



Machine Learning for Complex Networks

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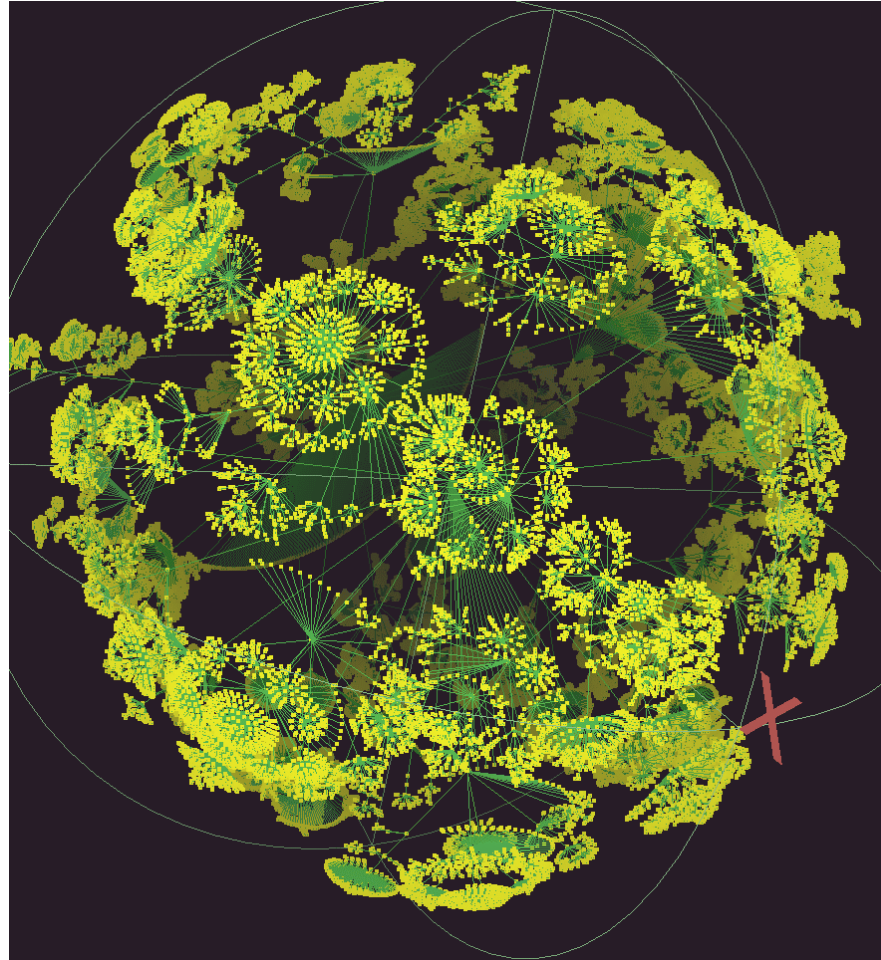


Roadmap

- Introduction
- Traffic collection, characterization, and modeling
- Case studies:
 - telecommunication network: BCNET
 - public safety wireless network: E-Comm
 - satellite network: ChinaSat
 - packet data networks: Internet
- 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 (unlike Poisson traffic)
 - 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

- 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

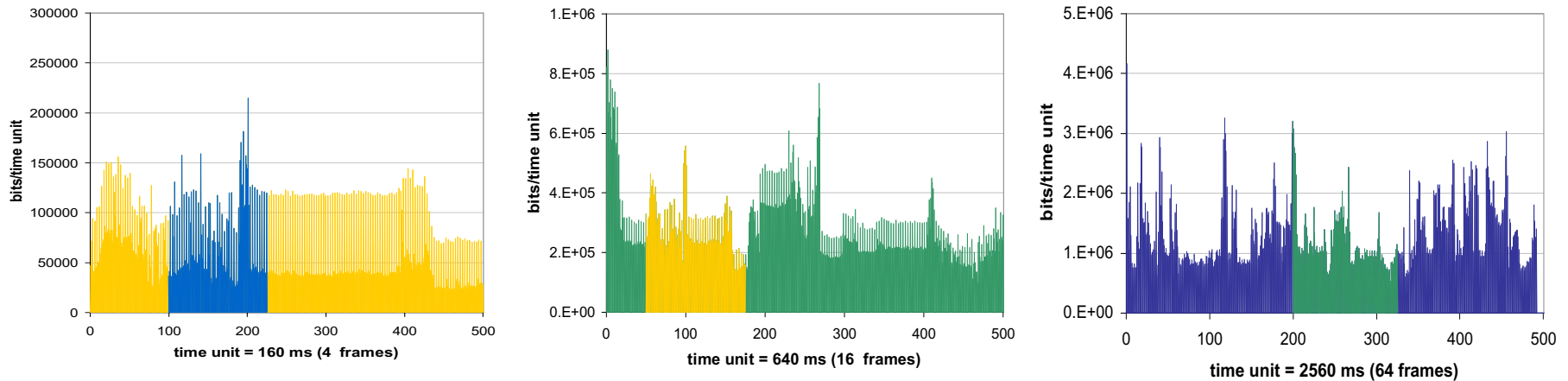


Self-similar processes

- 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 Hurst parameter increases

Self-similarity: influence of time-scales

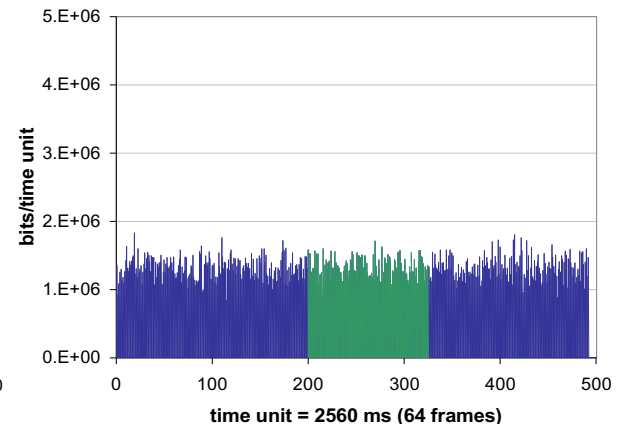
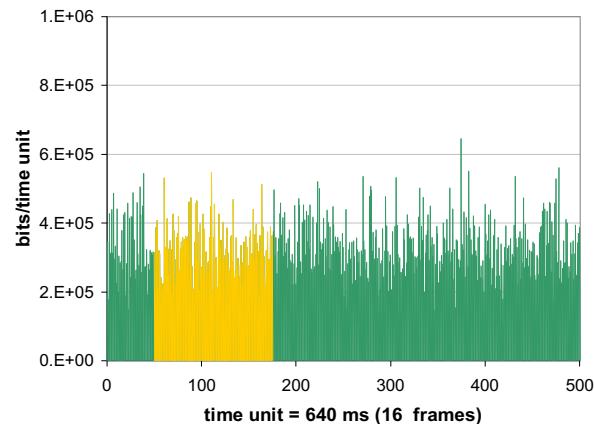
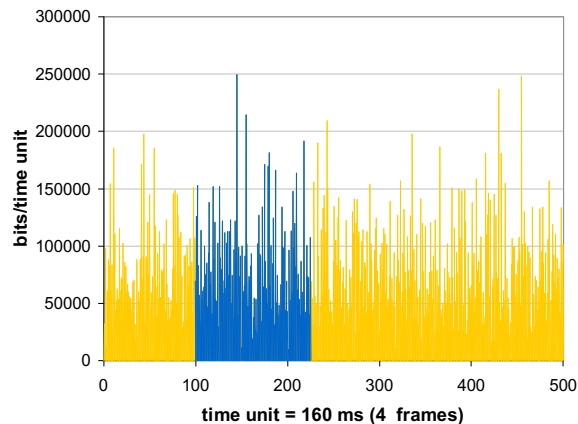
■ Genuine MPEG traffic trace



W. E. Leland, M. S. Taqqu, W. Willinger, and D. V. Wilson, "On the self-similar nature of Ethernet traffic (extended version)," *IEEE/ACM Trans. Netw.*, vol. 2, no 1, pp. 1-15, Feb. 1994.

Self-similarity: influence of time-scales

- Synthetically generated Poisson model



W. E. Leland, M. S. Taqqu, W. Willinger, and D. V. Wilson, "On the self-similar nature of Ethernet traffic (extended version)," *IEEE/ACM Trans. Netw.*, vol. 2, no 1, pp. 1-15, Feb. 1994.



Roadmap

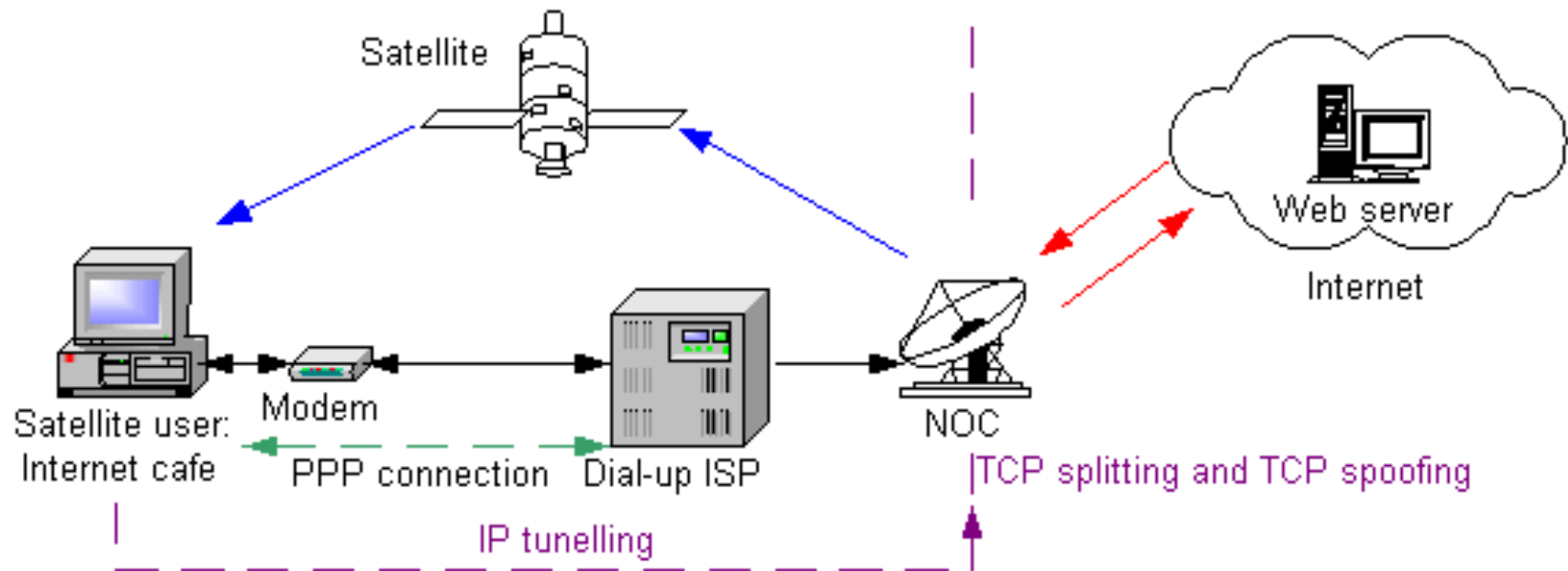
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Case study: ChinaSat DirecPC system

- 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 DirecPC system





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



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



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



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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:

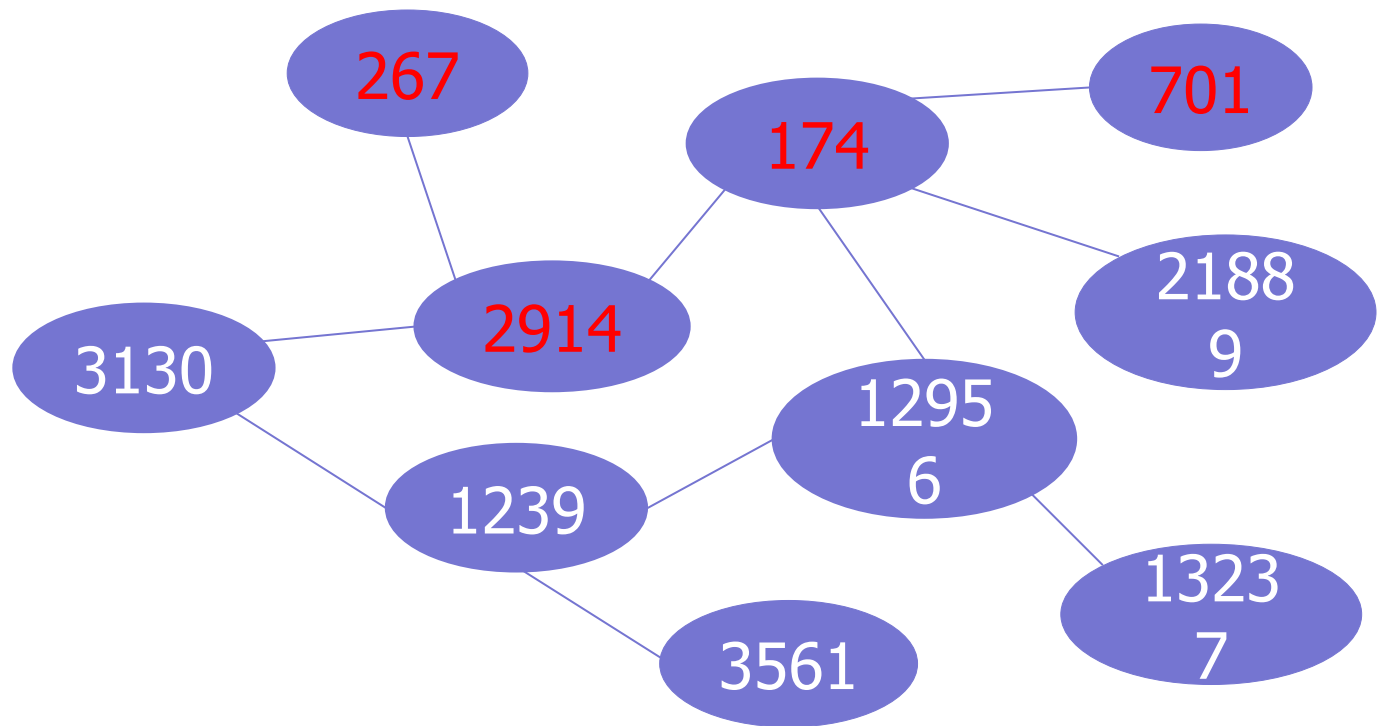
```
TABLE_DUMP| 1050122432| B| 204.42.253.253|  
267| 3.0.0.0/8| 267 2914 174 701| IGP|  
204.42.253.253| 0| 0| 267:2914 2914:420  
2914:2000 2914:3000| NAG| |
```

- 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



Traffic anomalies

- Slammer, Nimda, and Code Red I anomalies affected performance of the Internet Border Gateway Protocol (BGP)
- BGP anomalies also include: Internet Protocol (IP) prefix hijacks, miss-configurations, and electrical failures
- Techniques for detecting BGP anomalies have recently gained visible attention and importance



Anomaly detection techniques

- Classification problem:
 - assigning an “anomaly” or “regular” label to a data point
- Accuracy of a classifier depends on:
 - extracted features
 - combination of selected features
 - underlying model

Goal:

- Detect Internet routing anomalies using the Border Gateway Protocol (BGP) update messages



BGP features

Approach:

- Define a set of 37 features based on BGP update messages
- Extract the features from available BGP update messages that are collected during the time period when the Internet experienced anomalies:
 - Slammer
 - Nimda
 - Code Red I



Feature selection

- Select the most relevant features for classification using:
 - Fisher
 - Minimum Redundancy Maximum Relevance (mRMR)
 - Odds Ratio
 - Decision Tree
 - Fuzzy Rough Sets



Anomaly classification

- Train classifiers for BGP anomaly detection using:
 - Support Vector Machines (SVM)
 - Long Short-Term Memory (LSTM) Neural Network
 - Hidden Markov Models (HMM)
 - Naive Bayes (NB)
 - Decision Tree
 - Extreme Learning Machine (ELM)



Feature extraction: BGP messages

- Border Gateway Protocol (BGP) enables exchange of routing information between gateway routers using update messages
- BGP update message collections:
 - Réseaux IP Européens (RIPE) under the Routing Information Service (RIS) project
 - Route Views
 - Available in multi-threaded routing toolkit (MRT) binary format



BGP: known anomalies

Anomaly	Date	Duration (min)
Slammer	January 25, 2003	869
Nimda	September 18-20, 2001	3,521
Code Red I	July 19, 2001	600

Event	Date	Peers
Moscow power blackout	May 2005	AS 1853, AS 12793, AS 13237
AS 9121 routing table leak	Dec. 2004	AS 1853, AS 12793, AS 13237
AS 3561 improper filtering	Apr. 2001	AS 3257, AS 3333, AS 286
Panix domain hijack	Jan. 2006	AS 12956, AS 6762, AS 6939, AS 3549
As-path error	Oct. 2001	AS 3257, AS 3333, AS 6762, AS 9057
AS 3356/AS 714 de-peering	Oct. 2005	AS 13237, AS 8342, AS 5511, AS 16034



Training and test datasets

Dataset	Training dataset	Test dataset
1	Slammer and Nimda	Code Red I
2	Slammer and Code Red I	Nimda
3	Nimda and Code Red I	Slammer
4	Slammer	Nimda and Code Red I
5	Nimda	Slammer and Code Red I
6	Code Red I	Slammer and Nimda
7	Slammer, Nimda, and Code Red I	RIPE or BCNET



Feature extraction: BGP messages

- Define 37 features
- Sample every minute during a five-day period:
 - the peak day of an anomaly
 - two days prior and two days after the peak day
- 7,200 samples for each anomalous event:
 - 5,760 regular samples (non-anomalous)
 - 1,440 anomalous samples
 - Imbalanced dataset



BGP features

Feature	Definition	Category
1	Number of announcements	Volume
2	Number of withdrawals	Volume
3	Number of announced NLRI prefixes	Volume
4	Number of withdrawn NLRI prefixes	Volume
5	Average AS-PATH length	AS-path
6	Maximum AS-PATH length	AS-path
7	Average unique AS-PATH length	AS-path
8	Number of duplicate announcements	Volume
9	Number of duplicate withdrawals	Volume
10	Number of implicit withdrawals	Volume



BGP features

Feature	Definition	Category
11	Average edit distance	AS-path
12	Maximum edit distance	AS-path
13	Inter-arrival time	Volume
14-24	Maximum edit distance = n , where $n = (7, \dots, 17)$	AS-path
25-33	Maximum AS-path length = n , where $n = (7, \dots, 15)$	AS-path
34	Number of IGP packets	Volume
35	Number of EGP packets	Volume
36	Number of incomplete packets	Volume
37	Packet size (B)	Volume



Feature selection algorithms

- Employed to select the most relevant features:
 - Fisher
 - Minimum Redundancy Maximum Relevance (mRMR)
 - Odds Ratio
 - **Decision Tree**
 - Fuzzy Rough Sets



Feature selection: decision tree

Dataset	Training data	Selected Features
Dataset 1	Slammer + Nimda	1-21, 23-29, 34-37
Dataset 2	Slammer + Code Red I	1-22, 24-29, 34-37
Dataset 3	Code Red I + Nimda	1-29, 34-37

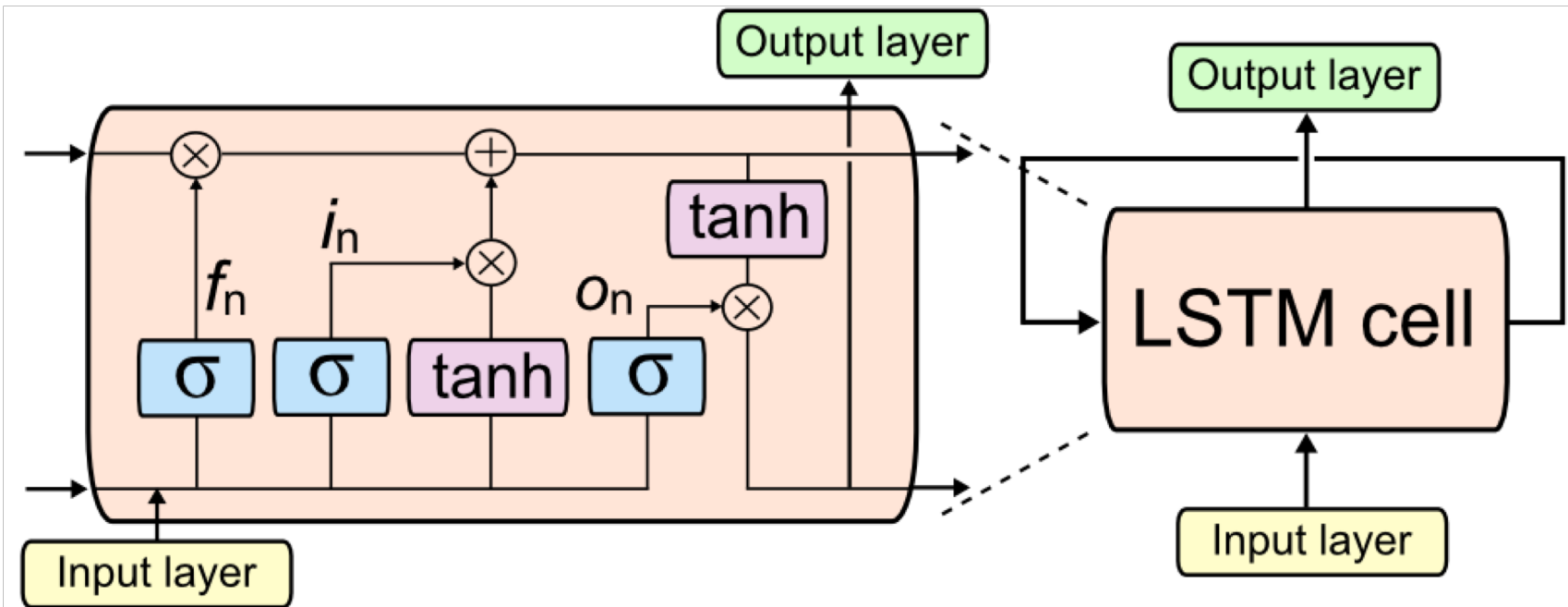
- Either four (30, 31, 32, 33) or five (22, 30, 31, 32, 33) features are removed in the constructed trees mainly because:
 - features are numerical and some are used repeatedly



Anomaly classification

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 - Hidden Markov Models (HMM)
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 - Decision Tree
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Anomaly classifiers: LSTM



- Repeating modules for the LSTM neural network: input layer, LSTM layer with one LSTM cell, and output layer.



Anomaly classifiers: LSTM

		Accuracy (%)			F-Score (%)
Test dataset			RIPE	BCNET	Test dataset
LSTMu 1	Code Red I	95.22	65.49	57.30	83.17
LSTMu 2	Nimda	53.94	51.53	50.80	11.81
LSTMu 3	Slammer	95.87	56.74	58.55	84.62

		Accuracy (%)			F-Score (%)
Test dataset			RIPE	BCNET	Test dataset
LSTMb 1	Code Red I	56.43	60.48	62.78	26.59
LSTMb 2	Nimda	53.32	44.27	53.58	65.96
LSTMb 3	Slammer	82.98	55.00	48.20	58.54



Anomaly classifiers: decision tree

		Accuracy (%)			F-Score (%)
Training dataset	Test dataset		RIPE	BCNET	Test dataset
Dataset 1	Code Red I	85.36	89.00	77.22	47.82
Dataset 2	Nimda	58.13	94.19	81.18	26.16
Dataset 3	Slammer	95.89	89.42	77.78	84.34

- Each path from the root node to a leaf node may be transformed into a decision rule
- A set of rules that are obtained from a trained decision tree may be used for classifying unseen samples



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Conclusions

- Data collected from deployed networks are used to:
 - evaluate network performance
 - characterize and model traffic (inter-arrival and call holding times)
 - identify trends in the evolution of the Internet topology
 - classify traffic and network anomalies



References: sources of data

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- University of Oregon Route Views project [Online]. Available:
[http:// www.routeviews.org/](http://www.routeviews.org/).
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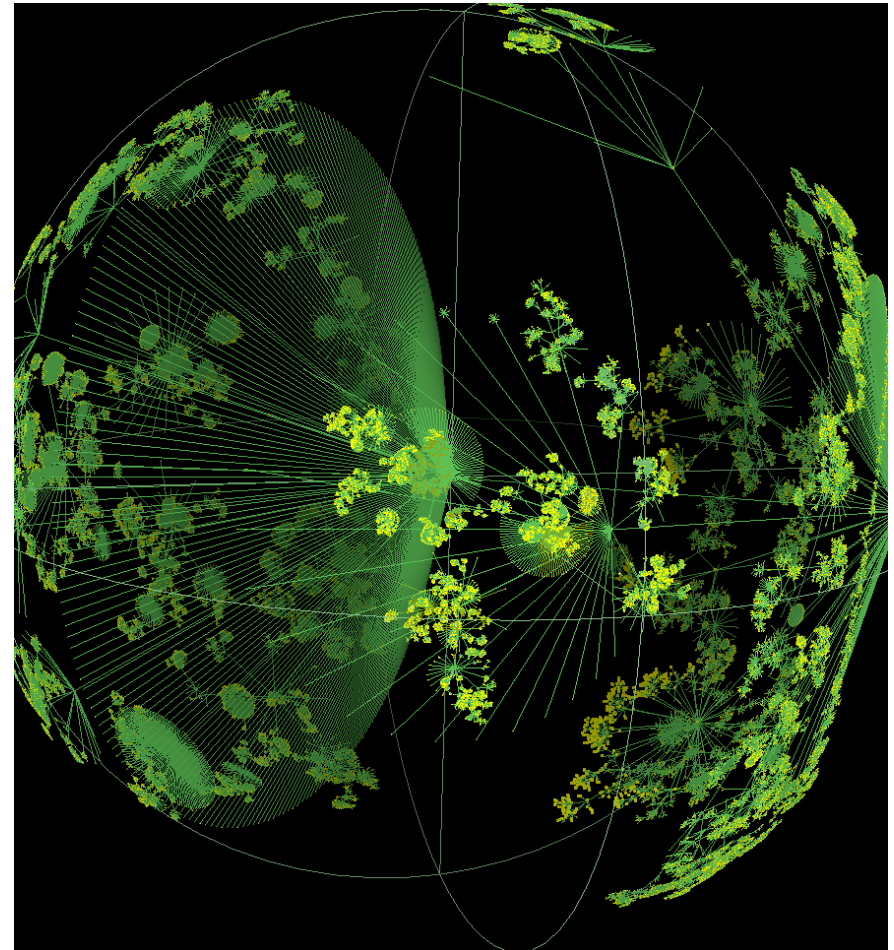
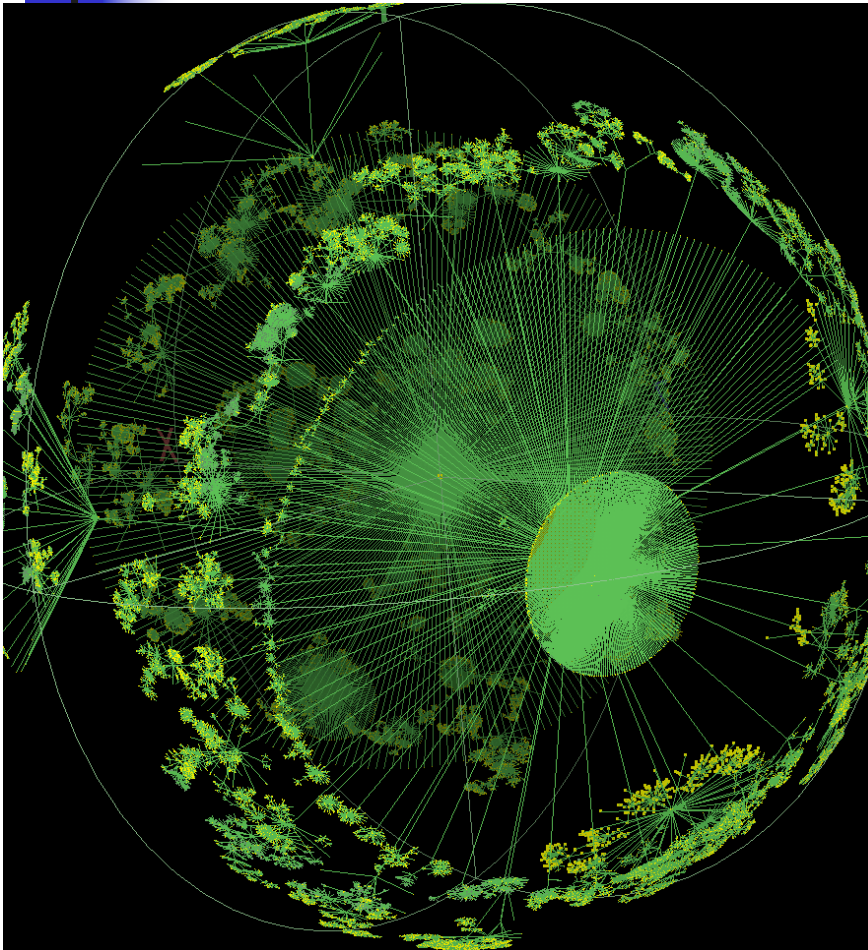


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