

518 **A Appendix**

519 **A.1 Datasets**

Table 4: Statistics of GRB datasets after new splitting scheme and feature normalization.

Dataset	Splitting	Avg. Deg.	Avg.Deg. (E / M / H / F)	Feature range	Feature range (Arctan norm.)
<i>grb-cora</i>		3.84	1.53/2.96/5.23/3.24	[-2.30, 2.40]	[-0.94, 0.94]
<i>grb-citeseer</i>	<b>Train / Val</b>	2.61	1.01/1.74/3.82/2.19	[-4.55, 1.67]	[-0.96, 0.89]
<i>grb-flickr</i>	0.6 / 0.1	10.08	5.00/6.02/11.03/7.35	[-0.90, 269.96]	[-0.47, 1.00]
<i>grb-reddit</i>	<b>Test: E / M / H / F</b>	99.65	29.23/68.36/150.99/82.86	[-28.19, 120.96]	[-0.98, 0.99]
<i>grb-aminer</i>	0.1 / 0.1 / 0.1 / 0.3	8.73	1.99/5.12/13.25/6.79	[-1.74, 1.62]	[-0.93, 0.93]

520 GRB includes five datasets of different scales, the details of them are as following:

- 521 • *grb-cora*: Small-scale citation networks. Each node represents a research paper, and each edge  
522 represents a citation relationship between two papers. Instead of using the popular version of  
523 Cora used in Planetoid [41], we use a refined version [38], which removes duplicated nodes  
524 and generates indirect pre-trained word embeddings as node features to solve the problem of  
525 information leakage in the original version. As a result, the features become 302-dimension  
526 continuous features rather than 1433-dimension binary features in the original version. The task  
527 is to classify papers into 7 categories.
- 528 • *grb-citeseer*: Small-scale citation networks. Similar to *grb-cora*, we use a refined version [38]  
529 of CiteSeer, which eliminates identical papers and generates text embeddings by pre-trained  
530 BERT [42] model. The resulting features are 768-dimension continuous features rather than  
531 3703-dimension binary features in the original version. The task is to classify papers into 6  
532 categories.
- 533 • *grb-flickr*: Medium-scale social networks. We adopt the Flickr dataset from [39], which contains  
534 descriptions and common properties of online images. The dataset is processed with a new  
535 splitting scheme and feature normalization mentioned in 4. The task is to classify images into 7  
536 categories.
- 537 • *grm-reddit*: We adopt the Reddit dataset from [39], which contains the communities of online  
538 posts based on user comments. The task is to classify communities into 41 categories.
- 539 • *grb-aminer*: Large-scale citation networks. The papers are collected from the academic searching  
540 engine Aminer [43], and the dataset was used in KDD-CUP 2020 Graph Adversarial Attack &  
541 Defense competition. The task is to classify papers into 18 categories.

542 All five datasets are processed by the new splitting scheme and feature normalization mentioned  
543 in 4. The datasets are saved in the format of numpy [44] zipped format (with .npz extension),  
544 and each has four files: adj.npz, features.npz, index.npz and labels.npz. The data can be  
545 loaded by using the *Dataset* module in GRB, the example is in <https://github.com/THUDM/grb>.  
546 All data are maintained and can be found in <https://cogdl.ai/grb/datasets>, where we will  
547 continuously update to ensure the accessibility for a long term. We use MIT license for data and  
548 codes.

549 **A.2 Related works**

550 In other domains like image classification, there are already standards [27] or benchmarks [45] [46] for  
551 evaluating adversarial robustness. Besides, there exists a toolkit like DeepRobust [47] that implements  
552 adversarial attacks and defenses for both image classification and graph ML tasks. There are currently  
553 several benchmarks in graph ML. Open Graph Benchmark (OGB) [23] develops a diverse set of  
554 scalable and realistic datasets, which facilitates the evaluation of graph ML models. Dwivedi et  
555 al. [24] proposes a reproducible GNN benchmarking framework to facilitate researchers to add new  
556 models conveniently for arbitrary datasets. These benchmarks mainly focus on the performance but  
557 not the robustness of GNNs. so far, there is no benchmark on evaluating the *adversarial robustness* of  
558 GNNs, i.e. the robustness in the presence of adversarial attacks. Nevertheless, it is an important but  
559 challenging task, which requires avoiding pitfalls in previous works and proposing a better solution.

560 **A.3 Methodology**

561 **A.3.1 GNN models**

562 GCN [1] introduces a layer-wise propagation rule for graph-structured data which is motivated from  
 563 a first-order approximation of spectral graph convolutions. GAT [3] leverages masked self-attention  
 564 layers where nodes can attend over their neighborhoods’ features with different weights. GIN [4] is a  
 565 theoretically guaranteed framework for analyzing the expressive power of GNNs to capture different  
 566 graph structures. APPNP [35] utilizes an improved propagation scheme based on personalized  
 567 PageRank to construct a simple model with fast approximation. TAGCN [15] provides a systematic  
 568 way to design a set of fixed-size learnable filters to perform convolutions on graphs. GraphSAGE [2]  
 569 is a general inductive framework that leverages node features to generate node embeddings for  
 570 previously unseen data. SGCN [36] removes nonlinearities and collapses weight matrices between  
 571 consecutive layers, resulting in a linear model.

572 **A.3.2 Adversarial attacks**

573 RND [9] is a random attack strategy that only modifies the structure of the graph. In the proposed  
 574 injection scenario, the features are randomly generated from the Gaussian distribution. FGSM [8]  
 575 linearizes the cost function around the current value of parameters, obtaining an optimal max-norm  
 576 constrained perturbation, which is called the “fast gradient sign method” of generating adversarial  
 577 examples. We use an iterative version of FGSM to conduct a graph injection attack. PGD [29] is a  
 578 universal “first-order adversary”, i.e., the strongest attack utilizing the local first-order information  
 579 about the network. The feature initialization is different from FGSM. SPEIT [26] is the first place  
 580 solution in KDD-CUP 2020 Graph Adversarial Attack & Defense competition. It consists of  
 581 adversarial adjacent matrix generation and enhanced feature gradient attacks, which are designed as a  
 582 universal black-box graph injection attack. TDGIA [17] is an effective graph injection attack that  
 583 tackles the topological defectiveness of graphs. By sequentially injecting malicious nodes around  
 584 nodes that are topologically vulnerable, TDGIA can significantly influence the accuracy of GNNs.  
 585 Since the proposed scenario in GRB is a *black-box* one, all the above attacks are first applied to  
 586 a surrogate model (trained by the attackers themselves), and then transfer to the target model. As  
 587 demonstrated in [17], the choice of surrogate model will influence the transferability of attacks. When  
 588 using raw GCN as the surrogate model, attacks can generally achieve better performance. Thus in  
 589 GRB experiments, we use GCN as the surrogate model for all attacks. Nevertheless, we encourage  
 590 future researchers to further investigate the effect of transferability by testing other methods.

591 **A.3.3 Adversarial defenses**

592 GNN-SVD [21] utilizes a low-rank approximation of the graph, that  
 593 uses only the top singular components for its reconstruction. GNN-  
 594 Guard [22] introduces the neighbor importance estimation and the  
 595 layer-wise graph memory for defenses. RobustGCN (R-GCN) [48]  
 596 is a GCN variant that is specially designed against adversarial at-  
 597 tacks on graphs. It adapts the random perturbation of features from  
 598 VAE [49] and encodes both the mean and variance of the node rep-  
 599 resentation thus makes the GNNs more robust. However, we found  
 600 that methods like GNN-SVD and GNNGuard are not scalable to  
 601 large-scale graphs due to the calculation of large dense matrices. To  
 602 have stronger baseline defenses, we propose two methods that are  
 603 scalable and can generally improve the performance of GNNs.

604 **The proposed layer normalization (LN).** LN [37] computes the  
 605 mean and variance used for normalization from all of the summed  
 606 inputs to the neurons in a layer on a single training case. It is  
 607 originally used to stabilize the hidden state dynamics in recurrent  
 608 networks. We found that it can also help to improve the adversarial  
 609 robustness of GNNs. Unlike the original version that is only used  
 610 after hidden layers, we use LN first on the input features, and then  
 611 after every graph convolutional layer except the last one. The process of the proposed LN is illustrated

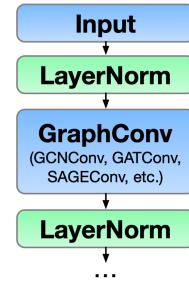


Figure 10: The proposed layer normalization in GRB. It is applied on the input and after every graph convolutional layer except the last one.

612 in Figure 10. The experiment results in Section 4 show that the proposed LN can generally improve  
613 the adversarial robustness of different types of GNNs.

614 **The proposed adversarial training (AT) in GRB scenario.** The AT [29] is originally designed for  
615 defending adversarial attacks in image classification. The idea is to generate adversarial examples  
616 during training to change the classification distribution of models, which makes it difficult to perturb  
617 the results. Previous works [30] show that AT is also helpful for GNNs, but it only considers the  
618 problem of graph modification attack, where the original graph can be modified. In our case, the  
619 defense is against graph injection attack, thus we propose a variant of AT that conduct graph injection  
620 attack during training. The procedure of the proposed AT is as following: (1) Initialization: the  
621 training graph is first used to train GNNs for a few iterations as a warm-up. (2) FGSM attack: we  
622 conduct FGSM attack for a few steps on the current model to inject malicious nodes to attack training  
623 nodes. (3) Update gradients: we then train on the injected graph and minimize the classification loss  
624 of training nodes (excluding the injected nodes). (4) Repetition: we repeat this AT process until the  
625 training loss converges. Finally, we are able to construct more robust GNNs. Interestingly, we found  
626 that AT with FGSM can also defend against other attacks, which shows great generality. Besides, the  
627 proposed AT can be easily adapt to any kind of GNNs and scalable to large graphs.

Table 5: Hyper-parameters for adversarial training for five datasets.

Dataset	Attack	Step size	# Steps/Iter	# Injection	# Edges	Feature range
<i>grb-cora</i>	FGSM	0.01	10	20	20	[-0.94, 0.94]
<i>grb-citeseer</i>	FGSM	0.01	10	30	20	[-0.96, 0.89]
<i>grb-flickr</i>	FGSM	0.01	10	200	100	[-0.47, 0.99]
<i>grb-reddit</i>	FGSM	0.01	10	500	200	[-0.98, 0.99]
<i>grb-aminer</i>	FGSM	0.01	10	500	100	[-0.93, 0.93]

#### 628 A.4 Reproducibility

629 Reproducibility is one of the main features of GRB. For reproducing results on leaderboards, all  
630 necessary components are available, including model weights, attack parameters, generated adver-  
631 sarial results, etc. Besides, GRB provides scripts that allow users to reproduce results by a single  
632 command line. All codes are available in <https://github.com/THUDM/grb>, where the implemen-  
633 tation details and examples can be found. GRB also provides full documentation for each module and  
634 function. All experiments can be reproduced in a single NVIDIA V100 GPU (with 32 GB memory).

##### 635 A.4.1 Hyper-parameter settings

636 **Hyper-parameters of GNNs and defenses.** The hyper-parameters of raw GNNs and defenses  
637 are shown in Table 6, 7, 8, 9, 10, where GCNGuard stands for GCN+GNNGuard, GATGuard for  
638 GAT+GNNGuard, GCN-SVD for GCN+GNN-SVD, and LN for the proposed layer normalization.  
639 For the proposed adversarial training (AT), the hyper-parameters are shown in Table 5. Under the  
640 proposed AT, GNNs are trained while being continuously attacked by FGSM attack for a few steps  
641 per training iterations. Note that in each iteration, the attack is independent of previous iterations,  
642 only based on the weights of the model in the current iteration. The other hyper-parameters are  
643 exactly the same as training GNNs.

644 **Hyper-parameters for adversarial attacks.** The hyper-parameters of attacks are shown in Table 11.  
645 To minimally ensure *unnoticeability* of attacks, GRB has constraints on the number of injected nodes  
646 and the range of their features. Nevertheless, more definitions of *unnoticeability* can be developed by  
647 attackers and defenders when using GRB. Since the proposed scenario in GRB is a *black-box* one, all  
648 the above attacks are first applied to a surrogate model (trained by the attackers themselves), and then  
649 transfer to the target model. As demonstrated in [17], the choice of surrogate model will influence the  
650 transferability of attacks. When using raw GCN as the surrogate model, attacks can generally achieve  
651 better performance. Thus in GRB experiments, we use GCN as the surrogate model for all attacks.

#### 652 A.5 Detailed experiment results

653 We conduct extensive experiments on all datasets and build a leaderboard for each dataset. Here  
654 we show the results of Top-5 attacks vs. Top-10 defenses, full leaderboards can be found in

Table 6: Hyper-parameters of GNN models for *grb-cora* dataset.

Model	#Params	Hidden sizes	LR	Dropout	Optimizer	Others
GCN	28167	64, 64, 64	0.01	0.5	Adam	
GCN+LN	29027	64, 64, 64	0.01	0.5	Adam	
SAGE	160320	64, 64, 64	0.01	0.5	Adam	full-batch
SAGE+LN	161180	64, 64, 64	0.01	0.5	Adam	full-batch
SGCN	28771	64, 64, 64	0.01	0.5	Adam	k=4
SGCN+LN	29027	64, 64, 64	0.01	0.5	Adam	k=4
R-GCN	56334	64, 64, 64	0.01	0.5	Adam	
TAGCN	84103	64, 64, 64	0.01	0.5	Adam	k=2
TAGCN+LN	84963	64, 64, 64	0.01	0.5	Adam	k=2
GAT	217940	64, 64, 64	0.01	0.5	Adam	num_heads=4
GAT+LN	219568	64, 64, 64	0.01	0.5	Adam	num_heads=4
APPNP	19847	64	0.01	0.5	Adam	alpha=0.01, k=10
APPNP+LN	20579	64	0.01	0.5	Adam	alpha=0.01, k=10
GIN	45194	64, 64, 64	0.01	0.5	Adam	
GIN+LN	46054	64, 64, 64	0.01	0.5	Adam	
GCNGuard	24010	64, 64	0.001	0.1	Adam	
GATGuard	151639	64, 64	0.001	0.1	Adam	num_heads=4
GCN-SVD	24007	64, 64	0.01	0.5	Adam	

Table 7: Hyper-parameters of GNN models for *grb-citeseer* dataset.

Model	#Params	Hidden sizes	LR	Dropout	Optimizer	Others
GCN	57926	64, 64, 64	0.01	0.5	Adam	
GCN+LN	59718	64, 64, 64	0.01	0.5	Adam	
SAGE	718924	64, 64, 64	0.01	0.5	Adam	full batch
SAGE+LN	720716	64, 64, 64	0.01	0.5	Adam	full batch
SCGN	59462	64, 64, 64	0.01	0.5	Adam	k=4
SCGN+LN	59718	64, 64, 64	0.01	0.5	Adam	k=4
R-GCN	115852	64, 64, 64	0.01	0.5	Adam	
TAGCN	173382	64, 64, 64	0.01	0.5	Adam	k=2
TAGCN+LN	175174	64, 64, 64	0.01	0.5	Adam	k=2
GAT	336200	64, 64, 64	0.01	0.5	Adam	num_heads=4
GAT+LN	338760	64, 64, 64	0.01	0.5	Adam	num_heads=4
APPNP	49606	64	0.01	0.5	Adam	
APPNP+LN	51270	64	0.01	0.5	Adam	alpha=0.01, k=10
GIN	74953	64, 64, 64	0.01	0.5	Adam	
GIN+LN	76745	64, 64, 64	0.01	0.5	Adam	
GCNGuard	53769	64, 64	0.001	0.1	Adam	
GATGuard	269899	64, 64	0.001	0.1	Adam	num_heads=4
GCN-SVD	53766	64, 64	0.01	0.5	Adam	

Table 8: Hyper-parameters of GNN models for *grb-flickr* dataset.

Model	#Params	Hidden sizes	LR	Dropout	Optimizer	Others
GCN	169863	256, 128, 64	0.01	0.5	Adam	
GCN+LN	171631	256, 128, 64	0.01	0.5	Adam	
SAGE	496146	128, 128, 128	0.01	0.5	Adam	full batch
SAGE+LN	497658	128, 128, 128	0.01	0.5	Adam	full batch
R-GCN	196110	128, 128, 128	0.01	0.5	Adam	
TAGCN	29383	128, 128, 128	0.01	0.5	Adam	k=2
TAGCN+LN	294895	128, 128, 128	0.01	0.5	Adam	k=2
GAT	799316	128, 128, 128	0.01	0.5	Adam	num_heads=4
GAT+LN	802364	128, 128, 128	0.01	0.5	Adam	num_heads=4
APPNP	65031	128	0.01	0.5	Adam	alpha=0.01, k=10
APPNP+LN	66287	128	0.01	0.5	Adam	alpha=0.01, k=10
GIN	164874	128, 128, 128	0.01	0.5	Adam	
GIN+LN	166386	128, 128, 128	0.01	0.5	Adam	
GCNGuard	81546	128, 128	0.001	0.1	Adam	

Table 9: Hyper-parameters of GNN models for *grb-reddit* dataset.

Model	#Params	Hidden sizes	LR	Dropout	Optimizer	Others
GCN	115497	128, 128, 128	0.01	0.5	Adam	
GCN+LN	117213	128, 128, 128	0.01	0.5	Adam	
SAGE	643536	128, 128, 128	0.01	0.5	Adam	full batch
SAGE+LN	645252	128, 128, 128	0.01	0.5	Adam	full batch
SCGN	116701	128, 128, 128	0.01	0.5	Adam	k=4
SCGN+LN	117213	128, 128, 128	0.01	0.5	Adam	k=4
R-GCN	230994	128, 128, 128	0.01	0.5	Adam	
TAGCN	345641	128, 128, 128	0.01	0.5	Adam	k=2
TAGCN+LN	347357	128, 128, 128	0.01	0.5	Adam	k=2
GAT	104950	64, 64	0.01	0.5	Adam	num_heads=2
GAT+LN	106410	64, 64	0.01	0.5	Adam	num_heads=2
APPNP	82473	128	0.01	0.5	Adam	
APPNP+LN	83933	128	0.01	0.5	Adam	alpha=0.01, k=10
GIN	182316	128, 128, 128	0.01	0.5	Adam	
GIN+LN	184032	128, 128, 128	0.01	0.5	Adam	

Table 10: Hyper-parameters of GNN models for *grb-aminer* dataset.

Model	#Params	Hidden sizes	LR	Dropout	Optimizer	Others
GCN	48274	128, 128, 128	0.01	0.5	Adam	
GCN+LN	48986	128, 128, 128	0.01	0.5	Adam	
SAGE	156184	128, 128, 128	0.01	0.5	Adam	full batch
SAGE+LN	156896	128, 128, 128	0.01	0.5	Adam	full batch
SCGN	48474	128, 128, 128	0.01	0.5	Adam	k=4
SCGN+LN	48986	128, 128, 128	0.01	0.5	Adam	k=4
R-GCN	96548	128, 128, 128	0.01	0.5	Adam	
TAGCN	144018	128, 128, 128	0.01	0.5	Adam	k=2
TAGCN+LN	144730	128, 128, 128	0.01	0.5	Adam	k=2
GAT	177624	64, 64, 64	0.01	0.5	Adam	num_heads=2
GAT+LN	178848	64, 64, 64	0.01	0.5	Adam	num_heads=2
APPNP	15250	128	0.01	0.5	Adam	alpha=0.01, k=10
APPNP+LN	15706	128	0.01	0.5	Adam	alpha=0.01, k=10
GIN	115093	128, 128, 128	0.01	0.5	Adam	
GIN+LN	115805	128, 128, 128	0.01	0.5	Adam	

Table 11: Hyper-parameters for adversarial attacks for five datasets.

Dataset	Attack	$\epsilon$	# Iter	# Injection (E/M/H/F)	# Edges	Feature Range	Others
<i>grb-cora</i>	RND	-	1				Random features
	PGD	0.01	1000				-
	FGSM	0.01	1000	20/20/20/60	20	[-0.94, 0.94]	-
	SPEIT	0.01	1000				-
	TDGIA	0.01	1000				Sequential
<i>grb-citeseer</i>	RND	-	1				Random features
	PGD	0.01	1000				-
	FGSM	0.01	1000	30/30/30/90	20	[-0.96, 0.89]	-
	SPEIT	0.01	1000				-
	TDGIA	0.01	1000				Sequential
<i>grb-flickr</i>	RND	-	1				Random features
	PGD	0.01	2000				-
	FGSM	0.01	2000	200/200/200/600	100	[-0.47, 0.99]	-
	SPEIT	0.01	2000				-
	TDGIA	0.01	2000				Sequential
<i>grb-reddit</i>	RND	-	1				Random features
	PGD	0.01	5000				-
	FGSM	0.01	5000	500/500/500/1500	200	[-0.98, 0.99]	-
	SPEIT	0.01	5000				-
	TDGIA	0.01	5000				Sequential
<i>grb-aminer</i>	RND	-	1				Random features
	PGD	0.01	5000				-
	FGSM	0.01	5000	500/500/500/1500	100	[-0.93, 0.93]	-
	SPEIT	0.01	5000				-
	TDGIA	0.01	5000				Sequential

655 <https://cogdl.ai/grb/leaderboard>. It can be seen that different methods vary performance in  
656 different datasets. And it is also hard for attacks to be generally effective, especially in the presence  
657 of the proposed strong defense baselines. We hope GRB leaderboards can provide insights for future  
658 research in this field. Both attacks and defenses are ranked by the weighted accuracy, where **red** and  
659 **blue** indicated the best results in each difficulty.

Table 12: GRB leaderboard (Top 5 Attacks vs. Top 10 Defenses) for *grb-cora* dataset.

Attack	Defenses	1 R-GCN <sub>AT</sub>	2 GAT <sub>AT</sub>	3 SGCN <sub>AT</sub>	4 R-GCN	5 TAGCN <sub>LN</sub>	6 GIN <sub>LN</sub>	7 APPNP <sub>LN</sub>	8 GIN <sub>AT</sub>	9 GATGuard	10 GCN <sub>LN</sub>	Avg. Accuracy	Avg. 3-Max Accuracy	Weighted Accuracy	
1 SPEIT	E	79.97 <sub>±0.16</sub>	66.16 <sub>±0.06</sub>	74.62 <sub>±0.20</sub>	55.60 <sub>±0.11</sub>	54.48 <sub>±0.06</sub>	64.93 <sub>±0.00</sub>	48.06 <sub>±0.38</sub>	52.01 <sub>±0.09</sub>	53.48 <sub>±0.25</sub>	53.44 <sub>±0.17</sub>				
	M	84.11 <sub>±0.38</sub>	84.55 <sub>±0.44</sub>	80.60 <sub>±1.10</sub>	81.16 <sub>±1.39</sub>	74.59 <sub>±0.86</sub>	64.10 <sub>±1.05</sub>	75.67 <sub>±1.12</sub>	63.36 <sub>±1.39</sub>	63.06 <sub>±1.26</sub>	69.18 <sub>±2.24</sub>	47.31 <sub>±0.09</sub>	50.35 <sub>±1.25</sub>	50.89 <sub>±0.24</sub>	
	H	88.51 <sub>±0.80</sub>	89.78 <sub>±1.00</sub>	89.74 <sub>±0.67</sub>	88.47 <sub>±0.54</sub>	89.85 <sub>±0.55</sub>	80.37 <sub>±1.10</sub>	80.64 <sub>±1.14</sub>	63.51 <sub>±0.22</sub>	88.55 <sub>±1.12</sub>	42.72 <sub>±0.07</sub>	47.34 <sub>±0.27</sub>	48.44 <sub>±0.12</sub>		
	F	85.21 <sub>±0.41</sub>	85.35 <sub>±0.75</sub>	75.65 <sub>±0.87</sub>	79.85 <sub>±0.48</sub>	71.73 <sub>±1.14</sub>	64.75 <sub>±0.62</sub>	73.11 <sub>±0.76</sub>	65.67 <sub>±0.00</sub>	59.45 <sub>±0.64</sub>	45.86 <sub>±0.05</sub>	48.56 <sub>±0.98</sub>	48.95 <sub>±0.12</sub>		
2 TDGIA	E	81.68 <sub>±0.14</sub>	80.52 <sub>±0.77</sub>	72.05 <sub>±3.01</sub>	68.13 <sub>±3.50</sub>	73.36 <sub>±3.86</sub>	68.77 <sub>±2.56</sub>	64.18 <sub>±1.71</sub>	63.02 <sub>±3.37</sub>	64.93 <sub>±0.00</sub>	65.93 <sub>±0.07</sub>	50.12 <sub>±0.14</sub>	53.22 <sub>±1.01</sub>	53.30 <sub>±0.12</sub>	
	M	83.96 <sub>±0.08</sub>	84.25 <sub>±0.40</sub>	81.49 <sub>±0.67</sub>	77.57 <sub>±1.86</sub>	82.17 <sub>±2.39</sub>	73.58 <sub>±2.81</sub>	74.44 <sub>±1.52</sub>	70.19 <sub>±1.84</sub>	83.06 <sub>±0.00</sub>	76.34 <sub>±2.16</sub>	47.21 <sub>±0.06</sub>	51.58 <sub>±0.22</sub>	51.06 <sub>±0.10</sub>	
	H	88.43 <sub>±0.18</sub>	90.30 <sub>±0.80</sub>	88.92 <sub>±2.00</sub>	87.39 <sub>±1.81</sub>	84.52 <sub>±1.28</sub>	78.58 <sub>±1.30</sub>	80.63 <sub>±1.06</sub>	69.03 <sub>±0.00</sub>	86.64 <sub>±1.63</sub>	45.17 <sub>±0.07</sub>	48.53 <sub>±1.14</sub>	48.68 <sub>±0.06</sub>		
	F	84.43 <sub>±0.27</sub>	84.55 <sub>±0.50</sub>	77.39 <sub>±1.05</sub>	74.58 <sub>±1.78</sub>	79.67 <sub>±1.53</sub>	76.14 <sub>±2.10</sub>	70.51 <sub>±1.58</sub>	65.67 <sub>±0.00</sub>	72.58 <sub>±2.71</sub>	46.24 <sub>±0.04</sub>	49.75 <sub>±0.84</sub>	49.73 <sub>±0.09</sub>		
3 PGD	E	83.02 <sub>±1.26</sub>	80.60 <sub>±1.00</sub>	73.88 <sub>±2.42</sub>	67.80 <sub>±2.24</sub>	74.78 <sub>±2.36</sub>	70.07 <sub>±1.79</sub>	66.19 <sub>±1.50</sub>	62.65 <sub>±1.33</sub>	64.93 <sub>±0.00</sub>	68.58 <sub>±3.00</sub>	50.11 <sub>±0.11</sub>	53.19 <sub>±0.98</sub>	53.29 <sub>±0.14</sub>	
	M	83.84 <sub>±1.15</sub>	84.81 <sub>±0.67</sub>	82.20 <sub>±1.10</sub>	78.51 <sub>±1.57</sub>	83.36 <sub>±1.39</sub>	77.35 <sub>±1.02</sub>	73.21 <sub>±1.83</sub>	69.25 <sub>±2.18</sub>	77.80 <sub>±1.26</sub>	47.24 <sub>±0.08</sub>	51.64 <sub>±0.20</sub>	51.11 <sub>±0.09</sub>		
	H	88.88 <sub>±0.50</sub>	90.48 <sub>±0.67</sub>	89.96 <sub>±0.67</sub>	89.48 <sub>±1.07</sub>	89.97 <sub>±0.82</sub>	78.47 <sub>±1.29</sub>	80.82 <sub>±0.89</sub>	69.03 <sub>±0.00</sub>	88.32 <sub>±0.56</sub>	45.18 <sub>±0.05</sub>	48.50 <sub>±1.14</sub>	48.68 <sub>±0.06</sub>		
	F	85.20 <sub>±0.88</sub>	85.43 <sub>±2.22</sub>	81.90 <sub>±0.60</sub>	78.58 <sub>±0.51</sub>	66.49 <sub>±0.61</sub>	71.30 <sub>±0.94</sub>	67.21 <sub>±0.68</sub>	78.21 <sub>±1.68</sub>	46.26 <sub>±0.04</sub>	49.81 <sub>±1.89</sub>	49.83 <sub>±1.08</sub>			
4 FGSM	E	82.35 <sub>±0.08</sub>	80.19 <sub>±0.97</sub>	73.95 <sub>±2.58</sub>	67.01 <sub>±1.40</sub>	74.03 <sub>±1.73</sub>	70.48 <sub>±1.60</sub>	67.46 <sub>±1.71</sub>	64.93 <sub>±0.00</sub>	68.39 <sub>±1.27</sub>	52.72 <sub>±0.03</sub>	54.71 <sub>±0.33</sub>	54.71 <sub>±0.07</sub>		
	M	84.25 <sub>±1.24</sub>	85.11 <sub>±0.67</sub>	82.46 <sub>±2.09</sub>	77.87 <sub>±1.43</sub>	84.29 <sub>±1.40</sub>	78.77 <sub>±1.09</sub>	73.10 <sub>±1.13</sub>	69.74 <sub>±1.60</sub>	63.06 <sub>±0.00</sub>	78.47 <sub>±1.30</sub>	48.71 <sub>±0.16</sub>	51.81 <sub>±0.67</sub>	51.93 <sub>±0.09</sub>	
	H	89.22 <sub>±0.59</sub>	90.59 <sub>±0.50</sub>	86.23 <sub>±2.16</sub>	89.55 <sub>±0.67</sub>	86.08 <sub>±0.78</sub>	89.04 <sub>±0.91</sub>	86.03 <sub>±0.78</sub>	87.13 <sub>±0.96</sub>	63.06 <sub>±0.00</sub>	87.13 <sub>±0.96</sub>	43.58 <sub>±0.08</sub>	48.20 <sub>±1.74</sub>	48.84 <sub>±0.08</sub>	
	F	85.01 <sub>±0.41</sub>	85.33 <sub>±0.78</sub>	81.53 <sub>±1.26</sub>	76.62 <sub>±0.98</sub>	80.33 <sub>±0.61</sub>	76.26 <sub>±0.88</sub>	67.09 <sub>±1.21</sub>	71.64 <sub>±1.27</sub>	65.67 <sub>±0.00</sub>	48.26 <sub>±0.03</sub>	51.45 <sub>±0.77</sub>	51.61 <sub>±0.06</sub>		
5 RND	E	82.28 <sub>±0.93</sub>	80.26 <sub>±1.24</sub>	76.57 <sub>±2.44</sub>	73.54 <sub>±1.44</sub>	78.36 <sub>±1.74</sub>	68.81 <sub>±0.82</sub>	67.95 <sub>±1.68</sub>	67.69 <sub>±1.05</sub>	64.93 <sub>±0.00</sub>	74.29 <sub>±1.86</sub>	52.31 <sub>±0.06</sub>	53.65 <sub>±0.24</sub>	53.65 <sub>±0.14</sub>	
	M	84.18 <sub>±1.00</sub>	84.44 <sub>±0.88</sub>	82.05 <sub>±0.77</sub>	79.33 <sub>±1.24</sub>	84.11 <sub>±0.34</sub>	76.68 <sub>±1.05</sub>	73.88 <sub>±1.64</sub>	72.72 <sub>±1.68</sub>	63.06 <sub>±0.00</sub>	80.11 <sub>±1.08</sub>	48.89 <sub>±0.05</sub>	51.70 <sub>±0.32</sub>	51.57 <sub>±0.11</sub>	
	H	88.99 <sub>±0.51</sub>	90.71 <sub>±0.31</sub>	90.19 <sub>±0.41</sub>	87.20 <sub>±0.75</sub>	90.04 <sub>±0.24</sub>	84.52 <sub>±0.73</sub>	80.03 <sub>±1.11</sub>	82.87 <sub>±0.83</sub>	69.03 <sub>±0.00</sub>	89.29 <sub>±0.75</sub>	44.74 <sub>±0.07</sub>	49.19 <sub>±0.26</sub>	48.77 <sub>±0.18</sub>	
	F	85.36 <sub>±0.41</sub>	84.95 <sub>±0.53</sub>	82.85 <sub>±1.25</sub>	79.53 <sub>±0.74</sub>	84.22 <sub>±0.58</sub>	76.75 <sub>±0.98</sub>	68.93 <sub>±0.92</sub>	74.11 <sub>±0.71</sub>	65.67 <sub>±0.00</sub>	61.81 <sub>±0.40</sub>	48.32 <sub>±0.04</sub>	50.98 <sub>±0.17</sub>	50.74 <sub>±0.07</sub>	
6 W/O Attack	E	84.70 <sub>±0.00</sub>	81.34 <sub>±0.00</sub>	82.09 <sub>±0.00</sub>	78.02 <sub>±0.00</sub>	79.10 <sub>±0.00</sub>	70.15 <sub>±0.00</sub>	77.99 <sub>±0.00</sub>	68.28 <sub>±0.00</sub>	64.93 <sub>±0.00</sub>	79.10 <sub>±0.00</sub>	52.04 <sub>±0.01</sub>	53.70 <sub>±0.88</sub>	54.15 <sub>±0.08</sub>	
	M	83.96 <sub>±0.00</sub>	84.33 <sub>±0.00</sub>	82.84 <sub>±0.00</sub>	83.21 <sub>±0.00</sub>	85.45 <sub>±0.00</sub>	76.87 <sub>±0.00</sub>	82.46 <sub>±0.00</sub>	73.51 <sub>±0.00</sub>	63.06 <sub>±0.00</sub>	81.72 <sub>±0.00</sub>	49.67 <sub>±0.01</sub>	52.67 <sub>±0.50</sub>	52.65 <sub>±0.09</sub>	
	H	89.95 <sub>±0.00</sub>	91.04 <sub>±0.00</sub>	91.04 <sub>±0.00</sub>	89.18 <sub>±0.00</sub>	90.67 <sub>±0.00</sub>	80.70 <sub>±0.00</sub>	88.06 <sub>±0.00</sub>	82.84 <sub>±0.00</sub>	69.03 <sub>±0.00</sub>	89.93 <sub>±0.00</sub>	45.94 <sub>±0.01</sub>	50.01 <sub>±0.56</sub>	49.99 <sub>±0.00</sub>	
	F	86.07 <sub>±0.00</sub>	85.57 <sub>±0.00</sub>	85.20 <sub>±0.00</sub>	84.83 <sub>±0.00</sub>	85.05 <sub>±0.00</sub>	85.07 <sub>±0.00</sub>	77.24 <sub>±0.00</sub>	82.84 <sub>±0.00</sub>	74.88 <sub>±0.00</sub>	65.67 <sub>±0.00</sub>	49.21 <sub>±0.01</sub>	51.82 <sub>±0.33</sub>	51.77 <sub>±0.04</sub>	
Avg. Accuracy	E	82.33 <sub>±0.40</sub>	80.65 <sub>±0.54</sub>	74.05 <sub>±1.00</sub>	72.20 <sub>±1.00</sub>	73.82 <sub>±1.00</sub>	67.31 <sub>±0.56</sub>	68.76 <sub>±0.54</sub>	63.10 <sub>±0.38</sub>	64.93 <sub>±0.00</sub>	67.39 <sub>±0.84</sub>	-	-	-	
	M	84.05 <sub>±0.34</sub>	84.58 <sub>±0.21</sub>	81.94 <sub>±0.96</sub>	79.61 <sub>±0.66</sub>	82.33 <sub>±0.49</sub>	74.56 <sub>±0.45</sub>	75.46 <sub>±0.45</sub>	69.80 <sub>±0.82</sub>	63.06 <sub>±0.00</sub>	77.27 <sub>±0.49</sub>	-	-	-	
	H	88.88 <sub>±0.21</sub>	90.49 <sub>±0.21</sub>	90.02 <sub>±0.27</sub>	87.29 <sub>±0.33</sub>	89.50 <sub>±0.41</sub>	84.36 <sub>±0.36</sub>	80.77 <sub>±0.23</sub>	78.60 <sub>±0.83</sub>	69.03 <sub>±0.00</sub>	88.31 <sub>±0.38</sub>	-	-	-	
	F	85.28 <sub>±0.23</sub>	85.20 <sub>±0.20</sub>	85.20 <sub>±0.20</sub>	85.20 <sub>±0.20</sub>	85.20 <sub>±0.20</sub>	78.69 <sub>±0.72</sub>	81.15 <sub>±0.42</sub>	75.29 <sub>±0.49</sub>	71.10 <sub>±1.40</sub>	65.67 <sub>±0.00</sub>	75.46 <sub>±0.49</sub>	-	-	-
Avg. 3-Min Accuracy	E	80.93 <sub>±0.61</sub>	79.91 <sub>±0.61</sub>	70.14 <sub>±1.00</sub>	67.61 <sub>±1.00</sub>	69.58 <sub>±1.00</sub>	62.92 <sub>±0.83</sub>	64.89 <sub>±0.88</sub>	59.17 <sub>±0.66</sub>	64.93 <sub>±0.00</sub>	60.34 <sub>±1.48</sub>	-	-	-	
	M	83.46 <sub>±0.31</sub>	84.14 <sub>±0.22</sub>	81.07 <sub>±0.76</sub>	77.74 <sub>±0.93</sub>	79.90 <sub>±0.82</sub>	73.09 <sub>±1.07</sub>	73.07 <sub>±0.83</sub>	67.10 <sub>±1.28</sub>	63.06 <sub>±0.00</sub>	74.28 <sub>±0.90</sub>	-	-	-	
	H	88.38 <sub>±0.28</sub>	90.06 <sub>±0.28</sub>	89.39 <sub>±0.37</sub>	86.17 <sub>±0.53</sub>	88.58 <sub>±0.80</sub>	82.97 <sub>±0.42</sub>	78.41 <sub>±0.38</sub>	74.66 <sub>±1.17</sub>	69.03 <sub>±0.00</sub>	87.16 <sub>±0.61</sub>	-	-	-	
	F	84.79 <sub>±0.23</sub>	84.77 <sub>±0.34</sub>	78.01 <sub>±0.50</sub>	75.99 <sub>±0.42</sub>	80.78 <sub>±0.78</sub>	72.46 <sub>±0.81</sub>	67.10 <sub>±0.76</sub>	68.12 <sub>±0.65</sub>	65.67 <sub>±0.00</sub>	69.83 <sub>±0.88</sub>	-	-	-	
Weighted Accuracy	E	80.19 <sub>±0.68</sub>	76.92 <sub>±0.61</sub>	68.40 <sub>±1.04</sub>	66.85 <sub>±1.06</sub>	66.67 <sub>±1.12</sub>	59.85 <sub>±0.17</sub>	70.09 <sub>±0.09</sub>	57.05 <sub>±0.00</sub>	64.93 <sub>±0.00</sub>	54.51 <sub>±1.73</sub>	-	-	-	
	M	83.27 <sub>±0.41</sub>	84.00 <sub>±0.30</sub>	70.74 <sub>±0.44</sub>	77.37 <sub>±0.12</sub>	77.02 <sub>±0.12</sub>	76.76 <sub>±0.13</sub>	72.10 <sub>±0.14</sub>	72.63 <sub>±0.14</sub>	65.40 <sub>±0.17</sub>	63.06 <sub>±0.00</sub>	71.83 <sub>±1.38</sub>	-	-	-
	H	88.22 <sub>±0.31</sub>	89.80 <sub>±0.60</sub>	89.15 <sub>±0.49</sub>	85.91 <sub>±0.56</sub>	88.05 <sub>±0.12</sub>	81.70 <sub>±0.69</sub>	78.00 <sub>±0.67</sub>	69.13 <sub>±0.25</sub>	69.03 <sub>±0.00</sub>	86.71 <sub>±0.94</sub>	-	-	-	
	F	84.65 <sub>±0.23</sub>	84.62 <sub>±0.33</sub>	76.86 <sub>±0.58</sub>	75.45 <sub>±0.96</sub>	74.96 <sub>±0.91</sub>	68.64 <sub>±0.68</sub>	66.79 <sub>±0.00</sub>	65.73 <sub>±0.89</sub>	65.67 <sub>±0.00</sub>	64.82 <sub>±0.60</sub>	-	-	-	
Table 13: GRB leaderboard (Top 5 Attacks vs. Top 10 Defenses) for <i>grb-citeese</i> dataset.	E	71.07 <sub>±0.47</sub>	67.56 <sub>±1.04</sub>	68.34 <sub>±0.54</sub>	65.52 <sub>±0.50</sub>	56.46 <sub>±0.37</sub>	52.38 <sub>±0.72</sub>	49.87 <sub>±2.29</sub>	52.29 <sub>±0.88</sub>	50.88 <sub>±4.49</sub>	56.61 <sub>±2.50</sub>	50.11 <sub>±0.01</sub>	53.19 <sub>±0.08</sub>	53.29 <sub>±0.04</sub>	
	M	72.54 <sub>±0.48</sub>	73.23 <sub>±0.51</sub>	71.25 <sub>±0.47</sub>	63.64 <sub>±0.60</sub>	62.67 <sub>±0.40</sub>	60.22 <sub>±0.19</sub>	58.53 <sub>±1.76</sub>	57.43 <sub>±1.55</sub>	61.76 <sub>±2.09</sub>	61.85 <sub>±1.49</sub>	45.17 <sub>±0.07</sub>	48.53 <sub>±1.13</sub>	48.68 <sub>±0.06</sub>	
	H	78.40 <sub>±0.38</sub>	79.94 <sub>±0.31</sub>	77.24 <sub>±0.96</sub>	72.10 <sub>±0.00</sub>	74.36 <sub>±0.75</sub>	71.03 <sub>±1.24</sub>	71.94 <sub>±2.16</sub>	70.72 <sub>±1.29</sub>	77.90 <sub>±1.40</sub>	71.66 <sub>±2.18</sub>	45.18 <sub>±0.07</sub>	48.50 <sub>±1.14</sub>	48.68 <sub>±0.06</sub>	
	F	73.86 <sub>±0.28</sub>	73.63 <sub>±0.50</sub>	72.40 <sub>±0.60</sub>	67.08 <sub>±0.00</sub>	64.56 <sub>±0.04</sub>	58.05 <sub>±0.88</sub>	57.09 <sub>±0.57</sub>	61.36 <sub>±0.11</sub>	63.59 <sub>±0.00</sub>	62.54 <sub>±0.81</sub>	46.26 <sub>±0.04</sub>	49.81 <sub>±0.88</sub>	49.83 <sub>±0.08</sub>	

Table 14: GRB leaderboard (Top 5 Attacks vs. Top 10 Defenses) for *grb-flickr* dataset.

Attack	Defenses	1	2	3	4	5	6	7	8	9	10	Avg.	Avg. 3-Max	Weighted
		R-GCN <sub>AT</sub>	GAT <sub>LN</sub>	SAGE <sub>LN</sub>	GIN <sub>LN</sub>	GCN <sub>AT</sub>	SAGE <sub>AT</sub>	GAT	GIN <sub>AT</sub>	SAGE	APPNP <sub>LN</sub>	Accuracy	Accuracy	Accuracy
1 SPEIT	E	53.41 <sub>±0.12</sub>	53.36 <sub>±0.22</sub>	51.43 <sub>±0.15</sub>	50.96 <sub>±0.29</sub>	52.89 <sub>±0.22</sub>	52.87 <sub>±0.13</sub>	53.62 <sub>±0.36</sub>	50.15 <sub>±0.14</sub>	51.65 <sub>±0.45</sub>	49.78 <sub>±0.03</sub>	52.01 <sub>±0.09</sub>	53.48 <sub>±0.25</sub>	53.44 <sub>±0.17</sub>
	M	49.79 <sub>±0.26</sub>	49.21 <sub>±0.26</sub>	47.83 <sub>±0.09</sub>	46.19 <sub>±0.14</sub>	48.05 <sub>±0.24</sub>	48.91 <sub>±0.12</sub>	52.04 <sub>±0.33</sub>	43.62 <sub>±0.10</sub>	44.54 <sub>±0.12</sub>	42.94 <sub>±0.09</sub>	47.31 <sub>±0.09</sub>	50.35 <sub>±0.13</sub>	50.89 <sub>±0.24</sub>
	F	47.14 <sub>±0.13</sub>	46.39 <sub>±0.13</sub>	47.62 <sub>±0.10</sub>	46.18 <sub>±0.08</sub>	43.52 <sub>±0.08</sub>	48.17 <sub>±0.14</sub>	49.91 <sub>±0.17</sub>	43.73 <sub>±0.05</sub>	43.66 <sub>±0.07</sub>	42.30 <sub>±0.08</sub>	45.86 <sub>±0.07</sub>	48.56 <sub>±0.07</sub>	48.95 <sub>±0.12</sub>
2 FGSM	E	53.99 <sub>±0.13</sub>	51.87 <sub>±0.49</sub>	50.89 <sub>±0.15</sub>	48.24 <sub>±0.13</sub>	53.79 <sub>±0.17</sub>	44.06 <sub>±0.23</sub>	48.23 <sub>±0.56</sub>	50.08 <sub>±0.16</sub>	49.99 <sub>±0.33</sub>	50.07 <sub>±0.08</sub>	50.12 <sub>±0.14</sub>	53.22 <sub>±0.10</sub>	53.30 <sub>±0.12</sub>
	M	51.79 <sub>±0.13</sub>	51.42 <sub>±0.20</sub>	47.89 <sub>±0.13</sub>	46.43 <sub>±0.13</sub>	51.54 <sub>±0.13</sub>	44.24 <sub>±0.17</sub>	46.17 <sub>±0.41</sub>	44.81 <sub>±0.14</sub>	44.24 <sub>±0.22</sub>	43.59 <sub>±0.08</sub>	47.21 <sub>±0.08</sub>	51.58 <sub>±0.22</sub>	51.06 <sub>±0.10</sub>
	F	50.20 <sub>±0.08</sub>	50.47 <sub>±0.15</sub>	47.58 <sub>±0.08</sub>	46.94 <sub>±0.07</sub>	48.58 <sub>±0.06</sub>	43.10 <sub>±0.14</sub>	42.78 <sub>±0.27</sub>	45.28 <sub>±0.10</sub>	43.33 <sub>±0.19</sub>	44.16 <sub>±0.09</sub>	46.24 <sub>±0.08</sub>	49.75 <sub>±0.09</sub>	49.73 <sub>±0.09</sub>
3 PGD	E	54.02 <sub>±0.18</sub>	51.88 <sub>±0.49</sub>	50.77 <sub>±0.19</sub>	48.36 <sub>±0.19</sub>	53.68 <sub>±0.18</sub>	43.95 <sub>±0.24</sub>	48.33 <sub>±0.71</sub>	50.04 <sub>±0.15</sub>	49.95 <sub>±0.42</sub>	50.05 <sub>±0.07</sub>	50.11 <sub>±0.11</sub>	53.19 <sub>±0.08</sub>	53.29 <sub>±0.14</sub>
	M	51.74 <sub>±0.22</sub>	51.65 <sub>±0.21</sub>	47.77 <sub>±0.16</sub>	46.69 <sub>±0.23</sub>	51.53 <sub>±0.10</sub>	44.26 <sub>±0.17</sub>	45.91 <sub>±0.40</sub>	44.95 <sub>±0.27</sub>	44.38 <sub>±0.43</sub>	43.56 <sub>±0.10</sub>	47.24 <sub>±0.20</sub>	51.64 <sub>±0.20</sub>	51.11 <sub>±0.09</sub>
	F	50.22 <sub>±0.11</sub>	50.62 <sub>±0.12</sub>	47.56 <sub>±0.11</sub>	46.94 <sub>±0.09</sub>	48.58 <sub>±0.08</sub>	43.09 <sub>±0.15</sub>	42.90 <sub>±0.24</sub>	45.24 <sub>±0.10</sub>	43.32 <sub>±0.14</sub>	44.14 <sub>±0.07</sub>	46.26 <sub>±0.07</sub>	49.81 <sub>±0.09</sub>	49.83 <sub>±0.08</sub>
4 TDGIA	E	55.13 <sub>±0.08</sub>	54.17 <sub>±0.17</sub>	51.83 <sub>±0.08</sub>	52.29 <sub>±0.08</sub>	54.35 <sub>±0.09</sub>	53.61 <sub>±0.08</sub>	54.66 <sub>±0.12</sub>	49.95 <sub>±0.02</sub>	51.50 <sub>±0.12</sub>	49.72 <sub>±0.00</sub>	52.72 <sub>±0.03</sub>	54.71 <sub>±0.07</sub>	-
	M	51.45 <sub>±0.12</sub>	51.30 <sub>±0.04</sub>	46.86 <sub>±0.08</sub>	48.54 <sub>±0.12</sub>	50.86 <sub>±0.13</sub>	50.03 <sub>±0.16</sub>	52.67 <sub>±0.24</sub>	43.20 <sub>±0.07</sub>	49.31 <sub>±0.16</sub>	42.88 <sub>±0.00</sub>	48.71 <sub>±0.16</sub>	51.81 <sub>±0.07</sub>	51.93 <sub>±0.09</sub>
	F	48.97 <sub>±0.05</sub>	51.25 <sub>±0.07</sub>	47.13 <sub>±0.07</sub>	49.05 <sub>±0.05</sub>	47.54 <sub>±0.06</sub>	49.52 <sub>±0.08</sub>	52.46 <sub>±0.09</sub>	43.77 <sub>±0.00</sub>	50.63 <sub>±0.08</sub>	42.30 <sub>±0.00</sub>	48.26 <sub>±0.00</sub>	51.45 <sub>±0.07</sub>	51.61 <sub>±0.06</sub>
5 RND	E	53.90 <sub>±0.20</sub>	53.31 <sub>±0.13</sub>	51.73 <sub>±0.14</sub>	51.16 <sub>±0.15</sub>	53.62 <sub>±0.10</sub>	53.19 <sub>±0.12</sub>	52.77 <sub>±0.22</sub>	50.36 <sub>±0.08</sub>	53.25 <sub>±0.13</sub>	49.83 <sub>±0.03</sub>	52.31 <sub>±0.06</sub>	53.65 <sub>±0.24</sub>	53.65 <sub>±0.14</sub>
	M	51.22 <sub>±0.15</sub>	50.01 <sub>±0.15</sub>	47.82 <sub>±0.12</sub>	48.21 <sub>±0.15</sub>	51.78 <sub>±0.11</sub>	49.84 <sub>±0.13</sub>	51.06 <sub>±0.30</sub>	44.11 <sub>±0.08</sub>	49.85 <sub>±0.18</sub>	43.04 <sub>±0.06</sub>	48.89 <sub>±0.07</sub>	51.70 <sub>±0.12</sub>	51.57 <sub>±0.11</sub>
	F	49.32 <sub>±0.11</sub>	49.33 <sub>±0.18</sub>	42.90 <sub>±0.13</sub>	46.79 <sub>±0.14</sub>	48.95 <sub>±0.12</sub>	49.03 <sub>±0.15</sub>	49.29 <sub>±0.25</sub>	39.10 <sub>±0.09</sub>	45.13 <sub>±0.28</sub>	34.50 <sub>±0.08</sub>	44.74 <sub>±0.07</sub>	49.19 <sub>±0.12</sub>	48.77 <sub>±0.18</sub>
6 W/O Attack	E	54.94 <sub>±0.12</sub>	52.58 <sub>±0.00</sub>	51.68 <sub>±0.00</sub>	50.48 <sub>±0.00</sub>	52.97 <sub>±0.00</sub>	53.18 <sub>±0.00</sub>	49.50 <sub>±0.00</sub>	50.72 <sub>±0.00</sub>	52.77 <sub>±0.00</sub>	51.55 <sub>±0.00</sub>	52.04 <sub>±0.01</sub>	53.70 <sub>±0.08</sub>	54.15 <sub>±0.08</sub>
	M	53.23 <sub>±0.13</sub>	52.75 <sub>±0.00</sub>	47.83 <sub>±0.00</sub>	48.05 <sub>±0.00</sub>	52.03 <sub>±0.00</sub>	51.27 <sub>±0.00</sub>	50.06 <sub>±0.00</sub>	44.87 <sub>±0.00</sub>	51.63 <sub>±0.00</sub>	45.01 <sub>±0.00</sub>	49.67 <sub>±0.00</sub>	52.67 <sub>±0.00</sub>	52.65 <sub>±0.09</sub>
	F	52.28 <sub>±0.06</sub>	51.66 <sub>±0.00</sub>	47.47 <sub>±0.00</sub>	48.31 <sub>±0.00</sub>	51.53 <sub>±0.00</sub>	50.52 <sub>±0.00</sub>	50.12 <sub>±0.00</sub>	45.23 <sub>±0.00</sub>	50.79 <sub>±0.00</sub>	44.23 <sub>±0.00</sub>	49.21 <sub>±0.00</sub>	51.82 <sub>±0.03</sub>	51.77 <sub>±0.04</sub>
Avg. Accuracy	E	54.23 <sub>±0.07</sub>	52.86 <sub>±0.16</sub>	51.38 <sub>±0.08</sub>	50.25 <sub>±0.09</sub>	53.55 <sub>±0.07</sub>	50.14 <sub>±0.07</sub>	51.19 <sub>±0.15</sub>	50.22 <sub>±0.04</sub>	51.52 <sub>±0.12</sub>	50.17 <sub>±0.07</sub>	-	-	-
	M	51.54 <sub>±0.07</sub>	51.39 <sub>±0.10</sub>	47.67 <sub>±0.08</sub>	47.35 <sub>±0.08</sub>	50.96 <sub>±0.08</sub>	48.09 <sub>±0.07</sub>	49.65 <sub>±0.09</sub>	44.26 <sub>±0.06</sub>	47.32 <sub>±0.19</sub>	43.50 <sub>±0.02</sub>	-	-	-
	F	49.69 <sub>±0.04</sub>	50.25 <sub>±0.08</sub>	47.47 <sub>±0.04</sub>	47.67 <sub>±0.04</sub>	48.46 <sub>±0.06</sub>	47.26 <sub>±0.04</sub>	48.17 <sub>±0.09</sub>	44.60 <sub>±0.03</sub>	46.79 <sub>±0.06</sub>	43.24 <sub>±0.01</sub>	-	-	-
Avg. 3-Min Accuracy	E	53.74 <sub>±0.09</sub>	52.11 <sub>±0.26</sub>	51.03 <sub>±0.10</sub>	49.03 <sub>±0.07</sub>	53.14 <sub>±0.09</sub>	46.96 <sub>±0.14</sub>	48.69 <sub>±0.25</sub>	50.00 <sub>±0.07</sub>	50.46 <sub>±0.22</sub>	49.78 <sub>±0.07</sub>	-	-	-
	M	50.23 <sub>±0.13</sub>	52.75 <sub>±0.00</sub>	47.83 <sub>±0.00</sub>	48.05 <sub>±0.00</sub>	52.03 <sub>±0.00</sub>	51.27 <sub>±0.00</sub>	50.06 <sub>±0.00</sub>	44.87 <sub>±0.00</sub>	51.63 <sub>±0.00</sub>	45.01 <sub>±0.00</sub>	49.67 <sub>±0.00</sub>	52.67 <sub>±0.00</sub>	52.65 <sub>±0.09</sub>
	F	48.48 <sub>±0.06</sub>	49.16 <sub>±0.04</sub>	47.35 <sub>±0.04</sub>	47.67 <sub>±0.04</sub>	48.46 <sub>±0.06</sub>	47.26 <sub>±0.04</sub>	48.17 <sub>±0.09</sub>	44.60 <sub>±0.03</sub>	46.79 <sub>±0.06</sub>	43.24 <sub>±0.00</sub>	-	-	-
Weighted Accuracy	E	53.62 <sub>±0.08</sub>	51.97 <sub>±0.33</sub>	50.92 <sub>±0.12</sub>	48.67 <sub>±0.09</sub>	53.02 <sub>±0.12</sub>	45.43 <sub>±0.10</sub>	48.62 <sub>±0.42</sub>	49.97 <sub>±0.06</sub>	50.22 <sub>±0.26</sub>	49.80 <sub>±0.01</sub>	-	-	-
	M	50.35 <sub>±0.18</sub>	50.62 <sub>±0.17</sub>	47.44 <sub>±0.07</sub>	46.44 <sub>±0.11</sub>	50.13 <sub>±0.09</sub>	45.81 <sub>±0.09</sub>	47.38 <sub>±0.19</sub>	43.65 <sub>±0.04</sub>	44.38 <sub>±0.21</sub>	42.95 <sub>±0.00</sub>	-	-	-
	F	45.15 <sub>±0.10</sub>	47.43 <sub>±0.17</sub>	42.37 <sub>±0.06</sub>	45.30 <sub>±0.13</sub>	45.55 <sub>±0.13</sub>	43.66 <sub>±0.07</sub>	45.92 <sub>±0.18</sub>	37.78 <sub>±0.04</sub>	39.72 <sub>±0.13</sub>	34.47 <sub>±0.01</sub>	-	-	-

Table 15: GRB leaderboard (Top 5 Attacks vs. Top 10 Defenses) for *grb-reddit* dataset.

Attack	Defenses	1	2	3	4	5	6	7	8	9	10	Avg.	Avg. 3-Max	Weighted
	gin_ln	tagen_ln	tagen_ln	gat_ln	robustgen_at	tagen	gen_ln	graphsgen_at	graphsgen	srgn_ln	scgn_ln	Accuracy	Accuracy	Accuracy
1 TDGIA	E	89.57 <sub>±0.05</sub>	80.59 <sub>±0.02</sub>	70.17 <sub>±0.28</sub>	84.18 <sub>±0.03</sub>	88.38 <sub>±0.02</sub>	78.83 <sub>±0.18</sub>	80.79 <sub>±0.17</sub>	86.29 <sub>±0.03</sub>	71.00 <sub>±0.11</sub>	76.36 <sub>±0.03</sub>	81.62 <sub>±0.08</sub>	89.52 <sub>±0.09</sub>	89.17 <sub>±0.03</sub>
	M	98.20 <sub>±0.01</sub>	97.79 <sub>±0.00</sub>	98.02 <sub>±0.01</sub>	96.20 <sub>±0.02</sub>	95.50 <sub>±0.01</sub>	96.62 <sub>±0.01</sub>	97.66 <sub>±0.01</sub>	94.07 <sub>±0.01</sub>	95.66 <sub>±0.02</sub>	92.27 <sub>±0.01</sub>	96.21 <sub>±0.00</sub>	98.03 <sub>±0.21</sub>	97.97 <sub>±0.01</sub>
	F	99.52 <sub>±0.01</sub>	99.16 <sub>±0.01</sub>	98.54 <sub>±0.01</sub>	98.17 <sub>±0.01</sub>	99.16 <sub>±0.01</sub>	95.68 <sub>±0.02</sub>	97.77 <sub>±0.01</sub>	90.60 <sub>±0.01</sub>	98.43 <sub>±0.02</sub>	93.33 <sub>±0.01</sub>	97.04 <sub>±0.01</sub>	99.28 <sub>±0.18</sub>	99.18 <sub>±0.00</sub>
2 SPEIT	E	91.92 <sub>±0.04</sub>	91.58 <sub>±0.03</sub>	91.73 <sub>±0.05</sub>	87.18 <sub>±0.08</sub>	88.81 <sub>±0.02</sub>	88.65 <sub>±0.01</sub>	90.75 <sub>±0.02</sub>	86.87 <sub>±0.03</sub>	88.10 <sub>±0.07</sub>	76.55 <sub>±0.10</sub>	87.57 <sub>±0.02</sub>	91.74 <sub>±0.14</sub>	91.35 <sub>±0.03</sub>
	M	98.27 <sub>±0.01</sub>	97.84 <sub>±0.01</sub>	97.98 <sub>±0.02</sub>	91.19 <sub>±0.16</sub>	95.28 <sub>±0.01</sub>	96.60 <sub>±0.00</sub>	97.77 <sub>±0.00</sub>	94.03 <sub>±0.01</sub>	96.74 <sub>±0.02</sub>	92.26 <sub>±0.03</sub>	96.30 <sub>±0.00</sub>	98.03 <sub>±0.08</sub>	97.97 <sub>±0.01</sub>
	F	99.31 <sub>±0.02</sub>	96.31 <sub>±0.02</sub>	95.77 <sub>±0.00</sub>	93.76 <sub>±0.00</sub>	93.59 <sub>±0.01</sub>	99.37 <sub>±0.00</sub>	95.57 <sub>±0.00</sub>	90.21 <sub>±0.01</sub>	92.96 <sub>±0.04</sub>	87.02 <sub>±0.03</sub>	93.53 <sub>±0.01</sub>	96.13 <sub>±0.26</sub>	95.96 <sub>±0.01</sub>
3 FGSIM	E	91.77 <sub>±0.06</sub>	91.53 <sub>±0.05</sub>	92.60 <sub>±0.04</sub>	87.38 <sub>±0.04</sub>	89.06 <sub>±0.01</sub>	90.52 <sub>±0.01</sub>	89.70 <sub>±0.01</sub>	86.78 <sub>±0.03</sub>	88.24 <sub>±0.06</sub>	78.51 <sub>±0.12</sub>	88.61 <sub>±0.02</sub>	91.97 <sub>±0.46</sub>	91.92 <sub>±0.03</sub>
	M	98.26 <sub>±0.01</sub>	97.74 <sub>±0.01</sub>	99.18 <sub>±0.01</sub>	95.47 <sub>±0.01</sub>	96.94 <sub>±0.01</sub>	97.68 <sub>±0.01</sub>	97.68 <sub>±0.01</sub>	94.01 <sub>±0.01</sub>	95.42 <sub>±0.04</sub>	92.65 <sub>±0.01</sub>	96.36 <sub>±0.01</sub>	98.04 <sub>±0.01</sub>	97.99 <sub>±0.01</sub>
	F	99.48 <sub>±0.01</sub>	99.02 <sub>±0.01</sub>	99.13 <sub>±0.01</sub>	98.17 <sub>±0.01</sub>	95.94 <sub>±0.01</sub>	99.32 <sub>±0.00</sub>	99.08 <sub>±0.00</sub>	91.01 <sub>±0.00</sub>	98.42 <sub>±0.03</sub>	93.65 <sub>±0.01</sub>	97.24 <sub>±0.00</sub>	99.27 <sub>±0.19</sub>	99.23 <sub>±0.01</sub>
4 RND	E	92.04 <sub>±0.04</sub>	91.75 <sub>±0.04</sub>	92.60 <sub>±0.04</sub>	87.09 <sub>±0.04</sub>	88.87 <sub>±0.05</sub>	90.00							

Table 16: GRB leaderboard (Top 5 Attacks vs. Top 10 Defenses) for *grb-aminer* dataset.

Attack	Defenses	1 GAT <sub>AT</sub>	2 R-GCN <sub>AT</sub>	3 SGCN <sub>LN</sub>	4 R-GCN	5 GCN <sub>LN</sub>	6 GAT <sub>LN</sub>	7 GIN <sub>LN</sub>	8 TAGCN <sub>LN</sub>	9 TAGCN <sub>AT</sub>	10 GAT	Avg. Accuracy	Avg. 3-Max Accuracy	Weighted Accuracy	
1 TDGIA	E	59.54 <sub>±0.05</sub>	56.83 <sub>±0.06</sub>	56.73 <sub>±0.06</sub>	56.12 <sub>±0.07</sub>	53.51 <sub>±0.21</sub>	43.93 <sub>±0.41</sub>	51.10 <sub>±0.12</sub>	54.63 <sub>±0.20</sub>	49.59 <sub>±0.50</sub>	42.40 <sub>±0.52</sub>	<b>52.44<sub>±0.17</sub></b>	<b>57.70<sub>±1.31</sub></b>	<b>58.08<sub>±0.04</sub></b>	
	M	68.39 <sub>±0.02</sub>	65.61 <sub>±0.03</sub>	66.11 <sub>±0.06</sub>	65.23 <sub>±0.06</sub>	66.78 <sub>±0.05</sub>	61.84 <sub>±1.20</sub>	64.49 <sub>±0.10</sub>	64.62 <sub>±0.02</sub>	67.27 <sub>±0.04</sub>	62.47 <sub>±1.01</sub>	<b>65.28<sub>±0.23</sub></b>	<b>67.48<sub>±0.68</sub></b>	<b>67.69<sub>±0.02</sub></b>	
	F	67.69 <sub>±0.03</sub>	63.62 <sub>±0.32</sub>	62.20 <sub>±0.15</sub>	61.99 <sub>±0.23</sub>	60.38 <sub>±1.46</sub>	59.69 <sub>±1.57</sub>	59.59 <sub>±0.42</sub>	59.06 <sub>±1.75</sub>	57.24 <sub>±3.04</sub>	56.63 <sub>±4.75</sub>	60.81 <sub>±1.71</sub>	<b>64.52<sub>±2.32</sub></b>	<b>65.74<sub>±0.21</sub></b>	
2 SPEIT	E	59.54 <sub>±0.07</sub>	56.80 <sub>±0.05</sub>	56.94 <sub>±0.10</sub>	55.64 <sub>±0.10</sub>	56.15 <sub>±0.06</sub>	56.13 <sub>±0.07</sub>	54.24 <sub>±0.09</sub>	56.61 <sub>±0.06</sub>	56.59 <sub>±0.09</sub>	57.36 <sub>±0.09</sub>	56.60 <sub>±0.04</sub>	57.95 <sub>±1.14</sub>	58.62 <sub>±0.05</sub>	
	M	68.37 <sub>±0.04</sub>	65.46 <sub>±0.03</sub>	66.20 <sub>±0.02</sub>	65.25 <sub>±0.03</sub>	66.75 <sub>±0.03</sub>	67.49 <sub>±0.06</sub>	65.05 <sub>±0.06</sub>	64.47 <sub>±0.04</sub>	66.95 <sub>±0.05</sub>	66.81 <sub>±0.04</sub>	66.28 <sub>±0.02</sub>	67.60 <sub>±0.59</sub>	67.86 <sub>±0.03</sub>	
	F	68.04 <sub>±0.03</sub>	64.05 <sub>±0.04</sub>	64.84 <sub>±0.06</sub>	64.06 <sub>±0.06</sub>	65.51 <sub>±0.02</sub>	64.02 <sub>±0.04</sub>	63.11 <sub>±0.02</sub>	62.59 <sub>±0.04</sub>	63.77 <sub>±0.06</sub>	63.58 <sub>±0.06</sub>	64.36 <sub>±0.02</sub>	66.13 <sub>±1.38</sub>	66.89 <sub>±0.02</sub>	
3 RND	E	59.56 <sub>±0.06</sub>	57.73 <sub>±0.06</sub>	57.41 <sub>±0.06</sub>	56.38 <sub>±0.11</sub>	57.76 <sub>±0.06</sub>	58.83 <sub>±0.10</sub>	54.41 <sub>±0.13</sub>	58.07 <sub>±0.12</sub>	58.14 <sub>±0.04</sub>	57.46 <sub>±0.10</sub>	57.55 <sub>±0.03</sub>	58.85 <sub>±0.57</sub>	59.09 <sub>±0.05</sub>	
	M	68.22 <sub>±0.04</sub>	65.86 <sub>±0.03</sub>	66.29 <sub>±0.03</sub>	65.34 <sub>±0.06</sub>	67.03 <sub>±0.03</sub>	68.62 <sub>±0.03</sub>	65.54 <sub>±0.06</sub>	64.98 <sub>±0.08</sub>	67.34 <sub>±0.08</sub>	67.71 <sub>±0.06</sub>	66.69 <sub>±0.02</sub>	68.18 <sub>±0.38</sub>	68.24 <sub>±0.03</sub>	
	F	75.94 <sub>±0.04</sub>	72.27 <sub>±0.03</sub>	72.36 <sub>±0.02</sub>	71.86 <sub>±0.03</sub>	73.41 <sub>±0.01</sub>	75.34 <sub>±0.03</sub>	72.87 <sub>±0.03</sub>	68.88 <sub>±0.05</sub>	73.98 <sub>±0.02</sub>	73.83 <sub>±0.04</sub>	<b>73.07<sub>±0.00</sub></b>	<b>75.08<sub>±0.82</sub></b>	75.33 <sub>±0.02</sub>	
4 PGD	E	59.70 <sub>±0.06</sub>	57.71 <sub>±0.06</sub>	57.73 <sub>±0.06</sub>	57.19 <sub>±0.06</sub>	57.60 <sub>±0.08</sub>	57.05 <sub>±0.17</sub>	54.69 <sub>±0.09</sub>	58.18 <sub>±0.07</sub>	58.27 <sub>±0.09</sub>	58.46 <sub>±0.11</sub>	57.66 <sub>±0.04</sub>	58.81 <sub>±0.64</sub>	59.14 <sub>±0.05</sub>	
	M	68.40 <sub>±0.05</sub>	66.12 <sub>±0.06</sub>	66.39 <sub>±0.06</sub>	65.67 <sub>±0.06</sub>	67.04 <sub>±0.05</sub>	68.24 <sub>±0.04</sub>	65.64 <sub>±0.08</sub>	65.17 <sub>±0.05</sub>	67.32 <sub>±0.03</sub>	67.85 <sub>±0.05</sub>	66.78 <sub>±0.06</sub>	68.16 <sub>±0.23</sub>	68.12 <sub>±0.03</sub>	
	F	75.83 <sub>±0.03</sub>	72.91 <sub>±0.04</sub>	72.47 <sub>±0.04</sub>	72.18 <sub>±0.06</sub>	73.52 <sub>±0.02</sub>	75.55 <sub>±0.05</sub>	73.58 <sub>±0.04</sub>	69.64 <sub>±0.06</sub>	73.89 <sub>±0.02</sub>	74.34 <sub>±0.04</sub>	73.39 <sub>±0.01</sub>	75.24 <sub>±0.65</sub>	75.36 <sub>±0.02</sub>	
5 FGSM	E	59.71 <sub>±0.05</sub>	57.69 <sub>±0.06</sub>	57.62 <sub>±0.06</sub>	57.16 <sub>±0.06</sub>	57.60 <sub>±0.06</sub>	56.97 <sub>±0.09</sub>	54.67 <sub>±0.08</sub>	58.20 <sub>±0.10</sub>	58.23 <sub>±0.06</sub>	58.46 <sub>±0.07</sub>	57.63 <sub>±0.04</sub>	58.81 <sub>±0.65</sub>	59.15 <sub>±0.04</sub>	
	M	68.37 <sub>±0.02</sub>	66.10 <sub>±0.03</sub>	66.38 <sub>±0.03</sub>	65.70 <sub>±0.05</sub>	67.03 <sub>±0.04</sub>	68.27 <sub>±0.04</sub>	65.61 <sub>±0.08</sub>	65.16 <sub>±0.05</sub>	67.30 <sub>±0.02</sub>	67.84 <sub>±0.07</sub>	66.78 <sub>±0.06</sub>	68.16 <sub>±0.23</sub>	68.11 <sub>±0.02</sub>	
	F	75.82 <sub>±0.02</sub>	72.92 <sub>±0.04</sub>	72.48 <sub>±0.04</sub>	72.18 <sub>±0.05</sub>	73.52 <sub>±0.02</sub>	75.55 <sub>±0.05</sub>	73.60 <sub>±0.04</sub>	69.64 <sub>±0.04</sub>	73.90 <sub>±0.01</sub>	74.34 <sub>±0.04</sub>	73.39 <sub>±0.01</sub>	75.23 <sub>±0.65</sub>	75.35 <sub>±0.02</sub>	
6 W/O Attack	E	59.67 <sub>±0.06</sub>	58.08 <sub>±0.06</sub>	60.22 <sub>±0.06</sub>	58.53 <sub>±0.06</sub>	58.14 <sub>±0.06</sub>	60.78 <sub>±0.06</sub>	56.83 <sub>±0.06</sub>	59.47 <sub>±0.06</sub>	59.62 <sub>±0.06</sub>	59.88 <sub>±0.06</sub>	59.12 <sub>±0.06</sub>	60.29 <sub>±0.37</sub>	60.42 <sub>±0.00</sub>	
	M	68.28 <sub>±0.06</sub>	66.14 <sub>±0.06</sub>	67.11 <sub>±0.06</sub>	66.35 <sub>±0.06</sub>	67.00 <sub>±0.06</sub>	68.98 <sub>±0.06</sub>	66.26 <sub>±0.06</sub>	65.41 <sub>±0.06</sub>	67.53 <sub>±0.06</sub>	68.41 <sub>±0.06</sub>	67.15 <sub>±0.06</sub>	68.56 <sub>±0.30</sub>	68.59 <sub>±0.00</sub>	
	F	75.85 <sub>±0.03</sub>	73.05 <sub>±0.04</sub>	72.69 <sub>±0.04</sub>	72.66 <sub>±0.06</sub>	73.46 <sub>±0.06</sub>	75.64 <sub>±0.06</sub>	73.69 <sub>±0.06</sub>	69.84 <sub>±0.06</sub>	74.10 <sub>±0.06</sub>	75.76 <sub>±0.06</sub>	73.67 <sub>±0.00</sub>	75.75 <sub>±0.09</sub>	75.52 <sub>±0.00</sub>	
Avg. Accuracy	E	<b>59.62<sub>±0.02</sub></b>	57.44 <sub>±0.06</sub>	57.77 <sub>±0.03</sub>	56.84 <sub>±0.04</sub>	56.79 <sub>±0.04</sub>	55.62 <sub>±0.06</sub>	54.33 <sub>±0.04</sub>	57.53 <sub>±0.05</sub>	56.74 <sub>±0.09</sub>	55.67 <sub>±0.10</sub>	-	-	-	
	M	68.34 <sub>±0.01</sub>	65.88 <sub>±0.03</sub>	66.41 <sub>±0.03</sub>	65.59 <sub>±0.03</sub>	66.94 <sub>±0.02</sub>	67.24 <sub>±0.19</sub>	65.43 <sub>±0.03</sub>	64.97 <sub>±0.02</sub>	67.28 <sub>±0.01</sub>	66.85 <sub>±0.18</sub>	-	-	-	
	F	<b>75.84<sub>±0.01</sub></b>	72.69 <sub>±0.04</sub>	72.42 <sub>±0.04</sub>	72.14 <sub>±0.05</sub>	73.47 <sub>±0.01</sub>	75.49 <sub>±0.01</sub>	73.33 <sub>±0.02</sub>	69.38 <sub>±0.02</sub>	73.98 <sub>±0.00</sub>	74.78 <sub>±0.02</sub>	-	-	-	
Avg. 3-Min Accuracy	E	<b>59.55<sub>±0.03</sub></b>	57.05 <sub>±0.06</sub>	57.02 <sub>±0.03</sub>	56.05 <sub>±0.07</sub>	55.73 <sub>±0.07</sub>	52.33 <sub>±0.12</sub>	53.25 <sub>±0.07</sub>	56.43 <sub>±0.07</sub>	54.77 <sub>±0.16</sub>	52.41 <sub>±0.17</sub>	-	-	-	
	M	<b>68.28<sub>±0.01</sub></b>	65.64 <sub>±0.03</sub>	66.20 <sub>±0.03</sub>	65.28 <sub>±0.03</sub>	66.84 <sub>±0.02</sub>	65.85 <sub>±0.40</sub>	65.02 <sub>±0.04</sub>	64.69 <sub>±0.03</sub>	67.17 <sub>±0.02</sub>	65.66 <sub>±0.34</sub>	-	-	-	
	F	<b>67.78<sub>±0.01</sub></b>	64.87 <sub>±0.06</sub>	65.02 <sub>±0.06</sub>	64.41 <sub>±0.04</sub>	65.12 <sub>±0.26</sub>	65.45 <sub>±0.36</sub>	63.65 <sub>±0.07</sub>	63.42 <sub>±0.29</sub>	64.53 <sub>±0.84</sub>	64.46 <sub>±0.13</sub>	-	-	-	
Weighted Accuracy	E	<b>59.53<sub>±0.04</sub></b>	56.93 <sub>±0.06</sub>	56.94 <sub>±0.06</sub>	55.93 <sub>±0.06</sub>	54.63 <sub>±0.14</sub>	48.21 <sub>±0.27</sub>	52.23 <sub>±0.08</sub>	55.55 <sub>±0.14</sub>	52.18 <sub>±0.33</sub>	47.45 <sub>±0.35</sub>	-	-	-	
	M	<b>68.25<sub>±0.02</sub></b>	65.57 <sub>±0.03</sub>	66.17 <sub>±0.03</sub>	65.28 <sub>±0.03</sub>	66.79 <sub>±0.02</sub>	63.85 <sub>±0.80</sub>	64.77 <sub>±0.07</sub>	64.60 <sub>±0.03</sub>	67.06 <sub>±0.01</sub>	64.07 <sub>±0.68</sub>	-	-	-	
	F	<b>67.73<sub>±0.03</sub></b>	63.96 <sub>±0.21</sub>	63.19 <sub>±0.10</sub>	62.80 <sub>±0.15</sub>	62.18 <sub>±0.08</sub>	61.58 <sub>±1.05</sub>	61.00 <sub>±0.28</sub>	60.54 <sub>±1.18</sub>	59.82 <sub>±3.38</sub>	59.37 <sub>±4.53</sub>	-	-	-	