Tracing Fake-News Footprints: Characterizing Social Media Messages by How They Propagate

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Overview

Overview

The big question

- When a message, such as a piece of news, spreads in social networks, how can we classify it into categories of interests, such as genuine or fake news ?

Overview

Some setbacks

- Content spread based on user belief system.
- Intentional content spread.
- Content modification to bring the fake content closer to the original content.
- Incentivized spread

Overview

Research question

- How can information diffusion traces be used to classify social media content ?
- Can this be done independent of the content ?

Overview

Experiment

- Learning embeddings based on network connectivity.
- Construct a sequence classifier with LSTM-RNN's.

- A social media message as a sequence of its spreaders.Use LSTM-RNN's to model the sequence, and the final hidden output are aggregated using softmax to produce a predicted class label.

Data

Table 2: Statistics of the datasest used in this study.

	Messages	Posts	Unique Users	Class Ratio
Real News	68,892	288,591	121,211	0.27(b):0.25(t):0.37(e):0.11(m)
Fake News	3,600	17,613	9,153	0.5:0.5

Experiment

Experiment

Sequence Modelling

- Modelled as a graph $G \in$ <V,E>
- $v_i \in V$, $e_{ij} \in E$ edge between i and j
- $m_i \in M$, message
- Each message has its spreaders sorted by time
- Spread sequence is fed to RNN in reverse
- Results are aggregated at the end with a softmax layer

Experiment

Word embeddings

- DeepWalk
- SimDoc
- Line
- TraceMiner

Experiment

Summary

- The first step utilizes network structures to embed social media users into space of low dimensionality, which alleviates the data sparsity of utilizing social media users as features.
- The second step represents user sequences of information diffusion, which allows for the classification of propagation pathways.

Results

News categorization

Table 3: The F_1-measure of different methods on the task of social media news categorization.

	Training Ratio	10%	20%	30%	40%	50%	60%	70%	80%	90%
Micro-F_1(%)	SVM	0.6967	0.7138	0.7447	0.7577	0.7988	0.8096	0.8499	0.8787	0.8996
	XGBoost	0.7121	0.7349	0.7512	0.7794	0.8248	0.8250	0.8638	0.8951	0.9047
	TM(DeepWalk)	0.7895	0.8081	0.8149	0.8374	0.8569	0.8627	0.8852	0.8917	0.9184
	TM(LINE)	0.7691	0.7926	0.8163	0.8379	0.8467	0.8744	0.8980	0.9106	0.9253
	TraceMiner	**0.8275**	**0.8460**	**0.8658**	**0.8835**	**0.8885**	**0.9141**	**0.9218**	**0.9357**	**0.9380**
Macro-F_1(%)	SVM	0.6988	0.7260	0.7425	0.7754	0.7665	0.7872	0.8118	0.8314	0.8722
	XGBoost	0.7305	0.7438	0.7857	0.7887	0.8144	0.8344	0.8726	**0.8941**	0.9044
	TM(DeepWalk)	0.7746	0.8010	0.8156	0.8313	0.8377	0.8611	0.8646	0.8734	0.8839
	TM(LINE)	0.7561	0.7895	0.8019	0.8138	0.8235	0.8568	0.8775	0.8896	**0.9153**
	TraceMiner	**0.8181**	**0.8347**	**0.8359**	**0.8549**	**0.8635**	**0.8788**	**0.8779**	0.8882	0.9064

Fake news detection

Table 4: The F_1-measure of different methods on the task of fake news detection.

Training Ratio	10%	20%	30%	40%	50%	60%	70%	80%	90%
SVM	0.5825	0.5779	0.6122	0.6194	0.6658	0.7114	0.7224	0.7252	0.7581
XGBoost	0.6558	0.7004	0.7002	0.7153	0.7288	0.7703	0.7984	0.8115	0.8226
TM(DeepWalk)	0.7804	0.7810	0.8078	0.8264	0.8194	0.8491	0.8542	0.8738	0.8894
TM(LINE)	0.7542	0.7547	0.7913	0.8015	0.8083	0.8485	0.8733	0.8936	0.8971
TraceMiner	**0.7867**	**0.7935**	**0.8344**	**0.8459**	**0.8547**	**0.8751**	**0.8988**	**0.9089**	**0.9124**

Discussion

Discussion

- Dataset is small
- Why not augment it ?
- No further details on the ground truth generation
- Why is metadata like demographics, age etc not considered ?
- I think that looking into different platforms improve the quality of fake-news tracing. - Nina