Explainable Movie Recommendation Systems by using Story-based Similarity

O-Joun Lee
Department of Computer Engineering,
Chung-Ang University
Dongjak-gu, Seoul, Republic of Korea
concerto34@cau.ac.kr

Jason J. Jung*
Department of Computer Engineering,
Chung-Ang University
Dongjak-gu, Seoul, Republic of Korea
j3ung@cau.ac.kr

ABSTRACT

The goal of this paper is to provide a story-based explanation for movie recommendation systems, achieved by a multi-aspect explanation and narrative analysis methods. We explain how and why particular movies are similar based on following two aspects: (i) composition of movie characters and (ii) interactions among the characters. These aspects correspond to story-based features of the movies that are extracted from character networks (i.e., social networks among the characters). By using the story-based features, we can explain the reason why two arbitrary movies are similar or not. We anticipate that the proposed method could improve the explainability of the recommender systems for movies.

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; J.5. Computer Applications: Arts and Humanities; I.2.4. Artificial Intelligence: Knowledge Representation Formalisms and Methods

Author Keywords

Explainable Recommender System; Movies; Character Network; Story Analysis; Computational Narrative.

INTRODUCTION

Various online services have been employing recommender module to provide users with the most relevant items. However, with only a list of recommended items, it is difficult for the users to understand why such items are selected. The users should spend additional resources (mostly time or money) for identifying whether the recommended items are really preferable. The problem becomes even worse for recommending narrative works (e.g., movies, TV series, novels, and so on). For example, we have experienced giving up watching TV series after a few episodes.

Hence, explaining the reason on the recommendation has been regarded as an important research issue. There have been various studies [7, 2] on building 'explainable' recommender systems.

*Corresponding author.

However, the previous studies could not identify what the users will gain or feel from the recommended items. Most of the studies only took into account the 'scrutability' for the recommended items. Moreover, content of the items were not considered.

For recommending the narrative works, in this work, we assume that the content of the items directly affect the users' preference. We focus on analyzing and exploiting the major characteristics of the content (such as drawing styles of comics or stories of movies).

We have conducted a simple user survey among 97 users of 'webtoon', which is a novel media distributing comics through the web. The survey simply consisted of one question, which allowed plural responses: "What are criteria that affect your preferences for webtoons?". Most of the users wrote two criteria: stories (98.96%) and drawing styles (97.93%); 96.90% of the users selected both the criteria. Also, we interviewed Lehzin Comics[1], which is one of the major webtoon publishers in Korea. For a question: "Why you do not use recommender engines for your platform?", they answered that users mostly consume webtoons within a few limited genres and drawing styles.

Based on the results, we have found out that the following patterns can be used for explaining the recommendations.

- stories contained in the narrative works
- how the stories are physically described.

The goal of this study is to improve the explainability of the recommender systems by using the similarity among the stories. Nevertheless, as an ongoing study, we limited our target domain into the movies. Also, using character networks (i.e., social networks among the characters), we preserved the expandability of the proposed method for other types of narrative works.

EXPLAINING STORY-BASED SIMILARITY

Expected results of the proposed method are similar to what Netflix[2] is already providing, as displayed in Fig. 1. Netflix recommends sets of movies or TV series with some reasons; e.g., "Because you watched Madam Secretary."

[1] https://www.lezhin.com/ko/
[2] https://www.netflix.com/browse

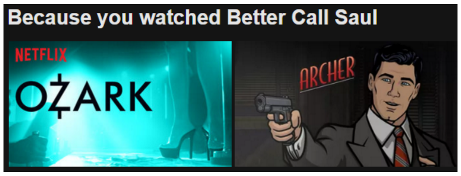

Figure 1: Examples of explanations provided by Netflix.

However, we targeted on more detailed explanations than Netflix's. Our proposed method focused on providing causal evidence based on the movies' stories. For example, when we recommend “Cinderella” for the users, we can say “Cinderella is similar with Snow White with focus on relationships among characters appearing in the movies.”

To achieve these goals, this study aimed for following objectives: (i) discovering story-based features, (ii) estimating story-based similarity among the movies, (iii) providing explainable recommendation on the basis of the story-based similarity, and (iv) making the proposed method expendable to other media.

For the former two objectives, we attempted to discover features with two aspects: composition of the characters and interactions among the characters. Based on the story-based features, we developed measurements to display the differences between two arbitrary stories. Also, with focus on the expandability, data sources of the features were limited within the character network.

Character Network

Our previous studies [1, 5, 4, 3] have proposed SNA-based methods for computationally analyzing the movies' stories. We modeled the stories by using the character network that was defined as follows;

Definition 1 (Character Network). *Suppose that N is the number of characters that appeared in a movie, $\mathbb{C}_\alpha$. When $N(\mathbb{C}_\alpha)$ indicates a character network of $\mathbb{C}_\alpha$, $N(\mathbb{C}_\alpha)$ can be described as a matrix $\in \mathbb{R}^{N\times N}$. It consists of $N \times N$ components which are social affinities among the characters where, $a_{i,j}$ is the social affinity of c_i for c_j when C_α is an universal set of characters that appeared in $\mathbb{C}_\alpha$ and c_i is an i-th element of C_α.*

In this study, we used frequency of the dialogues among the characters as the social affinity among them. The dialogues were extracted from the movies' scripts that were collected from the Internet Movie Script Database (IMSDb) [3].

Composition of the Characters

The directors have to compose characters with a focus on representation of their stories. In other words, the users might recognize the movies' stories from the composition of characters, whether it is intuitively or analytically. Hence, the similarity among movies' stories is recognizable from the difference among compositions of characters.

[3]http://www.imsdb.com/

In order to compare the compositions of characters, we classified the characters with two criteria: (i) importance of their roles and (ii) proximity with a protagonist. In our former studies, we proved that roles of the characters are easily distinguishable. We classified the characters' roles into three categories (i.e., main characters, minor characters, and extras) by using their centralities on the character networks [6]. The centralities were estimated by the linear combination of standard node centrality measurements: the degree centrality, closeness centrality, and betweenness centrality.

In addition, we distinguished the protagonists who are the most spotlighted and the antagonists who are secondly focused [6]. We considered the remaining ones as tritagonists. The tritagonists were categorized into three sides: friendly, neutral, and hostile ones for the protagonists.

The categorization was conducted by measuring social ties among the characters. If there are three characters (c_P, c_A, and c_i), c_P is a protagonist, and c_A is an antagonist, we can identify which character is closer with c_i than the other by comparing c_i's social ties for c_P and c_A. It can be formulated as

$$c_i \in \begin{cases} P, & \text{if } \begin{array}{c} \mathscr{T}(c_i,c_P) > \mathscr{T}(c_i,c_A), \\ \mathscr{T}(c_i,c_P) > \underset{\forall c_j}{\text{median}}\, \mathscr{T}(c_j,c_P), \end{array} \\ A, & \text{if } \begin{array}{c} \mathscr{T}(c_i,c_A) > \mathscr{T}(c_i,c_P), \\ \mathscr{T}(c_i,c_A) > \underset{\forall c_j}{\text{median}}\, \mathscr{T}(c_j,c_A), \end{array} \\ N, & \text{otherwise.} \end{cases}, \tag{1}$$

where $\mathscr{T}(c_j,c_k)$ indicates the degree of social tie between c_j and c_k, P and A indicate sets of the characters who are friendly with the protagonist and the antagonist, respectively, N denotes a set of the characters who take the neutral positions between the protagonist and the antagonist, $\text{median}_{\forall c_j} \mathscr{T}(c_j,c_P)$ and $\text{median}_{\forall c_j} \mathscr{T}(c_j,c_A)$ refer to median values of the social ties of all the characters for c_P and c_A, respectively.

To measure the degree of social ties, we considered the frequency of interactions and the number of paths between target characters. It is formulated as:

$$\mathscr{T}(c_i,c_j) = \sum_{\forall p_k \in \mathbb{P}_{i,j}} \prod_{l=2}^{|p_k|} f(n_{l-1},n_l), \tag{2}$$

where $\mathbb{P}_{i,j}$ is a set of possible paths between c_i and c_j, p_k indicates a k-th path in $\mathbb{P}_{i,j}$, n_l denotes a l-th node (character) on p_k, $|p_k|$ is the number of nodes included in the p_k, and $f(n_{l-1},n_l)$ means a weighting value (interaction frequency) between n_{l-1} and n_l.

By combining the two classification criteria, we categorized the characters into six groups, as displayed in Fig. 2.

The number of characters in each category was represented as a 2×3 matrix. We call this matrix a ‘character composition matrix’. As a naive approach, the difference between two movies can be estimated by the Frobenius distance among their character composition matrices as:

$$\mathscr{D}_{\mathscr{C}}(\mathbb{C}_\alpha,\mathbb{C}_\beta) = \| \mathscr{C}_\alpha - \mathscr{C}_\beta \|_F, \tag{3}$$

		Importance	
		Main	Minor
Proximity	Protagonist	Friendly Main Characters	Friendly Minor Characters
	Neutral	Neutral Main Characters	Neutral Minor Characters
	Antagonist	Hostile Main Characters	Hostile Minor Characters

Figure 2: The proposed category of the characters.

where $\|\cdot\|_F$ denotes the Frobenius norm. In here, $\mathscr{D}_{\mathscr{C}}(\mathbb{C}_\alpha, \mathbb{C}_\beta)$ has smaller value, as $\mathbb{C}_\alpha$ and $\mathbb{C}_\beta$ have more similar number of characters for all the categories. It means that $\mathscr{D}_{\mathscr{C}}$ is highly affected by the number of characters.

Therefore, we normalized the character composition matrix as:

$$\mathscr{C}_\alpha^{Norm} = \frac{\mathscr{C}_\alpha}{|C_\alpha|}, \tag{4}$$

where $|C_\alpha|$ is the number of characters that appeared in $\mathbb{C}_\alpha$. By comparing the normalized composition matrices, we got a scale-tolerant distance. Also, the number of characters was directly compared with other movie's. It can be formulated as:

$$\mathscr{D}_{\mathscr{C}}^{Norm}(\mathbb{C}_\alpha, \mathbb{C}_\beta) = \| \mathscr{C}_\alpha^{Norm} - \mathscr{C}_\beta^{Norm} \|_F, \tag{5}$$

$$\mathscr{D}_{\mathscr{C}}^{Scale}(\mathbb{C}_\alpha, \mathbb{C}_\beta) = \frac{\max(|C_\alpha|, |C_\beta|)}{\min(|C_\alpha|, |C_\beta|)}. \tag{6}$$

Thus, the explanations to the users can be composed by considering the (i) proximity and (ii) importance. For example, 'The Day After Tomorrow (2004)' and 'Gravity (2013)' are commonly disaster movies. In these two movies, nature takes the roles of antagonists. However, tritagonists within 'The Day After Tomorrow (2004)' are mostly main characters, while a protagonist of 'Gravity (2013)' almost solely appeared. Also, the number of character of 'The Day After Tomorrow (2004)' is bigger than that of 'Gravity (2013)'. because 'The Day After Tomorrow (2004)' is closer to a drama movie dealing with family affection and 'Gravity (2013)' is also a sort of thriller movie.

Interactions among the Characters

Although the protagonists and antagonists interact with most of the characters, the others are mostly bounded in particular communities. For example, acquaintances of the protagonists usually interact and appear with the protagonists. If they start appearing frequently with the antagonists, there is a possible indication that a conflict or a crisis (e.g., betrayal, convert, kidnapping, etc.) is likely to happen. In other words, interactions among the characters' groups reflect methods for developing the stories.

Based on this intuition, we compared the stories by using two criteria: (i) frequency: proportion of inter-group interactions and (ii) aggressiveness: external adjacency of the groups.

To utilize the two metrics, we had to discover the characters' groups. The groups were built on the basis of P, A, and N that were composed in Sect. 2.2. Procedures for discovering the groups can be summarized as follows.

1. Subsume extras under P, A, and N with the same method that is used for the main and minor characters.

2. Calculate the internal compactness and the external adjacency of each group.

3. If the external adjacency of a particular group is too high, compared with its internal compactness, partition the group.

4. Iterate Step. 2 and Step. 3, until the groups have adequate quality.

The external adjacency is measured on the basis of the external interactions' frequency and the out-degree of the groups, as:

$$\mathscr{I}(G_k) = \sum_{\substack{\forall c_i \in G_k,\\ \forall c_j \in G_k,\\ c_i \neq c_j}} a_{i,j} \times \frac{\sum_{c_l \in G_k} d(j,l)}{|G_k|}, \tag{7}$$

$$d(j,l) = \begin{cases} 1, & \text{if } a_{j,l} \neq 0, \\ 0, & \text{otherwise.} \end{cases}, \tag{8}$$

where G_k denotes a k-th group, $|G_k|$ indicates the number of characters included in G_k, and $d(j,l)$ refers to an indicator function that indicates existence of interactions between c_j and c_l. On the contrary, the internal compactness was estimated from the internal interactions' frequency and the in-degree of the groups.

$$\mathscr{E}(G_k) = \sum_{\substack{\forall c_i \in G_k,\\ \forall c_j \notin G_k}} a_{i,j} \times \frac{\sum_{c_l \notin G_k} d(j,l)}{\sum_{\forall c_l} d(j,l)}. \tag{9}$$

In order to compare $\mathscr{I}(G_k)$ with $\mathscr{E}(G_k)$, we defined a unified metric by the linear combination of $\mathscr{I}(G_k)$ and $\mathscr{E}(G_k)$. It can be formulated as:

$$\mathscr{Q}(G_k) = \alpha \times (\mathscr{I}(G_k)) - (1-\alpha) \times (\mathscr{E}(G_k)), \tag{10}$$

where $\alpha \in [0,1]$ is a weighting factor; in this study, we set $\alpha = 0.80$. Based on $\mathscr{Q}(G_k)$, we determined whether G_k had to be reconstructed or not.

Therefore, if $\mathscr{Q}(G_k)$ was lower than a user-defined minimum threshold, θ, we partitioned G_k into several groups. The method for partitioning the group is the same with Eq. 1. It can be summarized as follows:

1. Choose top-two characters as centers for new groups based on the characters' centralities.

2. Partition the target group into three new groups by using the same method with Eq. 1.

3. Calculate $\mathscr{Q}(G_k)$ of novel groups. If the average quality of the novel model is worse than previous model's, restore the model and designate next order as the center.

From the characters' groups, we measure the proposed metrics. The frequency can be measured by the proportion of inter-group interactions for the total interactions. It can be formulated as:

$$\mathscr{F}(\mathbb{C}_\alpha) = \frac{\sum\limits_{\forall G_k} \sum\limits_{\substack{\forall c_i \in G_k, \\ \forall c_j \notin G_k}} a_{i,j}}{\sum\limits_{\substack{\forall c_i, \forall c_j, \\ c_i \neq c_j}} a_{i,j}}, \tag{11}$$

where G_k indicates a group of the characters.

In order to formulate the aggressiveness, we considered both of the external adjacency and the internal compactness of the groups. It is formulated as:

$$\mathscr{A}(\mathbb{C}_\alpha) = \sum_{\forall G_k} \mathscr{E}(G_k) - \sum_{\forall G_k} \mathscr{I}(G_k). \tag{12}$$

Therefore, the explanations to the users can be generated by considering the (i) frequency and (ii) aggressiveness. With the same example in Sect. 2.2, stories of 'The Day After Tomorrow (2004)' and 'Gravity (2013)' are commonly led by two groups. However, groups in 'The Day After Tomorrow (2004)' are highly separated, while groups of 'Gravity (2013)' frequently interact with each other, relatively. In addition, groups within 'The Day After Tomorrow (2004)' commonly have high internal compactness and low external adjacency, since this movie describes an 'adventure', where a father rescues his son. On the other hand, groups of 'Gravity (2013)' show opposite characteristics, because 'Gravity (2013)' draws a person who has to save herself, relying on tritagonists' advice.

CONCLUSION

We propose a method for explaining the reason behind existence or non-existence of similarity between the two arbitrary movies. This method can improve explainability of the recommender systems for movies. Also, it is expandable to other media and formats, since the proposed method is built on the character network.

Nevertheless, the proposed method is not yet verified with a large scale dataset. Our future research will be focused on implementing appropriate datasets and conducting an evaluation for the proposed method. Also, we are planning to consider multiple features of the movies (e.g., genre and tempo) for generating explanation.

ACKNOWLEDGMENTS

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (NRF-2017R1A41015675).

REFERENCES

1. Tran Quang Dieu, Dosam Hwang, O-Joun Lee, and Jason J. Jung. 2016. A Novel Method for Extracting Dynamic Character Network from Movie. In *Proceedings of the 7th EAI International Conference on Big Data Technologies and Applications*. Seoul, Korea.

2. Xiangnan He, Tao Chen, Min-Yen Kan, and Xiao Chen. 2015. TriRank: Review-aware Explainable Recommendation by Modeling Aspects. In *Proceedings of the 24th ACM International on Conference on Information and Knowledge Management (CIKM 2015)*, James Bailey, Alistair Moffat, Charu C. Aggarwal, Maarten de Rijke, Ravi Kumar, Vanessa Murdock, Timos K. Sellis, and Jeffrey Xu Yu (Eds.). ACM, 1661–1670.

3. Jai E. Jung, O-Joun Lee, Eun-Soon You, and Myoung-Hee Nam. 2017. A computational model of transmedia ecosystem for story-based contents. *Multimedia Tools and Applications* 76, 8 (2017), 10371–10388.

4. O-Joun Lee and Jason J. Jung. To Appear. Modeling Affective Character Network for Story Analytics. *Future Generation Computer Systems* (To Appear).

5. Quang Dieu Tran, Dosam Hwang, O-Joun Lee, and Jai E. Jung. 2017. Exploiting Character Networks for Movie Summarization. *Multimedia Tools and Applications* 76, 8 (Apr 2017), 10357–10369.

6. Quang Dieu Tran and Jai E. Jung. 2015. CoCharNet: Extracting Social Networks using Character Co-occurrence in Movies. *Journal of Universal Computer Science* 21, 6 (2015), 796–815.

7. Yongfeng Zhang, Guokun Lai, Min Zhang, Yi Zhang, Yiqun Liu, and Shaoping Ma. 2014. Explicit factor models for explainable recommendation based on phrase-level sentiment analysis. In *Proceedings of The 37th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2014)*, Shlomo Geva, Andrew Trotman, Peter Bruza, Charles L. A. Clarke, and Kalervo Järvelin (Eds.). ACM, Gold Coast, QLD, Australia, 83–92.