Online algorithms with predictions

Spyros Angelopoulos

CoreLab Seminar, NTUA, March 29 2021

Leveraging predictions in a status of uncertainty

Online computation: the standard model

Online computation: the standard model

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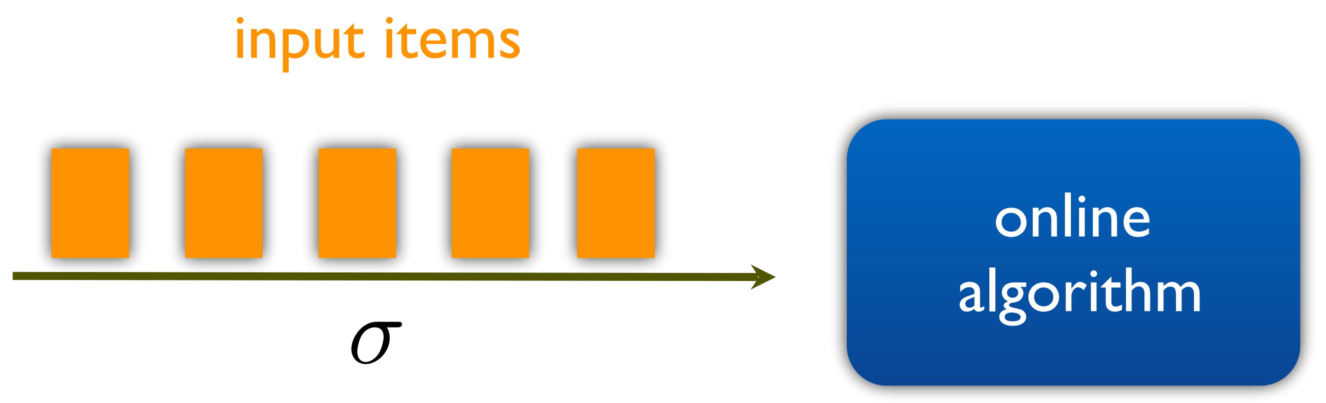

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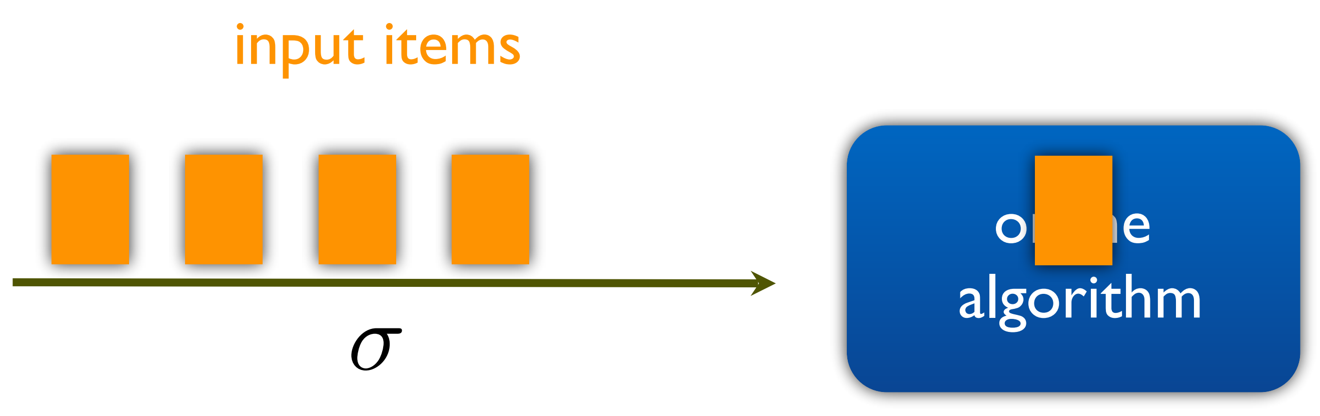

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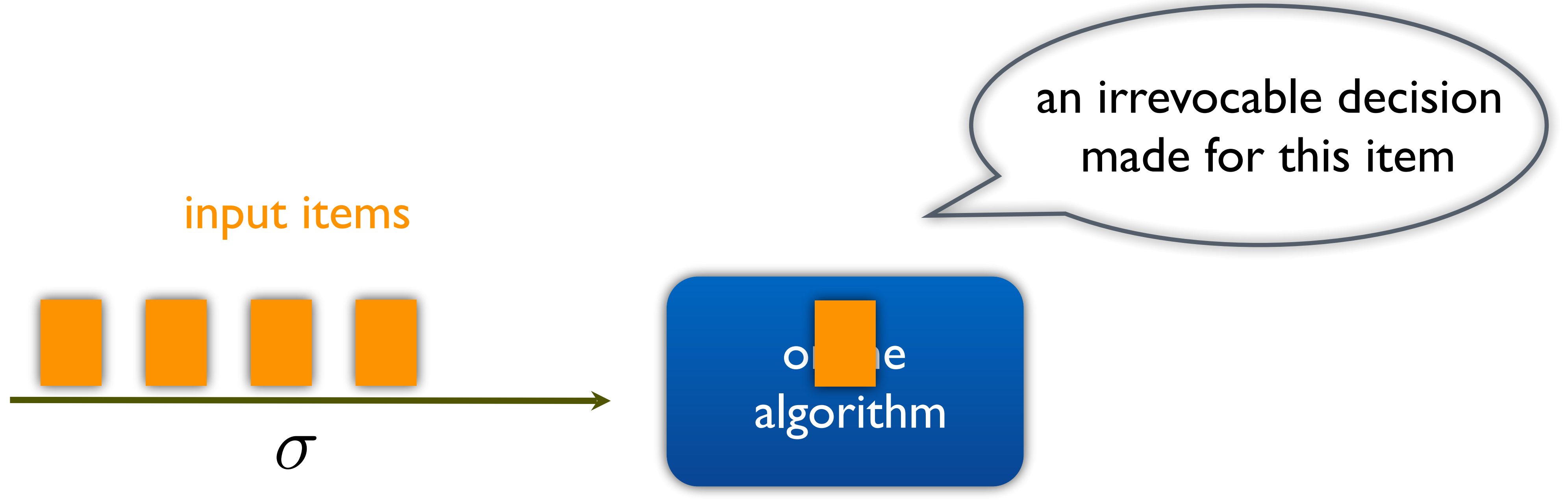

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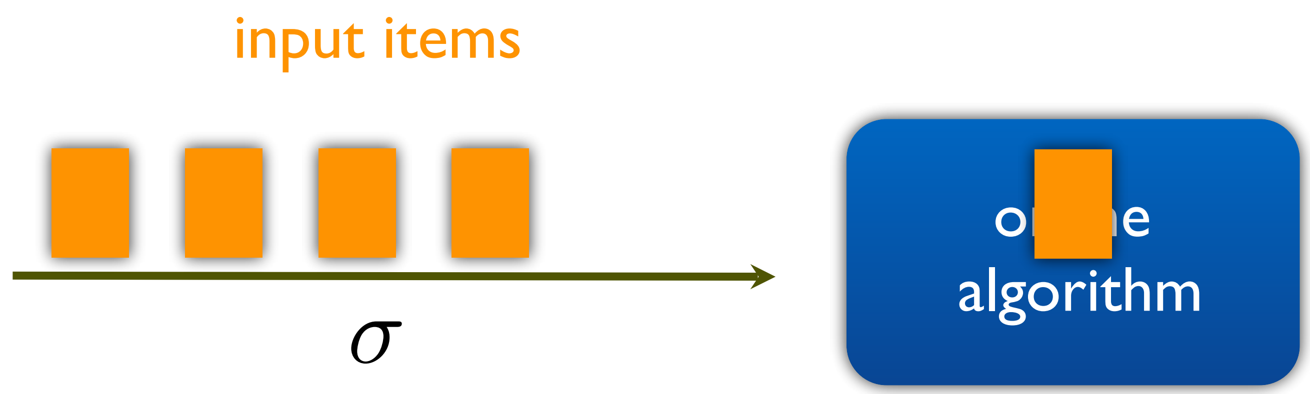

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In the standard model: No assumptions about the future input items

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Competitive analysis: main analysis technique since the mid 80s [Sleator and Tarjan 85]

Competitive ratio of algorithm A:

$$\sup_{\sigma} \frac{\text{cost of } A \text{ on } \sigma}{\mathrm{OPT}(\sigma)}$$

How to enhance the standard model of
online computation so as to deal with predictions
concerning the input?

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- If ϕ(σ) encodes the optimal decisions => Optimal offline performance

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General question: what lies between these two extremes ?

Advice complexity of online problems

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Definition [Dobrev et al. 2009, Böckenhauer et al. 2009, Emek et al. 2011]

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Applications in many problems: paging, list update, makespan scheduling, k-server, bin packing, graph colouring, Steiner trees and many, many others

[Komm: An introduction to online computation, Springer 2016]

[Boyar et al. Online computation with advice: A survey, ACM Computing Surveys, 2017]

Advice complexity model: mostly theoretical

- Focus on size of the encoded advice
- Advice oracle can be overly powerful
- Advice is guaranteed to be error-free and trustworthy

Advice in the real world

advice

/ədˈvʌɪs/

noun

1. guidance or recommendations offered with regard to prudent future action.
   "my advice is to see your doctor"
   synonyms: guidance, advising, counselling, counsel, help, direction, instruction, information, enlightenment; More
2. a formal notice of a financial transaction.
   "remittance advices"

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A **prediction** associated with the input which is inherently **erroneous**

The prediction has error η (unknown to the algorithm)

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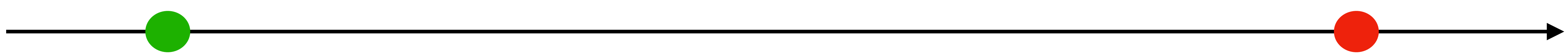

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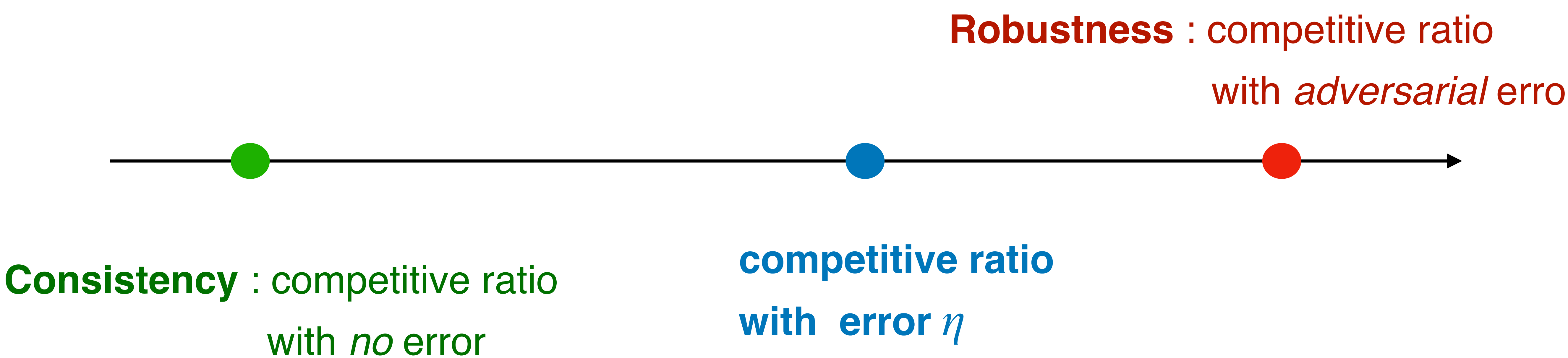

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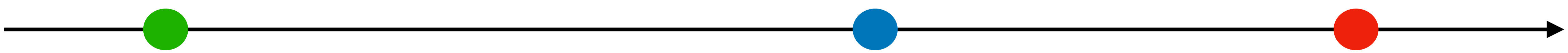

Consistency : competitive ratio with *no* error

competitive ratio with error η

objectives

Mostly upper bounds on the competitive ratio with error

"Smooth" degradation with error

Experimental validation

Related works

[Lykouris and Vassilvitskii, ICML 2018] : Introduced consistency, robustness in paging

[Purohit, Svitkina, Kumar, NeurIPS 2018] : Other online problems

Many other recent works…

[Mitzenmacher and Vassilvitskii 2020] : survey of (some) recent results

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Broader direction: Analysis of algorithms **beyond the worst case**

Summary of our work

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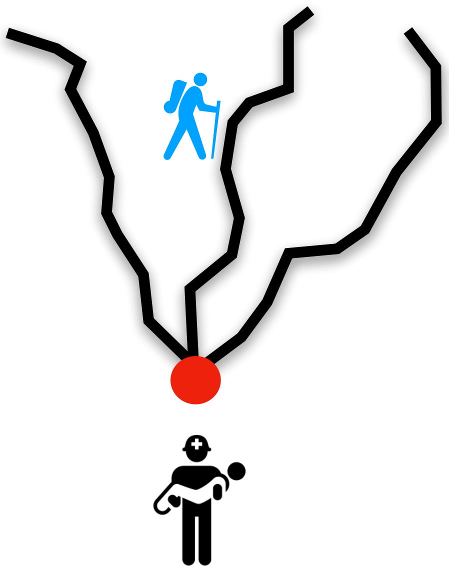
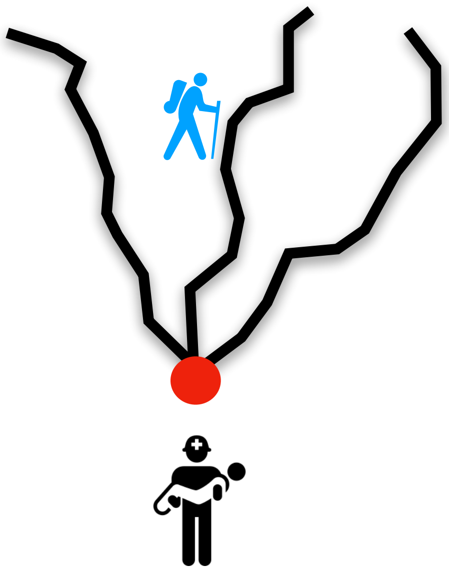


Part 1 : Searching with a hint



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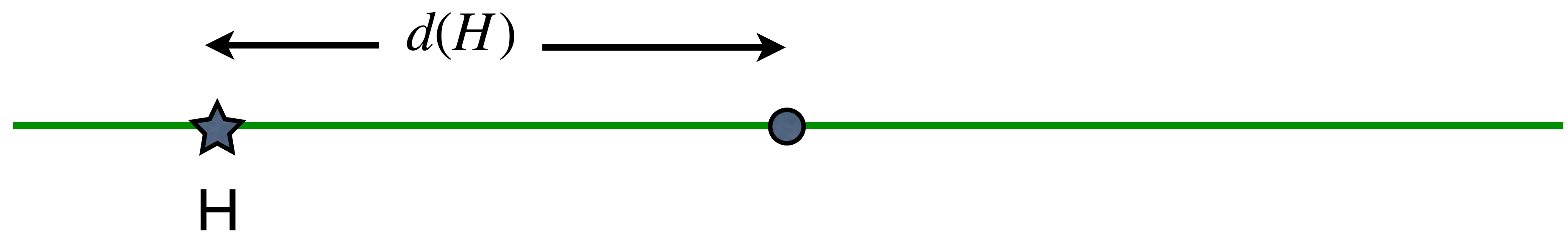

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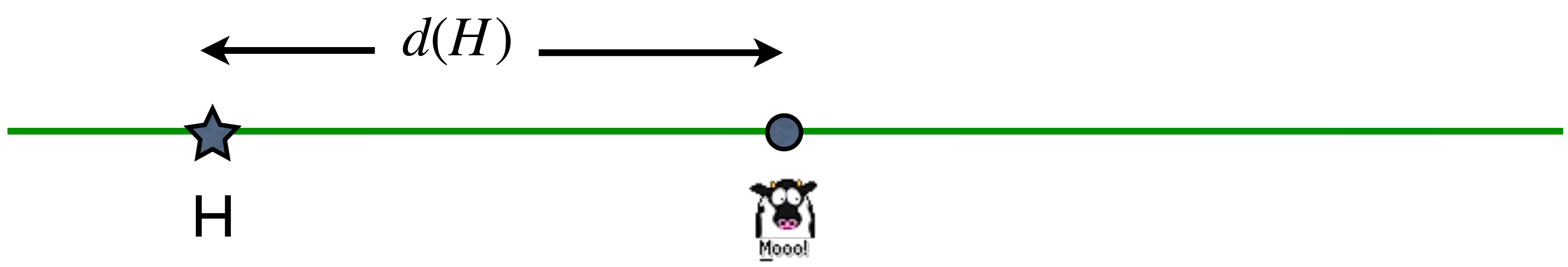

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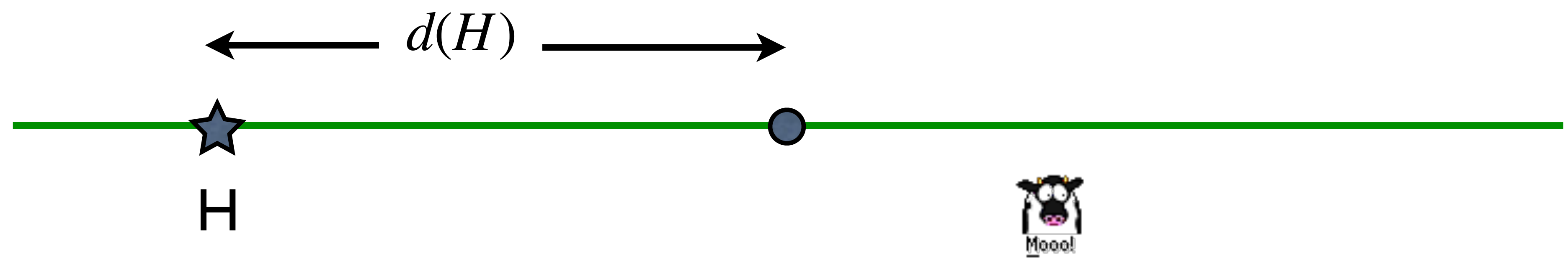

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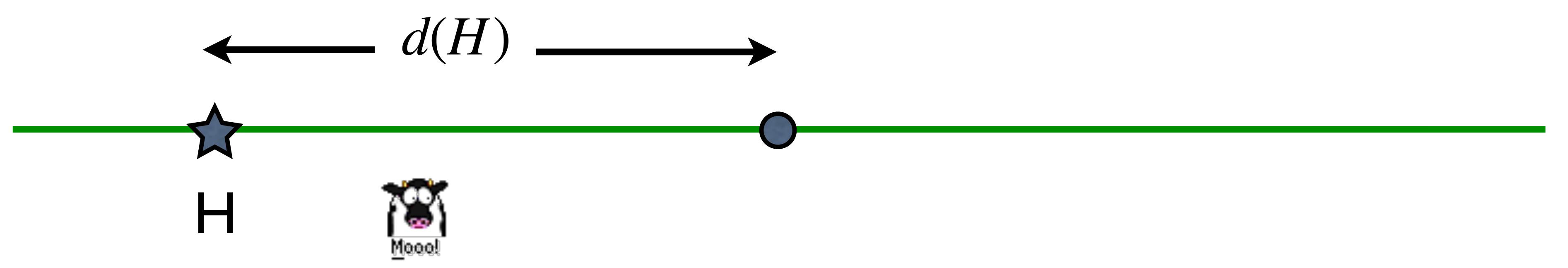

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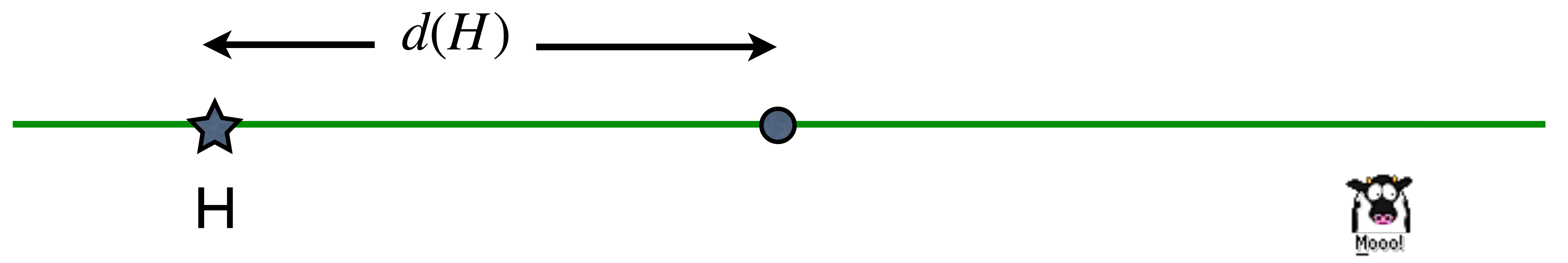

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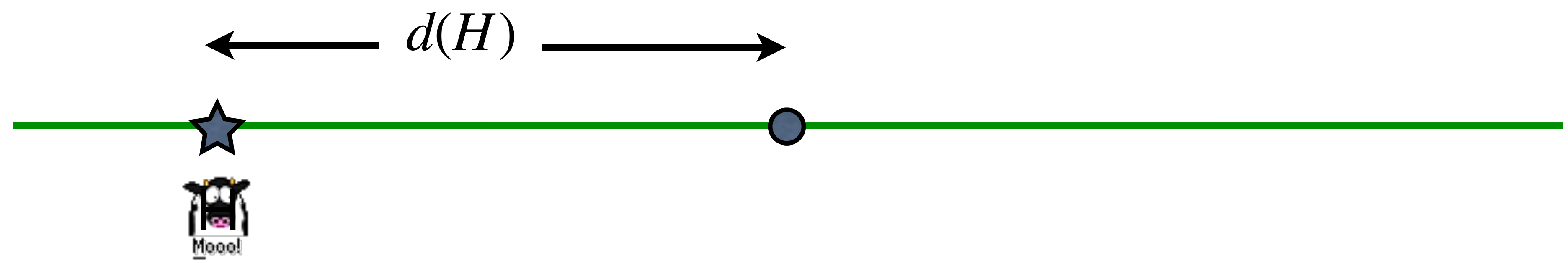

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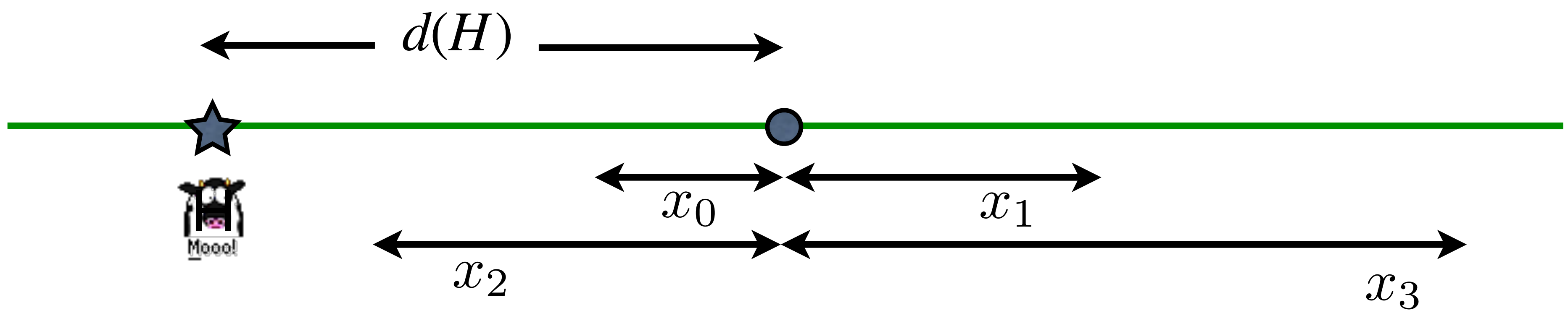

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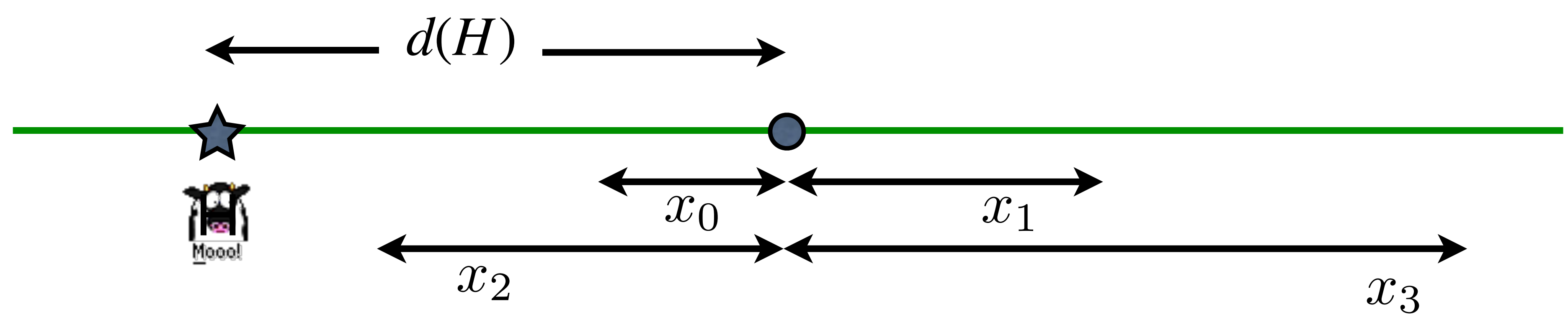

- Searcher aims to minimize the competitive ratio of its strategy S

$$\text{cr}(S) = \sup_H \frac{\text{distance traversed by the searcher using } S}{d(H)}$$

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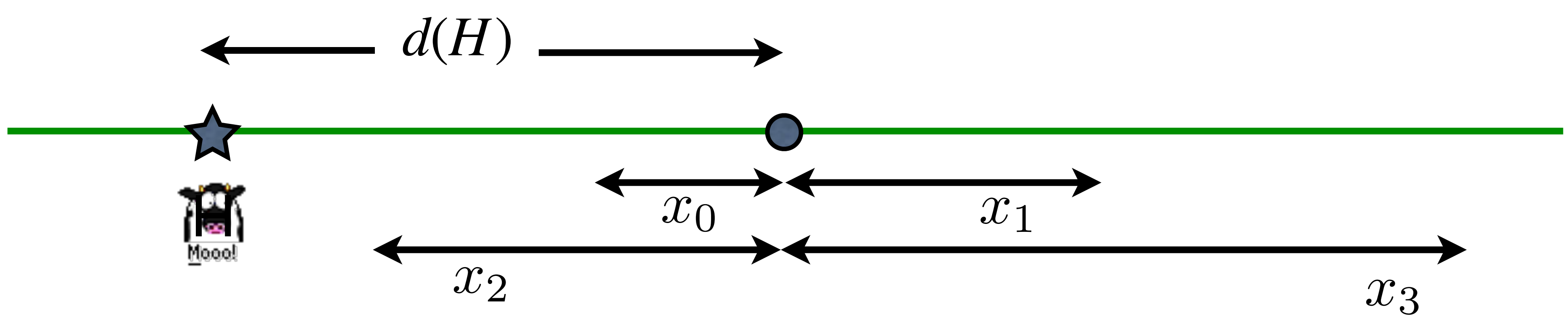

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- Optimal deterministic competitive ratio = 9 using $x_i = 2^i$ [Beck and Newman 70]

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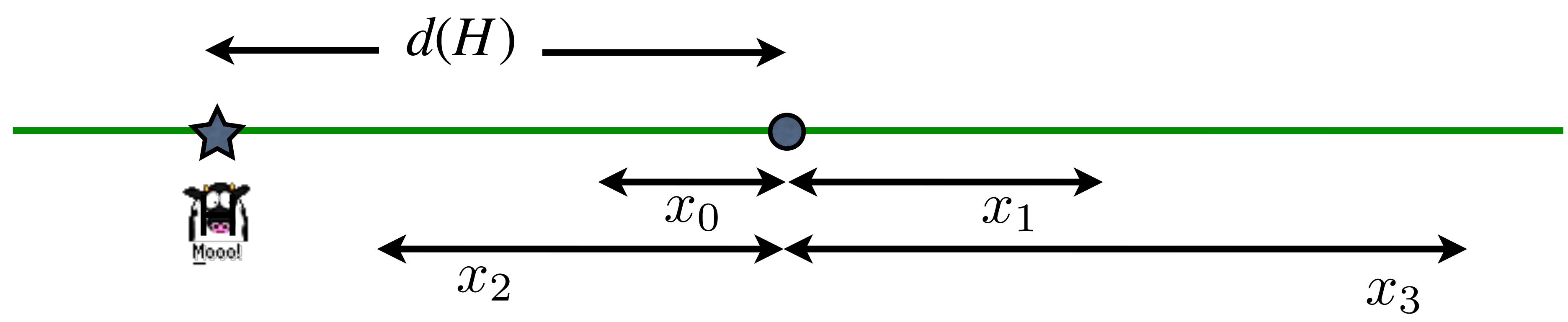

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- Many studies of extensions [Alpern and Gal, *The Theory of Search Games and Rendevous*, 2003]

Hints in online search

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Hint h: some information that is given to the searcher

The search strategy $S(h)$ is now a function of the hint

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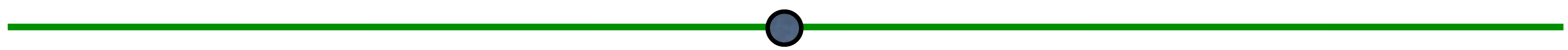

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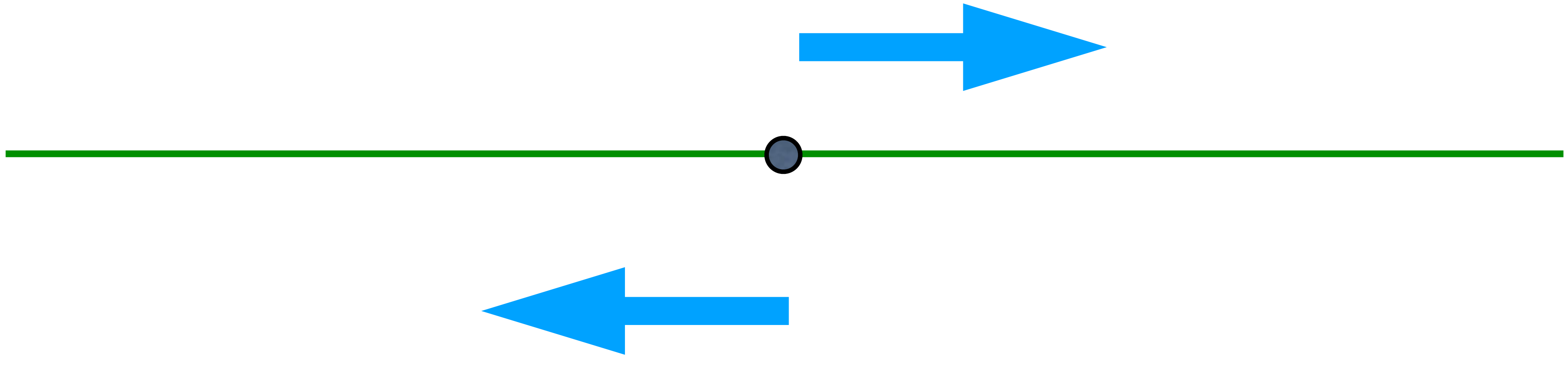

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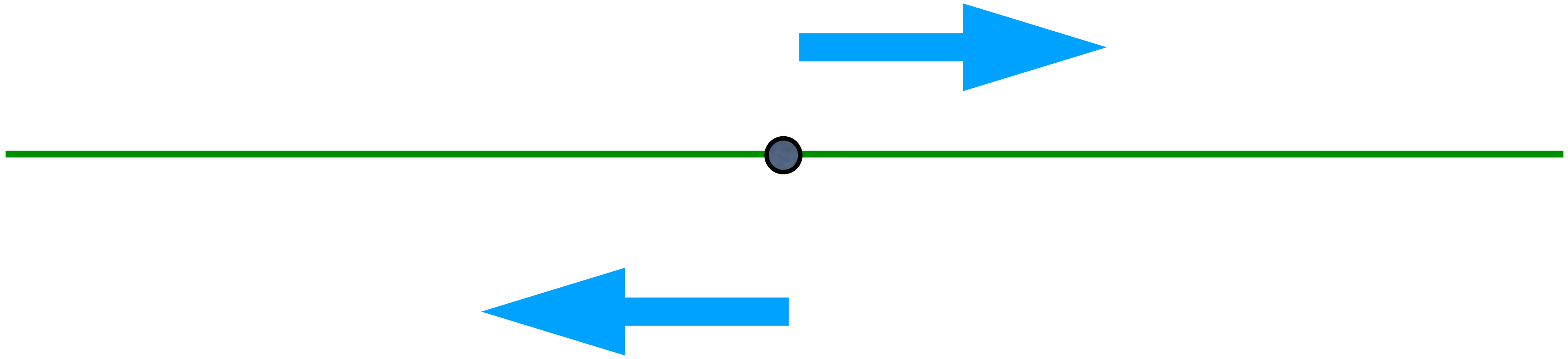

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- The doubling strategy that ignores the hint is $(9, 9)$ competitive

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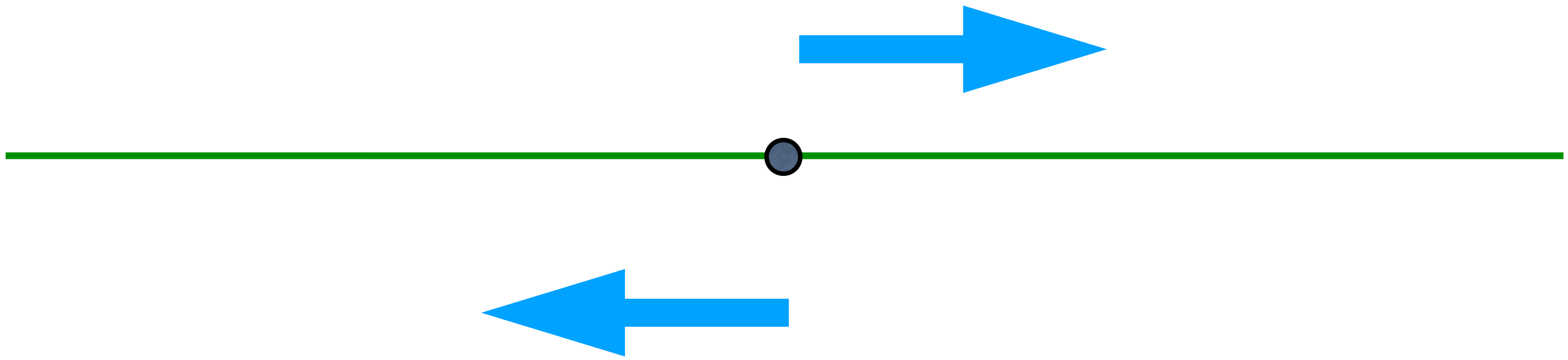

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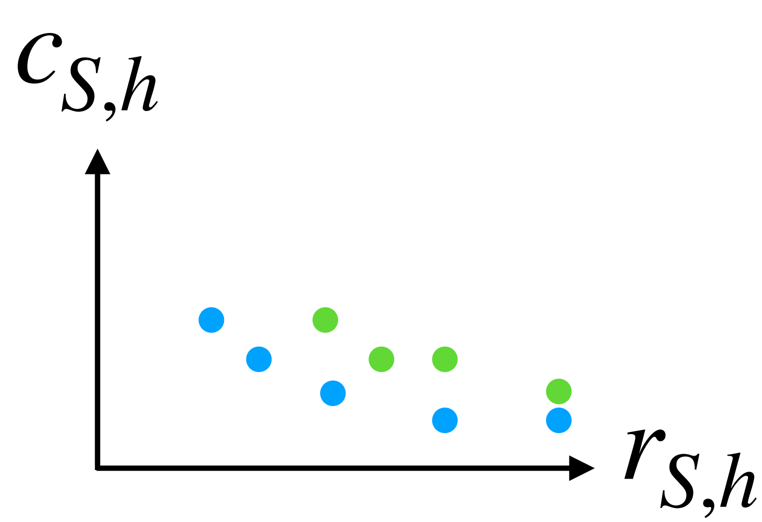
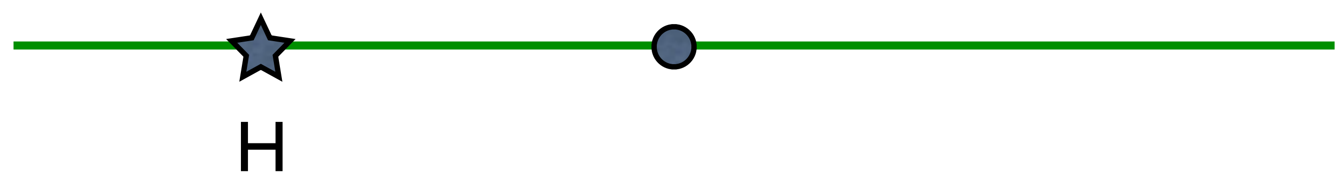
Pareto efficiency

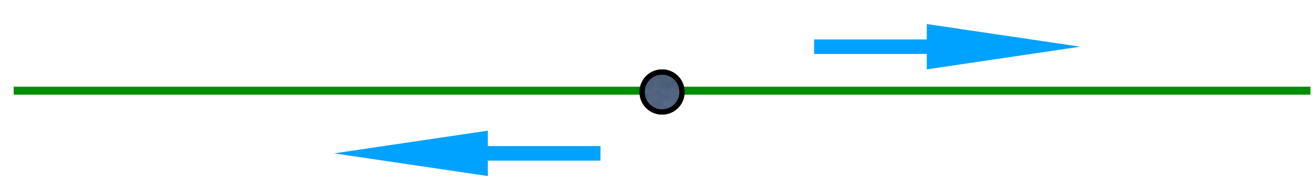


Types of hints

1 The hint is the exact **position** of the target



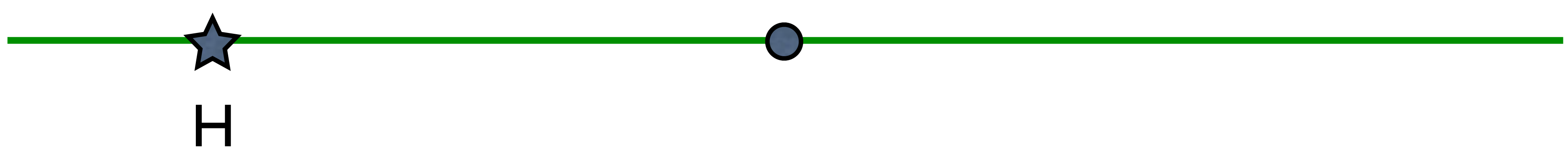
2 The hint is the **direction** of the search (left or right)

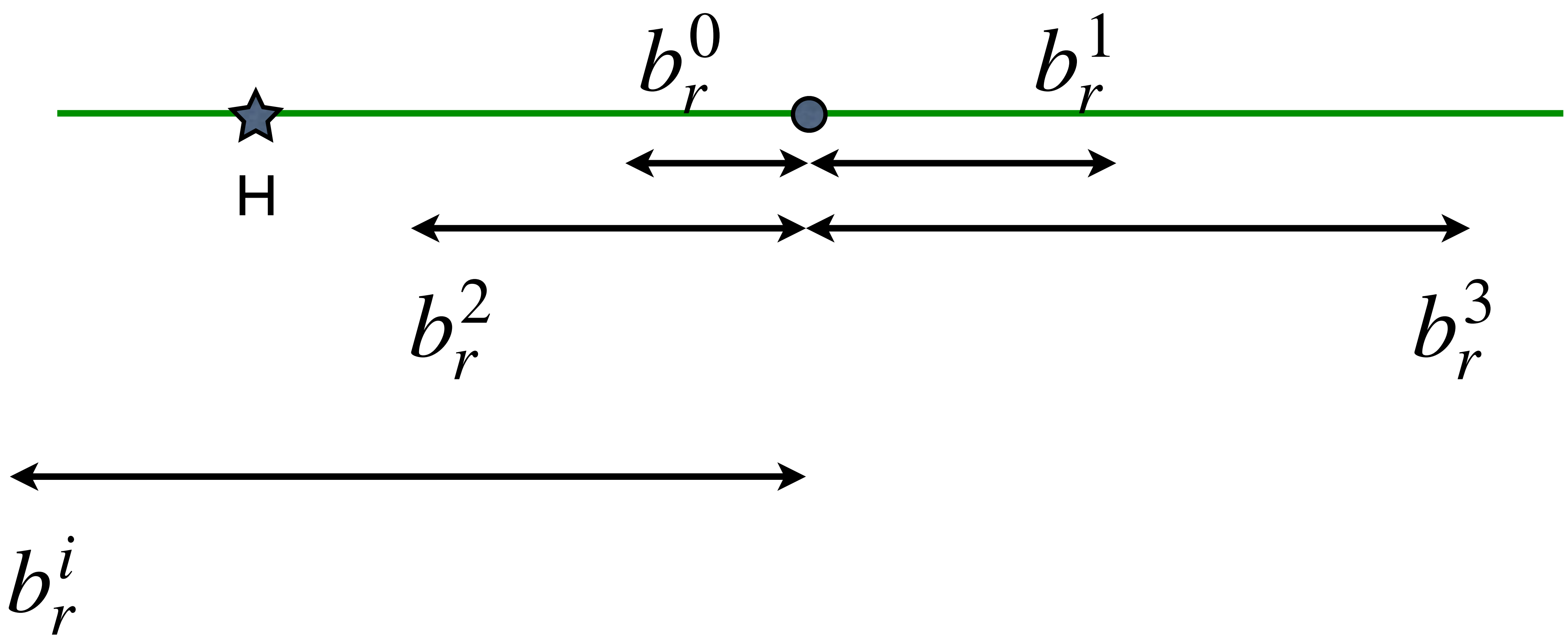


3 The hint is a **k-bit string**

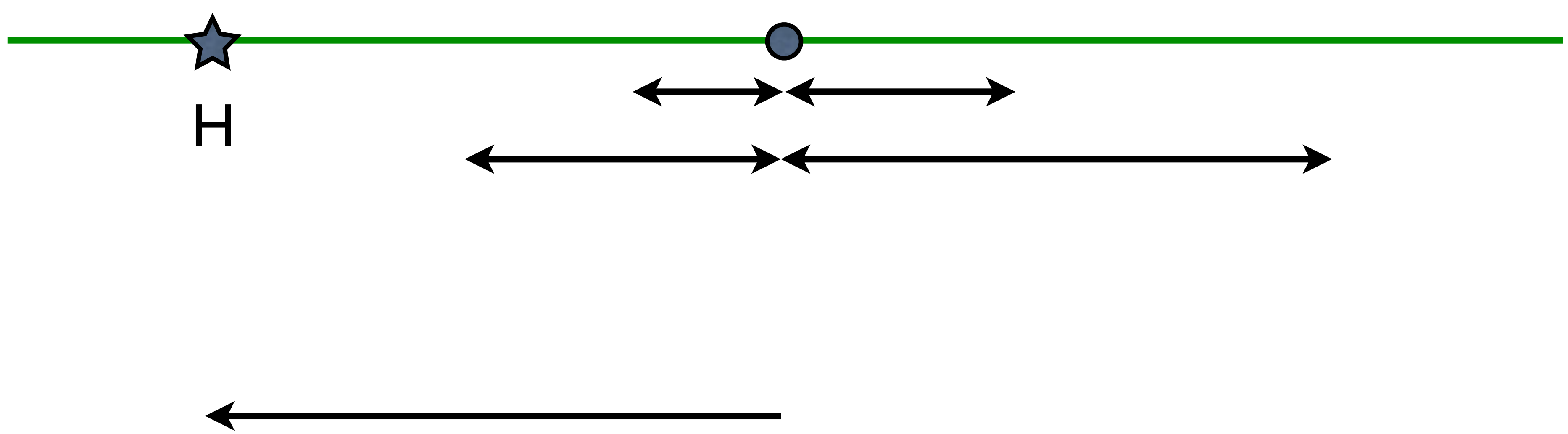
`01101...1`

1. The hint is the exact **position** of the target





$$b_r = \frac{r + \sqrt{r^2 - 4r}}{2}$$


H

Results for hint as position

Upper bound: The previous strategy is $\left(\frac{b_r + 1}{b_r - 1}, r\right)$-competitive

Lower bound: No other strategy is better (Pareto optimality)

Helpful lemma. For every r-robust strategy it holds that

$$x_i \leq \left(b_r + \frac{b_r}{i+1}\right) x_{i-1}, \text{ for every i}$$

Summary of results for the other settings

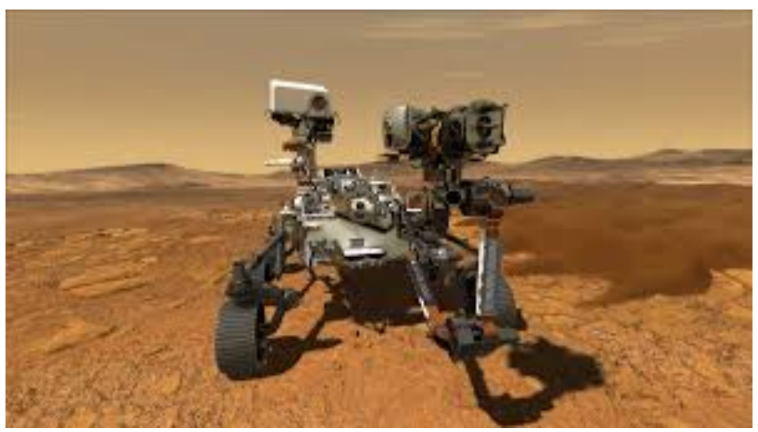
		Upper bounds	Lower bounds	Techniques
Hint= direction	Pareto-optimal strategies			Functional theorems [Schuierer 2001] and [Gal 1974]
Hint= k-bit string	k=1	$(1+4\sqrt{2},9)$ Upper bound for general r	No better than $(5,9)$ $(1+2\frac{b_r}{b_r-1},r)$ for restricted strategies	Information-theoretic arguments Adversary-algorithm games Relate the hint to multi-searcher strategies
	k>1	Upper bound for general r	$c \geq 3$	

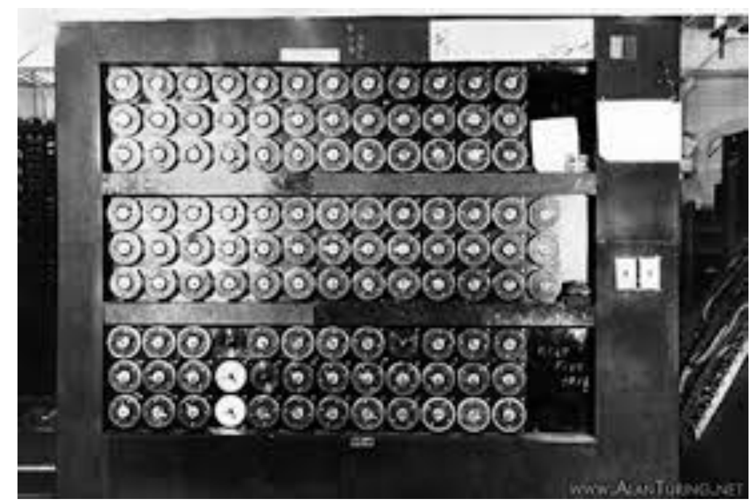
Part 2 : Contract scheduling with predictions

Motivation

Design of systems that are robust to interruptions

Integral requirement of many real-time and anytime applications





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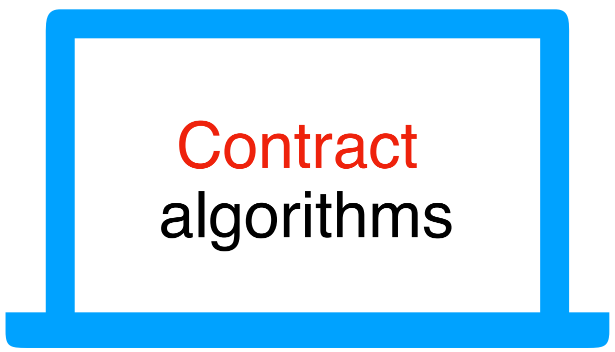

Execution time T given as input

If allowed to run up to T: output is correct

If interrupted prior to T, output
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Contract algorithms

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Interruptible algorithms

Return progressively better output as function of time

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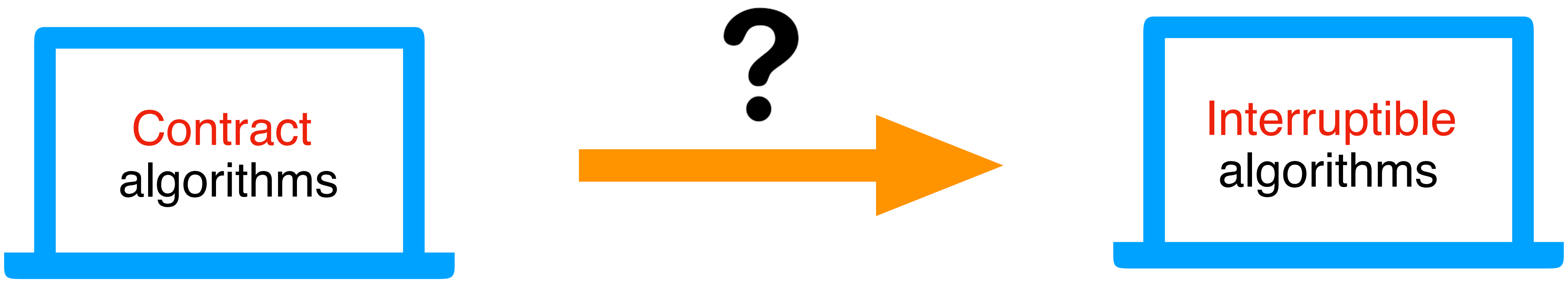

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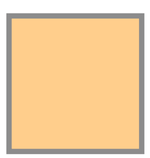

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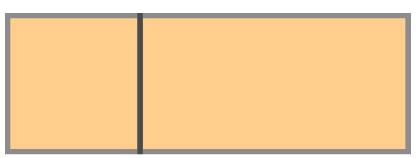

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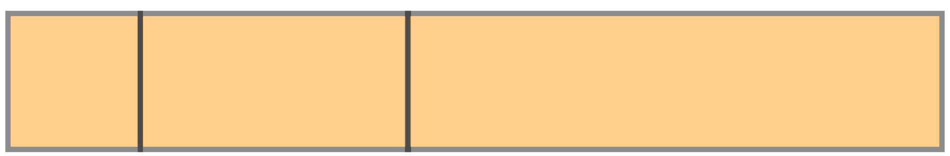

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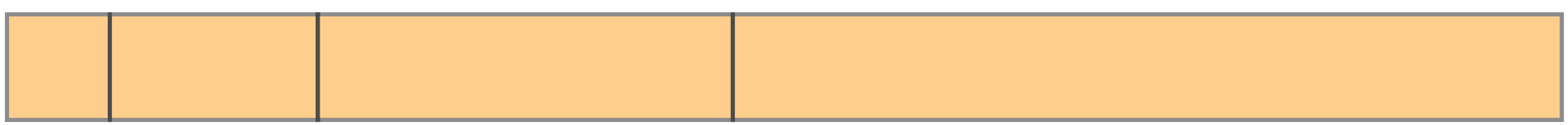

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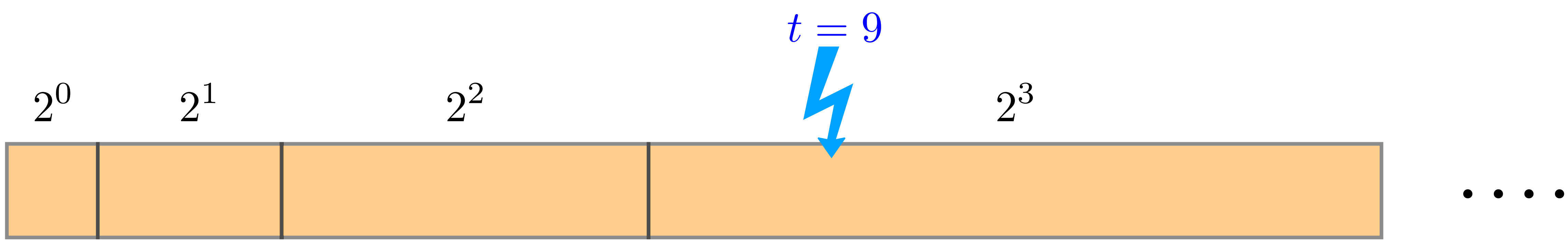

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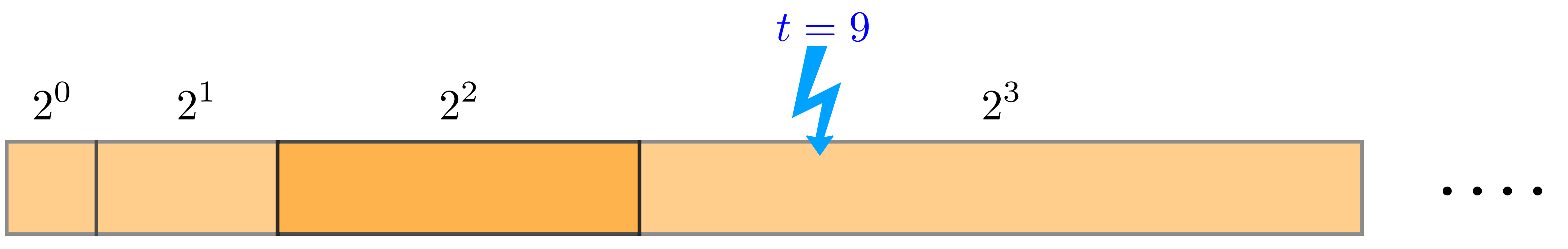

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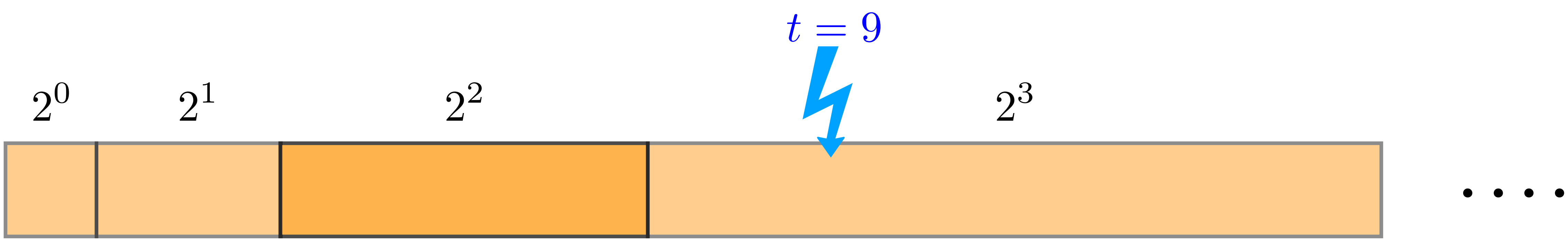

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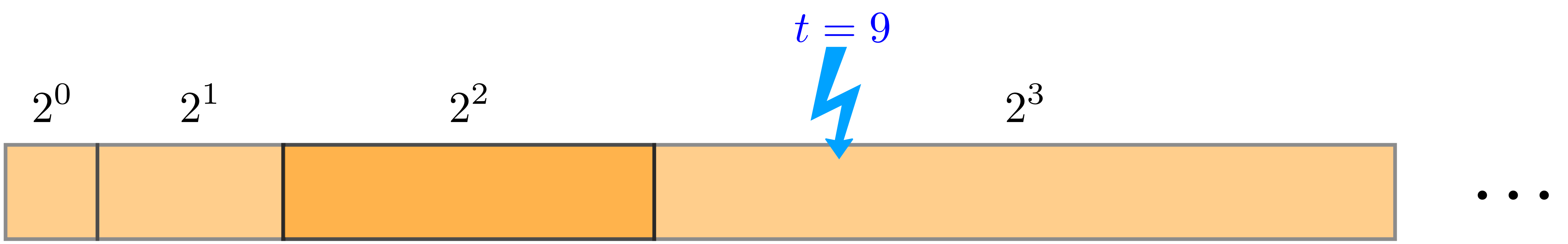

$$\texttt{acceleration ratio} = \sup_t \frac{t}{\text{largest contract completed by } t} = 4(\texttt{optimal})$$

[Russell and Zilberstein 1991]

Related work on contract scheduling

Setting	Reference
1 instance	Russell and Zilberstein 1991
n instances	Zillberstei, Charpillet and Chassaing 2003
1 instance, m processors	Bernstein, Perkins, Finkelstein and Zilberstein 2002
n instances, m processors	Bernstein Finkelstein and Zilberstein 2003
n instances, m processors	López-Ortiz, A, and Hamel 2014
Soft interruptions	A. and López-Ortiz 2017
Alternative measures	A. and López-Ortiz 2009
Connections to searching	Bernstein Finkelstein and Zilberstein 2003 and A. 2015
End guarantees	A. and Jin, 2019

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- Prediction is **the interruption**

- Prediction is the answer to **n binary queries**

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actual interruption

$$\tau(1-\eta) \leq T \leq \tau(1+\eta)$$

prediction

error $\in [0,1]$

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- Prediction is the answer to **n binary queries**

$\eta \in [0,1]$: fraction of the erroneous bits

Our setting: Contract scheduling with predictions

Information related to interruption

- Prediction is **the interruption**

actual interruption

$$\tau(1-\eta) \leq T \leq \tau(1+\eta)$$

prediction

error $\in [0,1]$

- Prediction is the answer to **n binary queries**

$\eta \in [0,1]$: fraction of the erroneous bits

- H : upper bound on η. Distinction between H-**aware** and H-**oblivious** schedules

Prediction is the interruption time

Start with an **ideal** setting: the prediction has **no error ($\eta = 0$)**

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For desired robustness r,

this schedule has consistency

$$c = \frac{r - \sqrt{r^2 - 4r}}{2}$$

E.g., for $r = 4$, c= 2

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Pareto optimal

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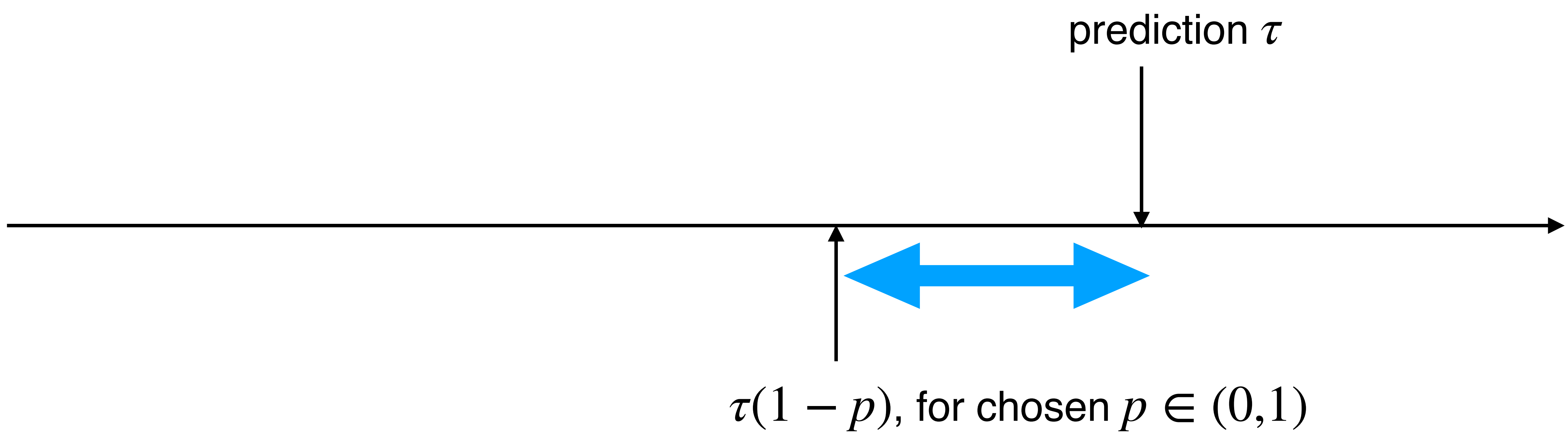

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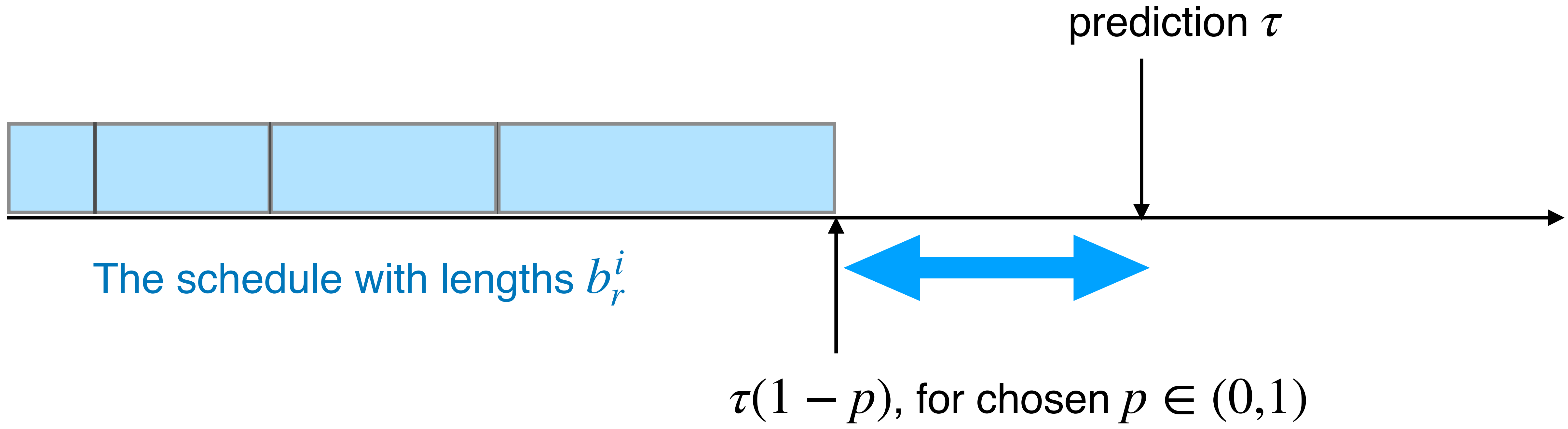

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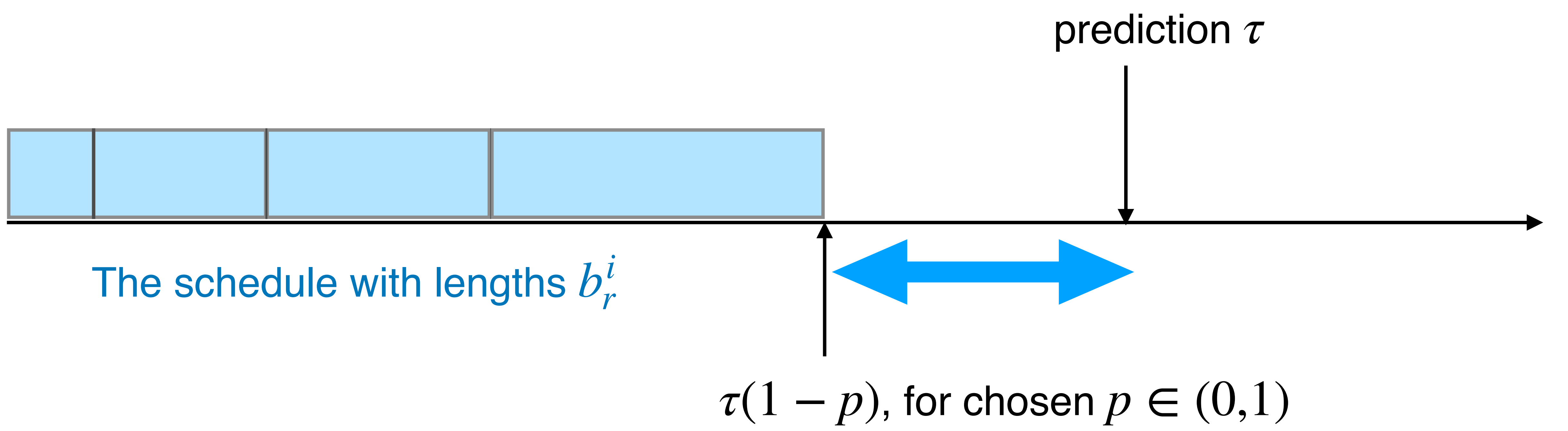
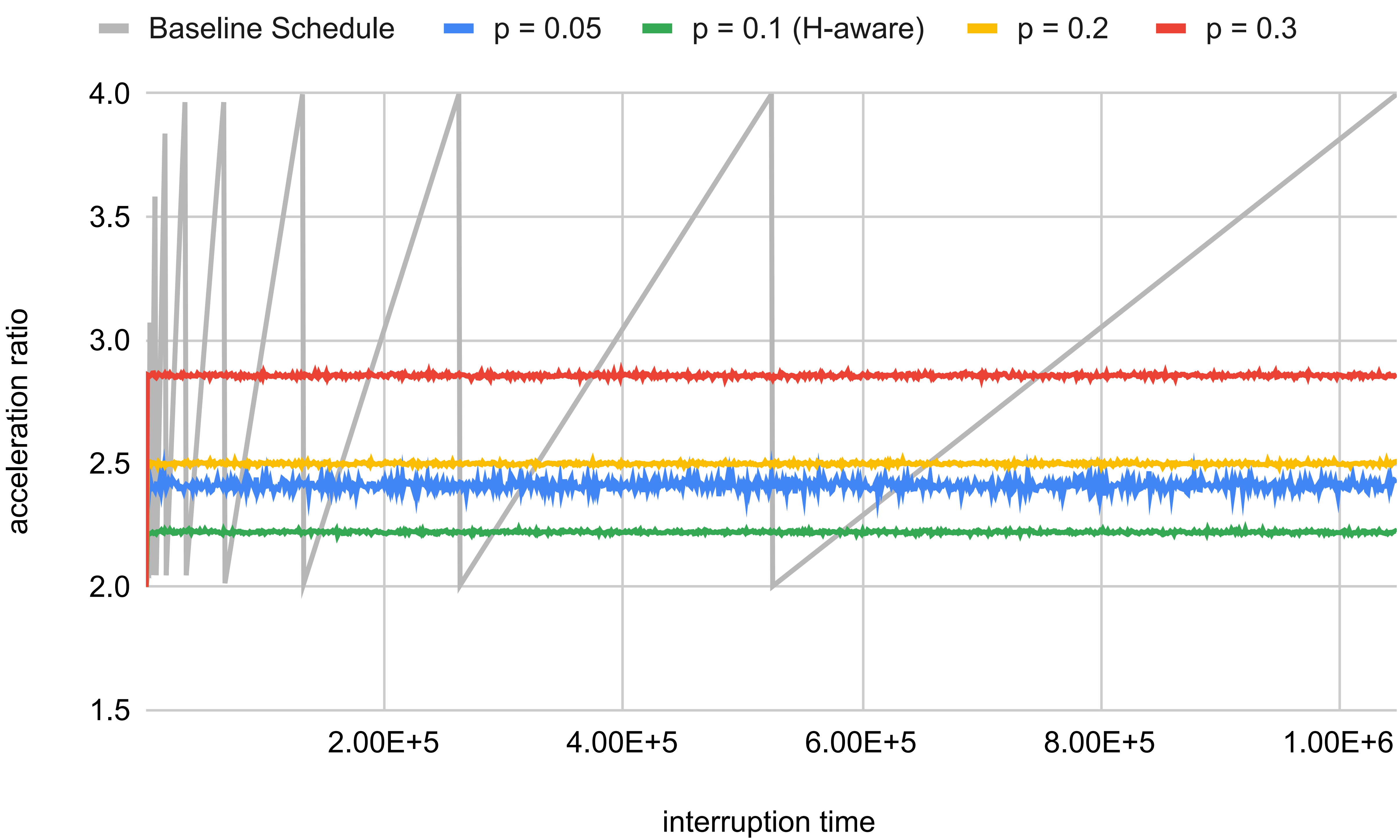


Results

- For H-**oblivious** schedules, this is near-optimal
- For H-**aware** schedules, choosing $p = H$ is near-optimal

Experimental results for r=4, H=0.1



Prediction comes from n binary queries

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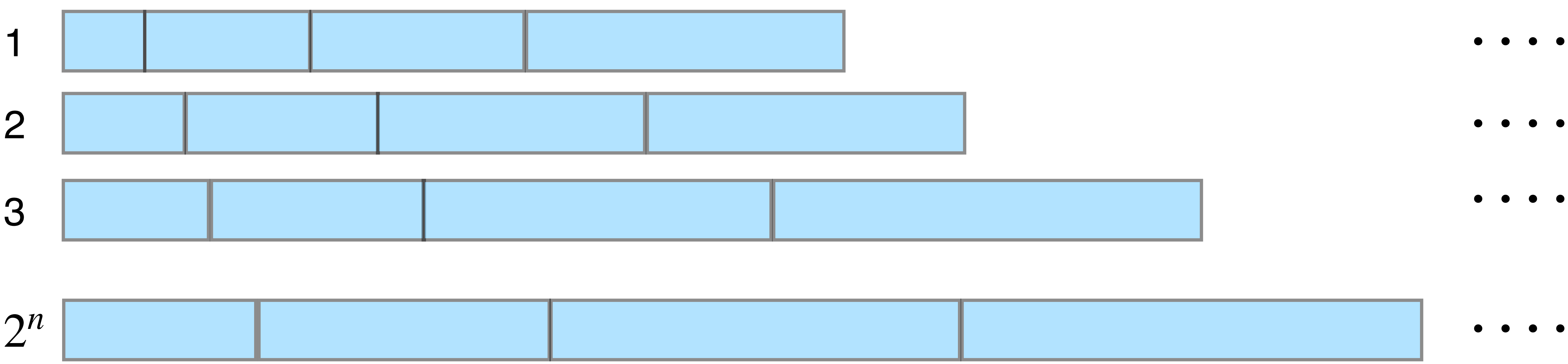

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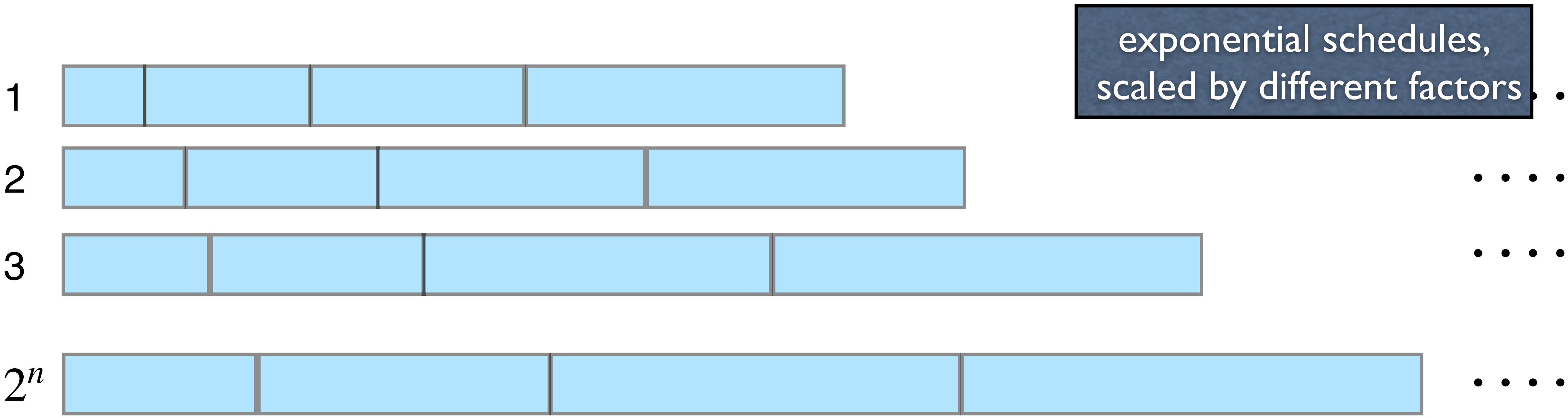

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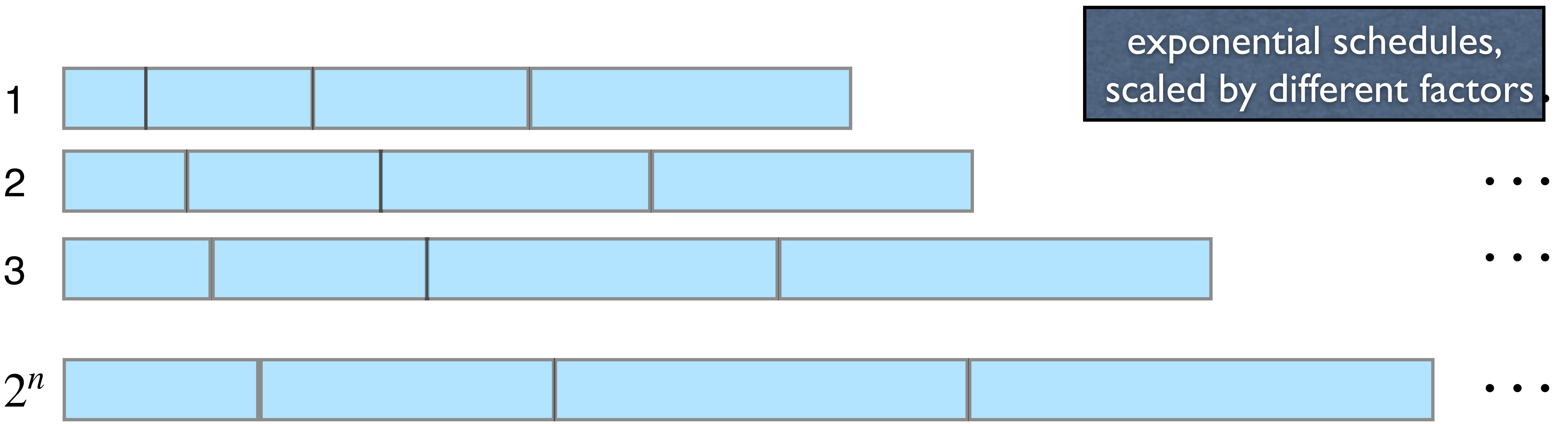

Results

- Tradeoff between robustness r and consistency c in terms of n
- E.g., for $r = 4$, we obtain $c = 2^{1+\frac{1}{2n}}$
- This is **Pareto-optimal** for $r = 4$

Prediction comes from n binary queries

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Outline of the approach

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- Tradeoff between robustness r and consistency c, in terms of n and p
- E.g., for $r = 4$, we obtain $c = 2^{1+\frac{1}{n}+2p}$

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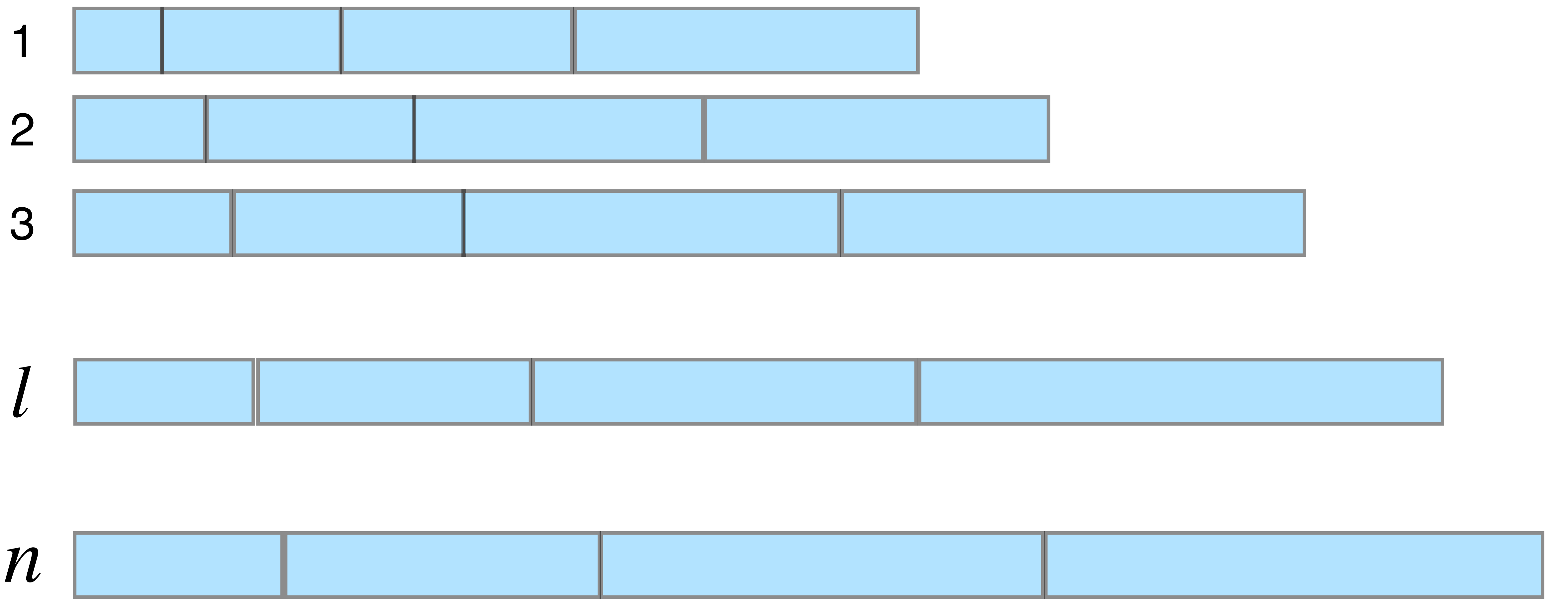

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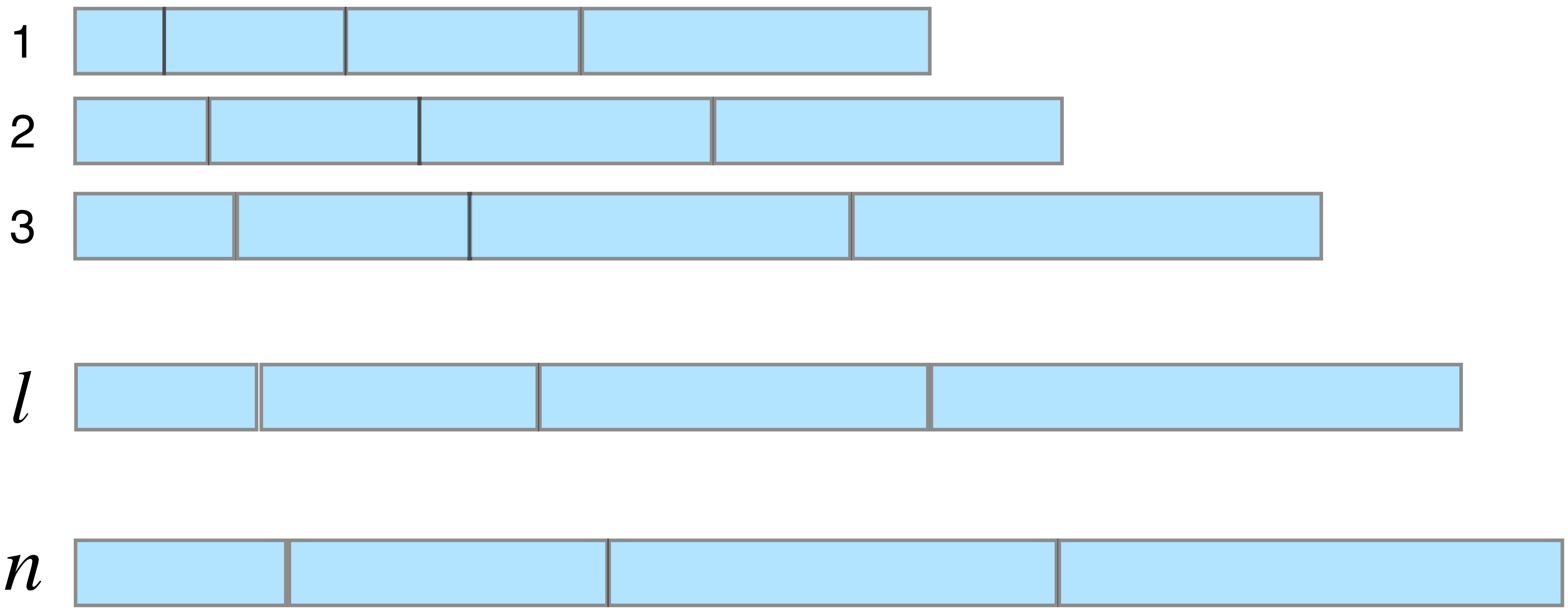

index of best schedule : l

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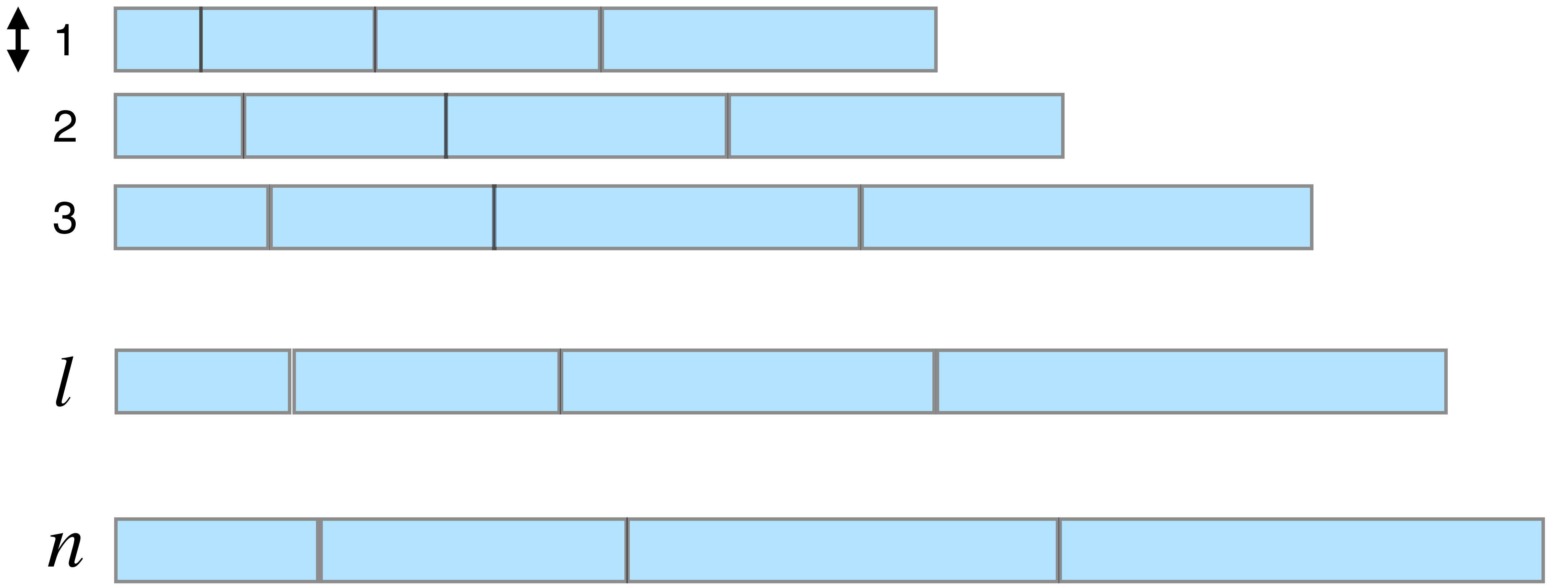

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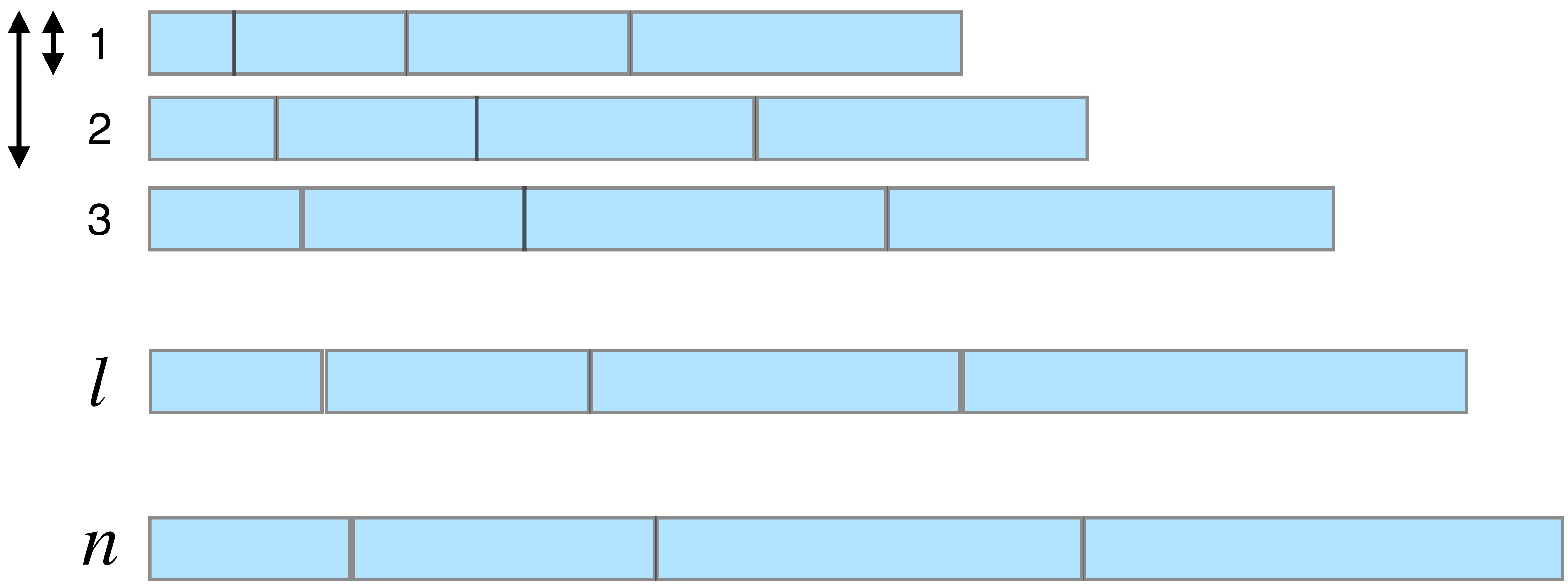

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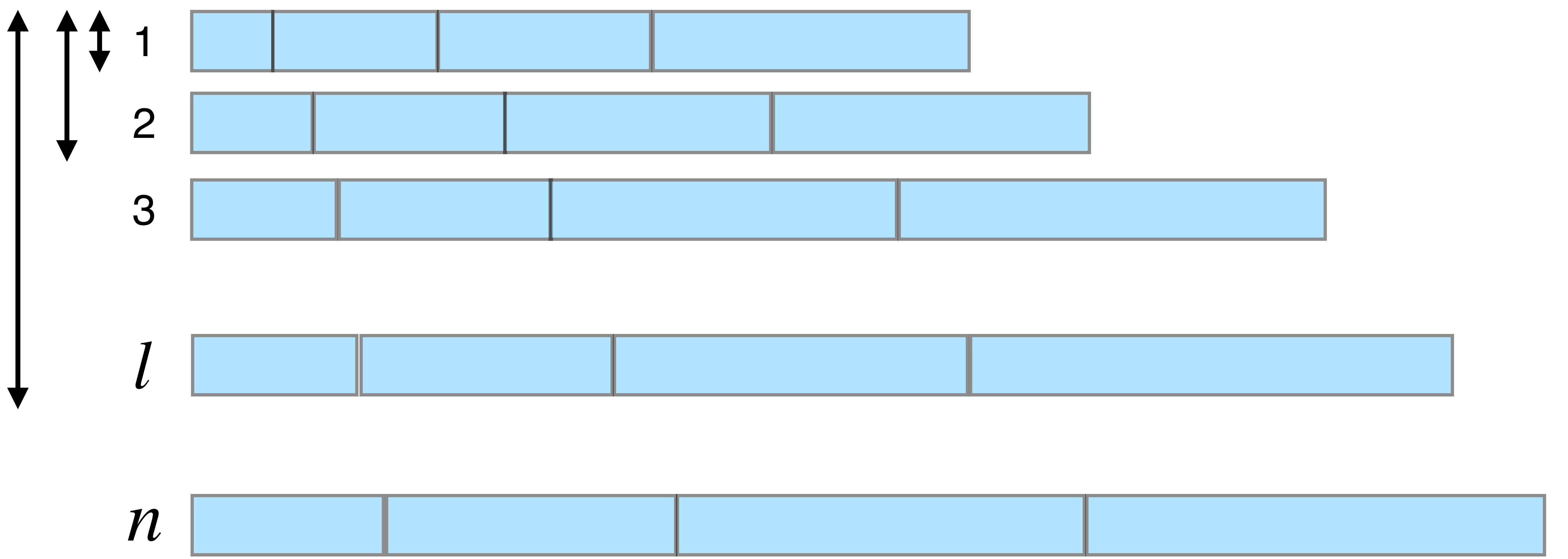

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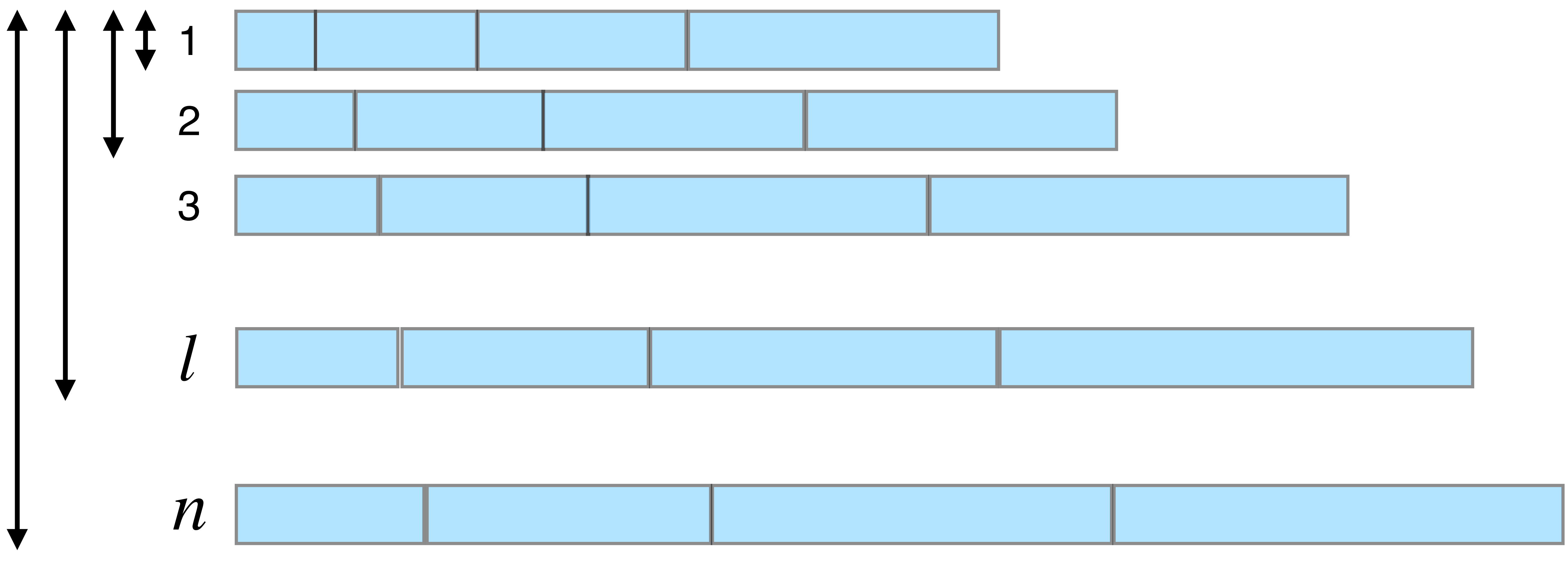

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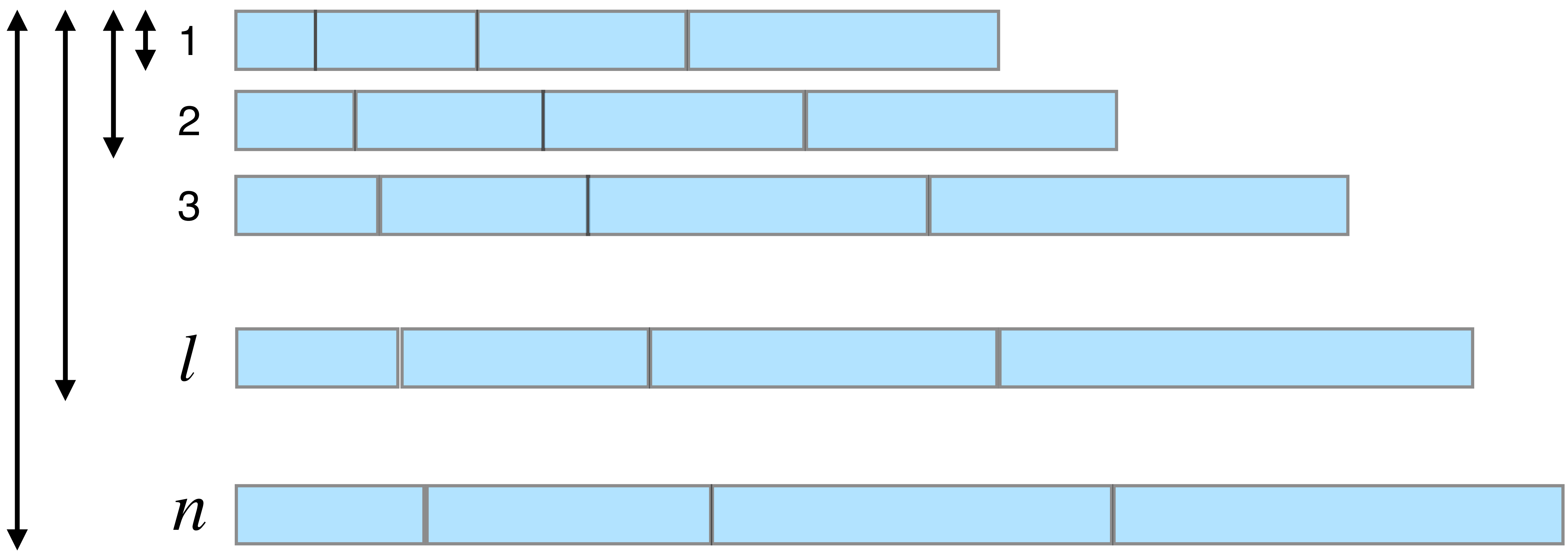

index of best schedule : l

index of chosen schedule : $N + 1 - p \cdot n$

N: number of ``no'' responses

p: tolerance (buffer)

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- In the previous discussion, queries are not very intuitive….
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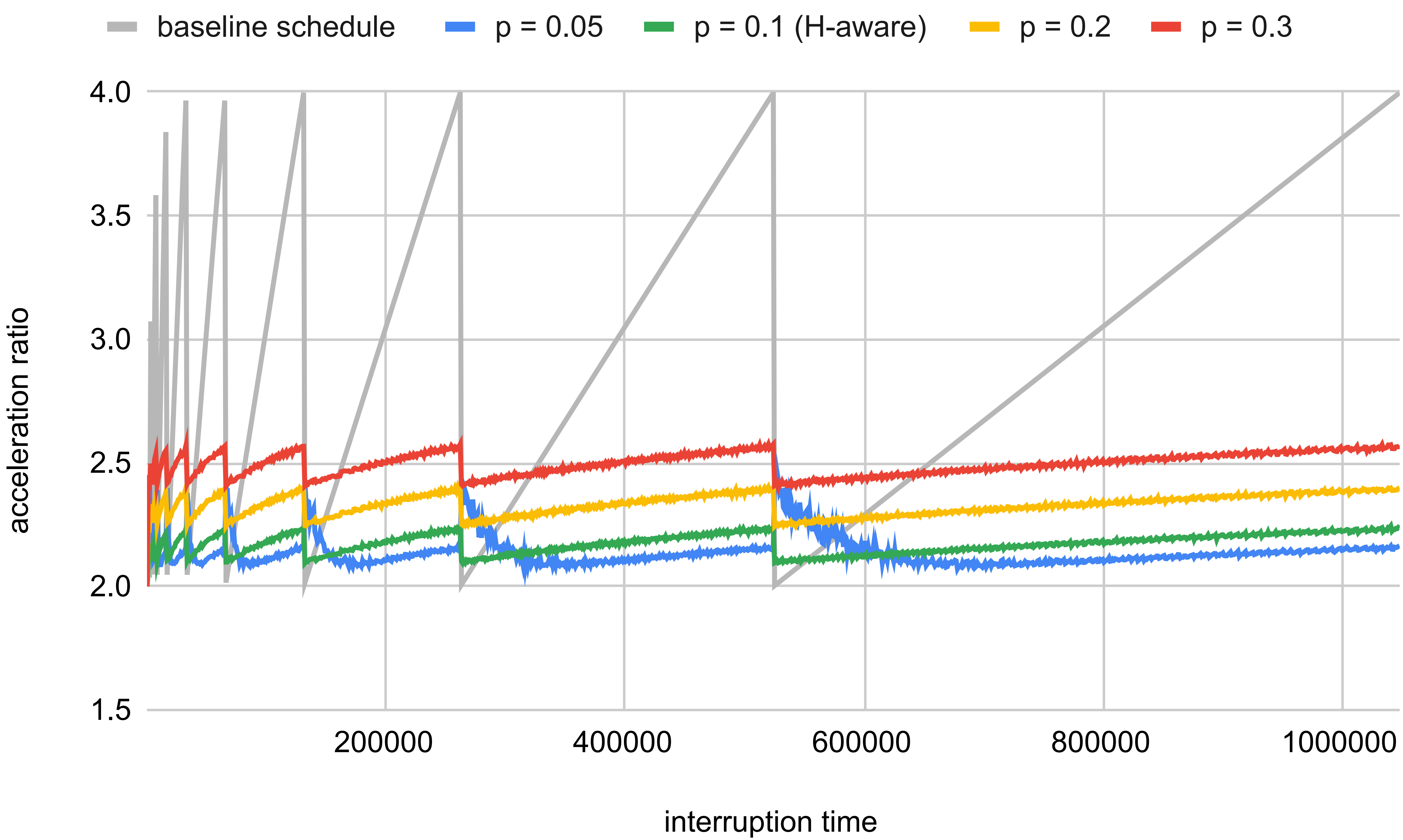
“Does the interruption occur in the red partition on in the orange partition?”

Experimental results for r=4, n=100, H=0.1



Part 3 : Online bin packing with predictions

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Pack a sequence of items (each with its own weight) into the minimum number of bins of a given capacity

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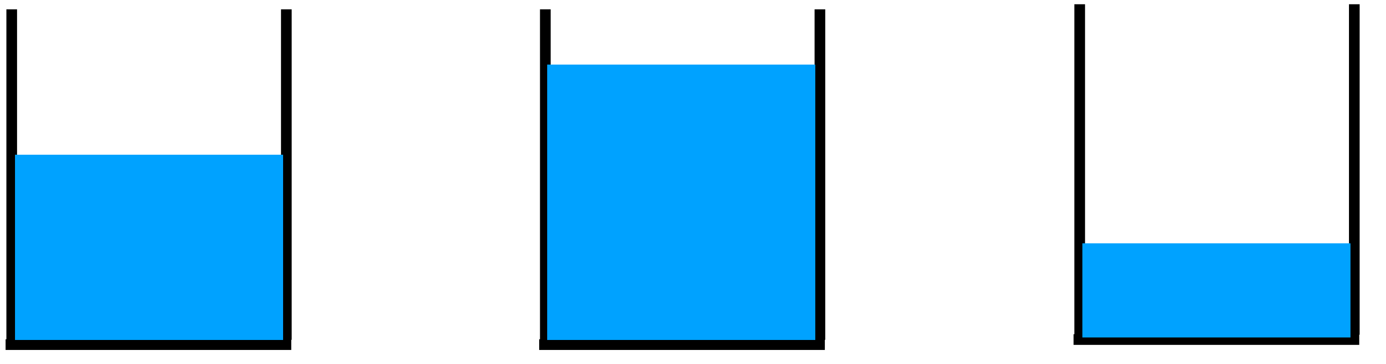

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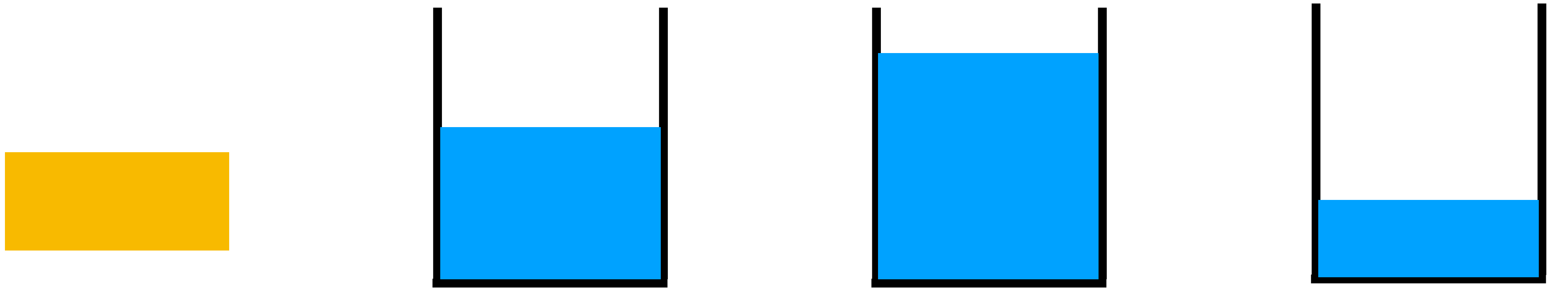

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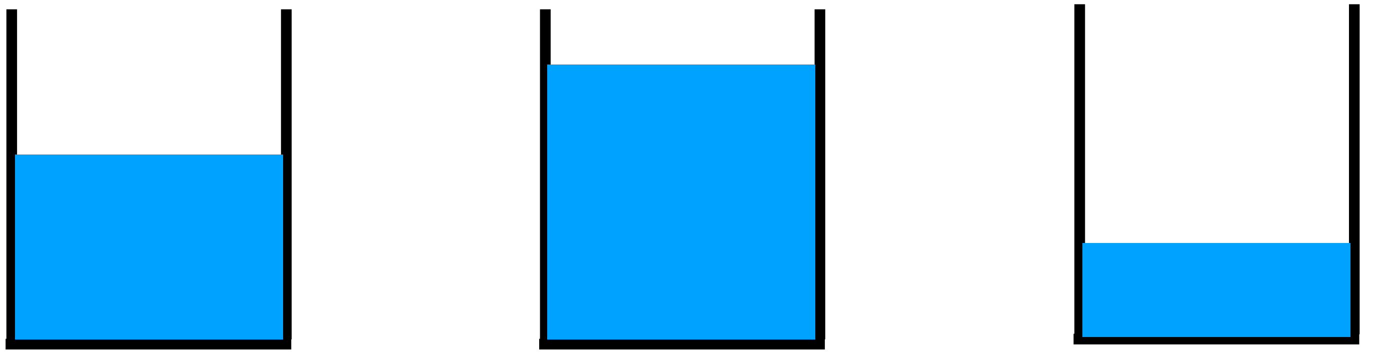

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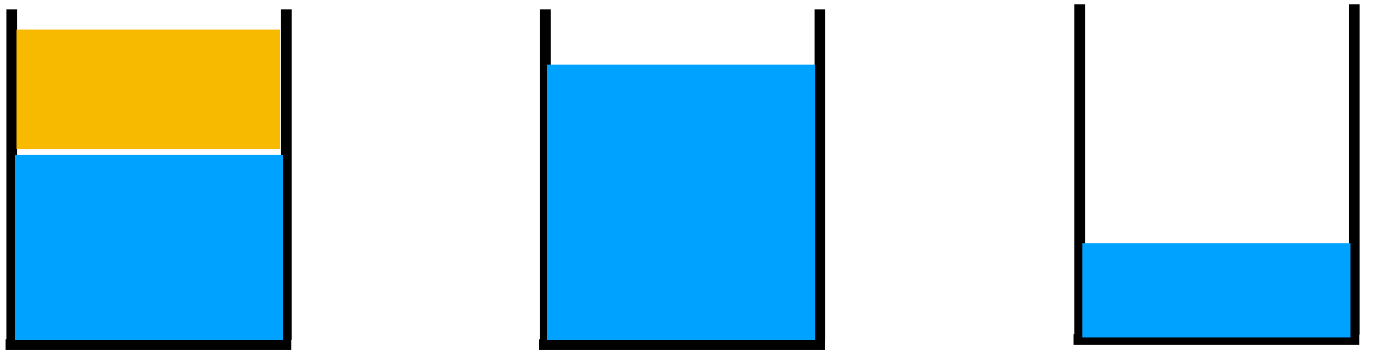

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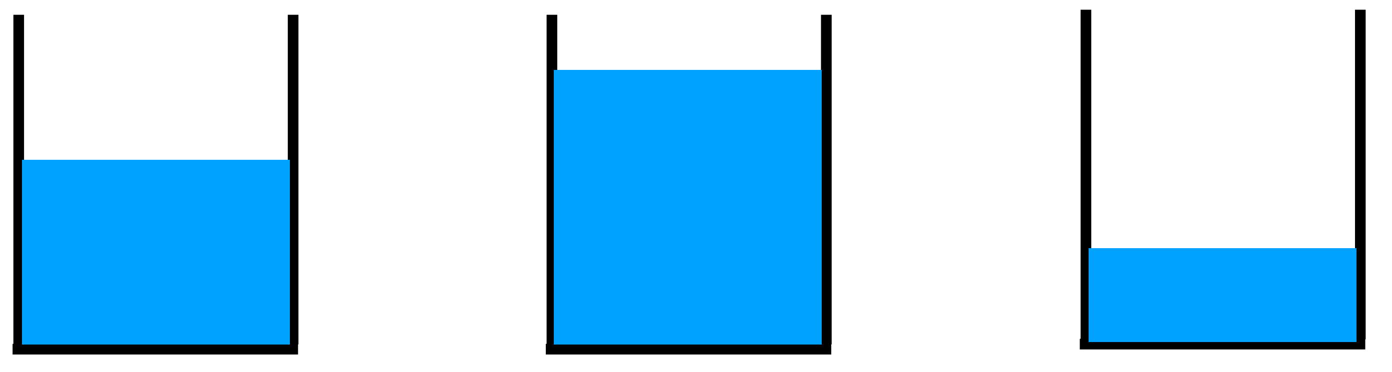

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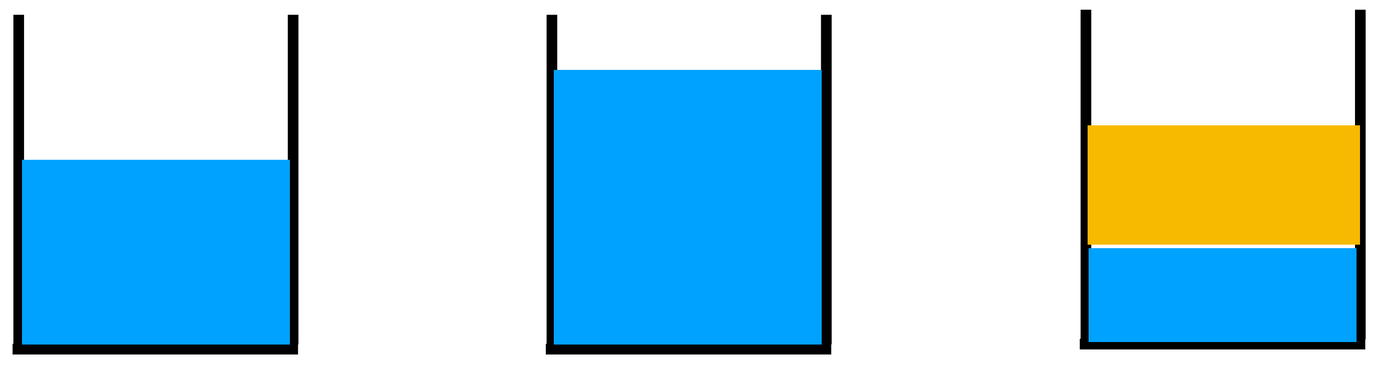

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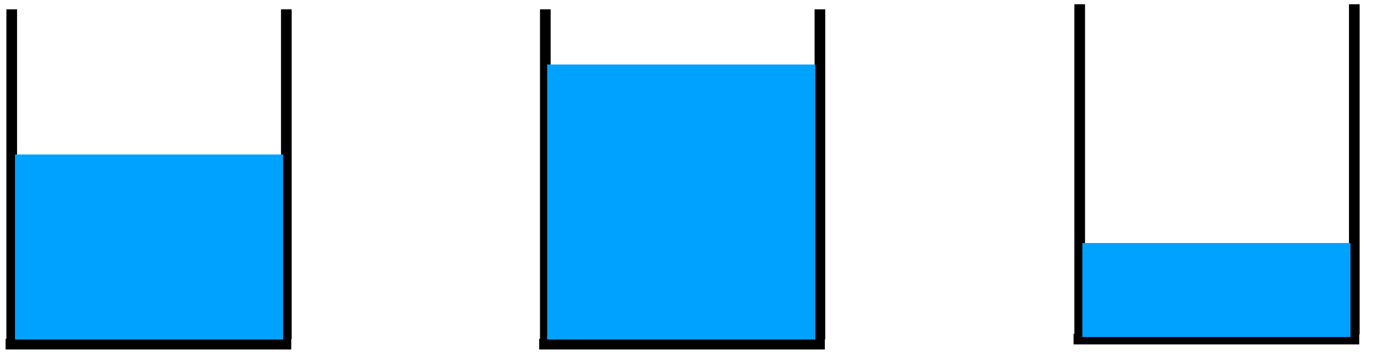

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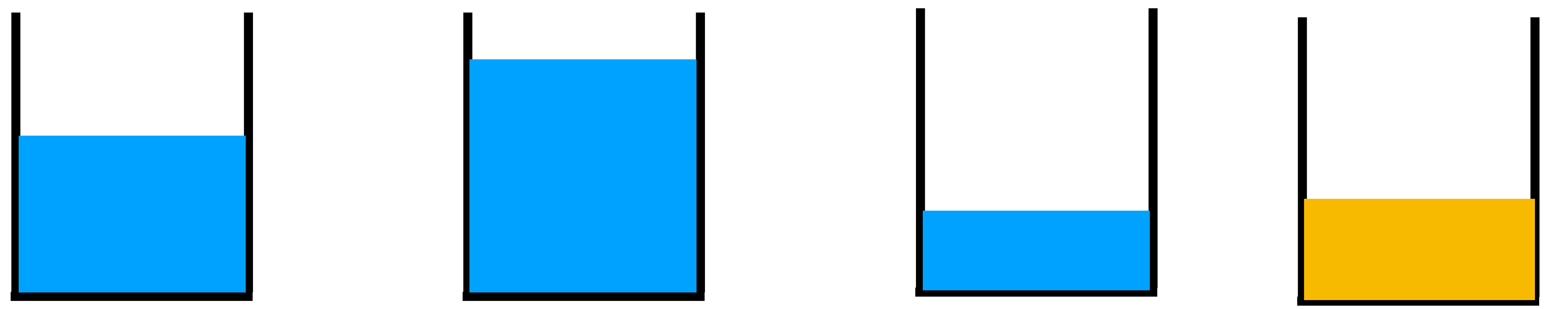

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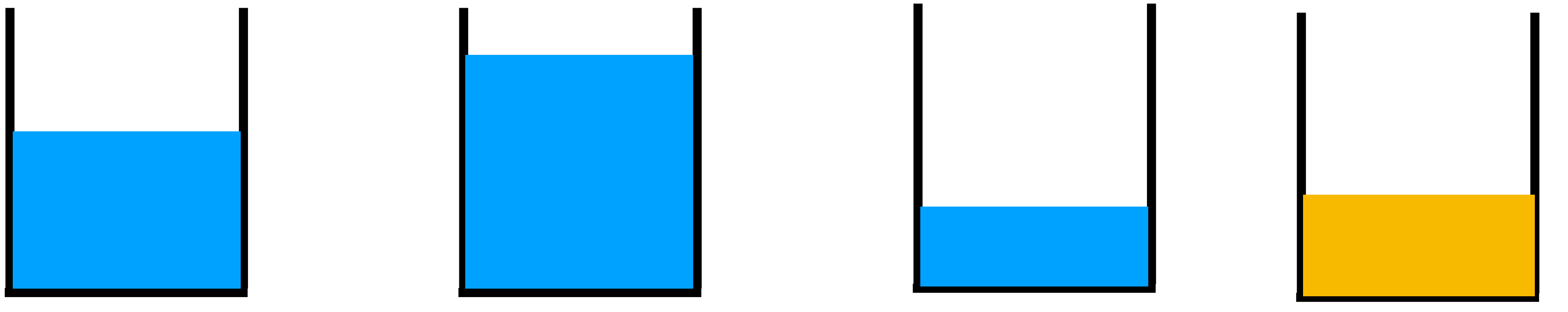

Online setting: Minimize the (asymptotic) competitive ratio

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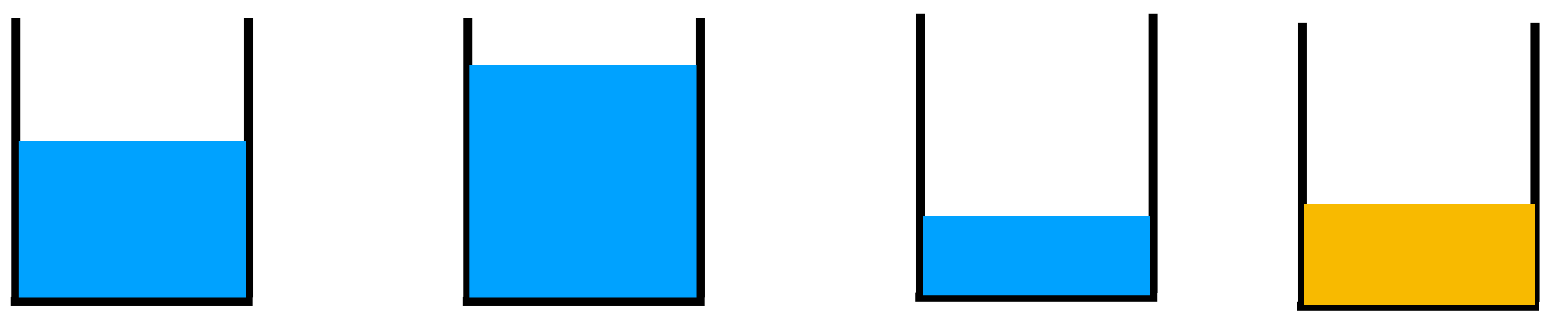

Online setting: Minimize the (asymptotic) competitive ratio

Many applications (from inventory management to cloud computing)

e.g., [Cohen et al : Overcommitment in Cloud Services: Bin Packing with Chance Constraints, *Management Science* 2019]

Some known results

Best known **upper** bound : 1.57829 [Balogh et al. 2018]

Best known **lower** bound : 1.54037 [Balogh, Békési and Galambos 2012]

FIRST-FIT, BEST-FIT have competitive ratio 1.7. [Johnson et al. 1974]

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In practice, FIRST-FIT and BEST-FIT perform very well

In practice, many competitively efficient algorithms do not perform as well as FIRST-FIT

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Prediction error: L_1 distance between the actual and the predicted frequencies

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Fix a (large) constant M. We call the multiset that consists of $\lceil f_{x,\sigma} \cdot M \rceil$ items of size x the **profile** of σ

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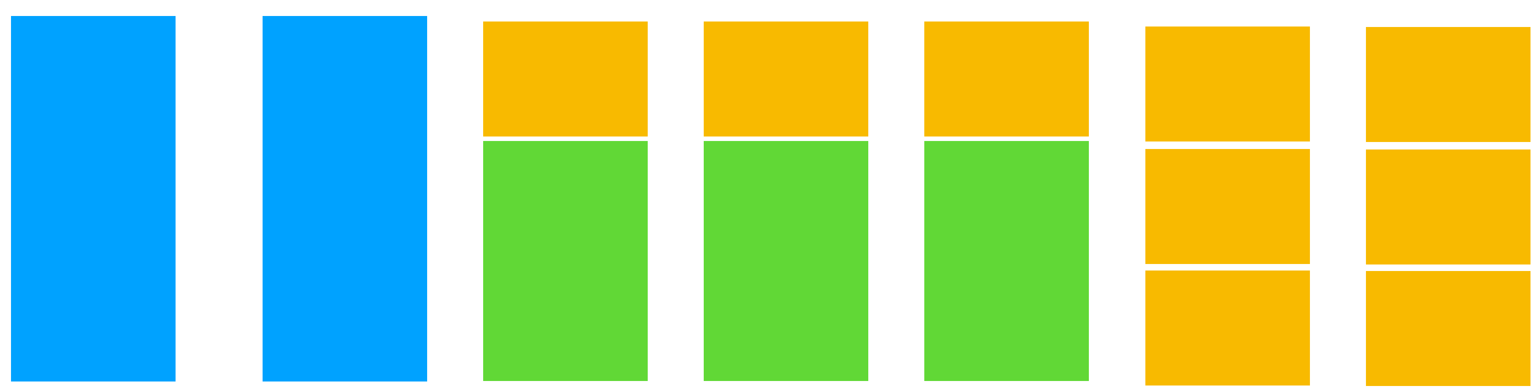

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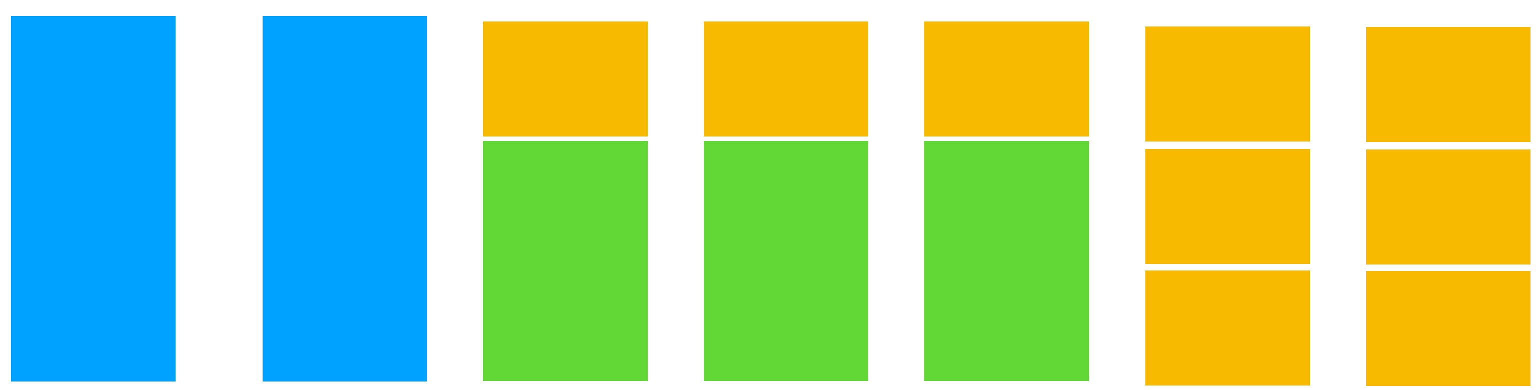

Profile Packing: A natural online algorithm based on this concept

Results

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(excellent consistency, bad robustness)

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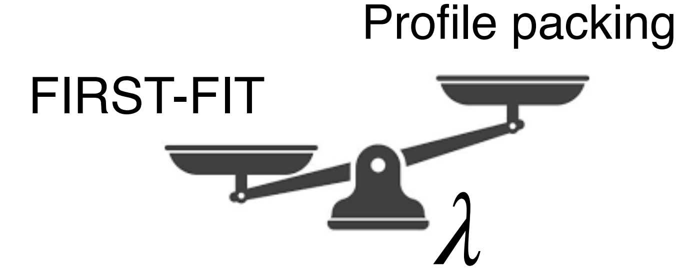
We propose an algorithm that offers a much better balance, which we call **HYBRID**(λ)**,** where $\lambda \in [0,1]$ is a parameter chosen by the user

Main idea: Some items are served using FIRST-FIT, others using Profile Packing



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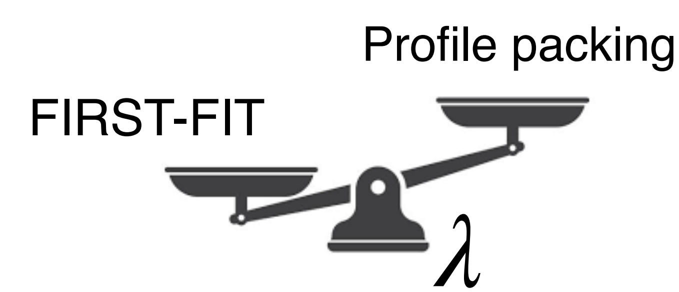
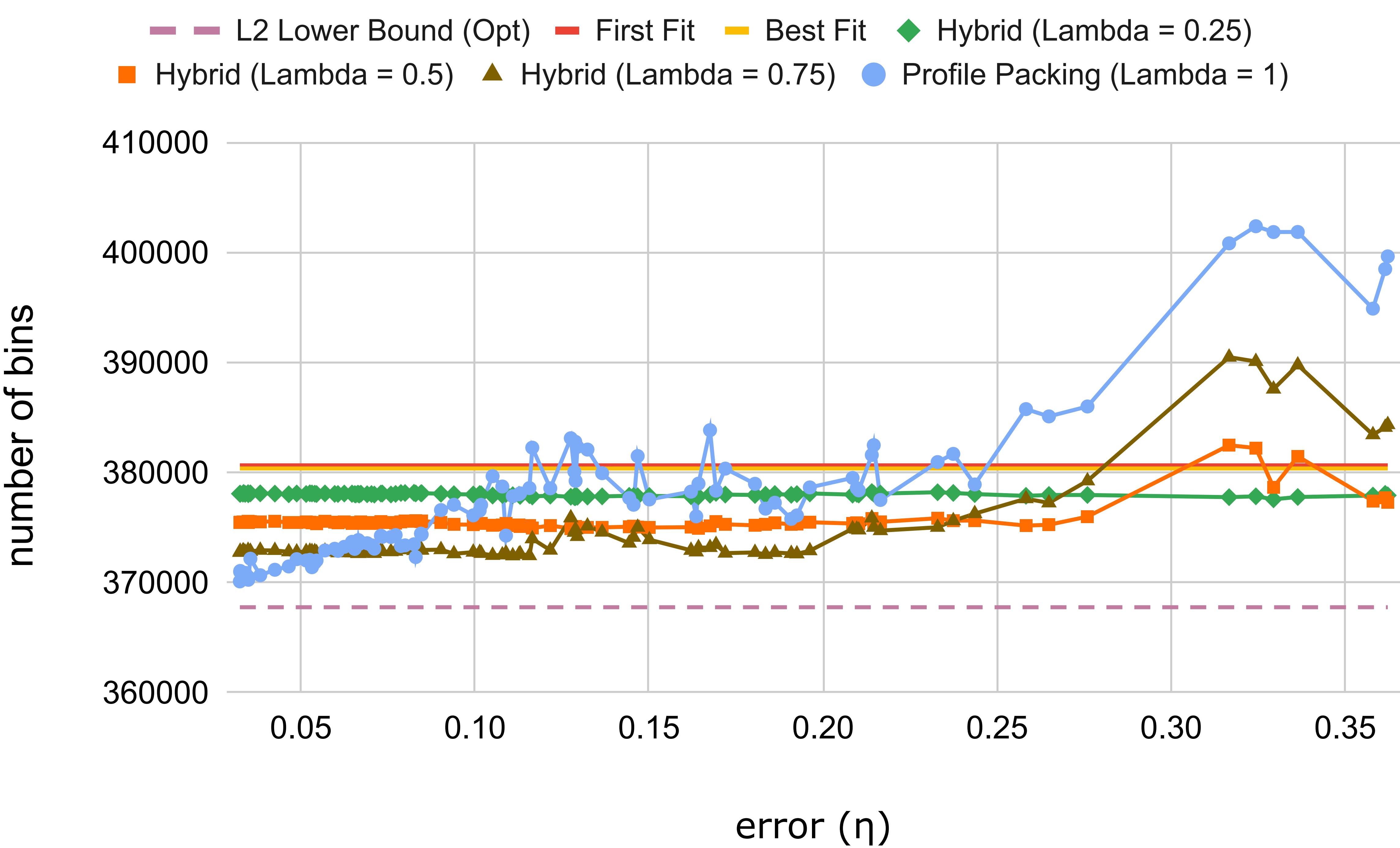


Theorem: HYBRID(λ) has competitive ratio arbitrarily close to $1.7 + \lambda(2\eta k - 0.7)$

Experimental evaluation (Weibull distribution)



Future work

- Bridge the gaps between the upper and the lower bounds for online search and contract scheduling (the upper bounds are likely tight)
- Challenge: information-theoretic lower bounds in the presence of errors
- Analysis beyond the competitive ratio (e.g. search optimization problems)
- Learning aspects of predictions

Potential PhD and postdoc opportunities

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