



Mathematical Foundations of Robust Distributionally Robust Optimization

Jianzhe Zhen,¹⁾ Wolfram Wiesemann,²⁾ Daniel Kuhn³⁾

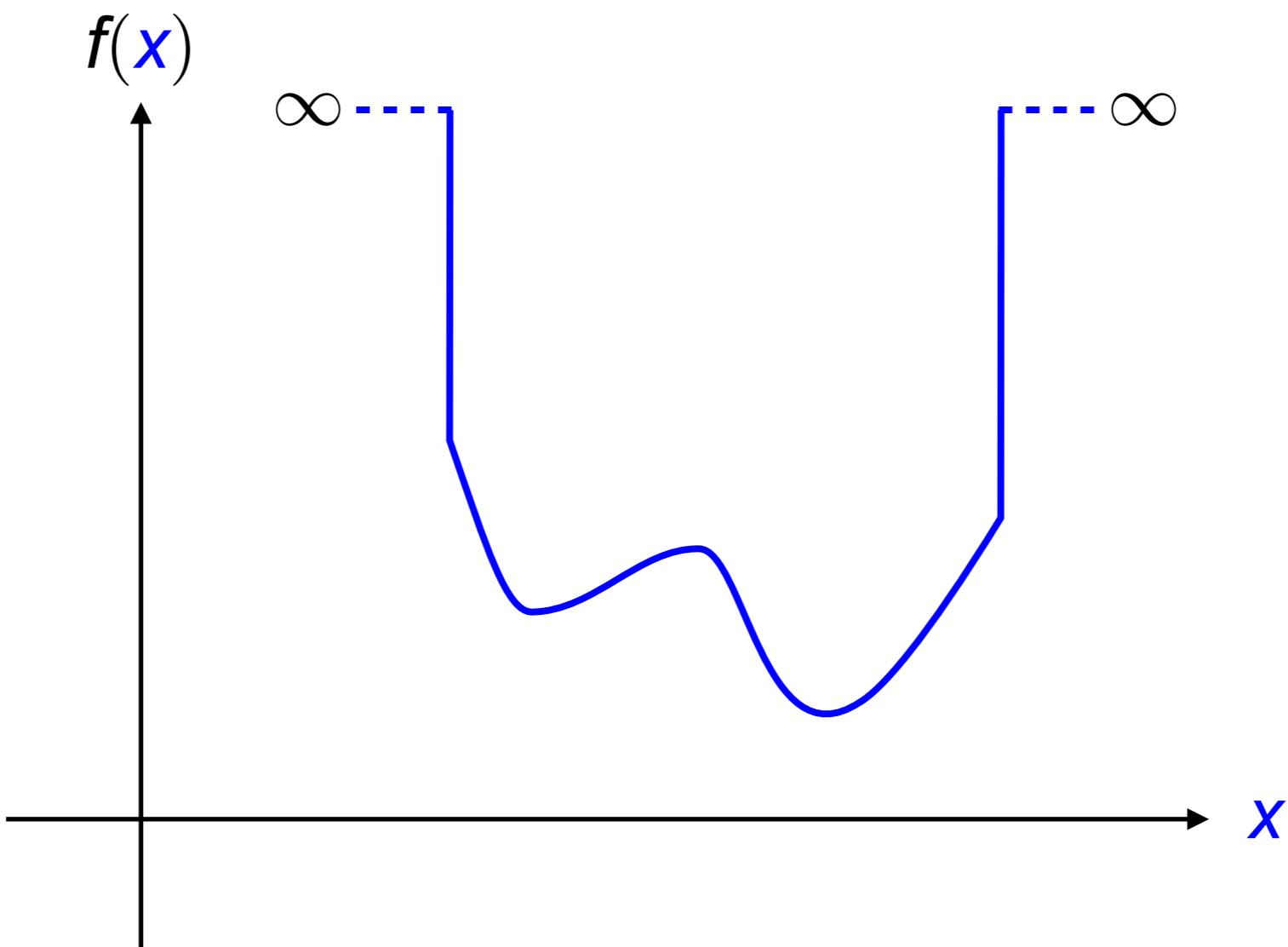
¹⁾ Automatic Control Laboratory, ETH Zurich
trevorzhen.com

²⁾ Imperial College Business School
wp.doc.ic.ac.uk/wwiesema/

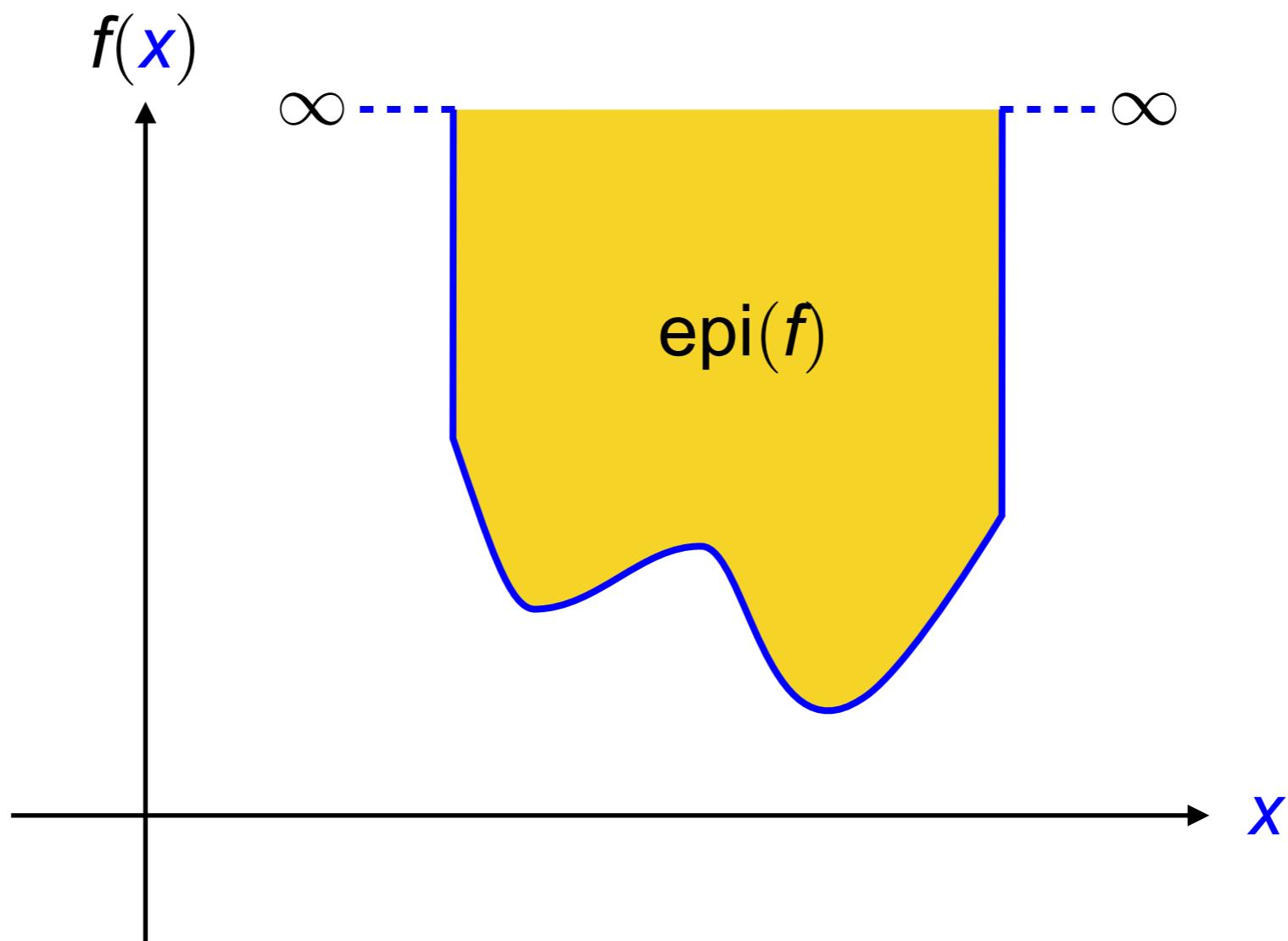
³⁾ Risk Analytics and Optimization Chair, EPFL
www.epfl.ch/labs/rao/

Extended Real-Valued Functions

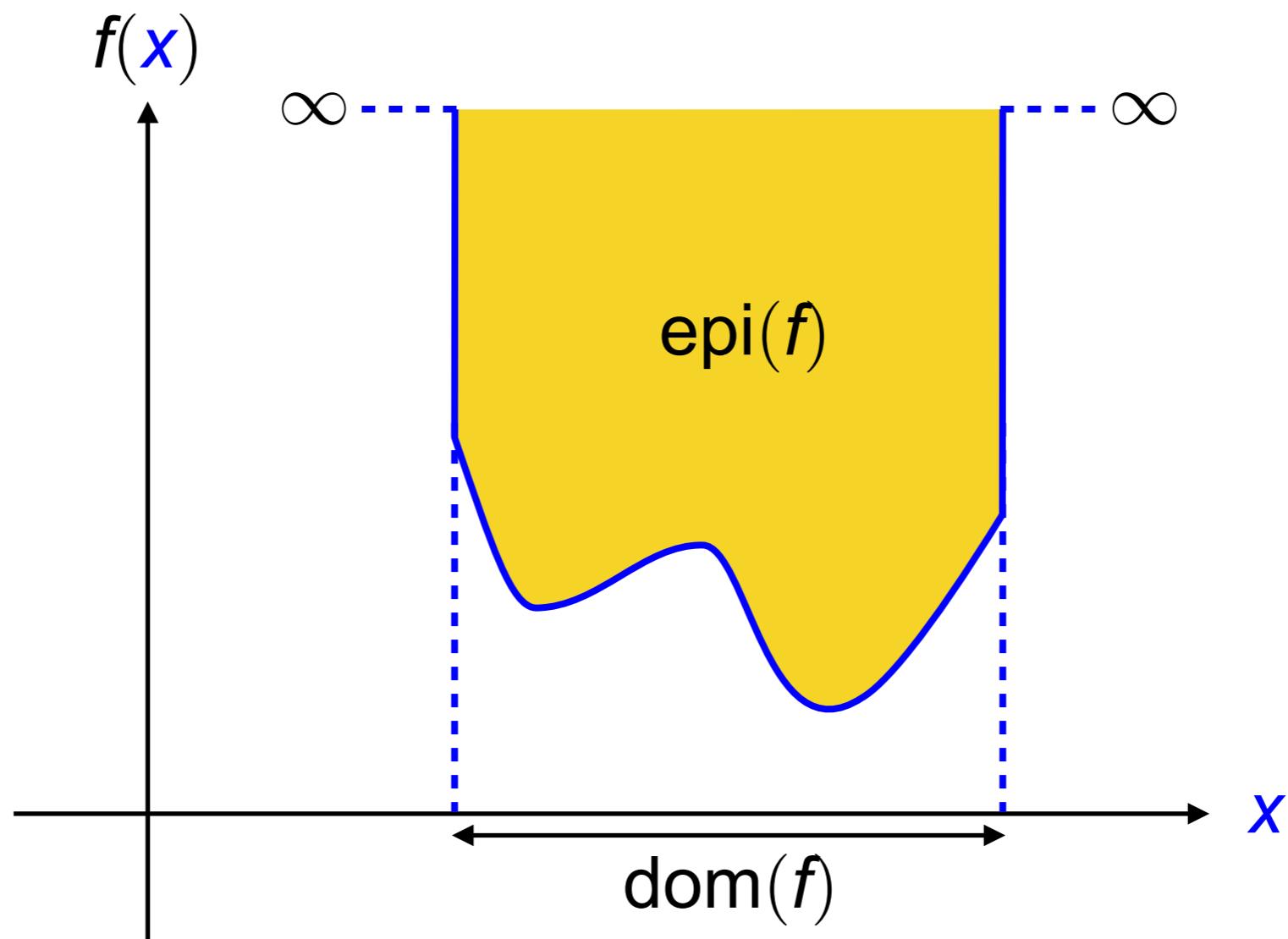
Proper Functions



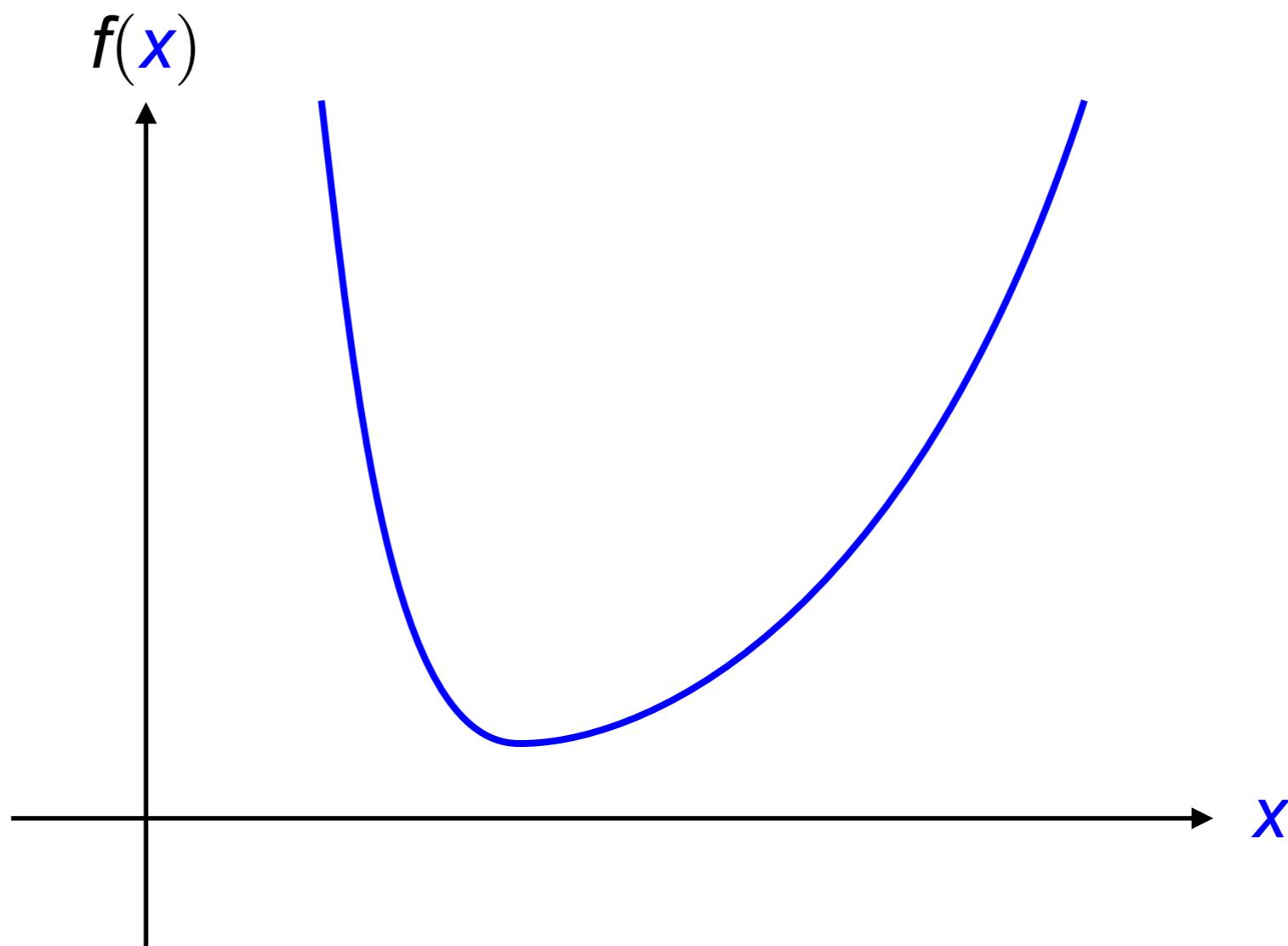
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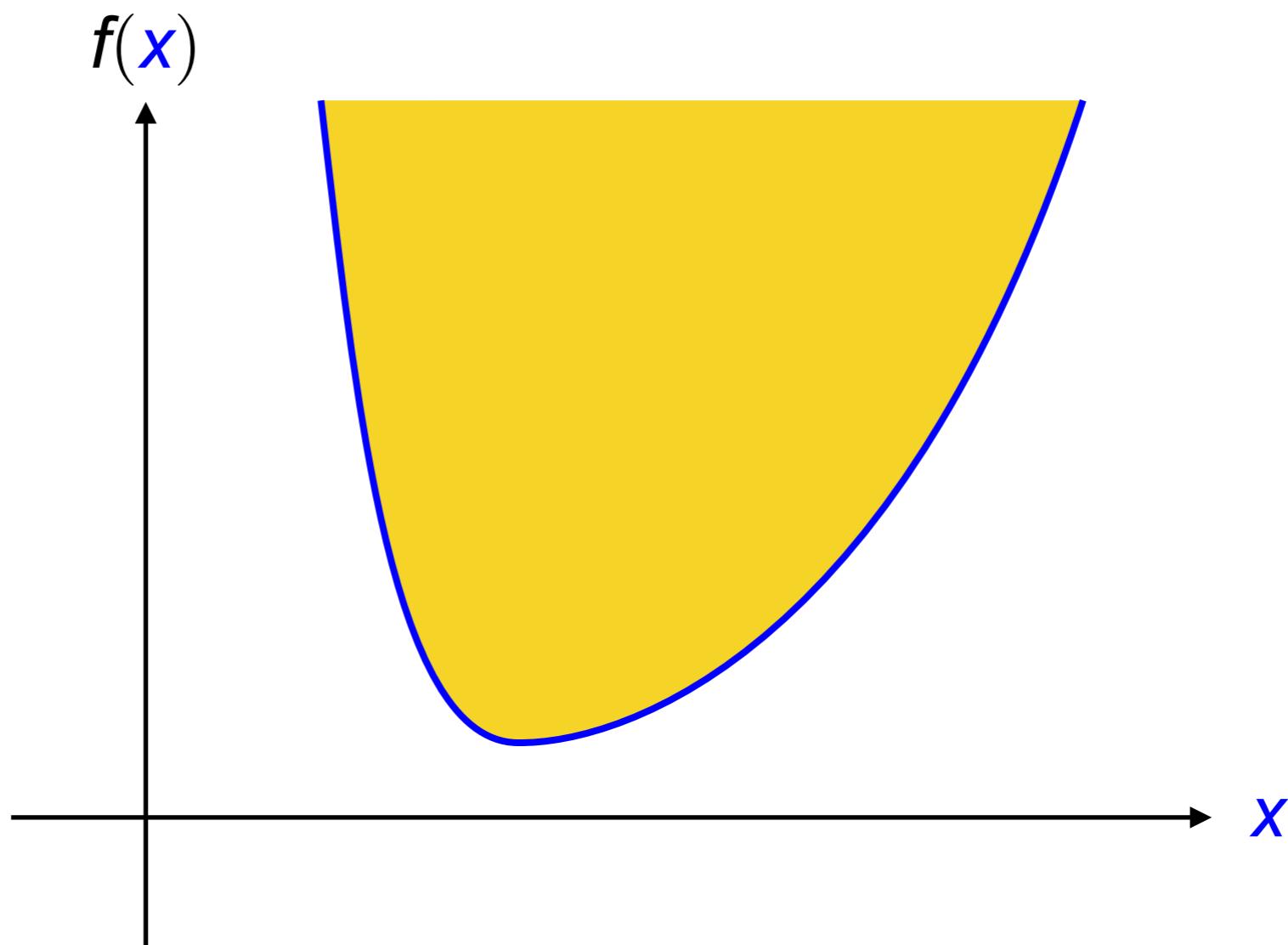
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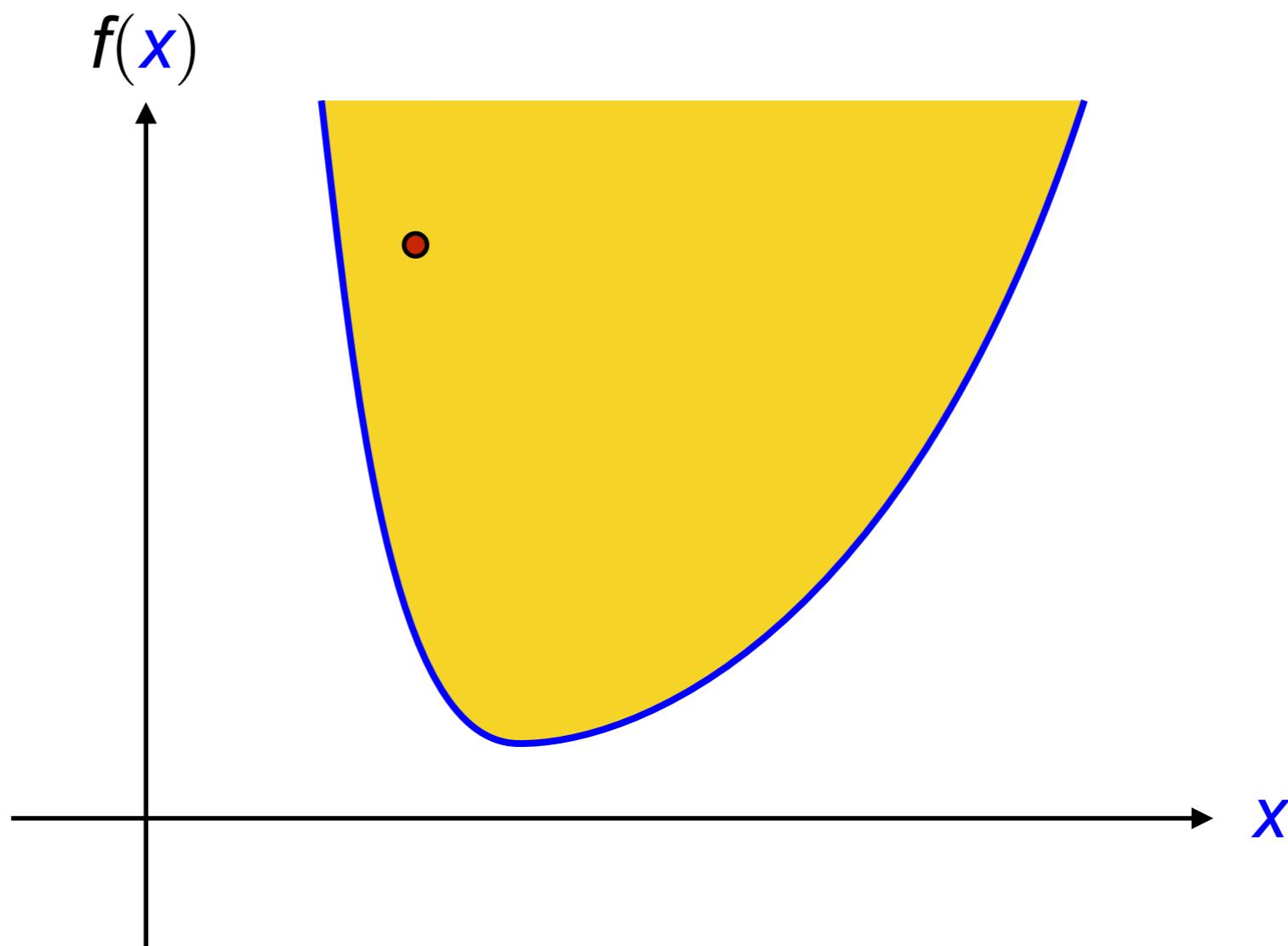
Convex Functions



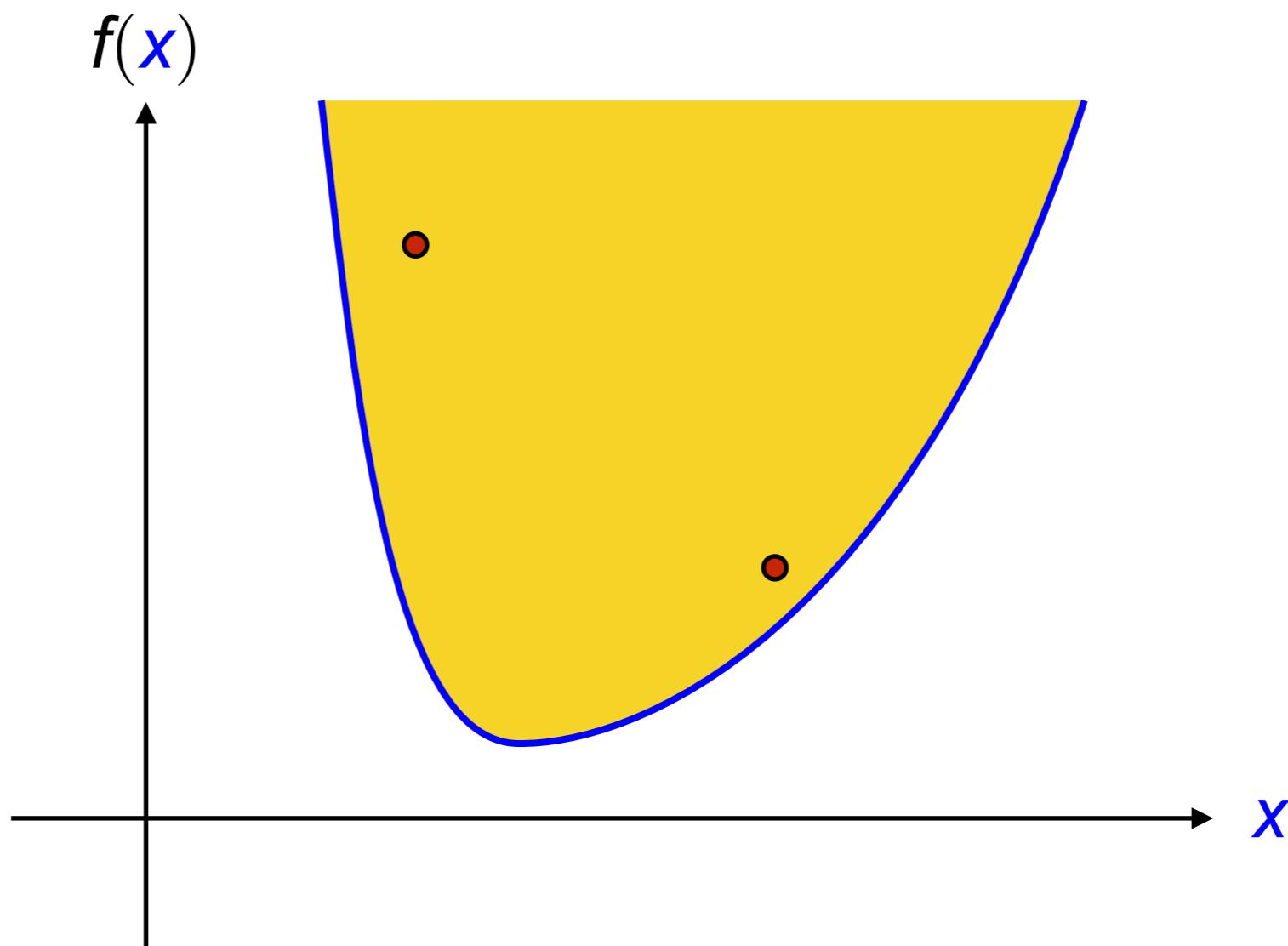
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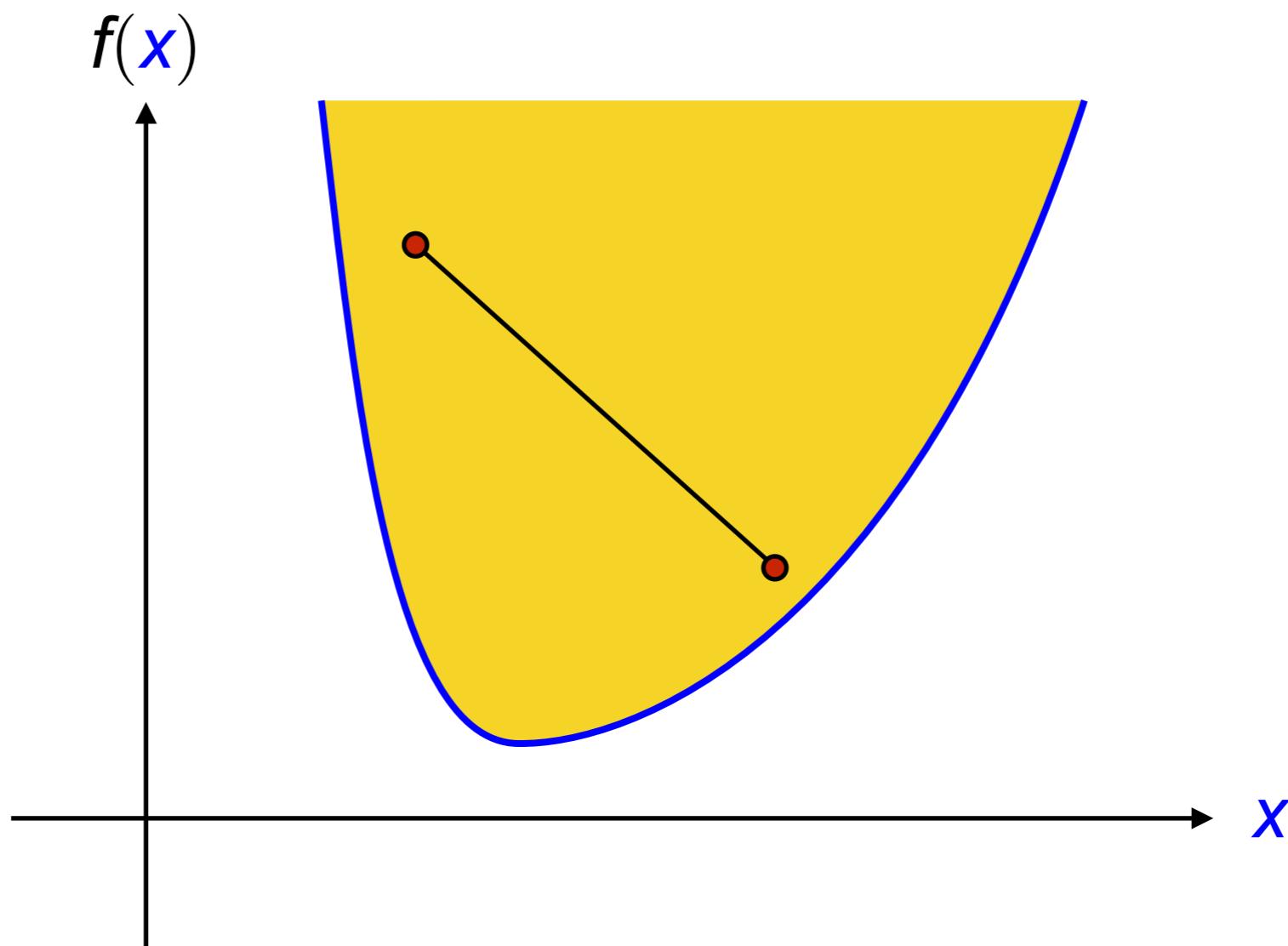
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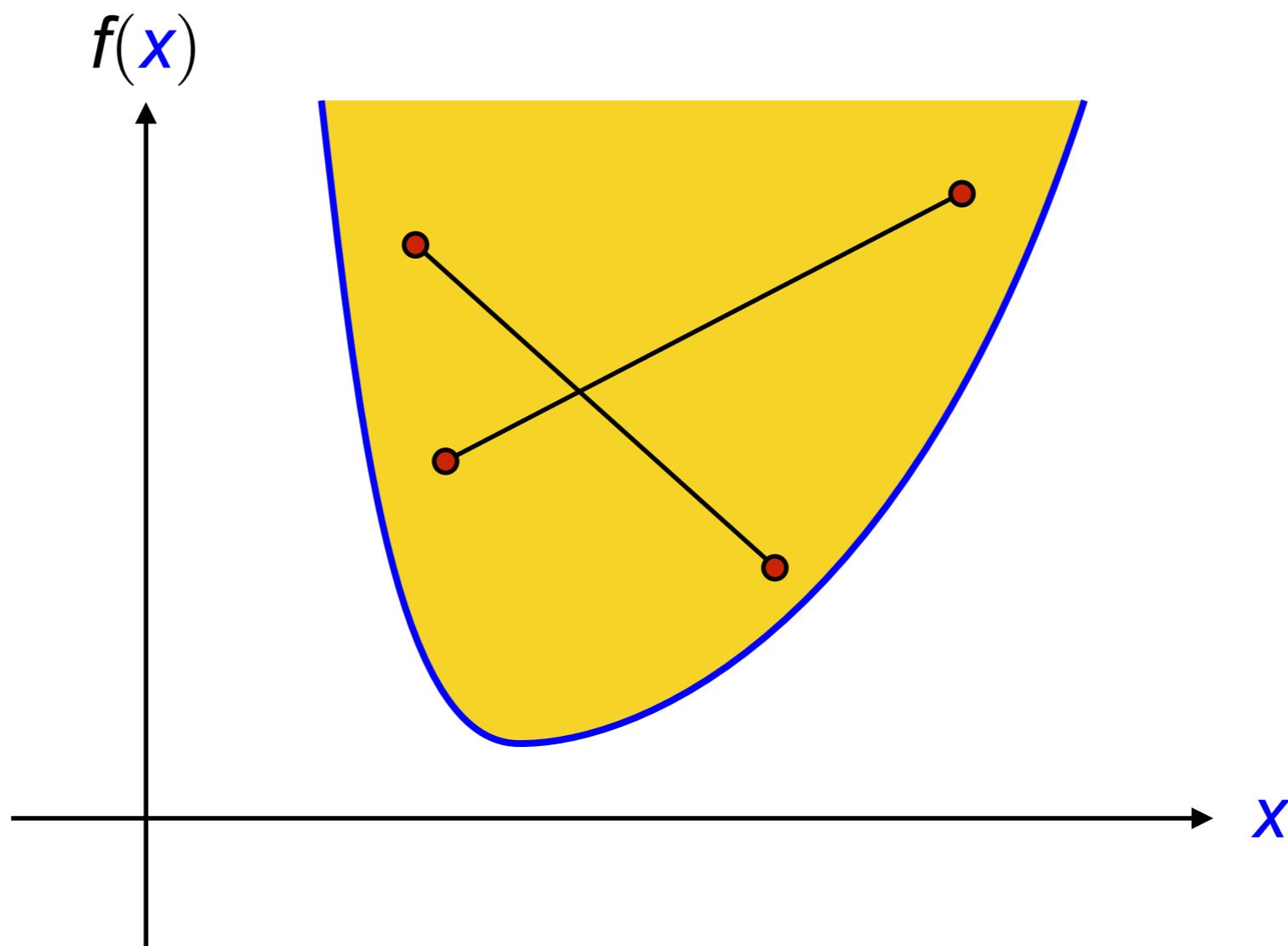
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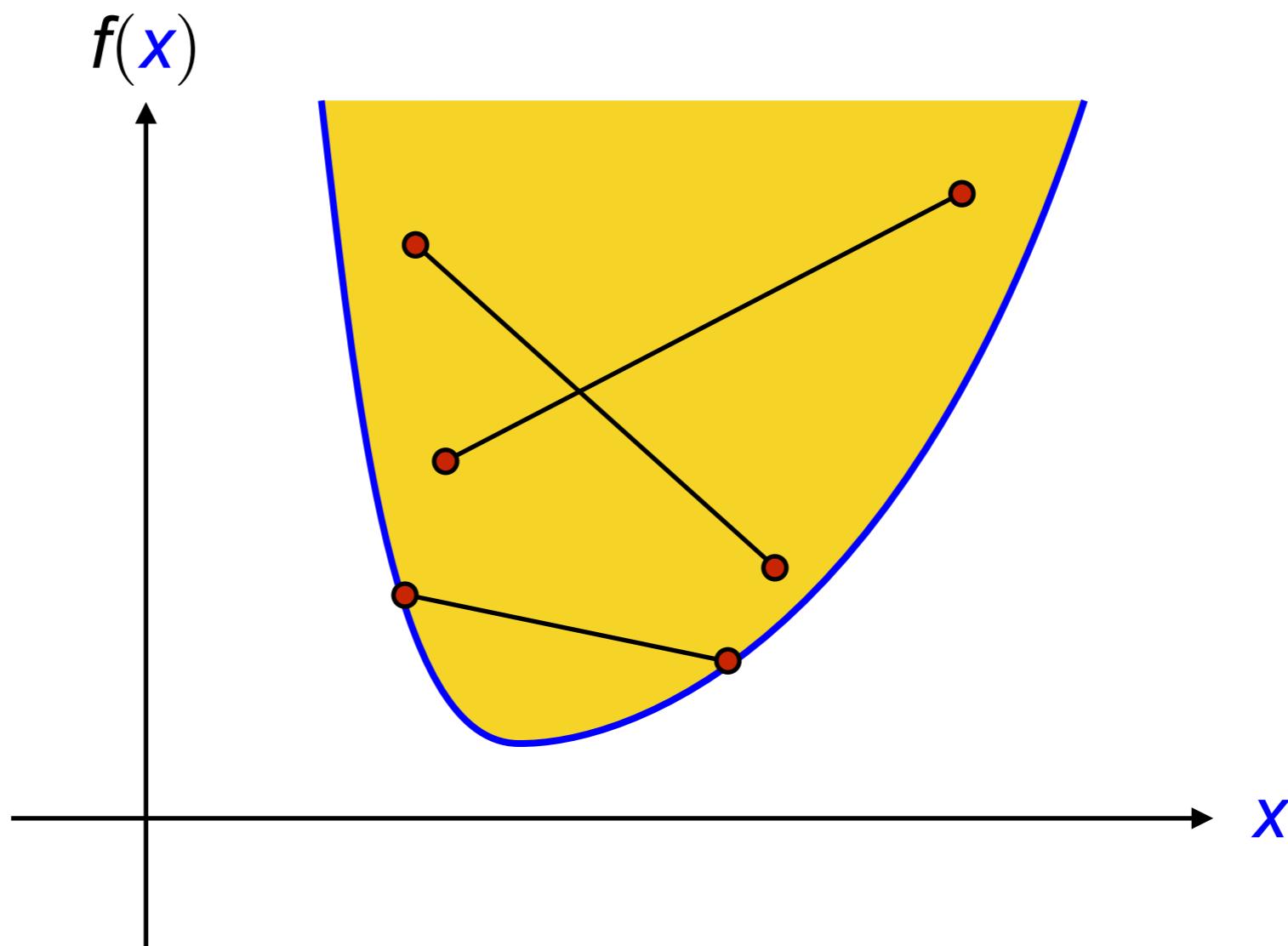
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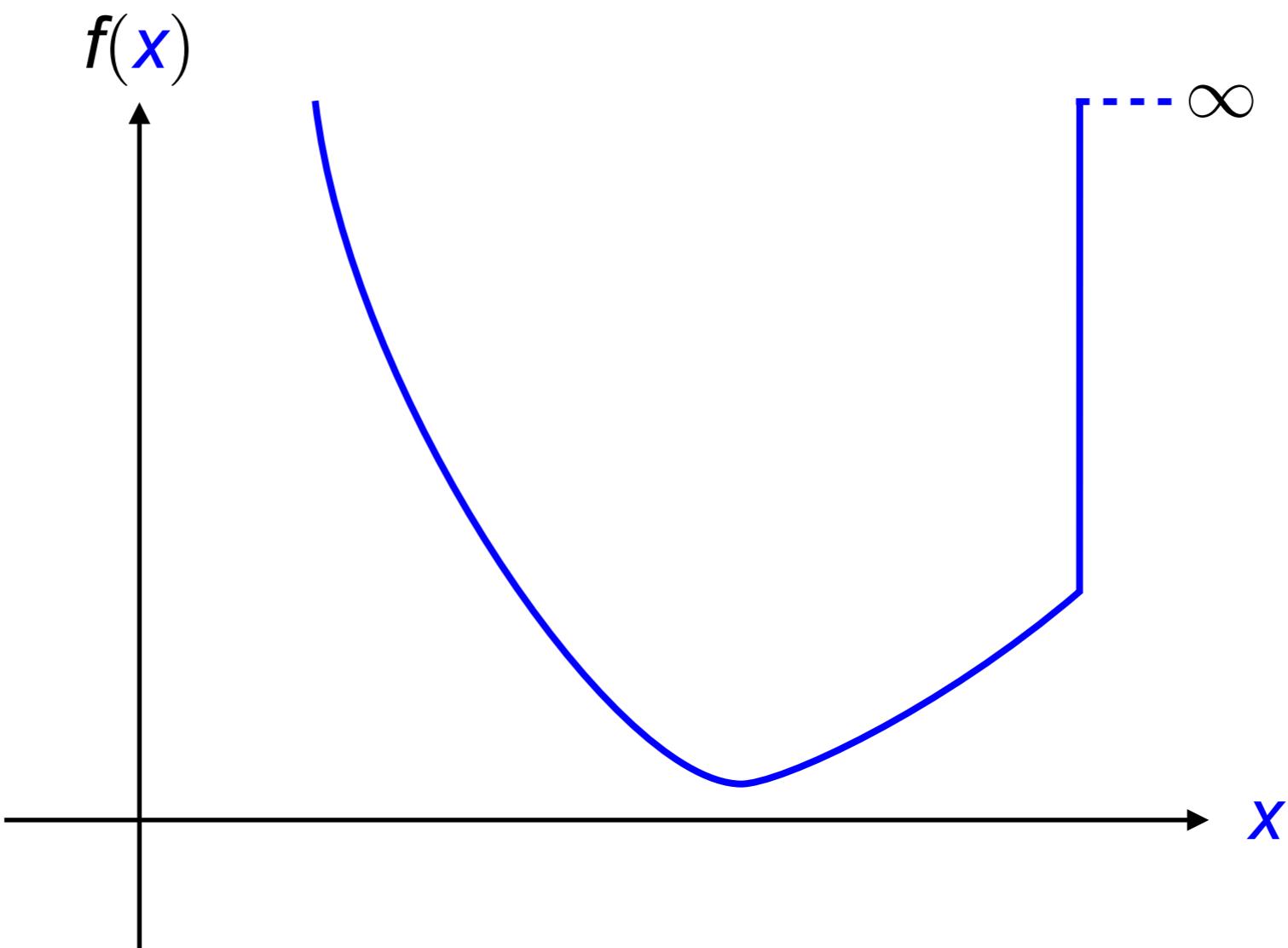
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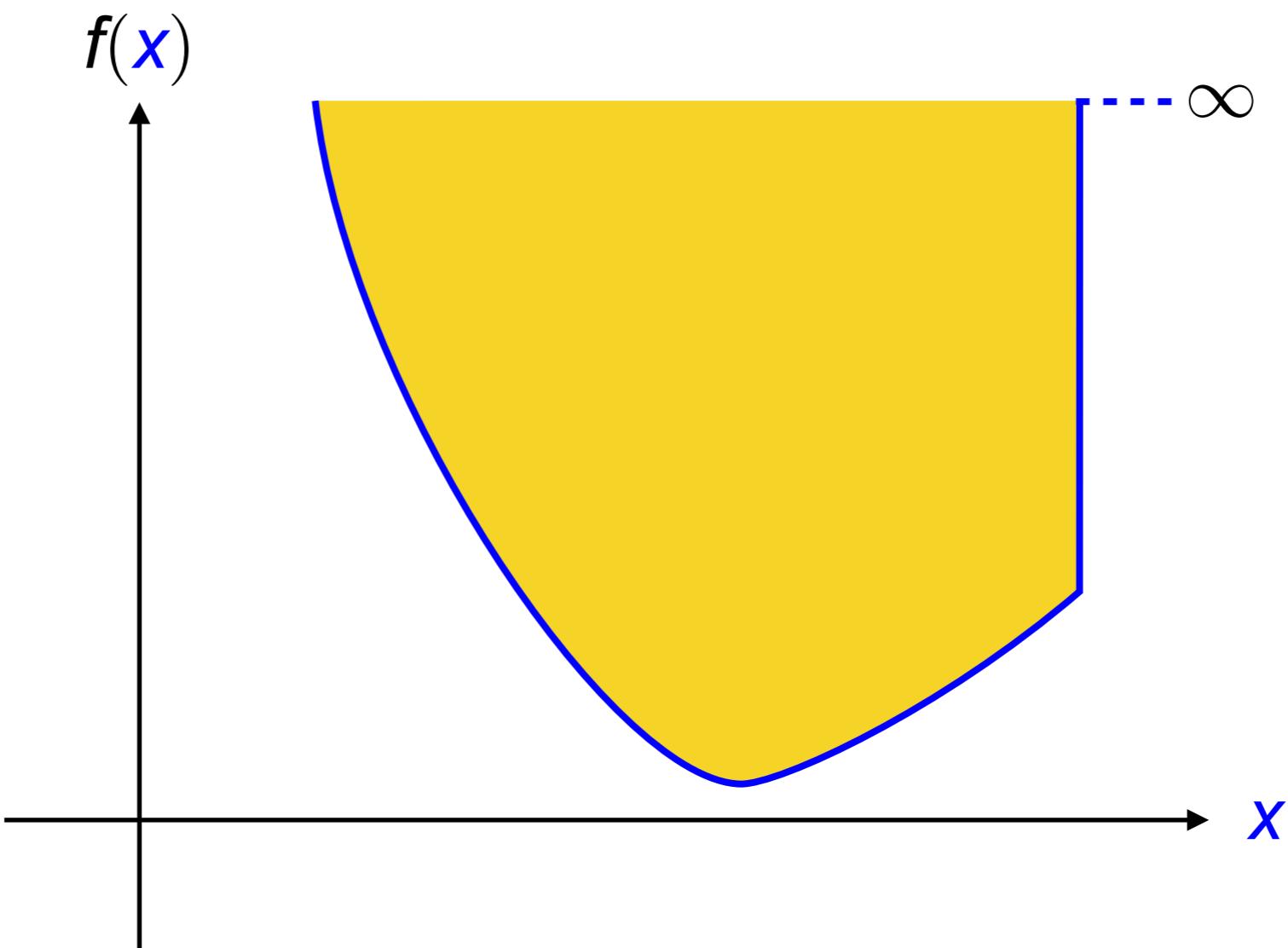
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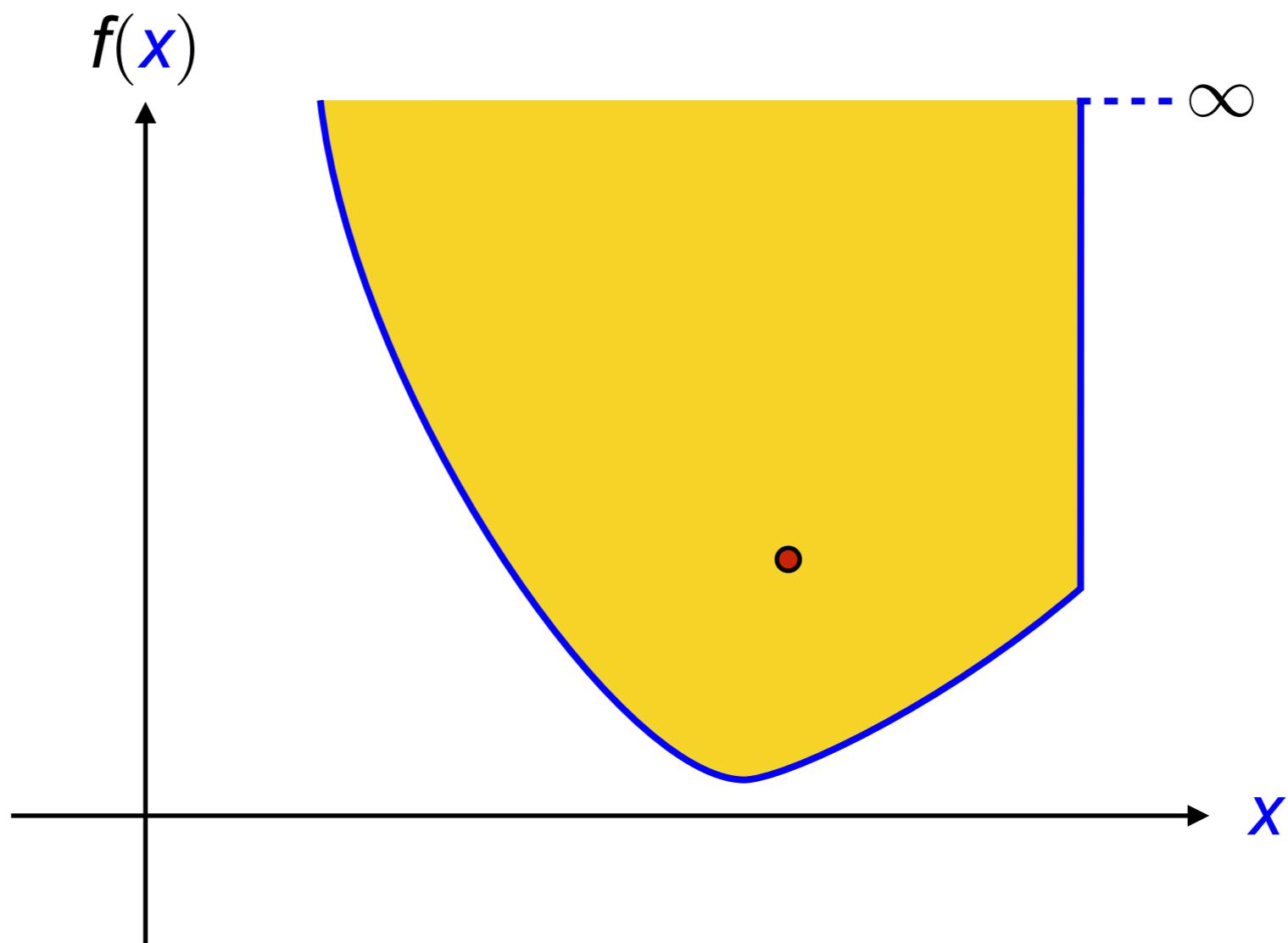
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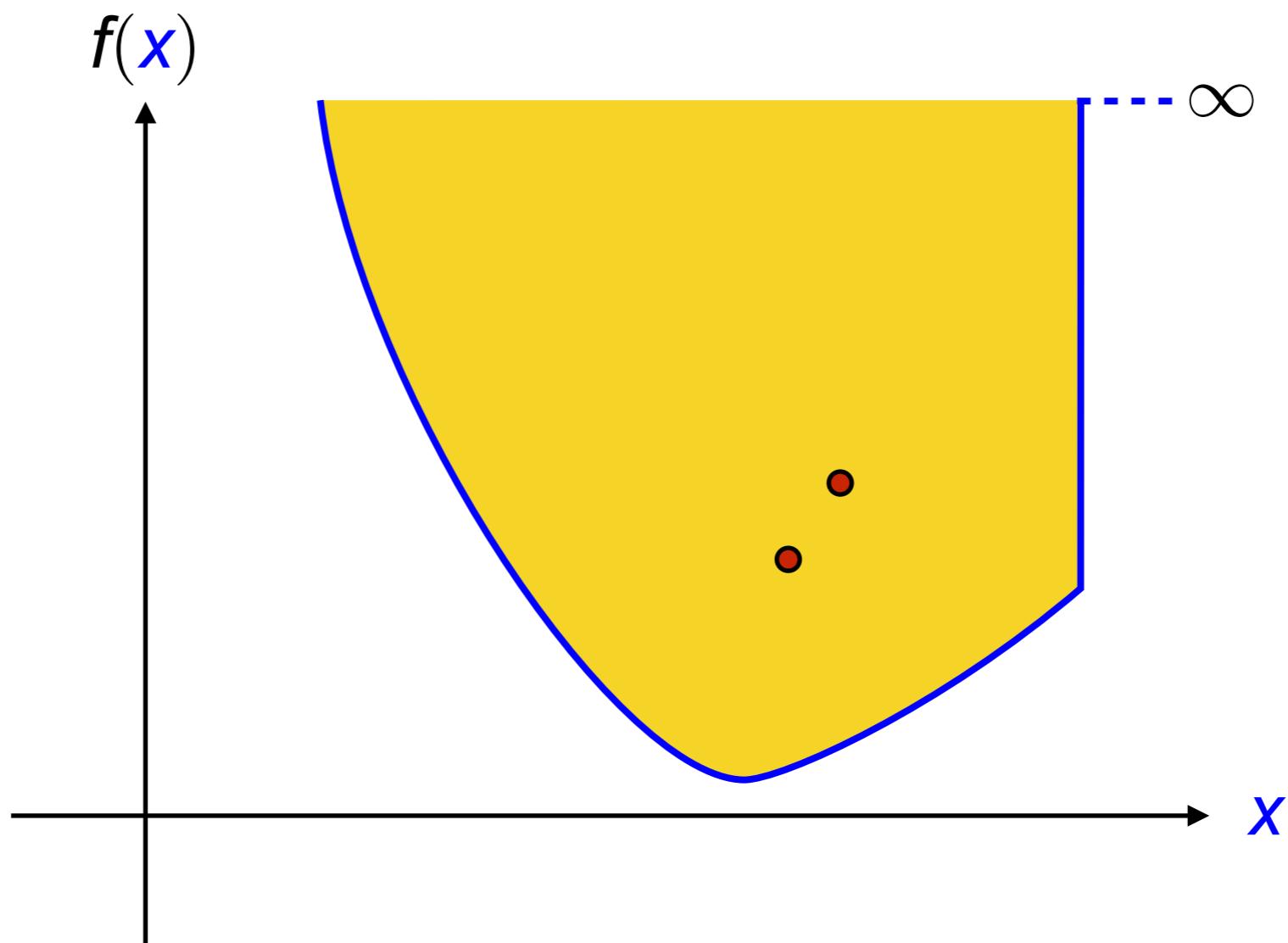
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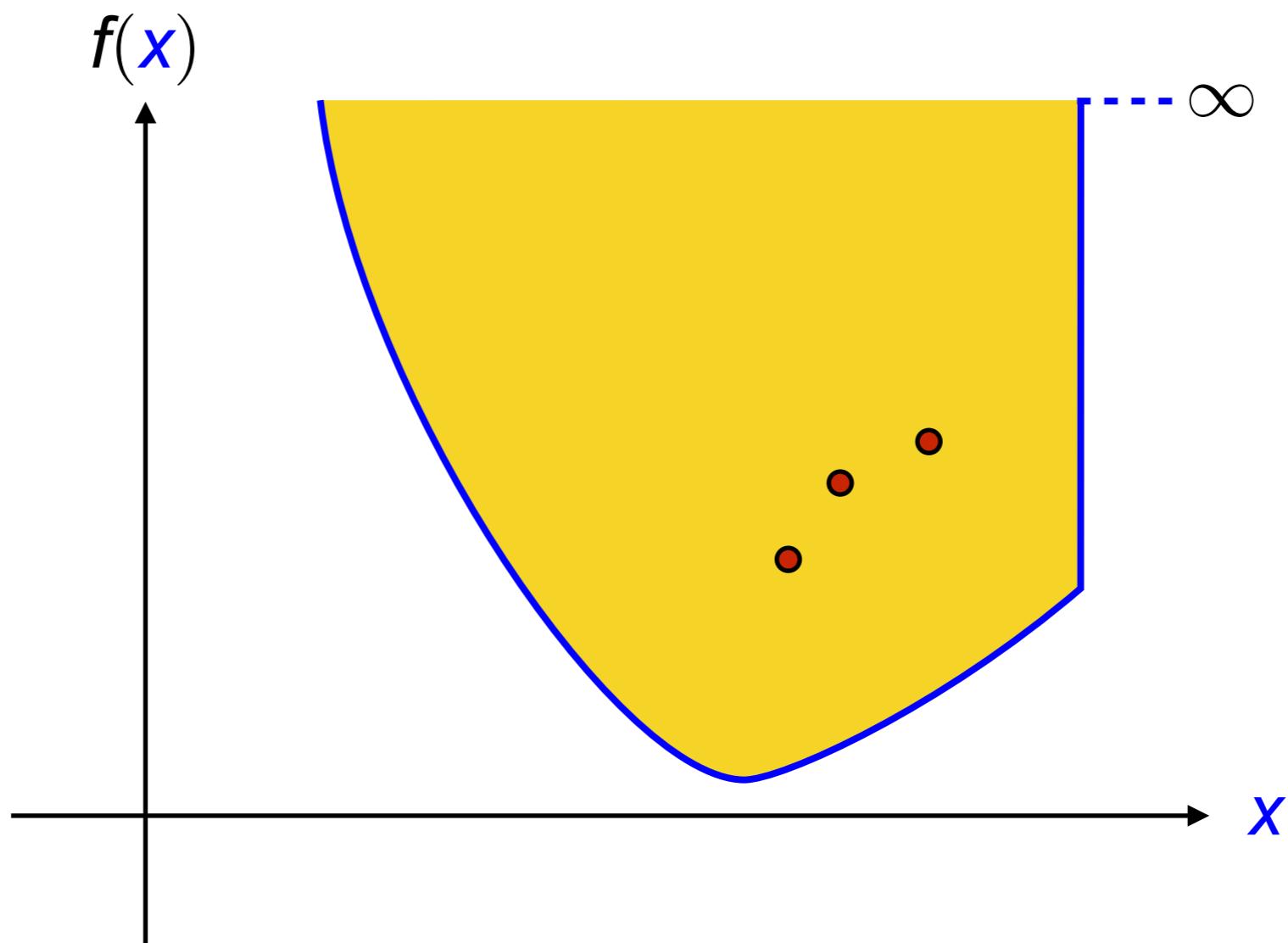
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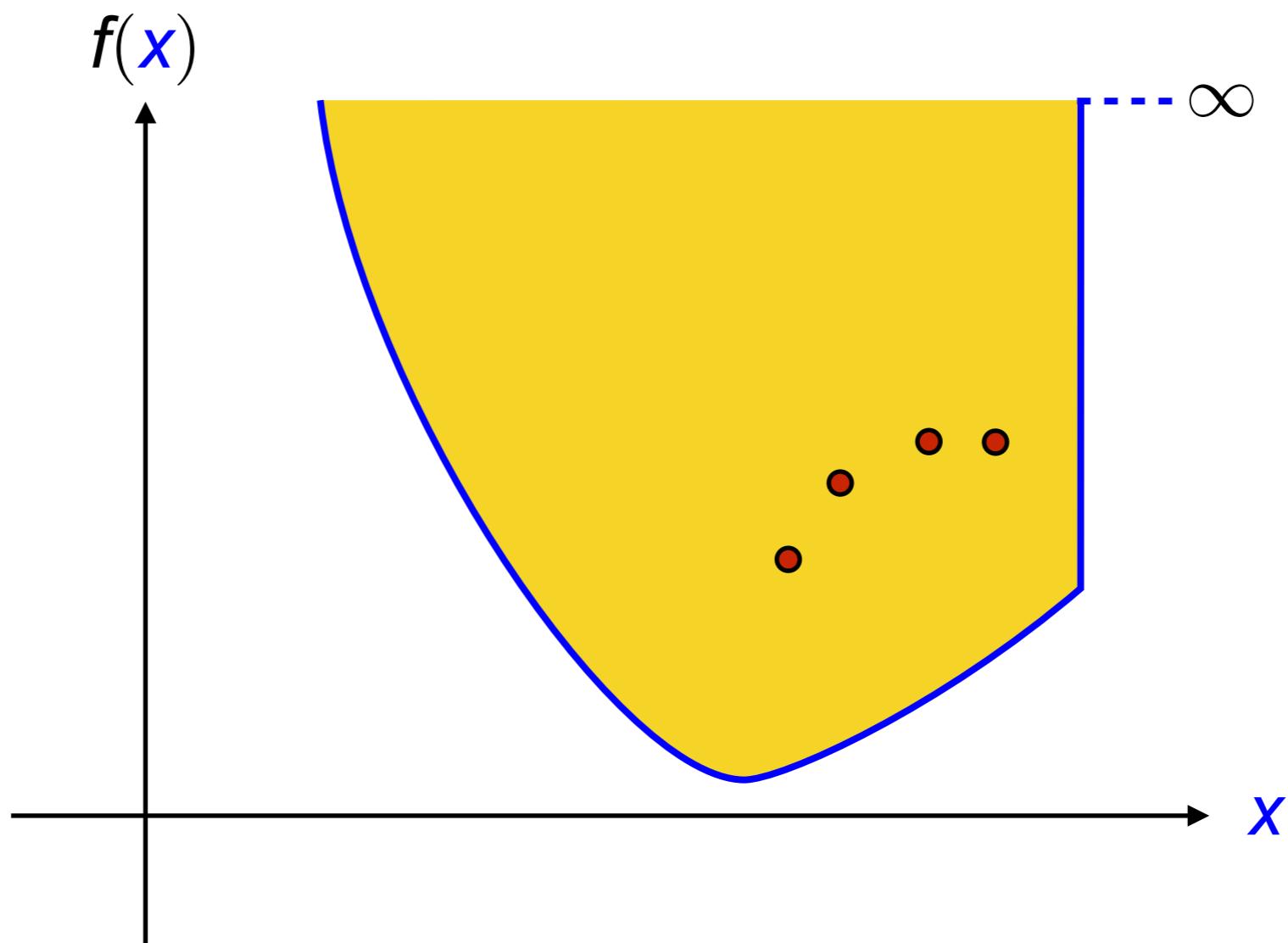
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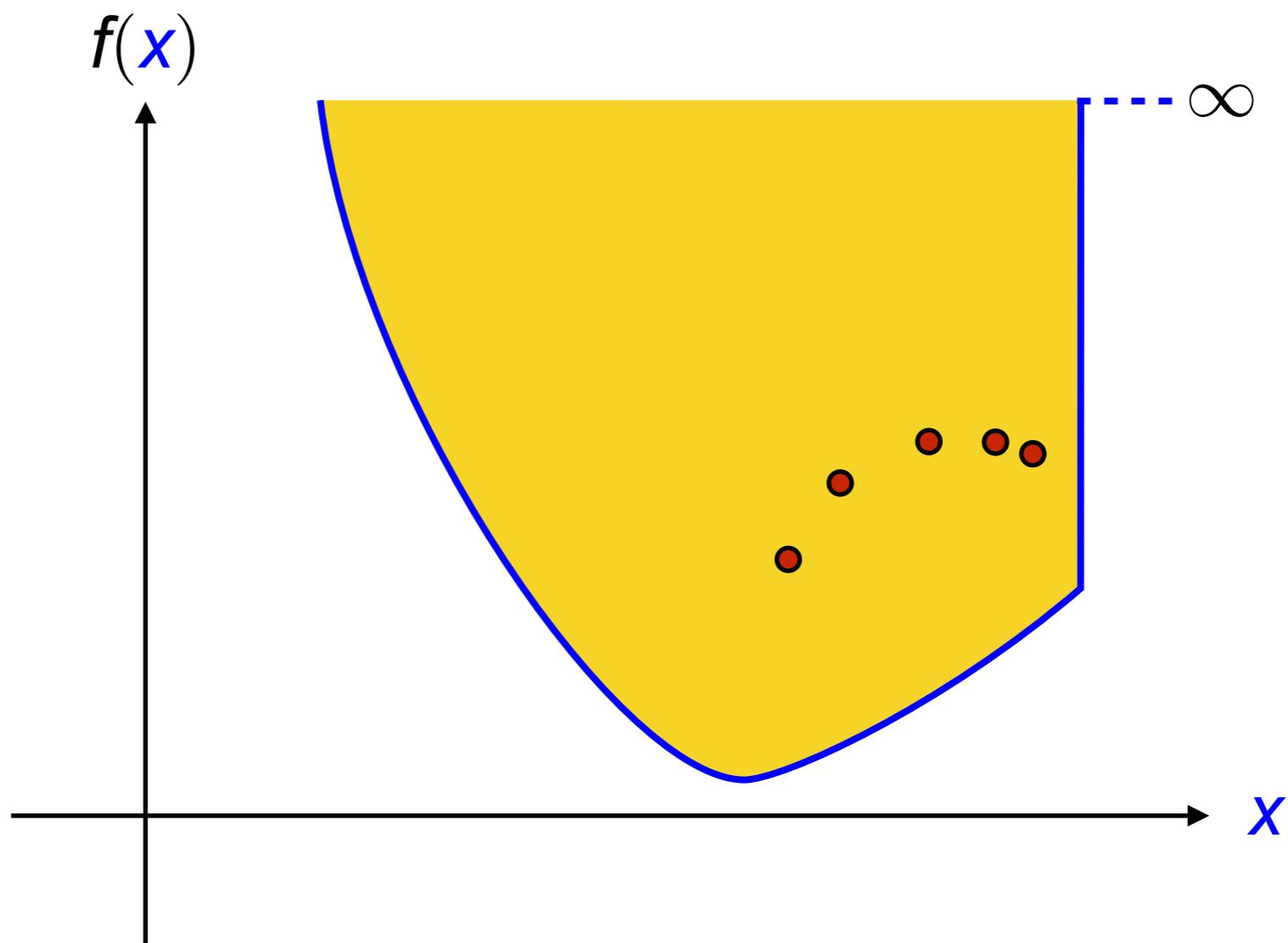
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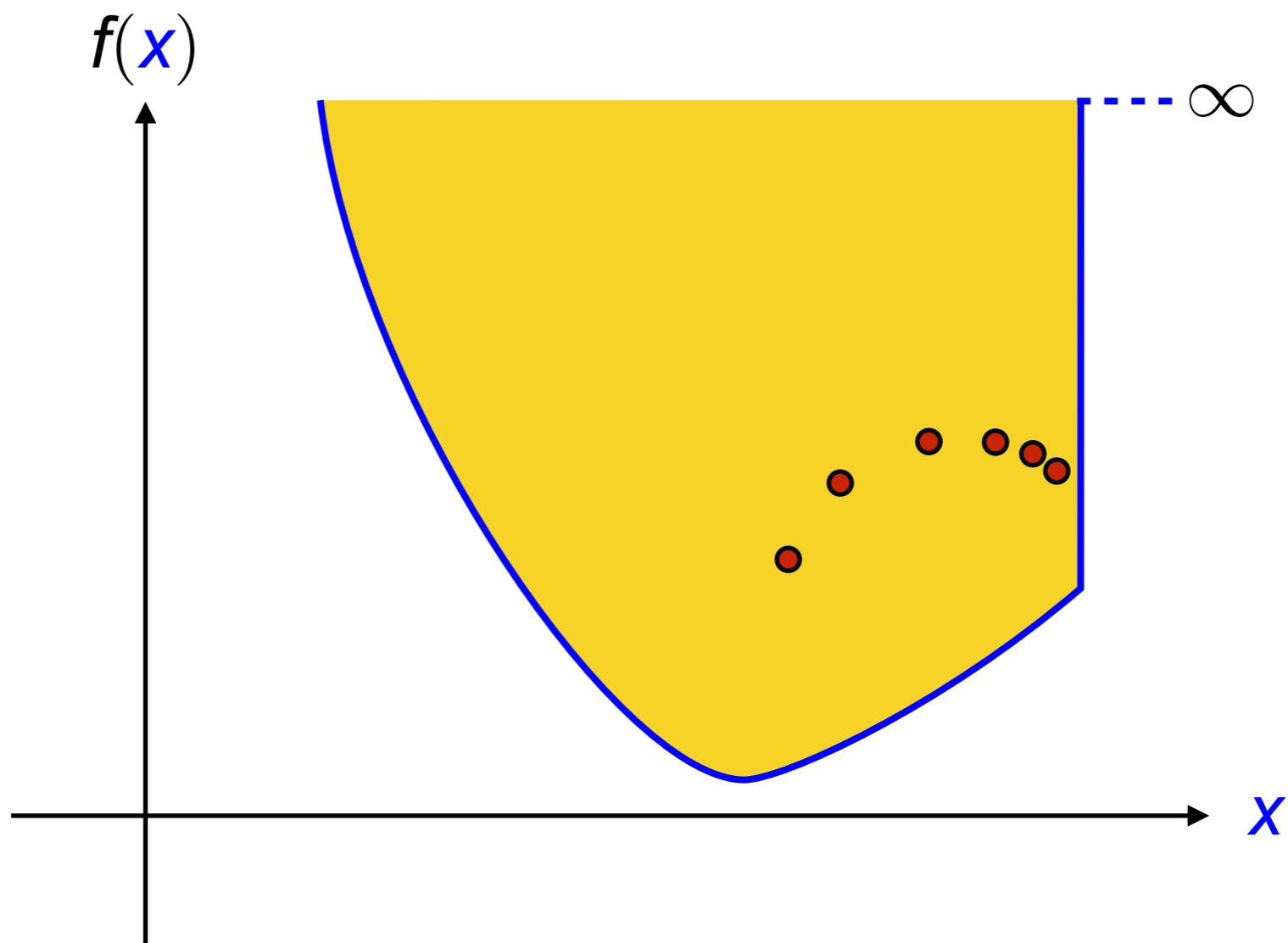
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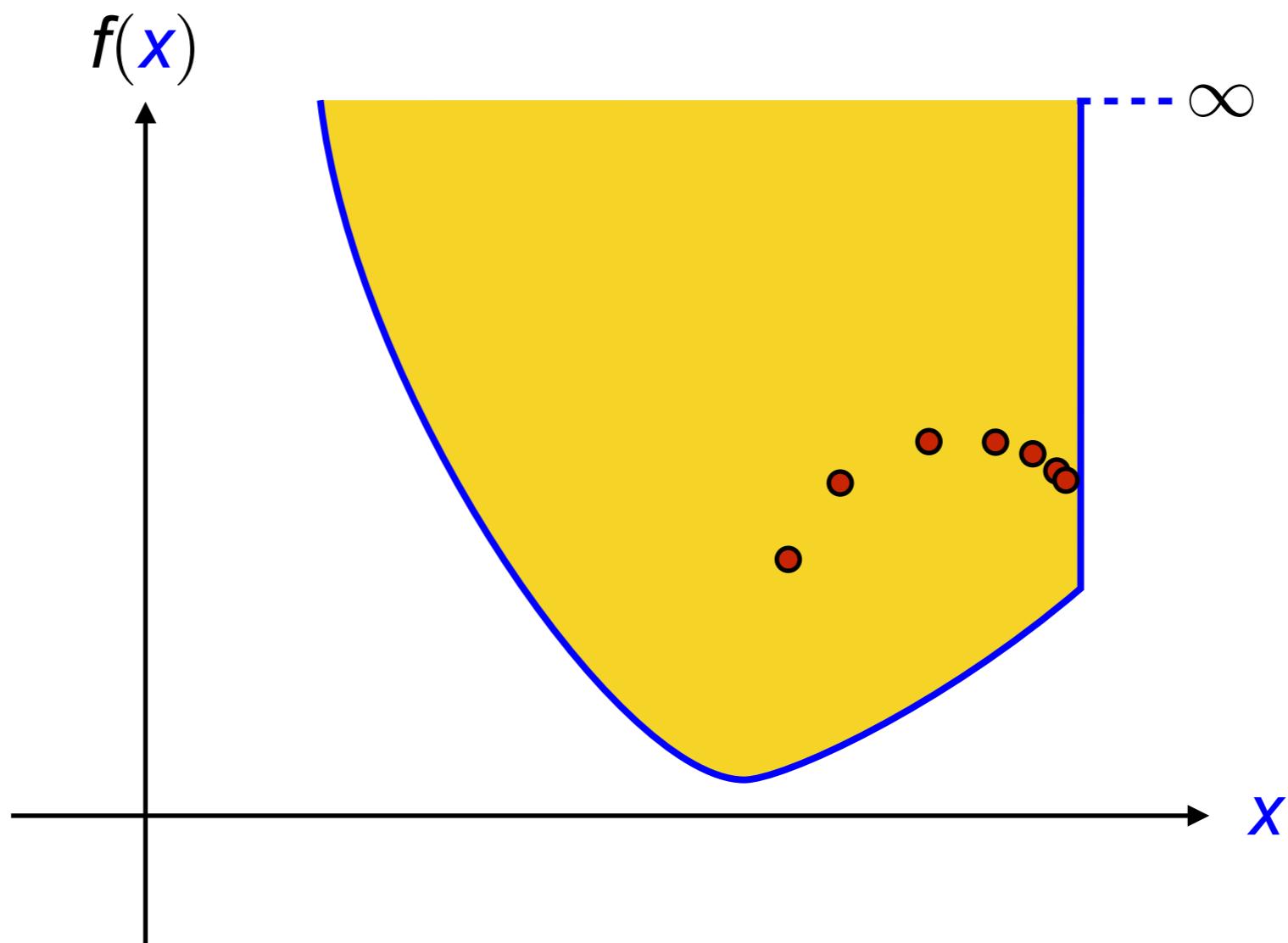
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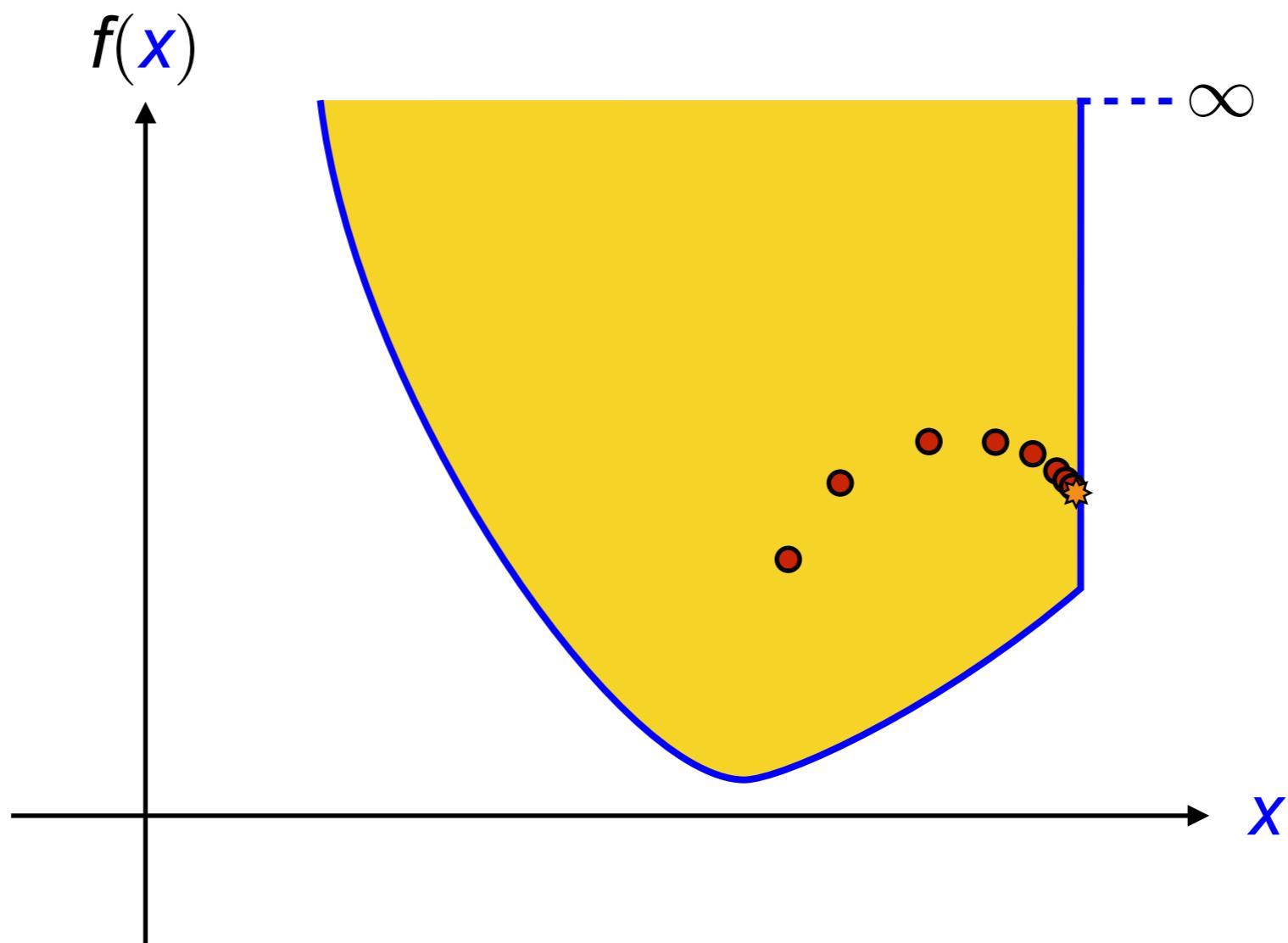
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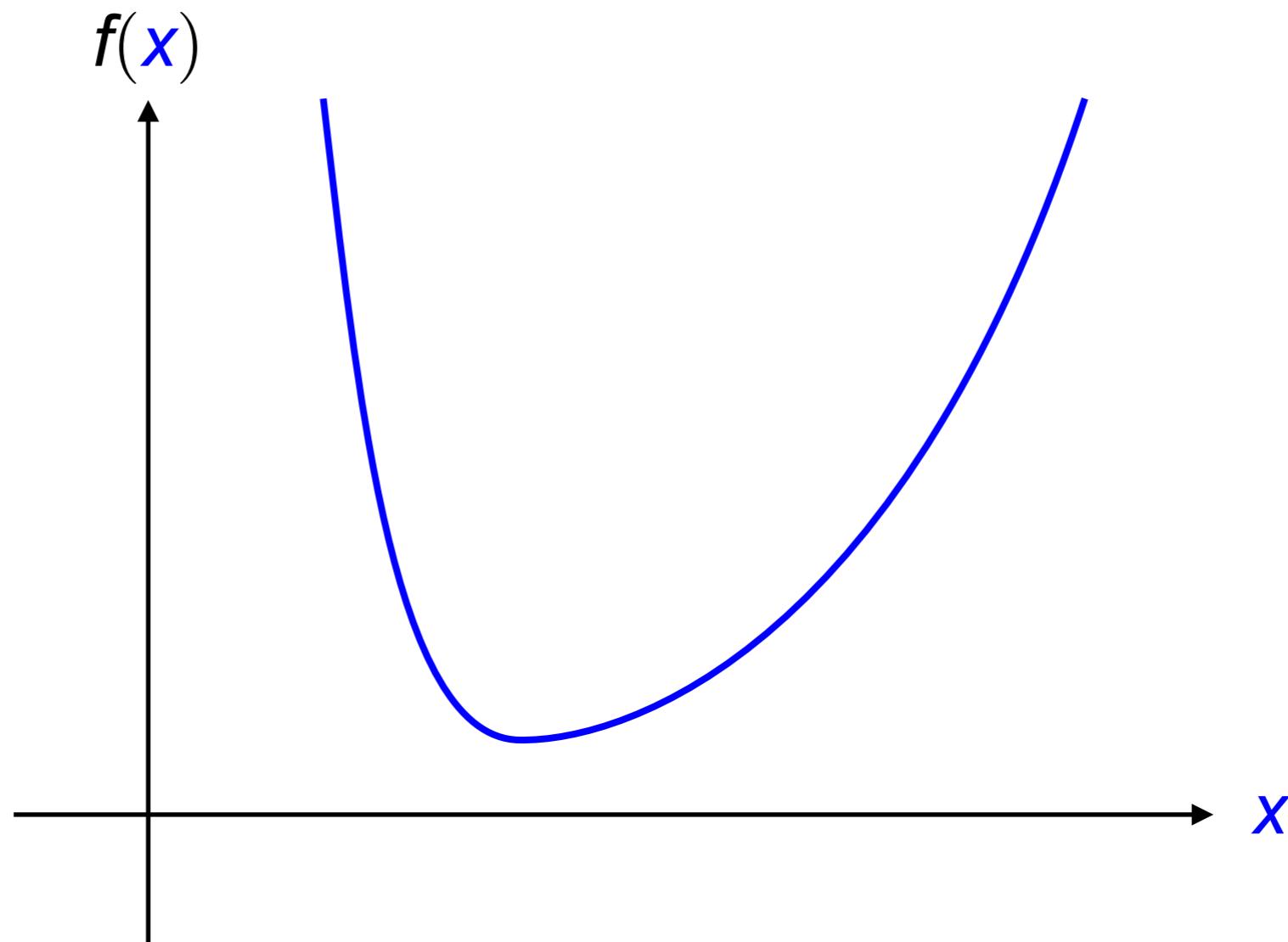


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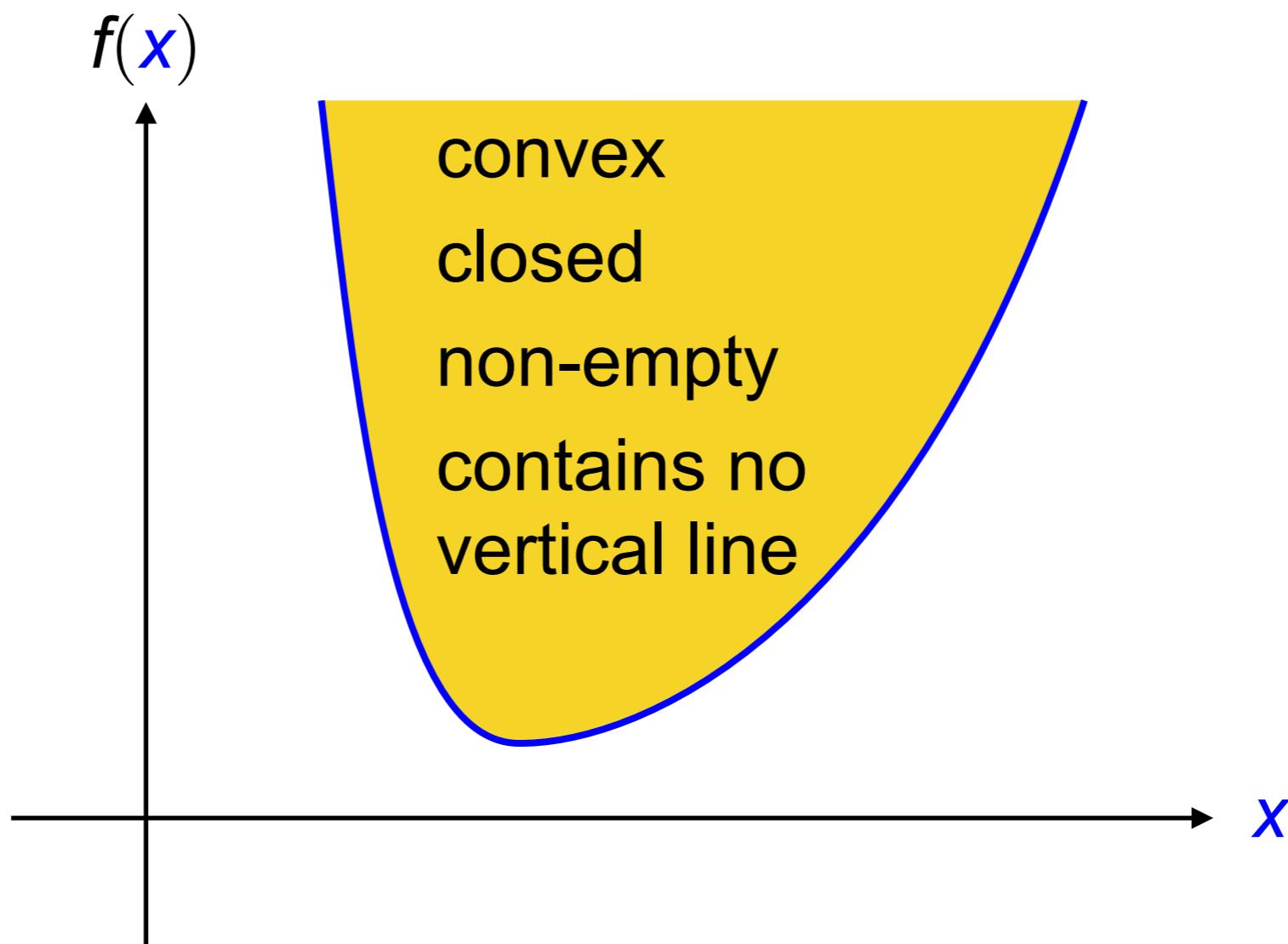
PCC Functions

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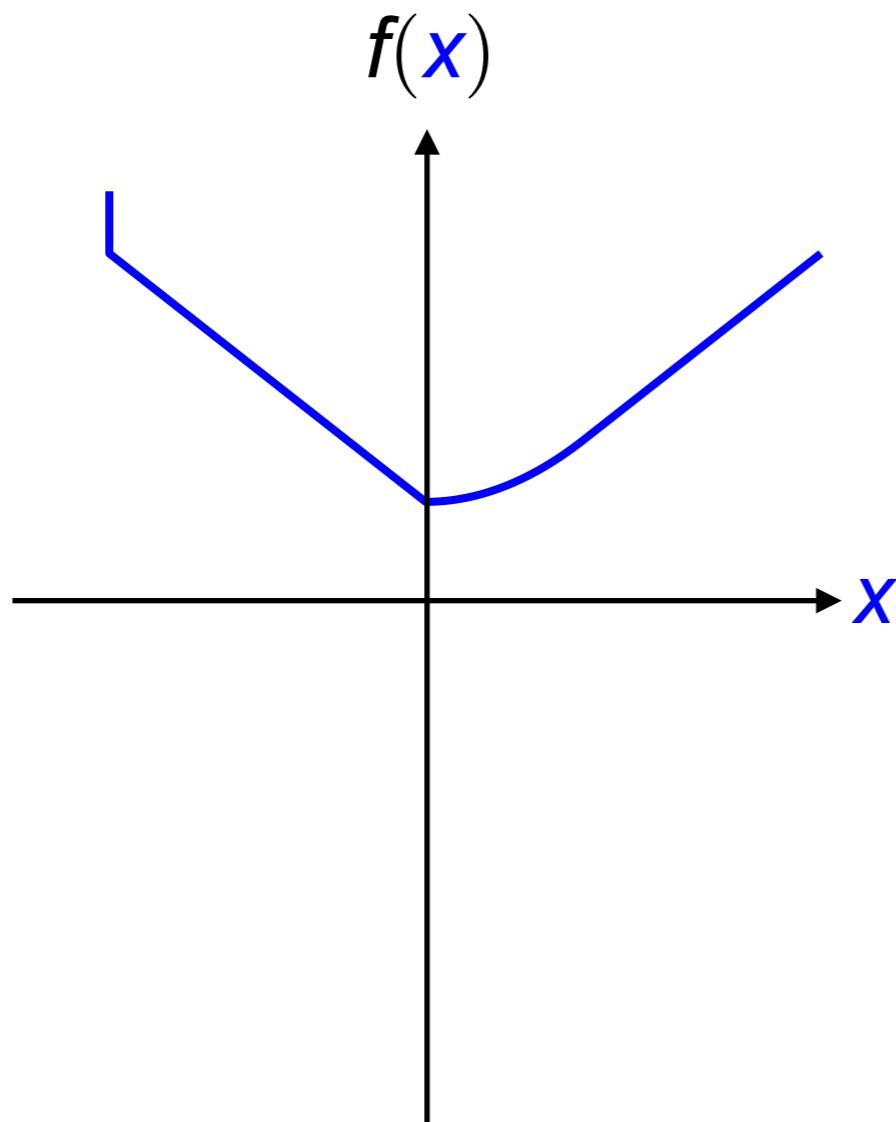
Convexity-Preserving Transformations

Conjugate Functions

$$f(\textcolor{blue}{x}) \quad \rightsquigarrow \quad f^*(\textcolor{red}{w}) = \sup_{\textcolor{blue}{x}} \left\{ \textcolor{red}{w}^\top \textcolor{blue}{x} - f(\textcolor{blue}{x}) \right\}$$

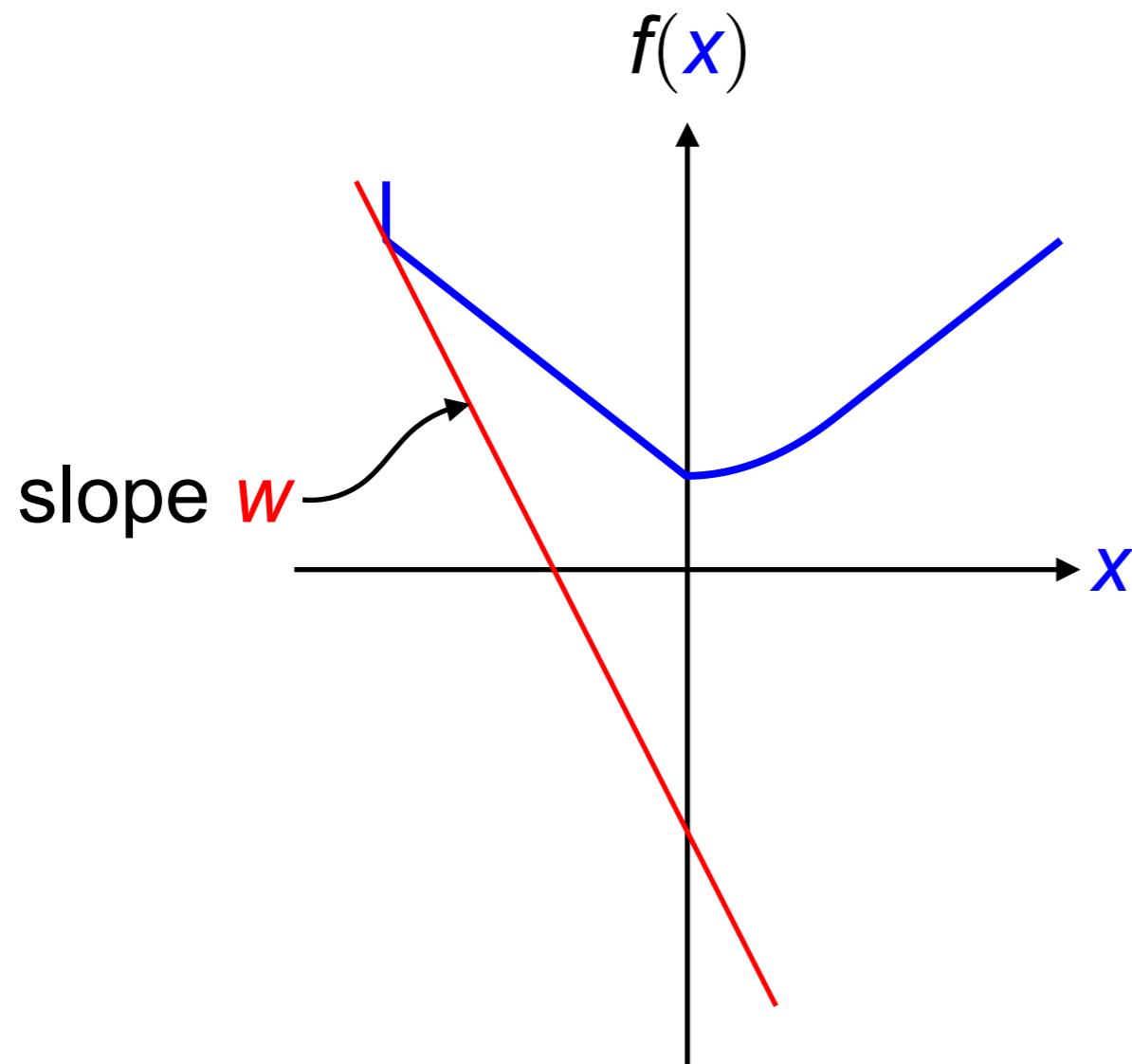
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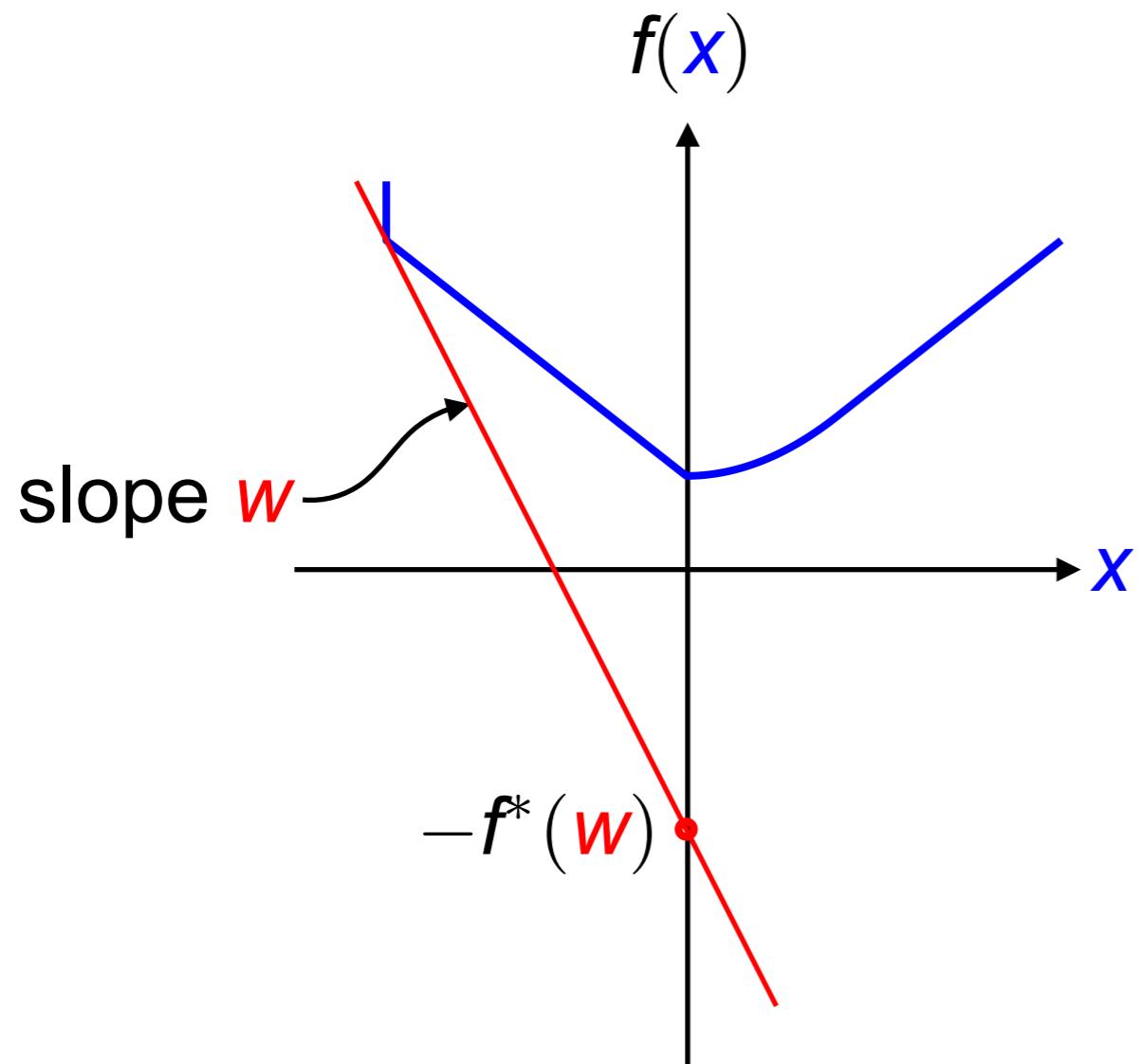
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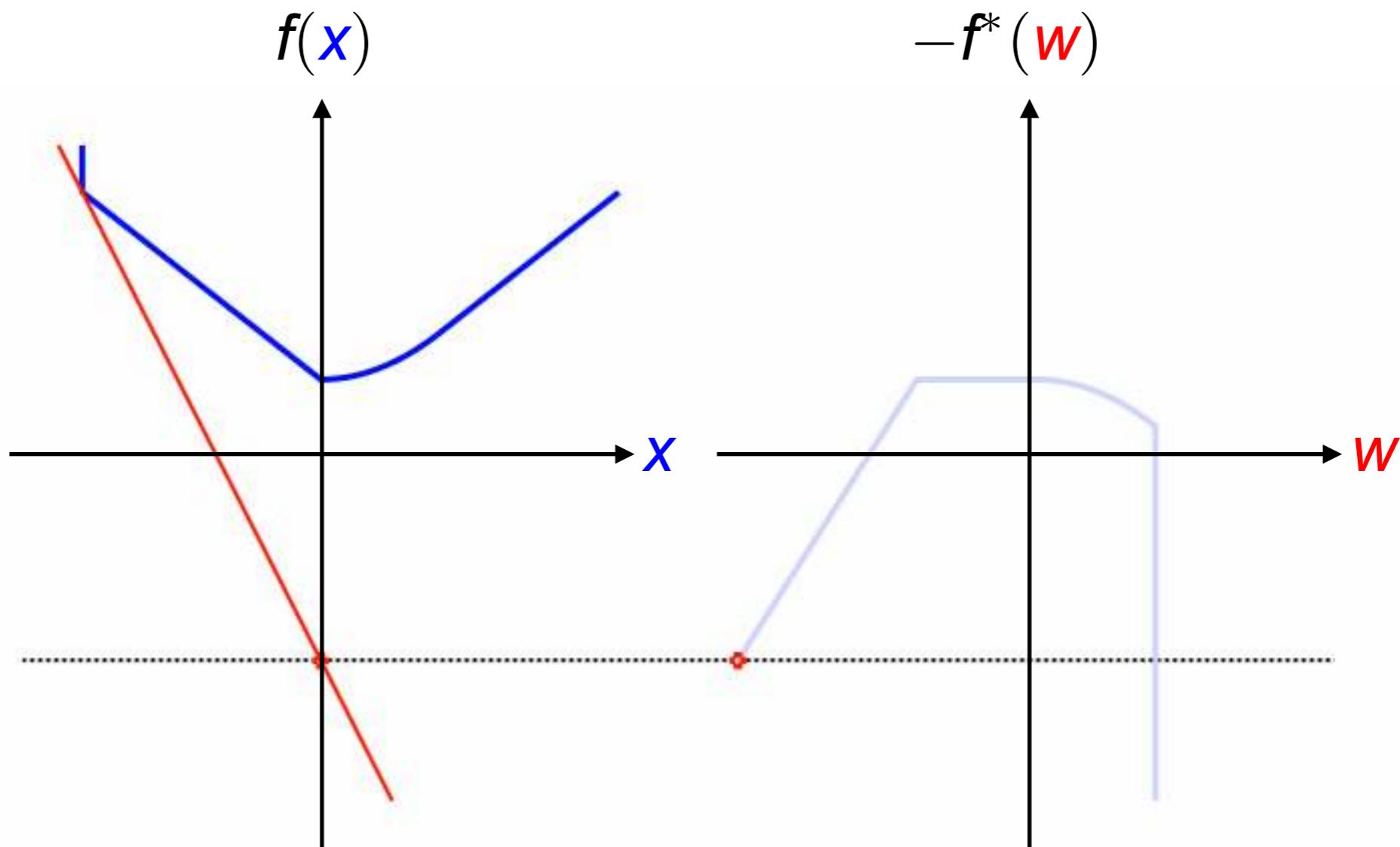
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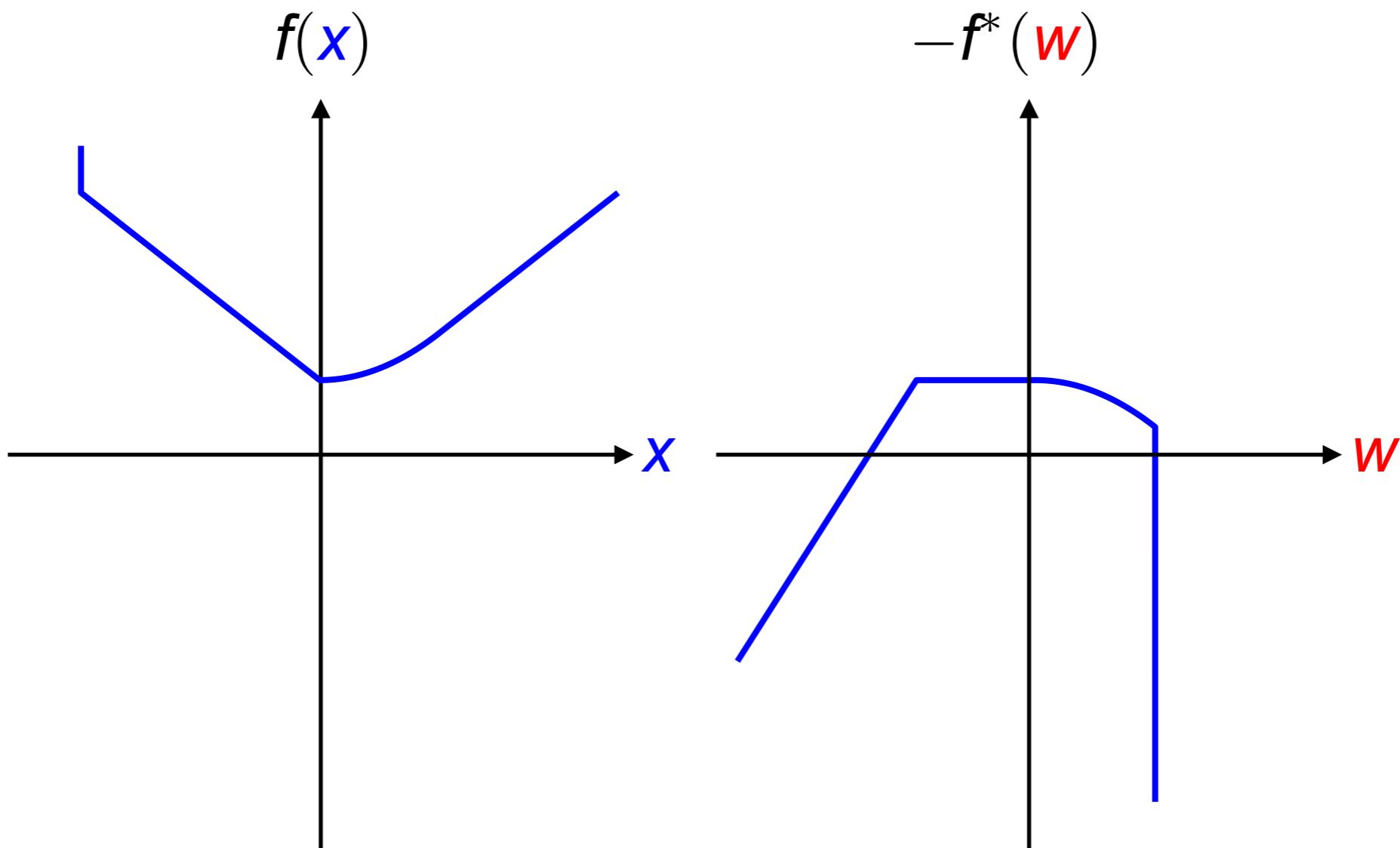
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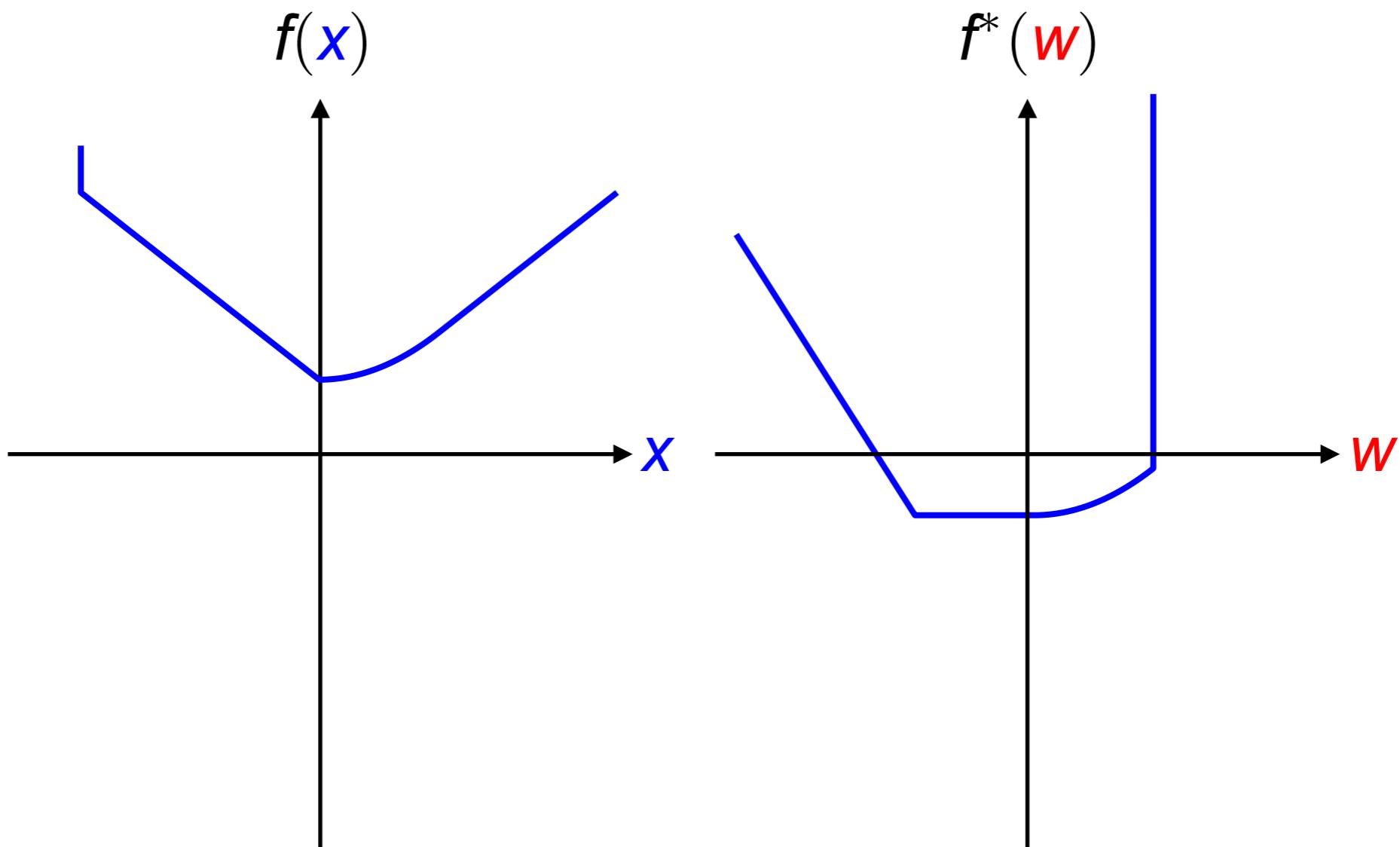
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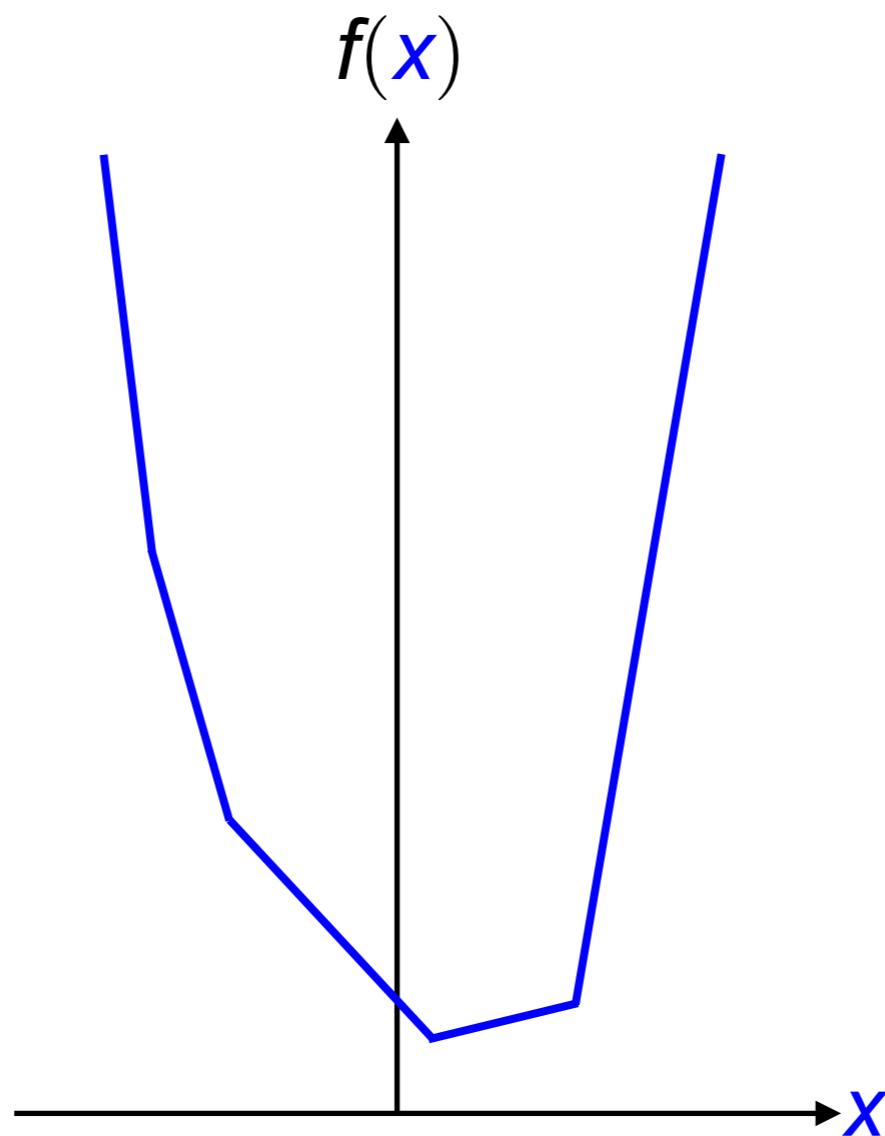


Perspective Functions

$$f(\textcolor{blue}{x}) \rightsquigarrow \underline{f}(x, t) = t \cdot f(\textcolor{blue}{x}/t)$$

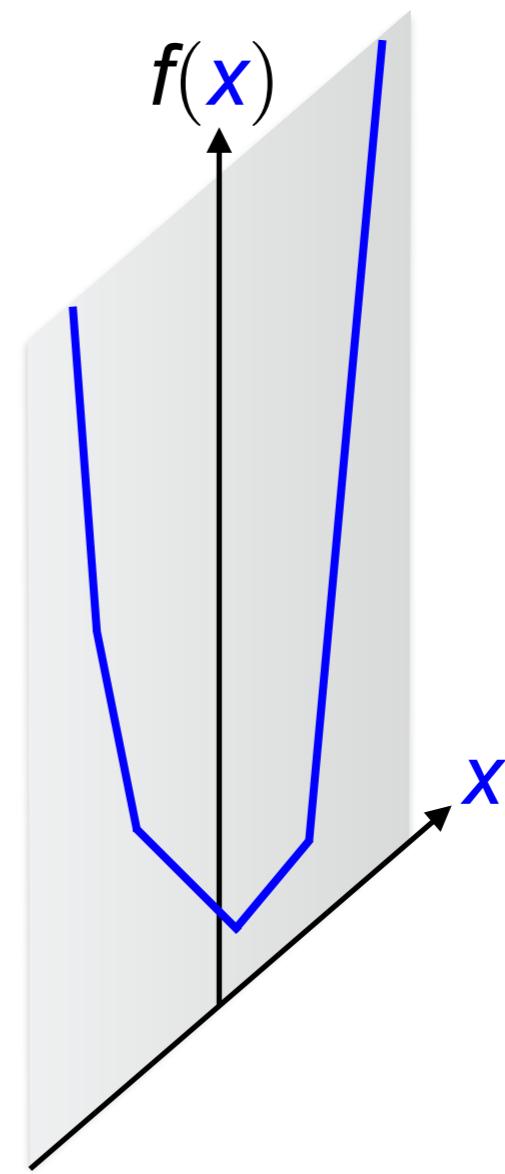
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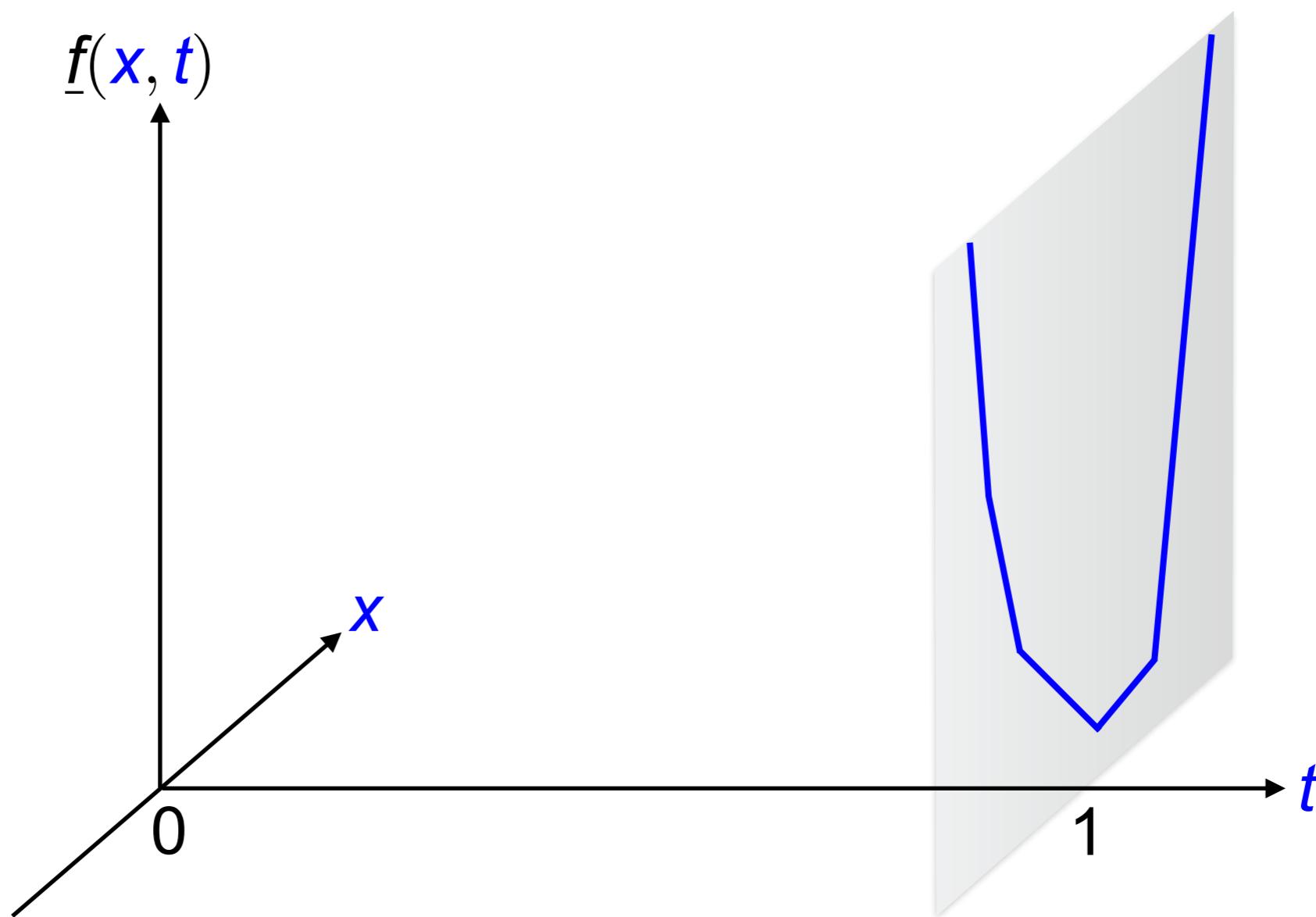
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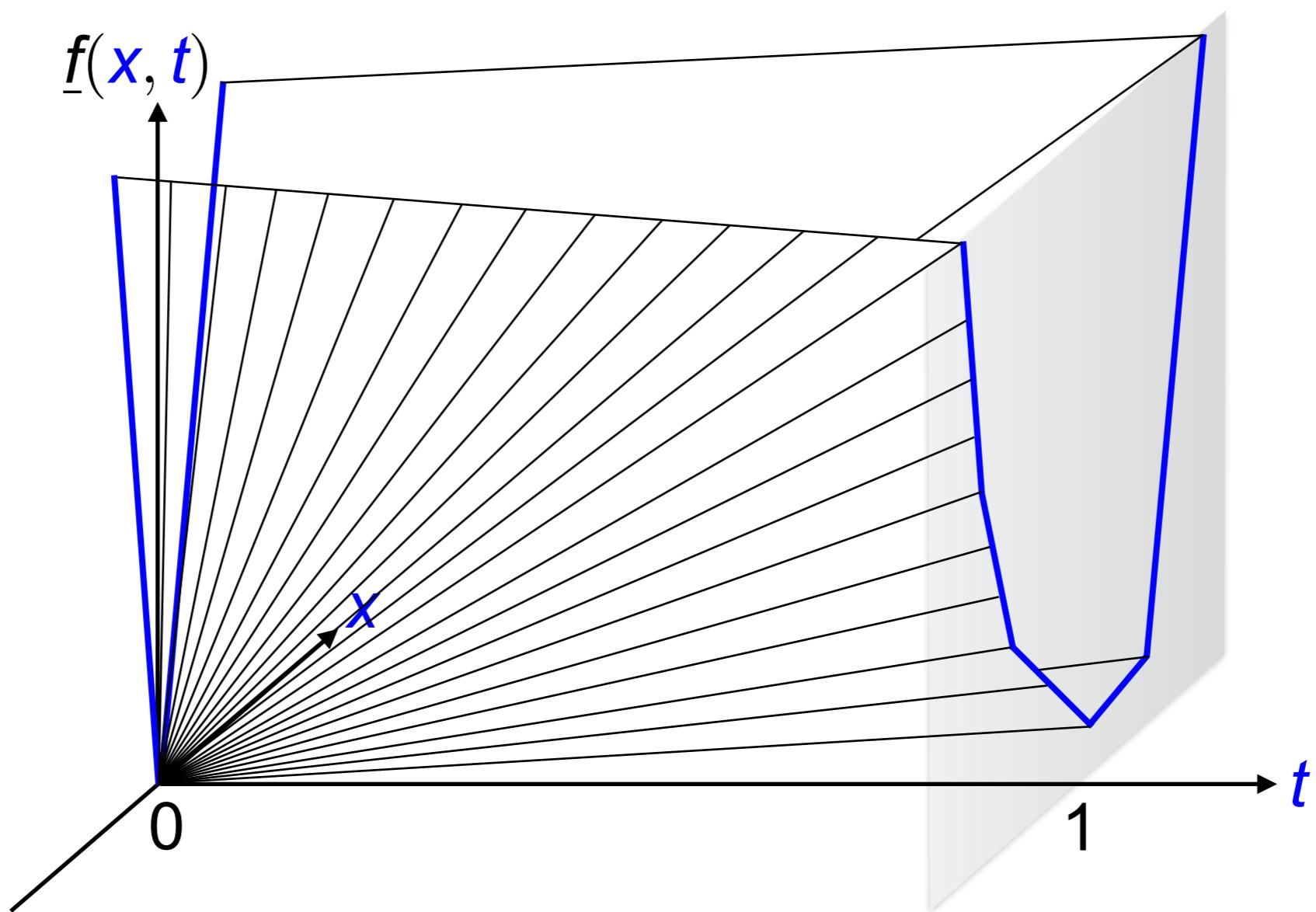
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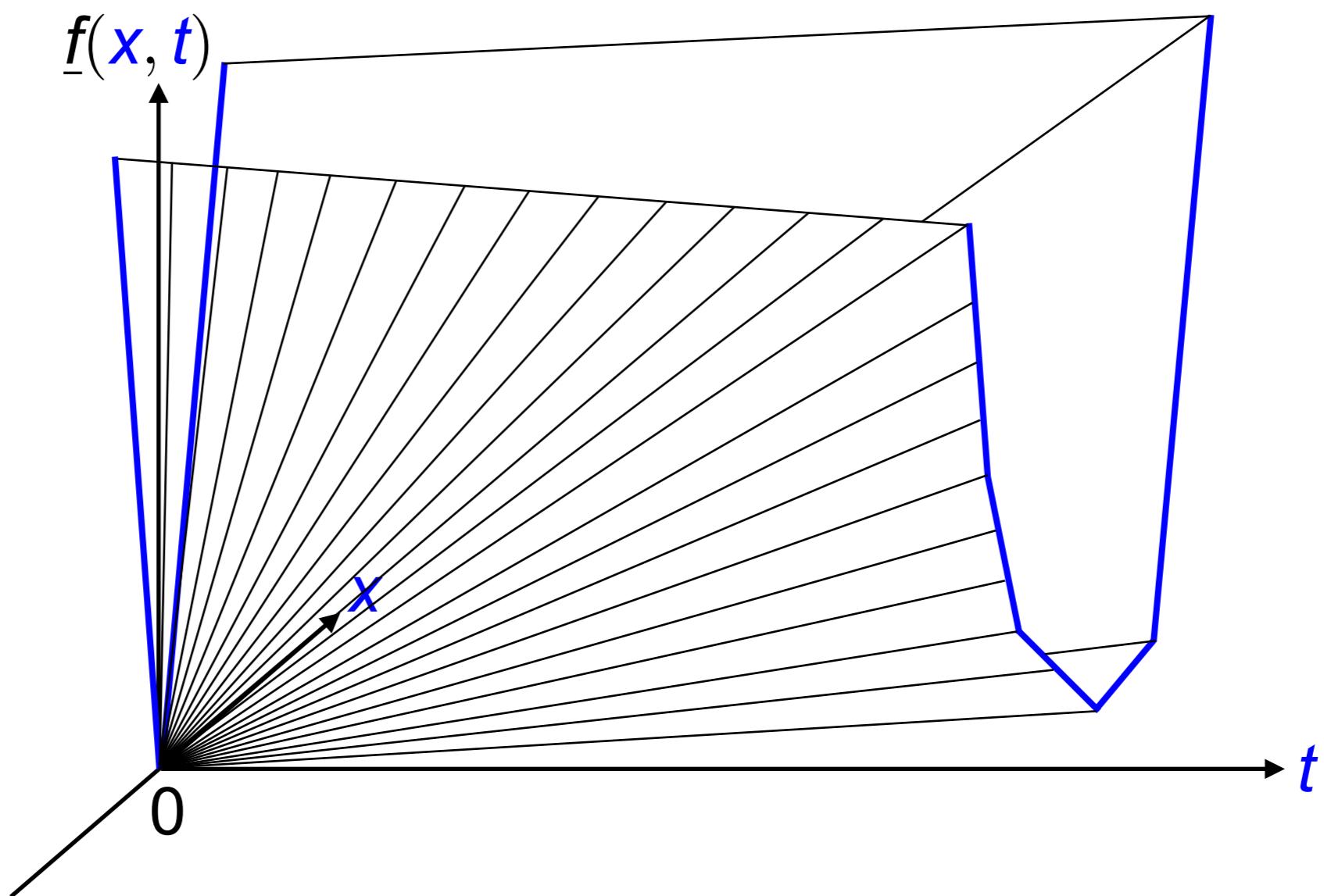
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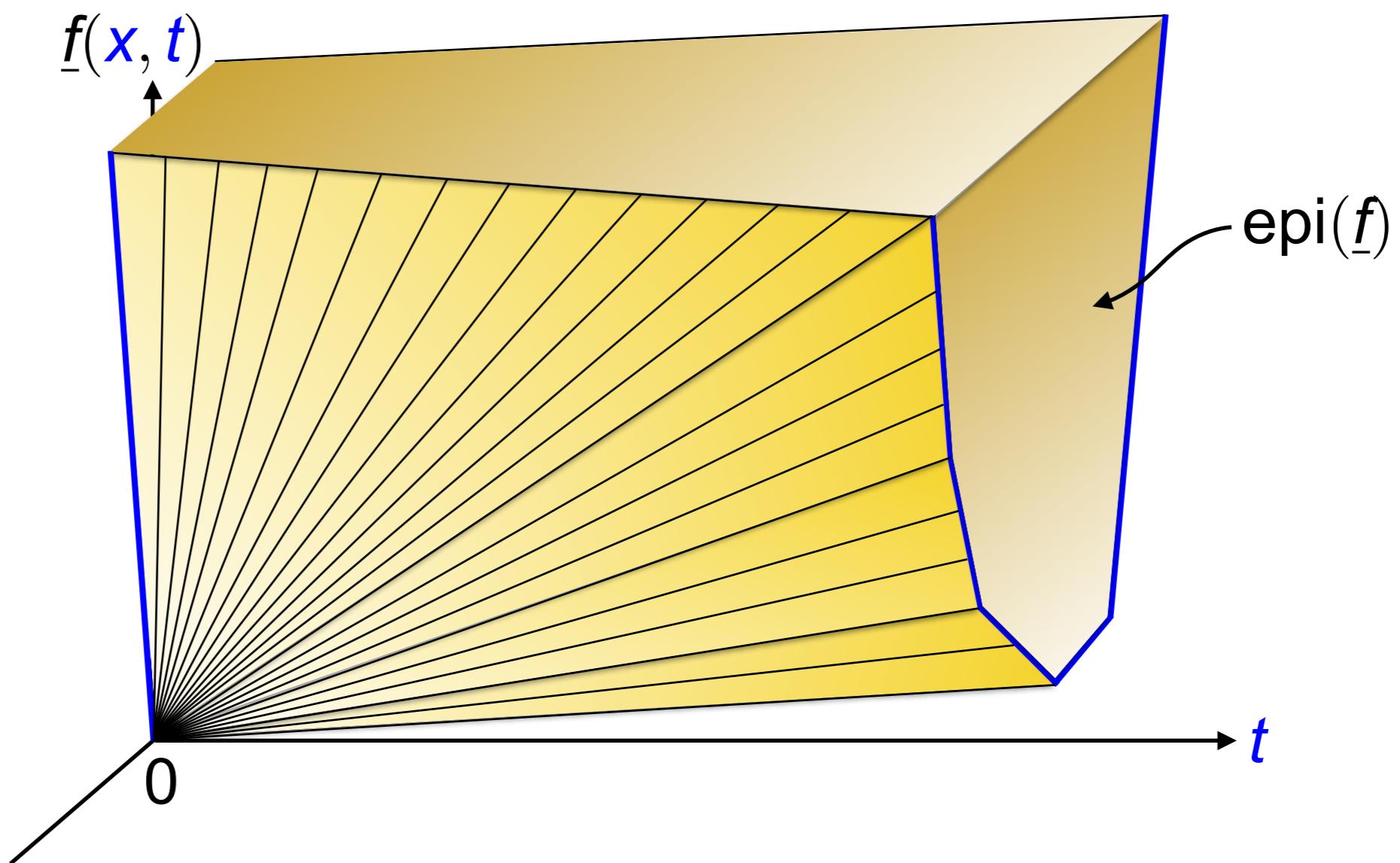
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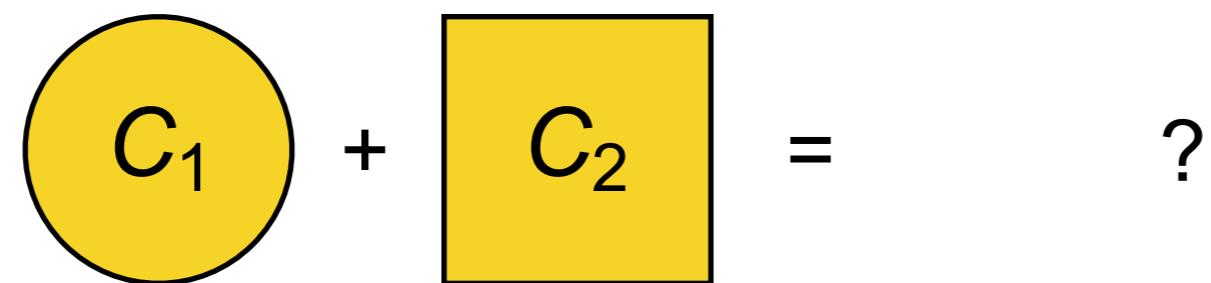


Minkowski Sums

$$C_1, C_2 \rightsquigarrow C_1 + C_2 = \{x_1 + x_2 : x_1 \in C_1, x_2 \in C_2\}$$

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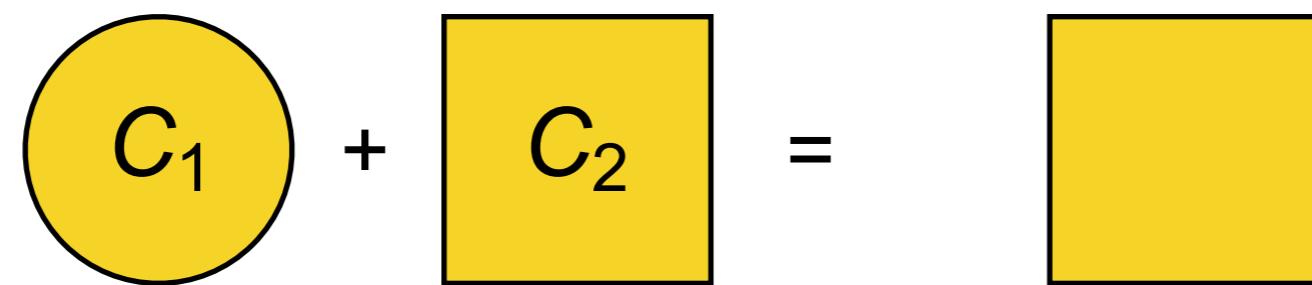
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A diagram illustrating the Minkowski sum of two sets, C_1 and C_2 . On the left, there is a yellow circle labeled C_1 . To its right is a plus sign ($+$). To the right of the plus sign is a yellow square labeled C_2 . To the right of the square is an equals sign ($=$). To the right of the equals sign is a question mark ($?$), indicating the result of the sum.

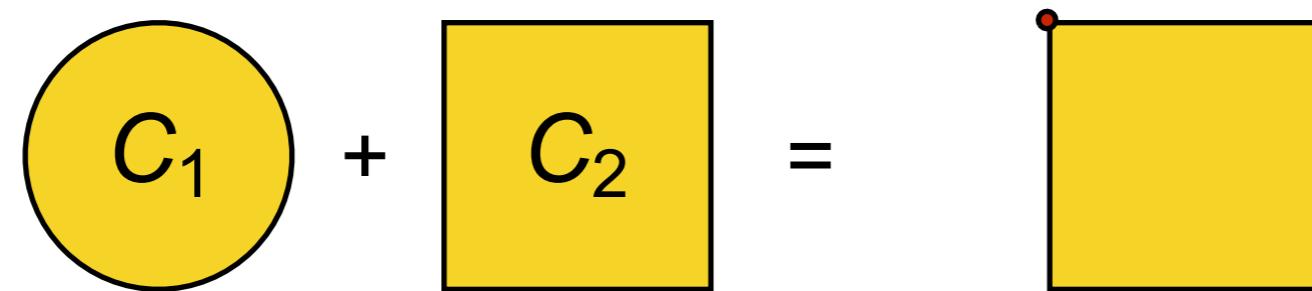
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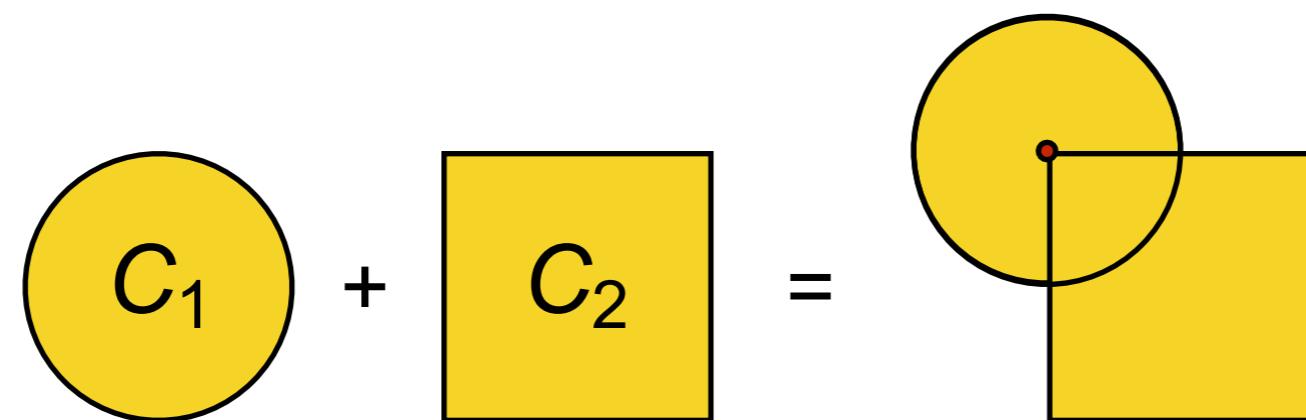
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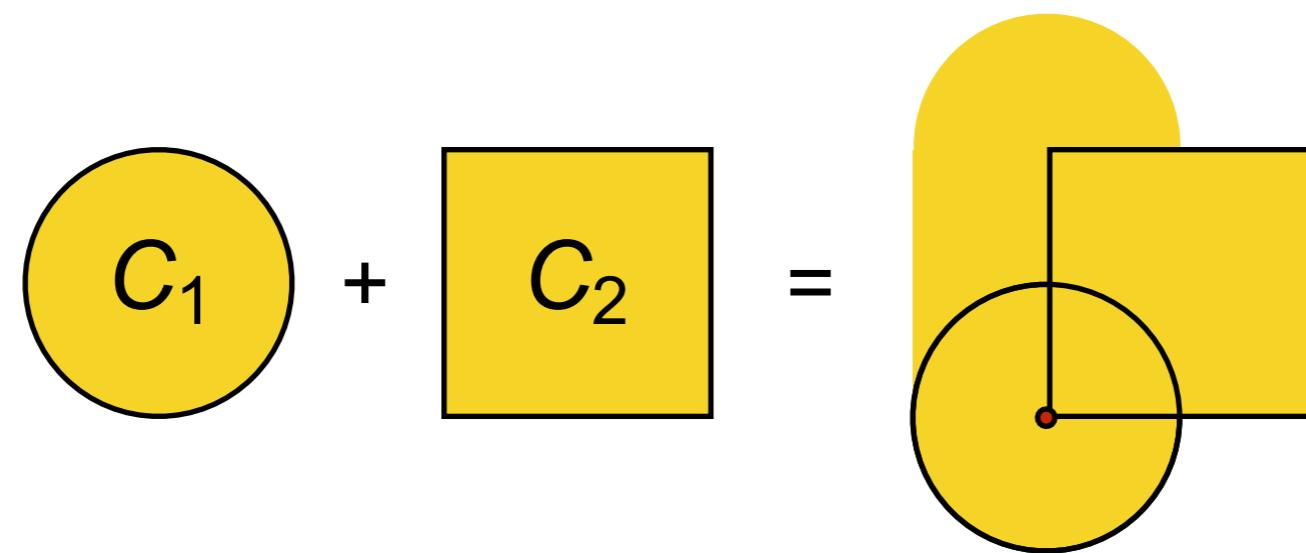
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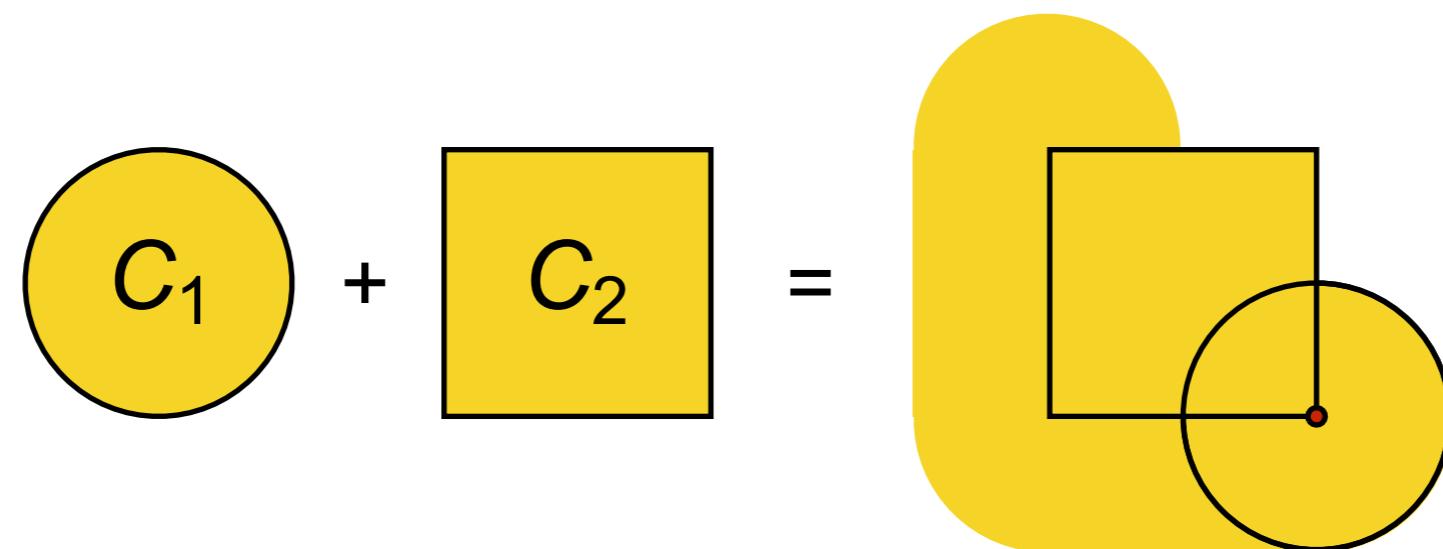
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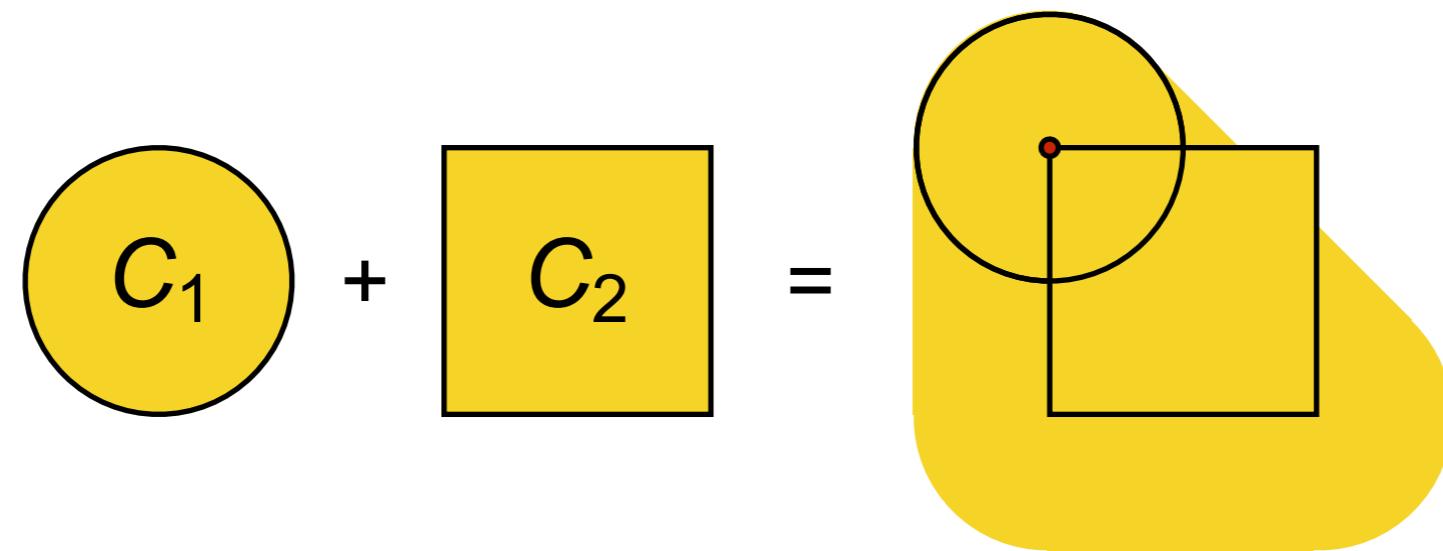
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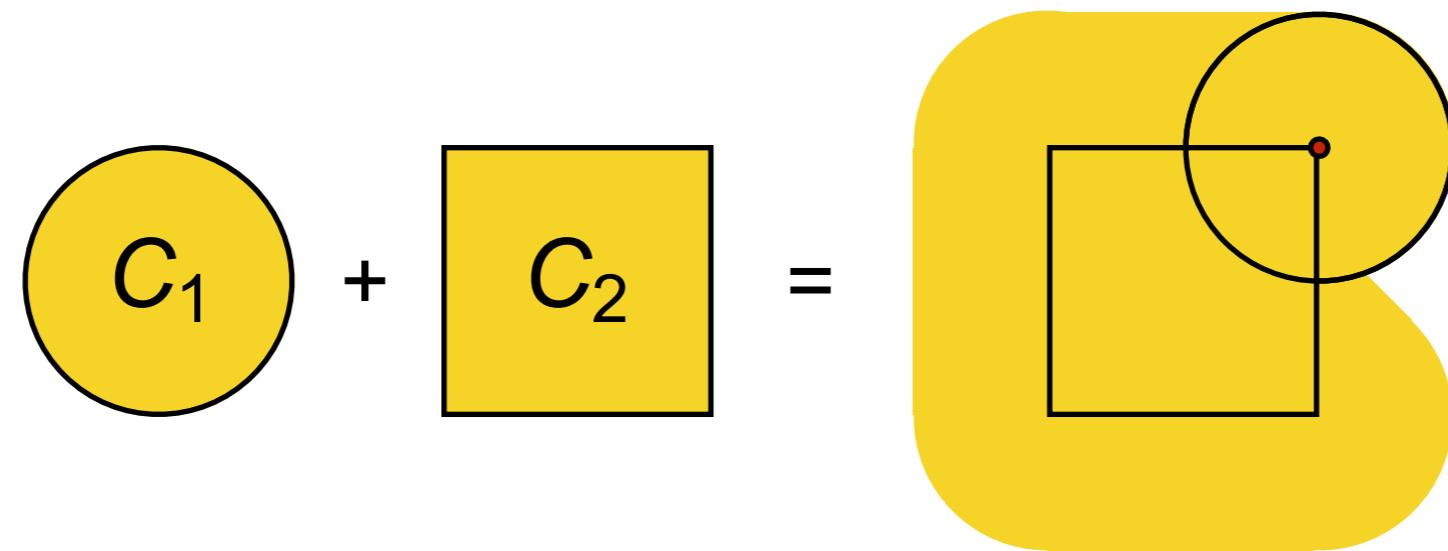
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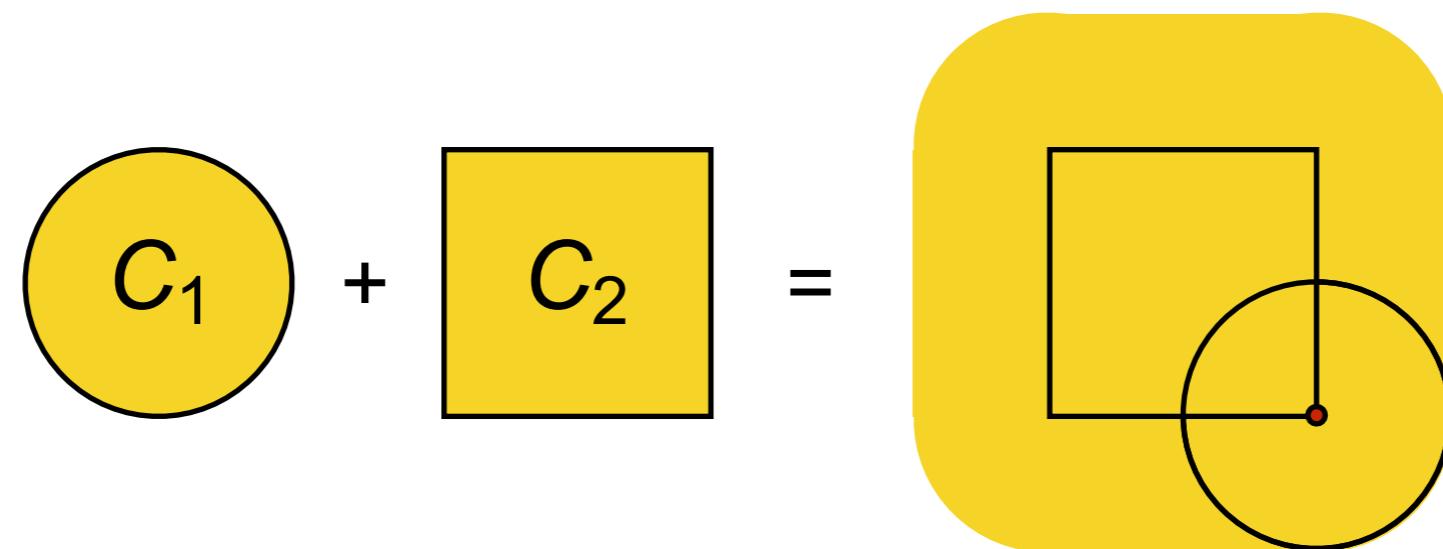
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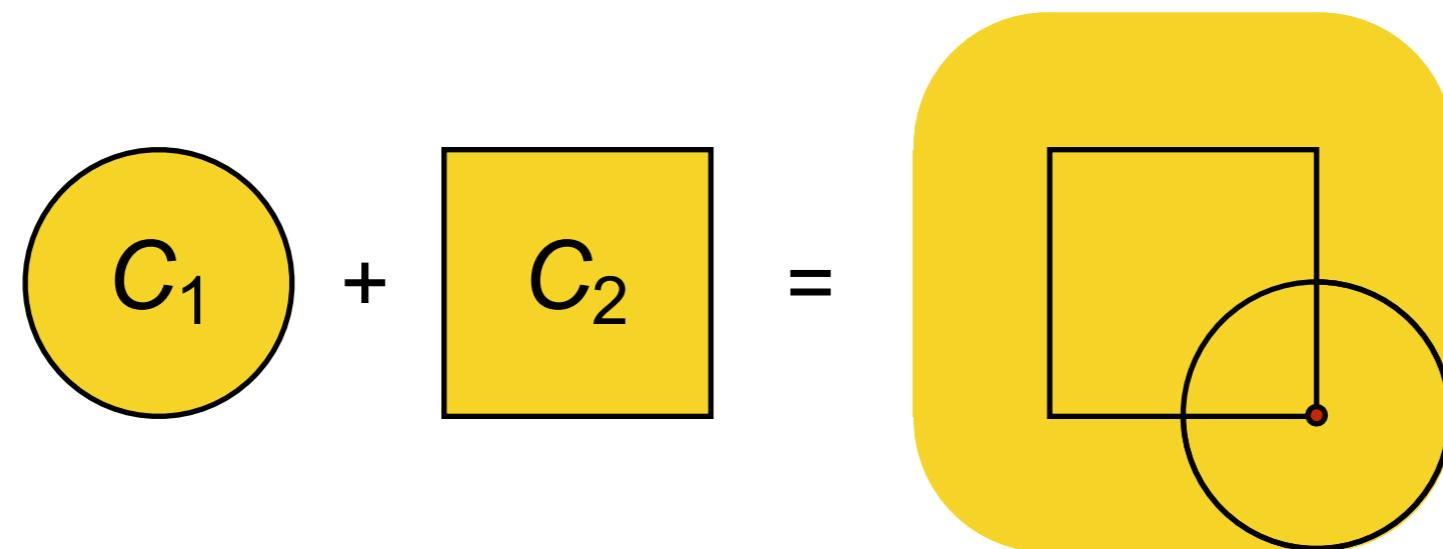
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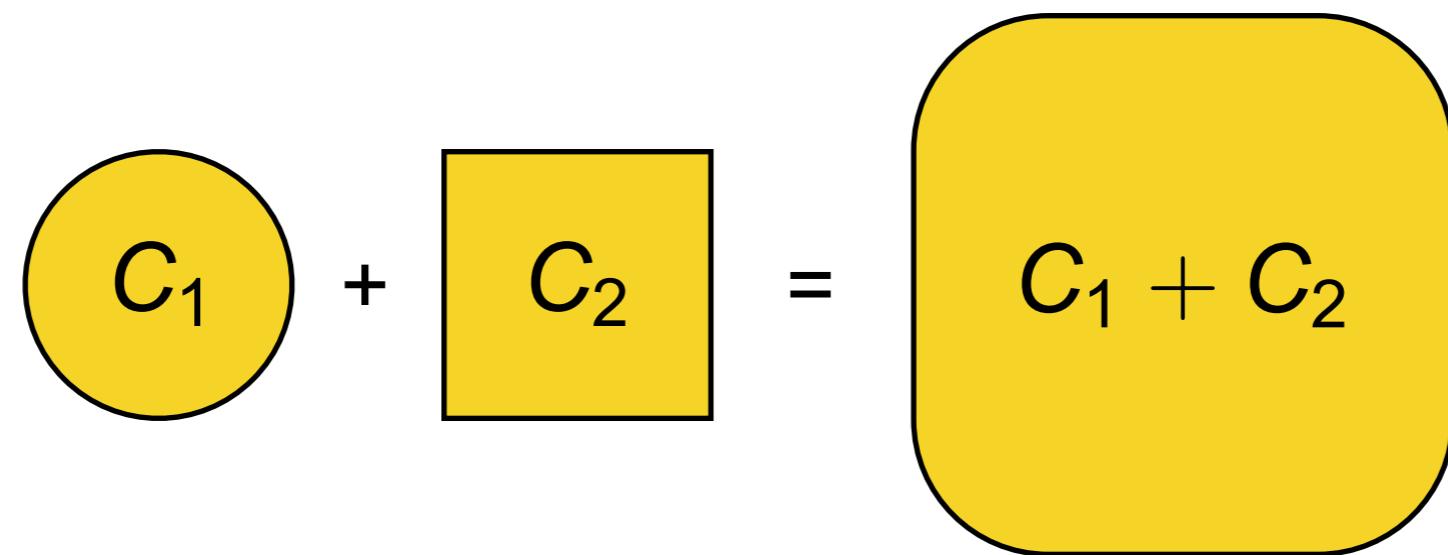
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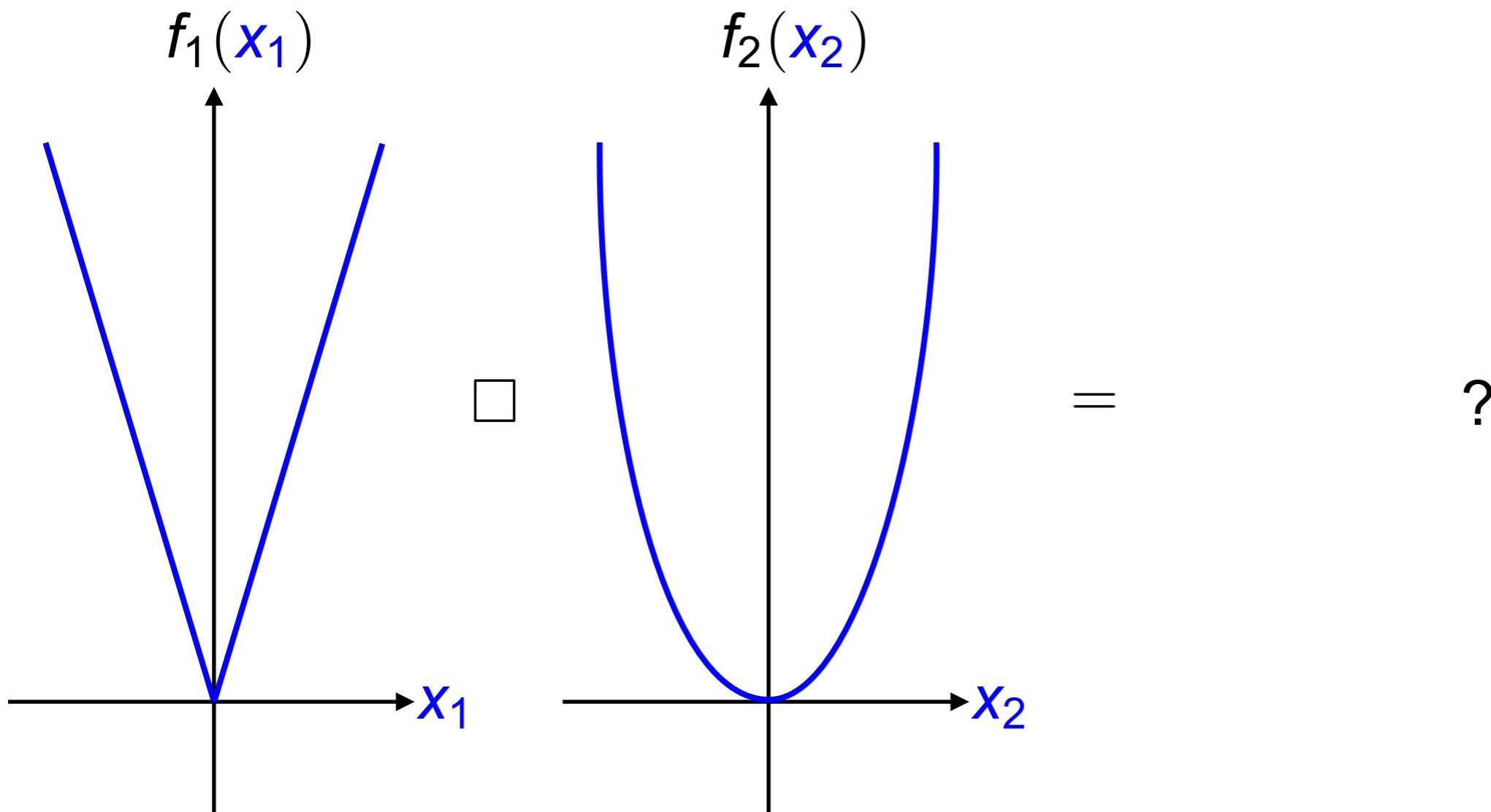


Infimal Convolution

$$f_1(\textcolor{blue}{x}_1), f_2(\textcolor{blue}{x}_2) \rightsquigarrow (f_1 \square f_2)(\textcolor{blue}{x}) = \inf_{x_1 + \textcolor{blue}{x}_2 = \textcolor{blue}{x}} f_1(\textcolor{blue}{x}_1) + f_2(\textcolor{blue}{x}_2)$$

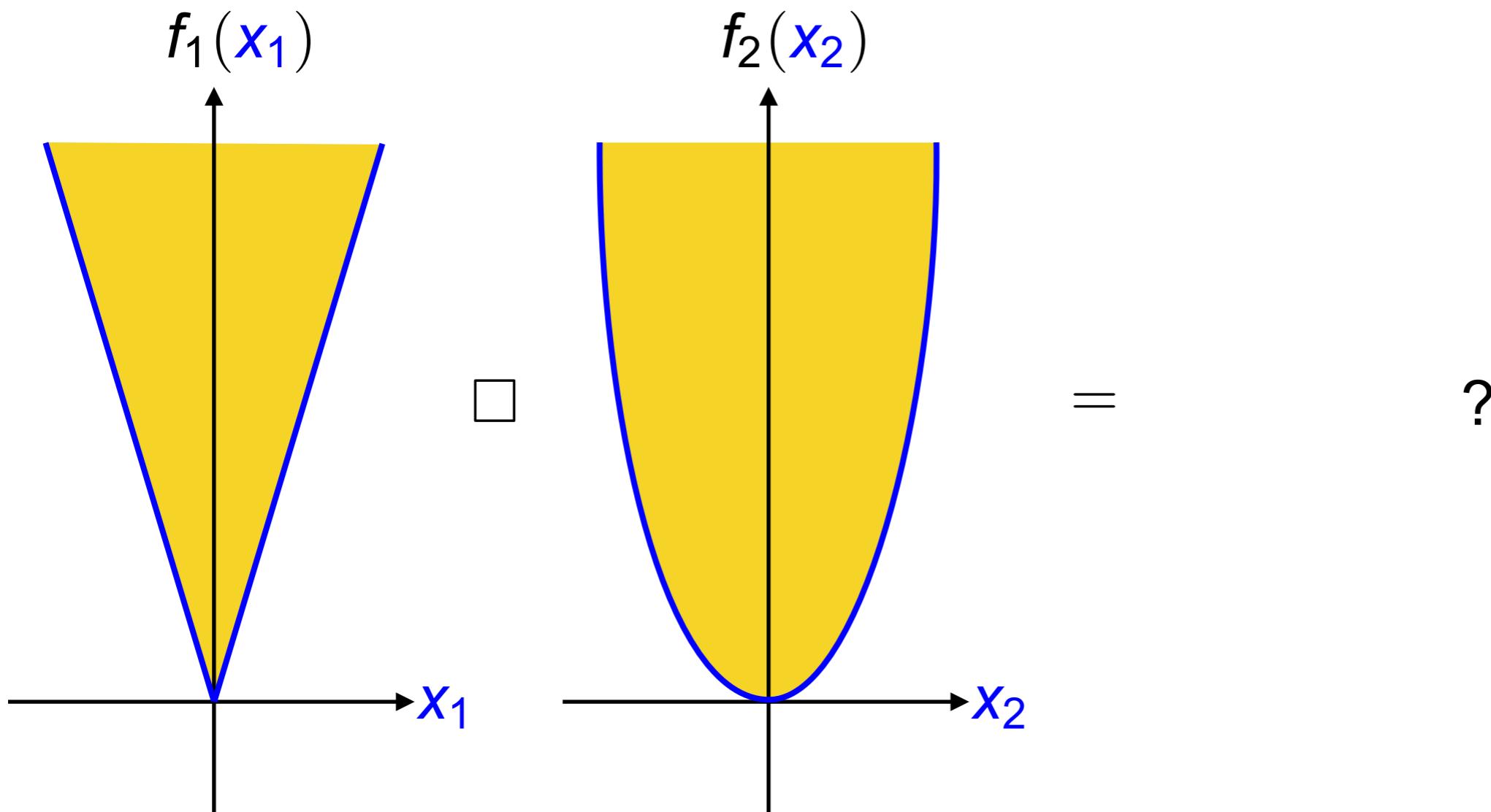
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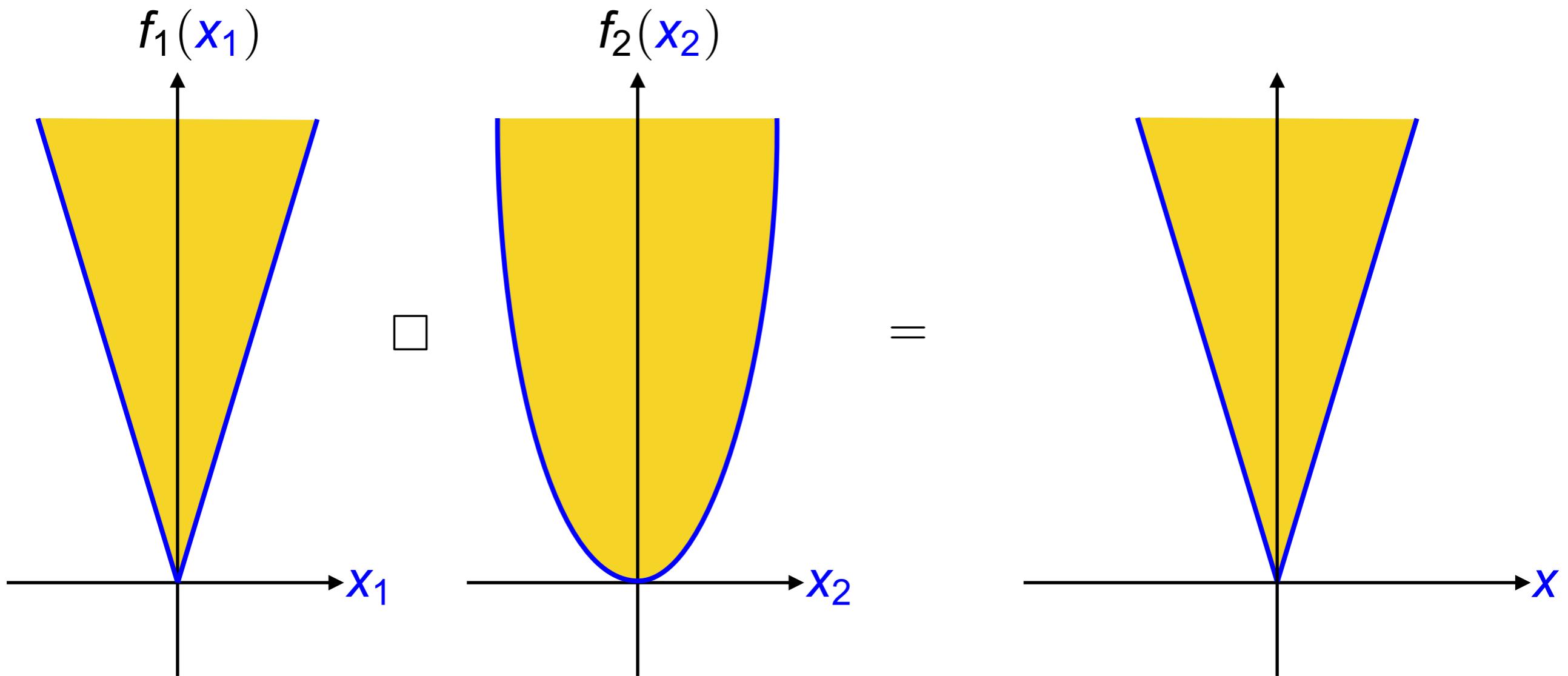
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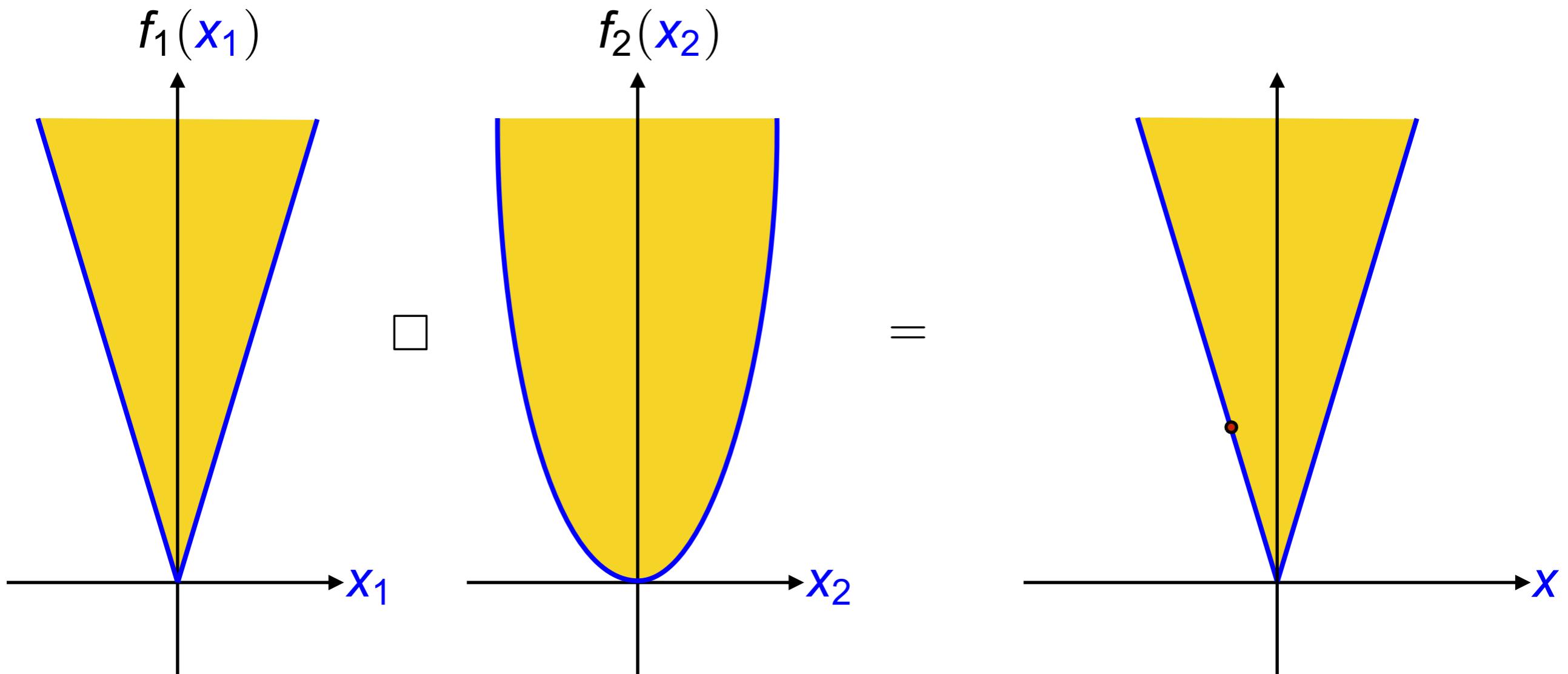
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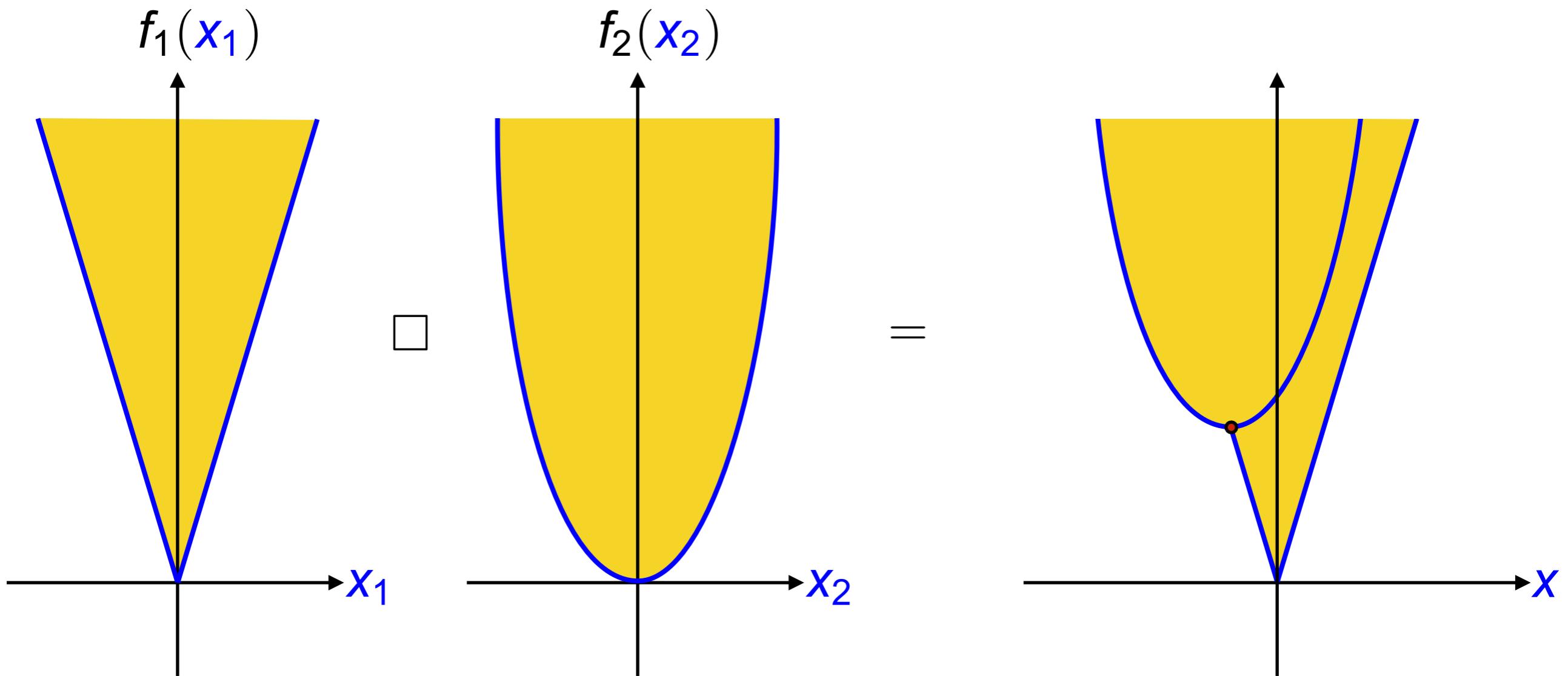
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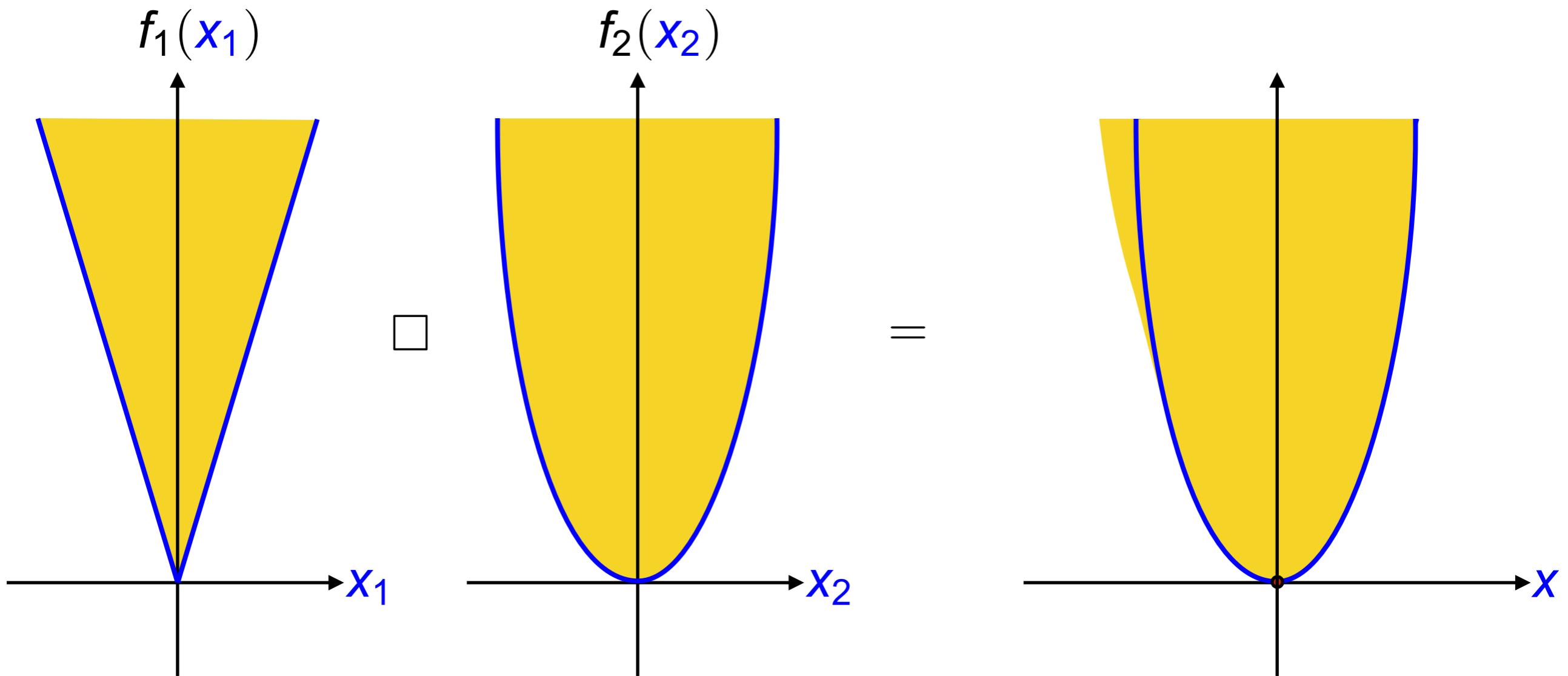
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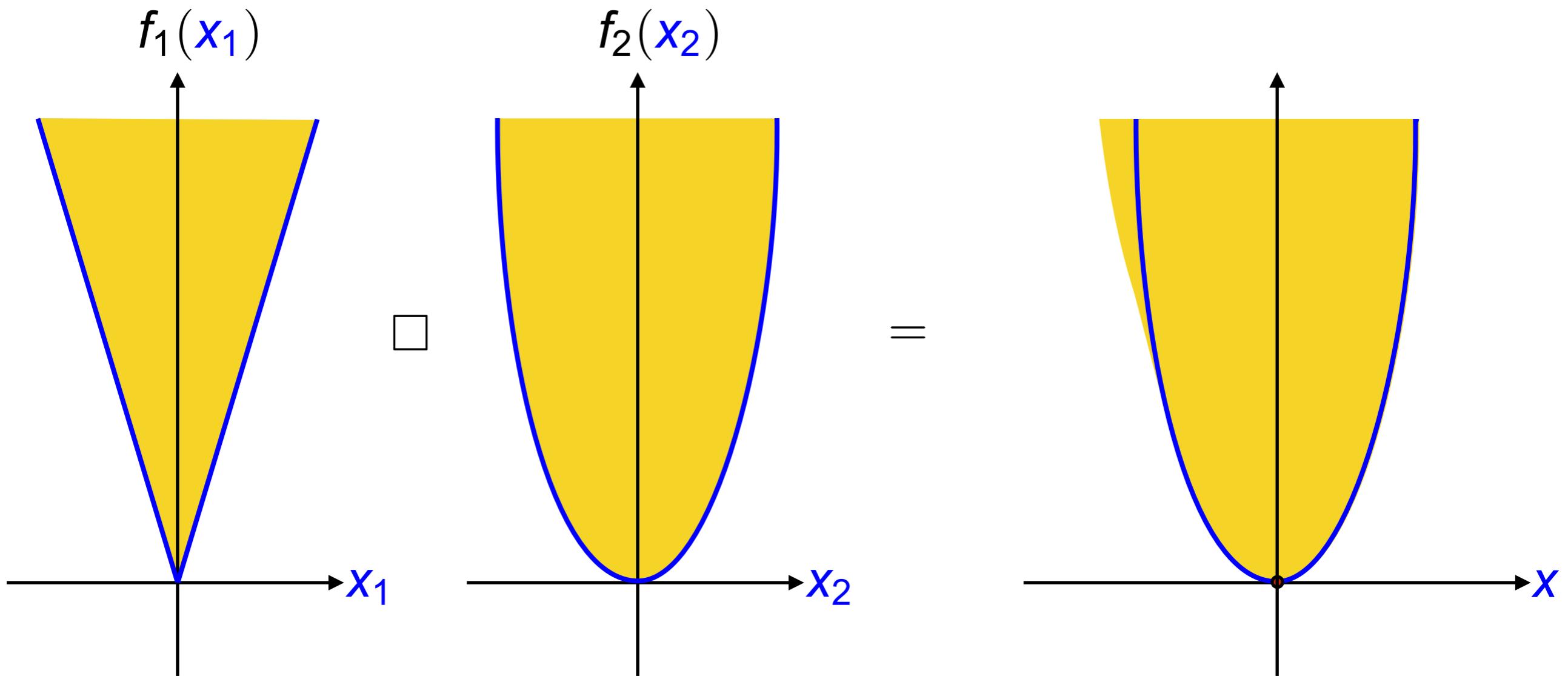
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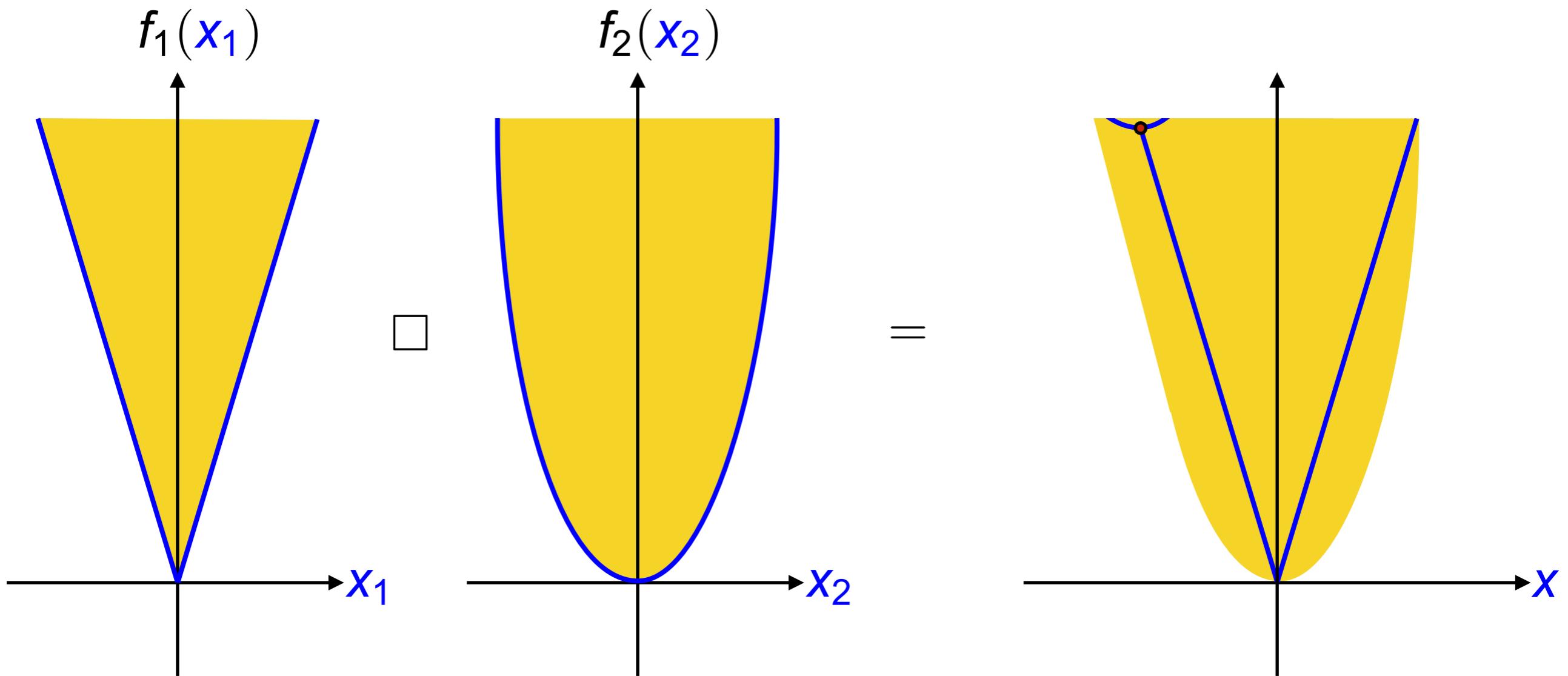
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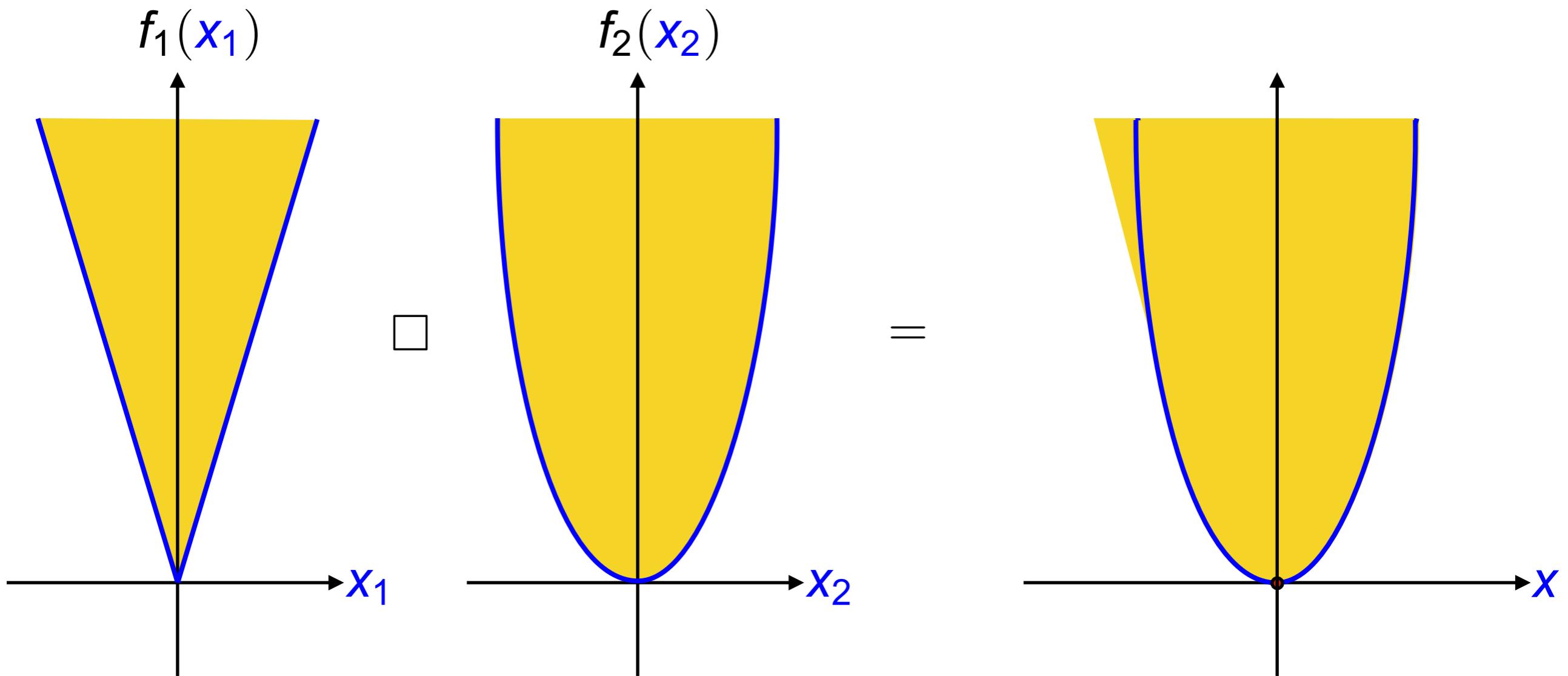
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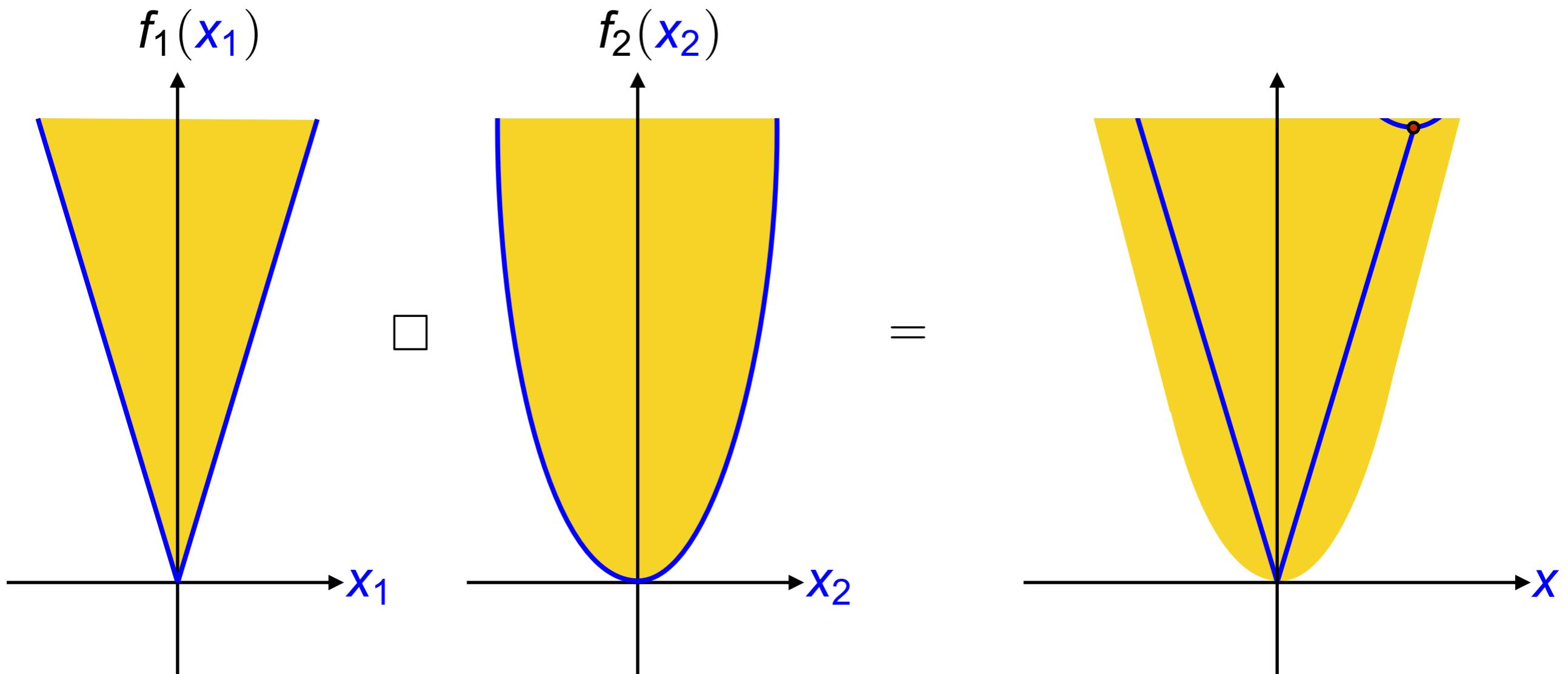
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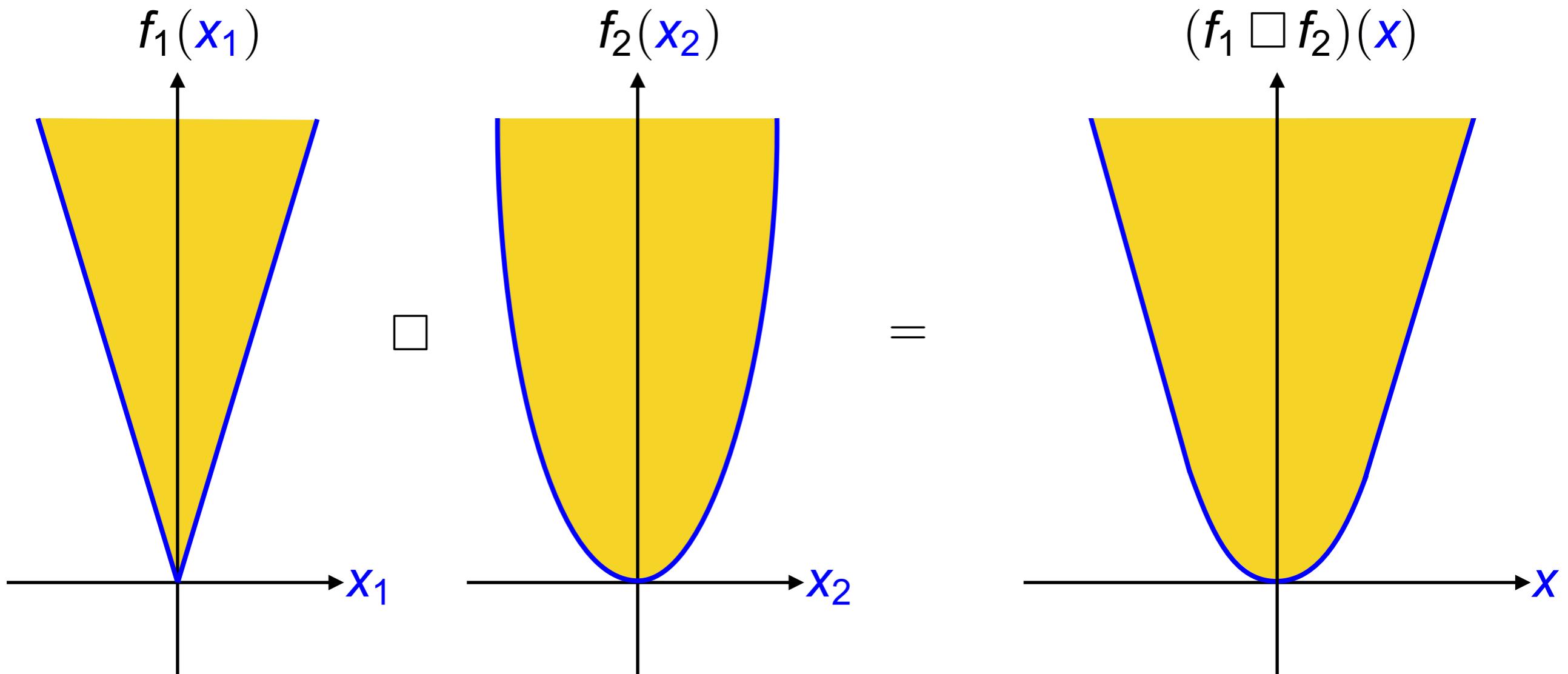
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Infimal Convolution

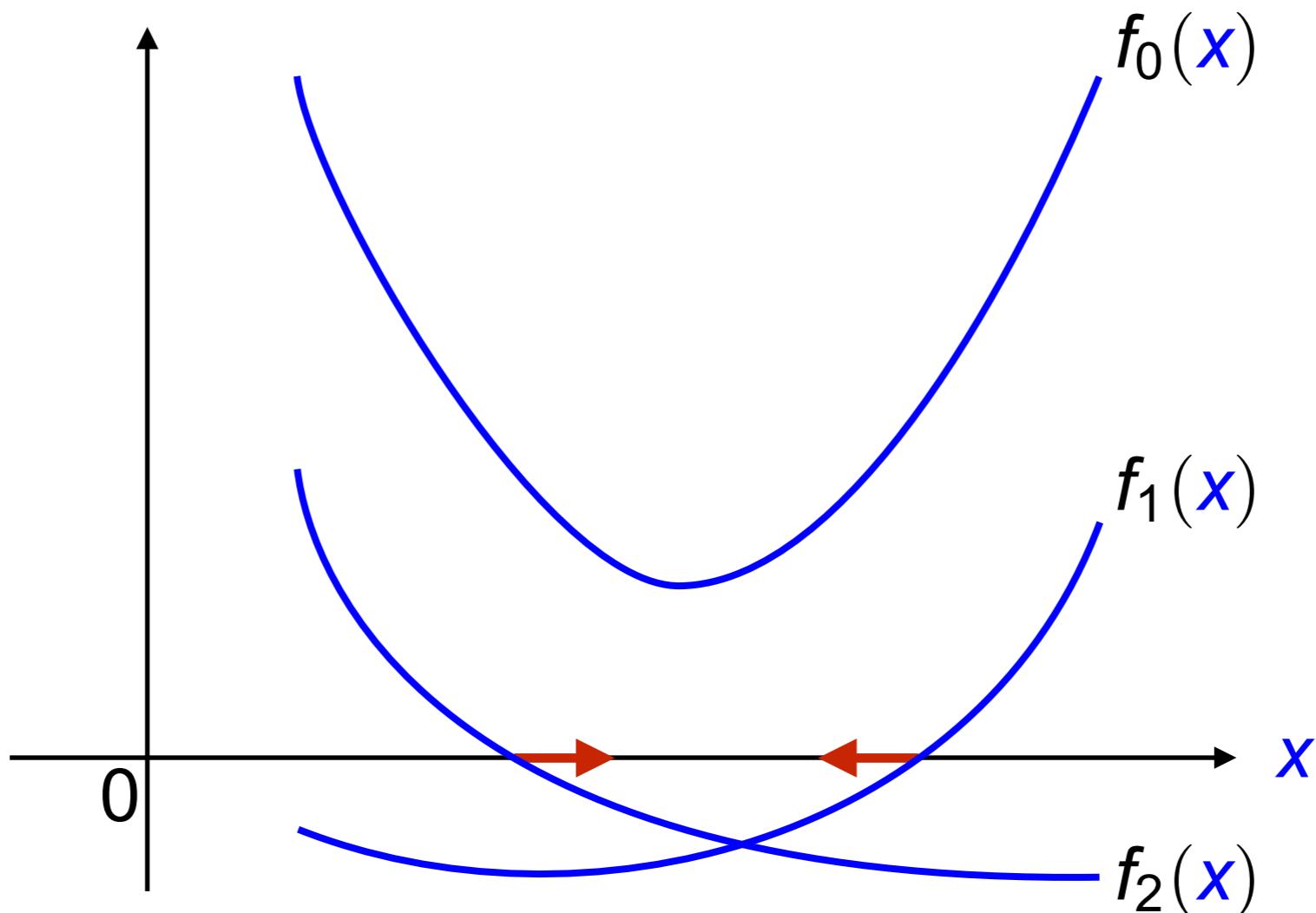
$$f_1(\textcolor{blue}{x}_1), f_2(\textcolor{blue}{x}_2) \rightsquigarrow (f_1 \square f_2)(\textcolor{blue}{x}) = \inf_{x_1 + \textcolor{blue}{x}_2 = \textcolor{blue}{x}} f_1(\textcolor{blue}{x}_1) + f_2(\textcolor{blue}{x}_2)$$



Convex Optimization

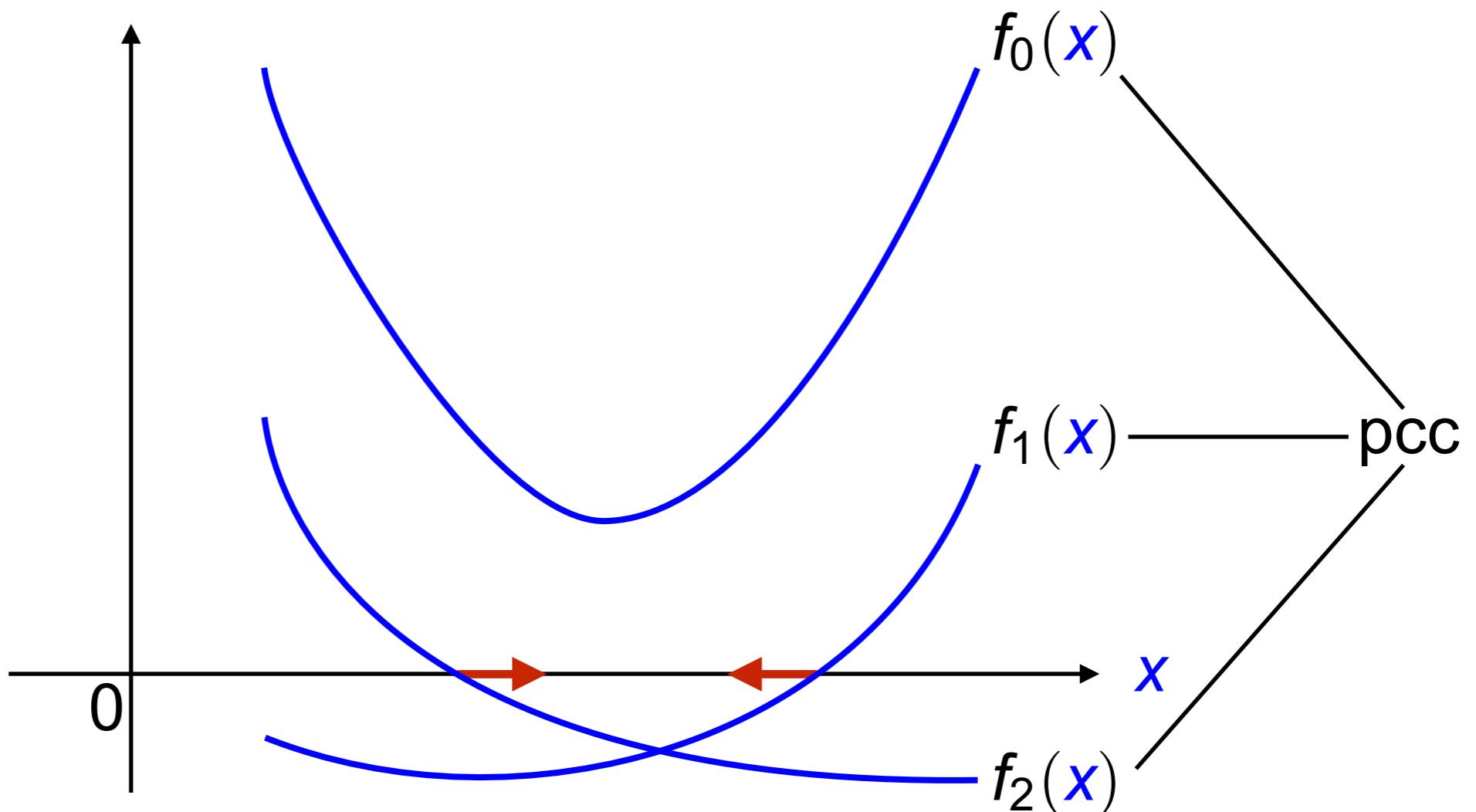
Primal Problem

$$\begin{array}{ll} \inf_{\mathbf{x}} & f_0(\mathbf{x}) \\ \text{s.t.} & f_i(\mathbf{x}) \leq 0 \quad \forall i = 1, \dots, I \end{array} \quad (\text{P})$$



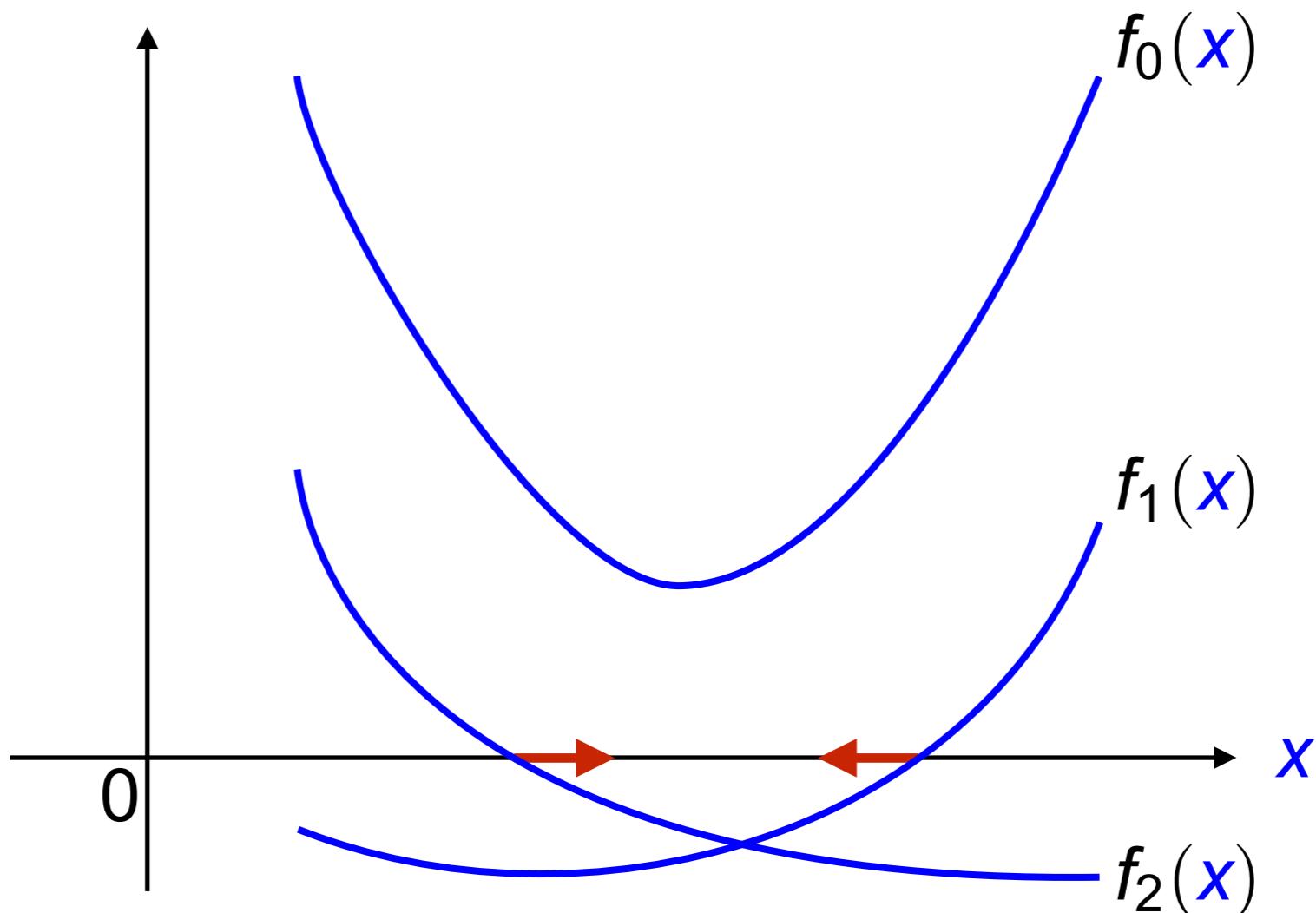
Primal Problem

$$\begin{array}{ll} \inf_{\mathbf{x}} & f_0(\mathbf{x}) \\ \text{s.t.} & f_i(\mathbf{x}) \leq 0 \quad \forall i = 1, \dots, I \end{array} \quad (\text{P})$$



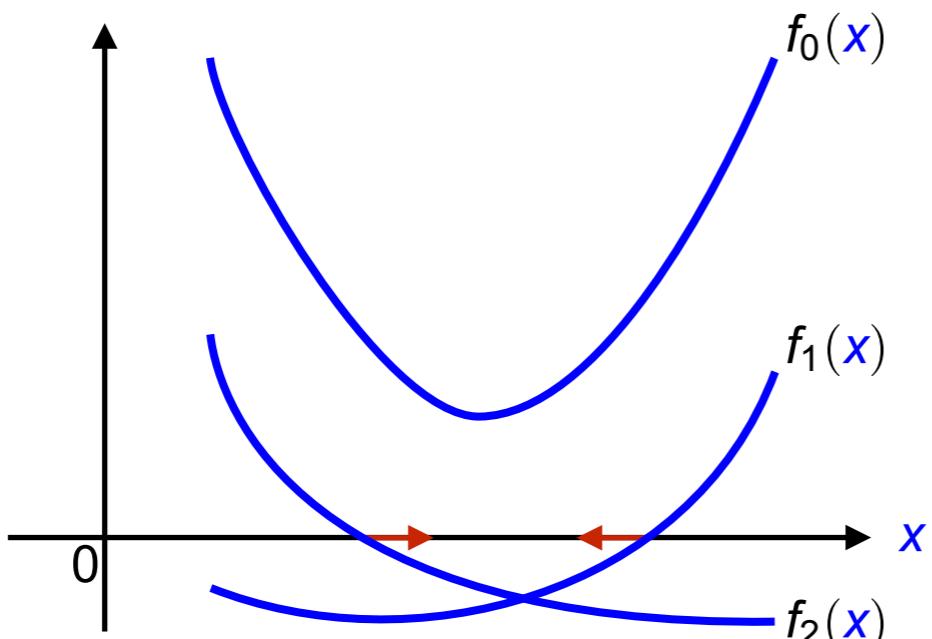
Primal Problem

$$\begin{array}{ll} \inf_{\mathbf{x}} & f_0(\mathbf{x}) \\ \text{s.t.} & f_i(\mathbf{x}) \leq 0 \quad \forall i = 1, \dots, I \end{array} \quad (\text{P})$$



Primal Problem

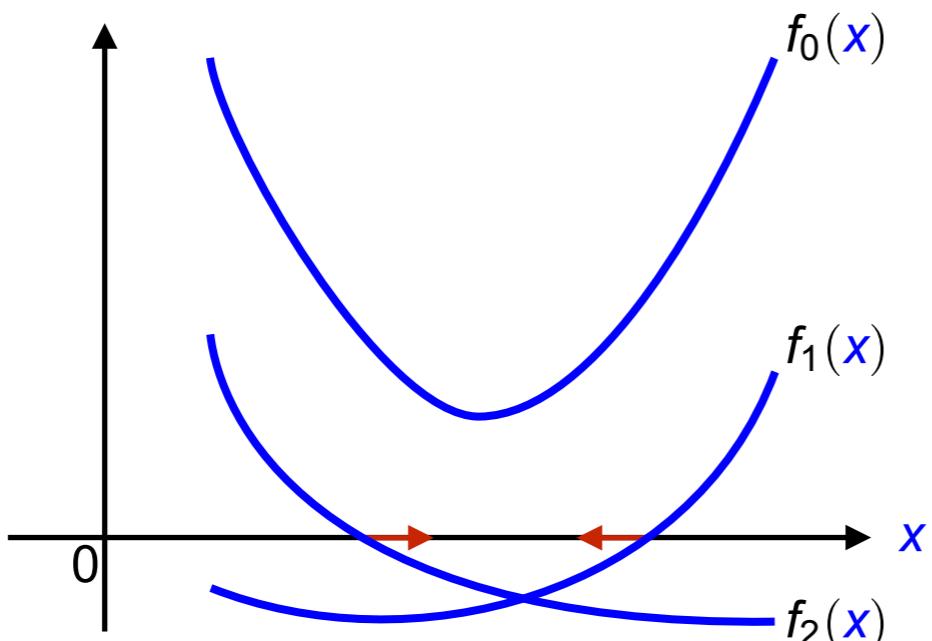
$$\begin{aligned} \inf_{\mathbf{x}} \quad & f_0(\mathbf{x}) \\ \text{s.t.} \quad & f_i(\mathbf{x}) \leq 0 \quad \forall i = 1, \dots, I \end{aligned} \quad \xleftarrow{\hspace{1cm}} \lambda_i$$



Joseph-Luis Lagrange

Primal Problem

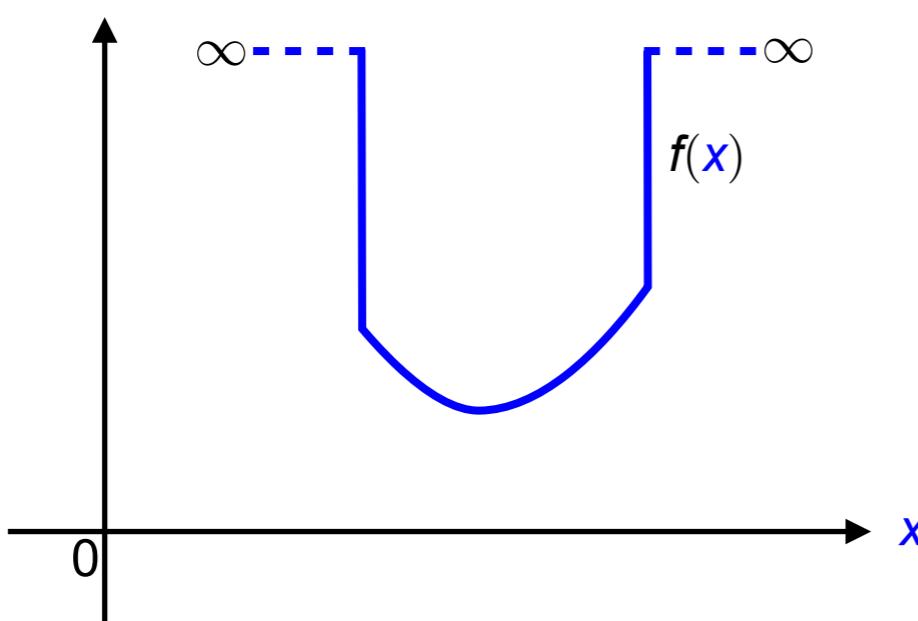
$$\inf_{\mathbf{x}} \sup_{\lambda \geq 0} f_0(\mathbf{x}) + \sum_{i=1}^I \lambda_i f_i(\mathbf{x})$$



Joseph-Luis Lagrange

Primal Problem

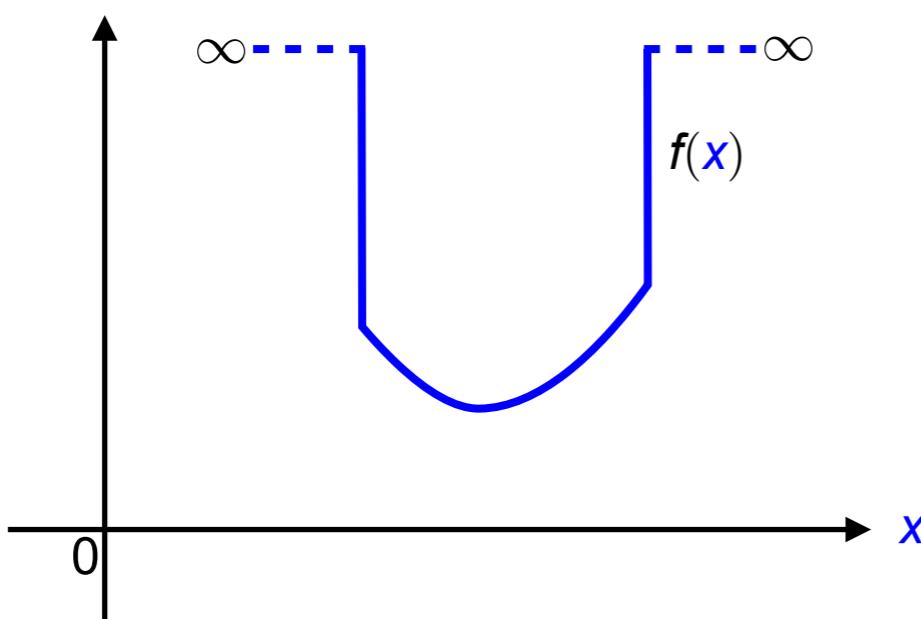
$$\inf_{\mathbf{x}} \sup_{\lambda \geq 0} f_0(\mathbf{x}) + \sum_{i=1}^I \lambda_i f_i(\mathbf{x}) = f(\mathbf{x})$$



Joseph-Luis Lagrange

Dual Problem

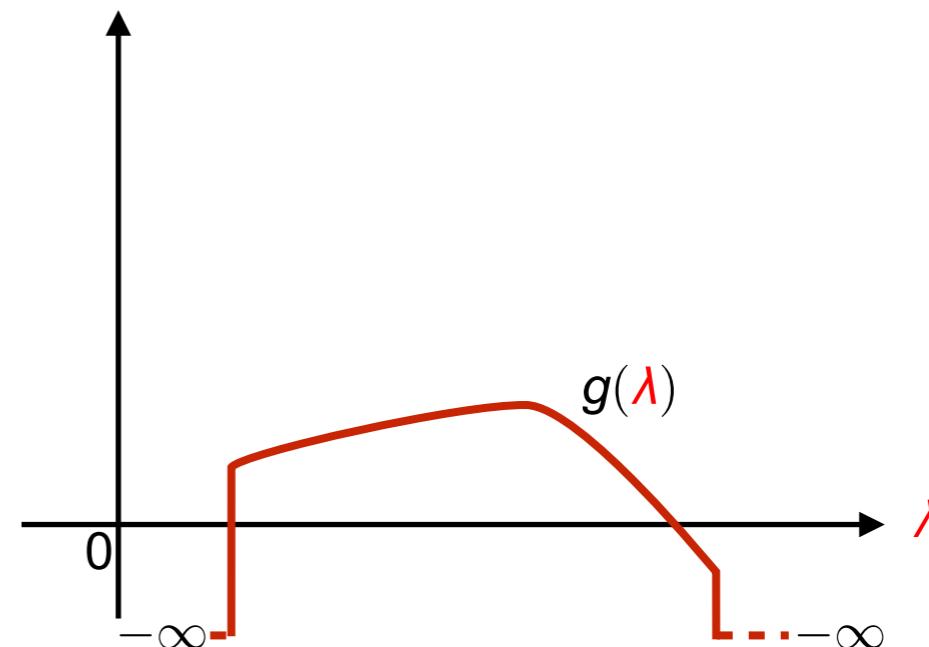
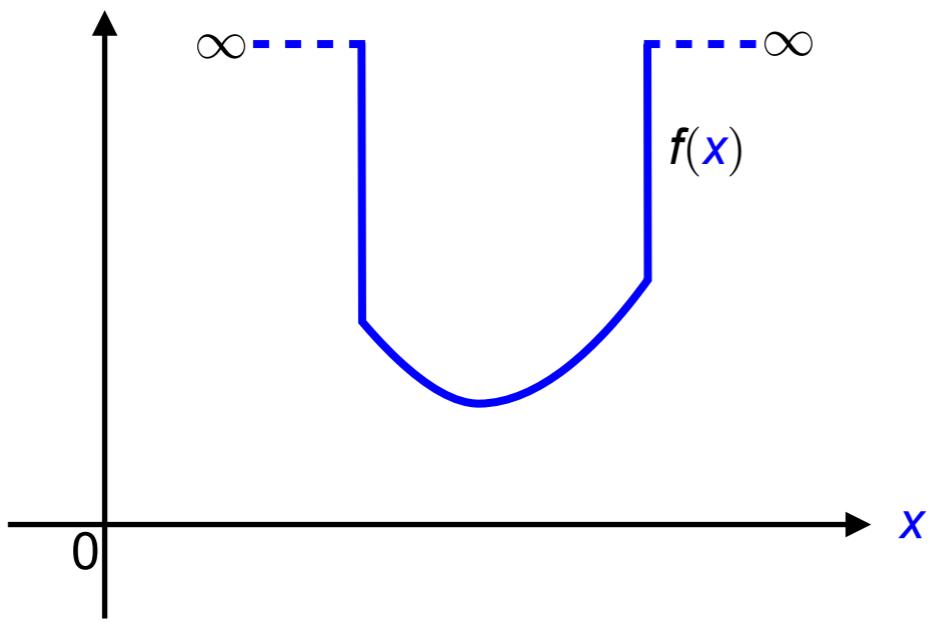
$$\sup_{\lambda \geq 0} \inf_{\mathbf{x}} f_0(\mathbf{x}) + \sum_{i=1}^I \lambda_i f_i(\mathbf{x})$$



Joseph-Luis Lagrange

Dual Problem

$$\sup_{\lambda \geq 0} \inf_{\mathbf{x}} f_0(\mathbf{x}) + \sum_{i=1}^l \lambda_i f_i(\mathbf{x}) = g(\lambda)$$



Dual Problem

$$\sup_{\lambda \geq 0} \inf_{\mathbf{x}} 0^\top \mathbf{x} + f_0(\mathbf{x}) + \sum_{i=1}^l \lambda_i f_i(\mathbf{x})$$



Werner Fenchel

Dual Problem

$$\sup_{\lambda \geq 0} - \sup_{\mathbf{x}} 0^\top \mathbf{x} - f_0(\mathbf{x}) - \sum_{i=1}^I \lambda_i f_i(\mathbf{x})$$



Werner Fenchel

Dual Problem

$$\sup_{\lambda \geq 0} - \boxed{\sup_{\mathbf{x}} 0^\top \mathbf{x} - f_0(\mathbf{x}) - \sum_{i=1}^I \lambda_i f_i(\mathbf{x})}$$

conjugate of Lagrangian



Werner Fenchel

Dual Problem

$$\sup_{\lambda \geq 0} - \boxed{\sup_{\mathbf{x}} 0^\top \mathbf{x} - f_0(\mathbf{x}) - \sum_{i=1}^I \lambda_i f_i(\mathbf{x})}$$

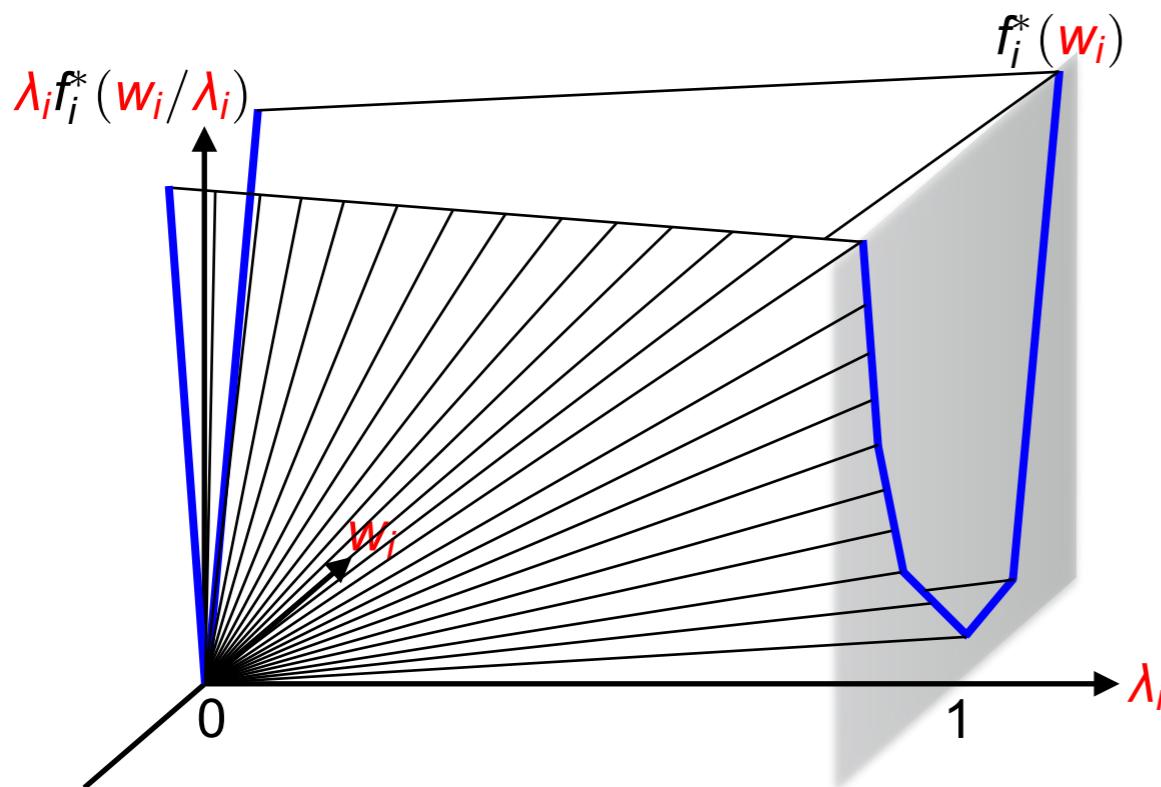
= inf-convolution of f_0^* and $(\lambda_i f_i)^*$, $i = 1, \dots, I$



Werner Fenchel

Dual Problem

$$\begin{aligned} \sup_{\mathbf{w}, \lambda \geq 0} \quad & -f_0^*(\mathbf{w}_0) - \sum_{i=1}^I \lambda_i f_i^*(\mathbf{w}_i / \lambda_i) \\ \text{s.t.} \quad & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned}$$



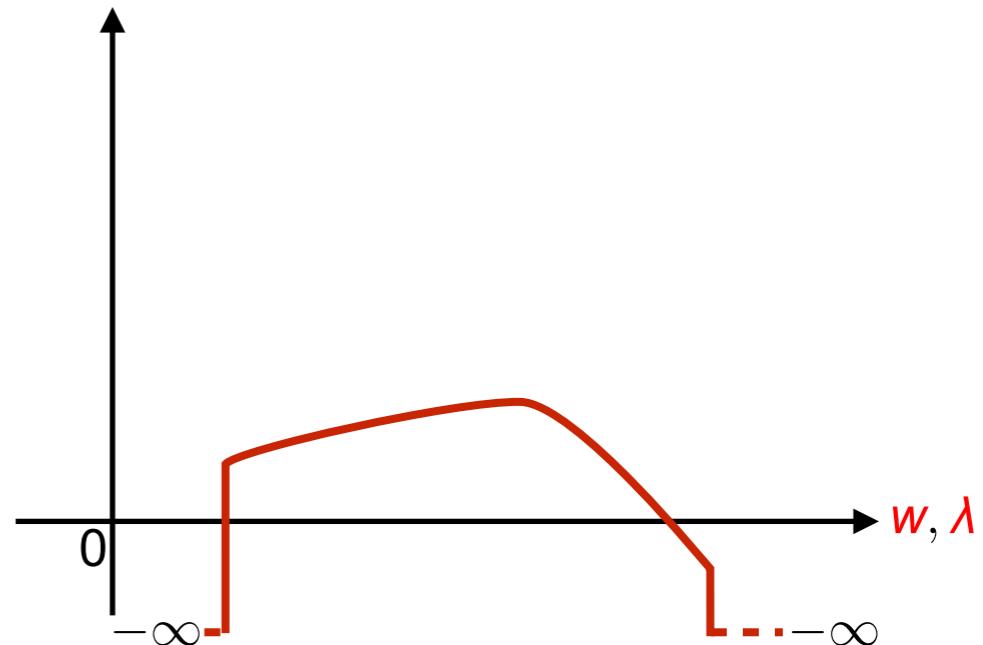
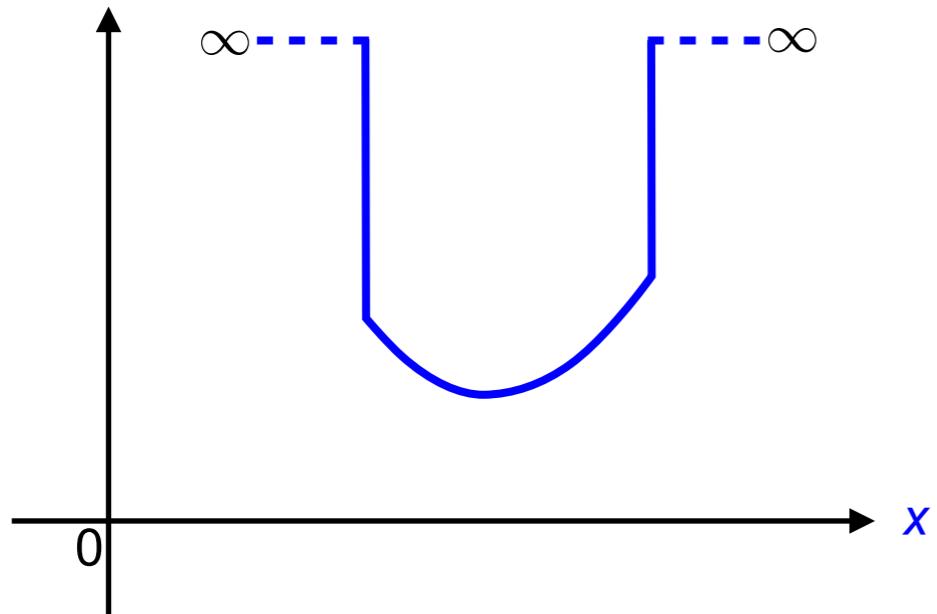
Werner Fenchel

Dual Problem

$$\begin{aligned} \sup_{\mathbf{w}, \lambda \geq 0} \quad & -f_0^*(\mathbf{w}_0) - \sum_{i=1}^I \lambda_i f_i^*(\mathbf{w}_i / \lambda_i) \\ \text{s.t.} \quad & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \tag{D}$$

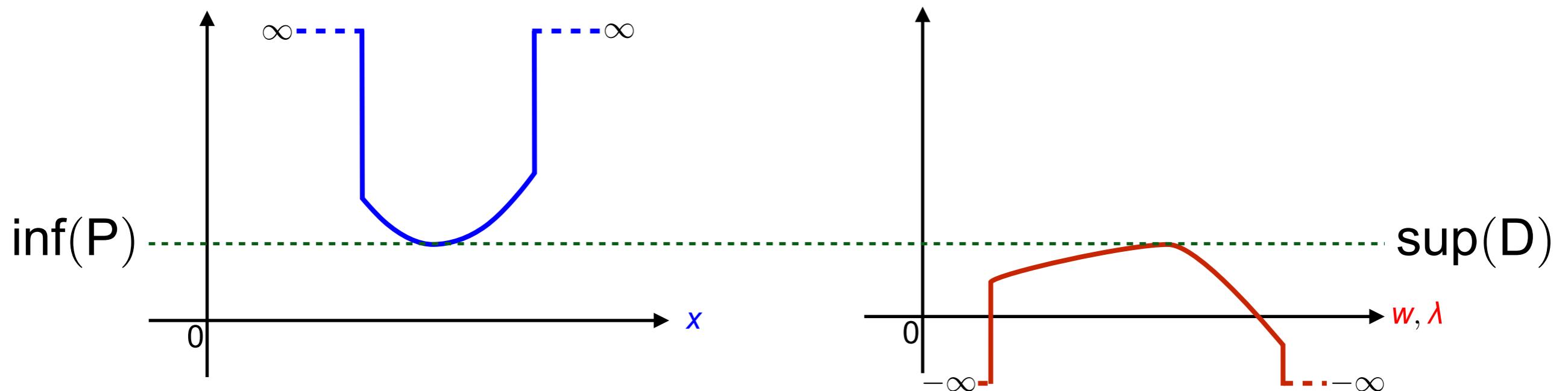
Strong Duality

$$\begin{aligned} \sup_{\substack{\mathbf{w}, \lambda \geq 0}} \quad & -f_0^*(\mathbf{w}_0) - \sum_{i=1}^I \lambda_i f_i^*(\mathbf{w}_i / \lambda_i) \\ \text{s.t.} \quad & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \quad (\text{D})$$



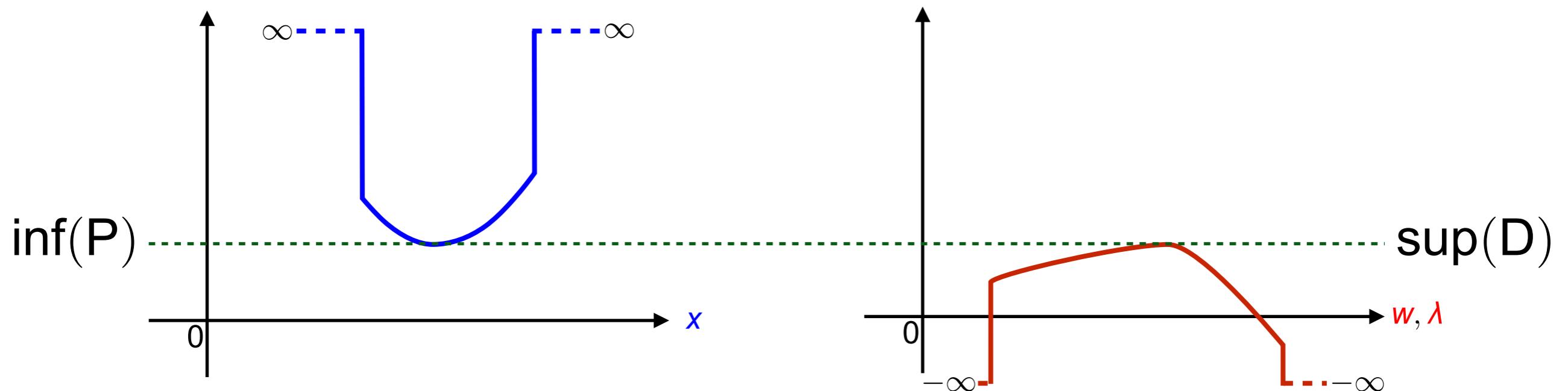
Strong Duality

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Strong Duality

$$\begin{aligned} \sup_{\mathbf{w}, \lambda \geq 0} \quad & -f_0^*(\mathbf{w}_0) - \sum_{i=1}^I \lambda_i f_i^*(\mathbf{w}_i / \lambda_i) \\ \text{s.t.} \quad & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \quad (\text{D})$$



if feasible set of (\mathcal{P}) or (\mathcal{D}) is bounded or has Slater point

Robust Convex Optimization

Optimization under Uncertainty



Pliny the Elder

The only
certainty is that
nothing is certain.

Optimization under Uncertainty



Pliny the Elder

The only
certainty is that
nothing is certain.

Real decision problems depend on uncertain parameters **z** .

Scenario Problems

Fix any uncertainty realization $\mathbf{z} = (z_0, \dots, z_I)$.

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Scenario Problems

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$$\begin{array}{ll}\inf_{\mathbf{x}} & f_0(\mathbf{x}, z_0) \\ \text{s.t.} & f_i(\mathbf{x}, z_i) \leq 0 \quad \forall i = 1, \dots, I\end{array} \quad (\mathbf{P}(\mathbf{z}))$$

pcc in \mathbf{x}

Scenario Problems

Fix any uncertainty realization $\mathbf{z} = (\mathbf{z}_0, \dots, \mathbf{z}_I)$.

$$\begin{aligned} & \inf_{\mathbf{x}} && f_0(\mathbf{x}, \mathbf{z}_0) \\ \text{s.t. } & && f_i(\mathbf{x}, \mathbf{z}_i) \leq 0 \quad \forall i = 1, \dots, I \end{aligned} \tag{P(z)}$$

$$\begin{aligned} & \sup_{\mathbf{w}, \lambda \geq 0} && -f_0^{*1}(\mathbf{w}_0, \mathbf{z}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i / \lambda_i, \mathbf{z}_i) \\ \text{s.t. } & && \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \tag{D(z)}$$

Scenario Problems

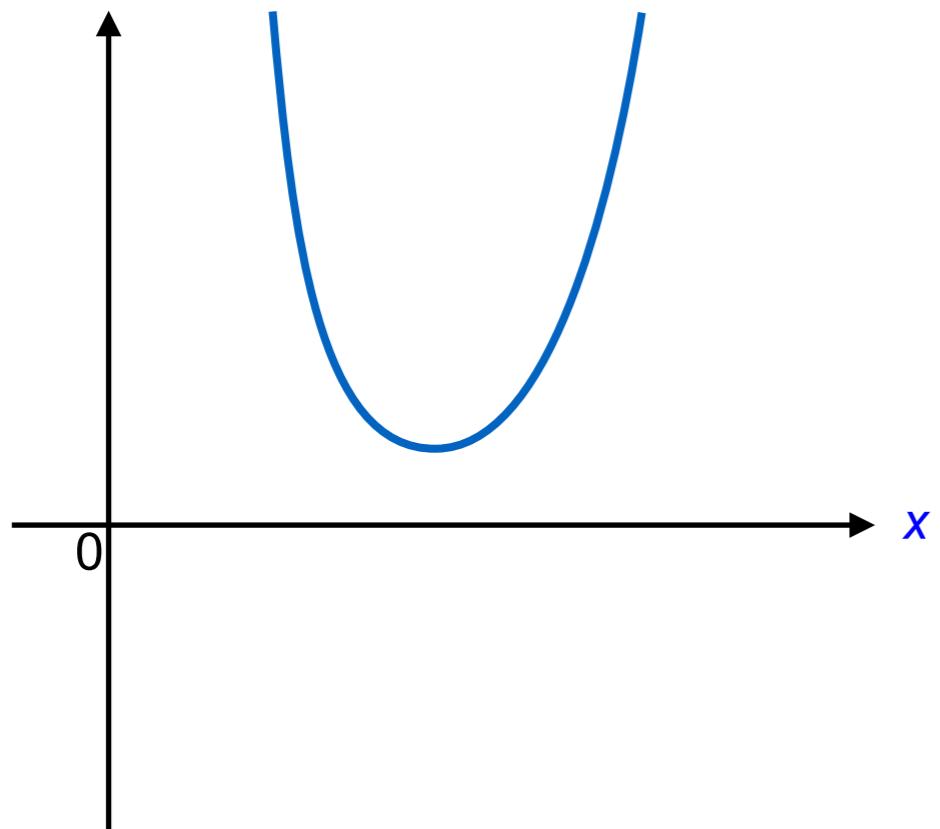
Fix any uncertainty realization $\mathbf{z} = (z_0, \dots, z_I)$.

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$$\begin{aligned} \sup_{w, \lambda \geq 0} \quad & -f_0^{*1}(w_0, z_0) - \sum_{i=1}^I \lambda f_i^{*1}(w_i/\lambda_i, z_i) \\ \text{s.t.} \quad & \sum_{i=0}^I w_i = 0 \end{aligned} \tag{D(z)}$$

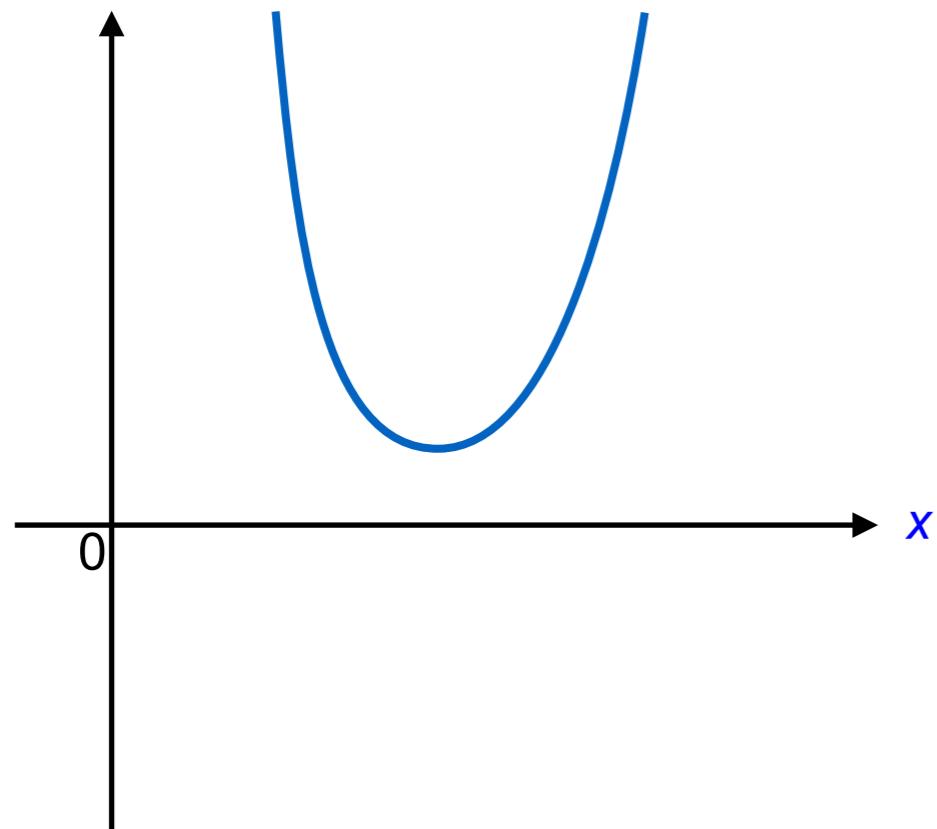
conjugates w.r.t. \mathbf{x}

Scenario Problems

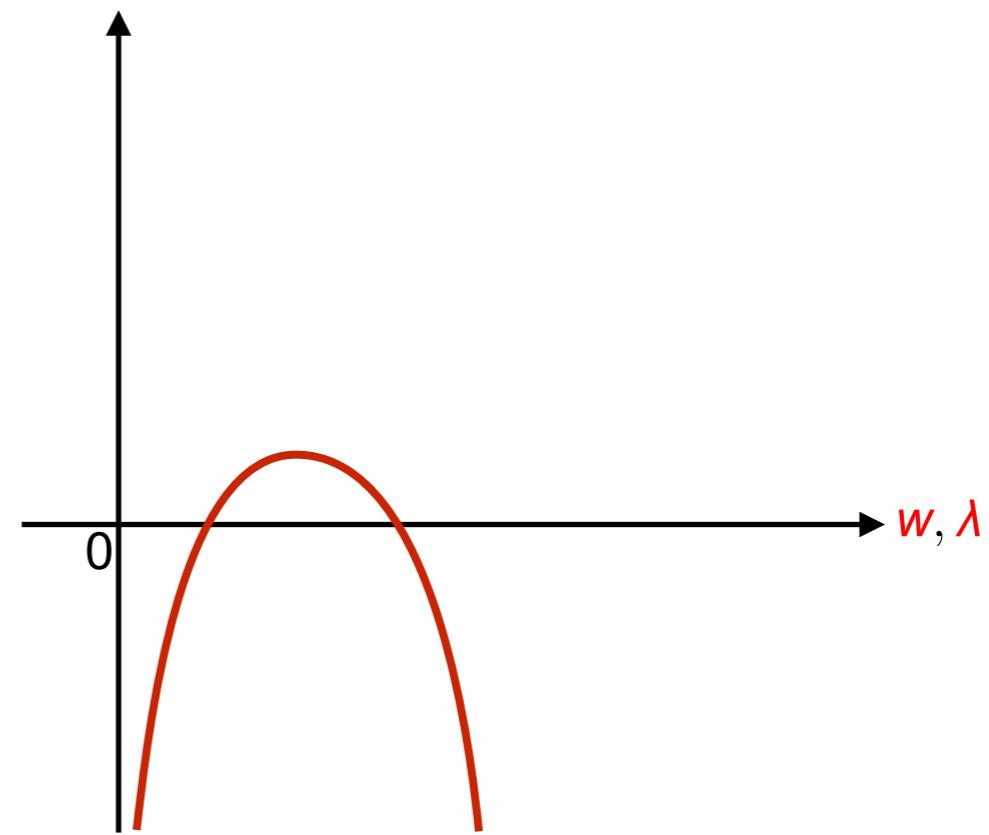


$$P(z^{(1)})$$

Scenario Problems



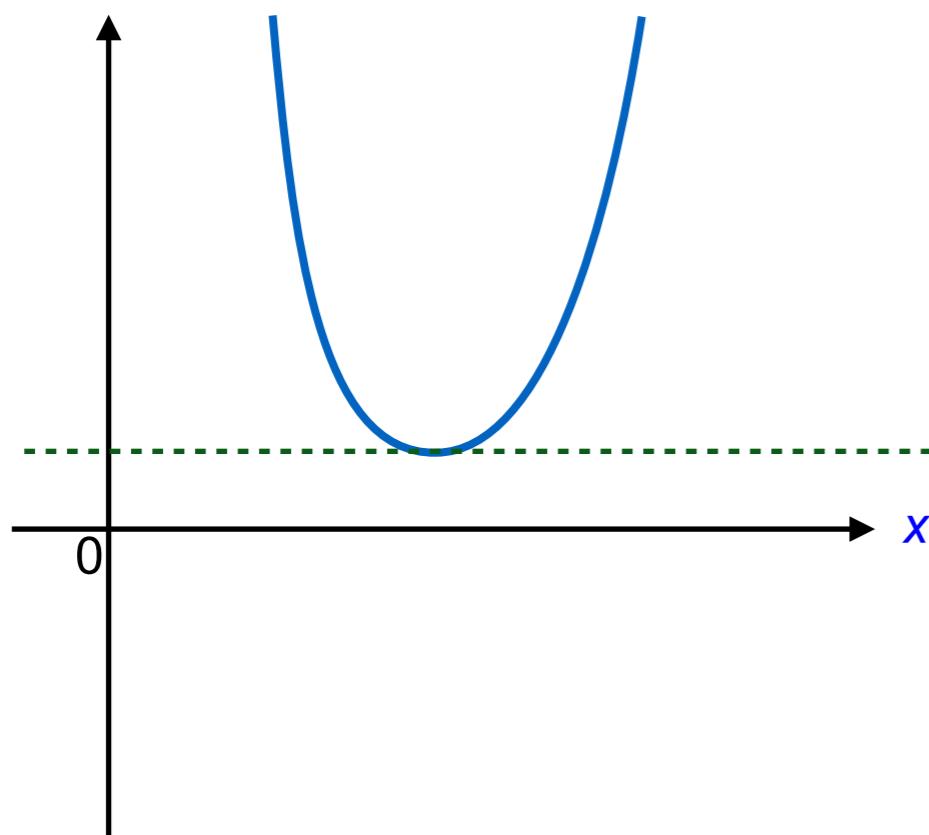
$P(z^{(1)})$



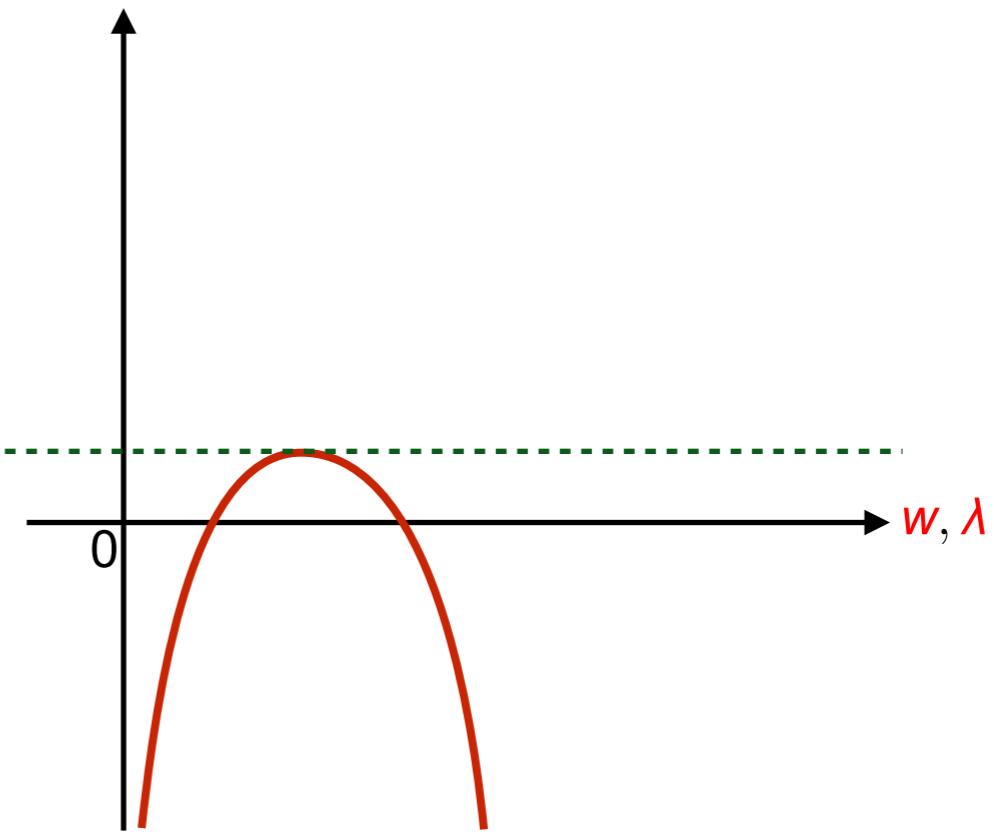
$D(z^{(1)})$

Scenario Problems

$$\inf P(z^{(1)}) = \sup D(z^{(1)})$$



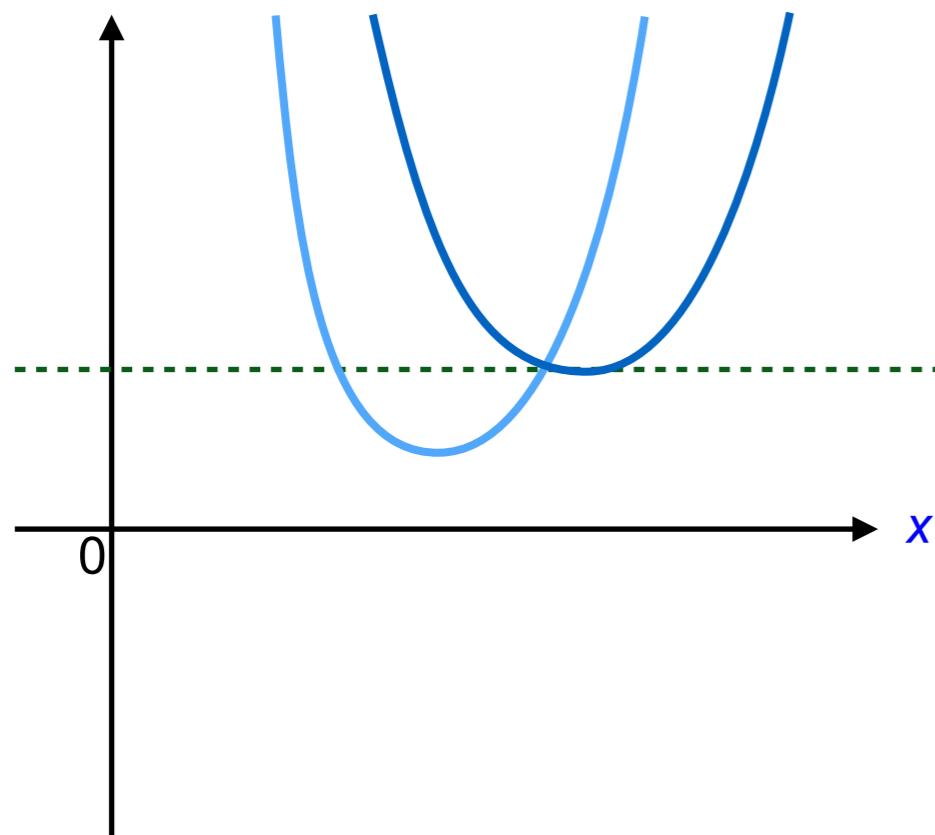
$P(z^{(1)})$



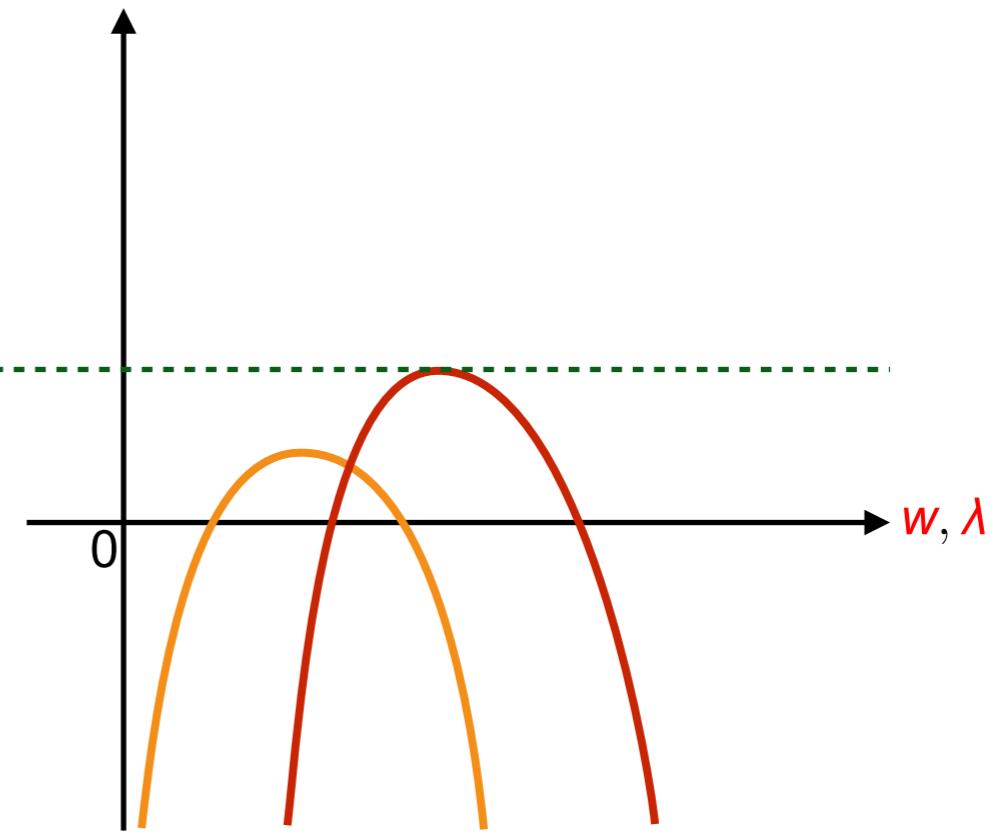
$D(z^{(1)})$

Scenario Problems

$$\inf P(z^{(2)}) = \sup D(z^{(2)})$$



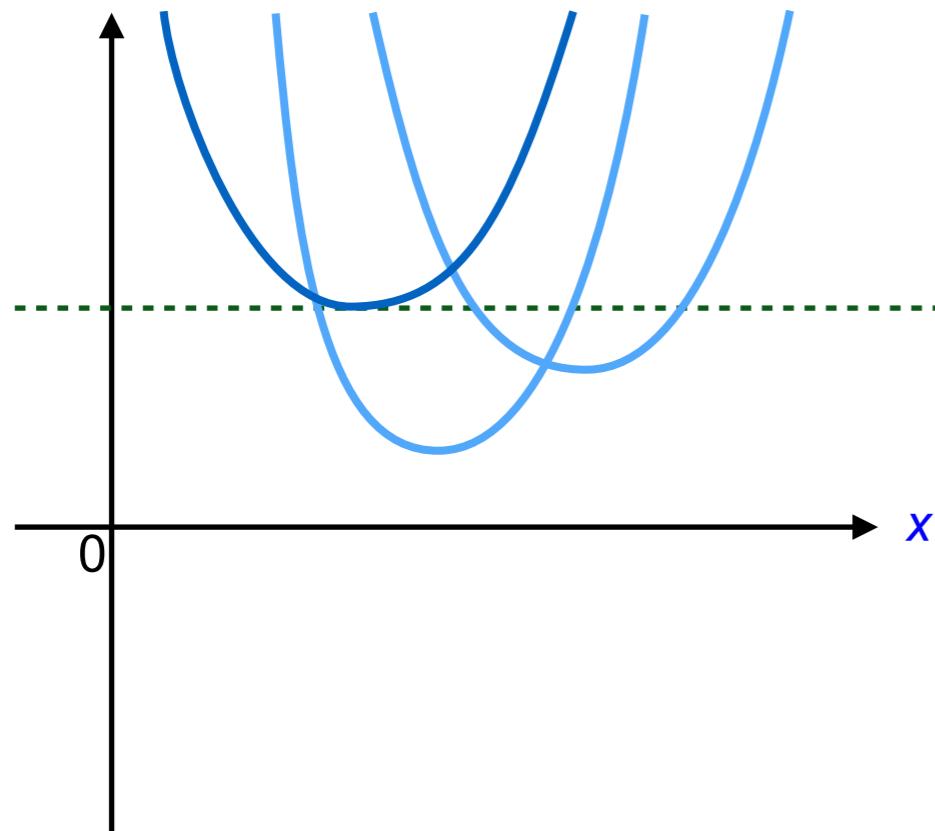
$P(z^{(2)})$



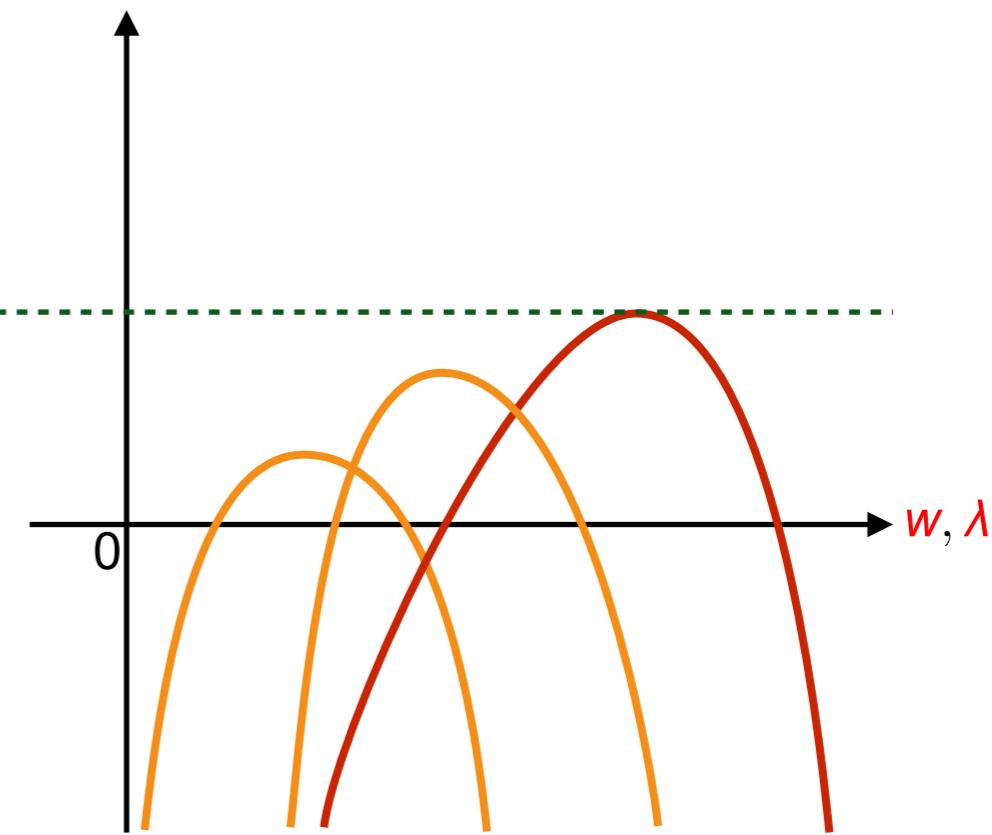
$D(z^{(2)})$

Scenario Problems

$$\inf P(z^{(3)}) = \sup D(z^{(3)})$$



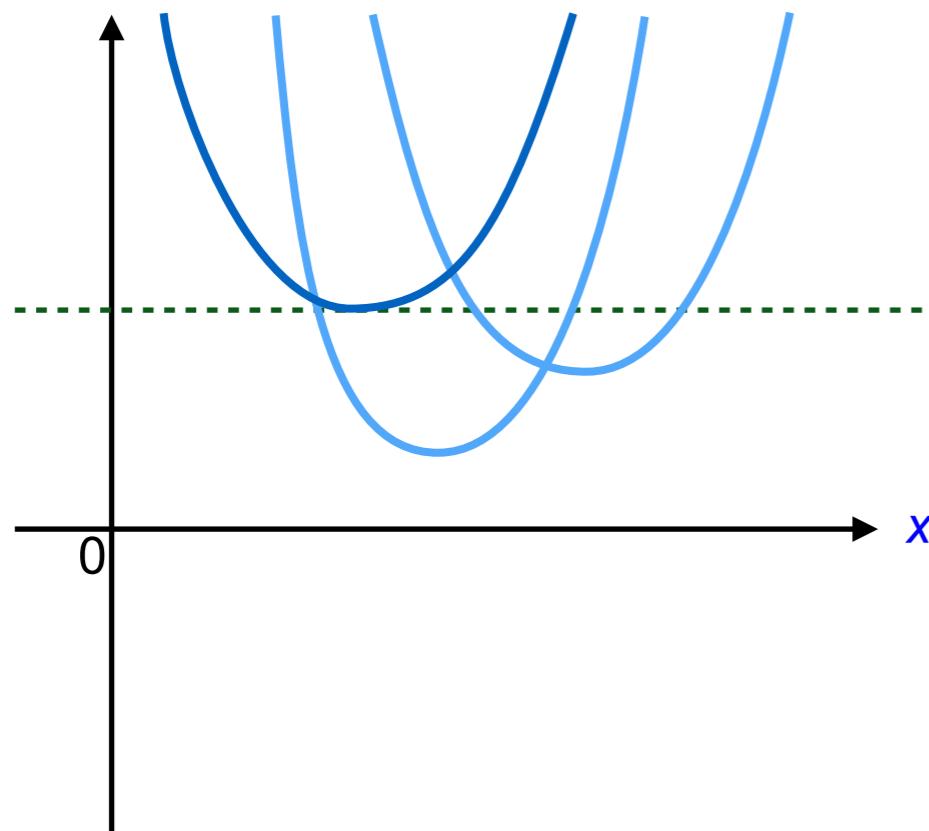
$P(z^{(3)})$



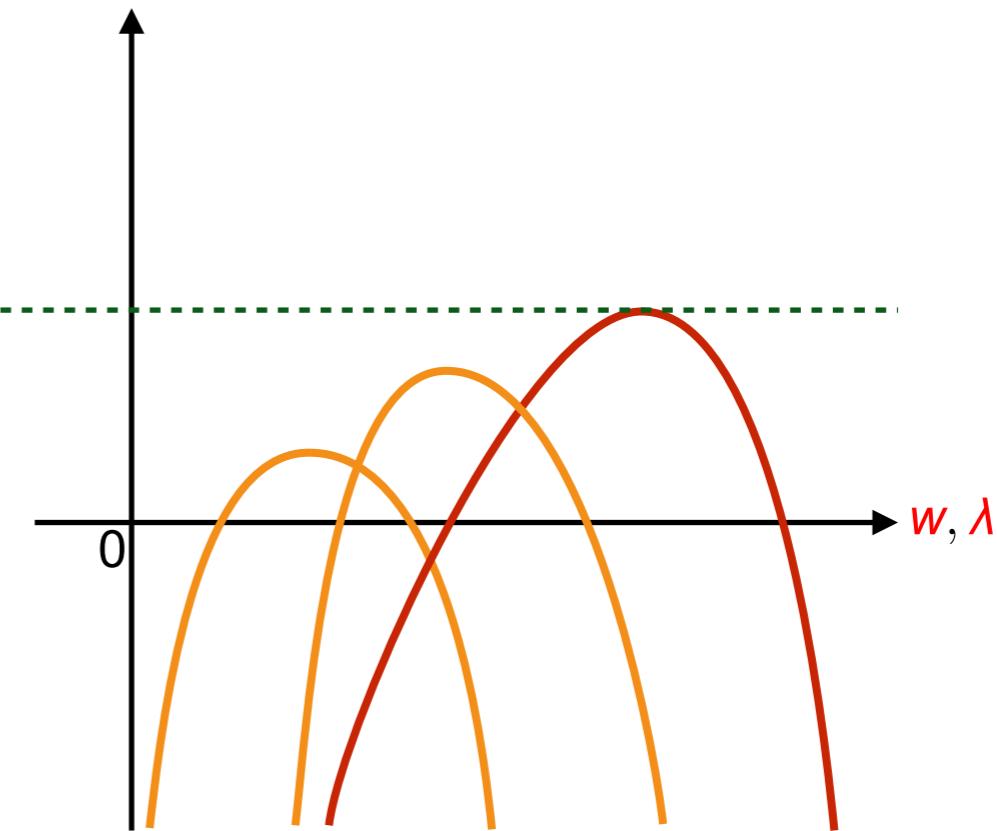
$D(z^{(3)})$

Duality of Robust Optimization

$$\sup_{z \in \mathcal{Z}} \inf P(z) = \sup_{z \in \mathcal{Z}} \sup D(z)$$



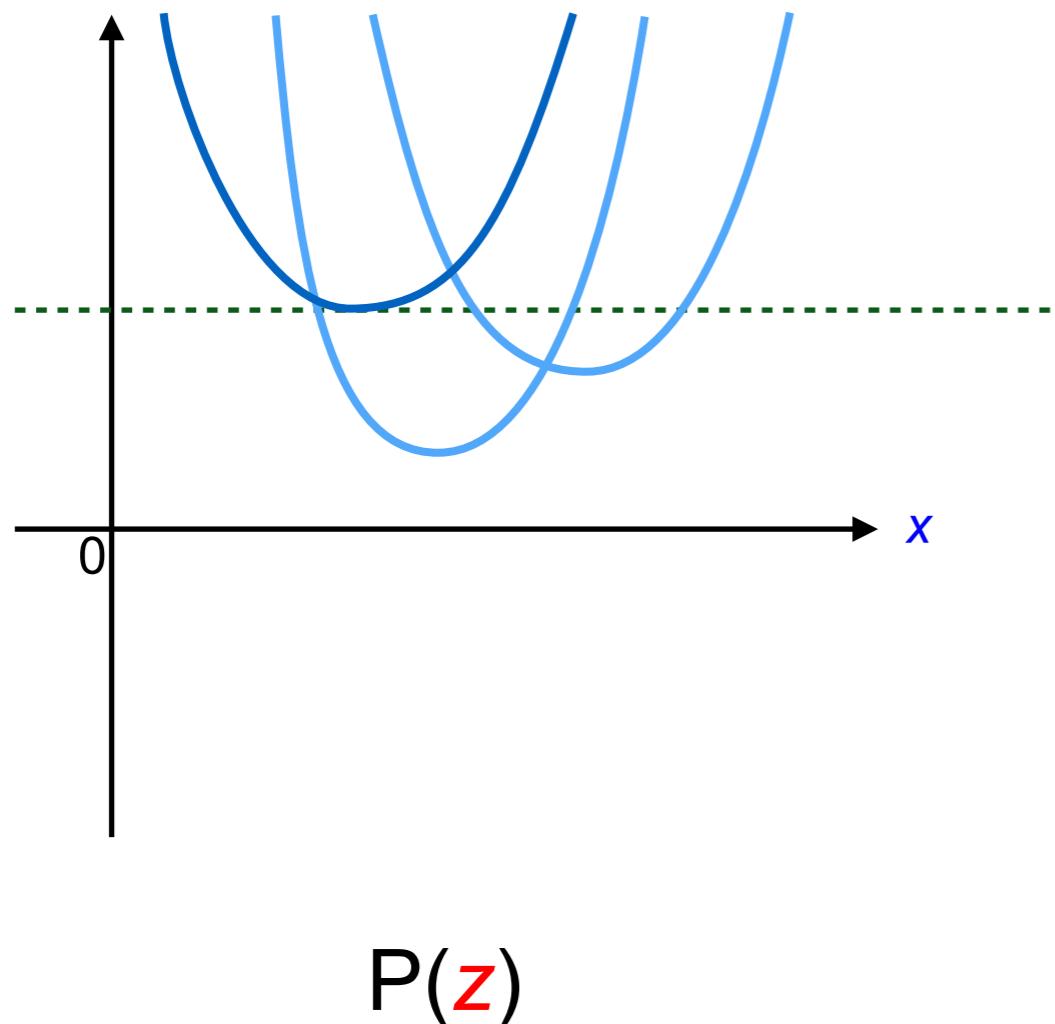
$P(z)$



$D(z)$

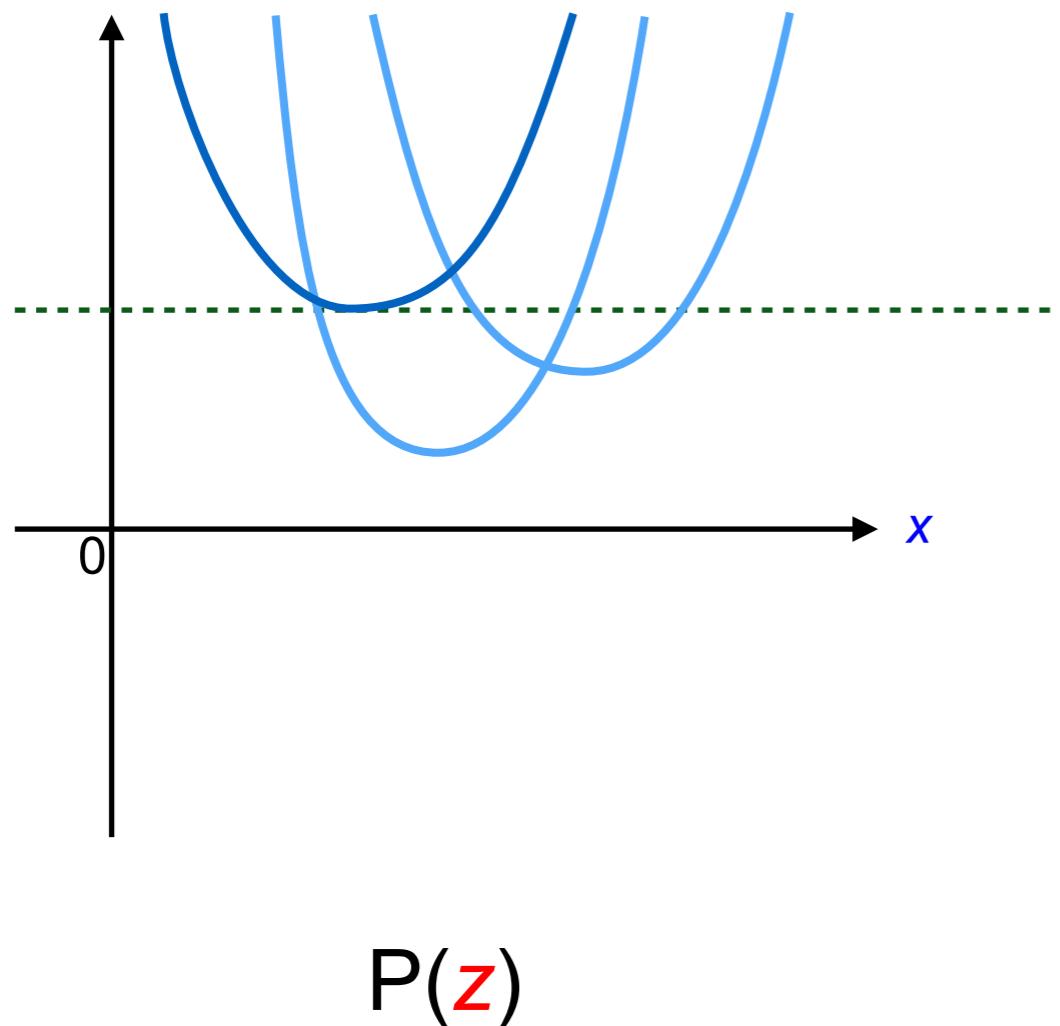
Primal Worst

$$\sup_{\mathbf{z} \in \mathcal{Z}} \inf \mathbf{P}(\mathbf{z}) = \sup_{\mathbf{z} \in \mathcal{Z}} \left\{ \begin{array}{ll} \inf_{\mathbf{x}} & f_0(\mathbf{x}, \mathbf{z}_0) \\ \text{s.t.} & f_i(\mathbf{x}, \mathbf{z}_i) \leq 0 \quad \forall i = 1, \dots, I \end{array} \right.$$



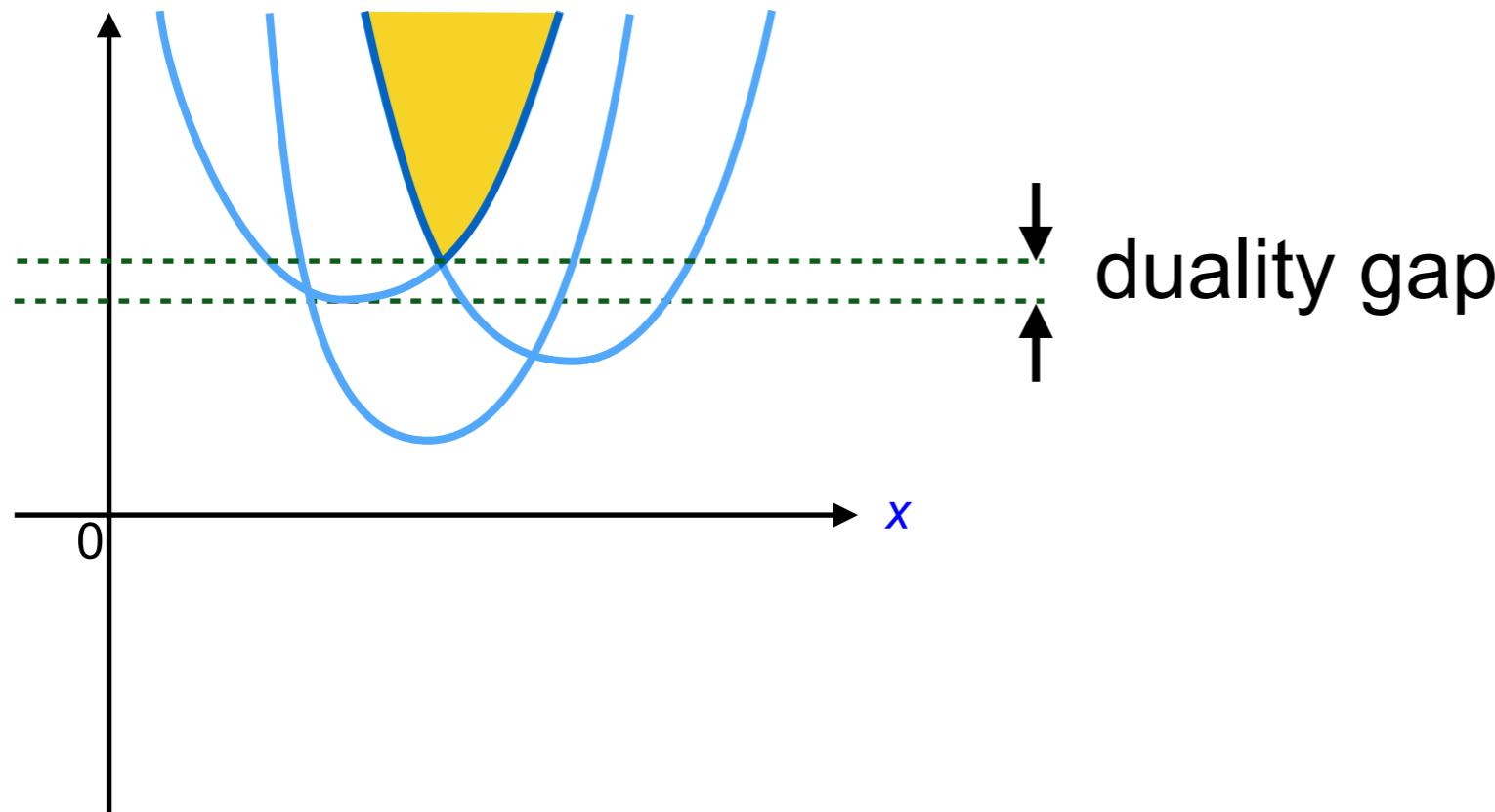
Primal Worst

$$\sup_{\mathbf{z} \in \mathcal{Z}} \inf \mathbf{P}(\mathbf{z}) \leq \left\{ \begin{array}{ll} \inf_{\mathbf{x}} & \sup_{\mathbf{z}_0 \in \mathcal{Z}} f_0(\mathbf{x}, \mathbf{z}_0) \\ \text{s.t.} & \sup_{\mathbf{z}_i \in \mathcal{Z}} f_i(\mathbf{x}, \mathbf{z}_i) \leq 0 \quad \forall i = 1, \dots, I \end{array} \right.$$



Primal Worst

$$\sup_{z \in \mathcal{Z}} \inf P(z) \leq \left\{ \begin{array}{ll} \inf_x & \sup_{z_0 \in \mathcal{Z}} f_0(x, z_0) \\ \text{s.t.} & \sup_{z_i \in \mathcal{Z}} f_i(x, z_i) \leq 0 \quad \forall i = 1, \dots, I \end{array} \right.$$

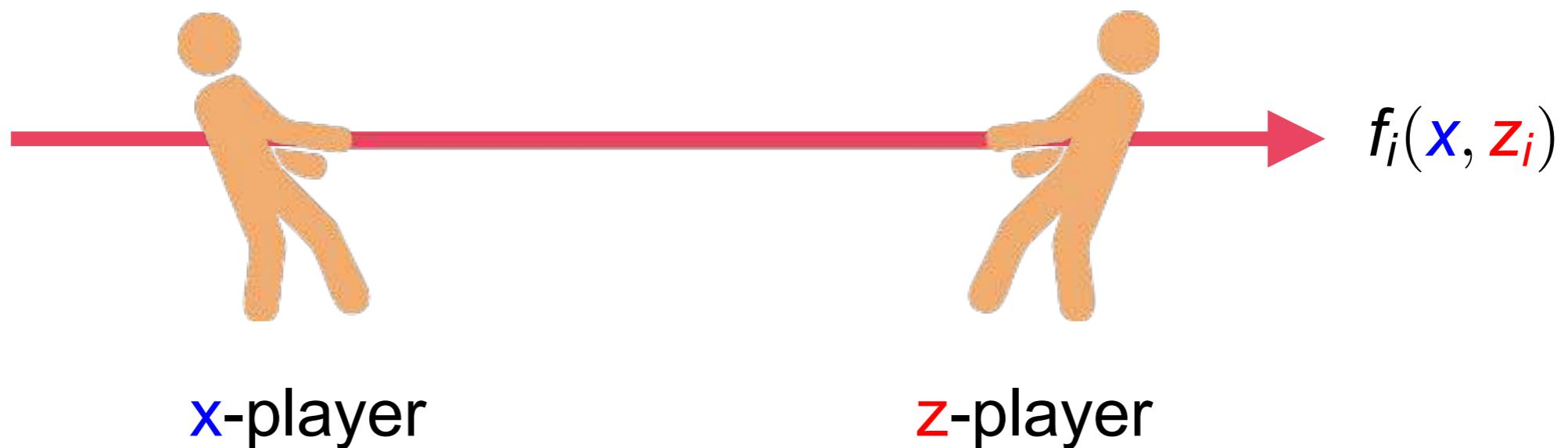


Primal Worst

$$\begin{aligned} \inf_{\textcolor{blue}{x}} \quad & \sup_{\textcolor{red}{z}_0 \in \mathcal{Z}} f_0(\textcolor{blue}{x}, \textcolor{red}{z}_0) \\ \text{s.t.} \quad & \sup_{\textcolor{red}{z}_i \in \mathcal{Z}} f_i(\textcolor{blue}{x}, \textcolor{red}{z}_i) \leq 0 \quad \forall i = 1, \dots, I \end{aligned} \tag{P-W}$$

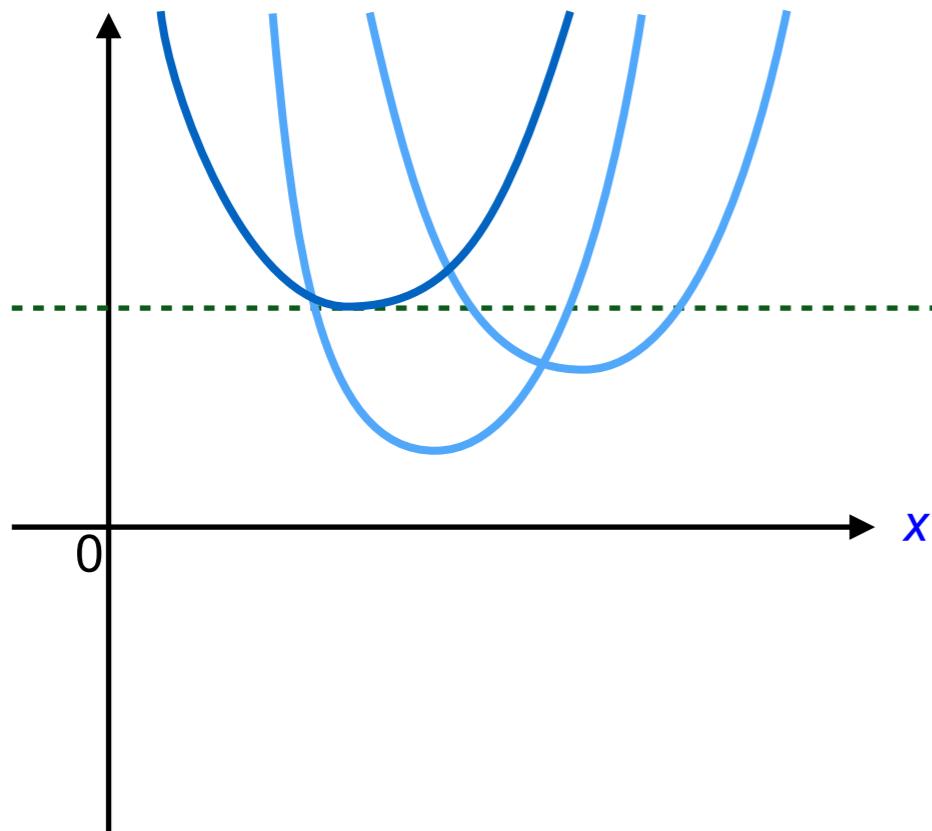
Primal Worst

$$\begin{array}{ll}\inf_{\color{blue}x} & \sup_{\color{red}z_0 \in \mathcal{Z}} f_0(\color{blue}x, \color{red}z_0) \\ \text{s.t.} & \sup_{\color{red}z_i \in \mathcal{Z}} f_i(\color{blue}x, \color{red}z_i) \leq 0 \quad \forall i = 1, \dots, I\end{array} \quad (\text{P-W})$$

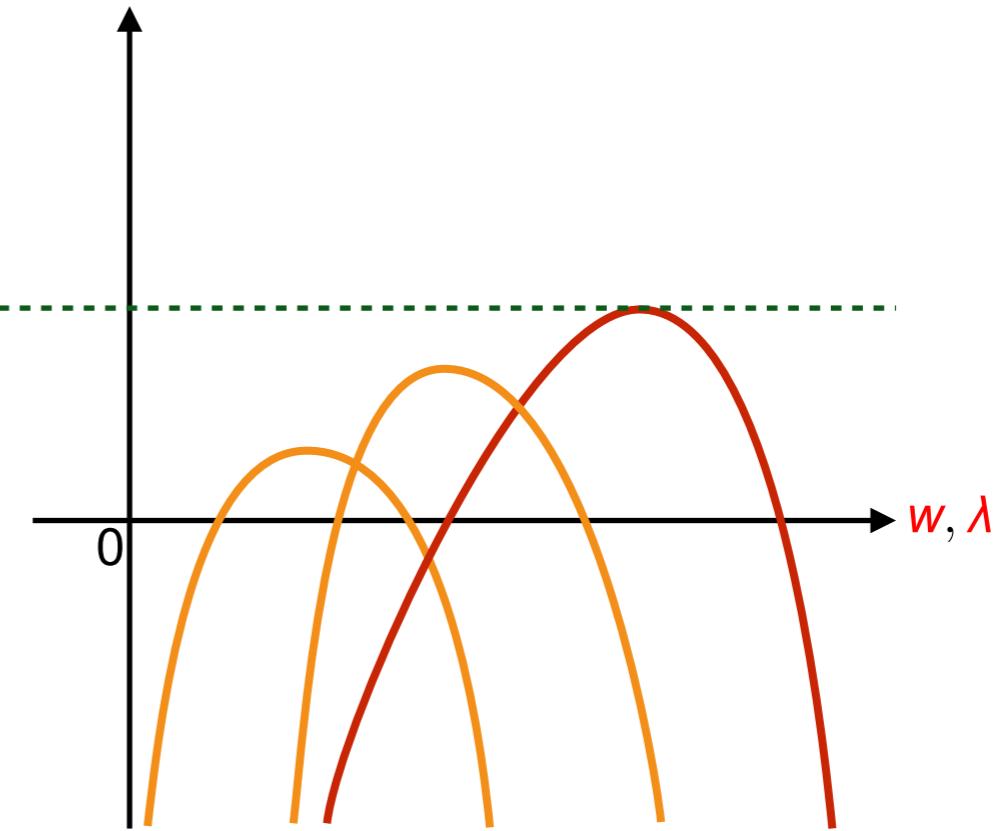


Duality of Robust Optimization

$$\sup_{z \in \mathcal{Z}} \inf P(z) = \sup_{z \in \mathcal{Z}} \sup D(z)$$



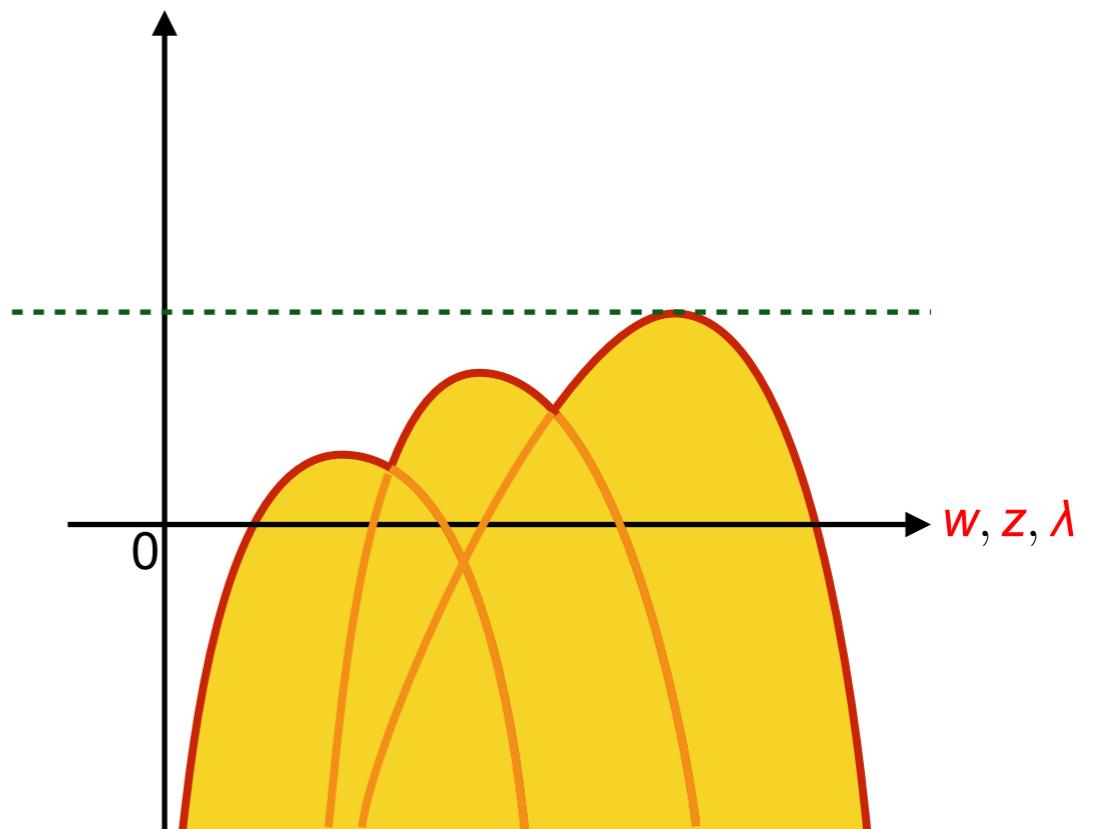
$P(z)$



$D(z)$

Dual Best

$$\sup_{\mathbf{z} \in \mathcal{Z}} \sup \mathbf{D}(\mathbf{z}) = \left\{ \begin{array}{ll} \sup_{w, z, \lambda \geq 0} & -f_0^{*1}(w_0, z_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(w_i/\lambda_i, z_i) \\ \text{s.t.} & \sum_{i=0}^I w_i = 0, \quad z_i \in \mathcal{Z} \quad \forall i = 0, \dots, I \end{array} \right.$$

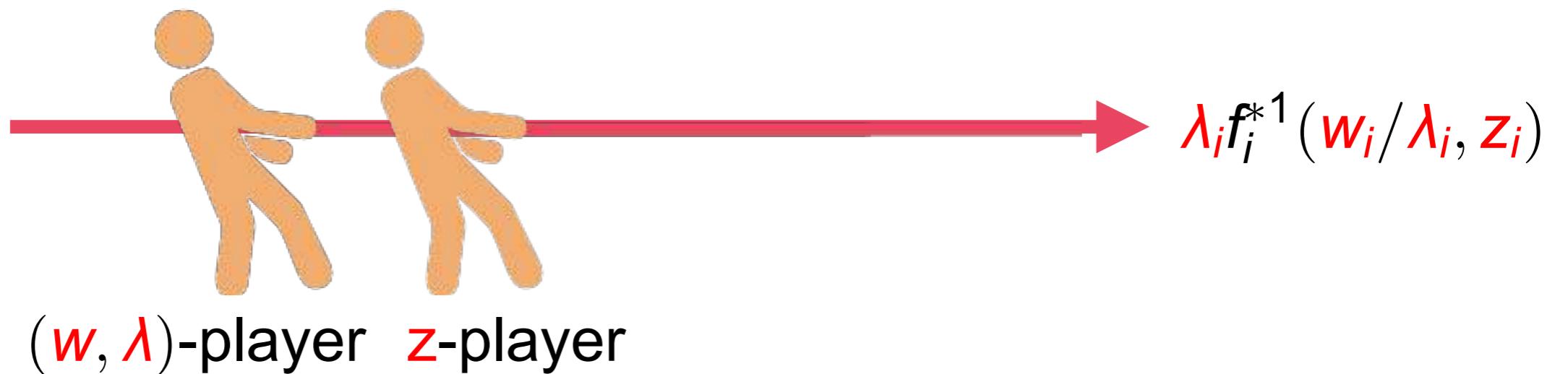


Dual Best

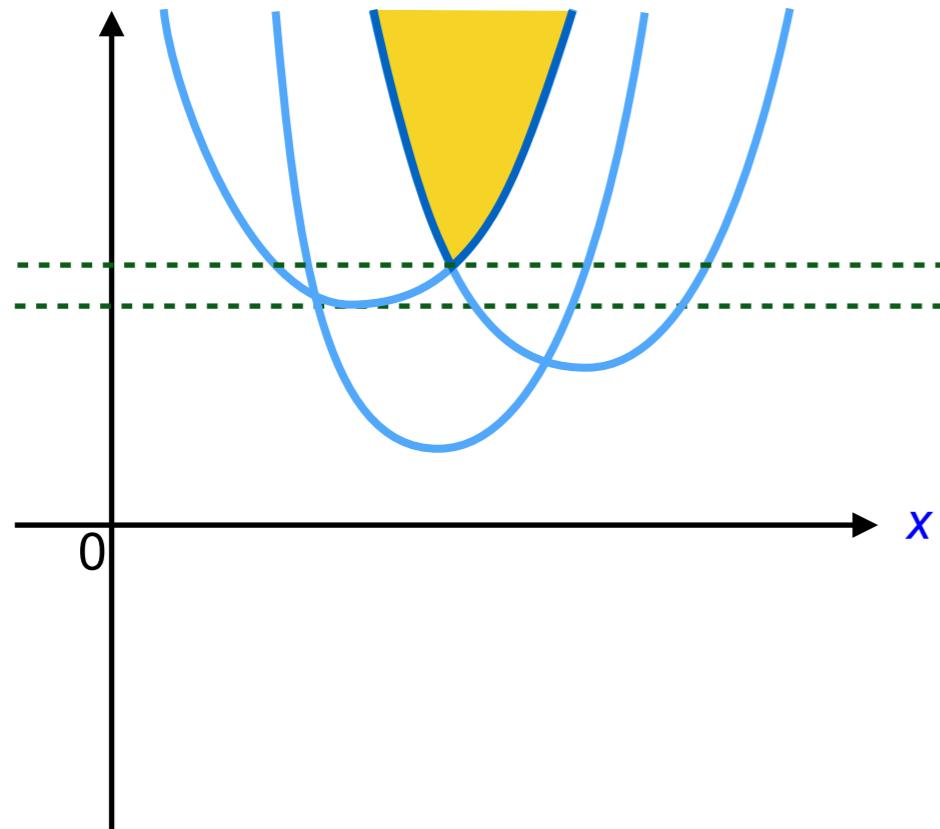
$$\begin{aligned} \sup_{\mathbf{w}, \mathbf{z}, \boldsymbol{\lambda} \geq 0} \quad & -f_0^{*1}(\mathbf{w}_0, \mathbf{z}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i / \lambda_i, \mathbf{z}_i) \\ \text{s.t.} \quad & \sum_{i=0}^I \mathbf{w}_i = 0, \quad \mathbf{z}_i \in \mathcal{Z} \quad \forall i = 0, \dots, I \end{aligned} \tag{D-B}$$

Dual Best

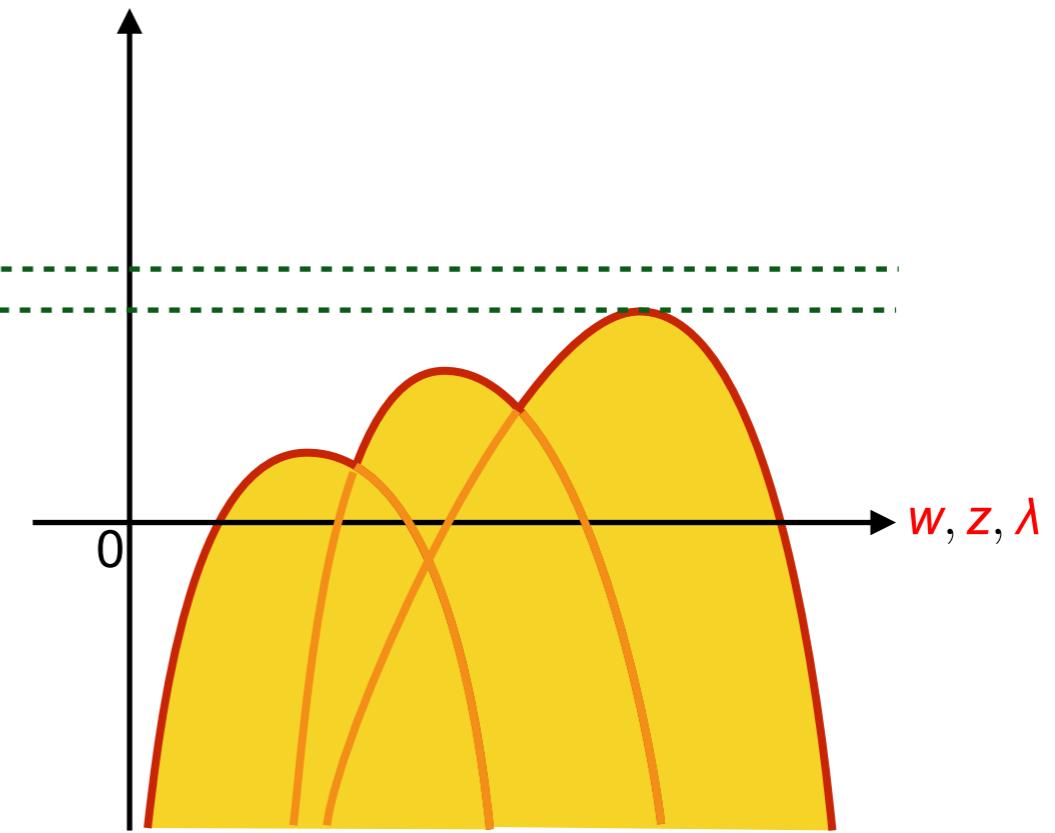
$$\begin{aligned} \sup_{\substack{\mathbf{w}, \mathbf{z}, \boldsymbol{\lambda} \geq 0}} \quad & -f_0^{*1}(\mathbf{w}_0, \mathbf{z}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i / \lambda_i, \mathbf{z}_i) \\ \text{s.t.} \quad & \sum_{i=0}^I \mathbf{w}_i = 0, \quad \mathbf{z}_i \in \mathcal{Z} \quad \forall i = 0, \dots, I \end{aligned} \tag{D-B}$$



Duality of Robust Optimization



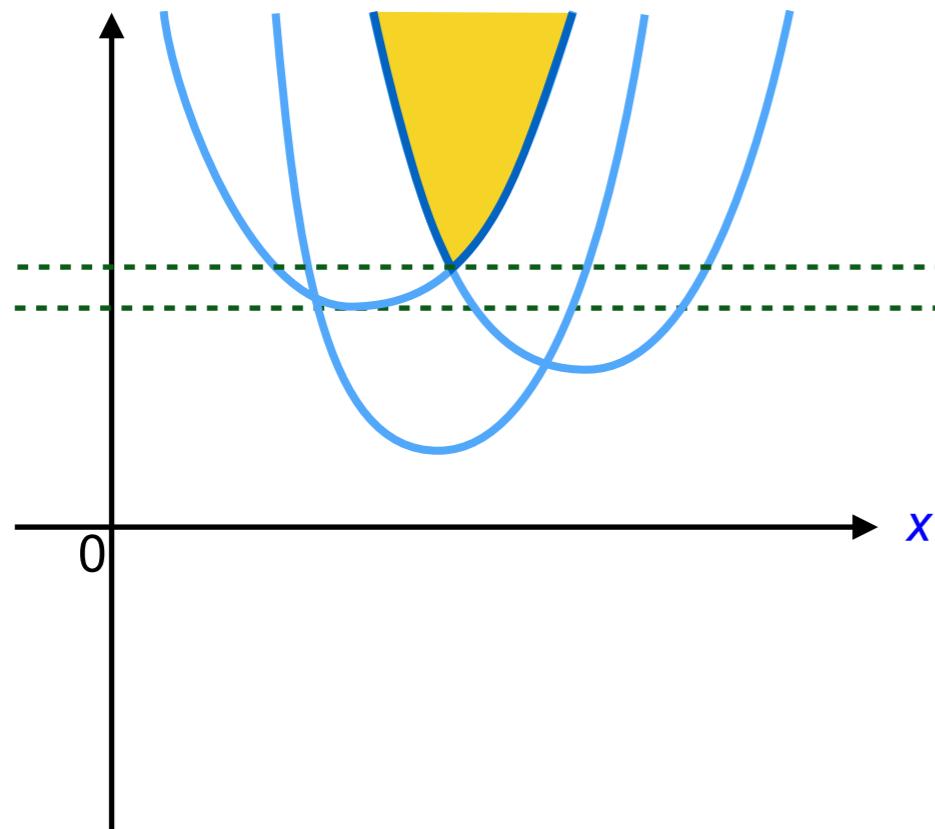
(P-W)



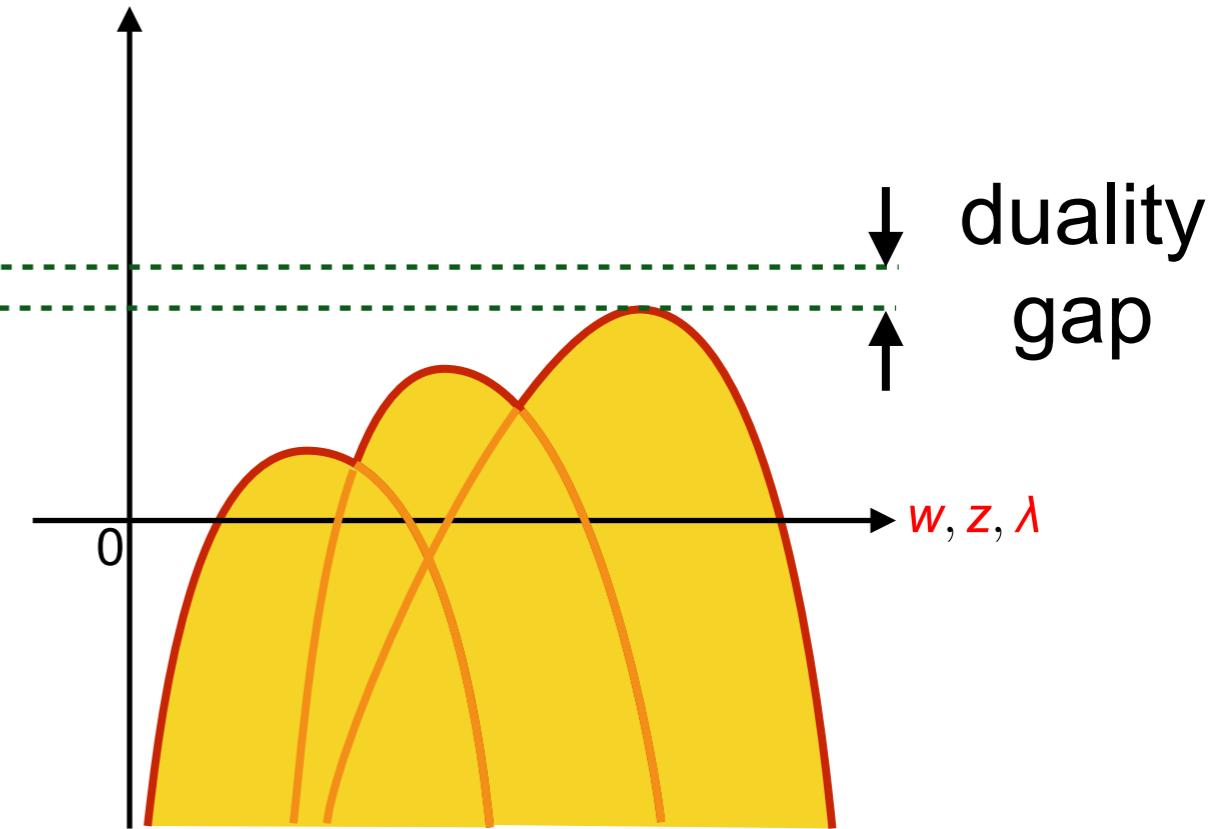
(D-B)

Duality of Robust Optimization

Conditions for gap-free duality?



(P-W)



(D-B)

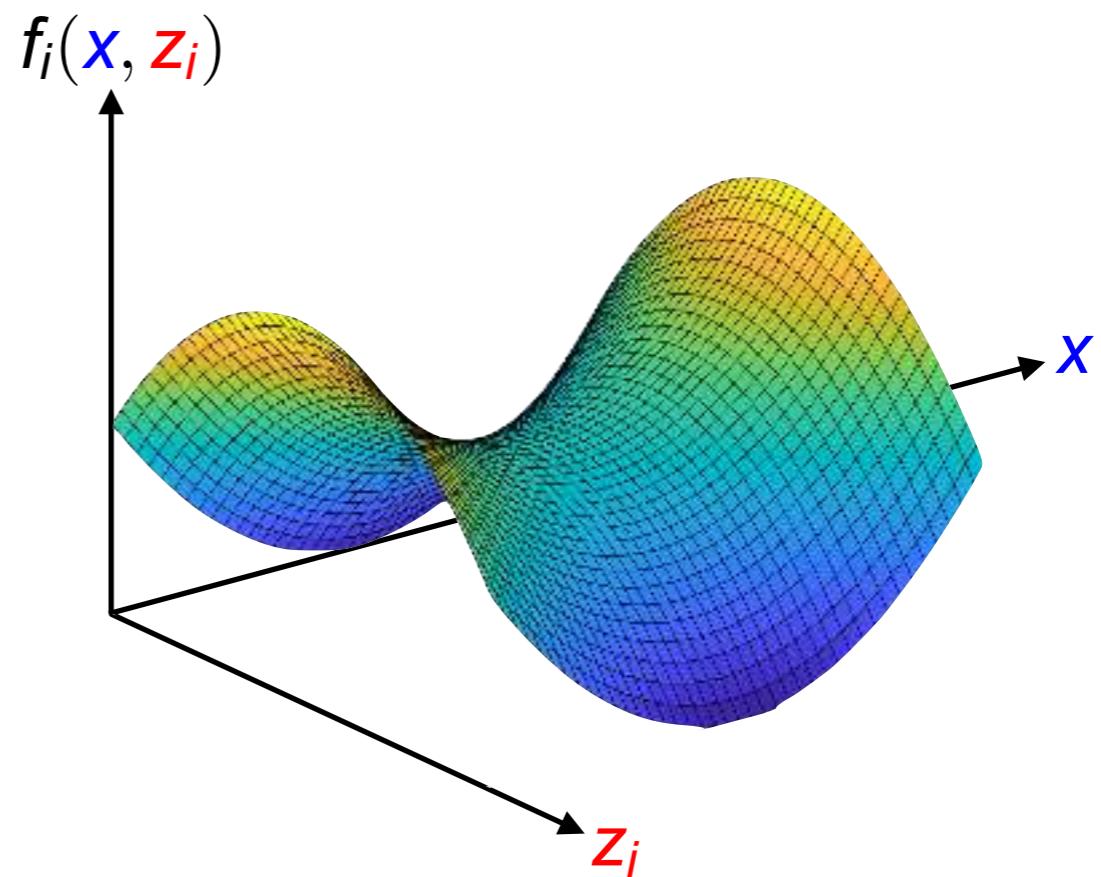
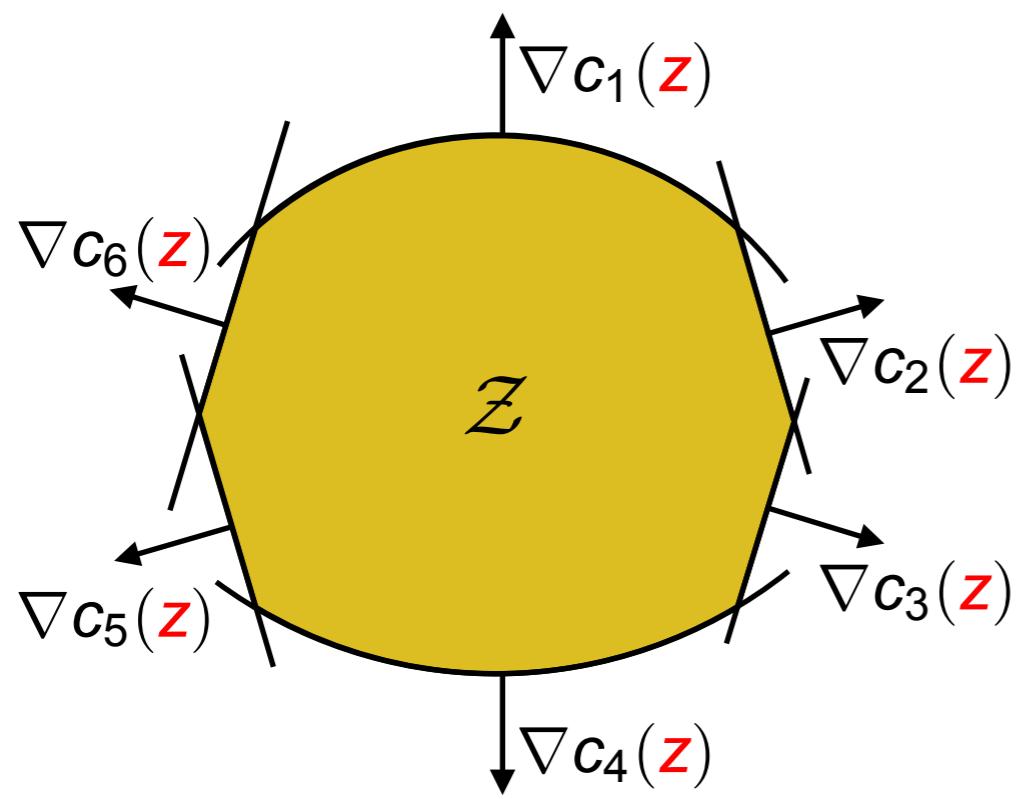
Convexity Assumptions

Uncertainty set: $\mathcal{Z} = \{\mathbf{z} : c_\ell(\mathbf{z}) \leq 0 \ \forall \ell = 1, \dots, L\}$

Constraint functions:

$c_\ell(\mathbf{z})$ pcc in \mathbf{z} for every ℓ

$-f_i(\mathbf{x}, z_i)$ pcc in z_i for every i



Convex Reformulation of (P-W)

$$\begin{aligned} \inf_{\textcolor{blue}{x}} \quad & \sup_{\textcolor{red}{z}_0 \in \mathcal{Z}} f_0(\textcolor{blue}{x}, \textcolor{red}{z}_0) \\ \text{s.t.} \quad & \sup_{\textcolor{red}{z}_i \in \mathcal{Z}} f_i(\textcolor{blue}{x}, \textcolor{red}{z}_i) \leq 0 \quad \forall i = 1, \dots, I \end{aligned}$$

Convex Reformulation of (P-W)

$$\sup_{\mathbf{z}_i \in \mathcal{Z}} f_i(\mathbf{x}, \mathbf{z}_i) = - \inf_{\mathbf{z}_i \in \mathcal{Z}} -f_i(\mathbf{x}, \mathbf{z}_i)$$

Convex Reformulation of (P-W)

$$\sup_{\mathbf{z}_i \in \mathcal{Z}} f_i(\mathbf{x}, \mathbf{z}_i) = - \left\{ \begin{array}{ll} \inf_{\mathbf{z}_i} & -f_i(\mathbf{x}, \mathbf{z}_i) \\ \text{s.t.} & c_\ell(\mathbf{z}_i) \leq 0 \quad \forall \ell = 1, \dots, L \end{array} \right.$$

Convex Reformulation of (P-W)

$$\sup_{\mathbf{z}_i \in \mathcal{Z}} f_i(\mathbf{x}, \mathbf{z}_i) = - \left\{ \begin{array}{ll} \sup_{\mathbf{y}, \mathbf{v} \geq 0} & -(-f_i)^{*2}(\mathbf{x}, \mathbf{y}_{i,\ell}) - \sum_{\ell=1}^L \mathbf{v}_{i\ell} \mathbf{c}_{\ell}^{*}(\mathbf{y}_{i\ell}/\mathbf{v}_{i\ell}) \\ \text{s.t.} & \sum_{\ell=0}^L \mathbf{y}_{i\ell} = 0 \end{array} \right.$$

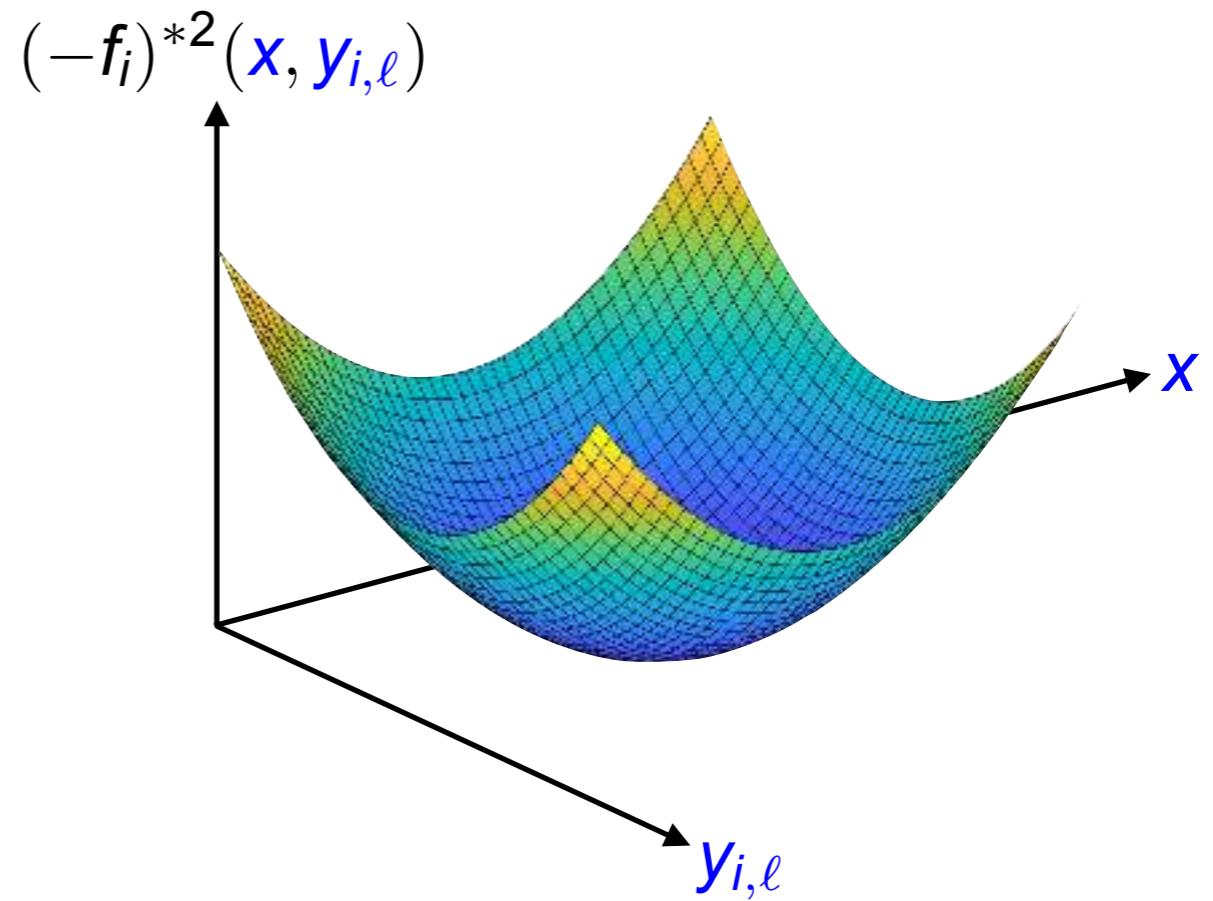
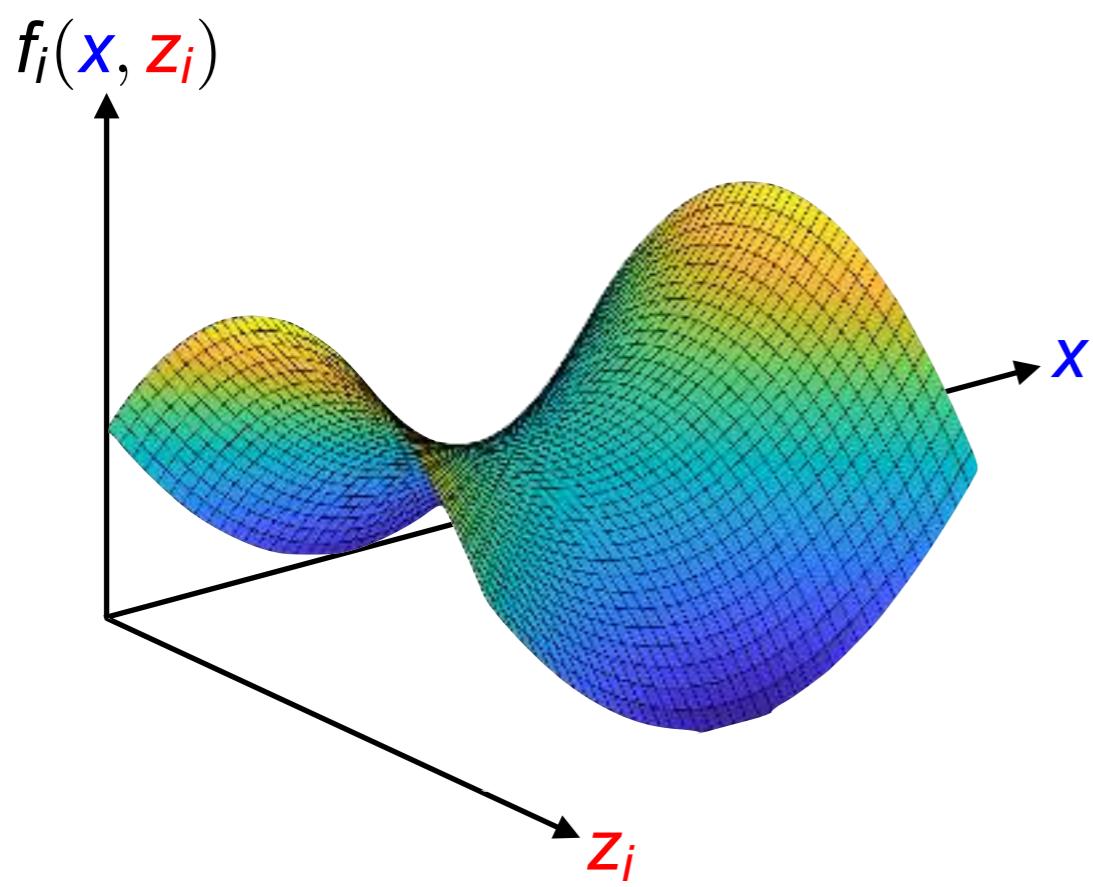
Convex Reformulation of (P-W)

$$\sup_{\mathbf{z}_i \in \mathcal{Z}} f_i(\mathbf{x}, \mathbf{z}_i) = - \left\{ \begin{array}{l} \sup_{\mathbf{y}, \mathbf{v} \geq 0} \quad -(-f_i)^{*2}(\mathbf{x}, \mathbf{y}_{i,\ell}) - \sum_{\ell=1}^L \mathbf{v}_{i\ell} \mathbf{c}_{\ell}^{*}(\mathbf{y}_{i\ell}/\mathbf{v}_{i\ell}) \\ \text{s.t.} \quad \sum_{\ell=0}^L \mathbf{y}_{i\ell} = 0 \end{array} \right.$$

conjugates w.r.t. \mathbf{z}_i

Convex Reformulation of (P-W)

$$\sup_{\mathbf{z}_i \in \mathcal{Z}} f_i(\mathbf{x}, \mathbf{z}_i) = - \left\{ \begin{array}{ll} \sup_{\mathbf{y}, \mathbf{v} \geq 0} & -(-f_i)^{*2}(\mathbf{x}, \mathbf{y}_{i,\ell}) - \sum_{\ell=1}^L \mathbf{v}_{i\ell} \mathbf{c}_{\ell}^{*}(\mathbf{y}_{i\ell}/\mathbf{v}_{i\ell}) \\ \text{s.t.} & \sum_{\ell=0}^L \mathbf{y}_{i\ell} = 0 \end{array} \right.$$



Convex Reformulation of (P-W)

$$\sup_{\mathbf{z}_i \in \mathcal{Z}} f_i(\mathbf{x}, \mathbf{z}_i) = \left\{ \begin{array}{ll} \inf_{\mathbf{y}, \mathbf{v} \geq 0} & (-f_i)^{*2}(\mathbf{x}, \mathbf{y}_{i,\ell}) + \sum_{\ell=1}^L v_{i\ell} c_{\ell}^{*}(\mathbf{y}_{i\ell}/v_{i\ell}) \\ \text{s.t.} & \sum_{\ell=0}^L \mathbf{y}_{i\ell} = 0 \end{array} \right.$$

Convex Reformulation of (P-W)

$$\begin{aligned} \inf_{\color{blue}{x}} \quad & \sup_{\color{red}{z_0} \in \mathcal{Z}} f_0(\color{blue}{x}, \color{red}{z_0}) \\ \text{s.t.} \quad & \sup_{\color{red}{z_i} \in \mathcal{Z}} f_i(\color{blue}{x}, \color{red}{z_i}) \leq 0 \quad \forall i = 1, \dots, I \end{aligned} \tag{P-W}$$

Convex Reformulation of (P-W)

$$\begin{aligned}
 & \inf_{\textcolor{blue}{x}} \quad \sup_{\textcolor{red}{z}_0 \in \mathcal{Z}} f_0(\textcolor{blue}{x}, \textcolor{red}{z}_0) \\
 \text{s.t.} \quad & \sup_{\textcolor{red}{z}_i \in \mathcal{Z}} f_i(\textcolor{blue}{x}, \textcolor{red}{z}_i) \leq 0 \quad \forall i = 1, \dots, I
 \end{aligned} \tag{P-W}$$

$$\begin{aligned}
 & \inf_{\textcolor{blue}{x}, \textcolor{blue}{y}, \textcolor{blue}{v} \geq 0} \quad (-f_0)^{*2}(\textcolor{blue}{x}, \textcolor{blue}{y}_{0,\ell}) + \sum_{\ell=1}^L \textcolor{blue}{v}_{0\ell} \mathbf{c}_\ell^*(\textcolor{blue}{y}_{0\ell} / \textcolor{blue}{v}_{0\ell}) \\
 \text{s.t.} \quad & (-f_i)^{*2}(\textcolor{blue}{x}, \textcolor{blue}{y}_{i,\ell}) + \sum_{\ell=1}^L \textcolor{blue}{v}_{i\ell} \mathbf{c}_\ell^*(\textcolor{blue}{y}_{i\ell} / \textcolor{blue}{v}_{i\ell}) \leq 0 \quad \forall i = 1, \dots, I \quad (\text{P-W}') \\
 & \sum_{\ell=0}^L \textcolor{blue}{y}_{i\ell} = 0 \quad \forall i = 1, \dots, I
 \end{aligned}$$

Convex Reformulation of (P-W)

$$\begin{aligned}
 & \inf_{\color{blue}x} \quad \sup_{\color{red}z_0 \in \mathcal{Z}} f_0(\color{blue}x, \color{red}z_0) \\
 \text{s.t.} \quad & \sup_{\color{red}z_i \in \mathcal{Z}} f_i(\color{blue}x, \color{red}z_i) \leq 0 \quad \forall i = 1, \dots, I
 \end{aligned} \tag{P-W}$$

\Updownarrow (subject to regularity conditions)

$$\begin{aligned}
 & \inf_{\color{blue}x, \color{blue}y, \color{blue}v \geq 0} \quad (-f_0)^{*2}(\color{blue}x, \color{blue}y_{0,\ell}) + \sum_{\ell=1}^L \color{blue}v_{0\ell} \mathbf{c}_\ell^*(\color{blue}y_{0\ell} / \color{blue}v_{0\ell}) \\
 \text{s.t.} \quad & (-f_i)^{*2}(\color{blue}x, \color{blue}y_{i,\ell}) + \sum_{\ell=1}^L \color{blue}v_{i\ell} \mathbf{c}_\ell^*(\color{blue}y_{i\ell} / \color{blue}v_{i\ell}) \leq 0 \quad \forall i = 1, \dots, I \quad (\text{P-W}') \\
 & \sum_{\ell=0}^L \color{blue}y_{i\ell} = 0 \quad \forall i = 1, \dots, I
 \end{aligned}$$

Convex Reformulation of (P-W)

$$\begin{aligned}
 & \inf_{\color{blue}x} \quad \sup_{\color{red}z_0 \in \mathcal{Z}} f_0(\color{blue}x, \color{red}z_0) \\
 \text{s.t.} \quad & \sup_{\color{red}z_i \in \mathcal{Z}} f_i(\color{blue}x, \color{red}z_i) \leq 0 \quad \forall i = 1, \dots, I
 \end{aligned} \tag{P-W}$$

\Updownarrow (subject to regularity conditions)

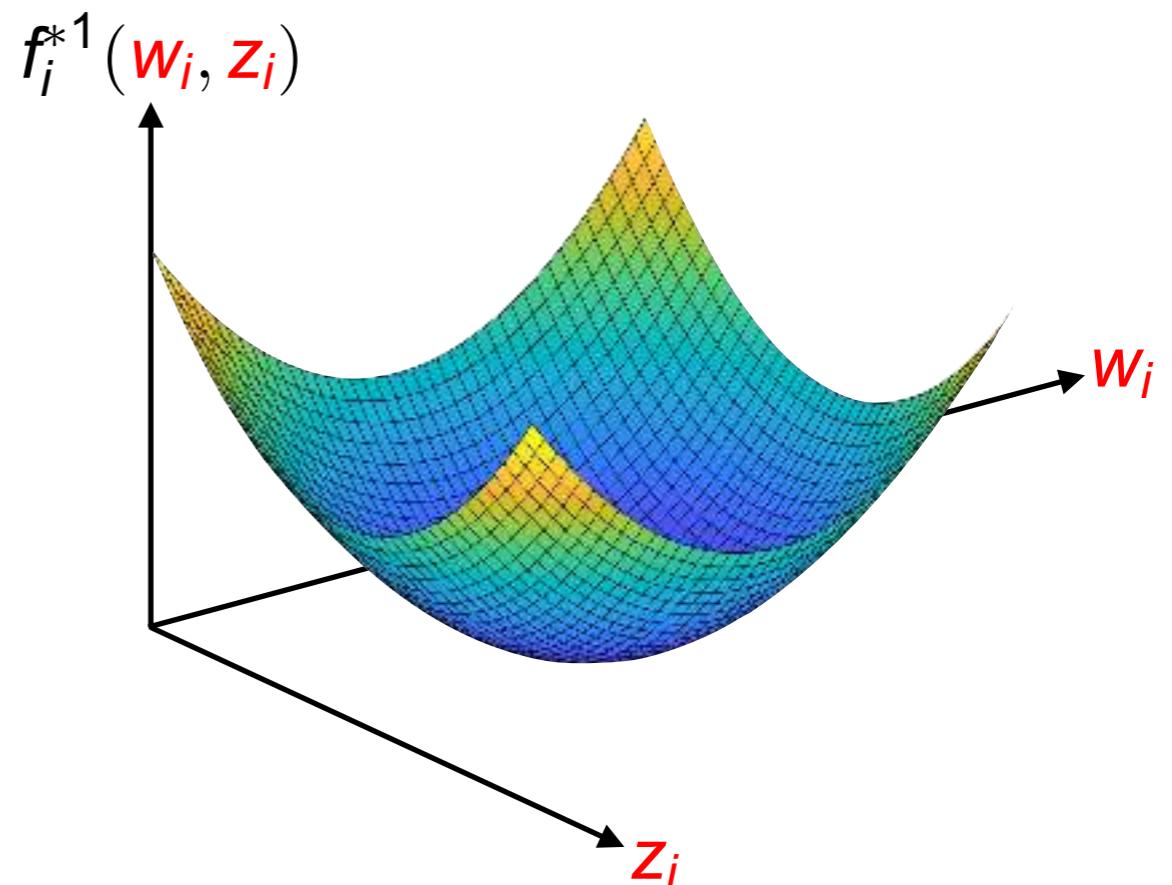
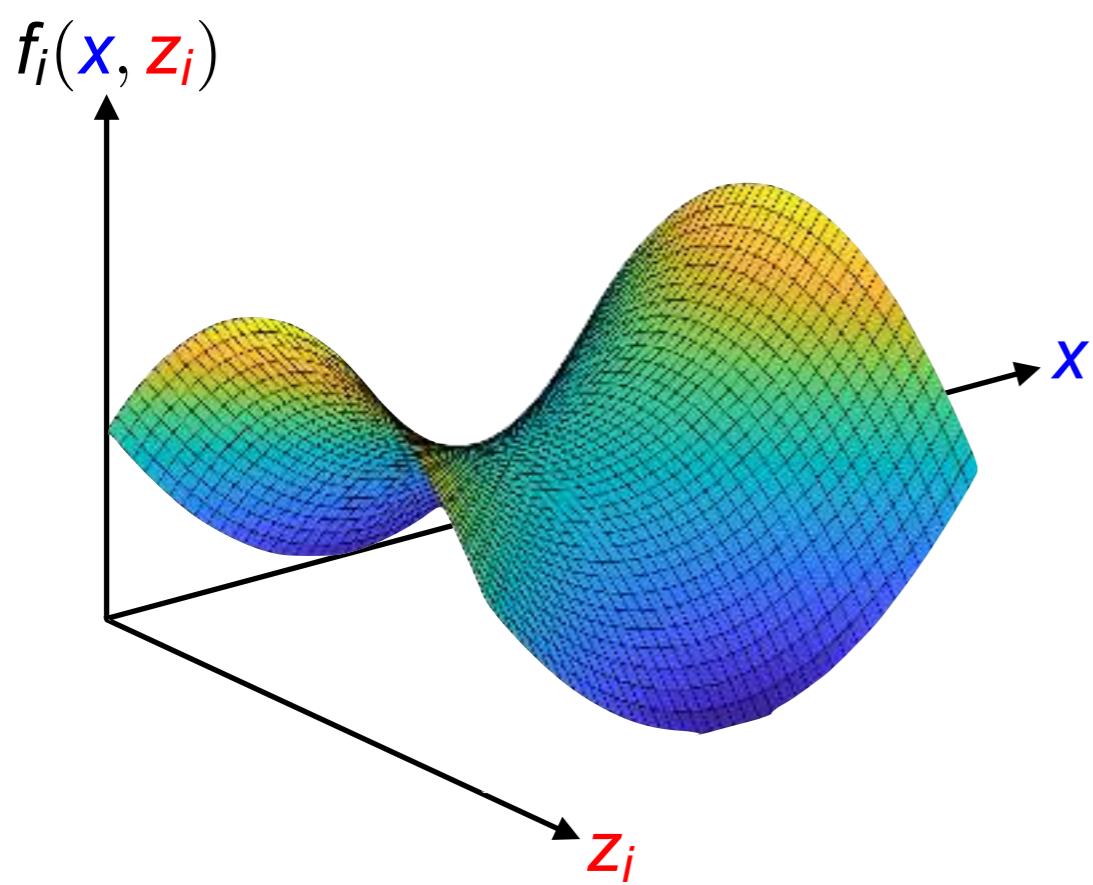
$$\begin{aligned}
 & \inf_{\color{blue}x, \color{blue}y, \color{blue}v \geq 0} \quad (-f_0)^{*2}(\color{blue}x, \color{blue}y_{0,\ell}) + \sum_{\ell=1}^L \color{blue}v_{0\ell} \mathbf{c}_{\ell}^{*}(\color{blue}y_{0\ell} / \color{blue}v_{0\ell}) \\
 \text{s.t.} \quad & (-f_i)^{*2}(\color{blue}x, \color{blue}y_{i,\ell}) + \sum_{\ell=1}^L \color{blue}v_{i\ell} \mathbf{c}_{\ell}^{*}(\color{blue}y_{i\ell} / \color{blue}v_{i\ell}) \leq 0 \quad \forall i = 1, \dots, I \quad (\text{P-W}') \\
 & \sum_{\ell=0}^L \color{blue}y_{i\ell} = 0 \quad \forall i = 1, \dots, I
 \end{aligned}$$

Convex Reformulation of (D-B)

$$\begin{aligned} \sup_{\substack{\mathbf{w}, \mathbf{z}, \boldsymbol{\lambda} \geq 0}} \quad & -f_0^{*1}(\mathbf{w}_0, \mathbf{z}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i / \lambda_i, \mathbf{z}_i) \\ \text{s.t.} \quad & c_\ell(\mathbf{z}) \leq 0 \quad \forall i = 0, \dots, I, \quad \forall \ell = 1, \dots, L \\ & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \tag{D-B}$$

Convex Reformulation of (D-B)

$$\begin{aligned} & \sup_{\substack{\mathbf{w}, \mathbf{z}, \lambda \geq 0}} -f_0^{*1}(\mathbf{w}_0, \mathbf{z}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i / \lambda_i, \mathbf{z}_i) \\ \text{s.t. } & c_\ell(\mathbf{z}) \leq 0 \quad \forall i = 0, \dots, I, \quad \forall \ell = 1, \dots, L \\ & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \tag{D-B}$$



Convex Reformulation of (D-B)

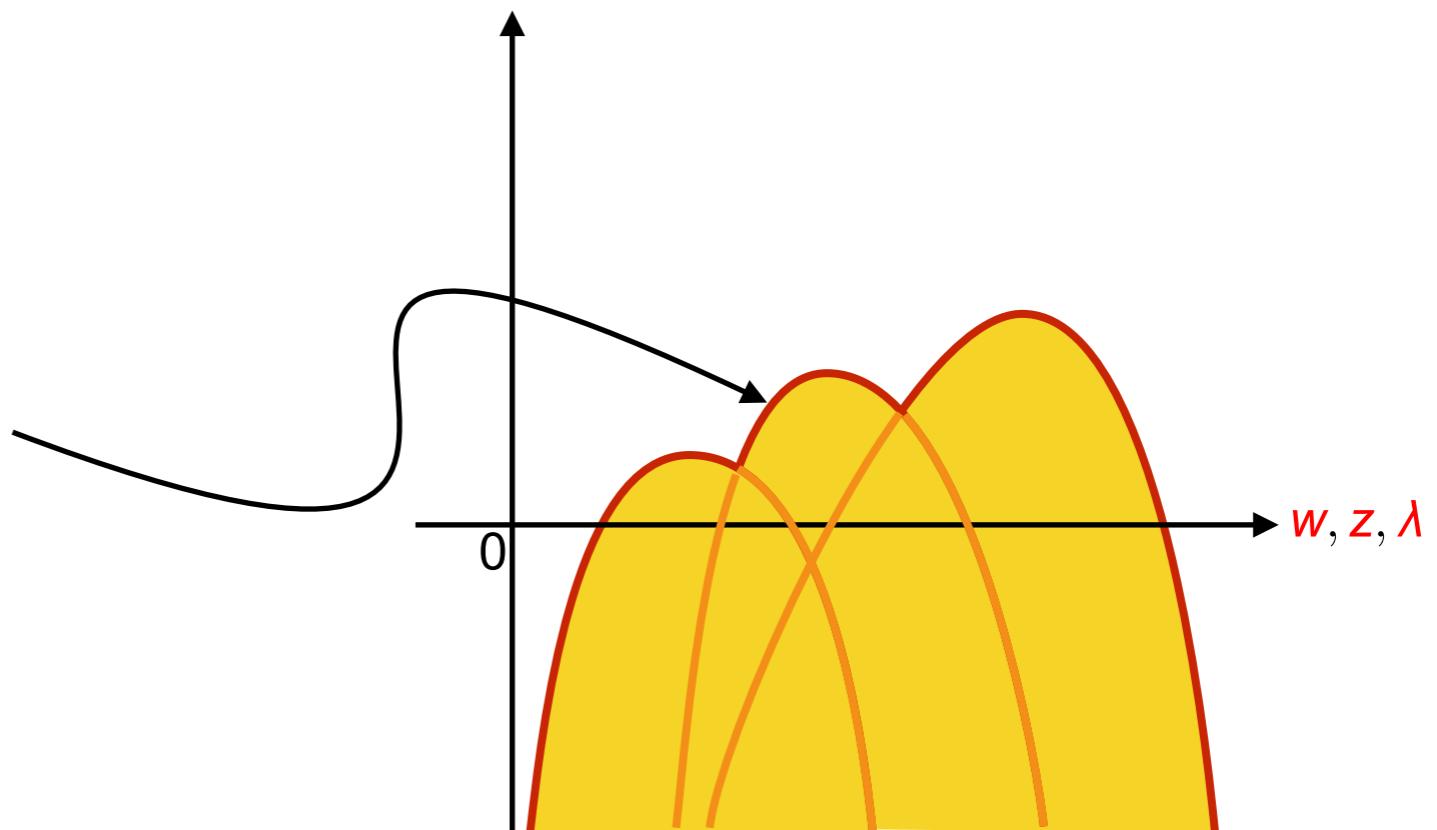
$$\begin{array}{ll} \sup_{\substack{\mathbf{w}, \mathbf{z}, \lambda \geq 0}} & -f_0^{*1}(\mathbf{w}_0, \mathbf{z}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i / \lambda_i, \mathbf{z}_i) \\ \text{s.t.} & c_\ell(\mathbf{z}) \leq 0 \quad \forall i = 0, \dots, I, \quad \forall \ell = 1, \dots, L \\ & \sum_{i=0}^I \mathbf{w}_i = 0 \end{array} \quad (\text{D-B})$$

nonconvex objective!

Convex Reformulation of (D-B)

$$\begin{aligned} \sup_{\substack{\mathbf{w}, \mathbf{z}, \lambda \geq 0}} \quad & -f_0^{*1}(\mathbf{w}_0, \mathbf{z}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i / \lambda_i, \mathbf{z}_i) \\ \text{s.t.} \quad & c_\ell(\mathbf{z}) \leq 0 \quad \forall i = 0, \dots, I, \quad \forall \ell = 1, \dots, L \quad (\text{D-B}) \\ & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned}$$

nonconvex objective!



Convex Reformulation of (D-B)

$$\begin{aligned} \sup_{\mathbf{w}, \mathbf{z}, \boldsymbol{\lambda} \geq 0} \quad & -f_0^{*1}(\mathbf{w}_0, \mathbf{z}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i / \lambda_i, \mathbf{z}_i) \\ \text{s.t.} \quad & c_\ell(\mathbf{z}) \leq 0 \quad \forall i = 0, \dots, I, \quad \forall \ell = 1, \dots, L \\ & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \quad (\text{D-B})$$

variable substitution: $v_i \leftarrow \lambda_i z_i$

Convex Reformulation of (D-B)

$$\begin{aligned} \sup_{\substack{\mathbf{w}, \mathbf{z}, \lambda \geq 0}} \quad & -f_0^{*1}(\mathbf{w}_0, \mathbf{z}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i/\lambda_i, \mathbf{z}_i) \\ \text{s.t.} \quad & c_\ell(\mathbf{z}) \leq 0 \quad \forall i = 0, \dots, I, \quad \forall \ell = 1, \dots, L \\ & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \quad (\text{D-B})$$

$$\begin{aligned} \sup_{\substack{\mathbf{w}, \mathbf{v}, \lambda \geq 0}} \quad & -f_0^{*1}(\mathbf{w}_0, \mathbf{v}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i/\lambda_i, \mathbf{v}_i/\lambda_i) \\ \text{s.t.} \quad & \lambda_i c_\ell(\mathbf{v}/\lambda_i) \leq 0 \quad \forall i = 0, \dots, I, \quad \forall \ell = 1, \dots, L \\ & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \quad (\text{D-B}')$$

Convex Reformulation of (D-B)

$$\begin{aligned} \sup_{\substack{\mathbf{w}, \mathbf{z}, \lambda \geq 0}} \quad & -f_0^{*1}(\mathbf{w}_0, \mathbf{z}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i/\lambda_i, \mathbf{z}_i) \\ \text{s.t.} \quad & c_\ell(\mathbf{z}) \leq 0 \quad \forall i = 0, \dots, I, \quad \forall \ell = 1, \dots, L \\ & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \quad (\text{D-B})$$

\Updownarrow (subject to regularity conditions)

$$\begin{aligned} \sup_{\substack{\mathbf{w}, \mathbf{v}, \lambda \geq 0}} \quad & -f_0^{*1}(\mathbf{w}_0, \mathbf{v}_0) - \sum_{i=1}^I \lambda_i f_i^{*1}(\mathbf{w}_i/\lambda_i, \mathbf{v}_i/\lambda_i) \\ \text{s.t.} \quad & \lambda_i c_\ell(\mathbf{v}/\lambda_i) \leq 0 \quad \forall i = 0, \dots, I, \quad \forall \ell = 1, \dots, L \\ & \sum_{i=0}^I \mathbf{w}_i = 0 \end{aligned} \quad (\text{D-B}')$$

Primal Worst = Dual Best

$\inf (P-W)$

$\sup (D-B)$

$\inf (P-W')$

$\sup (D-B')$

Primal Worst = Dual Best

robust

$\inf (P-W)$

nonconvex

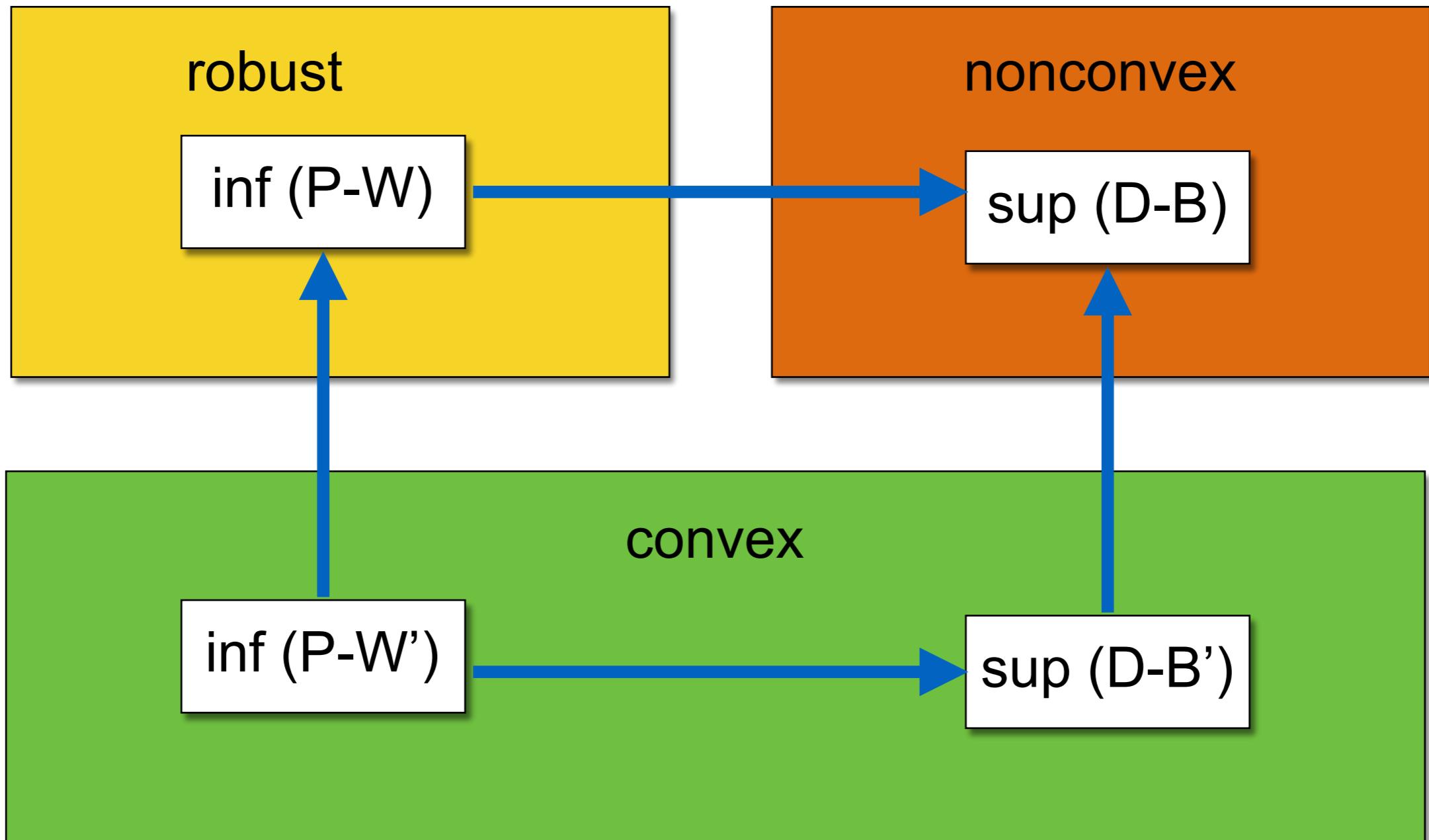
$\sup (D-B)$

convex

$\inf (P-W')$

$\sup (D-B')$

Primal Worst = Dual Best



Primal Worst = Dual Best

If (D-B) has a Slater point...

