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Impact of Packet Sampling on Anomaly Detection Metrics

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Motivation

- The general opinion about sampling:
  - With sampling valuable information lost about anomalies
  - But sampling needs to be used anyway...
    - Cannot get unsampled netflow from some routers
- Interesting questions arise:
  - *How much* information is actually lost?
  - Are all *anomalies* equally affected by sampling?
  - Are all *detection metrics* equally affected by sampling?
  - At which *sampling rate* is a certain anomaly still detectable?
  - Can we estimate the *original anomaly size* from a sampled view?

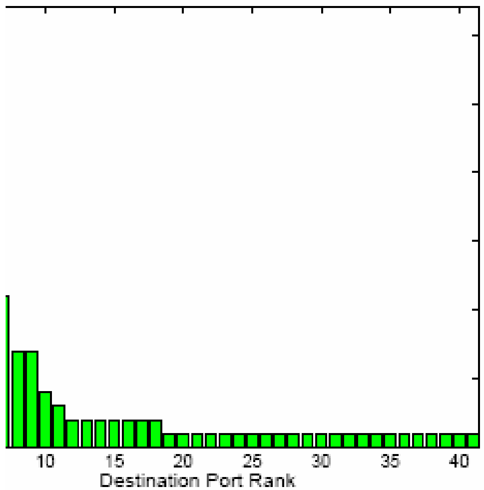
Data & Experiments

- A week-long dataset of ***unsampled Netflow records*** from a backbone router of a national ISP
- Known Blaster outbreak in our data

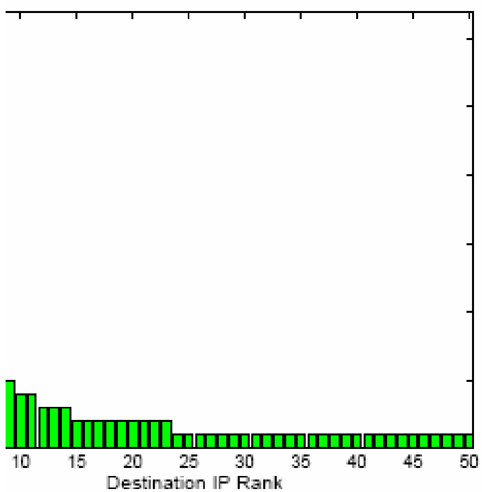
- **Goal:** Study impact of packet sampling on Blaster worm
  - Focus on visibility of Blaster worm
  - Focus on anomaly detection metrics
    - **Bytes, Packets, Flows, Traffic Features**, ...

Entropy as a Detection Metric [LCD:SIGCOMM05]

Dispersed Histogram
High Entropy



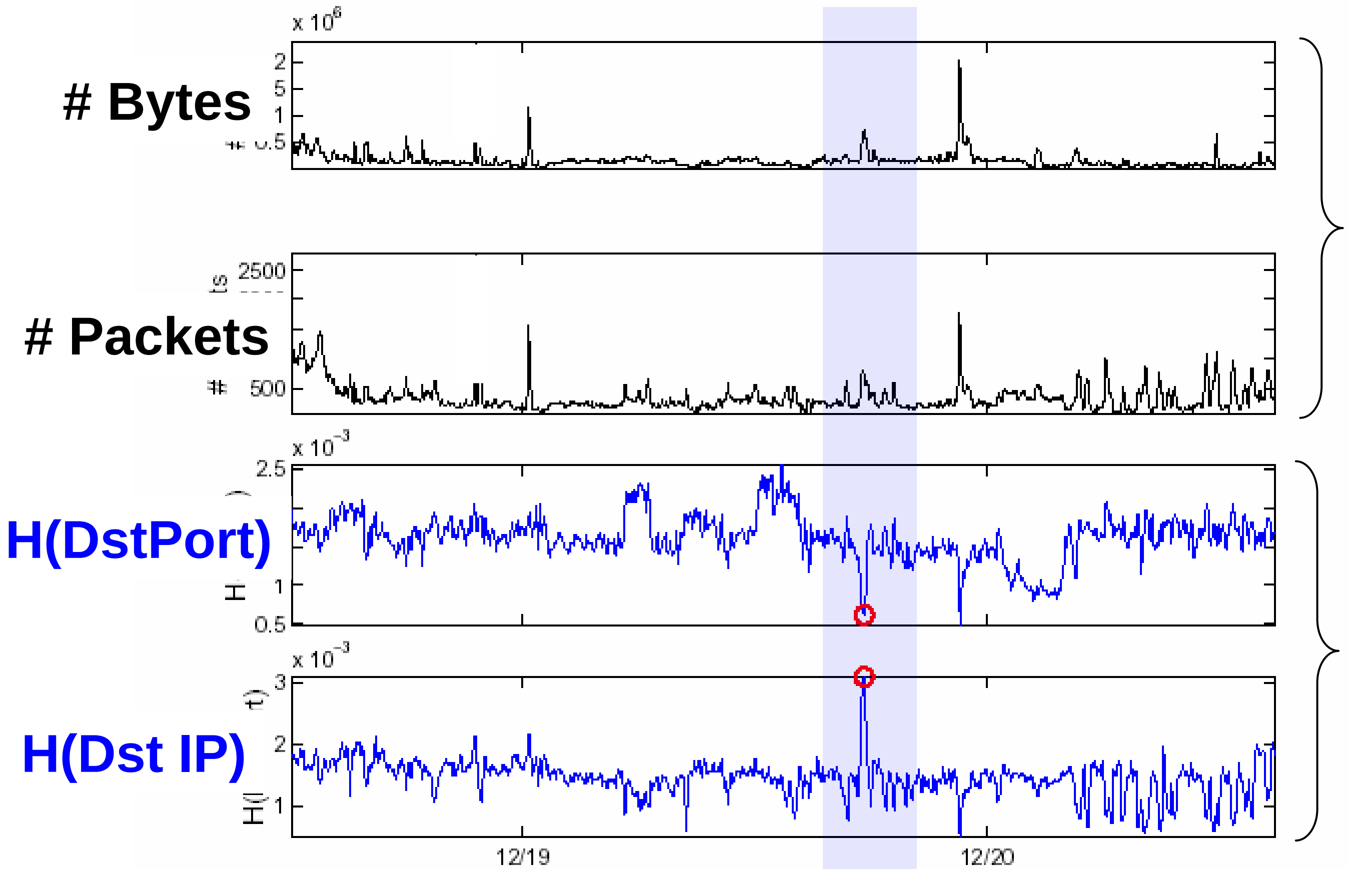
Concentrated Histogram
Low Entropy



ypical Traffic

Summarize using **sample entropy** of histogram *X*

The Power of Entropy

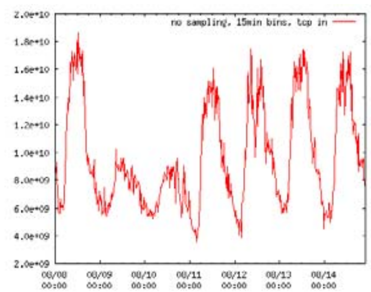
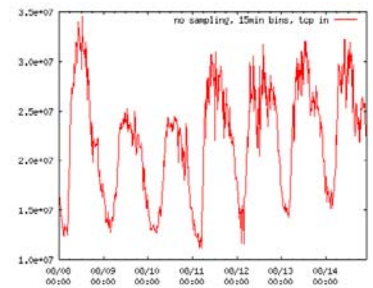
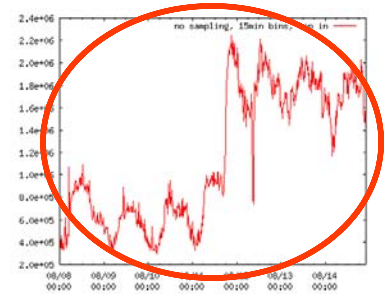


Traffic from SNVA to NYC

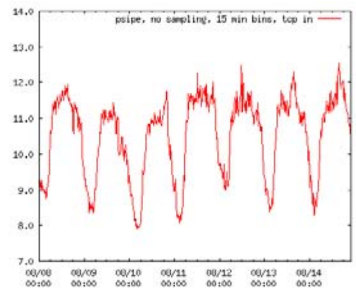
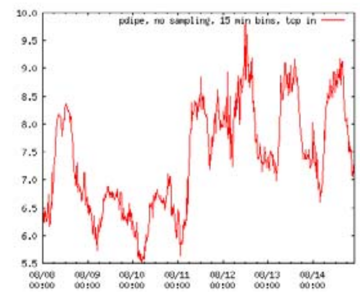
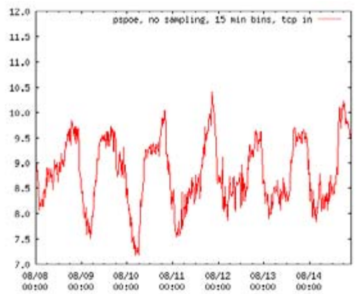
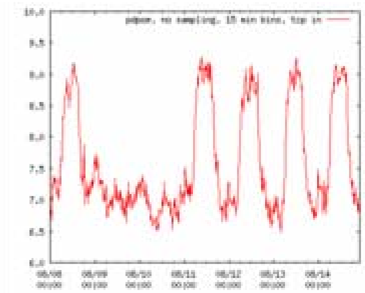
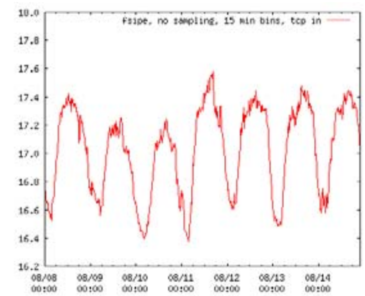
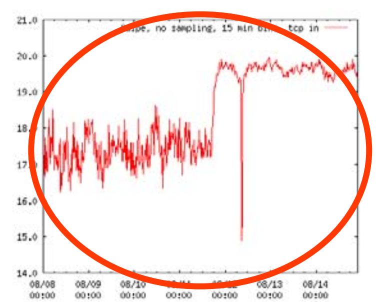
Worm scan dwarfed in volume metrics…

But stands out in feature entropy, which also reveals its structure

Which AD metrics to look at?

Flow counts

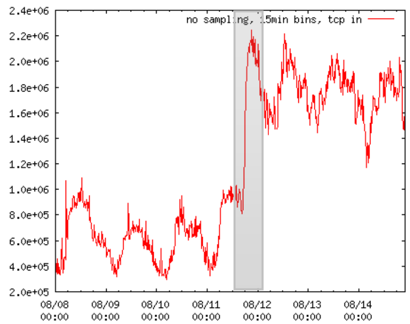
Flow destination IP entropy

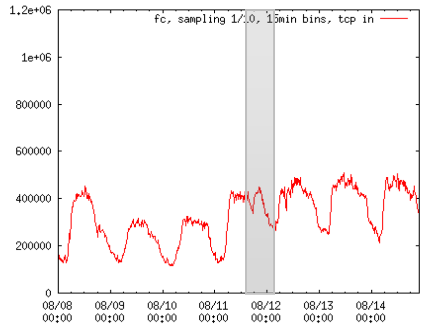
Methodology: Packet Sampling

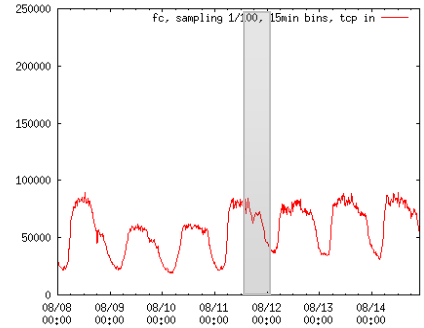
- Determine the *packet size* (bytes) and *timestamps* for individual packets in the flow trace
- Each packet of a flow is recorded in it‘s own flow record with
  - *packet_size = flow_size/num_packets (average packet size)*
  - timestamp randomly chosen within flow bounds
- Randomly sample every 10th, 100th, 250th, and 1000th packet
  - Not exactly what Cisco does, but pretty close...

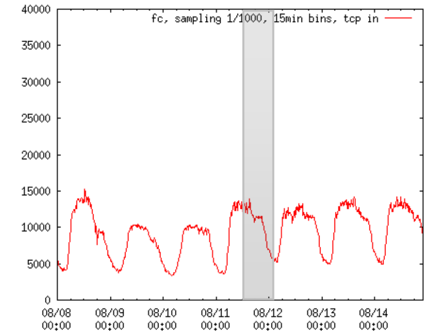
Timeseries of Detection Metrics

Flow counts

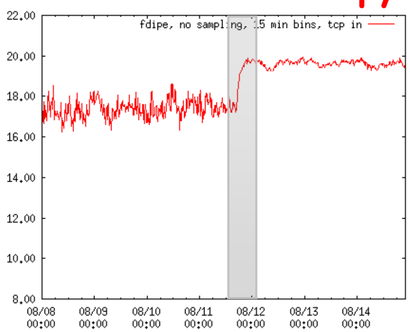


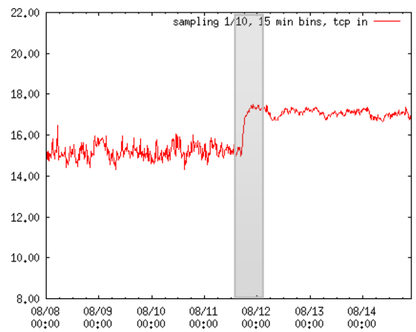


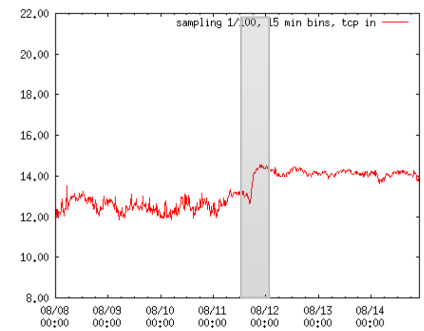


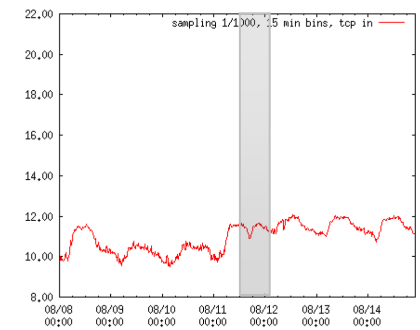


Flow dst IP entropy







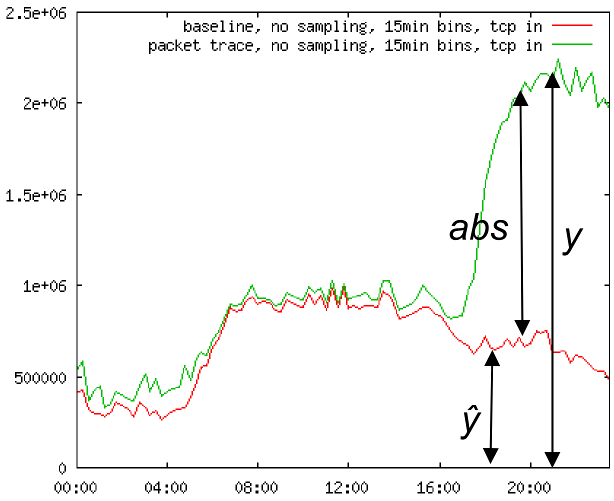


unsampled **10** **100** **1000**

Methodology: Determine the Baseline

- AD algorithms measure distance from (predicted) baseline to (actual) observed metrics
- Each AD method uses it‘s own handcrafted algorithm to determine the baseline model
- Since we know the anomaly very well we can construct an *„ideal baseline“* by removing all blaster packets from the observed trace
  - *Heuristic: blaster packet = packet with destination port 135, protocol TCP, and length of 40, 44, 48 bytes*
- One baseline per metric and *sampling rate*

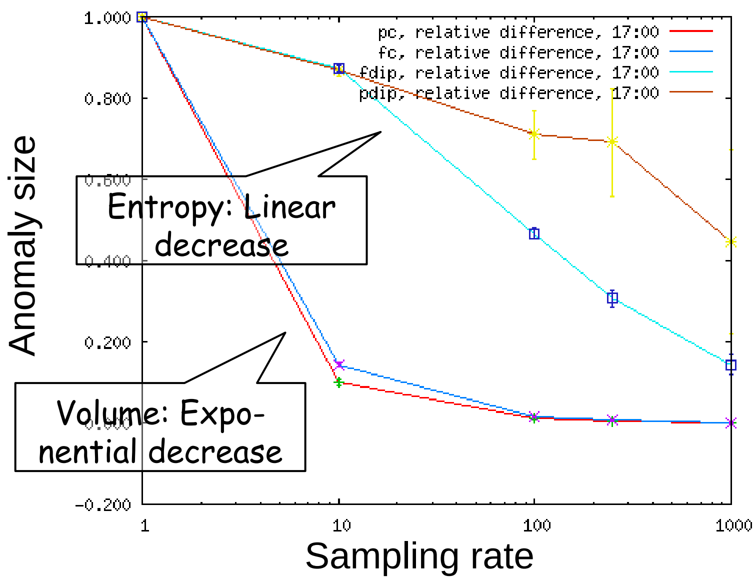
Methodology: Measure anomaly distance



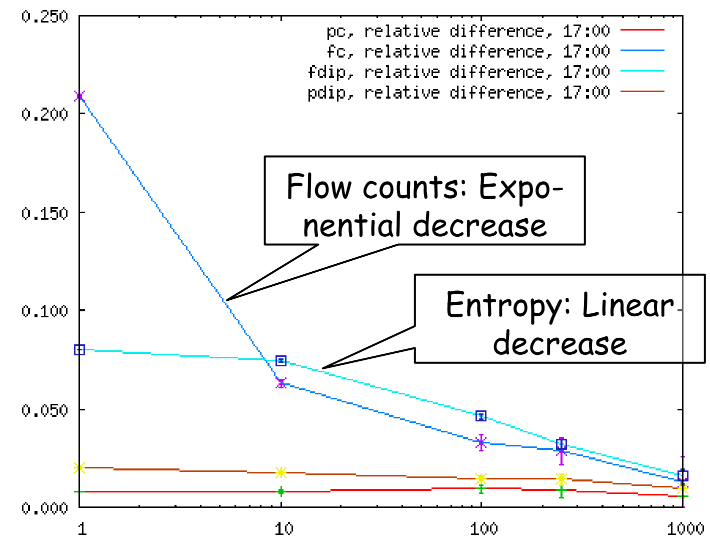
- Absolute difference between trace *y* and baseline *ŷ*
  - $abs = y - \hat{y}$
- Absolute difference normalized to the baseline *ŷ*
  - $rel = (y - \hat{y}) / \hat{y}$

Anomaly Distance vs Sampling Rate

Absolute distance



Relative distance



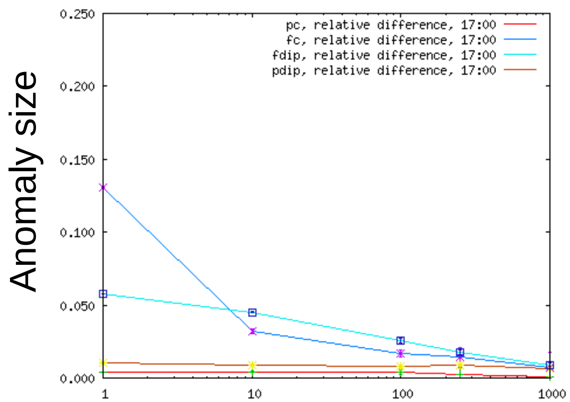
Q: What do these distance measures tell us?
A: In this scenario entropy is less disturbed by sampling…

Scaling the Blaster Worm

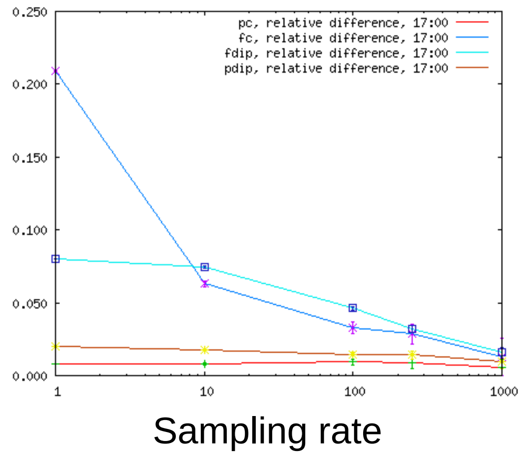
- *Identification* of Blaster packets based on heuristic
  - dst port, packet size, tcp
- *Amplification* of the Blaster worm
  - Insertion of new packets with same src IP, and dst IP randomly selected from SWITCH IP range
- *Attenuation* of the Blaster worm
  - Randomly throwing out of some of the Blaster packets (e.g., select each packet with probability of 50%)

Relative Distance for Scaled Blaster

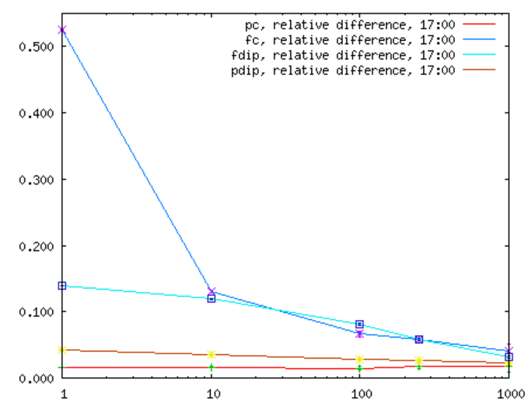
Scaling factor: 0.5



Scaling factor: 1



Scaling factor: 2



Q: What do these scaled distance measures tell us?
A: For faster and slower Blaster-like worms, entropy is less disturbed by sampling than flow counts…

Conclusion and Future Work

- What did we learn?
  - Some metrics are more resilient to sampling than others
  - Flow DST IP entropy is most resilient to sampling for Blaster-type anomalies (in our traces)

- What still needs to be studied...
  - Other types of anomalies, anomaly intensities
  - Other distance metrics (considering a metrics‘ variance)
  - Different bin sizes
  - Further anomaly metrics
  - Anomaly detectability at different sampling rates

Questions?

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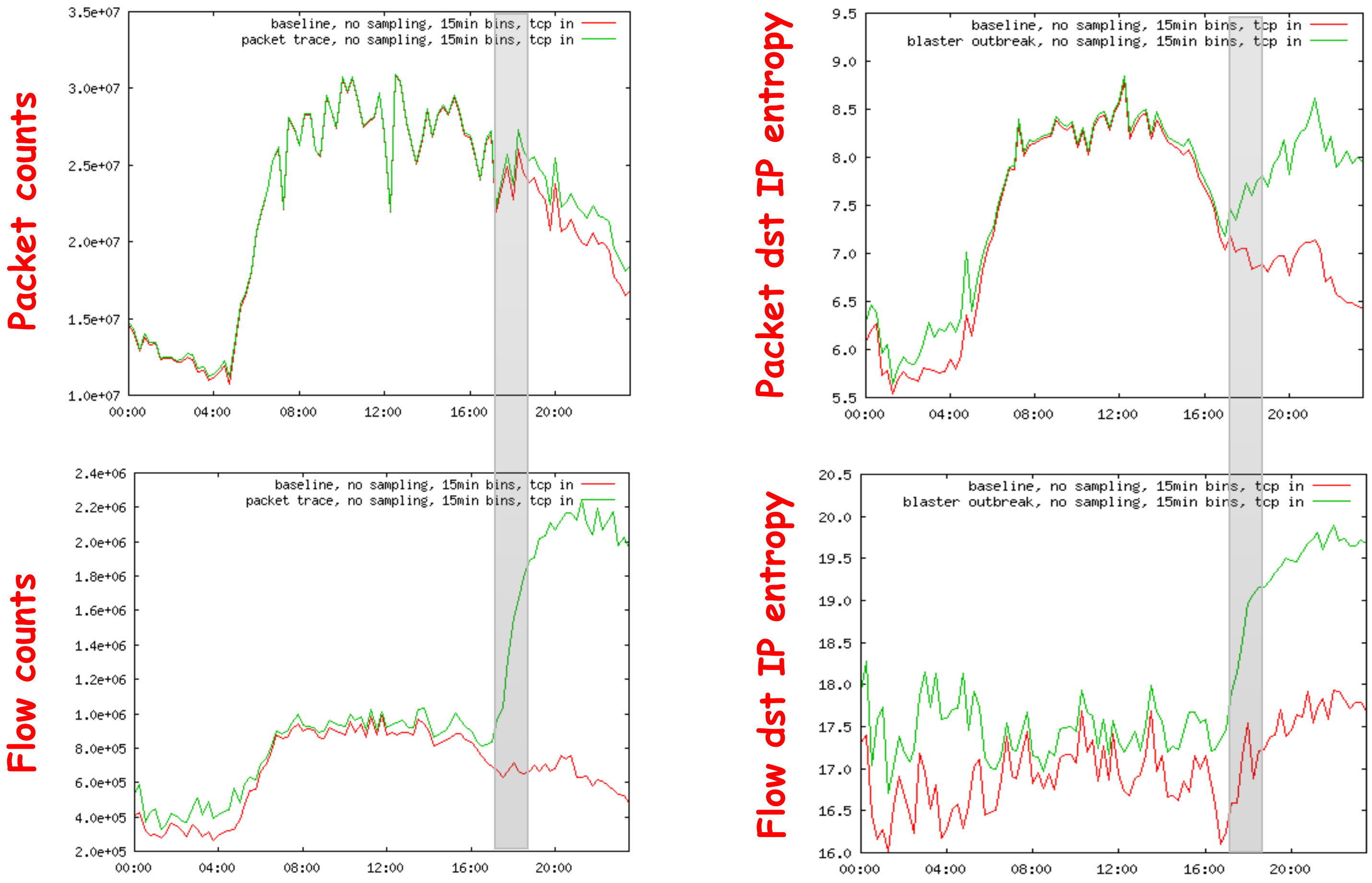
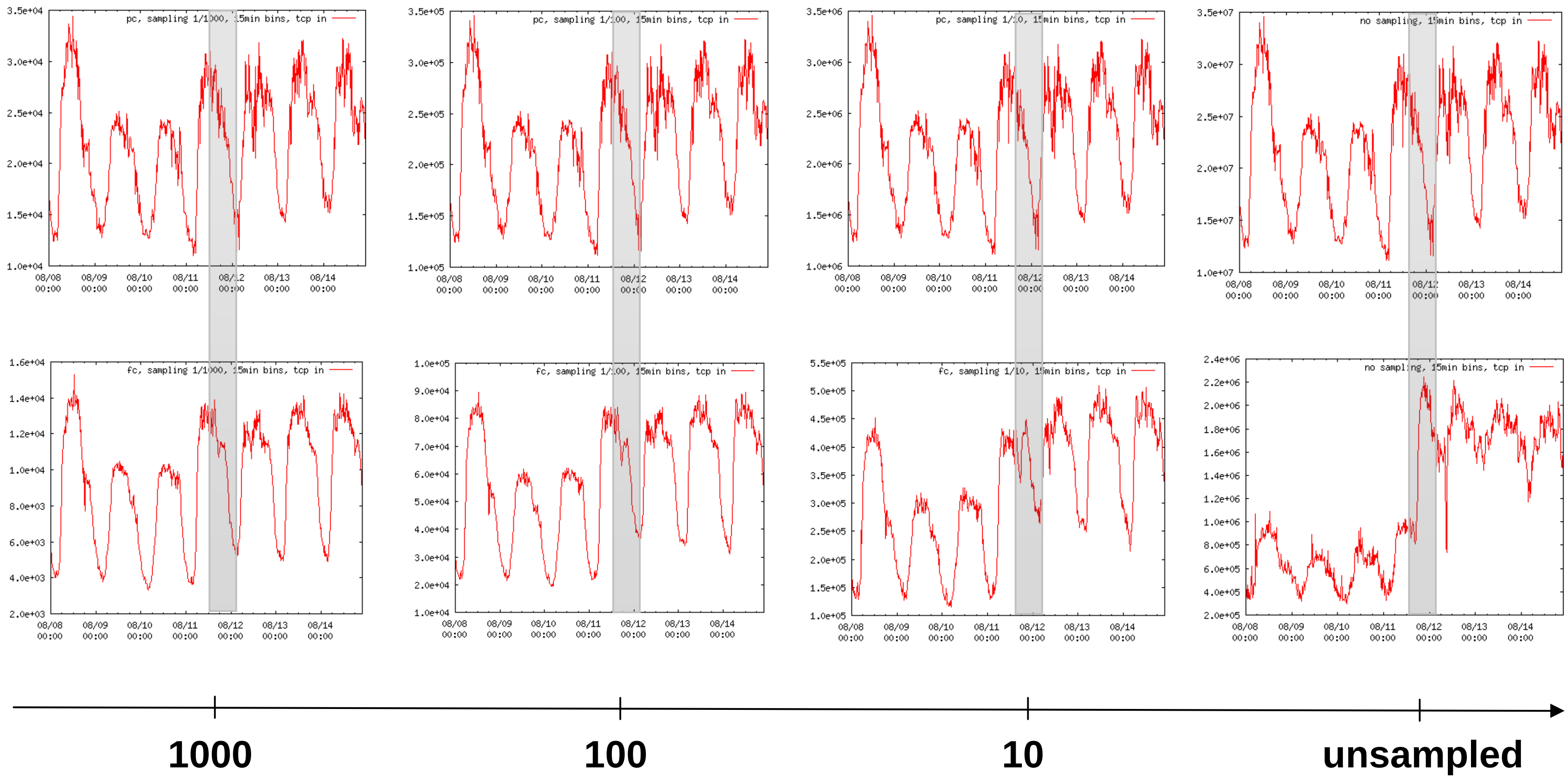
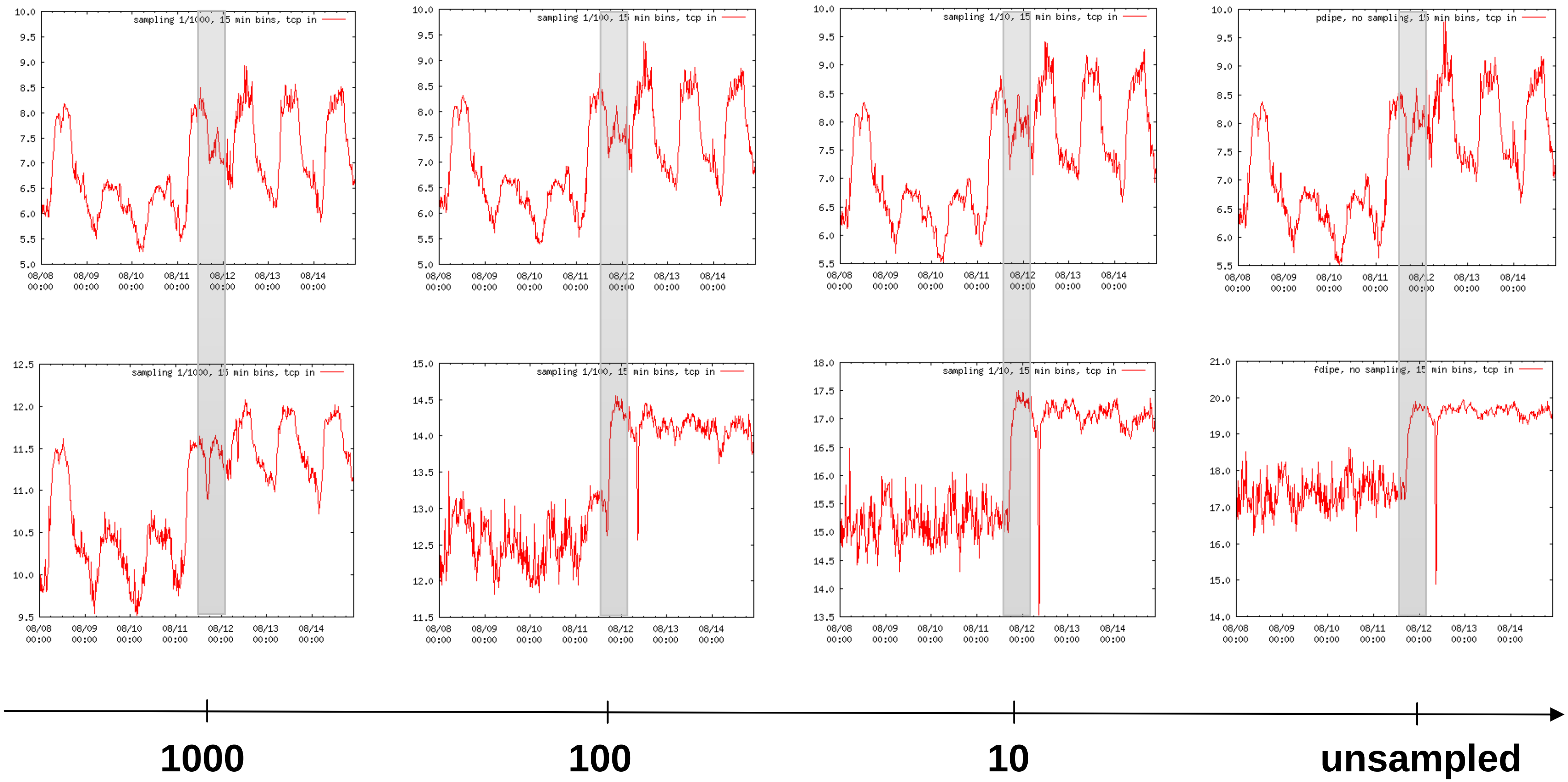
Baselines for AD Metrics (unsampled)



Volume Time Series



Entropy Time Series



Anomaly Distance vs Sampling Rate