On the Characteristics of Internet Traffic Variability: *Spikes and Elephants*

Tatsuya Mori,[1][2] Ryoichi Kawahara,[1]
Shozo Naito,[3] Shigeki Goto[2]

(1) NTT Service Integration Laboratories
(2) Waseda University
(3) NTT Information Sharing Platform Laboratories

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Outline:

- Overview
- Internet traffic model
- Measurement and analysis
  - Aggregated traffic
  - User traffic
  - Their relationship
- Summary

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Overview:

- We need a practical Internet traffic model
  - for efficient designing and controlling of networks
  - They should be realistic!
    → wide-range measurement is required!

- Measurement and analysis of traffic
  - Traditional traffic models cannot cover the characteristics of today's Internet traffic
  - What are they?

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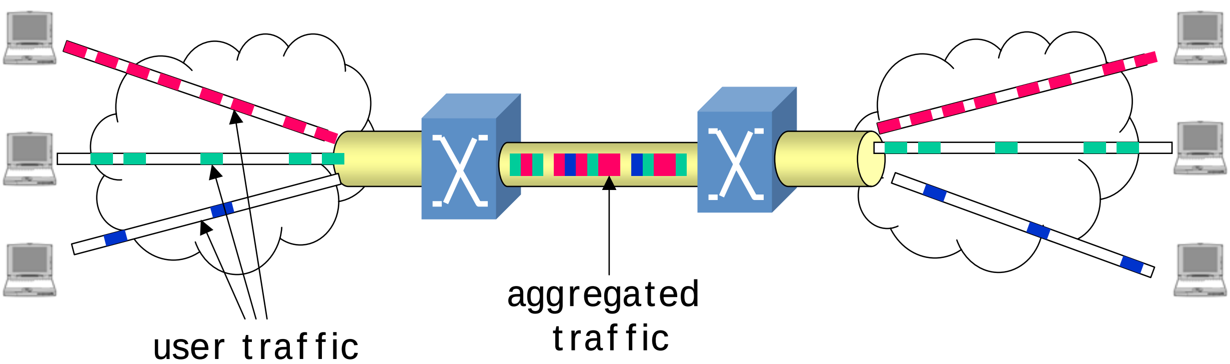
Internet traffic model:

- Aggregated traffic
  - aggregation of user traffic
- User traffic
  - Traffic produced by Application
  - Characterized by "flow"
    - flow = {srcIP, dstIP, srcPort, dstPort, protocol}



Internet traffic model (cont.):

- Characteristics of aggregated traffic
  - Essential metrics for controlling/designing network
    - Queuing behavior
    - Utilization monitoring

- Characteristics of user traffic
  - Essential metrics for traffic engineering
    - Router algorithms to control per-flow bandwidth
      - WFQ, CSFQ, RED, etc.
    - Adequate parameters are required
      - flow size, flow duration, etc.

Some invariant characteristics assumed in traditional traffic models:

- Aggregated traffic
  - Variability has "long-range dependence" (LRD)
    - since early 1990's [Willinger et. al]
    - significant effect on network performance

  - Marginal dist. of variability is assumed to be "Gaussian"
    - Also important metrics for network performance
    - Central limit theorem, fGn (fBm) models

Some invariant characteristics assumed in traditional traffic models:

- User traffic
  - Flow durations are "heavy-tailed"
    - well known Pareto ON/OFF model
      - Transmission rate of each flow is fixed in the model
    - related to LRD of aggregated traffic
      - Aggregation of Pareto on/off sources → LRD
    - related to file size distibution
      - Web objects follow zipf's law

Are they realistic in today's Internet? :

- Aggregated traffic
  - LRD: in most cases, YES
  - Gaussian: → ???
- User traffic
  - Heavy-tailed duration: YES
  - Fixed transmission rate: → ???

traditional traffic model can cover these? (NO)

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Measured traffic data:

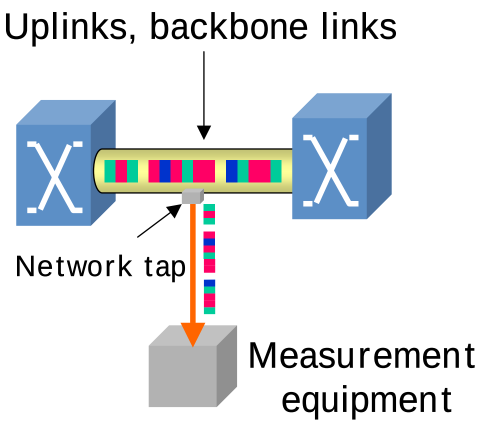
- Internet uplinks
  - NTTlab: corporation
  - Waseda: university
- Internet backbone links
  - OCN-SINET: domestic
  - APAN: international
  - WIDE: international

Total:
269 one-way traces
(each 300 sec long)

data	line	direction	bandwidth	# traces	avg packets	avg rate
NTTlab	ATM	incoming	12 Mbps	56	1.55×10^5	3.75 Mbps
Waseda	Ethernet	incoming	100 Mbps	71	1.84×10^6	23.31 Mbps
OCN-SINET	ATM	OCN-to-SINET	135 Mbps	32	8.06×10^5	12.50 Mbps
APAN	OC3	US-to-JP	155 Mbps	44	5.98×10^5	5.14 Mbps
WIDE	Ethernet	US-to-JP	100 Mbps	66	1.61×10^6	18.00 Mbps

Measured traffic data (cont.) :

- Passive measurement
  - captures headers of packets
  - can analyze aggregated/user traffic



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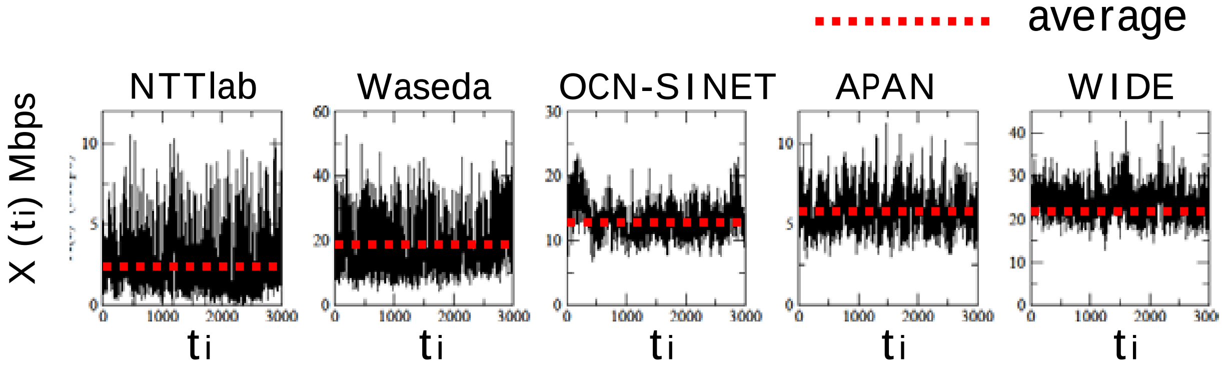
Aggregated traffic :

- Traffic variability
  - Variability of throughput
  - $X(t_i)$: throughput time series
  - Throughput time bin = 0.1 (s)

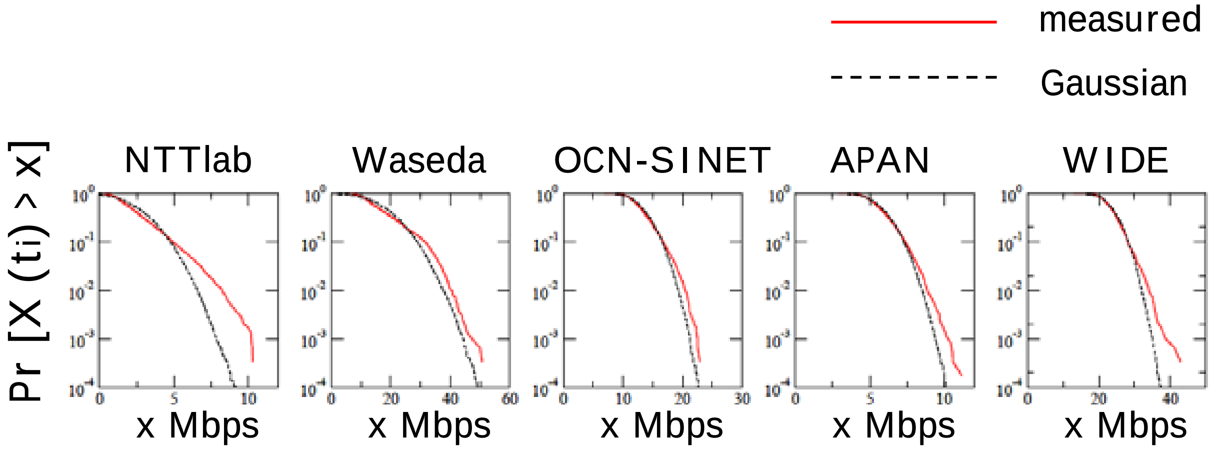
Throughput variability:



Throughput time series

<u>much higher values than the average.</u>

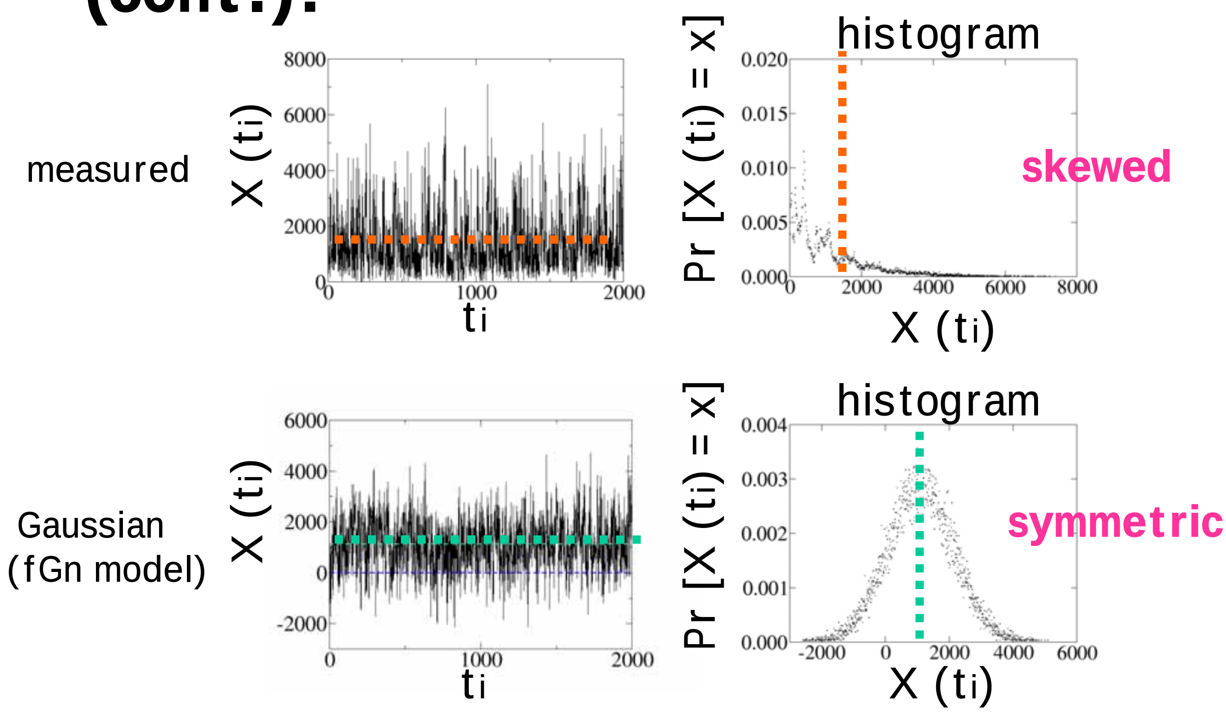
Marginal distribution of X(ti):



Complementary cumulative distribution

<u>They are all skewed (not Gaussian dist.)</u>

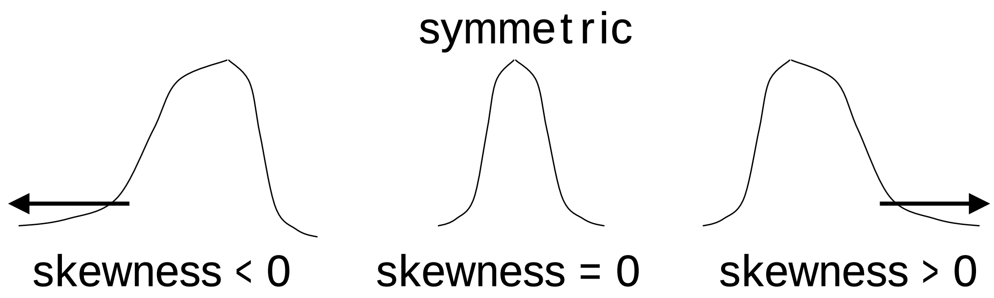
Marginal distribution of X(ti) (cont.):



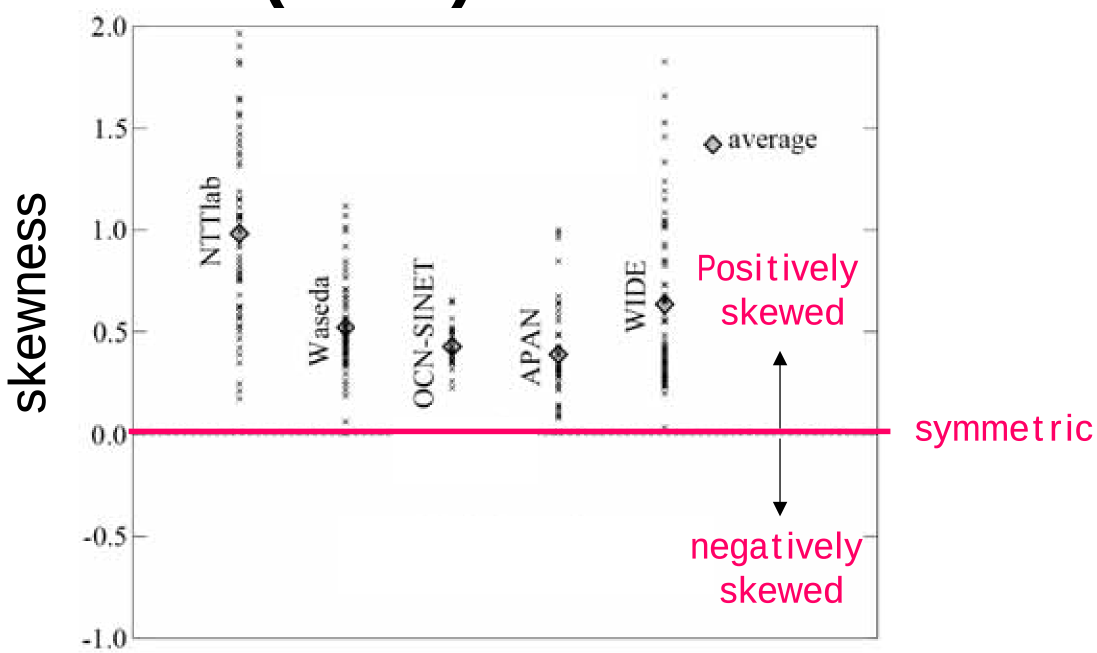
Skewness:

$$\text{skewness} = \frac{\left\langle \left(X(t_i) - \left\langle X(t_i) \right\rangle \right)^3 \right\rangle}{\sigma^3}$$

σ : standad deviation



Skewness (cont.) :

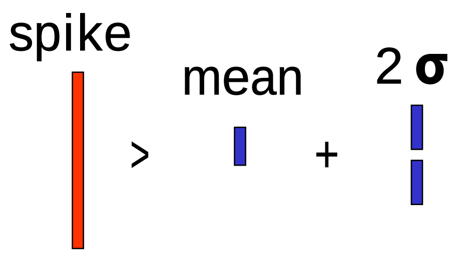


Most of traces are positively skewed

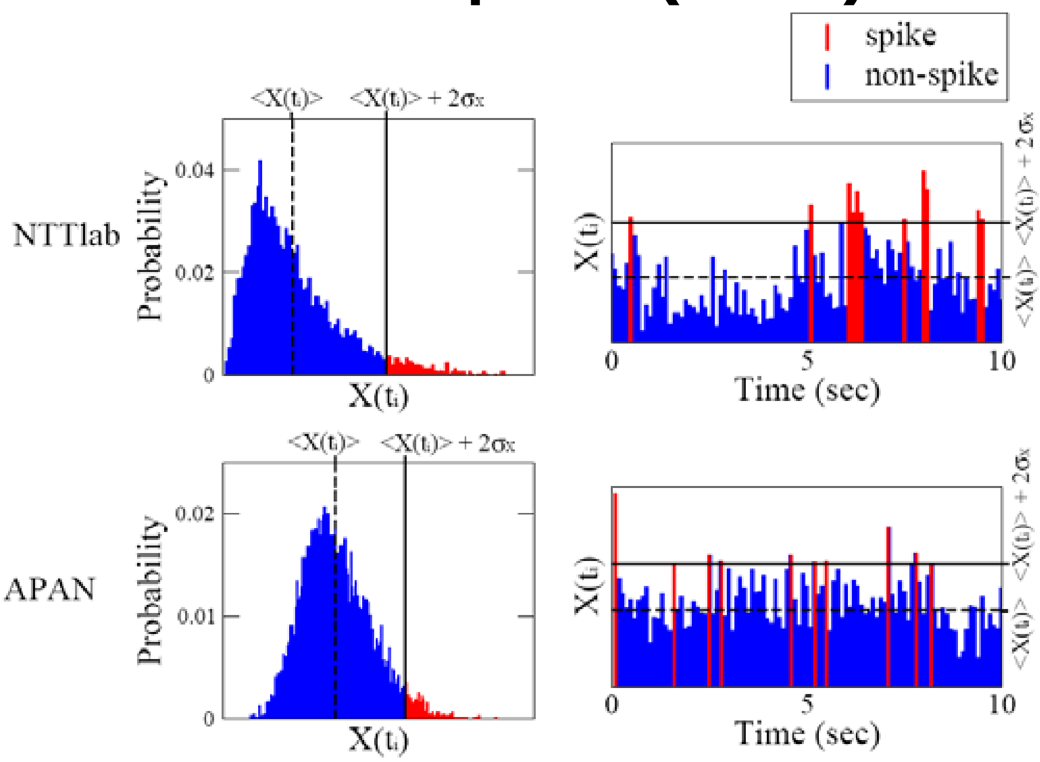
Skewness and spikes:

- Positively skewed distribution
  - Existence of <u>larger values</u> of throughput $X(t_i)$ →spikes

- Definition of spikes
  - $X(t_i)$ which exceeds mean + 2 **σ**
    - **σ** = standard deviation of $X(t_i)$



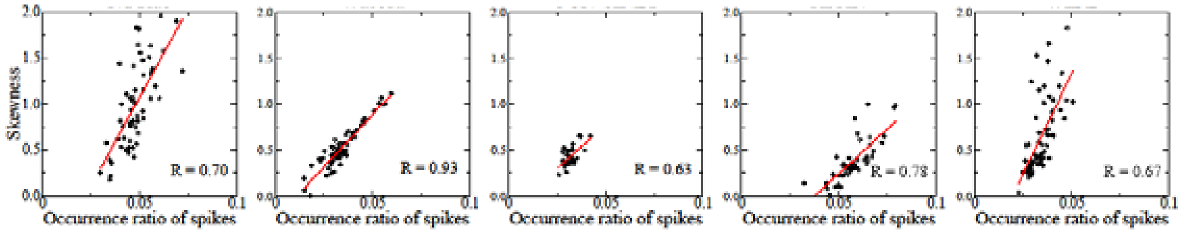
Skewness and spikes (cont.):



Skewness and spikes (cont.):

- Occurrence ratio of spikes vs. skewness

NTTlab Waseda OCN-SINET APAN WIDE



They are positively correlated!
<u>i.e., more spikes, more skewed</u>

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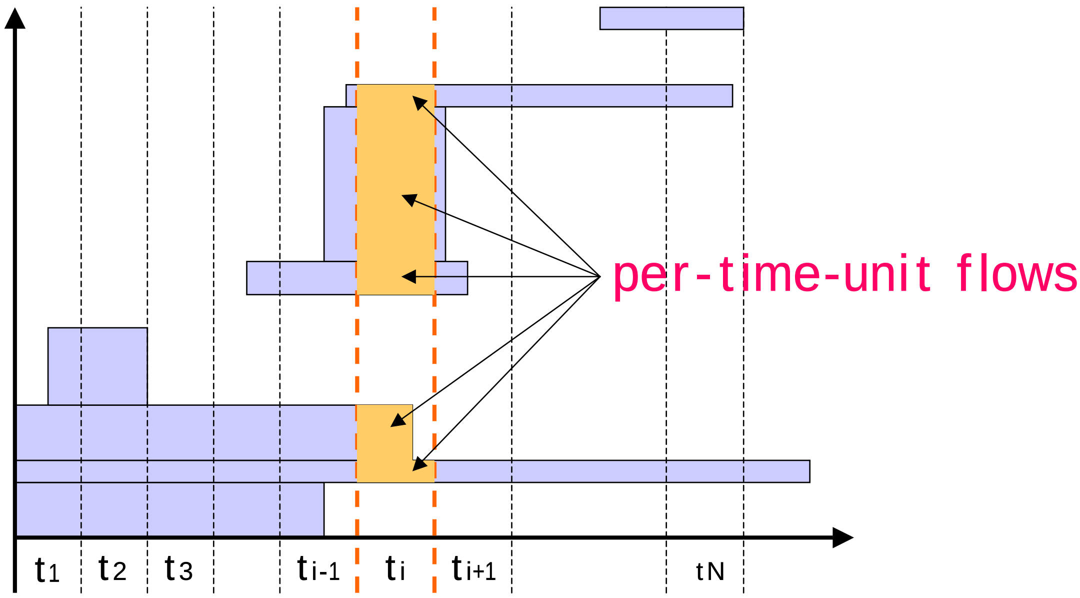
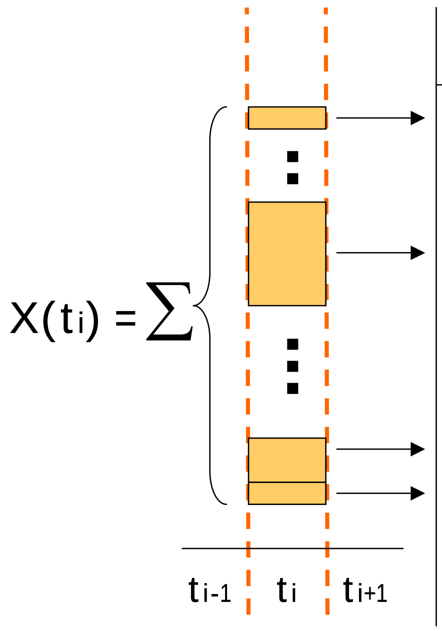
Per-time-unit flow:

- To see how each user traffic contributes to the aggregated traffic

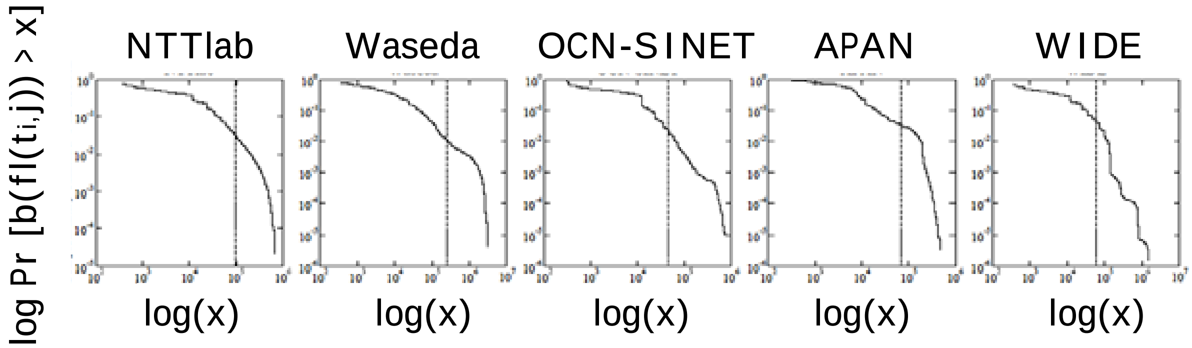


Per-time-unit flow (cont.):



#	ID	size (bit)
N_{t_i}	$fl(t_i, N_{t_i})$	$b(fl(T_i, N_{t_i}))$
⋮	⋮	⋮
j	$fl(t_i, j)$	$b(fl(t_i, j))$
⋮	⋮	⋮
2	$fl(t_i, 2)$	$b(fl(t_i, 2))$
1	$fl(t_i, 1)$	$b(fl(t_i, 1))$

Size dist. of Per-time-unit flow:

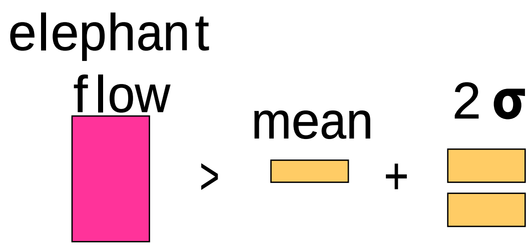


Size distributions of per-time-unit flows are heavy-tailed

i.e., quite large per-time-unit flows exist = elephant flows

Elephant flows:

- Definition of an elephant flow
  - A flow fl(ti,j) whose size b(fl(ti,j)) exceeds mean + 2 **σ**
    - **σ** = standard deviation of b(fl(ti,j))



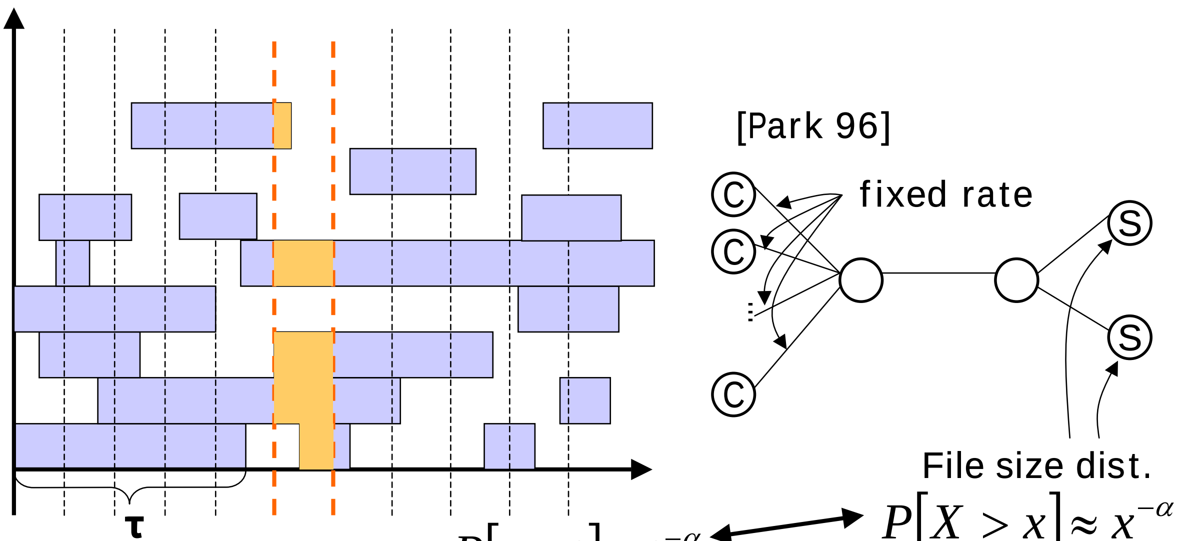
Elephant flows (cont.):

Occurrence/occupation ratio of elephant flows

	NTTlab	Waseda	OCN-SINET	APAN	WIDE
Occurrence ratio	3.01 %	1.15 %	2.35 %	3.22 %	4.65 %
Occupation ratio	35.72 %	39.07 %	25.59 %	41.22 %	41.30 %

1. **# of Elephant flows is not large.**
2. **Elephant flows occupy large part of traffic.**

[cf] Pareto ON/OFF model:



$$P[\tau > t] \approx t^{-\alpha} \longleftrightarrow P[X > x] \approx x^{-\alpha}$$

All b(fl(ti,j)) s are almost same

i.e., No elephant flows!

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Per-time-unit flow and spike/non-spike:

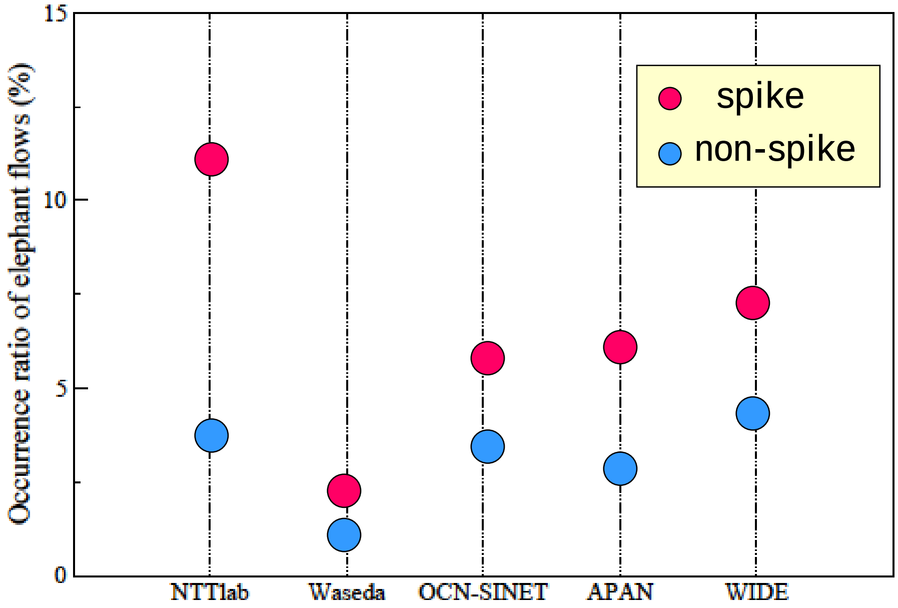
N_{ti} for each traces

	NTTlab	Waseda	OCN-SINET	APAN	WIDE
spike	17.8	80.9	191.7	50.9	253.6
non-spike	15.2	78.2	174.3	48.3	213.7

The difference between spikes and non-spikes is not remarkable

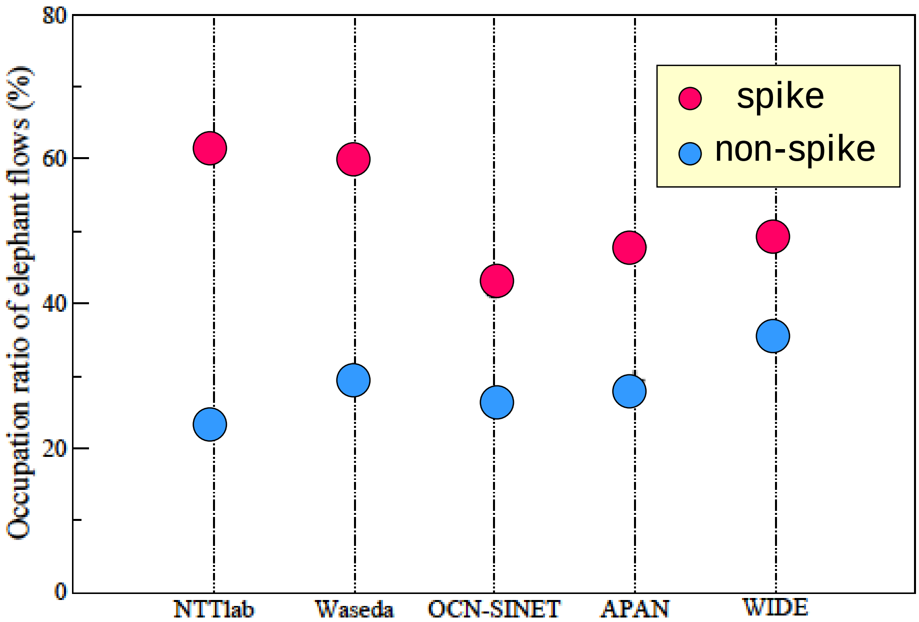
i.e., number of per-time-unit flows does NOT largely contribute to spikes

elephant flow and spike/non-spike:



Occurrence ratio of elephant flows

elephant flow and spike/non-spike (cont.):



Occupation ratio of elephant flows

elephant flow and spike/non-spike (cont.):

- # of elephant flows
  - within spikes > within non-spikes
  - about 1.7 – 2.9 times higher

- A large part of spikes are elephant flows
  - about 42 – 61 %
  - non-spikes → about 22 – 35 %

Thus, spikes and elephant flows are strongly related!

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Summary:

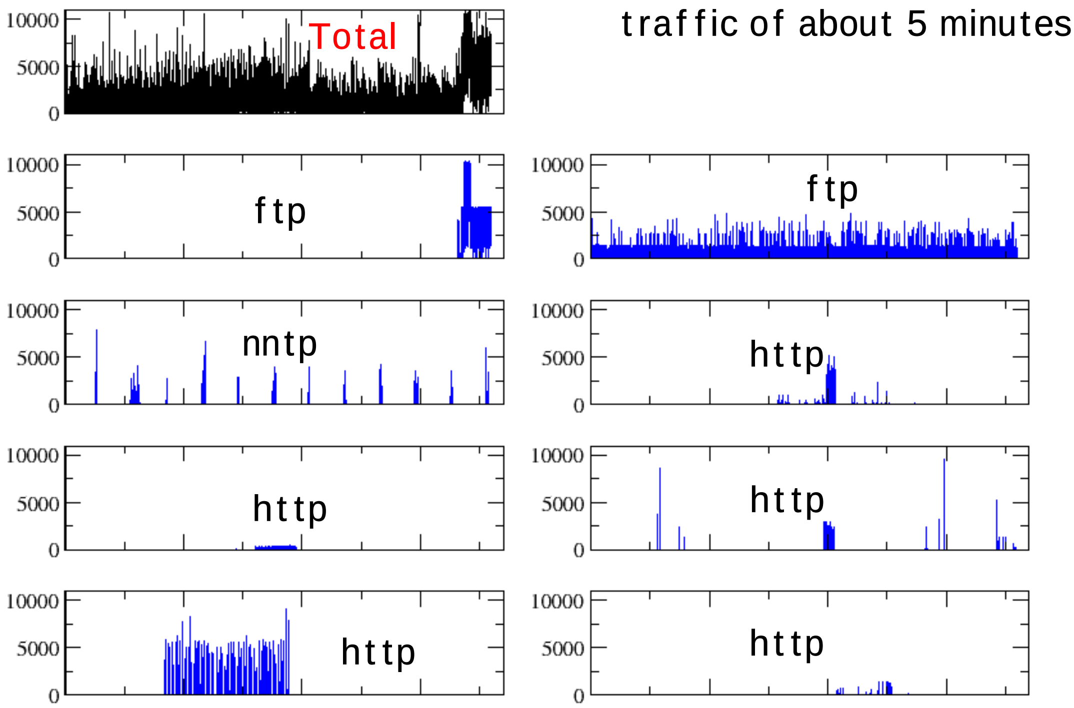
- Variability of aggregated traffic
  → positively skewed (non-Gaussian)

- User traffic
  → elephant flows exist
  – flow rates are NOT fixed

- Elephant flows are more likely within spikes

  <u>These findings are useful in constructing a practical and realistic traffic model.</u>

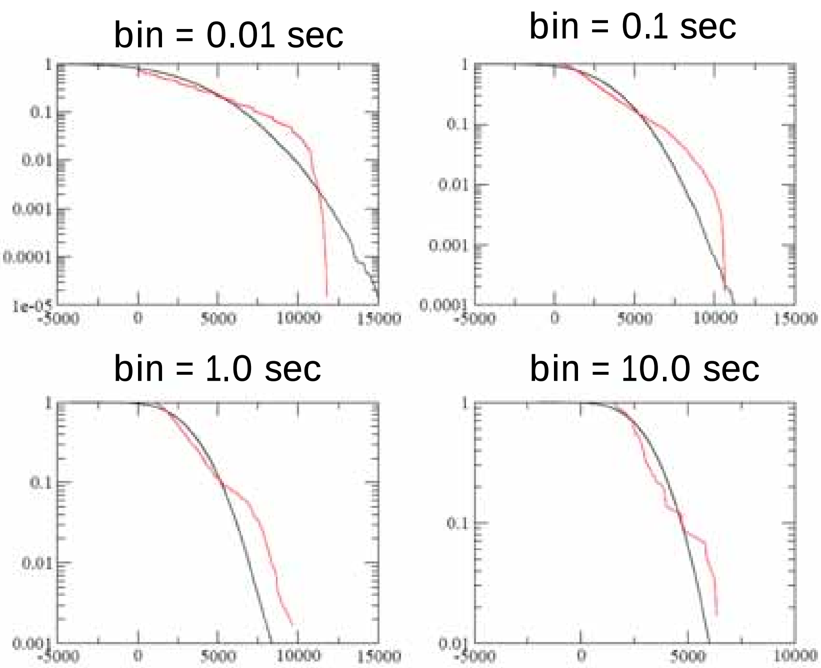
Appendix:
Example of aggregated traffic and flows



Appendix:
time-scale issue (aggregated traffic)

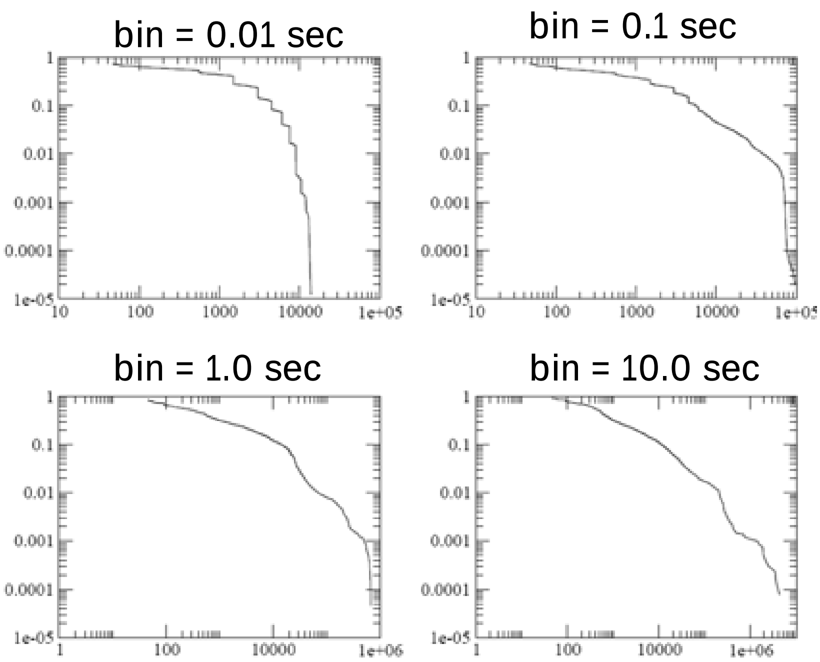
NTTlab trace: CCD plots of X(ti)

measured
Gaussian



Appendix:
time-scale issue (user traffic)

NTTlab trace: LLCD plots of b(fl(ti,j))



Appendix:
time-scale issue (spikes and elephants)

NTTlab trace: occupation ratio of elephant flows