

# Optimization for Machine Learning

## CS-439

### Lecture 3: Faster, and Projected Gradient Descent

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# Can we go even faster?

So far: Error decreases with  $1/\sqrt{T}$ , or  $1/T$ ...

Could it decrease exponentially in  $T$ ?

# Can we go even faster?

- ▶ On  $f(x) := x^2$ : Stepsize  $\gamma := \frac{1}{2}$  ( $f$  is  $L = 2$  - smooth)

$$x_{t+1} = x_t - \frac{1}{2} \nabla f(x_t) = x_t - x_t = 0,$$

- ▶ converged in one step!

- ▶ Same  $f(x) := x^2$ : Stepsize  $\gamma := \frac{1}{4}$  ( $f$  is  $L = 4$  - smooth)

$$x_{t+1} = x_t - \frac{1}{4} \nabla f(x_t) = x_t - \frac{x_t}{2} = \frac{x_t}{2},$$

so  $f(x_t) = f\left(\frac{x_0}{2^t}\right) = \frac{1}{2^{2t}} x_0^2$ .

- ▶ Exponential in  $t$  !

# Strongly convex functions

## “Not too flat”

### Definition

Let  $f : \mathbf{dom}(f) \rightarrow \mathbb{R}$  be a differentiable function,  $X \subseteq \mathbf{dom}(f)$  convex and  $\mu \in \mathbb{R}_+, \mu > 0$ . Function  $f$  is called **strongly convex** (with parameter  $\mu$ ) over  $X$  if

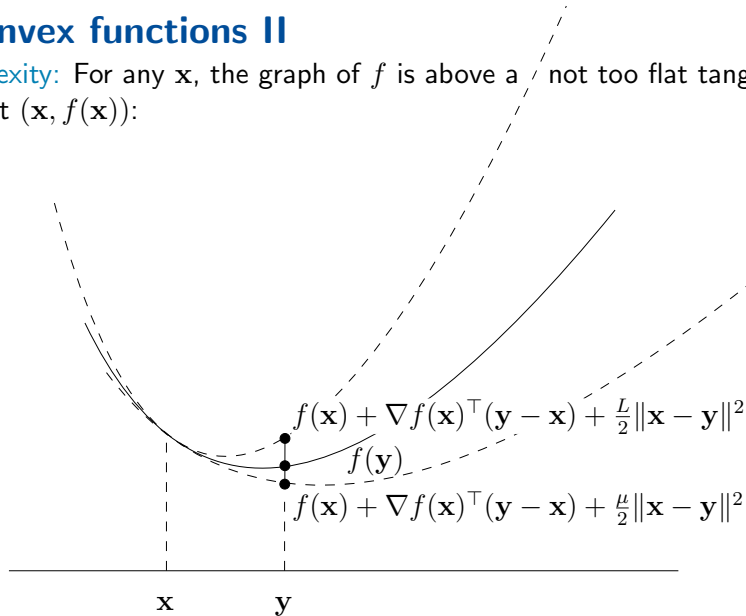
$$f(\mathbf{y}) \geq f(\mathbf{x}) + \nabla f(\mathbf{x})^\top (\mathbf{y} - \mathbf{x}) + \frac{\mu}{2} \|\mathbf{x} - \mathbf{y}\|^2, \quad \forall \mathbf{x}, \mathbf{y} \in X.$$

### Lemma (Exercise 17)

*If  $f$  is strongly convex with parameter  $\mu > 0$ , then  $f$  is strictly convex and has a unique global minimum.*

## Strongly convex functions II

**Strong convexity:** For any  $\mathbf{x}$ , the graph of  $f$  is above a not too flat tangential paraboloid at  $(\mathbf{x}, f(\mathbf{x}))$ :



## Smooth and strongly convex functions: $\mathcal{O}(\log(1/\varepsilon))$ steps

Want to show:  $\lim_{t \rightarrow \infty} \mathbf{x}_t = \mathbf{x}^\star$

Vanilla Analysis:

$$\nabla f(\mathbf{x}_t)^\top (\mathbf{x}_t - \mathbf{x}^\star) = \frac{\gamma}{2} \|\nabla f(\mathbf{x}_t)\|^2 + \frac{1}{2\gamma} (\|\mathbf{x}_t - \mathbf{x}^\star\|^2 - \|\mathbf{x}_{t+1} - \mathbf{x}^\star\|^2)$$

Now use **stronger** lower bound on left hand side, coming from **strong** convexity:

$$\nabla f(\mathbf{x}_t)^\top (\mathbf{x}_t - \mathbf{x}^\star) \geq f(\mathbf{x}_t) - f(\mathbf{x}^\star) + \frac{\mu}{2} \|\mathbf{x}_t - \mathbf{x}^\star\|^2$$

Putting it together:

$$f(\mathbf{x}_t) - f(\mathbf{x}^\star) \leq \frac{1}{2\gamma} (\gamma^2 \|\nabla f(\mathbf{x}_t)\|^2 + \|\mathbf{x}_t - \mathbf{x}^\star\|^2 - \|\mathbf{x}_{t+1} - \mathbf{x}^\star\|^2) - \frac{\mu}{2} \|\mathbf{x}_t - \mathbf{x}^\star\|^2.$$

Rewriting:

$$\|\mathbf{x}_{t+1} - \mathbf{x}^\star\|^2 \leq 2\gamma(f(\mathbf{x}^\star) - f(\mathbf{x}_t)) + \gamma^2 \|\nabla f(\mathbf{x}_t)\|^2 + (1 - \mu\gamma) \|\mathbf{x}_t - \mathbf{x}^\star\|^2.$$

## Smooth and strongly convex functions: $\mathcal{O}(\log(1/\varepsilon))$ steps II

$$\|\mathbf{x}_{t+1} - \mathbf{x}^*\|^2 \leq 2\gamma(f(\mathbf{x}^*) - f(\mathbf{x}_t)) + \gamma^2 \|\nabla f(\mathbf{x}_t)\|^2 + \underbrace{(1 - \mu\gamma)}_{\text{noise}} \|\mathbf{x}_t - \mathbf{x}^*\|^2.$$

**Squared distance to  $\mathbf{x}^*$  goes down by a constant factor, up to some “noise”.**

### Theorem

*Let  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  be differentiable with a global minimum  $\mathbf{x}^*$ ; suppose that  $f$  is smooth with parameter  $L$  and strongly convex with parameter  $\mu > 0$ . Choosing  $\gamma := \frac{1}{L}$ , gradient descent with arbitrary  $\mathbf{x}_0$  satisfies the following two properties.*

(i) *Squared distances to  $\mathbf{x}^*$  are geometrically decreasing:*

$$\|\mathbf{x}_{t+1} - \mathbf{x}^*\|^2 \leq \left(1 - \frac{\mu}{L}\right) \|\mathbf{x}_t - \mathbf{x}^*\|^2, \quad t \geq 0.$$

(ii) *The absolute error after  $T$  iterations is exponentially small in  $T$ :*

$$f(\mathbf{x}_T) - f(\mathbf{x}^*) \leq \frac{L}{2} \left(1 - \frac{\mu}{L}\right)^T \|\mathbf{x}_0 - \mathbf{x}^*\|^2, \quad T > 0.$$

## Smooth and strongly convex functions: $\mathcal{O}(\log(1/\varepsilon))$ steps III

$$\| \mathbf{x}_{t+1} - \mathbf{x}^* \|^2 \leq 2\gamma(f(\mathbf{x}^*) - f(\mathbf{x}_t)) + \gamma^2 \|\nabla f(\mathbf{x}_t)\|^2 + \underbrace{(1 - \mu\gamma) \|\mathbf{x}_t - \mathbf{x}^*\|^2}_{\text{noise}}.$$

Proof of (i).

Bounding the noise:

$\gamma = 1/L$  , sufficient decrease

$$\begin{aligned} 2\gamma(f(\mathbf{x}^*) - f(\mathbf{x}_t)) + \gamma^2 \|\nabla f(\mathbf{x}_t)\|^2 &= \frac{2}{L}(f(\mathbf{x}^*) - f(\mathbf{x}_t)) + \frac{1}{L^2} \|\nabla f(\mathbf{x}_t)\|^2 \\ &\leq \frac{2}{L}(f(\mathbf{x}_{t+1}) - f(\mathbf{x}_t)) + \frac{1}{L^2} \|\nabla f(\mathbf{x}_t)\|^2 \\ &\leq -\frac{1}{L^2} \|\nabla f(\mathbf{x}_t)\|^2 + \frac{1}{L^2} \|\nabla f(\mathbf{x}_t)\|^2 = 0. \end{aligned}$$

Hence, the noise is nonpositive, and we get (i):

$$\| \mathbf{x}_{t+1} - \mathbf{x}^* \|^2 \leq (1 - \mu\gamma) \|\mathbf{x}_t - \mathbf{x}^*\|^2 = \left(1 - \frac{\mu}{L}\right) \|\mathbf{x}_t - \mathbf{x}^*\|^2.$$



## Smooth and strongly convex functions: $\mathcal{O}(\log(1/\varepsilon))$ steps III

Proof of (ii).

From (i):

$$\|\mathbf{x}_T - \mathbf{x}^\star\|^2 \leq \left(1 - \frac{\mu}{L}\right)^T \|\mathbf{x}_0 - \mathbf{x}^\star\|^2.$$

Smoothness together with  $\nabla f(\mathbf{x}^\star) = \mathbf{0}$ :

$$f(\mathbf{x}_T) - f(\mathbf{x}^\star) \leq \nabla f(\mathbf{x}^\star)^\top (\mathbf{x}_T - \mathbf{x}^\star) + \frac{L}{2} \|\mathbf{x}_T - \mathbf{x}^\star\|^2 = \frac{L}{2} \|\mathbf{x}_T - \mathbf{x}^\star\|^2.$$

Putting it together:

$$f(\mathbf{x}_T) - f(\mathbf{x}^\star) \leq \frac{L}{2} \|\mathbf{x}_T - \mathbf{x}^\star\|^2 \leq \frac{L}{2} \left(1 - \frac{\mu}{L}\right)^T \|\mathbf{x}_0 - \mathbf{x}^\star\|^2.$$



## Smooth and strongly convex functions: $\mathcal{O}(\log(1/\varepsilon))$ steps IV

$$R^2 := \|\mathbf{x}_0 - \mathbf{x}^\star\|^2.$$

$$T \geq \frac{L}{\mu} \ln \left( \frac{R^2 L}{2\varepsilon} \right) \quad \Rightarrow \quad \text{error} \leq \frac{L}{2} \left( 1 - \frac{\mu}{L} \right)^T R^2 \leq \varepsilon.$$

**Conclusion:** To reach absolute error at most  $\varepsilon$ , we only need  $\mathcal{O}(\log \frac{1}{\varepsilon})$  iterations, e.g.

- ▶  $\frac{L}{\mu} \ln(50 \cdot R^2 L)$  iterations for error 0.01 ...
- ▶ ... as opposed to  $50 \cdot R^2 L$  in the smooth case

In Practice:

What if we don't know the smoothness parameter  $L$ ?

→ (similar to) **Exercise 15**

# Chapter 3

## Projected Gradient Descent

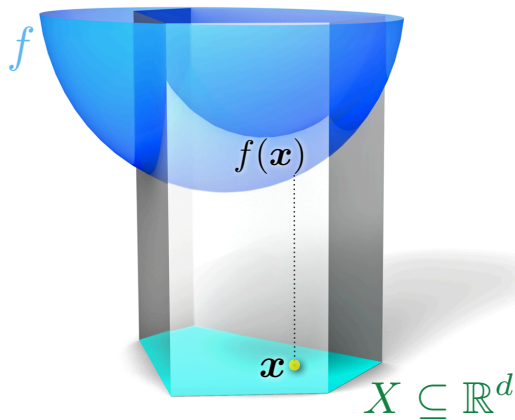
# Constrained Optimization

## Constrained Optimization Problem

$$\begin{array}{ll} \text{minimize} & f(\mathbf{x}) \\ \text{subject to} & \mathbf{x} \in X \end{array}$$

## Solving Constrained Optimization Problems

- A Projected Gradient Descent
- B Transform it into an *unconstrained* problem

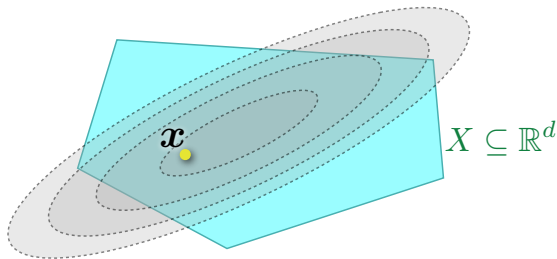


# Constrained Optimization

## Solving Constrained Optimization Problems

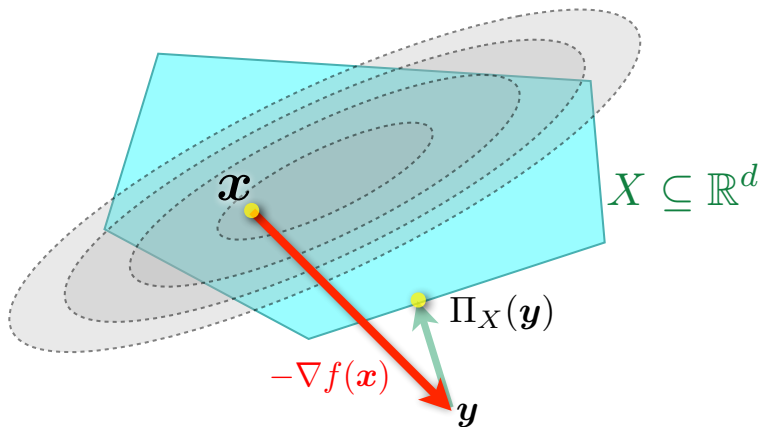
$$\begin{array}{ll} \text{minimize} & f(\mathbf{x}) \\ \text{subject to} & \mathbf{x} \in X \end{array}$$

- Here: Projected Gradient Descent



# Projected Gradient Descent

Idea: project onto  $X$  after every step:  $\Pi_X(\mathbf{y}) := \operatorname{argmin}_{\mathbf{x} \in X} \|\mathbf{x} - \mathbf{y}\|$



Projected gradient update  $\mathbf{x}_{t+1} \leftarrow \Pi_X[\mathbf{x}_t - \gamma \nabla f(\mathbf{x}_t)]$

# The Algorithm

Projected gradient descent:

$$\begin{aligned}\mathbf{y}_{t+1} &:= \mathbf{x}_t - \gamma \nabla f(\mathbf{x}_t), \\ \mathbf{x}_{t+1} &:= \Pi_X(\mathbf{y}_{t+1}) := \operatorname{argmin}_{\mathbf{x} \in X} \|\mathbf{x} - \mathbf{y}_{t+1}\|^2.\end{aligned}$$

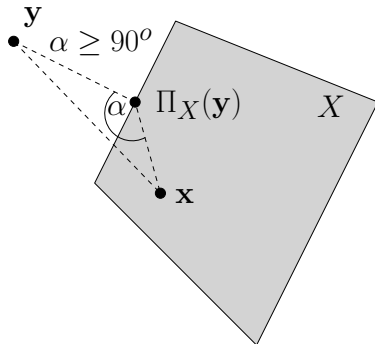
for **timesteps**  $t = 0, 1, \dots$ , and **stepsize**  $\gamma \geq 0$ .

# Properties of Projection

## Fact

Let  $X \subseteq \mathbb{R}^d$  be closed and convex,  $\mathbf{x} \in X, \mathbf{y} \in \mathbb{R}^d$ . Then

- (i)  $(\mathbf{x} - \Pi_X(\mathbf{y}))^\top (\mathbf{y} - \Pi_X(\mathbf{y})) \leq 0$ .
- (ii)  $\|\mathbf{x} - \Pi_X(\mathbf{y})\|^2 + \|\mathbf{y} - \Pi_X(\mathbf{y})\|^2 \leq \|\mathbf{x} - \mathbf{y}\|^2$ .





## Properties of Projection II

### Fact

Let  $X \subseteq \mathbb{R}^d$  be closed and convex,  $\mathbf{x} \in X, \mathbf{y} \in \mathbb{R}^d$ . Then

- (i)  $(\mathbf{x} - \Pi_X(\mathbf{y}))^\top (\mathbf{y} - \Pi_X(\mathbf{y})) \leq 0$ .
- (ii)  $\|\mathbf{x} - \Pi_X(\mathbf{y})\|^2 + \|\mathbf{y} - \Pi_X(\mathbf{y})\|^2 \leq \|\mathbf{x} - \mathbf{y}\|^2$ .

### Proof.

(i)  $\Pi_X(\mathbf{y})$  is minimizer of (differentiable) convex function  $d_{\mathbf{y}}(\mathbf{x}) = \|\mathbf{x} - \mathbf{y}\|^2$  over  $X$ .

By first-order characterization of optimality (**Lemma 1.22**),

$$\begin{aligned} 0 &\geq \nabla d_{\mathbf{y}}(\Pi_X(\mathbf{y}))^\top (\mathbf{x} - \Pi_X(\mathbf{y})) \\ &= 2(\Pi_X(\mathbf{y}) - \mathbf{y})^\top (\mathbf{x} - \Pi_X(\mathbf{y})) \\ \Leftrightarrow 0 &\leq 2(\mathbf{y} - \Pi_X(\mathbf{y}))^\top (\mathbf{x} - \Pi_X(\mathbf{y})) \\ \Leftrightarrow 0 &\leq (\mathbf{x} - \Pi_X(\mathbf{y}))^\top (\mathbf{y} - \Pi_X(\mathbf{y})) \end{aligned}$$

# Properties of Projection III

## Fact

Let  $X \subseteq \mathbb{R}^d$  be closed and convex,  $\mathbf{x} \in X, \mathbf{y} \in \mathbb{R}^d$ . Then

(i)  $(\mathbf{x} - \Pi_X(\mathbf{y}))^\top (\mathbf{y} - \Pi_X(\mathbf{y})) \leq 0$ .

(ii)  $\|\mathbf{x} - \Pi_X(\mathbf{y})\|^2 + \|\mathbf{y} - \Pi_X(\mathbf{y})\|^2 \leq \|\mathbf{x} - \mathbf{y}\|^2$ .

## Proof.

(ii)

$$\mathbf{v} := (\mathbf{x} - \Pi_X(\mathbf{y})), \quad \mathbf{w} := (\mathbf{y} - \Pi_X(\mathbf{y})).$$

By (i),

$$\begin{aligned} 0 \geq 2\mathbf{v}^\top \mathbf{w} &= \|\mathbf{v}\|^2 + \|\mathbf{w}\|^2 - \|\mathbf{v} - \mathbf{w}\|^2 \\ &= \|\mathbf{x} - \Pi_X(\mathbf{y})\|^2 + \|\mathbf{y} - \Pi_X(\mathbf{y})\|^2 - \|\mathbf{x} - \mathbf{y}\|^2. \end{aligned}$$

# Results for projected gradient descent over closed and convex $X$

The **same** number of steps as gradient over  $\mathbb{R}^d$ !

- ▶ Lipschitz convex functions over  $X$ :  $\mathcal{O}(1/\varepsilon^2)$  steps
- ▶ Smooth convex functions over  $X$ :  $\mathcal{O}(1/\varepsilon)$  steps
- ▶ Smooth and strongly convex functions over  $X$ :  $\mathcal{O}(\log(1/\varepsilon))$  steps

We will adapt the previous proofs for gradient descent.

BUT:

- ▶ Each step involves a projection onto  $X$
- ▶ may or may not be efficient (in relevant cases, it is)...

## Lipschitz convex functions over $X$ : $\mathcal{O}(1/\varepsilon^2)$ steps

Assume that all gradients of  $f$  are bounded in norm over **closed and convex**  $X$ .

- ▶ Equivalent to  $f$  being Lipschitz over  $X$ .
- ▶ **Many** interesting functions are Lipschitz over **bounded** sets  $X$ .

Theorem (same as the unconstrained one, but more useful)

Let  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  be convex and differentiable,  $X \subseteq \mathbb{R}^d$  closed and convex,  $\mathbf{x}^*$  a minimizer of  $f$  over  $X$ ; furthermore, suppose that  $\|\mathbf{x}_0 - \mathbf{x}^*\| \leq R$  with  $\mathbf{x}_0 \in X$ , and that  $\|\nabla f(\mathbf{x})\| \leq B$  for all  $\mathbf{x} \in X$ . Choosing the constant stepsize

$$\gamma := \frac{R}{B\sqrt{T}},$$

**projected** gradient descent yields

$$\frac{1}{T} \sum_{t=0}^{T-1} f(\mathbf{x}_t) - f(\mathbf{x}^*) \leq \frac{RB}{\sqrt{T}}.$$

## Lipschitz convex functions: $\mathcal{O}(1/\varepsilon^2)$ steps II

Proof.

- Replace  $\mathbf{x}_{t+1}$  in the vanilla analysis with  $\mathbf{y}_{t+1}$  (the unprojected gradient step):

$$\mathbf{g}_t^\top (\mathbf{x}_t - \mathbf{x}^\star) = \frac{1}{2\gamma} \left( \gamma^2 \|\mathbf{g}_t\|^2 + \|\mathbf{x}_t - \mathbf{x}^\star\|^2 - \|\underline{\mathbf{y}_{t+1}} - \mathbf{x}^\star\|^2 \right).$$

- Use Fact (ii):  $\|\mathbf{x} - \Pi_X(\mathbf{y})\|^2 + \|\mathbf{y} - \Pi_X(\mathbf{y})\|^2 \leq \|\mathbf{x} - \mathbf{y}\|^2$ .
- With  $\mathbf{x} = \mathbf{x}^\star, \mathbf{y} = \mathbf{y}_{t+1}$ , we have  $\Pi_X(\mathbf{y}) = \mathbf{x}_{t+1}$ , and hence

$$\|\mathbf{x}^\star - \mathbf{x}_{t+1}\|^2 \leq \|\mathbf{x}^\star - \mathbf{y}_{t+1}\|^2$$

- We go back to the original vanilla analysis and continue from there as before:

$$\mathbf{g}_t^\top (\mathbf{x}_t - \mathbf{x}^\star) \leq \frac{1}{2\gamma} \left( \gamma^2 \|\mathbf{g}_t\|^2 + \|\mathbf{x}_t - \mathbf{x}^\star\|^2 - \|\underline{\mathbf{x}_{t+1}} - \mathbf{x}^\star\|^2 \right).$$

# Smooth functions over $X$

Recall:

$f$  is called **smooth** (with parameter  $L$ ) over  $X$  if

$$f(\mathbf{y}) \leq f(\mathbf{x}) + \nabla f(\mathbf{x})^\top (\mathbf{y} - \mathbf{x}) + \frac{L}{2} \|\mathbf{x} - \mathbf{y}\|^2, \quad \forall \mathbf{x}, \mathbf{y} \in X.$$

# Sufficient decrease

## Lemma

Let  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  be differentiable and smooth with parameter  $L$  over  $X$ . Choosing stepsize

$$\gamma := \frac{1}{L},$$

*projected* gradient descent with arbitrary  $\mathbf{x}_0 \in X$  satisfies

$$f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2 + \frac{L}{2} \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2, \quad t \geq 0.$$

**Remark:** More specifically, this already holds if  $f$  is smooth with parameter  $L$  over the line segment connecting  $\mathbf{x}_t$  and  $\mathbf{x}_{t+1}$ .

## Sufficient decrease II

$$f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2 + \frac{L}{2} \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2.$$

Proof.

Use smoothness,  $\mathbf{y}_{t+1} - \mathbf{x}_t = -\nabla f(\mathbf{x}_t)/L$ ,  $2\mathbf{v}^\top \mathbf{w} = \|\mathbf{v}\|^2 + \|\mathbf{w}\|^2 - \|\mathbf{v} - \mathbf{w}\|^2$ :

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



## Smooth convex functions over $X$ : $\mathcal{O}(1/\varepsilon)$ steps

### Theorem

*Let  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  be convex and differentiable. Let  $X \subseteq \mathbb{R}^d$  be a closed convex set, and assume that there is a minimizer  $\mathbf{x}^\star$  of  $f$  over  $X$ ; furthermore, suppose that  $f$  is smooth over  $X$  with parameter  $L$ . Choosing stepsize*

$$\gamma := \frac{1}{L},$$

*gradient descent yields*

$$f(\mathbf{x}_T) - f(\mathbf{x}^\star) \leq \frac{L}{2T} \|\mathbf{x}_0 - \mathbf{x}^\star\|^2, \quad T > 0.$$

## Smooth convex functions over $X$ : $\mathcal{O}(1/\varepsilon)$ steps II

$$f(\mathbf{x}_T) - f(\mathbf{x}^\star) \leq \frac{L}{2T} \|\mathbf{x}_0 - \mathbf{x}^\star\|^2, \quad T > 0.$$

Proof.

As before, use sufficient decrease to bound sum of squared gradients in vanilla analysis:

$$\frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2 \leq f(\mathbf{x}_t) - f(\mathbf{x}_{t+1}) + \frac{L}{2} \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2$$

But now: **extra** term  $\frac{L}{2} \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2$ .

Compensate in the vanilla analysis itself!



## Recall: Lipschitz convex functions: $\mathcal{O}(1/\varepsilon^2)$ steps II

Proof.

- ▶ Replace  $\mathbf{x}_{t+1}$  in the vanilla analysis with  $\mathbf{y}_{t+1}$  (the unprojected gradient step):

$$\mathbf{g}_t^\top (\mathbf{x}_t - \mathbf{x}^\star) = \frac{1}{2\gamma} (\gamma^2 \|\mathbf{g}_t\|^2 + \|\mathbf{x}_t - \mathbf{x}^\star\|^2 - \|\mathbf{y}_{t+1} - \mathbf{x}^\star\|^2).$$

- ▶ Use Fact (ii):  $\|\mathbf{x} - \Pi_X(\mathbf{y})\|^2 + \|\mathbf{y} - \Pi_X(\mathbf{y})\|^2 \leq \|\mathbf{x} - \mathbf{y}\|^2$ .
- ▶ With  $\mathbf{x} = \mathbf{x}^\star$ ,  $\mathbf{y} = \mathbf{y}_{t+1}$ , we have  $\Pi_X(\mathbf{y}) = \mathbf{x}_{t+1}$ , and hence

$$\|\mathbf{x}^\star - \mathbf{x}_{t+1}\|^2 + \underbrace{\|\mathbf{y}_{t+1} - \Pi_X(\mathbf{y}_{t+1})\|^2}_{\leq \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2} \leq \|\mathbf{x}^\star - \mathbf{y}_{t+1}\|^2$$

- ▶ We get back to the vanilla analysis... but with a saving!

$$\mathbf{g}_t^\top (\mathbf{x}_t - \mathbf{x}^\star) \leq \frac{1}{2\gamma} \left( \gamma^2 \|\mathbf{g}_t\|^2 + \|\mathbf{x}_t - \mathbf{x}^\star\|^2 - \|\mathbf{x}_{t+1} - \mathbf{x}^\star\|^2 - \underbrace{\|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2}_{\leq \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2} \right)$$

## Smooth convex functions over $X$ : $\mathcal{O}(1/\varepsilon)$ steps III

$$f(\mathbf{x}_T) - f(\mathbf{x}^\star) \leq \frac{L}{2T} \|\mathbf{x}_0 - \mathbf{x}^\star\|^2, \quad T > 0.$$

Proof.

Use  $f(\mathbf{x}_t) - f(\mathbf{x}^\star) \leq \mathbf{g}_t^\top (\mathbf{x}_t - \mathbf{x}^\star)$  (convexity), vanilla analysis with saving,  $\gamma = 1/L$ :

$$\begin{aligned} \sum_{t=0}^{T-1} (f(\mathbf{x}_t) - f(\mathbf{x}^\star)) &\leq \sum_{t=0}^{T-1} \mathbf{g}_t^\top (\mathbf{x}_t - \mathbf{x}^\star) \\ &\leq \frac{1}{2L} \sum_{t=0}^{T-1} \|\mathbf{g}_t\|^2 + \frac{L}{2} \|\mathbf{x}_0 - \mathbf{x}^\star\|^2 - \frac{L}{2} \sum_{t=0}^{T-1} \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2. \end{aligned}$$

Use sufficient decrease to bound  $\frac{1}{2L} \sum_{t=0}^{T-1} \|\mathbf{g}_t\|^2$  by

$$\sum_{t=0}^{T-1} \left( f(\mathbf{x}_t) - f(\mathbf{x}_{t+1}) + \frac{L}{2} \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2 \right) = f(\mathbf{x}_0) - f(\mathbf{x}_T) + \frac{L}{2} \sum_{t=0}^{T-1} \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2.$$

## Smooth convex functions over $X$ : $\mathcal{O}(1/\varepsilon)$ steps IV

$$f(\mathbf{x}_T) - f(\mathbf{x}^\star) \leq \frac{L}{2T} \|\mathbf{x}_0 - \mathbf{x}^\star\|^2, \quad T > 0.$$

Proof.

Putting it together: extra terms cancel, and as in unconstrained case, we get

$$\sum_{t=1}^T (f(\mathbf{x}_t) - f(\mathbf{x}^\star)) \leq \frac{L}{2} \|\mathbf{x}_0 - \mathbf{x}^\star\|^2.$$

**Exercise 19:** again, we make progress in every step (not immediate from sufficient decrease here). Hence,

$$f(\mathbf{x}_T) - f(\mathbf{x}^\star) \leq \frac{1}{T} \sum_{t=1}^T (f(\mathbf{x}_t) - f(\mathbf{x}^\star)) \leq \frac{L}{2T} \|\mathbf{x}_0 - \mathbf{x}^\star\|^2.$$

# Smooth and strongly convex functions over $X$

Recall:

$f$  is **strongly convex** (with parameter  $\mu$ ) over  $X$  if

$$f(\mathbf{y}) \geq f(\mathbf{x}) + \nabla f(\mathbf{x})^\top (\mathbf{y} - \mathbf{x}) + \frac{\mu}{2} \|\mathbf{x} - \mathbf{y}\|^2, \quad \forall \mathbf{x}, \mathbf{y} \in X.$$

## Smooth and strongly convex functions over $X$ : $\mathcal{O}(\log(1/\varepsilon))$ steps

**Exercise 20:** a strongly convex function has a unique minimizer  $\mathbf{x}^\star$  of  $f$  over  $X$ .

### Theorem

Let  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  be convex and differentiable. Let  $X \subseteq \mathbb{R}^d$  be a nonempty closed and convex set and suppose that  $f$  is smooth over  $X$  with parameter  $L$  and strongly convex over  $X$  with parameter  $\mu > 0$ . Choosing  $\gamma := \frac{1}{L}$ , projected gradient descent with arbitrary  $\mathbf{x}_0$  satisfies the following two properties.

(i) Squared distances to  $\mathbf{x}^\star$  are geometrically decreasing:

$$\|\mathbf{x}_{t+1} - \mathbf{x}^\star\|^2 \leq \left(1 - \frac{\mu}{L}\right) \|\mathbf{x}_t - \mathbf{x}^\star\|^2, \quad t \geq 0.$$

(ii) The absolute error after  $T$  iterations is exponentially small in  $T$ :

$$\begin{aligned} f(\mathbf{x}_T) - f(\mathbf{x}^\star) &\leq \|\nabla f(\mathbf{x}^\star)\| \left(1 - \frac{\mu}{L}\right)^{T/2} \|\mathbf{x}_0 - \mathbf{x}^\star\| \quad \leftarrow \text{in general, } \nabla f(\mathbf{x}^\star) \neq \mathbf{0}! \\ &+ \frac{L}{2} \left(1 - \frac{\mu}{L}\right)^T \|\mathbf{x}_0 - \mathbf{x}^\star\|^2, \quad T > 0. \quad \leftarrow \text{as in unconstrained case} \end{aligned}$$

# Smooth and strongly convex functions over $X$ : $\mathcal{O}(\log(1/\varepsilon))$ steps I

Proof.

(i) Geometric decrease plus noise:  $\|\mathbf{x}_{t+1} - \mathbf{x}^*\|^2 \leq \dots$

► unconstrained case:

$$2\gamma(f(\mathbf{x}^*) - f(\mathbf{x}_t)) + \gamma^2 \|\nabla f(\mathbf{x}_t)\|^2 + \underbrace{(1 - \mu\gamma)\|\mathbf{x}_t - \mathbf{x}^*\|^2}_{\text{noise}}.$$

► constrained case (vanilla analysis with a saving):

$$2\gamma(f(\mathbf{x}^*) - f(\mathbf{x}_t)) + \gamma^2 \|\nabla f(\mathbf{x}_t)\|^2 - \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2 + \underbrace{(1 - \mu\gamma)\|\mathbf{x}_t - \mathbf{x}^*\|^2}_{\text{noise}},$$

□



## Smooth and strongly convex functions over $X$ : $\mathcal{O}(\log(1/\varepsilon))$ steps II

Proof.

To bound the noise, we use sufficient decrease.

► unconstrained case:

$$f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2, \quad t \geq 0.$$

► constrained case:

$$f(\mathbf{x}_{t+1}) \leq f(\mathbf{x}_t) - \frac{1}{2L} \|\nabla f(\mathbf{x}_t)\|^2 + \frac{L}{2} \|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2, \quad t \geq 0.$$

Putting it together, the terms  $\|\mathbf{y}_{t+1} - \mathbf{x}_{t+1}\|^2$  cancel, and we get

$$\|\mathbf{x}_{t+1} - \mathbf{x}^*\|^2 \leq (1 - \mu\gamma) \|\mathbf{x}_t - \mathbf{x}^*\|^2 = \left(1 - \frac{\mu}{L}\right) \|\mathbf{x}_t - \mathbf{x}^*\|^2.$$

in both cases.



## Smooth and strongly convex functions over $X$ : $\mathcal{O}(\log(1/\varepsilon))$ steps II

Proof.

(ii) Error bound from smoothness:

$$\begin{aligned} f(\mathbf{x}_T) - f(\mathbf{x}^*) &\leq \nabla f(\mathbf{x}^*)^\top (\mathbf{x}_T - \mathbf{x}^*) + \frac{L}{2} \|\mathbf{x}^* - \mathbf{x}_T\|^2 \\ &\leq \|\nabla f(\mathbf{x}^*)\| \|\mathbf{x}_T - \mathbf{x}^*\| + \frac{L}{2} \|\mathbf{x}^* - \mathbf{x}_T\|^2 \text{ (Cauchy-Schwarz)} \\ &\leq \|\nabla f(\mathbf{x}^*)\| \left(1 - \frac{\mu}{L}\right)^{T/2} \|\mathbf{x}_0 - \mathbf{x}^*\| + \frac{L}{2} \left(1 - \frac{\mu}{L}\right)^T \|\mathbf{x}_0 - \mathbf{x}^*\|^2. \text{ (i)} \end{aligned}$$

□

constrained error bound  $\approx \sqrt{\text{unconstrained error bound}}$

required number of steps roughly doubles.