1. Clarity, format and styling:
The text is well-structured with important subsections of research highlighted, such as work structure, method components, experiments pipeline and outcomes. Results and explanations are supported with visualizations or tables, what simplifies the understanding. However some plots are too simple or have too few samples and the author could try to express more information in them. Text has a detailed explanation of used algorithms and justification for different steps of the pipeline. The grammar is fine, but sometimes the text has mistakes, but they were probably made in a hurry of the final report preparation and do not influence the understanding of the explained ideas.

2. Repo quality:
Repository contains a description of the work that each of the presented scripts does. However it does not describe what parameters or input data are expected for each script and its components, what makes it harder to reuse this code in different experiments if one decides to continue the work. However for reproducibility the description is fine enough. Also, I would increase the project description and add some information on the results of the work in the README as well, so that one could compare them without using a paper as guidance. Another suggestion for improvement could be to use python scripts instead of plain notebooks because the latter sometimes are harder to analyze and overview in github.

3. Reproducibility:
In github most of the scripts run successfully without any errors. As I already said, scripts for reproduction do not contain descriptions for the components and it makes it harder to understand whether you should run every cell and wait for the result or not if you want to work only with the part of the project. Something can be guessed from the parameters, but this is not convenient.
Overall, the author compares two methods of extracting TDA features from BERT's attention maps: one focusing only on the last layer and last head, and another considering all layers and heads. TDA features from undirected graphs were found to be more beneficial when extracted from all layers and heads, while directed graph features did not show a significant improvement. Author claims to reach ~74% accuracy with the baseline on full dataset and 68% on half, while undirected TDA features improve accuracy on half dataset to 70% and get similar quality on full. Directed TDA features reached 73% accuracy on the full dataset and failed to compute the results for a greater amount of features on the half dataset. So, the results of the paper indicate a modest but noteworthy improvement in classification accuracy when utilizing TDA features from undirected graph representations of attention maps. This, on the one hand, does not support the initial motivation that described the potential of the graph analysis for attention features. On the other hand, author's initial aim of comparison of different models is reached, though with unfortunate results for the target methods and the author provides fair justification and analysis of the project outcomes. The study highlights the potential of undirected and directed TDA in enhancing model performance while also pointing out the practical challenges and limitations, especially for directed graphs. Results in the git correspond to the findings explained in paper.