EEE 586: Survey for the Term Project
Text Classification with Graph Neural Networks

Tuna Alikaşifoğlu
Dept. of Electrical and Electronics Engineering
Bilkent University
t.alikasifoglu@bilkent.edu.tr

Arda Can Aras
Dept. of Electrical and Electronics Engineering
Bilkent University
can.aras@bilkent.edu.tr

***Abstract*—Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.**

I. Introduction

- Introduction to Text Classification task, overview of the previous approaches, in Section II-A.
- Introduction to Graph Neural Networks (GNNs), what is GNN, why they are being utilized, in Section II-B.
- GNN in NLP, more specifically in Text Classification in Section III.

II. Previous Work

A. Text Classification

Text classification is the "procedure of designating pre-defined labels for the text". The task is to assign labels to the text based knowledge, where the labels are usually defined by humans, but can also be defined by the machine. This task is a fundamental part of Natural Language Processing (NLP), and it is significant to its applications such as sentiment analysis, question answering, text summarization, etc. [1]. Text classification task can be partitioned into five phases: preprocessing, feature extraction, dimensionality reduction (optional), classifier selection and evaluation:

1) Preprocessing: Text preprocessing is a crucial prerequisite for a successful feature extraction. The input of the text classification frameworks consists of raw text data, which are in the form of a sequence of sentences. In this step, "cleaning" of the text datasets is performed to transform the data into a form that is suitable for feature extraction. The cleaning process is usually performed by tokenization, capitalization, slang and abbreviation handling, noise removal, spelling correction, stemming and lemmatization [2].

2) Feature Extraction: After preprocessing step, another crucial step, feature extraction step is necessary. Two common methods of text based feature extraction are weighted word and word embedding techniques. In the weighted word aspect, we have old techniques like bag-of-words and term frequency-inverse document frequency (TF-IDF). In the relatively recent aspect, we have the word embedding techniques like *word2vec*, *GloVe*, *FastText*, etc. [1].

3) Dimensionality Reduction:

4) Classifier Selection:

5) Evaluation: GLUE [3], TweetEval [4], among others.

[1], [2], [5], [6]

B. Graph Neural Networks

[7]–[10].

III. Related Work

[11]–[15]

References

[1] Q. Li, H. Peng, J. Li, *et al.*, "A survey on text classification: From shallow to deep learning," *CoRR*, vol. abs/2008.00364, 2020. arXiv: 2008.00364. [Online]. Available: https://arxiv.org/abs/2008.00364.

[2] Kowsari, J. Meimandi, Heidarysafa, Mendu, Barnes, and Brown, "Text classification algorithms: A survey," *Information*, vol. 10, no. 4, p. 150, Apr. 2019, ISSN: 2078-2489. DOI: 10.3390/info10040150. [Online]. Available: http://dx.doi.org/10.3390/info10040150.

[3] A. Wang, A. Singh, J. Michael, F. Hill, O. Levy, and S. R. Bowman, "GLUE: A multi-task benchmark and analysis platform for natural language understanding," arXiv preprint 1804.07461, 2018. [Online]. Available: https://gluebenchmark.com/.

[4] F. Barbieri, J. Camacho-Collados, L. Espinosa-Anke, and L. Neves, "TweetEval: Unified Benchmark and Comparative Evaluation for Tweet Classification," in *Proceedings of Findings of EMNLP*, 2020.

[5] J. Devlin, M. Chang, K. Lee, and K. Toutanova, "BERT: pre-training of deep bidirectional transformers for language understanding," *CoRR*, vol. abs/1810.04805, 2018. arXiv: 1810.04805. [Online]. Available: http://arxiv.org/abs/1810.04805.

[6] J. Howard and S. Ruder, "Fine-tuned language models for text classification," *CoRR*, vol. abs/1801.06146, 2018. arXiv: 1801.06146. [Online]. Available: http://arxiv.org/abs/1801.06146.

[7] J. Zhou, G. Cui, S. Hu, *et al.*, "Graph neural networks: A review of methods and applications," *AI Open*, vol. 1, pp. 57–81, 2020, ISSN: 2666-6510. DOI: https://doi.org/10.1016/j.aiopen.2021.01.001. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666651021000012.

[8] Z. Wu, S. Pan, F. Chen, G. Long, C. Zhang, and P. S. Yu, "A comprehensive survey on graph neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 1, pp. 4–24, Jan. 2021, ISSN: 2162-2388. DOI: 10.1109/tnnls.2020.2978386. [Online]. Available: http://dx.doi.org/10.1109/TNNLS.2020.2978386.

[9] Z. Zhang, P. Cui, and W. Zhu, "Deep learning on graphs: A survey," *CoRR*, vol. abs/1812.04202, 2018. arXiv: 1812.04202. [Online]. Available: http://arxiv.org/abs/1812.04202.

[10] L. Sun, J. Wang, P. S. Yu, and B. Li, "Adversarial attack and defense on graph data: A survey," *CoRR*, vol. abs/1812.10528, 2018. arXiv: 1812.10528. [Online]. Available: http://arxiv.org/abs/1812.10528.

[11] L. Yao, C. Mao, and Y. Luo, *Graph convolutional networks for text classification*, 2018. arXiv: 1809.05679 [cs.CL].

[12] T. N. Kipf and M. Welling, *Semi-supervised classification with graph convolutional networks*, 2017. arXiv: 1609.02907 [cs.LG].

[13] H. Peng, J. Li, Q. Gong, *et al.*, *Hierarchical taxonomy-aware and attentional graph capsule rcnns for large-scale multi-label text classification*, 2019. arXiv: 1906.04898 [cs.IR].

[14] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Liò, and Y. Bengio, *Graph attention networks*, 2018. arXiv: 1710.10903 [stat.ML].

[15] Z. Guo, Y. Zhang, and W. Lu, "Attention guided graph convolutional networks for relation extraction," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, Florence, Italy: Association for Computational Linguistics, Jul. 2019, pp. 241–251. DOI: 10.18653/v1/P19-1024. [Online]. Available: https://aclanthology.org/P19-1024.