Bipartite Dynamic Representations for Abuse Detection

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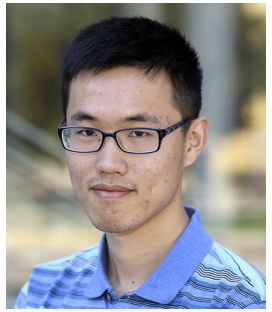

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Abusive Actors Harm Online Communities

WIKIPEDIA
The Free Encyclopedia

Social and collaboration networks:
Trolling, propagating misinformation, offensive language

E-commerce websites:
Fake reviews or purchases to inflate product rankings

Image source: Wikimedia Commons

Abusive Actors Harm Online Communities

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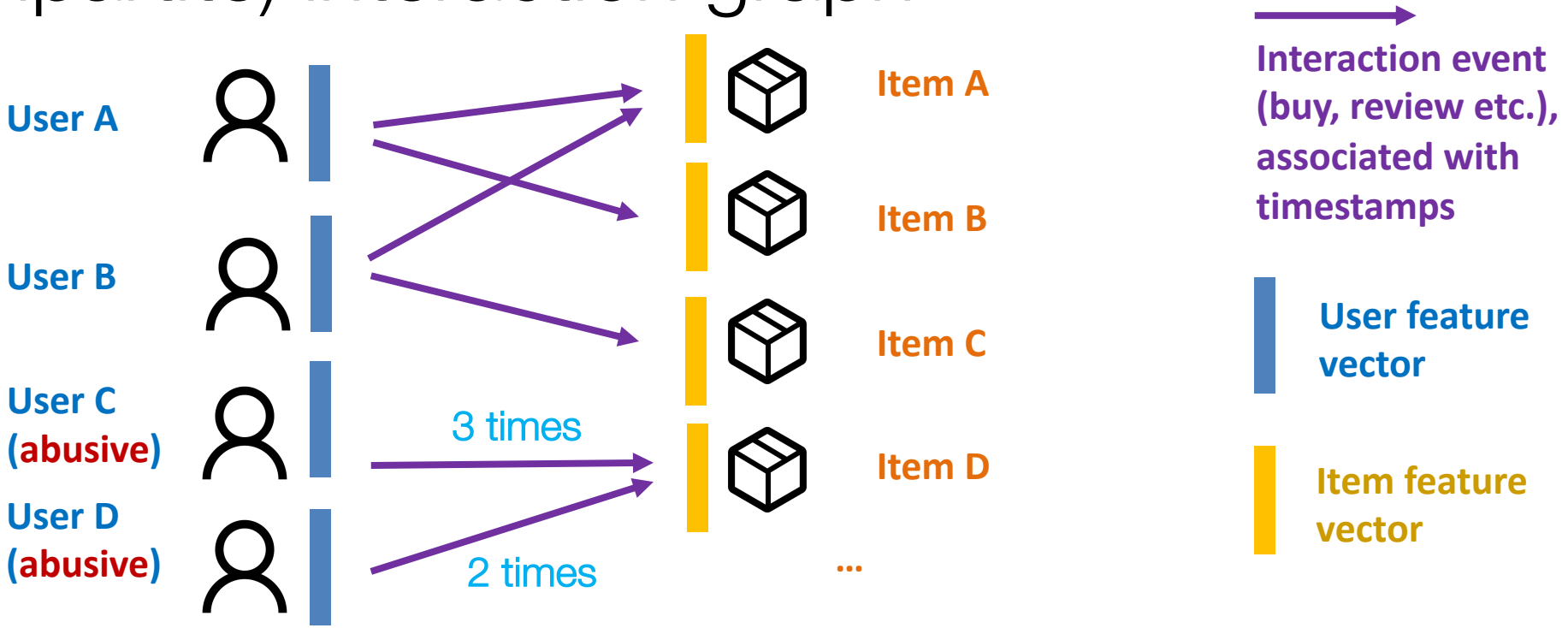
Effects of abuse:

- Hurts the experience of honest users
- Reduces customer engagement and revenue
- Reduces trust in the platform

Image source: Wikimedia Commons

Abuse Detection in E-commerce

- Abuse detection is an important problem in the E-commerce setting, where users and items form a (bipartite) interaction graph



Problem Setting: Detecting Abusive Actors

- Given:
  - Interaction data of users with items (e.g. products, subcommunities) over time
  - A subset of users labeled as abusive or non-abusive
- Goal:
  - For all unlabeled users, predict if each is abusive

Abuse Detection is Challenging

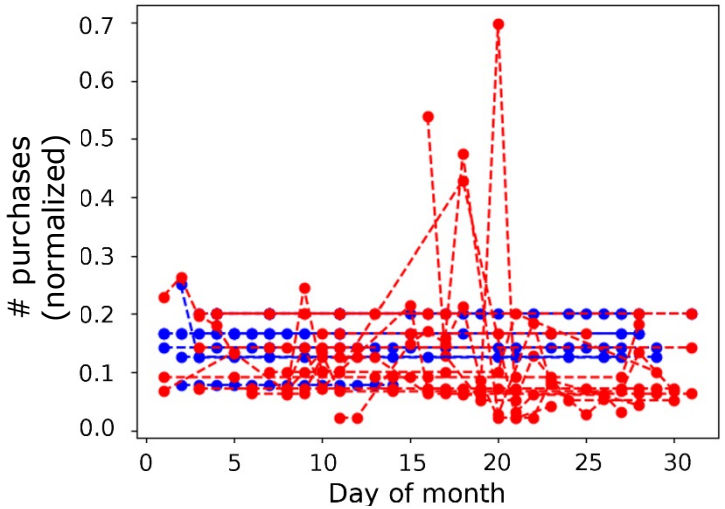
Complex dynamics:
Users interact with various items over time

Extremely large-scale interaction data

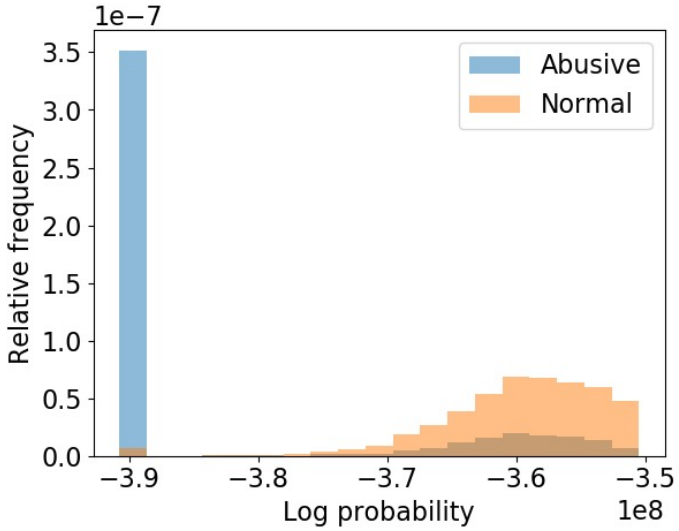
Collecting ground-truth labels is costly

Abuse Detection: Interactions Follow Complex Dynamics

1. Complex dynamics: users interact with various items over time



Time domain: abusive users (red) have more fluctuating activity than normal users (blue)



Graph domain: abusive users have less likely connections than normal users (as estimated by link prediction model)

e-commerce dataset

Abuse Detection: Scalability is Crucial

2. Extremely large-scale interaction data

- High volume (100M+) of interactions
- End-to-end training of graph neural networks (GNNs) is expensive:
  - The entire graph and features cannot be fit into GPU memory
  - Exponential memory cost $O(d^L)$ of minibatch training with increasing number of hops L, and fanout d
  - Require a dynamic model

Abuse Detection: Labeled Data is Sparse

3. Collecting ground-truth labels is costly

- Human annotation is expensive
- Positive labels are scarce due to rarity of abuse

Our work: bridge the gap via a comprehensive system for large-scale abuse detection on dynamic graphs

Our Work: Problem Framework

- Model data as a dynamic, bipartite graph $G = (U, V, E, f, g, h)$
  - User nodes $u \in U$, item nodes $v \in V$
  - Dynamic edges $(u, v, t) \in E$ $(u \in U, v \in V, t \in \mathbb{R})$ with timestamp t
  - Node features $f: U \to \mathbb{R}^{d_1}$, $g: V \to \mathbb{R}^{d_2}$
  - Edge features $h: E \to \mathbb{R}^{d_3}$

- Model learning problem as **transductive node classification**
  - Some users are known to be abusive or non-abusive
    - Partial function $f: U \to \{0,1\}$ known at training time
  - Goal: infer status of remaining users
    - Predict labels of all users $u \in U$

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Our Work: Detecting Abuse

Our approach: **BiDyn**

Complex dynamics: Users interact with various items over time	Joint modeling of time and graph information	*Model architecture*
Extremely large-scale interaction data	Scalable training scheme	*Training algorithm*
Collecting ground-truth labels is costly	Self-supervised pretraining framework	*Training objective*

Our Work: Detecting Abuse

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Complex dynamics: Users interact with various items over time → Joint modeling of time and graph information — *Model architecture*

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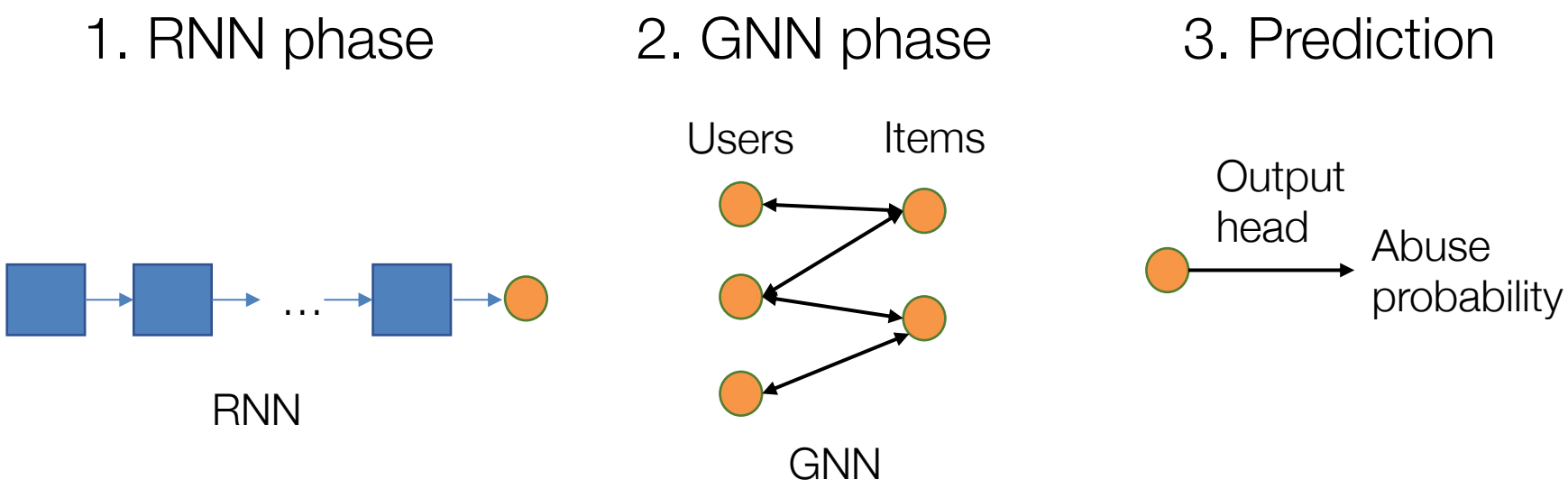
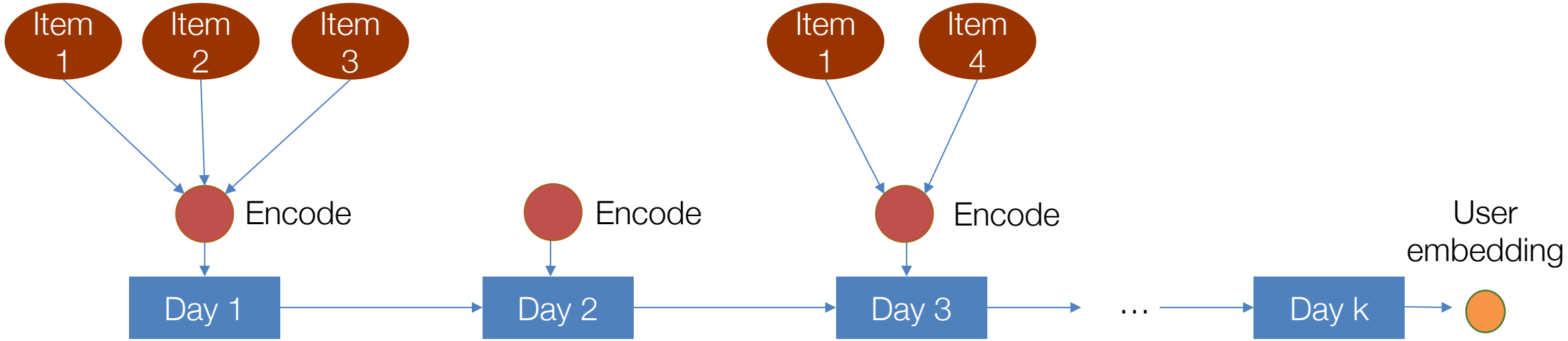
BiDyn Architecture: Joint Modeling of Graph and Time Information

- Motivation: preserve raw time series information (bursty behavior)
- BiDyn uses a three-phase model architecture:



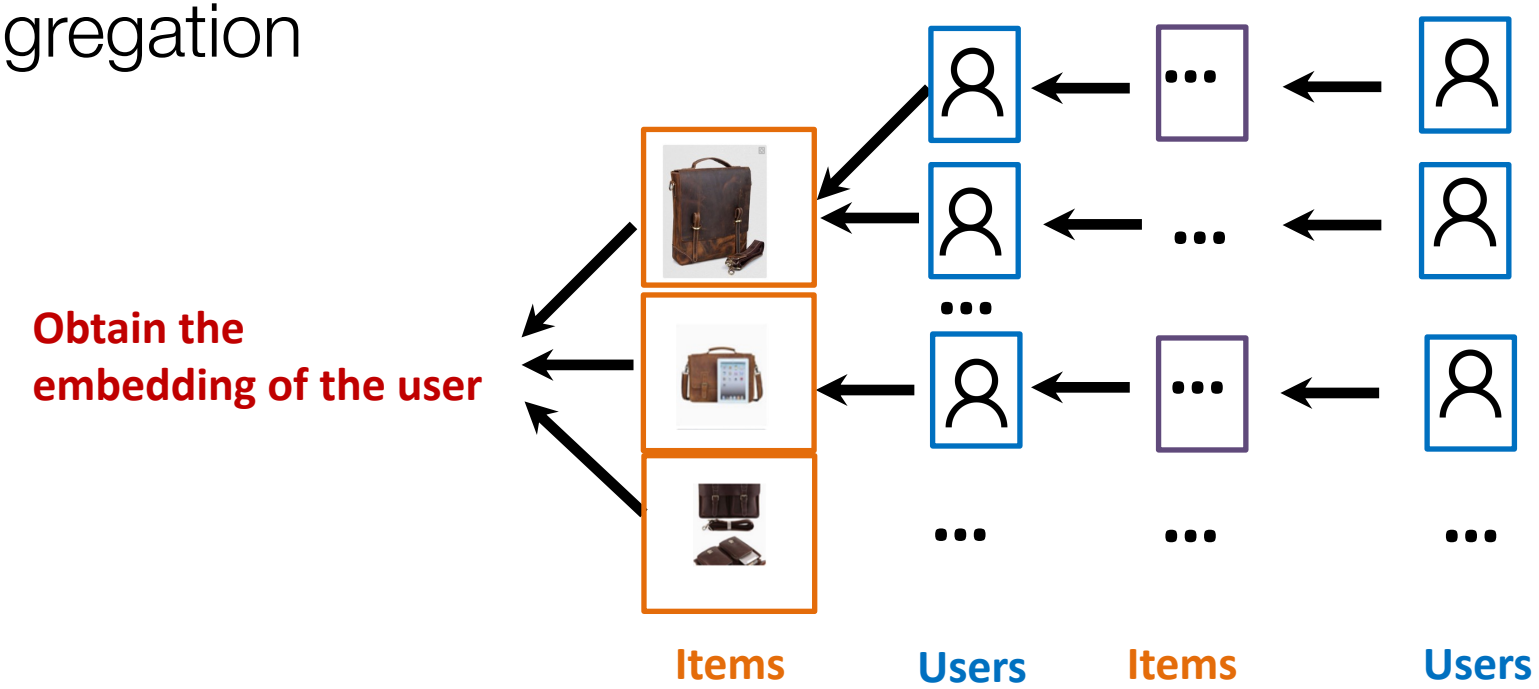
BiDyn Architecture: RNN Phase

- RNN: LSTM of all events associated with given node, in time order
- Aggregate simultaneous events using a deepset encoder
- Concatenate number of events on each day



BiDyn Architecture: GNN Phase

- Graph neural network: aggregate information from local neighborhood
  - Use convolution function without learnable parameters for aggregation



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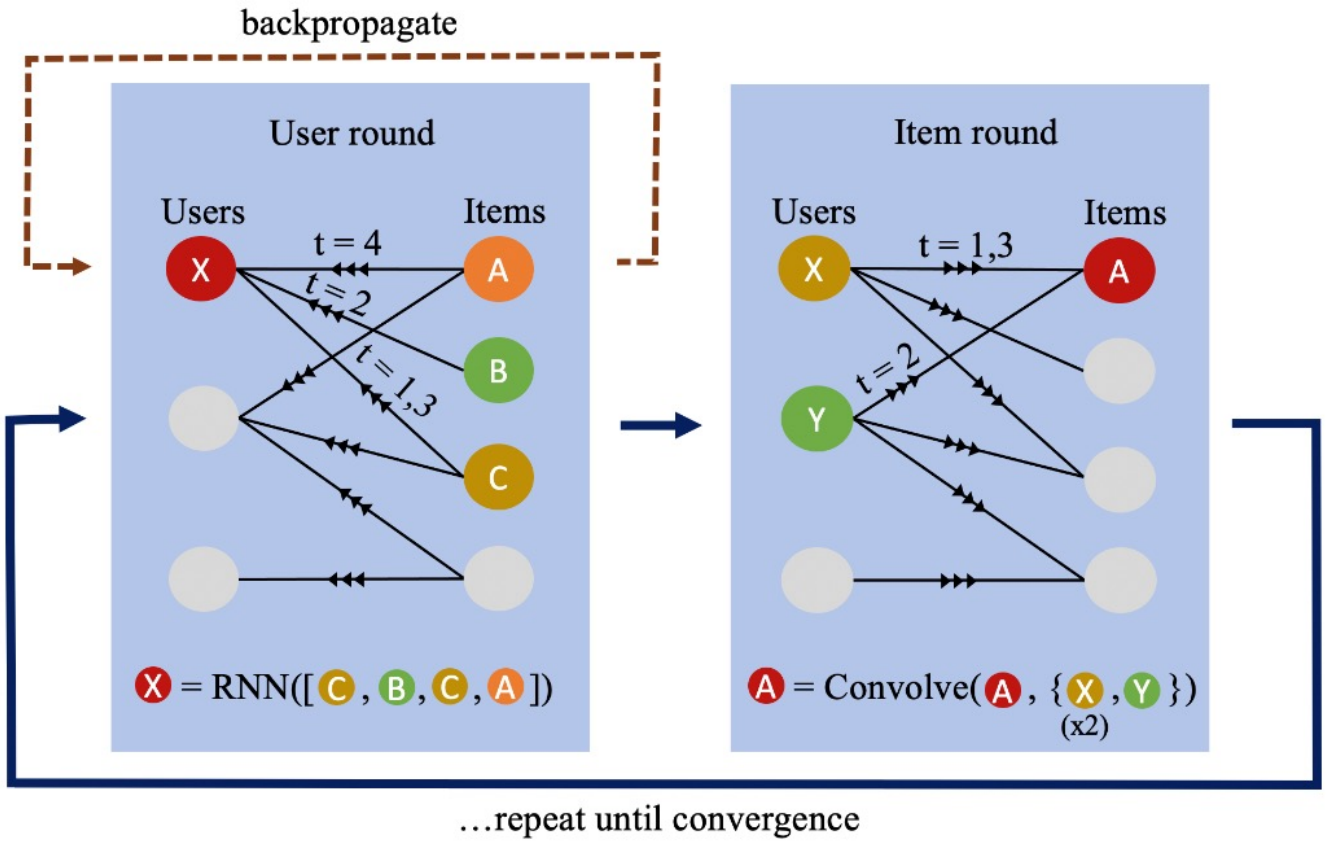
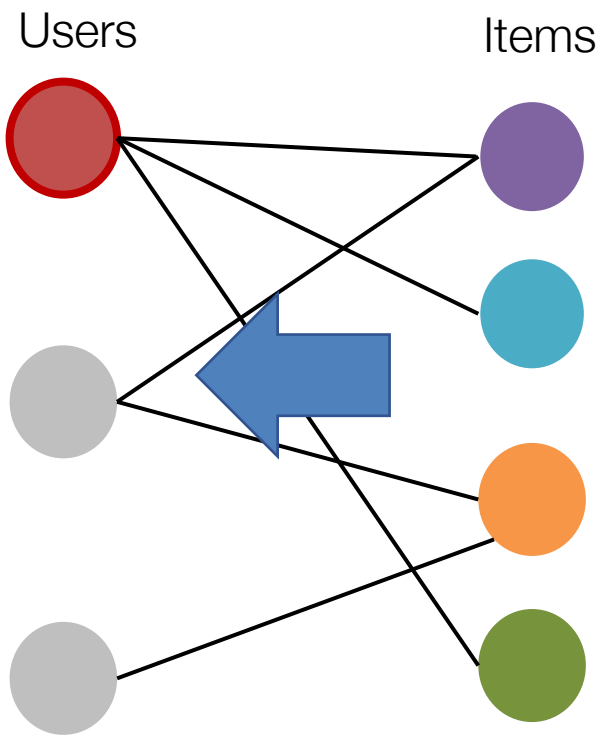
BiDyn: Scalable Training Scheme

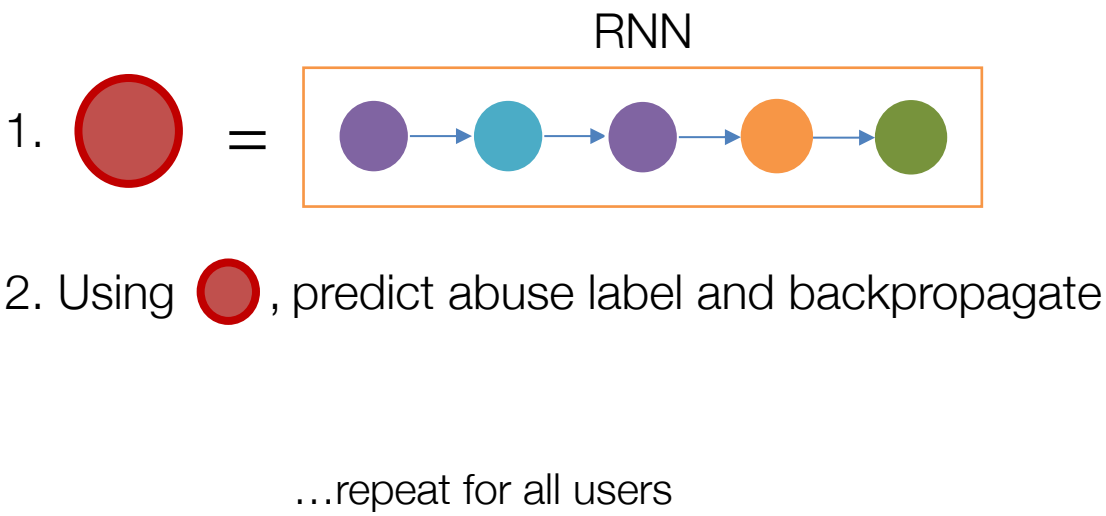
- Idea: *stacked* ensemble model
- Evolve node representations by alternating application of RNN phase (“**user round**”) and GNN phase (“**item round**”)



BiDyn: Alternating Training

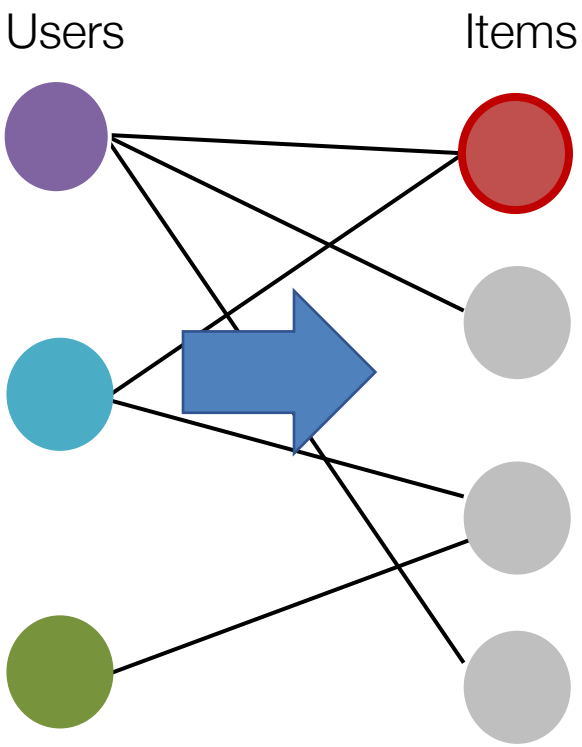
- User round: update user representations by aggregating representations of all items each user interacted with over time
  - RNN during user round ensures accurate modeling of bursty behavior

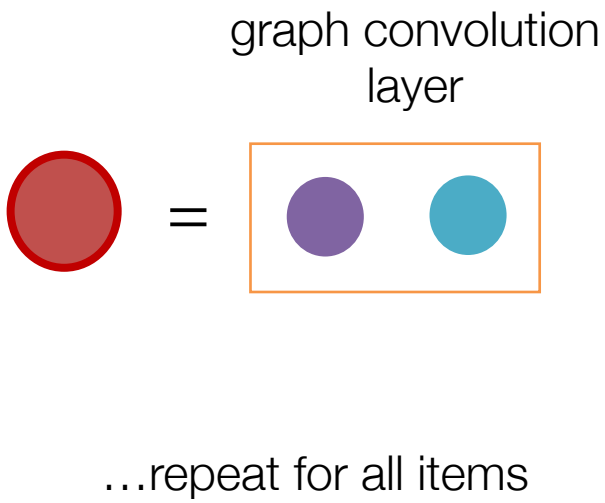




BiDyn: Alternating Training

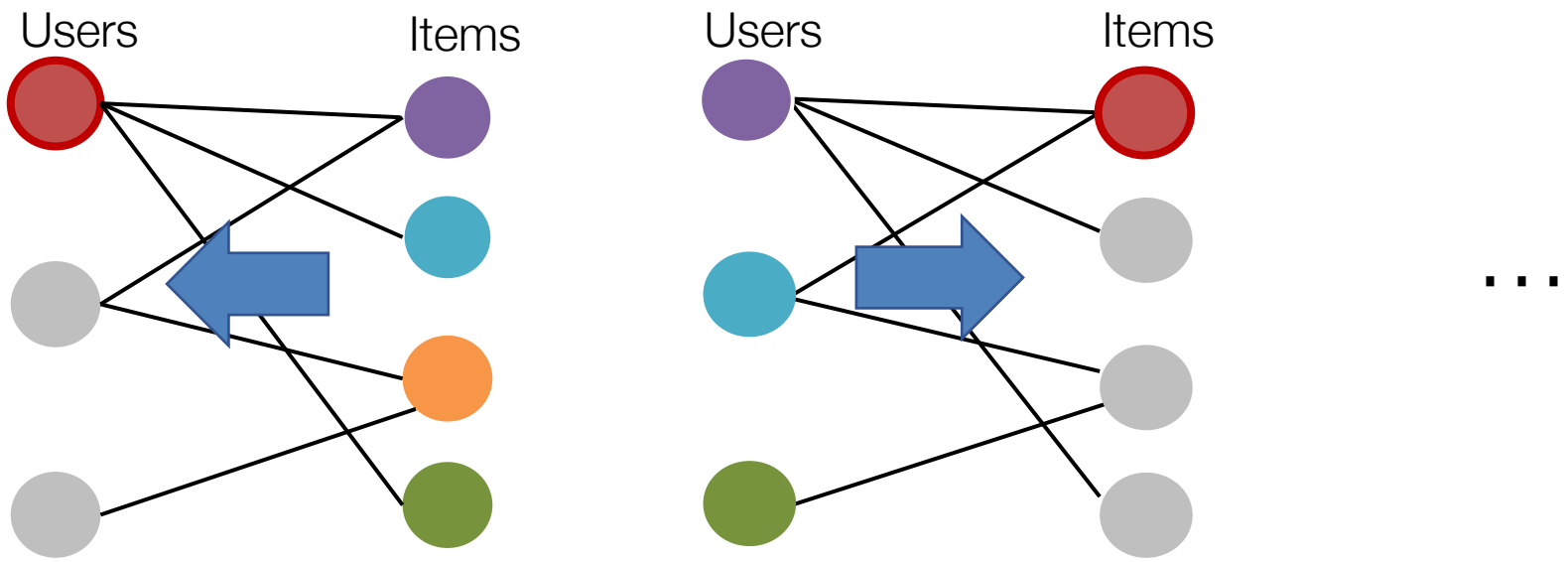
- **Item round:** update item representations by aggregating representations of all users that interacted with each item





BiDyn: Alternating Training

- Improved user representations give rise to improved item representations, and vice versa
- Alternating user and item updates ensure that each node can communicate with every other node in the graph



Our Work: Detecting Abuse

Our approach: **BiDyn**

Complex dynamics: Users interact with various items over time → Joint modeling of time and graph information — *Model architecture*

Extremely large-scale interaction data → Scalable training scheme — *Training algorithm*

Collecting ground-truth labels is costly → Self-supervised pretraining framework — *Pre-training framework*

Experiments: Datasets

- E-commerce
  - Purchases between buyers and products over two-month period
  - 400K users (0.2% abusive), 5.6M items, 113M edges
- Wikipedia
  - Edits between users and articles
  - 8K users (2.3% abusive), 1K items, 157K edges
- Reddit
  - Posts by users in communities
  - 10K users (3.3% abusive), 1K items, 672K edges

Experiments: Method Comparison

Baselines

- TGAT: temporal attention layers to attend to node history
- TGN: uses memory modules and graph-based operators
- DyRep: model dynamics jointly on small and large time scales
- JODIE: predict trajectories of node embeddings over time

Ablations

- RNN: use only the RNN phase of BiDyn
- GNN: use only the GNN phase of BiDyn
- RNN-GNN: use the RNN and GNN phases together, but train end-to-end

Experiments: Method Comparison

	AUROC	e-commerce	Wikipedia	Reddit
Baselines	TGAT	-4.0	73.6	51.5
	TGN	OOM	49.0	**67.0**
	DyRep	OOM	52.5	61.4
	JODIE	OOM	53.0	61.2
Ours	BiDyn	+1.2	86.5	56.0
	BiDyn + pretraining	**+4.5**	**87.5**	50.5

- BiDyn achieves comparable or better performance than existing dynamic graph models on small datasets (Wikipedia, Reddit)
- BiDyn scales to 100M-edge graphs (e-commerce), while baselines run out of memory (OOM)

5% of labels seen in training

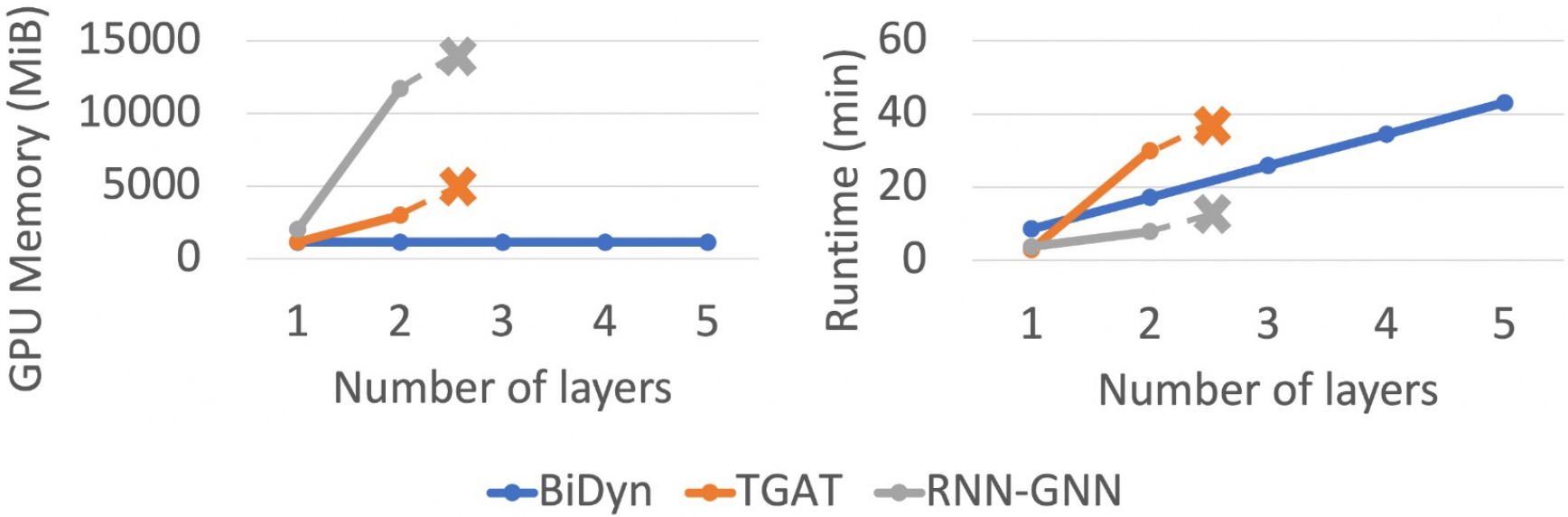
Experiments: Method Comparison

	AUROC	e-commerce	Wikipedia	Reddit
Ablations	GNN	+0.0	69.6	53.7
	RNN	+0.0	78.0	51.3
	RNN-GNN	-2.2	70.0	53.8
Ours	BiDyn	+1.2	86.5	**56.0**
	BiDyn + pretraining	**+4.5**	**87.5**	50.5

- BiDyn outperforms models that only use graph or time information alone (RNN, GNN)
- BiDyn outperforms end-to-end training (RNN-GNN) due to increased model depth
- Pretraining can lead to additional gains in label-sparse settings

5% of labels seen in training

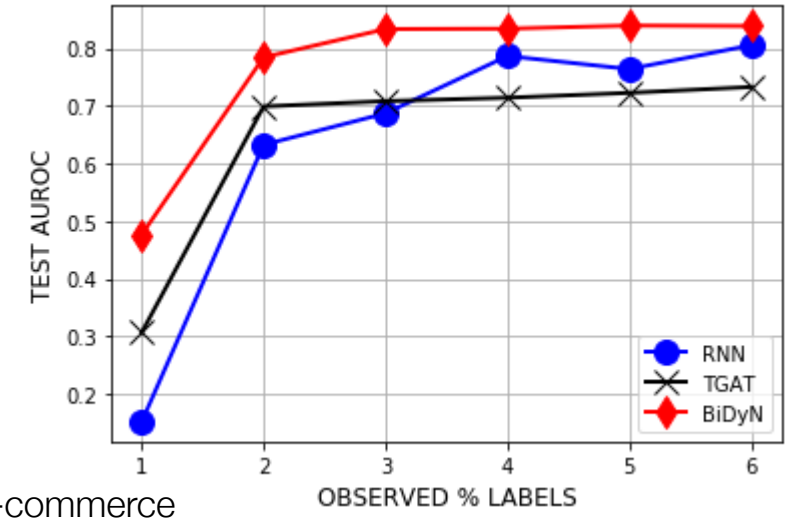
Experiments: Scalability



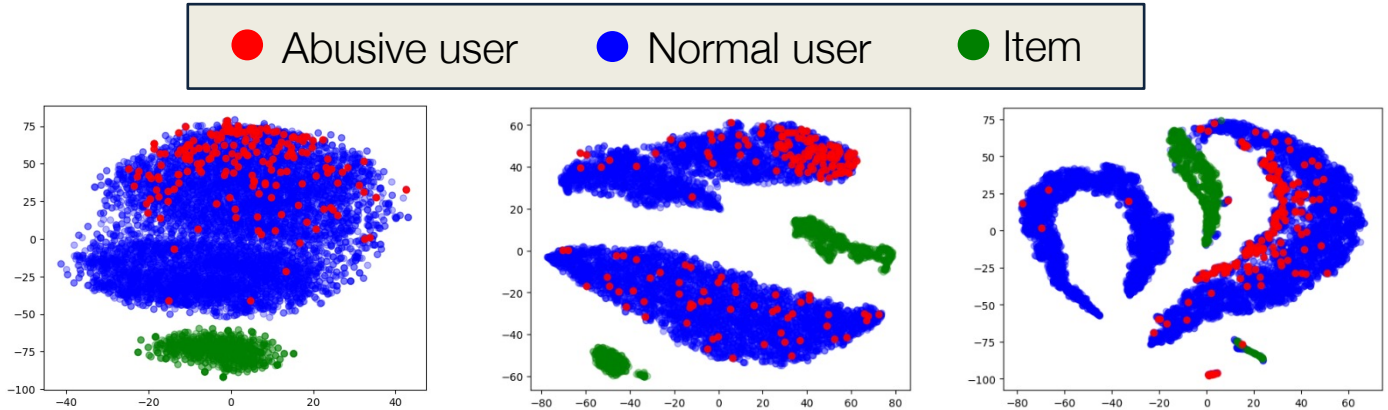
- BiDyn uses 10-100X less memory than baselines, with comparable runtime
- Enables training of deeper models

e-commerce. 5% of labels seen in training

Experiments: Pretraining



E-commerce



Before pretraining

After pretraining

After finetuning

Wikipedia

- BiDyn is robust to sparse training labels
- Pretraining gives initial separation of node classes

Conclusion

- Integrating time series and graph information leads to significant improvement in abuse detection
- Alternating training is a high-performing, scalable approach to node classification on dynamic graphs
- Pretraining on anomaly detection objectives can improve performance in label-sparse settings

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- Code: http://snap.stanford.edu/bidyn