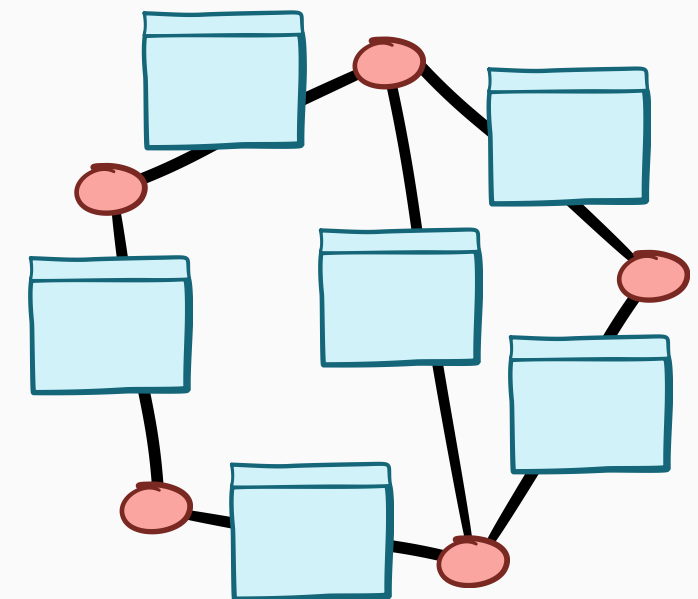


# Local Hedging *approximately solves* Pandora's Box Problems *with* Nonobligatory Inspection

Ziv Scully  
*Cornell ORIE*

Laura Doval  
*Columbia Business School*





*In uncertain environments, when is the*

# **value of new information**

*worth the cost of obtaining it?*



*In uncertain environments, when is the*

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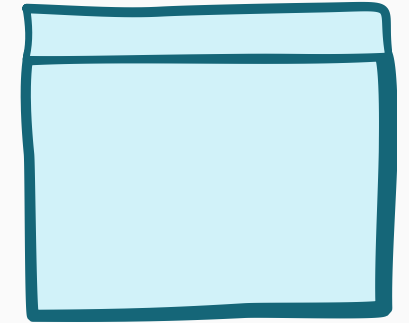
*In stochastic control, when can we*

**decompose hard problems**

*into more tractable subproblems?*

# Modeling cost of information

Pandora's box model:

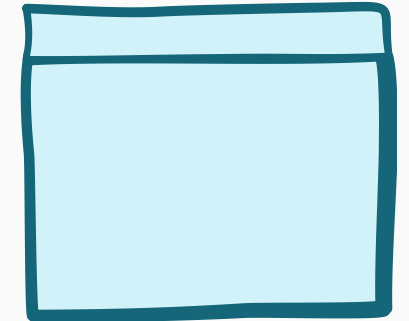




# Modeling cost of information

**Pandora's box model:**

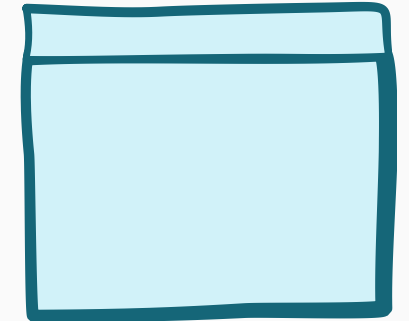
- Opening cost  $c$



# Modeling cost of information

**Pandora's box model:**

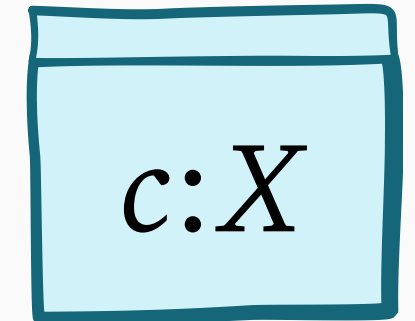
- Opening cost  $c$
- Hidden price  $X$



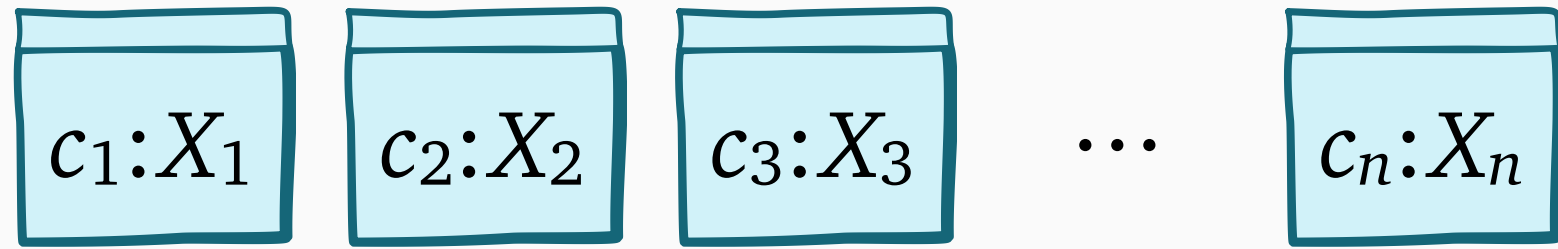
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**Pandora's box model:**

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- Hidden price  $X$

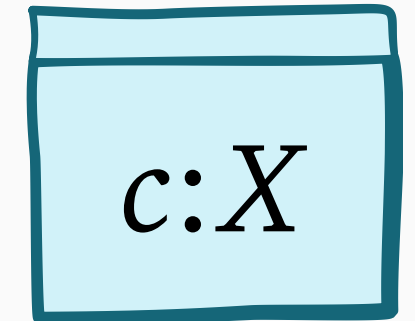


# Modeling cost of information

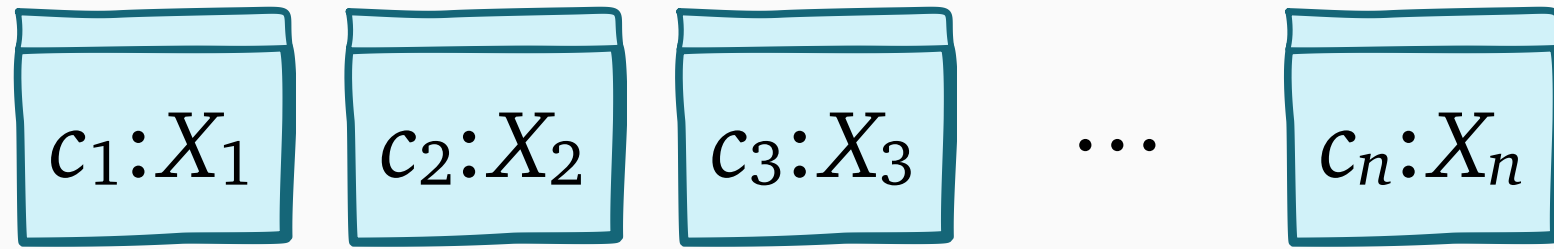


**Pandora's box model:**

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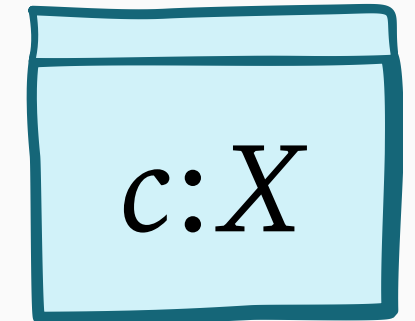


# Modeling cost of information



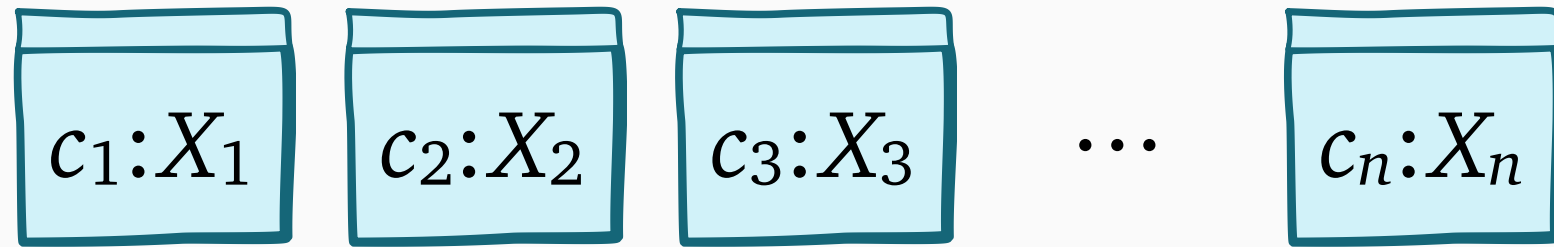
**Pandora's box model:**

- Opening cost  $c$
- Hidden price  $X$



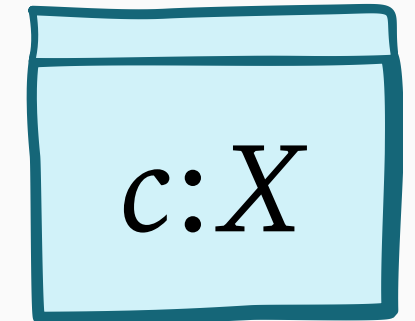
**Classic problem:**

# Modeling cost of information



**Pandora's box model:**

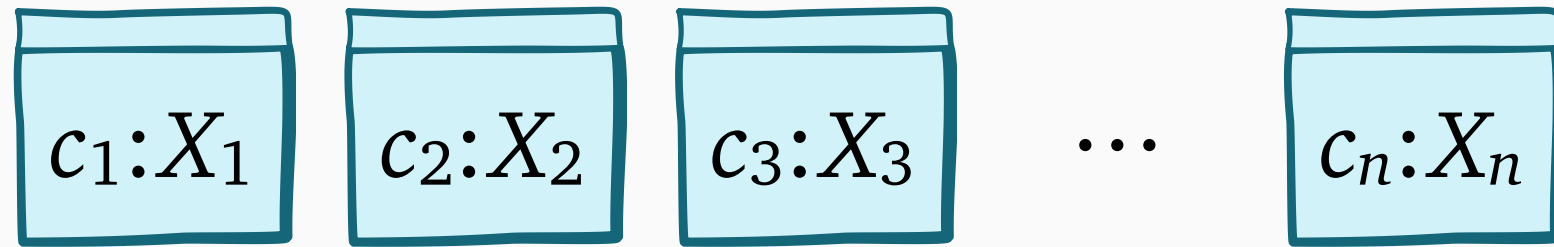
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**Classic problem:**

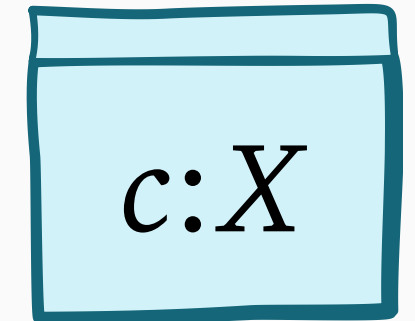
- Open boxes one at a time

# Modeling cost of information



**Pandora's box model:**

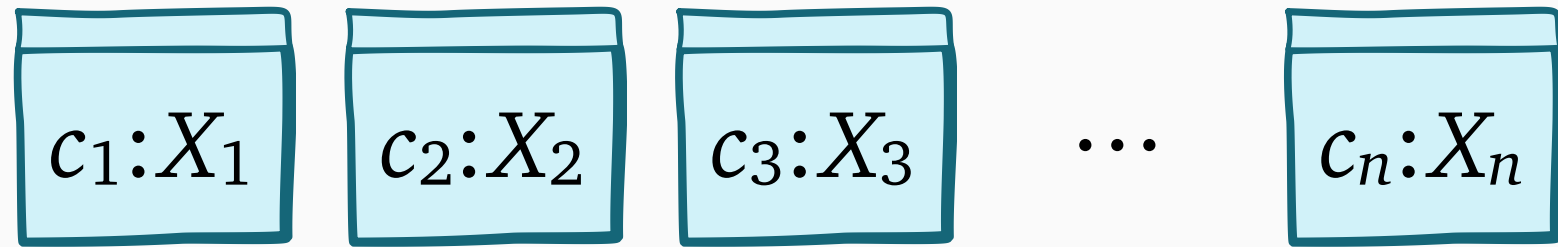
- Opening cost  $c$
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**Classic problem:**

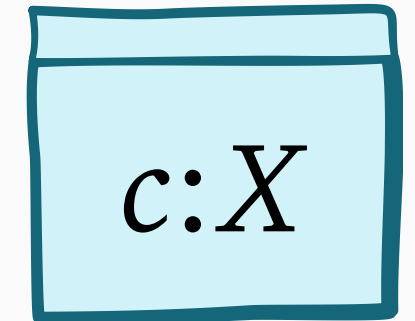
- Open boxes one at a time
- Stop by selecting open box

# Modeling cost of information



**Pandora's box model:**

- Opening cost  $c$
- Hidden price  $X$



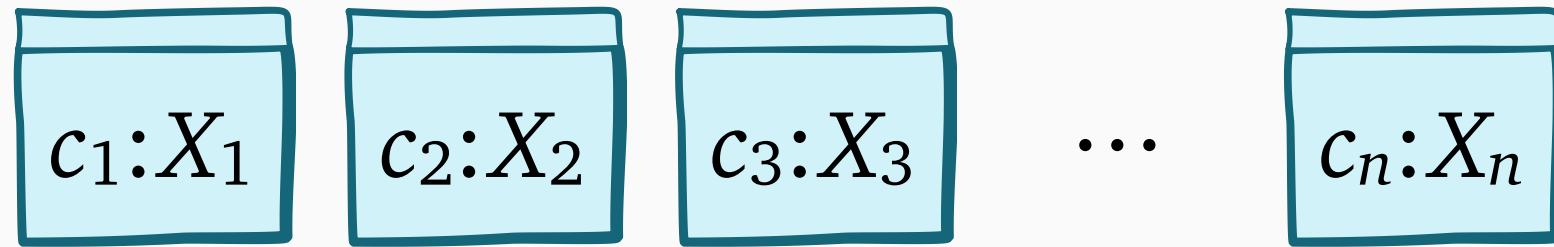
**Classic problem:**

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- Stop by selecting open box

**Goal:** minimize  $\mathbf{E} \left[ \sum_{i \text{ opened}} c_i + \sum_{j \text{ selected}} X_j \right]$

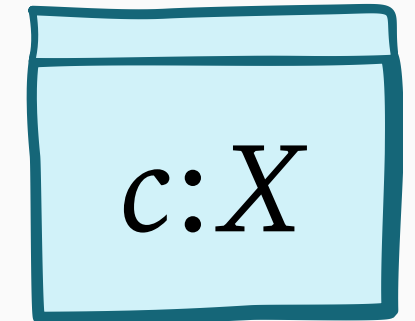


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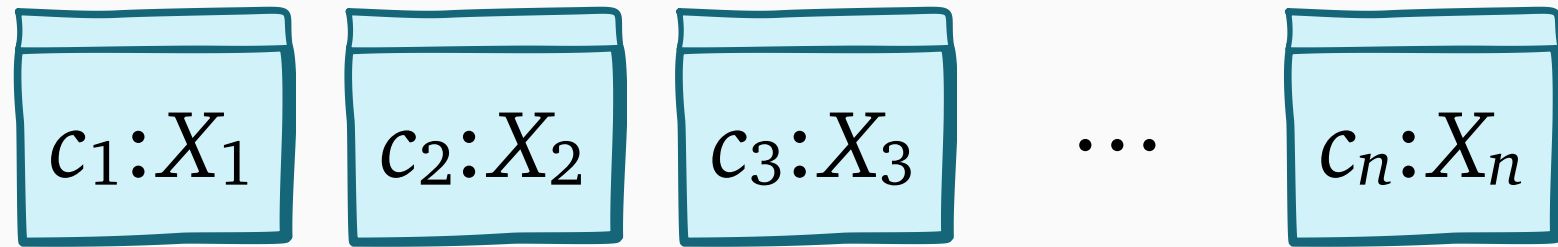
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**Combinatorial problems:**

select *admissible set* of open boxes

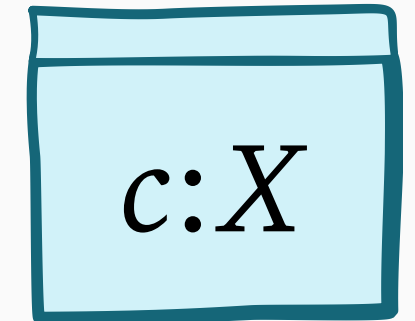
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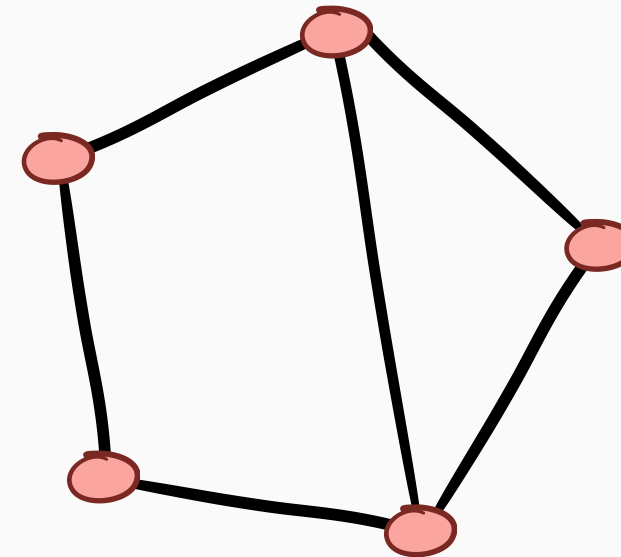
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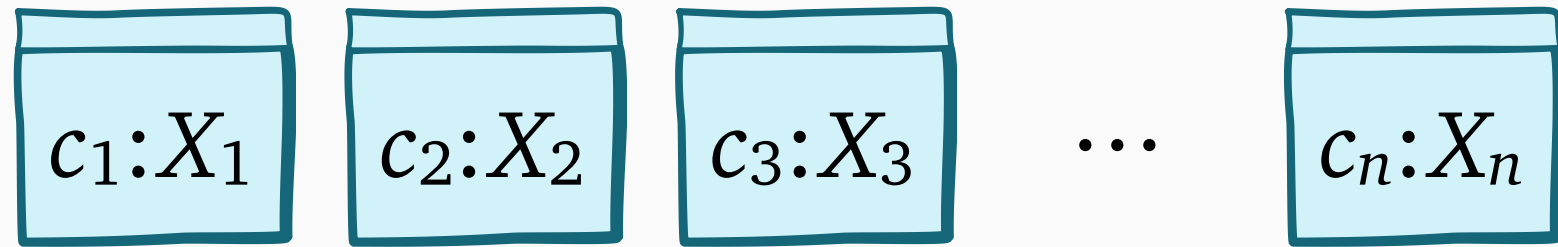
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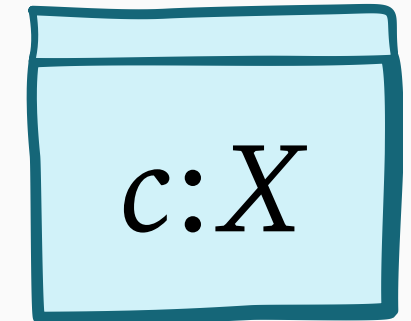
*Example:* build a spanning tree

# Modeling cost of information



**Pandora's box model:**

- Opening cost  $c$
- Hidden price  $X$



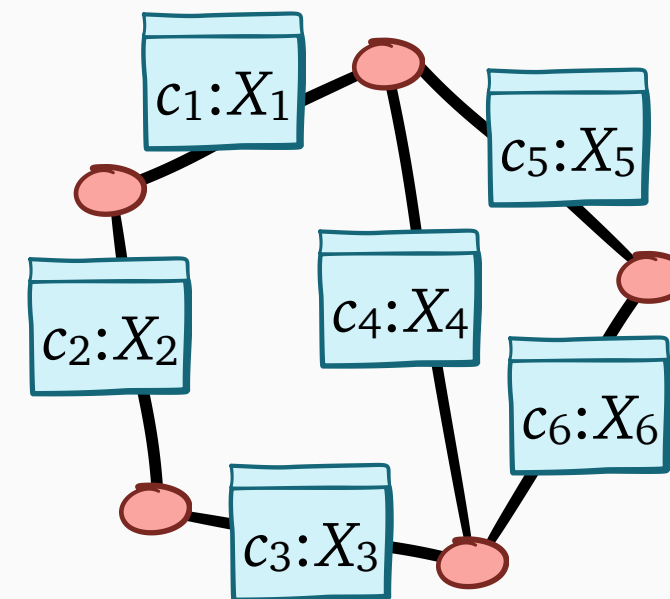
**Classic problem:**

- Open boxes one at a time
- Stop by selecting open box

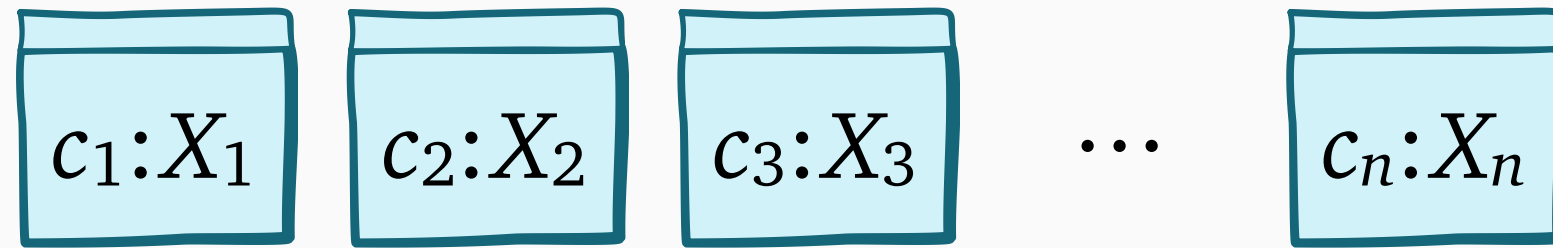
**Goal:** minimize  $\mathbf{E} \left[ \sum_{i \text{ opened}} c_i + \sum_{j \text{ selected}} X_j \right]$

**Combinatorial problems:**

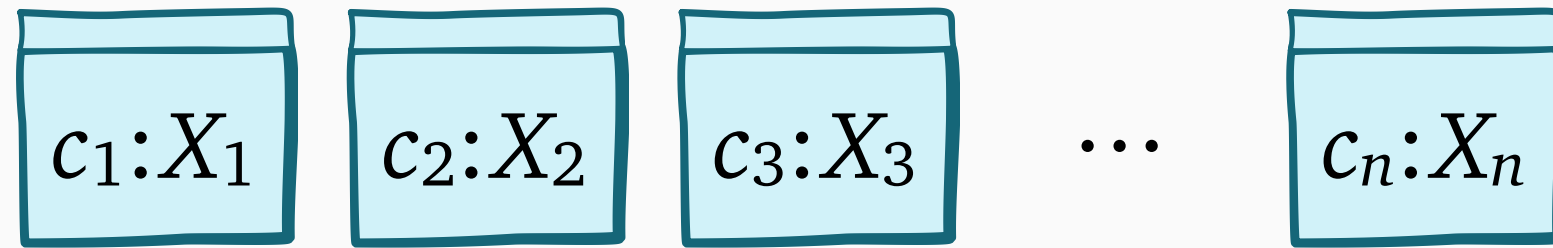
select *admissible set* of open boxes



*Example:* build a spanning tree



**Goal:** minimize  $\mathbf{E} \left[ \sum_{i \text{ opened}} c_i + \sum_{j \text{ selected}} X_j \right]$

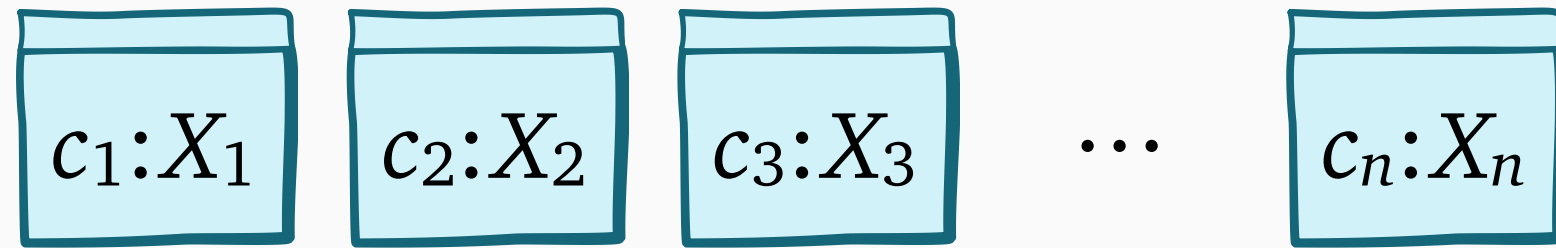


**Goal:** minimize  $\mathbf{E} \left[ \sum_{i \text{ opened}} c_i + \sum_{j \text{ selected}} X_j \right]$



## Multifaceted decision

Should we stop? If not, which box should we open?



**Goal:** minimize  $\mathbf{E} \left[ \sum_{i \text{ opened}} c_i + \sum_{j \text{ selected}} X_j \right]$



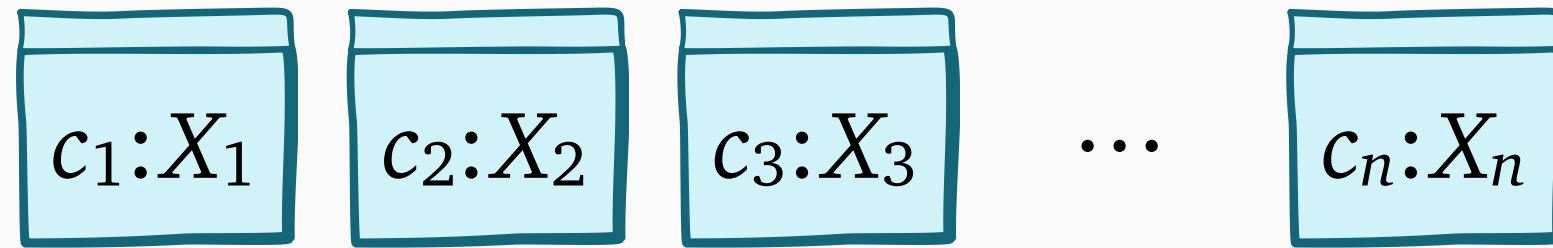
## Multifaceted decision

Should we stop? If not, which box should we open?



## Large state space

Grows exponentially with number of boxes  $n$



**Goal:** minimize  $\mathbf{E} \left[ \sum_{i \text{ opened}} c_i + \sum_{j \text{ selected}} X_j \right]$



## Multifaceted decision

Should we stop? If not, which box should we open?



## Large state space

Grows exponentially with number of boxes  $n$



## Combinatorial constraints

Can make problem hard even without uncertainty

# Decomposition for Pandora's box

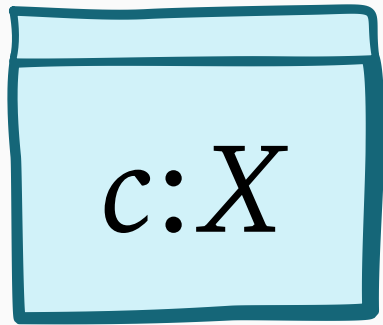
**Step 1:** *rate* each box separately

**Step 2:** *act* on box of best rating



# Decomposition for Pandora's box

**Step 1:** *rate* each box separately



**Step 2:** *act* on box of best rating

# Decomposition for Pandora's box

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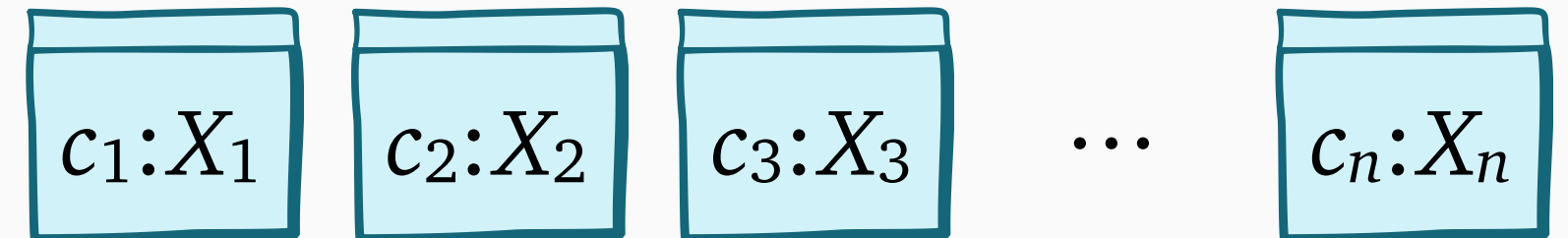
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# Decomposition for Pandora's box

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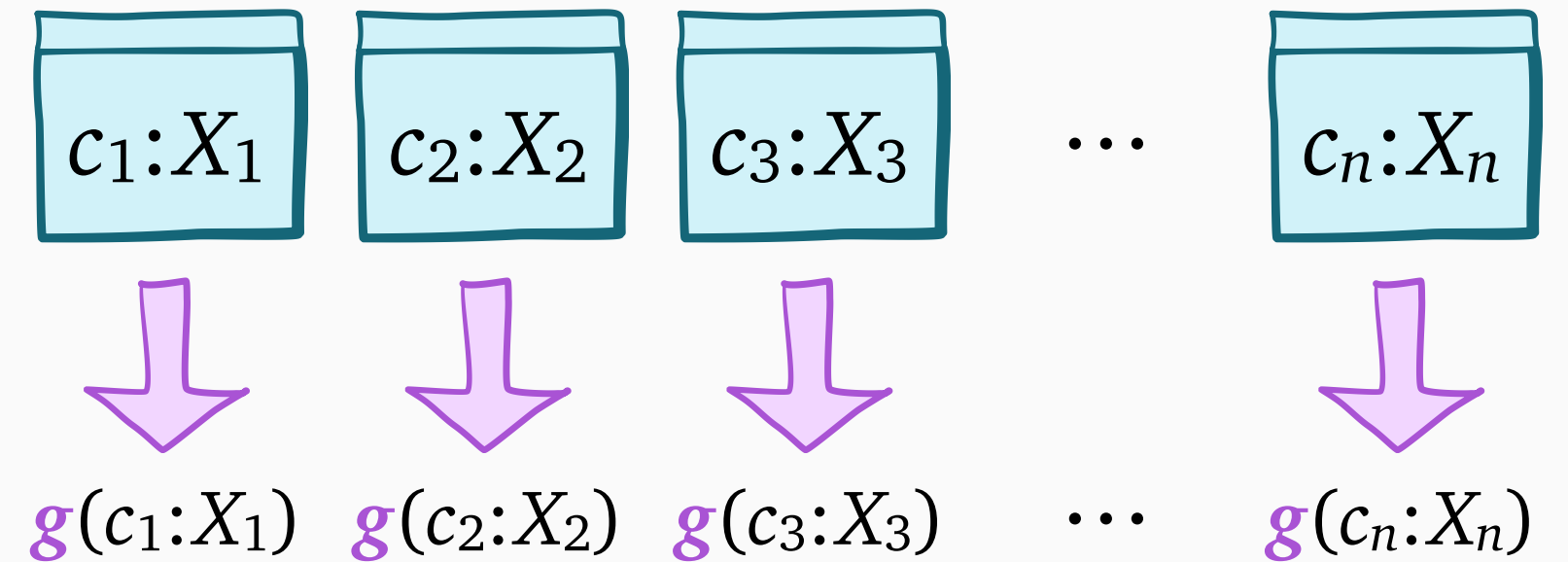


# Decomposition for Pandora's box

**Step 1:** *rate* each box separately



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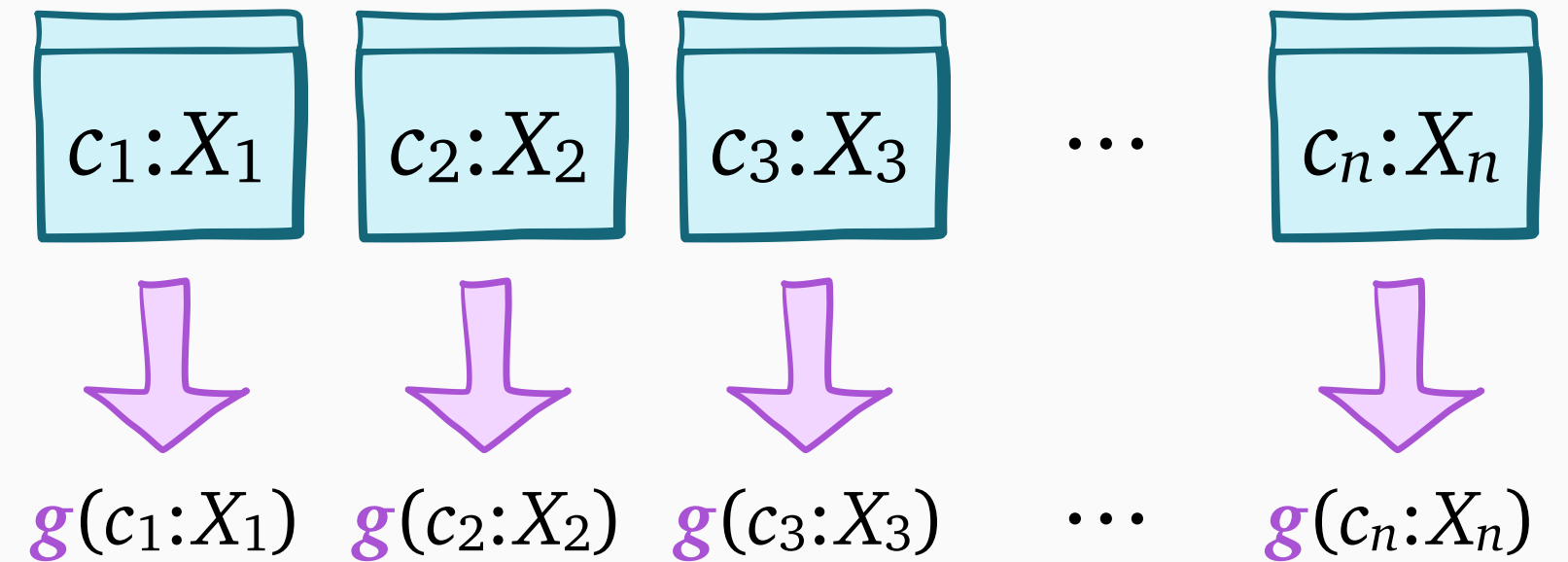


# Decomposition for Pandora's box

**Step 1:** *rate* each box separately



**Step 2:** *act* on box of best rating



**Gittins policy:** if box of least **Gittins** index is...

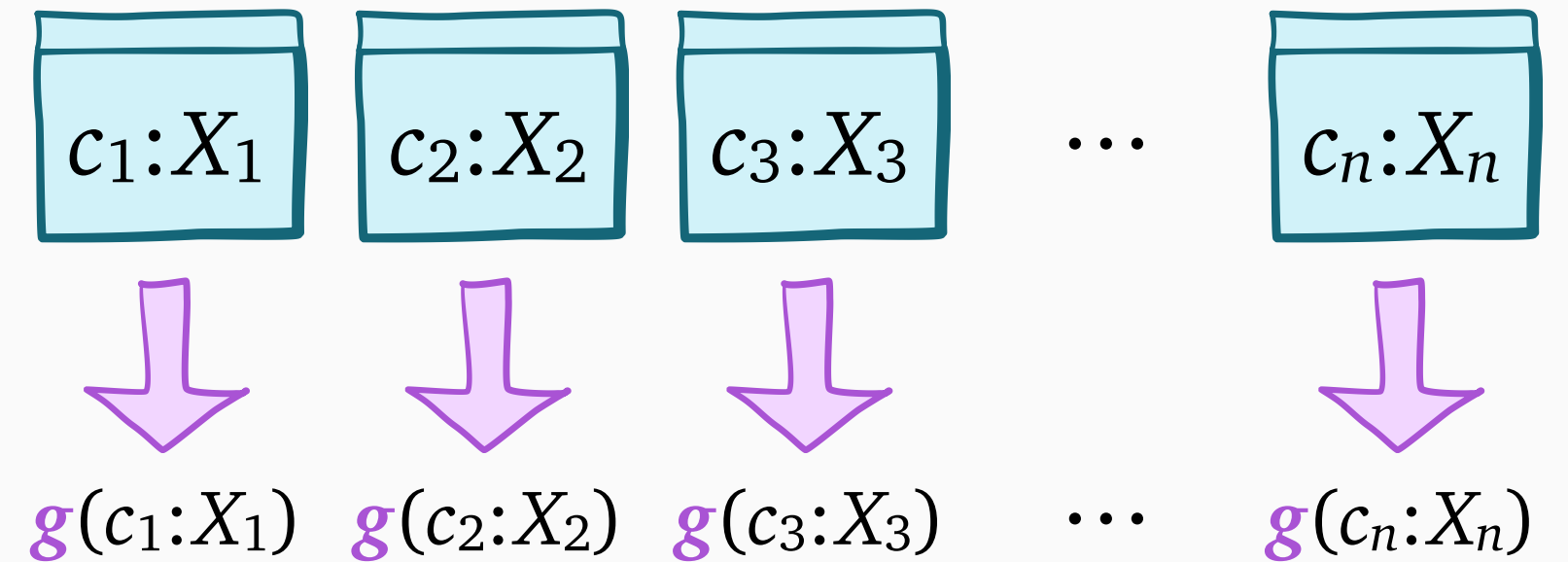
- *closed*: open it
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# Decomposition for Pandora's box

**Step 1:** *rate* each box separately



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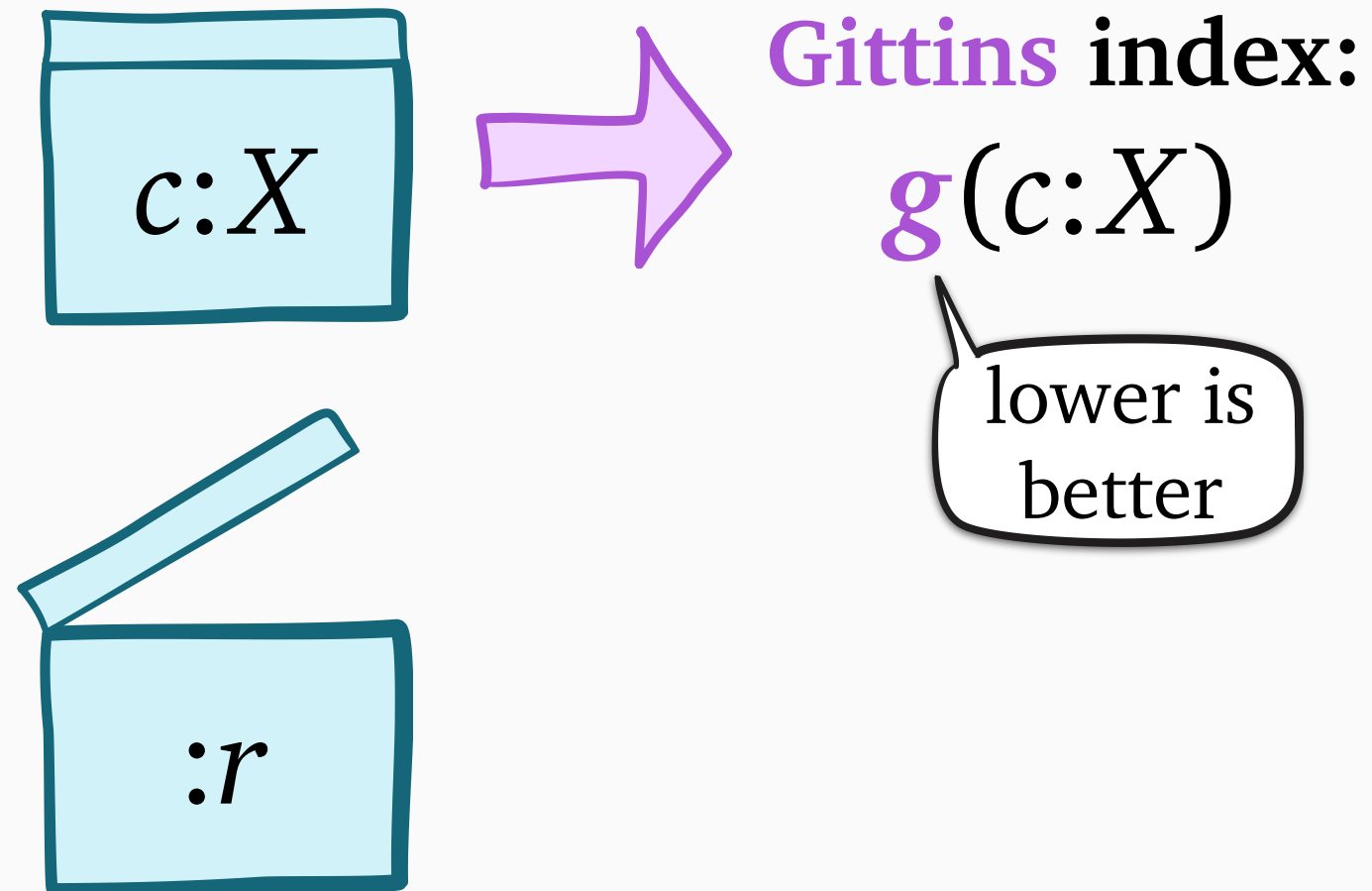


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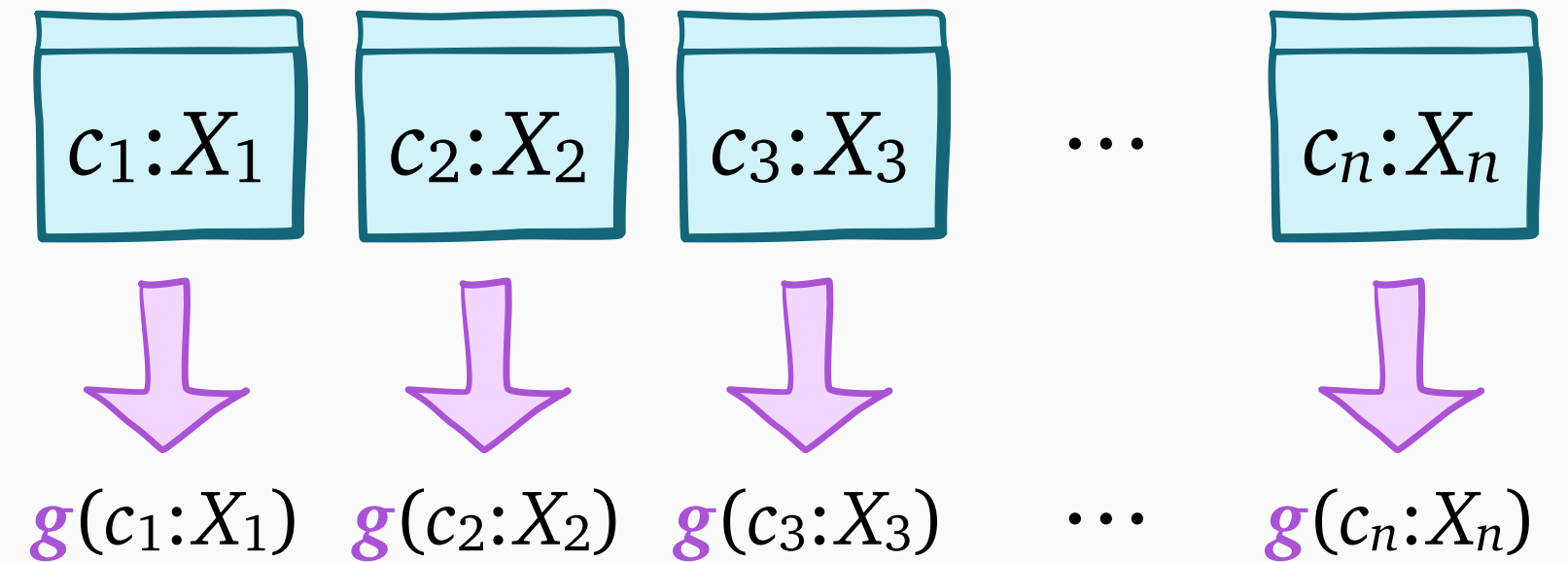
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**Step 1:** *rate* each box separately



**Step 2:** *act* on box of best rating



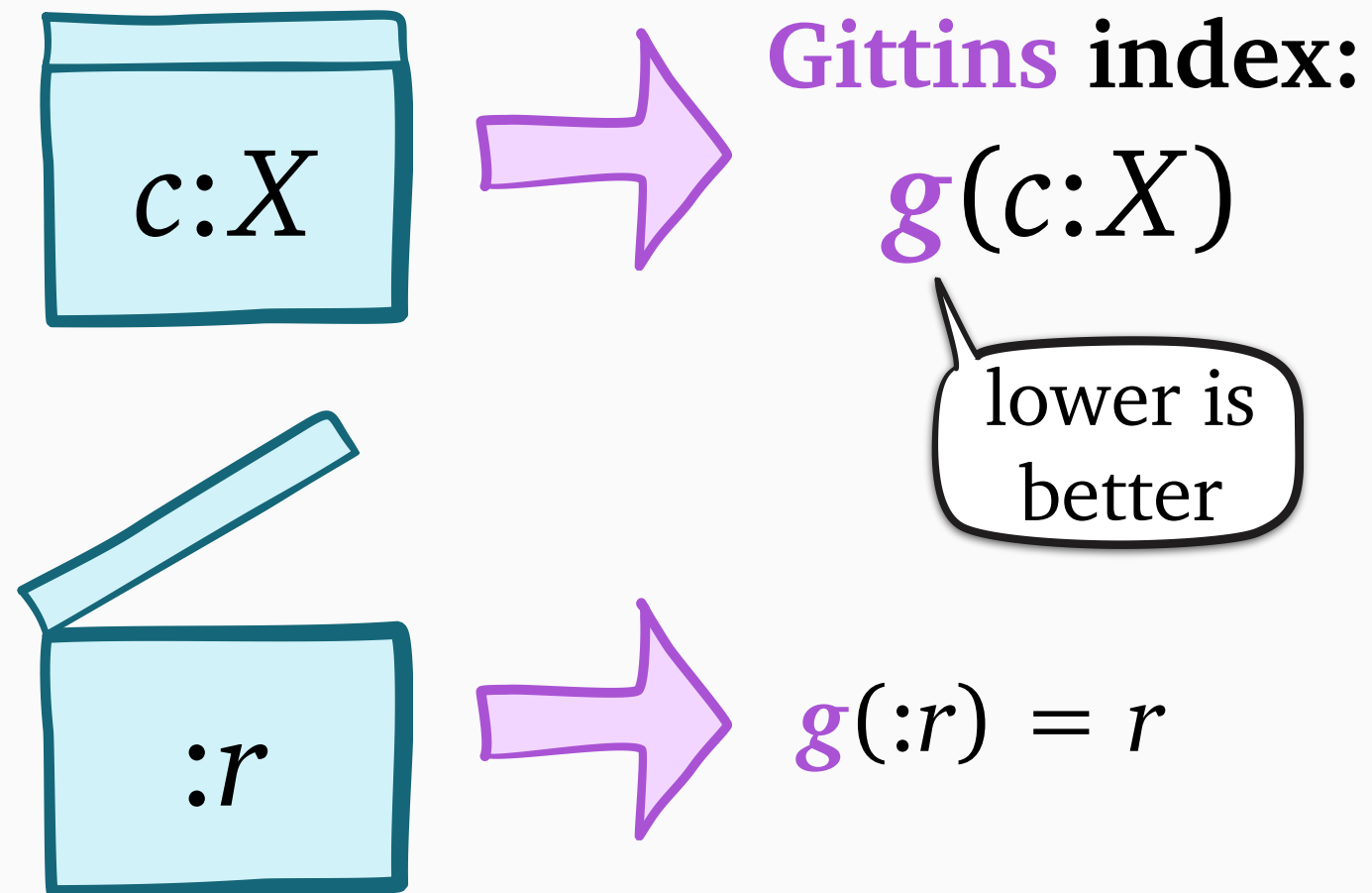
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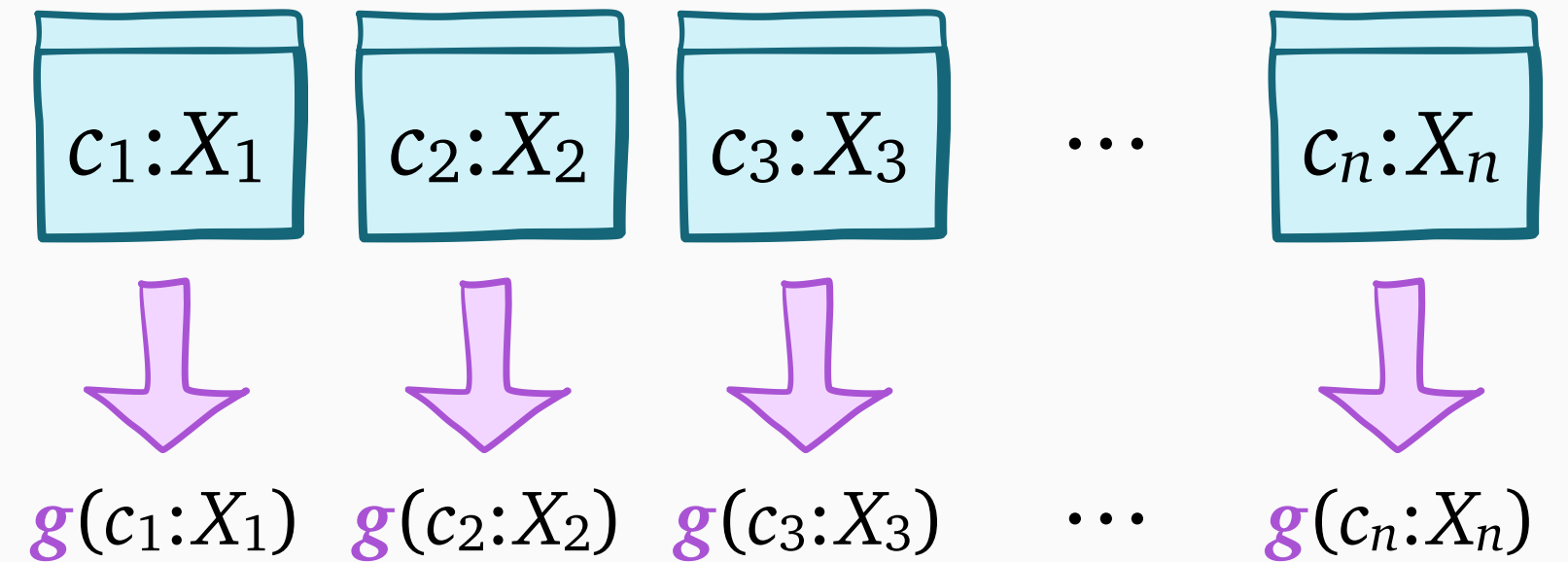


# Decomposition for Pandora's box

Step 1: *rate* each box separately



Step 2: *act* on box of best rating

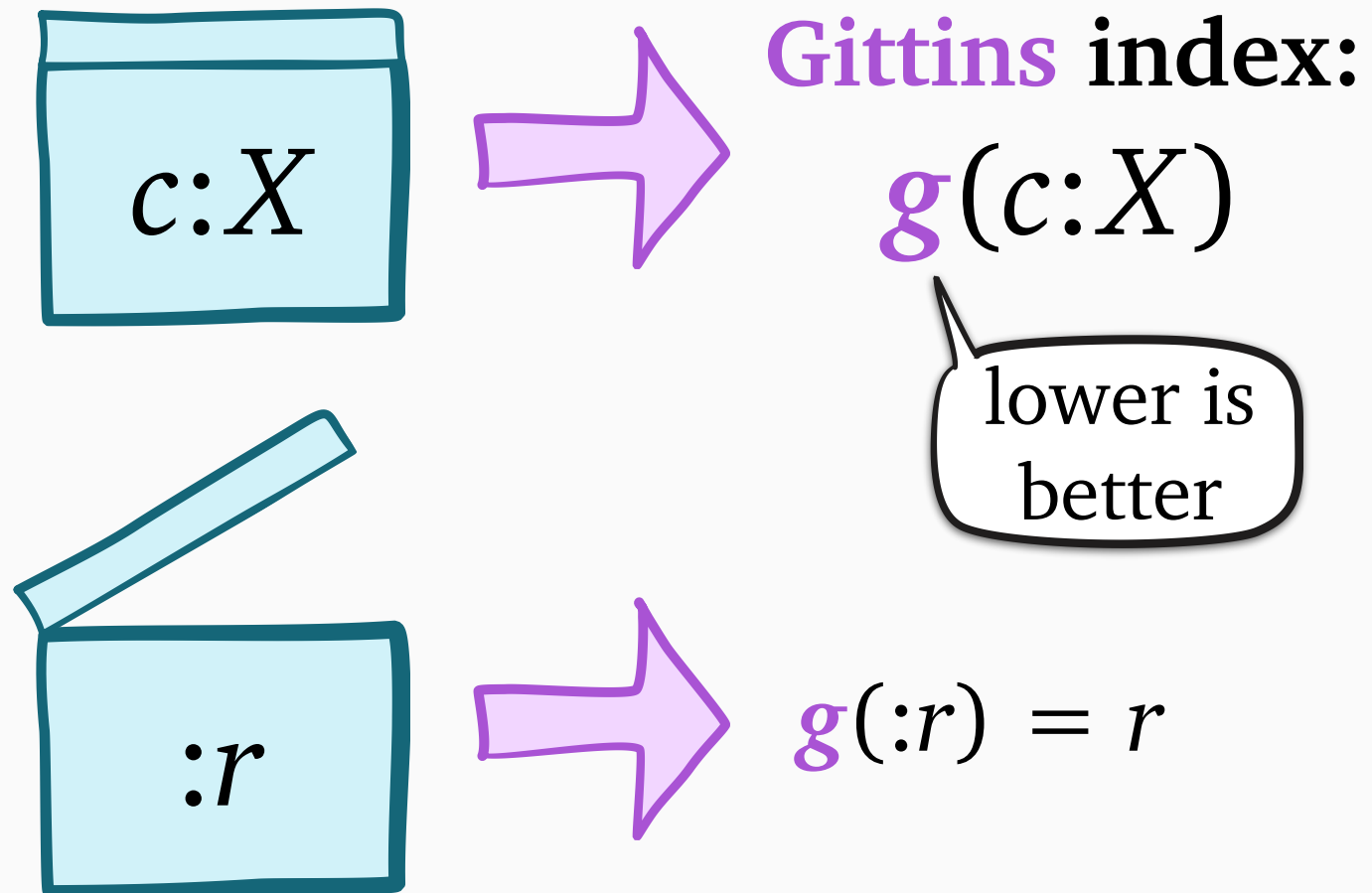


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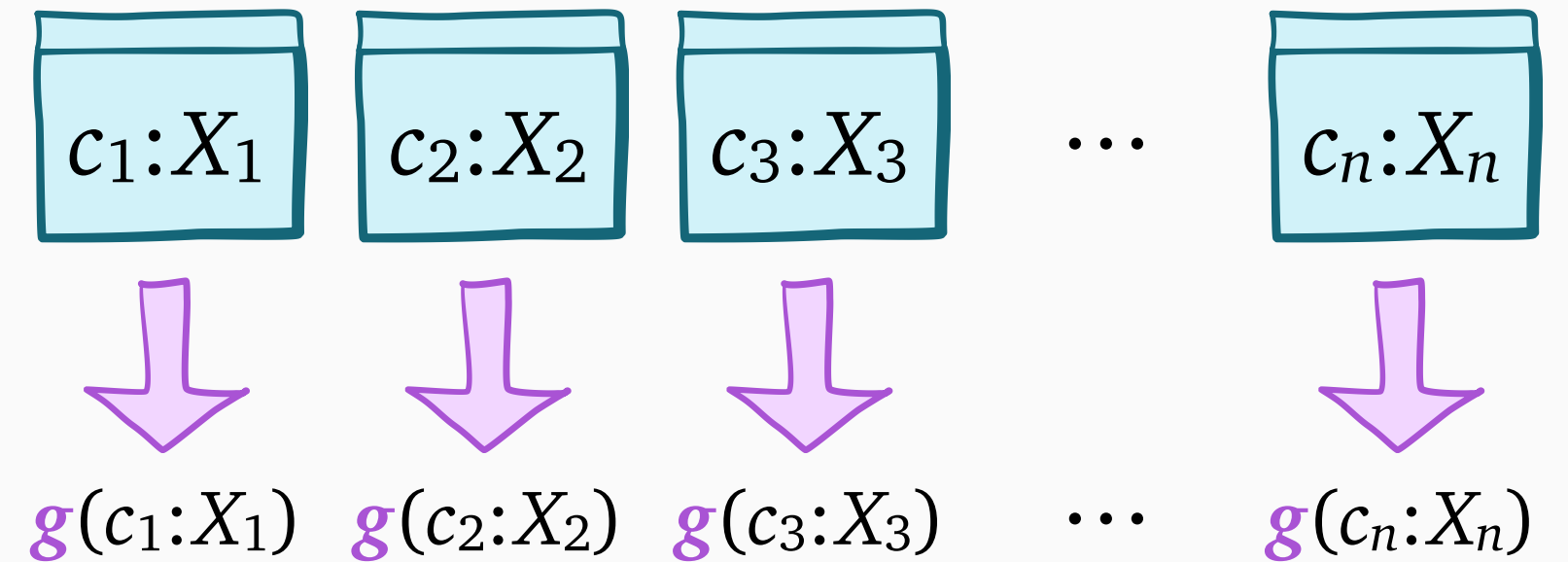
# Decomposition for Pandora's box

**Step 1:** *rate* each box separately



**Theorem** [Weitzman, 1979]:  
the **Gittins** policy is optimal

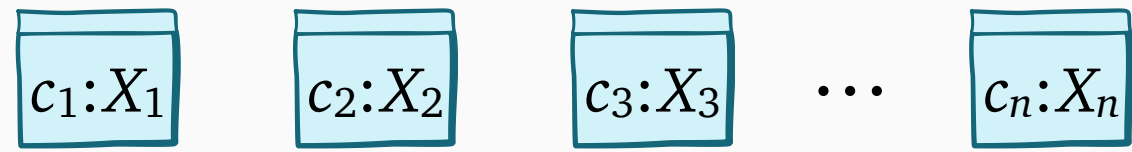
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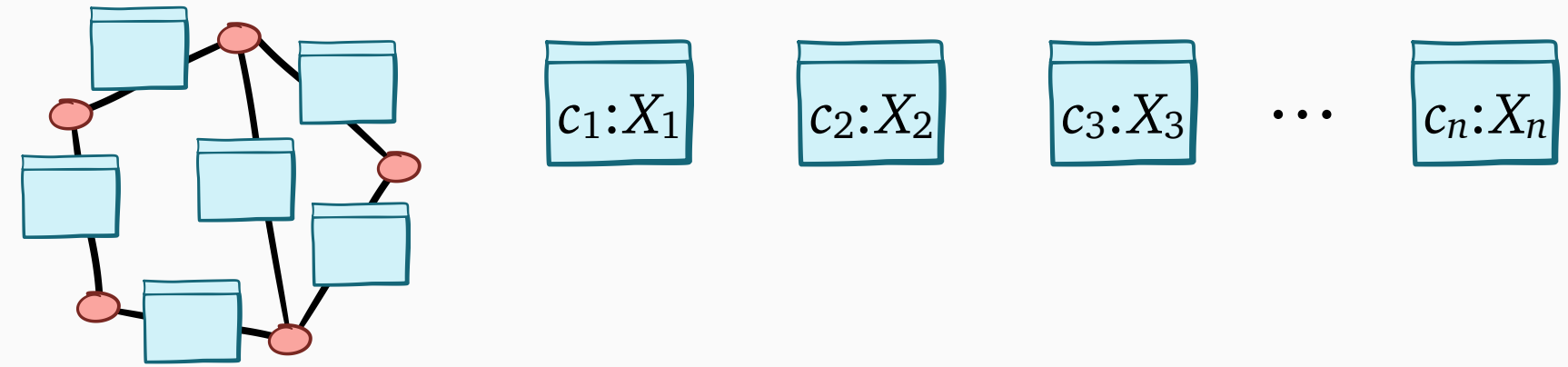
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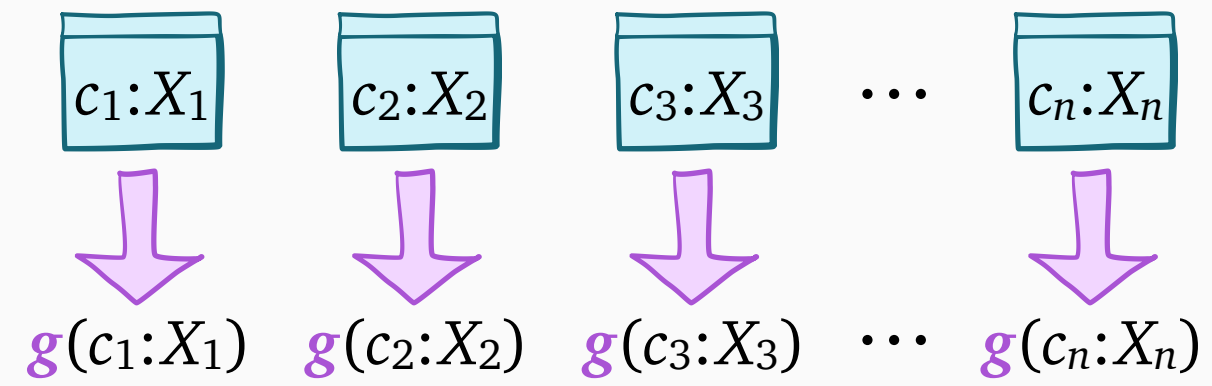
# Classic problem



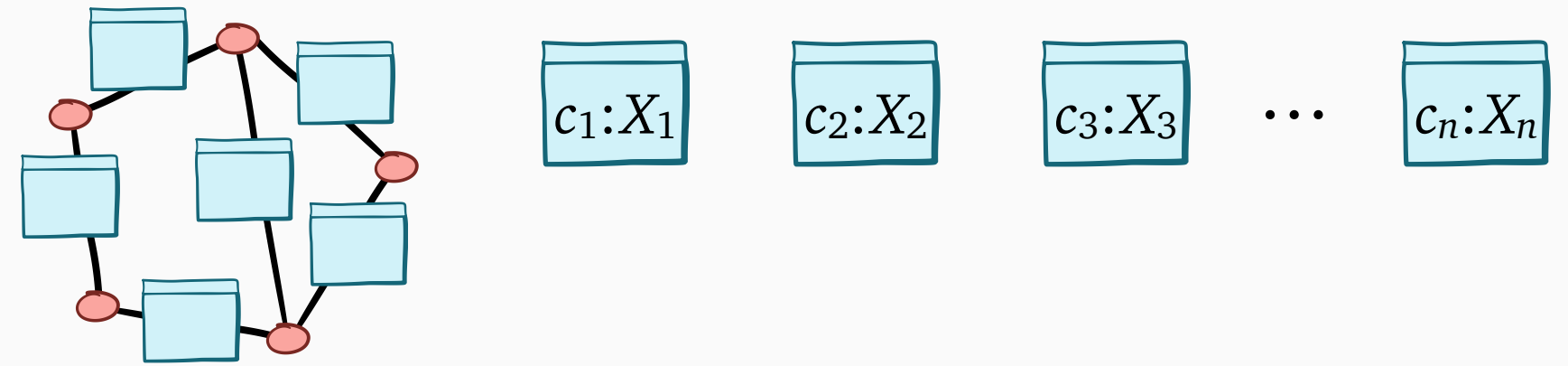
# Combinatorial problems



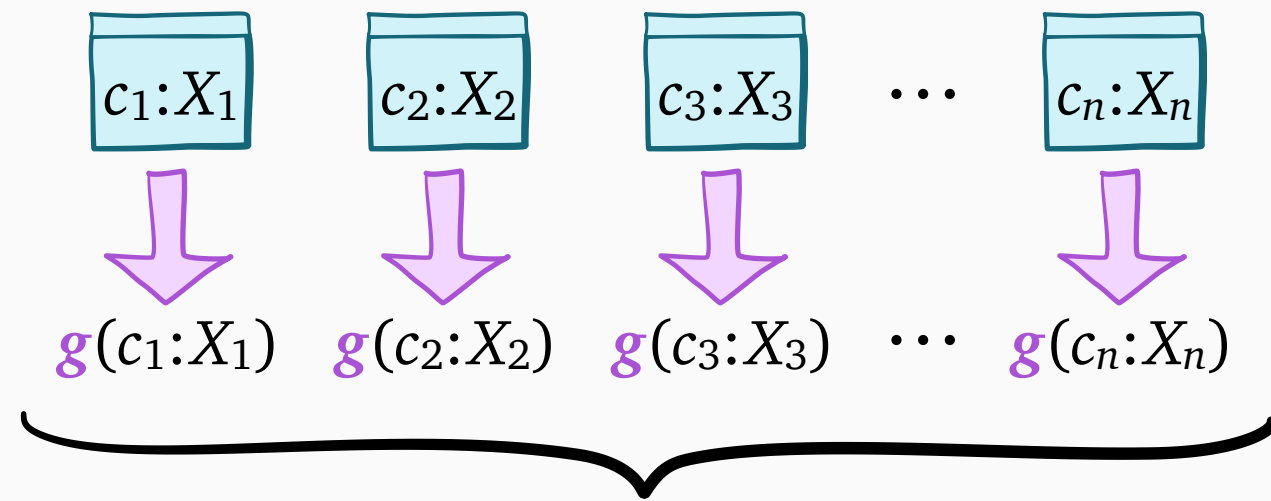
# Classic problem



# Combinatorial problems

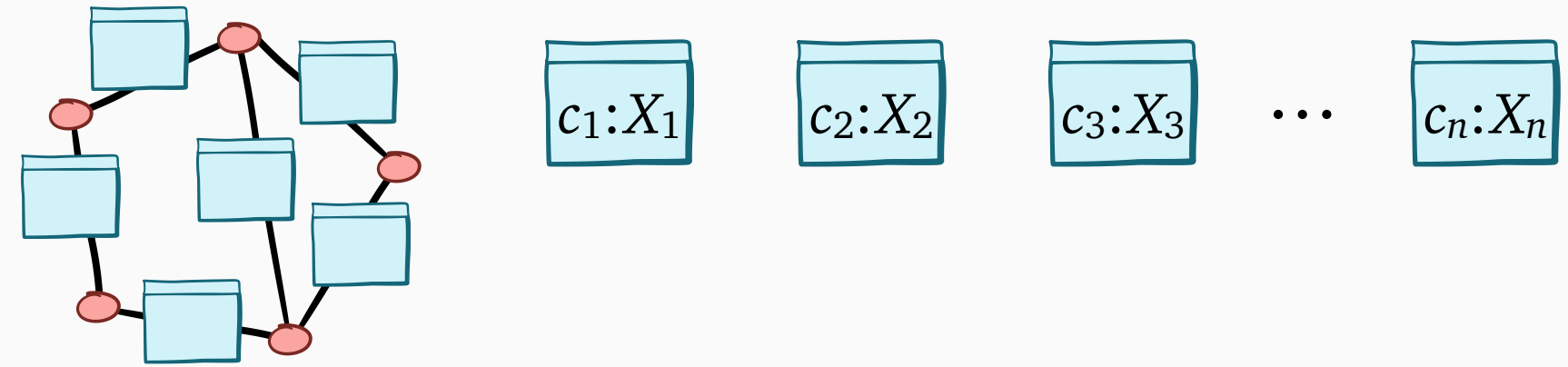


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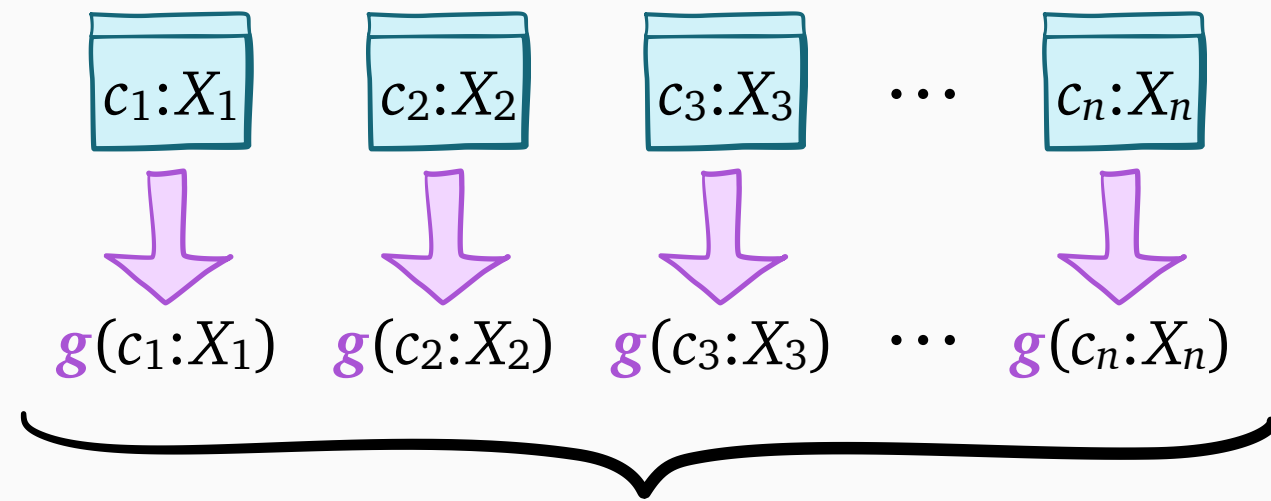


**Deterministic algorithm:**  
pick smallest number

# Combinatorial problems

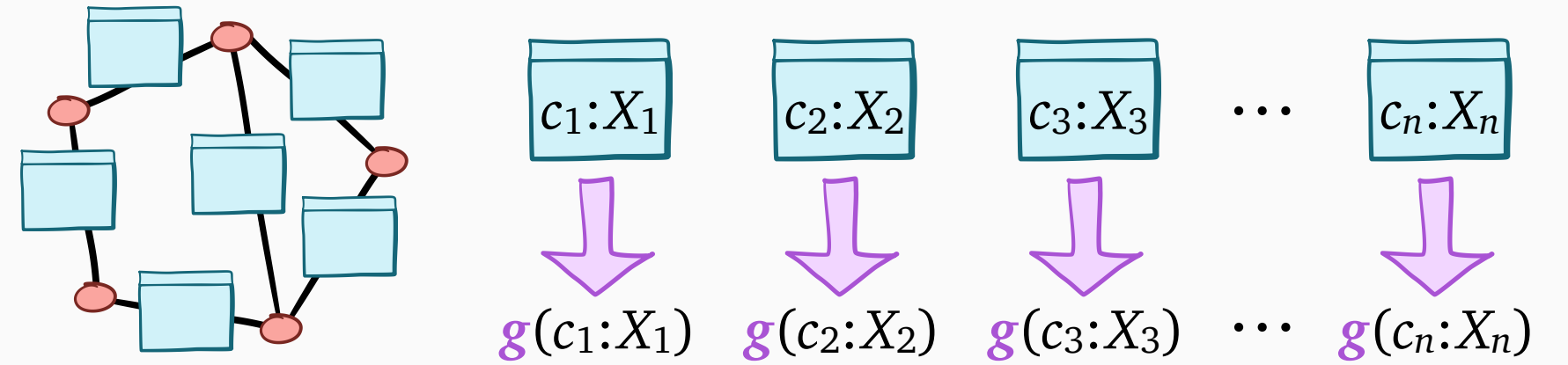


# Classic problem

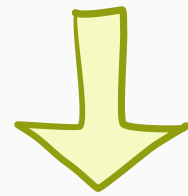
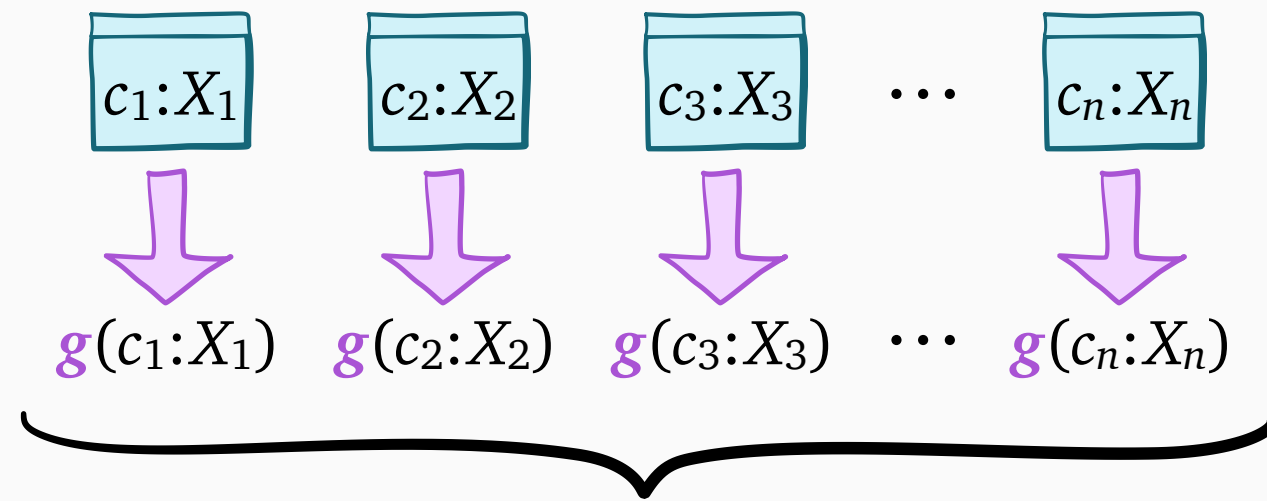


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# Combinatorial problems

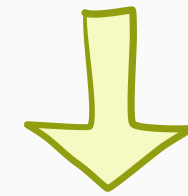
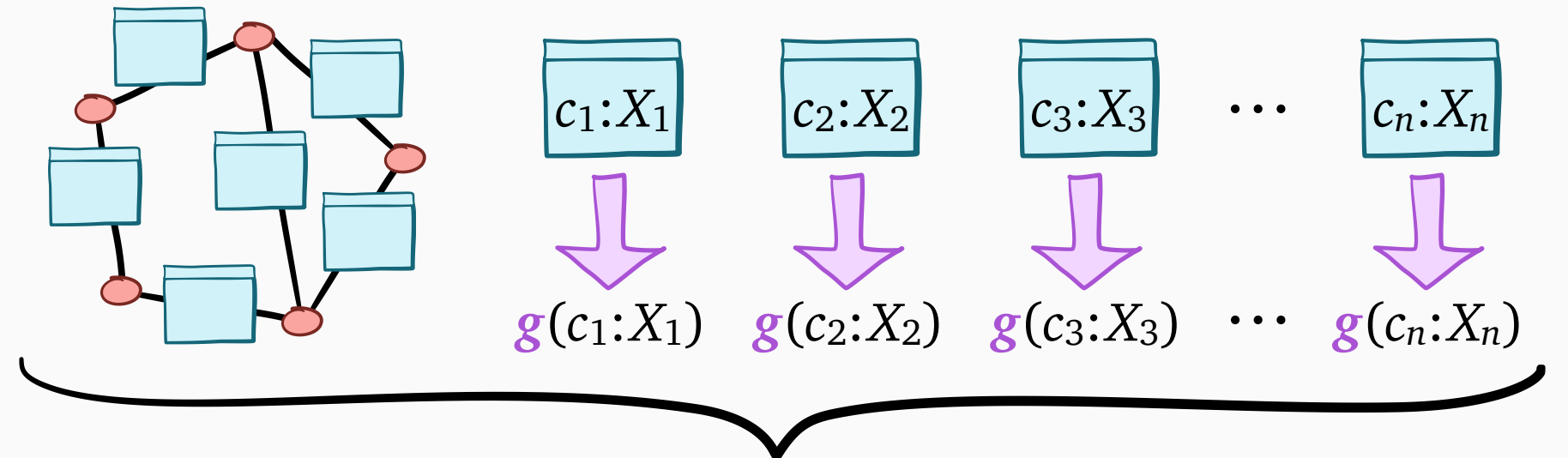


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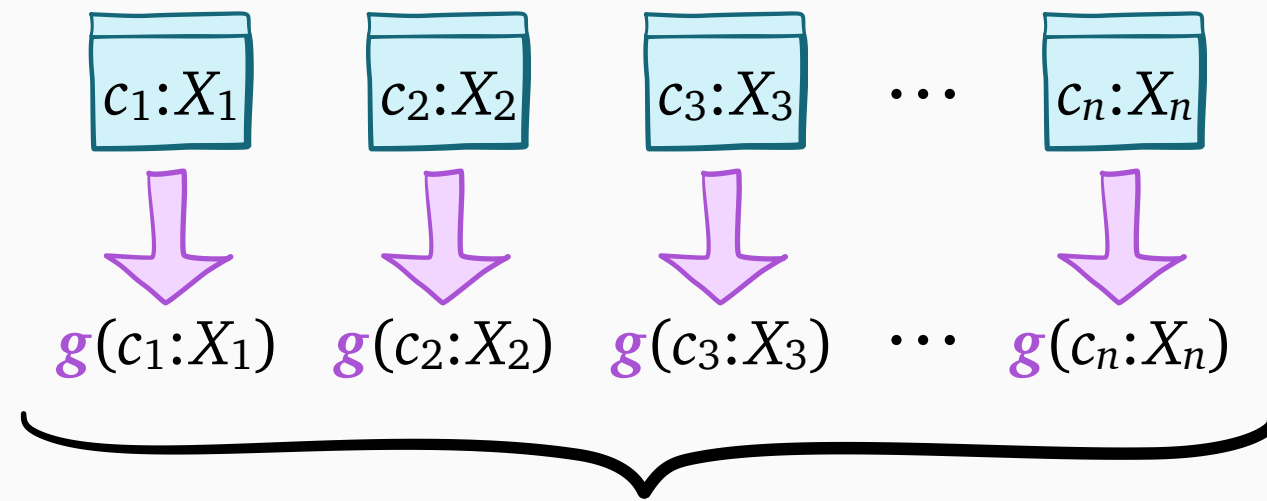
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# Combinatorial problems



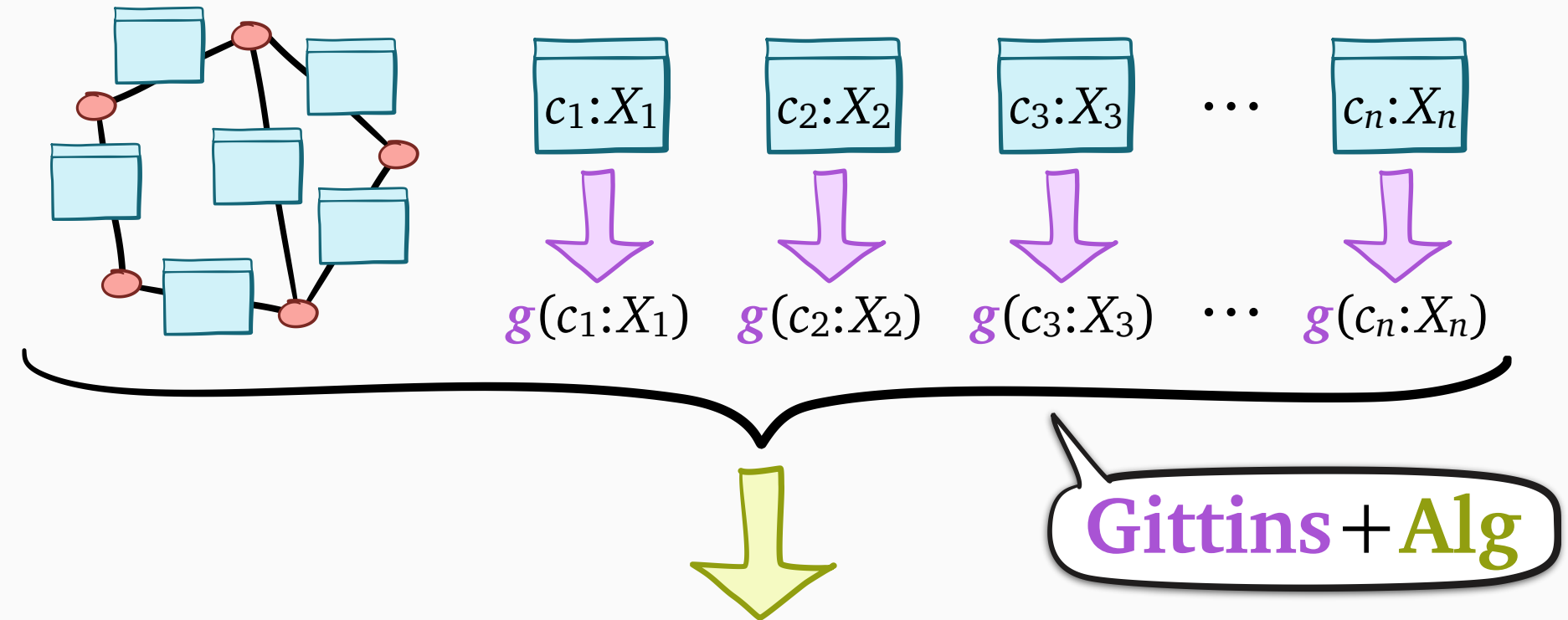
**Deterministic algorithm:**  
“greedy” algorithm **Alg**

# Classic problem



**Deterministic algorithm:**  
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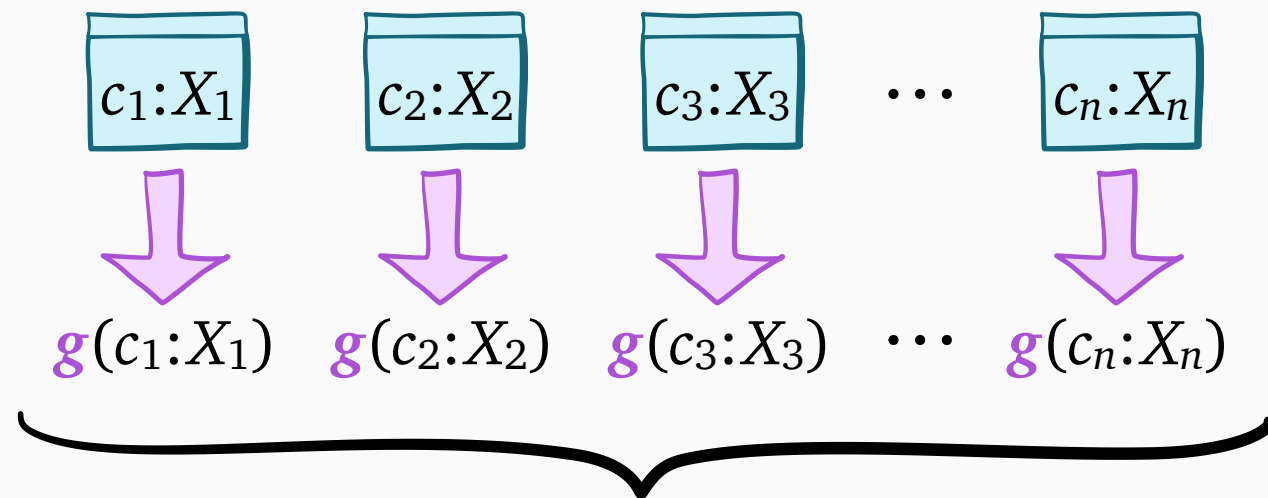
# Combinatorial problems



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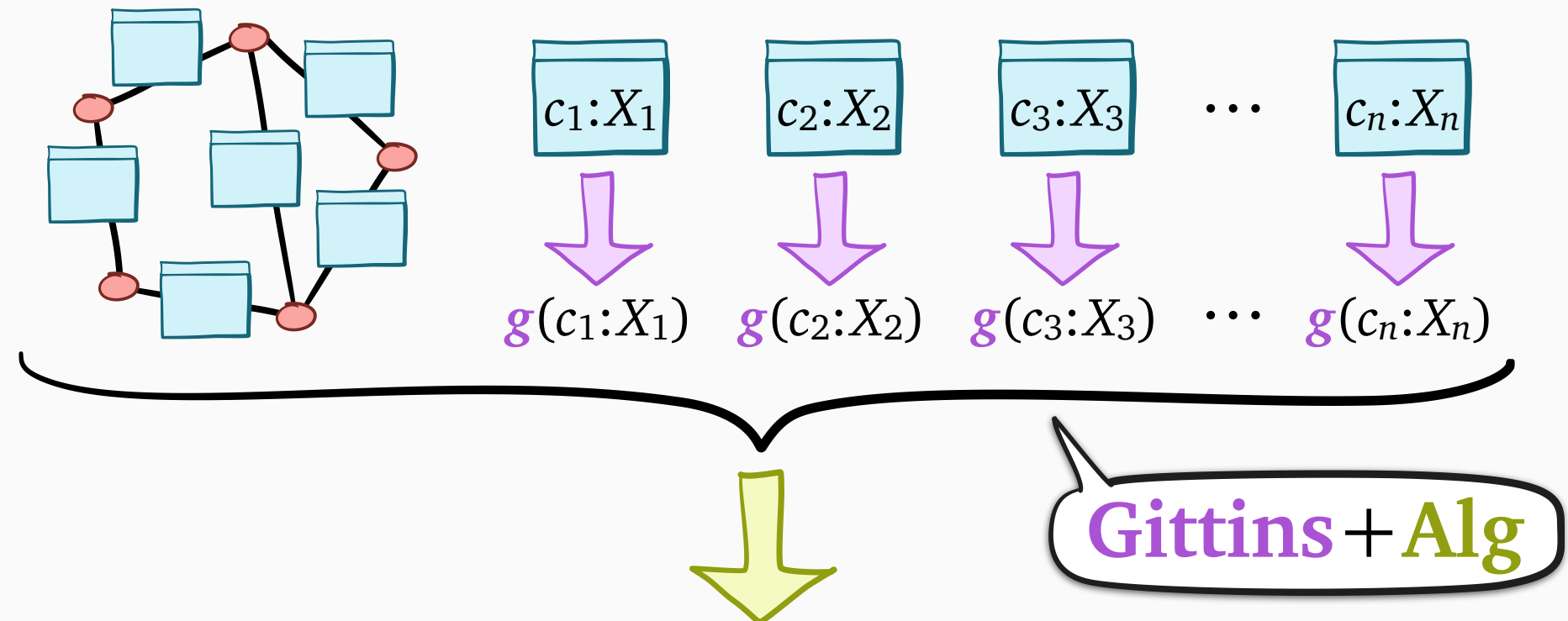


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**Deterministic algorithm:**  
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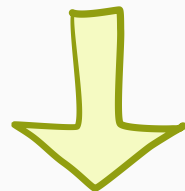
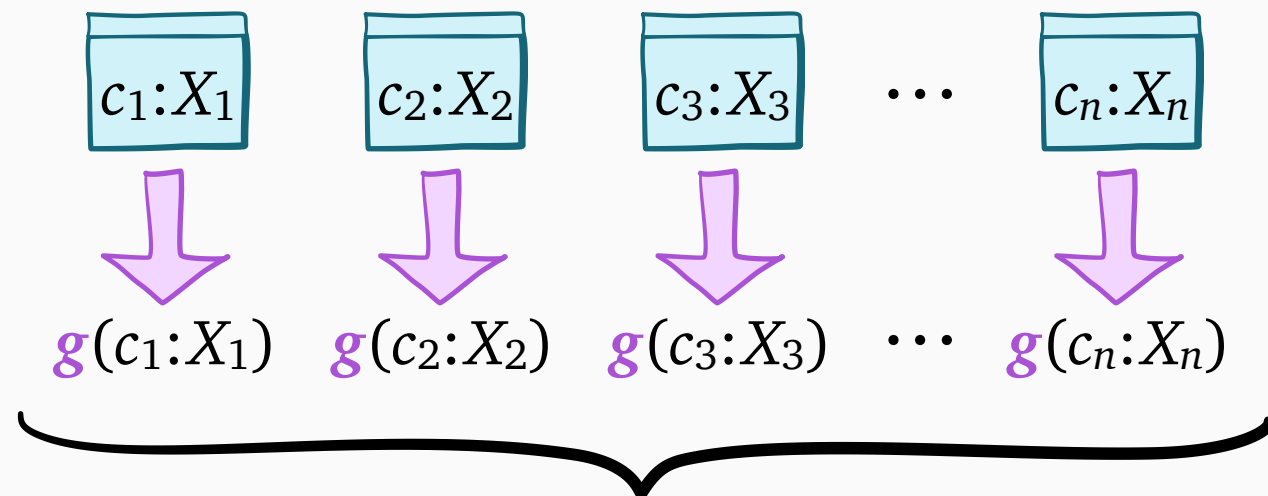
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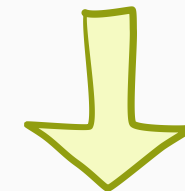
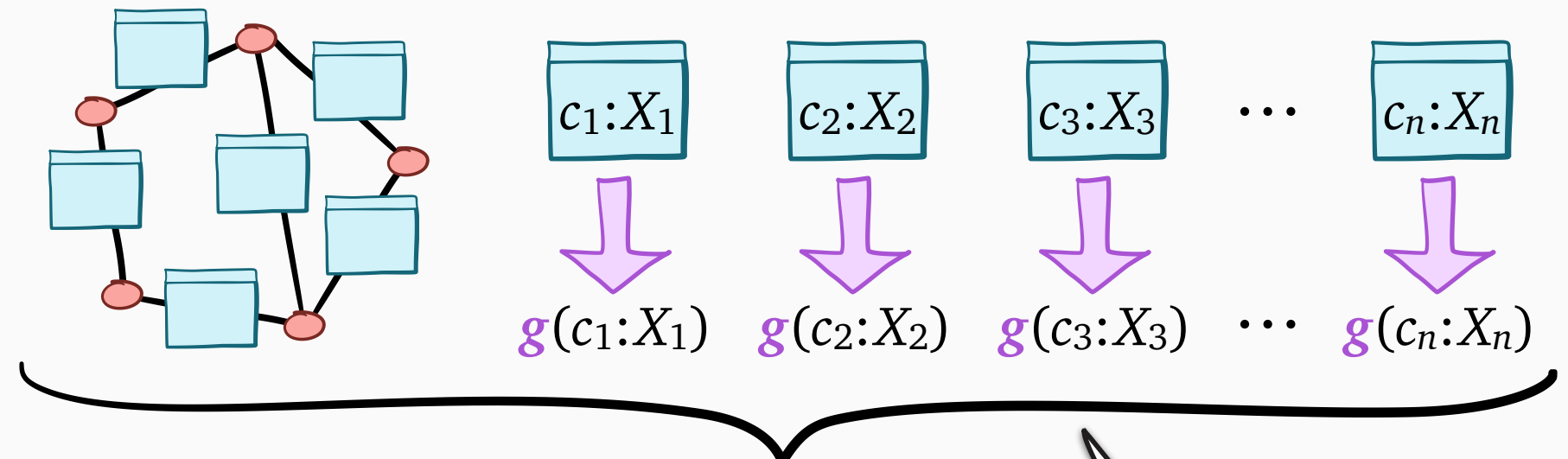
**Theorem** [Singla, 2018]: if **Alg** is a “greedy” algorithm, then **Gittins + Alg** and **Alg** have the same approximation ratio

# Classic problem



**Deterministic algorithm:**  
pick smallest number

# Combinatorial problems



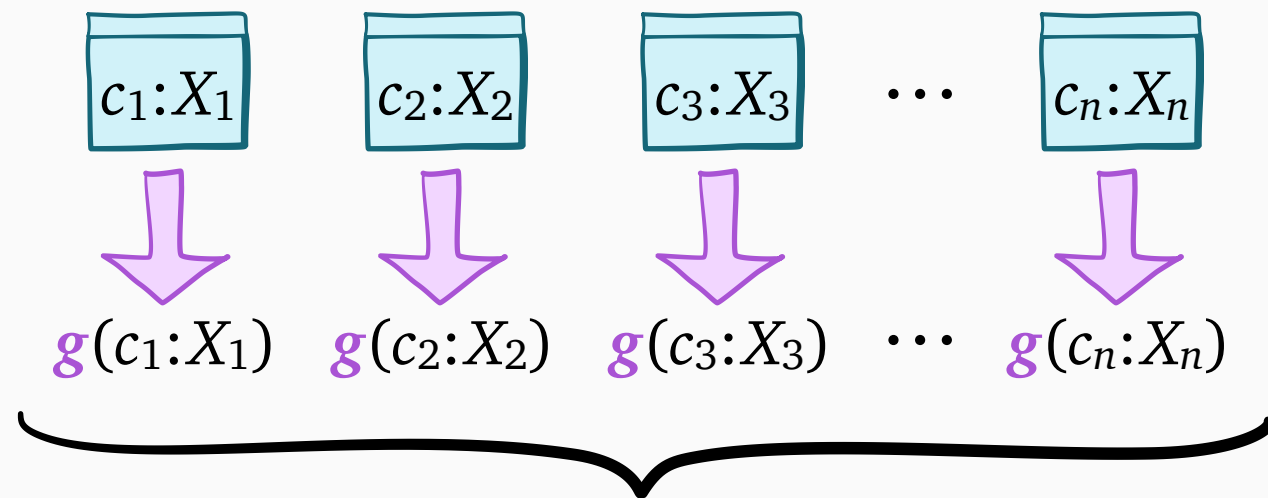
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**Gittins + Alg**

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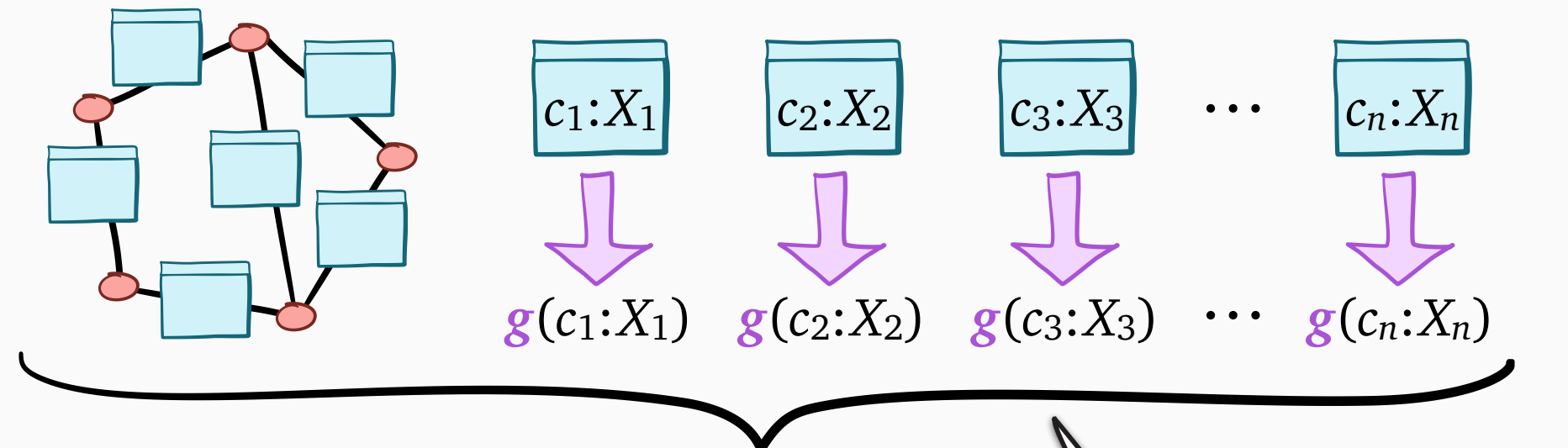
deterministic

# Classic problem



**Deterministic algorithm:**  
pick smallest number

# Combinatorial problems



**Gittins + Alg**

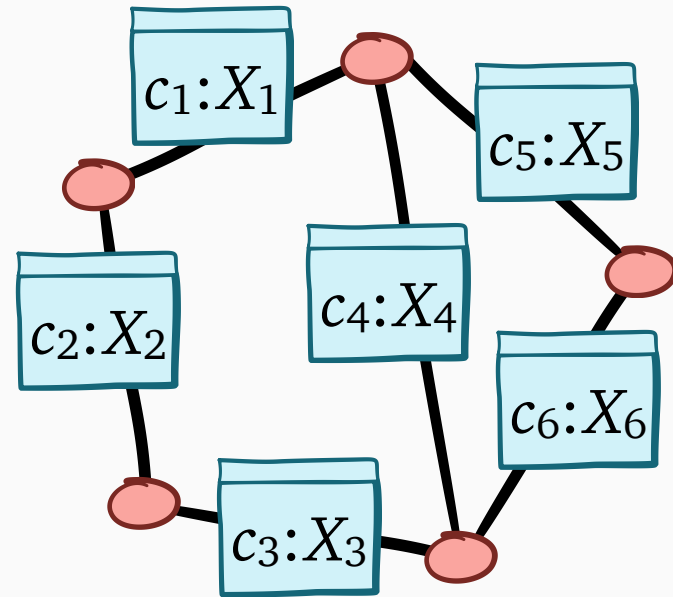
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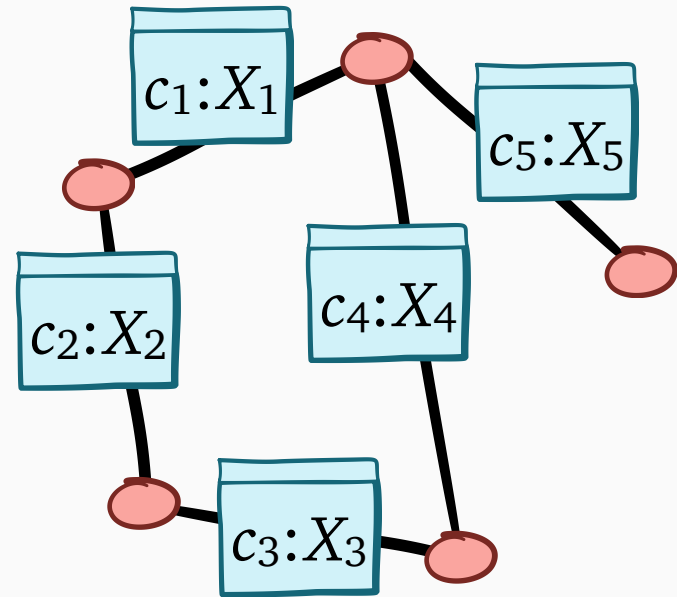
Pandora’s box

deterministic

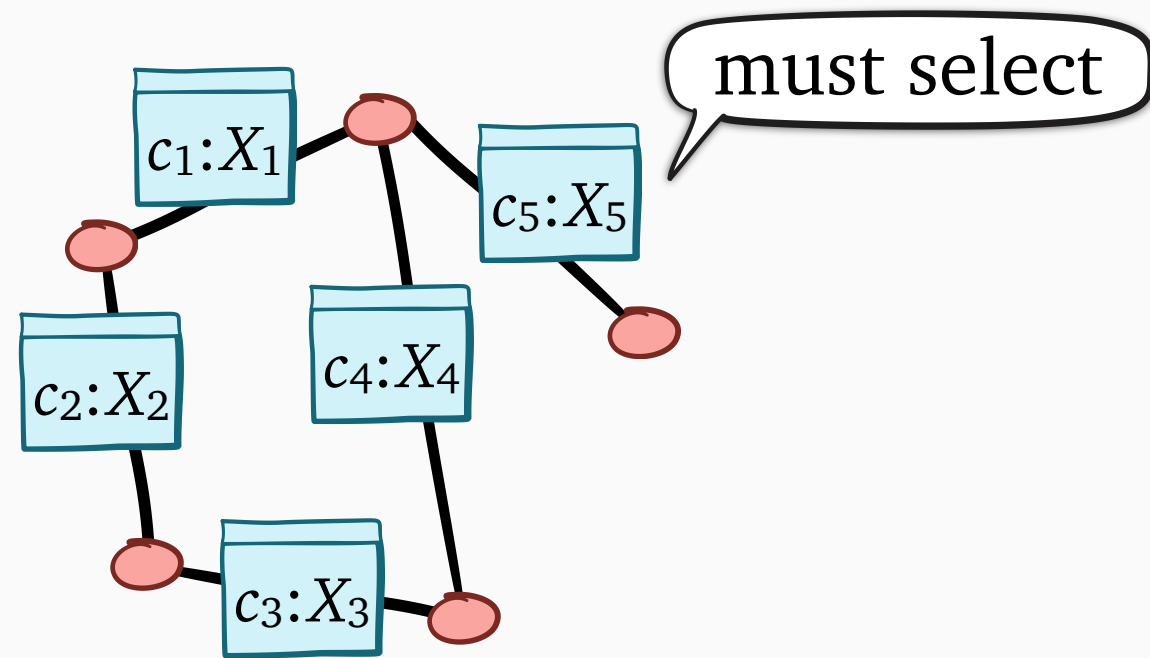
*Example:*  
build a spanning tree



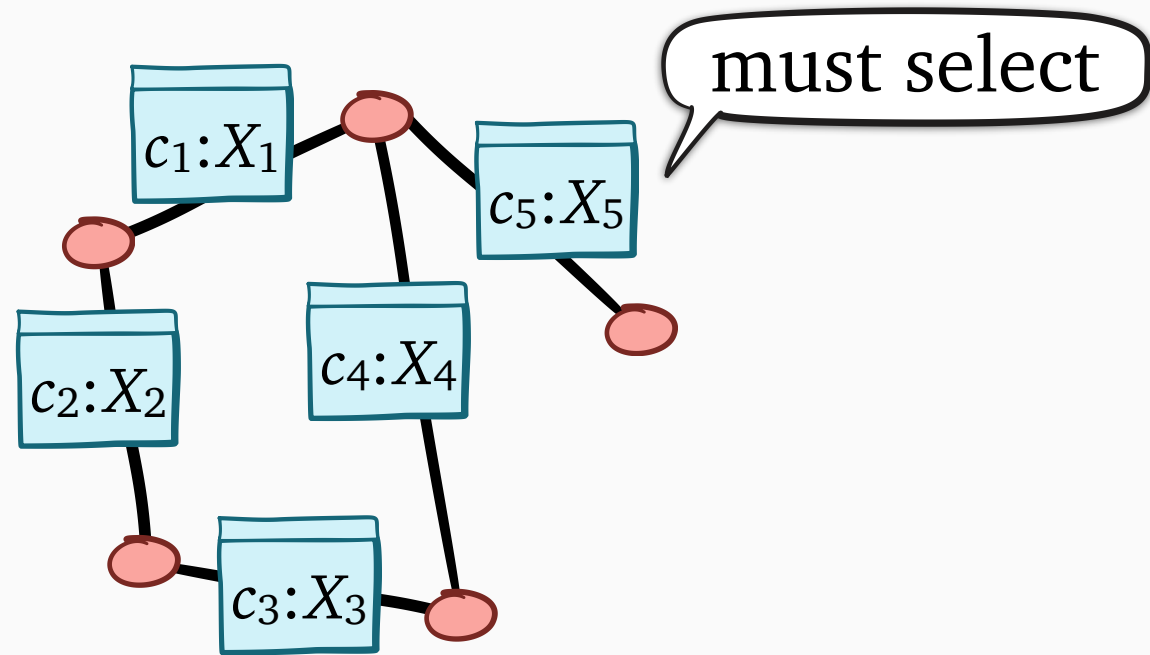
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*Example:*  
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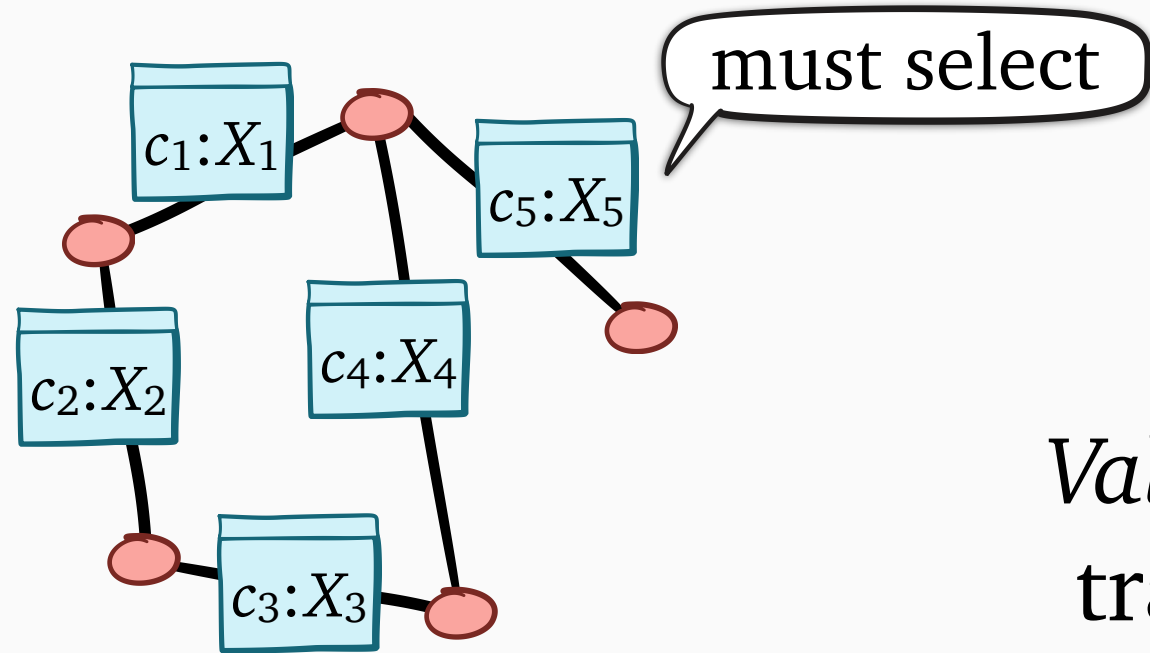


*Example:*  
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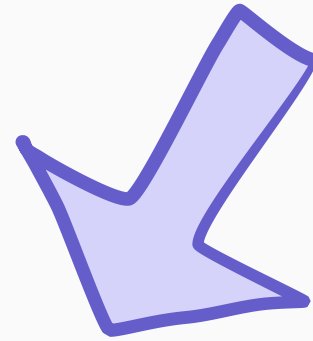


**Optional inspection:**  
allow selecting closed boxes

*Example:*  
build a spanning tree



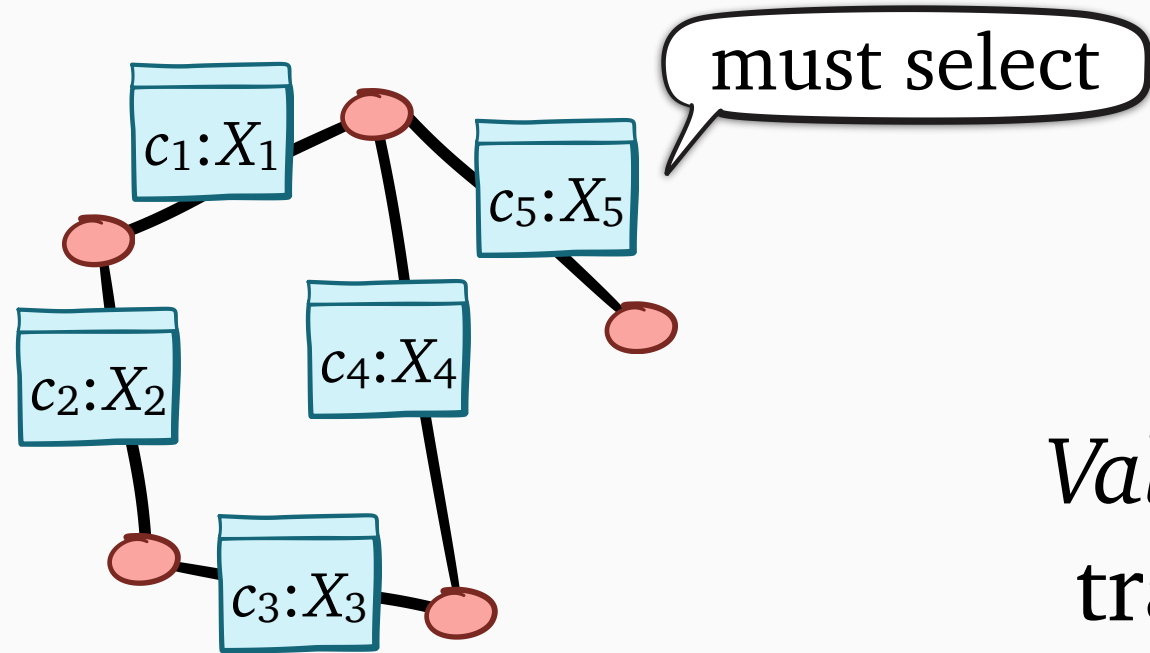
**Optional inspection:**  
allow selecting closed boxes



*Value of information:*  
tradeoff within box



*Example:*  
build a spanning tree



**Optional inspection:**  
allow selecting closed boxes

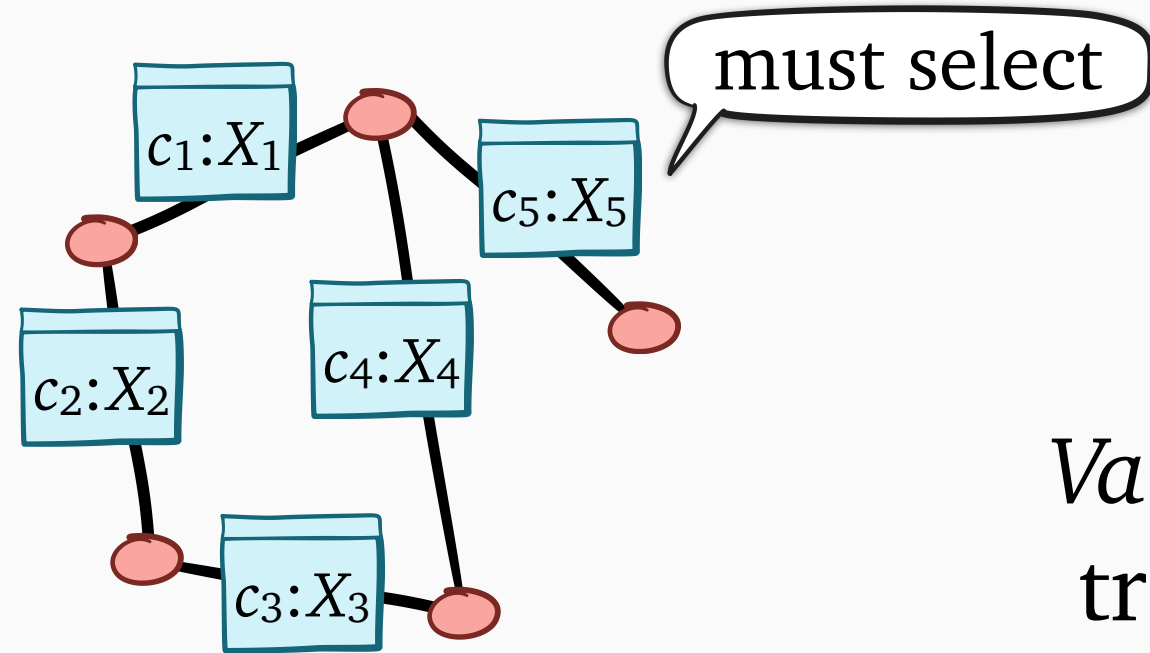


*Value of information:*  
tradeoff within box



*Decompose hard problems:*  
more actions within box

*Example:*  
build a spanning tree



**Optional inspection:**  
allow selecting closed boxes



*Value of information:*  
tradeoff within box

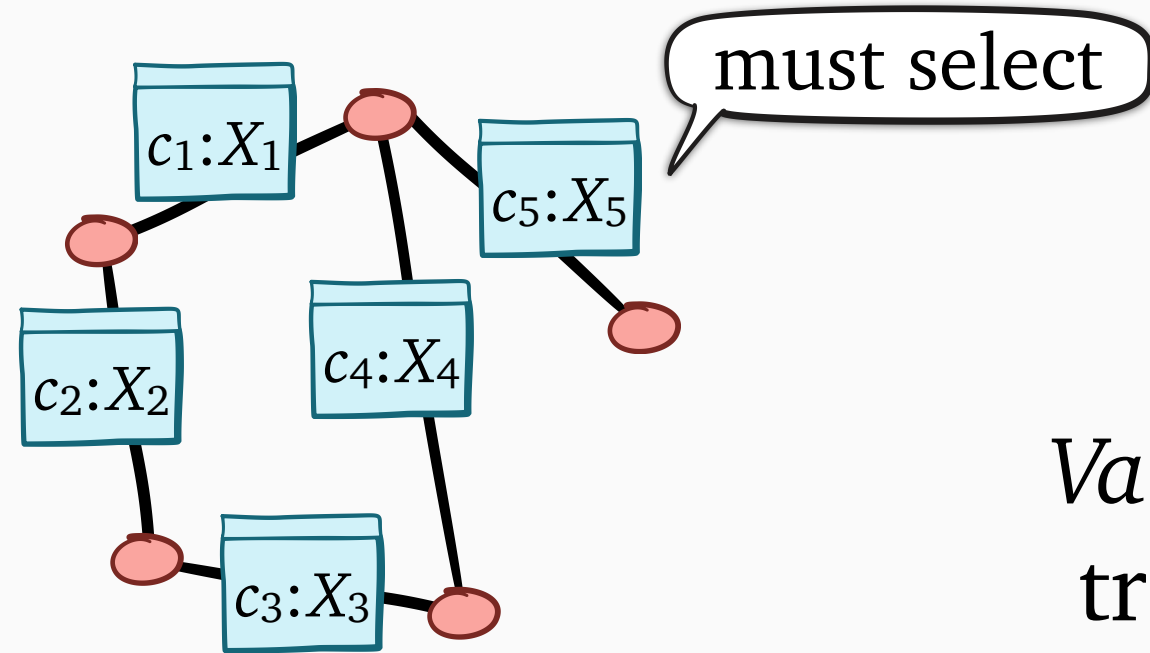


*Decompose hard problems:*  
more actions within box

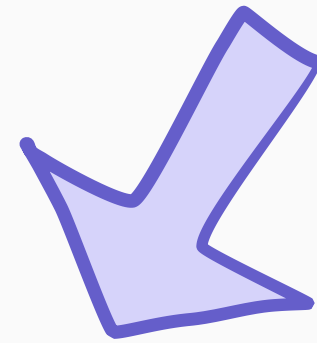


**Optional inspection is hard!**

*Example:*  
build a spanning tree



**Optional inspection:**  
allow selecting closed boxes



*Value of information:*  
tradeoff within box



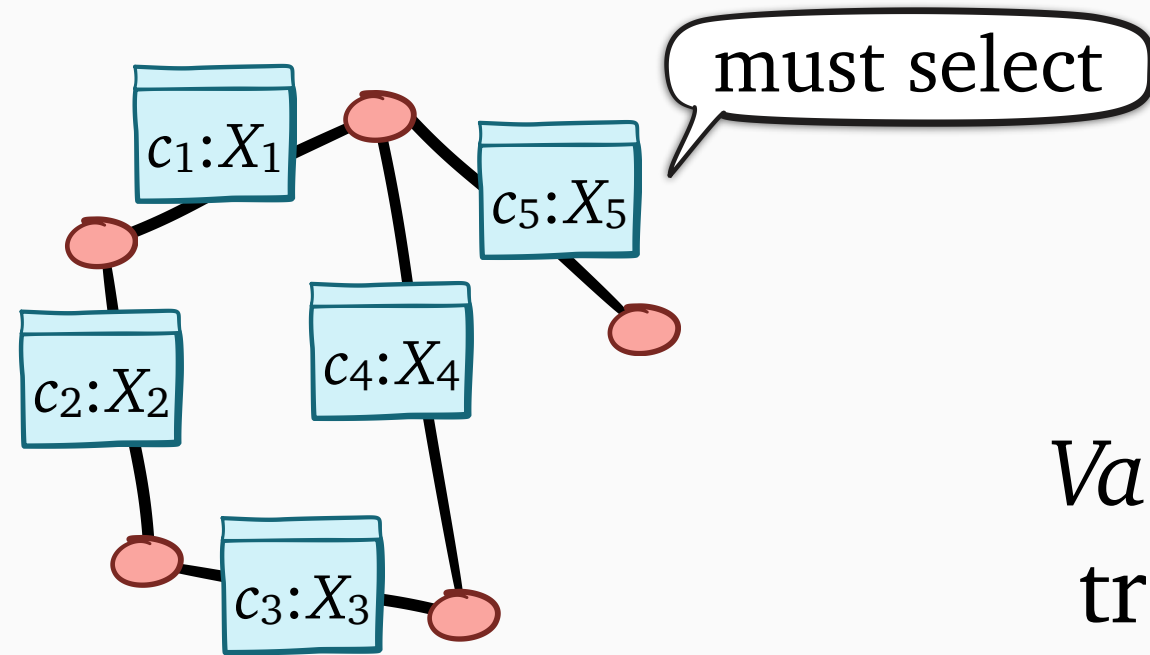
*Decompose hard problems:*  
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- **Gittins** optimality doesn't generalize

*Example:*  
build a spanning tree



**Optional inspection:**  
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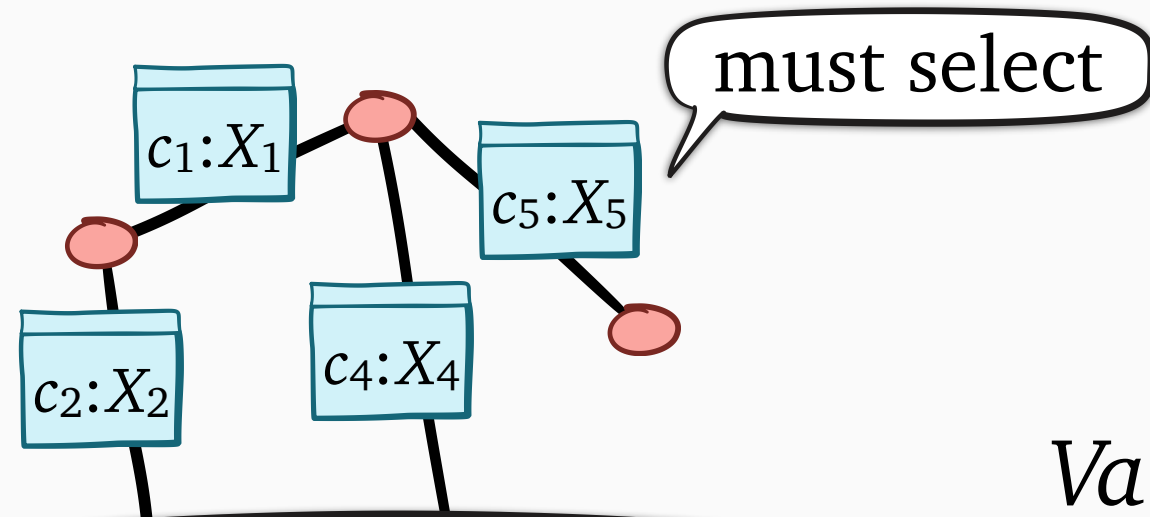
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**Optional inspection is hard!**

- **Gittins** optimality doesn't generalize
- Progress on classic problem, but combinatorial problems open

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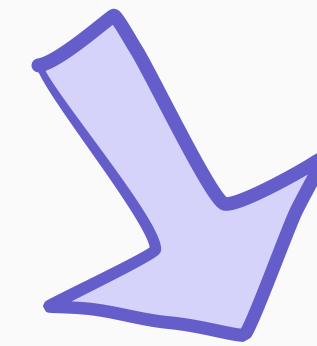


1 - 1/e [Beyhaghi & Kleinberg, 2019]  
4/5 [Guha, Munagala, & Sarkar, 2008]  
PTAS [Fu, Li, & Liu, 2023]  
PTAS [Beyhaghi & Cai, 2023]

**Optional inspection:**  
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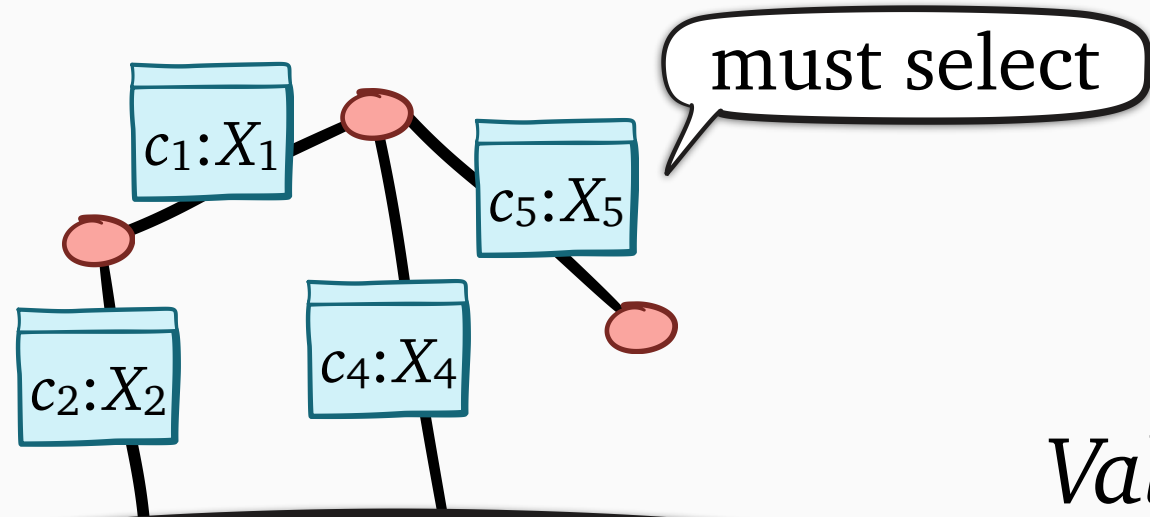
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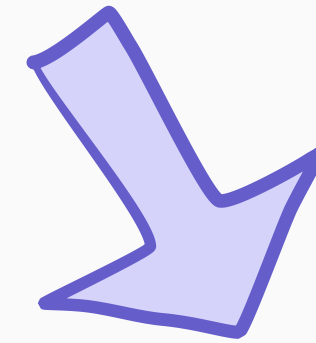


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*Decompose hard problems:*  
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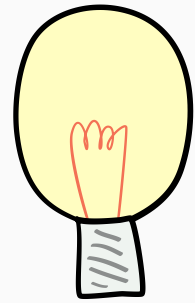
**Gittins**-y policy works in special cases [Doval, 2018]

**Optional inspection is hard.**

**Gittins** optimality doesn't generalize

- Progress on classic problem, but combinatorial problems open

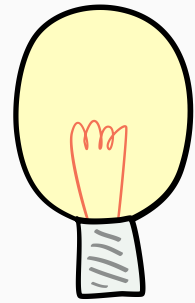
# Our contribution



## **Local Hedging (LH)**

New *decomposition-based* technique for optional inspection

# Our contribution



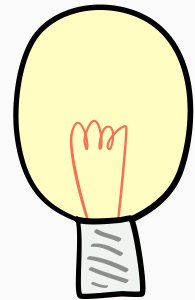
## Local Hedging (LH)

New *decomposition-based* technique for optional inspection

- Reduces problem to required-inspection case



# Our contribution

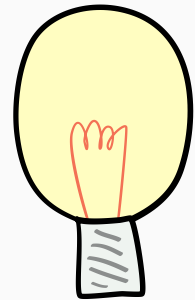


## Local Hedging (LH)

New *decomposition-based* technique for optional inspection

- Reduces problem to required-inspection case
- Naturally generalizes to combinatorial problems

# Our contribution



## Local Hedging (LH)

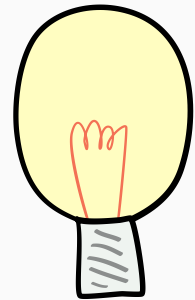
New *decomposition-based* technique for optional inspection

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**Theorem:** if **Alg** is a “greedy” algorithm, then the approximation ratio of **Gittins** + **Alg** + **LH** is  $\leq 4/3$  times that of **Alg**

# Our contribution



## Local Hedging (LH)

New *decomposition-based* technique for optional inspection

- Reduces problem to required-inspection case
- Naturally generalizes to combinatorial problems



**Theorem:** if **Alg** is a “greedy” algorithm, then the approximation ratio of **Gittins** + **Alg** + **LH** is  $\leq 4/3$  times that of **Alg**

price of reduction

# Rest of this talk



Why does **Gittins** work under required inspection?

# Rest of this talk

? Why does **Gittins** work under required inspection?

? What goes wrong under optional inspection?

# Rest of this talk

? Why does **Gittins** work under required inspection?

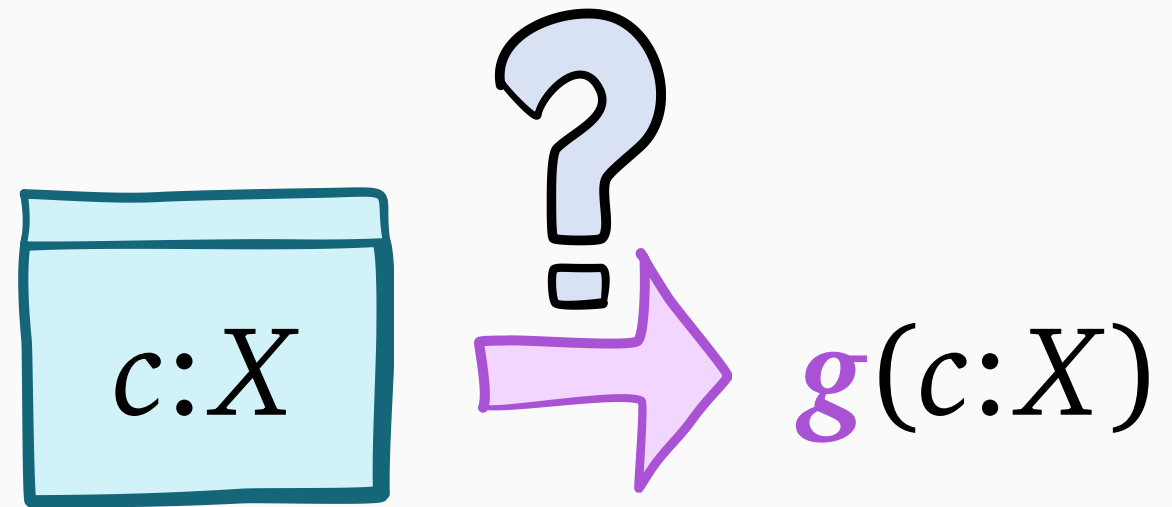
? What goes wrong under optional inspection?

? How does **Local Hedging** fix the problem?

# Defining the **Gittins** index

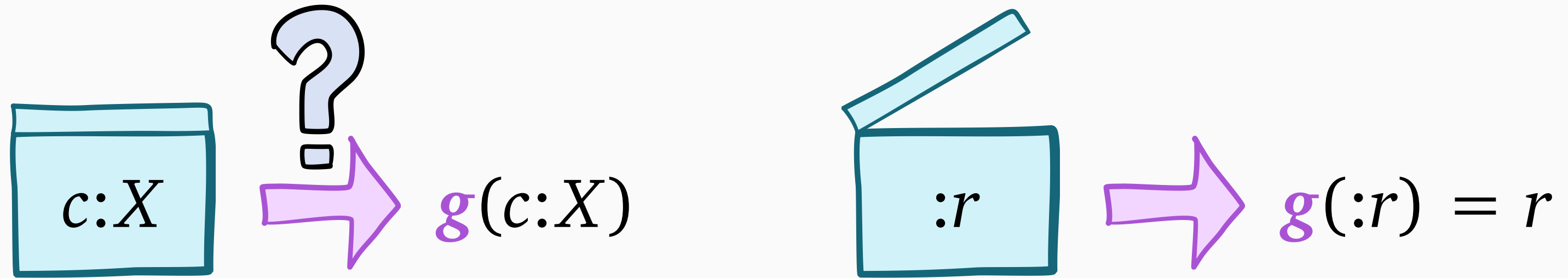


# Defining the **Gittins** index

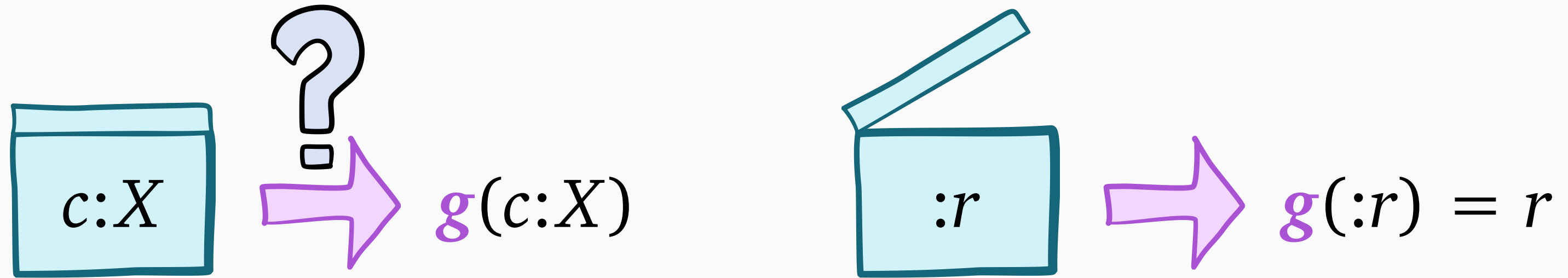




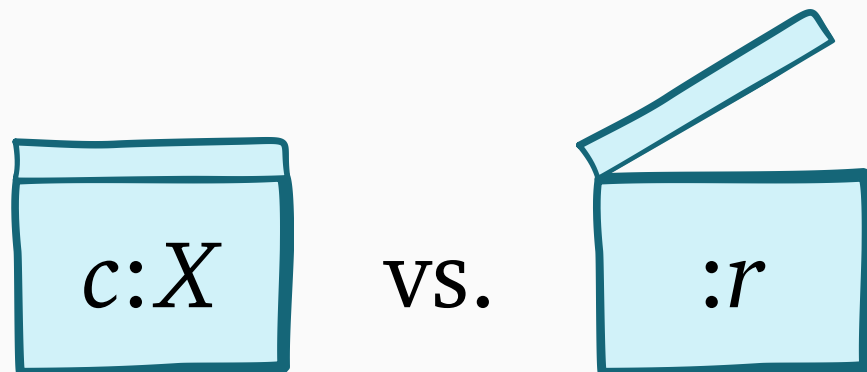
# Defining the **Gittins** index



# Defining the **Gittins** index



## 1.5-box problem

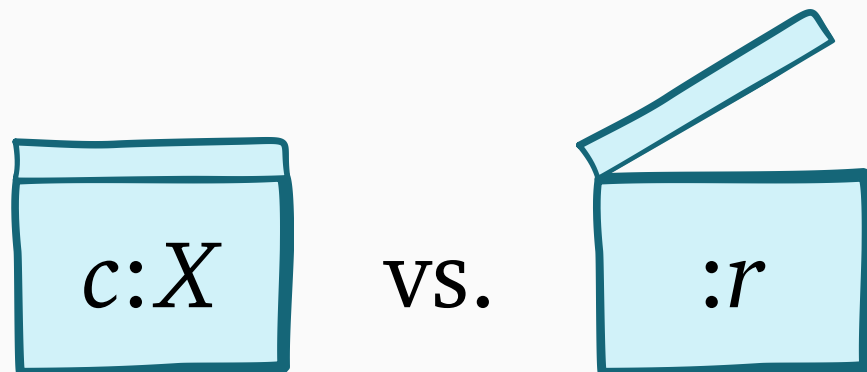


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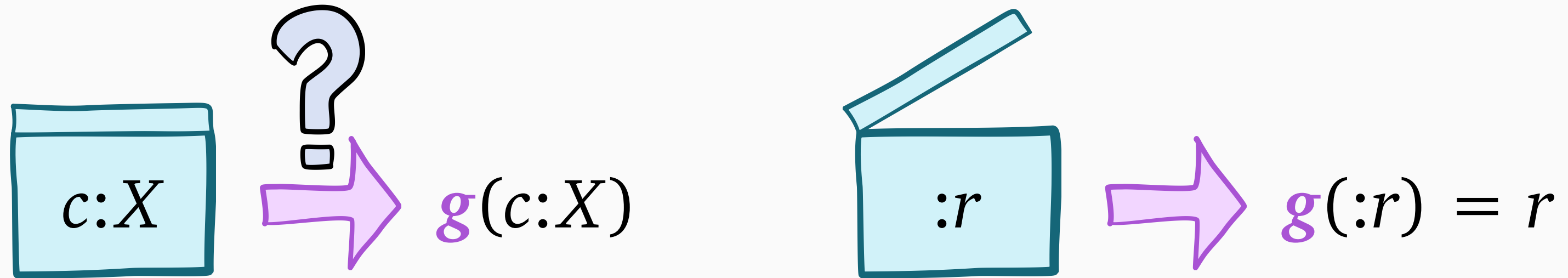


**1.5-box problem**

**Key question:** what to do in 1.5-box problem?

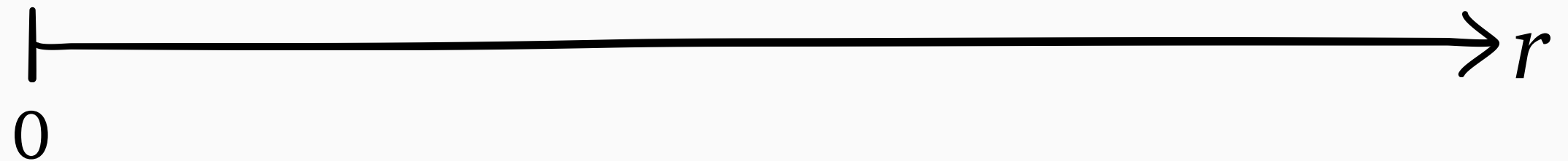
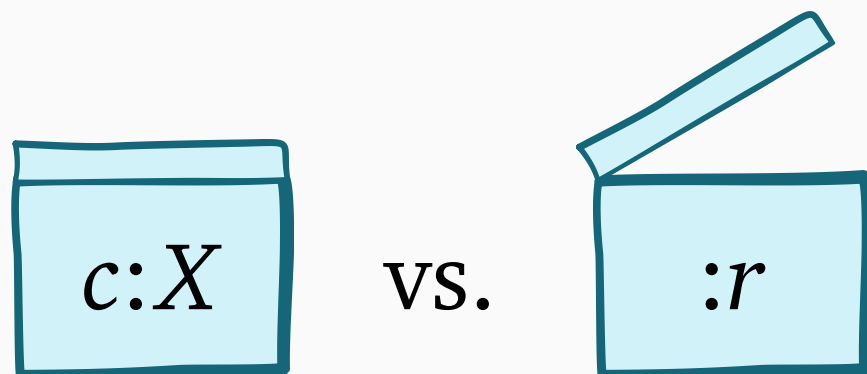


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**Key question:** what to do in 1.5-box problem?

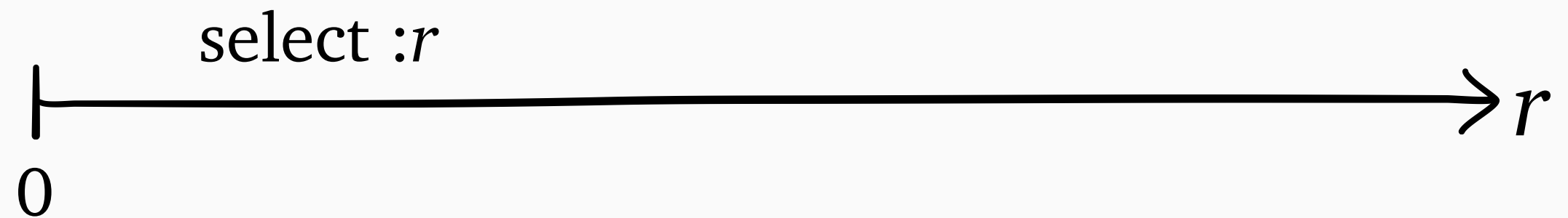
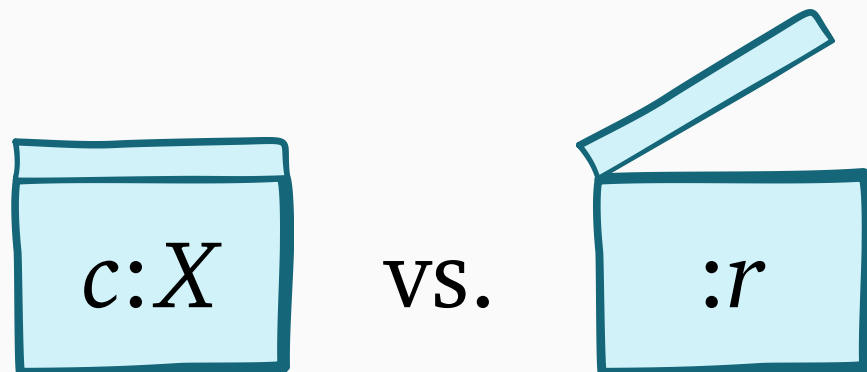


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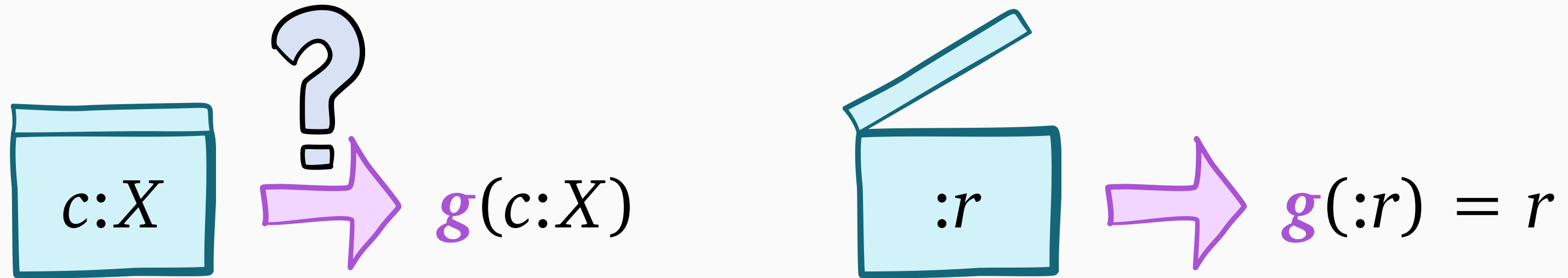


## 1.5-box problem

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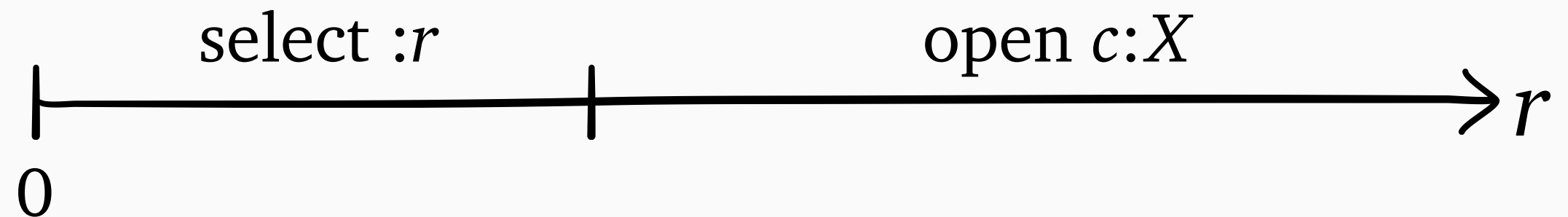
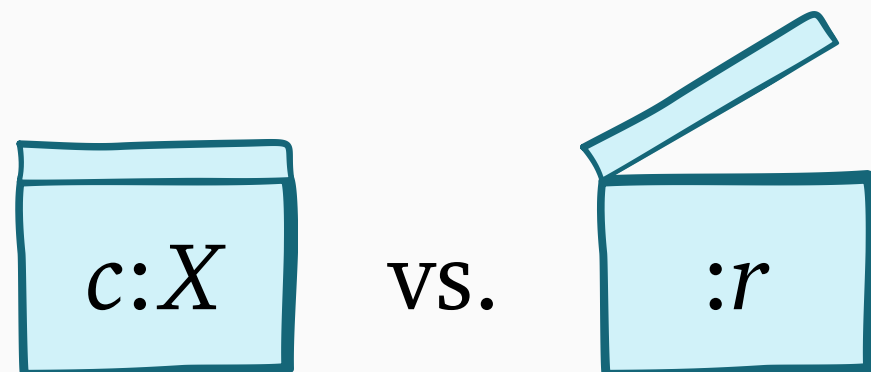


# Defining the **Gittins** index

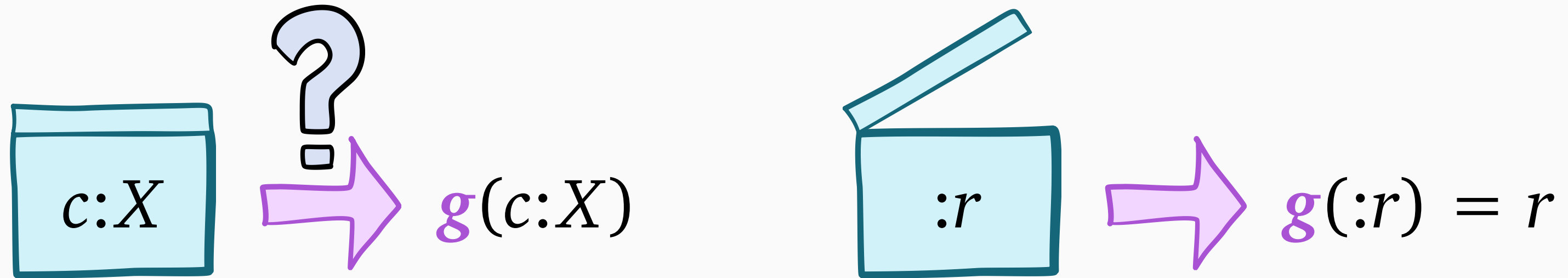


## 1.5-box problem

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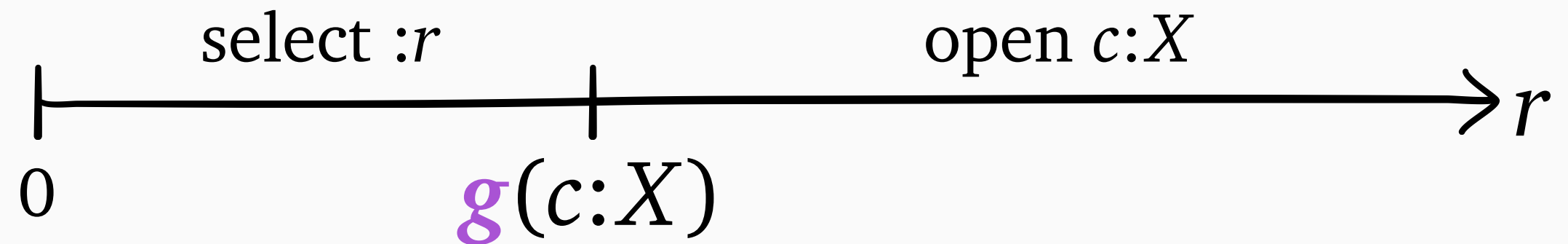
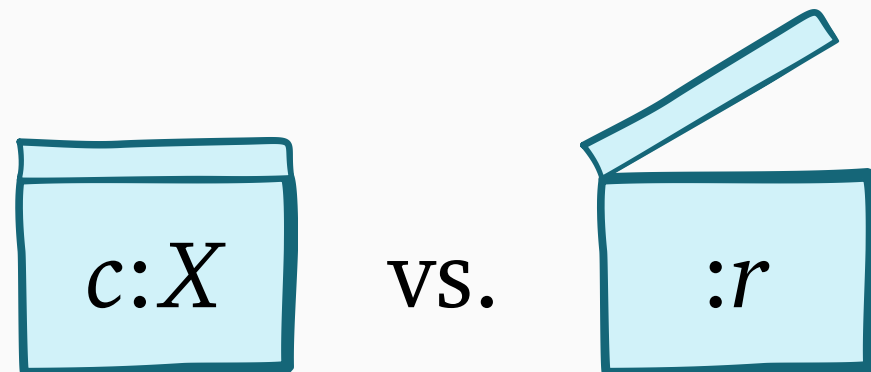


# Defining the **Gittins** index

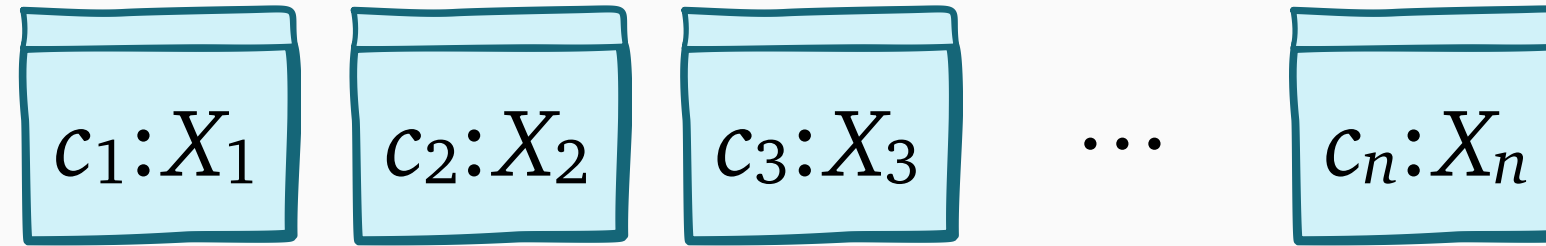


## 1.5-box problem

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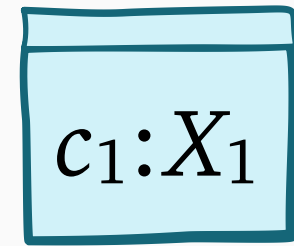


# Why **Gittins** works under required inspection

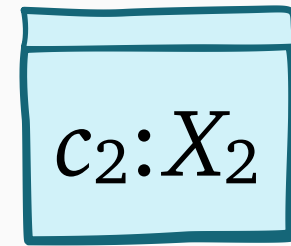




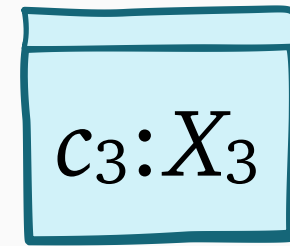
# Why **Gittins** works under required inspection



$c_1:X_1$

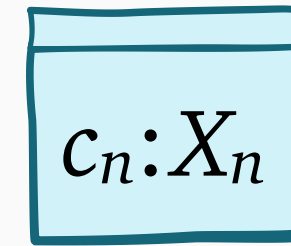


$c_2:X_2$



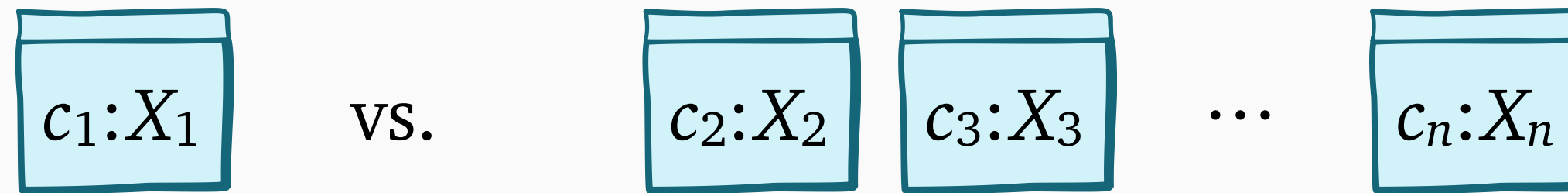
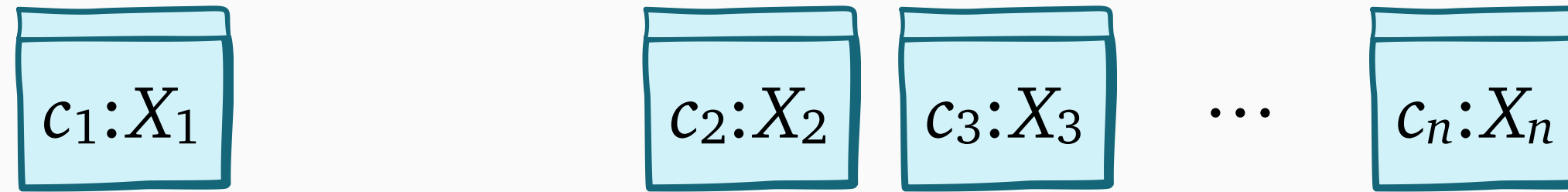
$c_3:X_3$

...

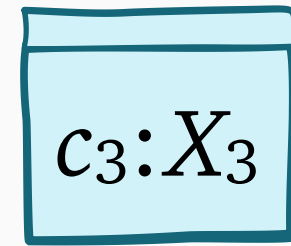
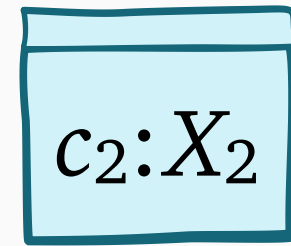
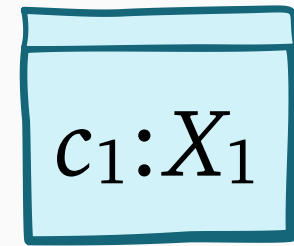


$c_n:X_n$

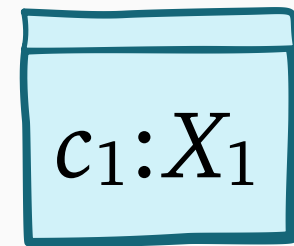
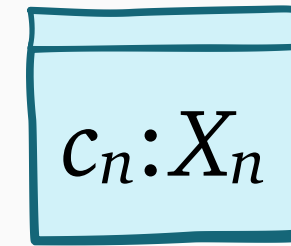
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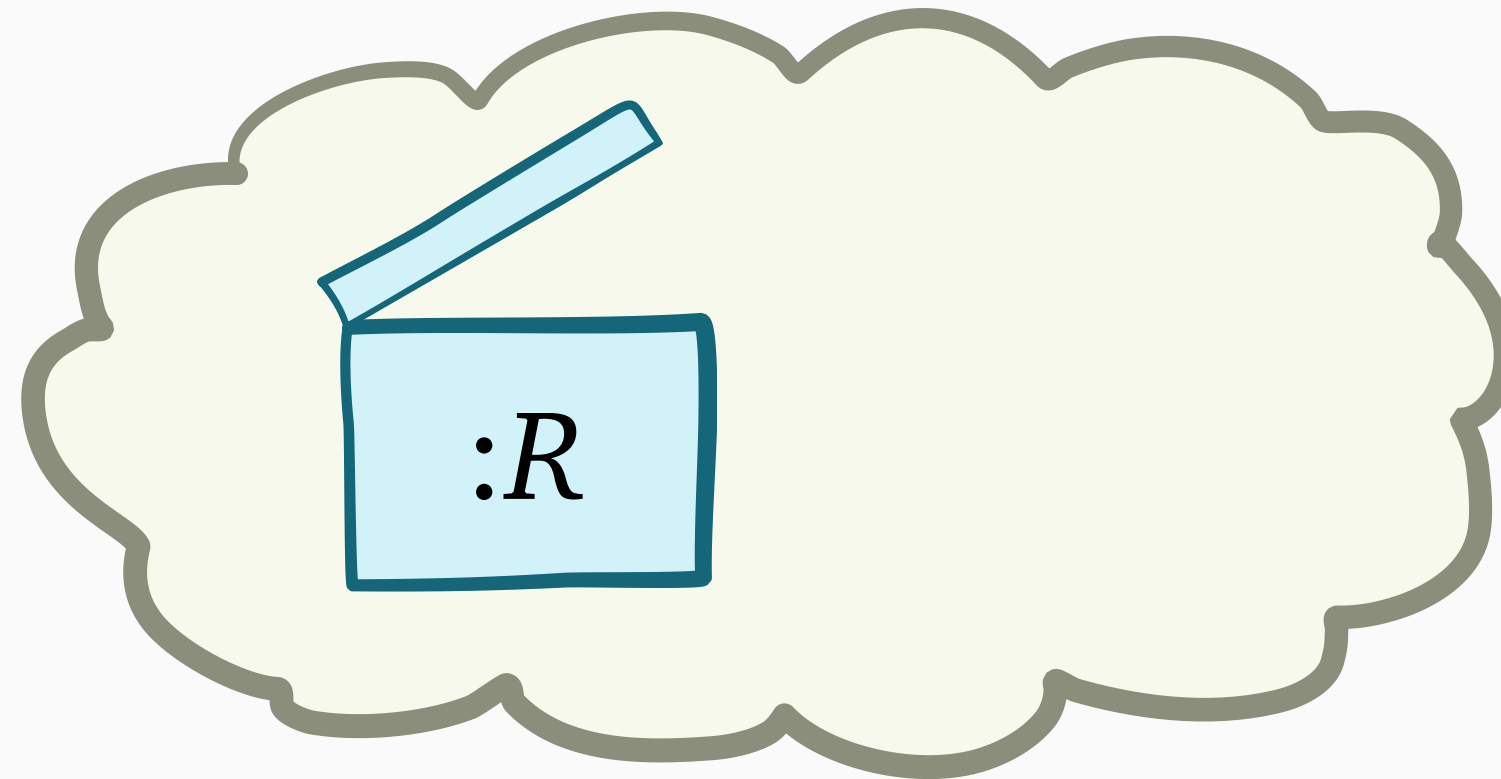
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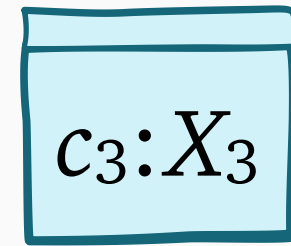
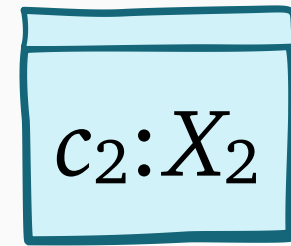
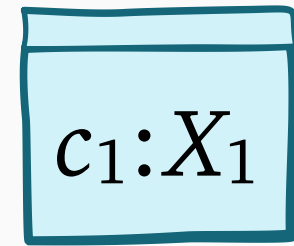
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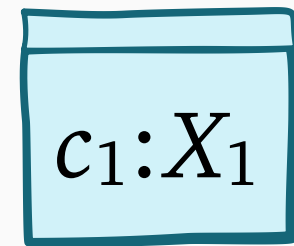
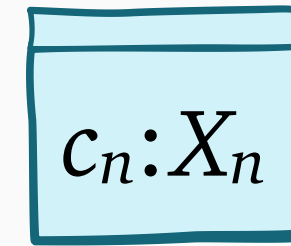
vs.



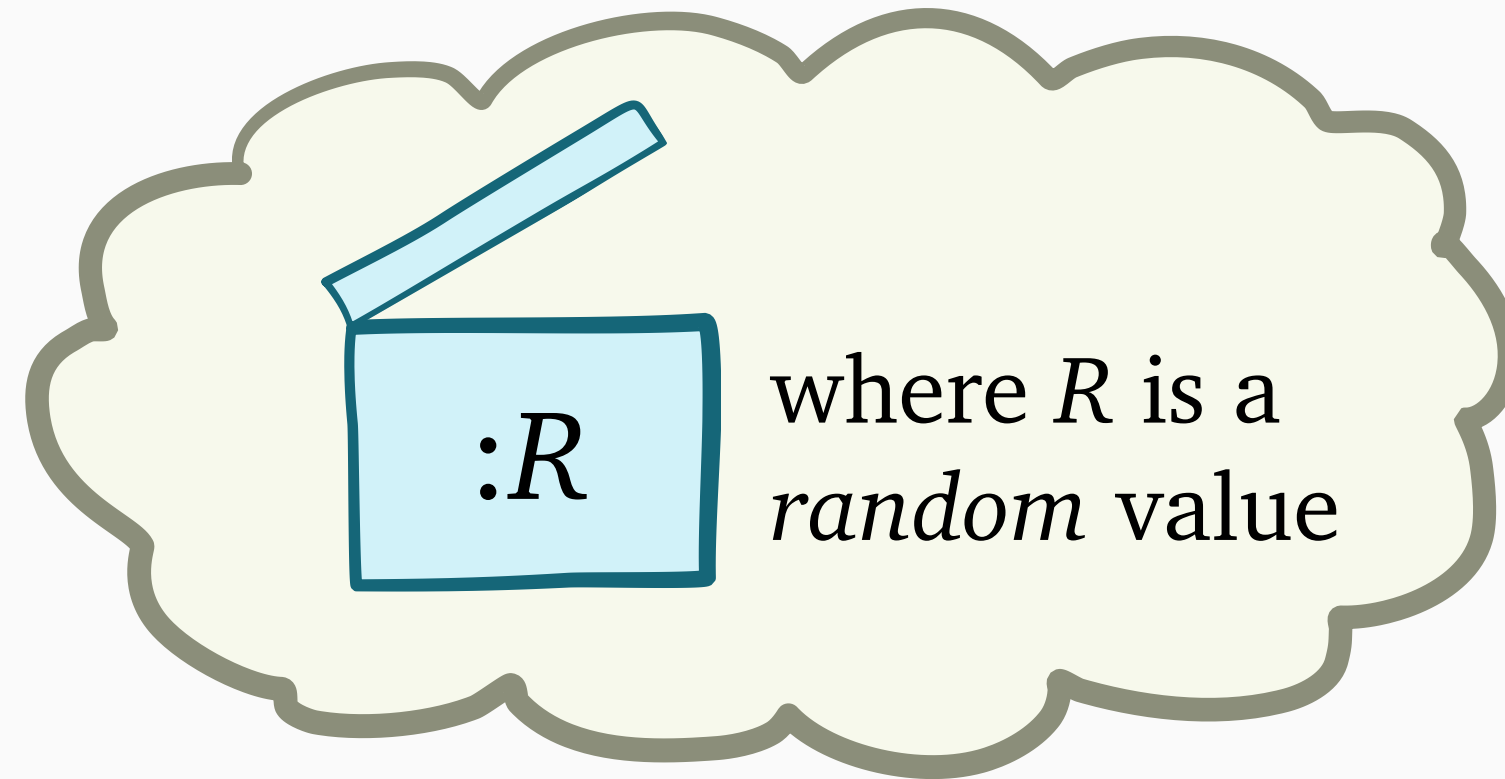
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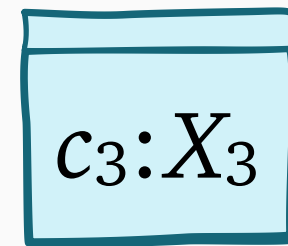
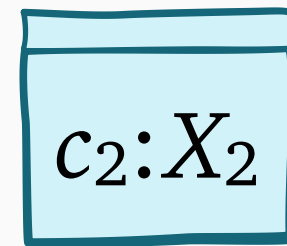
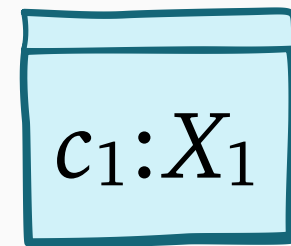
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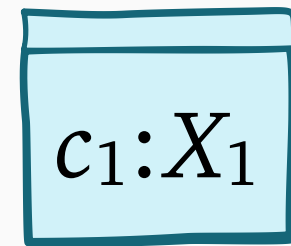
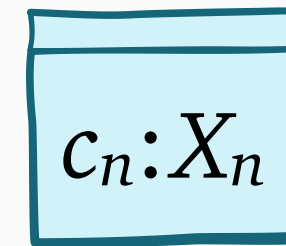
vs.



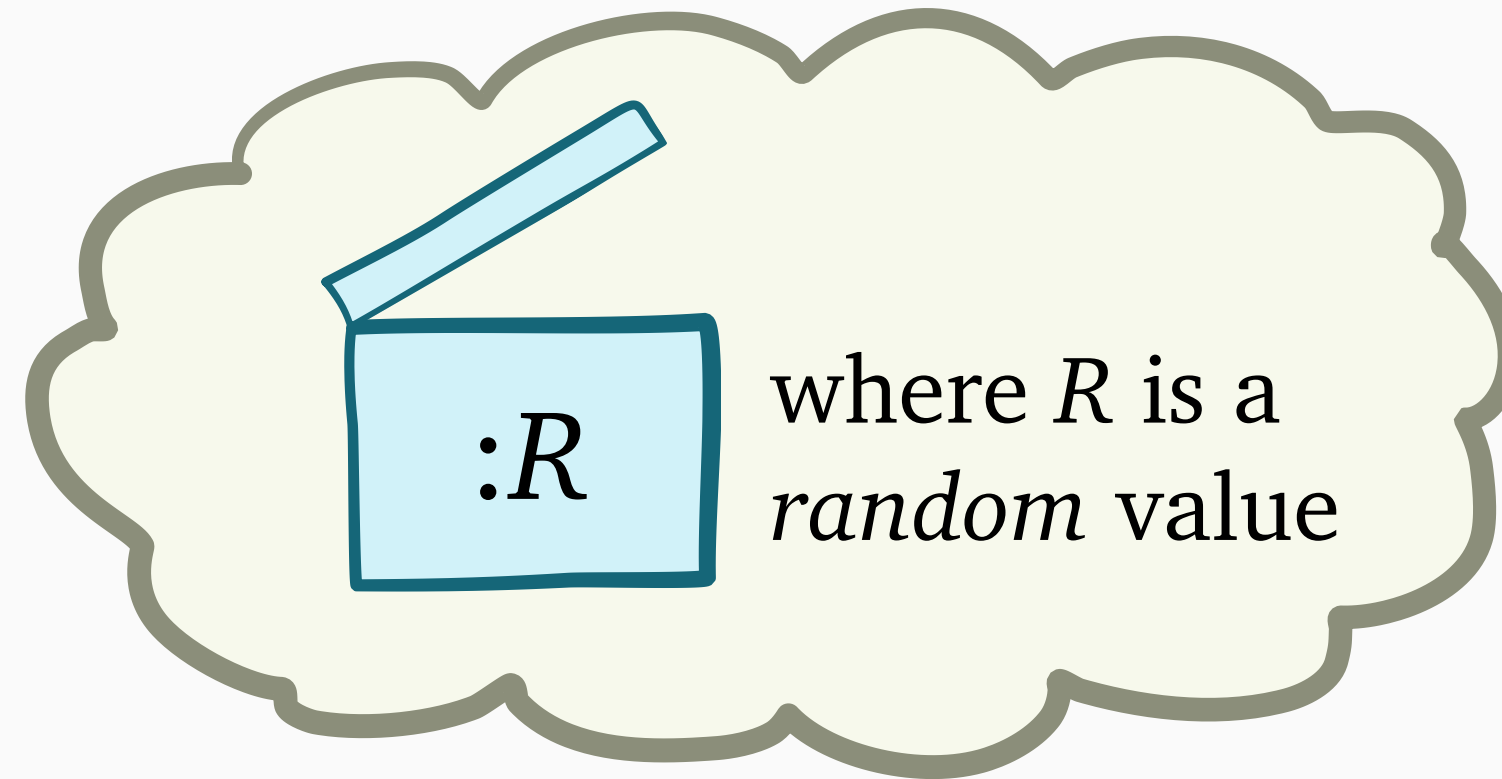
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...

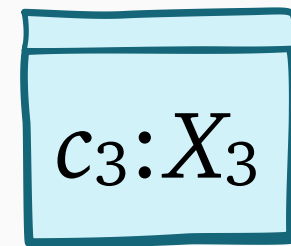
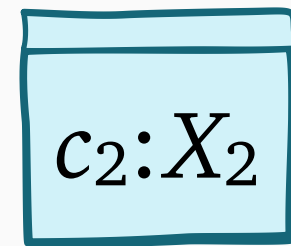
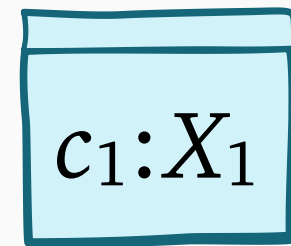


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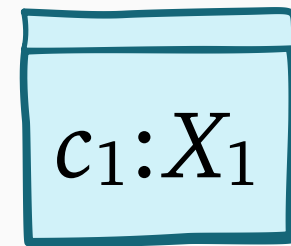
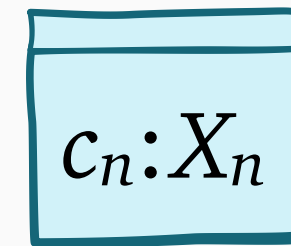


**Key property:**  $R \geq \min\{g(c_2:X_2), \dots, g(c_n:X_n)\}$

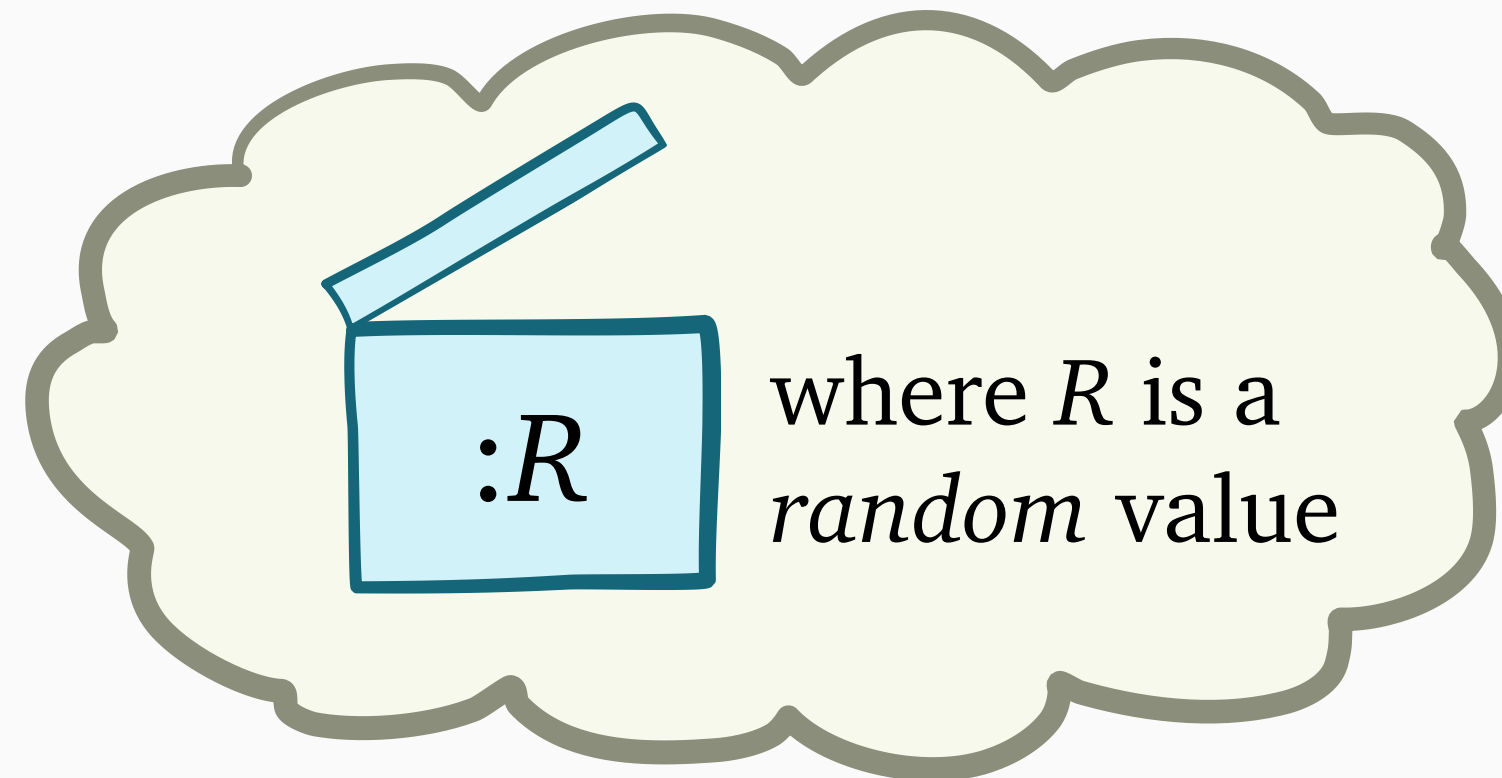
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...



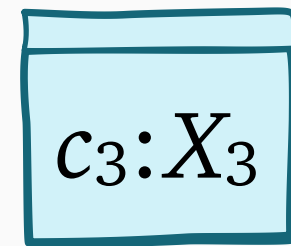
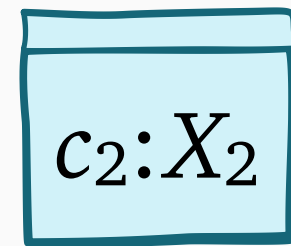
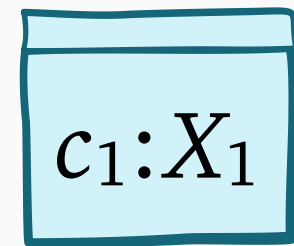
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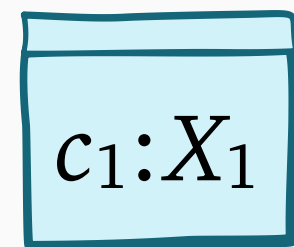
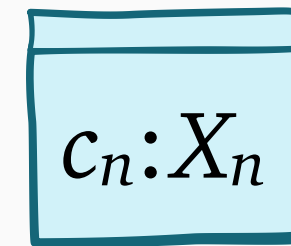
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$\Rightarrow$  If  $g(c_1:X_1)$  minimal, then  $g(c_1:X_1) \leq R$

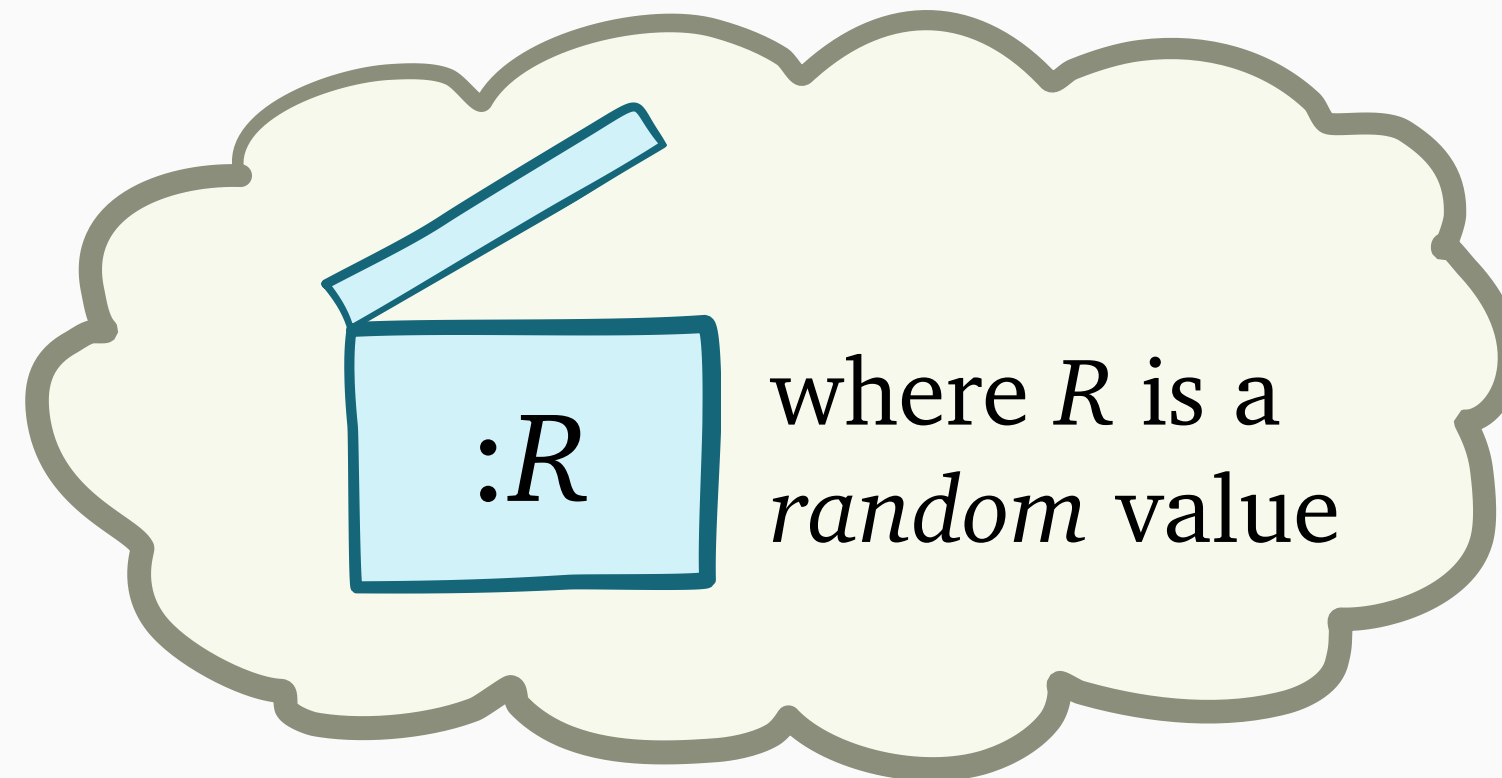
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...



vs.

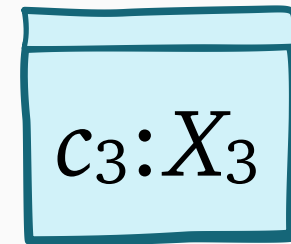
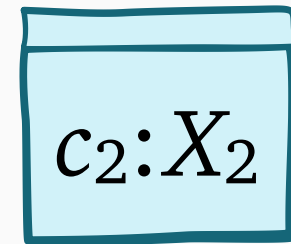
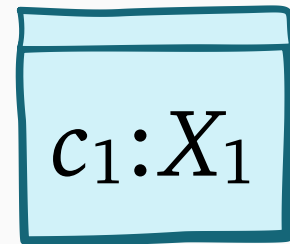


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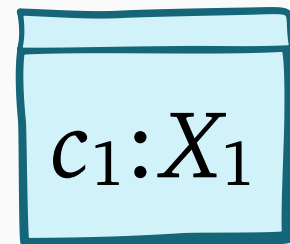
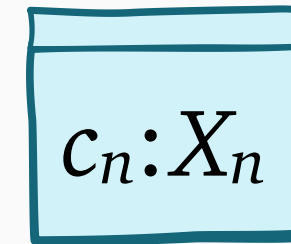
$\Rightarrow$  If  $g(c_1:X_1)$  minimal, then  $g(c_1:X_1) \leq R$

$\Rightarrow$  If  $g(c_1:X_1)$  minimal, optimal to open box 1

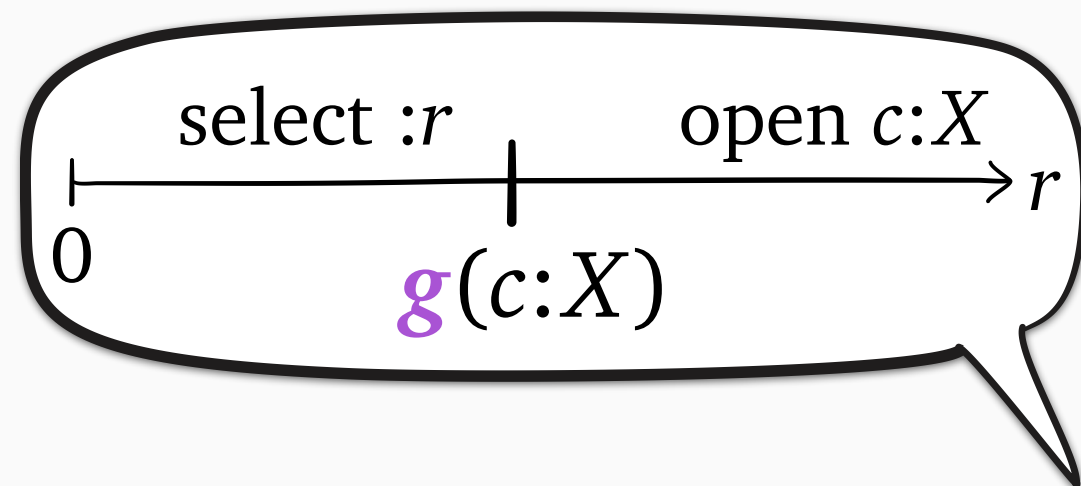
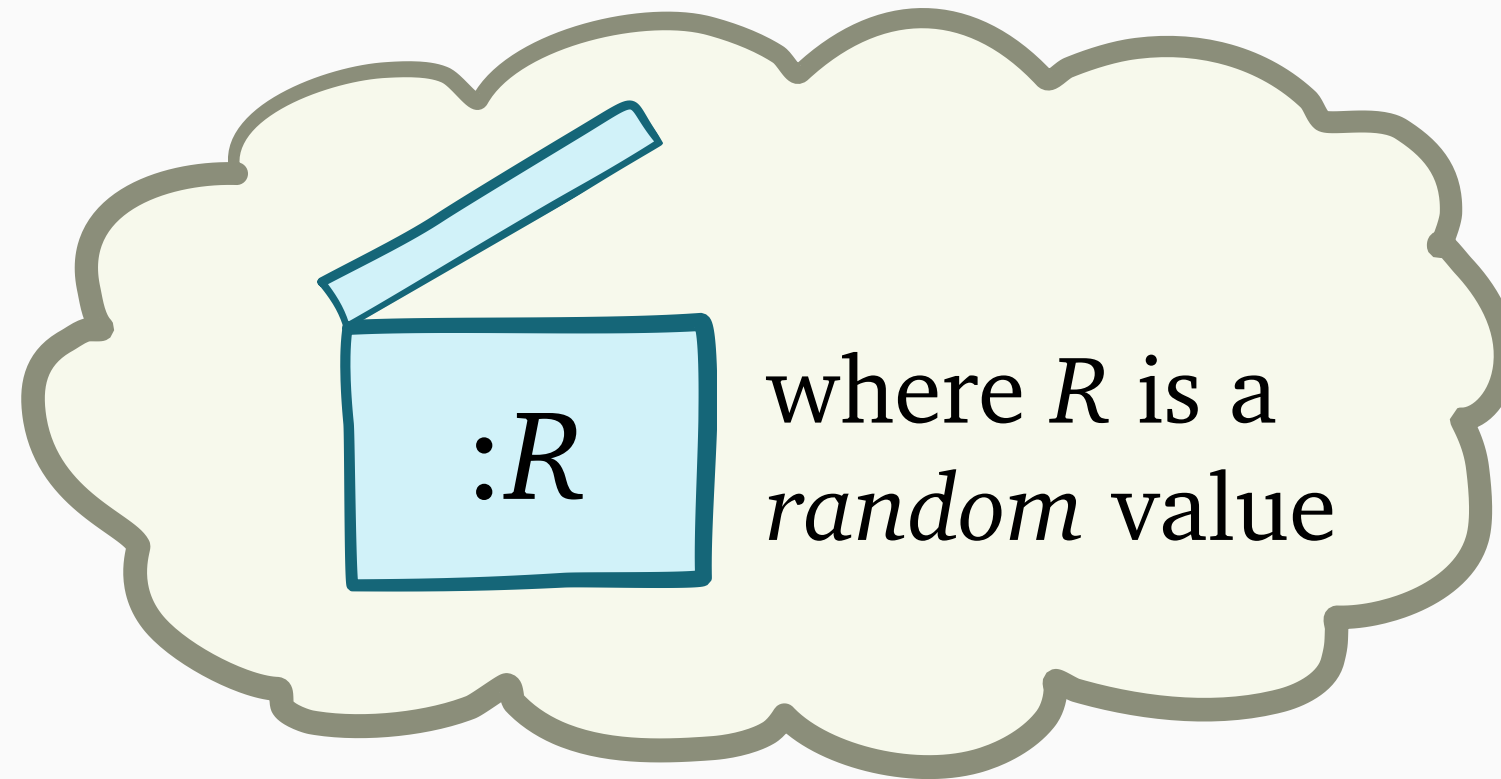
# Why **Gittins** works under required inspection



...



vs.



**Key property:**  $R \geq \min\{g(c_2:X_2), \dots, g(c_n:X_n)\}$

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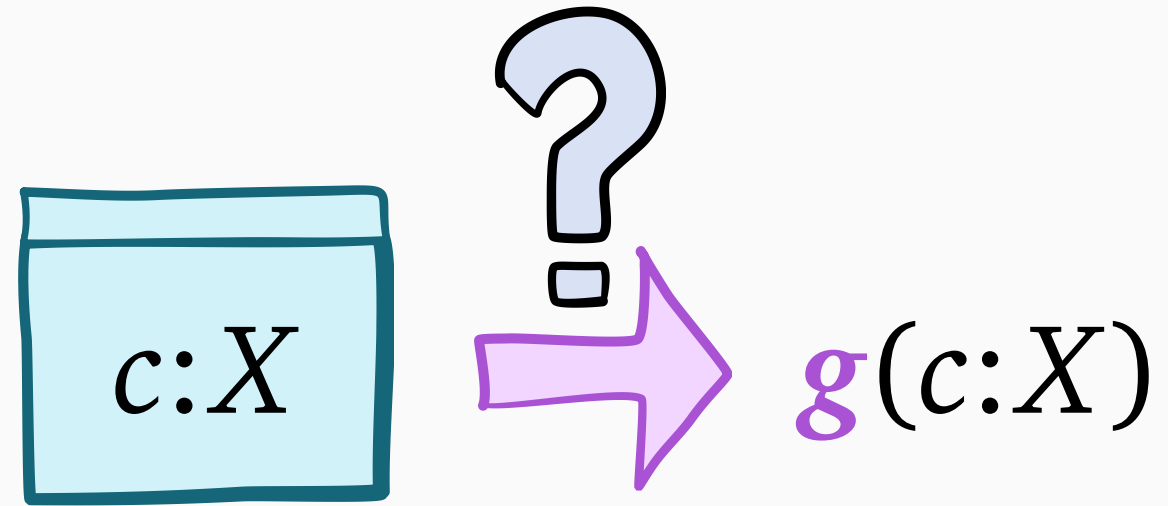
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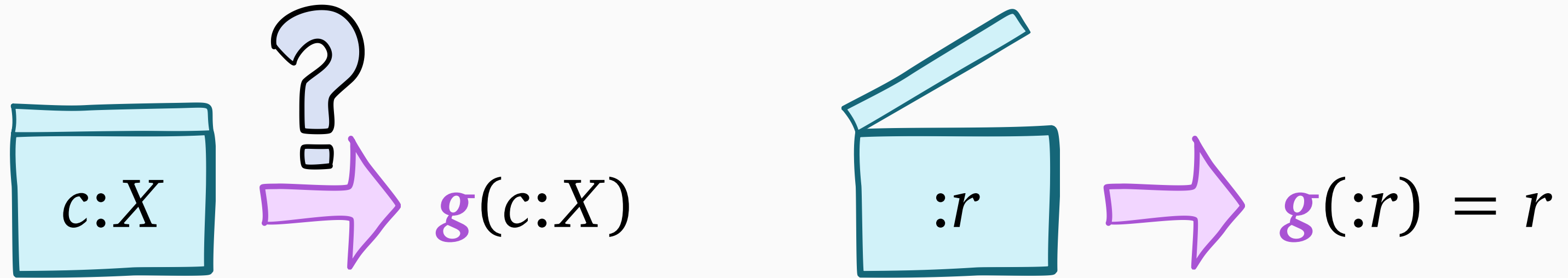
# What changes under optional inspection?



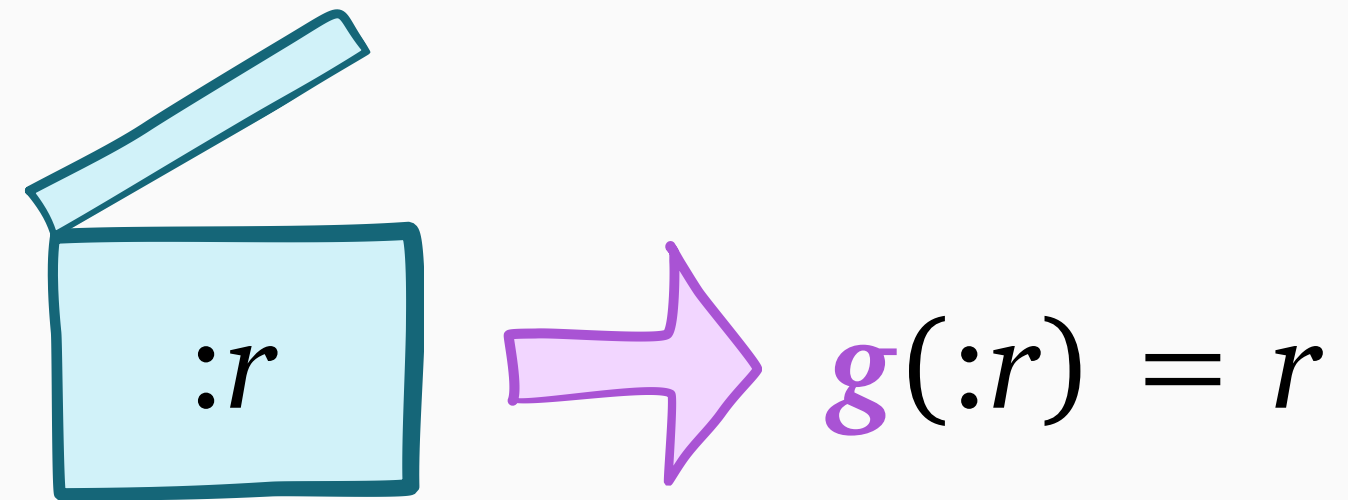
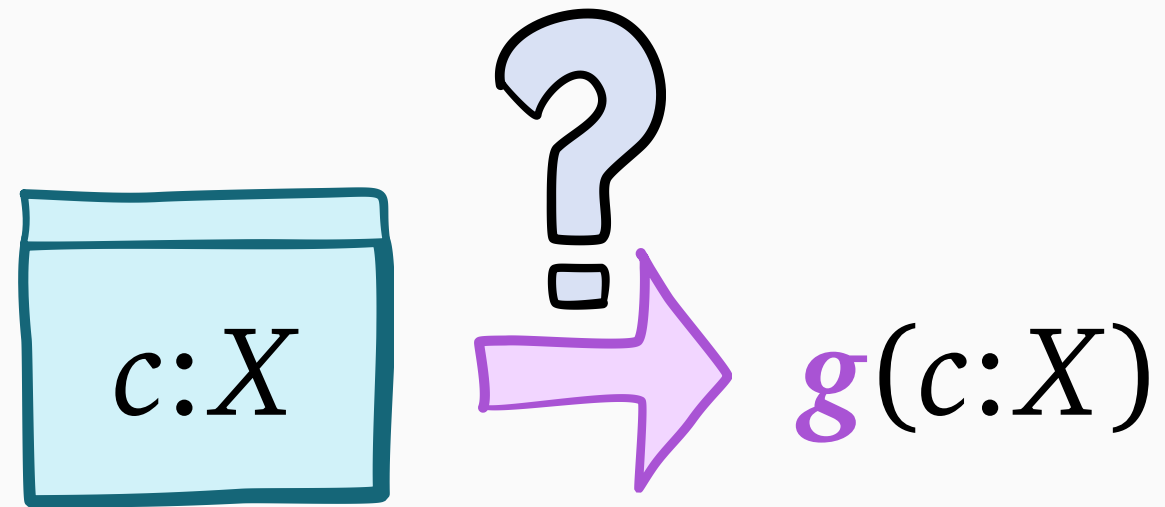
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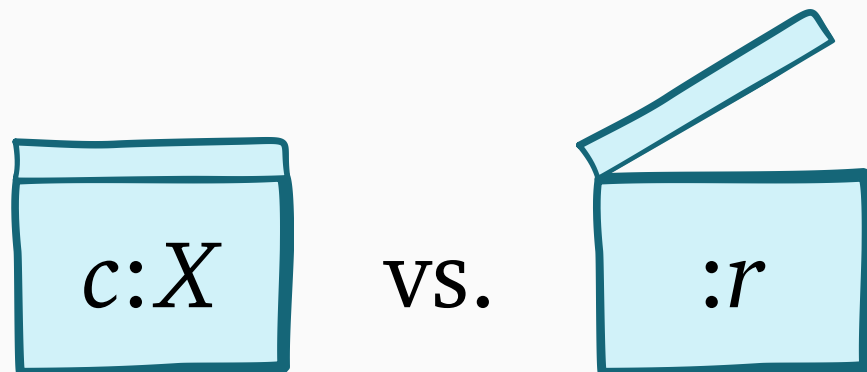
# What changes under optional inspection?



# What changes under optional inspection?



## 1.5-box problem

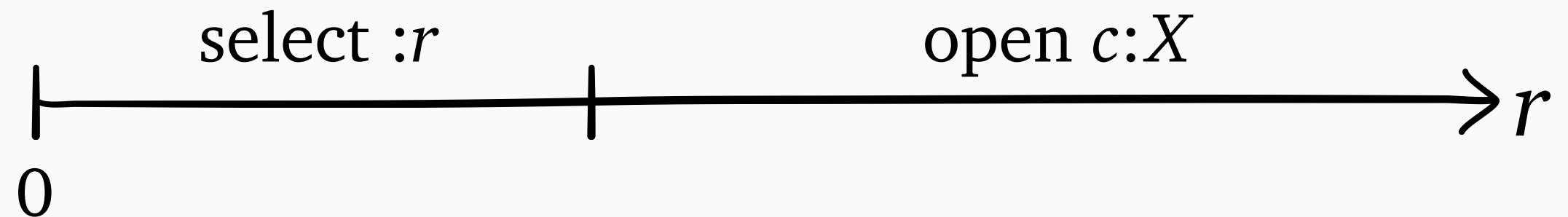
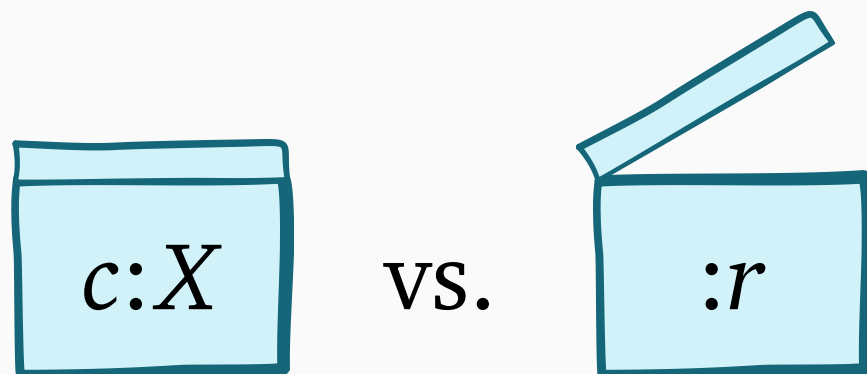


# What changes under optional inspection?

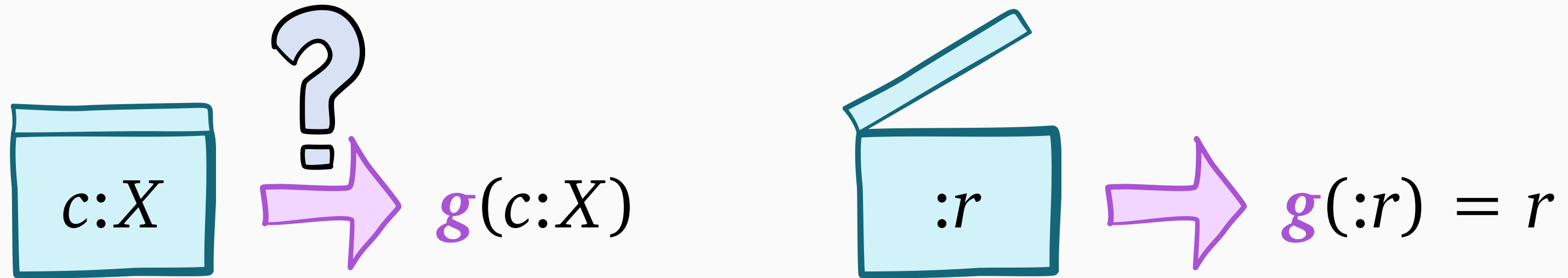


## 1.5-box problem

**Key question:** what to do in 1.5-box problem?

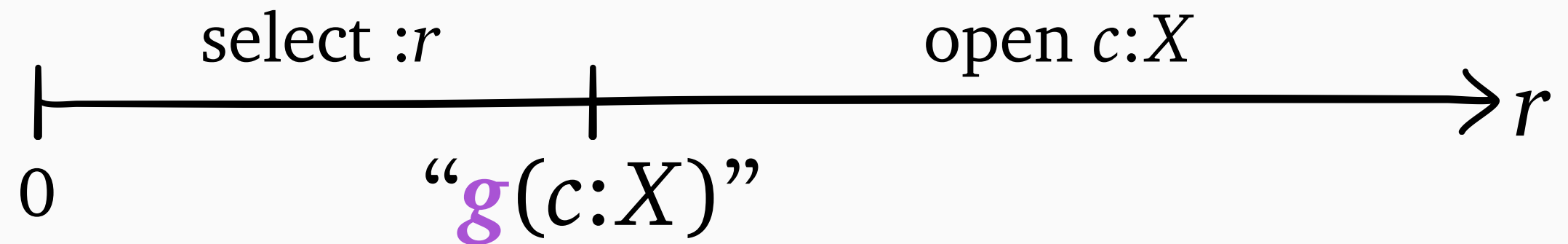
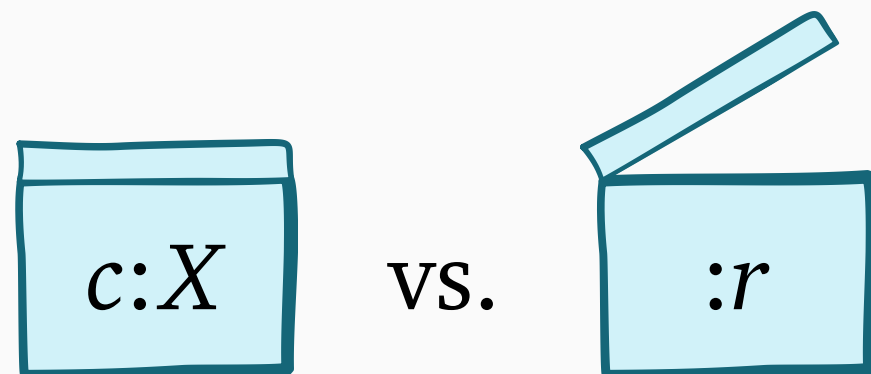


# What changes under optional inspection?

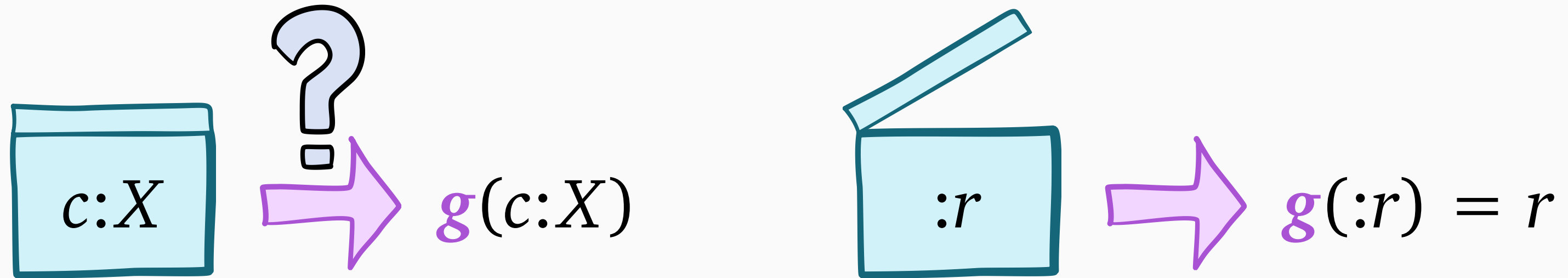


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**Key question:** what to do in 1.5-box problem?

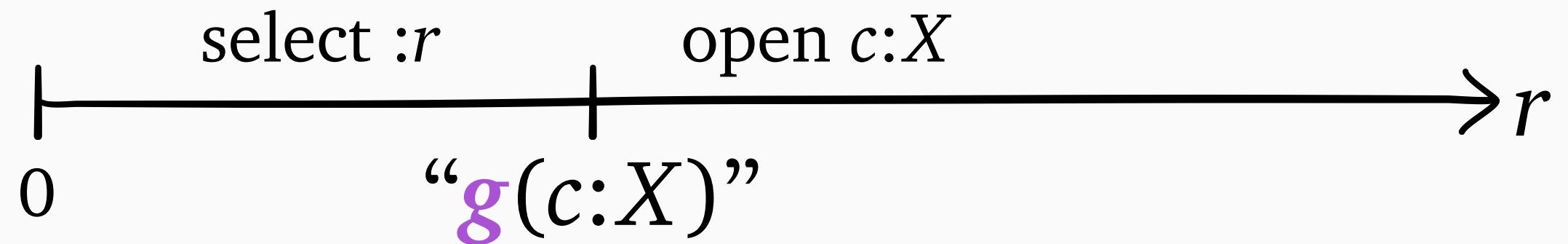
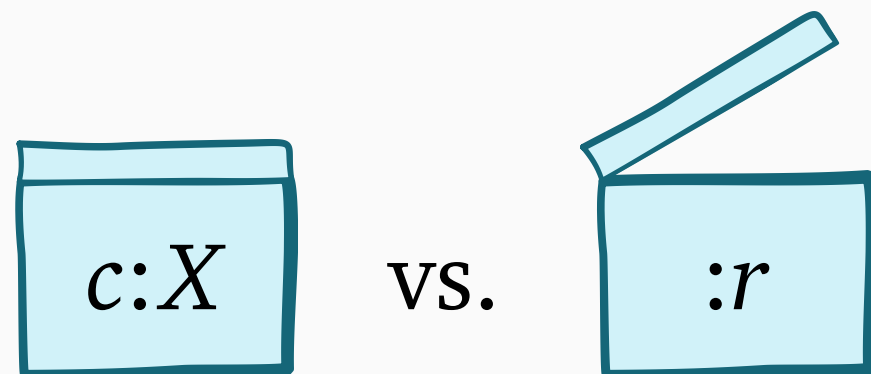


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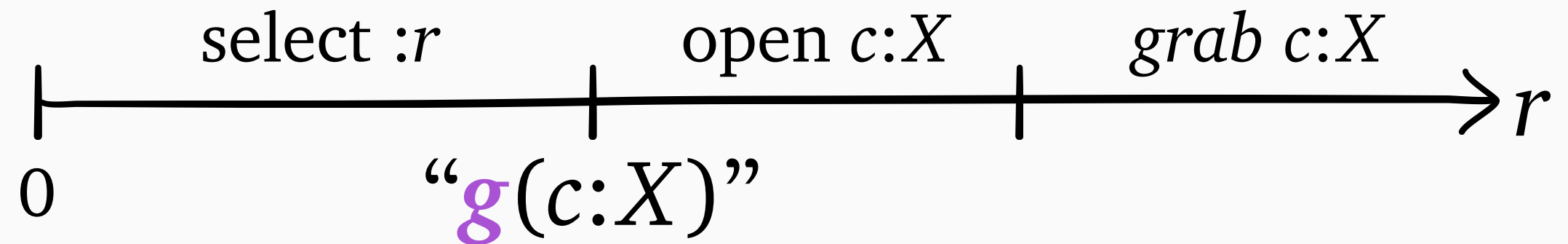
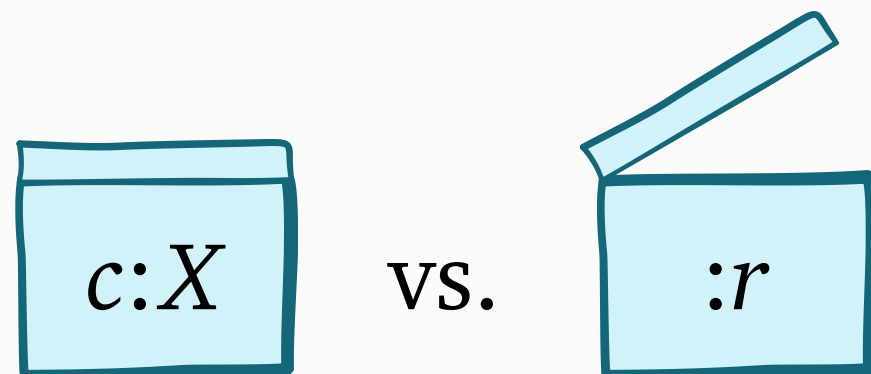


# What changes under optional inspection?



## 1.5-box problem

**Key question:** what to do in 1.5-box problem?



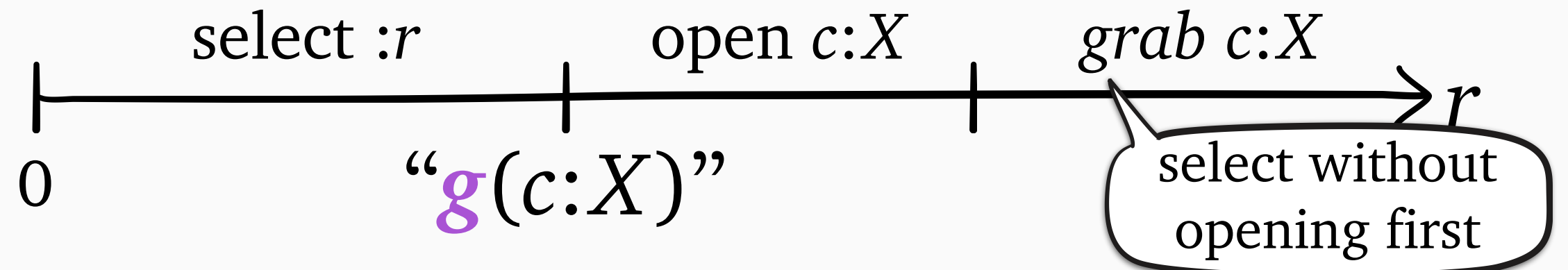
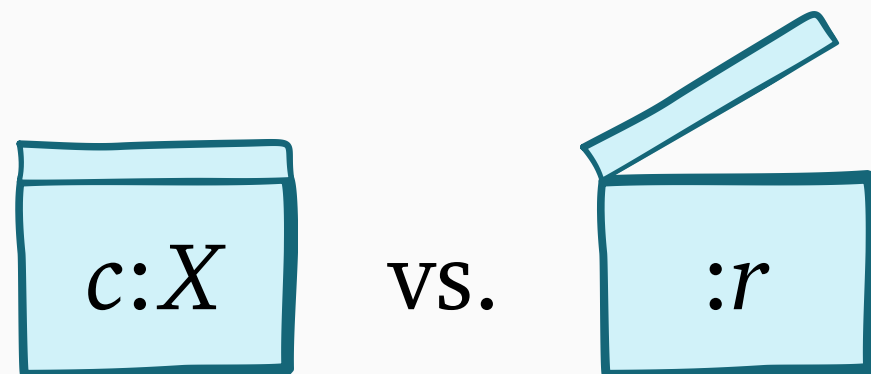


# What changes under optional inspection?



## 1.5-box problem

Key question: what to do in 1.5-box problem?



# What goes wrong under optional inspection?

$c_1:X_1$

$c_2:X_2$

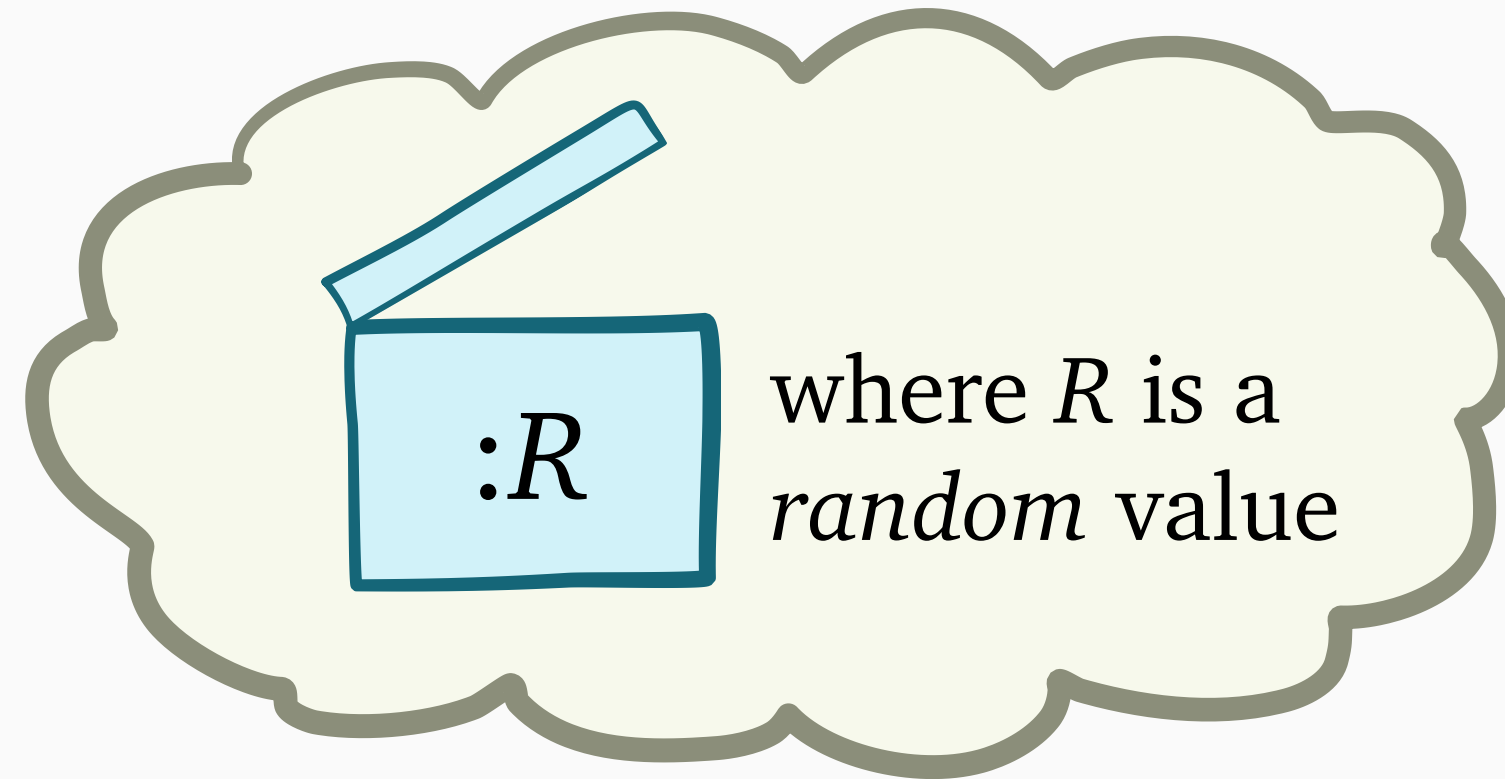
$c_3:X_3$

...

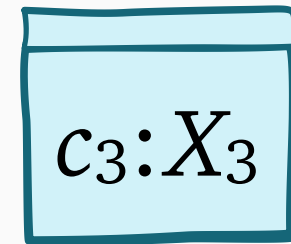
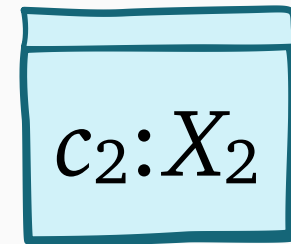
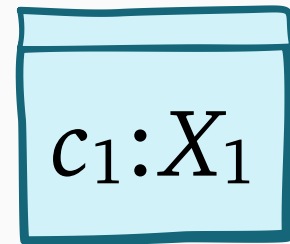
$c_n:X_n$

$c_1:X_1$

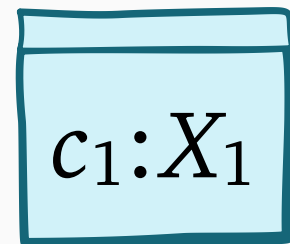
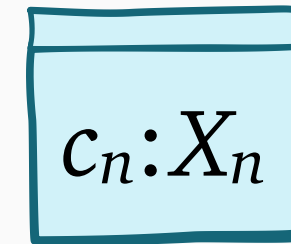
vs.



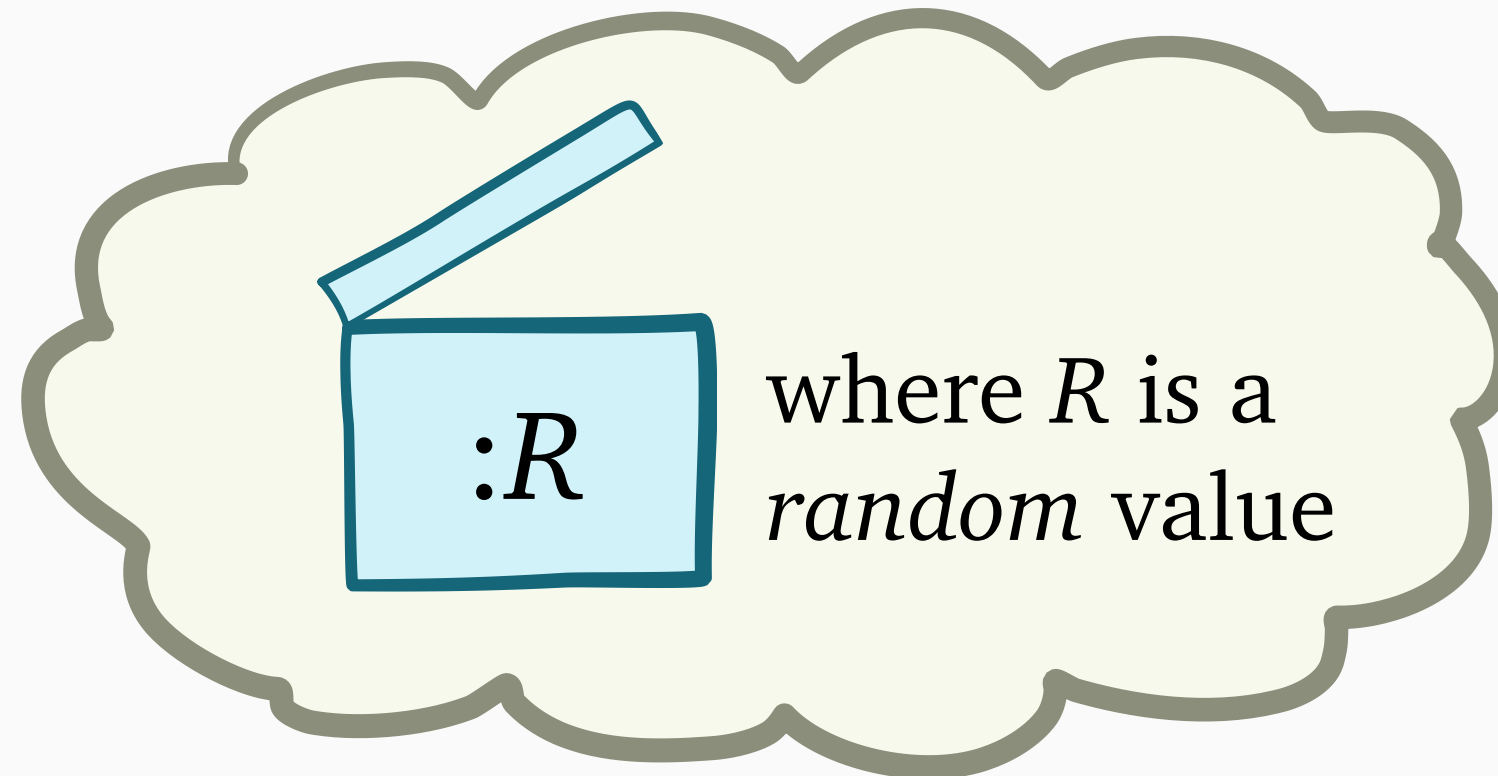
# What goes wrong under optional inspection?



...

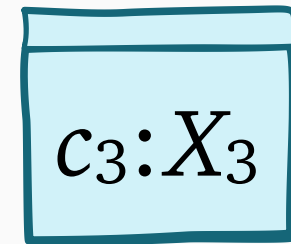
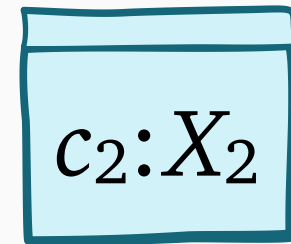
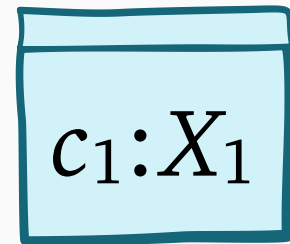


vs.

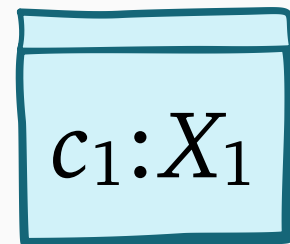
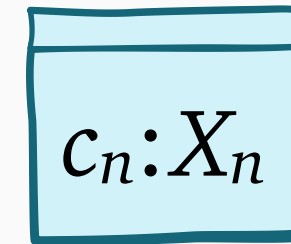


Open vs. grab  
for box 1  
depends on  $R$

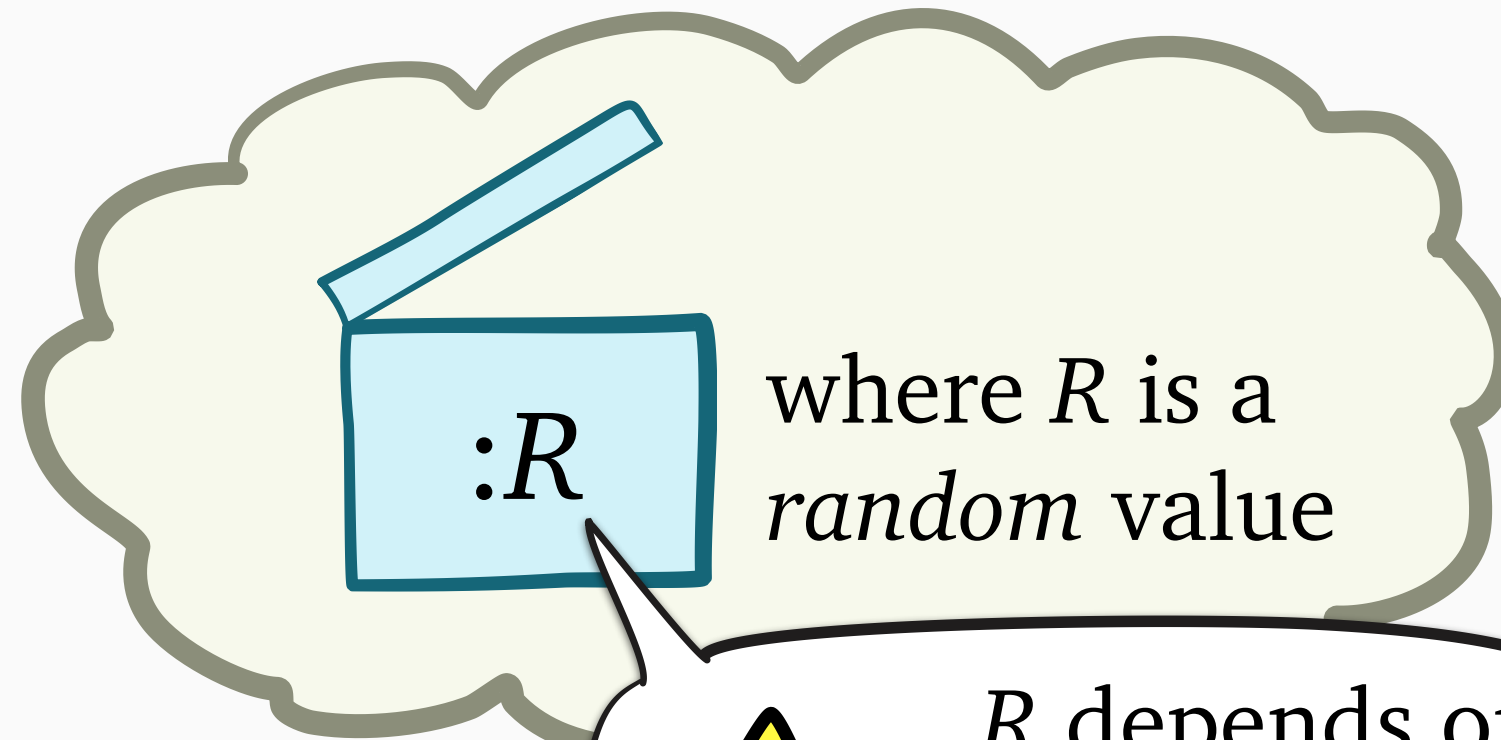
# What goes wrong under optional inspection?





...



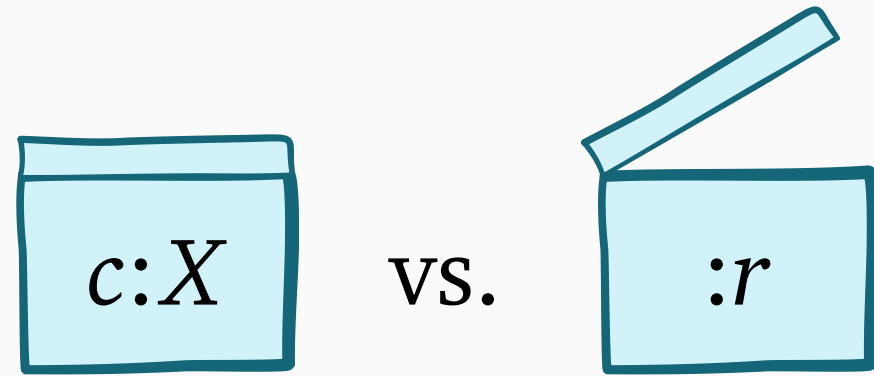
vs.



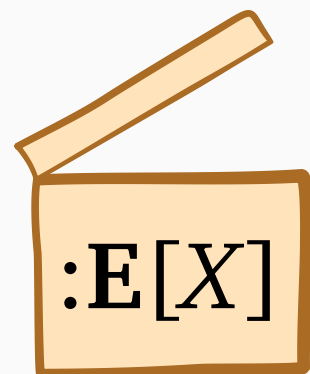
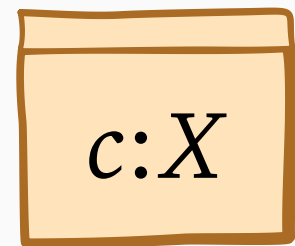
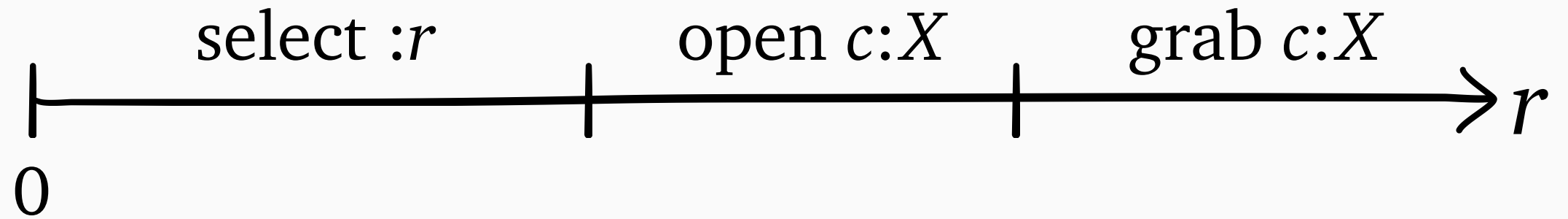
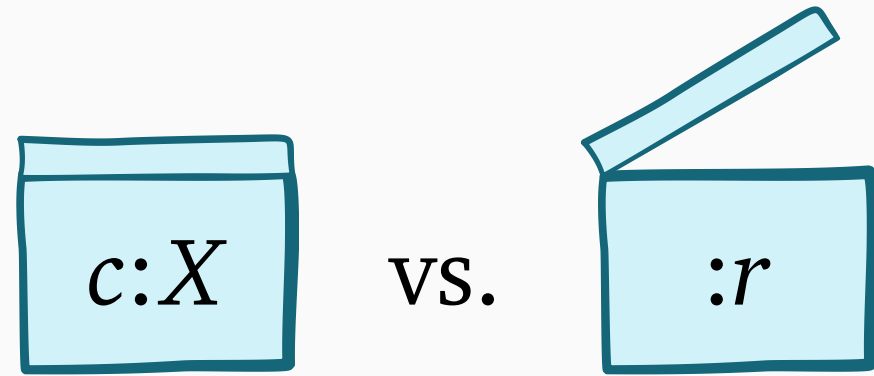
 Open vs. grab for box 1 depends on  $R$

  $R$  depends on open vs. grab for boxes 2 ...  $n$

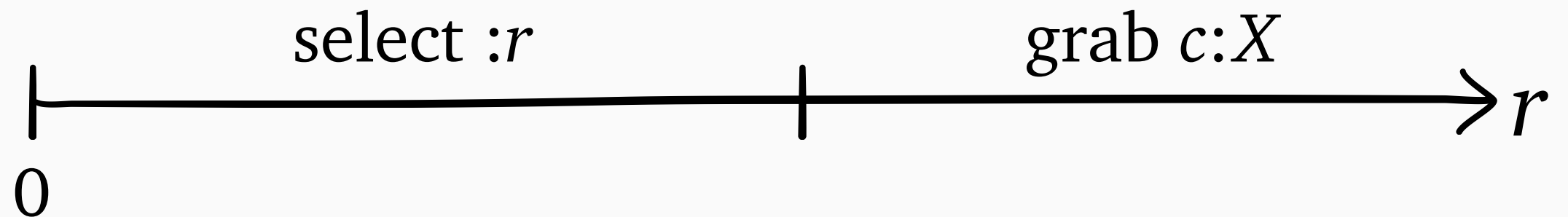
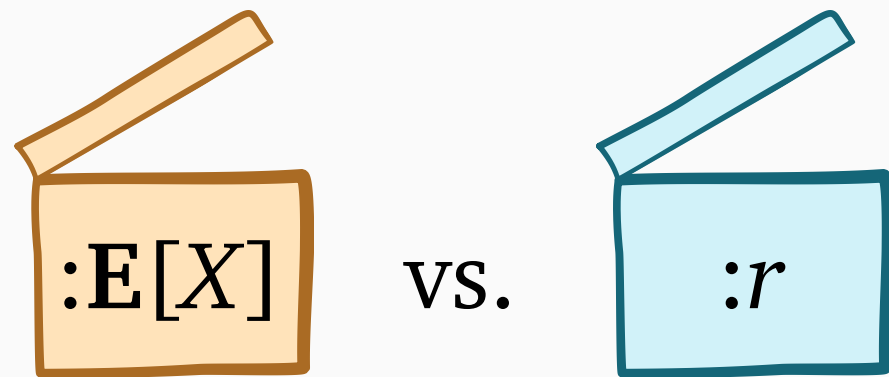
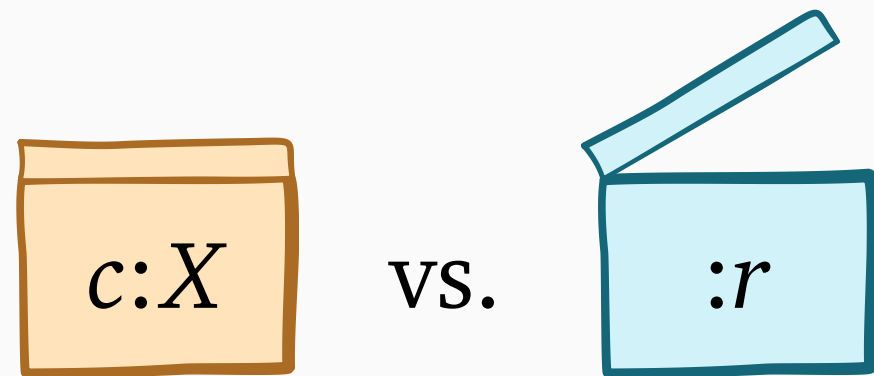
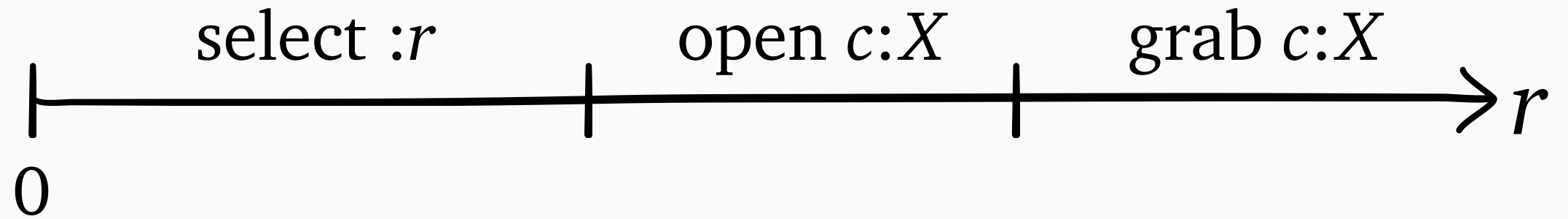
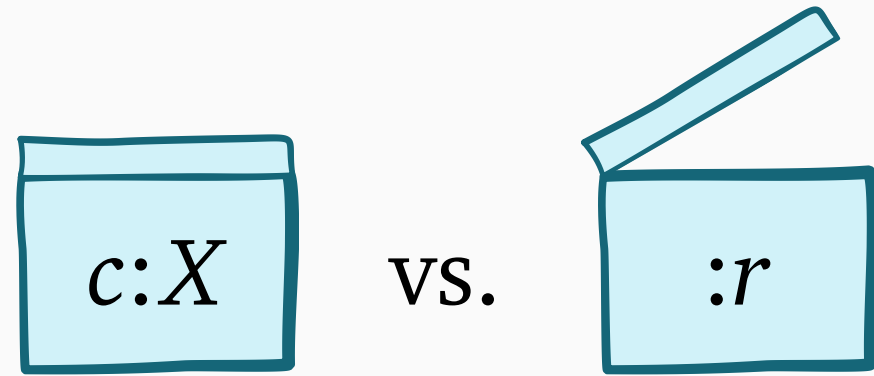
# Approximate solution with **Local Hedging**



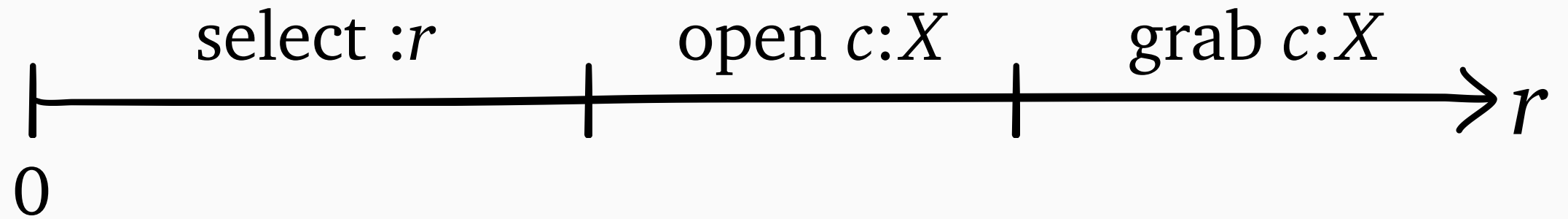
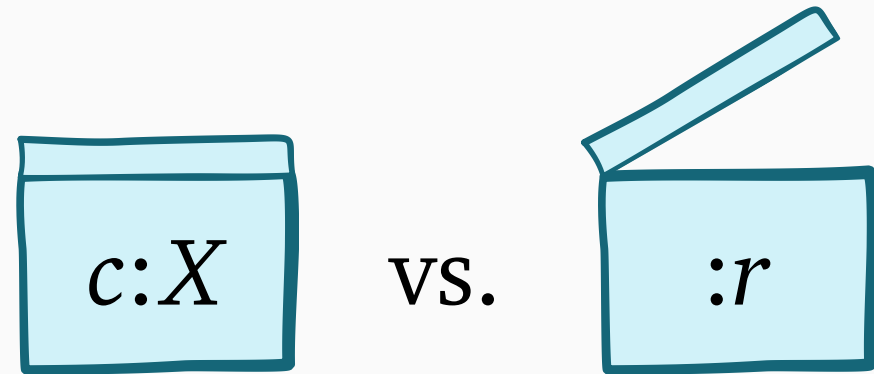
# Approximate solution with **Local Hedging**



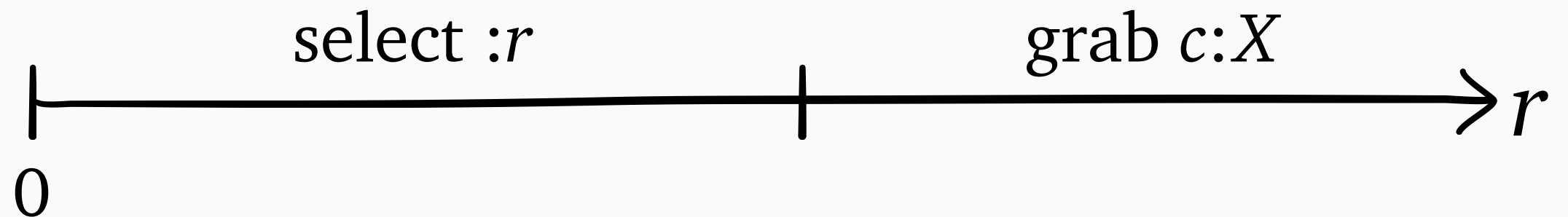
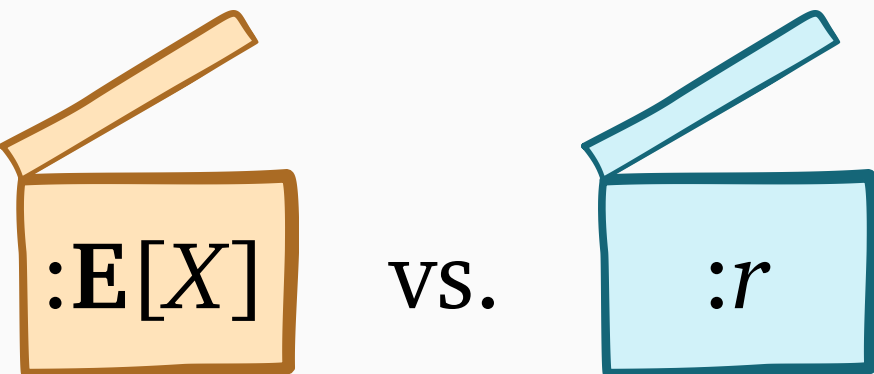
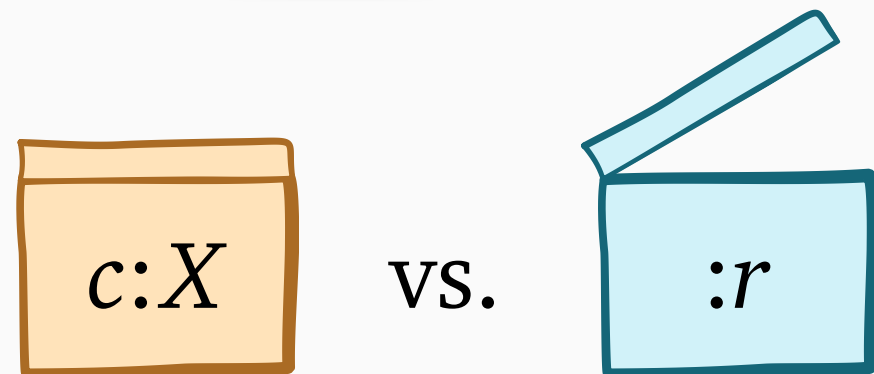
# Approximate solution with **Local Hedging**



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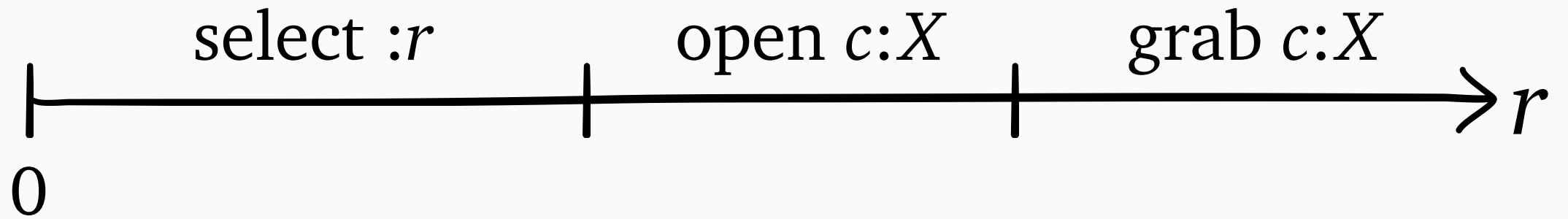
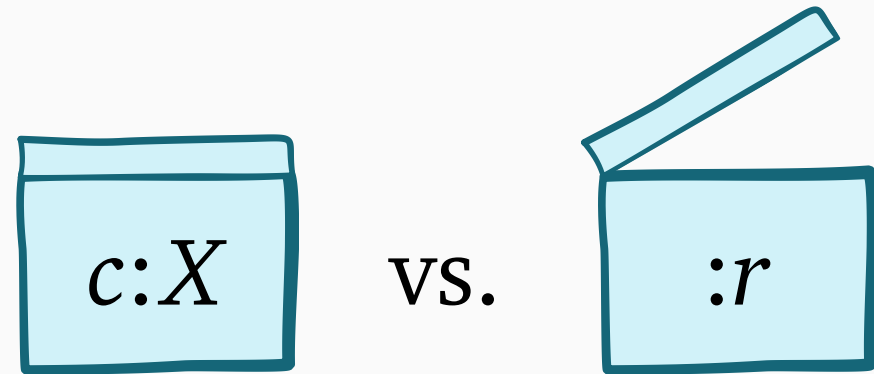
 randomize



LH

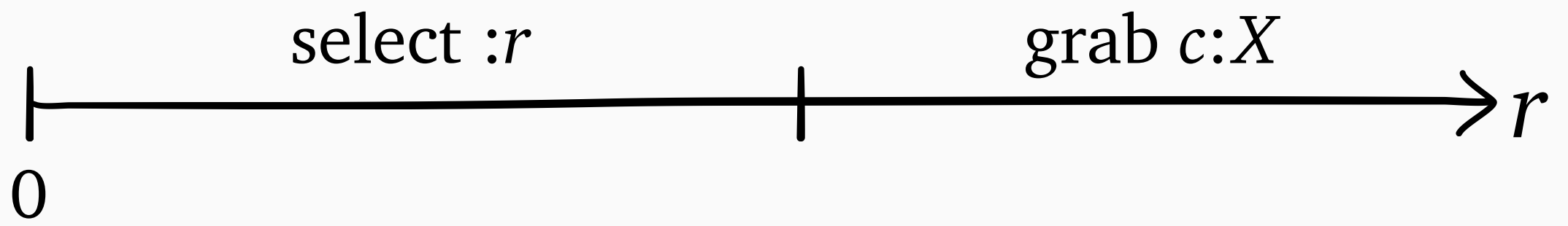
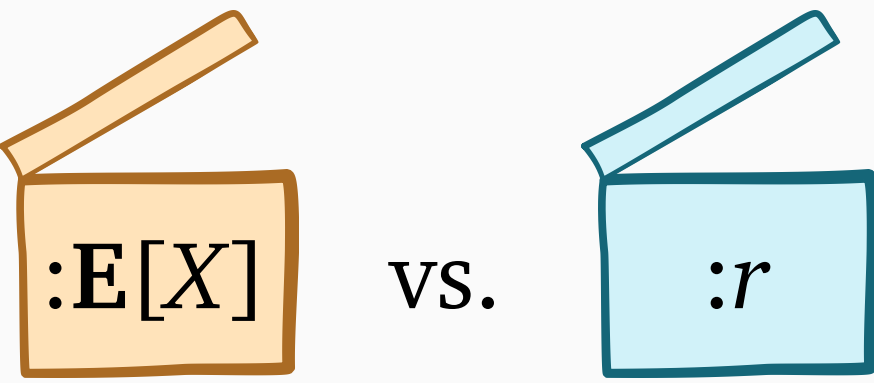
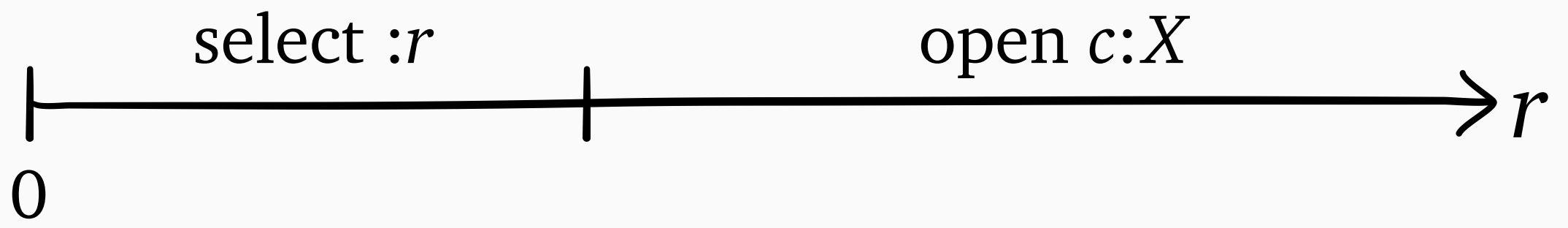
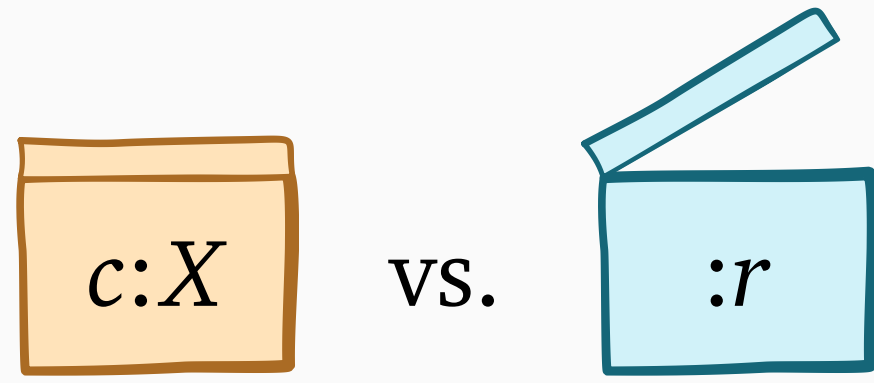


# Approximate solution with **Local Hedging**



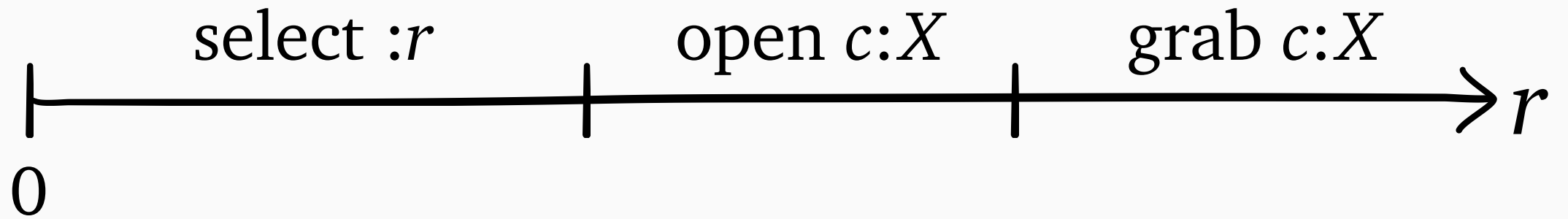
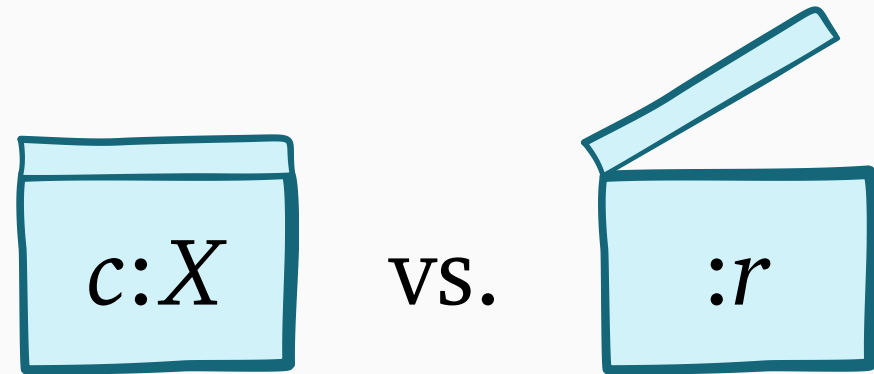
**Lemma:** exists prob. s.t. for all  $r \geq 0$ ,  
 ↓ has lower  $E[\text{cost}]$  than ↑

💡 randomize



LH

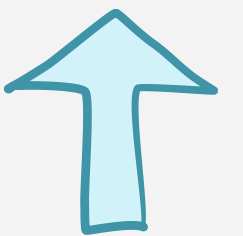
# Approximate solution with **Local Hedging**



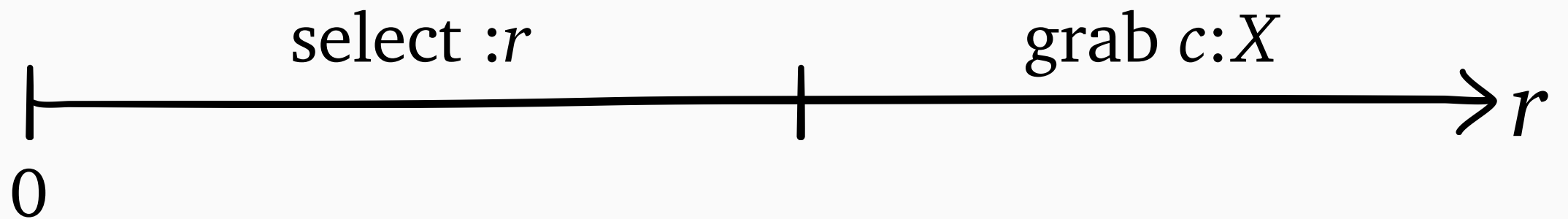
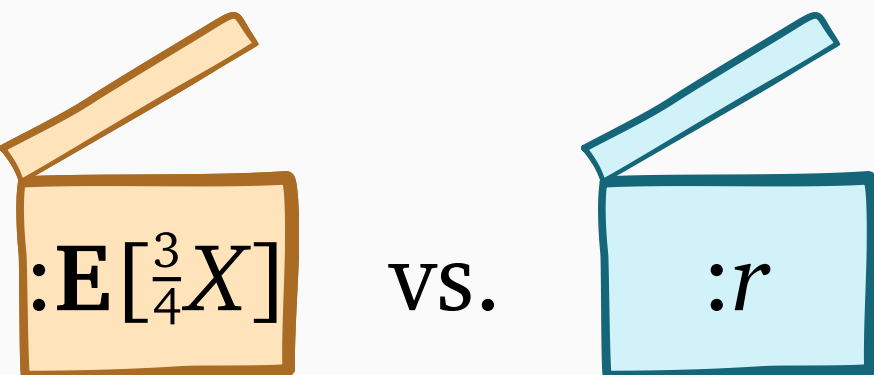
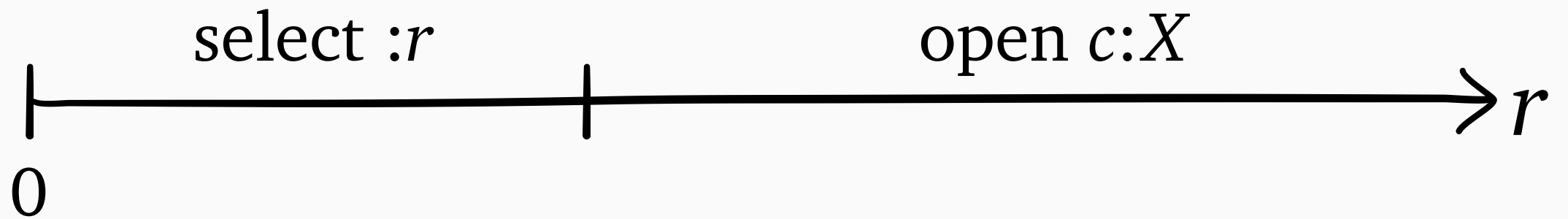
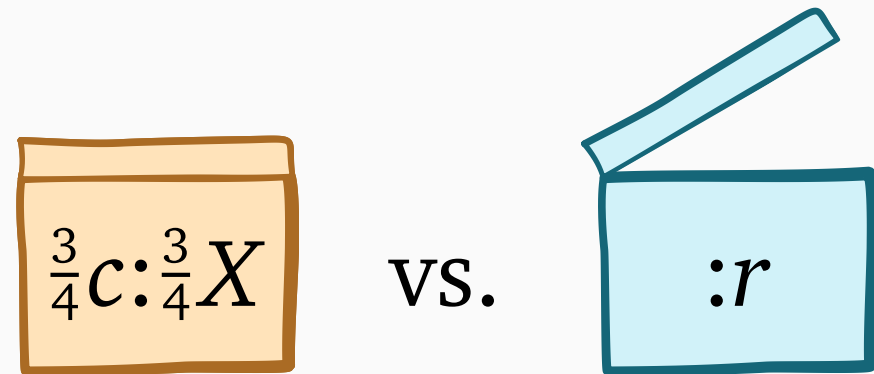
**Lemma:** exists prob. s.t. for all  $r \geq 0$ ,

with 3/4 discount

has lower  $E[\text{cost}]$  than

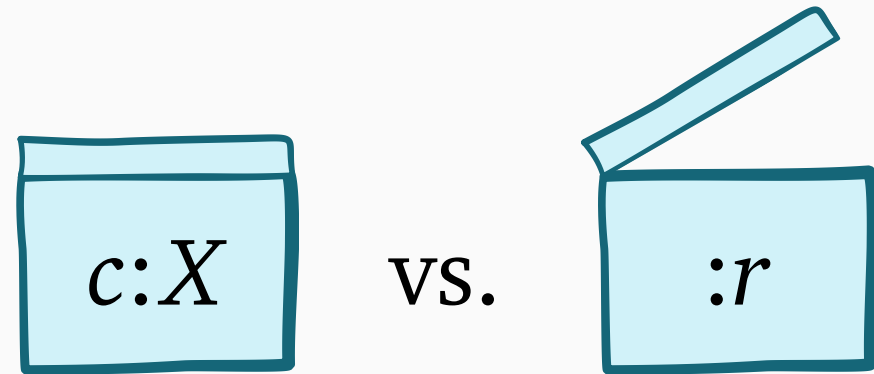


randomize



LH

# Approximate solution with Local Hedging

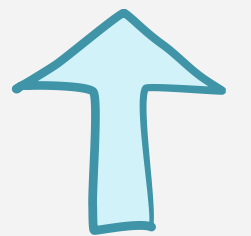


$$E[\text{cost}] = ?$$

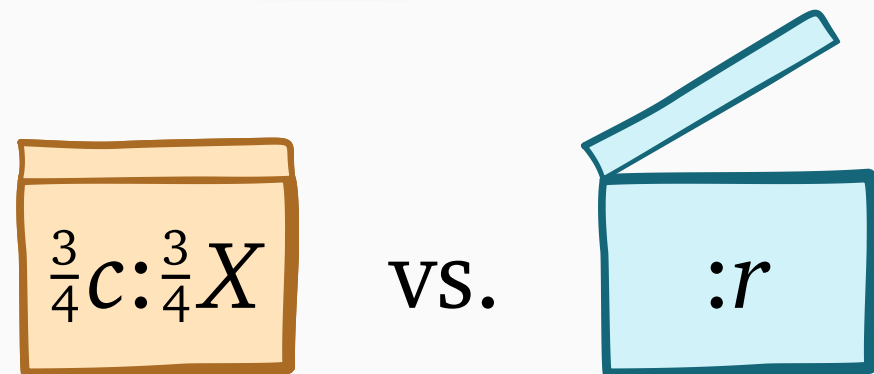
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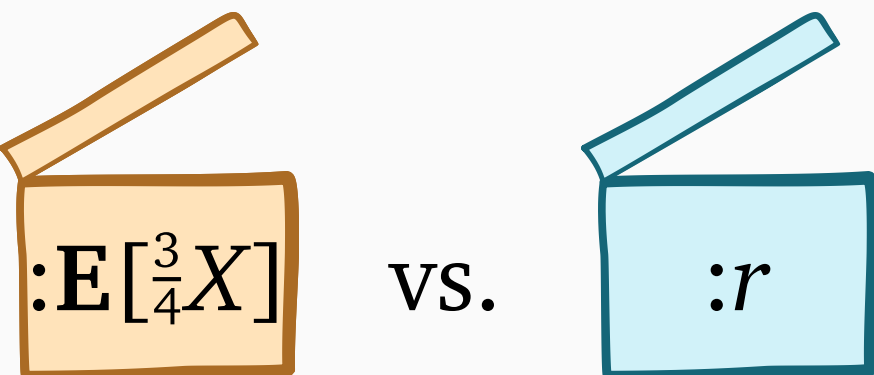
has lower  $E[\text{cost}]$  than



 randomize

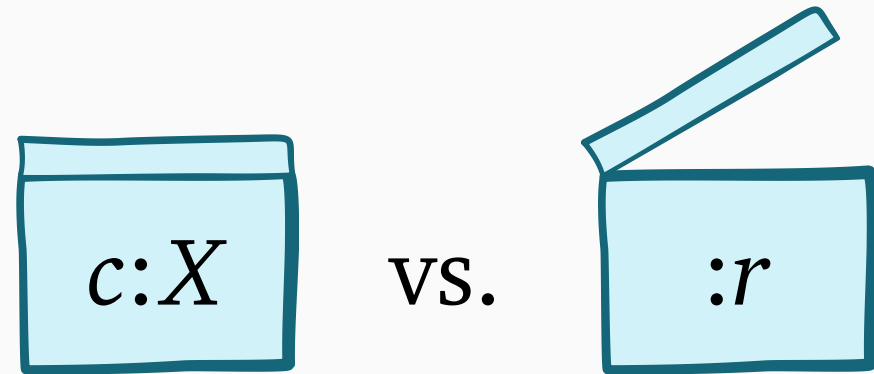


$$E[\text{cost}] = ?$$

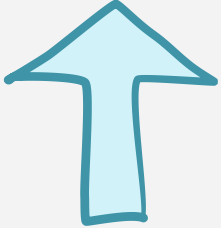


LH

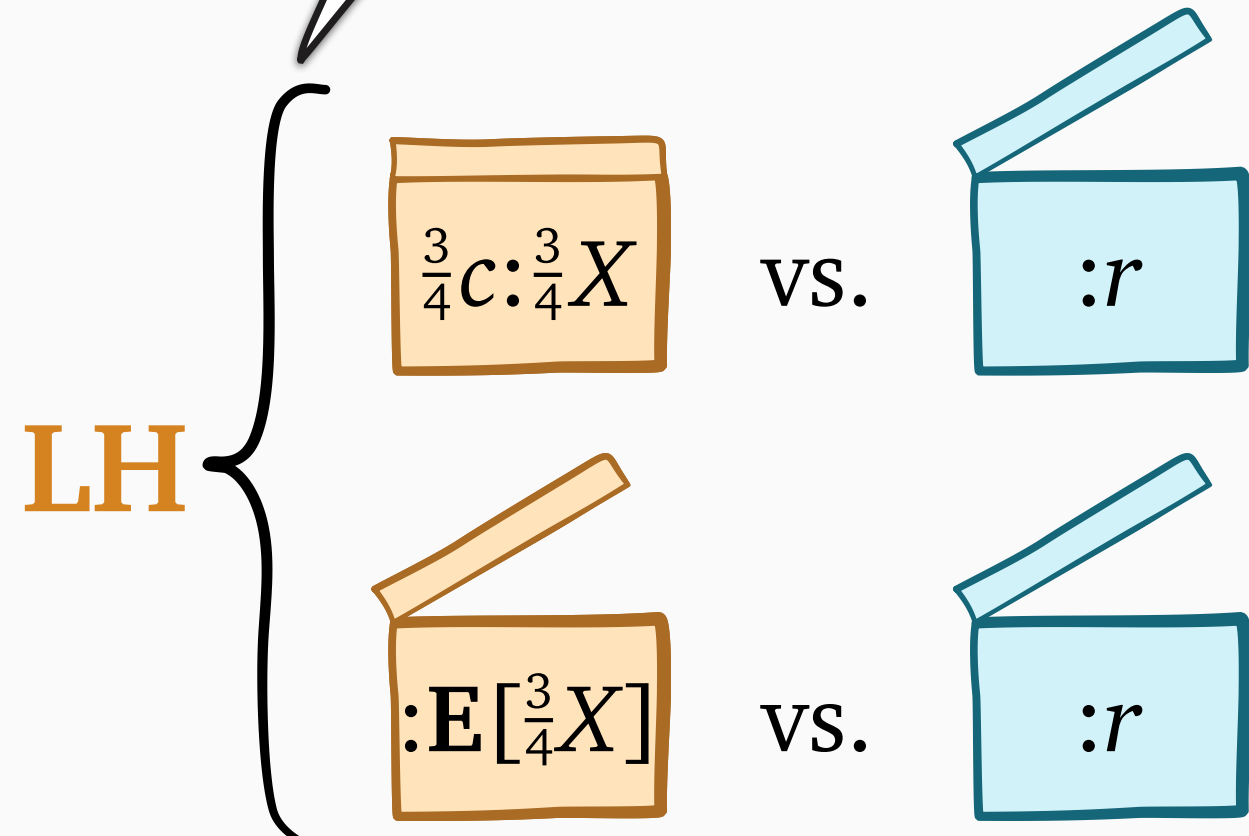
# Approximate solution with **Local Hedging**

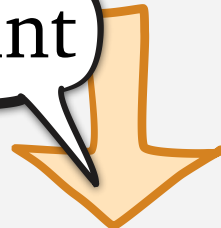


$$E[\text{cost}] = \min(r, E[X], c + E[\min(r, X)])$$

**Lemma:** exists prob. s.t. for all  $r \geq 0$ ,  
 with 3/4 discount has lower  $E[\text{cost}]$  than 

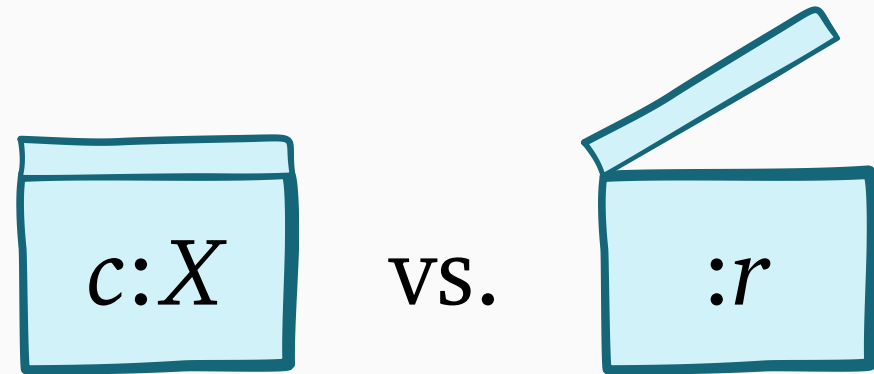
 randomize



with 3/4 discount 

$$E[\text{cost}] = ?$$

# Approximate solution with **Local Hedging**

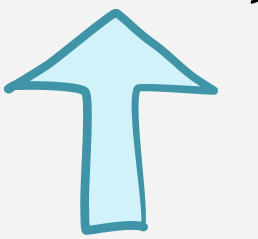


$$E[\text{cost}] = \min(r, E[X], c + E[\min(r, X)])$$

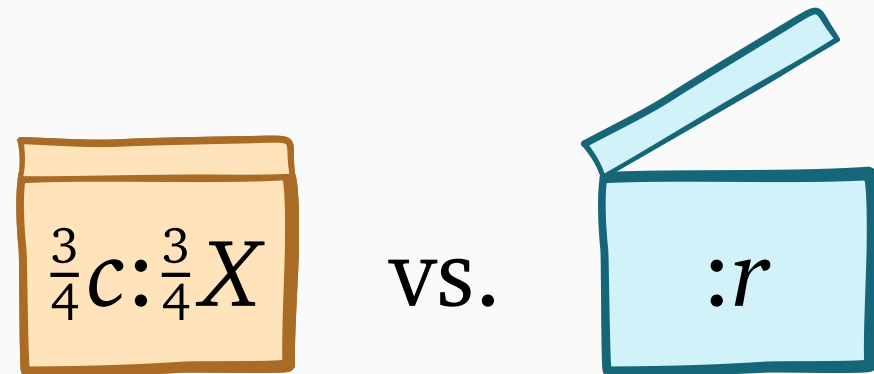
**Lemma:** exists prob. s.t. for all  $r \geq 0$ ,

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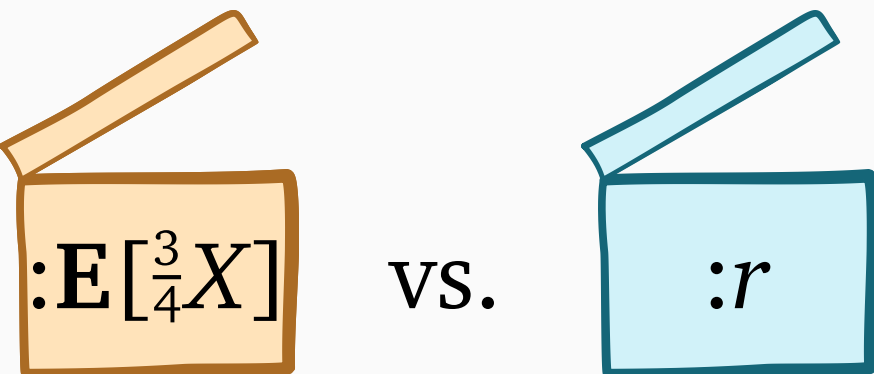


randomize



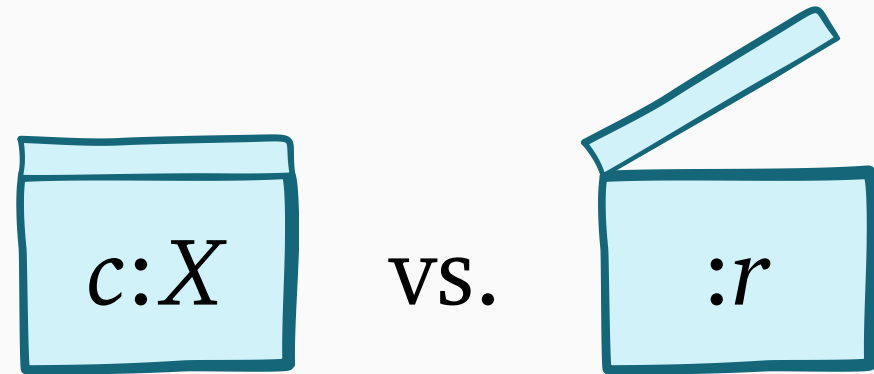
$$E[\text{cost} \mid \text{open}] = \min\left(r, \frac{3}{4}c + E\left[\min\left(r, \frac{3}{4}X\right)\right]\right)$$

LH



$$E[\text{cost}] = ?$$

# Approximate solution with **Local Hedging**

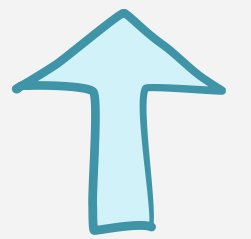


$$E[\text{cost}] = \min(r, E[X], c + E[\min(r, X)])$$

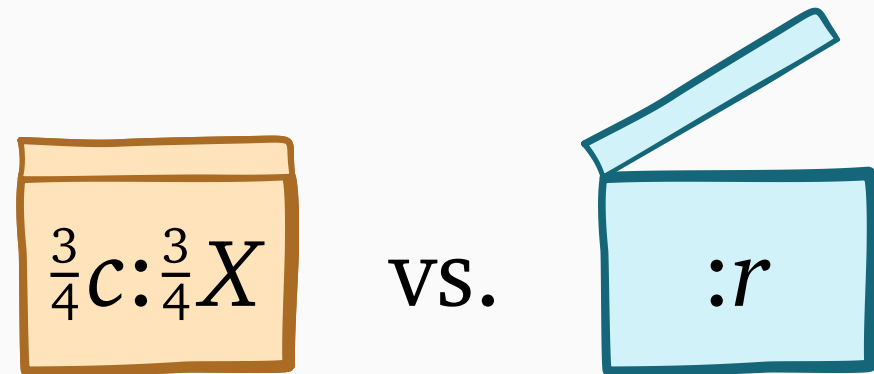
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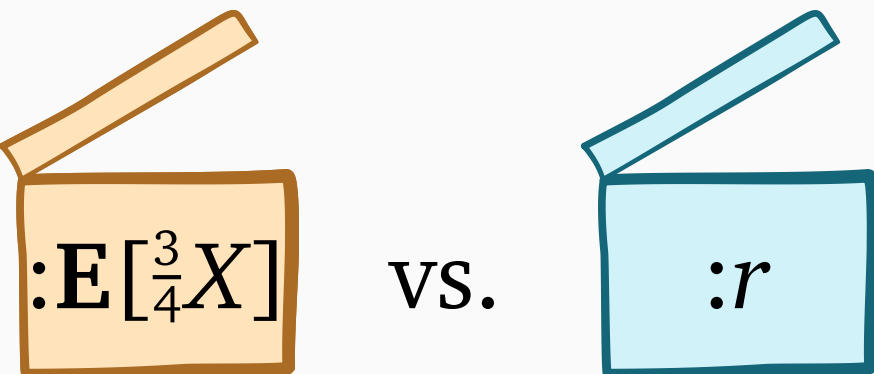


 randomize



$$E[\text{cost} \mid \text{open}] = \min\left(r, \frac{3}{4}c + E\left[\min\left(r, \frac{3}{4}X\right)\right]\right)$$

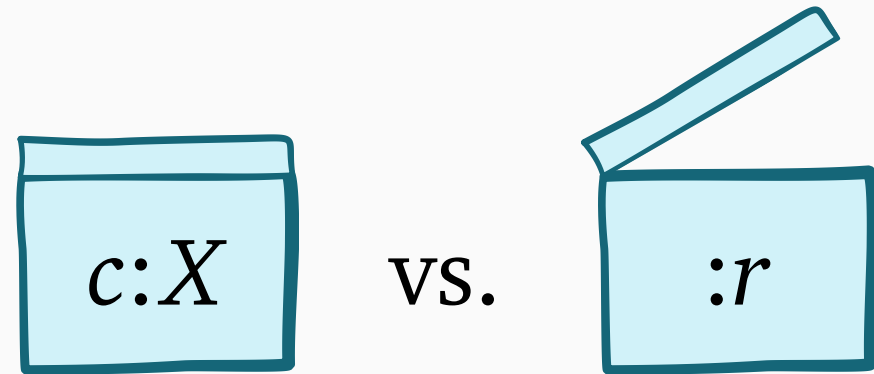
$$E[\text{cost}] = ?$$



$$E[\text{cost} \mid \text{grab}] = \min\left(r, E\left[\frac{3}{4}X\right]\right)$$

**LH**

# Approximate solution with **Local Hedging**

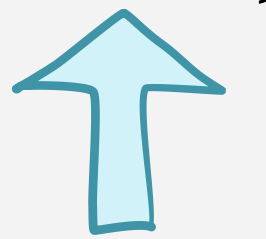


$$\mathbf{E}[\text{cost}] = \min\left(r, \mathbf{E}[X], c + \mathbf{E}[\min(r, X)]\right)$$

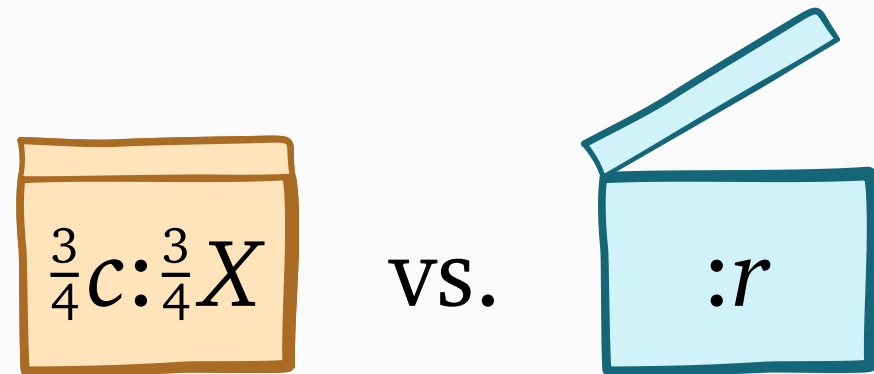
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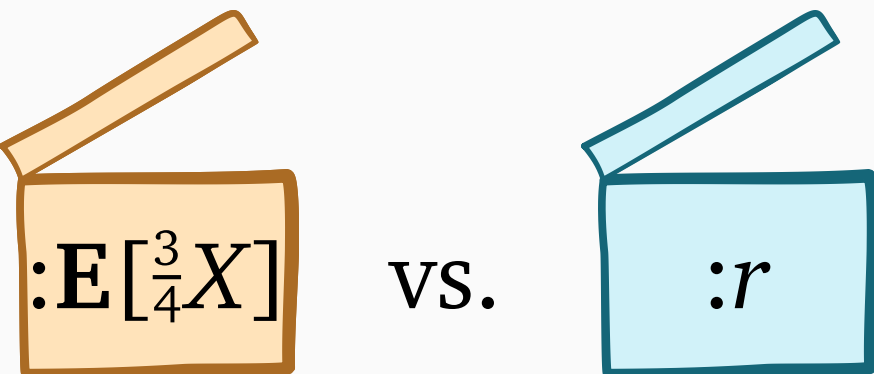


 randomize



$$\mathbf{E}[\text{cost} \mid \text{open}] = \min\left(r, \frac{3}{4}c + \mathbf{E}[\min(r, \frac{3}{4}X)]\right)$$

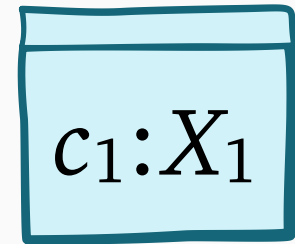
**LH**



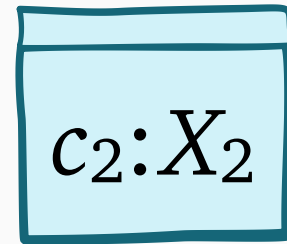
$$\mathbf{E}[\text{cost}] = p\mathbf{E}[\text{cost} \mid \text{open}] + (1 - p)\mathbf{E}[\text{cost} \mid \text{grab}]$$

$$\mathbf{E}[\text{cost} \mid \text{grab}] = \min\left(r, \mathbf{E}[\frac{3}{4}X]\right)$$

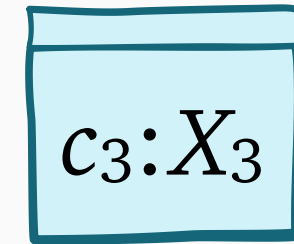
# How **Local Hedging** helps



$c_1: X_1$

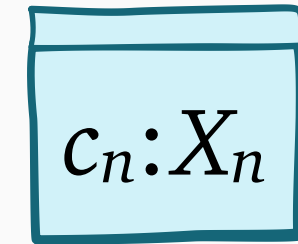


$c_2: X_2$



$c_3: X_3$

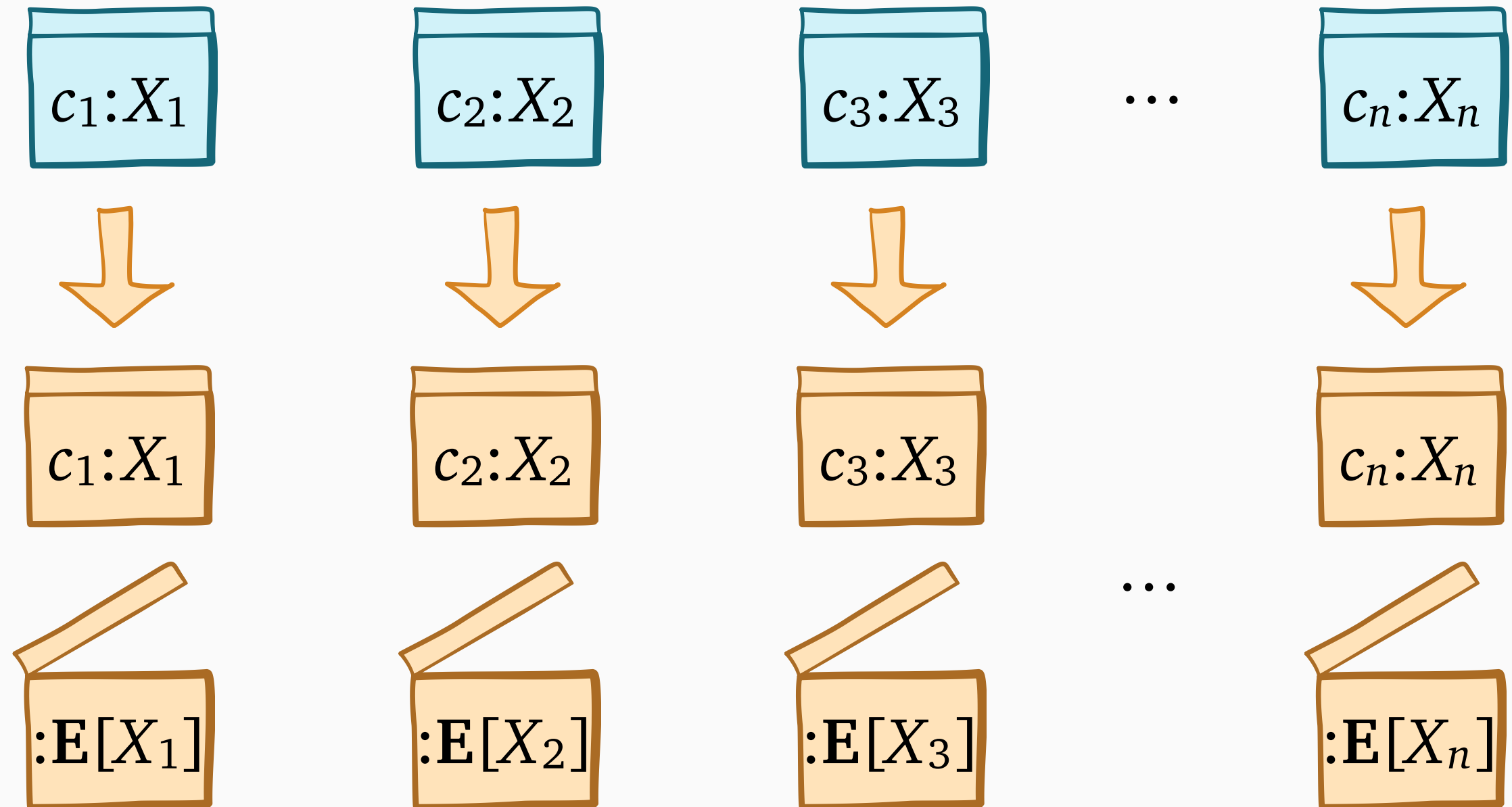
...



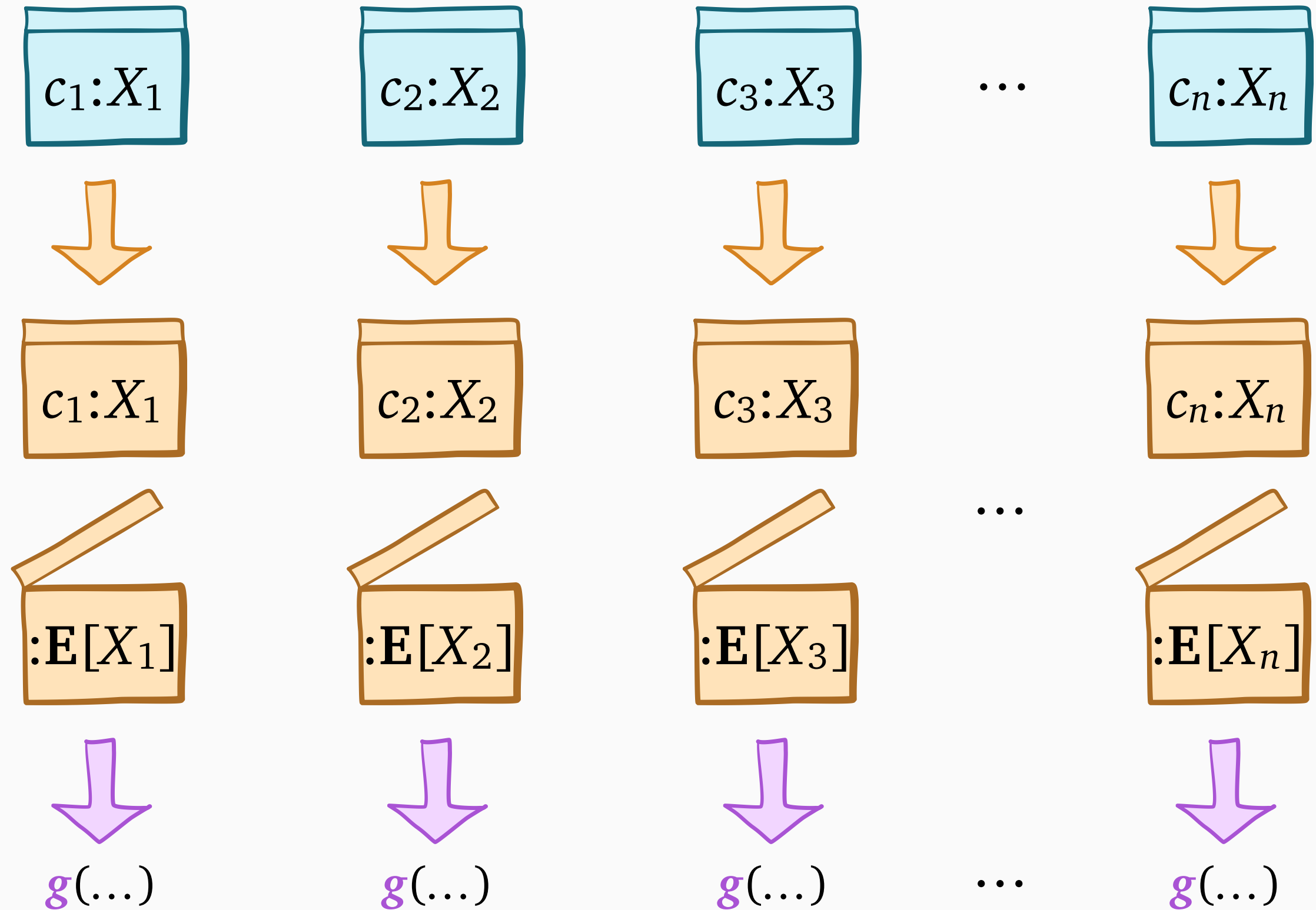
$c_n: X_n$



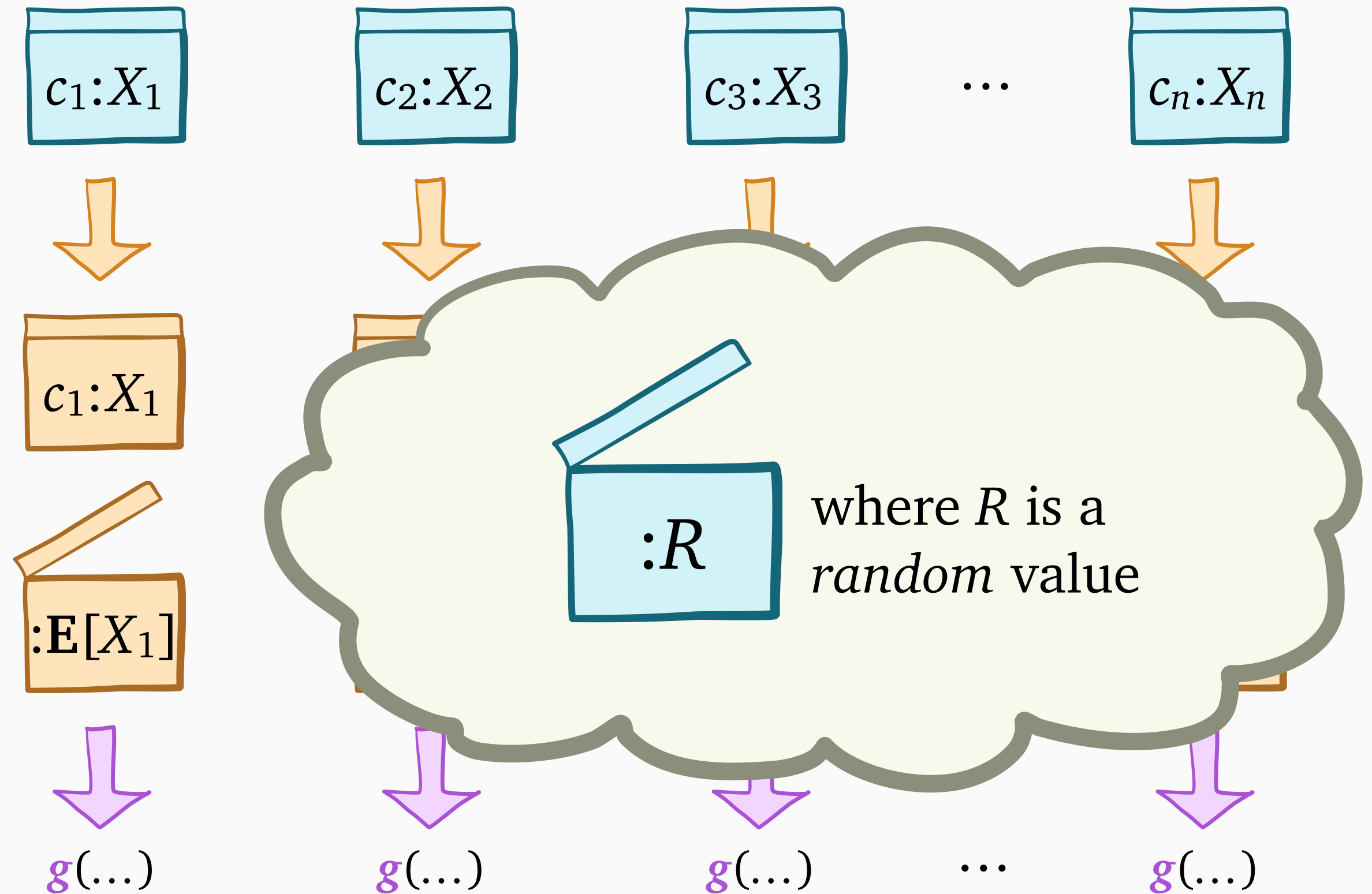
# How **Local Hedging** helps



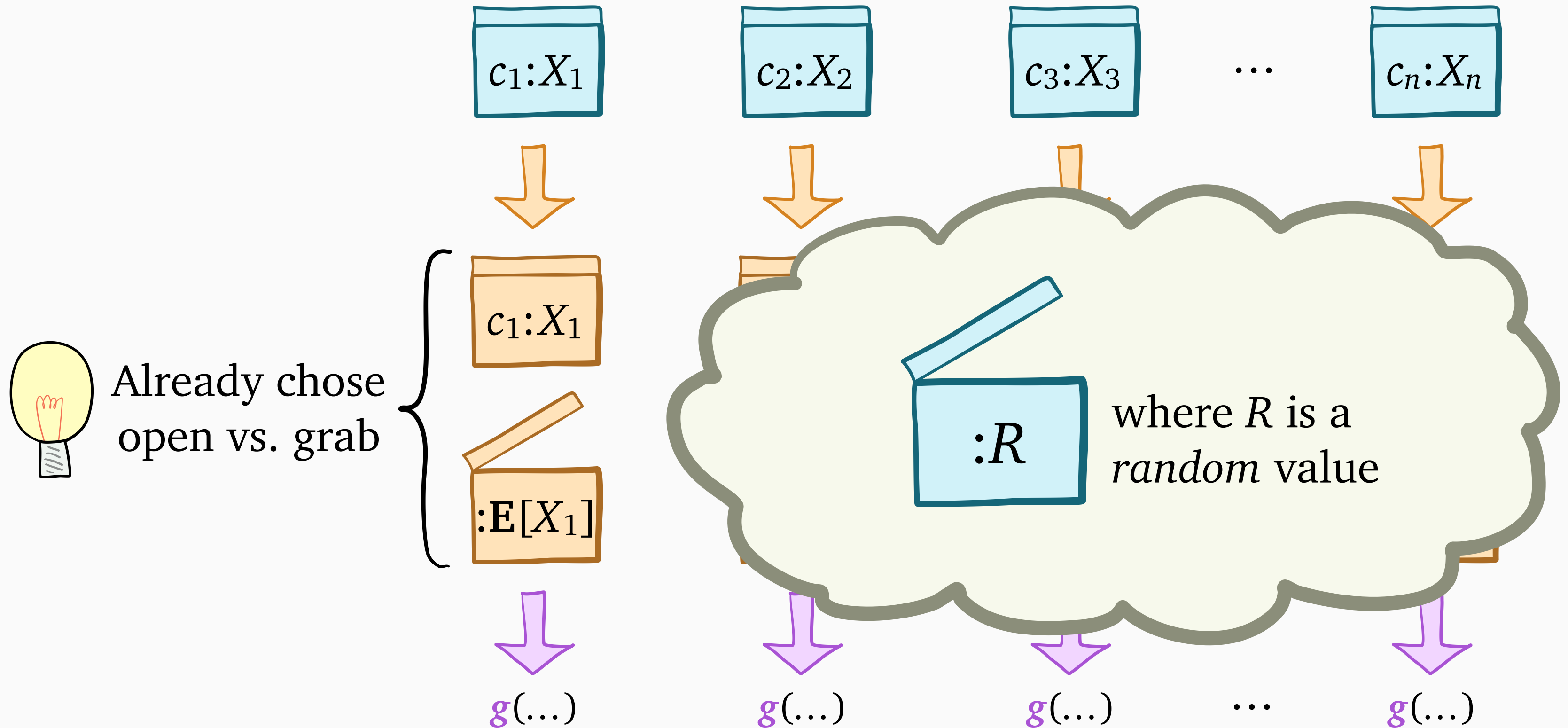
# How **Local Hedging** helps



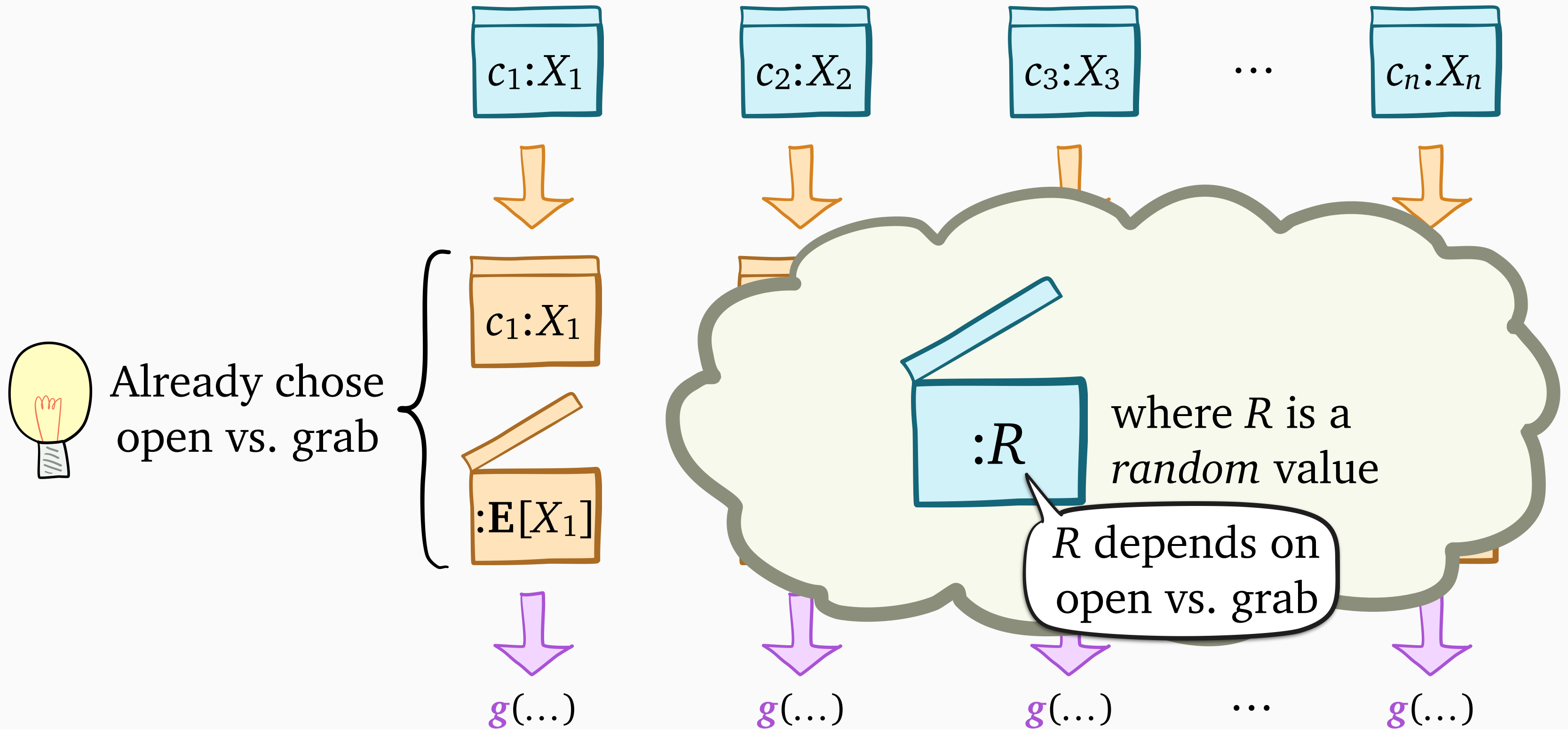
# How **Local Hedging** helps



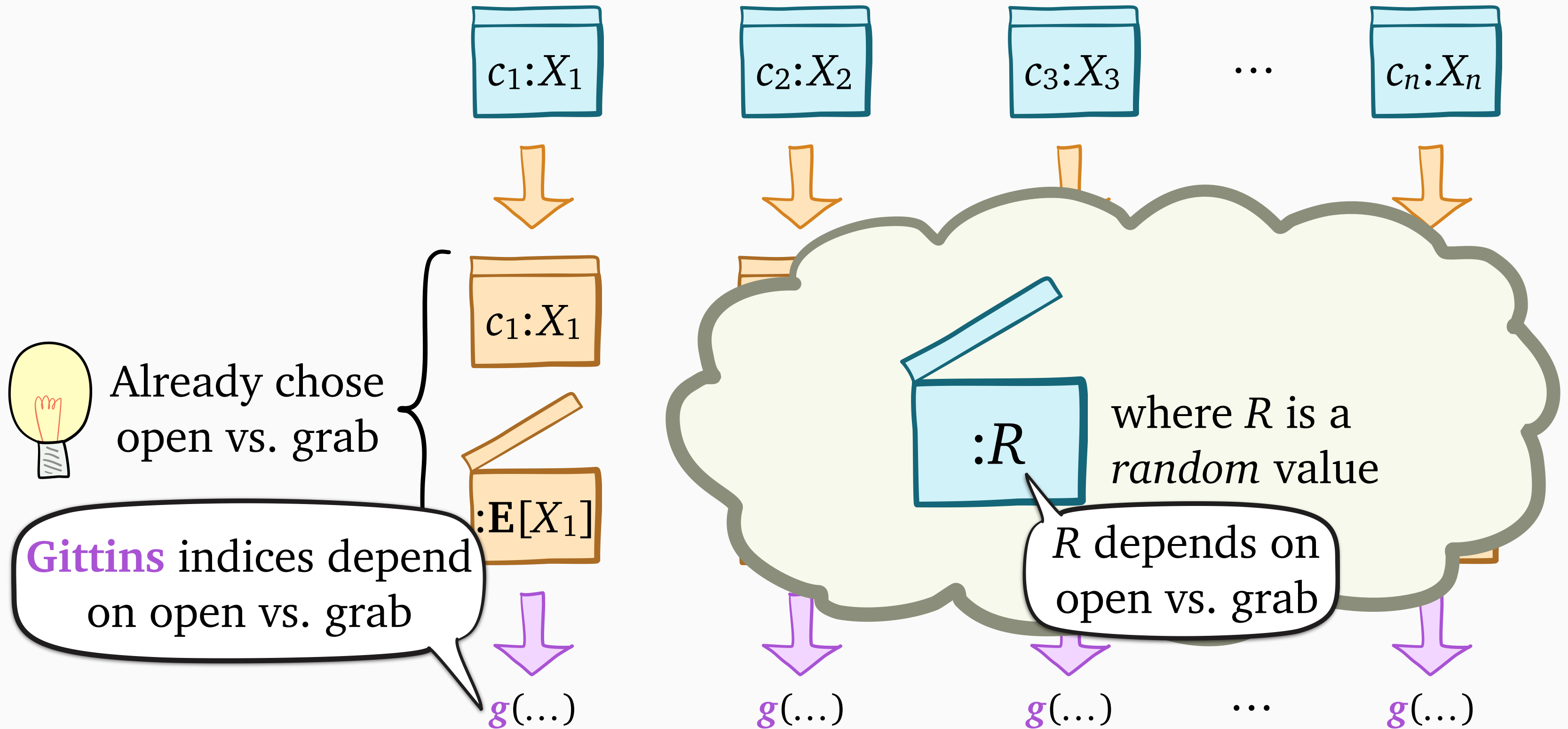
# How **Local Hedging** helps



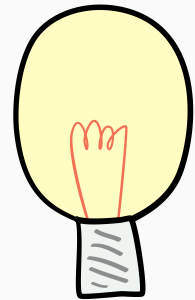
# How **Local Hedging** helps



# How **Local Hedging** helps



# Our contribution



## Local Hedging (LH)

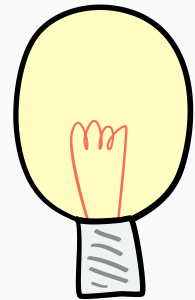
New *decomposition-based* technique for optional inspection

- Reduces problem to required-inspection case
- Naturally generalizes to combinatorial problems



**Theorem:** if **Alg** is a “greedy” algorithm, then the approximation ratio of **Gittins** + **Alg** + **LH** is  $\leq 4/3$  times that of **Alg**

# Our contribution



## Local Hedging (LH)

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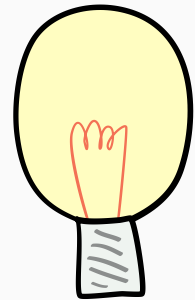
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price of reduction  
from 3/4 discount



# Our contribution

Key idea: randomization  
for “context-robustness”



## Local Hedging (LH)

New *decomposition-based* technique for optional inspection

- Reduces problem to required-inspection case
- Naturally generalizes to combinatorial problems



**Theorem:** if **Alg** is a “greedy” algorithm, then the approximation ratio of **Gittins** + **Alg** + **LH** is  $\leq 4/3$  times that of **Alg**

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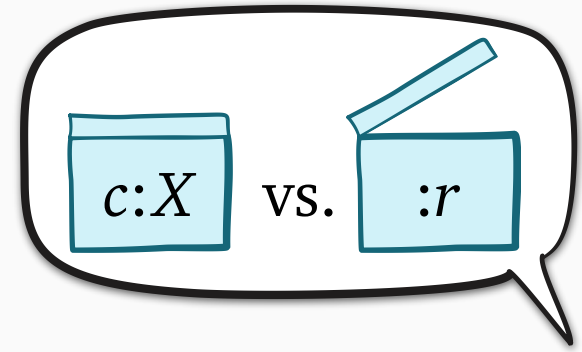
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**Technical tool:**  
*surrogate prices*

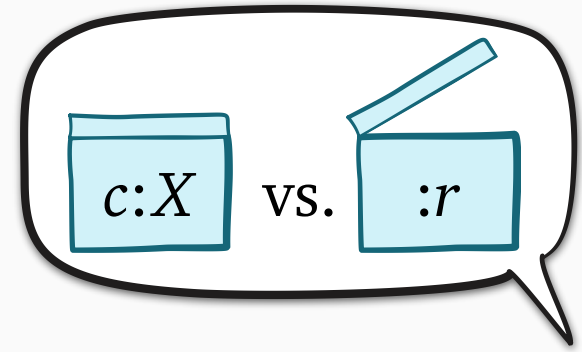
# Surrogate price: **required** inspection



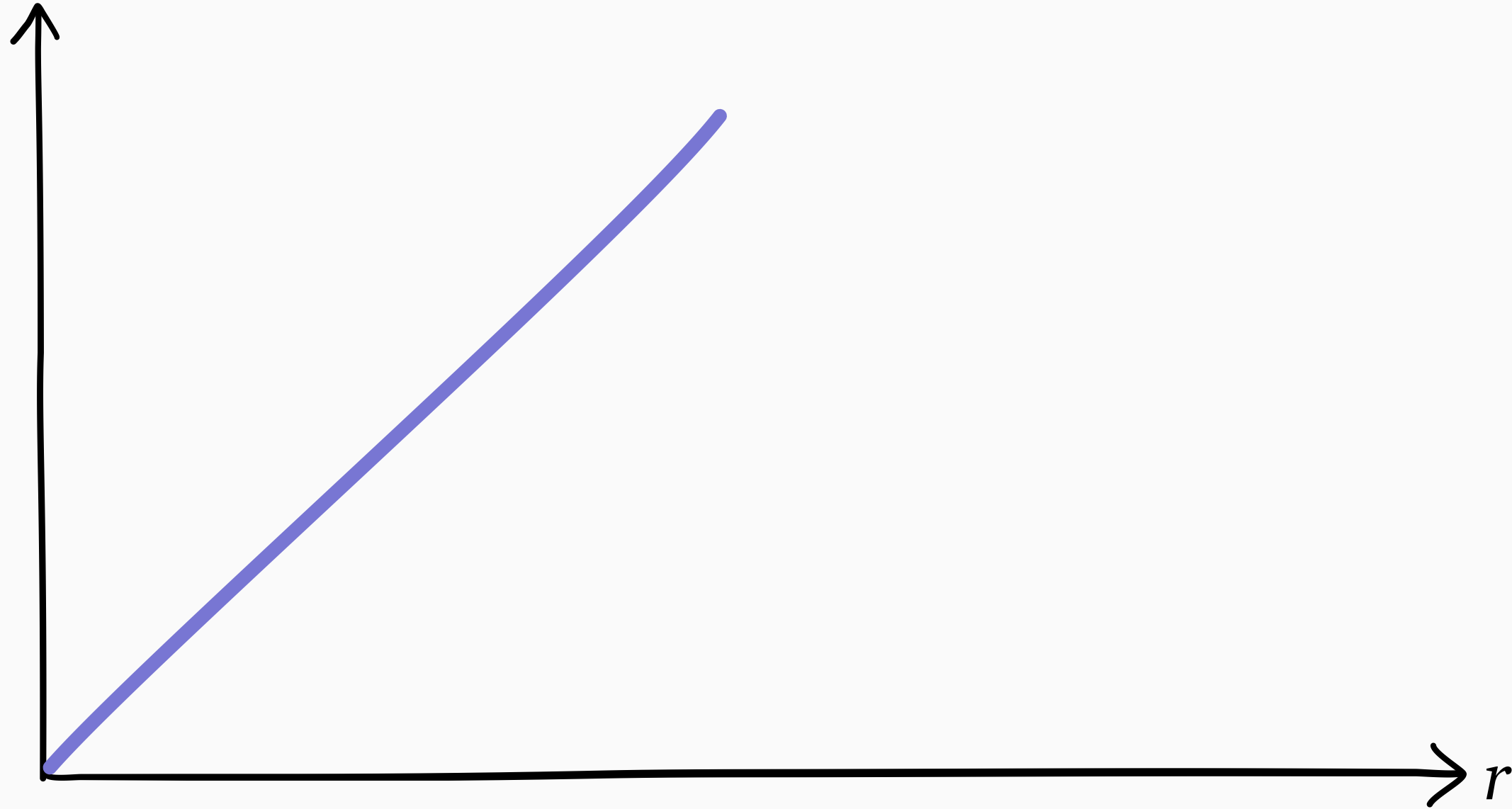
$E[\text{cost}(r)]$



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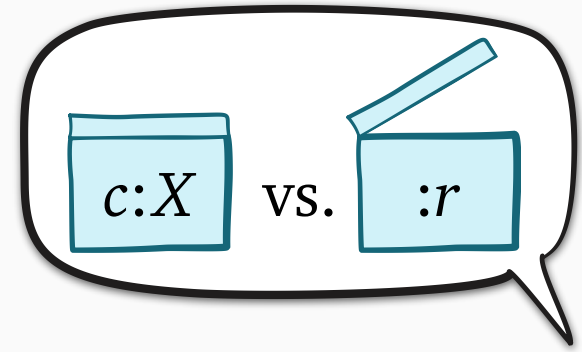


$E[\text{cost}(r)]$

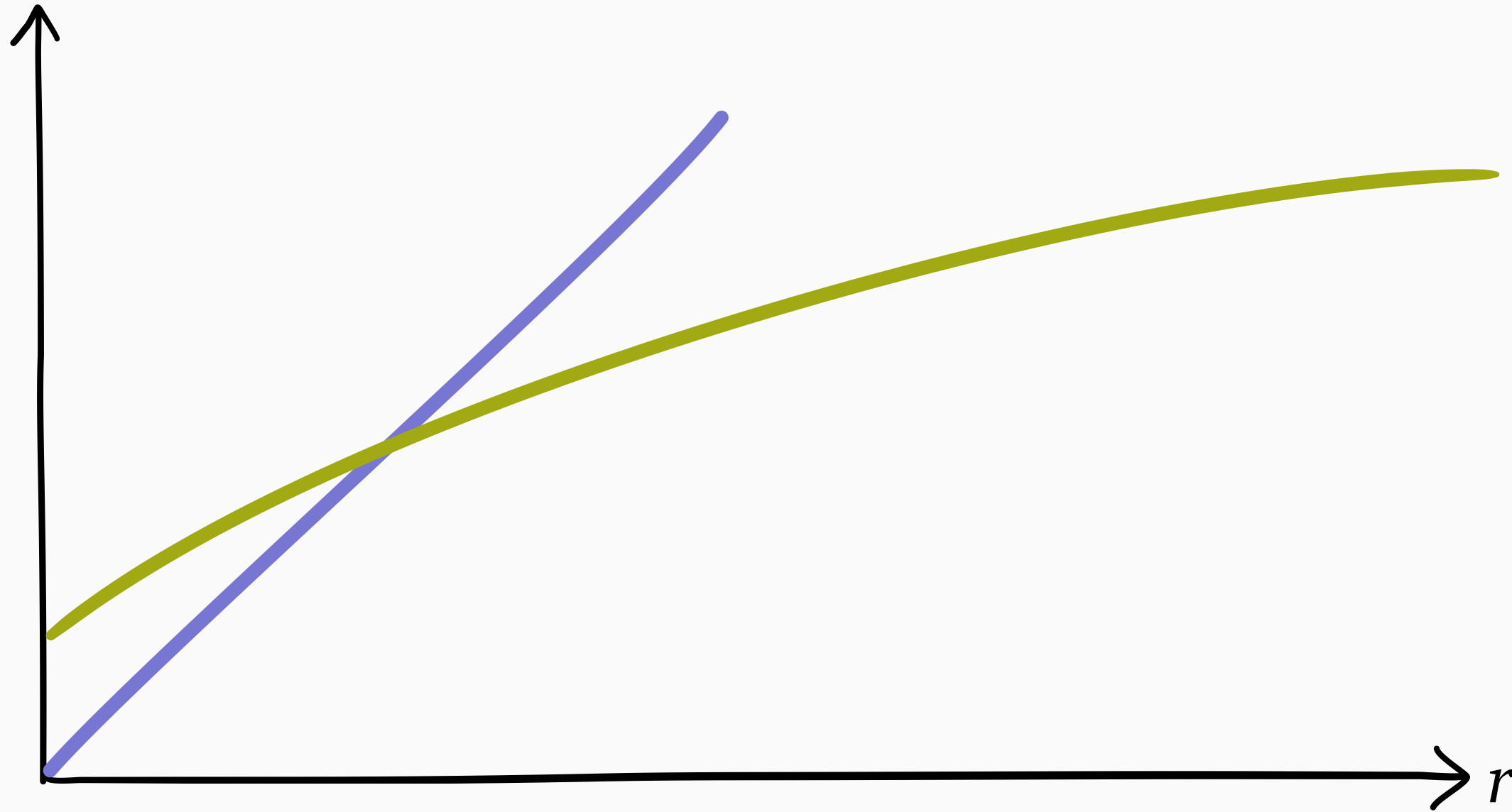


**select**  $:r$

# Surrogate price: **required** inspection



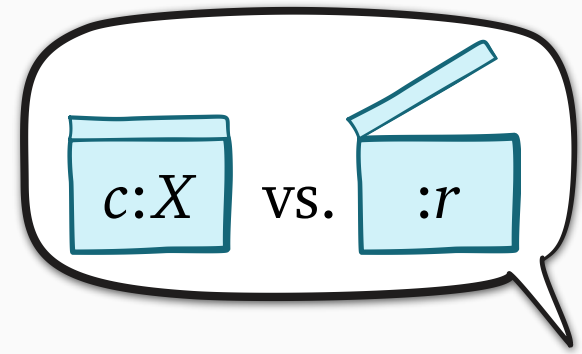
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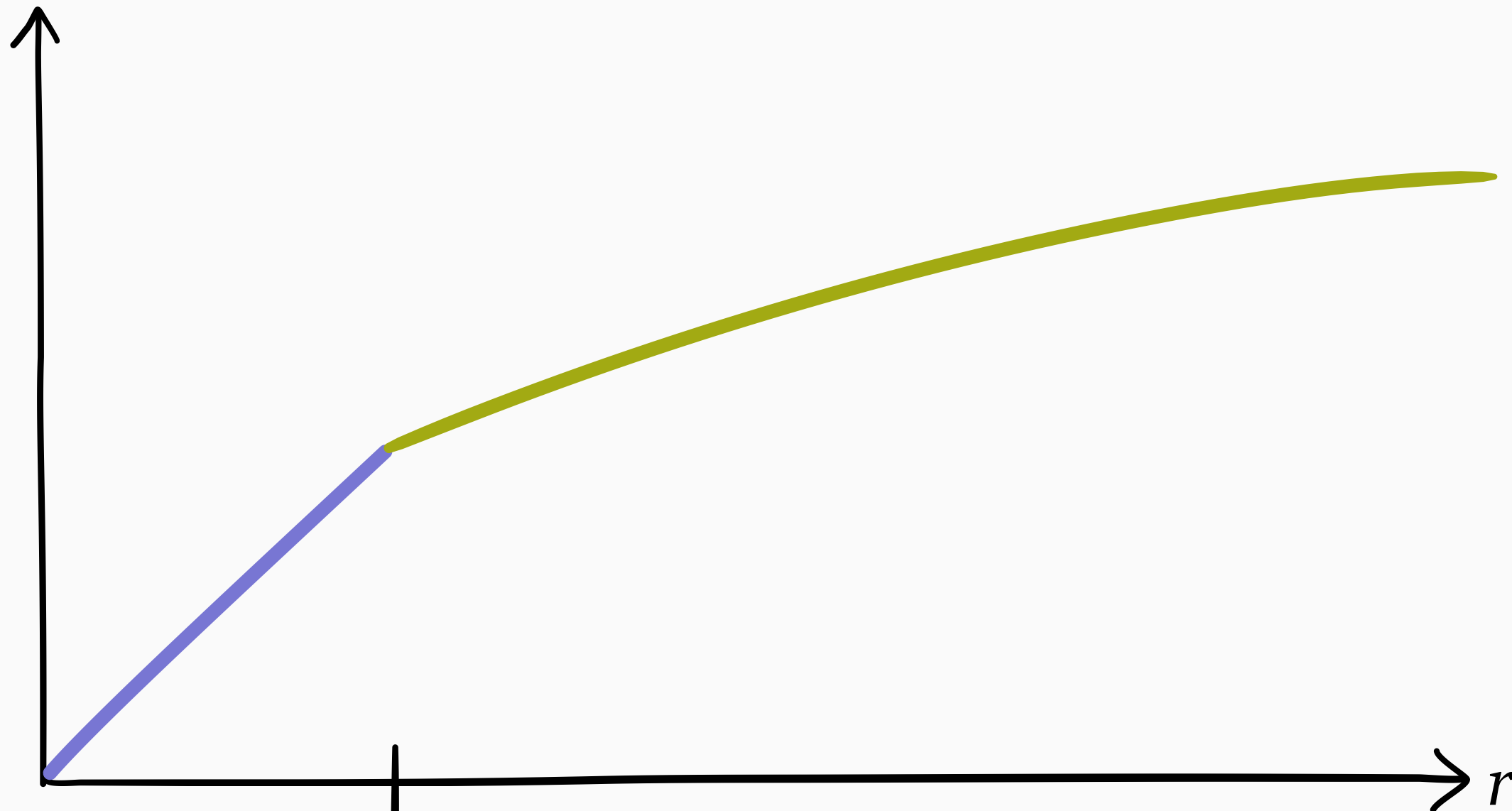
**select**  $:r$

**open**  $c:X$

# Surrogate price: **required** inspection



$E[\text{cost}(r)]$

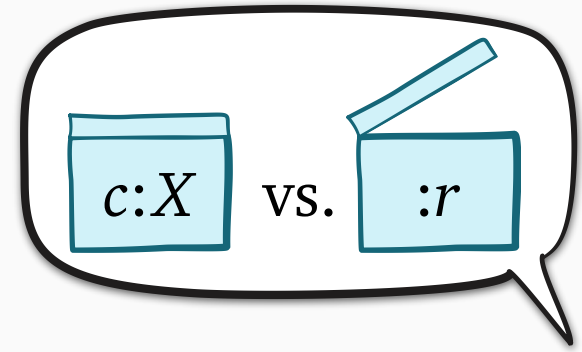


**select**  $:r$

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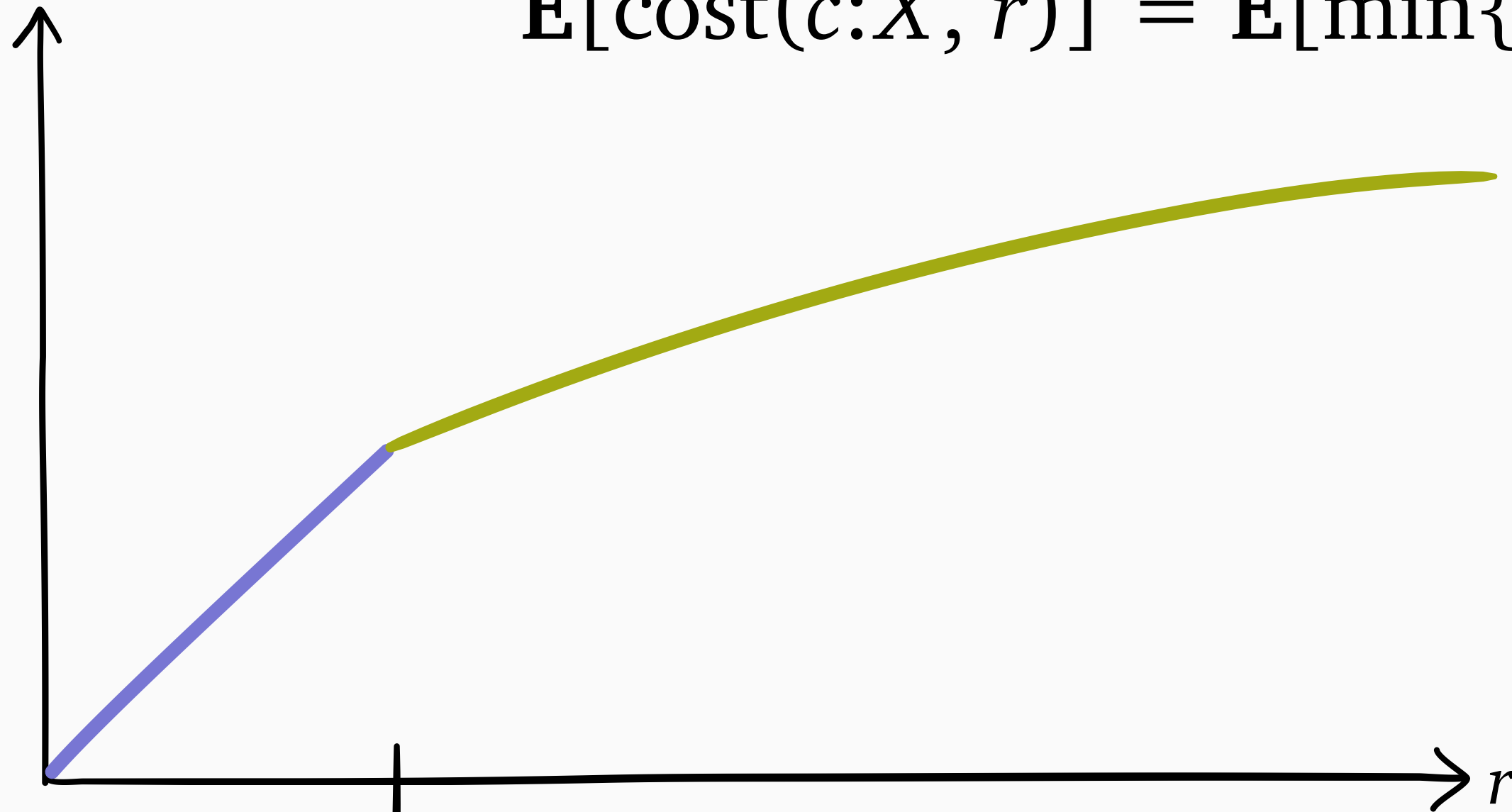
# Surrogate price: **required** inspection



Definition:  $W_{\text{reqd}}$  satisfies

$$\mathbf{E}[\text{cost}(c:X, r)] = \mathbf{E}[\min\{W_{\text{reqd}}, r\}]$$

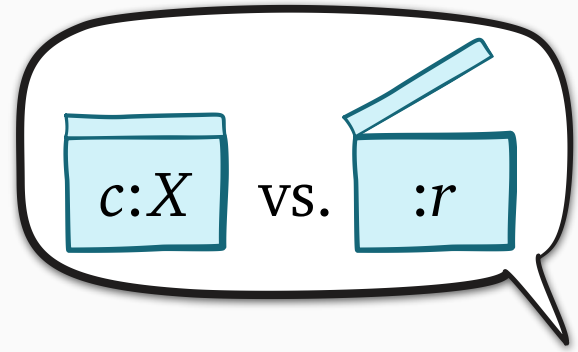
$\mathbf{E}[\text{cost}(r)]$



**select**  $:r$

**open**  $c:X$

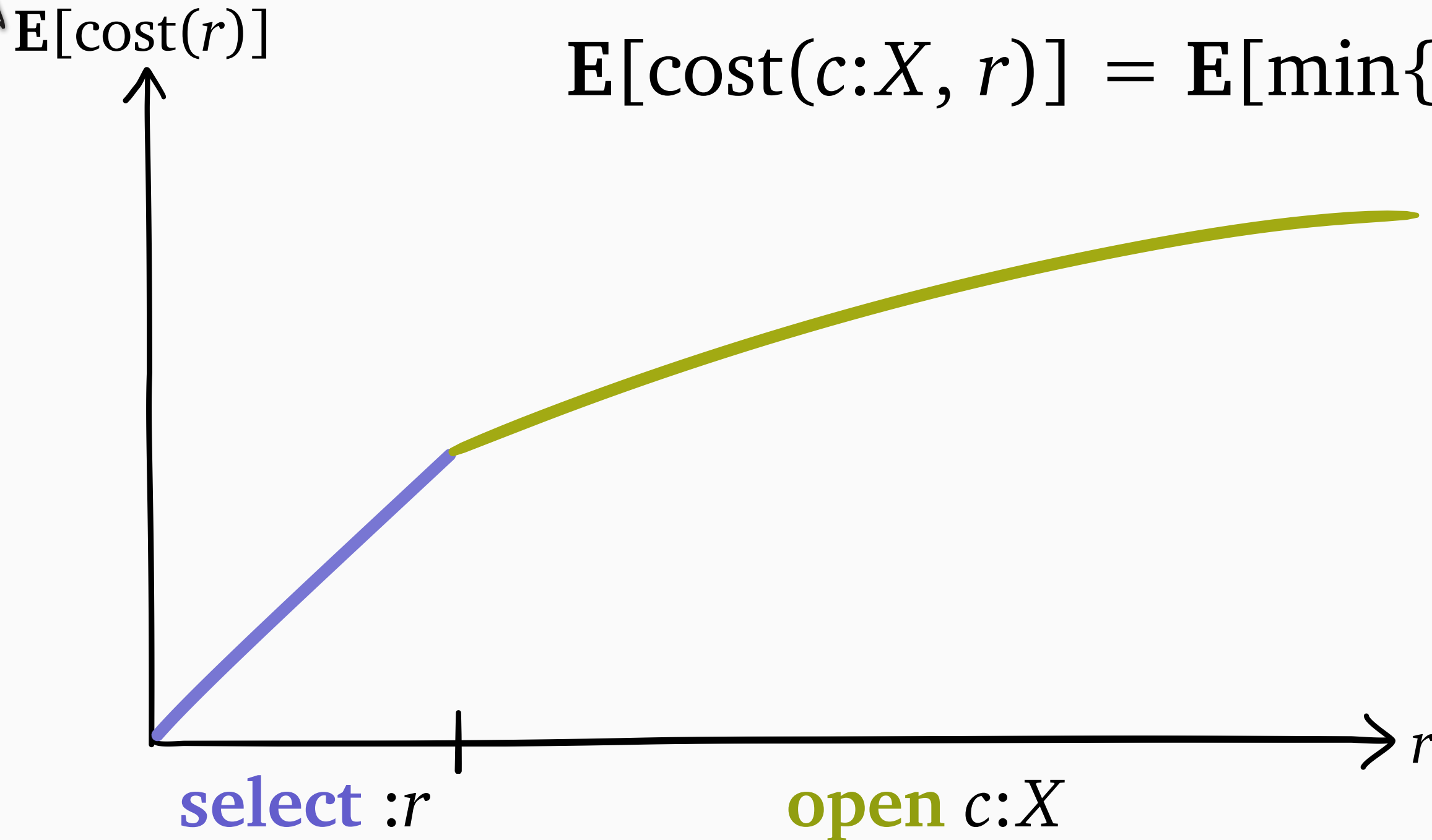
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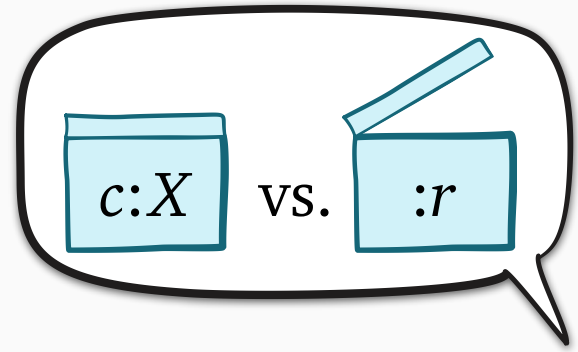
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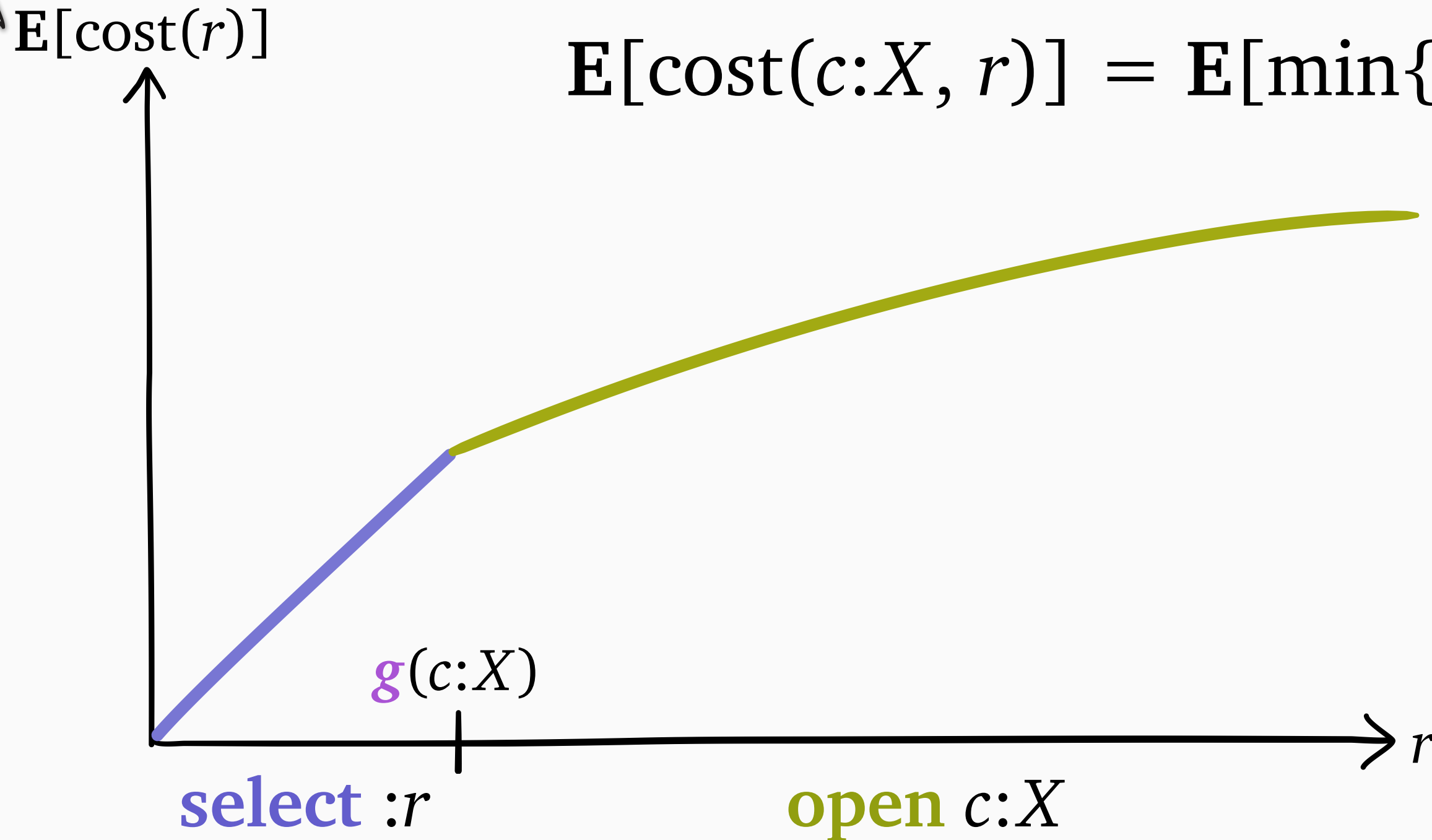
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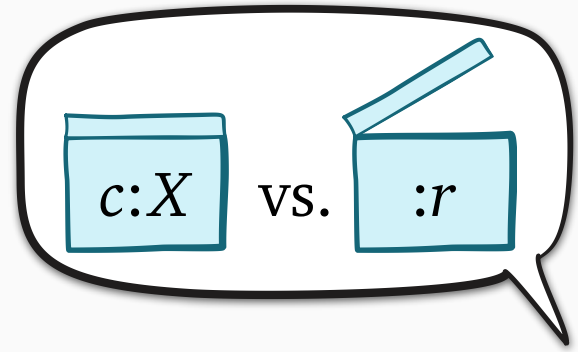
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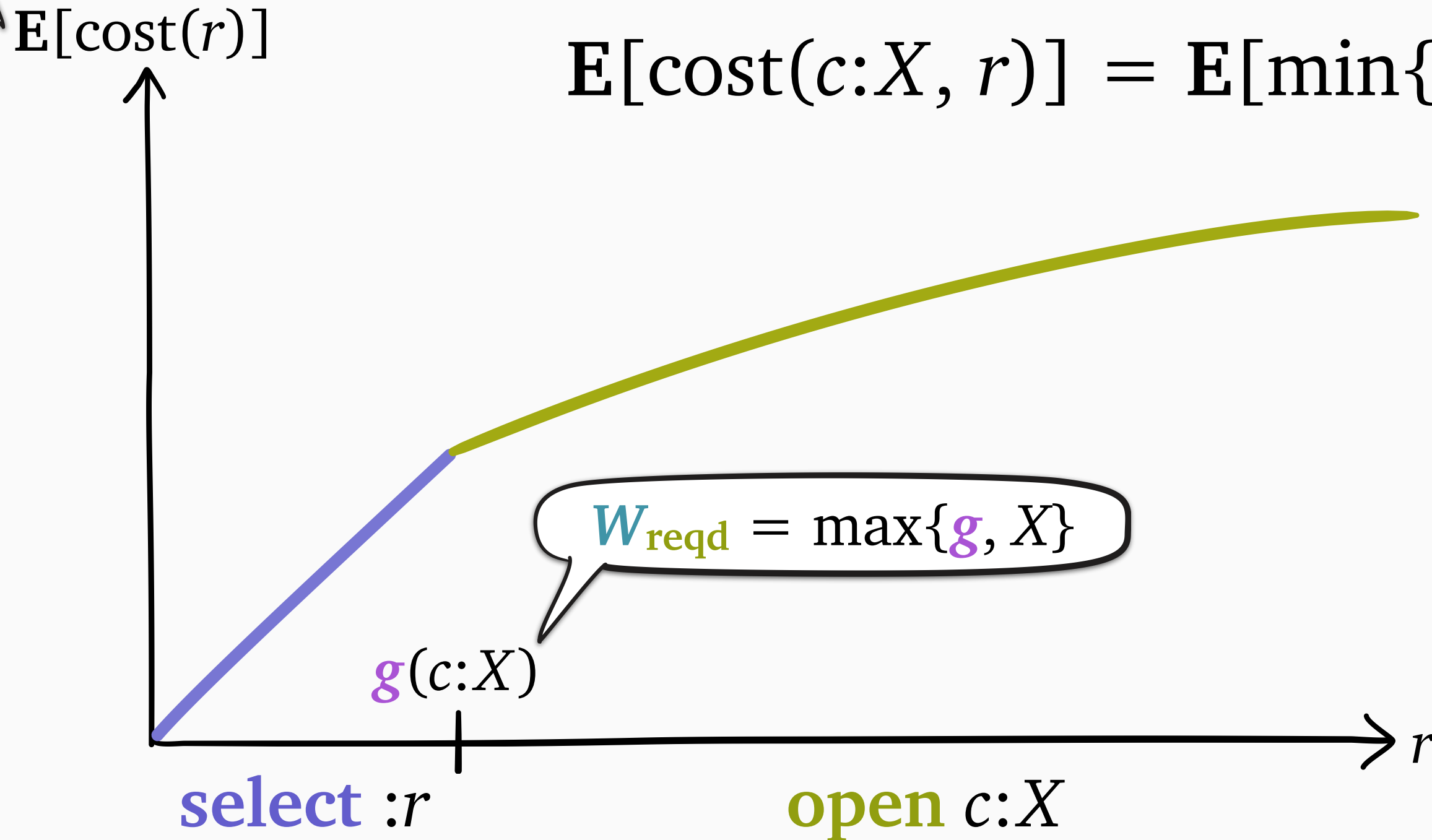
# Surrogate price: **required** inspection



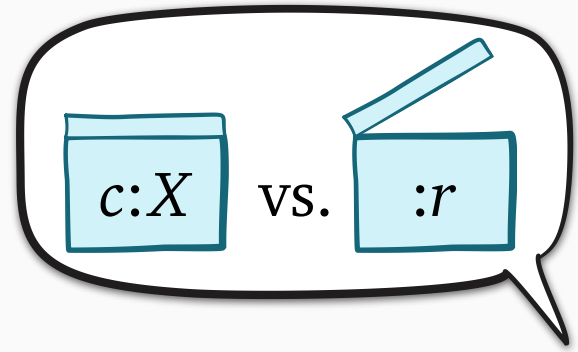
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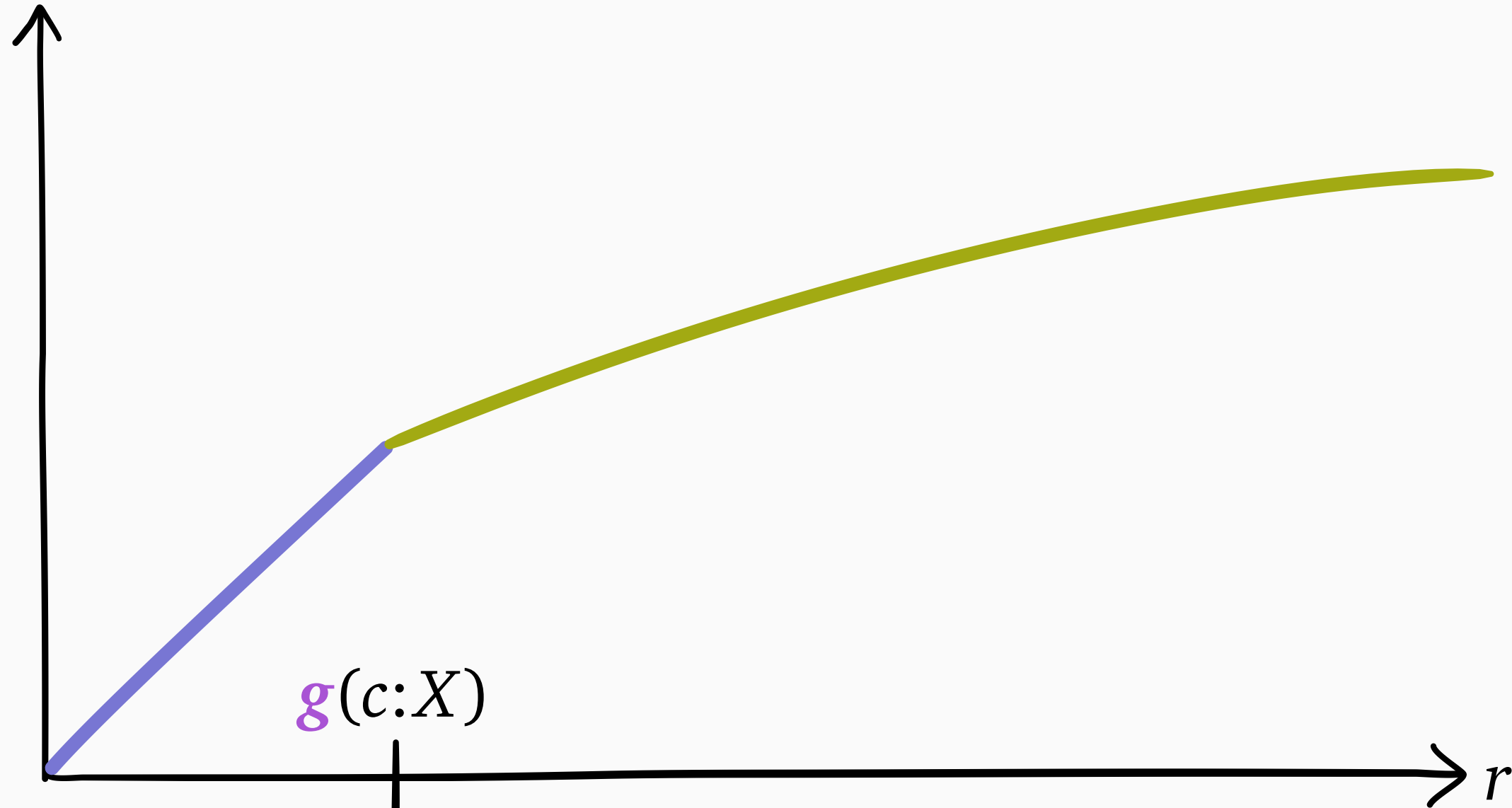
$W_{\text{reqd}}(c:X)$



# Surrogate price: optional inspection



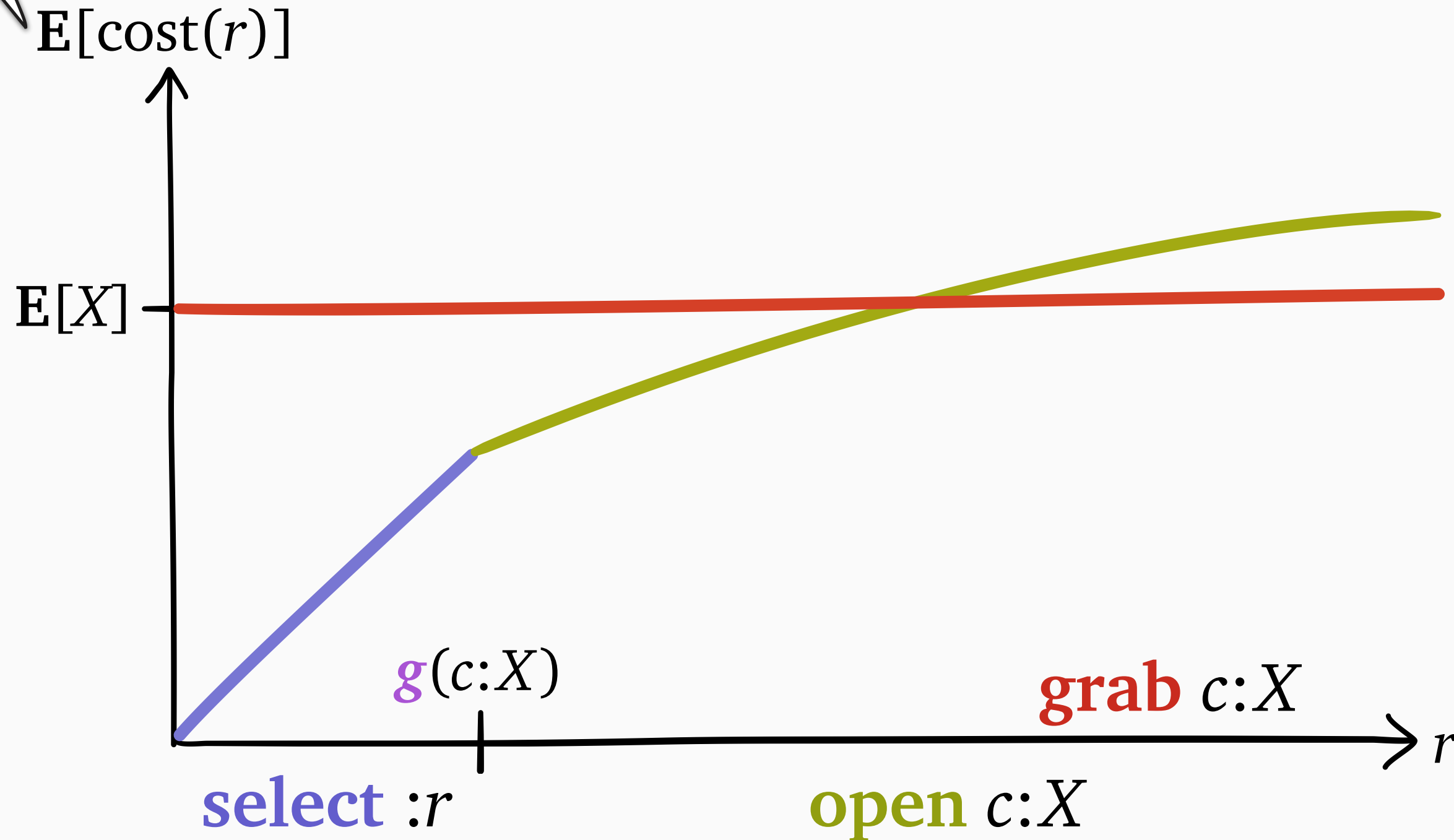
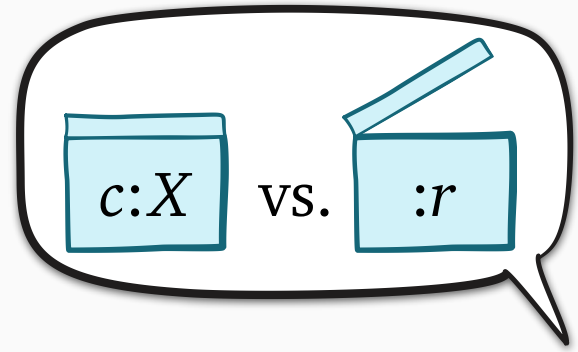
$E[\text{cost}(r)]$



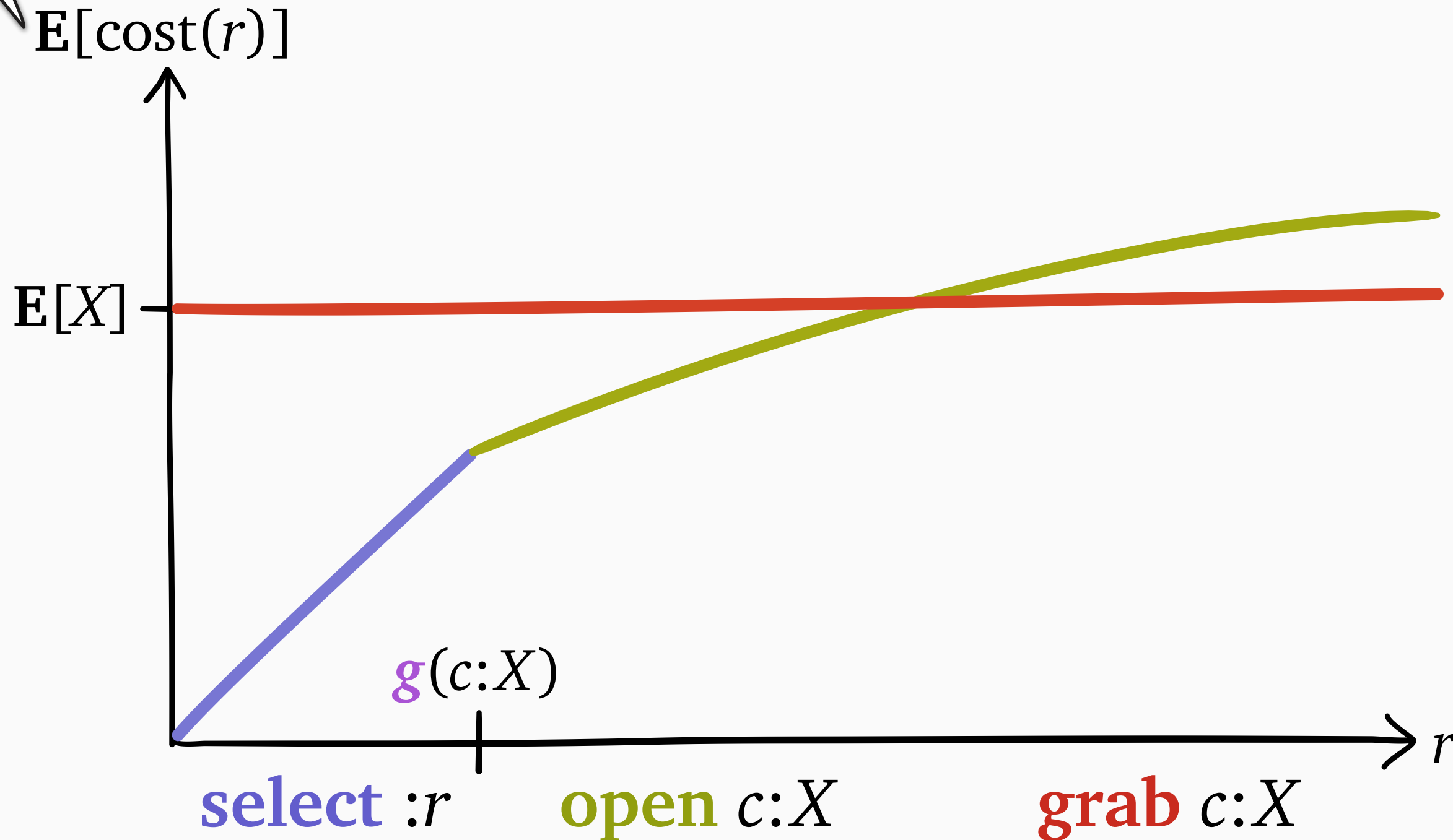
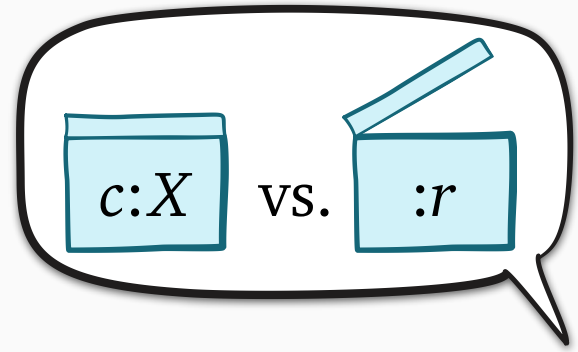
**select**  $:r$

**open**  $c:X$

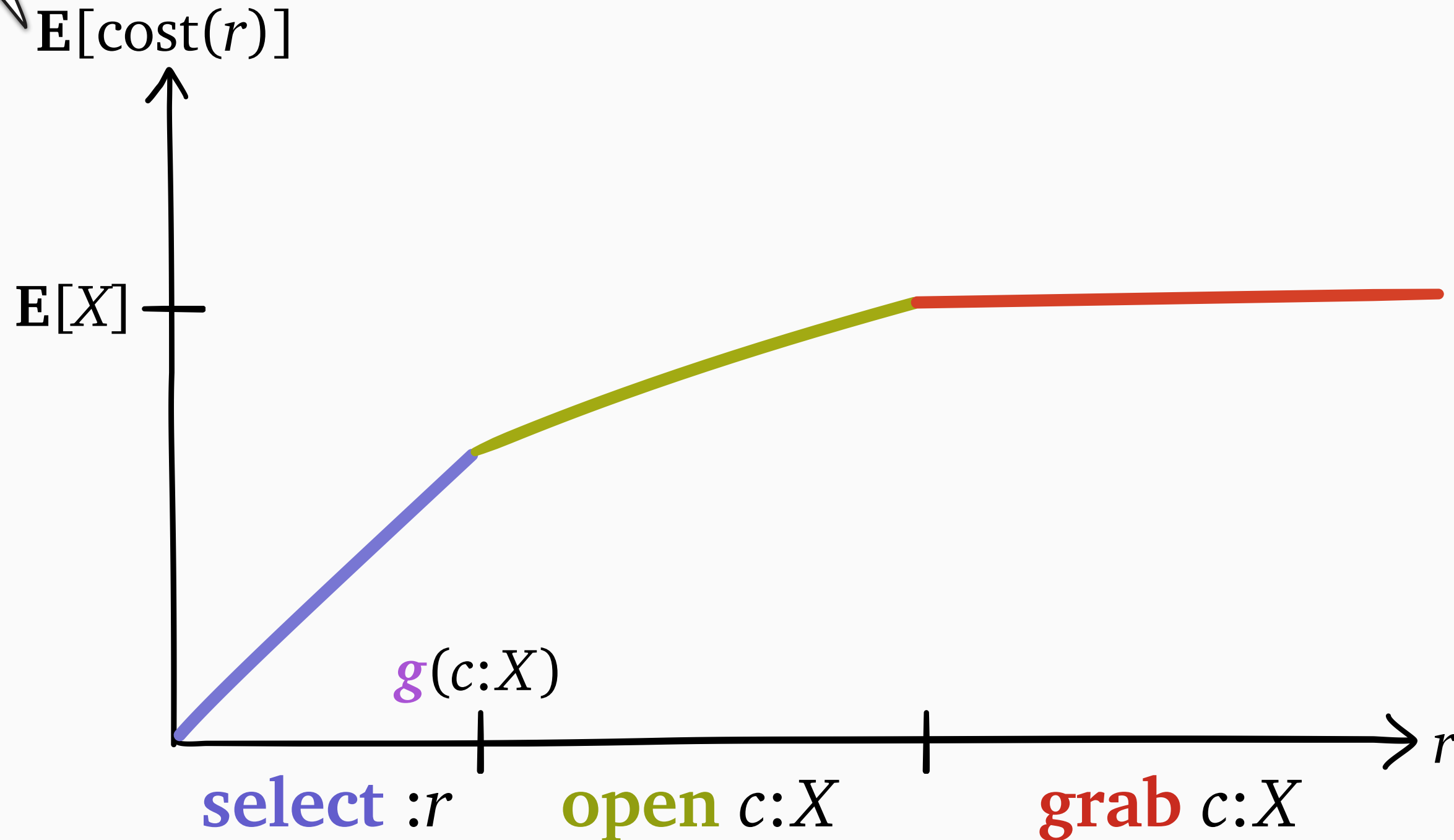
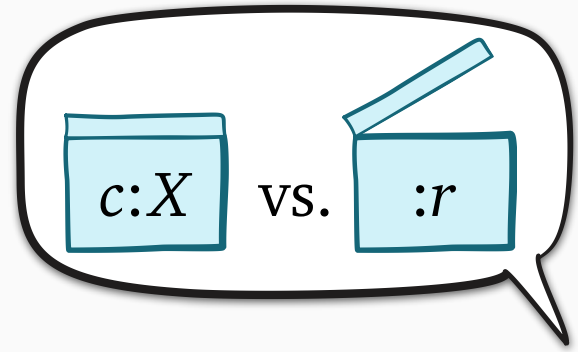
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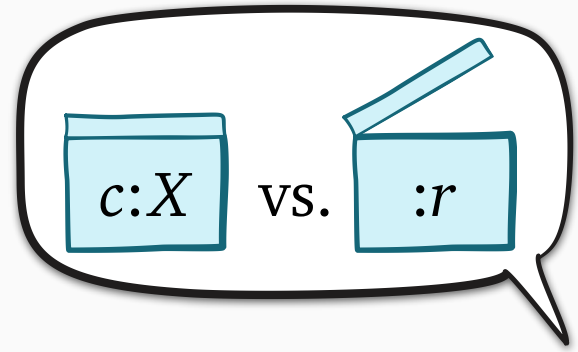


# Surrogate price: optional inspection



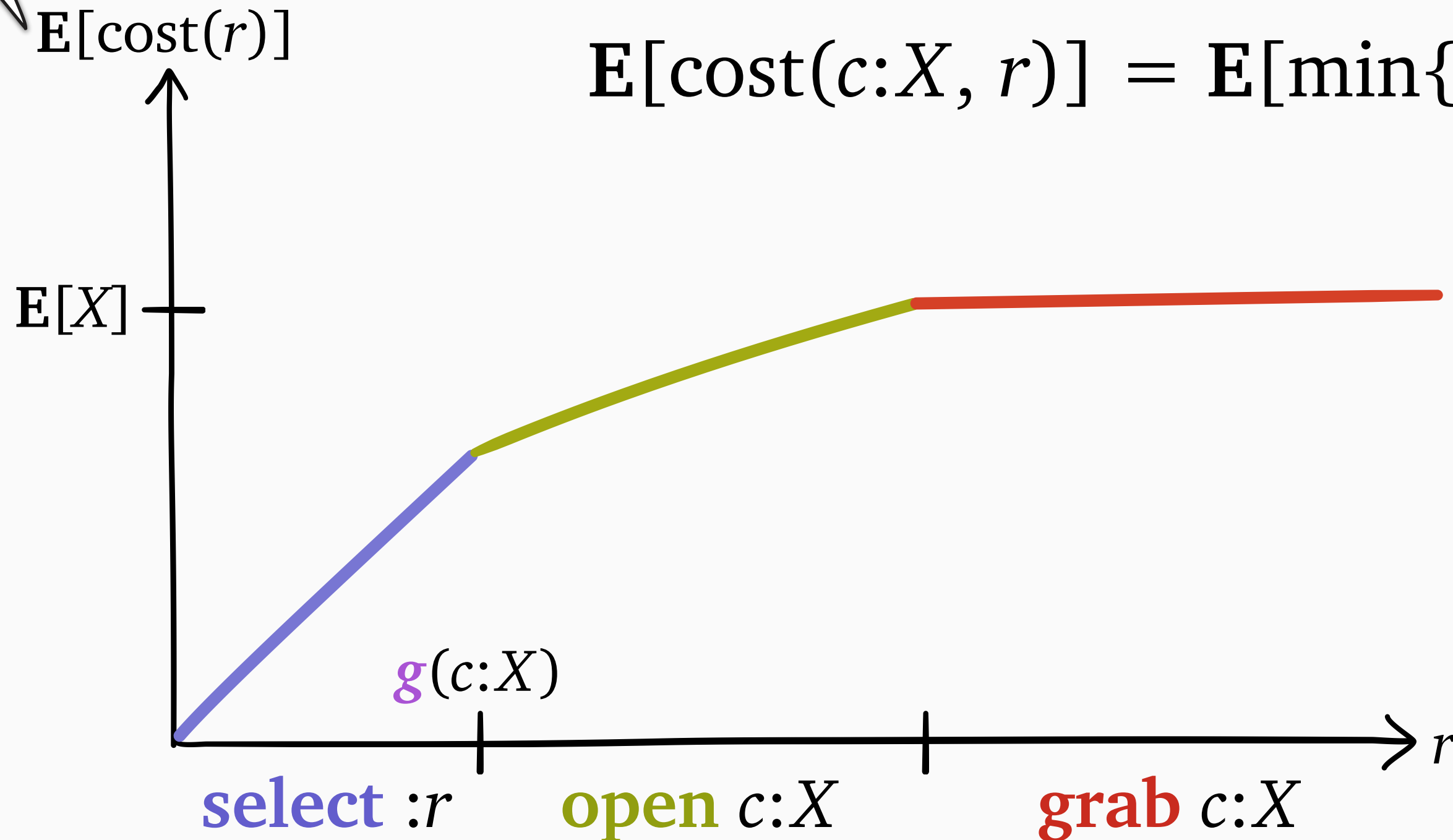


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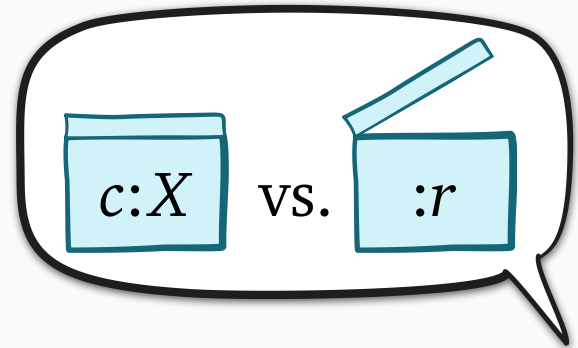


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$$\mathbf{E}[\text{cost}(c:X, r)] = \mathbf{E}[\min\{W_{\text{optn}}, r\}]$$

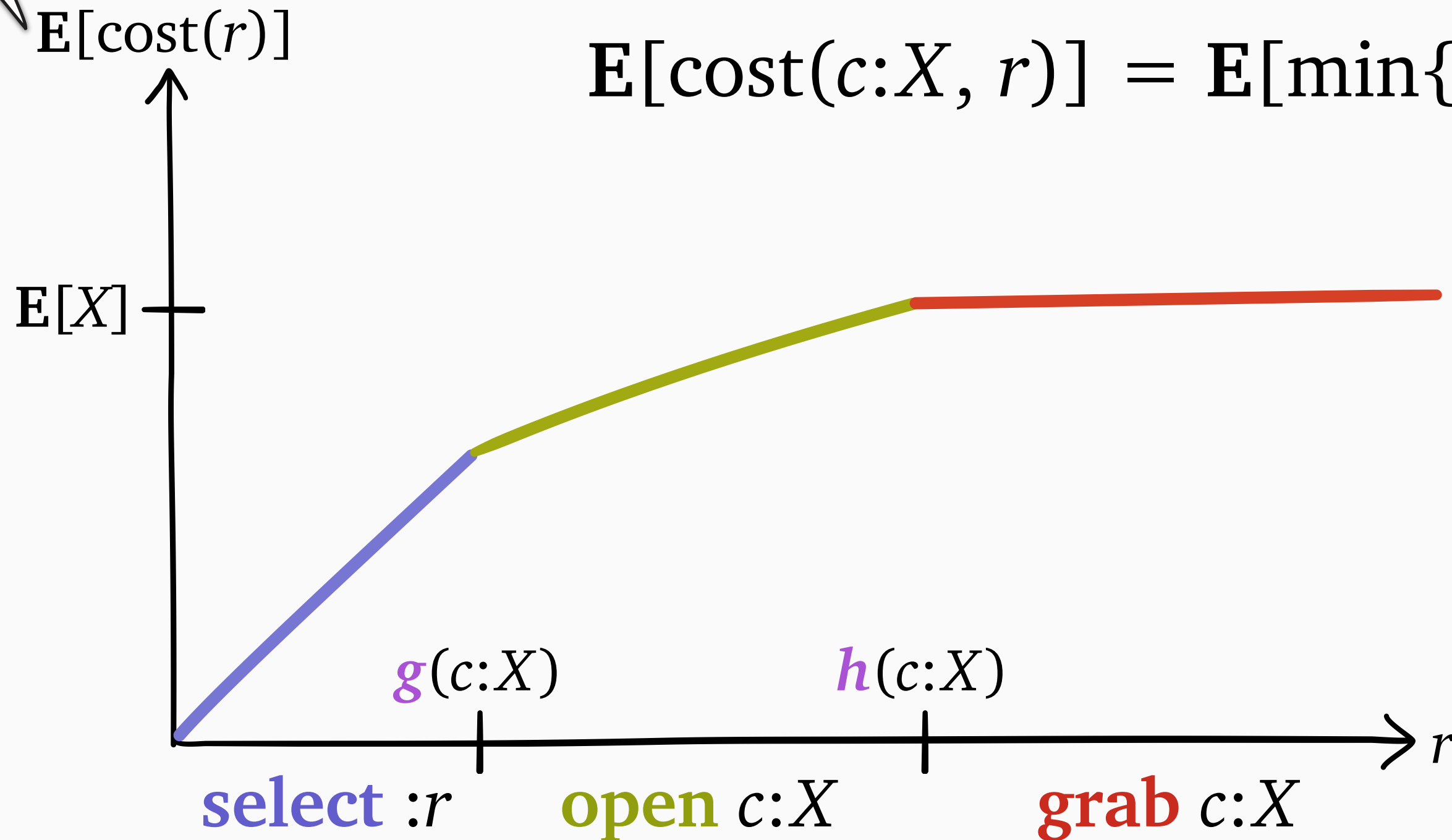


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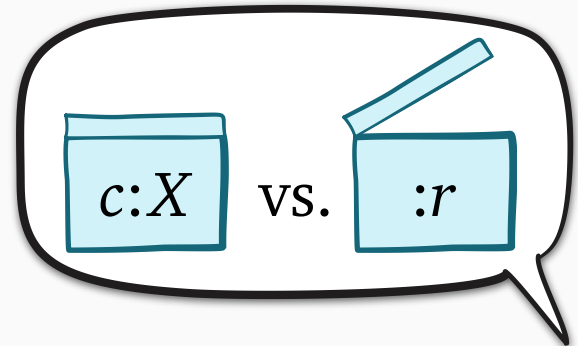


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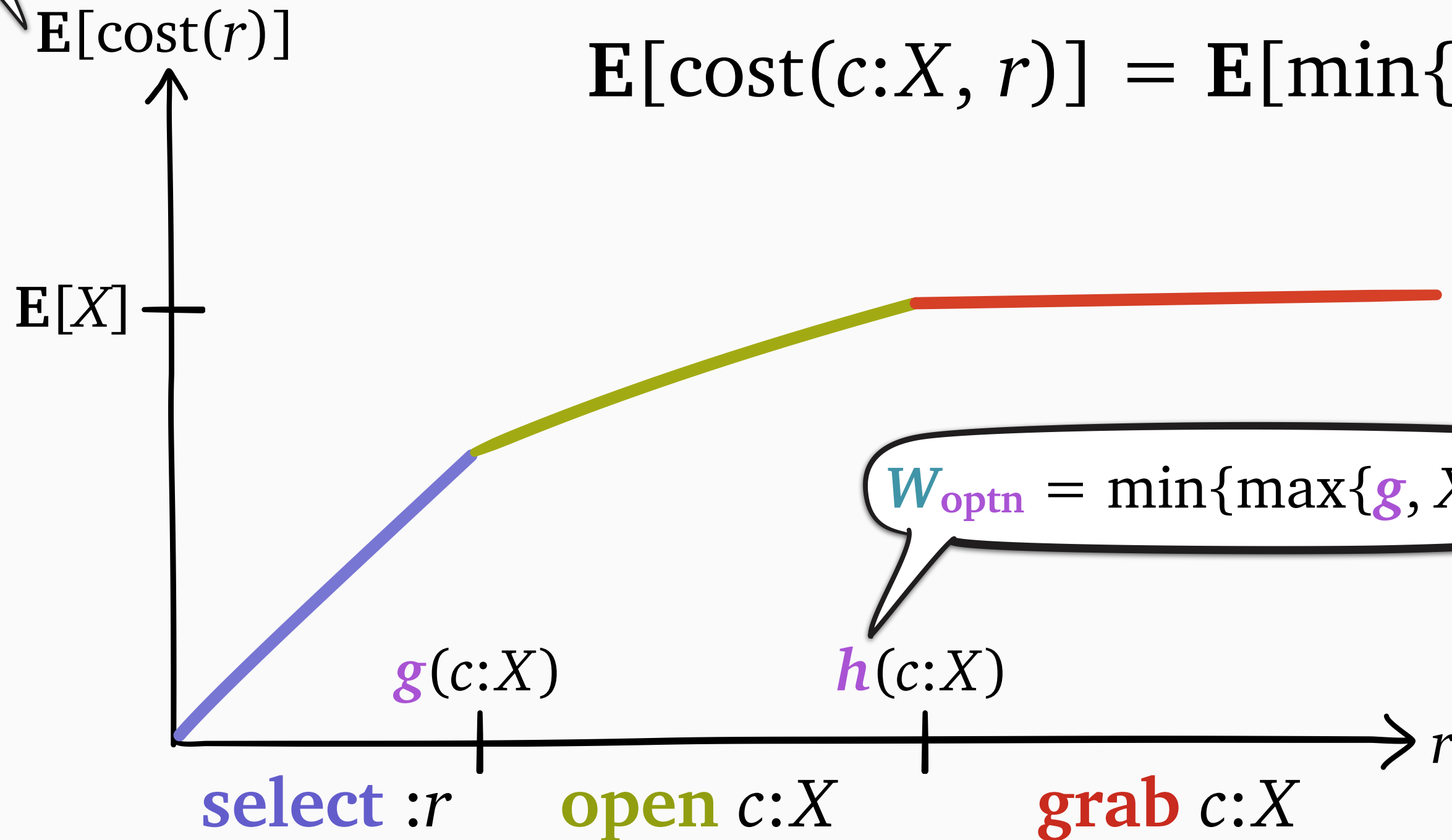


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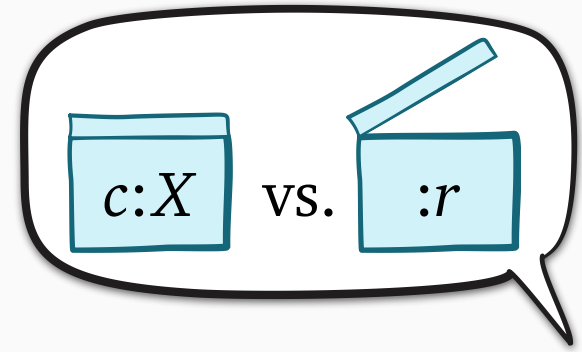


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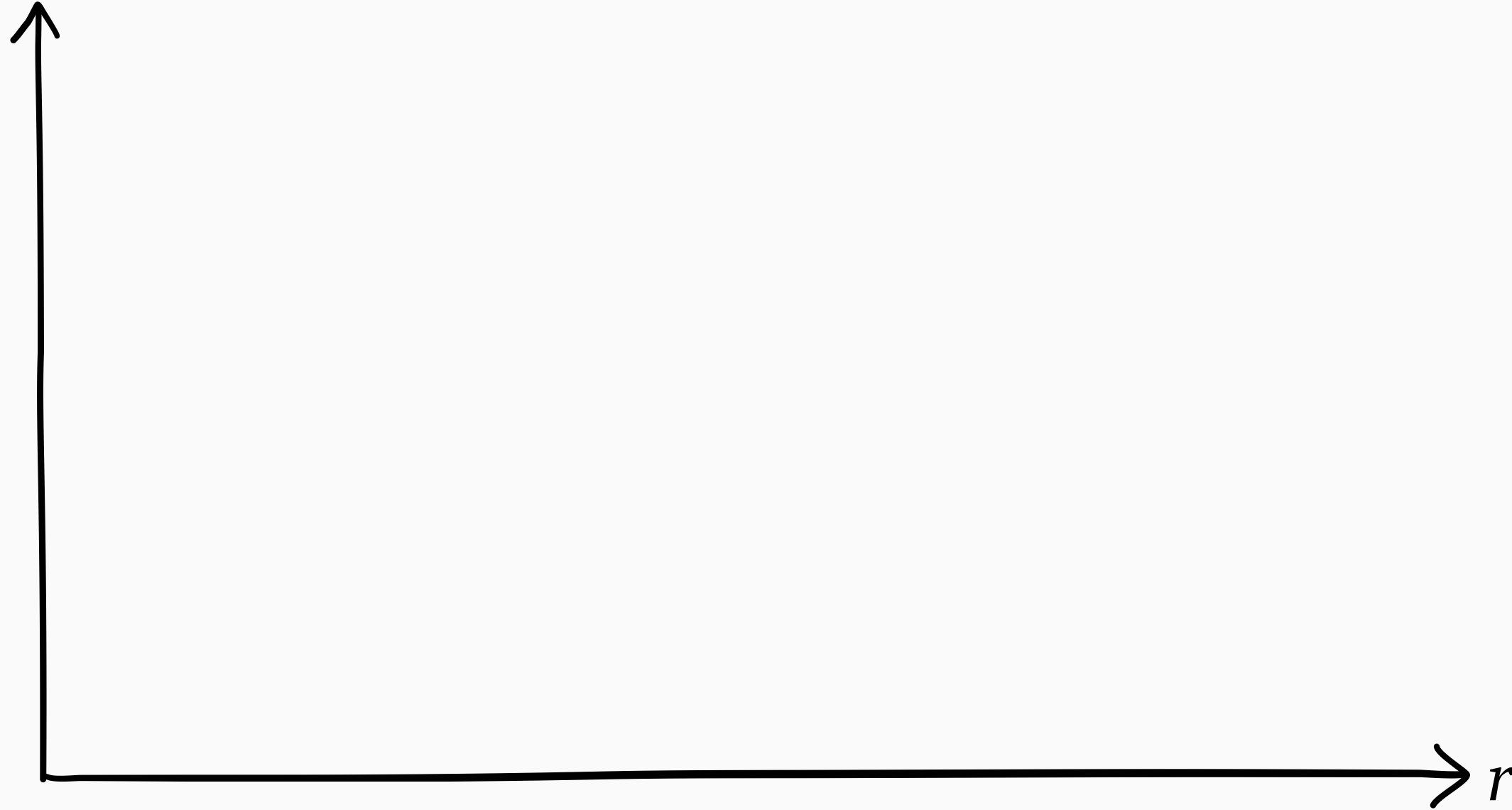
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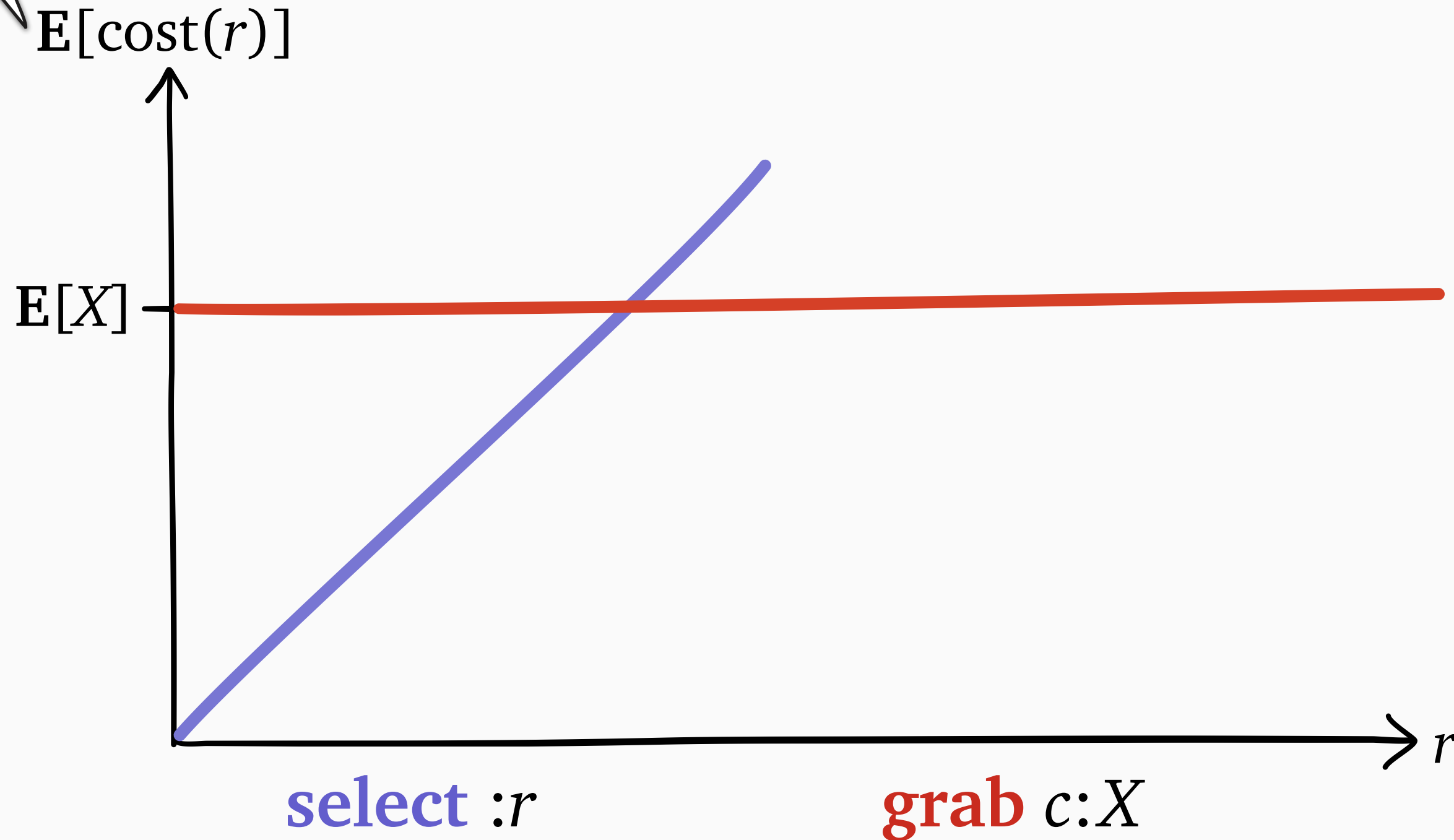
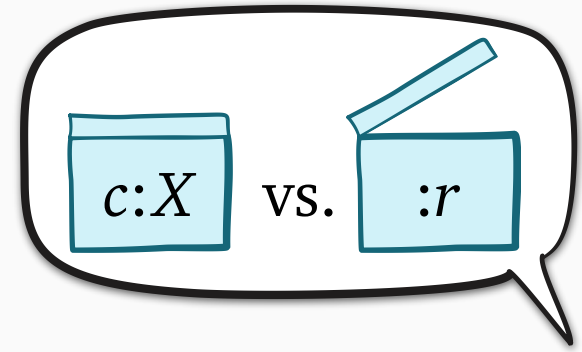
# Surrogate price: **grab** only



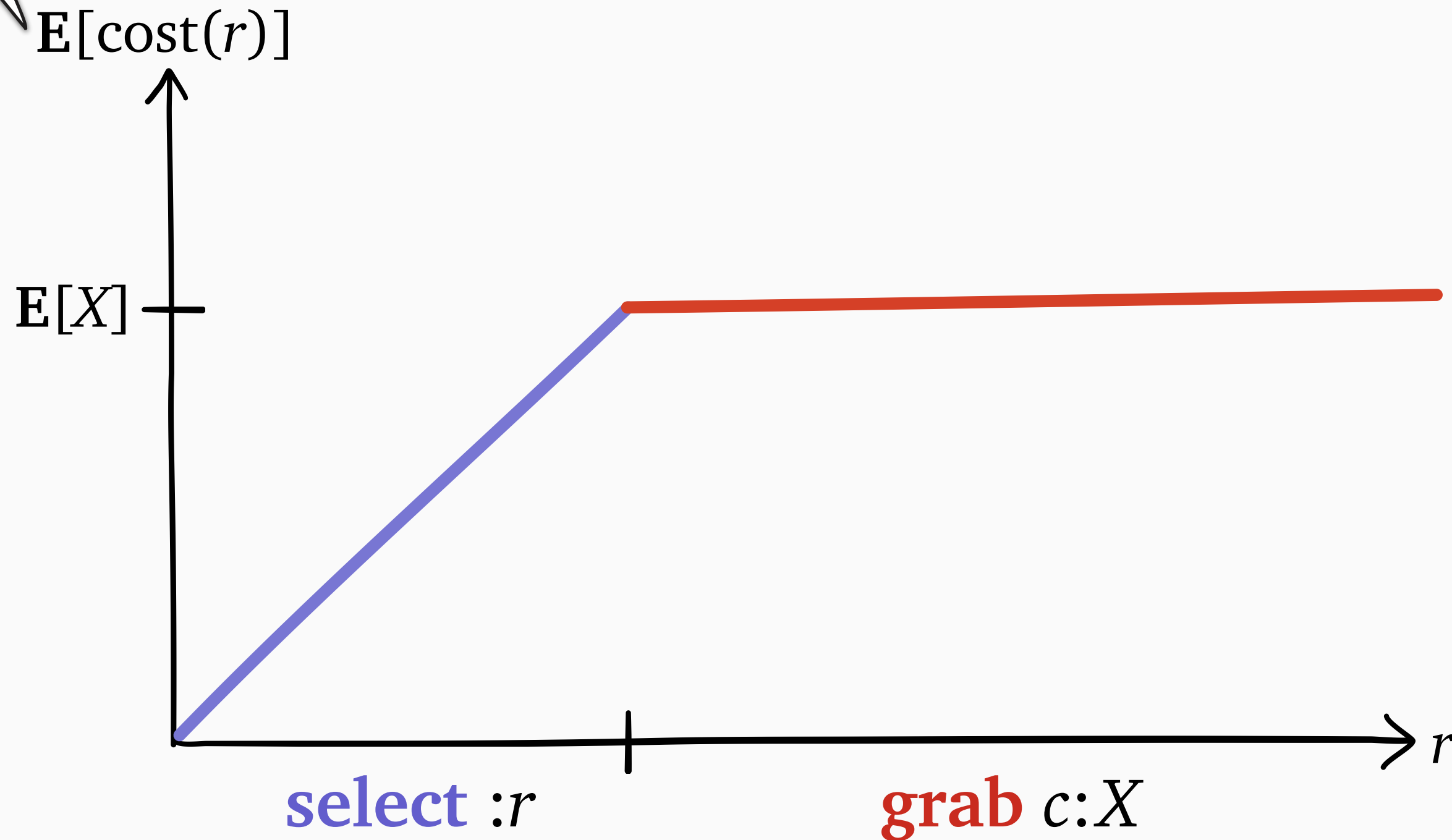
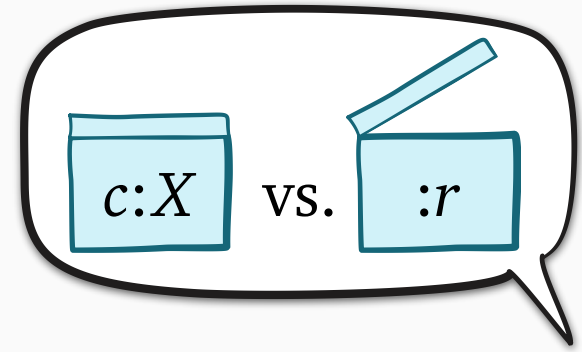
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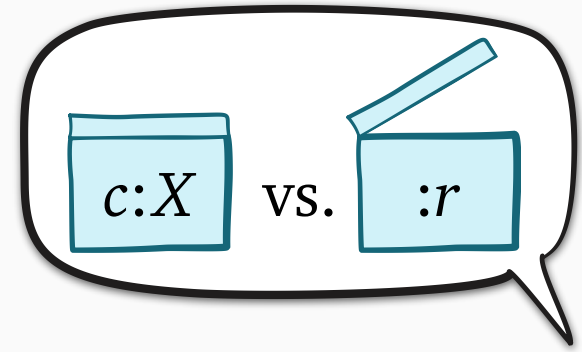
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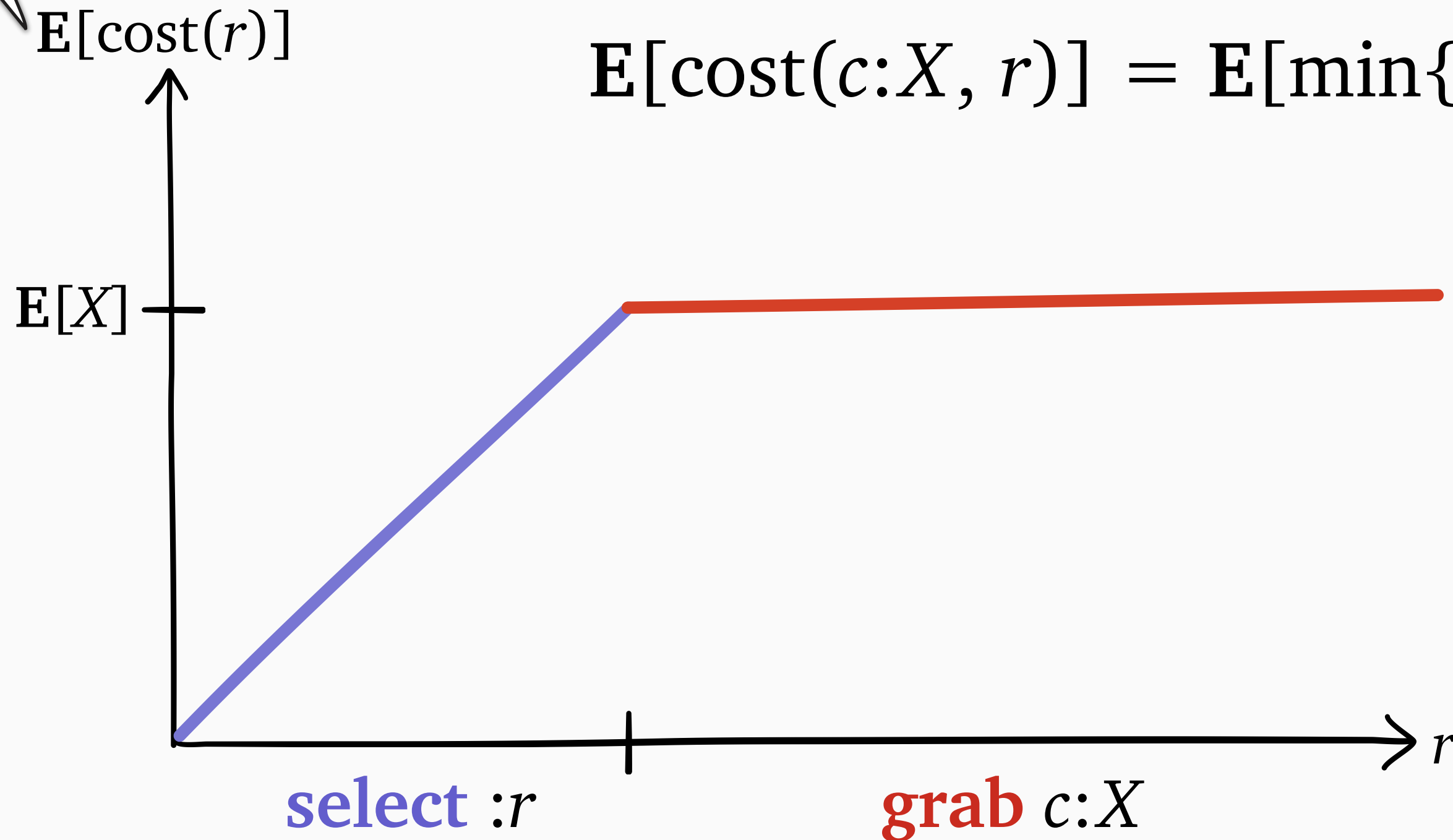


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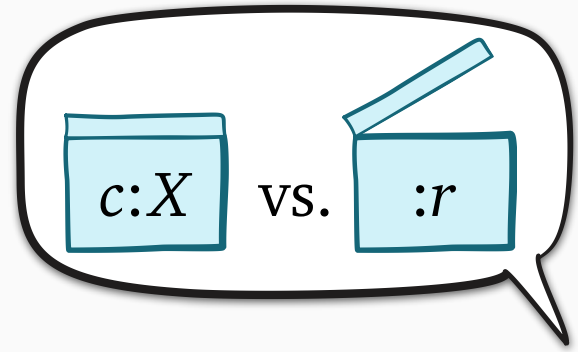


Definition:  $W_{\text{grab}}$  satisfies

$$\mathbf{E}[\text{cost}(c:X, r)] = \mathbf{E}[\min\{W_{\text{grab}}, r\}]$$

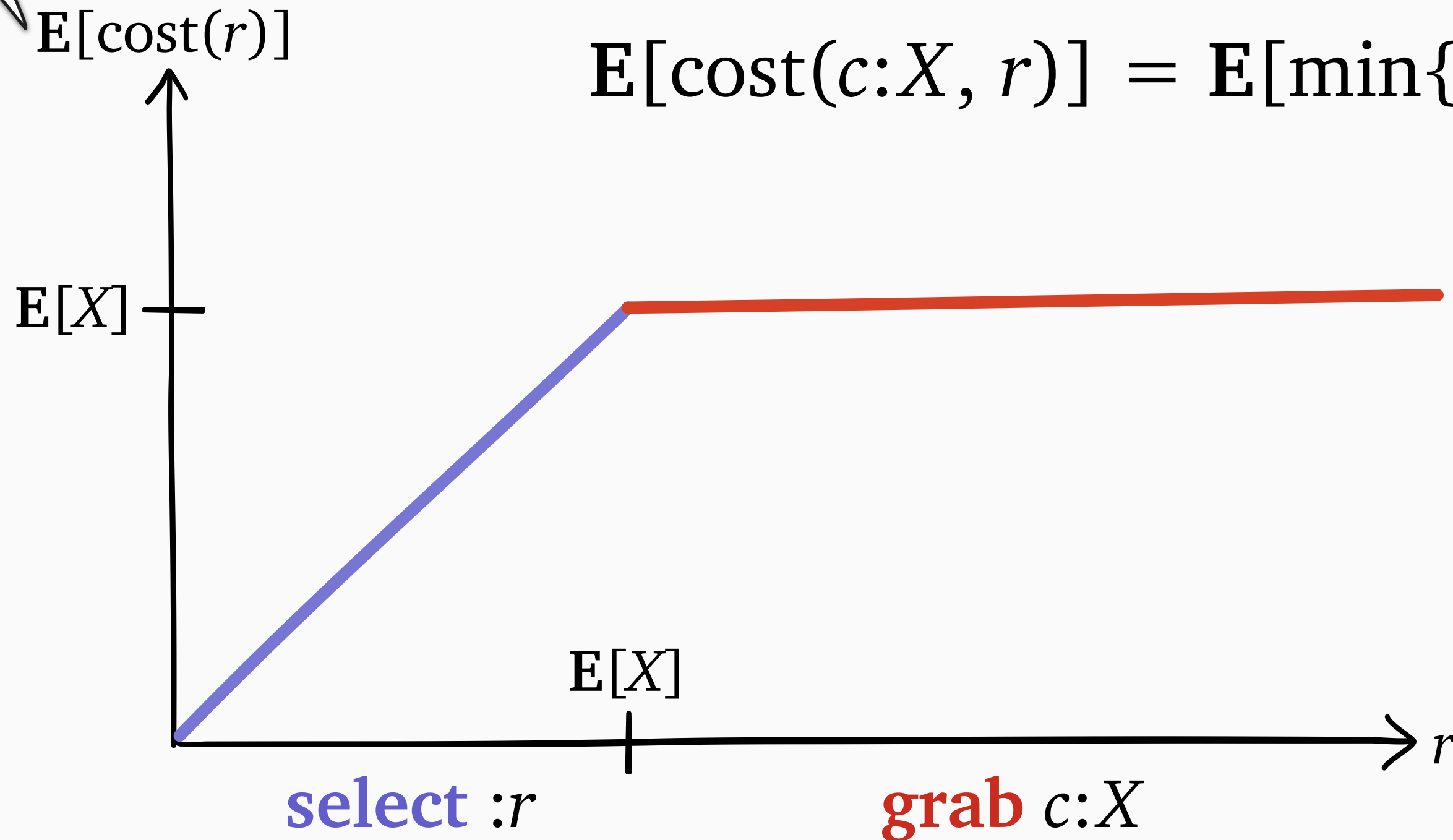


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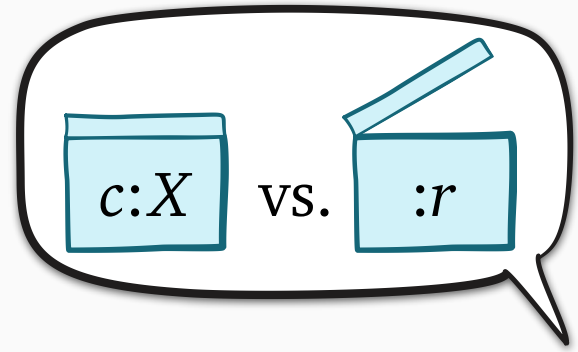
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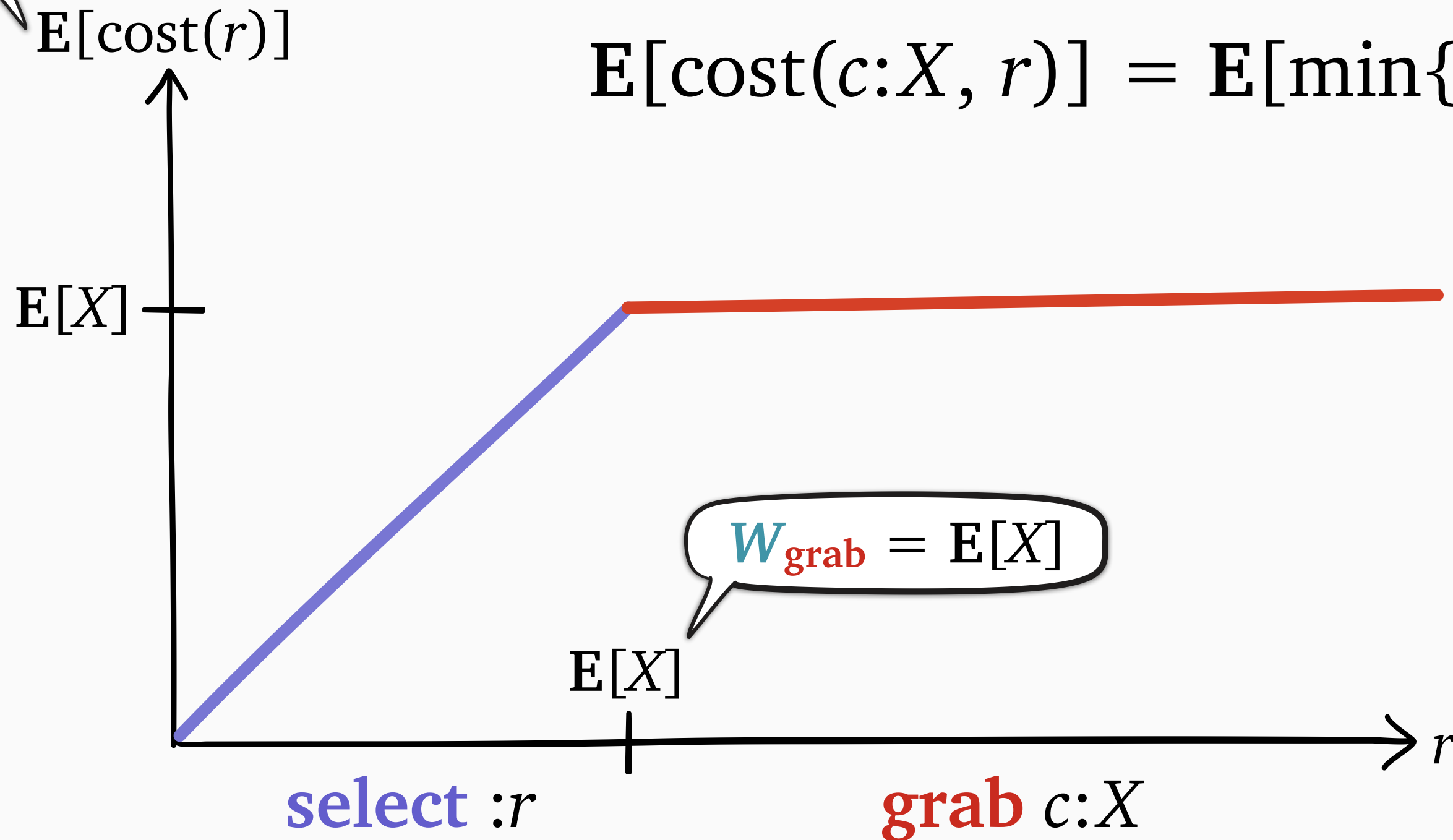


# Surrogate price: **grab** only

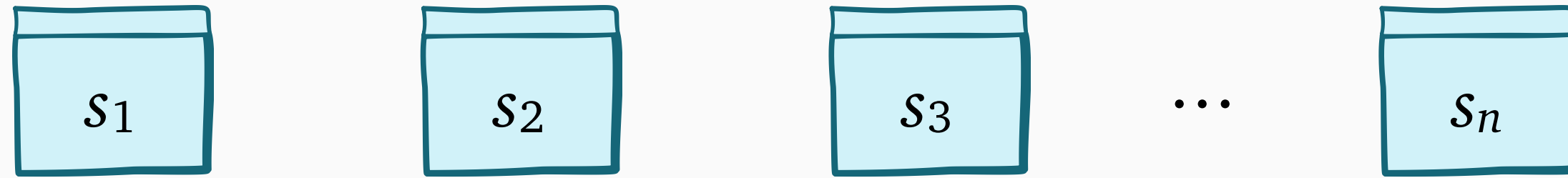


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$$\mathbf{E}[\text{cost}(c:X, r)] = \mathbf{E}[\min\{W_{\text{grab}}, r\}]$$



# Expressing cost using **surrogate** prices

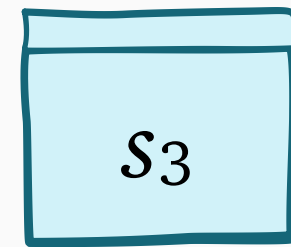
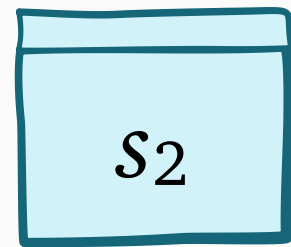
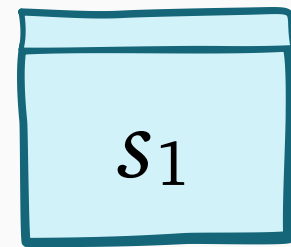


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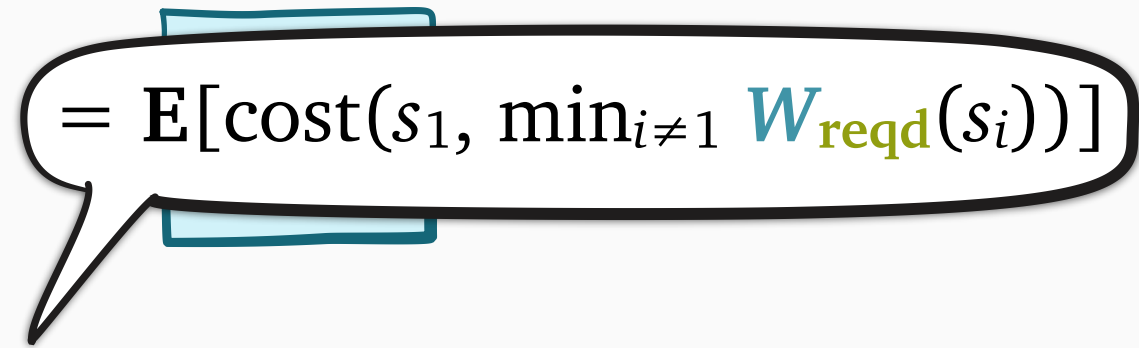


$$\mathbf{E}[\text{optimal required-inspection cost}] = \mathbf{E}[\min_i W_{\text{reqd}}(s_i)]$$

# Expressing cost using **surrogate** prices

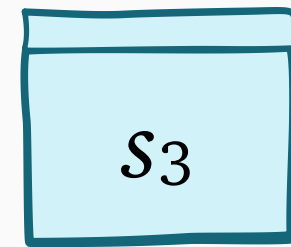
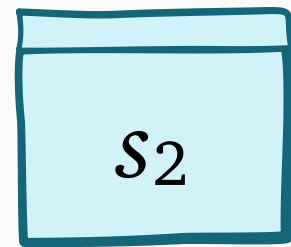
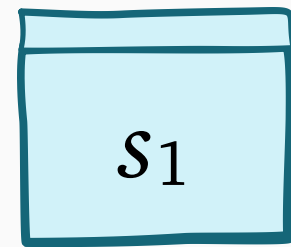


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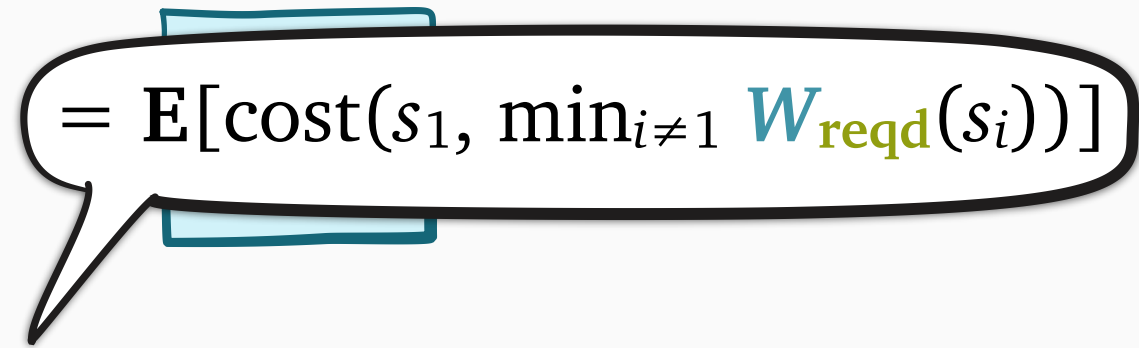


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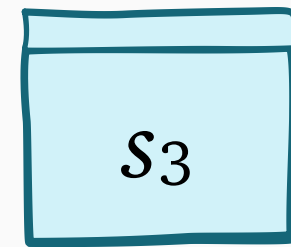
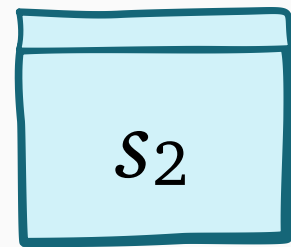
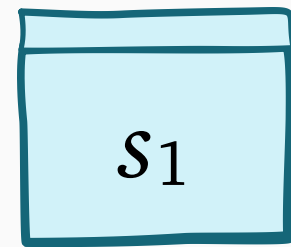
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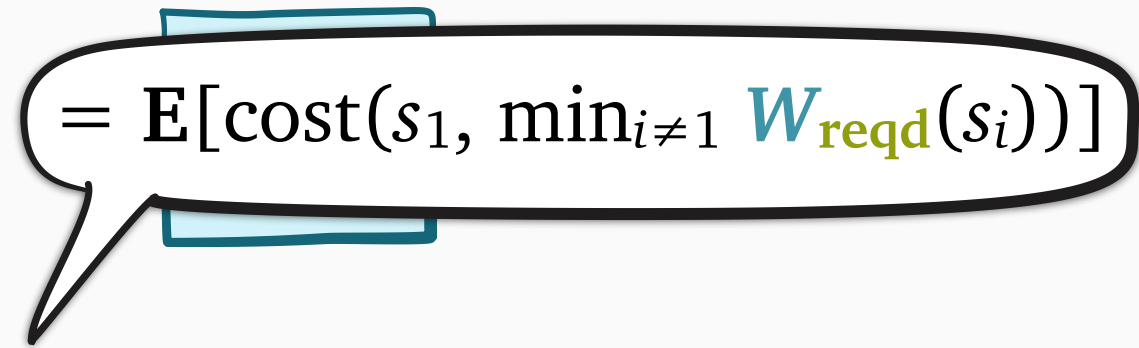
$$\mathbf{E}[\text{optimal required-inspection cost}] = \mathbf{E}[\min_i W_{\text{reqd}}(s_i)]$$

$$\mathbf{E}[\text{optimal optional-inspection cost}] \geq \mathbf{E}[\min_i W_{\text{optn}}(s_i)]$$

# Expressing cost using **surrogate** prices



...

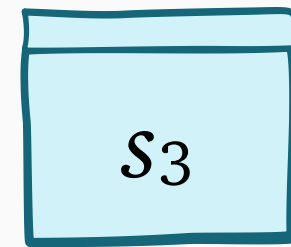
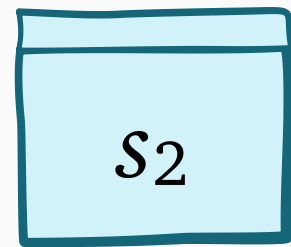
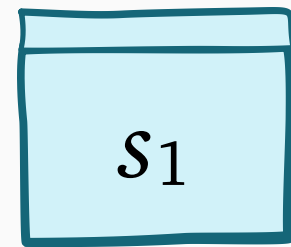


$$E[\text{optimal required-inspection cost}] = E[\min_i W_{\text{reqd}}(s_i)]$$



$$\text{newish } E[\text{optimal optional-inspection cost}] \geq E[\min_i W_{\text{optn}}(s_i)]$$

# Expressing cost using **surrogate** prices



...

$$= \mathbf{E}[\text{cost}(s_1, \min_{i \neq 1} W_{\text{reqd}}(s_i))]$$

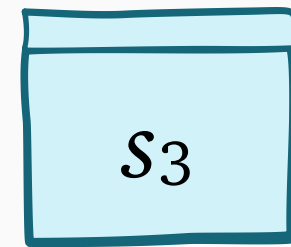
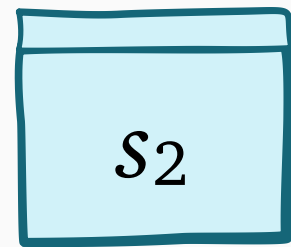
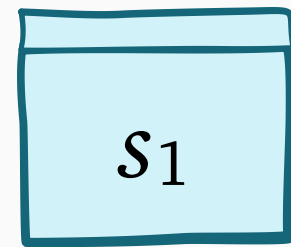
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$$\mathbf{E}[\text{optimal optional-inspection cost}] \geq \mathbf{E}[\min_i W_{\text{optn}}(s_i)]$$

$$\mathbf{E}[\text{cost under Local Hedging}] = \mathbf{E}[\min_i W_{\text{LH}}(s_i)]$$

# Expressing cost using **surrogate** prices



...  $= \mathbb{E}[\text{cost}(s_1, \min_{i \neq 1} W_{\text{reqd}}(s_i))]$

$$\mathbb{E}[\text{optimal required-inspection cost}] = \mathbb{E}[\min_i W_{\text{reqd}}(s_i)]$$



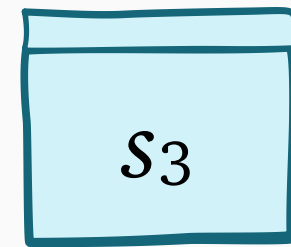
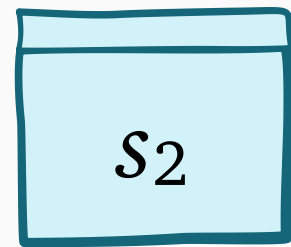
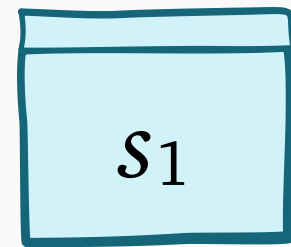
$$\mathbb{E}[\text{optimal optional-inspection cost}] \geq \mathbb{E}[\min_i W_{\text{optn}}(s_i)]$$

$$\mathbb{E}[\text{cost under Local Hedging}] = \mathbb{E}[\min_i W_{\text{LH}}(s_i)]$$

$$W_{\text{LH}} = \begin{cases} W_{\text{reqd}} & \text{w.p. } p \\ W_{\text{grab}} & \text{w.p. } 1 - p \end{cases}$$



# Expressing cost using **surrogate** prices



... =  $E[\text{cost}(s_1, \min_{i \neq 1} W_{\text{reqd}}(s_i))]$

$$E[\text{optimal required-inspection cost}] = E[\min_i W_{\text{reqd}}(s_i)]$$

**newish**  $E[\text{optimal optional-inspection cost}] \geq E[\min_i W_{\text{optn}}(s_i)]$

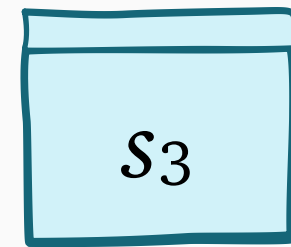
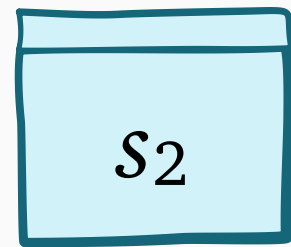
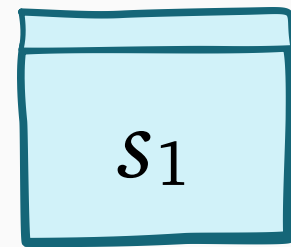
$$E[\text{cost under Local Hedging}] = E[\min_i W_{\text{LH}}(s_i)]$$



**Lemma:** exists prob  $p$  s.t. for all  $r$ ,  
 $E[\min\{\frac{3}{4}W_{\text{LH}}, r\}] \leq E[\min\{W_{\text{optn}}, r\}]$

$$W_{\text{LH}} = \begin{cases} W_{\text{reqd}} & \text{w.p. } p \\ W_{\text{grab}} & \text{w.p. } 1 - p \end{cases}$$

# Expressing cost using **surrogate** prices



... =  $E[\text{cost}(s_1, \min_{i \neq 1} W_{\text{reqd}}(s_i))]$

$$E[\text{optimal required-inspection cost}] = E[\min_i W_{\text{reqd}}(s_i)]$$



$$E[\text{optimal optional-inspection cost}] \geq E[\min_i W_{\text{optn}}(s_i)]$$

$$E[\text{cost under Local Hedging}] = E[\min_i W_{\text{LH}}(s_i)]$$



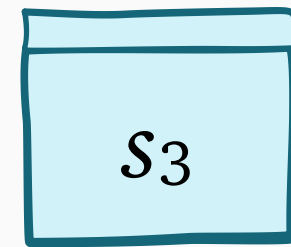
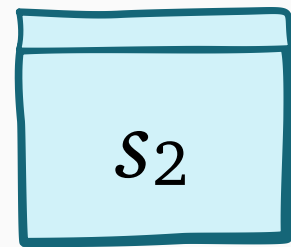
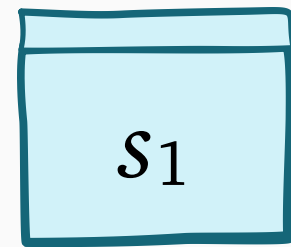
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# Expressing cost using **surrogate** prices



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**newish**  $E[\text{optimal optional-inspection cost}] \geq E[\min_i W_{\text{optn}}(s_i)]$

$$E[\text{cost under Local Hedging}] = E[\min_i W_{\text{LH}}(s_i)]$$



**Lemma:** exists prob  $p$  s.t. for all  $r$ ,  
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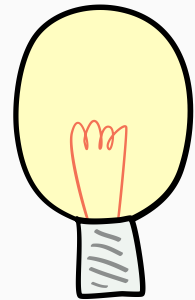
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 "local"

"context"

# Our contribution

Key idea: randomization  
for “context-robustness”



## Local Hedging (LH)

New *decomposition-based* technique for optional inspection

- Reduces problem to required-inspection case
- Naturally generalizes to combinatorial problems



**Theorem:** if **Alg** is a “greedy” algorithm, then the approximation ratio of **Gittins** + **Alg** + **LH** is  $\leq 4/3$  times that of **Alg**

price of reduction  
from  $3/4$  discount