Optimal Multiserver Scheduling

with Unknown Job Sizes in Heavy Traffic

Ziv Scully Isaac Grosof Mor Harchol-Balter

Carnegie Mellon University

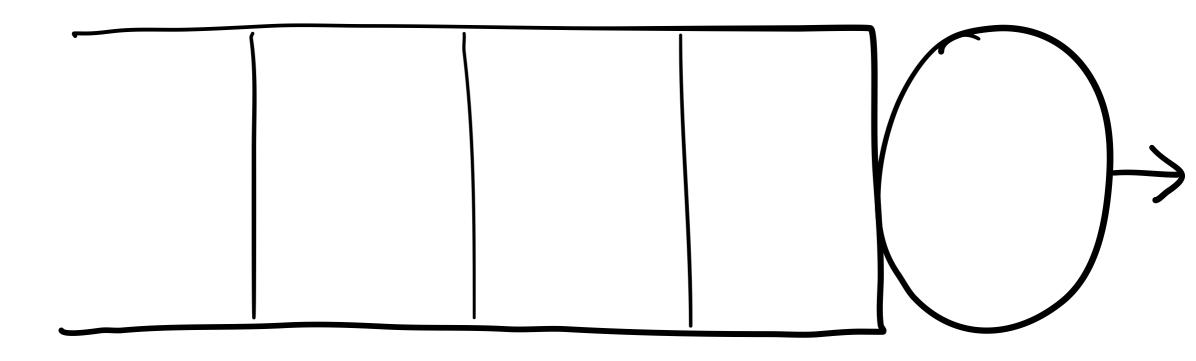


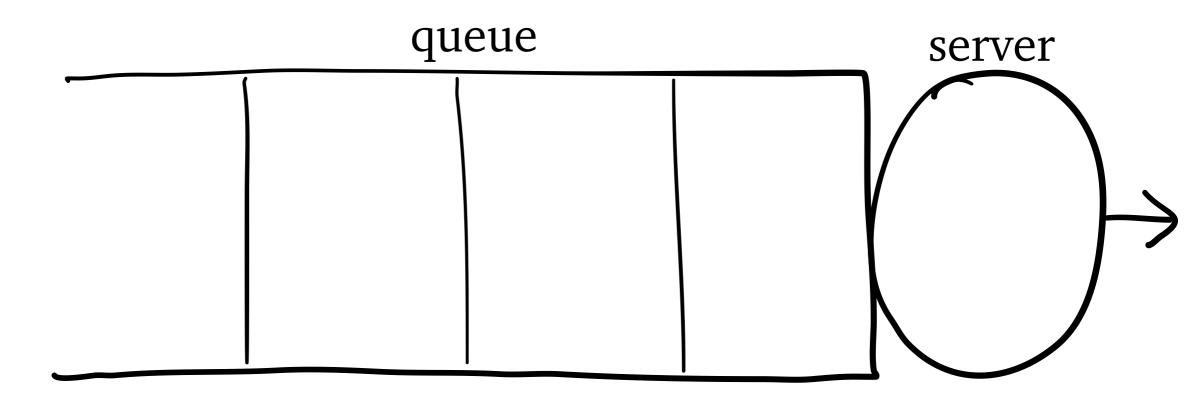
M/G/k Optimal Multiserver Scheduling with Unknown Job Sizes in Heavy Traffic

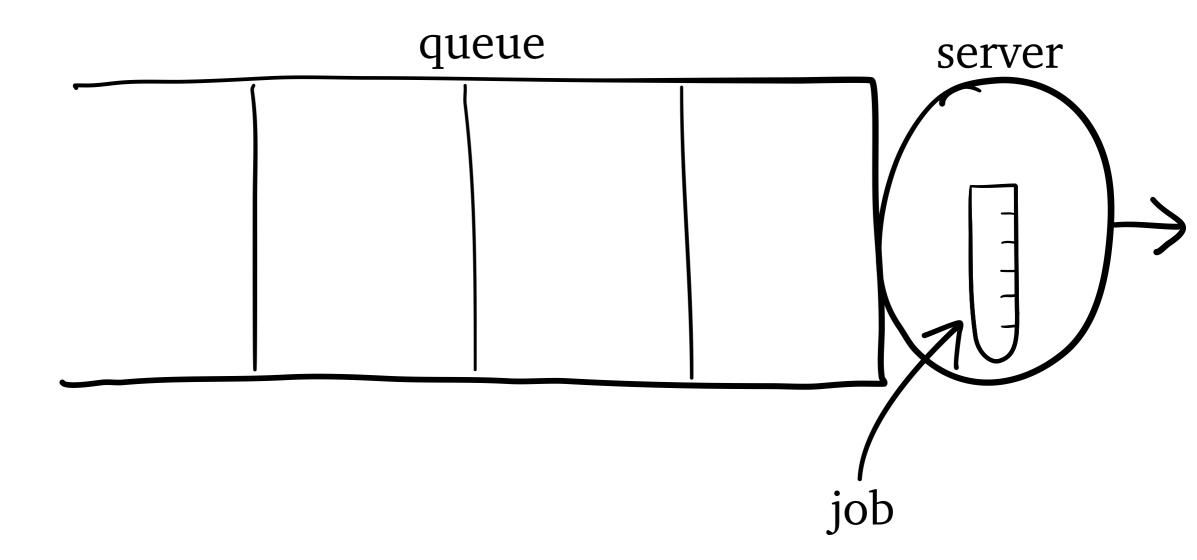
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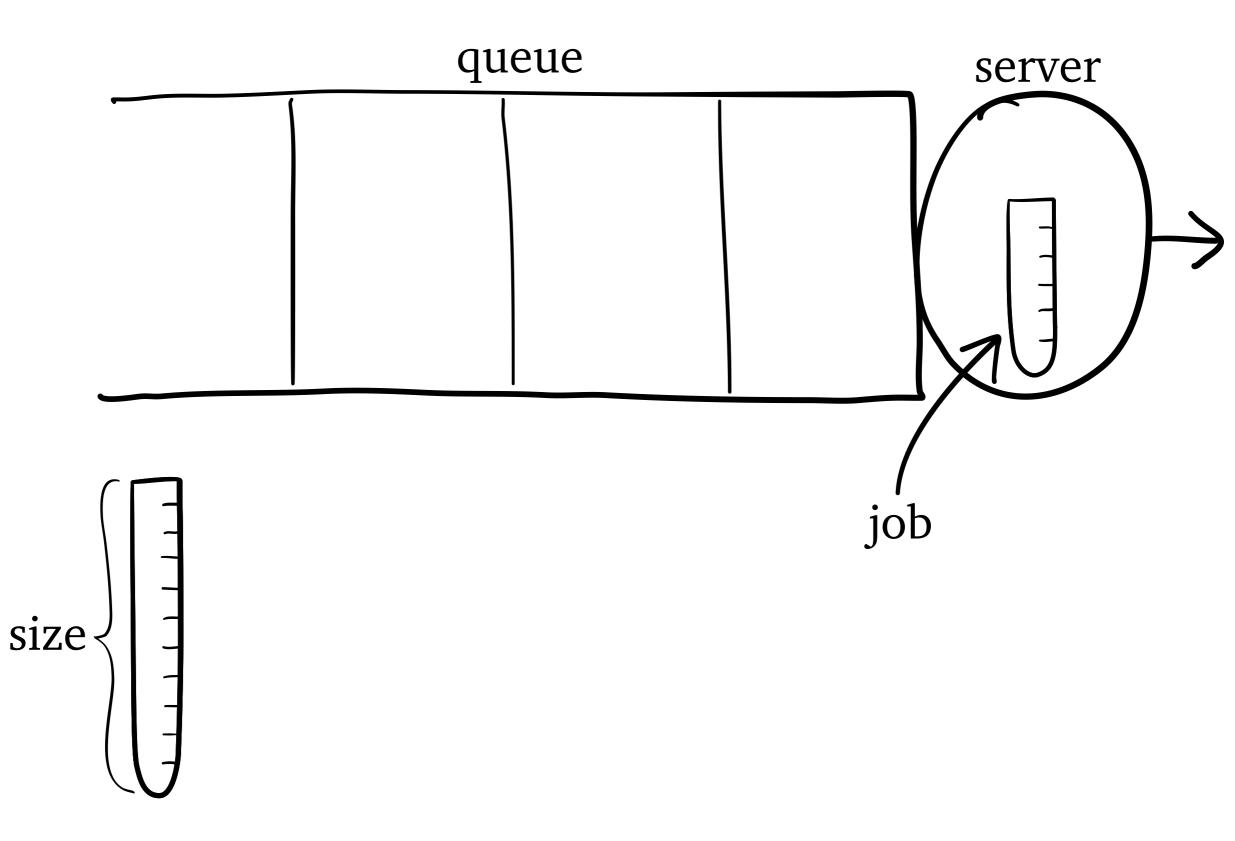
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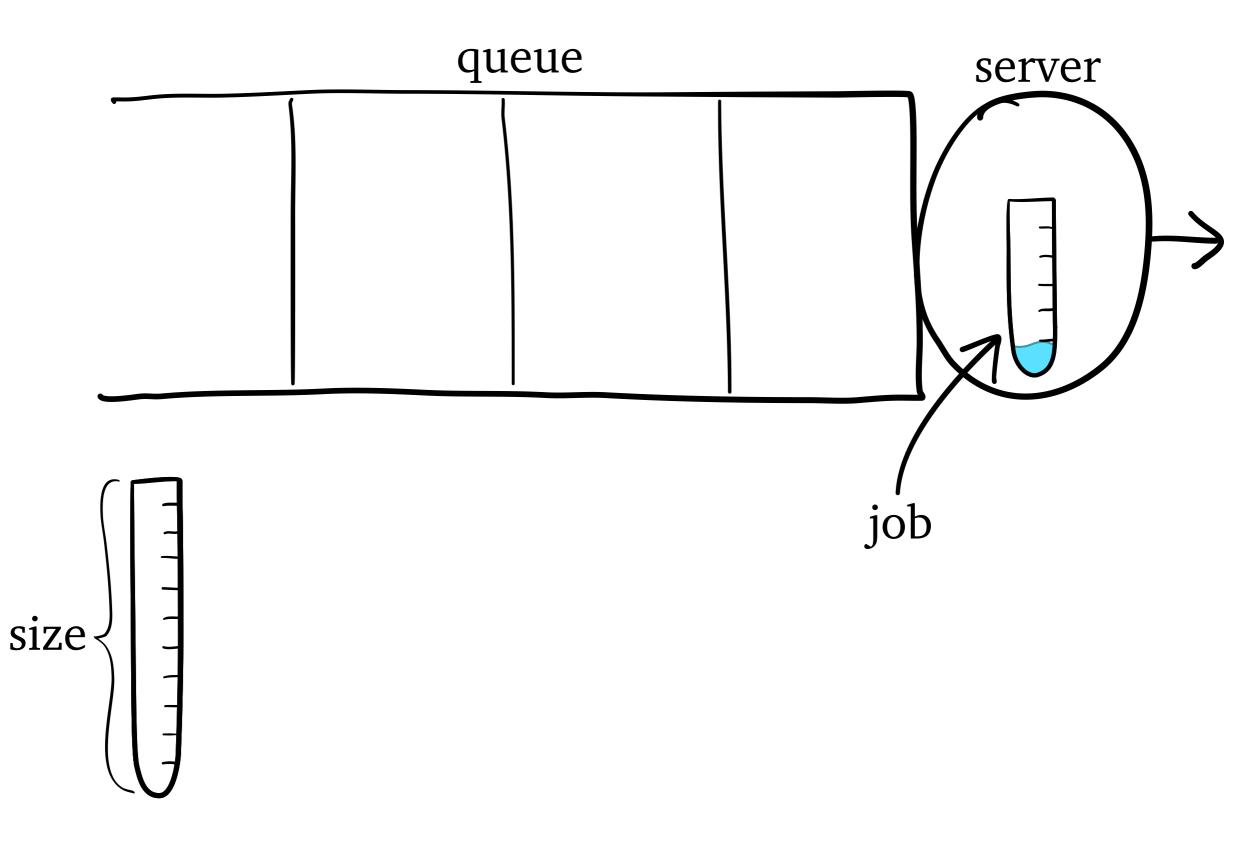


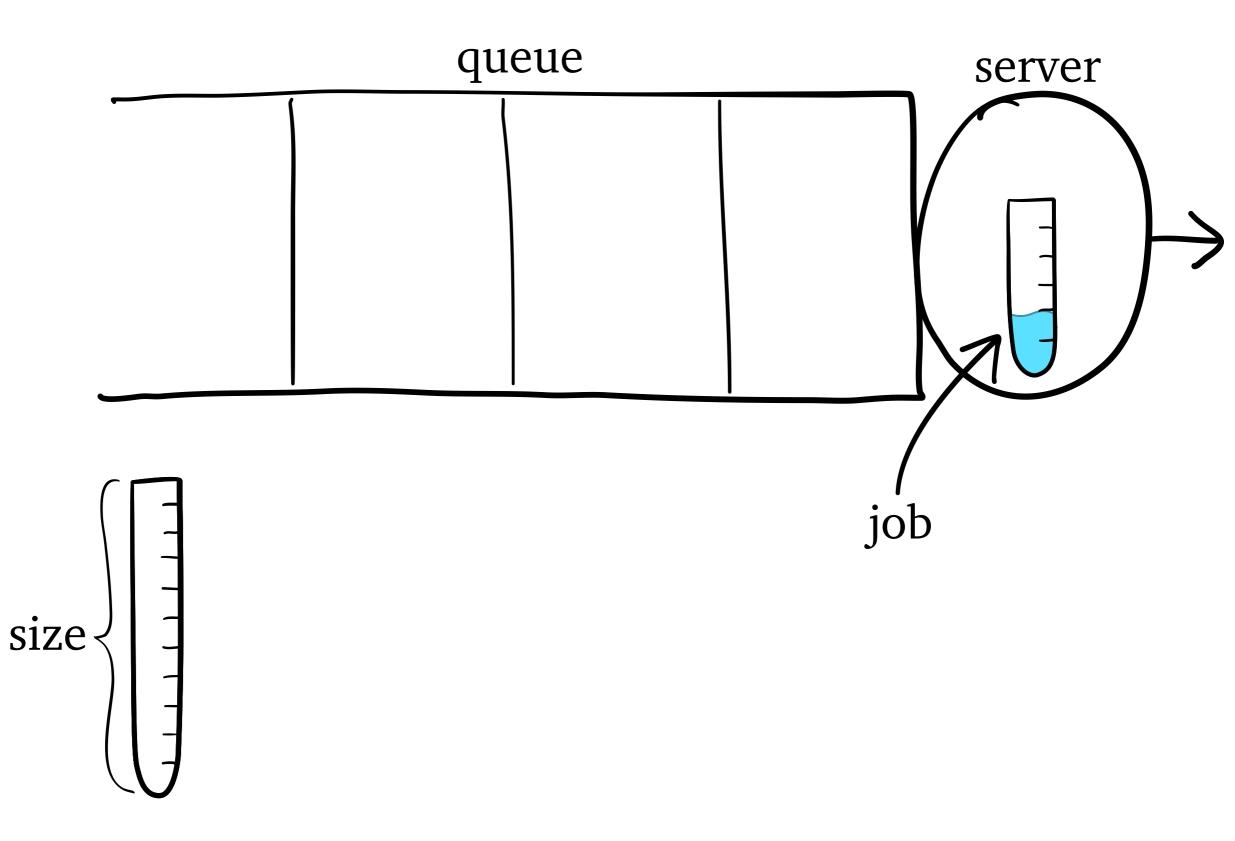


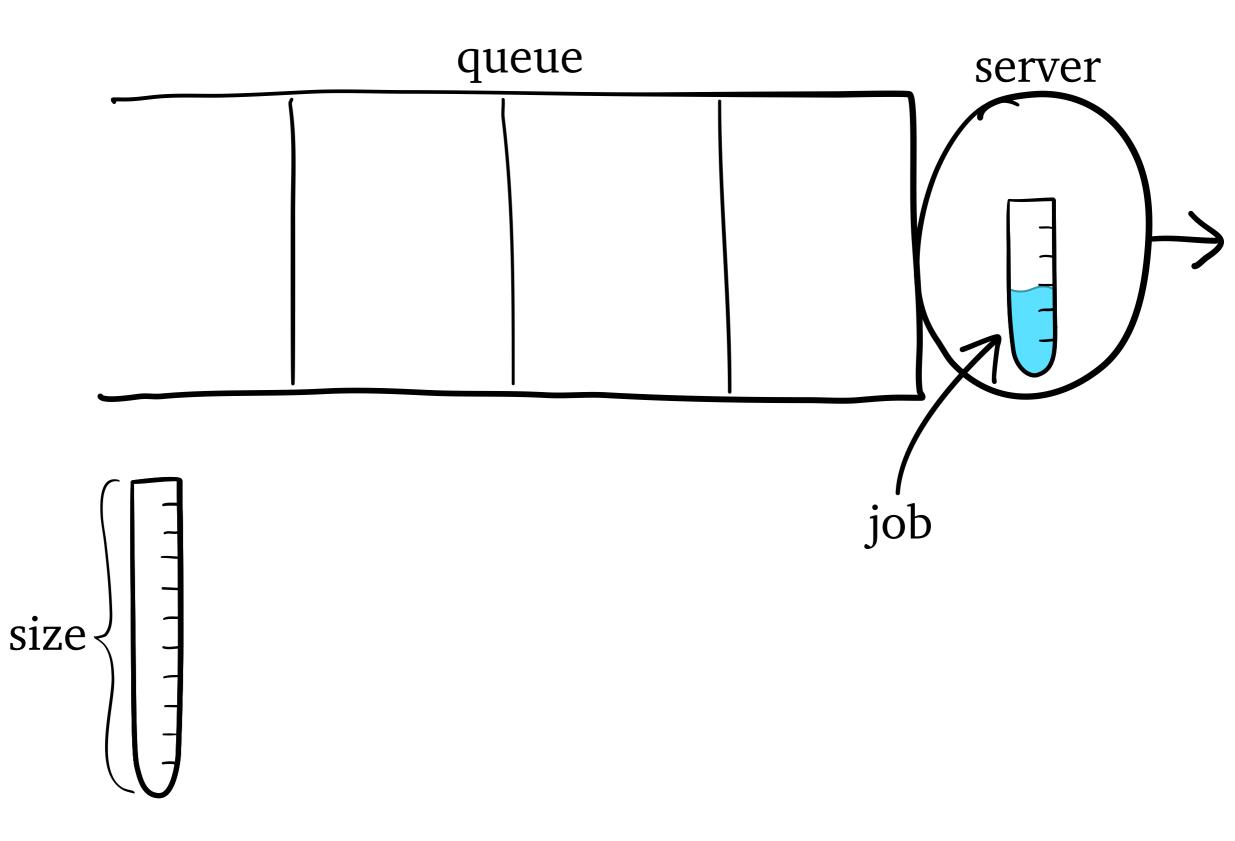


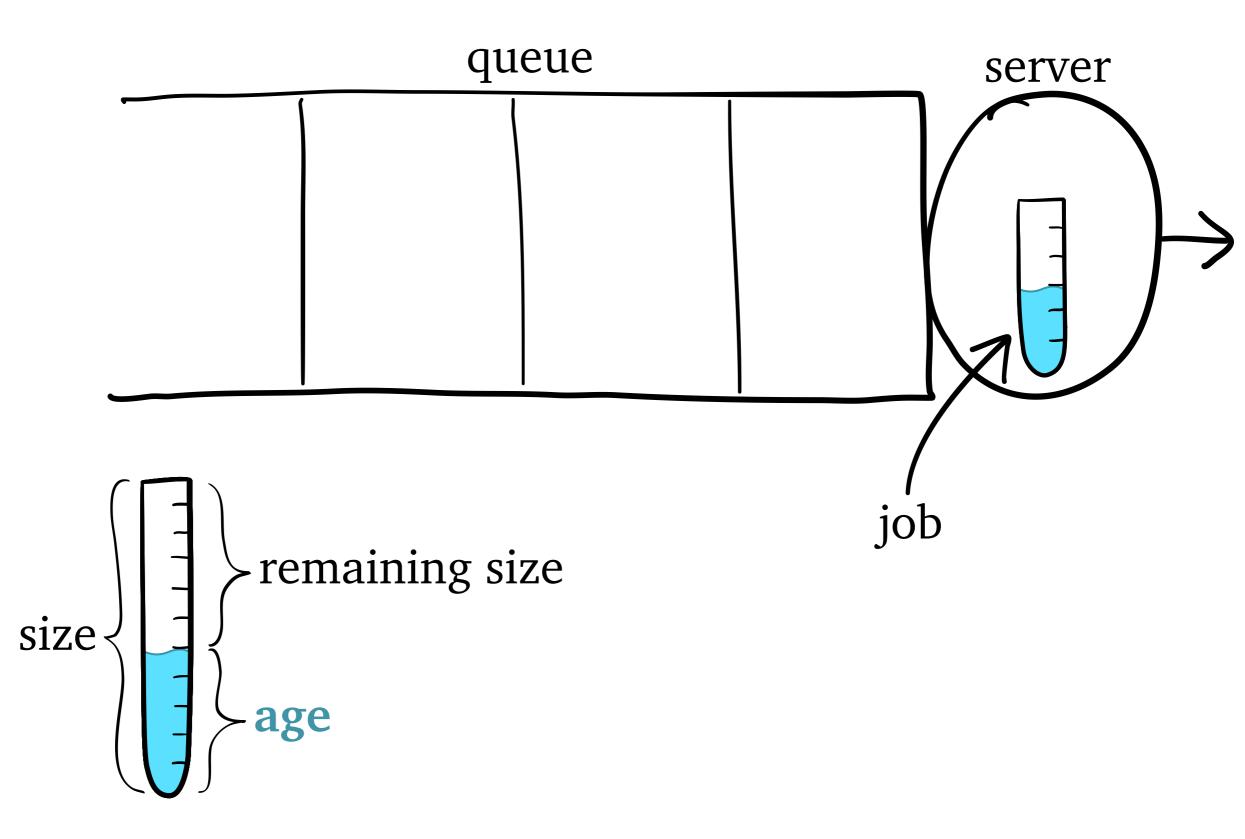


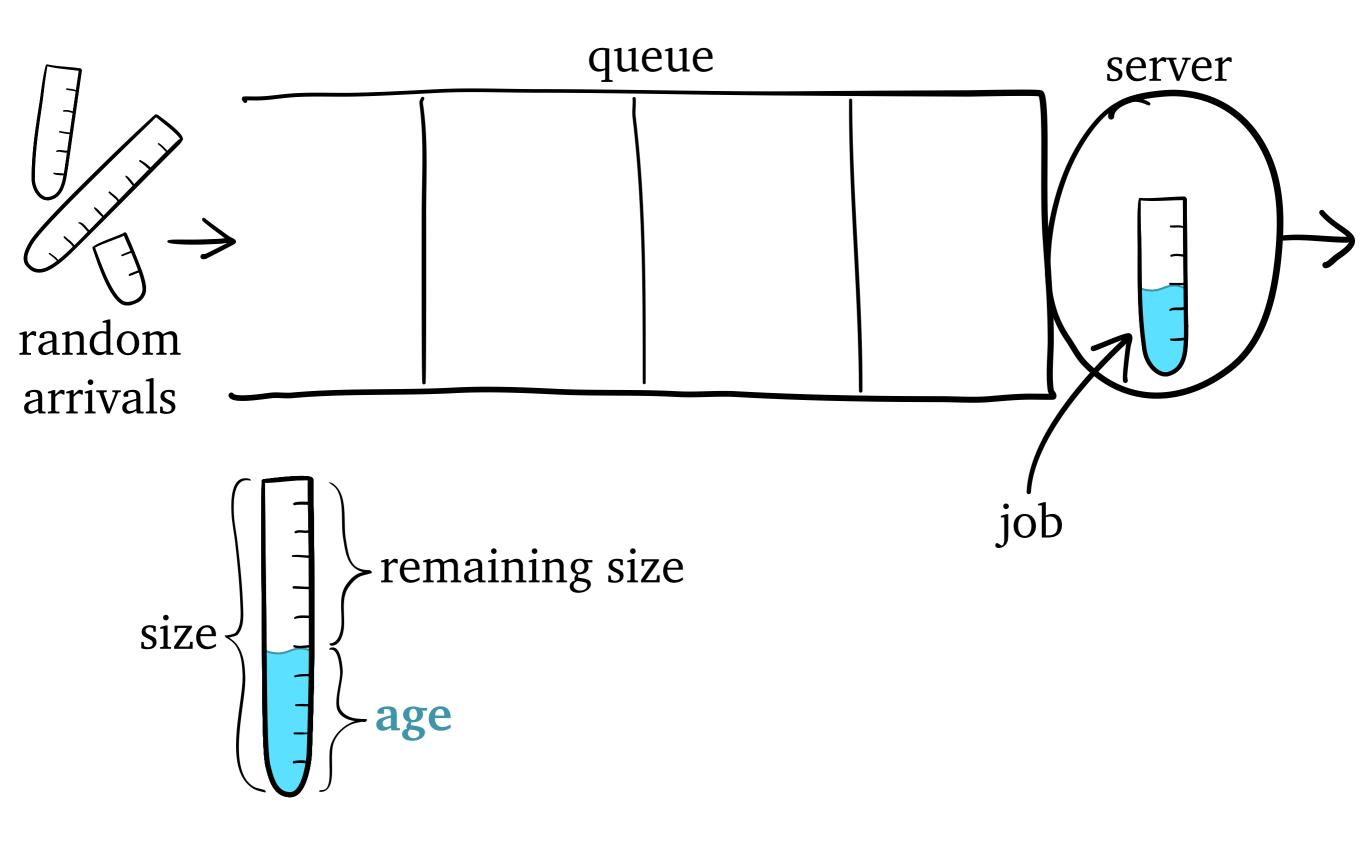


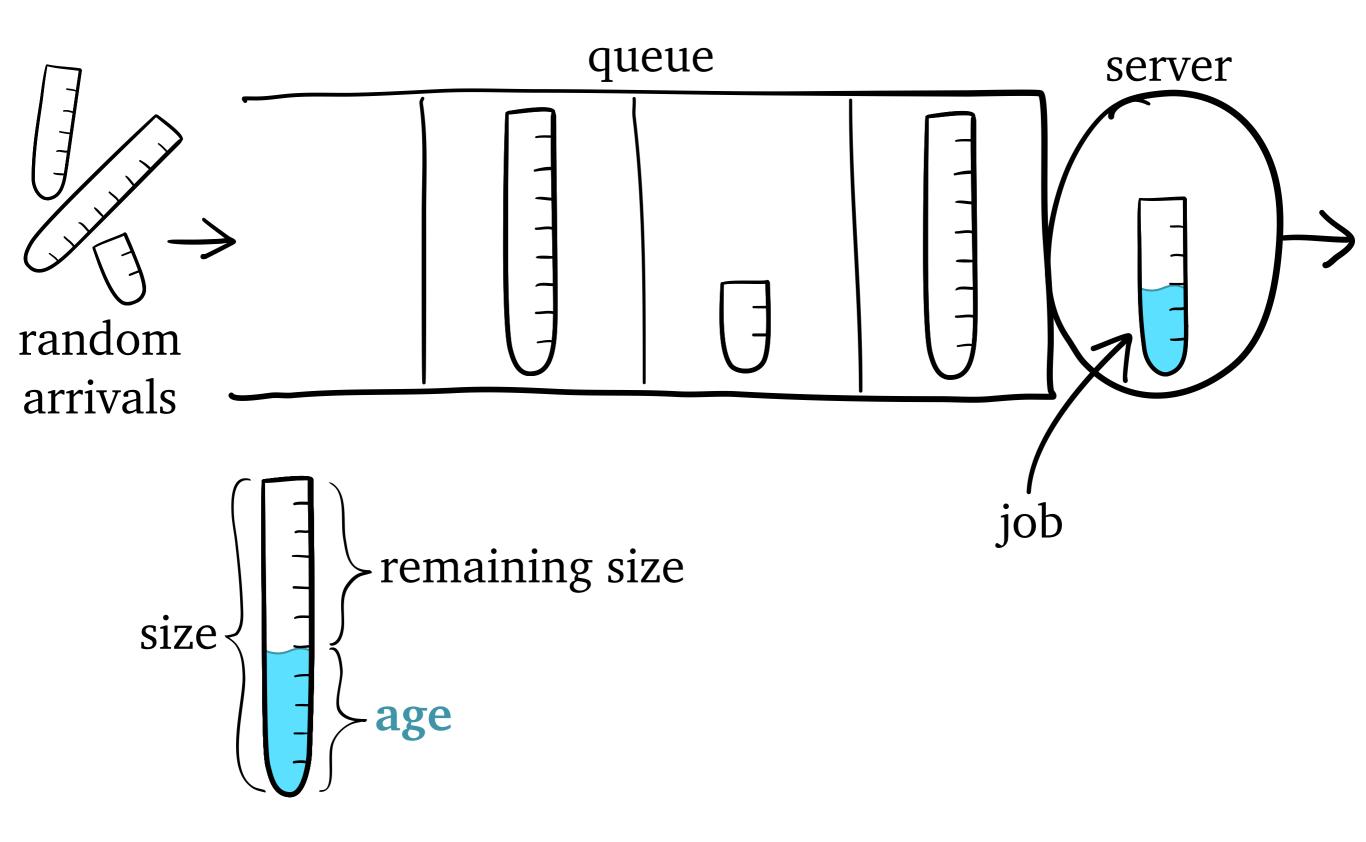


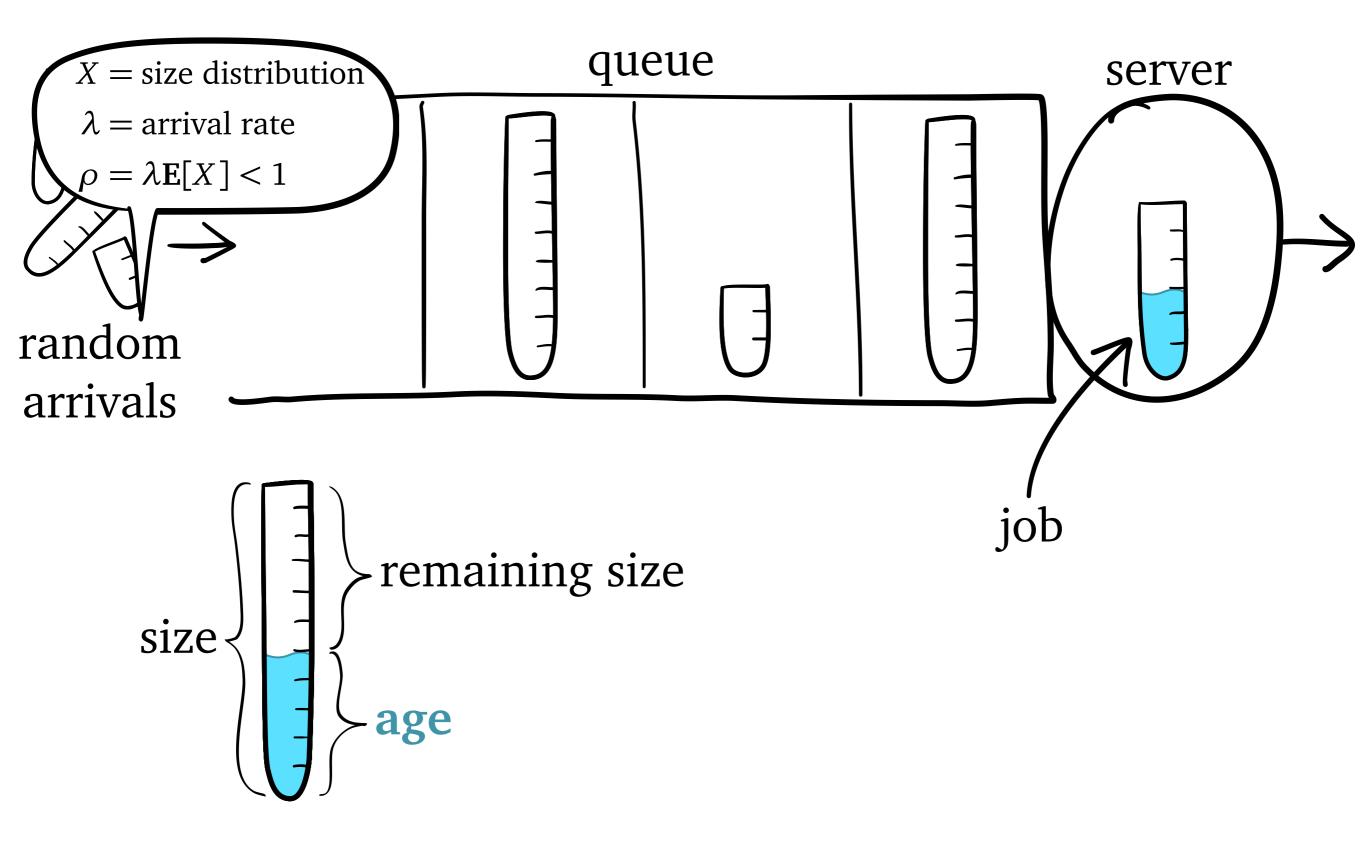


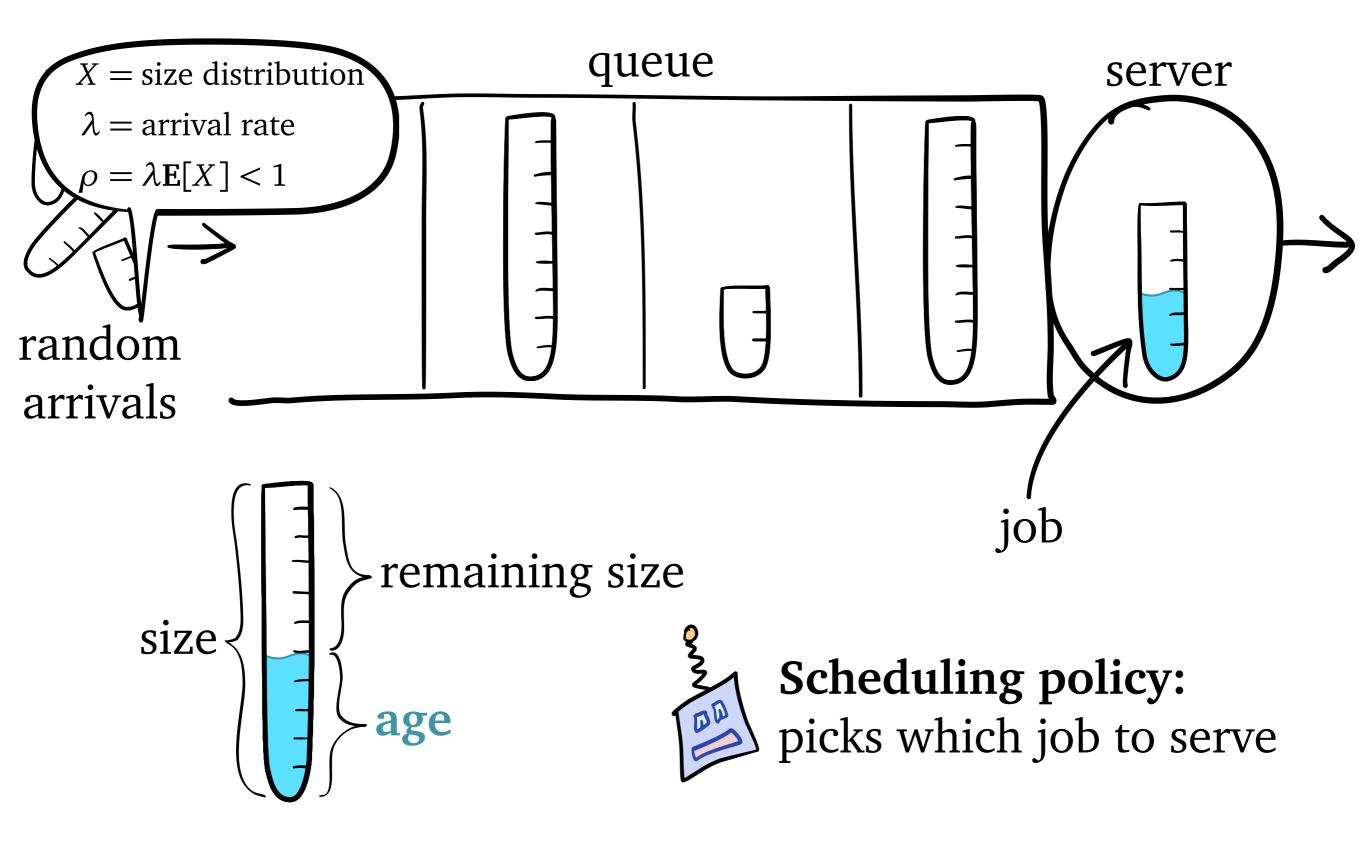


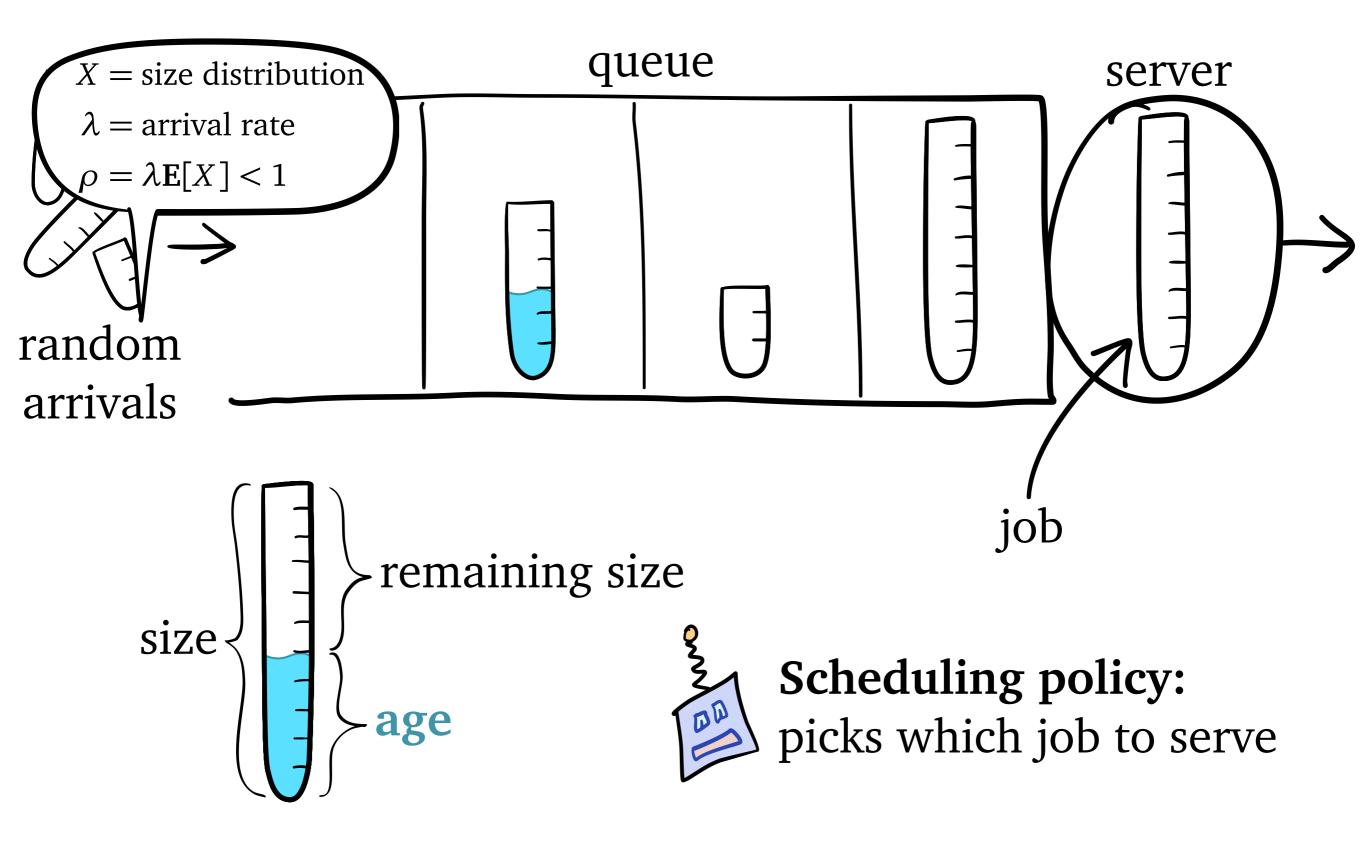


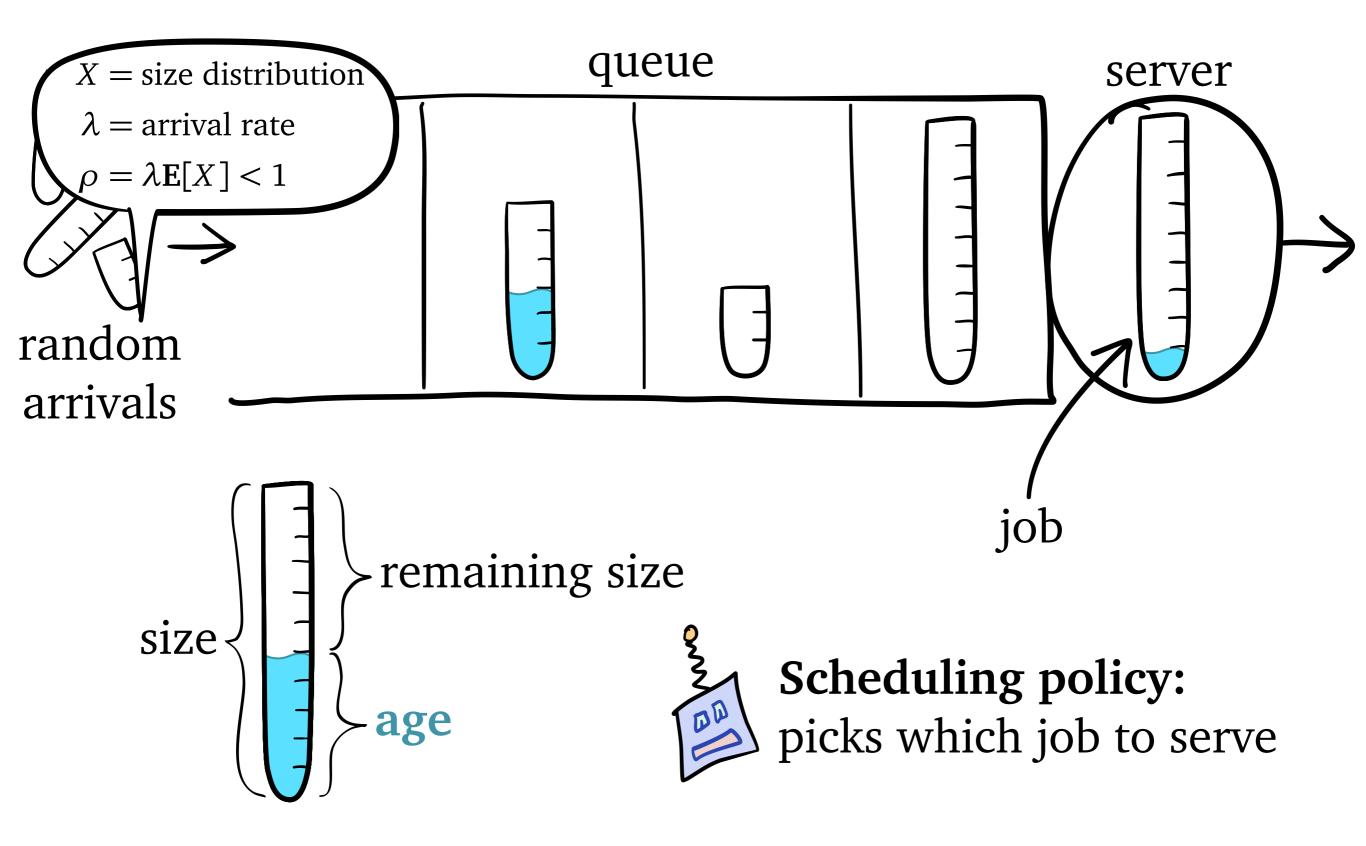


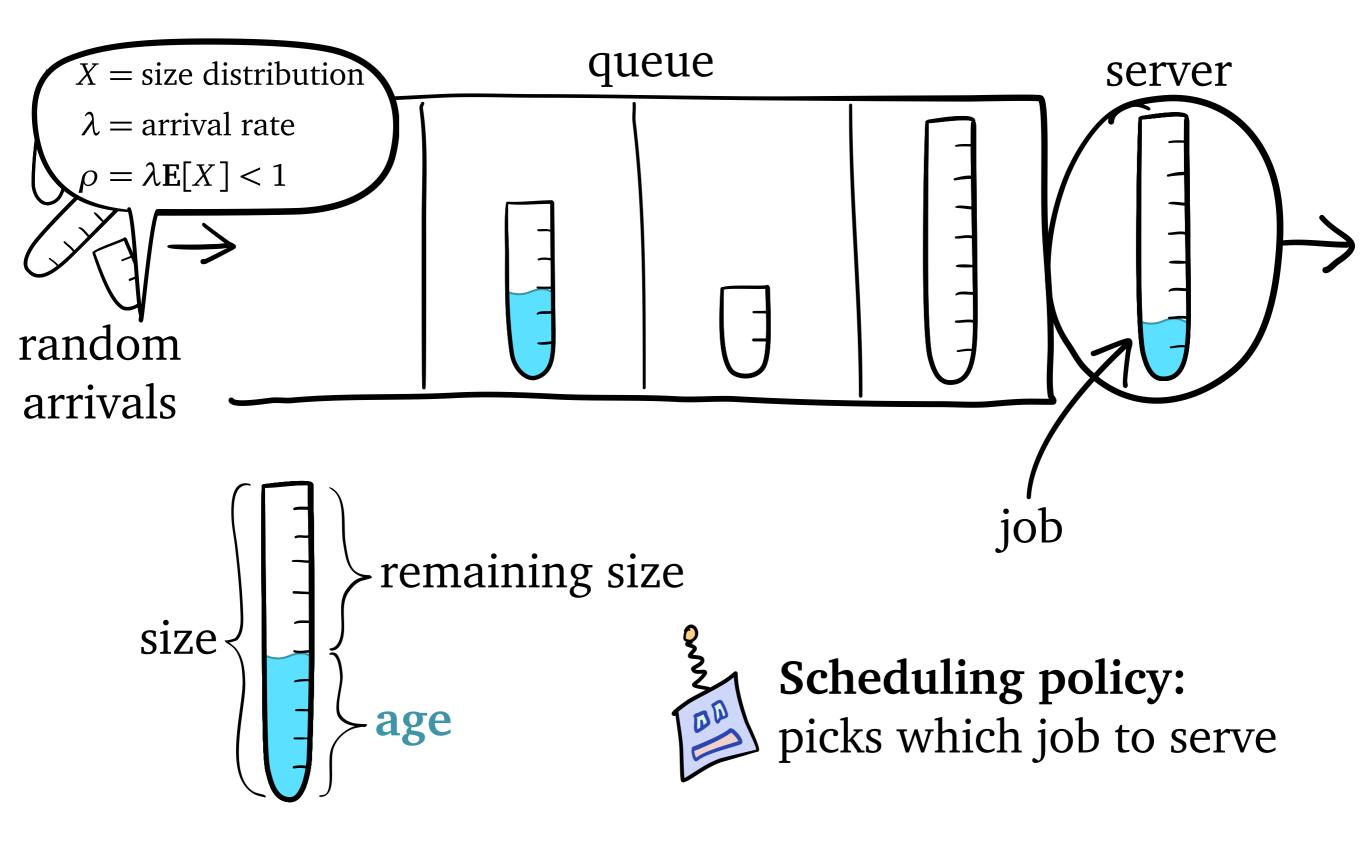


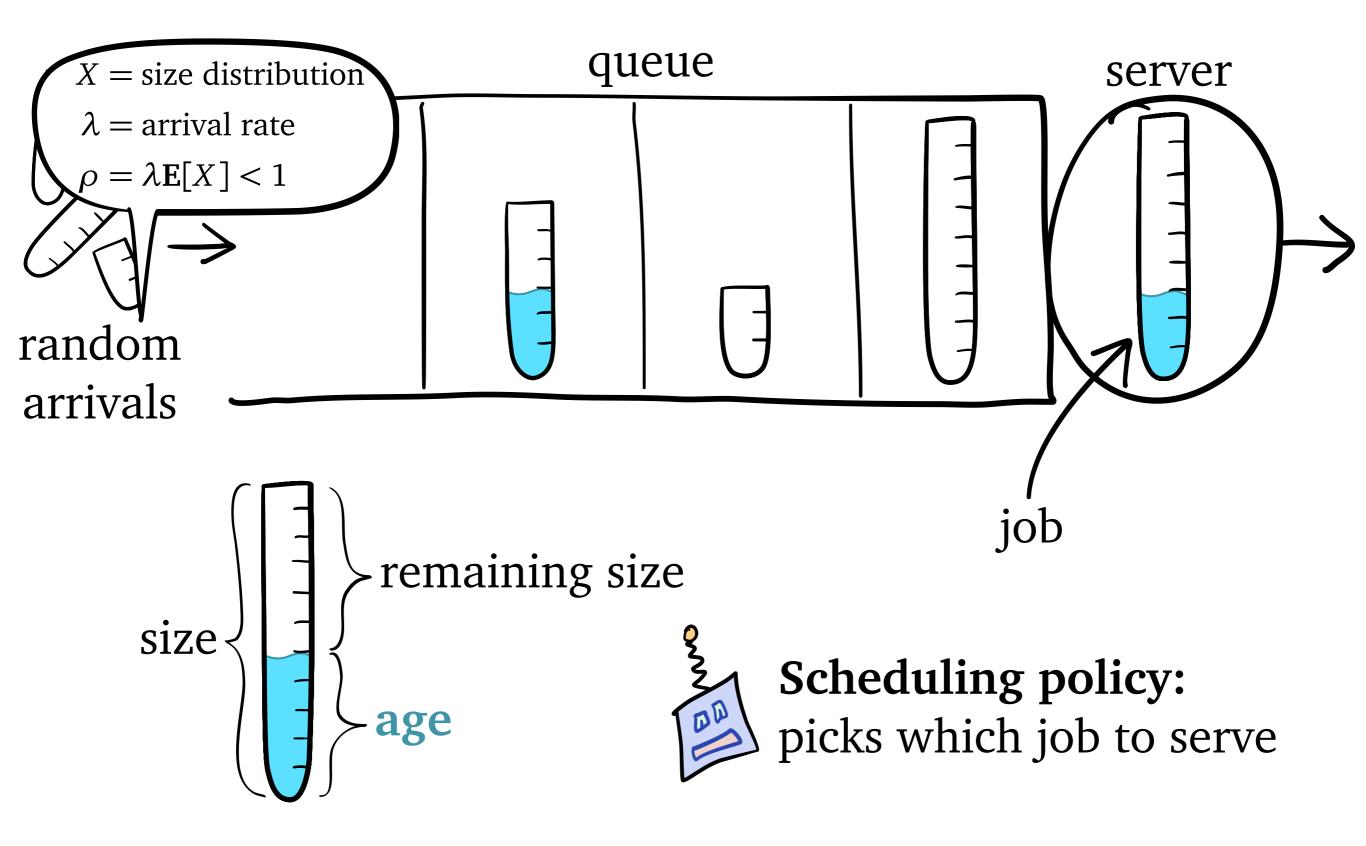


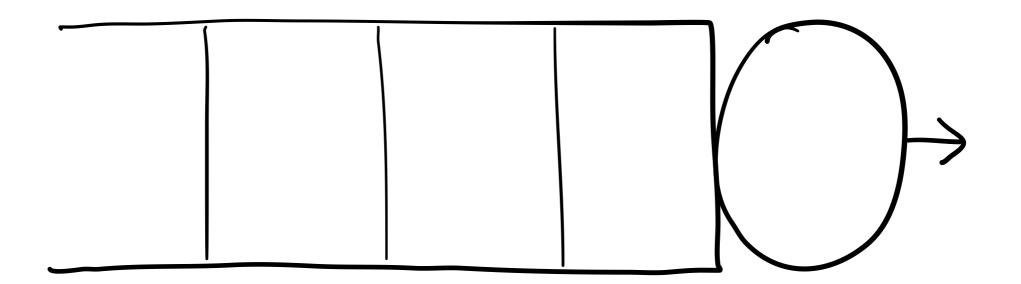


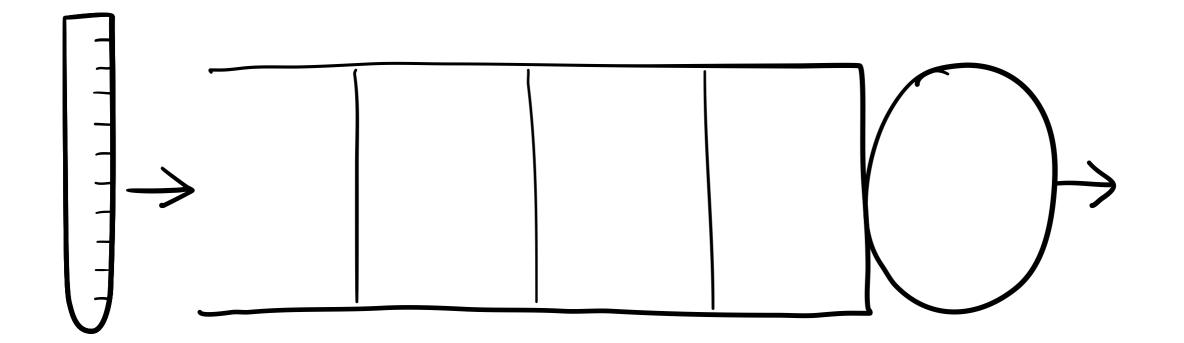


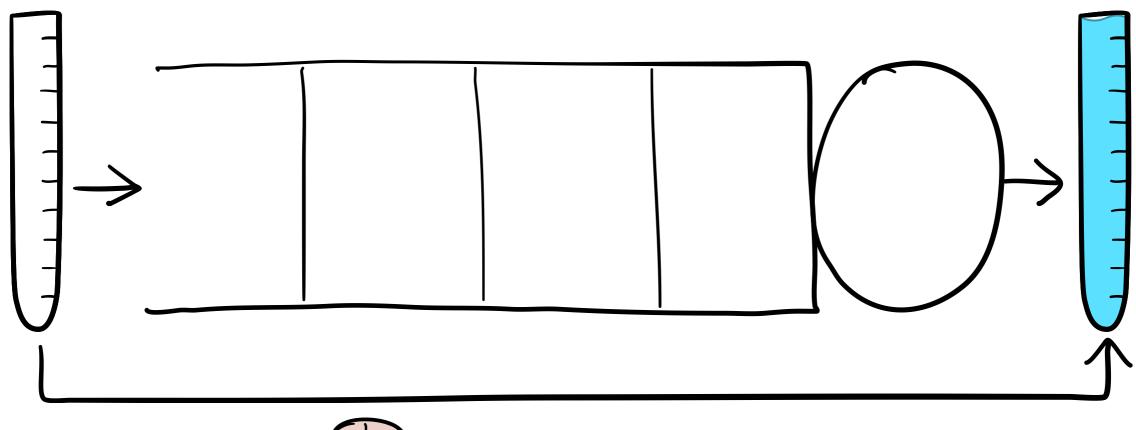




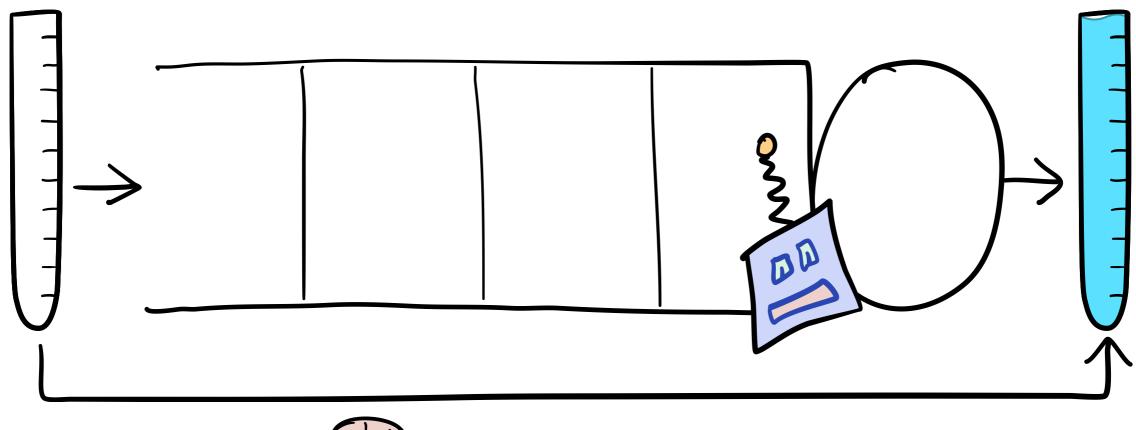




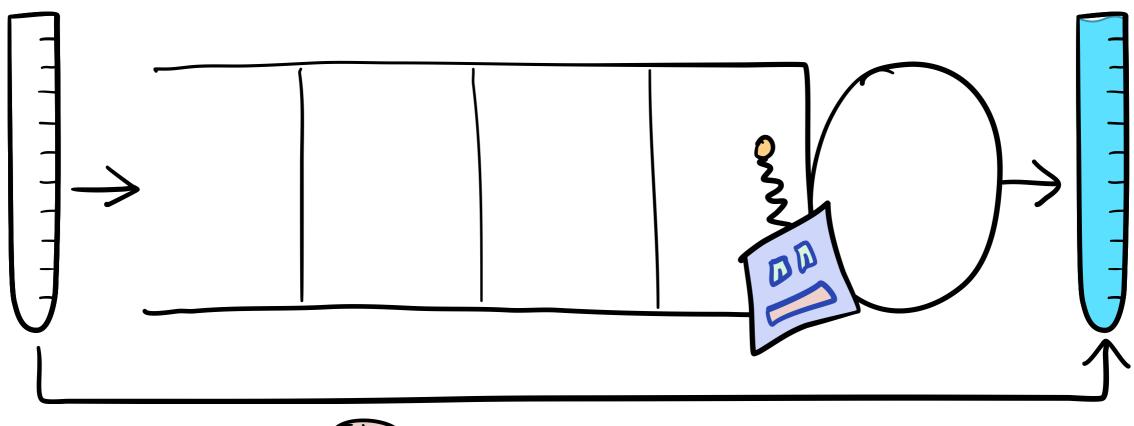




$$T = T = response time$$

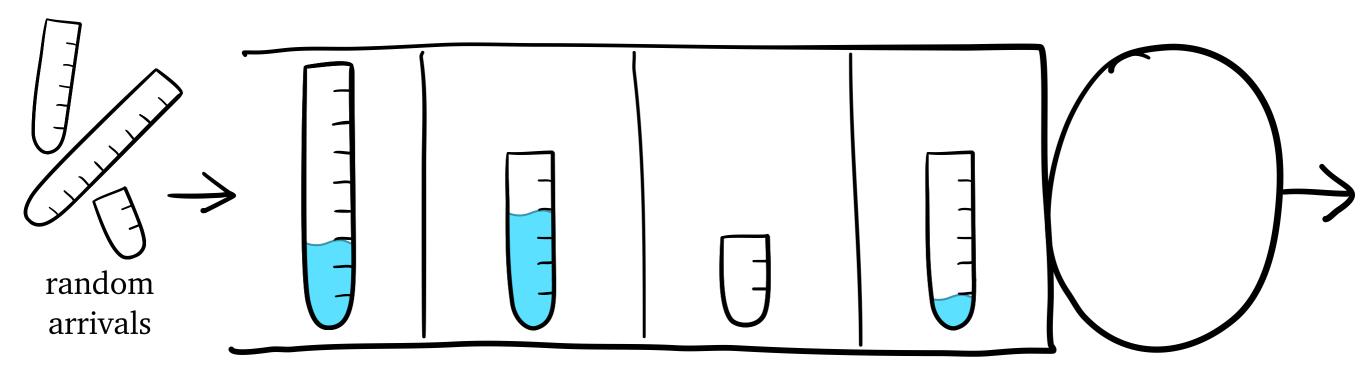


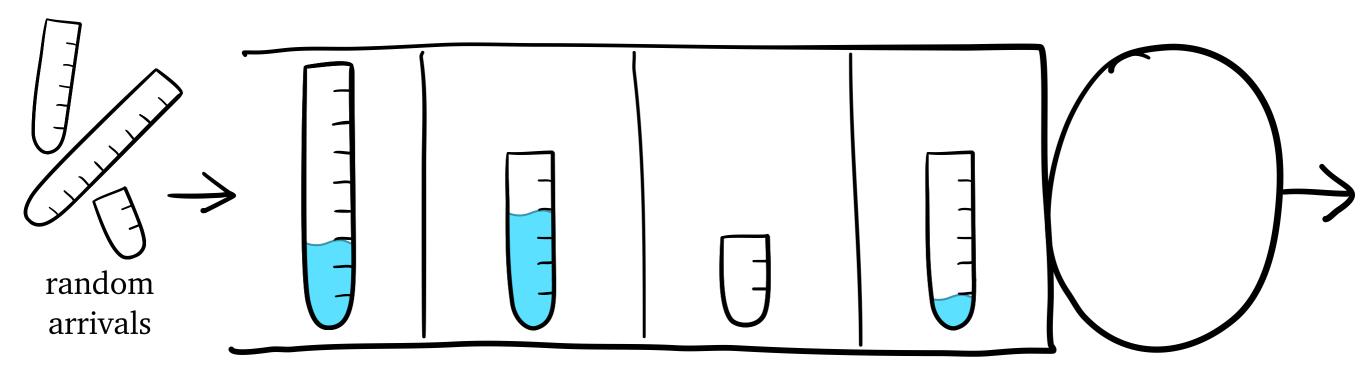
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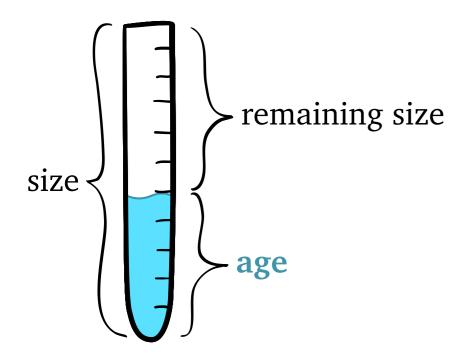


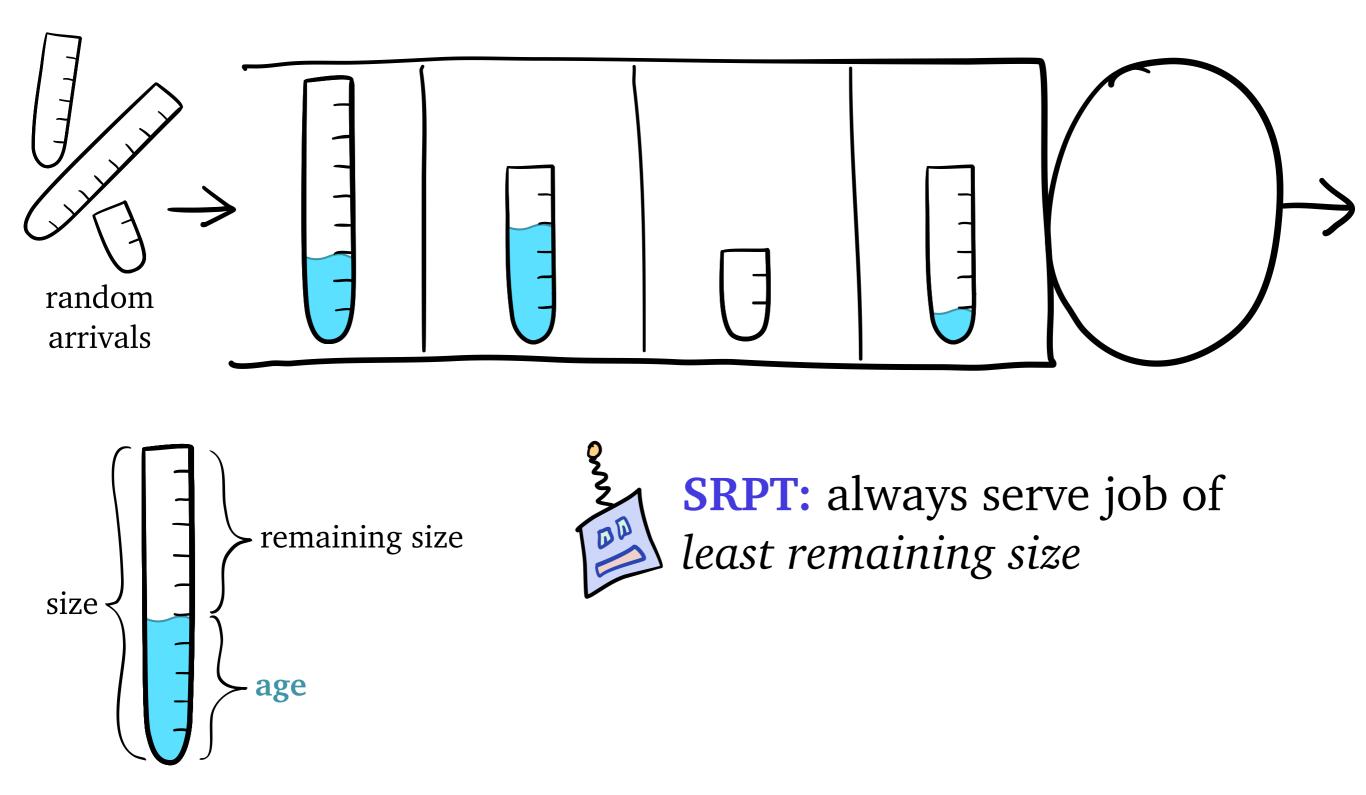
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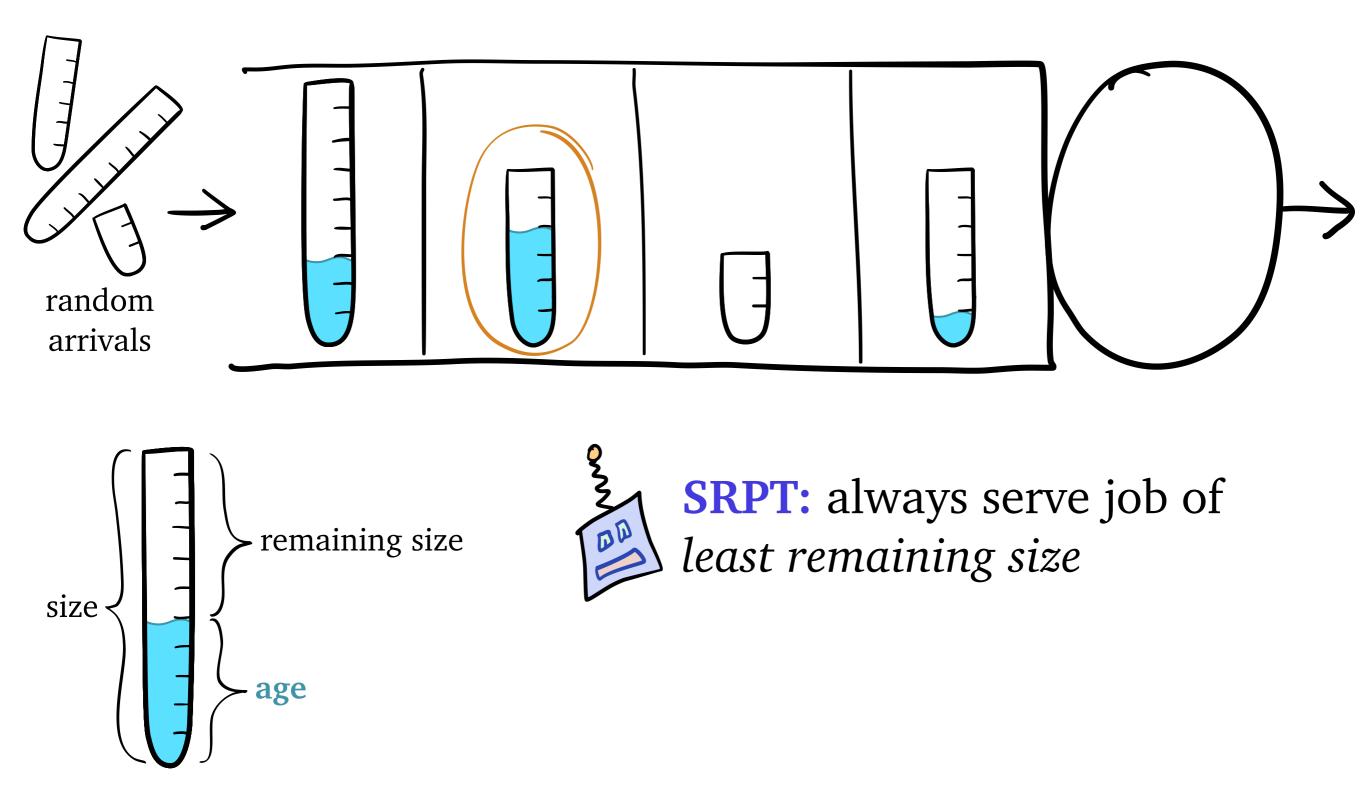
Goal: schedule to minimize *mean response time* **E**[*T*]

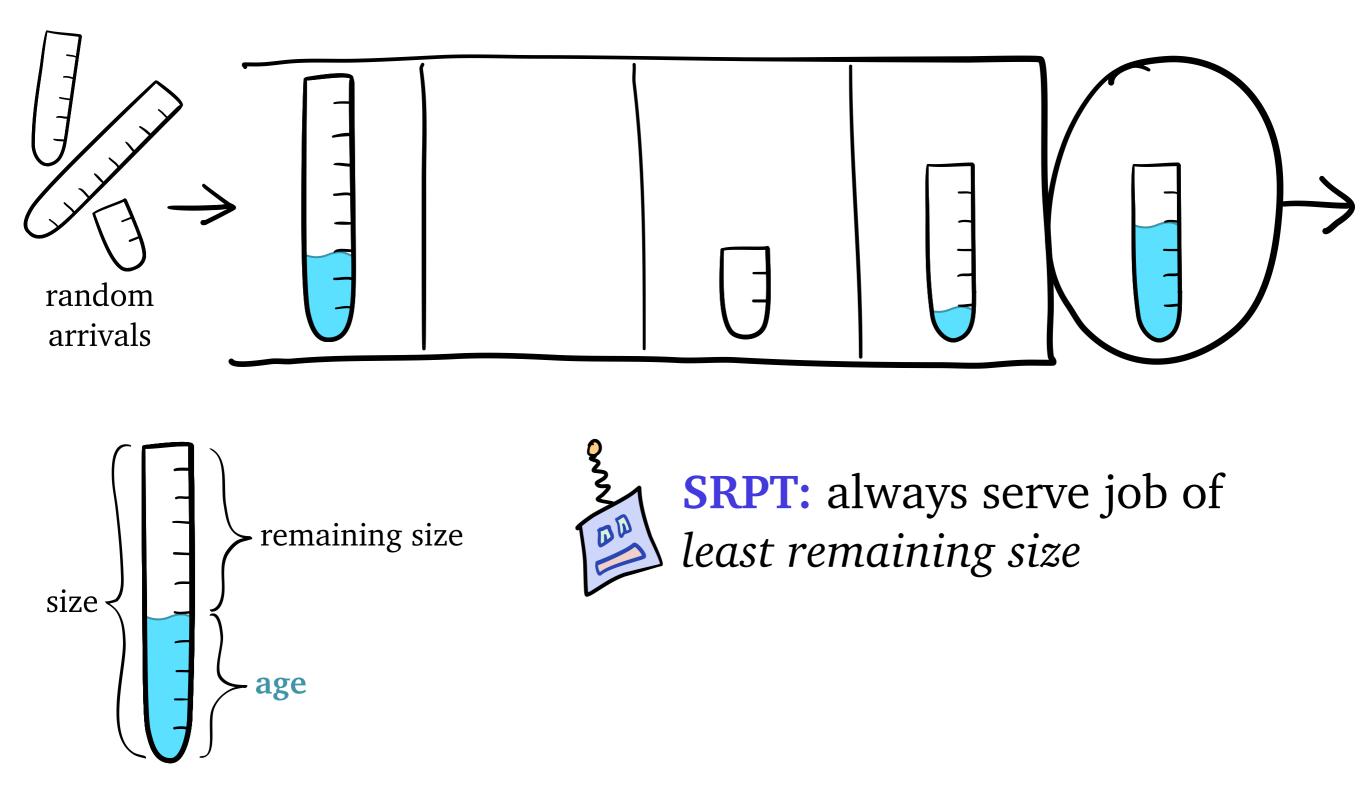


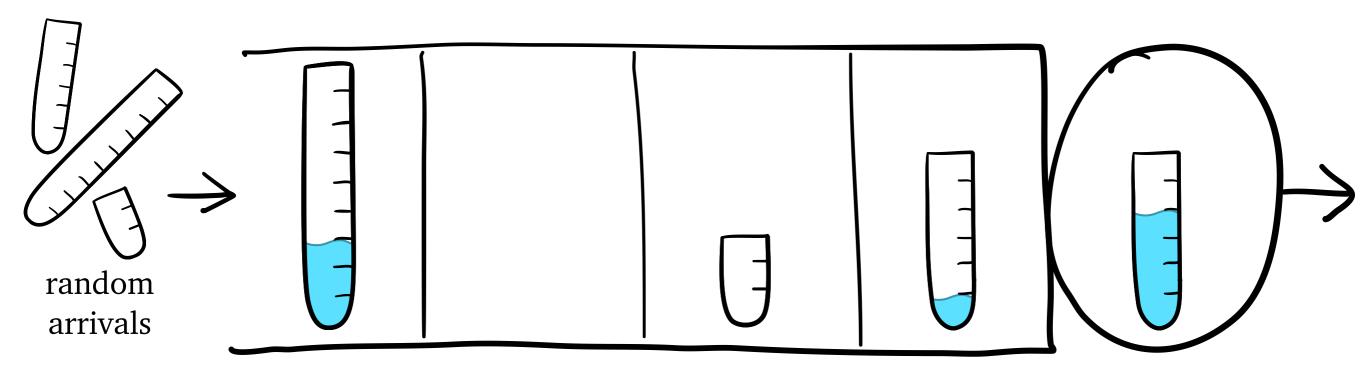












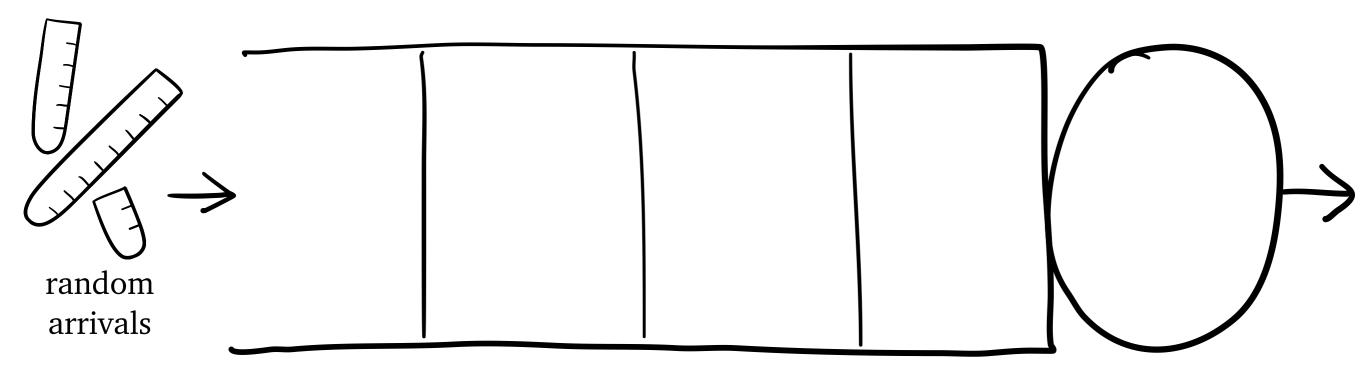
size age

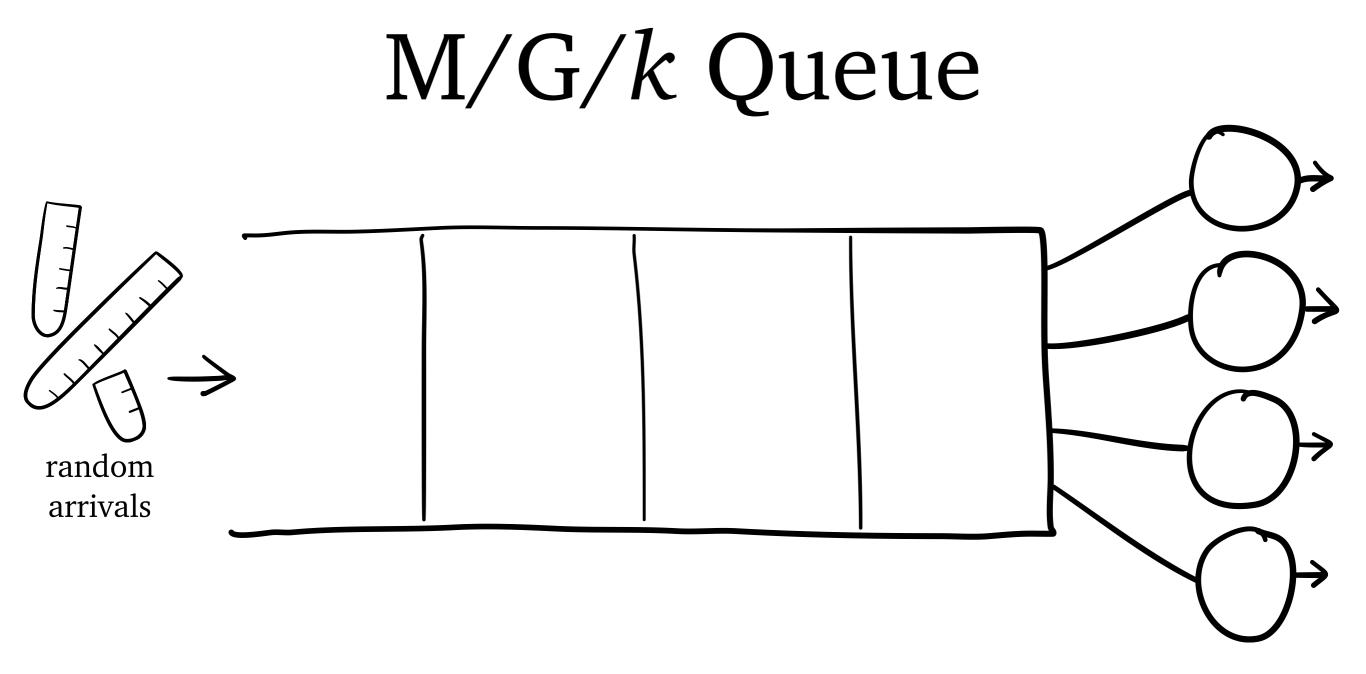


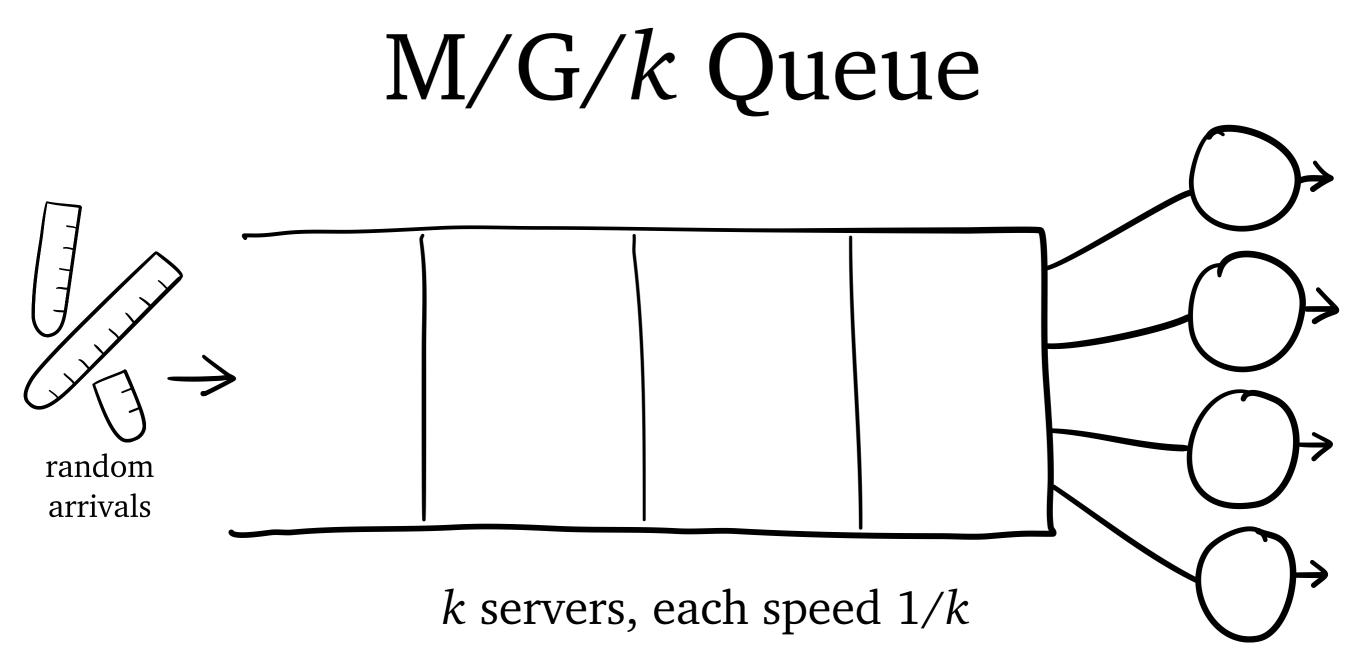
SRPT: always serve job of *least remaining size*

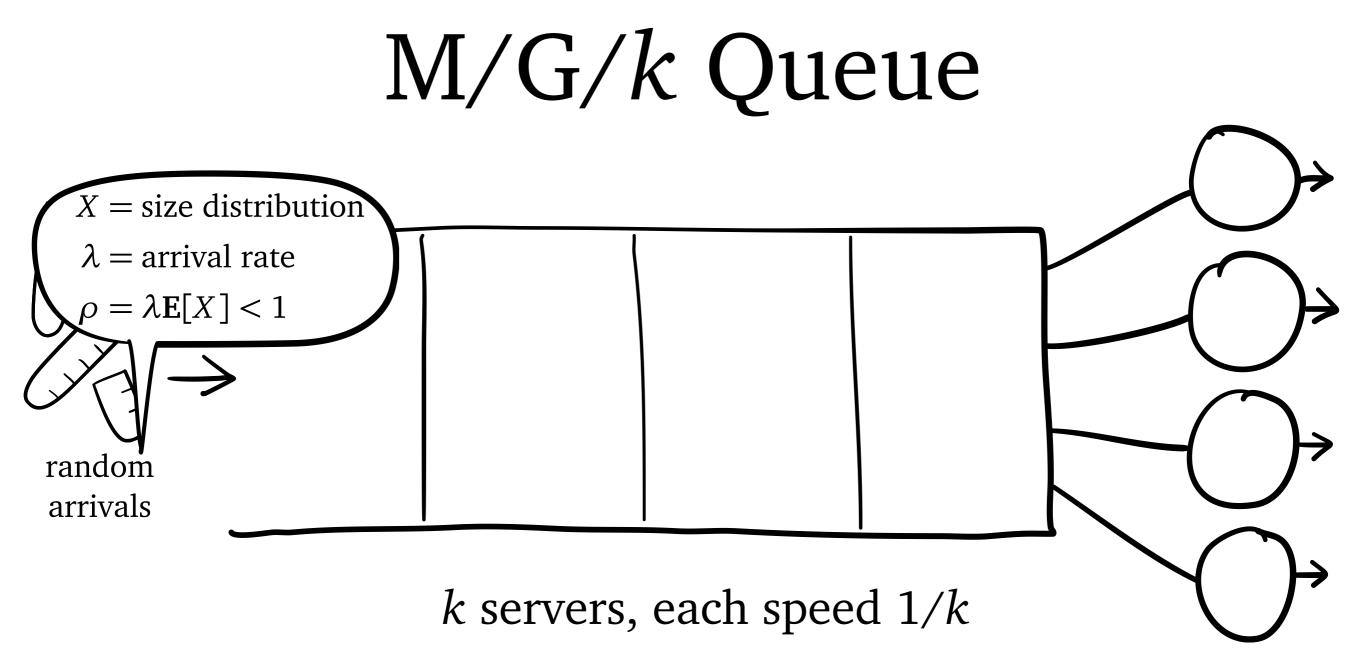


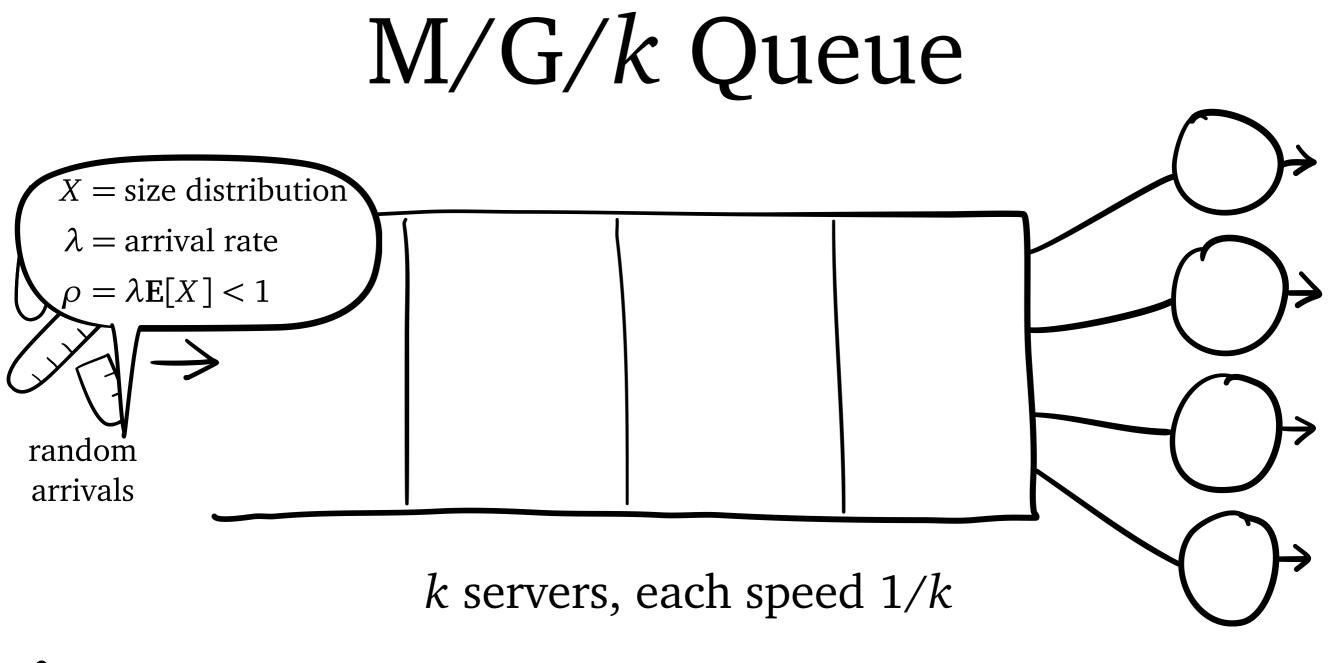
SRPT minimizes **E**[*T*]













SRPT-k: always serve k jobs of least remaining size

M/G/k Queue X = size distribution $\lambda = arrival rate$ $\rho = \lambda \mathbf{E}[X] < 1$ random arrivals k servers, each speed 1/k

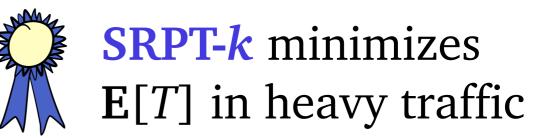


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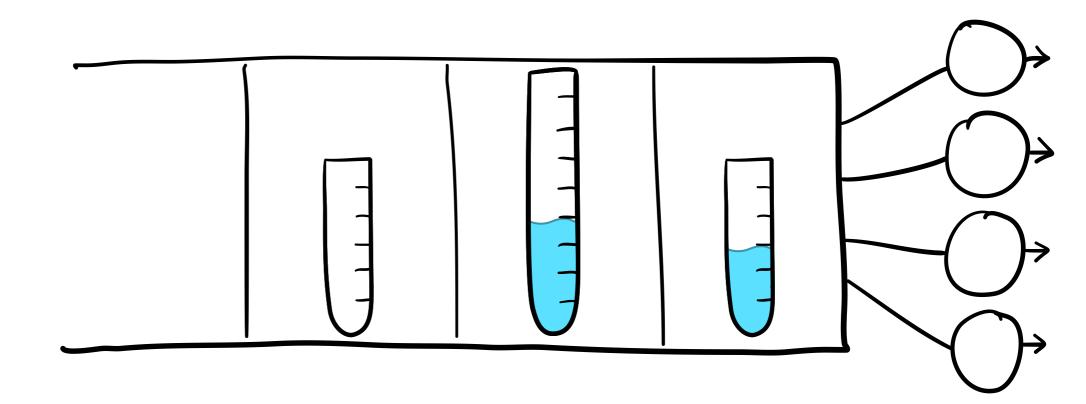


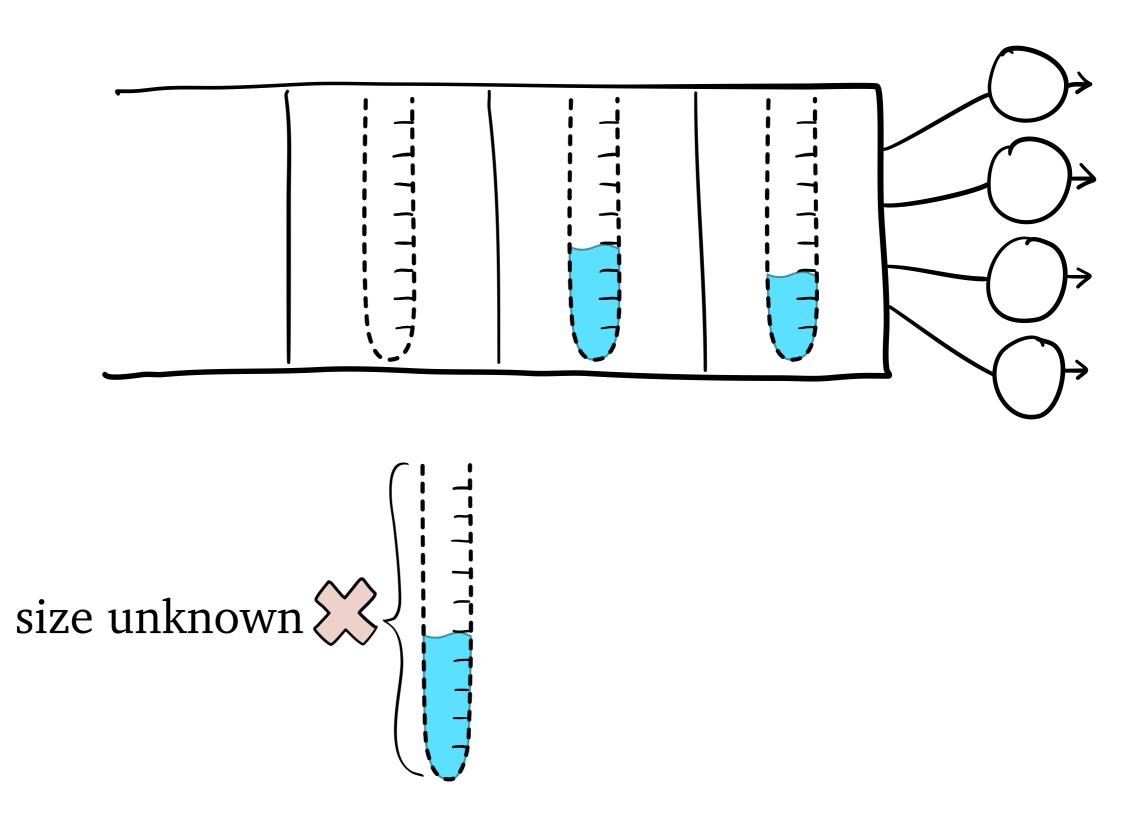
SRPT-k: always serve k jobs of least remaining size

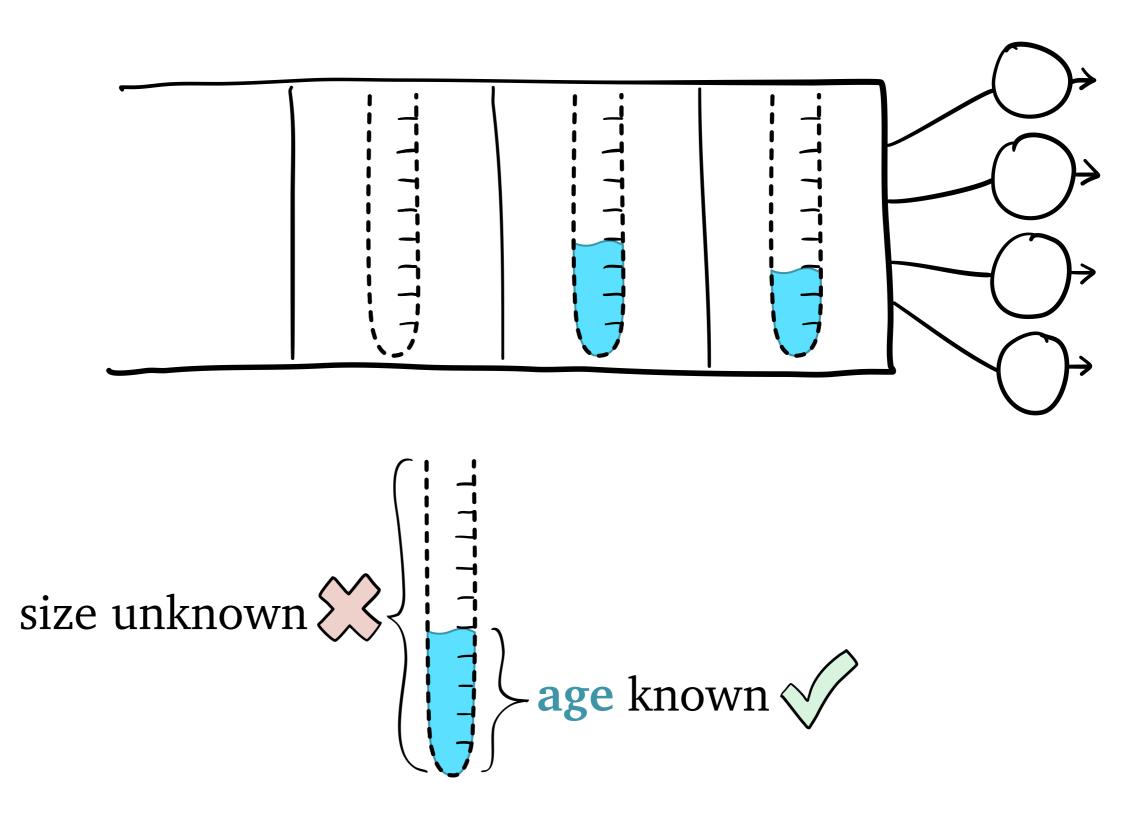
SRPT-*k* minimizes **E**[*T*] in heavy traffic $\lim_{\rho \to 1} \frac{\mathbf{E}[T_{\text{SRPT-}k}]}{\mathbf{E}[T_{\text{SRPT-}1}]} = 1$

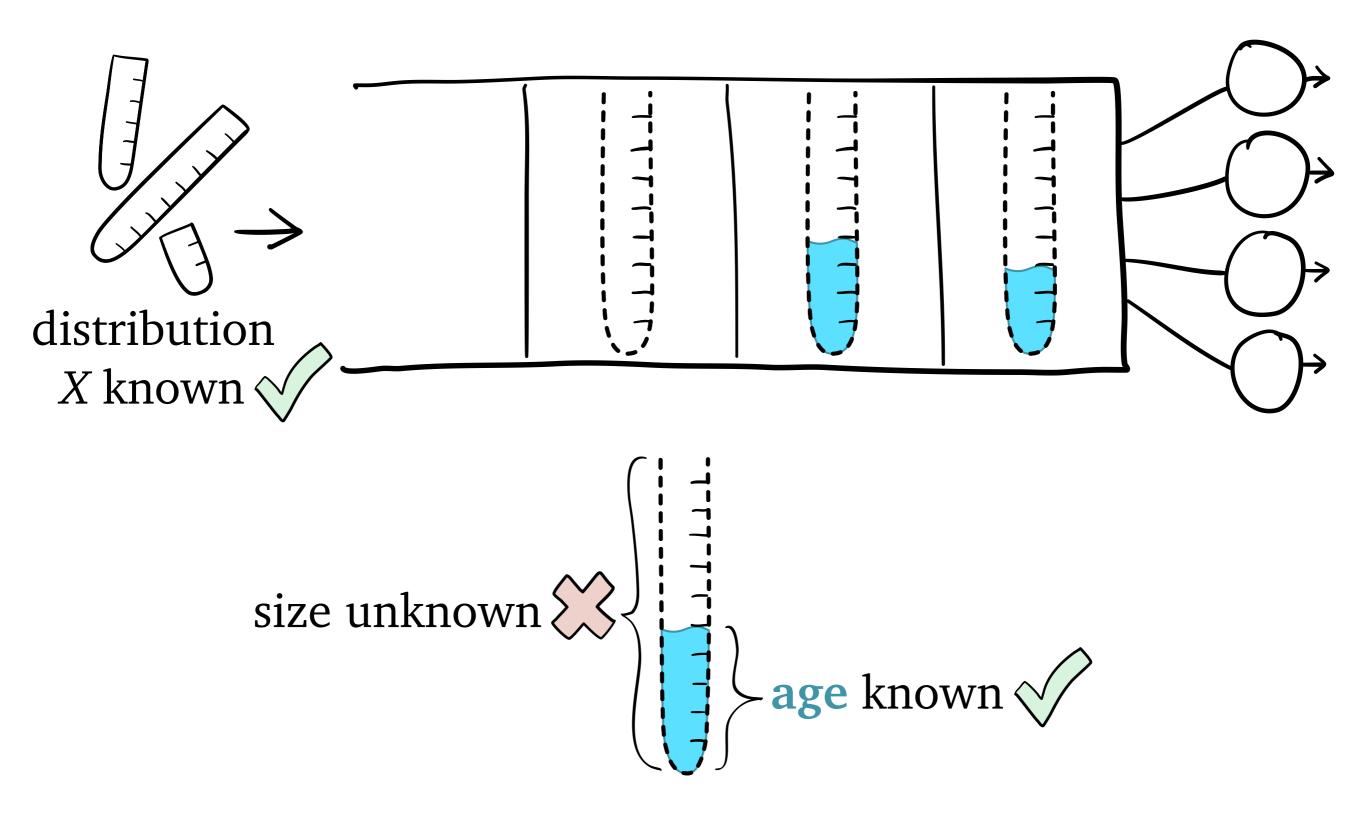
M/G/k Queue X = size distribution $\lambda = arrival rate$ $\rho = \lambda \mathbf{E}[X] < 1$ random arrivals k servers, each speed 1/k**SRPT-***k***:** always serve *k* jobs **SRPT-***k* minimizes A least remaining size **E**[*T*] in heavy traffic $\lim_{\rho \to 1} \frac{\mathbf{E}[T_{\text{SRPT-}k}]}{\mathbf{E}[T_{\text{SRPT-}1}]} = 1$ needs known job sizes

This talk: unknown job sizes





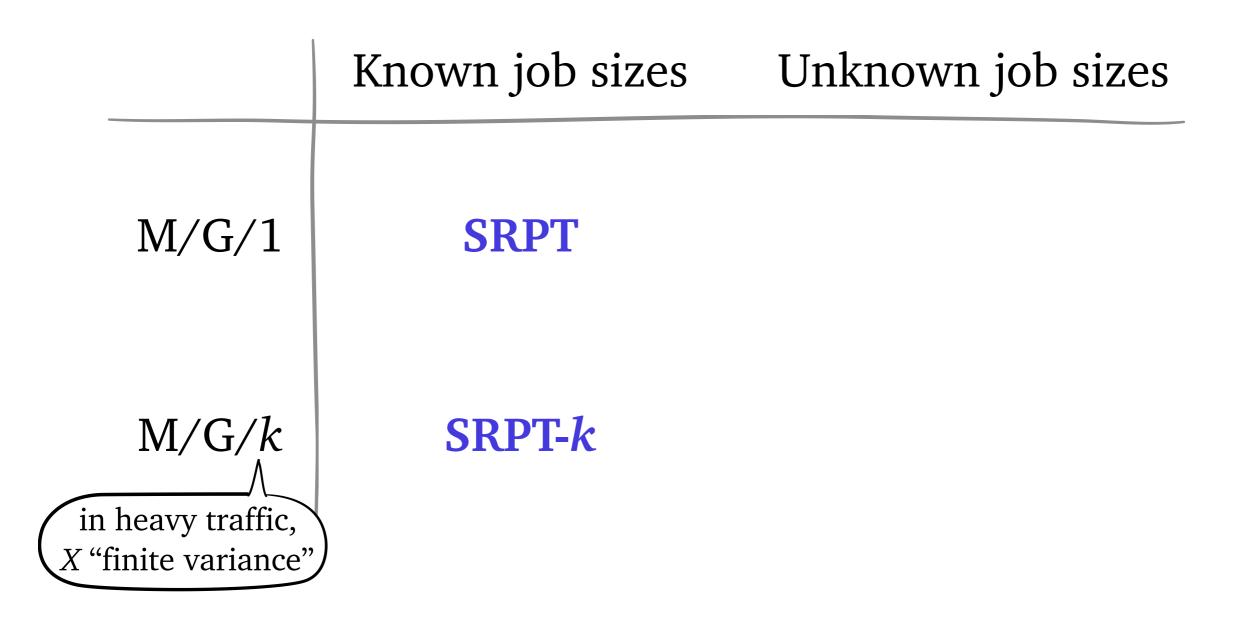


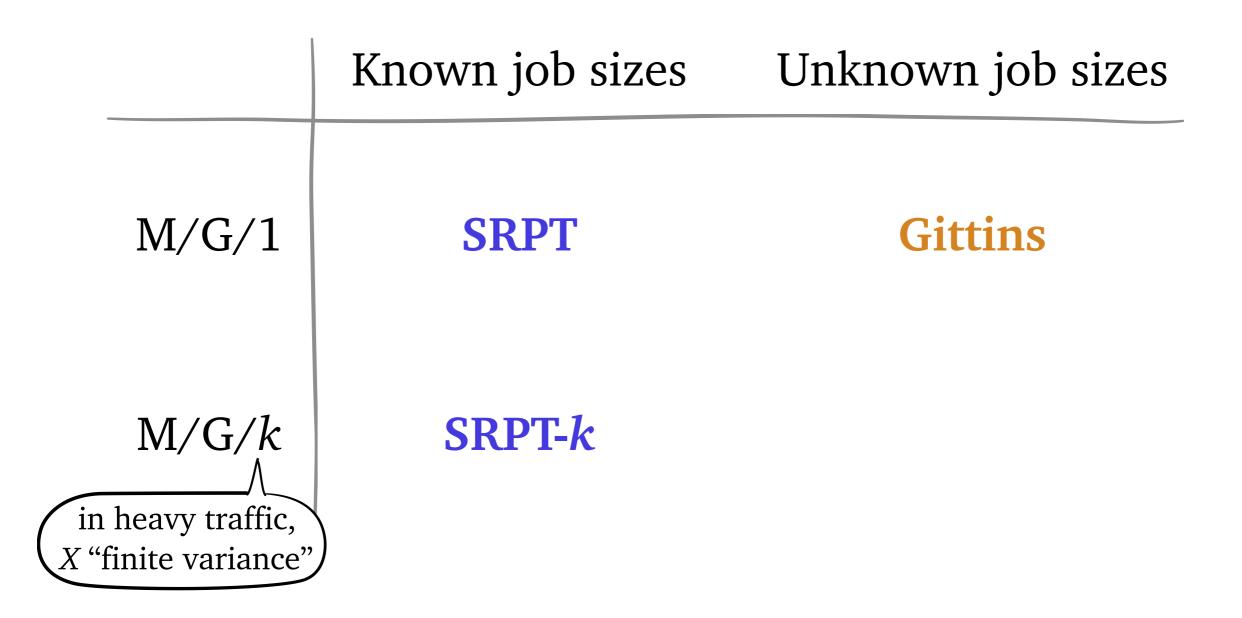


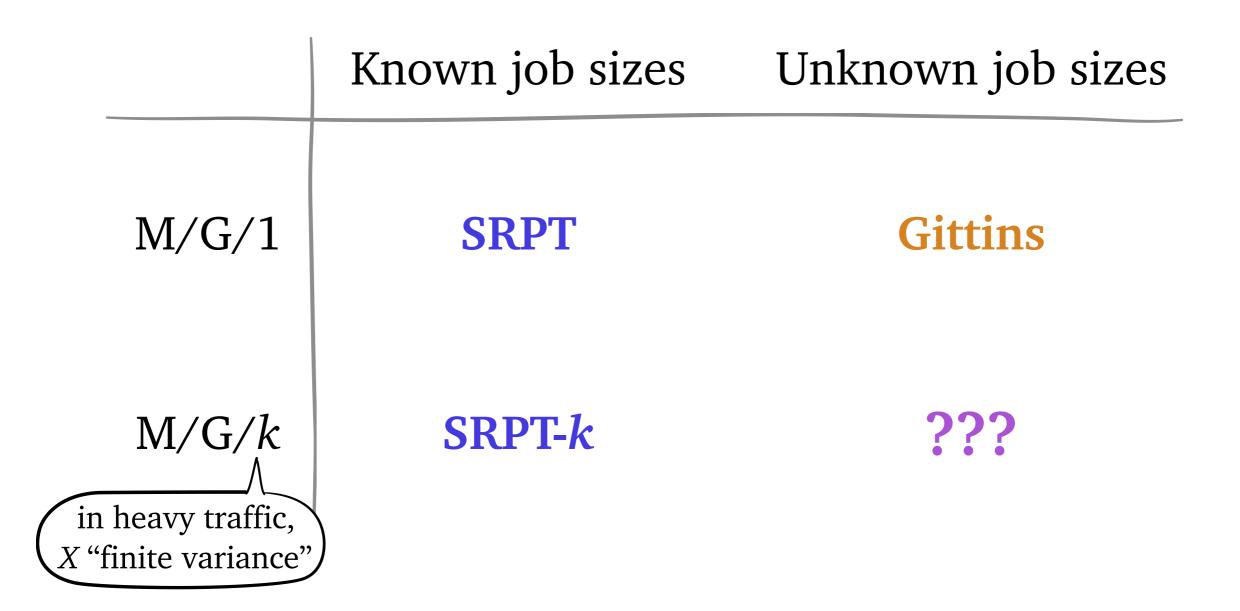
Minimizing $\mathbf{E}[T]$

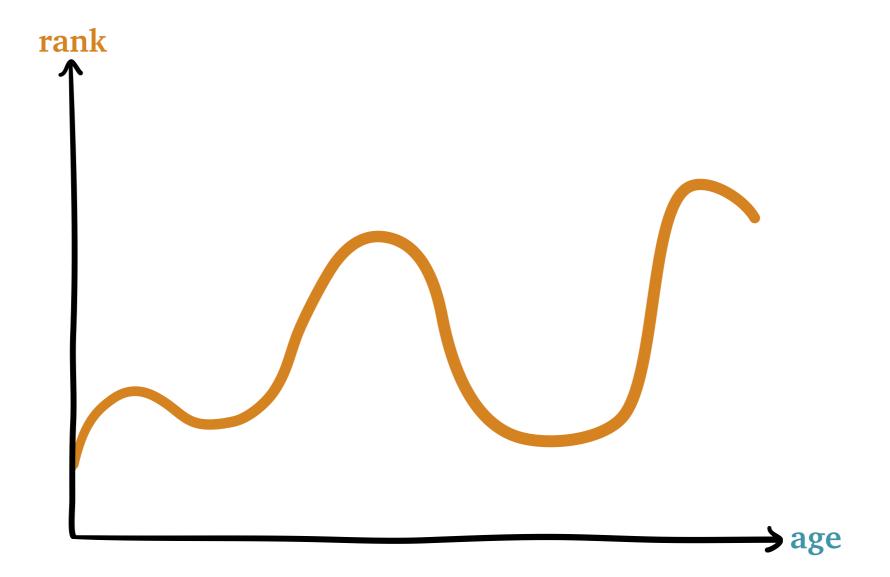
	Known job sizes	Unknown job sizes
M/G/1		
M/G/k		

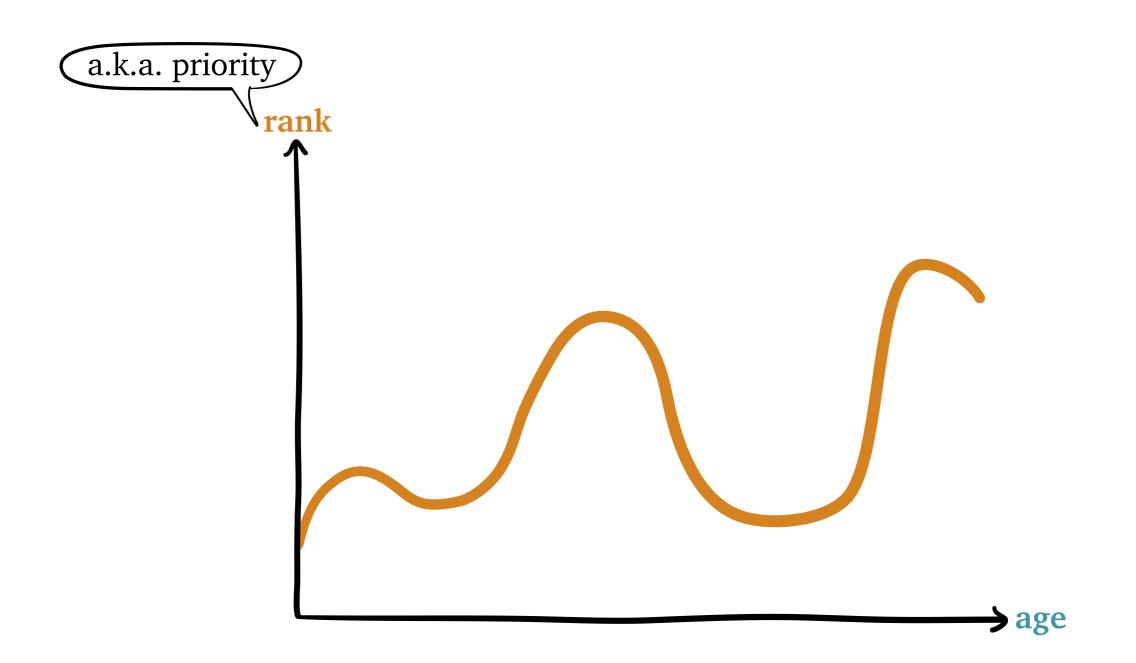
	Known job sizes	Unknown job sizes
M/G/1	SRPT	
M/G/k	SRPT-k	

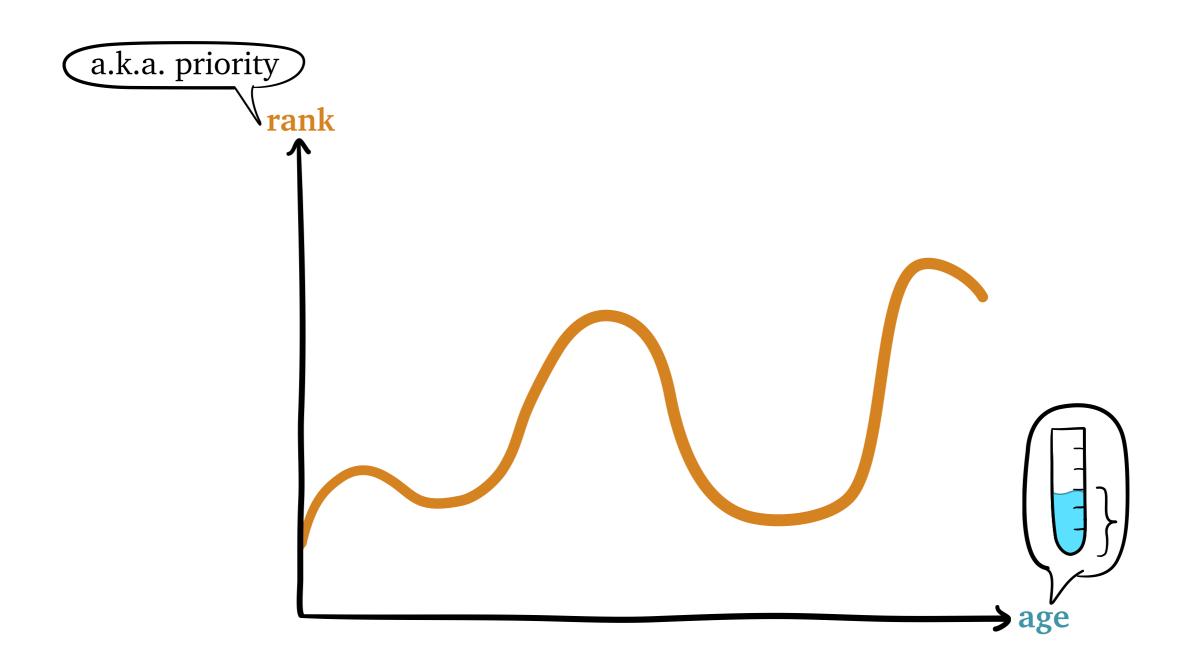


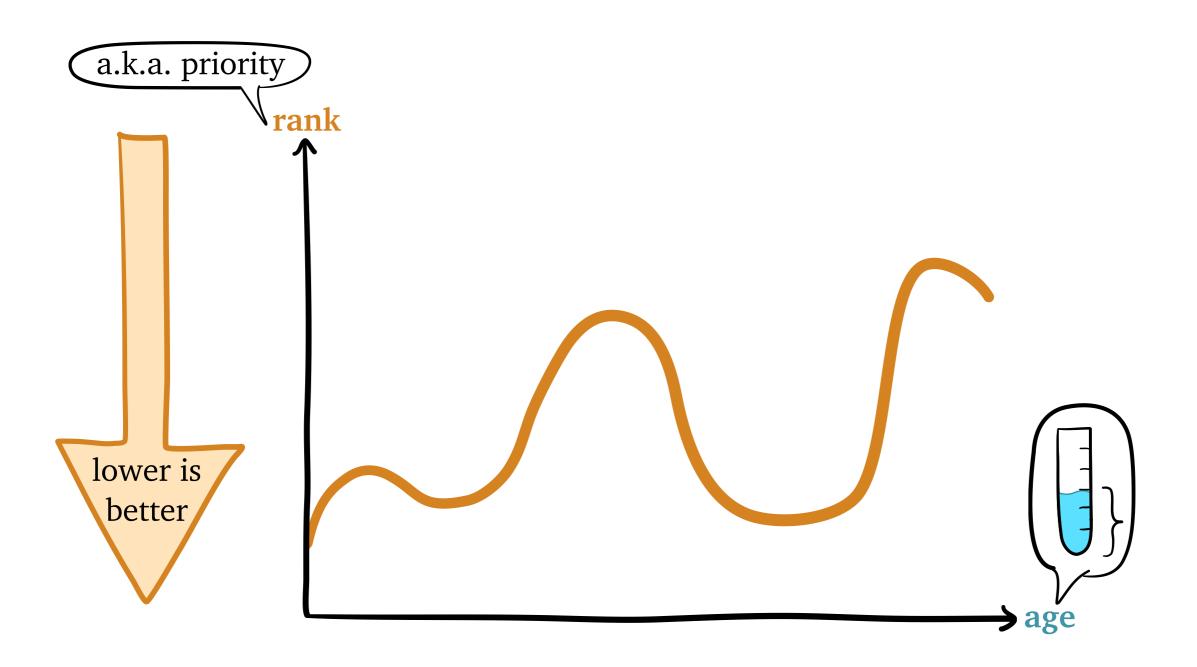


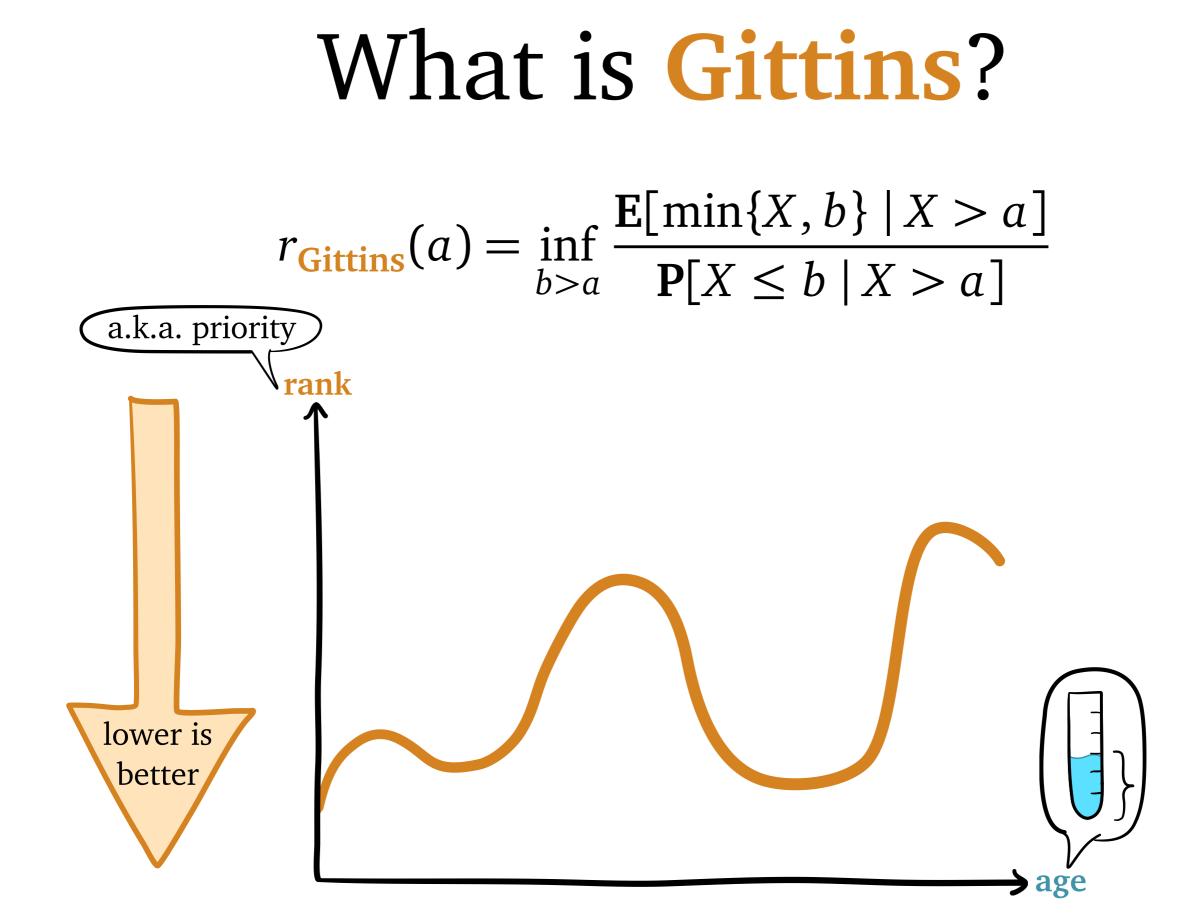


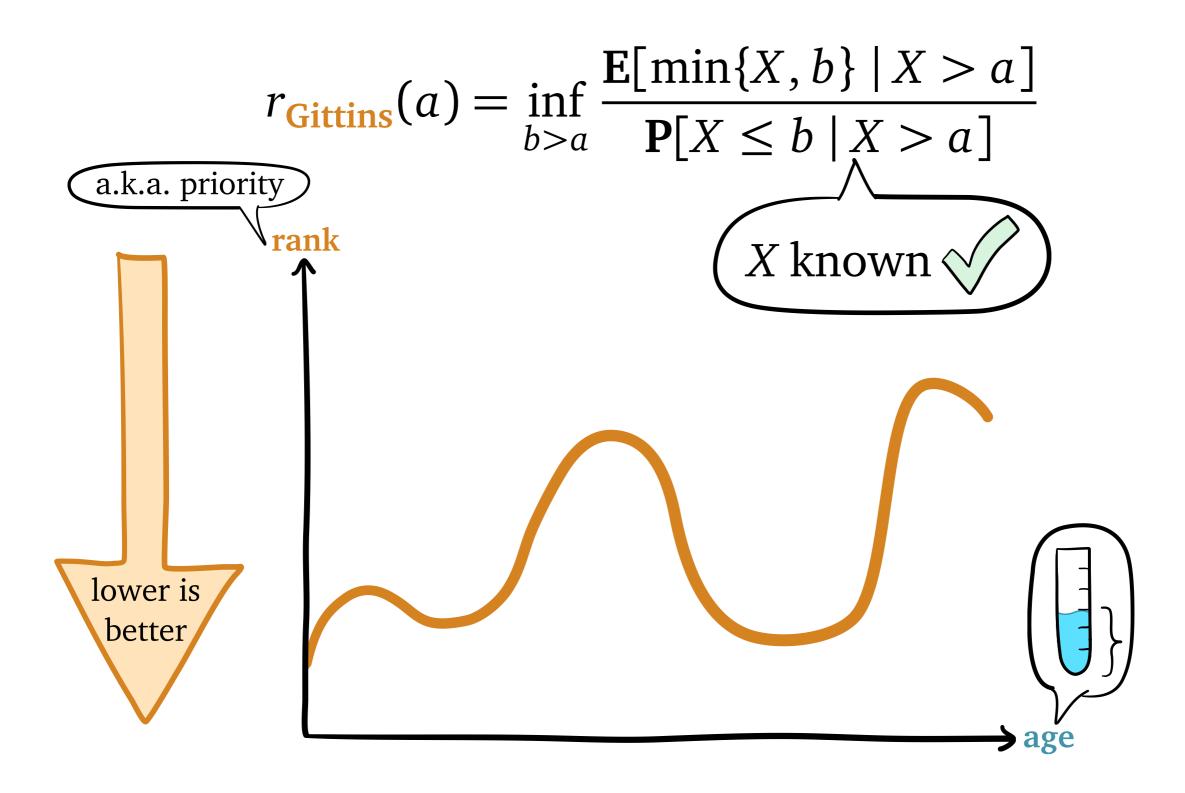


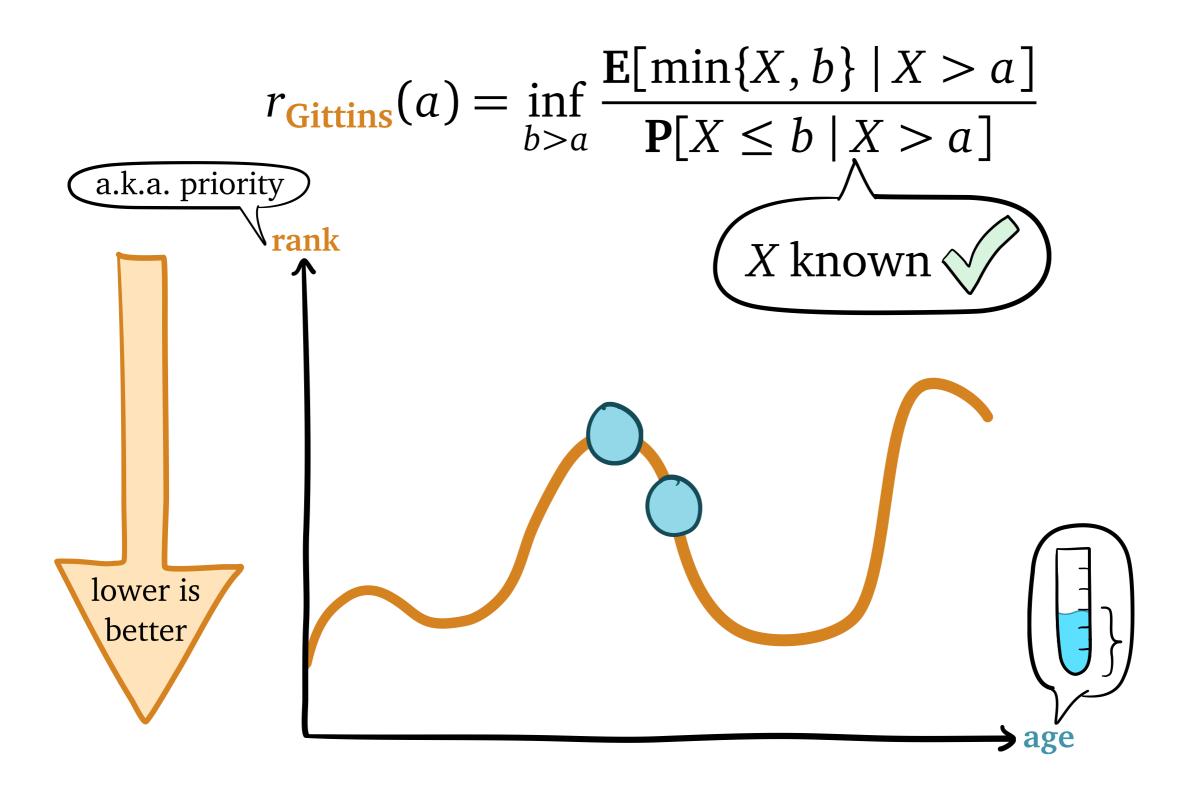


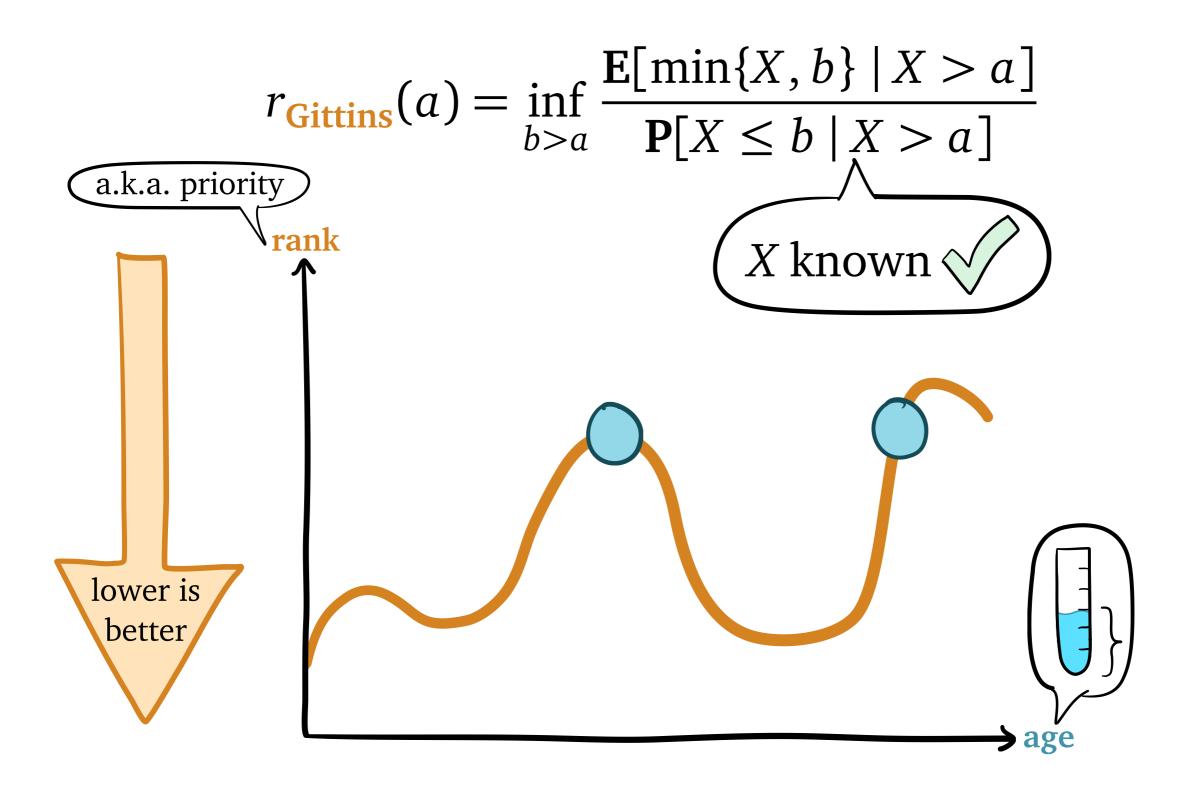


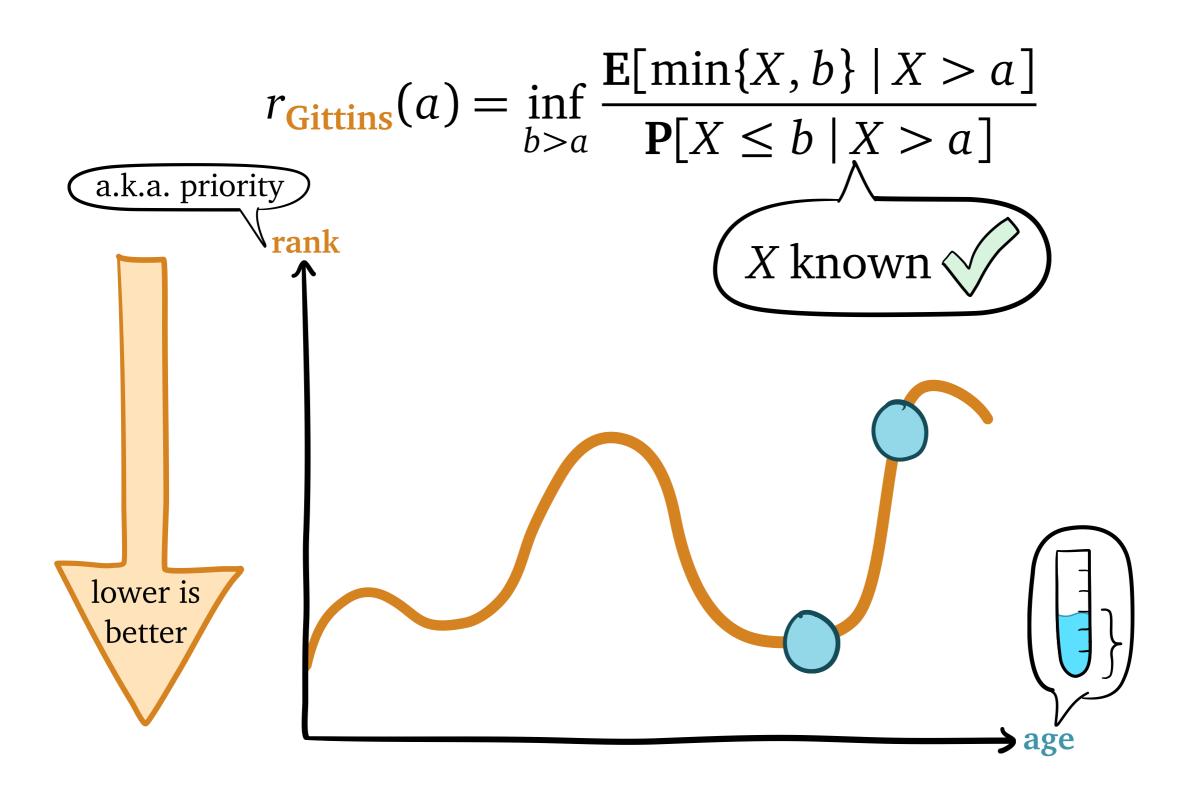


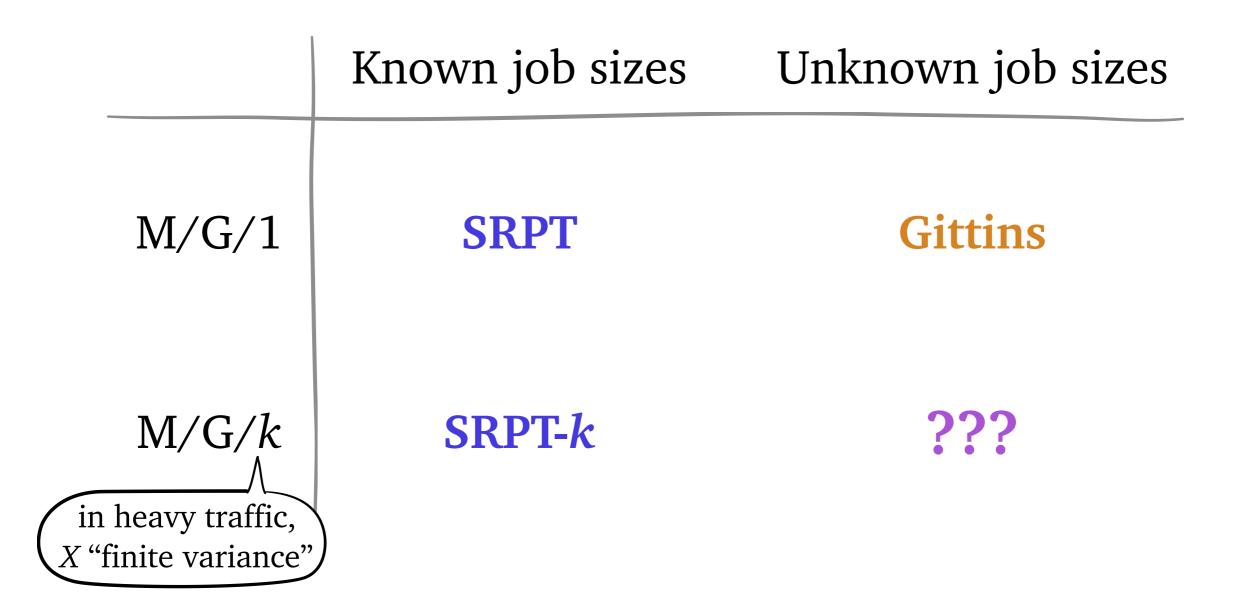


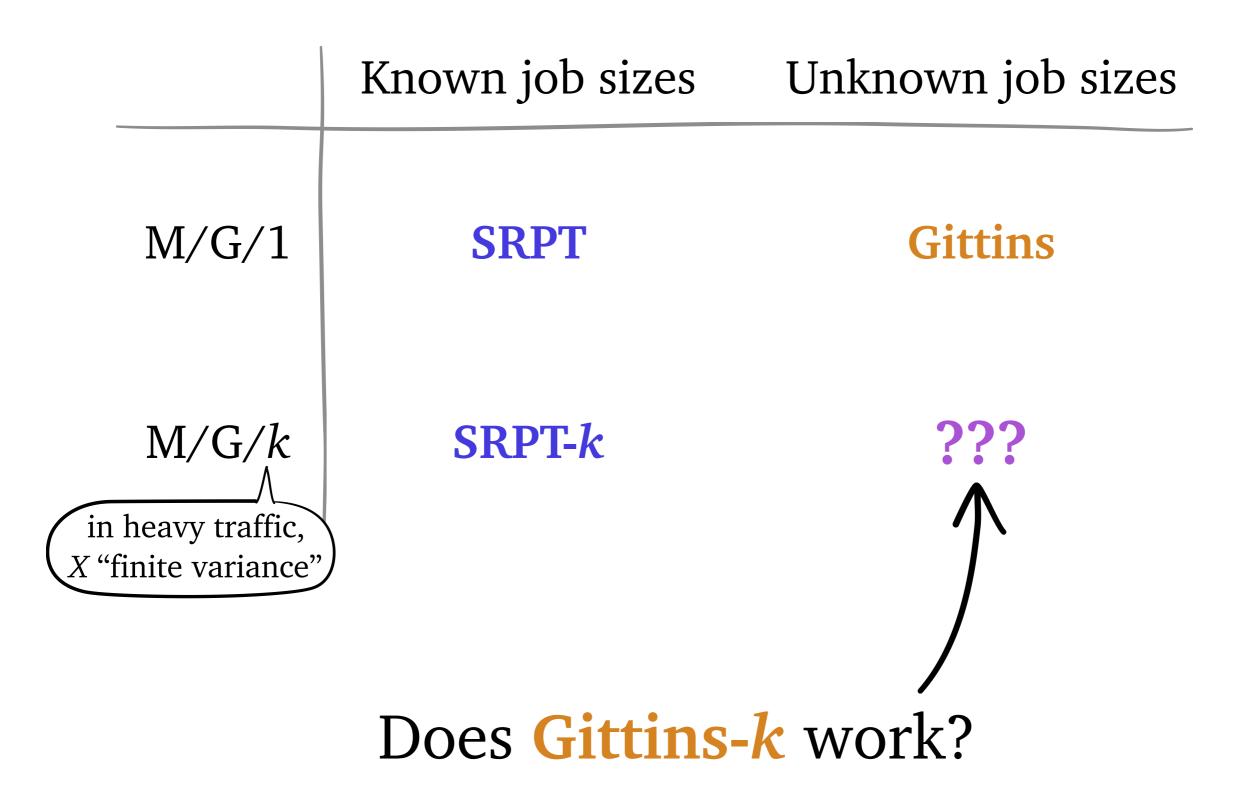








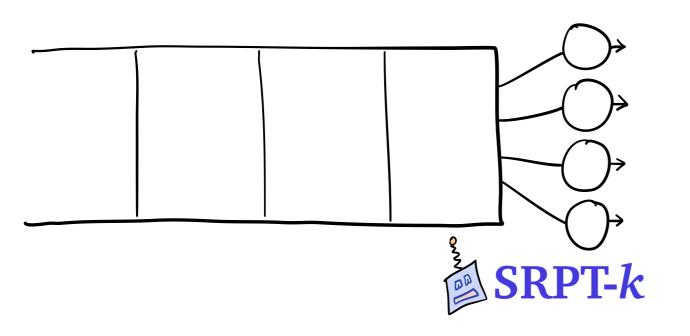


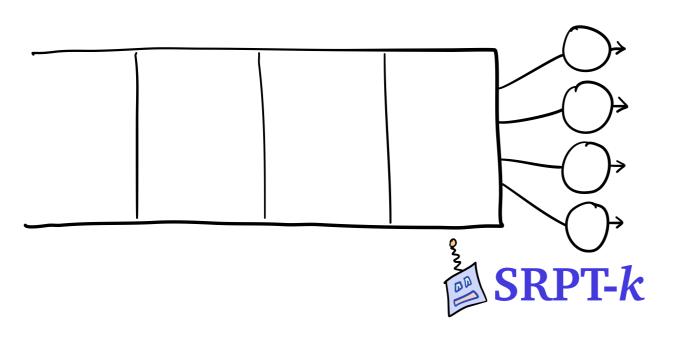


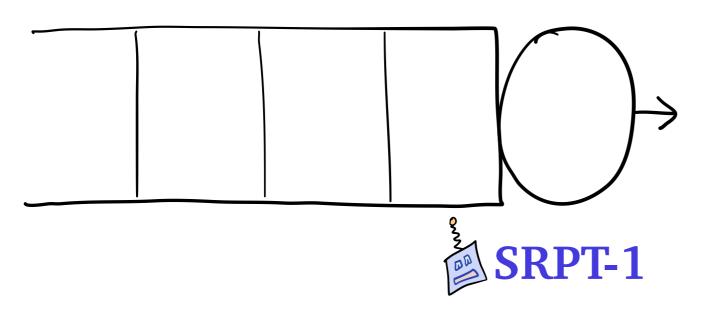
Background: SRPT-k optimality

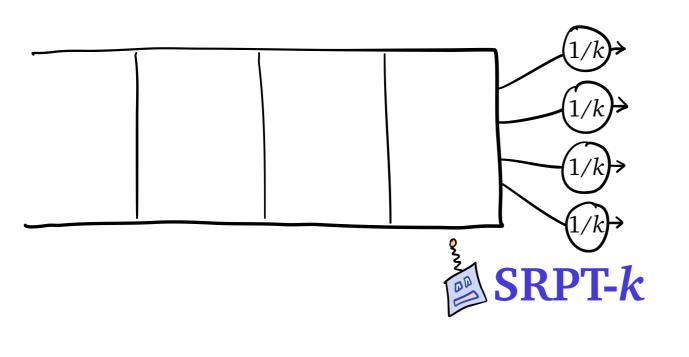
Background: SRPT-k optimality

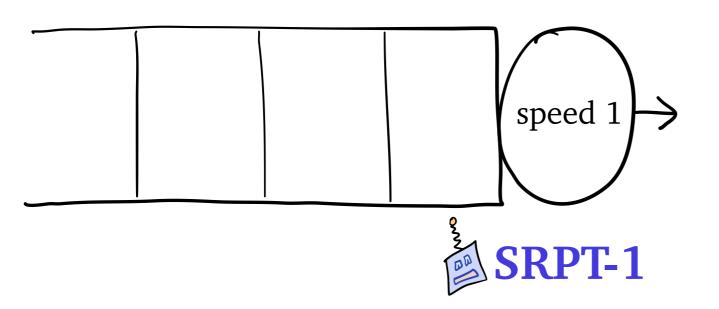
(Grosof, Scully, & Harchol-Balter, 2018)

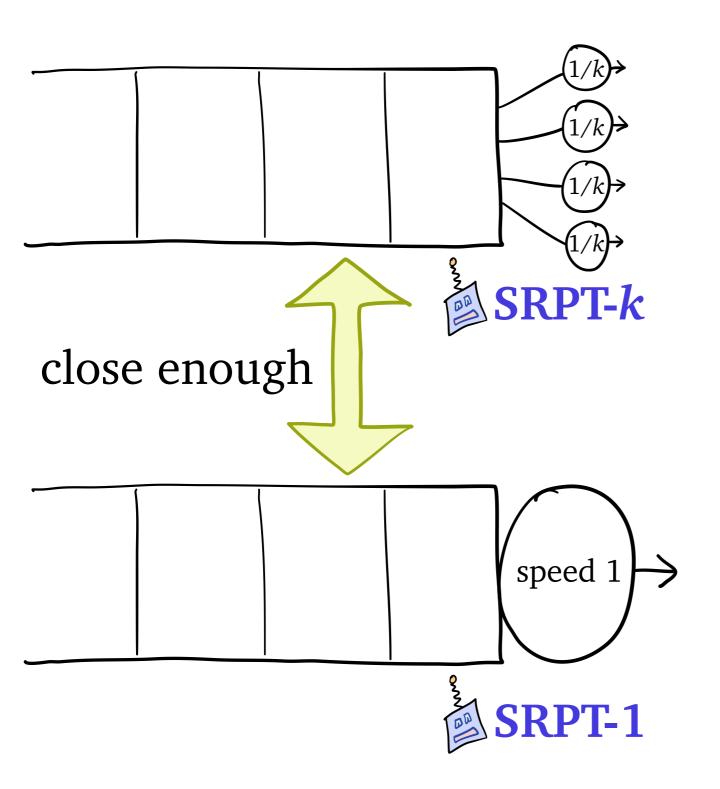


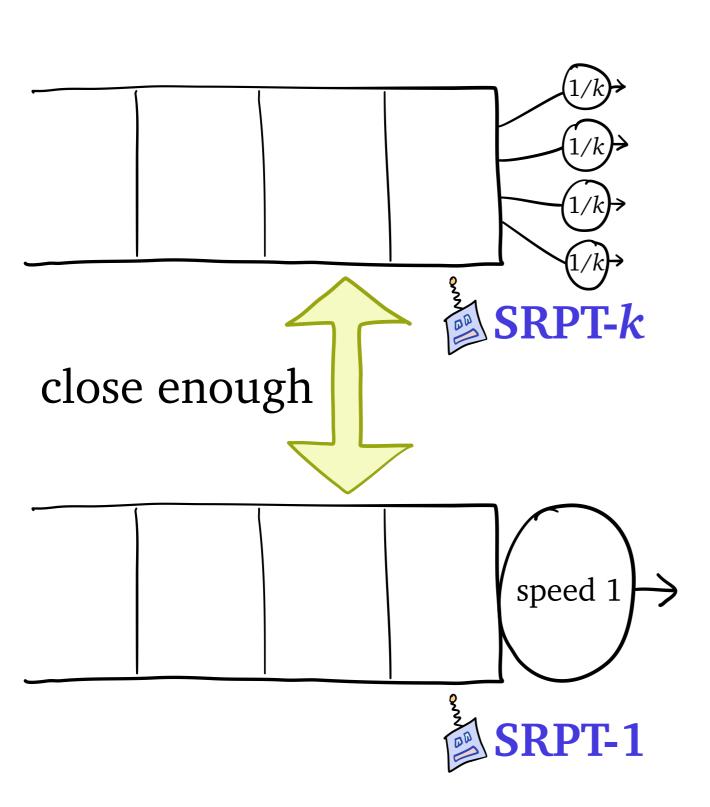






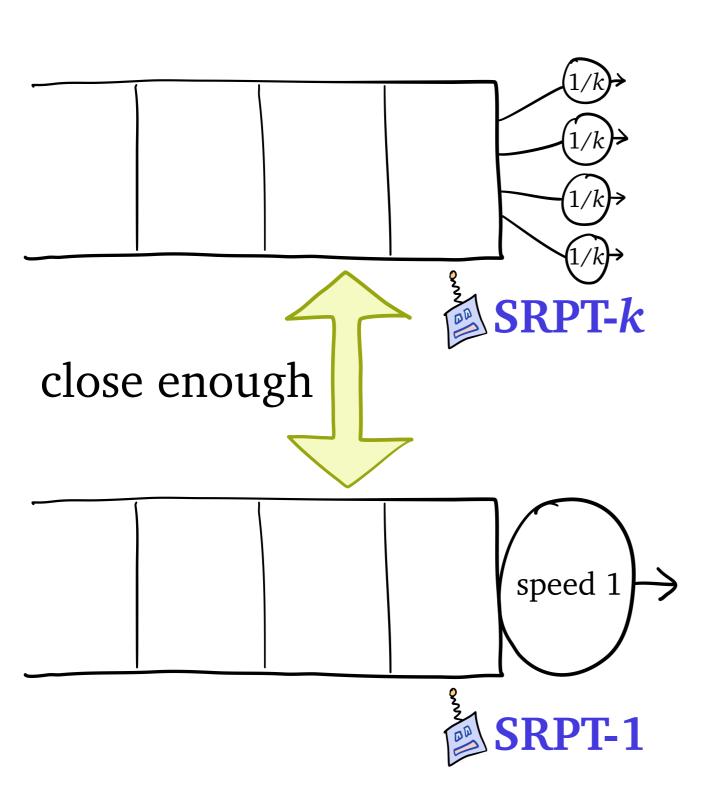






Step 1: link **SRPT-***k* to **SRPT-1**

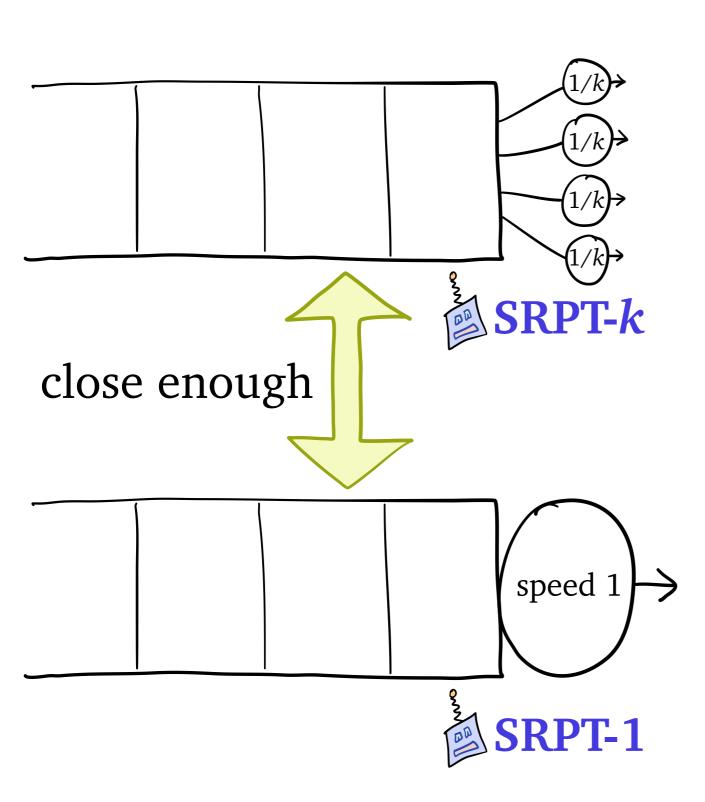
 $\mathbf{E}[T_{\mathbf{SRPT-}k}] \le \mathbf{E}[T_{\mathbf{SRPT-}1}] + k \cdot O\left(\log\frac{1}{1-\rho}\right)$



Step 1: link **SRPT-***k* to **SRPT-1**

 $\mathbf{E}[T_{\mathbf{SRPT-}k}] \le \mathbf{E}[T_{\mathbf{SRPT-}1}] + k \cdot O\left(\log\frac{1}{1-\rho}\right)$

Step 2: analyze heavy-traffic **SRPT-1** $E[T_{SRPT-1}] = \omega \left(\log \frac{1}{1-\rho} \right)$

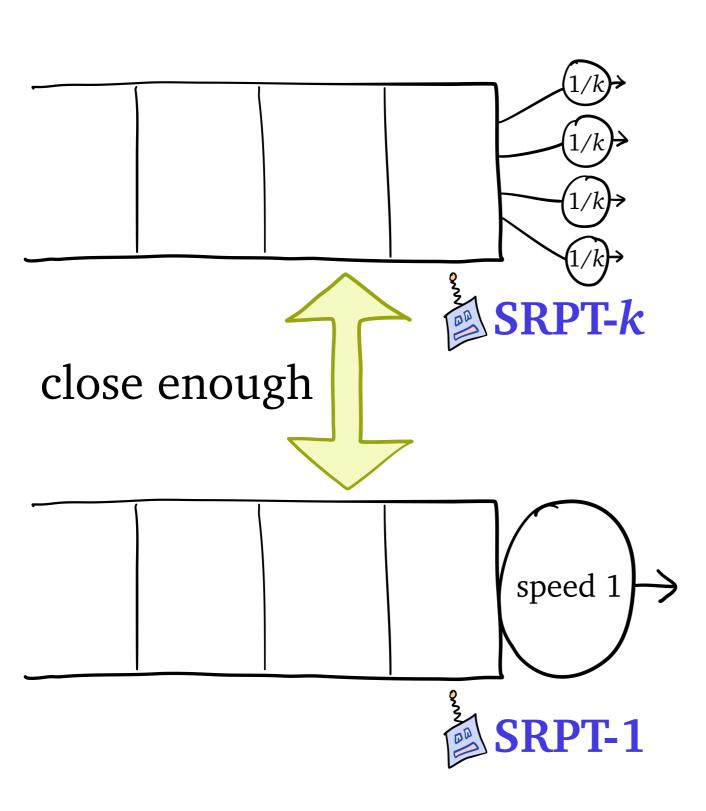


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 $\mathbf{E}[T_{\mathbf{SRPT-}k}] \le \mathbf{E}[T_{\mathbf{SRPT-}1}] + k \cdot O\left(\log\frac{1}{1-\rho}\right)$

Step 2: (Lin, Wierman, & Zwart, 2011) analyze heavy-traffic SRPT-1

$$\mathbf{E}[T_{\text{SRPT-1}}] = \omega \left(\log \frac{1}{1-\rho}\right)$$



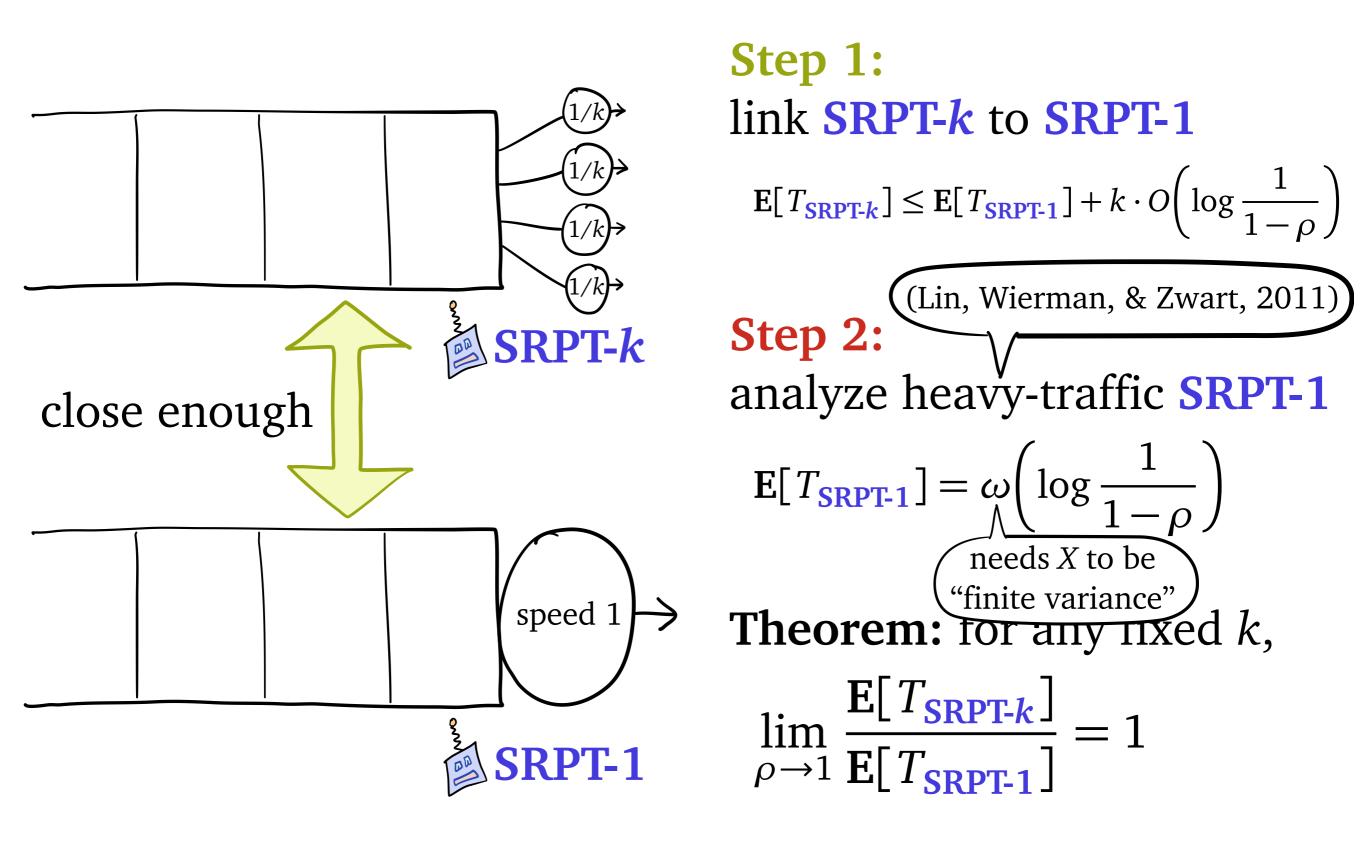
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$$\mathbf{E}[T_{\mathbf{SRPT-1}}] = \omega \left(\log \frac{1}{1-\rho}\right)$$

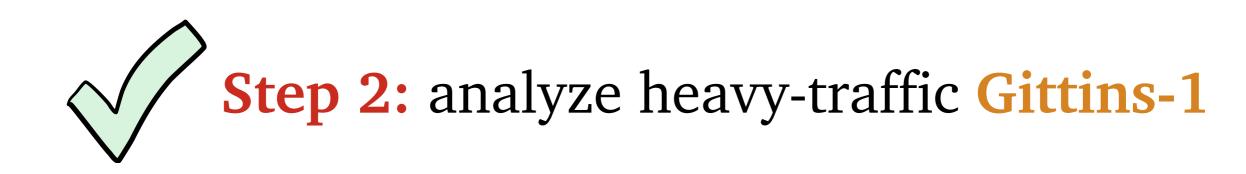
Theorem: for any fixed *k*, $\lim_{\rho \to 1} \frac{\mathbf{E}[T_{\text{SRPT-}k}]}{\mathbf{E}[T_{\text{SRPT-}1}]} = 1$



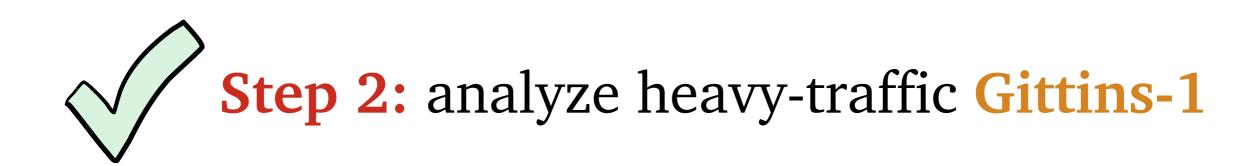
Step 1: link Gittins-k to Gittins-1

Step 2: analyze heavy-traffic **Gittins-1**

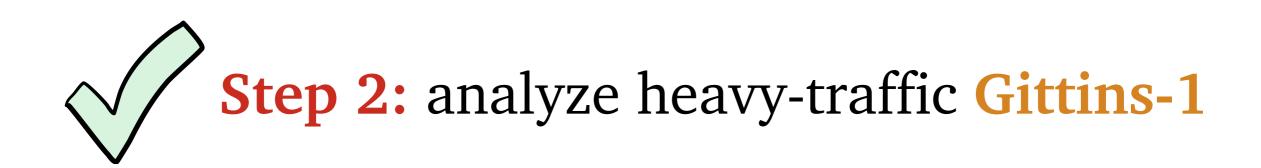
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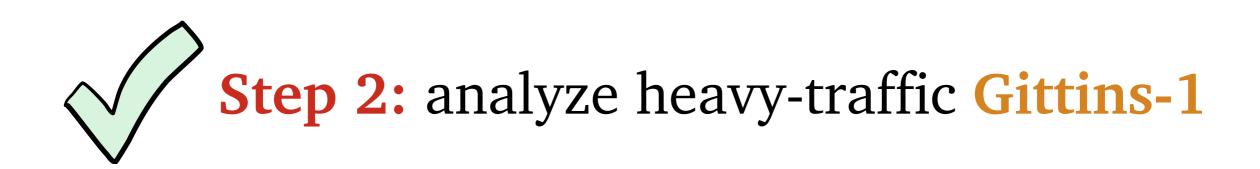




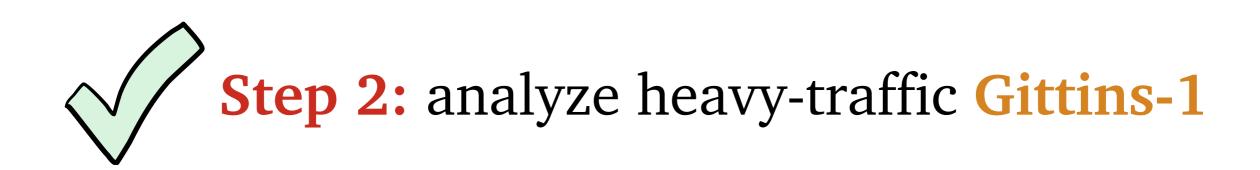




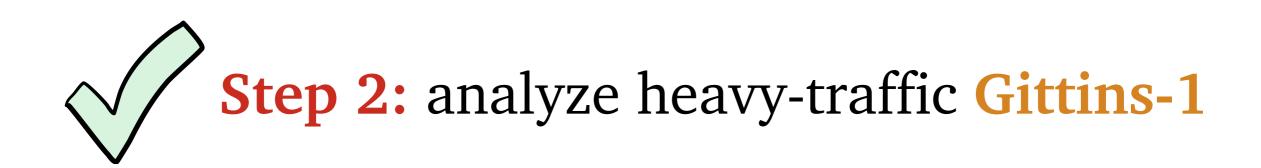














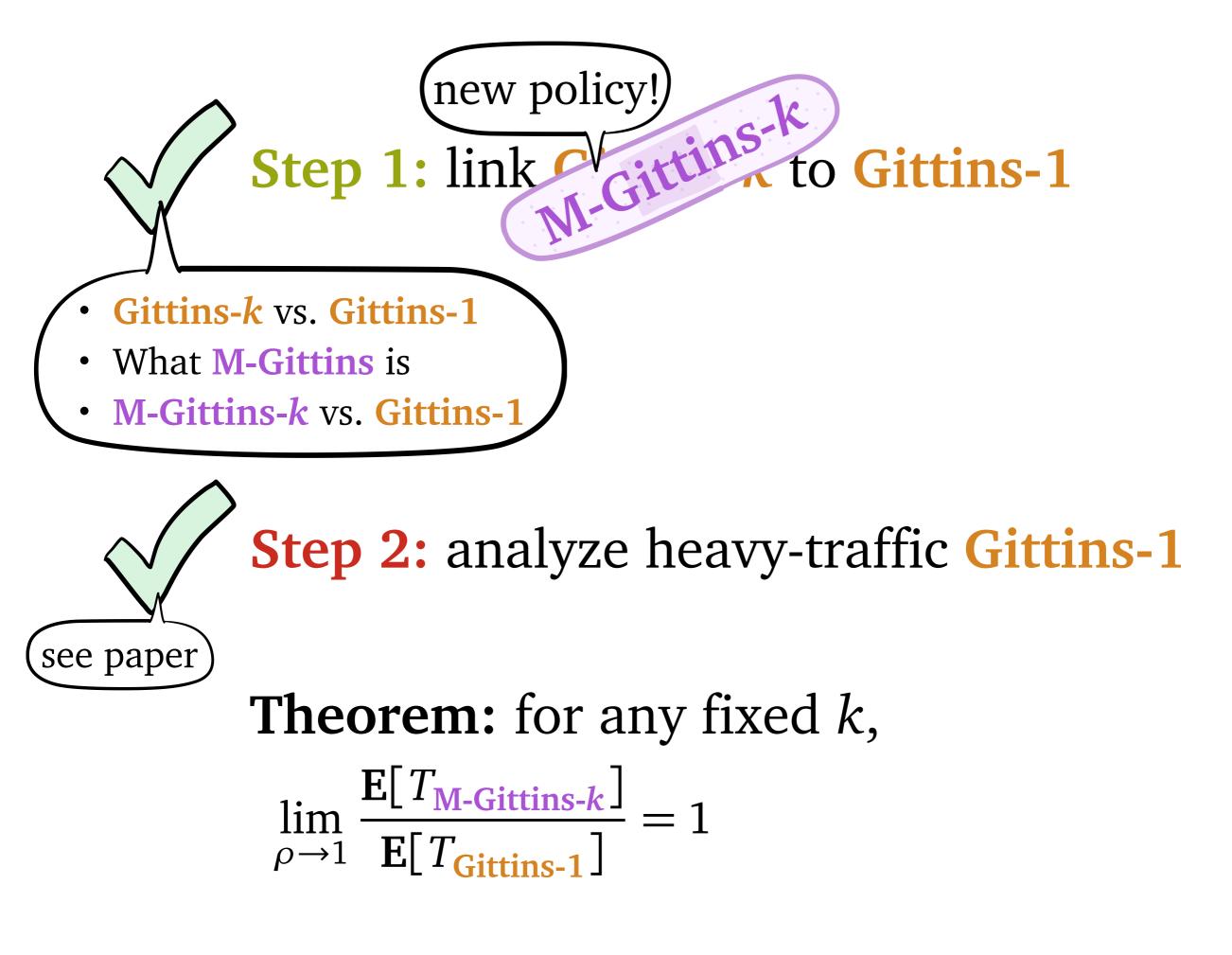
Step 2: analyze heavy-traffic **Gittins-1**

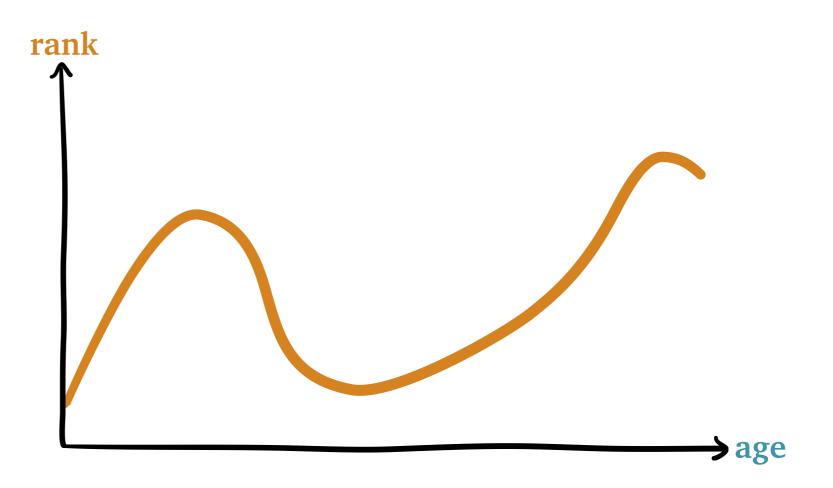
Theorem: for any fixed k, $\lim_{\rho \to 1} \frac{\mathbf{E}[T_{\mathbf{M}-\mathbf{Gittins}-k}]}{\mathbf{E}[T_{\mathbf{Gittins}-1}]} = 1$

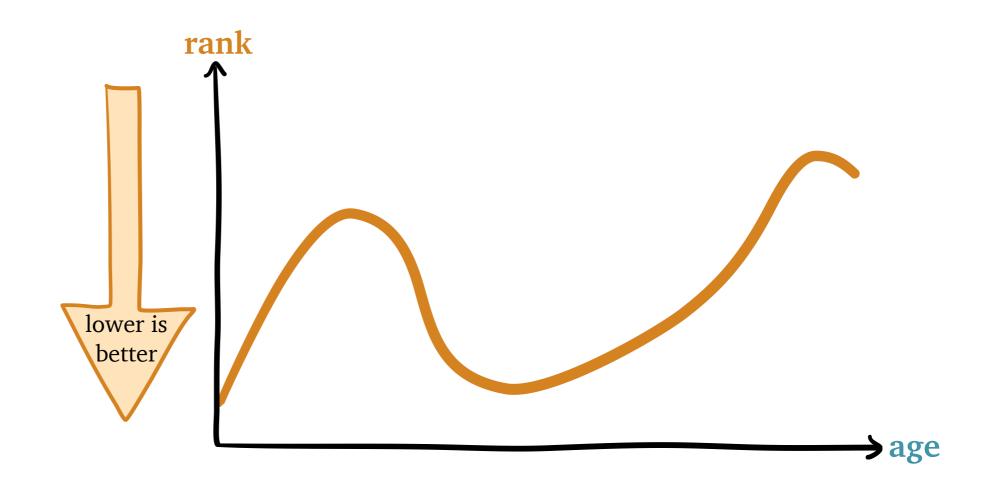


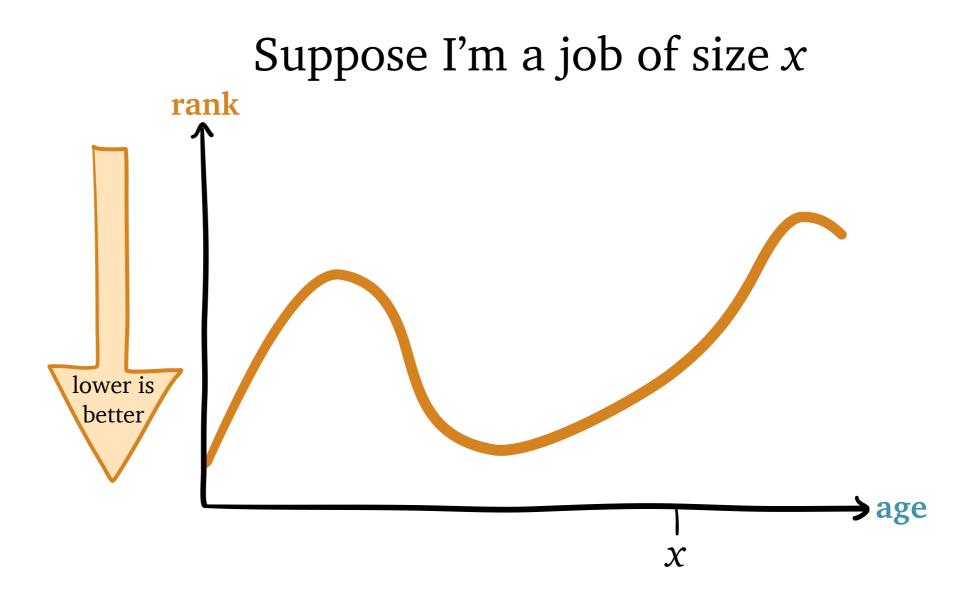
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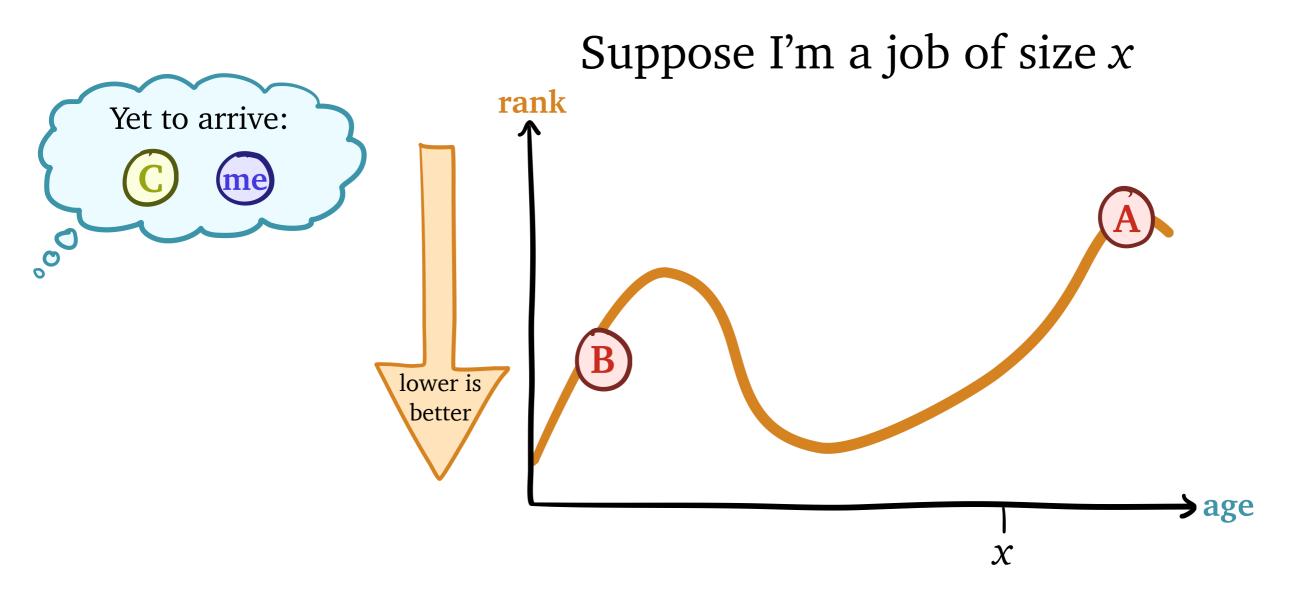
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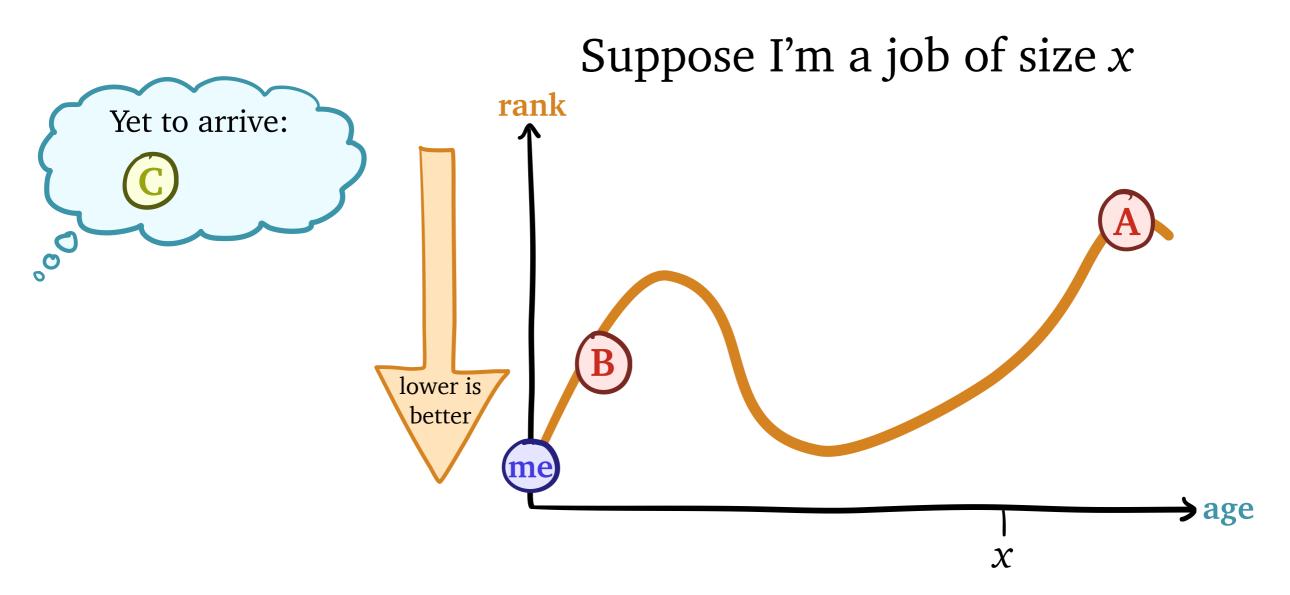


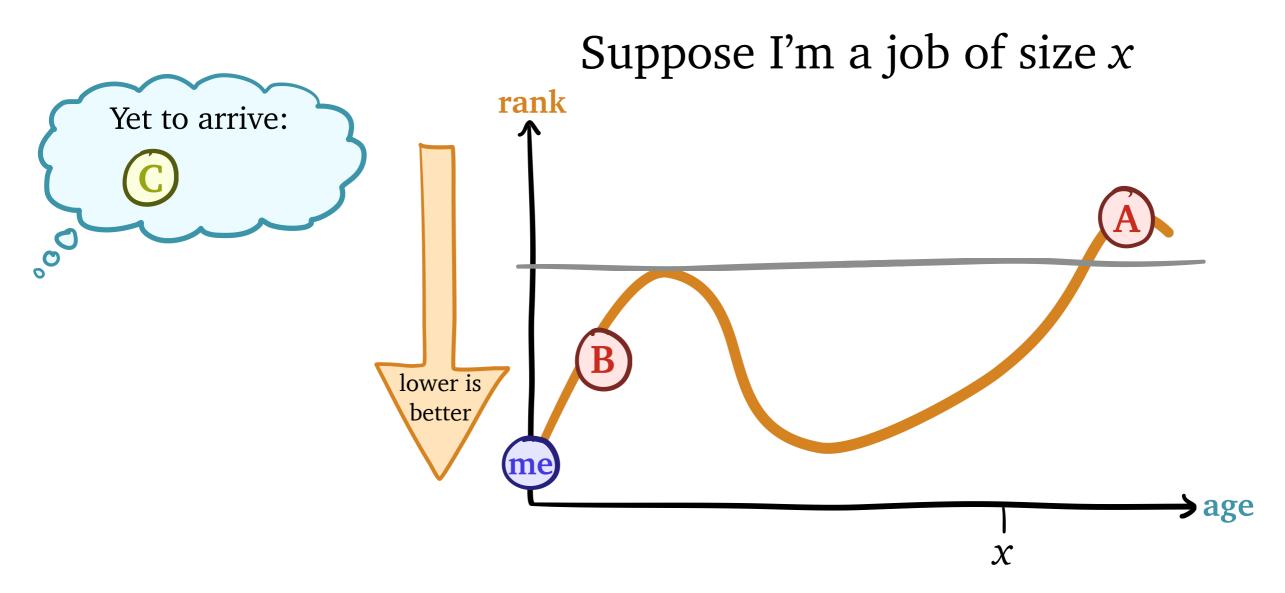


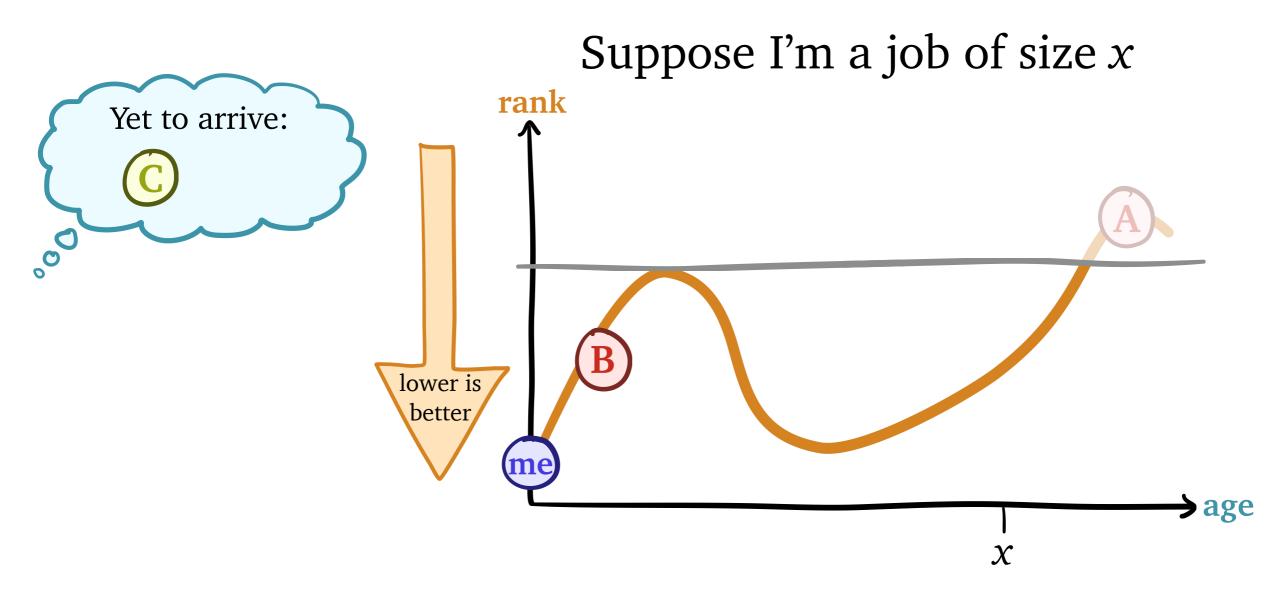


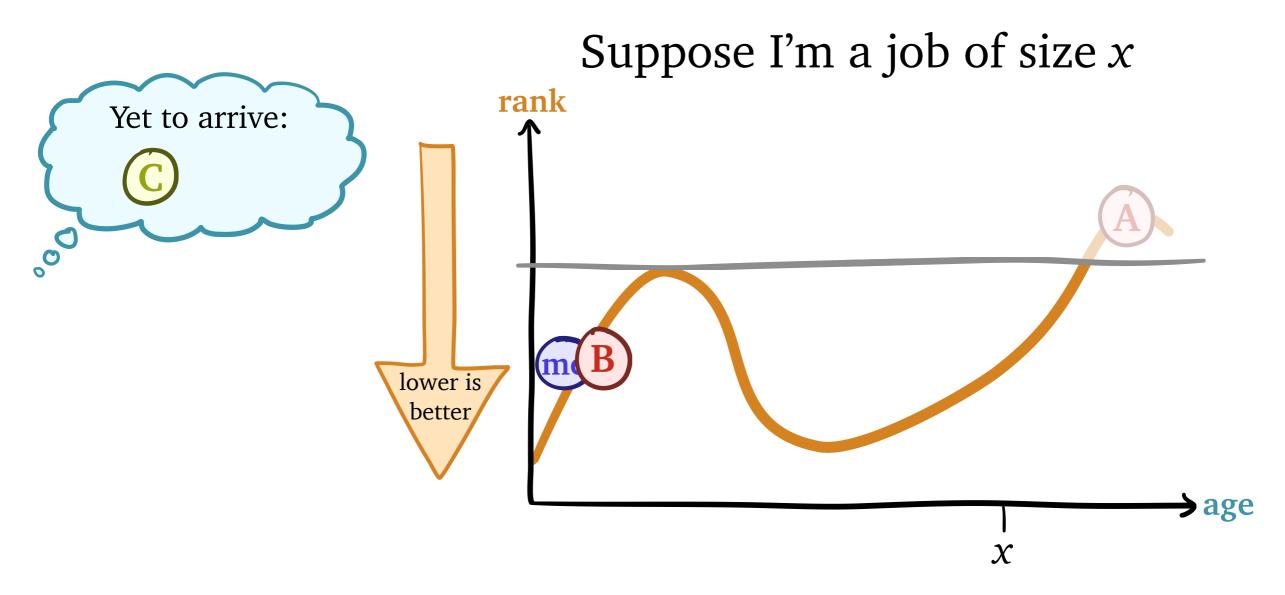


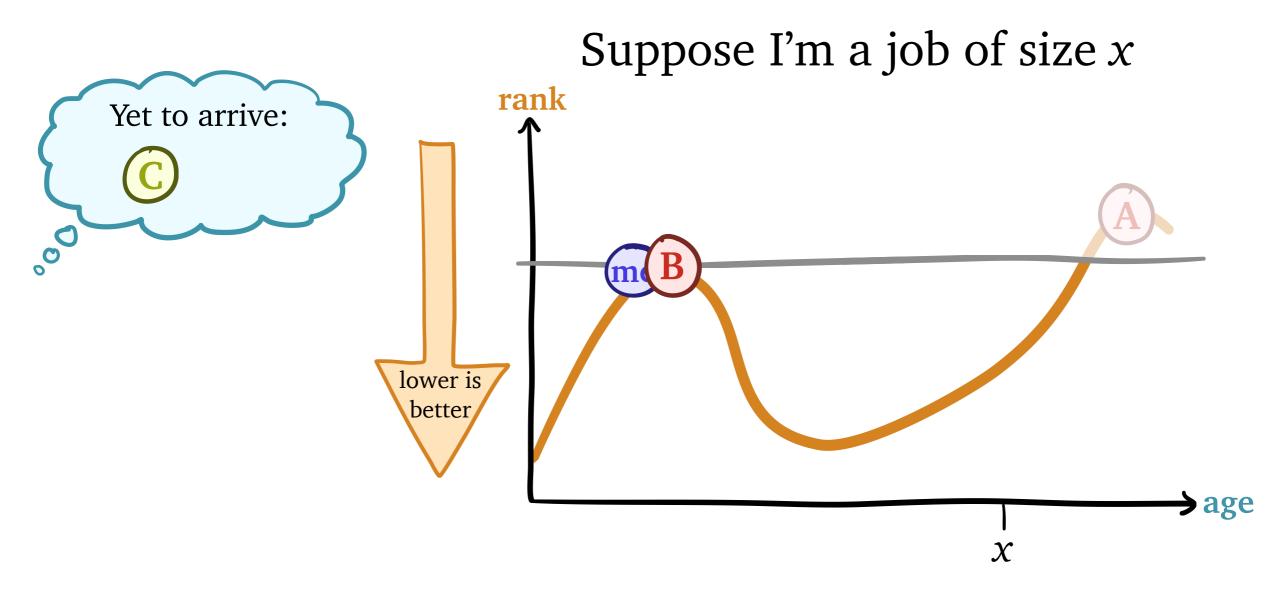


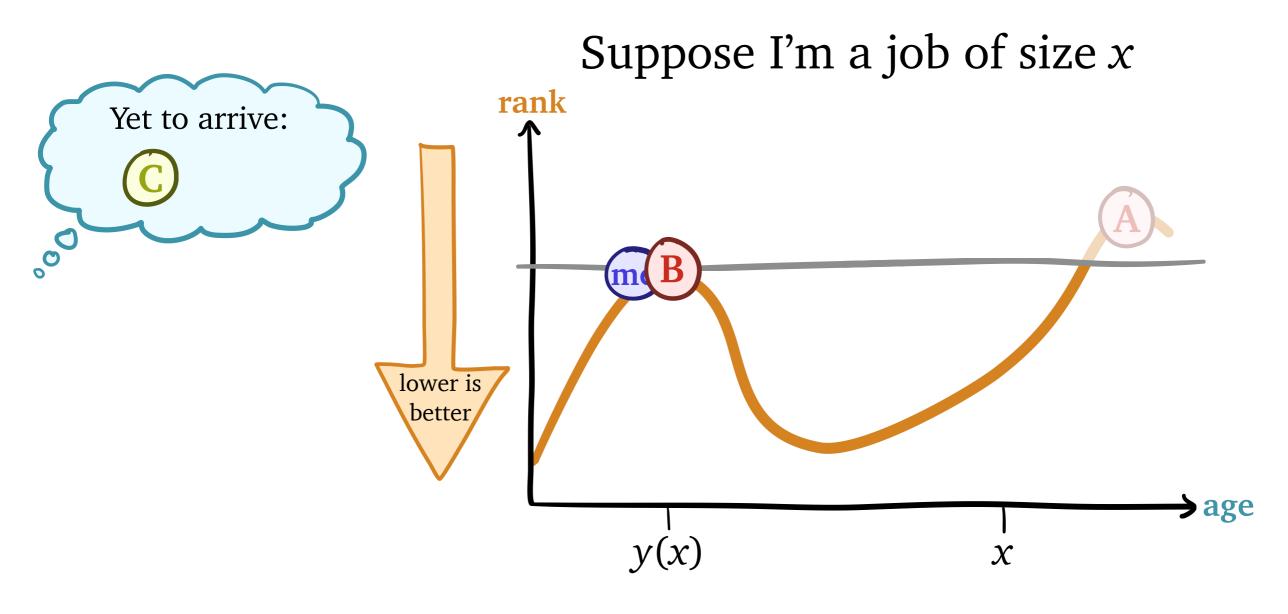


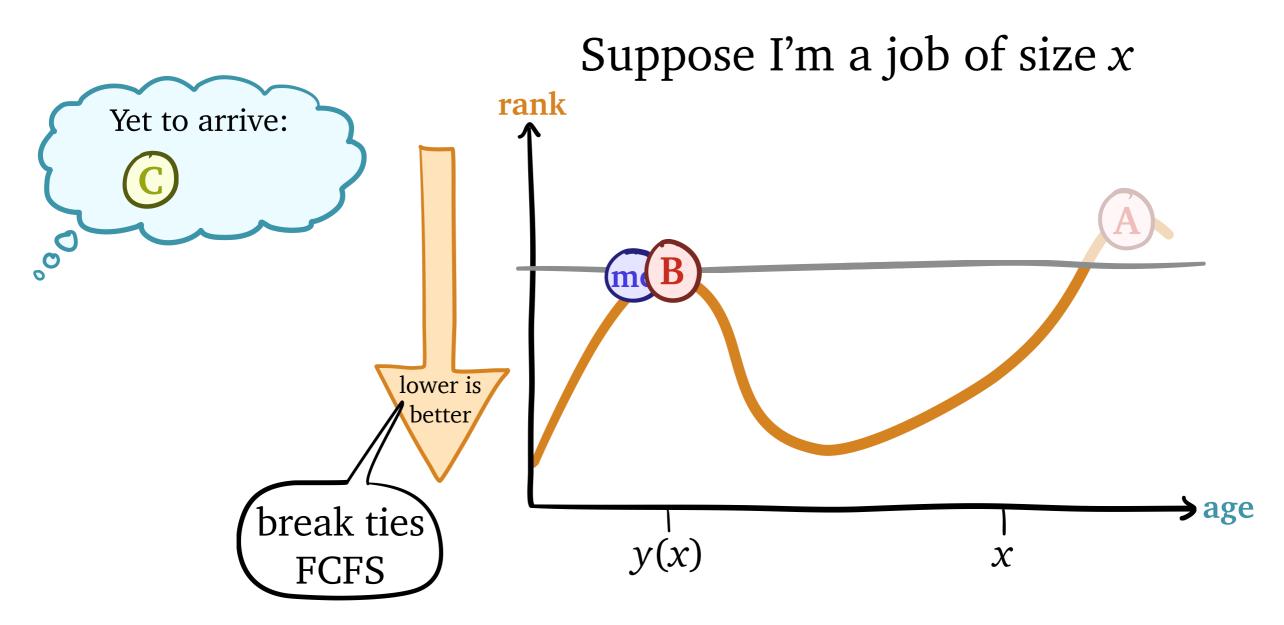


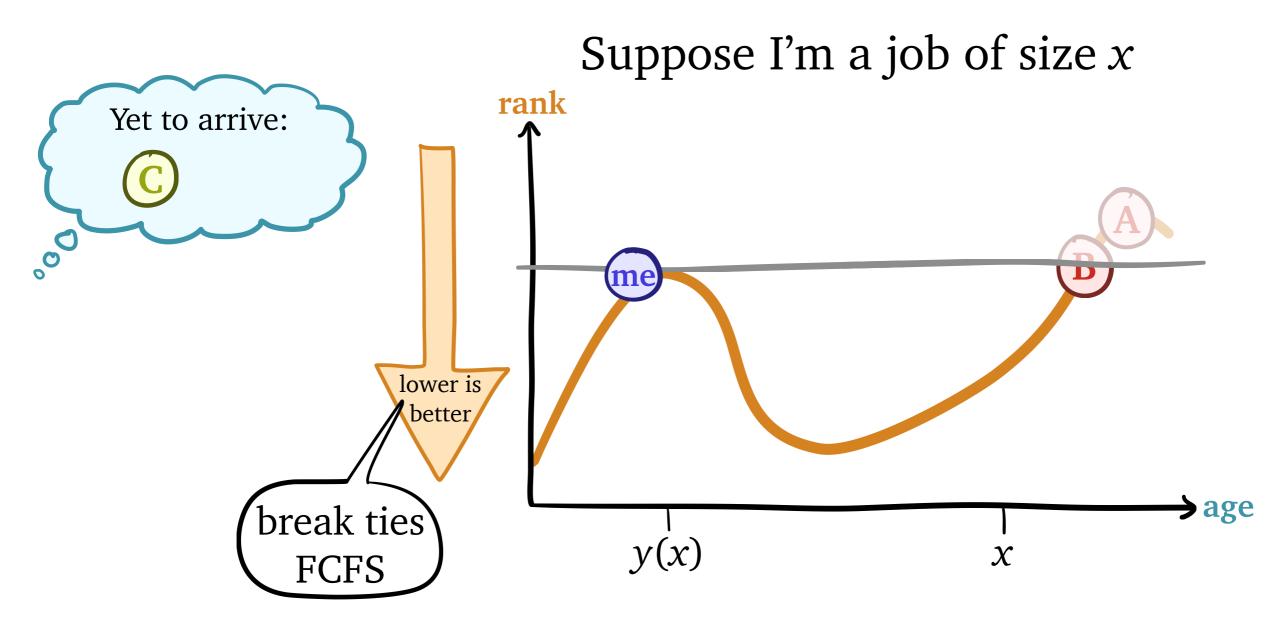


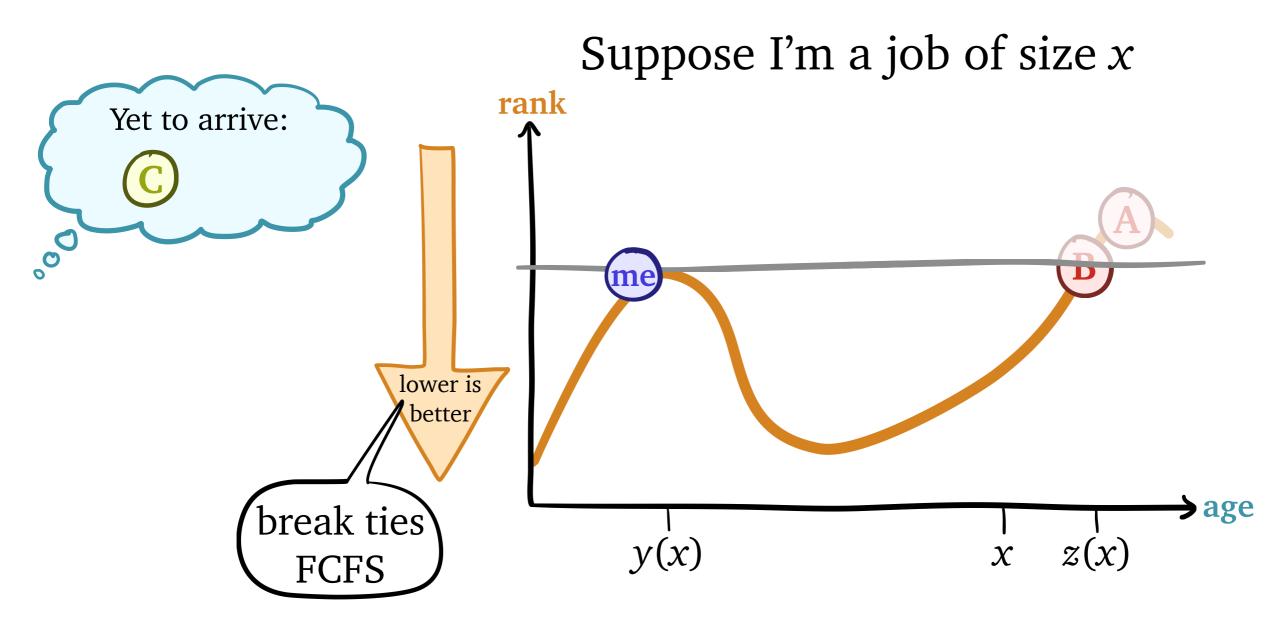


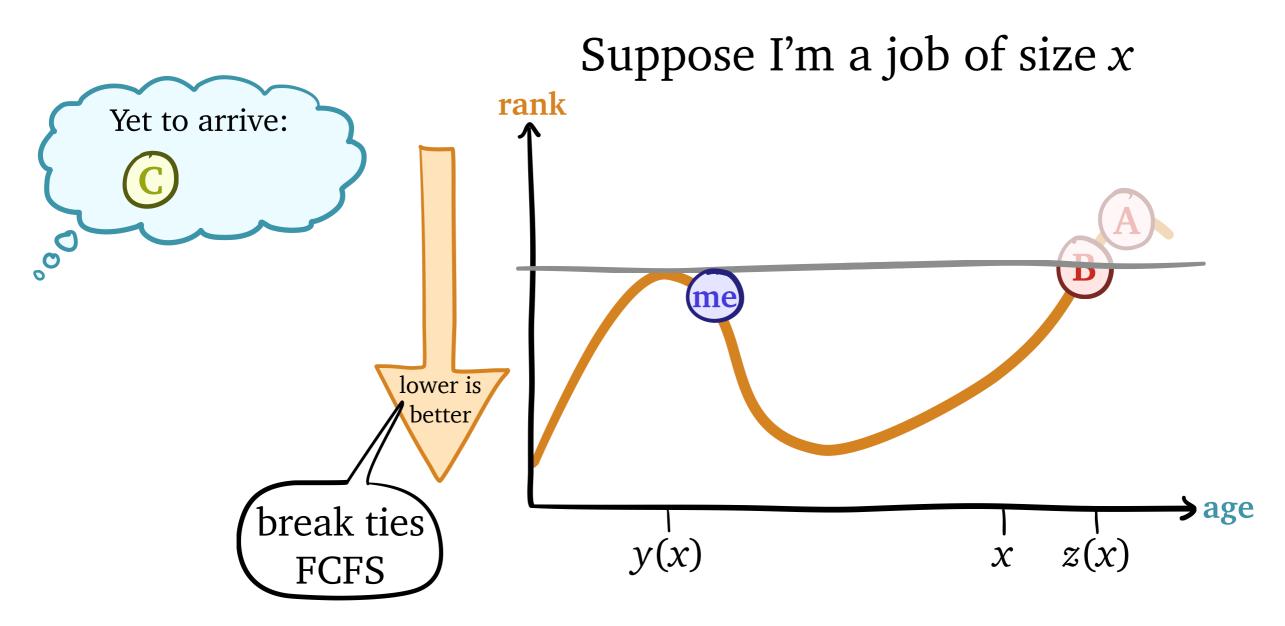


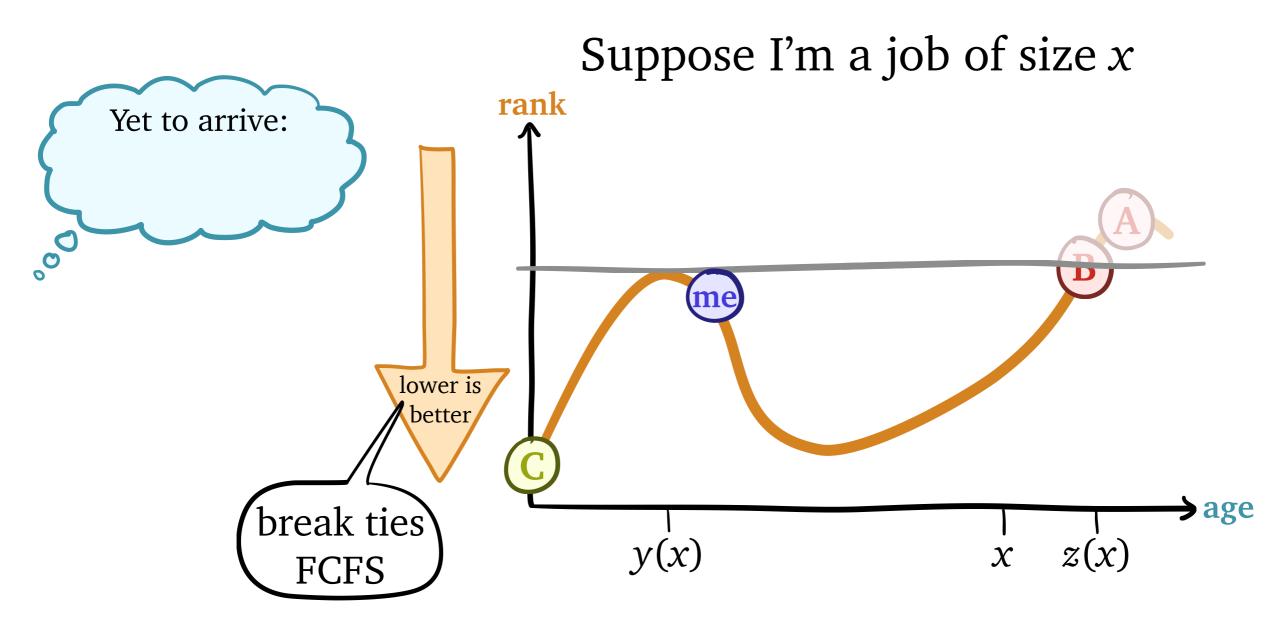


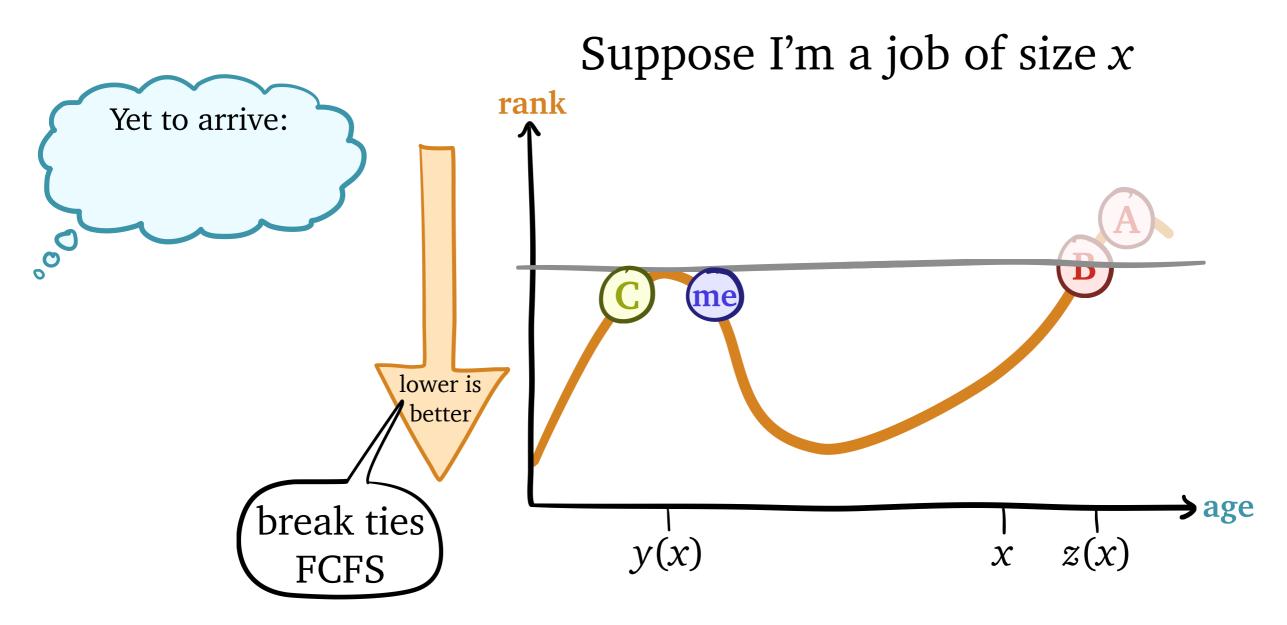


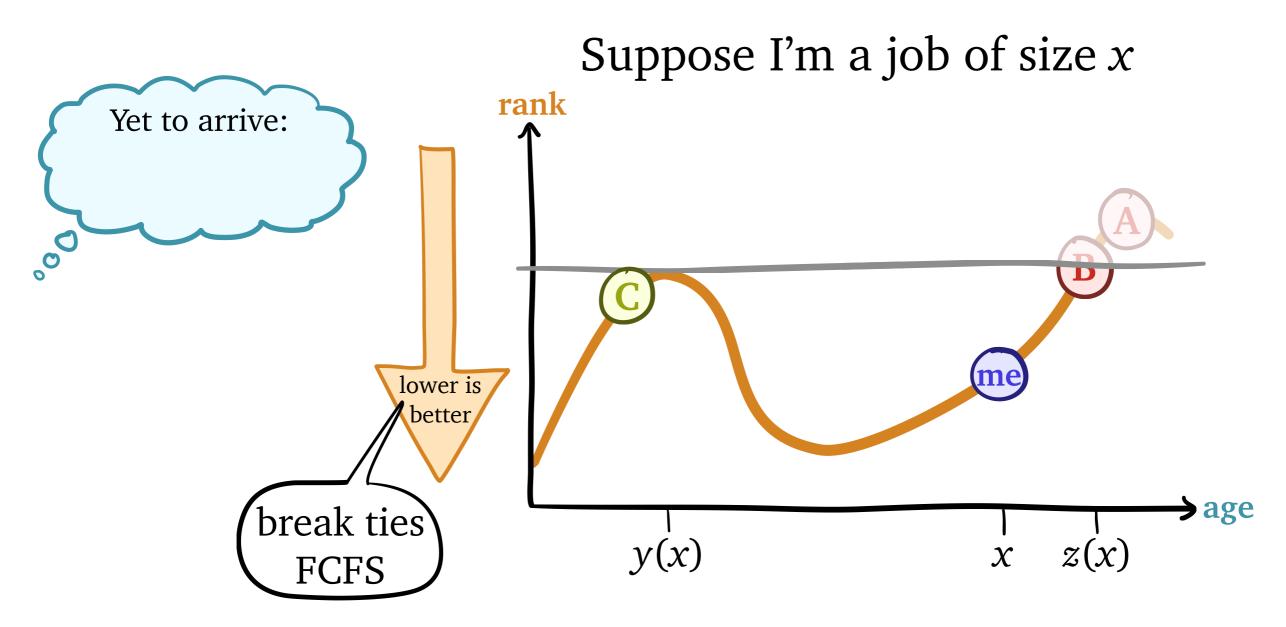


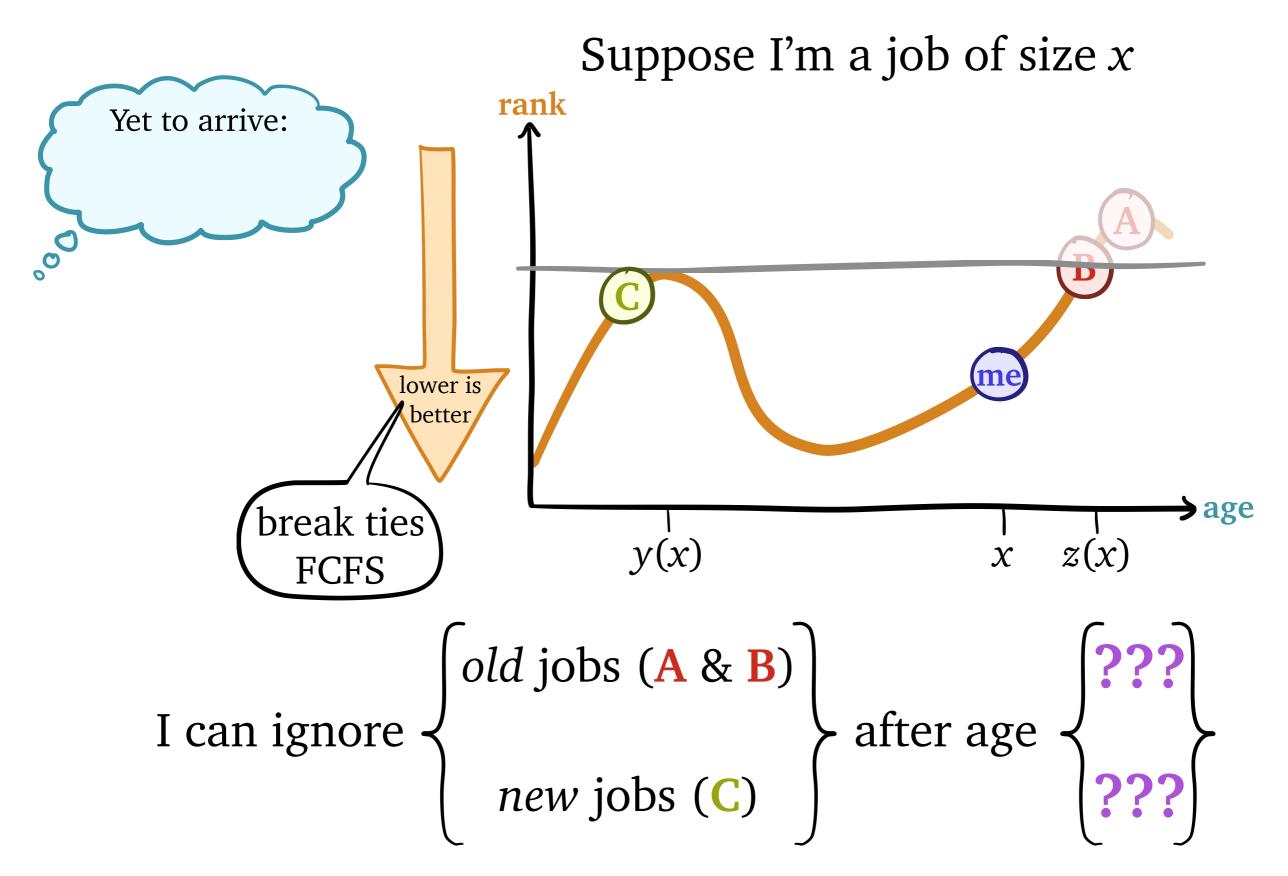


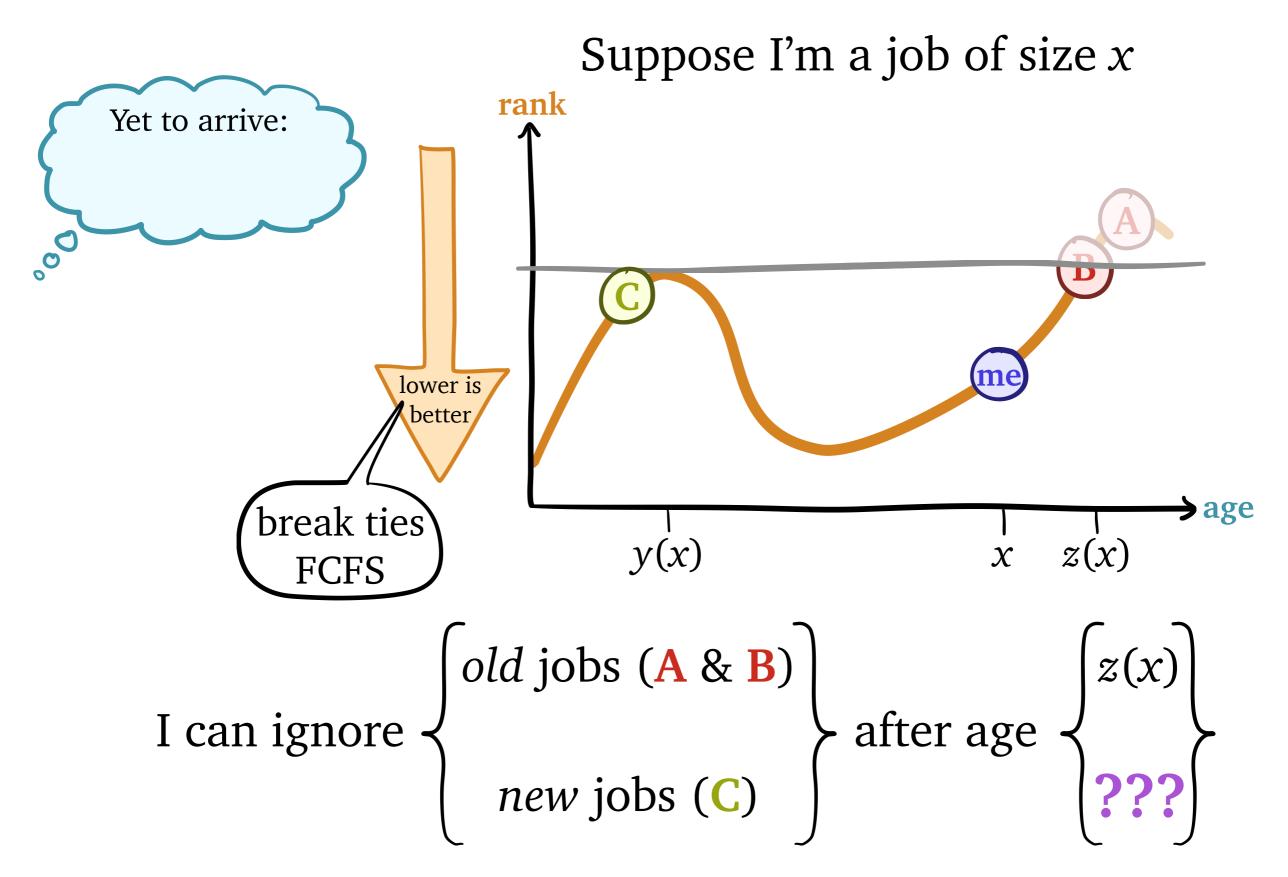


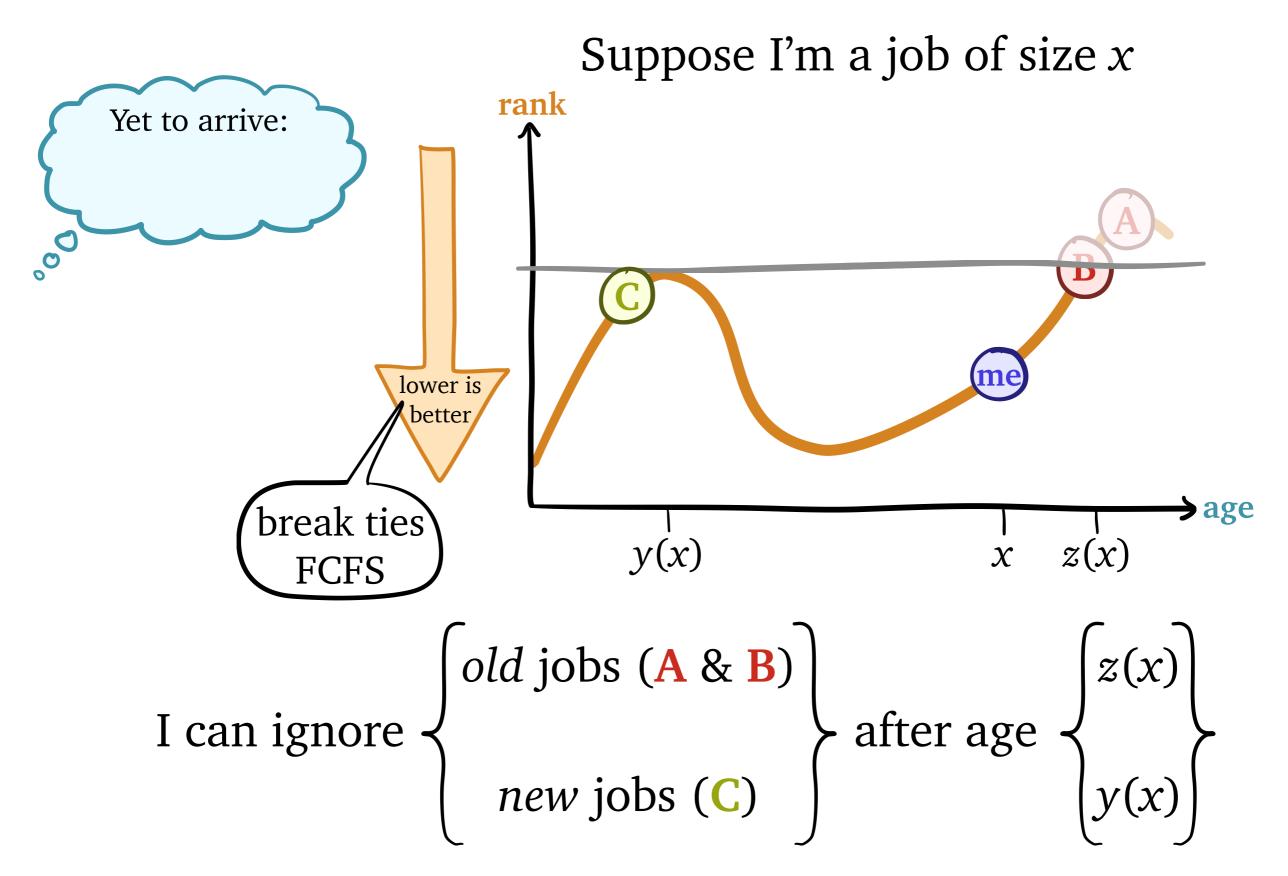




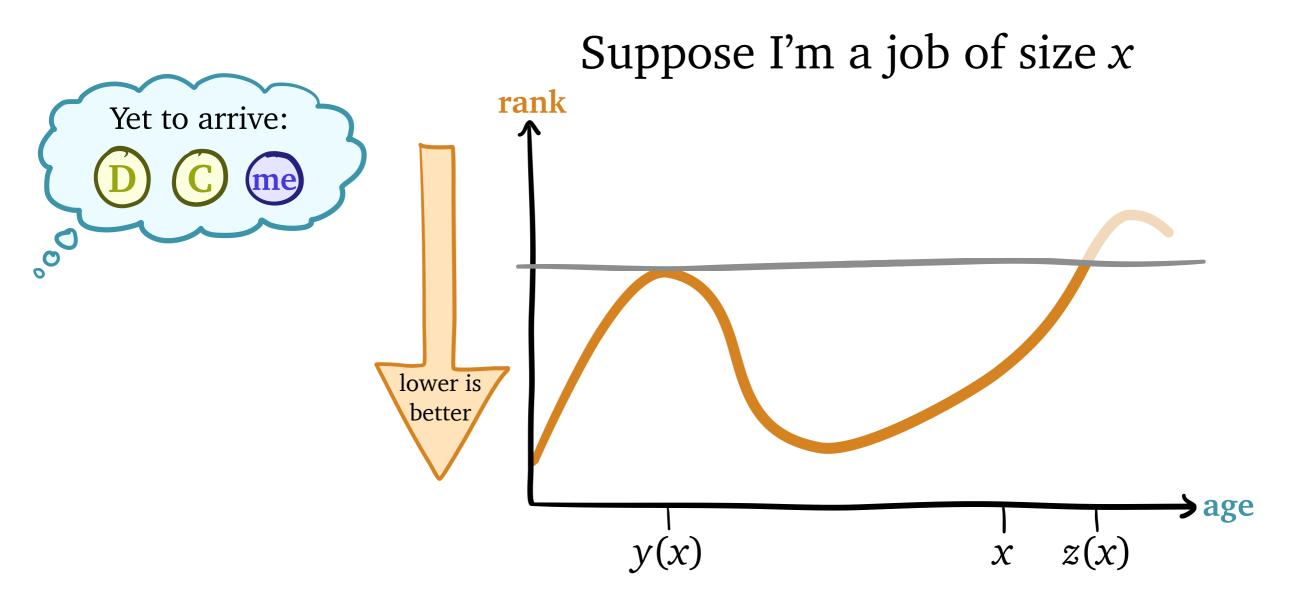


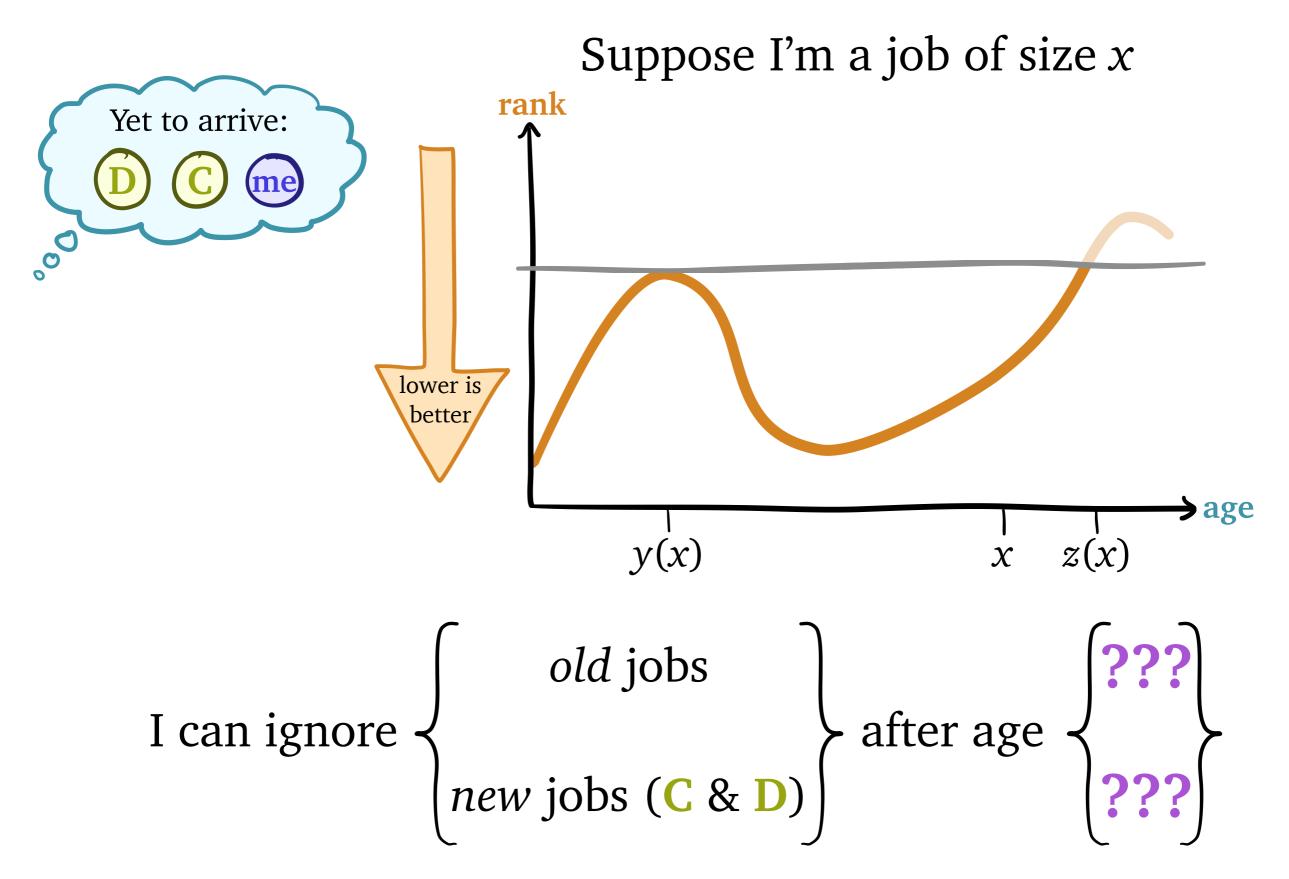


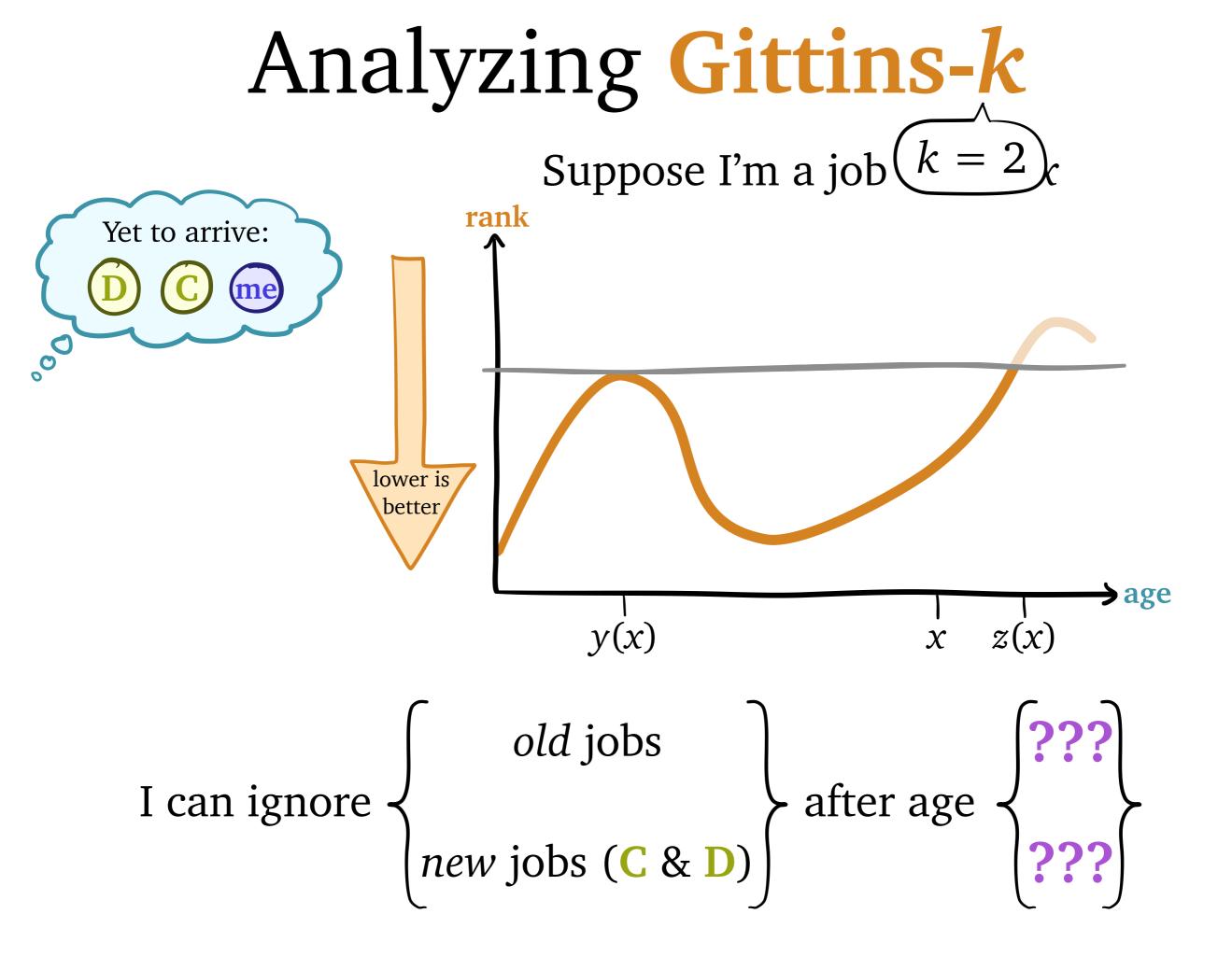


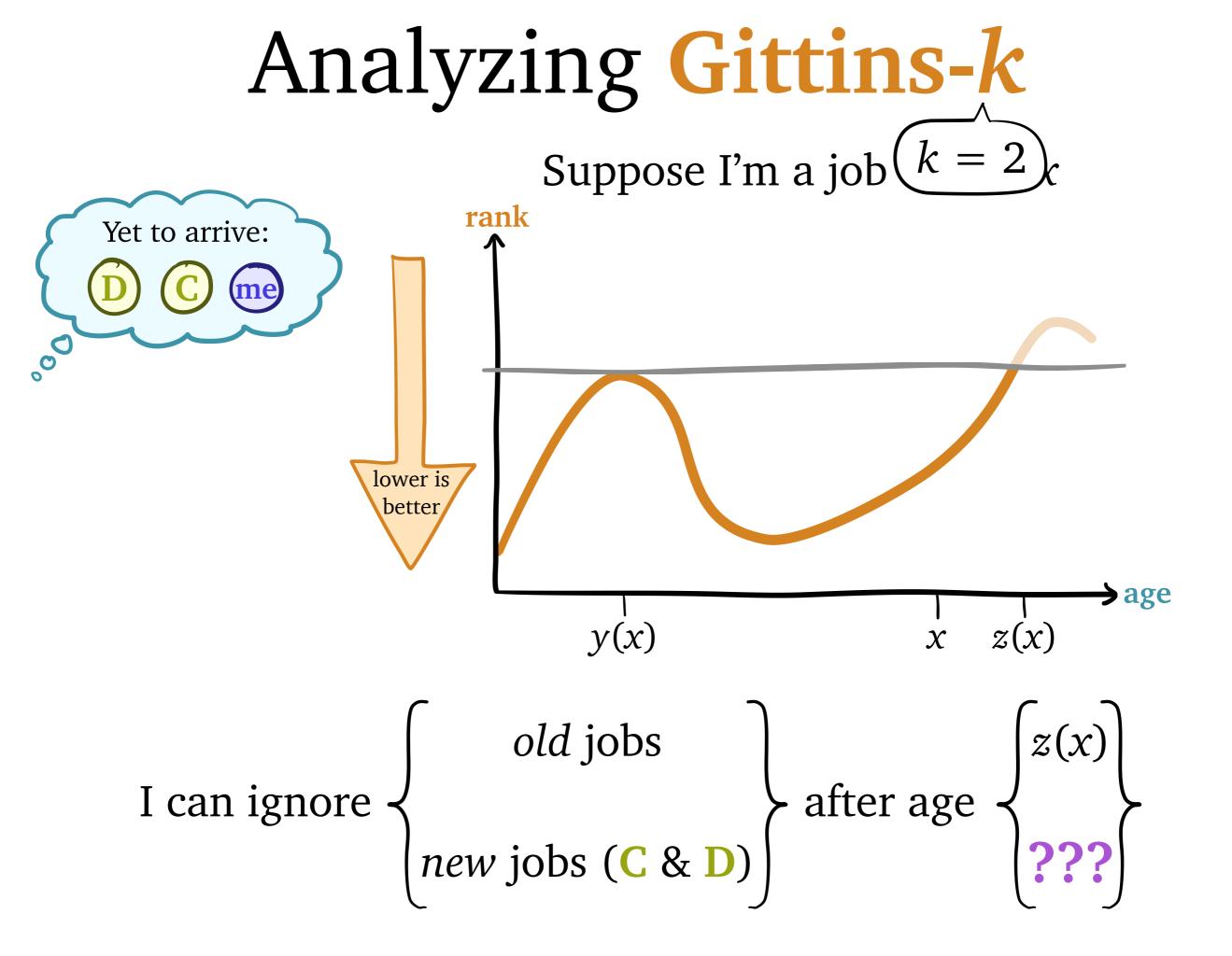


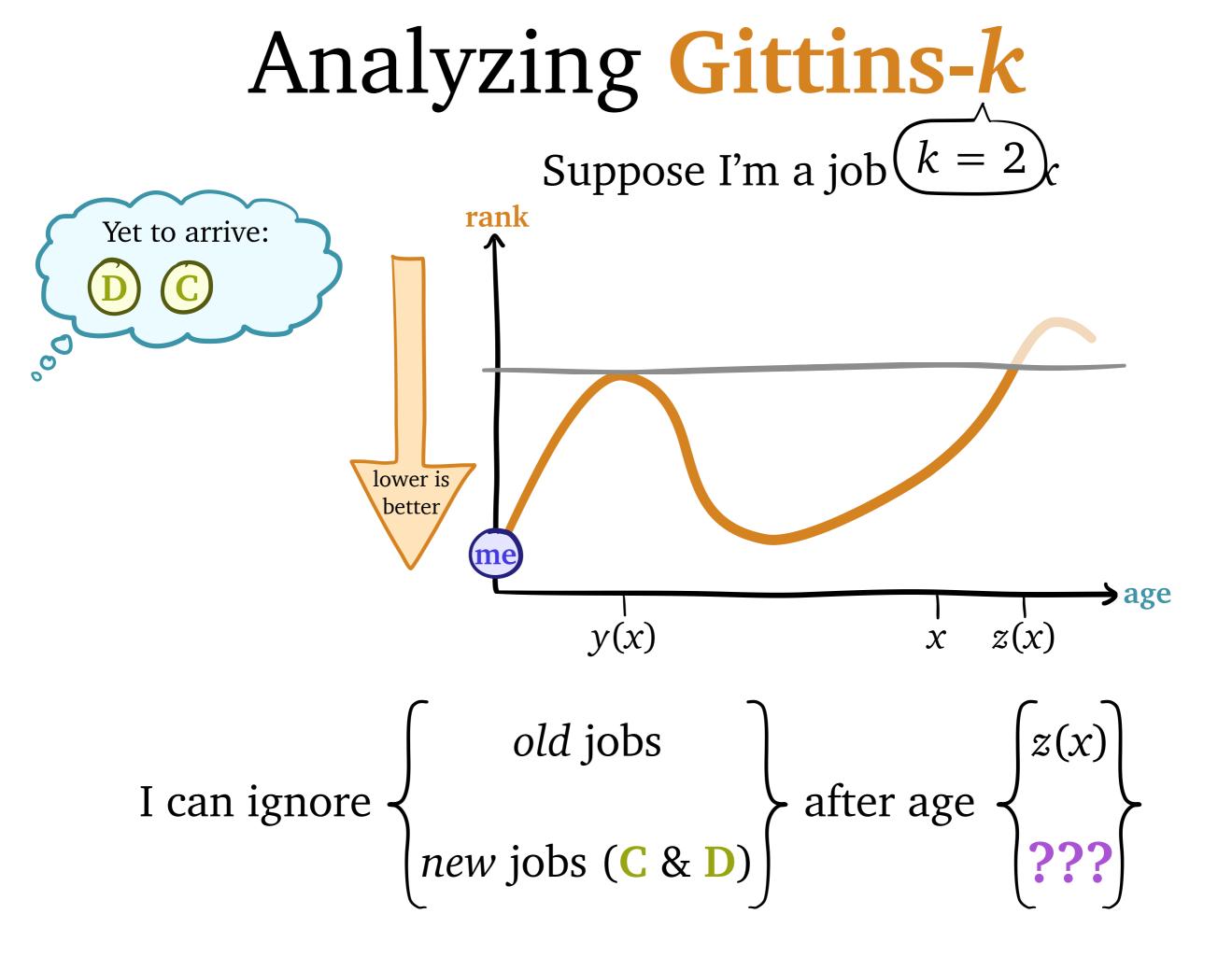
Question: What goes wrong for Gittins-k?

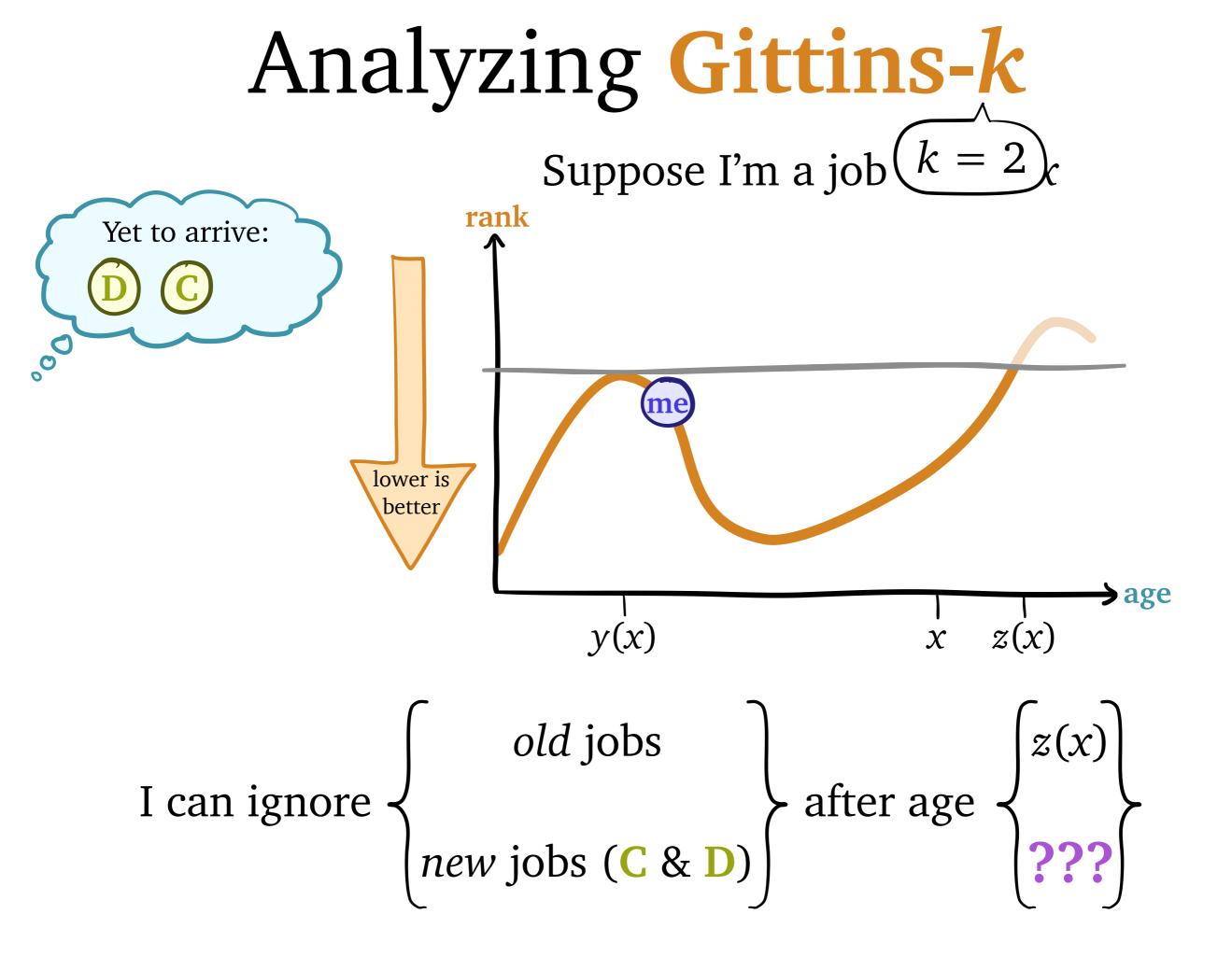


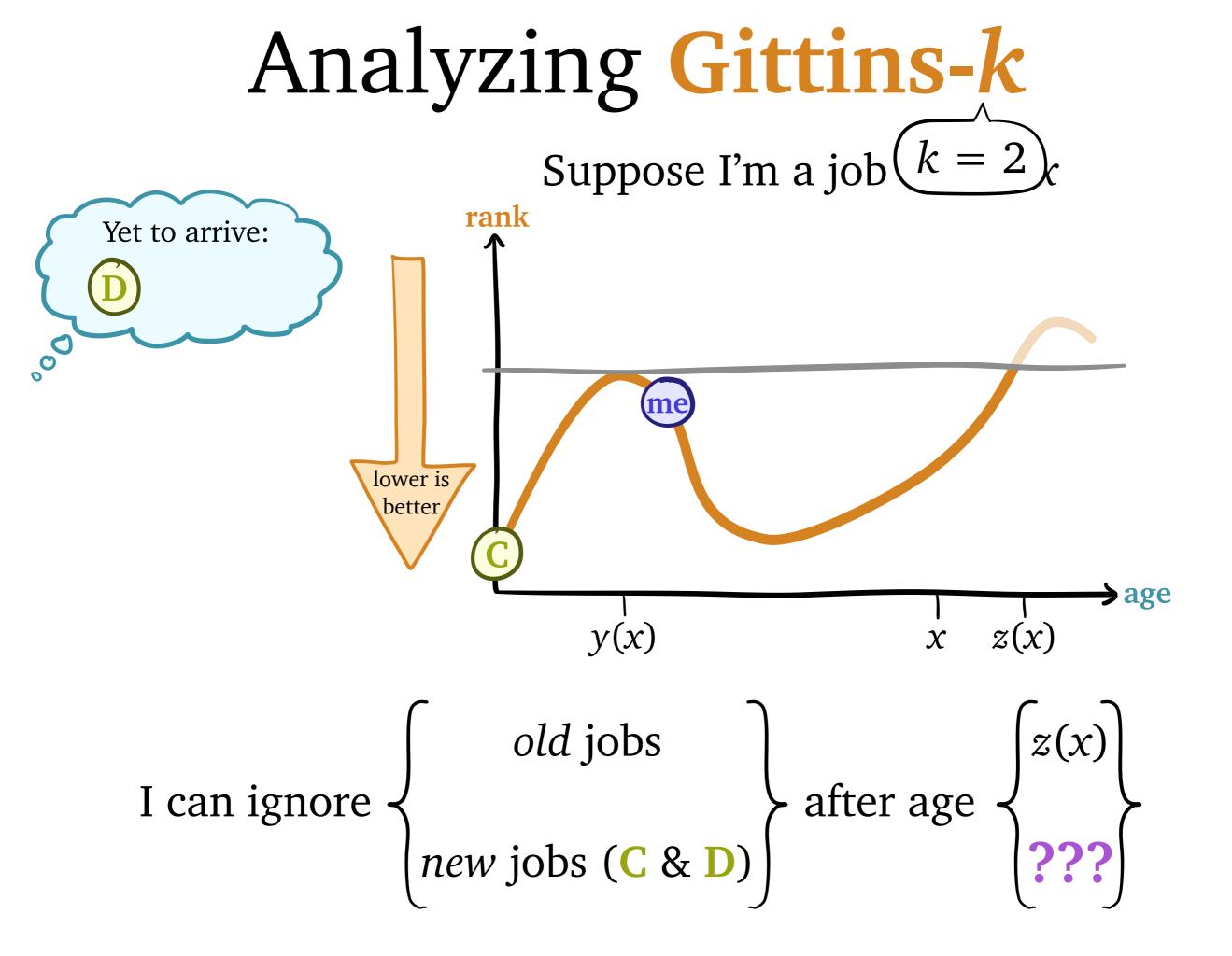


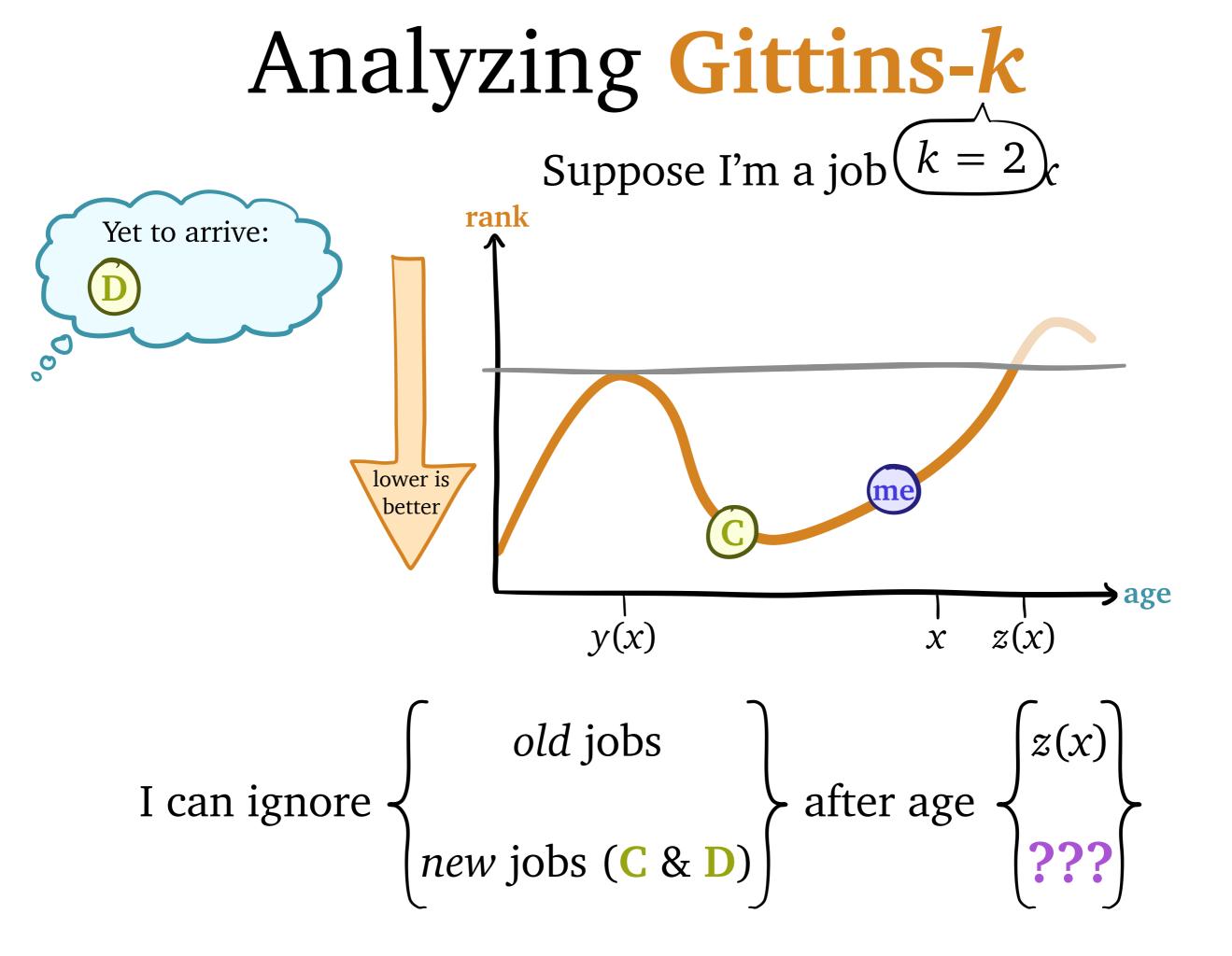


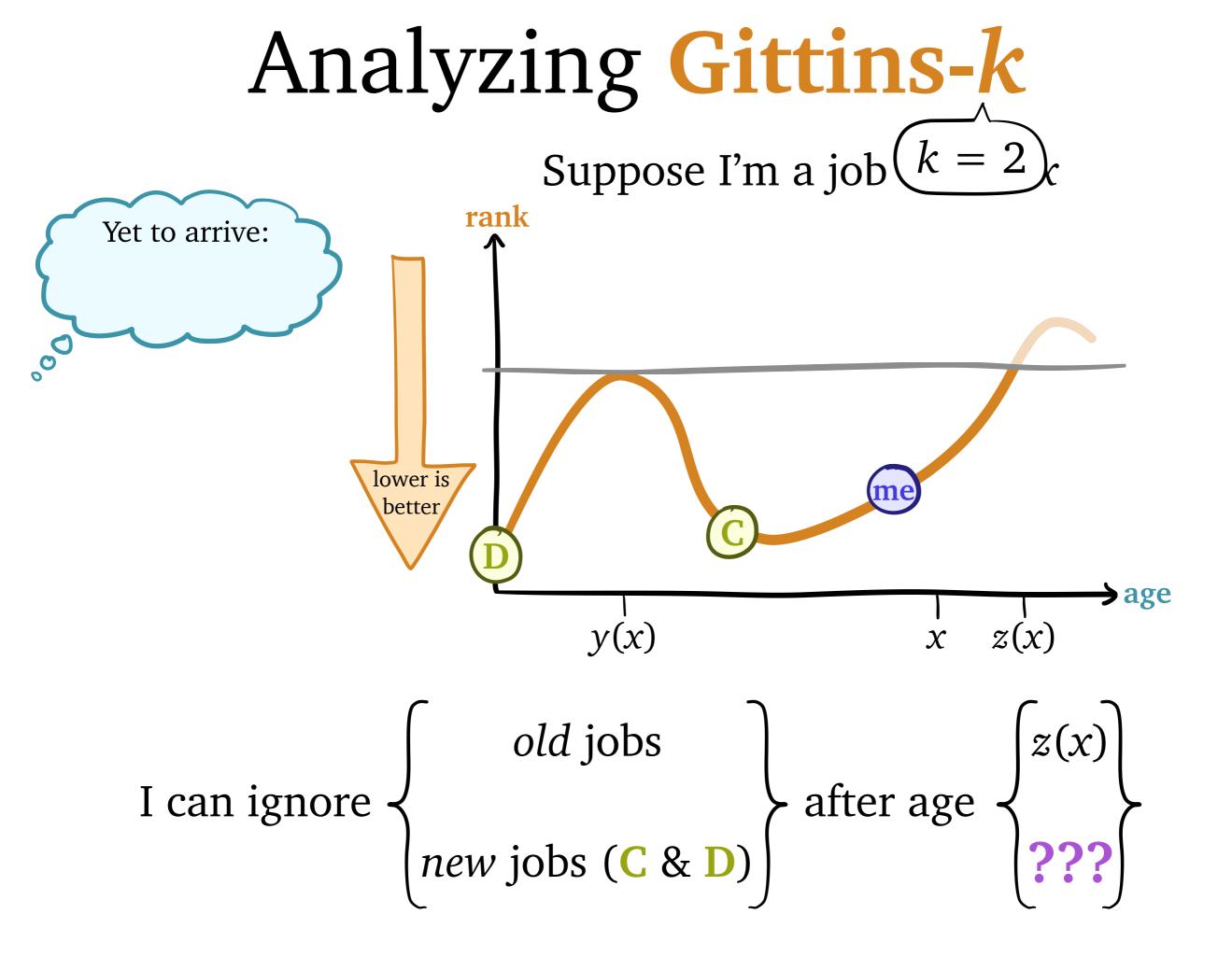


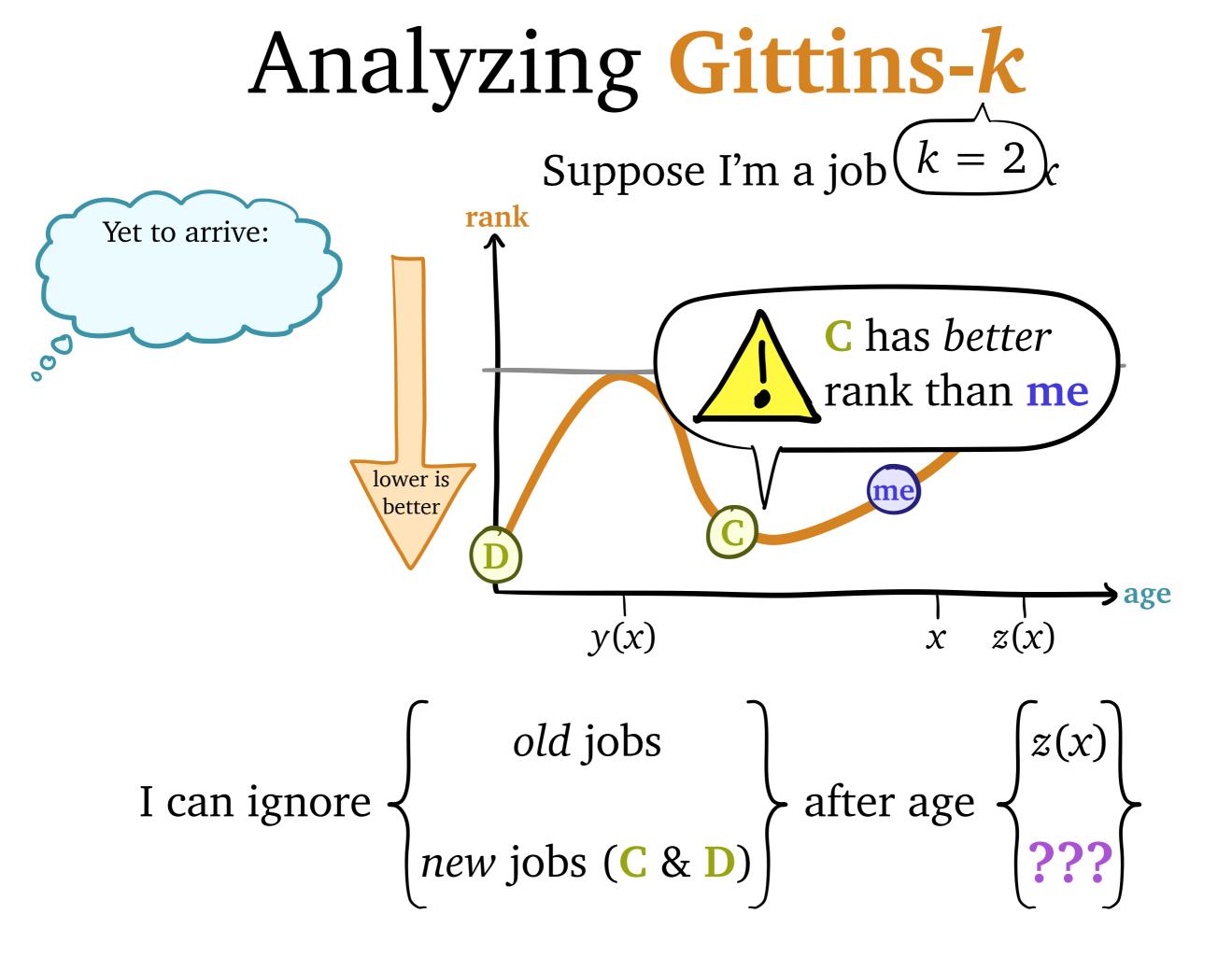


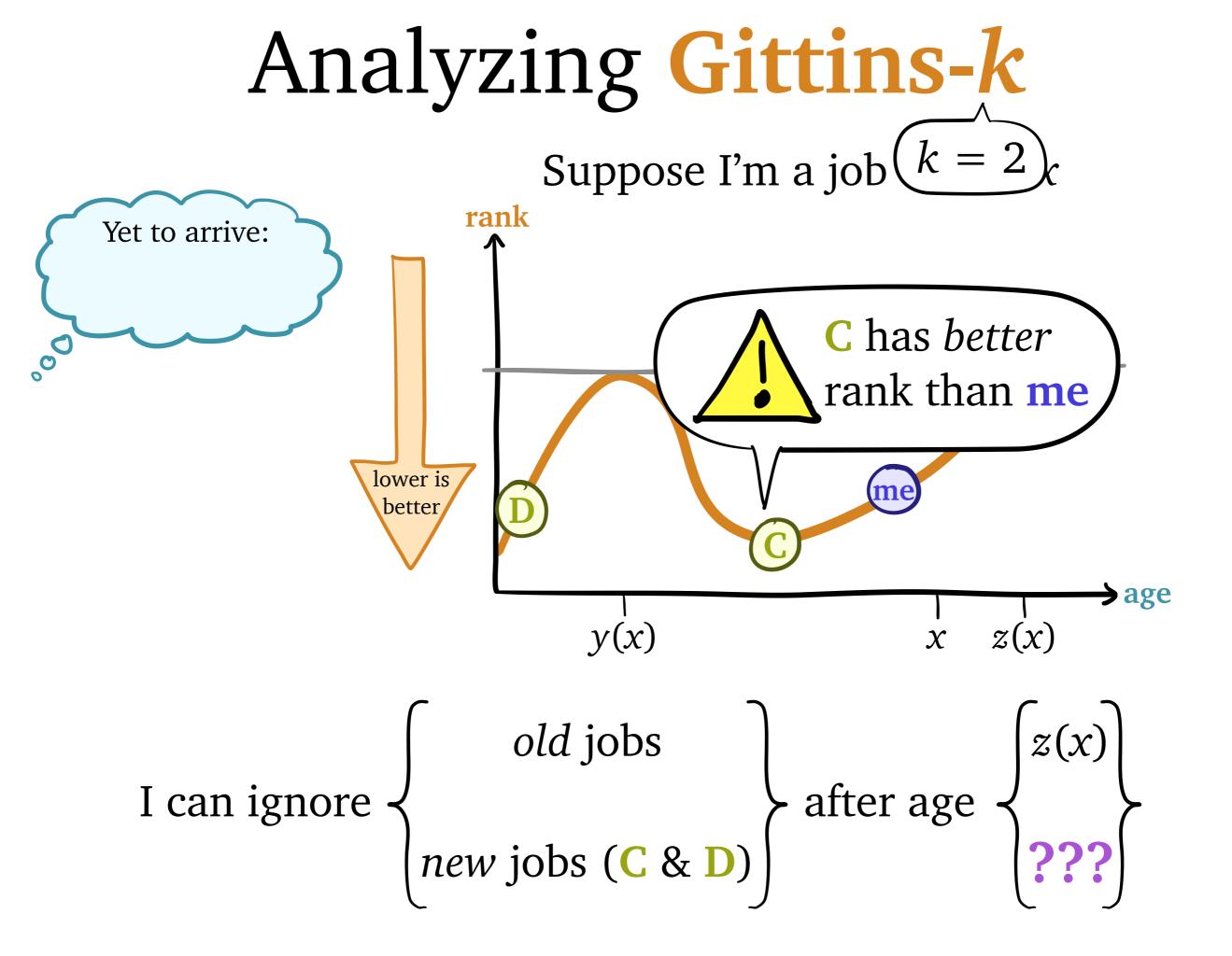


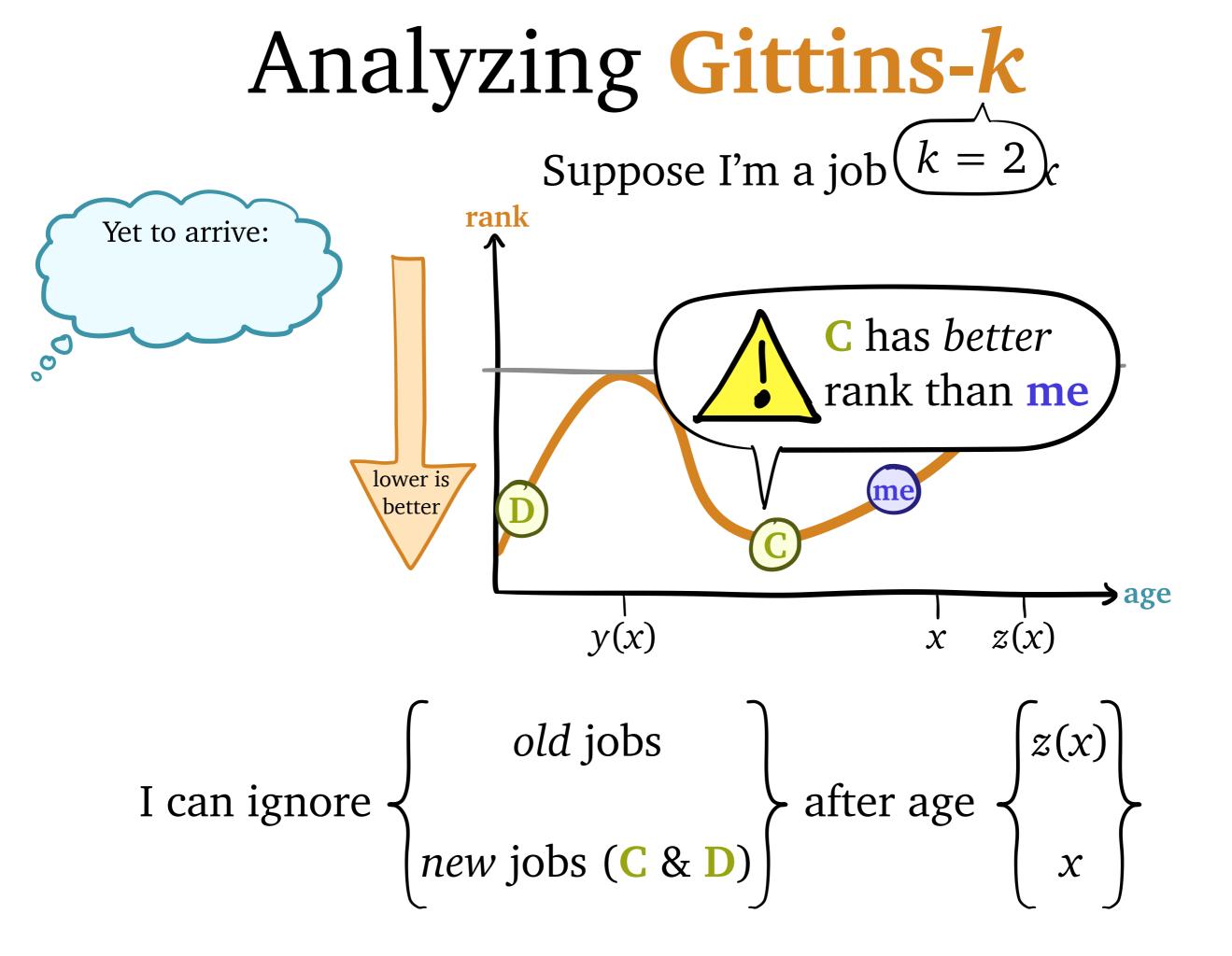


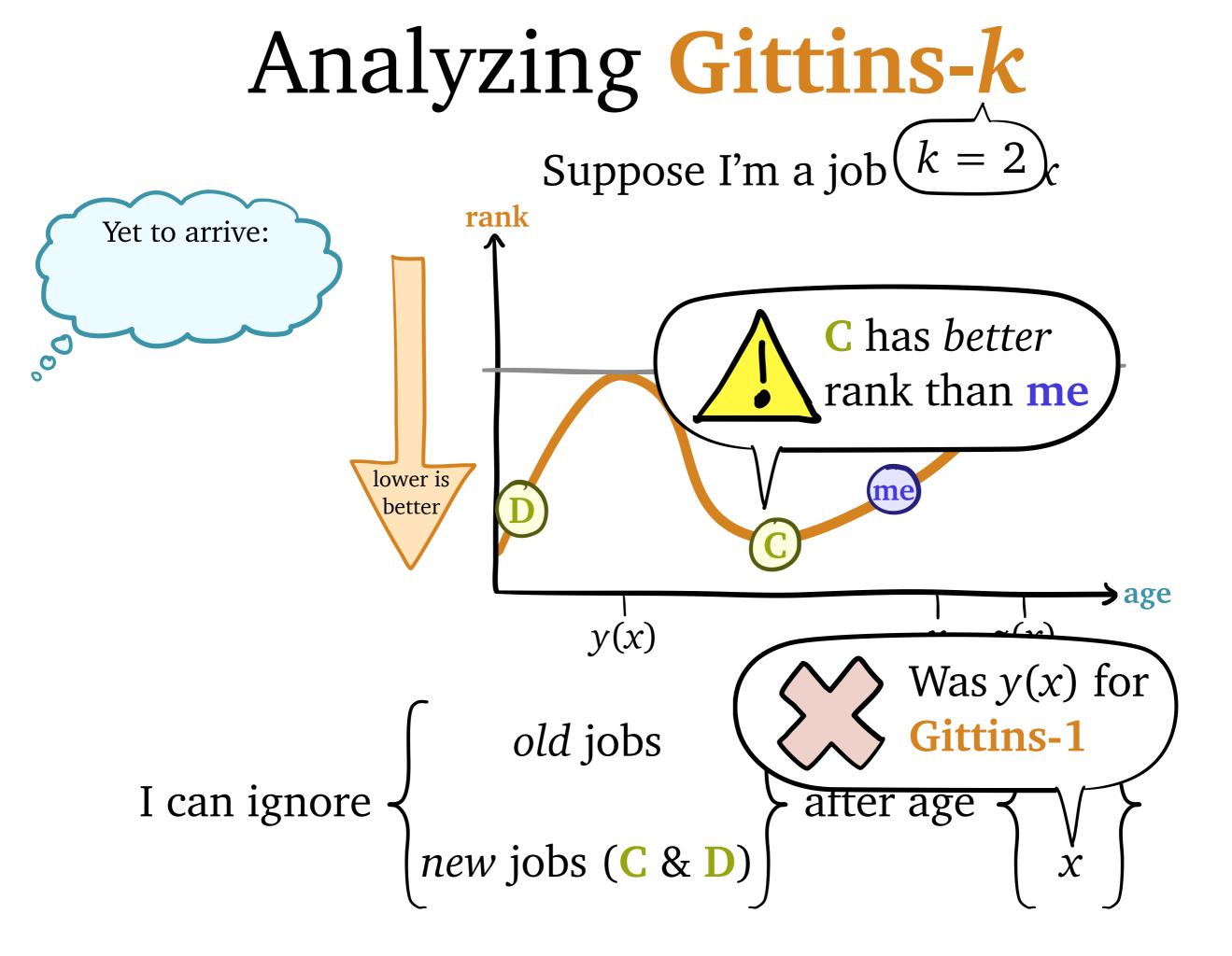




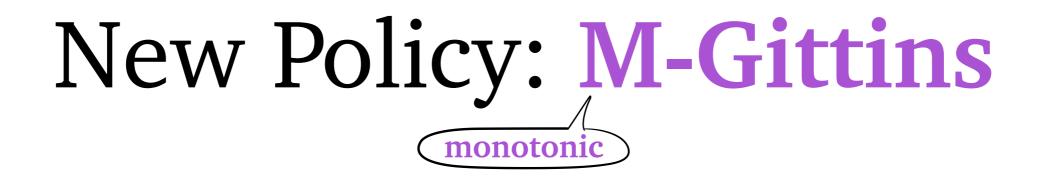


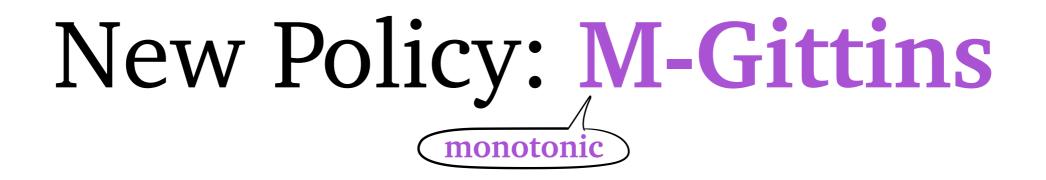


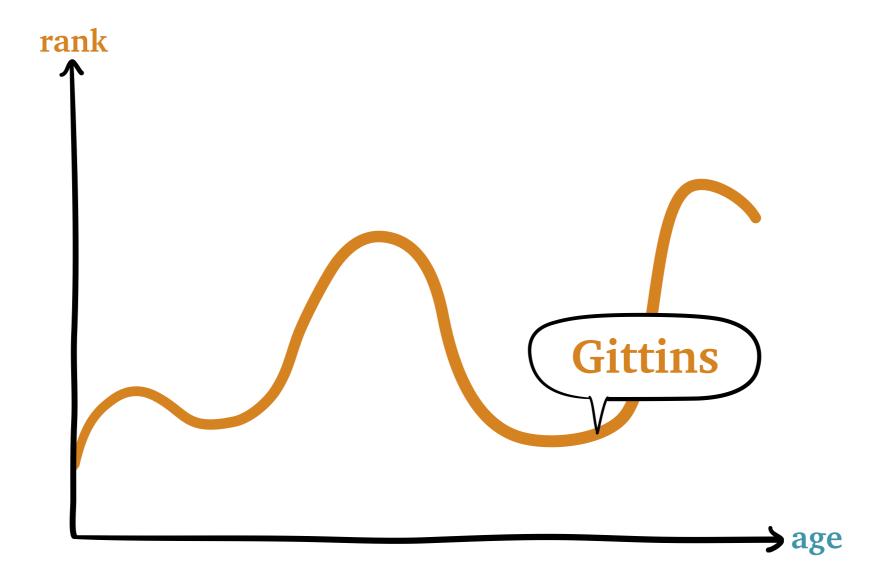


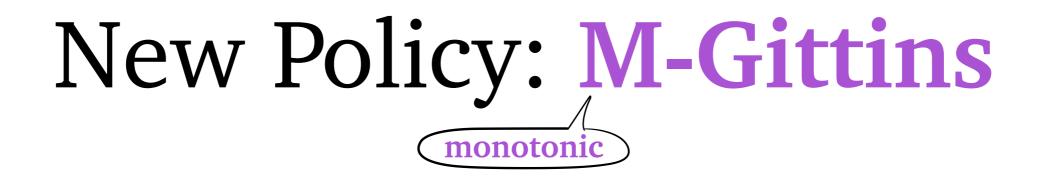


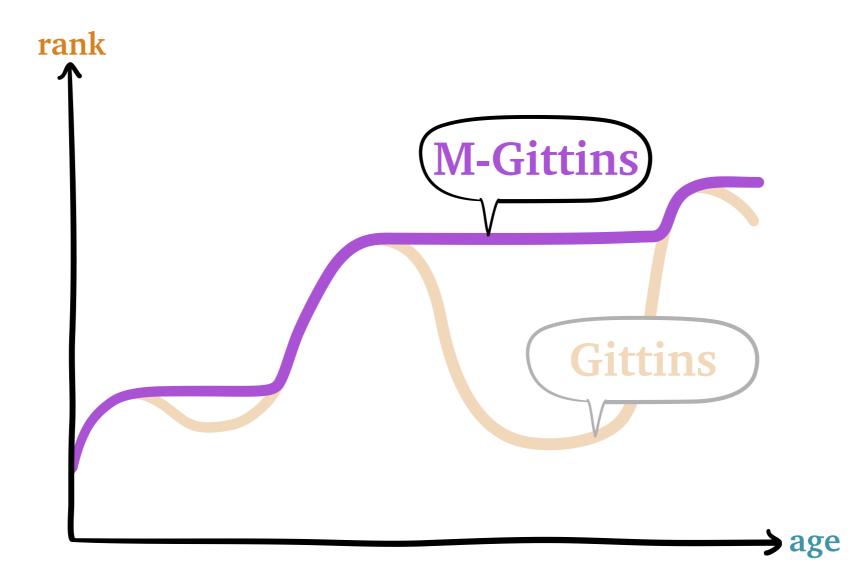
New Policy: M-Gittins

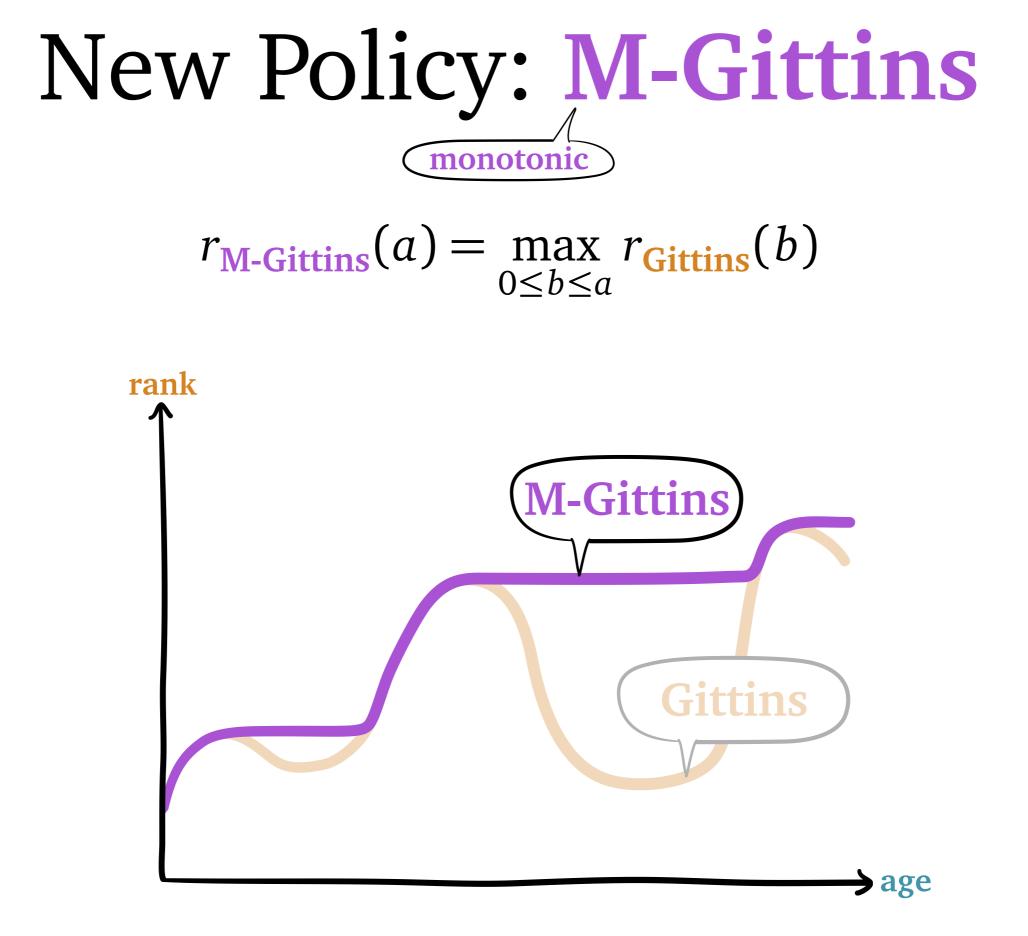




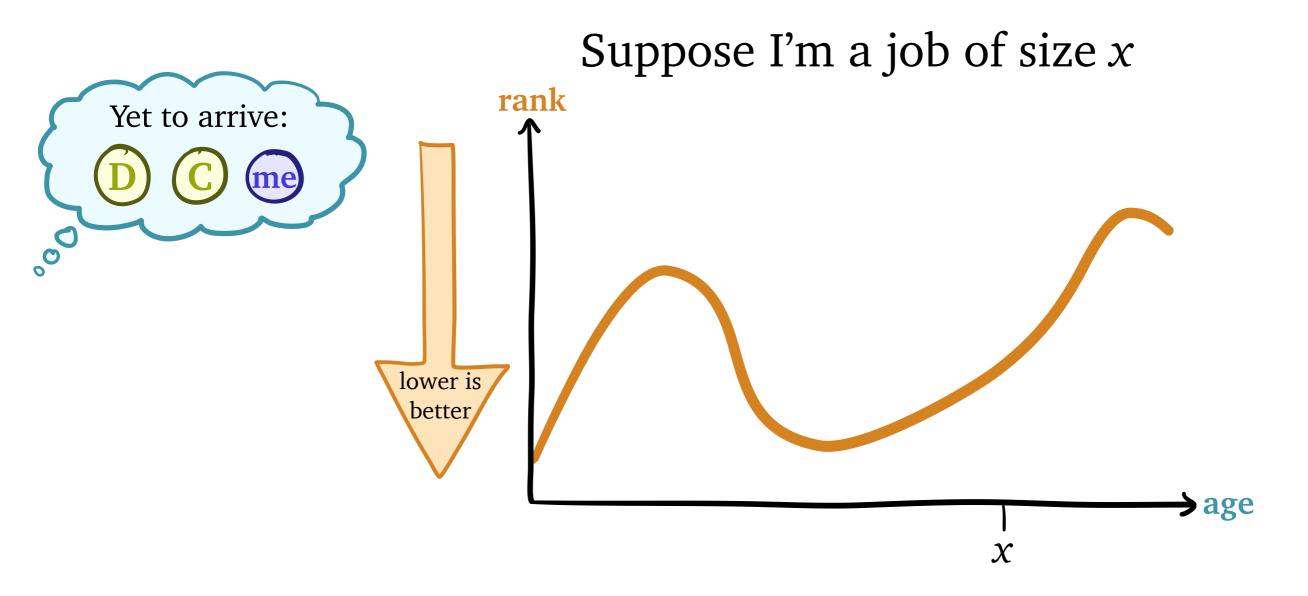




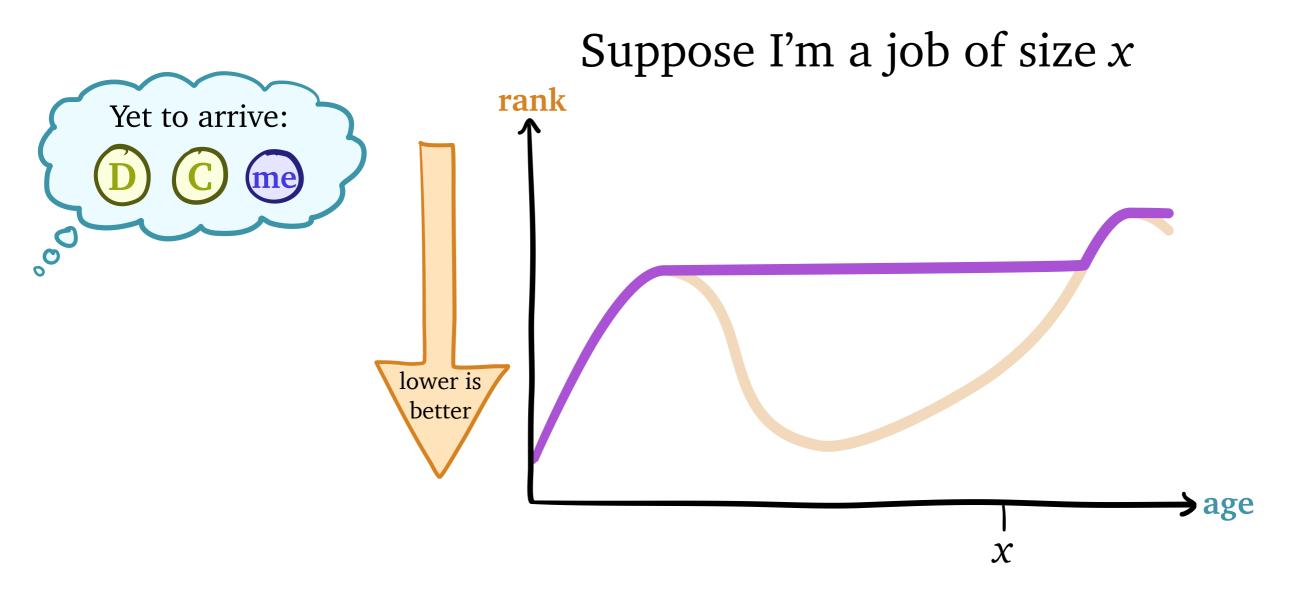




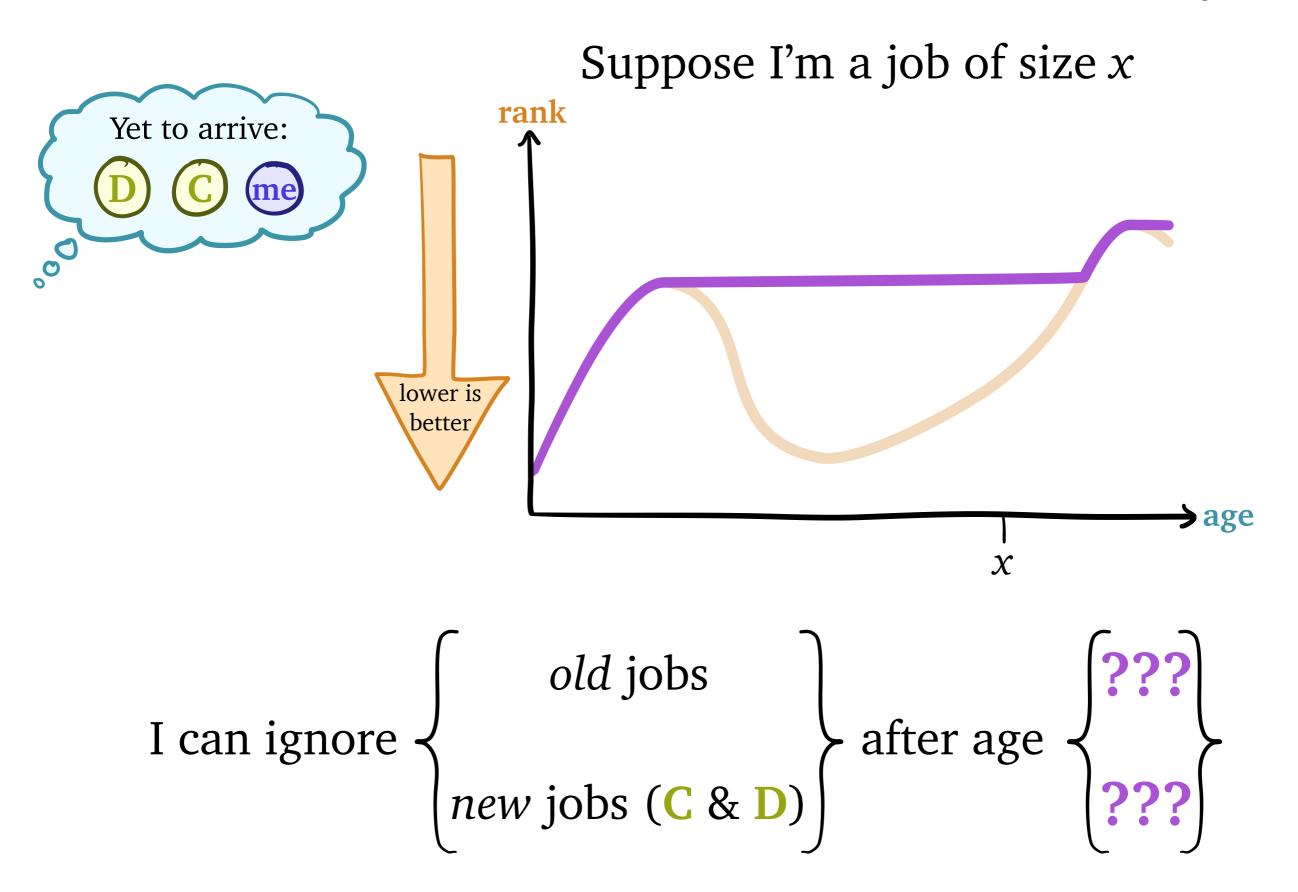
M-Gittins-k Saves the Day

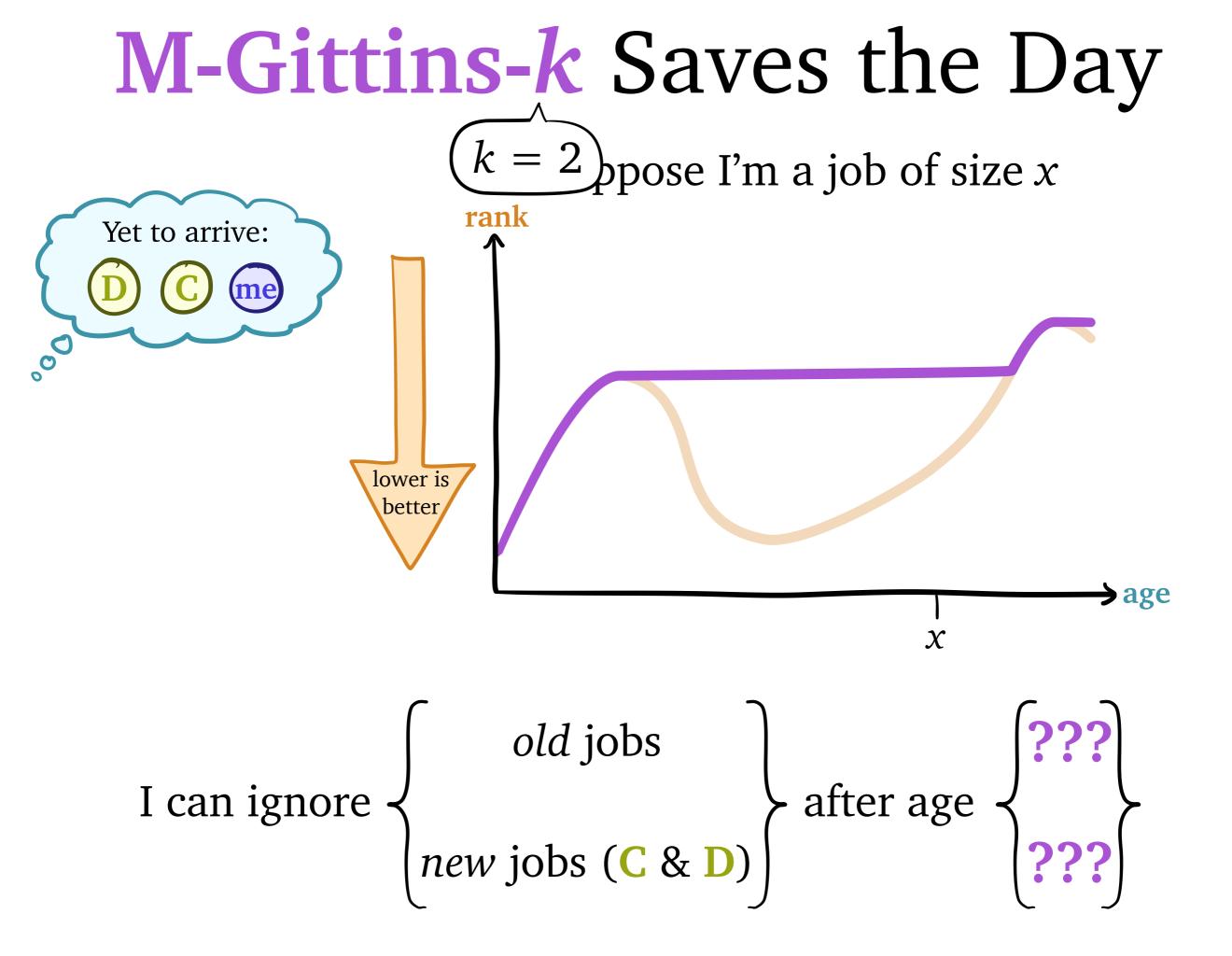


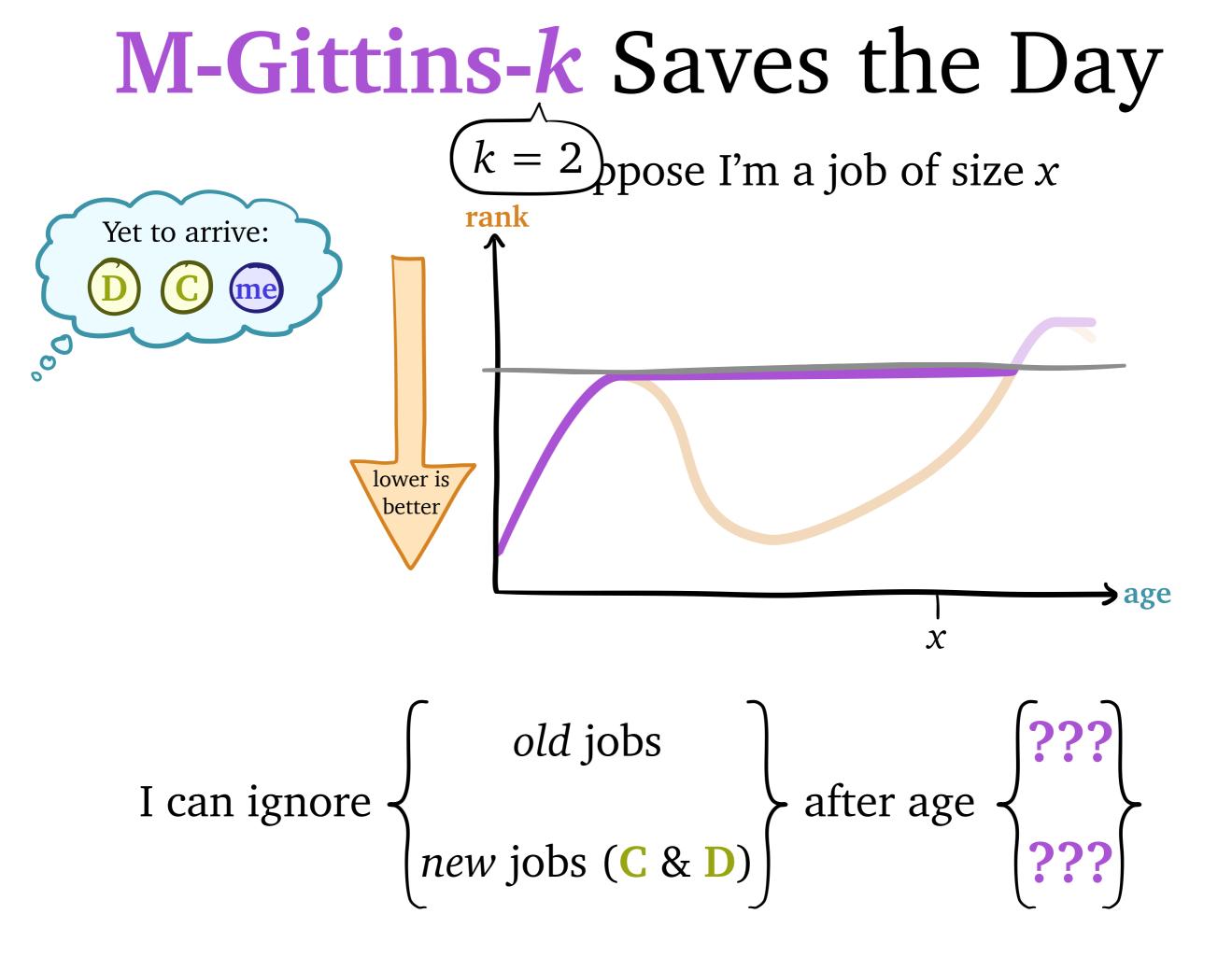
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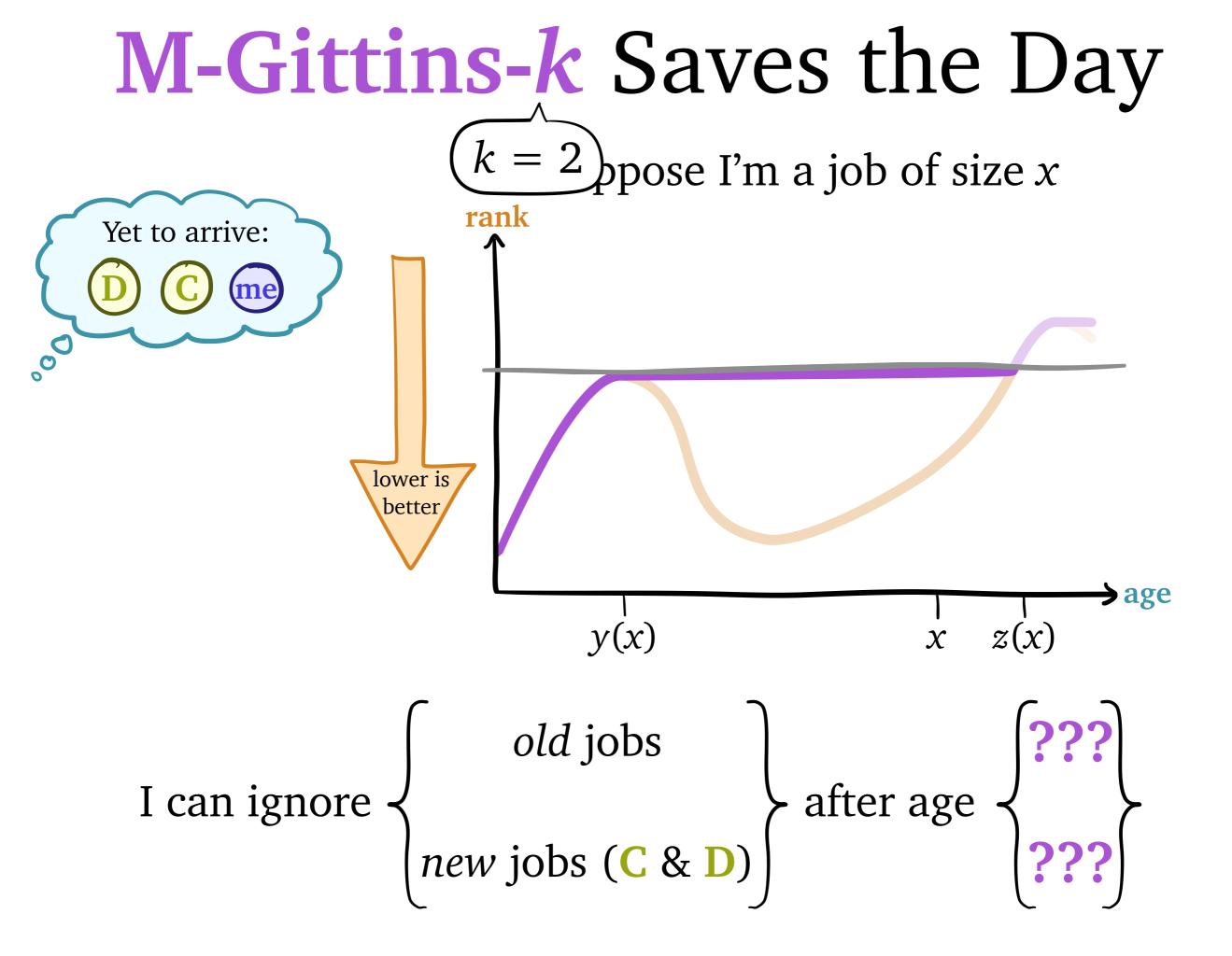


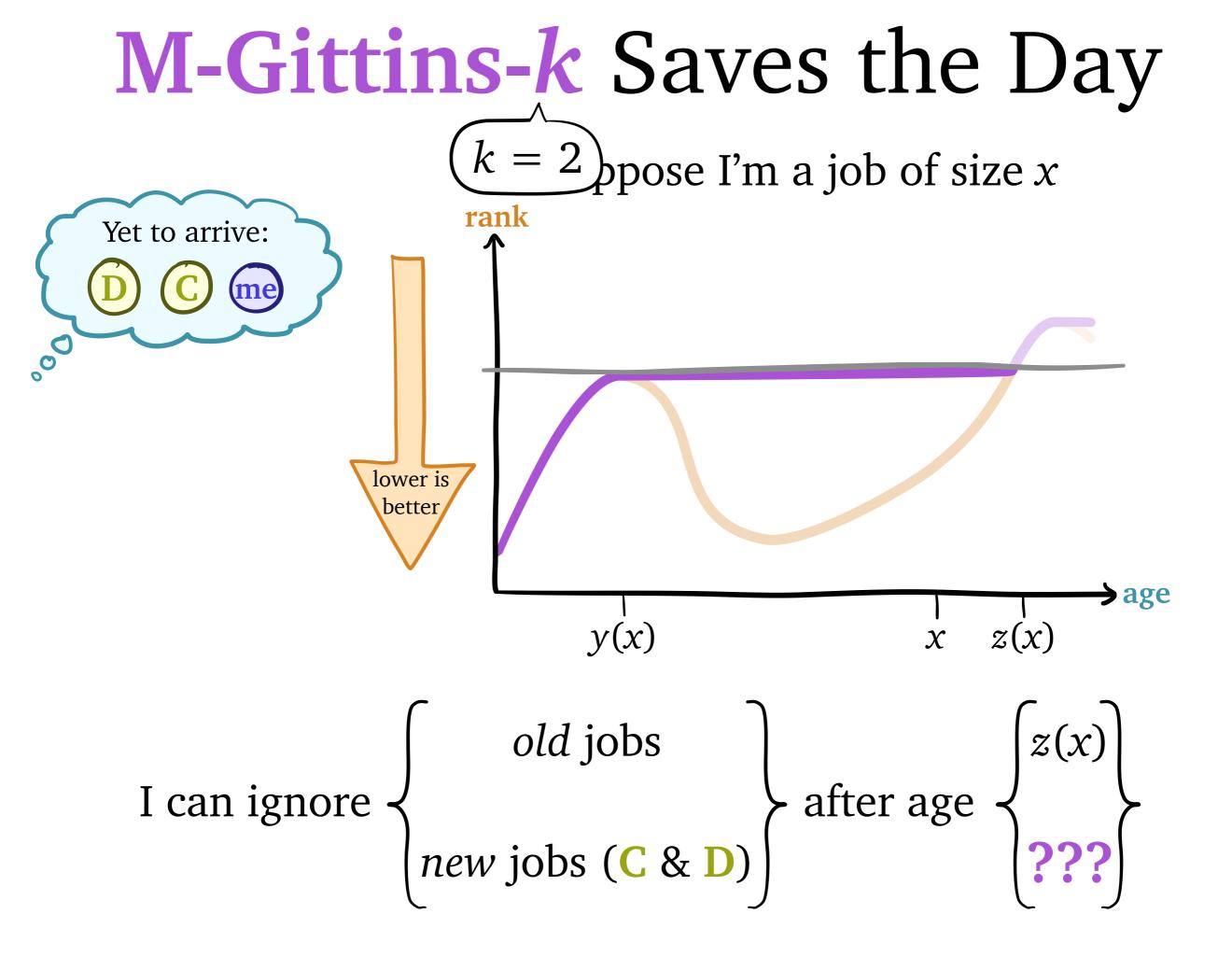
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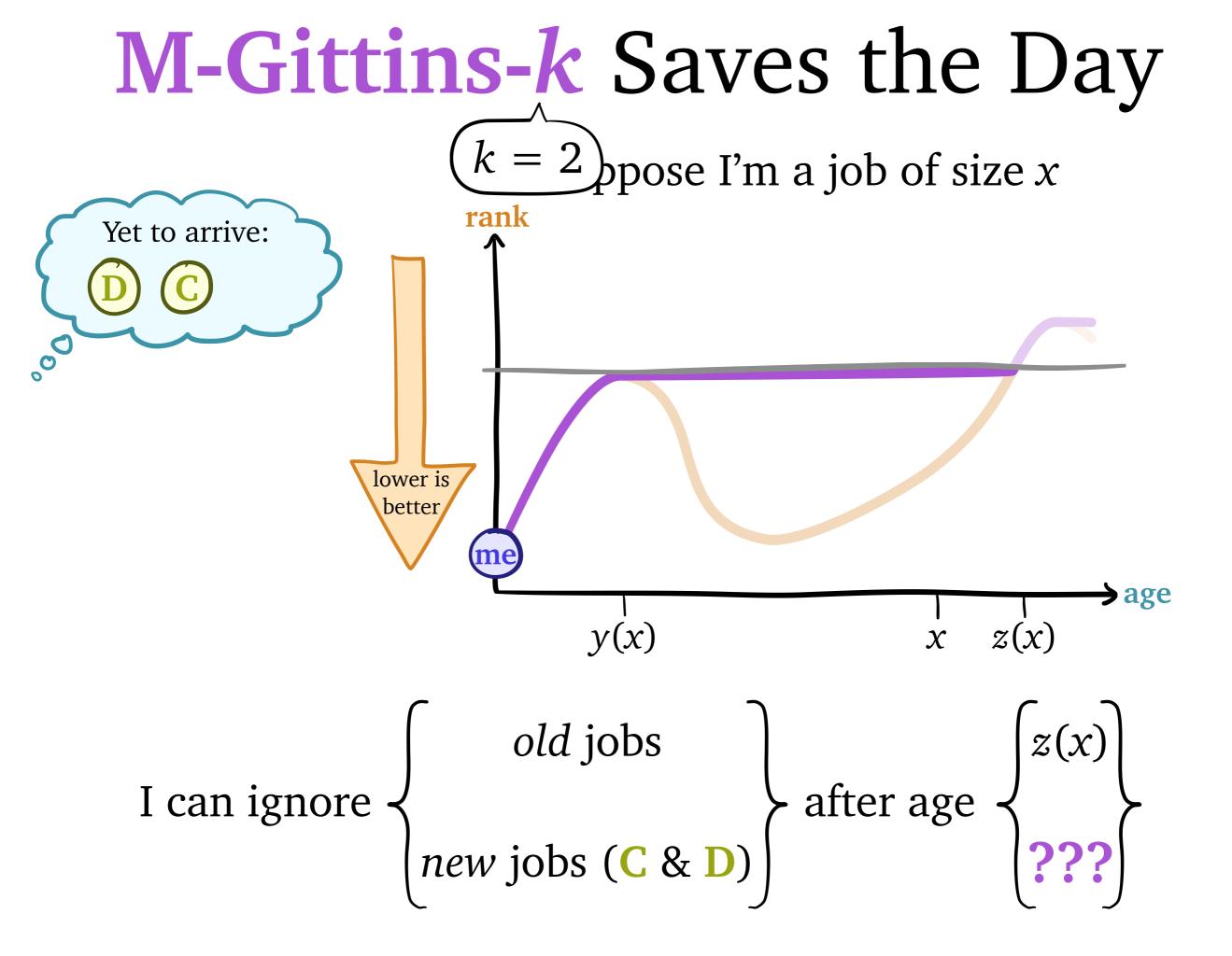


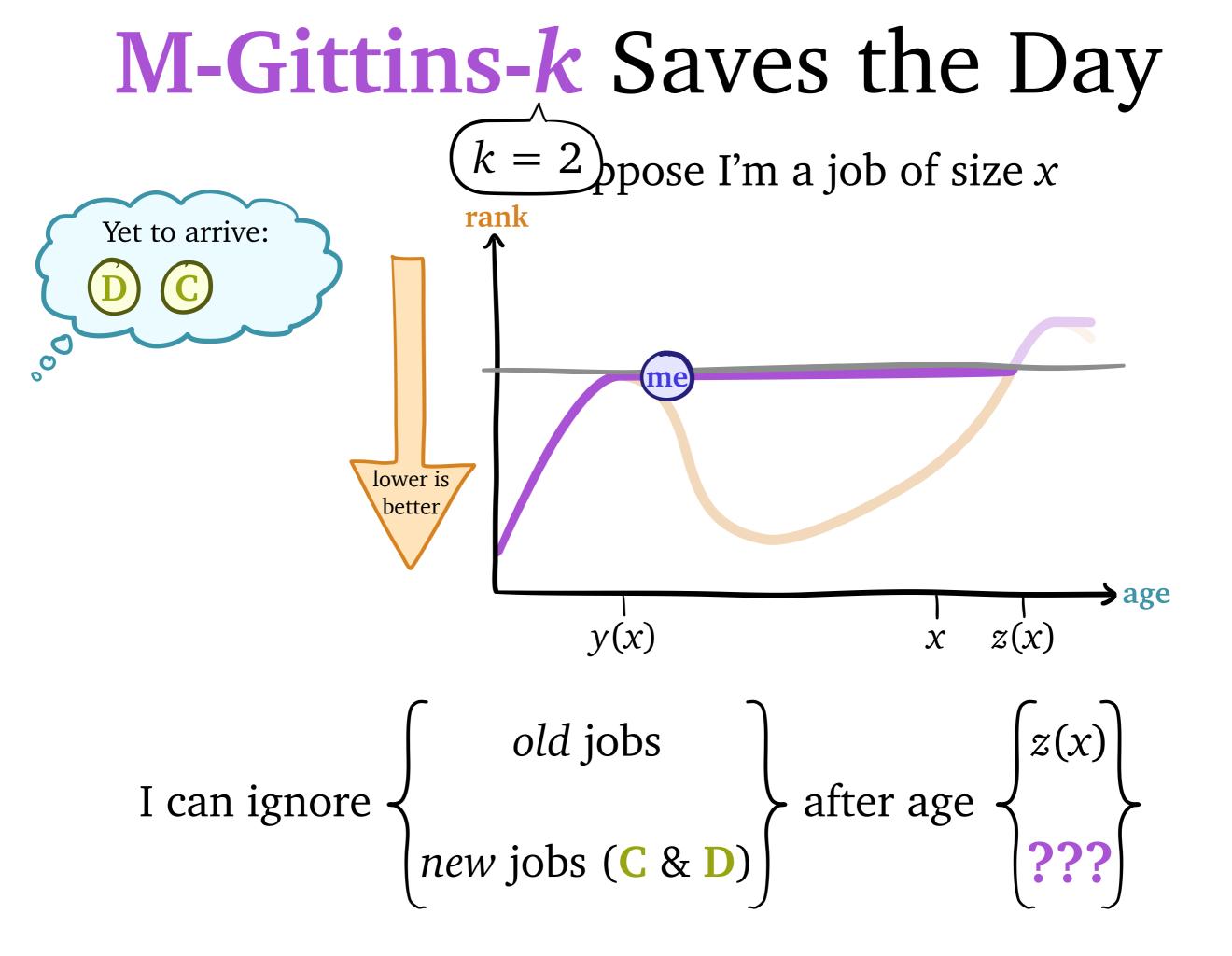


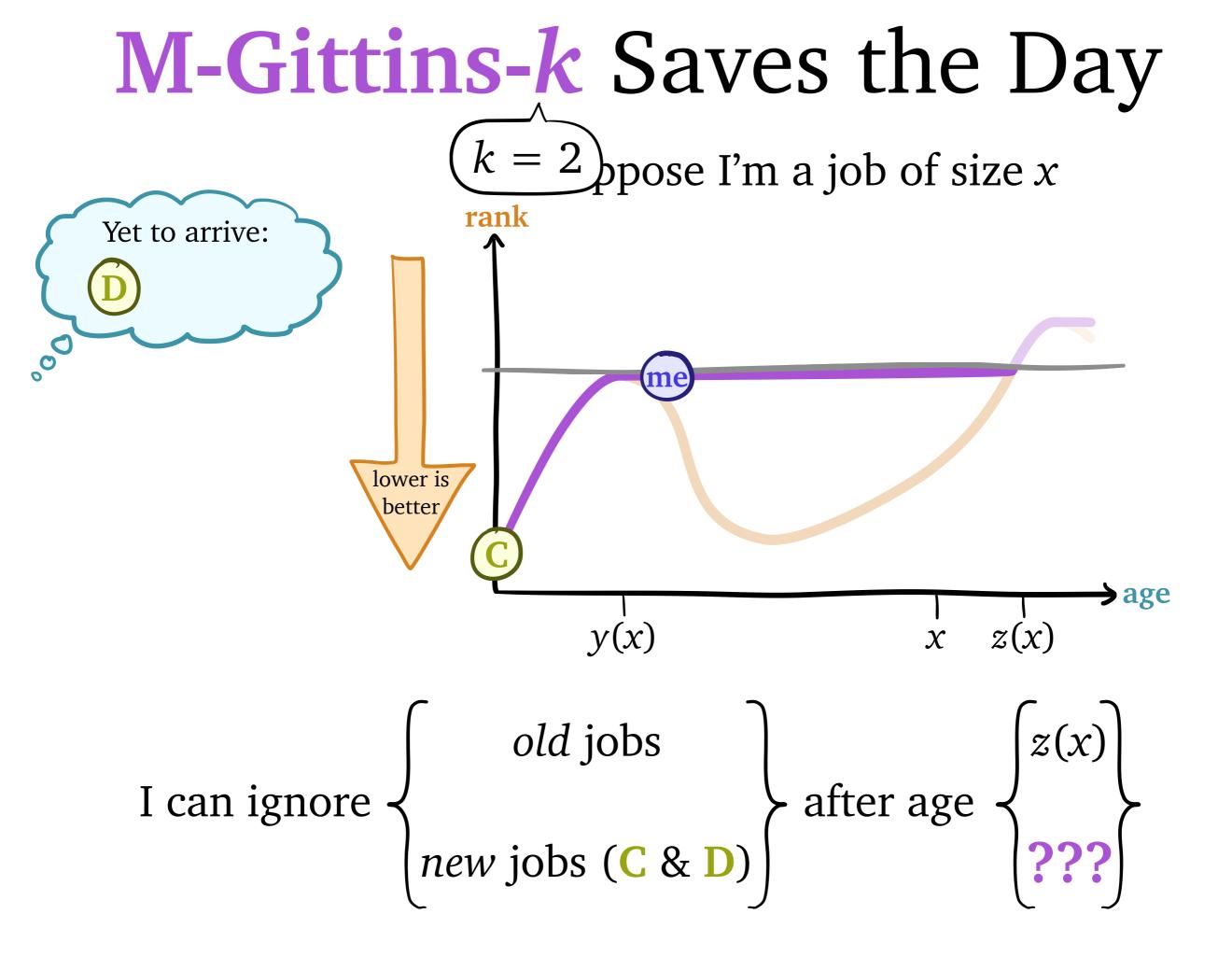


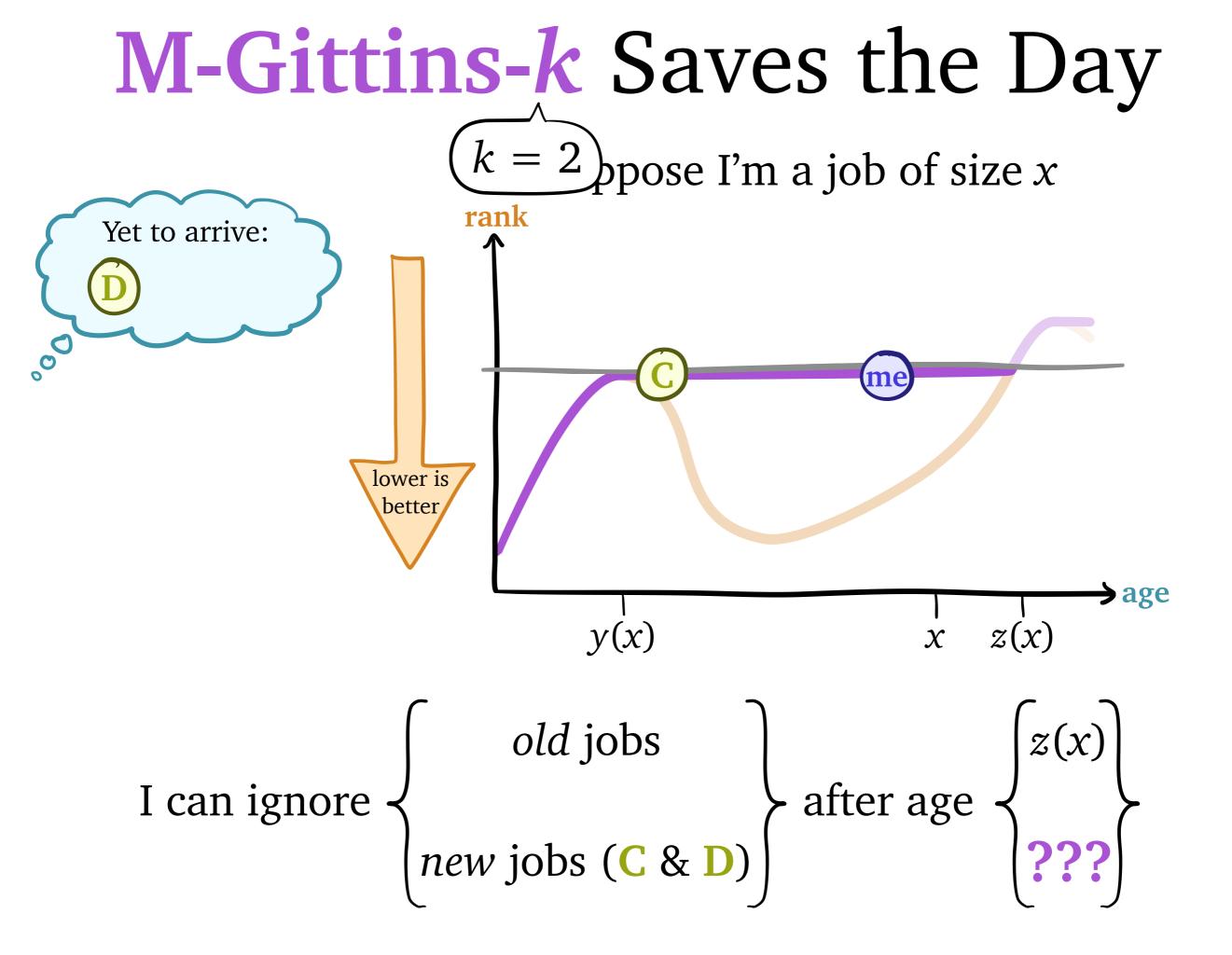


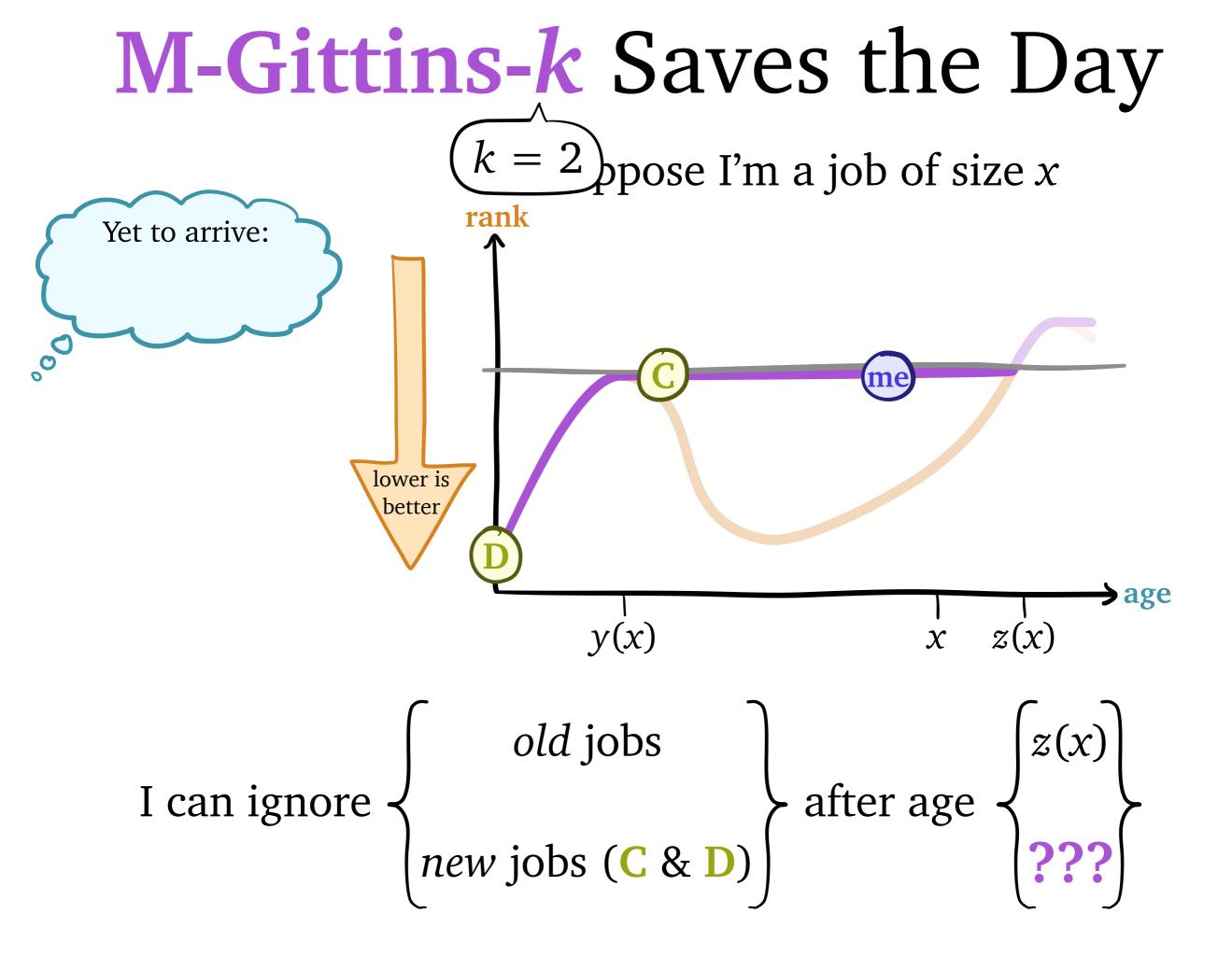


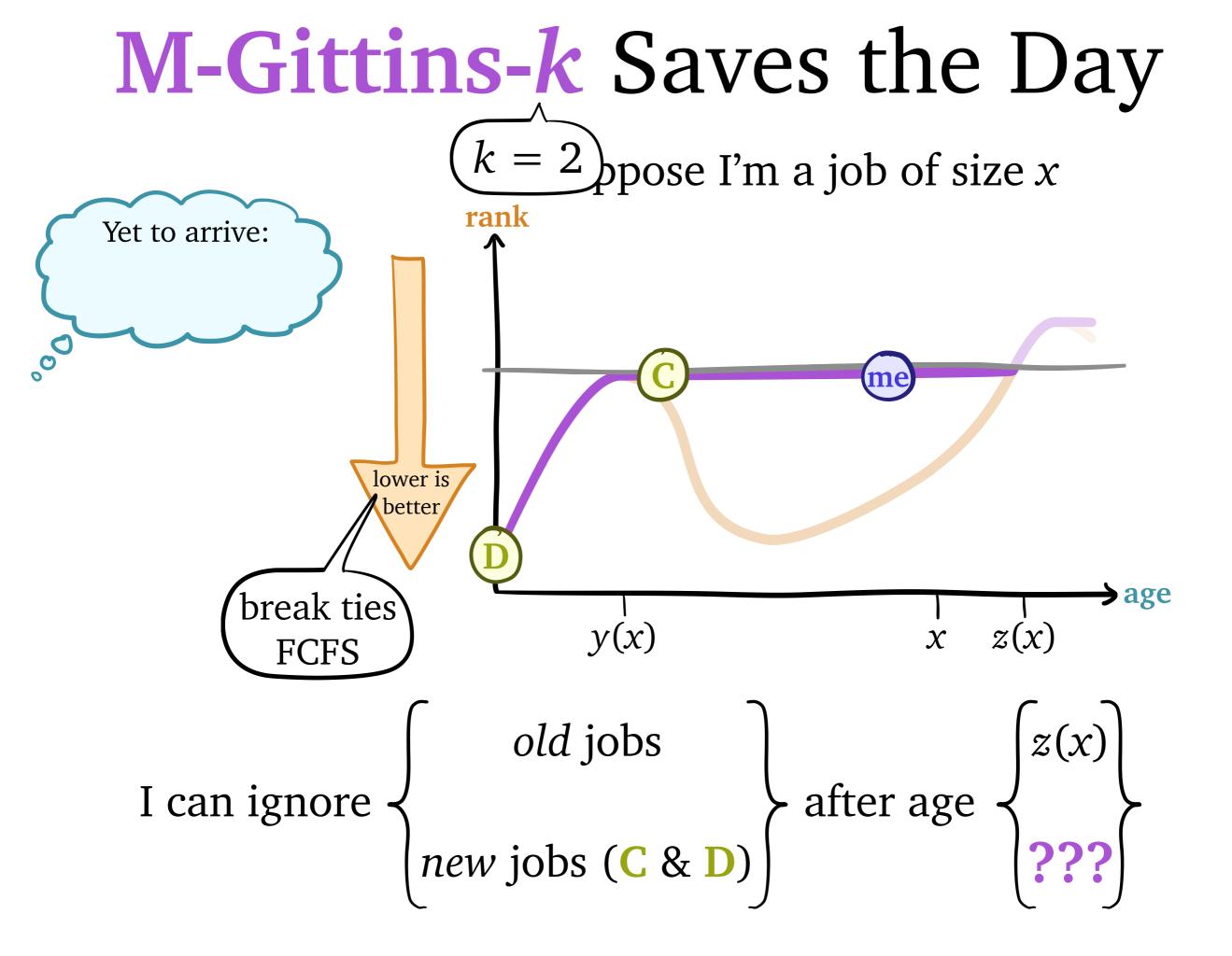


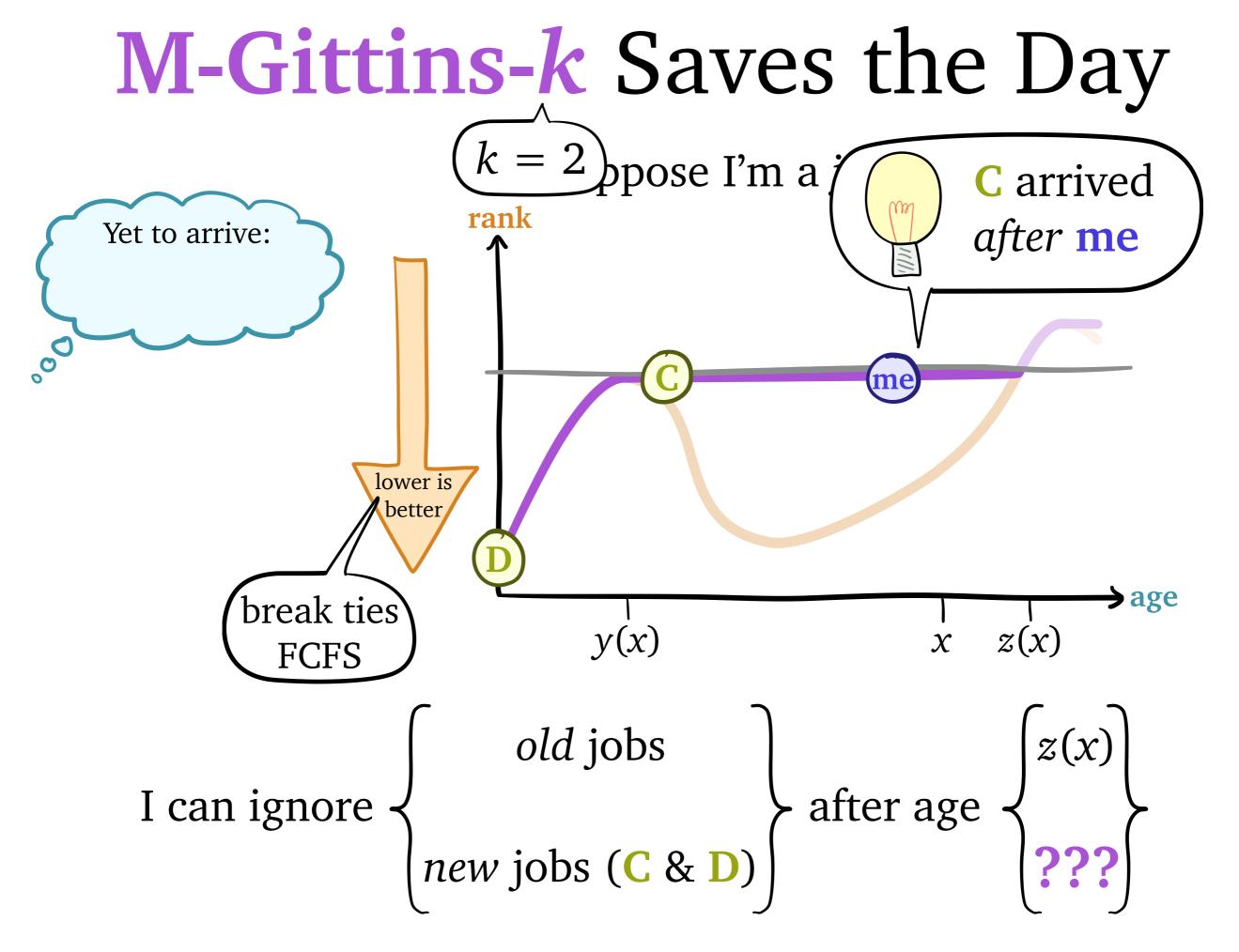


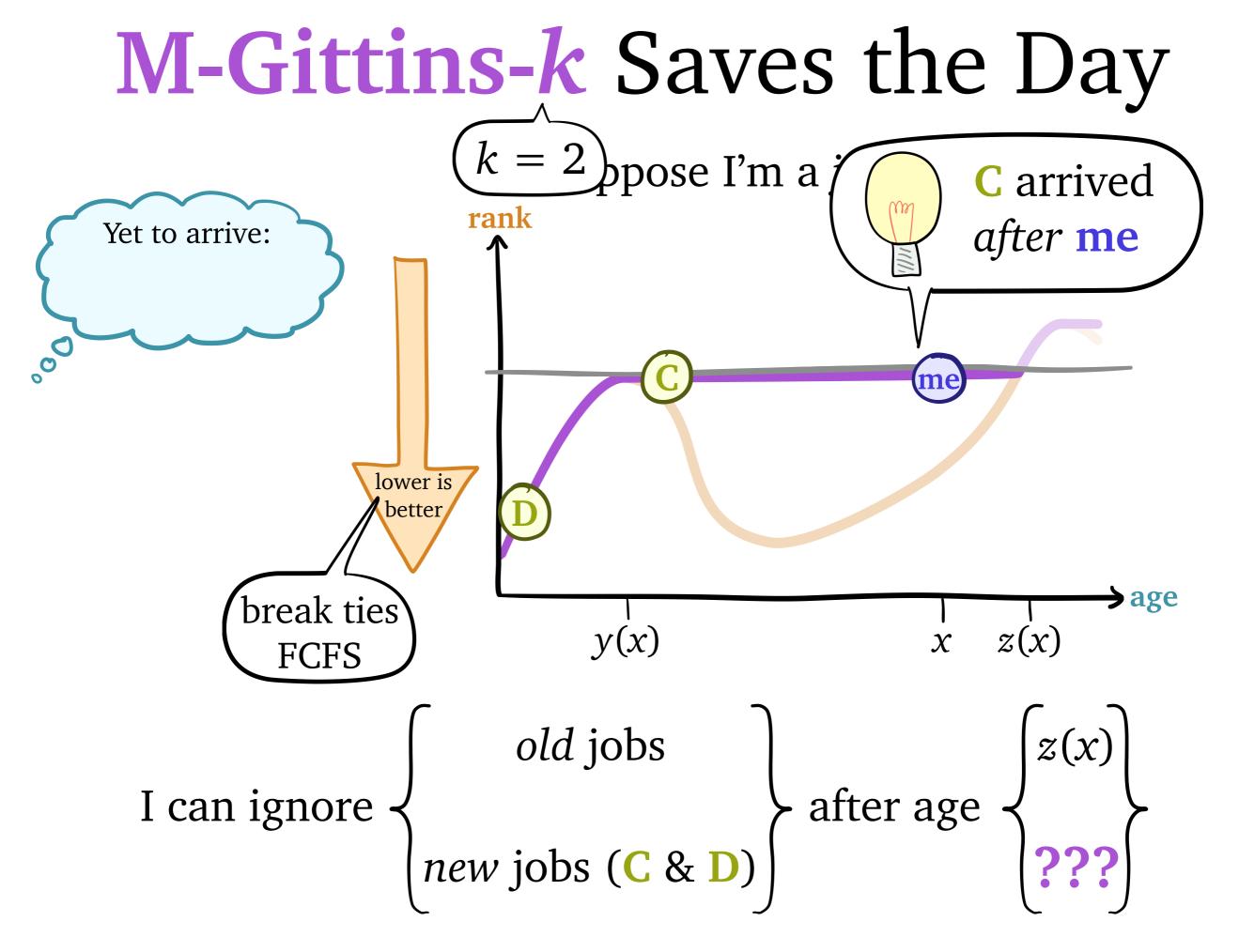


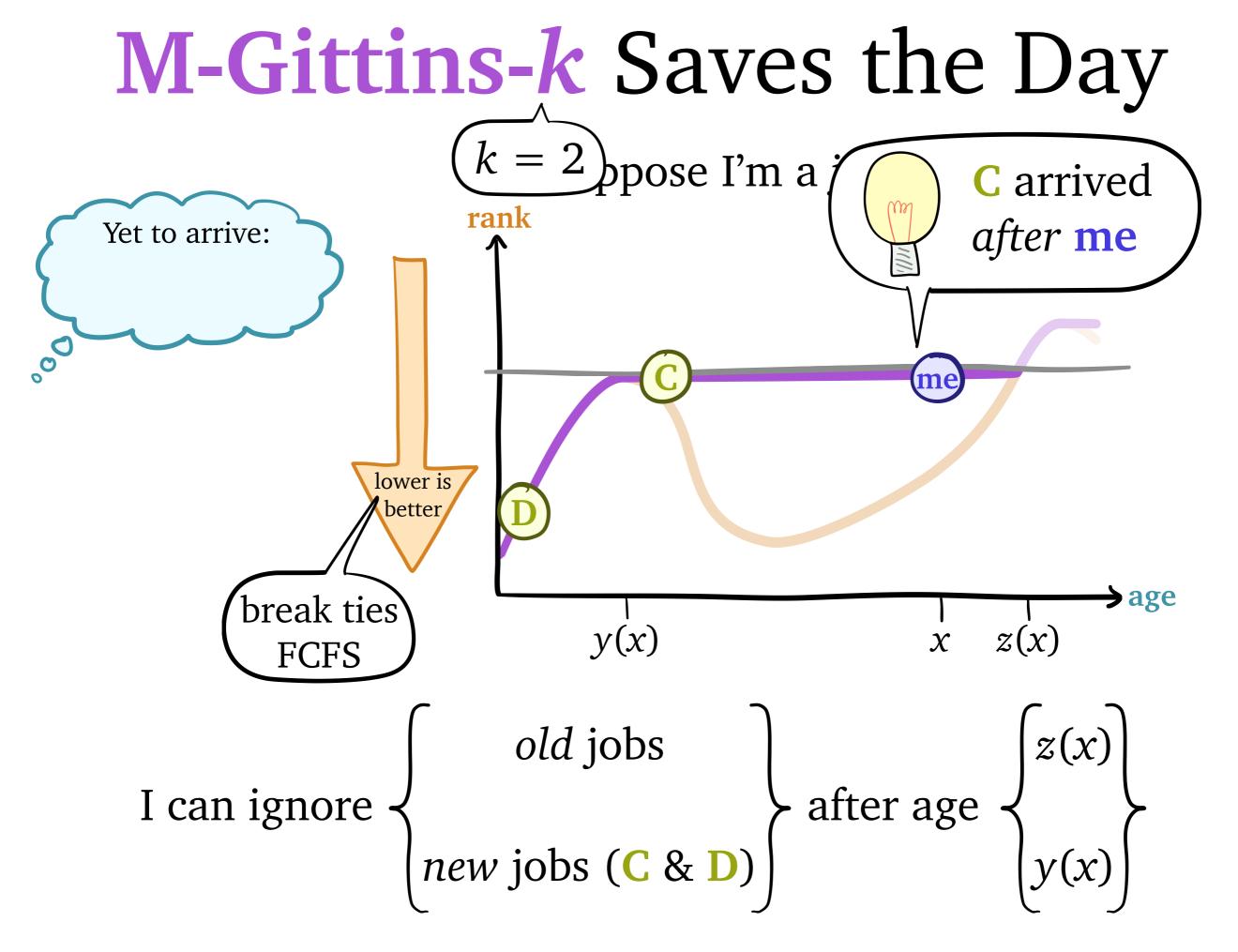


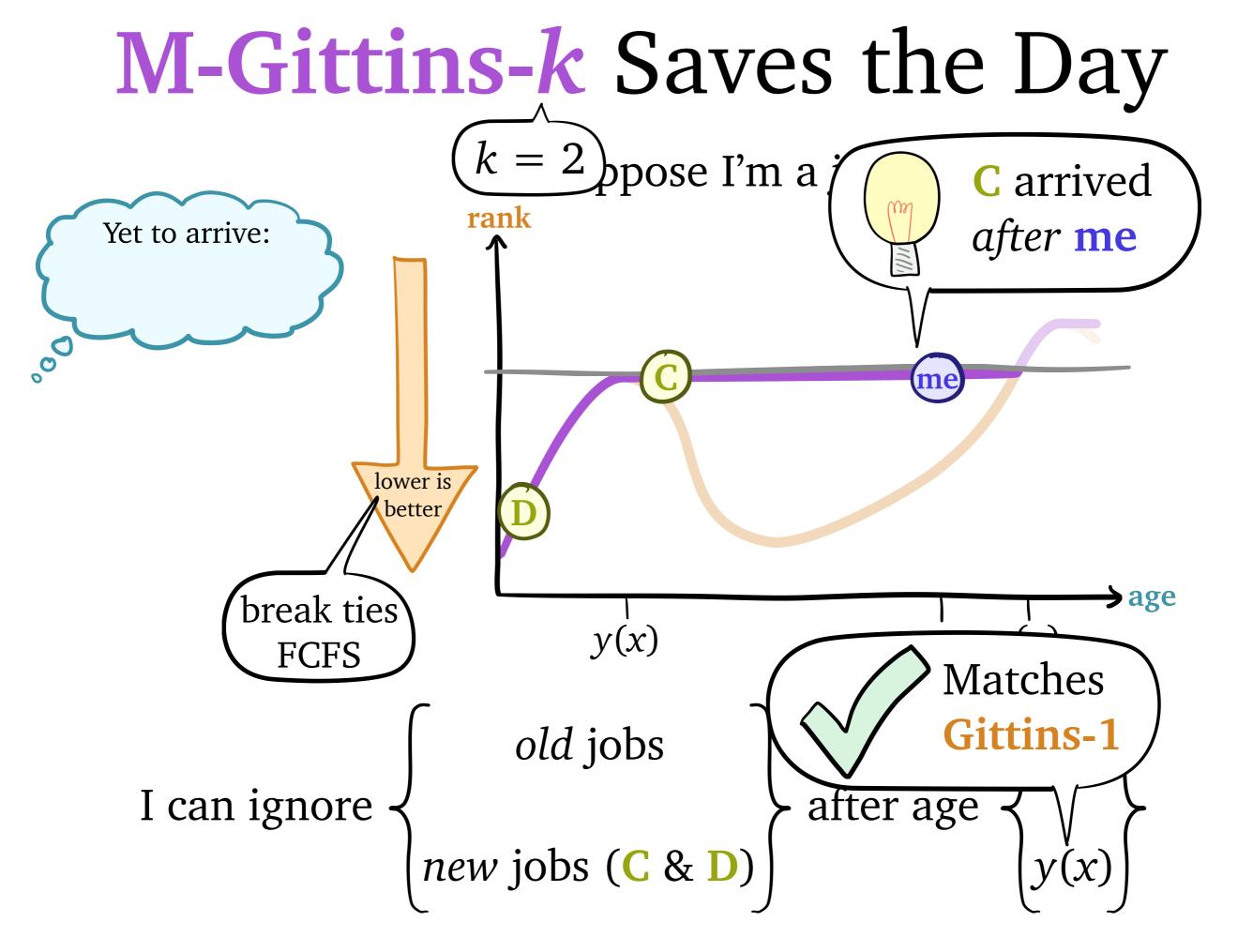












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similar results for some light-tailed *X* (see paper)

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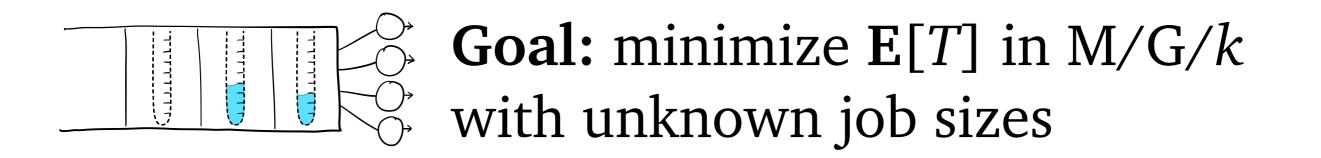
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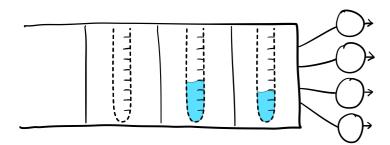
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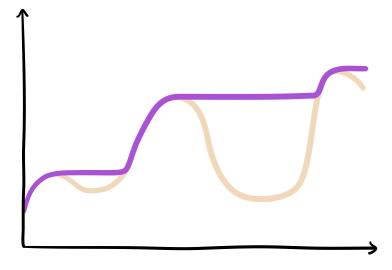
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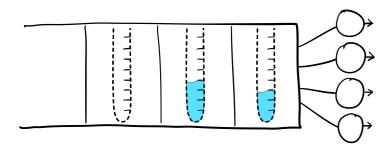




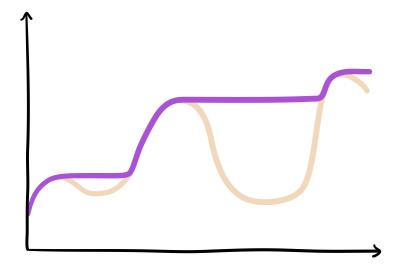
Goal: minimize E[T] in M/G/k with unknown job sizes



Key idea: new *monotonic* variant of **Gittins**, namely **M-Gittins**



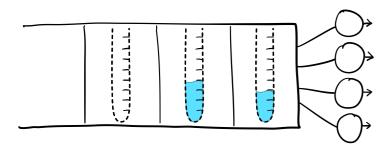
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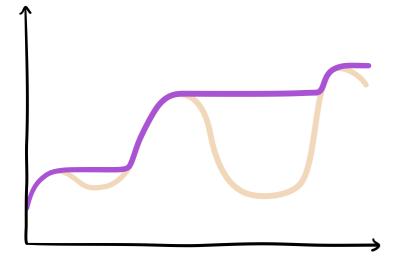
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Theorem:
$$\lim_{\rho \to 1} \frac{\mathbf{E}[T_{\mathbf{M}-\mathbf{Gittins}-k}]}{\mathbf{E}[T_{\mathbf{Gittins}-1}]} = 1$$



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Get in touch: zscully@cs.cmu.edu

Bonus Slides

Theorem:

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- MDA(Λ) with "quasi-decreasing hazard rate", e.g. $h(x) = \Theta(x^{-\gamma})$

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exponential, log-normal, Weibull...

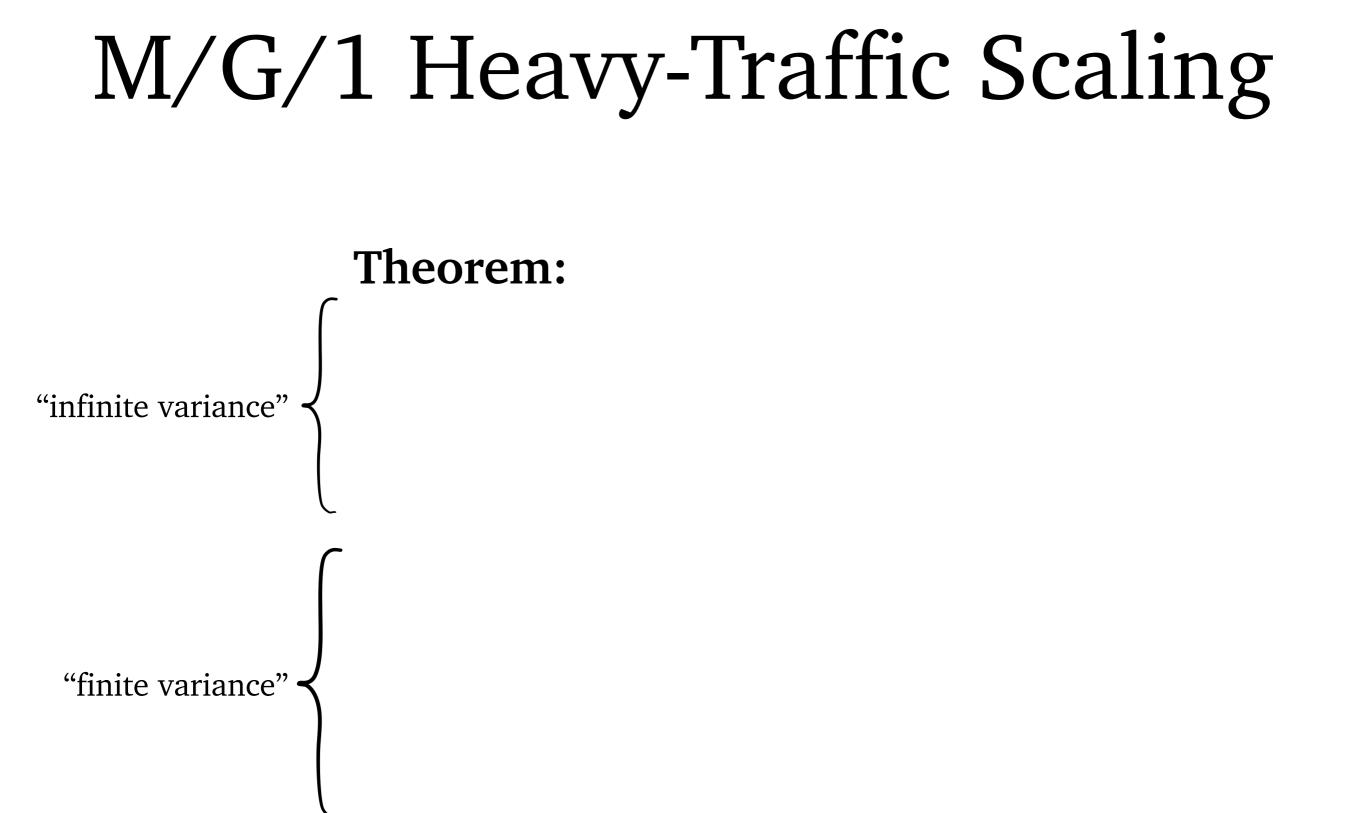
"finite-variance heavy-tailed"

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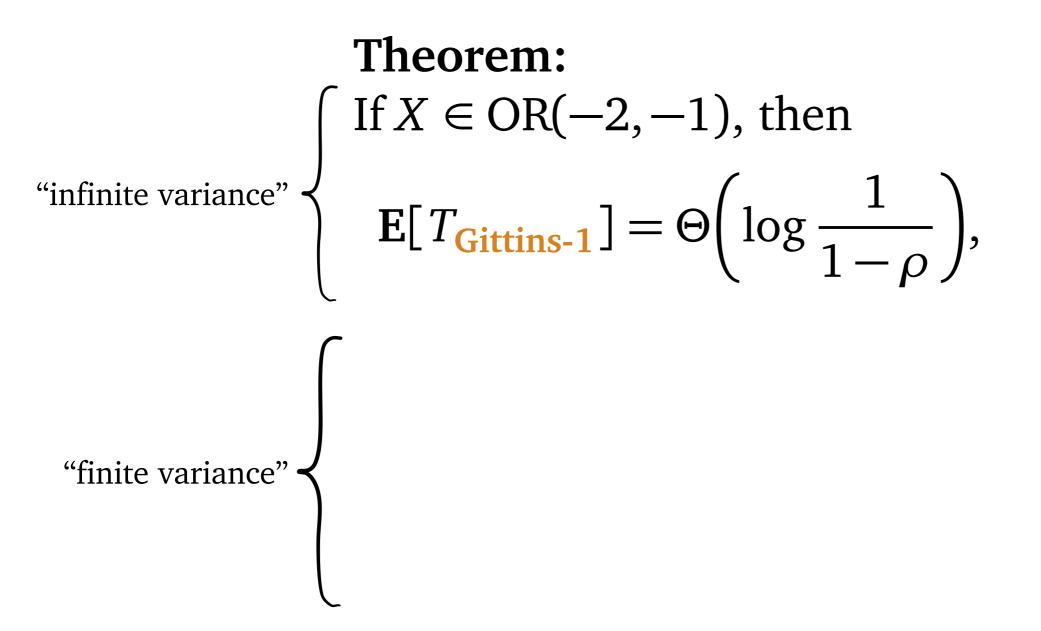
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M/G/1 Heavy-Traffic Scaling



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Theorem: "infinite variance" $\begin{cases} \text{If } X \in \text{OR}(-2, -1), \text{ then} \\ E[T_{\text{Gittins-1}}] = \Theta\left(\log\frac{1}{1-\rho}\right), \end{cases}$ "finite variance" $\begin{cases} \text{and if } X \in OR(-\infty, -2) \cup MDA(\Lambda) \cup ENBUE, \\ \text{then} \\ E[T_{\text{Gittins-1}}] = \Theta\left(\frac{1}{1-\rho} \middle/ \max_{0 \le b \le \overline{F}_e^{-1}(1-\rho)} E[X-b \mid X > b]\right). \end{cases}$