

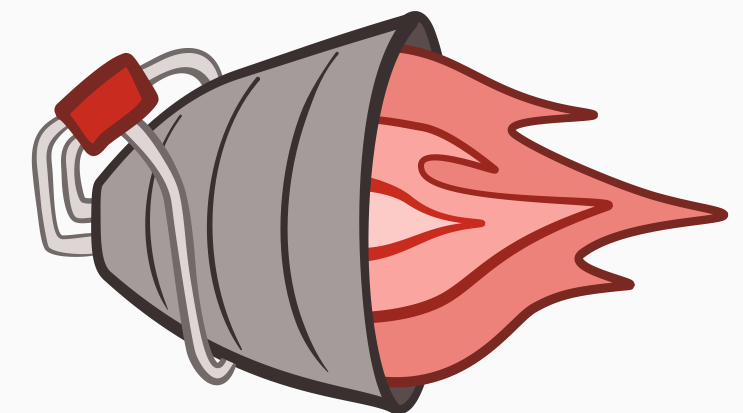
Strongly Tail-Optimal Scheduling *in the Light-Tailed M/G/1*

Ziv Scully Cornell ORIE

Joint work with

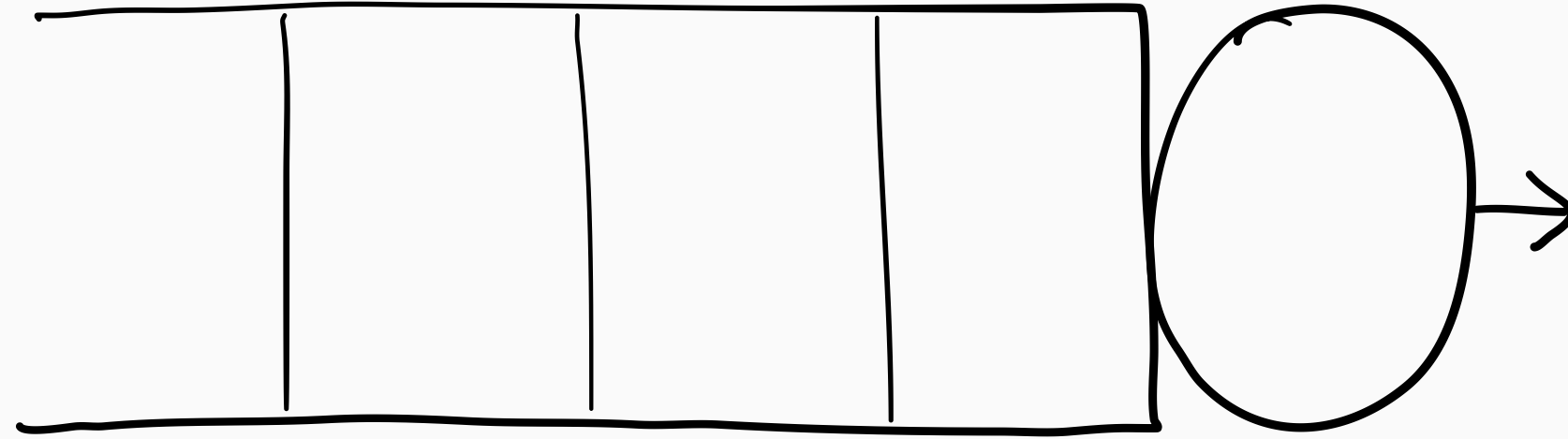
George Yu Cornell ORIE

Amit Harlev Cornell CAM

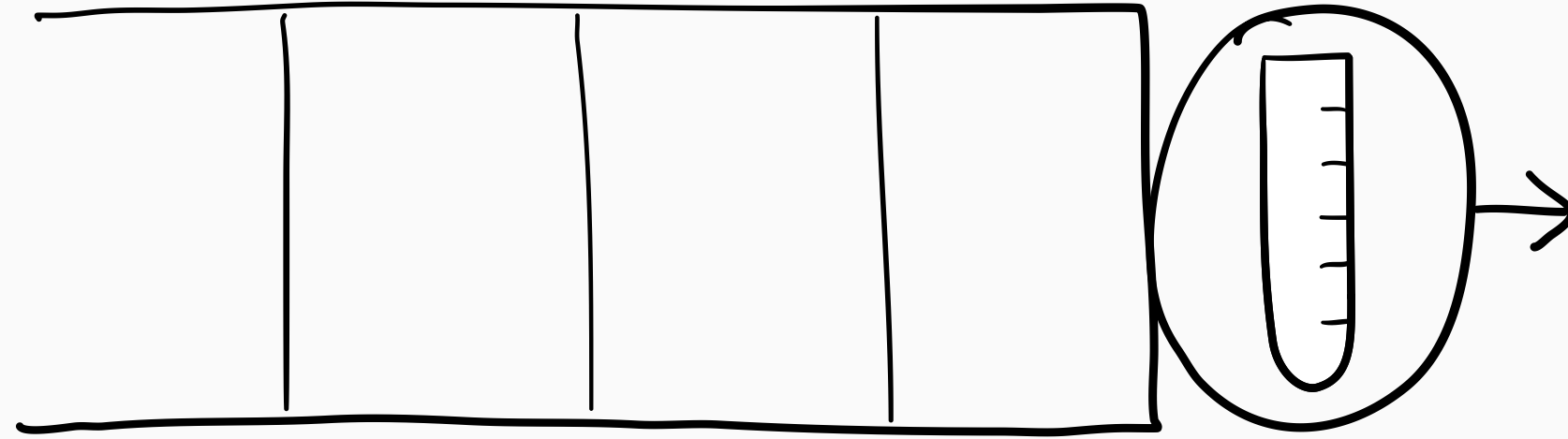


How should we schedule jobs to minimize delay?

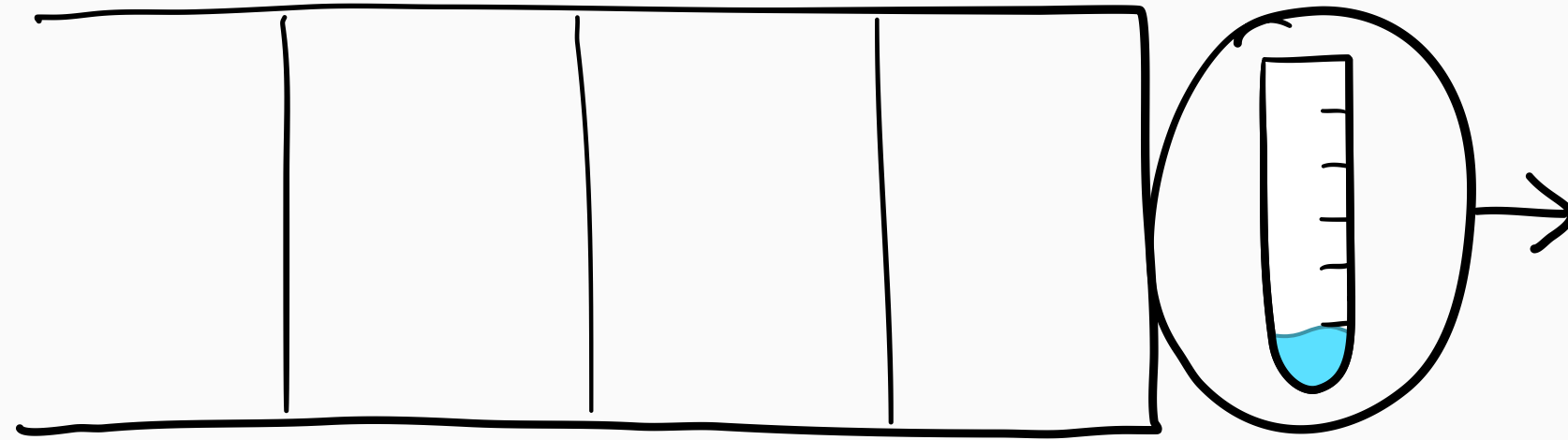
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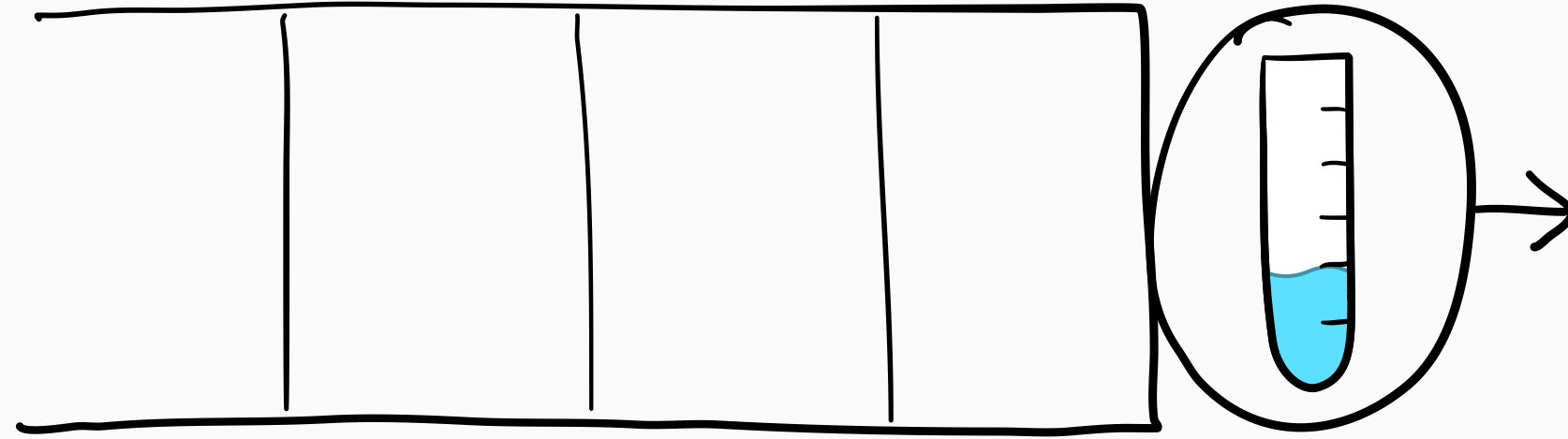
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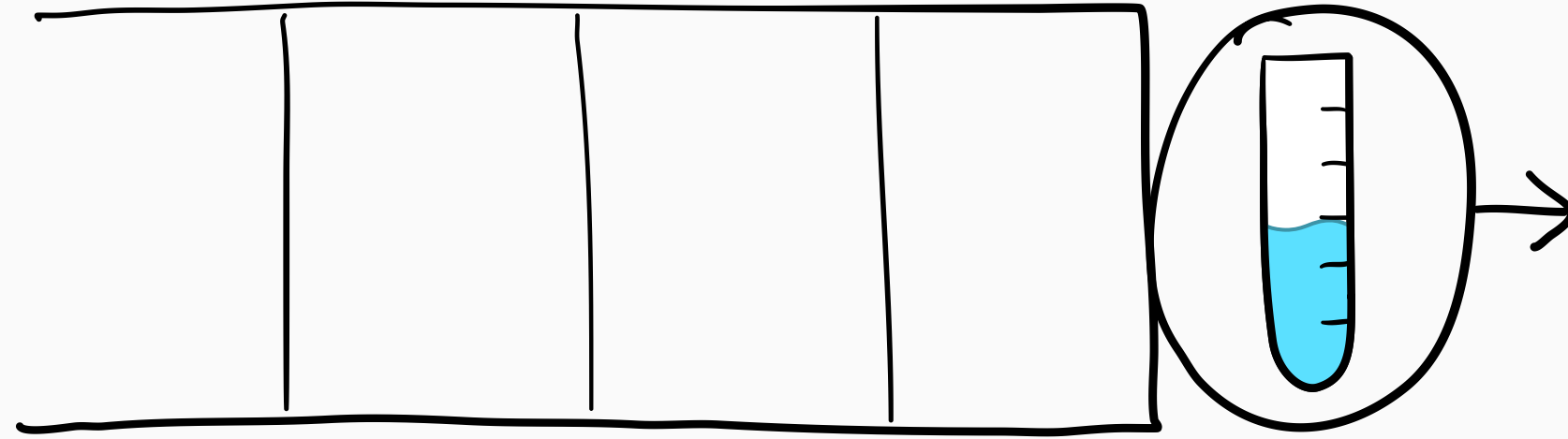
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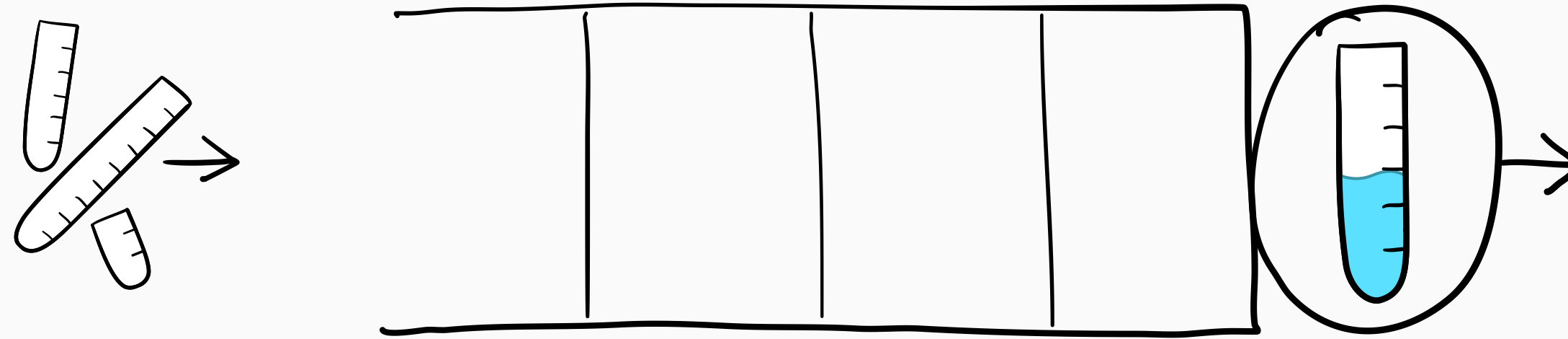
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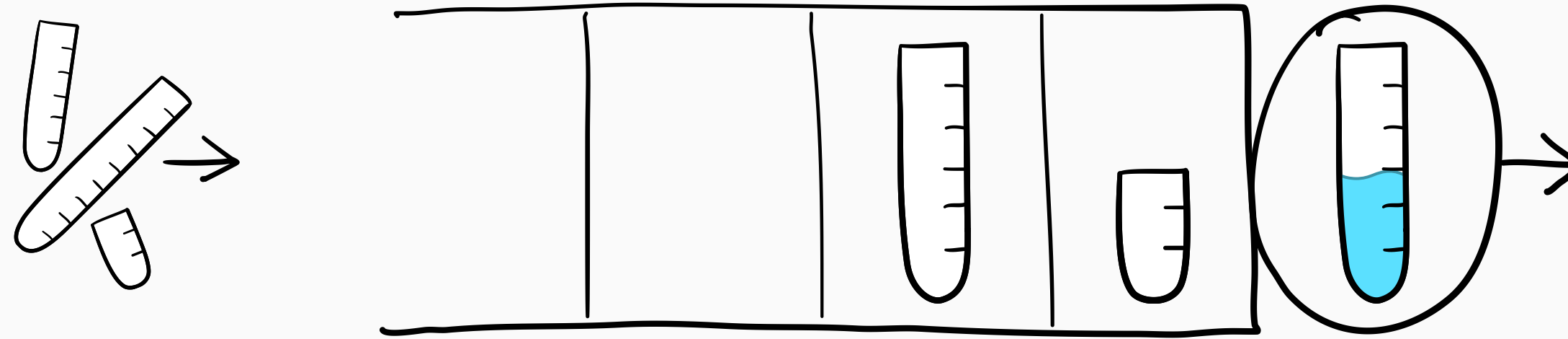
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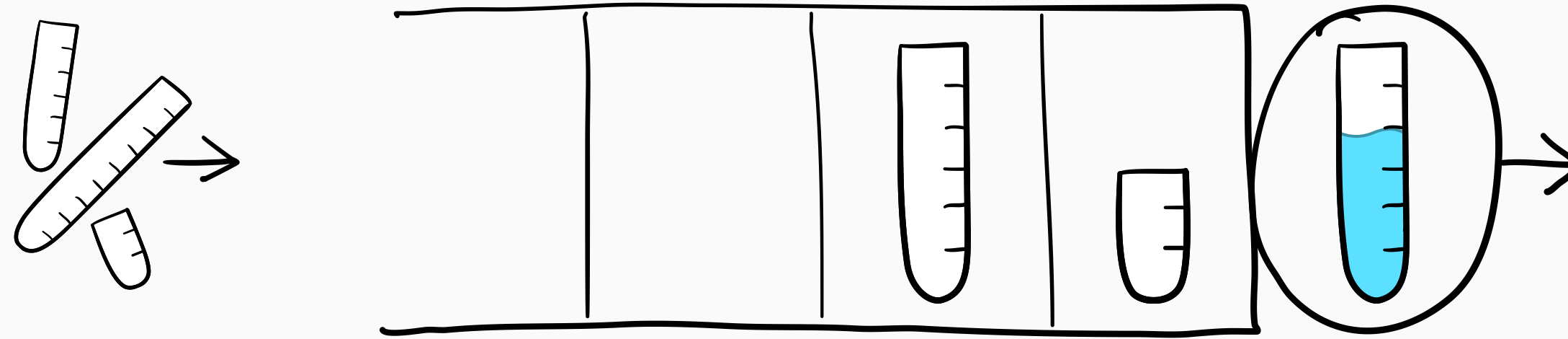
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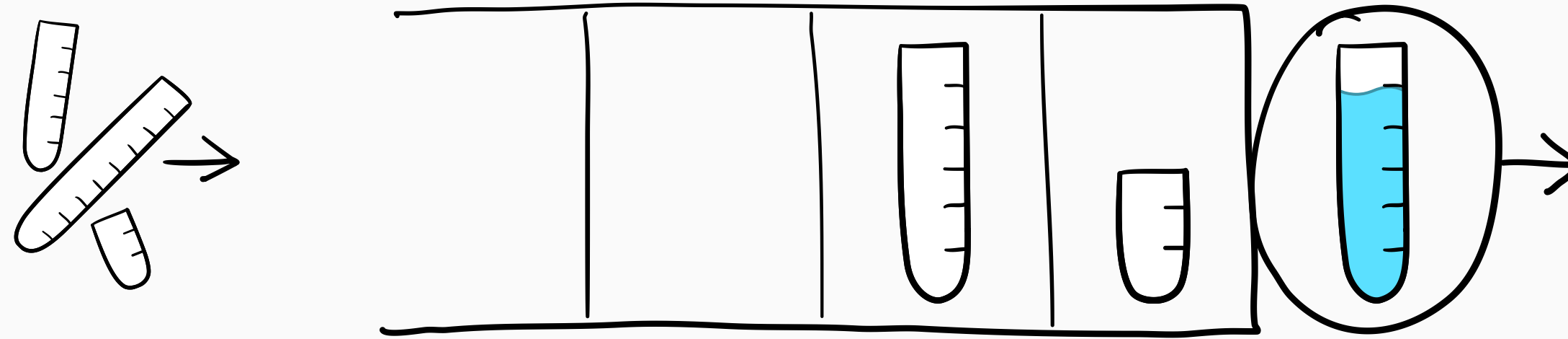
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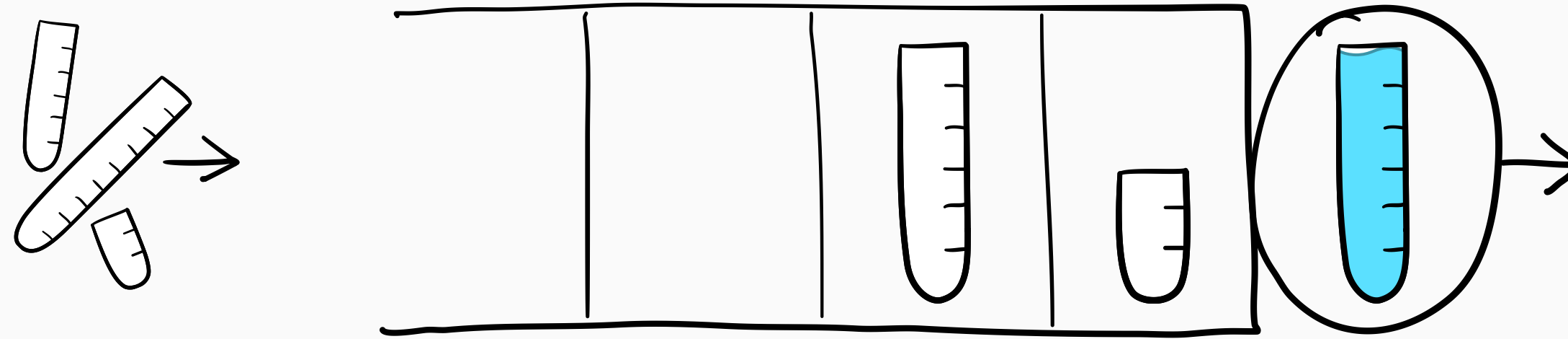
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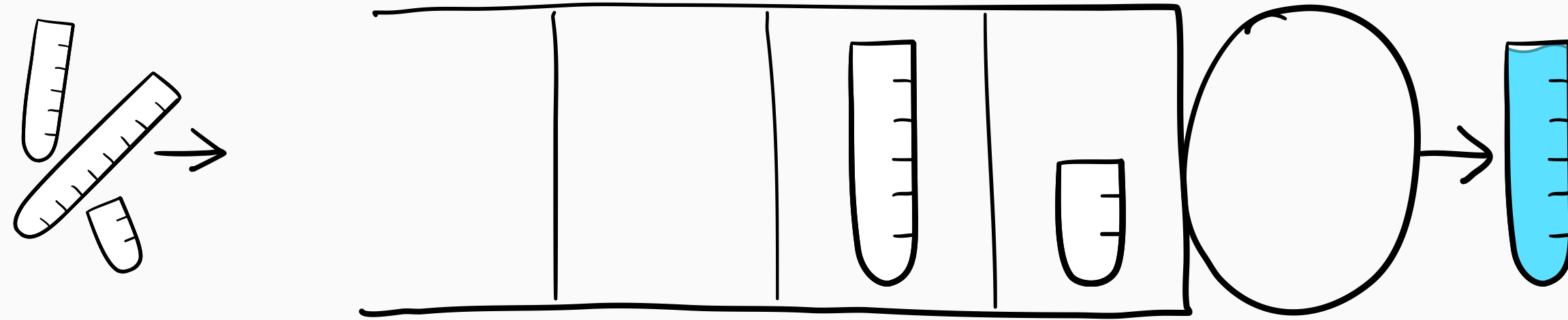
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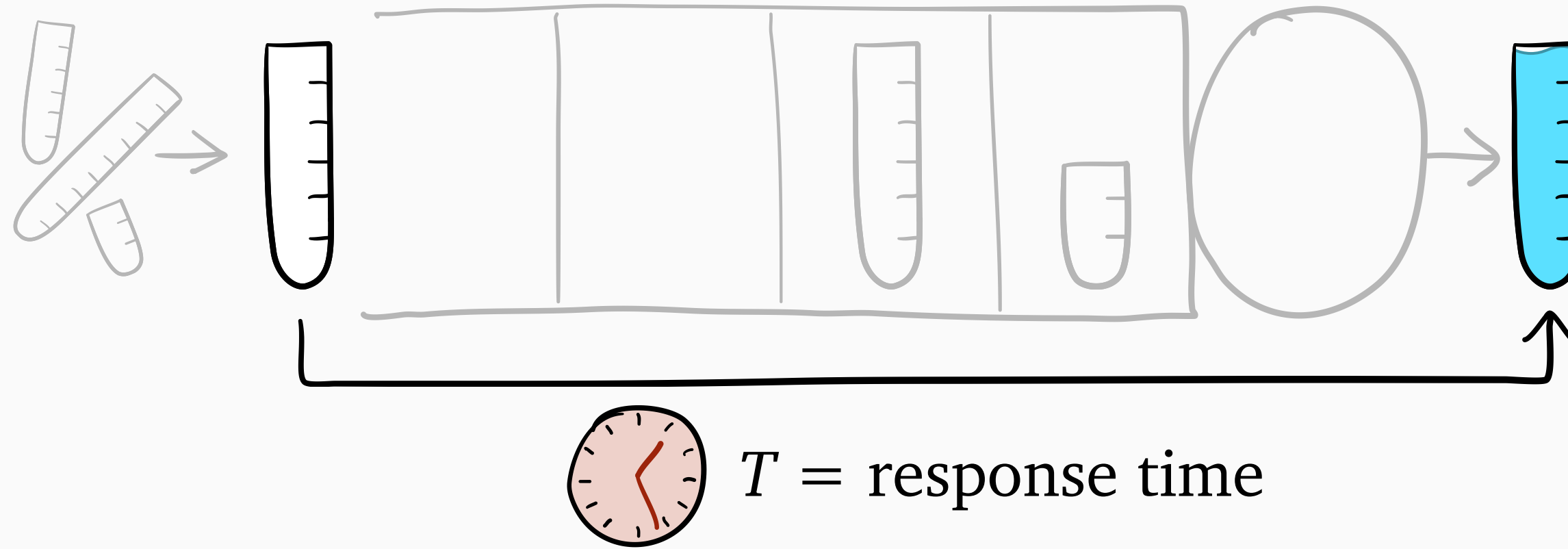
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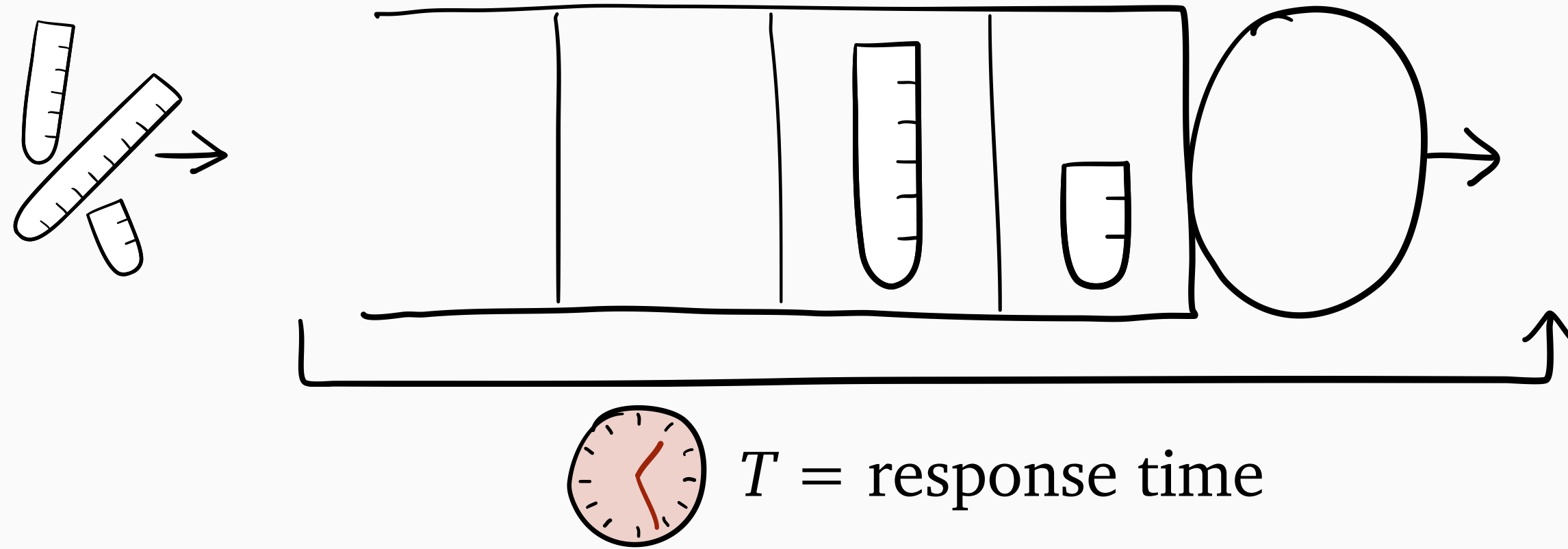
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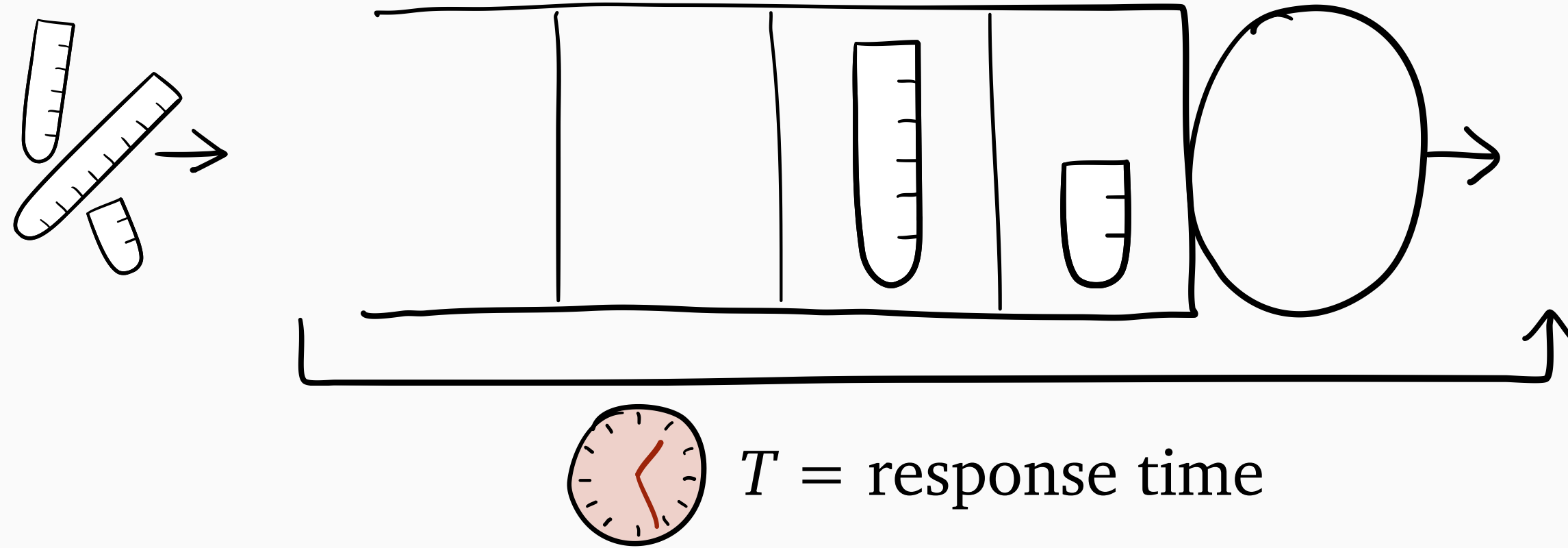
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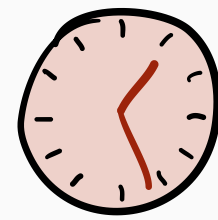
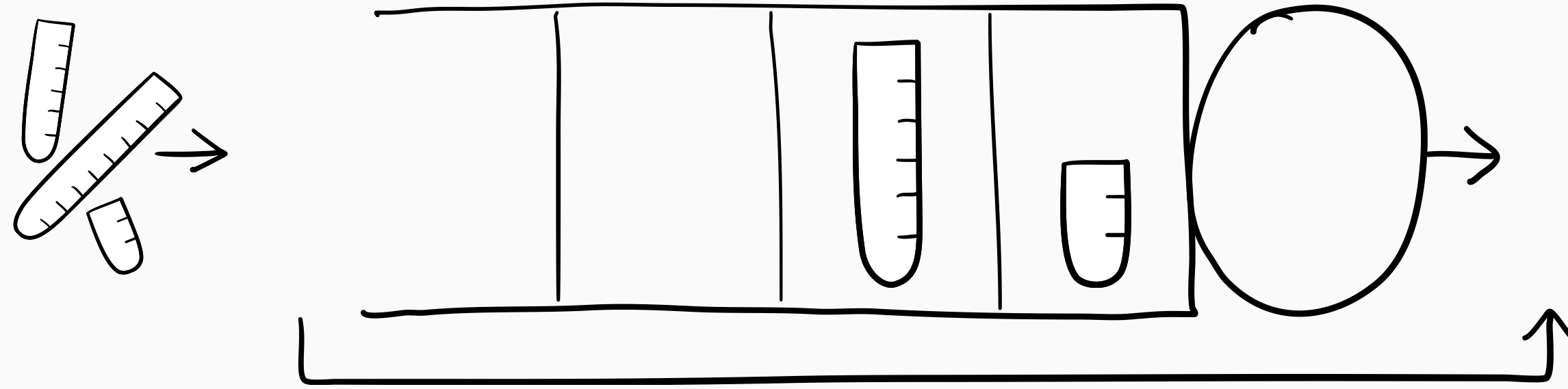


How should we schedule jobs to minimize delay?



? Minimize $E[T]$?

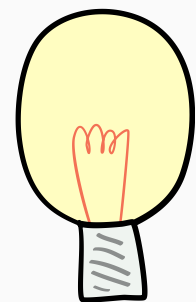
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$T =$ response time

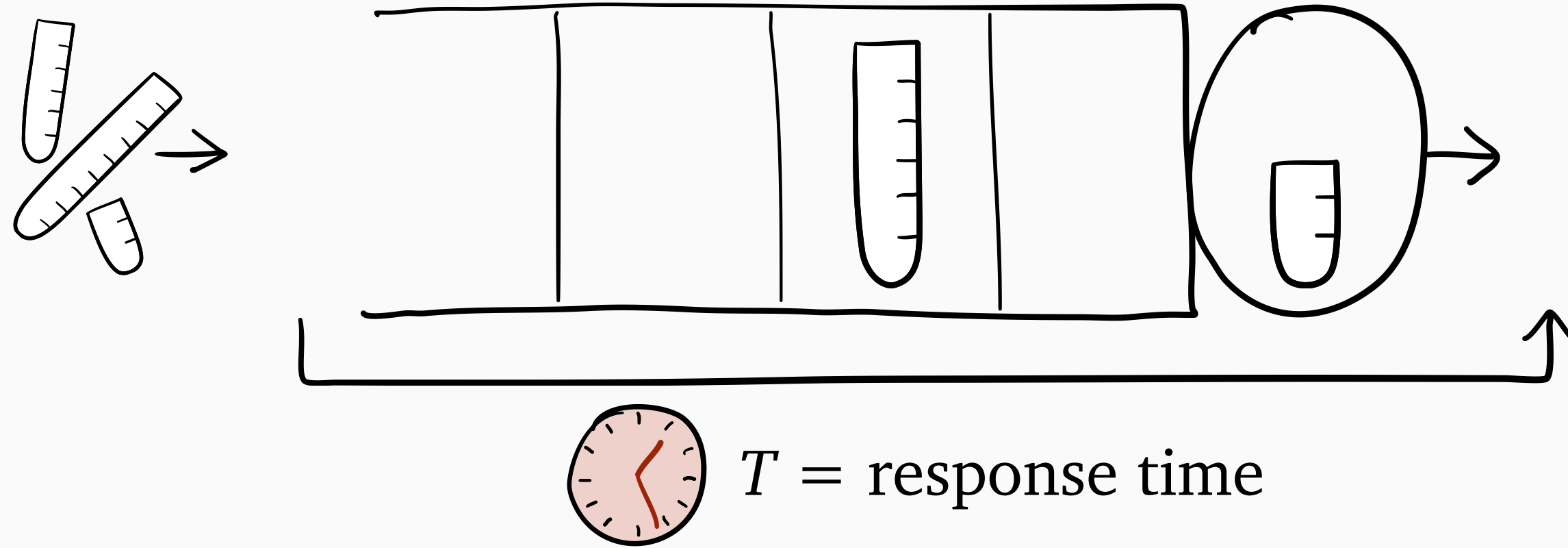


Minimize $E[T]$?



Serve short jobs
before long jobs

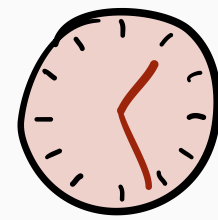
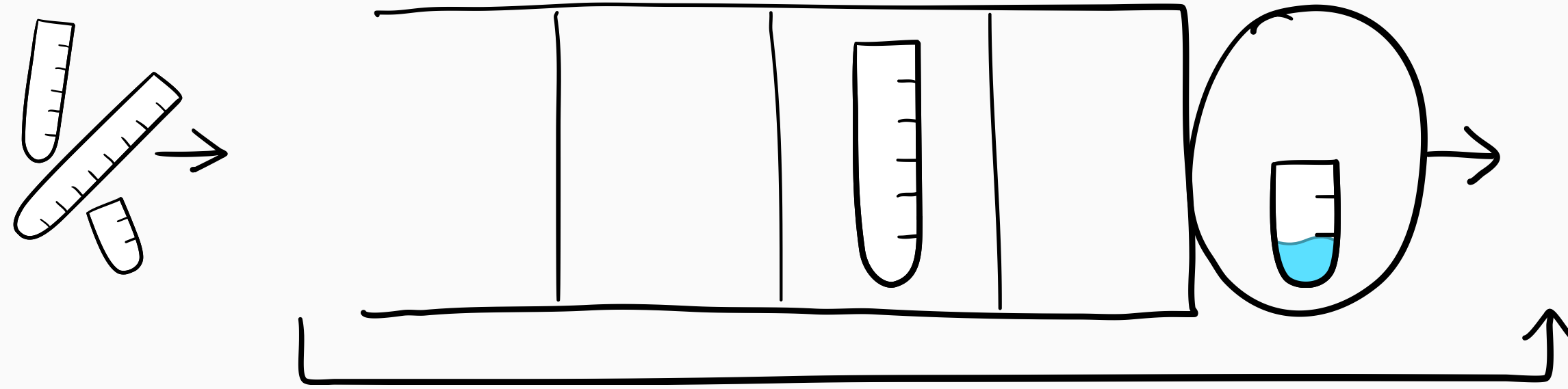
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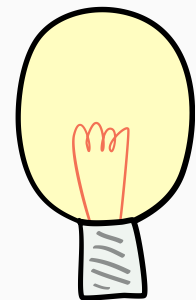
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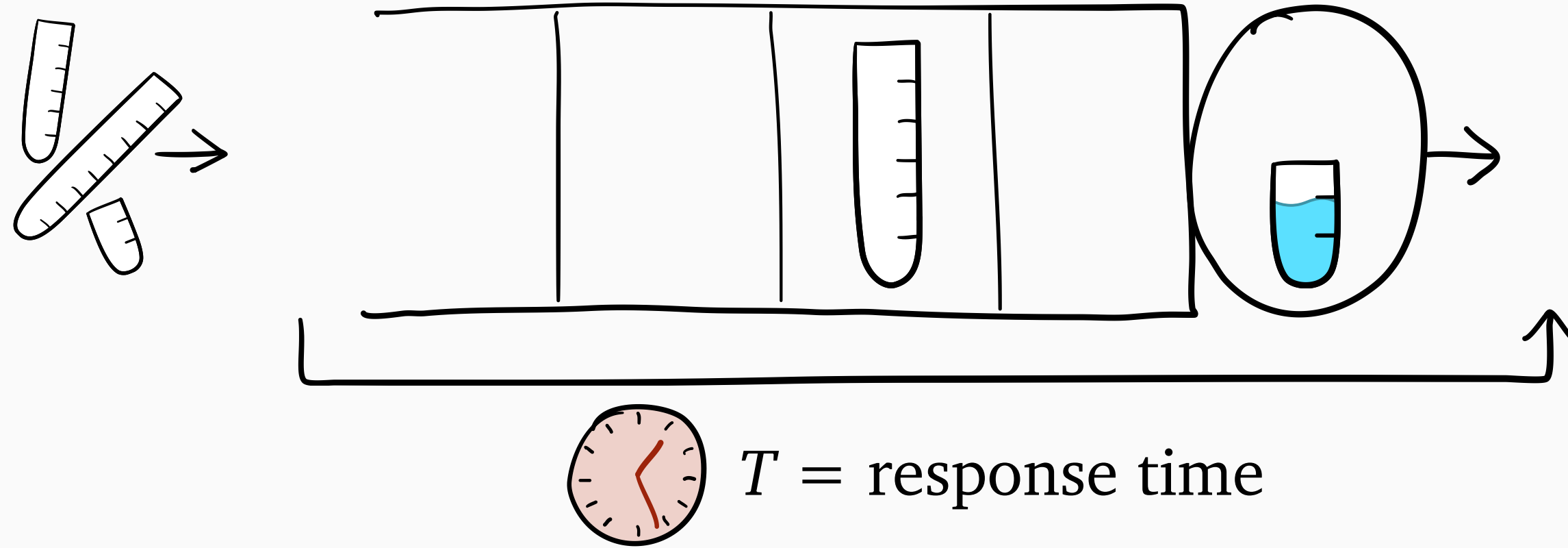


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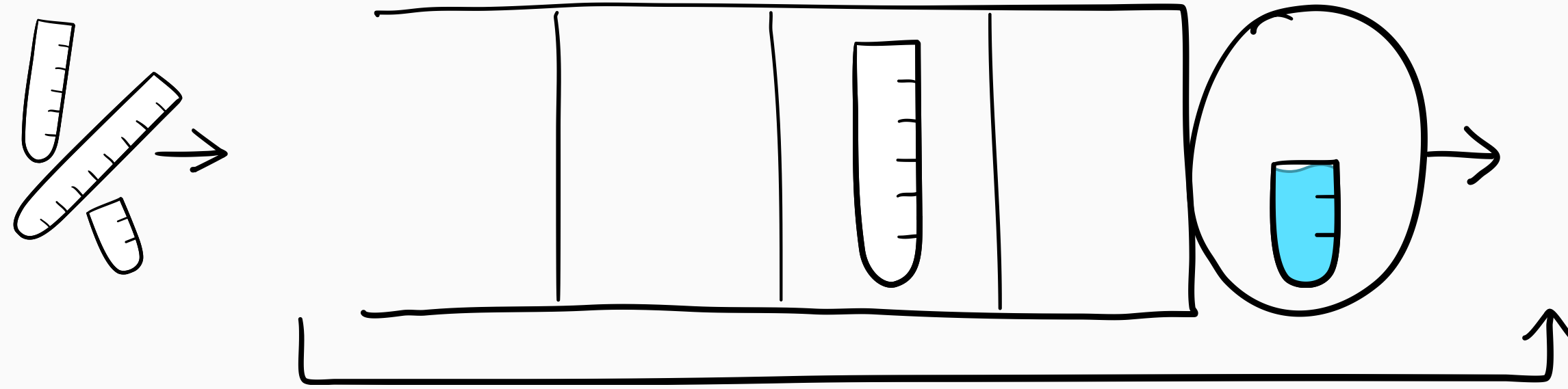
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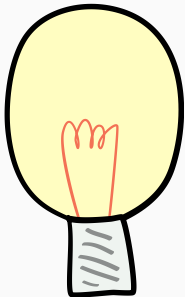
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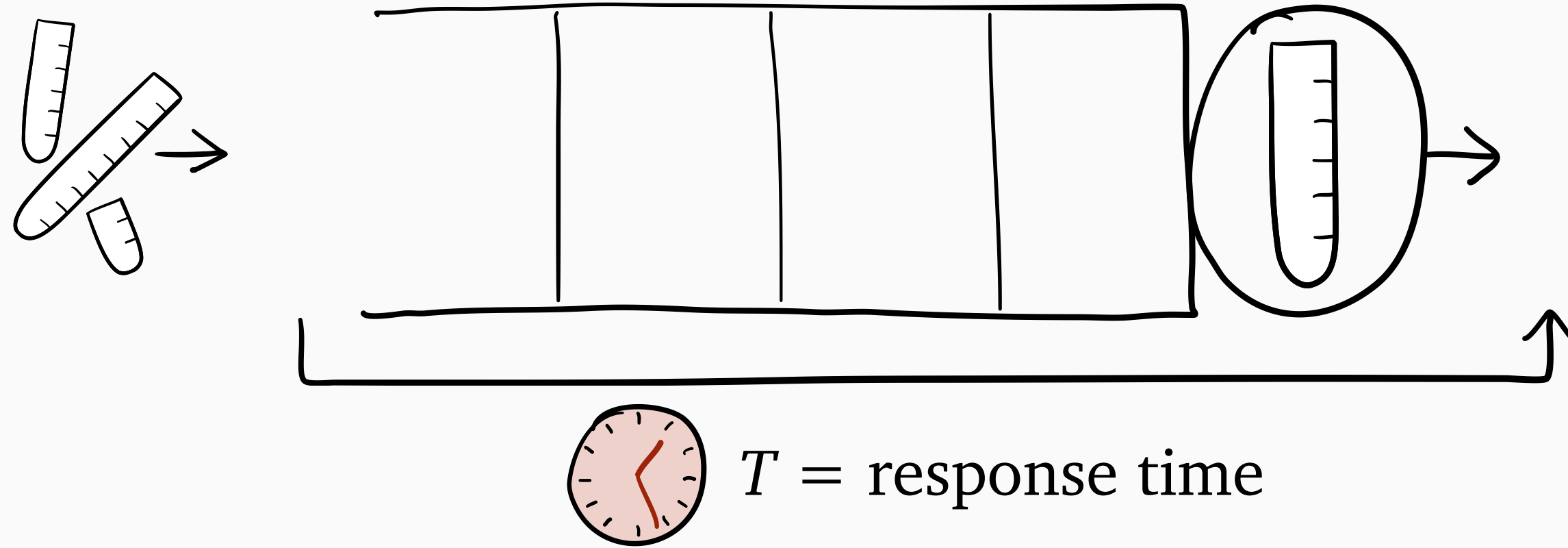


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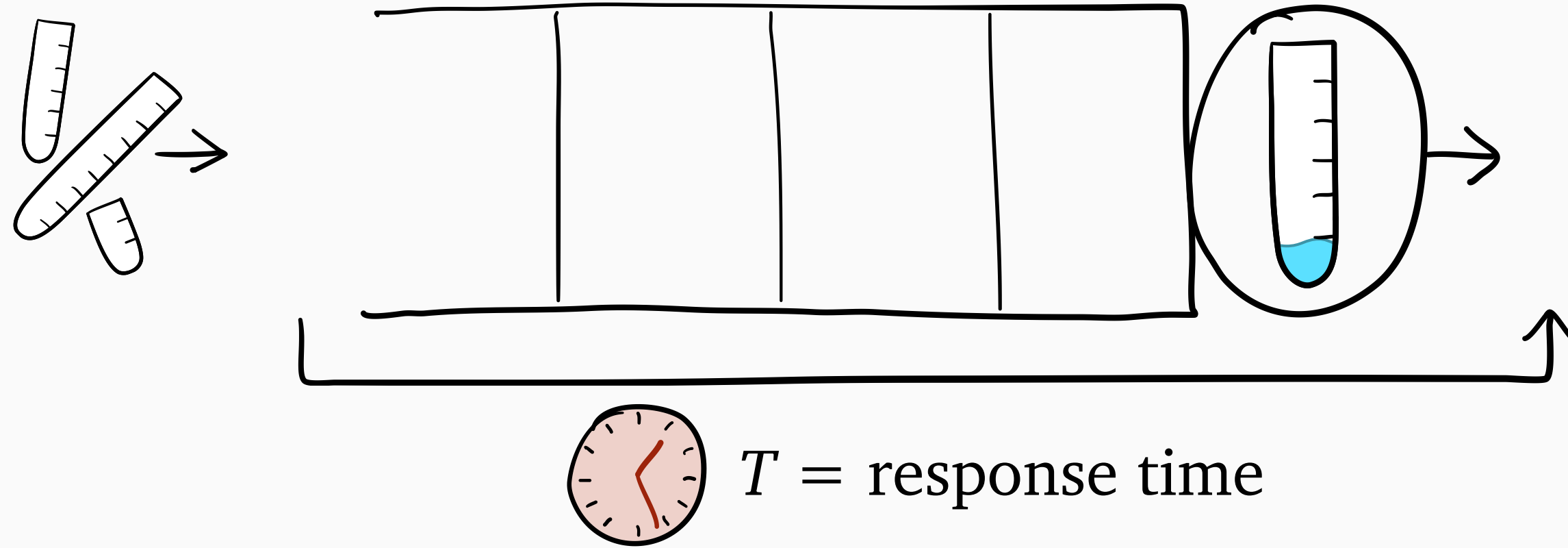
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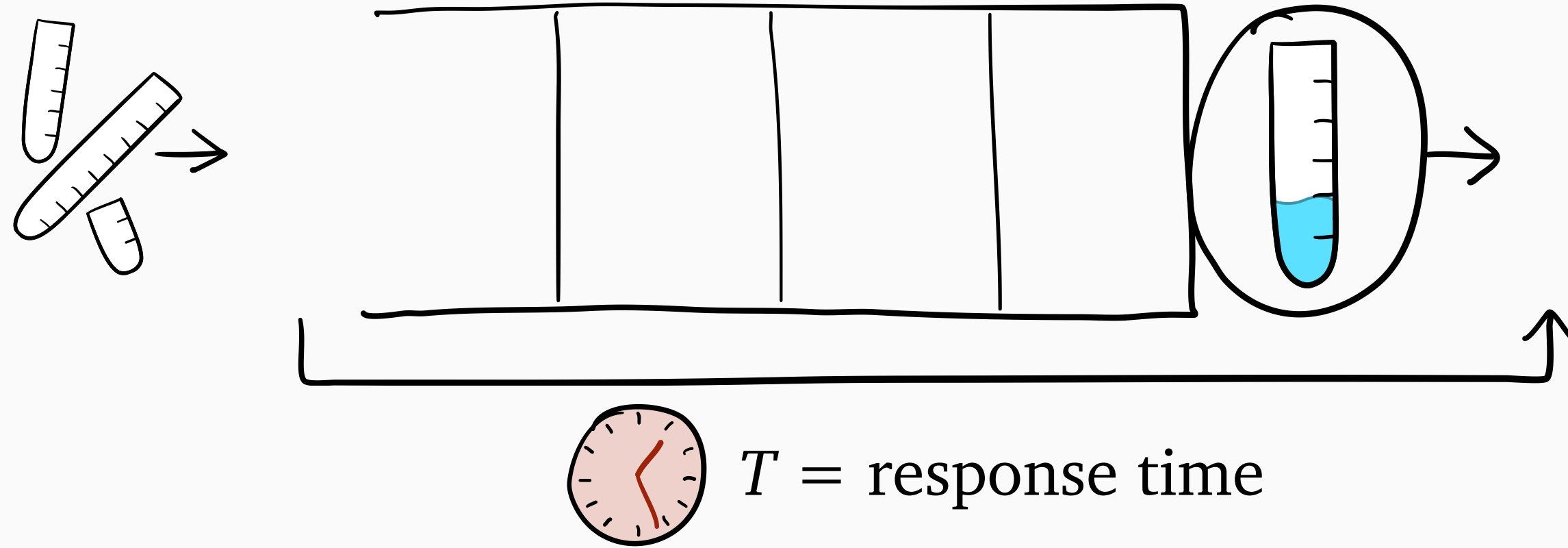
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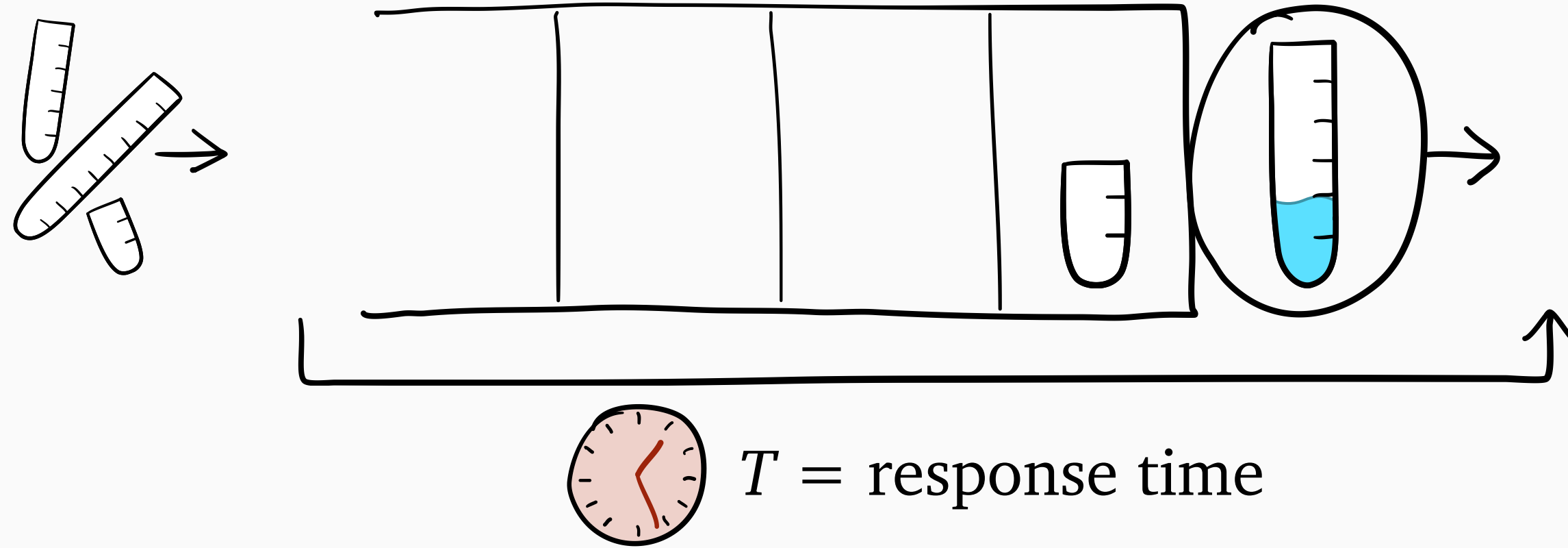
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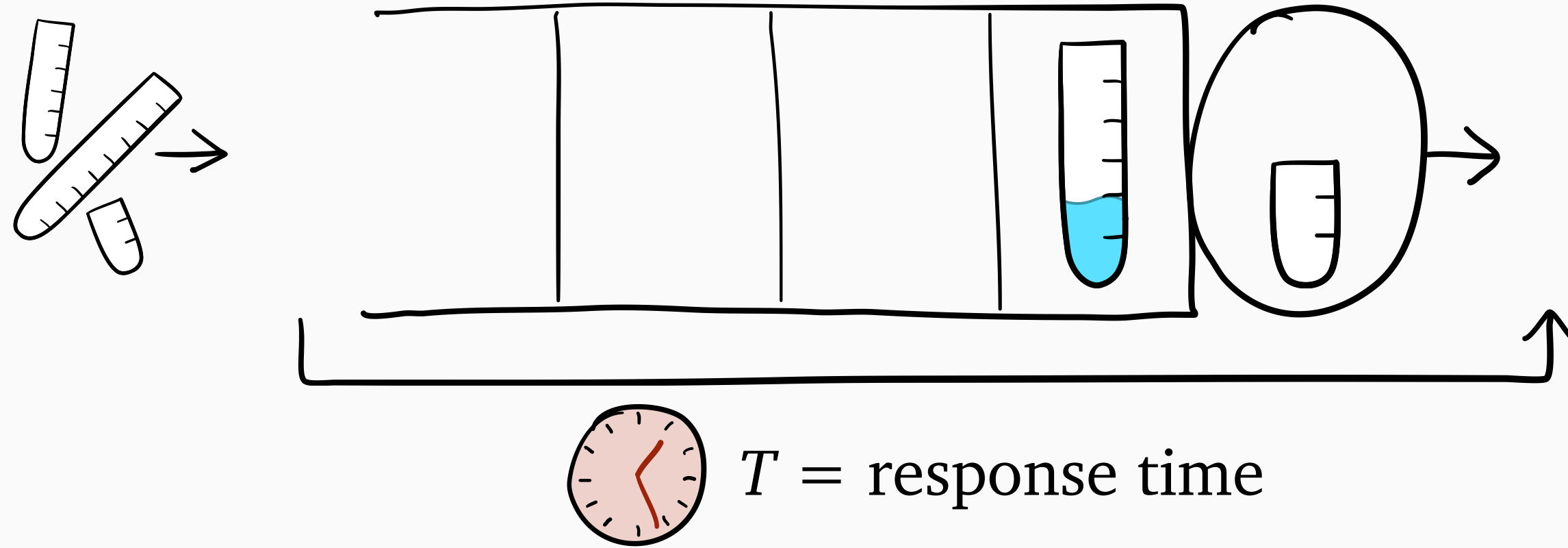
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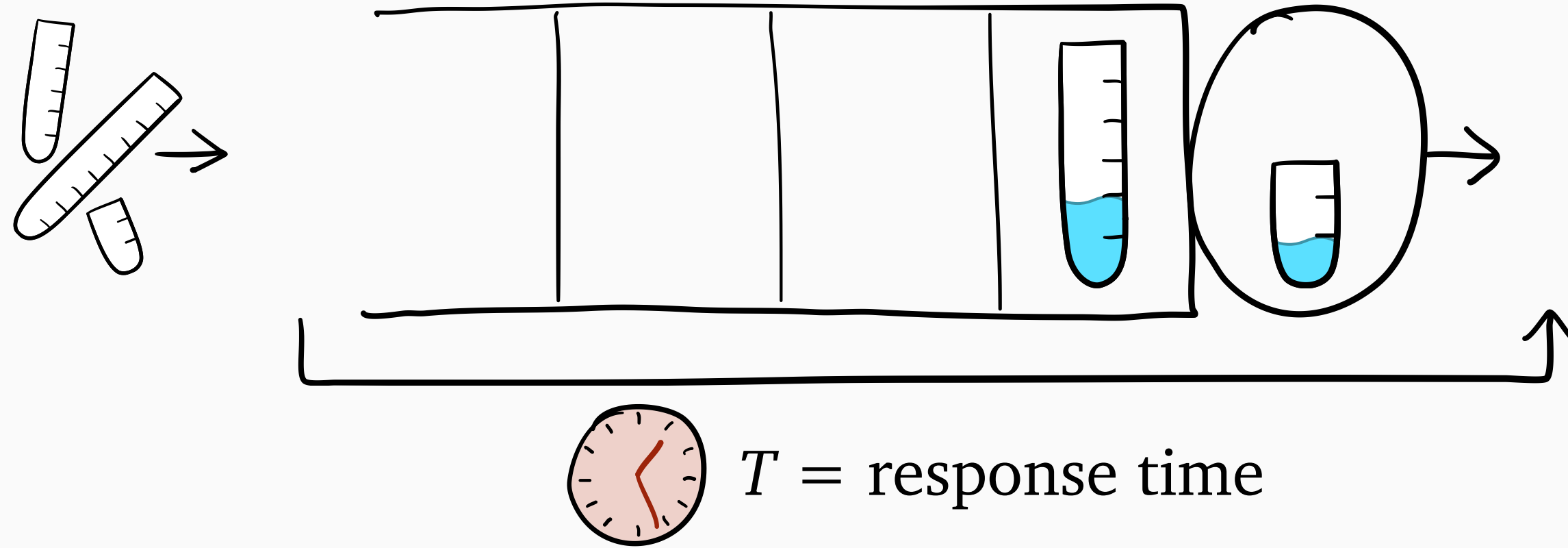
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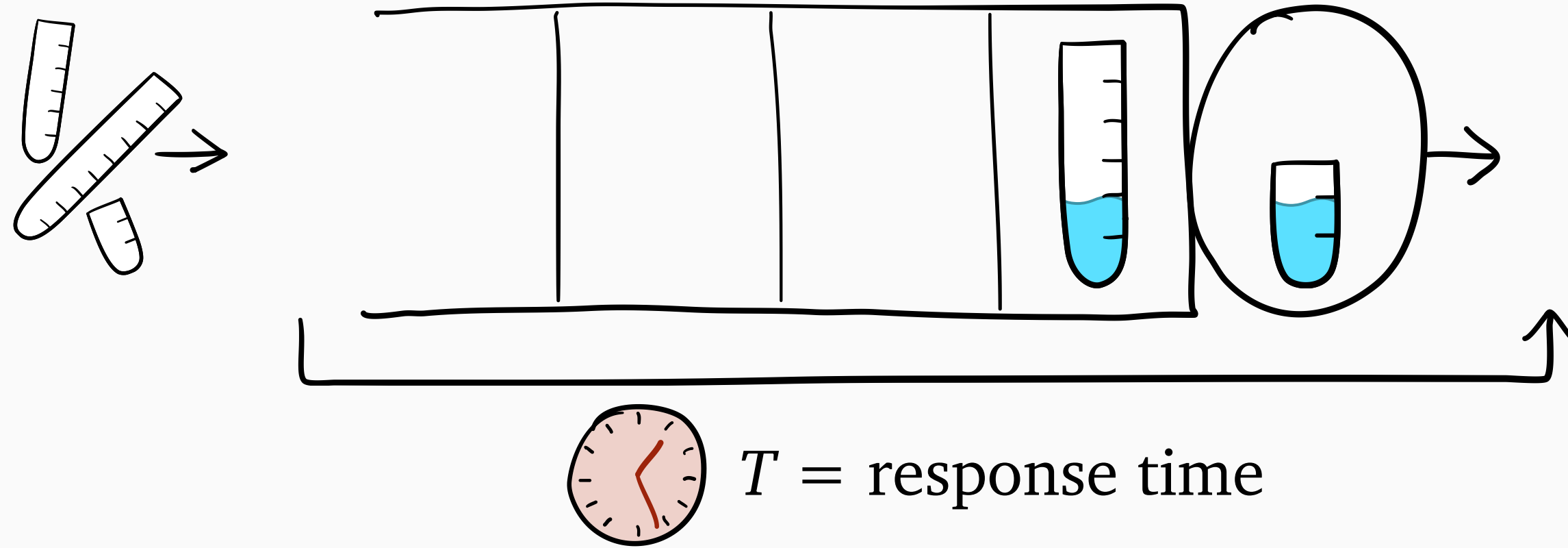
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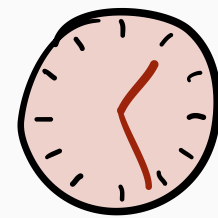
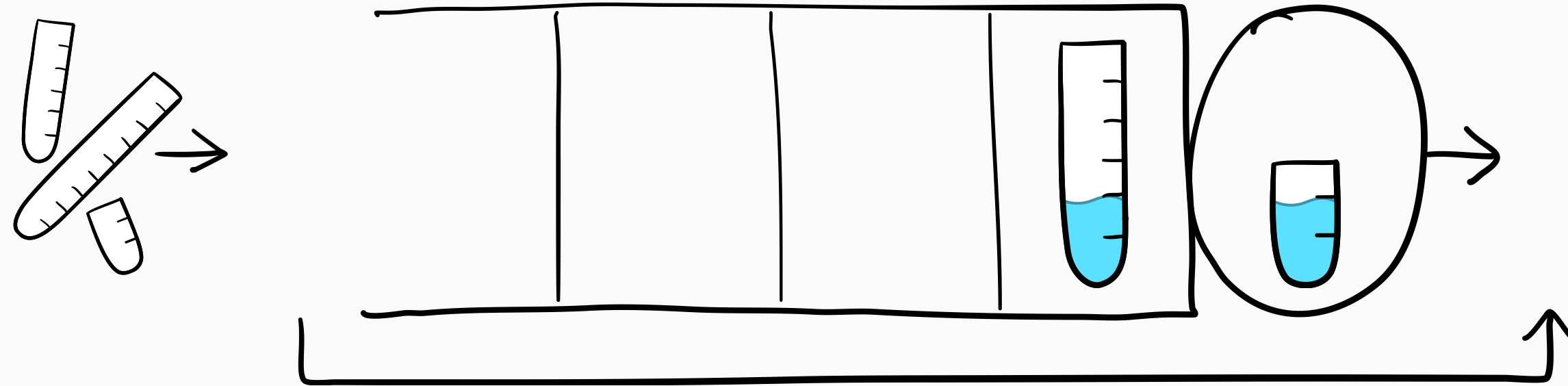
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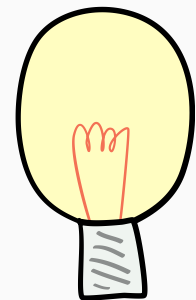
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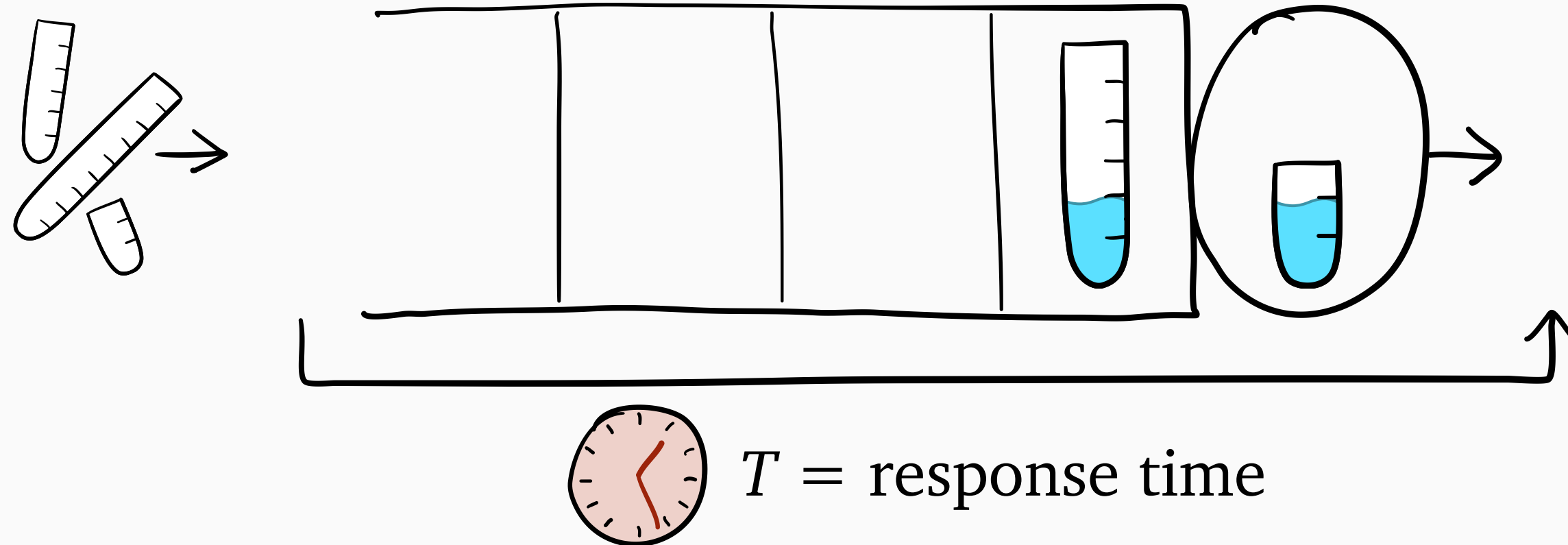
Serve short jobs
before long jobs



SRPT: minimizes $E[T]$

shortest remaining
processing time

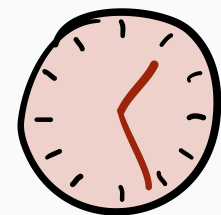
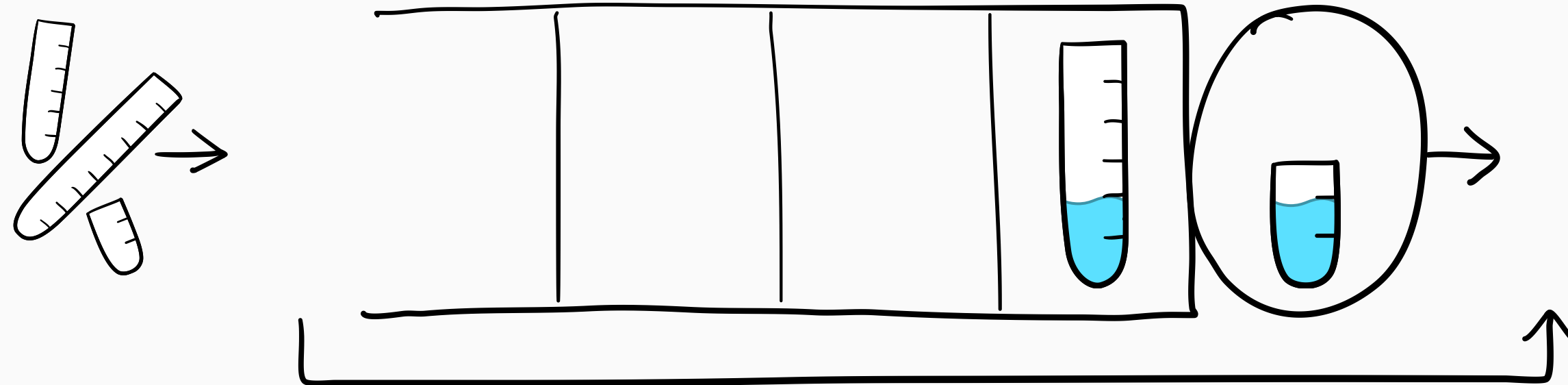
Beyond the mean: tail metrics



Beyond the mean: tail metrics



Minimize $\begin{cases} \mathbf{P}[T > t]? \\ \mathbf{E}[(T - t)^+]? \\ \text{quantiles of } T? \end{cases}$

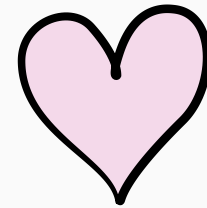


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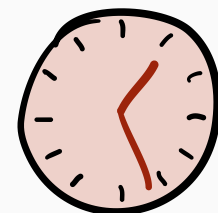
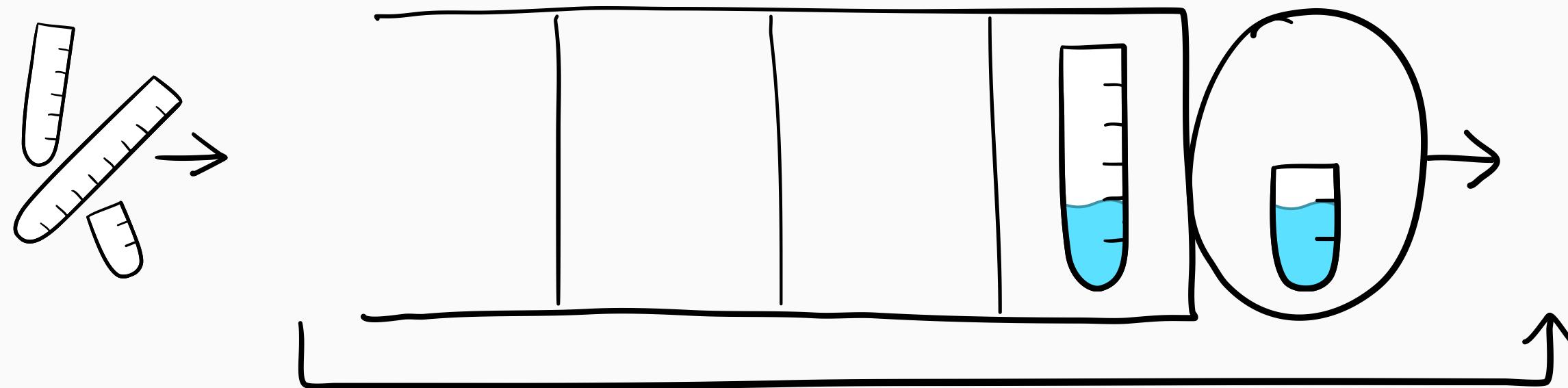
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Practice: important

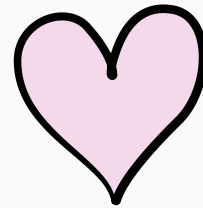


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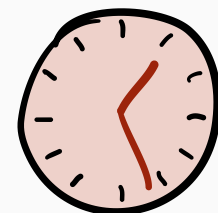
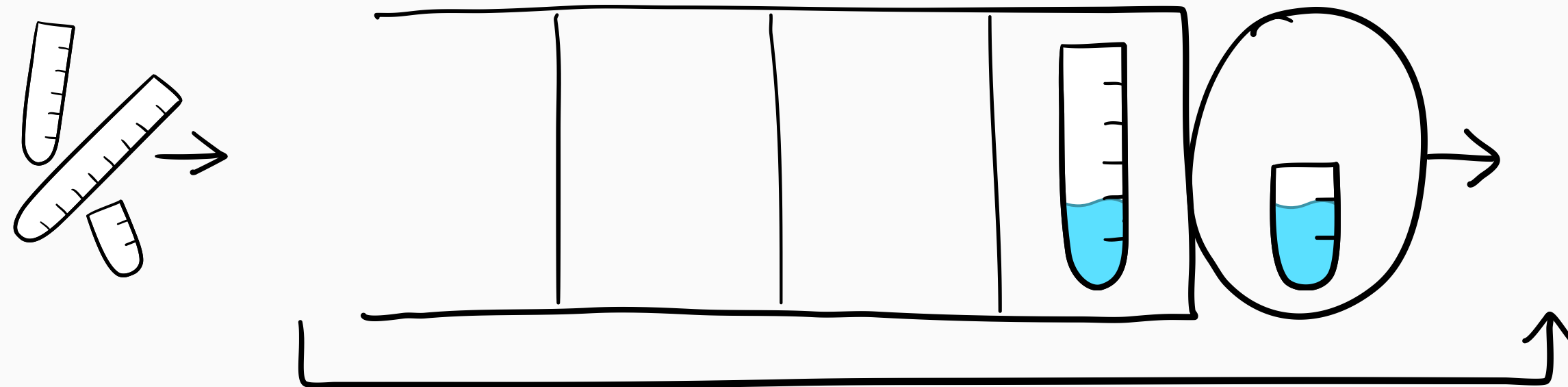
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Practice: important



Theory: very hard

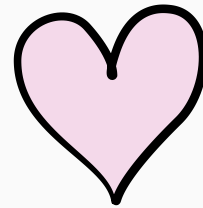


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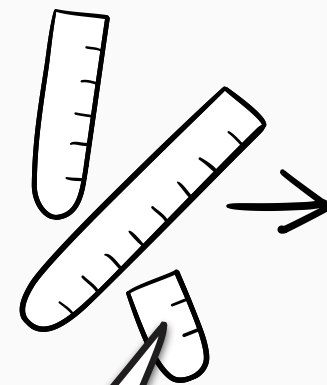
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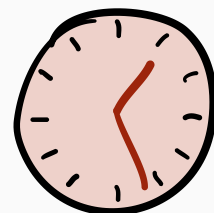
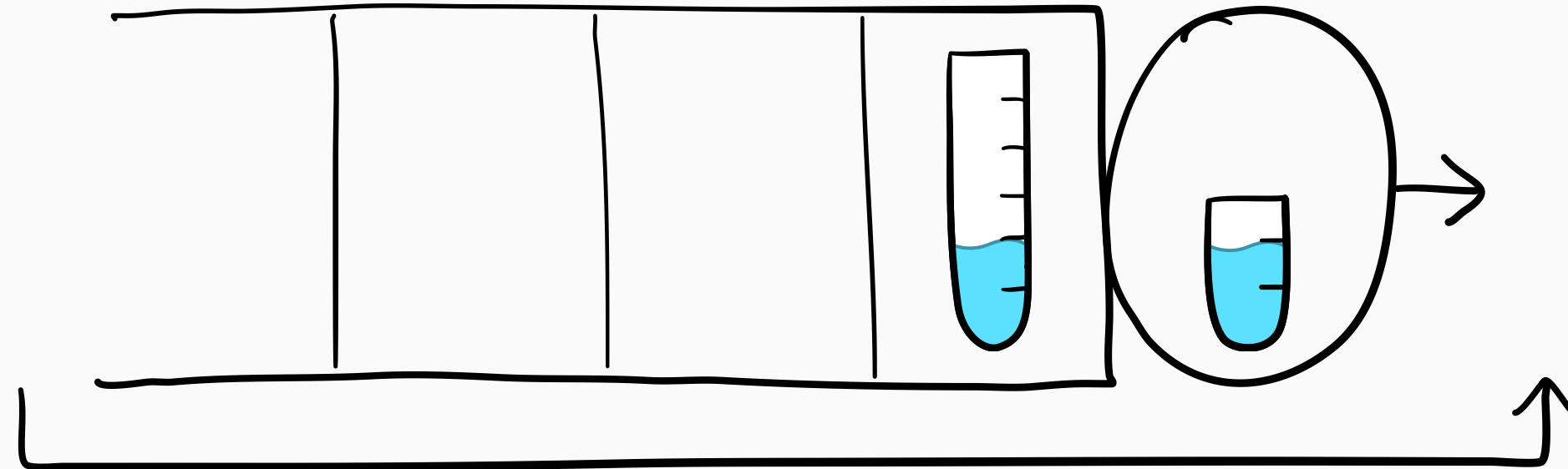


Theory: very hard



M/G arrivals

- arrival rate λ
- job size dist. S

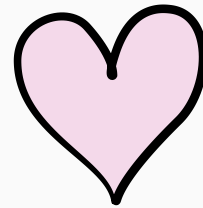


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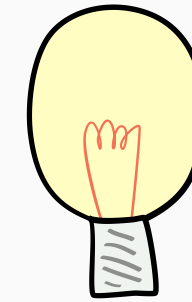
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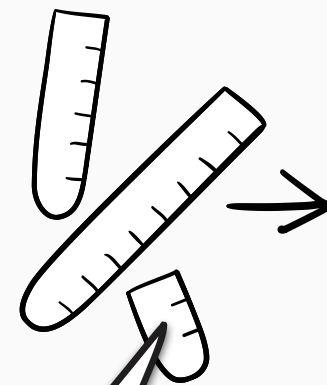
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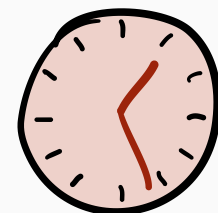
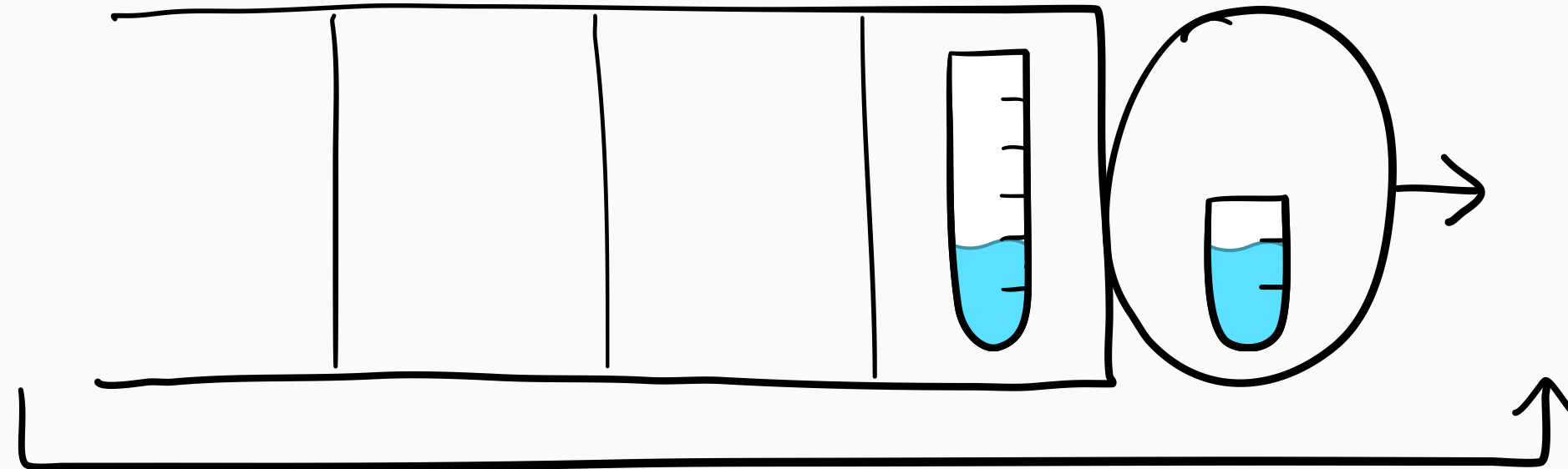


Tractable:
study $t \rightarrow \infty$
asymptotics



M/G arrivals

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Optimizing tail asymptotics

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Asymptotic tail ratio: $R_\pi = \sup_{\pi'} \limsup_{t \rightarrow \infty} \frac{\mathbf{P}[T_\pi > t]}{\mathbf{P}[T_{\pi'} > t]}$

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 Corollary of prior work
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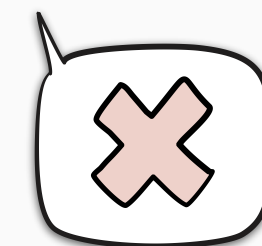
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Boost



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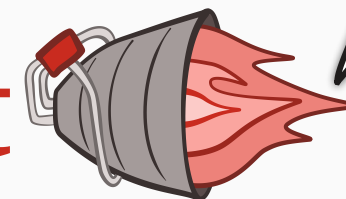
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Optimizing tail asymptotics

Asymptotic tail ratio: $R_\pi = \sup_{\pi'} \limsup_{t \rightarrow \infty} \frac{\mathbf{P}[T_\pi > t]}{\mathbf{P}[T_{\pi'} > t]}$

Heavy-tailed sizes



Light-tailed sizes



Weakly optimal

$$R_\pi < \infty$$

Preemptive LCFS

FCFS (first-come first-served)

Nudge [Grosf et al.]

Theorem:
 $R_{\text{Boost}} = 1$

Strongly optimal

$$R_\pi = 1$$

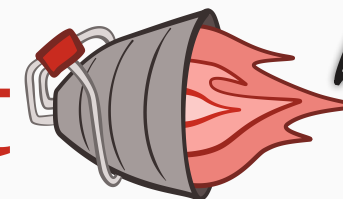
SRPT

PS (processor sharing)

LAS (least attained service)



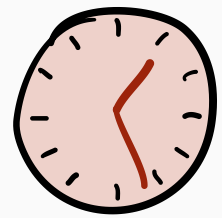
Boost



Our contributions:



Design the **Boost** scheduling policy



Analyze **Boost**'s performance



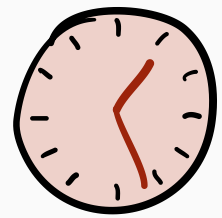
Prove **Boost** is *strongly tail-optimal* for light-tailed sizes

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actually a *family*
of many policies



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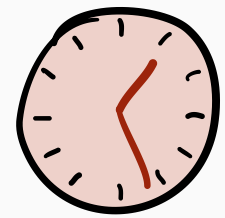
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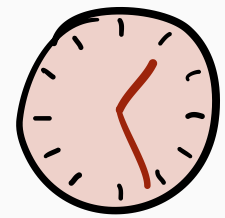
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specific instance
called **γ -Boost**



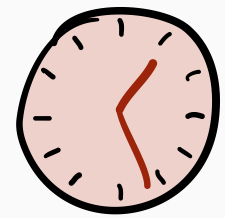
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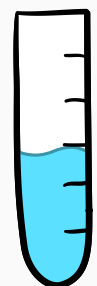
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Known job sizes

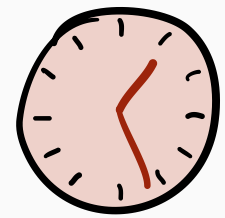
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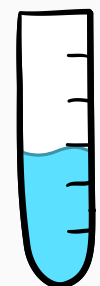
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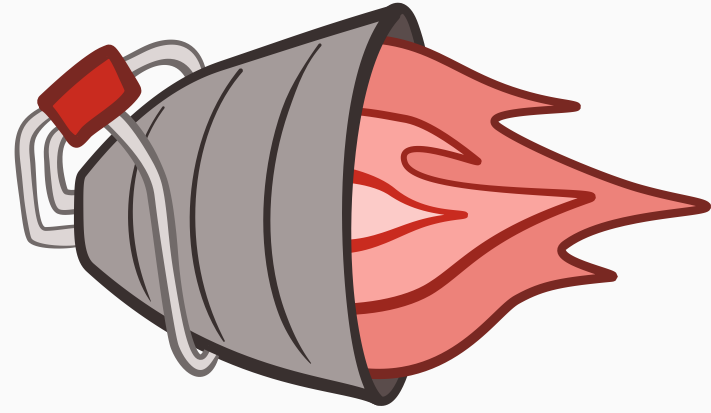
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Harlev, Yu, & Scully. *A Gittins Policy for Optimizing Tail Latency*. MAMA 2024.

Boost



Boost



How does the **Boost** policy family work?

Boost

? How does the **Boost** policy family work?

? How do we achieve strong tail optimality?

Boost



Why is achieving strong tail optimality hard?



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Heavy-tailed sizes

“ S Pareto-ish” (regularly varying)

$$\mathbf{P}[S > s] \sim As^{-\alpha}$$

Light-tailed sizes

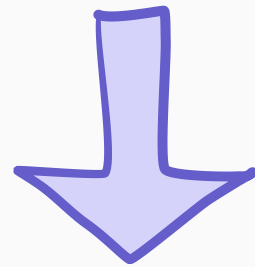
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$$\mathbf{P}[T > t] \sim Ct^{-\gamma}$$

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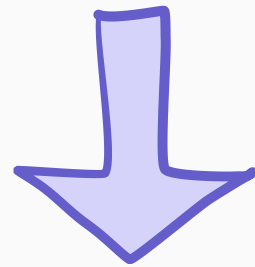
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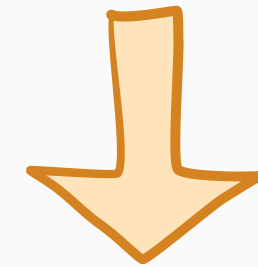


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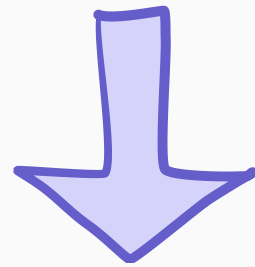


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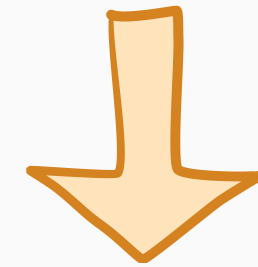


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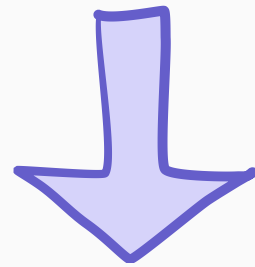


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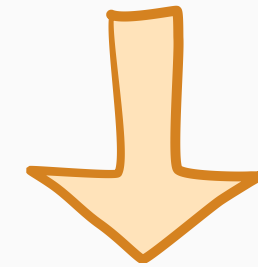


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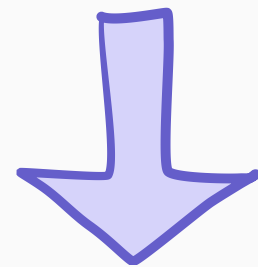
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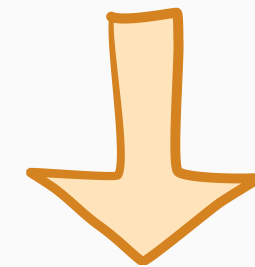


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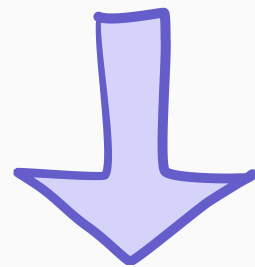
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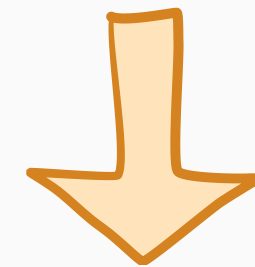


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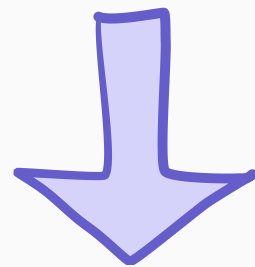
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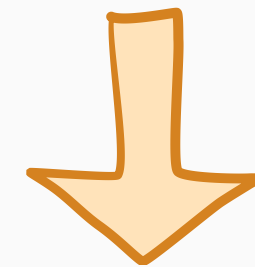


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$$R_{\pi} = \frac{C_{\pi}}{\inf_{\pi'} C_{\pi'}}$$

Background on decay rates

Heavy-tailed sizes

Light-tailed sizes

Background on decay rates

	Heavy-tailed sizes	Light-tailed sizes
SRPT, LAS, etc.		
FCFS		


Background on decay rates

	Heavy-tailed sizes	Light-tailed sizes
SRPT, LAS, etc.	optimal $\gamma = \alpha$	
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Background on decay rates

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 Main cause of large T ?		


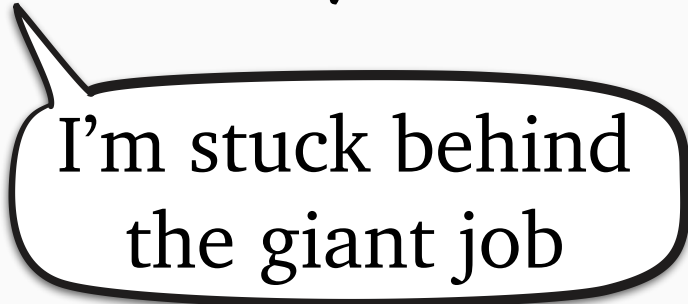
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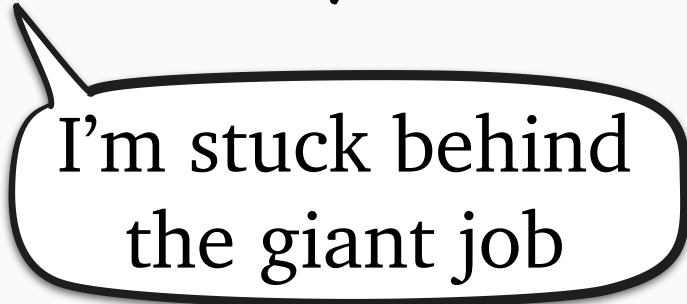
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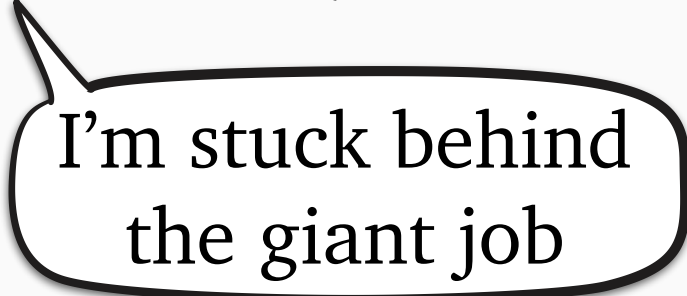
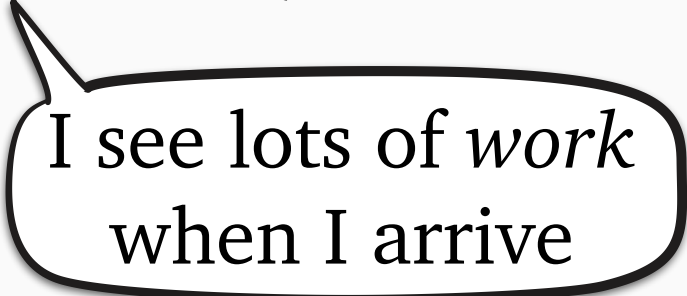
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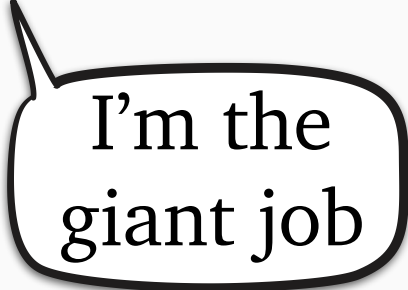
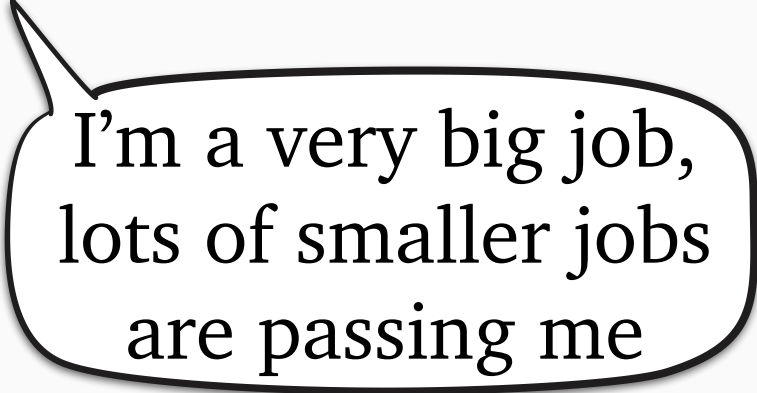
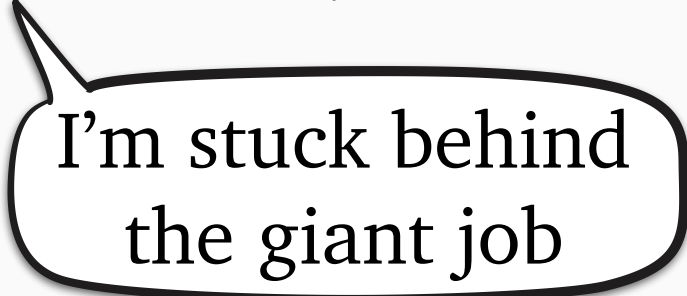
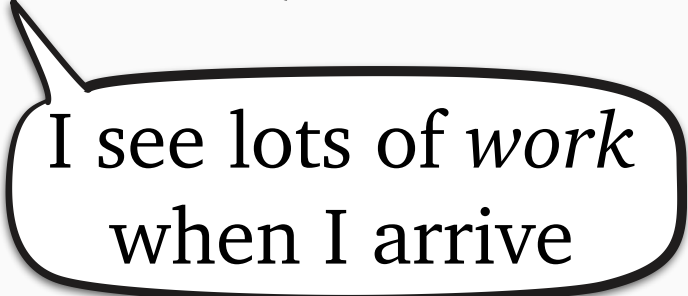
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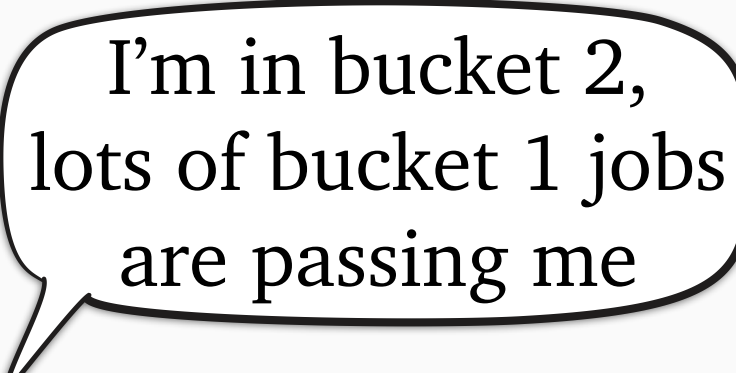
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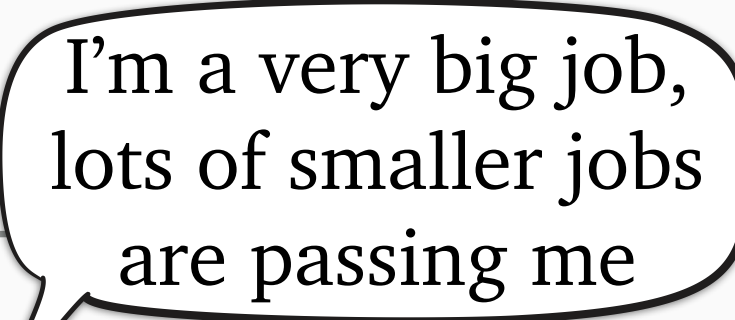
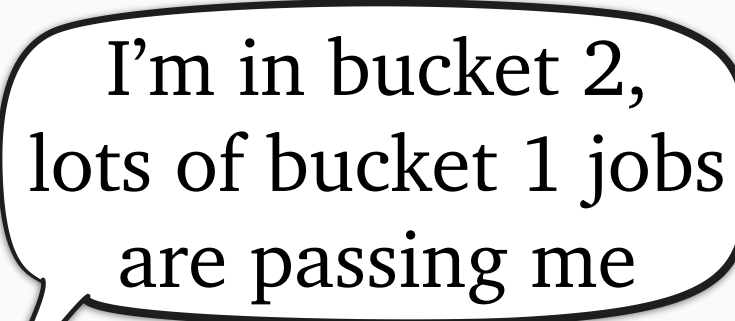
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Background on decay rates

SRPT, LAS, etc.

Light-tailed

I'm a very big job,
lots of smaller jobs
are passing me

pessimistic γ

FCFS

optimal γ

I'm in bucket 2,
lots of bucket 1 jobs
are passing me

SRPT or LAS with
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Background on decay rates

SRPT, LAS, etc.

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SRPT or LAS with
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? Main cause
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pessimist γ

 **Takeaway:**
for optimality, must
avoid strict priorities

optimal γ

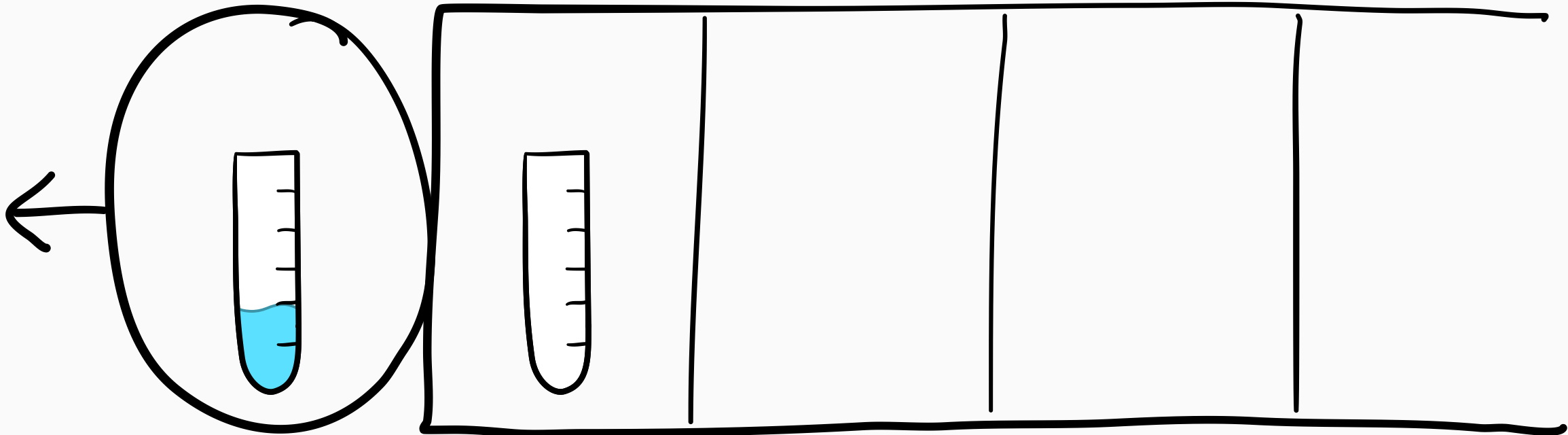
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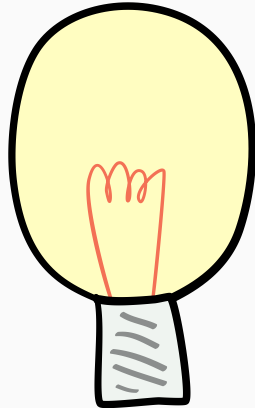
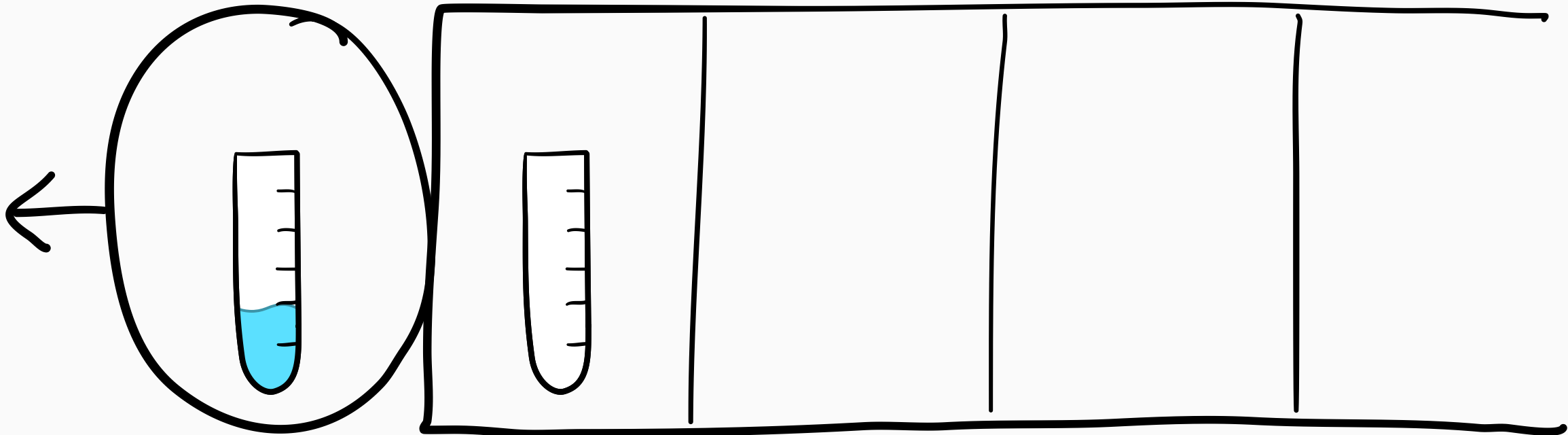
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Can we beat FCFS?

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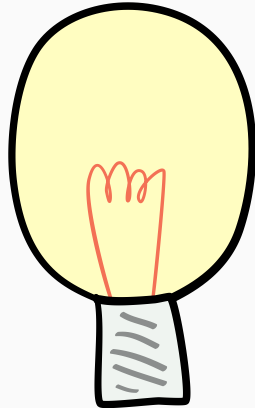
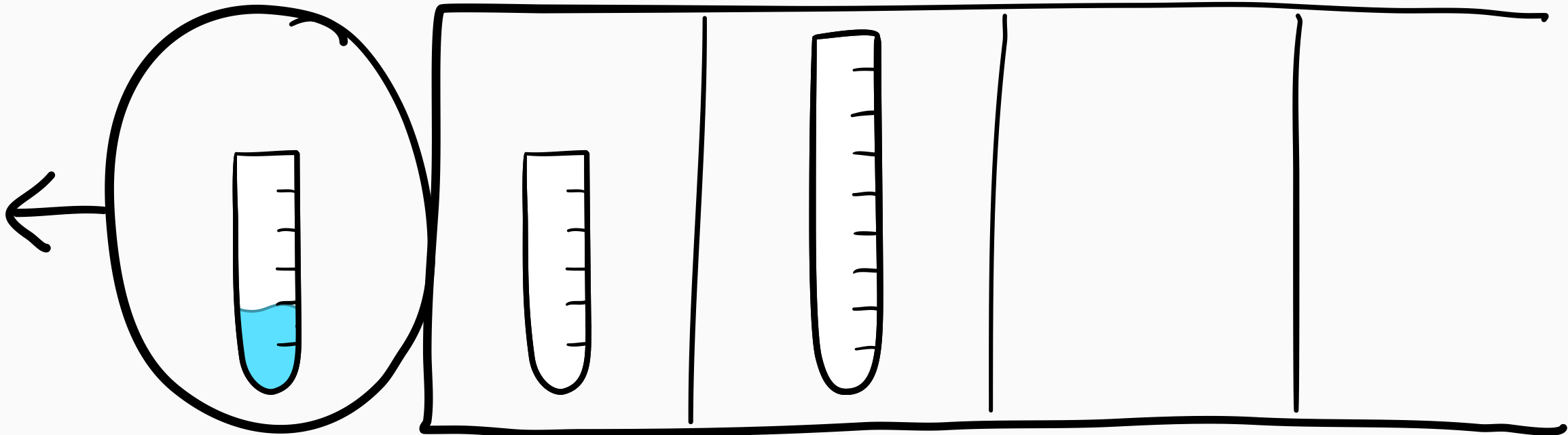


Can we beat FCFS?



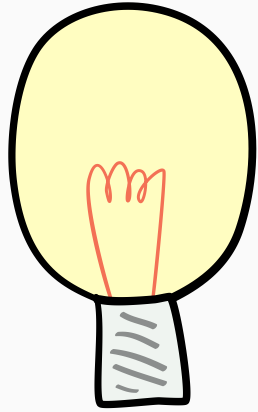
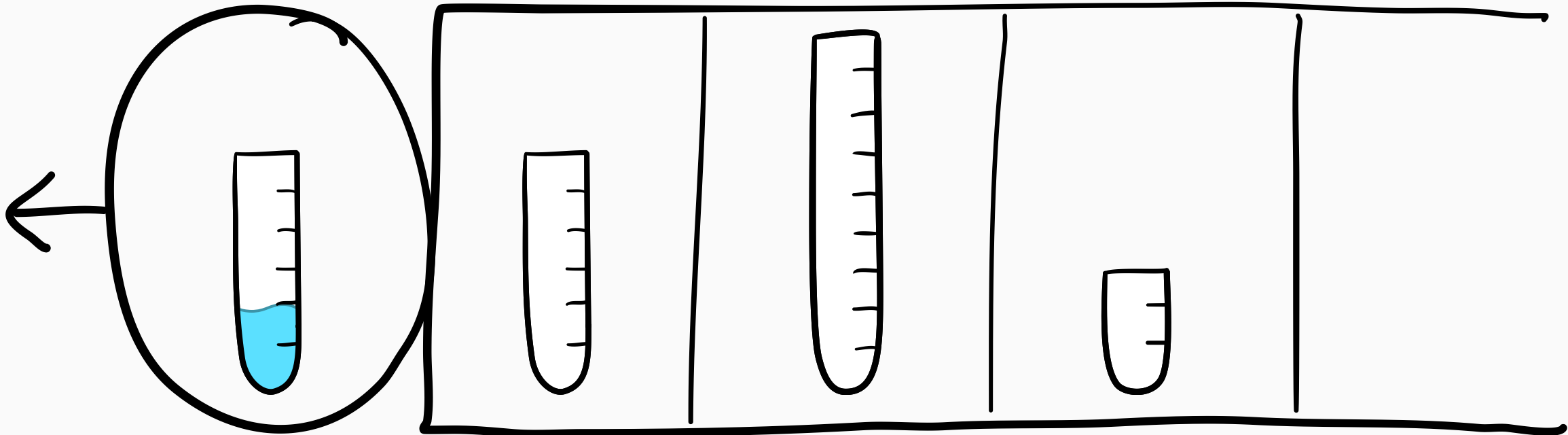
Nudge [Grosf et al., 2021]

Can we beat FCFS?



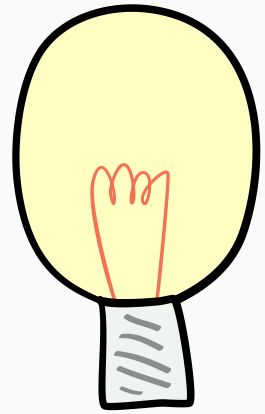
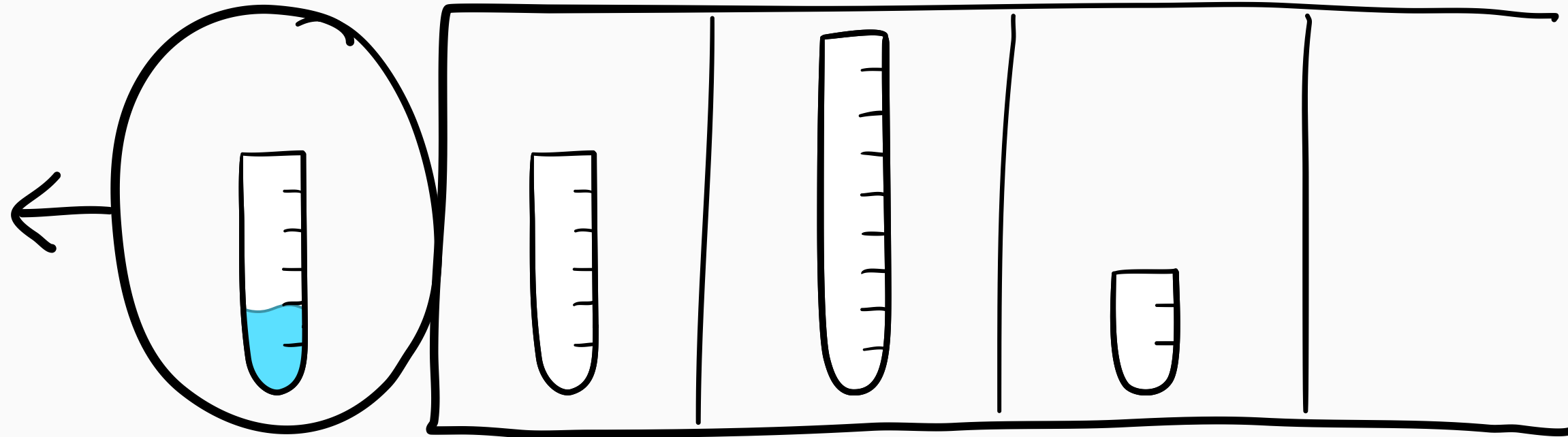
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Can we beat FCFS?



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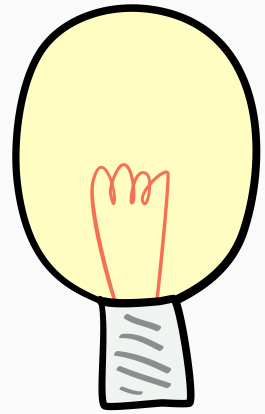
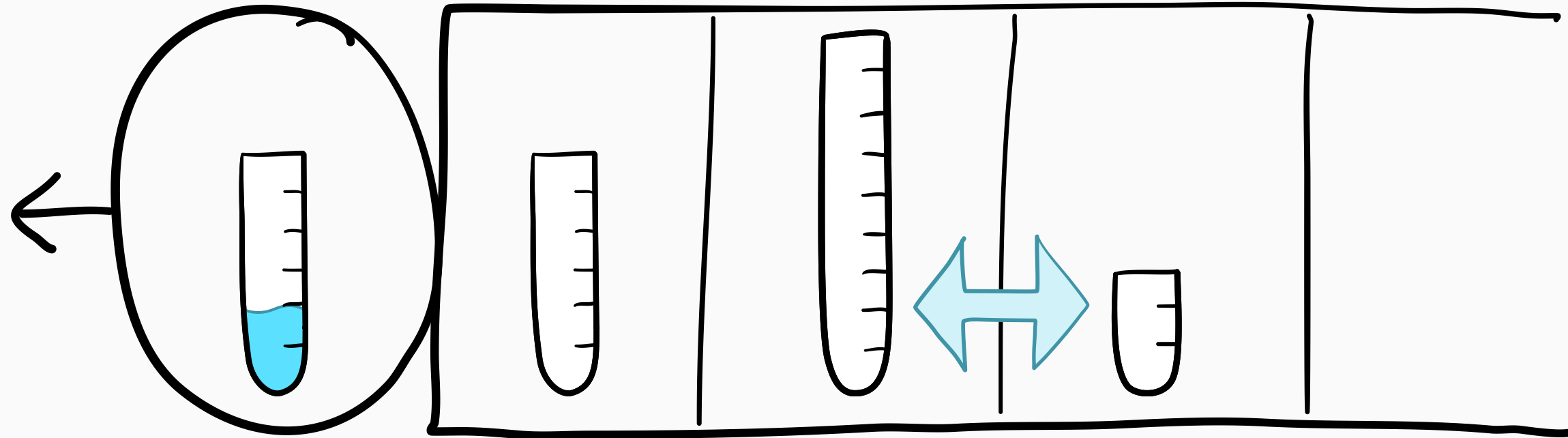
Can we beat FCFS?



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- small job can pass one large job

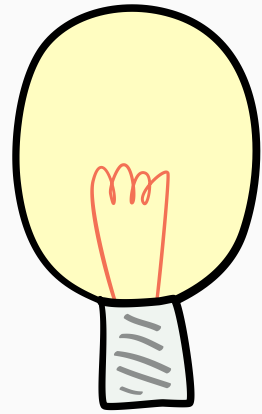
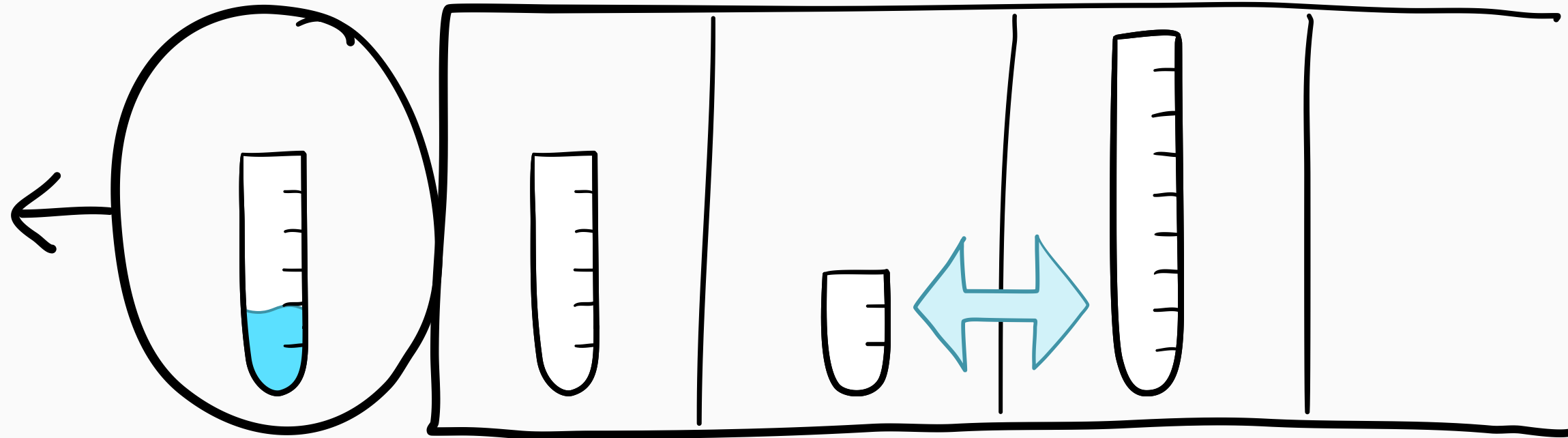
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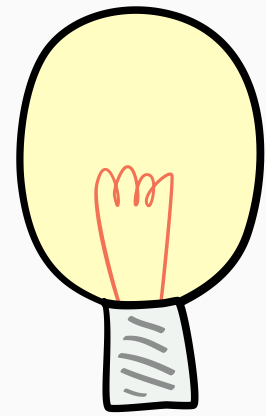
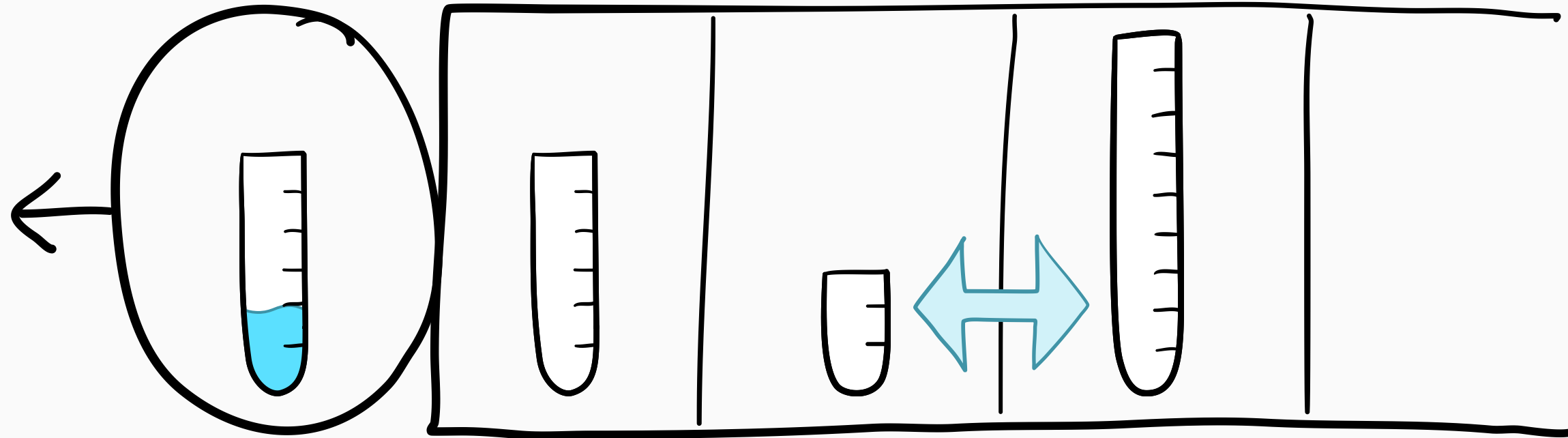
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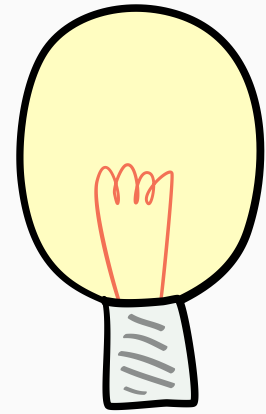
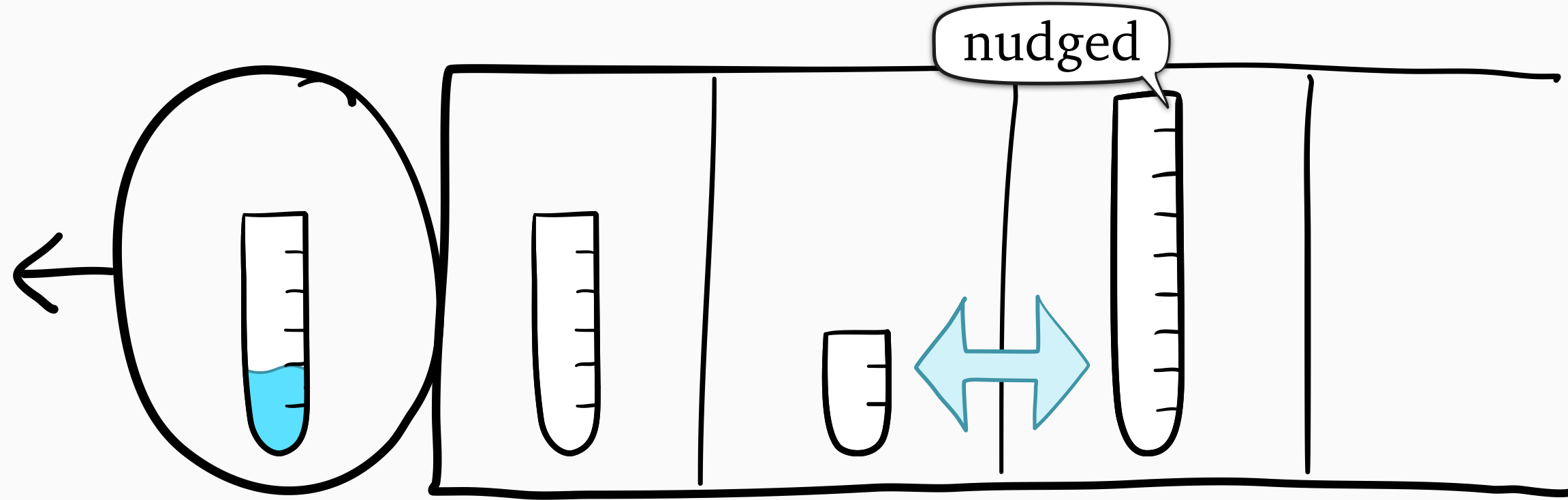
Can we beat FCFS?



Nudge [Grosf et al., 2021]

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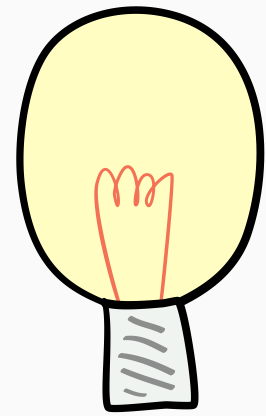
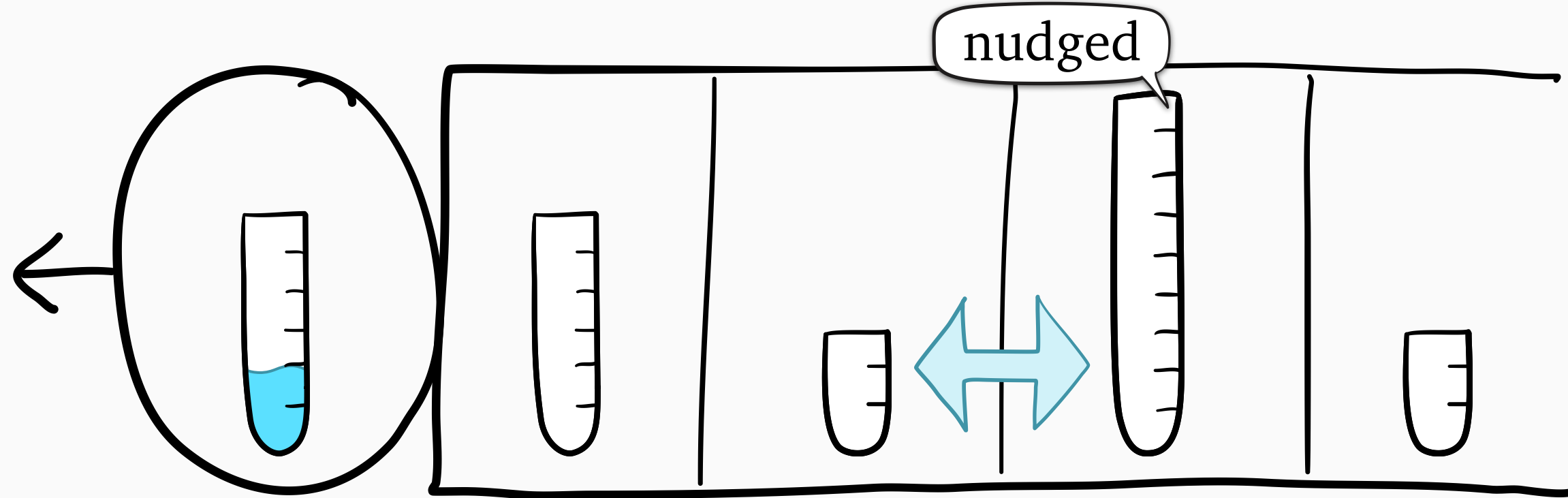
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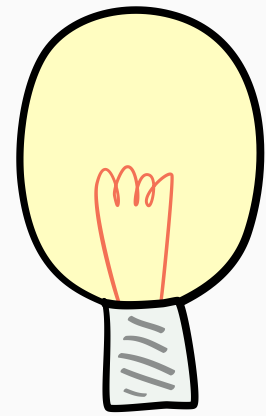
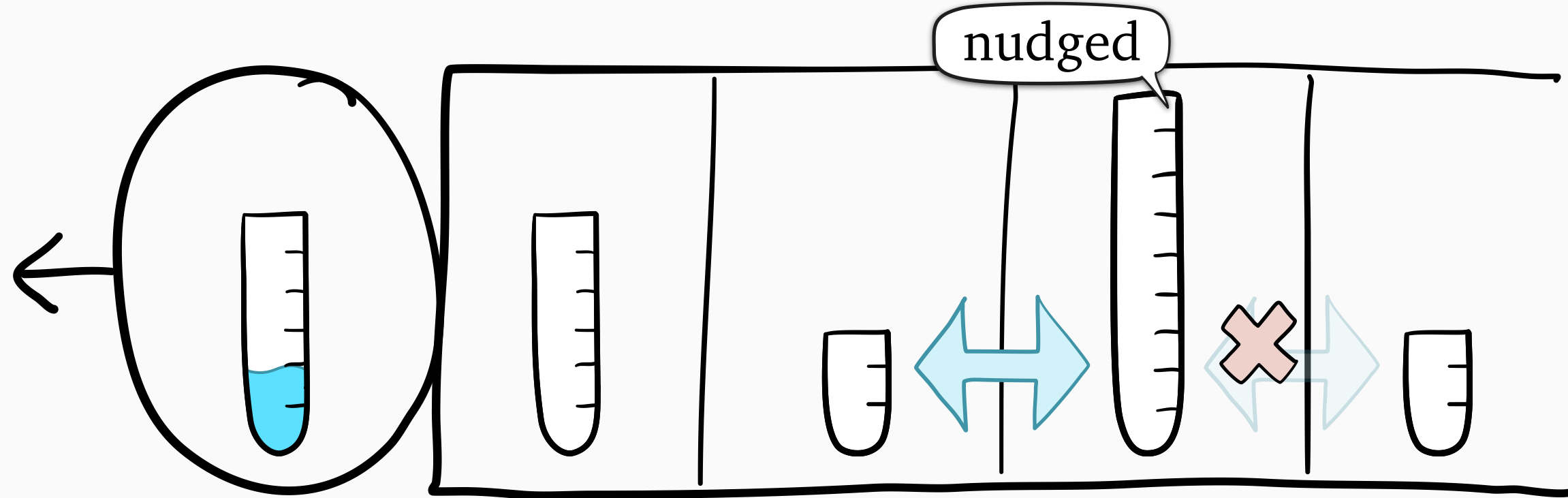
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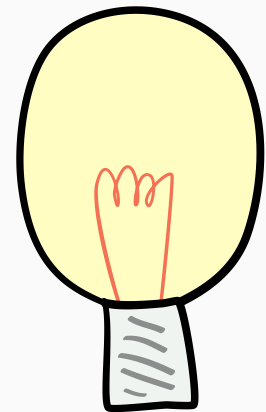
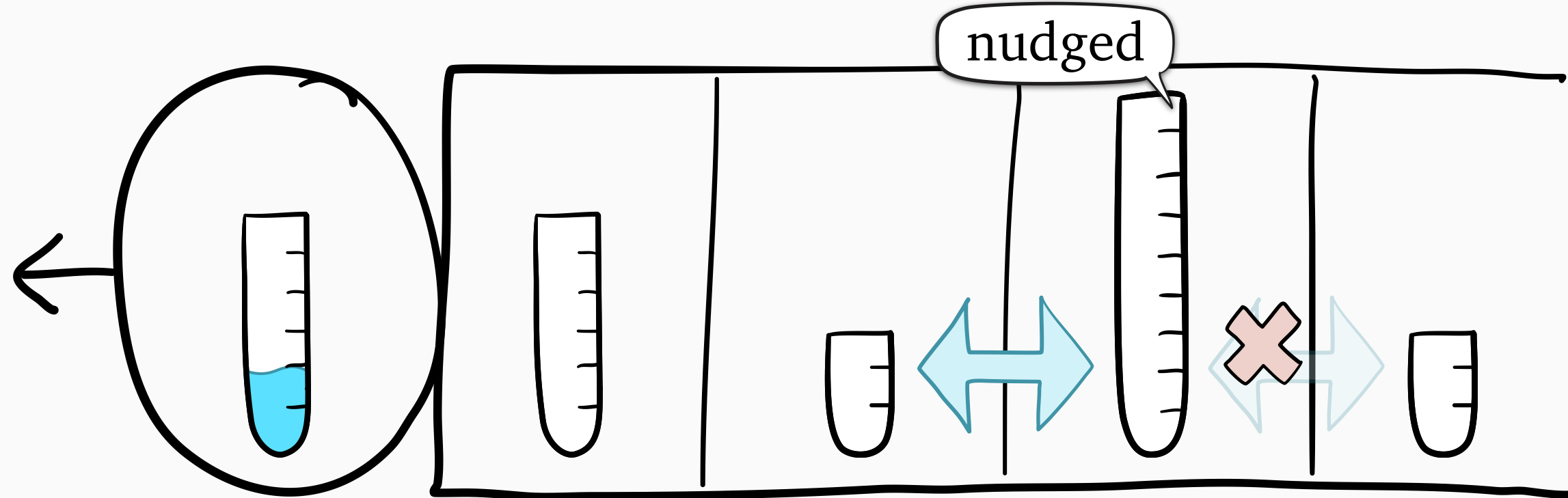
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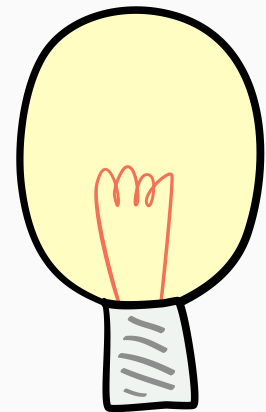
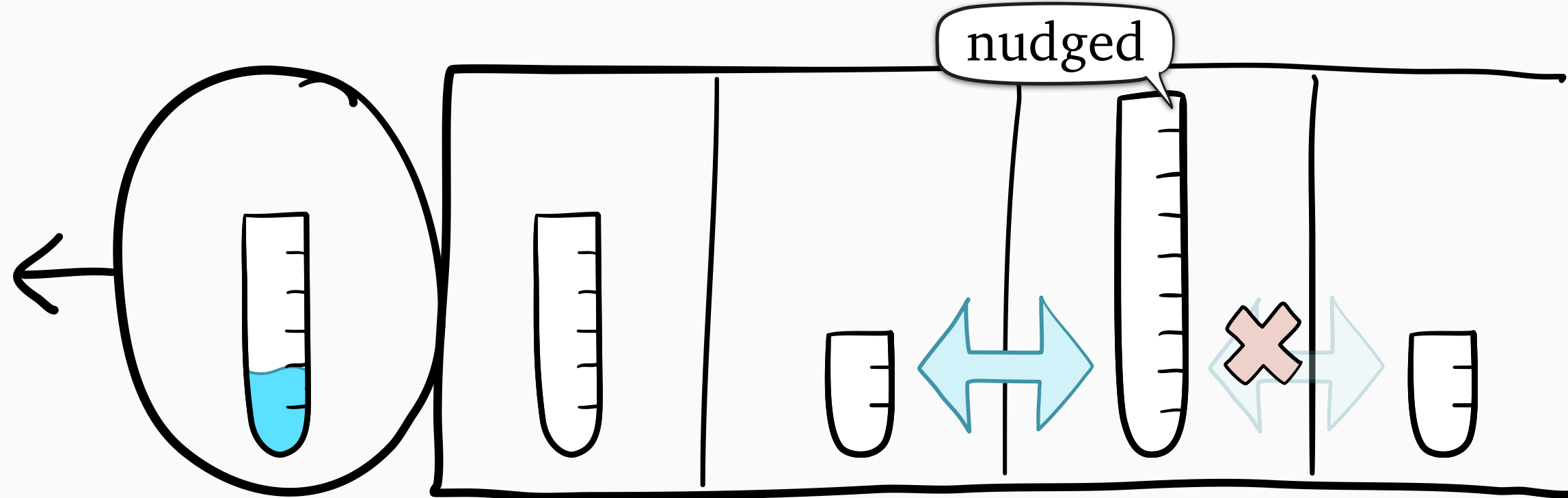
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Theorem:

$$C_{\text{Nudge}} < C_{\text{FCFS}}$$

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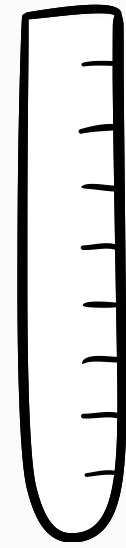
$$C_{\text{Nudge}} < C_{\text{FCFS}}$$

More complex variants get even lower C

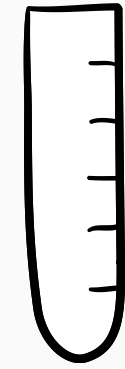
[Van Houdt, 2022; Charlet & Van Houdt, 2024]

Can we beat Nudge?

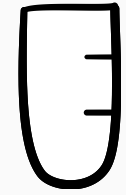
Can we beat Nudge?



1st



2nd

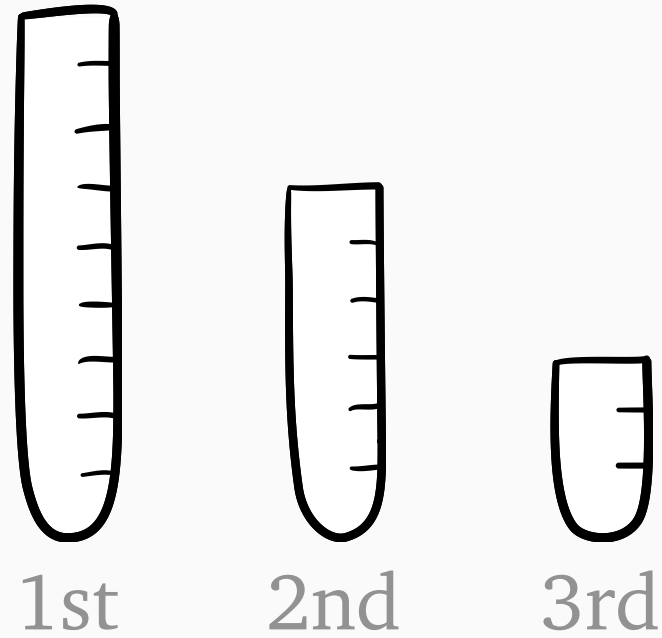


3rd



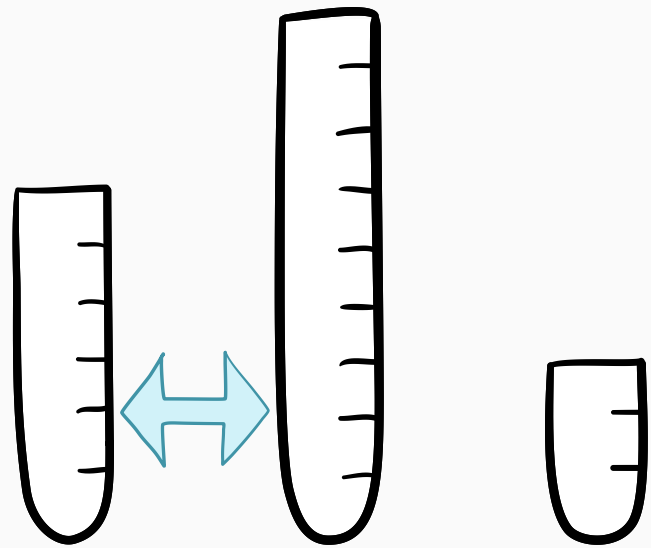
How to handle
range of sizes?

Can we beat Nudge?

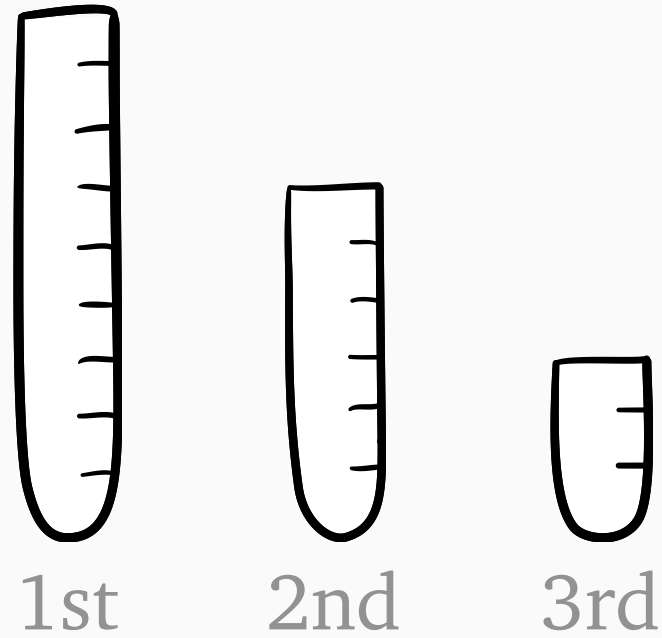


? How to handle range of sizes?

medium = small?

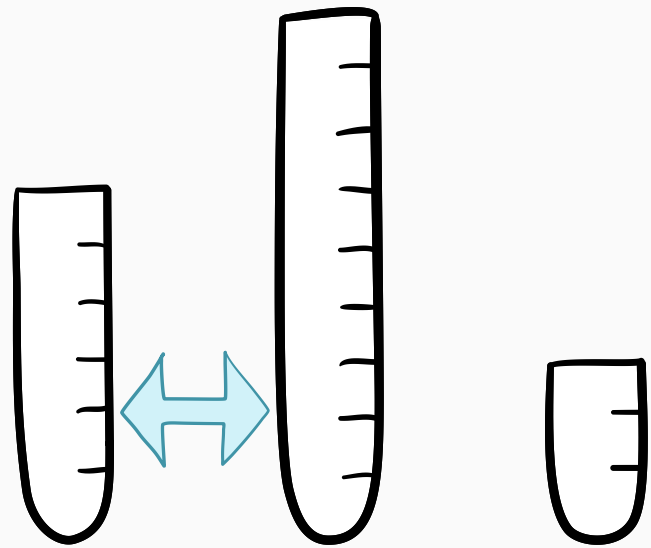


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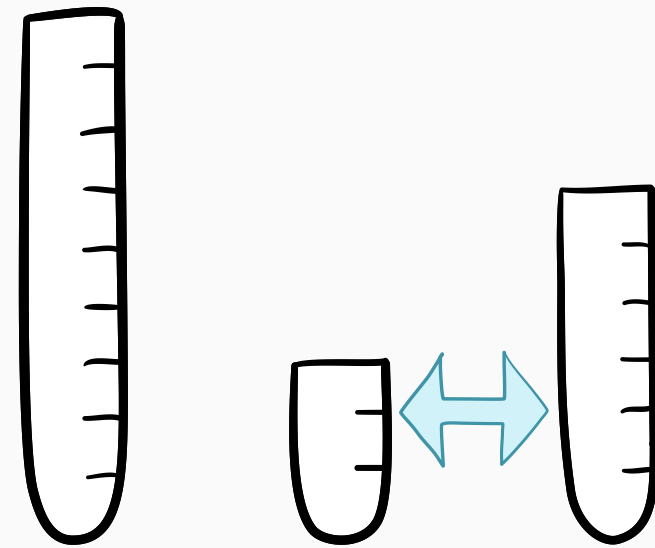


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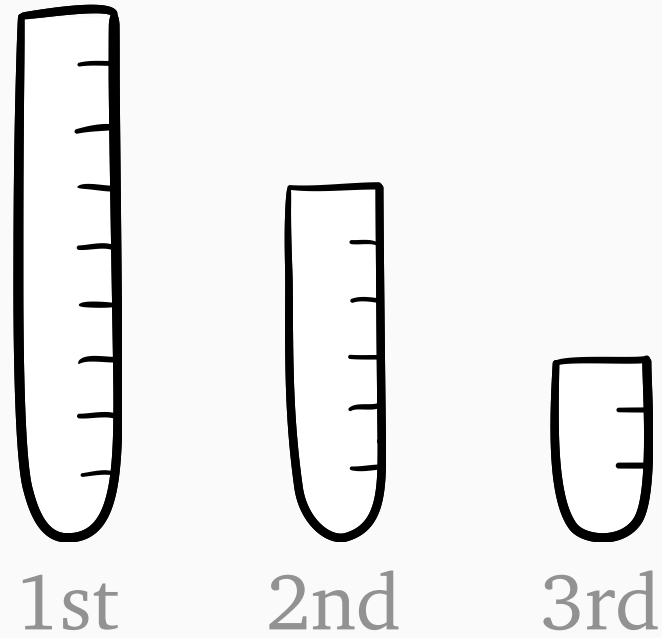
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medium = large?

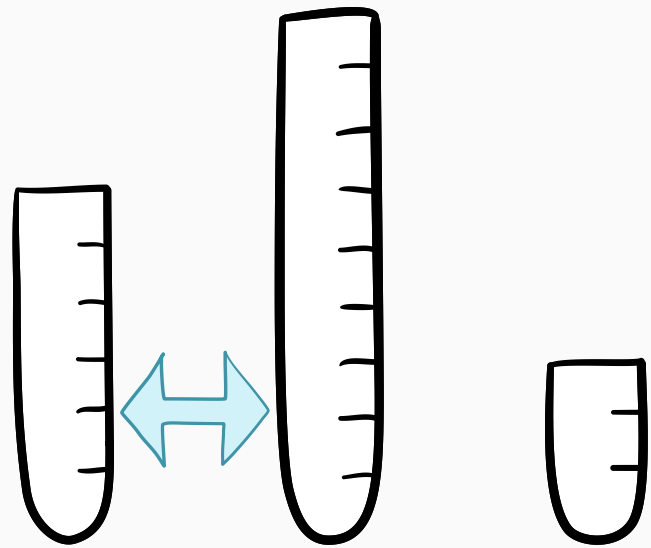


Can we beat Nudge?

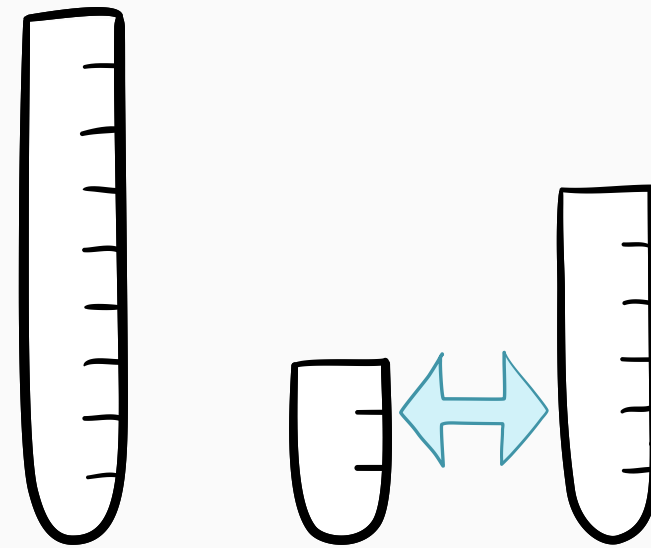


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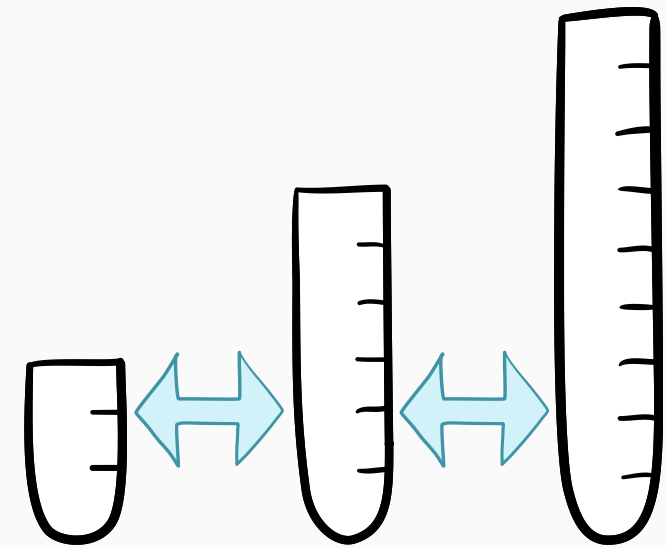
medium = small?



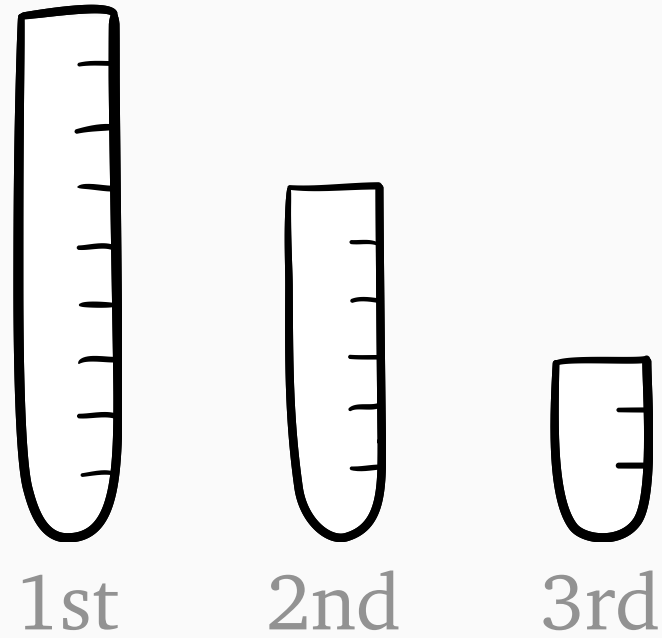
medium = large?



something else?



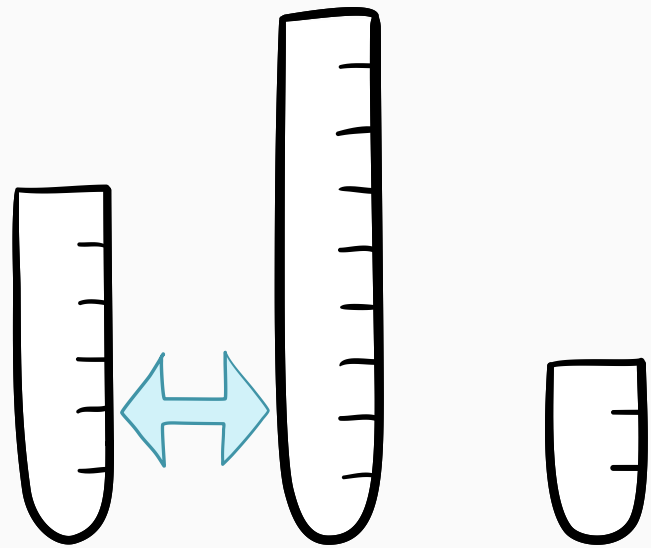
Can we beat Nudge?



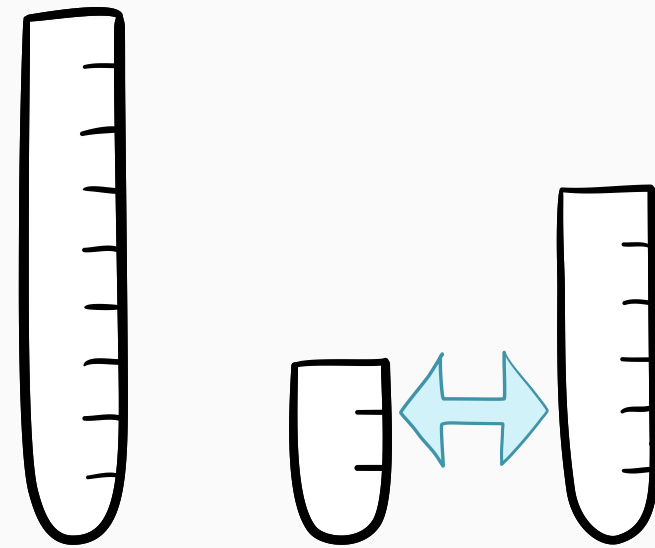
? How to handle range of sizes?

What info could help us decide?

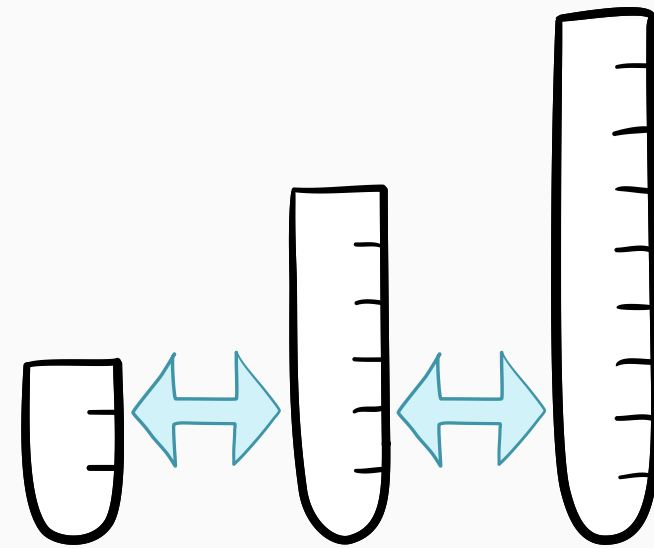
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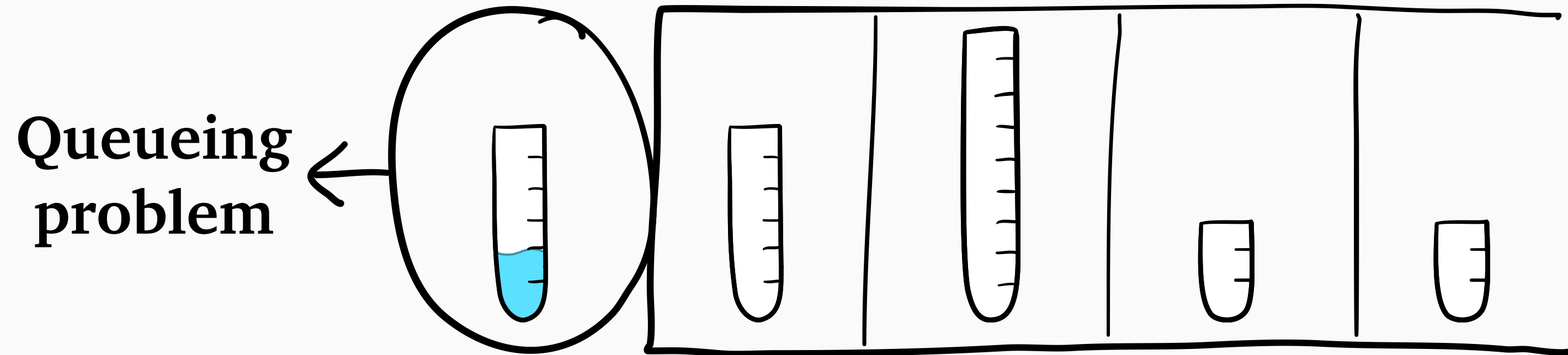


something else?

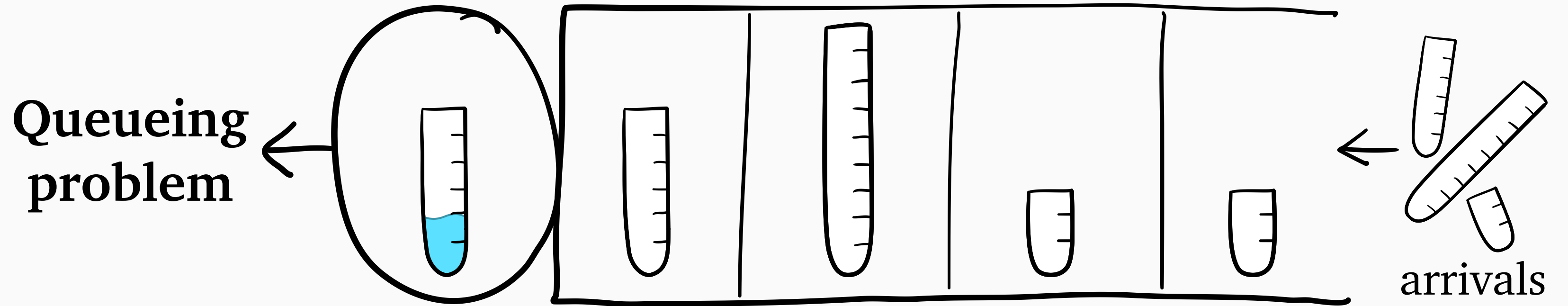


Where do optimal policies come from?

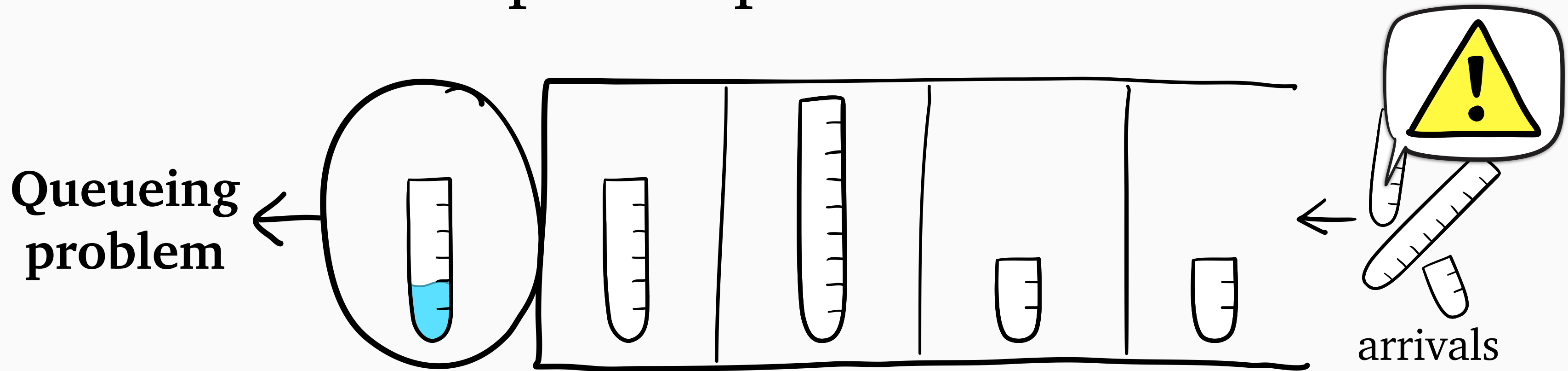
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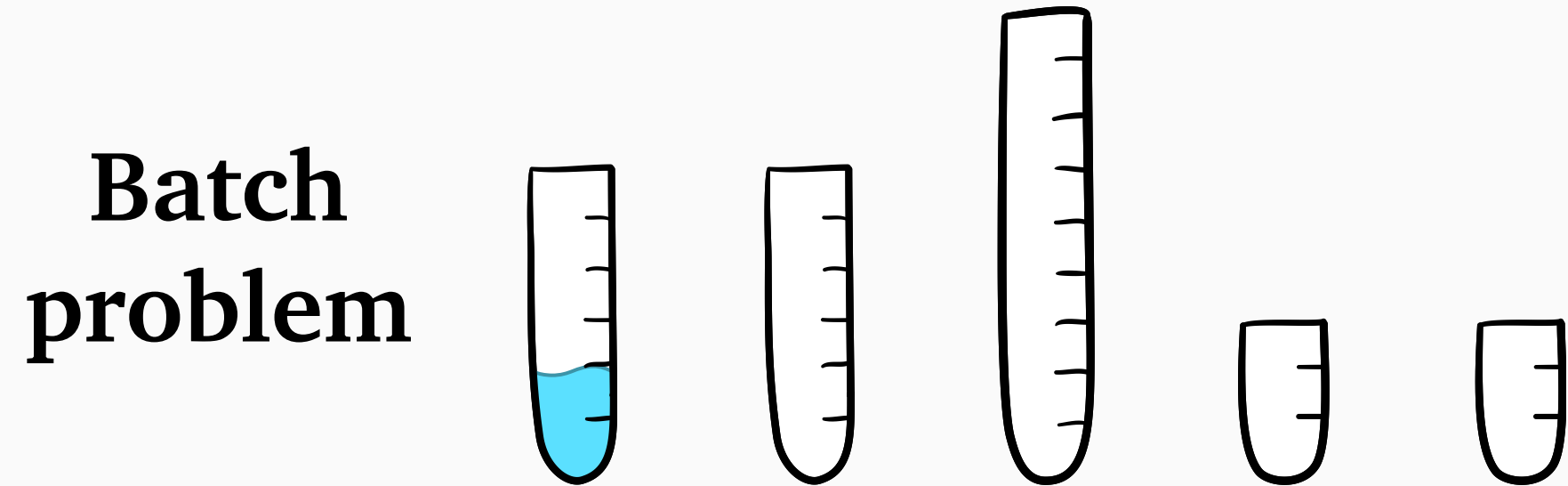
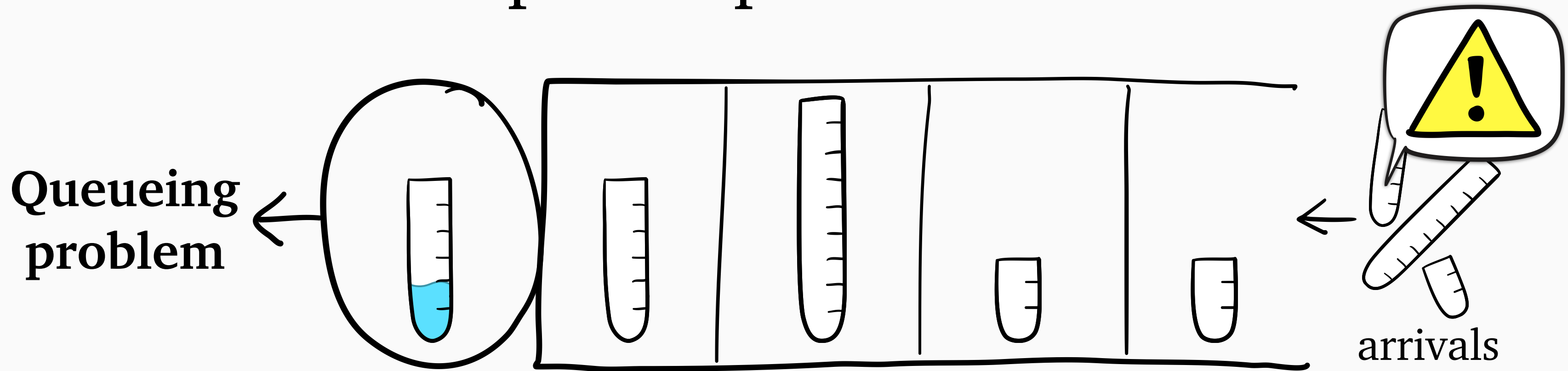
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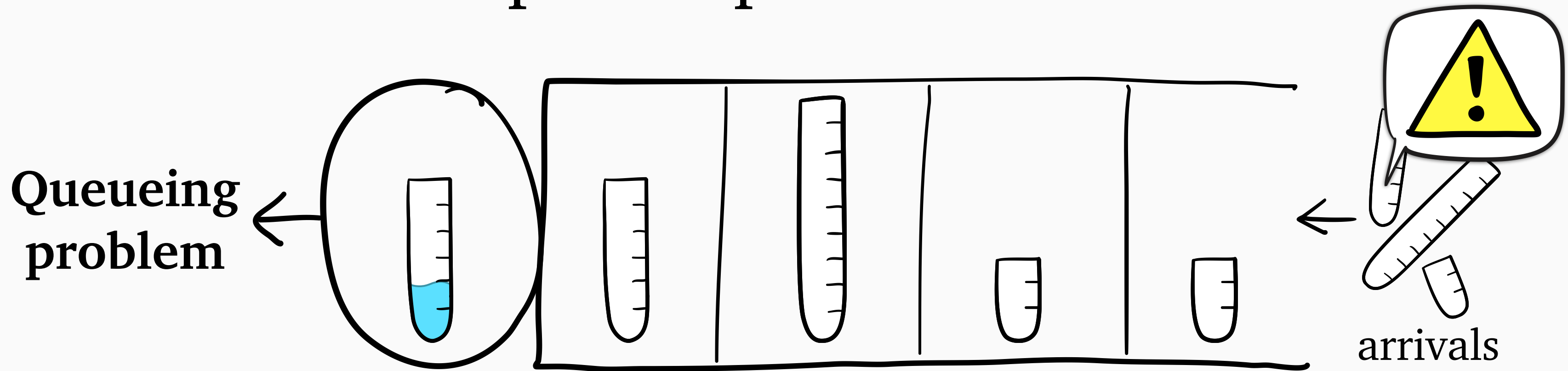
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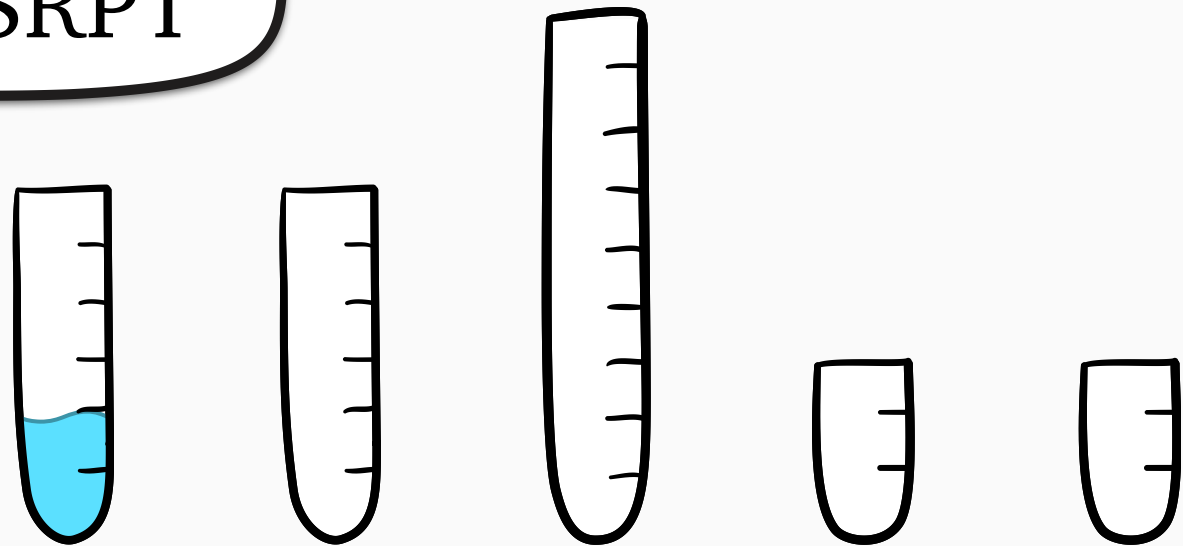


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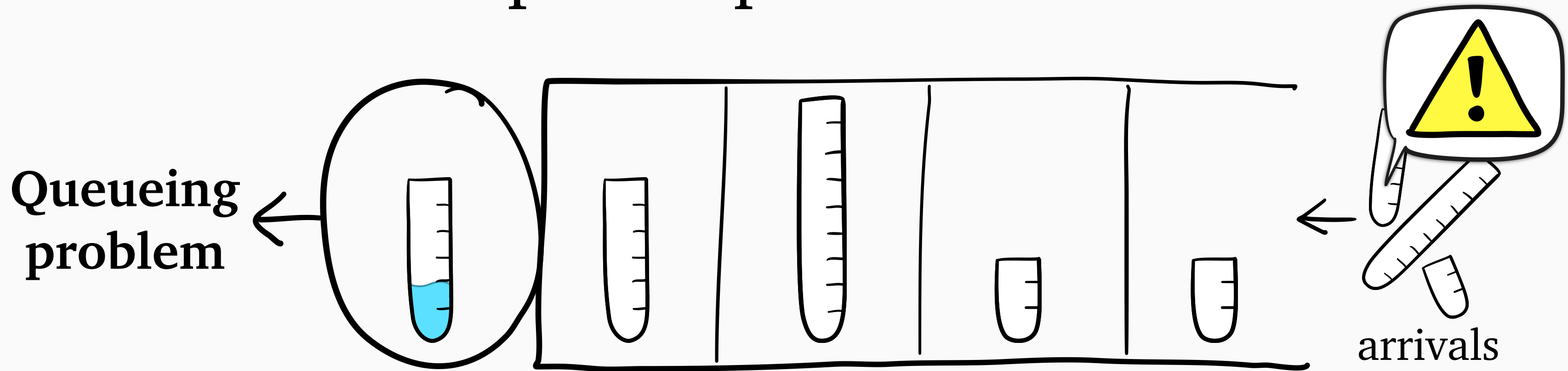


e.g. $\min E[T]$
yields SRPT

Batch
problem

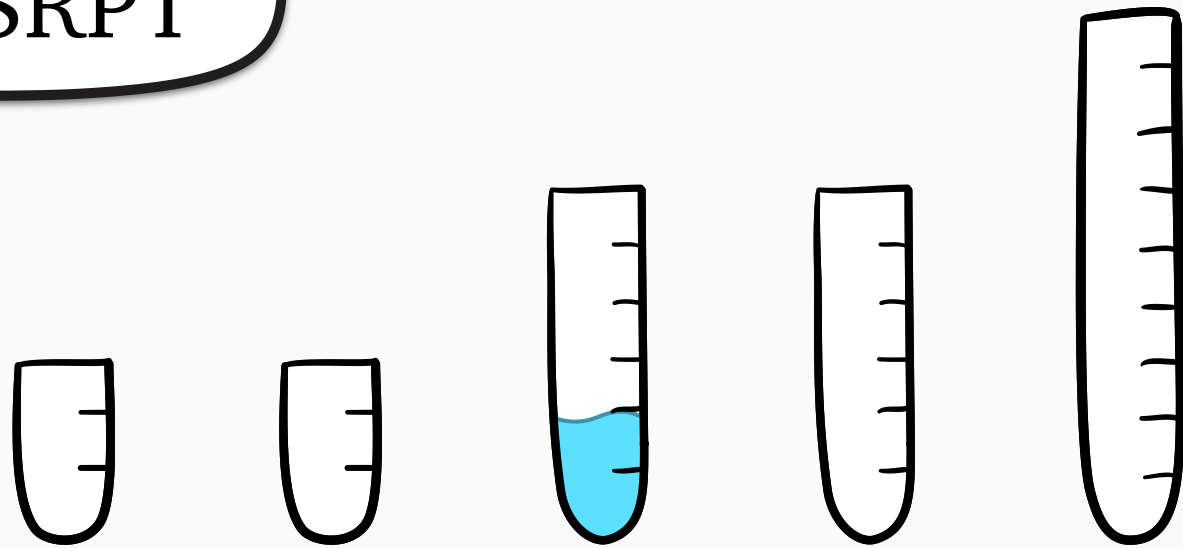


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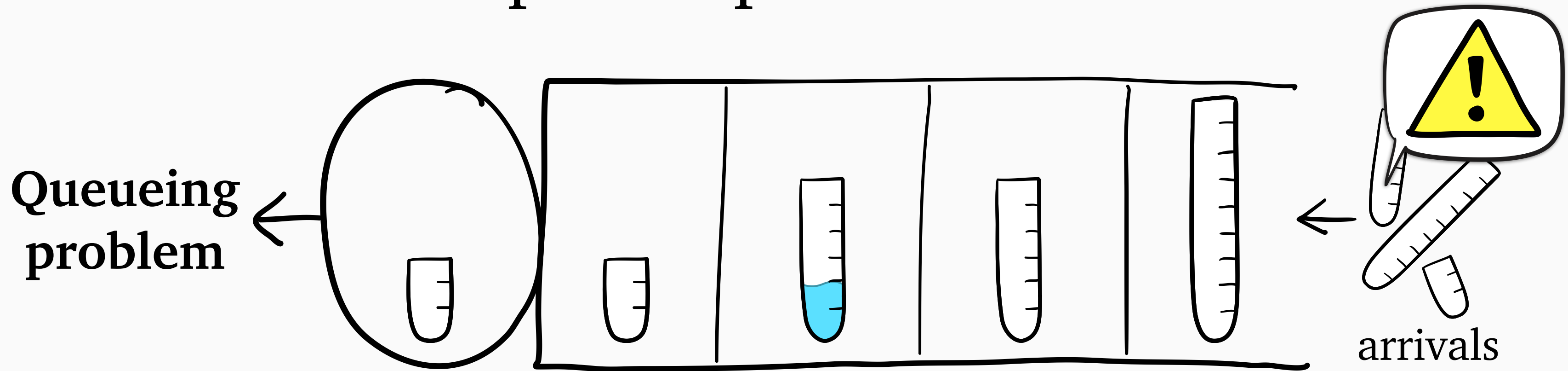


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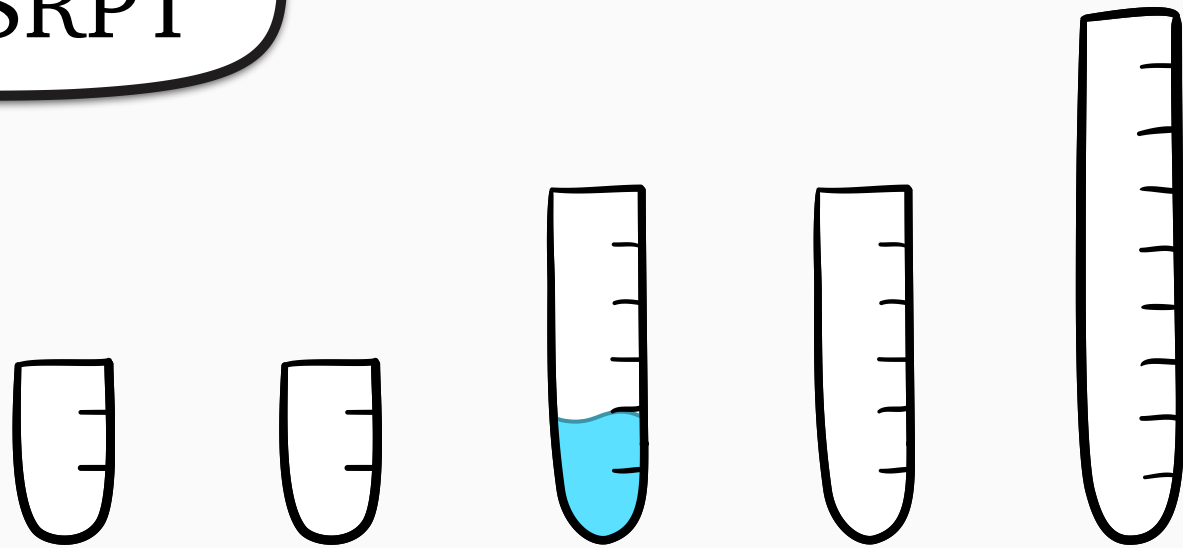


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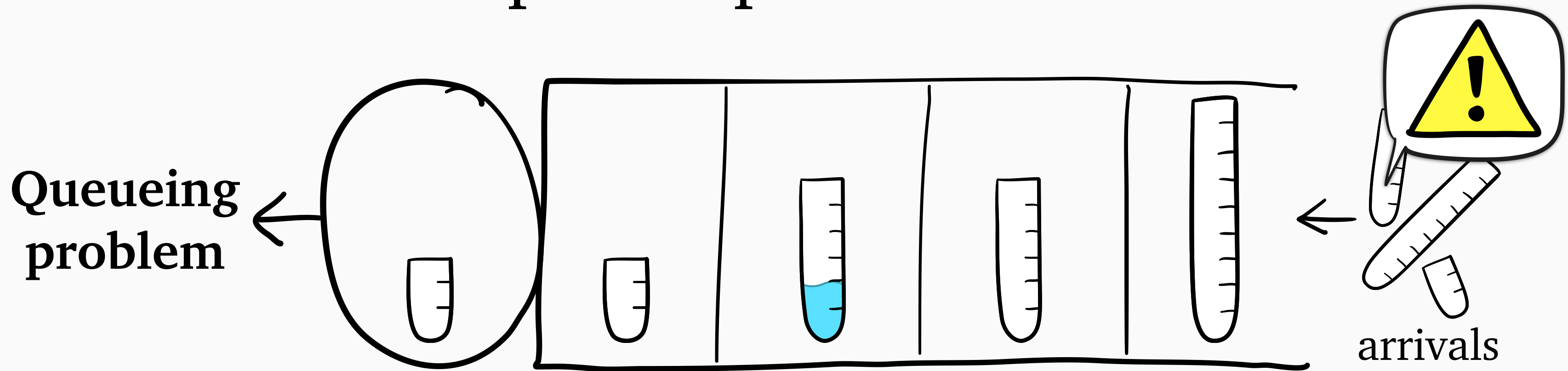


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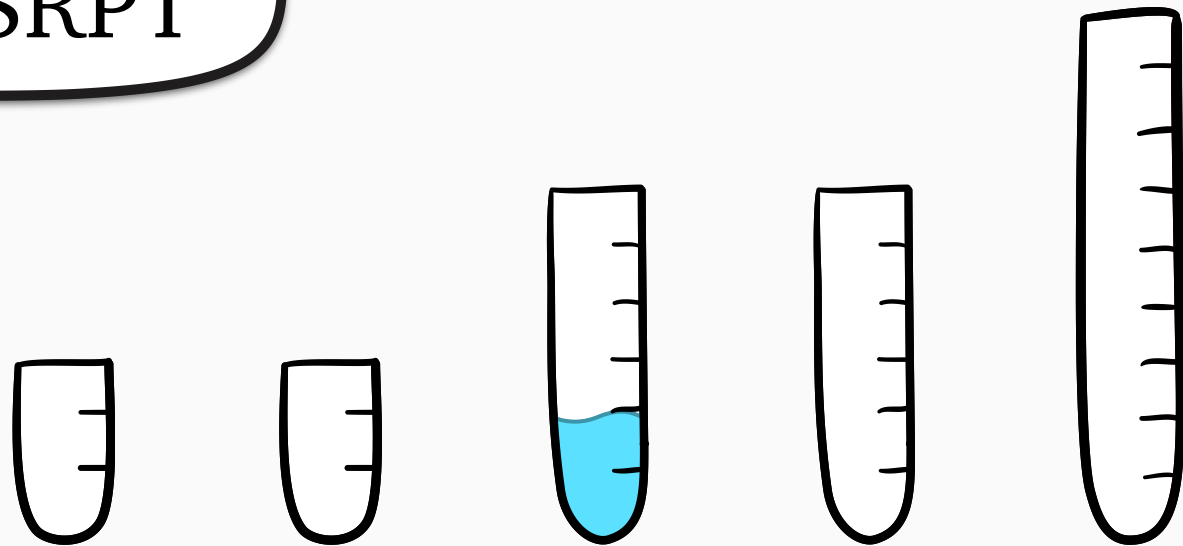


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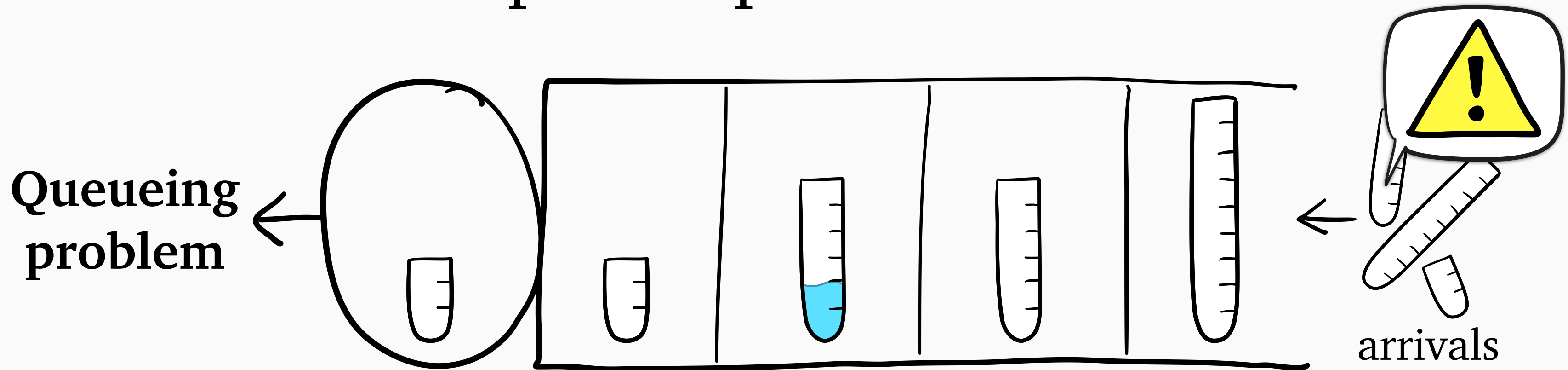
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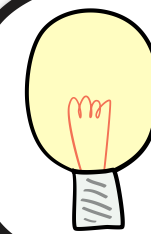
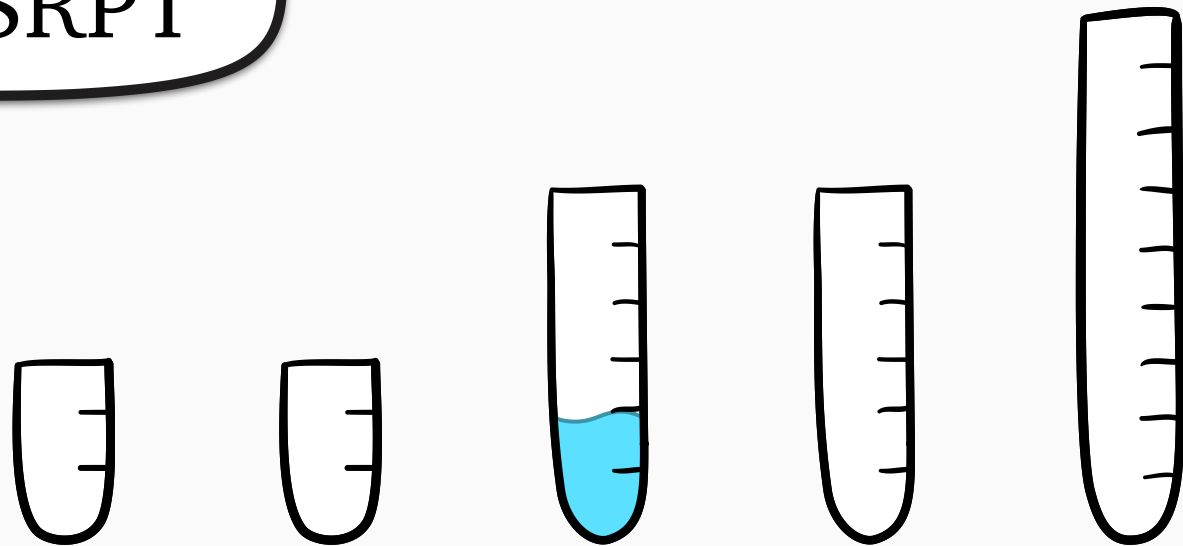
? Batch version of
minimizing C ?

Where do optimal policies come from?



e.g. $\min E[T]$
yields SRPT

Batch
problem



Non-asymptotic
version of metric?



Batch version of
minimizing C ?

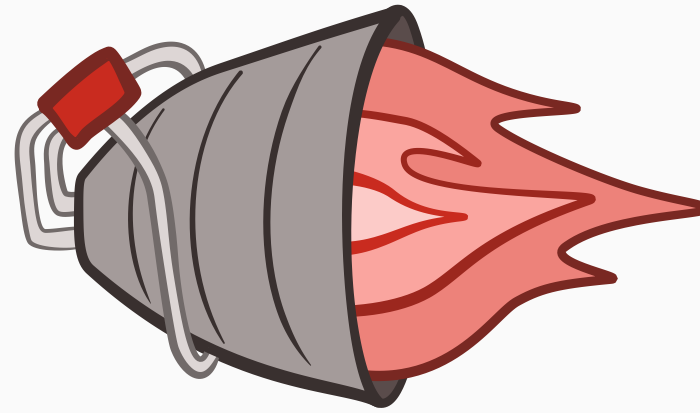
Boost

? Why is achieving strong tail optimality hard?

? How does the **Boost** policy family work?

? How do we achieve strong tail optimality?

Boost



Why is achieving strong tail optimality hard?

How to handle range of sizes?



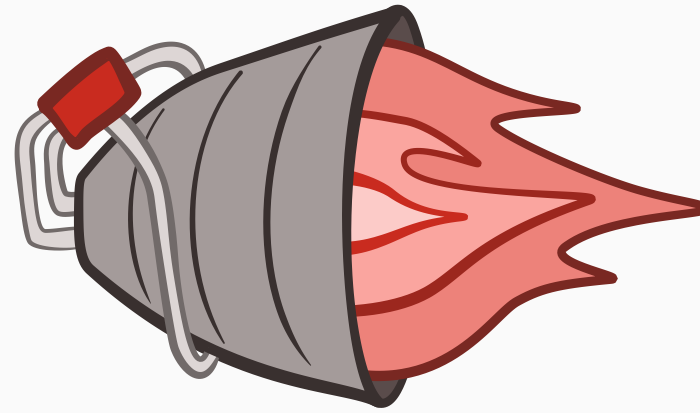
How does the **Boost** policy family work?

Batch version of minimizing C ?

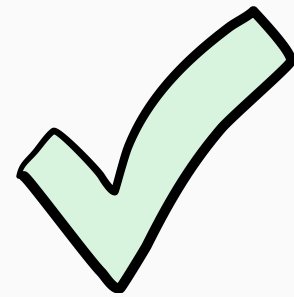


How do we achieve strong tail optimality?

Boost



How to handle range of sizes?



Why is achieving strong tail optimality hard?

Batch version of minimizing C ?

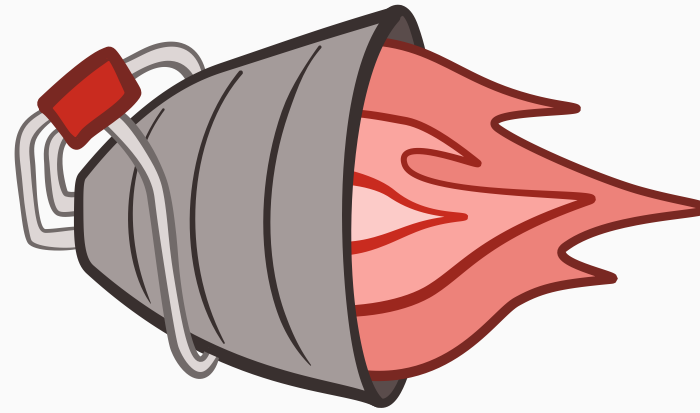


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Boost



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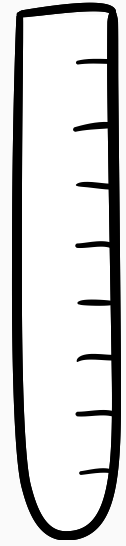


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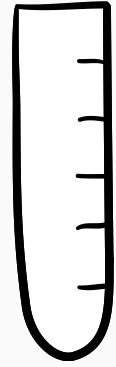


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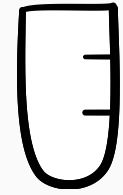
Key information:



1st



2nd

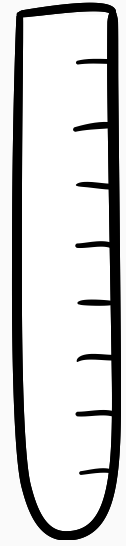


3rd

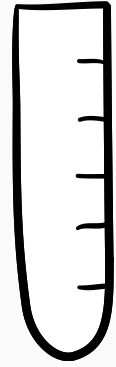


How to handle
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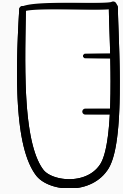
Key information: *arrival times*



1st



2nd

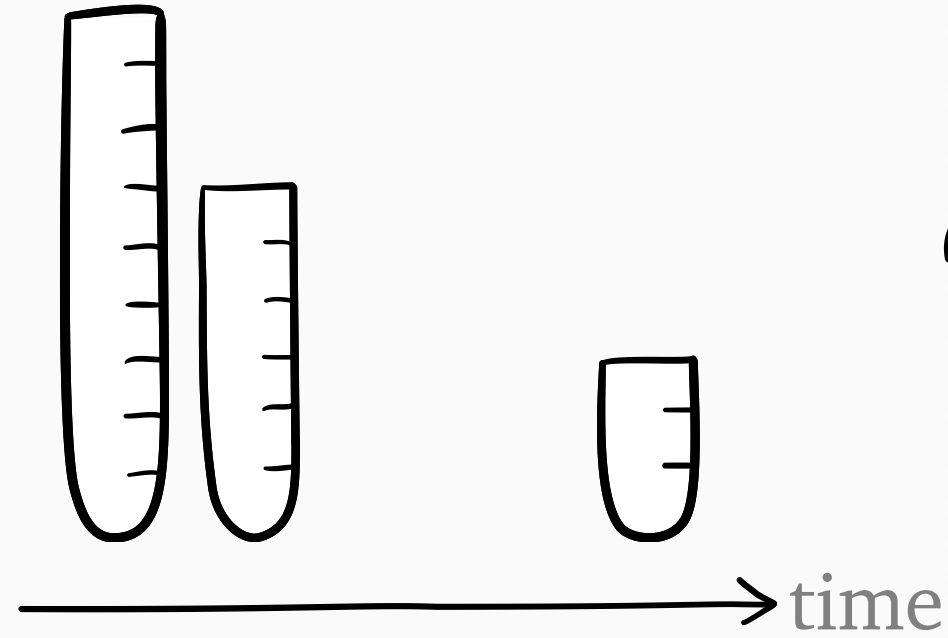


3rd



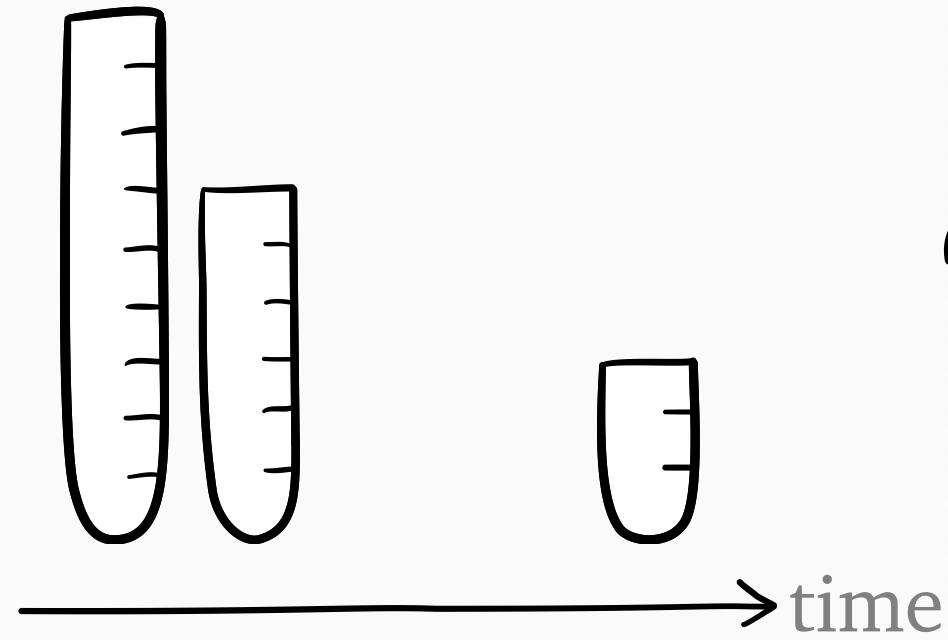
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Key information: *arrival times*

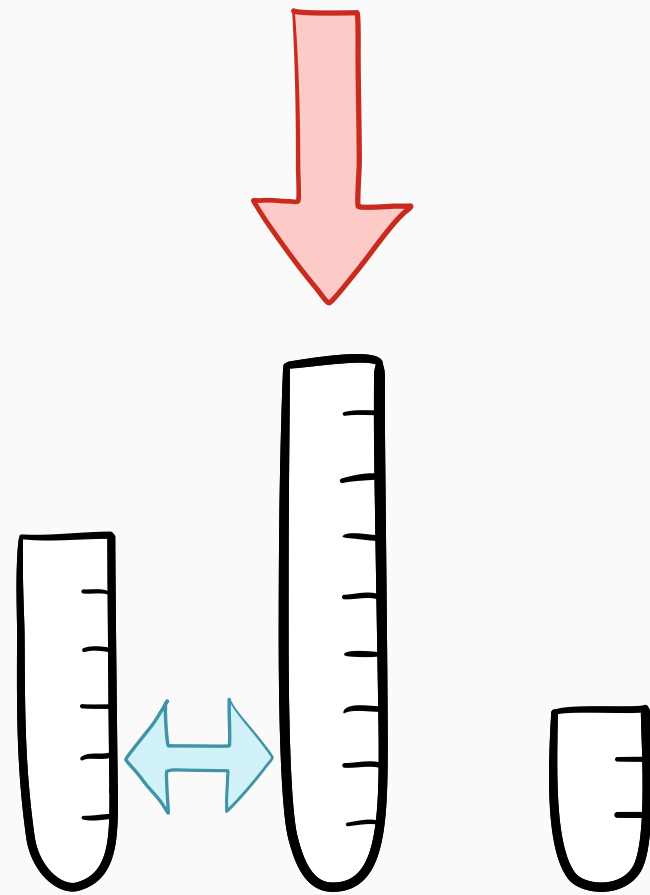


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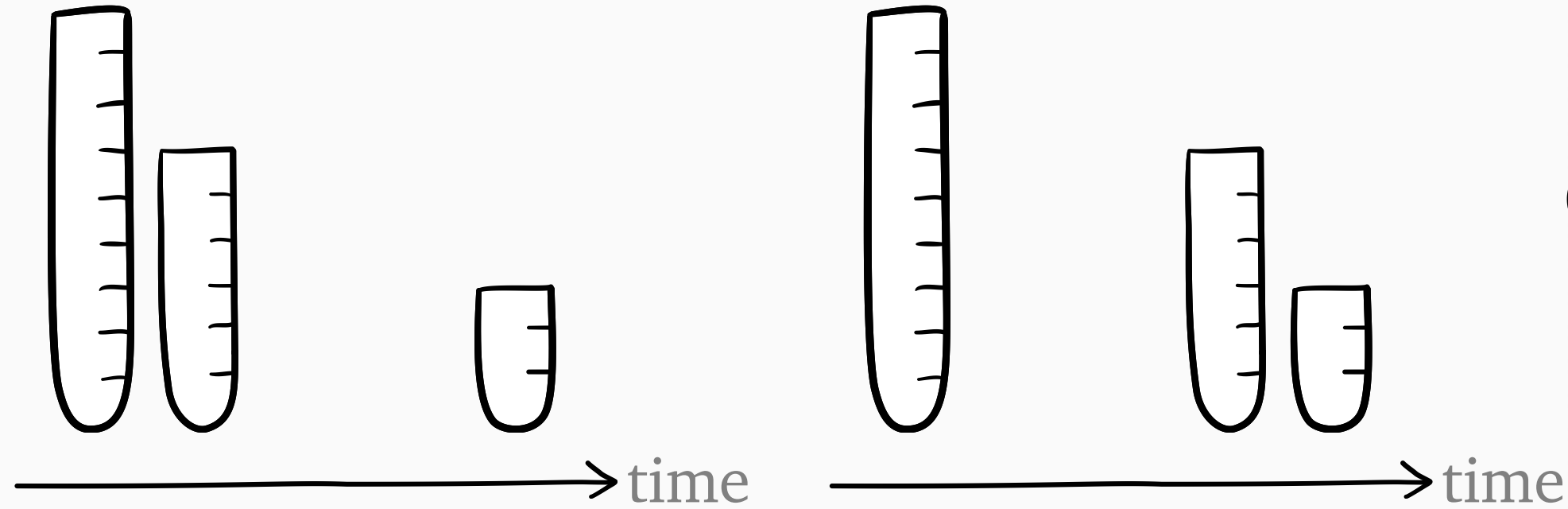
Key information: *arrival times*



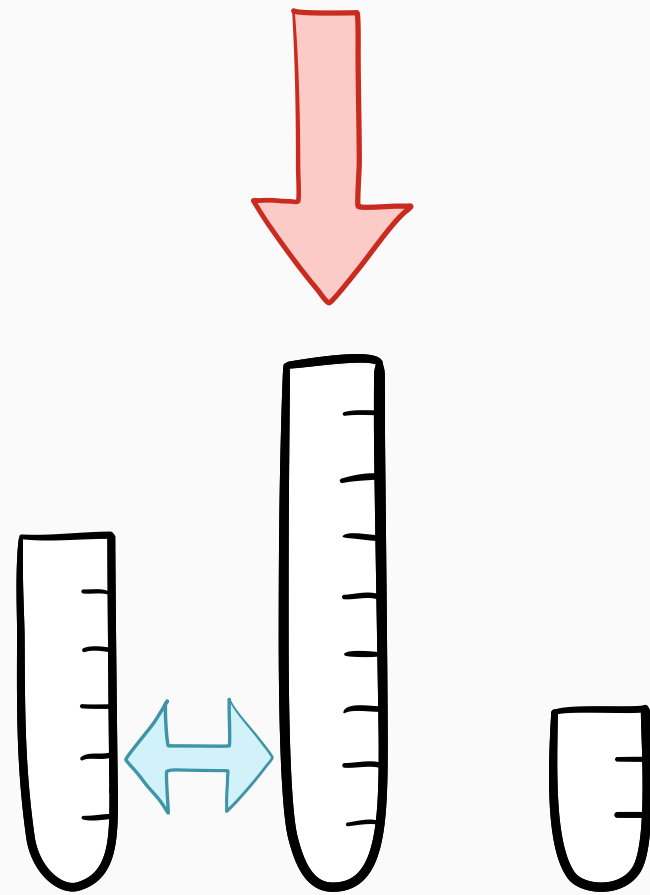
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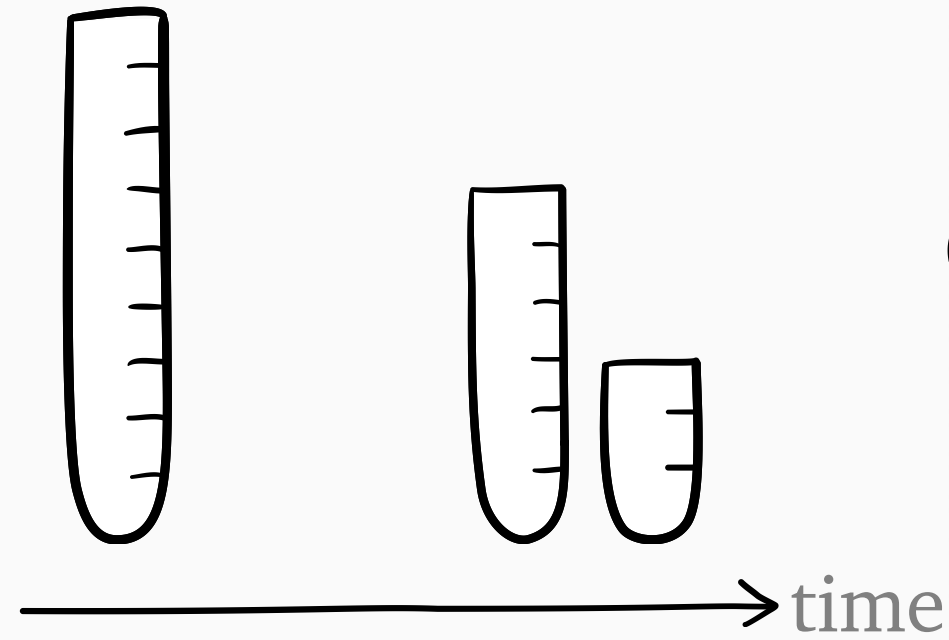
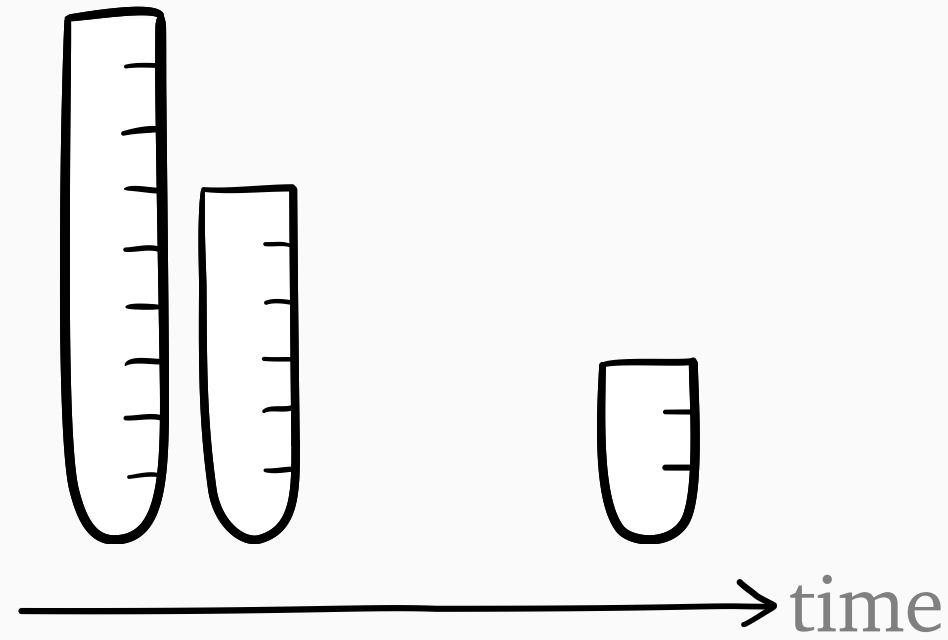
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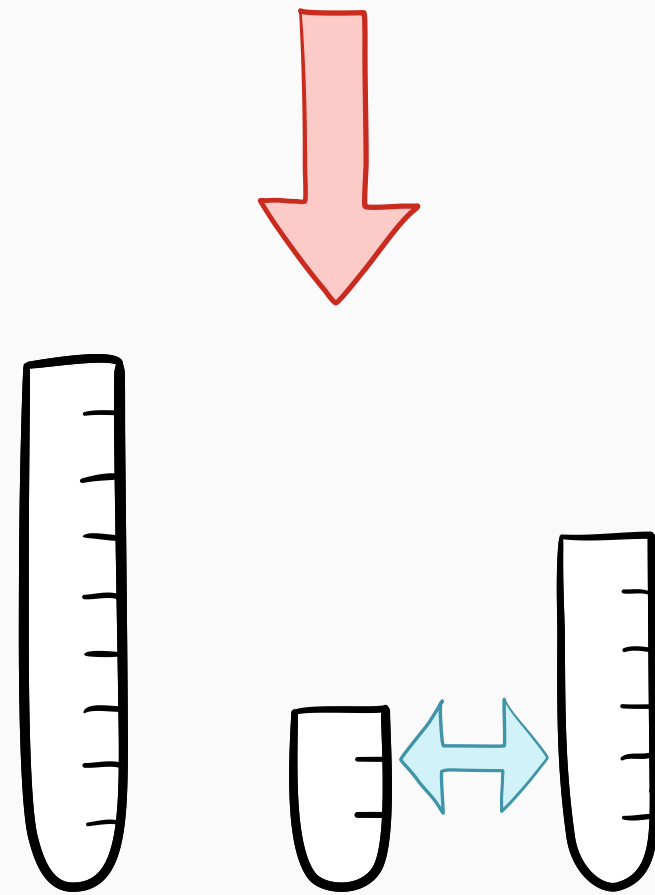
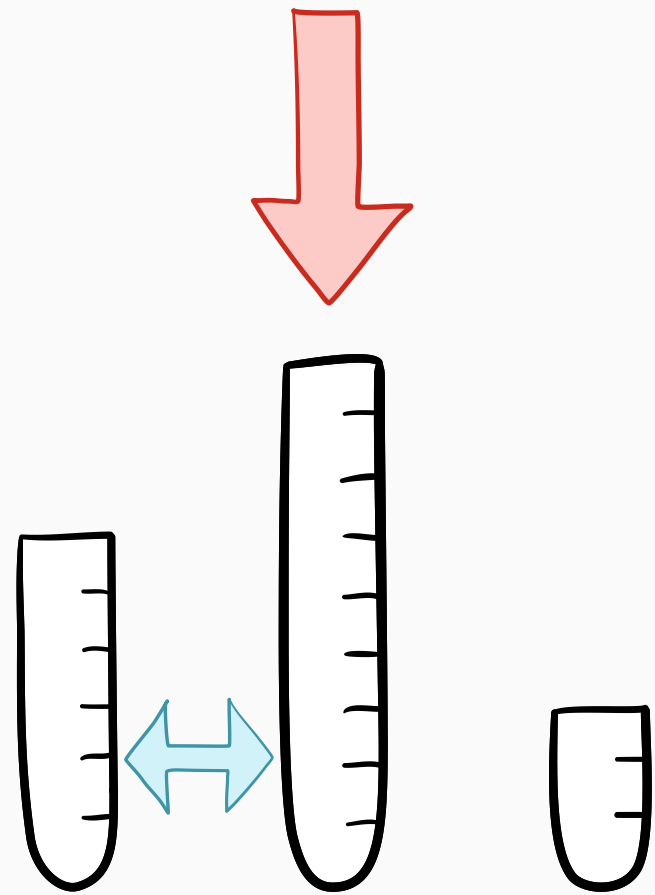
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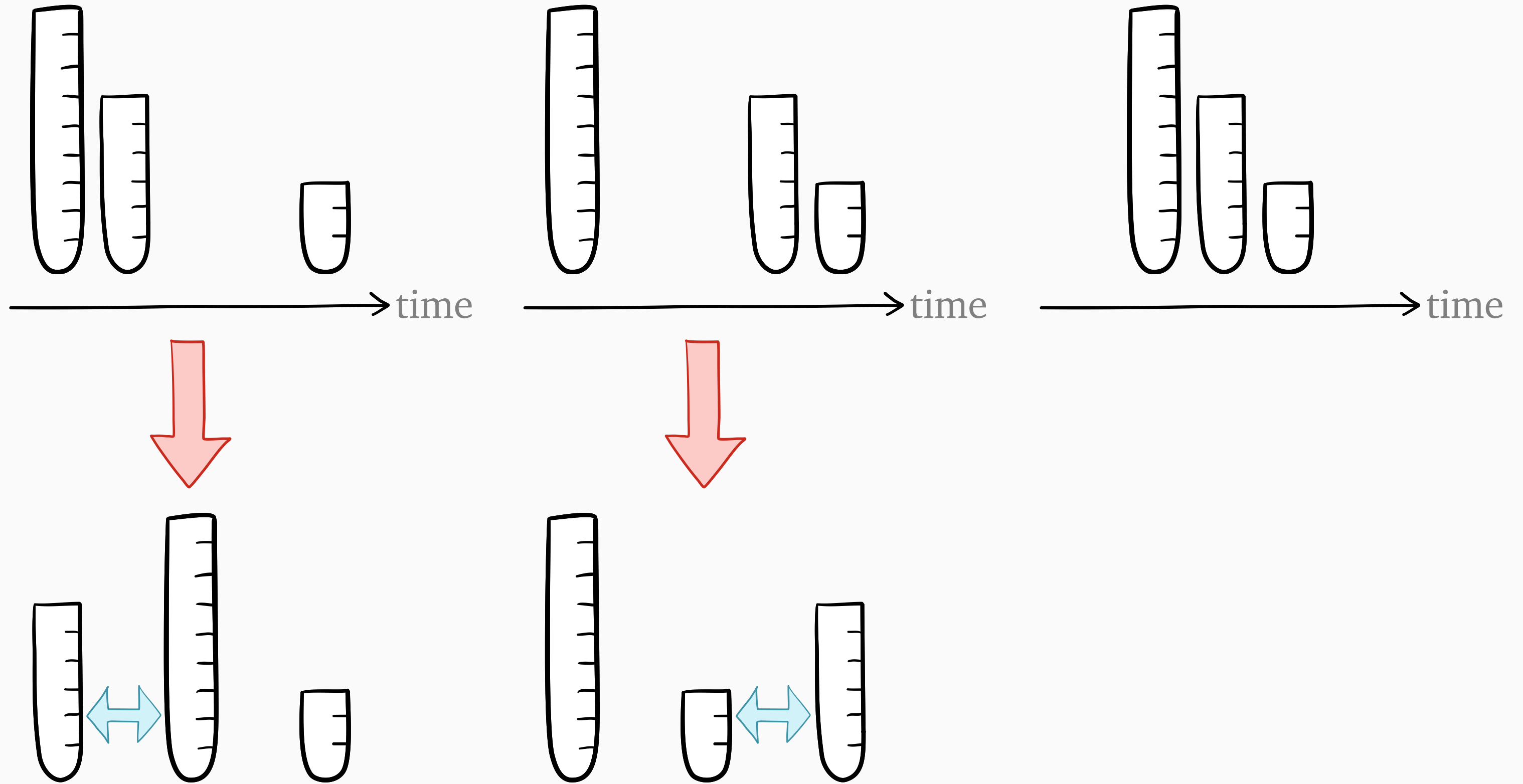
Key information: *arrival times*



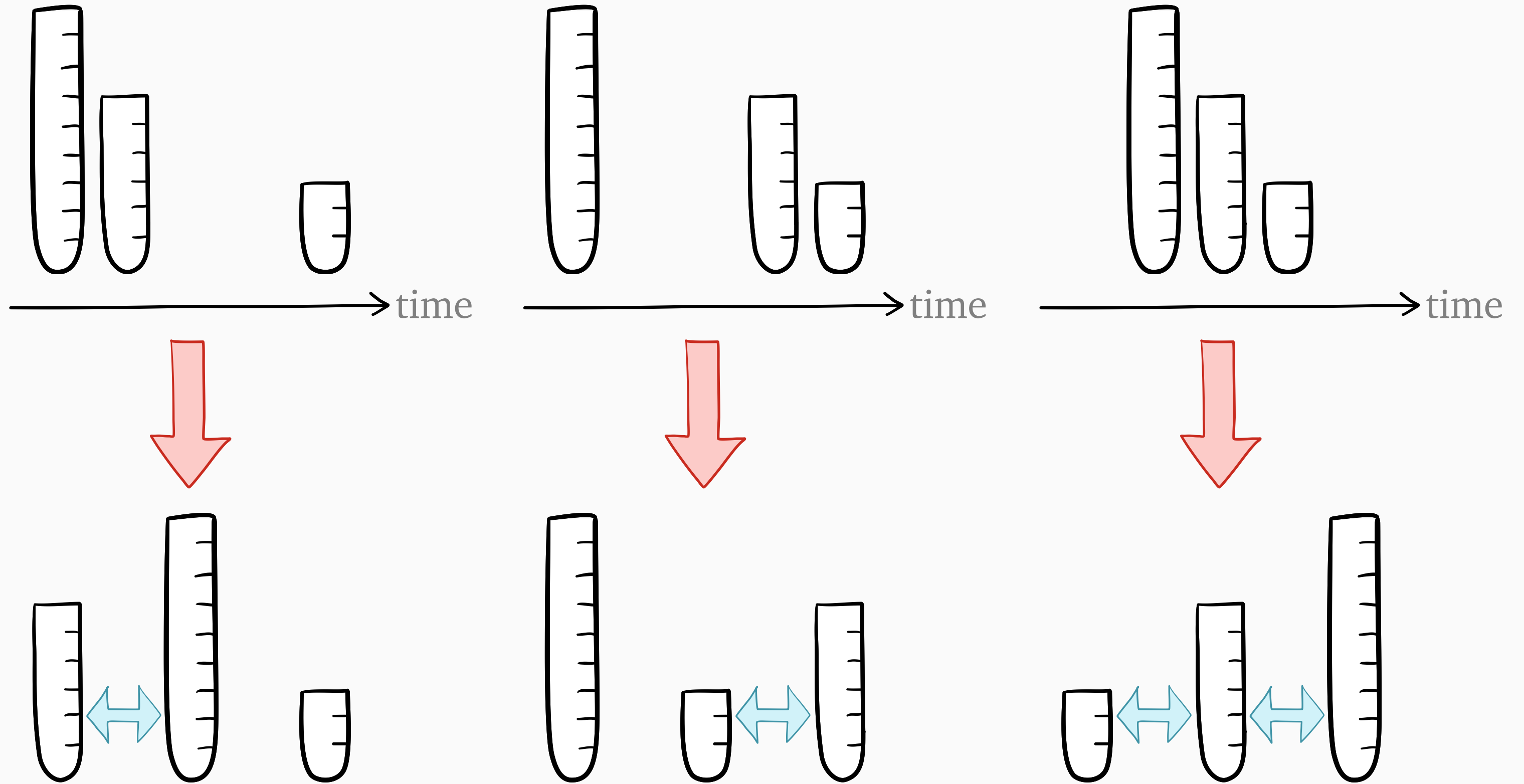
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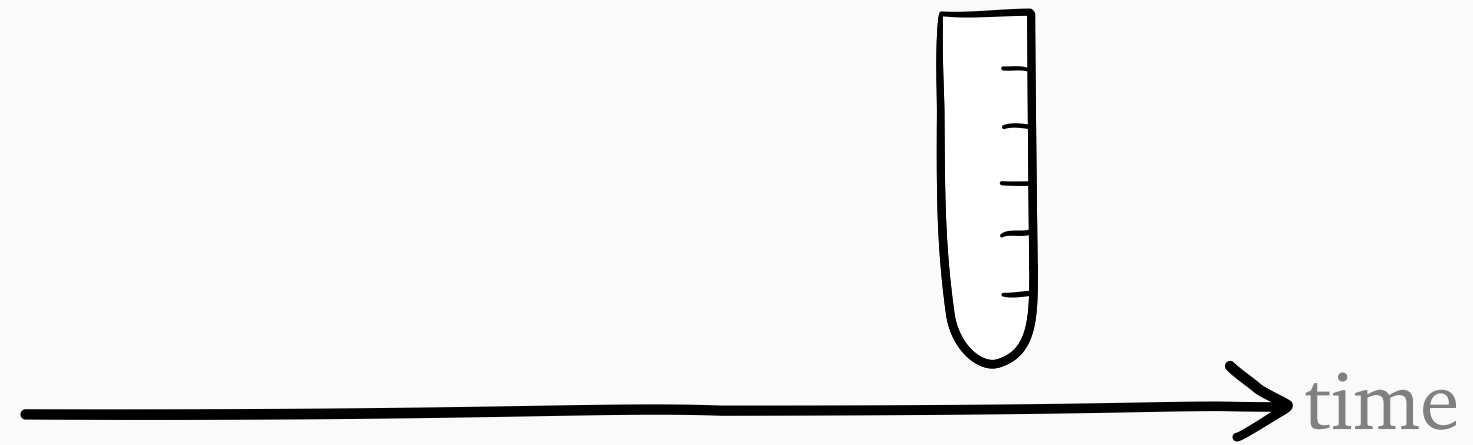
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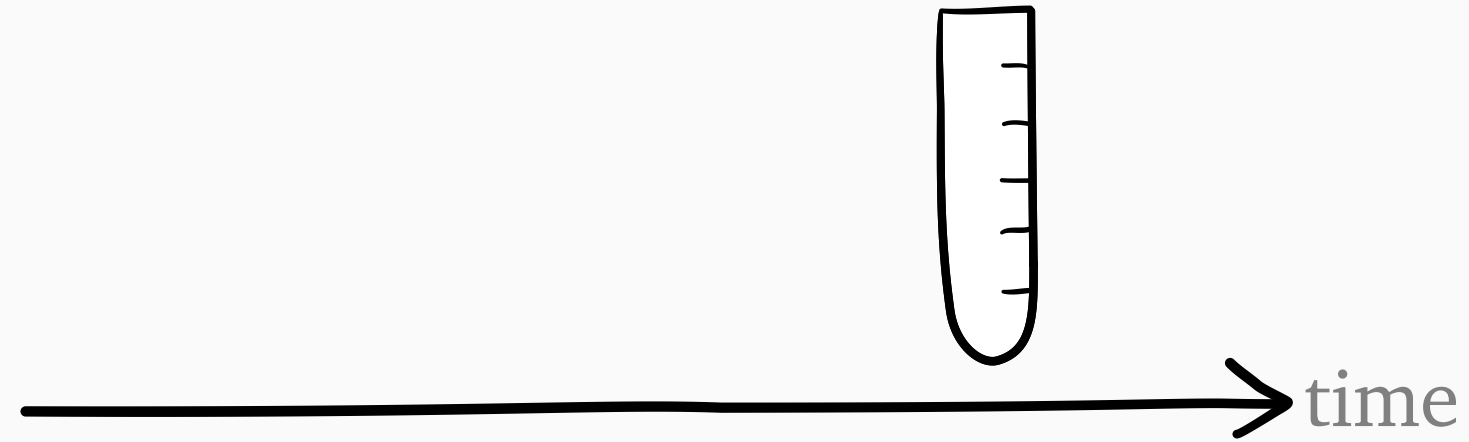
Key information: *arrival times*



Combining arrival time and size

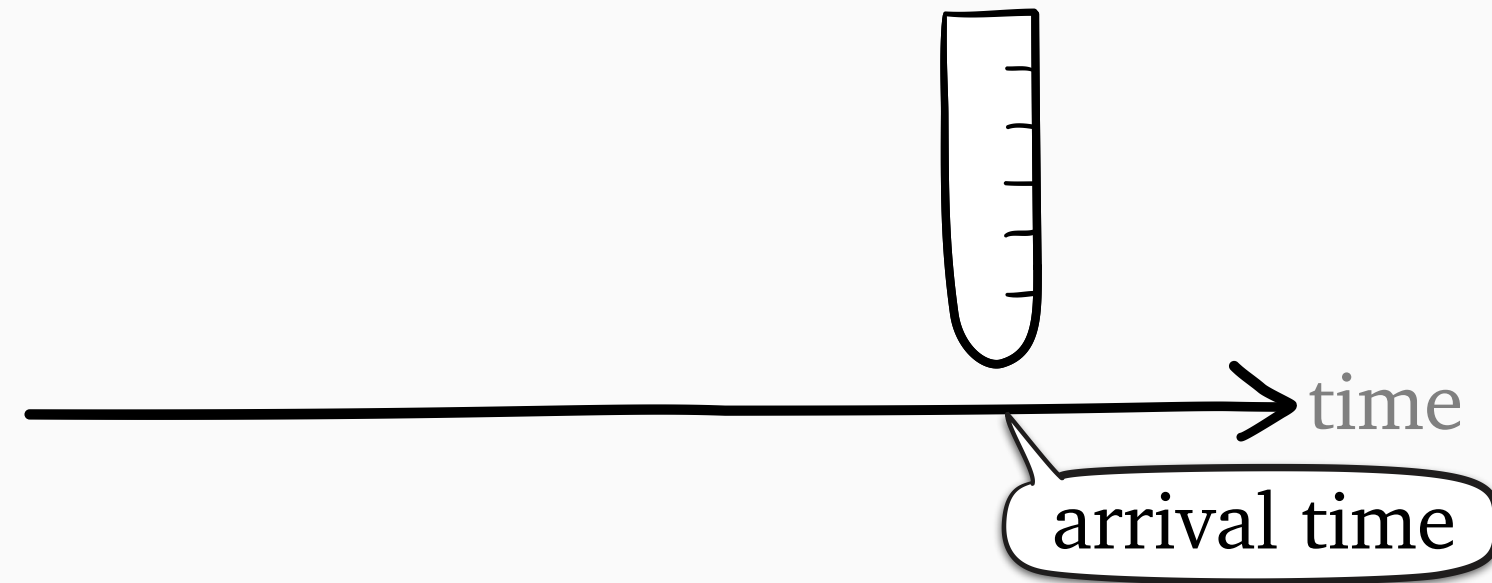


Combining arrival time and size



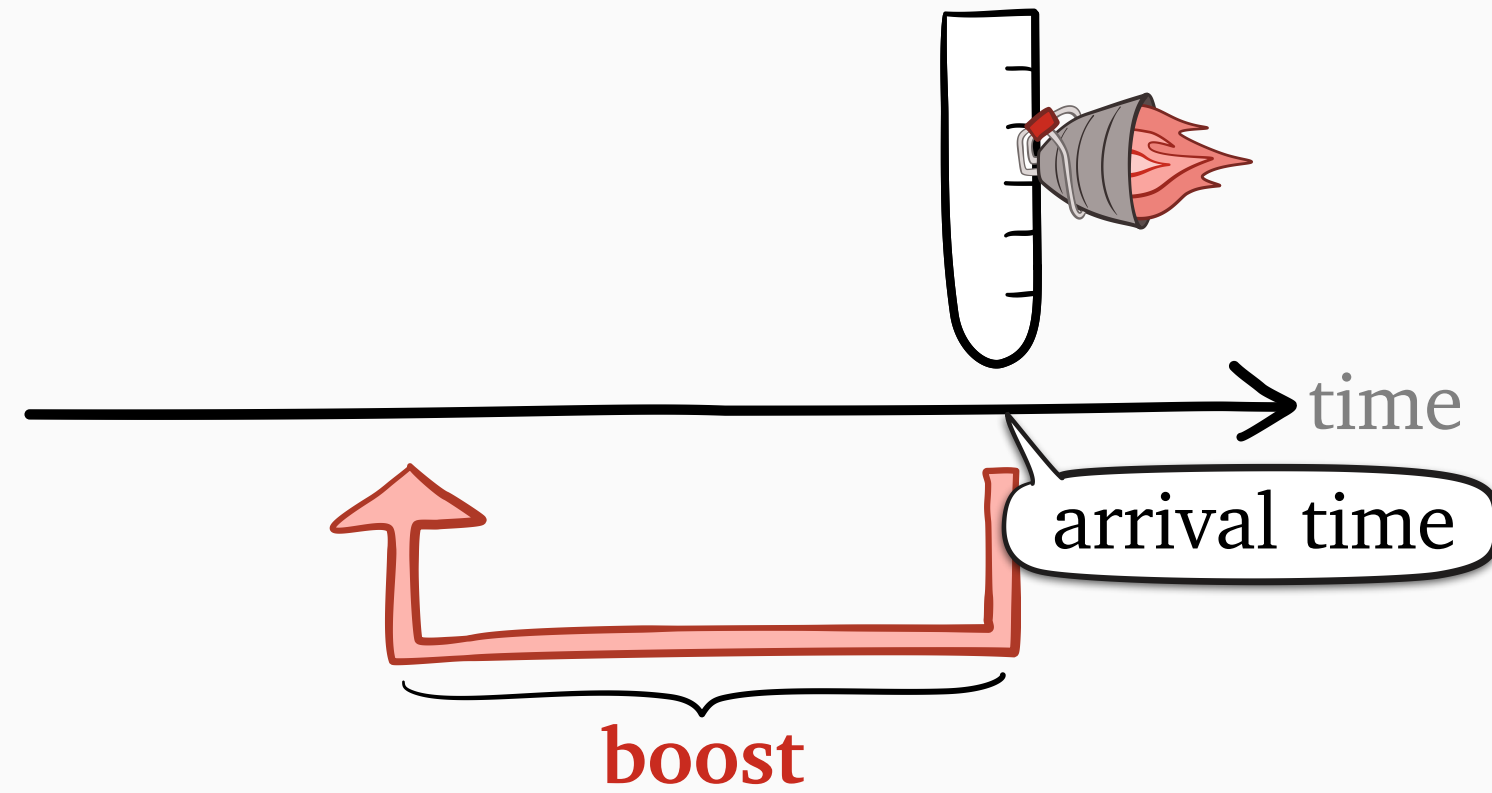
$$\text{boosted arrival time} \\ = \text{arrival time} - \text{boost}(\text{size})$$

Combining arrival time and size



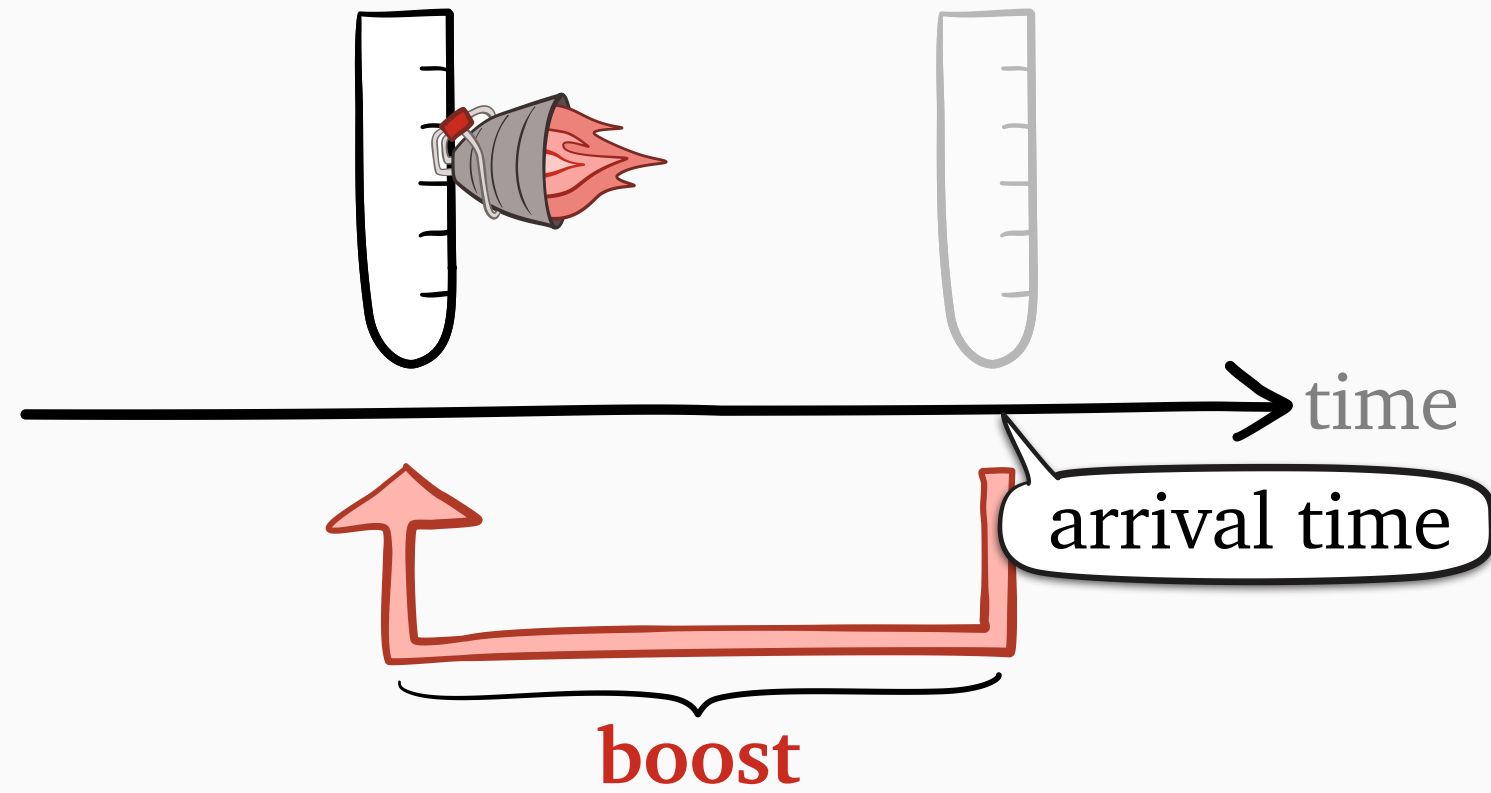
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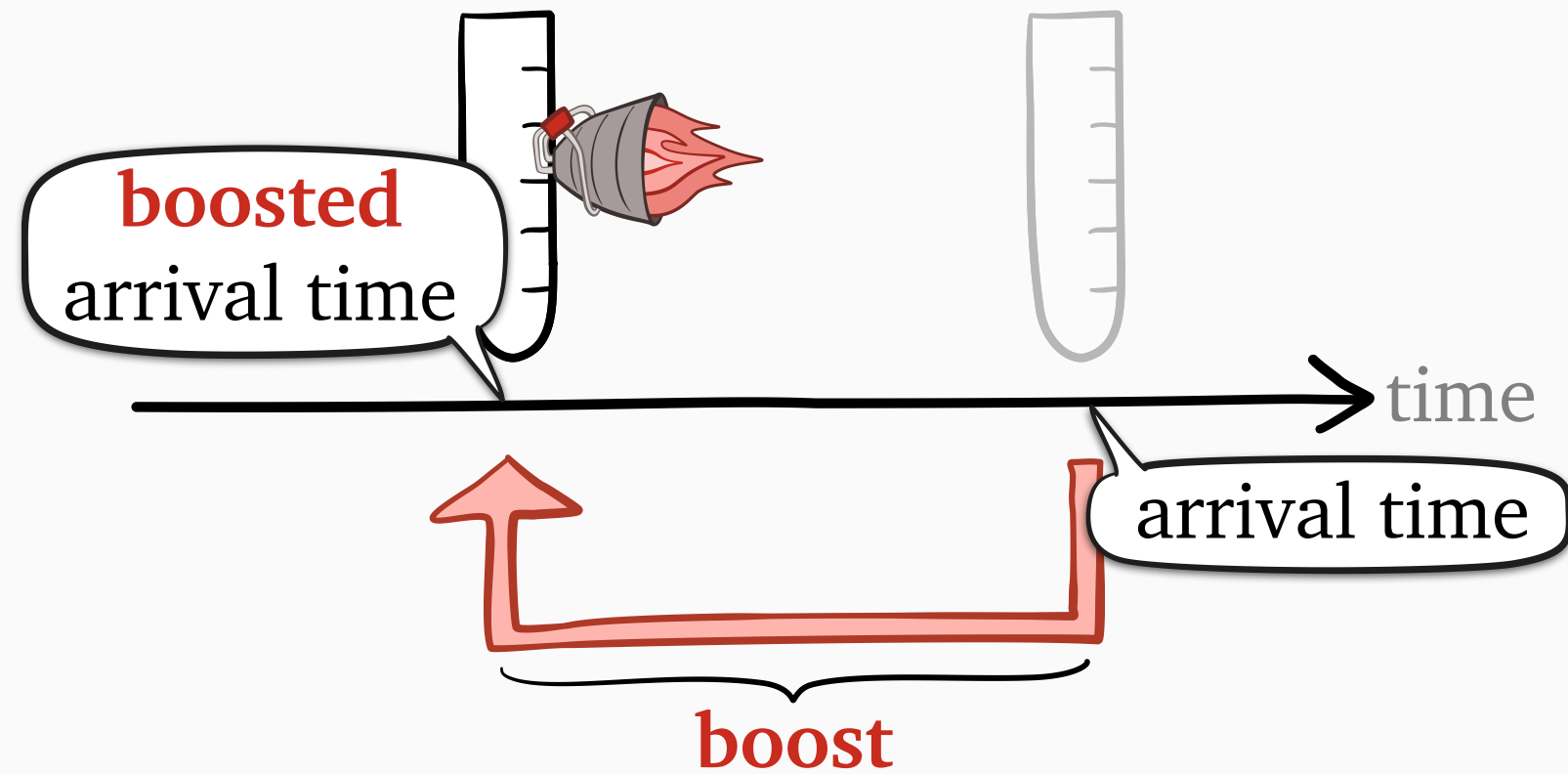
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Combining arrival time and size



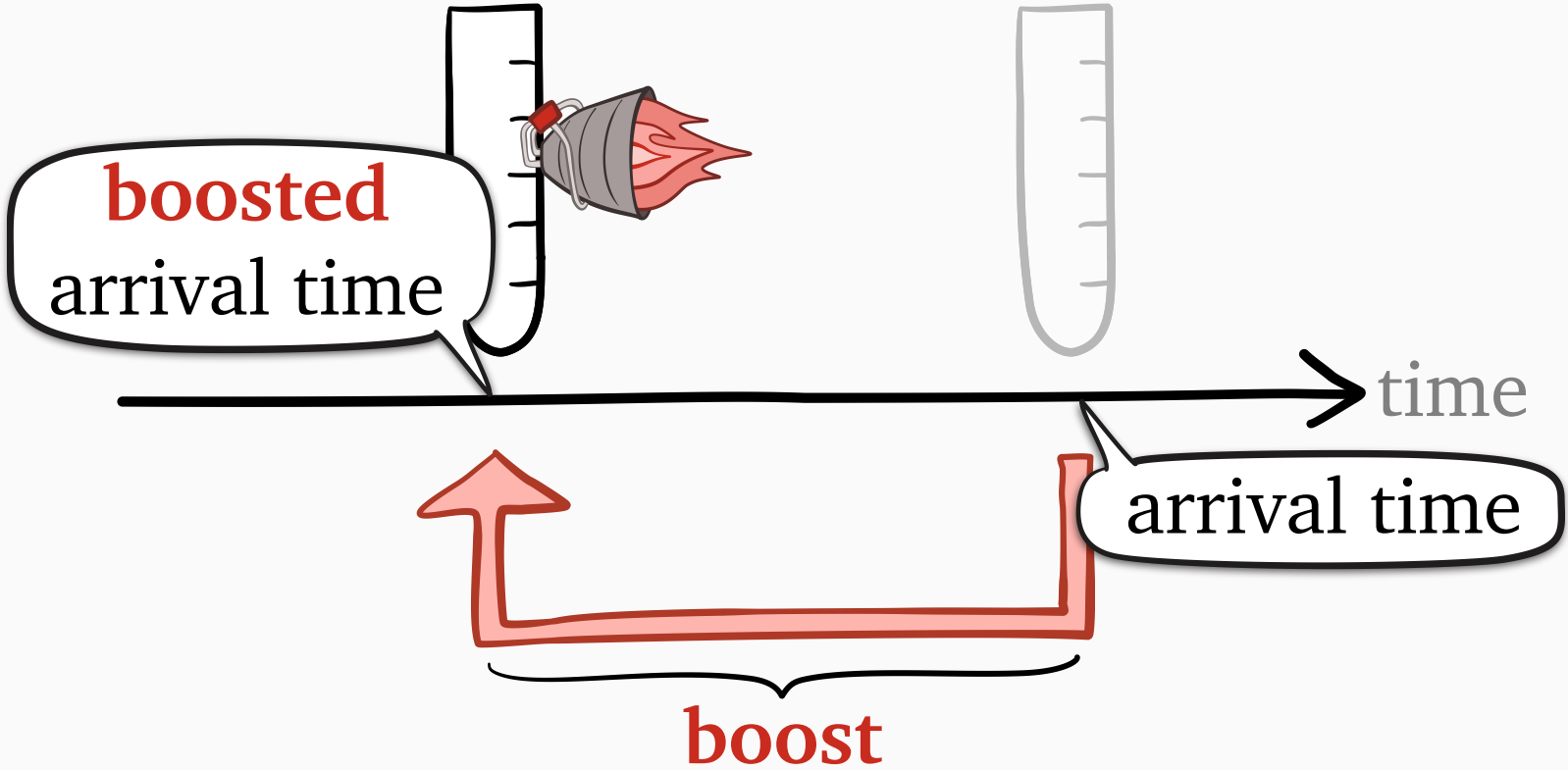
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Combining arrival time and size



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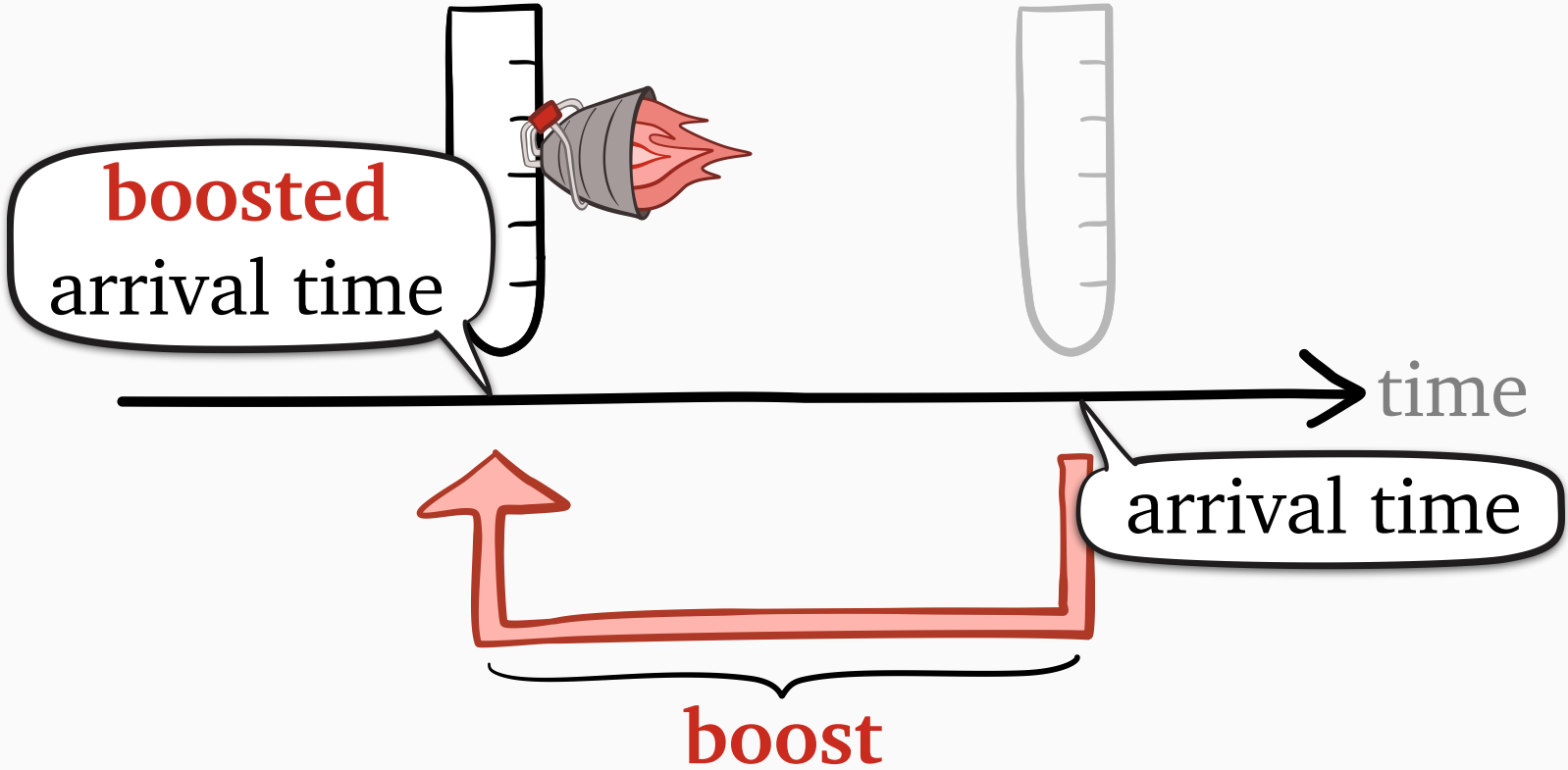
Combining arrival time and size



boosted arrival time
= arrival time - **boost**(size)

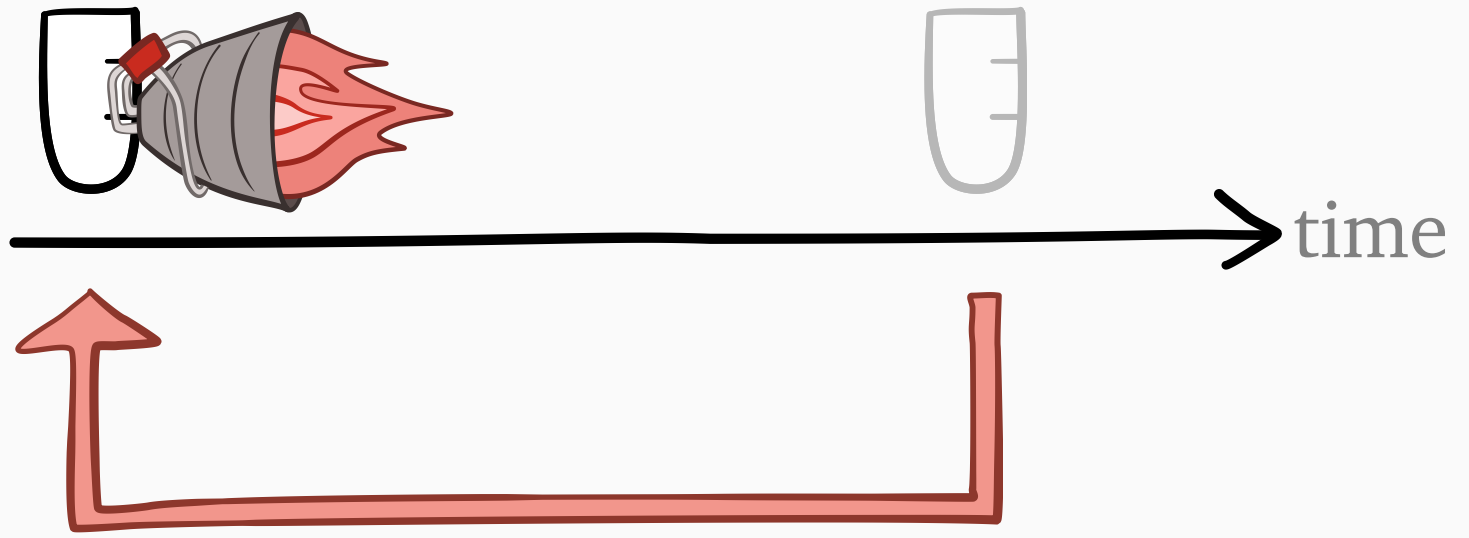
smaller sizes get bigger boosts

Combining arrival time and size

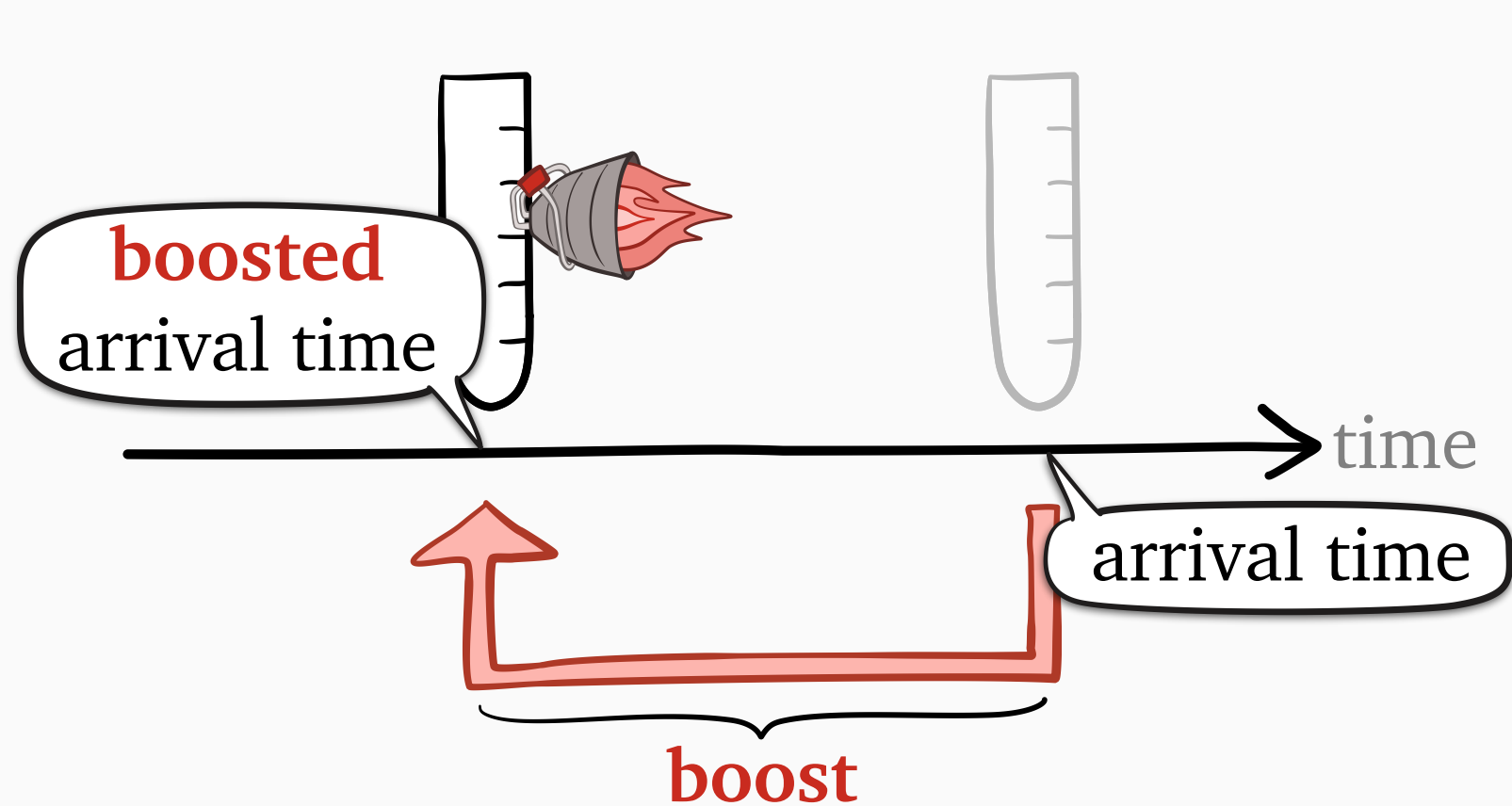


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$$\text{boosted arrival time} = \text{arrival time} - \text{boost}(\text{size})$$

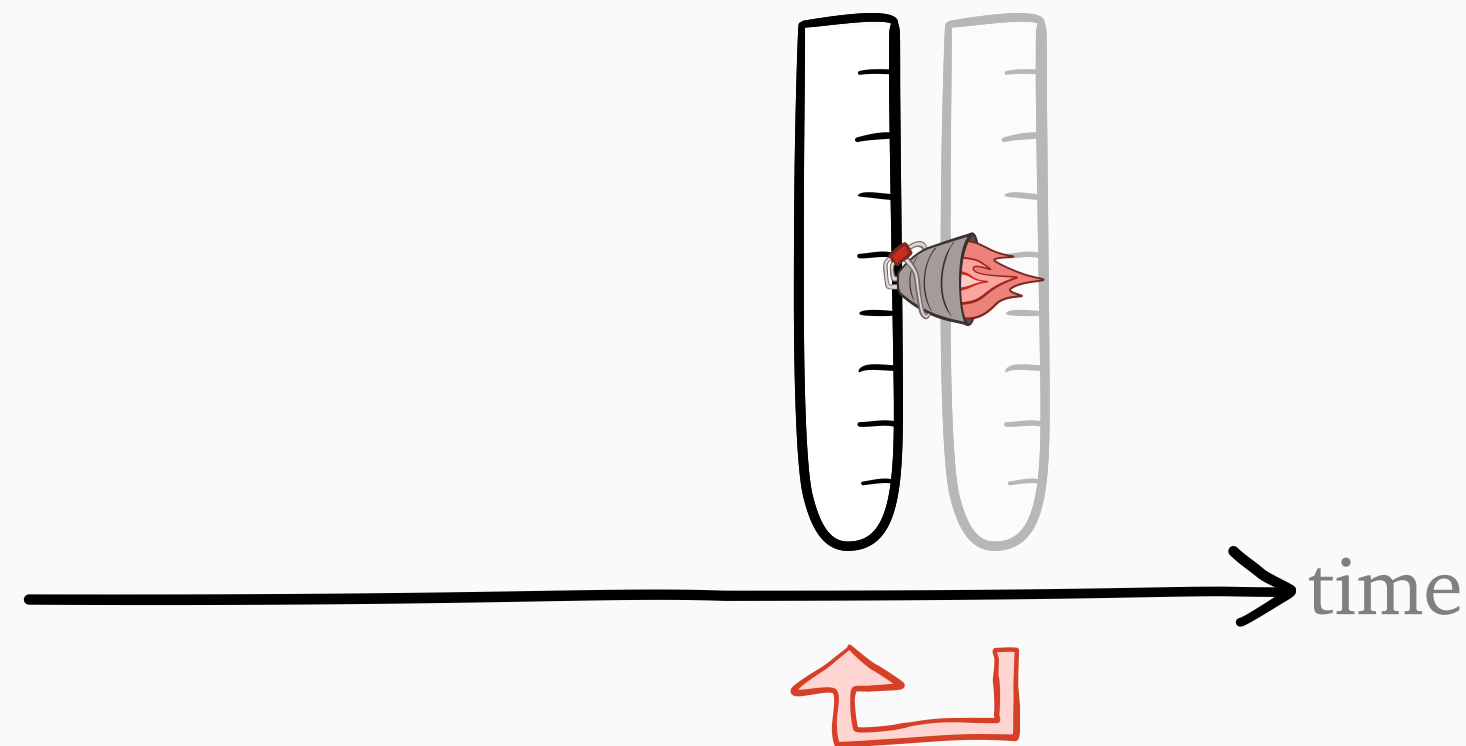
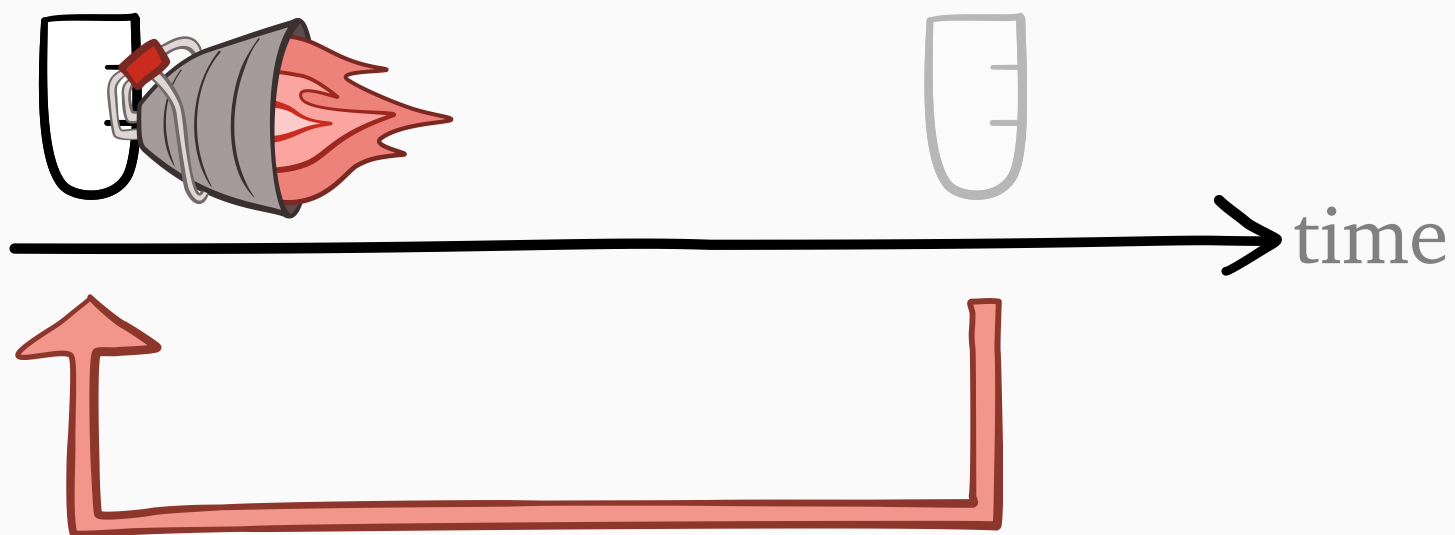


Combining arrival time and size

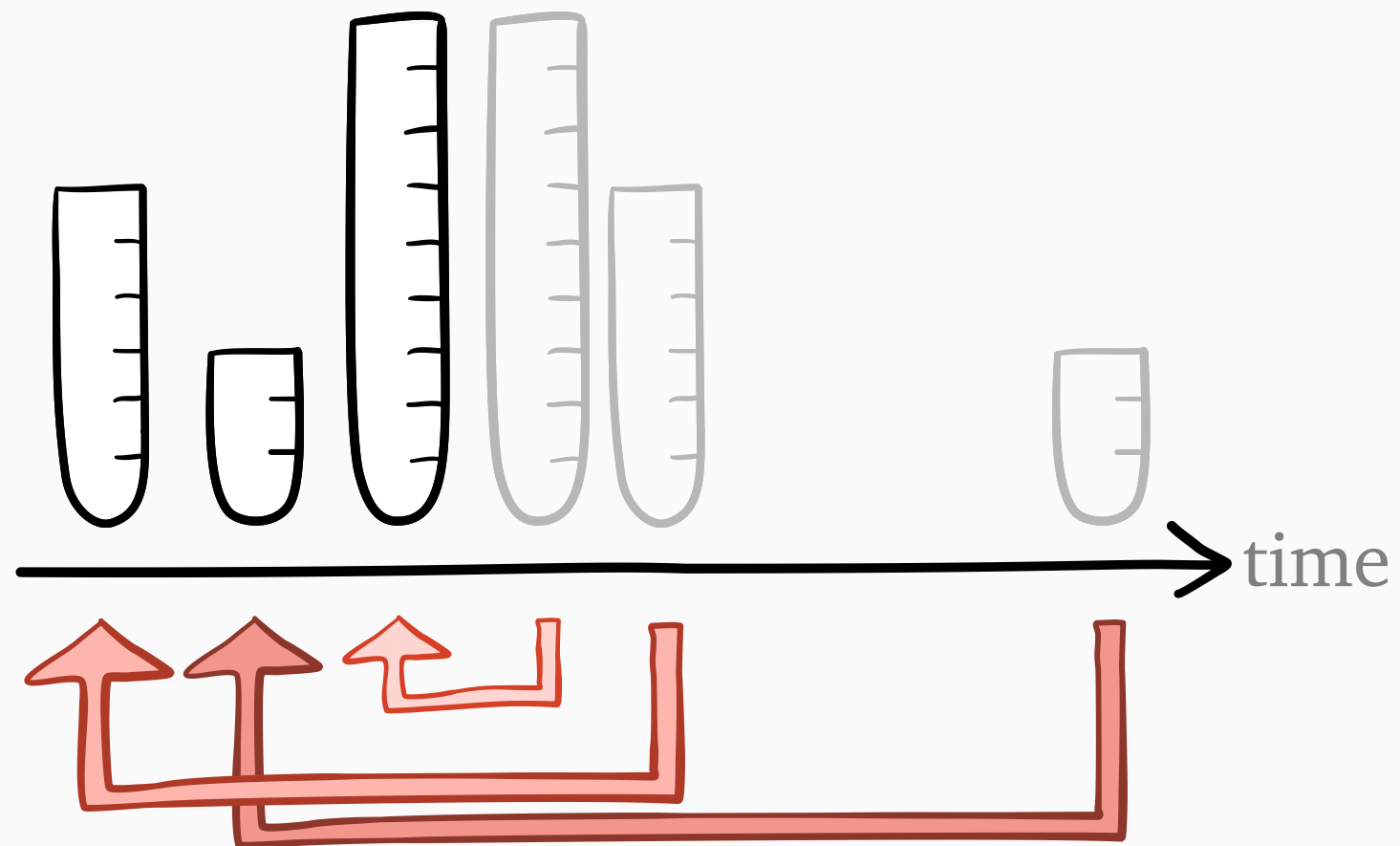


boosted arrival time
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smaller sizes get bigger boosts

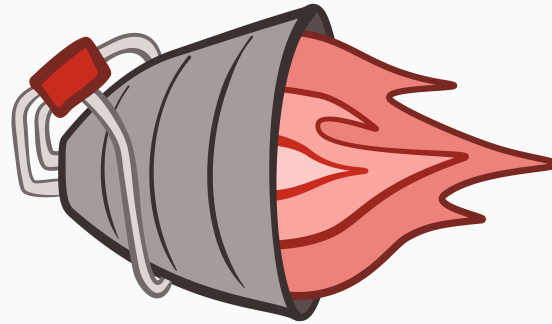


Boost policies

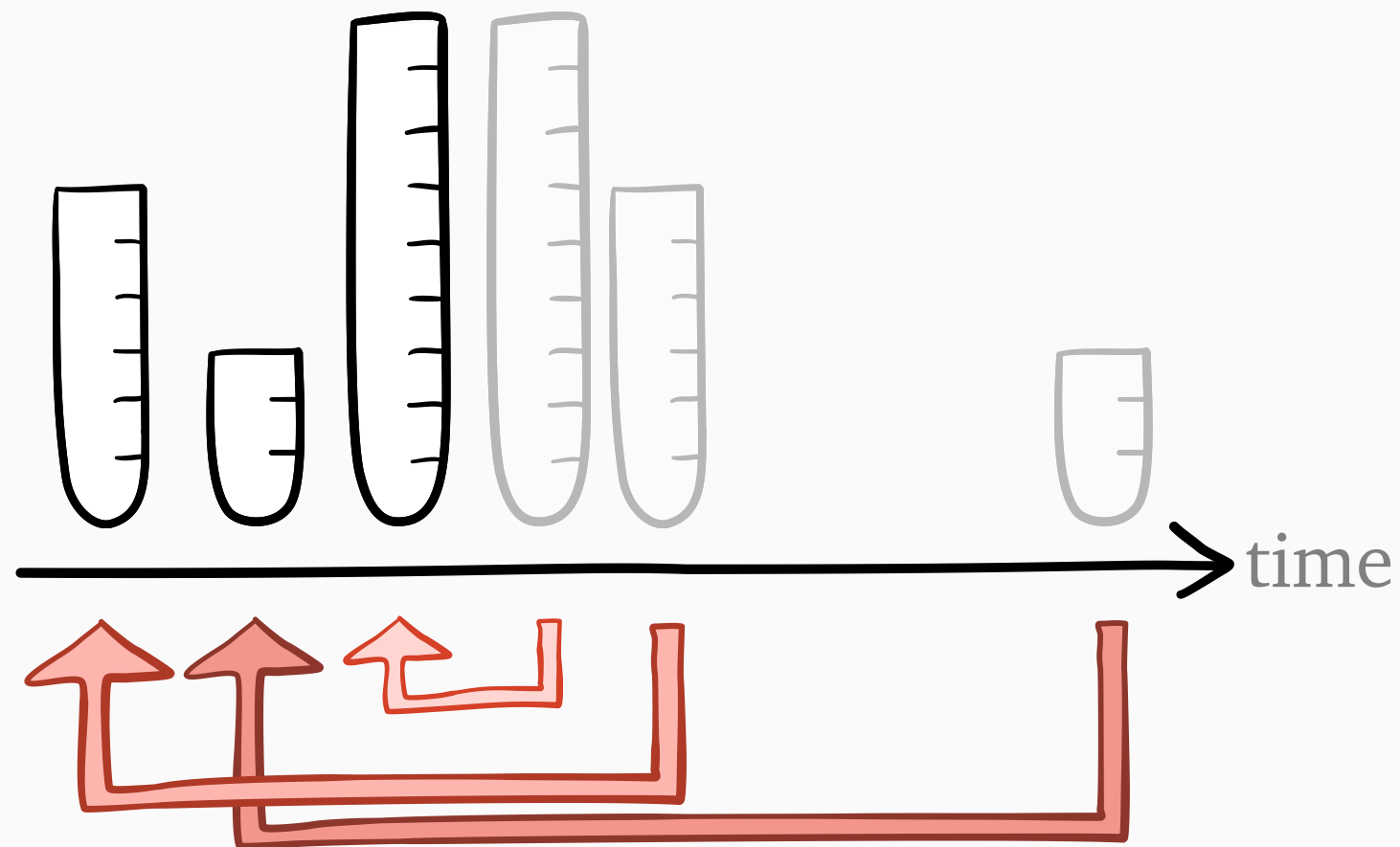


boosted arrival time
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Boost policies

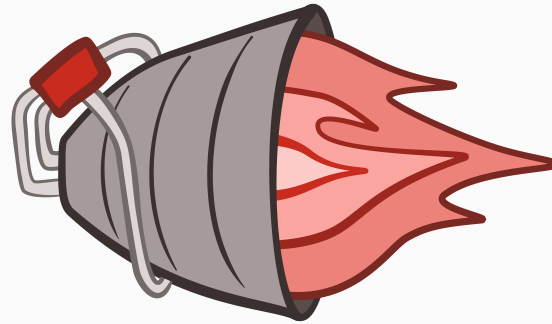


Scheduling rule: always serve job of *minimum **boosted** arrival time*

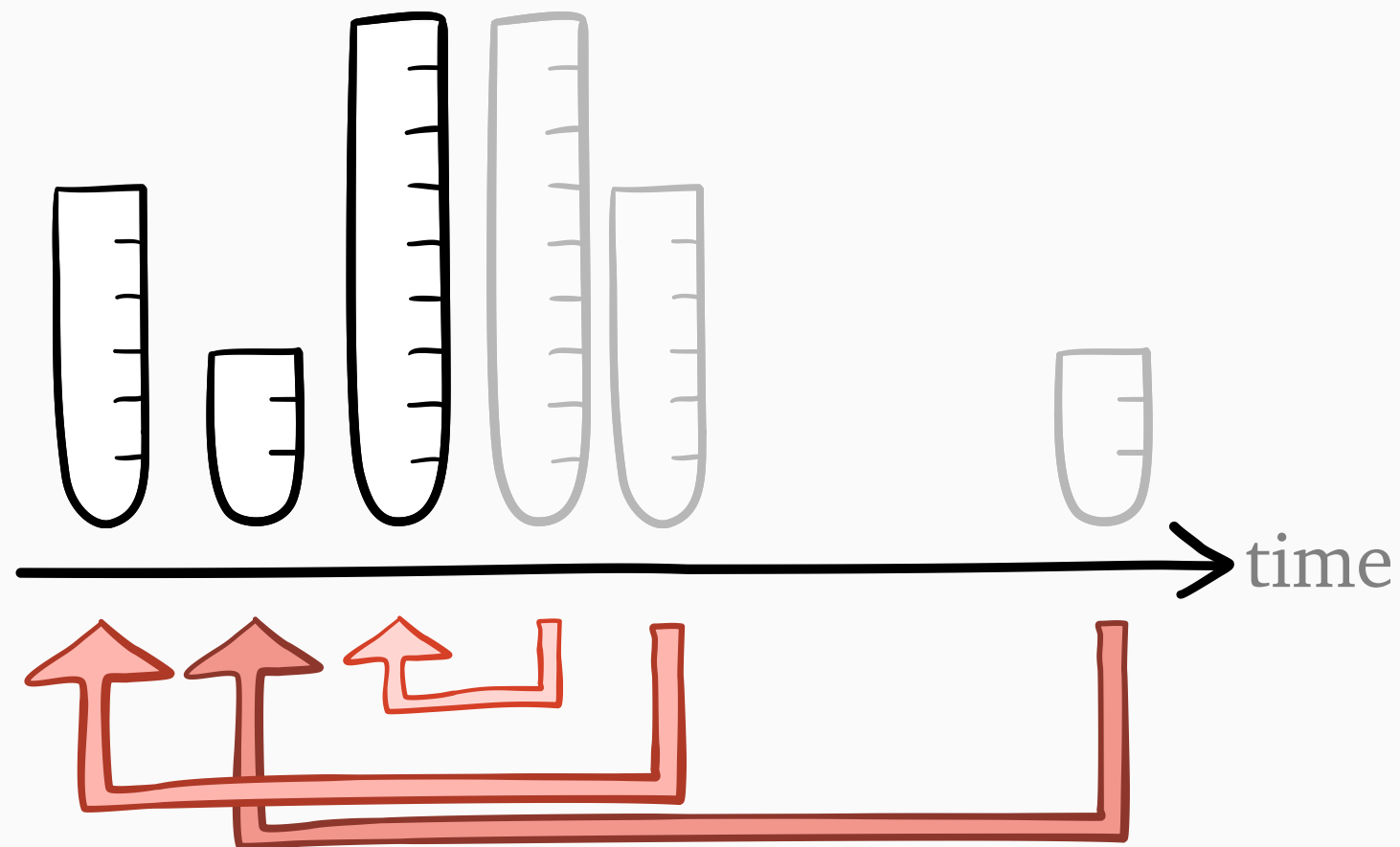


boosted arrival time
= arrival time - **boost**(size)

Boost policies



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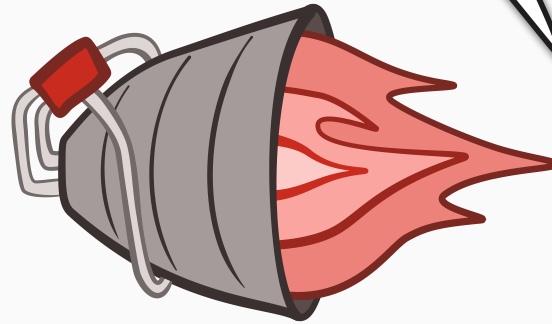


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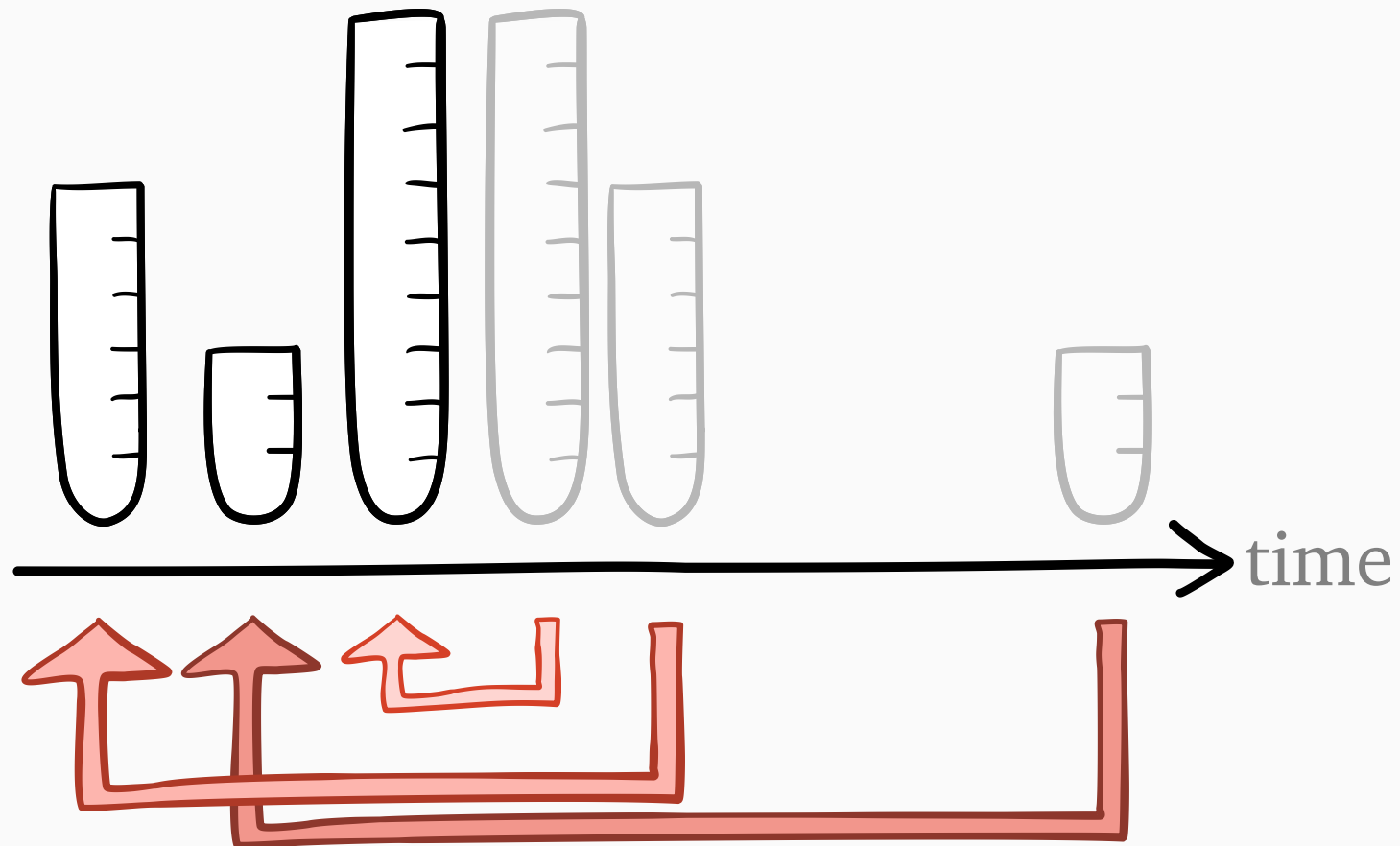
can vary choice of **boost** function

Boost policies

can be preemptive
or nonpreemptive



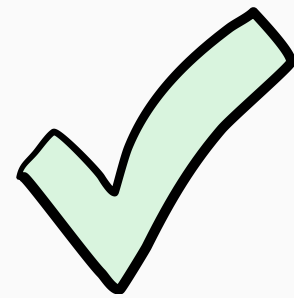
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Boost



Why is achieving strong tail optimality hard?



How does the **Boost** policy family work?



How do we achieve strong tail optimality?

Boost

✓ Why is achieving strong tail optimality hard?

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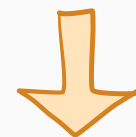
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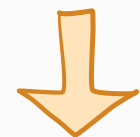
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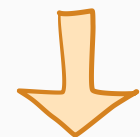
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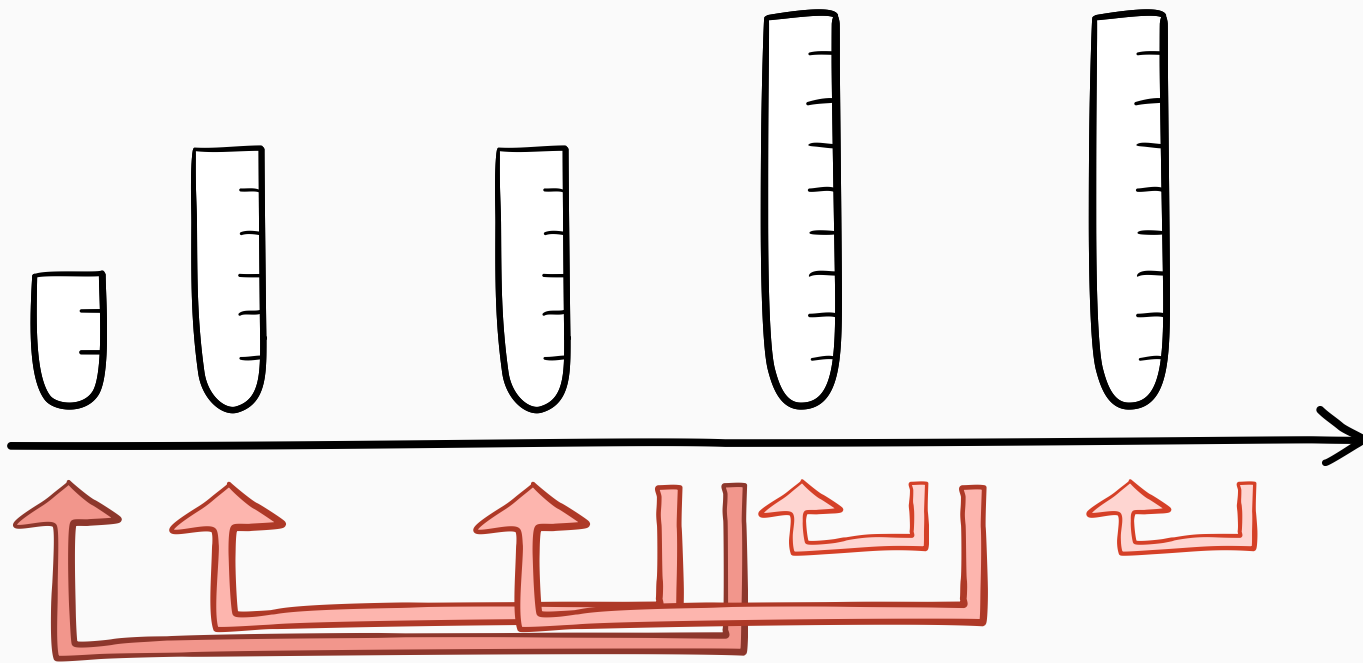
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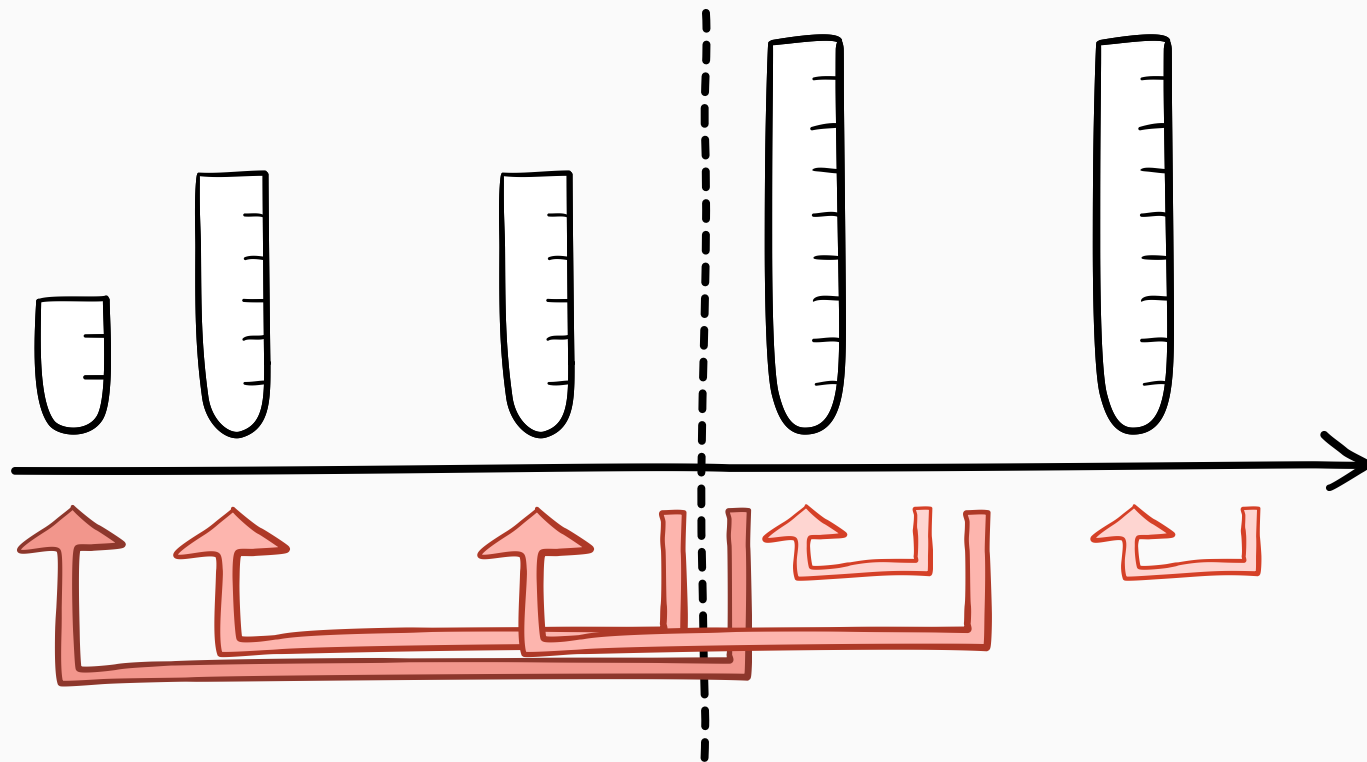
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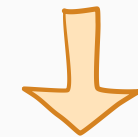
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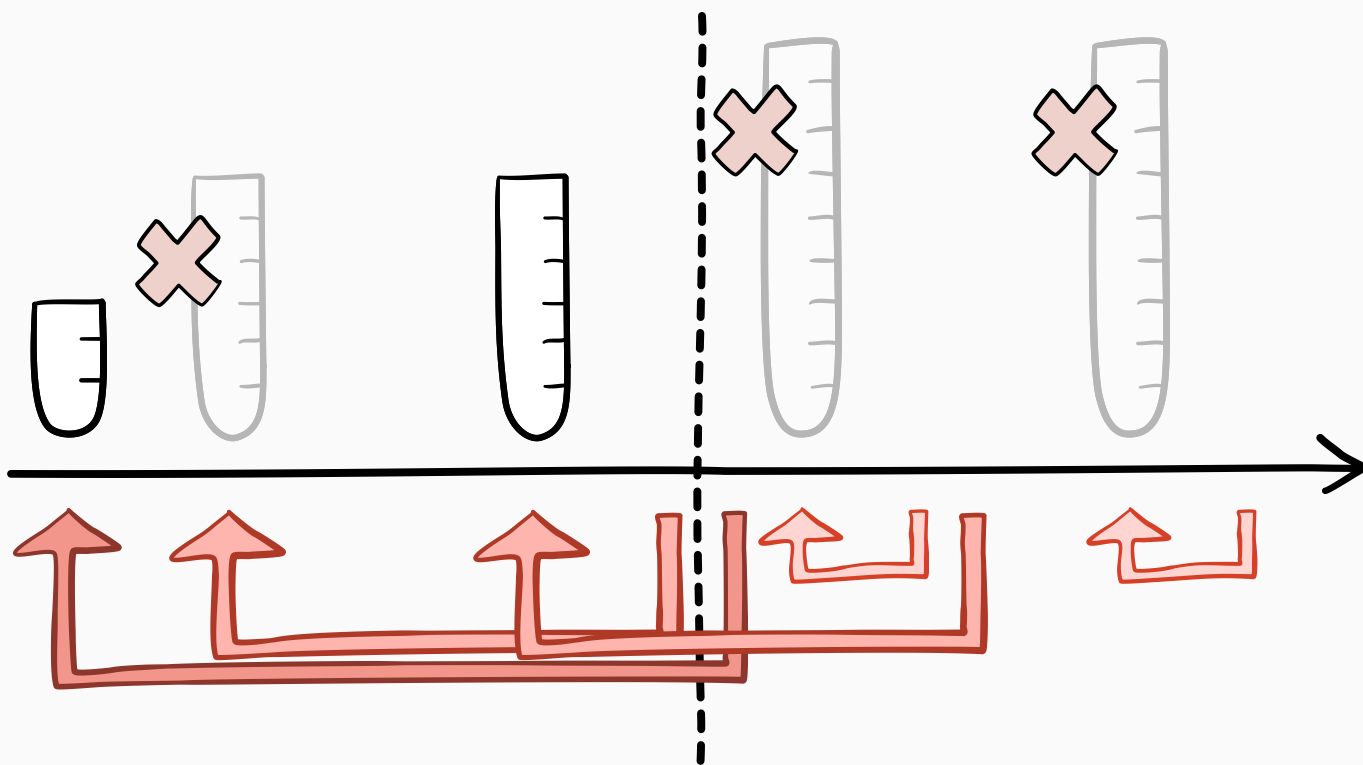
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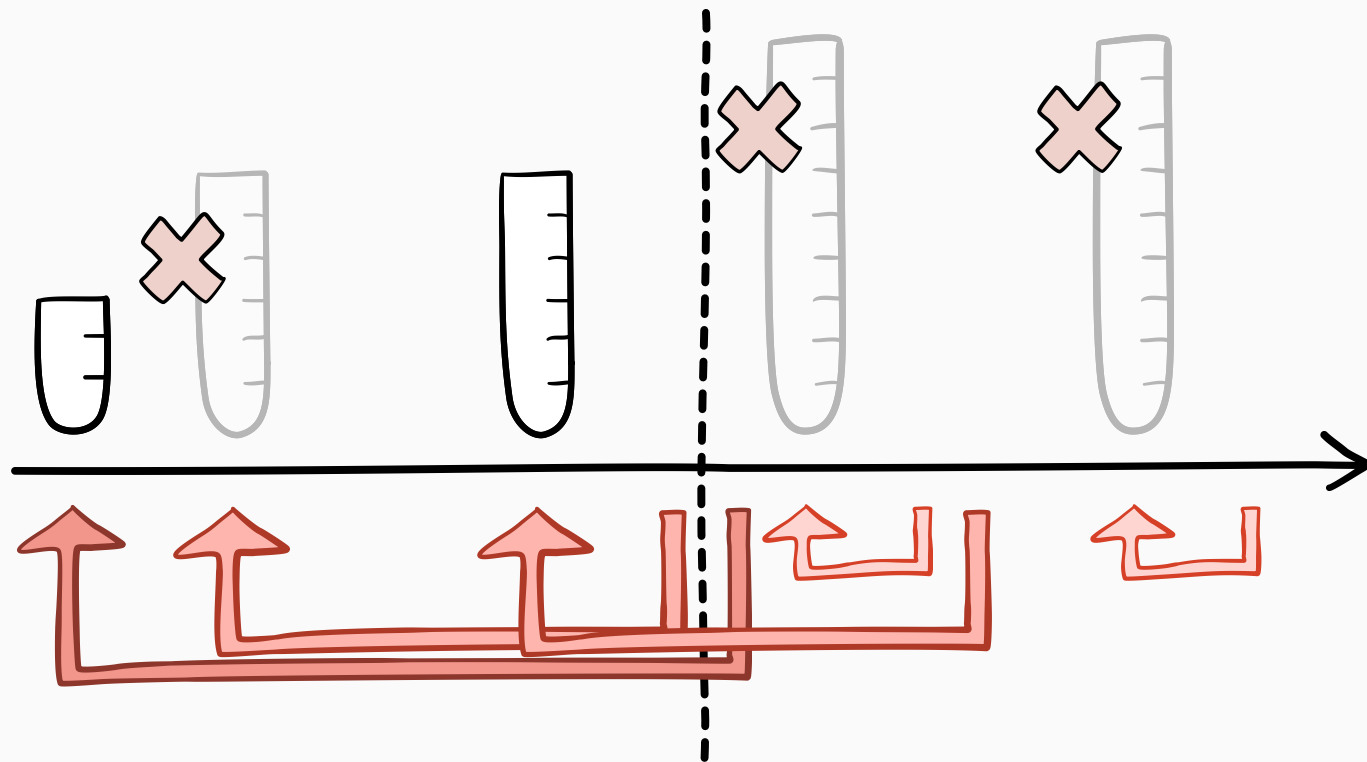
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Lemma: finite if $b(s) = O(1/s)$

A path to strong tail optimality

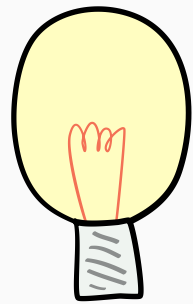
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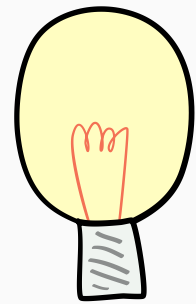
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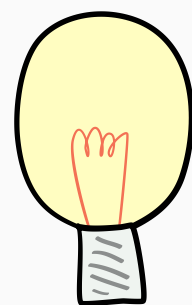


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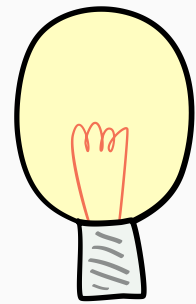
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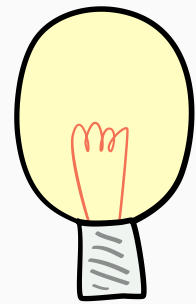
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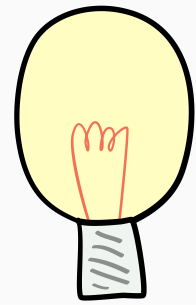
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almost classic problem

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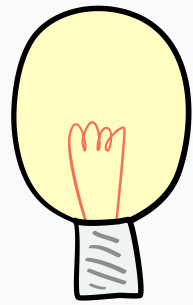
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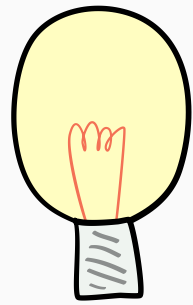
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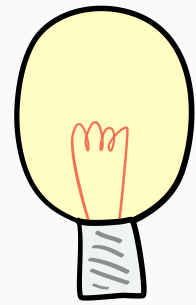


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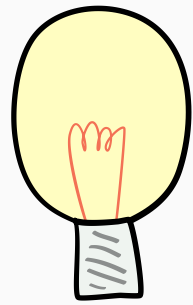


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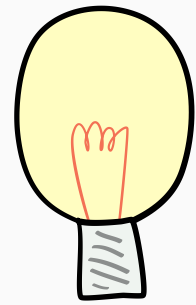


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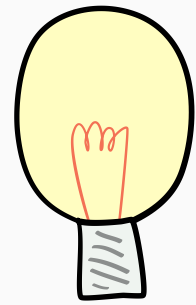


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Relaxation solved by WDSPT, which is **Boost** with

$$b(s) = \frac{1}{\gamma} \log \frac{1}{1 - e^{-\gamma s}}$$

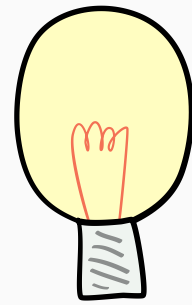


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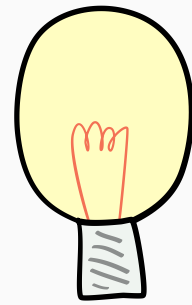


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$a_i =$ arrival

$d_i =$ depart

Unknown sizes:
swap WDSPT for Gittins

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Boost

✓ Why is achieving strong tail optimality hard?

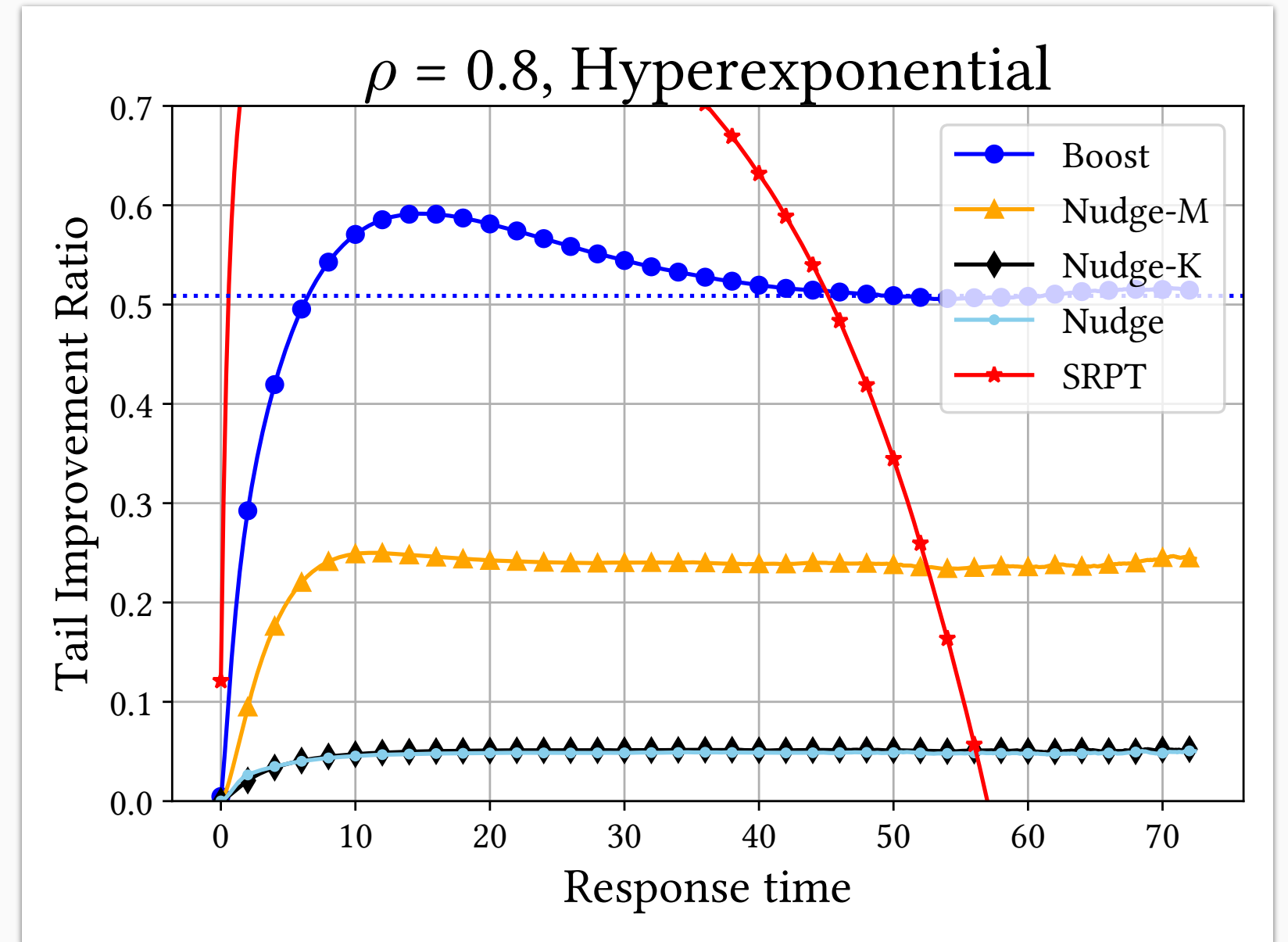
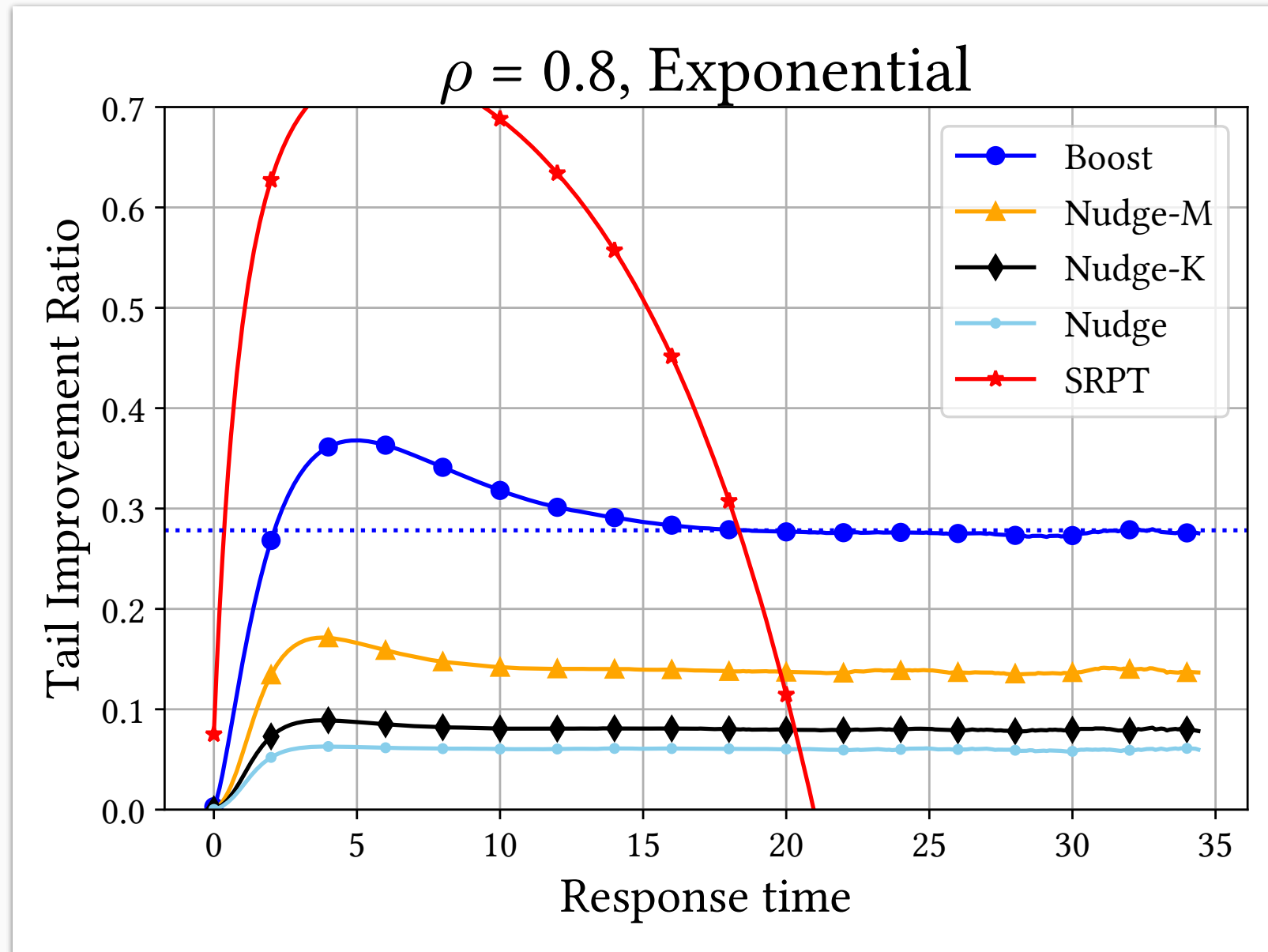
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? How do we achieve strong tail optimality?

Boost

- ✓ Why is achieving strong tail optimality hard?
- ✓ How does the **Boost** policy family work?
- ✓ How do we achieve strong tail optimality?

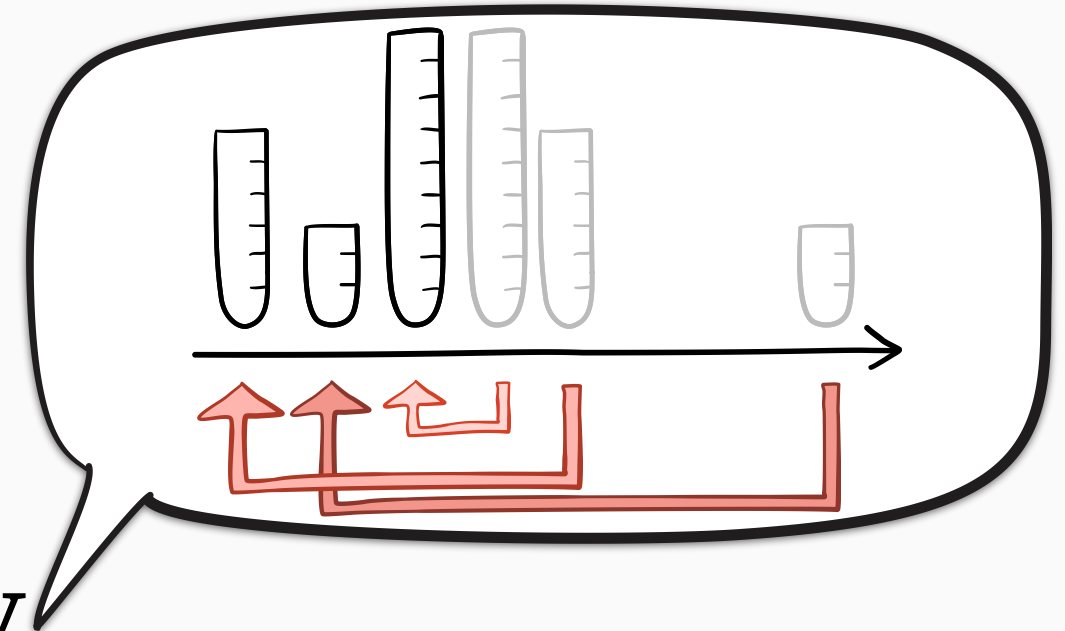
Empirical performance



Our contributions:



Design the **Boost** scheduling policy



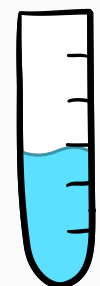
Analyze **Boost**'s performance

all instances

specific instance called **γ -Boost**



Prove **Boost** is *strongly tail-optimal* for light-tailed sizes



Known job sizes

Yu & Scully. *Strongly Tail-Optimal Scheduling in the Light-Tailed M/G/1*. SIGMETRICS 2024.



Unknown job sizes

Harlev, Yu, & Scully. *A Gittins Policy for Optimizing Tail Latency*. MAMA 2024.