Popularity Prediction on Social Platforms with Coupled Graph Neural Networks

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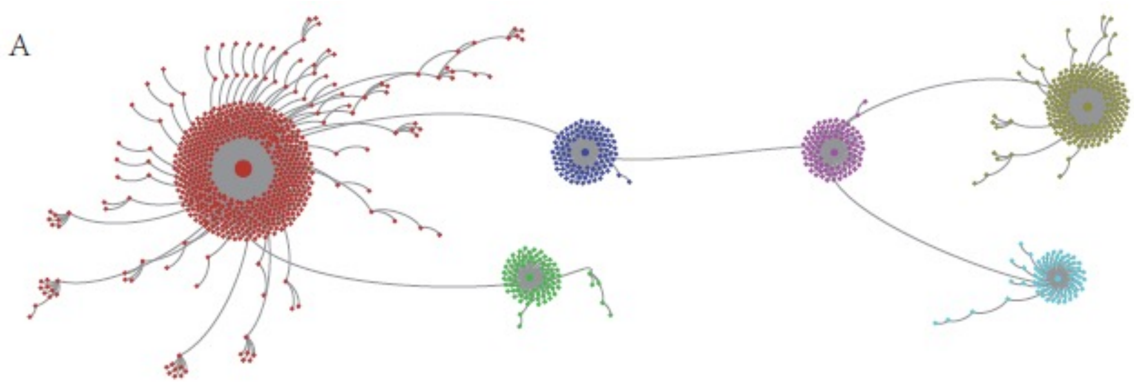
Background

- Online social platforms provide convenience for the production and delivery of information

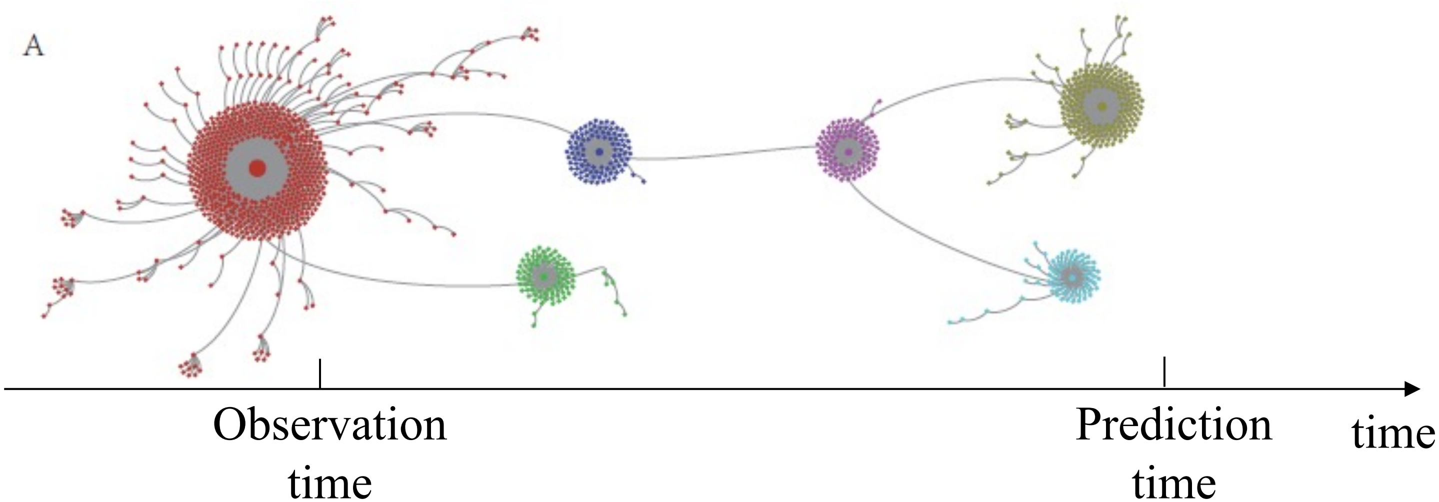
- Information cascades



Background

- Online social platforms provide convenience for the production and delivery of information

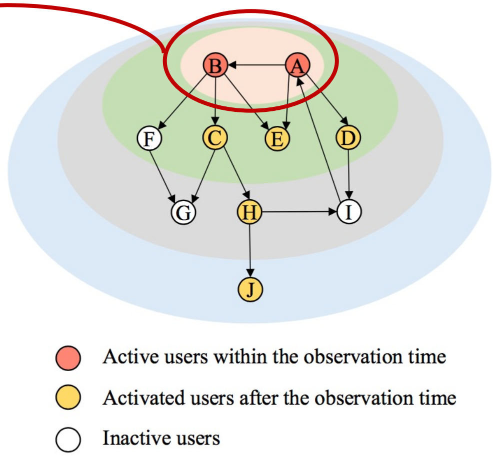
Predicting future popularity of information cascades on Social Platforms!



Outline

Motivation

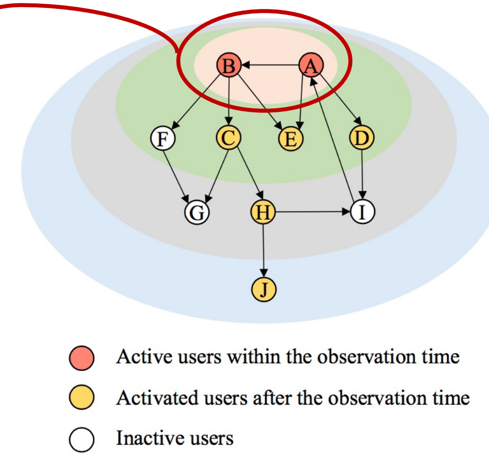
- Existing methods for popularity prediction mainly fall into three categories
  - ◆ Feature-based methods
    - Extract demographics, temporal and structural features of early adopters



Methods	consider early adopters	Approximate by statistics	Precisely capture cascading effect
Feature-based	✓	✗	✗
Deep learning-based			
Point process			

Motivation

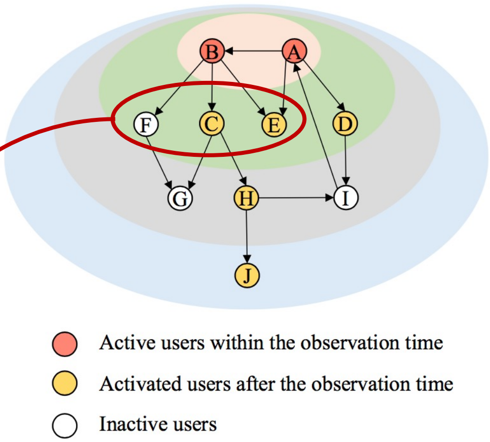
- Existing methods for popularity prediction mainly fall into three categories
  - Deep learning-based methods
    - Represent the subgraph of early adopters by deep learning



Methods	consider early adopters	Approximate by statistics	Precisely capture cascading effect
Feature-based	✓	✗	✗
Deep learning-based	✓	✗	✗
Point process			

Motivation

- Existing methods for popularity prediction mainly fall into three categories
  - Point process methods
    - Use average number of fans to approximate the impact of cascading effect in each generation



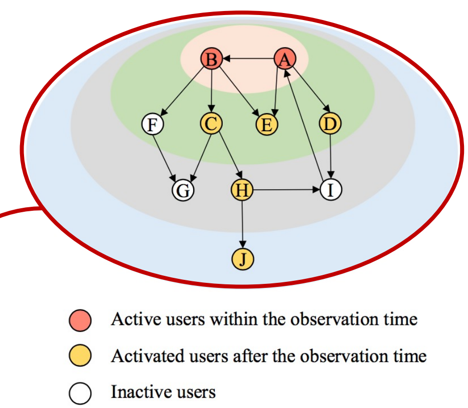
Methods	consider early adopters	Approximate by statistics	Precisely capture cascading effect
Feature-based	✓	✗	✗
Deep learning-based	✓	✗	✗
Point process	✗	✓	✗

Motivation

- Existing methods for popularity prediction mainly fall into three categories

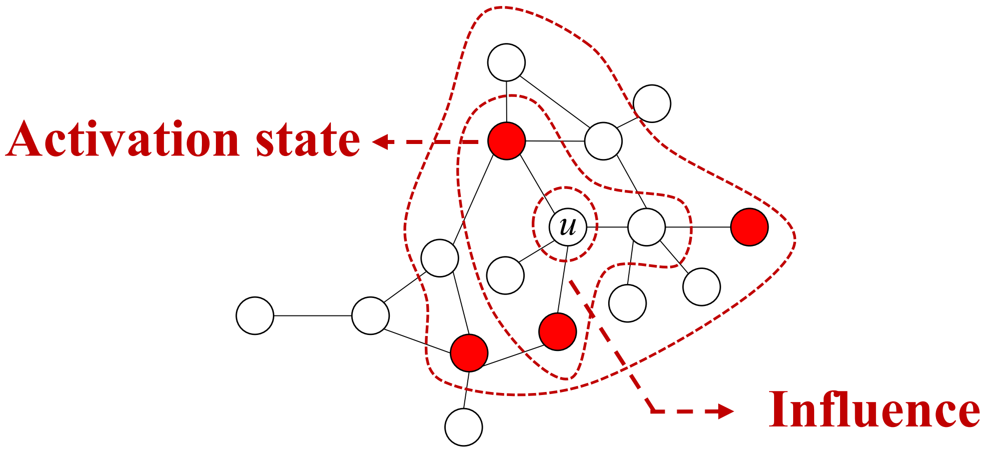
Methods	Only consider early adopters	Approximate by statistics	Precisely capture cascading effect
Feature-based	✓	✓	✗
Deep learning-based	✓	✗	✗
Point process	✗	✓	✗

- There still lack an effective method to **precisely capture the cascading effect** to predict the future popularity more accurately



Methods

- Cascading effect
  - The activation of a target user is **iteratively influenced by neighbors**.
  - The cascading effect is intrinsically the iterative interplay between **two key components**, i.e., **the state of neighbors** and **the spread of influence** over social networks.



Methods

- Framework of CoupledGNN
  - State Graph Neural Network
  - Influence Graph Neural Network

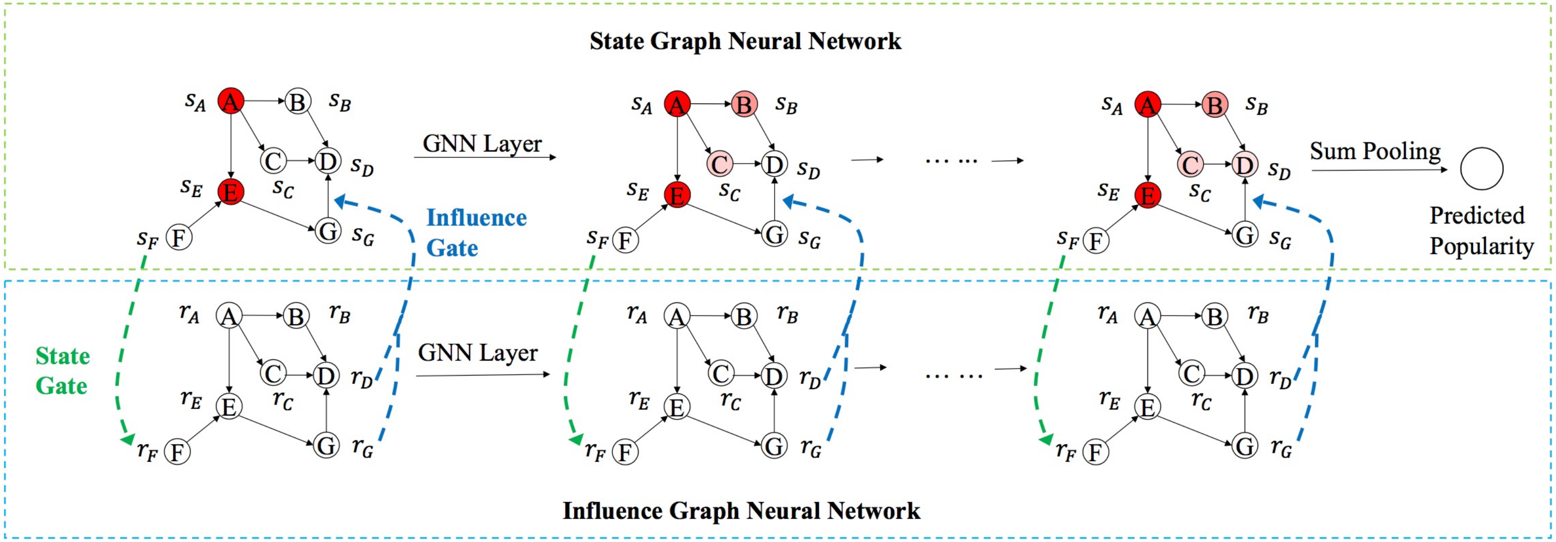


Figure 2: The framework of coupled graph neural networks for popularity prediction. s_* and r_* are the activation state and influence representation of user $*$ respectively.

Methods

- State Graph Neural Network
  - Model the activation state of user over network in a successive manner
    - Initial activation state

$$s_v^{(0)} = \begin{cases} 1, & v \in \boxed{C_T^m} \\ 0, & v \notin C_T^m \end{cases}$$

Active users within observation time

- Influence gating

$$\text{InfluGate}\left(\boldsymbol{r}_u^{(k)}, \boldsymbol{r}_v^{(k)}\right) = \boldsymbol{\beta}^{(k)}[\boldsymbol{W}^{(k)}\boldsymbol{r}_u^{(k)} \parallel \boldsymbol{W}^{(k)}\boldsymbol{r}_v^{(k)}],$$

Heterogeneous influence

- Aggregate

$$a_v^{(k)} = \boxed{\sum_{u \in \mathcal{N}(v)}} \text{InfluGate}\left(\boldsymbol{r}_u^{(k)}, \boldsymbol{r}_v^{(k)}\right) \boxed{s_u^{(k)}} + p_v,$$

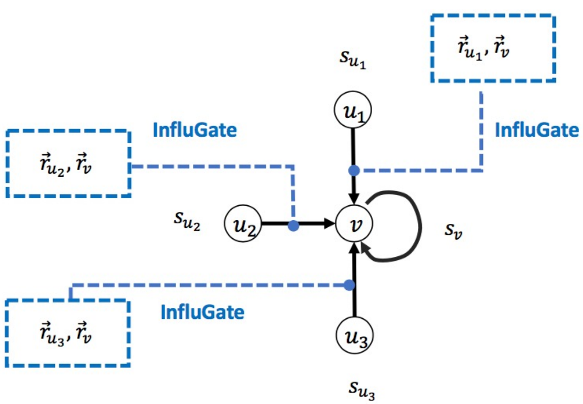
activation state

Expected activation state from neighborhood consider influence

- Combine

Update the activation state of user

$$s_v^{(k+1)} = \begin{cases} 1, & v \in C_T^m \\ \sigma\left(\mu_s^{(k)} s_v^{(k)} + \mu_a^{(k)} a_v^{(k)}\right), & v \notin C_T^m \end{cases}$$



Methods

- Influence Graph Neural Network
  - ◆ Model the diffusion of interpersonal influence in the social network
    - Initial influence representation $\boldsymbol{r}_v^{(0)}$
      - – node embedding & node features
    - Aggregate

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

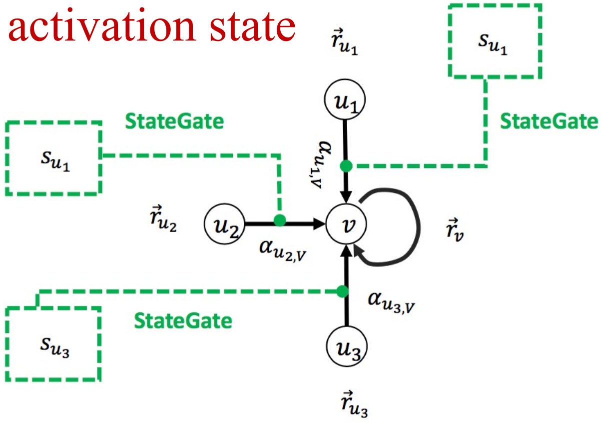
Influence representation

Expected influence representation from neighborhood gated by activation state

- Combine

$$\boldsymbol{r}_v^{(k+1)} = \boxed{\sigma\left(\zeta_r^{(k)} \boldsymbol{W}^{(k)} \boldsymbol{r}_v^{(k)} + \zeta_b^{(k)} \boldsymbol{b}_v^{(k)}\right)}$$

Update the influence representation of user



Methods

- Popularity prediction
  - Sum pooling mechanism

$$\hat{n}_{\infty}^{m} = \sum_{u \in \mathcal{V}} s_u^{(K)}$$

  - Loss function

$$L = L_{\mathrm{MRSE}} + L_{\mathrm{Reg}}$$

$$L_{\mathrm{MRSE}} = \frac{1}{M} \sum_{m=1}^{M} \left(\frac{\hat{n}_{\infty}^{m} - n_{\infty}^{m}}{n_{\infty}^{m}} \right)^2$$

$$L_{\mathrm{Reg}} = \eta \sum_{p \in \mathcal{P}} \| p \|_2 + \lambda L_{\mathrm{user}}$$

Experiments

- Datasets
  - 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)
    - Features of early adopters
  - DeepCas (Li et al., WWW'17)
    - Representative deep learning based method
  - SEISMIC (Zhao et al., KDD'15)
    - Representative point process method
- Evaluation metrics
  - Mean/Median Relative Square Error (MRSE)
  - Mean Absolute Percentage Error (MAPE)
  - Wrong Percentage Error (WroPerc)

$$MRSE = \frac{1}{M}\sum_{m=1}^{M}\left(\frac{\hat{n}_\infty^m - n_\infty^m}{n_\infty^m}\right)^2.$$

$$MAPE = \frac{1}{M}\sum_{m=1}^{M}\frac{|\hat{n}_\infty^m - n_\infty^m|}{n_\infty^m}.$$

$$WroPerc = \frac{1}{M}\sum_{m=1}^{M}\mathbb{I}\left[\frac{|\hat{n}_\infty^m - n_\infty^m|}{n_\infty^m} \geq \epsilon\right].$$

$\hat{n}_\infty^m$: predicted popularity

n_∞^m : true popularity

M : number of information

Evaluation metrics

Experiments

- Q1: How does CoupledGNN performs on popularity prediction?
  - CoupledGNN **outperforms all the baselines with different observation time**.
  - The **longer** the **observation time** is, the **smaller** the **prediction errors** are.

Table 1: Popularity prediction in Sina Weibo

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%**

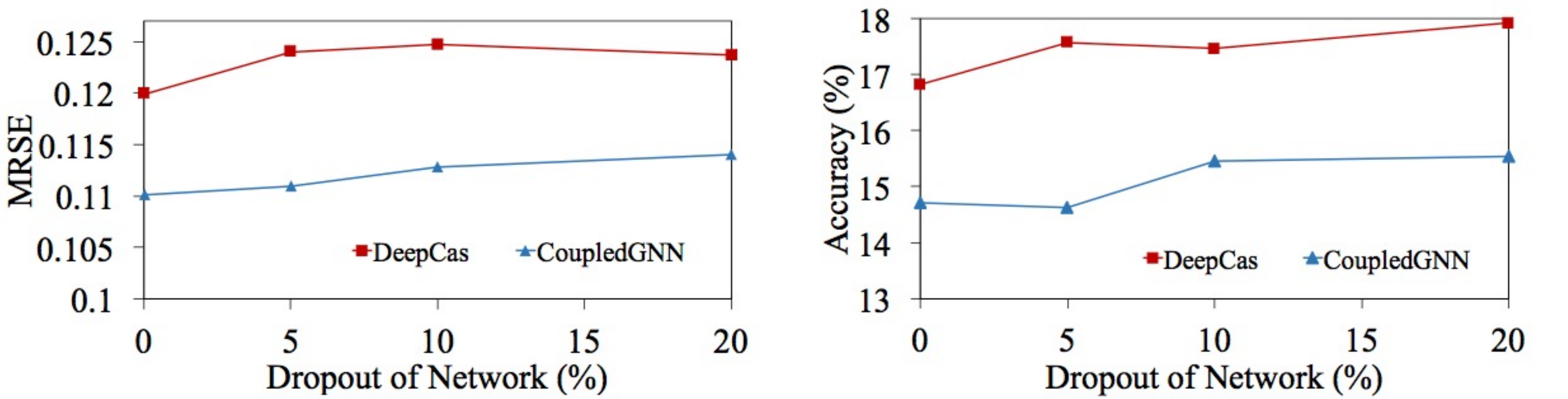
Experiments

- Q2: Is the coupled structure of our model effective?
  - **The coupled structure** of activation state and influence representation (CoupledGNN) **significantly improves the prediction performance** compared with the Single-GNN methods

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%**

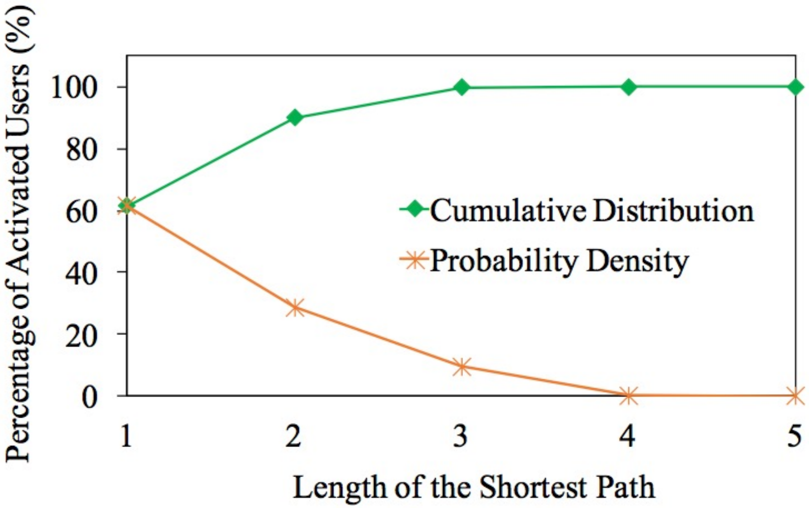
Experiments

- Q3: To what extent will a partial lack of network influences the prediction performance?
  - The **prediction performance** of both methods is **slightly degraded** by the dropout of the network
  - **CoupledGNN always significantly performs better** than DeepCas



Experiments

- Q4: Whether the learned CoupledGNN model can cover the scope of the cascading effect?
  - The **optimal number of layers** in CoupledGNN $K = 3$
  - **Almost all the activated users by cascading effect**, i.e., 99.76%, can be **covered within three-hops** in the neighborhood of early adopters.

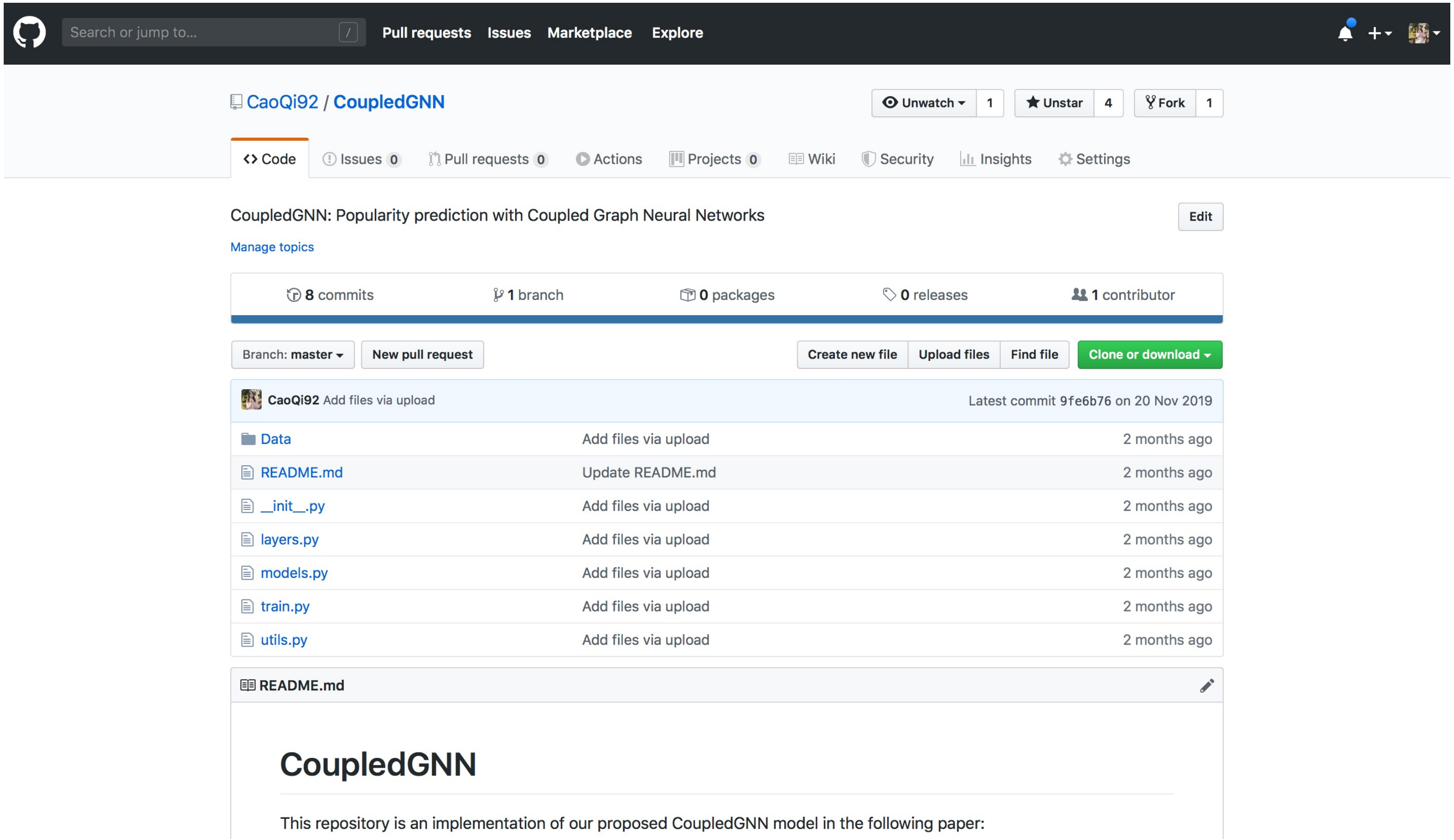


Conclusion

- 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 states and the spread of influence by **two graph neural networks** which **coupled** by gating mechanism

Public of Source Code

- We have made the source code of CoupledGNN public on github.



Contact Information

Thank you!
Welcome to contact us!

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