Text Mining
Project Report
How Similar Are Research Papers?

Shintaro Osuga

March 20, 2025

Introduction

With the increase in popularity within the the general public and in academic interest, machine learning and artificial intelligence as a to have have been steadily increasing. With this increase in interest, the number of research papers published each year has also been increasing. Alongside this increase in popularity as a topic, the platform called ArXiv has gained more and more popularity. This platform allows papers which haven't been published yet, therefore allowing for pre-prints of papers. Before ArXiv, gaining access to large quantities of research papers had been very expensive and time-consuming as multiple different publishing companies and platforms conquered the environment. This new environment allows for more experiments and analysis to be conducted on an ecosystem which could not be easily tapped into before. With this new platform, analysis of similarities of papers can now be conducted. In this experiment, similarities in the papers and trends within the topics or formulations of the papers are analyzed.

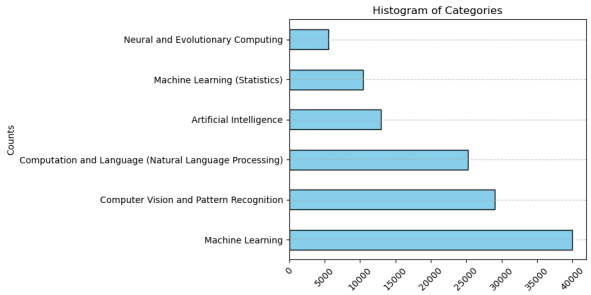
Data

The data set contains 125,548 rows of 10 columns. The columns are Id, title, category, category_code, published_date, update_date, authors, first_author, summary and summary_word_count. Of these, the columns on which this analysis will focus are title, category, published_date, and summary.

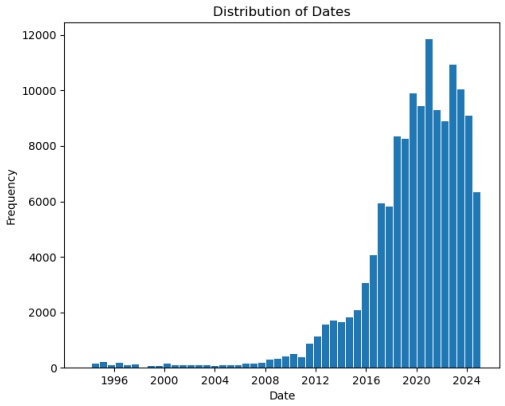
The distribution of the 2 of the most prominent and important categorical columns are shown below. As it can be seen in the distribution plots the most prominent category is "Machine Learning" with "Computer Vision and Pattern Recognition" and "Computation and Language (Natural Language Processing)" coming close behind it. Seen in the date distribution the number of papers published each year drastically increases around 2017 and before that there were less than a few hundred per year, but after 2017 the number published sky rockets and one year reaches close to 12,000 in one year. This is most likely due to the introduction of transformers in 2017 which brought attention back to AI as well as progress stagnant efforts in context encoding.

As the data is fed into a transformer model which can account for stopwords and also can benefit from keeping them, the data was not preprocessed and stopwords were not removed.

The embedded data can be provided upon request.



(a) Image 1



(b) Image 2

Processing

For processing, the columns title, category, published_date, and summary was fed into the SentenceTransformer model which encodes and embeds the input sentences into a 768 dimensional feature vector.

For calculating the cumulative score for aggregating the data to the most similar papers to the query values, the score cosine similarity score given for category and date were summed to create a column which represented the cumulative score for the similarity of a paper to the 2 query values.

0.1 Cosine Similarity

To calculate the similarity of 2 papers, the cosine similarity between every value of the encoded column and the encoded input query was calculated. This was done by using the sklearn cosine_similarity function, which calculates the cosine angle between the high dimensional vector of 2 vectors. This is a very prominent and often used technique to find the similarity between 2 high dimensional data points like images and words/sentences. This algorithm is used to first find papers which are similar to the input query and then again used to find how similar the papers within that subset of papers are to each other.

Models Used

0.2 Sentence Transformer

A pretrained Sentence Transformer model was used. This model utilizes the transformer encoder architecture and its attention mechanism to embed sentence information into higher dimensions. This model takes in an input of 384 and returns a vector of 768, deriving information from the input and casting it into a larger space. The model was originally trained on 1 billion training pairs from a variety of sources like Reddit, Wiki, Stack Exchange, etc.

Results

Analyzing the similarity of the summary of the papers which had a similar category and date to the query "Deep Learning Optimization" around the date of "11/13/17", the top 100 papers with the highest similarity scores were taken. This produced the below heat map of the similarity of a paper compared to another paper.

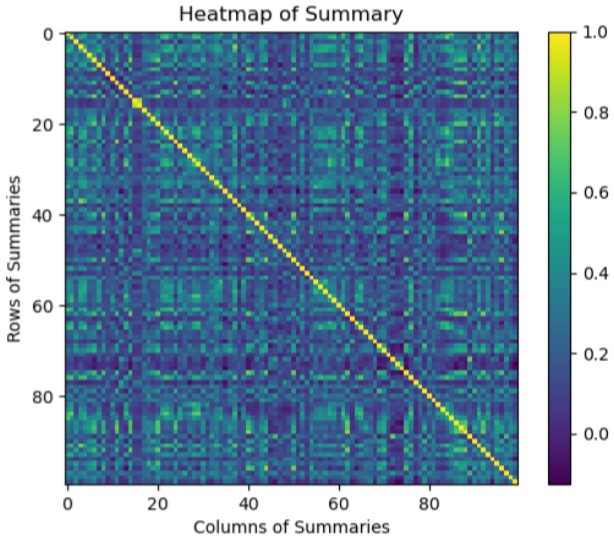


Figure 2: Heat Map of Top 100 Summary Similarities

Looking at the heat map above it can be seen that most of the values are darker being below 0.5, while some which are above 0.5 are scatter throughout. This shows that even the top 100 papers most similar in category and date published on average have a similarity score close to 0, showing even in the same category and time, the summaries are not too similar in wording.

0.2.1 Least Similar

The least similar of the top 100 papers with highest category and dates are as shown below. The two articles "Beyond RGB: Very High Resolution Urban Remote Sensing With Multi-modal Deep Networks" and "Haploid-Diploid Evolution: Nature's Memetic Algorithm" had the lowest similarity score of the top 100 papers which had the highest combined similarity score for category and date. These two had a summary similarity score of around -0.1261 which is very low considering that the score is from 1 to -1 and -1 suggests complete opposite direction for the two vectors. These two papers had the had category of "Neural and Evolutionary Computing" and a published date about 2 years apart. This would make sense why they were chosen to be in the top 100 of the most similar of those 2 categories as they would have received a 1 for category and a somewhat high score for published date.

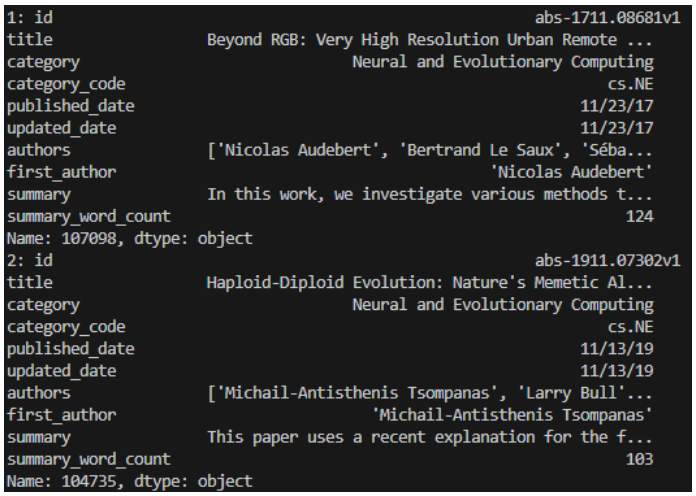


Figure 3: Least Similar Papers

0.2.2 Most Similar

The most similar of the top 100 papers with the highest combined similarity score for category and date was "Recurrent Neural Networks Hardware Implementation on FPGA" and "E-PUR: An Energy-Efficient Processing Unit for Recurrent Neural Networks". These two were part of the same category, "Neural and Evolutionary Computing" and were published about 2 years off from one another, which makes sense as they were chosen as the top 100 for the combined score of those two columns. The similarity score of the summary of the 2 papers was 0.8253, which is very high for 2 papers even if they are of the same category and subject since they are about 2 different things in this subject. This could have been brought about by a number of reasons but the most probable being that they are both about Recurrent Neural Networks and their hardware implementation. Since they are about the same architecture type and also about its hardware implementation it could be that the vocabulary used is very similar using words like "RNN", "efficient", "hardware", "performance", etc. This could most definitely increase the similarity of the 2 quite a lot, especially if you consider the filler words and connecting words around those key words which would most likely be the same or similar.

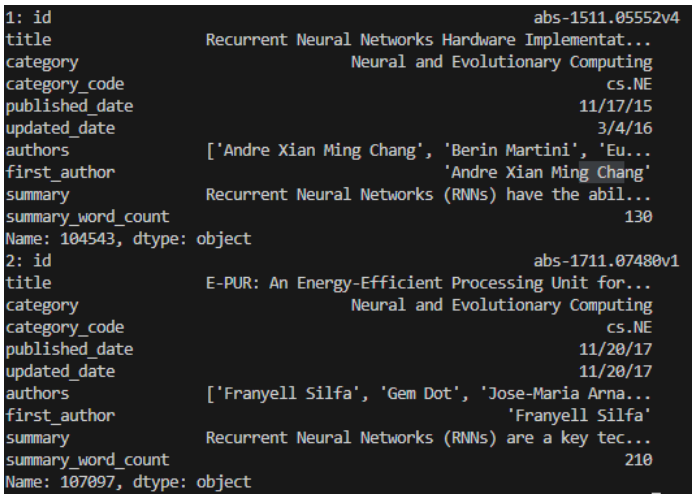


Figure 4: Most Similar Papers

Conclusion

The results given above are just a small subset of the dataset but generalizing the results it can be stated that for the majority of cases of papers and publications their summary's similarity is not very high with most of them being under -0.1 even when specifying into their corresponding category or date in time. This shows that even if there are thousands or even hundreds of thousands of papers published and made, there hasn't been any case of a converging structure or wording and that most papers are distinguishably dissimilar. Of the small number of papers which do possess a summary that is similar to one another, this only occurs when they are writing about the same niche in the same category as well as a niche use case for that niche in that category. This does not happen often but when it does, understandably the wording is very similar as naming conventions as well as measures, performance vocabulary, and connecting vocabulary can become very similar resulting in two papers with mathematically similar wording yet in concept very different.

As a final thought, there have been many research and articles pointing out the increasing use of AI, namely LLMs during the creation of papers after the introduction of high-perfomant language models like GPT. Utilizing the tools made for this project a simple analysis of the average similarity of the top 100 papers for the category "Deep Learning Optimization" during each of the 33 years, this results in the graph below. As can be seen over the 33 years the average similarity score has steadily increased going from a low of 0.19 to a high of around 0.26, increasing about 0.07 over 33 years. This shows an increase in the similarity of papers over 33 years, but at the same time, as it was shown above, the number of papers published each year was more than exponentially higher early on compared to recent years. This could have affected the increase in the average similarity of the papers over the years, as more papers allowed people to read and be inspired more by other papers subconsciously leading them to word things similarly. This could also be due to some average vocabulary used in each era being different and with the progressing of time people in recent years having a smaller vocabulary which they utilize making it seem like they are more similar, but in reality they are using a similar percentage of that person's total vocabulary. Again, all of these are speculation and cannot be proven at this point, further investigation as well as a more in-depth analysis and perhaps a model to compute better similarities could result in an answer to one or all of these questions.

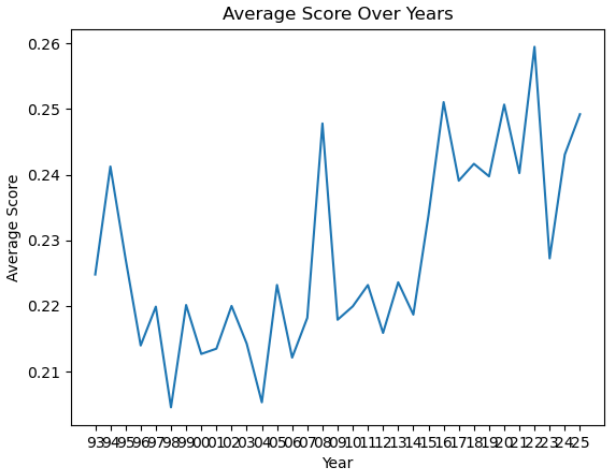


Figure 5: Average Similarity Score Over Years

0.3 References

a. Pretrained Sentence Transformer,
link: https://www.sbert.net/docs/sentence_transformer/pretrained_models.html