The Hidden Shape of Stories

Reveals Positivity Bias and Gender Bias

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Abstract: To capture the shape of stories is crucial for understanding the mind of human beings. In this research, we use word embeddings methods, a widely used tool in natural language processing and machine learning, in order to quantify and compare emotional arcs of stories over time. Based on trained Google News word2vec vectors and film scripts corpora (N =1109), we form the fundamental building blocks of story emotional trajectories. The results demonstrate that there exists only one universal pattern of story shapes in movies. Furthermore, there exists a positivity and gender bias in story narratives. More interestingly, the audience reveals a completely different preference from content producers.

Keywords: Story shape, story bias, story success, word embedding, emotional arc

Introduction

The communication power of stories to transfer information has been shown over time and thus seeking to better understand story narratives is very essential (Campbell, 2008; McKee, 1997). To be specific, in Kurt Vonnegut’s rejected master’s thesis, he defined the emotional arc of a story on the “beginning-end” and “ill fortune-great fortune” axes (1981, 1995). Inspired by this idea, Peter and his colleagues (2011, 2015, 2016, 2016) identified the emotions of the stories over time using sentiment analysis methods, and they found six core emotional arcs which form the essential building blocks of complex story trajectories. They also confirm that there is a positivity bias in human languages (Peter et al., 2014).

In this study, we employ word embeddings method to analyze the film scripts. First, we use two methods to validate our findings that there is only one main story trajectory, rather than six kinds of different story shapes. That is to say, there is a universal shape of stories which dominates the narrative of movies. Second, we extend our findings from the perspective of story bias in terms of
gender and emotion. Third, we offer a new insight to look upon the success of story in films by analyzing the ratings of the movies.

One of the most common approaches to computational social science is to develop predictive models. However, computational methods can not only be used for prediction, but also for explanation and understanding. In this research, we want to develop a narrative that helps us to understand qualitatively how cultural production reflects and shapes our social world.

**Methods**

**Data**

We have collected around more than one thousand ($N = 1109$) film Scripts from imsdb.com and relevant information, such as film genre (shown in figure 1) and user rating score. All of our codes are available publicly online and the data can be crawled from the website of imsdb (https://www.imsdb.com). Therefore, it is very convenient to reproduce our findings.

**Measures**

We apply the word embeddings as a quantitative lens through which to study emotional arcs. Word embedding is a powerful machine-learning framework that represents each word by a vector. The geometric relationship between these vectors can capture meaningful semantic relationships between corresponding words. Vectors being closer have been shown to correspond to more similar words (Collobert et al., 2011).

In this paper, we use Garg’s method (Garg et al., 2018) to demonstrate how temporal dynamics of the embeddings helps to quantify changes in emotional narratives of stories. The emotional arc construction includes three steps.

1. First, we choose several word lists to represent emotional arcs, one side fortune (‘success’, ‘succeed’, ‘lucky’, ‘fortunate’, ‘smile’, ‘happiness’) and the other side tragedy (‘failure’, ‘fail’, ‘unlucky’, ‘unfortunate’, ‘tear’, ‘sad’).
2. Second, we measure the average embedding distance that represents fortune and tragedy separately, using Google News word2vec vectors trained on the Google News dataset (Mikolov et al., 2013; Mikolov et al., 2013). If the average distance for fortunate side minus the average distance for unfortunate one is greater than 0, then the emotion is more positive.
3. Third, we average the stories into 10 (or 100, 200) parts based on word counts and repeat the step above on every part separately in order to get the temporal patterns of emotion.

After identifying the trajectory for each story, we regularize them with Z-score, namely, $z = (s' - s(\text{mean})) / s(\text{sd})$, where $s'$ is each story’s emotional time series, $s(\text{mean})$ and $s(\text{sd})$ are the mean and standard deviation of emotional trajectories for all considered stories. Figure 2 is an emotional arc visualization.
of cases based on embeddings and regularization. In figure 3, we show every regularized storyline.

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Insert Figure 2 and 3 here
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It is necessary to note that our approach behaves better in short text. For example, for the story of Cinderella, there is only a few hundred words, as it is shown in Figure 1, our approach has done a good job in identifying the fortunate/unfortunate hidden in the story.

Finally, we leverage the standard linear algebra technique Singular Value Decomposition (SVD) to find a decomposition of stories onto an orthogonal basis of emotional arcs. The SVD is \( A = U\Sigma V^T = WV^T \), where every row of \( A \) is the sentiment time series of each story. Here, we focus on the \( V \), which is the mode of stories. We combine \( \Sigma \) and \( V \) together as \( W \) to represents weighted mode coefficients.

**Findings**

**1. The shape of stories**

After sliding fixed size window through stories (smoothing) and differentiate between fortunate and tragic ending (classification), we can observe that the happy ending mode dominates in figure 4, nearly three times as much as the number of tragic ending.

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Insert Figure 4 here
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Using SVD method, we further validate our finding that the emotional arcs in the narrative of stories are dominated by one basic mode. Figure 5 and Table1 show the first mode (from fall to rise) is the most popular emotional trajectory.

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**2. The bias of stories**

As is shown in the figure 6 and 7, the average emotional trajectories for all considered films reveals story has a universal positivity bias in the ending, regardless of the film genre. Furthermore, comedy is the top three, next to drama and thriller. It indicates that the positive words are more diversely used for the description of the result.

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In terms of gender, we divide the trajectories into four categories, fortunate male films, tragic male films, fortunate female films and tragic female film. As is shown in figure 8A, the number of films with female protagonists is much less than those with male protagonists, regardless of the ending, which only accounts for 5.0% and 18.0% separately. For female films, the romance and family genres are more than the male films.

3. The success of stories
To examine how the emotional trajectory affects success, in figure 8B, we use the user rating score as the criteria for success. We find that while the number of films with female protagonists and tragic ending is the least, the user rating for this type is the highest. Shown in figure 9, the number of Sci-Fi, horror and family genres for the female tragic film is the most among four types. It is demonstrated the audience are more likely to speak highly of distinct films and produce aesthetic weariness to repeated things. Nowadays, the marketplace is producing more and more content, how to attract attention and avoid homogeneity deserves more thoughts and reflection.

Conclusion and Discussion
In all, the findings demonstrate that there exists only one universal pattern of story shapes in movies. And furthermore, there exists a positivity and gender bias in the movies’ story narratives. However, and more interestingly, the audience reveals a completely different preference from content producers. For example, the rating of female movies with tragedy endings is much larger than the other types even though this type has the least number. One possible explanation is to distinguish the movies into two kinds: the mass movies and the niche movies. The mass movie is written and cast for the majority of the society, while the niche ones are for the subgroups of the society. Though the story of the mass movies may be good, it is difficult to suit everyone's taste. That's why their ratings are not as high as the niche movies.

However, it does not mean that the niche movies can always do a good job. Just as Figure 8B has shown, the female movies with fortunate endings and the male movies with unfortunate movies are consistently low in both movie production and audience ratings. Actually, these two kinds of movies together represent almost half of the movies. And the ratings of these two kinds are the smallest, especially for the female movies with fortunate endings. Thus, our
findings may indicate that the gender bias still exits even in the mind of the audiences of the niche market.

We acknowledge that this present study is an on-going work of our research, and there are still many shortcomings. We will control more attributes of the movies in the future research, such as adding the box office income. And to test whether the so-called "the universal shape of stories" also exists in the other kinds of stories produced by human beings along the time, we will try the other kinds of narratives, such as the novels.
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Figure 1. The number of different film genres
Figure 2. Annotated emotional arc of Cinderella and Titanic story
Figure 3. Regularized emotional trajectories for 1109 stories
Figure 4. Two different endings for stories, red represents fortunate ending, green represents tragic ending.
Figure 5. First 6 SVD modes with closest stories to each
Figure 6. Average emotional trajectories for different genres
Figure 7. Average emotional trajectories over time, each shaded region is the standard error interval.
Figure 8. The comparison of four types of films for frequency distribution and user rating scores
Figure 9. Stacked bar graph of genres for four kinds of film