A Novel Approach to Detecting Covert DNS Tunnels Using Throughput Estimation

by

Michael Himbeault

A Thesis
Submitted to the Faculty of Graduate Studies
of the University of Manitoba
in partial fulfilment of the requirements
for the degree of

MASTER OF SCIENCE

Department of Electrical and Computer Engineering
University of Manitoba
Winnipeg, Manitoba, Canada

February 4, 2014

Background: Entropy

- Rough measure of the amount of information contained in a collection, *C:*

$$C = \{c_1, \ldots, c_n\}, P(c_i) = p_i$$

$$H(C) = -\sum_{i=1}^{n} p_i \log p_i$$

Background: Domain Name System (DNS)

- Translates text references to other forms of records. For example:
  - IP or IPv6 address (A or AAAA)
  - Another domain name (CNAME)
  - IP address to name (PTR)
  - Name to bulk data (TXT)

- Provides the human-interaction layer for the Internet
- Offers a great deal of flexibility for deploying automated services over existing infrastructure
  - For example: spam, malware, and address blacklists.

Background: Covert Channels

- Utilize standard means of transportation in non-standard ways
  - Often transporting unintended data types of existing protocols
  - Occasionally involves new custom protocols built on existing ones
- Intention is rarely benign, often circumventing existing security layers

Background: Covert Channels

- May or may not modify the standard protocols in ways that are conforming to specifications.
- May sacrifice ‘common’ features such as bidirectionality

- Examples:
  - IP timing channels
  - May use third party services such as Twitter, Facebook, or image hosting providers
    - Encoding information in JPEG headers
  - DNS tunnels

Background: DNS Tunnels

- Raw DNS tunnels
  - Utilize UDP/TCP port 53 for transmitting arbitrary data without respect for DNS protocol specifications
  - Not difficult to block
- Conforming DNS tunnels
  - Makes use of DNS packets that do not violate the protocol specifications to transmit arbitrary data
  - Can be very difficult to identify and block
  - The focus of this work

Background: DNS Tunnels

- Existing implementations are commonplace
  - Iodine
  - OzymanDNS
  - Dns2tcp
  - DNScat
  - DeNiSe
  - PSUDP
- A custom implementation was built to simulate a next-generation tunnel

Custom DNS Tunnel Application

- Prototype proof-of-concept implementation
- Implements encoding to match character frequencies to circumvent Born's approach to detection.
- Limited to client-to-server transfer only

State of the Art: DNS Tunnel Detection

- Fall into several categories
  - Signature based
  - Domain hash/blacklist
  - Flow data based
  - Character frequency analysis on queries
  - Behaviour of DNS queries on a per-domain basis
- The proposed approach falls into the last category

Context:
Goals and Objectives

- Be able to identify DNS tunnels that do not violate DNS RFCs or specifications in near real time with high accuracy.

Context: Motivation

- DNS tunnels are used in malware as botnet command-and-control channels
- DNS tunnels are used to in/ex-filtrate data through corporate security layers
- The ability to monitor the existence of these channels is important when securing a network.

Proposed Approach: Assumptions

- DNS tunnels move more data than benign traffic
- Attempt to detect this increase in data transmission volume

Proposed Approach: Theory

- Collect DNS queries into temporal buckets
  - Ten-second windows were used in the analysis
- Further group queries by top-level domain (TLD)
  - google.com
  - cbc.ca
  - Etc…
- For each TLD (in the current window), compute a measure of how much data was transmitted

Proposed Approach: Measuring Data Volume

- Since common domains may appear more than uncommon, simple character count is insufficient
  - Modulo caching effects as described in section 5.1.3
- Average character count is similarly uninformative
  - Tunnels can use any length queries, including modelling a length distribution of legitimate traffic

Proposed Approach: Measuring Data Volume

- DNS tunnels can be expected to have very few queries that appear more than once
  - Since they are transmitting arbitrary data
- Benign domains can have many queries that appear a great number of times
  - Such as www.google.com

Proposed Approach: Domain Length-Weighted Entropy (DLWE)

- Consider the collection of queries to a TLD in an interval
- Treat each query as a symbol, and compute the entropy of the collection.
- Multiply the result by the average query length for the TLD in the interval.

- Expect large values for tunnel domains, small values for benign domains.

Evaluation: Literature Candidates and Test Data

- Proposed approach was tested against candidates from the literature
  - *N*-gram detection proposed by Born
  - *Gzip* compression detection proposed by Paxson
  - Naïve counting of characters

- All approaches were implemented on a common Python framework
  - Analysis was done on approximately one billion UDP port 53 packets from a live ISP network as well as intentionally generated tunnel traffic

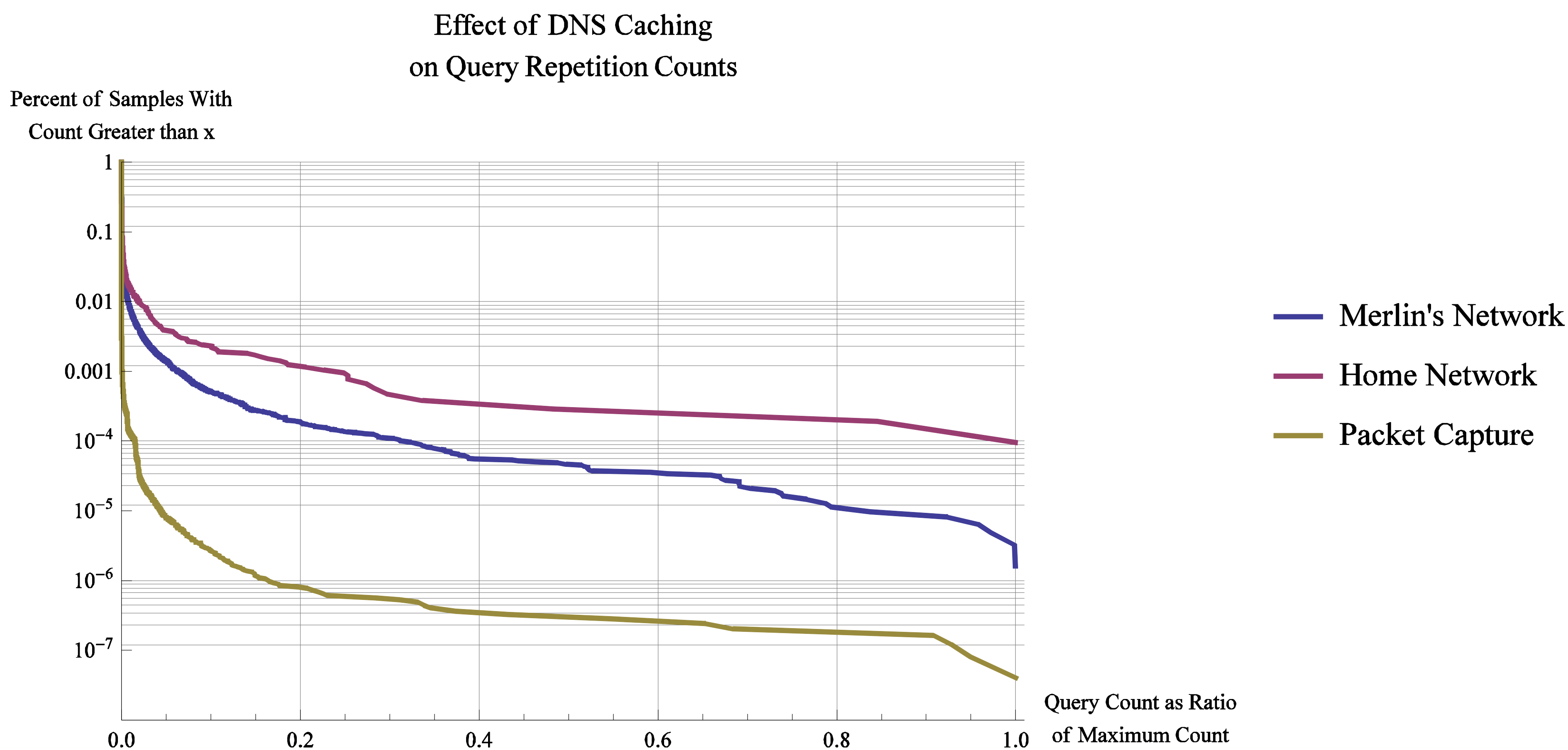
Evaluation Criteria

- Packet processing performance
  - A relative comparison, due to lack of optimized implementations no absolute target is chosen
- False positive rate
  - A relative ranking is employed
  - Intuitively, a false-positive rate of 1% will result in up to fifty alerts per second during average daytime traffic of the captured sample.

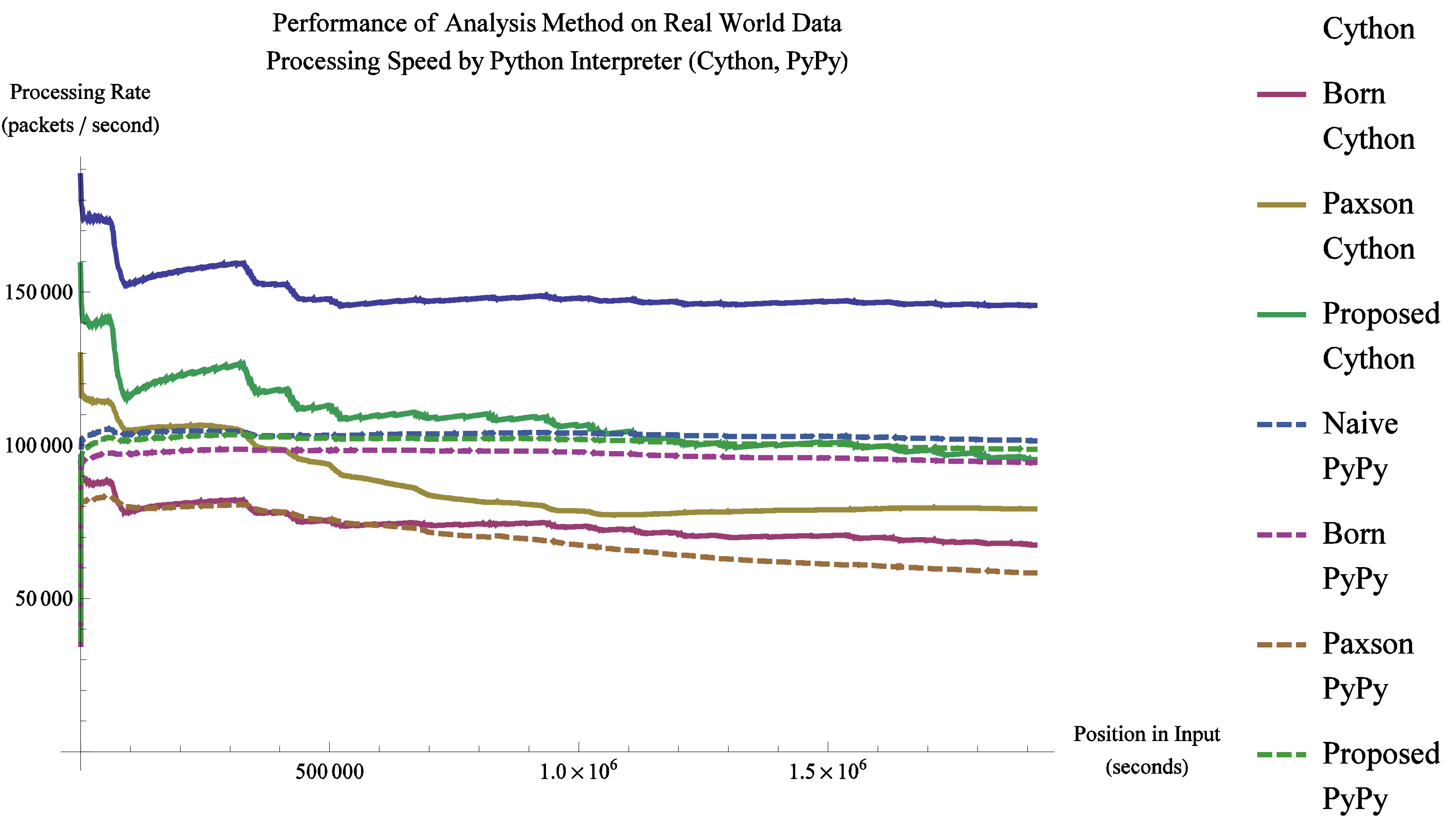
Sample Data

- May contain malicious traffic
  - In particular, DNS tunnels which will affect the false-positive rates of the detection methods.

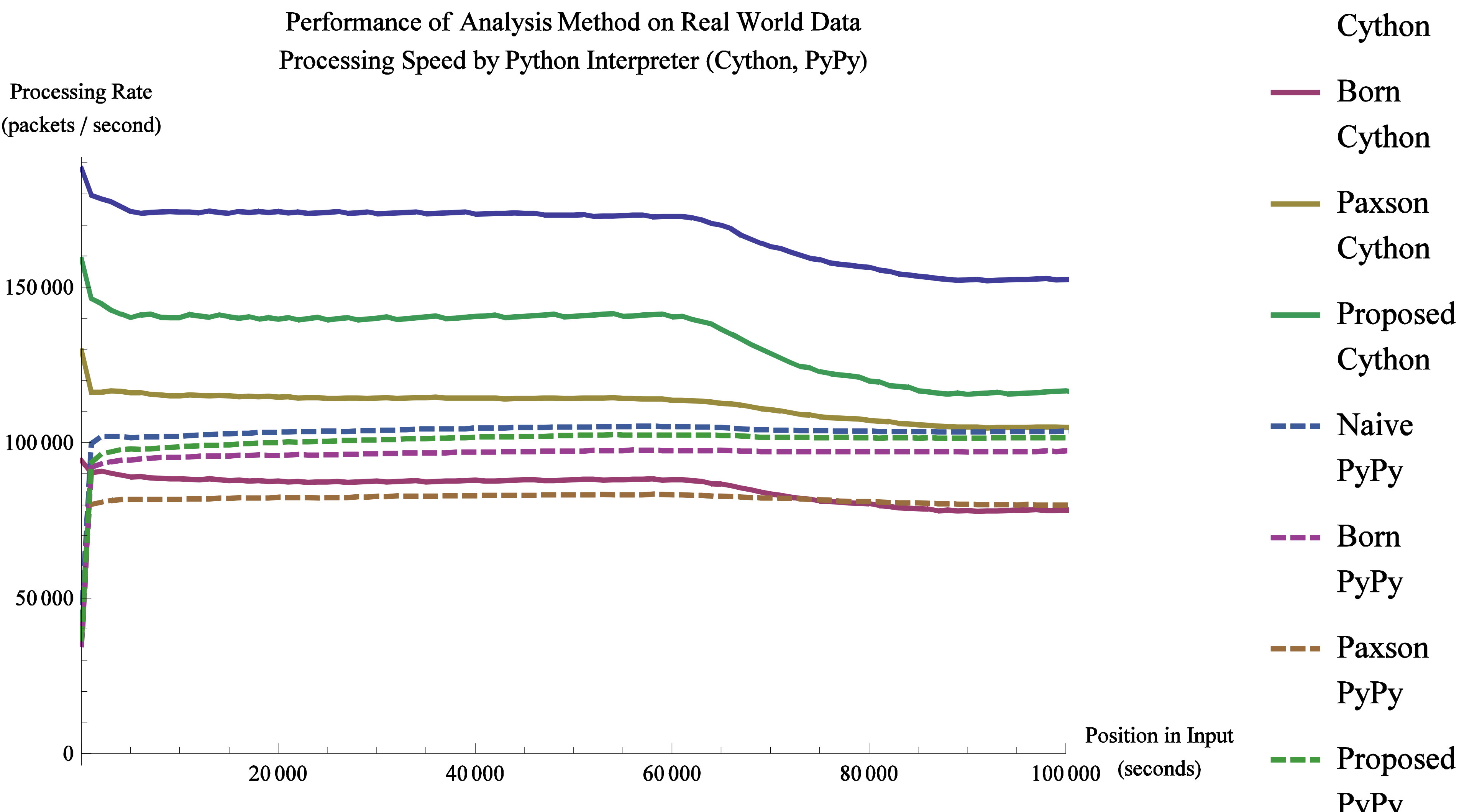
Confounding Factor: Effect of DNS Caching



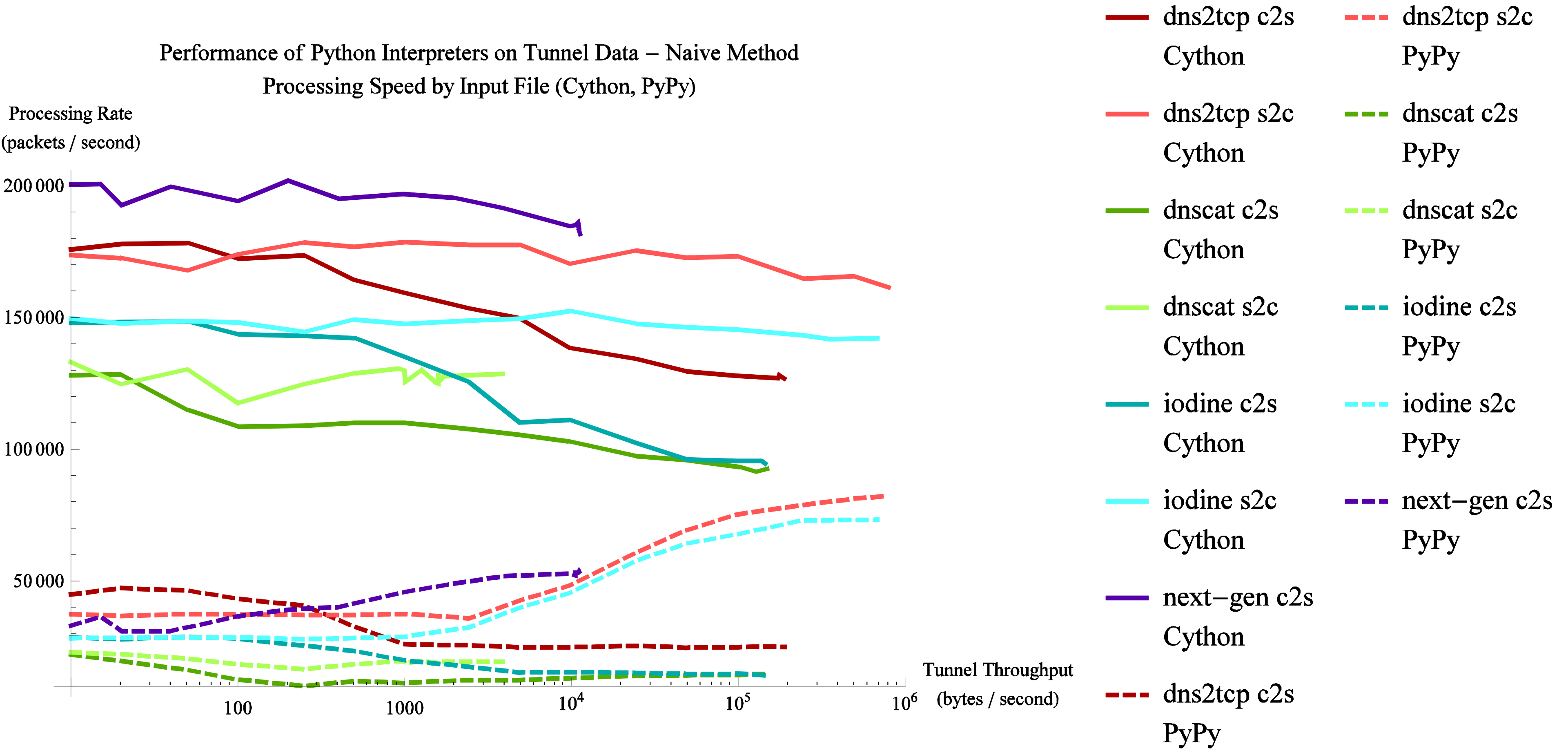
Processing Performance



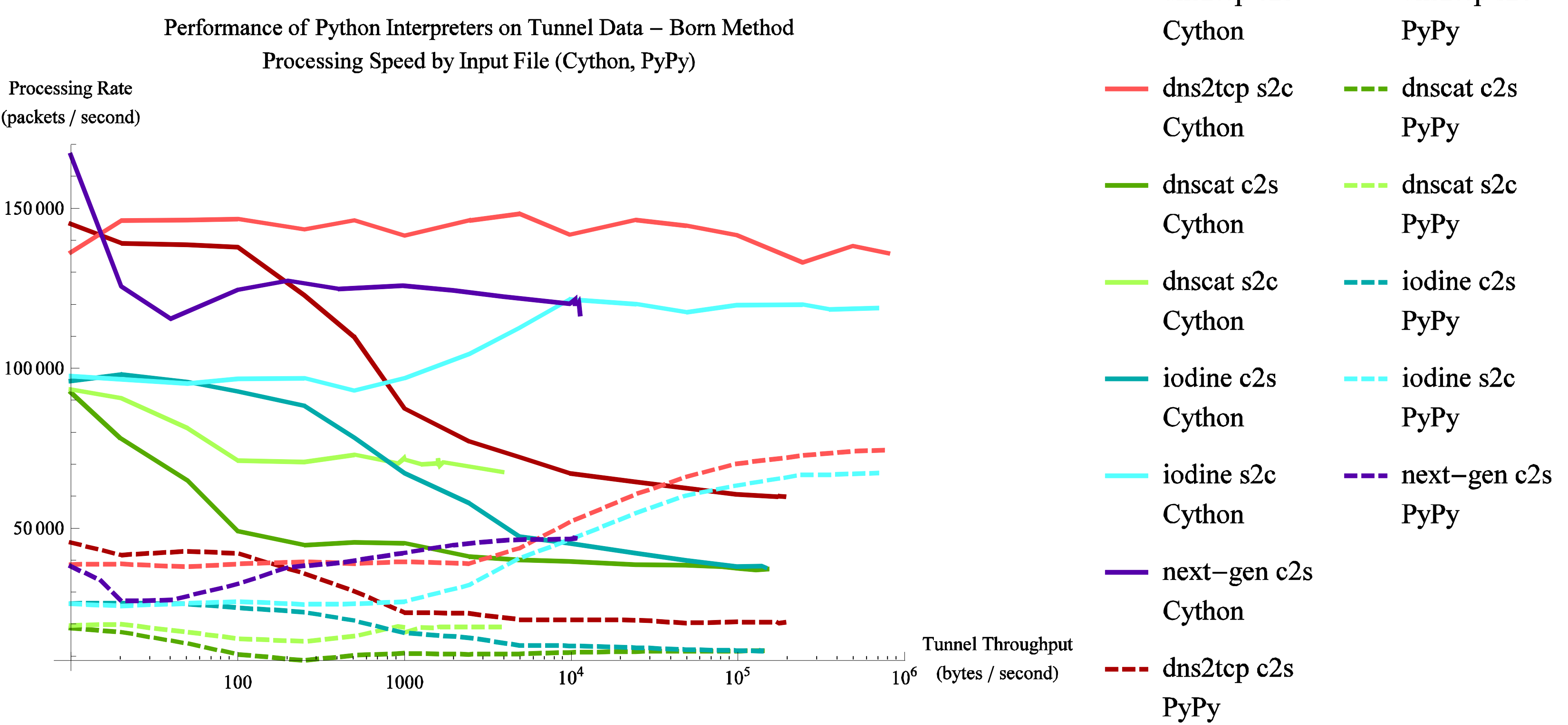
Processing Performance



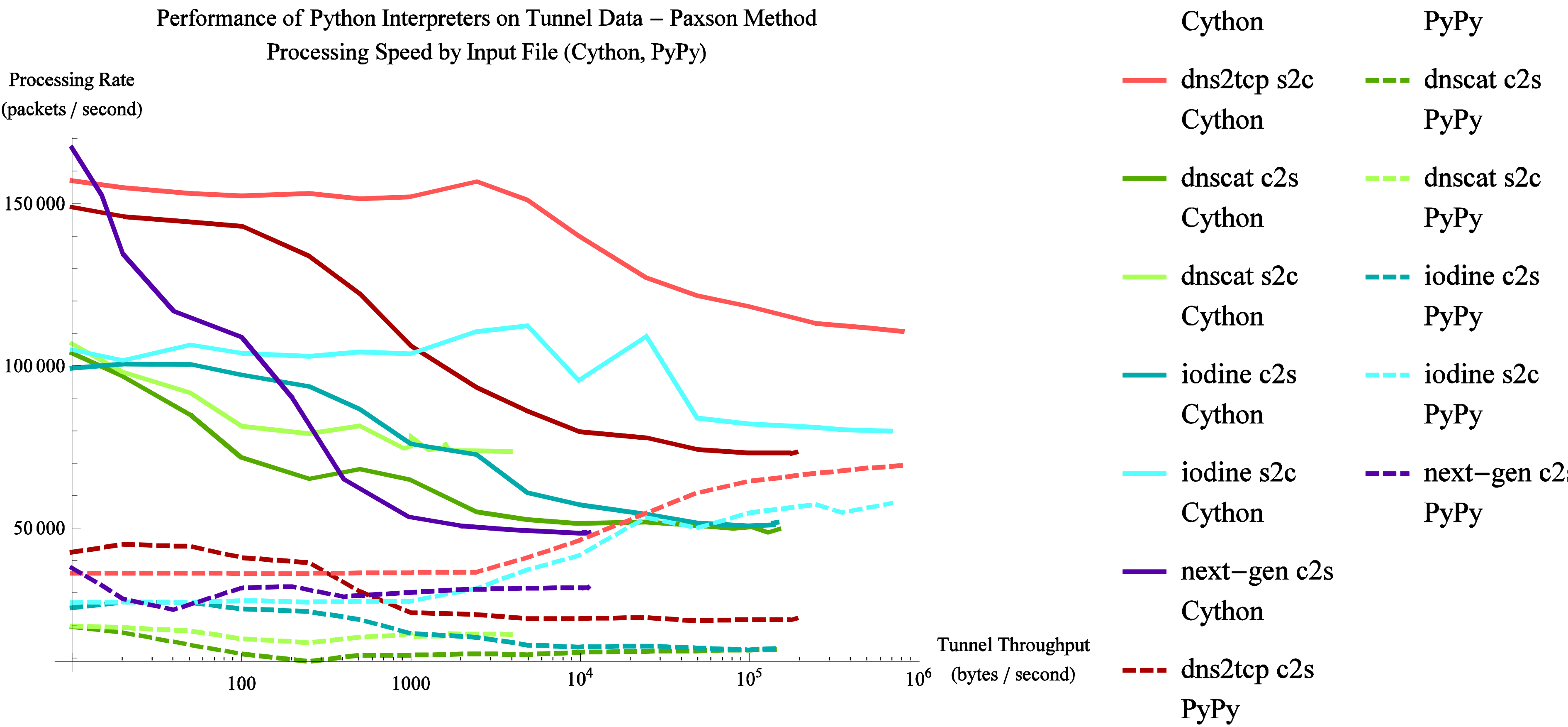
Processing Performance: Naïve Method



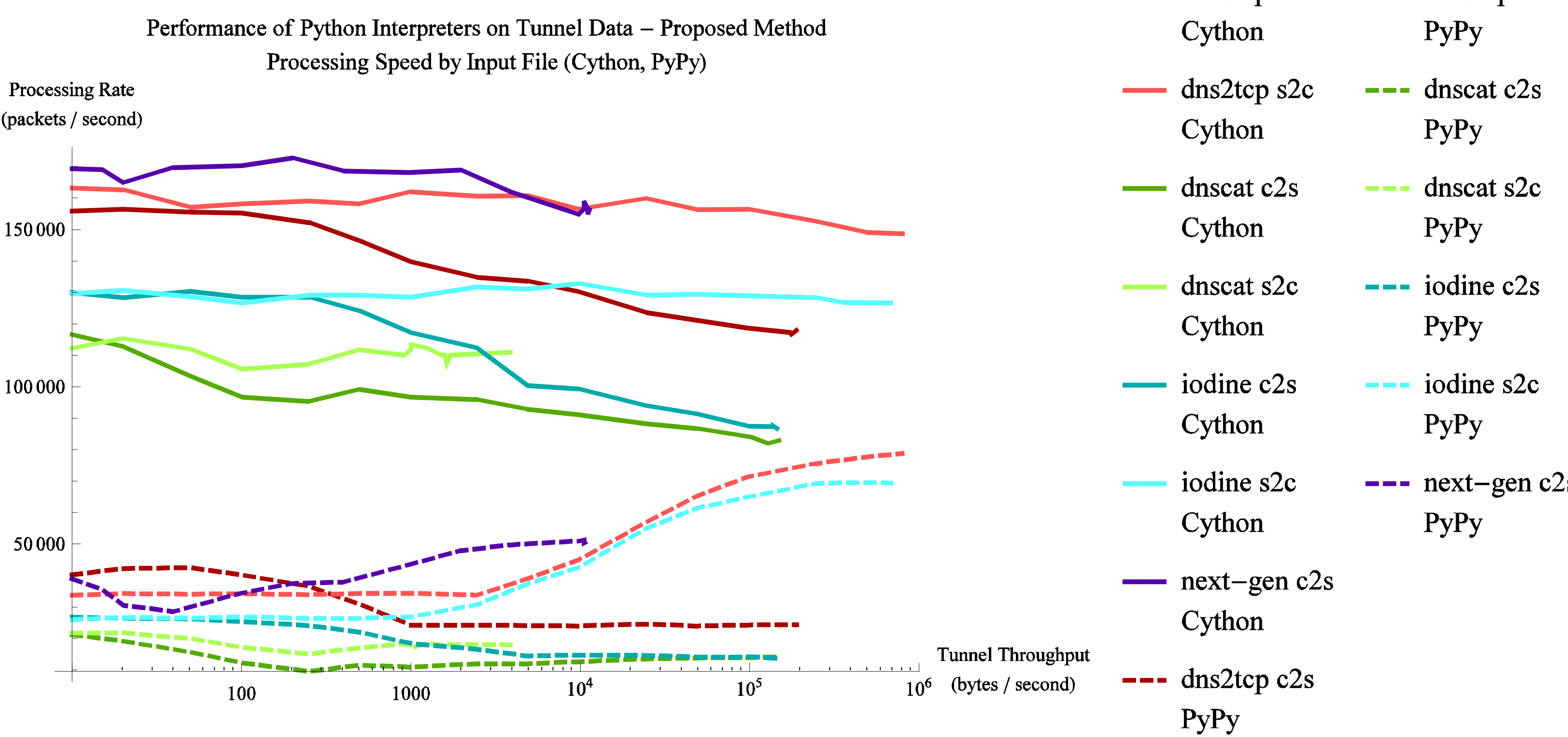
Processing Performance : Born Method



Processing Performance : Paxson Method



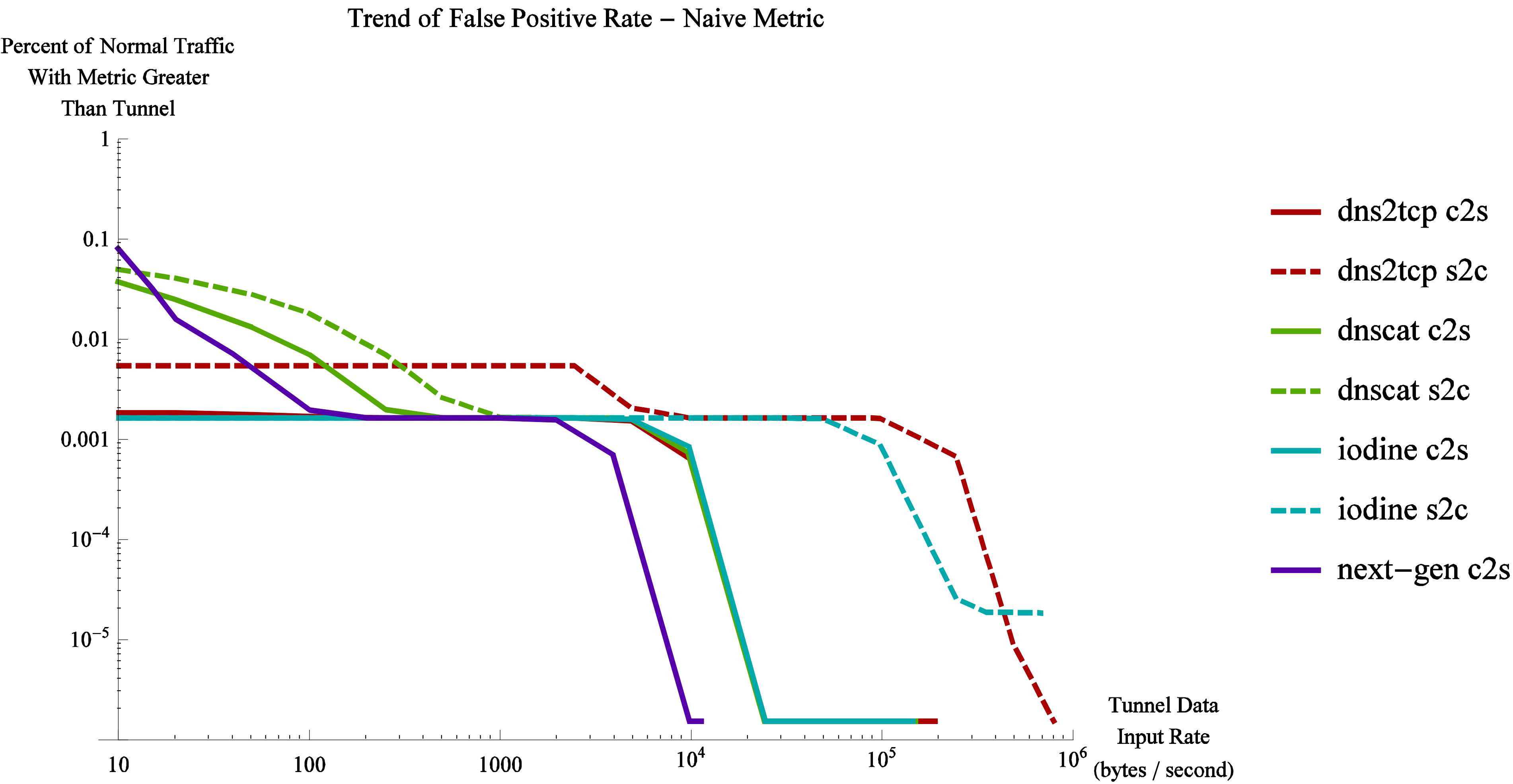
Processing Performance : Proposed Method



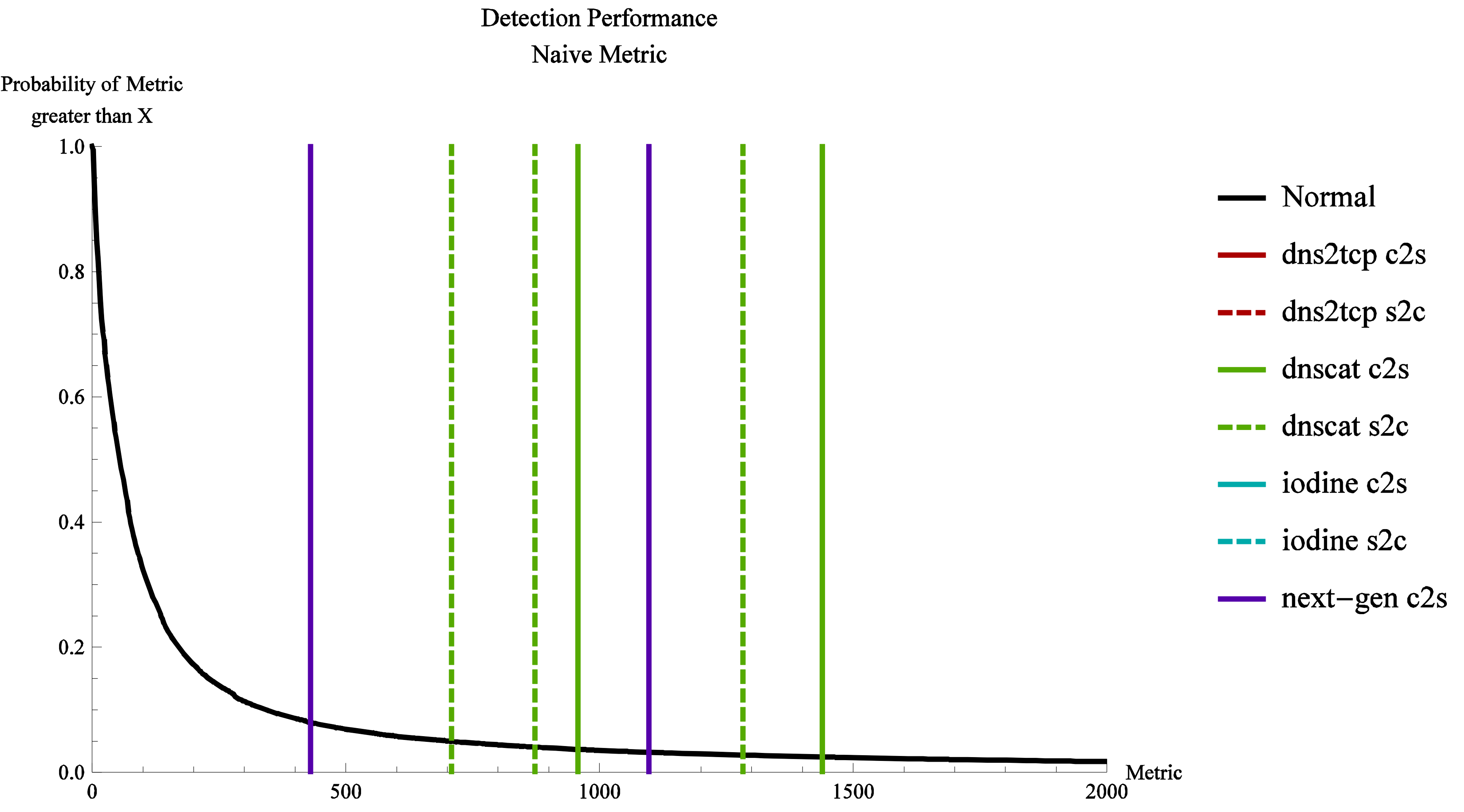
Processing Performance: Conclusions

- The naïve and proposed methods far outperform the other methods
- As throughput increases, both Paxson and Born approaches suffer severe degradation in performance.

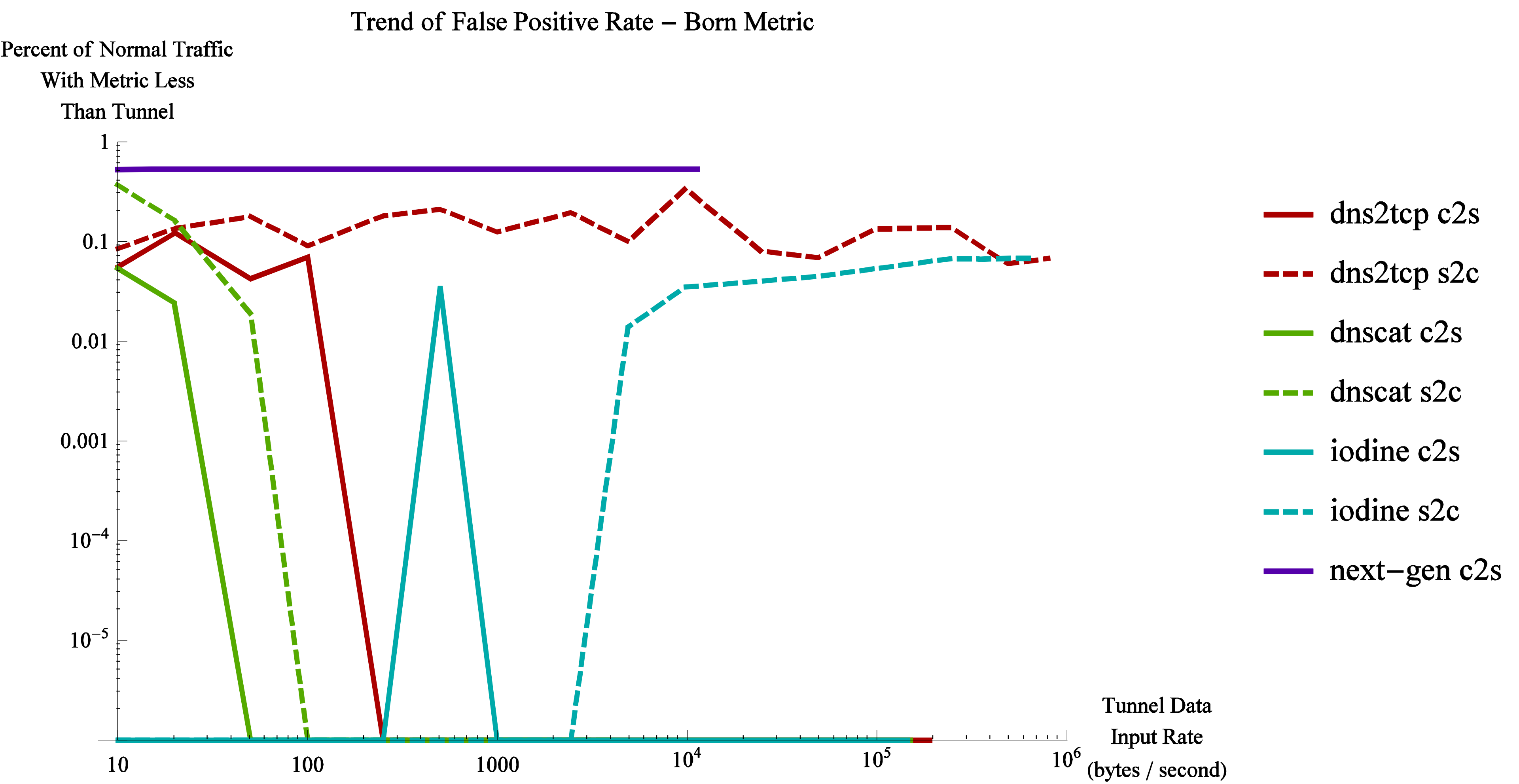
Detection Performance : Naïve Method



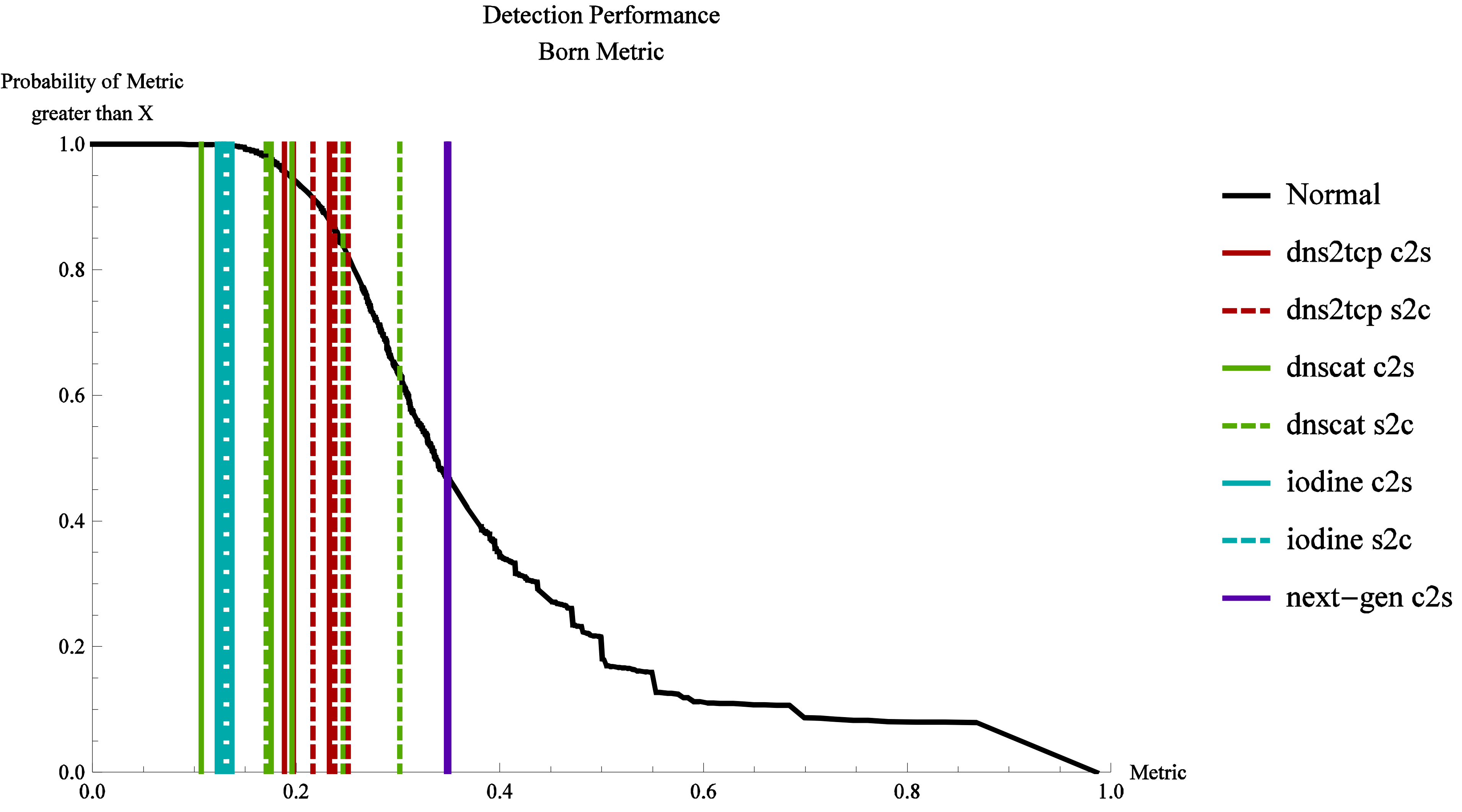
Detection Performance : Naïve Method



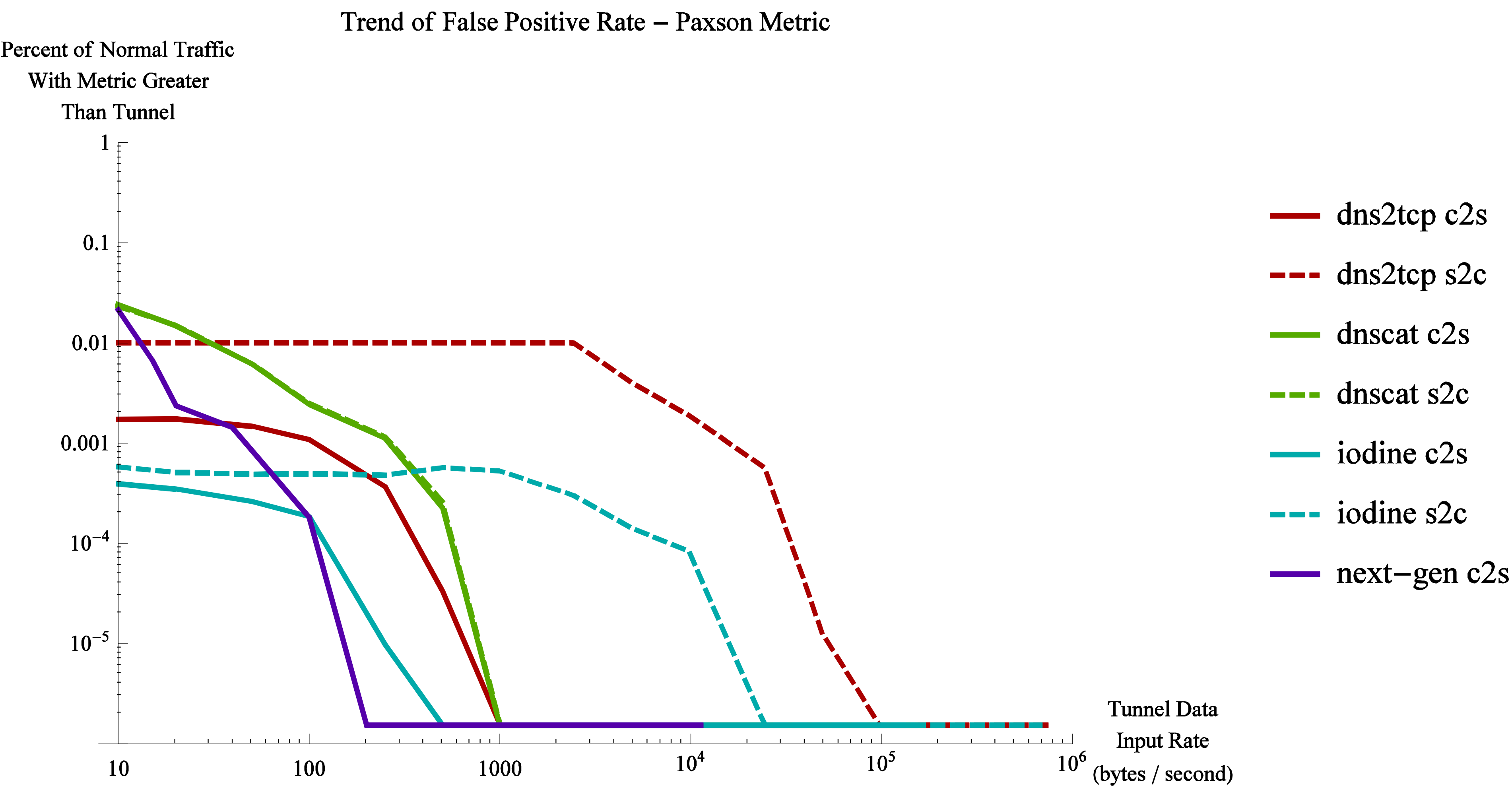
Detection Performance : Born Method



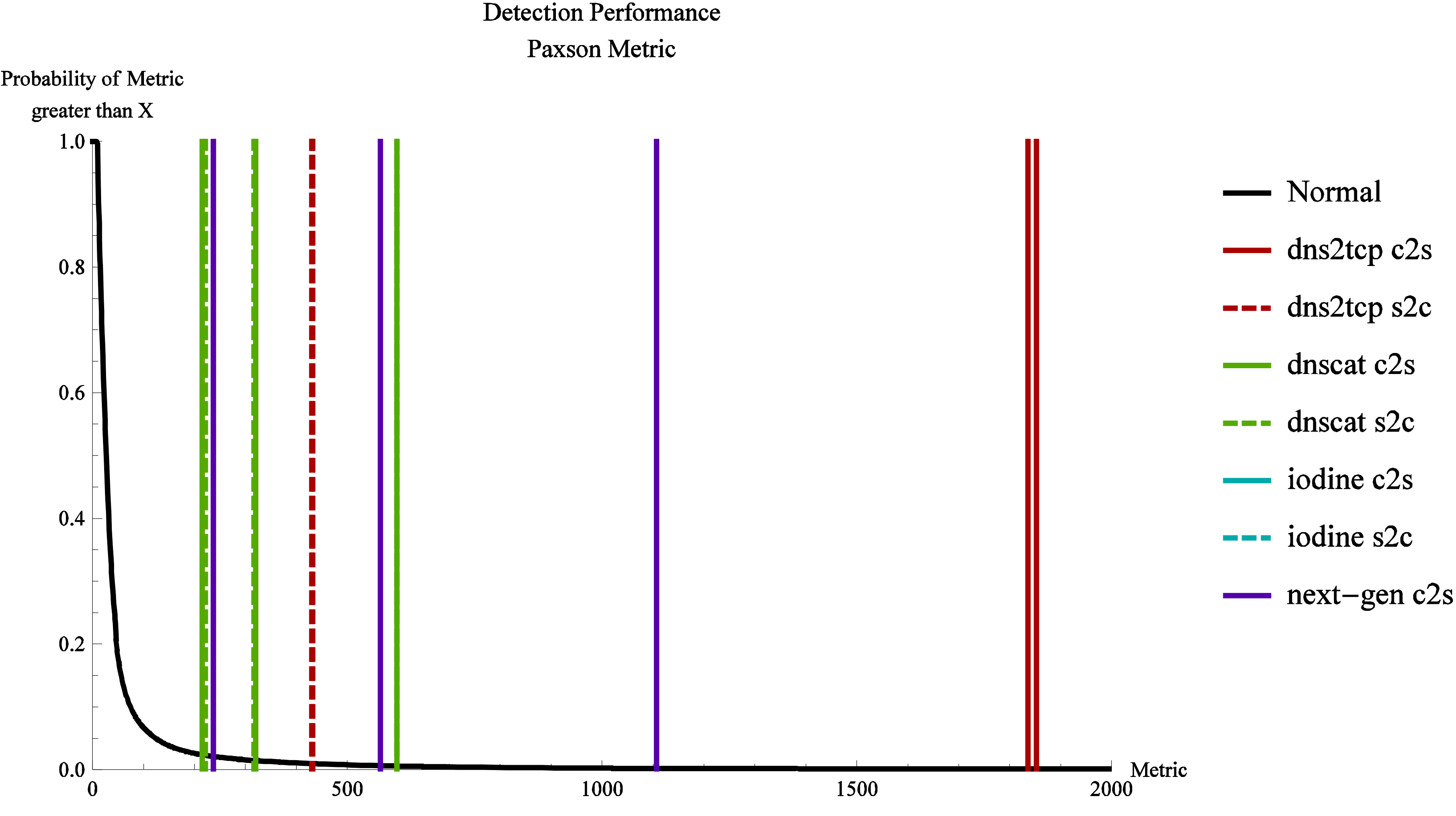
Detection Performance : Born Method



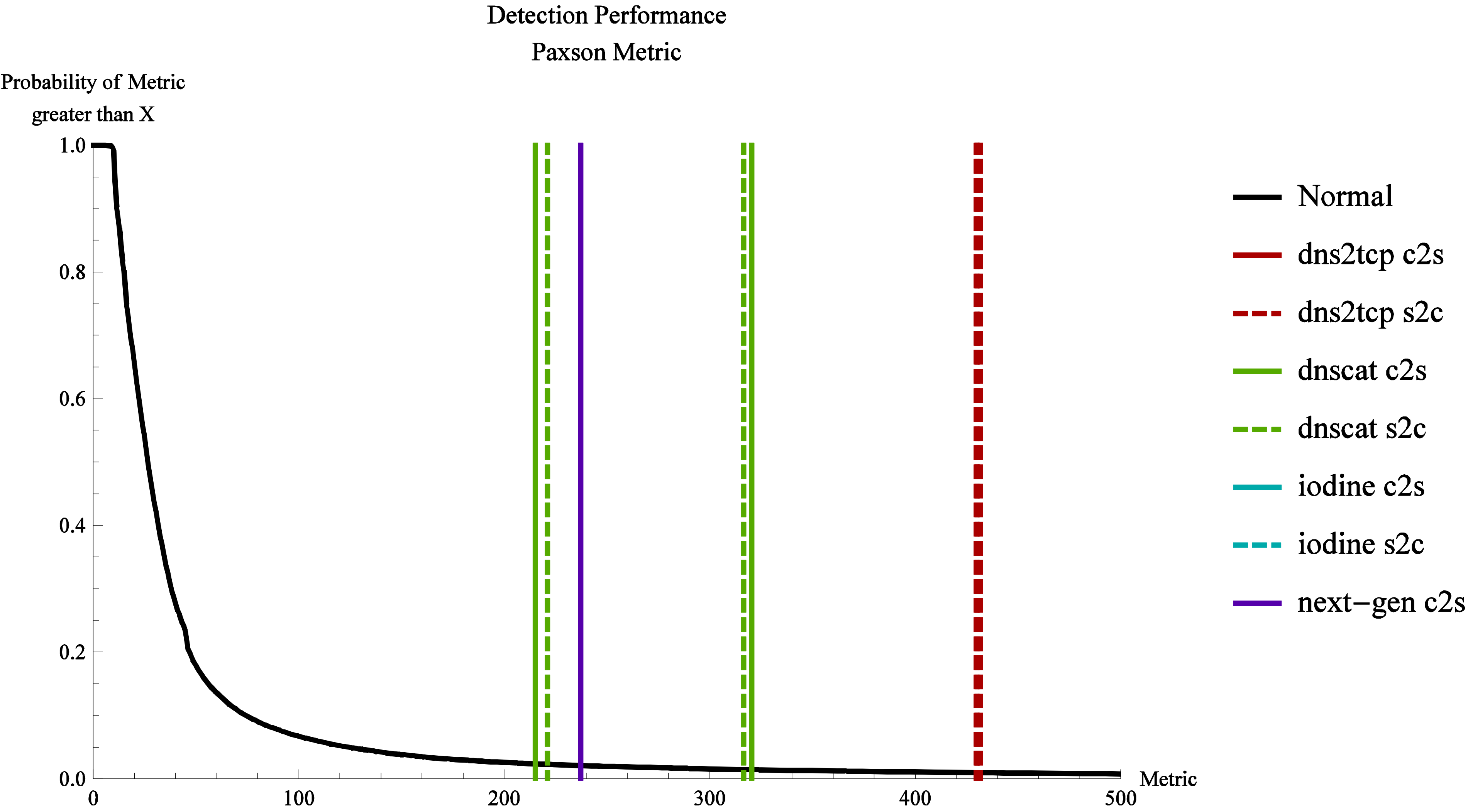
Detection Performance : Paxson Method



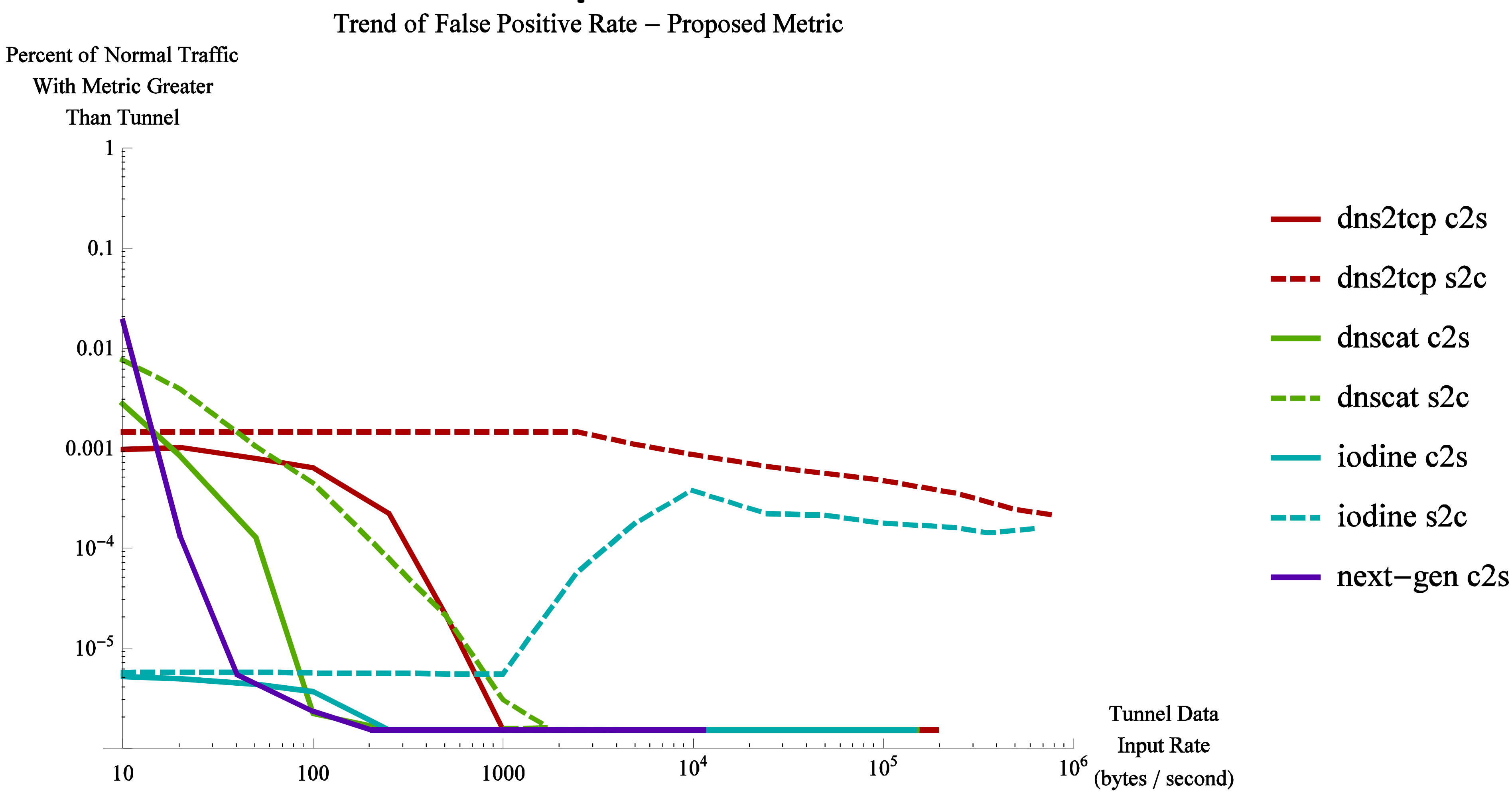
Detection Performance : Paxson Method



Detection Performance : Paxson Method

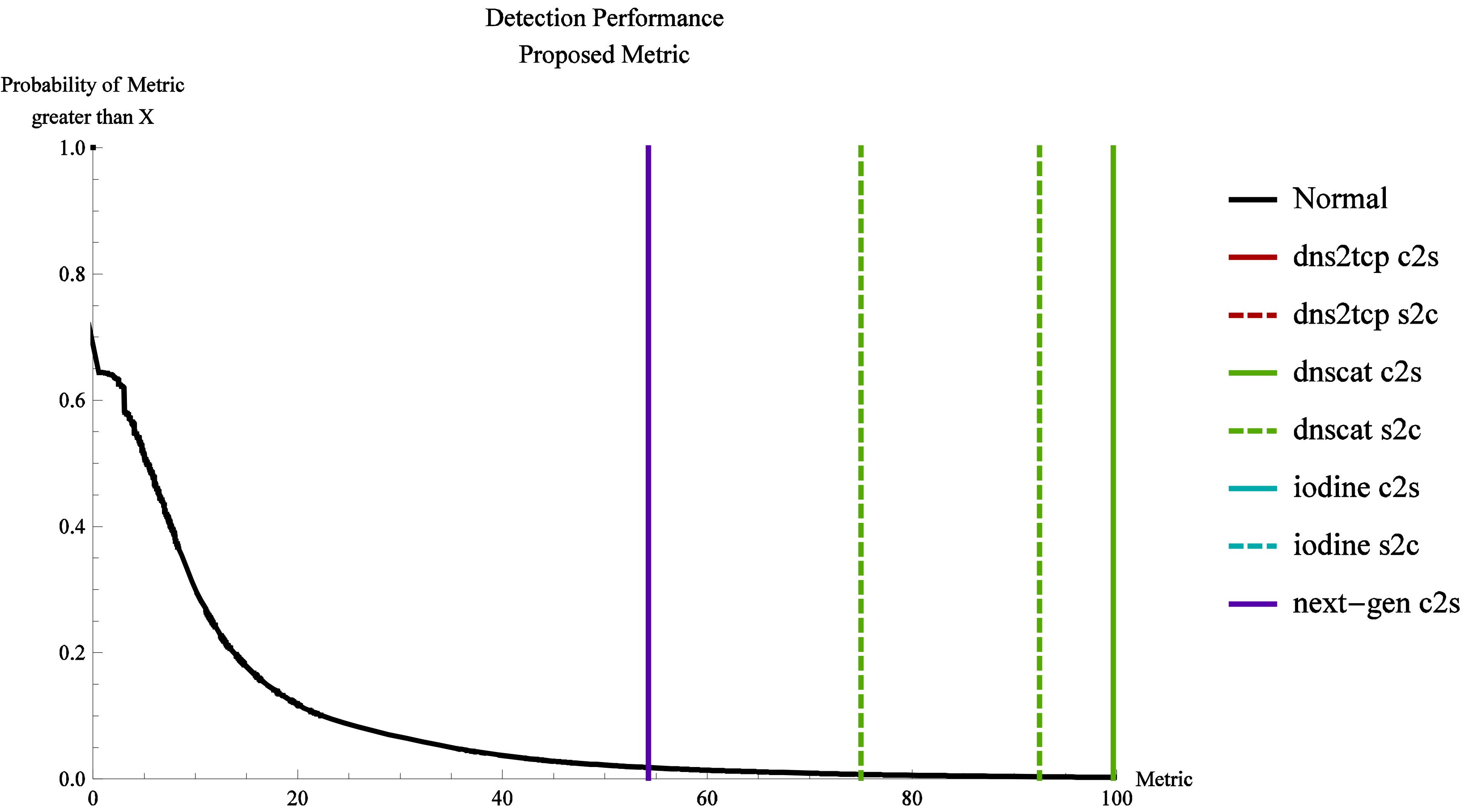


Detection Performance : Proposed Method

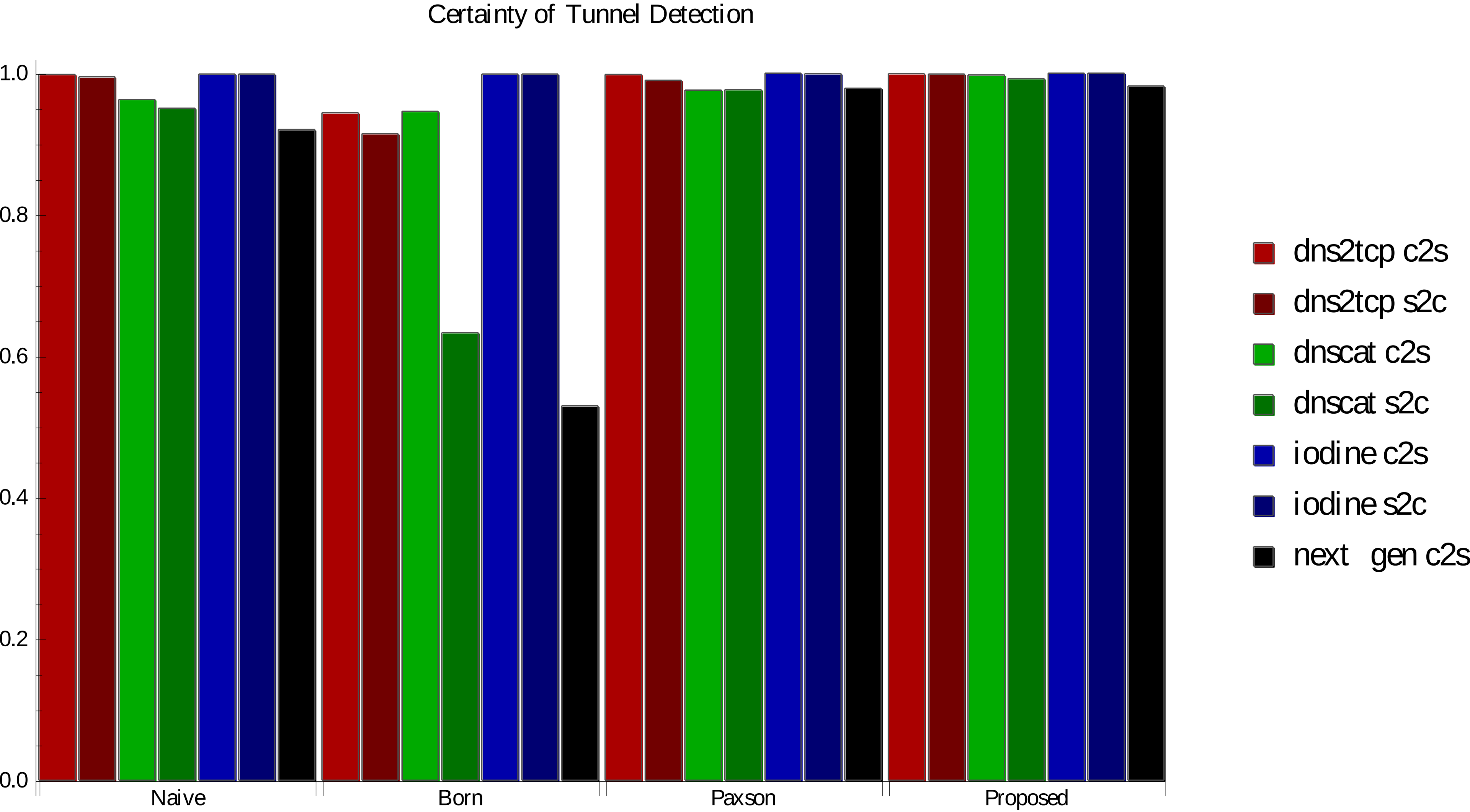


Detection Performance : ProposedMethod

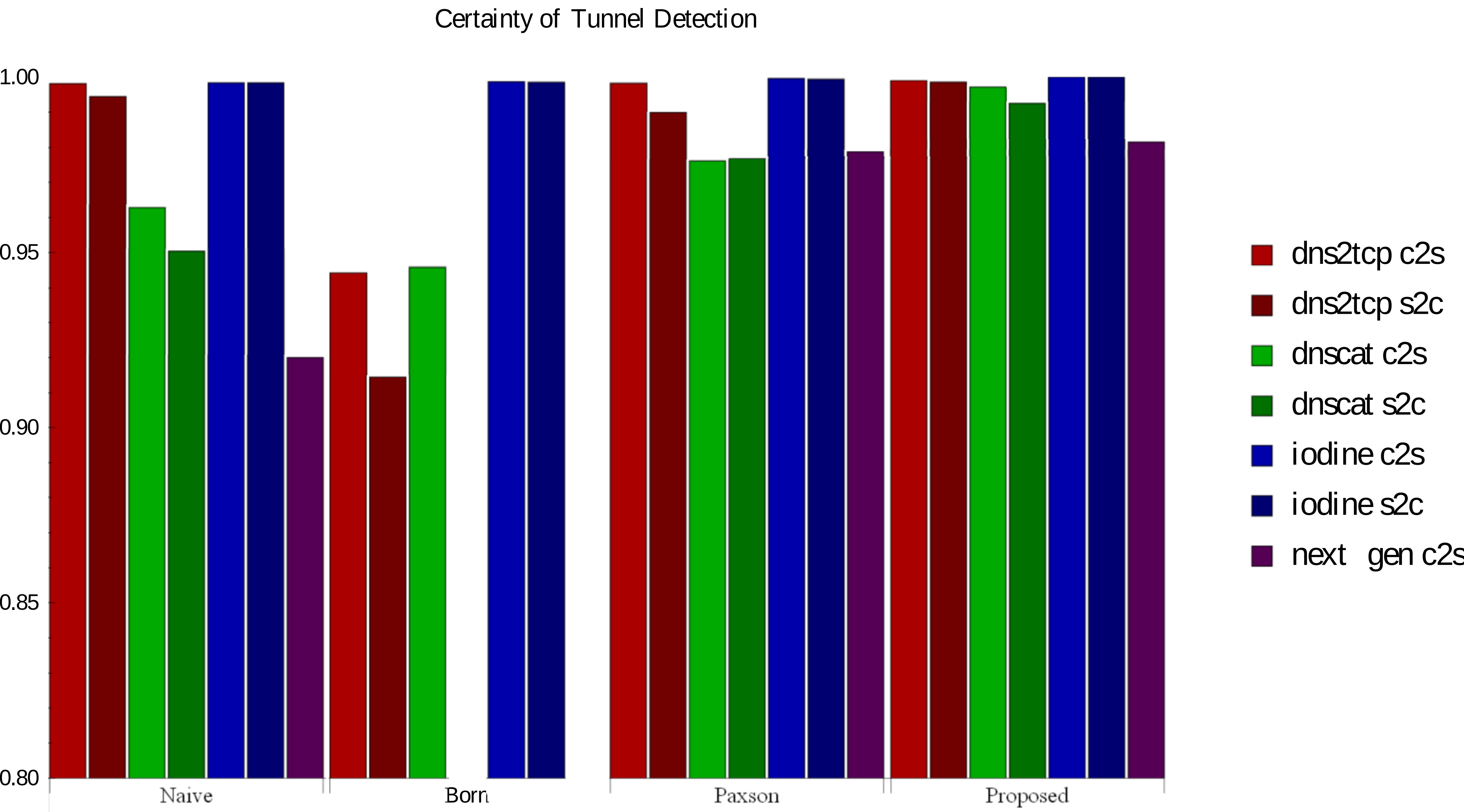
Detection Performance : Proposed Method



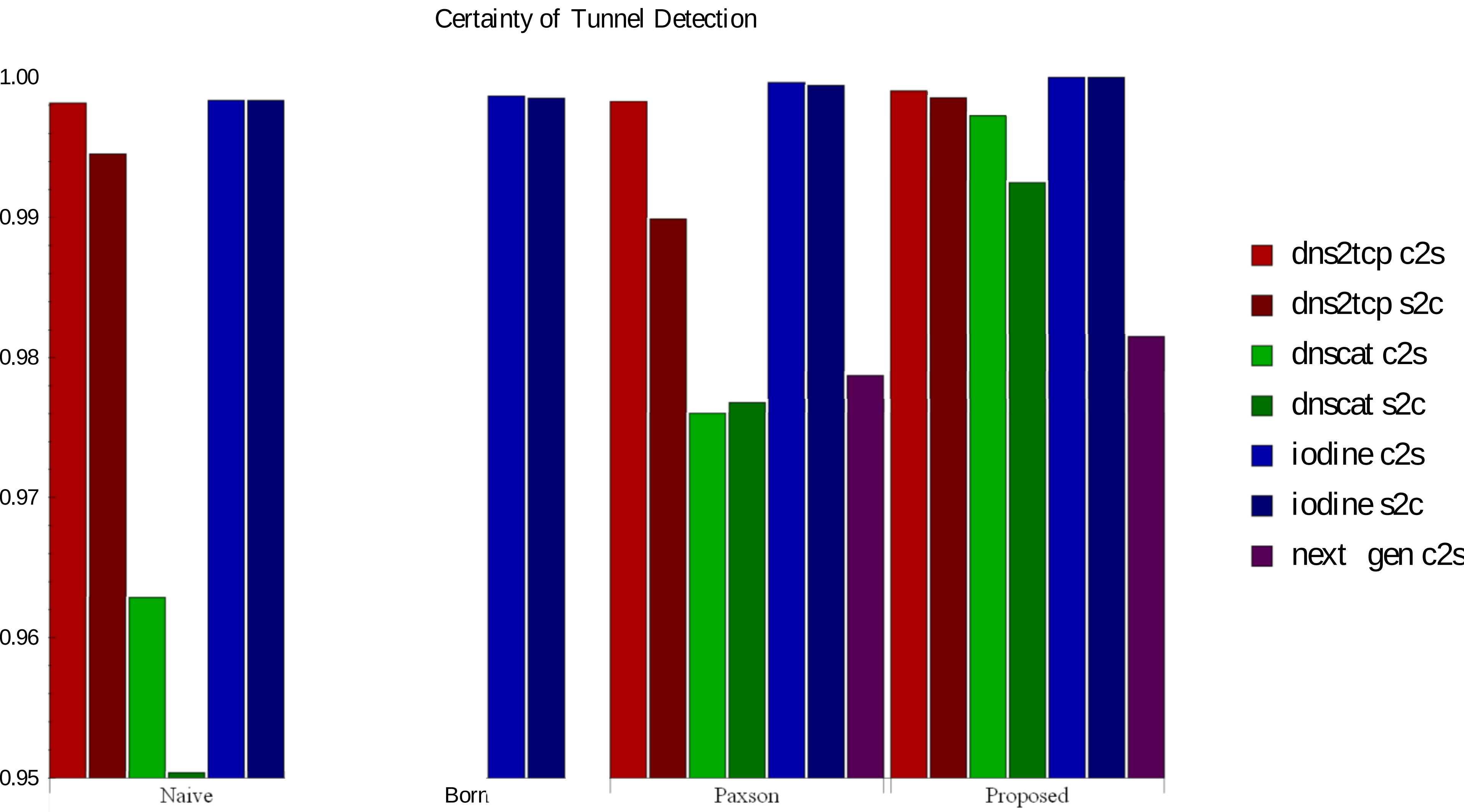
Detection Performance: Comparison of False Positive Rates



Detection Performance: Comparison of False Positive Rates



Detection Performance: Comparison of False Positive Rates



Detection Performance: Conclusions

- The proposed approach achieves categorically lower false positive rates than all other approaches.

- The prototype next-gen tunnel is the most difficult tunnel to detect by far.
  - Born’s approach has a false-positive rate little better than random chance.

Conclusions

- Proposed method:
  - Achieves the best detection performance, and nearly the best processing performance.
  - Represents a notable and novel contribution to the field.
  - Is already implemented in high-performance C/C++, making deployment possible.

Potential Future Work

- Test on more strictly curated data sets to remove confounding factors.
- Identify ways of improving false positive rate
  - Potentially with a more tailored metric
  - Potentially with more temporal knowledge and correlation

Thank you

- Questions