

Retraction

Retracted: Research on Characterization and Shaping of Chinese Heroic Characters in Online Media Based on Deep Neural Network Evaluation

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their

agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Z. Wang and J. Huang, "Research on Characterization and Shaping of Chinese Heroic Characters in Online Media Based on Deep Neural Network Evaluation," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 5485284, 12 pages, 2022.

Research Article

Research on Characterization and Shaping of Chinese Heroic Characters in Online Media Based on Deep Neural Network Evaluation

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Shaping the image of heroic characters is an important task of melodramatic films and TV dramas, whether they are revolutionary heroes, combat heroes, leader heroes, or civilian heroes, which have always been the key objects of melodramatic films and TV dramas. However, the traditional melodramatic films and TV dramas are facing many bottlenecks in the acceptance of heroic characters in the new era. In this paper, in order to obtain a richer character text, we divide the denotation elimination into two parts; one is the denotation elimination without considering the zero pronoun phenomenon, which is mainly done by the existing end-to-end neural codenotation algorithm, and the other is the attention-based algorithm model for the zero pronoun phenomenon. Analyzing this result from the perspective of the algorithmic model, it can be speculated that the lexical vector has a superior performance in the overall predicted character score, indicating that in the Big Five personality analysis for characters, the character's personality is more reflected in lexicality, and the scores on a person's Big Five personality dimensions can be indirectly reflected by the frequency of using different lexicalities. The similarities and differences among heroes are explored to create a popular hero image.

1. Introduction

Since ancient times, people's understanding of heroes is the image of those who sacrifice their lives for the country and have a heroic character. There is no doubt that the creation of melodramatic films and TV dramas coincides with the construction of the heroic character image [1]. But in the changing social values, moral rationality, and viewing needs, the old plot and story structure of traditional melodramas can no longer meet the appetite of the audience, the audience's taste for life; identity makes the traditional melodramas slowly fade from the screen in the market saturation and declining innovation. The "new melodramas" no longer show the public with the image of "fake, big, empty, tall, and righteous" characters, and the values and moral values brought about by the changing times have deeply

affected the contemporary view of heroes and also deeply affected the contemporary understanding of heroic characters [2, 3]. What is a hero in modern society? How to shape the heroes that the public likes to see? It is a question that contemporary media communicators need to think about.

The ego represents rationality; it feels external influences, satisfies instinctive requirements, and acts according to the "principle of reality" [4]. The superego represents the moral code of society, suppresses instinctive impulses, and operates according to the "principle of the best," which is developed from a part of the ego and represents the morality and conscience of the personality structure. A healthy personality is the harmonious unity of the ego, the ego and the superego. Most of the heroic characters in melodramas are characters with strong superego personalities [5]. Li Yunlong in "Bright Sword" has the disregard for life and

death of killing the enemy, the liver and guts of narrow-mindedness, and the bravado of grandeur, although he has the rustic character of a streamer and even the cunning of a businessman, but the mainstream character traits invariably account for the main line of multiple personalities [6]. In the name of the people, Li Dakang has the boldness to handle political affairs, the conscientiousness to work, and the struggle against bad practices, although he has a “small mind” in his political career and is extremely meticulous in his behavior, but the “label” type of purification will obscure his character [7]. The “flattening” of the character’s personality will obscure the diversity of his character. The “flattening” of character is not a characteristic needed by the spirit of the times, and too much of the character’s essence will lose the soul of the character, which is against the contemporary aesthetic interest and the contemporary character scale [8].

Marx raised the issue of “Shakespeareanization” in a letter to Raphael Lassalle in 1859, and Engels also envisioned the future of literature: “the depth of thought and the content of conscious thought, with the vividness and richness of the plots of Shakespeare’s plays. A perfect fusion of the vividness and richness of the plot of Shakespeare’s plays.” The so-called Shakespeareanization, specifically, is to draw on Shakespeare’s attitude toward reality and history, to use the realist method of creation, and to reveal our heroes organically with a rich and vivid plot and distinctive and prominent characters the heroic spirit, while romanticism will draw the characters into a more fleshed out, contradictory, and thus more touching broad future.

Shaping noble and heroic characters is the eternal theme of melodramas, but how to define and express the sublime is another topic that melodramas must pay attention to. Longinius believes that the sublime has two most essential elements: “The first and most important is a solemn and great thought, and the second is a strong and excited emotion.” Kant, in his Critique of Judgment, argues that the sublime is emotional. But both also believe that this emotion must be rooted in rational virtue; that is, only strong emotion based on rational virtue can lead to the sublime arising. It can be seen that the sublime of heroic characters is a combination of sensibility and rationality but also based on reason [9]. The “new melodrama” is to promote the main theme of the socialist era as the main theme of the film and television works, to undertake the important task of promoting the core values of socialism [10]. Deng Xiaoping once said, “Everything that promotes truth, goodness and beauty is a melodious film.” President Xi emphasized that to do a good job of ideological work in the new era, we should “carry forward the main melody and spread positive energy” [11]. How to effectively convey the core socialist values and shape the image of heroic characters that audiences recognize and love is the top priority for the creation of melodramatic films and dramas in the new era. Both “Bright Sword” and “In the Name of the People” are created and appreciated according to the “law of beauty,” which is in line with the important viewpoint of Marxist aesthetics [12]. At the same time, this law of beauty is combined with the requirements of the spirit of our times to form the aesthetic law of the

times, so that the melodramatic film and television dramas can achieve the proper aesthetic goals and missionary purposes [13].

2. Related Work

Through reviewing a large amount of information, I found that there are still many studies on the image of public figures, among which there are more studies on the social responsibility of public figures, privacy, relationship with the media, image design, and so on. However, there are few studies on the communication of public figures’ images in the political field [14]. In [15], we studied the process of virtual online communities on the formation of public figures’ images, in which we used the phenomenon of “spiral of silence” of audience theory, “opinion leaders,” and “secondary communication” of virtual community communication. The phenomenon of “spiral of silence” using audience theory, “opinion leaders,” and “secondary communication” through virtual communities is useful for this paper to study the communication of public figures in the new media environment. [16] analyzes the current situation of public figure image communication from the perspectives of communicator, media, audience, and information, which is very enlightening for this paper to study the relationship between public figures and information. [17] mentions personal branding and the great role it plays in practice, which is the same as this paper uses Peng Liyuan as an example to study the unique role played by public figures in specific occasions. [18] examines in detail the construction and communication of the public image of political public figures in the era of media politics. [19] specifically explains how influential public figures should portray themselves to the public and how they should operate in the information-rich, universal media era. In [20], the book explains in detail the role of the media in shaping people, companies, and events and shows how the media plays a role in shaping public figures, what communication principles are applied, and what issues public figures should pay attention to and deal with in the process of communicating and shaping their images through new media.

3. Design of Character Analysis Algorithm

In this subsection, the conception and construction of the whole algorithm model is completed first, and then, the algorithm is elaborated specifically according to the algorithms involved in each section.

In the task of character analysis of novel texts, the importance of characters in novels is first analyzed. Characters in novels can be mainly divided into core key characters and nonkey characters according to their importance, and the algorithm model of this thesis mainly takes key characters as an example for training and prediction of character analysis algorithms, and the main reasons for choosing to use key characters rather than nonkey characters are as follows.

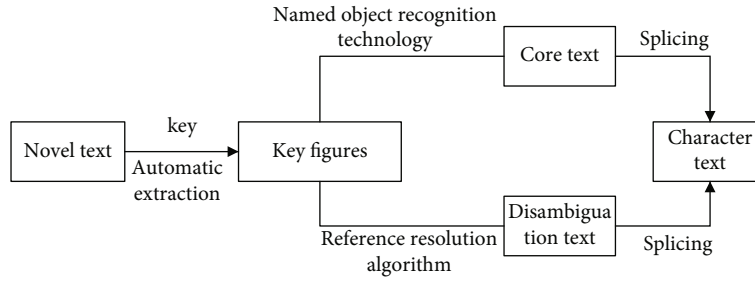


FIGURE 1: Flow chart of key person text automatic extraction algorithm.

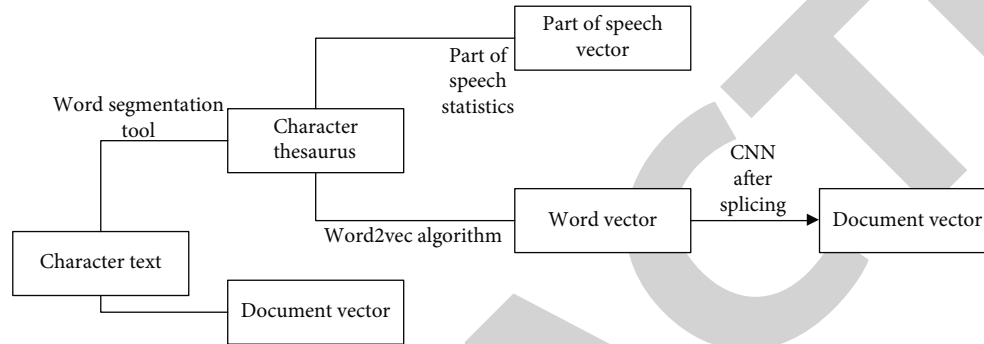


FIGURE 2: Flow chart of character text feature engineering algorithm.

- The number of core key character texts in the novel is large, and more character data output can be obtained when making predictions compared to nonkey characters, which is conducive to analyzing the five character scores of characters, while the number of texts of nonkey characters is small and the character scores are unstable
- In the literary creation of novels, nonkey characters are less portrayed in ink, character representation is not obvious, and there are fewer literary reviews, so it is difficult to obtain the character evaluation of the corresponding characters to verify the accuracy of the character scores output by the algorithm model

Third, from the analysis of the Big Five personality theory, the sentence-based Big Five personality scale has 240 self-assessments to obtain the Big Five personality score of characters and nonkey characters who do not meet the criteria of this scale to fully obtain their complete five-dimensional personality scores.

There are three main aspects that can be used as a basis for determining which key characters are described in a novel text. For example, in Lu Xun's "The Hometown," although the character of Leuntu is not in the text, the main character of the whole article is Leuntu, and other characters are just clues, because for the main character, he or she is bound to appear many times in many scenes in the article and has more or less connection with many characters; finally, we can look up information through references to explore the writer. Finally, we can explore the creative intent of the writer through reference search, so as to extract the

key characters precisely. The flow chart of the algorithm for the automatic acquisition of key characters in novels is shown in Figure 1.

After obtaining the relevant text of the core characters, the text is subjected to feature engineering operations, including document vectorization and lexical vector acquisition, and the flow chart of the algorithm is shown in Figure 2.

With the above algorithm flow, the Doc2vec document vector, Word2vec+CNN document vector, and lexical vector of the character text can be obtained.

4. Extraction of Text Related to Main Characters

When a text contains multiple characters, there are often descriptions of multiple characters by the author, and there are also descriptions of multiple characters among each other, etc. Therefore, in the text preprocessing session, it is necessary to use character-related text extraction techniques to complete the step of extracting the relevant description statements of the main characters studied.

In this paper, in order to obtain a richer character text, the denotational disambiguation is divided into two parts; one is the denotational disambiguation without considering the zero pronoun phenomenon, which is mainly done by using the existing end-to-end neural denotational disambiguation algorithm, and the other is an attention-based algorithmic model mainly for the zero pronoun phenomenon.

The end-to-end neural denotational disambiguation algorithm mainly adopts an unsupervised learning approach,

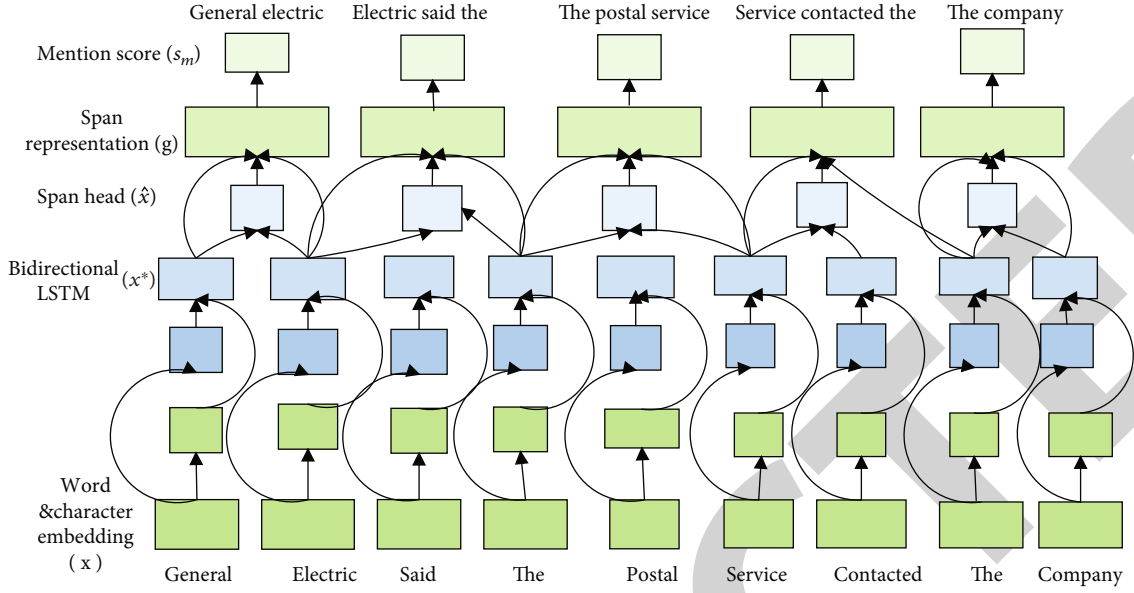


FIGURE 3: Overall algorithm model diagram.

formulating the task as a decision on all possible cases in a document, where the cases are written as spans, and if a document D contains T words, then the number of spans, that is, the number of possible phrases, is $T(T+1)/2$. The start (i) and end (j) are used to denote the number of spans in D , respectively (i) at the beginning and end of the index, the text to start (i) to number each span, for the same start (i) of the span (i), with end (j) to number. At this point, the task becomes for each span (i) to specify a prior y , and the set of possible values of y is $\{e, 1, \dots, i-1\}$, that is, a virtual prior and all previous spans, assuming that the real prior of span (i) is $\text{span}(j) (1 \leq j \leq i-1)$, which means that there is a co-indexed chain between i and j . The virtual prior means that there may be two cases; one is that the span is not an entity mention, and the other is that the span is an entity mention. The kind is that span is an entity mention but it does not have coreference with any of the preceding spans.

The goal of the model is to learn a conditional probability distribution P that is most likely to yield the correct equivalence class, as shown in

$$f(y_1, \dots, y_N | D) = \prod_{i=1}^N P(y_i | D) = \prod_{i=1}^N \frac{\exp(s(i, y_i))}{\sum_{y' \in Y(i)} \exp(s(i, y'))}, \quad (1)$$

where $s(i, j)$ is pairwise score of the coreference chain between span (i) and span (j) in D . It is generally determined by three factors: (1) whether span (i) is a mention, (2) whether span (j) is a mention, and (3) whether j is a prior of i , as shown in

$$s(i, j) = \begin{cases} 0, & j = \varepsilon, \\ s_m(i) + s_m(j) + s_a(i, j), & j \neq \varepsilon. \end{cases} \quad (2)$$

Here, $s_m(i)$ is the score of span (i) becoming a mention and $s_a(i, j)$ represents the pairwise score of span (j) becoming a prior of span (i).

The overall model diagram of the algorithm is shown in Figure 3.

Specifically, the first step is to calculate the vector representation of each span and use it to score each potential mention by slicing the encoded information into a set of sentence groups, constructing a deep learning model for each sentence independently, and inputting the feature matrix into a deep learning model, such as LSTM and CNN, to obtain the word vector representation for each of the words in the text composed of sentences. The word vector representation of each word in the text composed of sentences is obtained. For each span, the vector representation of span is obtained by combining each word in it, and then, the vector of span is mapped nonlinearly to obtain the score of each potential mention, and the mention is pruned by the size of the score to obtain a certain number of mentions, as shown in Figure 4.

The second step is to calculate the prior scores for each pair of span's vector representations. The final coreference score of a pair of spans is obtained by summing the mentioned score of two spans and their paired prior scores.

For the training process, since the prior is a hidden variable, the optimization objective consists of the marginal log-likelihood function of all correct prior generated by the standard equivalence class, as shown in

$$\log \prod_{i=1}^N \sum_{y \in Y(i) \cap \text{GOLD}(i)} P(y), \quad (3)$$

where $\text{GOLD}(i)$ is the set of all spans in the standard equivalence class including span (i), and if span (i) does not belong to the GOLD cluster or all its GOLD priors are

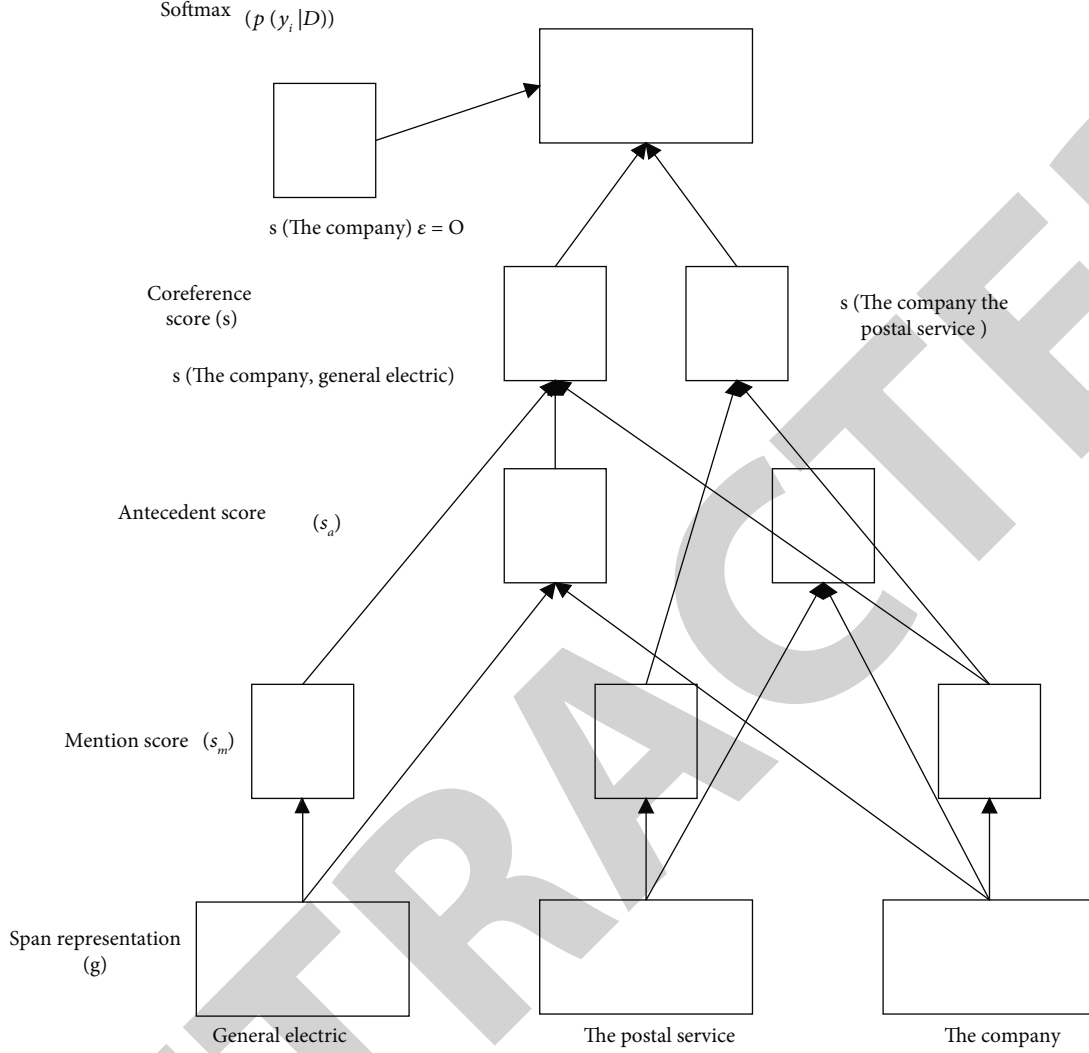


FIGURE 4: Diagram of the algorithm model for mention scoring.

cropped out. $GOLD(i) = \{e\}$. This objective function can be optimized using SGD, Adam, and other methods.

The above is the algorithmic idea of end-to-end neural coreference elimination used in this paper, and the following presents the algorithmic idea of the model based on attention mechanism used to solve the zero-reference phenomenon. For the modeling of candidate antecedents, a generalized attention model can be used so that it can automatically obtain the important components of the phrases. The traditional zero-reference approach is mainly divided into two steps: the identification of the disambiguity of zero-reference and the disambiguation of zero-reference, and here, the main focus is on the second task, as shown in Figure 5 in the specific flowchart.

In this paper, the self-attentive mechanism is used to model the contextual information of zero pronouns, and two recurrent neural networks are used to model the above and below of zero pronouns, respectively, and then, these vectors are used to model the self-attentive mechanism. For a zero pronoun, its corresponding contextual information is modeled as a sequential word embedding using RNN, as shown in

$$\begin{aligned}
 \text{Context}_{\text{precedding}} &= (w_1, w_2, \dots, w_{zp-1}), \\
 \text{Context}_{\text{following}} &= (w_{zp+1}, w_{zp+2}, \dots, w_n), \\
 h_t^{\text{pre}} &= \text{RNN}_{\text{pre}}(w_t, h_{t-1}^{\text{pre}}), \\
 h_t^{\text{fol}} &= \text{RNN}_{\text{fol}}(w_t, h_{t-1}^{\text{fol}}).
 \end{aligned} \tag{4}$$

Then, all the hidden layer information of the two separate RNNs is retained, as shown in

$$\begin{aligned}
 H_{\text{pre}} &= \{h_1^{\text{pre}}, h_2^{\text{pre}}, \dots, h_{\text{pre}}^{\text{pre}}\}, \\
 H_{\text{fol}} &= \{h_1^{\text{fol}}, h_2^{\text{fol}}, \dots, h_{\text{fol}}^{\text{fol}}\}.
 \end{aligned} \tag{5}$$

The self-attention mechanism is then used to compute a linear representation of the sum, using the sum as input, and outputting the attention matrix. After having the representation of zero pronouns, attention is computed for each word of a candidate prior using that representation as shown in

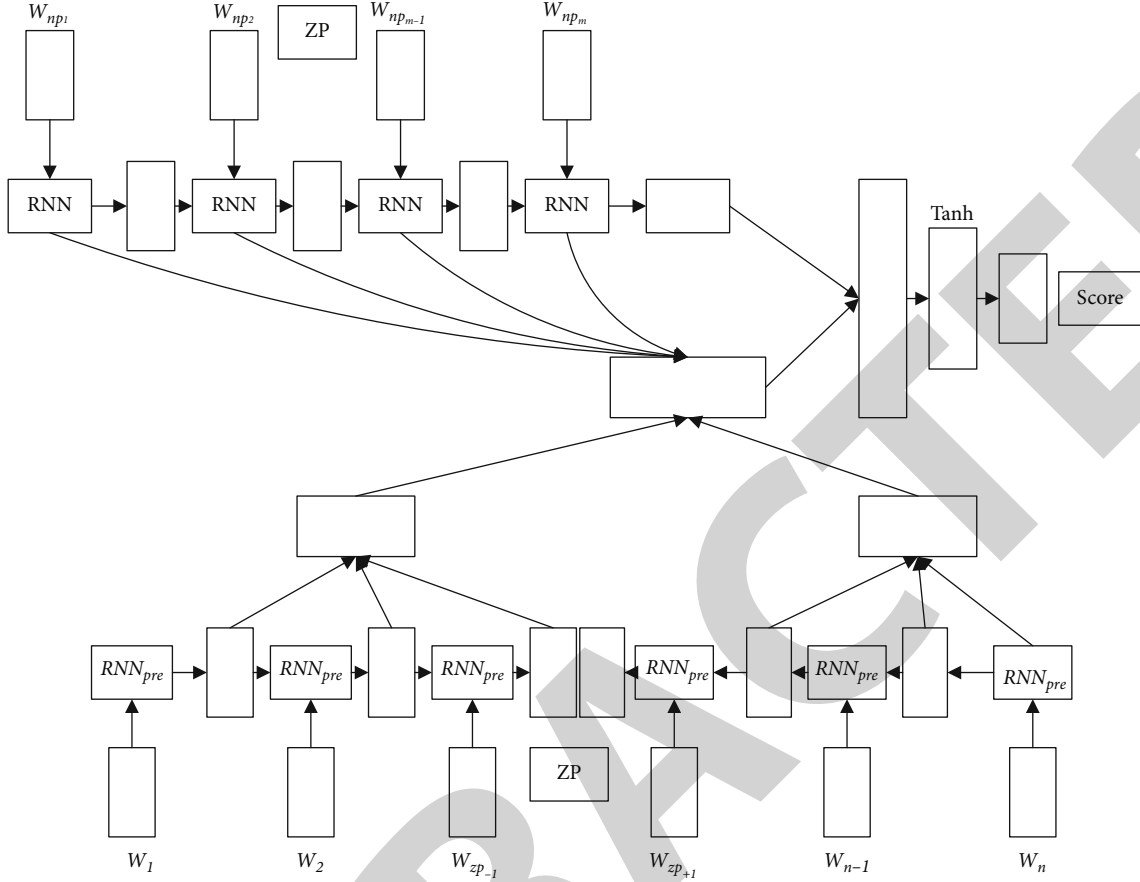


FIGURE 5: Model diagram of zero pronoun disambiguation algorithm.

$$s_t = \tanh \left(W^{(\text{att})} \cdot \left[e_t ; h_t^{(\text{np})} ; v^{(\text{zp})} \right] + b^{(\text{att})} \right), \quad (6)$$

$$\text{attention}_t = \frac{\exp(s_t)}{\sum_{t^*=1}^m \exp(s_{t^*})}.$$

After that, a weighted average is used to obtain the representation of the candidate prior, as shown in

$$\tilde{v}_{np} = \sum_{i=1}^m h_i^{(\text{np})} * \text{attention}_t. \quad (7)$$

By modeling the zero pronoun and the candidate prior, their representations are obtained here and denoted, respectively. The score of the disambiguation probability is then calculated by a feedforward neural network as shown in

$$s_j = \tanh \left(W_i^{(s)} \cdot s_{j-1} + b_j^{(s)} \right), \quad (8)$$

$$\text{score}_i = W^{(\text{sco})} \cdot s_{-1} + b^{(\text{sco})}.$$

Finally, a candidate prior with the highest probability is selected as the final result of the experiment.

5. Character Analysis Algorithm Prediction

In this subsection, the algorithm prediction is performed mainly using the personality analysis algorithm model trained in the previous subsection for a single dimension and the personality analysis algorithm model for five dimensions. The samples of the test set are selected mainly from two key characters, Tian Runye and Tian Xiaoxia, which also have the characteristics of large amount of sample data and distinctive personality [21, 22].

5.1. Model Prediction for a Single Personality Dimension. In this subsection, the model prediction of a single personality dimension will be conducted for each of the five personality dimensions in the Big Five. Since the overall idea of predicting each of the five personality dimensions is roughly the same, only differing in the numerical labeling, in this session, the overall prediction idea and result presentation are mainly elaborated using extroversion as a representative.

By using the prediction vectors trained by the five models for the extroversion dimension to predict Tian Runye with higher extroversion characteristics and Tian Xiaoxia with lower extroversion characteristics, according to the analysis of the works, it can be seen that Tian Runye and Sun Shaoan have similar scores in extroversion, while Tian Xiaoxia has lower extroversion compared to Shaoan,

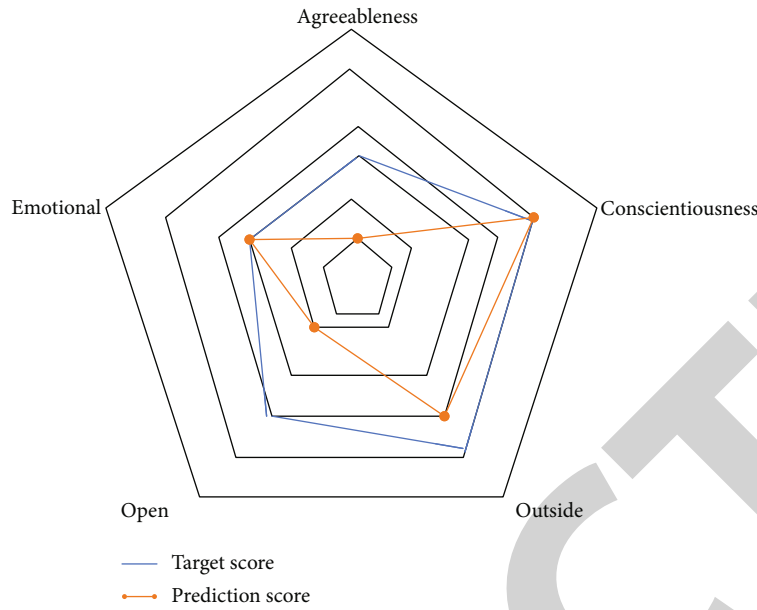


FIGURE 6: Comparison of prediction results of Tian Runye’s five personality dimensions-Doc2vec model.

so the extroversion score of Tian Runye is set to 95 and Tian Xiaoxia’s. The lower the RMSE, the more accurate the experimental results are, and the practicality of the algorithm is verified [23, 24].

(1) The output results of Doc2vec vectors are as follows

```
Tian Runye extroversion prediction score.
[ 84.37634435 84.44475251 84.50771158 8
4.55105547 83.35333941 83.82266533
84.83079264 85.06659382 84.79973825 8
4.38778243 85.11944887 84.83912866
```

The root mean square error was 10.282516.

```
Tian Xiaoxia’s extroversion prediction score.
[ 93.53856645 93.40279485 94.47830776 9
3.94026652 93.22148475 94.02033432
93.50247678 93.21516079 93.89203833 9
3.62953318 94.05450639 94.13169999
```

The root mean square error is 11.656244.

(2) Word2vec+CNN output results are as follows

```
Tian Runye extroversion prediction score.
[ 84.28172468 84.70457109 84.708115
84.67362891 84.40045191 84.40405639
85.71753076 84.63345581 84.96069185
84.50533099 85.12815465 84.88658313
```

The root mean square error was 10.289423.

```
Tian Xiaoxia’s predicted scores for extroversion.
[ 84.22324318 84.64945269 84.68575492
84.62021516 84.37303066 84.36238894
84.66459438 84.61013648 84.93252663 84.4
5972707 85.06710901 84.85060464
```

The root mean square error is 2.739378.

In the same way, the scores of predicted Tian Runye and Tian Xiaoxia for the lexical vector model, lexical vec-

tor+Doc2vec model, and lexical vector+Word2vec+CNN model and the root mean square error are obtained.

Similarly, openness, conscientiousness, agreeableness, and neuroticism were also predicted by the above ideas for Tian Runye and Tian Xiaoxia, respectively. Predictions of personality scores for the above four dimensions were conducted, and root mean square errors were obtained, which will be shown and analyzed for implications in the single personality dimension prediction results in this section [25, 26].

5.2. Model Prediction of the Big Five Personality Dimensions.

Based on the analysis of the works and the descriptions of the two main characters in the references, the scores of Tian Runye’s five personality dimensions of agreeableness, conscientiousness, extroversion, openness, and emotionality were set to 63, 96, 95, 74, and 64, and Tian Xiaoxia’s five personality dimensions of agreeableness, conscientiousness, extroversion, openness, and emotionality were set to 63, 96, 95, 74, and 64, and Tian Xiaoxia’s scores on the five personality dimensions of agreeableness, conscientiousness, extroversion, openness, and emotionality are set as 73, 66, 83, 94, and 61 to compare the effects of the prediction vectors and also to evaluate the generalization ability and to verify the practicality of the algorithm.

(1) The output of Doc2vec model is as follows

The personality radar plot of the five personality dimensions of Tian Runye combined with the target score and the predicted score is shown in Figure 6.

The personality radar plot of Tian Xiaoxia’s five personality dimensions combined with target scores and predicted scores is shown in Figure 7.

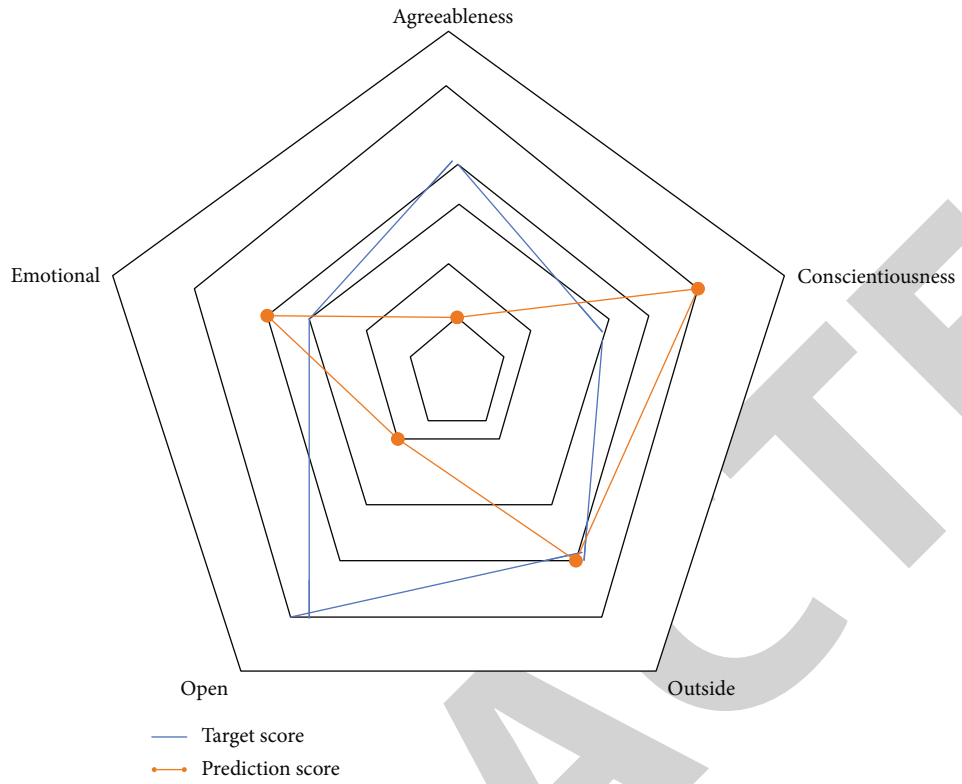


FIGURE 7: Comparison of prediction results of Tian Xiaoxia's five personality dimensions-Doc2vec model.

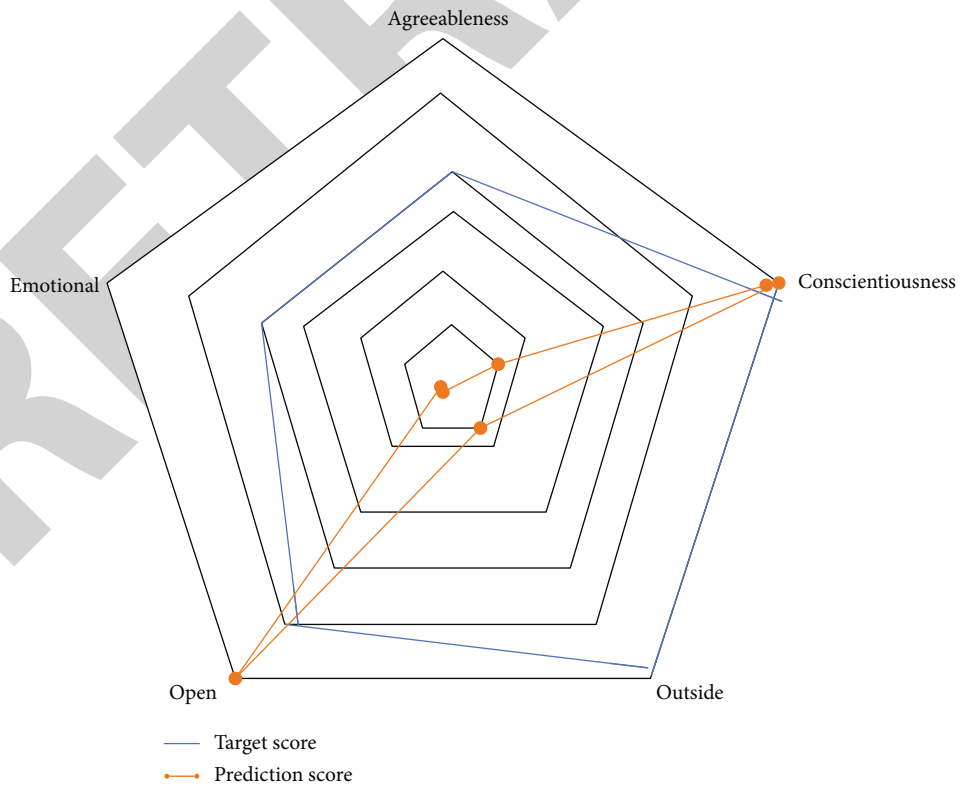


FIGURE 8: Comparison of prediction results of Tian Runye's five personality dimensions-Word2vec+CNN model.

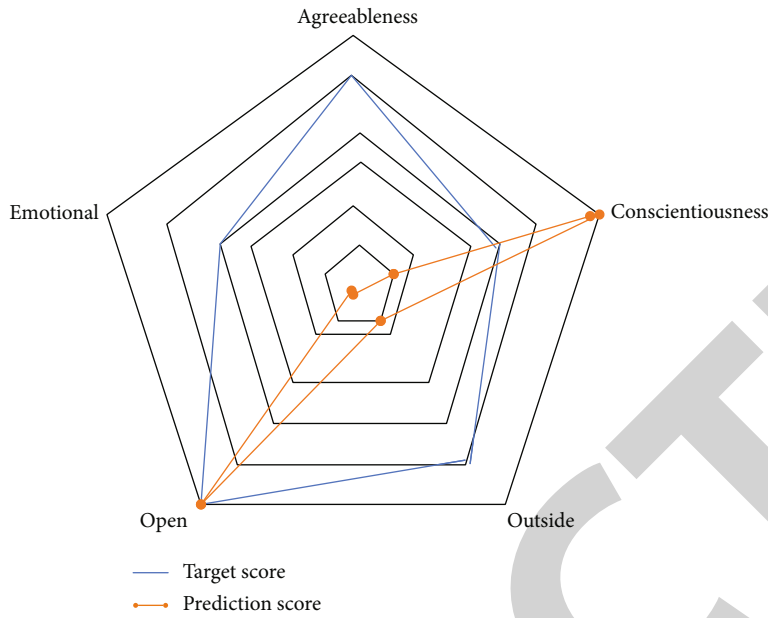


FIGURE 9: Comparison of prediction results of Tian Xiaoxia's five personality dimensions-Word2vec+CNN model.

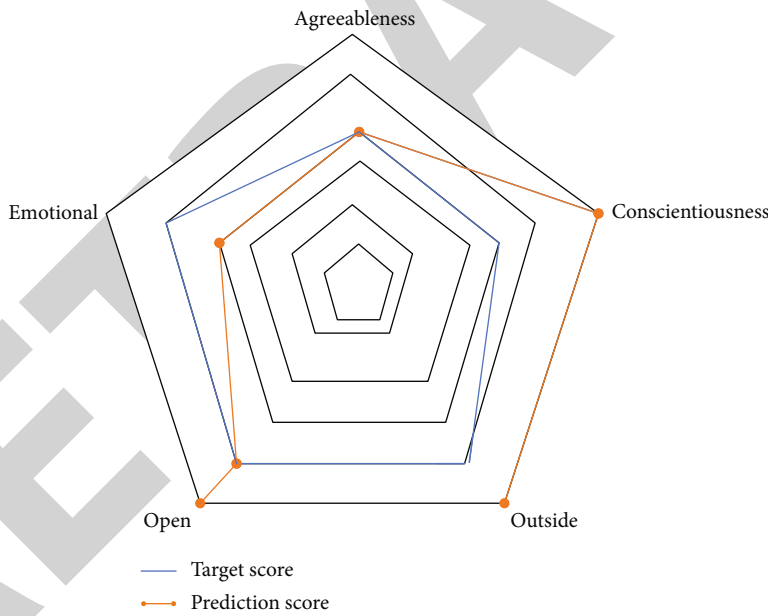


FIGURE 10: Tian Runye's five personality dimensions prediction results on lexical vector model.

(2) The output of the Word2vec+CNN model is as follows

The personality radar plot of Tian Runye's five major personality dimensions combined with the target score and predicted score is shown in Figure 8.

The personality radar plot of Tian Xiaoxia's five major personality dimensions combined with target scores and predicted scores is shown in Figure 9.

(3) The output results of the lexical vector model are as follows

The personality radar plot of Tian Runye's five major personality dimensions combined with the target score and the predicted score is shown in Figure 10.

5.3. Analysis of the Prediction Results of Single Personality Dimensions. Through the above experiments, it can be seen that in dimensions such as Big Five personality extraversion, Doc2vec and Word2vec+CNN, lexical vector, Doc2vec+lexical vector, and Word2vec+CNN+lexical vector can all train their respective feature vectors, and all of them can ensure

TABLE 1: List of root mean square errors of each model in predicting the scores of personality dimensions of agreeableness.

Character analysis algorithm model	Tian Runye root mean square error	Tian Xiaoxia root mean square error
Doc2vec	27.2899	14.3677
Word2vec+CNN	35.2691	6.3049
Part of speech vector	27.0193	13.9615
Doc2vec+part of speech vector	6.7839	14.3009
Word2vec+CNN+part of speech vector	35.3101	22.2625

TABLE 2: List of root mean square error of each model predicting due diligence personality dimension scores.

Character analysis algorithm model	Tian Runye root mean square error	Tian Xiaoxia root mean square error
Doc2vec	11.3128	1.7546
Word2vec+CNN	22.3398	6.6987
Part of speech vector	11.0308	2.1239
Doc2vec+part of speech vector	11.3023	1.8191
Word2vec+CNN+part of speech vector	6.3001	27.2927

TABLE 3: List of root mean square errors of each model predicting extraversion personality dimension scores.

Character analysis algorithm model	Tian Runye root mean square error	Tian Xiaoxia root mean square error
Doc2vec	10.2525	11.6545
Word2vec+CNN	10.2889	2.8312
Part of speech vector	10.0299	3.1059
Doc2vec+part of speech vector	1.4219	2.8112
Word2vec+CNN+part of speech vector	1.4179	11.7313

their experimental errors are small and guarantee the training data the ability to fit the training data and ensure a smaller bias.

Meanwhile, in the performance of the validation set delineated for the training set, it can be seen that the root mean square error of these models is relatively small, so for the unknown data on this training set, both models have good generalization ability and can predict the Big 5 personality scores of the characters on extraversion more accurately.

However, there is some variability in the performance of these five models in predicting the unknown data, as shown in Tables 1–5.

From the above table, it can be seen that when the five models trained were chosen to predict the five personality scores such as extraversion for two new characters, namely,

TABLE 4: List of root mean square error of each model predicting open personality dimension scores.

Character analysis algorithm model	Tian Runye root mean square error	Tian Xiaoxia root mean square error
Doc2vec	13.2998	0.7233
Word2vec+CNN	1.8289	14.7114
Part of speech vector	13.0291	0.5887
Doc2vec+part of speech vector	13.2888	0.7008
Word2vec+CNN+part of speech vector	1.8545	14.7772

TABLE 5: List of root mean square error of each model's predicted emotional personality dimension scores.

Character analysis algorithm model	Tian Runye root mean square error	Tian Xiaoxia root mean square error
Doc2vec	19.3114	19.2889
Word2vec+CNN	28.2779	15.3339
Part of speech vector	19.0239	5.9779
Doc2vec+part of speech vector	6.3914	6.3119
Word2vec+CNN+part of speech vector	28.2669	15.2428

Tian Runye and Tian Xiaoxia, the performance of the five models for agreeableness, dutifulness, and openness were not stable.

In terms of extraversion, Doc2vec, Word2vec+CNN and lexical vector were not good enough for prediction. Although Word2vec+CNN and lexical vectors have some prediction accuracy on Tian Xiaoxia's prediction score, the total error is higher compared to Doc2vec+lexical vector and Word2vec+CNN+lexical vector, and the error is higher in predicting Tian Runye with similar extraversion, which is not adopted. The error is around 1.4. In the prediction of Tian Xiaoxia with lower extraversion, the Doc2vec+lexical vector model outperforms the Word2vec+CNN+lexical vector model in predicting Tian Xiaoxia's character with lower extraversion, and the average score predicted by the Doc2vec+lexical vector model is 84.7261, while the average score predicted by the Word2vec+CNN+lexical vector model is 93.7016, which is better for the character Tian Xiaoxia. Her performance in the work has a lower extrapolation; obviously compared with Tian Xiaoxia, the score on extrapolation should be lower than hers, so the Doc2vec+lexical vector model performs better than the Word2vec+CNN+lexical vector model.

In terms of sentimentality, the Doc2vec+lexical vector model performs relatively well, with errors all around 6.3, which is within an acceptable and reasonable range, and the performance of the Doc2vec+lexical vector model is also relatively stable compared to other models for predicting sentimentality scores.

From the analysis of the algorithm structure, it can be speculated that the Doc2vec part of the Doc2vec+lexical

vector model directly uses text as input to obtain a document vector that is more generalizable, and no words are given higher attention, compared to the model trained by Word2vec+CNN+lexical vector in this training set and similar character scores on personality scores. The main reason is that the document vector stitched into the Word2vec obtained word vector which is more likely to highlight certain keywords after CNN processing, because CNN has the effect of highlighting local features, so when analyzing the unknown character personality, the model is easily influenced by the previous character training set, and it is difficult to achieve objective scoring [25–27].

6. Conclusion

In this paper, we analyze the results from the perspective of algorithmic model for the character of heroic characters in the media era, and we can speculate that the lexical vector has a better performance in the overall prediction of character score, indicating that in the Big Five personality analysis for characters, the character's personality is more reflected in lexicality, and the frequency of using different lexicalities can indirectly reflect a person's Big Five personality dimension on the score, and similarly, after using WOrd2veC+CNN with lexical vectors for splicing, the same effect of highlighting the importance of certain words can be achieved.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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