Complex Networks

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Roadmap

- Introduction
- Data processing
- Machine learning models
- Experimental procedure
- Performance evaluation
- Conclusions and references

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- Introduction:
  - Complex networks
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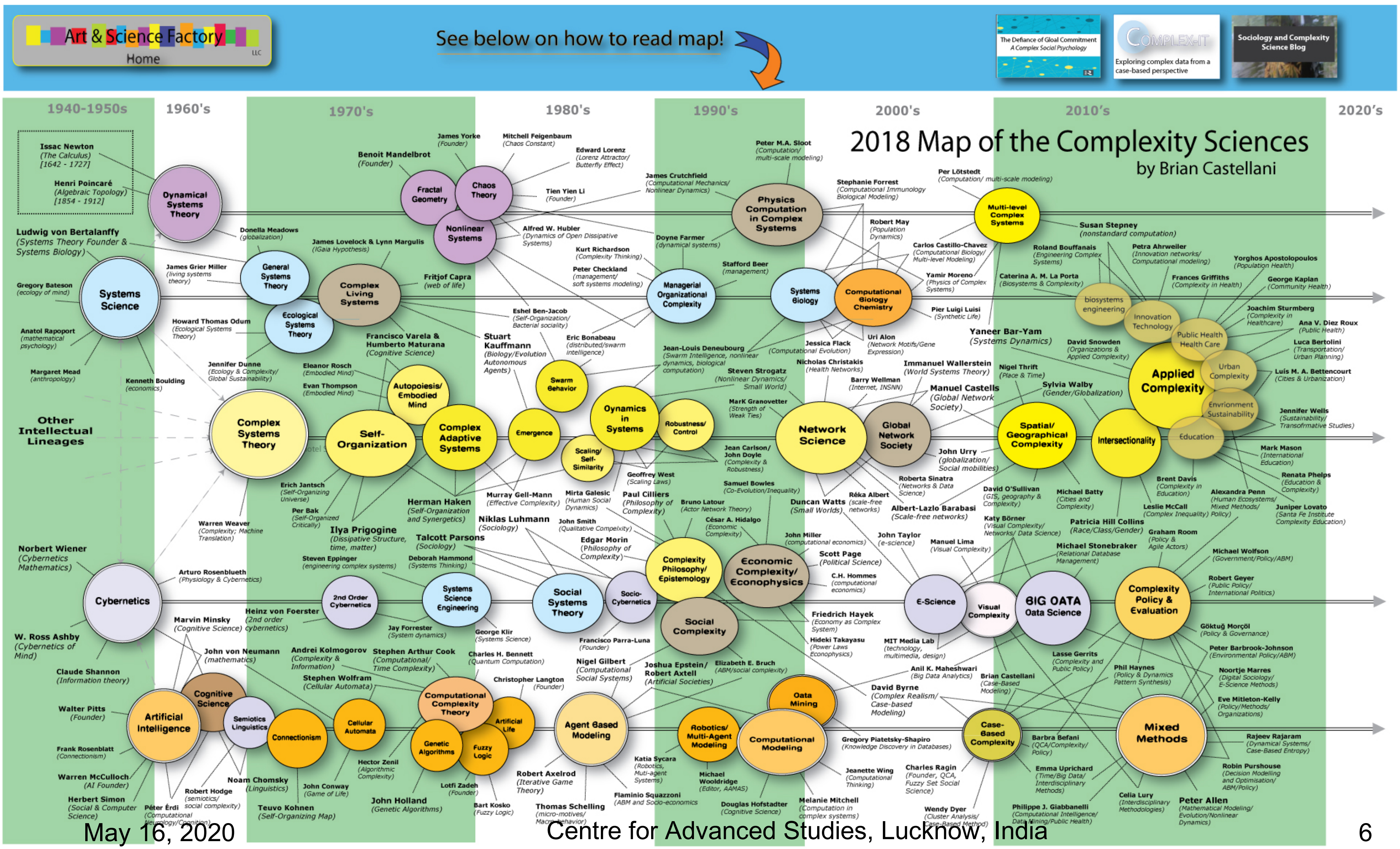
Complexity Sciences



Complexity Sciences

Please cite this map as follows:
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https://www.art-sciencefactory.com/complexity-map_feb09.html

HOW TO READ MAP:
This map is a macroscopic, trans-disciplinary introduction to the complexity sciences.

- Moving from left to right, the map is read in a roughly historical fashion -- but not literally, as we are compressing a n-dimensional intellectual space into a two-dimensional map grid.

- Also, in order to present some type of organizational structure, the history of the complexity sciences is developed along the field's five major intellectual traditions: dynamical systems theory (purple), systems science (blue), complex systems theory (yellow), cybernetics (grey) and artificial intelligence (orange). Again, the fit is not exact (and sometimes even somewhat forced); but it is sufficient to help those new to the field gain a sense of its evolving history.

- Placed along these traditions are the key scholarly themes and methods used across the complexity sciences. A theme's color identifies the historical tradition with which it is "best" associated, even if a theme is placed on a different trajectory. Themes were placed roughly at the point they became a major area of study; recognizing that, from there forward, researchers have continued to work in that area, in one way or another. For example, while artificial intelligence (AI) gained significant momentum in the 1940s and therefore is placed near the start of the map, it remains a major field of study, and is, circa 2018, going through a major resurgence.

- Also, themes in (brown) denote content/discipline specific topics, which illustrate how the complexity sciences are applied to different content. Finally, double-lined themes denote the intersection of a tradition with a new field of study, as in the case of visual complexity or agent-based modeling.

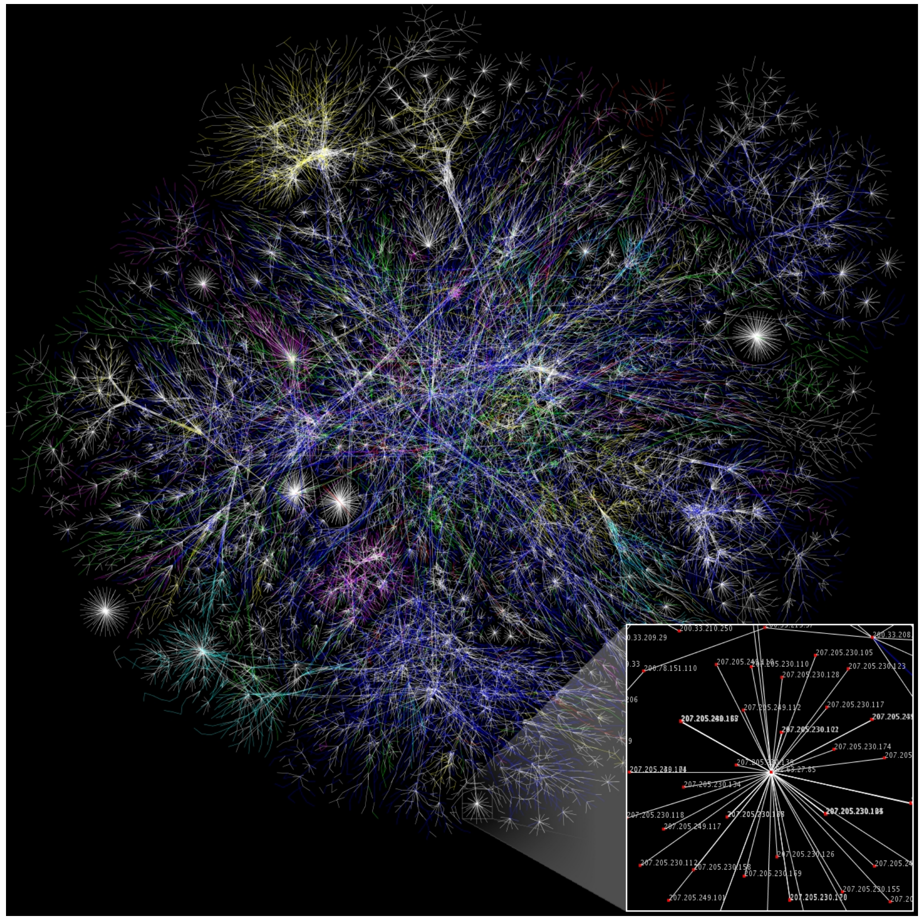
- Connected to themes are the scholars who "founded" or presently "exemplify" work in that area. In other instances, however, "up-and-coming scholars" are listed -- mainly to draw attention to scholars early in their work. There was also an attemt to showcase research from around the world, rather than just the global north. Also, while some scholars (as in the case of Bar-Yam, for example) impacted multiple areas of study, given their position on the map only a few of these links could be visualized -- which goes to the next point: unfortunately, there is no way to generate an educational map that has everyone and everything on it! As such, there is always someone who should be on the map who is not!

- Also, and again, it is important to point out that the positioning of scholars relative to an area of study does not mean they are from that time-period. It only means they are associated with that theme.

- Finally, remembering Foucault's famous argument that most history is really a history of the present as it looks back, who or what is considered an important theme or scholar is a function of time and place. Hence the reason this map has gone through so many revisions -- as the complexity sciences evolves, so does it history.

Durham University

The Internet



https://en.wikipedia.org/wiki/Complex_network#/media/File:Internet_map_1024.jpg
By The Opte Project - Originally from the English Wikipedia
https://commons.wikimedia.org/w/index.php?curid=1538544

The Internet

- Partial map of the Internet based on the January 15, 2005 data found on opte.org.
- Each line is drawn between two nodes, representing two IP addresses.
- The length of the lines are indicative of the delay between those two nodes.
- This graph represents less than 30% of the Class C networks reachable by the data collection program in early 2005.
- Lines are color-coded according to their corresponding RFC 1918 allocation as follows: Dark blue: net, ca, us; Green: com, org; Red: mil, gov, edu; Yellow: jp, cn, tw, au, de; Magenta: uk, it, pl, fr; Gold: br, kr, nl; White: unknown.

Scale-Free Networks

https://commons.wikimedia.org/w/index.php?curid=29364647

Scale-Free Network

- An example of complex scale-free network.
- Graph represents the metadata of thousands of archive documents, documenting the social network of hundreds of League of Nations personals.
- M. Grandjean, "La connaissance est un réseau," *Les Cahiers du Numérique,* vol. 10, no. 3, pp. 37-54, 2014.

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Machine Learning

- Using machine learning techniques to detect network intrusions is an important topic in cybersecurity.
- Machine learning algorithms have been used to successfully classify network anomalies and intrusions.
- Supervised machine learning algorithms:
  - Support vector machine: SVM
  - Long short-term memory: LSTM
  - Gated recurrent unit: GRU
  - Broad learning system: BLS

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- Data processing:
  - BGP datasets
  - NSL-KDD dataset
  - CICIDS2017
  - CSE-CIC-IDS2018
- Machine learning models
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BGP and NSL-KDD Datasets

- Used to evaluate anomaly detection and intrusion techniques
- BGP:
  - Routing records from Réseaux IP Européens (RIPE)
  - BCNET regular traffic
- NSL-KDD:
  - an improvement of the KDD’99 dataset
  - used in various intrusion detection systems (IDSs)

CICIDS2017 and CSE-CIC-IDS2018

- CICIDS2017 and CSE-CIC-IDS2018:
  - Testbed used to create the publicly available dataset that includes multiple types of recent cyber attacks.
  - Network traffic collected between:
    - Monday, 03.07.2017
    - Friday, 07.07.2017
    - Wednesday, 14.02.2018
    - Friday, 02.03.2018

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
- Best performance: 60% for training and 40% for testing

	Regular (min)	Anomaly (min)	Regular (training)	Anomaly (training)	Regular (test)	Anomaly (test)
Code Red I	6,599	600	3,678	362	2,921	239
Nimda	3,678	3,521	3,677	2,123	1	1,399
Slammer	6,330	869	3,209	531	3121	339

NSL-KDD Dataset

- KDDTrain+ and KDDTest+: training and test datasets
- KDDTest^{-21}: a subset of the KDDTest+ dataset that does not include records correctly classified by 21 models

	Regular	DoS	U2R	R2L	Probe	Total
KDDTrain^{+}	67,343	45,927	52	995	11,656	125,973
KDDTest^{+}	9,711	7,458	200	2,754	2,421	22,544
KDDTest^{-21}	2,152	4,342	200	2,754	2,402	11,850

CICD2017 Dataset: Types of Intrusion Attacks

Attack	Label	Day	Number of intrusions
Brute force	FTP, SSH	Tuesday	7,935; 5,897
Heartbleed	Heartbleed	Wednesday	11
Web attack	Brute force, XSS, SQL Injection	Thursday morning	1,507; 652; 21
Infiltration	Infiltration, PortScan	Thursday and Friday afternoons	36; 158,930
Botnet	Bot	Friday morning	1,956
DoS	Slowloris, Hulk, GoldenEye, SlowHTTPTest	Wednesday	5,796; 230,124; 10,293; 5,499
DDos	DDoS	Friday afternoon	128,027

CICD2017 Dataset: Number of Flows

Day	Valid flows	Total
Monday	529,481	529,918
Tuesday	445,645	445,909
Wednesday	691,406	692,703
Thursday (morning)	170,231	170,366
Thursday (afternoon)	288,395	288,602
Friday (morning)	190,911	191,033
Friday (afternoon, PortScan)	286,096	286,467
Friday (afternoon, DDoS)	225,711	225,745

CICD2018 Dataset: Types of Intrusion Attacks

Date	Attack	Day	Number of intrusions	Number of benign instances	Total
14.02.2018	FTP-BF, SSH-BF	Wednesday	667626	380949	1048575
15.02.2018	DoS-GE, DoS-Slowris	Thursday	52498	996077	1048575
16.02.2018	DoS-SlowHTTPTest, DoS-Hulk	Friday	601803	446772	1048575
20.02.2018	DDOS-LOIC-HTTP, DDoS-LOIC-UDP	Tuesday	576191	7372557	7948748
21.02.2018	DDOS-LOIC-UDP, DDOS-HOIC	Wednesday	687742	360833	1048575
22.02.2018	Web-BF, XSS-BF, SQL Injection	Thursday	362	1048213	1048575
23.02.2018	Web-BF, XSS-BF, SQL Injection	Friday	566	1048009	1048575
28.02.2018	Infiltration	Wednesday	68904	544200	613104
01.03.2018	Infiltration	Thursday	93088	238037	331125
02.03.2018	Bot	Friday	286191	762384	1048575

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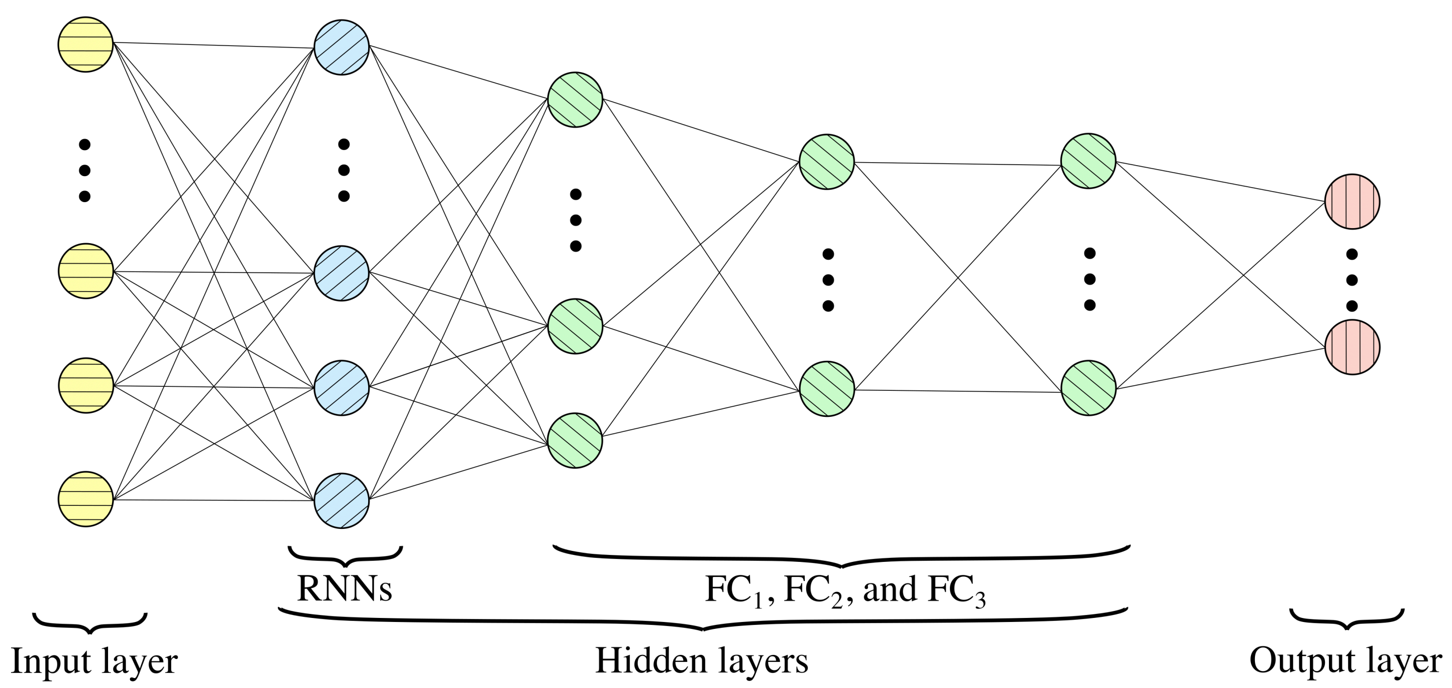
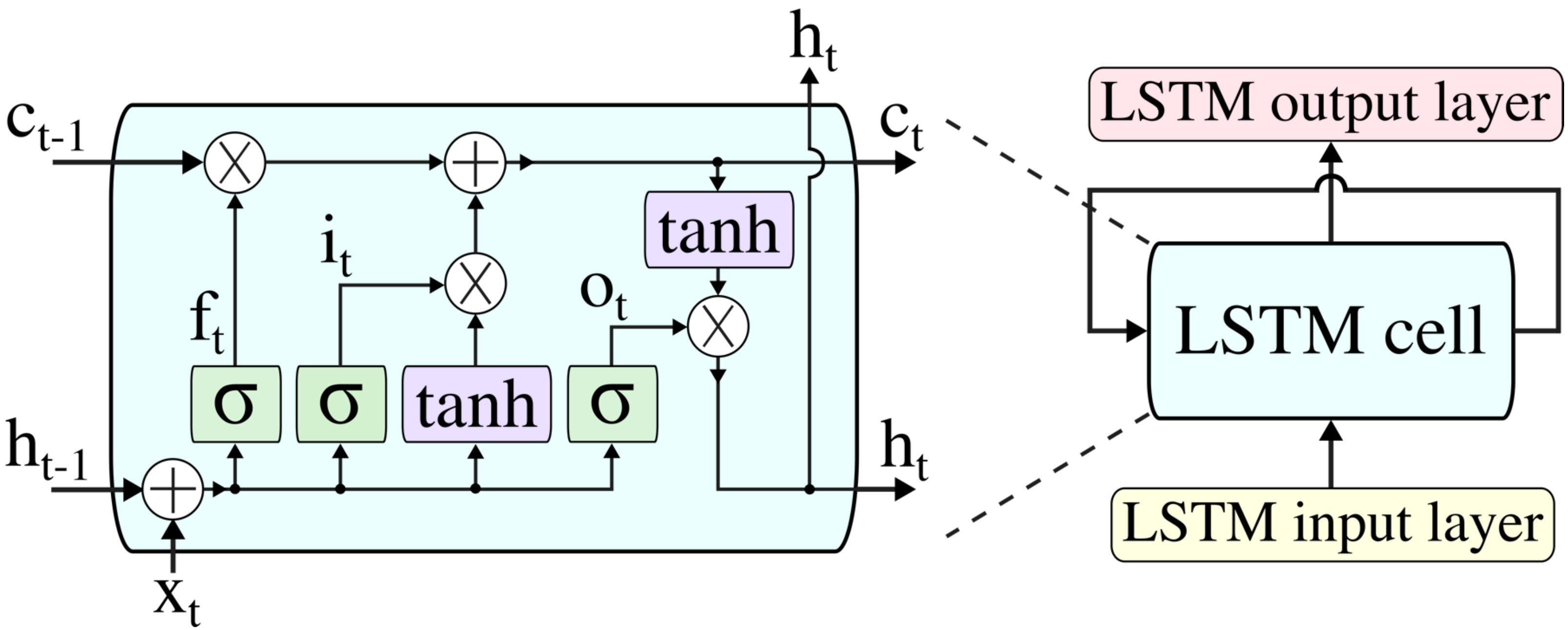
Deep Learning Neural Network

- 37 (BGP)/109 (NSL-KDD) RNNs, 80 FC_1, 32 FC_2, and 16 FC_3 fully connected (FC) hidden nodes:



Long Short-Term Memory

- Repeating module for the Long Short-Term Memory (LSTM) neural network:



Long Short-Term Memory: LSTM

- The outputs of the forget gate f_t, the input gate i_t, and the output gate o_t at time t are:

$$f_t = \sigma\left(W_{if}x_t + b_{if} + U_{hf}h_{t-1} + b_{hf}\right)$$
$$i_t = \sigma(W_{ii}x_t + b_{ii} + U_{hi}h_{t-1} + b_{hi})$$
$$o_t = \sigma(W_{io}x_t + b_{io} + U_{ho}h_{t-1} + b_{ho}),$$

where:

$\sigma(\cdot)$: logistic sigmoid function

x_t: current input vector

h_{t-1}: previous output vector

W_{if}, U_{hf}, W_{ii}, U_{hi}, W_{io} and U_{ho}: weight matrices

b_{if}, b_{hf}, b_{ii}, b_{hi}, b_{io}, and b_{ho}: bias vectors

Long Short-Term Memory: LSTM

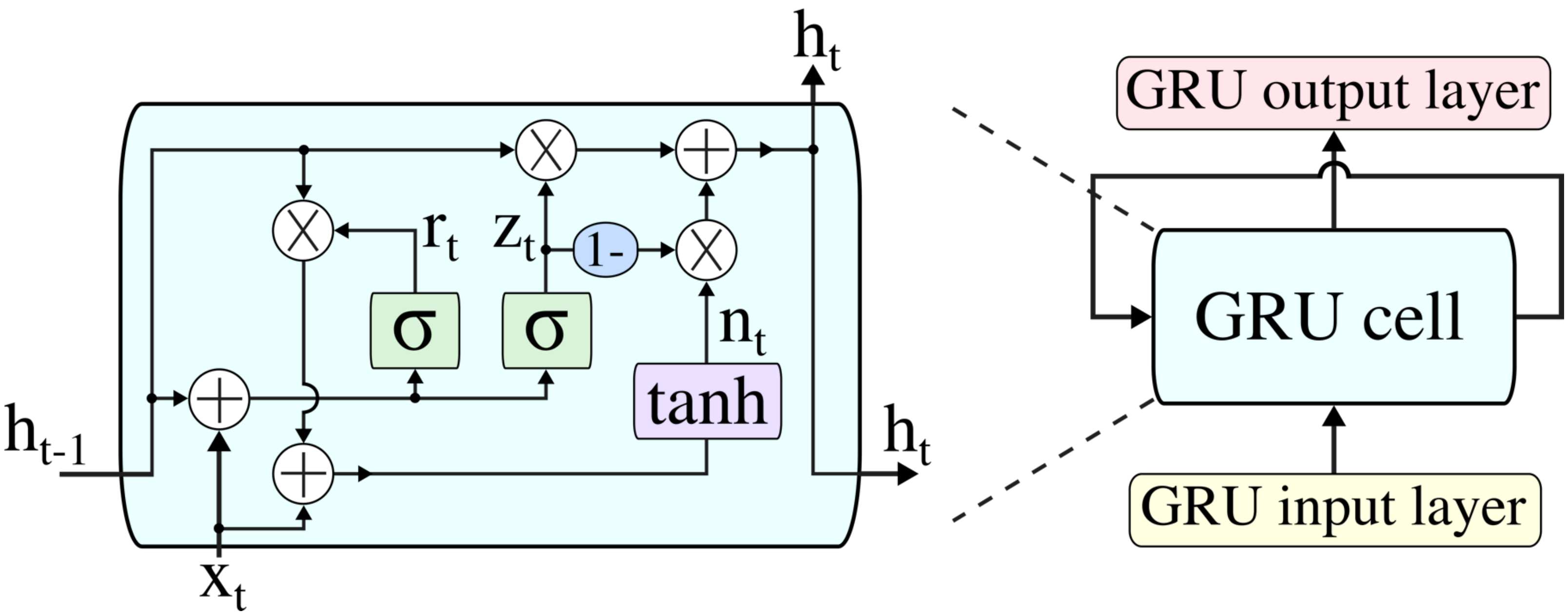
- Output i_t of the input gate decides if the information will be stored in the cell state. The sigmoid function is used to update the information.
- Cell state c_t:
  $$c_t = f_t * c_{t-1} + i_t * tanh(W_{ic}x_t + b_{ic} + U_{hc}h_{t-1} + b_{hc}),$$

where:

  - $*$ denotes element-wise multiplications
  - $tanh$ function: used to create a vector for the next cell state
- Output of the LSTM cell:
  $$h_t = o_t * tanh(c_t)$$

Gated Recurrent Unit

- Repeating module for the Gated Recurrent Unit (GRU) neural network:



Gated Recurrent Unit: GRU

- The outputs of the reset gate r_t and the update gate z_t at time t:

$$r_t = \sigma(W_{ir}x_t + b_{ir} + U_{hr}h_{t-1} + b_{hr})$$
$$z_t = \sigma(W_{iz}x_t + b_{iz} + U_{hz}h_{t-1} + b_{hz}),$$

where:

  - σ: sigmoid function
  - x_t: input, h_{t-1} is the previous output of the GRU cell
  - W_{ir}, U_{hr}, W_{iz}, and U_{hz}: weight matrices
  - b_{ir}, b_{hr}, b_{iz} +, and b_{hz} : bias vectors

Gated Recurrent Unit: GRU

- Output of the GRU cell:

$$h_t = (1 - z_t) * n_t + z_t * h_{t-1},$$

where n_t:

- $n_t = tanh(W_{in}x_t + b_{in} + r_t * (U_{hn}h_{t-1} + b_{hn}))$
- W_{in} and U_{hn}: weight matrices
- b_{in} and b_{hn}: bias vectors

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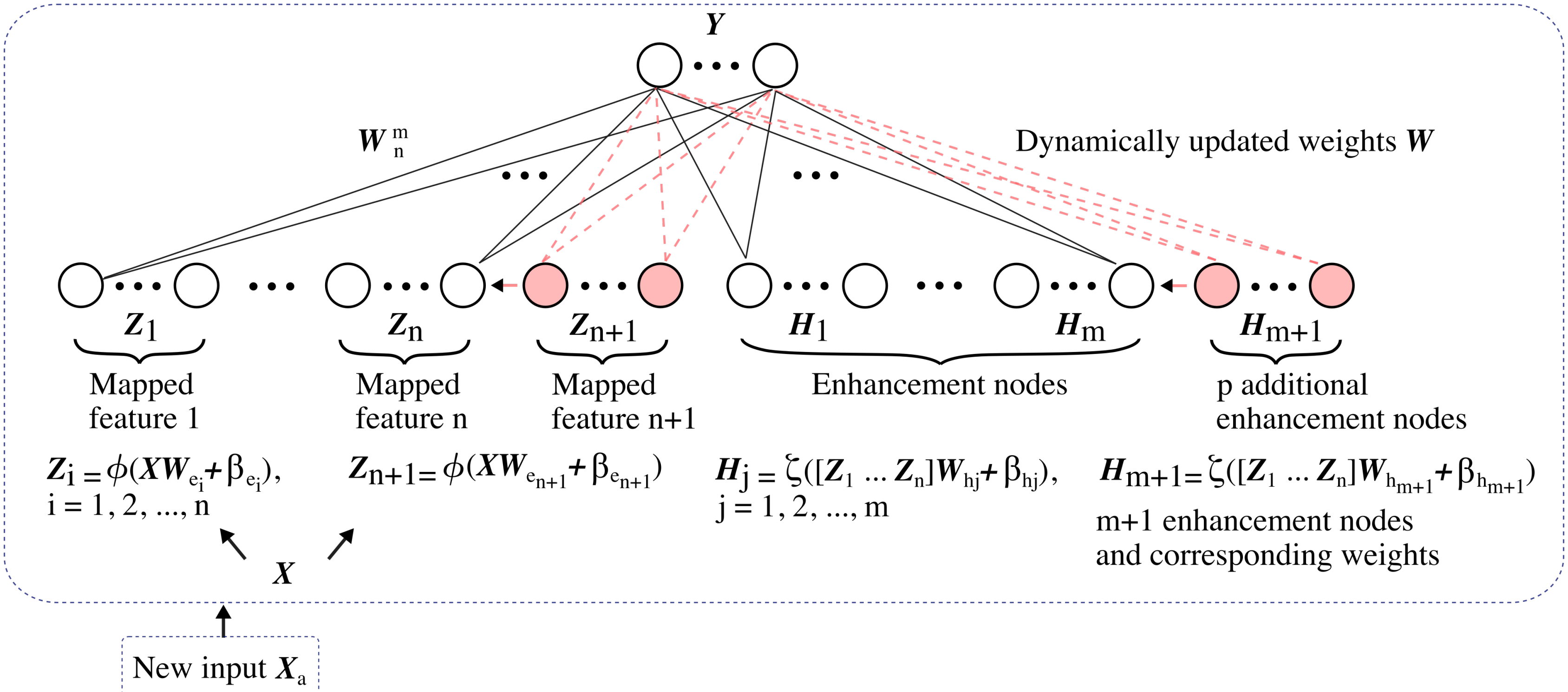
Broad Learning System

- Module of the Broad Learning System (BLS) algorithm with increments of mapped features, enhancement nodes, and new input data:



Original BLS

- Matrix $\boldsymbol{A}_x$ is constructed from groups of mapped features $\boldsymbol{Z}^n$ and groups of enhancement nodes $\boldsymbol{H}^m$ as:

$$\begin{aligned} A_x &= [\boldsymbol{Z}^n \mid \boldsymbol{H}^m] \\ &= \left[\phi\left(\boldsymbol{X}\boldsymbol{W}_{e_i} + \beta_{e_i}\right) \mid \xi\left(\boldsymbol{Z}_x^n \boldsymbol{W}_{h_j} + \beta_{h_j}\right)\right], \end{aligned}$$

where: $i = 1, 2, \dots, n$ and $j = 1, 2, \dots, m$

- ϕ and ξ: projection mappings
- $\boldsymbol{W}_{e_i}$, $\boldsymbol{W}_{h_j}$: weights
- β_{e_i}, β_{h_j}: bias parameters

Modified to include additional mapped features $\boldsymbol{Z}_{n+1}$, enhancement nodes $\boldsymbol{H}_{m+1}$, and/or input nodes $\boldsymbol{X}_a$

Original BLS

- Moore-Penrose pseudo inverse of matrix $\boldsymbol{A_x}$ is computed to calculate the weights of the output:

$$\boldsymbol{W_n^m} = [\boldsymbol{A_n^m}]^{+}\boldsymbol{Y}$$

- During the training process, data labels are deduced using the calculated weights $\boldsymbol{W_n^m}$, mapped features $\boldsymbol{Z}_n$, and enhancement nodes $\boldsymbol{H}_m$:

$$\begin{aligned}\boldsymbol{Y} &= \boldsymbol{A_n^m W_n^m} \\ &= [\boldsymbol{Z_1}, \dots, \boldsymbol{Z}_n | \boldsymbol{H}_1, \dots, \boldsymbol{H}_m]\boldsymbol{W_n^m}\end{aligned}$$

RBF-BLS Extension

- The RBF function is implemented using Gaussian kernel:

$$\xi(x) = exp\left(-\frac{||x - c||^2}{\gamma^2}\right)$$

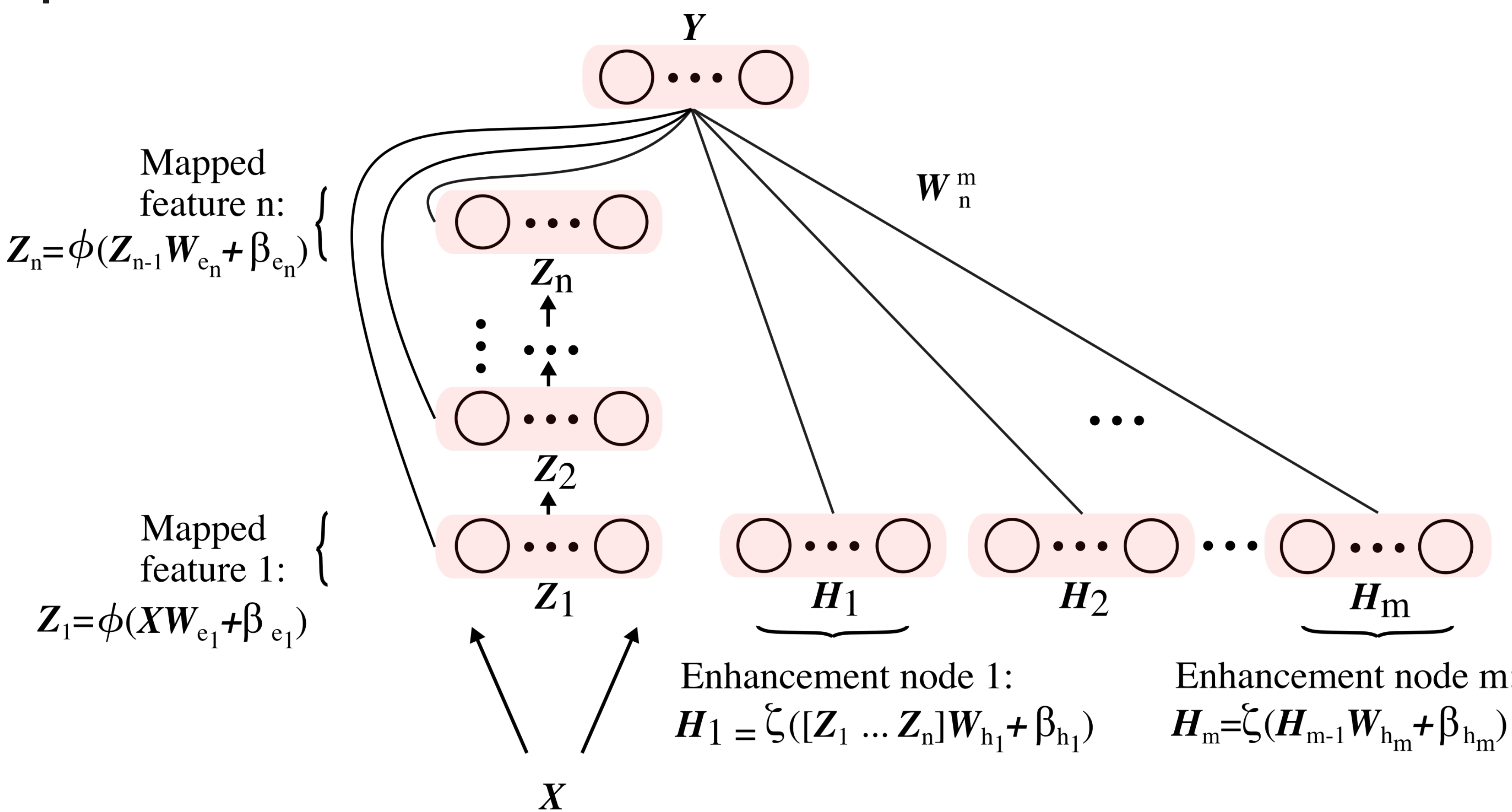
- Weight vectors of the output $\boldsymbol{HW}$ are deduced from:

$$\begin{aligned}\boldsymbol{W} &= (\boldsymbol{H}^T\boldsymbol{H})^{-1}\boldsymbol{H}^T\boldsymbol{Y} \\ &= \boldsymbol{H}^+\boldsymbol{Y},\end{aligned}$$

where:

- $\boldsymbol{W} = [\omega_1, \omega_2, \dots, \omega_k]$: output weights
- $\boldsymbol{H} = [\xi_1, \xi_2, \dots, \xi_k]$: hidden nodes
- $\boldsymbol{H}^+$: pseudoinverse of $\boldsymbol{H}$

Cascades of Mapped Features

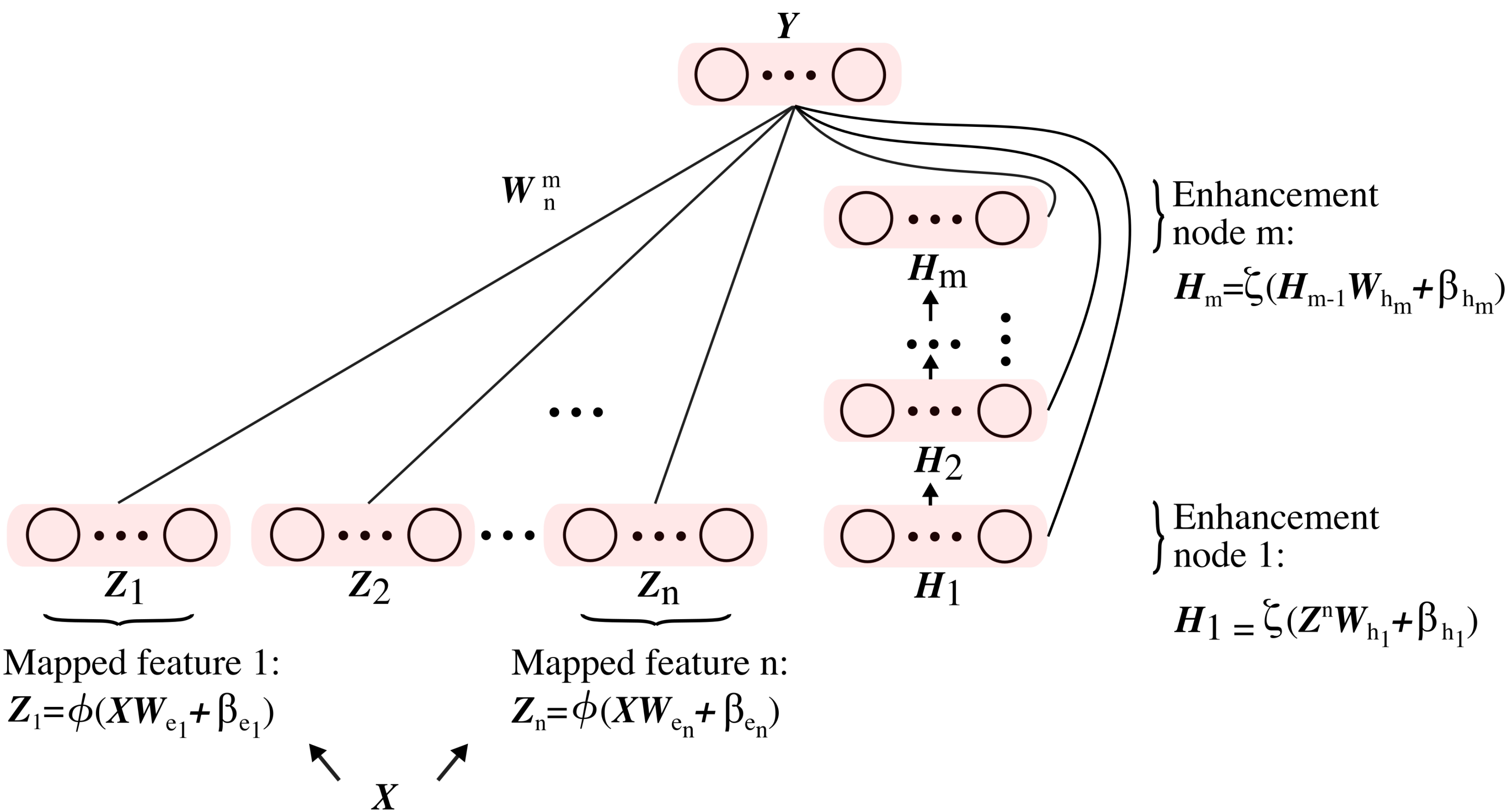


Cascades of Mapped Features

- Cascade of mapped features (CFBLS):
  the new group of mapped features is created by using the previous group $(k\ -1)$.
- Groups of mapped features are formulated as:

$$\boldsymbol{Z}_k = \phi(\boldsymbol{Z}_{k-1}\boldsymbol{W}_{e_k} + \beta_{e_k})$$
$$\triangleq \phi^k\left(\boldsymbol{X}\,; \{\boldsymbol{W}_{e_i}, \beta_{e_i}\}_{i=1}^{k}\right), for\ k = 1, \ldots, n$$

Cascades of Enhancement Nodes



Cascades of Enhancement Nodes

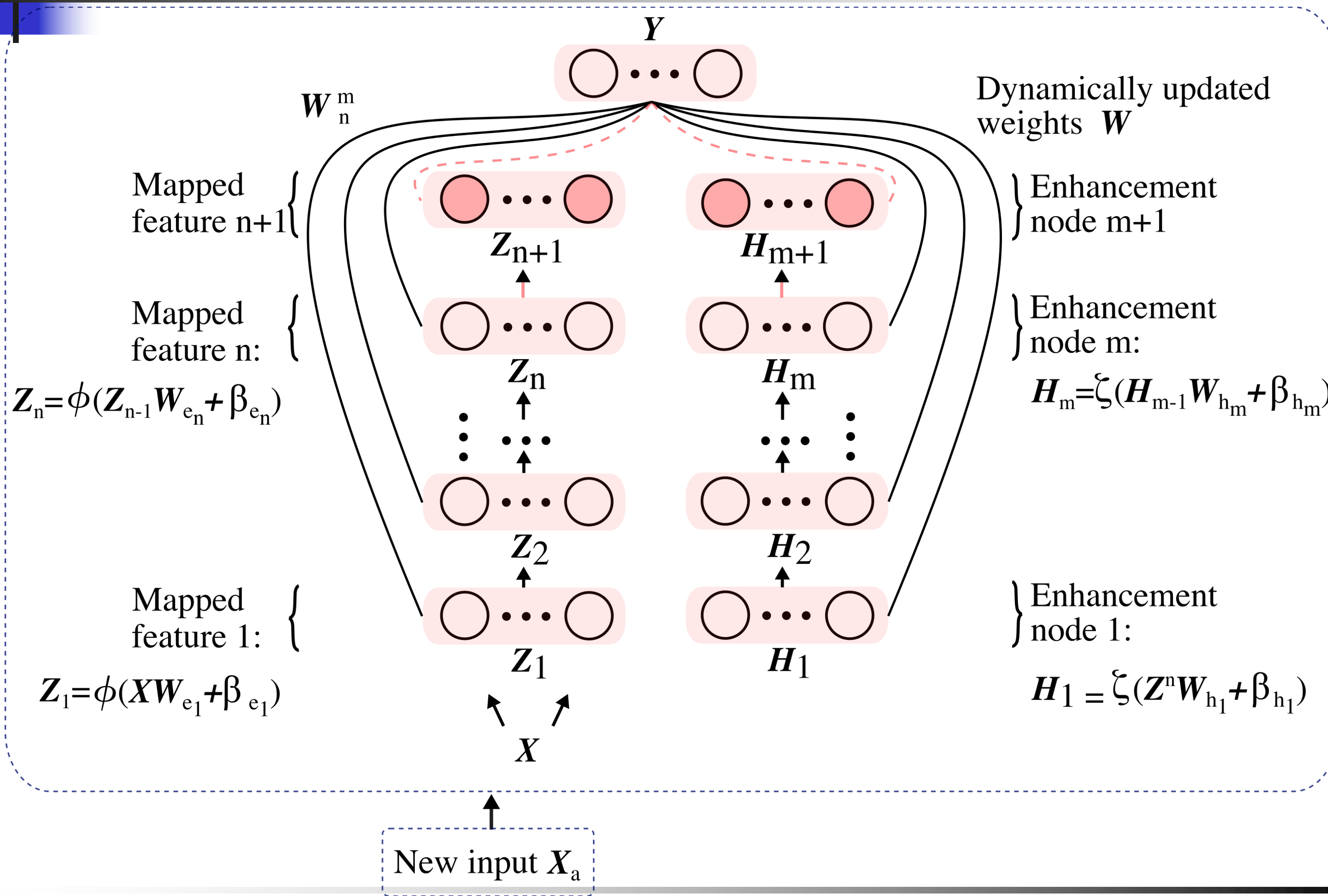
- The first enhancement node in cascade of enhancement nodes (CEBLS) is generated from mapped features.
- The subsequent enhancement nodes are generated from previous enhancement nodes creating a cascade:

$$H_u \triangleq \xi^u\left(\boldsymbol{Z}^n\,;\,\{\boldsymbol{W}_{h_i}, \beta_{h_i}\}_{i=1}^{u}\right), for\ u = 1, \ldots, m,$$

where:

  - $\boldsymbol{W}_{h_i}$ and β_{h_i}: randomly generated

Cascades with Incremental Learning



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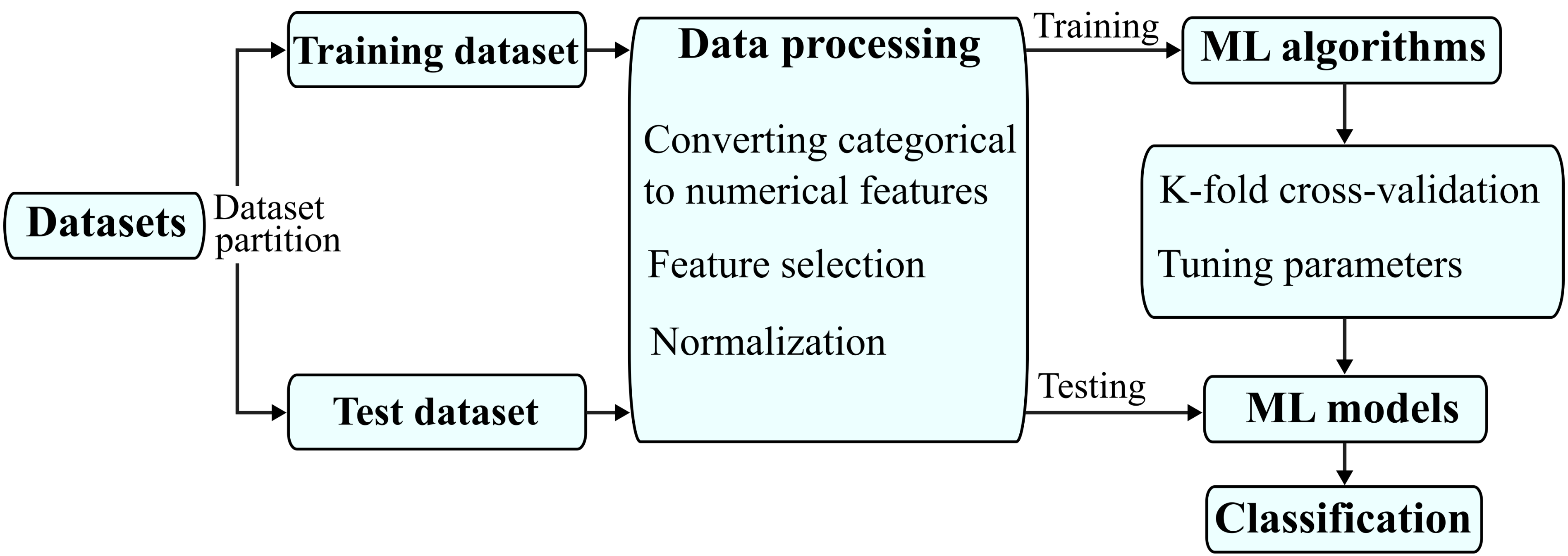
Intrusion Detection System

- Architecture:



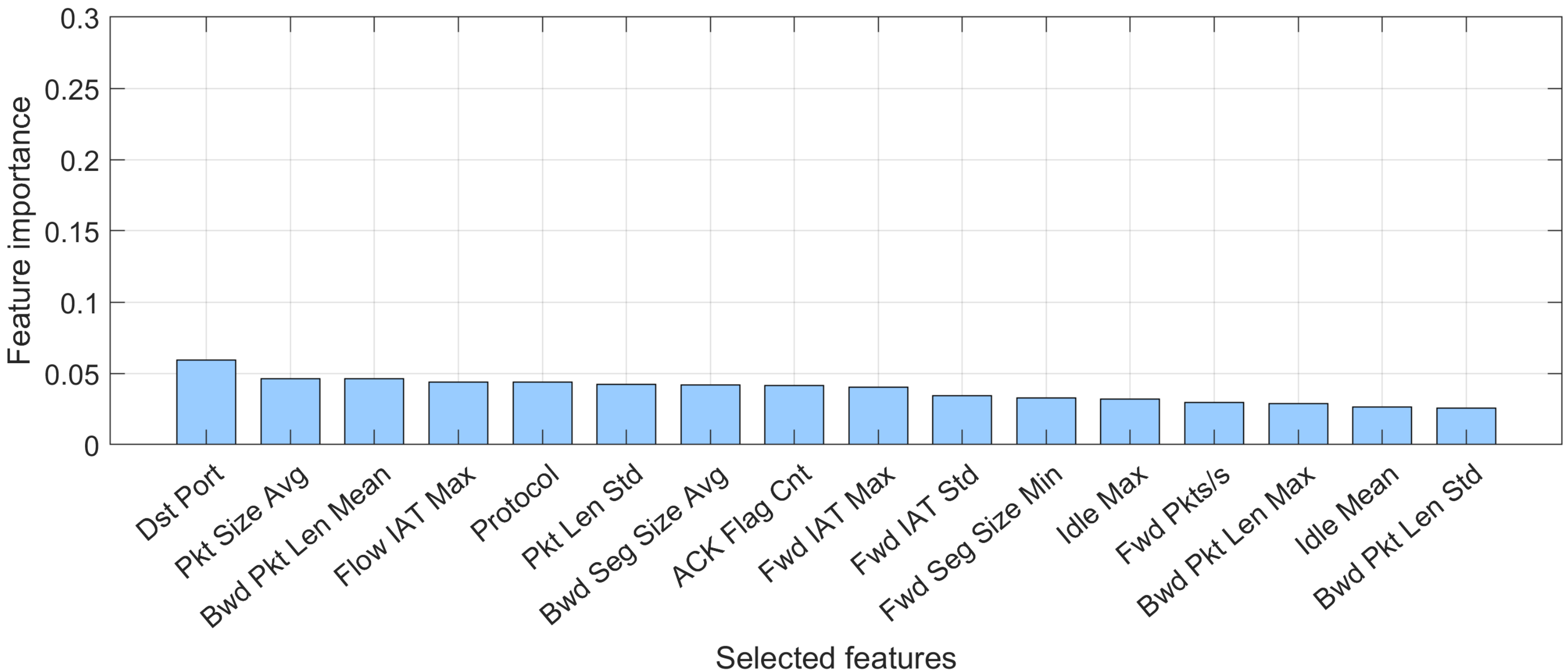
Experimental Procedure

- Step 1: Normalize training and test datasets.
- Step 2: Train the RNN models and BLS using 10-fold validation. Tune parameters of the RNN and BLS models.
- Step 3: Test the RNN and BLS models.
- Step 4: Evaluate models based on:
  - Accuracy
  - F-Score

*RNN: recurrent neural network
*BLS: broad learning system

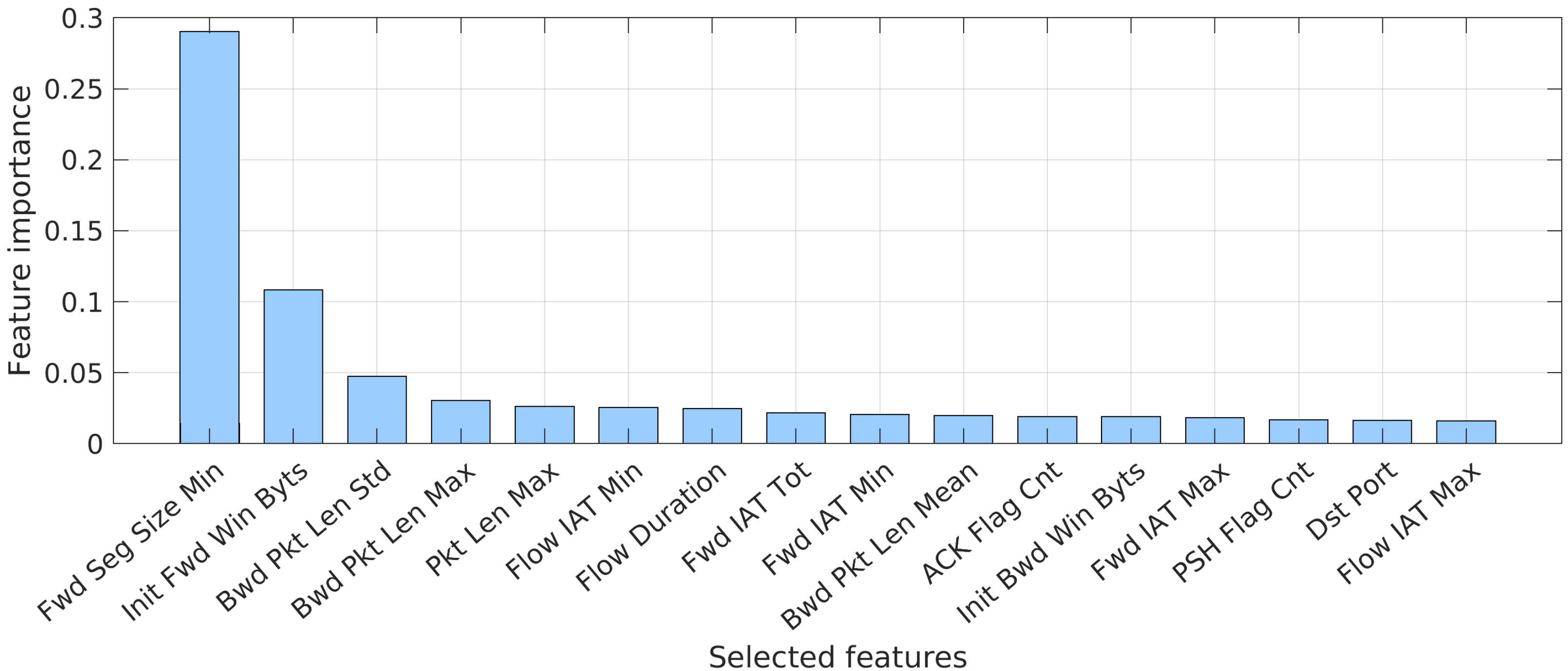
Most Relevant Features

- CICIDS 2017: 16 most relevant features



Most Relevant Features

- CSE-CIC-IDS2018: 16 most relevant features



Number of BLS Training Parameters

Parameters	Code Red I	Nimda	Slammer	NSL-KDD
Mapped features	100	500	100	100
Groups of mapped features	1	1	25	5
Enhancement nodes	500	700	300	100
Incremental learning steps	10	9	2	3
Data points/step	100	200	100	3,000
Enhancement nodes/step	10	10	50	60

Number of BLS Training Parameters

Parameters		CICIDS2017			CSE-CIC-IDS2018	
				Number of features		
BLS	**78**	**64**	**32**	**78**	**64**	**32**
Model	RBF-BLS	BLS	CEBLS	CFBLS	RBF-BLS	CEBLS
Mapped features	20	10	10	20	20	15
Groups of mapped features	30	30	10	10	10	20
Enhancement nodes	40	20	40	80	80	80

Number of Incremental BLS Training Parameters

Parameters	CICIDS2017			CSE-CIC-IDS2018		
	Number of features					
Incremental BLS	**78**	**64**	**32**	**78**	**64**	**32**
Model	CFBLS	CFEBLS	CEBLS	BLS	CEBLS	BLS
Mapped features	10	20	10	15	20	10
Groups of mapped features	20	20	20	30	10	20
Enhancement nodes	40	20	40	20	40	20
Incremental learning steps	2	2	2	2	2	2
Data points/step	55,680	55,680	55,680	49,320	49,320	49,320
Enhancement nodes/step	20	20	20	20	20	20

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Training Time: RNN Models

	Datasets	$LSTM_2$	$LSTM_3$	$LSTM_4$	GRU_2	GRU_3	GRU_4
				Python (CPU)			
Time (s)	BGP (Slammer)	224.52	259.91	819.78	54.12	60.76	759.82
	NSL-KDD	4,481.73	4,614.66	11,478.62	1,108.31	1,161.80	11,581.30
				Python (GPU)			
Time (s)	BGP (Slammer)	30.74	34.94	38.82	31.03	35.46	40.22
	NSL-KDD	344.93	355.86	394.55	317.53	345.04	369.86

Training Time: BLS Models

	Datasets	BLS	RBF-BLS	CFBLS	CEBLS	CFEBLS
				Python (CPU)		
Time (s)	BGP (Slammer)	21.53	18.68	18.89	32.36	32.13
	NSL-KDD	99.47	98.27	98.13	108.23	108.14
				MATLAB (CPU)		
Time (s)	BGP (Slammer)	1.36	1.20	1.03	5.49	5.98
	NSL-KDD	6.91	6.24	6.55	8.88	8.95

LSTM Models: BGP Datasets

Model	Training Dataset	Accuracy (%) Test	Accuracy (%) RIPE (regular)	Accuracy (%) BCNET (regular)	F-Score (%) Test
$LSTM_2$	Code Red I	94.08	83.75	60.49	68.89
	Nimda	78.36	47.15	48.61	87.87
	Slammer	92.98	92.99	85.97	72.42
$LSTM_3$	Code Red I	88.54	79.38	58.82	55.96
	Nimda	85.57	39.10	40.28	92.22
	Slammer	90.90	92.01	84.38	67.29
$LSTM_4$	Code Red I	86.96	75.00	57.01	51.53
	Nimda	92.00	26.94	35.21	95.83
	Slammer	92.49	92.22	86.18	70.72

GRU Models: BGP Datasets

Model	Training Dataset	Accuracy (%) Test	Accuracy (%) RIPE (regular)	Accuracy (%) BCNET (regular)	F-Score (%) Test
GRU_2	Code Red I	87.47	80.07	60.21	52.97
	Nimda	70.71	48.96	58.26	82.83
	Slammer	91.88	93.33	90.90	69.42
GRU_3	Code Red I	88.07	79.44	60.56	53.51
	Nimda	80.21	38.40	44.24	89.02
	Slammer	91.76	95.21	90.83	68.72
GRU_4	Code Red I	91.84	77.50	60.07	63.87
	Nimda	87.36	35.00	39.38	93.25
	Slammer	92.14	92.15	90.35	70.11

BLS Models: BGP Datasets

Model	Training Dataset	Accuracy (%) Test	Accuracy (%) RIPE (regular)	Accuracy (%) BCNET (regular)	F-Score (%) Test
BLS	Code Red I	94.97	69.79	65.21	66.38
	Nimda	76.57	70.69	54.93	86.73
	Slammer	87.65	75.62	68.40	57.68
RBF-BLS	Code Red I	95.92	90.69	73.96	70.07
	Nimda	57.92	70.63	57.22	73.36
	Slammer	91.21	90.55	70.76	64.57

BLS Models: BGP Datasets

Model	Training Dataset	Accuracy (%) Test	Accuracy (%) RIPE (regular)	Accuracy (%) BCNET (regular)	F-Score (%) Test
CFBLS	Code Red I	95.16	69.38	61.74	71.08
	Nimda	55.71	68.06	58.26	71.56
	Slammer	89.28	71.25	61.81	60.99
CEBLS	Code Red I	94.94	70.69	60.35	65.22
	Nimda	66.43	74.10	54.51	79.83
	Slammer	91.01	87.71	82.43	66.38
CFEBLS	Code Red I	95.66	70.07	59.51	71.75
	Nimda	64.29	70.83	57.43	78.24
	Slammer	86.36	71.11	57.71	55.30

RNN and BLS Models: NSL-KDD Dataset

	Accuracy (%)		F-Score (%)	
Model	**KDDTest^{+}**	**KDDTest^{-21}**	**KDDTest^{+}**	**KDDTest^{-21}**
$LSTM_4$	82.78	66.74	83.34	76.21
GRU_3	82.87	65.42	83.05	74.06
CFBLS	82.20	67.47	82.23	76.29

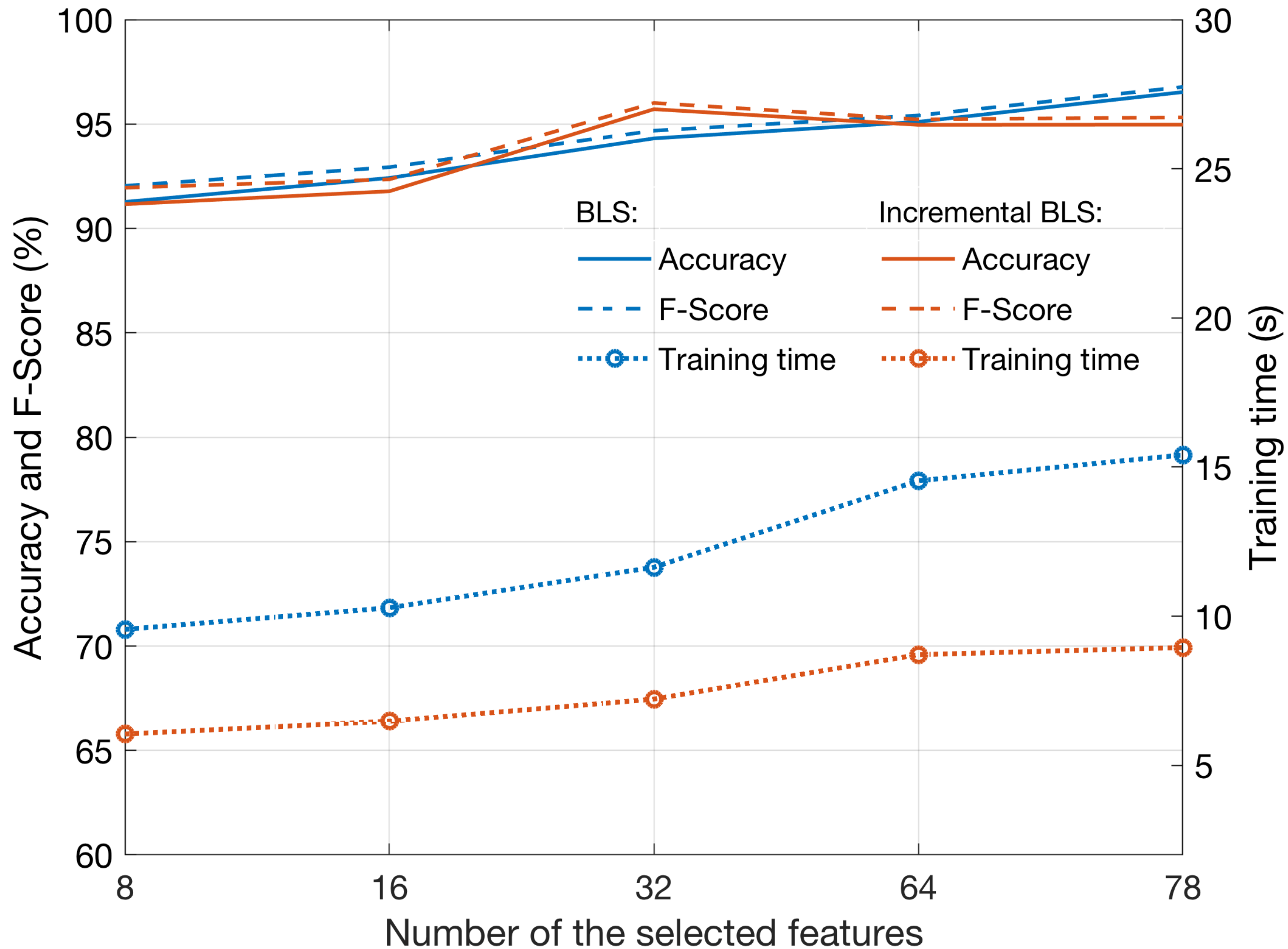
BLS Model: CICIDS2017 and CSE-CIC-IDS2018 Datasets

Number of features	Dataset	Accuracy (%)	F-Score (%)	Model	Training time (s)
BLS					
78	CICIDS2017	96.63	96.87	RBF-BLS	15.60
	CSE-CIC-IDS2018	97.46	81.46	CFBLS	4.13
64	CICIDS2017	96.10	96.35	BLS	8.97
	CSE-CIC-IDS2018	98.60	90.49	RBF-BLS	4.65
32	CICIDS2017	96.34	96.62	CEBLS	39.25
	CSE-CIC-IDS2018	98.83	92.26	CEBLS	33.46

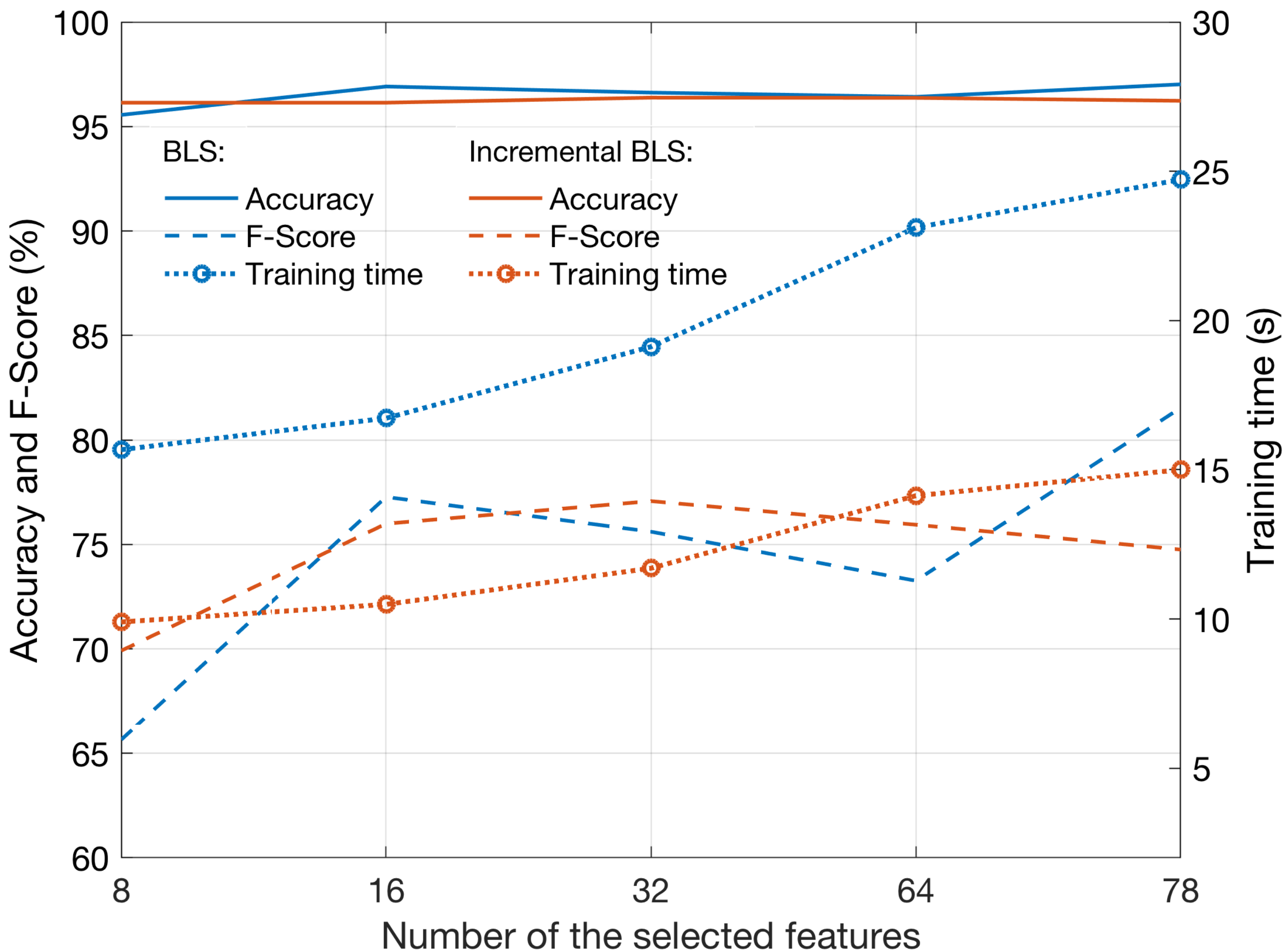
Incremental BLS Model: CICIDS2017 and CSE-CIC-IDS2018 Datasets

Number of features	Dataset	Accuracy (%)	F-Score (%)	Model	Training time (s)
Incremental BLS					
78	CICIDS2017	95.12	95.44	CFBLS	3.69
	CSE-CIC-IDS2018	97.47	81.35	BLS	6.78
64	CICIDS2017	94.44	95.38	CFBLS	7.39
	CSE-CIC-IDS2018	96.70	74.64	CEBLS	11.59
32	CICIDS2017	95.39	95.75	BLS	6.39
	CSE-CIC-IDS2018	97.08	77.89	BLS	5.65

Performance: BLS and Incremental BLS, CICIDS2017



Performance: BLS and Incremental BLS, CSE-CIC-IDS2018



Roadmap

- Introduction
- Data processing:
- Machine learning models:
- Experimental procedure
- Performance evaluation
- Conclusions and references

Conclusions

- We evaluated performance of:
  - LSTM and GRU deep recurrent neural networks with a variable number of hidden layers
  - BLS models that employ radial basis function (RBF), cascades of mapped features and enhancement nodes, and incremental learning
- BLS and cascade combinations of mapped features and enhancement nodes achieved comparable performance and shorter training time because of their wide and deep structure.

Conclusions

- BLS models:
  - consist of a small number of hidden layers and adjust weights using pseudoinverse instead of back-propagation
  - dynamically update weights in case of incremental learning
  - better optimized weights due to additional data points for large datasets (NSL-KDD)
- While increasing the number of mapped features and enhancement nodes as well as mapped groups led to better performance, it required additional memory and training time.

Roadmap

- Introduction
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References: Datasets

- BCNET :
  http://www.bc.net/
- RIPE RIS raw data:
  https://www.ripe.net/analyse/internet-measurements/routing-information-service-ris
- NSL-KDD dataset:
  https://www.unb.ca/cic/datasets/nsl.html
- CICIDS2017 dataset:
  https://www.unb.ca/cic/datasets/ids-2017.html
- CSE-CIC-IDS2018 dataset:
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References: Intrusion Detection

- Python:

  Pandas: https://pandas.pydata.org/

  PyTorch: https://pytorch.org/docs/stable/nn.html
- BLS:

  Broadlearning: http://www.broadlearning.ai/

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- Q. Ding, Z. Li, S. Haeri, and Lj. Trajković, "Application of machine learning techniques to detecting anomalies in communication networks: Datasets and Feature Selection Algorithms" in *Cyber Threat Intelligence,* M. Conti, A. Dehghantanha, and T. Dargahi, Eds., Berlin: Springer, pp. 47-70, 2018.
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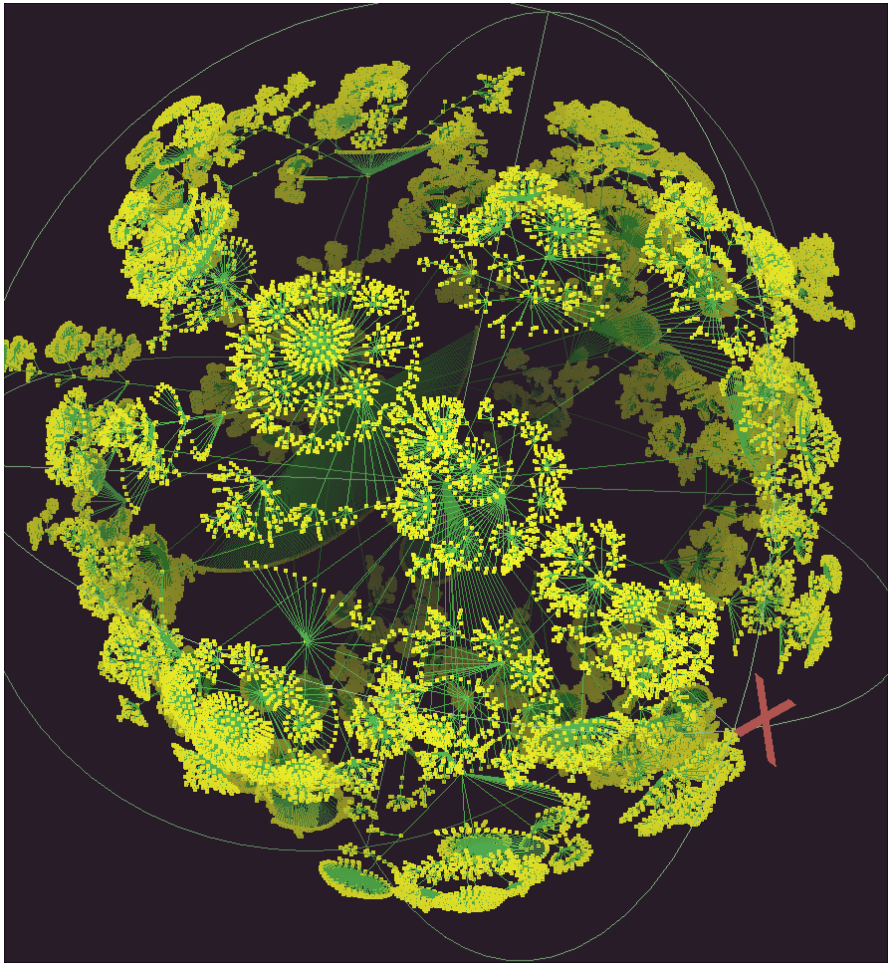
Ihr: 535,102 nodes and 601,678 links



http://www.caida.org/home/