Rumor Detection on Social Media with Out-In-Degree Graph Convolutional Networks

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CONTENT

01 Background

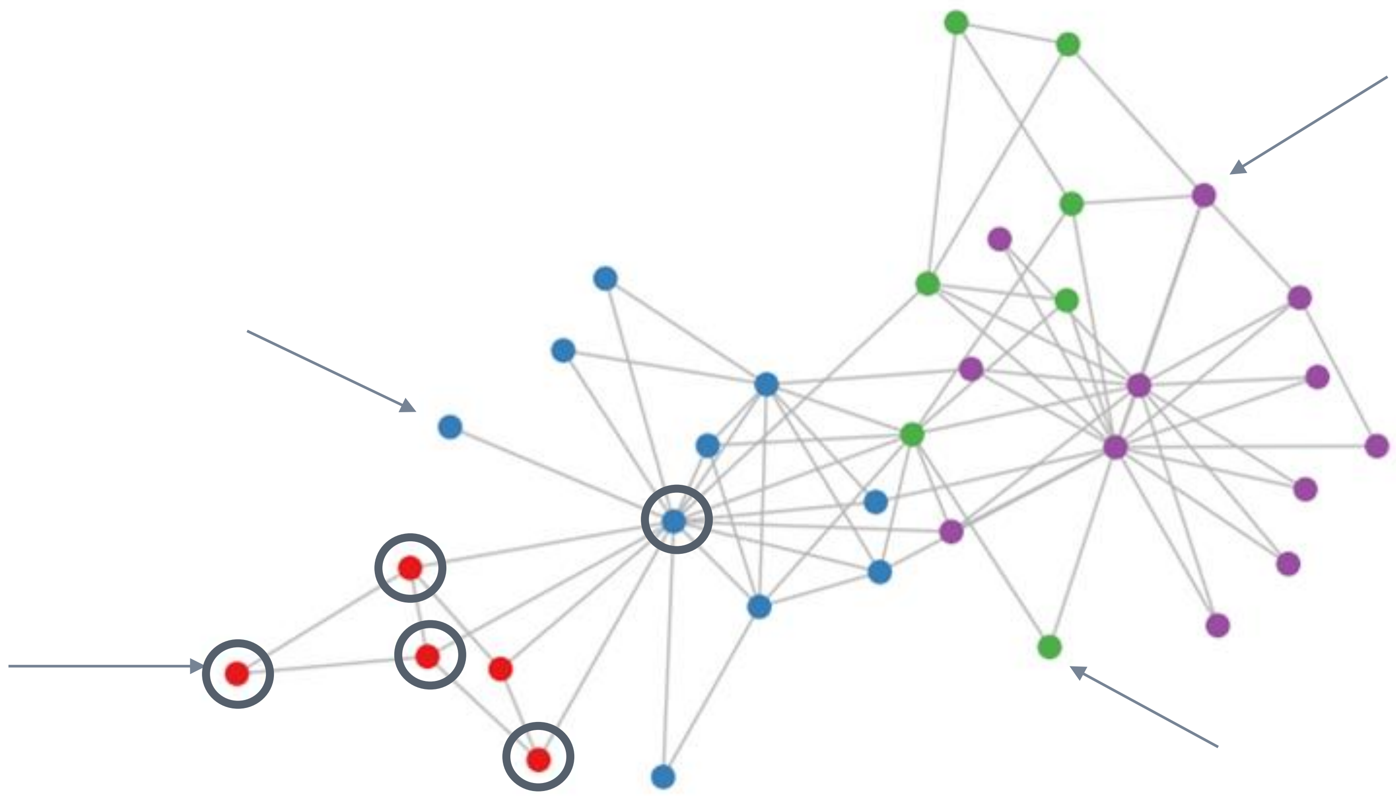
Rumor Detection

User number

Spread

Effect

Graph Neural Network



In rumor detection, every post in the event can be regarded as the node in the graph.

Graph neural network can process non Euclidean data and effectively represent node characteristics.

02 Related Work

Methods

Statistic learning methods

Labor intensive

Deep learning methods

Ignore graph structure

Low accuracy

Graph neural network methods

Capture graph structural information

Our motivation

The weaknesses of previous work

ignore the position contributions of nodes

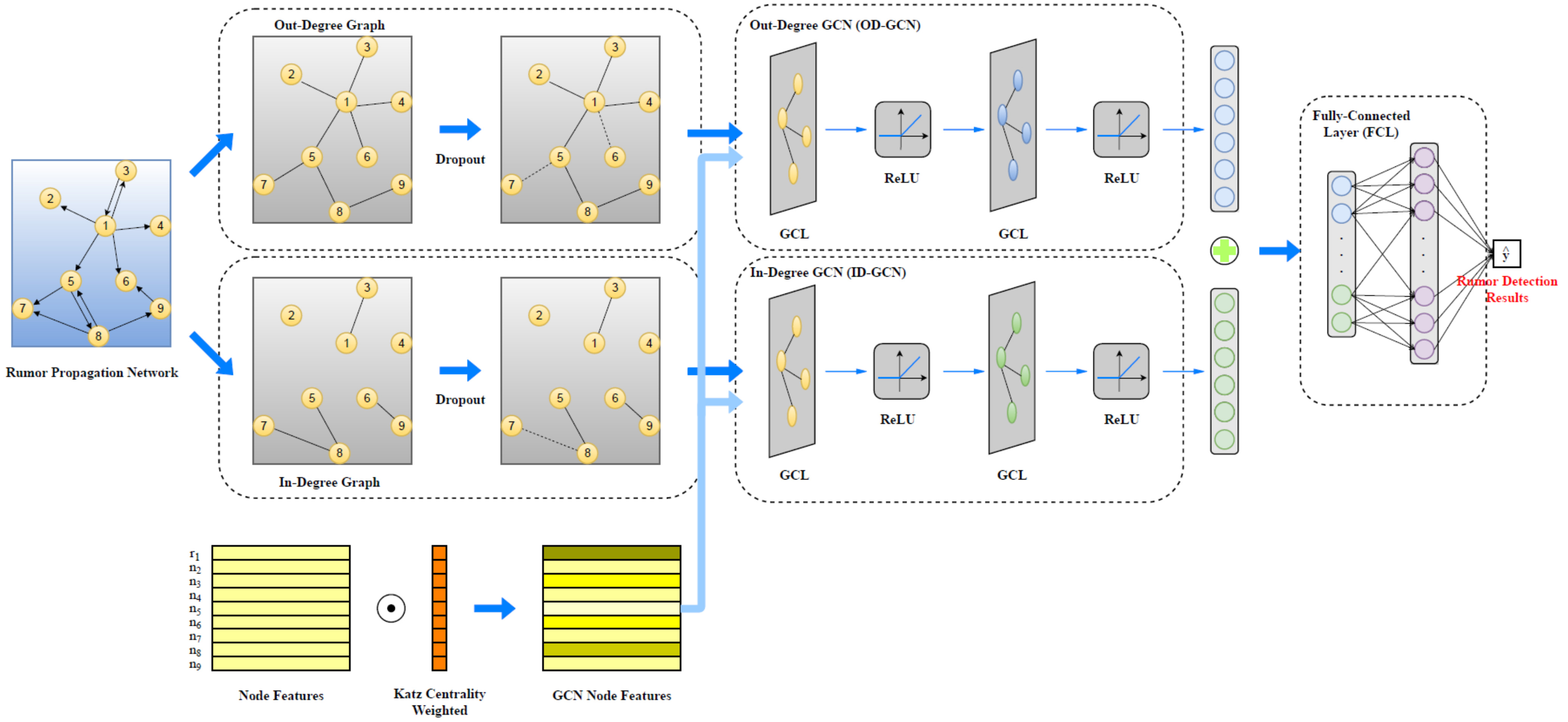
cannot efficiently process the imbalanced data

Our goal

a more accurate and flexible rumor detection model with GNN

03 Model

OID-GCN



Out-Degree Graph
Dropout
In-Degree Graph
Dropout
Rumor Propagation Network
Out-Degree GCN (OD-GCN)
GCL
ReLU
GCL
ReLU
In-Degree GCN (ID-GCN)
GCL
ReLU
GCL
ReLU
Fully-Connected Layer (FCL)
Rumor Detection Results
Node Features
Katz Centrality Weighted
GCN Node Features

04

Experiment

Dataset

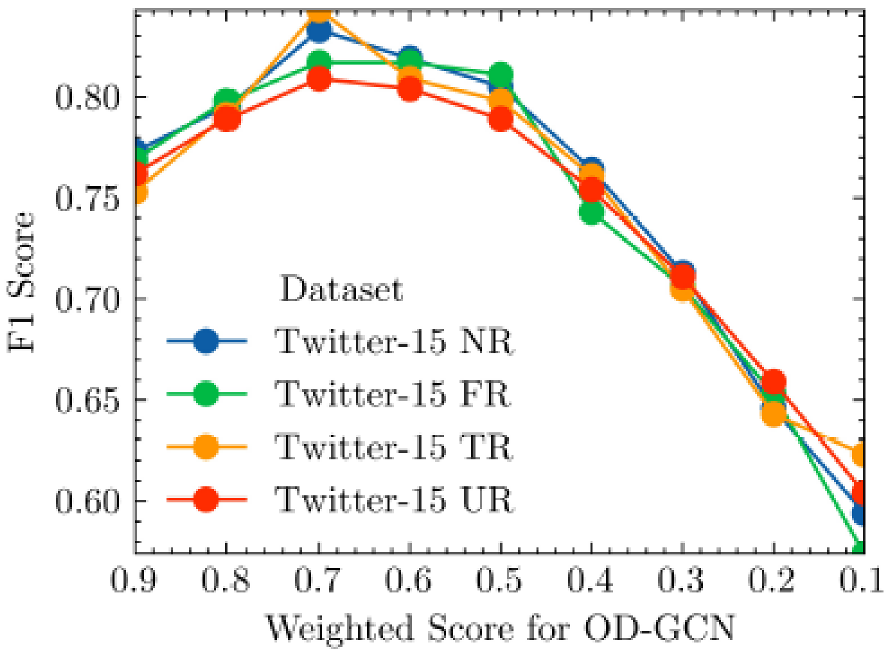
STATISTICS OF TWITTER-15 AND TWITTER-16

Statistic	*Twitter-15*	*Twitter-16*
# of posts	331,612	204,820
# of Users	276,663	173,487
# of events	1,490	818
# of **T**rue **R**umors	374	205
# of **F**alse **R**umors	370	205
# of **U**nverified **R**umors	374	203
# of **N**on-**R**umors	372	205
Avg. time length / event	1,337 Hours	848 Hours
Avg. # of posts / event	223	251
Max. # of posts / event	1,768	2,765
Min. # of posts / event	55	81

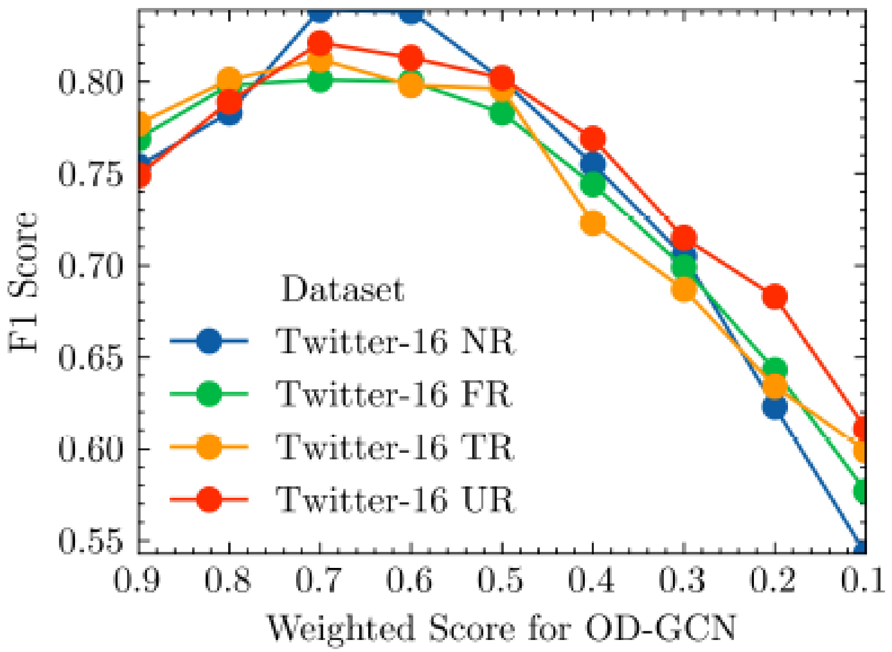
Accuracy performance

Dataset	*Twitter-15*					*Twitter-16*				
Method	Acc.	NR F1	FR F1	TR F1	UR F1	Acc.	NR F1	FR F1	TR F1	UR F1
DTR	0.409	0.501	0.311	0.364	0.473	0.414	0.394	0.273	0.630	0.344
DTC	0.454	0.733	0.355	0.317	0.415	0.465	0.643	0.393	0.419	0.403
RFC	0.565	0.810	0.422	0.401	0.543	0.585	0.752	0.415	0.547	0.563
CNN-OM	0.650	0.613	0.622	0.533	0.694	0.663	0.654	0.677	0.549	0.721
GRU-2	0.785	0.801	0.794	0.744	0.801	0.773	0.793	0.755	0.801	0.764
LSTM-2	0.733	0.711	0.745	0.624	0.761	0.752	0.749	0.766	0.733	0.747
BU-RvNN	0.708	0.695	0.728	0.759	0.653	0.718	0.723	0.712	0.779	0.659
TD-RvNN	0.723	0.682	0.758	0.821	0.654	0.737	0.662	0.743	0.835	0.708
TL-GCN	0.801	0.782	0.823	0.803	0.797	0.804	0.759	0.782	0.809	0.804
OID-GCN	**0.821**	**0.833**	**0.817**	**0.843**	**0.809**	**0.814**	**0.839**	**0.801**	**0.812**	**0.821**

Accuracy performance

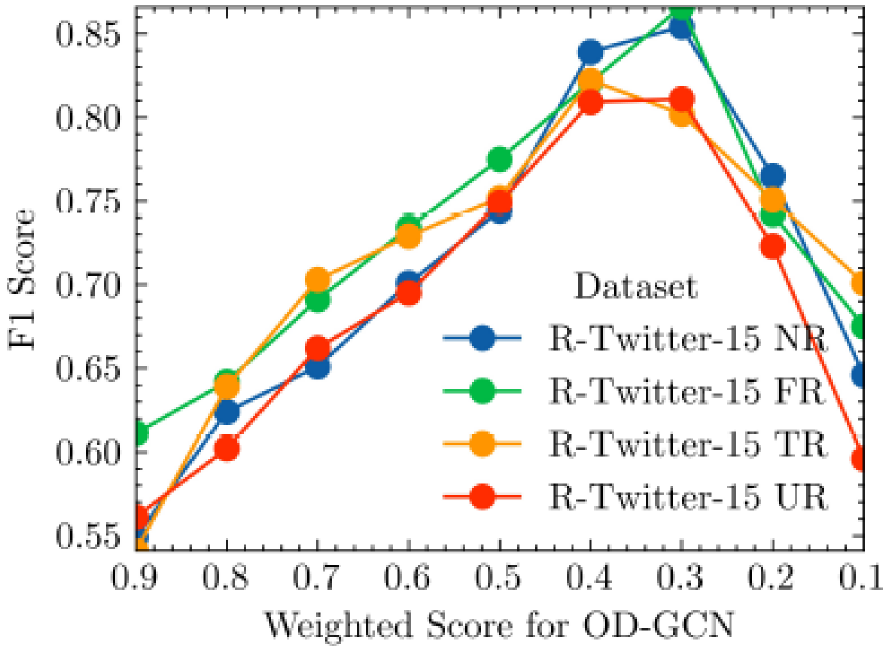


(a) Twitter-15

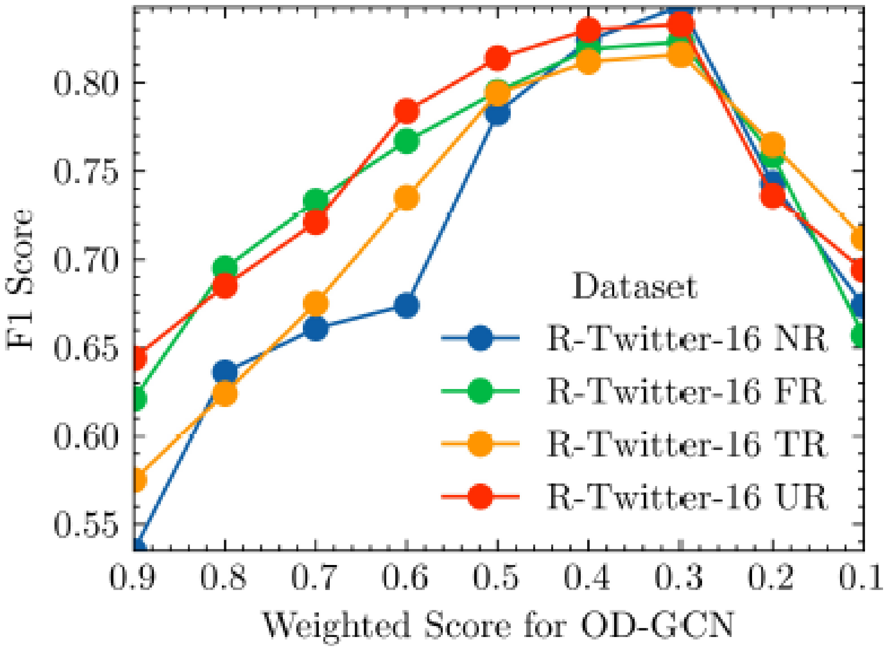


(b) Twitter-16

Flexibility experiment



(c) R-Twitter-15



(d) R-Twitter-16

Flexibility experiment

RESULTS OF FLEXIBILITY COMPARISON.

Method	Acc.	NR F1	FR F1	TR F1	UR F1
R-Twitter-15					
TL-GCN	0.799	0.804	0.827	0.765	0.772
Bi-GCN	0.692	0.710	0.723	0.695	0.685
OID-GCN	**0.834**	**0.854**	**0.866**	**0.802**	**0.811**
R-Twitter-16					
TL-GCN	0.806	0.763	**0.824**	0.793	0.765
Bi-GCN	0.707	0.744	0.737	0.696	0.678
OID-GCN	**0.827**	**0.843**	0.823	**0.816**	**0.833**

Thanks

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