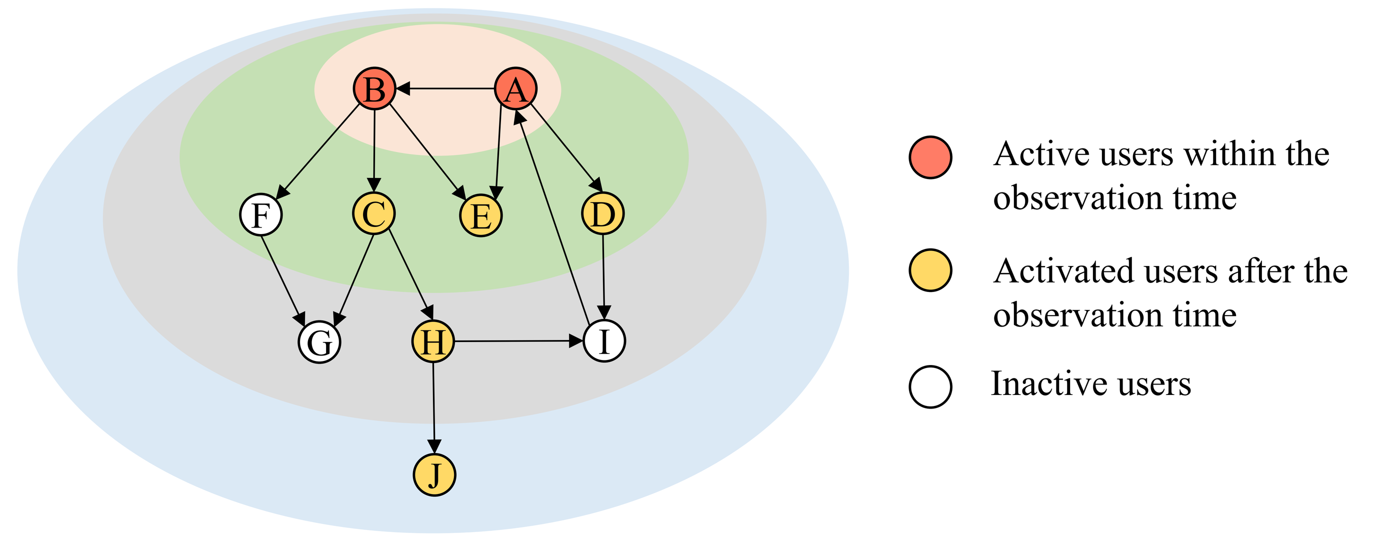
# Popularity Prediction on Social Platforms with Coupled Graph Neural Network

Qi Cao[1,2], Huawei Shen[1,2], Jinhua Gao[1], Bingzheng Wei[3], Xueqi Cheng[1]
{caoqi,shenhuawei,gaojinhua,cxq}@ict.ac.cn, coltonwei@tencent.com
[1] CAS Key Laboratory of Network Data Science and Technology, Institute of Computing Technology, Chinese Academy of Sciences
[2] University of Chinese Academy of Sciences [3] WeChat, Tencent Inc

## 1. Motivation

### 1.1Network-aware popularity prediction problem

- Given active users within observation time and network structure, this problem is to predict future popularity of information at prediction time.




### 1.2 Existing methods

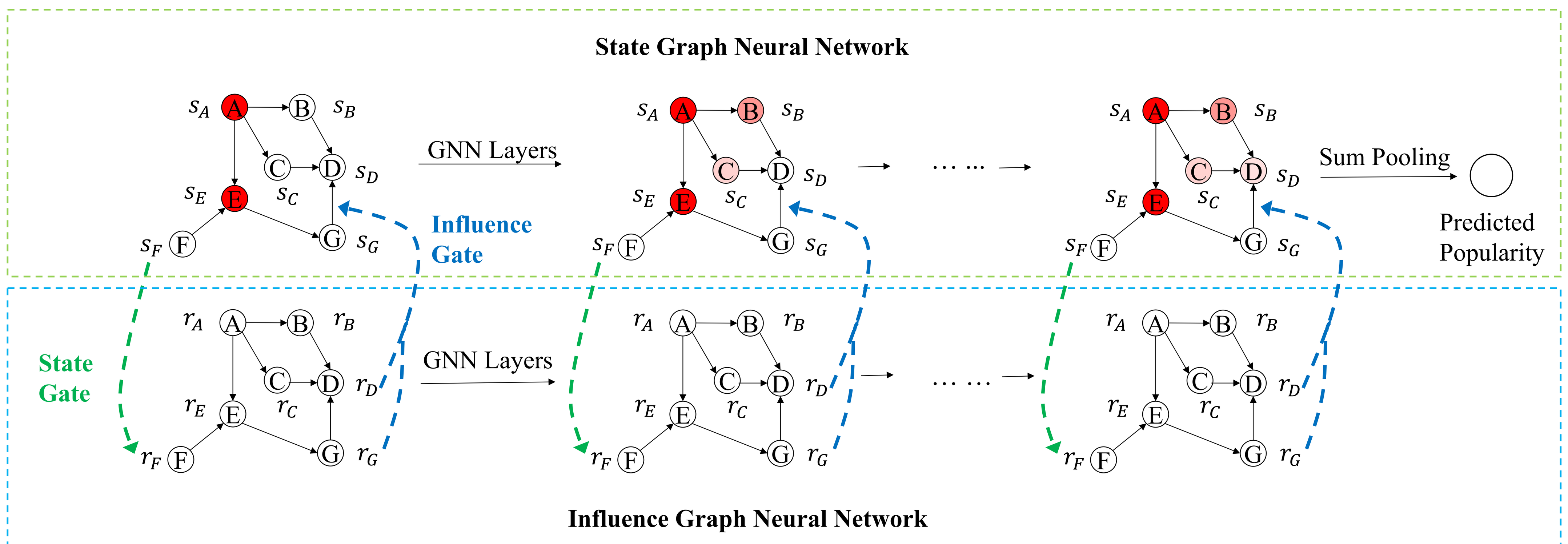
| | Feature-based methods | Deep learning-based methods | Point process methods |
|---|---|---|---|
| Characteristic | Extract features of early adopters | Represent the subgraph of early adopters | Use average #fans to approximate the impact of cascading effect |
| Drawbacks | Only focus on early adopters, ignoring the critical cascading effect to accurately predict future popularity | | Only adopt statistics to approximate, ignoring the explicit network structure governing the cascading effect |

- There still lack an effective method utilizing network structure to **precisely capture cascading effect** and predict future popularity more accurately.

## 2. Method

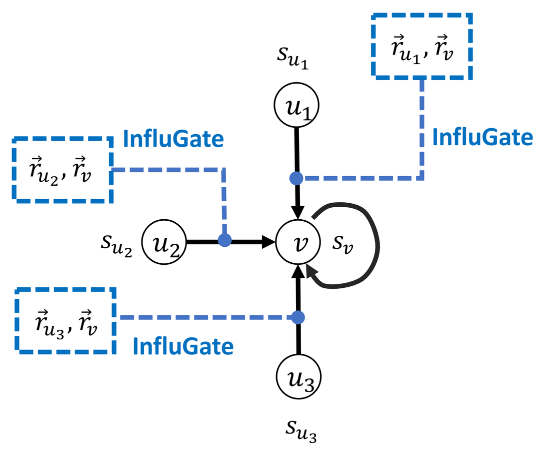
### 2.1 Framework

- Cascading effect is the **iterative interplay between state of neighbors** and **spread of influence** over networks.
- We propose **coupled graph neural networks (CoupledGNN)** to capture such cascading effect and predict future popularity.




### 2.2 State Graph Neural Network

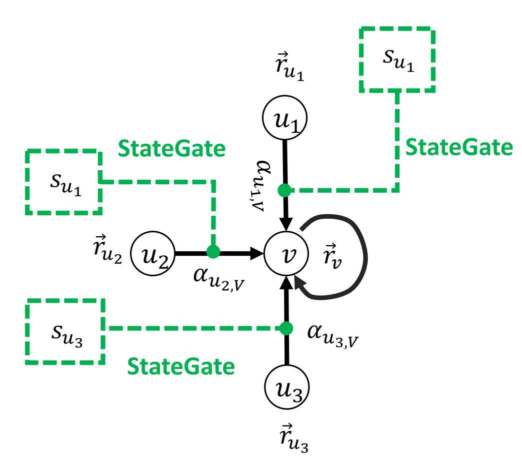
- Model the activation state of user over network in a successive manner
- Updated by the expected activation state from neighbors based on heterogeneous influence




$$a_v^{(k)} = \sum_{u \in \mathcal{N}(v)} \text{InfluGate}\left(\boldsymbol{r}_u^{(k)}, \boldsymbol{r}_v^{(k)}\right) s_u^{(k)} + p_v \qquad s_v^{(k+1)} = \begin{cases} 1, & v \in C_T^m \\ \sigma\left(\mu_s^{(k)} s_v^{(k)} + \mu_a^{(k)} a_v^{(k)}\right), & v \notin C_T^m \end{cases}$$

### 2.3 Influence Graph Neural Network

- Model the diffusion of interpersonal influence in the social network
- Updated by the expected influence representation from neighbors gated by user's activation state




$$\boldsymbol{b}_v^{(k)} = \sum_{u \in \mathcal{N}(v)} \text{StateGate}\left(s_u^{(k)}\right) \alpha_{uv}^{(k)} \boldsymbol{W}^{(k)} \boldsymbol{r}_u^{(k)}, \qquad \boldsymbol{r}_v^{(k+1)} = \sigma\left(\zeta_r^{(k)} \boldsymbol{W}^{(k)} \boldsymbol{r}_v^{(k)} + \zeta_b^{(k)} \boldsymbol{b}_v^{(k)}\right)$$

## 3. Experiment

### 3.1 Experiment settings

- Dataset: Synthetic Data Set & Sina Weibo Data Set
- Baselines: Feature-based (Cheng et al., WWW'14, Shulman et al., ICWSM'16, Gao et al., TKDD'19), DeepCas (Li et al., WWW'17), SEISMIC (Zhao et al., KDD'15).
- Evaluation metrics: MRSE, MAPE, Wrong Percentage Error (WroPerc)

### 3.2 Prediction performance

- CoupledGNN outperforms all baselines with different observation time.

| Observation Time | 1 hour | | | | 2 hours | | | | 3 hours | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Evaluation Metric | MRSE | mRSE | MAPE | WroPerc | MRSE | mRSE | MAPE | WroPerc | MRSE | mRSE | MAPE | WroPerc |
| SEISMIC | - | 0.2112 | - | 48.63% | - | 0.1347 | - | 34.59% | - | 0.0823 | - | 27.15% |
| Feature-based | 0.2106 | 0.1254 | 0.3749 | 35.17% | 0.1796 | 0.1041 | 0.3557 | 28.86% | 0.1581 | 0.0804 | 0.3147 | 18.97% |
| DeepCas | 0.2077 | **0.0930** | 0.3633 | 30.00% | 0.1650 | 0.0670 | 0.3134 | 20.55% | 0.1365 | 0.0361 | 0.2813 | 17.24% |
| CoupledGNN | **0.1816** | 0.0946 | **0.3515** | **25.68%** | **0.1397** | **0.0519** | **0.2989** | **17.81%** | **0.1120** | **0.0333** | **0.2611** | **13.01%** |

### 3.3 Effectiveness of the coupled structure

- The coupled structure of activation state and influence representation significantly improves the prediction performance.

| Observation Time | 1 hour | | | 2 hour | | | 3 hour | | |
|---|---|---|---|---|---|---|---|---|---|
| Evaluation Metric | MRSE | MAPE | WroPerc | MRSE | MAPE | WroPerc | MRSE | MAPE | WroPerc |
| Single-GCN | 0.1964 | 0.3707 | 29.11% | 0.1595 | 0.3201 | 22.26% | 0.1230 | 0.2653 | 16.10% |
| Single-GAT | 0.1999 | 0.3754 | 30.82% | 0.1569 | 0.3199 | 20.55% | 0.1222 | 0.2655 | 16.10% |
| CoupledGNN | **0.1816** | **0.3515** | **25.68%** | **0.1397** | **0.2989** | **17.81%** | **0.1120** | **0.2611** | **13.01%** |

## 4. Summary

- We propose **CoupledGNN** model to **precisely capture the cascading effect**, **improving the prediction performance** of future popularity
  - View the cascading effect as the iterative interplay between two key components, i.e., the state of neighbors and the spread of influence over social networks.
  - Model the iterative interplay between node activation states and the spread of influence by two graph neural networks which coupled by gating mechanism