MiningTraffic Data

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Roadmap

- Introduction
- Traffic data and analysis tools:
  - data collection, statistical analysis, clustering tools, prediction analysis
- Case studies:
  - satellite network: ChinaSat
  - packet data networks: Internet
  - BC.NET traffic measurements
  - public safety wireless network: E-Comm
- Conclusions and references

Graduate students

M.Sc. and M.Eng. students at SFU:

- ChinaSat data analysis:
  - Qing (Kenny) Shao
  - Savio Lau
- E-Comm data analysis:
  - Duncan Sharp
  - Hao (Leo) Chen
  - Bozidar Vujičić
  - Nikola Cackov
  - Svetlana Vujičić
  - Nenad Lasković
- Internet data analysis:
  - Hao (Johnson) Chen
- BC.NET measurements:
  - Mohamadreza Najiminaini
  - Laxmi Subedi

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Network traffic measurements

- Traffic measurements in operational networks help:
  - understand traffic characteristics in deployed networks
  - develop traffic models
  - evaluate performance of protocols and applications
- Analysis of traffic:
  - provides information about the user behavior patterns
  - enables network operators to understand the behavior of network users
- Traffic prediction: important to assess future network capacity requirements and to plan future network developments

Statistical properties: self-similarity

- Self-similarity implies a "fractal-like" behavior: data on various time scales have similar patterns
- A wide-sense stationary process X(n) is called (exactly second order) self-similar if its autocorrelation function satisfies:
  - $r^{(m)}(k) = r(k), k \geq 0, m = 1, 2, \ldots, n,$

    where m is the level of aggregation
- Implications:
  - no natural length of bursts
  - bursts exist across many time scales
  - traffic does not become "smoother" when aggregated (unlike Poisson traffic)

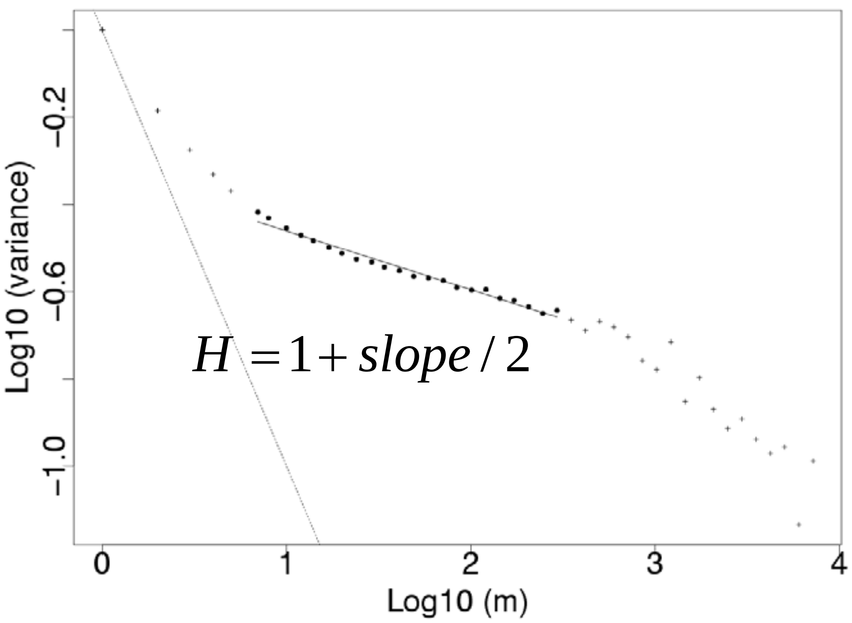
Self-similar processes

- Properties:
  - slowly decaying variance
  - long-range dependence
  - Hurst parameter (H)
- Processes with only short-range dependence (Poisson): $H = 0.5$
- Self-similar processes: $0.5 < H < 1.0$
- As the traffic volume increases, the traffic becomes more bursty, more self-similar, and the Hurst parameter increases

Estimation of H

Various estimators:

- variance-time plots
- R/S plots
- periodograms
- wavelets



Their performance often depends on the characteristics of the data trace under analysis

Clustering analysis

- Clustering analysis groups or segments a collection of objects into subsets or clusters
- Objects within a cluster are more similar to each other than objects in distinct clusters
- An object can be described by a set of measurements or by its relations to other objects
- Network users are classified into clusters, according to the similarity of their behavior patterns

Clustering analysis

- Groups collection of objects into subsets (clusters):
  - resulting intra-cluster similarity is high while inter-cluster similarity is low
- The inter-cluster distance reflects dissimilarity between clusters:
  - Euclidean distance between two cluster centroids (mean value of objects in a cluster, viewed as cluster's center of gravity)
- The intra-cluster distance expresses coherent similarity of data in the same cluster:
  - average distance of objects from their cluster centroids
- Better clustering:
  - large inter-cluster and small intra-cluster distances

Clustering quality

- Overall clustering quality: defined as difference between minimum inter-cluster and maximum intra-cluster distances
  - larger indicator implies better overall clustering quality
- Silhouette coefficient (x):

$$(b(x) - a(x)) / \max \{a(x), b(x)\}$$

  a(x) and b(x) are average distances between data point x and other data points in clusters A and B, respectively
  - independent of number of clusters K

Clustering algorithms

- Two approaches:
  - partitioning clustering (k-means)
  - hierarchical clustering
- Clustering tools:
  - k-means algorithm
  - AutoClass tool

L. Kaufman and P. J. Rousseeuw, *Finding Groups in Data: An Introduction to Cluster Analysis*. New York: John Wiley & Sons, 1990.

P. Cheeseman and J. Stutz, "Bayesian classification (AutoClass): theory and results," in *Advances in Knowledge Discovery and Data Mining*, U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy, Eds., AAAI Press/MIT Press, 1996.

Clustering algorithms: k-means

- The k-means algorithm is commonly used for data clustering
- The algorithm is well-known for its simplicity and efficiency
- Based on the input parameter k, it partitions a set of n objects into k clusters so that the resulting intra-cluster similarity is high and the inter-cluster similarity is low
- Similarity of clusters is measured with respect to the mean value of the objects in a cluster (viewed as the cluster's center of gravity)

Finding number of clusters

- The number of clusters k is not known a priori
- k-means algorithm is repeated for different k values
- Number of clusters is found by comparing average SC value for various values of k:
  - average SC is calculated for all objects
  - the natural number of clusters k is found at the local maxima

SC: silhouette coefficient

Traffic prediction: ARIMA model

- Auto-Regressive Integrated Moving Average (ARIMA) model:
  - general model for forecasting time series
  - past values: AutoRegressive (AR) structure
  - past random fluctuant effect: Moving Average (MA) process
- ARIMA model explicitly includes differencing
- ARIMA (p, d, q):
  - autoregressive parameter: p
  - number of differencing passes: d
  - moving average parameter: q

Traffic prediction: SARIMA model

- Seasonal ARIMA is a variation of the ARIMA model
- Seasonal ARIMA (SARIMA) model:

$$(p, d, q) \times (P, D, Q)_S$$

  - captures seasonal pattern
- SARIMA additional model parameters:
  - seasonal period parameter: S
  - seasonal autoregressive parameter: P
  - number of seasonal differencing passes: D
  - seasonal moving average parameter: Q

SARIMA models: selection criteria

- Order (p,d,q) selected based on:
  - time series plot of traffic data
  - autocorrelation and partial autocorrelation functions
- Validity of parameter selection:
  - Akaike's information criterion:
    - AIC
    - corrected AICc
  - Bayesian information criterion BIC

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ChinaSat data: analysis

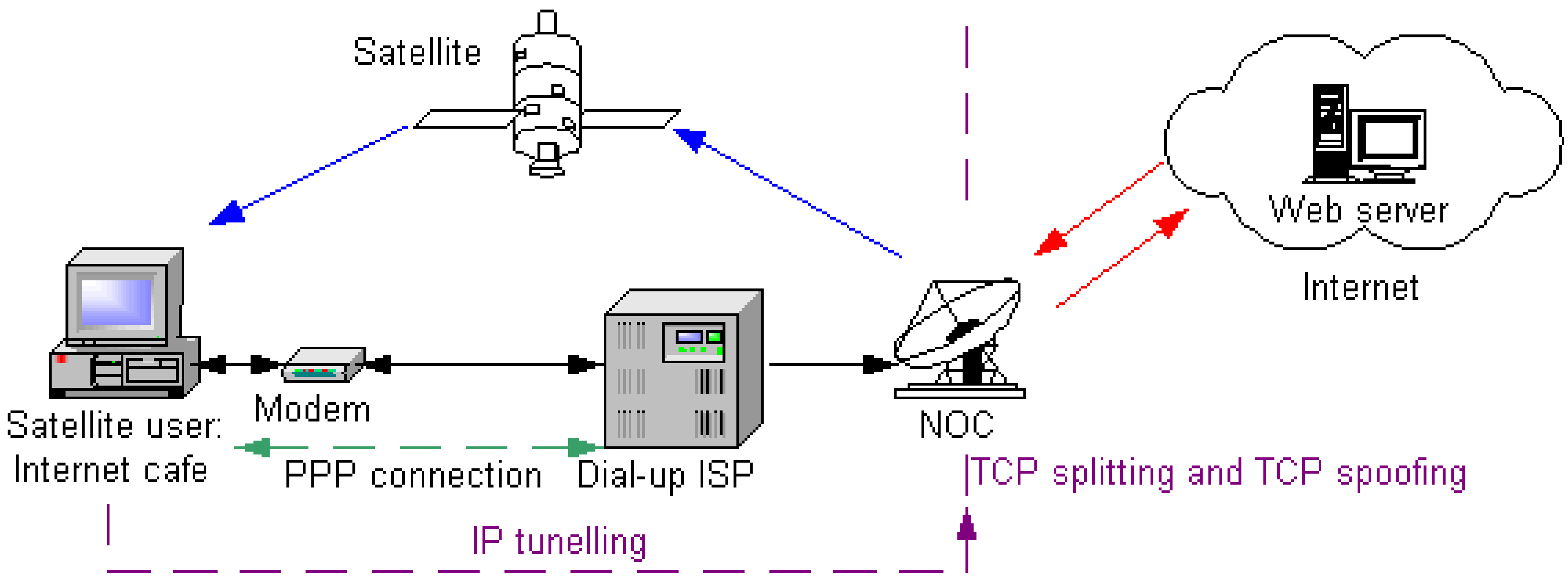
- Analysis of network traffic:
  - characteristics of TCP connections
  - network traffic patterns
  - statistical and cluster analysis of traffic
  - anomaly detection:
    - statistical methods
    - wavelets
    - principle component analysis

TCP: transport control protocol

Network and traffic data

- ChinaSat: network architecture and TCP
- Analysis of billing records:
  - aggregated traffic
  - user behavior
- Analysis of tcpdump traces:
  - general characteristics
  - TCP options and operating system (OS) fingerprinting
  - network anomalies

DirecPC system diagram



ChinaSat network

- ChinaSat hybrid satellite network
  - Employs geosynchrous satellites deployed by Hughes Network Systems Inc.
  - Provides data and television services:
    - DirecPC (Classic): unidirectional satellite data service
    - DirecTV: satellite television service
    - DirecWay (Hughnet): new bi-directional satellite data service that replaces DirecPC
  - DirecPC transmission rates:
    - 400 kb/s from satellite to user
    - 33.6 kb/s from user to network operations center (NOC) using dial-up
  - Improves performance using TCP splitting with spoofing

ChinaSat data: analysis

- ChinaSat traffic is self-similar and non-stationary
- Hurst parameter differs depending on traffic load
- Modeling of TCP connections:
  - inter-arrival time is best modeled by the Weibull distribution
  - number of downloaded bytes is best modeled by the lognormal distribution
- The distribution of visited websites is best modeled by the discrete Gaussian exponential (DGX) distribution

ChinaSat data: analysis

- Traffic prediction:
  - autoregressive integrative moving average (ARIMA) was successfully used to predict uploaded traffic (but not downloaded traffic)
  - wavelet + autoregressive model outperforms the ARIMA model

Q. Shao and Lj. Trajkovic, "Measurement and analysis of traffic in a hybrid satellite-terrestrial network," *Proc. SPECTS 2004*, San Jose, CA, July 2004, pp. 329–336.

Analysis of collected data

- Analysis of patterns and statistical properties of two sets of data from the ChinaSat DirecPC network:
  - billing records
  - tcpdump traces
- Billing records:
  - daily and weekly traffic patterns
  - user classification:
    - single and multi-variable k-means clustering based on average traffic
    - hierarchical clustering based on user activity

Analysis of collected data

- Analysis of tcpdump trace
  - tcpdump trace:
    - protocols and applications
    - TCP options
    - operating system fingerprinting
    - network anomalies
  - Developed C program pcapread:
    - processes tcpdump files
    - produces custom output
    - eliminates the need for packet capture library libpcap

Network anomalies

- Scans and worms:
  - packets are sent to probe network hosts
  - used to discover and exploit resources
- Denial of service:
  - large number of packets is directed to a single destination
  - makes a host incapable of handling incoming connections or exhausts available bandwidth along paths to the destination

Network anomalies

- Flash crowd:
  - high volume of traffic is destined to a single destination
  - caused by breaking news or availability of new software
- Traffic shift:
  - redirection of traffic from one set of paths to another
  - caused by route changes, link unavailability, or network congestion

Network anomalies

- Alpha traffic:
  - unusually high volume of traffic between two endpoints
  - caused by file transfers or bandwidth measurements
- Traffic volume anomalies:
  - significant deviation of traffic volume from usual daily or weekly patterns
  - classified as:
    - outages: caused by unavailable links, crashed servers, or routing problems
    - short term increases in demand: caused by short term events such as holiday traffic
  - involve multiple sources and destinations

Billing records

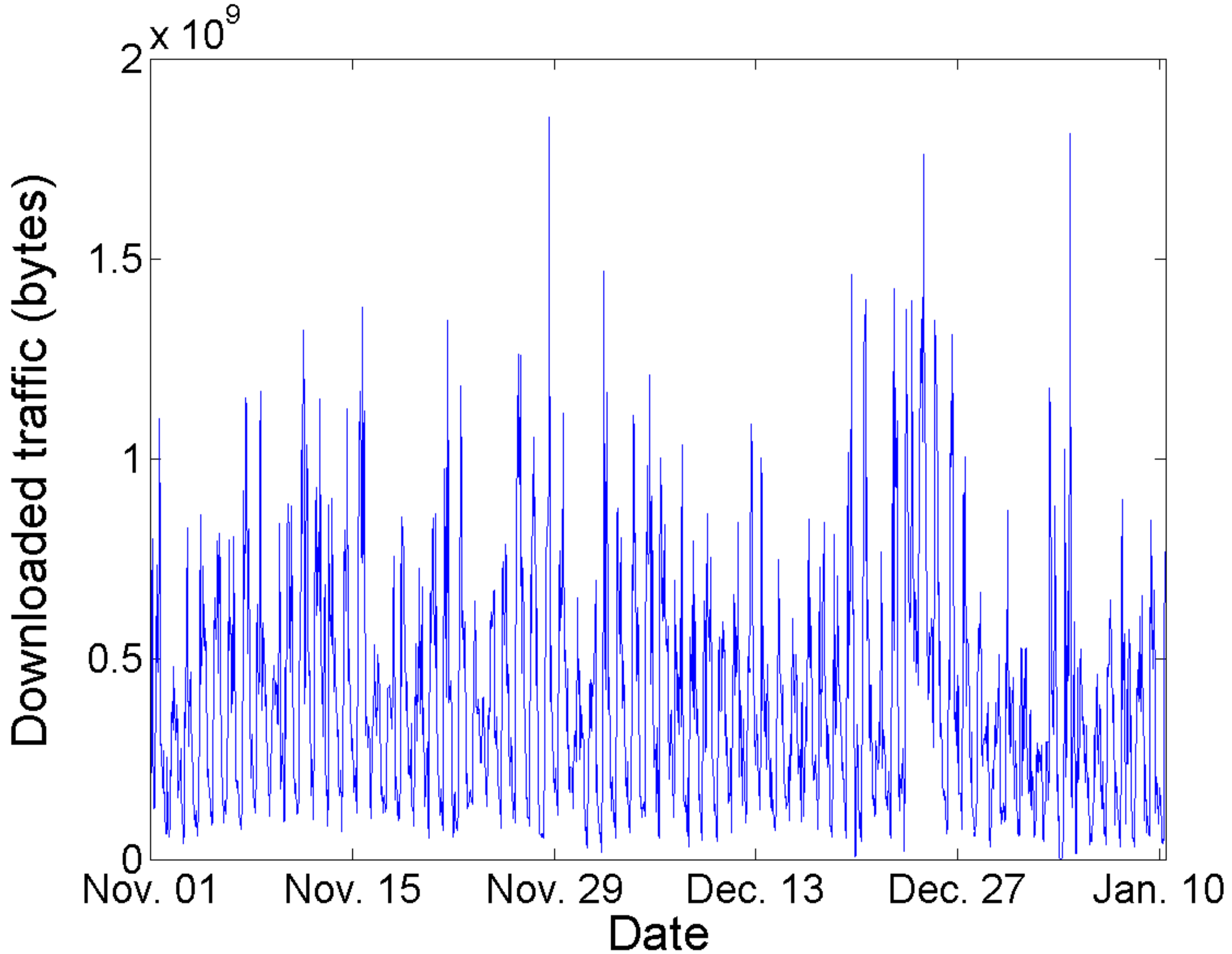
- Records were collected during the continuous period from 23:00 on Oct. 31, 2002 to 11:00 on Jan. 10, 2003
- Each file contains the hourly traffic summary for each user
- Fields of interests:
  - SiteID (user identification)
  - Start (record start time)
  - CTxByt (number of bytes downloaded by a user)
  - CRxByt (number of bytes uploaded by a user)
  - CTxPkt (number of packets downloaded by a user)
  - CRxPkt (number of packets uploaded by a user)

download: satellite to user
upload: user to NOC

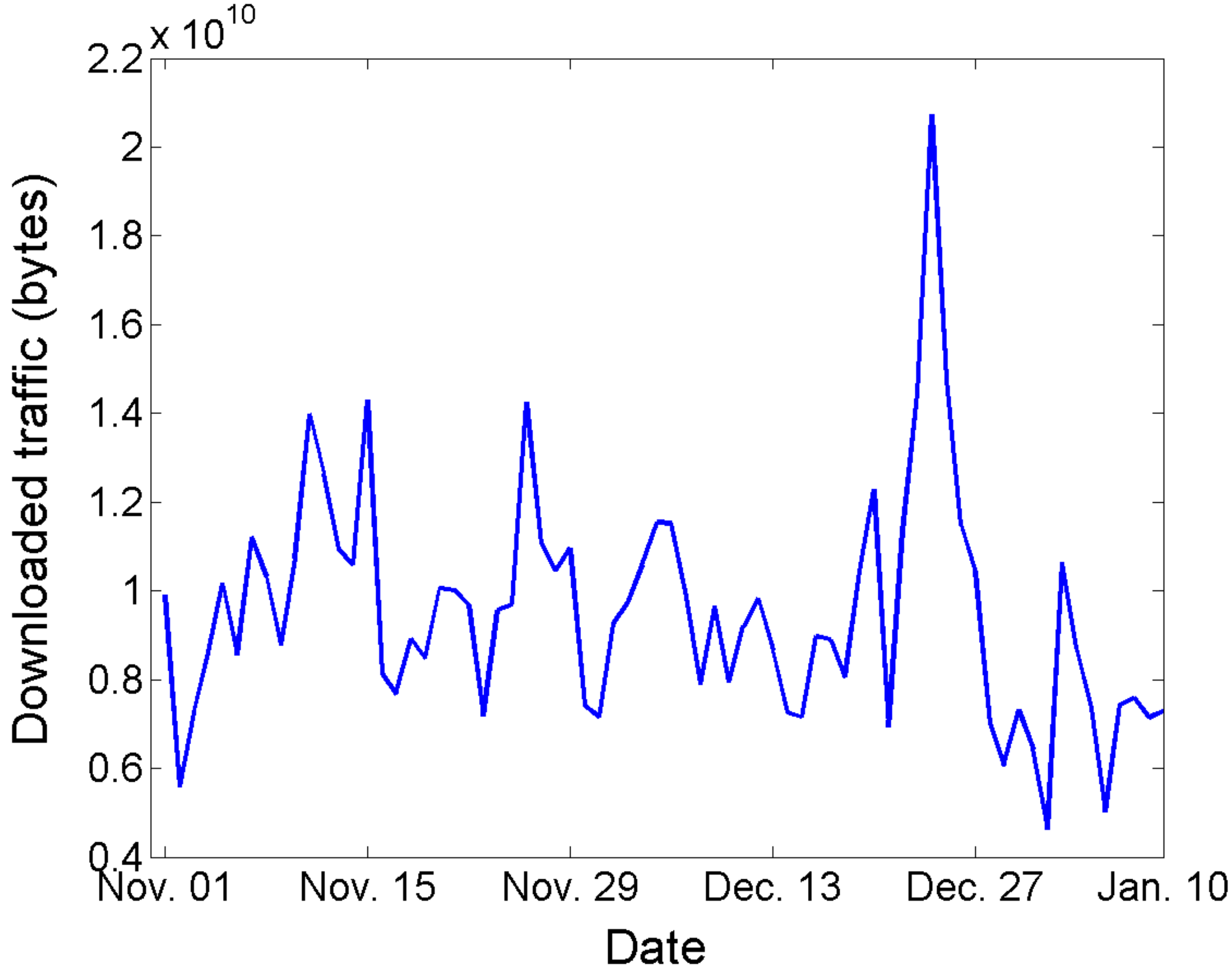
Billing records: characteristics

- 186 unique SiteIDs
- Daily and weekly cycles:
  - lower traffic volume on weekends
  - daily cycle starts at 7 AM, rises to three daily maxima at 11 AM, 3 PM, and 7 PM, then decrease monotonically until 7 AM
- Highest daily traffic recorded on Dec. 24, 2002
- Outage occurred on Jan. 3, 2003

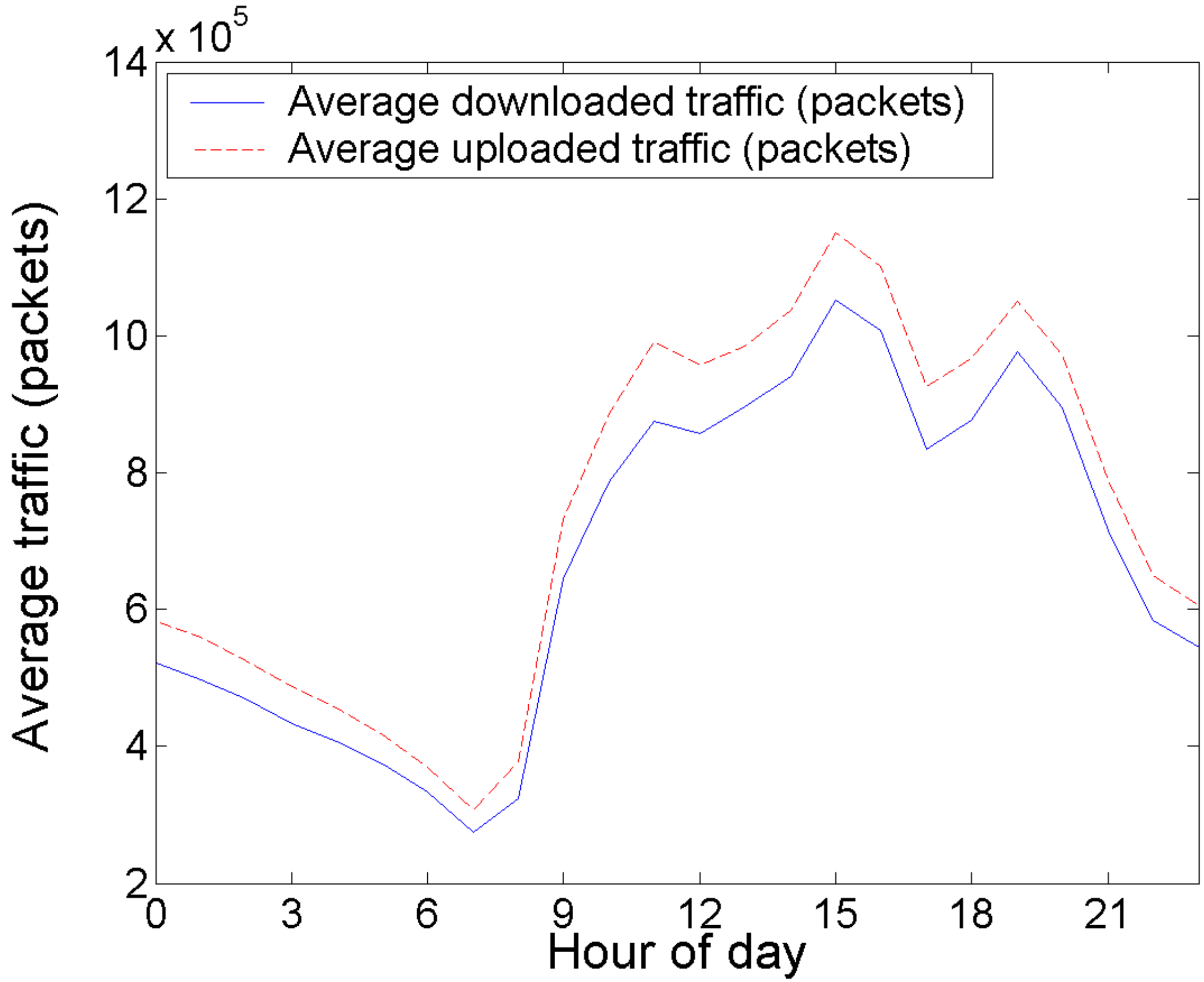
Aggregated hourly traffic



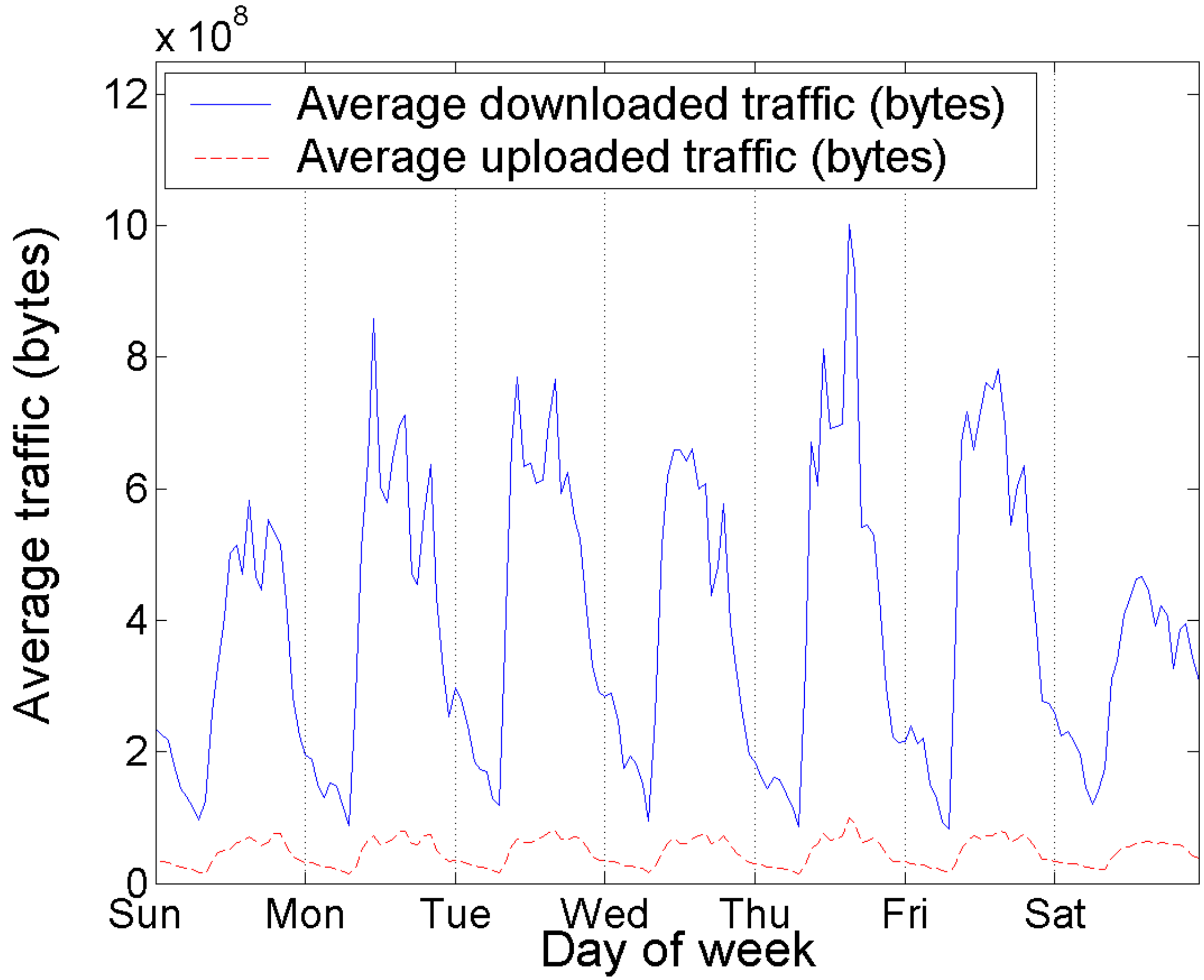
Aggregated daily traffic



Daily (diurnal) traffic: average downloaded bytes



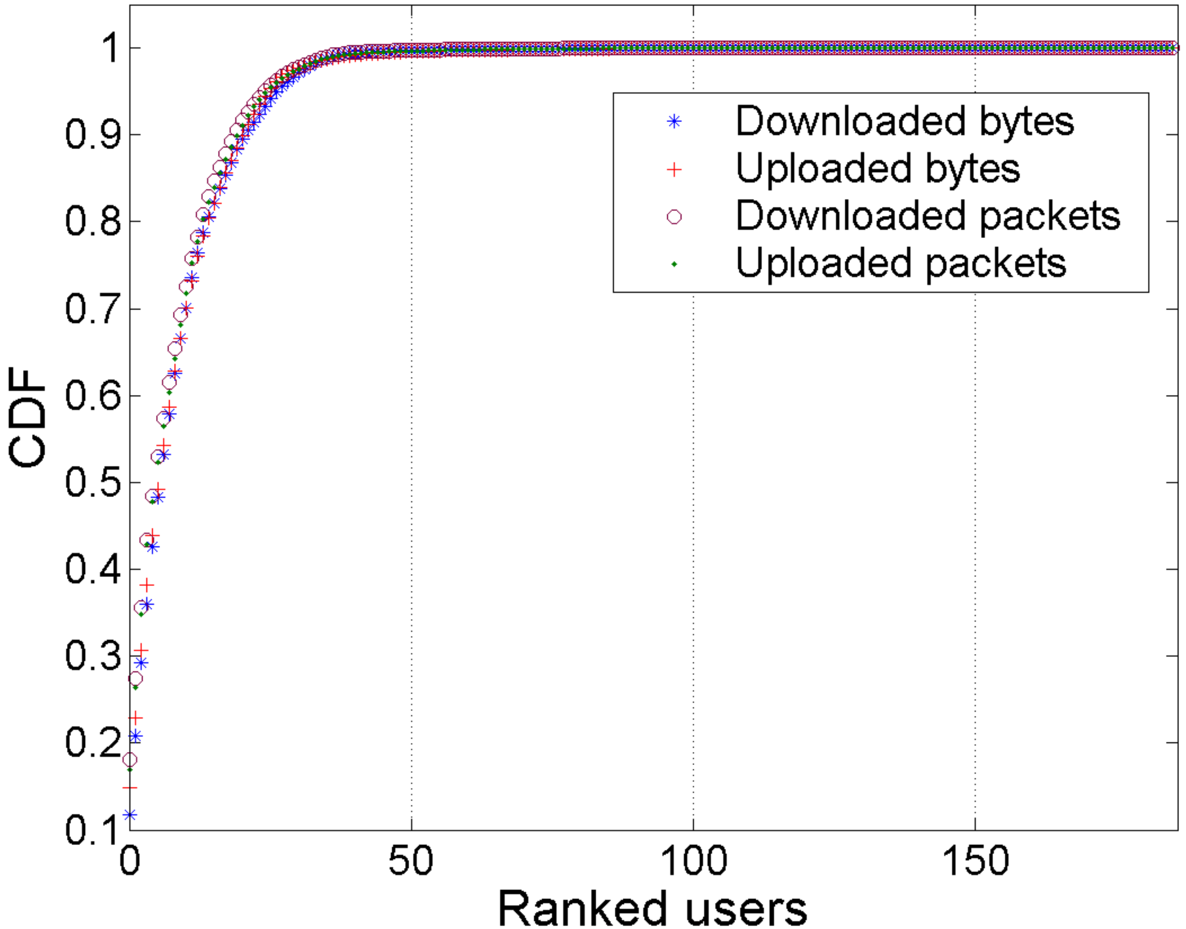
Weekly traffic: average downloaded bytes



Ranking of user traffic

- Users are ranked according to the traffic volume
- The top user downloaded 78.8 GB, uploaded 11.9 GB, and downloaded/uploaded ~205 million packets
- Most users download/uploaded little traffic
- Cumulative distribution functions (CDFs) are constructed from the ranks:
  - top user accounts for 11% of downloaded bytes
  - top 25 users contributed 93.3% of downloaded bytes
  - top 37 users contributed 99% of total traffic (packets and bytes)

Cumulative distribution functions



k-means: clustering results

- Natural number of clusters is k=3 for downloaded and uploaded bytes
- Most users belong to the group with small traffic volume
- For k=3:
  - 159 users in group 1 (average 0.0–16.8 MB downloaded per hour)
  - 24 users in group 2 (average 16.8–70.6 MB downloaded per hour)
  - 3 users in group 3 (average 70.6–110.7 MB downloaded per hour)

Refinement: clustering results

Traffic pattern	Number of users
Idle	162
Active	16
Semi-active	8
Total number of users	186

tcpdump traces

- Traces were continuously collected from 11:30 on Dec. 14, 2002 to 11:00 on Jan. 10, 2003 at the NOC
- The first 68 bytes of a each TCP/IP packet were captured
- ~63 GB of data contained in 127 files
- User IP address is not constant due to the use of the private IP address range and dynamic IP
- Majority of traffic is TCP:
  - 94% of total bytes and 84% of total packets
  - HTTP (port 80) accounts for 90% of TCP connections and 76% of TCP bytes
  - FTP (port 21) accounts for 0.2% of TCP connections and 11% of TCP bytes

Network anomalies

- Ethereal/Wireshark, tcptrace, and pcapread
- Four types of network anomalies were detected:
  - invalid TCP flag combinations
  - large number of TCP resets
  - UDP and TCP port scans
  - traffic volume anomalies

Analysis of TCP flags

TCP flag	Packet count	% of Total
SYN only	19,050,849	48.500
RST only	7,440,418	18.900
FIN only	12,679,619	32.300
*SYN+FIN	408	0.001
*RST+FIN (no PSH)	85,571	0.200
*RST+PSH (no FIN)	18,111	0.050
*RST+FIN+PSH	8,329	0.020
*Total number of packets with invalid TCP flag combinations	112,419	0.300
Total packet count	39,283,305	100.000

Large number of TCP resets

- Connections are terminated by either TCP FIN or TCP RST:
  - 12,679,619 connections were terminated by FIN (63%)
  - 7,440,418 connections were terminated by RST (37%)
- Large number of TCP RST indicates that connections are terminated in error conditions
- TCP RST is employed by Microsoft Internet Explorer to terminate connections instead of TCP FIN

M. Arlitt and C. Williamson, "An analysis of TCP reset behaviour on the Internet," *ACM SIGCOMM Comput. Commun. Rev.*, vol. 35, no. 1, pp. 37–44, Jan. 2005.

UDP and TCP port scans

- UDP port scans are found on UDP port 137 (NETBEUI)
- TCP port scans are found on these TCP ports:
  - 80 Hypertext transfer protocol (HTTP)
  - 139 NETBIOS extended user interface (NETBEUI)
  - 434 HTTP over secure socket layer (HTTPS)
  - 1433 Microsoft structured query language (MS SQL)
  - 27374 Subseven trojan
- No HTTP(S) servers were active in the ChinaSat network
- MSSQL vulnerability was discovered on Oct. 2002, which may be the cause of scans on TCP port 1433
- The Subseven trojan is a backdoor program used with malicious intents

TCP: transport control protocol
UDP: user defined protocol

UDP port scans originating from the ChinaSat network

192.168.2.30:137 - 195.x.x.98:1025
192.168.2.30:137 - 202.x.x.153:1027
192.168.2.30:137 - 210.x.x.23:1035
192.168.2.30:137 - 195.x.x.42:1026
192.168.2.30:137 - 202.y.y.226:1026
192.168.2.30:137 - 218.x.x.238:1025
192.168.2.30:137 - 202.y.y.226:1025
192.168.2.30:137 - 202.y.y.226:1027
192.168.2.30:137 - 202.y.y.226:1028
192.168.2.30:137 - 202.y.y.226:1029
192.168.2.30:137 - 202.y.y.242:1026
192.168.2.30:137 - 61.x.x.5:1028
192.168.2.30:137 - 219.x.x.226:1025
192.168.2.30:137 - 213.x.x.189:1028
192.168.2.30:137 - 61.x.x.193:1025
192.168.2.30:137 - 202.y.y.207:1028
192.168.2.30:137 - 202.y.y.207:1025
192.168.2.30:137 - 202.y.y.207:1026
192.168.2.30:137 - 202.y.y.207:1027
192.168.2.30:137 - 64.x.x.148:1027

- Client (192.168.2.30) source port (137) scans external network addresses at destination ports (1025-1040):
  - > 100 are recorded within a three-hour period
  - targeted IP addresses are variable
  - multiple ports are scanned per IP
  - may correspond to Bugbear, OpaSoft, or other worms

UDP port scans direct to the ChinaSat network

210.x.x.23:1035 - 192.168.1.121:137
210.x.x.23:1035 - 192.168.1.63:137
210.x.x.23:1035 - 192.168.2.11:137
210.x.x.23:1035 - 192.168.1.250:137
210.x.x.23:1035 - 192.168.1.25:137
210.x.x.23:1035 - 192.168.2.79:137
210.x.x.23:1035 - 192.168.1.52:137
210.x.x.23:1035 - 192.168.6.191:137
210.x.x.23:1035 - 192.168.1.241:137
210.x.x.23:1035 - 192.168.2.91:137
210.x.x.23:1035 - 192.168.1.5:137
210.x.x.23:1035 - 192.168.1.210:137
210.x.x.23:1035 - 192.168.6.127:137
210.x.x.23:1035 - 192.168.1.201:137
210.x.x.23:1035 - 192.168.6.179:137
210.x.x.23:1035 - 192.168.2.82:137
210.x.x.23:1035 - 192.168.1.239:137
210.x.x.23:1035 - 192.168.1.87:137
210.x.x.23:1035 - 192.168.1.90:137
210.x.x.23:1035 - 192.168.1.177:137
210.x.x.23:1035 - 192.168.1.39:137

- External address (210.x.x.23) scans for port (137) (NETBEUI) response within the ChinaSat network from source port (1035):
  - > 200 are recorded within a three-hour period
  - targets IP addresses are not sequential
  - may correspond to Bugbear, OpaSoft, or other worms

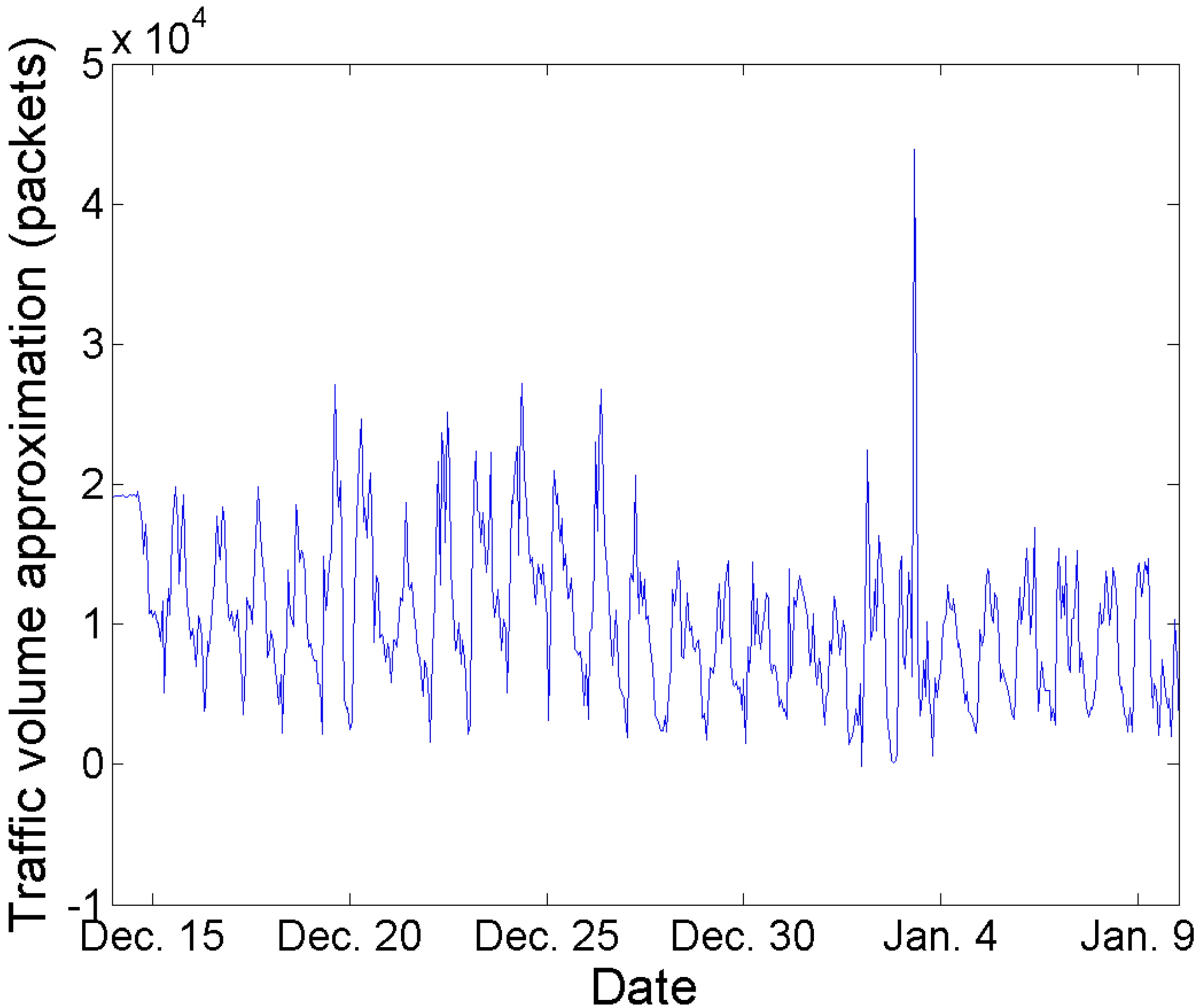
Detection of traffic volume anomalies using wavelets

- Traffic is decomposed into various frequencies using the wavelet transform
- Traffic volume anomalies are identified by the large variation in wavelet coefficient values
- The coarsest scale level where the anomalies are found indicates the time scale of an anomaly

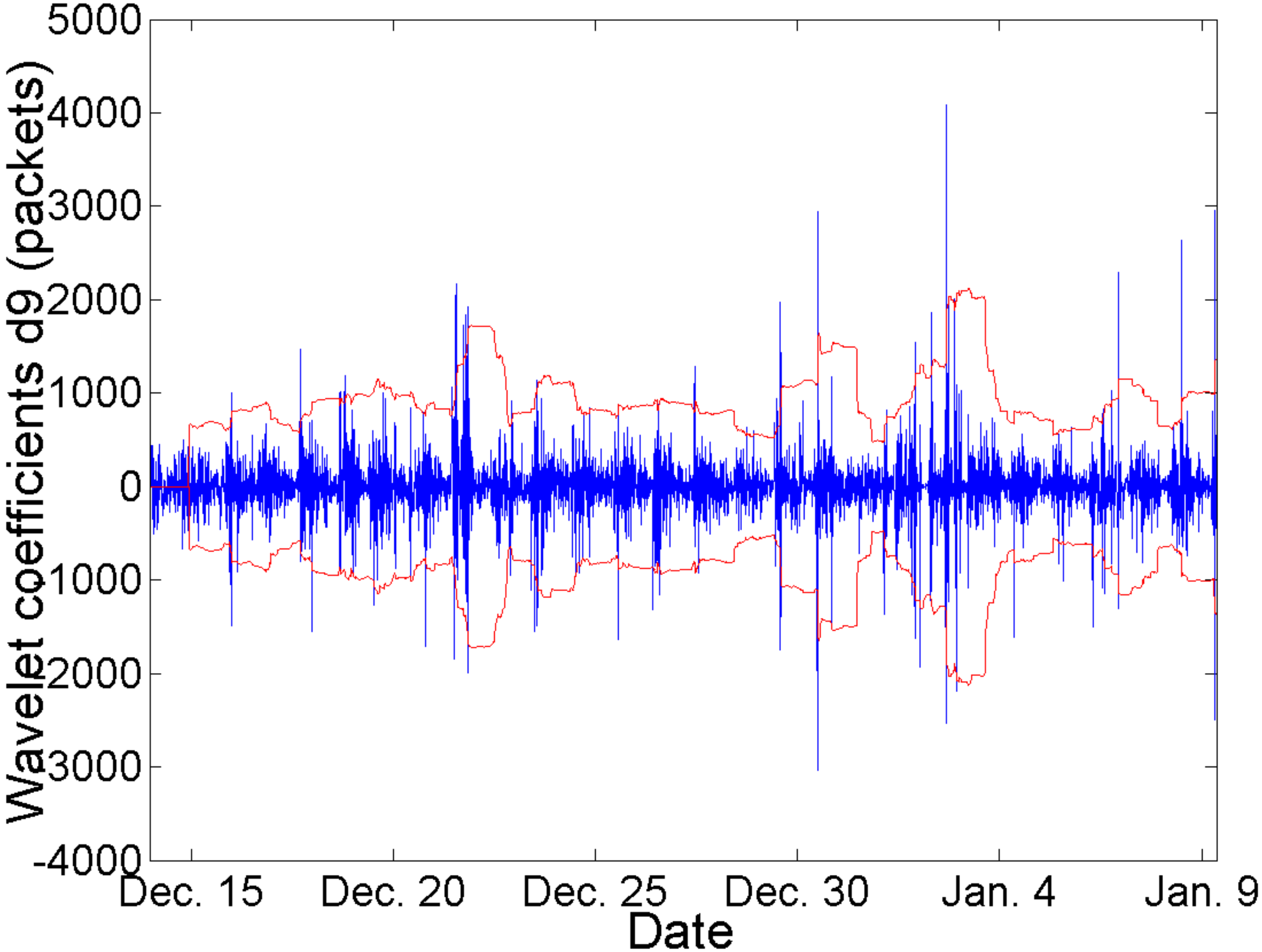
Detection of traffic volume anomalies using wavelets

- tcpdump traces are binned in terms of packets or bytes (each second)
- Wavelet transform of 12 levels is employed to decompose the traffic
- The coarsest level approximately represents the hourly traffic
- Anomalies are:
  - detected with a moving window of size 20 and by calculating the mean and standard deviation (σ) of the wavelet coefficients in each window
  - identified when wavelet coefficients lie outside the $\pm\ 3\sigma$ of the mean value

Wavelet approximation coefficients



Wavelet detail coefficients: d_9



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Autonomous System (AS)

- Internet is a network of Autonomous Systems:
  - groups of networks sharing the same routing policy
  - identified with Autonomous System Numbers (ASN)
- Autonomous System Numbers: http://www.iana.org/assignments/as-numbers
- Internet topology on AS-level:
  - the arrangement of ASs and their interconnections
- Border Gateway Protocol (BGP):
  - inter-AS protocol
  - used to exchange network reachability information among BGP systems
  - reachability information is stored in routing tables

Internet AS-level data

Source of data are routing tables:

- Route Views: http://www.routeviews.org
  - most participating ASs reside in North America
- RIPE (Réseaux IP européens): http://www.ripe.net/ris
  - most participating ASs reside in Europe

Data sets

Emerging concerns about the use of the two datasets:

- different observations about AS degrees:
  - power-law distribution: Route Views [Faloutsos, 1999]
  - Weibull distribution: Route Views + RIPE [Chang, 2001]
- data completeness:
  - RIPE dataset contains ~ 40% more AS connections and 2% more ASs than Route Views [Chang, 2001]

Route Views and RIPE: statistics

- Route Views and RIPE samples collected on May 30, 2003

Number of	Route Views	RIPE
AS paths	6,398,912	6,375,028
Probed ASs	15,418	15,433
AS pairs	34,878	35,225

- AS pair: a pair of connected ASs
- 15,369 probed ASs (99.7%) in both datasets are identical
- 29,477 AS pairs in Route Views (85%) and in RIPE (84%) are identical

Core ASs

- ASs with largest degrees
- 16 of the core ASs in Route Views and RIPE are identical
- Core ASs in Route Views have larger degrees than core ASs in RIPE

	Route Views		RIPE	
	AS	Degree	AS	Degree
1	701	2595	701	2448
2	1239	2569	1239	1784
3	7018	1999	7018	1638
4	3561	1036	209	861
5	1	999	3561	705
6	209	863	3356	673
7	3356	662	3549	612
8	3549	617	702	580
9	702	562	2914	561
10	2914	556	1	489
11	6461	498	4589	482
12	4513	468	6461	476
13	4323	315	8220	450
14	16631	294	3303	429
15	6347	291	13237	412
16	8220	289	6730	313
17	3257	277	4323	305
18	4766	263	3257	305
19	3786	263	16631	296
20	7132	258	6347	281

Spectral analysis of graphs

- Normalized Laplacian matrix N(G) [Chung, 1997]:

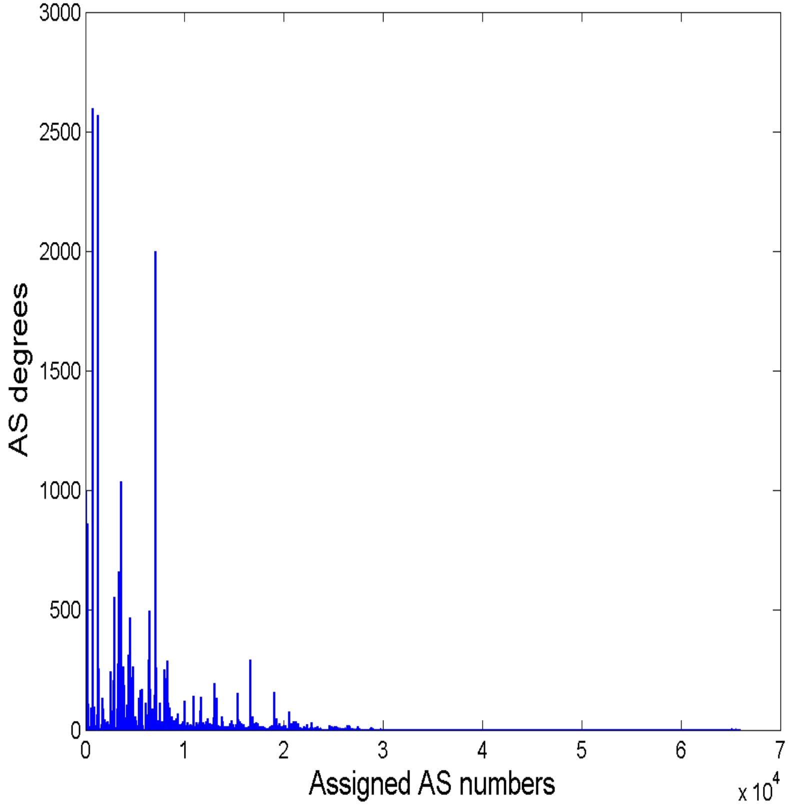
$$N(i,j)=\begin{cases} 1 & \text{if } i=j \text{ and } d_i \neq 0 \\ -\dfrac{1}{\sqrt{d_i d_j}} & \text{if } i \text{ and } j \text{ are adjacent} \\ 0 & \text{otherwise} \end{cases}$$

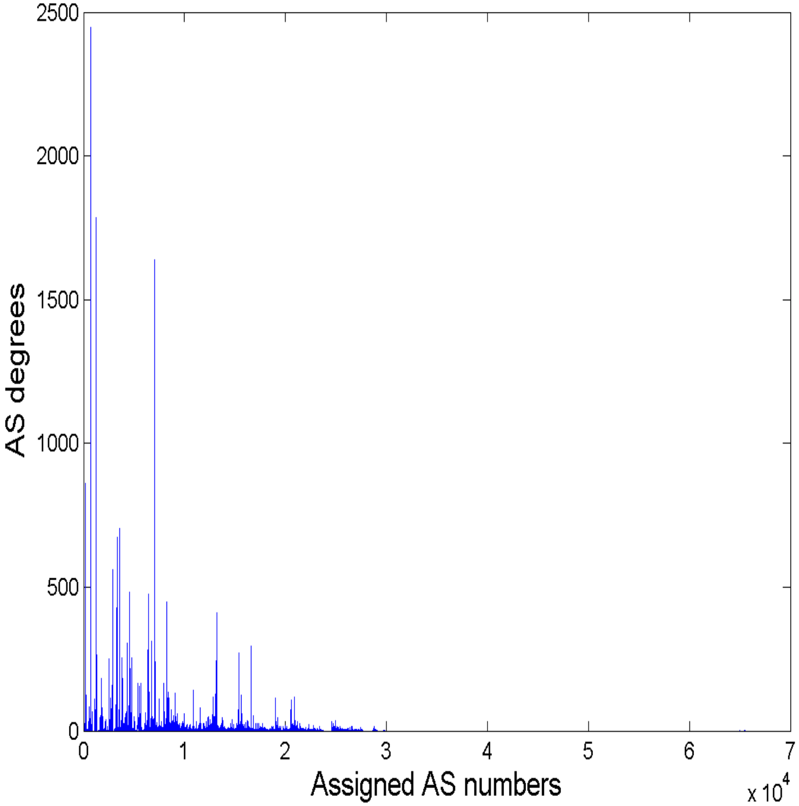
d_i and d_j are degrees of node *i* and *j*, *respectively*

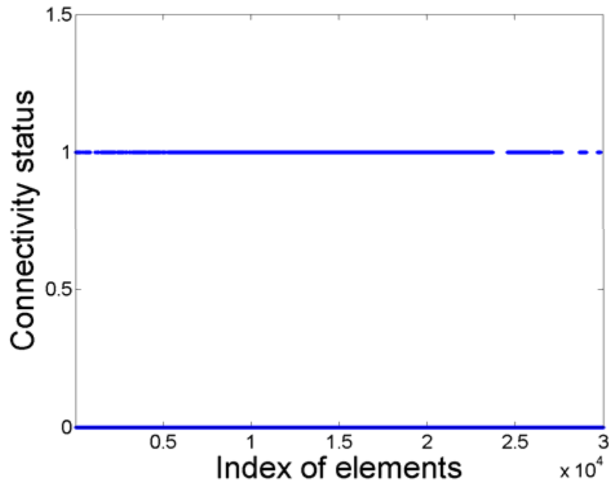
- The second smallest eigenvalue [Fiedler, 1973]
- The largest eigenvalue [Chung, 1997]
- Characteristic valuation [Fiedler, 1975]

Spectral analysis of topology data

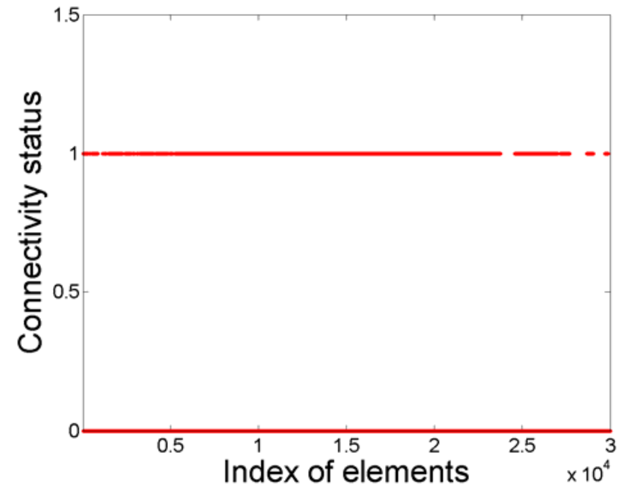
- Consider only ASs with the first 30,000 assigned AS numbers
- AS degree distribution in Route Views and RIPE datasets:





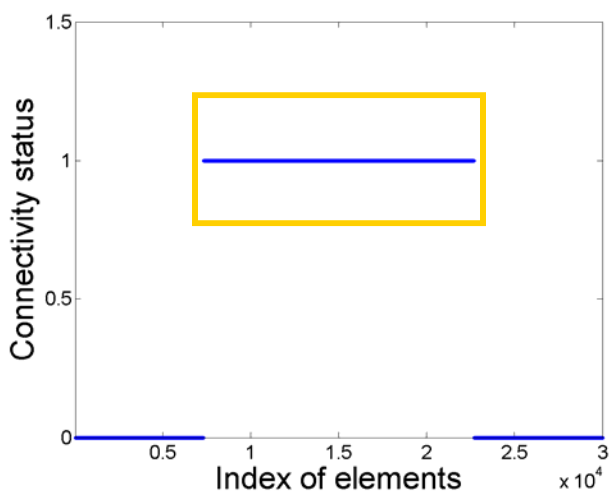


(a) RouteViews_original

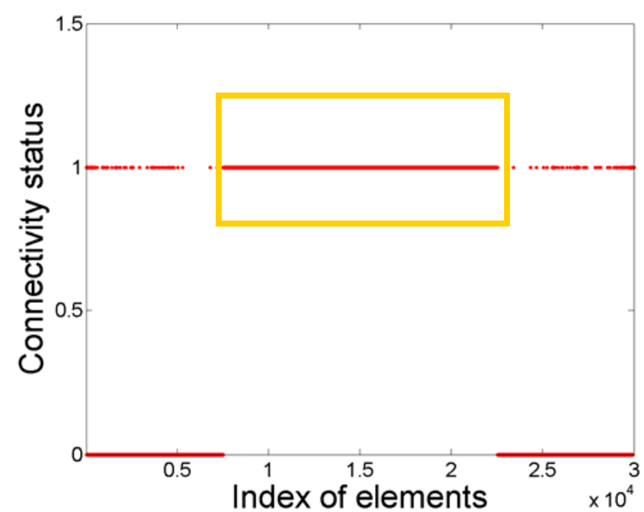


(b) RIPE_original

Before the sort

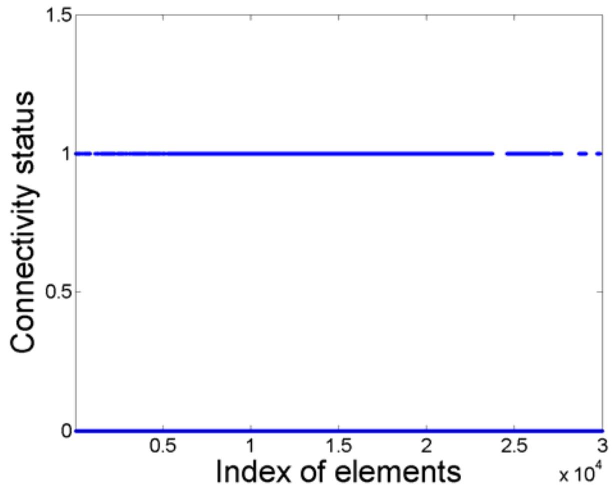


(c) RouteViews_min

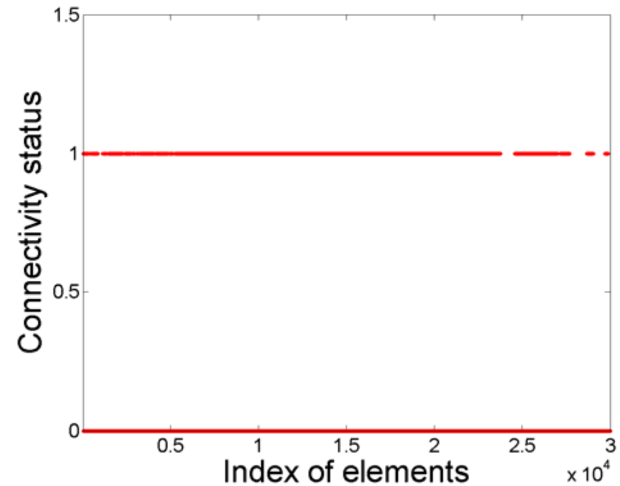


(d) RIPE_min

After the sort

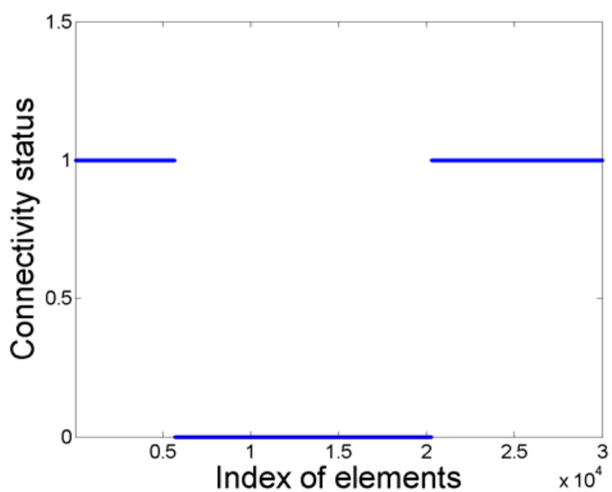


(a) RouteViews_original

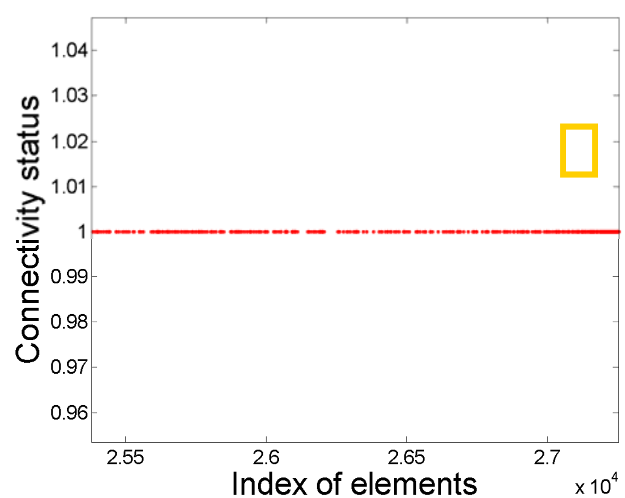


(b) RIPE_original

Before the sort



(c) RouteViews_max



(d) RIPE_max

After the sort

Data analysis results

- The second smallest eigenvector:
  - separates connected ASs from disconnected ASs
  - Route Views and RIPE datasets are similar on a coarser scale
- The largest eigenvector:
  - reveals highly connected clusters
  - Route Views and RIPE datasets differ on a finer scale

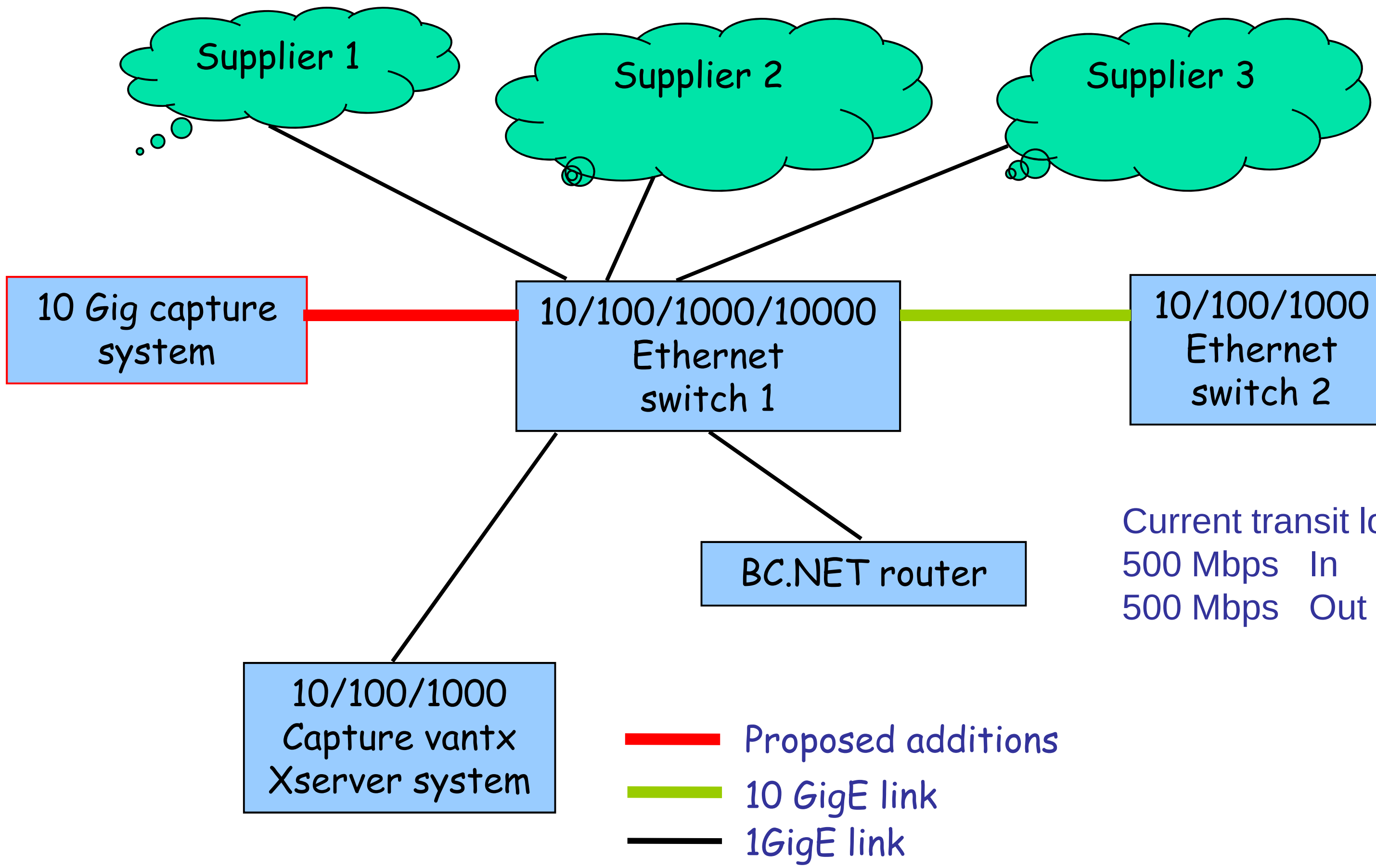
Observations

- The two datasets are similar on coarse scales:
  - number of ASs, number of AS connections, core ASs
- They exhibit different clustering characteristics:
  - Route Views data contain larger AS clusters
  - core ASs in Route Views have larger degrees than core ASs in RIPE
  - core ASs in Route Views connect a larger number of smaller ASs

Roadmap

- Introduction
- Traffic data and analysis tools:
  - data collection
  - statistical analysis, clustering tools, prediction analysis
- Case studies:
  - satellite network: ChinaSat
  - packet data network: Internet
  - BC.NET measurements
- Conclusions and references

BC.NET traffic measurements



Current transit loads:
500 Mbps In
500 Mbps Out

Project support

- Funding:
  - NSERC Equipment Grant
  - NSERC Discovery Grant
  - BC.NET funding
- Collaborators:
  - BC.NET Network Research Advisory Committee
  - UBC, UVic, UNBC, …

Roadmap

- Introduction
- Traffic data and analysis tools:
  - data collection
  - statistical analysis, clustering tools, prediction analysis
- Case studies:
  - satellite network: ChinaSat
  - packet data network: Internet
  - BC.NET measurements (in preparation)
- Conclusions and references

Conclusions

- We used simulation tools and analytical methods to analyze traffic data from three deployed networks: ChinaSat and the Internet (E-Comm)
- Network: evaluated network performance
- Traffic characterization and modeling: developed models of inter-arrival and call holding times
- Users: employed clustering algorithms to classify network users into user clusters
- Traffic prediction: used SARIMA models to predict network traffic based on aggregate user traffic and based on three user clusters
- Network anomalies: applied wavelet analysis to detect traffic anomalies

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