^2$.

o f_μ 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_μ : $\mathbf{x}_{t+1} = \text{prox}_{\lambda_t f}(\mathbf{x}_t)$.

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 γ_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 θ 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 θ 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 α 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 ϕ 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 ϵ -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 $(L\text{-smooth}, \text{C-C}, \gamma \leq \frac{1}{2L})$: $\hat{\epsilon}(\bar{\mathbf{x}}, \bar{\mathbf{y}}) \leq \frac{D_X^2 + D_Y^2}{2\gamma}$, 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 μ -**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 ϕ .
- 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