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# Empirically Based Analysis: The DDoS Case

**Jul 22nd, 2004**

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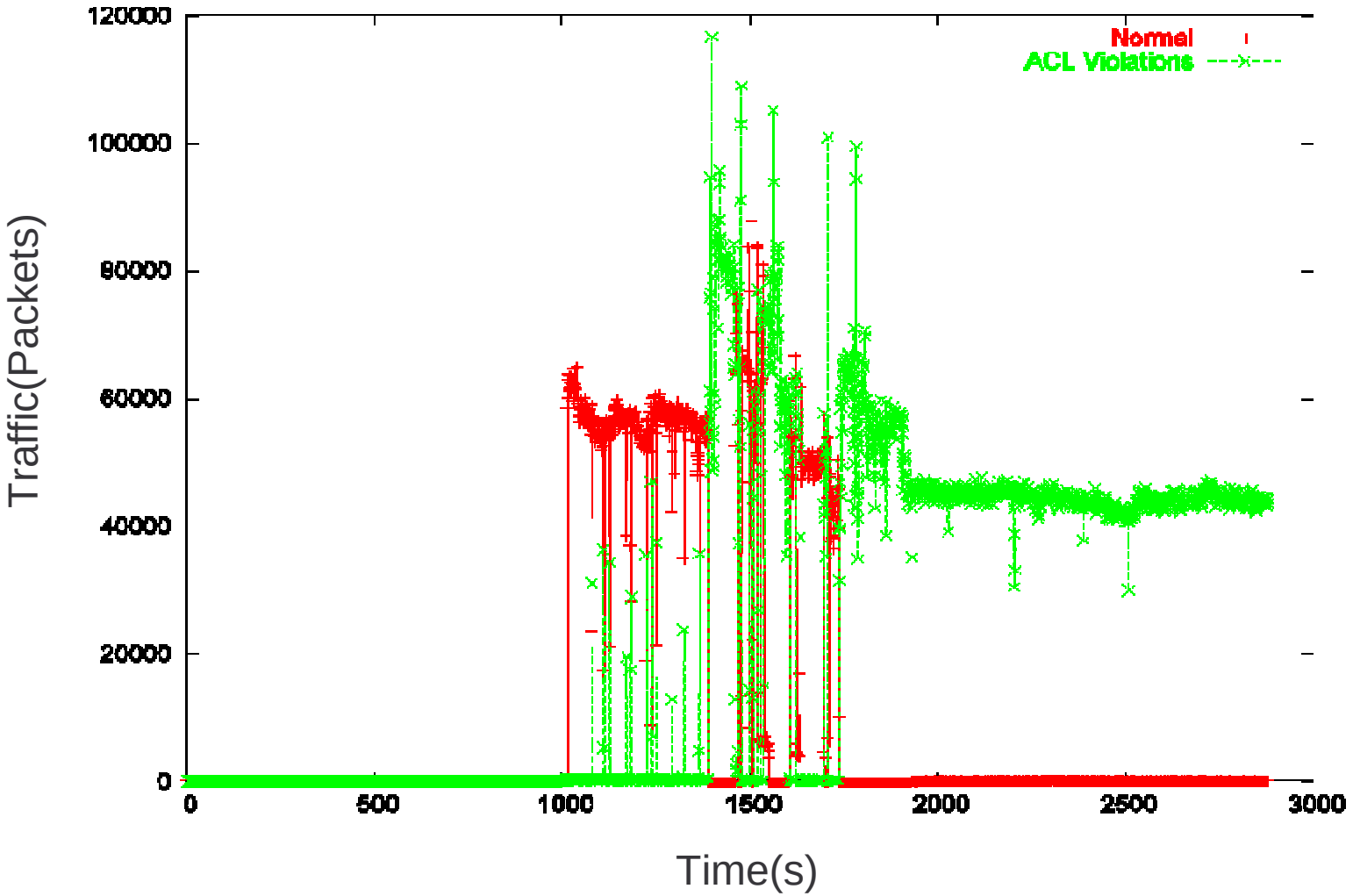
# Introduction

- Access to the dataset gives us a large enough record of traffic to test hypotheses in network security.
- Given this, we select and evaluate various security measures against real traffic
  - Or a reasonable facsimile thereof
- One example: target resident DDoS Filters
  - Heavily constrain the problem– not considering SYN floods, smurfing, reflection attacks…

# Attacks like this



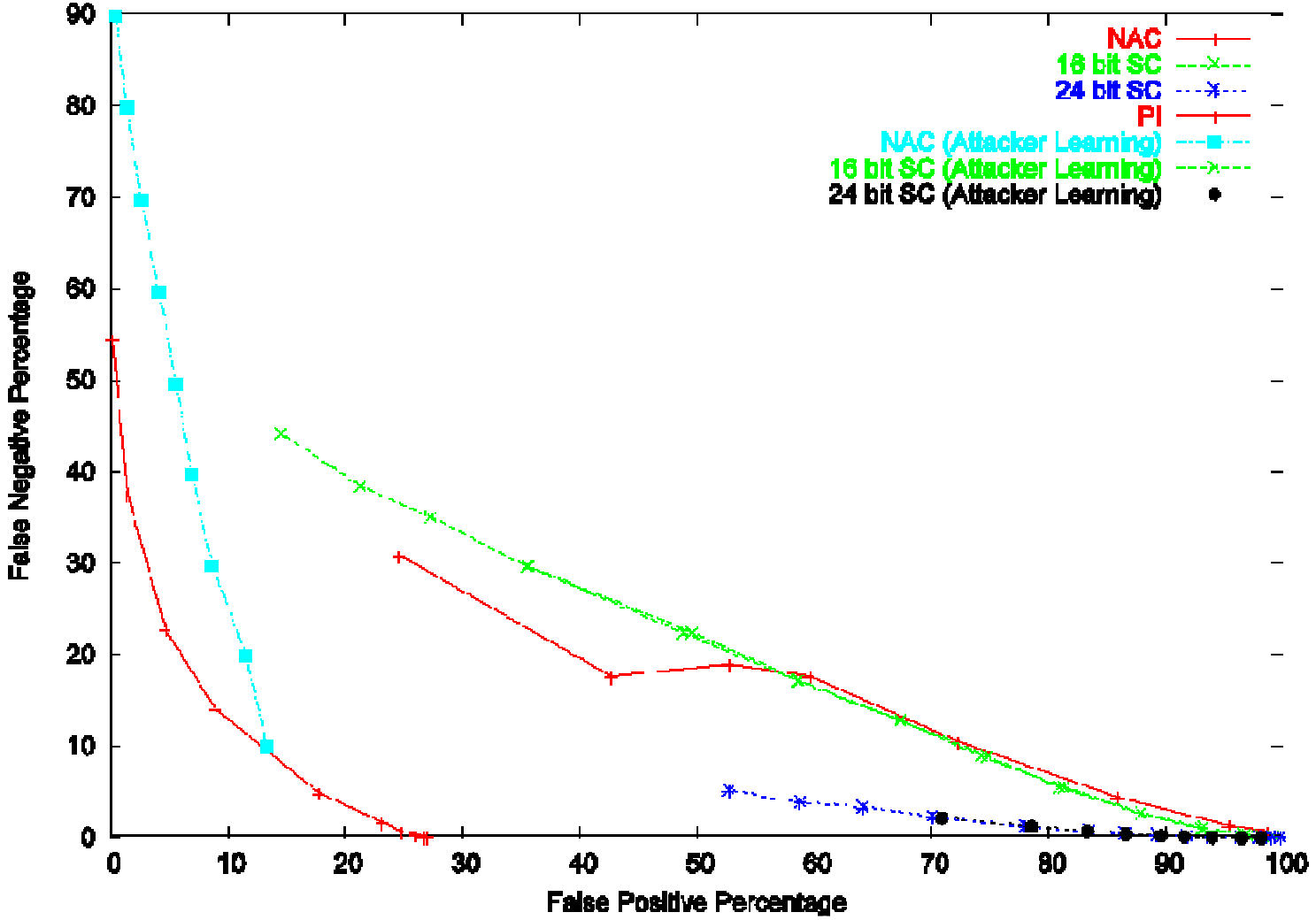
# How Do We Test?

- Any analysis opens a can of worms…err, "assumptions"
  - The network constantly changes
  - What is a representative host?
- Rerunning attacks is of debatable value
  - Most of the legitimate traffic is dropped, that's what a DoS is *for*
- We want our results to be representative
  - Test and summarize over multiple machines
- We want our results to be reproducible
  - Depend heavily on SiLK structures and tools

# Evaluation

- Trained filters on 15 days of legitimate traffic
  - Built a representation of IP address: volume relationship (via `rwaddrcount`)
- Then generated a simulated DoS
  - Botnet IPs collected with `rwset`
  - Normal traffic selected from another day
- Resulting traffic was then evaluated for failure rates
- Tested 2 types of filters:
  - Clustering – groups of adjacent IP addresses
  - PI – path marking approach

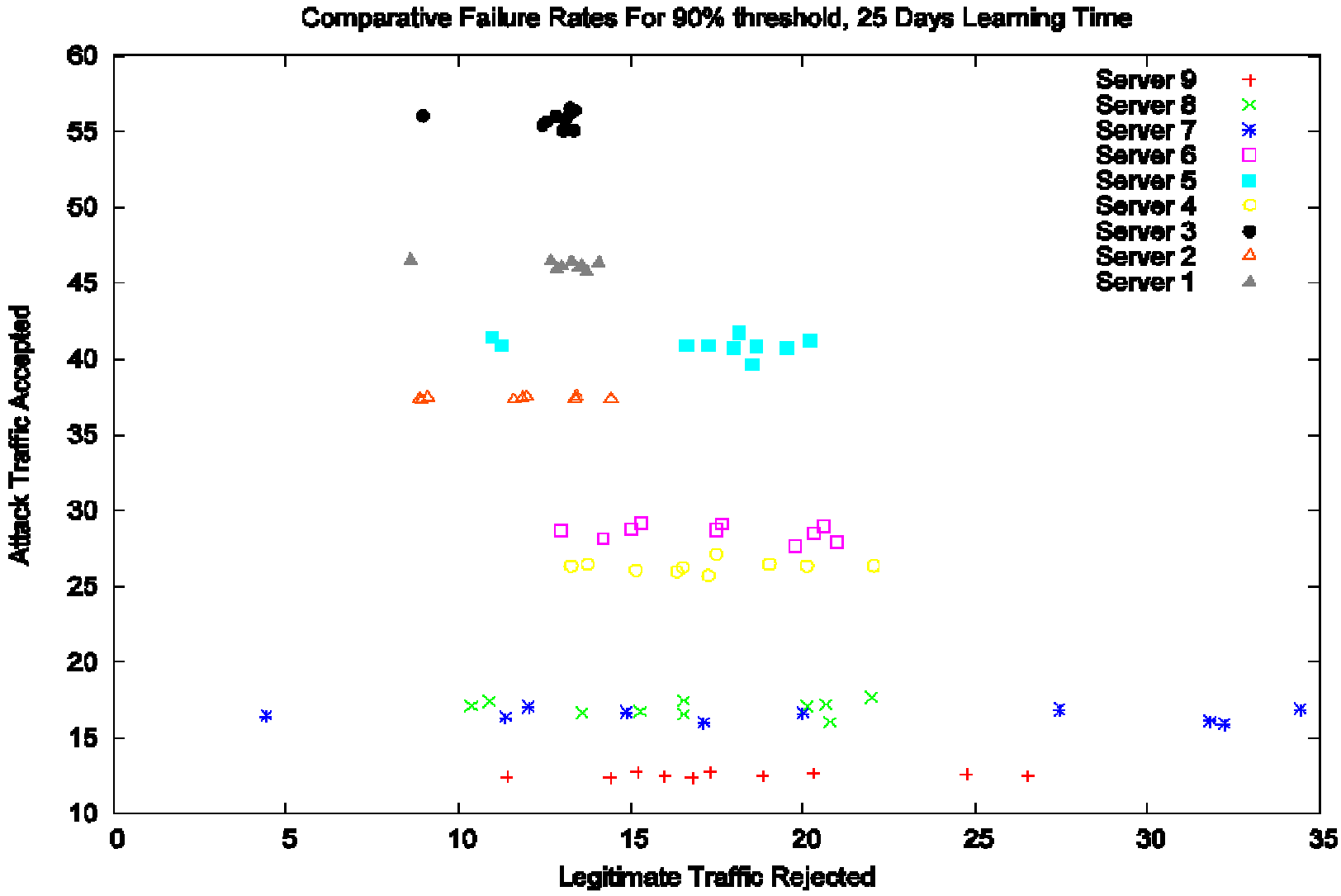
# DoS Filters



# Initial Observations

- Two groups
  - One group assumes a magic DoS Detection Oracle
    - That's the group with better results
- In general, the filters don't do well
  - Should we compare IP addresses, or packets?
  - Is traffic different for different servers?
- Let's look at one result in more depth

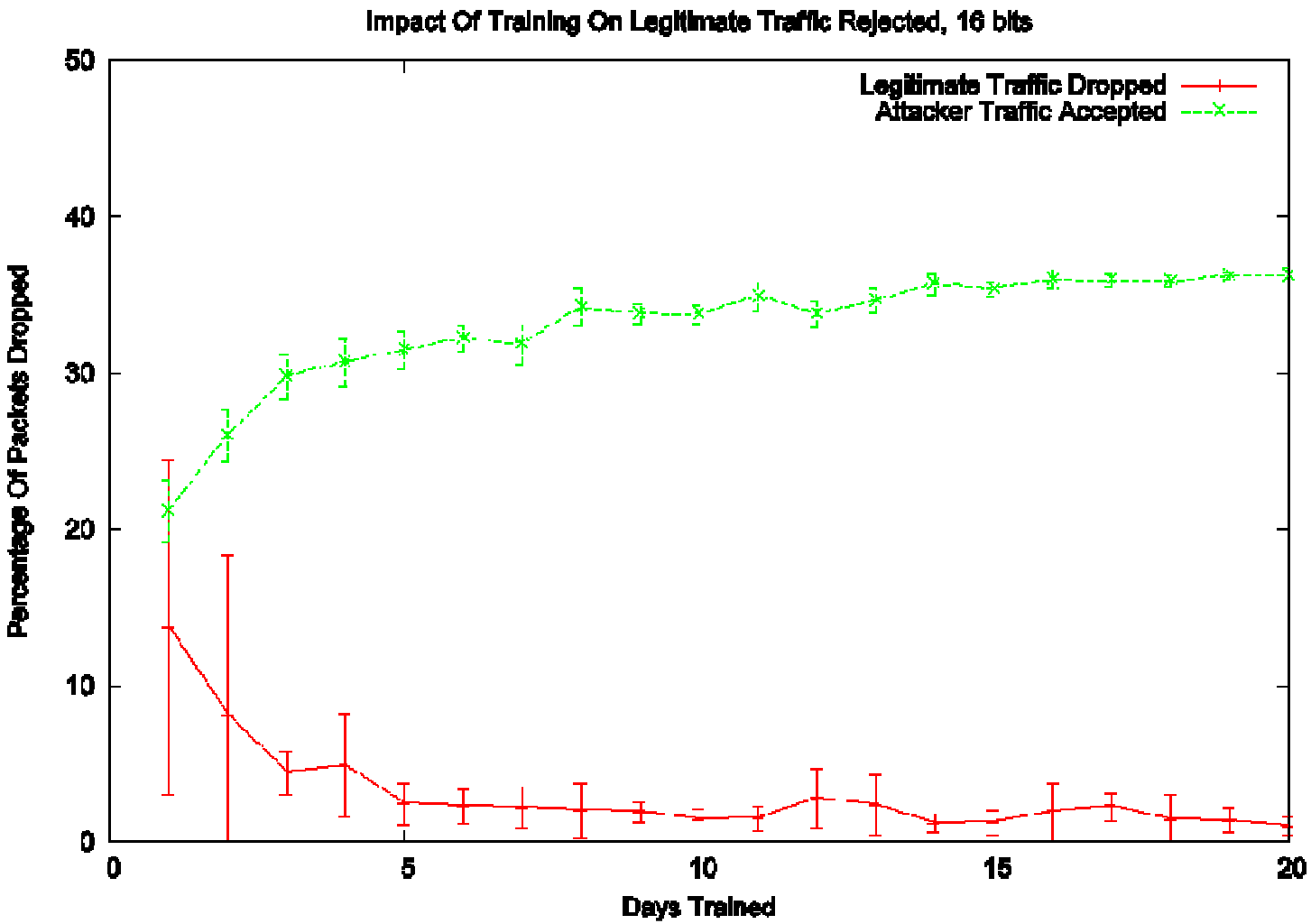
# One result in more depth



# Observations

- Normal traffic varies extensively
  - Although it seems to vary more with “smaller” servers
  - And it’s better when you look at packet counts
    - Which makes sense, given the absurd number of scanners we see.
- False negative rate (attackers accepted) seems to be related to server activity – the busier the higher.
  - Attackers don’t vary as much

# Learning Curves – 95% threshold



# Other Observations

- In the majority of cases, packets are dropped because they've never been seen before
  - Short learning curves – effectively no change in false positive rate after a week of learning.
  - Especially true for spoofed traffic
- Entropy is lower than expected
  - Filters that rely on spoof defense (HCF, PI) drop less than 10% of their packets because they detect a spoof

# Further Work

- Exploiting our DoS attack traffic records further
  - We know how the network reacts
  - We know how the attack starts and ends
    - Which impacts learning curve for defenses that *only* profile the attack
- Further use of other network maps
  - Skitter (used for PI), &c.
- Formalization of the techniques used
  - Developed a matrix based approach for the final iteration
  - Tools are going to be available publicly

# A Final Note

- URL for the SiLK tools:
  http://silktools.sourceforge.net