

# Convex Functions (II)

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# Outline

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- The Conjugate Function
- Quasiconvex Functions
- Log-concave and Log-convex Functions
- Convexity with Respect to Generalized Inequalities
- Summary



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# Conjugate Function

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□  $f: \mathbf{R}^n \rightarrow \mathbf{R}$ . Its conjugate function is

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

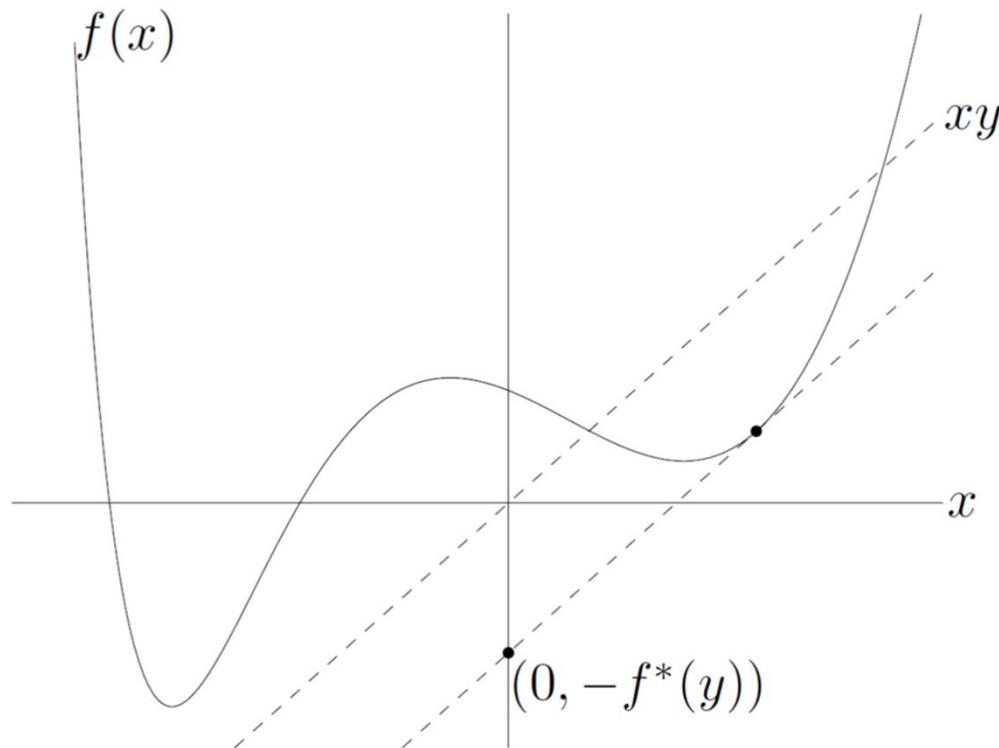
- $\text{dom } f^* = \{y | f^*(y) < \infty\}$
- $f^*$  is always convex



# Conjugate Function

□  $f: \mathbf{R}^n \rightarrow \mathbf{R}$ . Its conjugate function is

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





# Conjugate examples

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## □ Affine function

- $f(x) = ax + b$
- $f^*(y) = \sup_{x \in \mathbf{R}} (yx - ax - b)$
- $\text{dom } f^* = \{a\}, f^*(a) = -b$

## □ Negative logarithm

- $f(x) = -\log x$
- $f^*(y) = \sup_{x \in \mathbf{R}_{++}} (yx + \log x)$
- $\text{dom } f^* = -\mathbf{R}_{++}, f^*(y) = -\log(-y) - 1$



# Conjugate examples

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## □ Exponential

- $f(x) = e^x$
- $f^*(y) = \sup_{x \in \mathbf{R}} (xy - e^x)$
- $\text{dom } f^* = \mathbf{R}_+, f^*(y) = y \log y - y$

## □ Negative entropy

- $f(x) = x \log x$
- $f^*(y) = \sup_{x \in \mathbf{R}_+} (yx - x \log x)$
- $\text{dom } f^* = \mathbf{R}, f^*(y) = e^{y-1}$



# Conjugate examples

## □ Inverse

- $f(x) = 1/x$
- $f^*(y) = \sup_{x \in \mathbf{R}_{++}} (xy - 1/x)$
- $\text{dom } f^* = -\mathbf{R}_+, f^*(y) = -2(-y)^{1/2}$

## □ Strictly convex quadratic function

- $f(x) = \frac{1}{2} x^\top Q x, Q \in \mathbf{S}_{++}^n$
- $f^*(y) = \sup_{x \in \mathbf{R}^n} (y^\top x - \frac{1}{2} x^\top Q x)$
- $\text{dom } f^* = \mathbf{R}^n, f^*(y) = \frac{1}{2} y^\top Q^{-1} y$



# Conjugate examples

## □ Log-determinant

- $f(X) = \log \det X^{-1}, X \in \mathbf{S}_{++}^n$
- $f^*(Y) = \sup_{X \in \mathbf{S}_{++}^n} (\text{tr}(XY) + \log \det X)$
- $\text{dom } f^* = -\mathbf{S}_{++}^n, f^*(Y) = \log \det(-Y)^{-1} - n$

## □ Indicator function

- $I_S(x) = 0, \text{dom } I_S = S, S \subseteq \mathbf{R}^n$  is not necessarily convex
- $I_S^*(y) = \sup_{x \in S} y^\top x$
- $I_S^*(y)$  is the support function of the set  $S$



# Conjugate examples

## □ Norm

- $f(x) = \|x\|, x \in \mathbf{R}^n$ , with dual norm  $\|\cdot\|_*$
- $f^*(y) = \sup_{x \in \mathbf{R}^n} (x^\top y - \|x\|)$
- $\text{dom } f^* = \{y | \|y\|_* \leq 1\}, f^*(y) = 0$

## □ Norm squared

- $f(x) = \frac{1}{2} \|x\|^2, x \in \mathbf{R}^n$ , with dual norm  $\|\cdot\|_*$
- $f^*(y) = \sup_{x \in \mathbf{R}^n} (x^\top y - \frac{1}{2} \|x\|^2)$
- $\text{dom } f^* = \mathbf{R}^n, f^*(y) = \frac{1}{2} \|y\|_*^2$



# Basic properties

## □ Fenchel's inequality

- $\forall x \in \text{dom } f, y \in \text{dom } f^*, f(x) + f^*(y) \geq x^\top y$
- $f^*(y) = \sup_{x \in \mathbf{R}^n} (x^\top y - f(x))$
- $f(x) = \frac{1}{2} x^\top Q x, Q \in \mathbf{S}_{++}^n$   
 $\Rightarrow x^\top y \leq \frac{1}{2} x^\top Q x + \frac{1}{2} y^\top Q^{-1} y$

## □ Conjugate of the conjugate

- $f$  is convex and closed  $\Rightarrow f^{**} = f$



# Basic properties

## □ Differentiable functions

- $f$  is convex and differentiable,  $\text{dom } f = \mathbf{R}^n$
- $f^*(y) = \sup_{x \in \mathbf{R}^n} (x^\top y - f(x))$
- $x^* = \operatorname{argmax}(x^\top y - f(x)) \Rightarrow \nabla f(x^*) = y$
- $f^*(y) = {x^*}^\top \nabla f(x^*) - f(x^*) = {x^*}^\top y - f(x^*)$
- ✓  $x^* = \nabla^{-1}f(y)$



# Basic properties

## □ Scaling with affine transformation

- $a > 0, b \in \mathbf{R}, g(x) = af(x) + b$   
 $\Rightarrow g^*(y) = af^*\left(\frac{y}{a}\right) - b$
- $A \in \mathbf{R}^{n \times n}$  is nonsingular,  $b \in \mathbf{R}^n, g(x) = f(Ax + b) \Rightarrow g^*(y) = f^*(A^{-\top}y) - b^\top A^{-\top}y, \text{dom } g^* = A^\top \text{dom } f^*$

## □ Sums of independent functions

- $f(u, v) = f_1(u) + f_2(v), f_1, f_2$  are convex  $\Rightarrow f^*(w, z) = f_1^*(w) + f_2^*(z)$



# Outline

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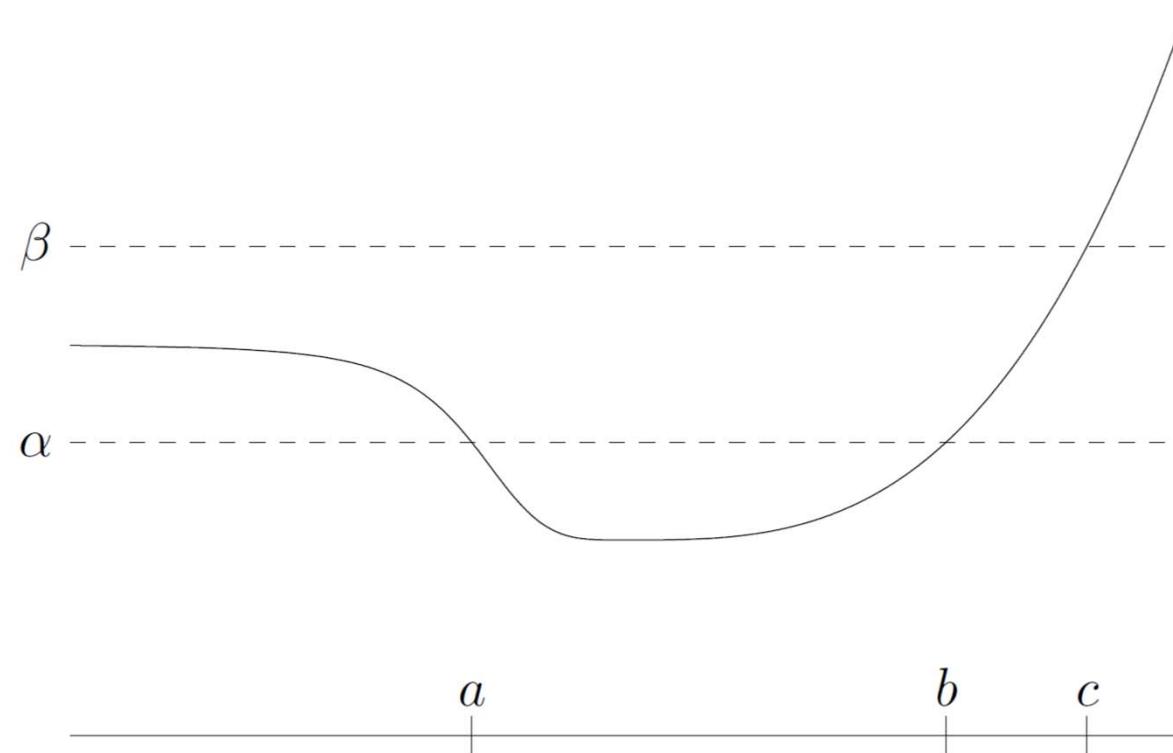
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# Quasiconvex functions

## □ Quasiconvex

- $f: \mathbf{R}^n \rightarrow \mathbf{R}$
- $S_\alpha = \{x \in \text{dom } f \mid f(x) \leq \alpha\}, \forall \alpha \in \mathbf{R}$  is convex





# Quasiconvex functions

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## □ Quasiconvex

- $f: \mathbf{R}^n \rightarrow \mathbf{R}$
- $S_\alpha = \{x \in \text{dom } f \mid f(x) \leq \alpha\}, \forall \alpha \in \mathbf{R}$  is convex

## □ Quasiconcave

- $-f$  is quasiconvex  $\Rightarrow f$  is quasiconcave

## □ Quasilinear

- $f$  is quasiconvex and quasiconcave  $\Rightarrow f$  is quasilinear



# Examples

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## □ Some example on $\mathbf{R}$

- Logarithm:  $\log x$  on  $\mathbf{R}_{++}$
- Ceiling function:  $\text{ceil}(x) = \inf\{z \in \mathbf{Z} \mid z \geq x\}$

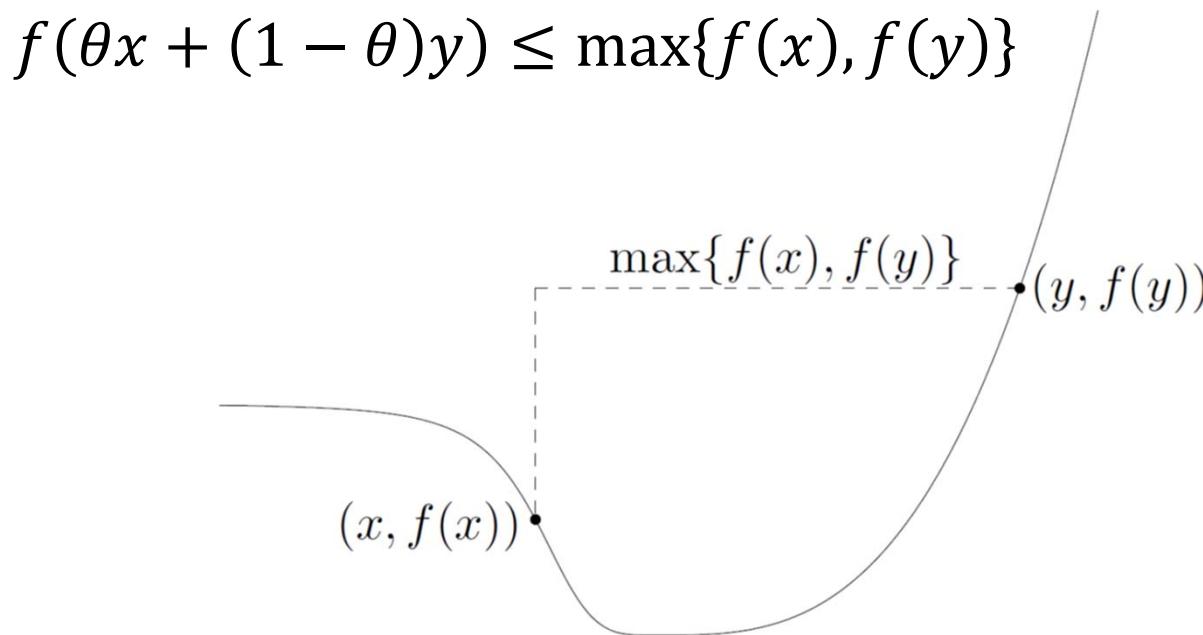
## □ Linear-fractional function

- $f(x) = \frac{a^\top x + b}{c^\top x + d}$ ,  $\text{dom } f = \{x \mid c^\top x + d > 0\}$
  - $\left\{x \mid c^\top x + d > 0, \frac{a^\top x + b}{c^\top x + d} \geq \alpha\right\}$  and  
 $\left\{x \mid c^\top x + d > 0, \frac{a^\top x + b}{c^\top x + d} \leq \alpha\right\}$  is convex
- $\Rightarrow f$  is Quasilinear



# Basic properties

- Jensen's inequality for quasiconvex functions
  - $f$  is quasiconvex  $\Leftrightarrow \text{dom } f$  is convex and
$$\forall x, y \in \text{dom } f, 0 \leq \theta \leq 1$$





# Basic properties

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## □ Condition

- $f$  is quasiconvex  $\Leftrightarrow$  its restriction to any line intersecting its domain is quasiconvex

## □ Quasiconvex functions on $\mathbf{R}$

- A continuous function  $f: \mathbf{R} \rightarrow \mathbf{R}$  is quasiconvex  $\Leftrightarrow$  one of the following conditions holds
  - $f$  is nondecreasing
  - $f$  is nonincreasing
  - $\exists c \in \text{dom } f, \forall t \in \text{dom } f, t \leq c, f$  is nonincreasing, and  $t \geq c, f$  is nondecreasing



# Differentiable quasiconvex functions

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## □ First-order conditions

- $f$  is differentiable
- $f$  is quasiconvex  $\Leftrightarrow \text{dom } f$  is convex,  $\forall x, y \in \text{dom } f, f(y) \leq f(x) \Rightarrow \nabla f(x)^\top (y - x) \leq 0$
- It is possible that  $\nabla f(x) = 0$ , but  $x$  is not a global minimizer of  $f$ .

## □ Second-order conditions

- $f$  is twice differentiable
- $\forall x \in \text{dom } f, \forall y \in \mathbf{R}^n, y^\top \nabla f(x) = 0 \Rightarrow y^\top \nabla^2 f(x) y > 0 \Rightarrow f$  is quasiconvex



# Operations that preserve quasiconvexity

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## □ Nonnegative weighted maximum

- $f_i$  is quasicovex,  $w_i \geq 0 \Rightarrow f = \max\{w_1f_1, \dots, w_nf_n\}$  is quasiconvex
  
- $g(x, y)$  is quasiconvex in  $x$  for each  $y, w(y) \geq 0 \Rightarrow f(x) = \sup_{y \in C} (w(y)f(x, y))$  is quasiconvex



# Operations that preserve quasiconvexity

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## □ Composition

- $g: \mathbf{R}^n \rightarrow \mathbf{R}$  is quasiconvex,  $h: \mathbf{R} \rightarrow \mathbf{R}$  is nondecreasing  $\Rightarrow f = h \circ g$  is quasiconvex
- $f: \mathbf{R}^n \rightarrow \mathbf{R}$  is quasiconvex  $\Rightarrow g(x) = f(Ax + b)$  is quasiconvex
- $f: \mathbf{R}^n \rightarrow \mathbf{R}$  is quasiconvex  $\Rightarrow g(x) = f(\frac{Ax+b}{c^\top x+d})$  is quasiconvex,  $\text{dom } g = \{x | c^\top x + d > 0, (Ax + b)/(c^\top x + d) \in \text{dom } f\}$

## □ Minimization

- $f(x, y)$  is **quasicovex** in  $x$  and  $y$ ,  $C$  is a convex set  $\Rightarrow g(x) = \inf_{y \in C} f(x, y)$  is quasiconvex



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# Log-concave and log-convex functions

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## □ Definition

- $f: \mathbf{R}^n \rightarrow \mathbf{R}, f(x) > 0, \forall x \in \text{dom } f, \log f(x)$  is concave (convex)  $\Rightarrow f$  is log-concave (convex)

## □ Condition

- $f: \mathbf{R}^n \rightarrow \mathbf{R}, f(x) > 0, \forall x \in \text{dom } f, f$  is log-concave  $\Leftrightarrow \forall x, y \in \text{dom } f, 0 \leq \theta \leq 1$ 
$$f(\theta x + (1 - \theta)y) \leq f(x)^\theta f(y)^{1-\theta}$$



# Examples

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- $f(x) = a^\top x + b, \text{dom } f = \{x | a^\top x + b > 0\}$  is log-concave
- $f(x) = x^a, \text{dom } f = \mathbf{R}_{++}, a \leq 0 \Rightarrow f$  is log-convex,  $a \geq 0 \Rightarrow f$  is log-concave
- $\phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-u^2/2} du$  is log-concave
- $\Gamma(x) = \int_0^\infty u^{x-1} e^{-u} du$  is log-convex for  $x \geq 1$
- $\det X$  and  $\frac{\det X}{\text{tr } X}$  are log-concave on  $S_{++}^n$



# Properties

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- Twice differentiable log convex/concave functions
  - $f$  is twice differentiable,  $\text{dom } f$  is convex
  - $\nabla^2 \log f(x) = \frac{1}{f(x)} \nabla^2 f(x) - \frac{1}{f(x)^2} \nabla f(x) \nabla f(x)^\top$
  - $f$  is log convex  $\Leftrightarrow f(x) \nabla^2 f(x) \geq \nabla f(x) \nabla f(x)^\top$
  - $f$  is log concave  $\Leftrightarrow f(x) \nabla^2 f(x) \leq \nabla f(x) \nabla f(x)^\top$



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# Convexity with respect to a generalized inequality

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## □ $K$ -convex

- $K \subseteq \mathbf{R}^m$  is a proper cone with associated generalized inequality  $\leqslant_K$
- $f: \mathbf{R}^n \rightarrow \mathbf{R}^m$  is  $K$ -convex if  $\forall x, y \in \text{dom } f, 0 \leq \theta \leq 1$   
$$f(\theta x + (1 - \theta)y) \leqslant_K \theta f(x) + (1 - \theta)f(y)$$
- $f: \mathbf{R}^n \rightarrow \mathbf{R}^m$  is strictly  $K$ -convex if  $\forall x \neq y \in \text{dom } f, 0 < \theta < 1$   
$$f(\theta x + (1 - \theta)y) <_K \theta f(x) + (1 - \theta)f(y)$$



# Examples

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## □ Componentwise inequality

- $K = \mathbf{R}_+^m$
- $f: \mathbf{R}^n \rightarrow \mathbf{R}^m$  is convex with respect to componentwise inequality  $\Leftrightarrow \forall x, y \in \text{dom } f, 0 \leq \theta \leq 1,$   
$$f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$$
- Each  $f_i$  is a convex function



# Examples

## □ Matrix convexity

- $f: \mathbf{R}^n \rightarrow \mathbf{S}^m$  is convex with respect to matrix inequality  $\Leftrightarrow \forall x, y \in \text{dom } f, 0 \leq \theta \leq 1$   
$$f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$$
- $f(X) = XX^\top, X \in \mathbf{R}^{m \times n}$  is matrix convex
- $X^p$  is matrix convex on  $\mathbf{S}_{++}^n$  for  $1 \leq p \leq 2$  or  $-1 \leq p \leq 0$ , and matrix concave for  $0 \leq p \leq 1$



# Convexity with respect to generalized inequalities

## □ Dual characterization of $K$ -convexity

- A function  $f$  is (strictly)  $K$ -convex  $\Leftrightarrow$  For every  $w \geqslant_{K^*} 0$ , the real-valued function  $w^\top f$  is (strictly) convex in the ordinary sense.

## □ Differentiable $K$ -convex functions

- A differentiable function  $f$  is  $K$ -convex  $\Leftrightarrow \text{dom } f$  is convex,  $\forall x, y \in \text{dom } f$ ,

$$f(y) \geqslant_K f(x) + Df(x)(y - x)$$

- A differentiable function  $f$  is strictly  $K$ -convex  $\Leftrightarrow \text{dom } f$  is convex,  $\forall x, y \in \text{dom } f, x \neq y$ ,

$$f(y) >_K f(x) + Df(x)(y - x)$$



# Convexity with respect to generalized inequalities

## □ Composition theorem

- $g: \mathbf{R}^n \rightarrow \mathbf{R}^p$  is  $K$ -convex,  $h: \mathbf{R}^p \rightarrow \mathbf{R}$  is convex, and  $\tilde{h}$  (the extended-value extension of  $h$ ) is  $K$ -nondecreasing  $\Rightarrow h \circ g$  is convex.

## □ Example

- $g: \mathbf{R}^{m \times n} \rightarrow \mathbf{S}^n$ ,  $g(X) = X^\top AX + B^\top X + X^\top B + C$  is convex, where  $A \geq 0, B \in \mathbf{R}^{m \times n}$  and  $C \in \mathbf{S}^n$
- $h: \mathbf{S}^n \rightarrow \mathbf{R}$ ,  $h(Y) = -\log \det(-Y)$  is convex and increasing on  $\text{dom } h = -\mathbf{S}_{++}^n$
- $f(X) = -\log \det(-(X^\top AX + B^\top X + X^\top B + C))$  is convex on  $\text{dom } f = \{X \in \mathbf{R}^{m \times n} | X^\top AX + B^\top X + X^\top B + C < 0\}$



# Monotonicity with respect to a generalized inequality

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- $K \subseteq \mathbf{R}^n$  is a proper cone with associated generalized inequality  $\leqslant_K$

- $f: \mathbf{R}^n \rightarrow \mathbf{R}$  is  $K$ -nondecreasing if

$$x \leqslant_K y \Rightarrow f(x) \leq f(y)$$

- $f: \mathbf{R}^n \rightarrow \mathbf{R}$  is  $K$ -increasing if

$$x \leqslant_K y, x \neq y \Rightarrow f(x) < f(y)$$



# Summary

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- The Conjugate Function
  - Definitions, Basic properties
- Quasiconvex Functions
- Log-concave and Log-convex Functions
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