Investigating bias in Agatha Christie's Detective Novels: relationship between Social Classes and Case Identity

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Abstract: This study delves into character analysis and bias detection in Agatha Christie's detective novels, focusing on the portrayal of social classes and case identities. By quantitatively analyzing the sentiment associated with characters across different social classes, we aim to uncover biases or stereotypes in Christie's narratives. Our methodology involves conducting sentiment analysis on the text associated with characters from various social classes, examining the adjectives and other parts of speech used to describe these characters, and exploring the relationship between social class and involvement in criminal activity. Specifically, we analyze the frequency and context of positive and negative sentiments, as well as the proportion of victims and offenders within different social groups, to reveal patterns and differences in characterization. This study provides insights into the portrayal of social classes in Christie's work, shedding light on the social attitudes and perceptions expressed in her detective novels.

Keywords: *bias, sentiment orientation, Agatha Christie, social classes*

Introduction

Agatha Christie, one of the most well-known crime fiction authors, has written numerous works throughout her lifetime, creating a vast array of characters. As Lidia Kyzlinková (1997) noted, being a well-bred upper-class lady herself, Christie often set her stories in the refined settings of upper-class society, such as tea parlours and country estates. This background raises the question of whether there is inherent bias in the way Christie portrayed characters from different social classes in her novels. This study aims to investigate potential biases in Christie's depiction of social classes and case identities within her detective novels, with a specific focus on the Hercule Poirot series, her most famous detective creation.

Our research leverages sentiment analysis to quantitatively assess the portrayal of characters across different social classes in Christie's works. By examining the adjectives and other parts of speech used to describe these characters, we seek to uncover patterns and biases that may exist in her narrative. We utilize the Semantic Orientation Calculator (SO-CAL) as developed by Taboada et al. (2011) to determine whether characters are portrayed positively or negatively. Additionally, we analyze the rate of offenders and victims among different social classes to further explore potential biases.

Related Work

Sentiment analysis is a crucial tool for understanding subjectivity and opinion in text, often capturing evaluative factors such as positivity, negativity, and the strength of these sentiments (Osgood et al. 1957). There are three primary methods for analyzing sentiment information: lexicon-based, machine learning, and hybrid approaches (Wankhade et al. 2022) .

Lexicon-based methods, such as SO-CAL (Taboada et al. 2011), SentiWordNet (Baccianella et al. 2010), and Semantic Orientation from Association (SO-A) (Turney & Littman 2003), rely on predefined dictionaries that assign sentiment scores to words. SO-CAL, for example, calculates sentiment polarity based on a comprehensive lexicon of adjectives, adverbs, nouns, and verbs. This method is advantageous for its interpretability and ease of use in identifying sentiment trends in text (Taboada et al. 2011).

Machine learning approaches, like those described by Socher et al. (2013), utilize complex models such as recursive deep learning to analyze sentiment. These models leverage syntactic information to provide a more nuanced understanding of sentiment at the phrase or sentence level. Techniques such as recursive deep models parse sentences to predict sentiment dynamically, benefiting from their ability to manage linguistic subtleties like irony and negation, though they require substantial data and computational power.

A hybrid approach combines machine learning and lexicon-based techniques for sentiment analysis, leveraging the strengths of both methods. This hybrid technique is extremely popular, with sentiment lexicons playing a significant role in the majority of systems. For instance, Hassonah et al. (2020) proposed a hybrid machine learning approach using SVM and two feature selection techniques: the multi-verse optimizer and the Relief algorithm (Chang et al. 2020). Similarly, Al Amrani et al. (2018) proposed a machine learning-based hybrid approach combining RF and SVM, demonstrating that the hybrid model had an accuracy close to 84%, outperforming the individual models. (Wankhade et al. 2022)

Character analysis, another critical aspect of our study, involves examining the linguistic features used to describe characters. Salim and Saad (2016) explored the use of adjectives in the Harry Potter series to understand how these descriptors contribute to the portrayal of protagonists. Their work highlights the importance of adjectives in character depiction, suggesting that further analysis of verbs and adverbs can provide deeper insights.

A significant challenge in sentiment analysis is accurately interpreting negation, modifiers, and irony. Negation can shift the polarity of a sentiment, making it difficult to assess the true sentiment of a statement. For instance, litotes involves conveying a mild positive by negating a negative item (e.g., "not bad") or a mild negative by negating a positive item (e.g., "not my best day"). This downtones the overall effect of the evaluation, whether positive or negative (Taboada 2016). Similarly, modifiers can amplify or diminish the sentiment strength, complicating the analysis. Irony adds another layer of complexity, as it often involves stating the opposite of what is meant, making it hard to detect without contextual understanding (Taboada 2016). These limitations highlight the intricacies involved in accurately measuring sentiment in literary texts, and currently, there is no effective method to fully account for these phenomena.

Our study builds on these existing literatures by applying sentiment analysis to the text of Christie's novels, focusing specifically on the Hercule Poirot series. By quantitatively analyzing the portrayal of social classes and case identities, we aim to provide a comprehensive understanding of potential biases in Christie's narrative and contribute to the broader discourse on social representation in literature.

Methodology

We focus on a quantitative analysis approach in this paper. We randomly select samples from Agatha Christie's Hercule Poirot series and conduct sentiment analysis on the text of each character. Sentiment computing tools are used to quantify the sentiment tendency of each character, and chi-square tests are employed to analyze the distribution of sentiment across social classes. This approach allows us to systematically evaluate the performance of sentiment in text and its differences across social classes.

We use Spacy to process the text and identify named entities tagged as "PERSON", collect all unique role names and initialize a dictionary with the key being the role name and the value being a list of sentences. We iterate over the sentences in the document and add the sentences containing the role name to the corresponding list. Then we write each character's sentences into a separate text file. These sentences are collected into a dictionary where the key is the character name and the value is the corresponding sentence list. Finally, each character's sentences are compiled into separate text files. The Stanford CoreNLP tool is used for text processing, including word segmentation and part-of-speech tagging, to ensure data integrity and accuracy.

During the data analysis phase, we use the Semantic Orientation Calculator (SO-CAL) (Taboada et al. 2011) to perform sentiment analysis. The SO-CAL method involves loading multiple dictionaries, including adjectives, adverbs, nouns, verbs, and intensifiers, to calculate sentiment polarity. The input text is split into word and label pairs, and an initial weight is assigned to each word. The program calculates the sentiment polarity of nouns, verbs, adjectives, and adverbs, adjusts the sentiment value of each word through dictionary lookup, stem extraction, negation, and intensifier detection, and finally calculates the overall sentiment score (SO) of the text. The results are written to a specified output file, including detailed sentiment calculation steps for each word and sentence.

We mark documents based on their sentiment scores, with scores greater than 0 marked as positive (1) and scores less than 0 marked as negative (0). And we classify the class of the sample based on the classification criteria of Max Weber in his book *Economy and Society (1978)*.

He proposed three types of class basis:

1. Property class: gaining advantages through monopoly capital, wealth accumulation, educational privileges, etc. It also includes landowners, industrial equipment owners, landless people, debtors, etc.
2. Business class: mainly entrepreneurs, bankers, etc., emphasizing the influence on business management and economic policies. It also includes skilled, semi-skilled and unskilled workers, such as doctors, lawyers, etc.
3. Social class: working class, including skilled workers and white-collar employees. There are also small business owners, technicians, civil servants, etc.

Our study collectively refers to these three categories as Upper class (Property class), Middle class (Commercial class) and Lower class (Social class).

The examples are as follows:

Filename	Score	Sentiment	Label	Class
33_William Boyd.txt	0.033164983	positive	1	Upper

Filename	Score	Sentiment	Label	Class
21_Alec Legge.txt	-0.7	negative	0	Middle

Filename	Score	Sentiment	Label	Class
33_Stephen Norton.txt	-0.625	negative	0	Lower

Figure 1 Marked documents based on their sentiment scores

Finally, chi-square tests are used to analyze the distribution of positive and negative sentiment labels across social classes, calculating chi-square values and p-values to determine differences in sentiment distribution. The null hypothesis is that the distribution of positive and negative sentiments is the same across different social classes. In other words, the distribution of positive and negative labels is independent of the social class, indicating no significant differences in their distribution.

Dataset

In this study, we randomly select 12 novels from Agatha Christie's Hercule Poirot series to provide a broad representation of Christie's work and include a diverse set of characters from various social classes. The criteria for selecting characters are based on their importance and frequency in the narrative. We identify the ten characters with the most sentences in each book to ensure the representativeness and diversity of the sample, resulting in a total of 120-character samples.

The text of each novel is processed to identify and isolate sentences related to the main characters. These sentences are compiled into separate text files for each character, ensuring sufficient contextual information for subsequent sentiment analysis. This comprehensive dataset allows us to perform detailed and representative sentiment analysis across different social classes in Christie's novels.

Results

This section presents the results of the sentiment analysis conducted on characters from Agatha Christie's Hercule Poirot series, focusing on the emotional language associated with different social classes. Utilizing the SO-CAL method for sentiment analysis and chi-square tests for statistical significance, we uncover notable patterns in the portrayal of characters from the upper, middle, and lower social classes.

1. Sentiment Distribution Across Social Classes

The distribution of positive and negative sentiments across social classes is visualized in the chart titled "Distribution of Positive and Negative Emotions in Different Social Classes" (Figure 2). The chart indicates clear differences in how characters from various social strata are depicted:

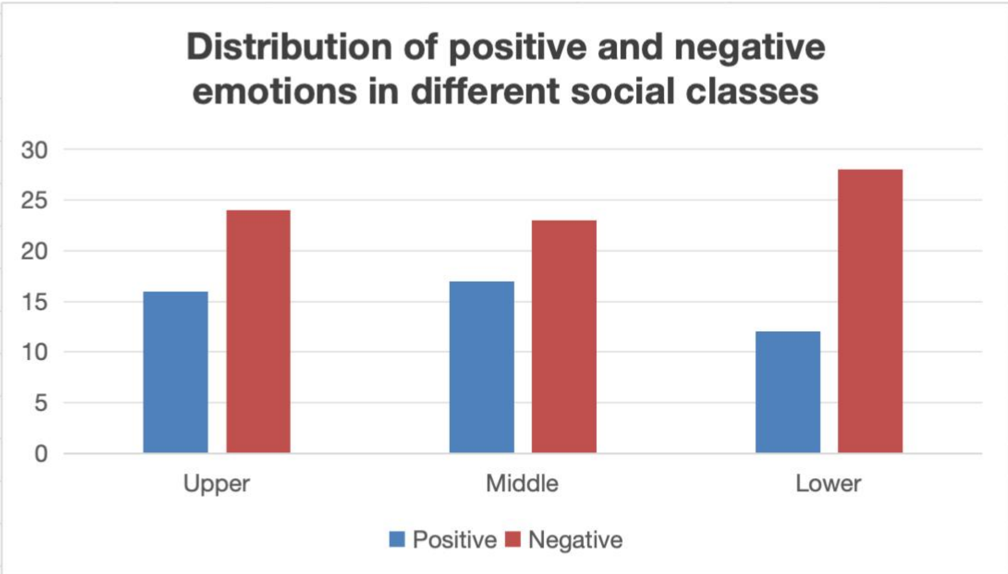

Figure 2 Distribution of Positive and Negative Emotions in Different Social Classes

1) Upper Class

The upper class is characterized by a higher frequency of negative sentiments compared to positive ones. This is reflected in the sentiment scores, which show a preponderance of negative descriptors. For instance, the character Rosalie Tamplin from the book The Mystery of the Blue Train has an overall sentiment score of -2.133, the lowest among the 120 characters analyzed. Significant negative contributions come from words such as "very faint," "uncomfortable," and "afraid."

Conversely, the character with the highest sentiment score also comes from the upper class. Margaret Ravenscroft from Elephants Can Remember has a score of 1.500. Despite the use of the word "dead," the sentence "But his affection shifted to the other sister, Margaret, whom he married" contributes 6 points to her overall sentiment score, making her the most positively depicted character.

Additionally, the character with the third highest sentiment score belongs to the upper class as well. Ariadne Oliver, also from Elephants Can Remember, has a score of 1.100. Positive words such as "friends," "warmth," "satisfaction," and "pleasure" outweigh negative words like "doubt," "danger," and "trouble," resulting in her high overall sentiment score.

2) Middle Class

Characters from the middle class exhibit a more balanced sentiment distribution, with a slight inclination towards positive sentiments. For example, Colonel Beck from The Clocks has the second lowest sentiment score of -1.933, due to negative words like "spectacles," "murder," and "refrained."

The second most positively depicted character belongs to the middle class. Dr. Willoughby from Elephants Can Remember has a sentiment score of 1.133. Despite receiving negative scores of -3.600 from the phrase "refuse absolutely" and -2.600 from the sentence containing this phrase, the positive score of 6 from "Good Heavens!" and the word "accept" contributing 1 point, make his overall sentiment score positive.

3) Lower Class

The lower class is predominantly depicted with negative sentiments. Characters such as Janet White have markedly negative sentiment scores, reflecting a less favorable portrayal. Janet White's sentiment score of -1.875, the third lowest overall, is indicative of the negative language used, with descriptors like "strangled" and "die."

The highest sentiment score among the lower class ranks fourth overall in the sentiment scores of the 120 characters. Eileen O'Brien from the book Sad Cypress has a score of 0.909. Although the average sentiment score of adjectives is 1.333, the presence of two neutral sentences out of five lowers the overall score to 0.909.

2. Statistical Analysis of Sentiment Distribution

To statistically assess the differences in sentiment distribution across social classes, Pearson's chi-squared test was conducted. The chi-squared test results, shown in Figure 3, indicate no significant differences in the distribution of positive and negative sentiments across social classes (X-squared = 1.4933, df = 2, p-value = 0.4739).

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        Pearson's Chi-squared test

data:  table_df
X-squared = 1.4933, df = 2, p-value = 0.4739
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Figure 3 Chi-square test result

Given that the p-value is greater than the significance level of 0.05, we fail to reject the null hypothesis. This suggests that there is no sufficient evidence to conclude that the distribution of positive and negative sentiments significantly differs across the upper, middle, and lower classes.

The observed frequency table (Figure 4) further supports this finding:

	0	1
Lower	28	12
Middle	23	17
Upper	24	16

Figure 4 Frequency table

These results indicate that the proportions of positive and negative sentiments are relatively similar across the different social classes, despite the differences in sentiment scores noted in the qualitative analysis.

3. Implications and Interpretation

The findings from the qualitative study suggest that Agatha Christie's portrayal of characters in the Hercule Poirot series is influenced by societal biases and stereotypes. Characters from the upper and lower social classes are more likely to be depicted with negative sentiments, whereas middle-class characters receive a more balanced portrayal.

However, the statistical analysis indicates that these differences are not significant enough to conclusively prove a bias in the distribution of sentiments across social classes.

The chi-squared test results further substantiate these observations, revealing no statistically significant differences in sentiment distribution across social classes. This analysis underscores the complexity of examining literary texts through the lens of sentiment analysis and highlights the need for a nuanced interpretation of the results.

Limitation of This Study

While this study provides valuable insights into the portrayal of social classes in Agatha Christie's Hercule Poirot series, several limitations should be noted. One significant limitation is the incomplete extraction of sentences related to each character. Due to the complex narrative structure and dialogue-heavy text typical of Christie's novels, not all sentences associated with a character were identified and analyzed, potentially leading to an underrepresentation of the full sentiment spectrum and biasing the results. Moreover, the sentiment analysis primarily focuses on individual words and phrases without fully accounting for the broader narrative context, which can significantly influence characters' sentiments through their development over a novel, interactions with other characters, and specific situations they encounter.

Additionally, the sample size, while broad in the context of selecting 12 novels and 120 characters, remains relatively small compared to Christie's extensive body of work. This limited sample may not fully capture the diversity of Christie's character portrayals and could affect the generalizability of the findings. Future studies could benefit from a more contextual approach to sentiment analysis and a larger, more comprehensive dataset to enhance the robustness of the results.

Another challenge in this study is the accurate interpretation of irony, negation, and modifiers in sentiment analysis. Sentences intended to be ironic may not be detected as such, leading to a misinterpretation where the literal meaning of the words is taken as the intended sentiment. Current sentiment analysis tools, including SO-CAL, often struggle with these nuances, potentially resulting in incorrect sentiment assessment of the text.

While the study analyzes various parts of speech, including adjectives, verbs, and adverbs, the emphasis on adjectives may lead to an overemphasis on certain types of sentiment expressions. Characters' actions and dialogue often carry substantial emotional weight, which may not be fully captured by focusing primarily on descriptive words.

Finally, classifying characters into distinct social classes based on textual evidence can be subjective and may not always reflect the complexities of social hierarchies in Christie's time. Some characters may exhibit traits or behaviors that straddle multiple social classes, complicating their classification and potentially influencing the analysis outcomes.

Conclusion

This study utilized a quantitative approach to conduct sentiment analysis of characters in Agatha Christie's novels, specifically focusing on the Hercule Poirot series. By randomly selecting a sample of characters and systematically processing the text, we extracted and analyzed the emotional tendencies associated with characters from different social classes. Employing the SO-CAL method for sentiment calculation and chi-square tests, we were able to quantify the distribution of positive and negative sentiments across various social classes.

Our qualitative findings reveal that characters from the upper and lower social classes are more frequently depicted with negative sentiments compared to middle-class characters, who exhibit a more balanced sentiment distribution. However, statistical analysis indicates that these differences are not significant enough to conclusively prove a bias in the sentiment distribution across social classes.

Despite providing valuable insights into the social attitudes and perceptions embedded in Christie's work, this study is not without limitations. Incomplete sentence extraction, a relatively small sample size, and challenges in accurately interpreting irony and complex linguistic phenomena such as negation and modifiers highlight the intricacies involved in sentiment analysis of literary texts. Additionally, the emphasis on adjectives and descriptors, and the subjective classification of social classes, further underscore the need for a more nuanced and comprehensive approach.

Future research should aim to address these limitations by employing more advanced text analysis techniques, expanding the dataset to include a broader range of Christie's work, and incorporating a deeper contextual understanding of the linguistic and social complexities within the narratives. By doing so, we can gain a more robust and nuanced understanding of the social and emotional dynamics in Agatha Christie's novels and further explore the potential biases in her portrayal of different social classes.

In summary, the differences observed in the sentiment distribution among different social classes in Agatha Christie’s novels are not significant enough to conclusively establish a bias. However, given the limitations of this study, future research should consider using a larger sample size and more effective methods for extracting character-related sentences to further investigate potential biases in her works.

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