Natural Language Processing CS-2385-1
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Assignment 2

Questions

1. What are the two real-world problems that the papers address? What are the similarities and differences between the two problems?
2. The methods applied for solving the problems. This section should include a comparative study on the similarities and differences of the methods.
3. Results - Key findings of each paper. How were the results evaluated?
4. Discussion and Extension - if you were given a chance to conduct similar research - what would be your problem statements? Why do you think the problem proposed by you is important? What would be the data that you would use for the research? How would you go about gathering the data?

Question 1

Real-World Problems Addressed

Paper 1: Quantifying 60 Years of Gender Bias in Biomedical Research with Word Embeddings (Rios, Joshi, and Shin)

- Problem: This paper addresses the issue of gender bias in biomedical research, focusing on how such bias can lead to disparities in health outcomes between genders. It highlights the historical preference for male subjects in research studies, leading to underrepresentation and inadequate investigation of health conditions affecting women, particularly older women and those from low-income backgrounds.
- Specific Focus: Temporal changes in gender bias in biomedical research articles are examined to understand how gender differences are reflected in medical studies over time and how these biases affect the representation of medical conditions associated with each gender.

Paper 2: School, Studying, and Smarts: Gender Stereotypes and Education Across 80 Years of American Print Media, 1930-2009 (Boutyline, Arseniev-Koehler, and Cornell)

- Problem: This study explores the evolution of education-related gender stereotypes in American print media over nearly 80 years. It investigates how stereotypes have shifted as women's educational attainment levels surpassed men's and examines the interplay between cultural perceptions of gender and educational roles.
- Specific Focus: The research tracks six specific stereotypes linked to academic outcomes, analyzing how these stereotypes have changed in response to societal shifts in gender roles within the educational sphere

Similarities and Differences

Similarities:

- Gender Bias and Stereotypes: Both papers tackle issues related to gender bias and stereotypes, focusing on how these biases and stereotypes manifest in significant societal domains: biomedical research and education.

- Temporal Analysis: Each study employs a longitudinal approach, analyzing changes in gender bias and stereotypes over several decades. This temporal aspect allows for an examination of trends and shifts in societal attitudes towards gender roles.
- Use of Computational Linguistics: Both research efforts utilize word embeddings—a form of computational linguistics—to analyze large corpora of text for implicit biases and associations related to gender.

Differences:	Paper 1 (Rios, Joshi, and Shin)	Paper 2 (Boutyline, Arseniev-Koehler, and Cornell)
Domain of Focus	Examines biomedical research to uncover biases in how health conditions are studied and reported in relation to gender.	Explores cultural stereotypes about gender and education, looking at societal perceptions and their impact on educational attitudes and achievements.
Nature of Bias	Concerned with gender bias in the context of scientific research and its implications for health disparities.	Explores cultural stereotypes about gender and education, looking at societal perceptions and their impact on educational attitudes and achievements.
Objective and Impact	Objective is to highlight and analyze the persistence of gender bias in biomedical literature, with a direct impact on healthcare practices and guidelines.	Aims to understand the evolution of educational stereotypes in media, which has broader implications for gender equality in educational attainment and perceptions of intelligence and capability.

Question 2

Paper 1: School, Studying, and Smarts: Gender Stereotypes and Education Across 80 Years of American Print Media, 1930-2009 (Boutyline, Arseniev-Koehler, and Cornell)
Paper 2: Quantifying 60 Years of Gender Bias in Biomedical Research with Word Embeddings (Rios, Joshi, and Shin)

When looking at both methodologies, various distinct approaches and objectives are revealed. Both methods focus on understanding a very similar problem - change in gender bias, albeit their objectives are slightly different. Below, we detail their similarities and differences across various aspects.

Firstly, let's analyze the data used to create deductions:

1) Paper 1 has used the Corpus of Historical American English which is a broad collection of texts from various domains over time, including books, articles, and online content, to capture general language use and societal changes in gender perceptions.

2) Paper 2 uses a more specialized dataset in the form of PubMed-indexed titles and abstracts from a specific range of years. This focus ensures that the analysis is deeply rooted in the context of medical literature and its unique linguistic characteristics.

This can be seen as the first major difference in application.

Methodology

Both methodologies reflect the adaptability of language models like Word2Vec in investigating linguistic trends and biases, yet they are tailored to suit distinct research objectives and contexts, this can be seen as follows.

Similarities

The primary similarity between the two papers is the use of the Word2Vec model. Both methodologies leverage this embedding model to analyze semantic relationships and biases within large text corpuses.Additionally, Both approaches are also concerned with identifying and quantifying biases—whether they are related to gender stereotypes in broader society or biases within the specialized domain of medical literature. The methodologies utilize computational techniques to systematically assess the presence and magnitude of these biases.

Differences

Although both approaches concern identifying and quantifying biases, the way they do it is very different.

In the first paper, The authors adapt Word2Vec to measure gender stereotypes by creating a "gender axis" in the vector space. This process aims to capture the linguistic context of femininity and masculinity. Following this, The relative gender association of specific terms is assessed by projecting their vectors onto the gender axis. This projection quantifies the extent to which terms are used in contexts that are more feminine or masculine, based on their proximity to either axes. Lastly, The authors detail their analytical strategy, including the use of bootstrapping to estimate model parameters across different time slices of the COHA dataset. The usage of bootstrapping and bagging is explained as means to enhance the vector's reliability.

In contrast, the second paper uses vector embedding to quantify gender biases in BioMedical literature. This method includes optimizing the Skip-Gram model's hyperparameters for each decade and then applying three distinct techniques to measure bias: the Word Embedding Association Test (WEAT), the Embedding Coherence Test (ECT), and the Relational Inner Product Association (RIPA), allowing for comparison of biases in different dimension.

The first paper creates a "gender axis" in the vector space to measure the association of terms with femininity or masculinity. This approach is somewhat direct, relying on the projection of term vectors onto this axis to quantify gender associations. The second paper optimizes Skip-Gram model hyperparameters for each decade and employs three distinct techniques (WEAT, ECT, RIPA) to measure bias. This multi-faceted approach allows for a more nuanced and comprehensive analysis of biases, considering different dimensions and relationships.

Additionally, the first paper uses techniques like bootstrapping and bagging as a strategy to enhance the reliability of vectors, focusing on statistical robustness and variability across second paper's use of three different techniques (WEAT, ECT, RIPA) suggests a diversified analytical strategy aimed at capturing various aspects of bias.

Question 3

Results - Key Findings and Evaluation

Paper 1 (Rios, Joshi, and Shin)

Key Findings:

- Traditional Gender Stereotypes: The study found variable bias scores across different stereotypes. Notably, there was a steady decrease in bias for Career vs Family, Science vs Art, and Strong vs Weak stereotypes over the decades. However, Math vs Art bias remained relatively static, and the 1990s and 2000s saw a substantial jump in the bias for Intelligence vs Appearance.
- Occupational and Mental Health Bias: The ECT results showed that better embedding quality correlated with lower bias. Occupational words showed a significant decrease in bias from the 1960s to the 1990s, while mental health-related words showed little change in bias over the decades.
- Biased Words Analysis: The RIPA analysis revealed significant changes in the bias of occupational-related words over time but little change in mental health-related words' bias. Notably, occupations associated with power tended to be male-biased, while disorders related to addictions were male-biased, and disorders related to appearance and emotions were female-biased.

Evaluation Methods:
The results were evaluated using a combination of methods designed to measure bias and embedding quality:

- UMLS-sim Dataset: Used to report the quality of each decade's embeddings, providing a direct measure of how well embeddings capture semantic similarity between words.
- WEAT (Word Embedding Association Test): Applied to understand traditional gender stereotypes' temporal bias by comparing the similarity of male and female words to target concept pairs.
- ECT (Embedding Coherence Test): Used to evaluate the bias in occupational and mental health-related words by measuring the coherence between gender words and a single set of target words.
- RIPA (Relational Inner Product Association): Employed to identify the most biased words for each gender in each decade, offering insight into how specific words' biases have evolved over time

Paper 2 (Boutyline, Arseniev-Koehler, and Cornell)

Key Findings:
- The study found significant shifts in the gender associations of terms related to schooling, intelligence, and academic behaviors over six decades.
- Schooling and related terms (like "classroom" and "student") became increasingly associated with femininity from the 1940s to the 2000s.
- Socio-behavioral skills maintained a consistent feminine association, while problem behaviors remained consistently masculine.
- The terms related to intelligence shifted from being slightly feminine or neutral to significantly masculine, mirroring changes in societal perceptions of intelligence.
- Unintelligence showed a transition from a feminine to a masculine association, indicating changing stereotypes about academic capabilities.
- The term “genius” was seen as the 146th most masculine word, more masculine than words like football and brother.

Evaluation Methods:
The research utilized a corpus-based textual analysis, examining the gender associations of specific terms in academic and educational contexts over time.
- The analysis was based on the frequency and context of words in a large corpus of written materials, including books, articles, and educational materials, spanning six decades.
- Statistical techniques, such as standardized projections and trend analysis, were used to quantify the gender associations of words and track their evolution over time.
- The study also compared the shifts in gender associations with historical changes in educational attainment and societal attitudes towards gender and intelligence.

Question 4

Given the opportunity to do similar research I would like to dig deeper into the political landscape and look into the shift of political ideologies across time and most importantly see how the advent of media has affected politics.

Problem statement - Analyzing the Impact of Digital Media on Political Discourse and Legislative Priorities: A Comparative Study

Importance of the problem

The advent of digital media has significantly altered the landscape of political communication, enabling politicians and political parties to engage directly with the electorate, bypassing traditional media channels. This direct connection has the potential to cause disruptive influence in legislative priorities for politicians and political discourse. Understanding this shift can be crucial in gaining an insight into modern politics and understanding how new age politicians approach important public matters and create voter expectations.

Data Requirements

1) Legislative Documents and Speeches - The most important part of data collection will be to get a comprehensive dataset of literature from the pre-digital era such as legislative texts, political speeches and government publishings.

2) Digital Media documents - Transcripts and data of digital media platforms commonly used by political parties and politicians, including social media engagement statistics, digital campaign strategies, newspaper transcripts and online media discourse.

3) Public Opinion data - To benchmark this data with the related outcomes, well require Surveys and polls reflecting public opinion on legislative priorities and political issues, spanning the pre-digital and post-digital eras.

Data Gathering

1) Historical and Contemporary Legislative Documents: Access archives of legislative bodies for historical documents and use official websites for contemporary records. This may involve collaboration with governmental archives and libraries.

2) Digital Media Analysis: Use API access or web scraping techniques to collect data from major social media platforms, focusing on accounts associated with political parties, politicians, and key political influencers.

3) Public Opinion Archives: Collaborate with research organizations, universities, and news outlets to access historical and contemporary public opinion data.