A flow aware packet sampling mechanism for high speed links

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Goal

- Enable for inline, real-time, application-centric traffic classification
  - Based upon a fixed number of packets at the start of all flows
- Permit implementation at 10+ Gbit/s

Motivation

- Studies* show that start of flow information allows for accurate identification of traffic
- Traditional packet sampling and NetFlow don’t provide required information
- Heavy-tailed nature of Internet traffic allows discarding of significant amount of data without processing

* For example:
[1] W. Li and A. W. Moore. A Machine Learning Approach for Efficient Traffic Classication. In Proceedings of the IEEE MASCOTS, October 2007.
[2] L. Bernaille, R. Teixeira, and K. Salamatian. Early Application Identication. In Proc. of ACM CoNEXT, December 2006.

Method

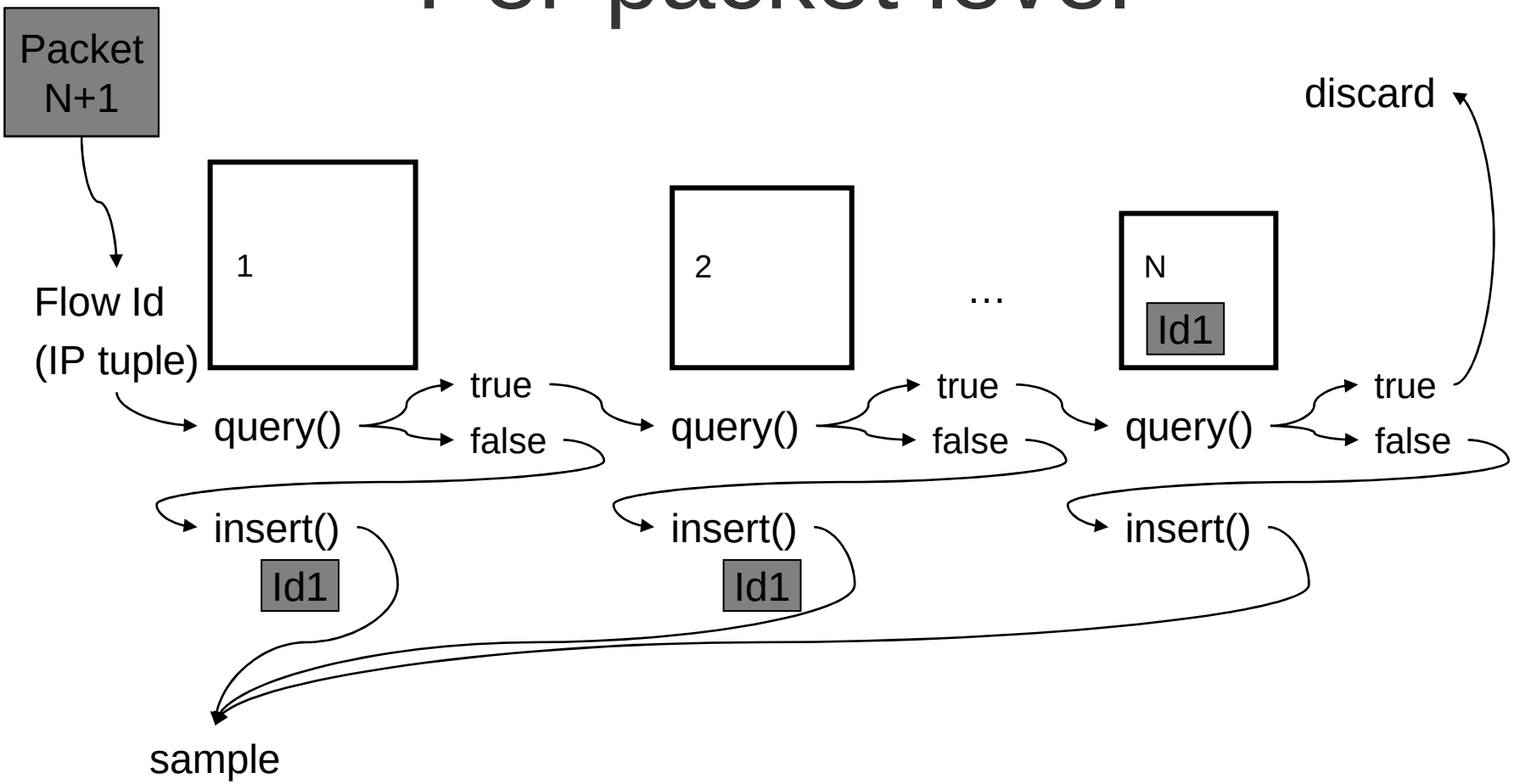
- Focus upon the sampling of a fixed number of packets at the start of all flows
- The scheme consists of two levels
- Per-packet level
  - Within a time window of length *W*, an algorithm based on Bloom filters identifies and samples the first *N* packets from each flow that occur in that window
- Per-window level
  - The memory allocation mechanism finds the parameters required in the sampling scheme

Bloom filter refresher

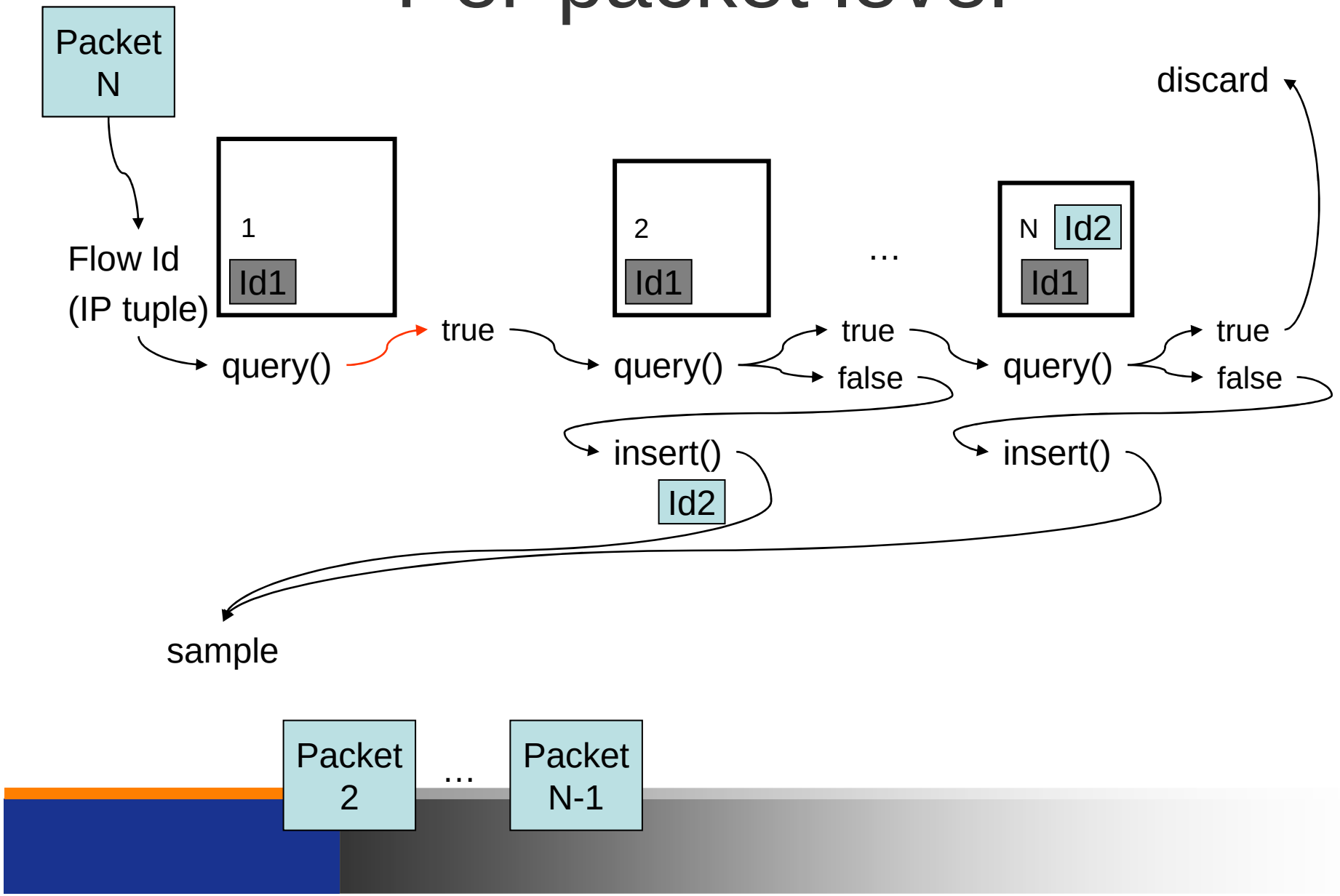
- Simple space-efficient probabilistic data structure for representing a set of elements
- Supports the insert() and query() operations
- False positives are possible
- False negatives are not possible

- Implemented with an array of *m* bits and uses *k* hash functions to map elements to [0,…,*m*-1]

Per-packet level



Per-packet level



False positives

- False positives introduce sampling errors
  - Packets that should have been sampled get discarded
  - Discarded are only ever at the end
- Reduce false positives by
  - Resetting the filters periodically
    - (at the end of each time window)
  - Optimize the memory based upon the traffic

Theory 1

After *n* elements have been inserted, the probability that a specific bit is still 0 is

$$p' = \left(1 - \frac{1}{m}\right)^{kn}$$

The probability of a false positive is approximated with

$$f' = \left(1 - \left(1 - \frac{1}{m}\right)^{kn}\right)^{k}$$ that is minimized for $$k = \ln(2) \cdot \frac{m}{n}$$

In this application we are interested in the number of false positives that occur as the Bloom filter is being filled. The expected number of false positives is

$$E[F] = \sum_{i=1}^{n} \left(1 - \left(1 - \frac{1}{m}\right)^{\ln(2)\cdot(m/n)\cdot i}\right)^{\ln(2)\cdot(m/n)}$$

where *n* is the expected number of elements that will be inserted within the current window

And considering a bank of *N* Bloom filters

$$E[F] = \sum_{j=1}^{N} \sum_{i=1}^{n_j} \left(1 - \left(1 - \frac{1}{m_j}\right)^{\ln(2)\cdot(m_j/n_j)\cdot i}\right)^{\ln(2)\cdot(m_j/n_j)}$$

Theory 2 : Per-window level

- Aim to divide a block of memory *M* into *N* different portions optimally
- The allocation of m_j is given by a system of linear equations

$$\begin{cases} \sum_{j=1}^{N} m_j = M \\ m_j - \alpha \cdot n_j = 0 \quad \forall j = 1 \ldots N \end{cases}$$

- However the number of elements that will be inserted in the filters, n_j, are unknown and have to be estimated (in our case using an AR model)

$$\hat{n}_j(k) = \theta_1 \hat{n}_j(k-1) + \sum_{i=2}^{r} \theta_i n_j(k-i) + \varepsilon_j(k)$$

Theory 3 : Window length

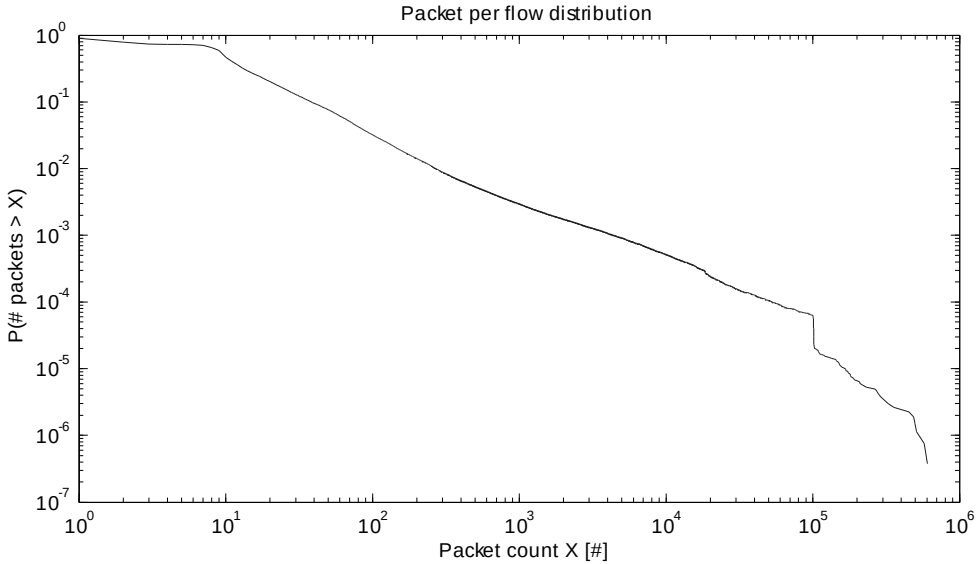
- Given an acceptable level of false positives the appropriate value of *W* can be estimated by use of a search algorithm as the number of false positives is a function of the window size

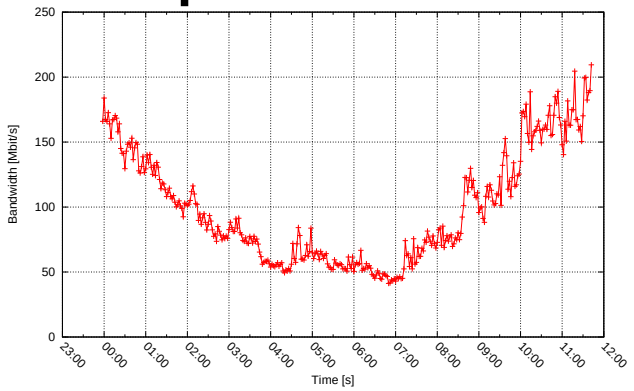
Theory Summary

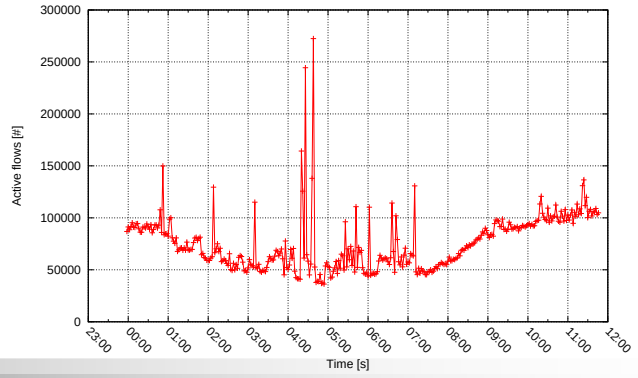
- Memory limits number of samples and size of Bloom filters
- False positive rate allows near-ideal sizing of Bloom filters (for a given amount of memory)
- False positive rate is estimated via AR
- Window length sets rate at which filters are reset

Results

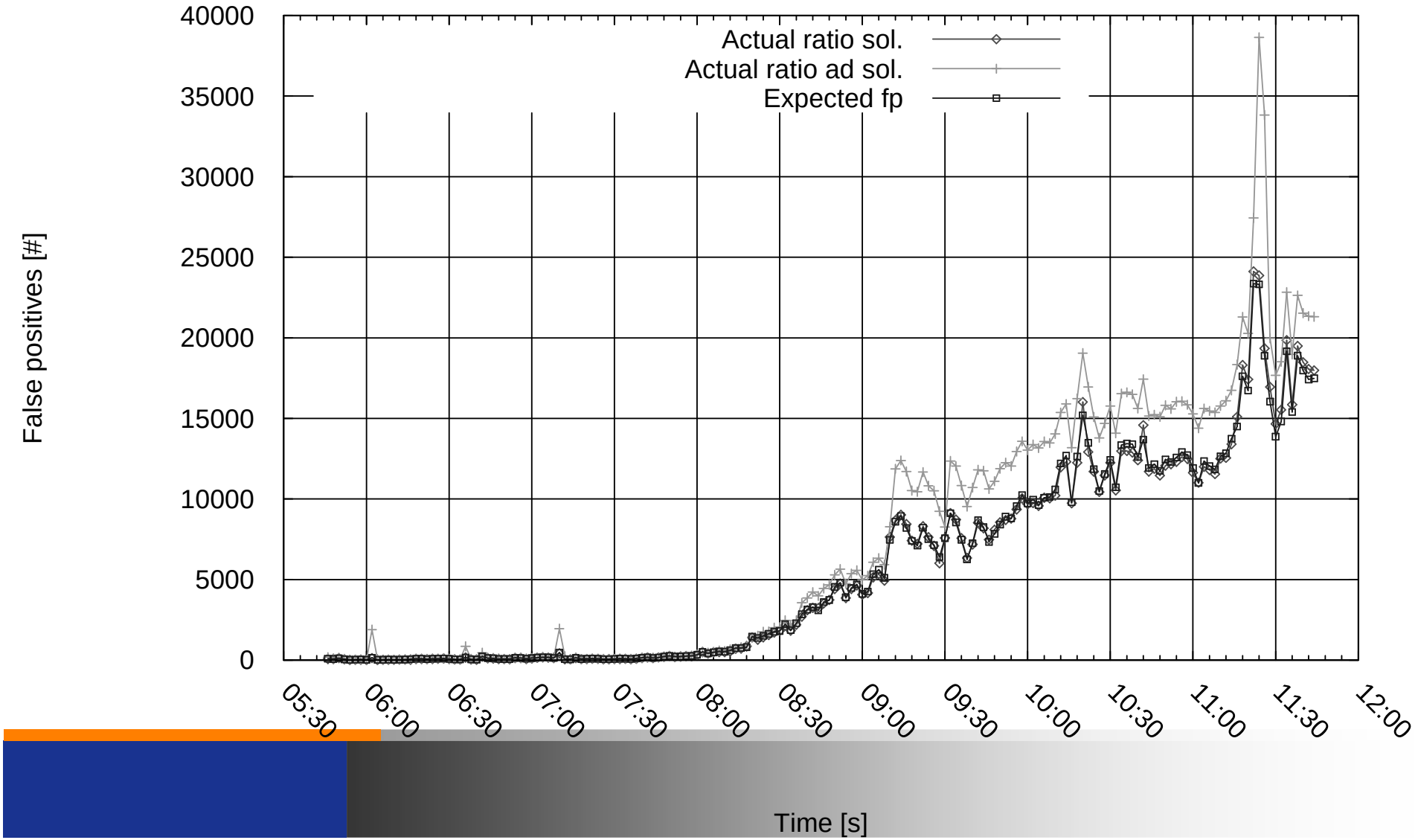
- Software implementation
- 12 hours trace from the edge of a research institute connected via a full-duplex 1 Gbit/s link



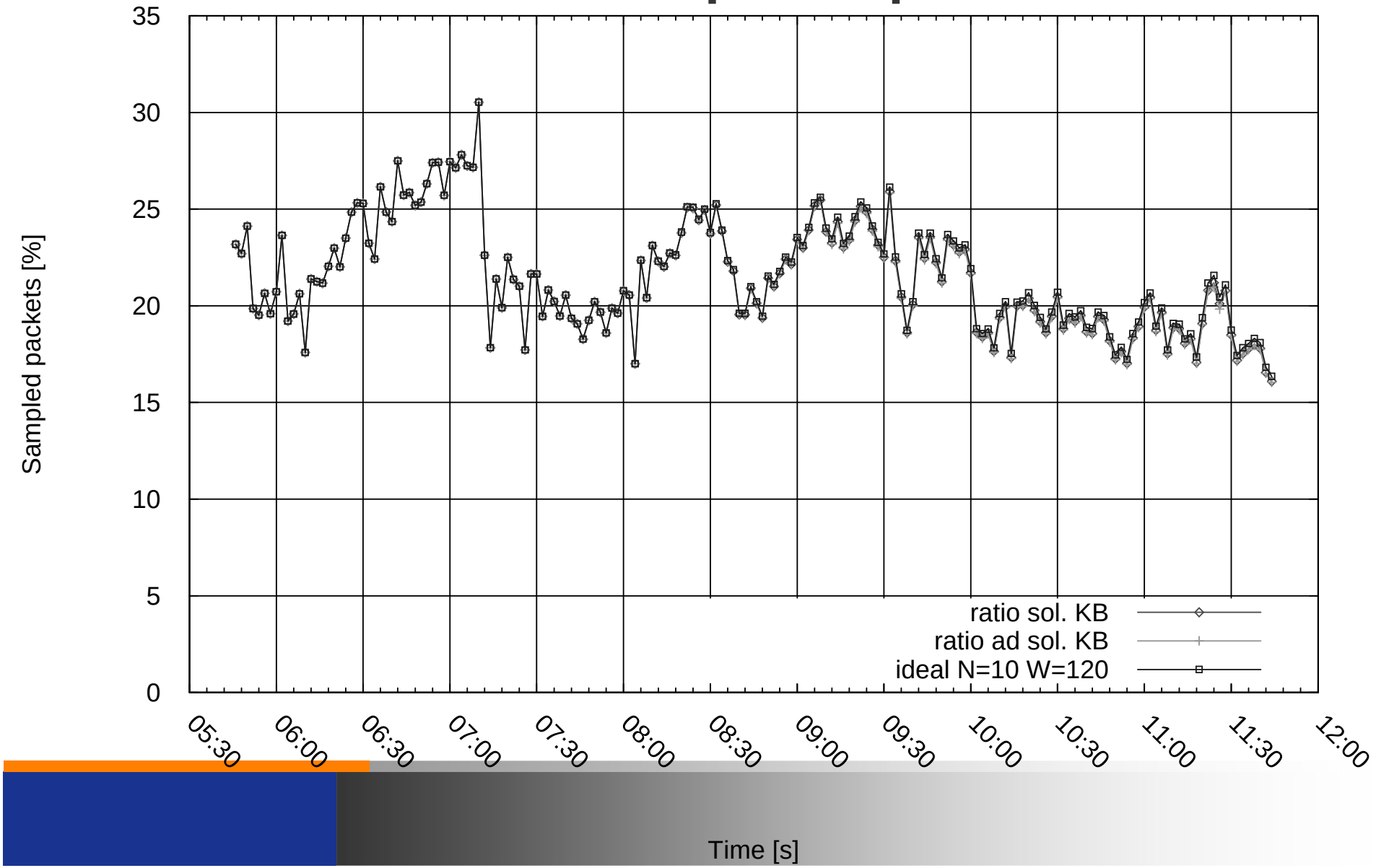




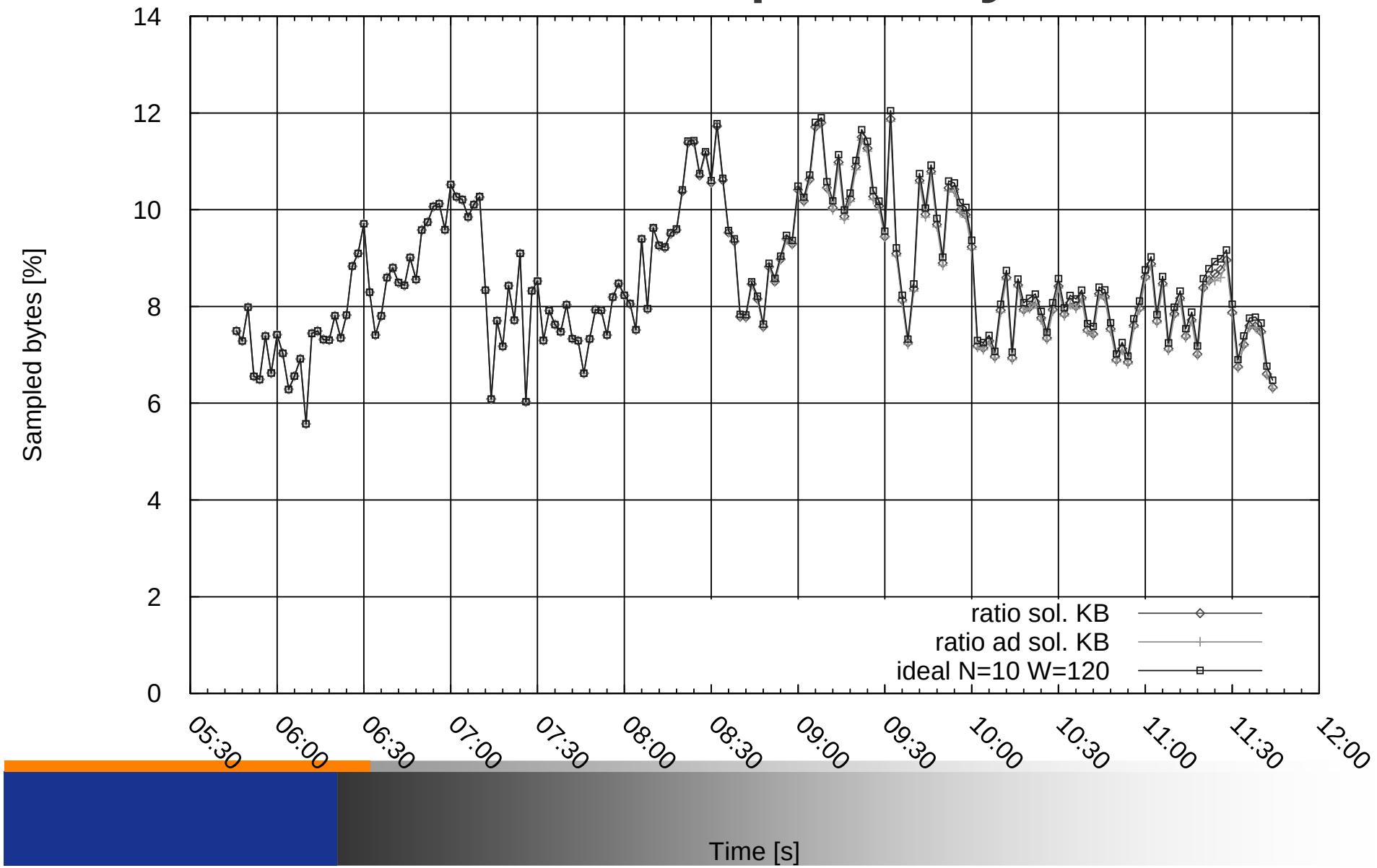
Results: false positives



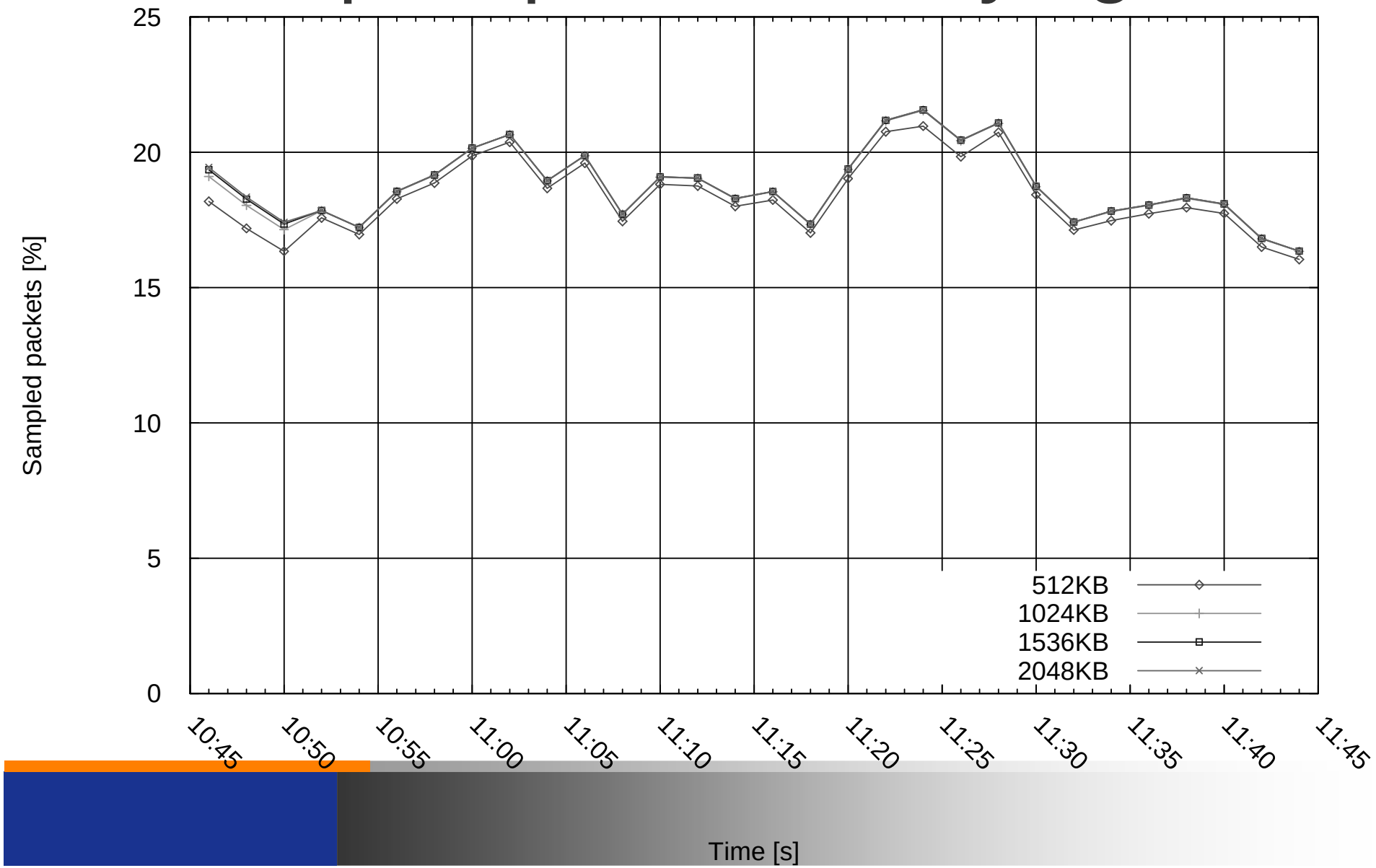
Results: sampled packets



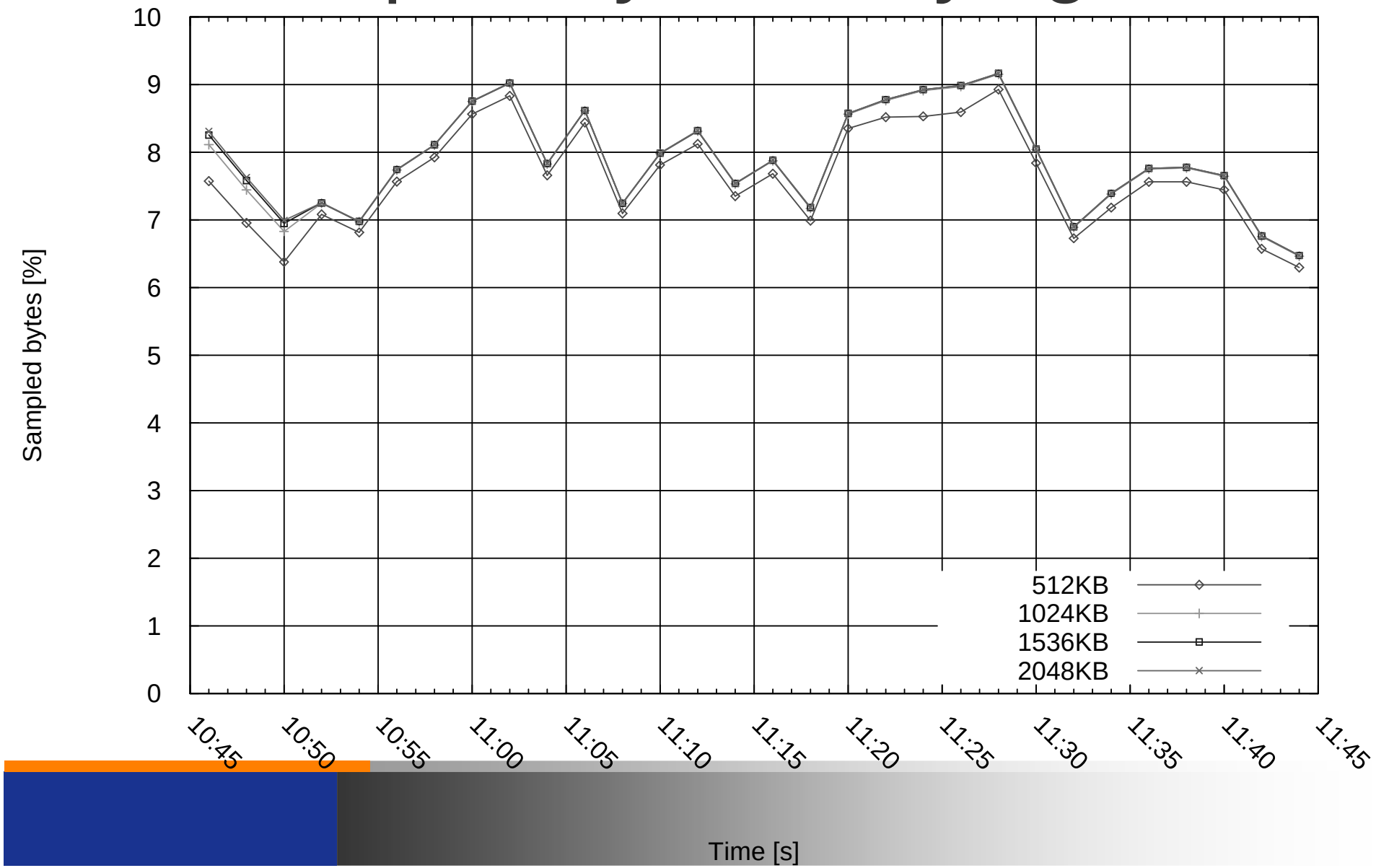
Results: sampled bytes



Sampled packets, varying M



Sampled bytes, varying M



Effects of false positives

M	Affected flows	Unsampled packets	Unsampled bytes
512KB	5529 (0.0021%)	517173 (0.0221%)	199167936 (0.0323%)
1024KB	4863 (0.0018%)	58007 (0.0024%)	22907748 (0.0037%)
1576KB	4274 (0.0016%)	15830 (0.0006%)	6535918 (0.0010%)
2048KB	4237 (0.0016%)	6086 (0.0003%)	2475934 (0.0004%)

Sampling plus flow classifier

- We used a pattern matching flow classifier derived from open source tool l7-filter
- Test data contains 2,642,841 flows
- With sampling (N = 10, W = 120, M = 512 KB) 2,636,549 flows are reported
- 6,292 (0.0024%) unreported flows
- 6,021 (0.0023%) flows had classifier error
- **Total error** is 12,323 **(0.0047%) flows**

Future Work

- FPGA based hardware implementation
- Flow sampling works
- Focus shifted to improving classification (identification) of applications