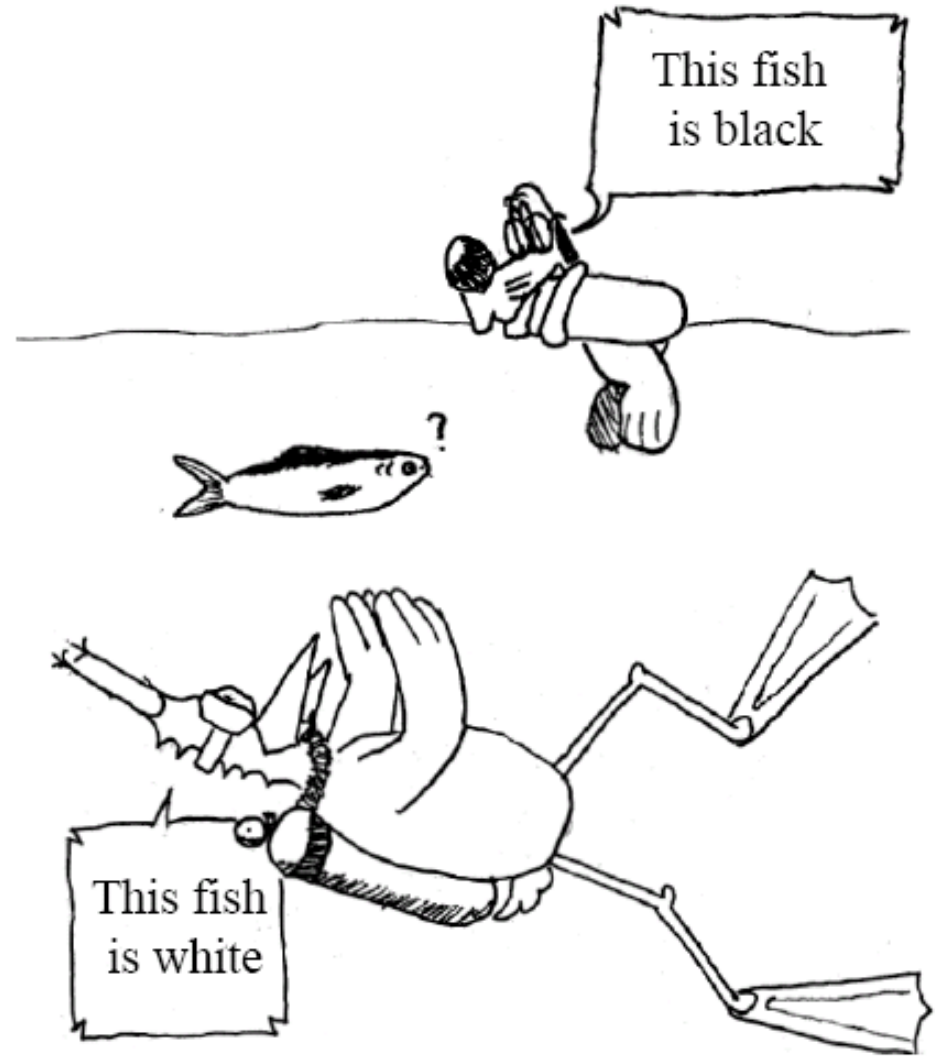


# Palm Calculus

## Part 1

### *The Importance of the Viewpoint*

JY Le Boudec



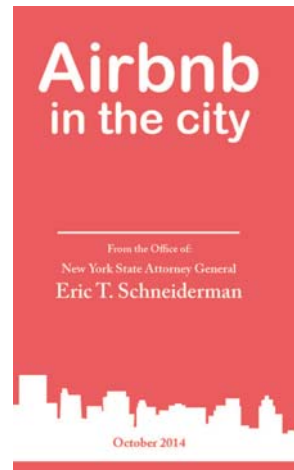
# Who says the truth ?

AirBnB claims:  
median occupancy of  
rented listings is 11%  
(40 days a year)

Airbnb. Data on the Airbnb community in New York City . Technical report, AirBnB corporation, Dec. 2015.

Insideairbnb.com  
claims:  
median occupancy of  
rented listings is 40-50%  
(165 days a year)

Lecuyer, M., Tucker, M. and Chaintreau, A., 2017, April. Improving the Transparency of the Sharing Economy. In Proceedings of the 26th International Conference on World Wide Web Companion (pp. 1043-1051). International World Wide Web Conferences Steering Committee.



# Who says the truth ?

SovRail: according to our systematic tracking system, probability of a train being late  $\leq 5\%$

BorduKonsum: according to our consumer survey, probability of being late  $\approx 30\%$

# 1. Event versus Time Averages

Consider a simulation, state  $S_t$

Assume simulation has a stationary regime

Consider an *Event Clock*: times  $T_n$  at which some specific changes of state occur

Ex: arrival of job; Ex. queue becomes empty

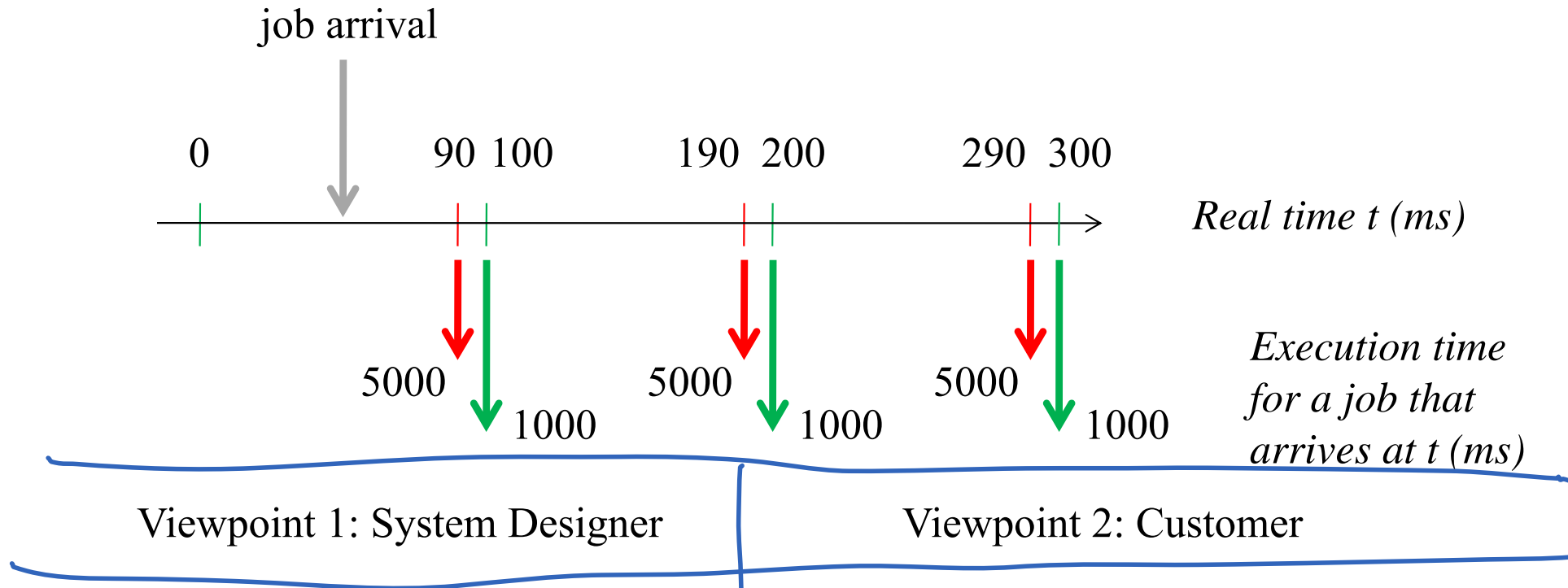
*Event average* statistic: mean queue length seen by an arriving

customer:  $\bar{Q}^0 = \frac{1}{N+1} \sum_{i=0}^N Q(T_n^-)$

*Time average* statistic: mean queue length (seen by an inspector):

$$\bar{Q} = \frac{1}{T_N - T_0} \int_{T_0}^{T_N} Q(s) ds$$

# Example: Gatekeeper; Average execution time



Two processes, with execution times 5000 and 1000

$$W_s = \frac{5000 + 1000}{2} = 3000$$

Inspector arrives at a random time  
red processor is used with proba  $\frac{90}{100}$

$$W_c = \frac{90}{100} \times 5000 + \frac{10}{100} \times 1000 = 4600$$

# Sampling Bias

$W_s$  and  $W_c$  are different, but both are *average execution times* !

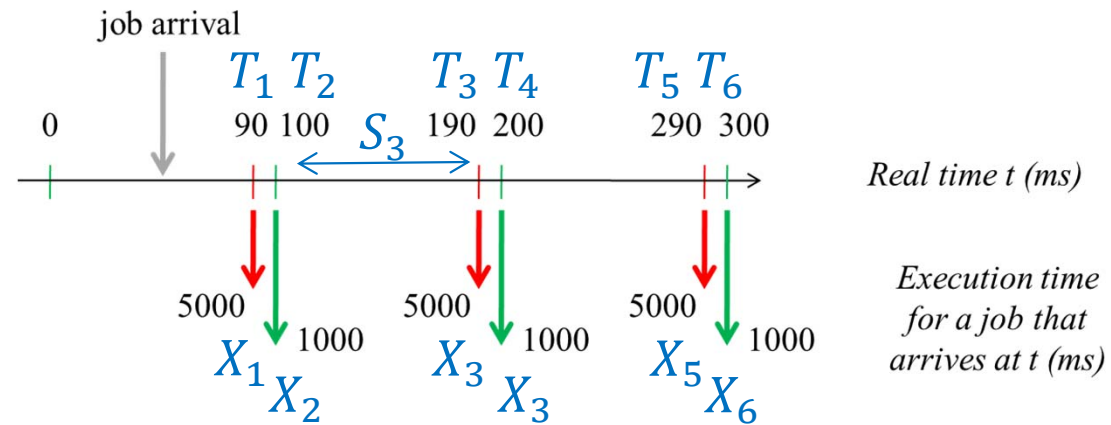
A metric definition should mention the sampling method  
(*viewpoint*)

Different sampling methods may provide different values: this is  
the *sampling bias*

*Palm Calculus* is a set of formulas for relating different viewpoints

Can often be obtained by means of the *Large Time Heuristic*

# Large Time Heuristic Explained on an Example



We want to relate  $W_s$  and  $W_c$

We apply the large time heuristic

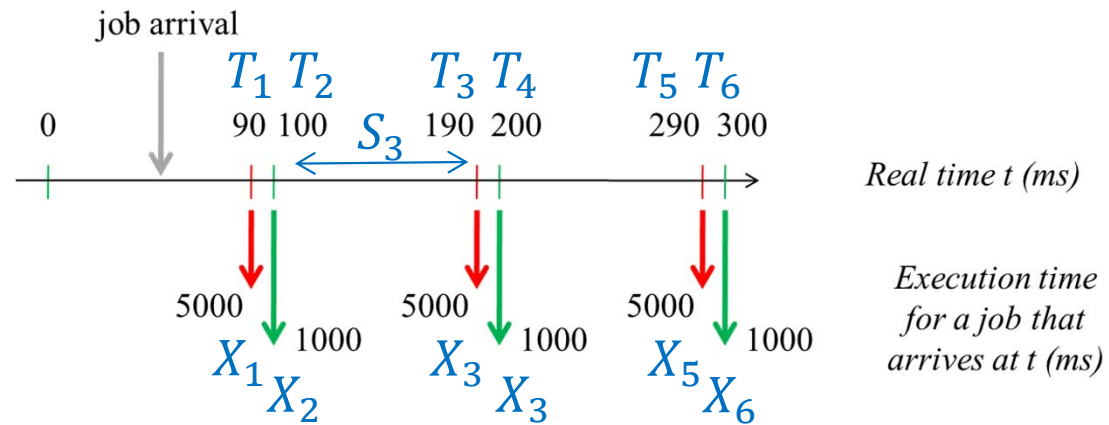
1. How do we evaluate these metrics in a simulation ?

$$W_s = \frac{1}{N} \sum_{n=1 \dots N} X_n = \bar{X}$$

$$W_c = \frac{1}{T} \int_0^T X_{N^+(t)} dt$$

where  $N^+(t)$  = index of next green or red arrow at or after  $T$

# Large Time Heuristic Explained on an Example



2. Break one integral into pieces that match the  $T_n$ 's:

$$W_s = \frac{1}{N} \sum_{n=1 \dots N} X_n = \bar{X}$$

$$W_c = \frac{1}{T} \int_0^T X_{N^+}(t) dt$$

$$W_c = \frac{1}{T} \left( \int_0^{T_1} X_{N^+}(t) dt + \int_{T_1}^{T_2} X_{N^+}(t) dt + \dots + \int_{T_{N-1}}^{T_N} X_{N^+}(t) dt \right)$$

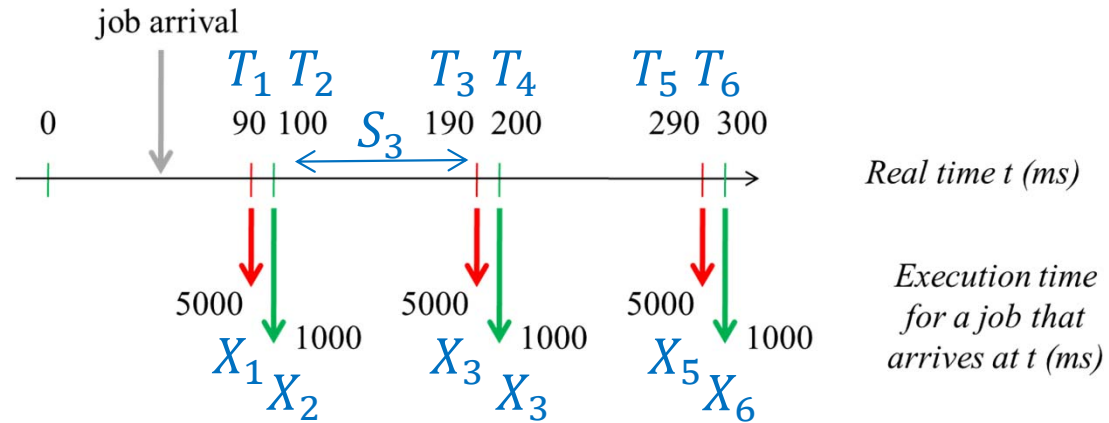
$$= \frac{1}{T} \left( \int_0^{T_1} X_1 dt + \int_{T_1}^{T_2} X_2 dt + \dots + \int_{T_{N-1}}^{T_N} X_N dt \right)$$

$$= \frac{1}{T} (T_1 X_1 + (T_2 - T_1) X_2 + \dots + (T_N - T_{N-1}) X_N)$$

$$= \frac{1}{T} (S_1 X_1 + S_2 X_2 + \dots + S_N X_N)$$



# Large Time Heuristic Explained on an Example



3. Compare

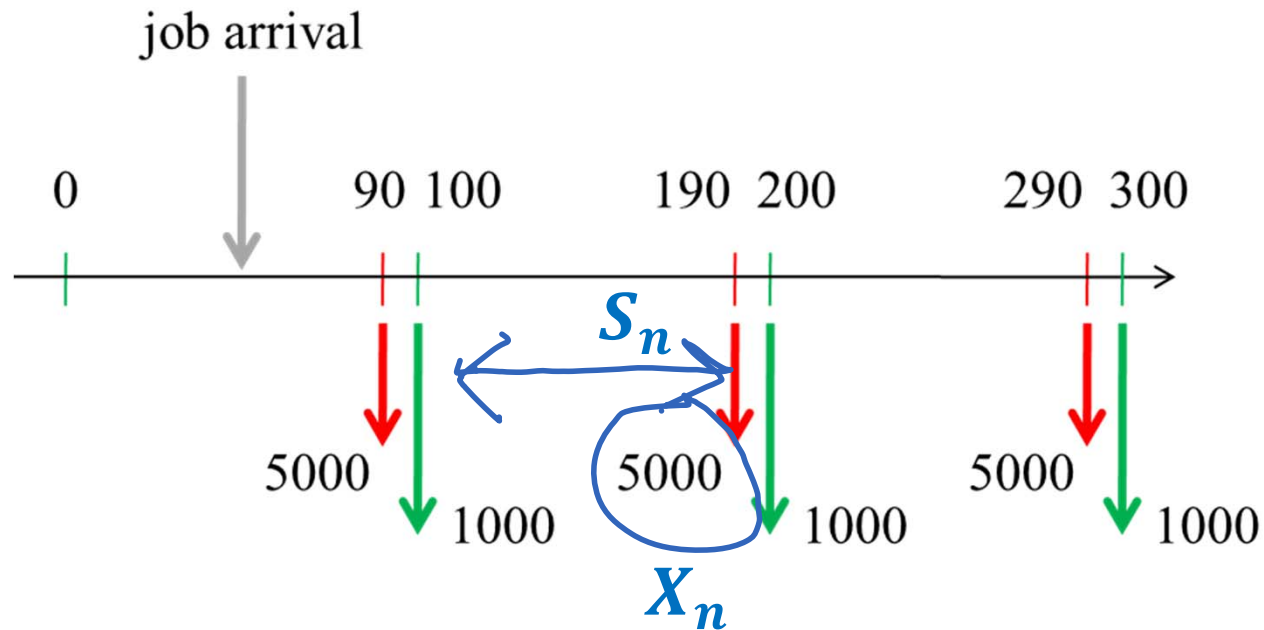
$$W_c = \frac{1}{T} (S_1 X_1 + S_2 X_2 + \dots + S_N X_N)$$

$$= \frac{N}{T} \times \frac{1}{N} (S_1 X_1 + S_2 X_2 + \dots + S_N X_N)$$

$$= \lambda \times (\text{cov}(S, X) + \bar{S} \bar{X}) = \lambda \times \left( \text{cov}(S, X) + \frac{1}{\lambda} \bar{X} \right)$$

$$W_c = \lambda \text{cov}(S, X) + W_s$$

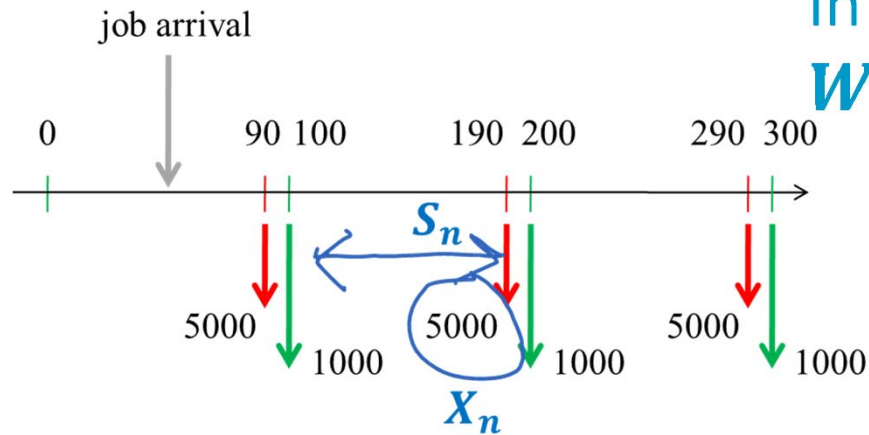
# This is Palm Calculus !



$$W_c = \lambda \text{cov}(S, X) + W_s$$

Viewpoint 1: System Designer	Viewpoint 2: Customer
<p>Two processes, with execution times 5000 and 1000</p> $W_s = \frac{5000 + 1000}{2} = 3000$	<p>Inspector arrives at a random time red processor is used with proba <math>\frac{90}{100}</math></p> $W_c = \frac{90}{100} \times 5000 + \frac{10}{100} \times 1000 = 4600$

In which case do we expect to see  $W_c > W_s$ ?



$$W_c = \lambda \text{cov}(S, X) + W_s$$

Viewpoint 1: System Designer	Viewpoint 2: Customer
<p>Two processes, with execution times 5000 and 1000</p> $W_s = \frac{5000 + 1000}{2} = 3000$	<p>Inspector arrives at a random time red processor is used with proba <math>\frac{90}{100}</math></p> $W_c = \frac{90}{100} \times 5000 + \frac{10}{100} \times 1000 = 4600$

- A.  $S_n = 90, 10, 90, 10, 90; X_n = 5000, 1000, 5000, 1000, 5000$
- B.  $S_n = 90, 10, 90, 10, 90; X_n = 1000, 5000, 1000, 5000, 1000$
- C. Both
- D. None
- E. I don't know

# Solution

In case A,  $S_n$  and  $X_n$  are positively correlated (when the interval is long, so is the processing time), i.e.  $\text{cov}(X, S) > 0$ . By the Palm calculus formula:  $W_c > W_s$

In case B, the correlation is negative, therefore  $W_c < W_s$

Answer A

# The Large Time Heuristic

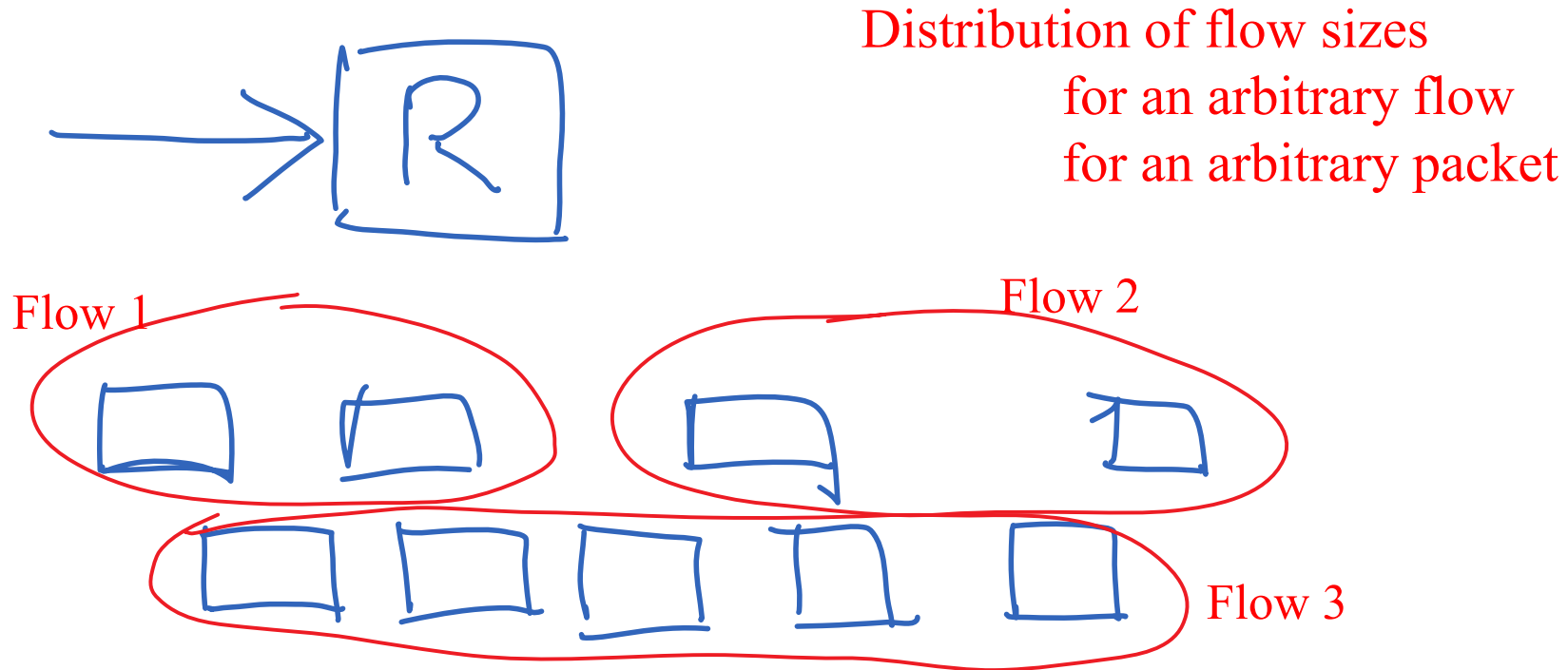
1. formulate each performance metric as a long run ratio, as you would do if you would be evaluating the metric in a discrete event simulation;
2. take the formula for the time average viewpoint and break it down into pieces, where each piece corresponds to a time interval between two selected events;
3. compare the two formulations.

Formally correct if simulation is stationary

It is a *robust* method, i.e. independent of assumptions on distributions (and on independence)

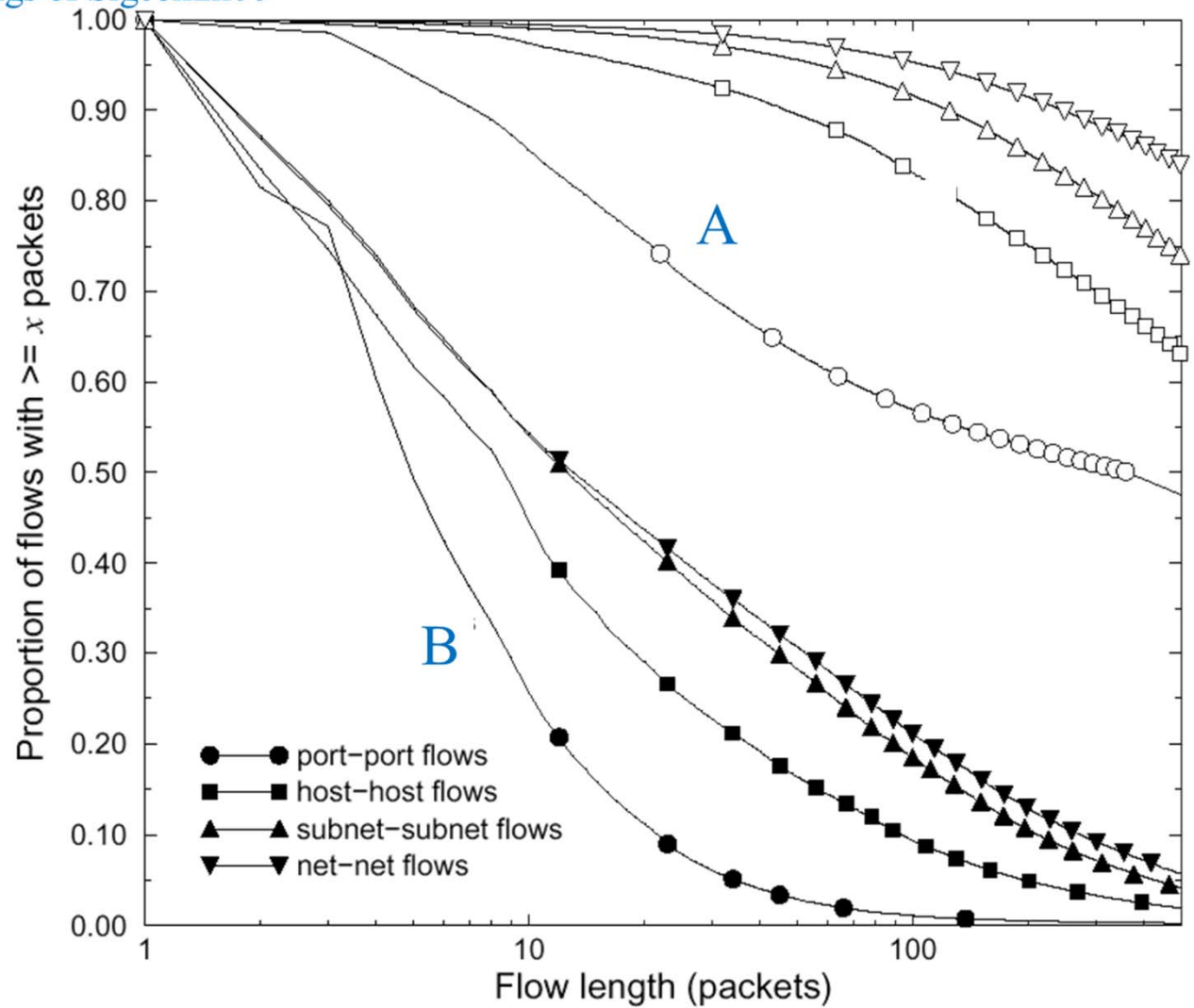
# Other «Clocks»

EXAMPLE 7.4: **FLOW VERSUS PACKET CLOCK [96]**. Packets arriving at a router are classified in “flows”. We would like to plot the empirical distribution of flow sizes, counted in packets. We measure all traffic at the router for some extended period of time. Our metric of interest is the probability distribution of flow sizes. We can take a flow “clock”, or viewpoint, i.e. ask: pick an arbitrary flow, what is its size? Or we could take a packet viewpoint and ask: take an arbitrary packet, what is the magnitude of its flow? We thus have two possible metrics (Figure 7.3):



Which curves are  
for the per-packet  
viewpoint ?

- A. A
- B. B
- C. It depends
- D. I don't know



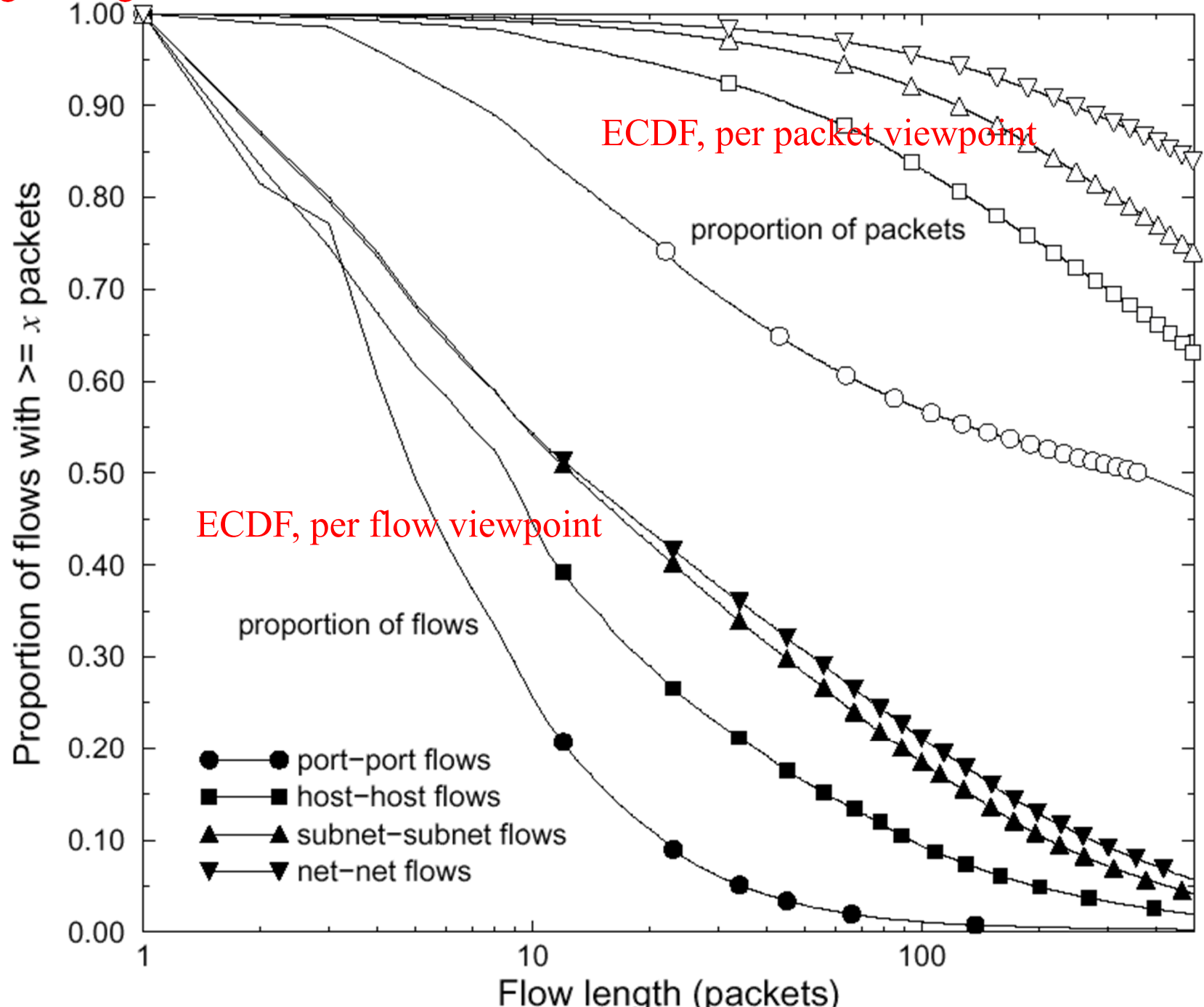
# Solution

Answer A

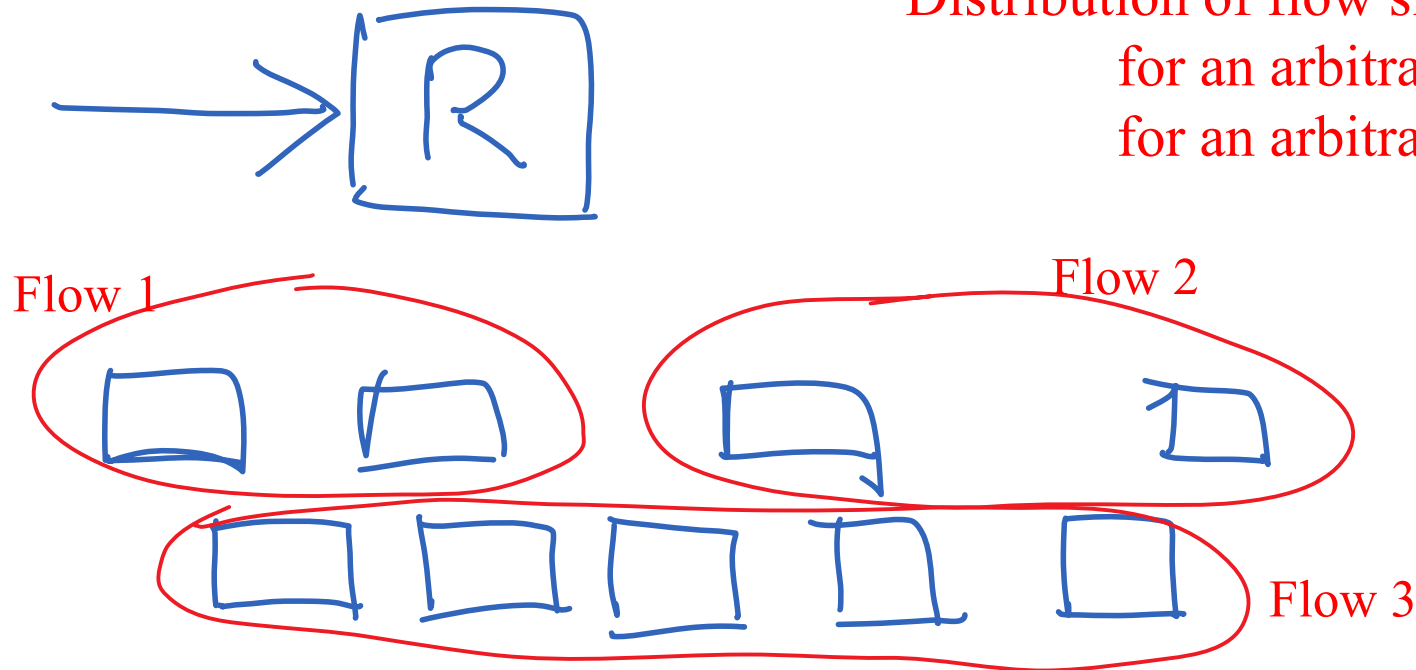
There are more packets in the large flows. So more packets experience a large flow size.



Load Sensitive Routing of Long-Lived IP Flows  
Anees Shaikh, Jennifer Rexford and Kang G. Shin  
Proceedings of Sigcomm'99



Distribution of flow sizes  
for an arbitrary flow  
for an arbitrary packet



Per flow  $f_F(s) = 1/N \times$  number of flows with length  $s$ , where  $N$  is the number of flows in the dataset;

Per packet  $f_P(s) = 1/P \times$  number of packets that belong to a flow of length  $s$ , where  $P$  is the number of packets in the dataset;

Mean flow size:

per flow  $S_F$

per packet  $S_P$

# Large «Time» Heuristic

1. How do we evaluate these metrics in a simulation ?

per flow  $S_F = \frac{1}{N} \sum_n S_n$

per packet  $S_P = \frac{1}{P} \sum_p S_{F(p)}$

where  $F(p) = n$  when packet  $p$  belongs to flow  $n$

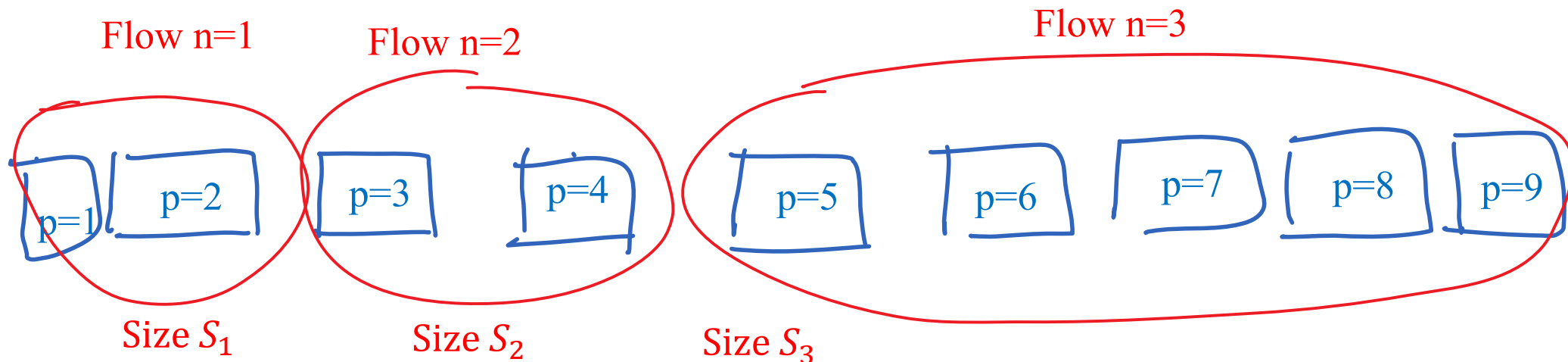
1. How do we evaluate these metrics in a simulation ?

per flow  $S_F = \frac{1}{N} \sum_n S_n$

per packet  $S_P = \frac{1}{P} \sum_p S_{F(p)}$

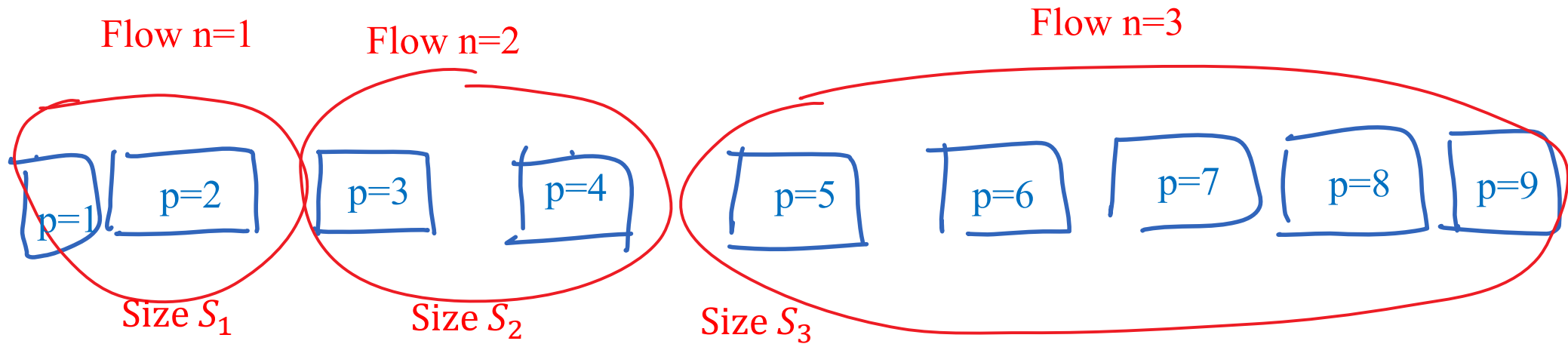
where  $F(p) = n$  when packet  $p$  belongs to flow  $n$

2. Put the packets side by side, sorted by flow



$$S_P = \frac{1}{P} (S_1 + S_1 + S_2 + S_2 + S_3 + S_3 + S_3 + S_3 + S_3 + \dots)$$

$$= \frac{1}{P} (S_1 \times S_1 + S_2 \times S_2 + S_3 \times S_3 + \dots) = \frac{1}{P} \sum_n S_n^2$$



3. Compare

$$S_P = \frac{1}{P} \sum_n S_n^2$$

$$S_F = \frac{1}{N} \sum_n S_n = \frac{1}{N} P$$

$$S_P = \frac{N}{P} \times \frac{1}{N} \sum_n S_n^2 = \frac{1}{S_F} \times \frac{1}{N} \sum_n S_n^2 = \frac{1}{S_F} \times \left( S_F^2 + \text{var}_F(S) \right)$$

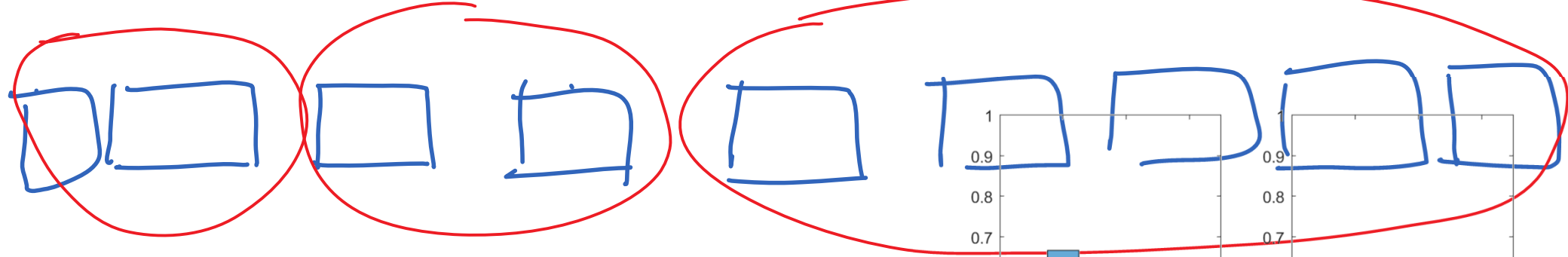
$$S_P = S_F + \frac{1}{S_F} \text{var}_F(S)$$

# PDFs of flow sizes

Flow n=1

Flow n=2

Flow n=3

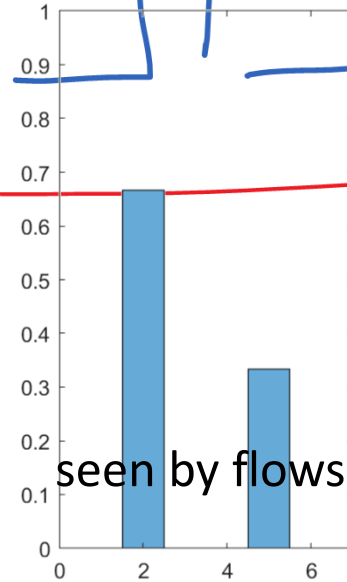


$f_F(s)$ : PDF of flow size, seen by flows

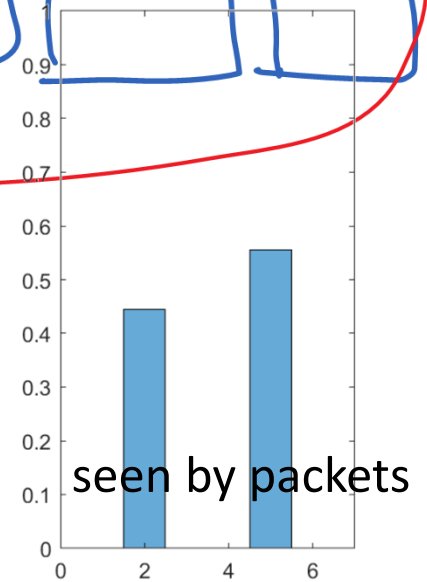
$f_P(s)$ : PDF of flow size, seen by packets

Using the same approach we obtain

$f_P(s) = \eta s f_F(s)$  where  $\eta$  is a normalization constant



seen by flows

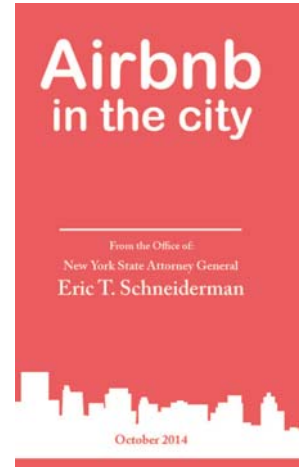


seen by packets

# AirBnB's Paradox

Occupancy PDF seen by an arbitrary object:

$f(s)$  = proportion of objects that are booked  $s$  nights per year



Occupancy PDF seen by an arbitrary traveller (estimated by insideairbnb.com)  $f_T(s)$  = proportion of bookings that occur in a object booked  $s$  nights per year

A.  $f_T(s) = \eta s f(s)$  where  $\eta$  is a normalizing constant

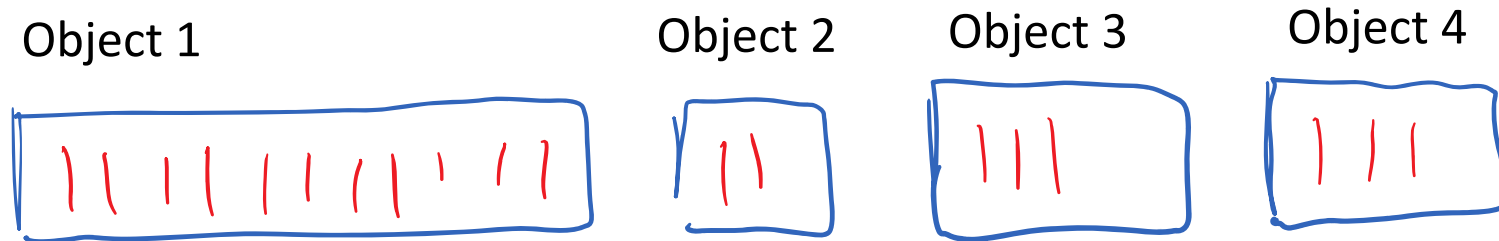
B.  $f_T(s) \approx f(s)$

C.  $f(s) = \eta s f_T(s)$  where  $\eta$  is a normalizing constant

D. I don't know

# Solution

This is the same case as with files (listings) and packets (bookings).



Therefore, with the same arguments  $f_T(s) = \eta s f(s)$

The median of the distribution with PDF  $f()$  is 40 days (reported by airbnb)

The median of the distribution with PDF  $f_T()$  is 165 days (reported by insideairbnb.com)

An arbitrary booking is more likely to fall in a listing that is often booked.



# Take-Home Message

How we sample data to compute a metric (the **viewpoint**) should be screened carefully.

Apparent paradoxes come from confusions in viewpoints.

Metrics may be misleading if sampling method is not appropriate.

Next we will see a formal theory (Palm Calculus) and its use in simulations.