

Detecting Internet Worms, Ransomware, and Blackouts Using Recurrent Neural Networks

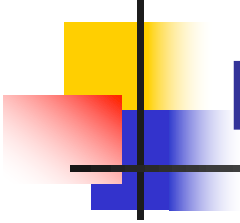
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<http://www.ensc.sfu.ca/cnl>

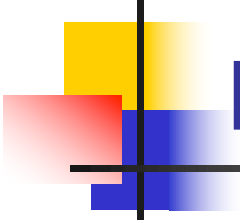
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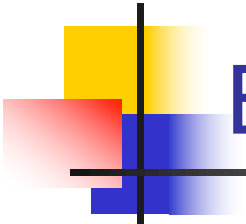
Roadmap

- Introduction
- BGP data collections: **RIPE**, **Route Views**
- BGP anomalies:
Slammer, **WannaCrypt**, **Moscow blackout**
- BGP datasets
- Experimental procedure
 - Deep learning: **multi-layer networks**
 - **BGP anomaly detection**
- Performance comparison: **LSTM**, **GRU**
- Conclusion and references



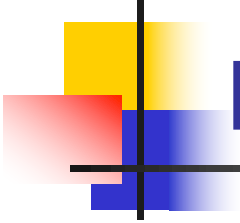
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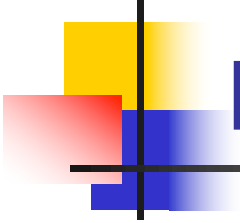
Border Gateway Protocol

- BGP's main function is to optimally route data between Autonomous Systems
- Types of BGP messages:
 - open, keepalive, update, and notification
- BGP anomalies:
 - worms, ransomware attacks, routing misconfigurations, Internet Protocol prefix hijacks, and link failures
- Collections of BGP update messages:
 - Réseaux IP Européens (RIPE)
 - Route Views



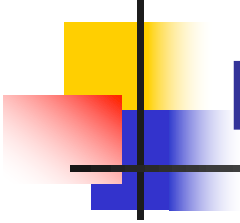
Machine Learning Algorithms

- Supervised machine learning algorithms:
 - Support vector machine: SVM
 - Broad learning system: BLS
 - Long short-term memory: LSTM
 - Gated recurrent unit: GRU



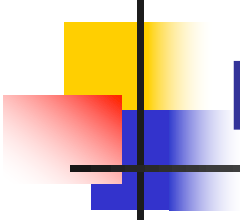
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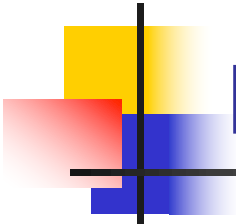
RIPE and Route Views

- RIPE:
 - RIPE Network Coordination Centre project established in 2001 to collect and store routing data from several ASes worldwide
 - Remote route collectors installed at major topologically interesting Internet points for collection of BGP data
- Route Views:
 - University of Oregon project to collect real-time BGP routing data from various backbone routers and locations worldwide



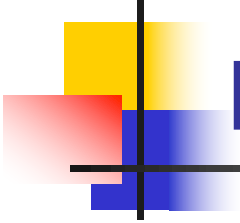
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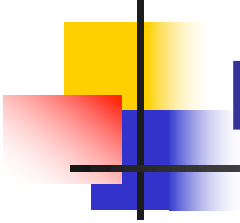
BGP Anomalies

- Slammer:
 - The fastest worm that self-propagated by using the User Datagram Protocol
 - Infected Microsoft SQL servers through a small piece of code that generated IP addresses at random
- WannaCrypt:
 - Data files are encrypted
 - Ransom is requested
- Moscow blackout:
 - Caused a complete shutdown of the Chagino substation of the Moscow energy ring
 - Caused the failure of the Internet traffic exchange



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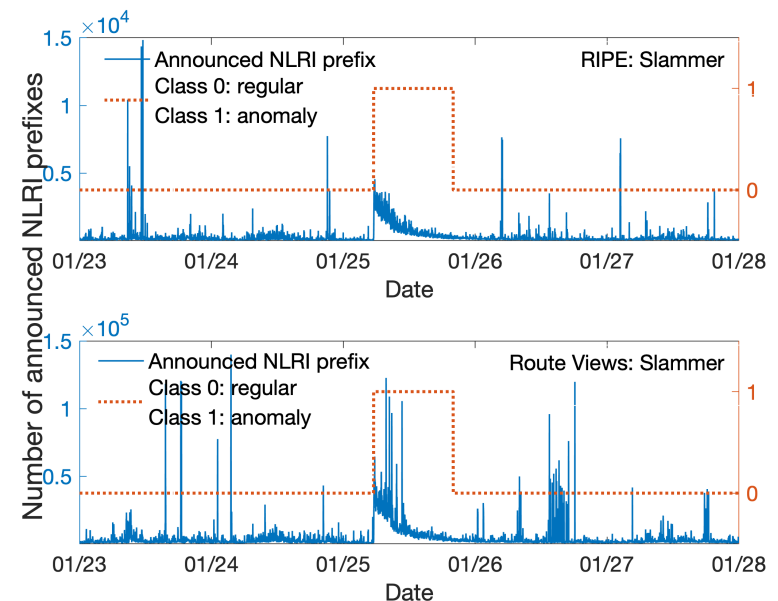
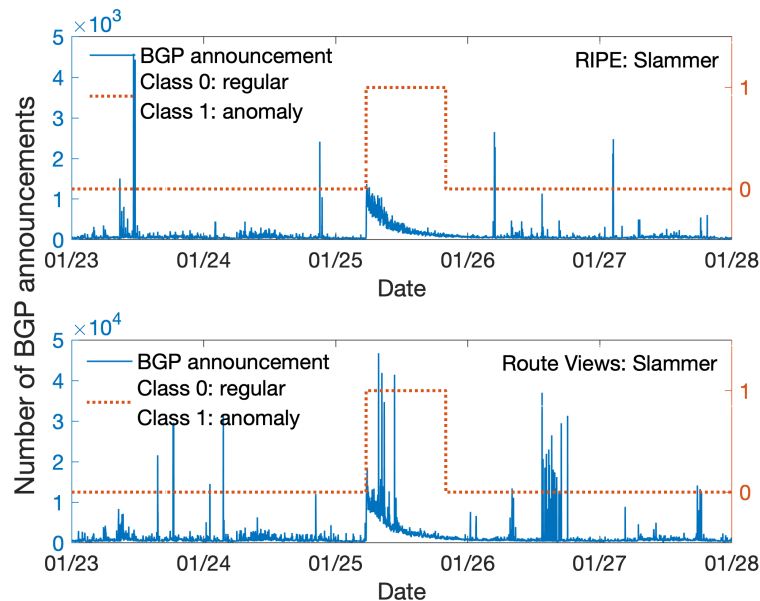


BGP Datasets

- Anomalous data: days of the attack
- Regular data: two days prior and two days after the attack
- 37 numerical features from BGP update messages
- Training and test datasets are created based on the percentages of anomalous data:
 - training: 60%
 - testing: 40%

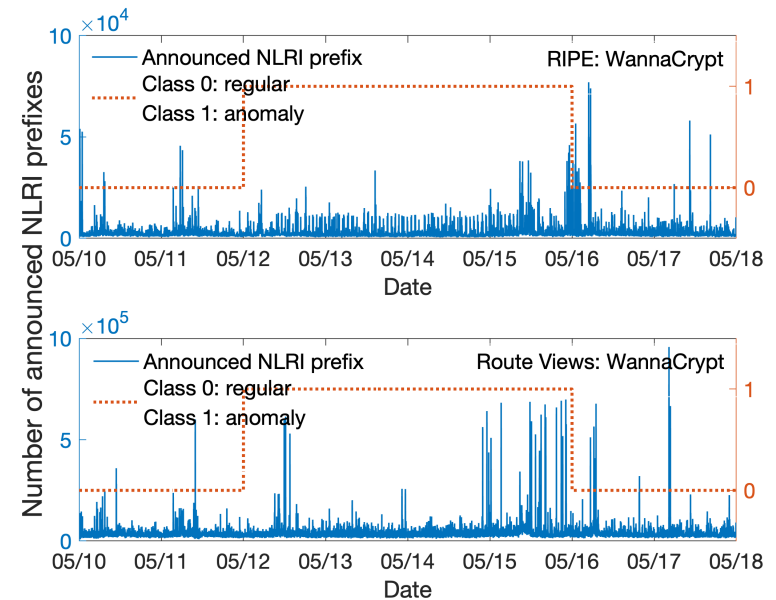
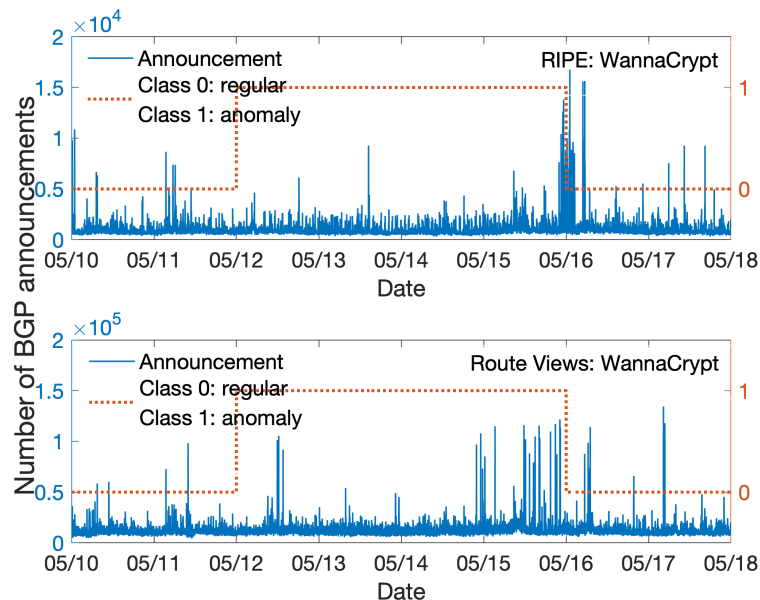
BGP Dataset: Slammer

- BGP announcements and announced NLRI prefixes:



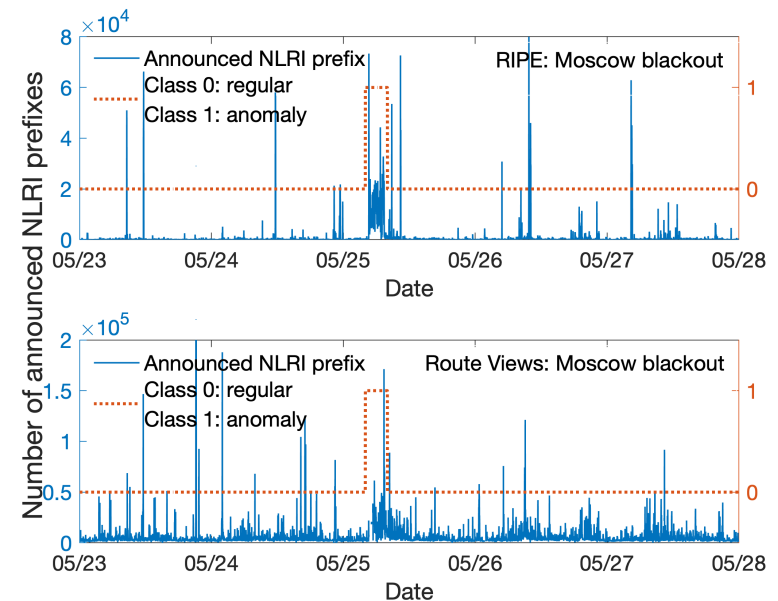
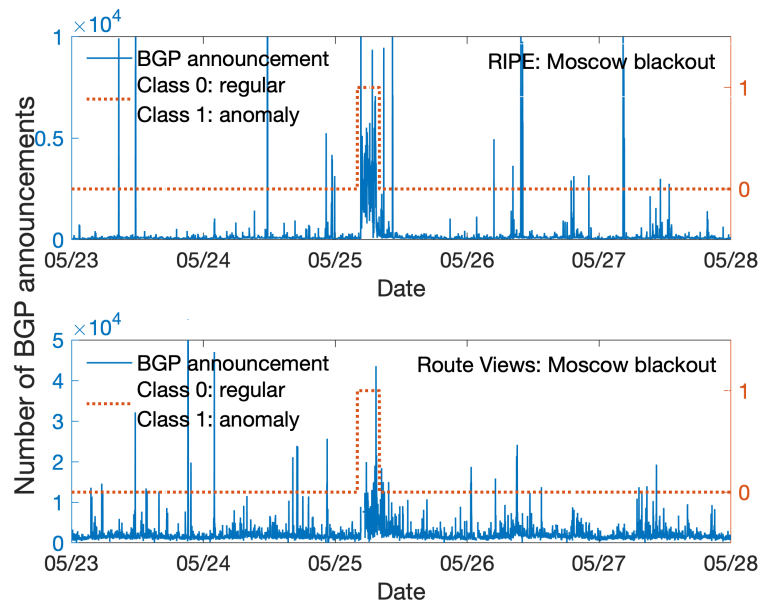
BGP Dataset: WannaCrypt

■ BGP announcements and announced NLRI prefixes:



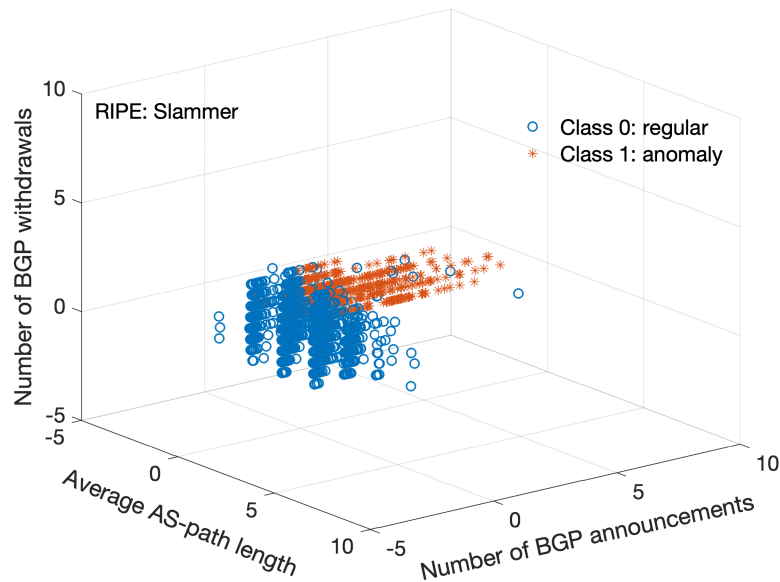
BGP Dataset: Moscow Blackout

■ BGP announcements and announced NLRI prefixes:



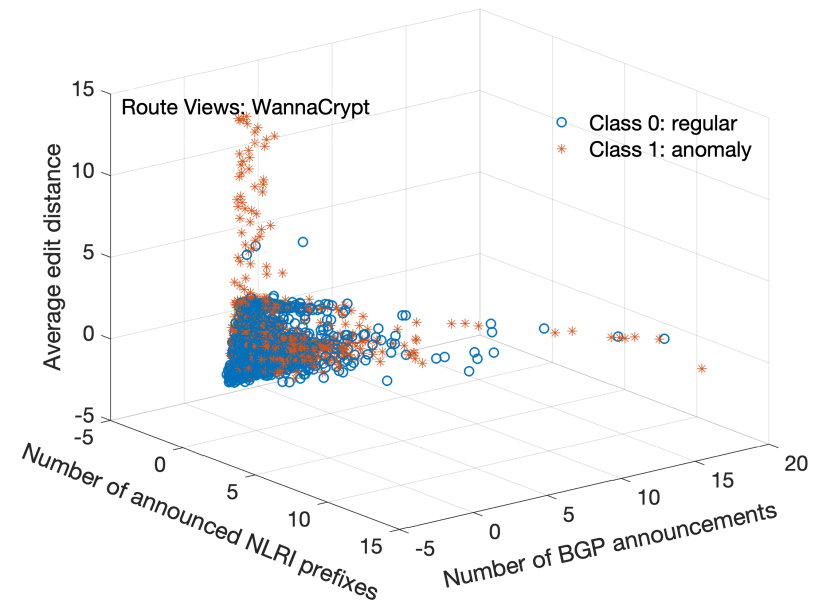
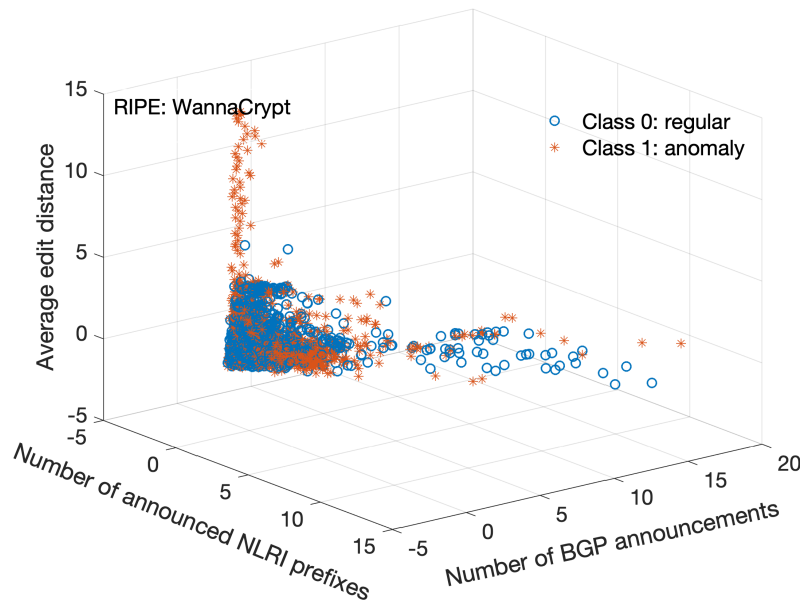
BGP Dataset: Slammer

- Average AS-path length vs. number of BGP announcements vs. number of BGP withdrawals:



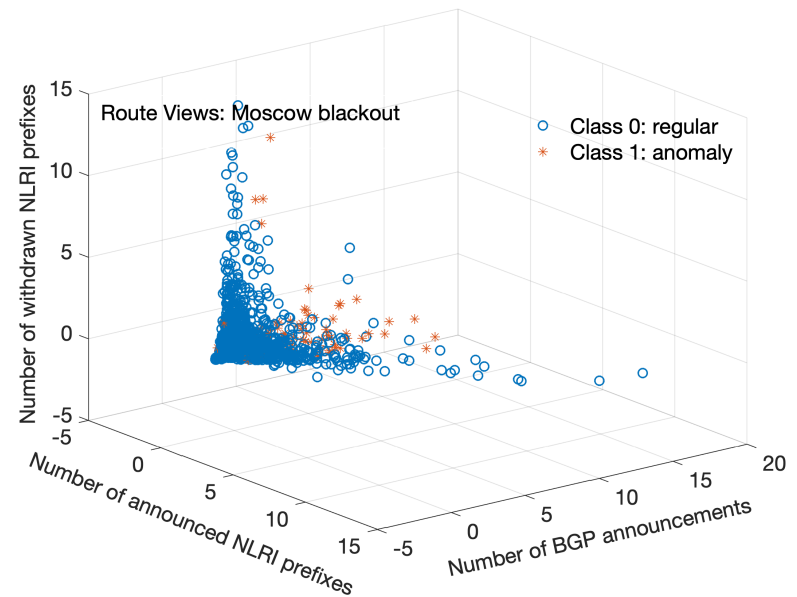
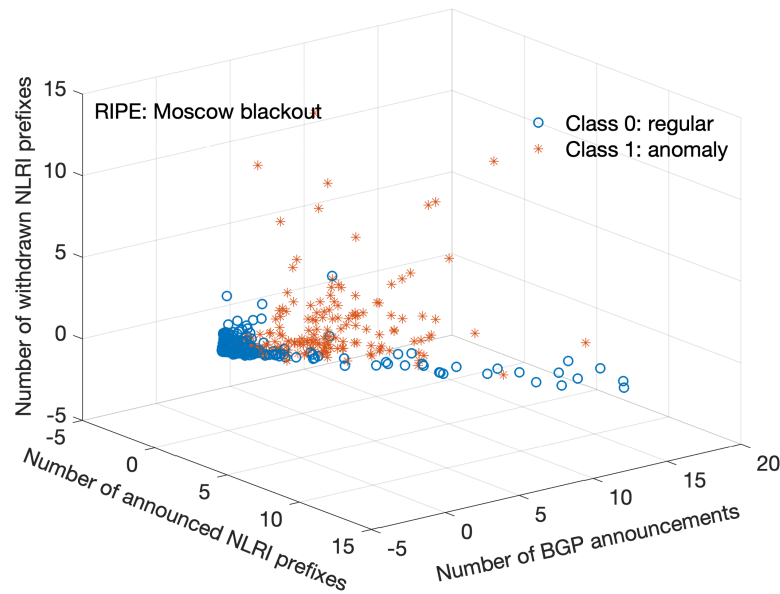
BGP Dataset: WannaCrypt

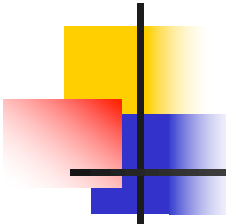
- Number of announced NLRI prefixes vs. number of BGP announcements vs. average edit distance:



BGP Dataset: Moscow Blackout

- Number of announced NLRI prefixes vs. number of BGP announcements vs. number of withdrawn NLRI prefixes:

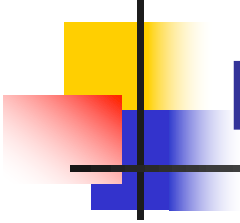




BGP Datasets

- Duration of BGP events and number of data points

Collection site	Dataset	Regular (min)	Anomaly (min)	Regular (training)	Anomaly (training)	Regular (test)	Anomaly (test)	Collection date	
								Start	End
RIPE	Slammer	6,331	869	3,210	530	3,121	339	23.01.2003 00:00:00	27.01.2003 23:59:59
	WannaCrypt	5,760	5,760	2,880	3,420	2,880	2,340	10.05.2017 00:00:00	17.05.2017 23:59:59
	Moscow b/o	6,960	240	3,120	180	3,840	60	23.05.2005 00:00:00	27.05.2005 23:59:59
Route Views	Slammer	6,319	869	3,198	530	3,121	339	23.01.2003 00:00:00	27.01.2003 23:59:59
	WannaCrypt	5,760	5,760	2,880	3,420	2,880	2,340	10.05.2017 00:00:00	17.05.2017 23:59:59
	Moscow b/o	6,865	130	3,075	85	3,790	45	23.05.2005 00:00:00	27.05.2005 23:59:59

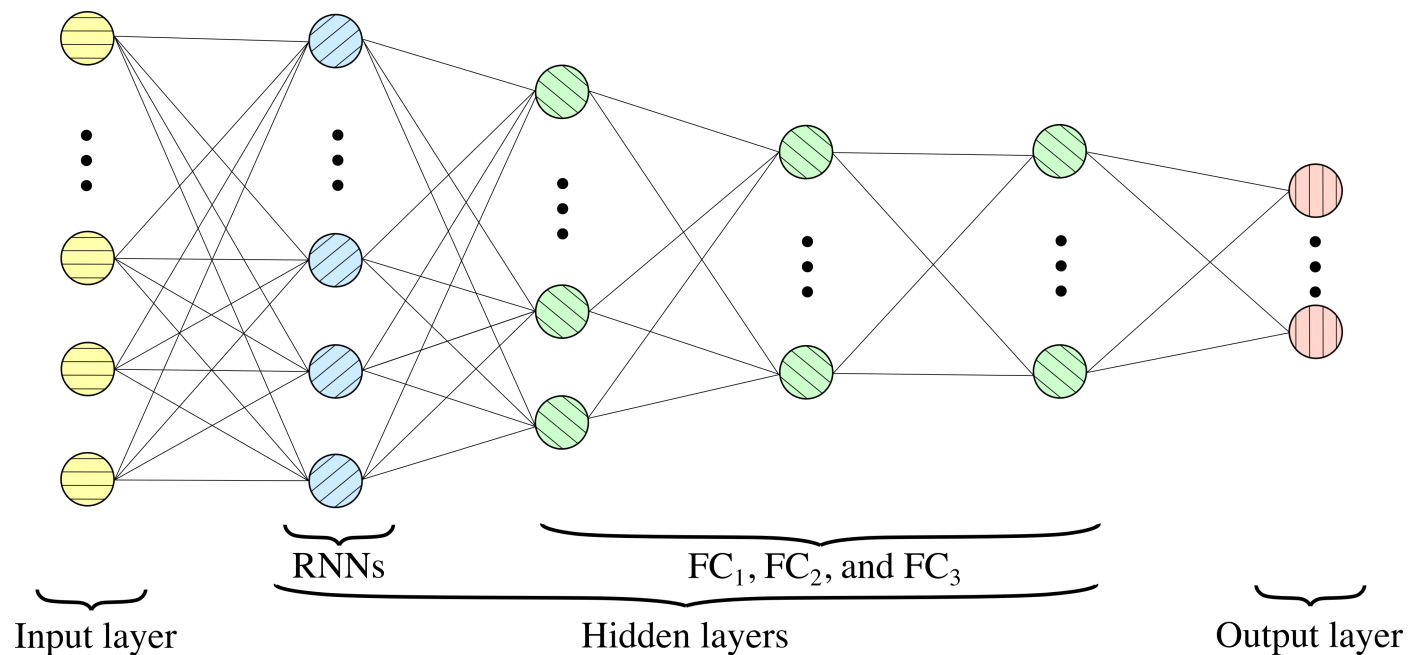


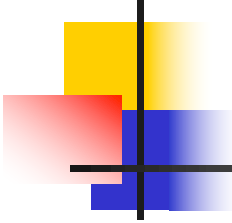
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Deep Learning: Multi-Layer Networks

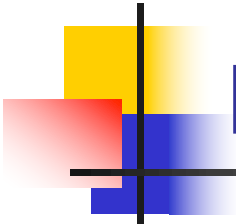
- 37 RNNs, 80 (**Slammer**)/64 (**WannaCrypt**)/64 (**Moscow blackout**) FC1, 32 FC2, and 16 FC3 fully connected (FC) hidden nodes



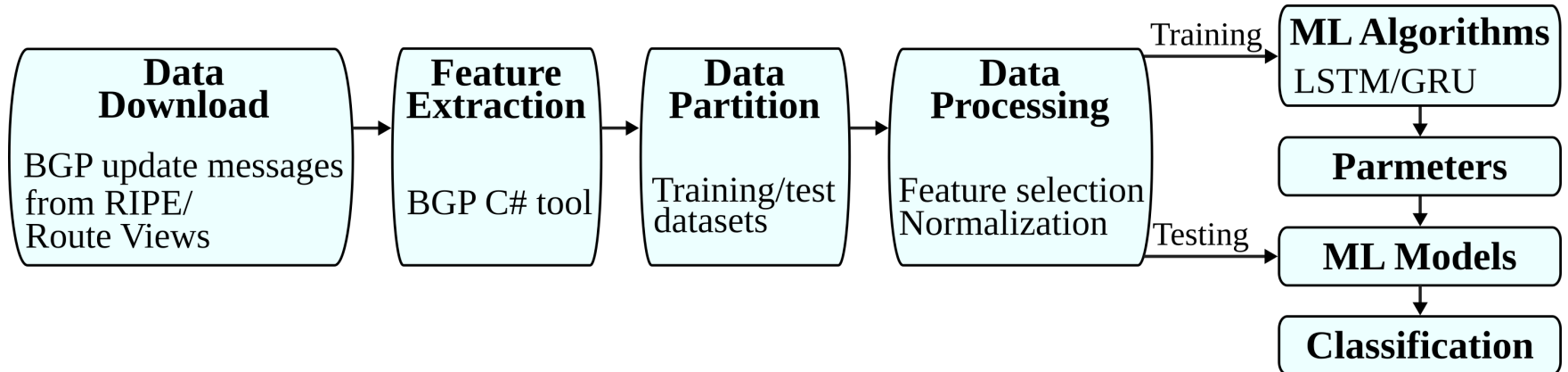


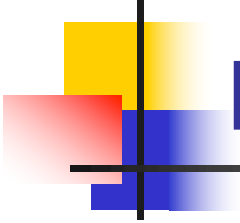
RNN Model Parameters

Parameter	Value	Best selection
Length of input sequence	5, 10, 20, 50, 100	Slammer: 10 WannaCrypt: 100 Moscow b/o: 100 (RIPE), 20 (Route Views)
Number of epochs	30, 50, 100	30
Number of hidden nodes	80, 64, 32, 16	Slammer: FC1 = 80, FC2 = 32, FC3 = 16 WannaCrypt/Moscow b/o: F11 = 64, FC2 = 32, FC3 = 16
Dropout rate	0.2, 0.4, 0.6	0.4
Learning rate	0.01, 0.1	0.01



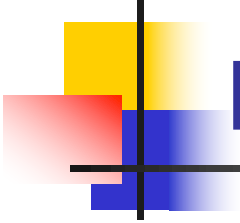
BGP Anomaly Detection





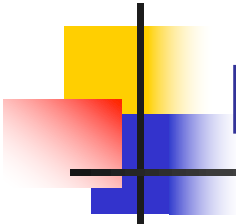
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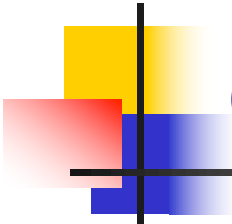
LSTM and GRU RNN Models

- We evaluate performance of LSTM and GRU models with various of hidden layers:
 - 2: LSTM2 and GRU2
 - 3: LSTM3 and GRU3
 - 4: LSTM4 and GRU4
- Performance evaluation is based on:
 - Accuracy
 - F-Score



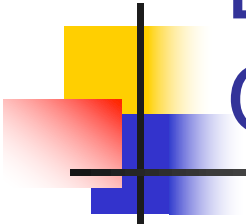
LSTM RNN Models

Model	Dataset	Accuracy (%)		F-Score (%)	
		RIPE	Route Views	RIPE	Route Views
LSTM ₂	Slammer	92.98	91.24	72.42	69.11
	WannaCrypt	58.08	67.23	61.48	70.14
	Moscow b/o	99.21	96.23	75.20	5.26
LSTM ₃	Slammer	90.90	95.72	67.29	81.77
	WannaCrypt	65.48	64.35	63.22	67.16
	Moscow b/o	98.38	97.77	55.94	32.00
LSTM ₄	Slammer	92.49	91.39	70.72	69.34
	WannaCrypt	57.94	72.29	62.42	73.86
	Moscow b/o	97.46	95.81	36.94	18.37



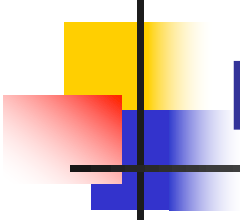
GRU RNN Models

Model	Dataset	Accuracy (%)		F-Score (%)	
		RIPE	Route Views	RIPE	Route Views
GRU ₂	Slammer	91.88	92.60	69.42	72.59
	WannaCrypt	57.27	72.58	60.56	74.21
	Moscow b/o	97.64	98.30	41.77	32.99
GRU ₃	Slammer	91.76	93.24	68.72	74.34
	WannaCrypt	52.85	72.63	53.96	74.14
	Moscow b/o	98.38	97.51	57.14	28.57
GRU ₄	Slammer	92.14	93.15	70.11	74.04
	WannaCrypt	52.15	68.71	52.70	71.61
	Moscow b/o	97.92	97.20	49.06	35.15



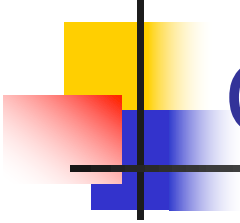
LSTM and GRU RNN Models: Observations

- Increasing the number of the hidden layers in LSTM₄ model may have resulted in over-fitting
- The best accuracy and F-Score generated by RNN models using Slammer and WannaCrypt data collected by Route Views are higher than data collected by RIPE
- Better classification results were achieved using Moscow blackout data collected by RIPE being more reliable than Route Views data



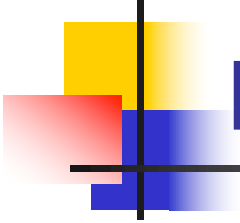
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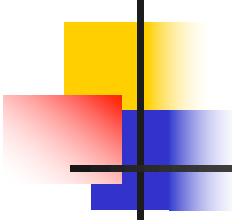
Conclusion

- BGP update messages collected by RIPE and Route Views data collection sites were used to classify Slammer, WannaCrypt, and Moscow blackout anomalous events
- RNN models with two and three hidden layers often exhibited the best performance
- BGP update messages collected by Route Views generated the best accuracy and F-Score for Slammer and WannaCrypt
- Classification models for Slammer dataset offered better results due to better spatial separation between regular and anomalous classes



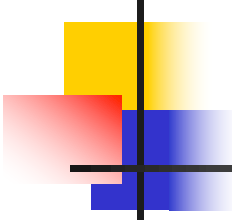
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References: Data Sources and Tools

- RIPE NCC:
<https://www.ripe.net>
- University of Oregon Route Views project:
<http://www.routeviews.org>
- PyTorch
<https://pytorch.org/docs/stable/nn.html>
- zebra-dump-parser:
<https://github.com/rfc1036/zebra-dump-parser>
- BGP C# tool:
http://www.sfu.ca/~ljilja/cnl/projects/BGP_datasets/index.html
- IEEE DataPort
Border Gateway Protocol (BGP) datasets:
<https://ieee-dataport.org/open-access/border-gateway-protocol-routing-records-reseaux-ip-europeens-ripe-and-bcnet>



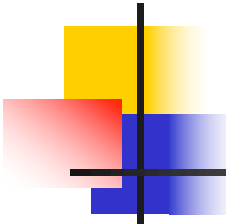
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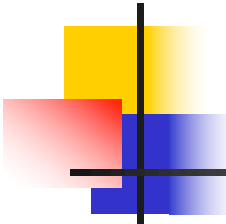
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