Fake news: an algorithmic perspective on fact-checking

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Abstract

Contents

1 Introduction

- Bevat je onderzoeksvraag (of vragen)

- Plaatst je vraag in de bestaande literatuur.

Je onderzoeksvraag is leidend voor je hele scriptie. Alles wat je doet moet uiteindelijk terug te voeren zijn op 1 doel: het beantwoorden van die vraag.

Typisch zal je het dan ook zo doen:

Mijn onderzoeksvraag is onderverdeeld in de volgende deelvragen:

RQ1 ... We beantwoorden deze vraag door het volgende te doen/ antwoord op de volgende vragen te vinden/ ...

  1. Vragen op dit niveau kan je echt beantwoorden, en dat doe je in je Evaluatie sectie.

RQ2 ...

RQ3 ...

Je Evaluatie sectie bevat evenveel subsecties als je deelvragen hebt. En in elke sectie beantwoord je dan die deelvraag met behulp van de vragen op het onderste niveau.

In je conclusies kan je dan je hoofdvraag gaan beantwoorden op basis van al het eerder vergaarde bewijs.

Overview of thesis   Hier geef je even kort weer wat in elke sectie staat.

2 Related Work

2.1 RQ1

Fake news as a term only caught public attention starting from the end of 2016, during the Presidential Elections of the United States [7].

2.2 RQ2

In the last couple of years, using transfer learning for natural language processing has given promisable results. The following sentence embeddings will be used to detect fake news:

- Bag of Words as a baseline for performance of non-pretrained embeddings;

- Facebook's InferSent [1];

- ELMo from the Allen Institute for Artificial Intelligence [5];

- OpenAI's GPT-2 [6];

- Transformer-XL [2];

- Microsoft's MT-DNN [4];

- and Google's BERT [3].

2.3 RQ3

Aligned with the original research on this dataset by Wang [8], the following machine learning algorithms will be used to test the applicability of the abovementioned embedding techniques:

- SVMs;

- Logistic regression;

- Bi-LSTMs;

- CNNs.

3 Methodology

3.1 Description of the data

3.2 Data charts

3.3 Methods

3.3.1 RQ1

3.3.2 RQ2

4 Evaluation

Evaluation.

5 Conclusions

Conclusions.

5.1 Acknowledgements

Many thanks.

References

[1] Alexis Conneau, Douwe Kiela, Holger Schwenk, Loïc Barrault, and Antoine Bordes. Supervised learning of universal sentence representations from natural language inference data. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 670–680, Copenhagen, Denmark, September 2017. Association for Computational Linguistics.

[2] Zihang Dai, Zhilin Yang, Yiming Yang, Jaime G. Carbonell, Quoc V. Le, and Ruslan Salakhutdinov. Transformer-xl: Attentive language models beyond a fixed-length context. *CoRR*, abs/1901.02860, 2019.

[3] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

[4] Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. Multi-task deep neural networks for natural language understanding. *arXiv preprint arXiv:1901.11504*, 2019.

[5] Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. *CoRR*, abs/1802.05365, 2018.

[6] Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. 2019.

[7] Google Trends. Explore. `https://trends.google.nl/trends/explore?date=today%205-y&q=fake%20news`, 2019. Retrieved on 16th of April, 2019.

[8] William Yang Wang. "liar, liar pants on fire": A new benchmark dataset for fake news detection. *CoRR*, abs/1705.00648, 2017.