OTTO VON GUERICKE UNIVERSITÄT MAGDEBURG

INF

FAKULTÄT FÜR INFORMATIK

Databases and Software Engineering

Master Thesis

Multi-Modal Fake News Detection with Word Embeddings and Deep Graph Learning

February 28, 2023

Reviewers:
Prof. Dr. rer. nat. habil. Gunter Saake
Dr. Claudia Krull

Supervisor: MSc. Gabriel Campero Durand

Presented by:
Saloni Verma
Matr. No. 225871
Data and Knowledge Engineering

Agenda

1. Motivation
2. Research Questions
3. Background
4. Design
5. Setup & Evaluation
6. Conclusion

Introduction

- **Explosion** of news content online

Washington Post	1200/day
NYTimes.com	150/weekday (250 Sunday) ~65 blogs/day
Germany [28]	5500 (150 EN)

- 68% of Americans get news from social media
- Biased information **amplified** on social media like Twitter [4,27]
  - 70% more likely to be retweeted, spreads ~6x quicker [23]
- Media landscape
  - Old: Newspaper editors, expert fact-checkers
  - Now: Everyone shares without thought

What to believe?


FBI REDUX: What's Behind New Probe into Hillary Clinton Emails?

OCTOBER 28, 2016 BY SHAWN HELTON 10 COMMENTS

21st Century Wire says...

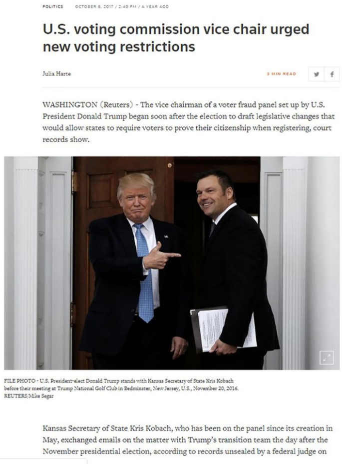
In a stunning turn of events 11 days before the 2016 presidential election, the FBI announced it is reopenning its investigation into Hillary Clinton's email server case, by probing newly emerging emails linked to Hillary Clinton.

'NEW PROBE' – The FBI gives Hillary Clinton a second look. (Photo illustraion 21WIRE)

FBI October Surprise?

According to reports, in a letter written today, FBI Director **James Comey**, stated that the FBI has begun a new probe into Hillary Clinton related emails once again. Comey offered scant details about the new probe, but due to an unrelated case, additional classified material may have been mishandled on Clinton's personal email server.

CNBC reported the latest FBI developments, including a passage from Comey's letter discussing


POLITICS OCTOBER 6, 2017 / 2:40 PM / A YEAR AGO

U.S. voting commission vice chair urged new voting restrictions

Julia Harte 3 MIN READ

WASHINGTON (Reuters) - The vice chairman of a voter fraud panel set up by U.S. President Donald Trump began soon after the election to draft legislative changes that would allow states to require voters to prove their citizenship when registering, court records show.

FILE PHOTO - U.S. President-elect Donald Trump stands with Kansas Secretary of State Kris Kobach before their meeting at Trump National Golf Club in Bedminster, New Jersey, U.S., November 20, 2016. REUTERS/Mike Segar

Kansas Secretary of State Kris Kobach, who has been on the panel since its creation in May, exchanged emails on the matter with Trump's transition team the day after the November presidential election, according to records unsealed by a federal judge on

Example of Political News (a) FAKE (b) REAL news story

What is Fake News?

- False or misleading information presented as news, to **damage reputation**
- Purpose: alter people's perceptions, attitudes, or beliefs in order to influence behaviour

Type	Definition	Possible Impact
Misinformation	False information	Unharmful, but misleading
Fake News [33]	Intentionally misleading facts	Racial discrimination, financial loss [24]
Hoax	False news	Public scare [24,25]

..Conspiracy Theory, Deepfakes and more [26]

- Filtering manually is not enough

How to detect?

- Research for labelling **FAKE** and **REAL** news
- Automate this with ML/DeepL models

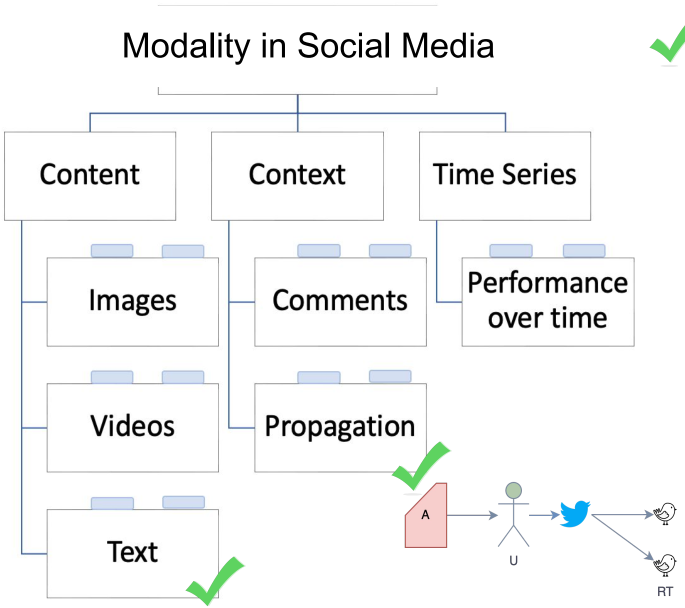
State-of-the-Art

Dataset: Politifact

Paper	Year	Concept	Accuracy (Text)	Accuracy (Multi-Modality)
Fakeddit [6]	2019	Hybrid models (text+image)	86.44	89.09
XGB-RF [4]	2020	XGB, Random Forest	**87.7**	86.5
Spotfake+ [7]	2020	Transfer learning for semantic + contextual	74	84.6
MM-RF [1]	2021	Random Forest (text+image)	86.24	**95.18**

Multi-Modality

"Modality" refers to an experience that we perceive [10]



Concepts

RepresentationFusion

Co-learning

Source: [Overview of online fake news]

Non-Transformer NLP & Word Embeddings

1 Motivation

2 **Research Questions**

3 Background

4 Design

5 Setup & Evaluation

6 Conclusion

Research Questions

1. To what extent can **traditional machine learning** approaches perform (XGBoost, fastText, basic Neural Nets) on the detection of fake news using textual features?

2. How does the performance of **node embeddings and graph embeddings** on the **User-Article graph** feature extracted from the dataset compare?

3. Does the use of a **Graph Neural Network** contribute to the detection of fake news, compared to the node embedding approach?

1 Motivation

2 Research Questions

3 **Background**

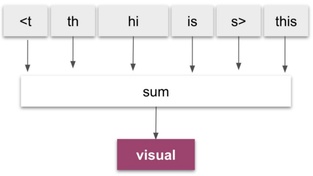
4 Design

5 Setup & Evaluation

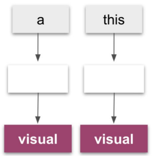
6 Conclusion

Representation Models (Text Embeddings)

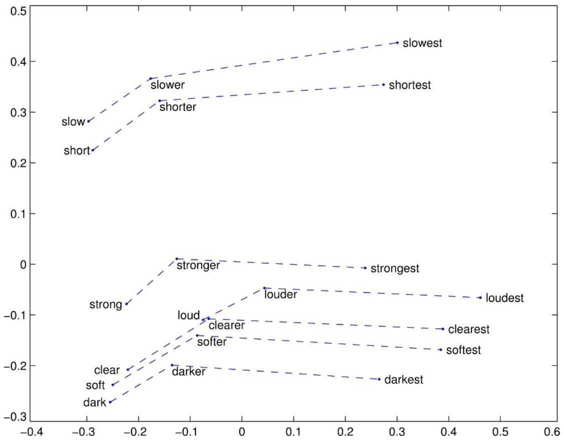
fastText



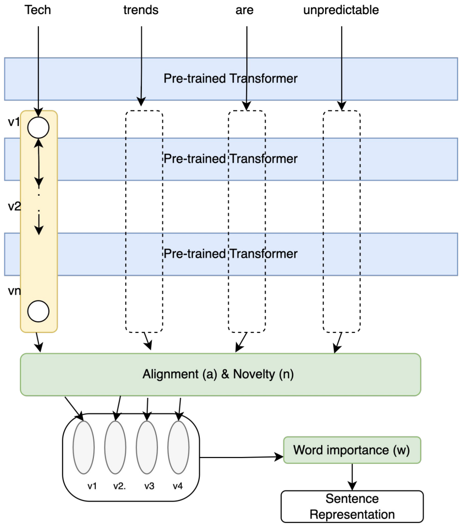
Word2Vec



Source: [kavita-ganesan]



Source: [Stanford]



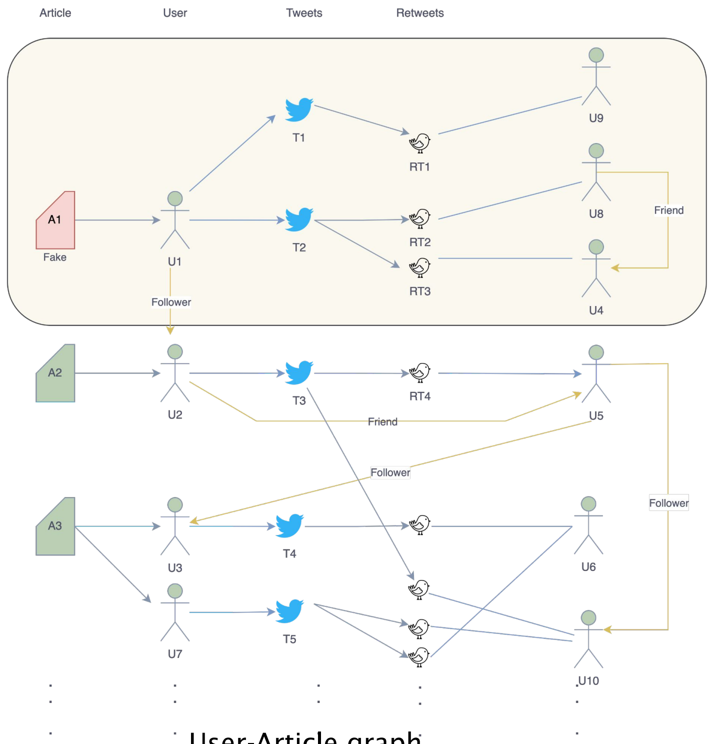
FastText FB, 2015

Word2Vec Google, 2013

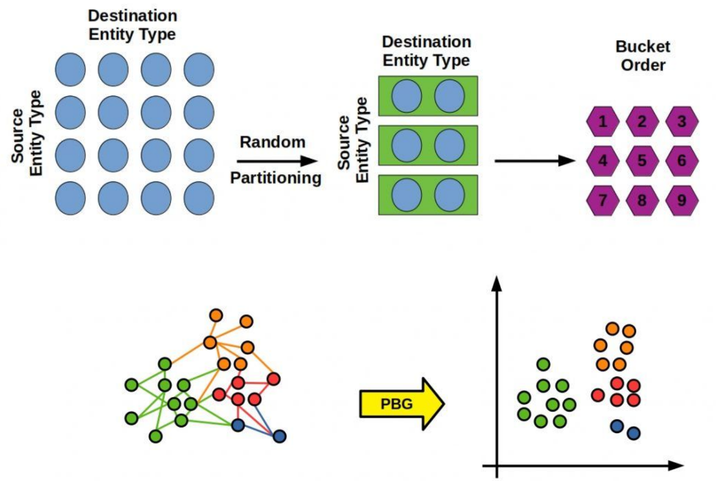
GloVe Stanford, 2014

SBERT [TU] Darmstadt, 2019

Representation Models (Graph Embeddings)



User-Article graph



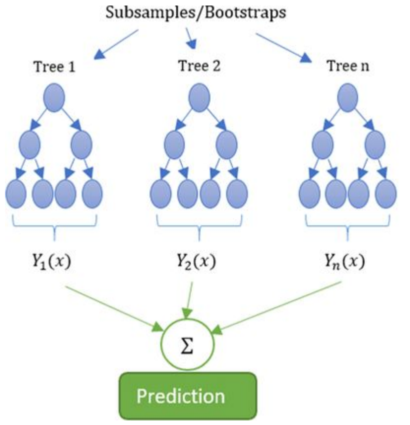
Source: [Starship-knowledge]

Pytorch Big Graph Facebook 2019

OTTO VON GUERICKE UNIVERSITÄT MAGDEBURG INF FAKULTÄT FÜR INFORMATIK

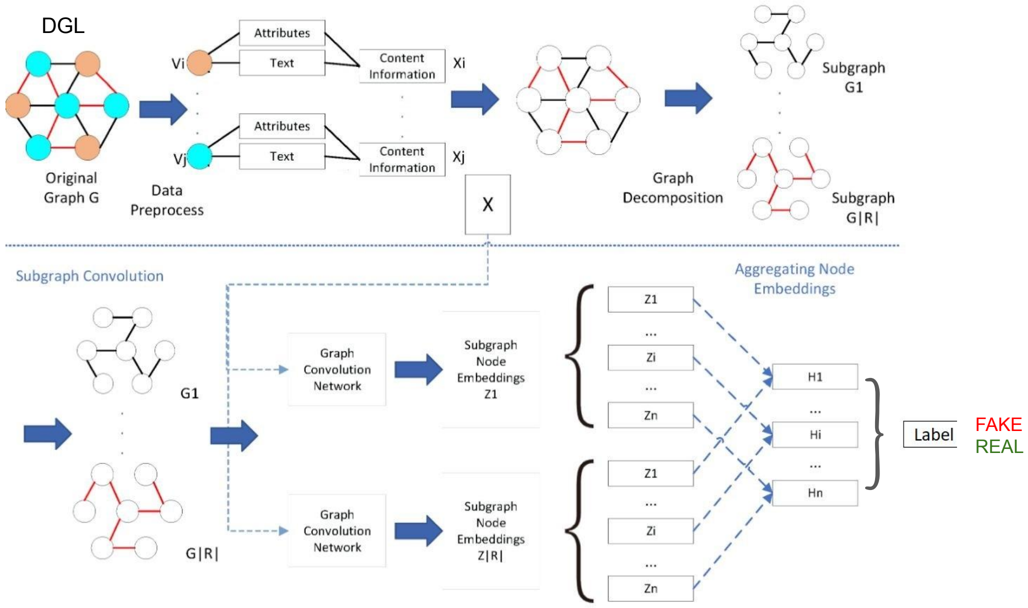
Classification Models

- **Neural Network (MLP)**
- **XGBoost (eXtreme Gradient Boosting)**
  Gradient-boosted decision tree implementation for speed + performance[9]



Source:ML for KPIs[37]

- **Heterogeneous Graph Neural Network**
  Relational Graph Convolution Network[16]



1 — 2 — 3 — 4 — 5 — 6

Motivation
Research Questions
Background
Design
Setup & Evaluation
Conclusion

Dataset Choices

Features	News Content		Social Context		SpatioTemporal			
	Linguistic	Visual	User	Post	Response	Network	Spatial	Temporal
Buzzfeed News y	✓							
Liar	✓							
Buzzface	✓			✓	✓			✓
BS Detector	✓							
CREDBANK	✓		✓				✓	✓
Facebook Hoax	✓		✓	✓				
FakeNewsNet (FNN)	✓	✓	✓	✓	✓	✓	✓	✓

Dataset

[FakeNewsNet](#)

- Data from 244 websites
- 12,999 news pieces
- Source: BS Detector [21]
- FAKE |REAL labelled

Fake: 22% bots
Real: 9% bots

[PolitiFact](#)

(Political news)

Journalists & domain experts review evaluation results[18,19]

Fake: 473
Real: 797

[GossipCop](#)

(Gossip/Entertainment news)

Evaluates + assigns truth values from 0-10 (wrt E! online)[18]

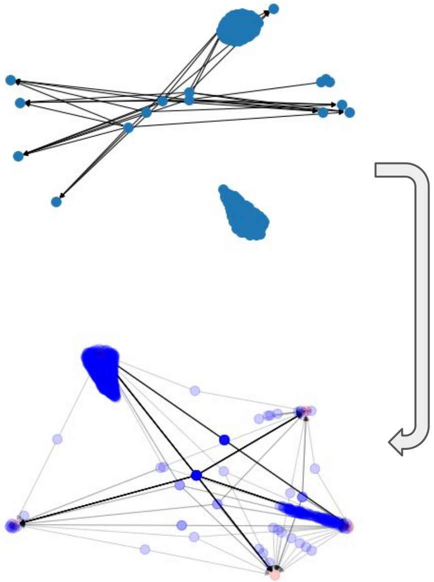
Fake: 5335
Real: 16790

Data Augment using Twitter Developer API

- User-Article graph <u>not</u> fully connected
  - Data decay (Missing tweets, news articles..)
  - Fraction of news articles not found 9%[11]

- Script
  - Map *TweetID* to its *UserID* (t2u)
  - Map user’s *friends/followers* if UserID present

➔ Less sparse data



Unconnected → Highly connected graph

Dataset: Extracted Features

News Article (Text)

Title/Headline , Text (Content)

Tweets (Social Context)

No. of Tweets, No. of Retweets
(Non-tuned embeddings)

Text Embeddings

PBG embeddings
for RQ2 Multi-Modal FND
(Tuned Embeddings)
Mid-level Fusion

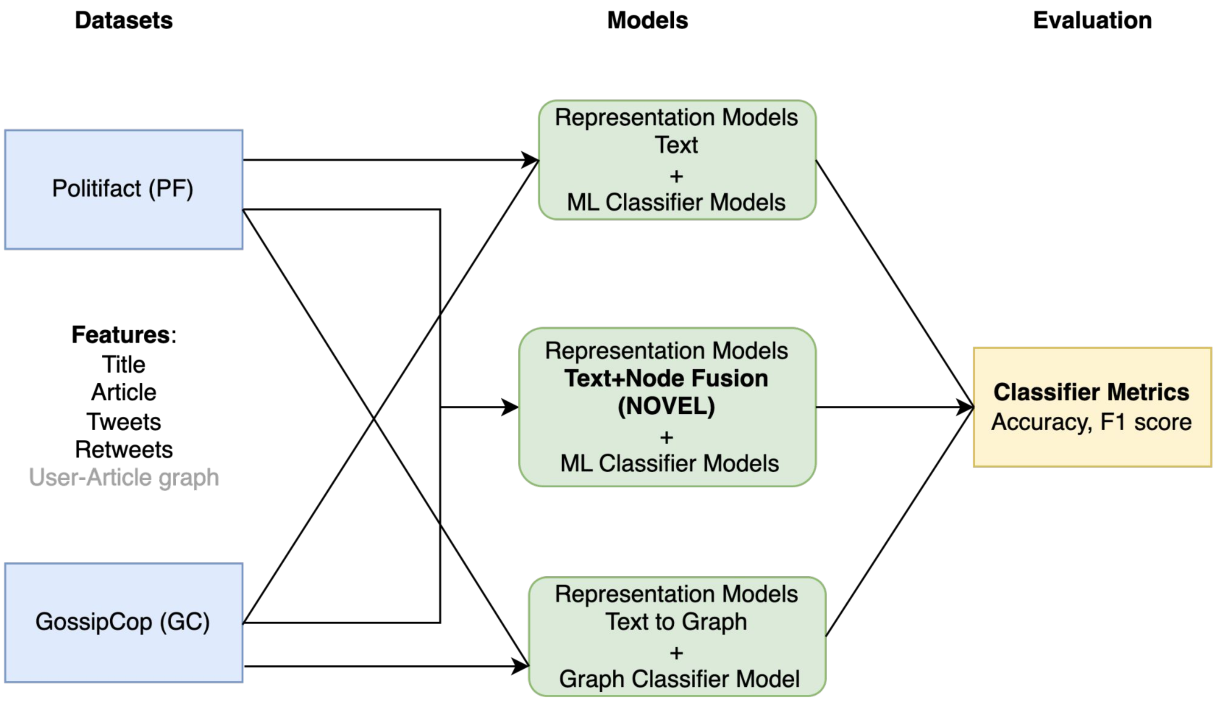
User-Article Graph

Through DGL
for RQ3 Graph Learning

Output in Classification Setting

News Label : **REAL** or **FAKE**

Design


Datasets
Models
Evaluation
Politifact (PF)
Features:
Title
Article
Tweets
Retweets
User-Article graph
GossipCop (GC)
Representation Models
Text
+
ML Classifier Models
Representation Models
Text+Node Fusion
(NOVEL)
+
ML Classifier Models
Representation Models
Text to Graph
+
Graph Classifier Model
Classifier Metrics
Accuracy, F1 score

FAKULTÄT FÜR INFORMATIK

1 — 2 — 3 — 4 — 5 — 6

Motivation

Research Questions

Background

Design

Setup & Evaluation

Conclusion

FAKULTÄT FÜR INFORMATIK

RQ 1: Machine Learning Approaches

Setup:

Embeddings: FasText 300d / SBERT 768d / Glove 300d

Classifiers: 1. XGB

```
num_boost_round=200, early_stopping_rounds=None
Binary Cross Entropy
```

2. NN Keras Hybrid Neural Network

```
"Epochs":200, "bs":128’,‘lr’:1e-3

Dropout, Conv1D, MaxPooling1D
2 LSTM layers Dense
```

Hyperparameter Evaluation: Activation Function, Dropout, Optimizer

Dataset Statistics

Number of Articles: 1056 (894)
Unique users: 31792
Fake: 411 (138) **Real:** 483 (179)

Number of Articles: 5323
Number of Tweets: 5135
Number of Retweets: 22140
Unique users: 639764
Fake: 3086 **Real:** 908

RQ 1: Machine Learning Approaches

Hypotheses:

1. Increasing features will increase model performance
2. NN would have best performance

Feature	Emb	F1-F	F1	Acc
Title (T)	Gl	.8409	.8462	84.36
T	SB	.8165	.8360	82.68
T	FT	.7560	.7917	77.53
T+Article(A)	Gl	.8654	.8770	87.15
T+A	**SB**	**.8764**	**.8778**	**87.71**
T+A	FT	.7950	.8308	81.46
T+A+T+RT	Gl (300d)	.8588	.8723	86.59
T+A+T+RT	FT	.8437	.8632	85.39

Results:
XGB

Feature	Emb	F1-F	F1	Acc
T	Gl	.4861	.8905	81.95
T	SB	.5856	.9024	84.20
T	FT	.5122	.8260	89.41
T+A	Gl	.5402	.8989	83.43
T+A	SB	.5856	.5829	84.2
T+A	FT	.8074	.8410	82.58
T+A+T+RT	Gl	.6945	.9232	87.73
T+A+T+RT	**FT**	**.7014**	**.9245**	**87.95**

RQ 1: Analysis

Hypotheses:

1. Increasing features will increase model performance: GC ✓ PF ✗ Title+Article enough to learn underlying patterns
2. NN would have best performance: GC ✗ could not learn PF ✓

Feature	DS	Model	Emb	F1-F	F1	Acc
T+A		XGB	SB	.8764	.8778	87.71
T+A		**NN** ★	**SB**	**.9142**	**.9180**	**91.62**
T+A+T+RT		NN	FT	.6449	.9153	86.33
T+A+T+RT		**XGB** ★	**GI**	**.6945**	**.9232**	**87.73**

Vs. State of the Art

Paper	Accuracy (Text)
XGB-RF [4] 2020	 87.7 *4% or 0.4x* ⇧
Spotfake+ [7] 2020	 74 0.18x ⇧  83.6 *0.7x* ⇧
Fakeddit [6] 2019	 86.44 0.6x ⇧
MM-RF [1] 2021	 86.24 ≈ 0.5x ⇧

- Models are **significantly dependent on word embeddings** used
- NN adapts well to any number of features it is fed → Could be good for generalisation to other datasets and FND tasks

RQ2: Multi-Modal Fake News Detection MoON architecture

Embeddings: SBERT + Pytorch BigGraph

Setup:

1. SBERT 128d (Title + Text)
2. Create **PBG** Node embeddings for User, Tweet, Retweet relationships
3. Concatenate: SBERT + PBG (Fusion) NOVEL
4. Classifiers: **XGB** and **NN -** Same as RQ1
   MultimodalOnlineNews classifier MoON architecture

```
988529911873921024    961251714857828357    follows
961635897929359360    961251714857828357    follows
159717173    961251714857828357    follows
4737344780    961251714857828357    follows
87696866    961251714857828357    follows
3936393793    961251714857828357    follows
79165215    775168554459070468    follows
1249663912439623680    775168554459070468    follows
```

Snapshot of PBG edges.txt for PF

Dataset	#Nodes	#Edges
	31896	49576
	314,262	308,798

RQ2: Results

Hypothesis: Using 2 modalities (Text+Graph) will give superior model than just text models (RQ1)

Epochs	Model	F1	Acc
200	XGB	91.489	.8764
400	XGB	91.489	.9142
200	NN	94.737	.6449
400	NN	95.531	.6945
600	**NN** ★	**96.296**	**96.089** A96.607

Epochs	Model	F1	Acc
200	XGB	93.250	89.23
400	**XGB** ★	**93.266**	**89.259**
600	XGB	89.484	93.405
200	NN	92.754	88.433
400	NN	92.689	88.332
600	NN	92.903	88.658

- **Results better than RQ1**
  - Amalgamation of textual and graphical features infuses more details
- MoON model **scalable**

Results SB+PBG embeddings for all features (T+A+TW+RT) fed through MLP and XGB (MoON)

OTTO VON GUERICKE UNIVERSITÄT MAGDEBURG

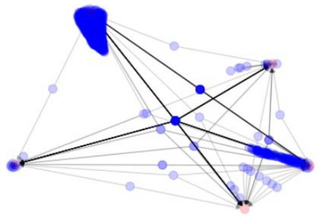
INF FAKULTÄT FÜR INFORMATIK

RQ2: Analysis wrt SOTA

Paper	Accuracy (Text)	Accuracy (Multi-Modal)
Spotfake+ [7] 2020	 74  83.6	 84.6 ~12% ⇧  85.6 ~ 8% ⇧
Fakeddit [6] 2019	 86.44	 89.09 7% ⇧
MM-RF [1] 2021	 86.24	 95.18 1% ⇧
SentimentAware[31] 2020	-	 F76.32 20% ⇧  F81.58 8% ⇧
dEFEND 2019 [19]	-	 90.04 6.18% ⇧  80.8 10.39% ⇧
Our Results	 91.62 (F91.80)  87.95 (F92.45)	 **96.08** (F96.29) 5.46% ⇧  **89.25** (F93.26) 1.47% ⇧

Note: Comparing multi-modality, others show results for text+image modalities

RQ3: Graph Learning Approach



Graph Visualised: GC 100 nodes

Hypothesis:

1. Graph approach will give superior results than just text models (RQ1)

Embeddings: FT / SB

Setup: Deep Graph Library

`StratifiedKFold` ✓ ∵ Class imbalance for GC

```
sampler = dgl.dataloading.NeighborSampler([10, 10])
batch_size=64
```

```
dgl.nn.GraphConv(64, 64, allow_zero_in_degree=True)
```

I/P, O/P features

- Residual function handles zero degree nodes

Node/Relation		
article	19968	894
user, follow, user (user, followed-by, user)	48409	695148
user	31792	639764
user, tweet, article (article, tweeted-by, user)	588	4587

RQ3: Results

Epochs	**Emb**	**F1**	**Acc**
100	FT	90.909	90.503
200	FT	87.50	89.385
400	FT	90.217	89.944
200	**SB**	**94.737**	**94.413**
400	SB	94.505	94.413

Epochs	Model	F1	Acc
100	FT	89.724	83.225
200	FT	89.752	83.225
400	FT	89.72	83.15
100	**SB**	**90.949**	**85.503**
200	SB	90.892	85.303
400	SB	90.83	87.414

Results All features (T+A+TW+RT) fed to HetGCN (with Cross Validation)

Comparison wrt. Our Research

RQ	**Accuracy (Best)**			
RQ1		91.62 **3.2%** ↑		87.95 **2.6%** ↓
RQ2		96.08 **1.6%** ↓		89.25 **3.7%** ↓
RQ3		94.413		85.503

- GCN models *highly sensitive* to size & type of DS, including class imbalance
- *Responsive to hyperparameter tuning*
- Model marginally outperformed by novel Multi-modal MoON

Takeaways

- RQ1
  - Increasing features generally makes the model learn better
  - XGB outperforms in some cases
  - Models dependent on word embeddings  SB>GI>FT  GI>SB>FT
- RQ2
  - MoON model outperforms all (marginally), adding features enhance pre-trained knowledge of models
  - Scarcity of PF sample having ALL 4 features affects model performance
  - Multi-modal models are capable of **capturing underlying data distribution**
- RQ3
  - GCN models **highly sensitive** to class imbalance
    ∵ some articles/users could be over-represented

1 Motivation

2 Research Questions

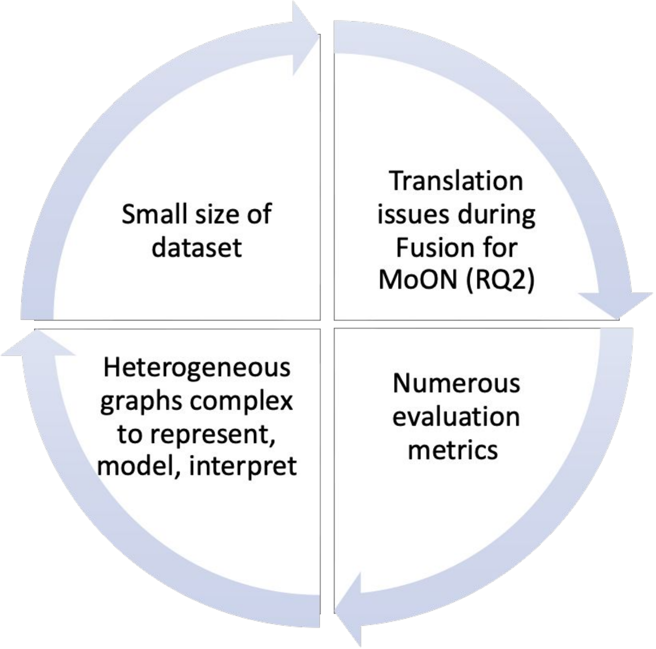
3 Background

4 Design

5 Setup & Evaluation

6 **Conclusion**

Challenges



→ Problem of incremental improvements

Conclusion

- Perils of fake news on social media
- Binary classification problem: REAL or FAKE labels for news online
- Exhaustive number of experiments (Engineering, Enrichment API,..)
- Common assumptions are not always true
- Amalgamation of Text + Relationship features infuses more details → Better model (Unimodal, Multi-modal & Graph)
  - MoON results best → Multi-modality reliable approach for complex problems like Fake News Detection
    - Scientifically find the **right mix** of *Content* and *Context*
- Future Work

Google Gato	Increasing modalities	Tuning of Transformers	Create UI for FND tool + Explanability

OTTO VON GUERICKE UNIVERSITÄT MAGDEBURG INF FAKULTÄT FÜR INFORMATIK

References

1. Vivek K. Singh, Isha Ghosh, and Darshan Sonagara. Detecting fake news stories via multimodal analysis. Journal of the Association for Information Science and Technology, 72(1):3–17, jan 2021. doi:10.1002/asi.24359. §
2. Xichen Zhang, Ali A. Ghorbani, An overview of online fake news: Characterization, detection, and discussion, Information Processing & Management, Volume 57, Issue 2, 2020, 102025, ISSN 0306-4573, https://doi.org/10.1016/j.ipm.2019.03.004. §
3. FakeNewsNet:
4. Xinyi Zhou and Reza Zafarani. A Survey of Fake News: Fundamental Theories, Detection Methods, and Opportunities. ACM Computing Surveys, 53(5), sep 2020. arXiv:1812.00315, doi:10.1145/3395046.
5. Awan Mohanty. Multi layer perceptron (mlp) models on real world banking data. becoming human: Artificial intelligence magazine. https://becominghuman.ai/multi-layer-perceptron-mlp-models-on-real-world-banking-data-f6dd3d7e998f, May 15 2019. (Accessed on 09/17/2022)
6. Kai Nakamura, Sharon Levy, and William Yang Wang. r/Fakeddit: A New Multimodal Benchmark Dataset for Fine-grained Fake News Detection. nov 2019. URL: http://arxiv.org/abs/1911.03854, arXiv:1911.03854.
7. Shivangi Singhal, Anubha Kabra, Mohit Sharma, Rajiv Shah, Tanmoy Chakraborty, and Ponnurangam Kumaraguru. Spotfake+: A multimodal framework for fake news detection via transfer learning (student abstract). Proceedings of the AAAI Conference on Artificial Intelligence, 34:13915–13916, 04 2020. doi:10.1609/aaai.v34i10.7230.
8. J Keller. 2013. A fake AP tweet sinks the DOWfor an instant. Bloomberg Businessweek (2013)
9. Jason Brownie. A gentle introduction to xgboost for applied machine learning. https://machinelearningmastery.com/ gentle-introduction-xgboost-applied-machine-learning/, August 2016. (Accessed on 11/23/2022).
10. https://courses.lumenlearning.com/waymaker-psychology/chapter/multi-modal-perception/
11. Kai Shu, Amy Sliva, Suhang Wang, Jiliang Tang, and Huan Liu. Fake news detection on social media: A data mining perspective. SIGKDD Explor. Newsl., 19(1):22–36, sep 2017. doi:10.1145/3137597.3137600
12. Tadas Baltrušaitis, Chaitanya Ahuja, and Louis-Philippe Morency. Multimodal Machine Learning: A Survey and Taxonomy. may 2017. URL: http://arxiv.org/ abs/1705.09406, arXiv:1705.09406.
13. Hanghang Tong, Jingrui He, Mingjing Li, Changshui Zhang, and Wei-Ying Ma. Graph Based Multi-Modality Learning*. Technical report, 2005
14. Verónica Pérez-Rosas, Bennett Kleinberg, Alexandra Lefevre, and Rada Mihalcea. Automatic Detection of Fake News. aug 2017. URL: http://arxiv.org/abs/ 1708.07104, arXiv:1708.07104.
15. Karishma Sharma, Feng Qian, He Jiang, Natali Ruchansky, Ming Zhang, and Yan Liu. Combating fake news: A survey on identification and mitigation techniques, apr 2019. arXiv:1901.06437, doi:10.1145/3305260
16. Thomas N. Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. CoRR, abs/1609.02907, 2016. URL: http://arxiv.org/ abs/1609.02907, arXiv:1609.02907.

OTTO VON GUERICKE UNIVERSITÄT MAGDEBURG INF FAKULTÄT FÜR INFORMATIK

References

17. Kai Shu, Deepak Mahudeswaran, Suhang Wang, Dongwon Lee, and Huan Liu. FakeNewsNet: A Data Repository with News Content, Social Context, and Spa- tiotemporal Information for Studying Fake News on Social Media. *Big Data*, 8(3):171–188, 2020. arXiv:1809.01286, doi:10.1089/big.2020.0062.
18. https://www.politifact.com/factchecks/list/?ruling=true , https://www.eonline.com/
19. Kai Shu, Limeng Cui, Suhang Wang, Dongwon Lee, and Huan Liu. defend: Explainable fake news detection. June 2019. URL: dl.acm.org/doi/10.1145/ 3292500.3330935, doi:doi/10.1145/3292500.3330935.
20. Twitter icon: flaticon.com, Bird icon: Clipartmax.com
21. Chen, J.; Huang, F.; Peng, J. MSGCN: Multi-Subgraph Based Heterogeneous Graph Convolution Network Embedding. *Appl. Sci.* 2021, *11*, 9832. https://doi.org/10.3390/app11219832
22. Image Credits: Reese Witherspoon fashiongonerogue.com, Chris Wallace: nbcnews.com
23. Diba Roy Sourush Vosoughi, Sinan Aral. The spread of true and false news on- line. March 2018. (Accessed on 08/11/2022). doi:10.1126/science.aap955
24. Nyhan B Flynn DJ and Reifler J. *The nature and origins of misperceptions: Understanding false and unsupported beliefs about politics. Political Psychology 38(S1*. 2017.
25. David M.J.Lazer, Matthew A.Baum, Yochai Benkler, Adam J.Berinsky, KellyM. Greenhill, Filippo Menczer, Miriam J. Metzger, Brendan Nyhan, Gordon Pennycook, David Rothschild, Michael Schudson, Steven A. Sloman, Cass R. Sunstein, Emily A. Thorson, Duncan J. Watts, and Jonathan L. Zittrain. The science of fake news: Addressing fake news requires a multidisciplinary effort. *Science*, 359(6380):1094–1096, mar 2018. doi:10.1126/science.aao2998.
26. Xia Hu and Huan Liu. In Charu C. Aggarwal and ChengXiang Zhai, editors, *Mining Text Data*. doi:https://doi.org/10.1007/978-1-4614-3223-4
27. Kathleen Hall Jamieson,Yu-Gang Jiang Joseph N Cappella Zhiwei Jin, JuanCao, and Yongdong Zhang. News credibility evaluation on microblog with a hierarchical propagation model. page 230–239. Oxford University Press, 2014
28. Felix Hamborg, Norman Meuschke, and Bela Gipp. Bias-aware news analysis using matrix-based news aggregation. *International Journal on Digital Libraries*, 21, 06 2020. doi:10.1007/s00799-018-0239-9
29. KaiShu and Huan Liu. Detecting fake news on social media.*Synthesis Lectures on Data Mining and Knowledge Discovery*, 2019.
30. Xinyi Zhou, Atishay Jain, Vir V Phoha, and Reza Zafarani. 2019a. Fake News Early Detection: A Theory-driven Model. arXiv preprint arXiv:1904.11679 (2019).
31. Limeng Cui, Suhang Wang, and Dongwon Lee. 2020. SAME: sentiment-aware multi-modal embedding for detecting fake news. In Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM '19). Association for Computing Machinery, New York, NY, USA, 41–48. https://doi.org/10.1145/3341161.3342894
32. Machine learning for KPIs prediction: a case study of the overall equipment effectiveness within the automotive industry, 10.1007/s00500-020-05348-y, Choumicha EL Mazgualdi et al.
33. Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks, 2019. URL: https://arxiv.org/abs/1908.10084, doi:10. 48550/ARXIV.1908.10084

Thank you!

Let’s delve into the questions