



Understanding Communication Networks

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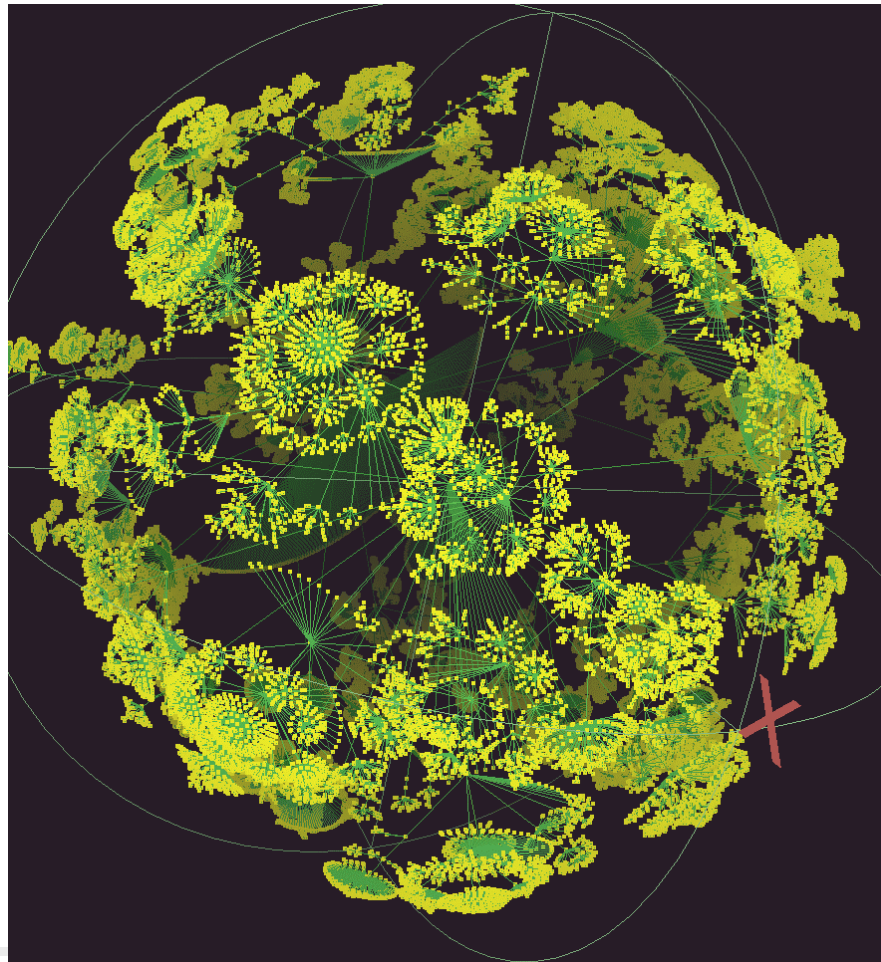


Roadmap

- Introduction
- Traffic measurements and analysis tools
- Case study:
 - public safety wireless network: E-Comm
- Collection of BCNET traffic
- Internet topology and spectral analysis of Internet graphs
- Conclusions



lhr (535,102 nodes and 601,678 links)





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Measurements of network traffic

- **Traffic measurements:**
 - help understand characteristics of network traffic
 - are basis for developing traffic models
 - are used to evaluate performance of protocols and applications
- **Traffic analysis:**
 - provides information about the network usage
 - helps understand the behavior of network users
- **Traffic prediction:**
 - important to assess future network capacity requirements
 - used to plan future network developments

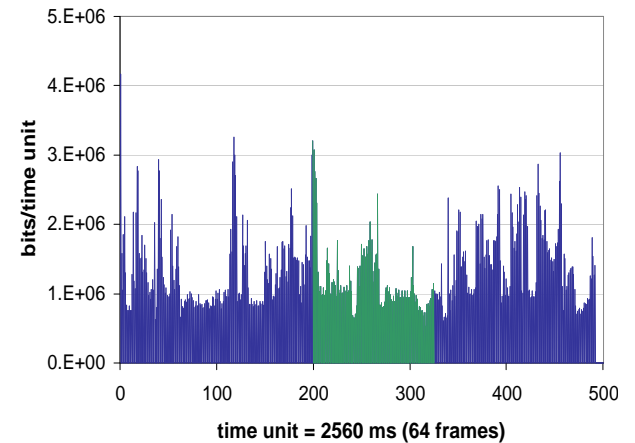
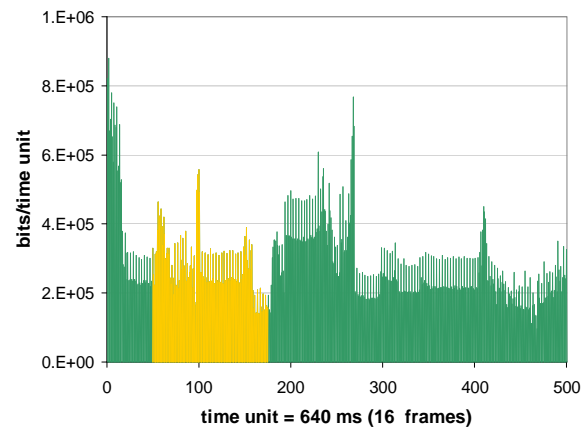
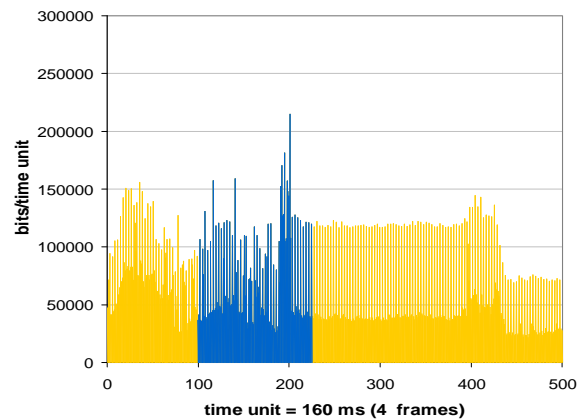


Traffic modeling: self-similarity

- Self-similarity implies a "fractal-like" behavior
- Data on various **time scales** have similar patterns
- Implications:
 - no natural length of bursts
 - bursts exist across many time scales
 - traffic does not become "smoother" when aggregated
 - it is unlike Poisson traffic used to model traffic in telephone networks
 - as the traffic volume increases, the traffic becomes more bursty and more self-similar

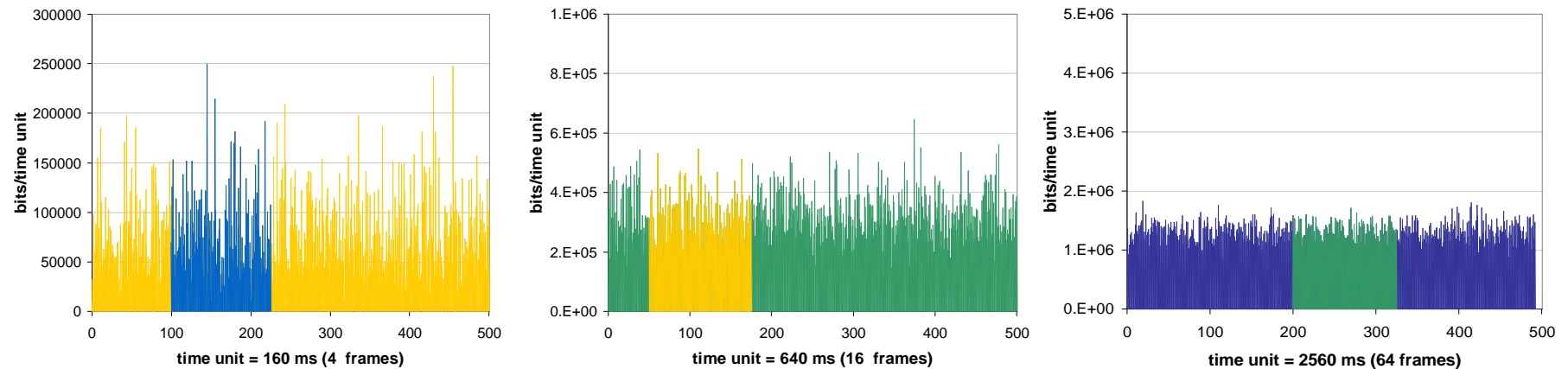
Self-similarity: influence of time-scales

- Genuine MPEG traffic trace



Self-similarity: influence of time-scales

- Synthetically generated Poisson model





Traffic analysis: clustering analysis

- Clustering generates groups (**clusters**) of similar objects
- An object is described by a set of measurements
- Clustering algorithms can be used to analyze behavior of network users
- Users are grouped into clusters based on the similarity of their behavior
- Traffic prediction based on clusters is simplified to predicting users' traffic from few clusters
- Clustering tools:
 - **k-means** algorithm
 - **AutoClass** tool



Traffic prediction: SARIMA 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
- Seasonal ARIMA (SARIMA) is a variation of the ARIMA model:
 - it captures seasonal patterns



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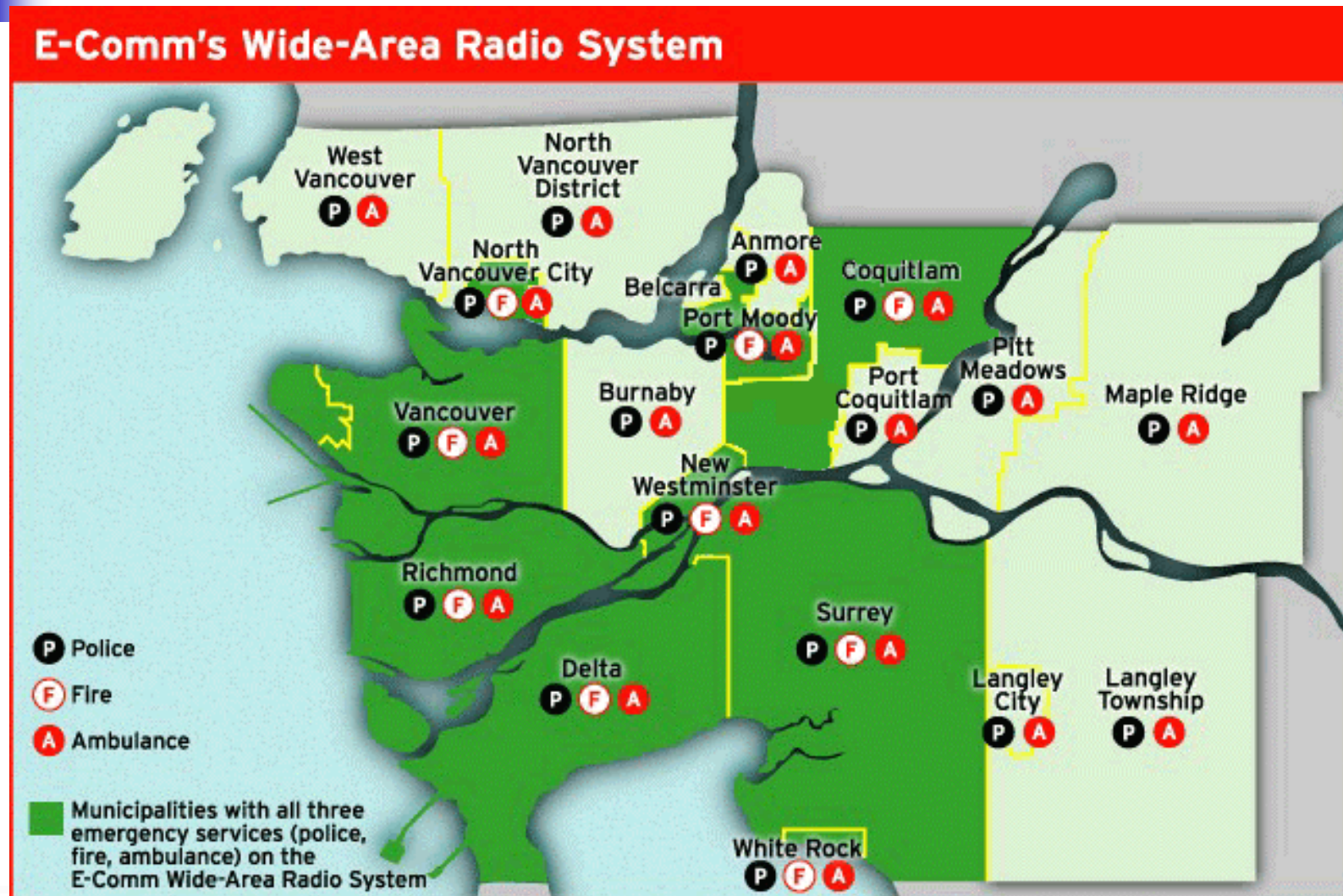
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Case study: E-Comm network

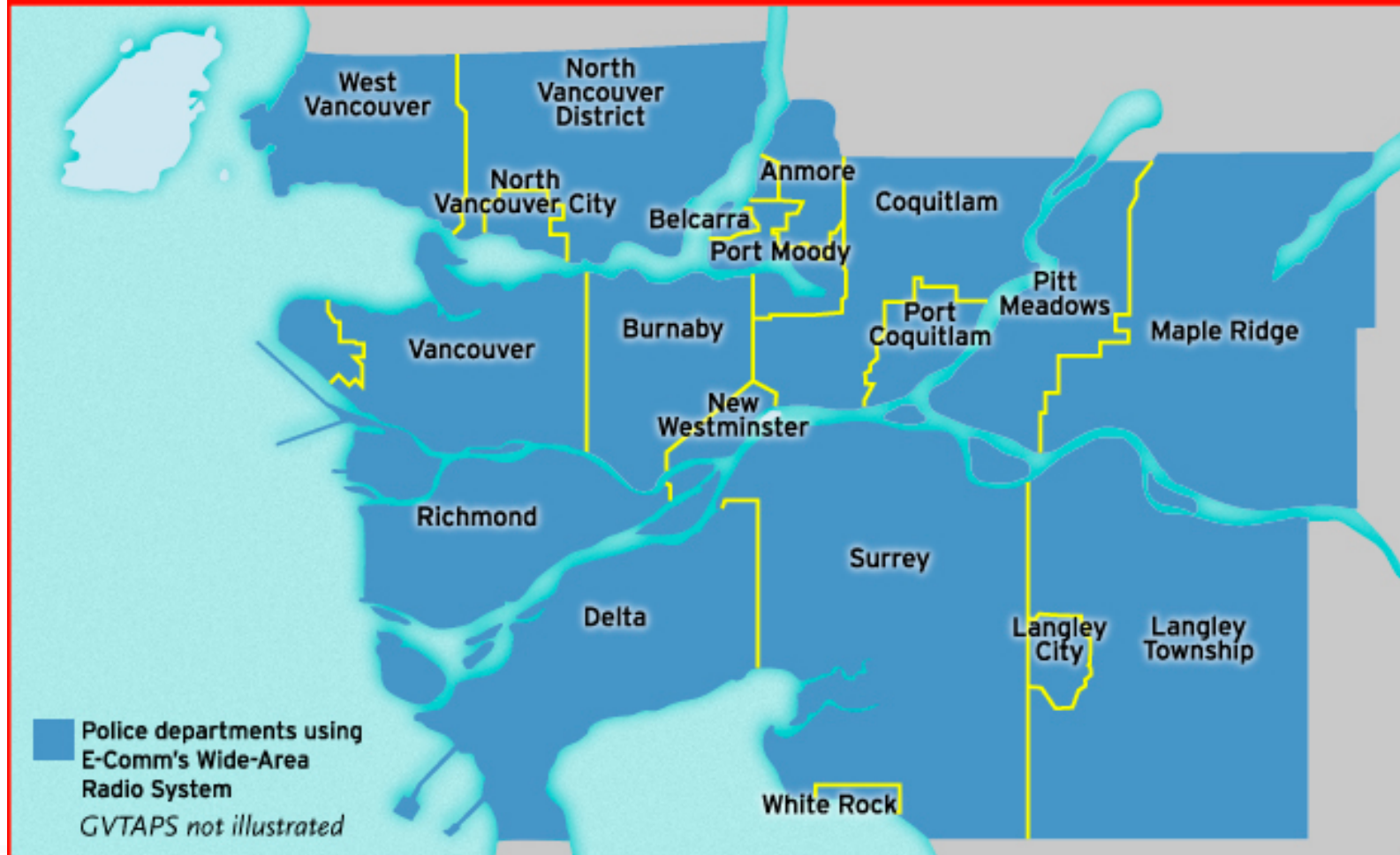
- An operational trunked radio system serving as a regional emergency communication system
- The E-Comm network is capable of both voice and data transmissions
- Voice traffic accounts for over 99% of network traffic
- A group call is a standard call made in a trunked radio system
- More than 85% of calls are group calls
- A distributed event log database records every event occurring in the network: call establishment, channel assignment, call drop, and emergency call

E-Comm network



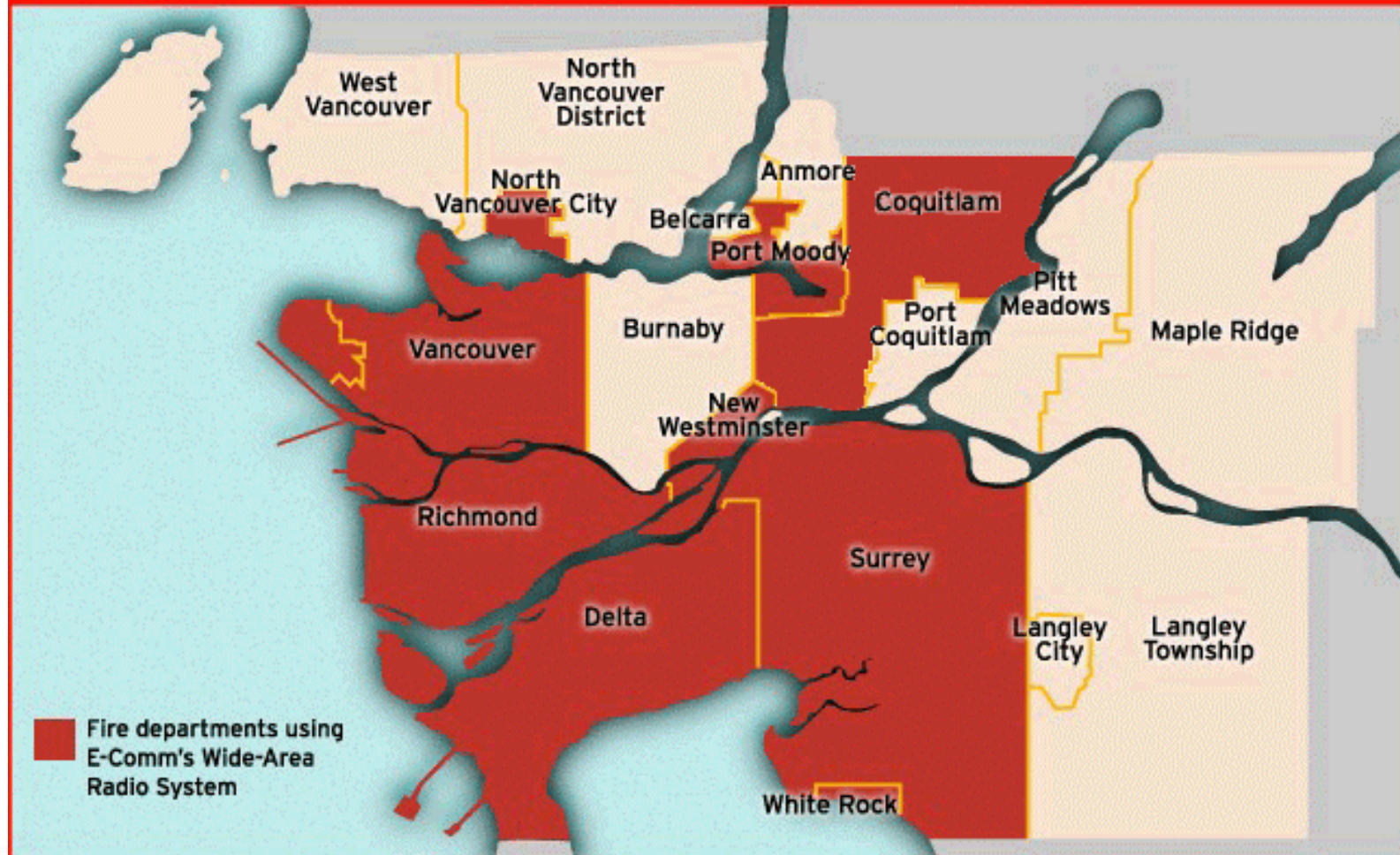
E-Comm network

E-Comm's Wide-Area Radio System: Police Customers



E-Comm network

E-Comm's Wide-Area Radio System: Fire Departments

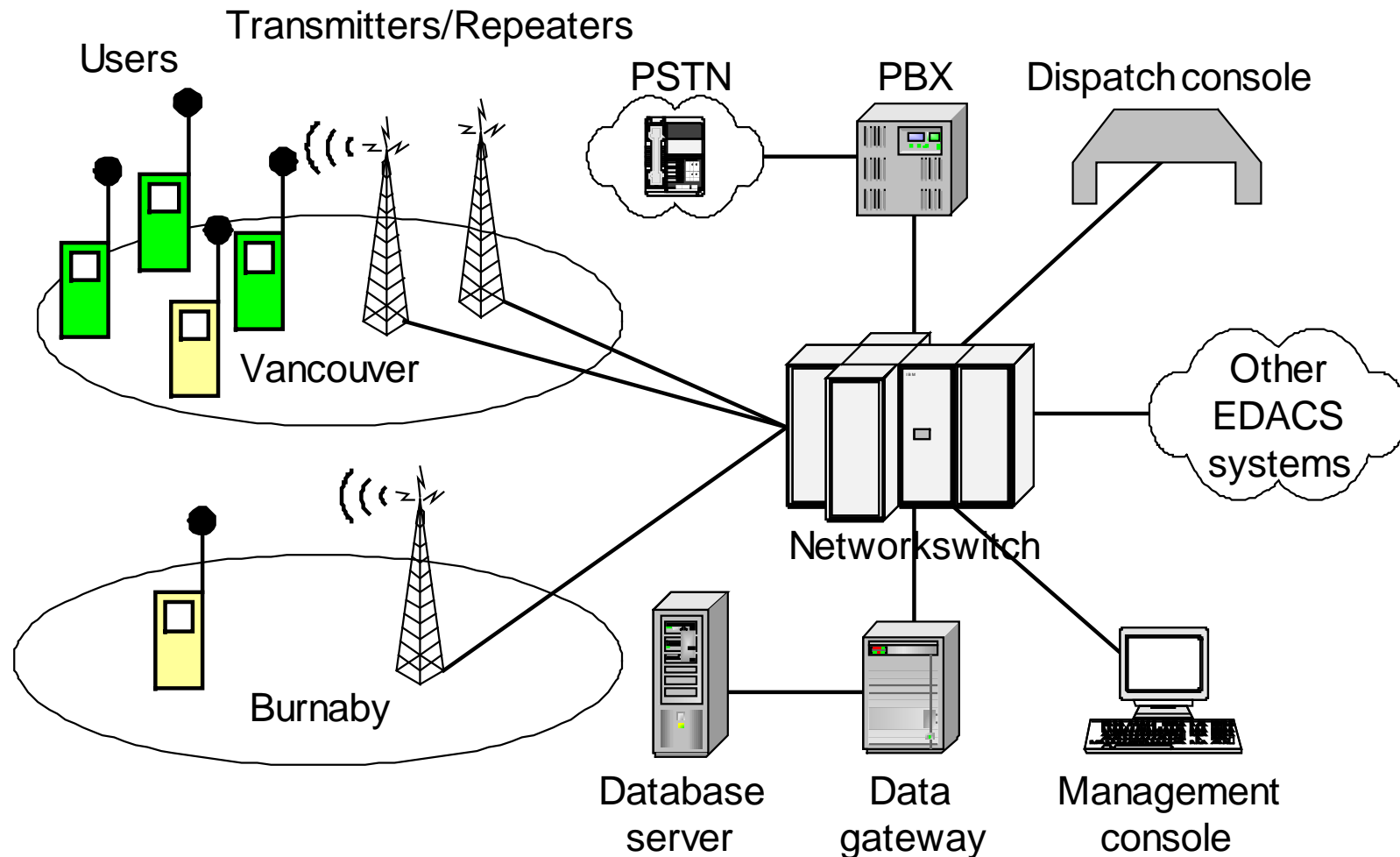


E-Comm network

E-Comm's Wide-Area Radio System: Ambulance Service



E-Comm network architecture





E-Comm traffic data

- 2001 data set:
 - 2 days of traffic data
 - 2001-11-1 to 2001-11-02 (110,348 calls)
- 2002 data set:
 - 28 days of continuous traffic data
 - 2002-02-10 to 2002-03-09 (1,916,943 calls)
- 2003 data set:
 - 92 days of continuous traffic data
 - 2003-03-01 to 2003-05-31 (8,756,930 calls)



E-Comm traffic data

- Records of network events:
 - established, queued, and dropped calls in the **Vancouver** cell
- Traffic data span periods during:
 - **2001, 2002, 2003**

Trace (dataset)	Time span	No. of established calls
2001	November 1–2, 2001	110,348
2002	March 1–7, 2002	370,510
2003	March 24–30, 2003	387,340



E-Comm traffic: observations

- Presence of daily cycles:
 - minimum utilization: ~ 2 PM
 - maximum utilization: 9 PM to 3 AM
- 2002 sample data:
 - cell 5 is the busiest
 - others seldom reach their capacities
- 2003 sample data:
 - several cells (2, 4, 7, and 9) have all channels occupied during busy hours
- The busiest hour: around midnight
- The busiest day: Thursday
- Useful for scheduling periodical maintenance tasks



E-Comm traffic: hourly traces

- Call holding and call inter-arrival times from the **five busiest hours** in each dataset (2001, 2002, and 2003)

2001		2002		2003	
Day/hour	No.	Day/hour	No.	Day/hour	No.
02.11.2001 15:00–16:00	3,718	01.03.2002 04:00–05:00	4,436	26.03.2003 22:00–23:00	4,919
01.11.2001 00:00–01:00	3,707	01.03.2002 22:00–23:00	4,314	25.03.2003 23:00–24:00	4,249
02.11.2001 16:00–17:00	3,492	01.03.2002 23:00–24:00	4,179	26.03.2003 23:00–24:00	4,222
01.11.2001 19:00–20:00	3,312	01.03.2002 00:00–01:00	3,971	29.03.2003 02:00–03:00	4,150
02.11.2001 20:00–21:00	3,227	02.03.2002 00:00–01:00	3,939	29.03.2003 01:00–02:00	4,097



E-Comm traffic: statistical distributions

- Fourteen candidate distributions:
 - exponential, Weibull, gamma, normal, lognormal, logistic, log-logistic, Nakagami, Rayleigh, Rician, t-location scale, Birnbaum-Saunders, extreme value, inverse Gaussian
- Parameters of the distributions: calculated by performing maximum likelihood estimation
- Best fitting distributions are determined by:
 - visual inspection of the distribution of the trace and the candidate distributions
 - Kolmogorov-Smirnov test of potential candidates

Call inter-arrival and call holding times: observations

	2001		2002		2003	
	Day/hour	Avg. (s)	Day/hour	Avg. (s)	Day/hour	Avg. (s)
inter-arrival	02.11.2001	0.97	01.03.2002	0.81	26.03.2003	0.73
holding	15:00–16:00	3.78	04:00–05:00	4.07	22:00–23:00	4.08
inter-arrival	01.11.2001	0.97	01.03.2002	0.83	25.03.2003	0.85
holding	00:00–01:00	3.95	22:00–23:00	3.84	23:00–24:00	4.12
inter-arrival	02.11.2001	1.03	01.03.2002	0.86	26.03.2003	0.85
holding	16:00–17:00	3.99	23:00–24:00	3.88	23:00–24:00	4.04
inter-arrival	01.11.2001	1.09	01.03.2002	0.91	29.03.2003	0.87
holding	19:00–20:00	3.97	00:00–01:00	3.95	02:00–03:00	4.14
inter-arrival	02.11.2001	1.12	02.03.2002	0.91	29.03.2003	0.88
holding	20:00–21:00	3.84	00:00–01:00	4.06	01:00–02:00	4.25

Avg. call inter-arrival times: 1.08 s (2001), 0.86 s (2002), 0.84 s (2003)

Avg. call holding times: 3.91 s (2001), 3.96 s (2002), 4.13 s (2003)



Busy hour: best fitting distributions

Busy hour	Distribution					
	Call inter-arrival times				Call holding times	
	Weibull		Gamma		Lognormal	
	a	b	a	b	μ	σ
02.11.2001 15:00–16:00	0.9785	1.1075	1.0326	0.9407	1.0913	0.6910
01.11.2001 00:00–01:00	0.9907	1.0517	1.0818	0.8977	1.0801	0.7535
02.11.2001 16:00–17:00	1.0651	1.0826	1.1189	0.9238	1.1432	0.6803
01.03.2002 04:00–05:00	0.8313	1.0603	1.1096	0.7319	1.1746	0.6671
01.03.2002 22:00–23:00	0.8532	1.0542	1.0931	0.7643	1.1157	0.6565
01.03.2002 23:00–24:00	0.8877	1.0790	1.1308	0.7623	1.1096	0.6803
26.03.2003 22:00–23:00	0.7475	1.0475	1.0910	0.6724	1.1838	0.6553
25.03.2003 23:00–24:00	0.8622	1.0376	1.0762	0.7891	1.1737	0.6715
26.03.2003 23:00–24:00	0.8579	1.0092	1.0299	0.8292	1.1704	0.6696



E-Comm traffic: clustering

- E-Comm network and traffic data:
 - data preprocessing and extraction
- Data clustering
- Traffic prediction:
 - based on aggregate traffic
 - cluster based



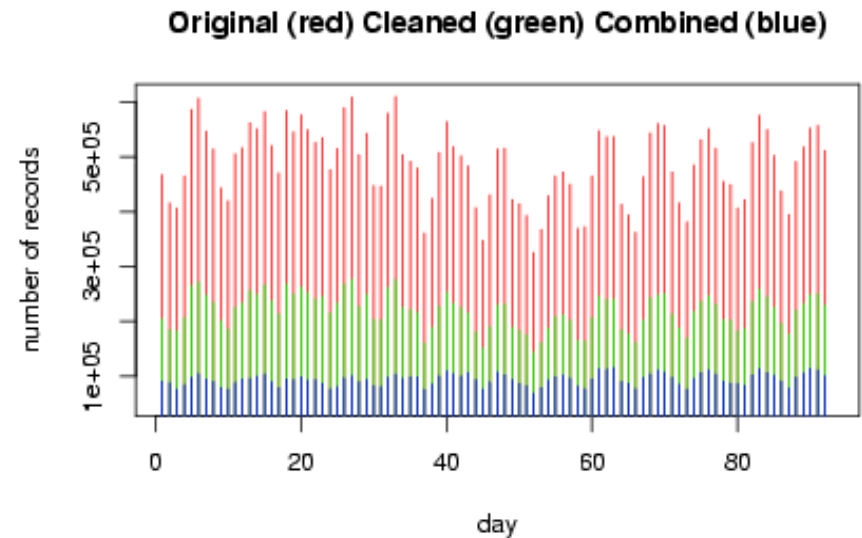
E-Comm traffic: preprocessing

- Original database: ~6 GBytes, with 44,786,489 record rows
- Data pre-processing:
 - cleaning the database
 - filtering the outliers
 - removing redundant records
 - extracting accurate user calling activity
- After the data cleaning and extraction, number of records was reduced to only 19% of original records

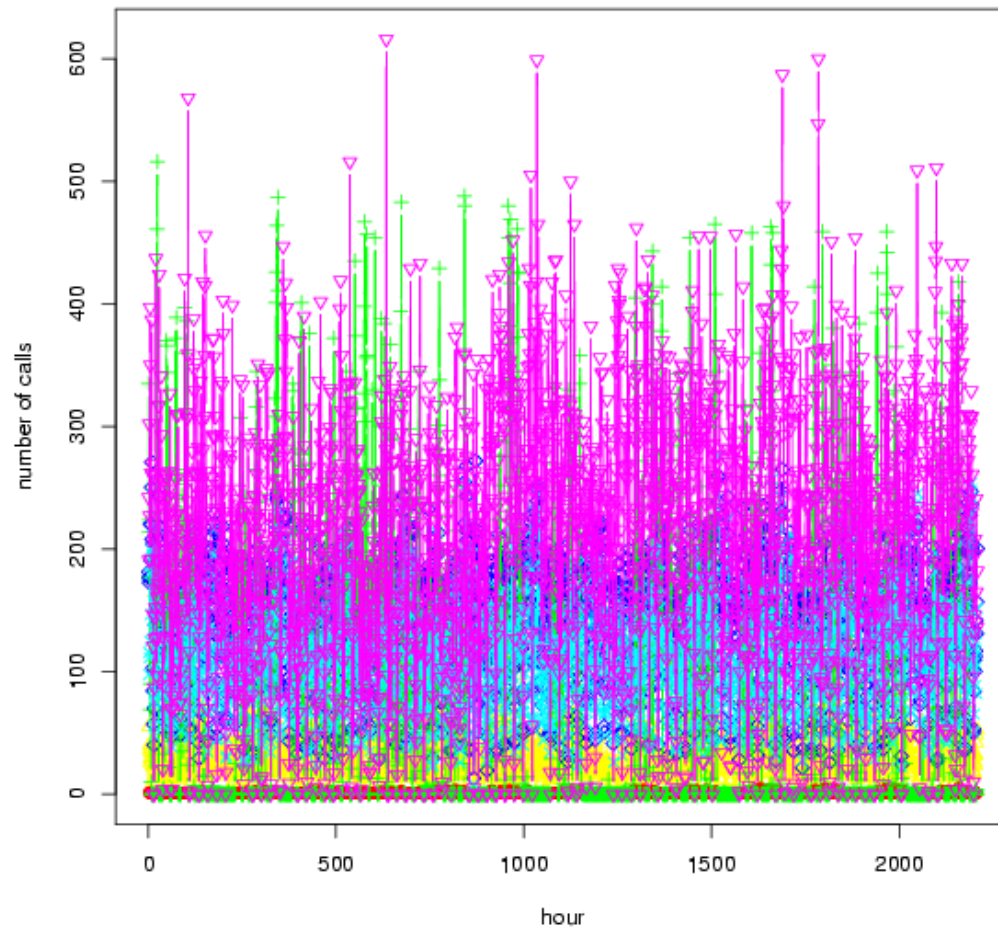
E-Comm traffic: data preparation

Date	Original	Cleaned	Combined
2003/03/01	466,862	204,357	91,143
2003/03/02	415,715	184,973	88,014
2003/03/03	406,072	182,311	76,310
2003/03/04	464,534	207,016	84,350
2003/03/05	585,561	264,226	97,714
2003/03/06	605,987	271,514	104,715
2003/03/07	546,230	247,902	94,511
2003/03/08	513,459	233,982	90,310
2003/03/09	442,662	201,146	79,815
2003/03/10	419,570	186,201	76,197
2003/03/11	504,981	225,604	88,857
2003/03/12	516,306	233,140	94,779
2003/03/13	561,253	255,840	95,662
2003/03/14	550,732	248,828	99,458

Total 92 Days	44,786,489	20,130,718	8,663,586
		44.95%	19.34%



User clusters with K-means: $k = 6$





Clustering results

- Cluster sizes:
 - 17, 31, and 569 for $K = 3$
 - 17, 33, 4, and 563 for $K = 4$
 - 13, 17, 22, 3, 34, and 528 for $K = 6$
- $K = 3$ produces the best clustering results (based on overall clustering quality and silhouette coefficient)
- Interpretations of three clusters have been confirmed by the E-Comm domain experts



E-Comm traffic: prediction

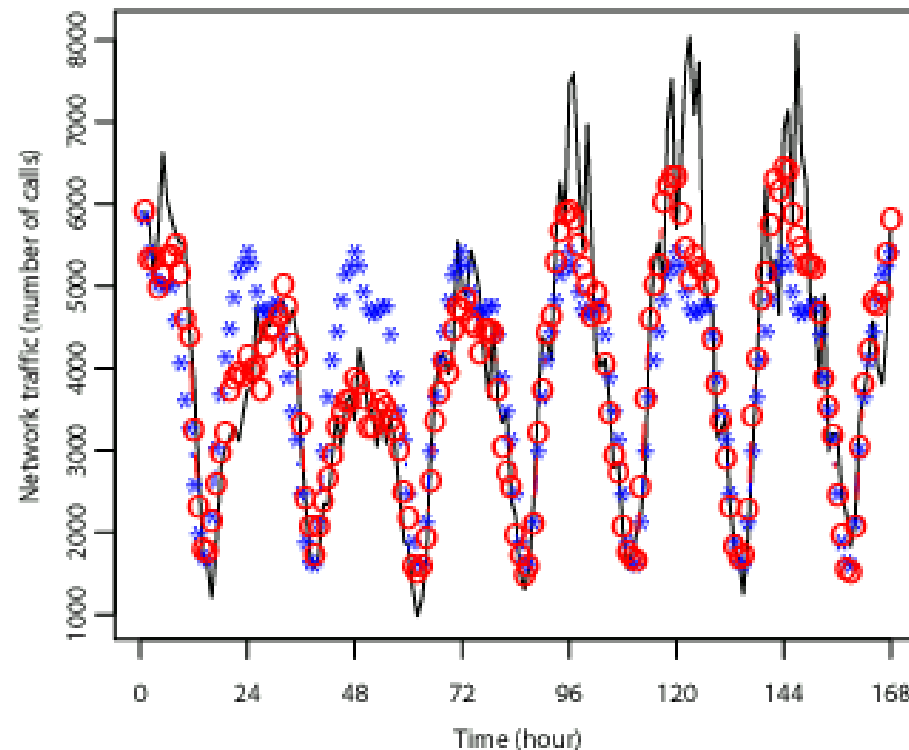
- Important to assess future network capacity requirements and to plan future network developments
- A network traffic trace consists of a series of observations in a dynamical system environment
- Traditional prediction: considers **aggregate traffic** and assumes a constant number of network users
- Approach that focuses on **individual users** has high computational cost for networks with thousands of users
- Employing **clustering techniques** for predicting aggregate network traffic bridges the gap between the two approaches



Prediction: based on the aggregate traffic

- Two groups of models, with 24-hour and 168-hour seasonal periods:
 - SARIMA $(2, 0, 9) \times (0, 1, 1)_{24 \text{ and } 168}$
 - SARIMA $(2, 0, 1) \times (0, 1, 1)_{24 \text{ and } 168}$
- Models with a 168-hour seasonal period provided better prediction than the four 24-hour period based models, particularly when predicting long term traffic data
- Prediction of traffic in networks with a variable number of users is possible, as long as the new users could be classified within the existing clusters

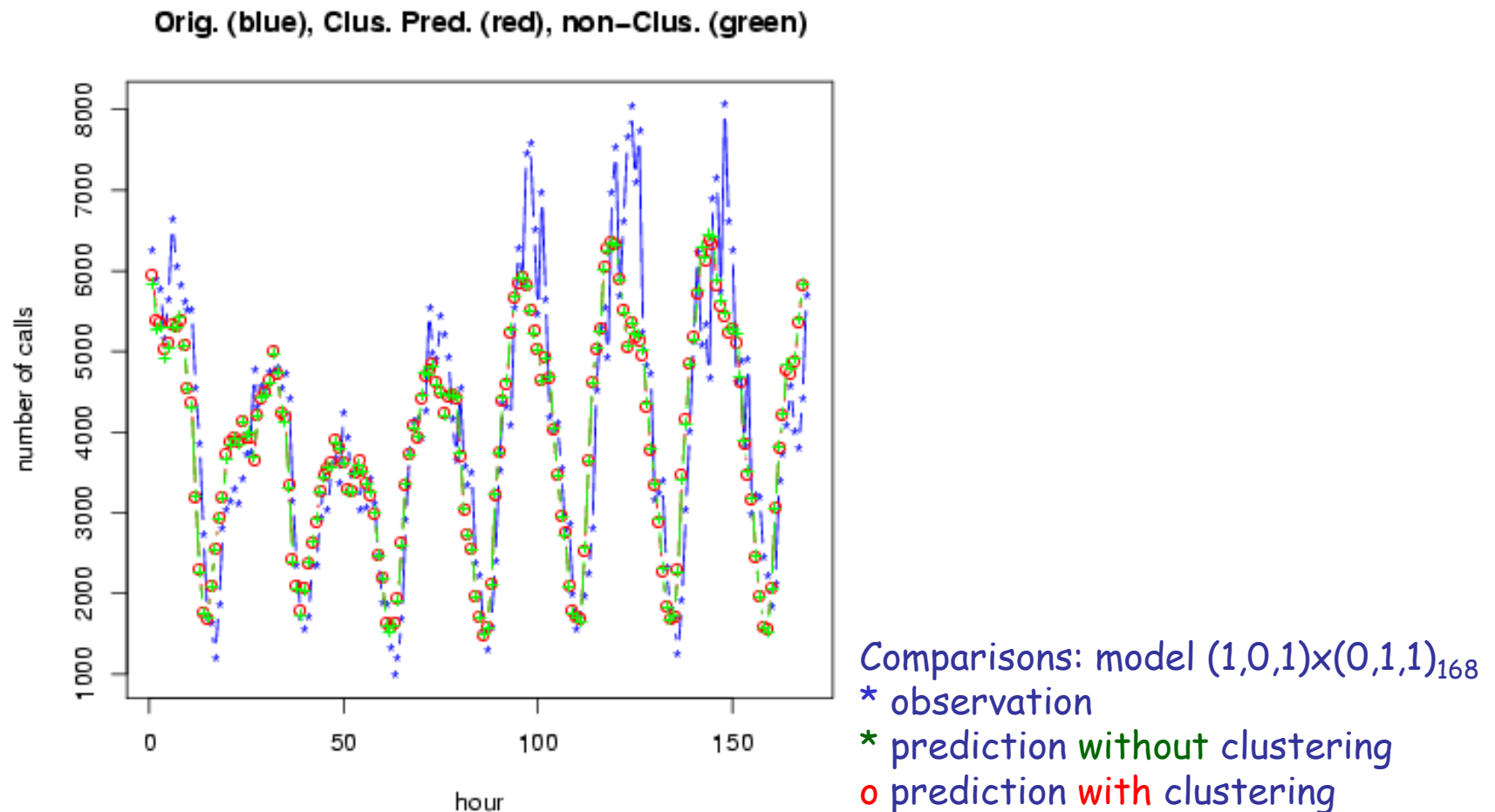
Prediction of 168 hours of traffic based on 1,680 past hours: sample



Comparison of the 24-hour and the 168-hour models

- Solid line: observation
- ○: prediction of 168-hour seasonal model
- *: prediction of 24-hour seasonal model

Prediction of 168 hours of traffic based on 1,680 past hours



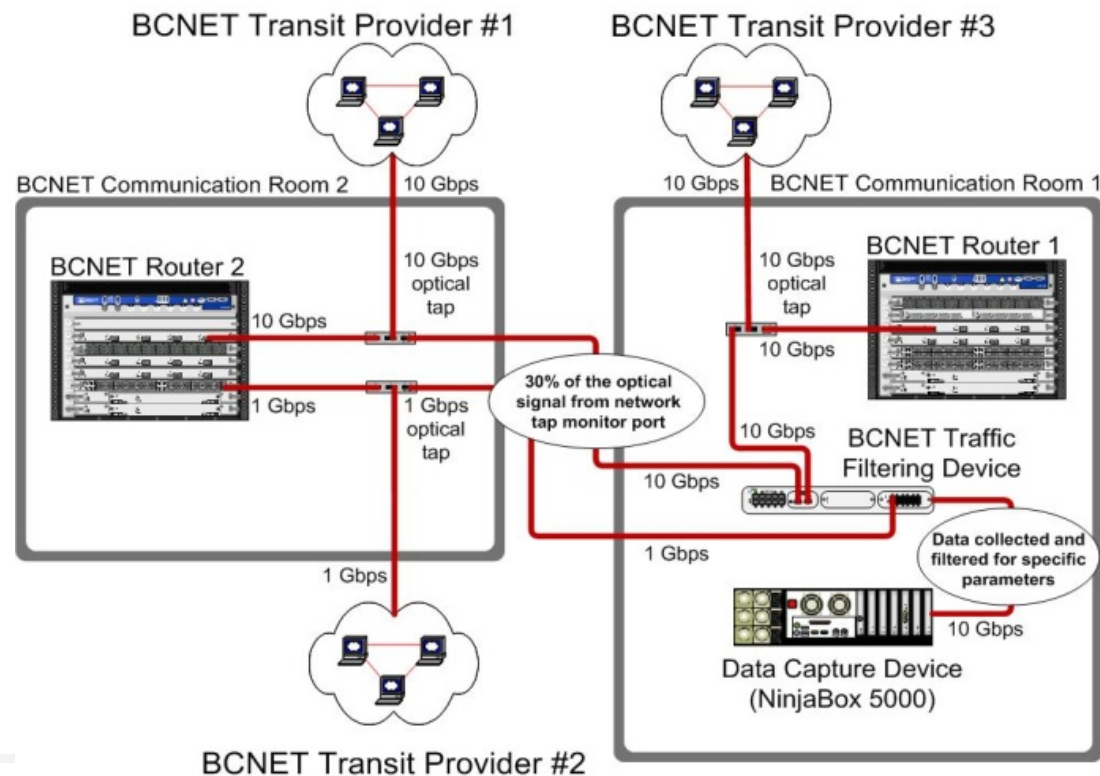


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BCNET packet capture: physical overview

- BCNET is the hub of advanced telecommunication network in British Columbia, Canada that offers services to research and higher education institutions



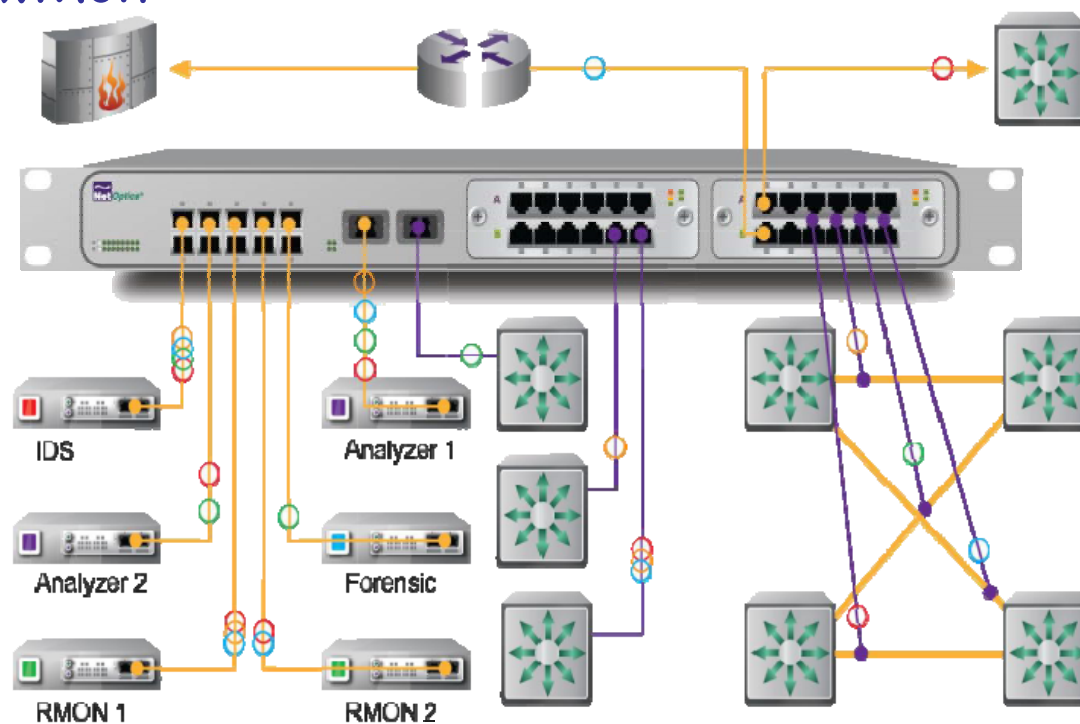


BCNET packet capture

- BCNET transits have two service providers with 10 Gbps network links and one service provider with 1 Gbps network link
- Optical Test Access Point (TAP) splits the signal into two distinct paths
- The signal splitting ratio from TAP may be modified
- The Data Capture Device (NinjaBox 5000) collects the real-time data (packets) from the traffic filtering device

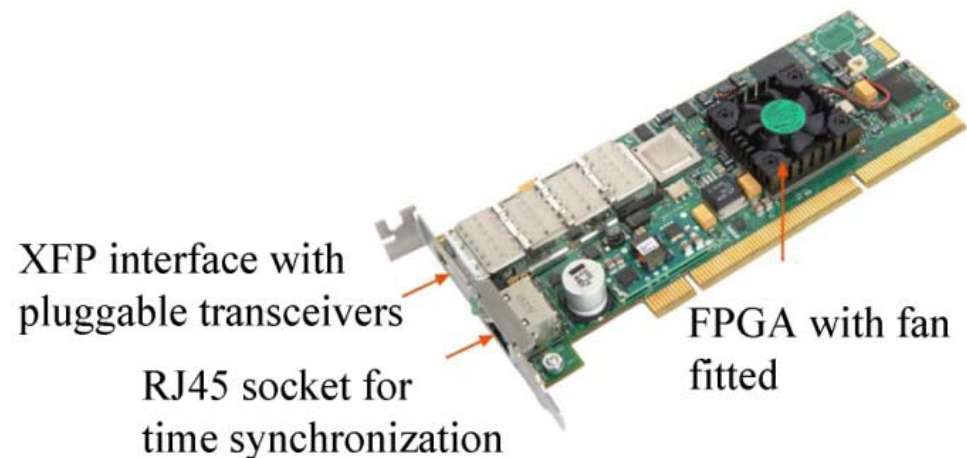
Net Optics Director 7400: application diagram

- Net Optics Director 7400 is used for BCNET traffic filtering
- It directs traffic to monitoring tools such as NinjaBox 5000 and FlowMon



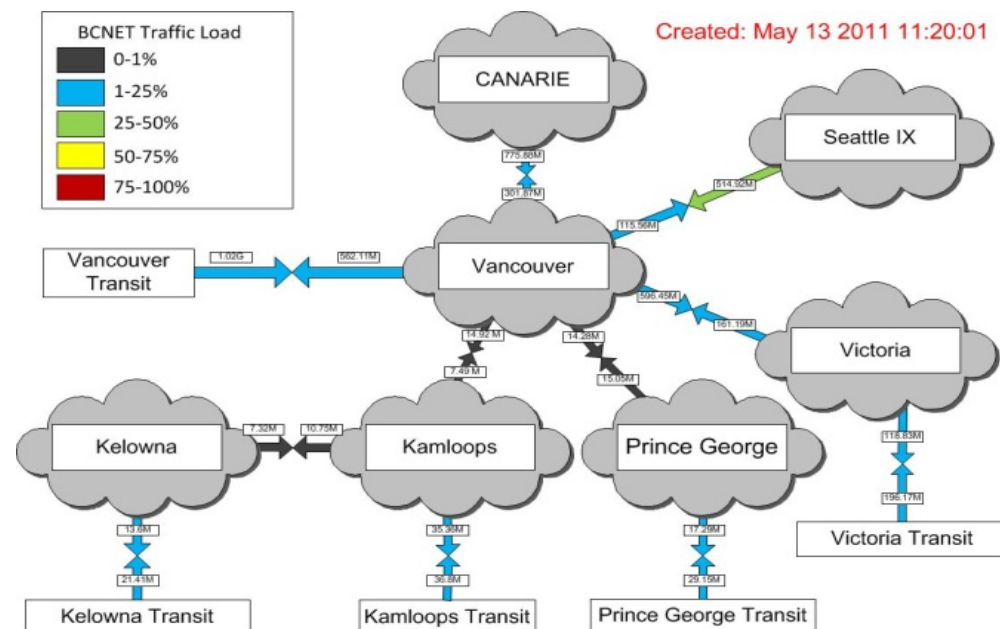
Network monitoring and analyzing: Endace card

- Endace Data Acquisition and Generation (DAG) 5.2X card resides inside the NinjaBox 5000
- It captures and transmits traffic and has time-stamping capability
- DAG 5.2X is a single port Peripheral Component Interconnect Extended (PCIe) card and is capable of capturing on average Ethernet traffic of 6.9 Gbps



Real time network usage by BCNET members

- The BCNET network is high-speed fiber optic research network
- British Columbia's network extends to 1,400 km and connects Kamloops, Kelowna, Prince George, Vancouver, and Victoria





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Internet topology

- 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 ASes and their interconnections
- Analyzing the Internet topology and finding properties of associated graphs rely on mining data and capturing information about Autonomous Systems (ASes)



Variety of graphs

- **Random** graphs:
 - nodes and edges are generated by a random process
 - Erdős and Rényi model
- **Small world** graphs:
 - nodes and edges are generated so that most of the nodes are connected by a small number of nodes in between
 - Watts and Strogatz model (1998)



Scale-free graphs

- **Scale-free** graphs:
 - graphs whose node degree distribution follow power-law
 - rich get richer
 - Barabási and Albert model (1999)
- Analysis of **complex networks**:
 - discovery of spectral properties of graphs
 - constructing matrices describing the network connectivity



Analyzed datasets

- Sample datasets:

- Route Views:

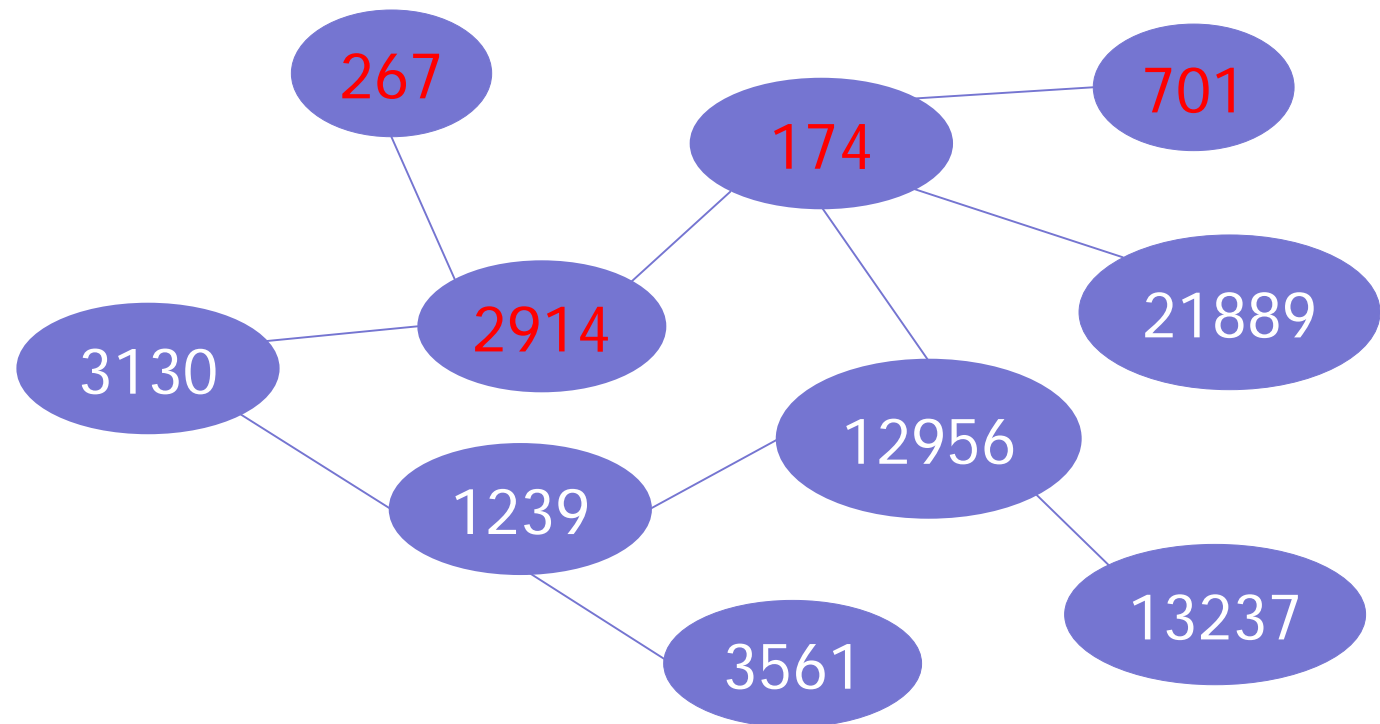
```
TABLE_DUMP| 1050122432| B| 204.42.253.253|  
267| 3.0.0.0/8| 267 2914 174 701| IGP|  
204.42.253.253| 0| 0| 267:2914 2914:420  
2914:2000 2914:3000| NAG| |
```

- RIPE:

```
TABLE_DUMP| 1041811200| B| 212.20.151.234|  
13129| 3.0.0.0/8| 13129 6461 7018 | IGP|  
212.20.151.234| 0| 0| 6461:5997 13129:3010| NAG|  
|
```

Internet topology at AS level

- Datasets collected from Border Gateway Protocols (BGP) routing tables are used to infer the Internet topology at AS-level





Internet topology

- The Internet topology is characterized by the presence of various power-laws:
 - node degree vs. node rank
 - eigenvalues of the matrices describing Internet graphs (adjacency matrix and normalized Laplacian matrix)
- **Power-laws exponents** have not significantly changed over the years
- **Spectral analysis** reveals new historical trends and notable changes in the connectivity and clustering of AS nodes over the years



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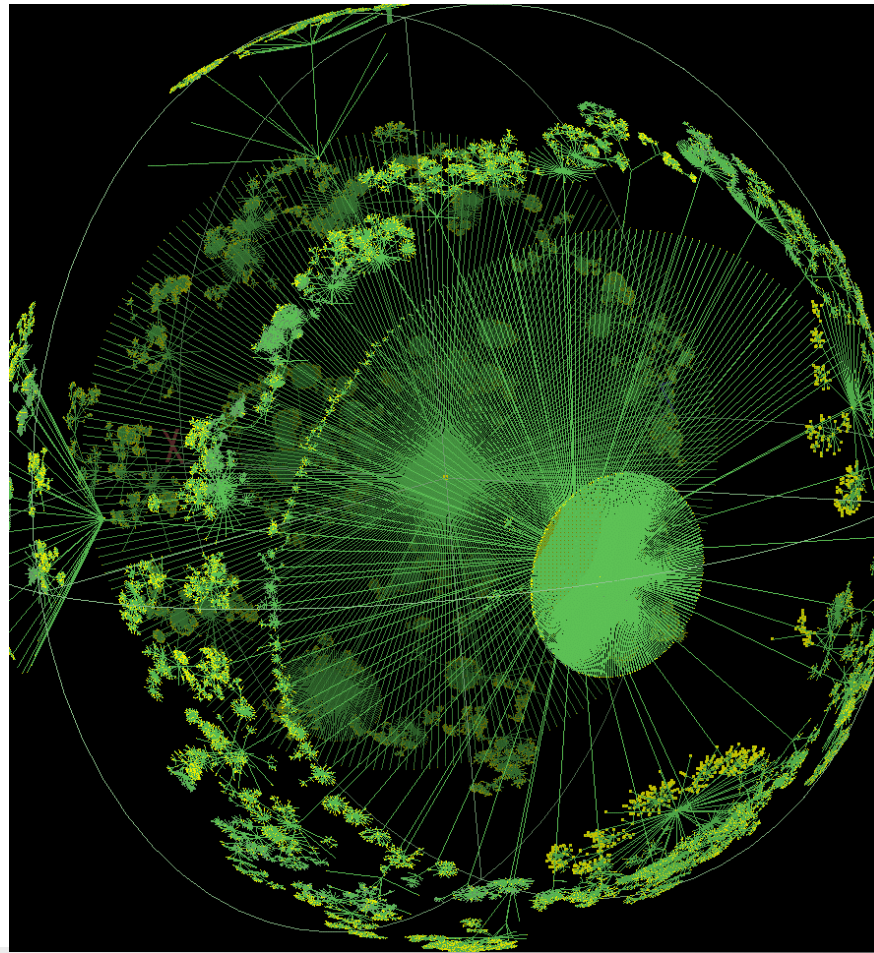


Conclusions

- Traffic data from deployed networks can be 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 models based on aggregate user traffic and user clusters
- **Internet** datasets reveal trends in the evolution of the Internet topology
- **Spectral analysis** indicate that clusters of connected Internet nodes have changed over time



lhr (535,102 nodes and 601,678 links)





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