

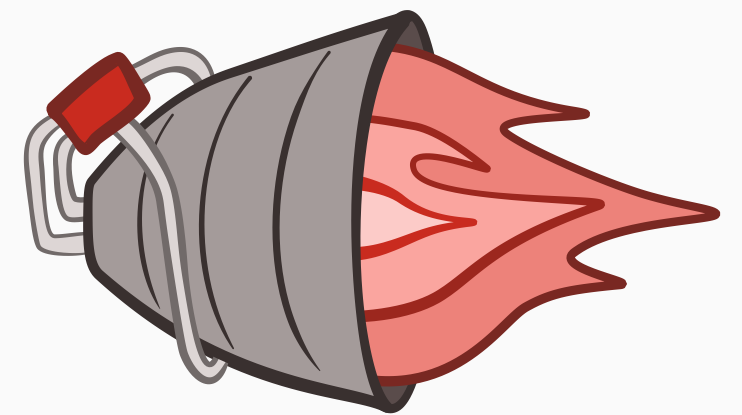
Strongly Tail-Optimal Scheduling *in the Light-Tailed $M/G/1$*

Ziv Scully Cornell ORIE

Joint work with

George Yu Cornell ORIE

Amit Harlev Cornell CAM



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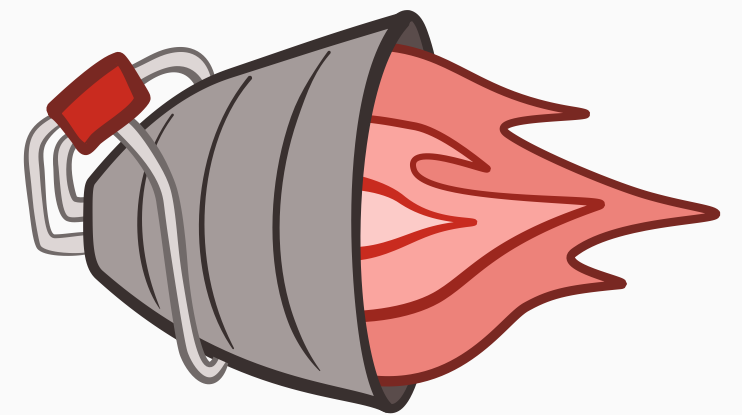
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Best paper award at
SIGMETRICS 2024



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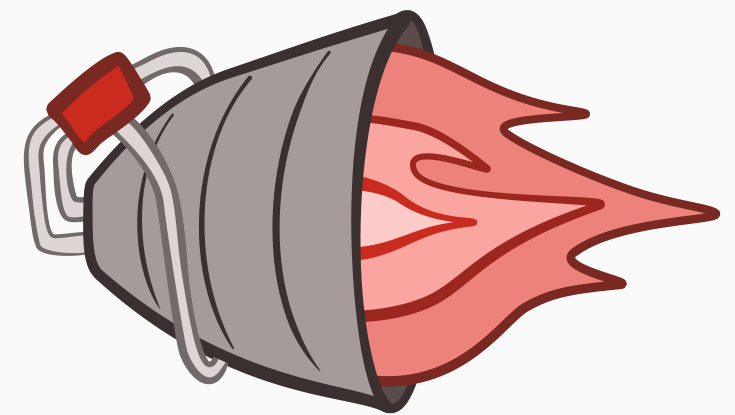
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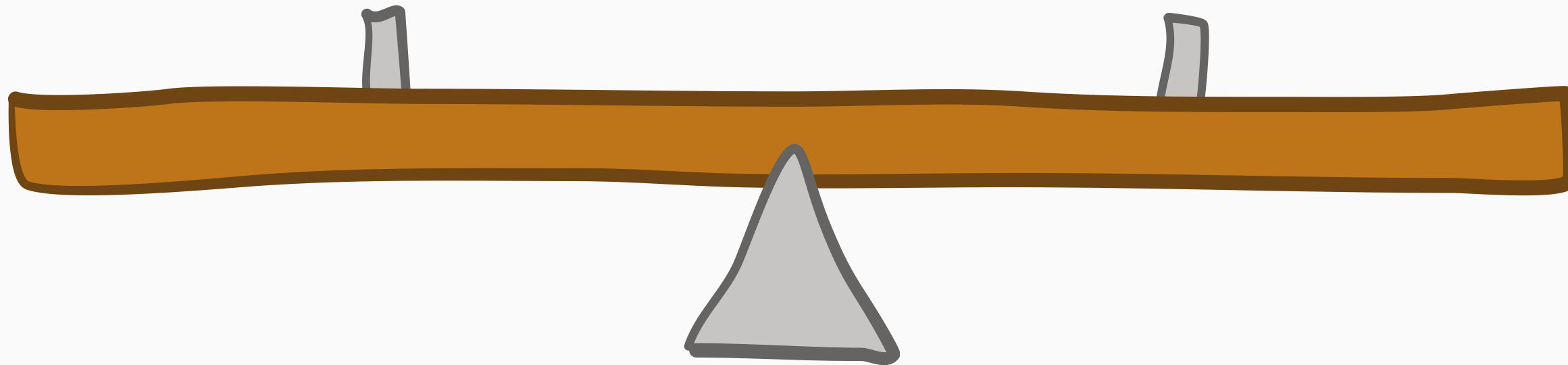


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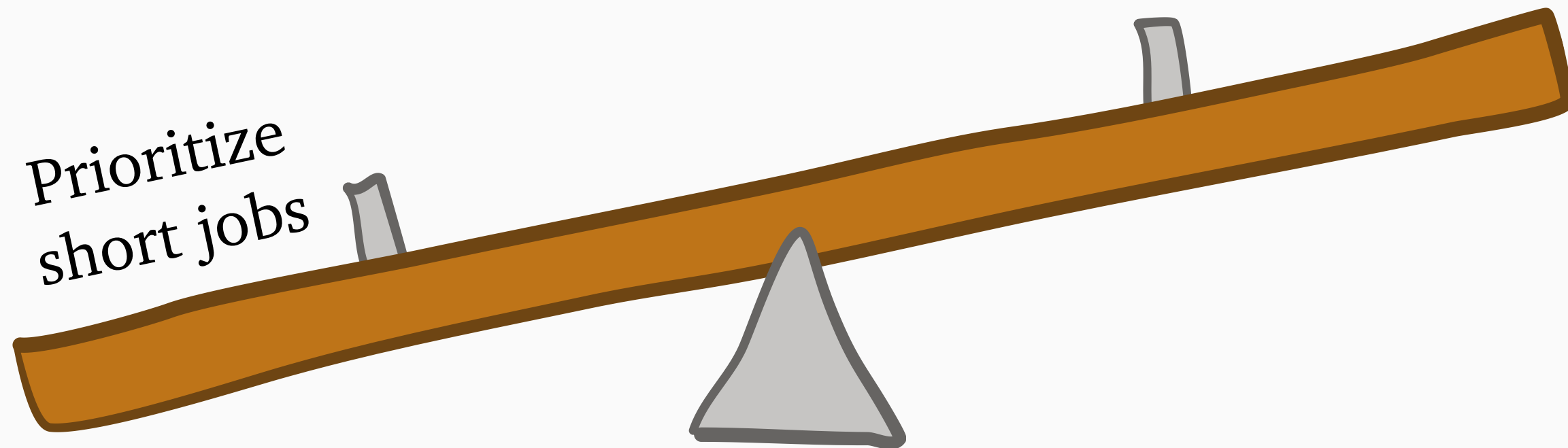
Preprint coming soon...



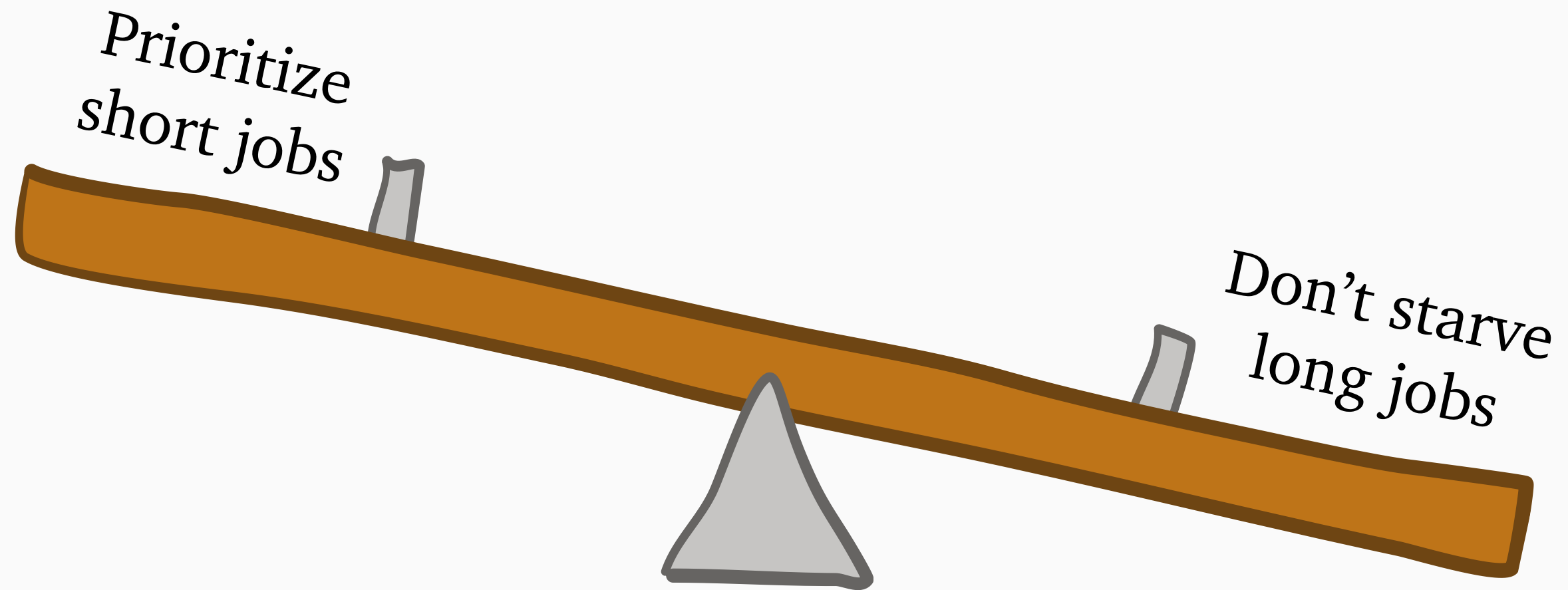
Tradeoff: priority vs. starvation



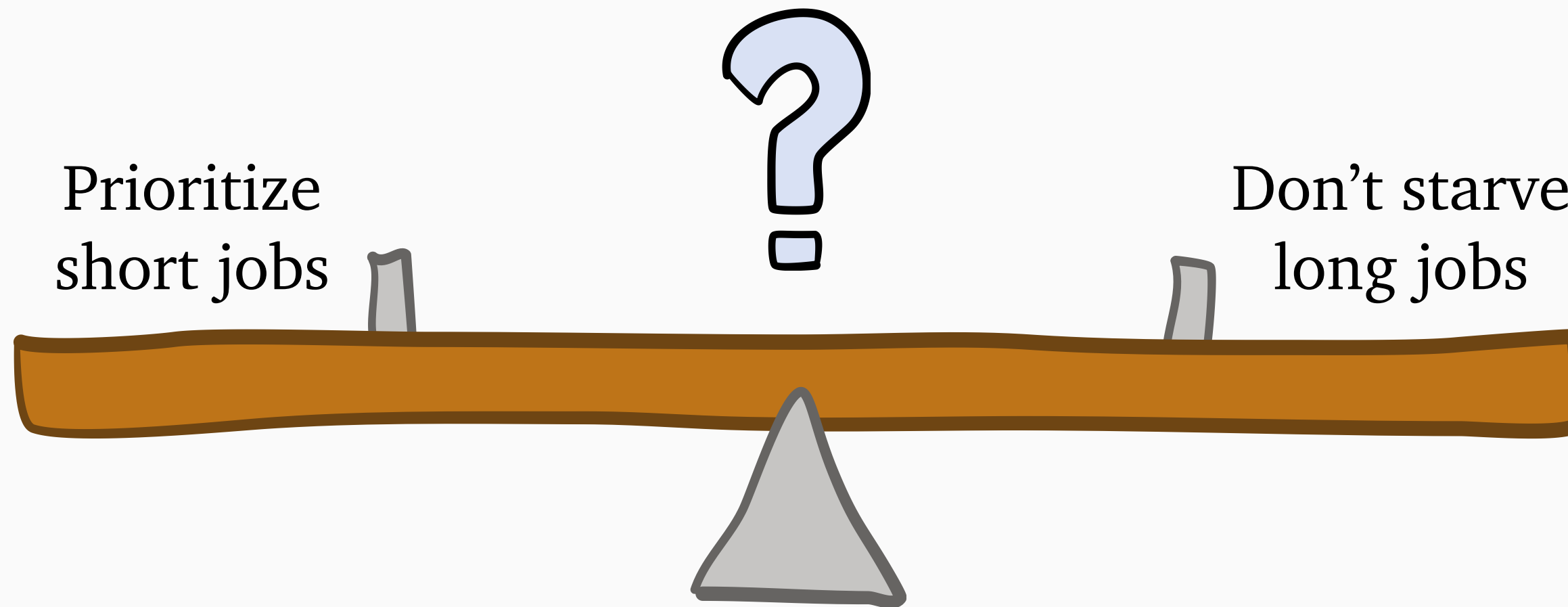
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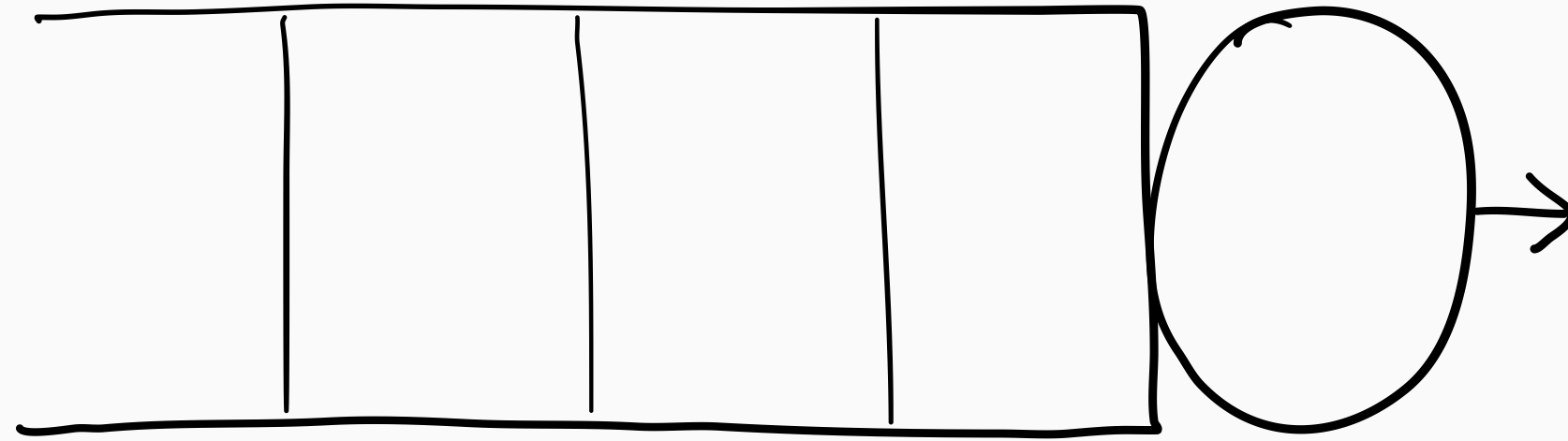


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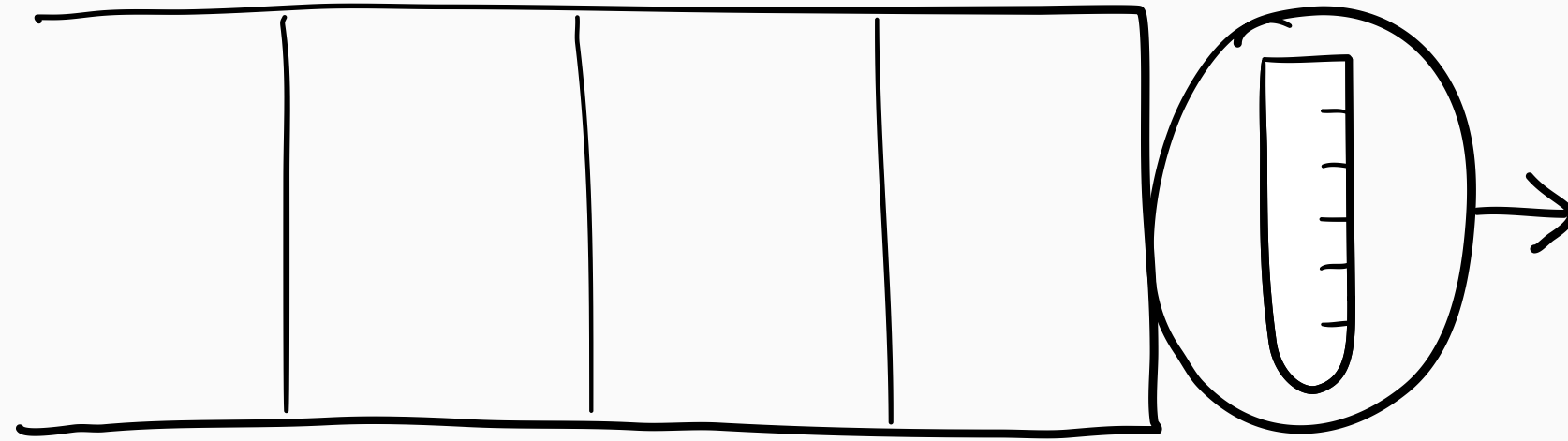


How should we schedule jobs to minimize delay?

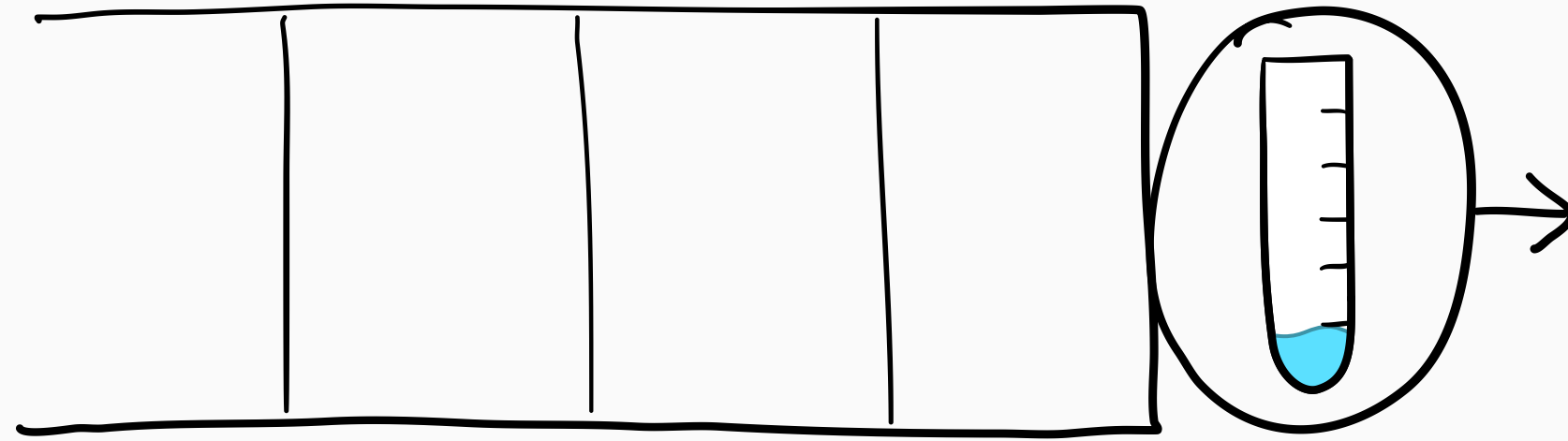
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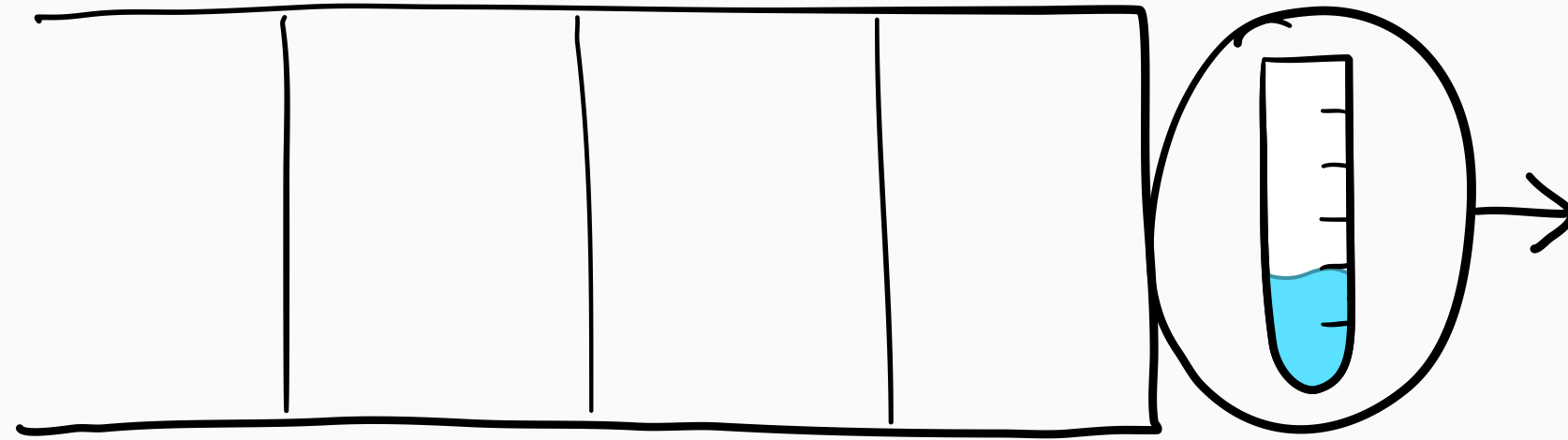
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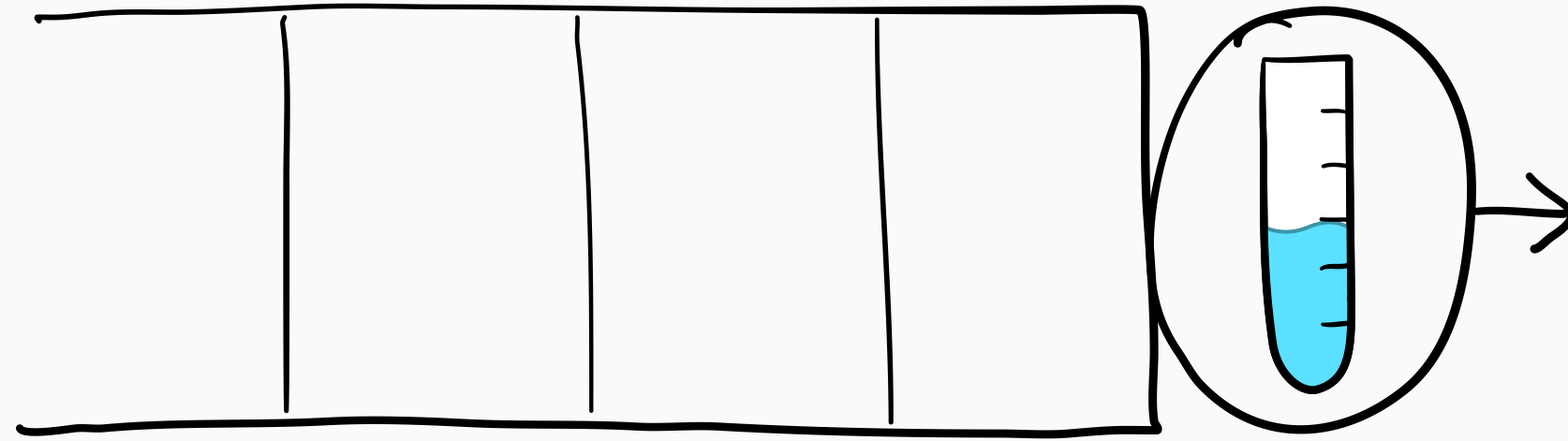
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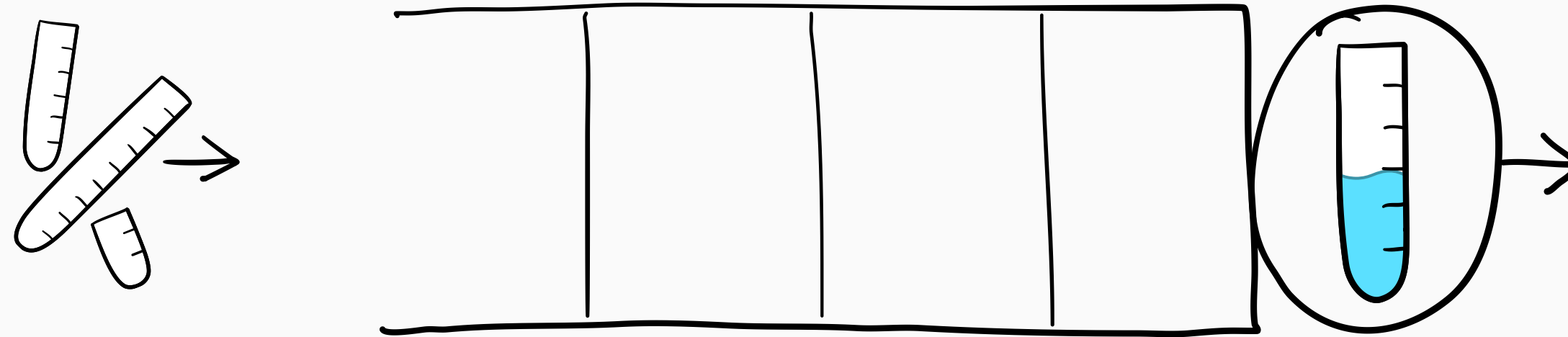
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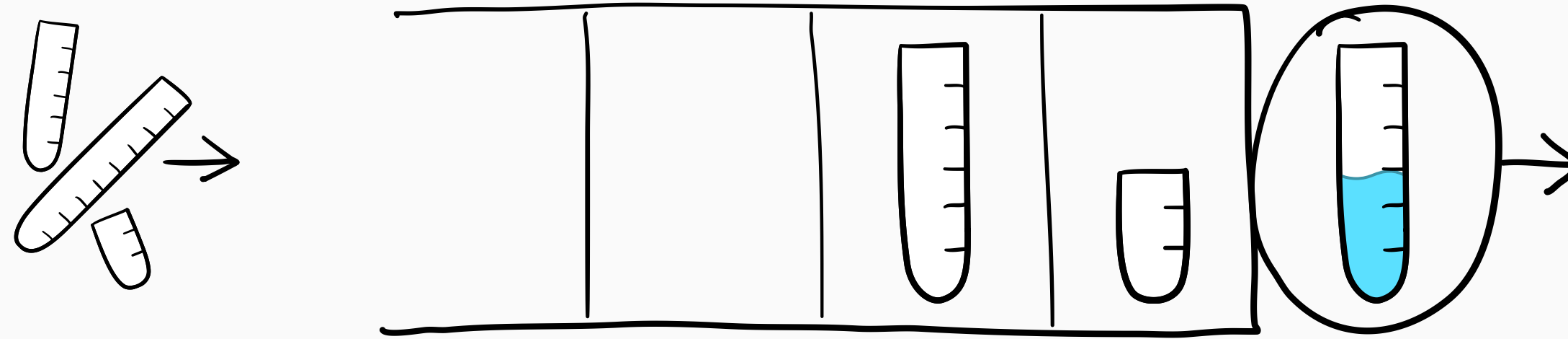
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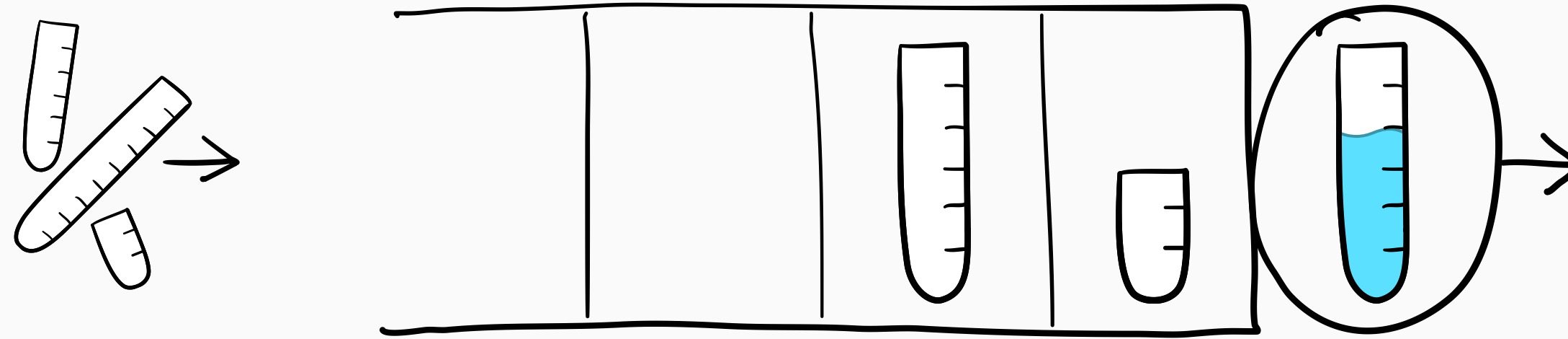
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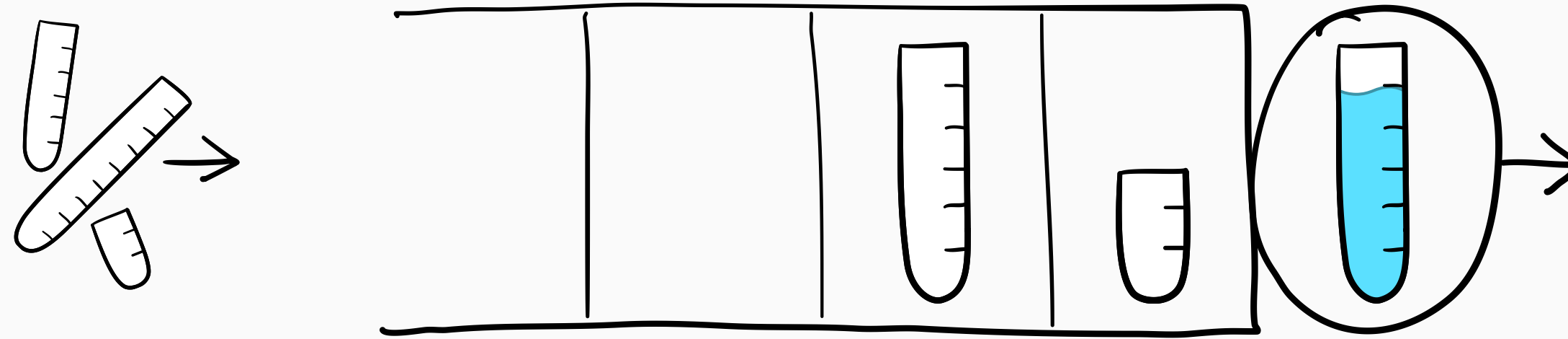
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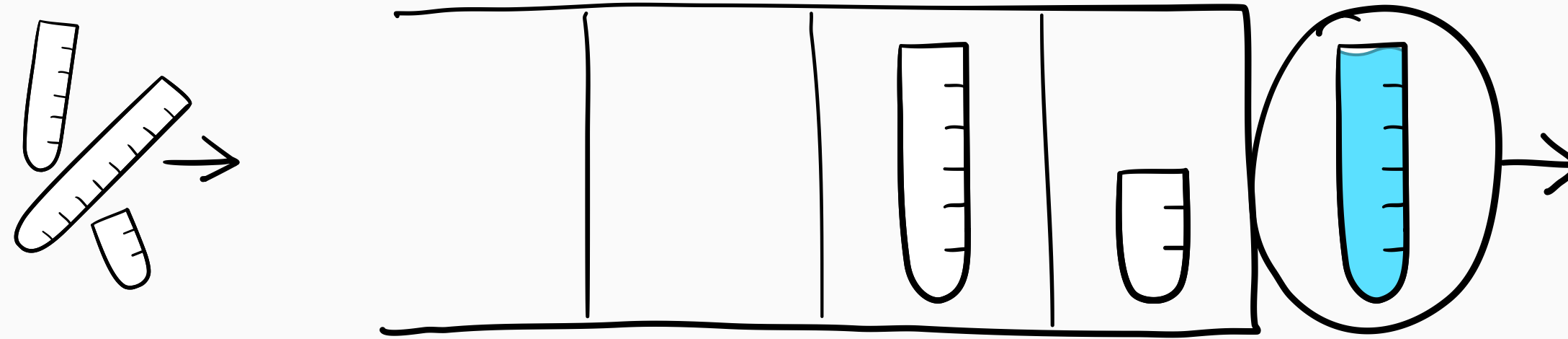
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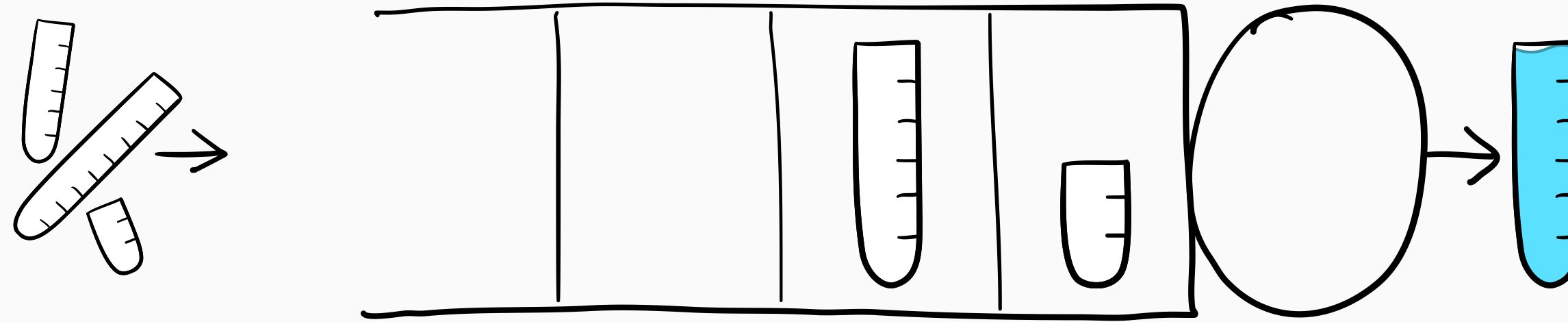
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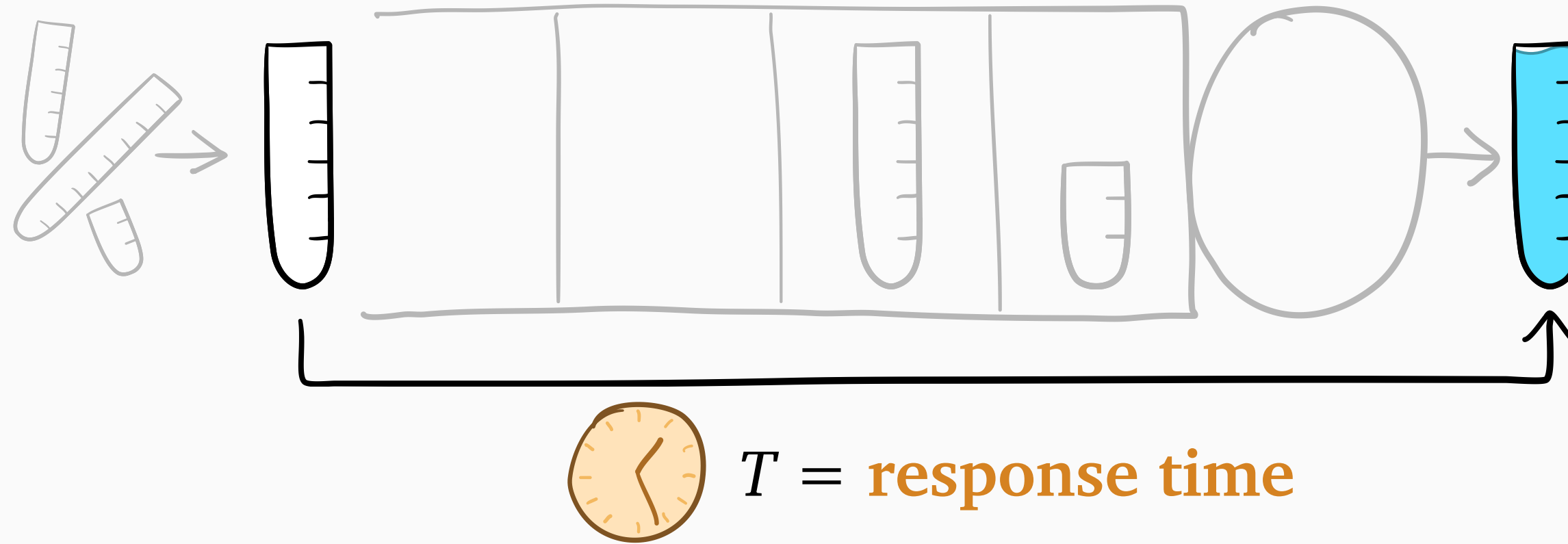
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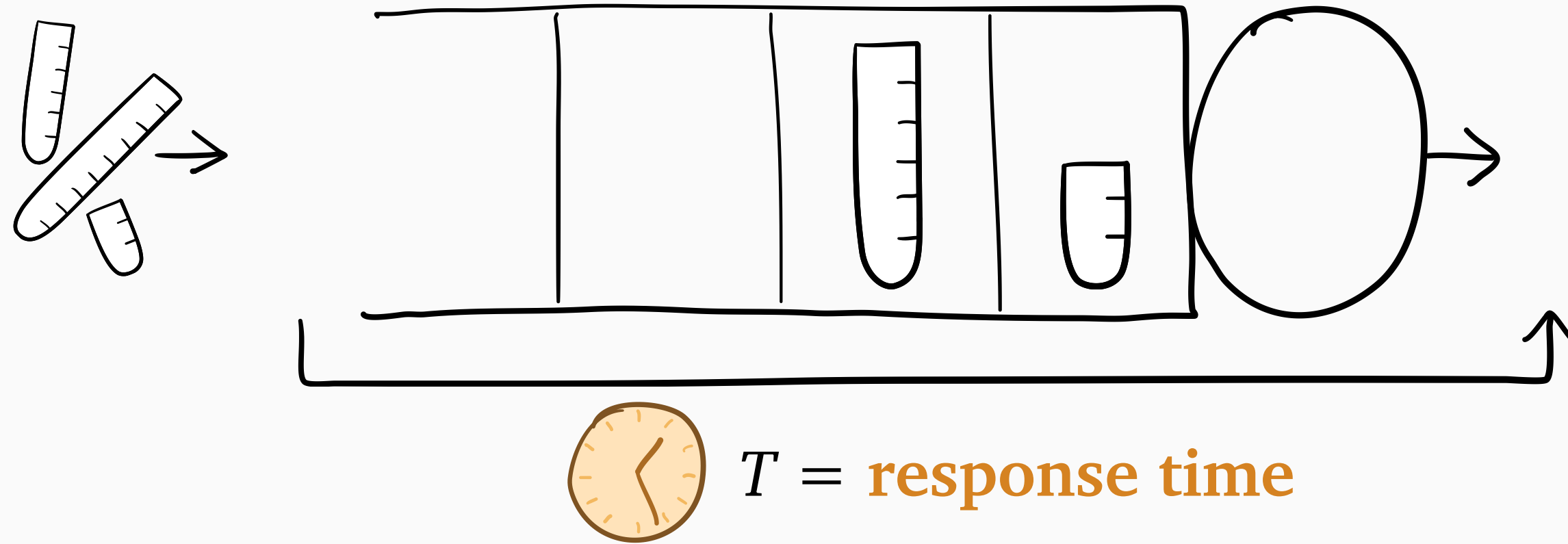
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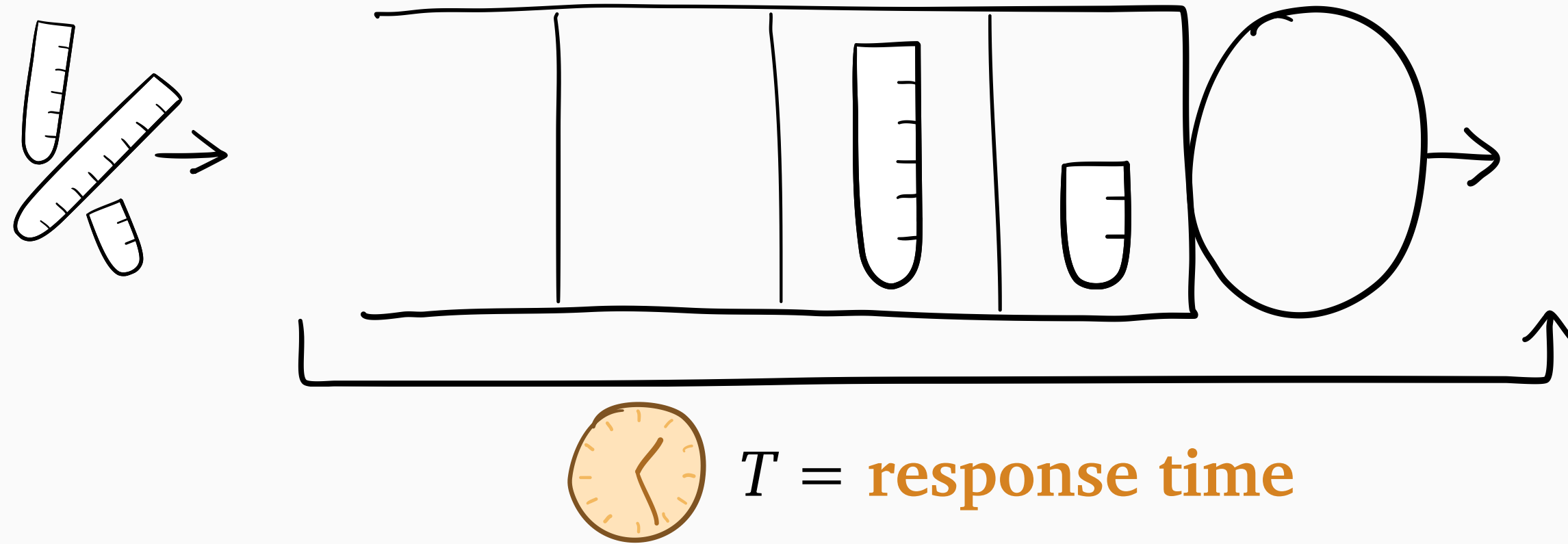
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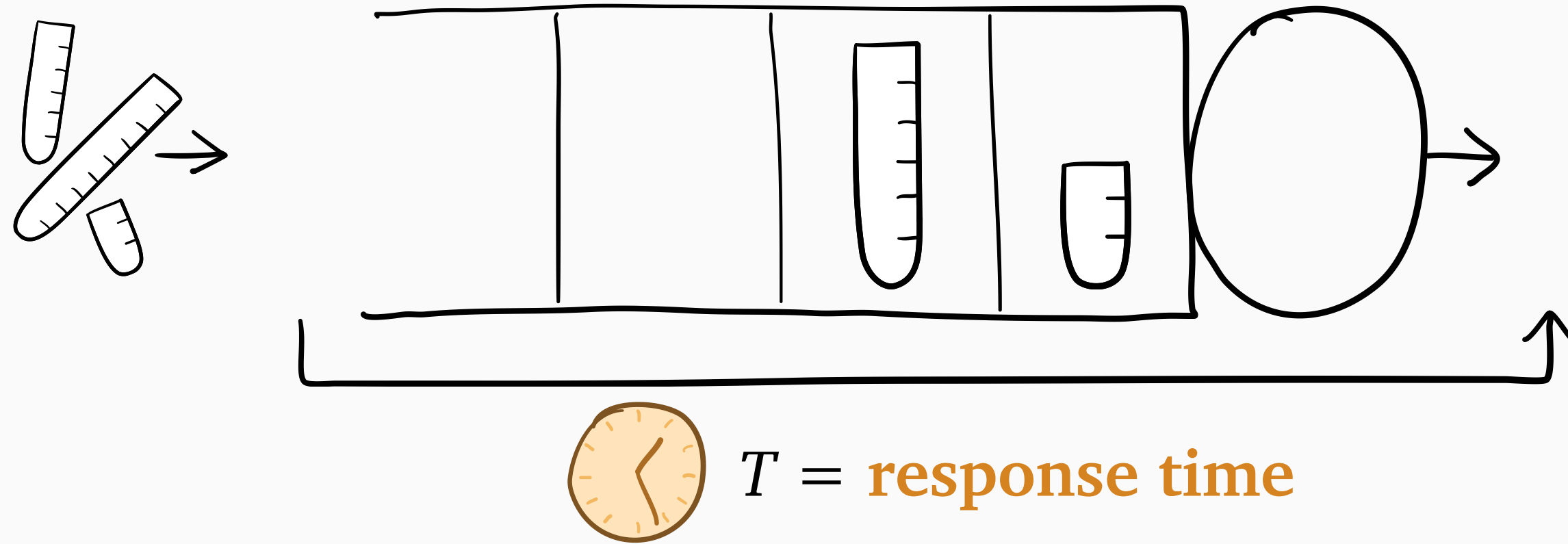


How should we schedule jobs to minimize delay?



? Minimize $E[T]$?

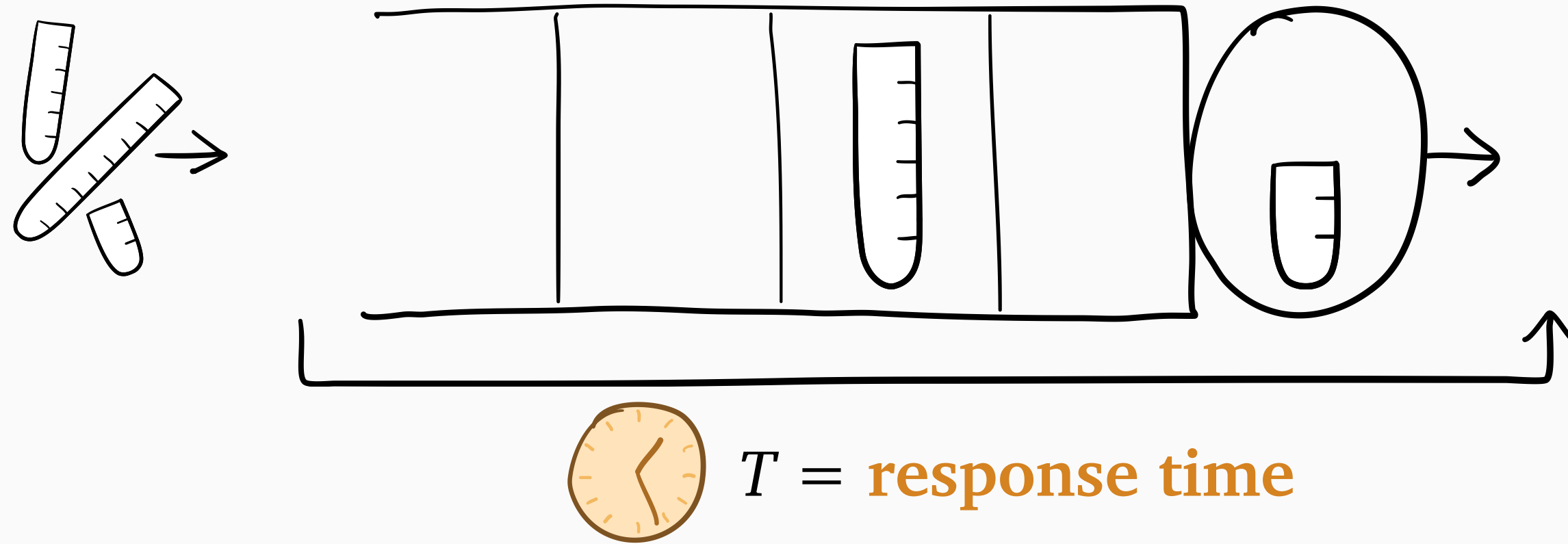
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💡 Serve short jobs
before long jobs

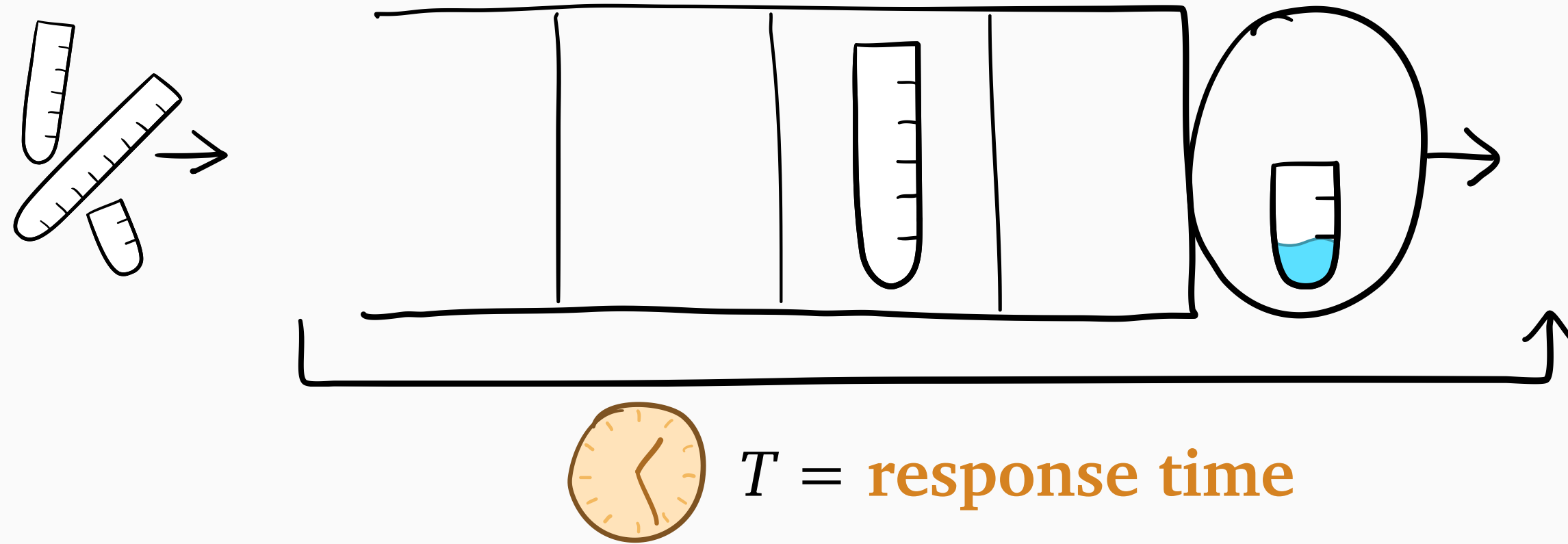
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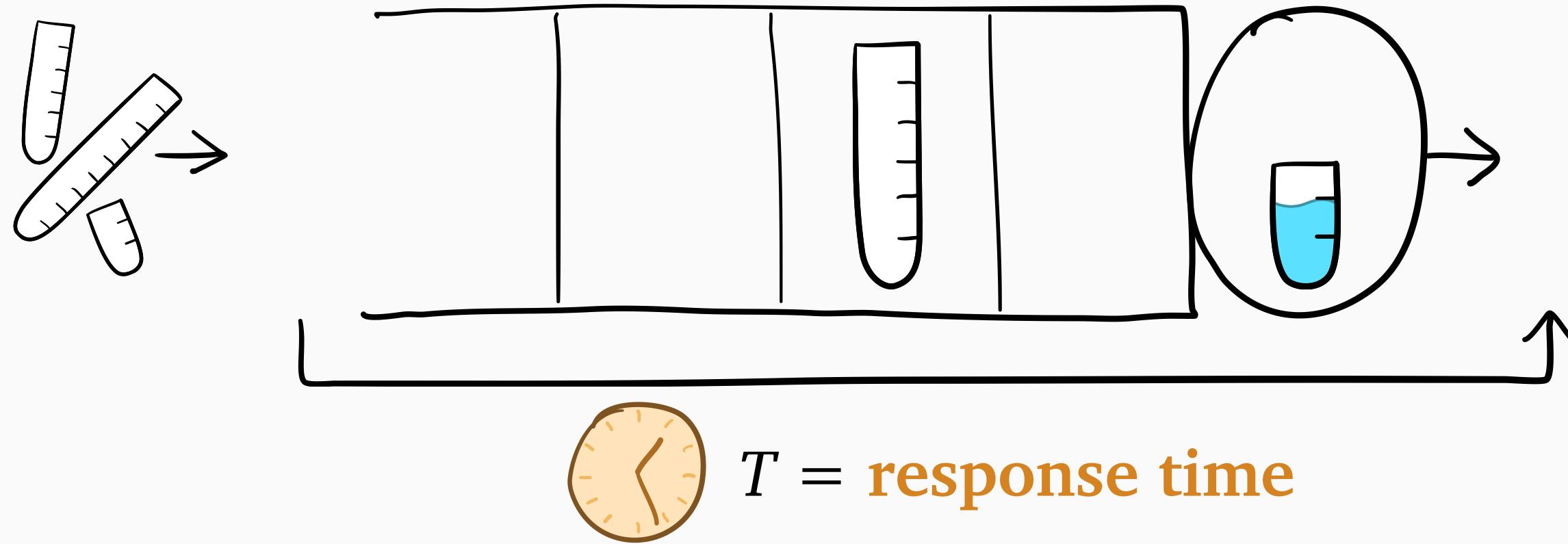
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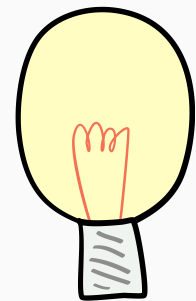
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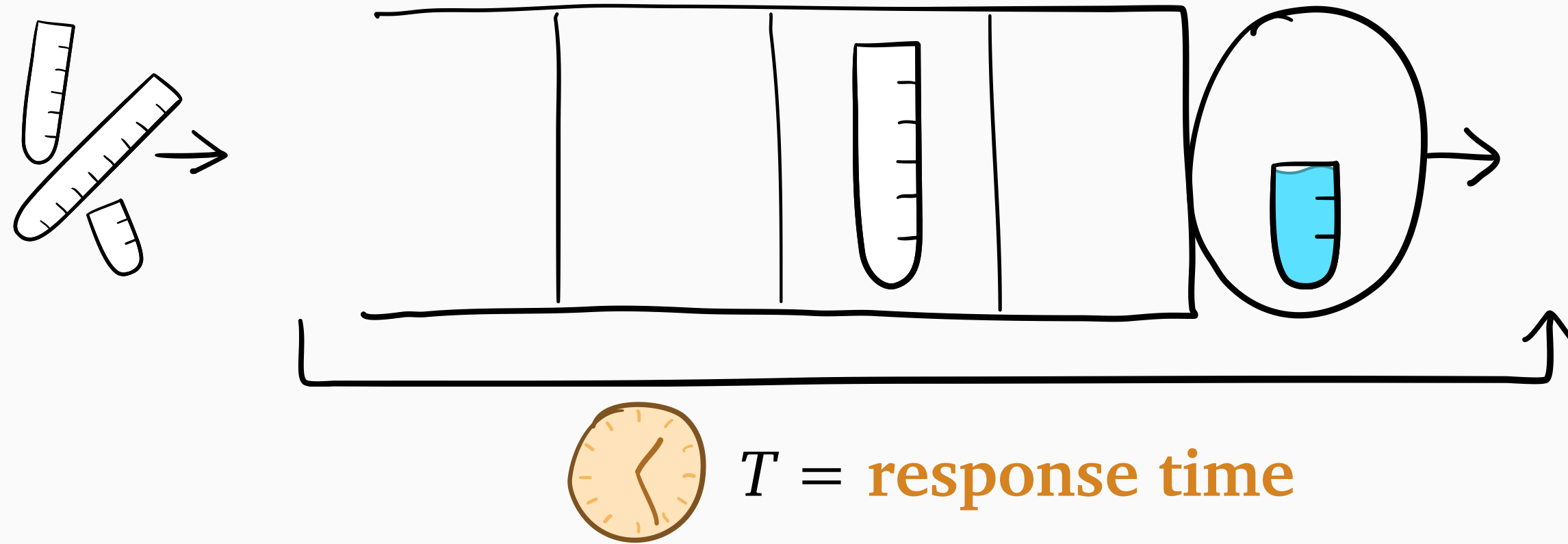


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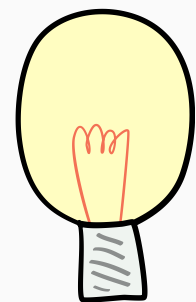


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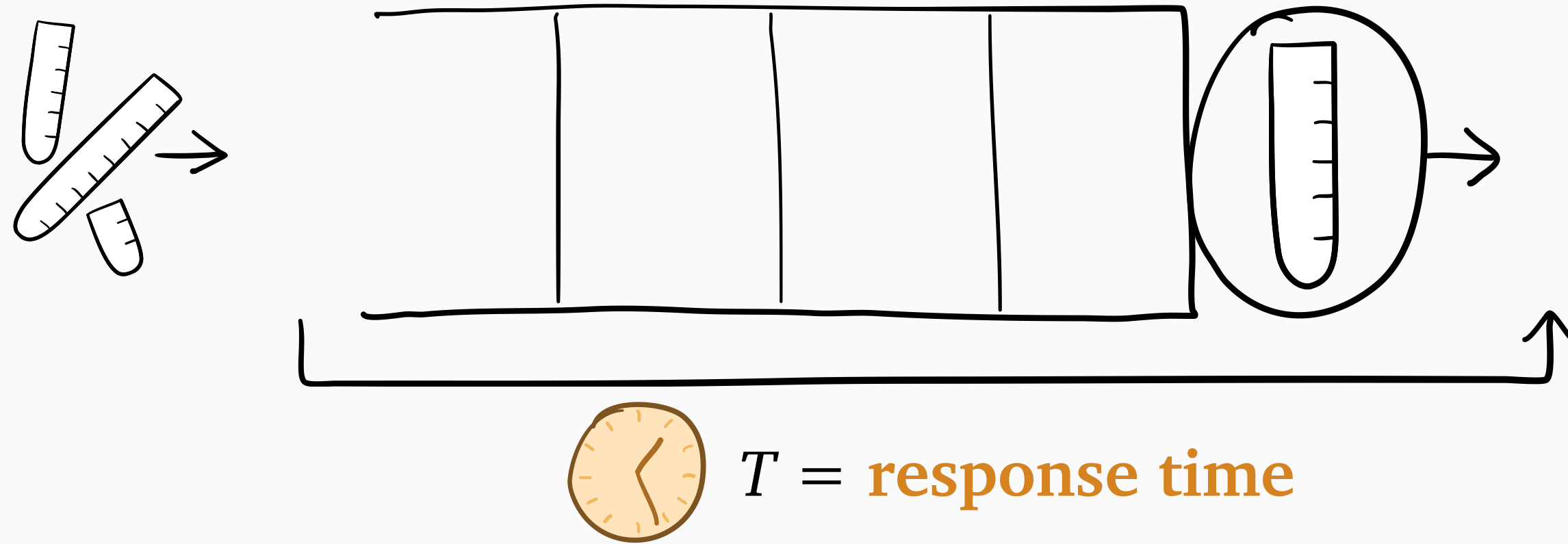


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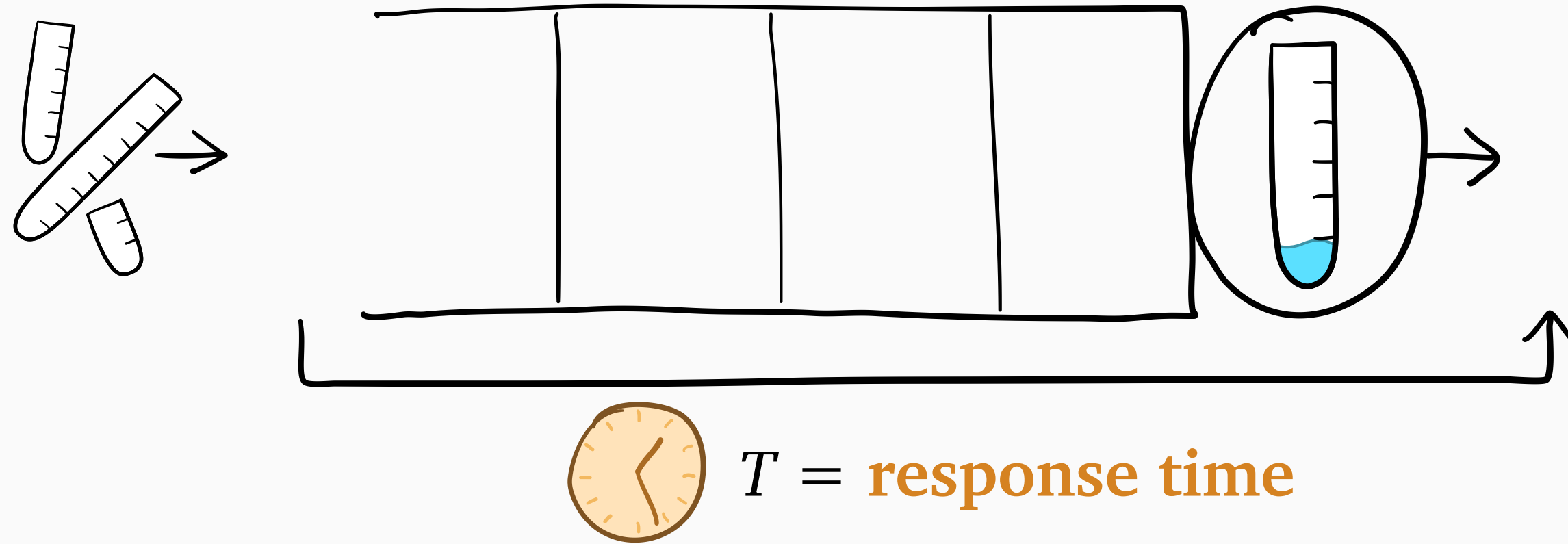
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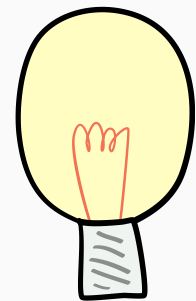
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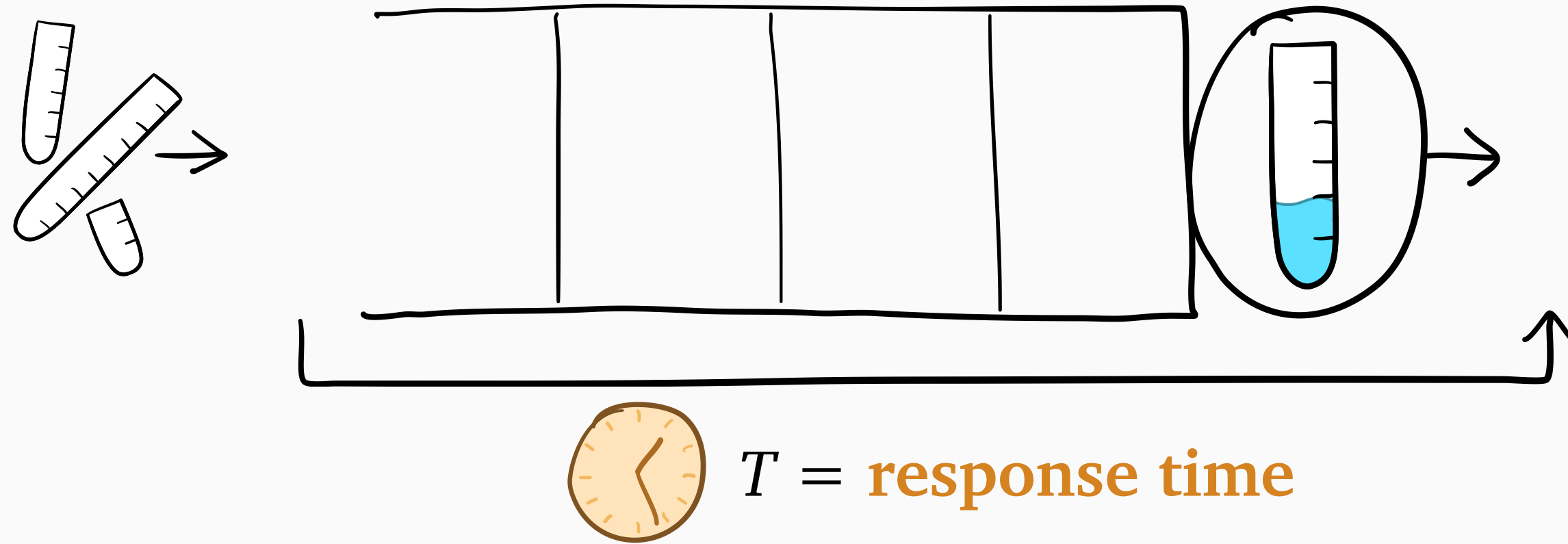


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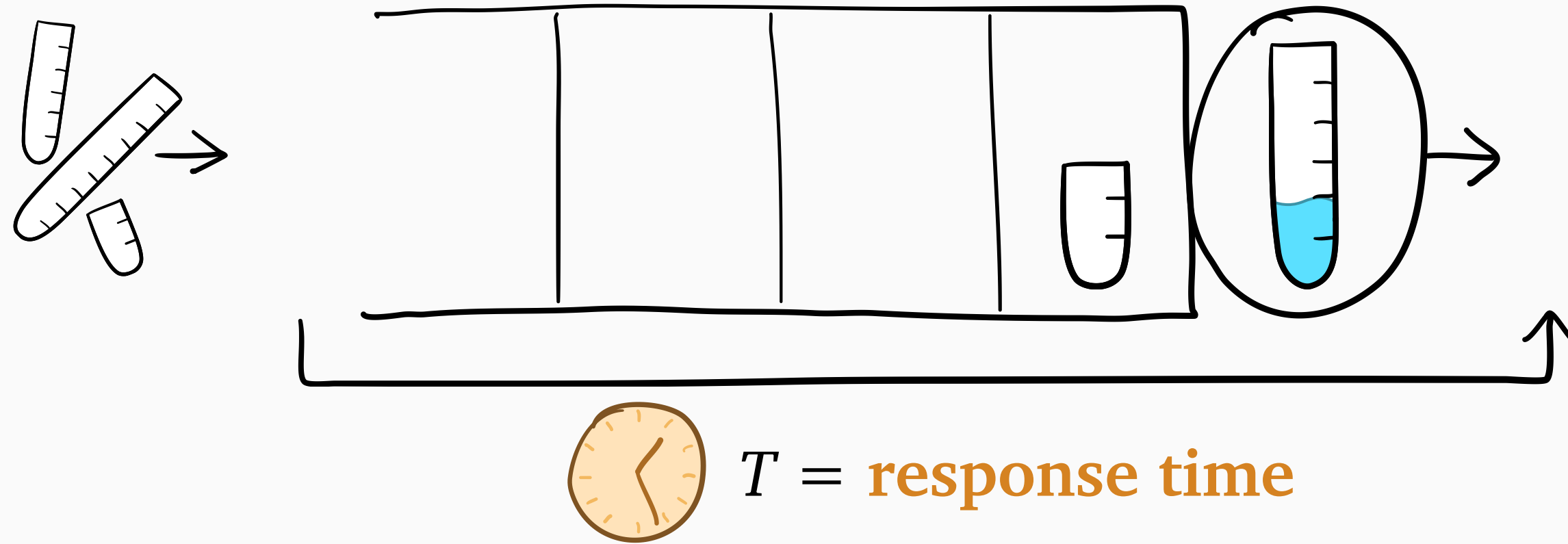
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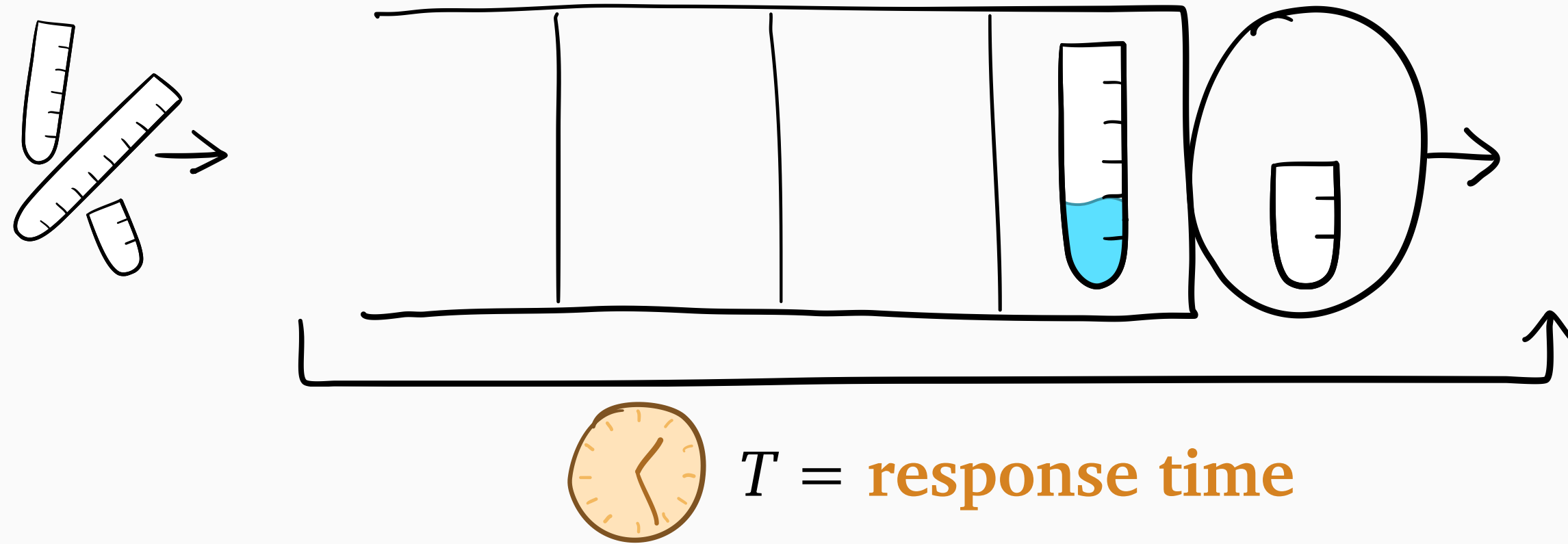
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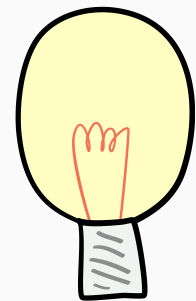
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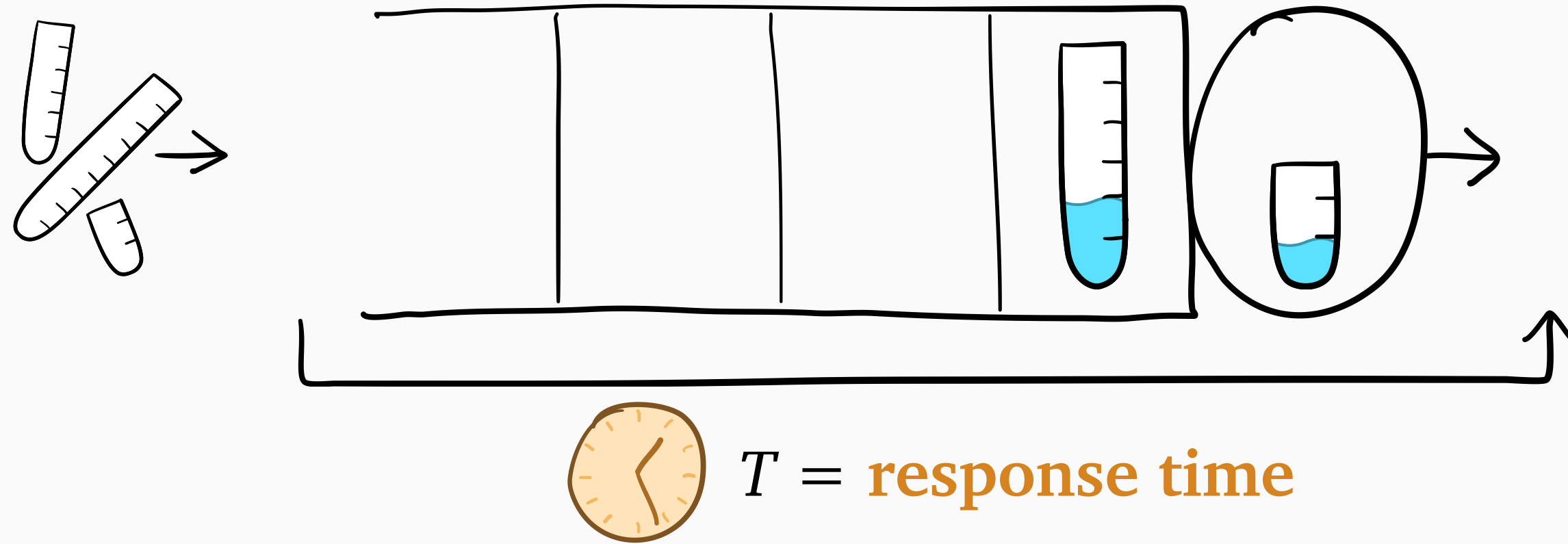


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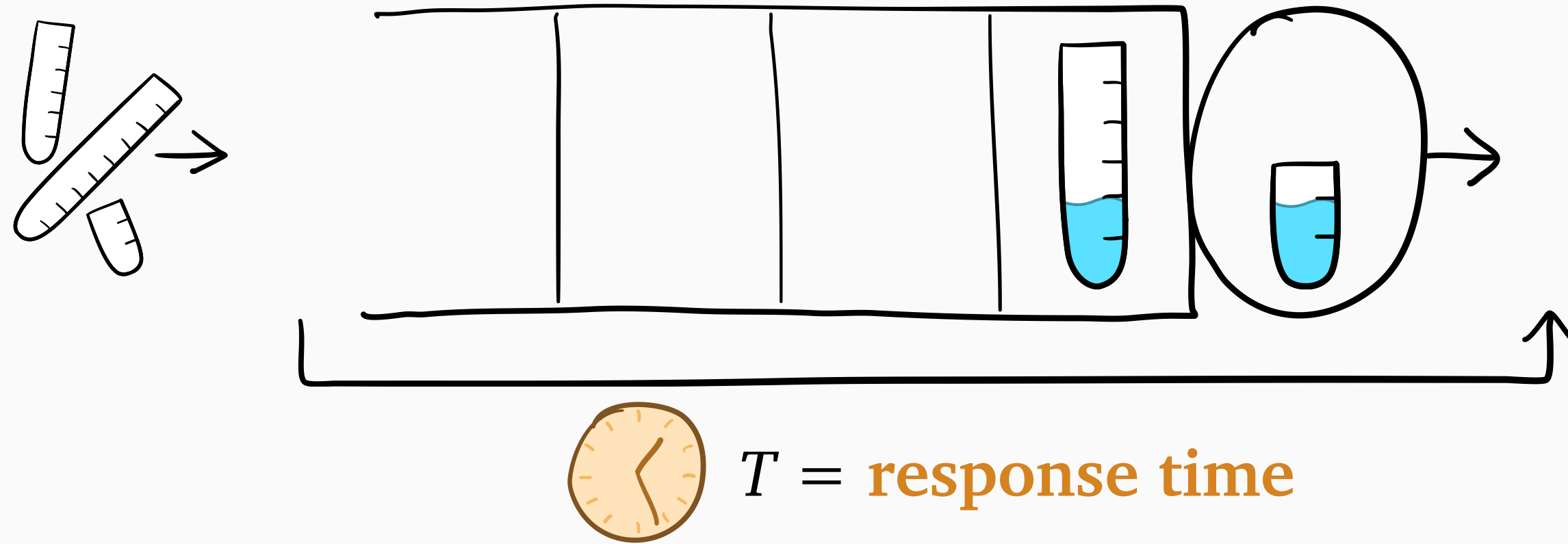
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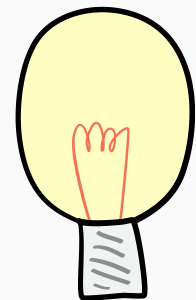
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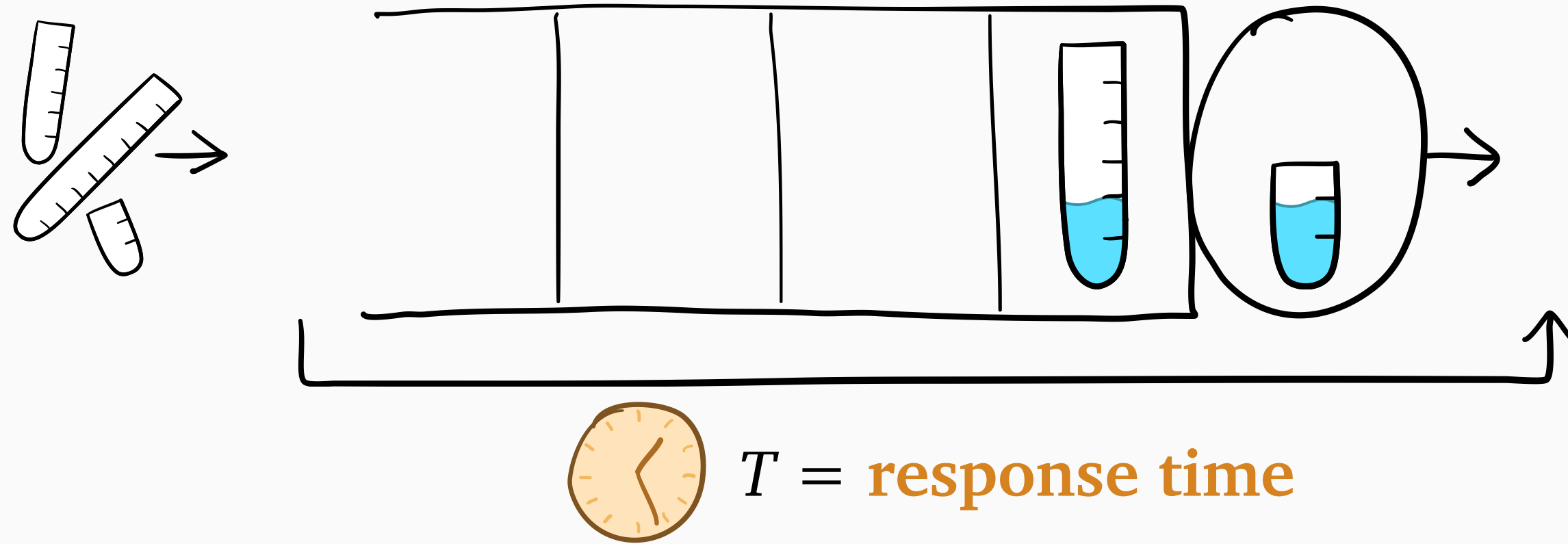


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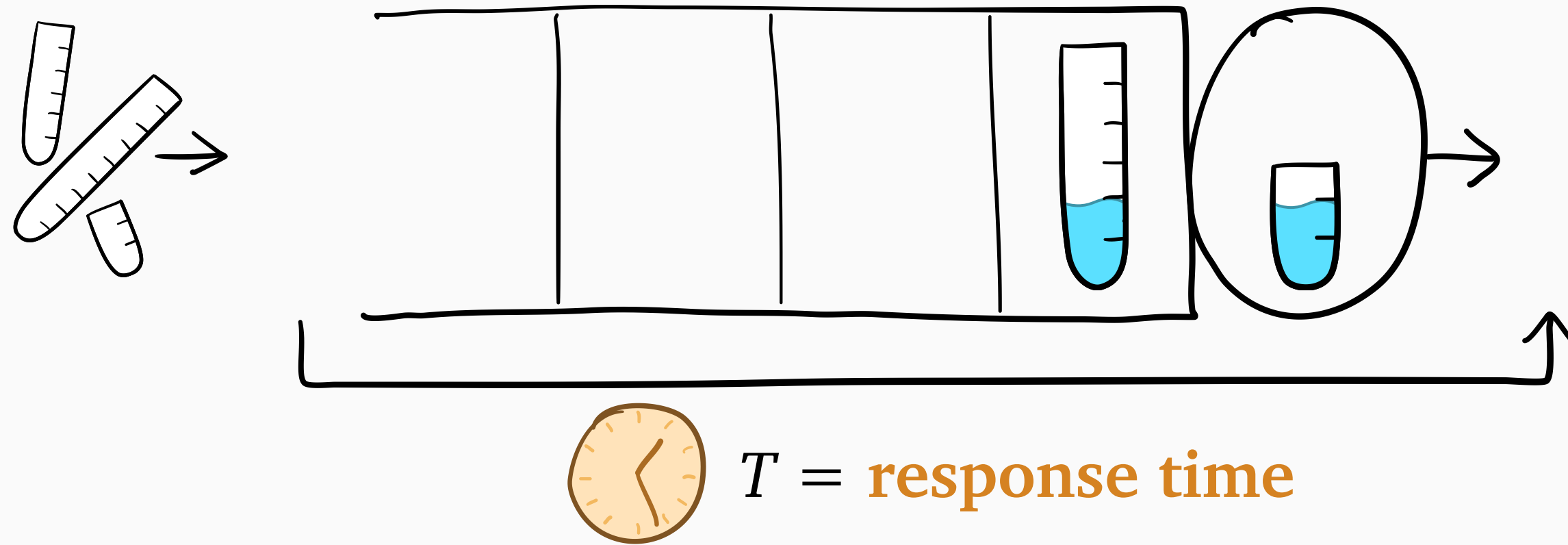


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🏆 **SRPT**: minimizes $E[T]$
shortest remaining
processing time

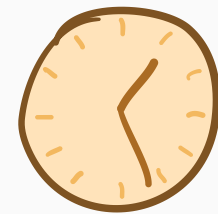
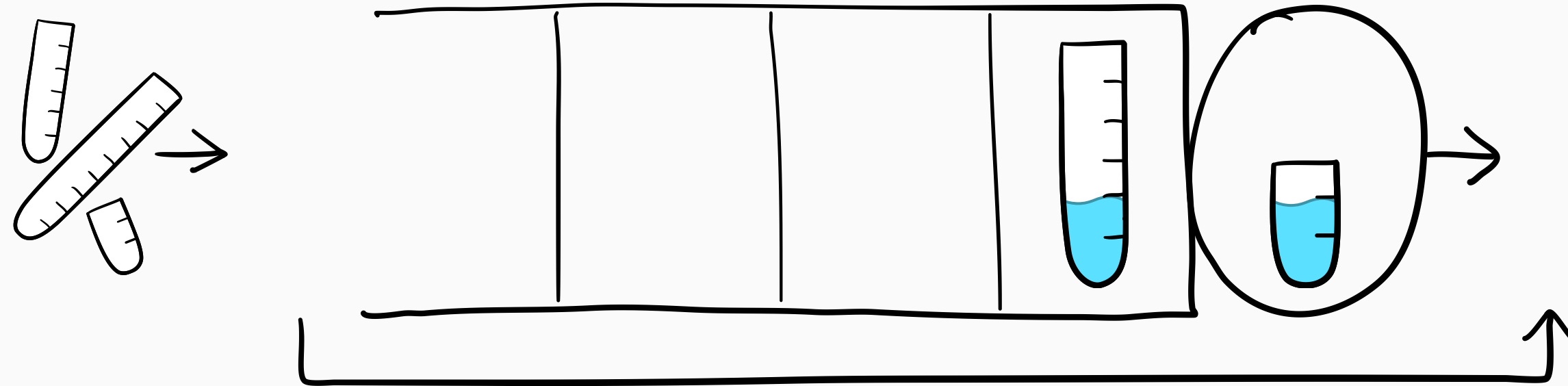
Beyond the mean: tail metrics



Beyond the mean: tail metrics



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

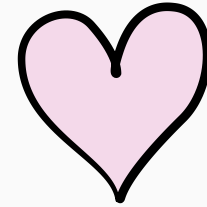


$T = \text{response time}$

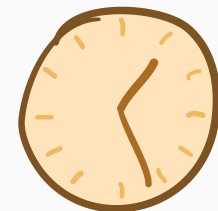
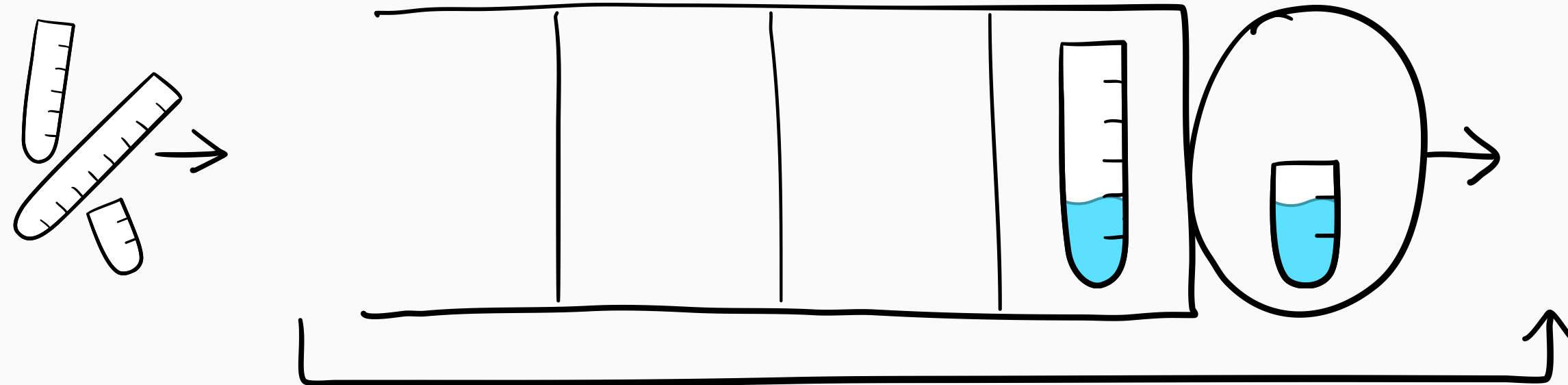
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Practice: important

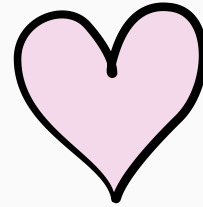


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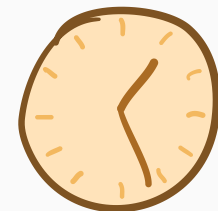
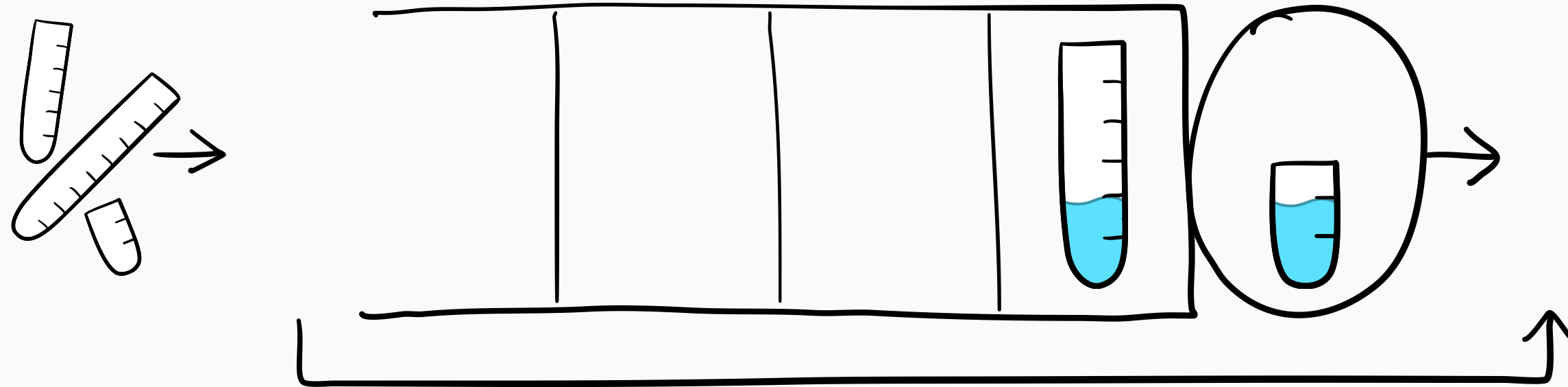
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Theory: very hard

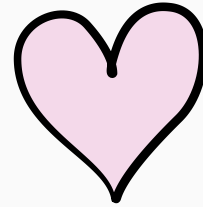


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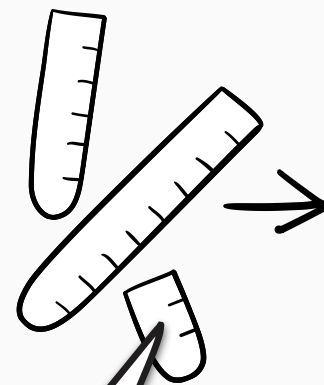
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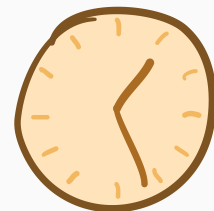
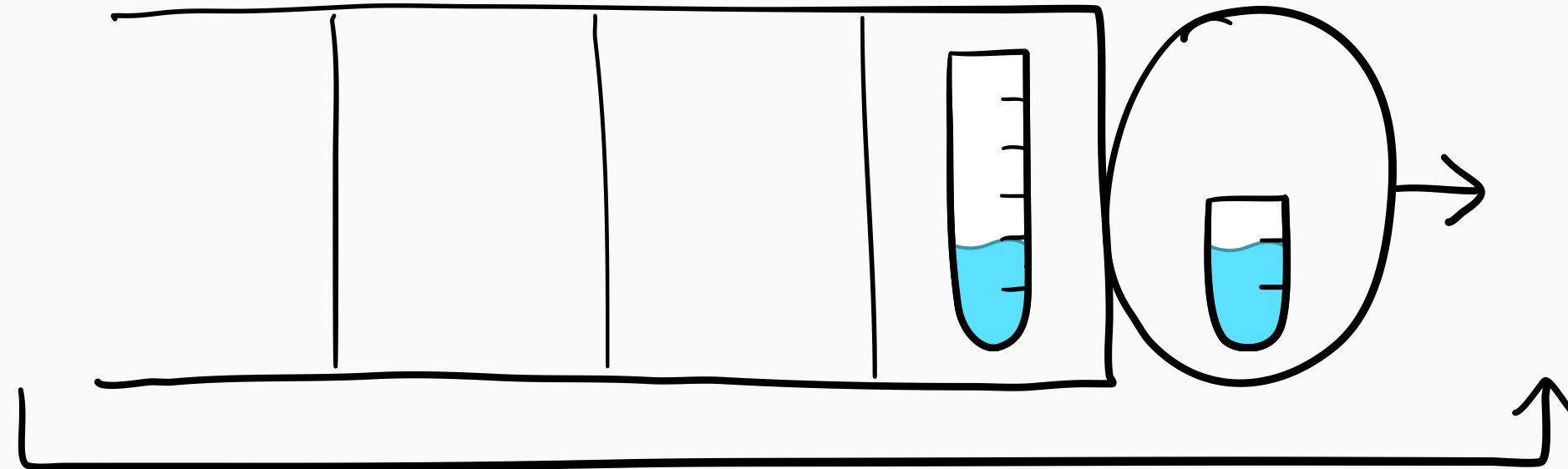


Theory: very hard



M/G arrivals

- arrival rate λ
- job size dist. S

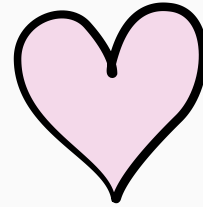


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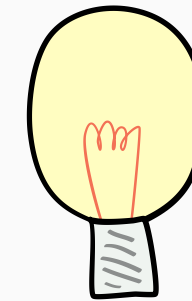
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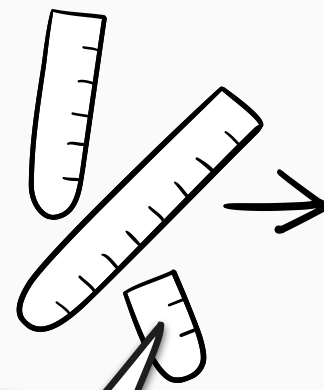
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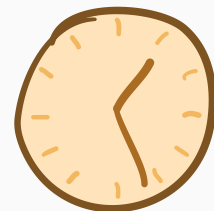
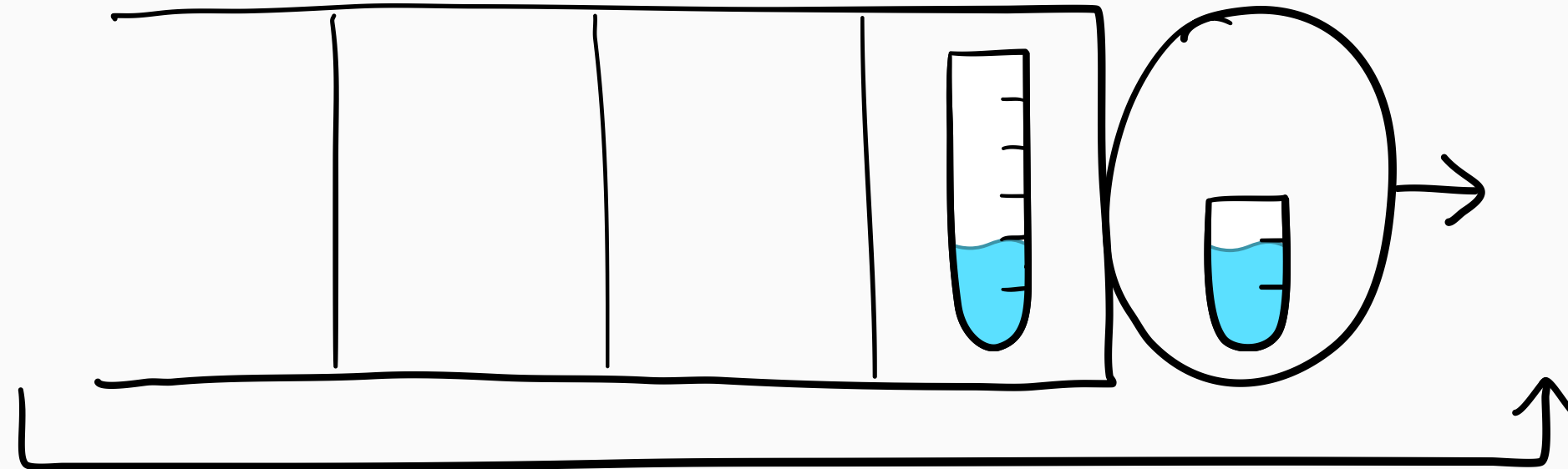


Tractable:
study $t \rightarrow \infty$
asymptotics



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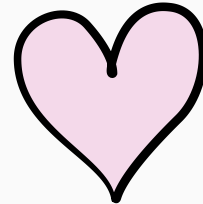
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Beyond the mean: tail metrics

no single t value
is most important



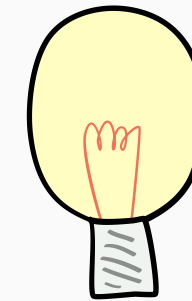
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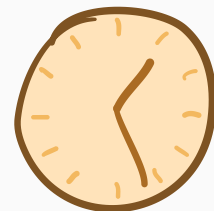
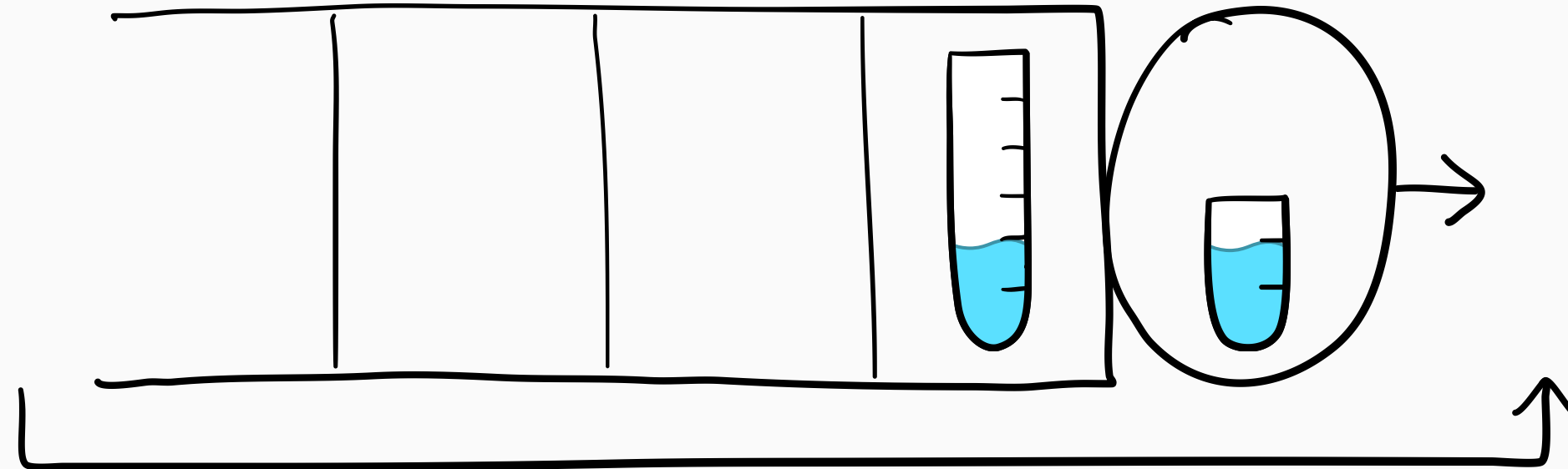
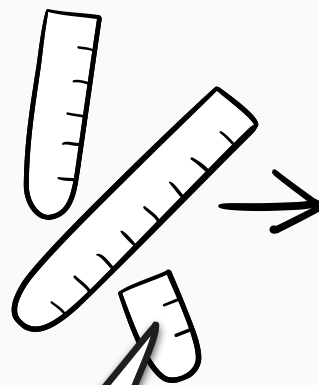
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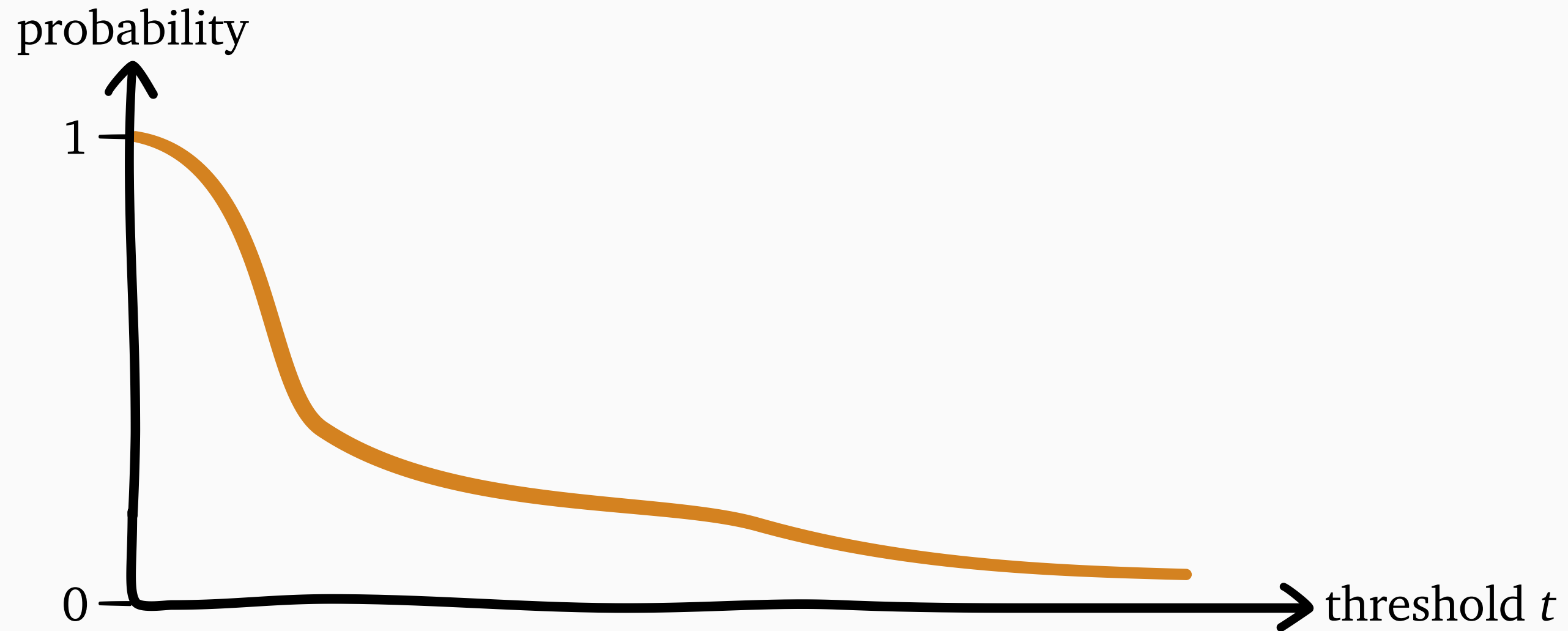
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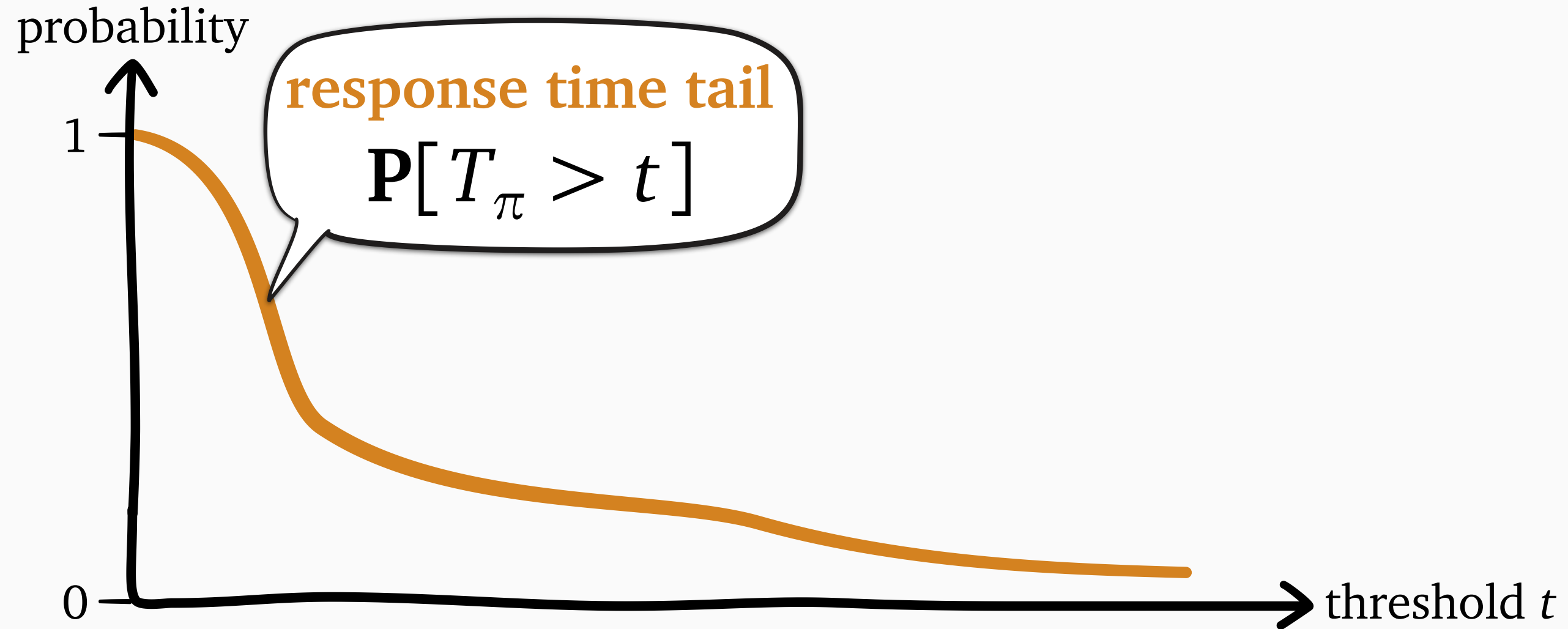


$T =$ **response time**

Asymptotic response time tail



Asymptotic response time tail



Asymptotic response time tail

depends on
policy π

probability

response time tail

$$\mathbf{P}[T_{\pi} > t]$$

1

0

threshold t

Asymptotic response time tail

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1

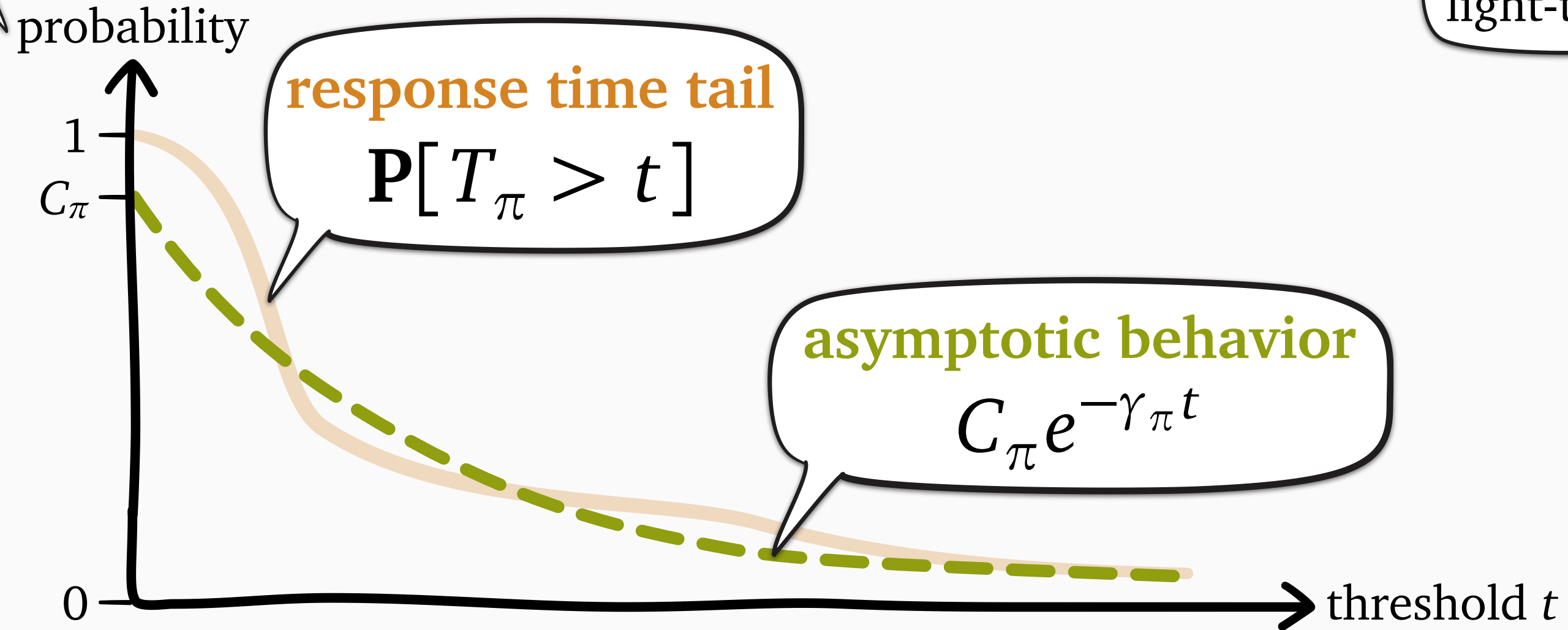
0

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Asymptotic response time tail

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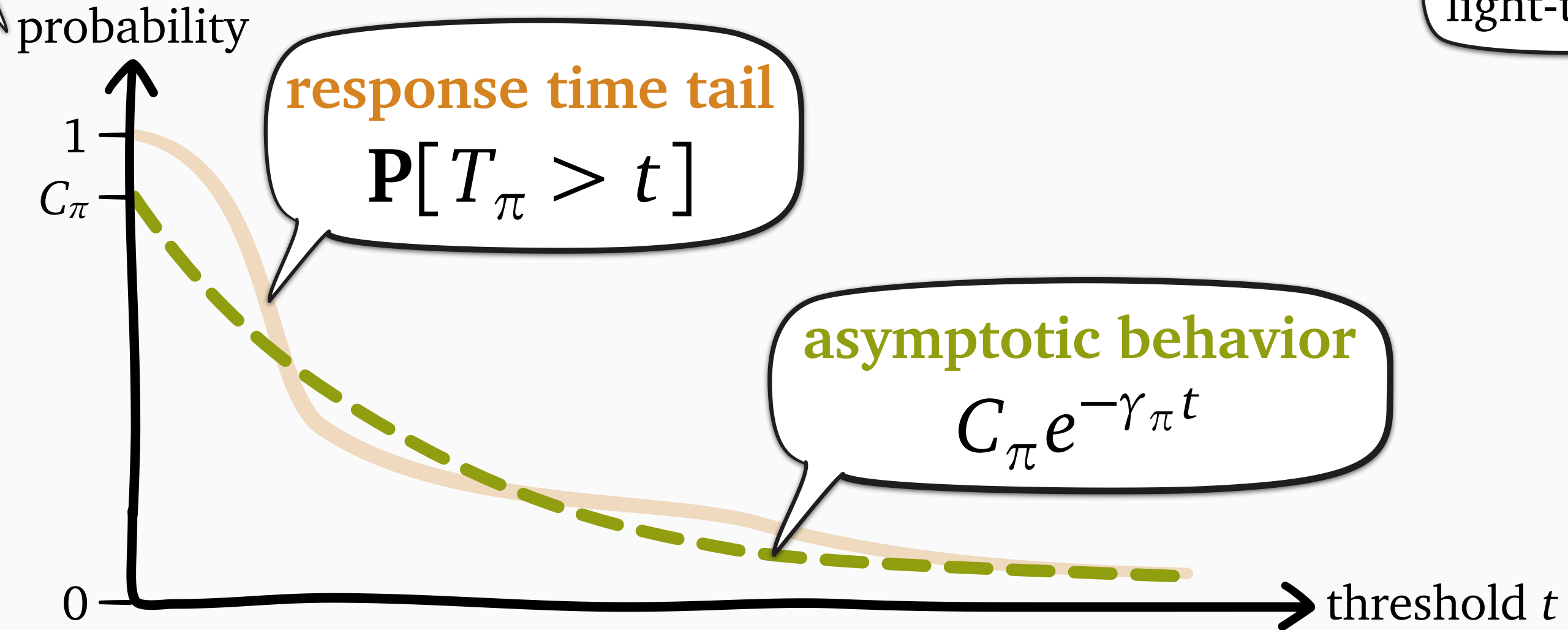
when S is
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Asymptotic response time tail

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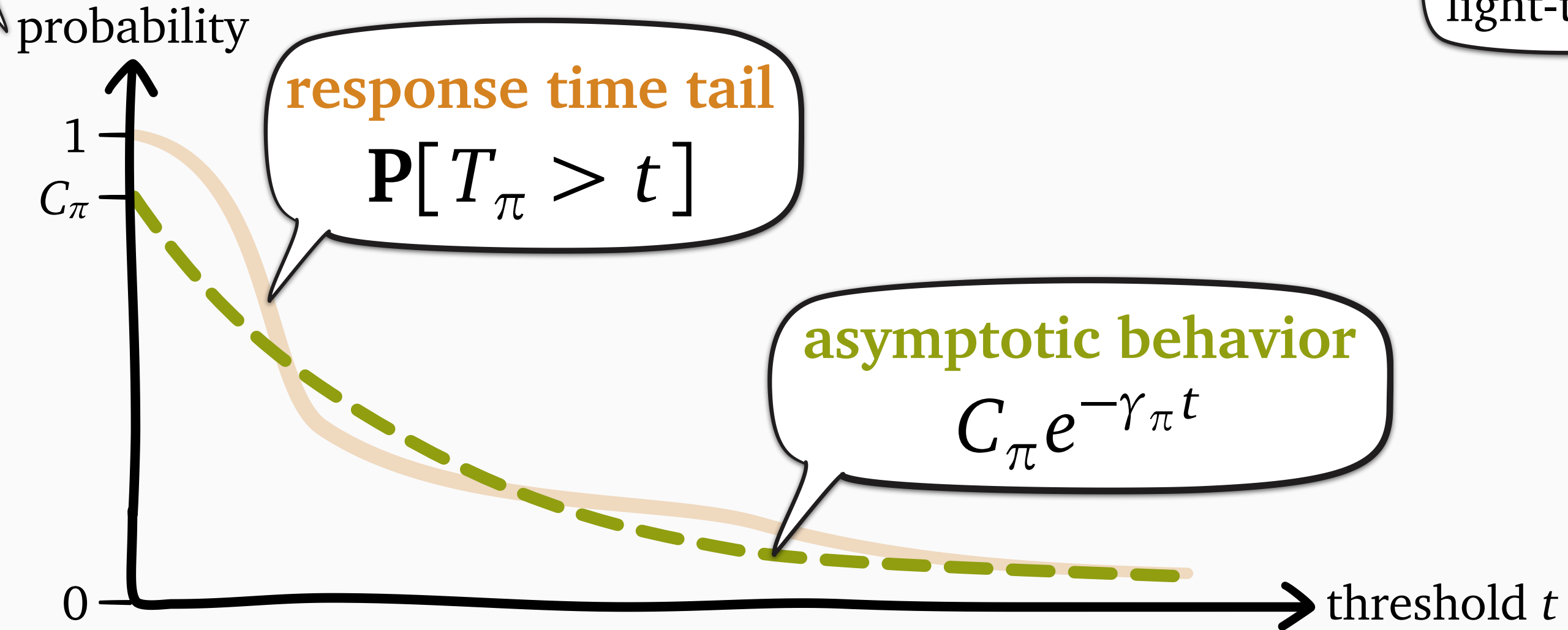
$\gamma_\pi = \text{decay rate of } \pi$

$C_\pi = \text{tail constant of } \pi$

Asymptotic response time tail

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Weak optimality: ←

optimal γ_π

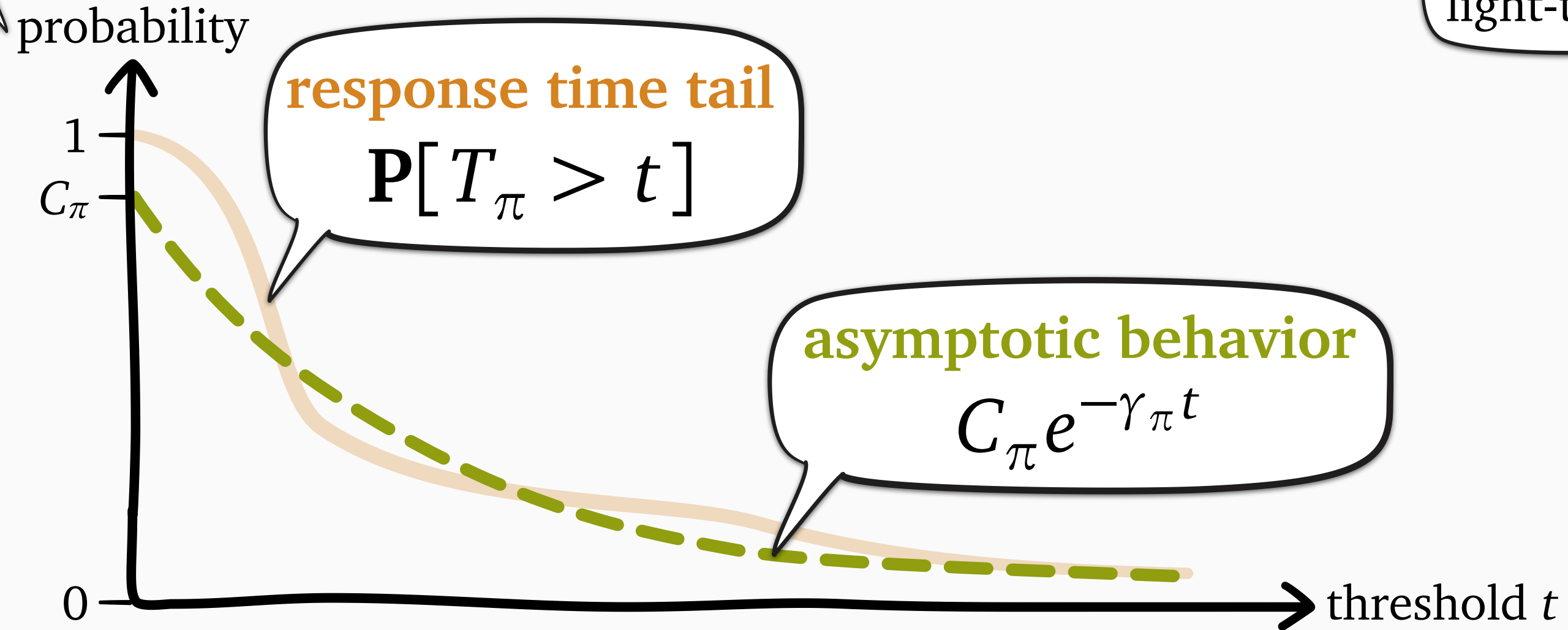
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Weak optimality: \leftarrow
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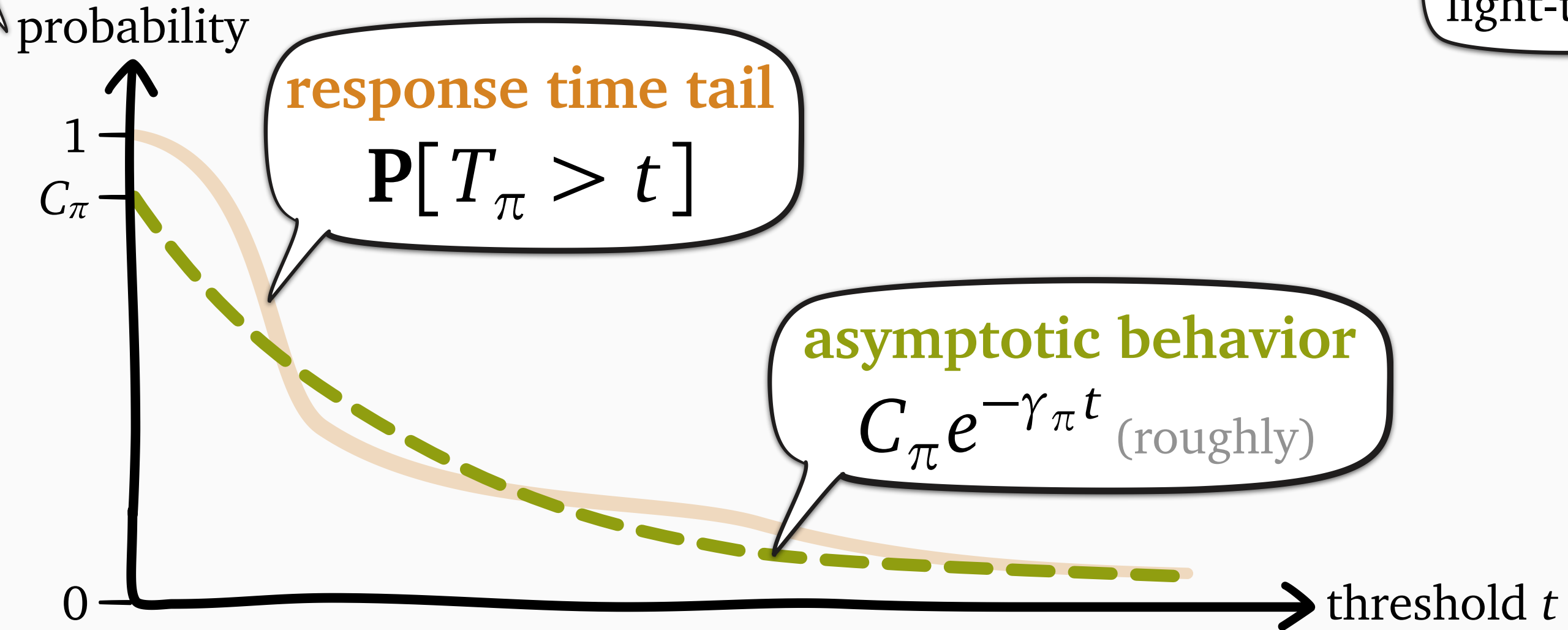
$\gamma_\pi = \text{decay rate of } \pi$
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\rightarrow **Strong optimality:**
optimal γ_π and C_π

Asymptotic response time tail

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Weak optimality: ←
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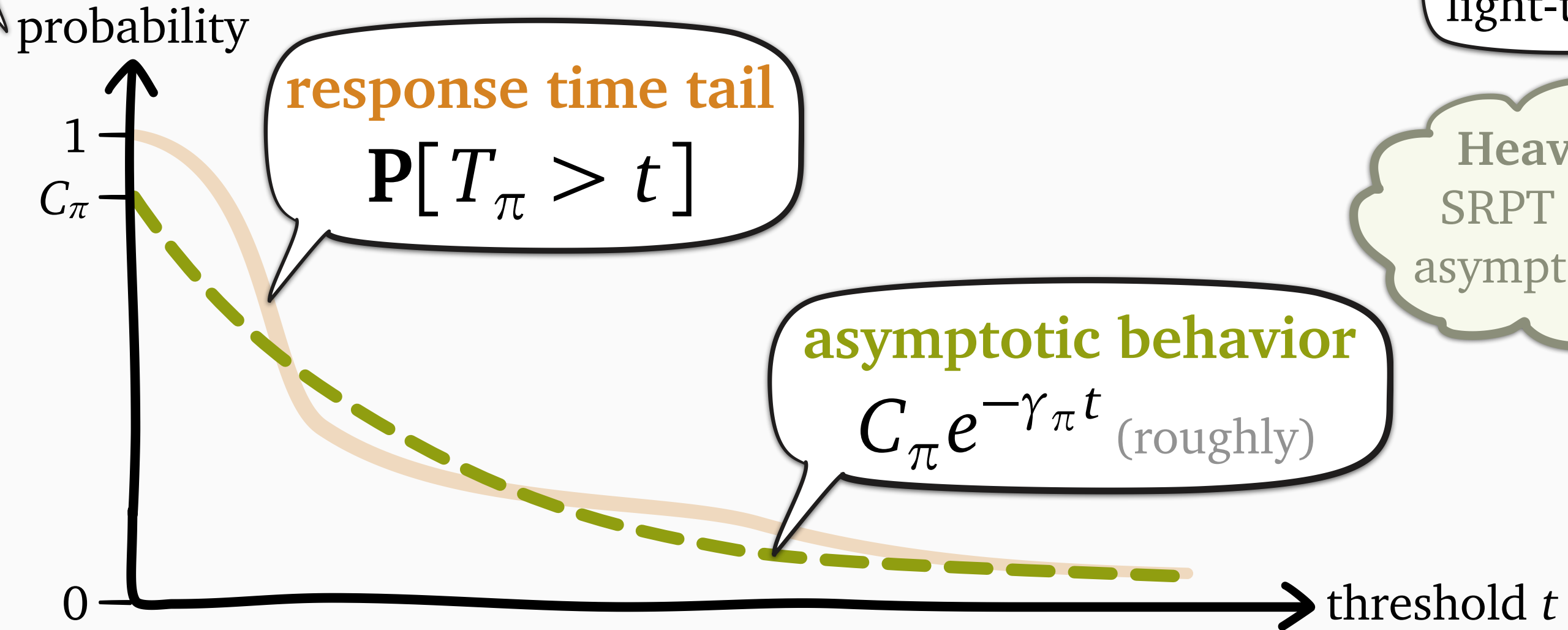
→ **Strong optimality:**
optimal γ_π and C_π

Asymptotic response time tail

depends on
policy π

when S is
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Heavy-tailed S :
SRPT has optimal
asymptotic behavior

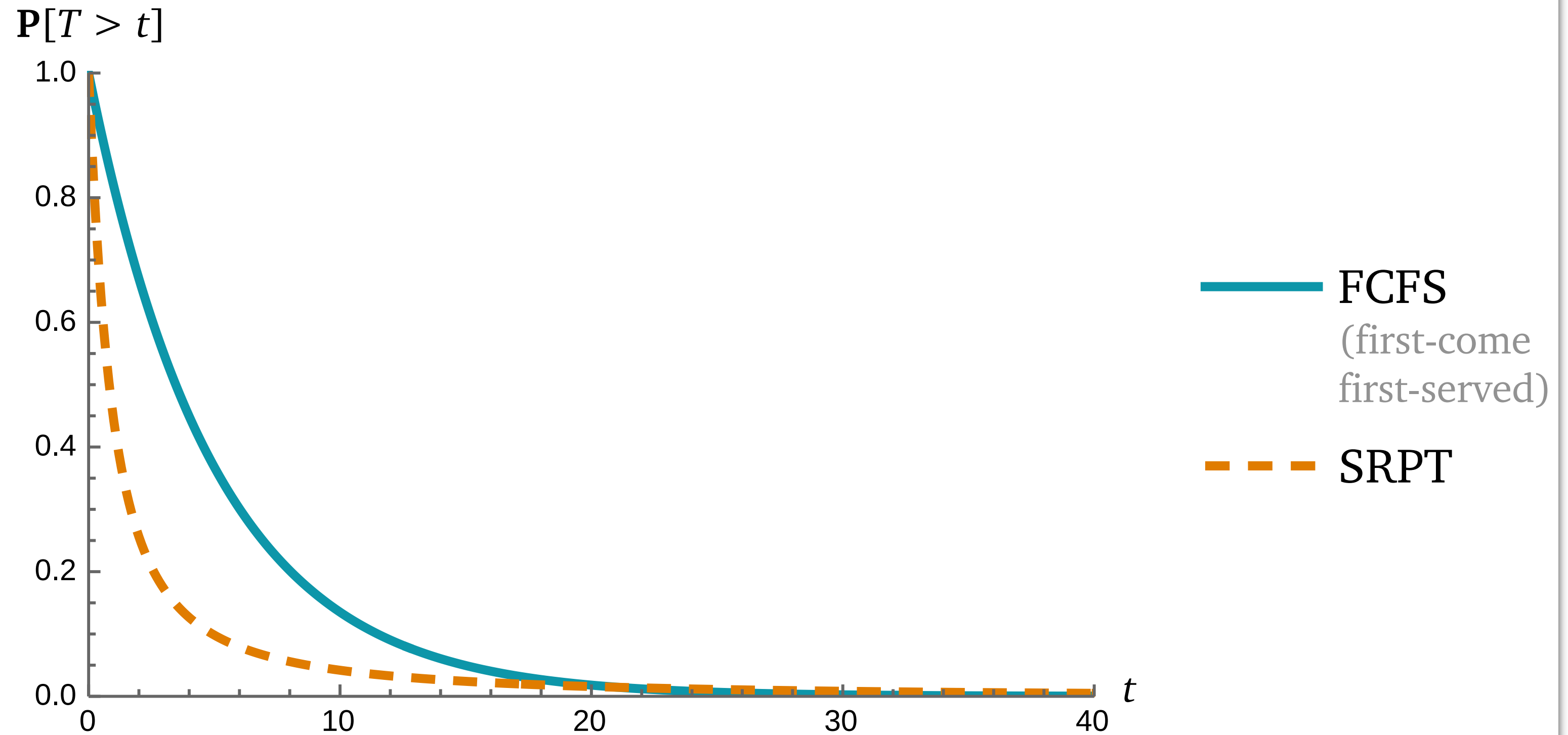


Weak optimality: ←
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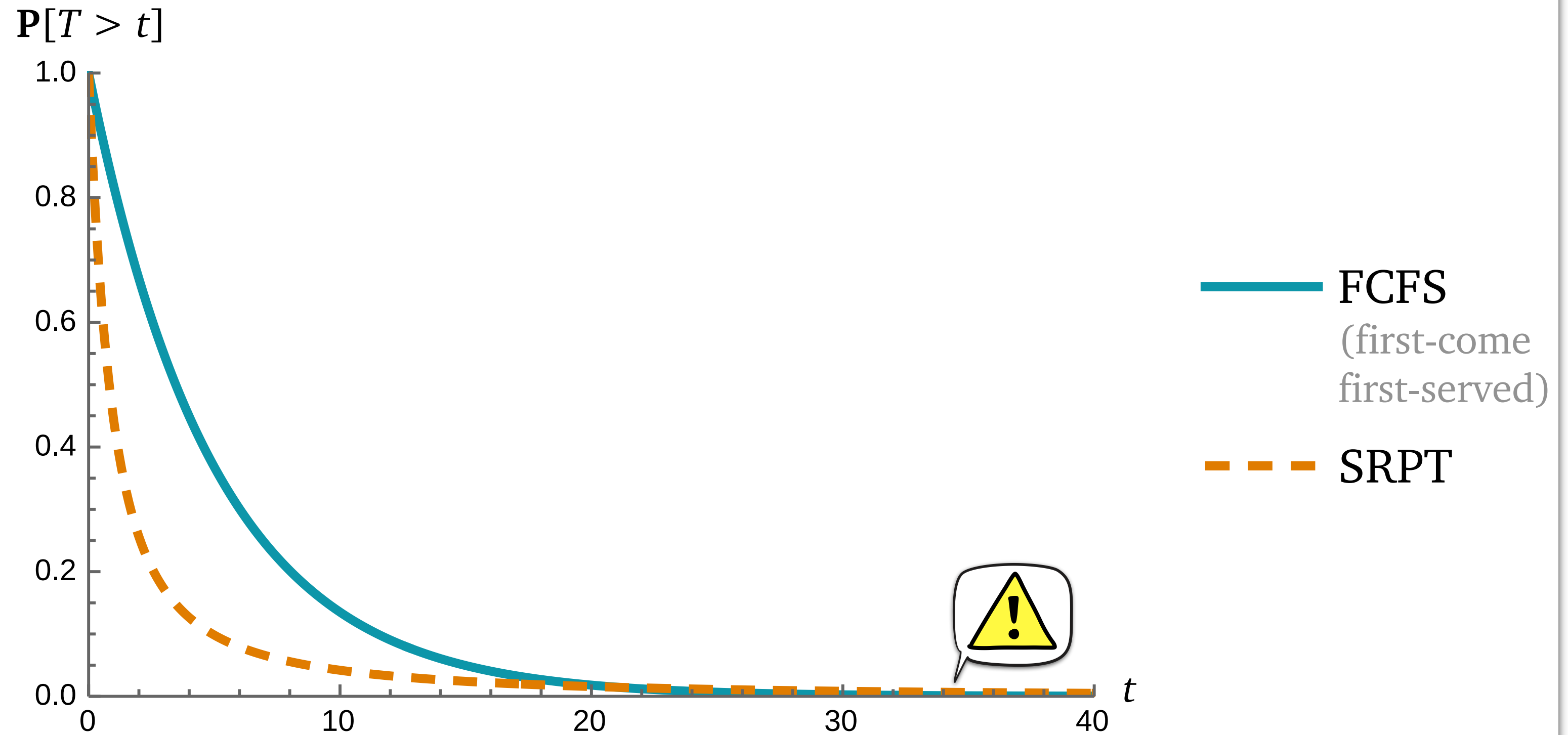
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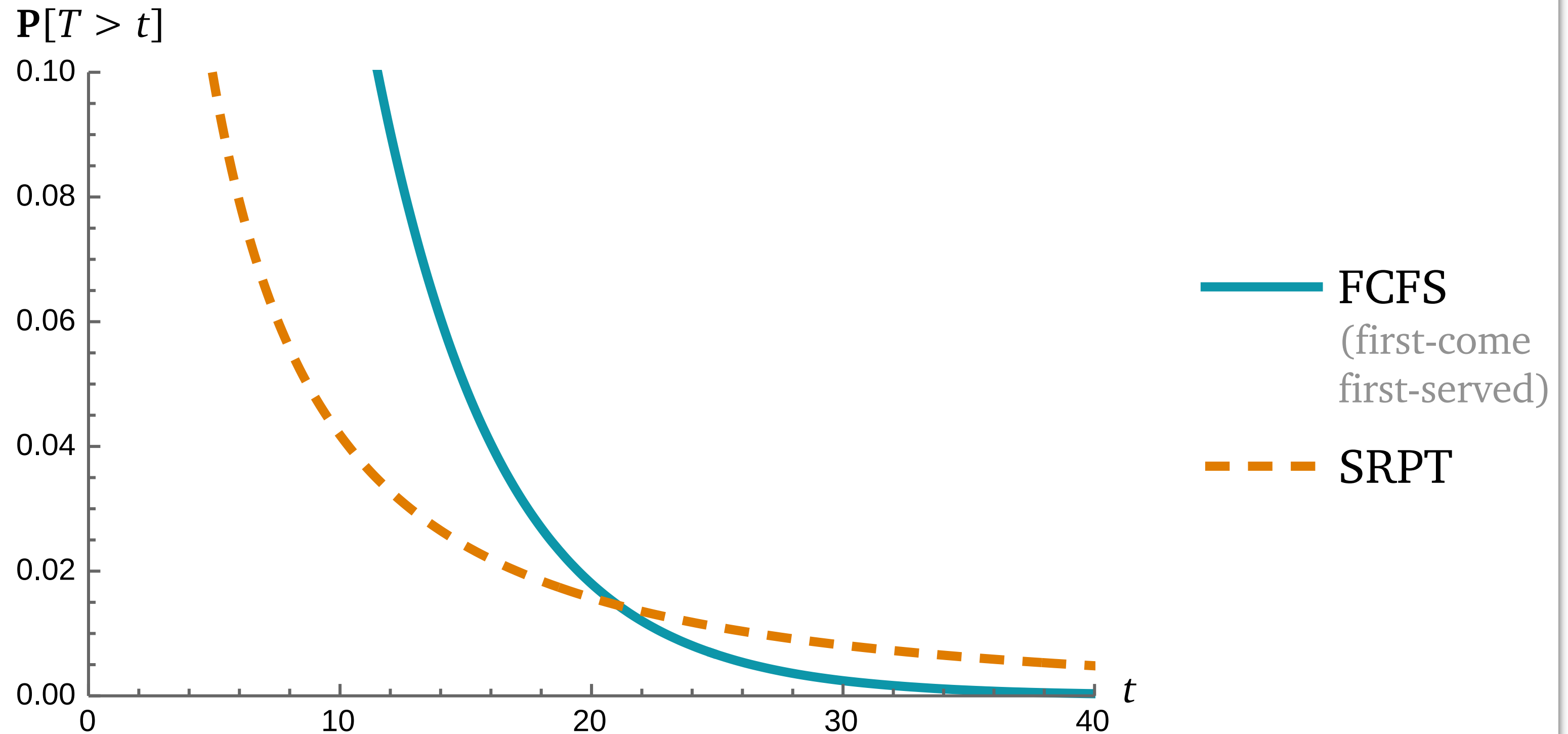
FCFS vs. SRPT



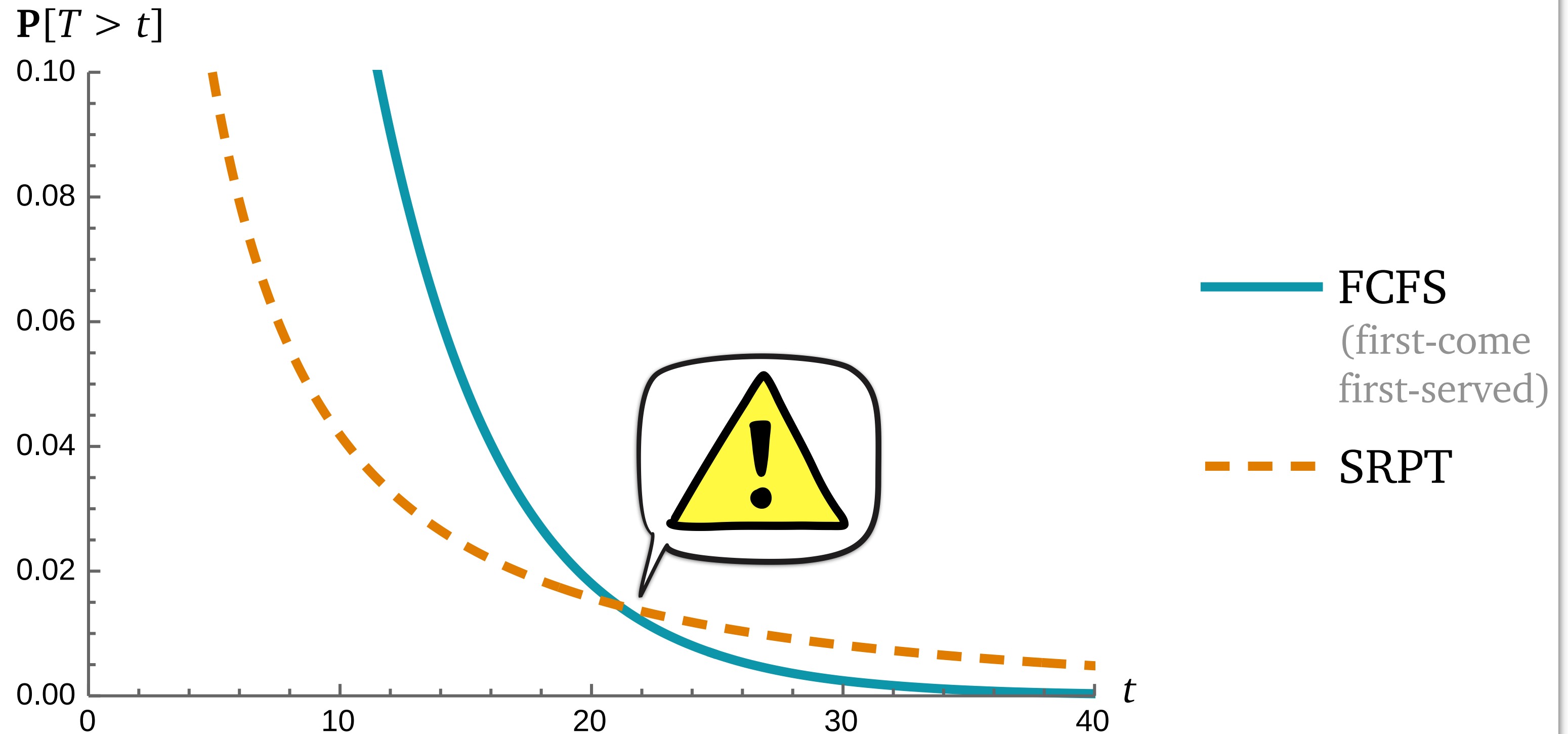
FCFS vs. SRPT



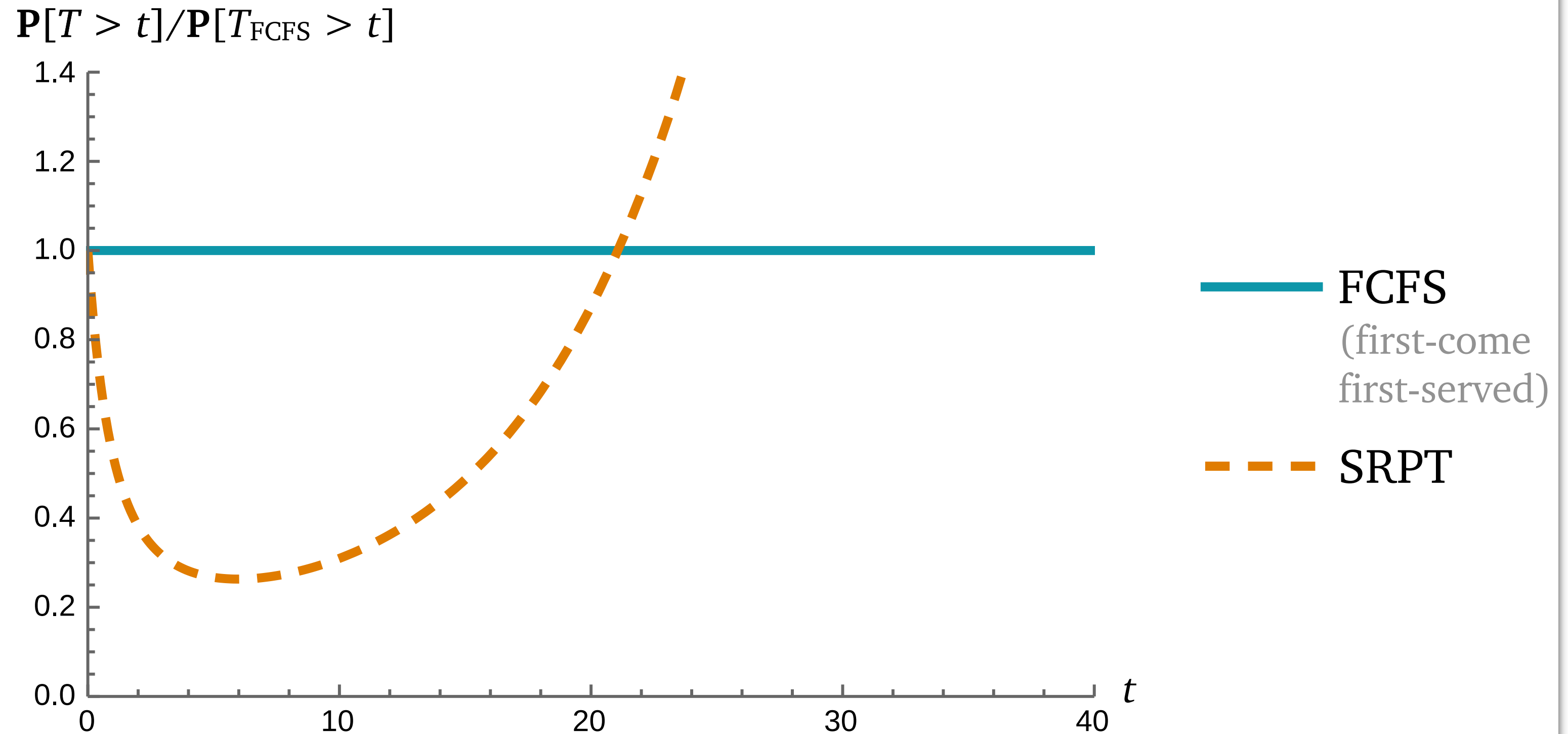
FCFS vs. SRPT



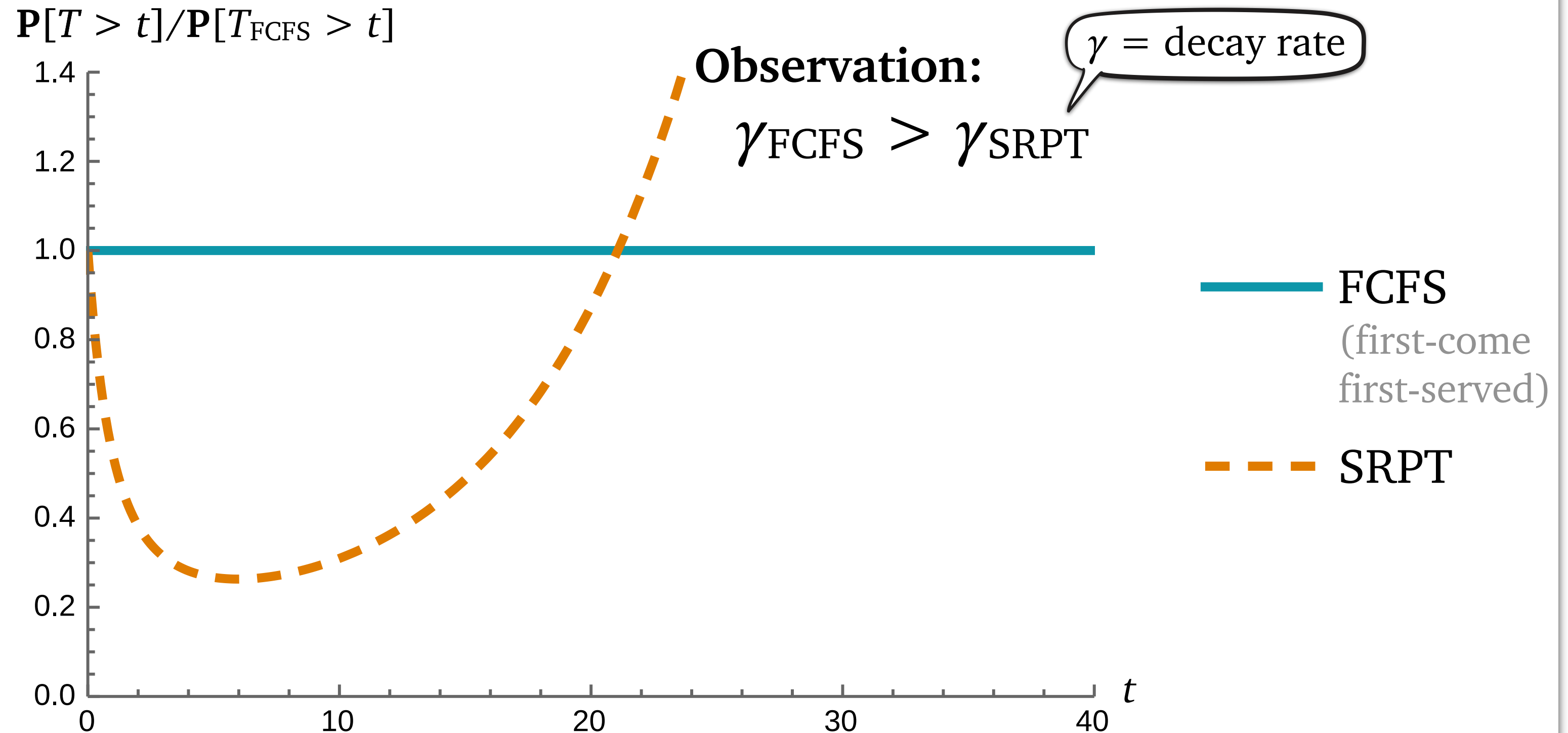
FCFS vs. SRPT



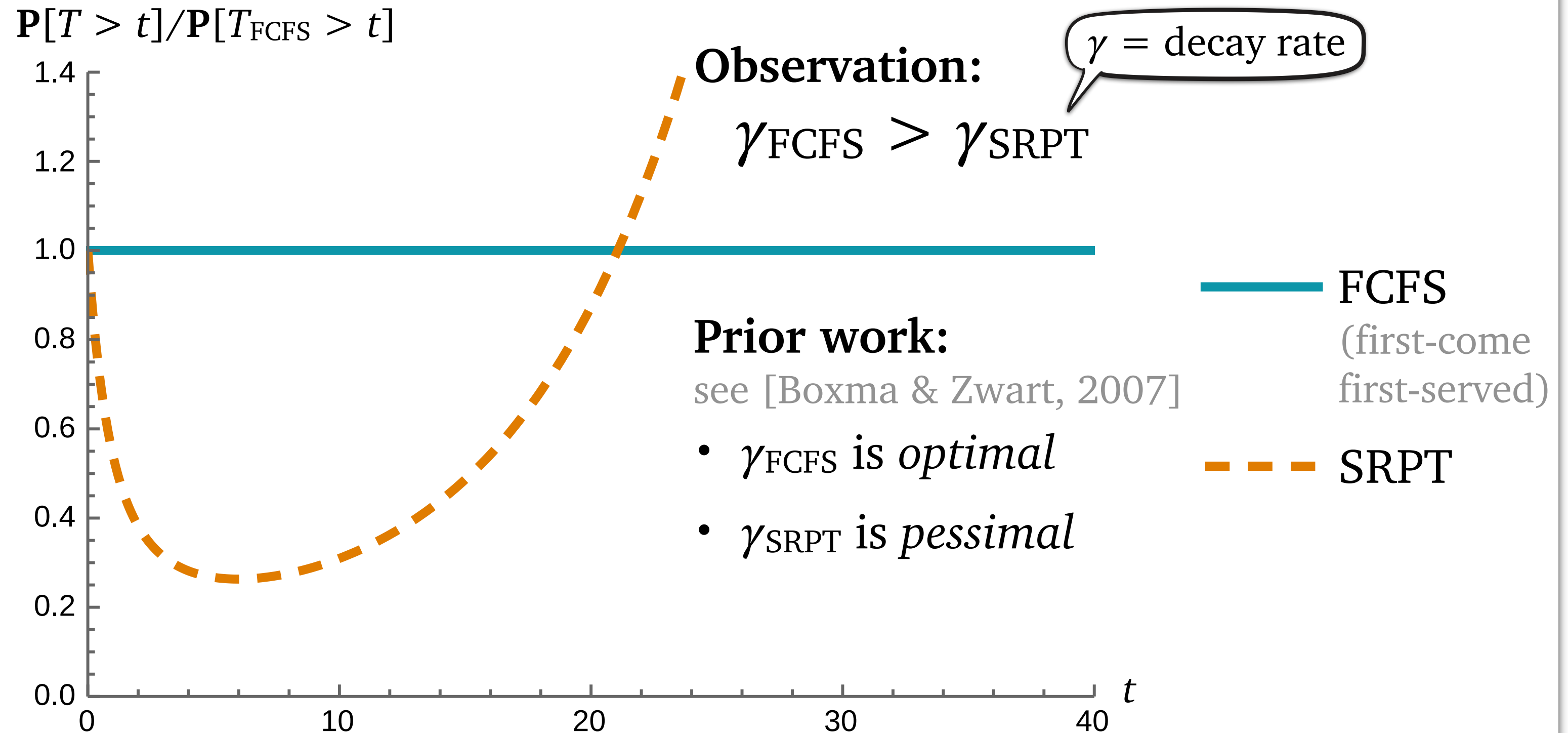
FCFS vs. SRPT



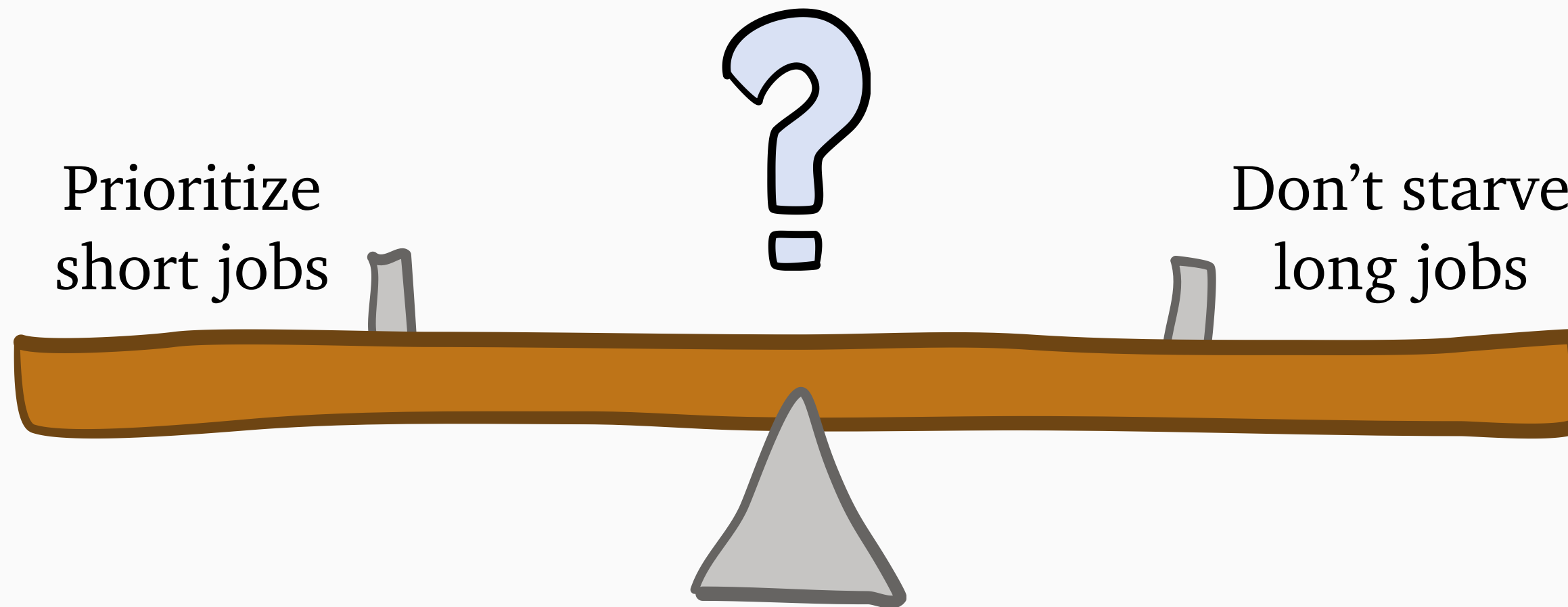
FCFS vs. SRPT



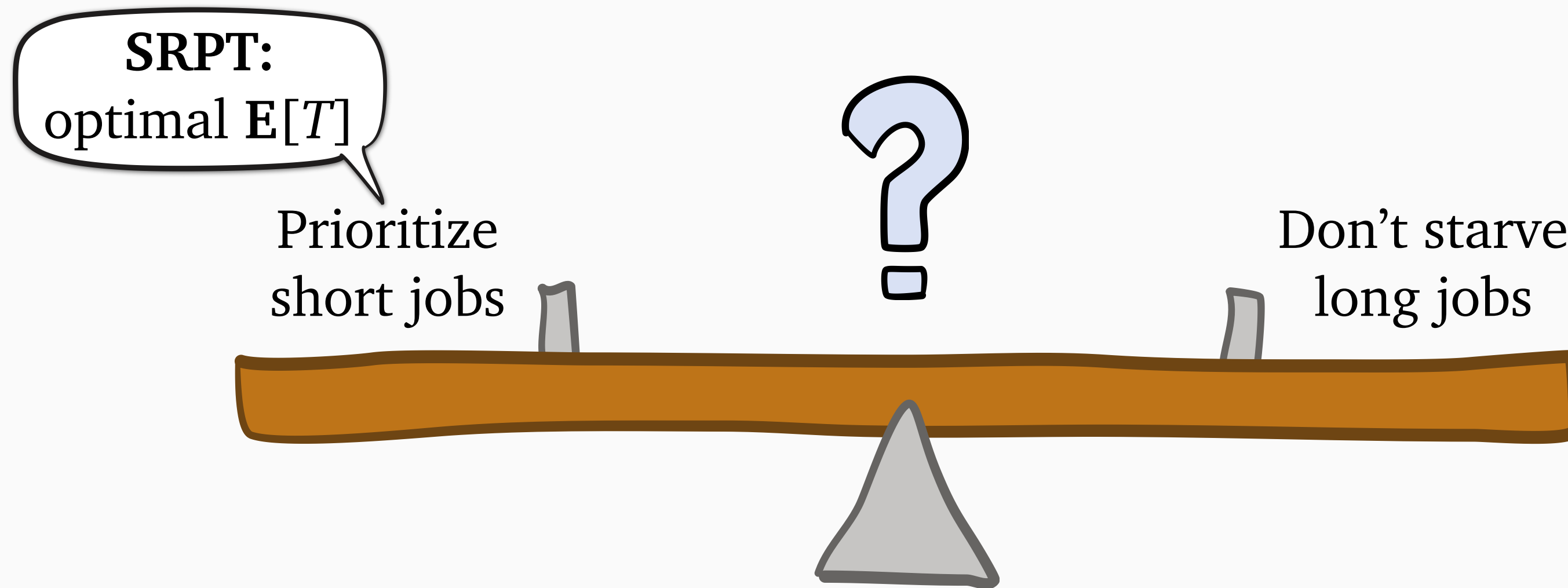
FCFS vs. SRPT



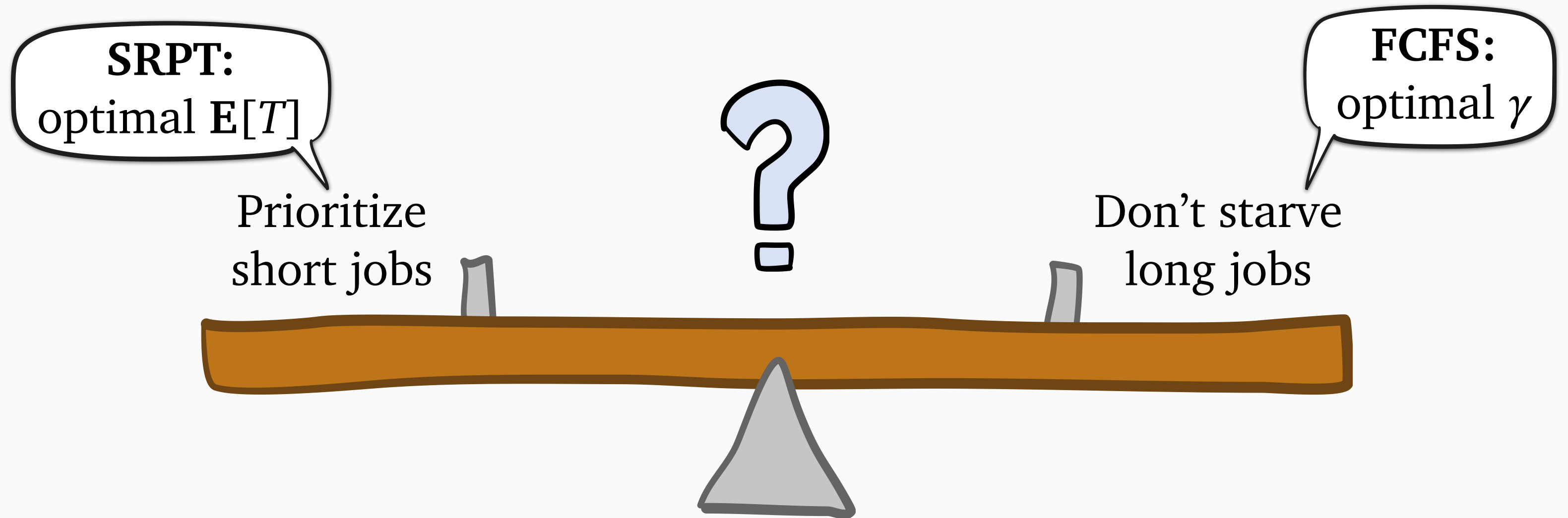
Tradeoff: priority vs. starvation



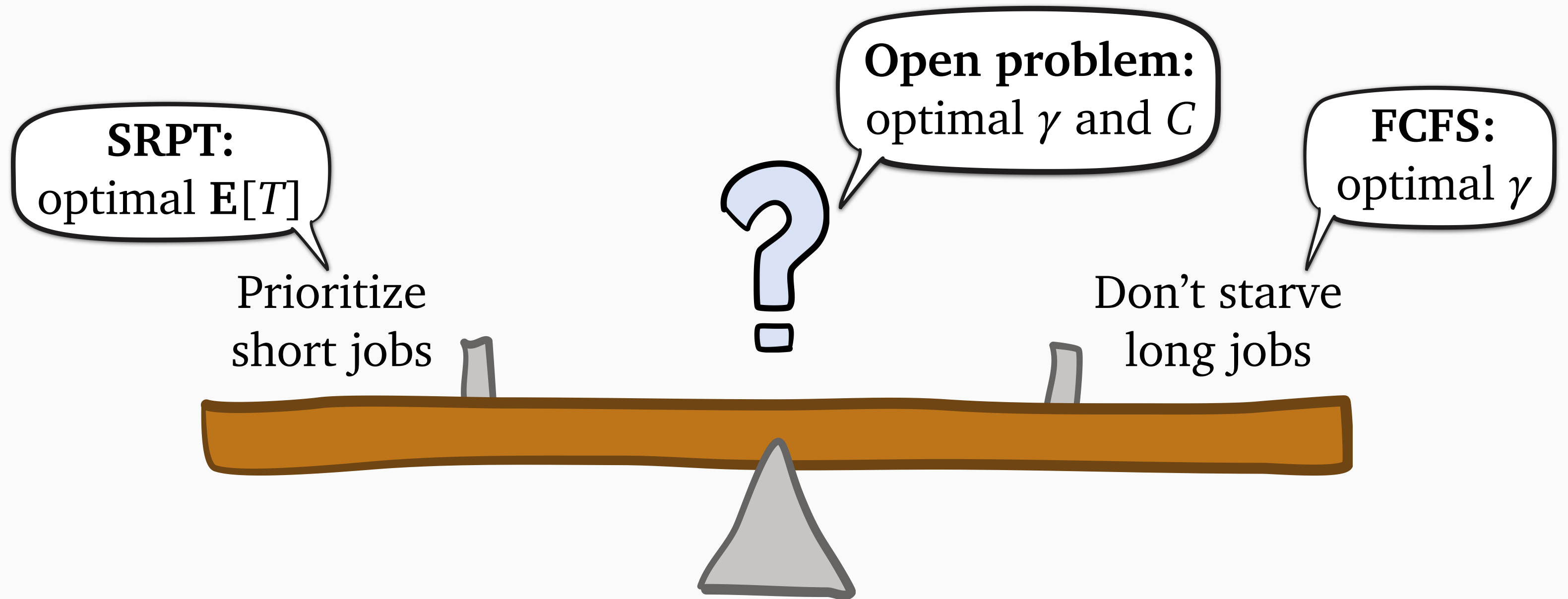
Tradeoff: priority vs. starvation



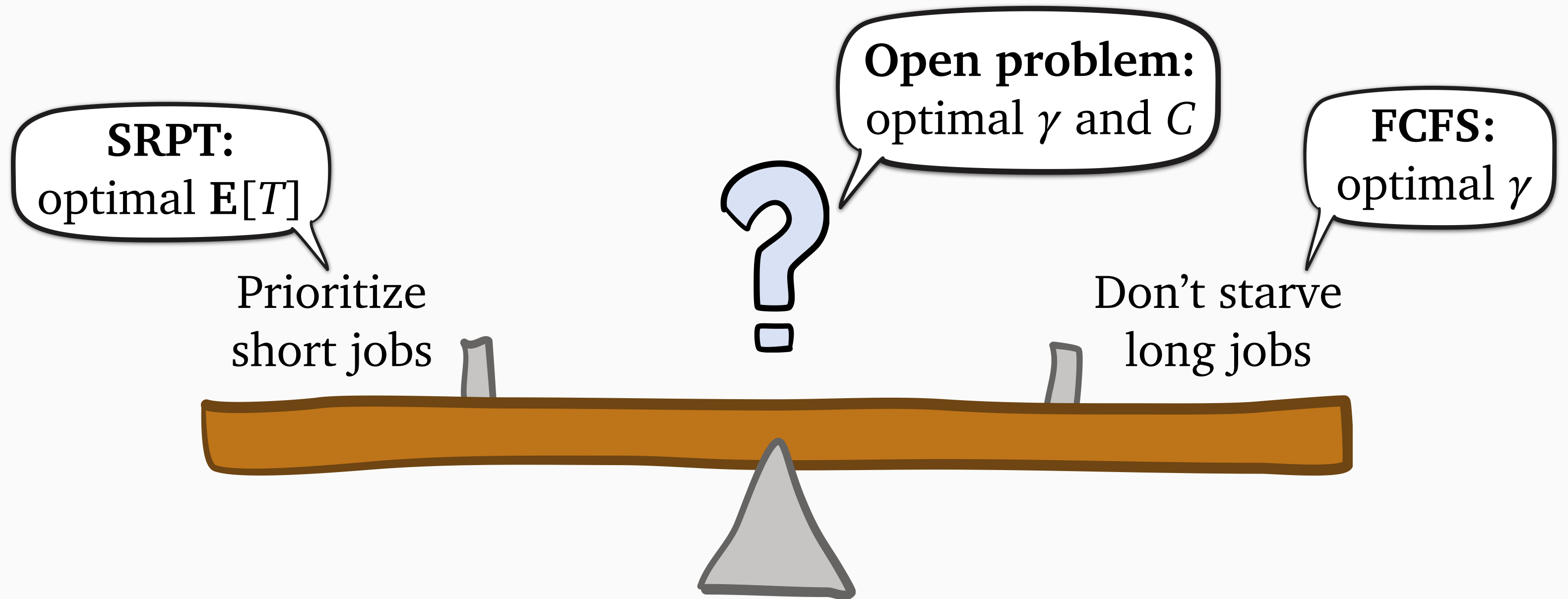
Tradeoff: priority vs. starvation



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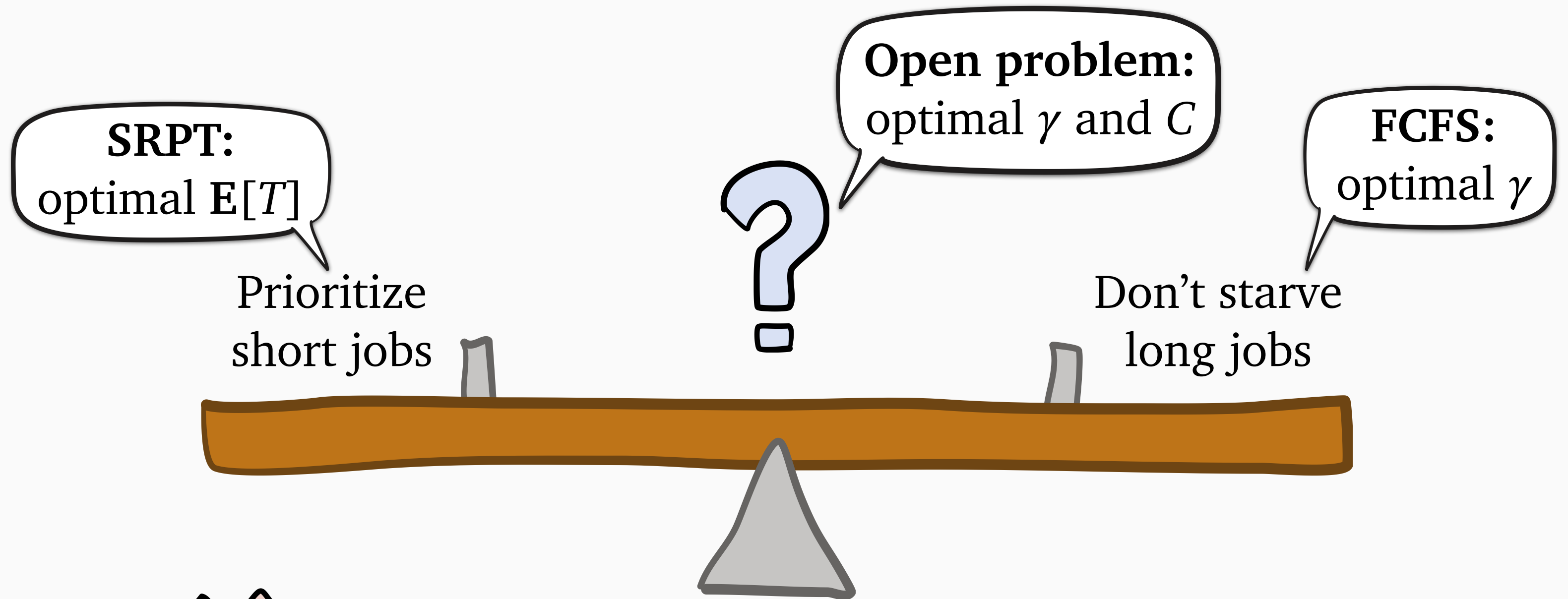
Tradeoff: priority vs. starvation



Conjecture: FCFS optimizes C , too

[Wierman & Zwart, 2012]

Tradeoff: priority vs. starvation



 **Conjecture: FCFS optimizes C , too**
[Wierman & Zwart, 2012]

Tradeoff: priority vs. starvation

SRPT:
optimal $E[T]$

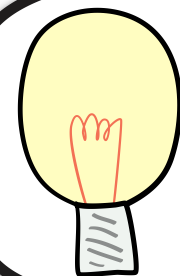
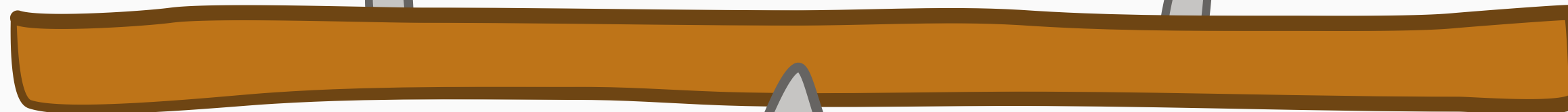
Prioritize
short jobs

Open problem:
optimal γ and C

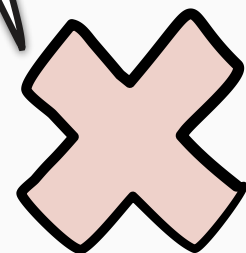


FCFS:
optimal γ

Don't starve
long jobs



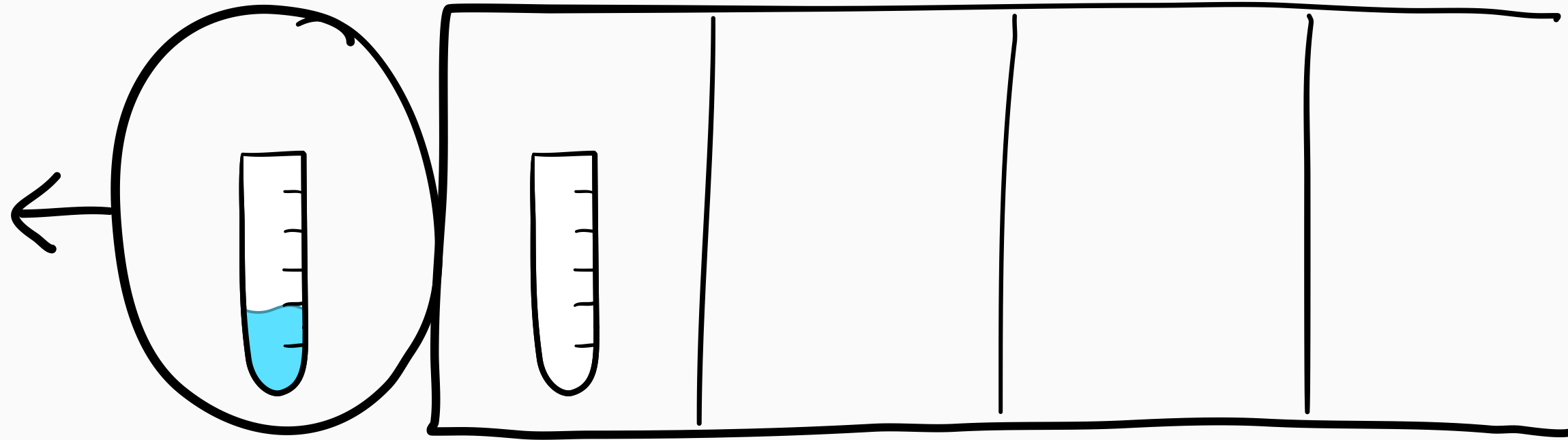
*partial
priority*



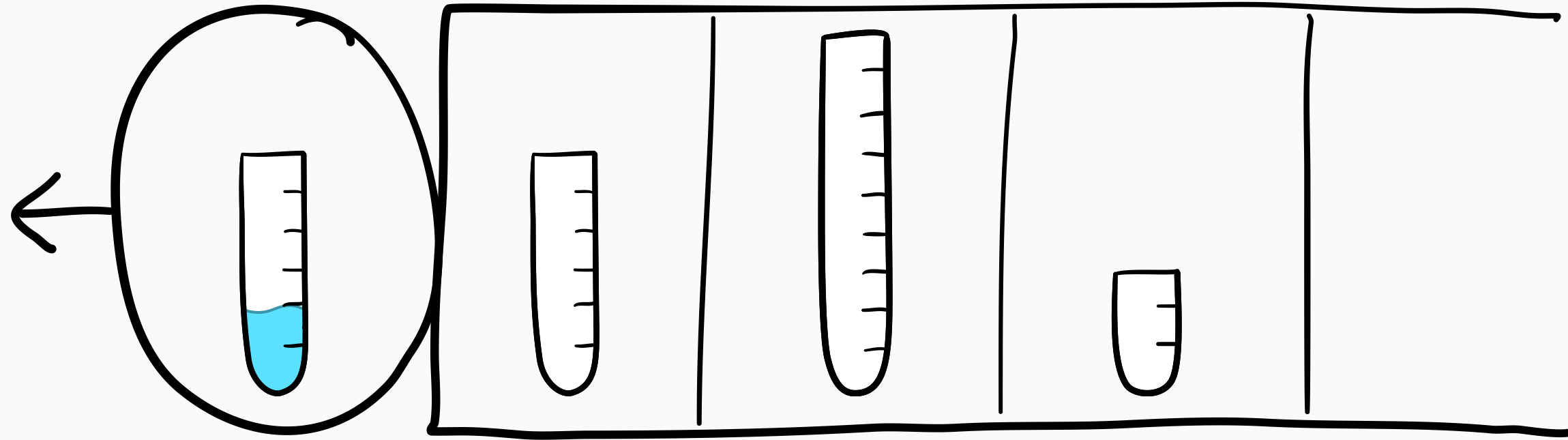
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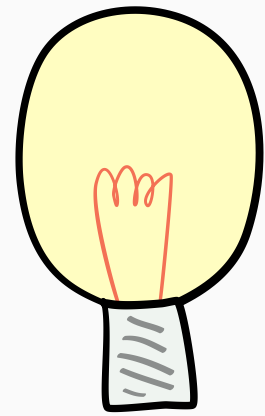
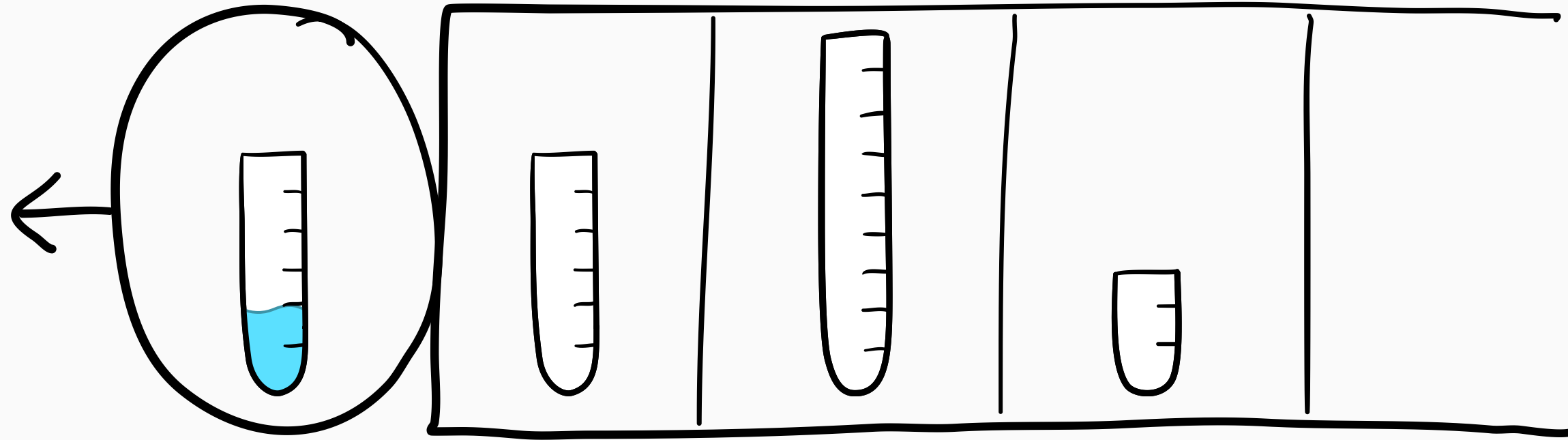
Can we beat FCFS?



Can we beat FCFS?

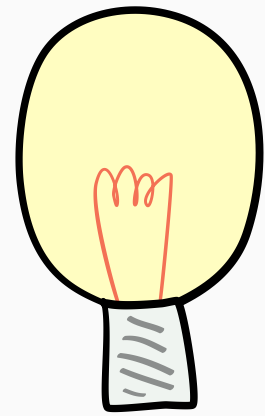
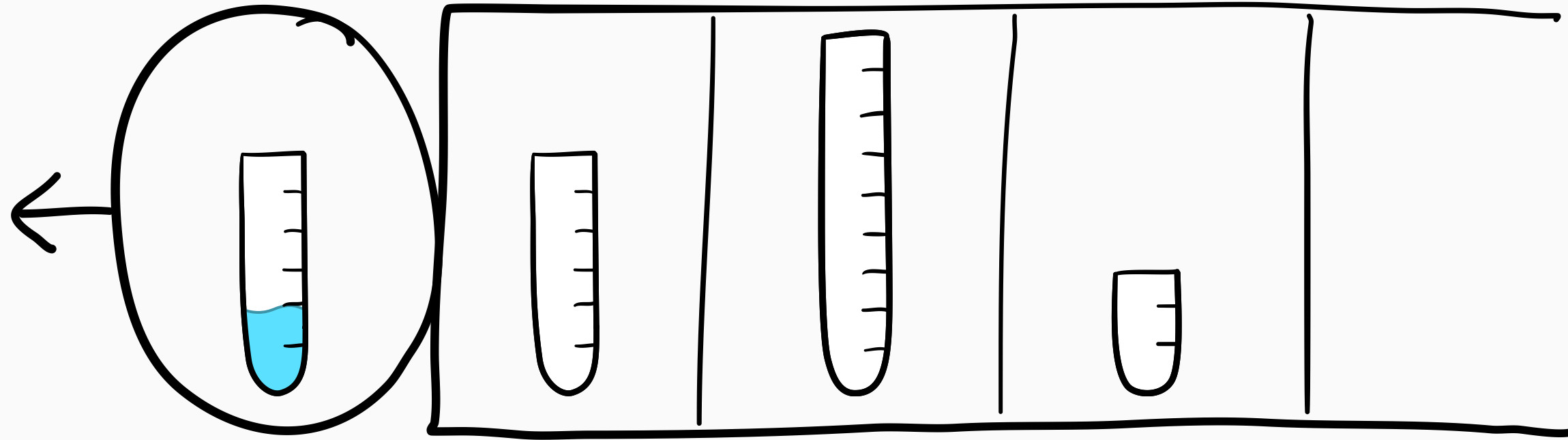


Can we beat FCFS?



Nudge [Grosz et al., 2021]

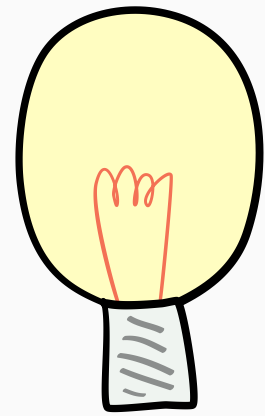
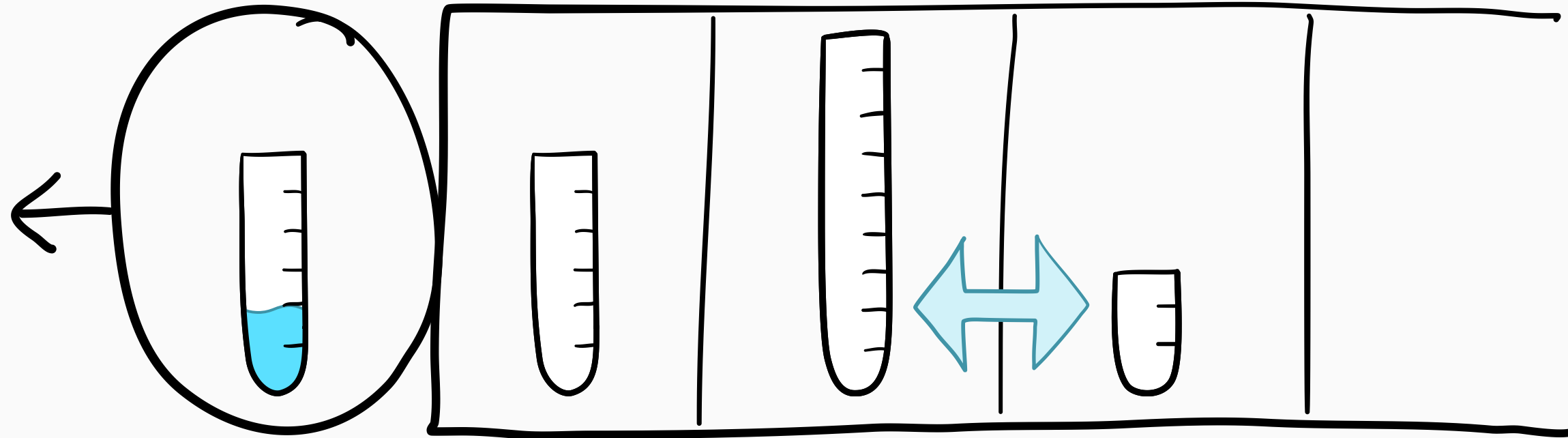
Can we beat FCFS?



Nudge [Grosz et al., 2021]

- small job can pass one large job

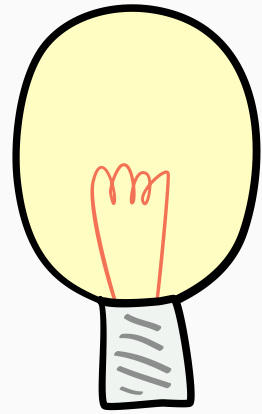
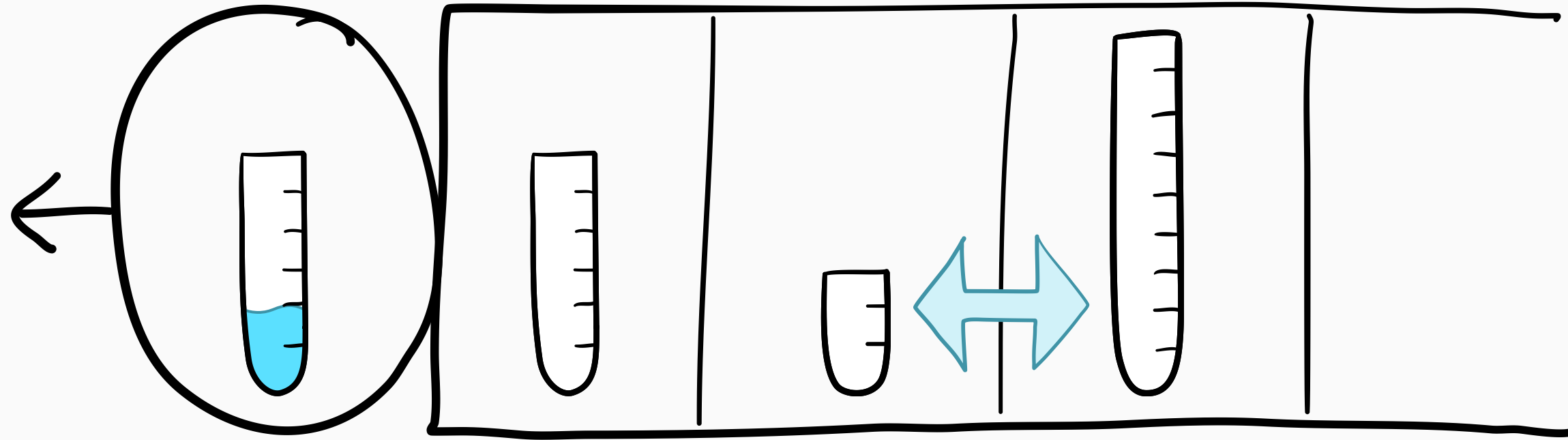
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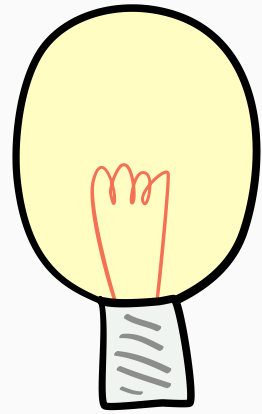
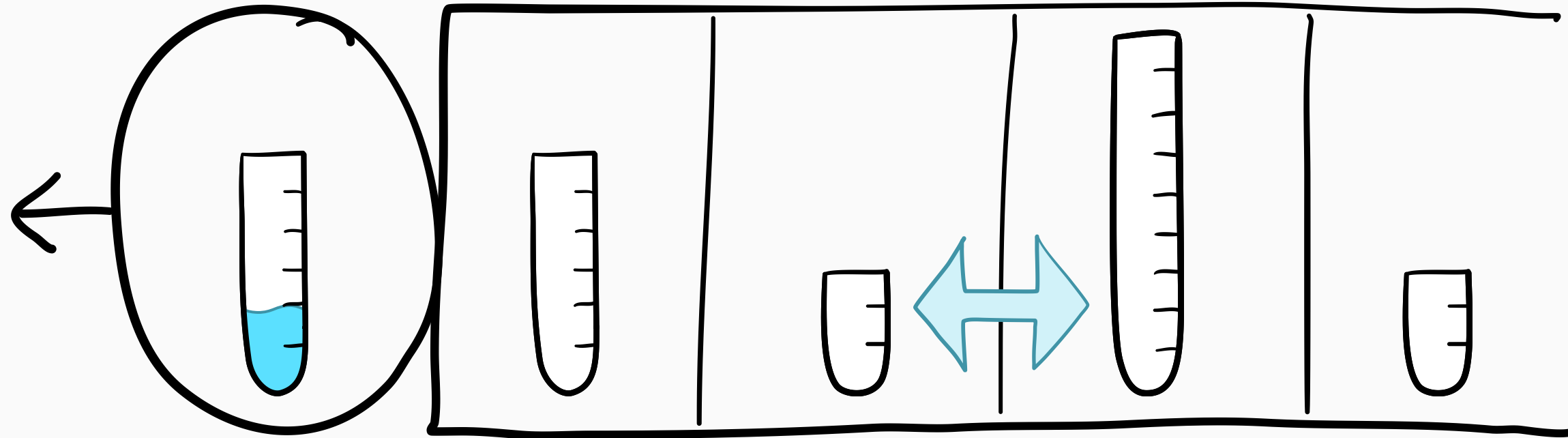
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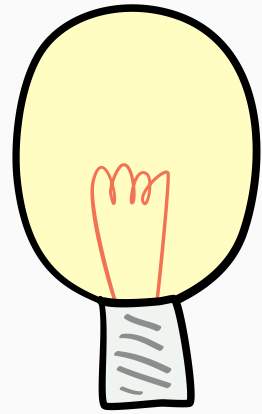
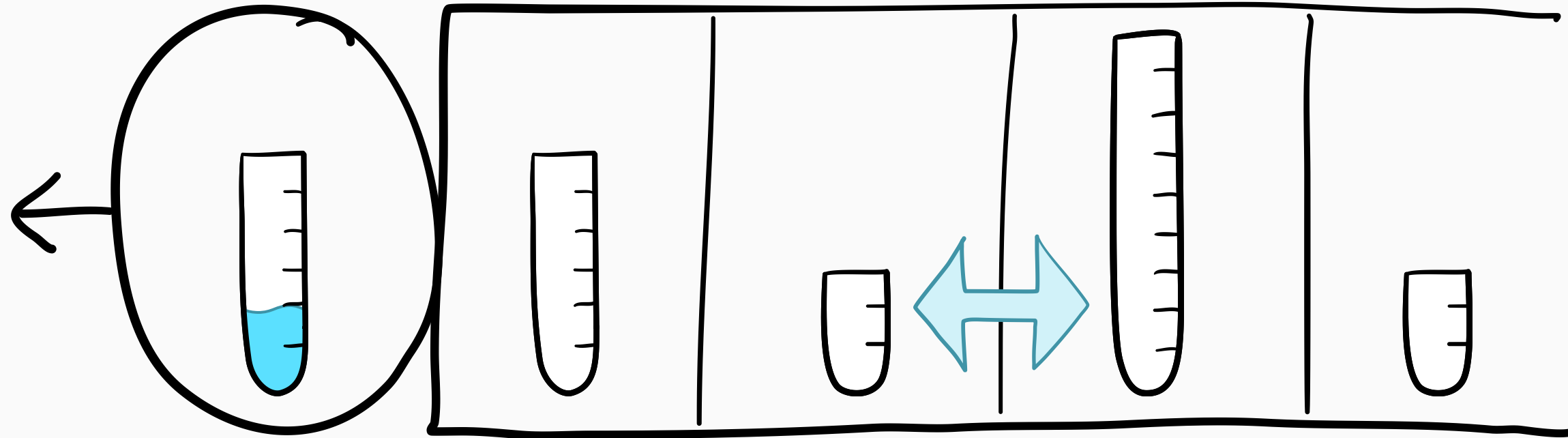
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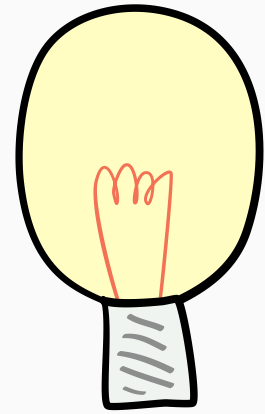
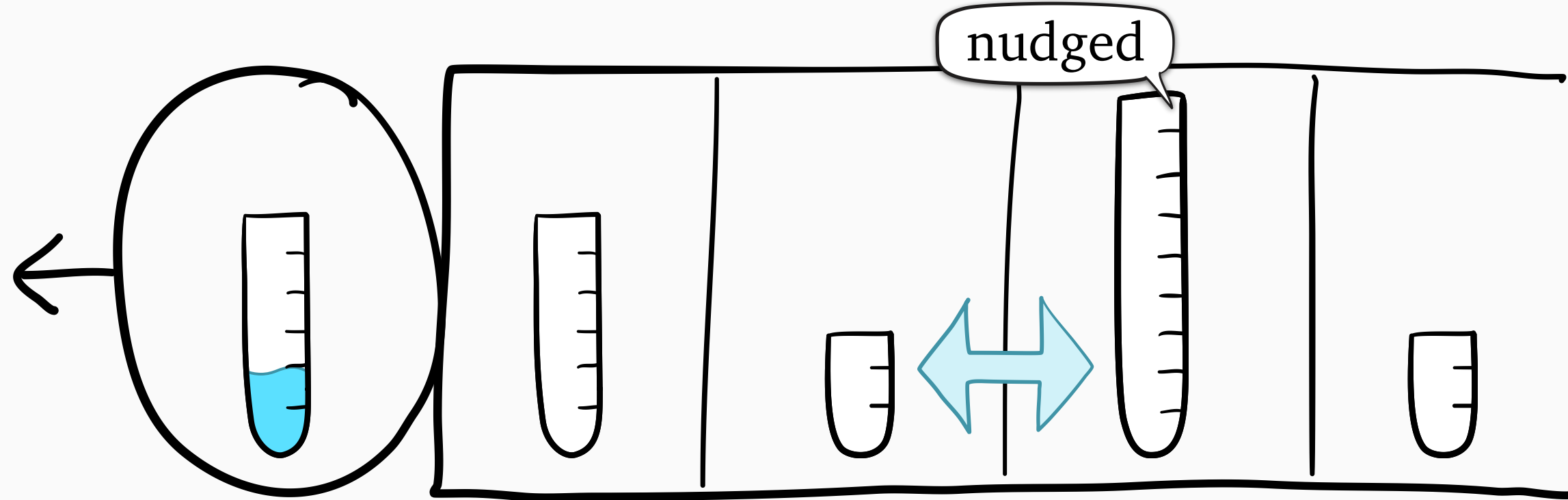
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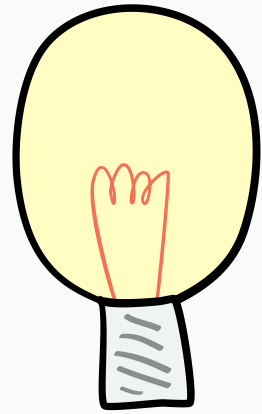
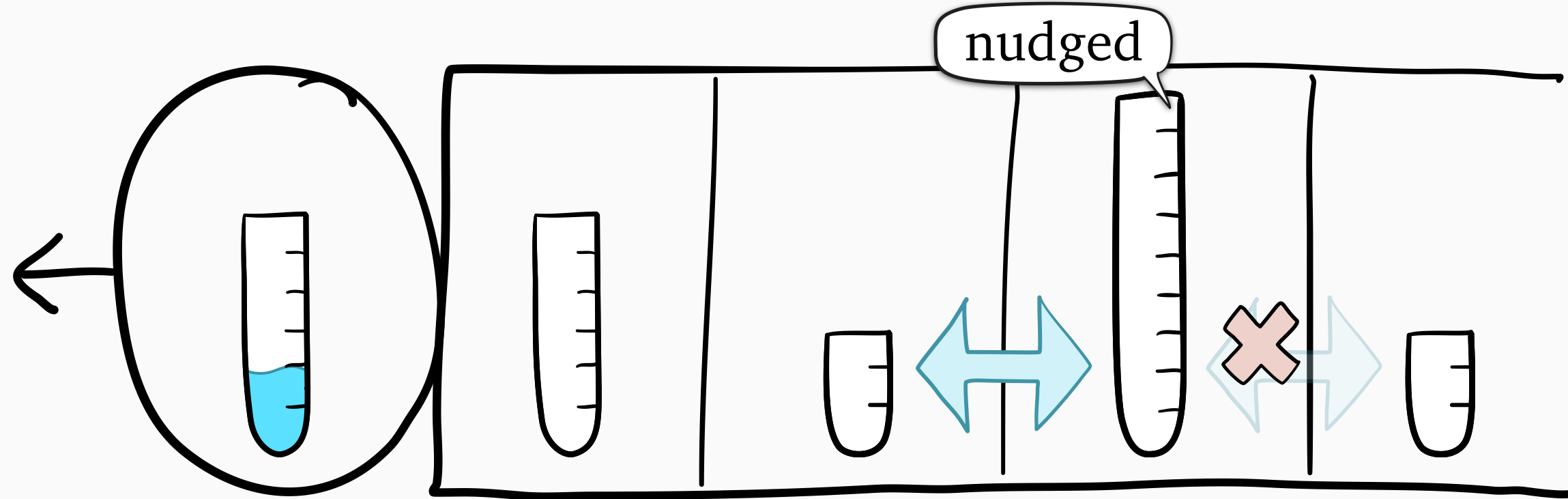
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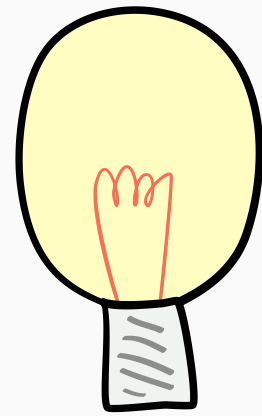
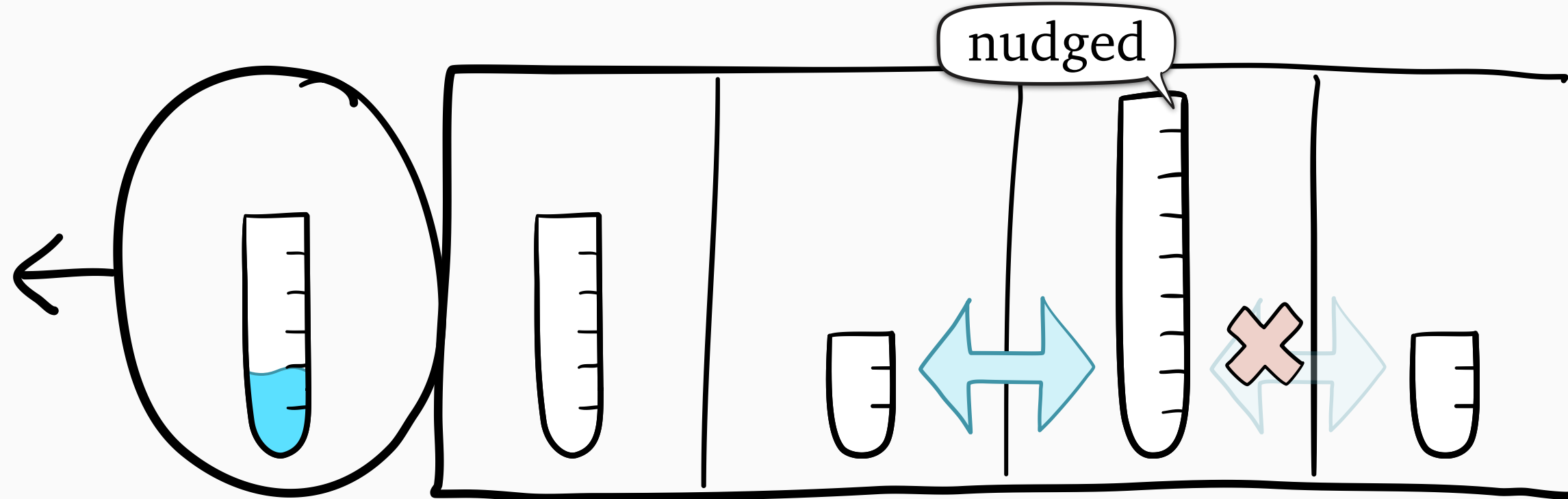
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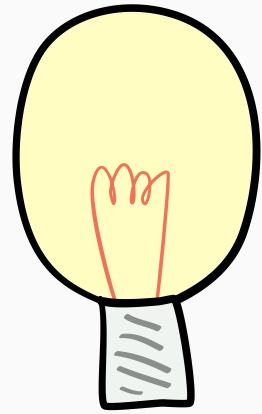
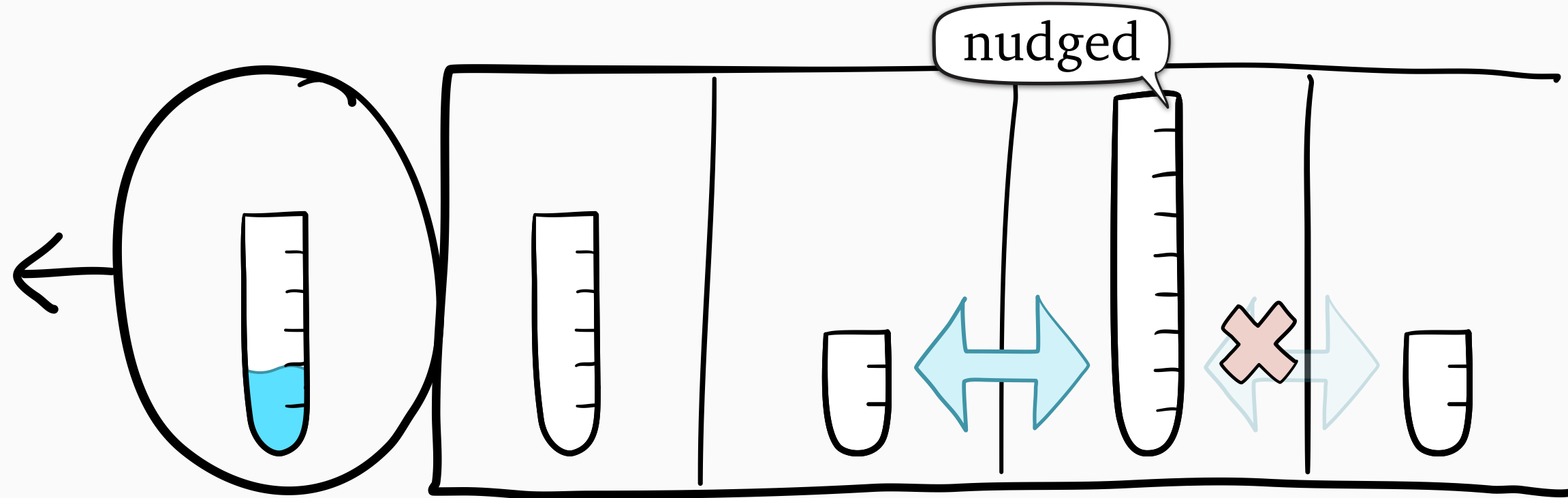
Nudge [Grosz et al., 2021]

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Theorem:

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

Can we beat FCFS?



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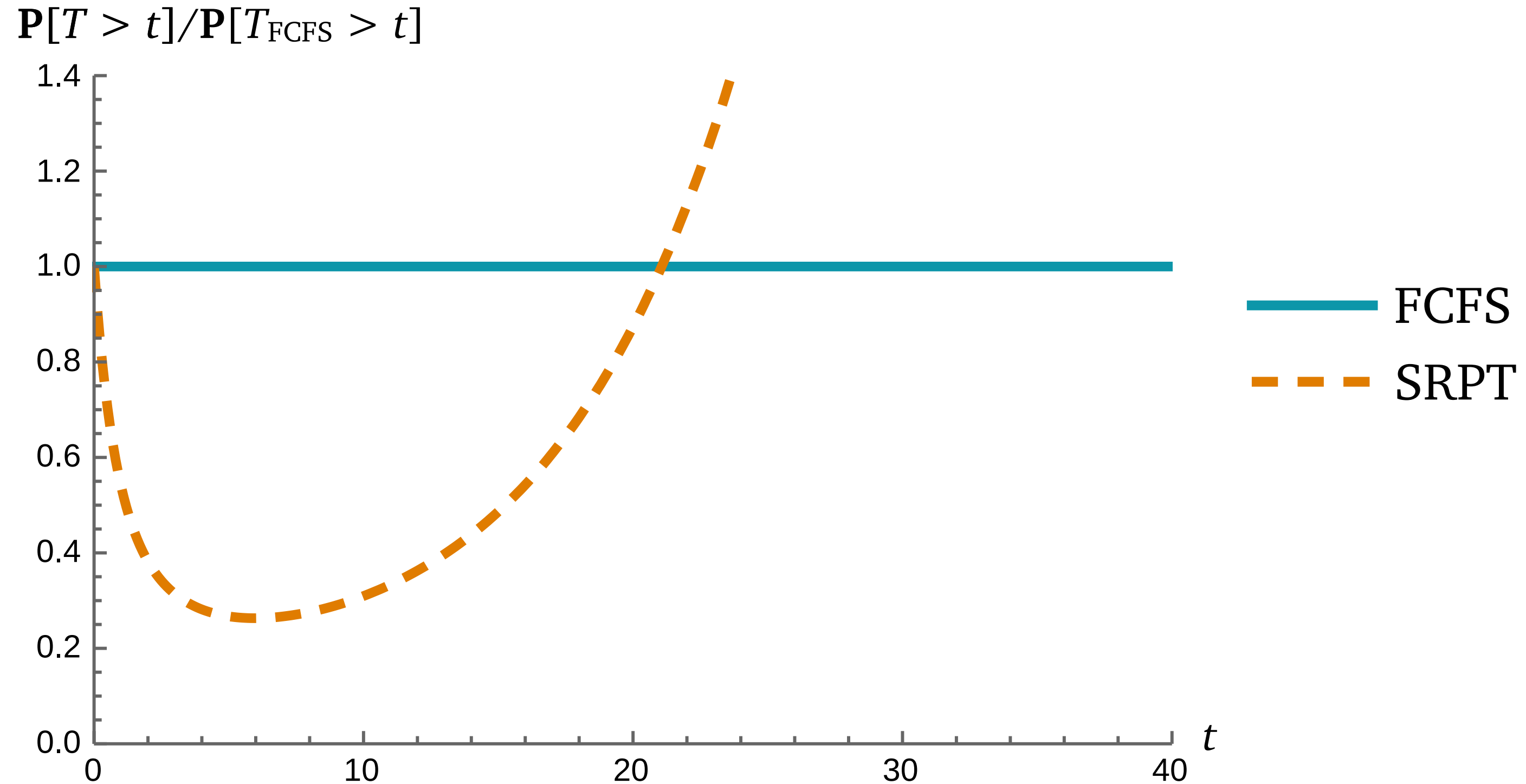
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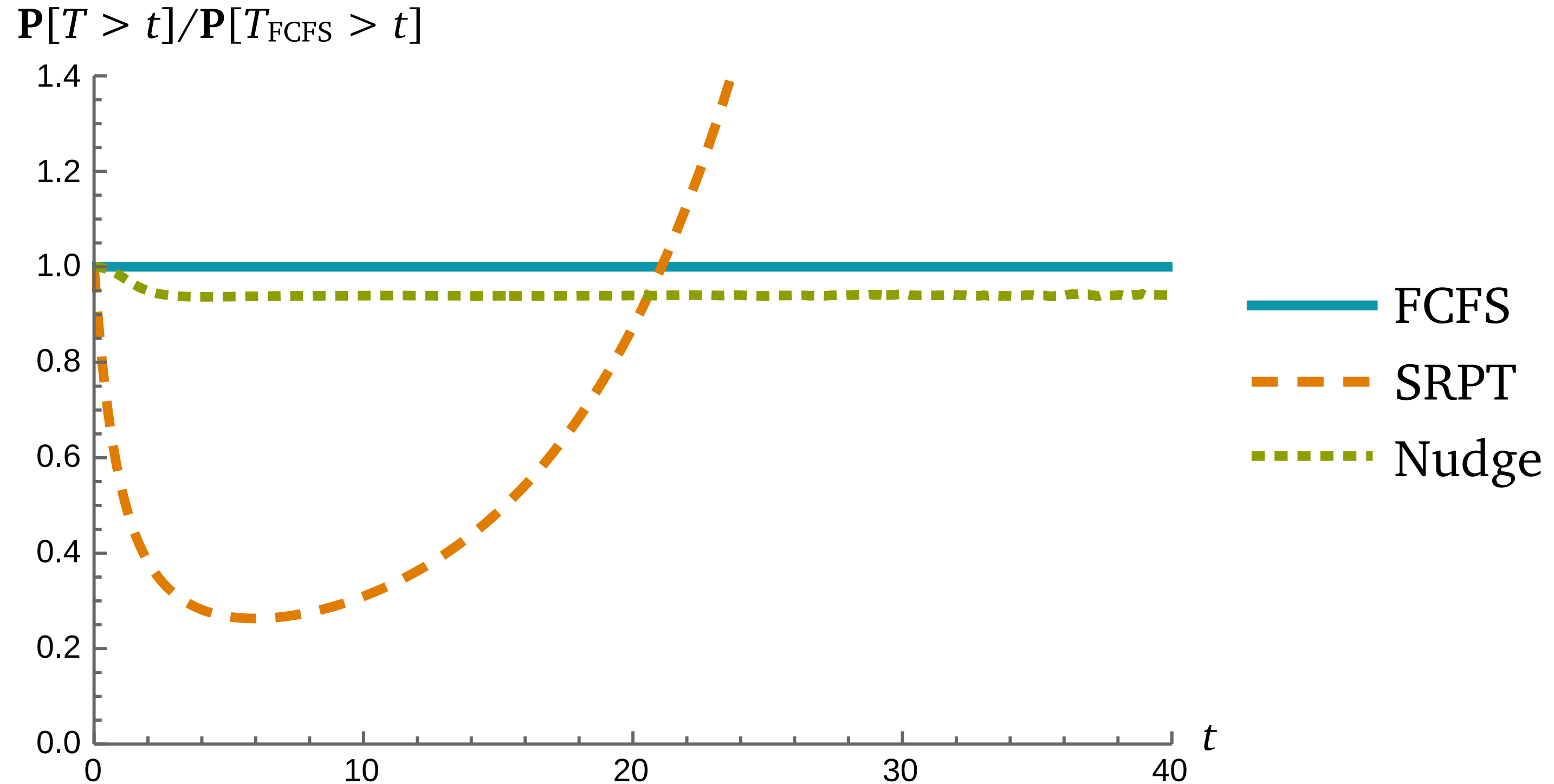
More complex variants get even lower C

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

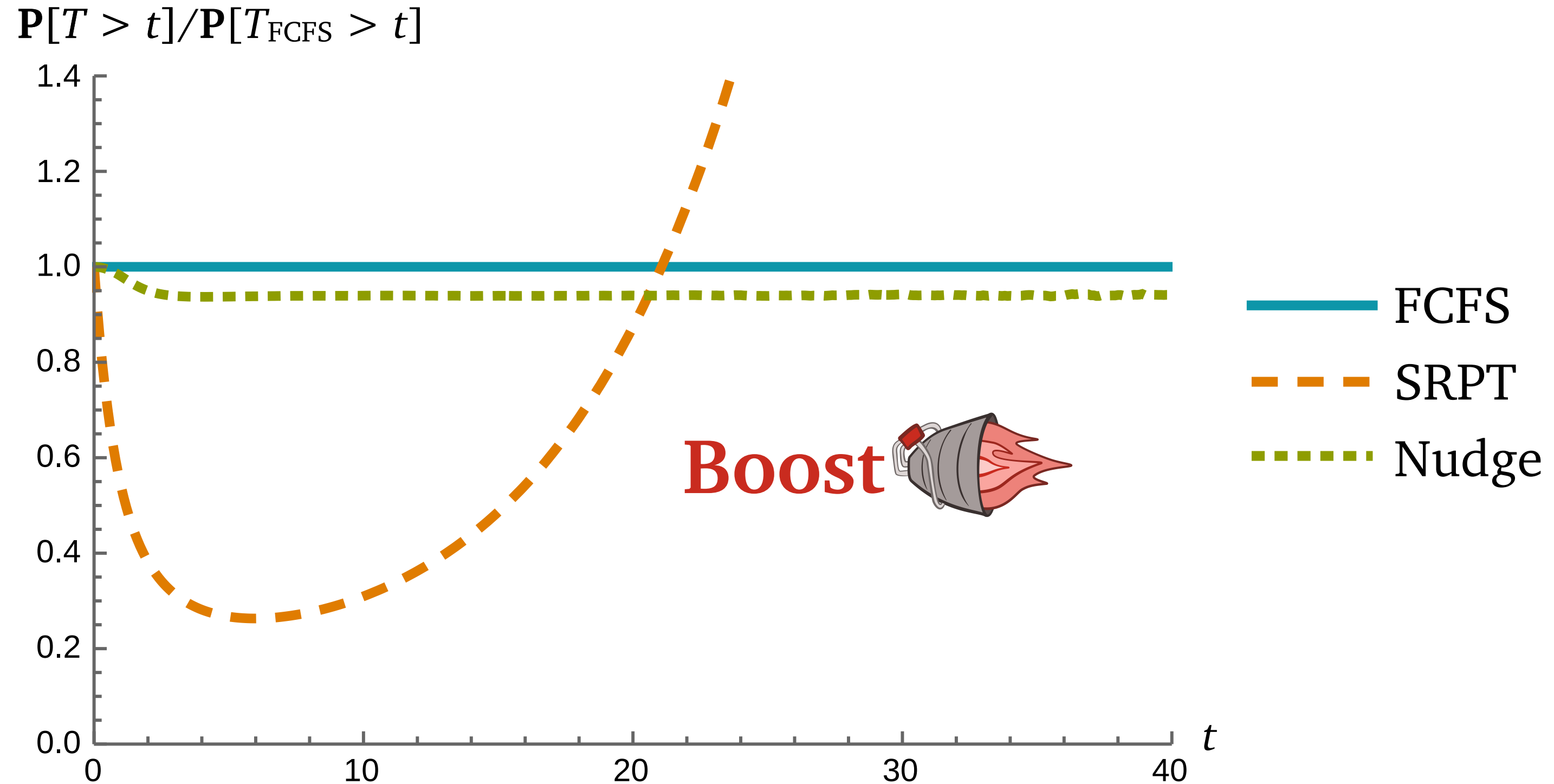
Optimizing the tail constant C



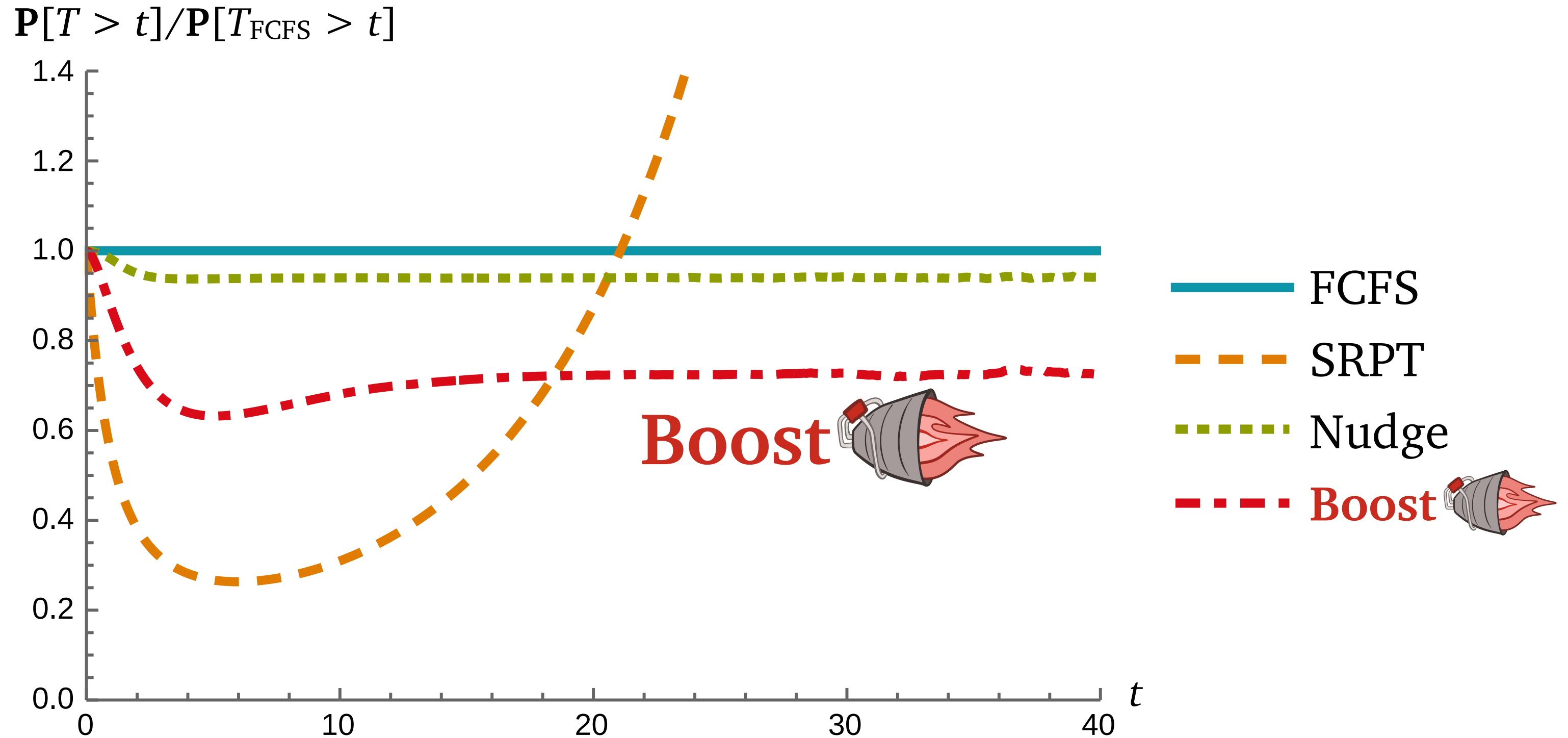
Optimizing the tail constant C



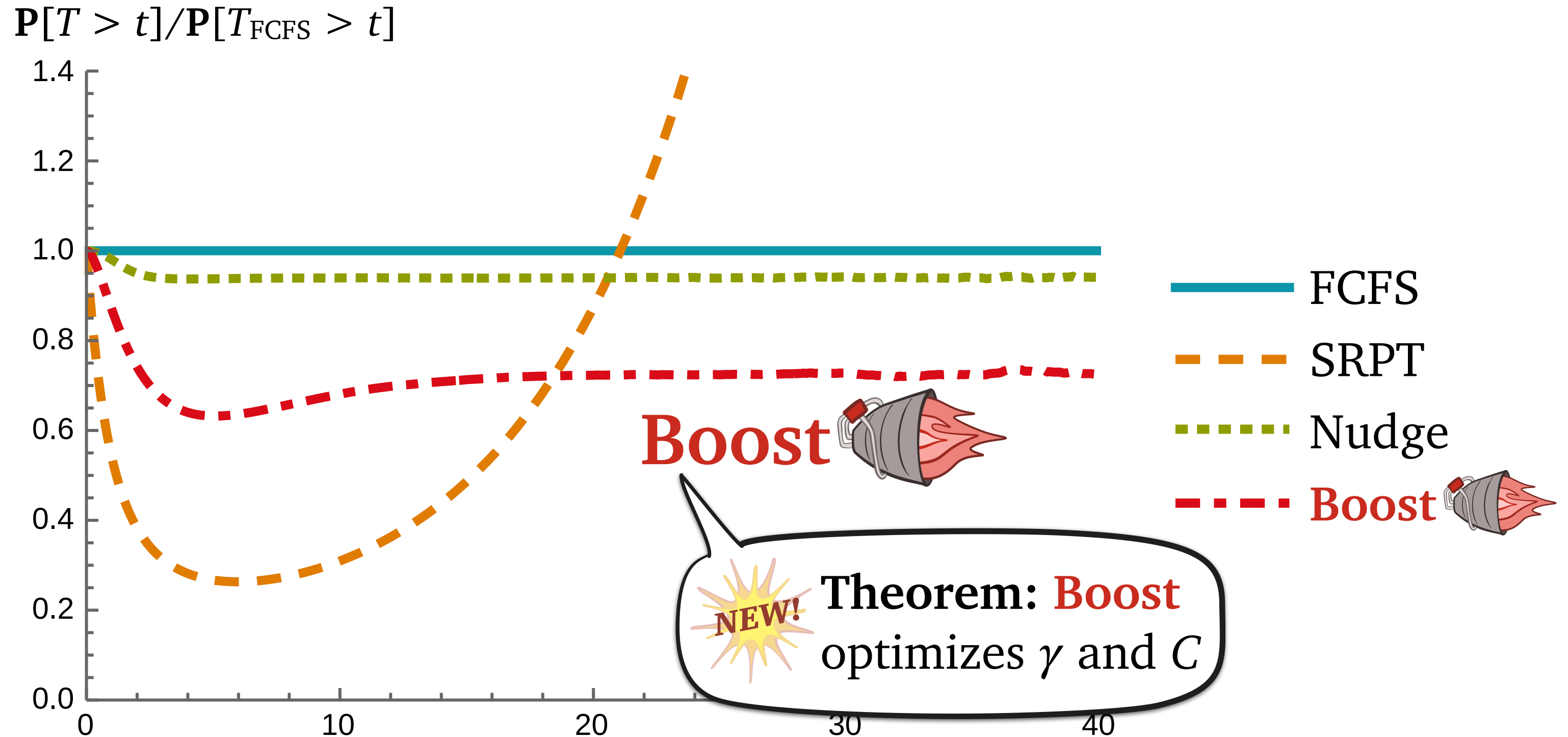
Optimizing the tail constant C



Optimizing the tail constant C



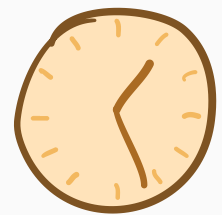
Optimizing the tail constant C



Our contributions:



Design the **Boost** scheduling policy



Analyze **Boost**'s performance



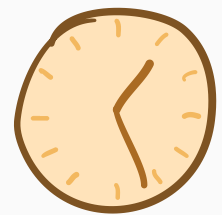
Prove **Boost** is *strongly tail-optimal* for light-tailed sizes

Our contributions:

actually a *family*
of many policies



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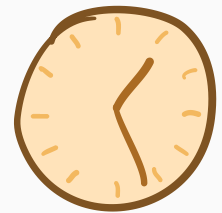
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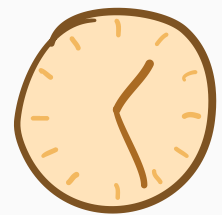
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specific instance
called γ -**Boost**



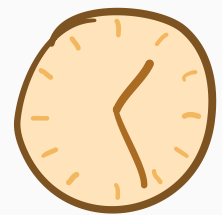
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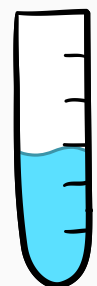
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Known job sizes

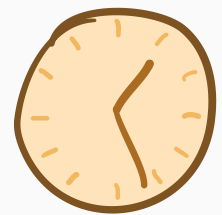
Yu & Scully. *Strongly Tail-Optimal Scheduling
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Our contributions:



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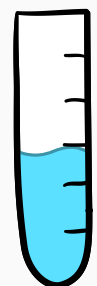
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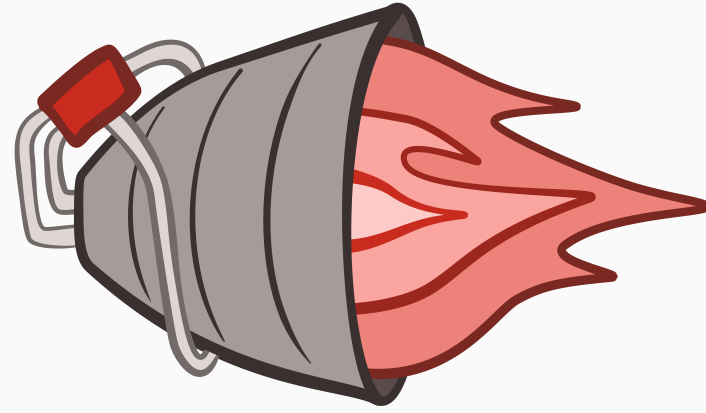
Yu & Scully. *Strongly Tail-Optimal Scheduling in the Light-Tailed M/G/1*. SIGMETRICS 2024.



Unknown job sizes

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

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?

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

? How do we achieve strong tail optimality?

Boost

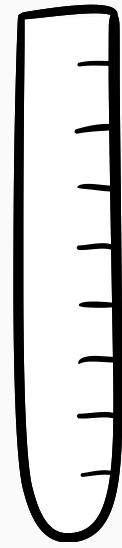
? Why is achieving strong tail optimality hard?

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

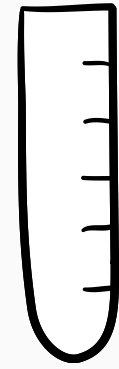
? How do we achieve strong tail optimality?

Can we beat Nudge?

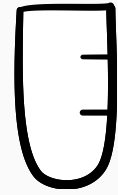
Can we beat Nudge?



1st



2nd

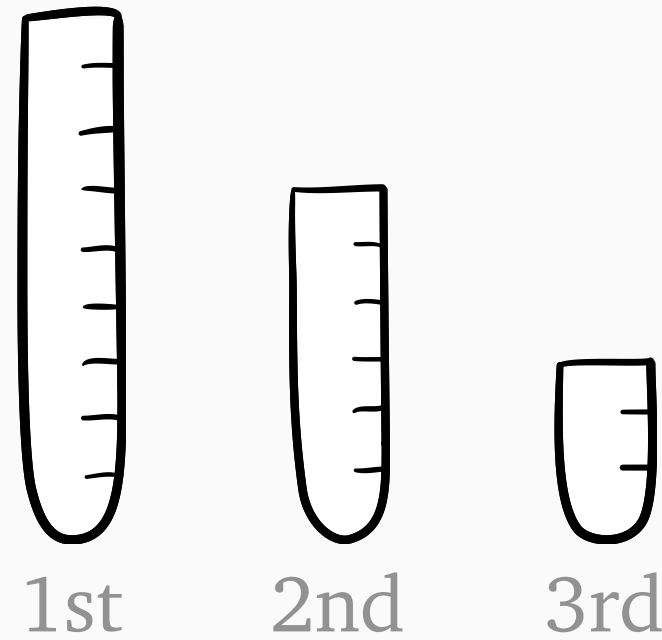


3rd



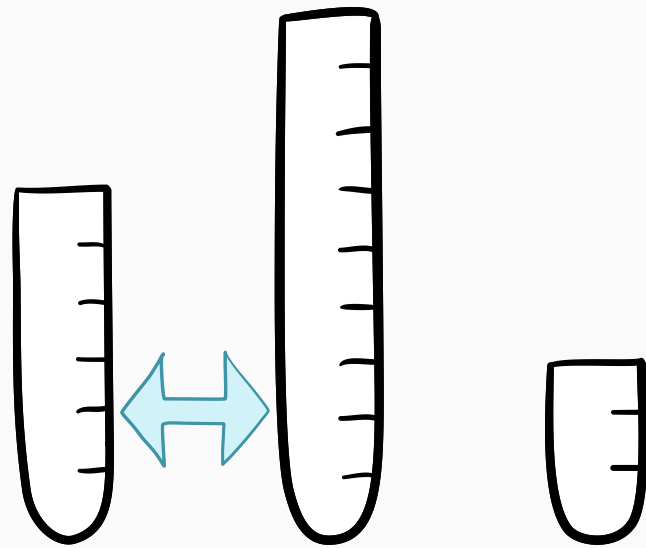
How to handle
range of sizes?

Can we beat Nudge?

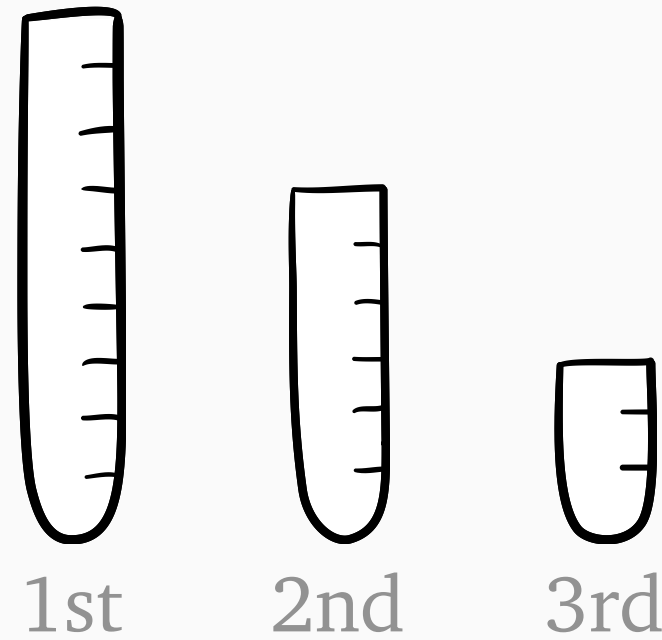


? How to handle
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medium = small?

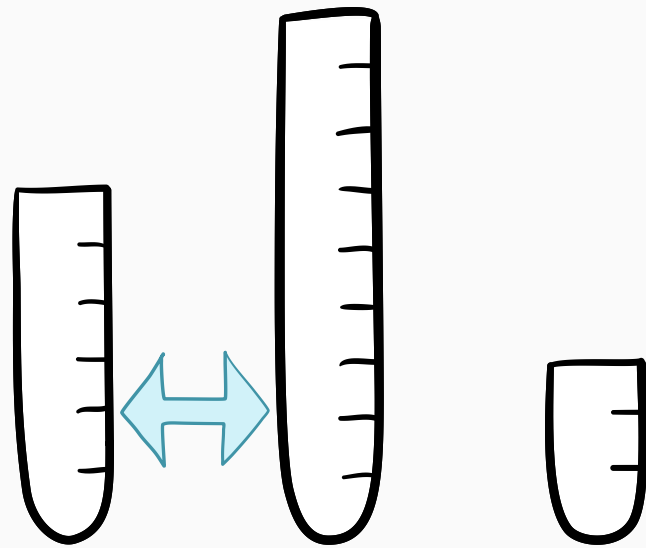


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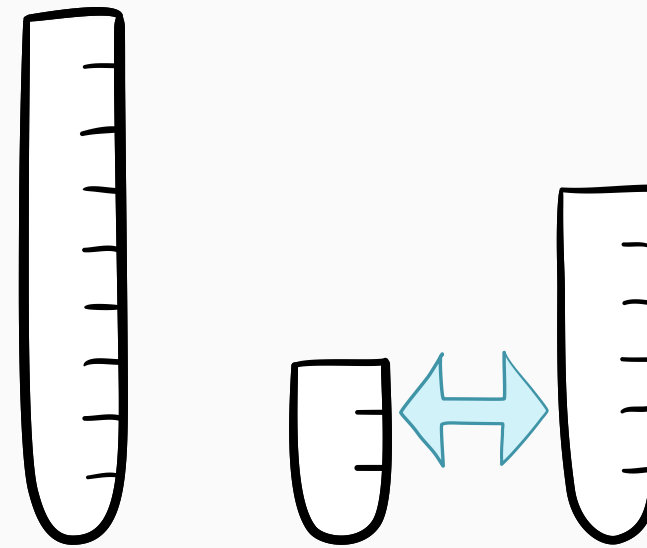


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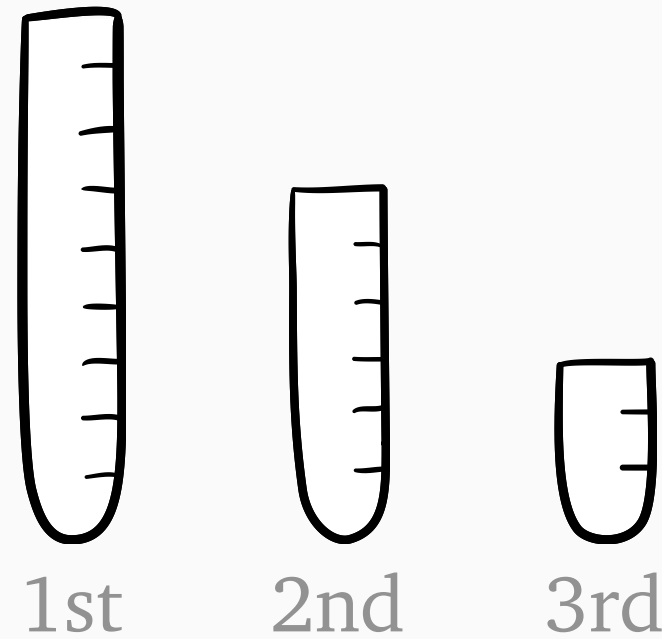
medium = small?



medium = large?

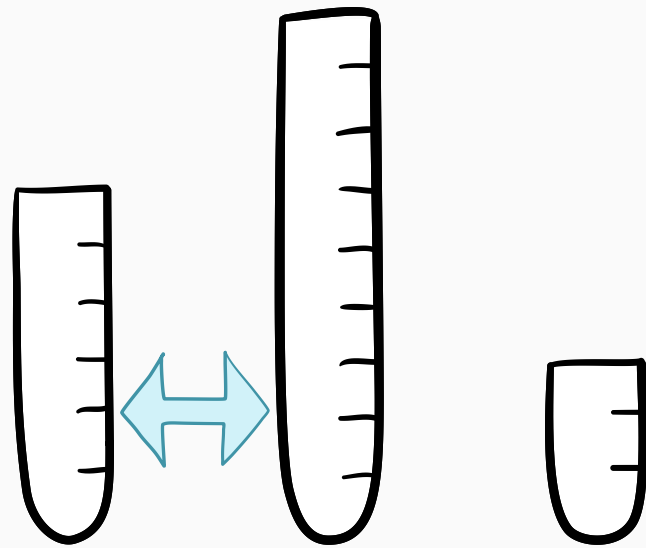


Can we beat Nudge?

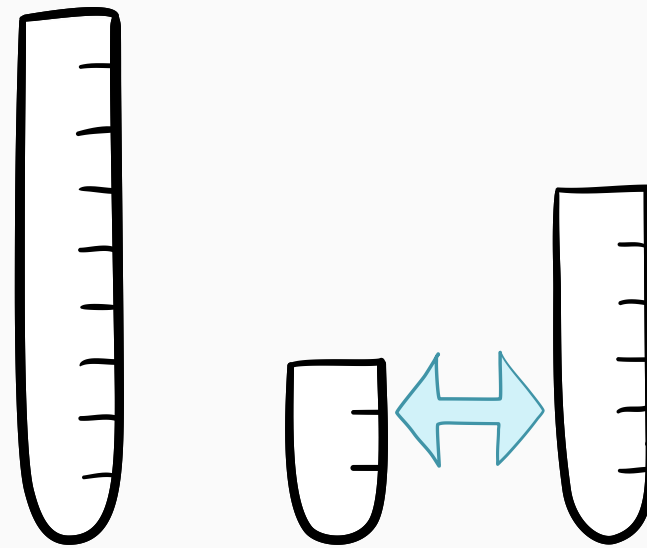


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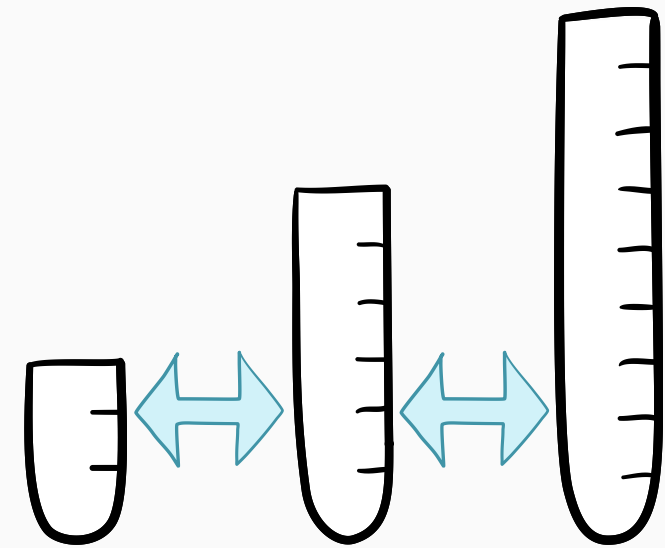
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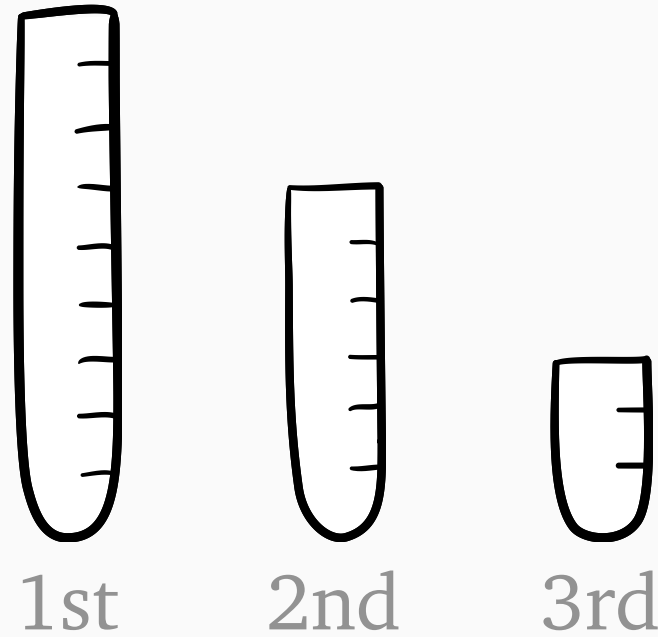
medium = large?



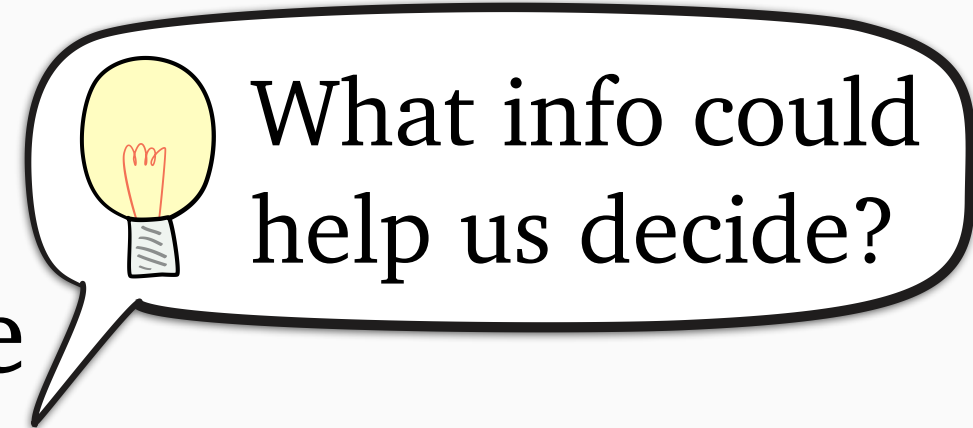
something else?



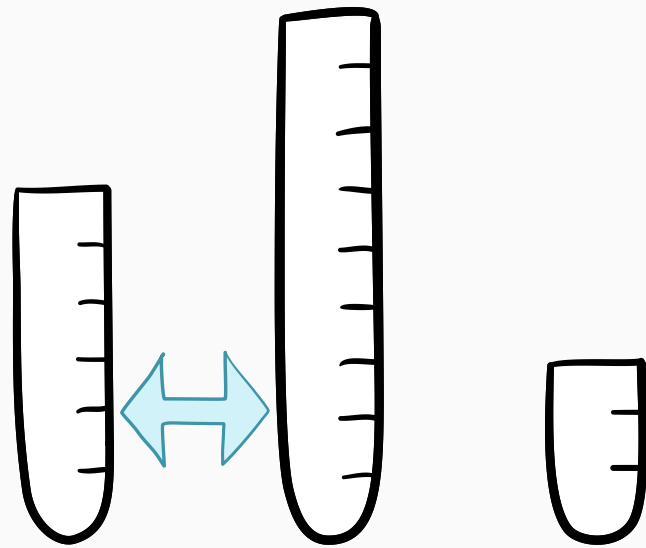
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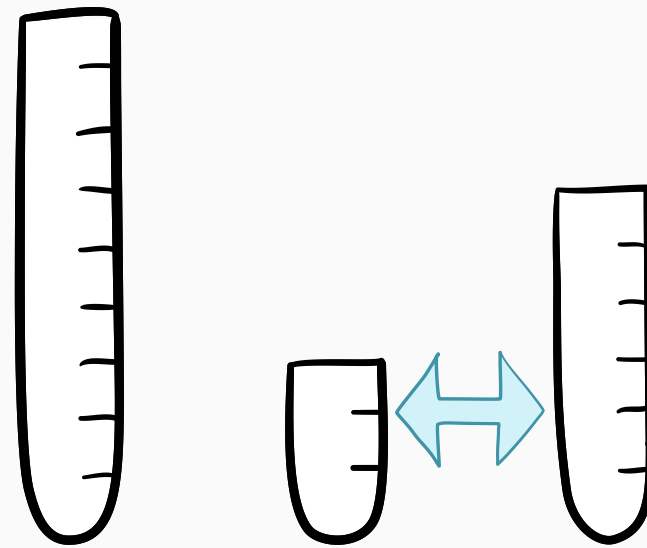
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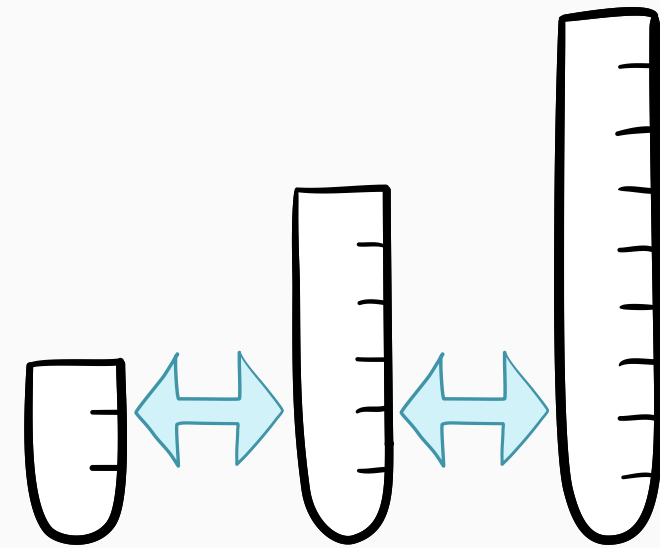
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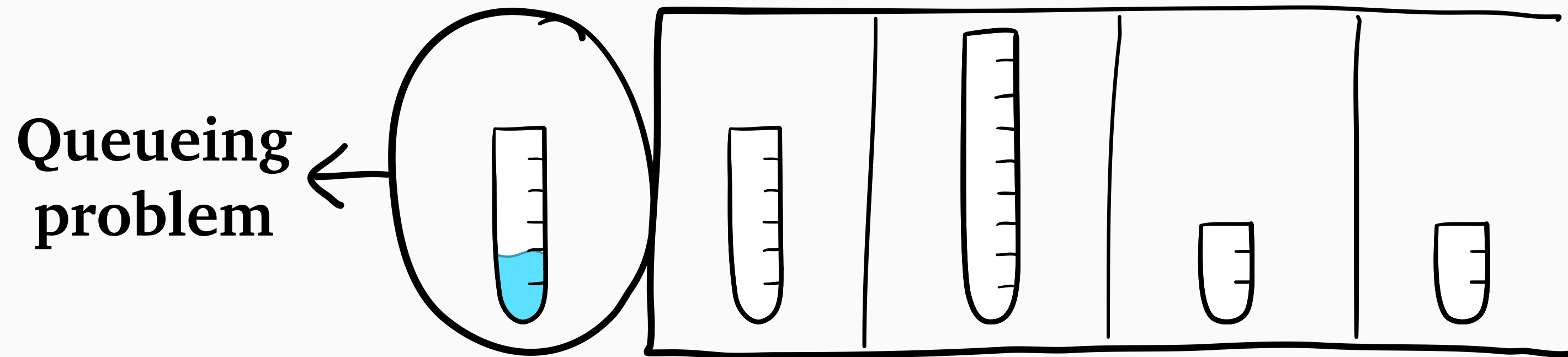


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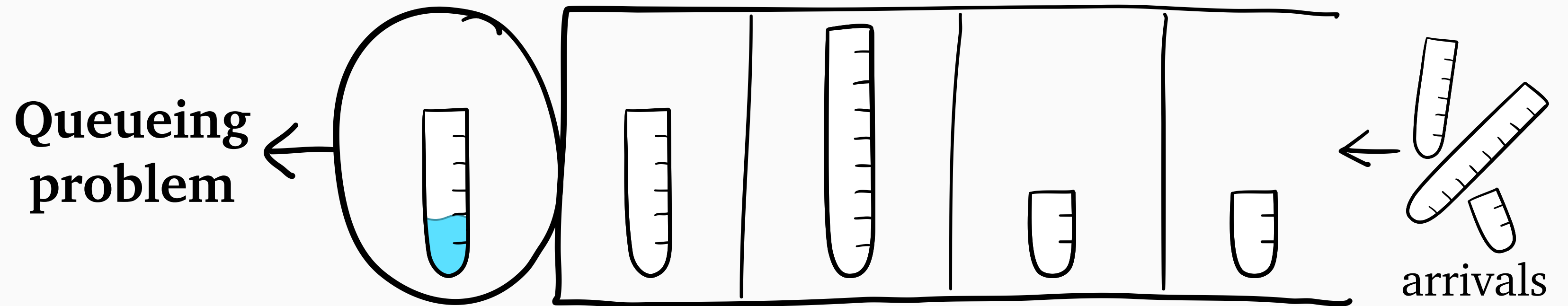


Where do optimal policies come from?

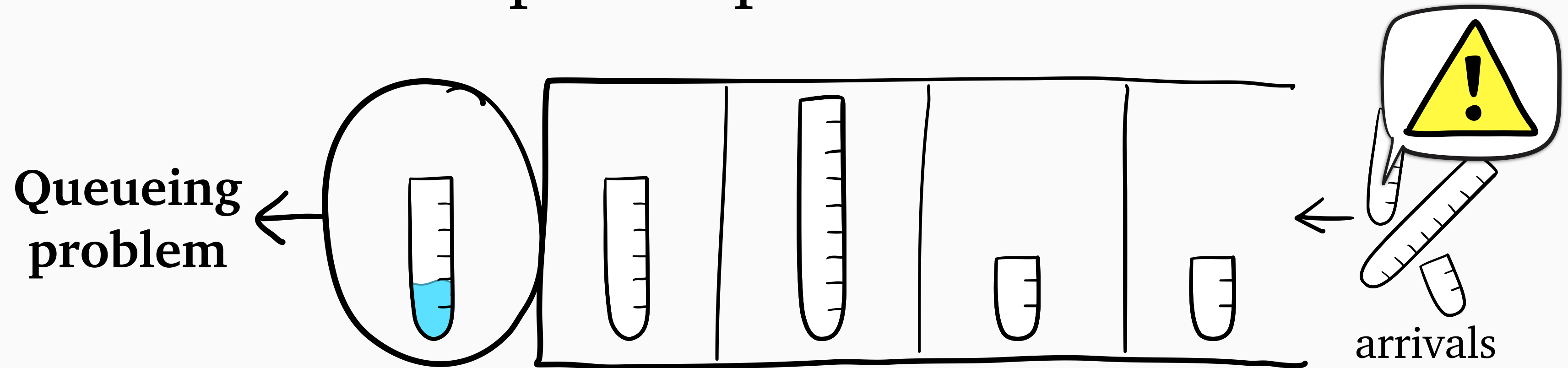
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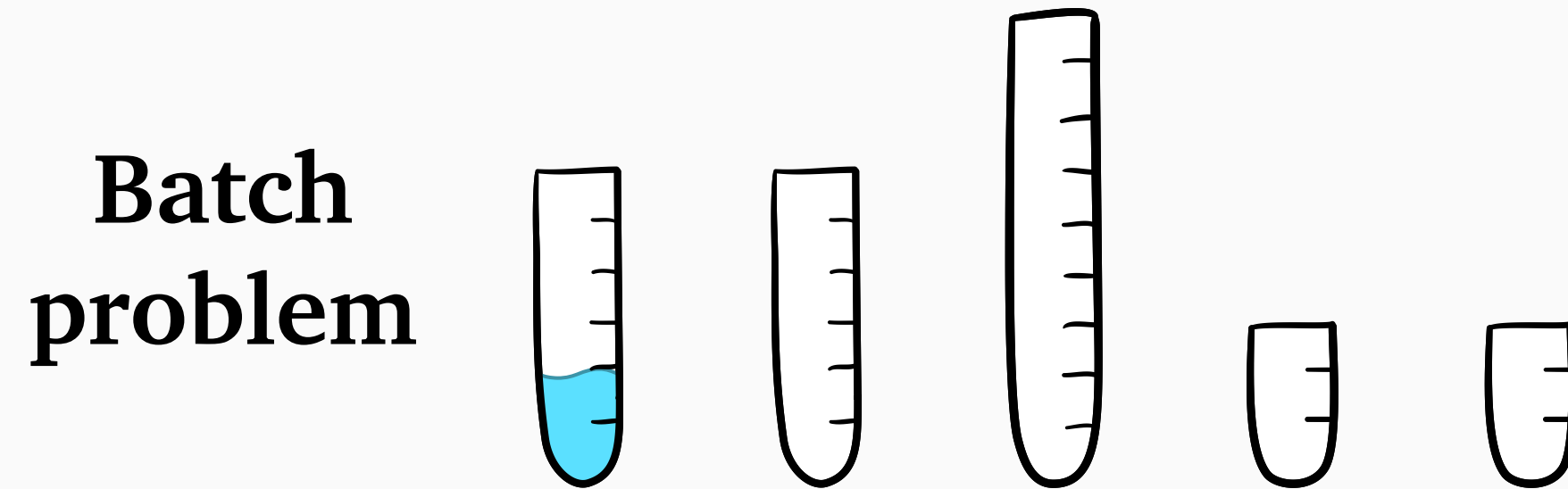
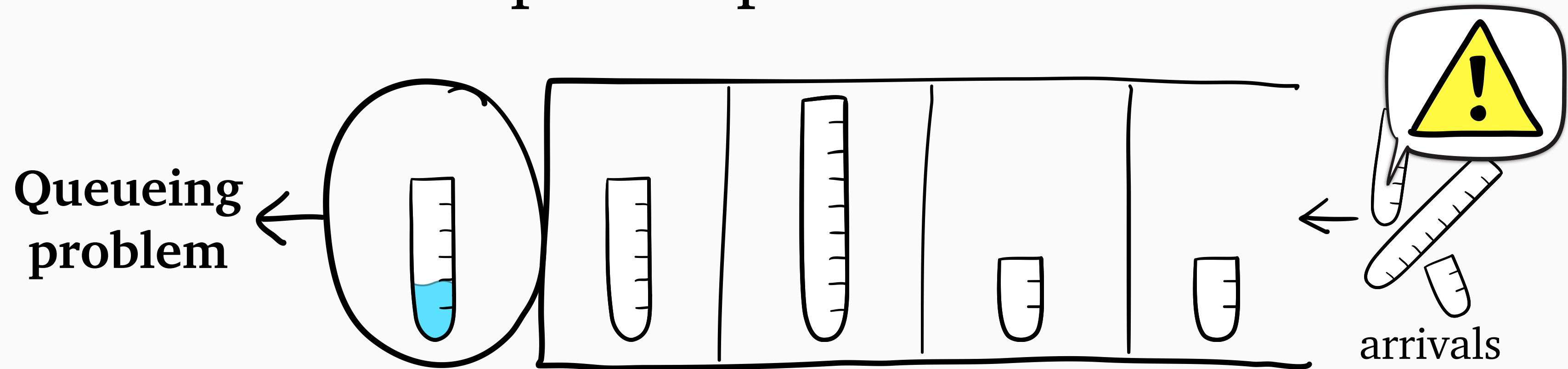
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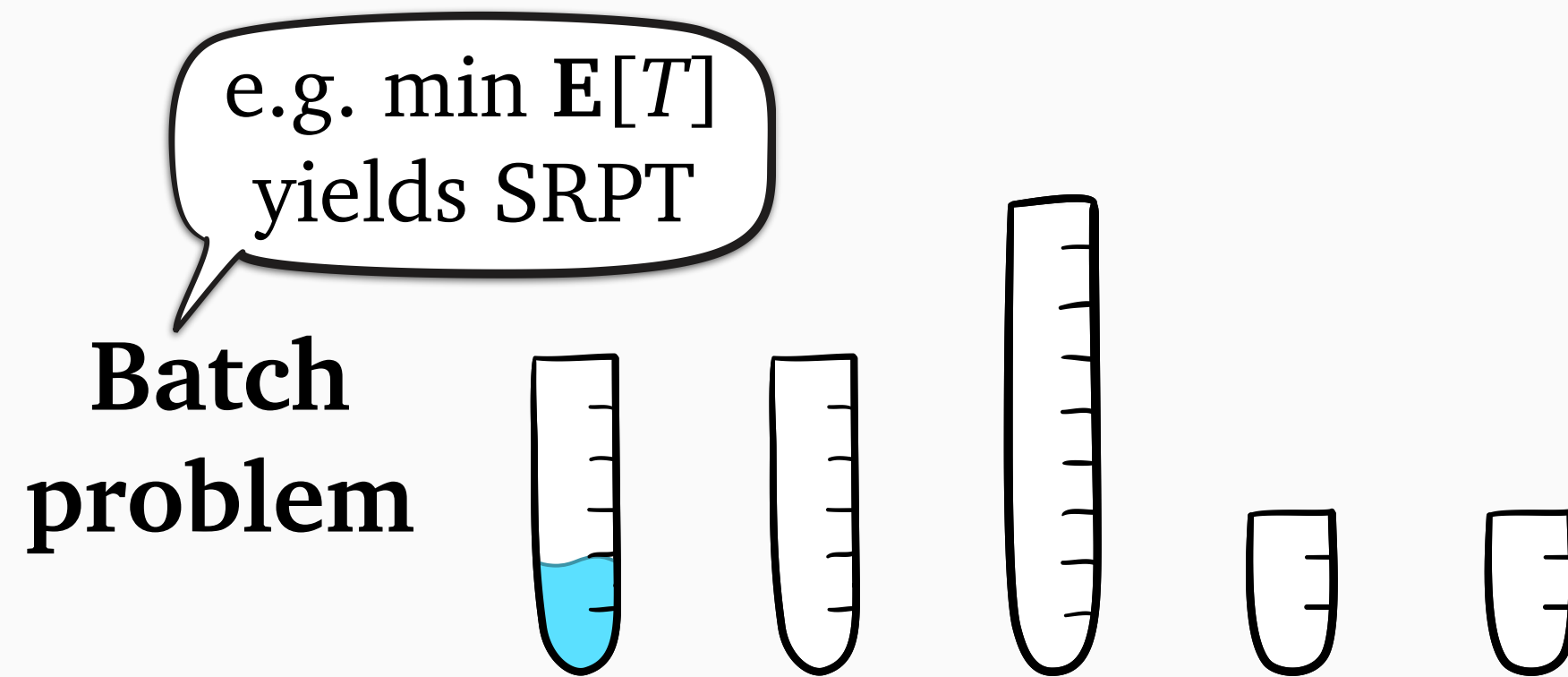
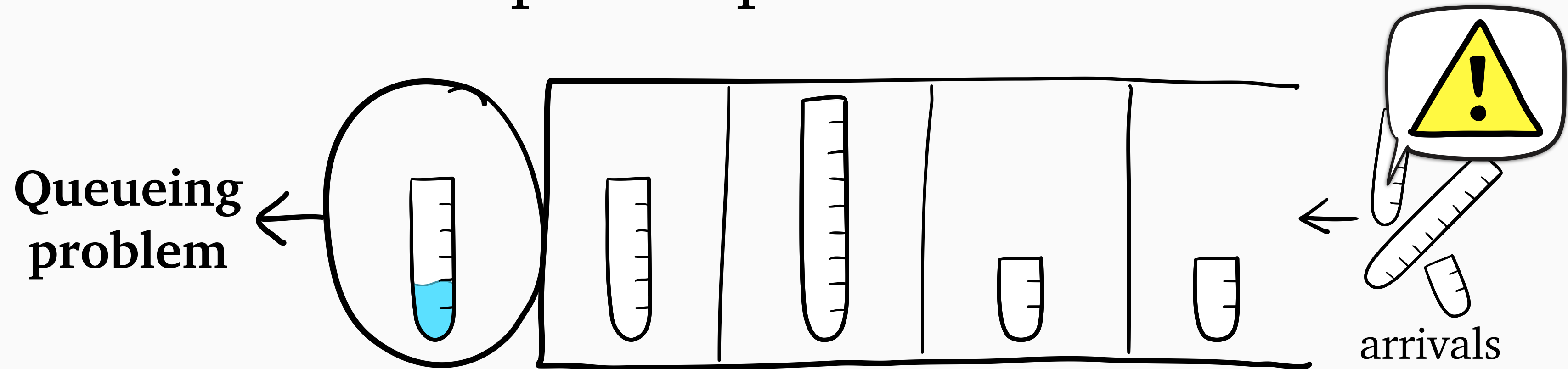
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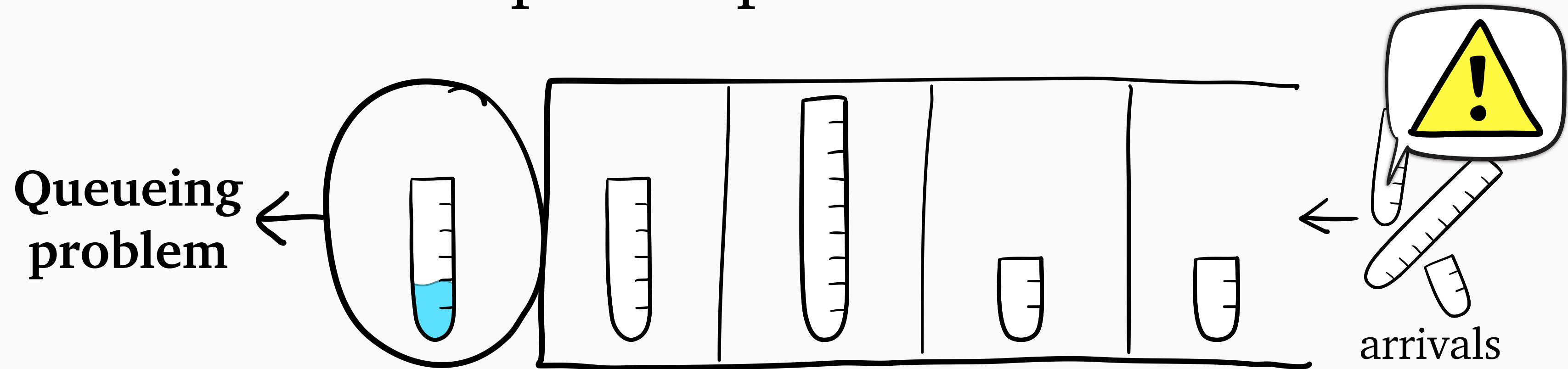
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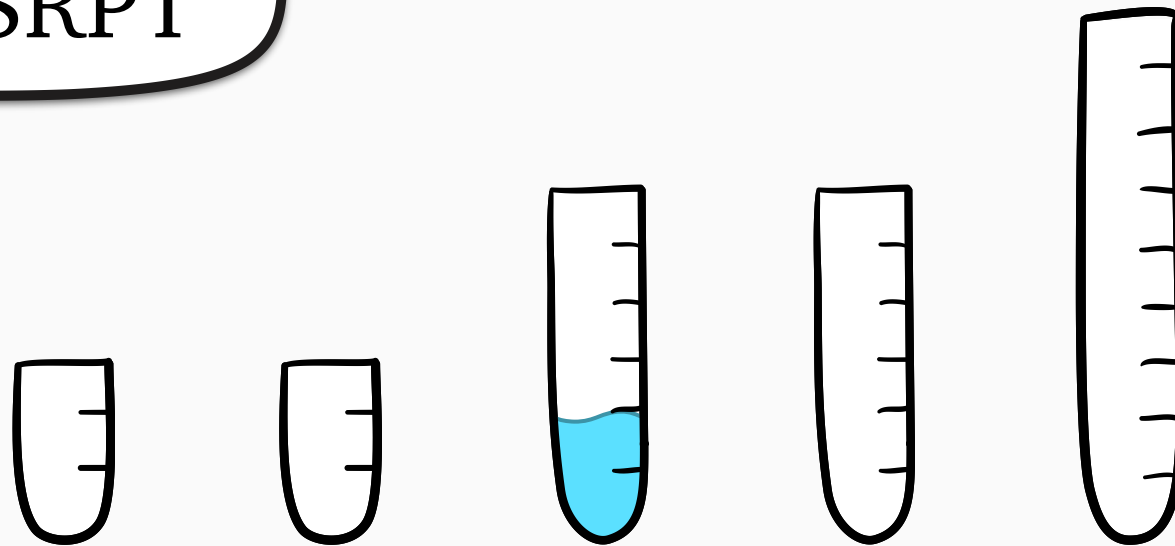


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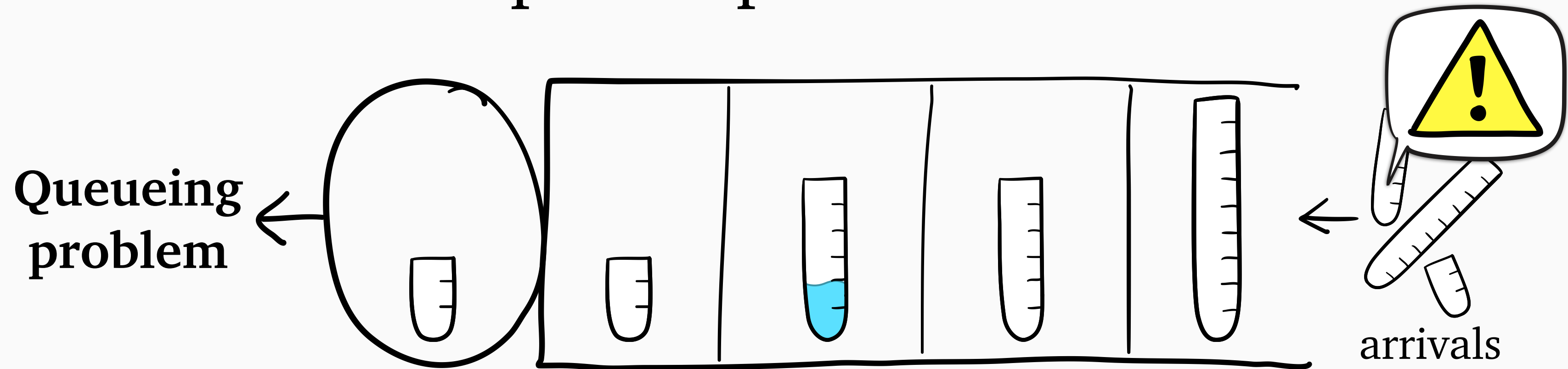


e.g. $\min E[T]$
yields SRPT

Batch problem

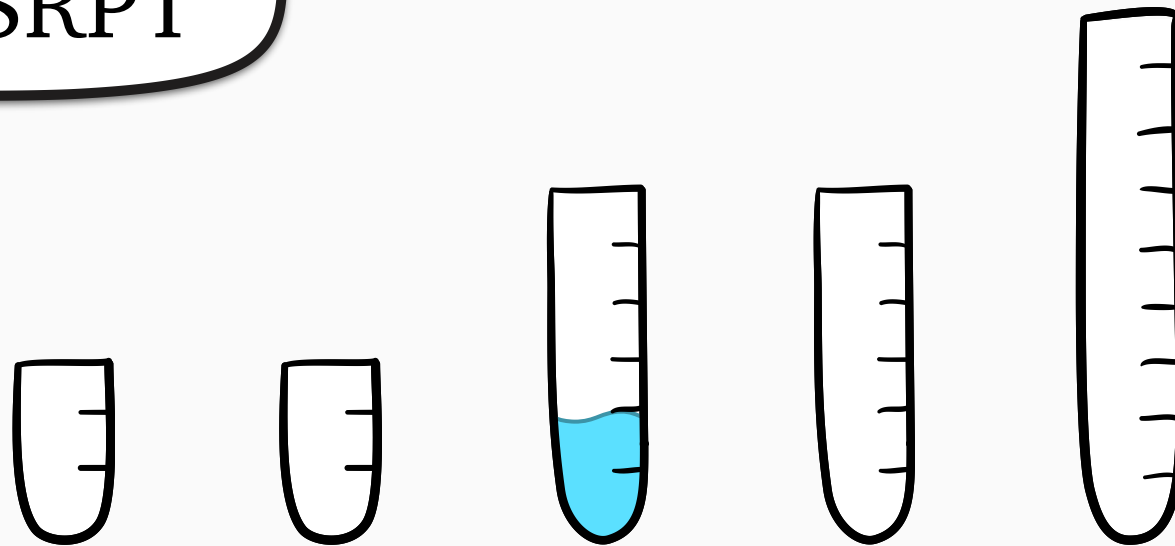


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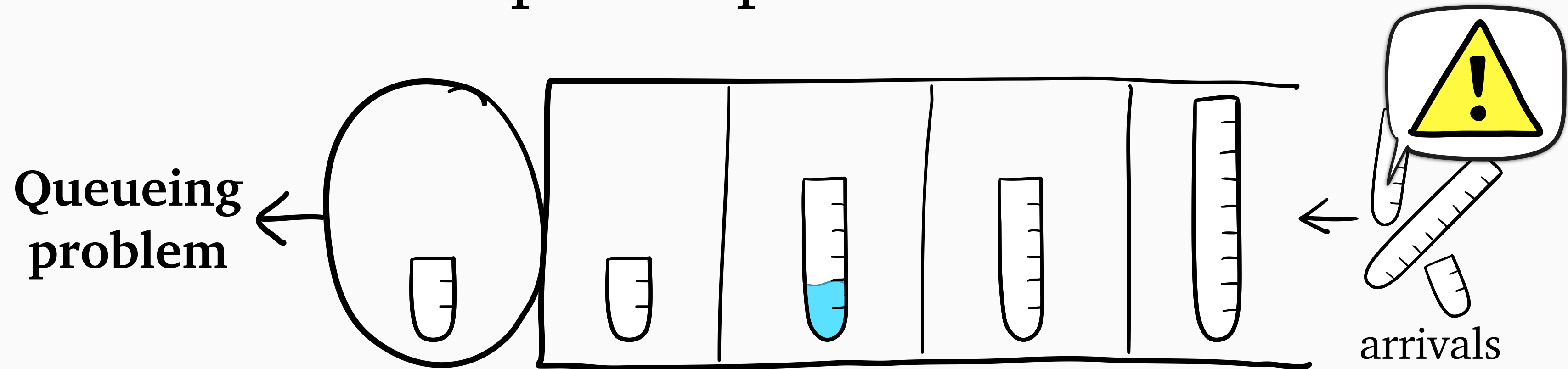


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Batch
problem

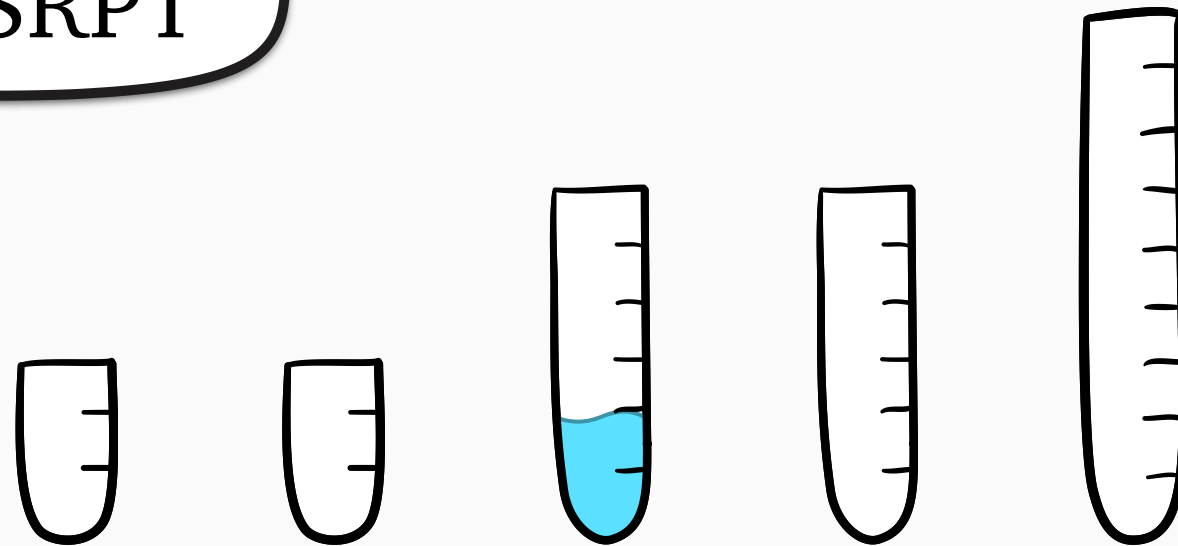


Where do optimal policies come from?



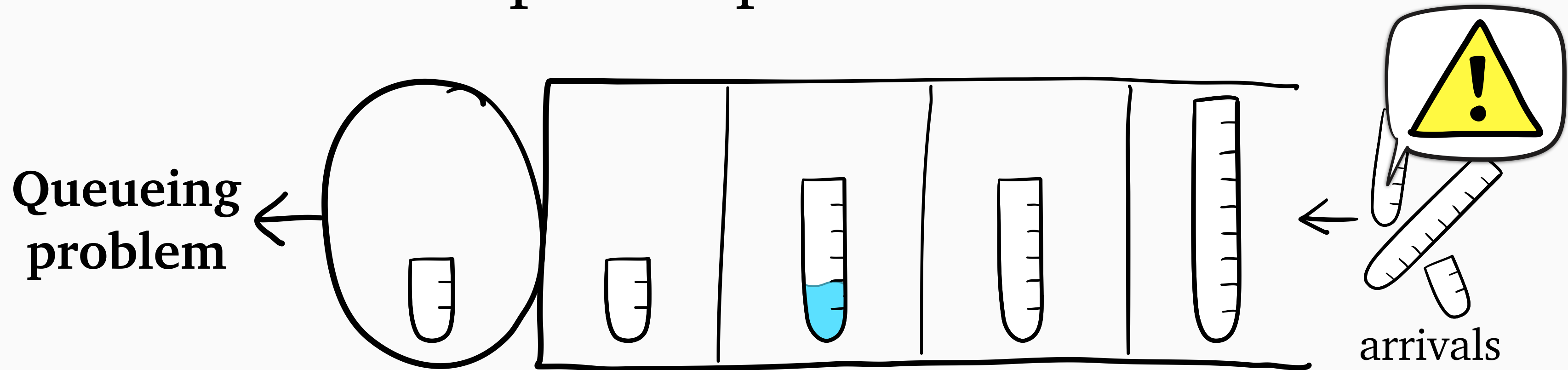
e.g. $\min E[T]$
yields SRPT

Batch
problem



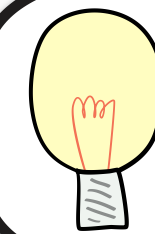
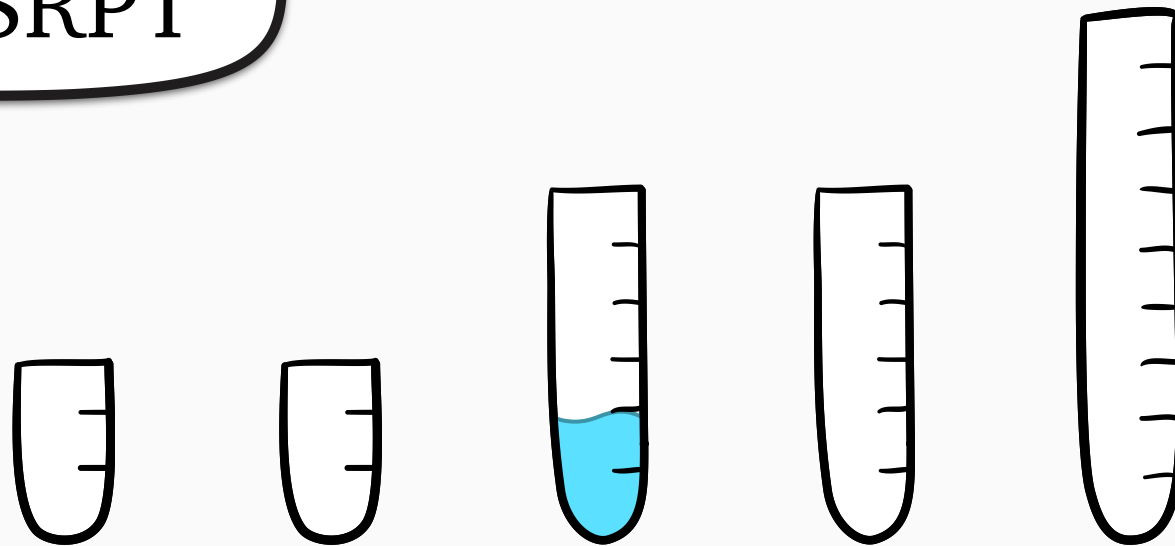
? Batch version of
minimizing C ?

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e.g. $\min E[T]$
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Batch
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Non-asymptotic
version of metric?



Batch version of
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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?

How to handle range of sizes?



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

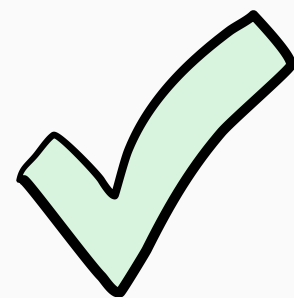
Batch version of minimizing C ?



How do we achieve strong tail optimality?

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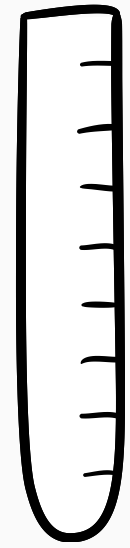


How does the **Boost** policy family work?

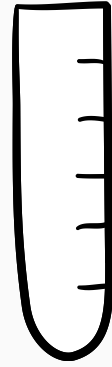


How do we achieve strong tail optimality?

Key information:



1st



2nd

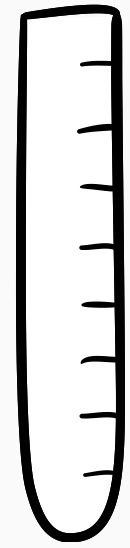


3rd

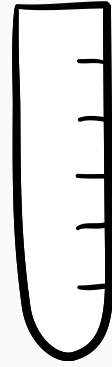


How to handle
range of sizes?

Key information: *arrival times*



1st



2nd

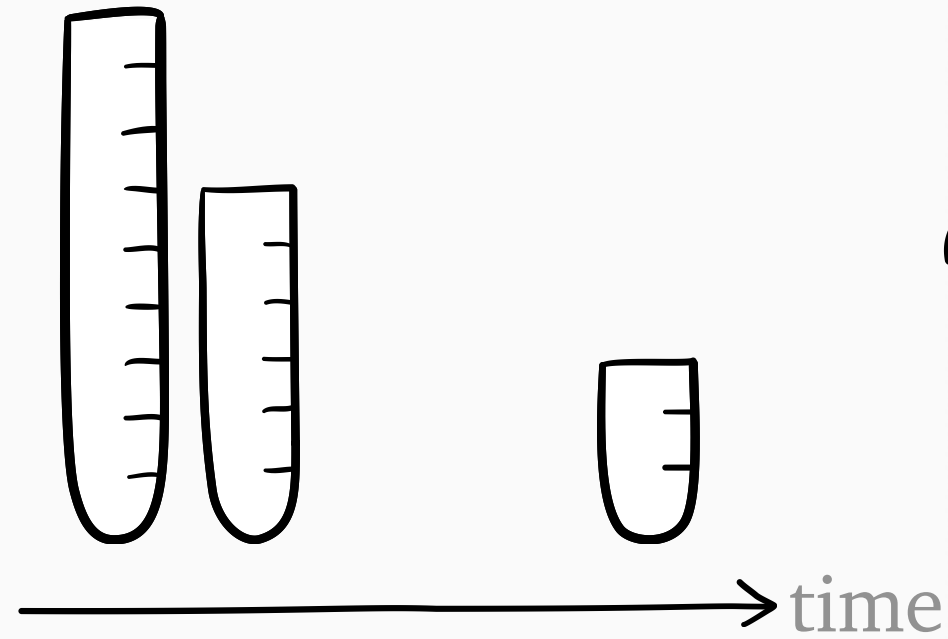


3rd



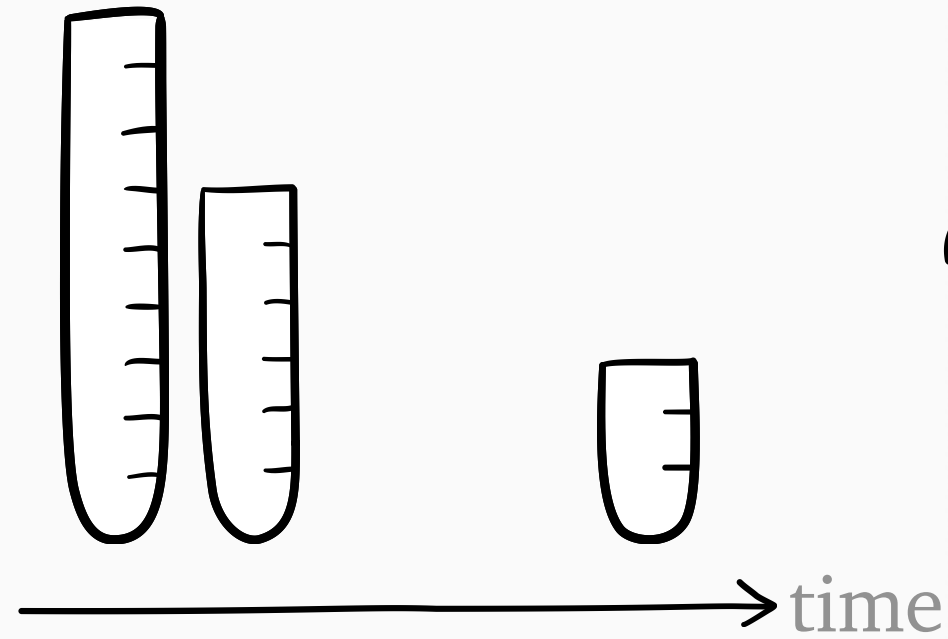
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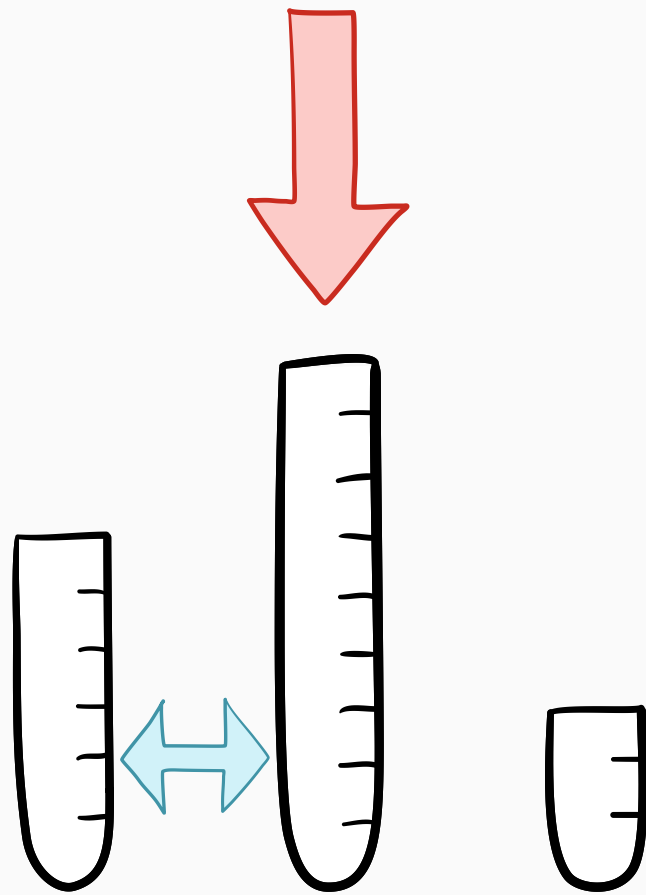


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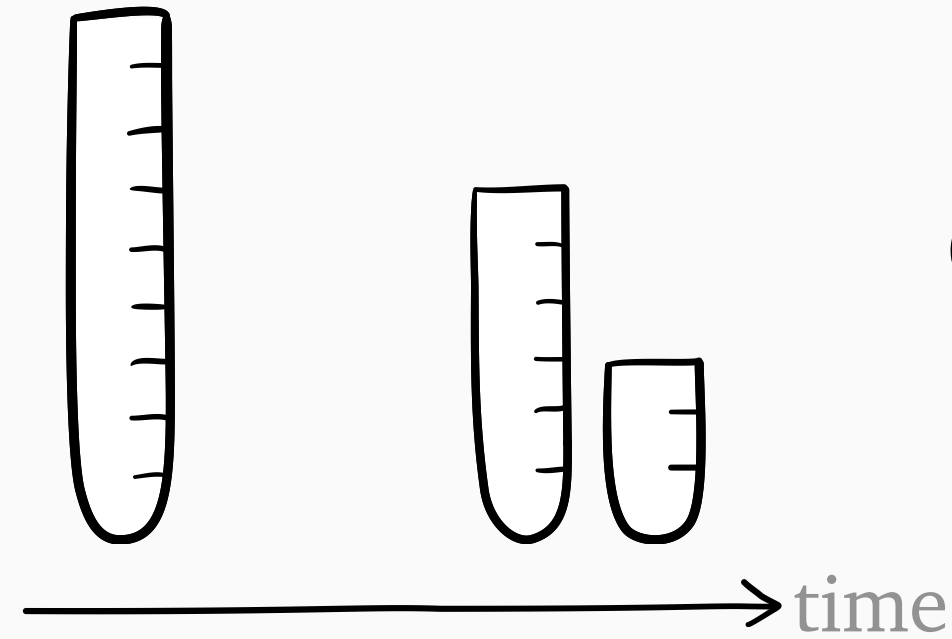
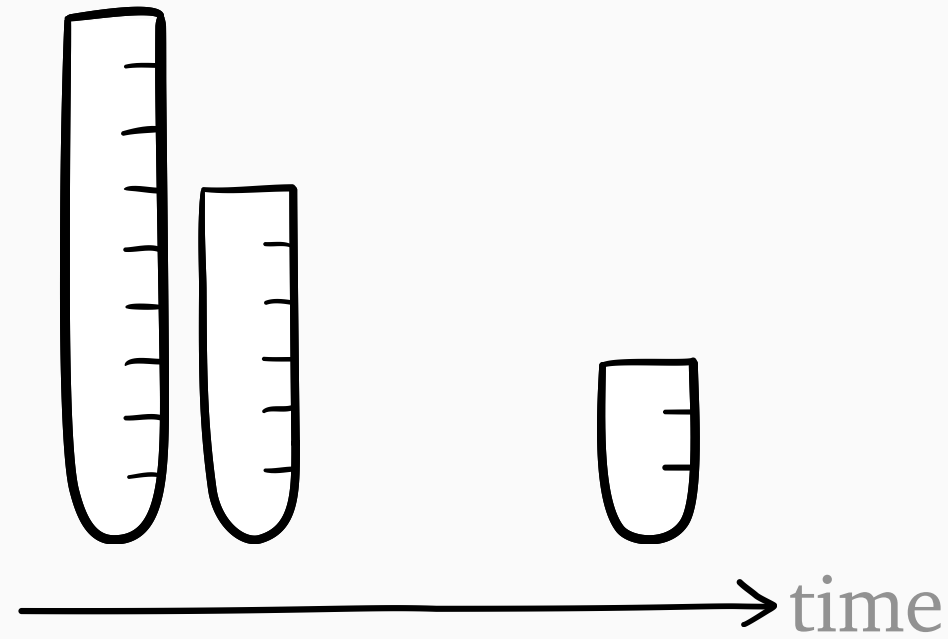
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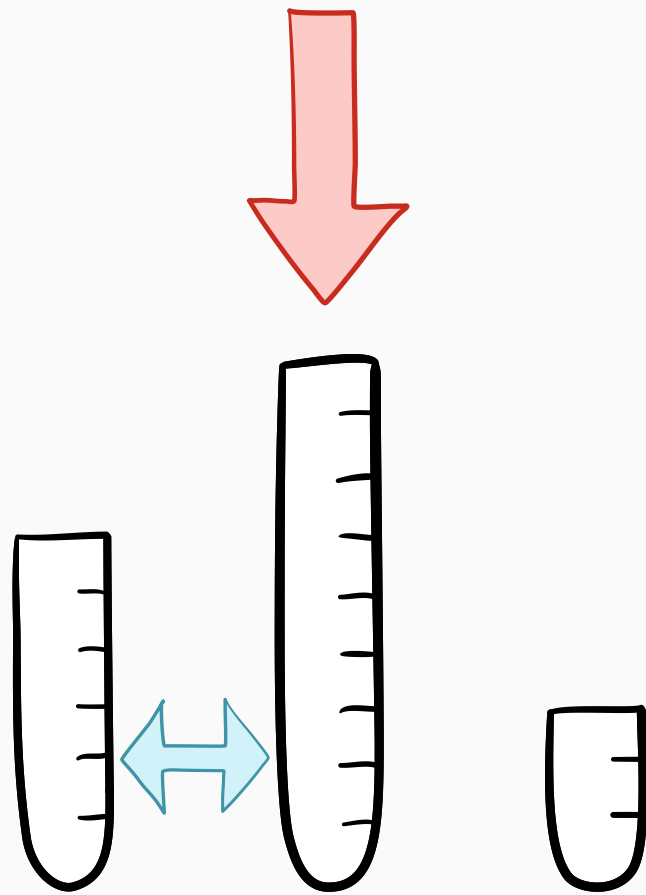
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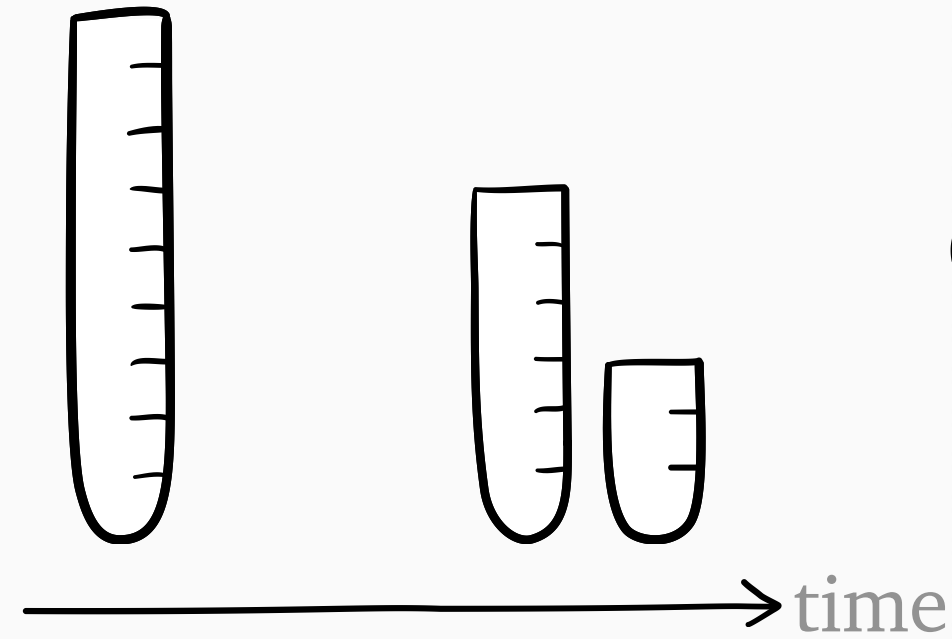
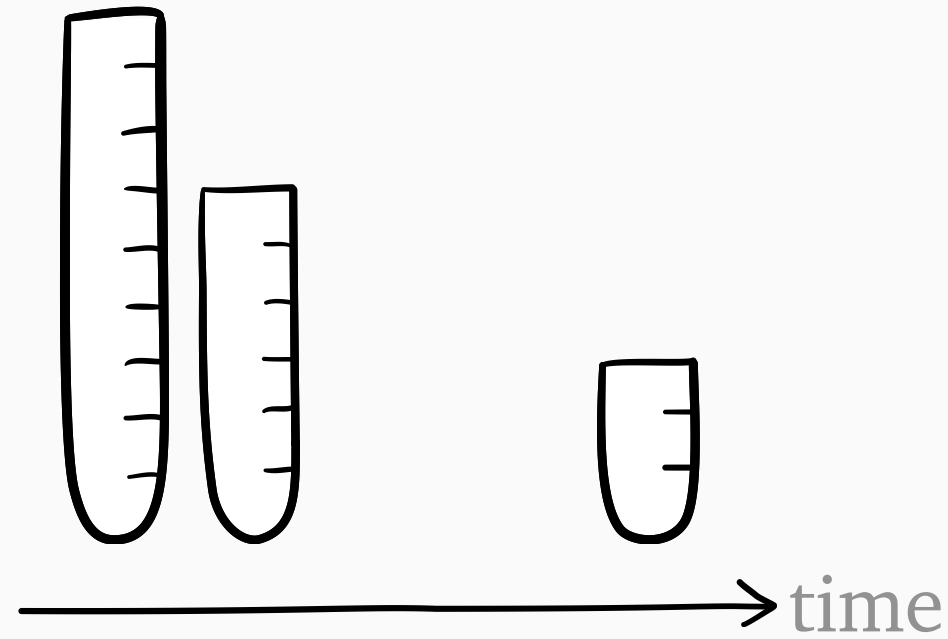
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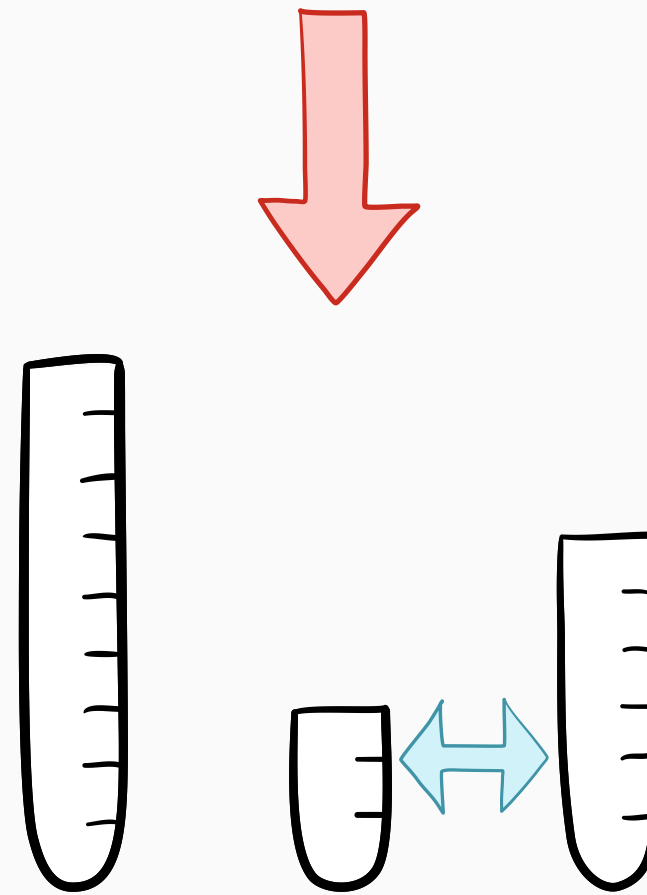
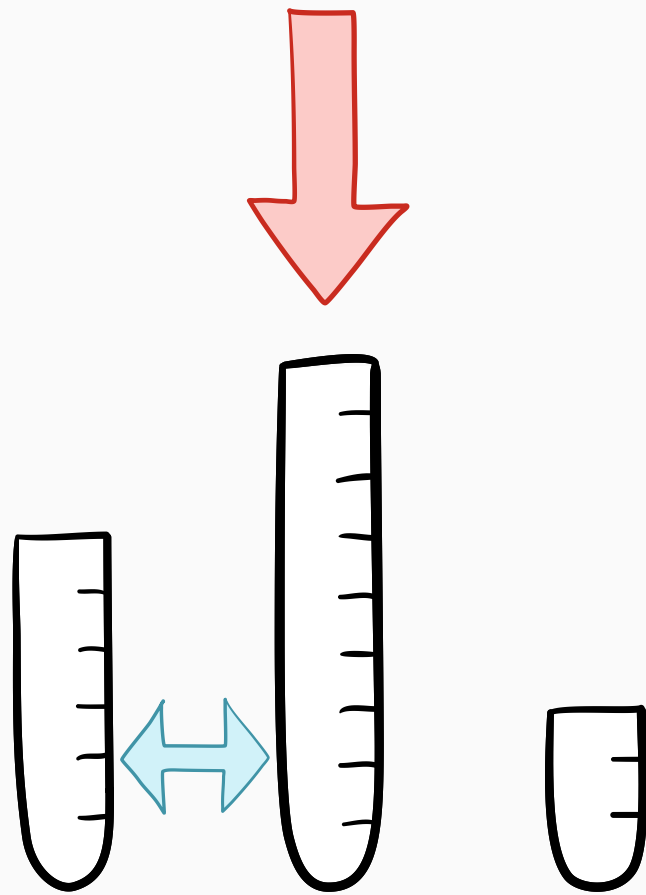
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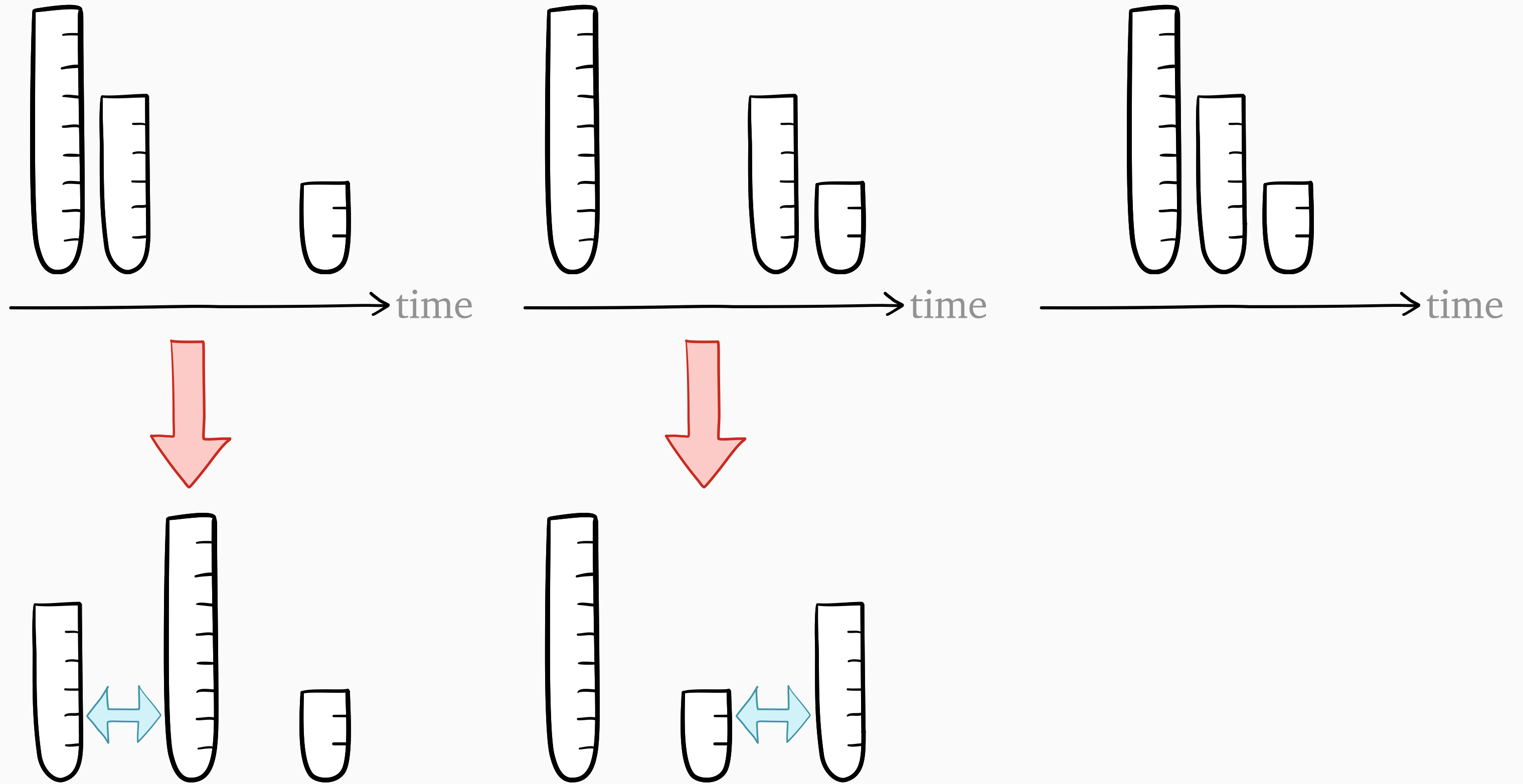
Key information: *arrival times*



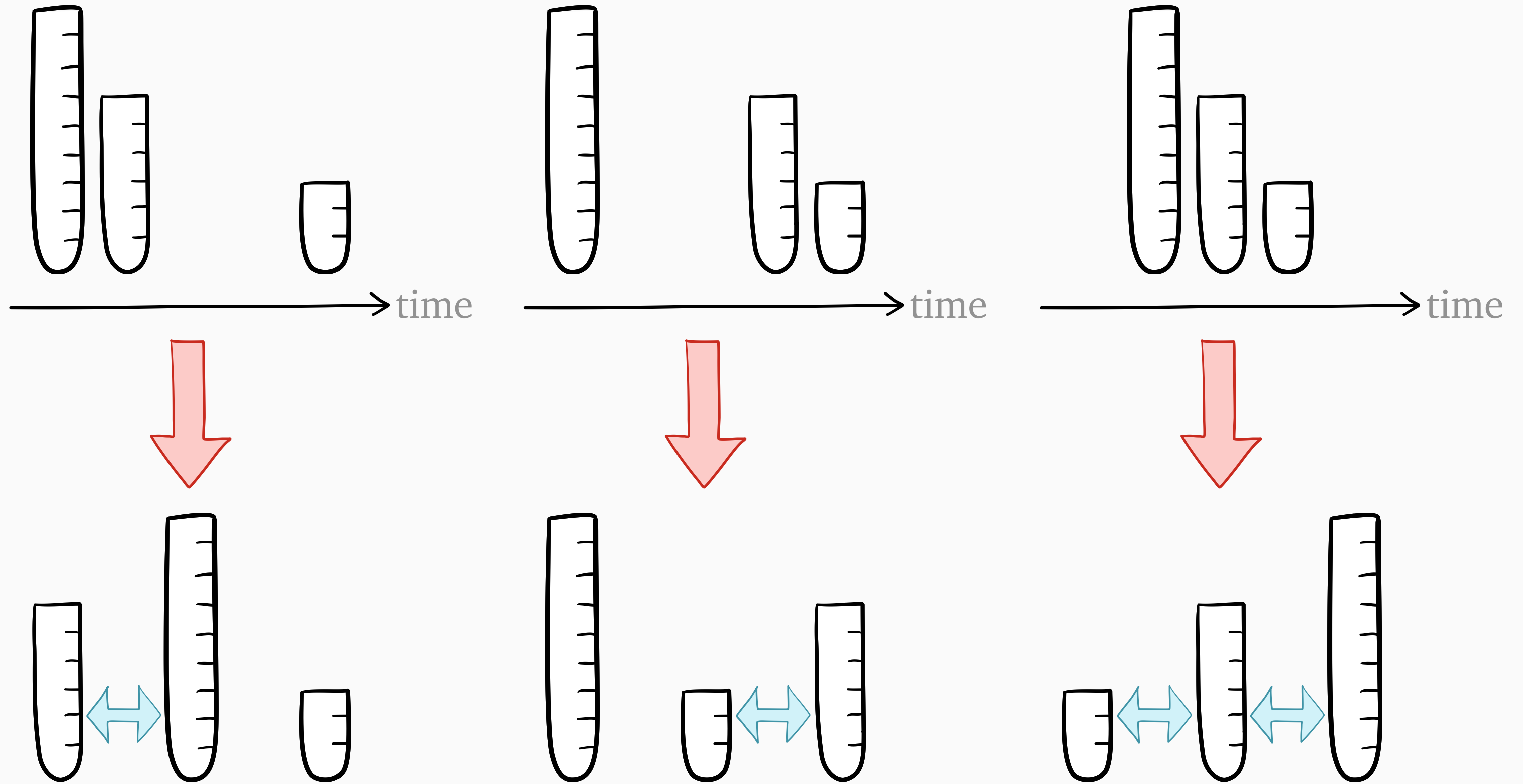
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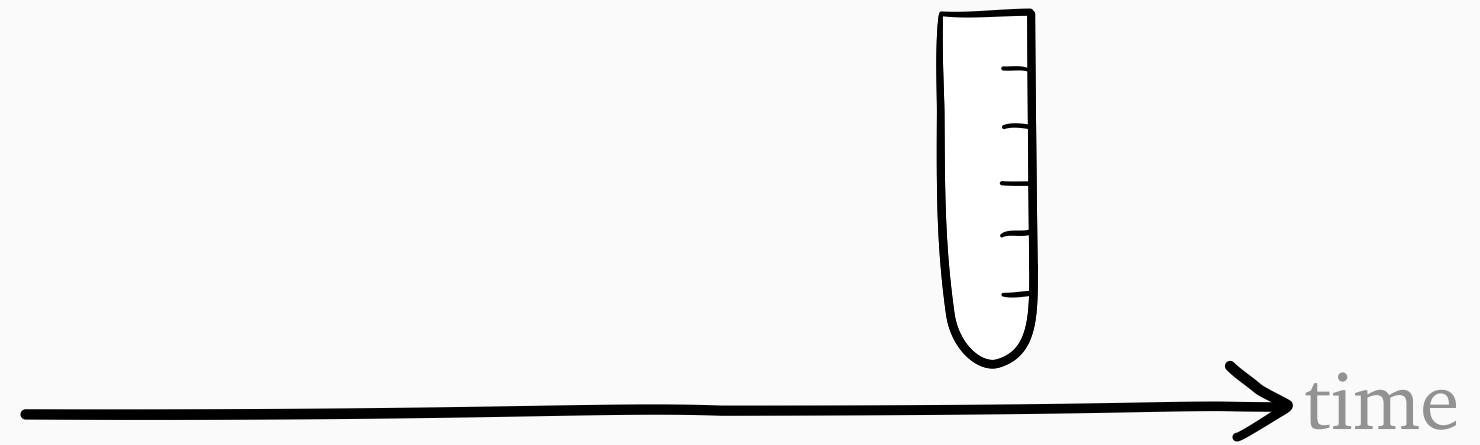
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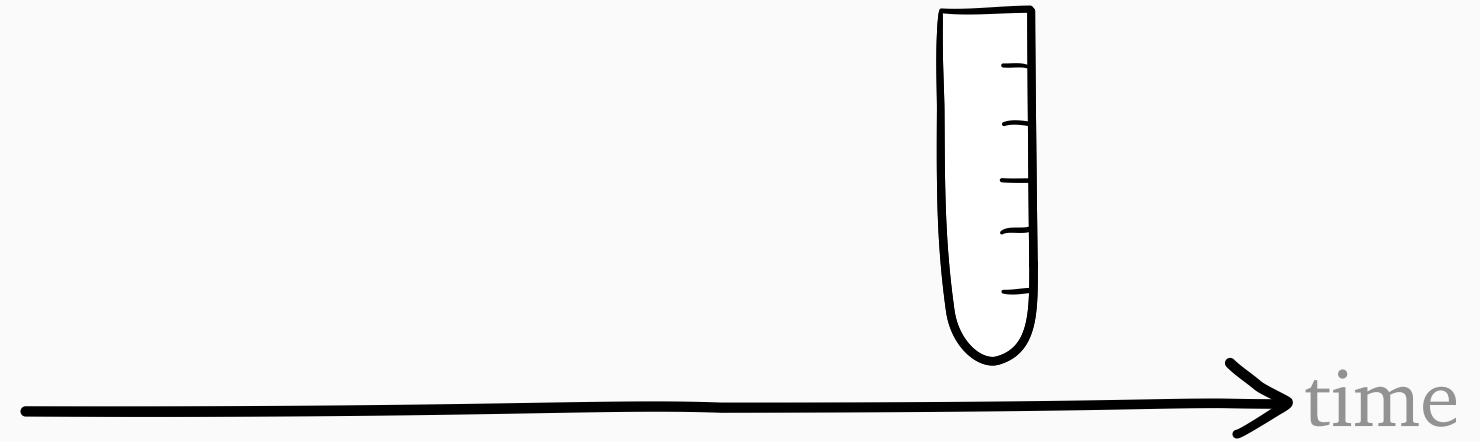
Key information: *arrival times*



Combining arrival time and size

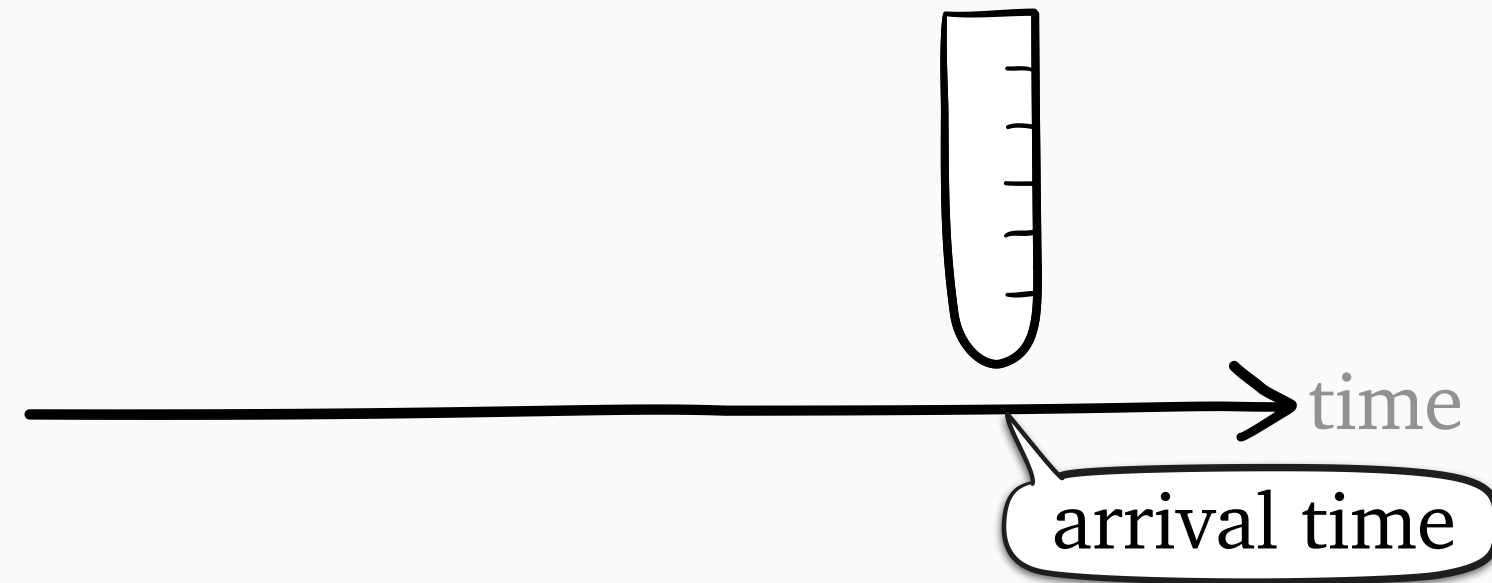


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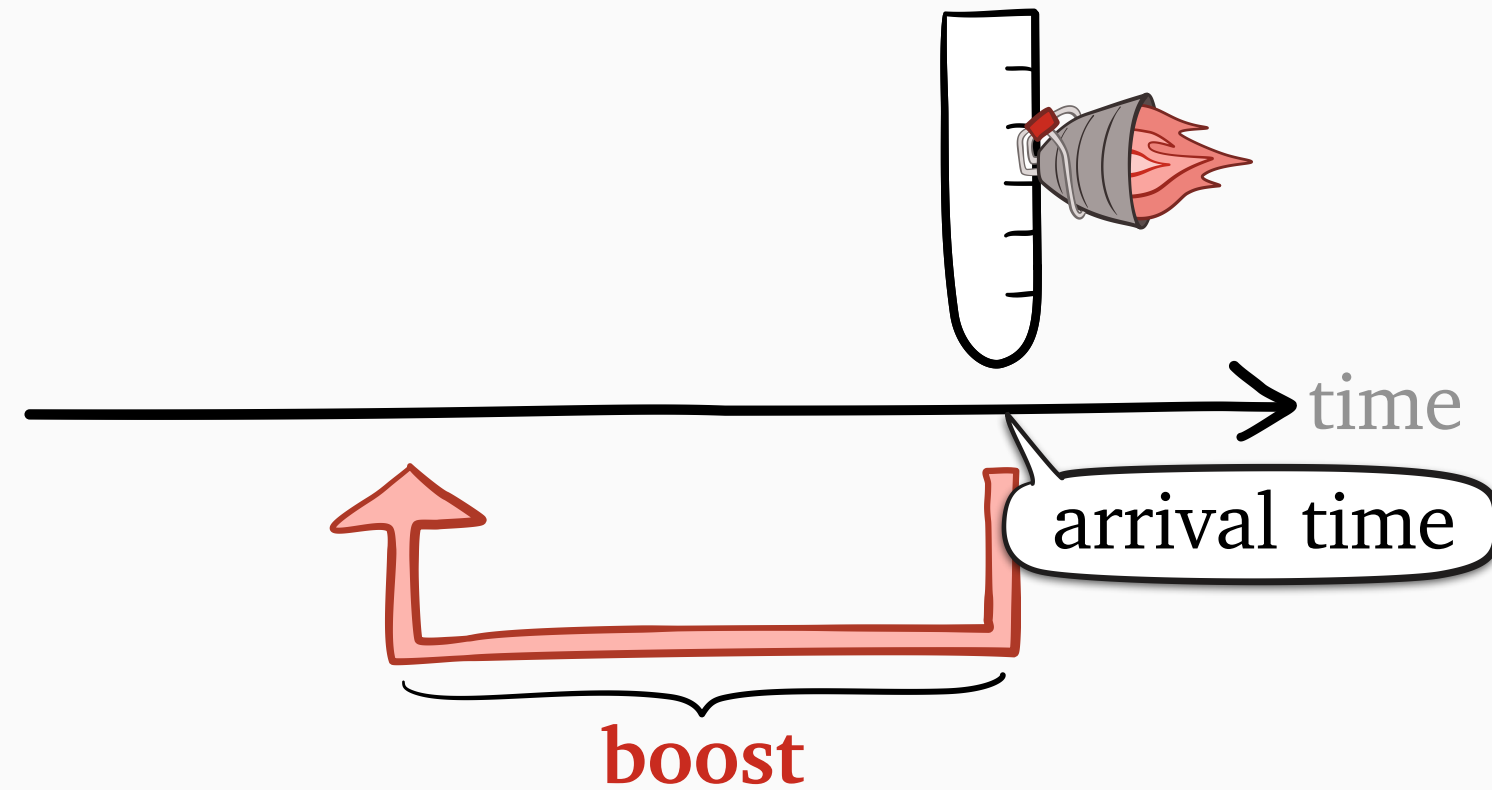
$$\text{boosted arrival time} \\ = \text{arrival time} - \text{boost}(\text{size})$$

Combining arrival time and size



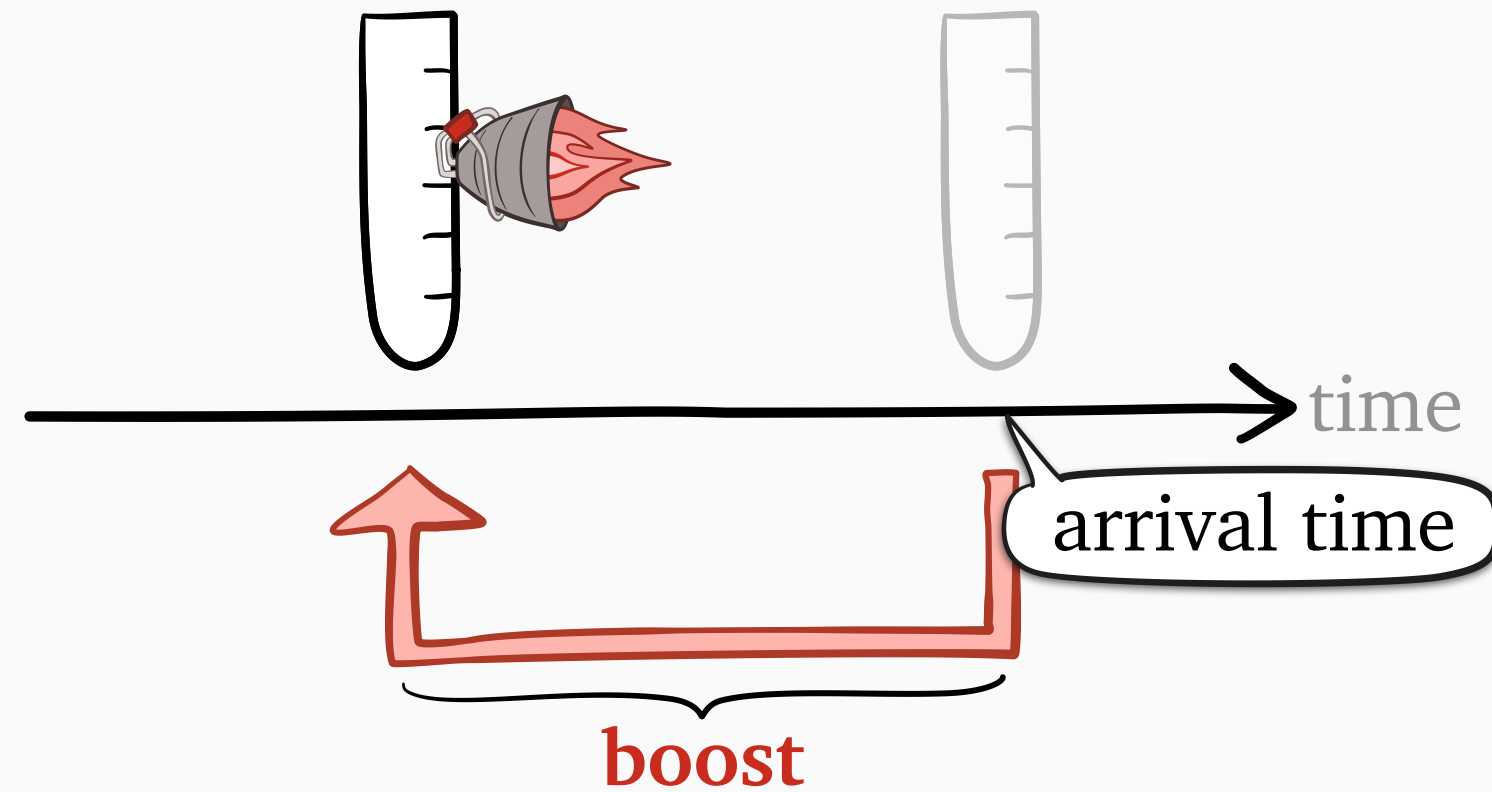
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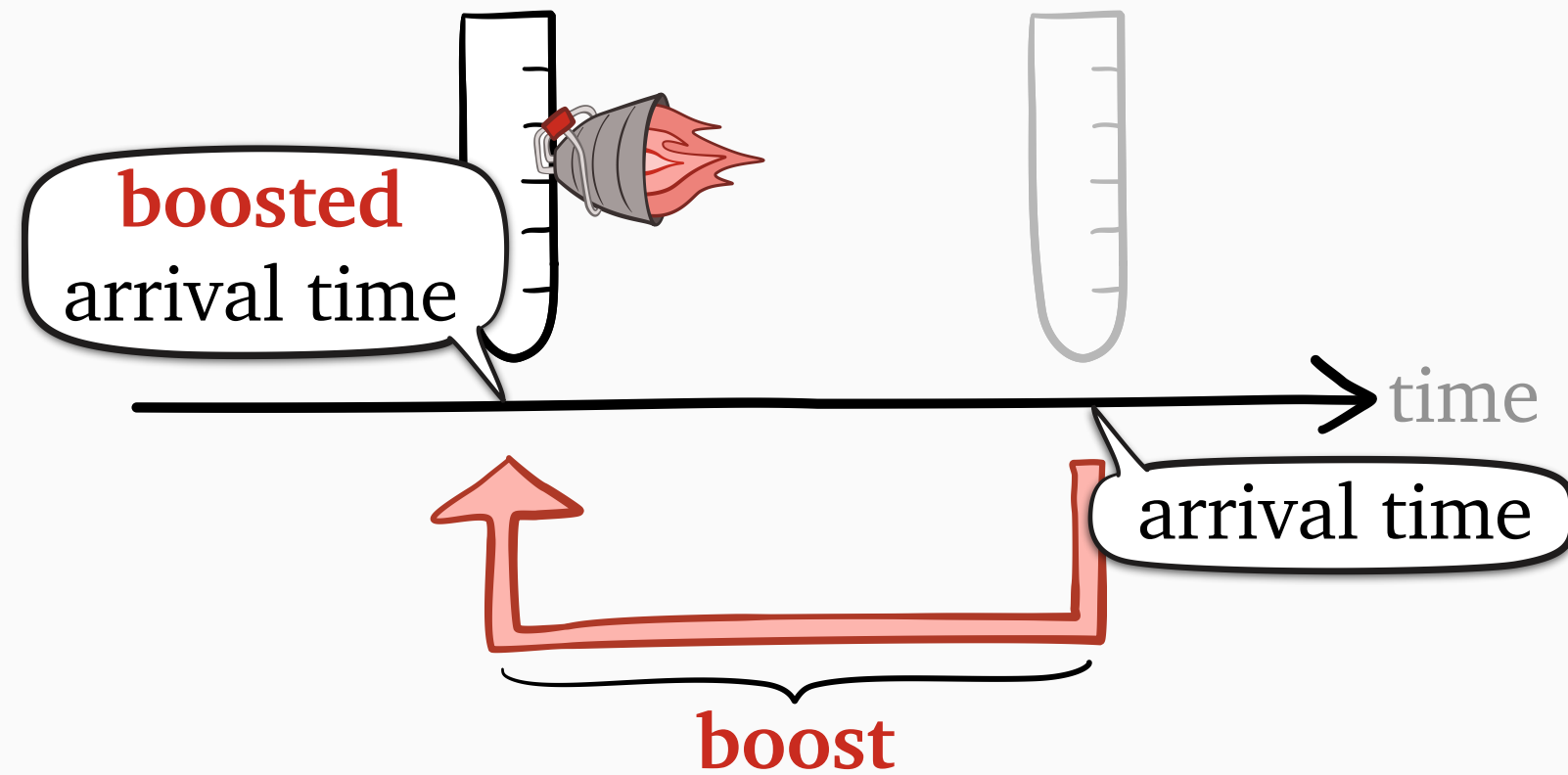
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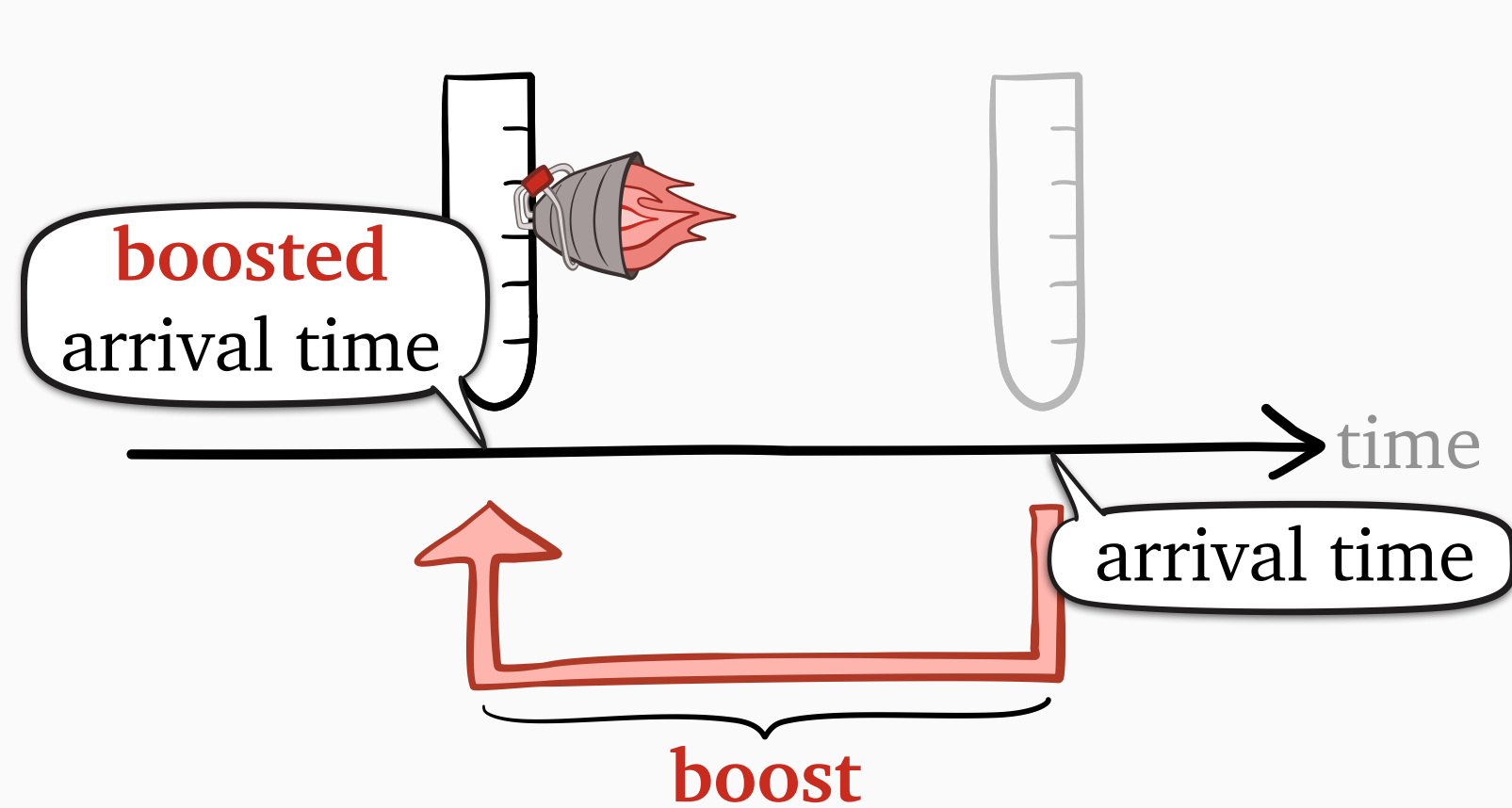
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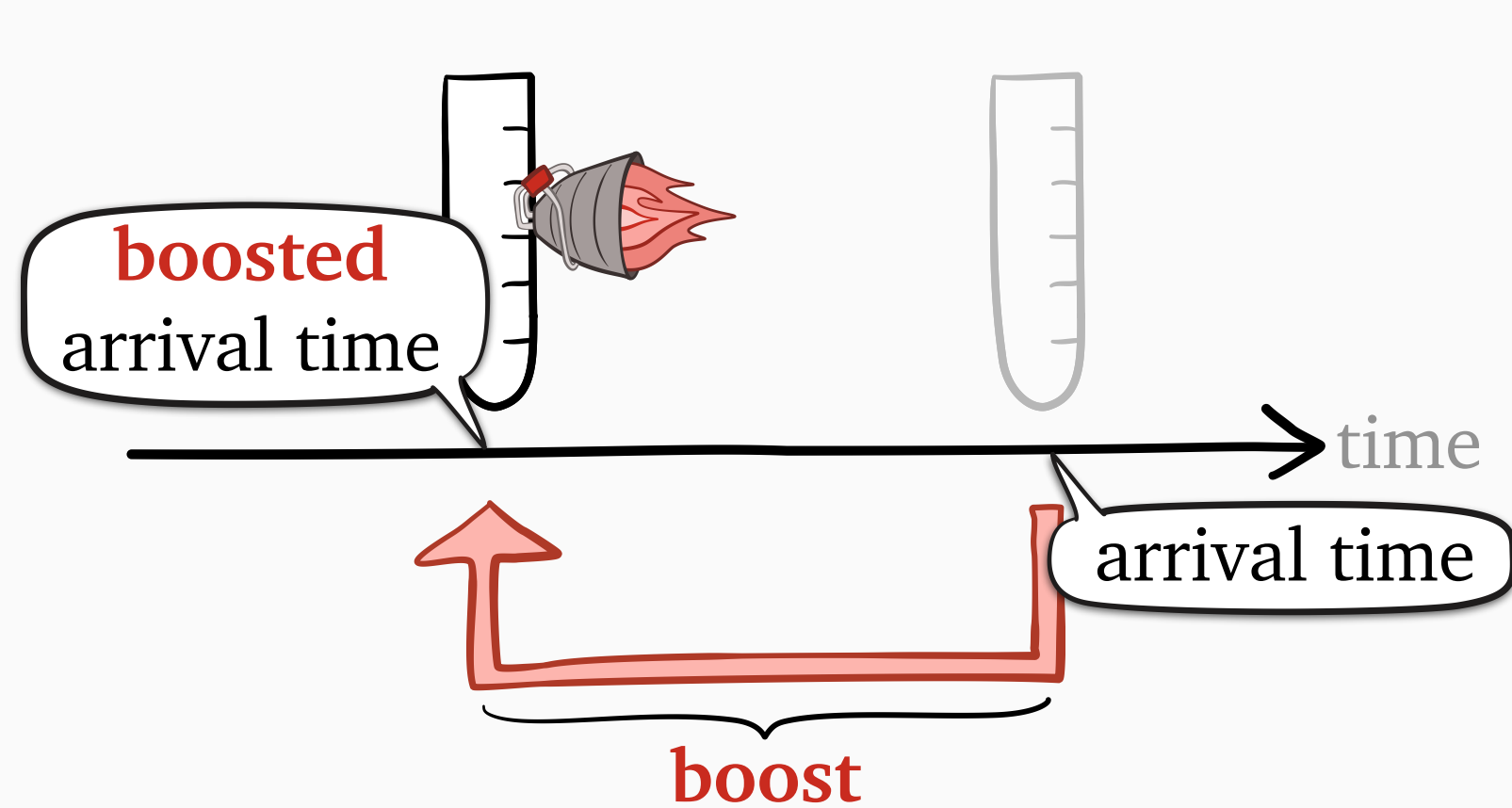
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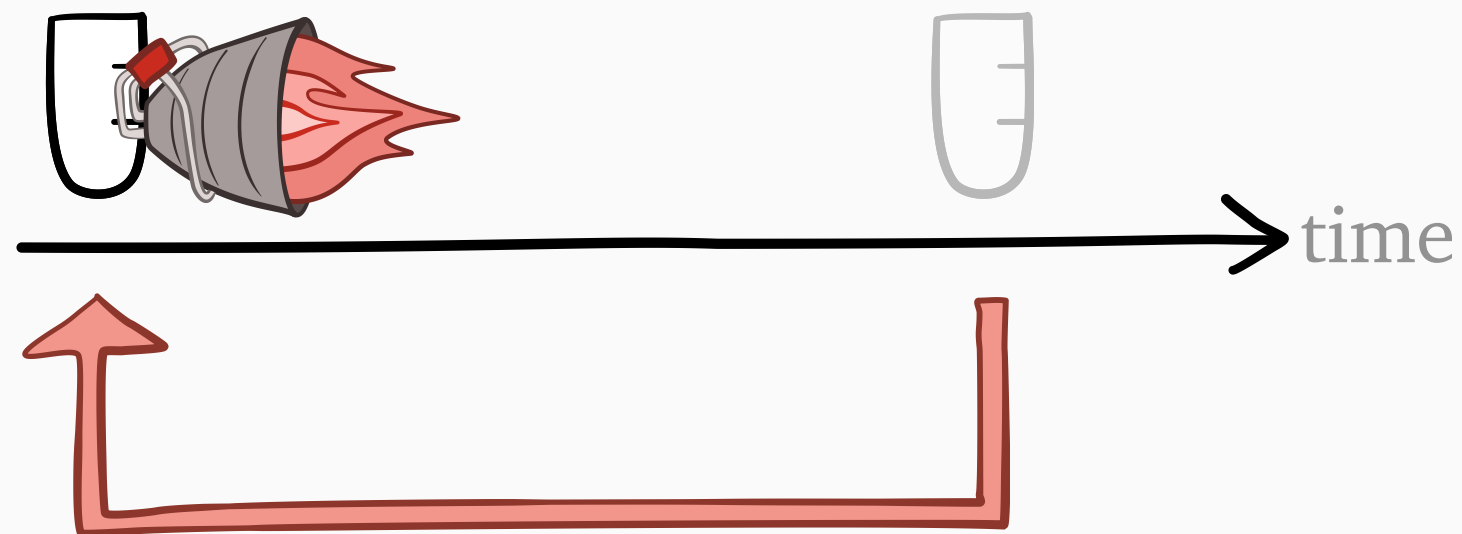
smaller sizes get
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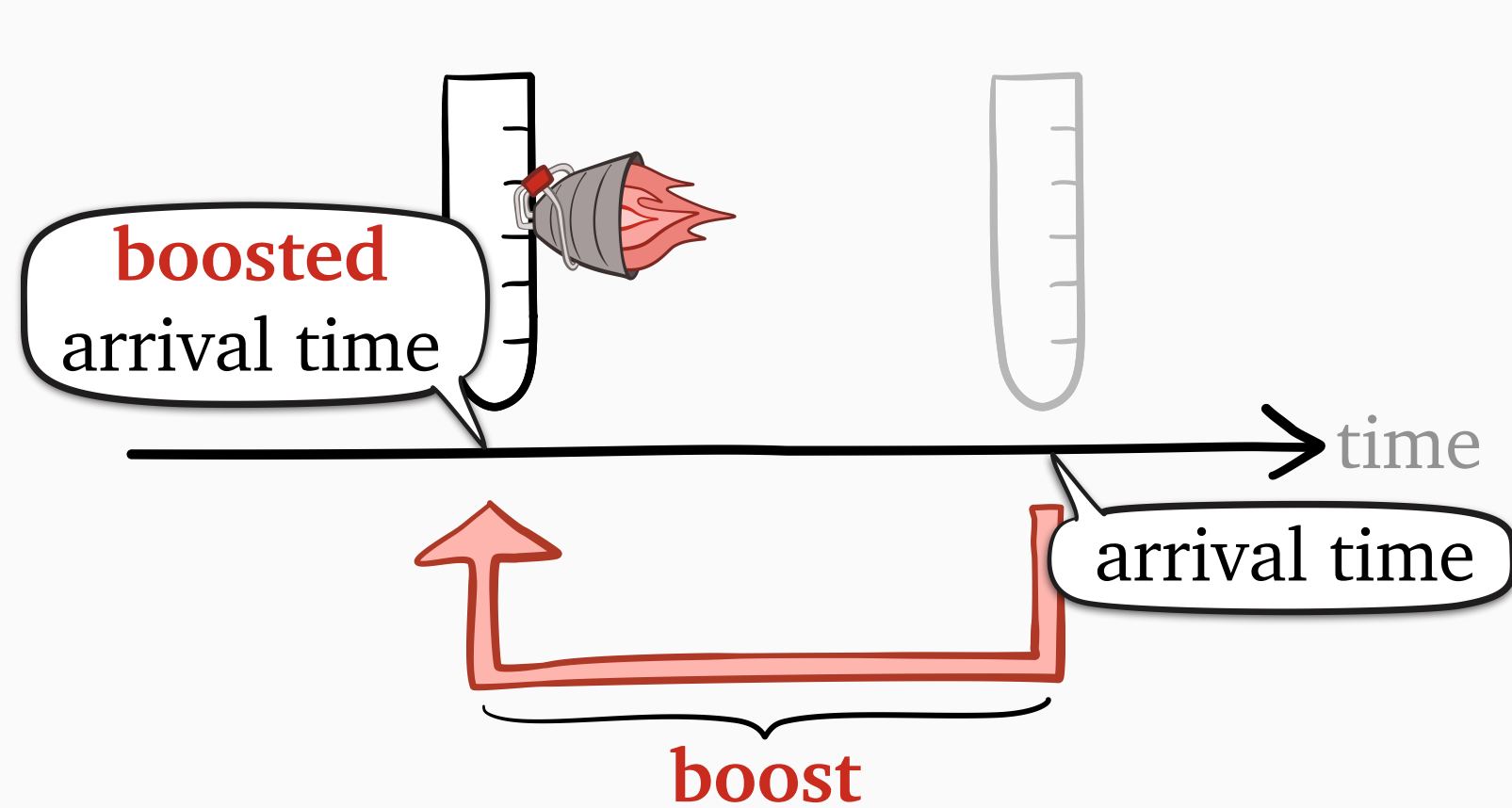


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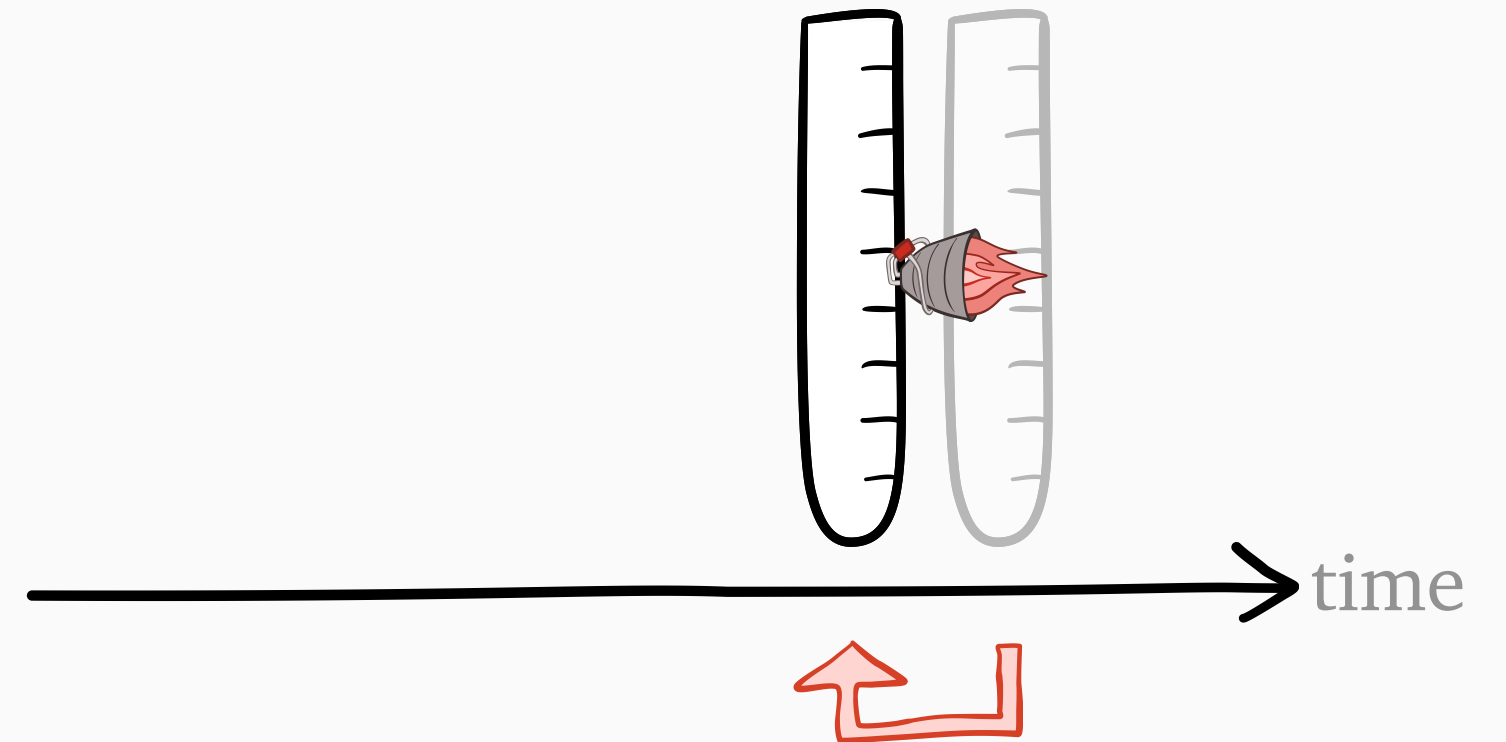
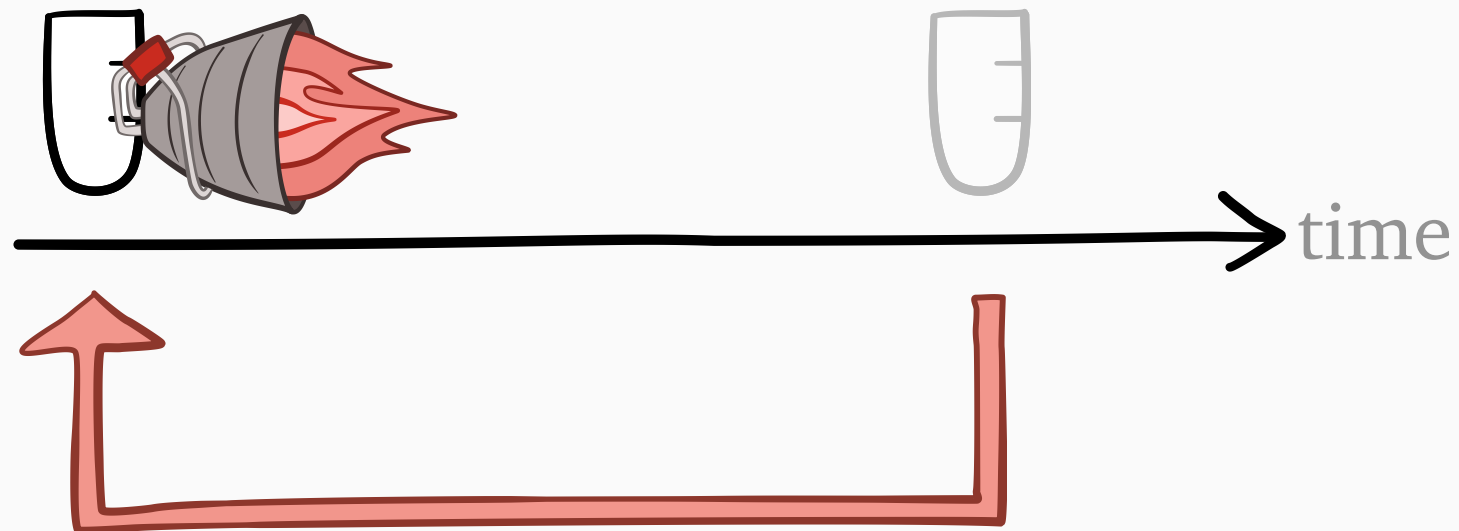


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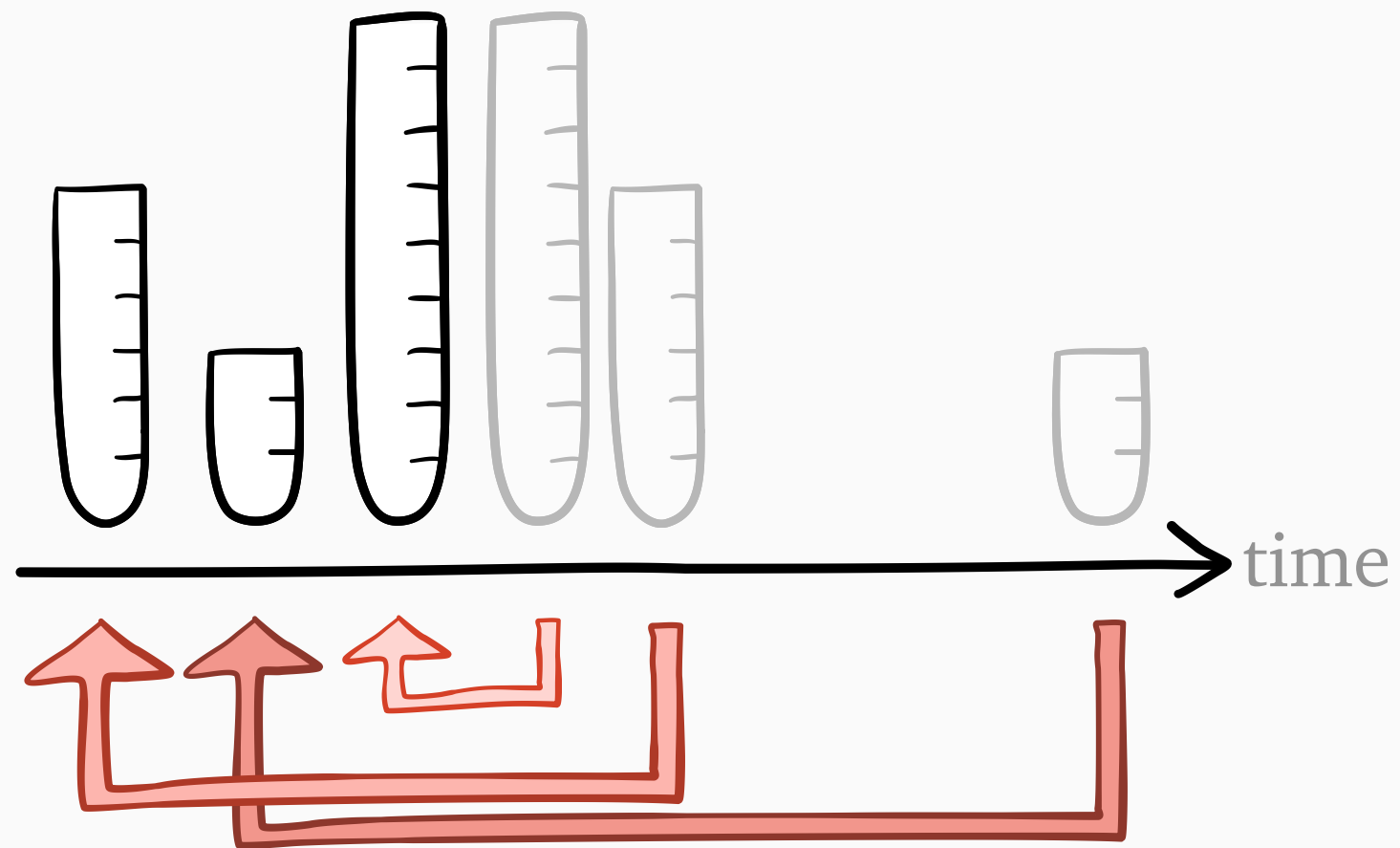


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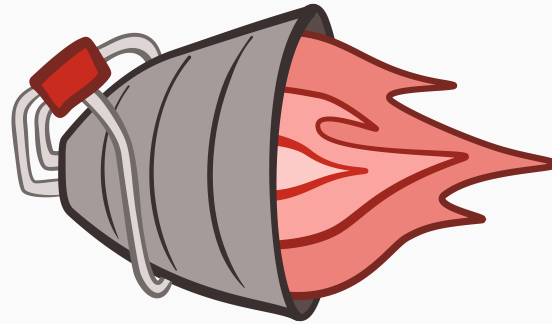


Boost policies

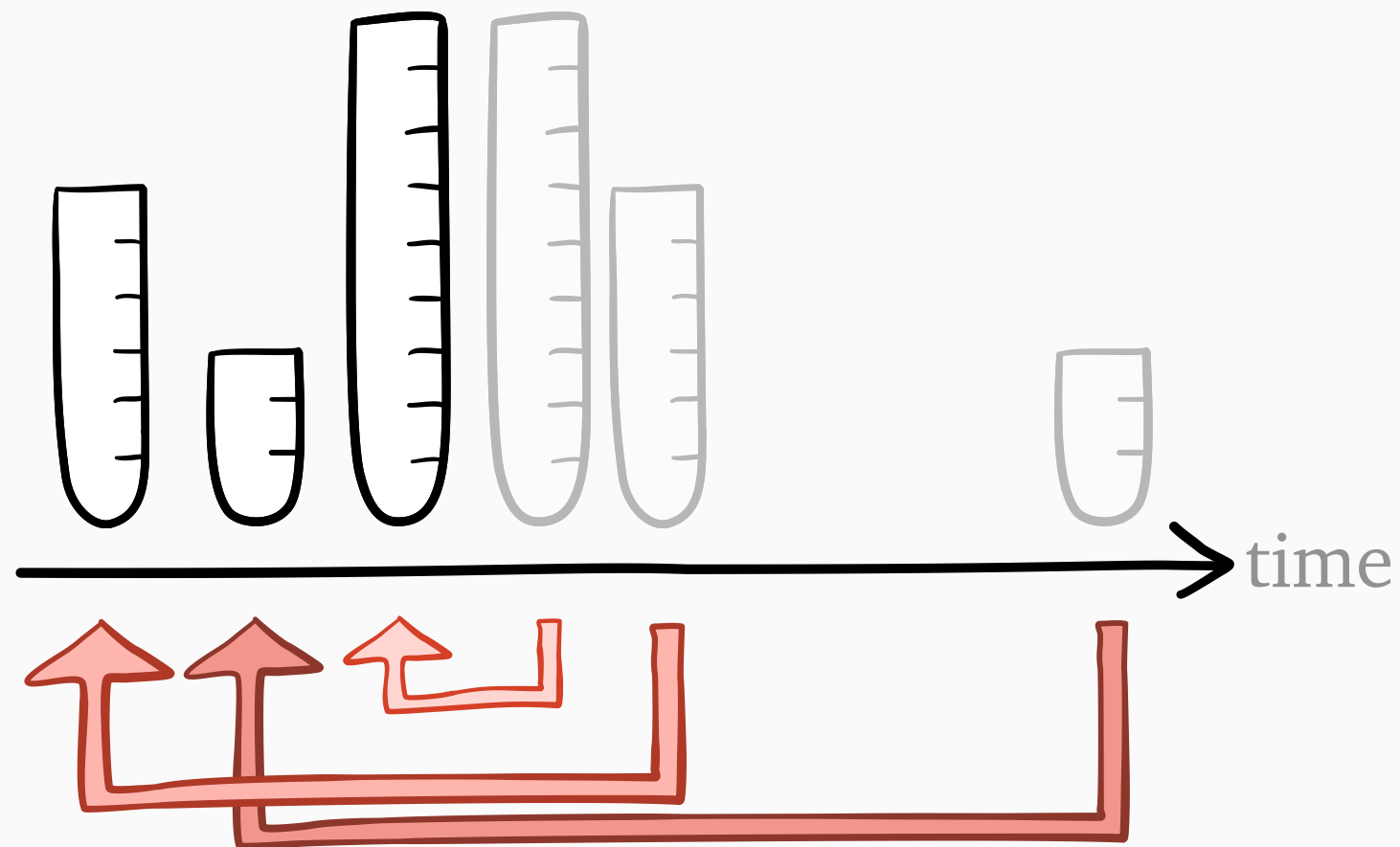


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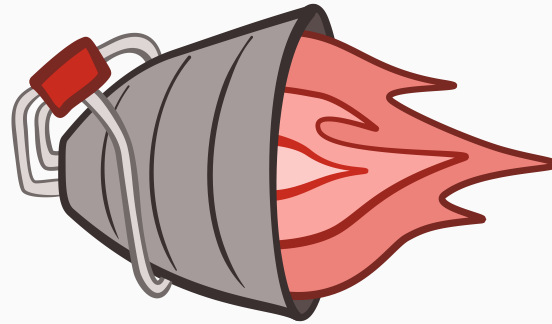


Scheduling rule: always serve job of *minimum **boosted** arrival time*

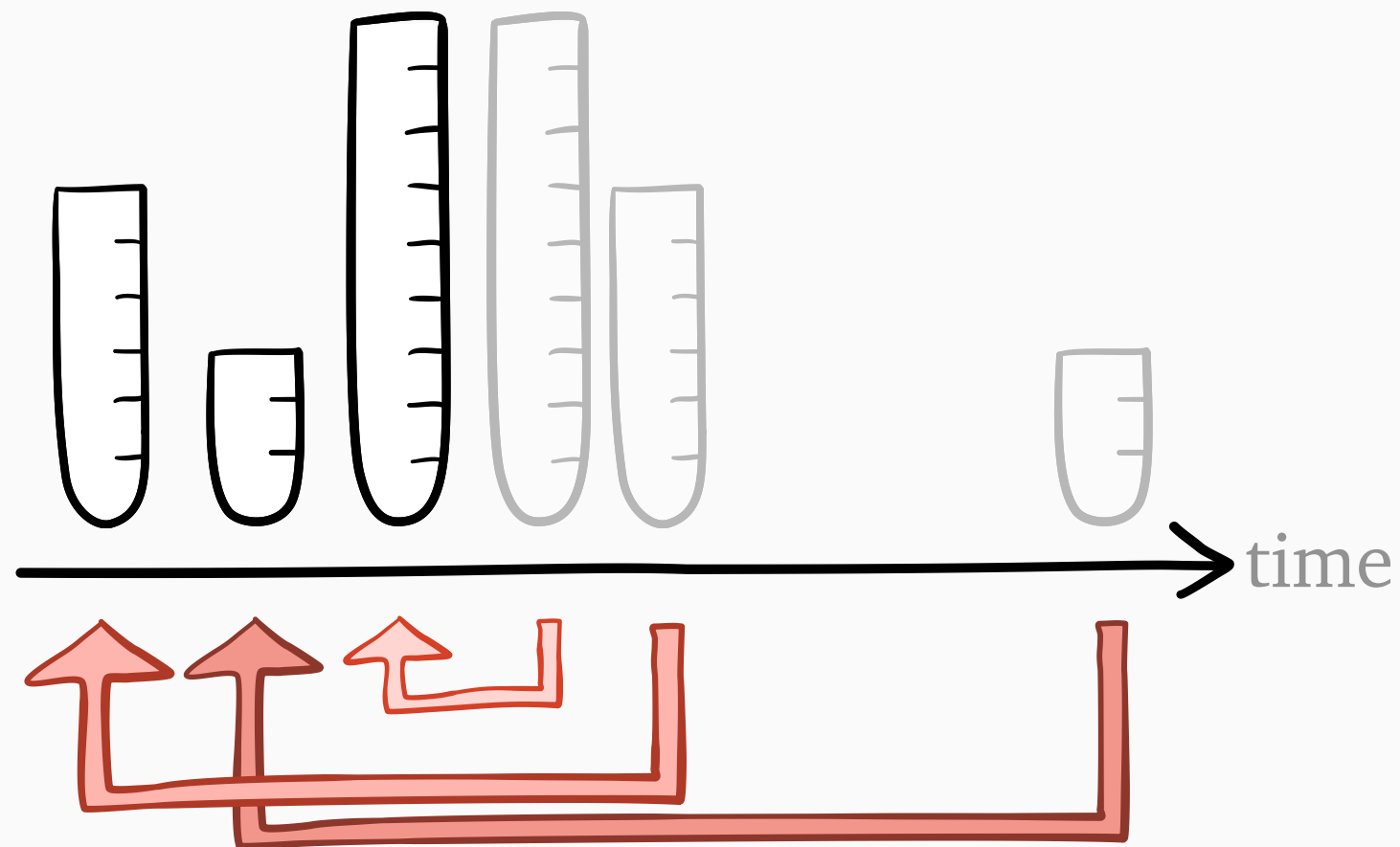


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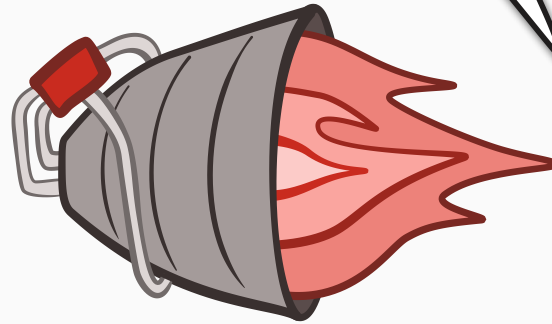


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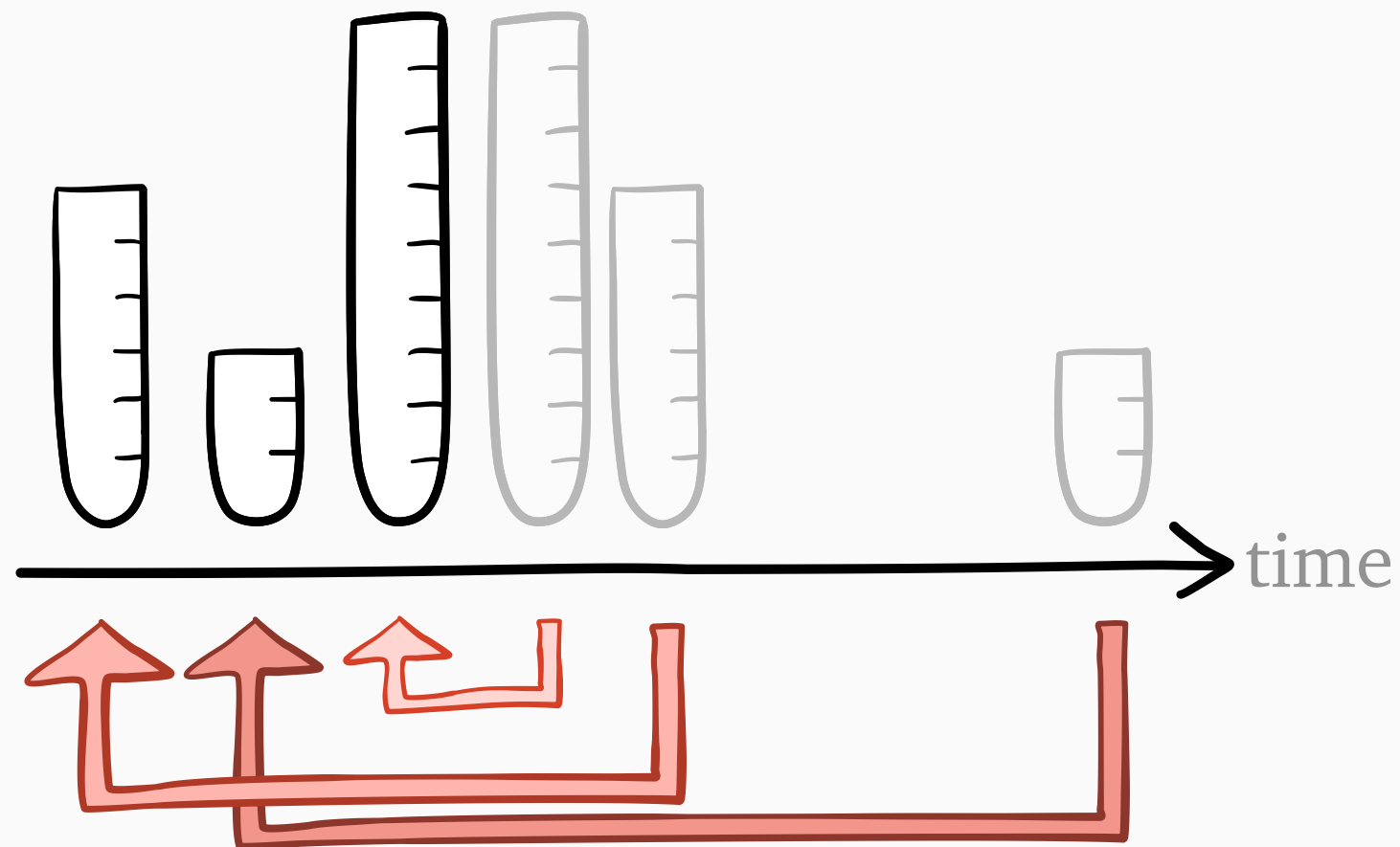
can vary choice of
boost function

Boost policies

can be preemptive
or nonpreemptive



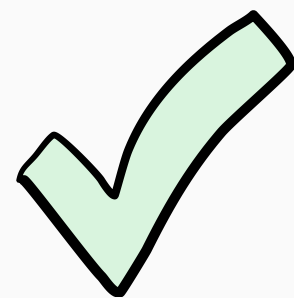
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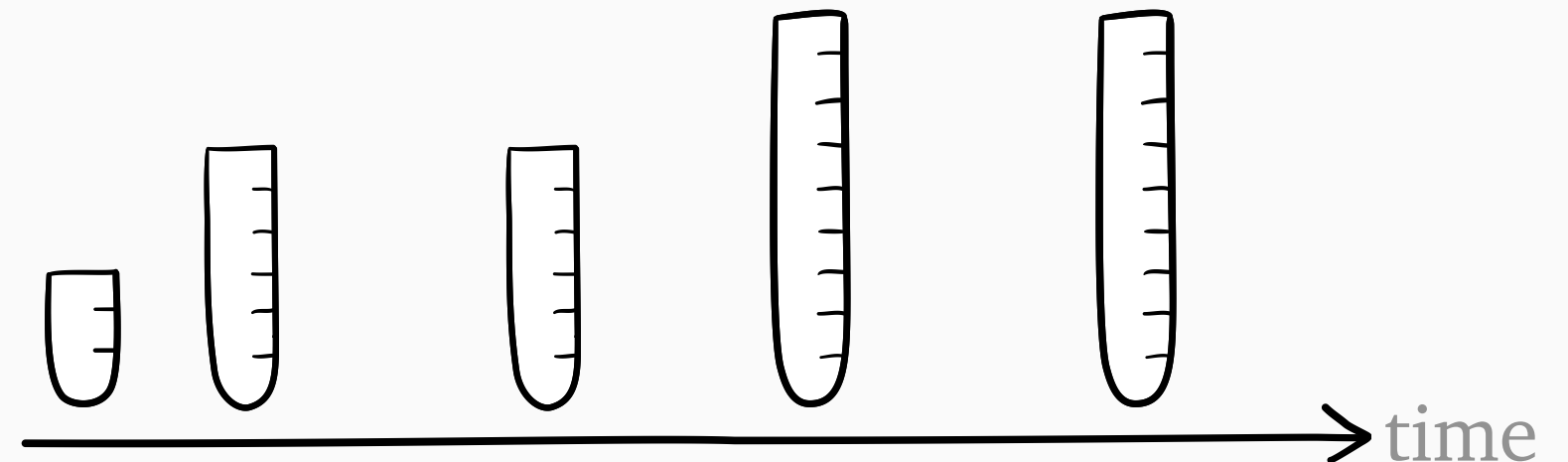
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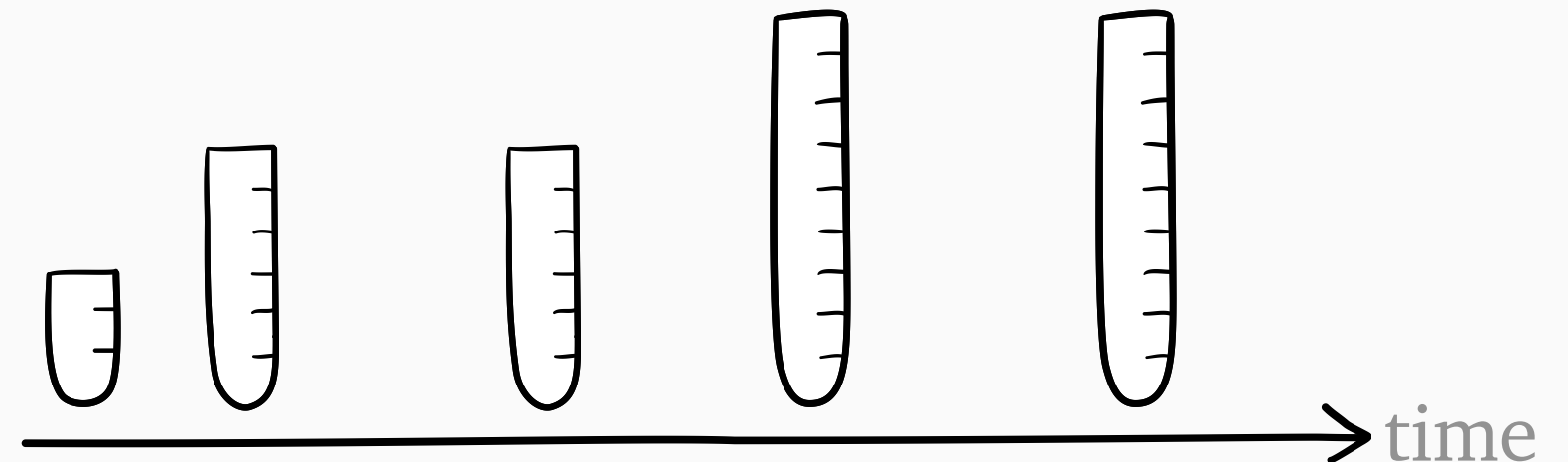
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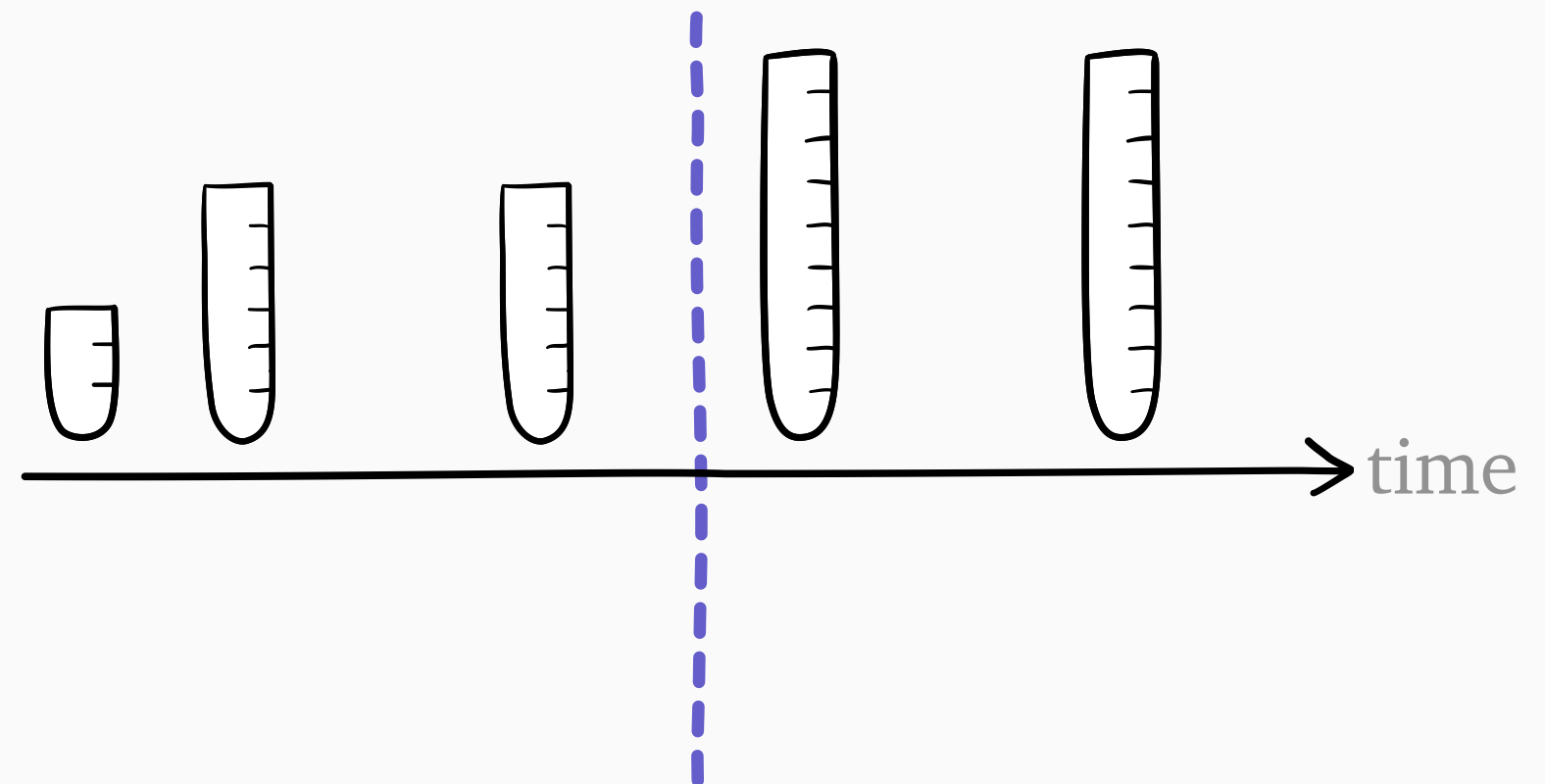
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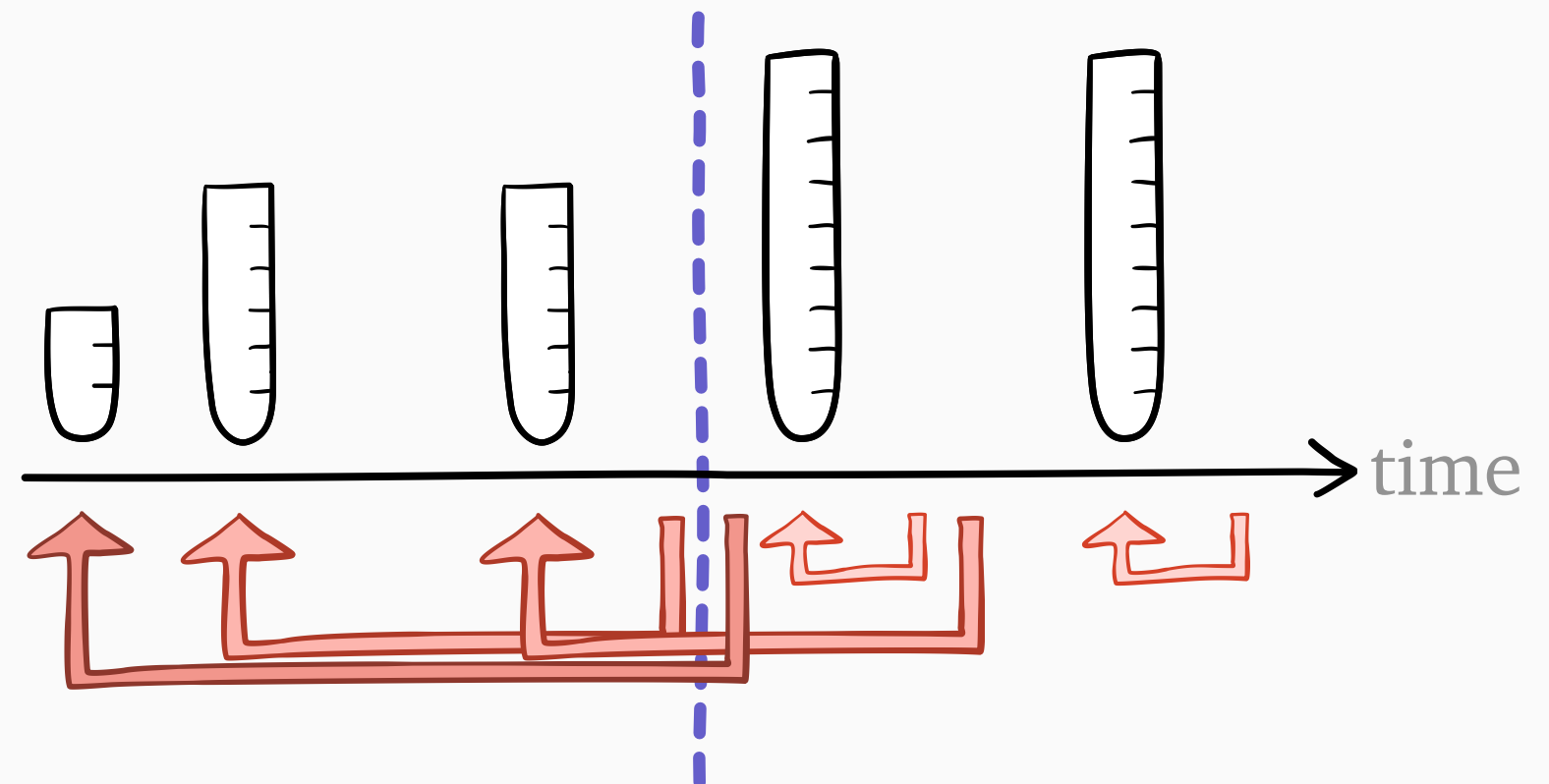
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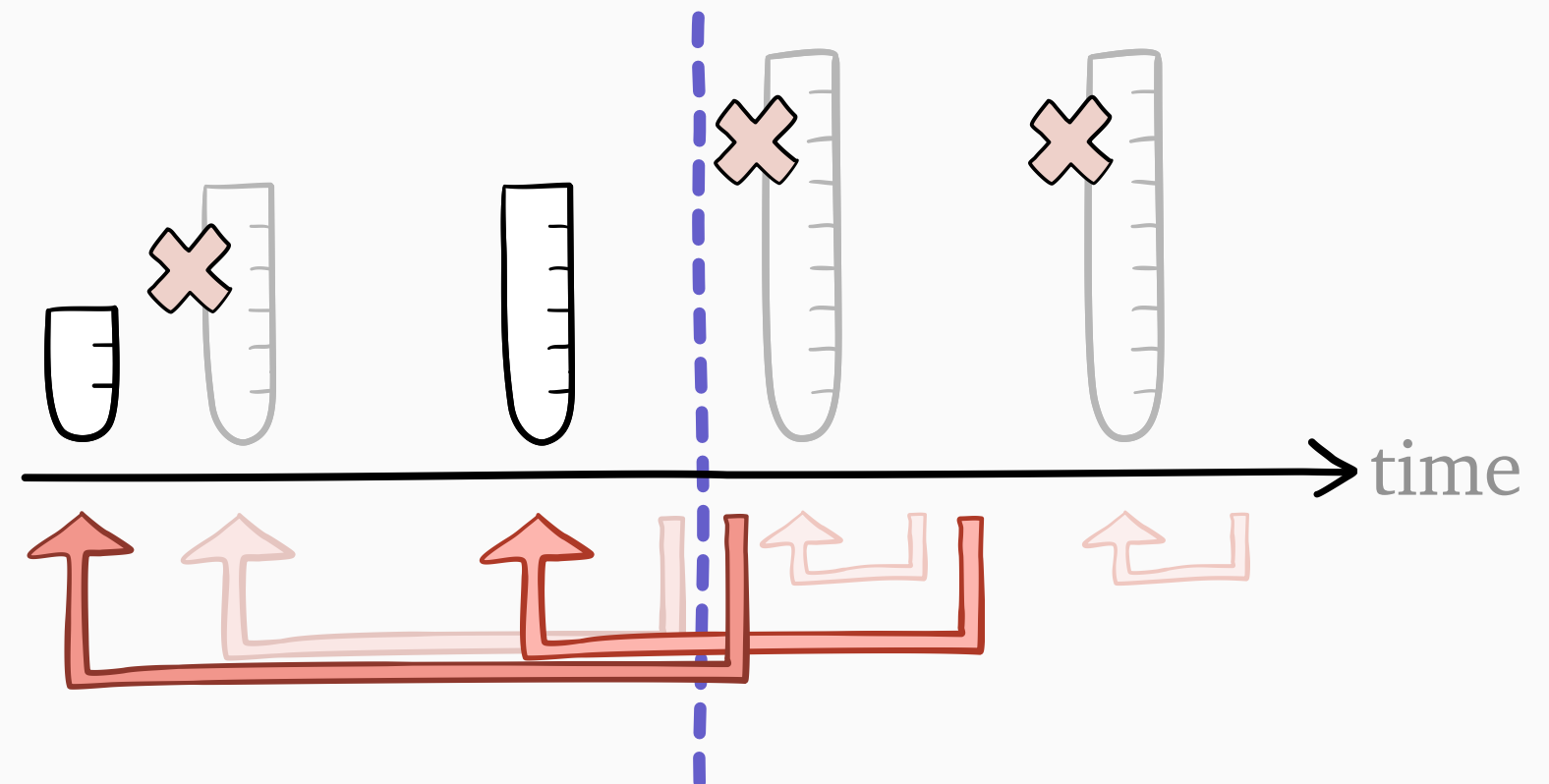
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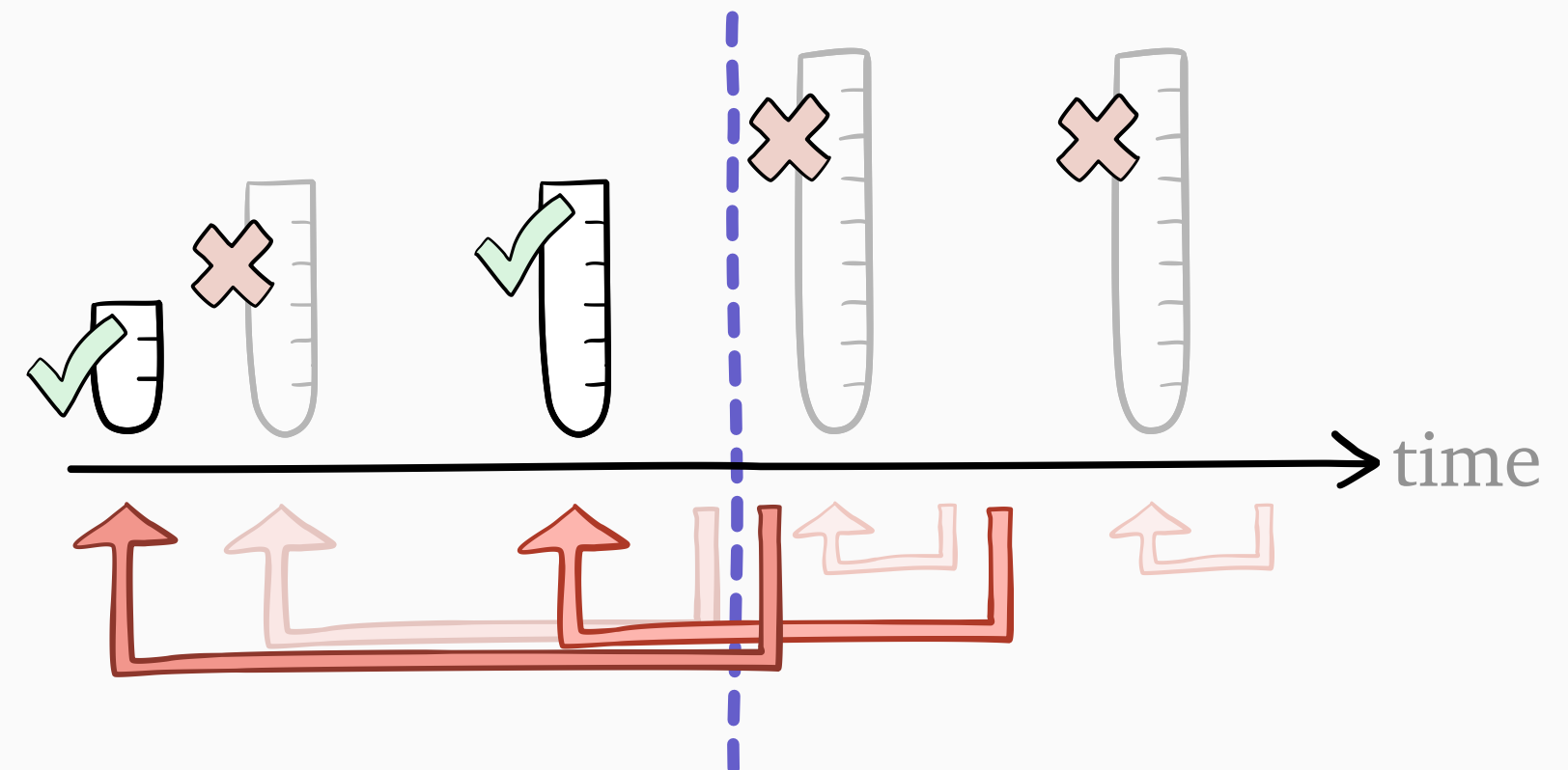
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final value theorem

Boost **boost** function

$$T_{\text{Boost}} \approx W + S - b(S) + V$$

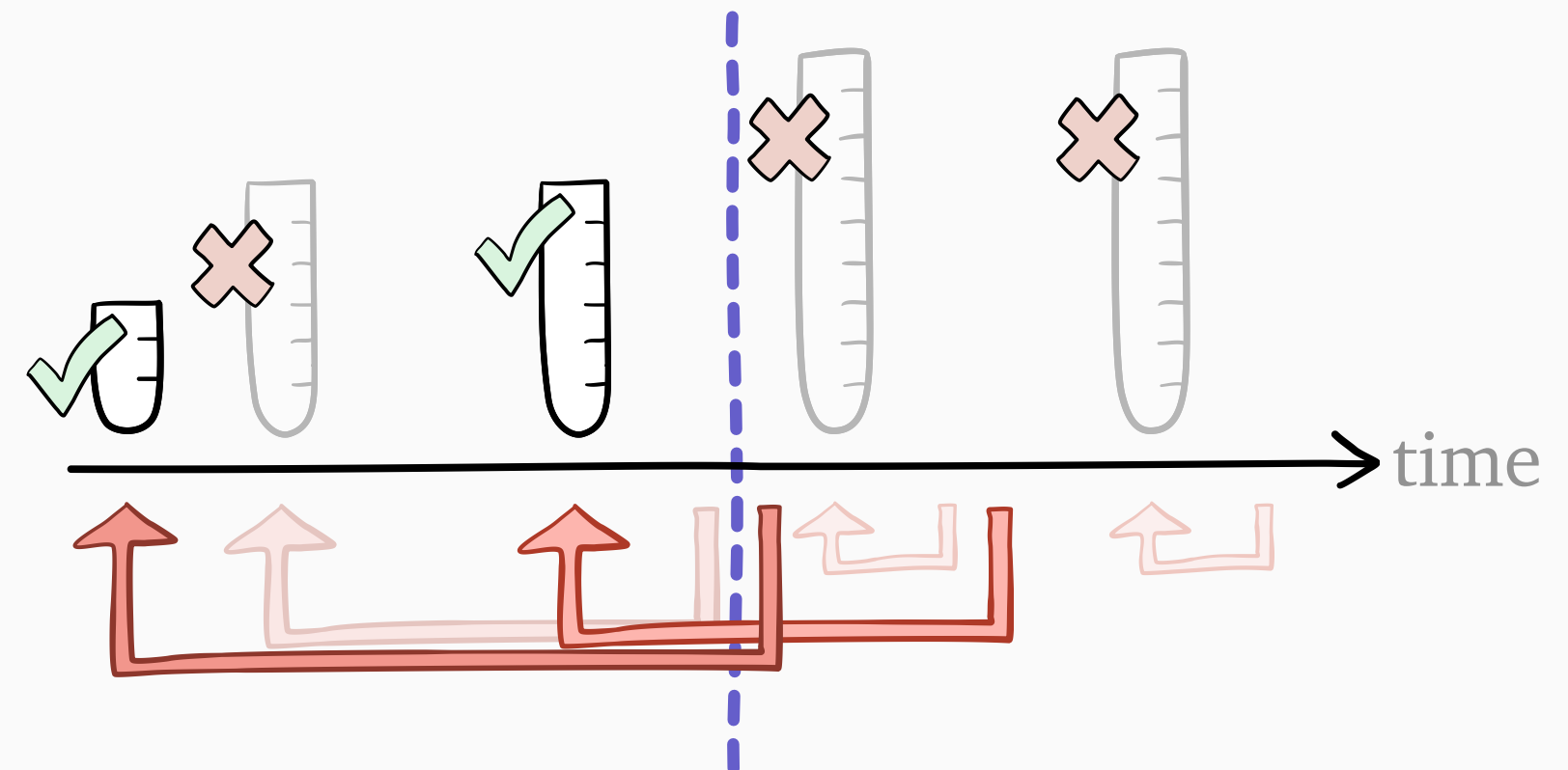
crossing work

$$C_{\text{Boost}} = C_W \mathbf{E}[e^{\gamma(S-b(S))}] \mathbf{E}[e^{\gamma V}]$$

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

$V =$ **crossing work**

work that “boosts past” a given time



How to achieve *strong* tail optimality?

$$C = \lim_{t \rightarrow \infty} e^{\gamma t} \mathbf{P}[T > t] = \lim_{\theta \rightarrow \gamma} \frac{\gamma - \theta}{\gamma} \mathbf{E}[e^{\theta T}]$$

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Finite batch
problem?

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$\underbrace{\hspace{10em}}$
“ $\infty \cdot \mathbf{P}[T > \infty]$ ”

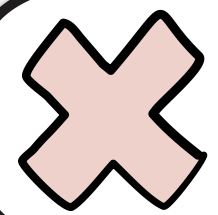
 Finite batch problem?

How to achieve *strong* tail optimality?

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 Finite batch problem?

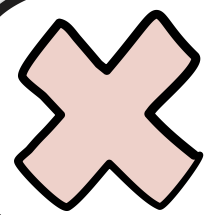


Always zero in batch setting

How to achieve *strong* tail optimality?

$$C = \underbrace{\lim_{t \rightarrow \infty} e^{\gamma t} \mathbf{P}[T > t]}_{\text{"}\infty \cdot \mathbf{P}[T > \infty]\text{"}} = \underbrace{\lim_{\theta \rightarrow \gamma} \frac{\gamma - \theta}{\gamma} \mathbf{E}[e^{\theta T}]}_{\text{"}0 \cdot \mathbf{E}[e^{\gamma T}]\text{"}}$$

 Finite batch problem?

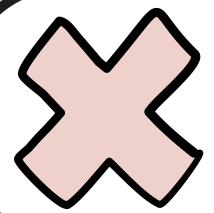


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Always zero in batch setting



Makes sense in batch setting!

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? Finite batch problem?



Always zero in batch setting



Makes sense in batch setting!

$$t_i = d_i - a_i$$

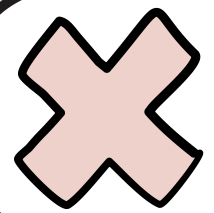
a_i = arrival time of job i

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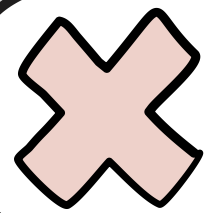
$$\mathbf{E}[e^{\gamma T}] = \frac{1}{n} \sum_{i=1}^n e^{\gamma t_i} = \frac{1}{n} \sum_{i=1}^n e^{-\gamma a_i} e^{\gamma d_i}$$

Batch problem: minimize

How to achieve *strong* tail optimality?

$$C = \underbrace{\lim_{t \rightarrow \infty} e^{\gamma t} \mathbf{P}[T > t]}_{\text{"}\infty \cdot \mathbf{P}[T > \infty]\text{"}} = \lim_{\theta \rightarrow \gamma} \underbrace{\frac{\gamma - \theta}{\gamma} \mathbf{E}[e^{\theta T}]}_{\text{"}0 \cdot \mathbf{E}[e^{\gamma T}]\text{"}}$$

? Finite batch problem?



Always zero in batch setting



Makes sense in batch setting!

almost classic problem

Batch problem: minimize

$t_i = d_i - a_i$
 a_i = arrival time of job i
 d_i = departure time of job i



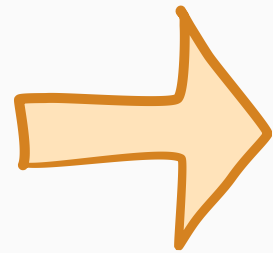
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 $\mathbf{E}[e^{\gamma T}] = \frac{1}{n} \sum_{i=1}^n e^{\gamma t_i} = \frac{1}{n} \sum_{i=1}^n e^{-\gamma a_i} e^{\gamma d_i}$


Classic metric: mean weighted discounted departure time

$$\frac{1}{n} \sum_{i=1}^n w_i e^{-\theta d_i}$$

How to achieve *strong* tail optimality?

Batch problem: minimize

$t_i = d_i - a_i$
 $a_i =$ arrival time of job i
 $d_i =$ departure time of job i


$$\mathbf{E}[e^{\gamma T}] = \frac{1}{n} \sum_{i=1}^n e^{\gamma t_i} = \frac{1}{n} \sum_{i=1}^n e^{-\gamma a_i} e^{\gamma d_i}$$




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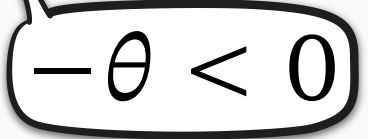
$t_i = d_i - a_i$
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 $d_i = \text{departure time of job } i$

 $\mathbf{E}[e^{\gamma T}] = \frac{1}{n} \sum_{i=1}^n e^{\gamma t_i} = \frac{1}{n} \sum_{i=1}^n e^{-\gamma a_i} e^{\gamma d_i}$



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Batch problem: minimize

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$$\gamma > 0$$



Classic metric: mean weighted discounted departure time

$$\frac{1}{n} \sum_{i=1}^n w_i e^{-\theta d_i}$$

$$-\theta < 0$$

How to achieve *strong* tail optimality?

$$t_i = d_i - a_i$$

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Batch problem: minimize

$$\mathbf{E}[e^{\gamma T}] = \frac{1}{n} \sum_{i=1}^n e^{\gamma t_i} = \frac{1}{n} \sum_{i=1}^n e^{-\gamma a_i} e^{\gamma d_i}$$

can't start i
before a_i

$$\gamma > 0$$



Classic metric: mean weighted
discounted departure time

$$\frac{1}{n} \sum_{i=1}^n w_i e^{-\theta d_i}$$

$$-\theta < 0$$

How to achieve *strong* tail optimality?

$$t_i = d_i - a_i$$

a_i = arrival time of job i

d_i = departure time of job i



Batch problem: minimize

$$\mathbf{E}[e^{\gamma T}] = \frac{1}{n} \sum_{i=1}^n e^{\gamma t_i} = \frac{1}{n} \sum_{i=1}^n e^{-\gamma a_i} e^{\gamma d_i}$$

can't start i
before a_i

$$\gamma > 0$$



Classic metric: mean weighted discounted departure time

$$\frac{1}{n} \sum_{i=1}^n w_i e^{-\theta d_i}$$

$$-\theta < 0$$

Relaxation solved by (sign-flipped) WDSPT, which is **Boost** with

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

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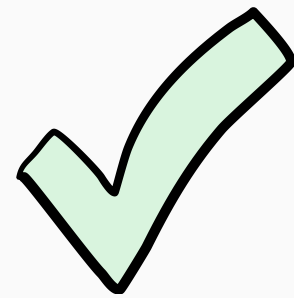
Relaxation solved by (sign-flipped) WDSPT, which is **Boost** with

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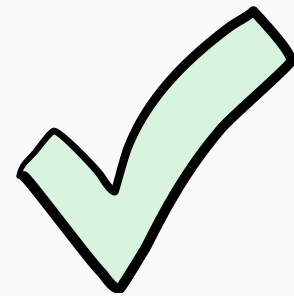
γ -Boost

Unknown sizes:
swap WDSPT for Gittins

Boost



Why is achieving strong tail optimality hard?

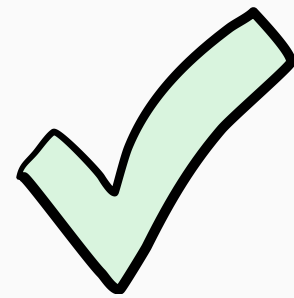


How does the **Boost** policy family work?

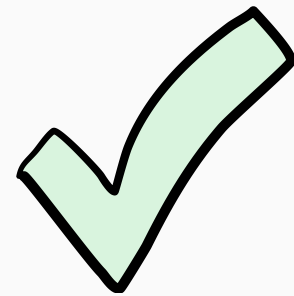


How do we achieve strong tail optimality?

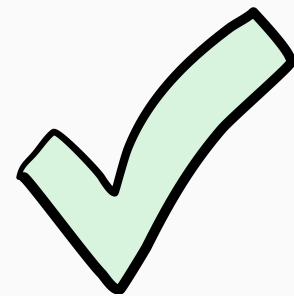
Boost



Why is achieving strong tail optimality hard?



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

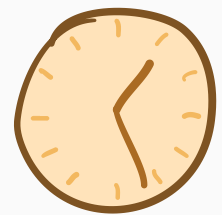


How do we achieve strong tail optimality?

Our contributions:



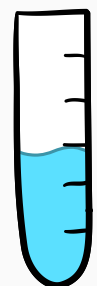
Design the **Boost** scheduling policy



Analyze **Boost**'s performance



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



Known job sizes

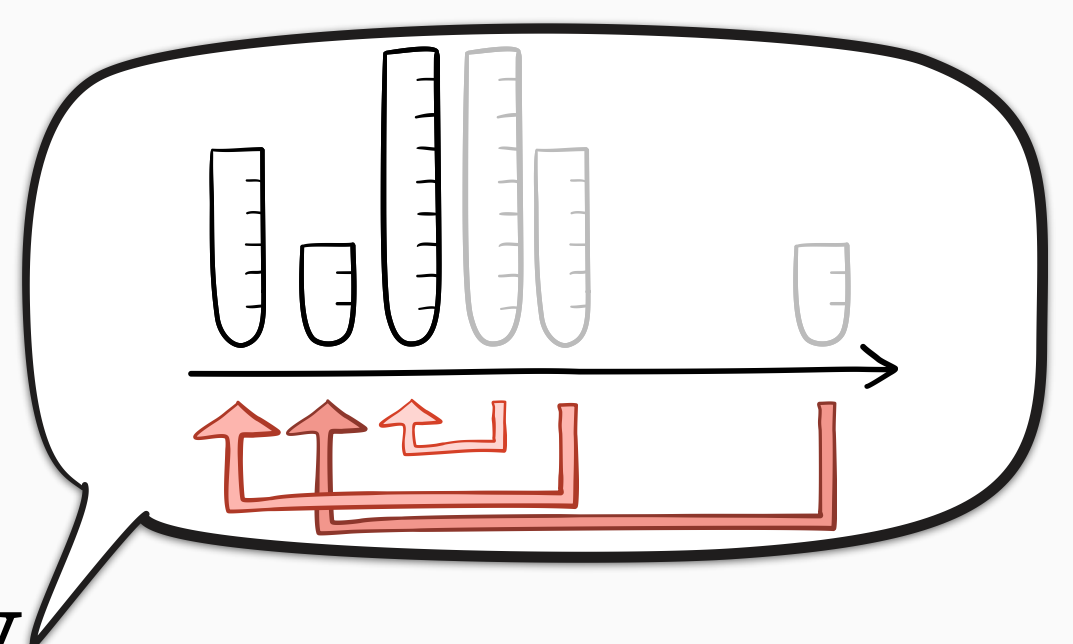
Yu & Scully. *Strongly Tail-Optimal Scheduling in the Light-Tailed M/G/1*. SIGMETRICS 2024.



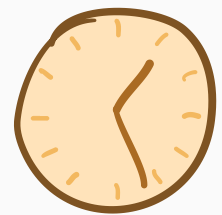
Unknown job sizes

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

Our contributions:



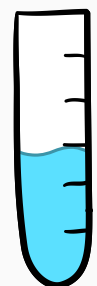
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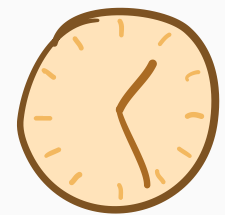
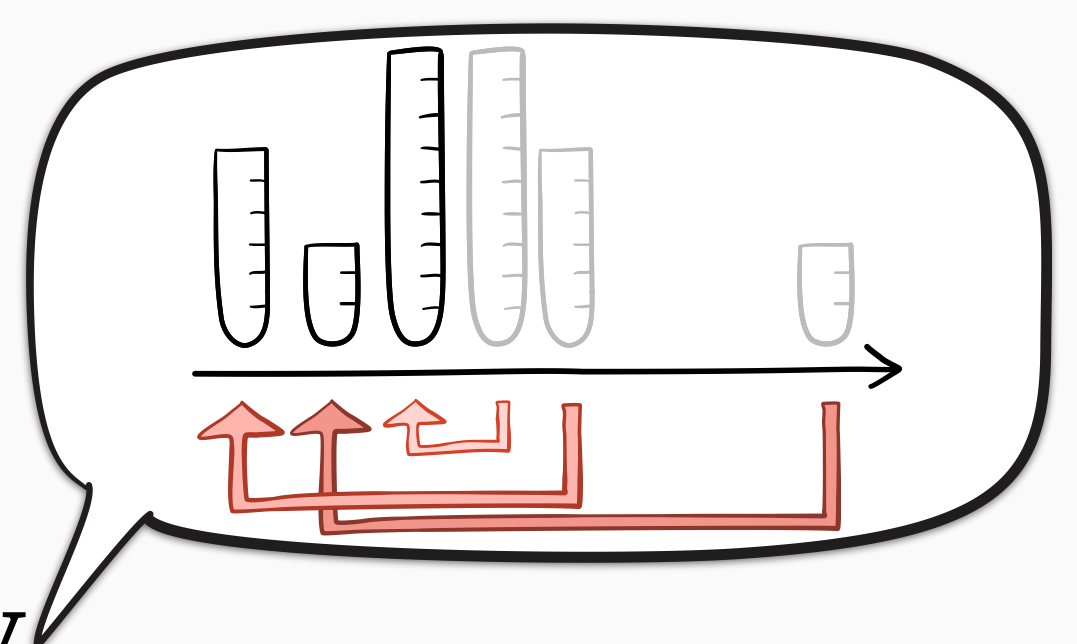
Unknown job sizes

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Our contributions:



Design the **Boost** scheduling policy

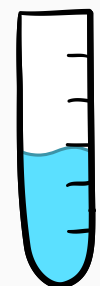


Analyze **Boost**'s performance

compute C_{Boost}



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



Known job sizes

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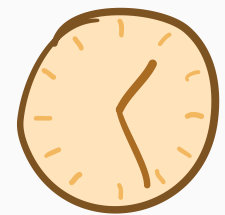
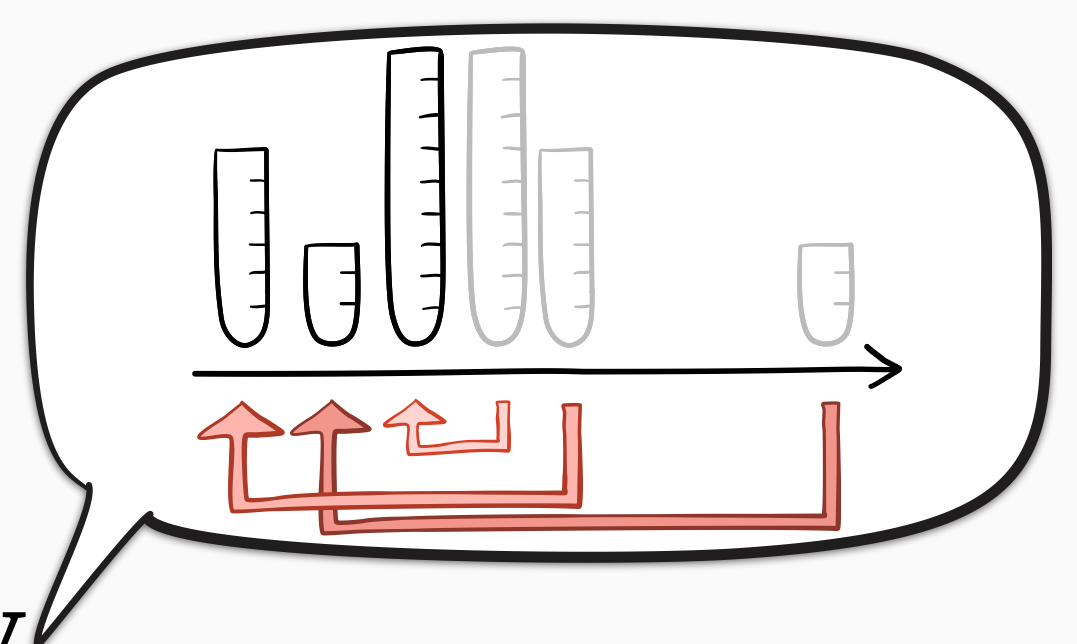
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Analyze **Boost**'s performance

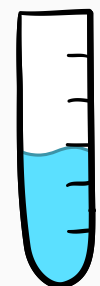
compute C_{Boost}

γ -Boost:

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



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



Known job sizes

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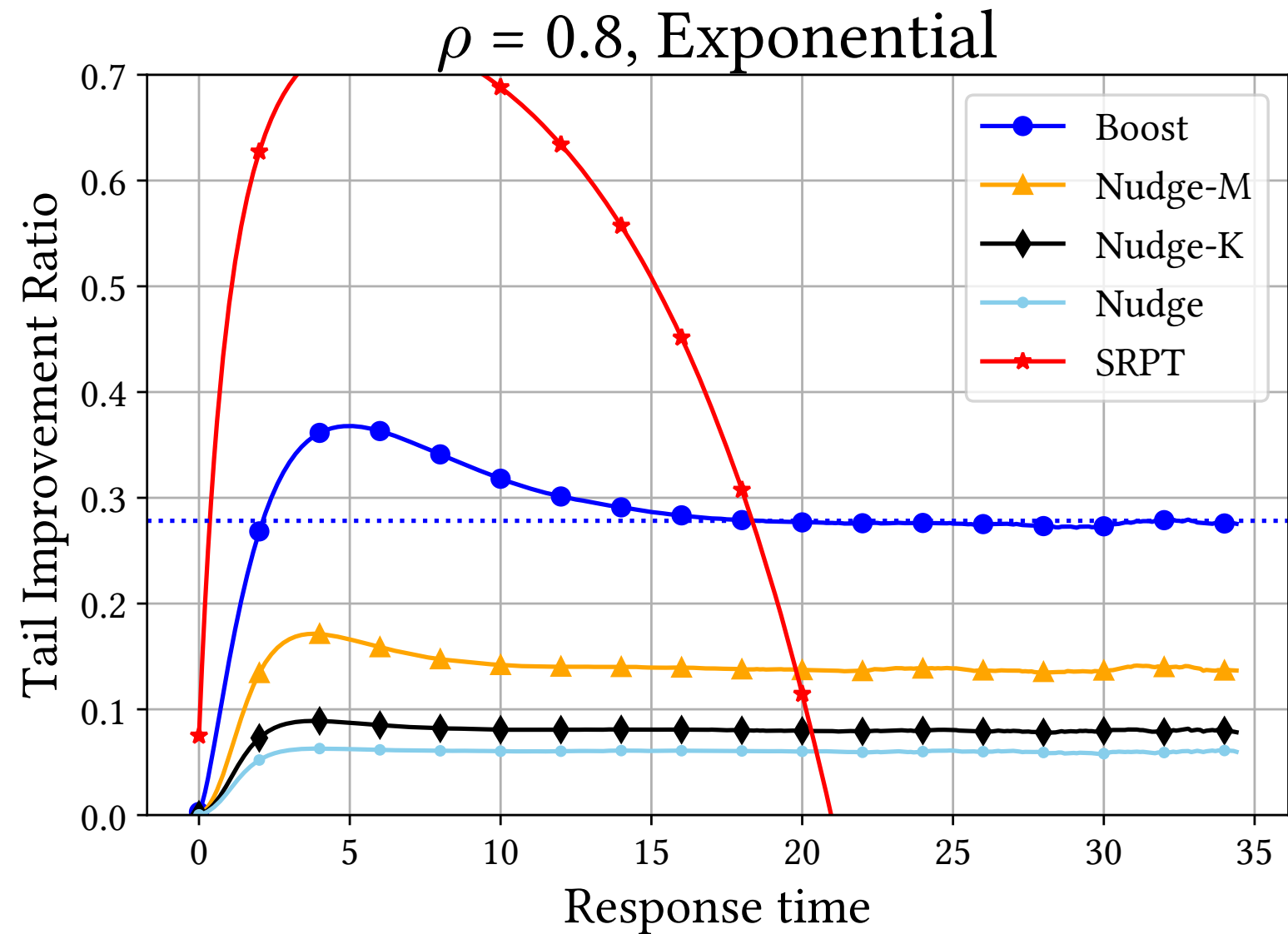
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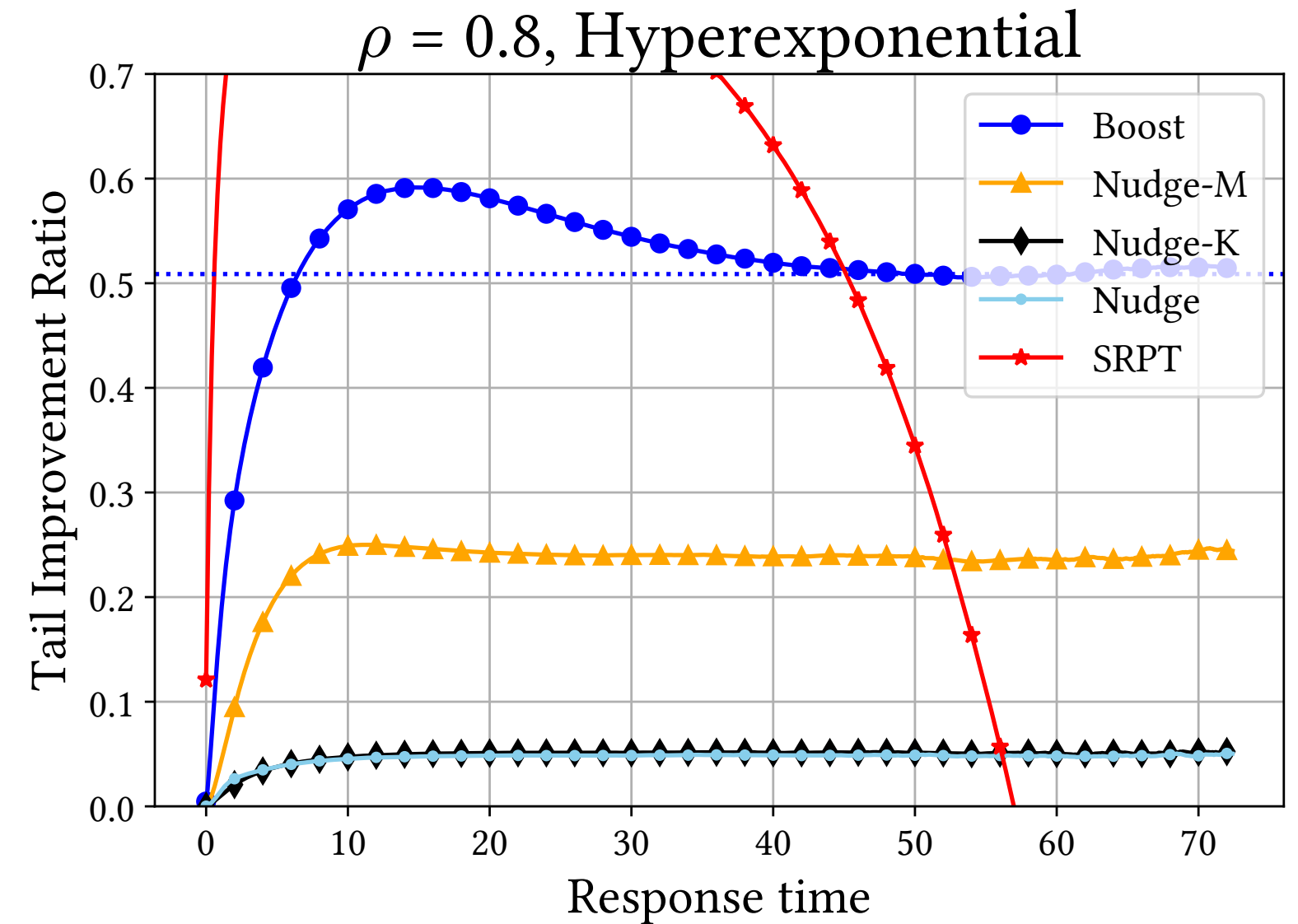
Bonus slides

Impact of job size variance

Low variance

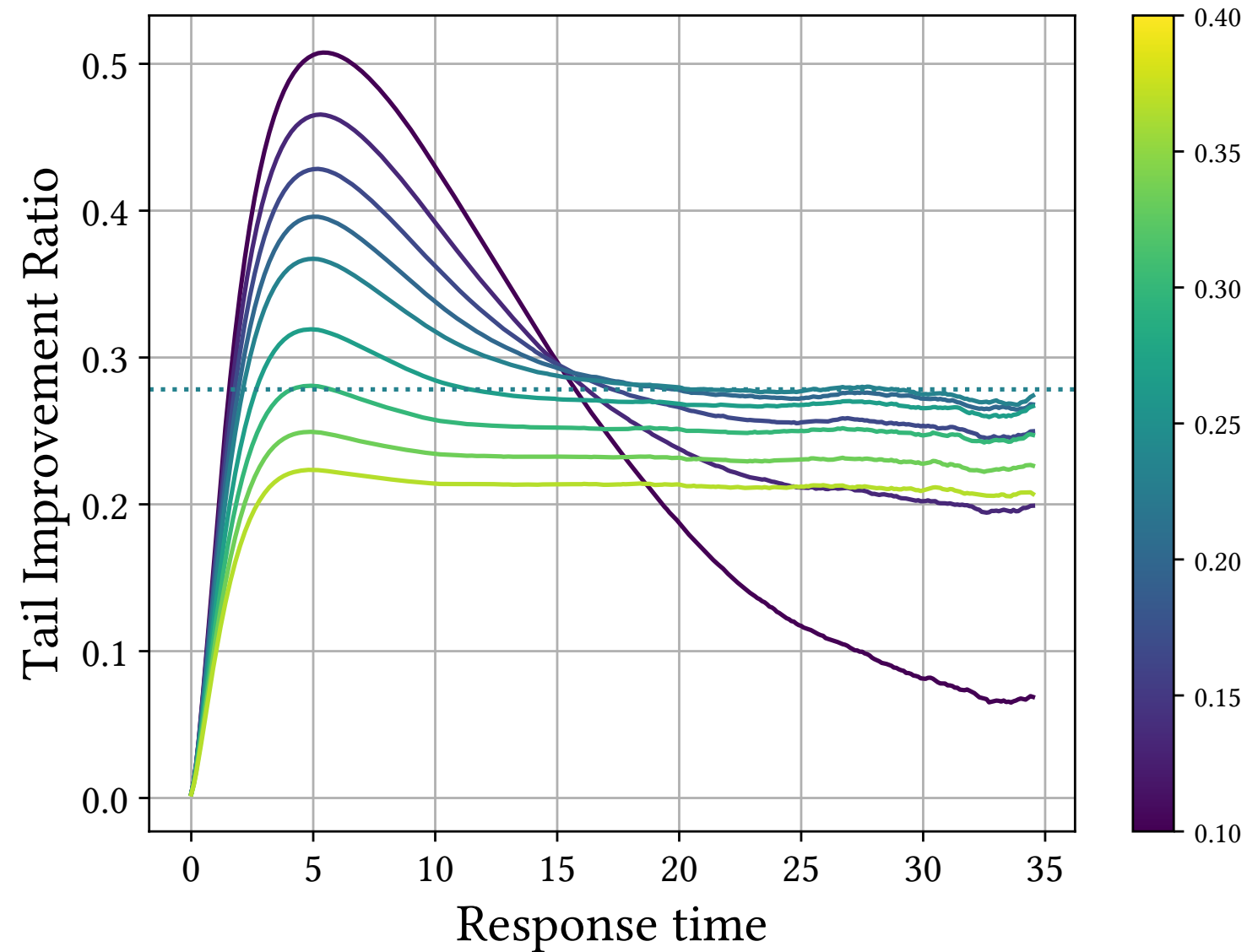


High variance

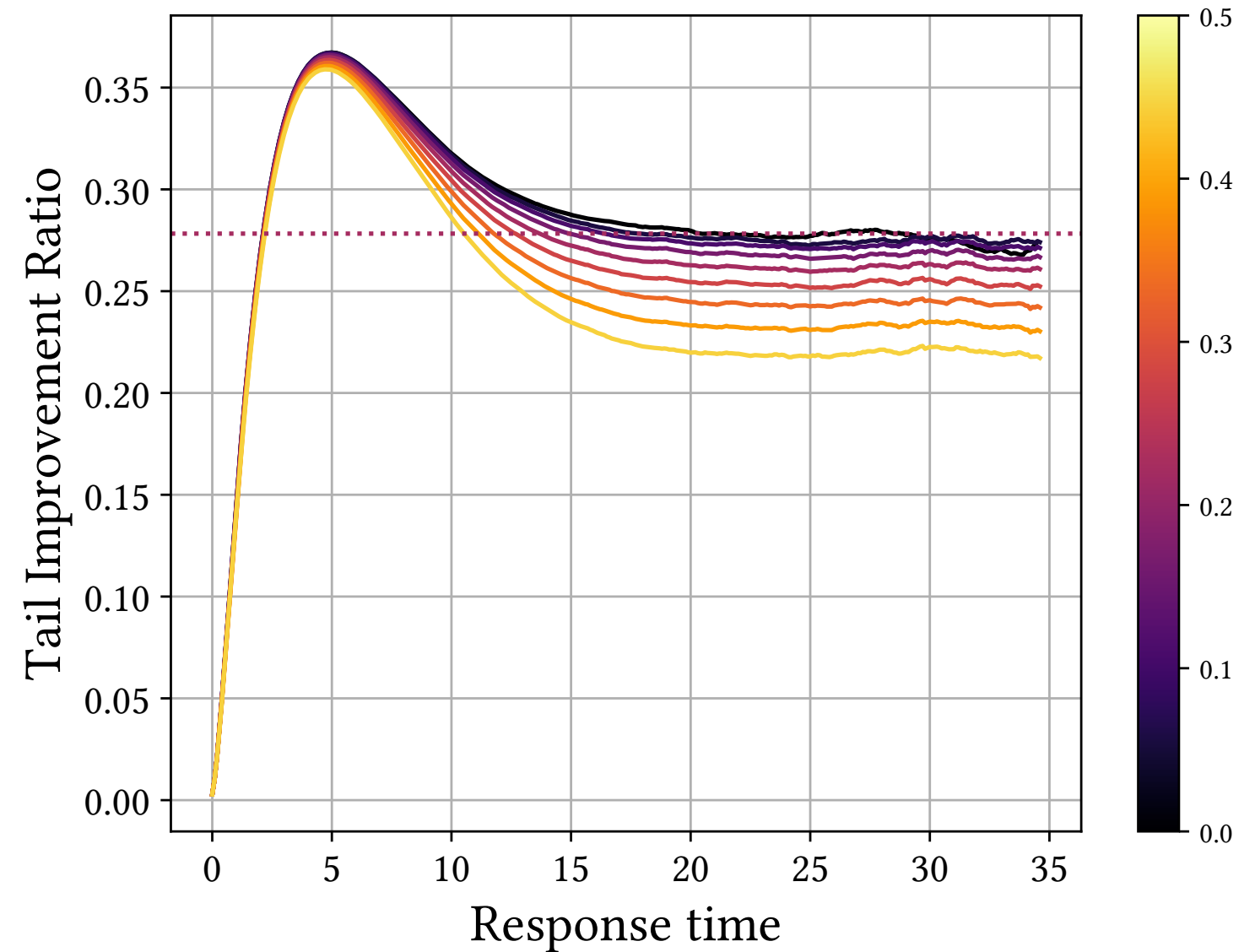


Sensitivity analysis

Misspecified γ



Noisy size information



Heavy-tailed sizes

“ S Pareto-ish” (regularly varying)

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

Light-tailed sizes

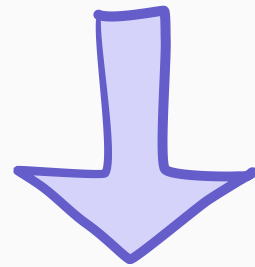
“ S exponential-ish or lighter” (class I)

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

Heavy-tailed sizes

“ S Pareto-ish” (regularly varying)

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



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

Light-tailed sizes

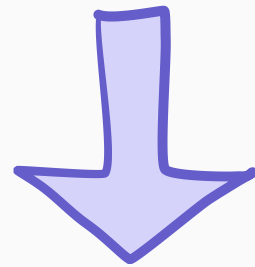
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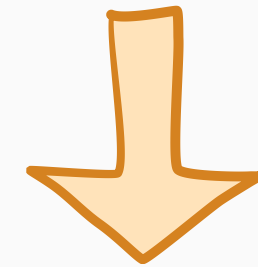


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Light-tailed sizes

“ S exponential-ish or lighter” (class I)

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

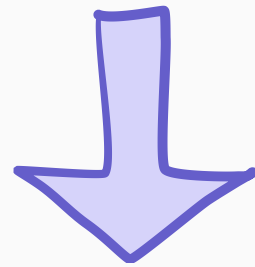


$$\mathbf{P}[T > t] \sim Ce^{-\gamma t}$$

Heavy-tailed sizes

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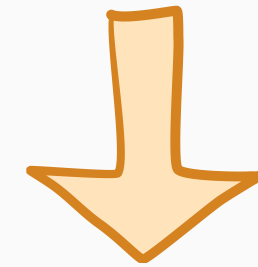


$$\mathbf{P}[T_{\pi} > t] \sim C_{\pi} t^{-\gamma_{\pi}}$$

Light-tailed sizes

“S exponential-ish or lighter” (class I)

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

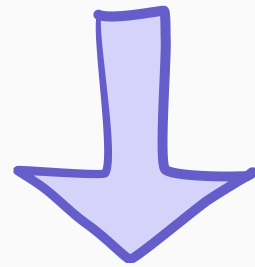


$$\mathbf{P}[T_{\pi} > t] \sim C_{\pi} e^{-\gamma_{\pi} t}$$

Heavy-tailed sizes

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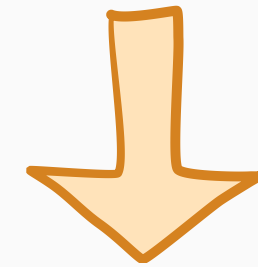


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Light-tailed sizes

“S exponential-ish or lighter” (class I)

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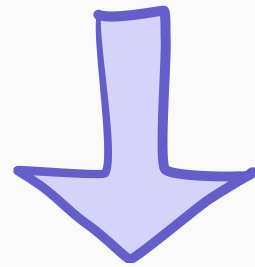
$$\mathbf{P}[T_{\pi} > t] \sim C_{\pi} e^{-\gamma_{\pi} t}$$

γ_{π} = decay rate of π
 C_{π} = tail constant of π

Heavy-tailed sizes

“S Pareto-ish” (regularly varying)

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

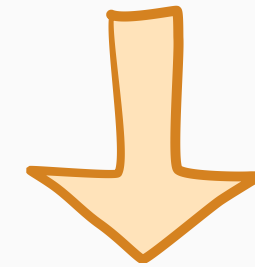


$$\mathbf{P}[T_{\pi} > t] \sim C_{\pi} t^{-\gamma_{\pi}}$$

Light-tailed sizes

“S exponential-ish or lighter” (class I)

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



$$\mathbf{P}[T_{\pi} > t] \sim C_{\pi} e^{-\gamma_{\pi} t}$$

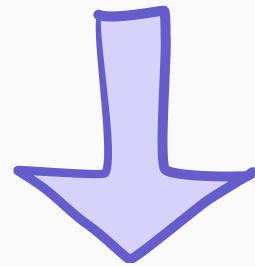
γ_{π} = decay rate of π
 C_{π} = tail constant of π

Weak optimality:
maximize γ_{π}

Heavy-tailed sizes

“S Pareto-ish” (regularly varying)

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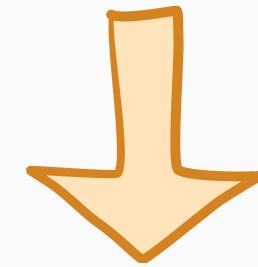


$$\mathbf{P}[T_{\pi} > t] \sim C_{\pi} t^{-\gamma_{\pi}}$$

Light-tailed sizes

“S exponential-ish or lighter” (class I)

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$$\mathbf{P}[T_{\pi} > t] \sim C_{\pi} e^{-\gamma_{\pi} t}$$

γ_{π} = decay rate of π
 C_{π} = tail constant of π

Weak optimality:

maximize γ_{π}

Strong optimality:

maximize γ_{π} , minimize C_{π}

Background on decay rates

Heavy-tailed sizes

Light-tailed sizes

Background on decay rates

	Heavy-tailed sizes	Light-tailed sizes
SRPT, LAS, etc. (least attained service)		
FCFS		

Background on decay rates

	Heavy-tailed sizes	Light-tailed sizes
SRPT, LAS, etc. (least attained service)	optimal $\gamma = \alpha$	
FCFS		optimal γ

Background on decay rates

	Heavy-tailed sizes	Light-tailed sizes
SRPT, LAS, etc. (least attained service)	optimal $\gamma = \alpha$	pessimal γ
FCFS	pessimal $\gamma = \alpha - 1$	optimal γ

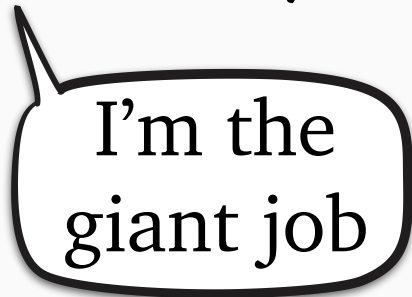
Background on decay rates

	Heavy-tailed sizes	Light-tailed sizes
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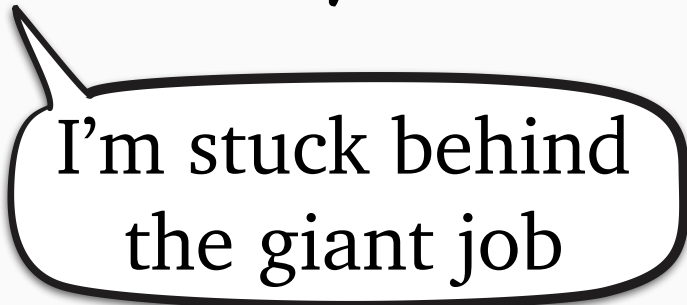
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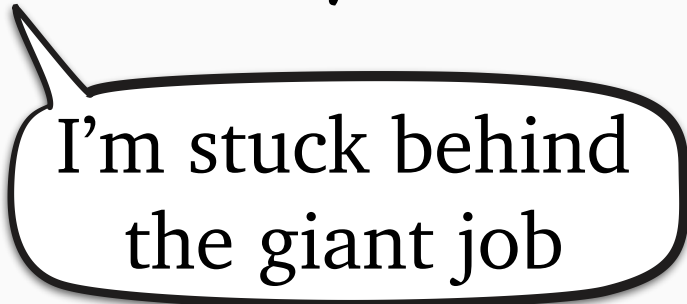
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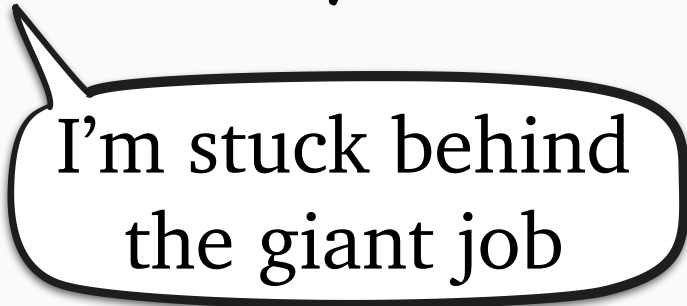
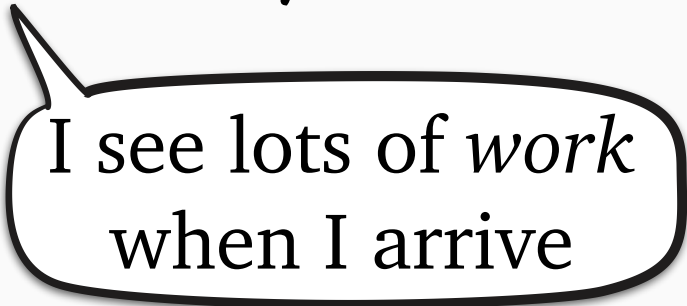
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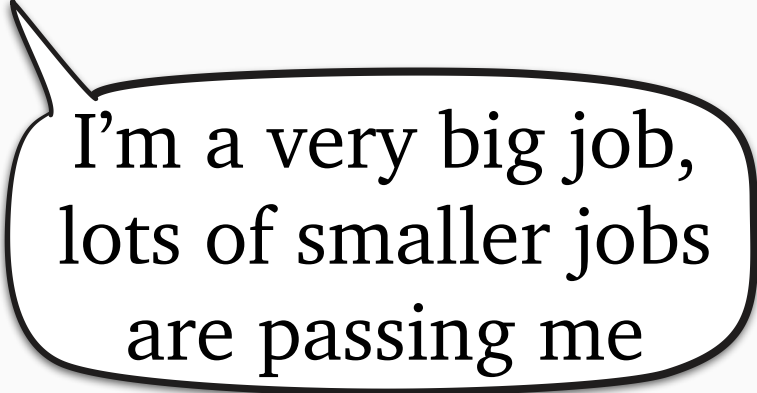
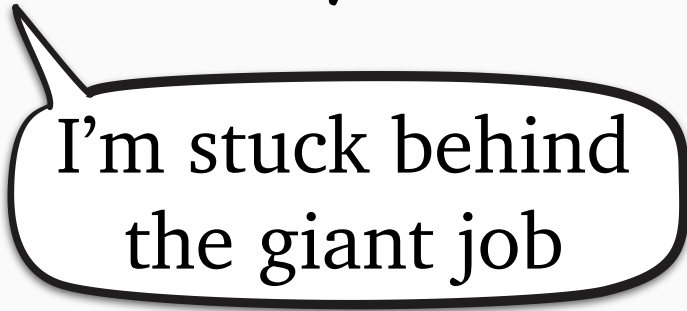
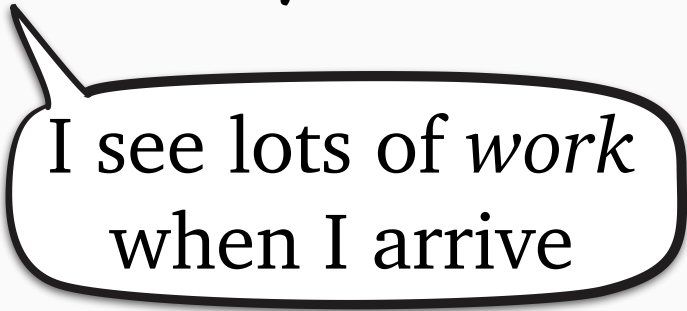
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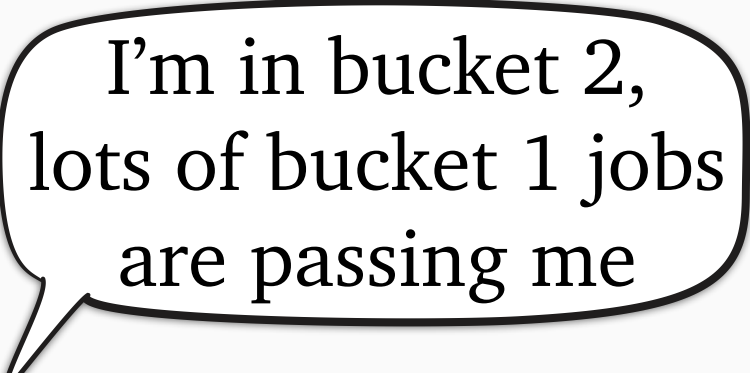
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I’m a very big job,
lots of smaller jobs
are passing me

I’m in bucket 2,
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SRPT, LAS, etc.
(least attained service)

FCFS

SRPT or LAS with
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Light-tailed

pessimistic γ

optimal γ

intermediate γ

“Conspiracy”
lots of biggish jobs

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SRPT or LAS with
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Light-tailed

I'm a very big job,
lots of smaller jobs
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pessimal γ

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

optimal γ

I'm in bucket 2,
lots of bucket 1 jobs
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intermediate γ

“Conspiracy”
lots of biggish jobs

Background on weak and strong optimality

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Corollary of prior work
[Wierman & Zwart, 2012]

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Light-tailed sizes

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Theorem:

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

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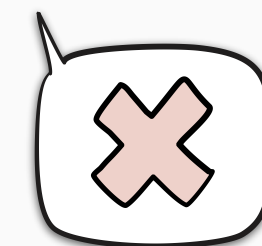
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Boost



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FCFS (first-come first-served)

Nudge [Grosf et al.]

Theorem:

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

Strongly optimal

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SRPT

PS (processor sharing)

LAS (least attained service)



Boost

