Traffic Monitoring and Application Classification: A Novel Approach

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QuickTime™ and a
TIFF (Uncompressed) decompressor
are needed to see this picture.

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are needed to see this picture.

Thomas Karagiannis

Marios Iliofotou

General Problem Definition

We don't know what goes on in the network

- Measure and monitor:
  - Who uses the network? For what?
  - How much file-sharing is there?
  - Can we observe any trends?
- Security questions:
  - Have we been infected by a virus?
  - Is someone scanning our network?
  - Am I attacking others?

Problem in More Detail

- Given network traffic in terms of flows
  - Flow: tuple (source IP, port; dest IP, port; protocol)
  - Flow statistics: packet sizes, interarrival etc
- Find which application generates each flow
  - Or which flows are P2P
  - Or detect viruses/worms
- Issues:
  - Definition of flow hides subtleties
  - Monitoring tools, netflow, provide this

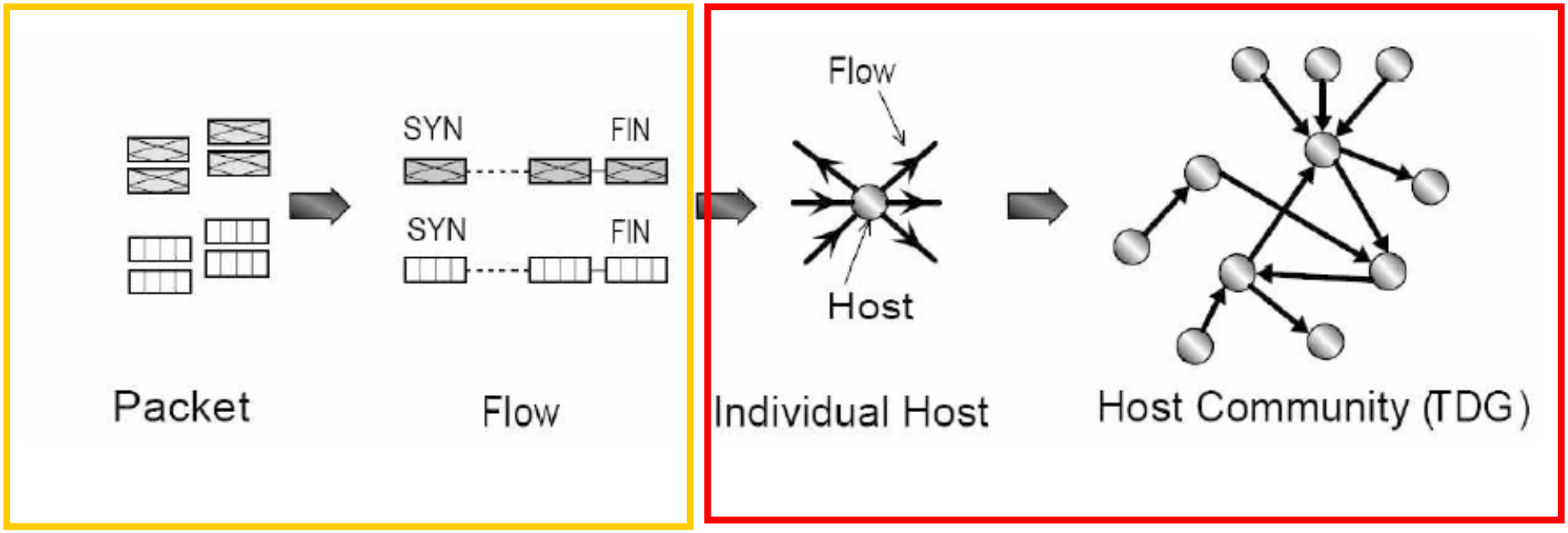
State of the Art Approaches

- Port-based: some apps use the same port
  - Works well for legacy applications, but not for new apps
- Statistics-based methods:
  - Measure packet and flow properties
    - Packet size, packet interarrival time etc
    - Number of packets per flow etc
  - Create a profile and classify accordingly
  - Weakness: Statistical properties can be manipulated
- Packet payload based:
  - Match the signature of the application in payload
  - Weakness
    - Require capturing the packet load (expensive)
    - Identifying the “signature” is not always easy
- IP blacklist/whitelist filtering

Our Novelty, Oversimplified

- We capture the intrinsic behavior of a user
  - Who talks to whom
- Benefits:
  - Provides novel insight
  - Is more difficult to fake
  - Captures intuitively explainable patterns
- Claim: our approach can give rise to a new family of tools

How our work differs from others



Previous work

Our work

- BLINC: Profile behavior of user (host level)
- TDGs: Profile behavior of the whole network (network level)

Motivation: People Really Care

- We started by measuring P2P traffic
  - which explicitly tries to hide
  - Karagiannis (UCR) at CAIDA, summer 2003
- How much P2P traffic is out there?
  - RIAA claimed a drop in 2003
  - We found a slight increase
    - "Is P2P dying or just hiding?" Globecom 2004

The Reactions

- RIAA did not like it
  - Respectfully said that we don't know what we are doing
- The P2P community loved it
  - Without careful scrutiny of our method

More People Got Interested

- Wired: ``Song-Swap Networks Still Humming" on Karagiannis work.
- ACM news, PC Magazine, USA Today,...
- Congressional Internet Caucus (J. Kerry!)
- In litigation docs as supporting evidence!

Structure of the talk

- Part I:
  - BLINC: A host-based approach for traffic classification
- Part II:
  - Monitoring using the network-wide behavior: Traffic Dispersion Graphs, TDGs

Part I: BLINC Traffic classification

- The goal:
  - Classify Internet traffic flows according to the applications that generate them
- Not as easy as it sounds:
  - Traffic profiling based on TCP/UDP ports
    - Misleading
  - Payload-based classification
    - Practically infeasible (privacy, space)
  - Can require specialized hardware

Joint Work with: Thomas Karagiannis, UC Riverside/ Microsoft

Konstantina Papagiannaki, Nina Taft, Intel

The State of the Art

- Recent research approaches
  - Statistical/machine-learning based classification
    - Roughan et al., IMC'04
    - McGregor et al., PAM'05
    - Moore et al., SIGMETRICS'05
  - Signature based
    - Varghese, Fingerhut, Bonomi, SIGCOMM'06
    - Bonomi, et al. SIGCOMM'06
  - IP blacklist/whitelist filtering to block bad traffic
    - Soldo+, Markopoulou, ITA'08
  - UCR/CAIDA a systematic study in progress:
    - What works, under which conditions, why?

Our contribution: BLINC

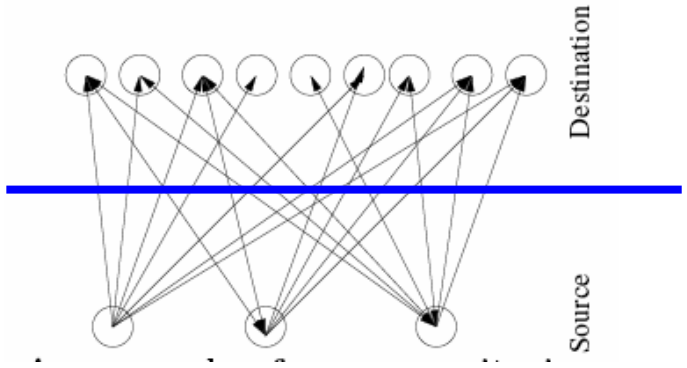
- BLINd Classification
  - ie without using payload
- We present a fundamentally different “in the dark” approach
  - We shift the focus to the host
- We identify “signature” communication patterns
  - Difficult to fake

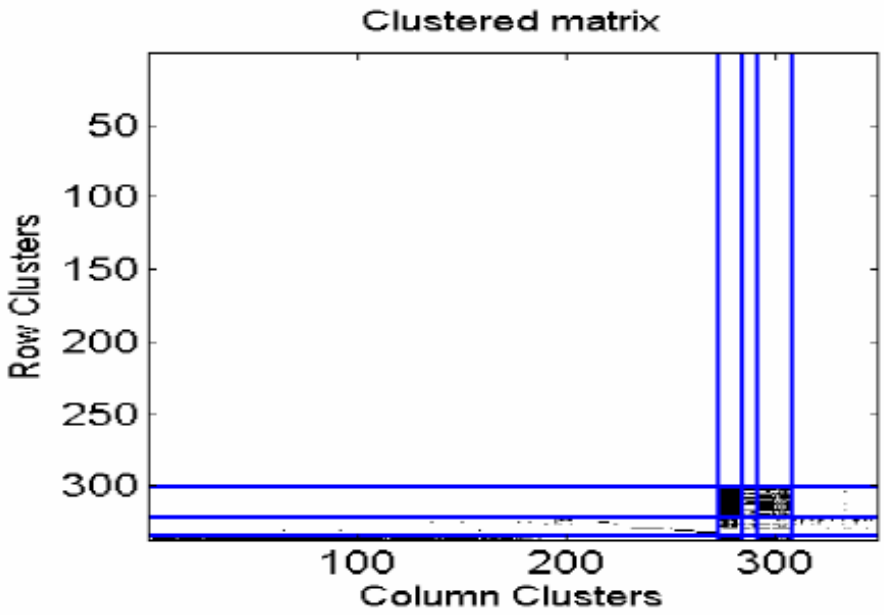
BLINC overview

- Characterize the host
  - Insensitive to network dynamics (wire speed)
- Deployable: Operates on flow records
  - Input from existing equipment
- Three levels of classification
  - Social : Popularity
  - Functional : Consumer/provider of services
  - Application : Transport layer interactions

Social Level

- Social:
  - Popularity
  - Bipartite cliques
- Gaming communities identified by using data mining:
  - fully automated cross-association
  - Chakrabarti et al KDD 20 (C. Faloutsos CMU)



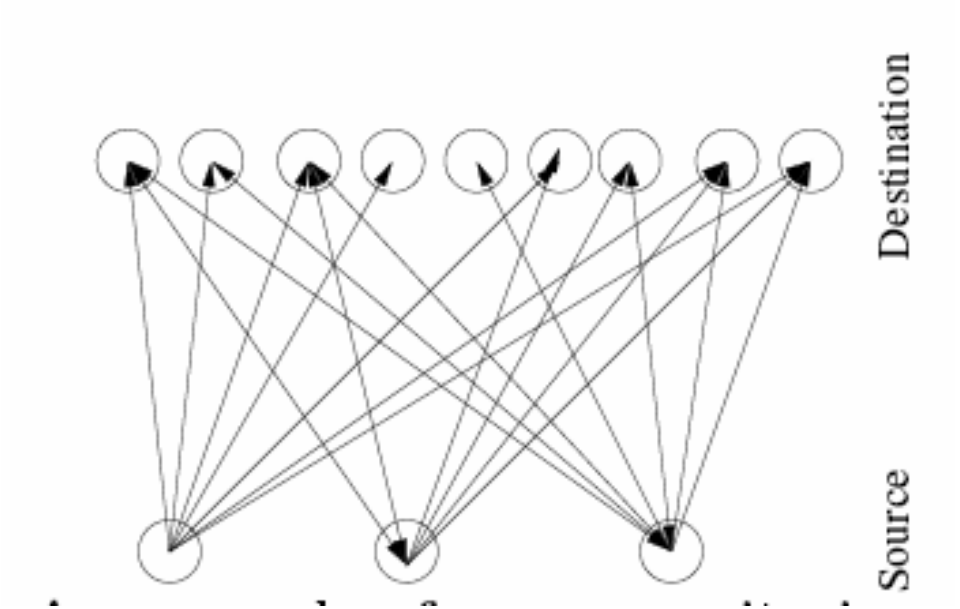


Functional level

- Functional:
  - Infer role of node
    - Server
    - Client
    - Collaborator
  - One way: #source ports vs. # of flows

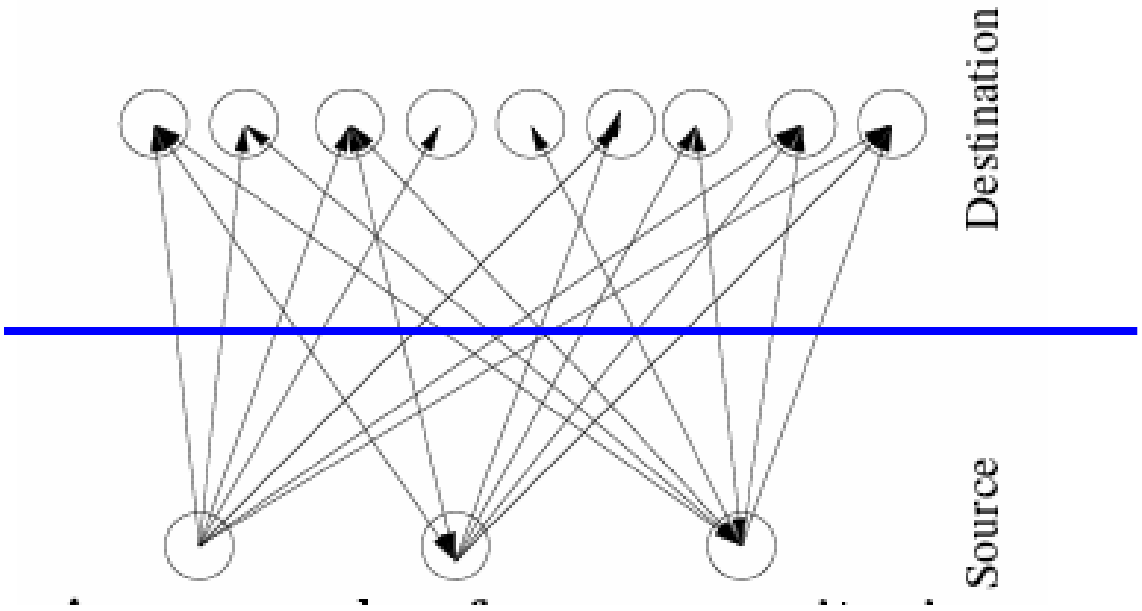
Social level

- Characterization of the popularity of hosts
- Two ways to examine the behavior:
  - Based on number of destination IPs
  - Analyzing communities



Social level: Identifying Communities

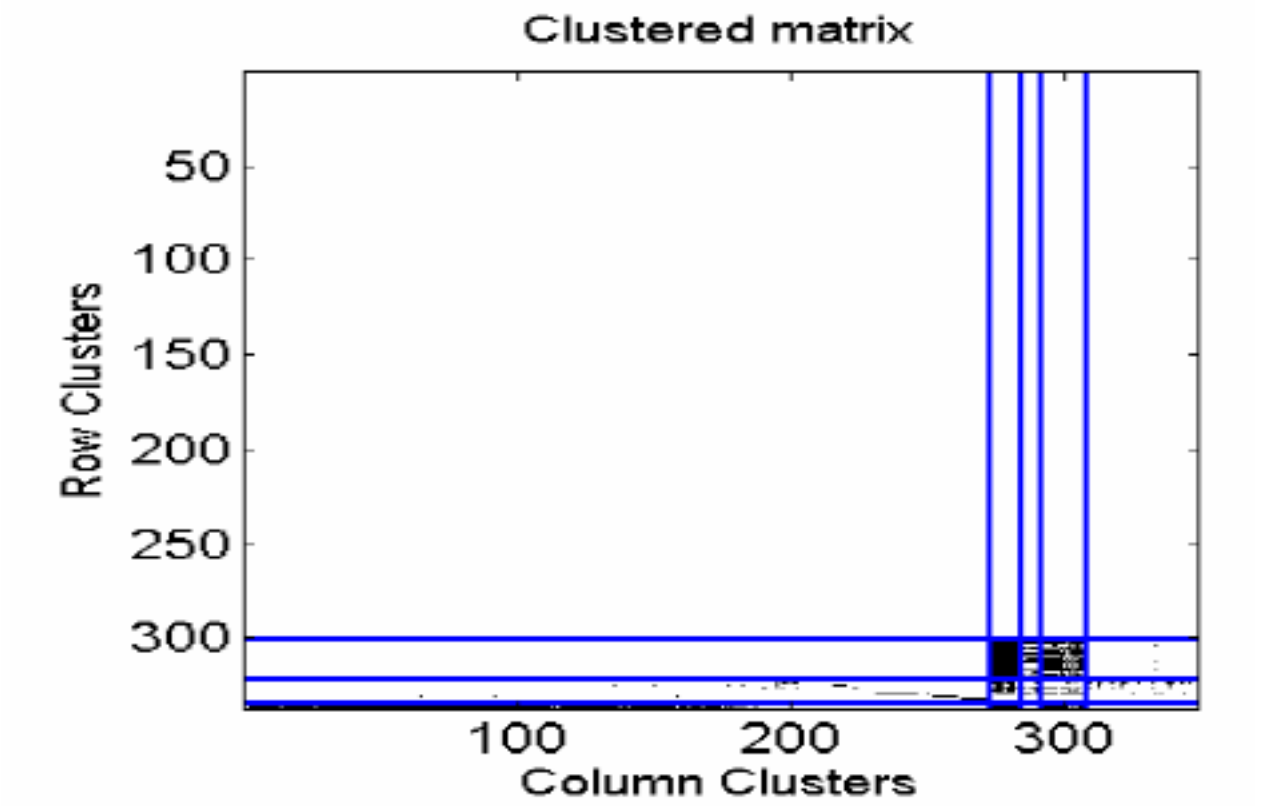
- Find bipartite cliques



Social Level: What can we see

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

Social Level: Finding communities in practice



- Gaming communities identified by using data mining: fully automated cross-association

Chakrabarti et al KDD 2004 (C. Faloutsos CMU)

Functional level

- Characterization based on tuple (IP, Port)
- Three types of behavior
  - Client
  - Server
  - Collaborative

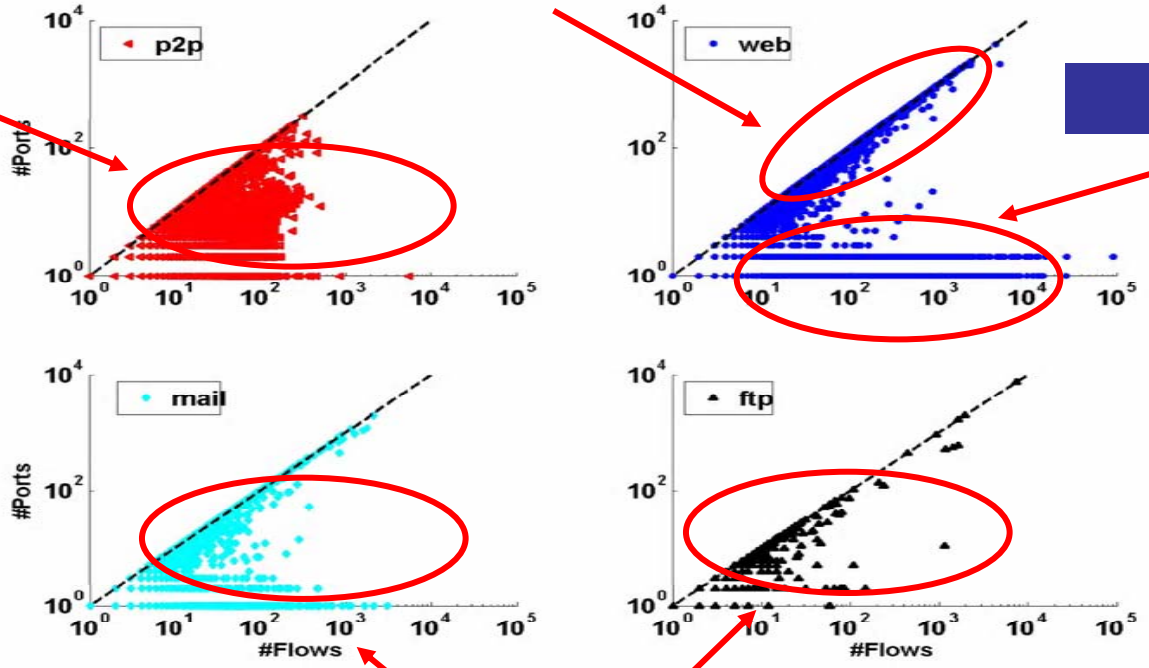
Functional level: Characterizing the host

Y-axis: number of source ports X-axis: number of flows

Collaborative applications: No distinction between servers and clients

Clients

Servers



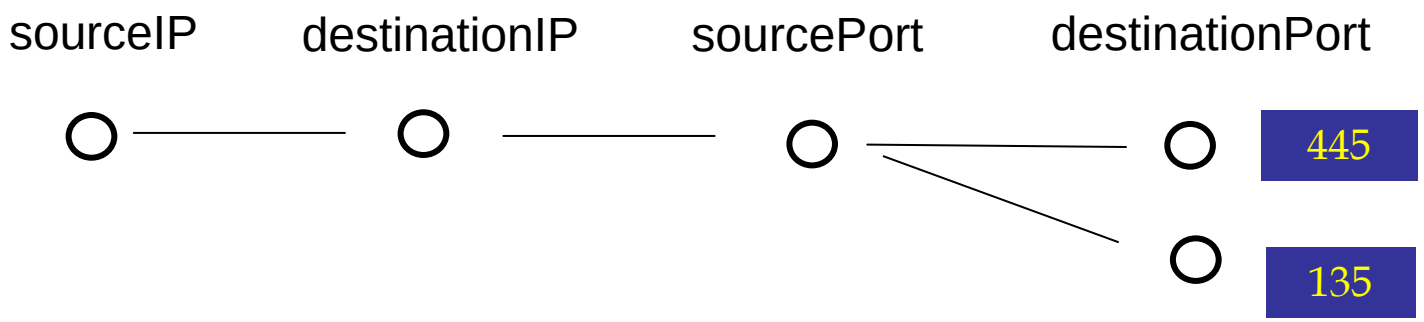
Obscure behavior due to multiple mail protocols and passive ftp

Application level

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

- We capture patterns using *graphlets*:
  - Most typical behavior
  - Relationship between fields of the 5-tuple

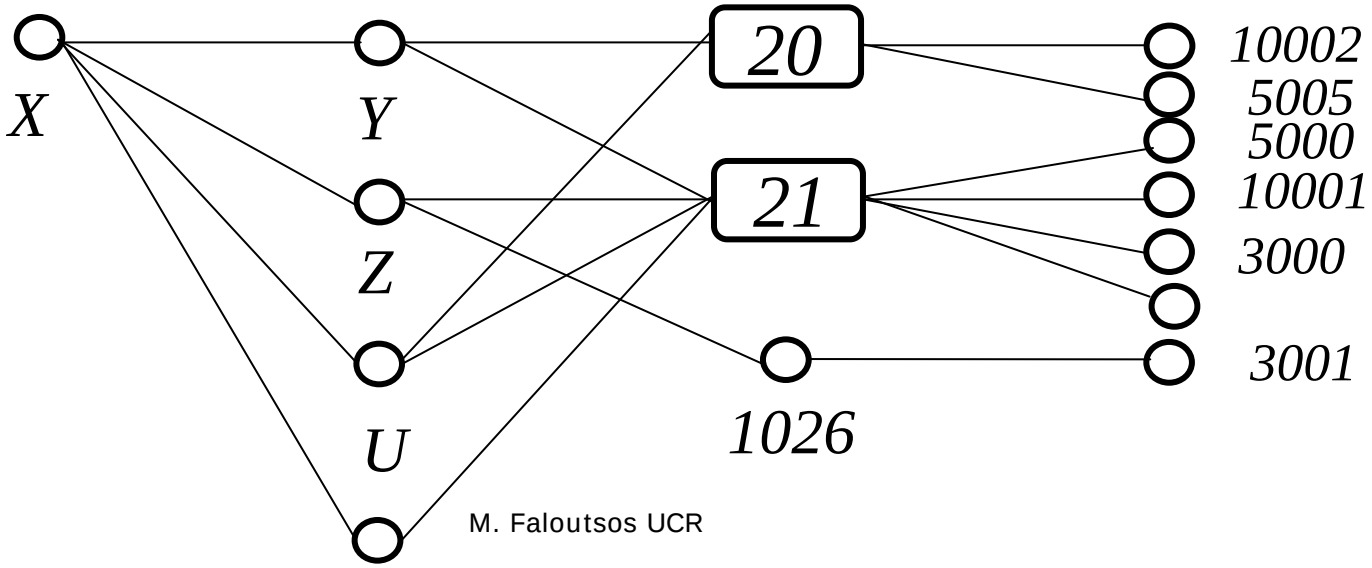
Application level: Graphlets



- Capture the behavior of a single host (IP address)
- Graphlets are graphs with four "columns":
  - src IP, dst IP, src port and dst port
- Each node is a distinct entry for each column
  - E.g. destination port 445
- Lines connect nodes that appear on the same flow

Graphlet Generation (FTP)

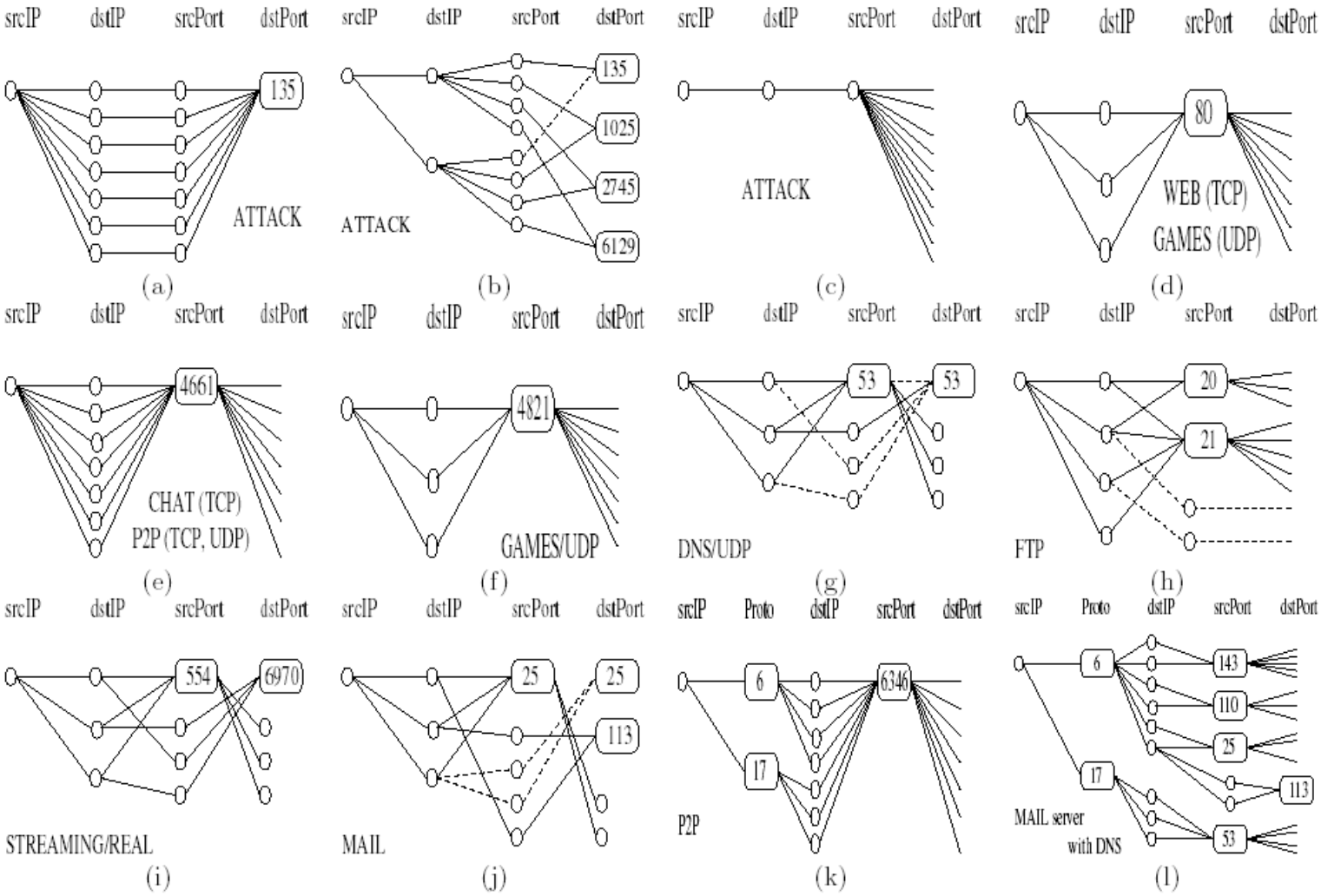
sourceIP	destinationIP	sourcePort	destinationPort
X	Z	21	3000
X	Z	1026	3001
X	U	21	5000
X	**U**	**20**	**5005**



What can Graphlets do for us?

- Graphlets
  - are a compact way to profile of a host
  - capture the intrinsic behavior of a host
- Premise:
  - Hosts that do the same, have similar graphlets
- Approach
  - Create graphlet profiles
  - Classify new hosts if they match existing graphlets

Training Part:
Create a Graphlet Library



Additional Heuristics

- In comparing graphlets, we can use other info:
  - the transport layer protocol (UDP or TCP).
  - the relative cardinality of sets.
  - the communities structure:
    - If X and Y talk to the same hosts, X and Y may be similar
    - Follow this recursively
- Other heuristics:
  - Using the per-flow average packet size
  - Recursive (mail/dns servers talk to mail/dns servers, etc.)
  - Failed flows (malware, p2p)

Evaluating BLINC

- We use real network traces
- Data provided by Intel:
  - Residential (Web, p2p)
  - Genome campus (ftp)
- Train BLINC on a small part of the trace
- Apply BLINC on the rest of the trace

Compare with what?

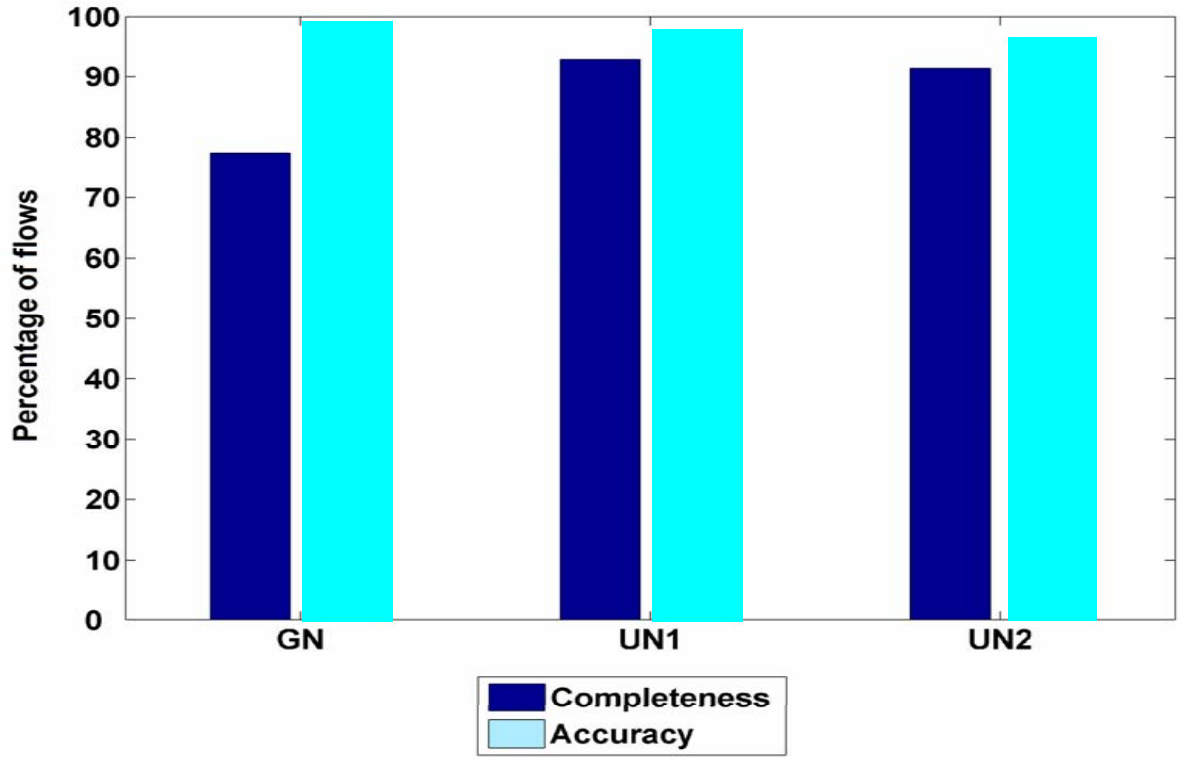
- Develop a reference point
  - Collect and analyze the whole packet
  - Classification based on payload signatures
- Not perfect but nothing better than this

Classification Results

- Metrics
  - Completeness
    - Percentage classified by BLINC relative to benchmark
    - “Do we classify most traffic?”
  - Accuracy
    - Percentage classified by BLINC correctly
    - “When we classify something, is it correct?”
  - Exclude unknown and nonpayload flows

Classification results : Totals

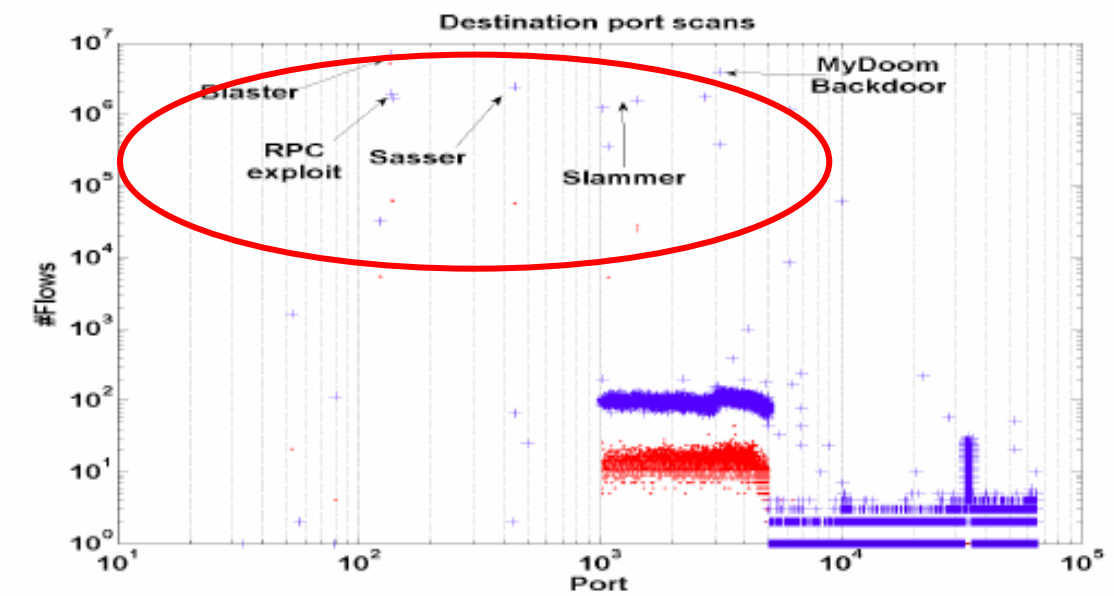
80%-90% completeness !
>90% accuracy !!



- BLINC works well

Characterizing the unknown: Non-payload flows

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

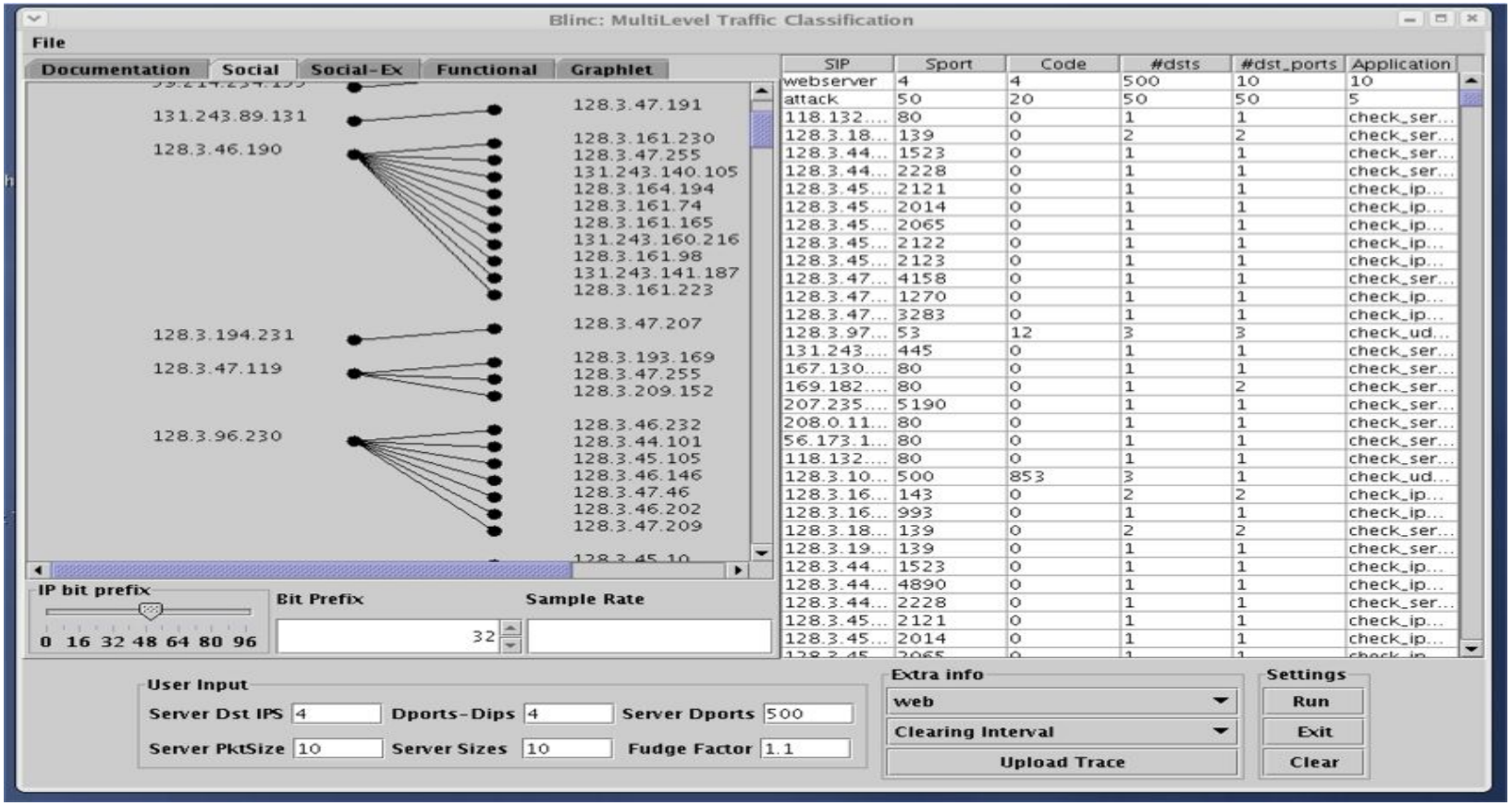


Flows classified as attacks reveal known exploits

BLINC issues and limitations

- How do we compare graphlets?
  - "Graph similarity" is difficult to define
  - Currently, based on heuristics and training
- What if a node runs two apps at the same time?
- Extensibility
  - Creating and incorporating new graphlets
- Application sub-types
  - e.g., BitTorrent vs. Kazaa
- Access vs. Backbone networks?
  - Works better for access networks (e.g. campus)

Developing a Useable Tool



SIP	Sport	Code	#dsts	#dst_ports	Application
webserver	4	4	500	10	10
attack	50	20	50	50	5
118.132....	80	0	1	1	check_ser...
128.3.18...	139	0	2	2	check_ser...
128.3.44...	1523	0	1	1	check_ser...
128.3.44...	2228	0	1	1	check_ser...
128.3.45...	2121	0	1	1	check_ip...
128.3.45...	2014	0	1	1	check_ip...
128.3.45...	2065	0	1	1	check_ip...
128.3.45...	2122	0	1	1	check_ip...
128.3.45...	2123	0	1	1	check_ip...
128.3.47...	4158	0	1	1	check_ser...
128.3.47...	1270	0	1	1	check_ip...
128.3.47...	3283	0	1	1	check_ip...
128.3.97...	53	12	3	3	check_ud...
131.243....	445	0	1	1	check_ser...
167.130....	80	0	1	1	check_ser...
169.182....	80	0	1	2	check_ser...
207.235....	5190	0	1	1	check_ser...
208.0.11...	80	0	1	1	check_ser...
56.173.1...	80	0	1	1	check_ser...
118.132....	80	0	1	1	check_ser...
128.3.10...	500	853	3	1	check_ud...
128.3.16...	143	0	2	2	check_ip...
128.3.16...	993	0	1	1	check_ip...
128.3.18...	139	0	2	2	check_ser...
128.3.19...	139	0	1	1	check_ser...
128.3.44...	1523	0	1	1	check_ip...
128.3.44...	4890	0	1	1	check_ip...
128.3.44...	2228	0	1	1	check_ser...
128.3.45...	2121	0	1	1	check_ip...
128.3.45...	2014	0	1	1	check_ip...

- Java front-end by Dhiman Barman UCR

Follow up work: Profiling the end user

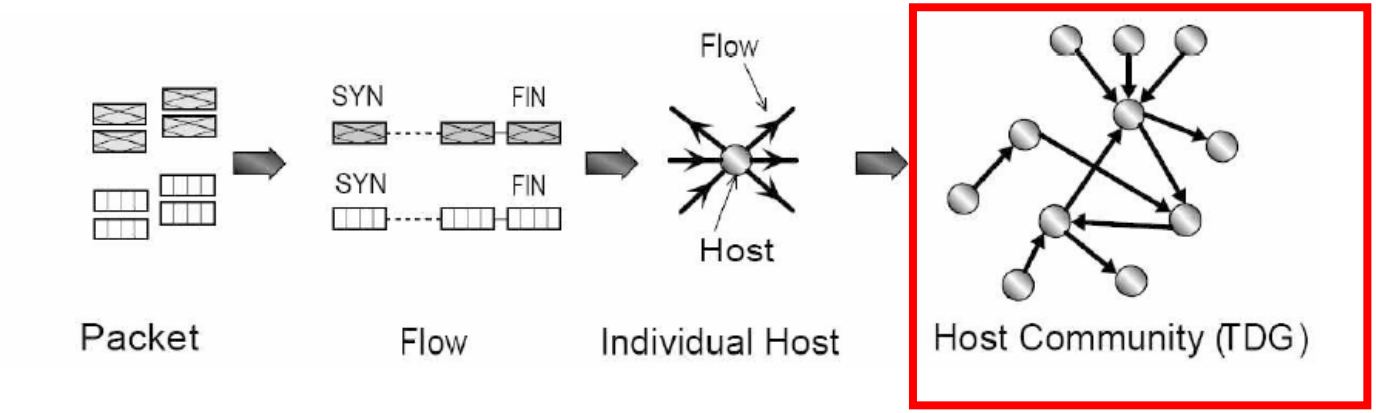
- We examine the dynamics of profiling
- How much variability exists
  - Per node over time
  - Among nodes in a network
- How can I summarize a graphlet
  - So that I can compare it with others?
- The answers in PAM 2007

Conclusions - I

- We shift the focus from flows to hosts
  - Capture the intrinsic behavior of a host
- Multi-level analysis:
  - each level provides more detail
- Good results in practice:
  - BLINC classifies 80-90% of the traffic with greater than 90% accuracy

Part II: Traffic Dispersion Graphs

- Monitoring traffic as a network-wide phenomenon

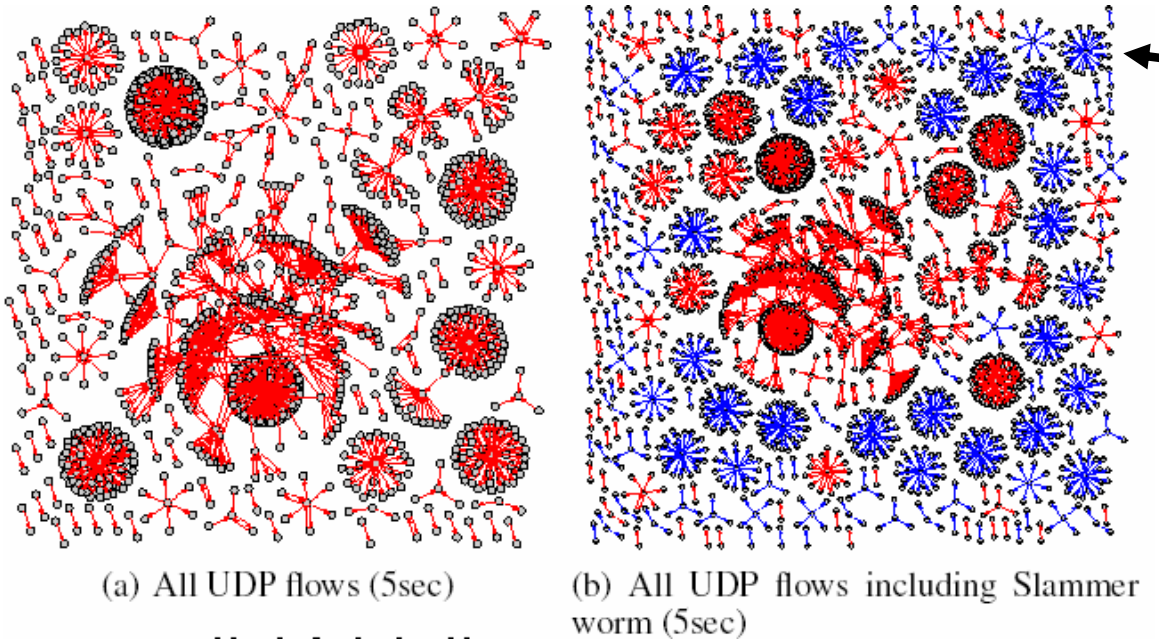


Paper at Internet Measurement Conference (IMC) 2007

Joint work with: Marios Iliofotou UC Riverside, G. Varghese UCSD

Prashanth Pappu, Sumeet Singh (Cisco) M. Mitzenmacher (Harvard)

Traffic Dispersion Graphs



(a) All UDP flows (5sec)

(b) All UDP flows including Slammer worm (5sec)

- Traffic Dispersion Graphs:
  - Who talks to whom
- Deceptively simple definition
- Provides powerful visualization and novel insight

Defining TDGs

- A node is an IP address (host, user)
- A key issue: define an edge (**Edge filter**)
  - Edge can represent different communications
  - Simplest: edge = the exchange of any packet
  - Edge Filter can be more involved:
    - A number of pkts exchanged
    - TCP with SYN flag set (initiating a TCP connection)
    - sequence of packets (e.g., TCP 3-way handshake)
    - Payload properties such as a content signature

Generating a TDG

- Pick a monitoring point (router, backbone link)
- Select an edge filter
  - Edge Filter = “What constitutes an edge in the graph?”
  - E.g., TCP SYN Dst. Port 80
- If a packet satisfies the edge filter, create the link
  - srcIP → dstIP
- Gather all the links and generate a graph
  - within a time interval, e.g., 300 seconds (5 minutes)

TDGs are a New Kind of Beast

- TDGs are
  - Directed graphs
  - Time evolving
  - Possibly disconnected
- TDGs are not yet another scalefree graph
- TDGs are not a single family of graphs
  - TDGs with different edge filters are different
- TDGs hide a wealth of information
  - Make “cool” visualizations
  - Can be “mined” to provide novel insight

TDGs and Preliminary Results

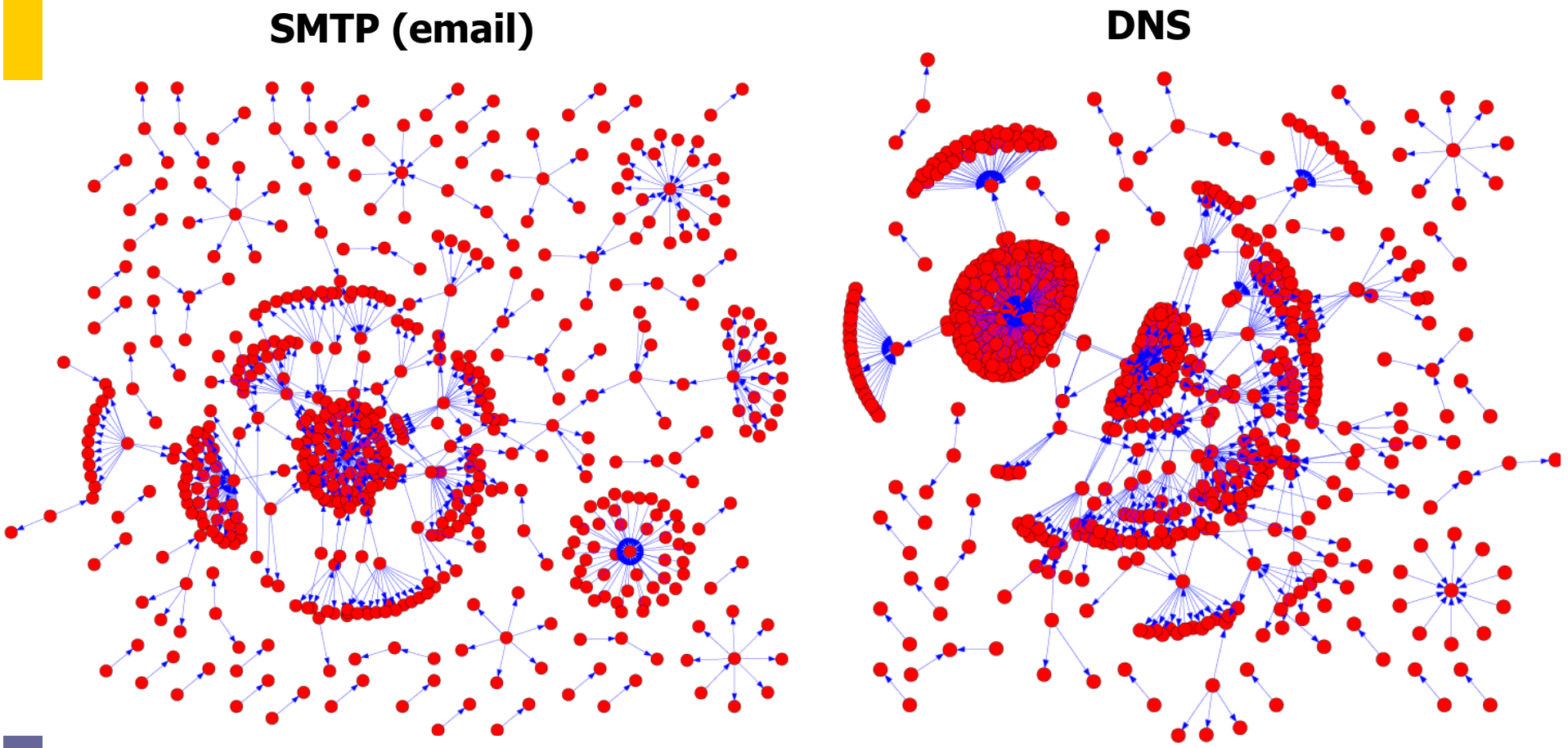
- We focus on studying **port-based TDGs**
  - Even that can give interesting information
- We study destination ports of known applications:
  - **UDP** ports: we generate an edge based on the first packet between two hosts
  - **TCP** we add an edge on a TCP SYN packet for the corresponding destination port number
    - e.g., port 80 for HTTP, port 25 for SMTP etc.

Data Used

- Real Data: typical duration = 1 hour
  - OC48 from CAIDA (22 million flows, 3.5 million IPs)
  - Abilene Backbone (23.5 million flows, 6 million IPs)
  - WIDE Backbone (5 million flows, 1 million IPs)
  - Access links traces (University of Auckland) + UCR traces were studied but not shown here (future work)

TDGs as a Visualization Tool

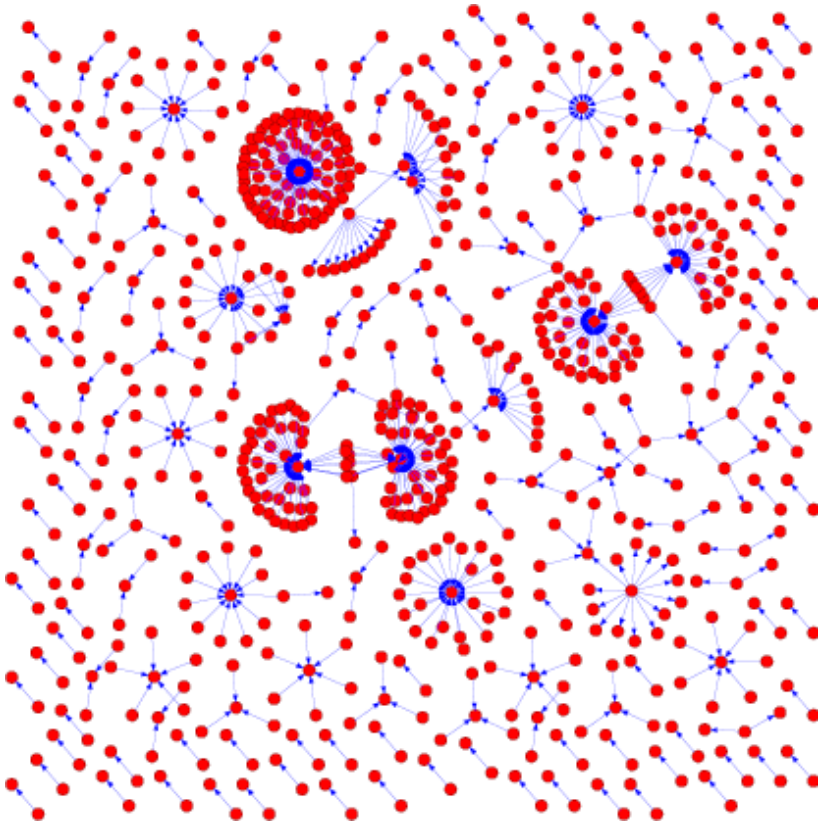
Identifying Hierarchies



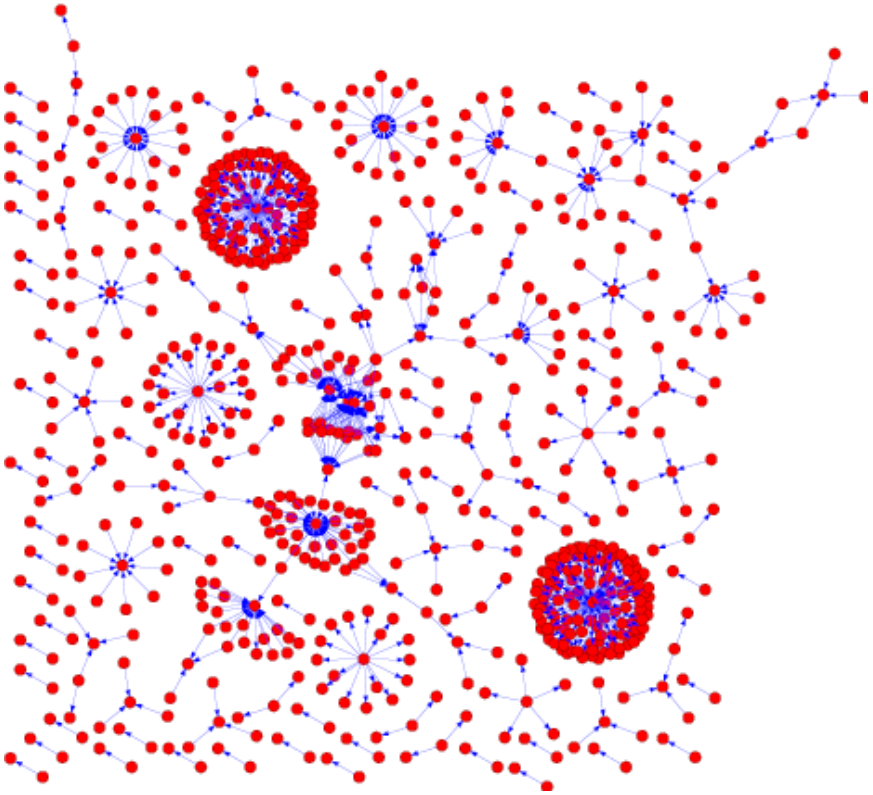
•Hierarchical structure with multiple levels of hierarchy

Web Traffic

Web: https



Web: port 8080



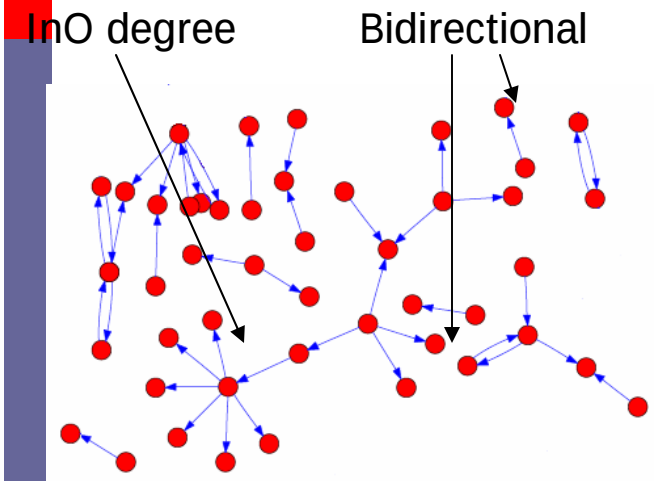
TDG Visualizations (Peer-to-Peer)

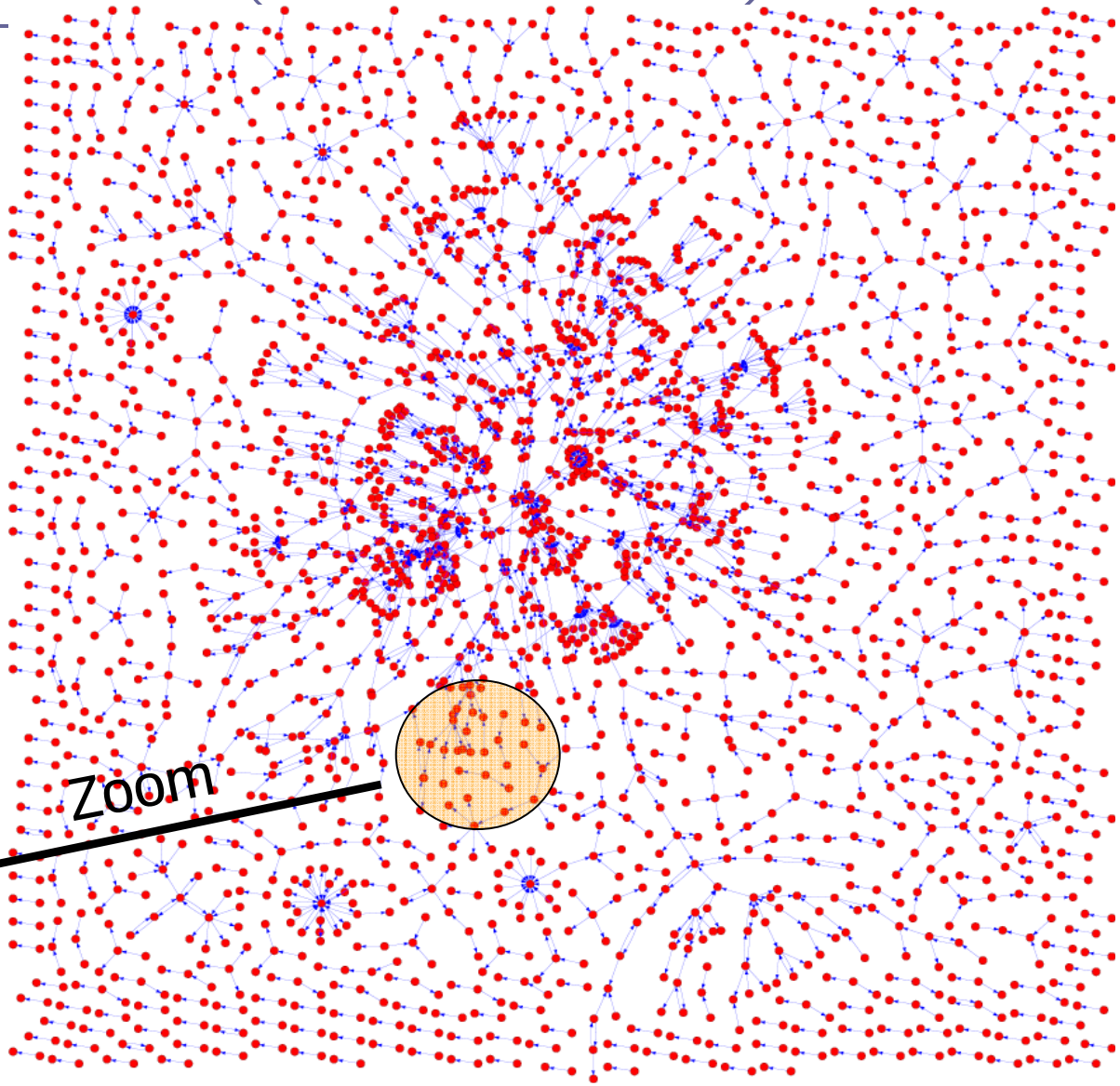
WinMX P2P App

- UDP Dst. Port 6257
- 15 sec

Observations

- Many nodes with in-and-out degree **(InO)**
- One large connected component
- Long chains

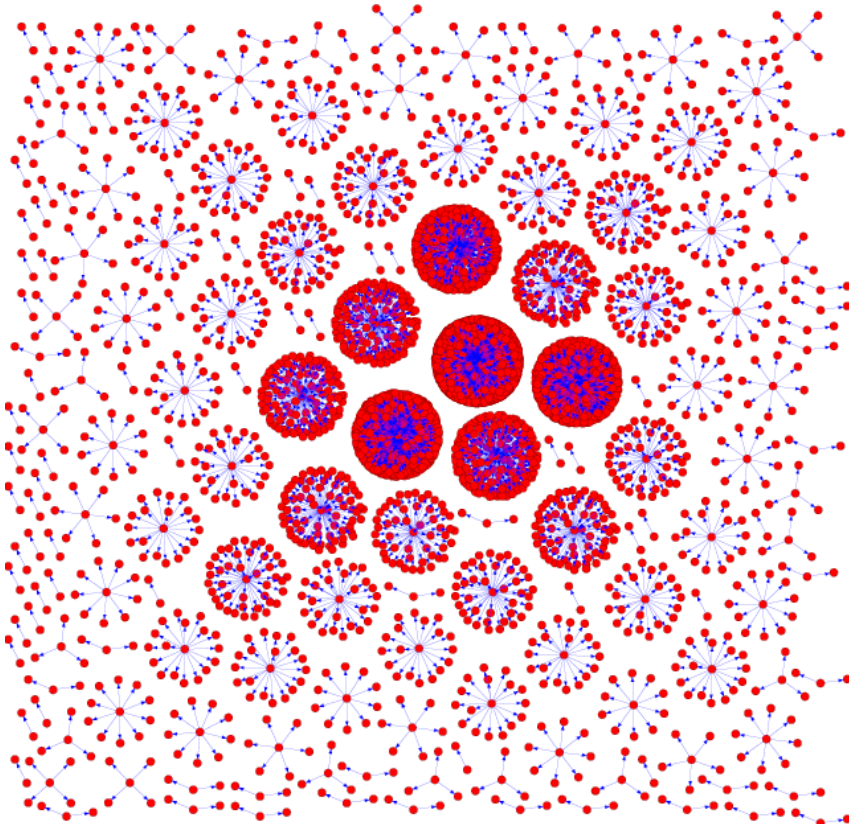




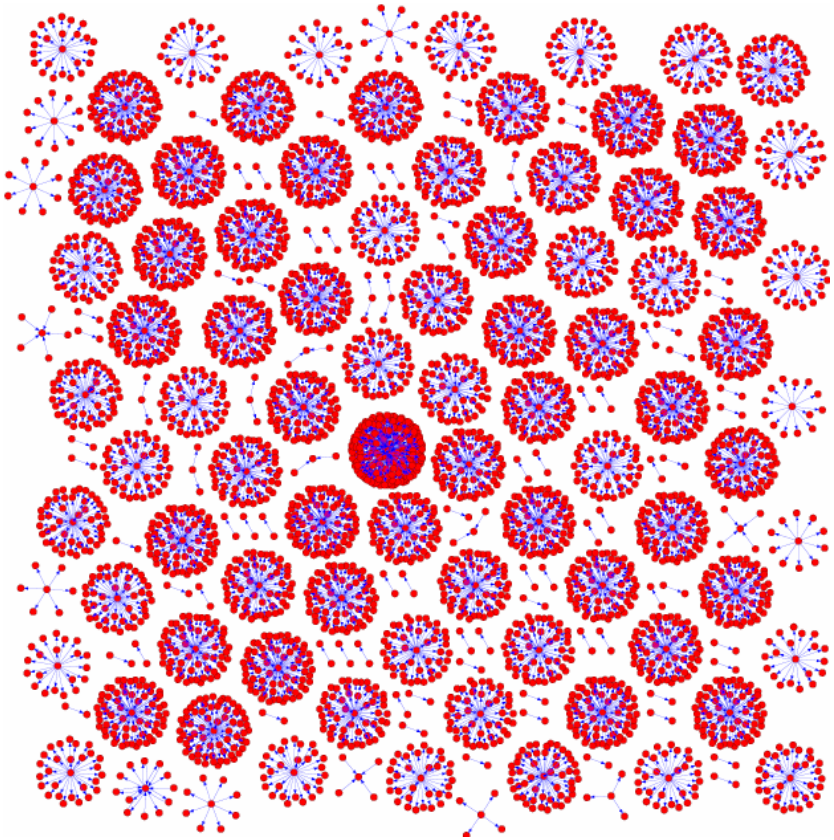
Detecting Viruses and Unusual Activities

Random IP range scanning activity?

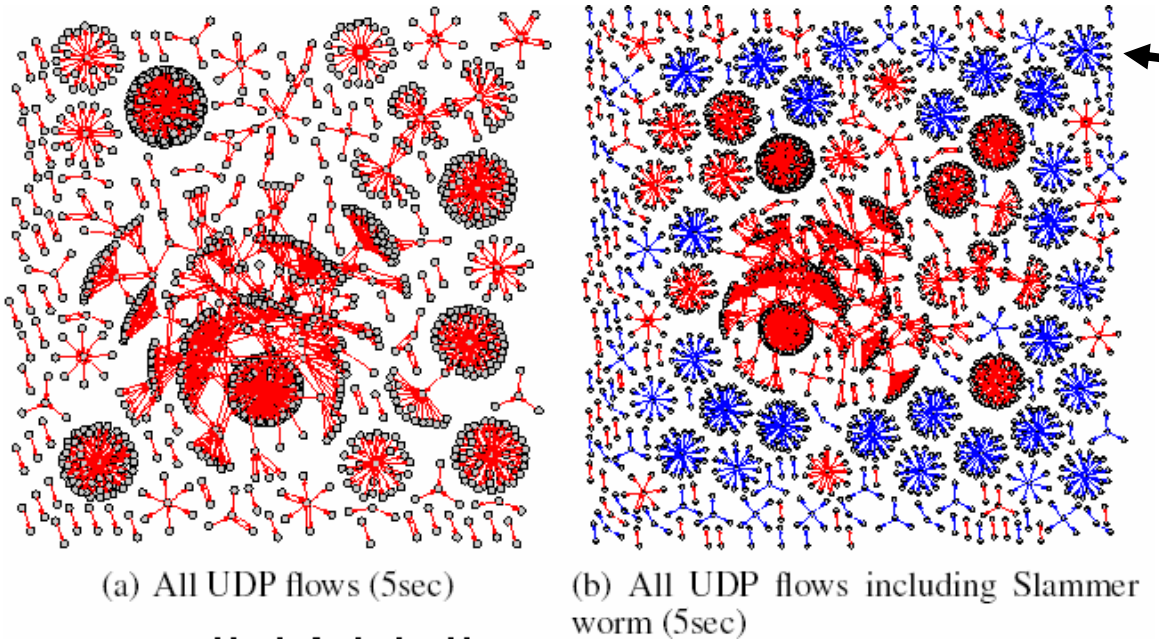
Slammer: port 1434



NetBIOS: port 137



Visually detecting virus activity



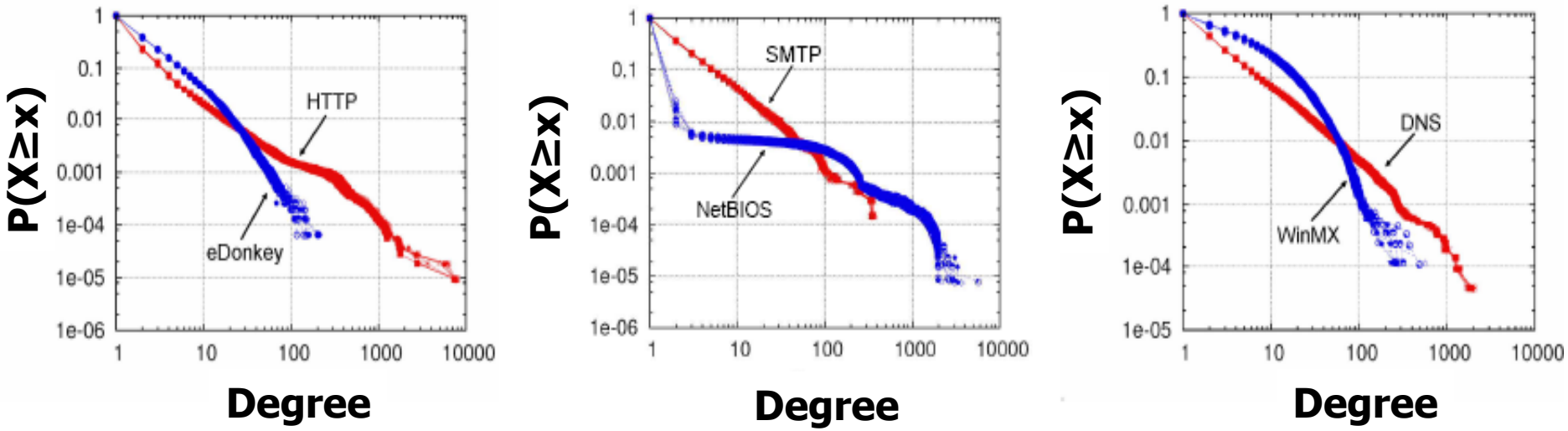
- Virus (slammer) creates more “star” configurations
- Directivity makes it clearer
  - Center node -> nodes, for virus “stars”

Quantitative Study of TDGs

Using Graph Metrics

- We use **new** and commonly used metrics
- Degree distribution
- Giant Connected Component
  - Largest connected subgraph
- Number of connected components
- In-Out nodes
  - Node with in- and out- edges
- Joint Degree Distribution

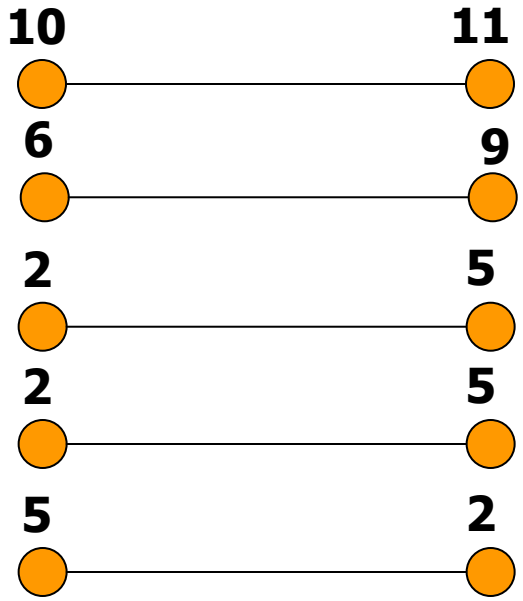
Degree Distribution



(a) HTTP Vs eDonkey (b) NetBIOS Vs SMTP (c) DNS Vs WinMX

- **The degree distributions of TDGs varies a lot.**
- Only some distributions can be modeled by power-laws (HTTP, DNS).
- P2P communities (eDonkey) have many medium degree nodes (4 to 30).
- HTTP and DNS have few nodes with very high degrees.
- NetBIOS: Scanning activity: 98% of nodes have degree of one, few nodes with very high degree → scanners

Joint Degree Distribution (JDD)

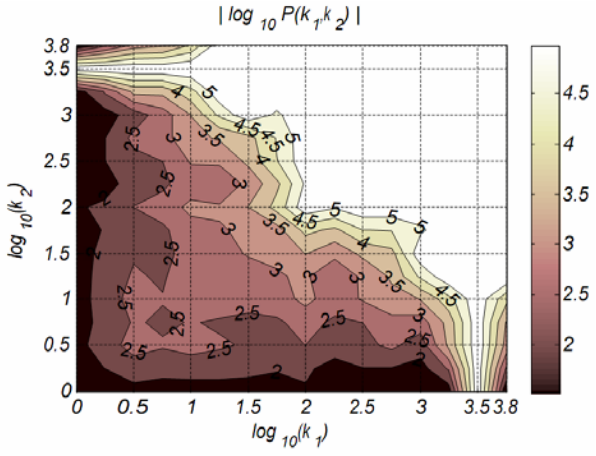


11										1	
10											1
9						1					
8											
7											
6									1		
5		3									
4											
3											
2					3						
1											
	1	2	3	4	5	6	7	8	9	10	11

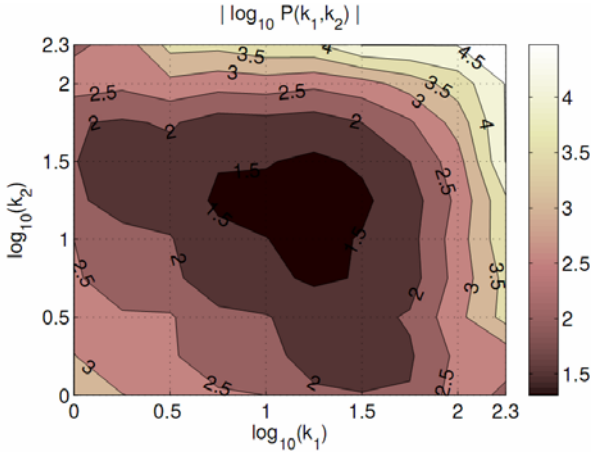
- **JDD: $P(k_1,k_2)$, the probability that a randomly selected edge connects nodes of degrees k_1 and k_2**
  - Normalized by the total Number of links

Joint Degree Distribution (JDD)

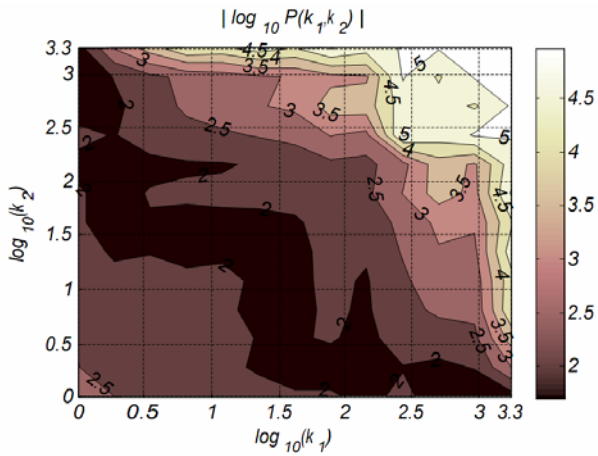
HTTP (client-server)



WinMX (peer-to-peer)



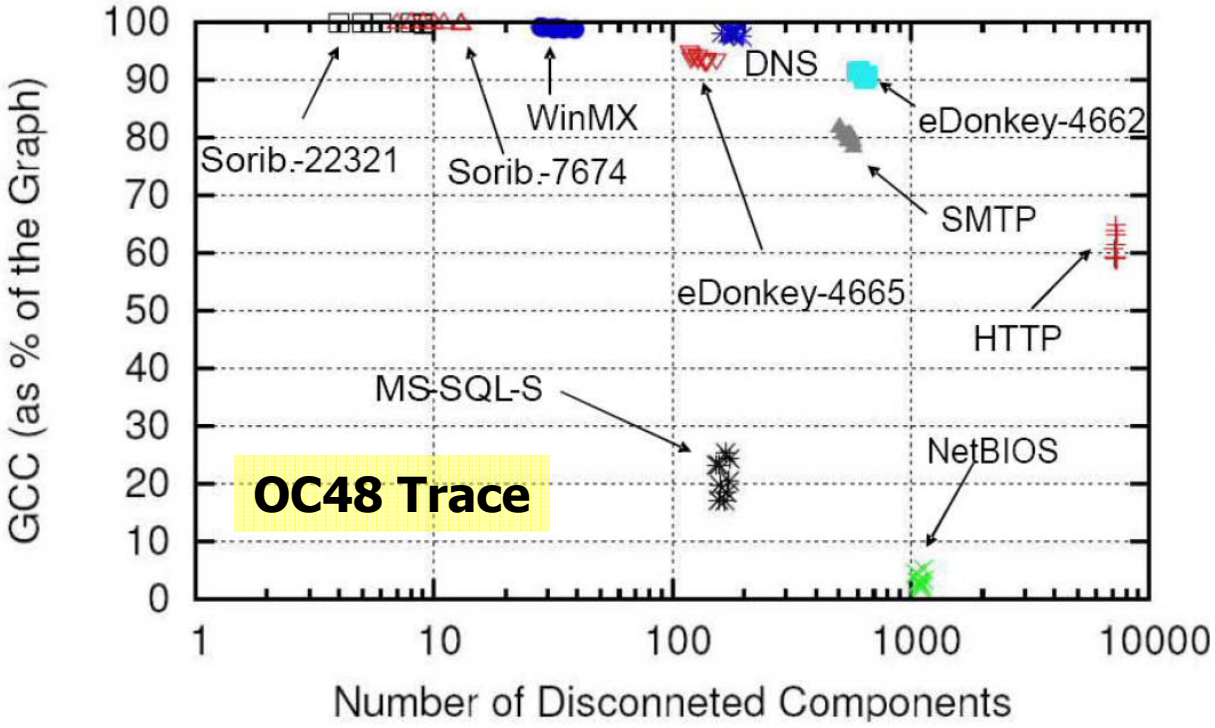
DNS (c-s and p2p)



- Couture plots (log-log scale due to high variability)
  - x-axis: Degree of the node on the one end of the link
  - y-axis: Degree of the other node
- Observations:
  - HTTP: low degree client to low to high degree servers
  - WinMX: medium degree nodes are connected
  - DNS: sings of both client server and peer-to-peer behavior
- Top degree nodes are not directly connected (top right corner)

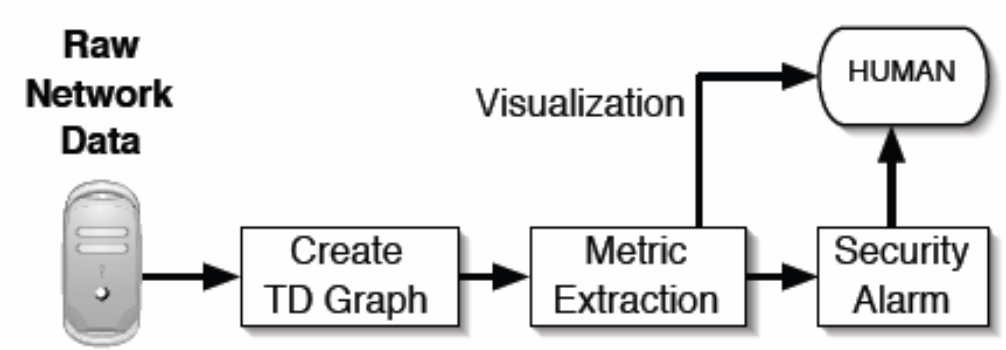
TDGs Can Distinguish Applications

- Monitor the top 10 ports number in number of flows.
- Scatter Plot:
  - Size of GCC Vs number of connected components.
- **Stable over Time!**
- We can separate apps!



- Soribada
  - UDP port 22321
  - UDP port 7674
- WinMX
  - UDP port 6257
- eDonkey
  - TCP port 4662
  - UDP port 4665
- NetBIOS
  - UDP port 137
- MS-SQL-S
  - TCP port 1433

TDGs as a Monitoring/Security Tool



- Two modes of operation:
  - Classification: based on previously observed thresholds.
  - Security: calculate TDGs and trigger an alarm on large change
- How do we choose which TDGs to monitor?
  - Manually,
  - Automatically-adaptively,
  - Using automatically extracted signatures of content (Earlybird)

Final Conclusions

- The “behavior” of hosts hides a information
  - Studying the transport-layer can provide insight
- We can do this at two levels
  - Host level using using BLINC
  - Network-wide level using TDGs
- Advantages:
  - More difficult to fake
  - More intuitive to interpret and deploy
- It can be used to monitor and secure

My Areas of Research

- Measurements and models for the Internet
  - Network Topology: models and patterns [ToN03, CSB06, NSDI07]
  - Traffic monitoring: models and classification [sigcomm05] [PAM07]
- Routing Security
  - Modeling and Securing BGP routing NEMECIS: [Infocom04, 07]
  - Adhoc routing security: [ICNP 06][ICNP07]
- Quantifying and protecting against URL hijacking [miniInfocom08]
- Design and capacity of WLANs and hybrid nets [mobicom07, infocom08]

- DART: A radical network layer for ad hoc [Infocom04] [ToN06]
- Cooperative Diversity in ad hoc networks [JSAC06, Infocom06]

Extras

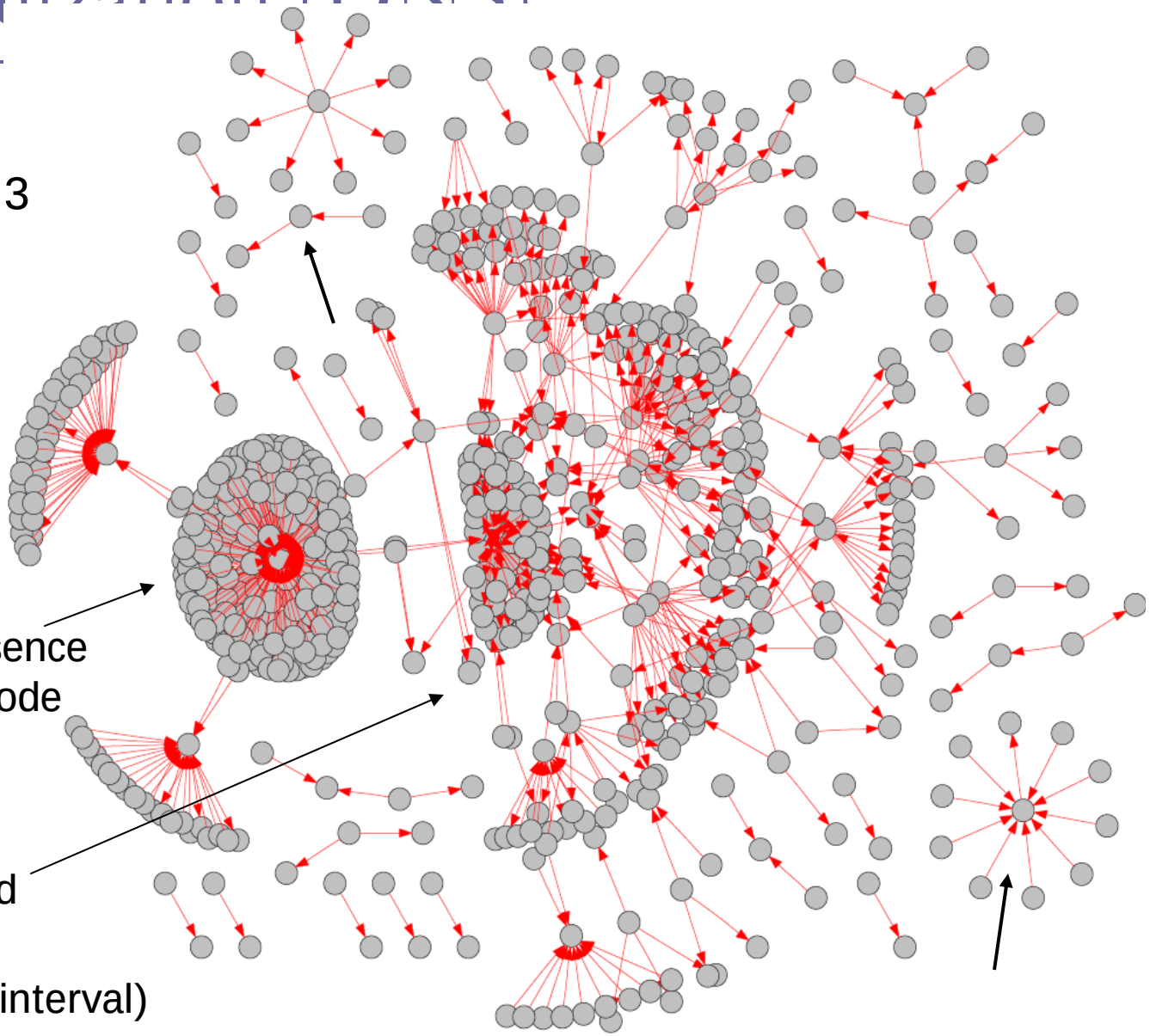
Main research areas

- Measurements
  - Traffic, BGP routing and topology, ad hoc
- Routing
  - scalable ad hoc, BGP instability
- Security
  - DoS, BGP attacks, ad hoc DoS
- Designing the future network
  - Rethinking the network architecture

TDG Visualization (DNS)

DNS TDG

- UDP Dst. Port 53
- 5 seconds



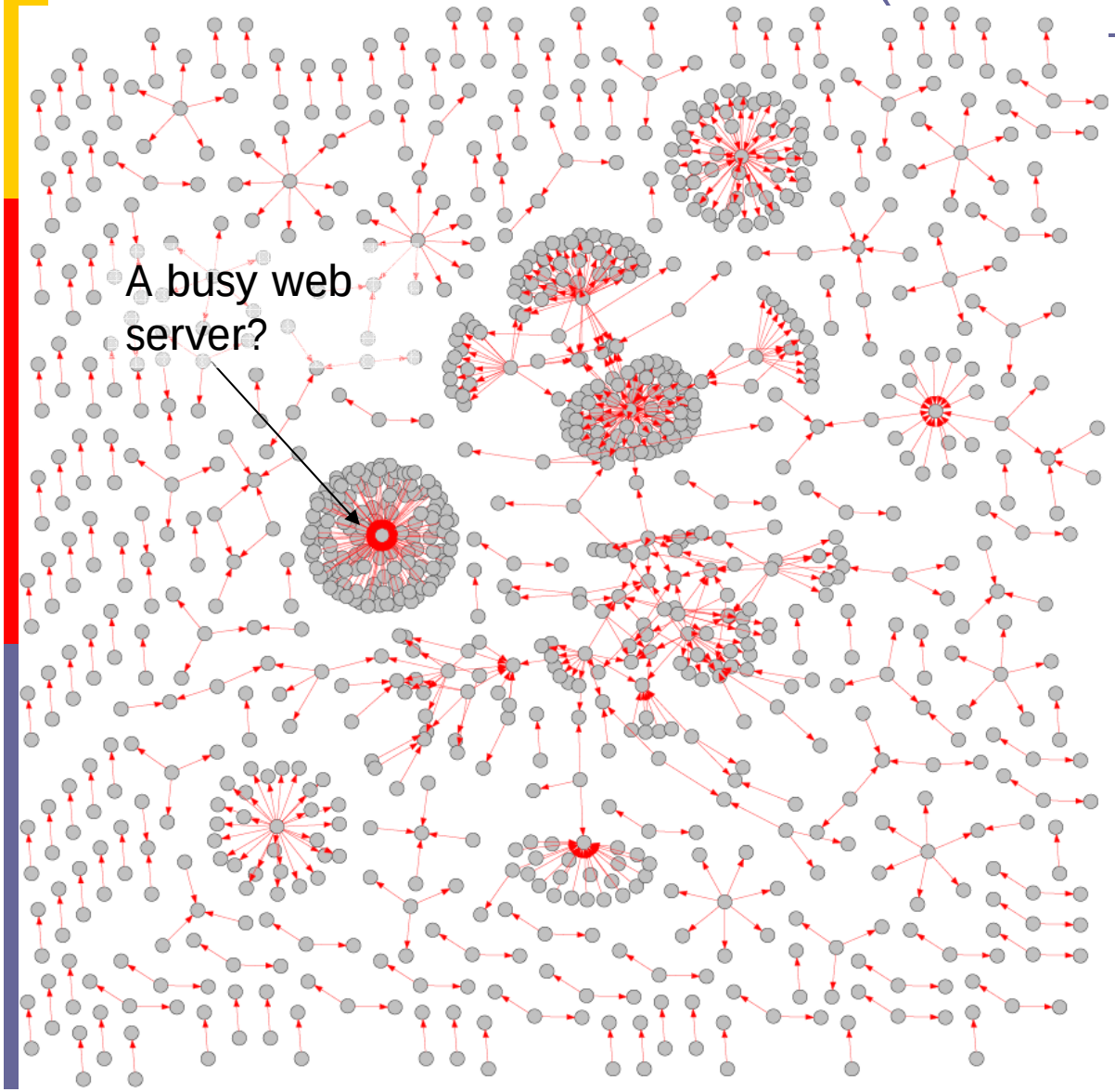
In- and Out-degree nodes

Very common in DNS, presence of few very high degree node

One large Connected Component!

(even in such small interval)

TDG Visualization (HTTP)



HTTP TDG

- **TCP SYN Dst. Port 80**
- **30 seconds**

Observations

- There is <u>not</u> a large connected component as in DNS
- Clear roles
  - very few nodes with in-and-out degrees)
    - Web caches?
    - Web proxies?
- Many disconnected components

TDG Visualization (Slammer Worm)

Slammer Worm

- UDP Dst. port 1434
- 10 seconds
- About:
  - Jan 25, 2003. MS-SQL-Server 2000 exploit.
    - Trace: April 24th
- Observations (Scanning Activity)
  - Many high out-degree nodes
  - Many disconnected components
  - The majority of nodes have **only in-degree** (nodes being scanned)