



Mining Network Traffic Data

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Roadmap

- Introduction
- Traffic data and analysis tools:
 - data collection, statistical analysis, clustering tools, prediction analysis
- Case studies:
 - wireless network: **Telus Mobility**
 - public safety wireless network: **E-Comm**
 - satellite network: **ChinaSat**
 - packet data networks: **Internet**
- Conclusions and references



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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
- Traffic **analysis**:
 - **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



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:
 - $r^{(m)}(k) = r(k)$, $k \geq 0$, $m = 1, 2, \dots, n$,
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)

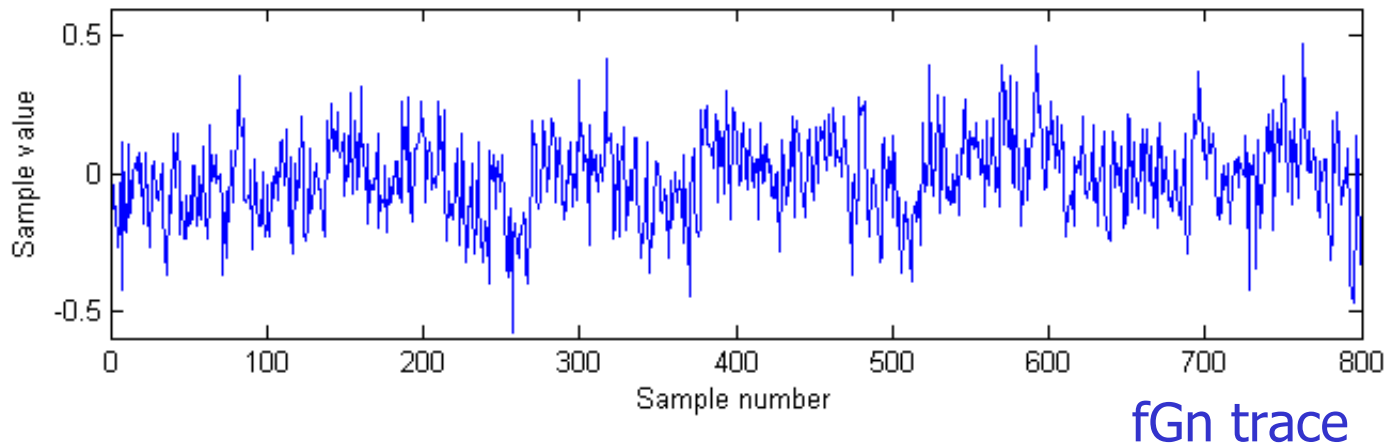


Self-similar processes

- 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

Long-range dependence: properties

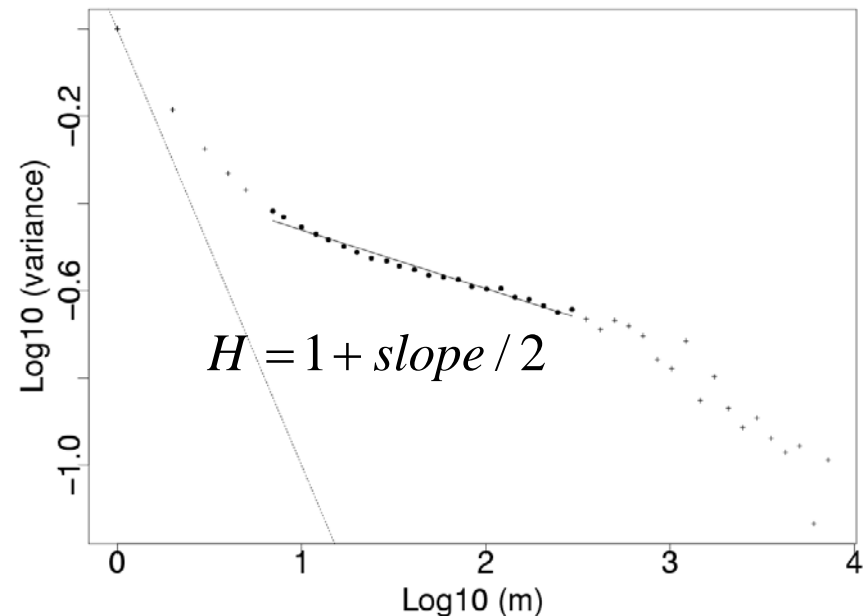
- High variability:
 - when the sample size increases, variance of the sample mean decays more slowly than expected
- Burstiness over a range of timescales:
 - long runs of large values followed by long runs of small values, repeated in aperiodic patterns



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** based on similarity
- An object can be described by a set of measurements or by its relations to other objects
- Clustering algorithms can be employed to analyze network user behaviors
- Network users are classified into clusters, according to the similarity of their behavior patterns
- With user clusters, traffic prediction is reduced to predicting and aggregating users' traffic from few clusters



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:
 - **AutoClass** tool
 - **k-means** algorithm

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.

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



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)



k-means: partitioning clustering

- Constructs k partitions of the data from n objects, where $k \leq n$
- Two constraints:
 - each cluster must contain at least one object
 - each object must belong to exactly one group
- Requires exhaustive enumeration of all possible combinations to find the optimal cluster solution



k-means clustering

- Generates k clusters from n objects
- Requires two inputs:
 - k : number of desired partitions
 - n objects
- Uses random placement of initial clusters
- Determines clustering results through an iteration technique to relocate objects to the most similar cluster:
 - similarity is defined as the distance between objects
 - objects that are closer to each other are more similar
- Computational complexity of $O(nkt)$, where t is the maximum number of iterations



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

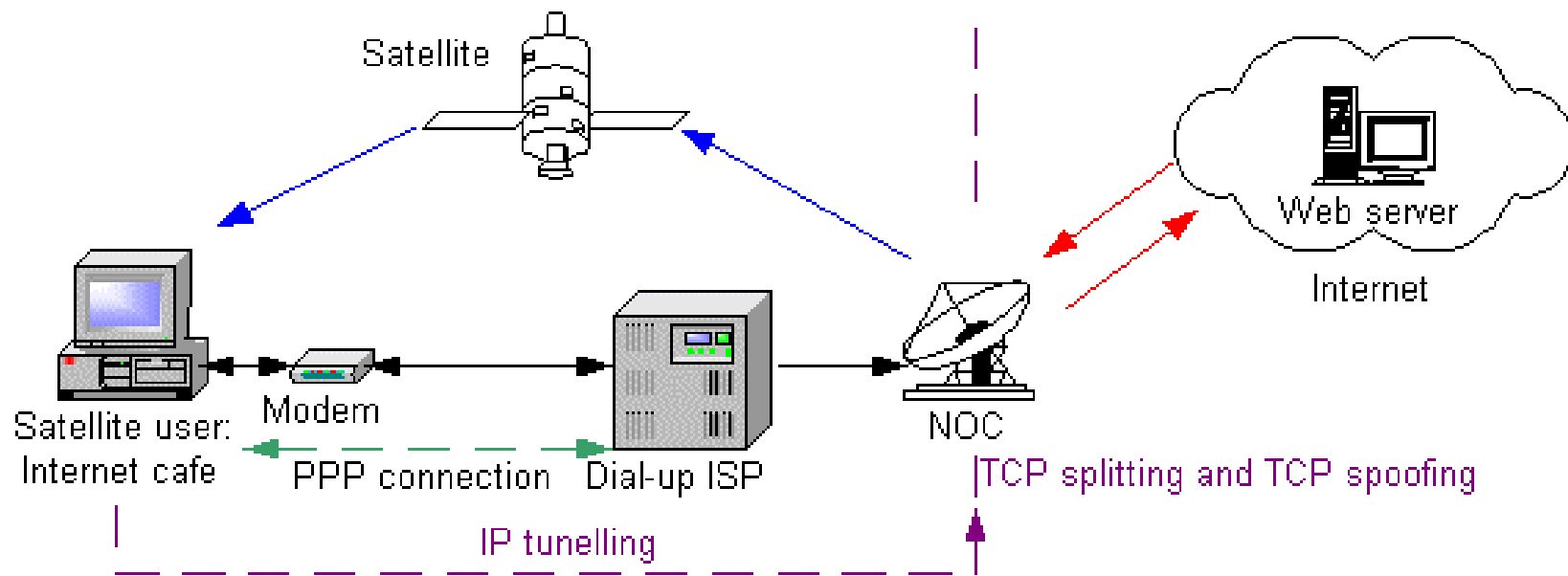
TCP: transport control protocol



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





Characteristics of satellite links

- Large coverage area
- High bandwidth
- Long propagation delay
- Large bandwidth-delay product
- High bit error rates:
 - 10^{-6} without error correction
 - 10^{-3} or 10^{-2} due to extreme weather and interference
- Path asymmetry



Characteristics of satellite links

- ChinaSat hybrid satellite network
 - Employs geosynchronous 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," in *Proc. SPECTS 2004*, San Jose, CA, July 2004, pp. 329-336.

S. Lau and Lj. Trajkovic, "Analysis of traffic data from a hybrid satellite Q. terrestrial network," in *Proc. QShine 2007*, Vancouver, BC, Canada, Aug. 2007.



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)

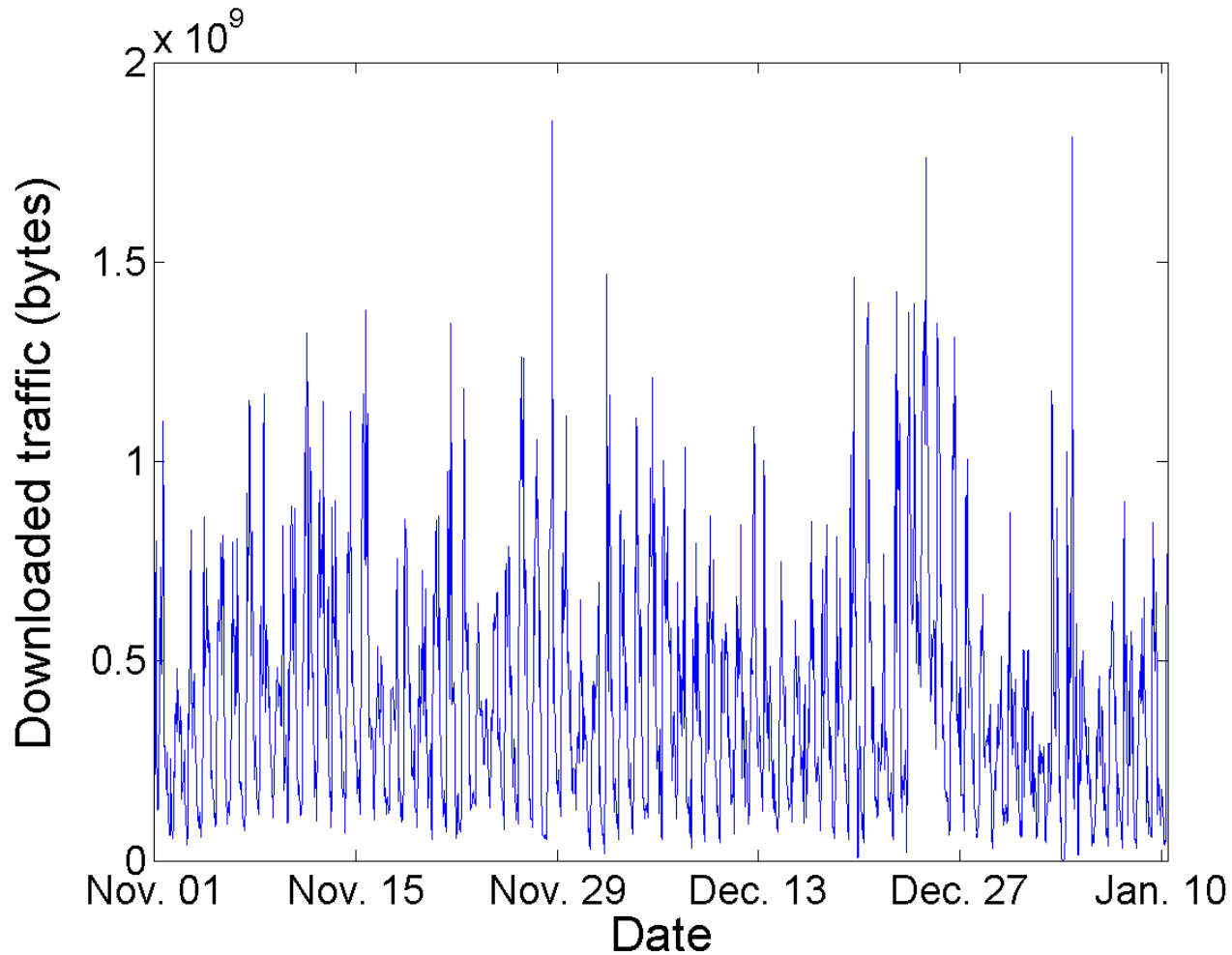
download: satellite to user
upload: user to NOC



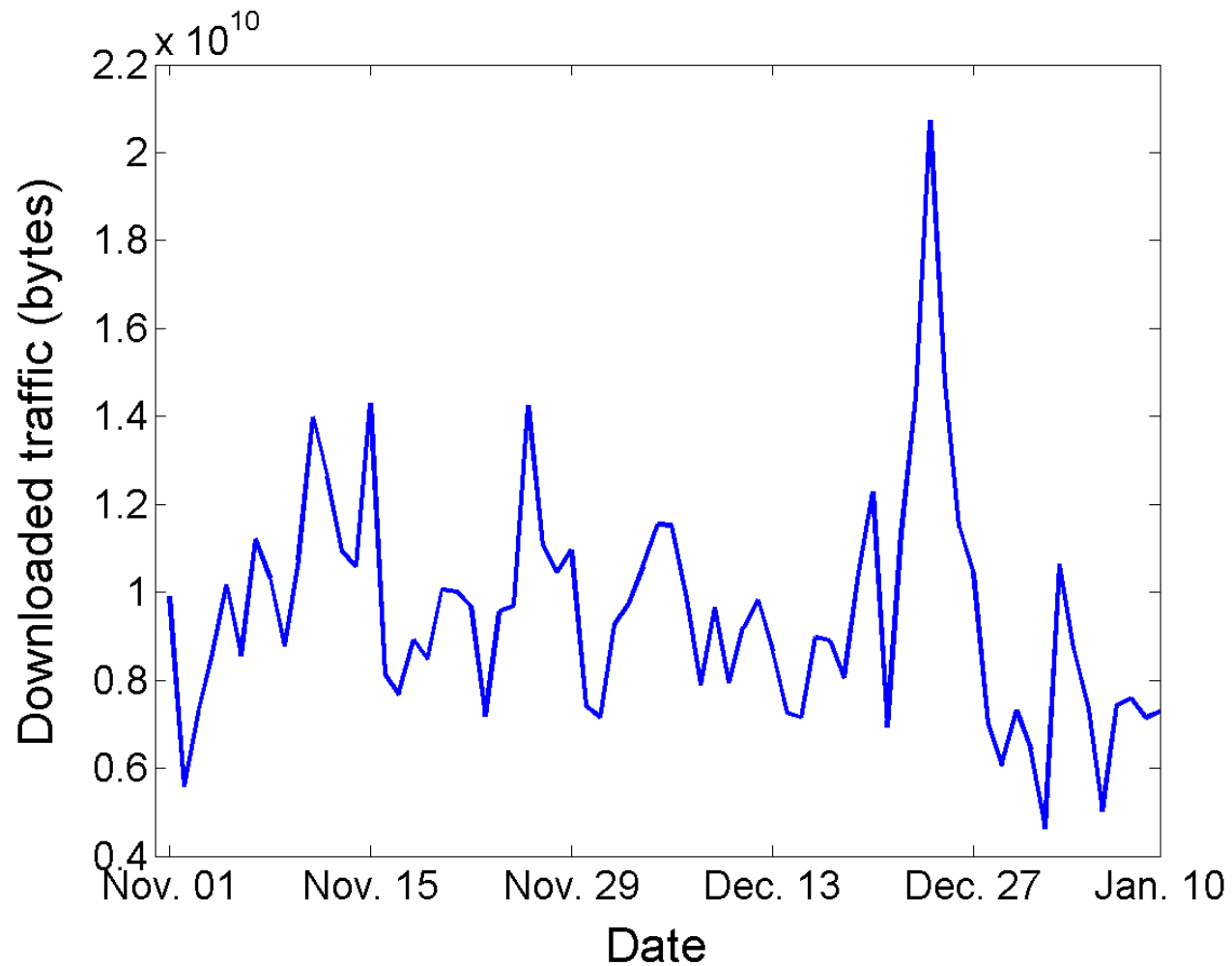
Billing records: characteristics

- 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

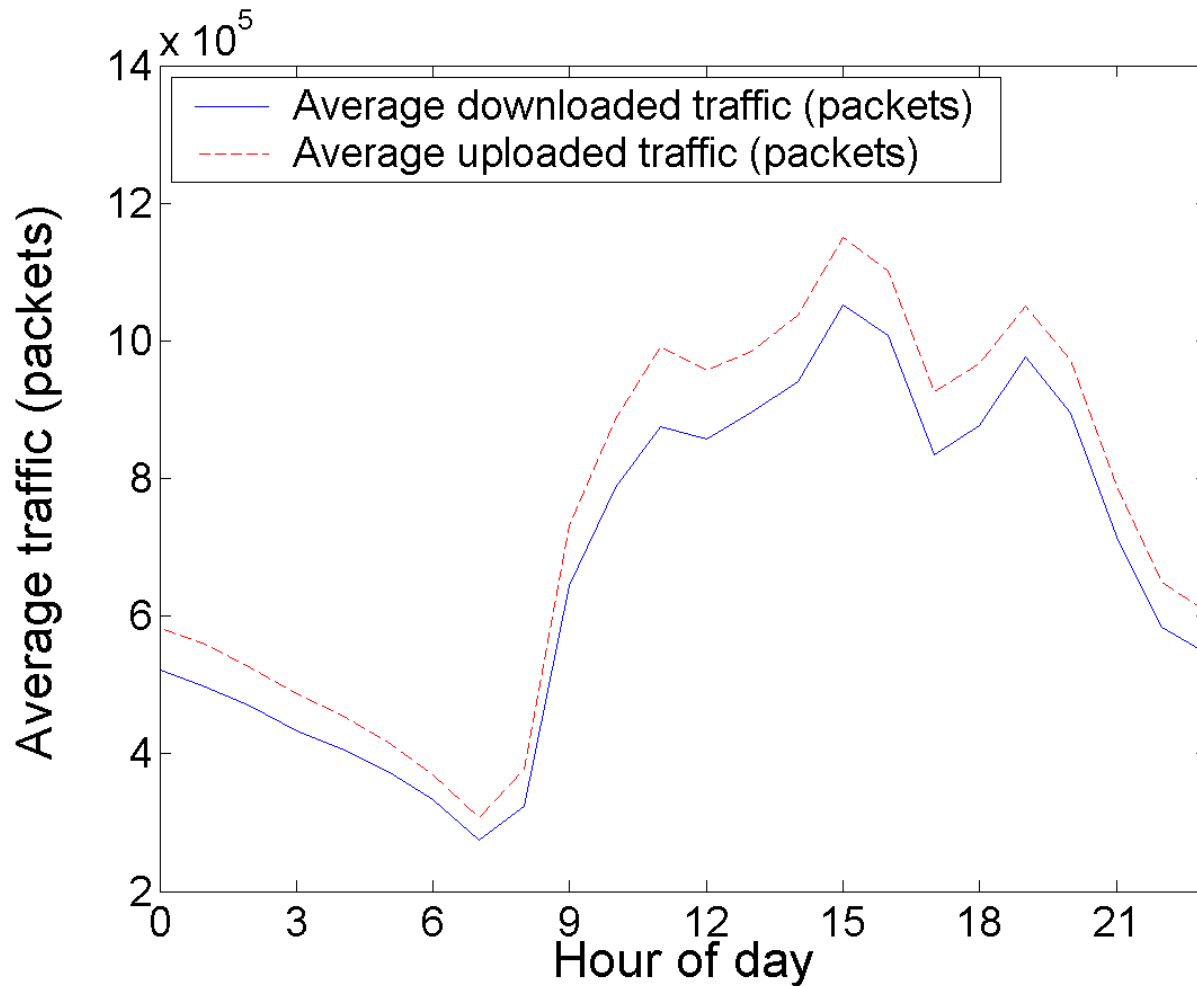
Aggregated hourly traffic



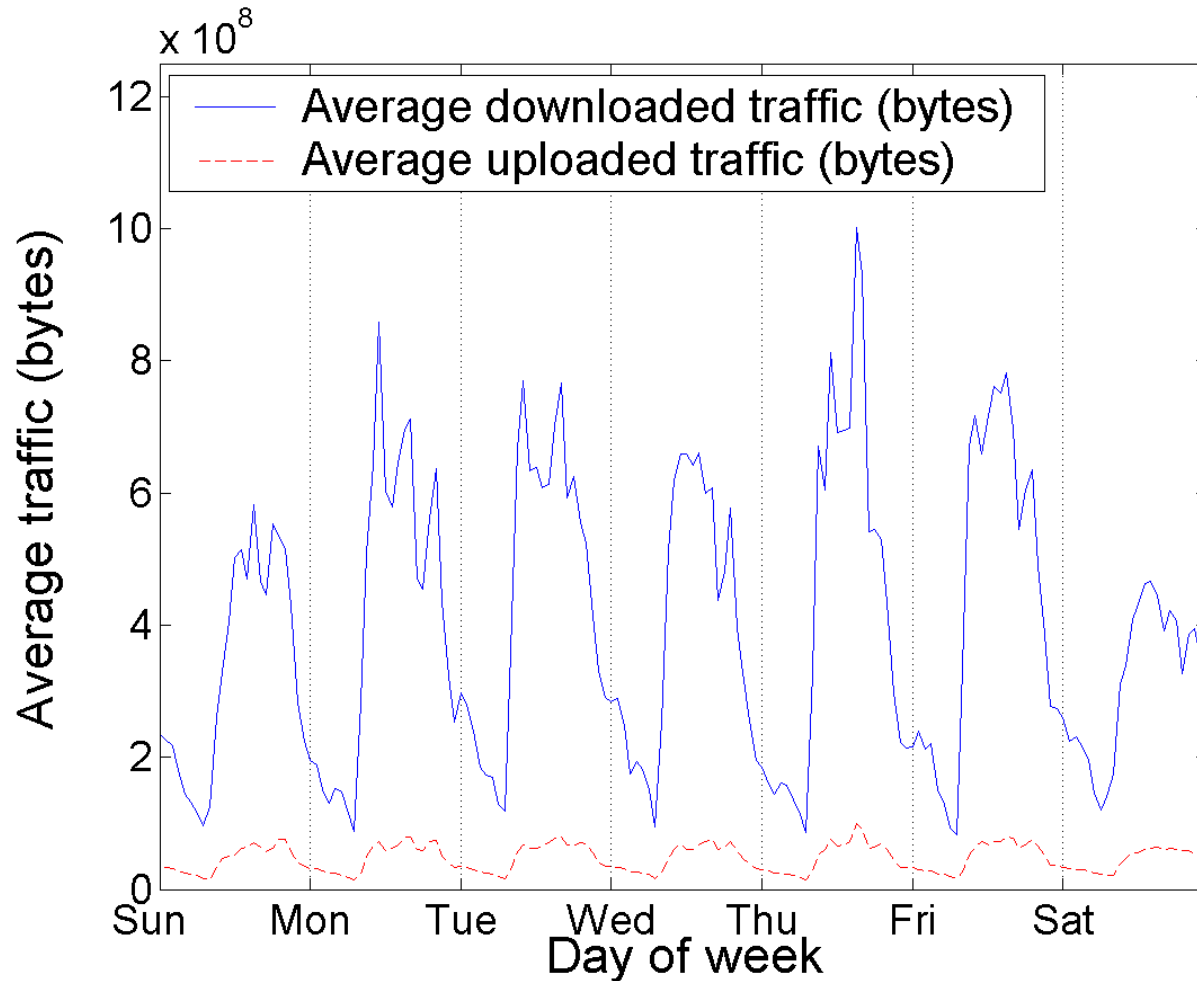
Aggregated daily traffic



Daily diurnal traffic: average downloaded bytes



Weekly traffic: average downloaded bytes

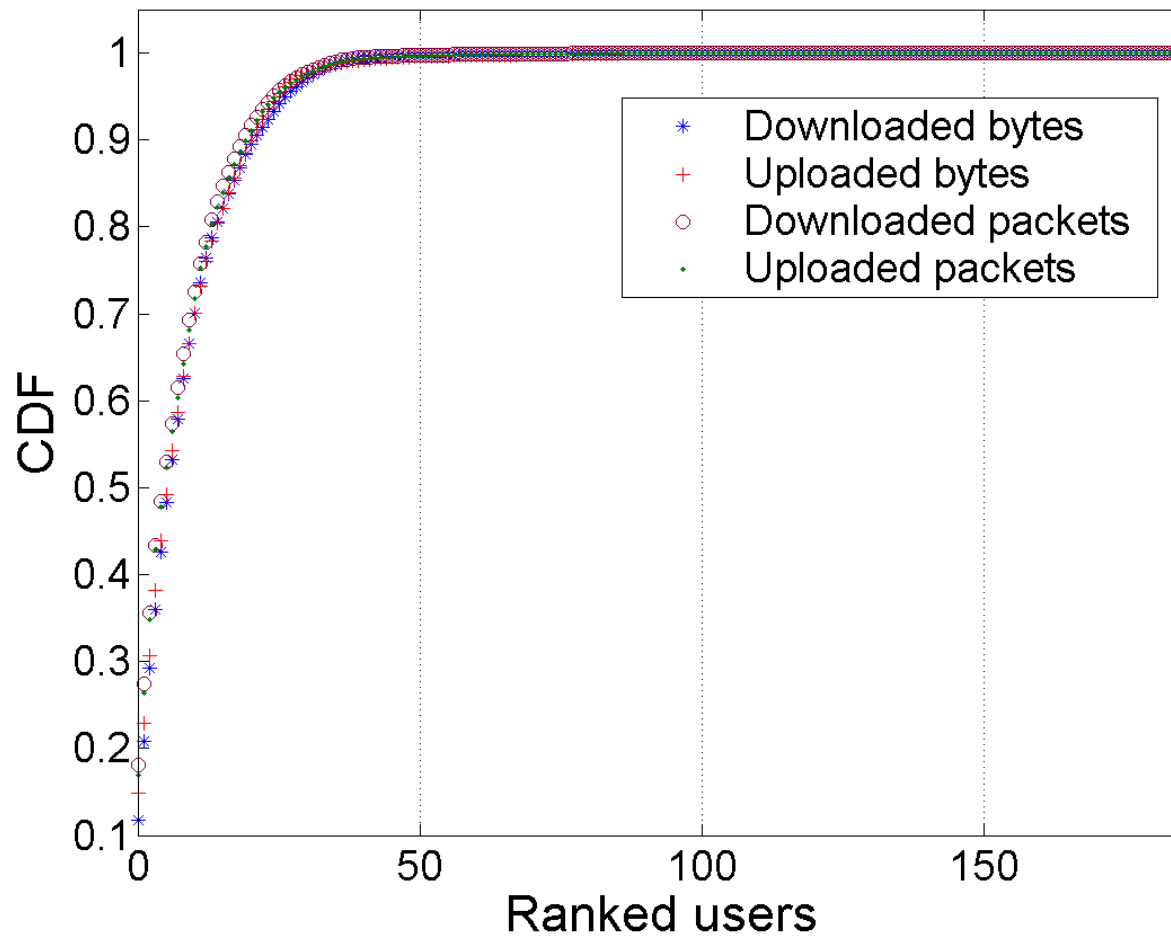




Ranking of user traffic

- 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:

three most common traffic patterns

- **Idle** users:
 - rarely download/upload traffic
 - represented by zero traffic
- **Active** users:
 - download/upload traffic for more than 18 hours a day
 - represented by traffic over 24 hours each day
- **Semi-active** users:
 - download/upload traffic for 8-12 hours a day
 - represented by a cycle of 10 hours **ACTIVE**/14 hours **IDLE** cycle for each day



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



OS fingerprinting results

- Analyzed 9 hours of `tcpdump` trace on Dec. 14, 2002 using the open-source tool `p0f v2`
- Assumed constant IP addresses
- Detected 171 users:
 - 137 users did not initiate any connections and cannot be identified (no SYN packets)
 - 14 users employ Microsoft Windows
 - 2 users employ Linux
 - 1 user employs an unknown OS (identified as an MSS-modifying proxy)

OS: operating system



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

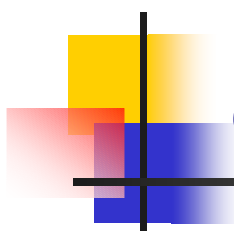
TCP: transport control protocol
UDP: user defined protocol



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

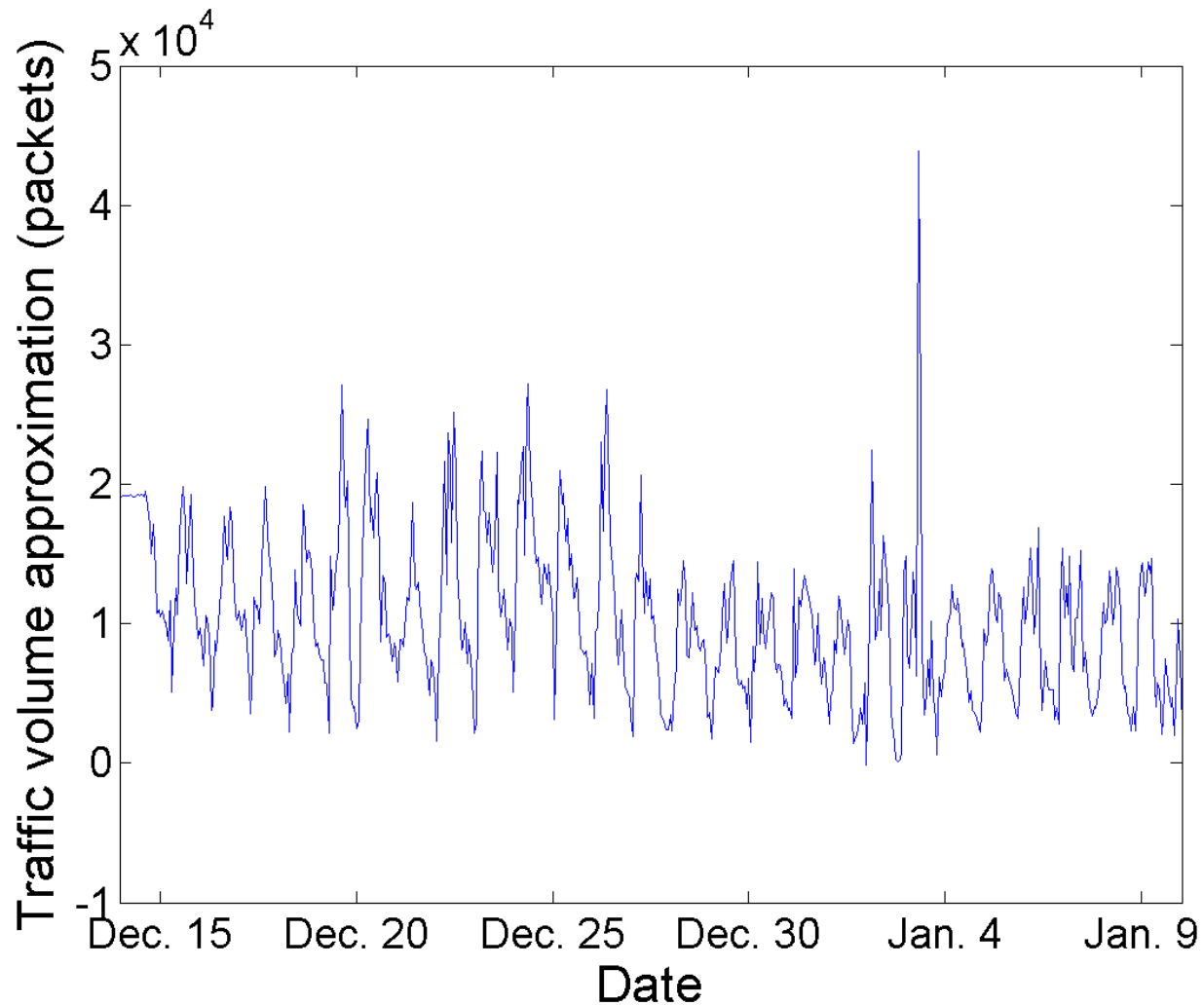
- Traffic is decomposed into various frequencies using the wavelet transform
- Traffic volume anomalies are identified by the large variation in wavelet coefficient values
- The coarsest scale level where the anomalies are found indicates the time scale of an anomaly



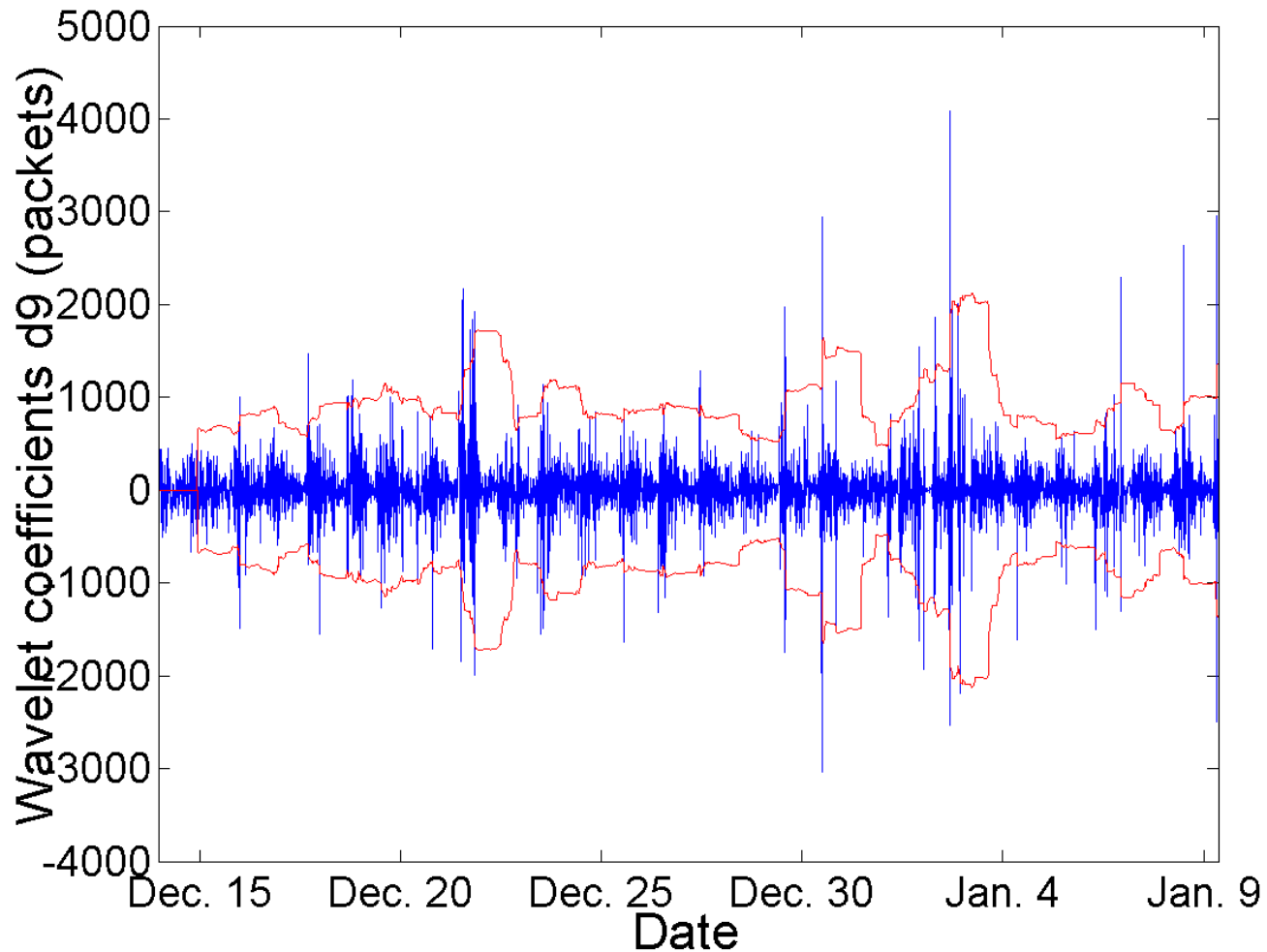
Detection of traffic volume anomalies using wavelets

- `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

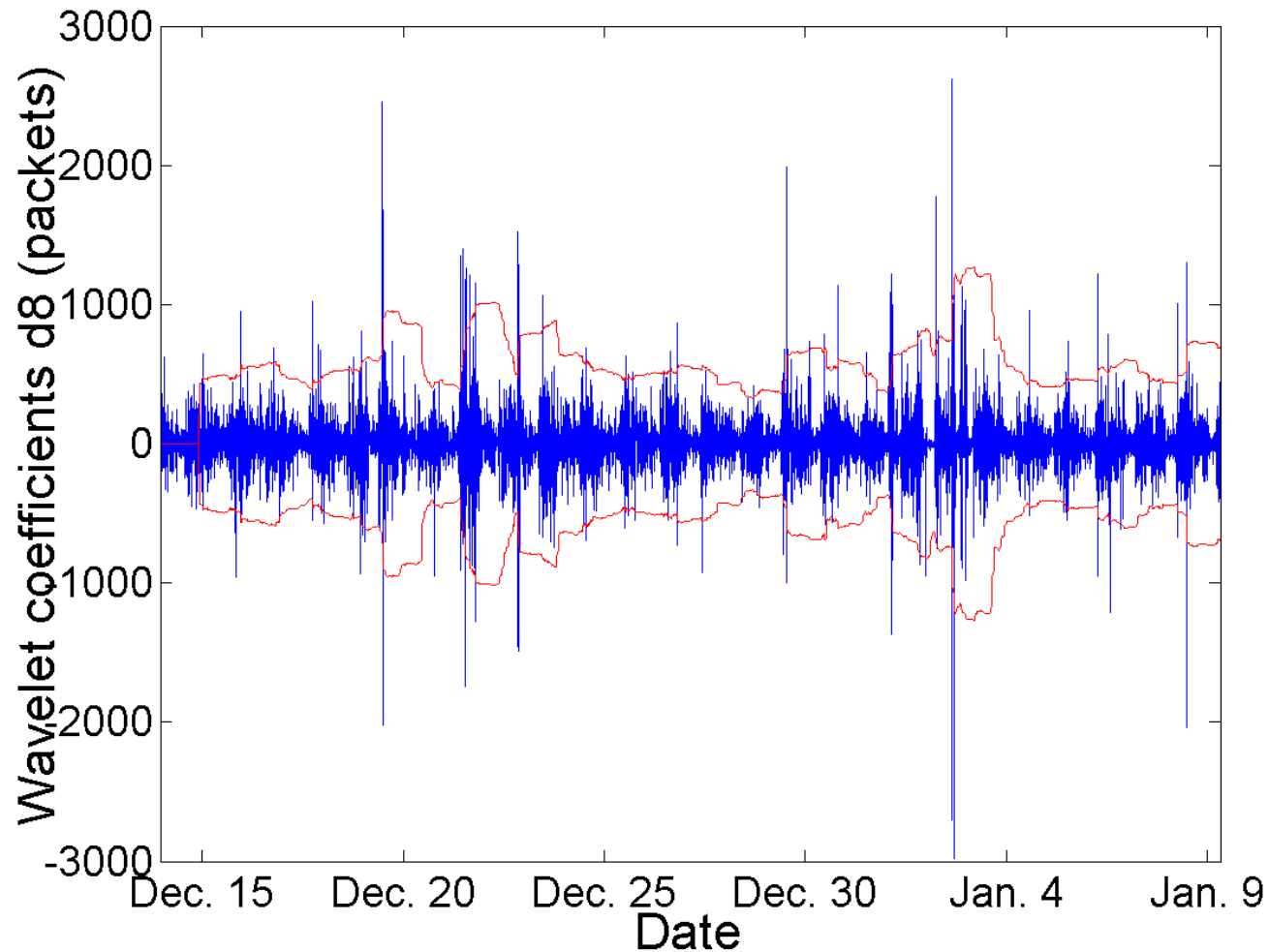


Wavelet detail coefficients: d_9





Wavelet detail coefficients: d_8





Roadmap

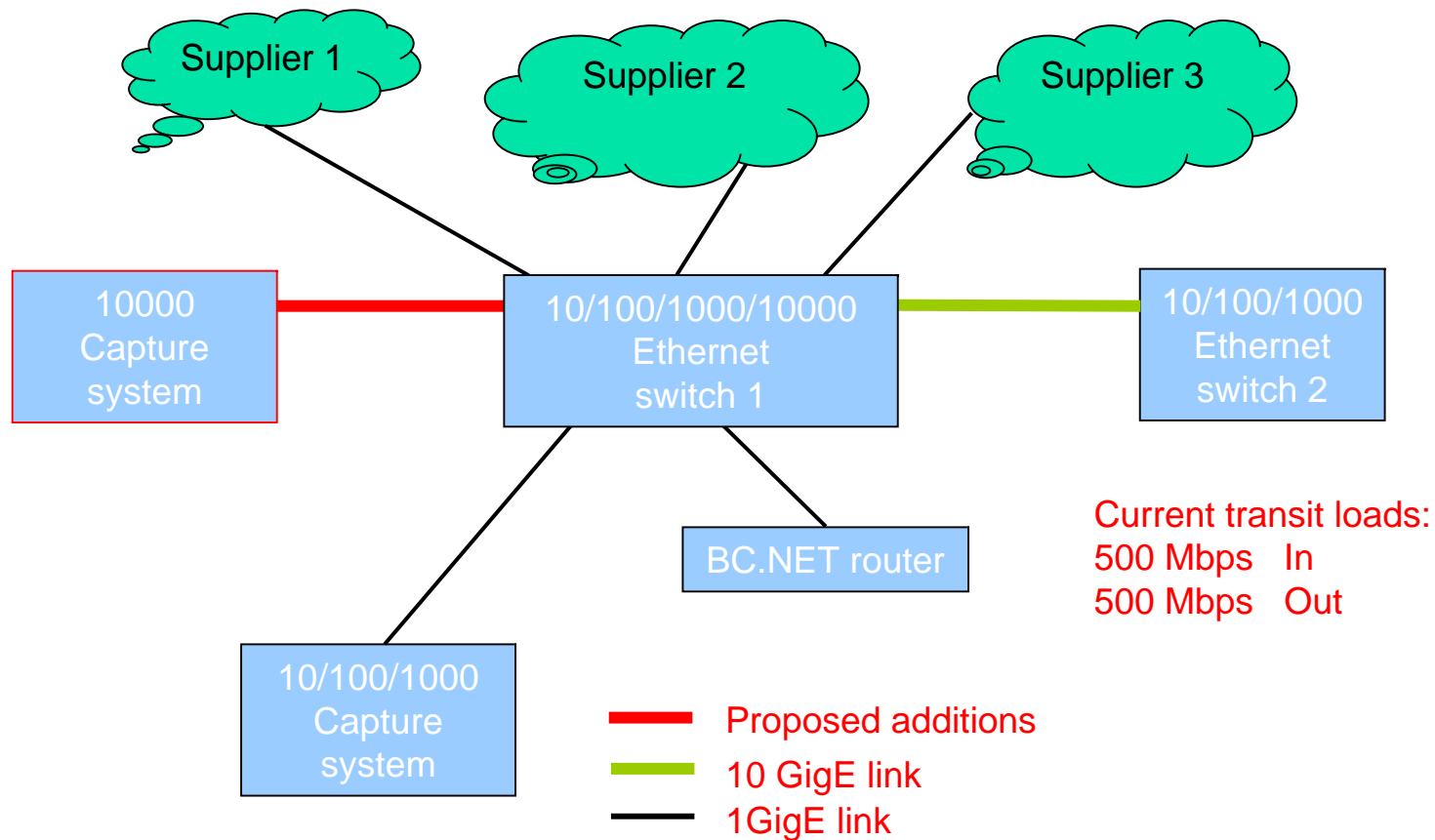
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 - packet data networks:
- **Conclusions, future work, and references**



Conclusions

- Traffic data from deployed networks (Telus Mobility, E-Comm, **ChinaSat**, the Internet) were used to:
- **evaluate network performance**
- **characterize and model traffic** (inter-arrival and call holding times)
- **classify network users** using clustering algorithms
- **predict network traffic** by employing SARIMA models based on aggregate user traffic and user clusters
- **detect network anomalies** using wavelet analysis

BC.NET traffic measurements





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http://www.ensc.sfu.ca/~ljilja/publications_date.html

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