Methods On The Effects of Sexism in Academic Literature

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Abstract

Over 10.8 million workers in the U.S. are involved in STEM occupations yet merely 27% are filled by women.

Despite the increasing demand for workers, the issue remains that women are far less likely to enter a career in STEM compared to their male counterparts.

In this study, we explored the underlying influences on gender inequality by processing textual analysis of academic literature.

Introduction

- Textbooks provide a comprehensive understanding of a branch of study, which allows for future independent development.
- Foundational influences may establish long-lasting effects that **differ** between men and women:
  - Self-identification,
  - Social ideology,
  - Cultural ideology
- 1960's Feminist Movement led to non-sexist guidelines for publishers.
- **Objective:** Use text-mining and sentiment analysis to evaluate emotional bias of textbooks with respect to gender pronouns.

Methodology

Project Overview

Pre-process Dataset → Create Bigrams → TidyText Analysis → Sentiment Analysis → ANOVA Test

Fig. 1: Flowchart of Summarized Steps

Step 1: Data Pre-processing

- 30 open-source literature:
  - 20 textbooks and 10 articles from journals
  - Natural sciences: Mathematics, Physics, Biology
  - Social Sciences: Humanities, History, and Business

Step 2: Create Bigrams

- Tokenized text into bigrams (consecutive pairs of words)
- pronoun + word = 'tidy data'
  - Example: She cries or He smiles

Step 3: TidyText Analysis

- Pronoun and Proper Noun frequencies were calculated:
  - Masculine: He, Him, His, Himself, Top 30 Names
  - Feminine: She, Her, Hers, Herself, Tops 30 Names
- Frequency = $\frac{occurence}{total}$

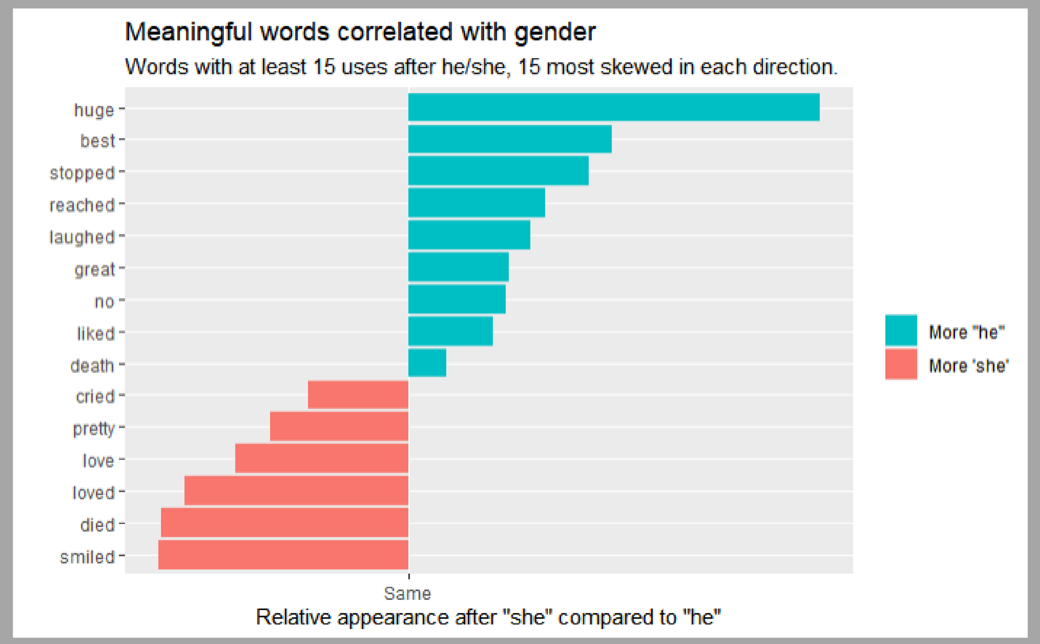

Fig. 2: Skewed Words Based on Frequency

Step 4: Sentiment Analysis

- AFINN lexicon was used to extract sentiment from each word
  - Integer rating between -5 and +5
- Evaluation Metric:
  - Sentiment Severity = *sentiment score* × *frequency*

Step 5: ANOVA Test

- Dependent variable:
  - Sentiment Severity (numeric)
- Independent variables:
  - Gender: M or F (2 levels)
  - Post-1960: T or F (2 levels)
  - Hard vs. Soft: H or S (2 levels)

Alpha level (significance level) – 0.05

Positive Words

Variable	F-Value	P-Value
Gender	0.3085	0.5787
Post1960	0.1159	0.7336
Hard vs. Soft	0.1926	0.6609

Fig. 3: Results of ANOVA on Positive Words

Negative Words

Variable	F-Value	P-value
Gender	0.1850	0.66720
Post1960	0.4008	0.52685
Hard vs. Soft	2.8854	0.08979

Fig. 4: Results of ANOVA on Negative Words

- Accepted Null Hypothesis: There is no interaction between the variables.

Step 6: Top 20 Most Contributing Words

- Same verbs and adjectives
- Similar levels of sentiment severity

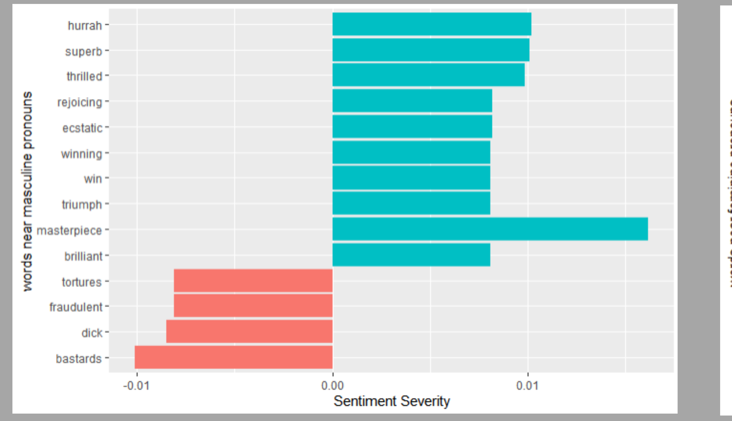

Fig. 5: Male Characterization

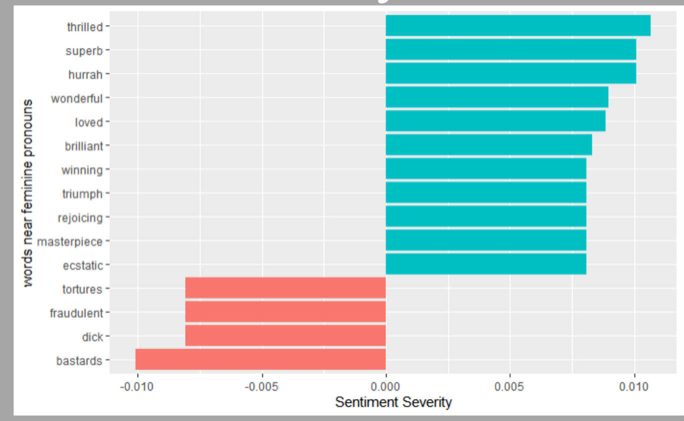

Fig. 6: Female Characterization

Positive Words: Thrilled, Ecstatic, Triumph, Win

Negative Words: Tortures, Fraudulent, Bastards

Results

- No statistical influence of variables on sentiment severity of words.
  - But there are skews in the usage of some words (in accordance with previous research on Fairy-tales).
  - More "masculine"
    - Best
    - Great
  - More "feminine"
    - Pretty
    - Cried
- Skewed words are not statistically influential.

Conclusion

Results demonstrate that academic subject nor publication year has an influence on sentiment severity of gender-associated words. However, gender characterization may be differentiated in another dataset.

Future Works

- Obtain unbiased dataset
- Account for visuals (computer vision application)

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