

Convex Optimization

CS5491: Artificial Intelligence
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Content Credits: Prof. Wei's CS4486 Course
and Prof. Boddeti's AI Course

TODAY

Convexity

Convex Optimization

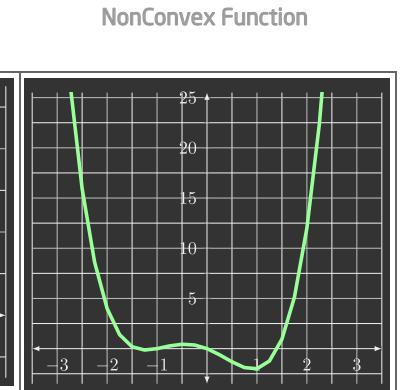
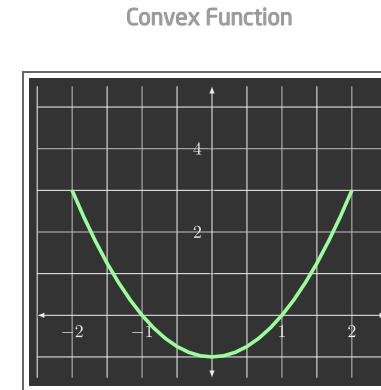
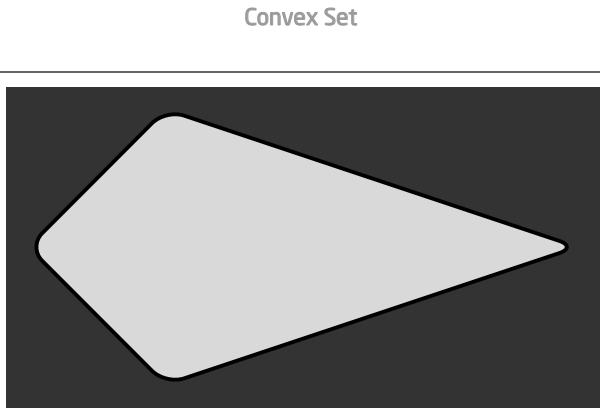
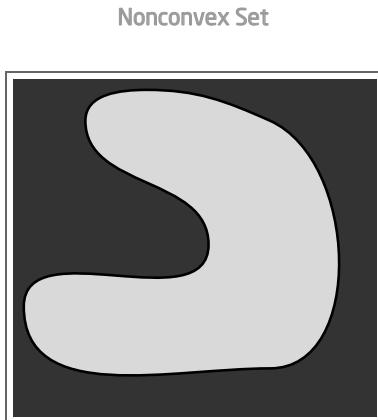
CONVEX OPTIMIZATION: DEFINITION

Convex Optimization Problem:

$$\begin{aligned} \min_{\mathbf{x}} \quad & f(\mathbf{x}) \\ \text{s.t. } & \mathbf{x} \in \mathcal{F} \end{aligned}$$

A special class of optimization problem

An optimization problem whose optimization objective f is a convex function and feasible region \mathcal{F} is a convex set.



CONVEX COMBINATION

A point between two points

Given $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, a convex combination of them is any point of the form $\mathbf{z} = \theta\mathbf{x} + (1 - \theta)\mathbf{y}$ where $\theta \in [0, 1]$.

When $\theta \in (0, 1)$, \mathbf{z} is called a strict convex combination of \mathbf{x}, \mathbf{y} .

CONVEX SETS

Conceptually: Any convex combination of two points in the set is also in the set

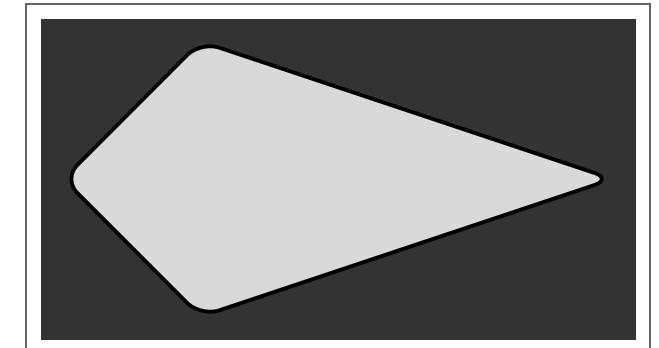
Mathematically: A set \mathcal{F} is convex if $\forall x, y \in \mathcal{F}, \forall \theta \in [0, 1]$,

$$z = \theta x + (1 - \theta)y \in \mathcal{F}$$

Nonconvex Set



Convex Set



QUIZ: CONVEX SET

Which of the following sets are convex?

- › $\mathcal{F} = \mathbb{R}^n$
- › $\mathcal{F} = \emptyset$
- › $\mathcal{F} = \{\mathbf{x}_0\}, \mathbf{x}_0 \in \mathbb{R}^n$
- › $\mathcal{F} = \mathcal{F}_1 \cap \mathcal{F}_2$, where \mathcal{F}_1 and \mathcal{F}_2 are convex sets.
- › $\mathcal{F} = \mathcal{F}_1 \cup \mathcal{F}_2$, where \mathcal{F}_1 and \mathcal{F}_2 are convex sets.
- › $\mathcal{F} = \mathbb{Z}^n$

CONVEX FUNCTION

Value in the middle point is lower than average value

Let \mathcal{F} be a convex set. A function $f : \mathcal{F} \rightarrow \mathbb{R}$ is convex in \mathcal{F} if $\forall x, y \in \mathcal{F}, \forall \theta \in [0, 1]$,

$$f(\theta \mathbf{x} + (1 - \theta) \mathbf{y}) \leq \theta f(\mathbf{x}) + (1 - \theta) f(\mathbf{y})$$

If $\mathcal{F} = \mathbb{R}^n$, we simply say f is convex.

HOW TO DETERMINE IF A FUNCTIONS IS CONVEX?

Prove by definition

Use properties of convex functions

- Sum of convex functions is convex

If $f(\mathbf{x}) = \sum_i w_i f_i(\mathbf{x})$, $w_i \geq 0$, $f_i(\mathbf{x})$ convex, then $f(\mathbf{x})$ is convex.

- Convexity is preserved under a linear transformation

If $f(\mathbf{x}) = g(A\mathbf{x} + b)$, if $g(\mathbf{x})$ is convex, then $f(\mathbf{x})$ is convex.

- If f is a twice differentiable function of one variable, f is convex on an interval $[a, b] \subseteq \mathbb{R}$ iff (if and only if) its second derivative $f''(x) \geq 0$ in $[a, b]$

CONVEX OPTIMIZATION: DEFINITION

If f is a twice continuously differentiable function of n variables, f is convex on \mathcal{F} iff its Hessian matrix of second partial derivatives is positive semidefinite on the interior of \mathcal{F} .

$$H(\mathbf{x}) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \frac{\partial^2 f}{\partial x_1 \partial x_2} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2 \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_1 \partial x_n} & \frac{\partial^2 f}{\partial x_2 \partial x_n} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}$$

H is positive semidefinite in S if $\forall \mathbf{x} \in S, \forall \mathbf{z} \in \mathbb{R}^n, \mathbf{z}^T H(\mathbf{x}) \mathbf{z} \geq 0$

H is positive semidefinite in \mathbb{R}^n iff all eigenvalues of H are non-negative.

Alternatively, prove $\mathbf{z}^T H(\mathbf{x}) \mathbf{z} = \sum_i g_i^2(x, z)$

CONCAVITY AND CONVEXITY

Concave function

- › A function f is concave if $-f$ is convex
- › Let \mathcal{F} be a convex set. A function $f : \mathcal{F} \rightarrow \mathbb{R}$ is concave in \mathcal{F} if $\forall \mathbf{x}, \mathbf{y} \in \mathcal{F}, \forall \theta \in [0, 1]$,

$$f(\theta \mathbf{x} + (1 - \theta) \mathbf{y}) \geq \theta f(\mathbf{x}) + (1 - \theta) f(\mathbf{y})$$

The following is a convex optimization problem if f is a concave function and \mathcal{F} is a convex set

$$\begin{aligned} & \max_{\mathbf{x}} f(\mathbf{x}) \\ & \text{s.t. } \mathbf{x} \in \mathcal{F} \end{aligned}$$

QUIZ 2: CONVEX FUNCTION

Which of the following functions are convex?

- › $f(x) = e^{ax}, a \in \mathbb{R}$
- › $f(x) = \log x, x \in (0, +\infty)$
- › $f(x) = \|\mathbf{x}\|_2 = \sqrt{\sum_i^n x_i^2}$
- › $f(\mathbf{x}, \mathbf{y}) = \mathbf{x}^T \mathbf{A} \mathbf{y}, \mathbf{A} \in \mathbb{R}^{m \times n}, \mathbf{x} \in \mathbb{R}^m, \mathbf{y} \in \mathbb{R}^n$
- › $f(x) = x^3, x \in \mathbb{R}$

CONVEX OPTIMIZATION: LOCAL OPTIMA=GLOBAL OPTIMA

$$\begin{aligned} \min_{\mathbf{x}} \quad & f(\mathbf{x}) \\ \text{s.t. } & \mathbf{x} \in \mathcal{F} \end{aligned}$$

Given an optimization problem, a point $\mathbf{x} \in \mathbb{R}^n$ is **globally optimal** if $\mathbf{x} \in \mathcal{F}$ and $\forall \mathbf{y} \in \mathcal{F}, f(\mathbf{x}) \leq f(\mathbf{y})$

Given an optimization problem, a point $\mathbf{x} \in \mathbb{R}^n$ is **locally optimal** if $\mathbf{x} \in \mathcal{F}$ and $\exists R > 0$ such that $\forall \mathbf{y} : \mathbf{y} \in \mathcal{F}$ and $\|\mathbf{x} - \mathbf{y}\|_2 \leq R, f(\mathbf{x}) \leq f(\mathbf{y})$

Theorem 1: For a convex optimization problem, all locally optimal points are globally optimal

OPTIMIZATION



CONVEX OPTIMIZATION: HOW TO SOLVE?

Recall discrete setting

- › Local search
- › Iteratively improving an assignment

Continuous and differentiable setting

- › Iteratively improving value of \mathbf{x}
- › Based on gradient

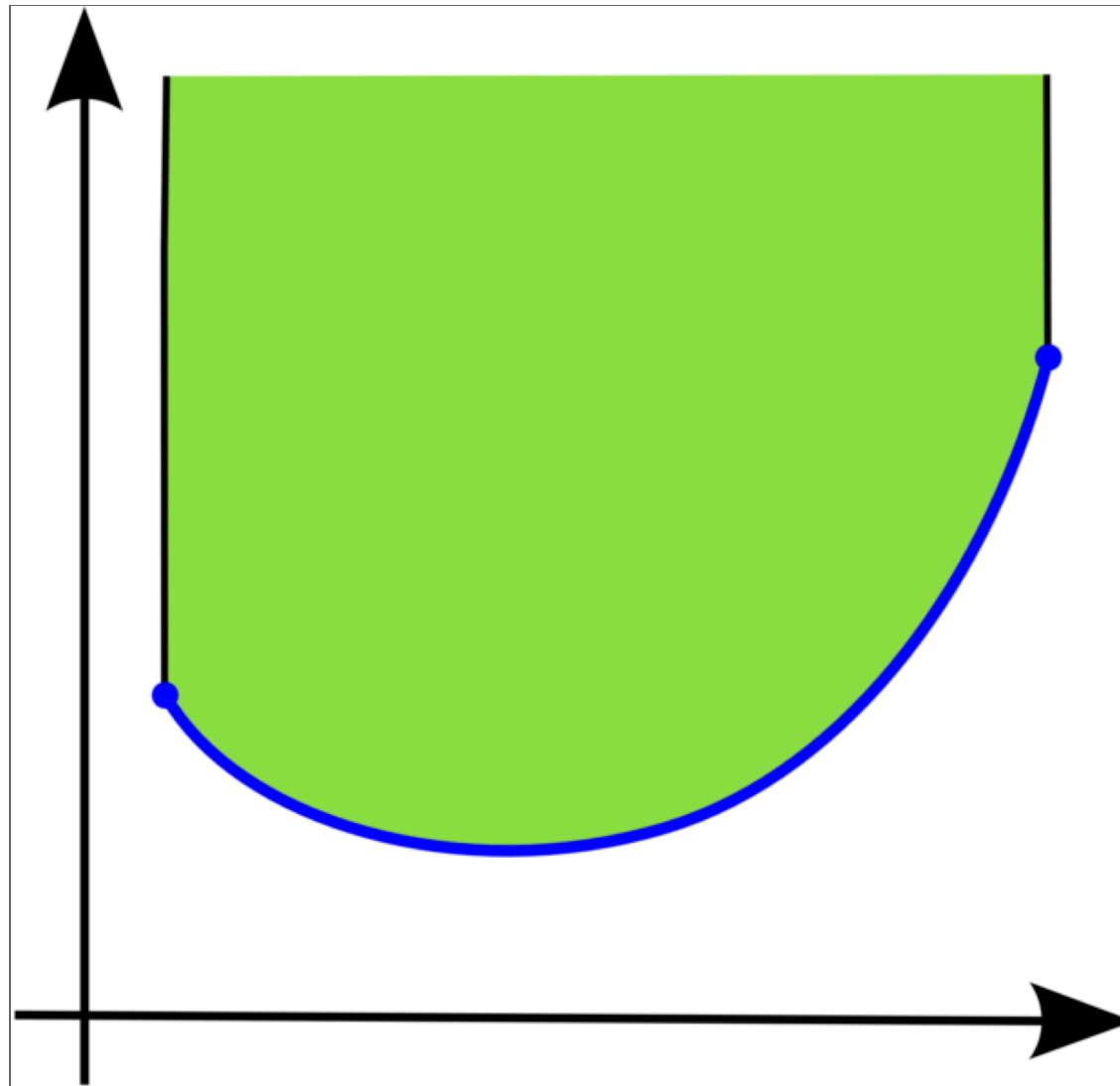
CONVEX OPTIMIZATION: HOW TO SOLVE?

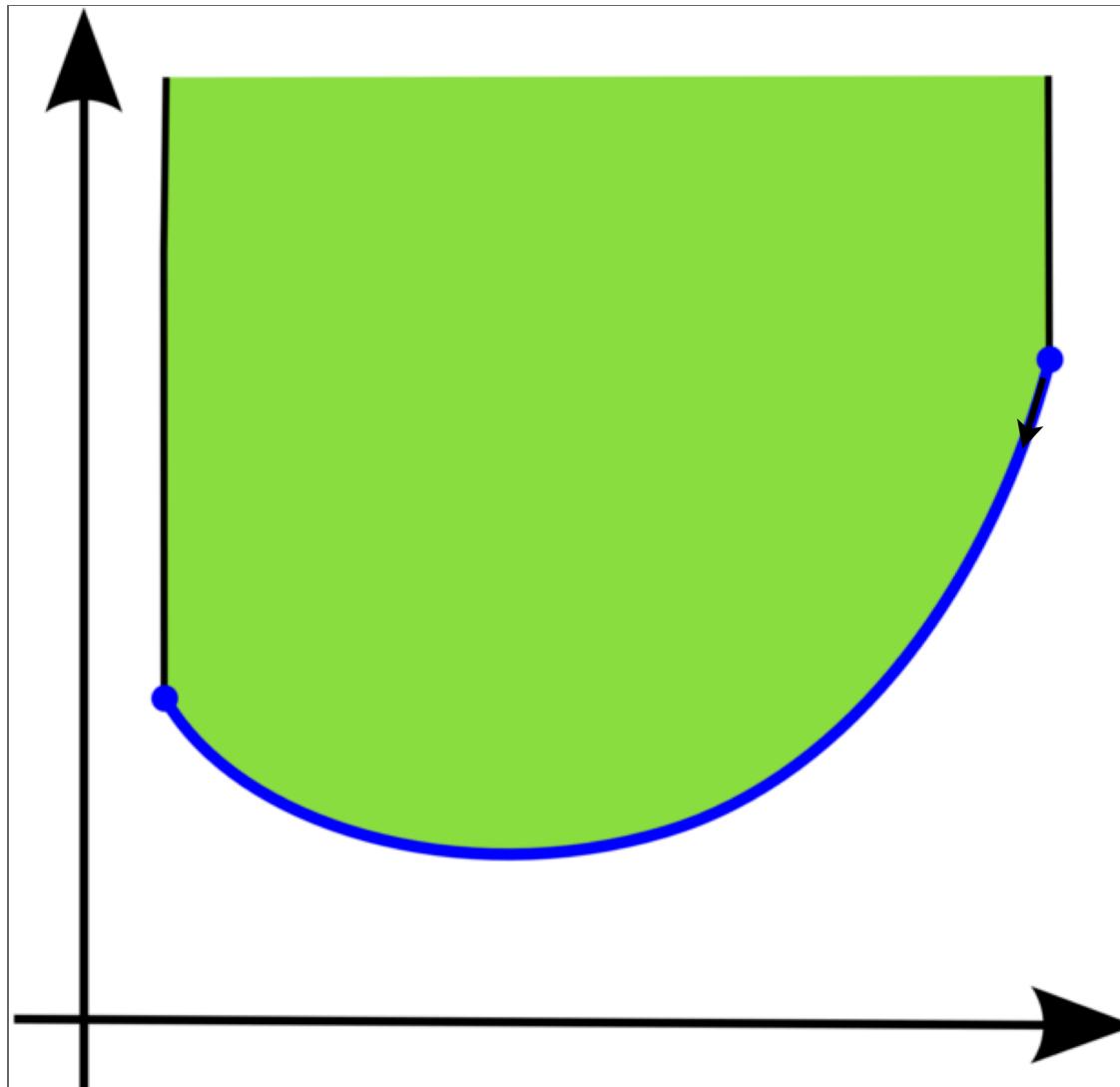
For $f : \mathbb{R}^n \rightarrow \mathbb{R}$, gradient is the vector of partial derivatives

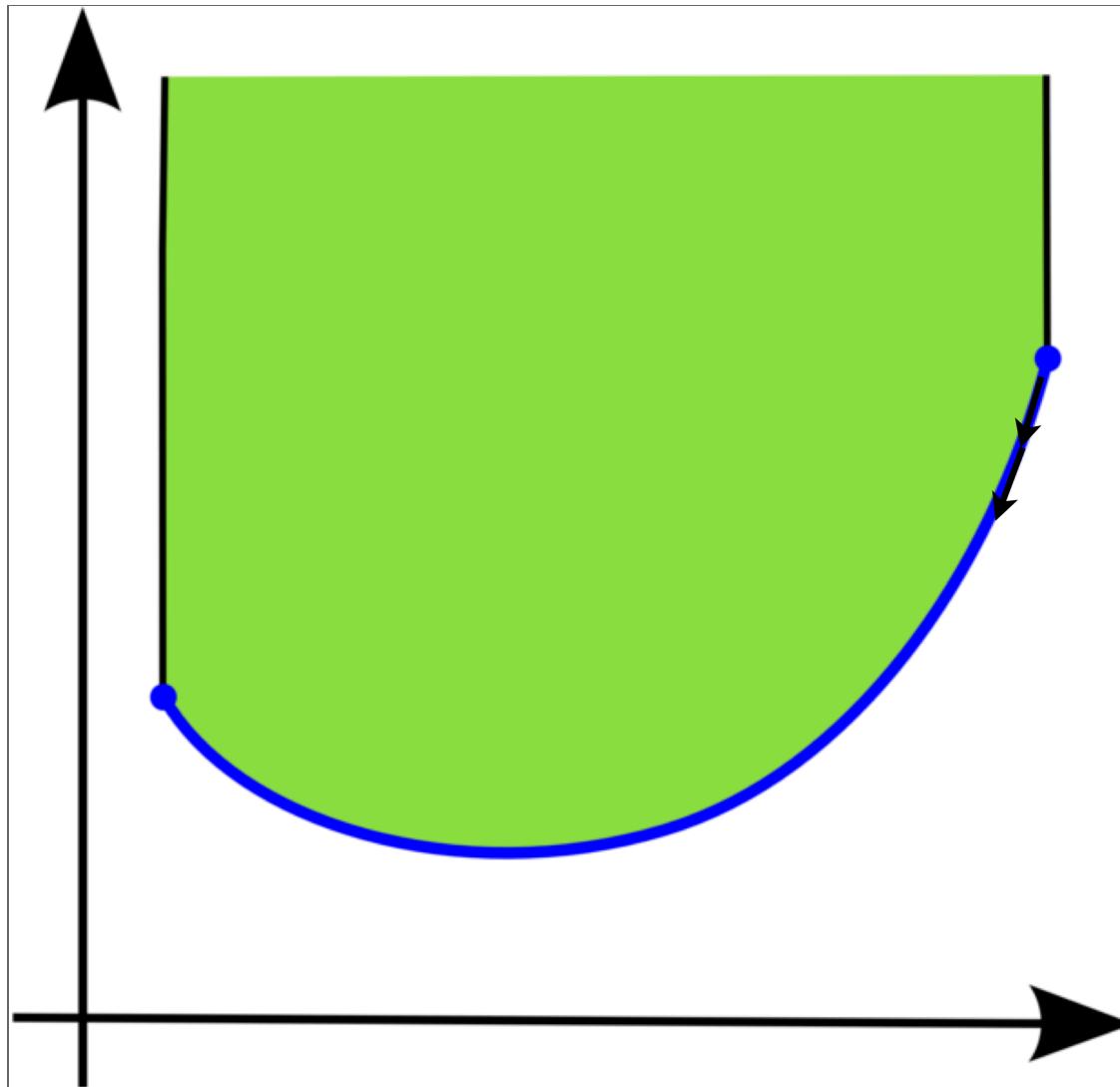
- › A multi-variable generalization of the derivative
- › Point in the direction of steepest increase in f

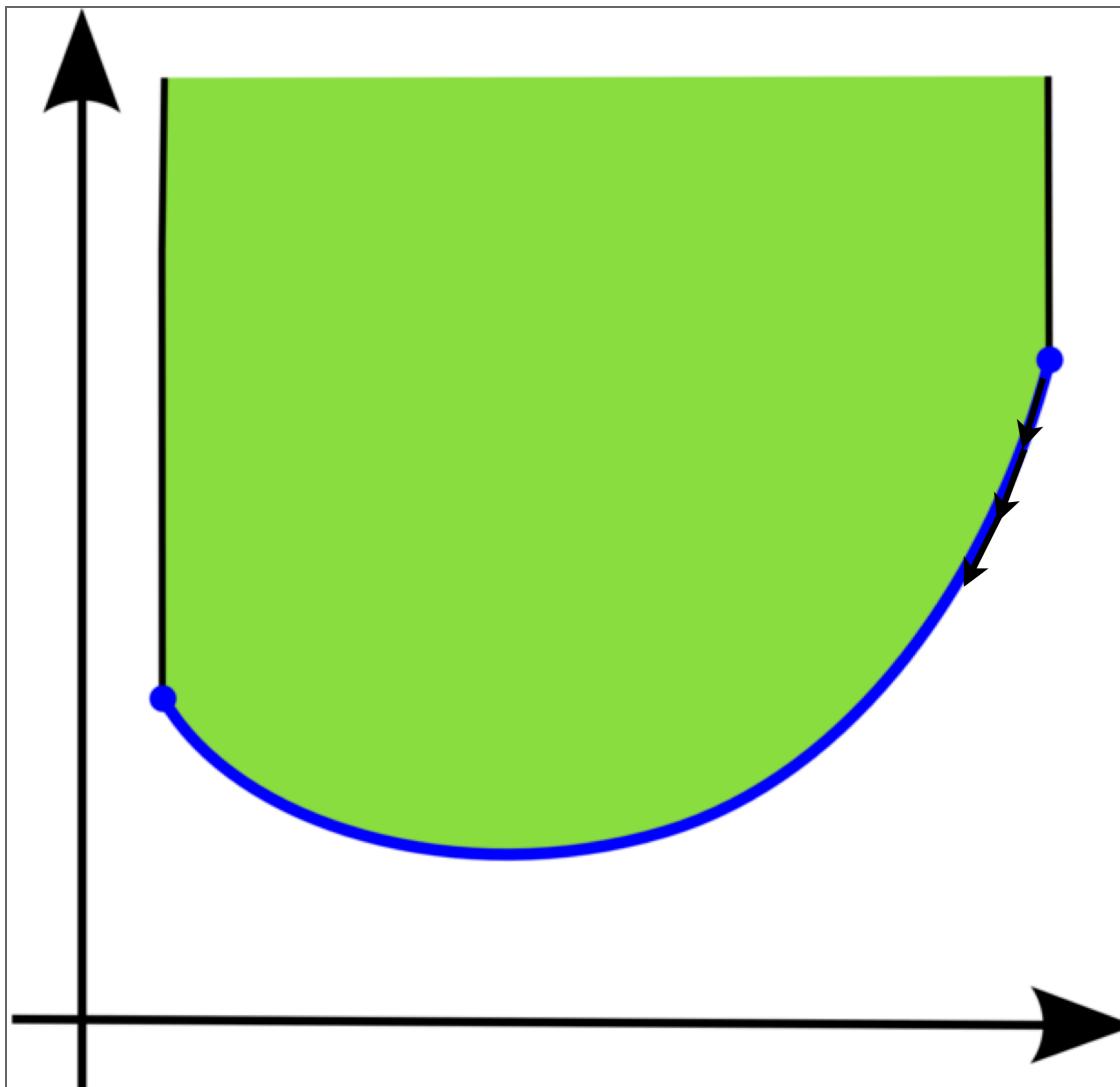
$$\nabla f(\mathbf{x}) \in \mathbb{R}^n = \begin{bmatrix} \frac{\partial f(\mathbf{x})}{\partial x_1} \\ \frac{\partial f(\mathbf{x})}{\partial x_2} \\ \vdots \\ \frac{\partial f(\mathbf{x})}{\partial x_n} \end{bmatrix}$$

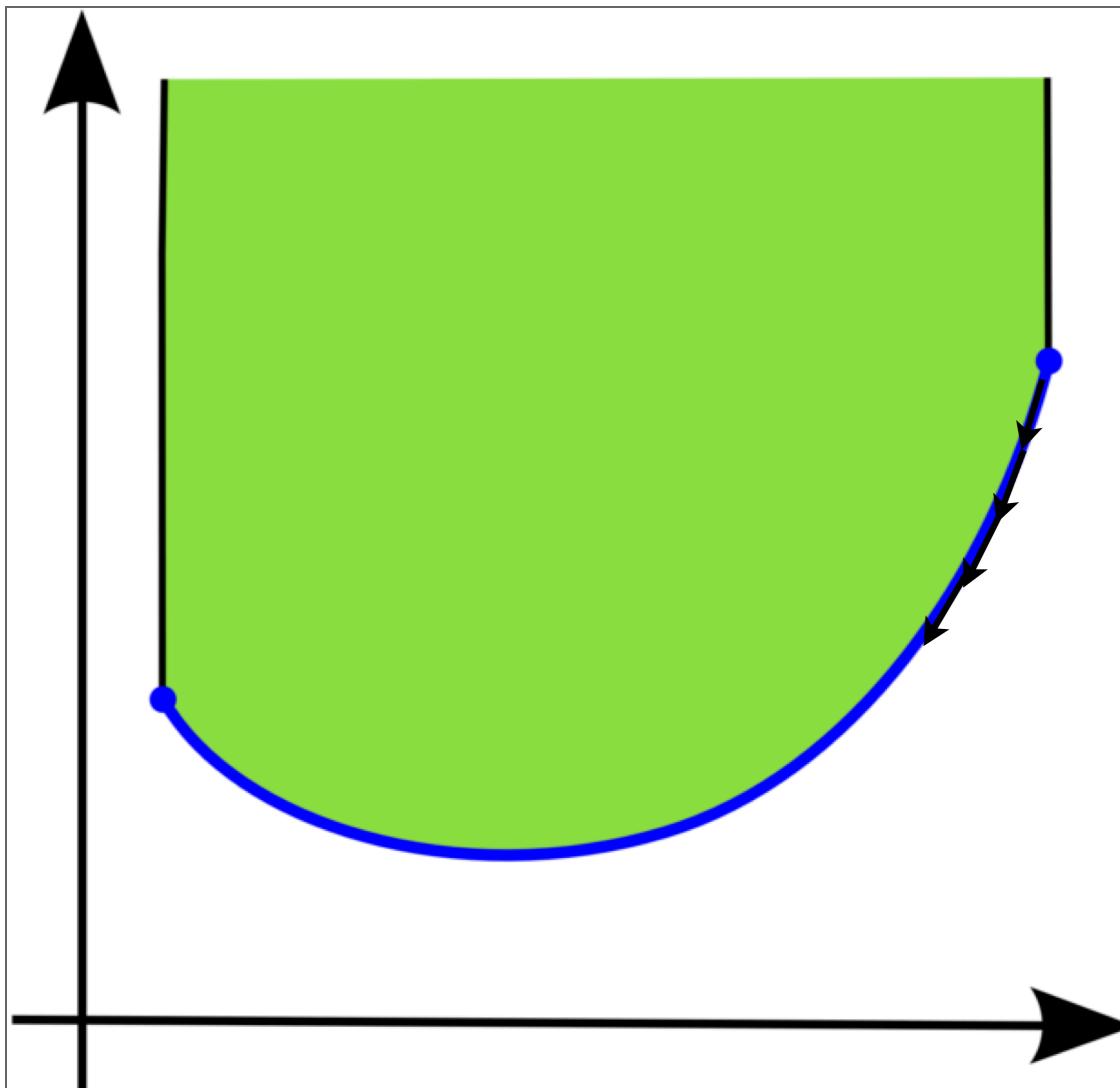
GRADIENT DESCENT

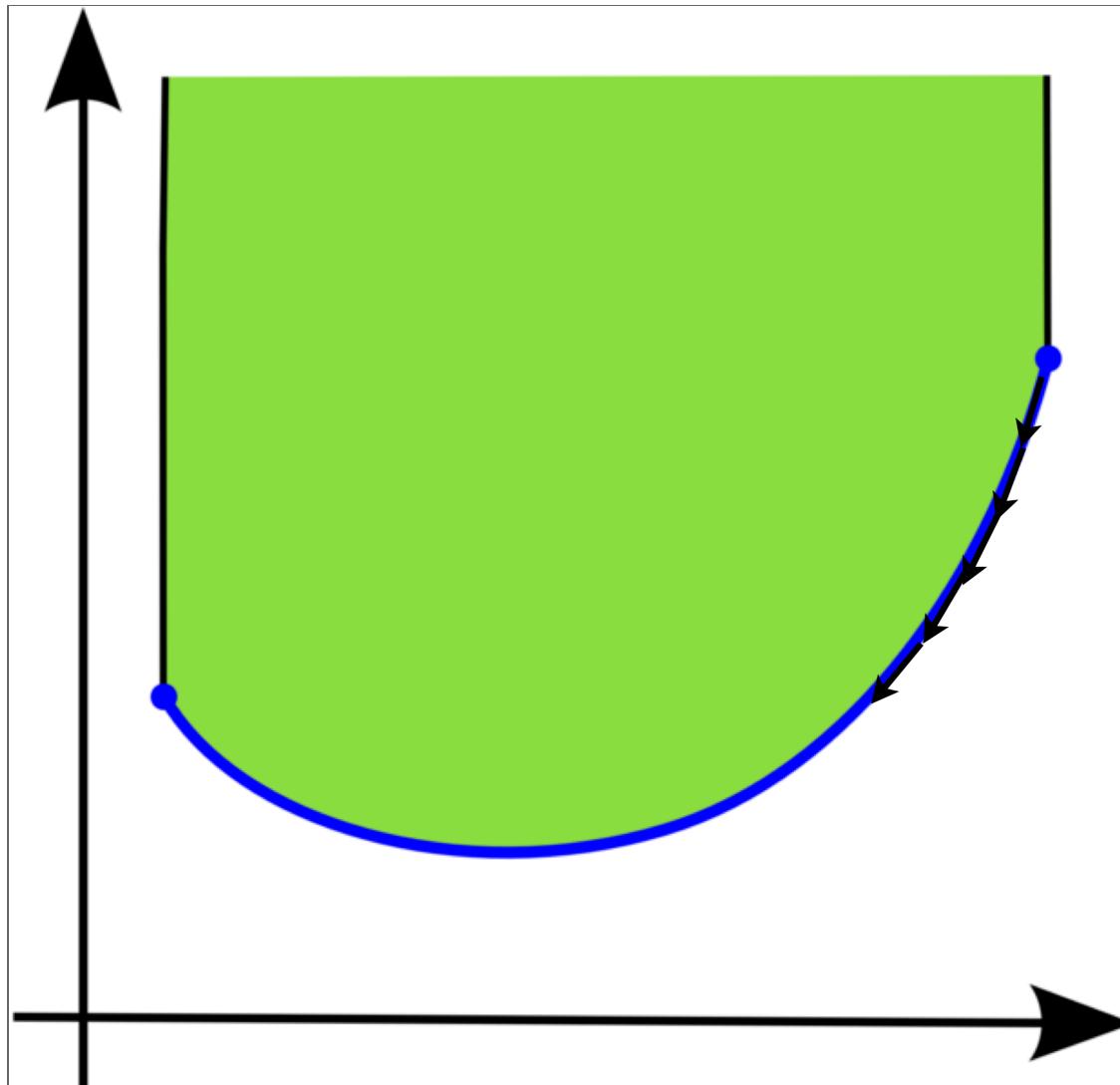


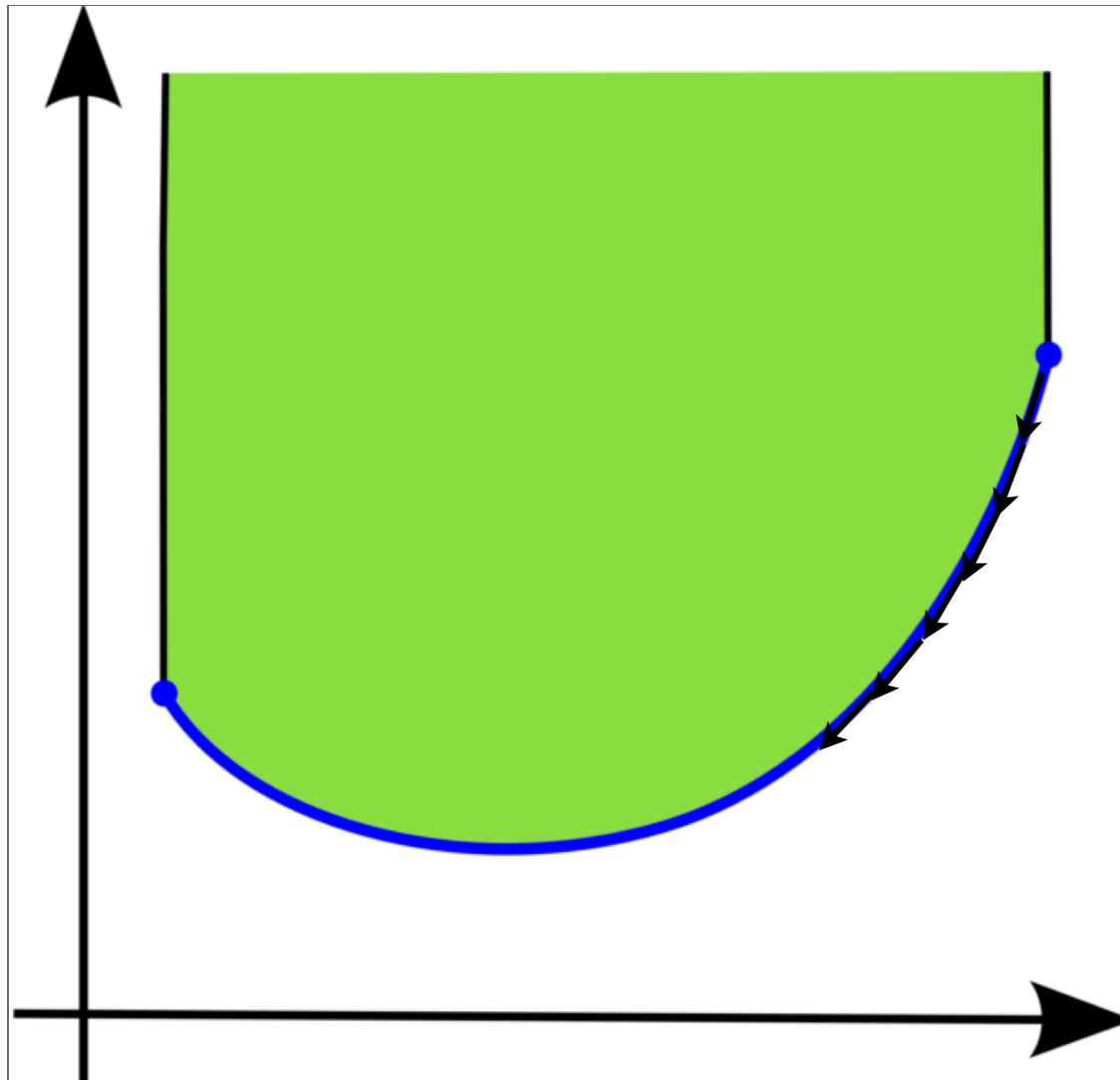












CONVEX OPTIMIZATION: HOW TO SOLVE?

Gradient descent: iteratively update the value of \mathbf{x}

- › A simple algorithm for unconstrained optimization $\min_{\mathbf{x} \in \mathbb{R}^n} f(\mathbf{x})$

```
Gradient Descent:  
Initialize  $x \leftarrow x_0$ ;  
repeat  
|  $x \leftarrow x - \alpha \nabla_x f(x)$ ;  
until convergence;
```

- › Variants
- › How to choose \mathbf{x}_0 , e.g., $\mathbf{x}_0 = \mathbf{0}$
- › How to choose and update step-size α , e.g., trial and error, line-search methods etc.
- › How to define "convergence", e.g., $\|\mathbf{x}^{i+1} - \mathbf{x}^i\| \leq \epsilon$

PROJECTED GRADIENT DESCENT

Iteratively update the value of \mathbf{x} while ensuring $\mathbf{x} \in \mathcal{F}$

Gradient Descent:

```
Initialize  $x \leftarrow x_0$ ;  
repeat  
|  $x \leftarrow P_{\mathcal{F}}(x - \alpha \nabla_x f(x))$ ;  
until convergence;
```

- › $P_{\mathcal{F}}$ projects a point to the constraint set.
- › Variant:
- › How to choose $P_{\mathcal{F}}$, e.g., $P_{\mathcal{F}} = \operatorname{argmin}_{\mathbf{x}' \in \mathcal{F}} \|\mathbf{x} - \mathbf{x}'\|_2^2$

CONVEX OPTIMIZATION: HOW TO SOLVE?

Unconstrained and differentiable

- › Gradient descent
- › Set derivative to be 0
- › Closed form solution
- › (Not covered) Newton's Method (if twice differentiable)

Constrained and differentiable

- › (Not covered) Projected gradient descent
- › (Not covered) Interior Point Method

(Not covered) Non-differentiable

- › ϵ -Subgradient Method

› Cutting Plane Method

CONVEX OPTIMIZATION: APPLY

Model a problem as a convex optimization problem

- › Define variable, feasible set, objective function
- › Prove it is convex (convex function + convex set)

Solve the convex optimization problem

- › Build up the model
- › Call a solver
- › Examples: fmincon (MATLAB), cvxpy (Python), cvxopt (Python), cvx (MATLAB)

Map the solution back to the original problem

Q & A



XKCD

Speaker notes

