

Topics in Applied Optimization

Optimization Algorithms for ML and Data Sciences

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Conjugate Function

Conjugate Function

$$\rightarrow \underline{y^T x - f(x)}$$

Conjugate Function: Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$. The function $f^* : \mathbb{R}^n \rightarrow \mathbb{R}$ defined as

$$f^*(y) = \sup_{x \in \text{dom } f} (y^T x - f(x))$$

is called **conjugate** of the function f . The **domain** of the conjugate function consists of $y \in \mathbb{R}^n$ for which the sum is **finite**, i.e., the difference $y^T x - f(x)$ is **bounded** above.

Conjugate Function

For a fixed x ,
Is $y^T x - f(x)$ convex?

$\sup \{ \underbrace{y^T x_1 - f(x_1)}_{x_1}, \underbrace{y^T x_2 - f(x_2)}_{x_2}, \dots \}$
 $\{g_1, g_2, \dots\}$ are convex
 $\sup \{g_1, g_2, \dots\}$ is convex.

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$$f(x) = Ax + b$$

$$f^*(y) \geq 0$$

- f^* is a convex function since it is a pointwise supremum of a family of convex functions

Linear fun
of y .

$$h(y) =$$

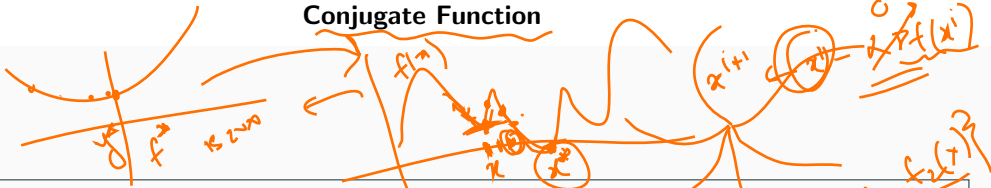
$$y^T x - f(x)$$

$$\nabla_y h(y) = x,$$

$$h(\theta y_1 + (1-\theta)y_2) \leq \theta h(y_1) + (1-\theta)h(y_2)$$

$$\nabla_y^2 h(y) = 0$$

Conjugate Function



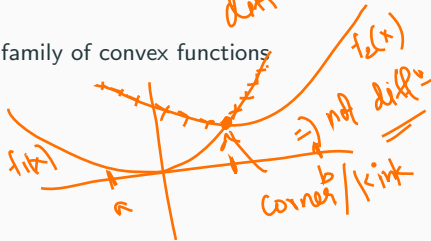
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- f^* is convex **regardless** of whether f is convex or not

(non-smooth opt problem). We need Sub-differentiable \rightarrow



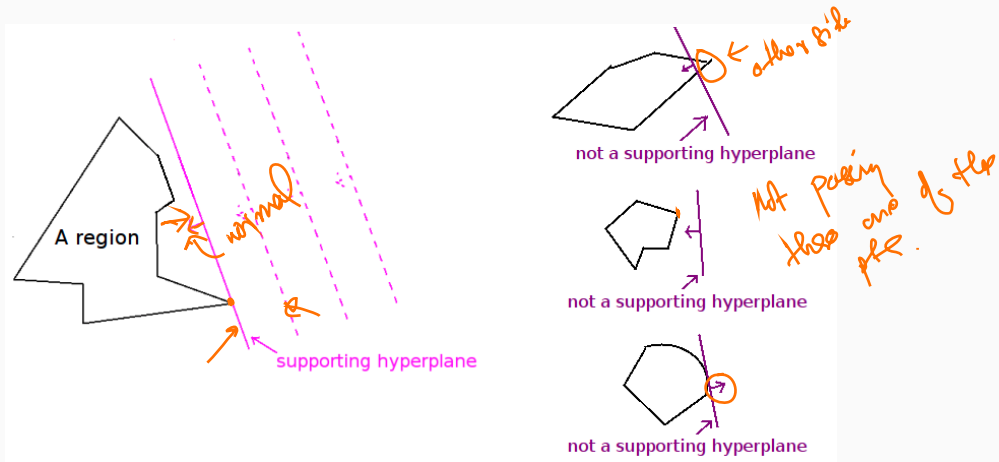
History and Geometric Intuition of Conjugates

History and Geometric Intuition of Conjugates

Recall supporting hyperplanes:

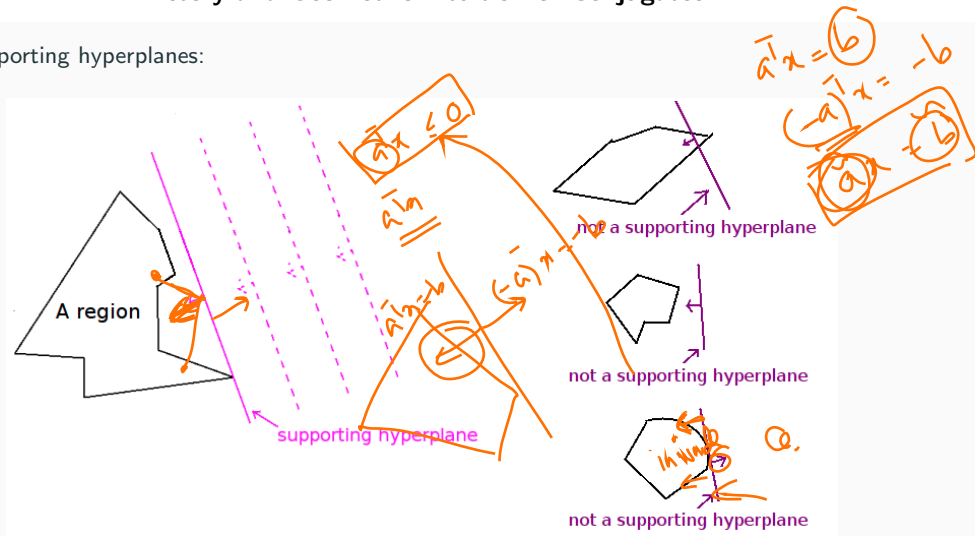
History and Geometric Intuition of Conjugates

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History and Geometric Intuition of Conjugates

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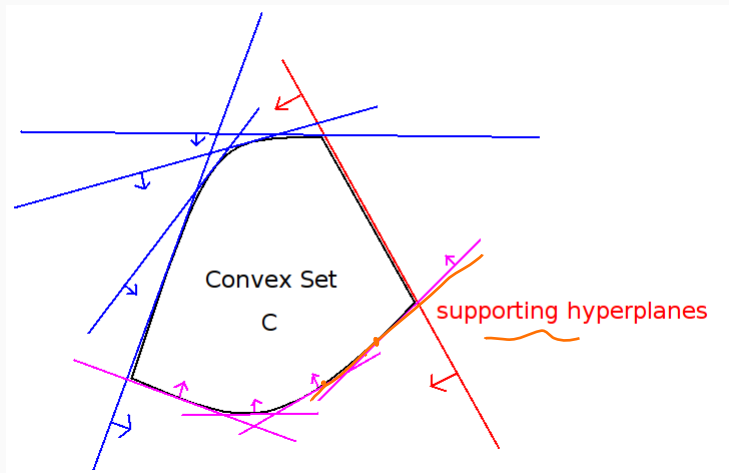


- Last one is not, because normal is pointing outwards

History and Geometric Intuition of Conjugates

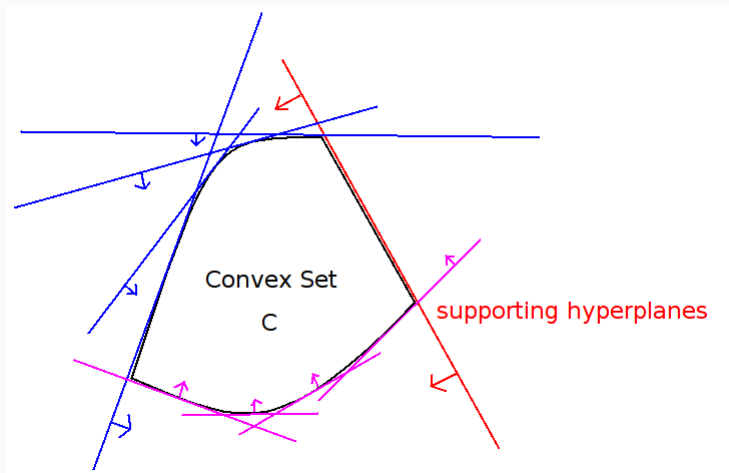
History and Geometric Intuition of Conjugates

A closed convex set can be represented by hyperplanes:



History and Geometric Intuition of Conjugates

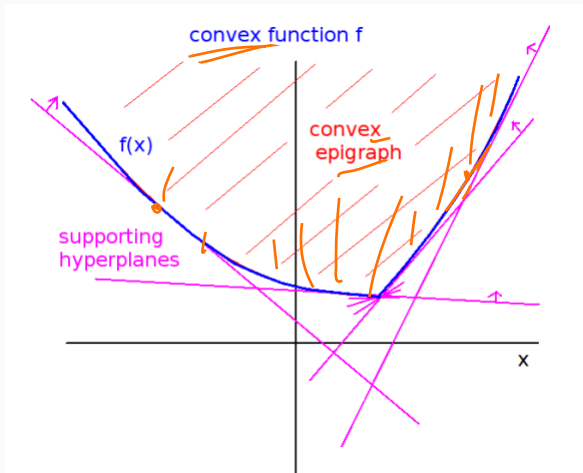
A closed convex set can be represented by hyperplanes:



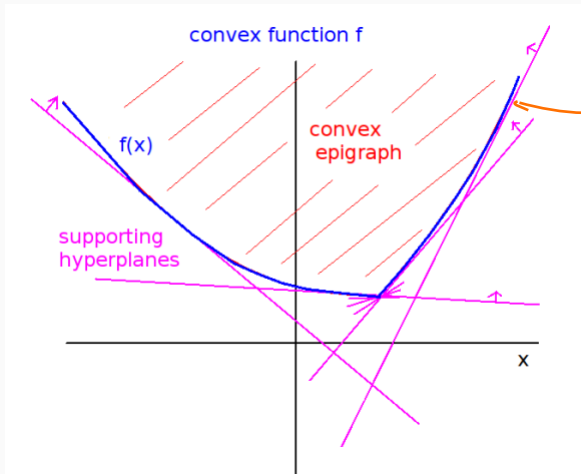
Note: At each point of a convex set, there is a unique supporting hyperplane

Supporting Hyperplanes for Convex Sets

Supporting Hyperplanes for Convex ~~Sets~~ Function



Supporting Hyperplanes for Convex Sets



- A closed convex set is **uniquely** determined by lower hyperplanes

Geometric intuition of Fenchel/Legendre's Transform

In 1D, Fenchel/Legendre's transform is:

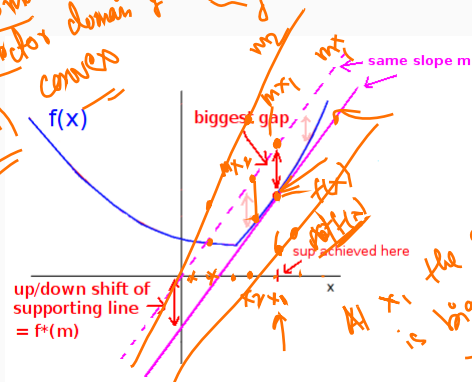
Primal
x-domain
↑

Dual
Slope-domain
normal-vector domain
 $f^*(m)$

$$f^*(m) = \sup_{x \in \mathbb{R}} (mx - f(x))$$

conjugate $\rightarrow f^*(y) = \sup_{x \in \mathbb{R}^n} (y^T x - f(x))$

$mx \leftarrow$ line passing through origin



$f(m_1) = \text{---}$
 $f(m_2) = \text{---}$

At x_1 the gap is biggest

time \leftrightarrow frequency

- Pick a plane with slope m and passing through origin
- Move the plane parallel to above plane until it becomes supporting hyperplane

Conjugates of Some Convex Functions on \mathbb{R}

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Find the conjugates of the following functions:

Conjugates of Some Convex Functions on \mathbb{R}

Find the conjugates of the following functions:

- Affine function: $f(x) = ax + b$.
- Negative logarithm: $f(x) = -\log x$
- Exponential. $f(x) = e^x$
- Negative Entropy. $f(x) = x \log x$
- Inverse. $f(x) = 1/x$

See classnotes for solutions.

Solution to previous problem...

Find conjugate of the affine function $f(x) = ax + b$

$yx - f(x) = yx - ax - b$ is bounded $x \in \mathbb{R}$.

$$\underline{\underline{f^*(y) = \sup_x (y^T x - f(x))}}$$

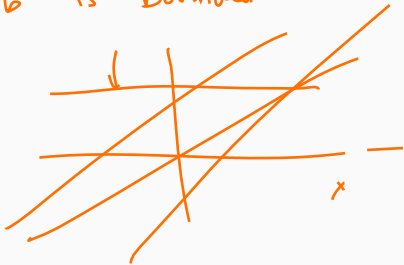
$y^T x - f(x)$ must be bounded.

Are linear fns bounded?

if $y = a$

$\text{dom } f^* = \{a\}$

$$f^*(a) = \underline{\underline{-b}}$$



$$f^*(y) = y \cdot \left(-\frac{1}{y}\right) + \log\left(-\frac{1}{y}\right) = -\log(-y) - 1 \quad \forall y < 0$$

Solution to previous problem...

Find conjugate of the negative logarithm $f(x) = -\log x$,

$$f(y) = yx - f(x) = yx + \log x$$

Case - I: $y > 0$

$$y + \frac{1}{x} > 0 \Rightarrow f(y) \text{ is strictly incr. for } y > 0$$

$$\Rightarrow f'(y) = 0$$

unbounded case

Case - II: $y < 0$

$$f'(x) = y + \frac{1}{x} \leq 0 \quad \geq 0$$

Critical point

$$f'(x) = 0 \Rightarrow$$

$$f''(x) = -\frac{1}{x^2} < 0$$

$$\Rightarrow f''(x) \big|_{x=-1/y} =$$

$$\text{dom } f^* = \{y \mid y < 0\} = \mathbb{R}_{++}$$

$$y + \frac{1}{x} = 0 \Rightarrow y = -\frac{1}{x} \Rightarrow x = -\frac{1}{y} \Rightarrow -\frac{1}{(-1/y)^2} = -y^2 < 0$$

