

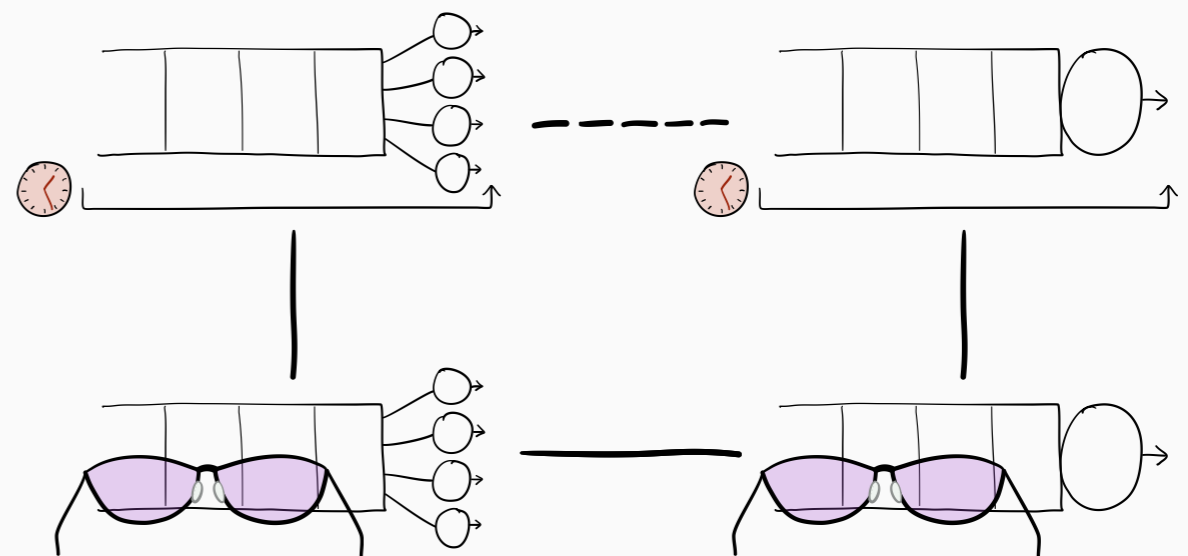
The Gittins Policy is Nearly Optimal in the $M/G/k$ *under Extremely General Conditions*

Ziv Scully

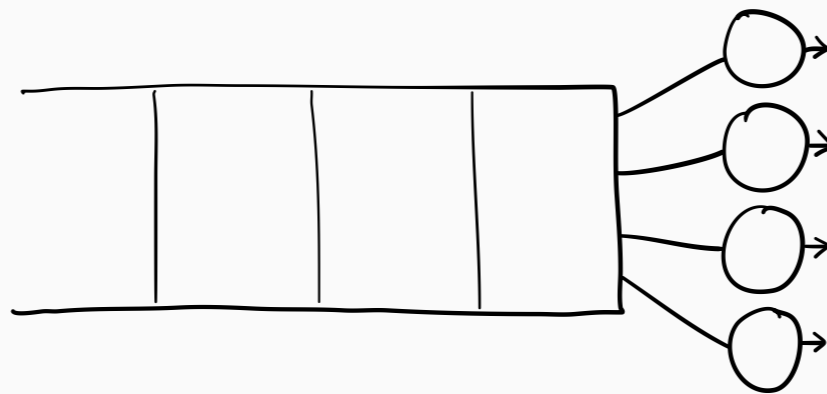
Isaac Grosf

Mor Harchol-Balter

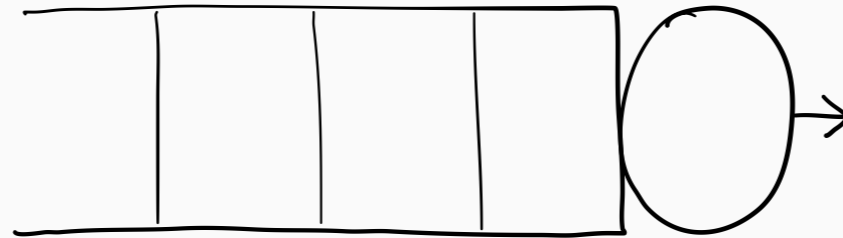
Carnegie Mellon University



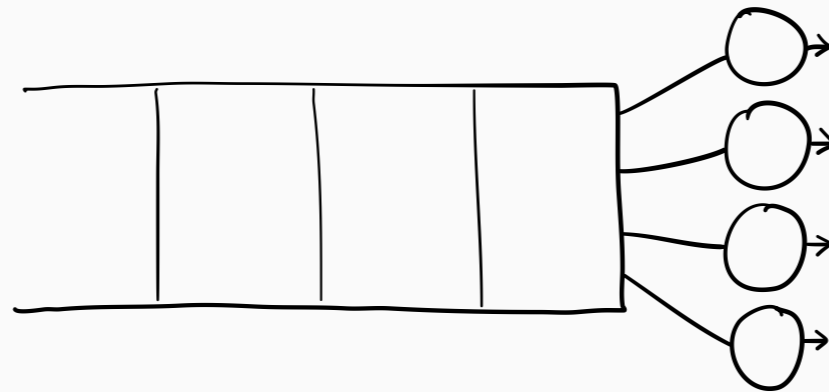
This talk: near-optimal *multiserver* scheduling



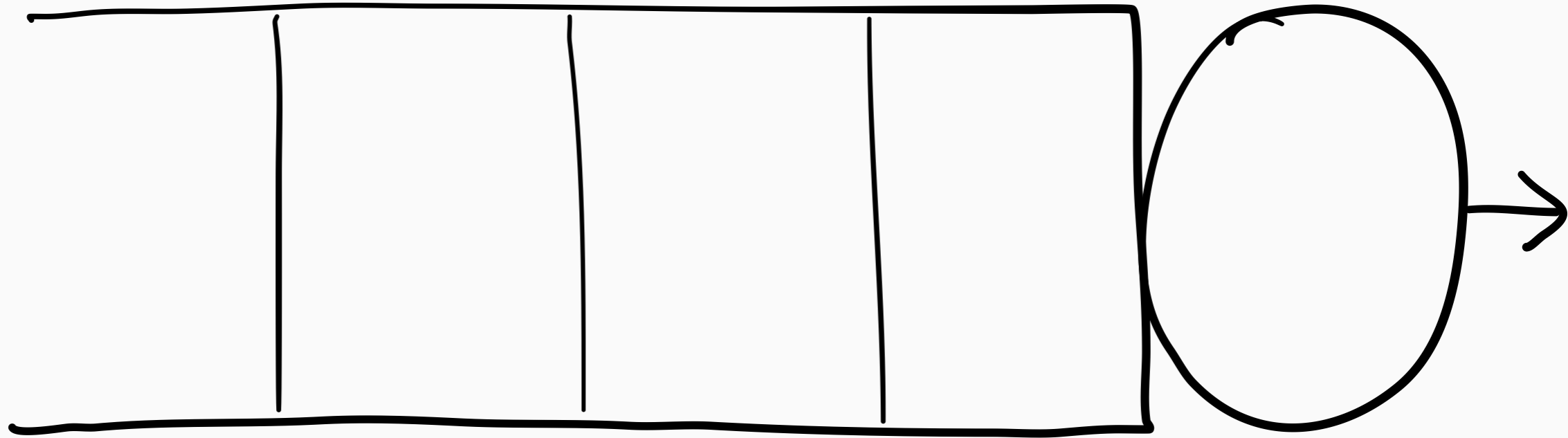
First: background on
single-server scheduling



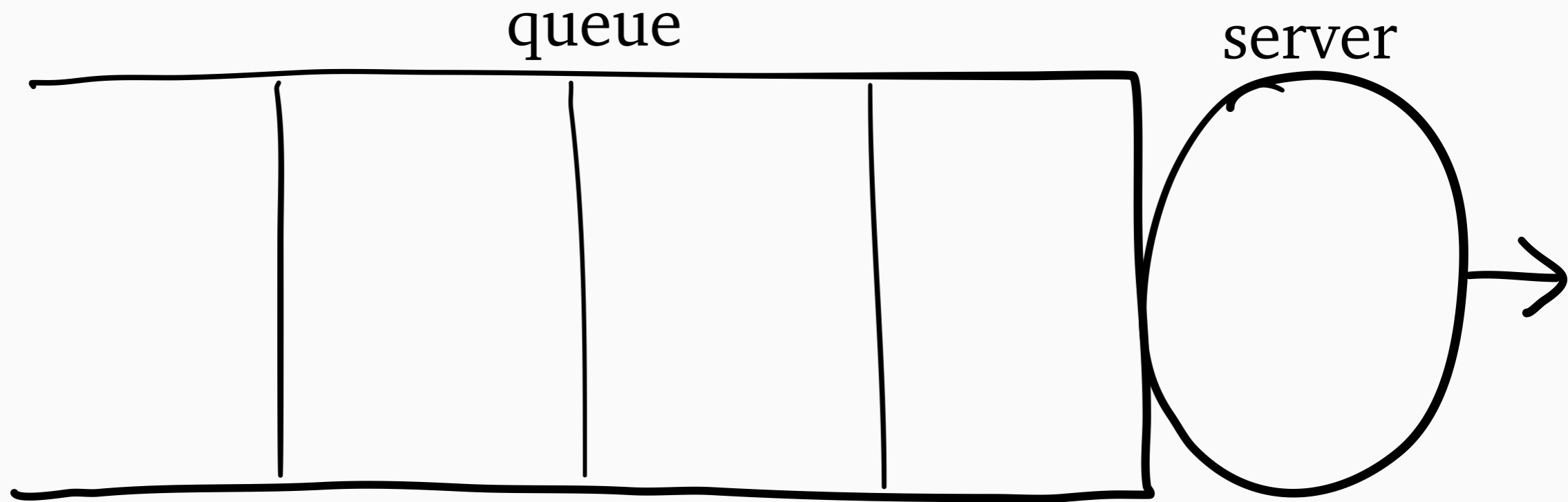
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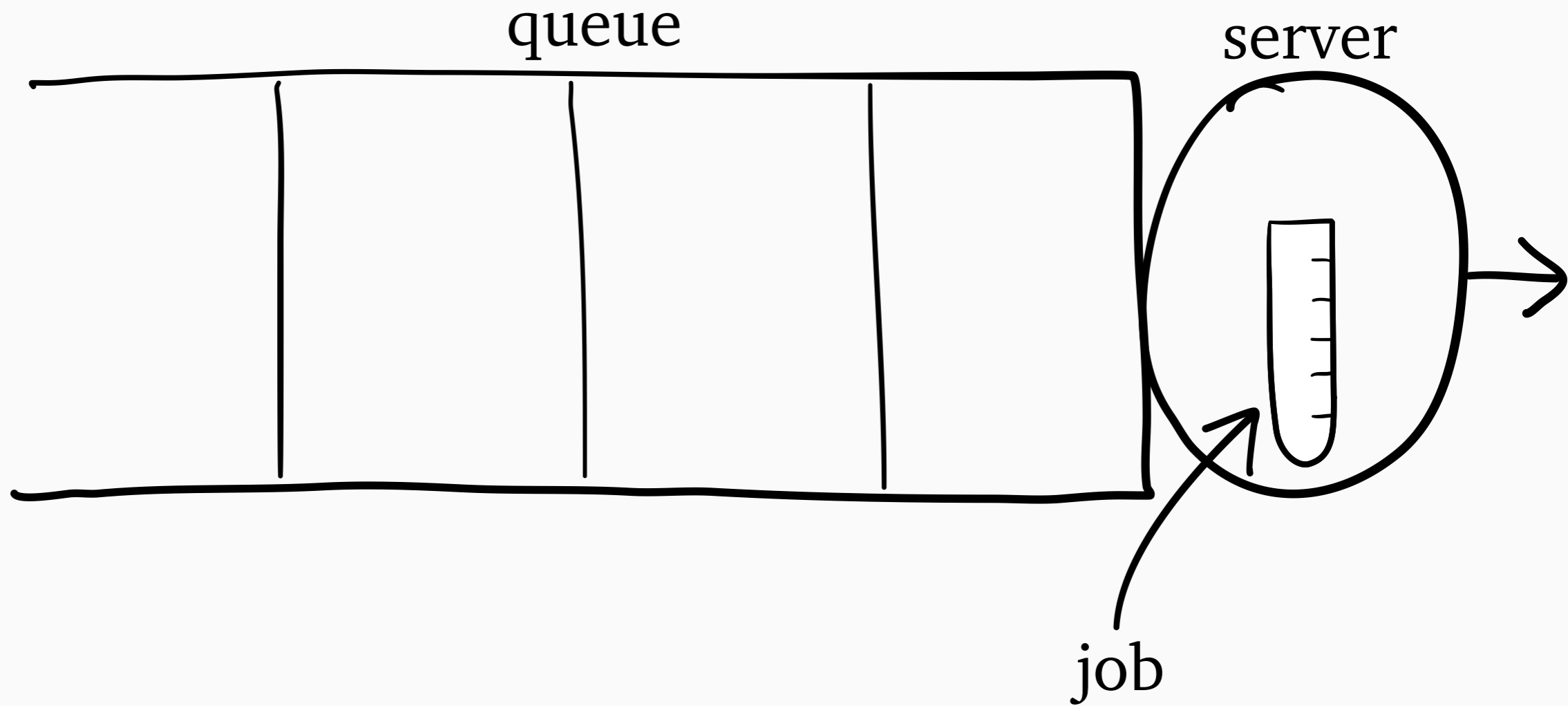
M/G/1 Queue



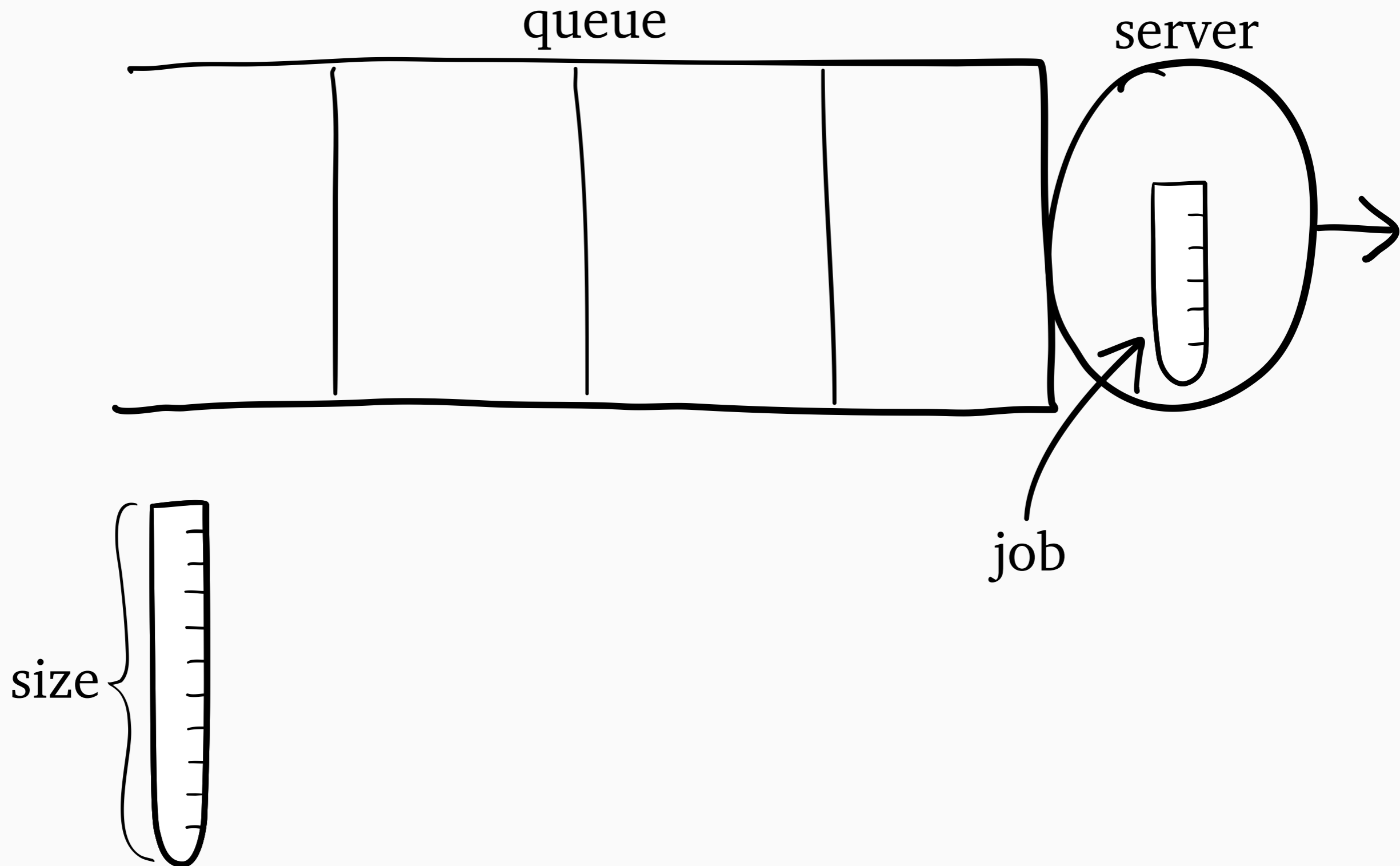
M/G/1 Queue



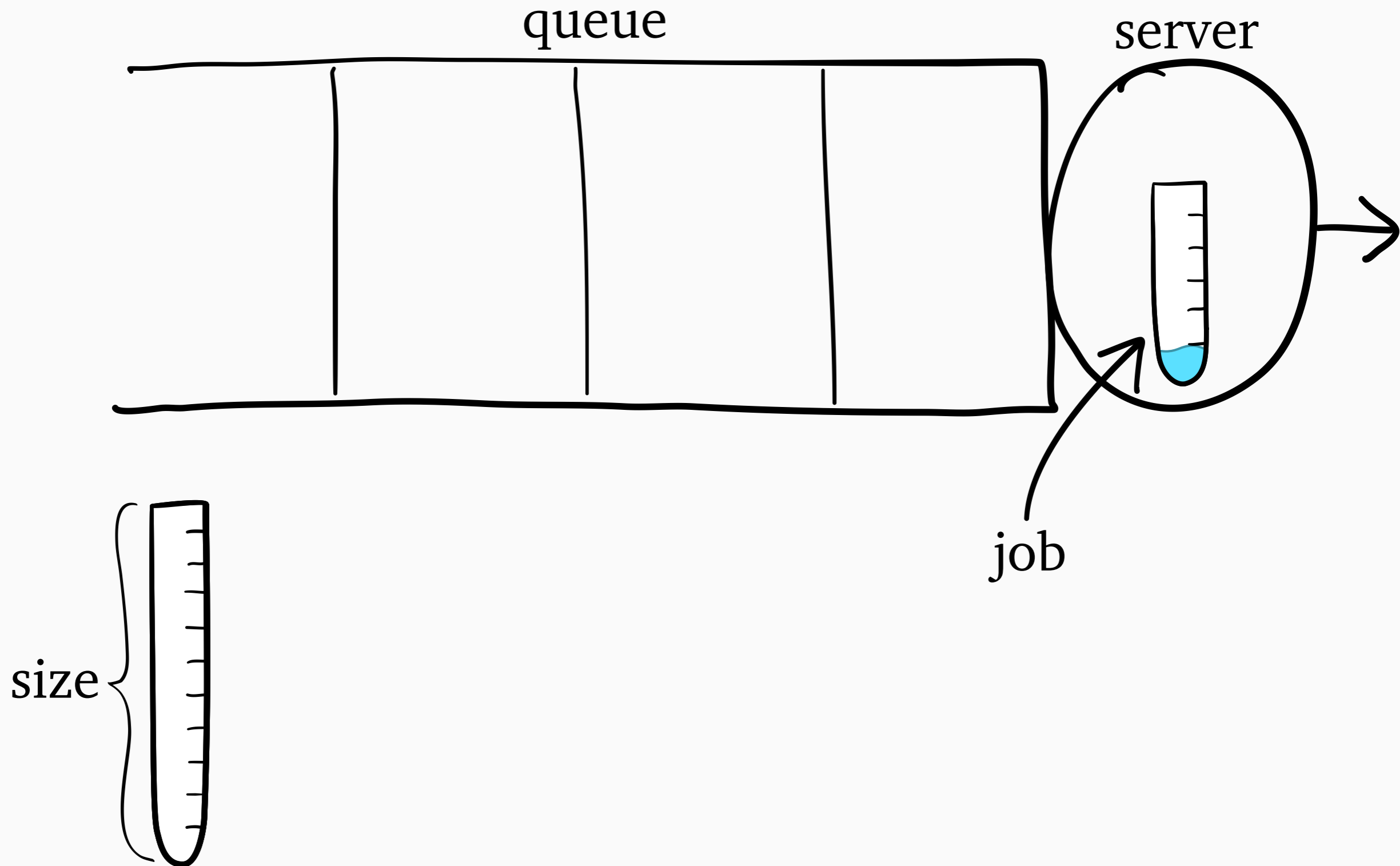
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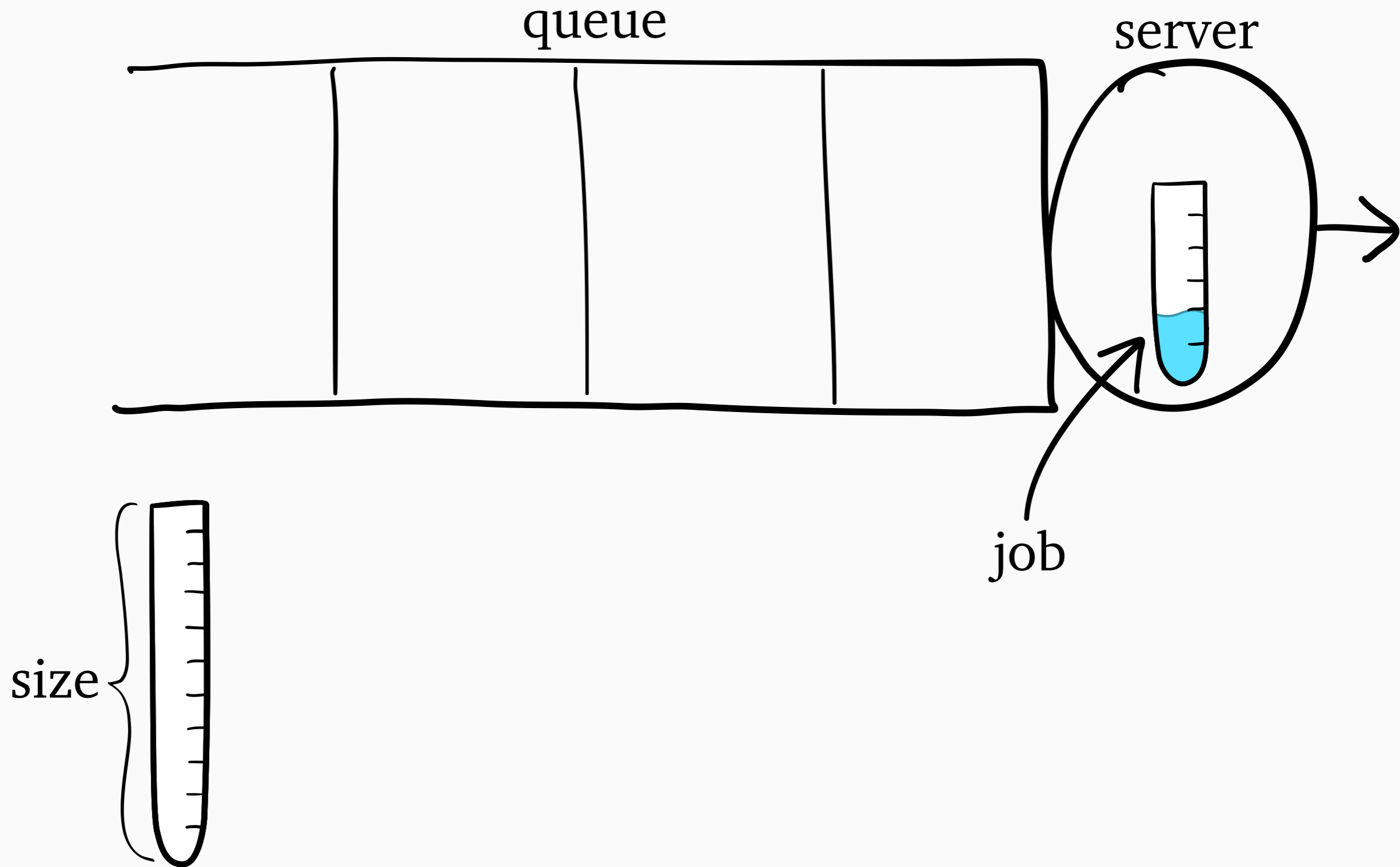
M/G/1 Queue



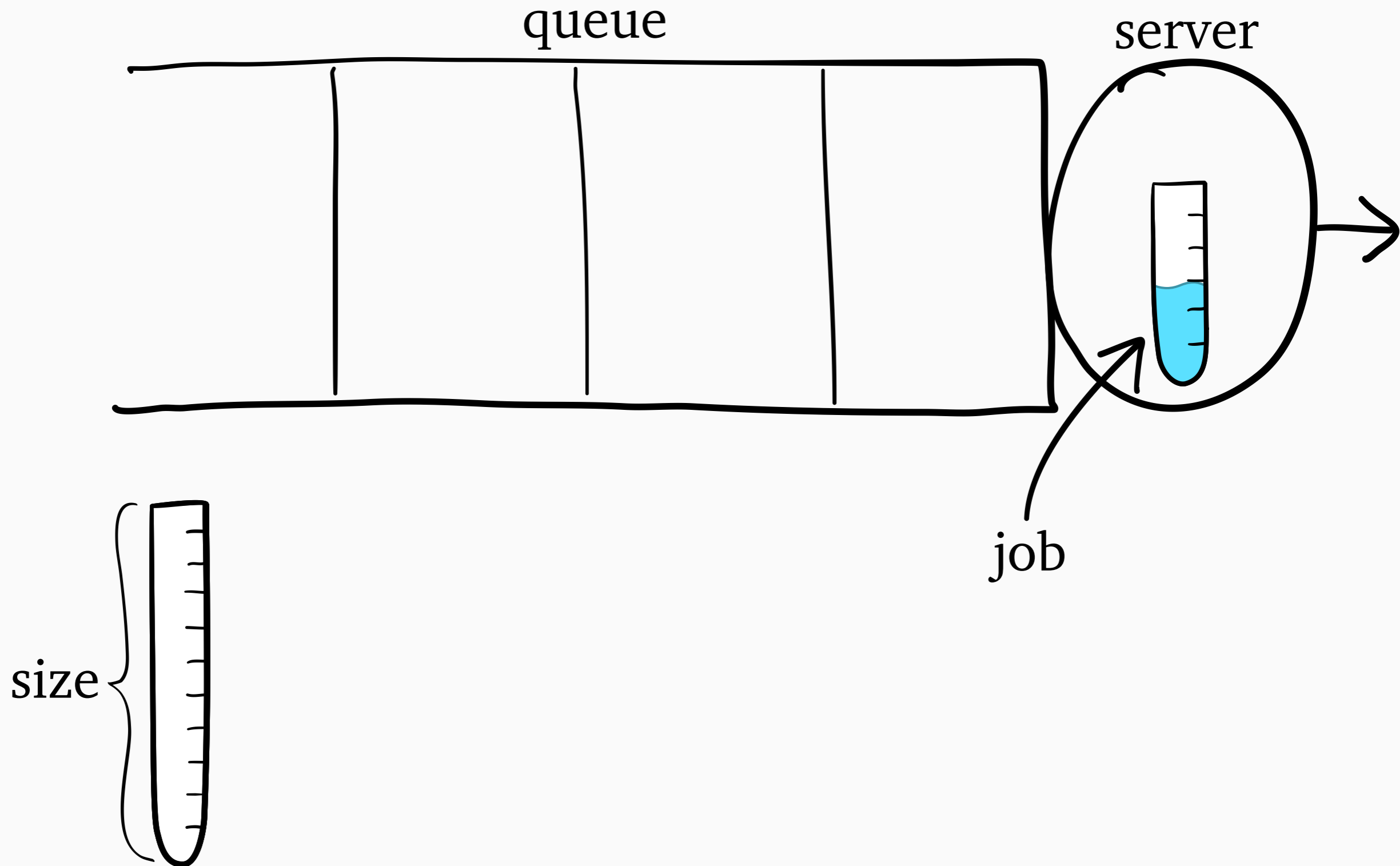
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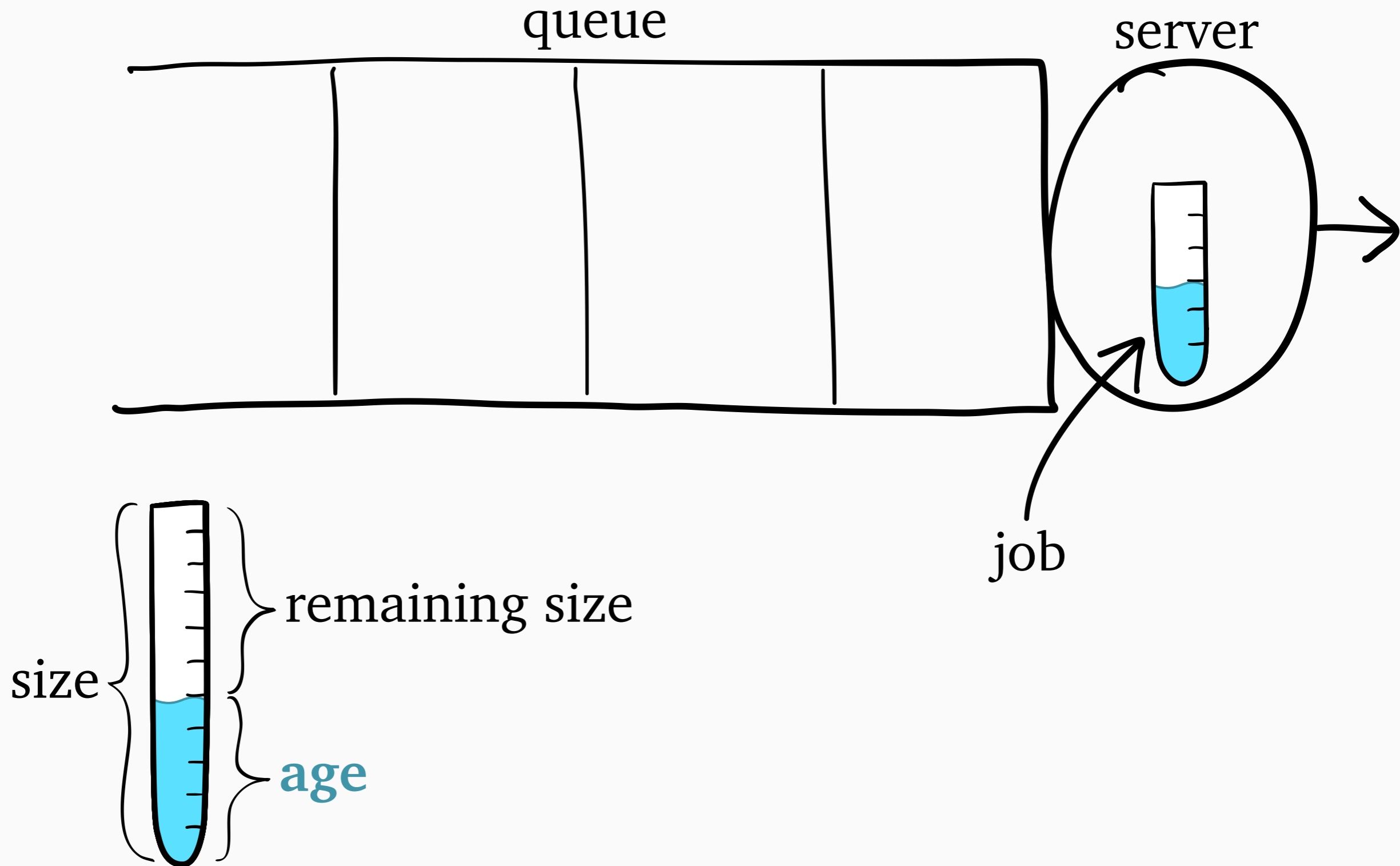
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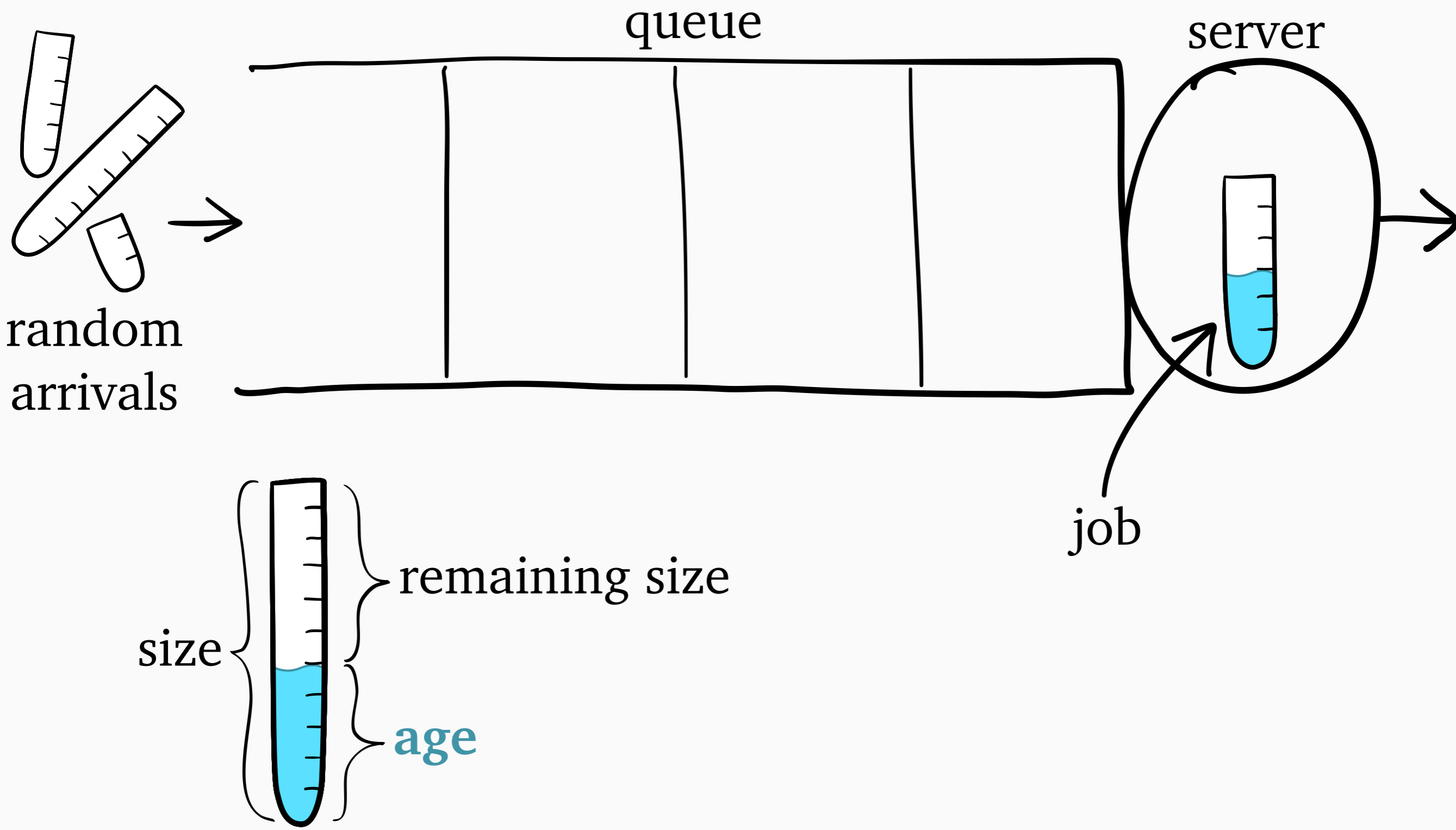
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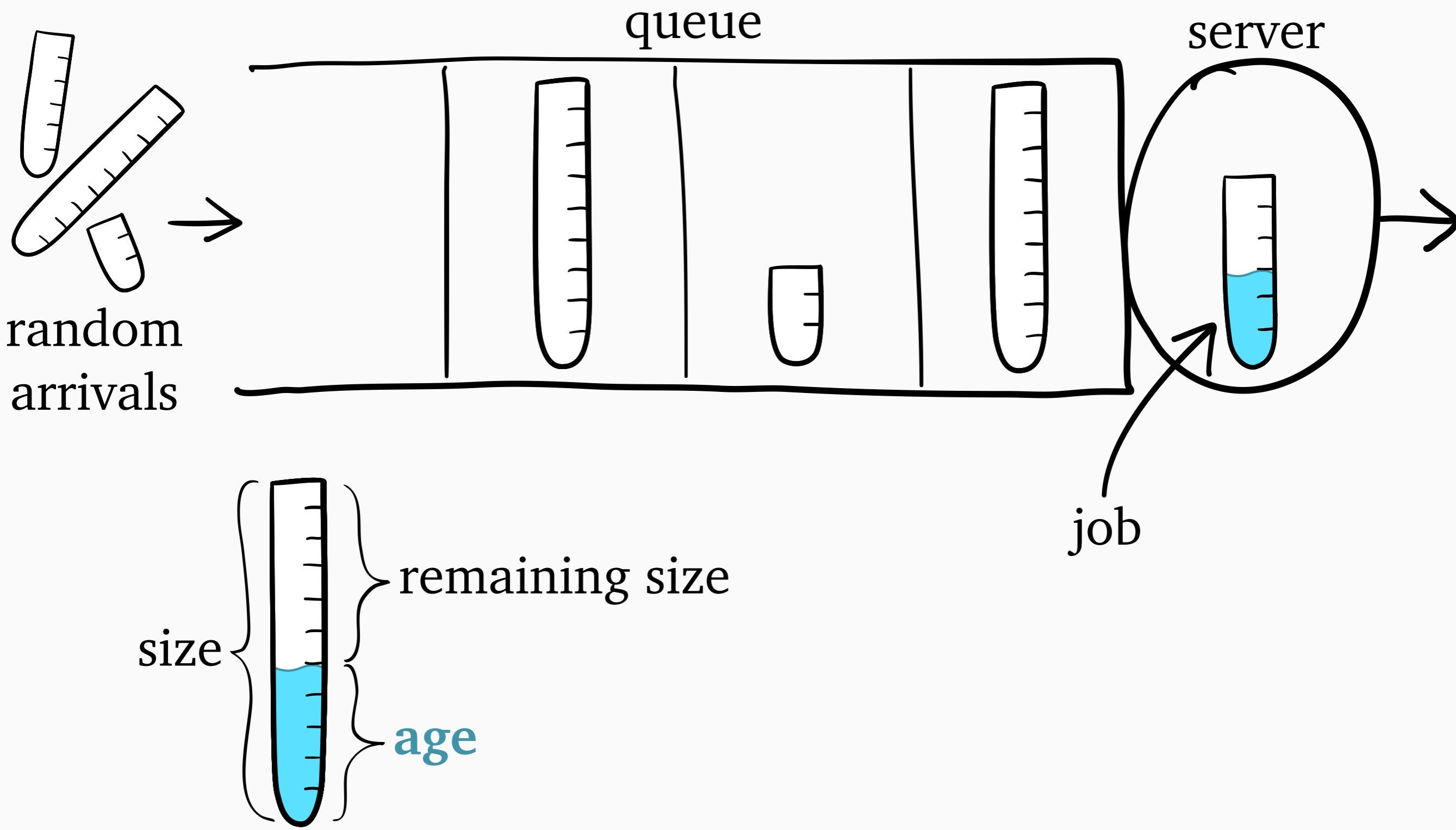
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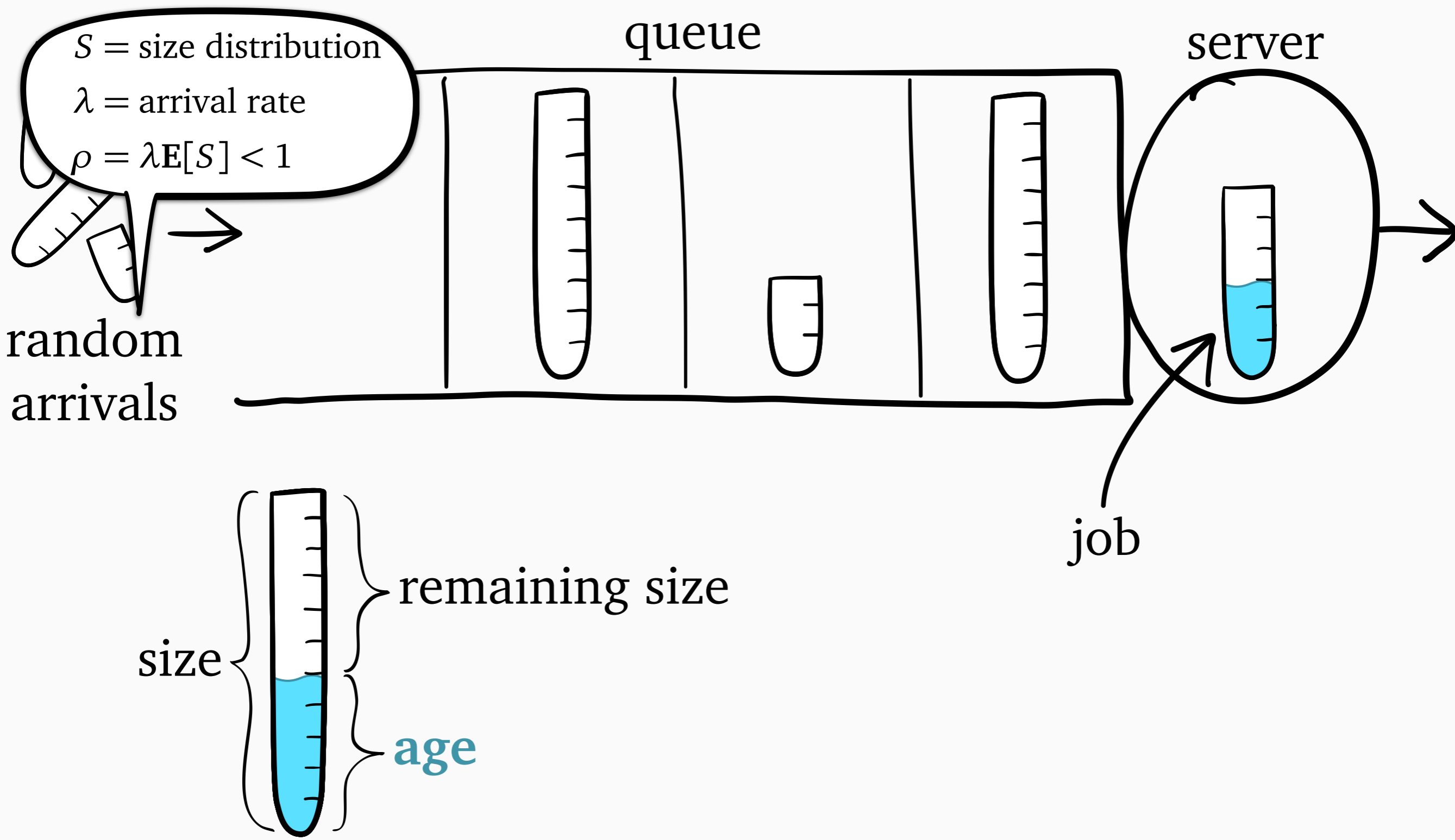
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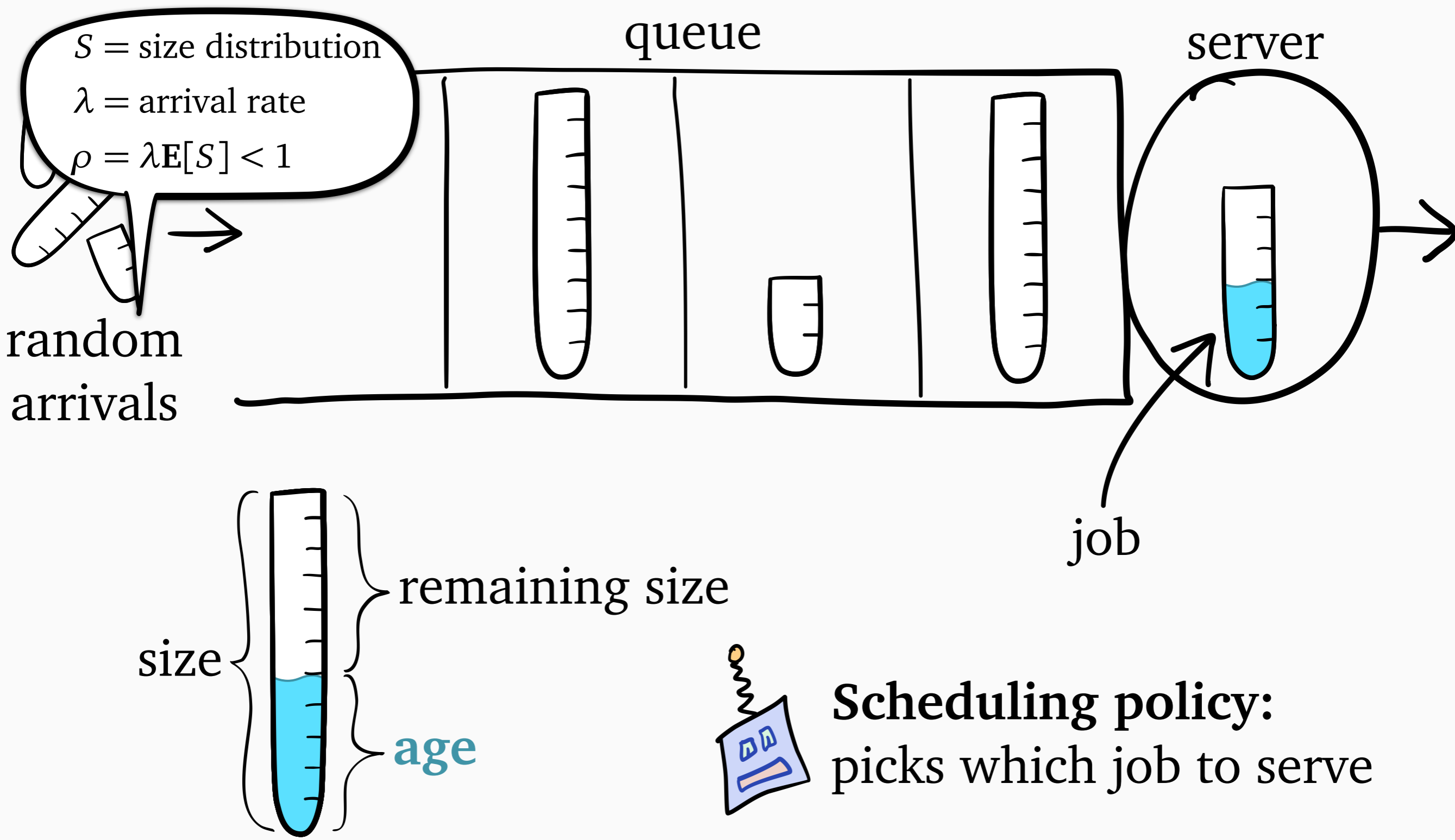
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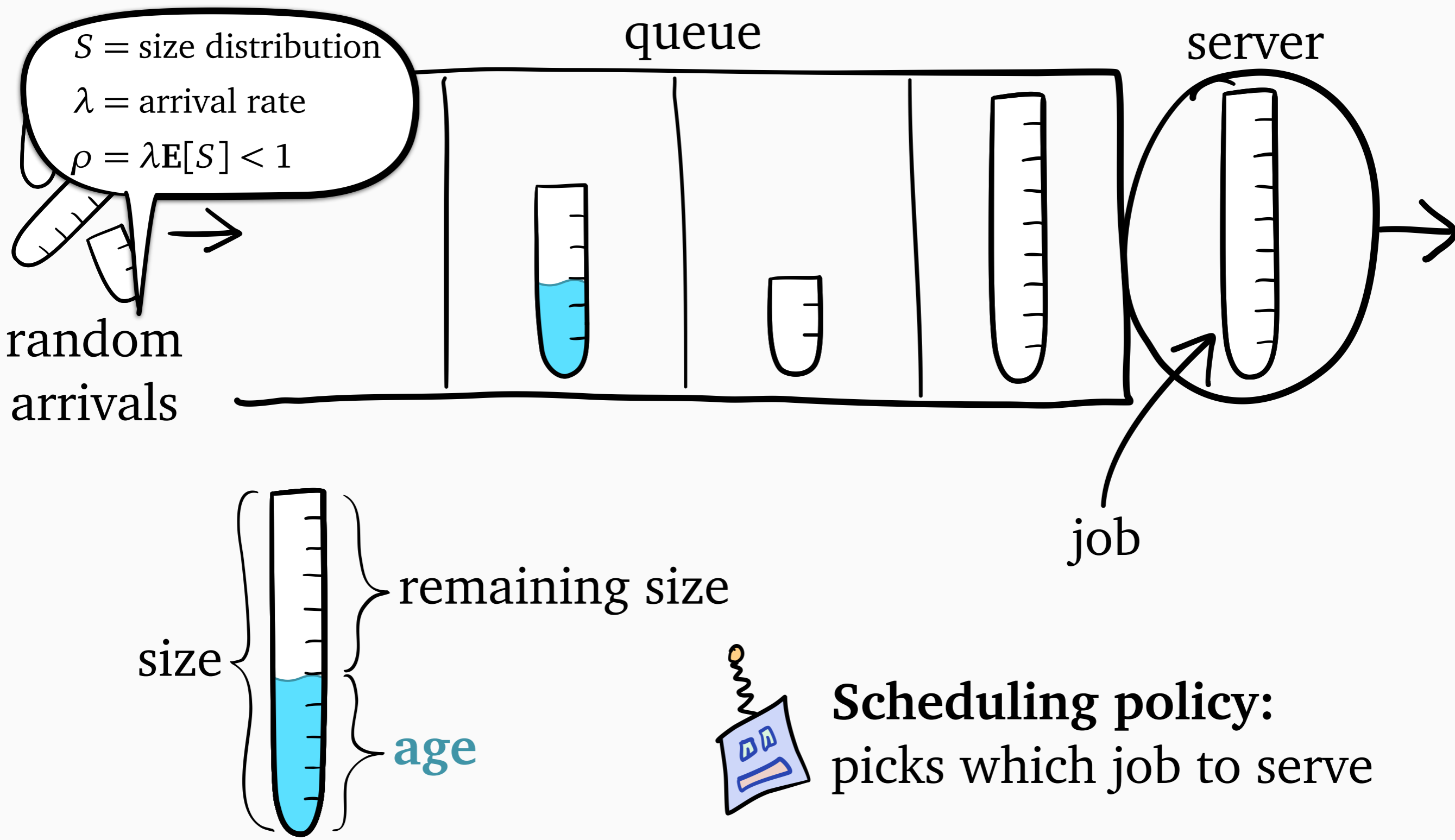
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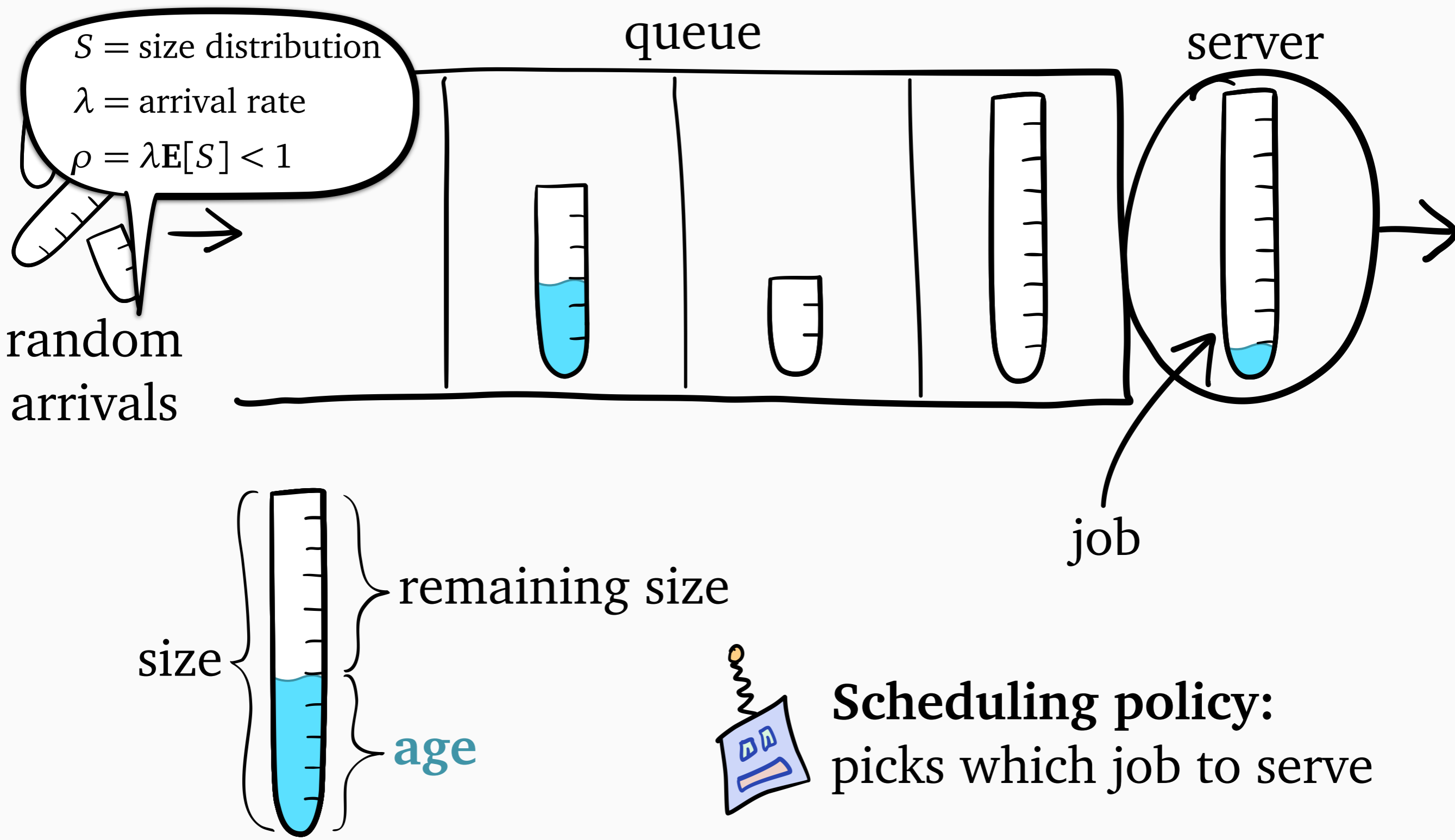
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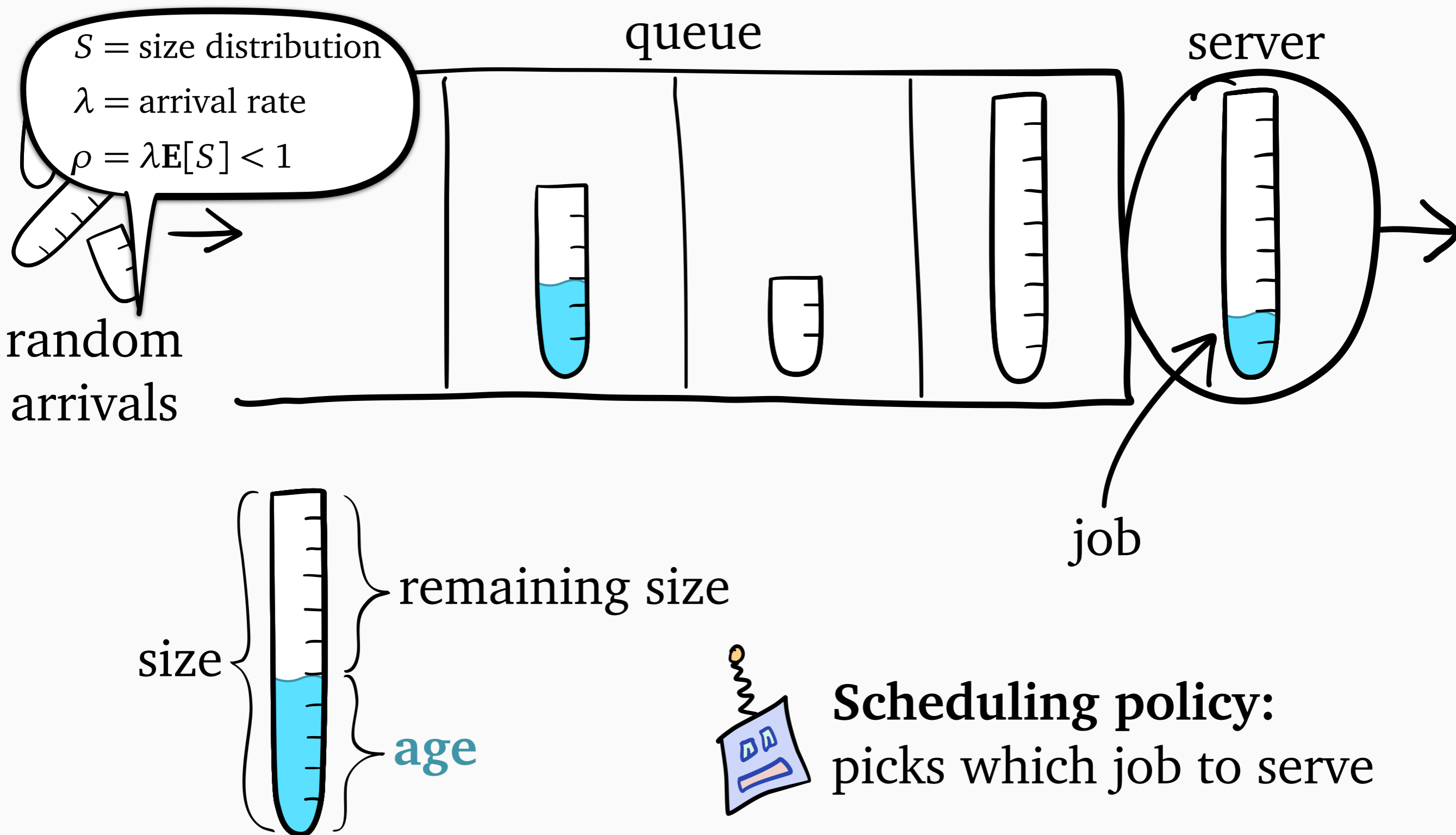
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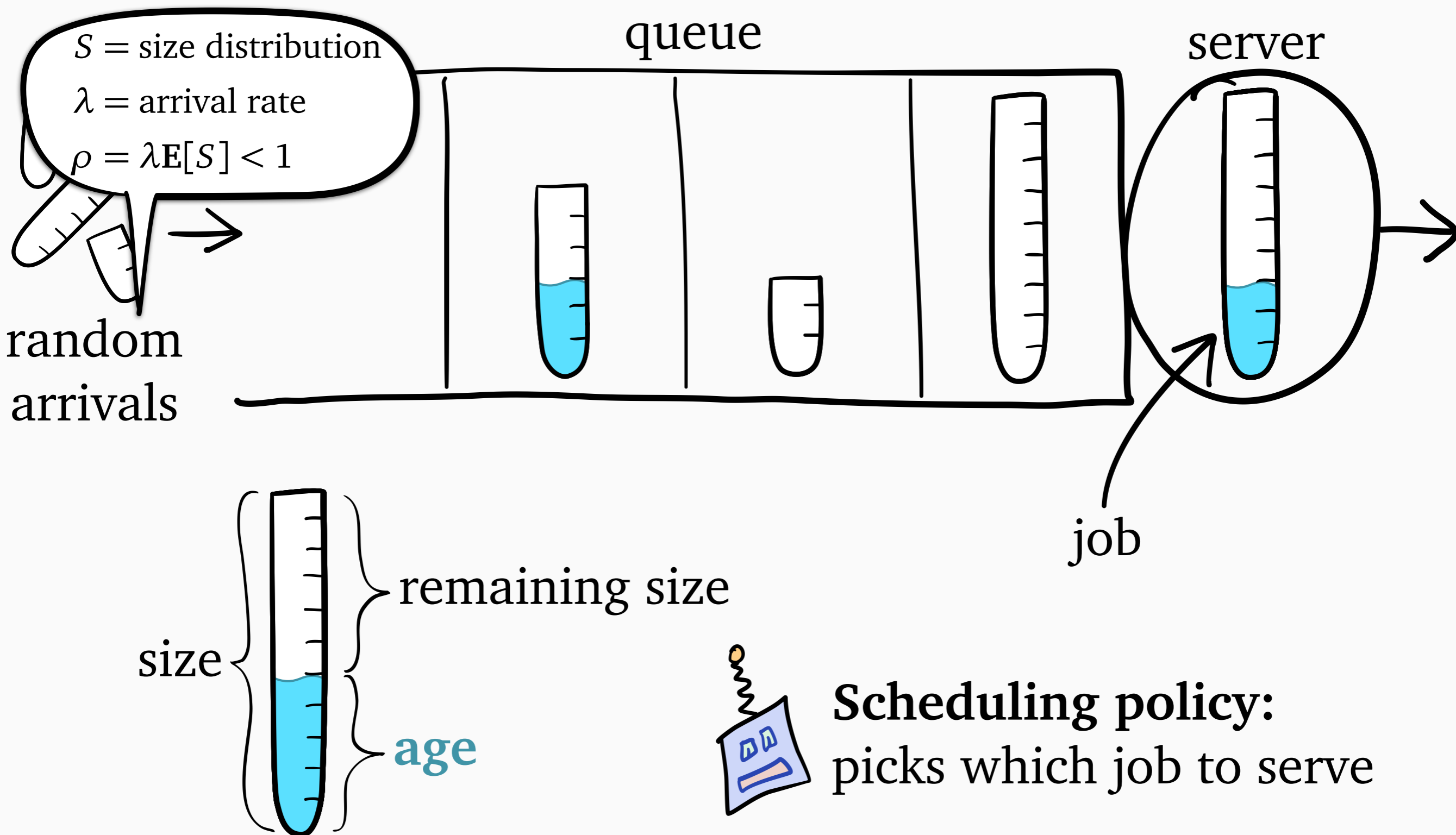
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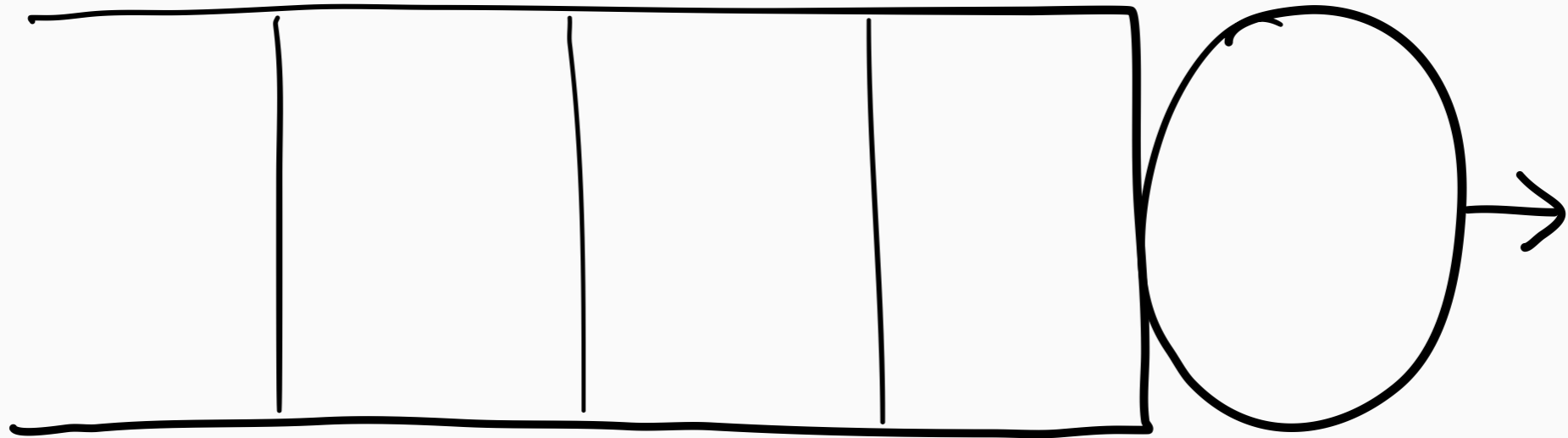
M/G/1 Queue



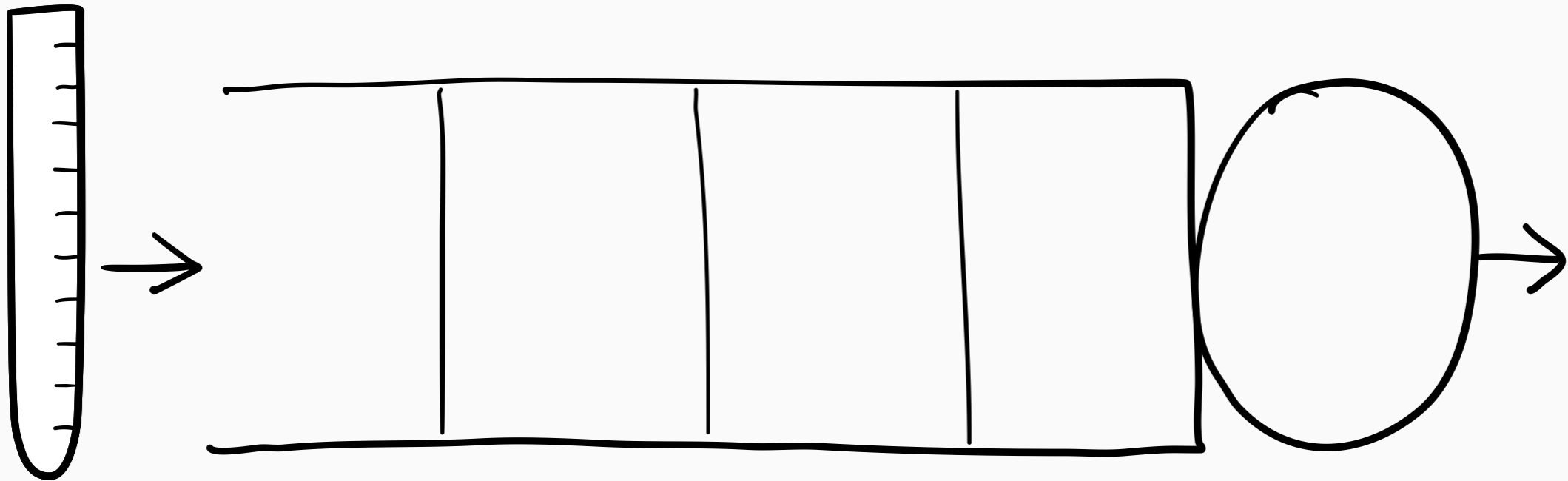
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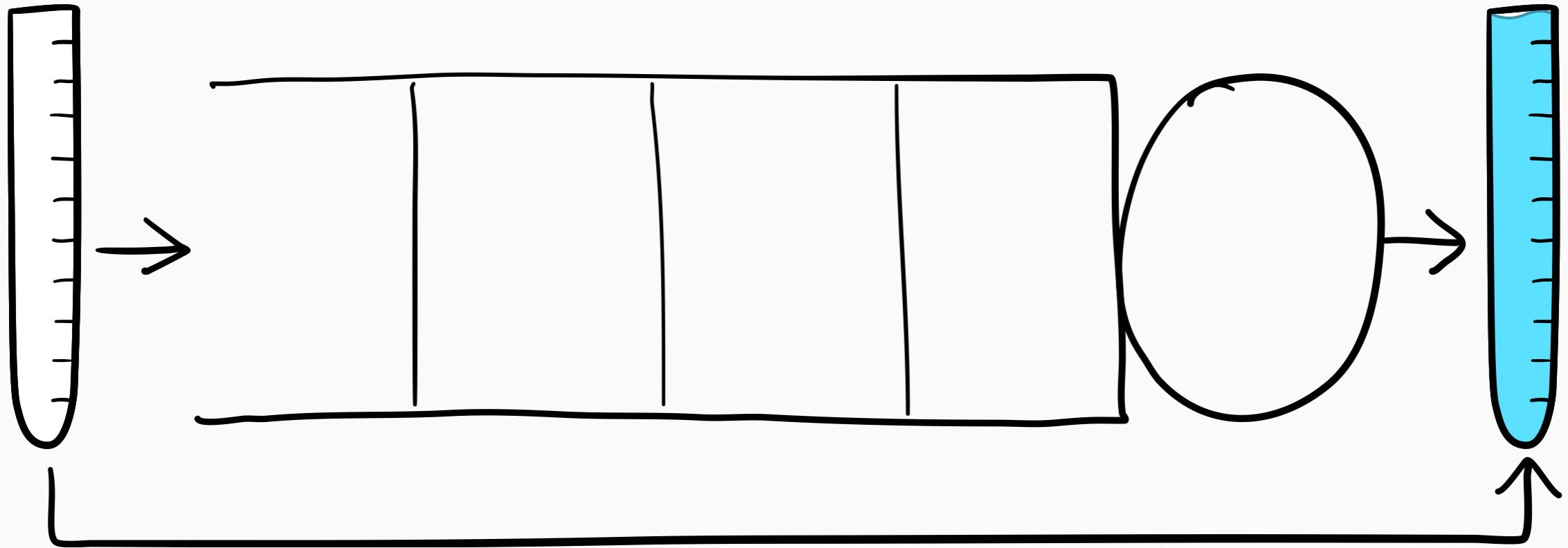
Response Time




Response Time

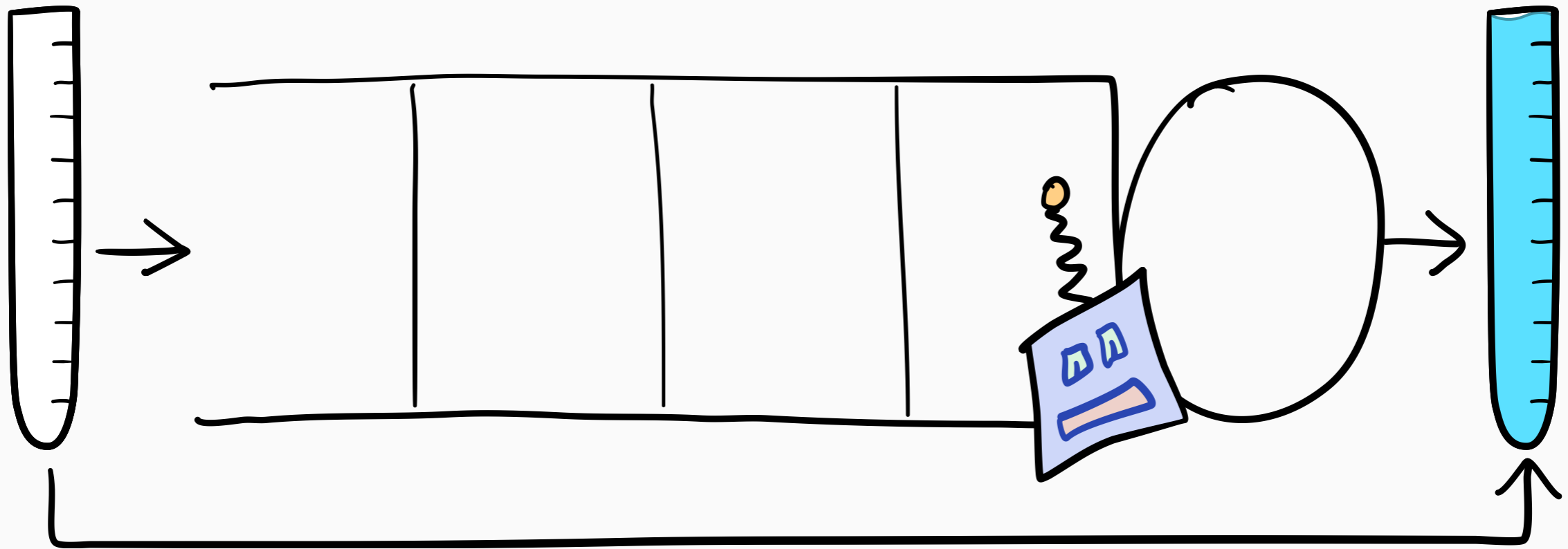



Response Time



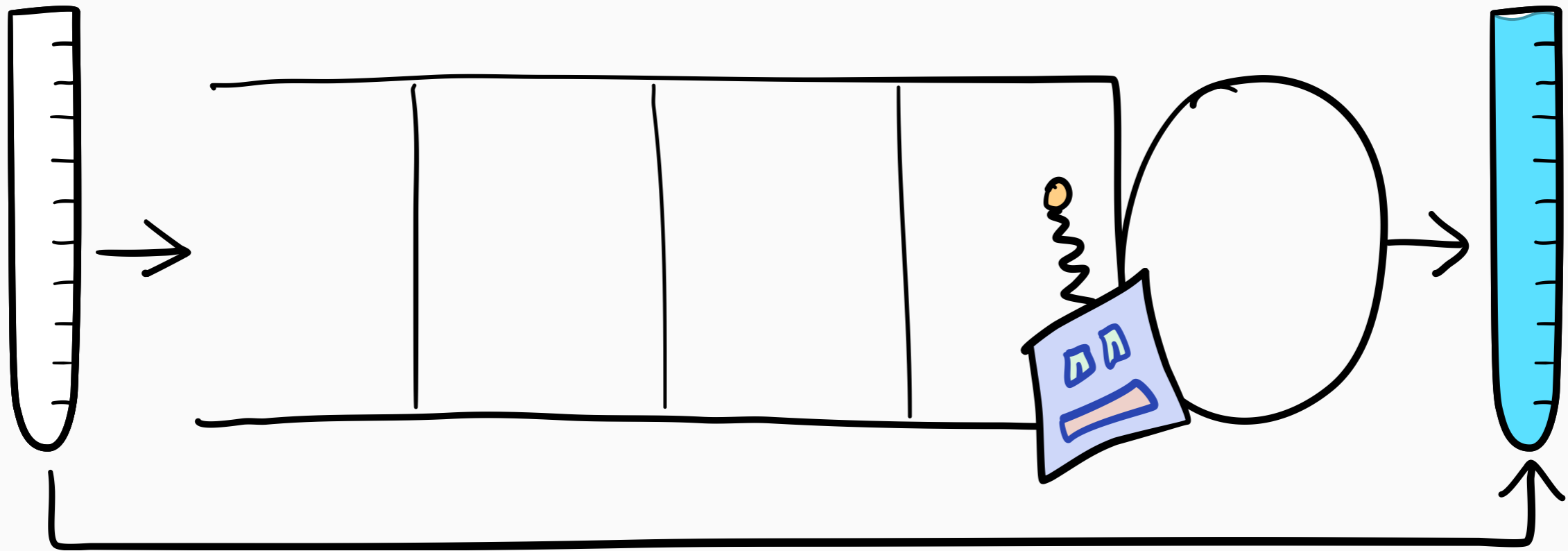
 = T = *response time*


Response Time



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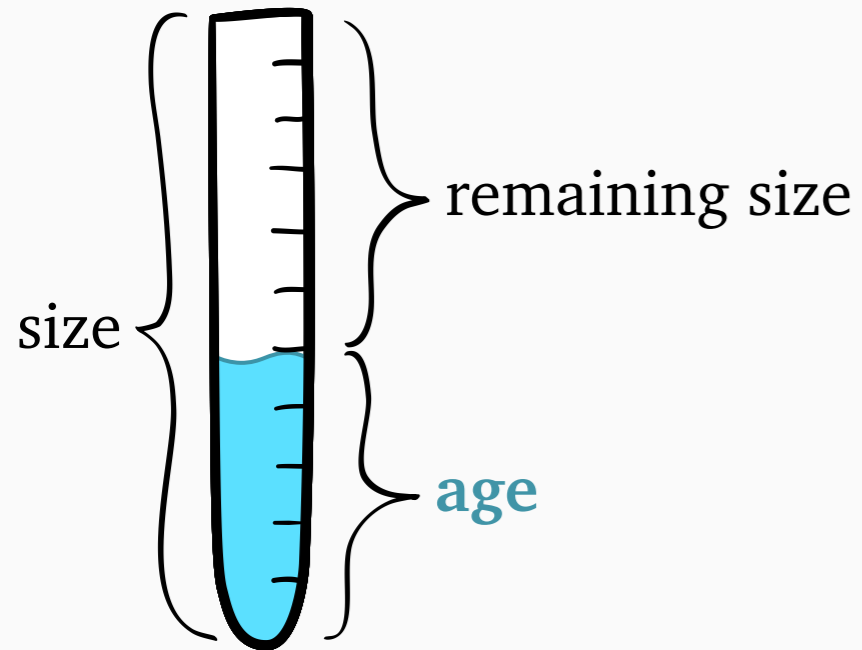
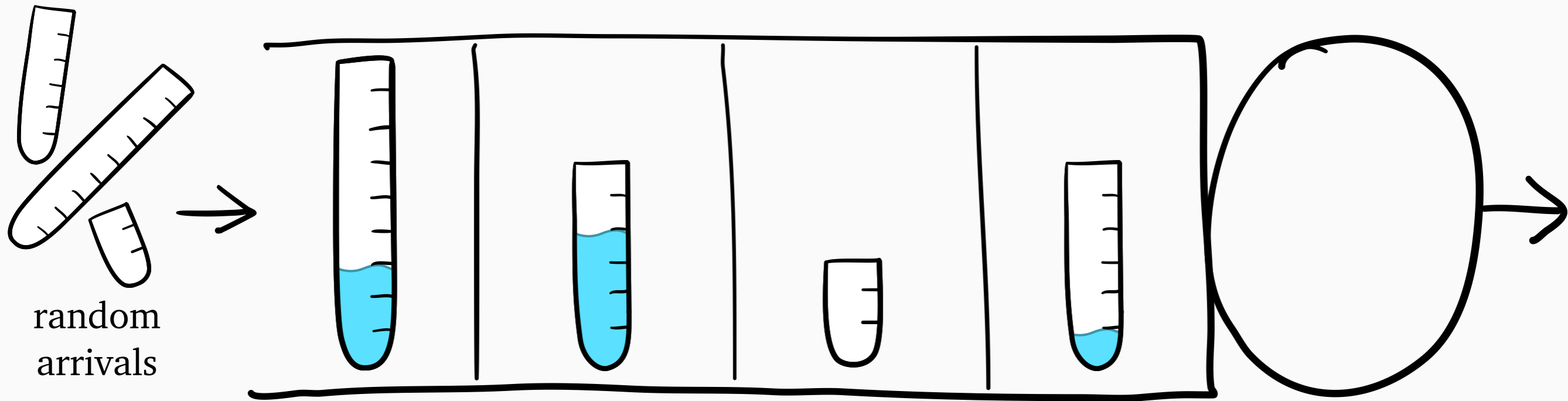
Response Time



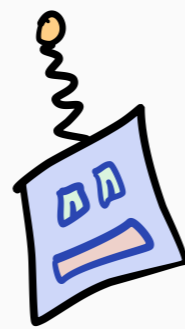
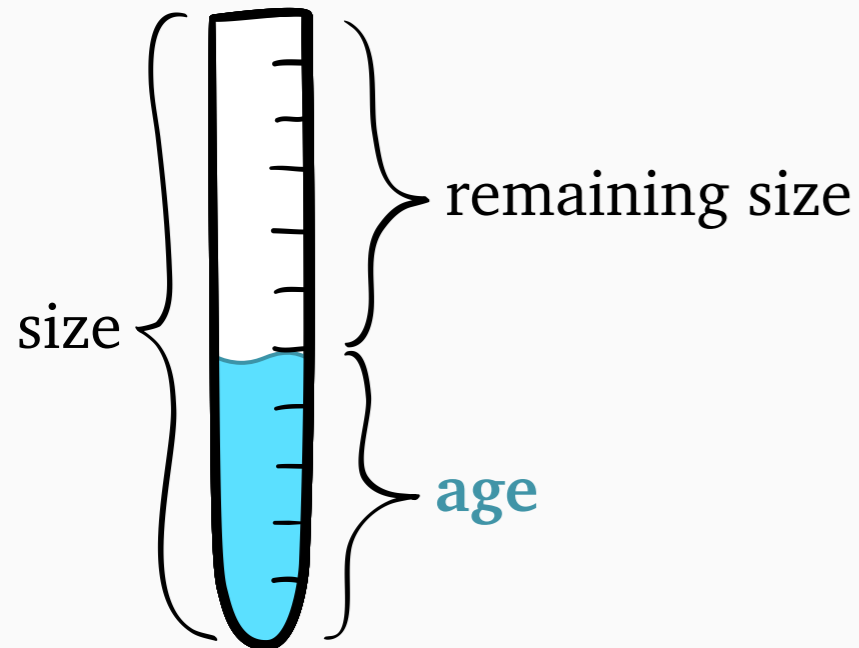
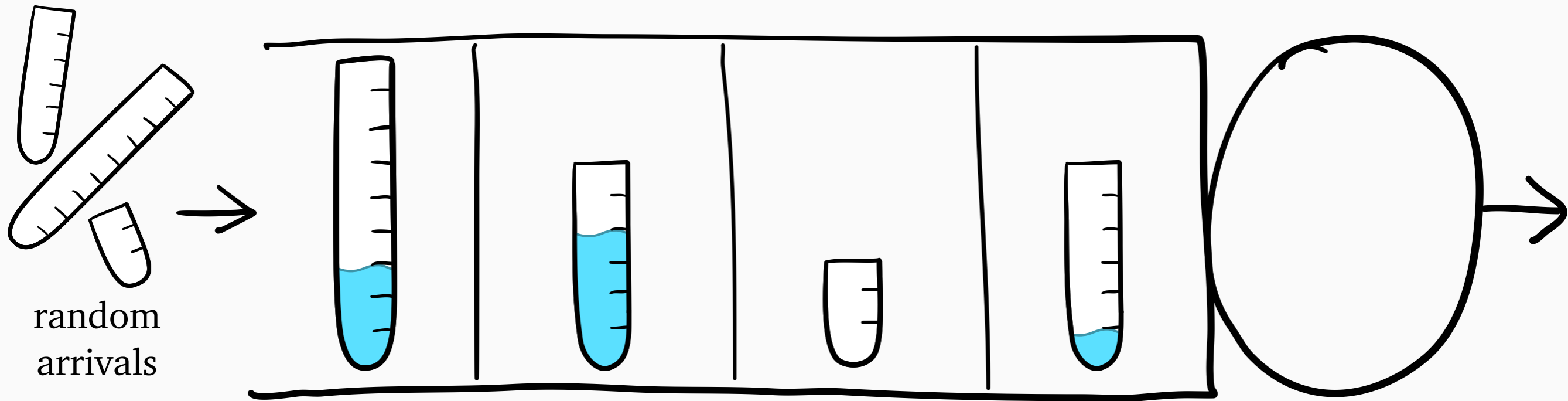
 = T = *response time*

Goal: schedule to minimize
mean response time $E[T]$

How to Schedule?

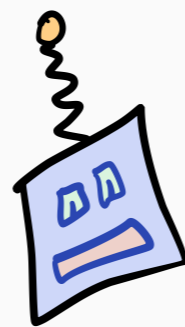
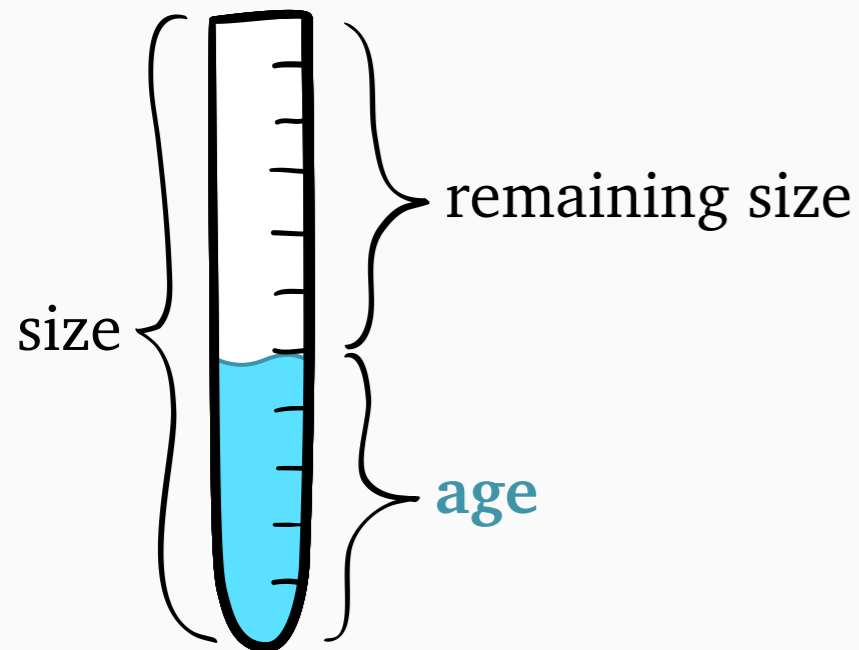
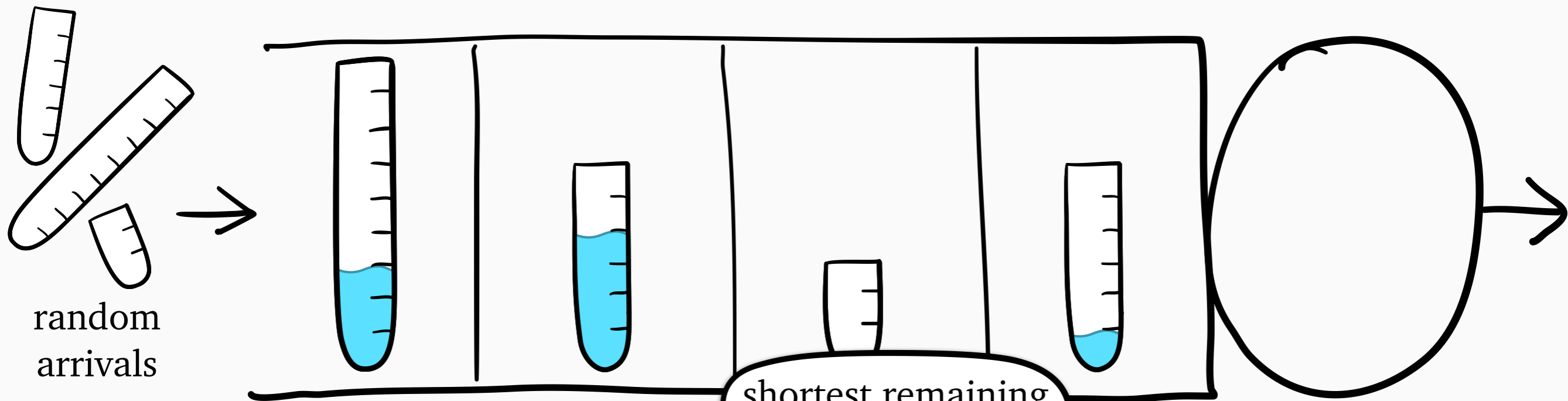


How to Schedule?



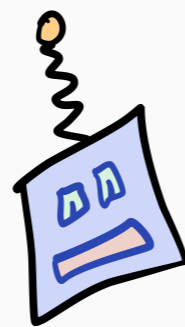
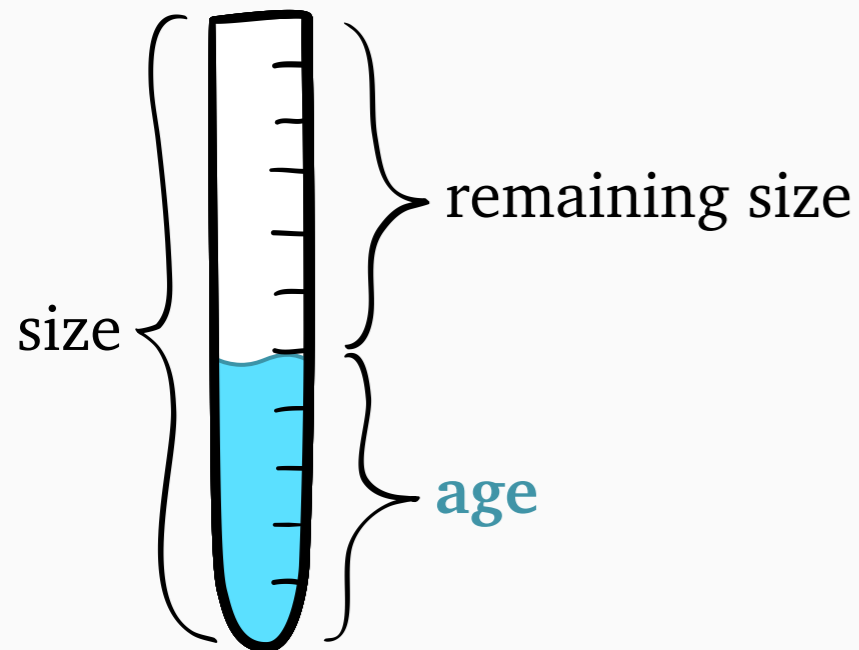
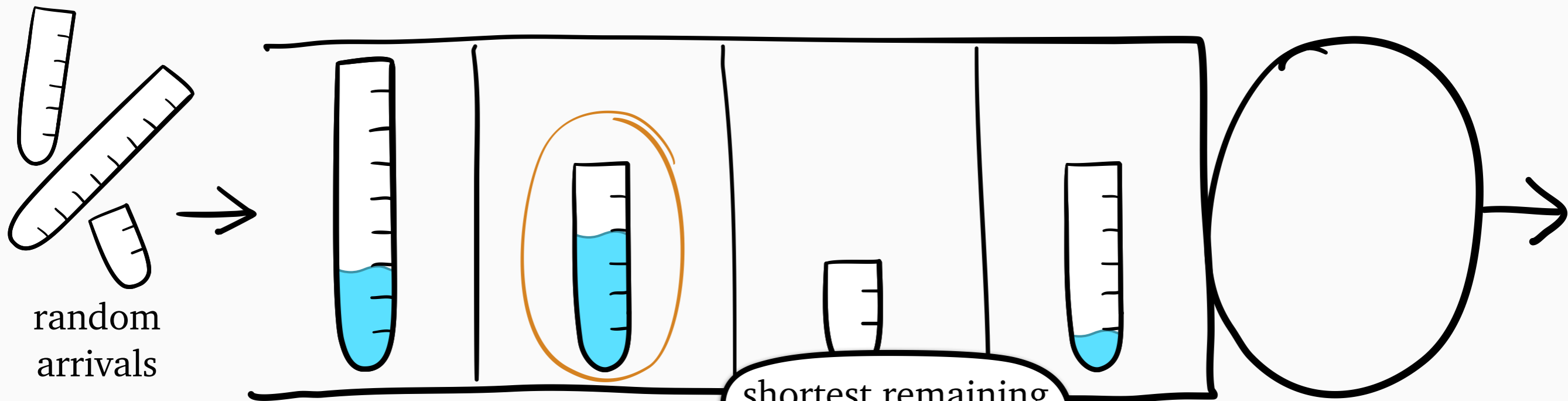
SRPT: always serve job of *least remaining size*

How to Schedule?



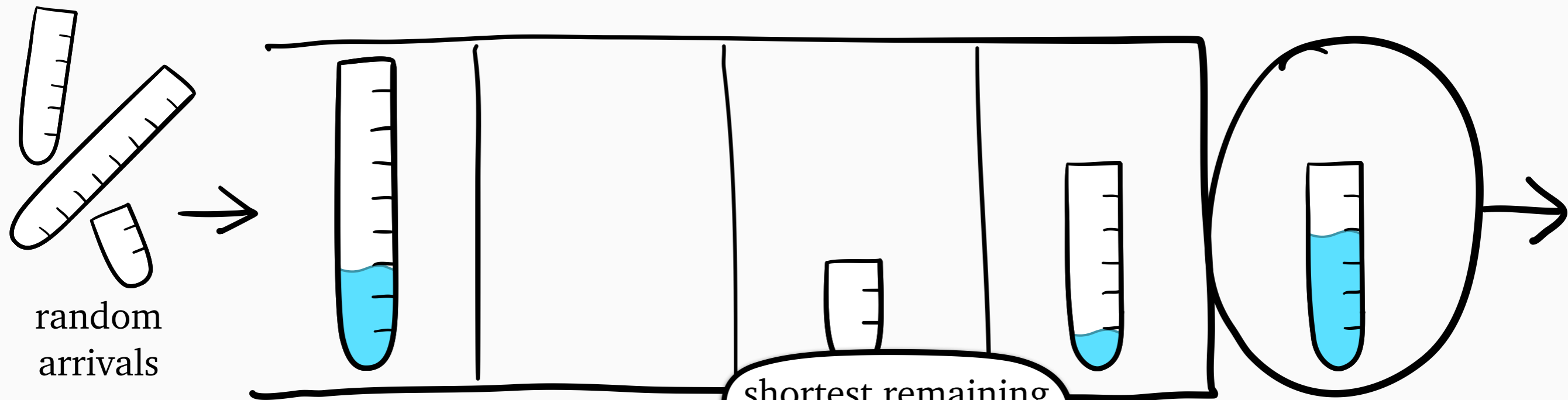
SRPT: always serve job of *least remaining size*

How to Schedule?



SRPT: always serve job of *least remaining size*

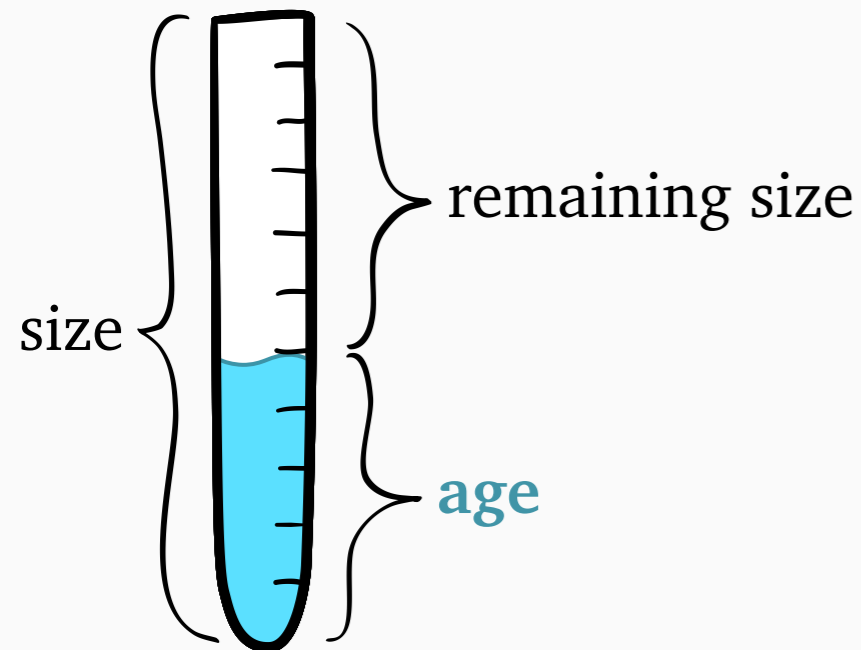
How to Schedule?



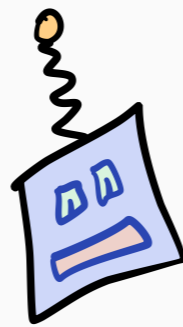
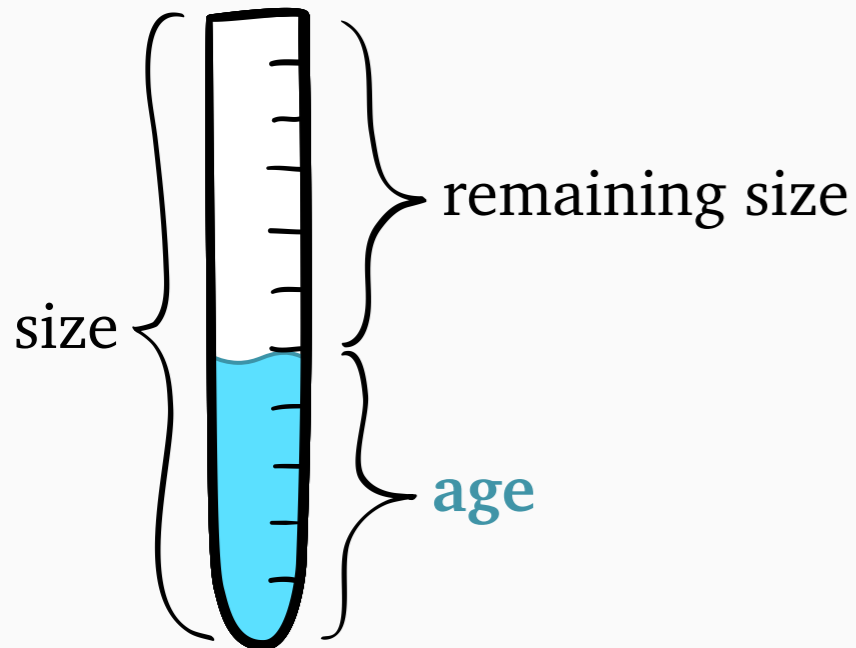
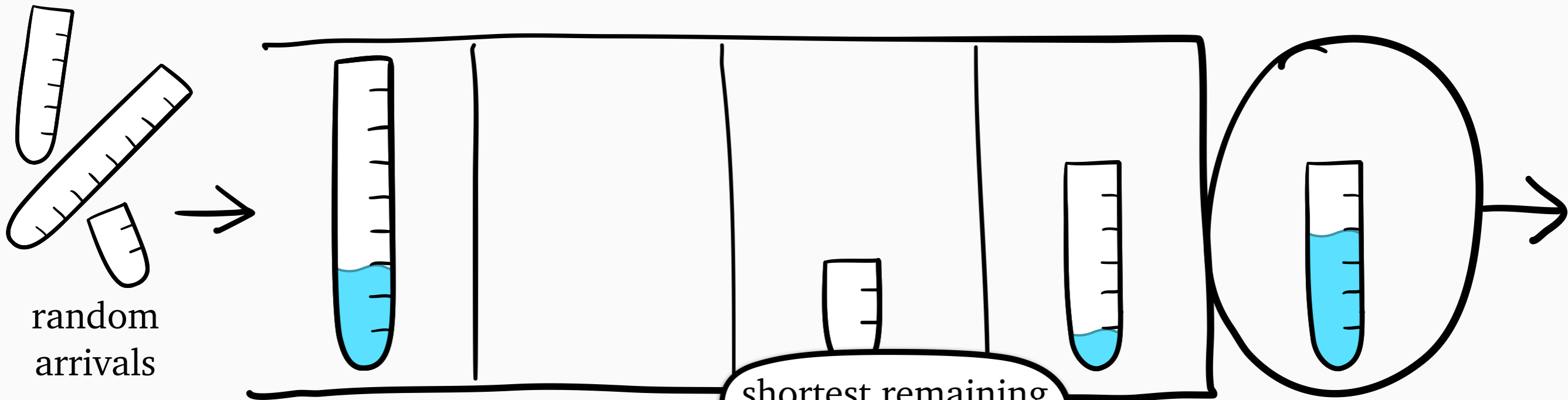
random arrivals

shortest remaining processing time

SRPT: always serve job of *least remaining size*



How to Schedule?

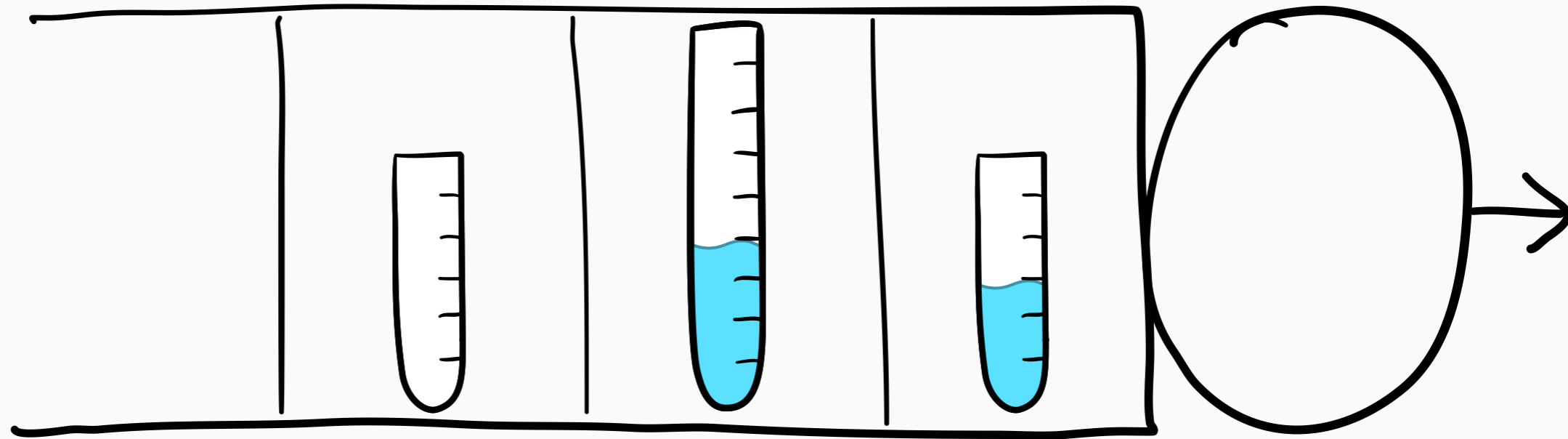


SRPT: always serve job of *least remaining size*

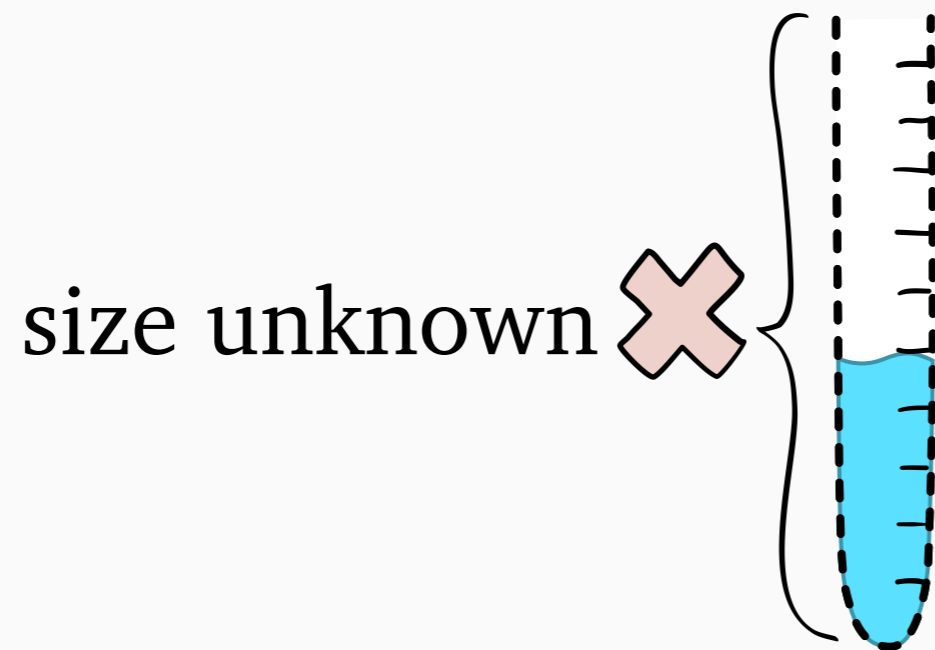
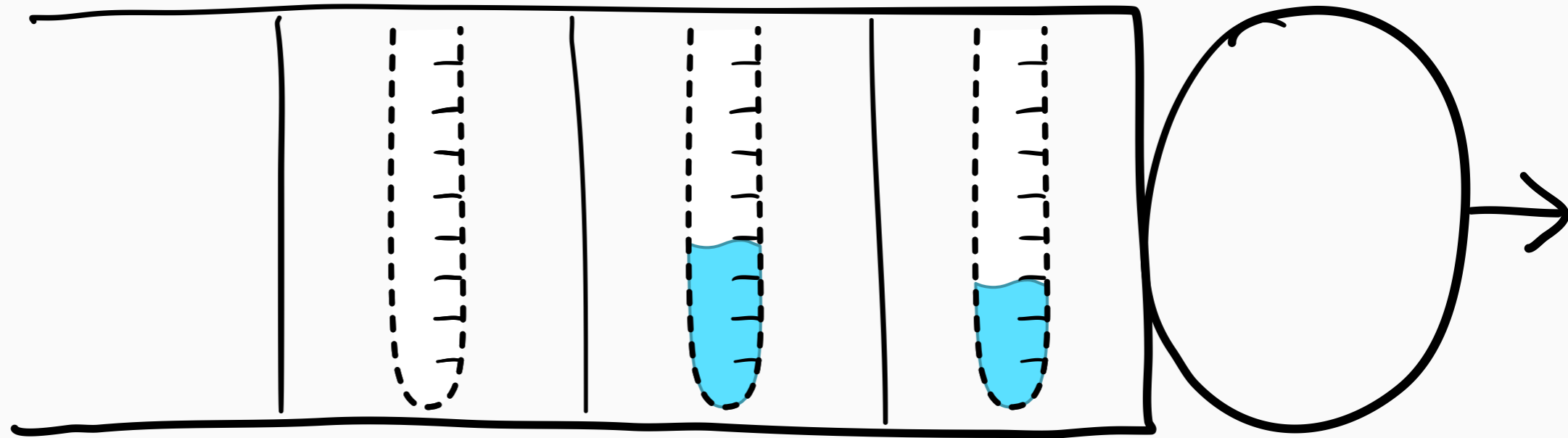


SRPT minimizes $E[T]$
(Schrage 1968)

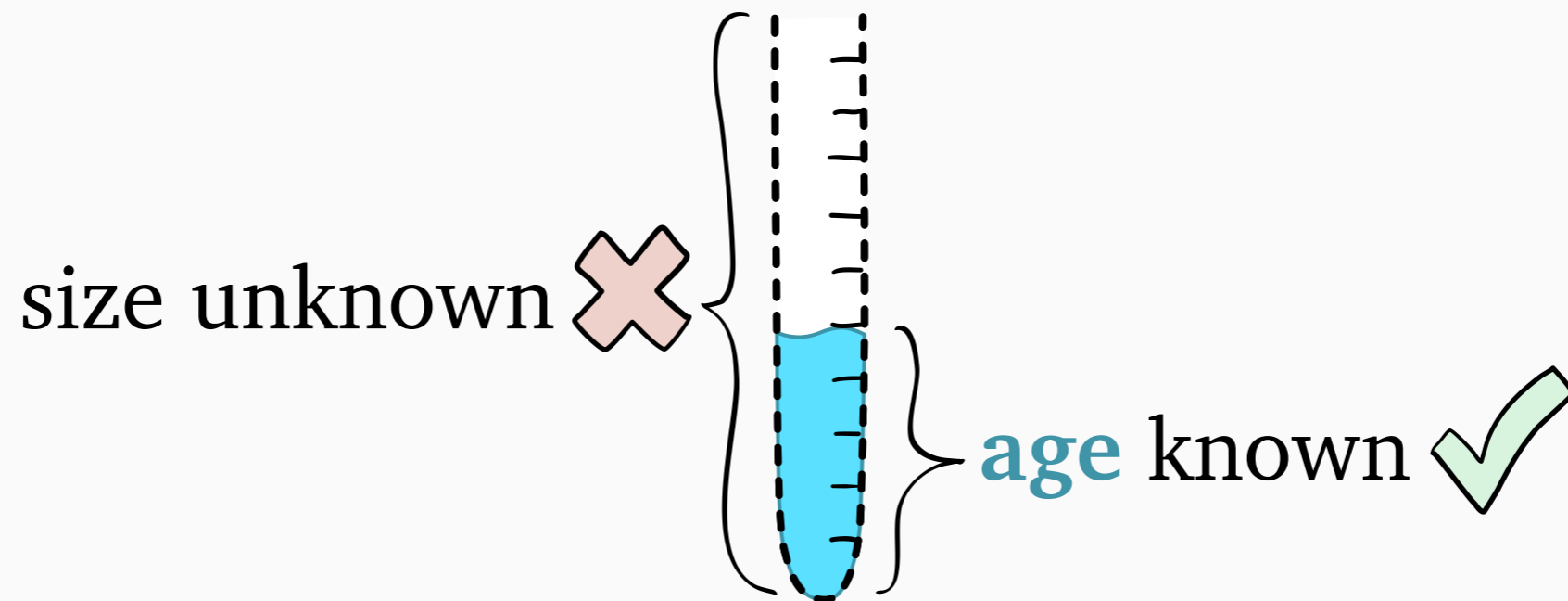
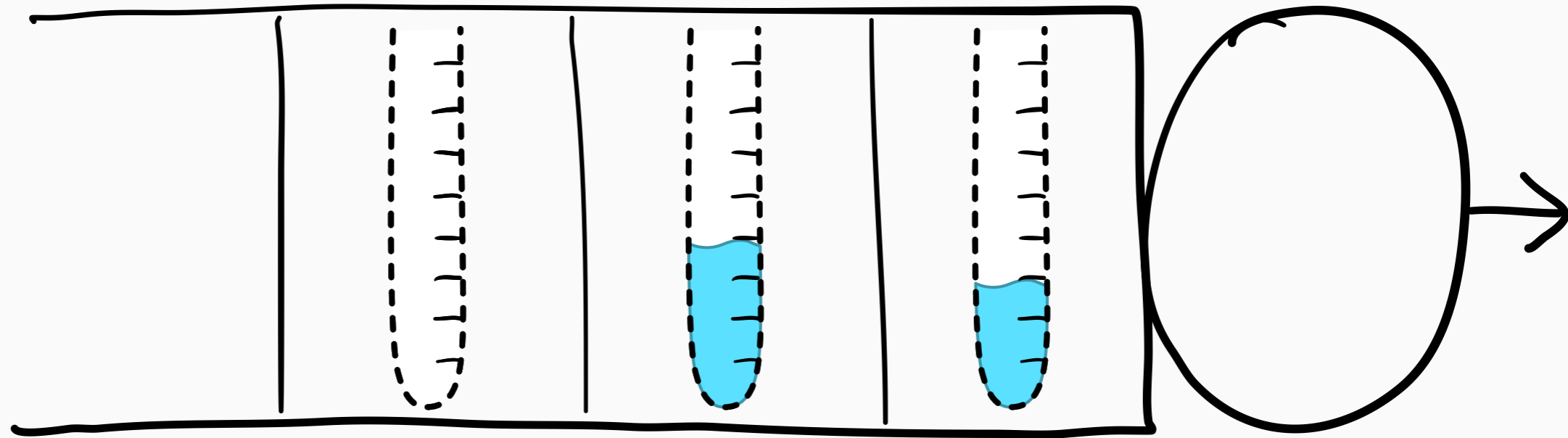
Unknown Job Sizes



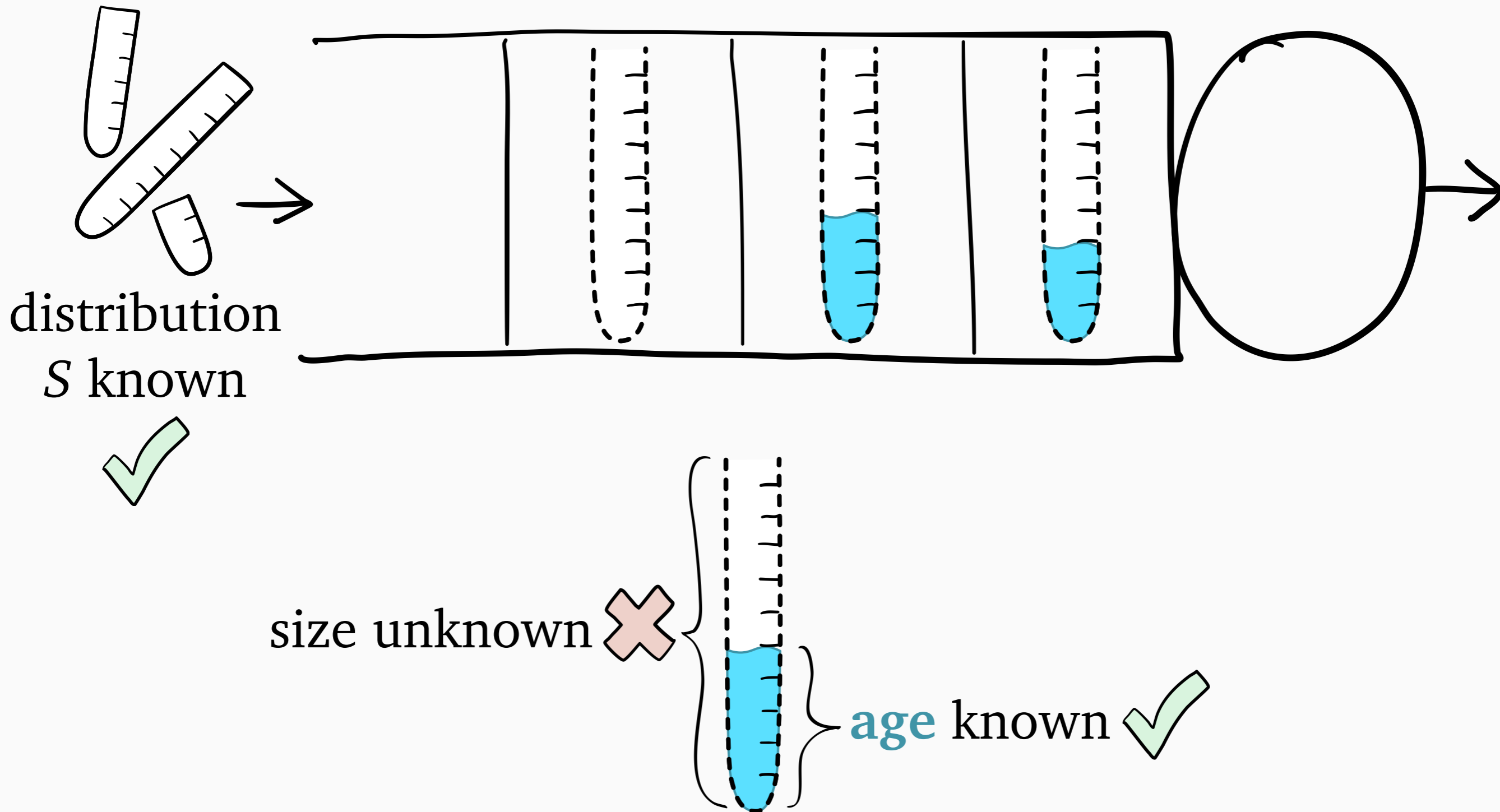
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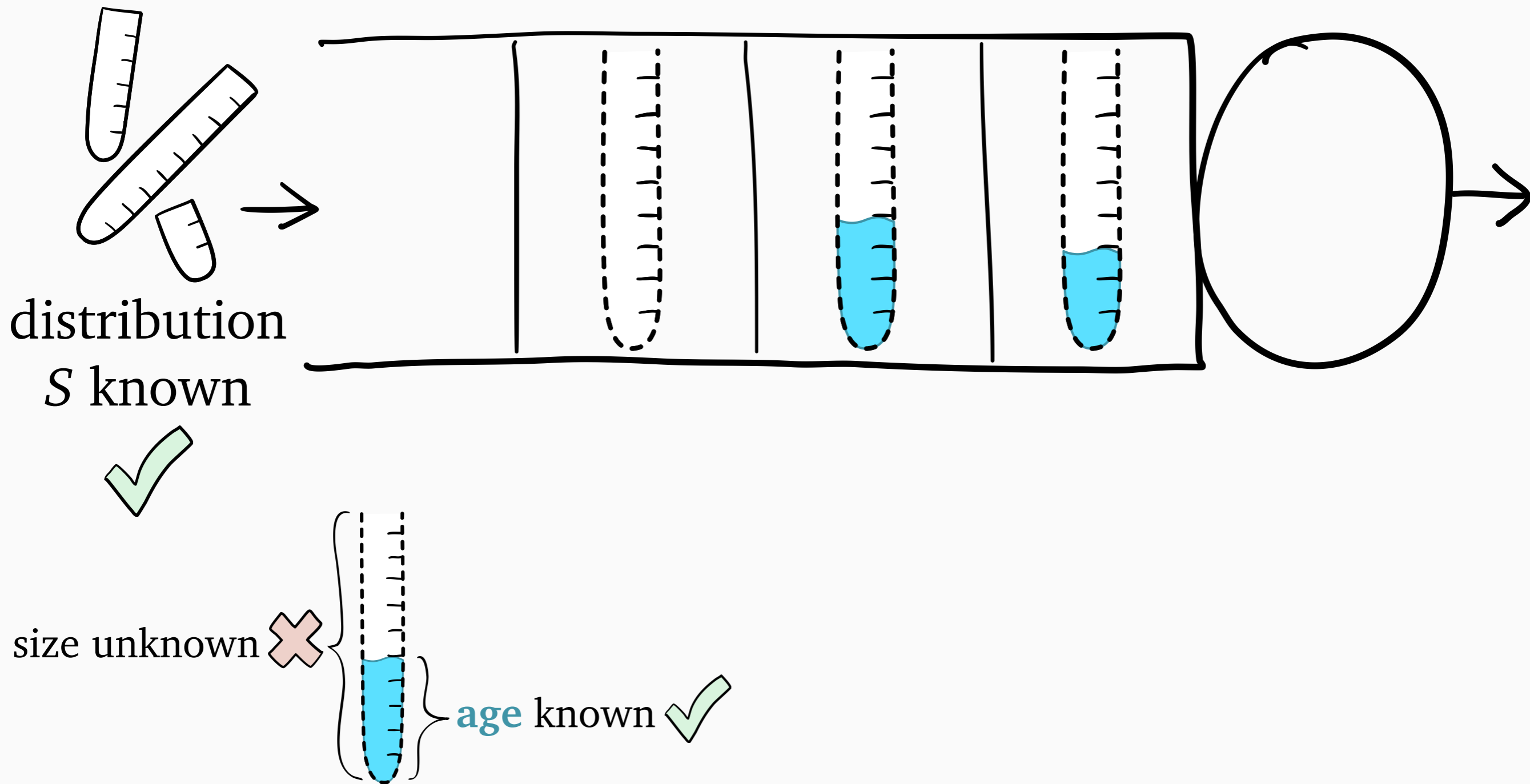
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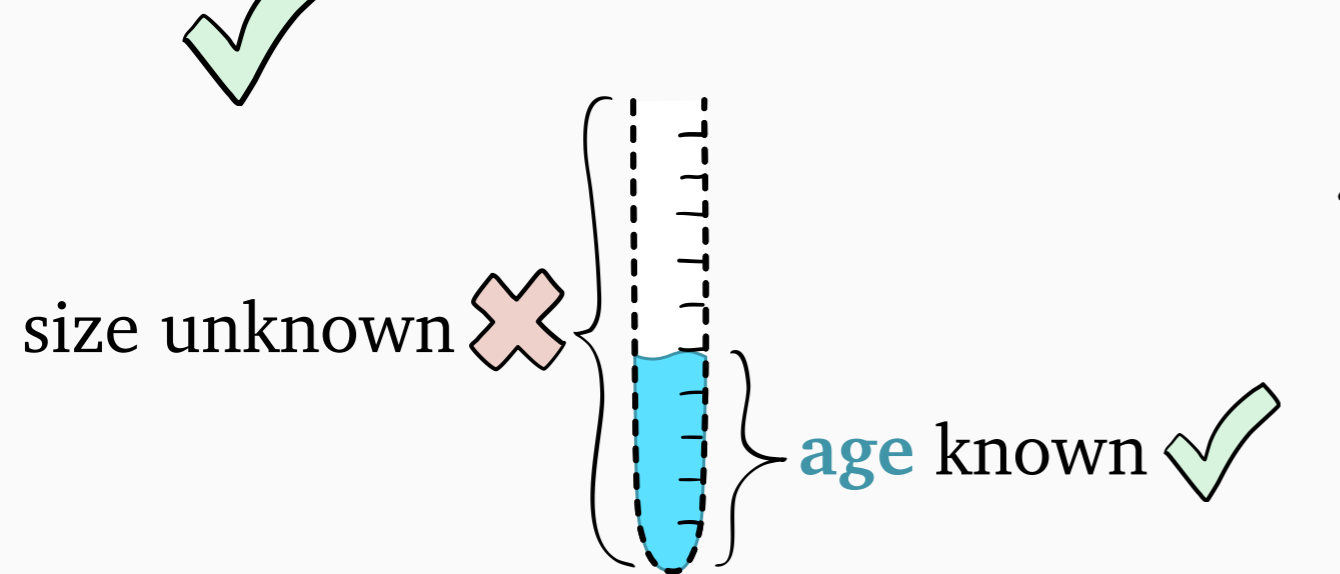
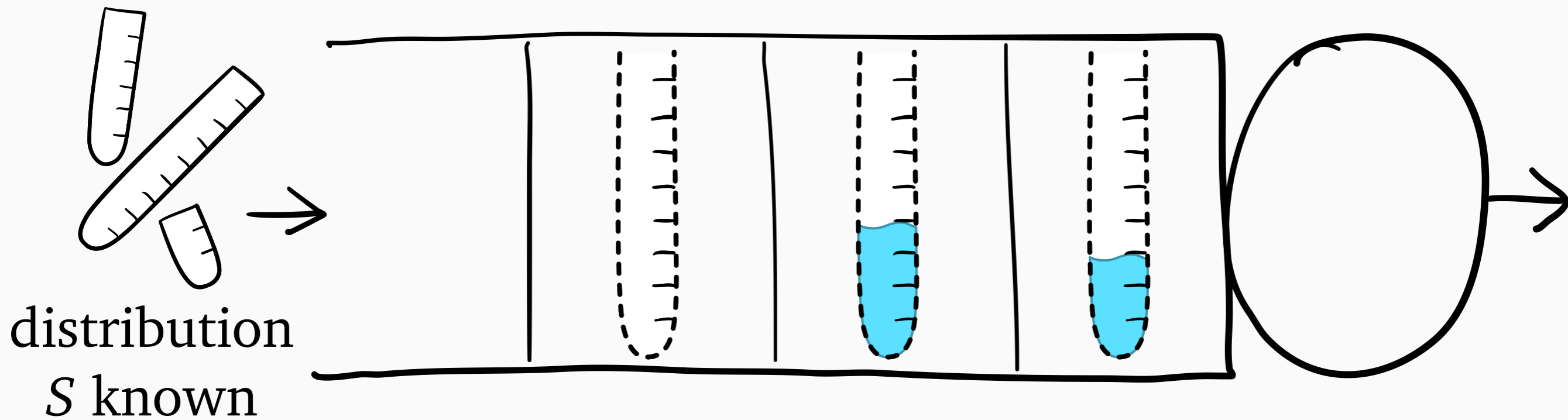
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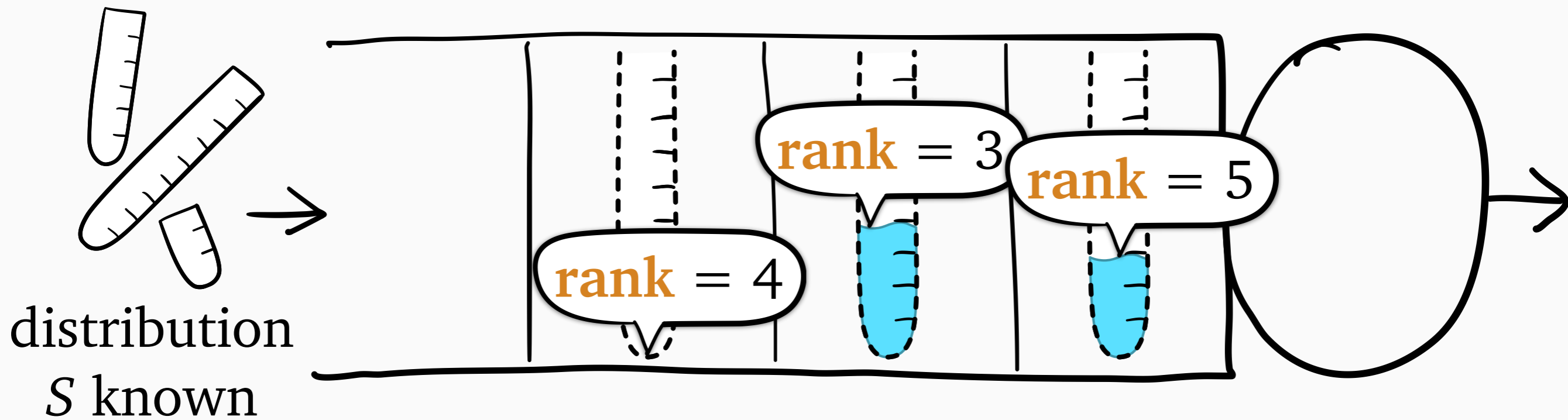


Unknown Job Sizes

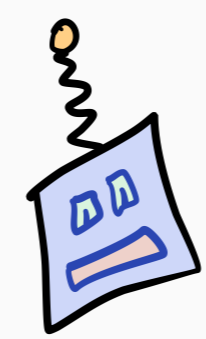
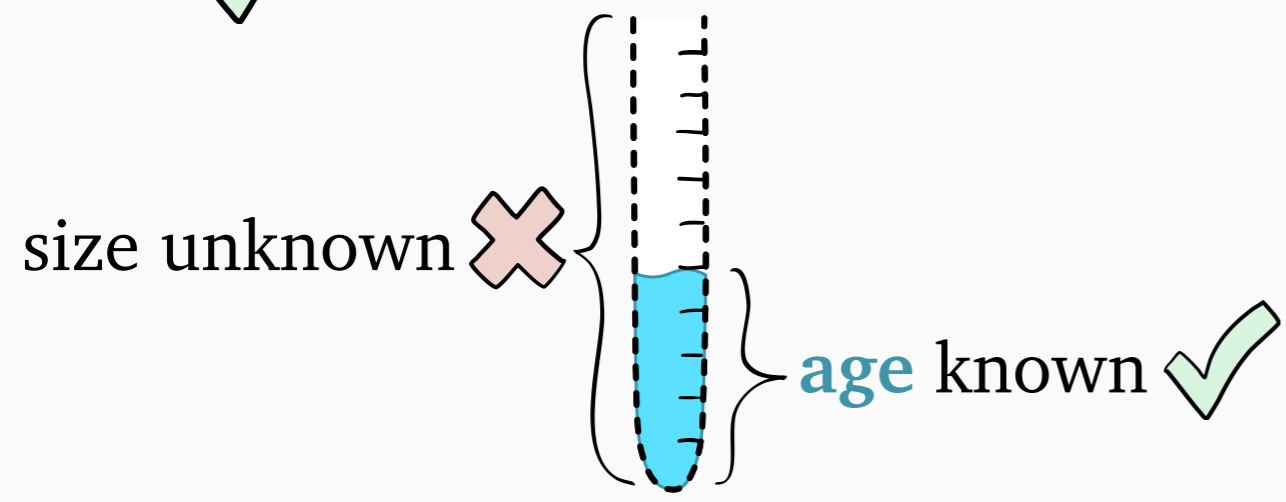


Gittins: assign each job a **rank** based on **age** and S (lower is better)

Unknown Job Sizes

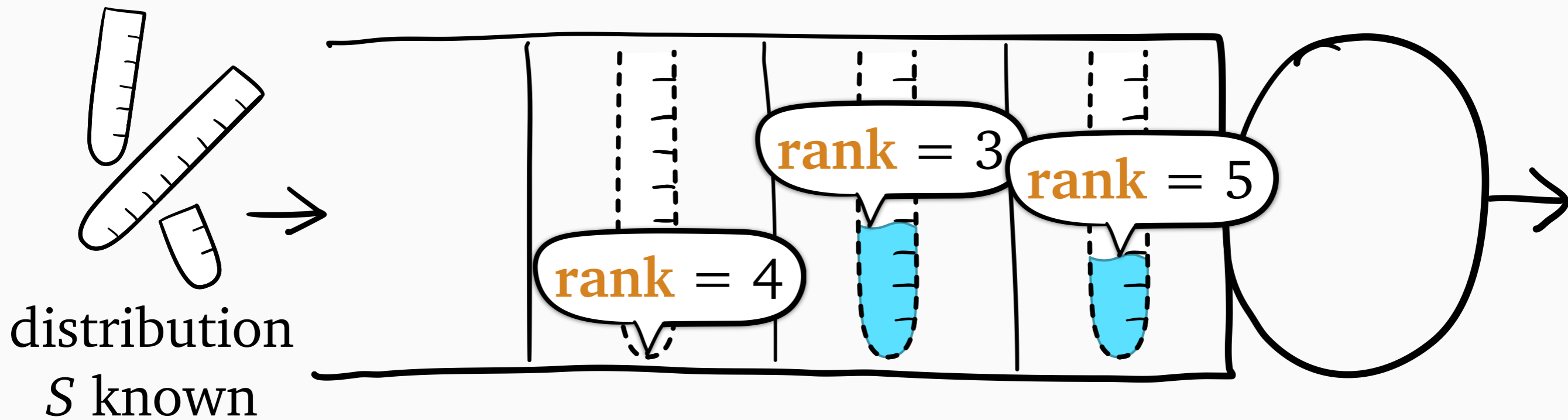


distribution
 S known
✓



Gittins: assign each job a **rank** based on **age** and S
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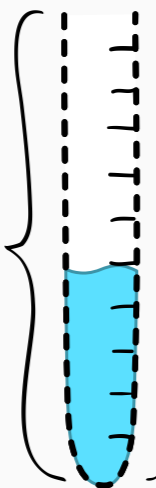
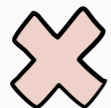
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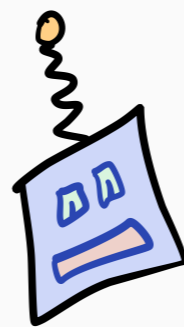
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size unknown



age known

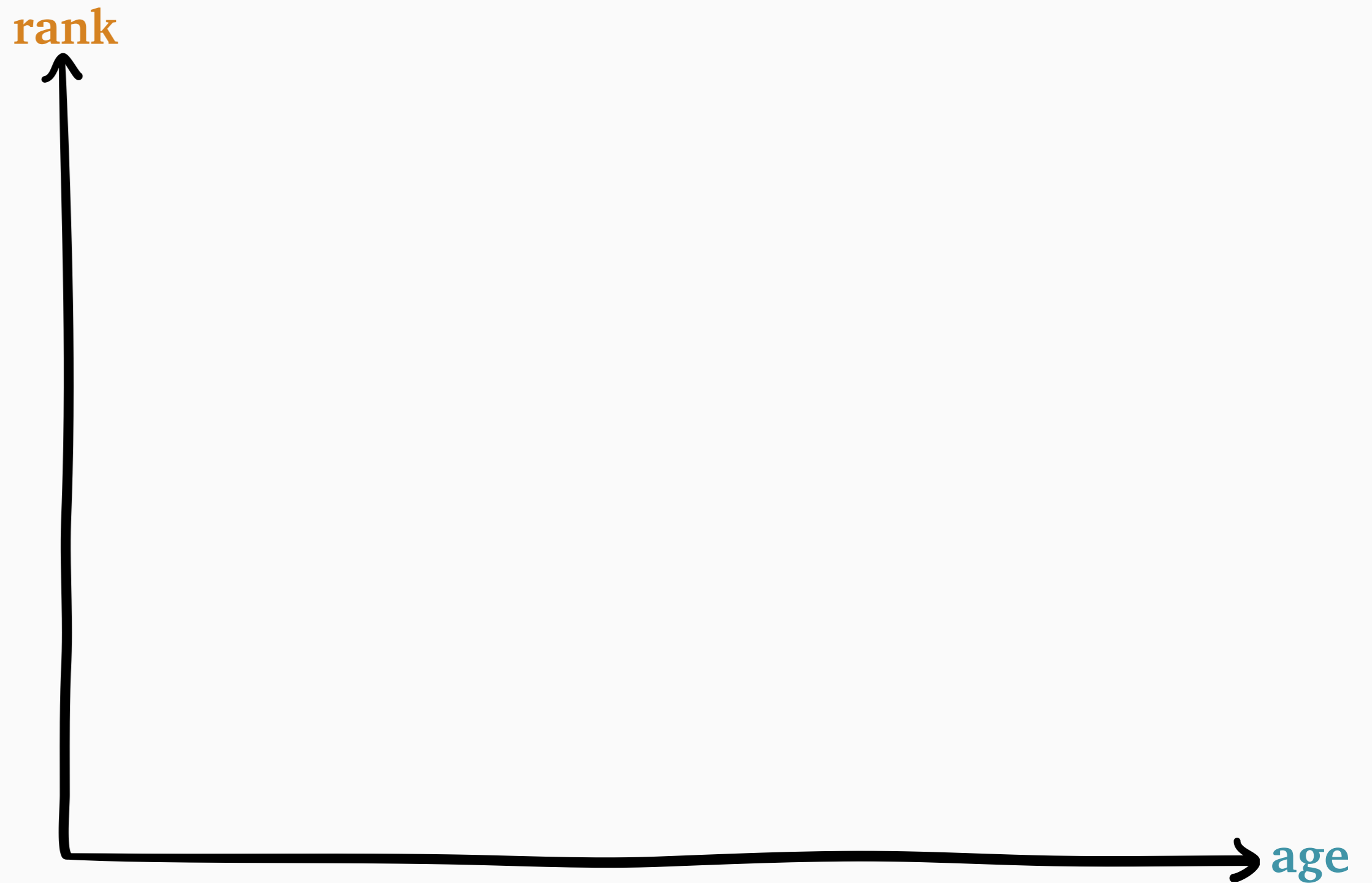


Gittins: assign each job a **rank** based on **age** and S (lower is better)



Gittins minimizes $E[T]$ (Gittins 1989)

Gittins Policy



Gittins Policy

a.k.a. priority

rank



age

Gittins Policy

a.k.a. priority

rank

lower is
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age

Gittins Policy

a.k.a. priority

rank

$$\text{rank}(a) = \inf_{b > a} \frac{\mathbb{E}[\min\{S, b\} - a \mid S > a]}{\mathbb{P}[S \leq b \mid S > a]}$$

lower is
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age

Gittins Policy

a.k.a. priority

rank

$$\text{rank}(a) = \inf_{b>a} \frac{\mathbb{E}[\min\{S, b\} - a \mid S > a]}{\mathbb{P}[S \leq b \mid S > a]}$$

Job size distribution:

$$S = \begin{cases} 1 & \text{w.p. } \frac{1}{3} \\ 6 & \text{w.p. } \frac{1}{3} \\ 14 & \text{w.p. } \frac{1}{3} \end{cases}$$

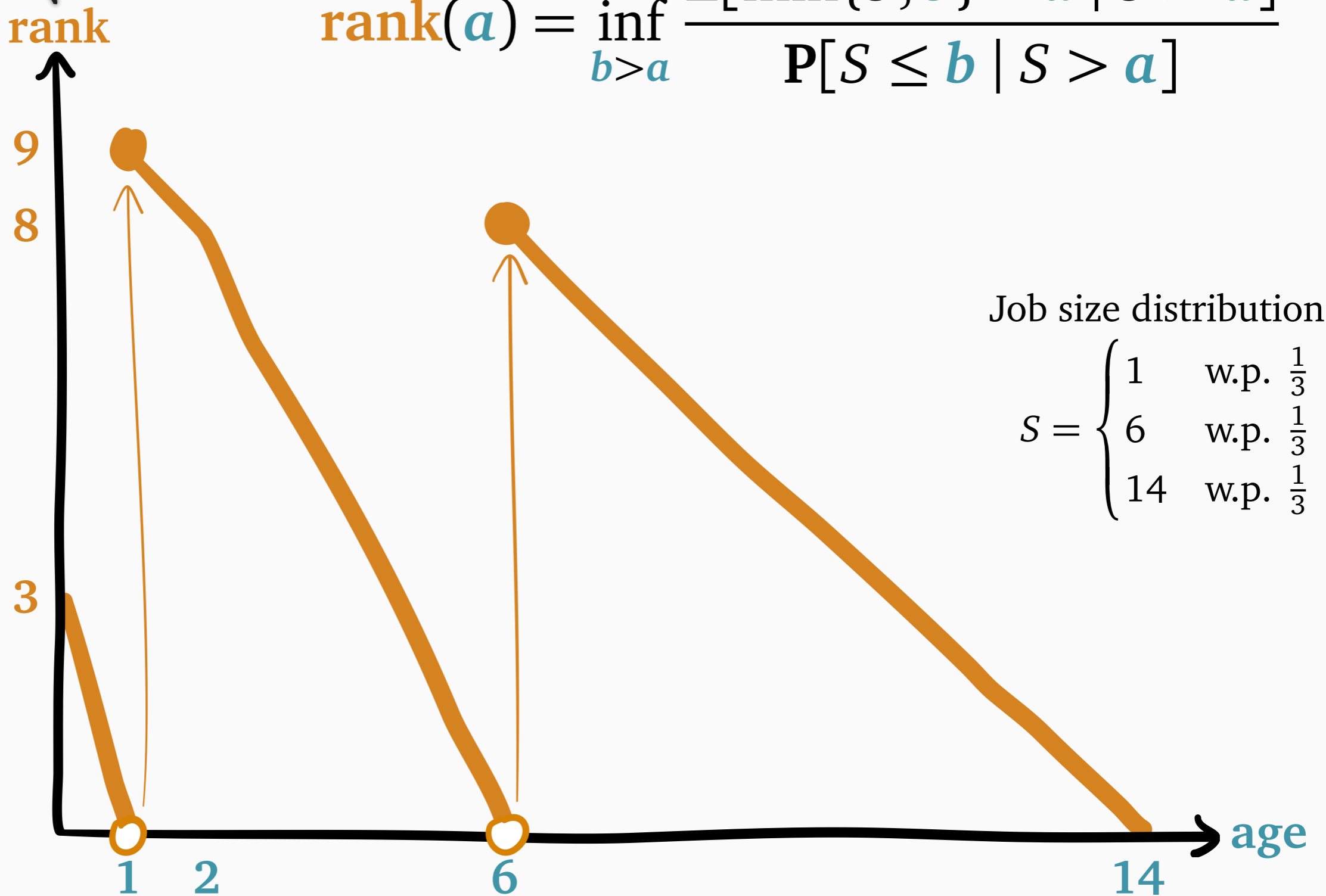
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Optimal Policies

Known Sizes

Unknown Sizes

M/G/1

SRPT

Gittins

Optimal Policies

Known Sizes

Partial Info

Unknown Sizes

M/G/1

SRPT

Gittins

Optimal Policies

Known Sizes

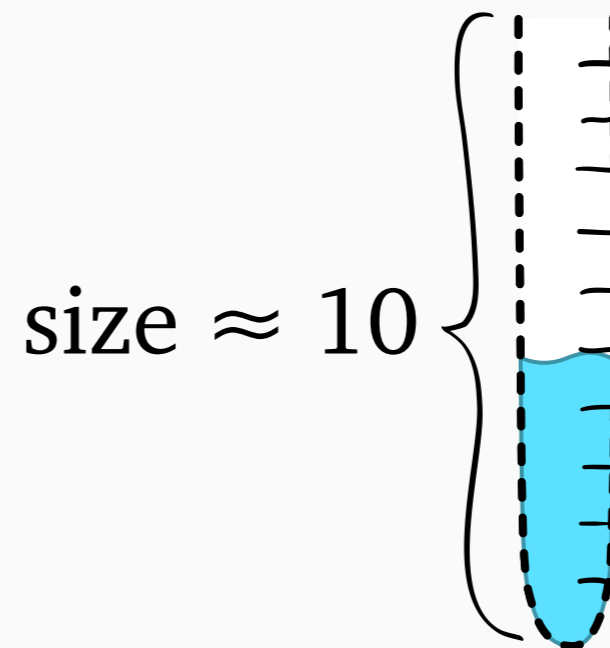
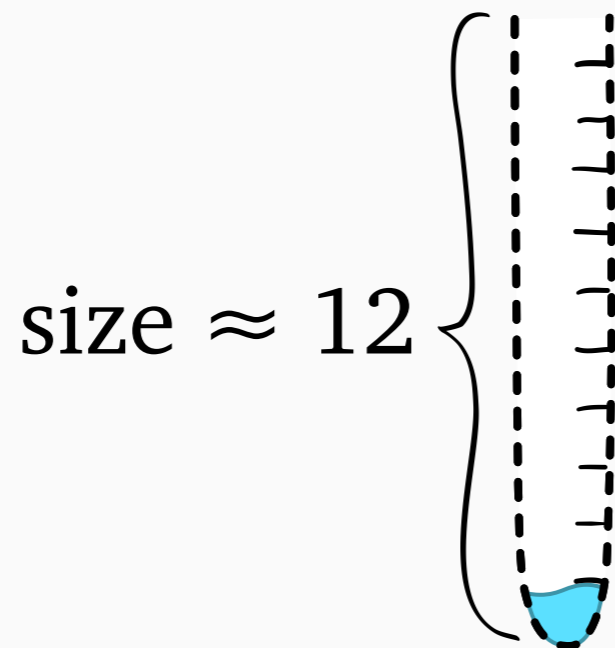
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Optimal Policies

Known Sizes

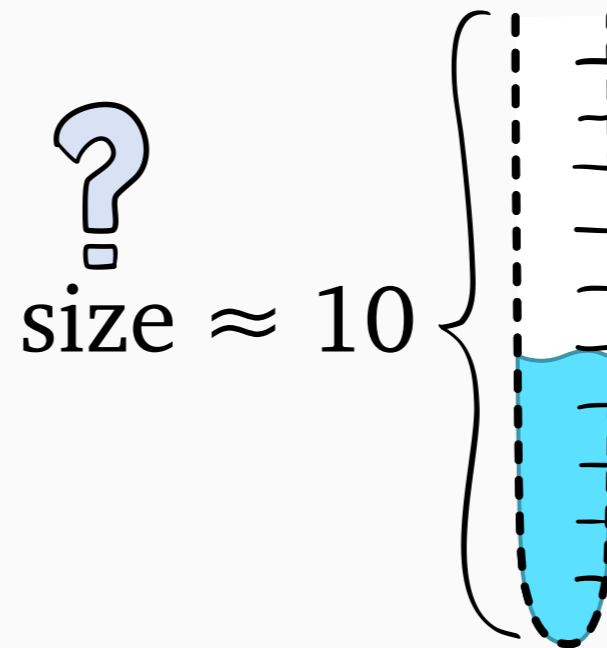
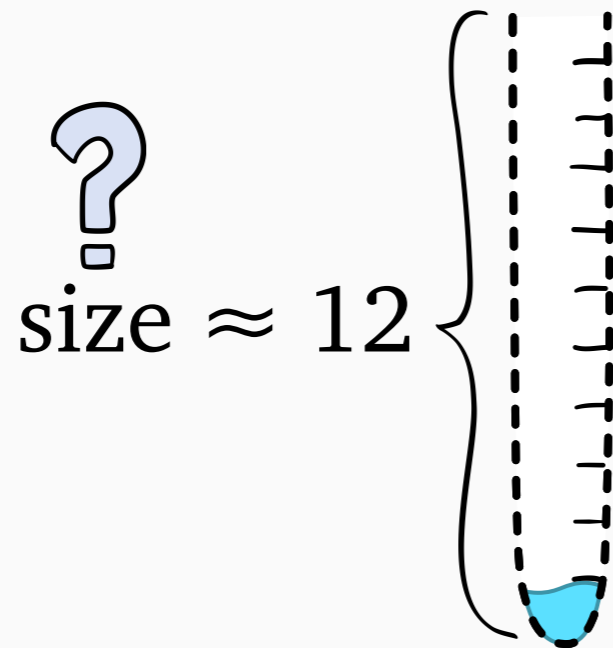
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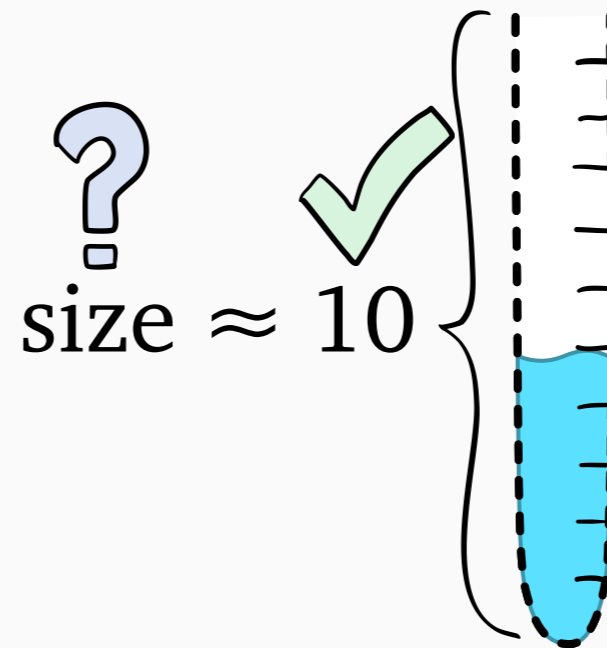
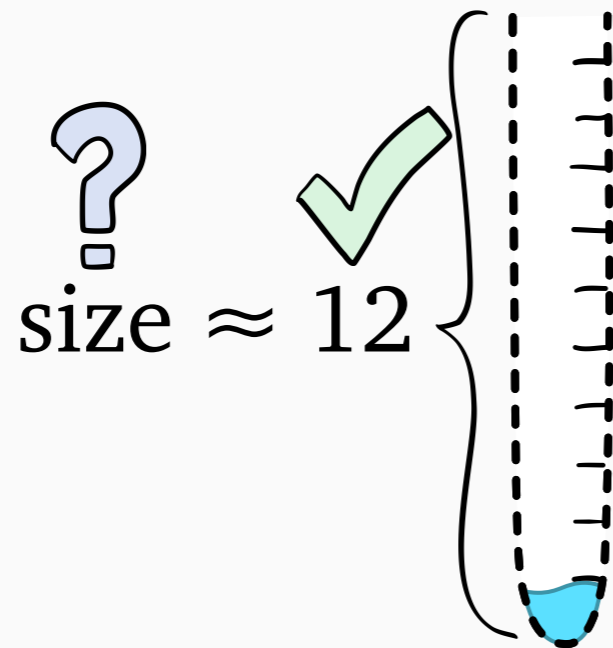
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Optimal Policies

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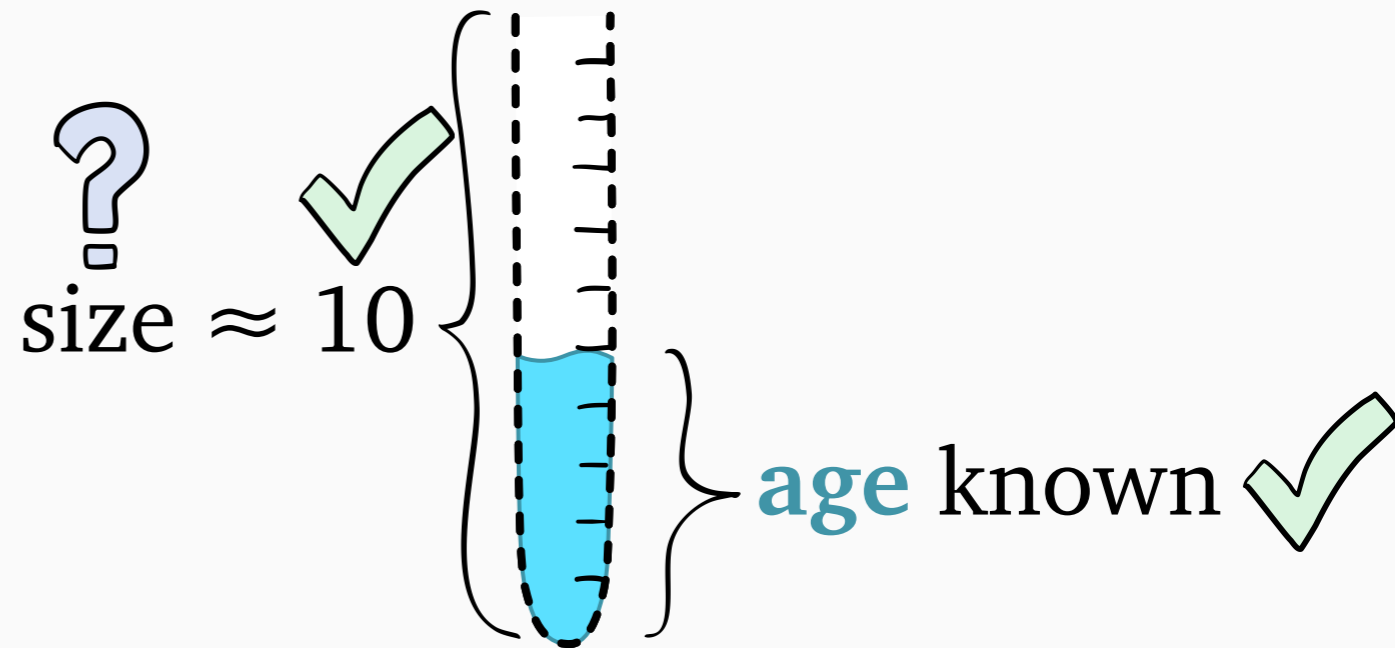
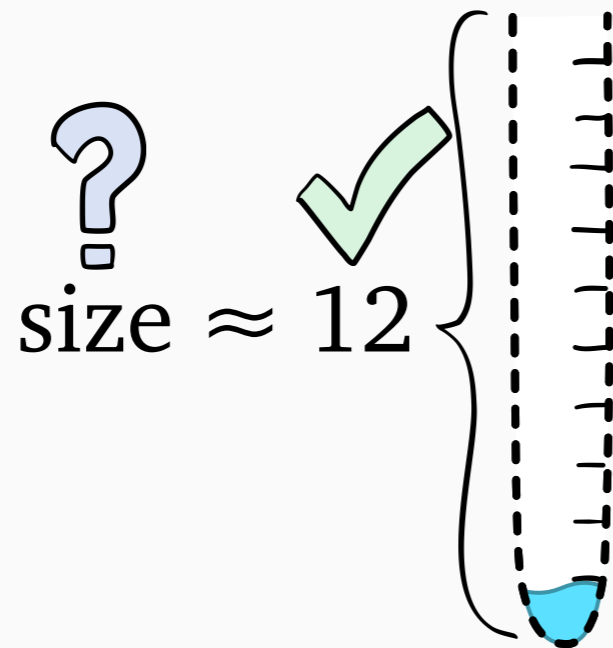
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Optimal Policies

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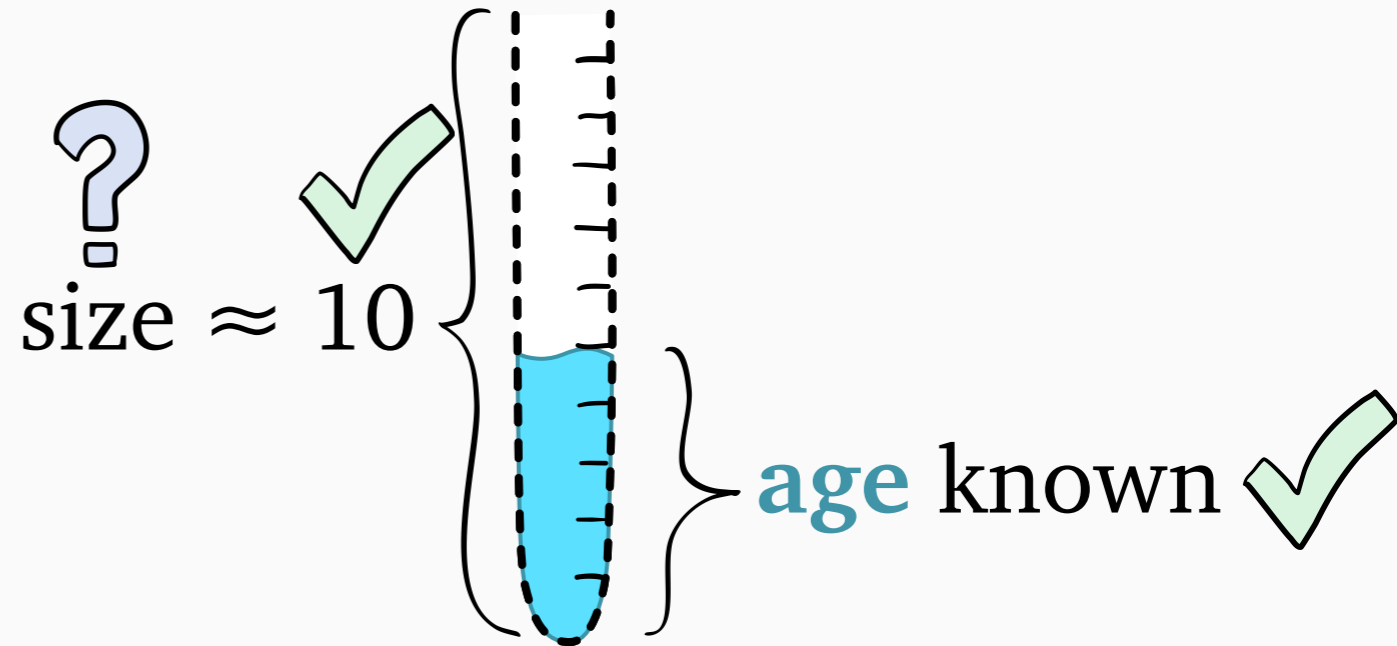
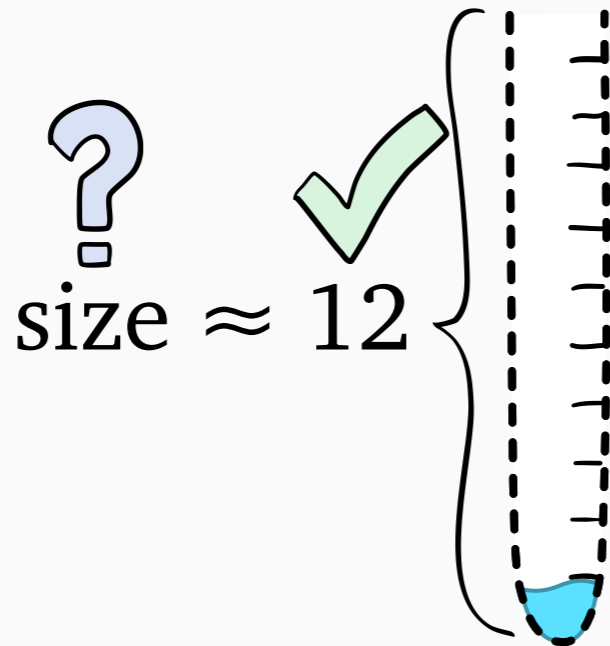
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M/G/1

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Gittins

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Optimal Policies

Known Sizes

Partial Info

Unknown Sizes

M/G/1

SRPT

Gittins

huge variety
of scenarios

Gittins

Optimal Policies

Known Sizes

Partial Info

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M/G/1

SRPT

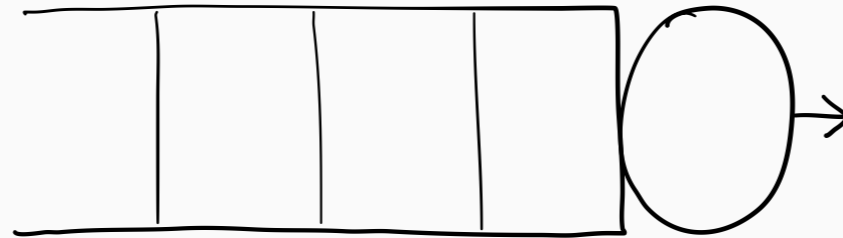
Gittins

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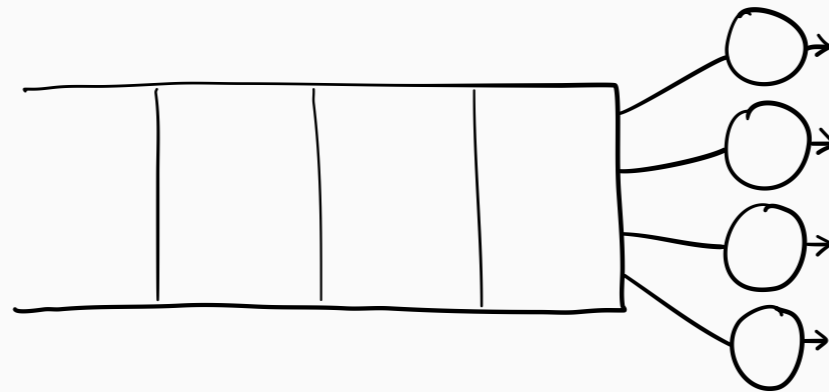
Gittins

special case of **Gittins**:
rank = remaining size

First: background on
single-server scheduling

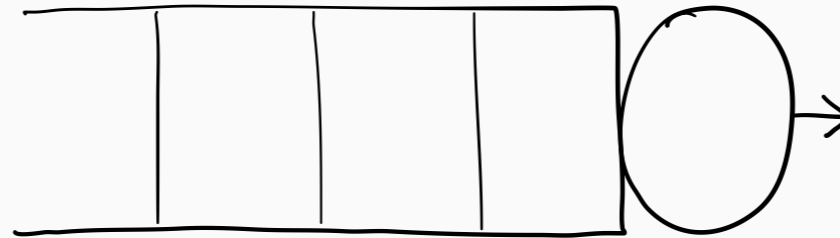


This talk: near-optimal
multiserver scheduling

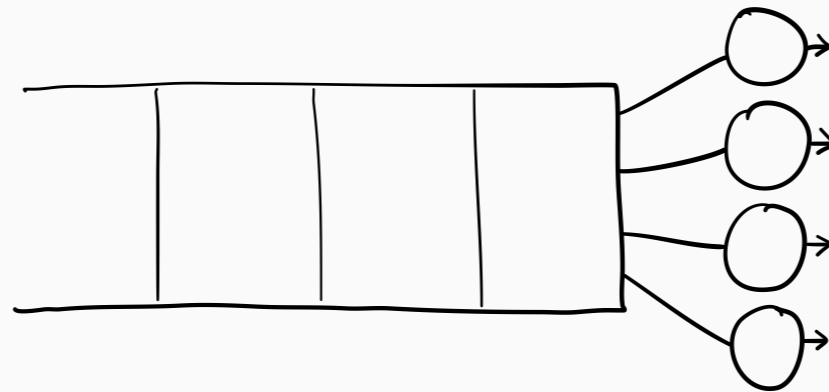




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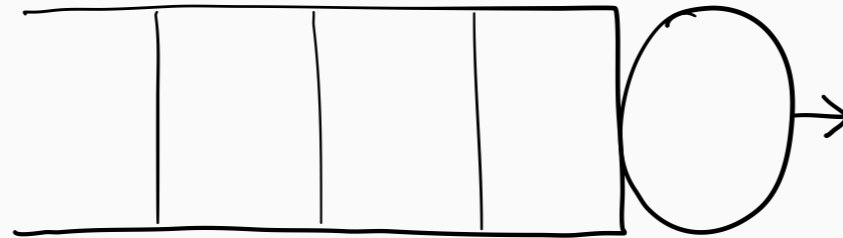


This talk: near-optimal *multiserver* scheduling

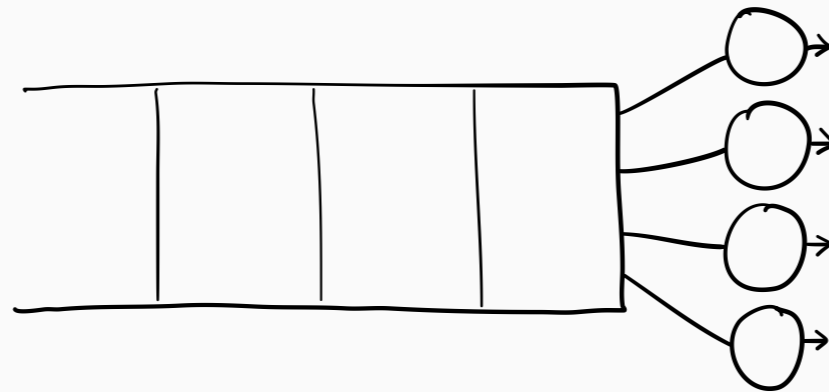


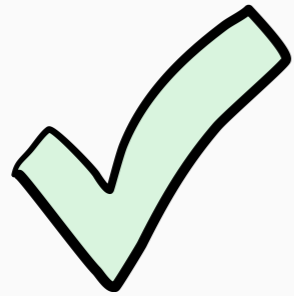


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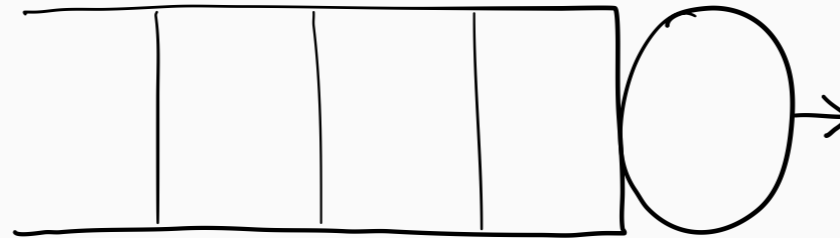
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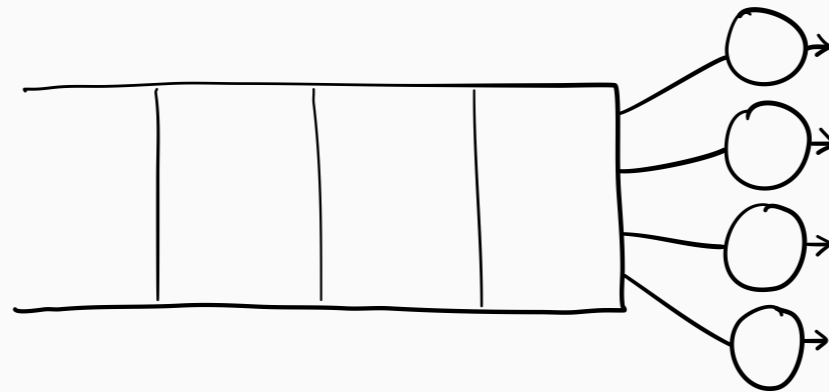


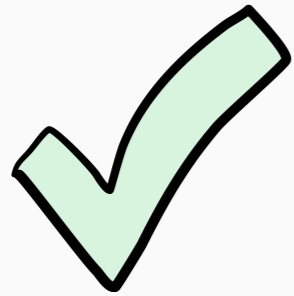
First: background on *single-server* scheduling

use **Gittins!**



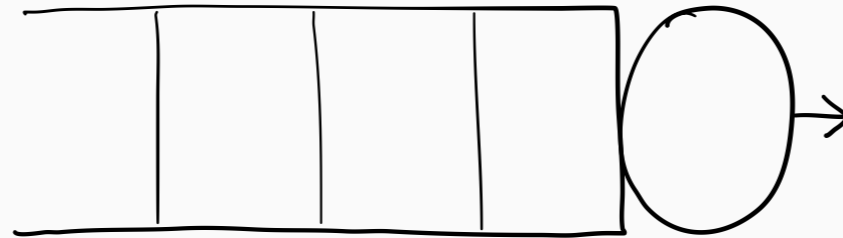
This talk: near-optimal *multiserver* scheduling





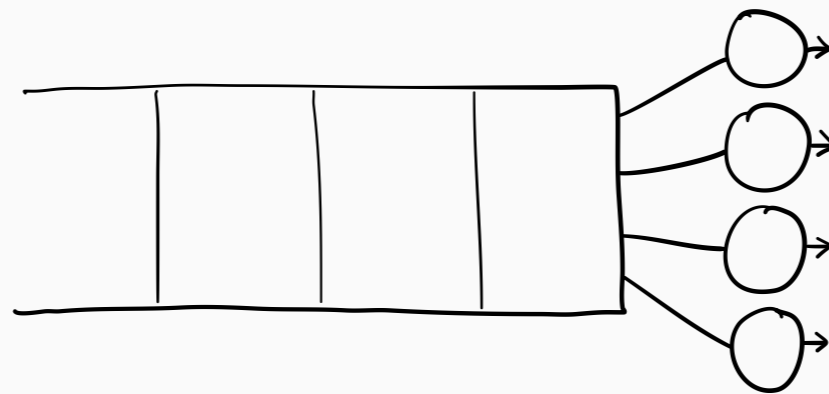
First: background on
single-server scheduling

use **Gittins!**

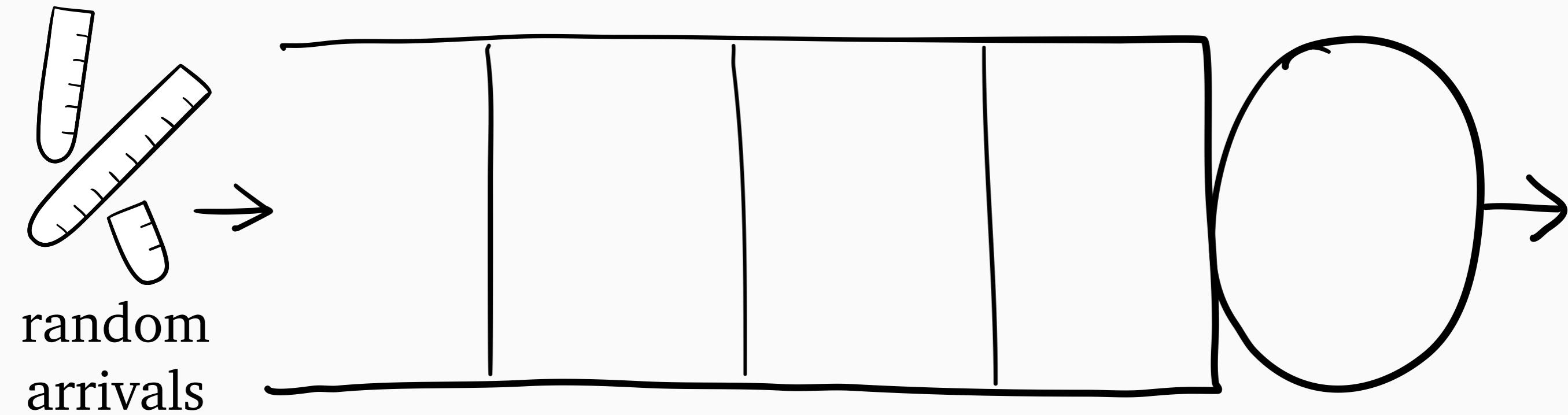


This talk: near-optimal
multiserver scheduling

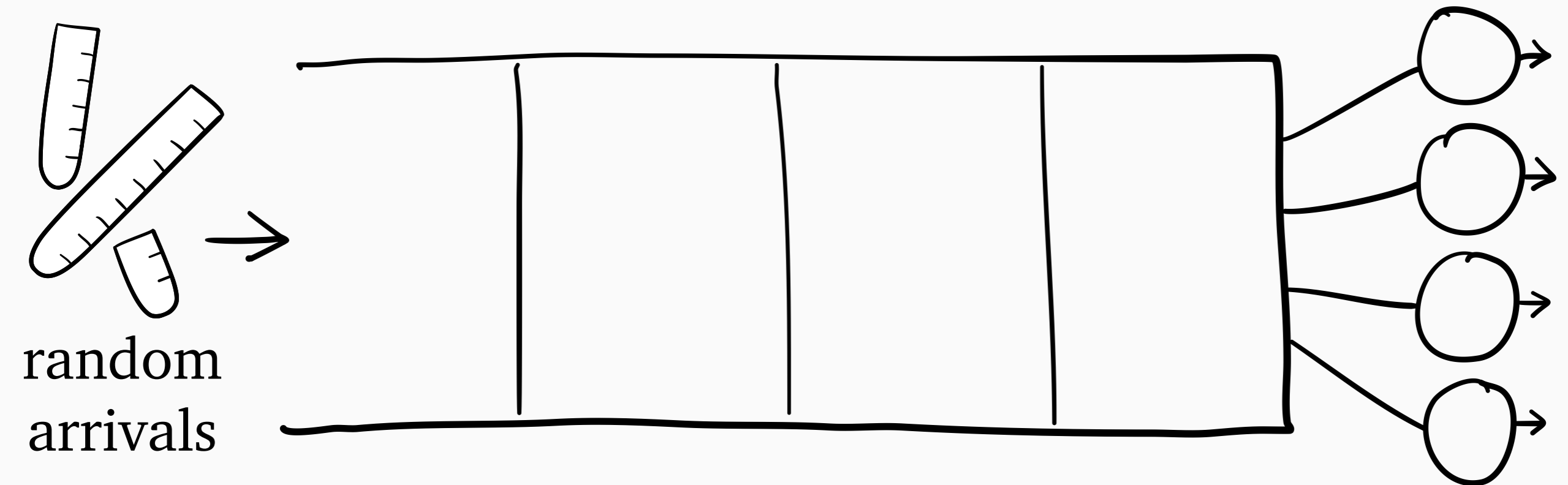
use **Gittins?**



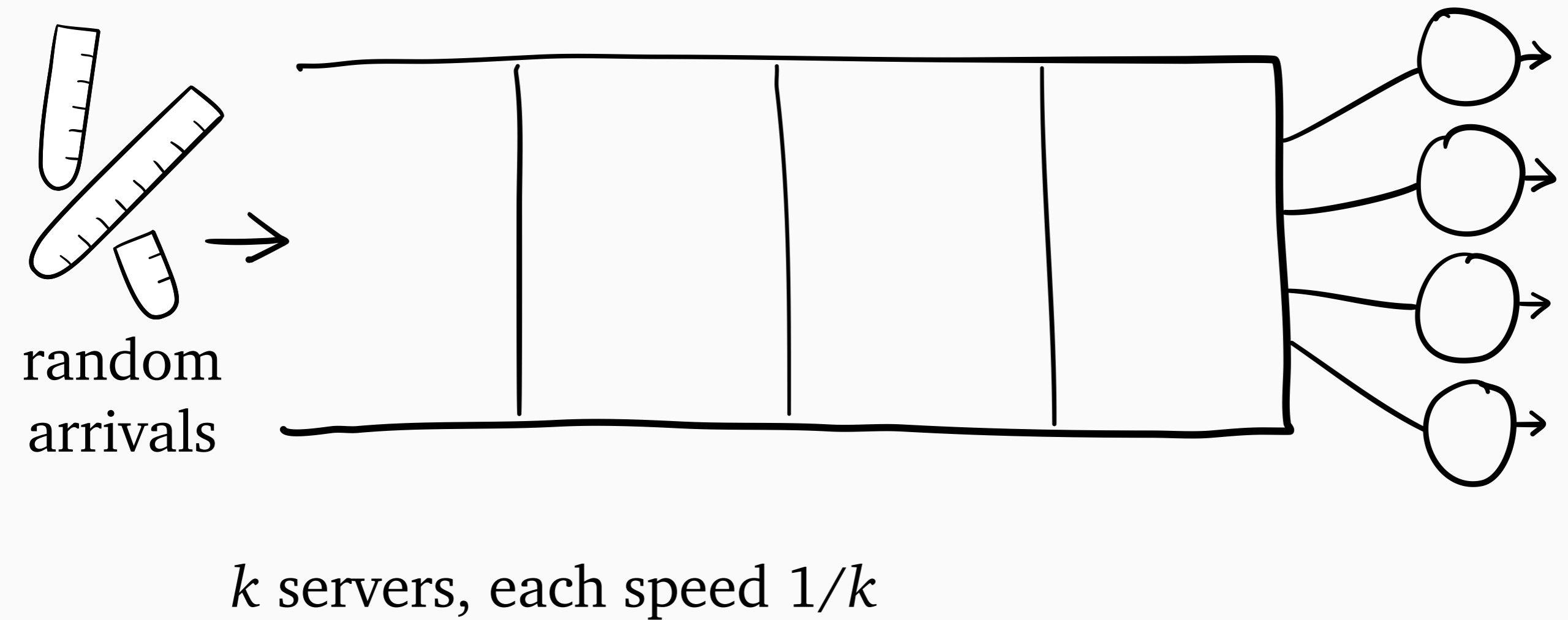
M/G/k Queue



M/G/k Queue



M/G/k Queue



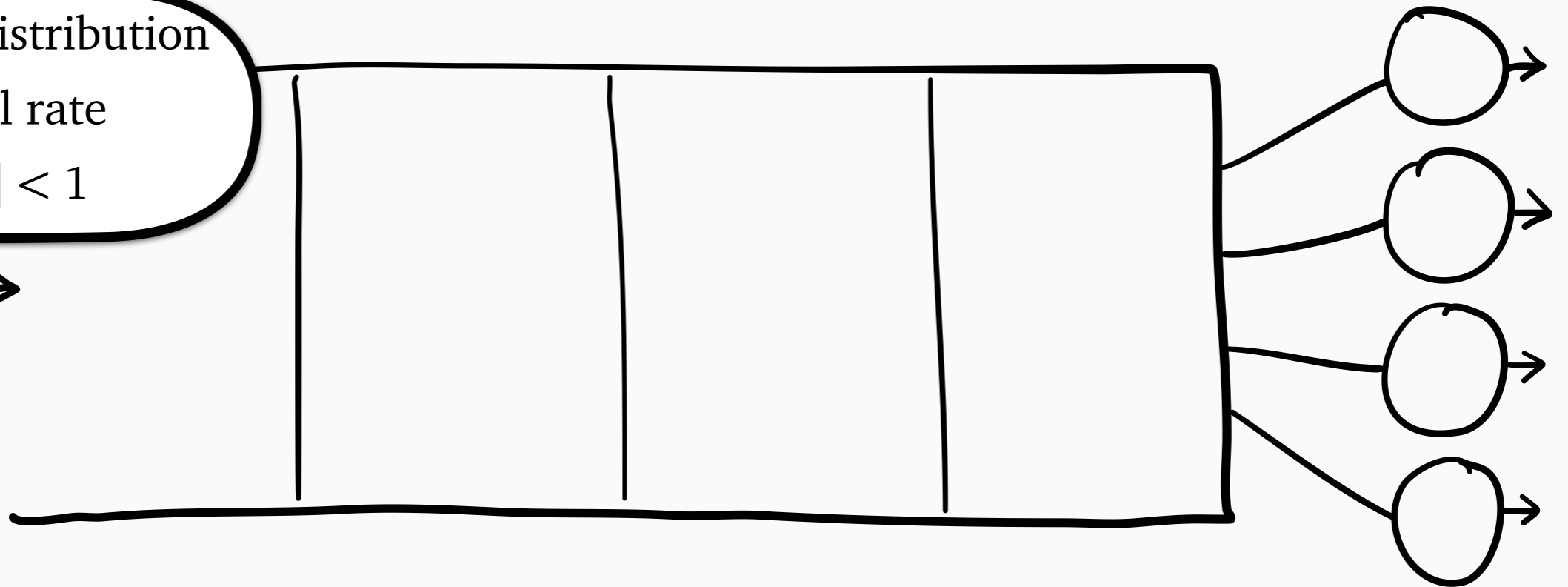
M/G/k Queue

S = size distribution

λ = arrival rate

$\rho = \lambda \mathbf{E}[S] < 1$

random
arrivals



k servers, each speed $1/k$

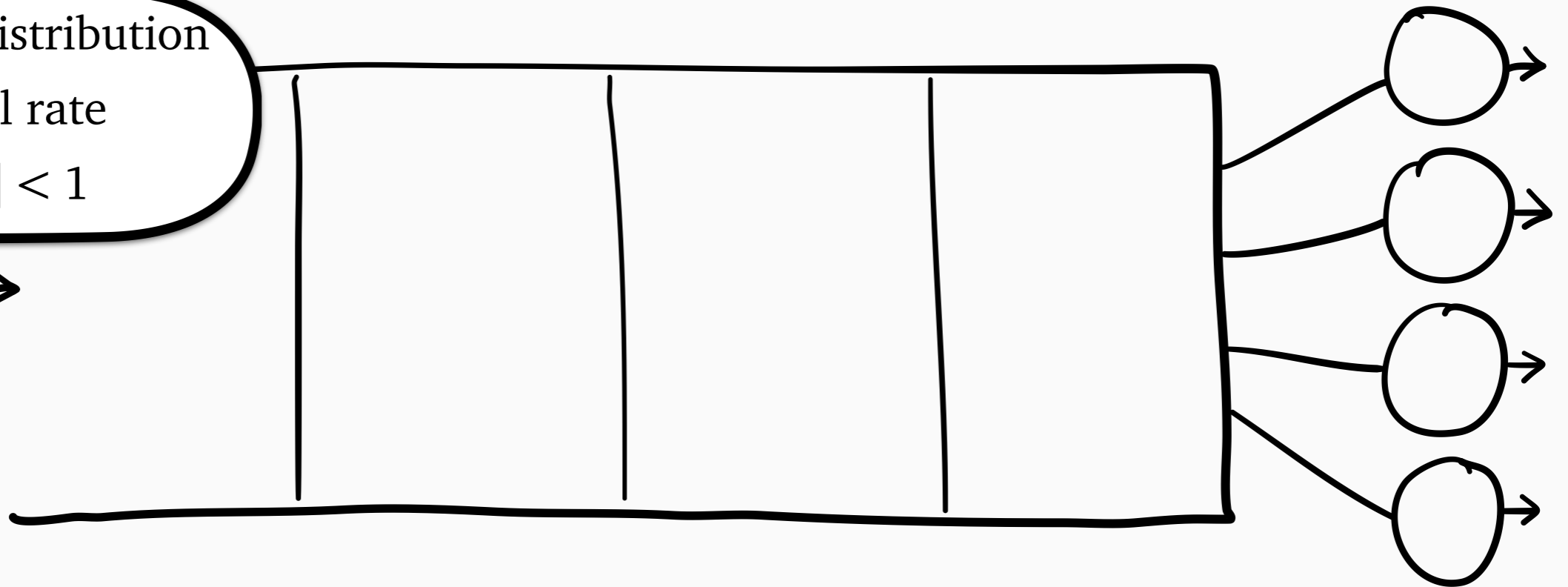
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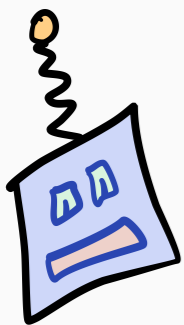
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k servers, each speed $1/k$



Scheduling policy:

picks which k jobs to serve

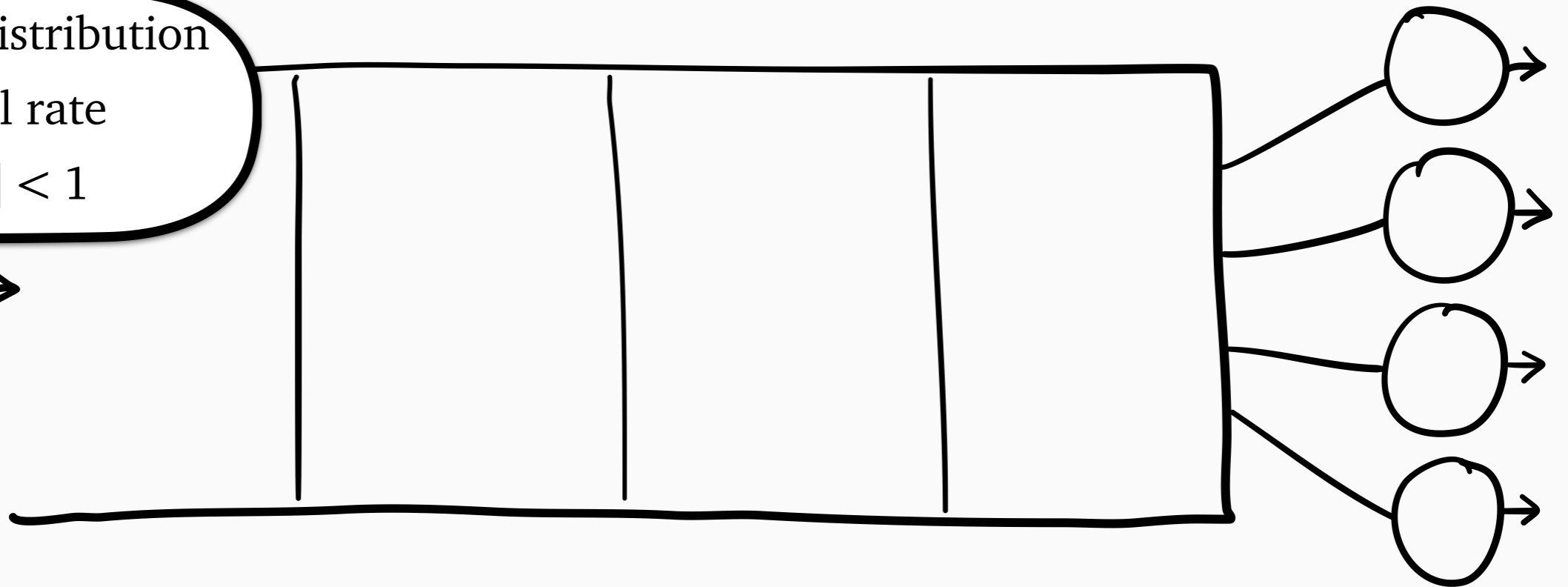
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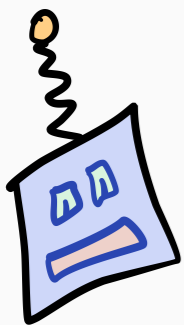
$\rho = \lambda \mathbf{E}[S] < 1$

random
arrivals



k servers, each speed $1/k$

Multiserver Gittins:
serves the k jobs with
the k lowest **ranks**



Scheduling policy:

picks which k jobs to serve



M/G/1 vs. M/G/*k*

$$\mathbf{E}[T_1^{\min}] \leq \mathbf{E}[T_k^{\min}]$$

M/G/1 vs. M/G/k

$$\mathbf{E}[T_1^{\text{Gittins}}] = \mathbf{E}[T_1^{\min}] \leq \mathbf{E}[T_k^{\min}]$$

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Goal 1: “near-optimality” bound

$$\mathbf{E}[T_k^{\text{Gittins}}] \leq \mathbf{E}[T_1^{\text{Gittins}}] + \text{something “small”}$$

M/G/1 vs. M/G/k

$$\mathbf{E}[T_1^{\text{Gittins}}] = \mathbf{E}[T_1^{\min}] \leq \mathbf{E}[T_k^{\min}] \leq \mathbf{E}[T_k^{\text{Gittins}}]$$

Goal 1: “near-optimality” bound

$$\mathbf{E}[T_k^{\text{Gittins}}] \leq \mathbf{E}[T_1^{\text{Gittins}}] + \text{something “small”}$$

Goal 2: heavy-traffic optimality


$$\lim_{\rho \rightarrow 1} \frac{\mathbf{E}[T_k^{\text{Gittins}}]}{\mathbf{E}[T_1^{\text{Gittins}}]} = 1$$

Near-Optimal Policies

	Known Sizes	Partial Info	Unknown Sizes
M/G/1	SRPT	Gittins	Gittins
M/G/ <i>k</i> (prior work)			


Near-Optimal Policies

	Known Sizes	Partial Info	Unknown Sizes
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 Generalize M/G/1
E[T] analysis

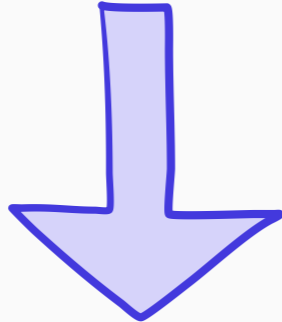
Near-Optimal Policies


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 Generalize M/G/1
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 Generalize M/G/1
 $E[T]$ analysis

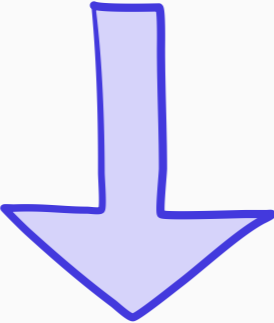
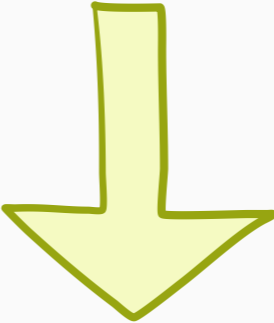
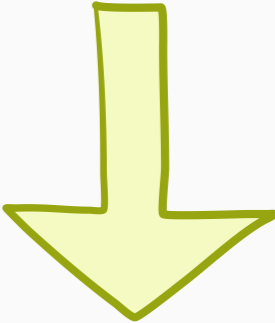


$$E[T_k] \leq E[T_1] + (k - 1) \cdot O\left(\log \frac{1}{1 - \rho}\right)$$

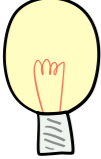
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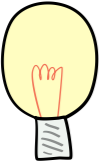
Near-Optimal Policies

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 Generalize M/G/1 E[T] analysis

Near-Optimal Policies


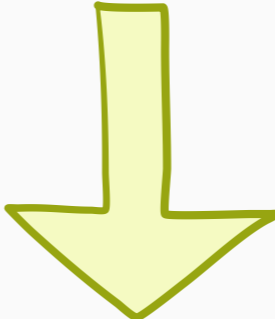
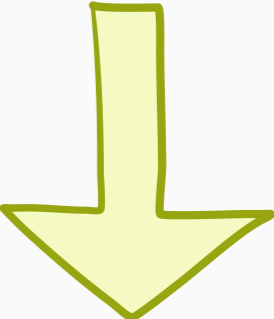


	Known Sizes	Partial Info	Unknown Sizes
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 Generalize M/G/1
E[T] analysis



Problem: existing M/G/1-to-M/G/k strategy uses **worst-case** techniques

Near-Optimal Policies


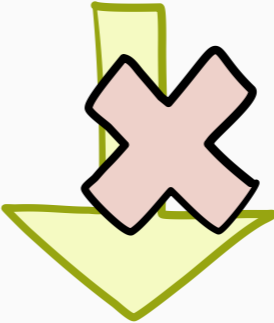
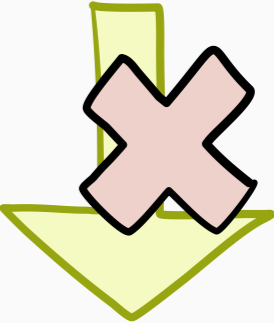


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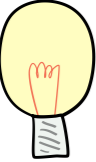
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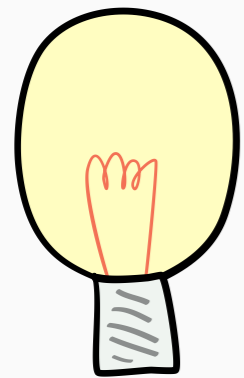
 Generalize M/G/1
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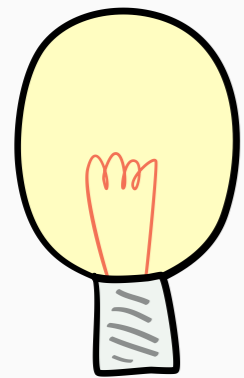
Our contributions:

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Introduce *new techniques* for analyzing $E[T]$ in the $M/G/k$

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Introduce *new techniques* for analyzing $E[T]$ in the $M/G/k$



Prove that **Gittins** has *near-optimal* $E[T]$ in the $M/G/k$

Near-Optimal Policies

	Known Sizes	Partial Info	Unknown Sizes
M/G/1	SRPT	Gittins	Gittins
M/G/k (prior work)	SRPT	?	?
M/G/k (new result)			

Near-Optimal Policies

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Near-Optimal Policies

	Known Sizes	Partial Info	Unknown Sizes
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$$E[T_k] \leq E[T_1] + (k-1) \cdot O\left(\log \frac{1}{1-\rho}\right)$$

Near-Optimal Policies

	Known Sizes	Partial Info	Unknown Sizes	
M/G/1	SRPT	$\mathbf{E}[T_k] \leq \mathbf{E}[T_1] + (k-1) \cdot O\left(\log \frac{1}{1-\rho}\right)$		Gittins
M/G/k (prior work)	SRPT	?	?	
M/G/k (new result)	SRPT	Gittins	Gittins	

$$\mathbf{E}[T_k] \leq \mathbf{E}[T_1] + (k-1) \cdot O\left(\log \frac{1}{1-\rho}\right)$$

Theorem: under **Gittins**,

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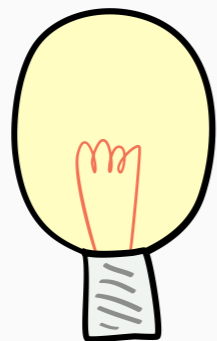
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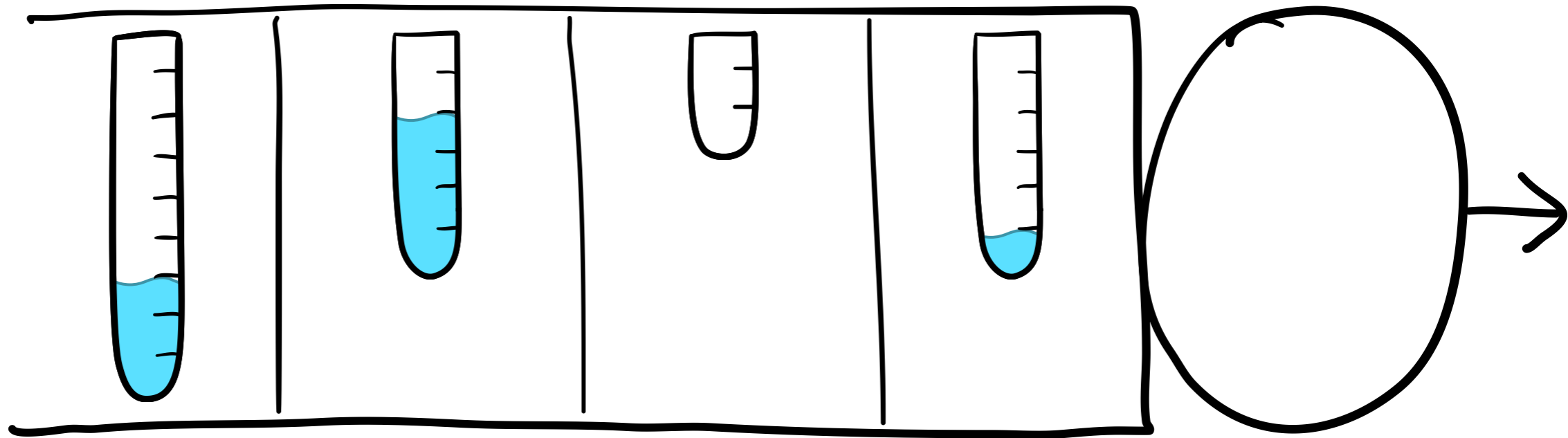
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New concept: *r*-work

What is *r-Work*? (SRPT)

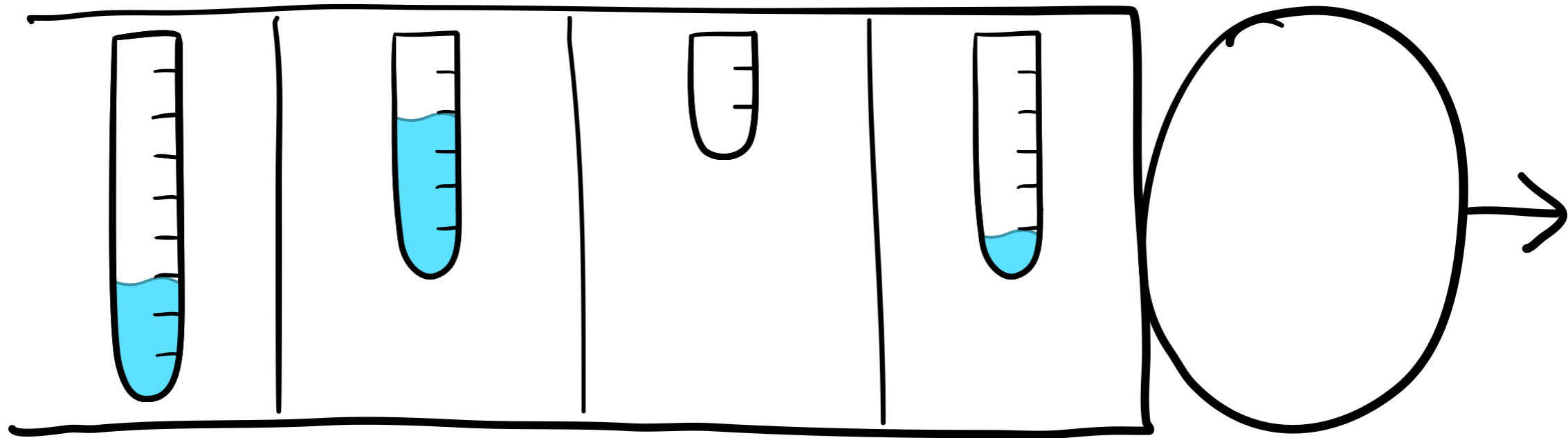
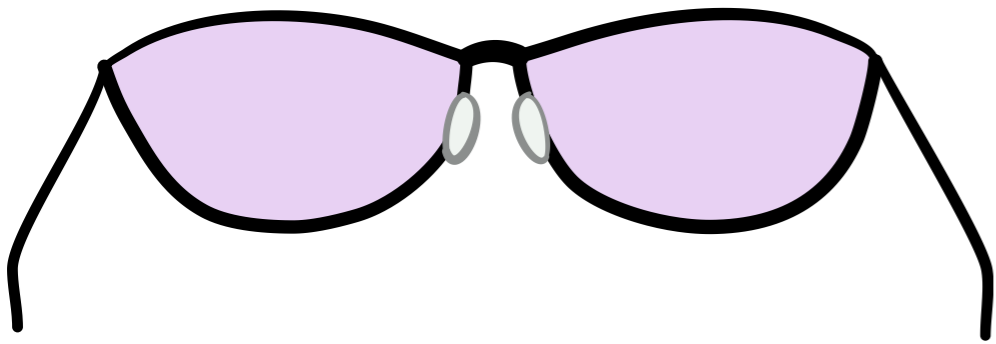
W = work = total remaining size of all jobs



What is *r*-Work? (SRPT)

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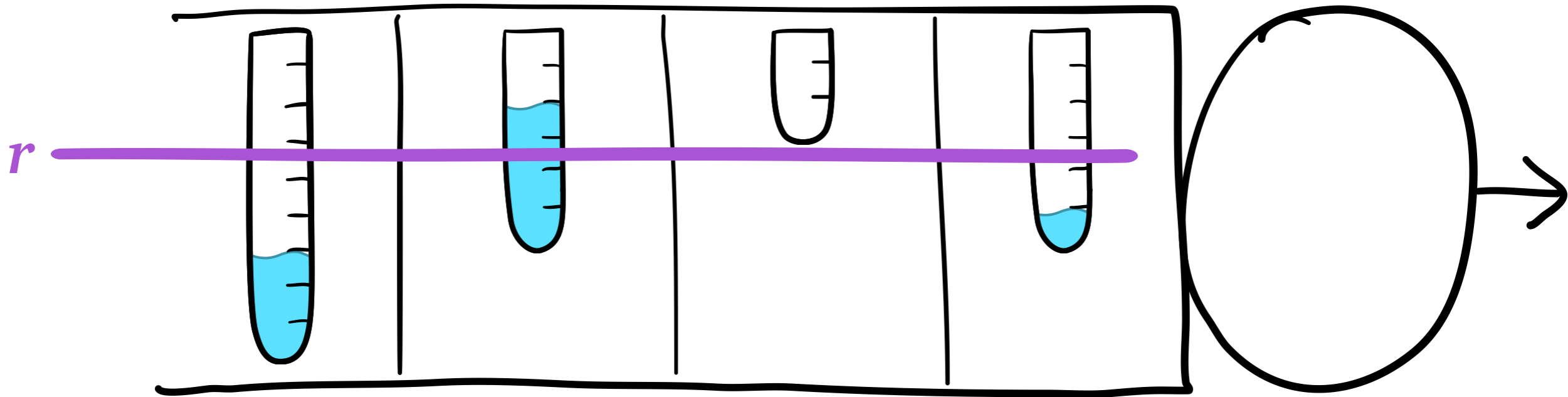
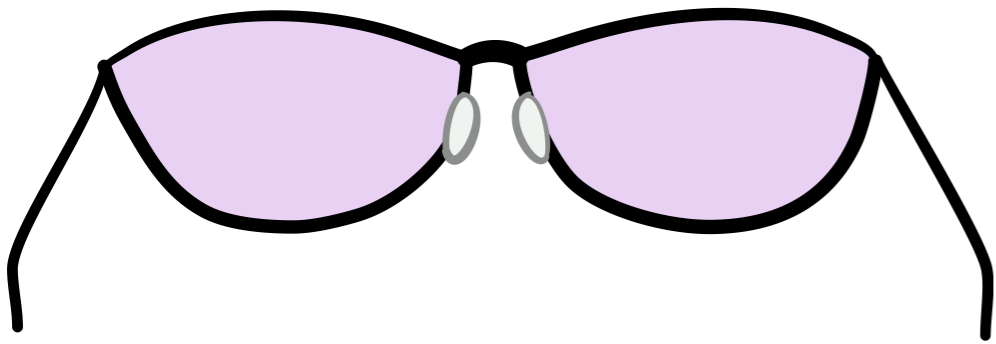
$W(r)$ = *r*-work = total remaining size of all jobs that have remaining size $\leq r$



What is *r*-Work? (SRPT)

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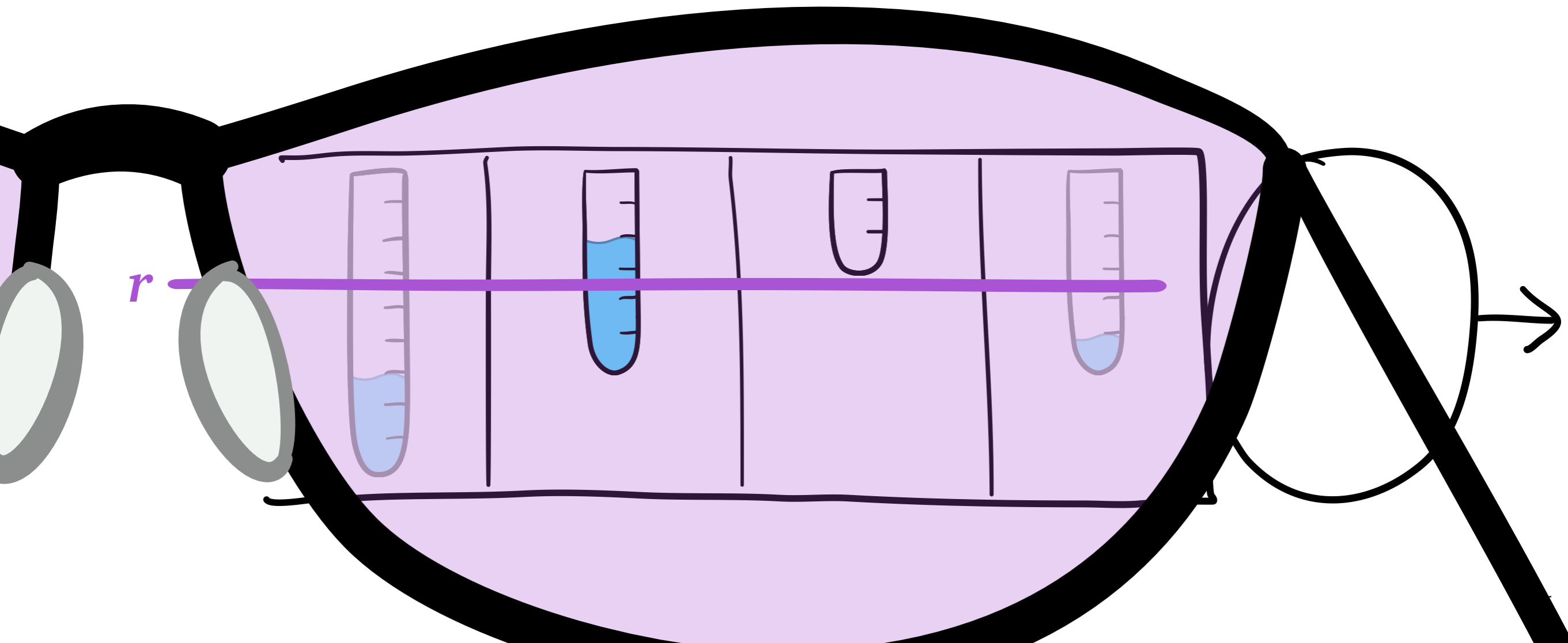
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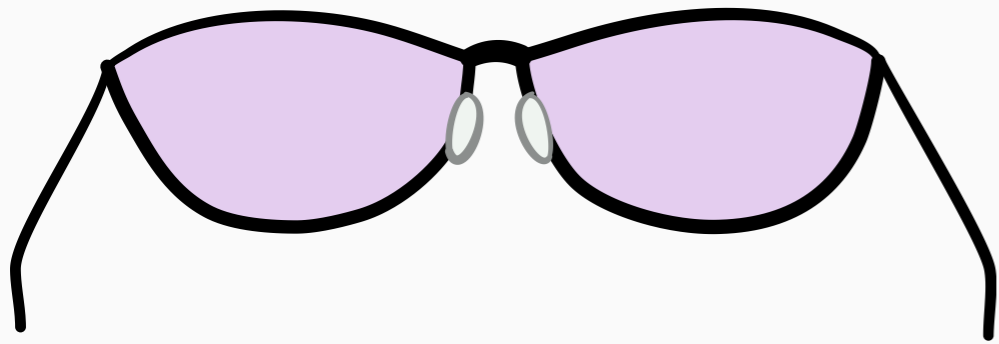
What is *r-Work*? (Gittins)

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What is *r*-Work? (Gittins)

W = work = total remaining size of all jobs

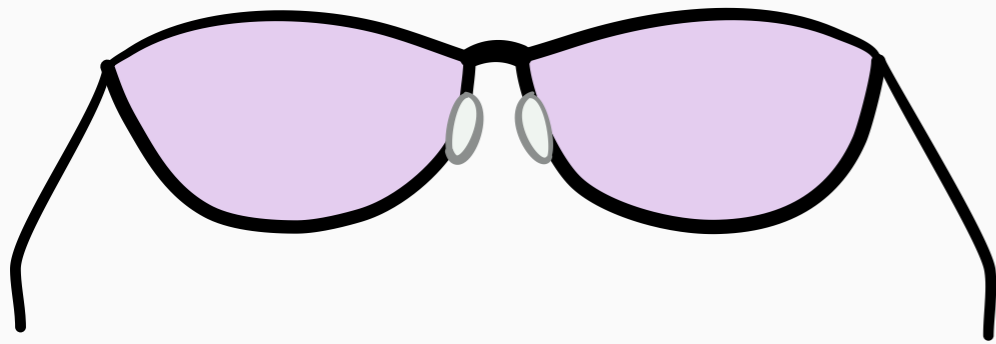
$W(r)$ = *r*-work = work “relevant” to rank r



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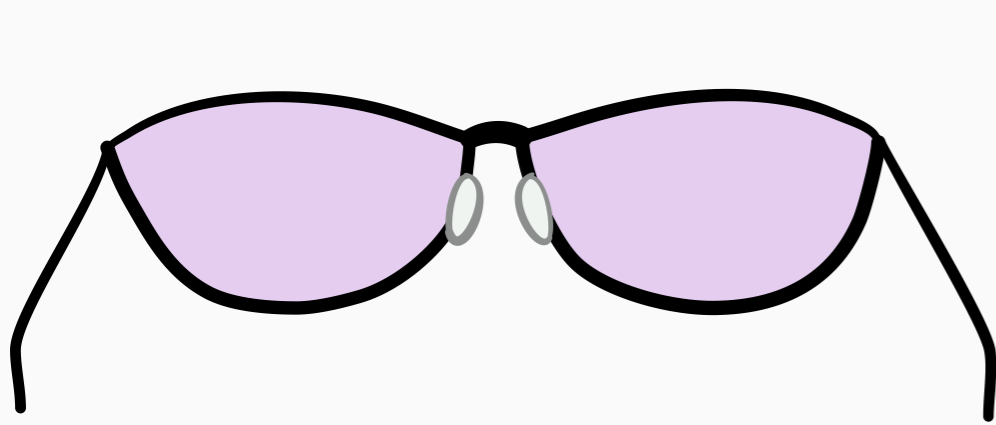


until job completes
or exceeds rank r

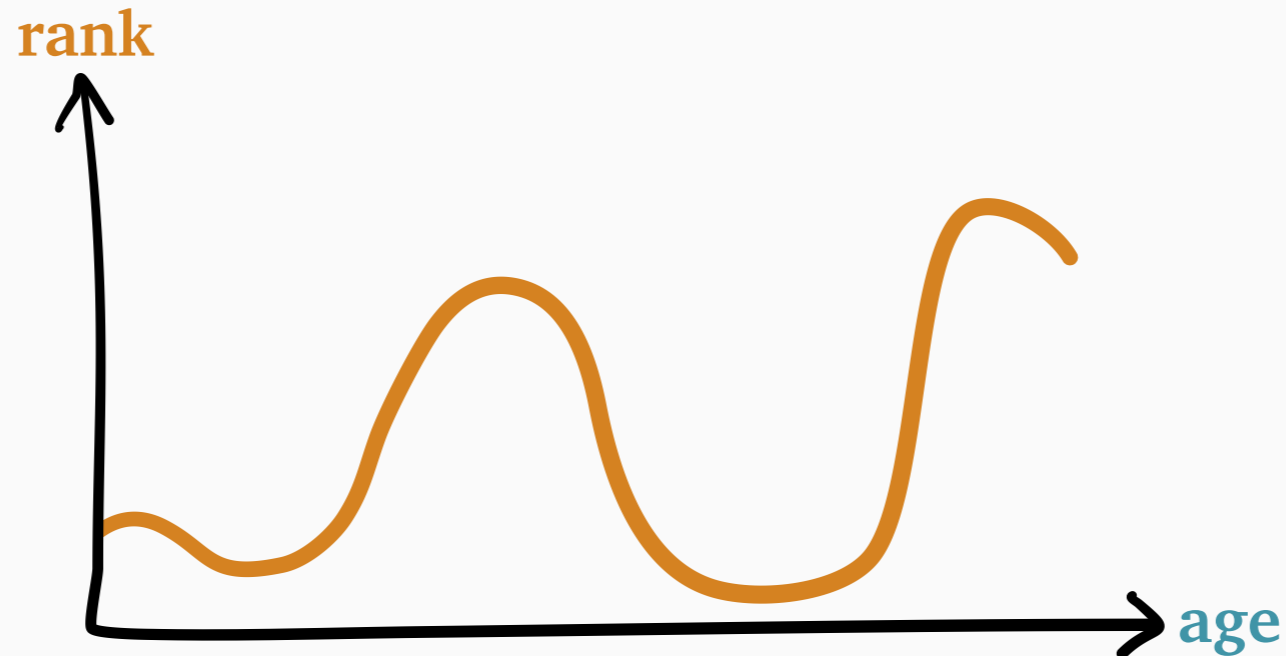
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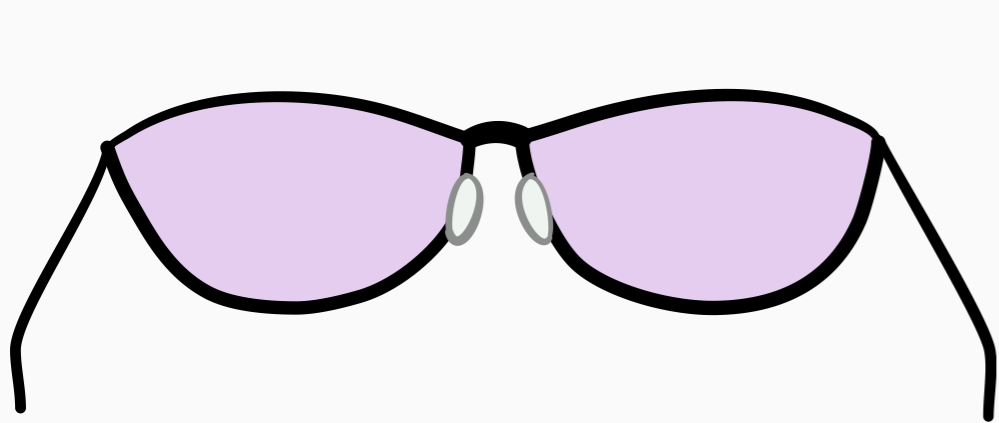
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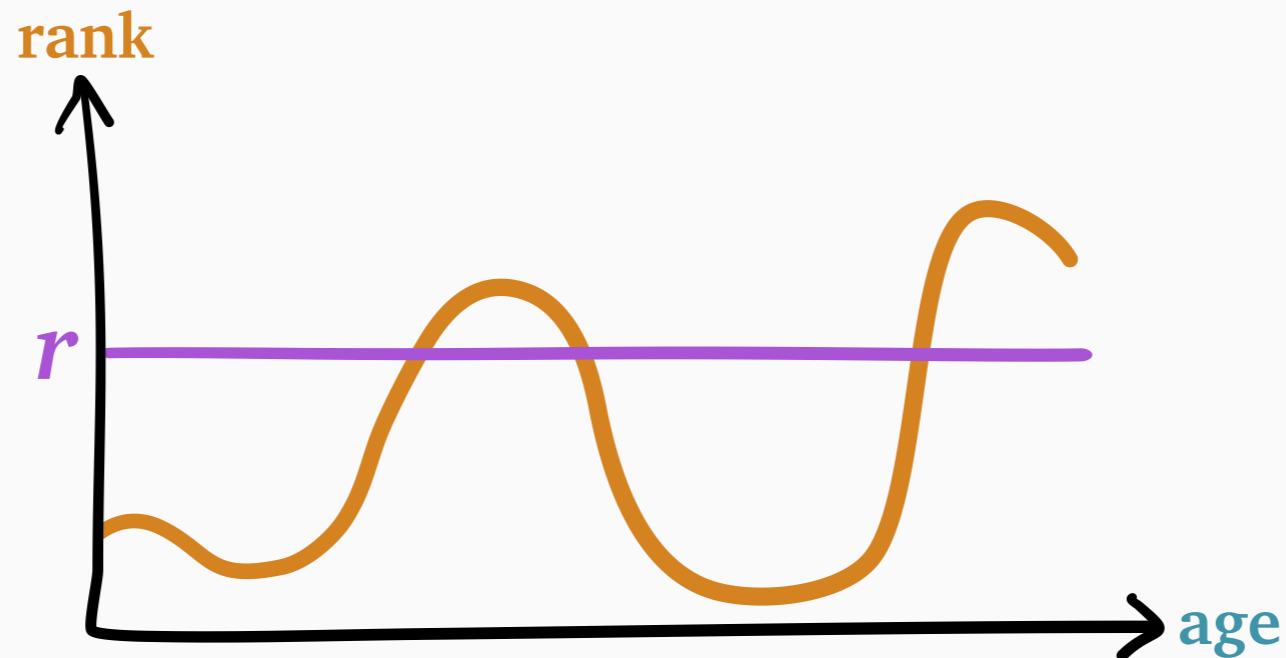
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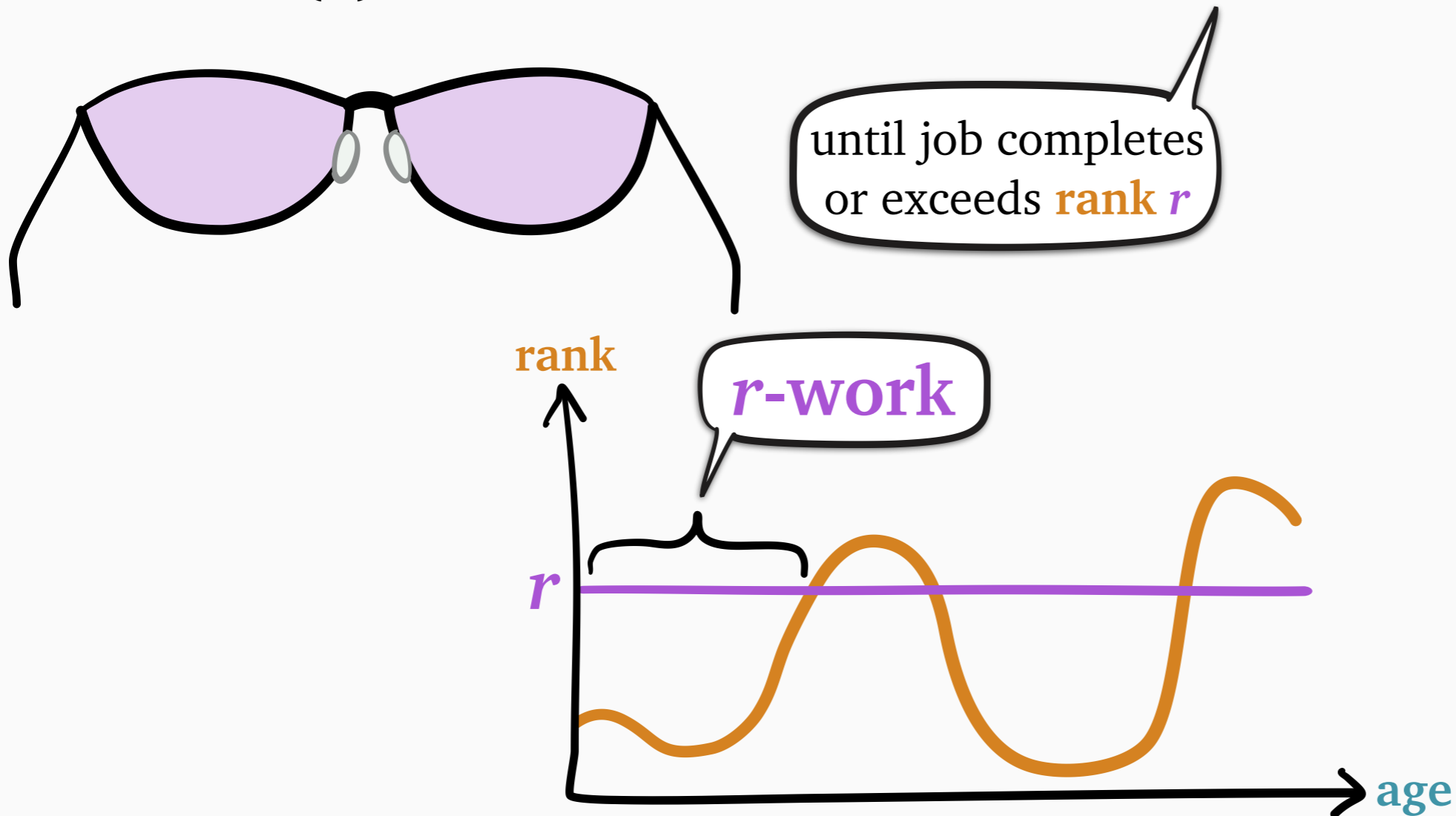
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What is *r*-Work? (Gittins)

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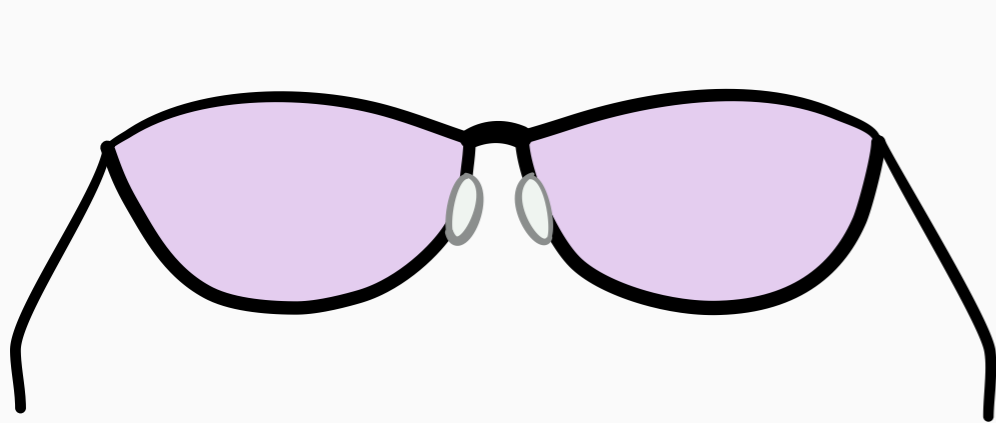
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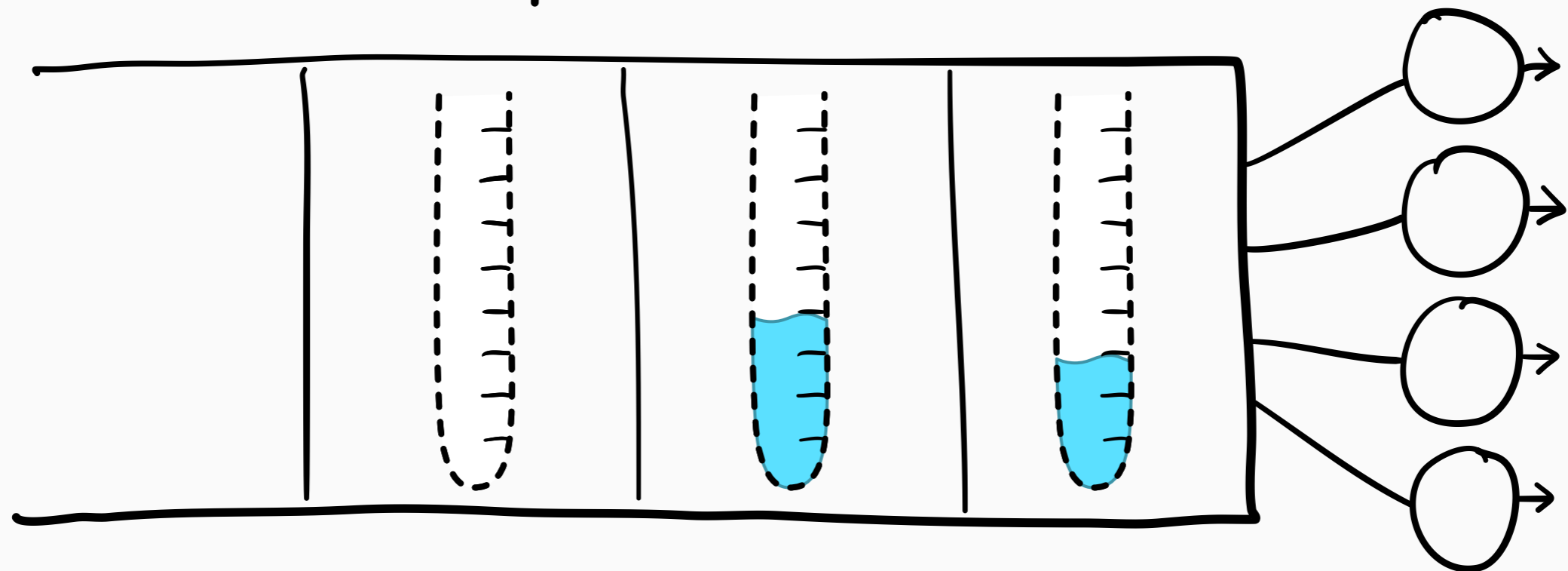
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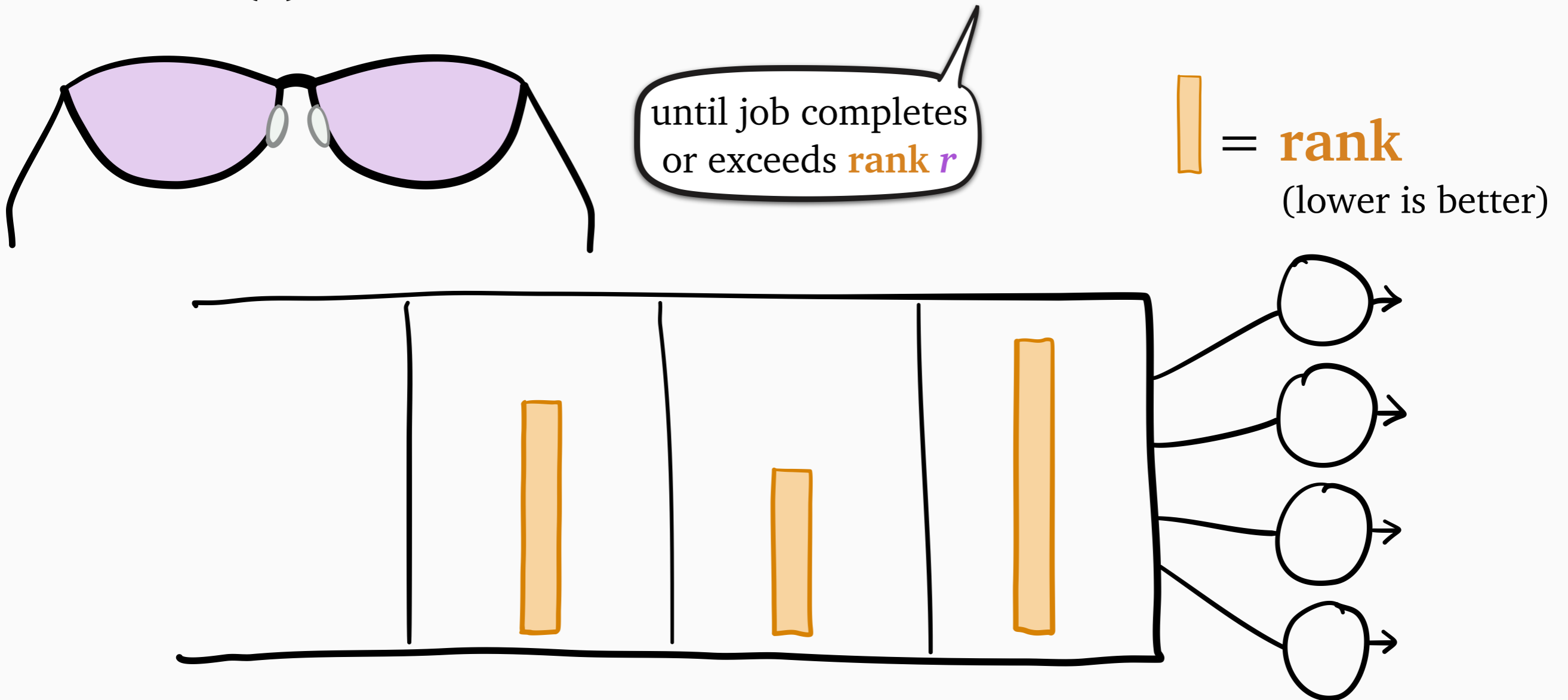
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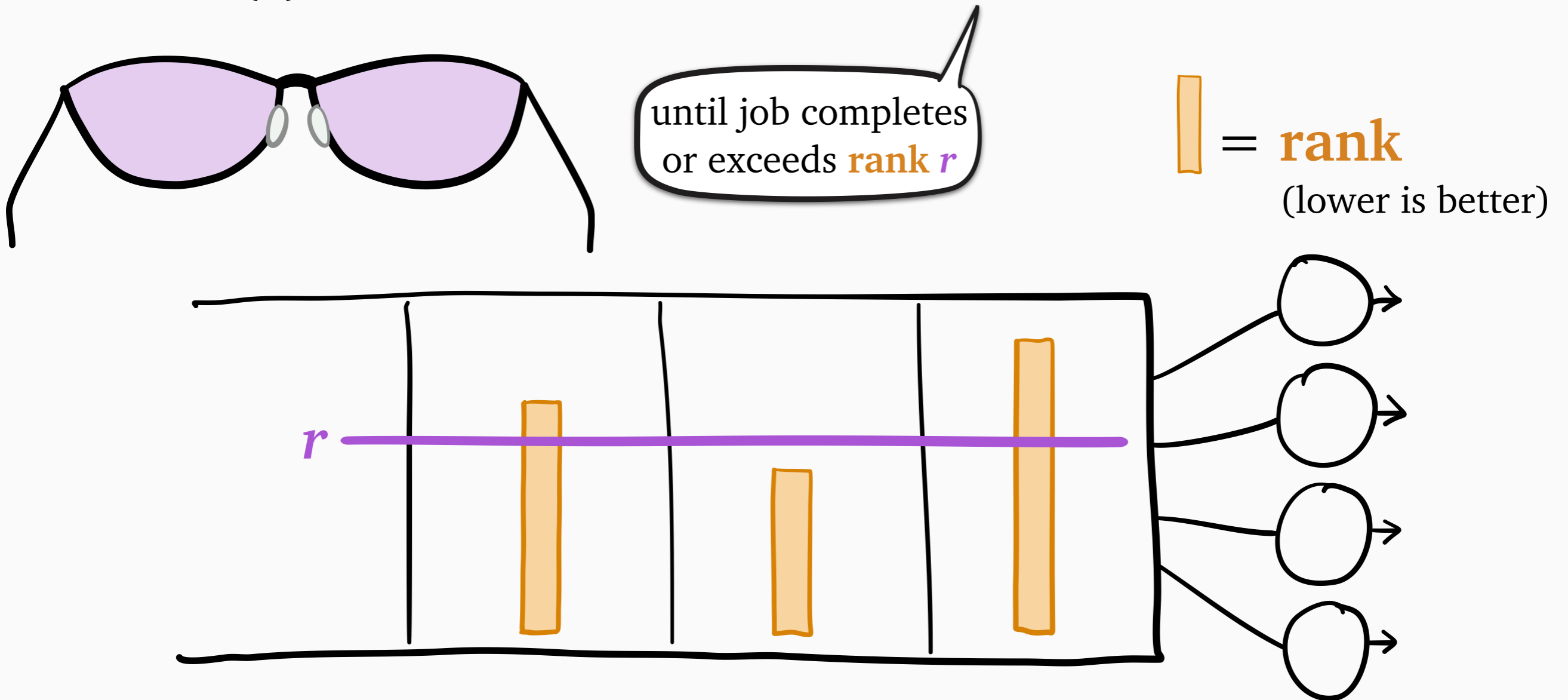
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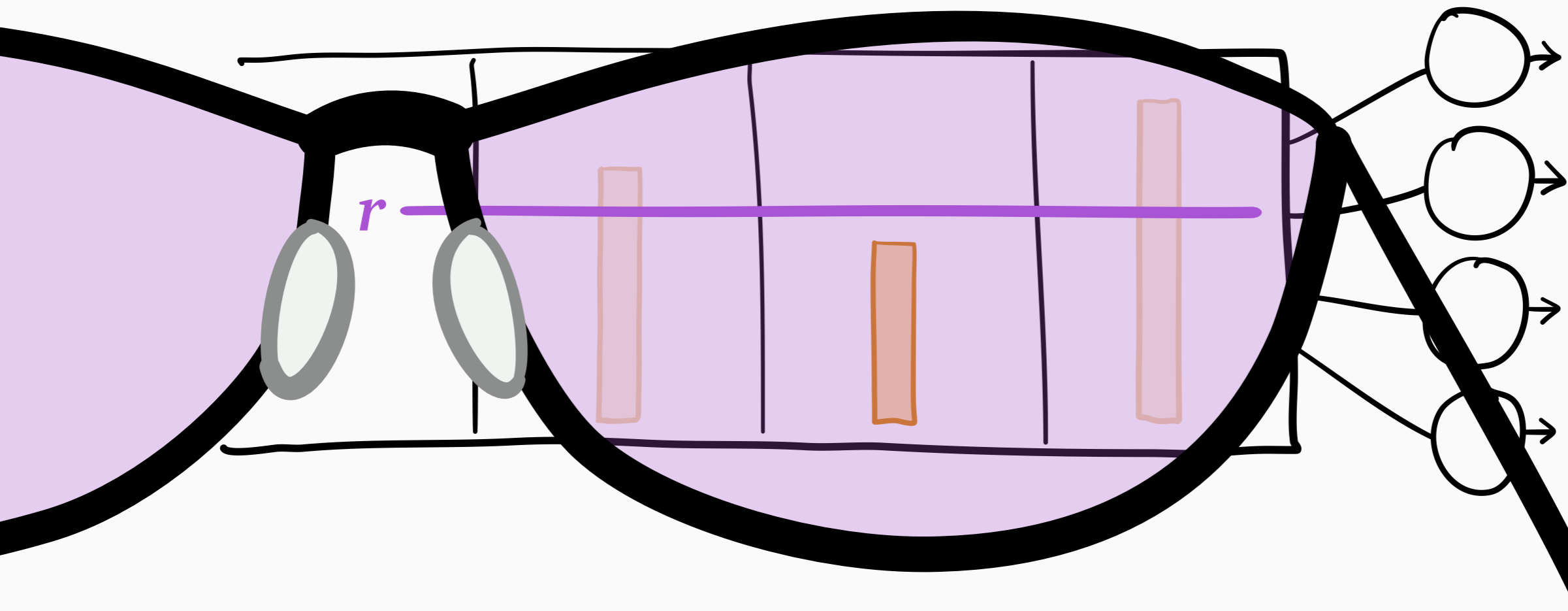
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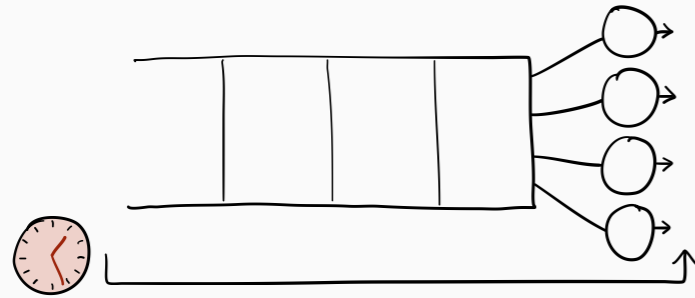
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until job completes
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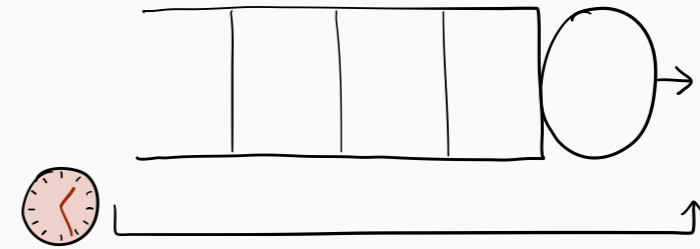
 = rank
(lower is better)



Response Time via *r*-Work

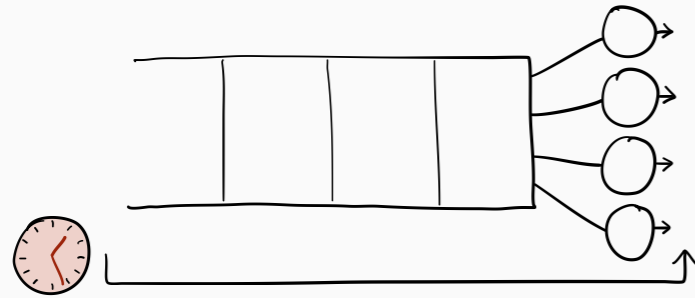


mean response
time in $M/G/k$

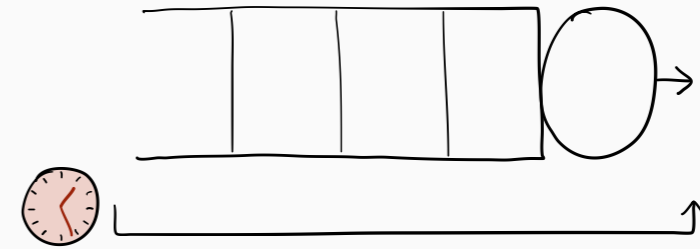


mean response
time in $M/G/1$

Response Time via *r*-Work

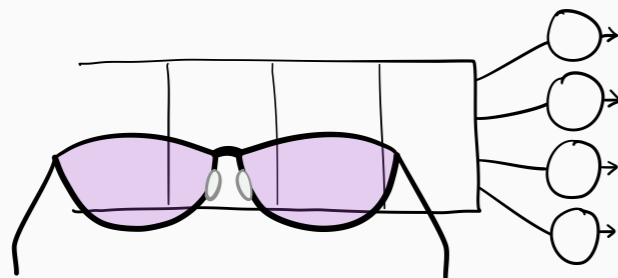


mean response
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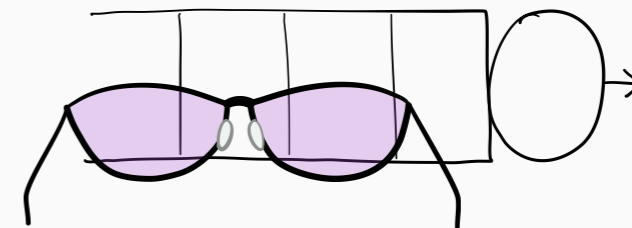


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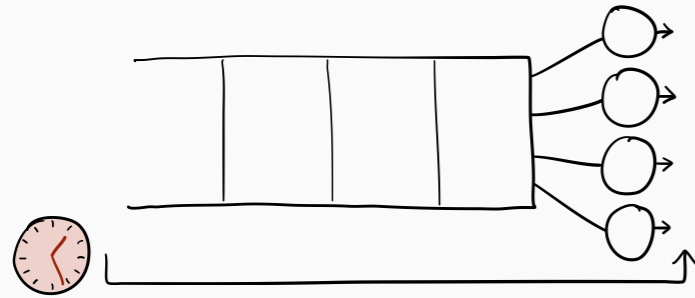
mean *r*-work
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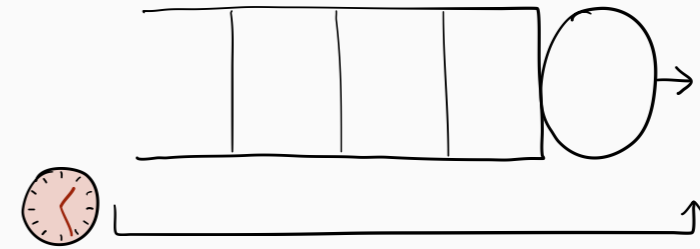
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Response Time via *r*-Work



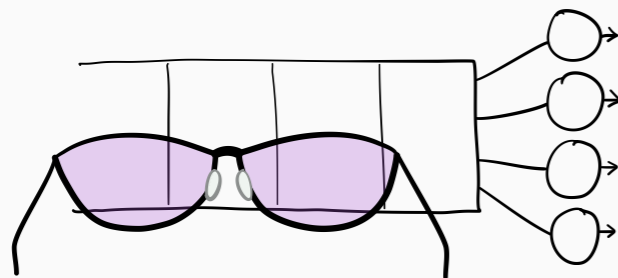
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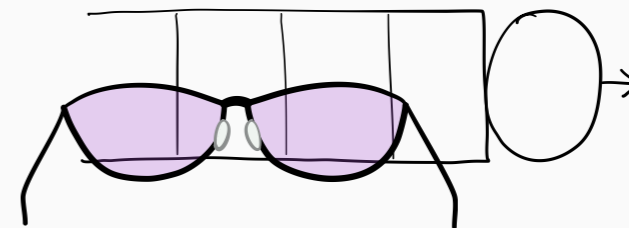
mean response
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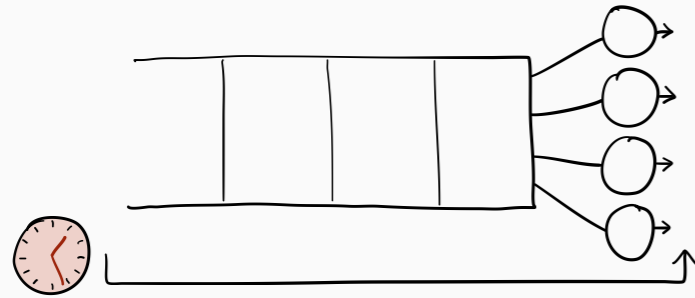
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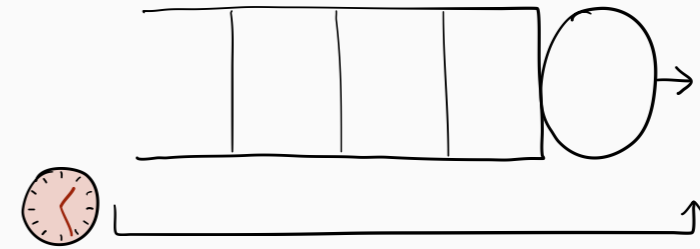
mean *r*-work
in M/G/1



Response Time via *r*-Work



mean response
time in M/G/*k*



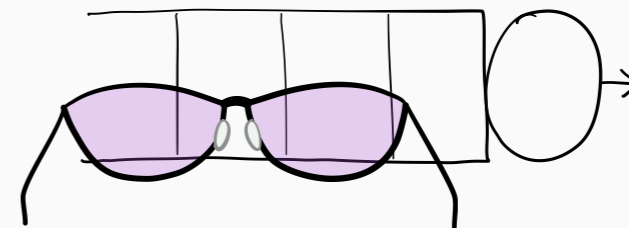
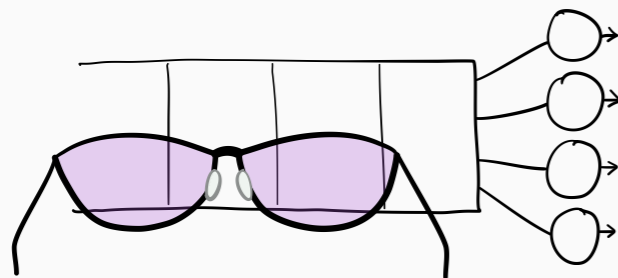
mean response
time in M/G/1



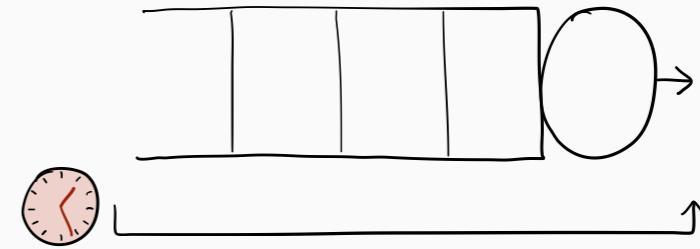
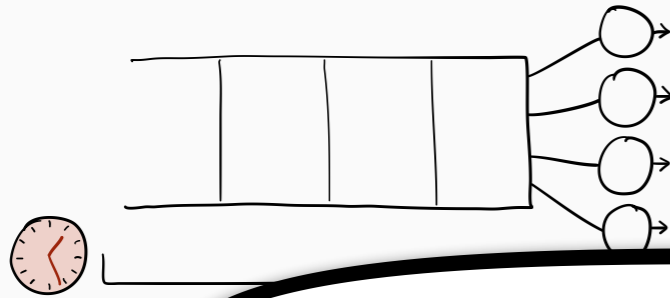
mean *r*-work
in M/G/*k*



mean *r*-work
in M/G/1



Response Time via *r*-Work



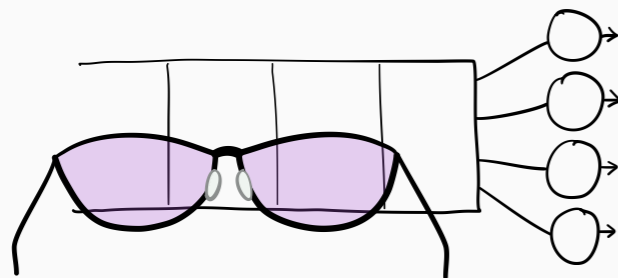
mean
response
time

Theorem:

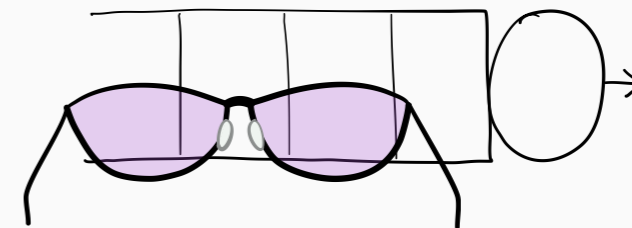
$$E[T] = \frac{1}{\lambda} \int_0^{\infty} \frac{E[W(r)]}{r^2} dr$$

mean response
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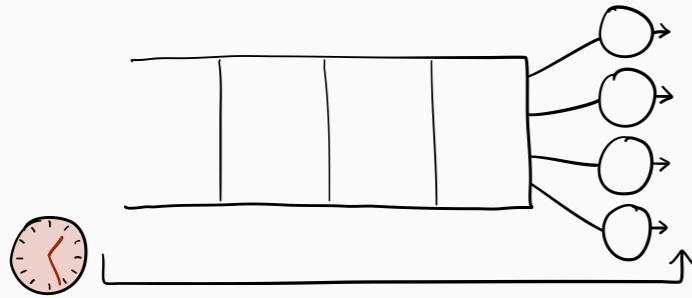
mean *r*-work
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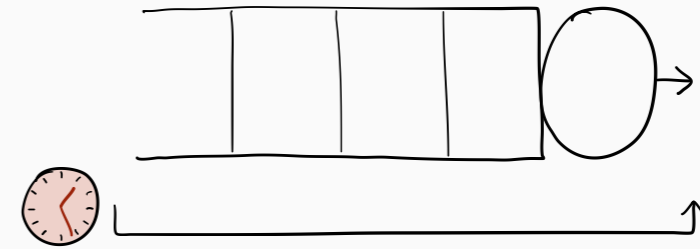
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Response Time via *r*-Work



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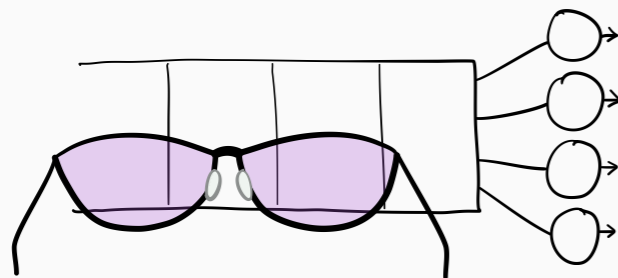


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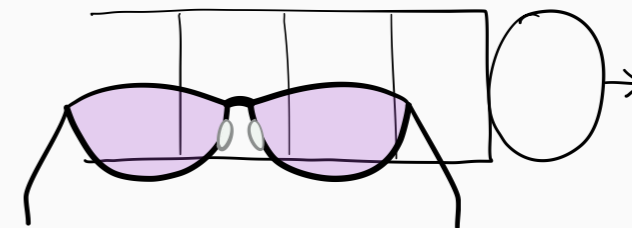
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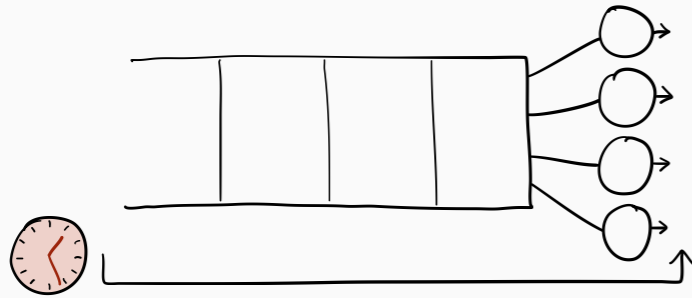
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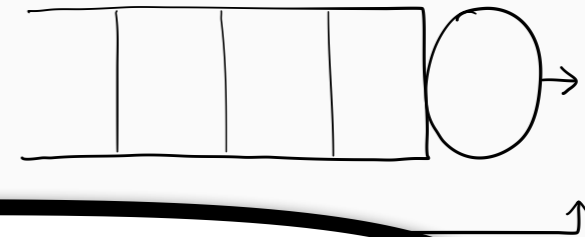
mean *r*-work
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Response Time via *r*-Work



mean response time in M/G/k



mean response time in M/G/1

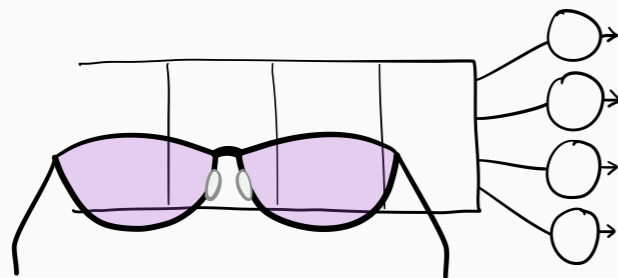
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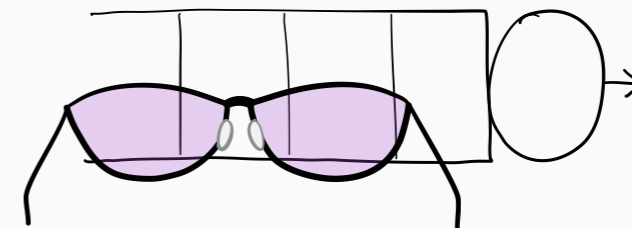
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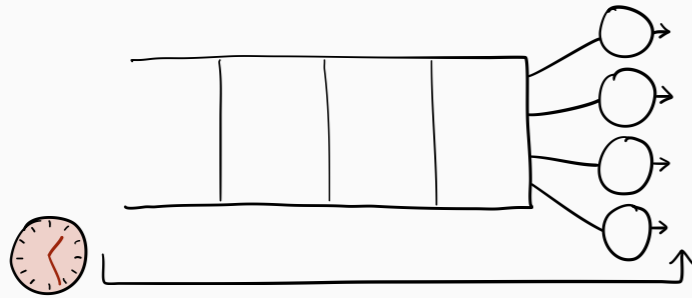
mean *r*-work in M/G/k



mean *r*-work in M/G/1



Response Time via *r*-Work

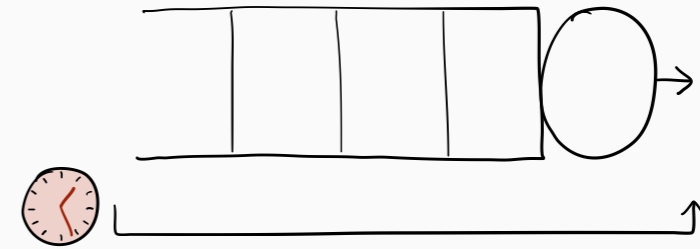
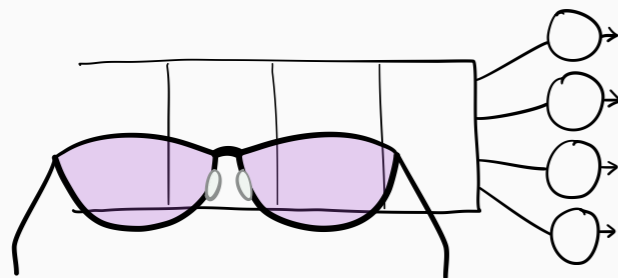


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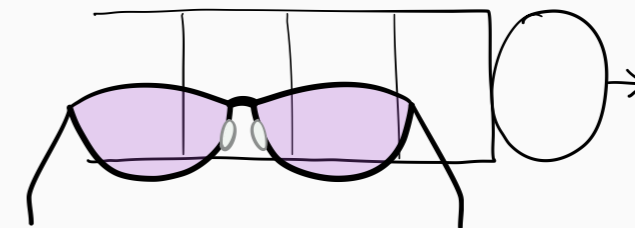


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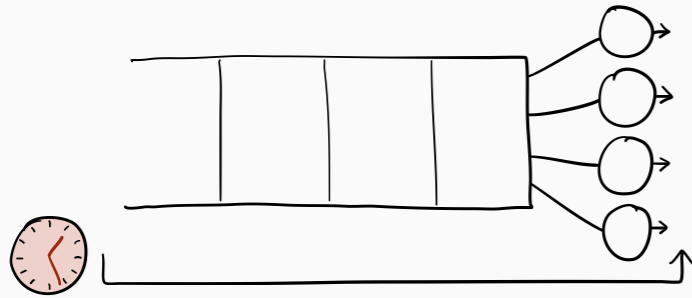
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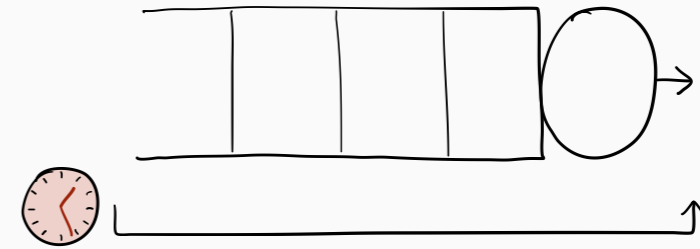
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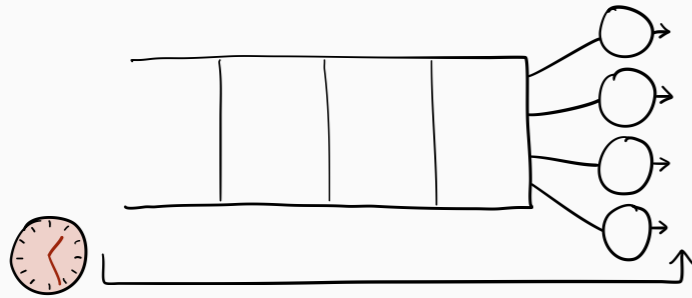
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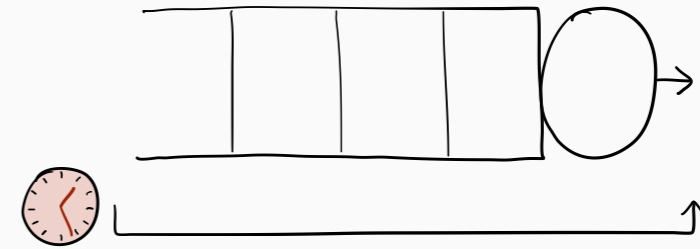


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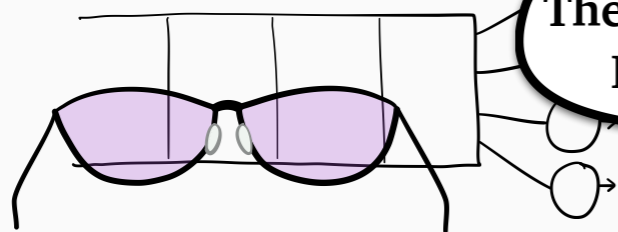


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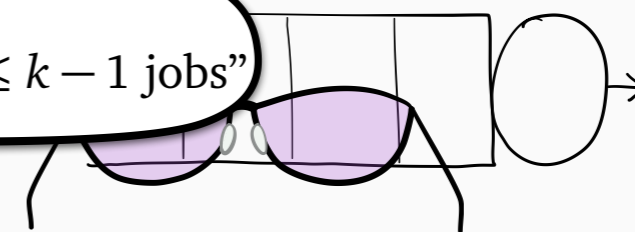
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mean *r-work*

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mean *r*-work

Holds for *any* queueing system:
M/G/k, G/G/k, load-balancing, ...

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New $E[T]$ Formula

Th

for **SRPT** case, in which
rank = remaining size

$$\frac{1}{\lambda} \int_0^{\infty} \frac{E[W(r)]}{r^2} dr$$

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Proof:

$$\int_0^{\infty} \frac{E[W(r)]}{r^2} dr = \int_0^{\infty} \frac{E\left[\sum_{i=1}^N \text{job } i\text{'s } r\text{-work}\right]}{r^2} dr$$

New $E[T]$ Formula

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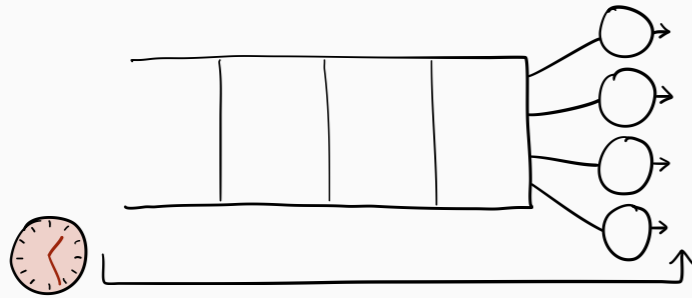
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Little's law

Response Time via *r*-Work

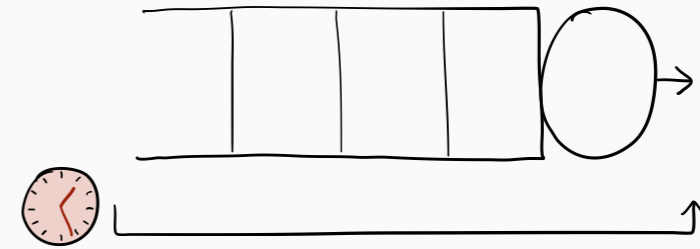


mean response time in M/G/k

Theorem:

$$E[T] = \frac{1}{\lambda} \int_0^{\infty} \frac{E[W(r)]}{r^2} dr$$

mean *r*-work in M/G/k

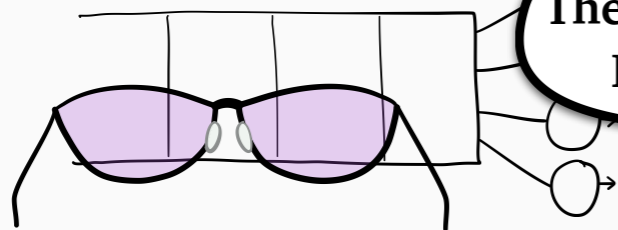


mean response time in M/G/1

Theorem:

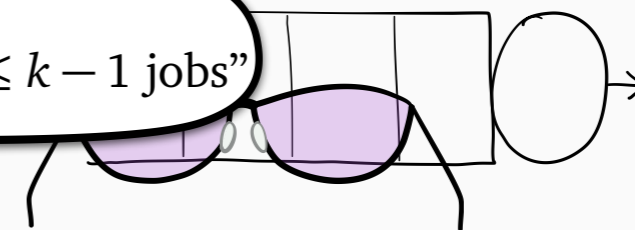
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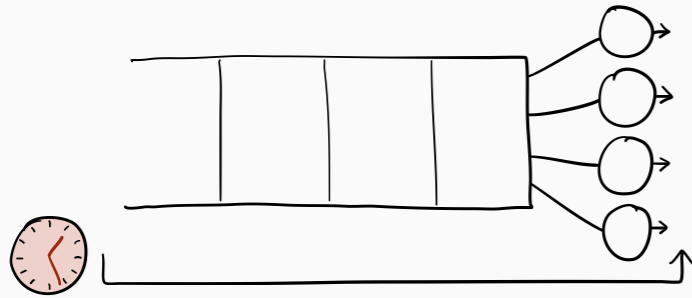


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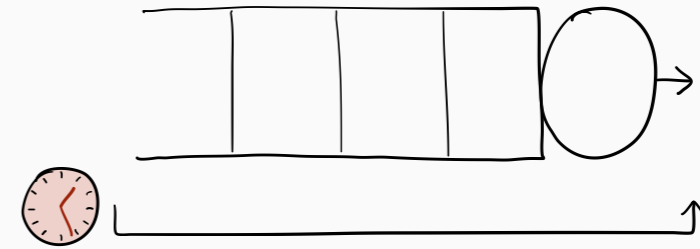
$$E[W_k(r)] = E[W_1(r)] + \text{"r-work of } \leq k - 1 \text{ jobs"}$$



Response Time via *r*-Work



mean response time in M/G/*k*



mean response time in M/G/1

✓

Theorem:

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mean *r*-work in M/G/*k*

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✓

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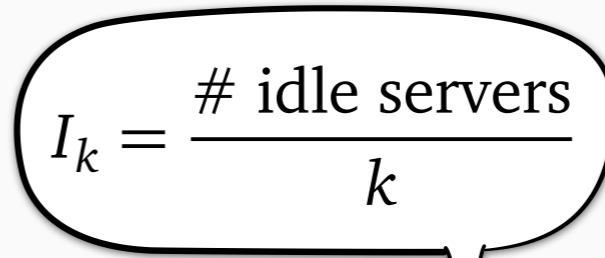
The diagram shows two queue configurations side-by-side. On the left is an M/G/k queue with four servers, and on the right is an M/G/1 queue with one server. Both diagrams have a pair of purple sunglasses drawn over the server area.

Work in $M/G/k$ vs. $M/G/1$

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Theorem:
$$\mathbf{E}[W_k] = \mathbf{E}[W_1] + \frac{\mathbf{E}[I_k W_k]}{1 - \rho}$$

Work in M/G/k vs. M/G/1

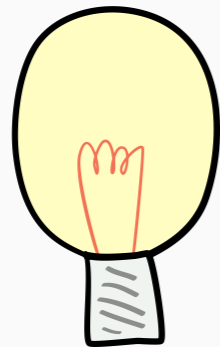

$$I_k = \frac{\# \text{ idle servers}}{k}$$

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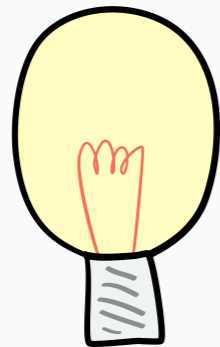


Whenever $I_k > 0$, a server is idle, so system has at most $k - 1$ jobs

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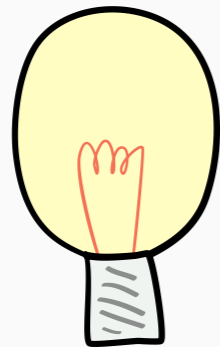
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“work of $\leq k - 1$ jobs”



Whenever $I_k > 0$, a server is idle, so system has at most $k - 1$ jobs

Can generalize to *any* system with Poisson arrivals

r-Work in M/G/*k* vs. M/G/1

Theorem:

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r-Work in M/G/*k* vs. M/G/1

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Theorem:

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r-Work in M/G/*k* vs. M/G/1

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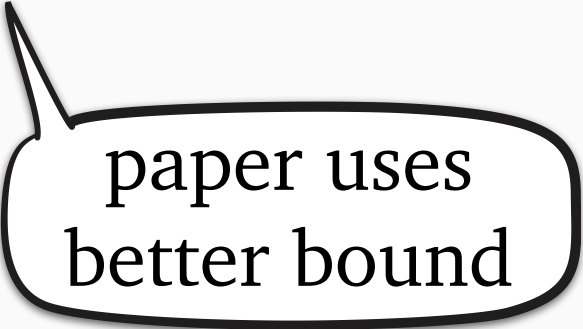
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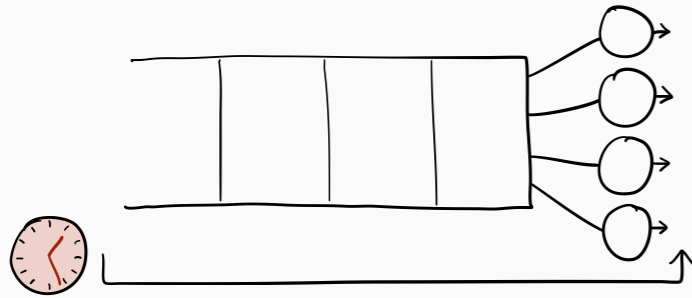
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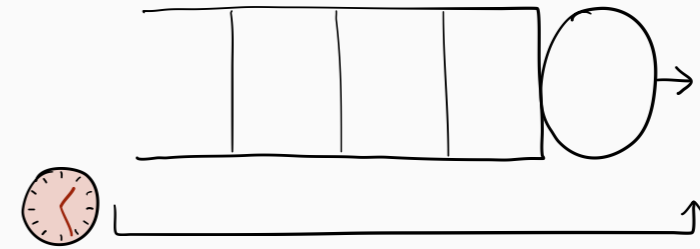


paper uses
better bound

Response Time via *r*-Work



mean response time in M/G/k



mean response time in M/G/1

✓

Theorem:

$$E[T] = \frac{1}{\lambda} \int_0^{\infty} \frac{E[W(r)]}{r^2} dr$$

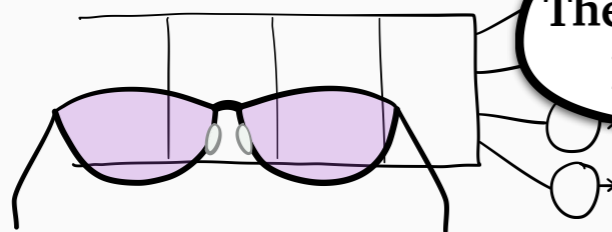
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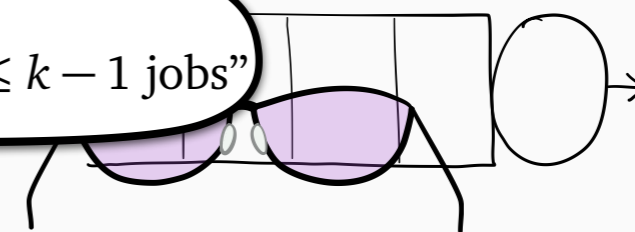
✓

mean *r*-work in M/G/1

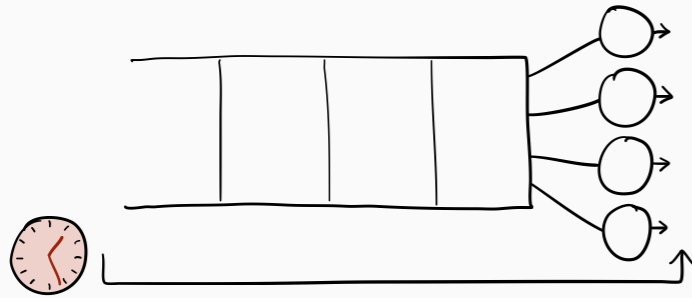


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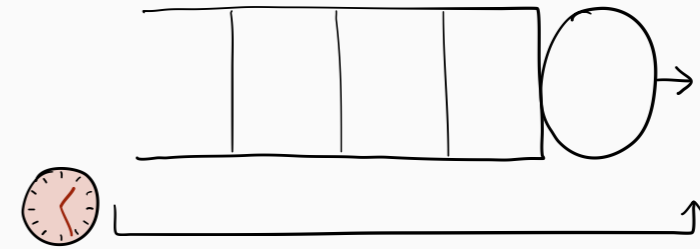
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Response Time via *r*-Work



mean response time in M/G/k



mean response time in M/G/1

✓

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mean *r*-work in M/G/k

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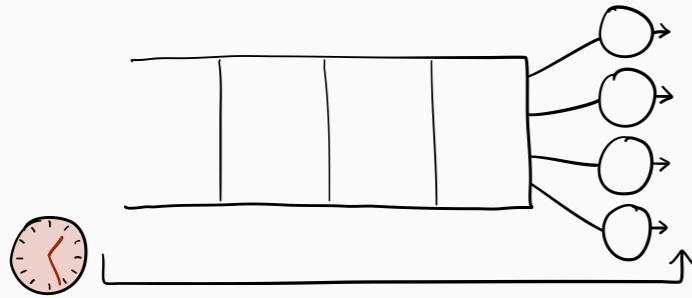
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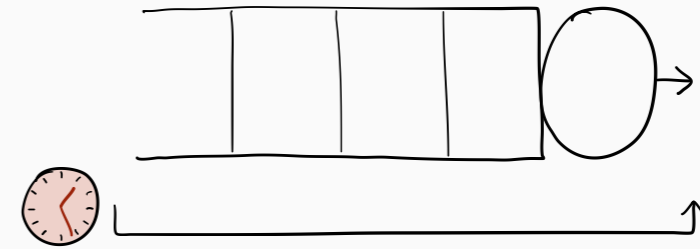
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$$E[T] = \frac{1}{\lambda} \int_0^{\infty} \frac{E[W(r)]}{r^2} dr$$

mean *r*-work in M/G/*k*

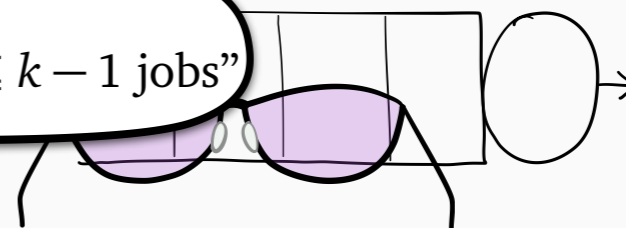
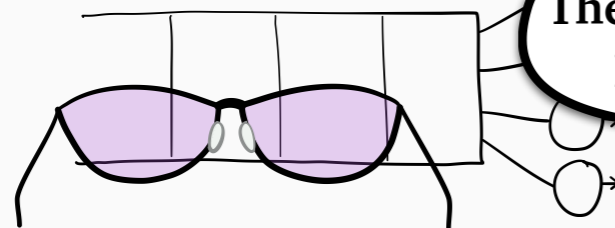
Theorem:

$$E[T] = \frac{1}{\lambda} \int_0^{\infty} \frac{E[W(r)]}{r^2} dr$$

mean *r*-work in M/G/1

Theorem:

$$E[W_k(r)] = E[W_1(r)] + \text{"r-work of } \leq k - 1 \text{ jobs"}$$



Summary

? Minimize $E[T]$ in $M/G/k$
without known job sizes

Summary

? Minimize $E[T]$ in M/G/k
without known job sizes

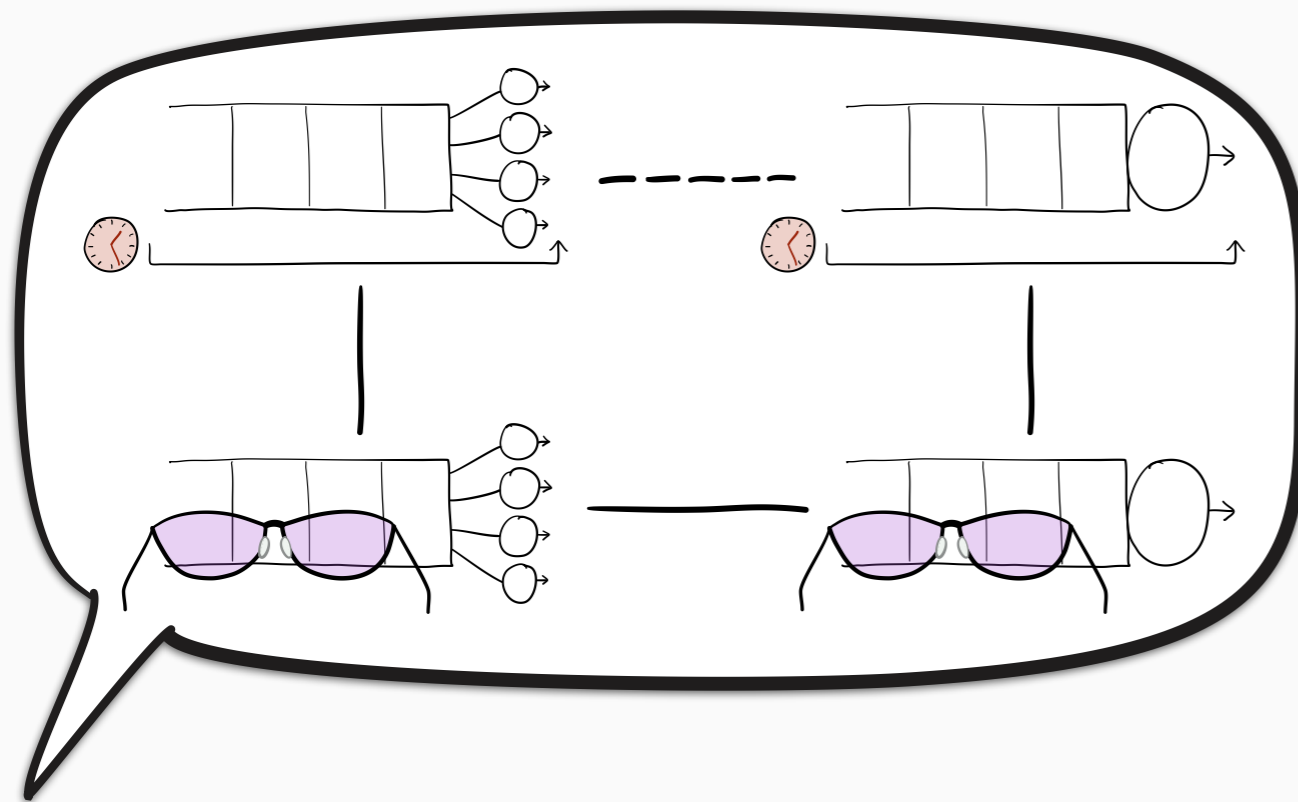


Prior M/G/k techniques
need known job sizes

Summary

? Minimize $E[T]$ in M/G/k without known job sizes

! Prior M/G/k techniques need known job sizes

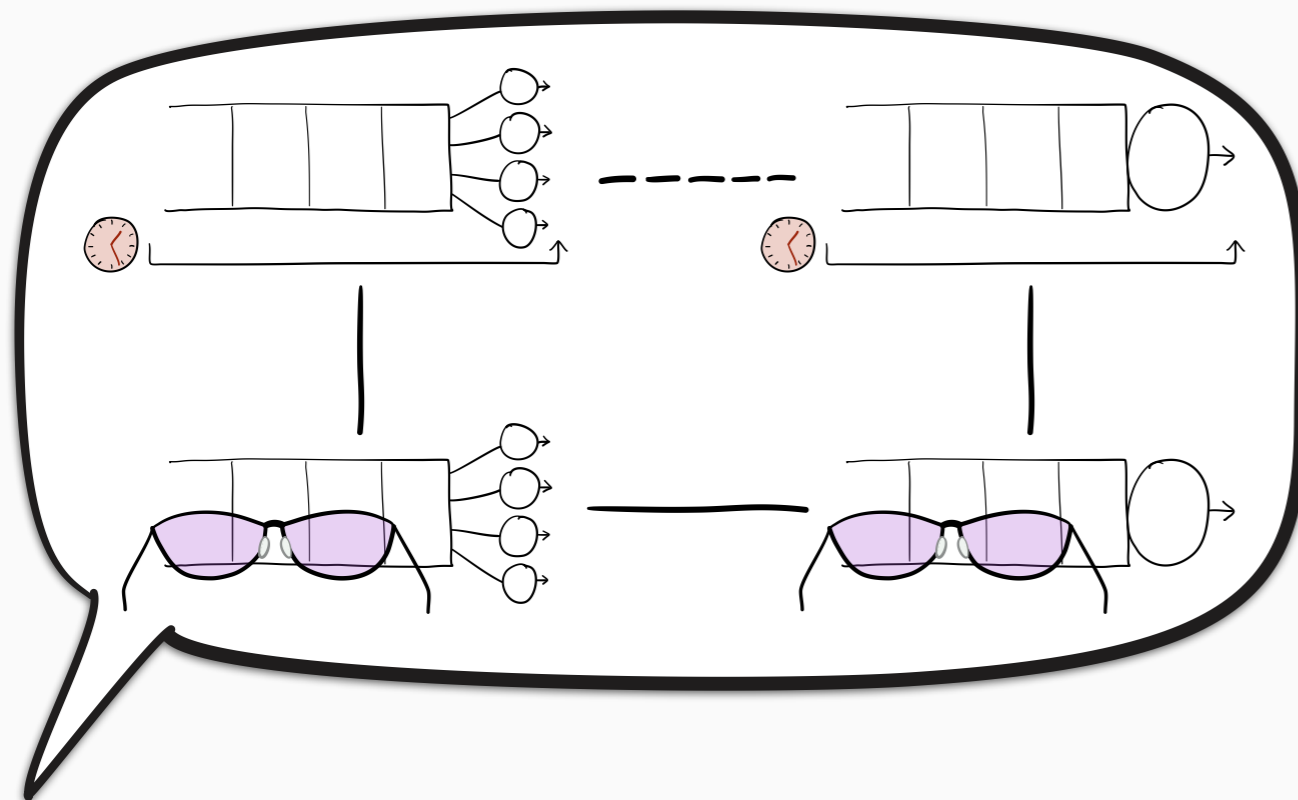


💡 New technique based on relating $E[T]$ to *r-work*

Summary

? Minimize $E[T]$ in M/G/k without known job sizes

! Prior M/G/k techniques need known job sizes



💡 New technique based on relating $E[T]$ to *r-work*

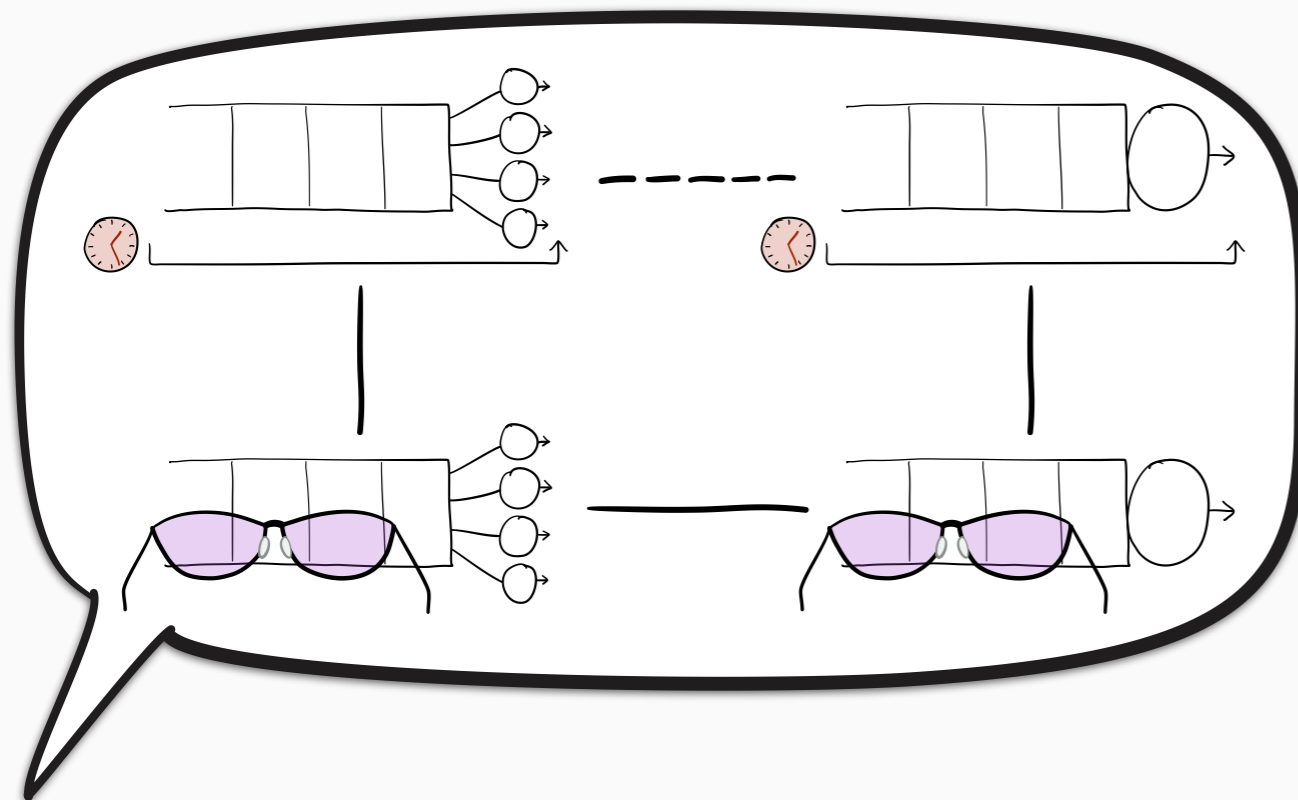
$$E[T_k] \leq E[T_1] + (k-1) \cdot O\left(\log \frac{1}{1-\rho}\right)$$

🏆 **Gittins** has near-optimal $E[T]$ in M/G/k

Summary

? Minimize $E[T]$ in M/G/k without known job sizes

! Prior M/G/k techniques need known job sizes



💡 New technique based on relating $E[T]$ to **r-work**

$$E[T_k] \leq E[T_1] + (k-1) \cdot O\left(\log \frac{1}{1-\rho}\right)$$

🏆 **Gittins** has near-optimal $E[T]$ in M/G/k

Get in touch: zscully@cs.cmu.edu

Bonus Slides

Levels of Size Information

less info

more info



Levels of Size Information

less info

more info



Known Size

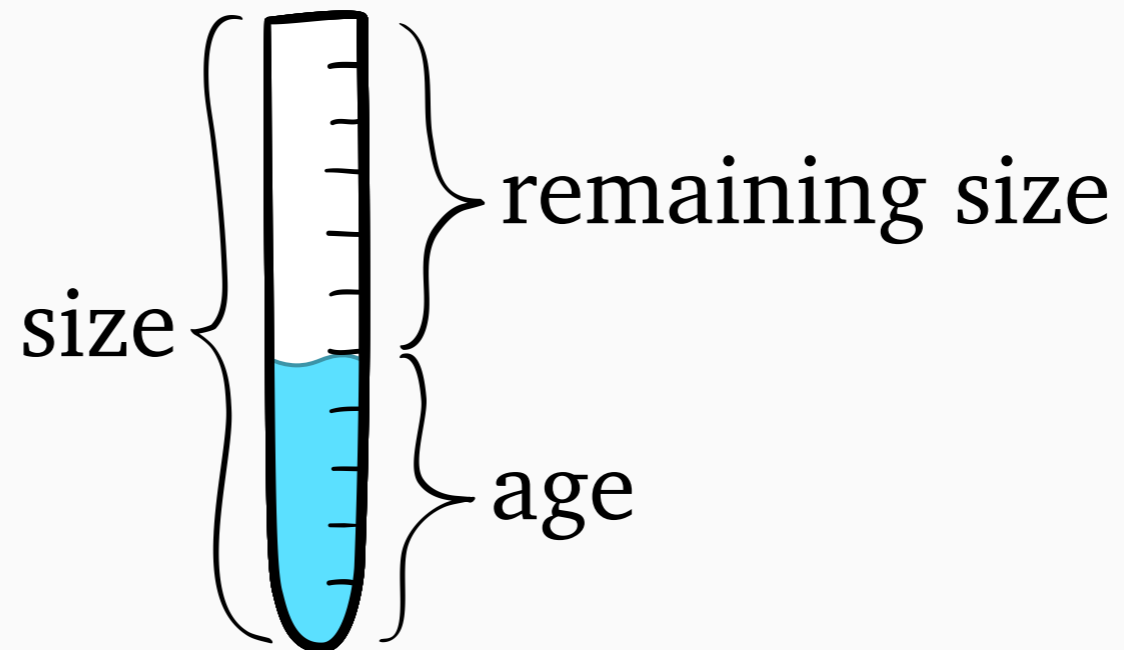
Levels of Size Information

less info

more info



Known Size



Levels of Size Information

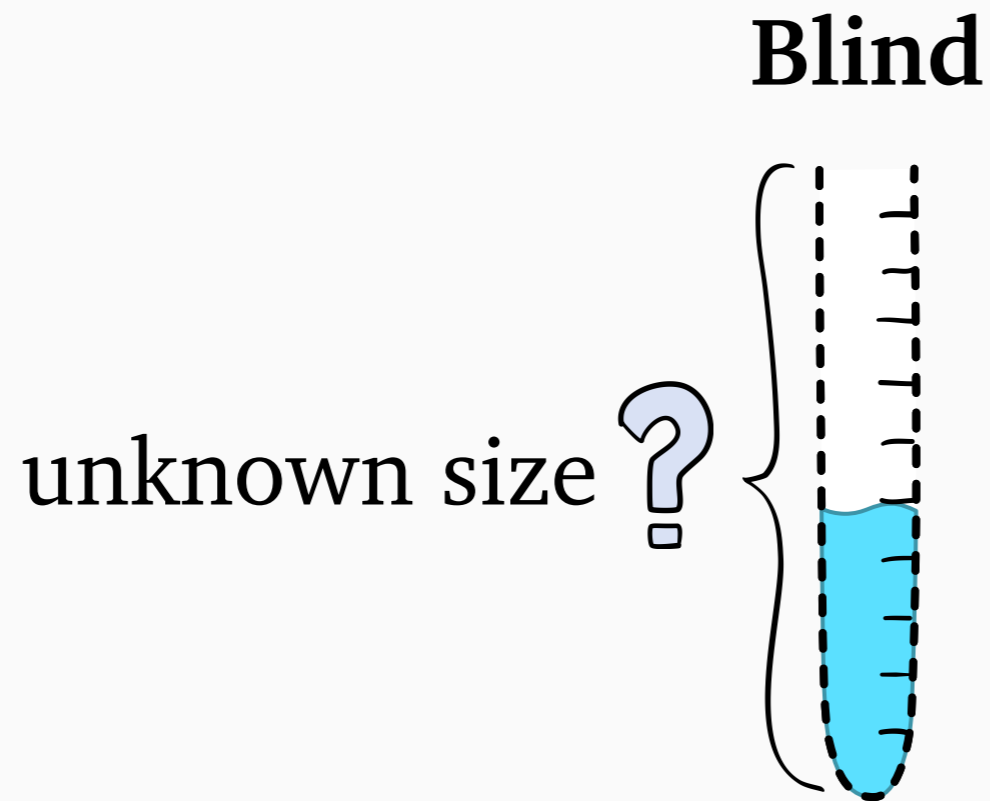


Levels of Size Information

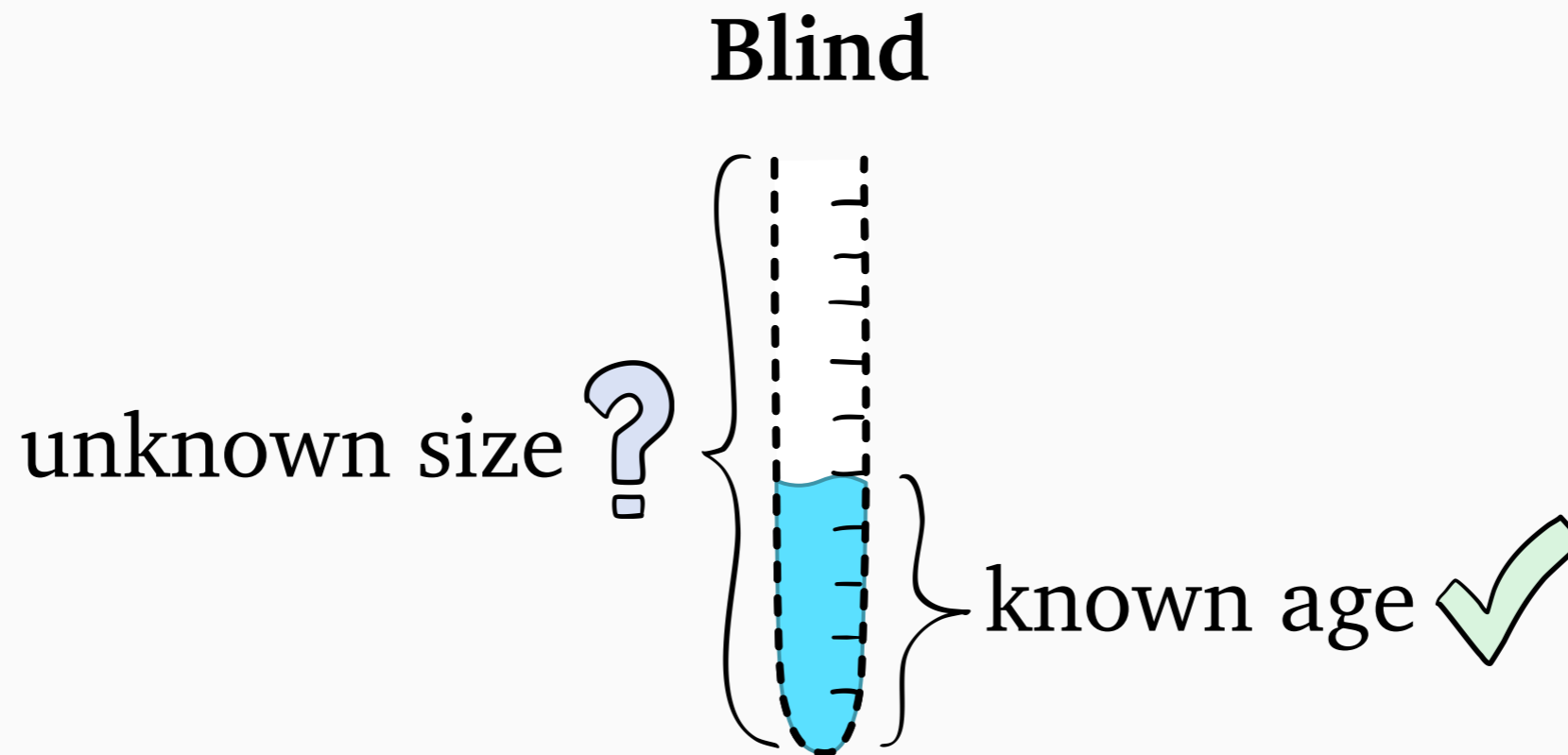


Blind

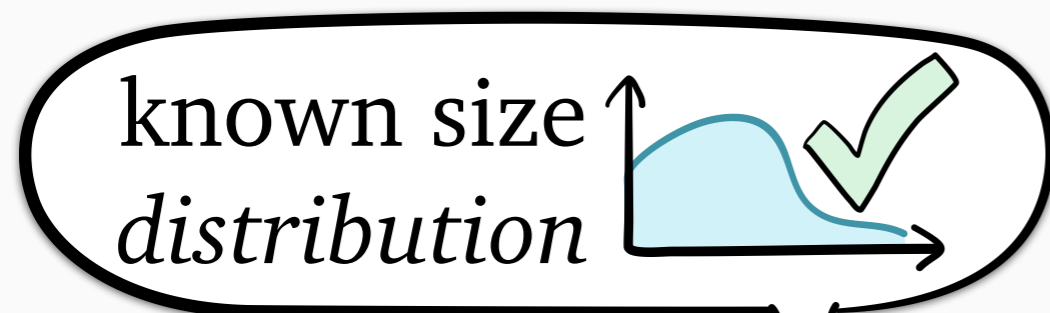
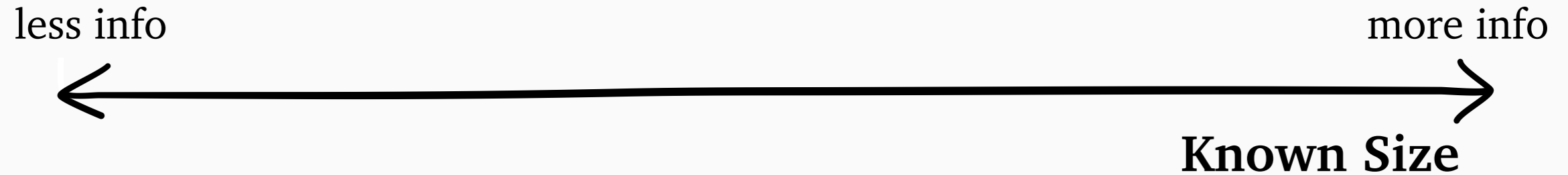
Levels of Size Information



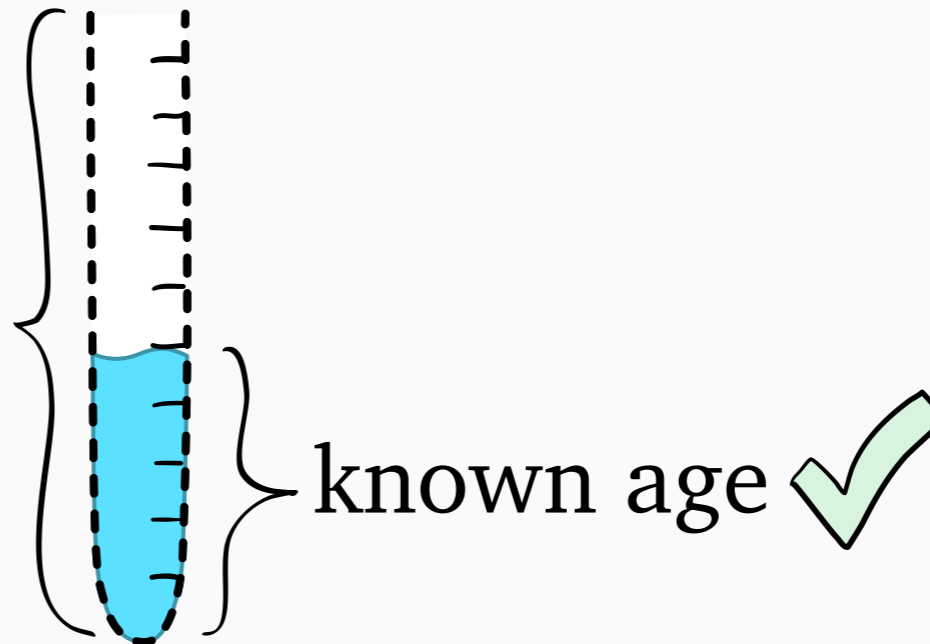
Levels of Size Information



Levels of Size Information



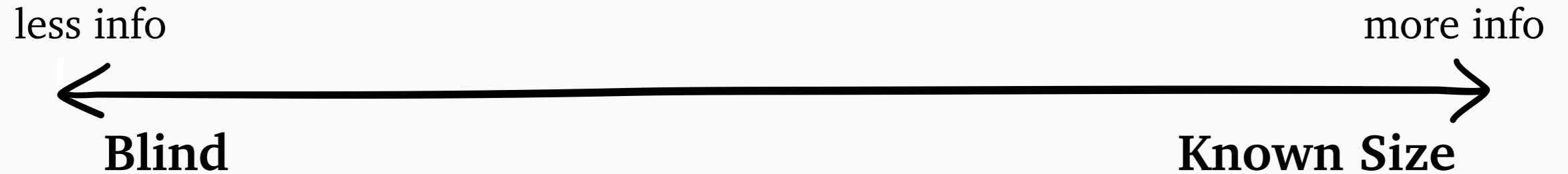
Blind



Levels of Size Information



Levels of Size Information

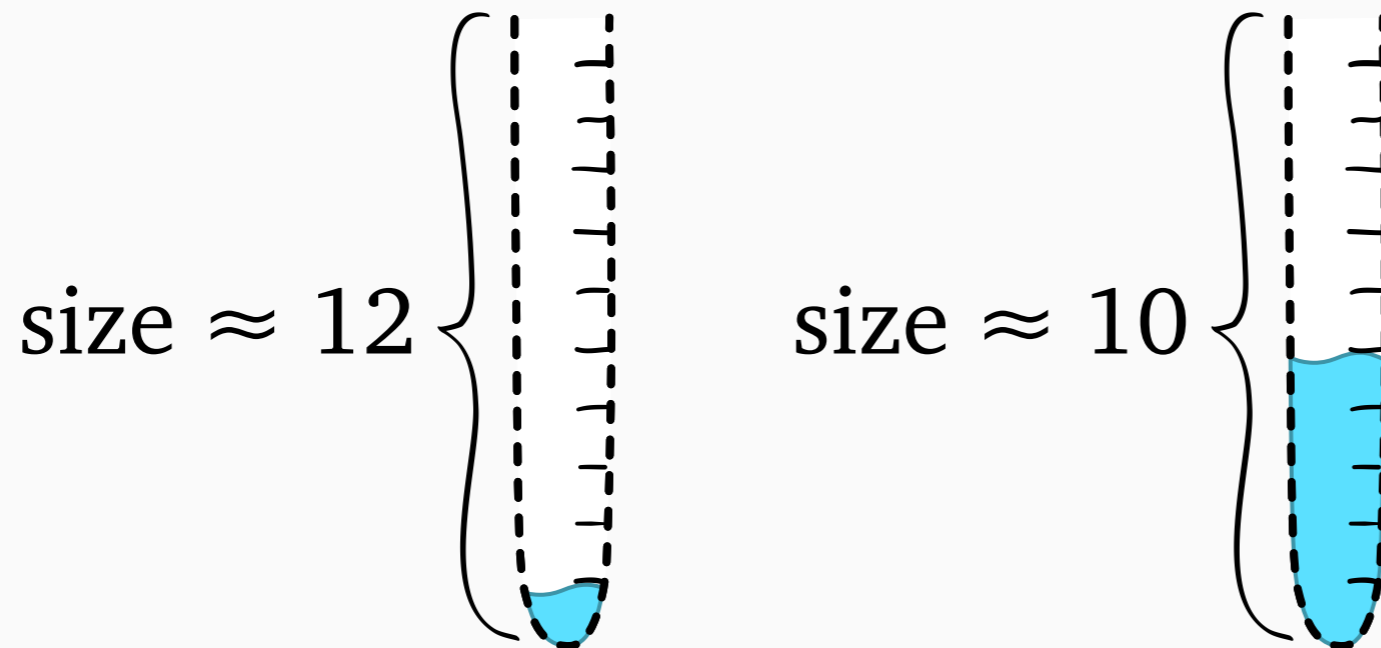


Noisy Estimates

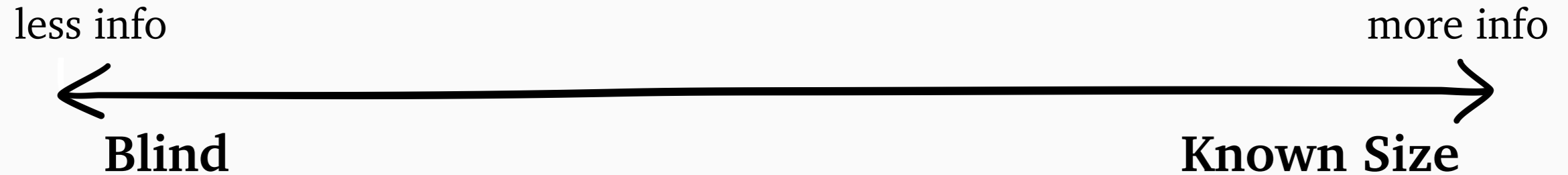
Levels of Size Information



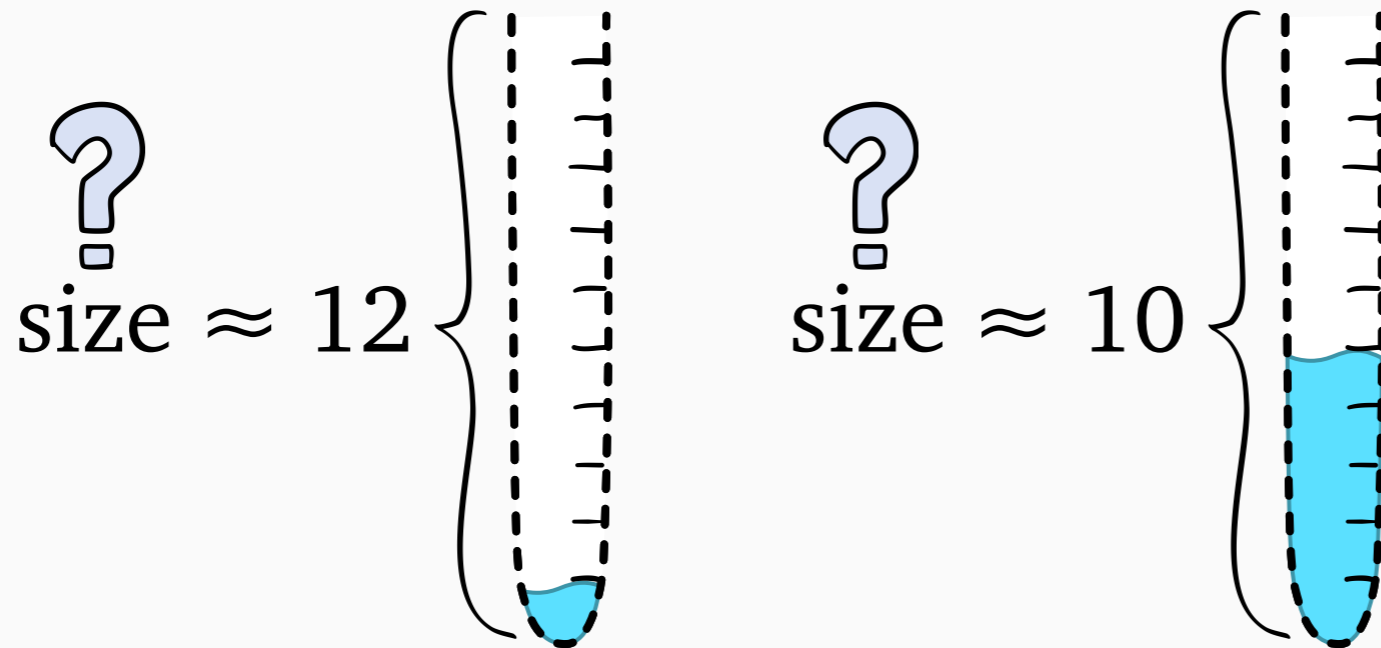
Noisy Estimates



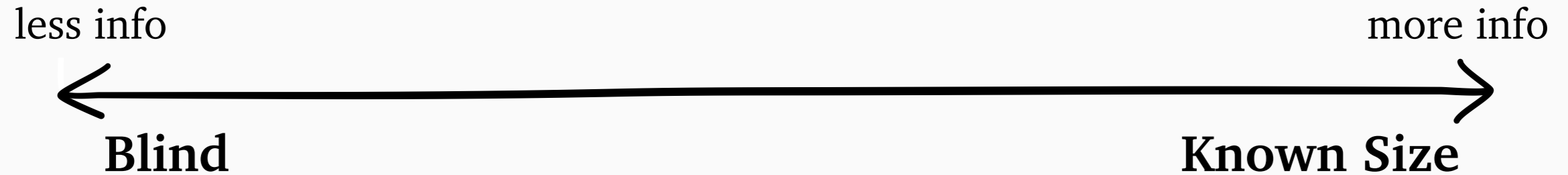
Levels of Size Information



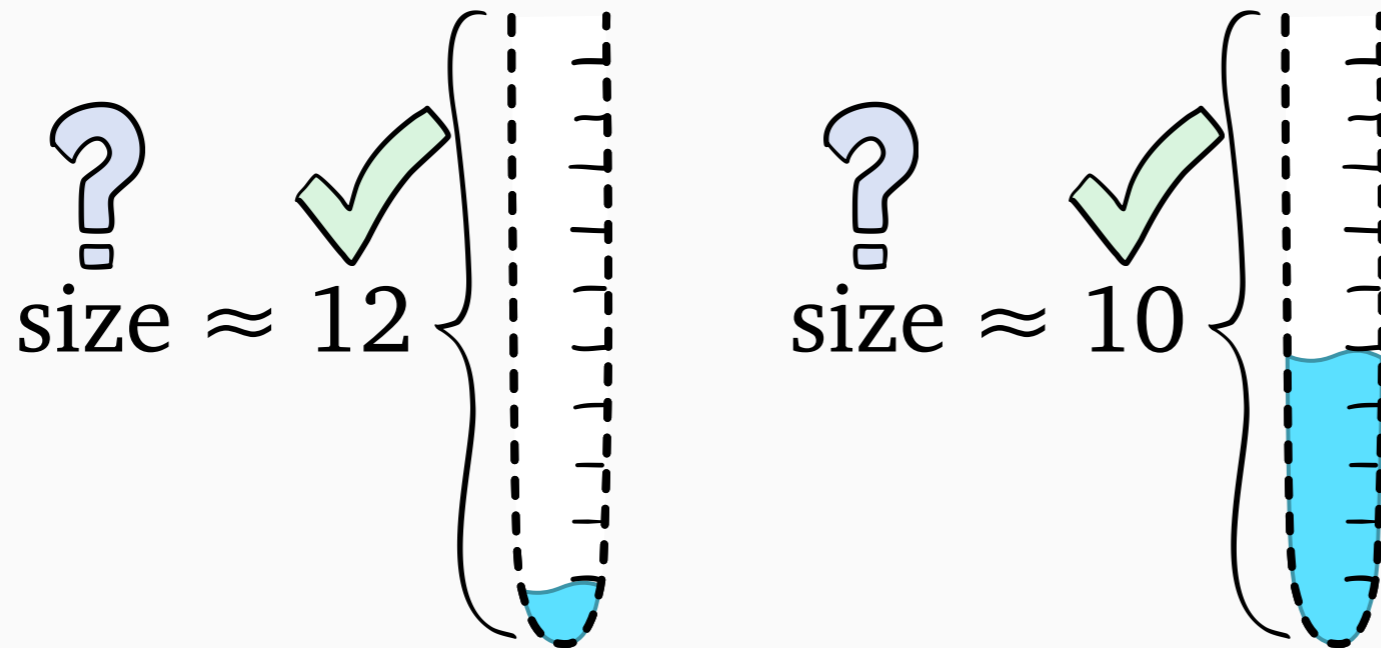
Noisy Estimates



Levels of Size Information



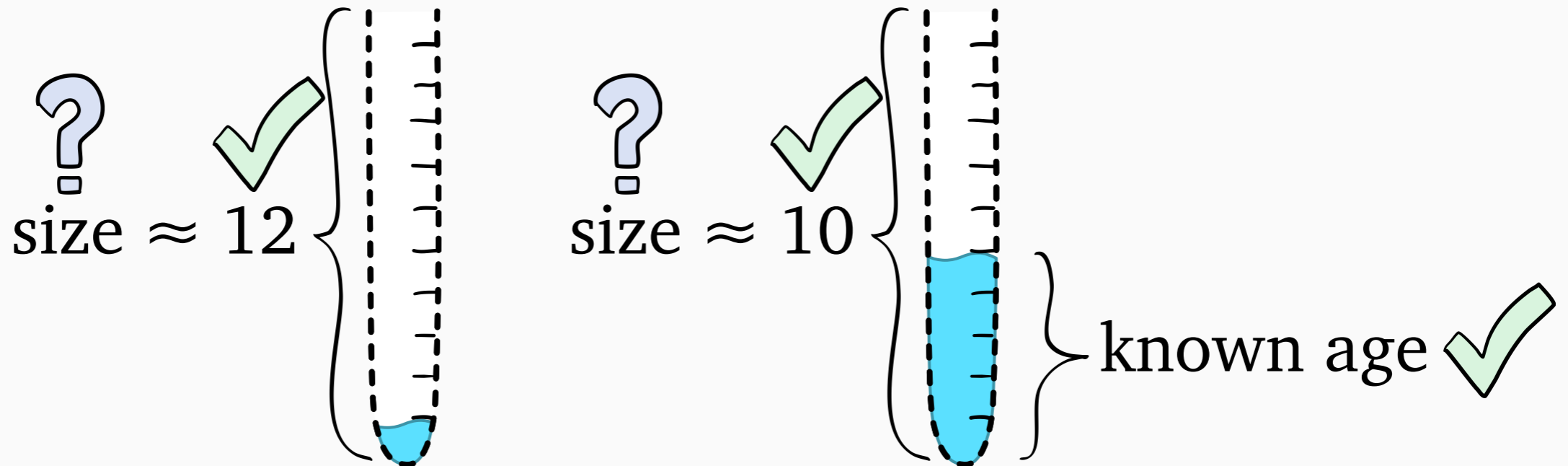
Noisy Estimates



Levels of Size Information



Noisy Estimates



Levels of Size Information

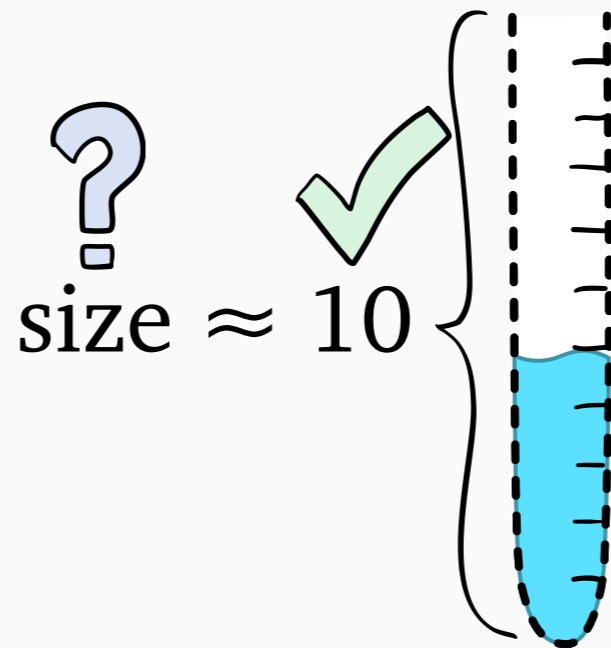
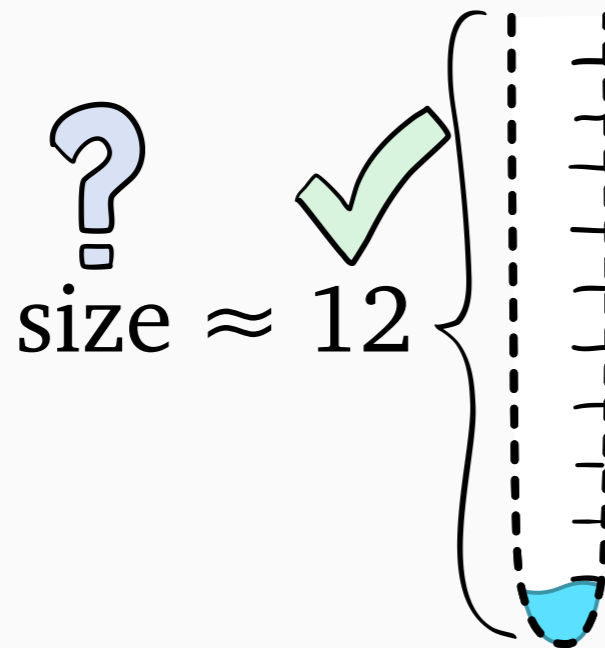


Blind

known joint distribution of true/estimated sizes ✓

Known Size

Noisy Estimates

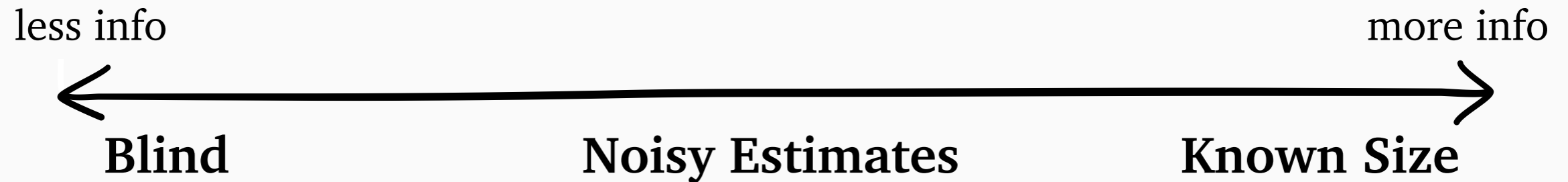


known age ✓

Levels of Size Information

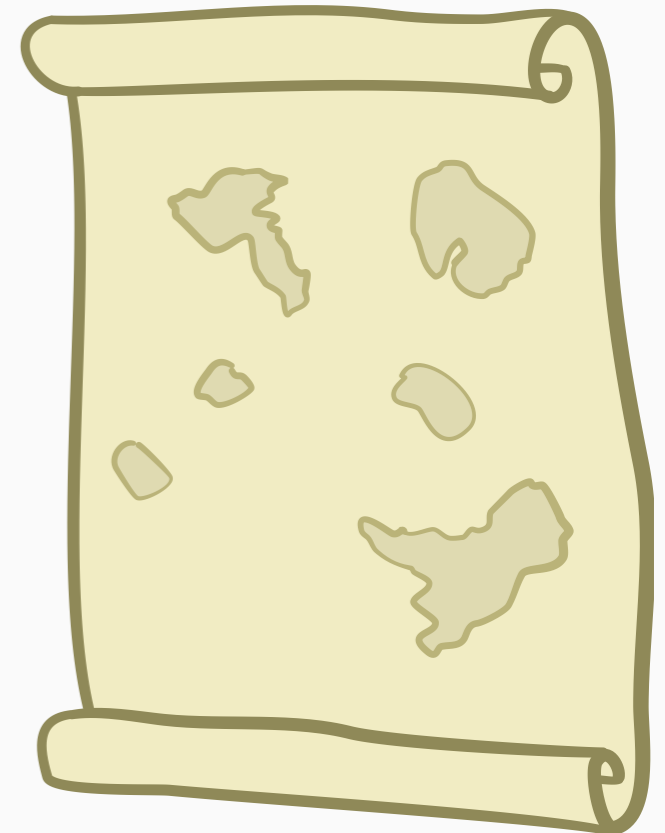


Levels of Size Information



General case: a job is a *Markov process*

 *general state space*



Levels of Size Information



General case: a job is a *Markov process*

 general *state space*

 job's *state* encodes all known info



Levels of Size Information

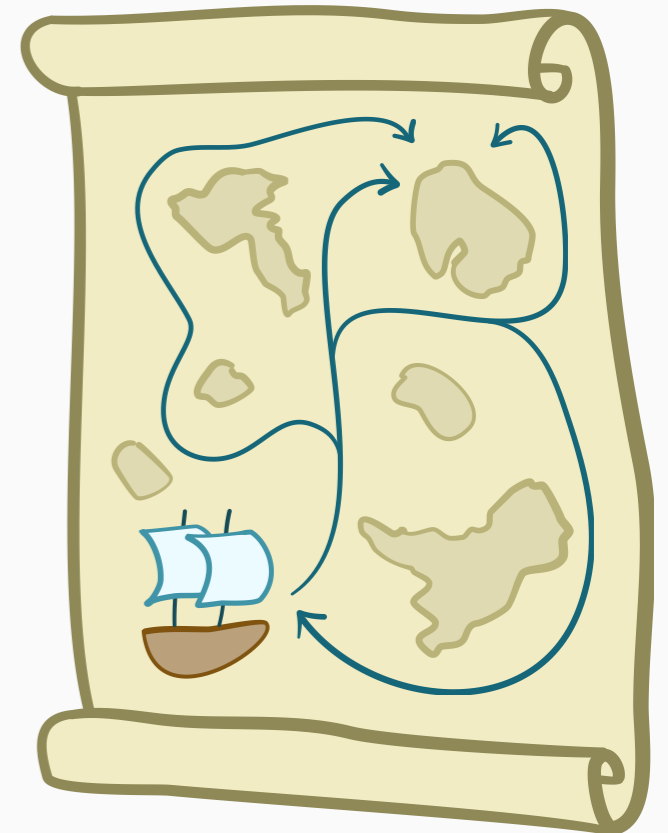


General case: a job is a *Markov process*

 general *state space*

 job's *state* encodes all known info

 *state* *stochastically evolves* with service



Levels of Size Information



General case: a job is a *Markov process*



general *state space*



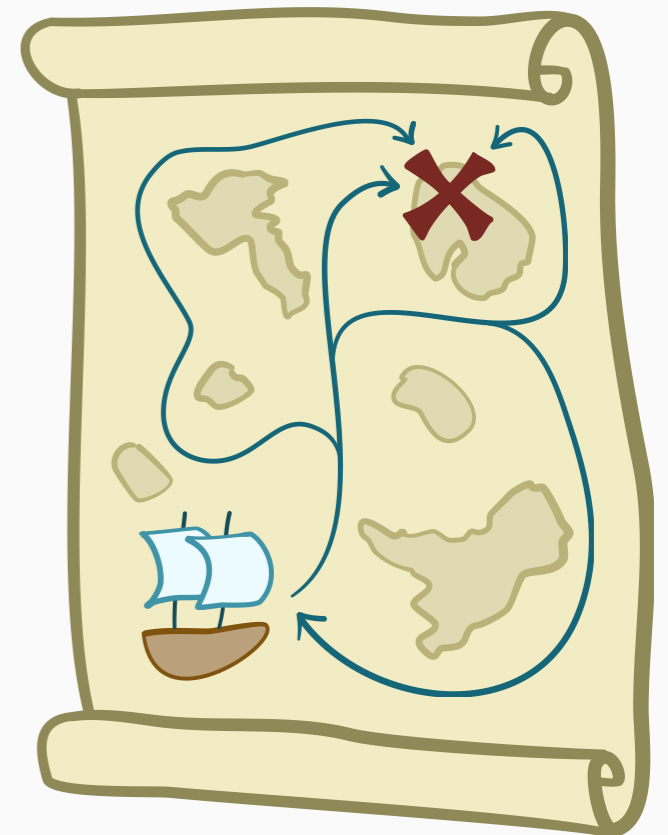
job's *state* encodes all known info



state *stochastically evolves* with service







completes upon entering *goal state*

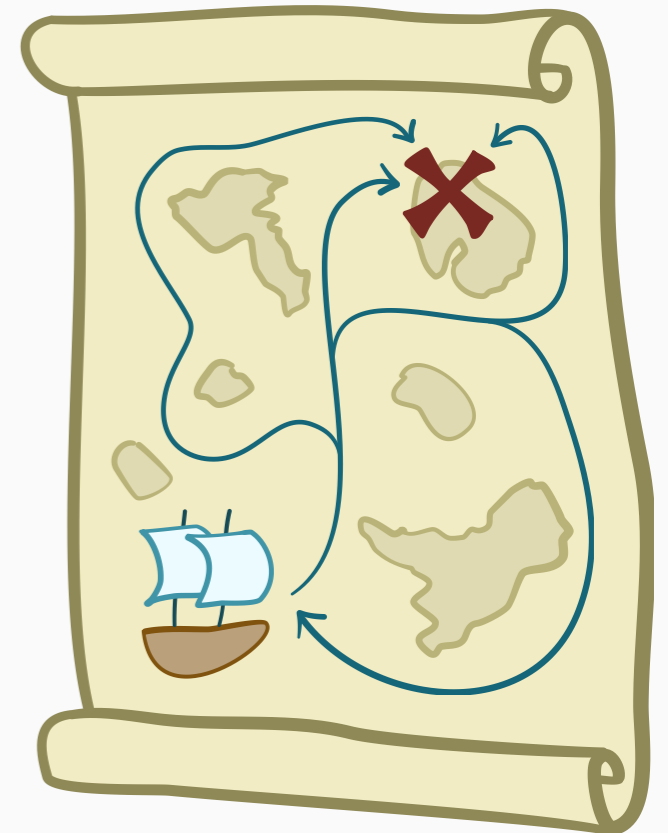


Levels of Size Information



General case: a job is a *Markov process*









- ✓  general *state space*
- ✓  job's *state* encodes all known info
-  *state* *stochastically evolves* with service
- ✓  completes upon entering *goal state*

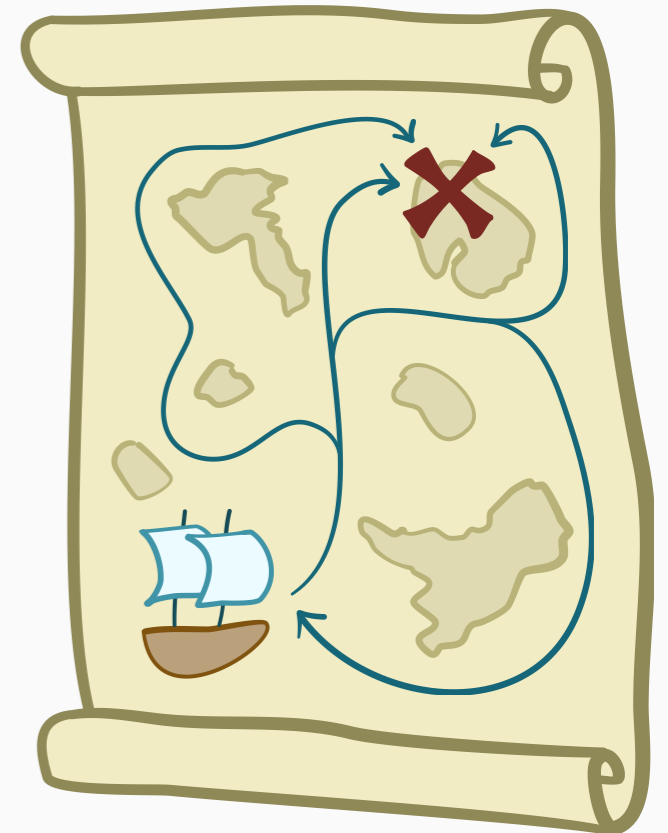


Levels of Size Information



General case: a job is a *Markov process*

-   general *state space*
-   job's *state* encodes all known info
-   *state* *stochastically evolves* with service
-   completes upon entering *goal state*



Levels of Size Information



General case: a job is a *Markov process*

- ✓ general *state space*
- ✓ job's *state* encodes all known info
- ? *state* stochastically evolves with service
- ✗ complete upon entering goal *state*

but *probabilities*
known ✓

