BLINC: Multilevel Traffic Classification in the Dark

Thomas Karagiannis, UC Riverside
Konstantina Papagiannaki, Intel Research Cambridge
Michalis Faloutsos, UC Riverside

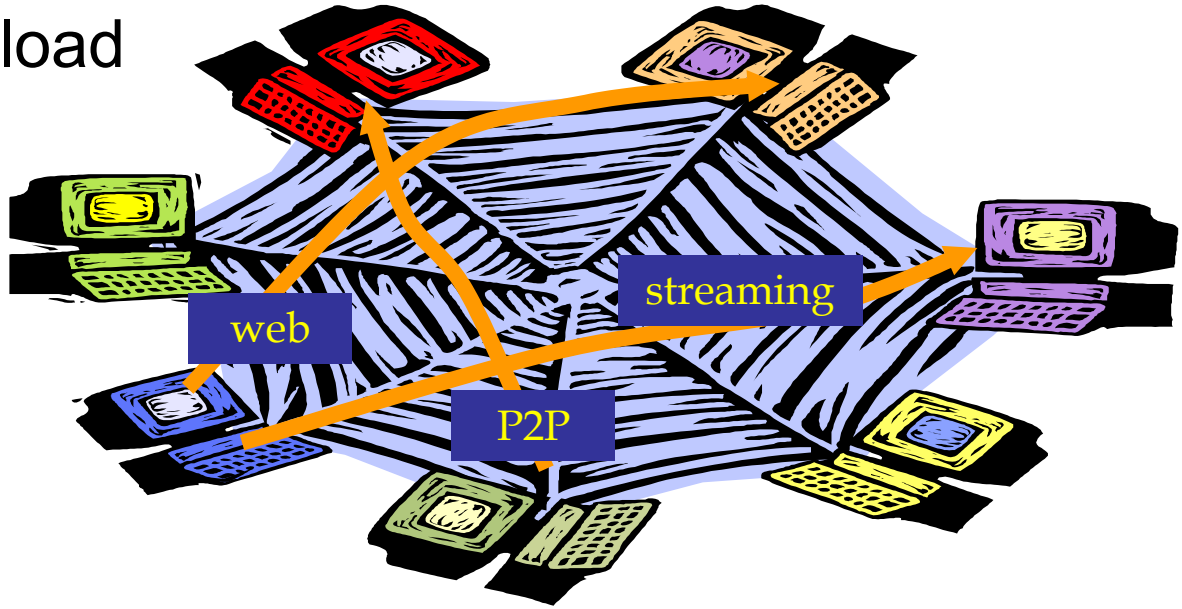
intel

UNIVERSITY of CALIFORNIA Riverside

Intel Research

The problem of workload characterization

- The goal: Classify Internet traffic flows according to the applications that generate them "*in the dark*"
  - No port numbers
  - No payload



The problem of workload characterization – Why in the dark?

- Traffic profiling based on TCP/UDP ports
  - Misleading
- Payload-based classification
  - Practically infeasible
- Applications are “hiding” their traffic
  - P2P applications, skype, etc.
- Recent research approaches
  - Statistical/machine-learning based classification (Roughan et al. IMC’04, Moore et al. SIGMETRICS’05)
  - Sensitive to network dynamics such as congestion

Our contributions

- We present BLINC (BLINd Classification), a fundamentally different “in the dark” approach
  - We shift the focus to the Internet host
  - We analyze host behavior at three levels
    - Social
    - Functional
    - Application
- We identify “signature” communication patterns
- Highly accurate classification

Outline

- Developing a classification benchmark
  - Payload-based classification
- BLINC design
  - Multilevel classification
  - Signature communication patterns
- BLINC evaluation

Classification benchmark

- Packet-traces with machine readable headers
  - Residential (2 traces)
    - 25 hours & 34 hours, 110 Mbps
    - web (35%), p2p (32%)
  - Genome campus
    - 44 hours, 25 Mbps, ftp (67%)
- Classification based on payload signatures
  - Caveats : Nonpayload (1%-2%), Unknown (6%-16%)

BLINC overview

- In the dark classification
  - No examination of port numbers
  - No examination of user payload
- Characterize the host
  - Insensitive to congestion and path changes
- Deployable with existing equipment
  - Operates on flow records

BLINC: Classification process

- Characterize the host
  - Social : Popularity/Communities
  - Functional : Consumer/provider of services
  - Application : Transport layer interactions
- Identify signature communication patterns
- Match observed behavior to signatures

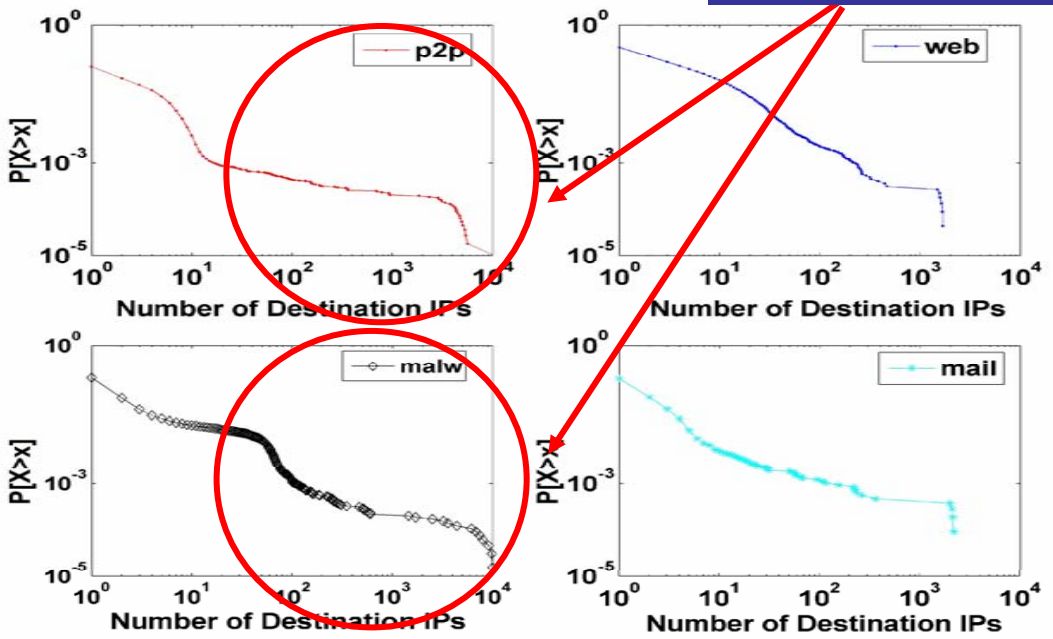
1. Social level

- Characterization of the popularity of hosts
- Two types of behavior:
  - Based on number of destination IPs
  - Communities: Groups of communicating hosts

1. Social level: Popularity

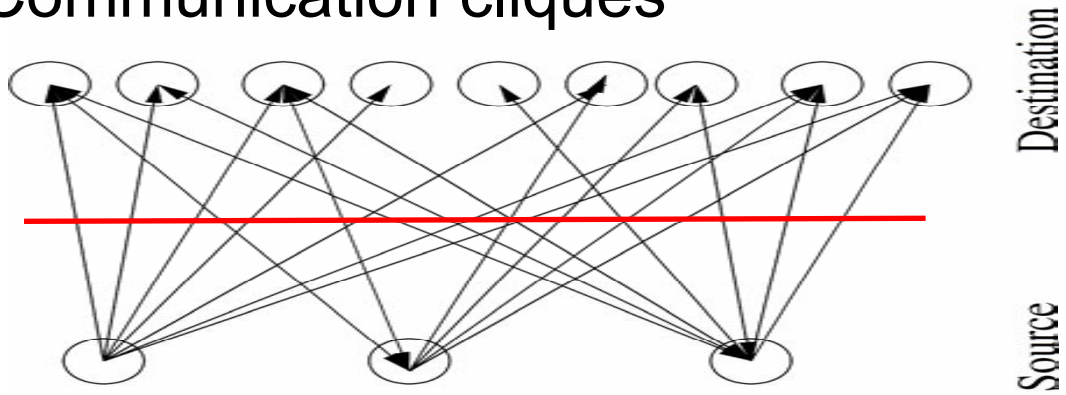
- Reveals only basic application traffic properties

Heavier tail of CCDF of destination IPs for P2P and malware



1. Social level: Communities

- Communication cliques

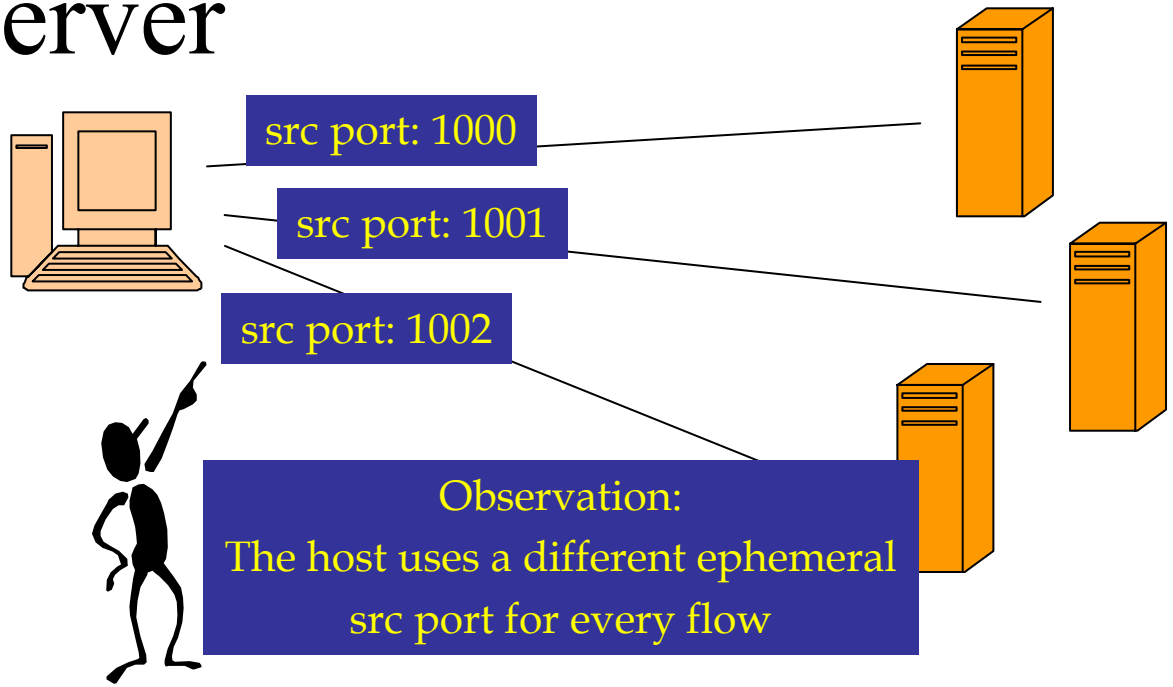


- Perfect cliques
  - Attacks
- Partial cliques
  - Collaborative applications (p2p, games)
- Partial cliques with same domain IPs
  - Server farms (e.g., web, dns, mail)

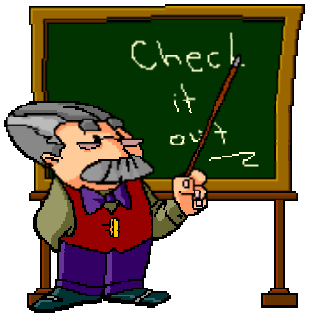
2. Functional level

- We characterize based on tuple (IP, Port)
- We identify three types of behavior
  - Client: Consumer of services
  - Server: Provider of services
  - Collaborative

2. Functional level: Client vs. Server

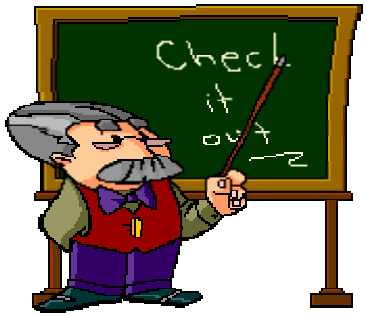


Observation:
The host uses a different ephemeral src port for every flow



Rule:
Hosts that use a large number of source ports are clients

2. Functional level: Client vs. Server

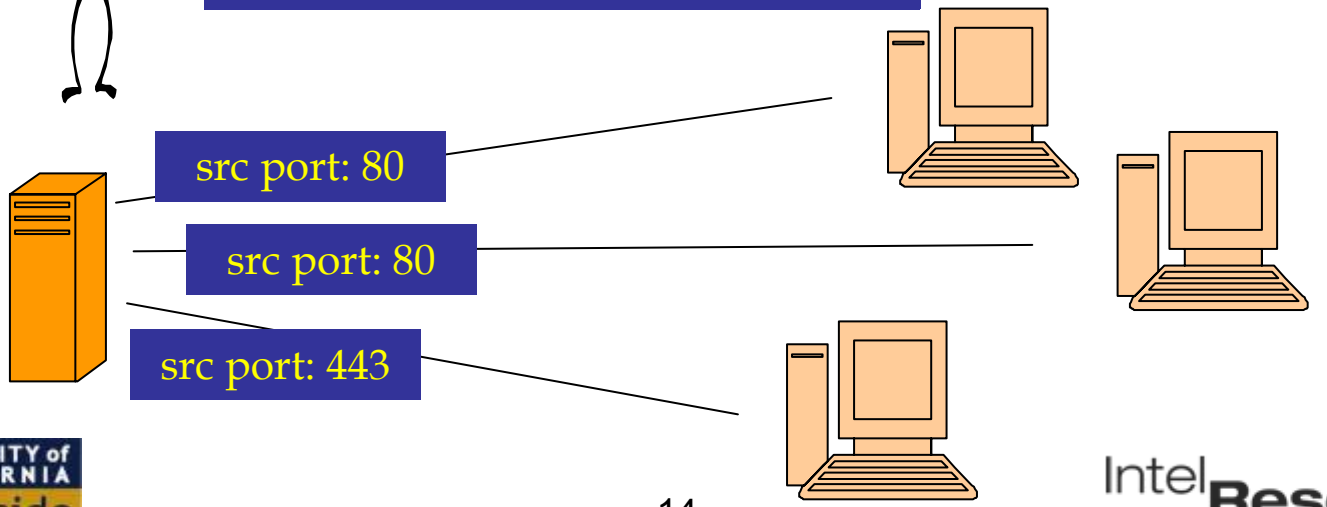


Rule:

Hosts that use a small number of source ports are offering services on these ports

Observation:

The host uses only two src ports for all flows

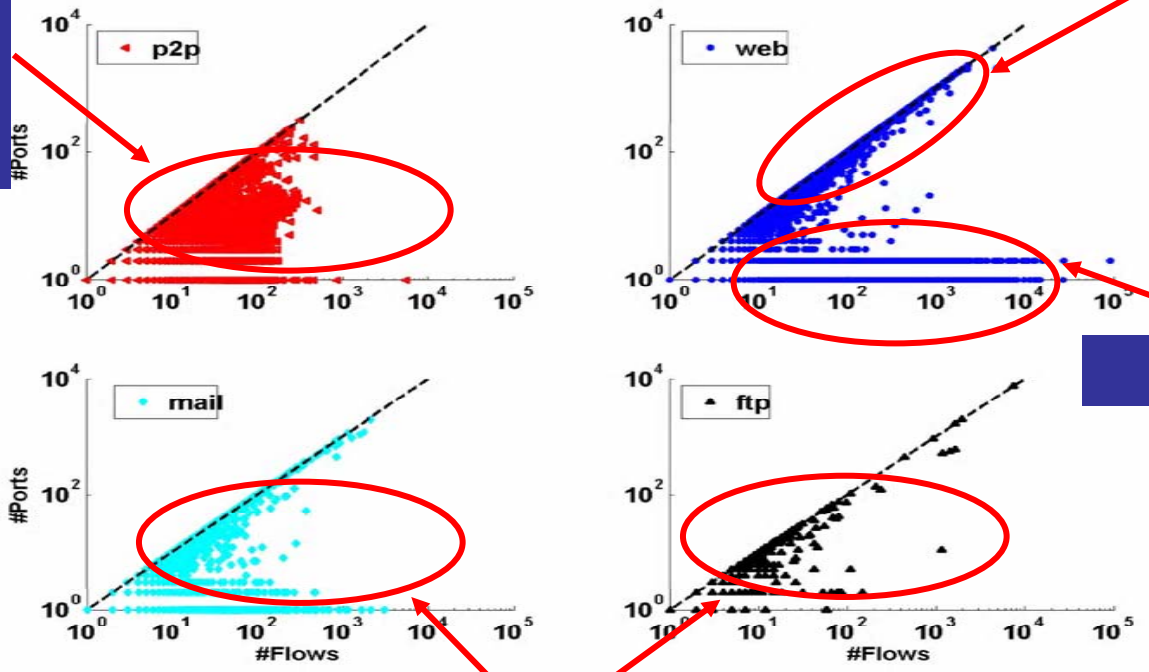


2. Functional level: Characterizing the host

flows vs. source ports per application

Collaborative applications: No distinction between servers and clients

Clients



Servers

Obscure behavior due to multiple mail protocols and passive ftp

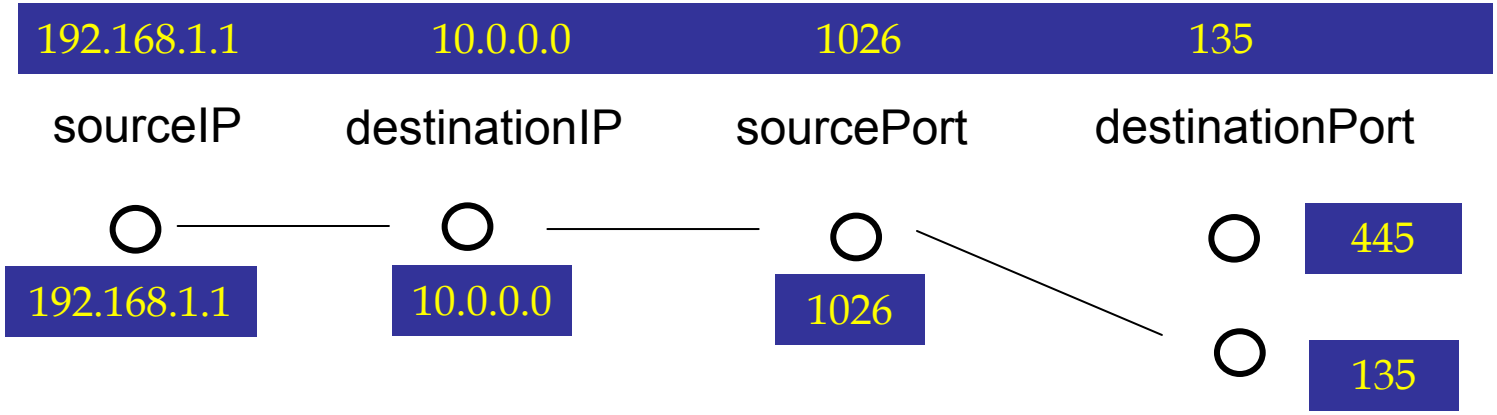
3. Application level

- Interactions between network hosts display diverse patterns across application types.

- We capture patterns using *"graphlets"*
  - Target most typical behavior
  - Relationship between fields of the 4-tuple

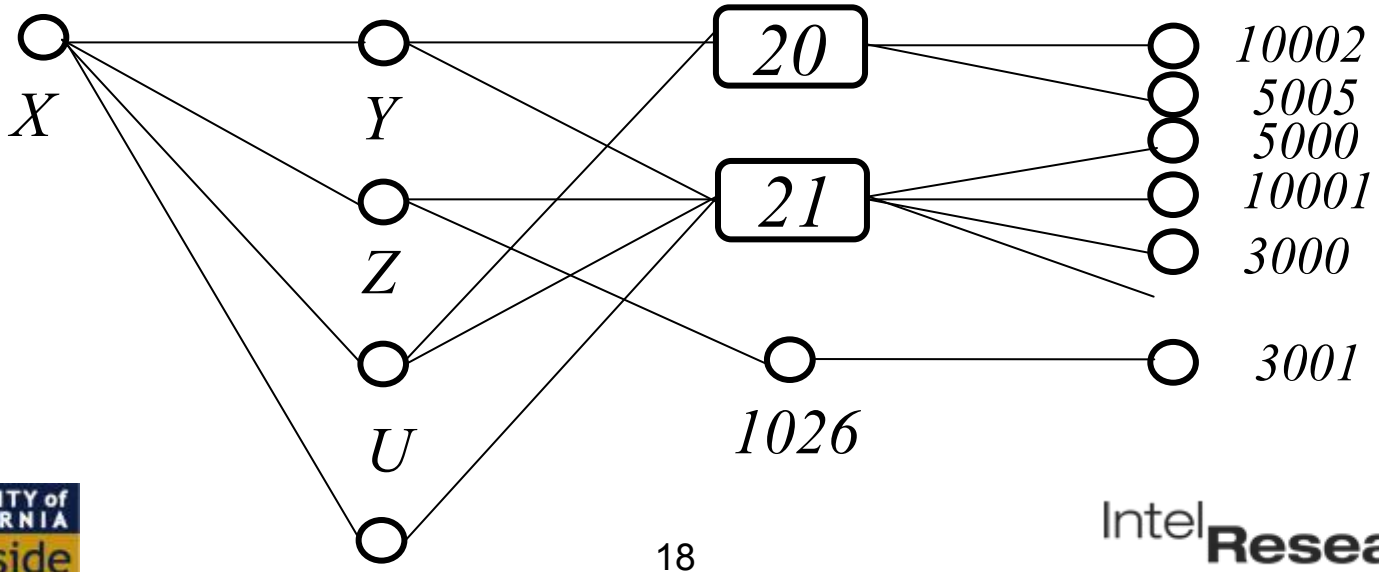
3. Application level: Graphlets

- Graphlets have four columns corresponding to the 4-tuple: src IP, dst IP, src port and dst port
- Each node is a distinct entry for each column
- Lines connect nodes when flows contain the specific field values

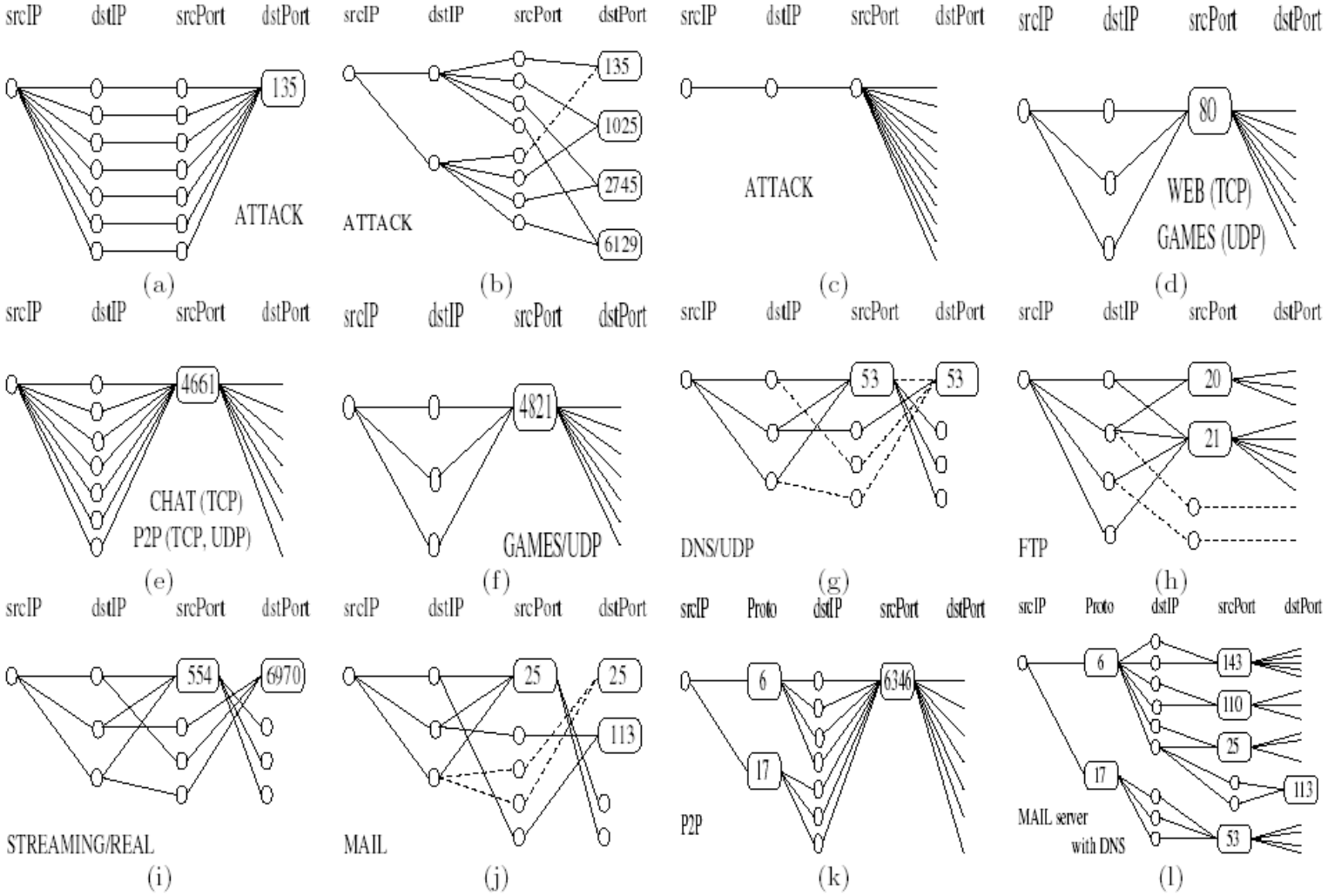


3. Graphlet Generation (FTP)

sourceIP	destinationIP	sourcePort	destinationPort
X	Y	21	10001
X	Y	20	10002
X	Z	21	3000
X	**Z**	**1026**	**3001**

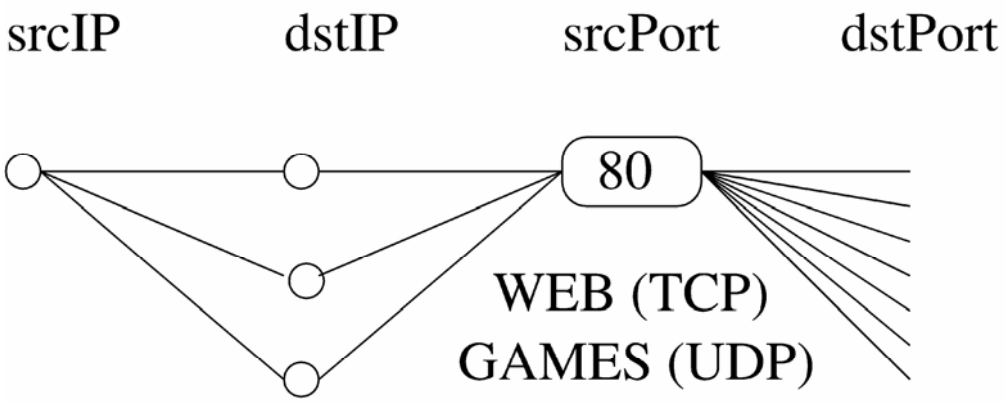


3. Graphlet Library



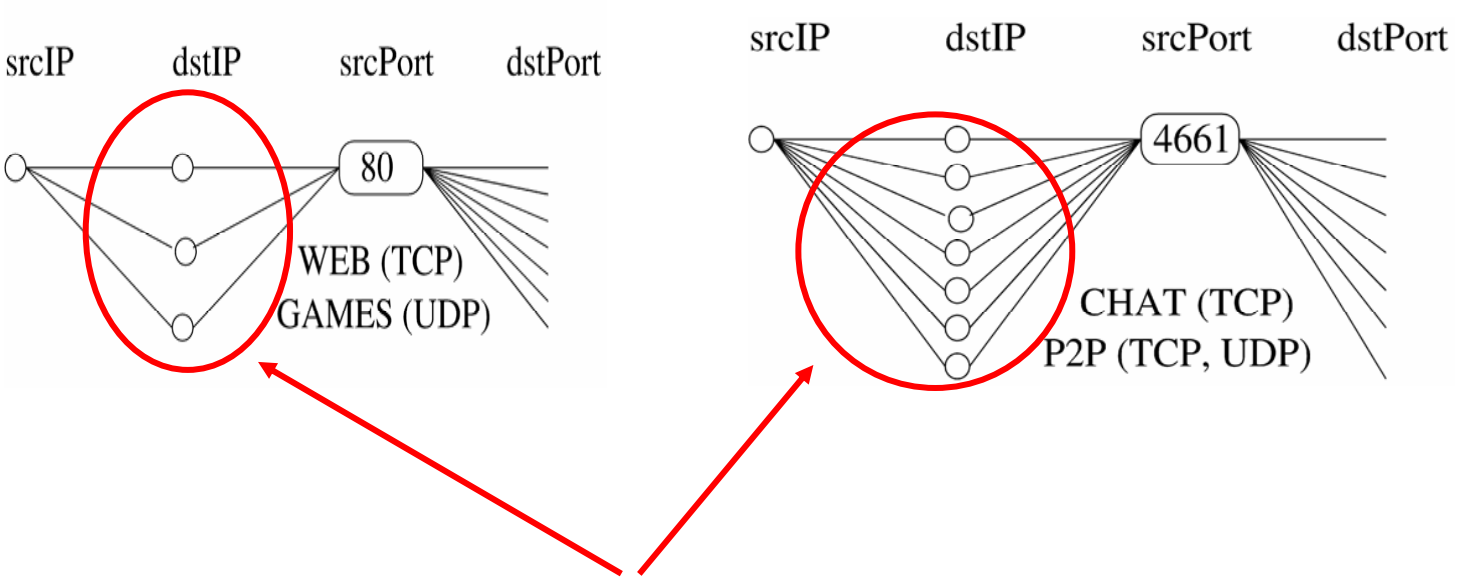
Heuristics: Further improving performance

- Using the transport layer protocol.



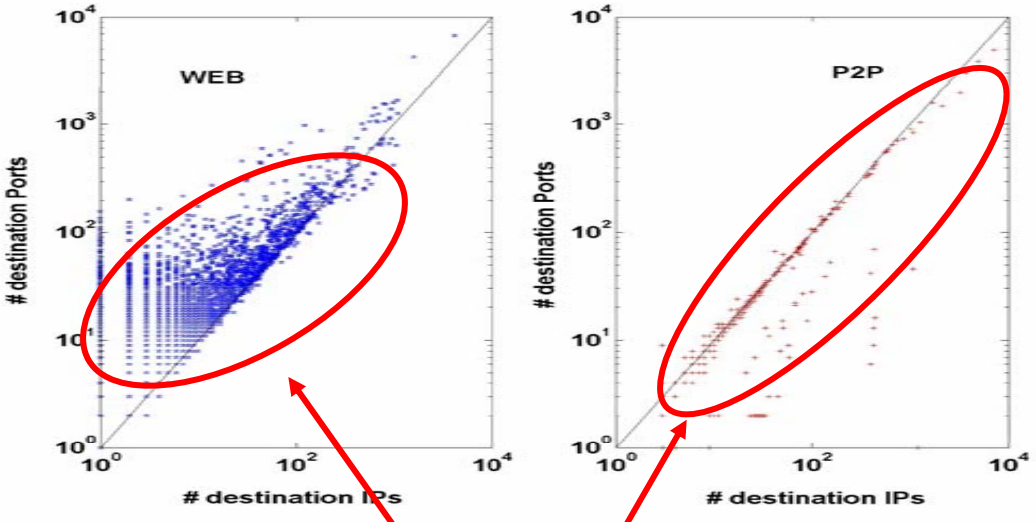
Heuristics: Further improving performance

- Using the relative cardinality of sets.



Heuristics: Further improving performance

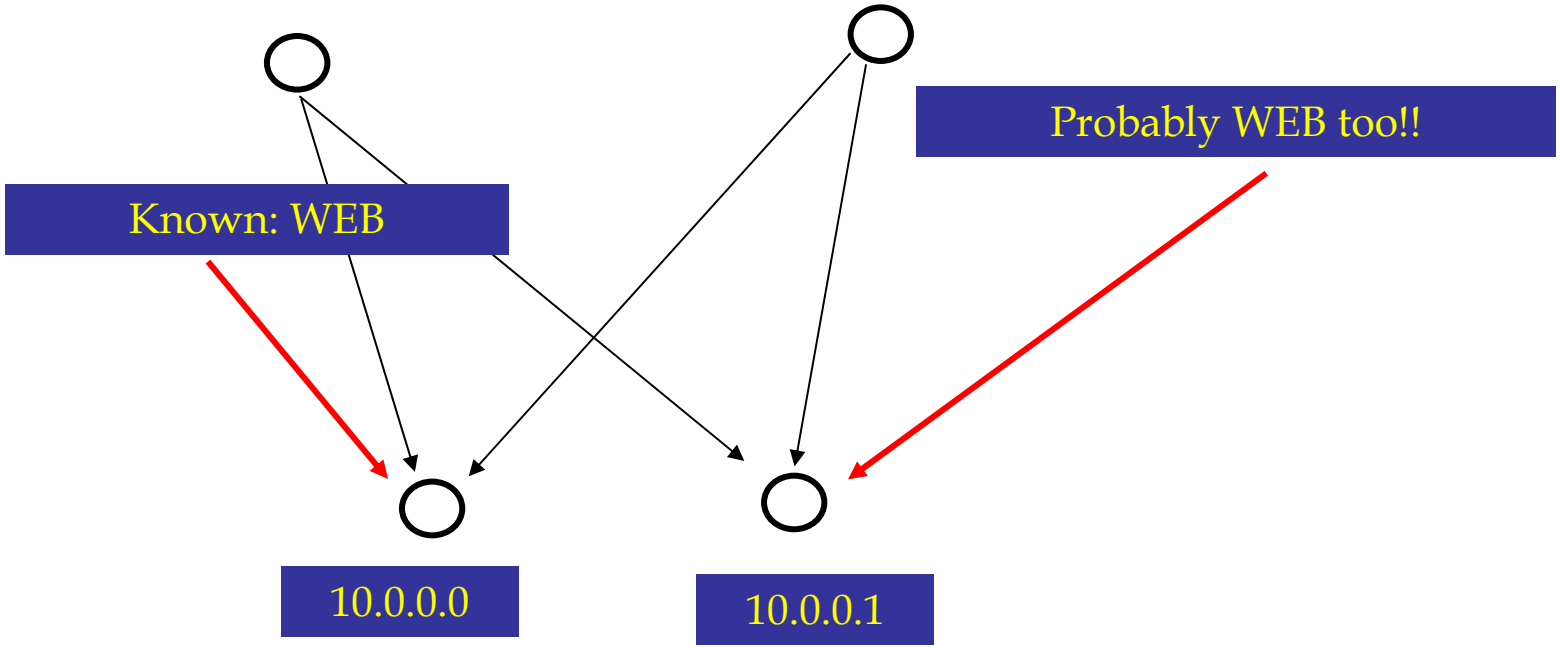
- Using the relative cardinality of sets.



WEB: #dst ports >> # dst IPs
P2P: #dst ports <= # dst IPs

Heuristics: Further improving performance

- Using the communities



Heuristics: Further improving performance

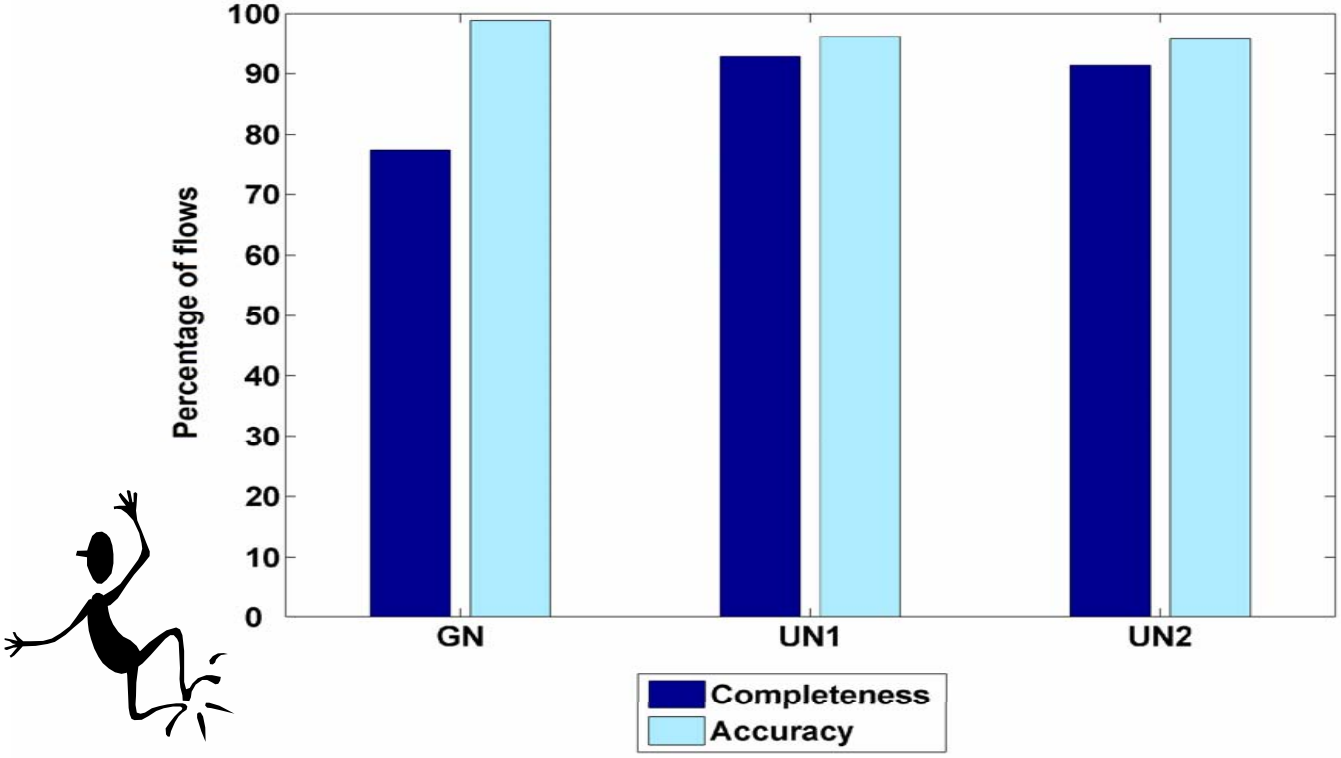
- Other heuristics:
  - Using the per-flow average packet size
  - Recursive (mail/dns servers talk to mail/dns servers, etc.)
  - Failed flows (malware, p2p)

Classification Results

- We evaluate BLINC using two metrics:
  - Completeness
    - Percentage classified by BLINC
  - Accuracy
    - Percentage classified by BLINC correctly
- We compare against payload classification
  - Exclude unknown and nonpayload flows

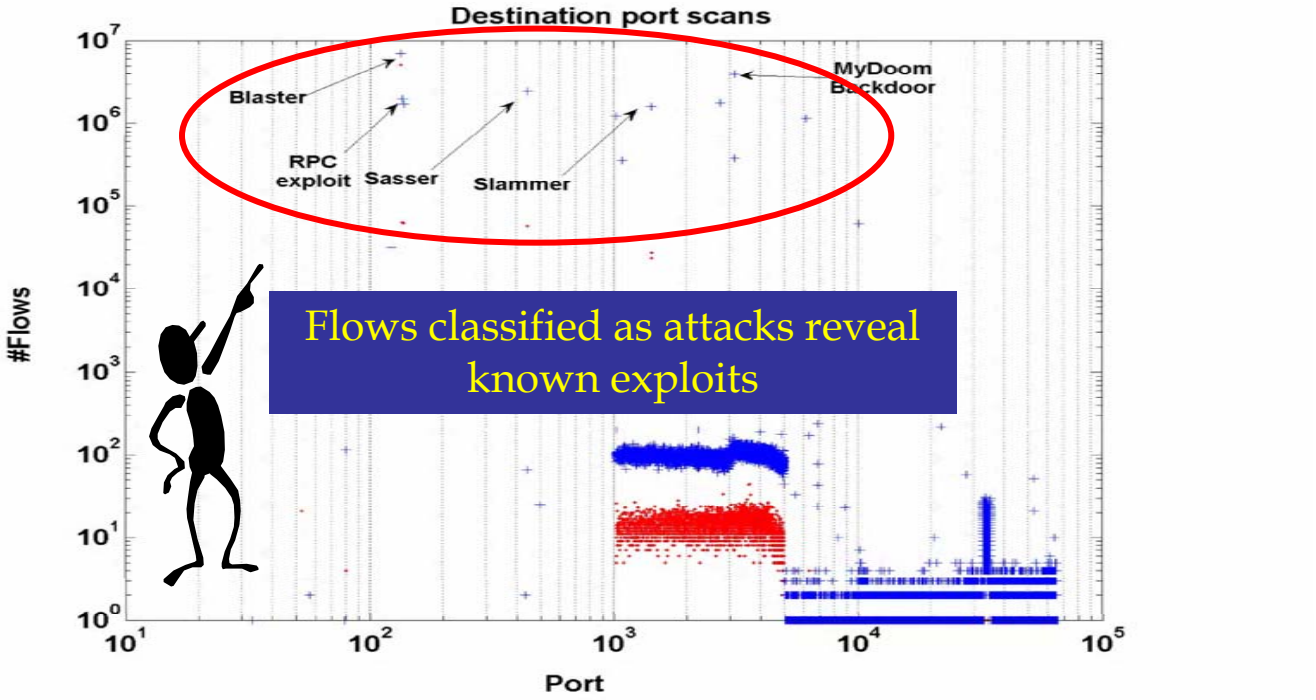
BLINC achieves highly accurate classification

80%-90% completeness !
>90% accuracy !!



Characterizing the unknown: Non-payload flows

BLINC is not limited by non-payload flows or unknown signatures



BLINC issues and limitations

- Extensibility
  - Creating and incorporating new graphlets
- Application sub-types
  - e.g., BitTorrent vs. Kazaa
- Transport-layer encryption
  - then what?
- NATS
  - Should handle most cases
- Access vs. Backbone networks?
  - Should handle but no data to test

Conclusions

- A new way of thinking of the classification problem
  - Classify nodes instead of flows
  - Multi-level analysis:
    - social, functional, transport-layer characteristics
    - each level provides corroborative evidence or insight
- BLINC works well in practice
  - classifies 80-90% of the traffic
  - with >90% accuracy
- Going beyond payload-based classification
  - Nonpayload/unknown flows
- Building block for security applications