

Two-Stage Robust Integer Programming

Wolfram Wiesemann,¹ Grani A. Hanasusanto,² Daniel Kuhn³

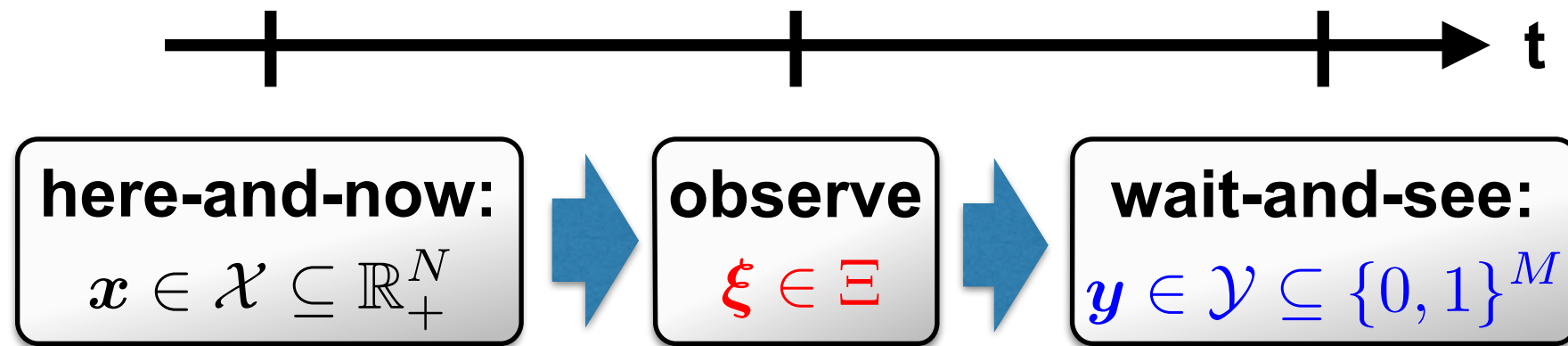
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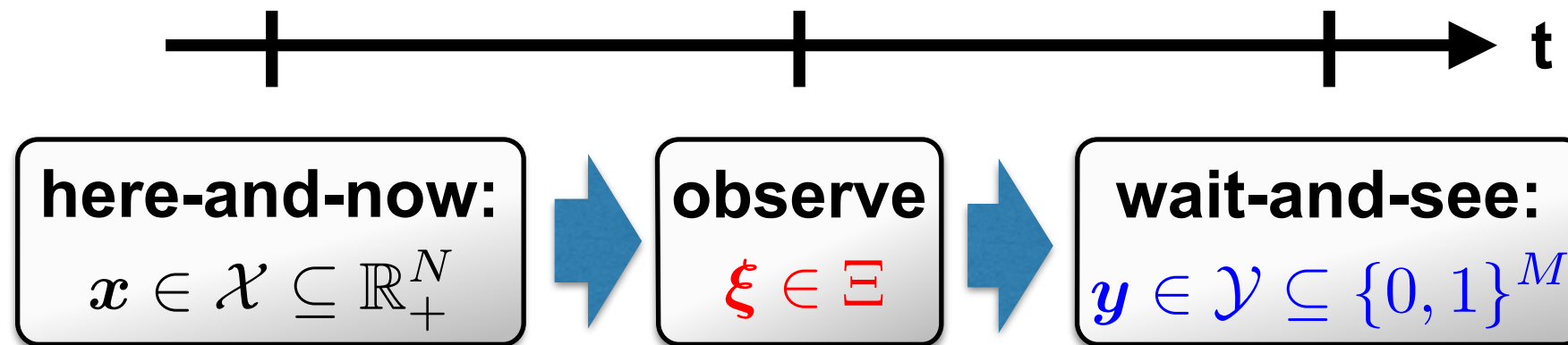
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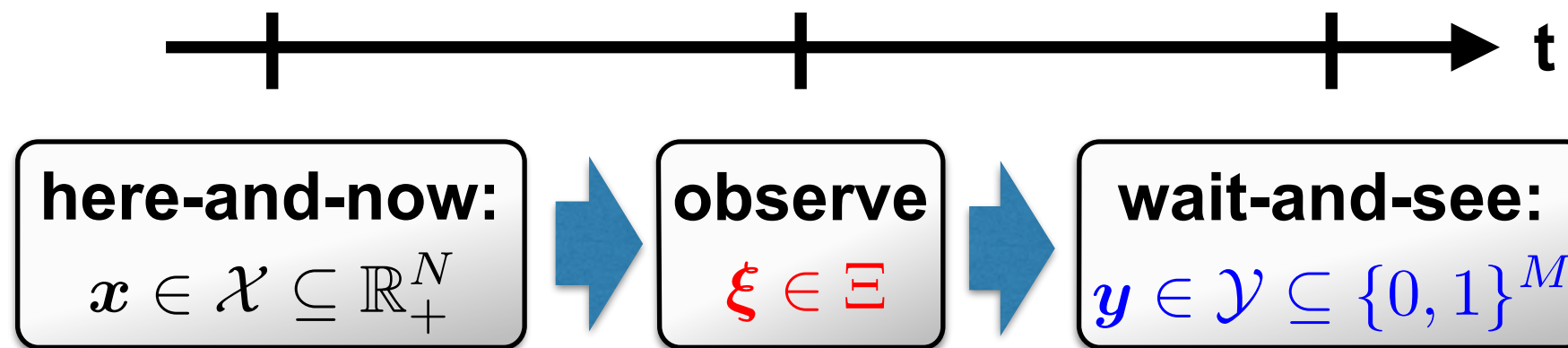


Mathematical Formulation:

$$\begin{aligned} &\text{minimize} && \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{y \in \mathcal{Y}} \{ \xi^\top Q y : Tx + Wy \leq H\xi \} \right] \\ &\text{subject to} && x \in \mathcal{X} \end{aligned}$$

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Applications:



operations mgmt.



investment planning



game theory

Literature Review

$$\begin{array}{ll} \text{minimize} & \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{y \in \mathcal{Y}} \{ \xi^\top Q y : Tx + Wy \leq H\xi \} \right] \\ \text{subject to} & x \in \mathcal{X} \end{array}$$

Literature Review

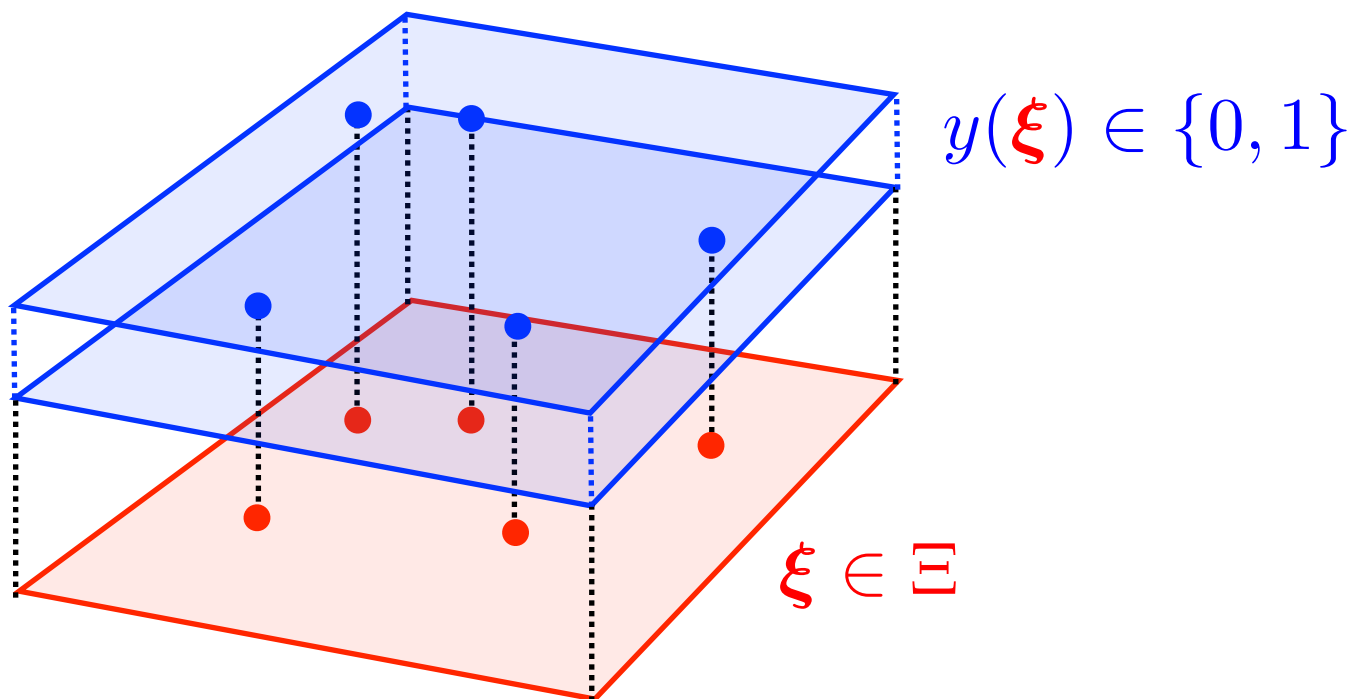
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1 Exact Approaches: not available

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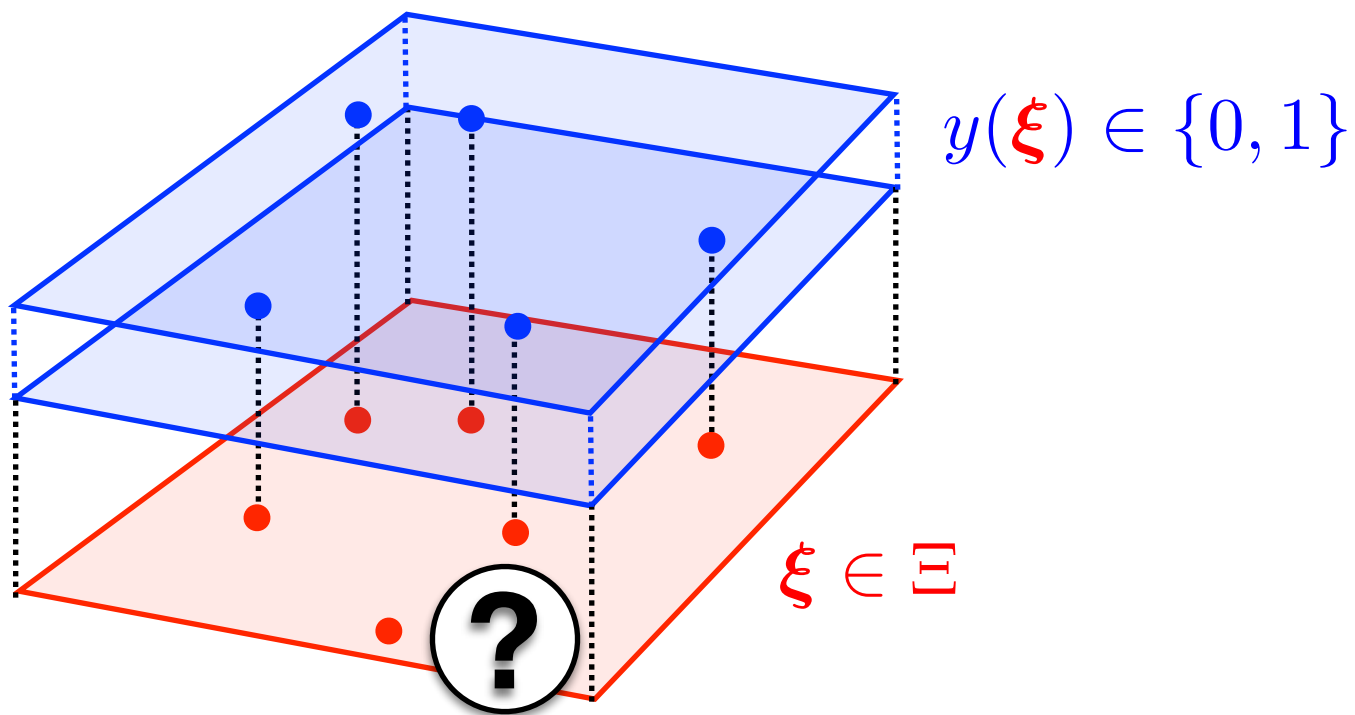
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- 2 **Sampling-Based Approximations:**



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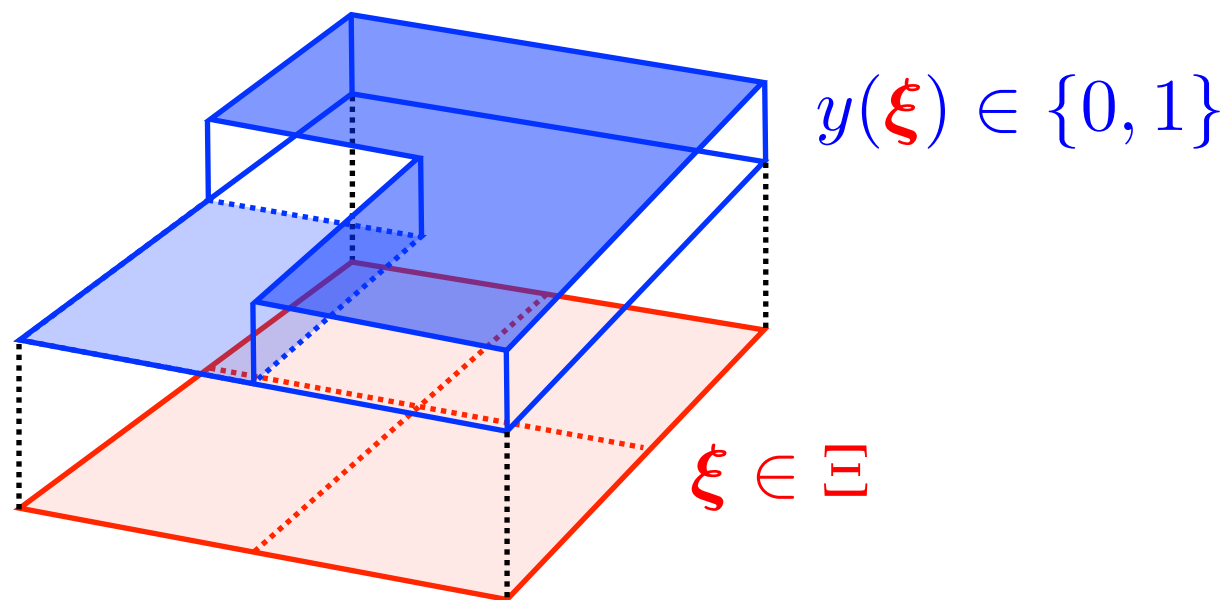
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- 1 **Exact Approaches:** not available
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- 3 **Space-Partitioning Approximations:**

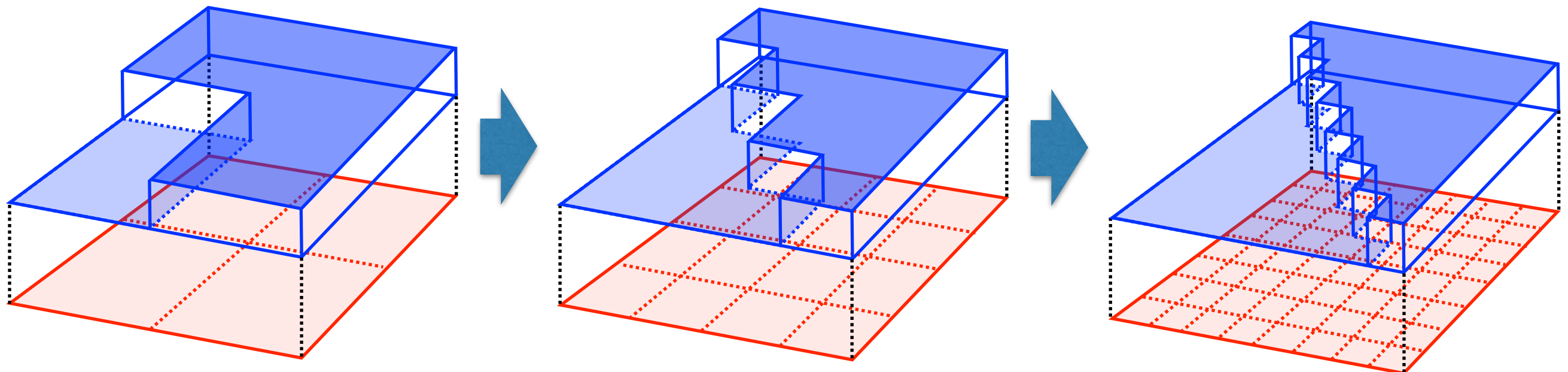


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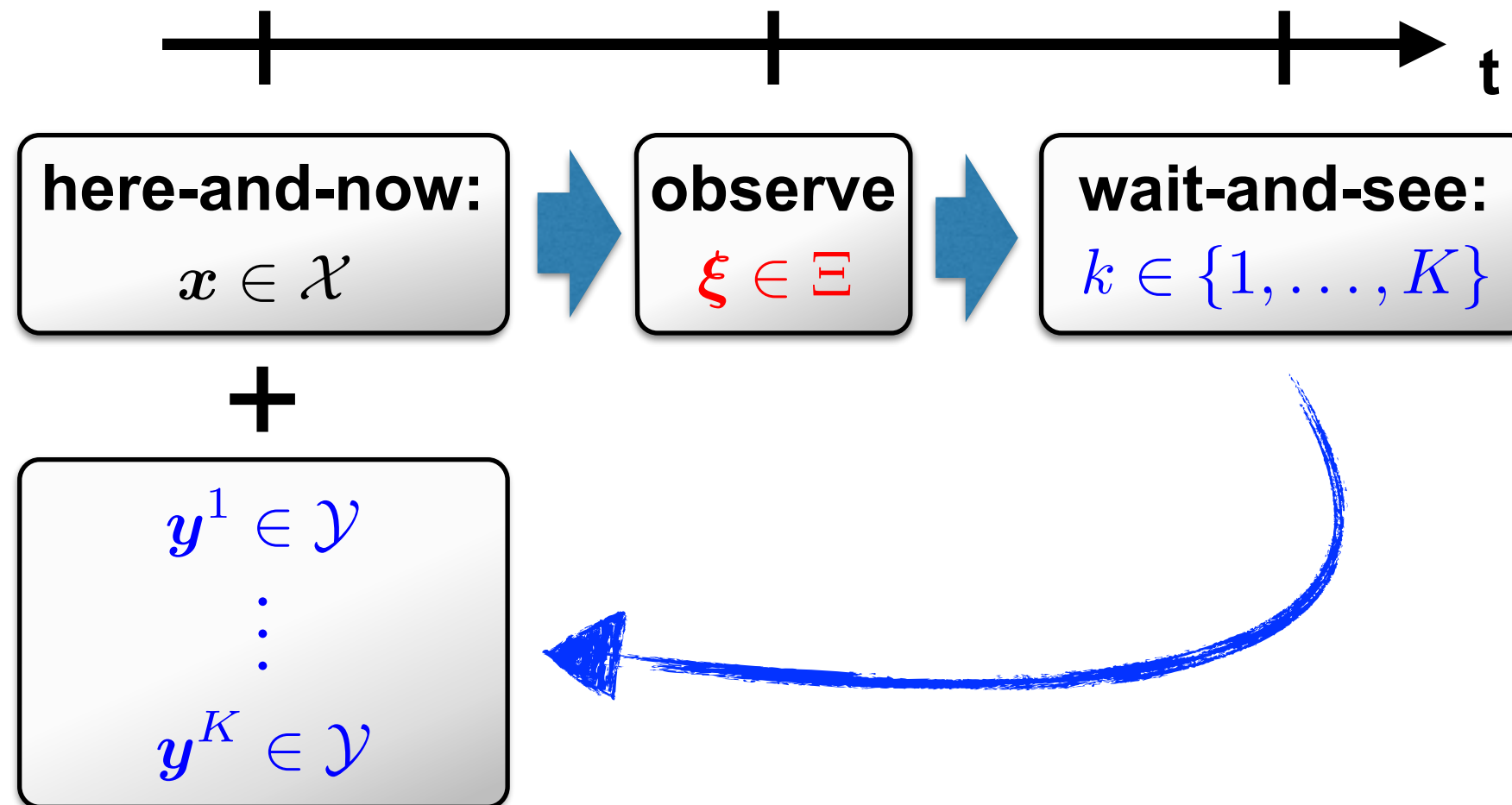
- 1 **Exact Approaches:** not available
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- 3 **Space-Partitioning Approximations:** exponential growth

$$\max_{\xi \in [0,1]^2} \min_{y \in \{0,1\}} \{ y - \xi_1 - \xi_2 : y \geq \xi_1 + \xi_2 - 1 \}$$



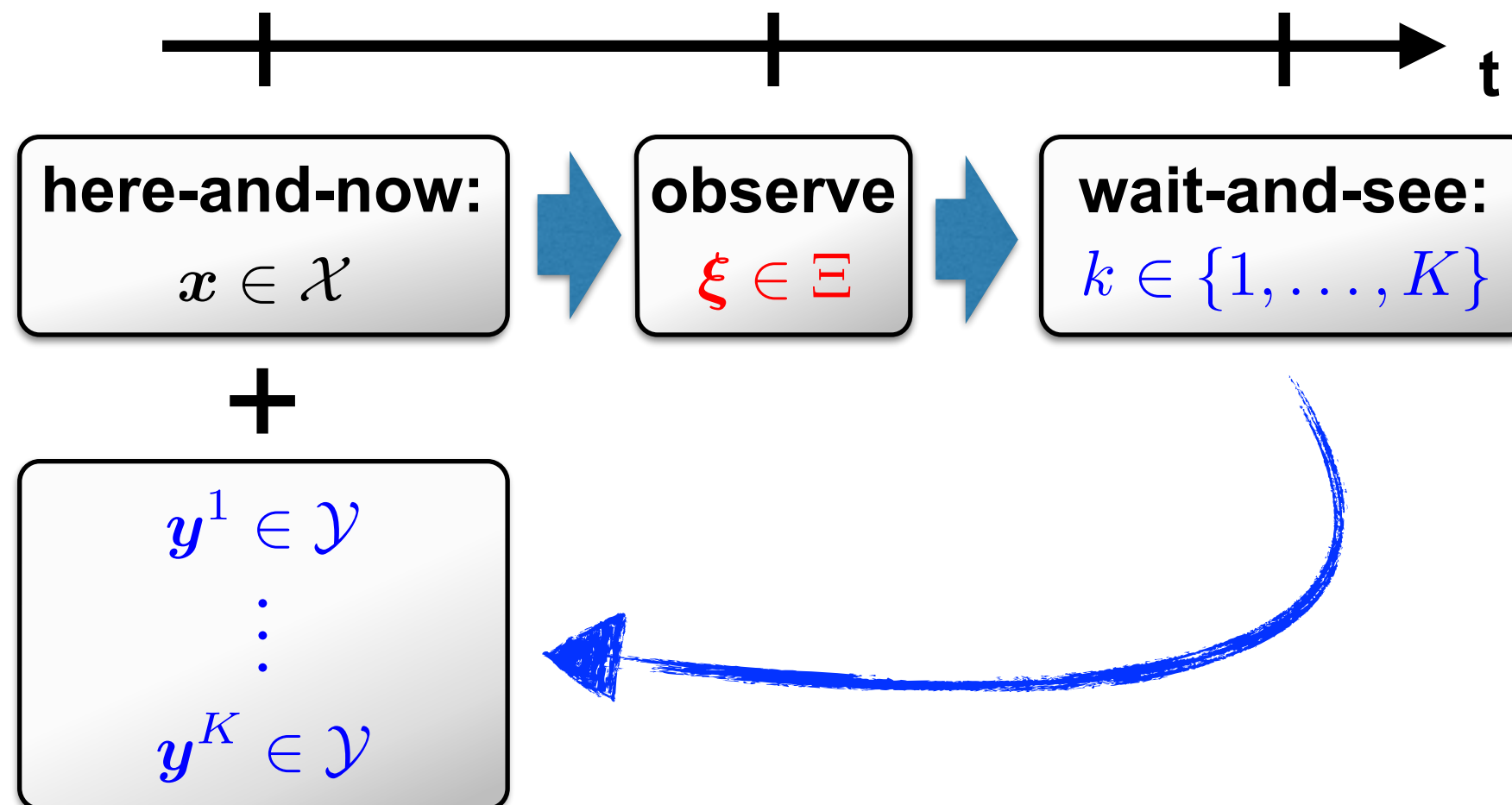
The K -Adaptability Problem

K -Adaptability Problem: Bertsimas and Caramanis (2010)



The K -Adaptability Problem

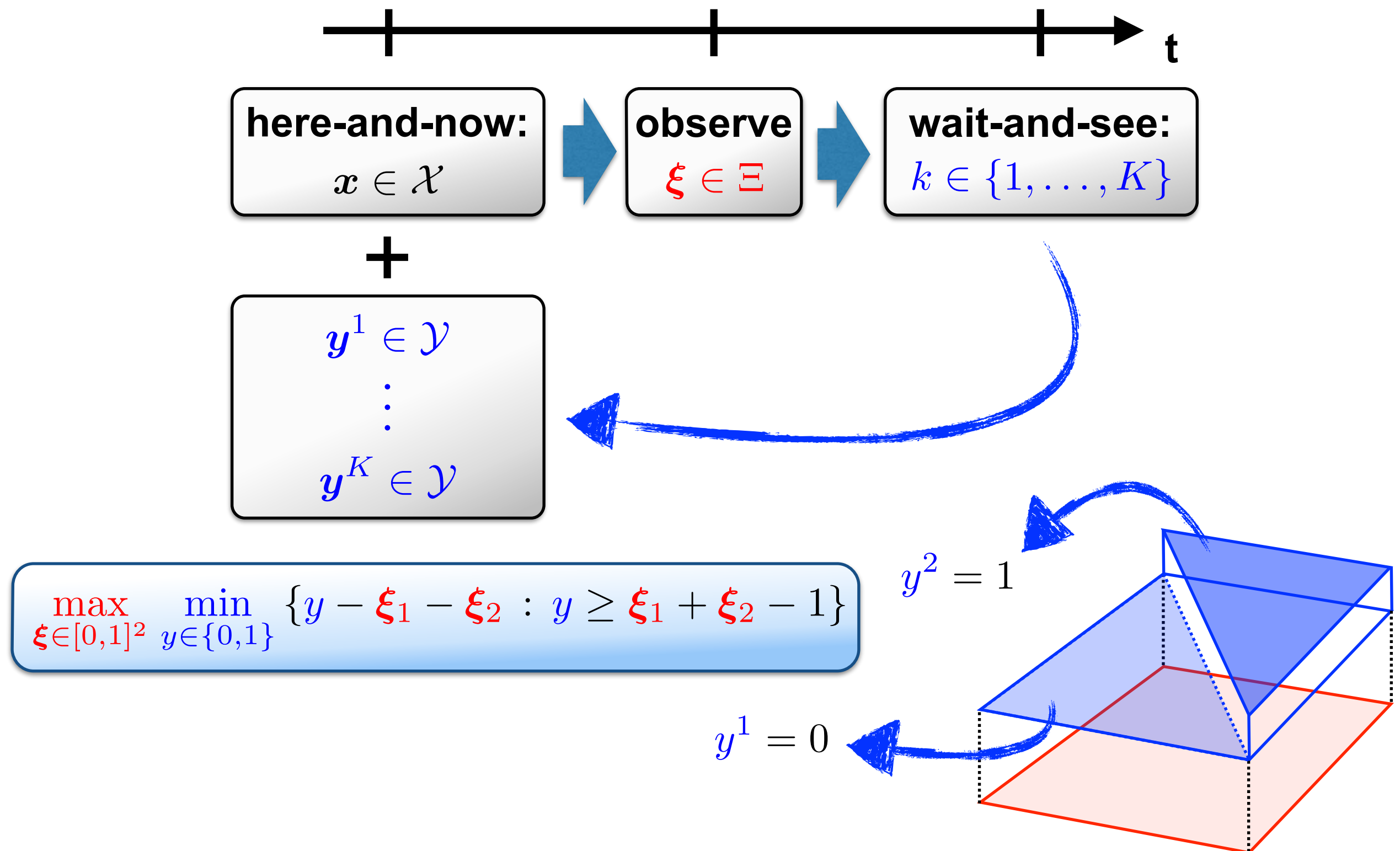
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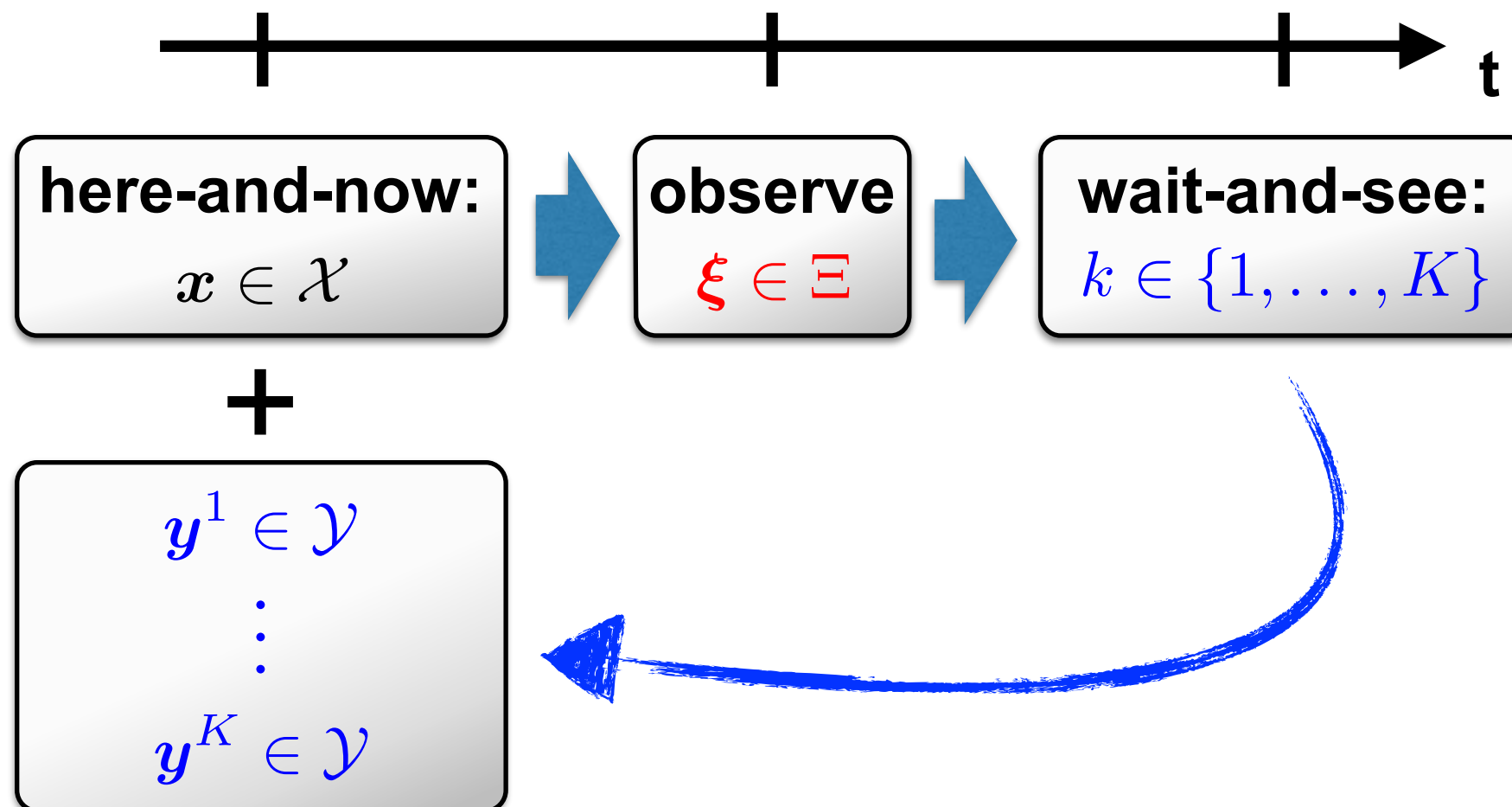
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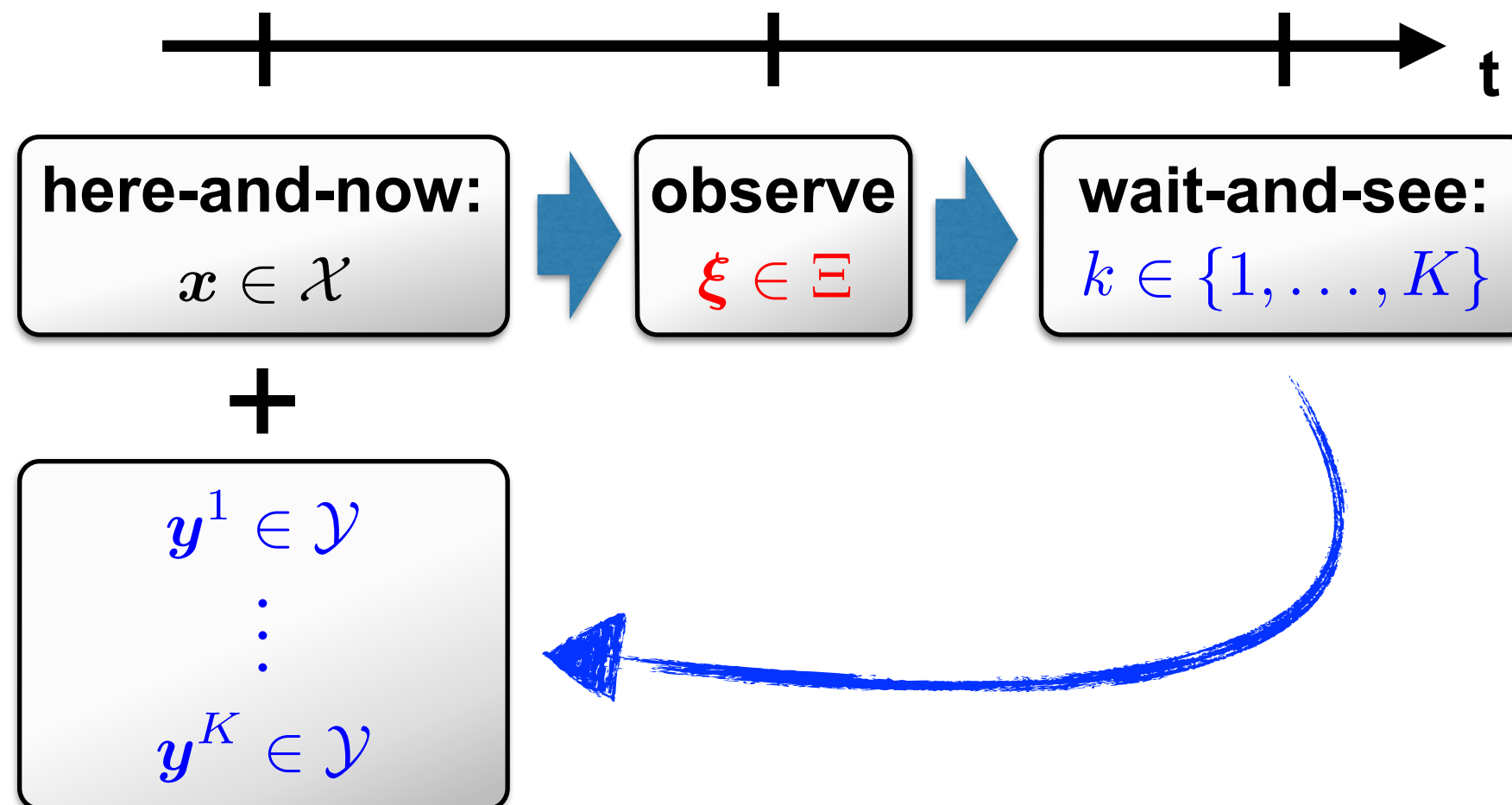


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How good is the approximation?

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How good is the approximation, and can we solve it?

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Objective Uncertainty

The K -Adaptability Problem **with Objective Uncertainty**:

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Objective Uncertainty: Approximation Quality

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How good is the approximation?

Theorem (Objective Uncertainty): The K -Adaptability Problem attains the same objective value as the Two-Stage Robust Integer Program whenever $K \geq \min\{\dim \mathcal{Y}, \dim \Xi\} + 1$.

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Theorem (Objective Uncertainty): The K -Adaptability Problem attains the same objective value as the Two-Stage Robust Integer Program whenever $K \geq \min\{\dim \mathcal{Y}, \dim \Xi\} + 1$.

Proof Outline: for $K \geq \dim \mathcal{Y} + 1$

Consider the \bar{K} -Adaptability Problem with $\bar{\mathcal{K}} = \{1, \dots, \bar{K} = |\mathcal{Y}|\}$:

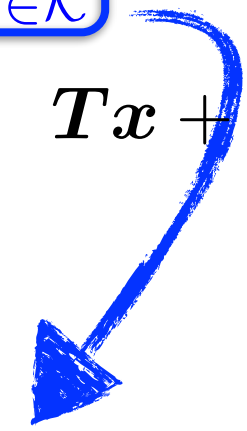
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$$\min_{k \in \bar{\mathcal{K}}} \xi^\top Q y^k = \min_{\lambda \in \Delta_{\bar{\mathcal{K}}}} \sum_{k \in \bar{\mathcal{K}}} \lambda_k \cdot \xi^\top Q y^k$$

\bar{K} -Adaptability Problem

where $\Delta_{\bar{\mathcal{K}}}$ denotes the unit simplex in $\mathbb{R}^{\bar{K}}$.

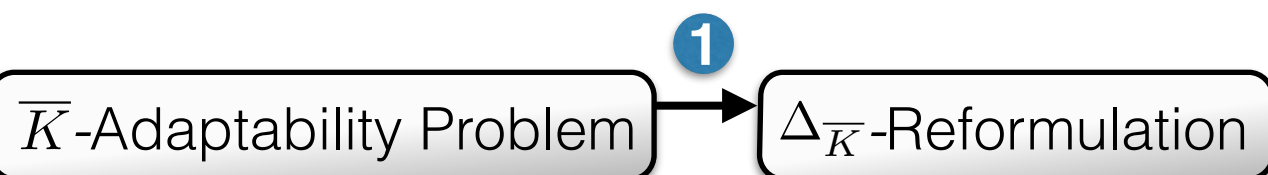
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Proof Outline: for $K \geq \dim \mathcal{Y} + 1$

Use Minimax Theorem to exchange order of max and min:

$$\begin{array}{ll} \text{minimize} & \min_{\lambda \in \Delta_{\bar{K}}} \max_{\xi \in \Xi} \left[\xi^\top C x + \sum_{k \in \bar{K}} \lambda_k \cdot \xi^\top Q y^k \right] \\ \text{subject to} & x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad Tx + Wy^k \leq h, \quad k \in \bar{K} \end{array}$$



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Combine minimization problems:

$$\begin{array}{ll} \text{minimize} & \max_{\xi \in \Xi} \left[\xi^\top C x + \sum_{k \in \bar{K}} \lambda_k \cdot \xi^\top Q y^k \right] \\ \text{subject to} & x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad Tx + Wy^k \leq h, \quad k \in \bar{K}, \\ & \lambda \in \Delta_{\bar{K}} \end{array}$$



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Reformulate objective function:

$$\begin{array}{ll} \text{minimize} & \max_{\xi \in \Xi} \left[\xi^\top C x + \xi^\top Q \cdot \sum_{k \in \bar{K}} \lambda_k y^k \right] \\ \text{subject to} & x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad T x + W y^k \leq h, \quad k \in \bar{K}, \\ & \lambda \in \Delta_{\bar{K}} \end{array}$$



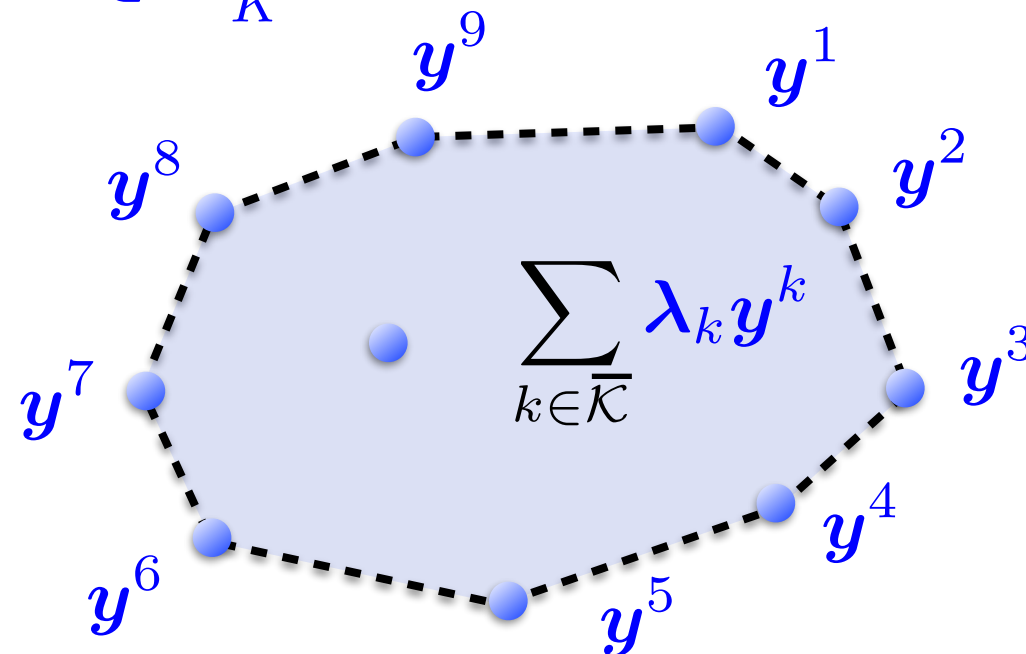
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Proof Outline: for $K \geq \dim \mathcal{Y} + 1$

Apply Carathéodory's Theorem:

$$\begin{array}{ll} \text{minimize} & \max_{\xi \in \Xi} \left[\xi^\top C x + \xi^\top Q \cdot \sum_{k \in \bar{K}} \lambda_k y^k \right] \\ \text{subject to} & x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad Tx + Wy^k \leq h, \quad k \in \bar{K}, \\ & \lambda \in \Delta_{\bar{K}} \end{array}$$



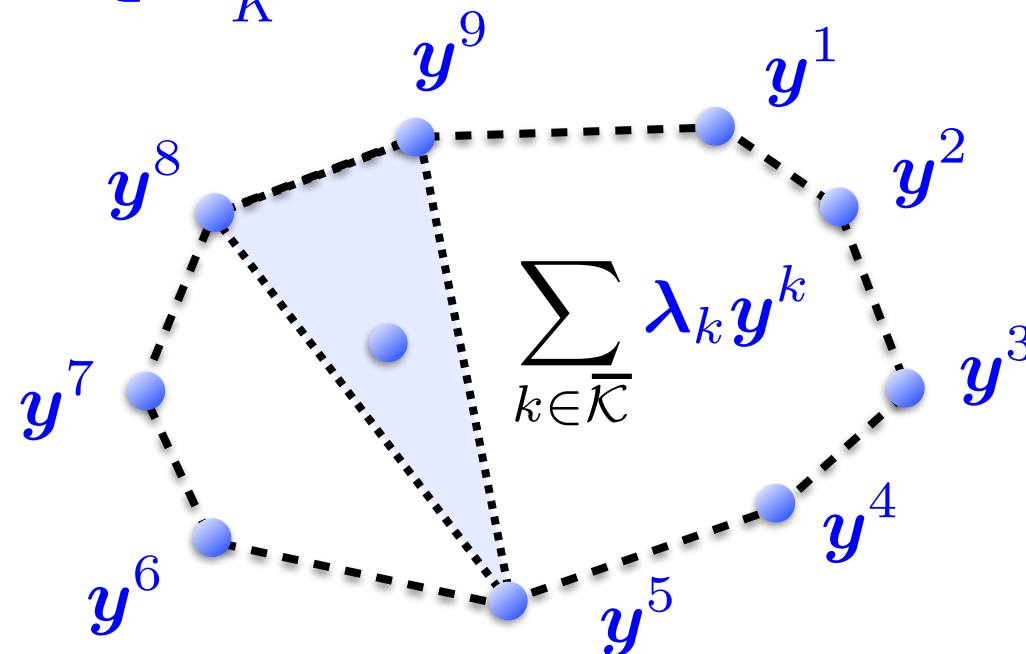
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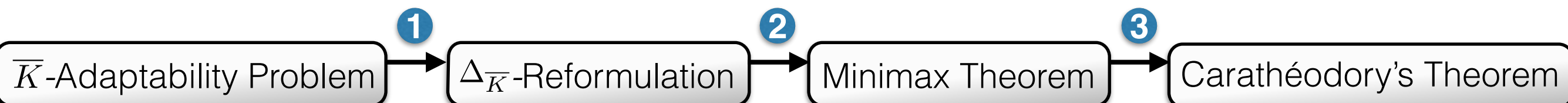
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where $\mathcal{K} = \{1, \dots, K = \dim \mathcal{Y} + 1\}$.



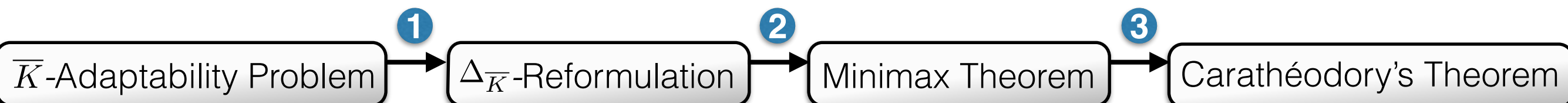
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Proof Outline: for $K \geq \dim \mathcal{Y} + 1$

Separate the two minimizations:

$$\begin{aligned} &\text{minimize} && \min_{\lambda \in \Delta_K} \max_{\xi \in \Xi} \left[\xi^\top C x + \sum_{k \in \mathcal{K}} \lambda_k \cdot \xi^\top Q y^k \right] \\ &\text{subject to} && x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad Tx + Wy^k \leq h, \quad k \in \mathcal{K} \end{aligned}$$



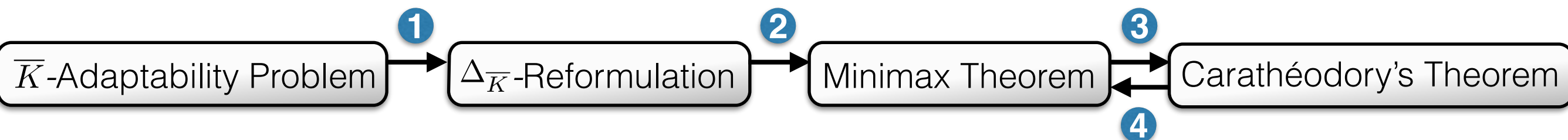
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Proof Outline: for $K \geq \dim \mathcal{Y} + 1$

Use Minimax Theorem to exchange order of min and max:

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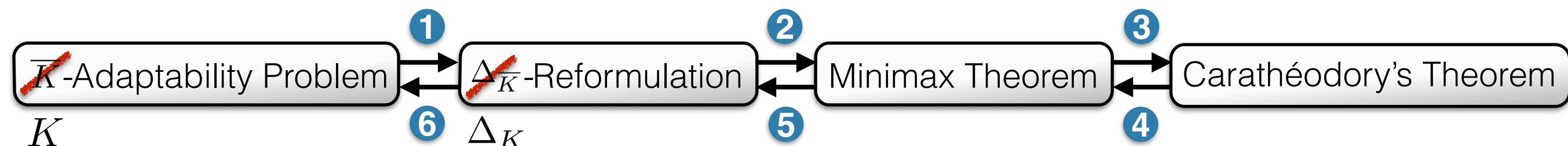
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Proof Outline: for $K \geq \dim \mathcal{Y} + 1$

We recover the K -Adaptability Problem:

$$\begin{aligned} &\text{minimize} && \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \mathcal{K}} \xi^\top Q y^k \right] \\ &\text{subject to} && x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad Tx + Wy^k \leq h, \quad k \in \mathcal{K} \end{aligned}$$



Objective Uncertainty: Tractability

The K -Adaptability Problem **with Objective Uncertainty**:

$$\begin{array}{ll} \text{minimize} & \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \mathcal{K}} \xi^\top Q y^k \right] \\ \text{subject to} & x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad Tx + Wy^k \leq h, \quad k \in \mathcal{K} \end{array}$$

Can we solve the approximation?

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Can we solve the approximation?

Theorem (Objective Uncertainty): The K -Adaptability Problem has equivalent MILP reformulation whose size scales *polynomially* in the problem data.

Objective Uncertainty: Tractability

Theorem (Objective Uncertainty): The K -Adaptability Problem has equivalent MILP reformulation whose size scales *polynomially* in the problem data.

Proof Outline:

Consider the K -Adaptability Problem:

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Objective Uncertainty: Tractability

Theorem (Objective Uncertainty): The K -Adaptability Problem has equivalent MILP reformulation whose size scales *polynomially* in the problem data.

Proof Outline:

Epigraph reformulation of inner min:

$$\begin{aligned} &\text{minimize} && \max_{\substack{\xi \in \Xi, \\ \tau \in \mathbb{R}}} [\xi^\top C x + \tau : \tau \leq \xi^\top Q y^k \quad \forall k \in \mathcal{K}] \\ &\text{subject to} && x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad Tx + Wy^k \leq h, \quad k \in \mathcal{K} \end{aligned}$$

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Epigraph Reformulation

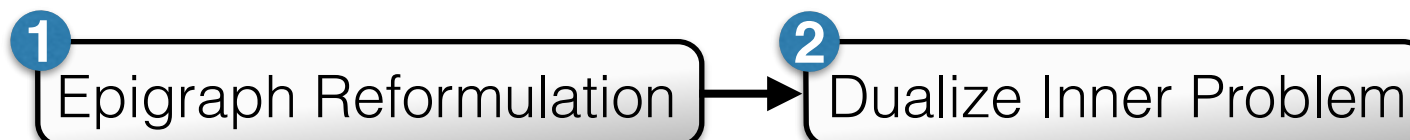
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Theorem (Objective Uncertainty): The K -Adaptability Problem has equivalent MILP reformulation whose size scales *polynomially* in the problem data.

Proof Outline:

Strong LP duality:

$$\begin{aligned} &\text{minimize} \quad \min_{\substack{\alpha \in \mathbb{R}_+^R, \\ \beta \in \mathbb{R}_+^K}} \left[b^\top \alpha : A^\top \alpha = Cx + \sum_{k \in \mathcal{K}} \beta_k Q y^k, \quad e^\top \beta = 1 \right] \\ &\text{subject to} \quad x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad Tx + Wy^k \leq h, \quad k \in \mathcal{K} \end{aligned}$$



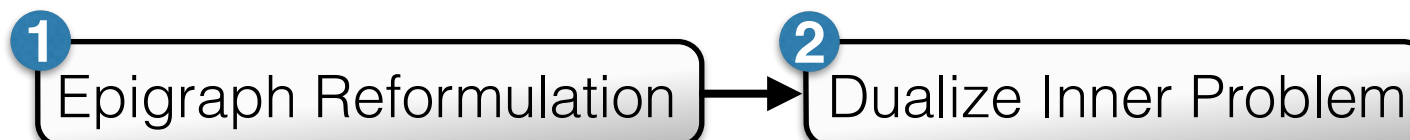
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Proof Outline:

Strong LP duality:

$$\begin{aligned} &\text{minimize} && \mathbf{b}^\top \boldsymbol{\alpha} \\ &\text{subject to} && \mathbf{x} \in \mathcal{X}, \mathbf{y}^k \in \mathcal{Y}, \mathbf{T}\mathbf{x} + \mathbf{W}\mathbf{y}^k \leq \mathbf{h}, k \in \mathcal{K} \\ &&& \boldsymbol{\alpha} \in \mathbb{R}_+^R, \boldsymbol{\beta} \in \mathbb{R}_+^K, \mathbf{A}^\top \boldsymbol{\alpha} = \mathbf{C}\mathbf{x} + \sum_{k \in \mathcal{K}} \beta_k \mathbf{Q}\mathbf{y}^k, \mathbf{e}^\top \boldsymbol{\beta} = 1 \end{aligned}$$



Objective Uncertainty: Tractability

Theorem (Objective Uncertainty): The K -Adaptability Problem has equivalent MILP reformulation whose size scales *polynomially* in the problem data.

Proof Outline:

Strong LP duality:

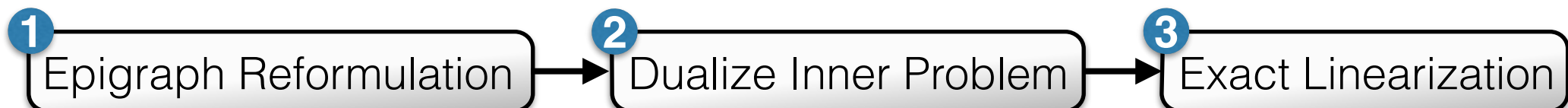
$$\text{minimize} \quad \mathbf{b}^\top \boldsymbol{\alpha}$$

$$\text{subject to} \quad \mathbf{x} \in \mathcal{X}, \quad \mathbf{y}^k \in \mathcal{Y}, \quad \mathbf{T}\mathbf{x} + \mathbf{W}\mathbf{y}^k \leq \mathbf{h}, \quad k \in \mathcal{K}$$

$$\boldsymbol{\alpha} \in \mathbb{R}_+^R, \quad \boldsymbol{\beta} \in \mathbb{R}_+^K, \quad \mathbf{A}^\top \boldsymbol{\alpha} = \mathbf{C}\mathbf{x} + \sum_{k \in \mathcal{K}} \boldsymbol{\beta}_k \mathbf{Q}\mathbf{y}^k, \quad \mathbf{e}^\top \boldsymbol{\beta} = 1$$

Linearize bilinear terms: via auxiliary variables $\mathbf{z}^k \in \mathbb{R}_+^M, k \in \mathcal{K}$

$$\mathbf{z}^k = \boldsymbol{\beta}_k \mathbf{y}^k \iff \mathbf{z}^k \leq \mathbf{y}^k, \quad \mathbf{z}^k \leq \boldsymbol{\beta}_k \mathbf{e}, \quad \mathbf{z}^k \geq (\boldsymbol{\beta}_k - 1)\mathbf{e} + \mathbf{y}^k$$



The K -Adaptability Problem:

$$\begin{array}{ll} \text{minimize} & \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \mathcal{K}} \left\{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \right\} \right] \\ \text{subject to} & x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad k \in \mathcal{K} \end{array}$$

Objective Uncertainty:

- ★ *strong* approximation guarantees
- ★ MILP reformulation that scales *polynomially*

Constraint Uncertainty

The K -Adaptability Problem **with Constraint Uncertainty**:

$$\begin{aligned} &\text{minimize} && \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \mathcal{K}} \left\{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \right\} \right] \\ &\text{subject to} && x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad k \in \mathcal{K} \end{aligned}$$

Constraint Uncertainty: Approximation Quality

The K -Adaptability Problem **with Constraint Uncertainty**:

$$\begin{array}{ll} \text{minimize} & \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \mathcal{K}} \left\{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \right\} \right] \\ \text{subject to} & x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad k \in \mathcal{K} \end{array}$$

How good is the approximation?

Constraint Uncertainty: Approximation Quality

The K -Adaptability Problem **with Constraint Uncertainty**:

$$\begin{aligned} &\text{minimize} && \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \mathcal{K}} \left\{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \right\} \right] \\ &\text{subject to} && x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad k \in \mathcal{K} \end{aligned}$$

How good is the approximation?

Theorem (Constraint Uncertainty): The K -Adaptability Problem can attain a *strictly larger objective value* than the Two-Stage Robust Integer Program whenever $K < |\mathcal{Y}|$.

Constraint Uncertainty: Tractability

The K -Adaptability Problem **with Constraint Uncertainty**:

$$\begin{aligned} &\text{minimize} && \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \mathcal{K}} \left\{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \right\} \right] \\ &\text{subject to} && x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad k \in \mathcal{K} \end{aligned}$$

Can we solve the approximation?

Constraint Uncertainty: Tractability

The K -Adaptability Problem **with Constraint Uncertainty**:

$$\begin{aligned} &\text{minimize} && \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \mathcal{K}} \{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \} \right] \\ &\text{subject to} && x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad k \in \mathcal{K} \end{aligned}$$

Can we solve the approximation?

Theorem (Constraint Uncertainty): The K -Adaptability Problem has an equivalent MILP reformulation that scales *exponentially* in the number of policies K (but *polynomially* in other problem data).

Constraint Uncertainty: Tractability

Theorem (Constraint Uncertainty): The K -Adaptability Problem has an equivalent MILP reformulation that scales *exponentially* in the number of policies K (but *polynomially* in other problem data).

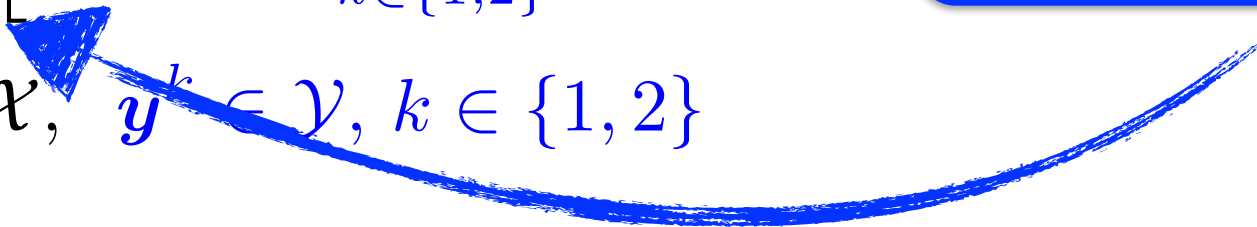
Proof Outline: Consider the 2-Adaptability Problem:

$$\begin{aligned} &\text{minimize} && \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \{1,2\}} \{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \} \right] \\ &\text{subject to} && x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad k \in \{1,2\} \end{aligned}$$

Constraint Uncertainty: Tractability

Theorem (Constraint Uncertainty): The K -Adaptability Problem has an equivalent MILP reformulation that scales *exponentially* in the number of policies K (but *polynomially* in other problem data).

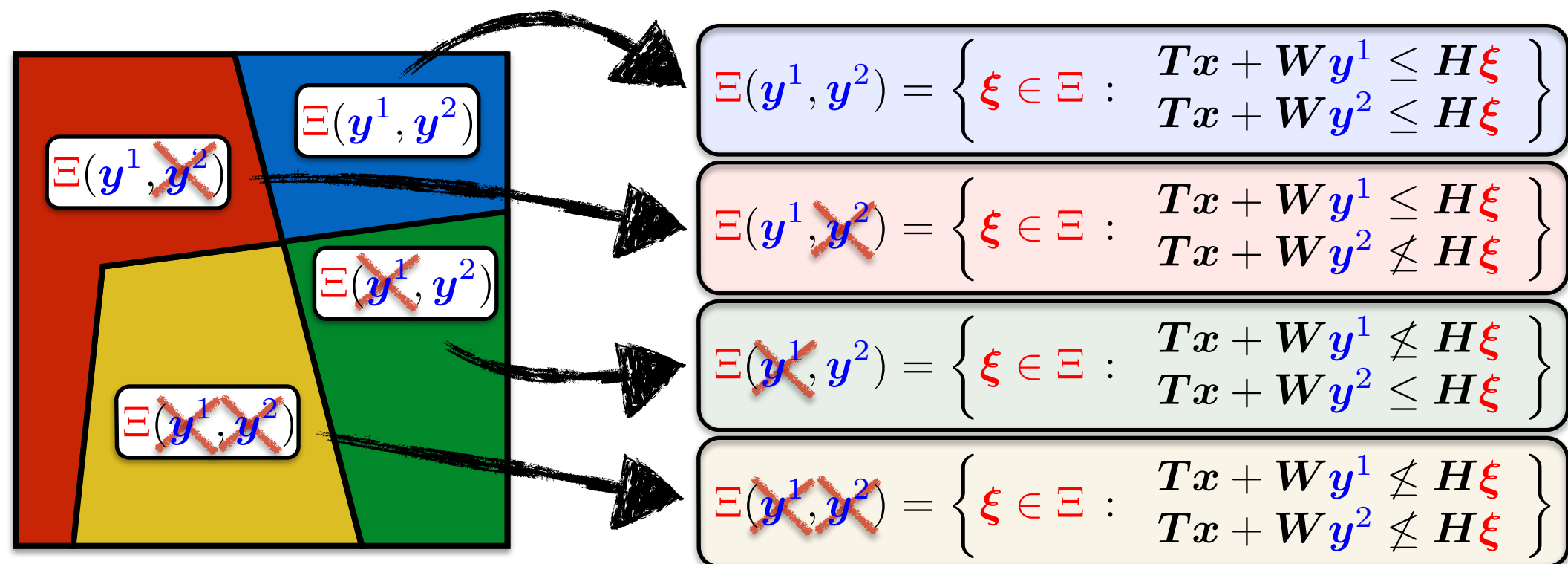
Proof Outline: Move second-stage constraints to uncertainty set:

$$\begin{array}{ll} \text{minimize} & \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \{1,2\}} \{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \} \right] \\ \text{subject to} & x \in \mathcal{X}, y^k \in \mathcal{Y}, k \in \{1,2\} \end{array}$$


Constraint Uncertainty: Tractability

Theorem (Constraint Uncertainty): The K -Adaptability Problem has an equivalent MILP reformulation that scales *exponentially* in the number of policies K (but *polynomially* in other problem data).

Proof Outline: Move second-stage constraints to uncertainty set:



$$\Xi = \Xi(y^1, y^2) \cup \Xi(\cancel{y^1}, y^2) \cup \Xi(y^1, \cancel{y^2}) \cup \Xi(\cancel{y^1}, \cancel{y^2})$$

Constraint Uncertainty: Tractability

Theorem (Constraint Uncertainty): The K -Adaptability Problem has an equivalent MILP reformulation that scales *exponentially* in the number of policies K (but *polynomially* in other problem data).

Proof Outline: Move second-stage constraints to uncertainty set:

$$\max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \{1,2\}} \{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \} \right]$$

$$= \max \left\{ \begin{array}{l} \max_{\xi \in \Xi(y^1, y^2)} \left[\xi^\top C x + \min_{k \in \{1,2\}} \{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \} \right], \\ \max_{\xi \in \Xi(y^1, \cancel{y^2})} \left[\xi^\top C x + \min_{k \in \{1,2\}} \{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \} \right], \\ \max_{\xi \in \Xi(\cancel{y^1}, y^2)} \left[\xi^\top C x + \min_{k \in \{1,2\}} \{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \} \right], \\ \max_{\xi \in \Xi(\cancel{y^1}, \cancel{y^2})} \left[\xi^\top C x + \min_{k \in \{1,2\}} \{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \} \right], \end{array} \right\}$$

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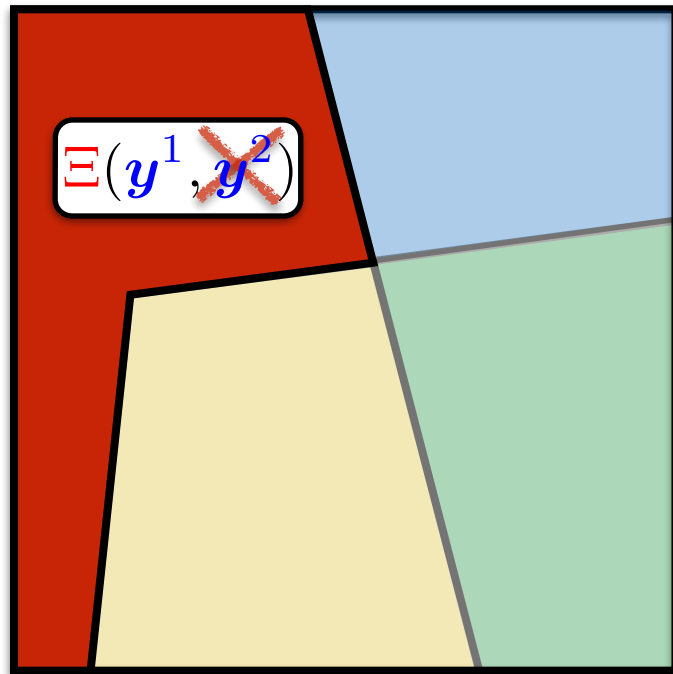
$$\max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \{1,2\}} \{ \xi^\top Q y^k : T x + W y^k \leq H \xi \} \right]$$

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Constraint Uncertainty: Tractability

Theorem (Constraint Uncertainty): The K -Adaptability Problem has an equivalent MILP reformulation that scales *exponentially* in the number of policies K (but *polynomially* in other problem data).

Proof Outline: Uncertainty sets have become non-convex:

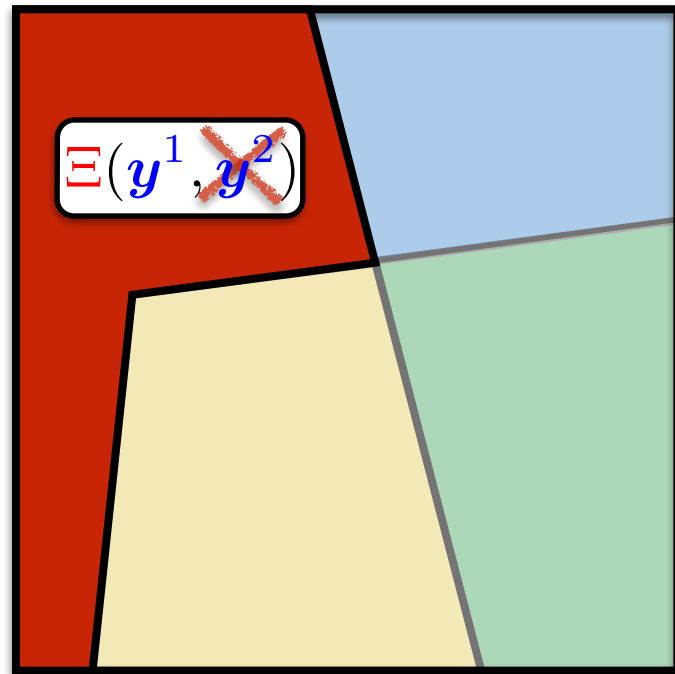


$$\Xi(y^1, y^2) = \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ Tx + Wy^2 \not\leq H\xi \end{array} \right\}$$

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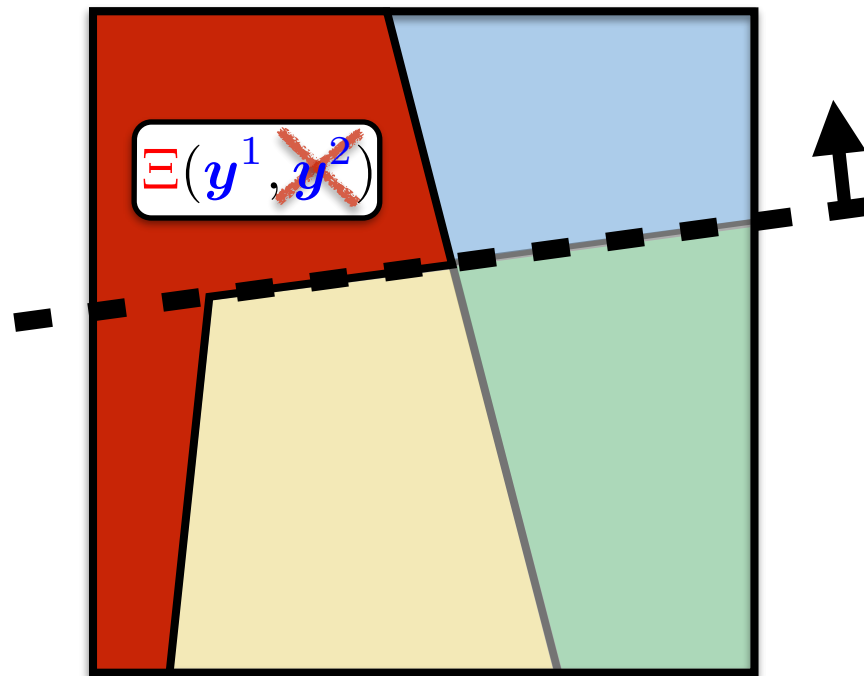


$$\begin{aligned} \Xi(y^1, \cancel{y^2}) &= \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ Tx + Wy^2 \not\leq H\xi \end{array} \right\} \\ &= \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ [Tx + Wy^2]_1 > [H\xi]_1 \vee \\ [Tx + Wy^2]_2 > [H\xi]_2 \end{array} \right\} \end{aligned}$$

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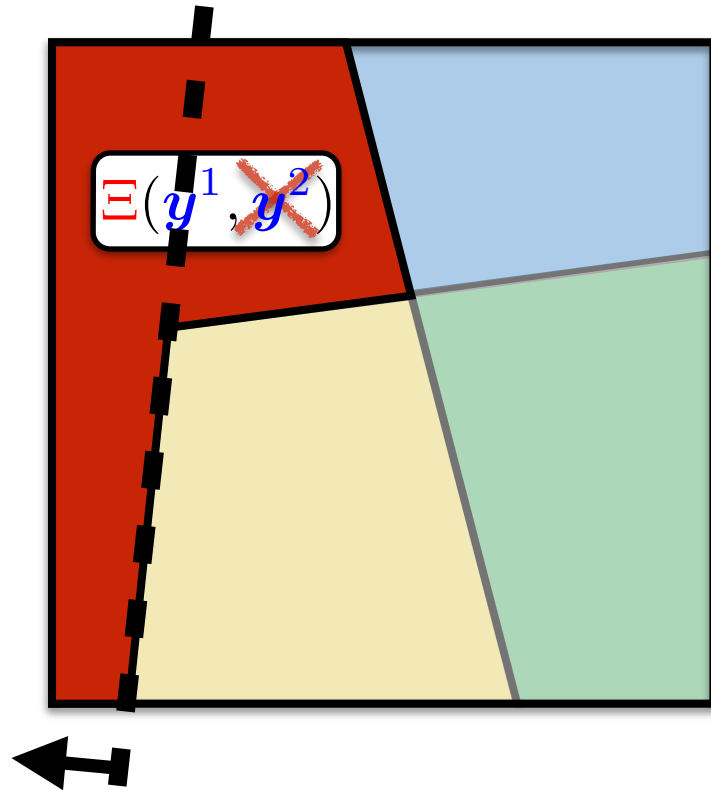


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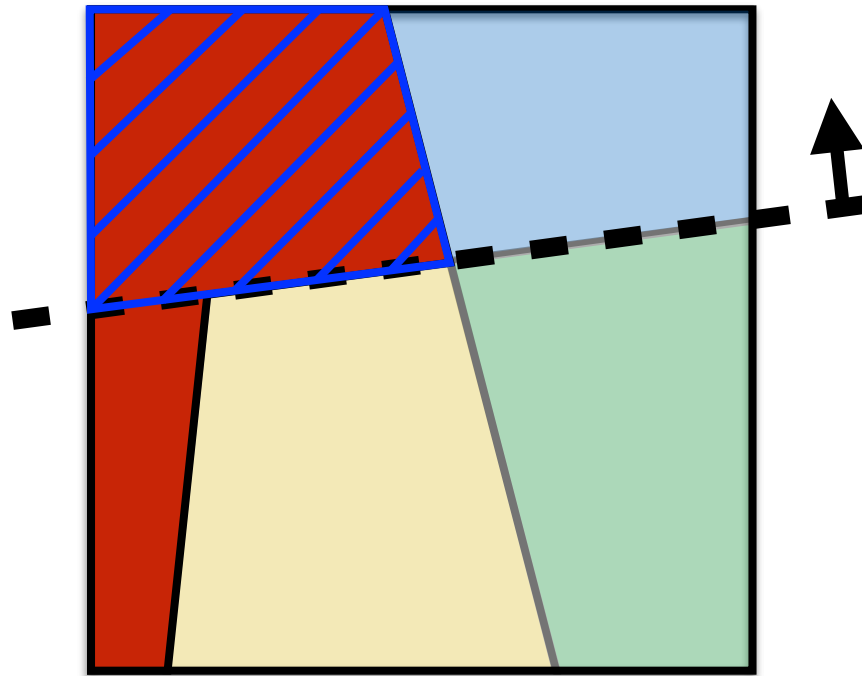


$$\begin{aligned} \Xi(y^1, y^2) &= \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ Tx + Wy^2 \not\leq H\xi \end{array} \right\} \\ &= \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ [Tx + Wy^2]_1 > [H\xi]_1 \vee \\ [Tx + Wy^2]_2 > [H\xi]_2 \end{array} \right\} \end{aligned}$$

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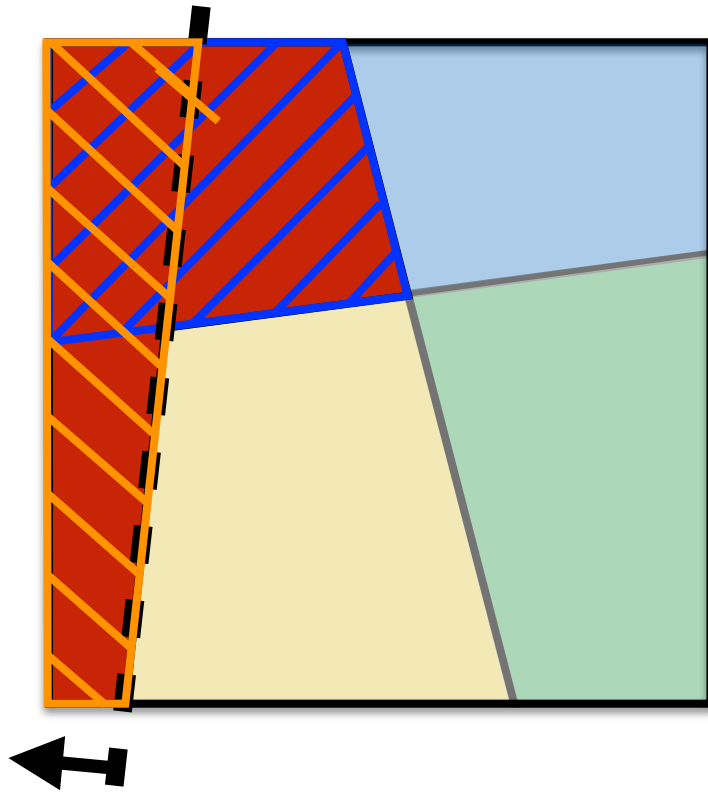


$$\begin{aligned}
 \Xi(y^1, \cancel{y^2}) &= \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ Tx + Wy^2 \not\leq H\xi \end{array} \right\} \\
 &= \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ [Tx + Wy^2]_1 > [H\xi]_1 \vee \\ [Tx + Wy^2]_2 > [H\xi]_2 \end{array} \right\} \\
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 \end{aligned}$$

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Proof Outline: Uncertainty sets have become non-convex:



$$\begin{aligned}
 \Xi(y^1, \cancel{y^2}) &= \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ Tx + Wy^2 \not\leq H\xi \end{array} \right\} \\
 &= \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ [Tx + Wy^2]_1 > [H\xi]_1 \vee \\ [Tx + Wy^2]_2 > [H\xi]_2 \end{array} \right\} \\
 &= \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ [Tx + Wy^2]_1 > [H\xi]_1 \end{array} \right\} \cup \\
 &\quad \left\{ \xi \in \Xi : \begin{array}{l} Tx + Wy^1 \leq H\xi \\ [Tx + Wy^2]_2 > [H\xi]_2 \end{array} \right\}
 \end{aligned}$$

The K -Adaptability Problem:

$$\begin{array}{ll} \text{minimize} & \max_{\xi \in \Xi} \left[\xi^\top C x + \min_{k \in \mathcal{K}} \{ \xi^\top Q y^k : Tx + Wy^k \leq H\xi \} \right] \\ \text{subject to} & x \in \mathcal{X}, \quad y^k \in \mathcal{Y}, \quad k \in \mathcal{K} \end{array}$$

Objective Uncertainty:

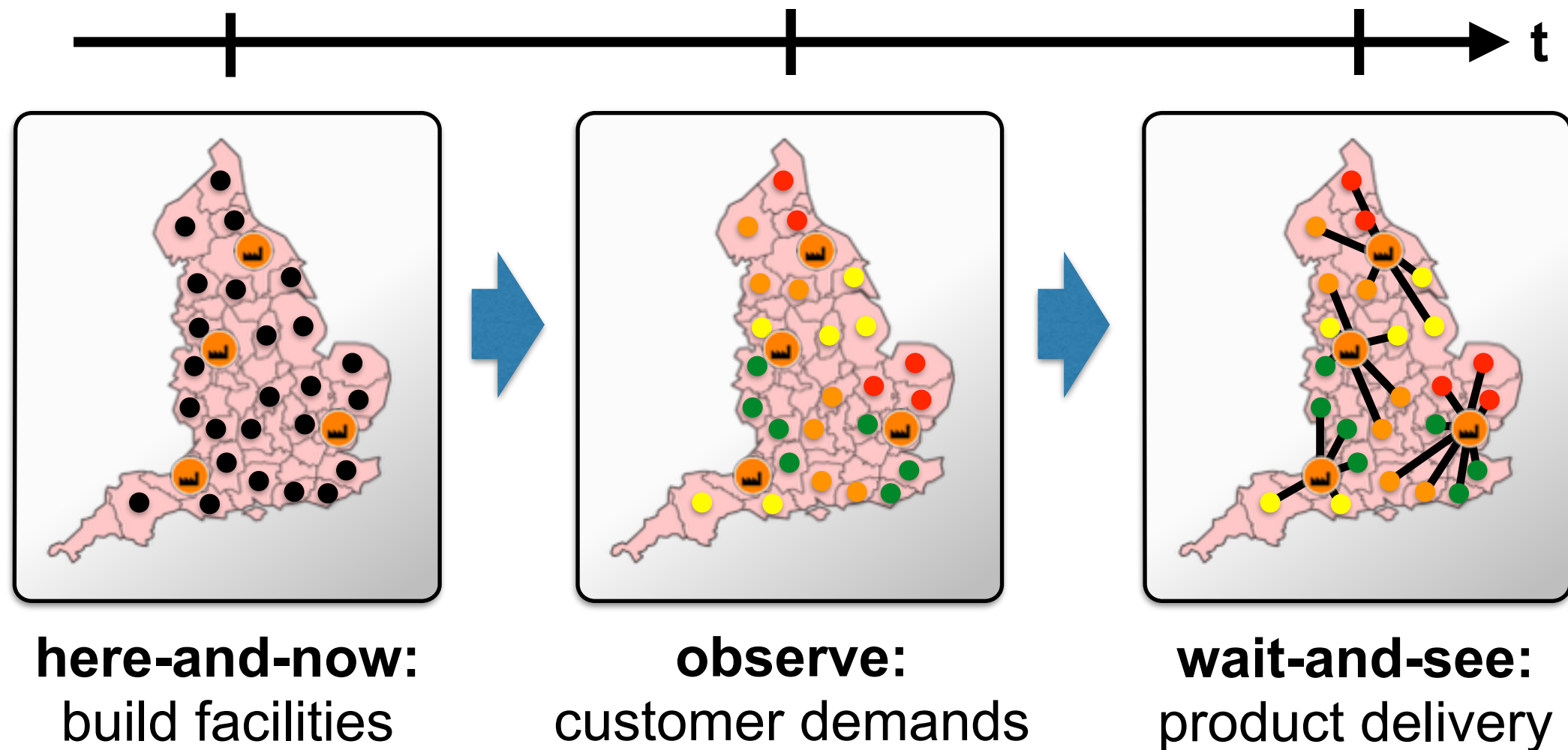
- ★ *strong* approximation guarantees
- ★ MILP reformulation that scales *polynomially*

Constraint Uncertainty:

- ★ *weak* approximation guarantees
- ★ MILP reformulation that scales
 - ✧ *exponentially* in K
 - ✧ *polynomially* in rest

Numerical Experiments

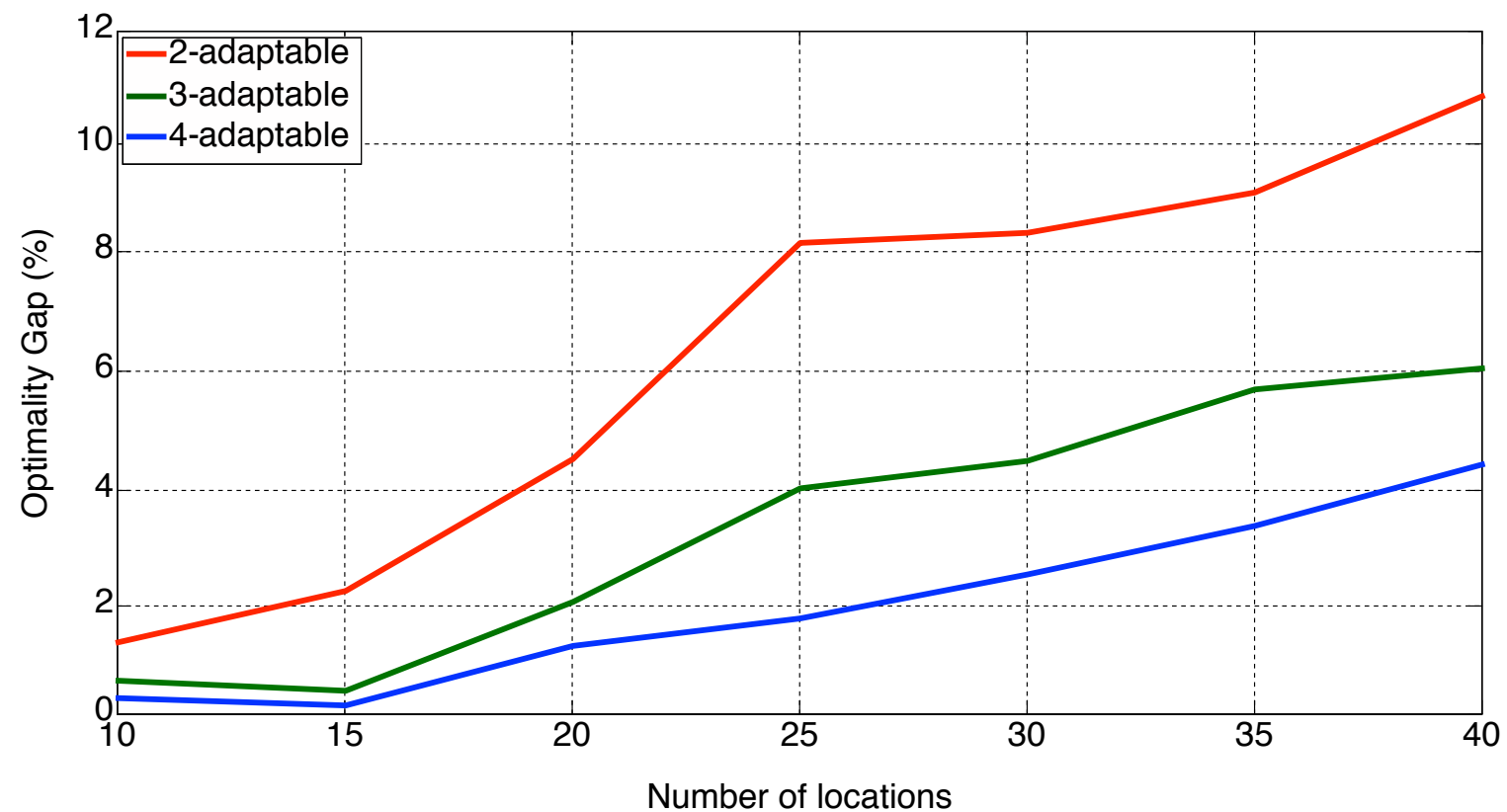
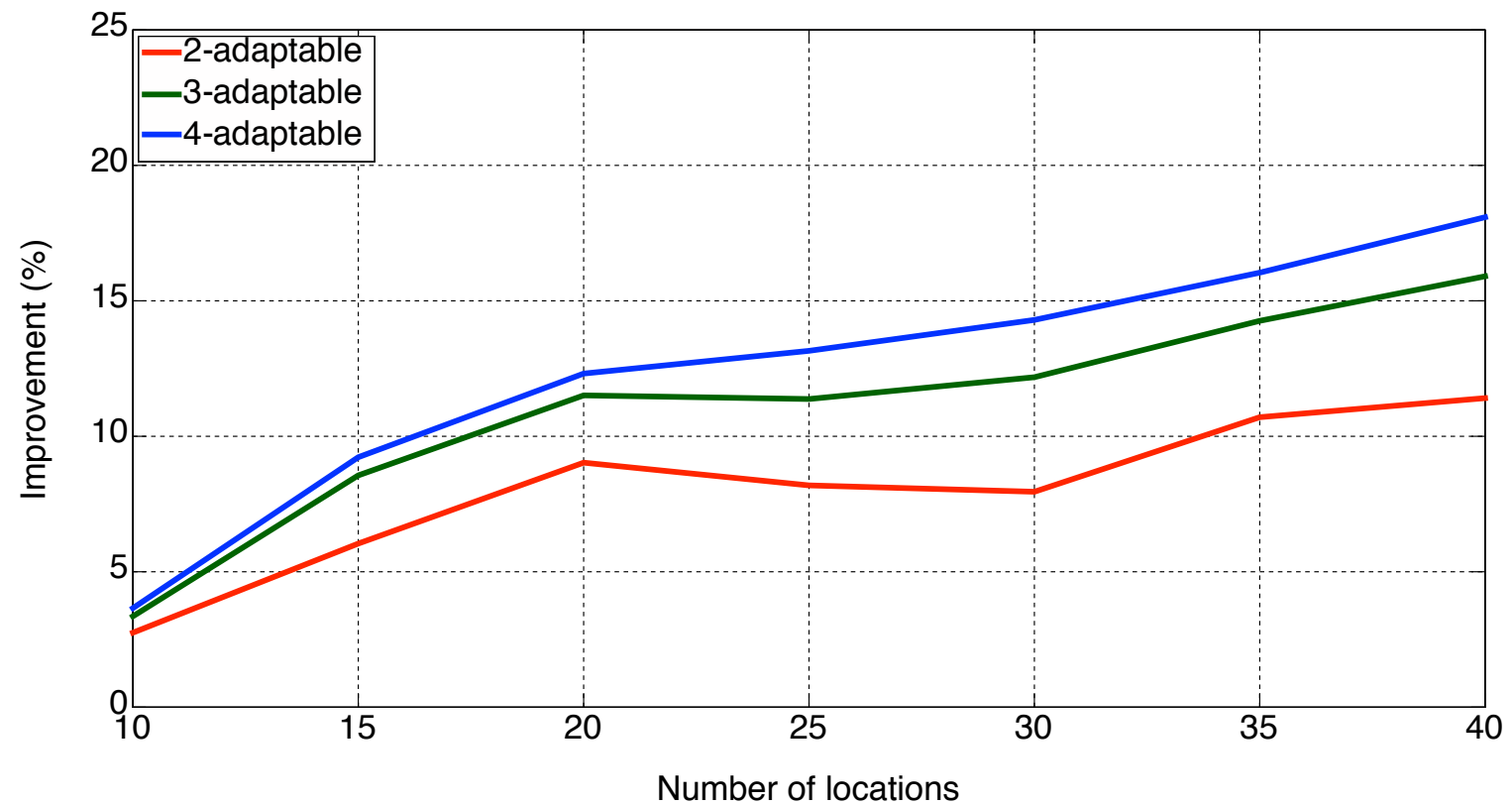
Supply Chain Design:



*Can be modeled as two-stage robust integer program
with **objective uncertainty**!*

Numerical Experiments

Supply Chain Design:



Numerical Experiments

Investment Planning:



here-and-now:
early-stage investment
(*first mover advantage*)

$$\begin{array}{ll} \text{costs:} & c(\xi)^{\top} x \\ \text{profits:} & r(\xi)^{\top} x \end{array}$$

observe:
risk factors

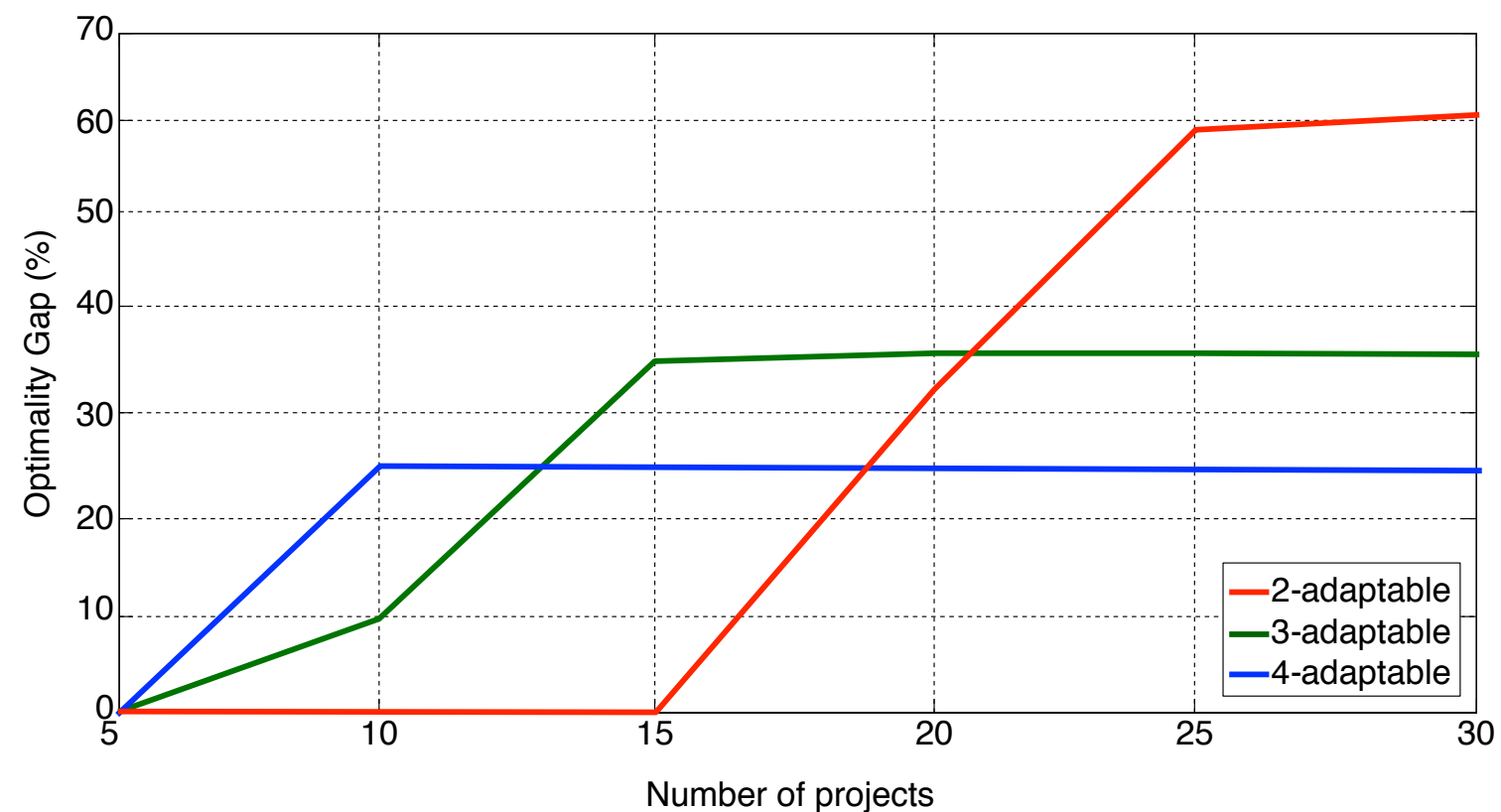
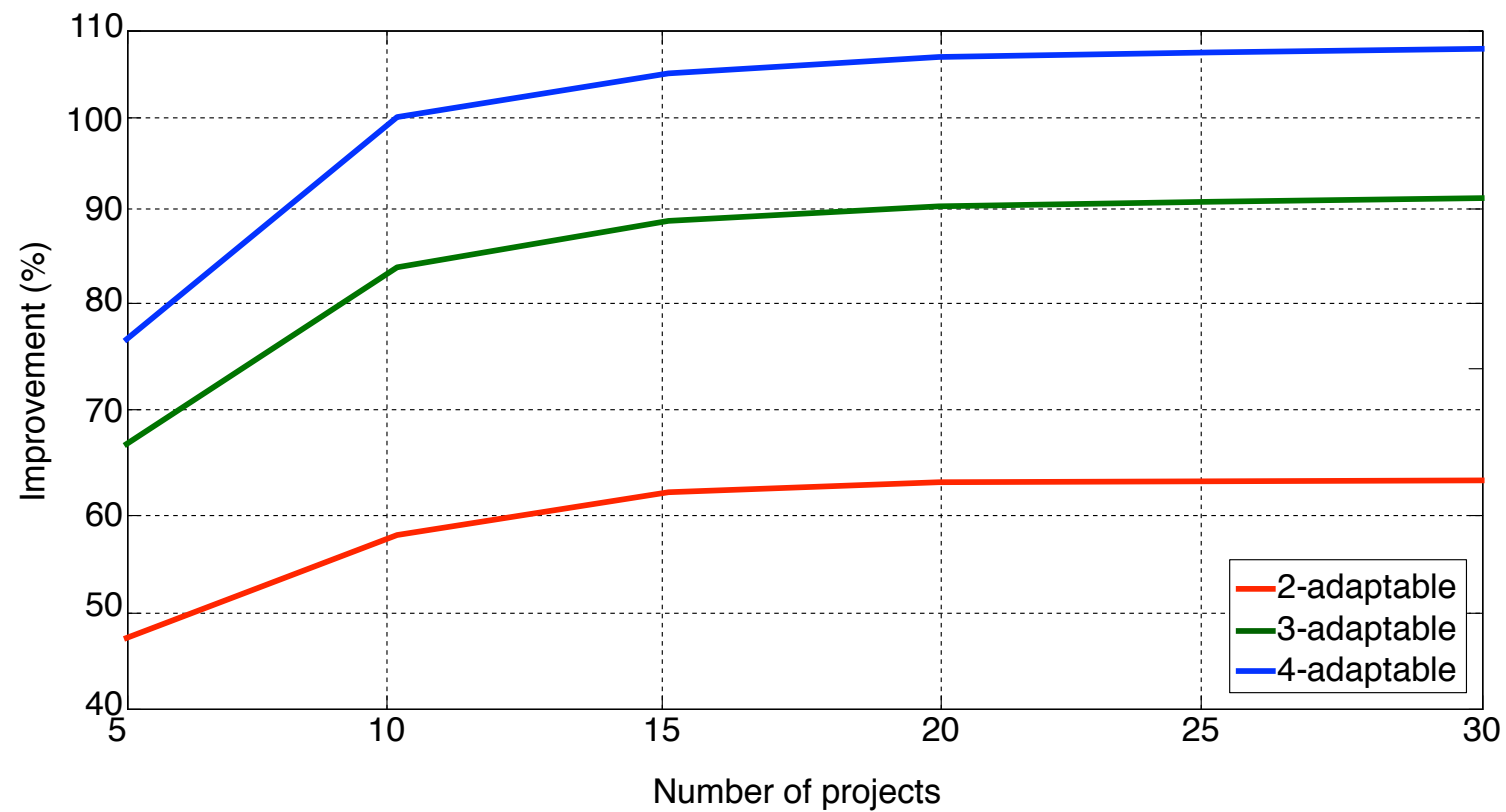
wait-and-see:
late-stage investment
(*no advantage*)

$$\begin{array}{ll} \text{costs:} & c(\xi)^{\top} y(\xi) \\ \text{profits:} & 0.8 \cdot r(\xi)^{\top} y(\xi) \end{array}$$

Can be modeled as two-stage robust integer program
with **constraint uncertainty!**

Numerical Experiments

Investment Planning:



References

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