MONSTOR: An Inductive Approach for Estimating and Maximizing Influence over Unseen Networks

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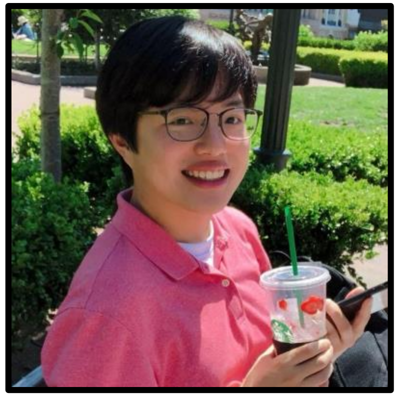

Kijung Shin

Noseong Park

Social relationship can be represented as graph!

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Information cascade in social relationship

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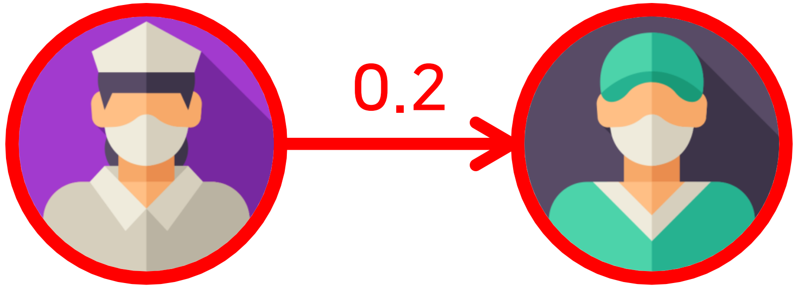
Influence Maximization

- Find a certain number of seed nodes to maximize the spread of information through a social network

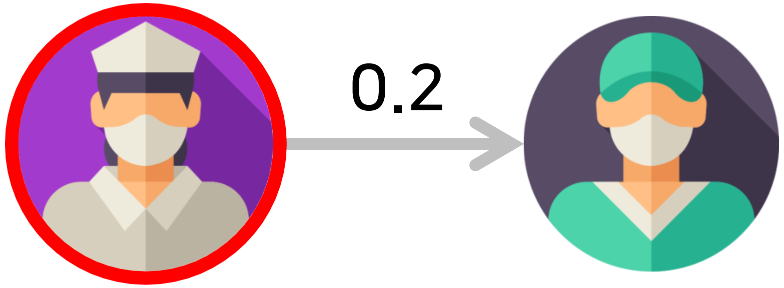
- Two major issues
  1) How to model the information cascade
  2) How to solve the problem based on information cascade model

How to model the information cascade

- Independent Cascade (IC)
  - When node v becomes active, it has a single chance of activating each currently inactive neighbor w
  - The activation attempt succeeds with some probability p_{vw}



with probability 0.2



with probability (1 - 0.2)

- Linear Threshold (LT)
  - Each node v has threshold p_v, and it is activated by its neighbors when at least p_v fraction of its neighbors are active

How to solve the problem based on IC model

- Greedy approach [KKT03]
  - Greedily choose nodes using Monte-Carlo simulations repeatedly
  - Guarantees the approximation ratio of $\left(1-\frac{1}{e}\right)$
  - d (usually set to 10,000) simulations takes $O(d|\mathcal{E}|)$ time!

    => performance bottleneck
  - CELF [LKGFVG07], UBLF [ZZGZG13] still rely heavily on MC simulations!
    - CELF significantly reduced MC simulations using submodular property
    - UBLF derived upper bound of marginal gain for every node at initialization step

How to solve the problem based on IC model

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<u>Solution</u>: Estimate results from repeated MC simulations in fast!

Outline

- Preliminaries
- Proposed method: MONSTOR
- Experimental Results
- Summary

Preliminaries

- Activation Probability from u to v
  - The success probability that the node u activates its neighbor v when u is infected
  - Bernoulli Trial (BT):

$$p_{uv} = \frac{|actions(u,*) \cap actions(v,*)|}{|actions(u,*)|}$$

  - Jaccard Index (JI):

$$p_{uv} = \frac{|actions(u,*) \cap actions(*,v)|}{|actions(u,*) \cup actions(*,v)|}$$

  - Linear Probability (LP):

$$p_{uv} = \frac{|actions(u,*) \cap actions(*,v)|}{|actions(*,v)|}$$

Notation

$actions(x,*)$: the set of actions done by node x

$actions(*,x)$: the set of actions whose object is node x

Preliminaries

- Activation probability matrix
  - The adjacency matrix when weighting each directional edge (u, v) by $p_{(u,v)}$
- Infection Probability for node v given a seed set S
  - The probability that v is infected under the IC model with S
  - Defined as $\rho(v)$
- Infection probability vector
  - $\pi \coloneqq [\rho(v)] \in [0,1]^{|\mathcal{V}|}$ be the vector of $\rho(v)$
  - π_i be the infection probability vector during the first i steps

Our problems

- Influence Estimation (IE)
  - Given a seed set S,
  - Estimate its influence $\sum_{v \in \mathcal{V}} \rho(v)$ (the expected number of infected nodes)

- Influence Maximization (IM)
  - Given the number of seed nodes k,
  - Find the set S of k seed nodes
  - to Maximize the influence $\sum_{v \in \mathcal{V}} \rho(v)$

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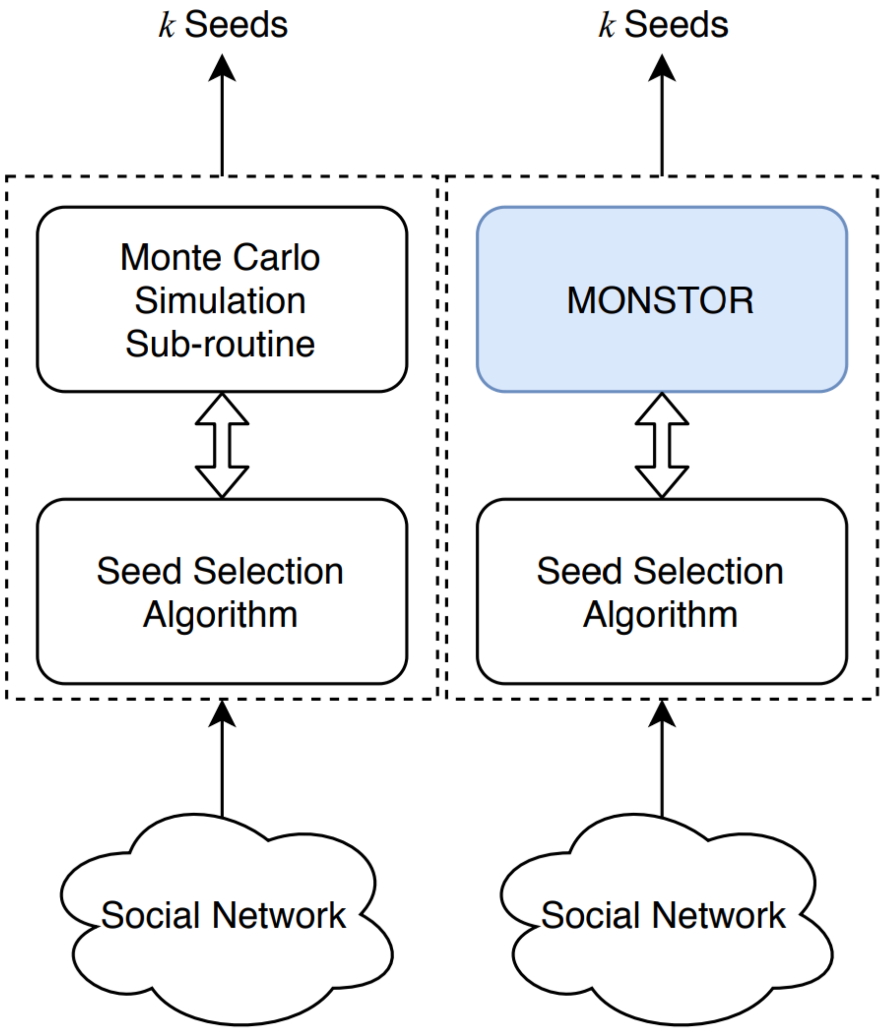
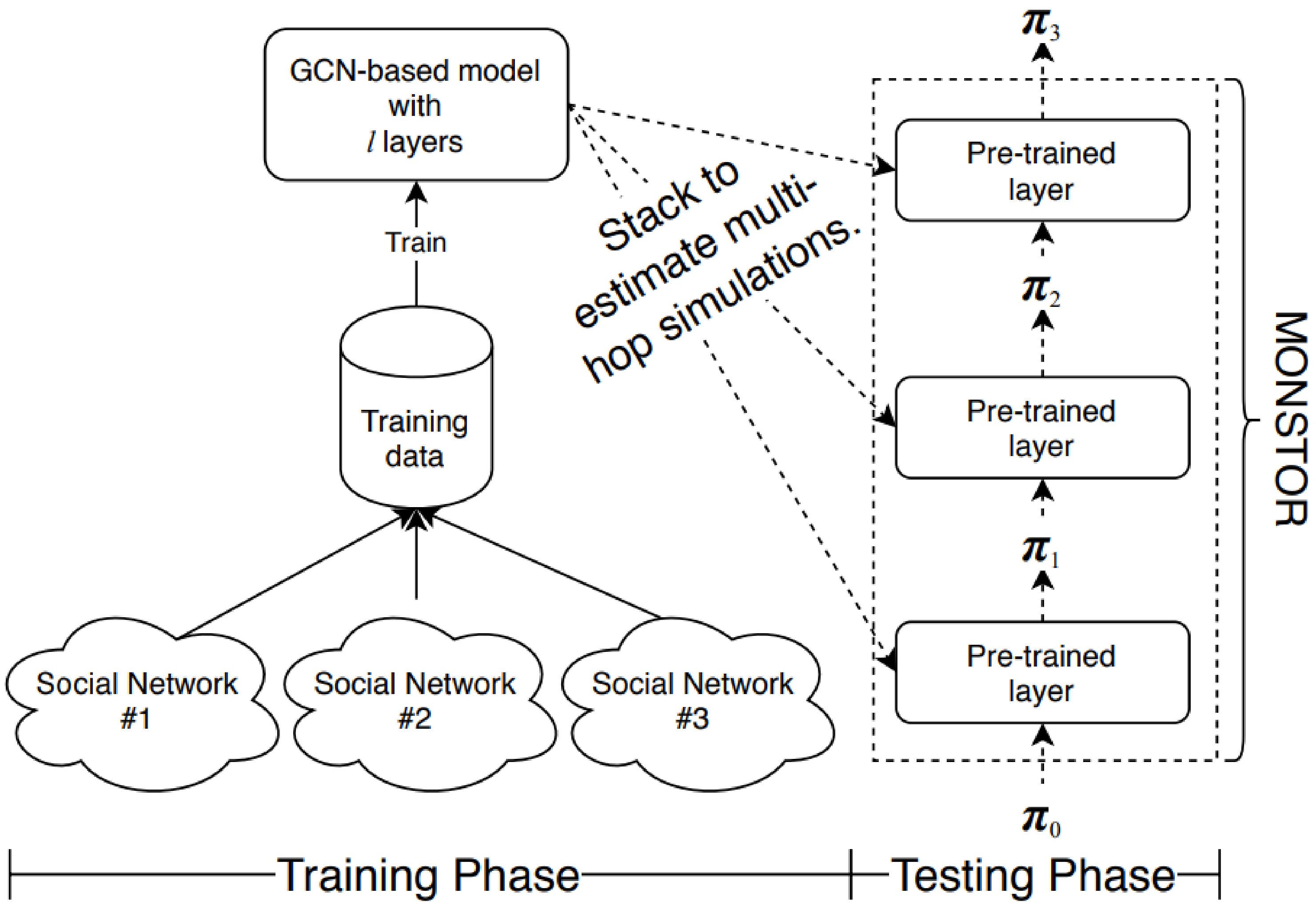
Proposed method: MONSTOR

- Neural network-based method for estimating MC simulation results under IC model
- MONSTOR can estimate MC simulation results in social networks unseen during training
- Significantly speeds up existing IM methods by replacing simulations

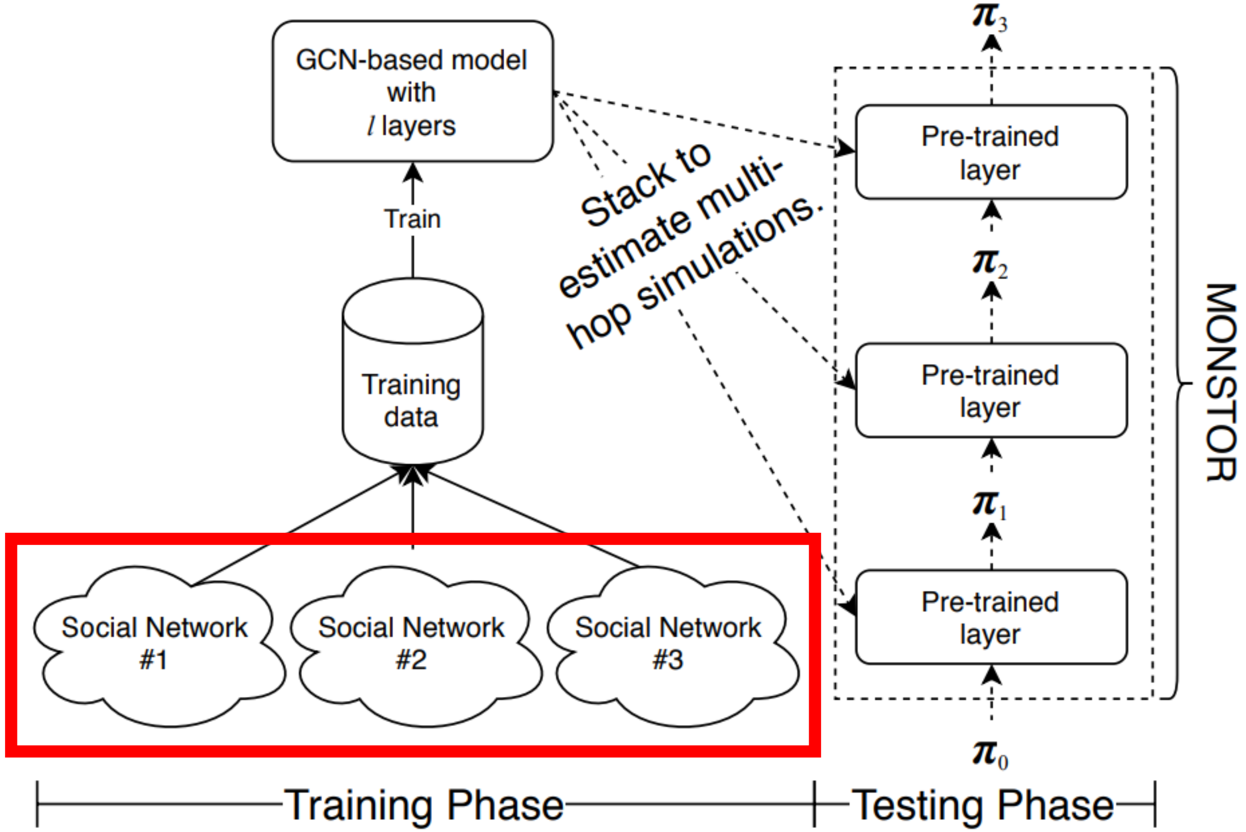


Overall Workflow



Overall Workflow

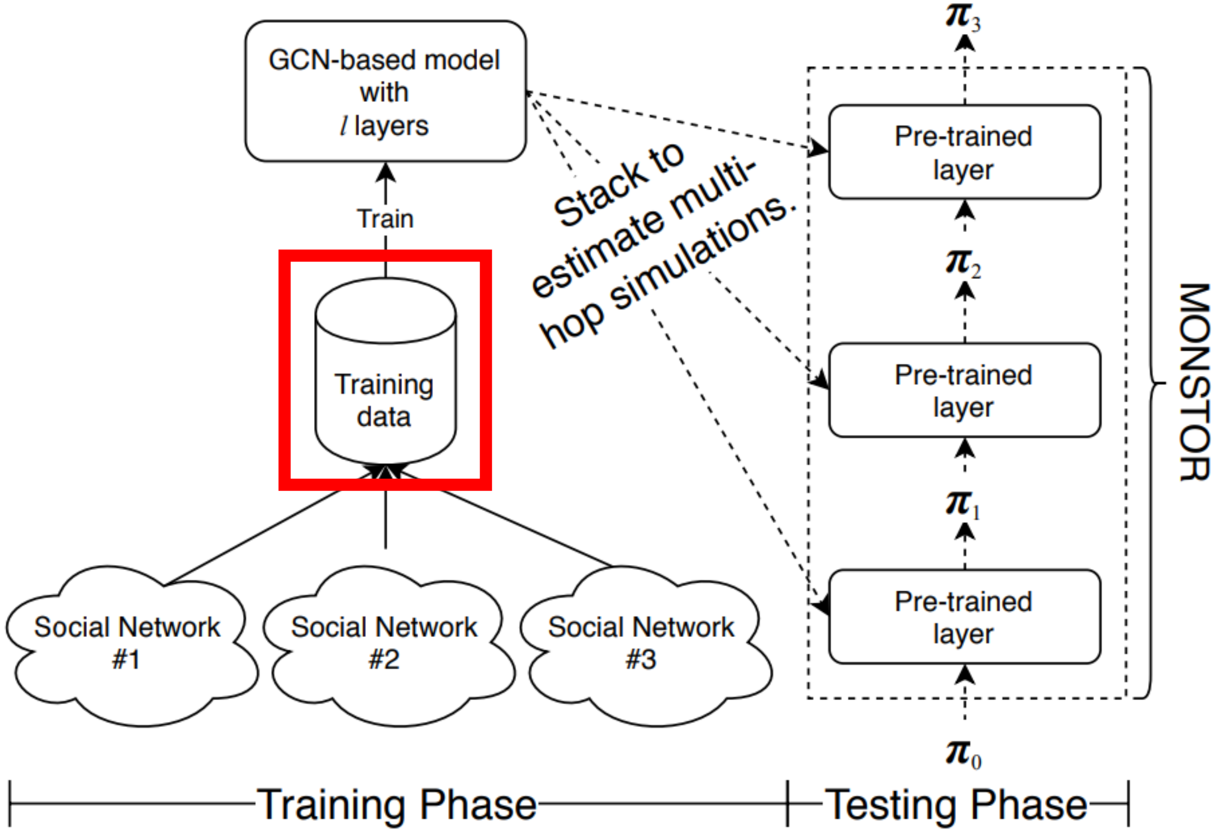
1) Collect one or more social networks $\{\mathcal{G}_1, \mathcal{G}_2, \dots\}$

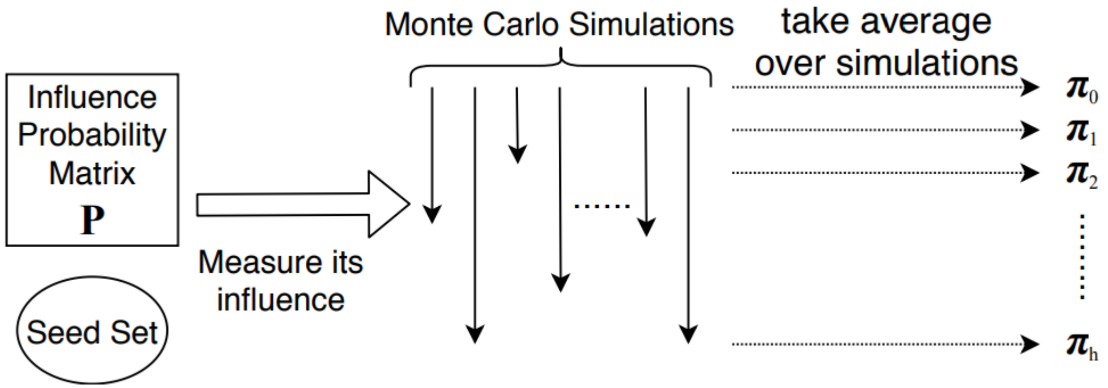


	$\lvert\mathcal{V}\rvert$	$\lvert\mathcal{E}\rvert$	$\sum p_{(u,v)}/\lvert\mathcal{E}\rvert$ in BT		$\sum p_{(u,v)}/\lvert\mathcal{E}\rvert$ in JI		$\sum p_{(u,v)}/\lvert\mathcal{E}\rvert$ in LP	
			Train	Test	Train	Test	Train	Test
Extended	11,409	58,972	0.0797	0.0919	0.0335	0.0410	0.1614	0.1837
WannaCry	35,627	169,419	0.0726	0.0947	0.0298	0.0449	0.1979	0.1630
Celebrity	15,184	56,638	0.0321	0.0279	0.0016	0.0016	0.2614	0.256

Overall Workflow

2) From each $\mathcal{G}_j$, collect the tuples $\{(\pi_i, \pi_{i-1}, \cdots, \pi_{i-e}, \mathbf{P}_j) : i \geq e\}$, after choosing a seed set S randomly
   - $e > 1$ is a hyperparameter
   - $\mathbf{P}_j \in \{\mathrm{BT}, \mathrm{JI}, \mathrm{LP}\}$
   - Repeat multiple times with different seed sets



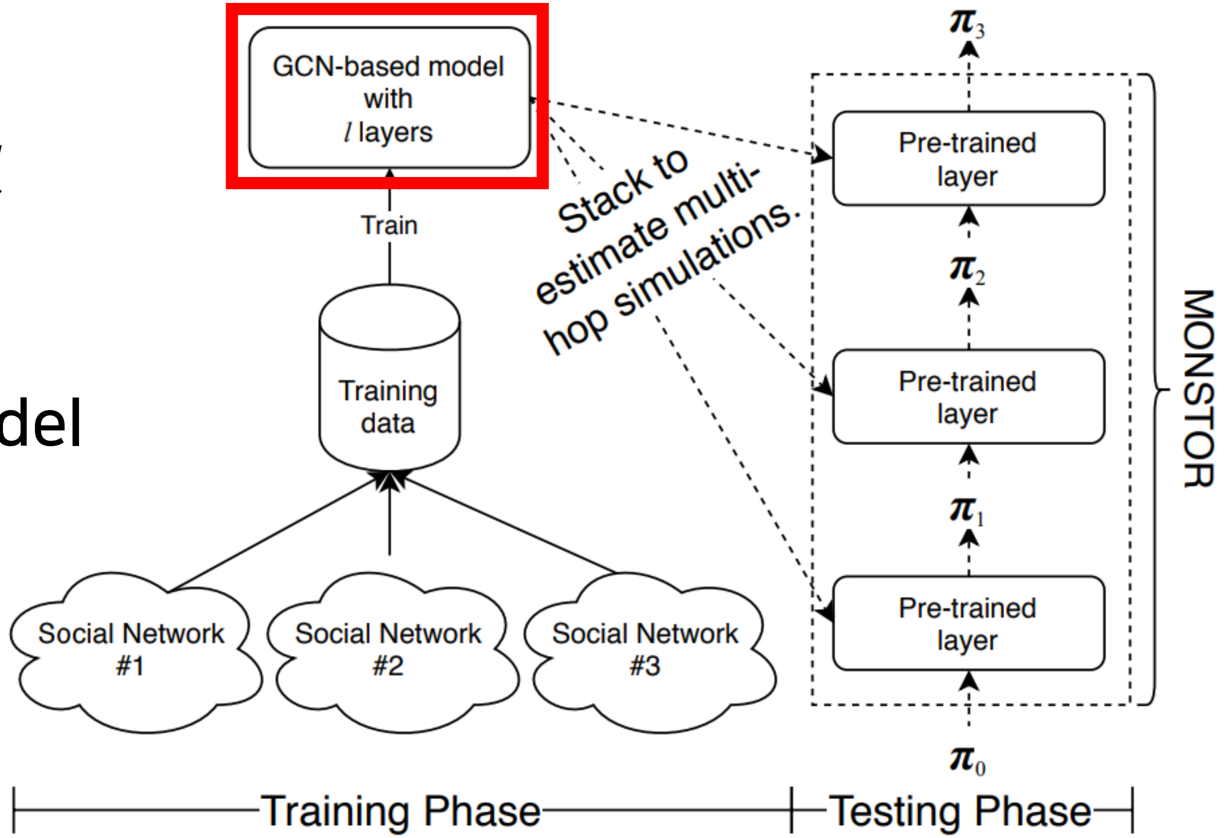


Notation

π_i be the infection probability vector during the first i steps

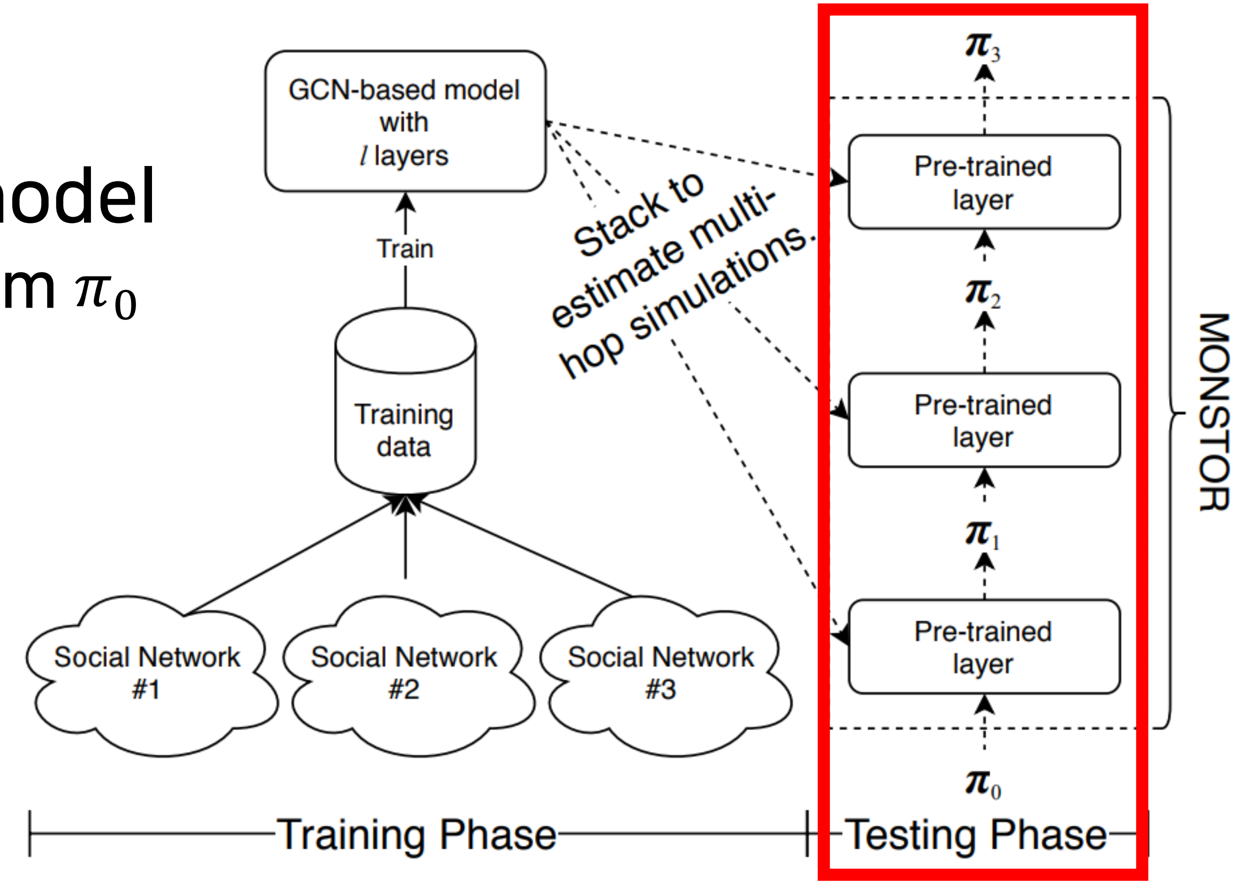
Overall Workflow

3) Train GCN-based model M with l layers, estimating π_i given $\pi_{i-1}, \cdots, \pi_{i-e}$
   - Estimates a single step of the IC model



Overall Workflow

4) Stack s times the pre-trained model
- The stacked model estimates π_s from π_0
- Estimates end-to-end simulations



5-1) For IE problem, compute $\langle \mathbf{1}, \boldsymbol{\pi}_s \rangle$

5-2) For IM problem, replace the MC simulation subroutine of existing IM algorithms with MONSTOR

Detailed Design

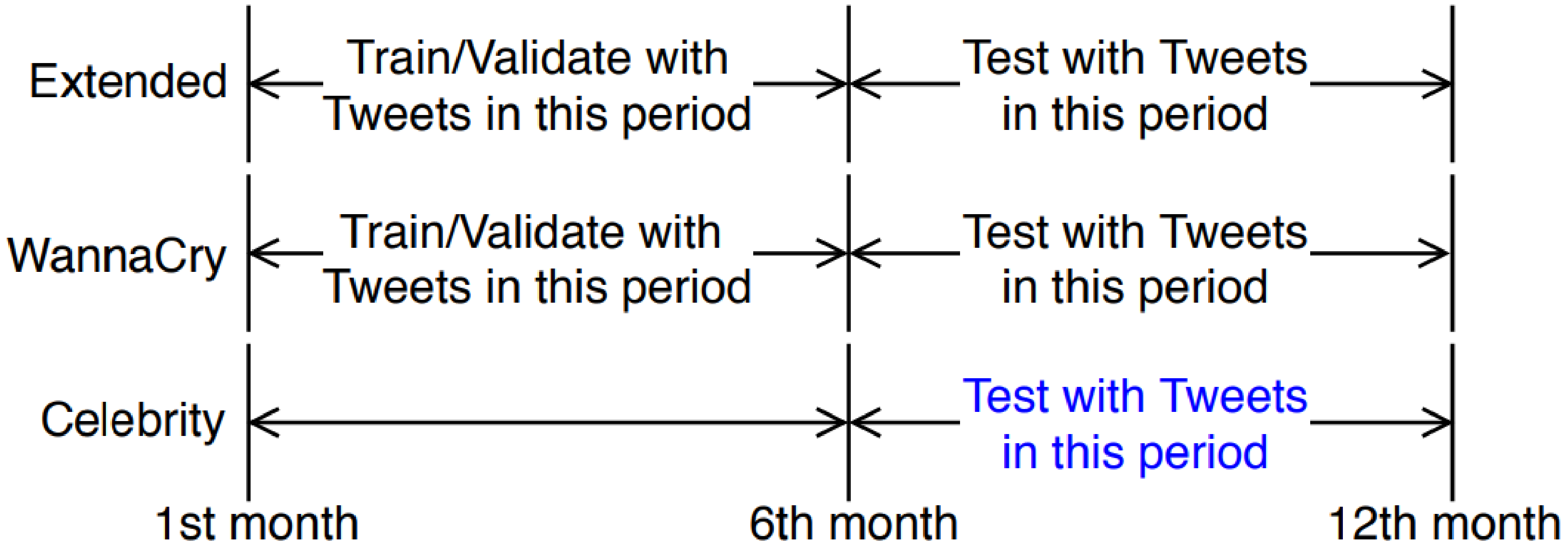
- Final output of our model is determined to

$$M(\pi_{i-1}, \ldots, \pi_{i-e}, \mathbf{P}; \boldsymbol{\theta}) \coloneqq \min\{\pi_{i-1} + h^l, u_i\}$$

, where $u_i \coloneqq \pi_{i-1} + (\pi_{i-1} - \pi_{i-2})\mathbf{P}$ (theoretical upper bound)

Detailed Design

- Training/Validation: online postings (and their cascade logs) during the first 50% of time (1,600 training / 400 validation tuples)
- Test: those during the remaining 50% of time (2000 testing tuples)



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Experiments

- Q1. Accuracy in Influence Maximization
- Q2. Accuracy in Influence Estimation
- Q3. Scalability
- Q4. Submodularity

Competitors

- Simulation-based algorithms: Greedy with MC simulations
  - UBLF for BT, JI
  - CELF for LP

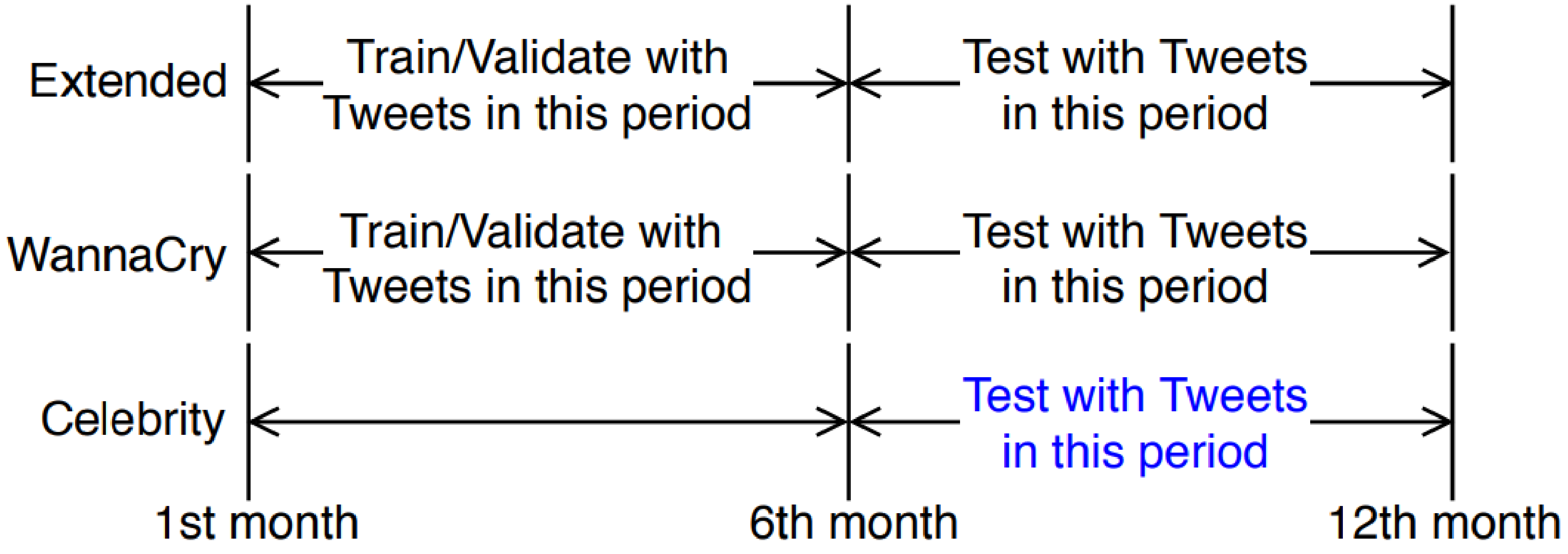
- Non-simulation-based algorithms
  - SSA / D-SSA [NTD16]
  - PMIA [CWW10] / IRIE [JHC12]

- **Our proposed approach**
  - **For BT, JI: U-MON (UBLF with MONSTOR)**
  - **For LP: C-MON (CELF with MONSTOR)**

Experimental Settings

- For training: two out of three networks
- For testing: Choose each of the three networks

- Inductive setting: testing with the graph unseen during training
  - Ex) U/C-MON (E+W)



Q1. Influence Maximization (IM)

- **Question**: How accurate are simulation-based IM algorithms equipped with MONSTOR, compared to competitors?
- **Answer**: Test with BT/JI - U-MON was most accurate in most cases

Test with BT

	Extended			WannaCry			Celebrity		
	k=10	50	100	10	50	100	10	50	100
Target Influence	244.4	529.3	706.6	533.9	1238.5	1648.0	43.7	90.3	140.2
U-MON (E+W)	244.5	529.1	706.8	**534.2**	**1239.2**	1647.4	43.7	90.4	140.4
U-MON (E+C)	244.5	**529.2**	706.6	**534.2**	1239.1	1647.4	43.7	**90.5**	140.4
U-MON (W+C)	244.4	529.1	706.8	534.1	1239.1	1647.3	43.7	90.4	**140.5**
D-SSA	244.5	521.2	682.8	532.3	1213.6	1589.7	43.6	89.9	139.9
SSA	244.5	521.2	682.8	532.3	1213.7	1589.8	43.6	89.9	139.9
IRIE	244.3	**529.2**	**707.3**	**534.2**	1239.0	**1647.8**	**43.8**	90.4	140.3
PMIA	**244.6**	529.1	705.4	534.1	1239.0	1646.8	42.7	90.4	140.3

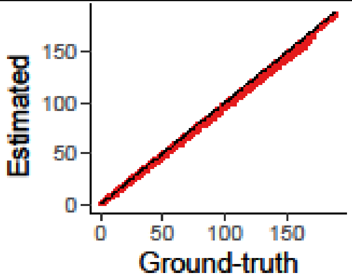
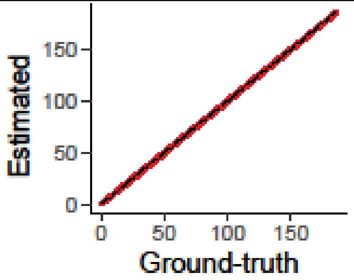
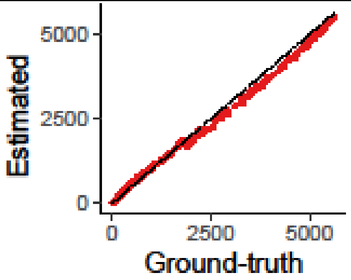
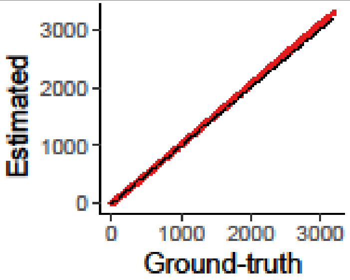
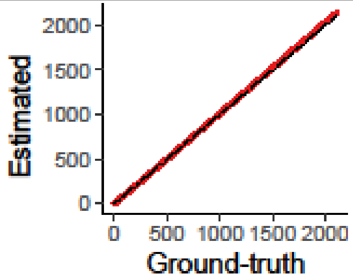
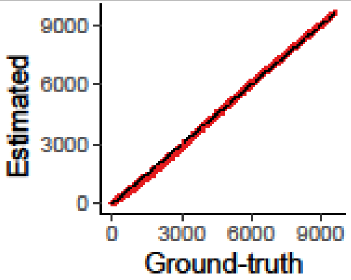
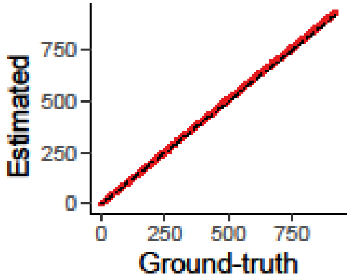
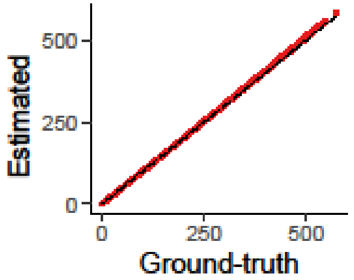
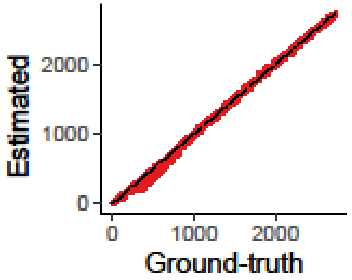
Q1. Influence Maximization (IM)

- **Question**: How accurate are simulation-based IM algorithms equipped with MONSTOR, compared to competitors?
- **Answer**: Test with LP - C-MON was most accurate in most cases

	Extended			WannaCry			Celebrity		
	k=10	50	100	10	50	100	10	50	100
Target Influence	1852.4	2876.5	3264.9	5271.6	7880.0	9098.3	5508.4	5616.7	5657.7
C-MON (E+W)	1843.0	**2863.0**	**3253.8**	5246.4	**7862.1**	**9073.5**	5508.9	5615.0	5664.9
C-MON (E+C)	1840.6	2848.5	3236.5	5253.0	7844.5	9041.7	5508.8	5616.4	5666.4
C-MON (W+C)	1839.5	2853.1	3242.0	5248.6	7850.7	9045.7	5508.8	5615.0	5665.0
D-SSA	**1844.3**	2858.7	3236.1	5256.7	7783.4	8977.3	5509.0	5606.2	5633.8
SSA	1843.8	2858.6	3236.1	**5257.2**	7783.6	8977.0	5508.8	5606.3	5633.9
IRIE	1816.2	2829.8	3201.2	5109.1	7714.1	8840.1	**5509.1**	**5617.4**	**5667.4**
PMIA	1830.0	2828.9	3243.2	5196.7	7807.6	8981.8	5508.5	5604.2	5630.2

Q2. Influence Estimation (IE)

- The ground-truth influences of test seed sets and the estimated influences were highly correlated

Model	Target graph	BT	JI	LP
U-MON (E+W) or C-MON (E+W)	Celebrity (Unseen)			
U-MON (E+C) or C-MON (E+C)	WannaCry (Unseen)			
U-MON (W+C) or C-MON (W+C)	Extended (Unseen)			

Q3. Scalability

- **Question**: How rapidly does the estimation time grow as the size of the input graph increase?
- **Answer**: The runtime per stacked GCN was near-linear in the number of edges in the input graph

$\lvert\mathcal{E}\rvert$	2^{20}	2^{21}	2^{22}	2^{23}	2^{24}	2^{25}	2^{26}
Estimation time (sec)	11.5	17.7	31.0	56.3	108.9	411.0	819.7

Q4. Submodularity

- **Question**: Is MONSTOR submodular as the ground-truth influence function is?
- Using each pair S and T of the seed sets, we tested whether

$$f(S) + f(T) \geq f(S \cup T) + f(S \cap T)$$

is met or not

- **Answer**: Influence estimation by MONSTOR can be considered as submodular in practice

	Extended	WannaCry	Celebrity
C-MON (E+W)	0.9993	0.9997	0.9938
C-MON (E+C)	0.9994	0.9997	0.9970
C-MON (W+C)	0.9992	0.9996	0.9945

The ratio of the cases where the submodularity holds (Tested with LP)

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Summary

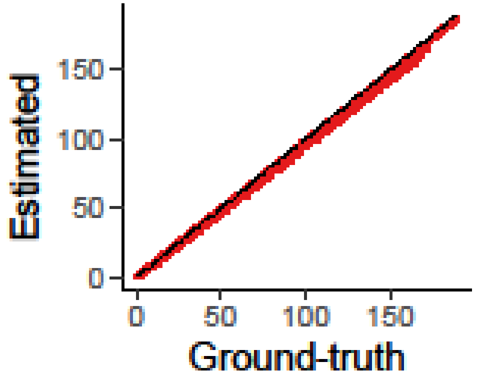
we present MONSTOR, an inductive learning algorithm for estimating the influence of seed nodes under the IC model.

Accurate in IM/IE Tasks

Most accurate in

17/27

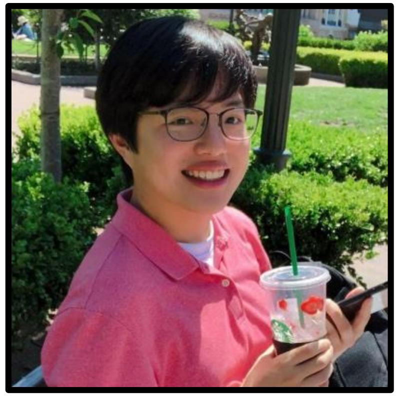
Cases



Scalable & Submodular

The code and datasets used in the paper are available at
https://github.com/jihoonko/asonam20-monstor/

MONSTOR: An Inductive Approach for Estimating and Maximizing Influence over Unseen Networks



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