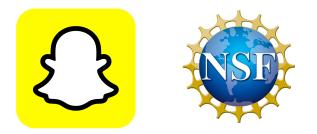


#### Action Sequence Augmentation for Early Graph-based Anomaly Detection

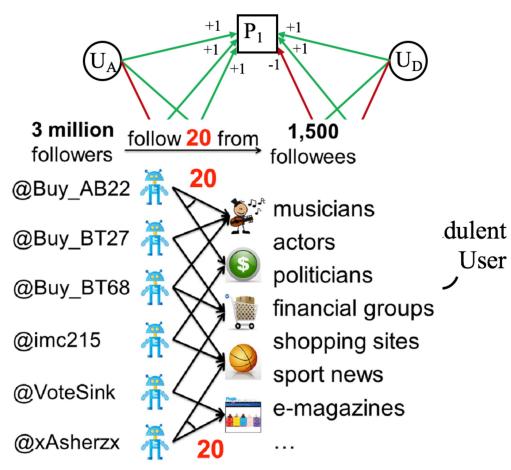
Tong Zhao<sup>+</sup>, Bo Ni<sup>+</sup>, Wenhao Yu<sup>+</sup>, Zhichun Guo<sup>+</sup>, Neil Shah<sup>‡</sup>, and Meng Jiang<sup>+</sup> <sup>+</sup> Department of Computer Science and Engineering, University of Notre Dame, Notre Dame, IN 46556, USA <sup>±</sup> Snap Research, Snap Inc., Santa Monica, CA 90405, USA





#### Background on Graph Anomaly Detection

- Graph anomaly detection:
  - Identify anomalous nodes in the graph.
- Many anomaly detection applications are better solved with graph anomaly detection approaches. E.g.,
  - Bad buyer detection
  - Bot account detection

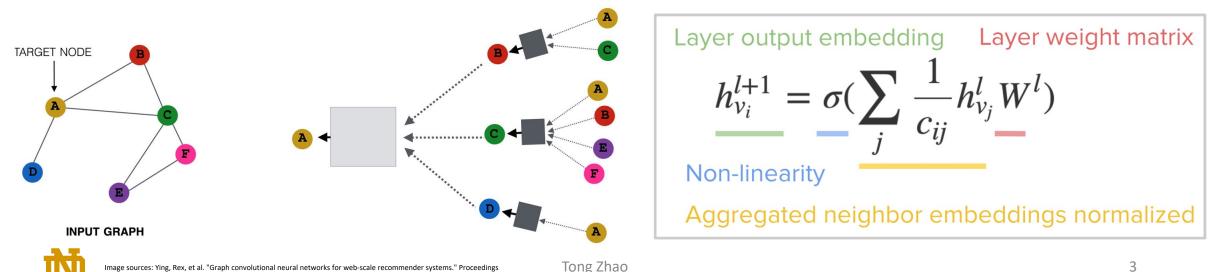




#### Background on Graph Neural Networks

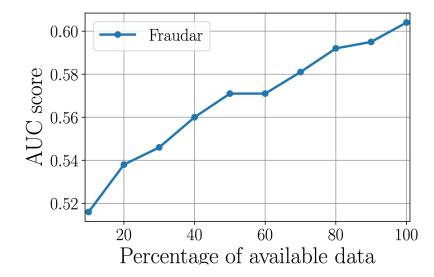
- Given: graph G = (V, E), node features  $\mathbf{x}_v \in \mathbb{R}^m, \forall v \in V$ .
- Learn: low dimensional node representations  $\mathbf{z}_v \in \mathbb{R}^d, \forall v \in V$ .
- Neighborhood aggregation: generate node representations based on local neighborhoods.

International Conference on Knowledge Discovery & Data Mining, 2018



### Early Graph Anomaly Detection

- The performances of existing graph anomaly detection methods might not be satisfactory when observations are limited.
- At the time when existing methods detects the anomalies, they may have already achieved their goals.



#### www.cbsnews.com

How fake news becomes a popular, trending topic -CBS News



Local Guide · 64 reviews · 60 photos

★★★★★ a week ago

They do a great job when they complete it. Price wise they are very expensive. Only great thing is they are for some reason insurance approved so no need to wait to get an estimate and they have on location.

1

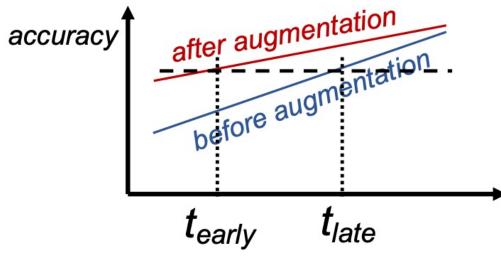
#### Response from the owner a week ago

Hi \_\_\_\_\_\_. We don't seem to have your name in our records. Is there any chance you are writing on behalf of someone else? Either way, can you let us know which location you visited, and a little bit more about what the problem was - you mentioned "when they complete it". If you like you can call me



#### Research Problem

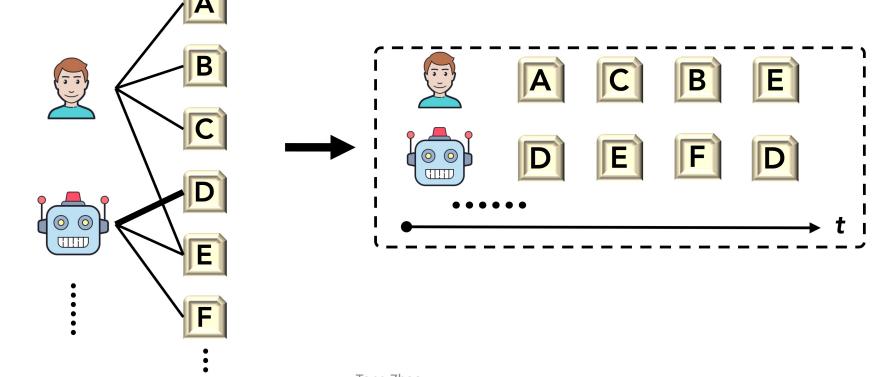
- Can we detect the anomalies before they achieve their goals?
- Given: a user-item bipartite graph at an early-time  $t_{early}$ .
- **Design:** a framework that can help any anomaly detection methods to achieve a comparable performance at time  $t_{early}$ .





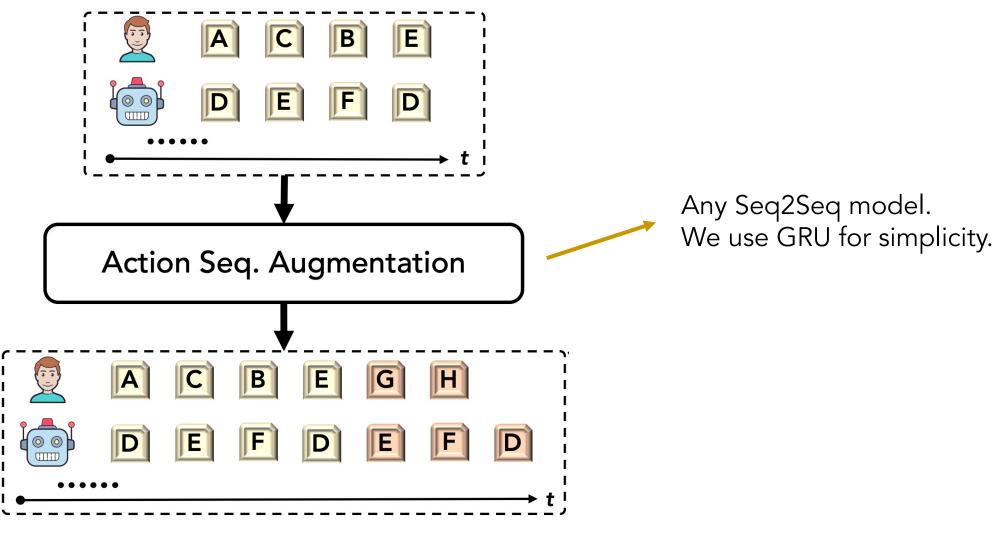
#### Action Sequence Augmentation

- Idea: Predict the future user actions to augment the data.
  - "Forecast the future"



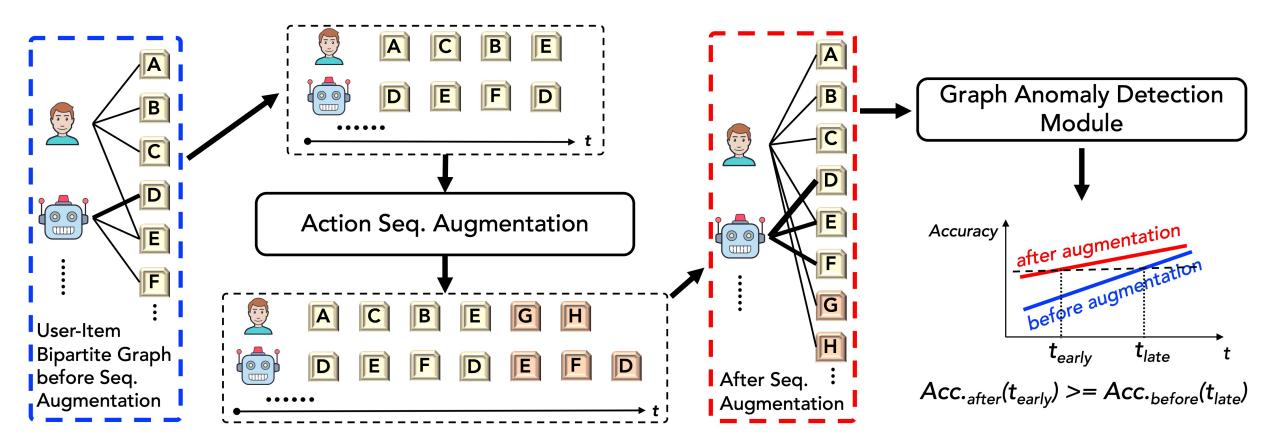


#### Action Sequence Augmentation





#### Proposed Framework: Eland





# **Eland-itr**: Bootstrapping iterative training strategy.

- Iteratively train both modules independently.
- Both modules benefit from the output of the other module.
  - Anomaly detection module makes better prediction with the enriched data.
  - Augmentation module use the predicted suspiciousness  $\hat{y}$  to determine the number of predicted actions.

Algorithm 1: ELAND-ITR **Input** : Adjacency matrix **A**; node feature matrix **X**; number of iterations *I*; anomaly detection module  $g \in \{g_{ad}, g_{ad-gnn}\}$ ; action sequence augmentation module *f<sub>aug</sub>*. **Output**: User prediction results  $\hat{\mathbf{y}}$ . 1  $X_{orig} = X$ ; <sup>2</sup> if g is  $g_{ad-qnn}$  then  $\hat{\mathbf{y}}, \mathbf{Z} = q(\mathbf{A}, \mathbf{X});$ // Defined in Eq.(4)  $\mathbf{X} = \operatorname{concat}(\mathbf{X}_{orig}, \mathbf{Z});$ 4 79.579.0score 78.5AUC 78.0 77.5 GCN+Eland-itr 77.0  $\mathbf{2}$ 8 10 Iteration  $\hat{\mathbf{y}} = q(\mathbf{A}', \mathbf{X});$ 17 end 18 19 end 20 return  $\hat{\mathbf{y}}$ ;



## **Eland-e2e**: End-to-End training of the whole framework.

- Enables end-to-end training.
- Avoids potential error propagation issue brought by bootstrapping.
- Anomaly detection module benefits from the graph with augmented actions.
- Augmentation module benefits from anomaly detection module's decisions.

Tong Zhao

• Train jointly with losses for both modules for stability.

<b>Input</b> : Adjacency matrix <b>A</b> ; node	feature matrix <b>X</b> ; action						
sequence augmentation module $f_{auq-e2e}$ ;							
GNN-based anomaly detection module $g_{ad-gnn}$ ;							
number of training epoch	5						
<b>Output</b> : User prediction results $\hat{\mathbf{y}}$ .							
/* model training	*/						
1 Initialize $\Theta_{aug-e2e}$ in $f_{aug-e2e}$ and	$\Theta_{ad-ann}$ in $q_{ad-ann}$ ;						
<sup>2</sup> <b>for</b> epoch in range(n_epochs) <b>do</b>	uu ynn 5uu ynn i						
	/ Defined in Eq.(13)						
$\hat{y}, Z = g_{ad-qnn}(A', X);$ // Defined in Eq. (4)							
5 Calculate $\mathcal{L}_{e2e}$ with Eq.(16);							
<b>I</b> , ,	with Control						
6 Update $\Theta_{aug-e2e}$ and $\Theta_{ad-gnn}$	with $\mathcal{L}e2e$ ,						
7 end							
<pre>/* model inferencing</pre>	*/						
	,						
8 $\mathbf{A'} = f_{aug-e2e}(\mathbf{A}, \mathbf{X});$	,						
8 $A' = f_{aug-e2e}(A, X);$ 9 $\hat{y}, Z = g_{ad-gnn}(A', X);$	,						
5	,						
9 $\hat{\mathbf{y}}, \mathbf{Z} = g_{ad-gnn}(\mathbf{A'}, \mathbf{X});$ 0 return $\hat{\mathbf{y}};$ 0.40							
9 $\hat{\mathbf{y}}, \mathbf{Z} = g_{ad-gnn}(\mathbf{A}', \mathbf{X});$ 0 return $\hat{\mathbf{y}};$ 0.40 0.38	82.5 80.0						
9 $\hat{\mathbf{y}}, \mathbf{Z} = g_{ad-gnn}(\mathbf{A}', \mathbf{X});$ 0 return $\hat{\mathbf{y}};$ 0.40 0.38 0.36 0.36	82.5						
9 $\hat{\mathbf{y}}, \mathbf{Z} = g_{ad-gnn}(\mathbf{A}', \mathbf{X});$ 0 return $\hat{\mathbf{y}};$ 0.40 0.38 0.36 0.36	82.5 D 80.0 D 77.5 U 75.0 U						
9 $\hat{\mathbf{y}}, \mathbf{Z} = g_{ad-gnn}(\mathbf{A'}, \mathbf{X})$ ; 0 return $\hat{\mathbf{y}}$ ; 0.40 0.38 0.36 0.36 0.34 0.32 0.30	82.5 O 80.0 D 77.5 T 75.0 T 72.5 T						
9 $\hat{\mathbf{y}}, \mathbf{Z} = g_{ad-gnn}(\mathbf{A'}, \mathbf{X})$ ; 0 return $\hat{\mathbf{y}}$ ; 0.40 0.38 0.36 0.34 0.32 0.30 0.28	82.5 O 80.0 O 77.5 V 75.0 v 72.5 tep 70.0 pi						
9 $\hat{\mathbf{y}}, \mathbf{Z} = g_{ad-gnn}(\mathbf{A'}, \mathbf{X})$ ; 0 return $\hat{\mathbf{y}}$ ; 0.40 0.38 0.36 0.36 0.34 0.32 0.30	82.5 O 80.0 D 77.5 T 75.0 T 72.5 T						

Epoch



#### **Consistent Gains with Augmentation**

Anomaly detection	Method	Weibo		Amazon Reviews		Reddit	
module $g_{ad}$		AUC	AP	AUC	AP	AUC	AP
	RNNfd [3]	$54.52 \pm 0.12$	$17.44 \pm 0.10$	60.22±0.29	$28.61 \pm 0.11$	66.08±0.36	$26.45 \pm 0.83$
	Grand [15]	$82.58 \pm 2.11$	$40.12 \pm 2.99$	81.71±2.56	$57.66 \pm 2.98$	79.09±0.18	$42.37 \pm 0.72$
GCN [21]	Original	81.78±0.78	41.21±1.36	80.28±0.09	$57.73 \pm 0.21$	78.01±0.71	41.21±0.69
	+JODIE [24]	$67.80 \pm 1.30$	$17.12 \pm 2.72$	-	-	$73.12 \pm 2.13$	$31.62 \pm 3.98$
	+GAug [53]	$82.04 \pm 0.40$	$48.17 \pm 0.59$	81.91±0.02	$60.12 \pm 0.15$	$78.78 \pm 0.07$	$40.74 {\pm} 0.72$
	+Eland-itr	$82.76 \pm 0.71$	$48.51 \pm 1.06$	$80.85 \pm 0.67$	$58.14 \pm 0.39$	$78.94 \pm 0.83$	$43.11 \pm 1.22$
	+Eland-e2e	<b>84.14</b> ±0.50	<b>54.15</b> ±0.83	<b>85.54</b> ±0.46	<b>65.48</b> ±0.14	<b>79.58</b> ±0.38	<b>44.60</b> ±0.43
GRAPHSAGE [18]	Original	81.87±0.56	$45.26 \pm 2.54$	78.67±0.09	$58.00 \pm 0.07$	81.06±0.02	$47.71 {\pm} 0.01$
	+JODIE [24]	69.44±0.95	$16.01 \pm 2.09$	_	-	$74.66 \pm 0.09$	$34.70 \pm 0.06$
	+GAug [53]	$82.10 \pm 0.46$	$47.81 \pm 1.29$	80.79±0.02	$56.38 \pm 0.03$	$81.37 \pm 0.01$	$43.83 {\pm} 0.01$
	+Eland-itr	$82.34 \pm 0.50$	$48.40 {\pm} 0.91$	81.59±0.23	<b>59.91</b> ±0.12	<b>81.62</b> ±0.10	$48.25 \pm 0.11$
	+Eland-e2e	83.41±0.37	<b>50.61</b> ±0.93	79.92±0.19	$58.21 \pm 0.31$	79.83±0.02	$44.38 \pm 0.02$
HetGNN [48]	Original	81.33±0.43	39.66±1.48	86.24±0.13	67.98±0.25	91.51±0.13	$67.51 {\pm} 0.17$
	+JODIE [24]	68.99±0.44	$17.38 \pm 1.87$	-	-	$92.02 \pm 0.36$	$68.16 {\pm} 0.30$
	+GAug [53]	82.09±0.21	$47.05 \pm 0.51$	87.26±0.12	$71.76 \pm 0.33$	$91.99 \pm 0.02$	$66.30 {\pm} 0.25$
	+Eland-itr	$81.46 \pm 0.57$	$40.20 \pm 1.19$	<b>90.58</b> ±0.86	<b>75.08</b> ±0.57	<b>92.44</b> ±0.07	<b>69.31</b> ±0.29
	+Eland-e2e	84.09±0.55	<b>54.07</b> ±1.64	87.57±0.26	68.46±0.35	84.24±0.22	55.34±0.88

Anomaly detection	Method	We	ibo	Reddit		
module $g_{ad}$		AUC	AP	AUC	AP	
Dominant [7] (Unsupervised)	Original	56.77±1.96	$13.73 \pm 1.22$	61.23±0.35	$18.30 \pm 0.21$	
	+JODIE [24]	58.18±0.77	$11.09 \pm 0.13$	61.64±0.09	$18.81 {\pm} 0.06$	
	+GAug [53]	61.22±1.86	$14.15 \pm 2.38$	$62.26 \pm 2.70$	$17.09 \pm 1.39$	
	+Eland-itr	<b>65.44</b> ±1.78	$19.42 \pm 1.29$	<b>62.96</b> ±0.10	$18.90{\pm}0.04$	
	+Eland-e2e	63.91±0.92	<b>21.90</b> ±0.87	$61.73 \pm 0.27$	<b>18.91</b> ±0.14	
	Original	$56.10 \pm 2.01$	$12.65 \pm 1.31$	61.94±0.39	18.29±0.13	
DEEPAE [55] (Unsupervised)	+JODIE [24]	57.74±0.87	$11.16 \pm 0.73$	$61.57 \pm 0.32$	$18.93 {\pm} 0.06$	
	+GAug [53]	$61.18 \pm 2.03$	$11.58 \pm 1.27$	$61.29 \pm 0.82$	$18.23 \pm 0.53$	
	+Eland-itr	<b>63.34</b> ±0.82	$15.88 \pm 0.73$	<b>62.87</b> ±0.37	<b>19.02</b> ±0.11	
	+Eland-e2e	$62.80 \pm 3.60$	<b>16.99</b> ±3.87	$62.47 \pm 0.11$	$18.88 {\pm} 0.04$	

Up to 15% AUC improvement.

Codes and datasets are available at: https://github.com/DM2-ND/Eland



#### Achieving Early Graph Anomaly Detection

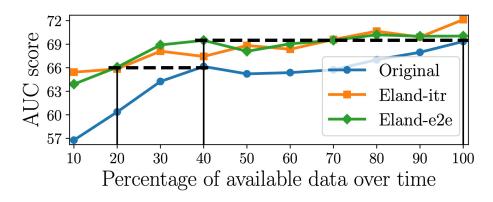
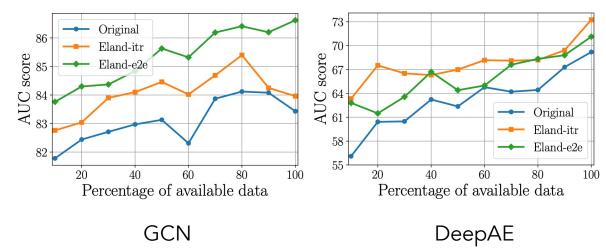


Figure 1: Performance of DOMINANT [7] and ELAND on a social media dataset considering the *earliest* 10%-100% data from each user's action sequence. Both our ELAND-ITR and ELAND-E2E with only 20% (40%) of available data can achieve the same performance as DOMINANT with 40% (100%) of data.





## Thank you for listening!

- Any questions?
- Feel free to email me any further questions at <u>tzhao2@nd.edu</u>



#### COLLEGE OF ENGINEERING



### Case Study

