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Modeling affective character network for story analytics☆

O-Joun Lee, Jason J. Jung *

Department of Computer Engineering, Chung-Ang University, Heunseok-Dong, Dongjak-gu, Seoul, 156-756, Republic of Korea

HIGHLIGHTS

- The paper presents a novel model and methods for analyzing stories of narrative works.
- The proposed methods are focusing on detecting affective events described in the stories.
- The affective events are detected by temporal changes of tensions per flows of the stories.
- The tensions are measured by affective relationships among characters appeared in the stories.
- It has shown its efficiency on recommendation system for the narrative works.

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ABSTRACT

Consideration of the stories included in the narrative works is important for analyzing and providing narrative works (e.g., movies, novels, and comics) to users. In this study, we analyzed the stories in a narrative work with three goals: (i) eliciting, (ii) modeling, and (iii) utilizing the stories. Based upon our previous studies regarding 'character networks' (i.e., social networks among characters in the stories), we elicited the stories with three methods: (i) composing affective character networks with affective relationships among the characters, (ii) measuring temporal changes in tension according to the flows of the stories, and (iii) detecting affective events which refer to dramatic changes in the tension. The affective relationships contain emotional changes of the characters on each segment of the stories. By aggregating the characters' emotional changes, we measured the tension of each segment. We called it 'Affective Fluctuation' and represented it as a discrete function (Affective Fluctuation Function, AFF). The AFFs enable us to detect affective events by using gradients of them and measure similarities among the stories by comparing their shapes. Also, we proposed a computational model of the stories by annotating the affective events and characters involved in those events. Finally, we demonstrated a practical application with a recommendation method which exploited the similarities between stories. Additionally, we verified the reliabilities and efficiencies of the proposed method for narrative works in the real world.

1. Introduction

With the advent of smart devices and extension of web accessibility, a massive amount of narrative works (i.e., artworks which involve storytellings) in various formats (e.g., TV series, short film, and transmedia) is distributed through diverse media (e.g., film, TV, book, online streaming, etc.). Narrative works contain stories that consist of three components: characters, events, and backgrounds. It causes many challenges for content providing services (e.g., retrieval, recommendation, and curation services) that address narrative works (e.g., movies, novels, comics, graphic novels, animations, etc.). One of the major issues is that the existing content analysis methods have difficulty reflecting the contents of the narrative works, since the narrative works are humanistic items which are manufactured, analyzed, and consumed by human beings.

To address this issue, various approaches have been attempted. The simplest solution is to apply external data which are manually annotated by humans (e.g., meta-data, tags, etc.) [1]. One of the representative attempts of this approach is Netflix.[1] The Netflix's recommender engine is highly dependent on multiple and detailed tags which are manually attached to the narrative works [2]. In order to implement a large amount of tags, Netflix has hired

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* Corresponding author.
E-mail addresses: concerto34@cau.ac.kr (O.-J. Lee), j3ung@cau.ac.kr (J.J. Jung).

1 https://www.netflix.com/.

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employees to specifically be Netflix taggers.[2] It is indisputable that small and middle-sized businesses would have difficulty affording the same method as Netflix. As such, the demand for an automated analysis method for the contents of narrative works exists.

There have been attempts to affectively analyze narrative works [3]. Some of them have been focused not on the affective features within the narrative works, but rather on the reactions of users. Users' reactions have been used for an approach that inversely connects the affective characteristics of the narrative works from the emotional states of the users who used the narrative works based on their physiological reactions like EMG (ElectroMyoGraphy), ECG (ElectroCardioGram), and more [4,5]. Other approaches have attempted to extract the affective features from the physical characteristics of the narrative works (e.g., beats of sounds, brightness of colors, etc.) [6,7]. However, it also cannot ascertain the contents of narrative works in a majority of the stories.

Different than the former two approaches, a few studies have attempted to analyze the stories of the narrative works directly by applying SNA (Social Network Analysis) methods and partially using NLP (Natural Language Processing) [8,9] and image processing [10,11] methods. These methods, which is referred to as character networks, compose the social networks among the characters within the narrative works and analyze them with SNA techniques. The character network is meaningful in terms of enabling the use of sufficiently verified techniques in a SNA domain. Nevertheless, these studies also have the following limitations: (i) dependencies on media, domains, and formats and (ii) difficulties reflecting the affective features of the stories. First, generalization of the World Wide Web (WWW) and personal smart devices causes the appearances of novel media like web comics or web drama, which can include particular physical features that limits the use and reuse of these types of methods. Although the character network is independent of the physical features, the existing studies have limited their applicable area by their data collection methods. Furthermore, the character network is only reflecting how frequently the characters are interacting, which makes it difficult to outline stories that represent sequences of events that occurred among the characters. Changes in the characters' interactions can be the result of the events, however, they do not directly represent the events.

To deal with this challenge, we proposed a novel SNA-based content analysis method for narrative works. It is based on an affective character network which is an extension of the former SNA-based methods: character network, dynamic character network, and more. The affective character network is developed by attaching affective relationships among the characters that appear in the narrative works. By observing changes in both affective and social relationships among the characters, we measured the fluctuations of tensions expressed in the narrative works according to the flows of the stories, and detected affective events that made the tensions heighten. Finally, we modeled the stories by using the detected affective events and transitions of the characters between them.

Furthermore, in order to prove utility and efficiency of the affective character network and the proposed story model, we proposed a similarity measurement among the stories of the narrative works. Similarity was estimated by the sequences of the affective events and temporal changes of the tensions. In addition, in order to utilize the similarity measurement, we suggested a preliminary story-based recommender system. The recommendation method is composed on the basis of the conventional item clustering-based collaborative filtering (ICCF) algorithm. We applied the story-based similarity measurement for clustering the narrative works.

The contributions of this study can be categorized, as follows:

1. Novel representation of the affective relationships among the characters that appeared in the narrative works and the temporal changes of the affective relationships (Section 3.2.1),
2. Method to measure the tensions within the stories and detect the affective events from the temporal changes of the tensions (Section 3.2.2),
3. Computational model of the story which displays the sequence of affective events within the narrative works and the transitions of the characters among them (Section 3.3), and,
4. Story-based recommender system based on a story-based similarity measurement (Section 4).

The remainder of this paper is organized in the following manners. In Section 2, we describe the raising problem and introduce the definition of the affective character network and how it is extended from the character network and the dynamic character network. Also, we present a conceptual design of the story model based on the affective character network. In Section 3, the proposed representation for the affective relationships among the characters is depicted with the methods for exposing the affective relationships among the characters. Also, we introduce the measurement of the tensions according to the flows of the stories and depict the detection of the affective events from the temporal changes in the tension. Furthermore, we represent the proposed model of the stories with the detected affective events. In Section 4, we describe the method for measuring the similarities among the narrative works by using the affective character network and the proposed story model. Moreover, we introduce a simple method to recommend the narrative works on the basis of the story-based similarity measurement. In Section 5, we evaluate the efficiency and reliability of the affective character network, the story model, the story-based similarity measurement, and the story-based recommender system. Finally, we present related studies with a focus on the content analysis methods in Section 6, and then in Section 7, we conclude our work and present a direction for future studies.

2. Problem description

To deal with narrative works that are distributed through various media, the content providing services require automated content analysis methods which are independent from domains, formats, and media. Although various methods have been proposed to improve it, most of them are focused on the physical features of the narrative works which are mainly visual or audible [12–14]. These methods are not only dependent on formats and media, but also has an obvious limitation of a gap between the low level physical features and high level semantics [15–17,6,3]. In this section, we extended and re-defined character networks, which was introduced in our previous studies [10,11,18,19], to achieve two main purposes: (i) represent the stories of the narrative works and (ii) minimize its dependencies on domains, formats, and media.

First, we newly define the character network which is a social network among characters that appear in the narrative works. Previous studies [20,8,11] have commonly defined and composed the character networks as dependent on various data sources, including the co-occurrences of the characters, dialogues, and more. Nevertheless, they demonstrated how strongly arbitrary that two characters are connected. To reduce the dependencies and emphasize the significance, which is the social relationships among the characters, we generalized the concepts of the character networks, as follows.

2 https://www.washingtonpost.com/news/arts-and-entertainment/wp/2015/06/11/netflix-tagging-yes-its-a-real-job.

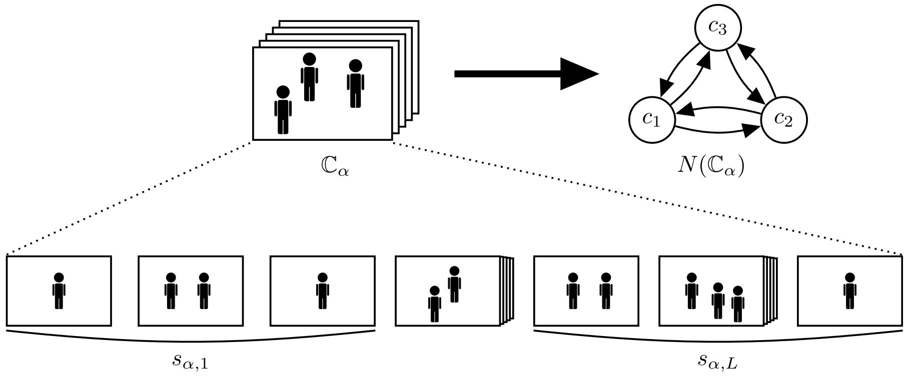


Fig. 1. An example of relationships between a narrative work ($\mathbb{C}_\alpha$), characters (c_1, c_2, c_3), segments ($s_{\alpha,1}, \ldots, s_{\alpha,L}$), and a character network ($N(\mathbb{C}_\alpha)$). If we suppose that $\mathbb{C}_\alpha$ is a movie, rectangular boxes represent the frames and symbols which look like people denote the characters appeared in each frame. In this circumstance, the segment is a set of frames which are temporally continuous. For example, $s_{\alpha,1}$ includes frames from first one to third one. When we compose $N(\mathbb{C}_\alpha)$ which is a character network of $\mathbb{C}_\alpha$, we have to consider all the frames contained within $\mathbb{C}_\alpha$. On the other hand, if we compose $N(s_{\alpha,l})$, we only need to take account of frames included by $s_{\alpha,l}$.

Definition 1 (*Character Network*)**.** Suppose that $n \in [1, N]$ is the number of characters that occurred in a narrative work, $\mathbb{C}_\alpha$. 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 $n \times n$ elements which are social affinities among the characters as:

$$N(\mathbb{C}_\alpha) = \begin{bmatrix} a_{1,1} & \cdots & a_{1,n} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,n} \end{bmatrix}, \tag{1}$$

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 ith element of C_α.

However, the character network has an inherent limitation in that it is difficult to represent the temporal dynamics of the stories within the narrative work. To solve this issue, we proposed a concept, dynamic character network, in a previous study [19]. This method is based on the segmentation of the narrative works by using the character network [11,18].

The segmentation means automatically extracting scenes from the narrative works. The scene is a part of the narrative works, which describes a particular event within the stories of narrative works. The users easily recognize the scenes based on the stories, however it is a hard task for computers. Therefore, in our previous study [18], we automatically extracted the scenes by using occurrences of the characters. We called these automatically extracted scenes 'segments'. Since the method for extracting the segments is out of this article's coverage, we do not describe it in detail.

Also, the scene consists of 'units' of the narrative work. The units are different with types of the narrative works' formats and media. For example, units of the movies are frames, and sentences or paragraphs can be used for units of the novels. The relationships between the narrative works, the characters, the segments, and the character networks can be illustrated as Fig. 1.

By segmenting, the narrative works are transformed into a sequence of segments (to simplify notations, we notate a relationship between an lth segment of $\mathbb{C}_\alpha$ ($s_{\alpha,l}$) and a narrative work including it ($\mathbb{C}_\alpha$) as $s_{\alpha,l} \in \mathbb{C}_\alpha$). The dynamic character network represents the temporal changes of the character networks by composing them segment by segment. Nevertheless, the existing definition of the dynamic character network in the previous study [19] is accumulative; a dynamic character network on $s_{\alpha,l}$ is a character network composed for a period which is from $s_{\alpha,1}$ to $s_{\alpha,l}$.

This definition is useful when we want to display temporal changes in the social relationships among the characters. However, it also has limitations for processing it to other formats. For example, in the existing definition, if we want to see interactions among the characters in only a single segment, we have to compare prior and posterior character networks. Furthermore, since its definition is isolated from the original character network, it causes confusion. Therefore, we re-defined the dynamic character network as follows.

Definition 2 (*Dynamic Character Network*)**.** Let L the total number of segments found in an arbitrary narrative work, $\mathbb{C}_\alpha$. When $D(\mathbb{C}_\alpha)$ means a dynamic character network of $\mathbb{C}_\alpha$, $D(\mathbb{C}_\alpha)$ can be represented as:

$$D(\mathbb{C}_\alpha) = \left\{ N(s_{\alpha,l}) | s_{\alpha,l} \in \mathbb{C}_\alpha, l \in [1, L] \right\}, \tag{2}$$

where $N(s_{\alpha,l})$ is a character network only for $s_{\alpha,l}$.

Although the dynamic character network represents temporal changes of the social relationships between the characters, it is not enough to reflect the story lines of the narrative work. The reason is that the social affinities cannot be directly matched with the emotional intimacies among the characters. Furthermore, the social affinities are only able to represent growths in the strength of the relationships since they are measured by the number of interactions.

Therefore, we defined a novel concept, affective character network by attaching the affective relationships of the characters on the dynamic character networks. Through it, we expected two outcomes: (i) representing emotional intimacies and conflicts among the characters, and (ii) connoting changes in the tension according to the flows of the stories. More simply, the tension refers to an overall emotional conflict among the characters.

Prior to annotating the affective relationships on the character network, we have to extract the emotional states of the characters at each segment. Data sources of the emotional states can be in different forms in the narrative works. If narrative works include visual features, we can apply the facial expressions of the characters. In other cases, if they are linguistic, we can analyze the emotional words used.

From the collected emotional states, we transformed them into the affective relationships. To conduct it, we supposed three assumptions. The emotion of a character will be directed to characters which (i) have high connectivity with him/her, (ii) are included in a common social group with him/her, and (iii) have a connection with him/her. By using the composed affective relationships as edges, we defined the affective character network, as follows.

Definition 3 (*Affective Character Network*)**.** An affective character network is a modification of dynamic character network which includes the affective relationships among the characters. Therefore,

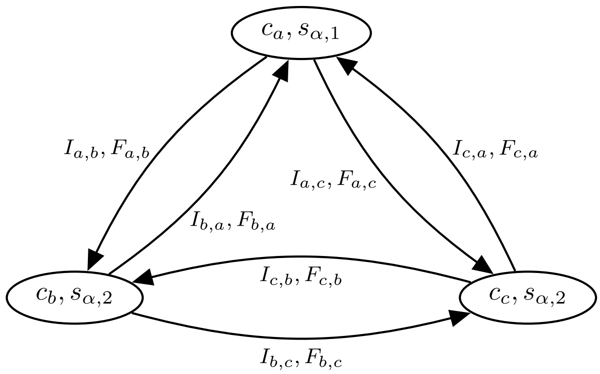


Fig. 2. An example of the affective character network.

similar to the dynamic character networks, an affective character network of $\mathbb{C}_\alpha$ also can be defined as a sequence of affective character networks for all the segments within $\mathbb{C}_\alpha$. It can be formulated as:

$$\mathcal{A}(\mathbb{C}_\alpha) = \left\{\mathcal{A}(s_{\alpha,l}) | s_{\alpha,l} \in \mathbb{C}_\alpha\right\}, \tag{3}$$

where $\mathcal{A}(\mathbb{C}_\alpha)$ indicates an affective character network of $\mathbb{C}_\alpha$ and $\mathcal{A}(s_{\alpha,l})$ means an affective character network for a lth segment within $\mathbb{C}_\alpha$.

If we suppose that three characters are appeared on $s_{\alpha,l}$, $\mathcal{A}(s_{\alpha,l})$ can be illustrated as Fig. 2, where c_a indicates an ath character appeared in $\mathbb{C}_\alpha$, $I_{a,b}$ means an emotional state of c_a for c_b, and $F_{a,b}$ denotes a change in emotional state of c_a for c_b during $s_{\alpha,l}$. Detailed definitions and descriptions of the parameters are provided in Section 3.

Finally, based on the character networks defined in Definitions 1, 2, and 3, we defined a model for the stories of the narrative works. To model and visualize the stories of the narrative works, we (i) detected the affective events that occurred within the narrative work from the changes in the tensions, and (ii) located the detected affective events in the order in which it was described in the narrative work. Also, by annotating characters involved in each event, we developed the model such that it had the capability to represent the logical linkages between the characters. The story model can be defined as follows.

Definition 4 (*Story Model*)**.** A story model is a lattice graph, where each node of the graph means each affective event occurred in the narrative work. The graph is organized with the following three rules: (i) locating the affective events as nodes according to their temporal order from left to right, (ii) laying out the affective events which are sharing a common spatial background on the same rows, and (iii) annotating commonly appeared characters by the edges among the nodes.

Fig. 3 is an example of the proposed computational model of the stories, where $m_{\alpha,i}$ indicates an ith major affective event occurred in $\mathbb{C}_\alpha$, $m_{\alpha,j}$ denotes a jth turning point of story line appeared in $\mathbb{C}_\alpha$, and G_A is an Ath community of characters within $\mathbb{C}_\alpha$. Detailed explanations of the notations are illustrated in Section 3.

3. Affective character network

In this section, we focus on extracting social and affective information about the stories of the narrative work by using the character networks. To discover and represent the stories of a narrative work, we extended the SNA-based content analysis methods that we focused on in our previous studies. The SNA-based content analysis methods have an advantage in that they can be applied on most kinds of media and formats.

To annotate the dynamic changes of the social and affective relationships among the characters and detect the affective events described in the stories, we applied three approaches: (i) segmenting the narrative work based on the occurrences of the characters, (ii) detecting the affective events from the changes in the characters' affective relationships, and (iii) modeling the stories with the detected affective events and the transitions of the characters among them. With these approaches, the stories are elicited by the following procedures:

1. Extract the social information among the characters in the narrative work based on the character network.
2. Segment the narrative work by using the social information.
3. Annotate the affective relationships between the characters at each segment of the narrative work.
4. Detect the affective events described in the narrative work by seeking changes in the affective relationships.
5. Model the stories of the narrative work with the affective events and the characters involved in the affective events.

To compose the character network and segment the narrative works, we applied methods which were slightly modified from the methods introduced in our former studies [10,11,18,19]. To compose the character network, we applied the CoCharNet system proposed in our previous study [10]. Also, we used heuristics that were introduced in two of our previous studies [11,18] to segment the narrative works. Finally, we extended a concept of the dynamic character network into the affective character network based on our previous study [19].

3.1. Extracting social information from the character network

In this section, we introduce how we composed the character network and extract the social information from it as a basis of the affective character network. The extracted information can be categorized into (i) the centralities and roles of the characters, (ii) segments within the narrative works, and (iii) communities among the characters. We first construct the character network and define the occurrence functions of the characters. In this work, we used co-occurrence frequencies between the characters as the social affinities among them. It can be formulated as:

$$N(\mathbb{C}_\alpha) = \begin{bmatrix} a_{1,1} & \cdots & a_{1,n} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \cdots & a_{n,n} \end{bmatrix} = \begin{bmatrix} f_{1,1} & \cdots & f_{1,n} \\ \vdots & \ddots & \vdots \\ f_{n,1} & \cdots & f_{n,n} \end{bmatrix}, \tag{4}$$

where $f(i,j)$ is the frequency of the co-occurrence between c_i and c_j. $f(i,j)$ was estimated by the following procedures:

$$f(i,j) = \sum_{\forall t} O^{co}_{c_i,c_j}(t), \tag{5}$$

$$O_{c_i}(t) = \begin{cases} 1, & \text{if } c_i \text{ is occurred on } t \\ 0, & \text{otherwise,} \end{cases} \quad t \in [0, T], \tag{6}$$

$$O^{co}_{c_i,c_j}(t) = \begin{cases} 1, & \text{if } O_{c_i}(t) = 1 \text{ and } O_{c_j}(t) = 1 \\ 0, & \text{otherwise,} \end{cases} \tag{7}$$

where $O_{c_i}(t)$ indicates an occurrence function of c_i, $O^{co}_{c_i,c_j}(t)$ means a co-occurrence function between c_i and c_j, and T is the total length of the narrative work. $O_{c_i}(t)$ and $O^{co}_{c_i,c_j}(t)$ return whether the characters are occurred and co-occurred on a certain time point, respectively. In this study, we set a unit of t as 10 s.

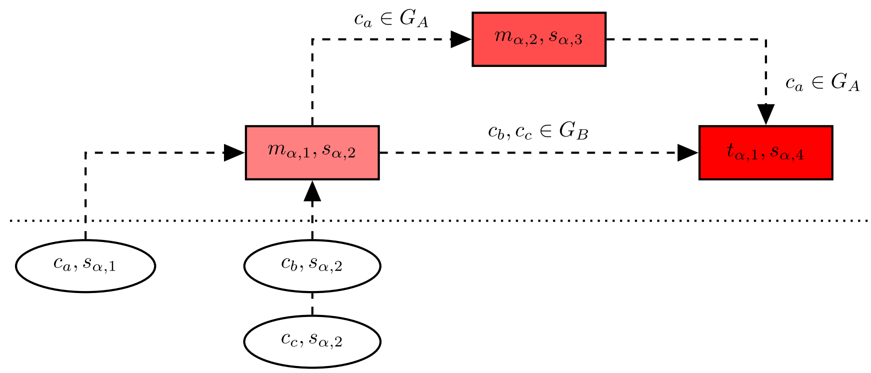


Fig. 3. An example of the computational model of the stories.

3.1.1. Centralities and roles of the characters

After composing the character network, we extracted information from the social relationships among the characters. First, the characters annotated in $N(\mathbb{C}_\alpha)$ were ordered by their centralities. A centrality of c_i during whole $\mathbb{C}_\alpha$, C_i^{all} was estimated by using the linear combinations of the degree centrality, closeness centrality, and betweenness centrality which are the well-known and widely-used node centrality measurements [21], based on the experimental results of a previous study [10]. The C_i^{all} can be calculated as:

$$\begin{aligned} C_i^{all} &= \frac{1}{3} \times \{B^{norm}(c_i) + C(c_i) + D(c_i)\} \\ &= \frac{1}{3} \times \left\{ \frac{B(c_i) - \operatorname{argmin}_{\forall c_j} B(c_j)}{\operatorname{argmax}_{\forall c_j} B(c_j) - \operatorname{argmin}_{\forall c_j} B(c_j)} + C(c_i) + D(c_i) \right\}, \end{aligned} \tag{8}$$

where $B(c_i)$, $C(c_i)$, and $D(c_i)$ are betweenness centrality, closeness centrality, and degree centrality of c_i, respectively, and $B^{norm}(c_i)$ is a normalized value of $B(c_i)$. If c_i has a more important role in the story of $\mathbb{C}_\alpha$, a value of C_i^{all} is larger, and vice versa.

Furthermore, we extracted the roles of the characters based on the centralities of them, since there were gaps of the centrality between the roles of characters, as described in our former research [10]. Thus, a role of c_i can be identified by:

$$C_\alpha^{Main} = \left\{ c_i \middle| C_i^{all} \geq \frac{1}{n} \times \sum_{\forall c_j} C_j^{all} \right\}, \tag{9}$$

where n is the number of characters and C_α^{Main} is a set of the main characters that appeared in $\mathbb{C}_\alpha$.

3.1.2. Segmentation of the narrative works

Given a character network, we can segment the narrative works with a similar approach depicted in two previous studies [11,18]. It is conducted on the basis of the characters' occurrences and lengths of no-occurrence areas (i.e., time intervals that not any of the characters occur). A procedure of segmenting narrative works can be described as Alg. 1. Parameters within Alg. 1 are calculated as:

$$i_{\alpha,k} = [t_{\alpha,k}^{pre}, t_{\alpha,k}^{por}], \tag{10}$$

$$I_\alpha = \left\{ i_{\alpha,k} \middle| \sum_{\forall c_i} O_{c_i}(t) = 0, \forall t_{\alpha,k}^{pre} \leq t \leq t_{\alpha,k}^{por} \right\}, \tag{11}$$

$$\mu(I_\alpha) = \frac{\sum_{\forall i_{\alpha,k}} t_{\alpha,k}^{por} - t_{\alpha,k}^{pre}}{|I_\alpha|}, \tag{12}$$

$$\mathcal{B}_\alpha = \{ i_{\alpha,k} | (t_{\alpha,k}^{por} - t_{\alpha,k}^{pre}) \geq \mu(I_\alpha) \}, \tag{13}$$

where $i_{\alpha,k}$ is a kth no-occurrence area within $\mathbb{C}_\alpha$ which has a starting point $t_{\alpha,k}^{pre}$ and an ending point $t_{\alpha,k}^{por}$, I_α indicates a set of the

Algorithm 1 Segmenting the Narrative Works based on Occurrences of the Characters

procedure SEGMENTING NARRATIVE WORKS
  Set $Flag \leftarrow 0, |I_\alpha| \leftarrow 0, |S_\alpha| \leftarrow 0$
  for $t : 0 \rightarrow T$ **do**
    if $\sum_{\forall c_i} O_{c_i}(t) = 0$ **then**
      if Flag != 1 **then**
        $n \leftarrow |I_\alpha| + 1$
        put $i_{\alpha,n}$ into I_α, $t_{\alpha,n}^{pre} \leftarrow t$
        $Flag \leftarrow 1, |I_\alpha| \leftarrow n$
    else
      if Flag = 1 **then**
        $n \leftarrow |I_\alpha|, t_{\alpha,n}^{por} \leftarrow t$
        $Flag \leftarrow 0$
  Calculate $\mu(I_\alpha)$ according to Eq. 12
  for $i_{\alpha,m} \in I_\alpha$ **do**
    if $t_{\alpha,m}^{por} - t_{\alpha,m}^{pre} \geq \mu(I_\alpha)$ **then**
      Put $i_{\alpha,m}$ into $\mathcal{B}_\alpha$
  for $i_{\alpha,o}, i_{\alpha,o+1} \in \mathcal{B}_\alpha$ **do**
    $l \leftarrow |S_\alpha| + 1, s_{\alpha,l} \leftarrow [t_{\alpha,o}^{por}, t_{\alpha,o+1}^{pre}]$
    Put $s_{\alpha,l}$ into S_α
    $|S_\alpha| \leftarrow l$

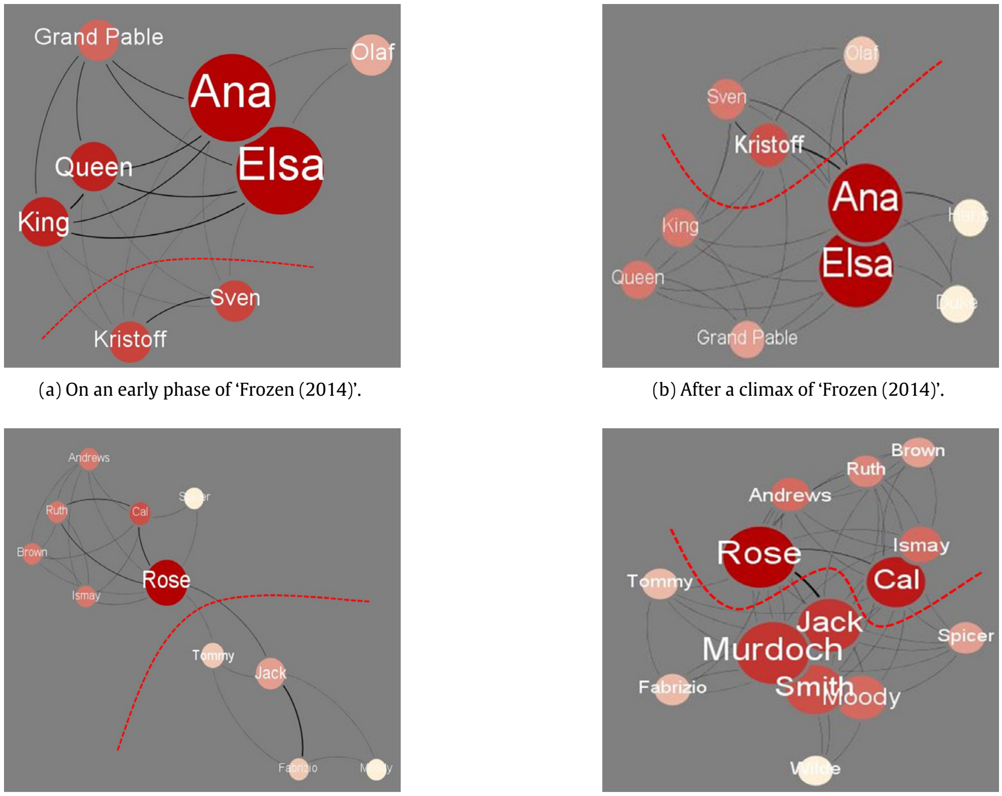
no-occurrence areas included in $\mathbb{C}_\alpha$, $\mu(I_\alpha)$ denotes an average length of the no-occurrence areas appeared in $\mathbb{C}_\alpha$, $|I_\alpha|$ is the number of elements included in I_α, $\mathcal{B}_\alpha$ indicates a set of boundaries of the segments, and S_α means a set of the segments found within $\mathbb{C}_\alpha$.

Through the segmentation, we can represent the narrative work $\mathbb{C}_\alpha$ as a set of segments $\mathbb{C}_\alpha = \{s_{\alpha,l} | l \in [1, L]\}$, where L is the number of segments found in $\mathbb{C}_\alpha$. With this representation, when we define that $N(s_{\alpha,l})$ is a character network composed within a segment $s_{\alpha,l}$, an accumulative summation for all $s_{\alpha,l}$ was the same as the character network of $\mathbb{C}_\alpha$. It can be formulated as:

$$N(\mathbb{C}_\alpha) = \sum_{\forall s_{\alpha,i}} N(s_{\alpha,i}). \tag{14}$$

3.1.3. Communities among the characters

In this study, we added more social information regarding the communities of characters to deeply represent the social relationships among them. We can understand the changes of the characters' stances for each other from the changes in the communities. Since in narrative works, most of the characters are peripheral ones of protagonists or their opponents (antagonists or tritagonists) as shown in Fig. 4. To detect the growths of the communities dynamically, we first measured accumulative centralities on each segment for each character. When $C_{l,i}^{acc}$ indicates an accumulative



(a) On an early phase of 'Frozen (2014)'.

(b) After a climax of 'Frozen (2014)'.

(c) On an early phase of 'Titanic (1997)'.

(d) After a climax of 'Titanic (1997)'.

Fig. 4. Accumulative character networks on early phases and after climaxes of 'Titanic (1997)' and 'Frozen (2014)' with the communities of characters detected within them; the nodes indicate characters, darker color of the nodes indicate that nodes' degree centralities are higher, bigger sizes of the nodes indicate that their betweenness centralities are higher, and the thickness of edges denotes how frequently both ends are co-occurred. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

centrality for c_i on $s_{\alpha,l}$, $C^{acc}_{l,i}$ is estimated within a period from $s_{\alpha,1}$ to $s_{\alpha,l}$. This period can be represented as:

$$N^{acc}(s_{\alpha,l}) = \sum_{i=1}^{l} N(s_{\alpha,i}), \tag{15}$$

where $N^{acc}(s_{\alpha,l})$ is an accumulative character network from $s_{\alpha,1}$ to $s_{\alpha,l}$. A method to calculate $C^{acc}_{l,i}$ is the same as C^{all}_{i}, as described in Eq. (8).

Based on the accumulative character networks and centralities, we detected communities among the characters based on the divisive algorithm proposed by Girvan and Newman [22,23]. Although it is a traditional and well-known algorithm [24,25], the reason that we adopted it was that there was no need to use state-of-the-art algorithms. The character networks were relatively much smaller than the social networks in the real world; the number of characters within the character networks is lower than 20 on average. Therefore, it is not necessary to pursue the low computational complexity and reasonable approximation, as different from the state-of-the-art algorithms. We are sure that we can discover out a global optima in a reasonable amount of time. When we detected communities within $s_{\alpha,l}$, the algorithm can be depicted as three steps:

1. Estimate the centralities of all edges on $N^{acc}(s_{\alpha,l})$.
2. Remove the edge that has the largest centrality.
3. Iterate Step. 1 and 2 until the $N^{acc}(s_{\alpha,l})$ is partitioned.

However, this algorithm was not appropriate when the densities of the character networks were high as displayed in Fig. 4(a), (b), and (d); although, it exhibited good performance in the case of Fig. 4(c). Therefore we modified the Girvan and Newman's divisive algorithm. First, (i) we composed the communities by conducting the divisive algorithm only among the main characters. Next (ii) we calculated the memberships of the other characters that were not the main characters for the communities composed in the first step. Then, (iii) we placed the characters into communities with the highest membership value. The centralities of the edges and the memberships of the characters were respectively estimated as:

$$C^{acc}_{l,e_{j,k}} = \min\{B^{norm}(c_j), B^{norm}(c_k)\}, \tag{16}$$

$$\mu_{G_i}(c_j) = \sum_{c_k \in G_i} f(j,k) \times \frac{\sum_{c_k \in G_i} d(j,k)}{\sum_{\forall c_k} d(j,k)}, \tag{17}$$

$$d(j,k) = \begin{cases} 1, & \text{if } f(j,k) \neq 0 \\ 0, & \text{otherwise}, \end{cases} \tag{18}$$

where $C^{acc}_{l,e_{j,k}}$ is a centrality of an edge between c_j and c_k, and $\mu_{G_i}(c_j)$ denotes a membership of c_j for ith community, G_i; $B^{norm}(c_j)$ and $f(j,k)$ (defined in Eqs. (8) and (5), respectively) in the above equations are calculated on the basis of a target segment $s_{\alpha,l}$ and its accumulative character network $N^{acc}(s_{\alpha,l})$.

Finally, (iv) we validated the quality of the composed community model based on its internal and external connectivities in the communities. (v) If the estimated quality was lower than the user-defined minimum threshold, we conducted the proposed community detection algorithm onto one of the elicited communities that had lower quality. The quality of community can be formulated

Table 2
A list of the narrative works within the dataset.

Notation	Title	Publish year
$\mathbb{C}_1$	Star Wars: Episode III: Revenge of the Sith	2005
$\mathbb{C}_2$	Star Wars Episode VI: Return of the Jedi	1983
$\mathbb{C}_3$	Frozen	2014
$\mathbb{C}_4$	Titanic	1997
$\mathbb{C}_5$	Snow White and the Seven Dwarfs	1937
$\mathbb{C}_6$	The Man from Earth	2007
$\mathbb{C}_7$	7 años	2016
$\mathbb{C}_8$	The Usual Suspects	1995
$\mathbb{C}_9$	Memento	2000
$\mathbb{C}_{10}$	No Country for Old Men	2007

as:

$$\mathcal{Q}(G_i) = \sum_{c_j \in G_i} \left\{ \sum_{c_k \in G_i} f(j,k) \times \frac{\sum_{c_k \in G_i} d(j,k)}{|G_i|} \right\} \times w_{\mathcal{Q}} - \sum_{c_j \in G_i} \left\{ \sum_{c_k \notin G_i} f(j,k) \times \frac{\sum_{c_k \notin G_i} d(j,k)}{\sum_{\forall c_k} d(j,k)} \right\} \times (1 - w_{\mathcal{Q}}), \quad (19)$$

where $\mathcal{Q}(G_i)$ is a quality of community for G_i and $w_{\mathcal{Q}} \in [0.5, 1]$ is a weighting factor for the internal connectivity. The quality of the whole model was estimated by an average of $\mathcal{Q}(G_i), \forall G_i$. As displayed in a range of $w_{\mathcal{Q}}$, we considered the internal connectivities more important than the external connectivities, since most of the characters were connected with each other. Fig. 4 is an example of outputs from the proposed community detection method. The number of communities detected on the character networks was usually the same as the number of major characters which were 'Protagonists' and 'Antagonists' (i.e., most of the conventional narrative works had two communities).

Conclusively, the communities including each character were represented as a vector for each segment. If we suppose that $G(s_{\alpha,l})$ represents the communities of characters on $s_{\alpha,l}$, it can be formulated as:

$$G(s_{\alpha,l}) = \begin{bmatrix} G_1 \\ \vdots \\ G_n \end{bmatrix}, \quad (20)$$

where G_i denotes a community including c_i.

3.2. Analyzing the affective relationships among the characters

In Section 3.1, we extracted the social information from the character networks. In this section, we introduce how to build the affective character networks and elicit the stories of the narrative works by using the affective character networks. The method to expose the stories consists of the following three steps.

1. Compose the affective character network for the narrative works.
2. Detect the affective events from the narrative works from changes in the tensions.
3. Model the stories of the narrative works by using the affective events.

Following these steps, we introduce how to transform the emotional states of the characters into the affective relationships among them in Section 3.2.1. In Section 3.2.2, we depict the method for detecting the affective events from the narrative works by using the affective character networks. Finally, we describe the model of a story and present examples of a real narrative work in Section 3.3.

We collected the emotional states of the characters according to the running time of the narrative work. In our previous studies, we extracted the social affinities among the characters from the number of their interactions (e.g., the number of dialogues exchanged [8,9], the frequencies of co-occurrences [10,11,18], etc.). These approaches have respectively focused on linguistic and visual data sources. In addition, in a previous study [9], we attempted to extract the emotional states of the characters based on the emotional words used by them and WordNet [26].

In this study, since we aimed to propose a domain-independent content analysis methodology, we collected the emotional states from both kinds of data sources: dialogues and facial expressions. The emotional states were semi-automatically extracted, which was the same as composing the character network and dynamic character network. The dialogues spoken by the characters were collected from the scripts of movies or speech bubbles of comics. In the case of visual narrative works, we collected rectangular boxes around the characters' faces every 60 frames. For processing these linguistic and visual data, various libraries and application programming interfaces (APIs) have been developed and distributed. As examples, we used "Text Analytics API[3] " and "Emotion API[4] " of 'Microsoft Cognitive Service', respectively.

However, the accuracy of the data collection processes was not perfect. As show in one of our previous studies [27], our semi-automated data collection system has difficulty detecting characters who are in darkness or hidden by other objects. In the case of our experimental dataset, which is presented in Table 2, the system could not detect 6.37% of characters' occurrences. It was much worse for animations such as 'Frozen (2014)' (17.61%). In addition, this problem increases difficulty for collecting emotional data, either. Following responses from a user group, which is composed for the evaluation, 10.15% of emotional states were wrongly detected. They mentioned about causes of this problem as "Facial expressions of actors/actresses sometimes do not match with dialogues among the characters". For example, when characters were in darkness, wearing sunglasses, or were not human beings, the facial recognition methods often failed to detect anything. Also, if rhetoric or metaphorical expressions were included in the dialogues, it was difficult to extract the emotional states considering only the superficial semantics. Therefore, we manually corrected the errors that occurred when automatically collecting the emotional states. Our data collection system is surely capable of improvement. However, the improvement for collecting data is out of the coverage, since this study pursued a generalization of the character network in order to handle all the types of narrative works.

By using the collected data, we annotated the characters' emotional states that occurred in each segment with two numerical values: (i) an average and (ii) a range of fluctuation of the emotional states. We called this affective annotation, and it is defined, as follows.

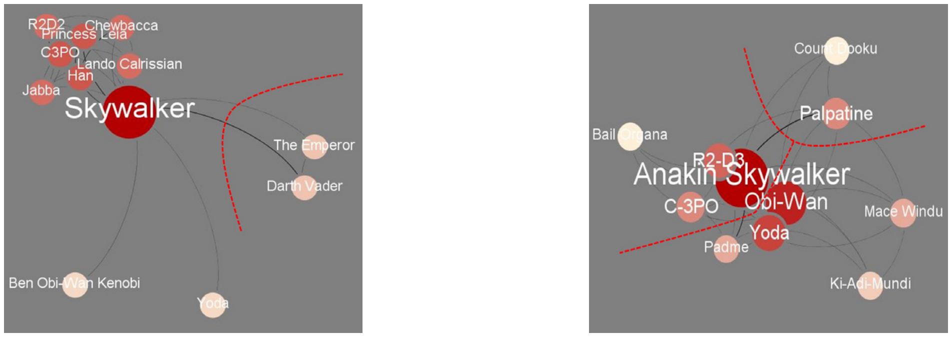
Definition 5 (*Affective Annotation*)**.** Let $I_l(c_i) \in [-1, 1]$ an average emotional state of c_i all across a segment $s_{\alpha,l}$ and $F_l(c_i) \in [0, 2]$ means a range of emotional fluctuation of c_i at the same segment. When $A_l(c_i)$ indicates an affective annotation of c_i on $s_{\alpha,l}$, it is described as:

$$A_l(c_i) = \langle I_l(c_i), F_l(c_i) \rangle. \quad (21)$$

3.2.1. Composing the affective character network

We composed the affective character network based on the affective annotation. Therefore, we transformed the emotional states of the characters which were undirected into directed forms, since

3 https://www.microsoft.com/cognitive-services/en-us/text-analytics-api.
4 https://www.microsoft.com/cognitive-services/en-us/emotion-api.



(a) 'Star Wars Episode VI: Return of the Jedi (1983)'.

(b) 'Star Wars: Episode III: Revenge of the Sith (2005)'.

Fig. 5. Communities of characters detected on the final phases of 'Star Wars Episode VI: Return of the Jedi (1983)' and 'Star Wars: Episode III: Revenge of the Sith (2005)'.

the affective annotation was only including the emotional states of each character in each segment.

Basically, the character network is a representation of relationships between the characters, whether it is based on dialogues, co-occurrences, or anything else. With Definition 5 to add affective information on the character network, we defined $\mathcal{A}(s_{\alpha,l})$ as a vector composed of three matrices and one vector. The matrices indicate the social relationships, intensities of the affective relationships, and ranges of fluctuation of the affective relationships within $s_{\alpha,l}$, respectively. The vector means the communities of characters on $s_{\alpha,l}$. It can be represented as:

$$\mathcal{A}(s_{\alpha,l}) = \langle N(s_{\alpha,l}), G(s_{\alpha,l}), I(s_{\alpha,l}), F(s_{\alpha,l})\rangle \tag{22}$$
$$= \left\langle \begin{bmatrix} f_{1,1} & \cdots & f_{1,n} \\ \vdots & \ddots & \vdots \\ f_{n,1} & \cdots & f_{n,n} \end{bmatrix}, \begin{bmatrix} G_1 \\ \vdots \\ G_n \end{bmatrix}, \begin{bmatrix} I_{1,1} & \cdots & I_{1,n} \\ \vdots & \ddots & \vdots \\ I_{n,1} & \cdots & I_{n,n} \end{bmatrix}, \begin{bmatrix} F_{1,1} & \cdots & F_{1,n} \\ \vdots & \ddots & \vdots \\ F_{n,1} & \cdots & F_{n,n} \end{bmatrix} \right\rangle,$$

where $I_{i,j}$ means a c_i's average emotion for c_j and $F_{i,j}$ indicates a range of fluctuation of c_i's emotion for c_j. Also, $N(s_{\alpha,l})$ is the same with itself in Definition 2 and $G(s_{\alpha,l})$ is equal to itself in Eq. (20).

Although $N(s_{\alpha,l})$ and $G(s_{\alpha,l})$ were respectively conducted from Sections 3.1.2 and 3.1.3, $I(s_{\alpha,l})$ and $F(s_{\alpha,l})$ were extracted from the affective annotation $A_l(c_i)$. However, to compose matrices for the affective relationships, we converted the affective annotation into relationships. To transform them, we made a simple assumption as defined below.

Assumption 1 (*Affective Relationship*). An affective relationship from an arbitrary character to another character will be as intense as their social relationship. It is actualized into three premises: (i) a social affinity between c_i and c_j is proportional to an intensity of the affective relationship of c_i for c_j, (ii) a probability that c_i and c_j are included in same community is proportional to a probability that c_i has a positive emotion for c_j, and (iii) a probability that c_i and c_j are included in different communities from each other is proportional to a probability that c_i's affective relationship for c_j changed. The premises can be formulated as:

$$f_{i,j} \propto I_{i,j} \text{ and } F_{i,j}, \tag{23}$$
$$\mu_{(0,1]}(I_{i,j}) \propto \mu_{G_k}(c_i) \oplus \mu_{G_k}(c_j),\ c_i \in G_k, \tag{24}$$
$$F_{i,j} \propto \{1 - \mu_{G_k}(c_i) \oplus \mu_{G_k}(c_j)\},\ c_i \in G_k, \tag{25}$$

where $\mu_{(0,1]}(I_{i,j})$ indicates a degree of how possibly $I_{i,j}$ is included in a range, (0, 1], $\mu_{G_k}(c_i)$ denotes a degree of how possibly c_i is included within G_k, and $\oplus$ means the triangular norm.

Therefore, we estimated an affective relationship from c_i to c_j at $s_{\alpha,l}$ by applying the social relationships between them as a weighting factor on an affective annotation for c_i. The social relationships between c_i and c_j on $s_{\alpha,l}$ was estimated by three terms. The first term focused on how frequently c_i and c_j interact with each other within $s_{\alpha,l}$. For example, in Eqs. (26) and (27), the preceding terms indicate a proportion of a social affinity between c_i and c_j for a maximum social affinity of c_i with all characters. This term corresponds to the first premise in Assumption 1.

Second, we considered the degree of how possibly c_i and c_j were included in a same community, $\mu_{G_k}(c_i) \oplus \mu_{G_k}(c_j)$. As shown in Fig. 5(a) which is an example of 'Star Wars Episode VI: Return of the Jedi (1983)', members of a community around a protagonist 'Skywalker' and members of the other community around an antagonist 'Darth Vader' hardly ever interacted with each other. Also, the protagonist maintained companionship with his community and was hostile to the opposite community, and vice versa. Therefore, we divided this problem into two cases. As shown in the second terms of Eq. (26), we applied $\mu_{G_k}(c_i) \oplus \mu_{G_k}(c_j)$ as a weighting factor when c_i has a positive emotion. In the other case when c_i has a negative emotion, we applied how possibly c_i and c_j were included in different communities from each other as a weighting factor.

Finally, we used $\mu_{G_k}(c_i) \oplus \mu_{G_k}(c_j)$ to estimate how possibly the affective relationship from c_i to c_j had changed. Fig. 5(b) provides an example of a well-known movie, 'Star Wars: Episode III: Revenge of the Sith (2005)'. In this movie, although the protagonist 'Skywalker' has changed his position (i.e., a dramatic change of his affective relationships), the opponents of the change have been mainly included in different communities from 'Skywalker' (e.g., 'Obi-Wan Kenobi', 'Palpatine', etc.). Thus we applied a weighting factor $1 - \mu_{G_k}(c_i) \oplus \mu_{G_k}(c_j)$ which means how possibly c_i and c_j were included in different communities with each other, when we estimated a fluctuation of the affective relationship as shown in Eq. (27). Conclusively, the method for estimating $I_{i,j}$ and $F_{i,j}$ on $\mathcal{A}(s_{\alpha,l})$ can be formulated as:

$$I_{i,j} = \begin{cases} \dfrac{N(s_{\alpha,l})_{i,j}}{\max_{\forall c_k} N(s_{\alpha,l})_{i,k}} \times \{\mu_{G_k}(c_i) \oplus \mu_{G_k}(c_j)\} \\ \times I_l(c_i), & \text{if } I_l(c_i) > 0 \\ \dfrac{N(s_{\alpha,l})_{i,j}}{\max_{\forall c_k} N(s_{\alpha,l})_{i,k}} \times \{1 - \mu_{G_k}(c_i) \oplus \mu_{G_k}(c_j)\} \\ \times I_l(c_i), & \text{otherwise,} \end{cases} \tag{26}$$

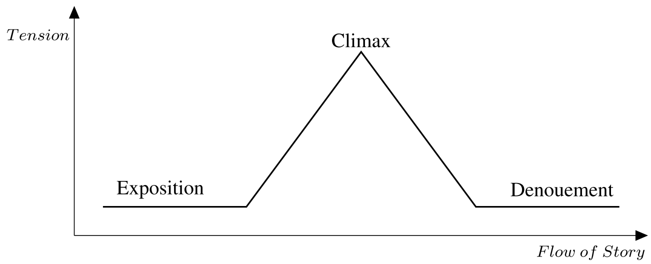


Fig. 6. A model of growth and resolution of tensions in stories.

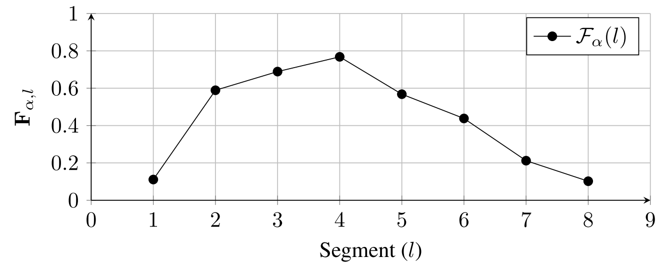


Fig. 7. An example of affective fluctuation function.

$$F_{i,j} = \frac{N(s_{\alpha,l})_{i,j}}{\max_{\forall c_k} N(s_{\alpha,l})_{i,k}} \times \{1 - \mu_{G_k}(c_i) \oplus \mu_{G_k}(c_j)\} \times F_l(c_i), \tag{27}$$

where

$$\mu_{G_k}(c_i) = \frac{\sum_{c_j \in G_k} N(s_{\alpha,l})_{i,j}}{\sum_{\forall c_j} N(s_{\alpha,l})_{i,j}} \times \frac{\sum_{c_j \in G_k} N^{acc}(s_{\alpha,l})_{i,j}}{\sum_{\forall c_j} N^{acc}(s_{\alpha,l})_{i,j}}, \tag{28}$$

$$\mu_{G_k}(c_i) \oplus \mu_{G_k}(c_j) = \min\{\mu_{G_k}(c_i), \mu_{G_k}(c_j)\}. \tag{29}$$

3.2.2. *Detecting affective events*

Conventionally, in the narrative works, emotional conflicts or tensions among the characters may keep increasing in the early phases of their story lines. Then, during climaxes, dramatic changes or reversals occur. In this moment, characters' ranges of affective fluctuation have mostly high values. The emotional conflicts tend to gradually decrease until the end of the stories. We were able to model it in Fig. 6, which is called 'Freytag's Pyramid' [28].

Nevertheless, narrative works in the real world do not possess a perfect pyramid, as displayed in Fig. 6. In the case of a whole series of a soap opera which is a group of narrative works related to each other, there can be multiple climaxes. To make a model which can represent various formats of stories, we have to represent the dynamic changes of the tensions within the stories. Therefore, we suggest Affective Fluctuation which marks the tension at certain points in the stories. We supposed that the affective fluctuation is a physical trace of the tension. It is defined as follows.

Definition 6 (*Affective Fluctuation*)**.** An affective fluctuation $\mathbf{F}_{\alpha,l}$ indicates a total emotional change for all the characters in a segment $s_{\alpha,l}$. As different from $F_l(c_i)$ defined in Definition 5 and $F(s_{\alpha,l})$ presented in Eq. (22), we represent it as a single value to compare it with other segments.

However, to estimate $\mathbf{F}_{\alpha,l}$, simply aggregating the ranges of the affective fluctuation is not appropriate since the importance of the characters (i.e., the centrality on character networks) were different from each other. To solve this issue, we considered two options: (i) a weighted average of $F_l(c_i)$ and (ii) a Frobenius norm of $F(s_{\alpha,l})$. We applied the weighted summation of $F_l(c_i)$ to reduce the uncertainty of the proposed methodology, since $F(s_{\alpha,l})$ is already an estimated variable from $F_l(c_i)$.

Therefore, we calculated $\mathbf{F}_{\alpha,l}$ as the weighted average of $F_l(c_i)$ for all c_i appeared in $s_{\alpha,l}$, by using the centralities of the characters as the weighting values. It can be formulated as:

$$\mathbf{F}_{\alpha,l} = \sum_{\forall c_i} C_i^{all} \times C_{l,i}^{seg} \times F_l(c_i) \times \frac{1}{\sum_{\forall c_i} C_i^{all} \times C_{l,i}^{seg}}, \tag{30}$$

where C_i^{all} indicates a centrality of c_i during whole $\mathbb{C}_\alpha$ as described in Eq. (8) and $C_{l,i}^{seg}$ means a centrality of c_i only within $s_{\alpha,l}$. The centralities of characters were measured by using linear combinations of the degree centrality, closeness centrality, and betweenness centrality, similar to a previous study [10]. They were estimated based on $N(\mathbb{C}_\alpha)$ and $N(s_{\alpha,l})$, respectively.

From the definition of affective fluctuation, we composed a discrete function $\mathcal{F}_\alpha(l)$ which provides a degree of affective fluctuation on each $s_{\alpha,l}$. We called it Affective Fluctuation Function (AFF). It can be defined as Eq. (31) and plotted as in Fig. 7.

$$\mathcal{F}_\alpha(l) = \mathbf{F}_{\alpha,l} \tag{31}$$

By using AFF, we detected the affective events that happened during the progression of the stories. It is conducted based on two assumptions, as follows.

Assumption 2 (*Affective Event*)**.** During important affective events, the characters may exhibit high ranges of affective fluctuation. Also, it may be high around the climaxes of the narrative works, and the climaxes might be turning points of the stories. It can be specified as the following two premises. (i) As the range of affective fluctuation increases, a corresponding segment will contain more important events. We called these kinds of events 'Major Affective Events.' (ii) Before and after major turning points of the stories, the direction of the affective fluctuation might change.

Based on these assumptions, we were able to find the turning points of stories and the major affective events. The major affective events were detected by a minimum threshold of the affective fluctuation. In this study, we defined this threshold as an average degree of the affective fluctuation. A set of the major events consists of segments which are describing them. It can be formulated as:

$$M_\alpha = \Bigg\{ s_{\alpha,l} \Bigg| \, |\mathcal{F}_\alpha(l) - \mathcal{F}_\alpha(l-1)| \geq \frac{1}{L} \times \sum_{\forall 1 < \mathbb{N} < L} |\mathcal{F}_\alpha(n) - \mathcal{F}_\alpha(n-1)| \Bigg\}, \tag{32}$$

where M_α is a set of the segments in $\mathbb{C}_\alpha$ which are corresponding with the major affective events. Also for convenience, we notate an ith major affective event in $\mathbb{C}_\alpha$ as $m_{\alpha,i}$.

Second, we extracted the turning points based on the derivatives of the AFF. If a left derivative and a right derivative on $s_{\alpha,l}$ had different signs from each other, we determined $s_{\alpha,l}$ to be one of the turning points. The left and right derivatives are approximated by the average gradients of the AFF. A set of the turning points is composed of segments which are depicting them. When T_α is a set of the segments within $\mathbb{C}_\alpha$ which are including the turning points, it can be defined as:

$$T_\alpha = \{s_{\alpha,l} | I^-(\alpha, l) \neq I^+(\alpha, l), s_{\alpha,l} \in \mathbb{C}_\alpha\}, \tag{33}$$

where $I^-(\alpha, l)$ and $I^+(\alpha, l)$ indicate the average gradients of the AFF on the left and right sides of $s_{\alpha,l}$, respectively. For readability, we notate an ith turning point in $\mathbb{C}_\alpha$ as $t_{\alpha,i}$. $I^-(\alpha, l)$ and $I^+(\alpha, l)$ are

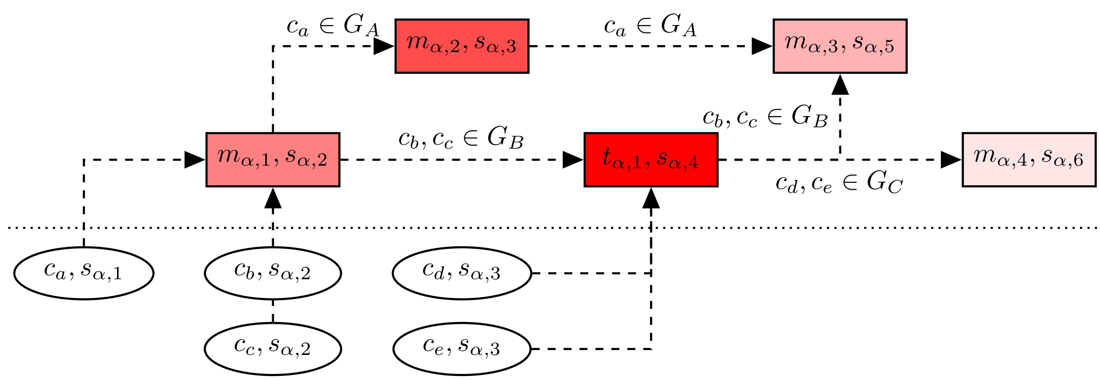


Fig. 8. An example of a story model, $S(\mathbb{C}_\alpha)$; blocks indicate affective events detected within $S(\mathbb{C}_\alpha)$, ellipses mean initial appearances of characters in $S(\mathbb{C}_\alpha)$, arrows denote involvements of the characters for the affective events, and colors of the blocks mean degrees of affective fluctuation at each affective event. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

calculated as:

$$I^-(\alpha, l) = \begin{cases} 1, & \text{if } \mathbf{F}_{\alpha,l} - \mathbf{F}_{\alpha,l-1} \geq 0 \\ 0, & \text{otherwise,} \end{cases} \tag{34}$$

$$I^+(\alpha, l) = \begin{cases} 1, & \text{if } \mathbf{F}_{\alpha,l+1} - \mathbf{F}_{\alpha,l} \geq 0 \\ 0, & \text{otherwise.} \end{cases} \tag{35}$$

After composing T_α and M_α, we excluded members of T_α from M_α, since the turning points might mostly be the major affective events. Also, we composed T_α^+ and T_α^- as subsets of T_α, which are indicators of the local maximums and local minimums, respectively. These two types of the turning points indicate different meanings from each other: (i) the starting points of the resolutions of in-progress stories (or sub-stories), and (ii) the starting points of new stories (or sub-stories).

Most of the stories progressed from an exposition to a denouncement via a climax, as shown in Fig. 6. Most single narrative works (e.g., a movie, a book, an episode of a TV series, etc.) had a single climax. However, when we targeted a set of narrative works sharing their narrative worlds (e.g., transmedia storytelling [29]), their common story lines had multiple turning points. As such, we captured the local maximums and minimums for detecting the turning points, instead of using the global maximums and minimums.

3.3. Modeling stories of the narrative works

In a previous study [29], Jung et al. modeled stories of narrative works that were related to each other as lattice graphs. We applied this scheme to describe the stories (or story lines) of the narrative works based on the major affective events and the turning points which were detected in Section 3.2.2. With this concept, the affective events were denoted as nodes on a graph; a horizontal order among the nodes represented their temporal order and a vertical distinction between them displayed their spatial backgrounds.

To model the stories of the narrative works, we used only the main characters (including protagonists) of them which $c_i \in C_\alpha^{Main}$. For example, suppose that $\mathbb{C}_\alpha$ has five main characters which belong to three different communities, a single turning point, and four major affective events. We can model $\mathbb{C}_\alpha$'s AFF $\mathcal{F}_\alpha(l)$ and its story model $S(\mathbb{C}_\alpha)$ as Figs. 7 and 8, respectively.

As shown in Fig. 8, a horizontal order of the nodes corresponds with their temporal order on $\mathbb{C}_\alpha$'s story line. The elliptical nodes below a dotted line and rectangular nodes above the dotted line, respectively, indicate the main characters and the affective events within $\mathbb{C}_\alpha$. The horizontal locations of the main characters' indicate the time points of their initial appearance, and the horizontal location of the affective events denote their occurred time. A vertical order of affective events indicates the difference in their spatial location where they have occurred. Also, we annotated their degrees of affective fluctuation by using colors of the nodes. The darker color means that stronger affective fluctuation occurred in a corresponding affective event. Furthermore, we notated the involvements of the main characters during the affective events by using arrows. The starting and ending points of the arrows denote involvements and movements of characters. Lastly, changes in the communities of the main characters are also notated on the arrows.

Based on this model, we present an example of a real narrative work, 'Star Wars: Episode III: Revenge of the Sith (2005)' as shown in Fig. 9; to increase readability, we wrote the descriptions of the affective events on the nodes instead of the segment numbers.

4. Story-based recommender system

In this section, we introduce a practical appliance for the affective character network: a story-based recommender system. It is difficult for conventional recommender systems, which mostly apply collaborative filtering (CF), to utilize the substantial information of stories within narrative works [30]. Even in cases of content-based filtering (CBF), they are highly domain-dependent or only consider implicit information in the narrative works [1,31].

Therefore, we suggest a novel recommendation method which can be applied independent of the domain for every narrative work regardless of their formats and media. To realize it, we first designed a new similarity measurement to estimate how similar the stories are. Also, we applied the similarity measurement on a preliminary story-based recommendation algorithm.

4.1. Story-based similarity measurement

To measure similarities among the stories of the narrative works, we used multiple metrics extracted from the affective character networks. The simplest way to measure how similar the stories are is to compare their AFFs, which are defined by Eq. (31). Nevertheless, it has a limitation of not being able to consider the affective events and the characters involved in them. Therefore, we propose two kinds of similarity metrics: (i) one based on the temporal sequences of the affective events and (ii) the other based on applying the shapes of the AFFs.

4.1.1. Sequence of the affective events and involved main characters

We proposed the model of stories for the narrative works in Section 3.3. The story model presents the affective events within the narrative works and the characters who are involved in the affective events. However, it is challenging to measure similarities among the story models, since the proposed model is represented as a lattice graph which is atypical and unstructured. Therefore, we

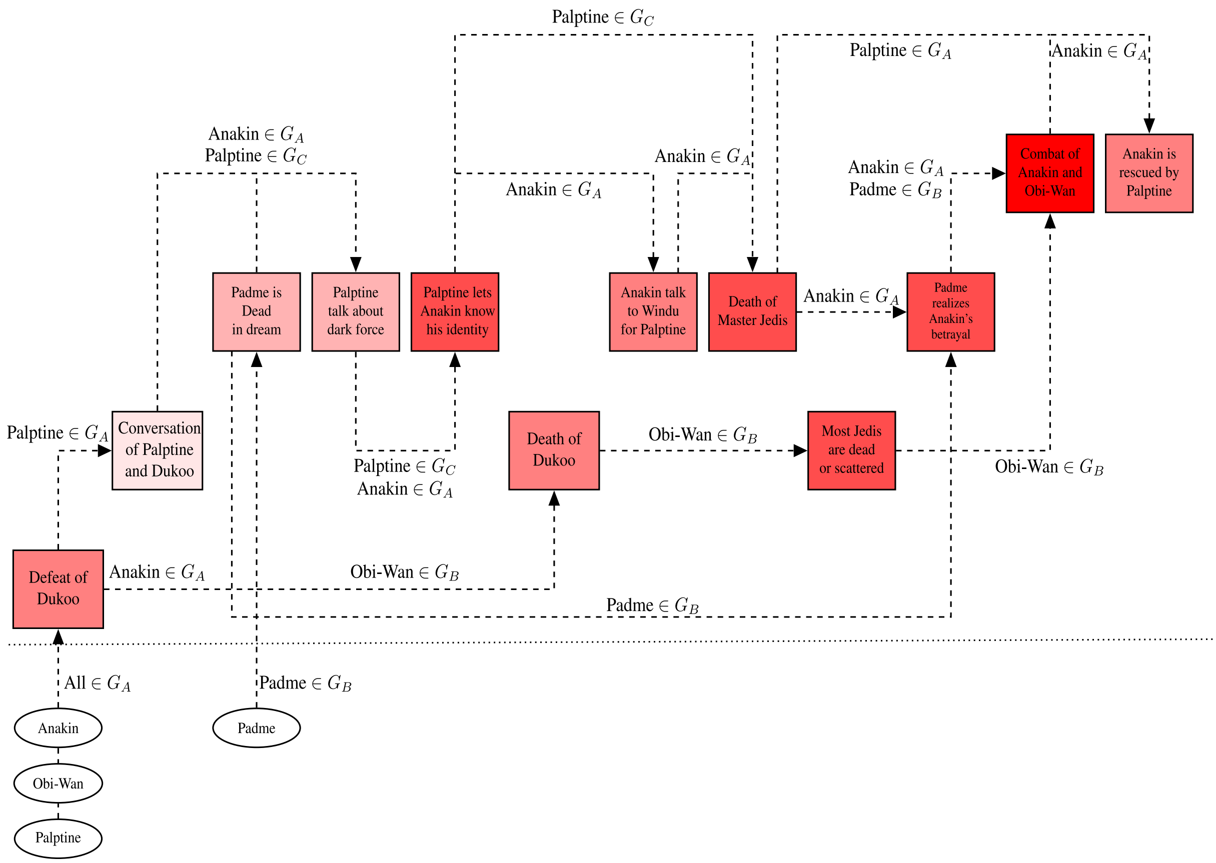


Fig. 9. A story model of 'Star Wars: Episode III: Revenge of the Sith (2005)'.

simplified the story models by reducing the information included in them.

It was conducted by 'summarizing' the involvements of the main characters based on a production of (i) their average emotional states on corresponding segments with the affective events, (ii) their centralities on the corresponding segments, and (iii) the degrees of affective fluctuation in the corresponding segments. By using these productions as elements of a matrix, we summarized the story models into matrices that easily can be compared to each other. $S(\mathbb{C}_\alpha)$ which is a story model of $\mathbb{C}_\alpha$ can be transformed into a matrix $\mathcal{M}(\mathbb{C}_\alpha) \in \mathbb{R}^{M\times K}$ as:

$$\mathcal{M}(\mathbb{C}_\alpha) = \begin{bmatrix} m_{1,1} & \cdots & m_{1,M} \\ \vdots & \ddots & \vdots \\ m_{K,1} & \cdots & m_{K,M} \end{bmatrix}, \tag{36}$$

where M is the number of main characters that appeared in $\mathbb{C}_\alpha$, K is the number of affective events that occurred in $\mathbb{C}_\alpha$, and $m_{i,j}$ indicates a relevancy between c_j and $e_{\alpha,i}$ which is an ith element of $E_\alpha = M_\alpha \cup T_\alpha$. When an affective event $e_{\alpha,i}$ corresponds with $s_{\alpha,l}$, an arbitrary element of $\mathcal{M}(\mathbb{C}_\alpha)$ ($m_{i,j}$) is estimated by multiplying c_j's average emotion on $s_{\alpha,l}$ ($I_l(c_j)$), c_j's centrality on $s_{\alpha,l}$ ($C^{seg}_{l,j}$), and a degree of affective fluctuation on $s_{\alpha,l}$ ($\mathcal{F}_\alpha(l)$). It can be formulated as:

$$m_{i,j} = I_l(c_j) \times C^{seg}_{l,j} \times \mathcal{F}_\alpha(l). \tag{37}$$

Nevertheless, it still has a problem in that the number of rows (events) and columns (characters) are different from each narrative work. To solve this problem, we reduced the number of rows and columns of a bigger story matrix in accordance with the number included in the smaller story matrices.

First, in order to reduce the number of affective events, we located a point of reference by using the climax which had the highest AFF value in each narrative work; it was one of the turning points which belongs to $T_\alpha \subset E_\alpha$. Then, we calculated the relative positions of other affective events on the basis of the climaxes. When we supposed that $\mathbb{C}_\alpha$'s climax $t_{\alpha,c}$ was on $s_{\alpha,l}$, $\mathcal{R}(e_{\alpha,i})$ which is a relative location of $e_{\alpha,i}$ corresponding with $s_{\alpha,m}$ can be calculated as:

$$\mathcal{R}(e_{\alpha,i}) = \begin{cases} \dfrac{m}{l}, & \text{if } m < l \\ \dfrac{m}{L_\alpha - l}, & \text{otherwise,} \end{cases} \tag{38}$$

where L_α is the number of segments included in $\mathbb{C}_\alpha$. Based on the relative location, we found matches from a narrative work which had a smaller number of affective events than the opponent one. These matching processes were conducted separately according to the kinds of affective events and between the front and the back of the climaxes. If we found a match for $m_{\alpha,i}$ which is on the front of climax, it was formulated as:

$$match(m_{\alpha,i}) = \underset{m_{\beta,j}\in M_\beta}{\mathrm{argmin}} \left\| \mathcal{R}(m_{\alpha,i}) - \mathcal{R}(m_{\beta,j}) \right\|_2, \tag{39}$$

where $\left\| \mathcal{R}(m_{\alpha,i}) - \mathcal{R}(m_{\beta,j}) \right\|_2$ indicate an euclidean distance between $\mathcal{R}(m_{\alpha,i})$ and $\mathcal{R}(m_{\beta,j})$ and $match(m_{\alpha,i})$ means a match of $m_{\alpha,i}$. With the matches, we made the number of rows of the story matrix for both target narrative works the same by deleting affective events which were not matched.

As an example, suppose $\mathbb{C}_\alpha$ and $\mathbb{C}_\beta$ which have AFFs, in the same manner as $\mathcal{F}_\alpha(l)$ and $\mathcal{F}_\beta(l)$ in Fig. 10. In this case, a climax of $\mathbb{C}_\alpha$ may have been located in $s_{\alpha,4}$ and there were no more other turning points in $\mathbb{C}_\alpha$. Also, the major events within $\mathbb{C}_\alpha$ would be $s_{\alpha,2}$, $s_{\alpha,3}$, $s_{\alpha,5}$ and $s_{\alpha,6}$. However, a climax of $\mathbb{C}_\beta$ was on $s_{\beta,10}$ and it had two other turning points: $s_{\beta,4}$ and $s_{\beta,5}$. Furthermore, it included eight

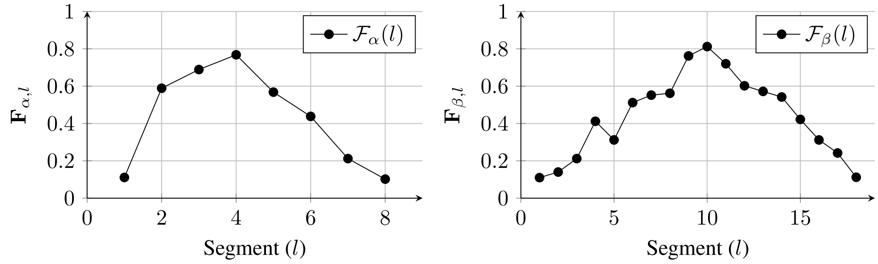


Fig. 10. Affective fluctuation functions of $\mathbb{C}_\alpha$ and $\mathbb{C}_\beta$.

Table 1
An example of reducing the number of $\mathbb{C}_\alpha$'s main characters in accordance with $\mathbb{C}_\beta$.

(a) List of main characters in $\mathbb{C}_\alpha$				(b) List of main characters in $\mathbb{C}_\beta$		
	G_A	G_B	G_C		G_O	G_P
c_a	1			c_o	1	
c_b		1		c_p		1
c_c	1			c_q	1	
c_d			1			
c_e			1			

major affective events: $s_{\beta,6}$, $s_{\beta,7}$, $s_{\beta,8}$, $s_{\beta,9}$, $s_{\beta,11}$, $s_{\beta,12}$, $s_{\beta,13}$, and $s_{\beta,14}$.

Since $\mathbb{C}_\beta$ contained many more affective events than $\mathbb{C}_\alpha$ in both of the turning points and the major affective events, in order to compare them, we reduced the number of affective events in $\mathbb{C}_\beta$. All of the turning points in $\mathbb{C}_\beta$, excluding its climax, were deleted, since $\mathbb{C}_\alpha$ did not have any extra turning points. Then, the major affective events, $s_{\beta,6}$ and $s_{\alpha,2}$ were matched in front of the climaxes. Though, $s_{\beta,7}$ and $s_{\beta,8}$ had the same distance with $s_{\alpha,3}$. In this case, we chose $s_{\beta,8}$ which had a higher degree of affective fluctuation. For the same reason, we chose $s_{\beta,12}$ and $s_{\beta,14}$ on the back of the climaxes.

To reduce characters, we used the communities and centralities of them. To conduct it, we developed two objectives: (i) a reduced list of characters should include as many communities as possible and (ii) characters in the list should have as high centralities as possible. For instance, suppose that $\mathbb{C}_\alpha$ and $\mathbb{C}_\beta$ contain the main characters displayed in Table 1. In this example, $\mathcal{M}(\mathbb{C}_\alpha)$ can have the same number of columns as $\mathcal{M}(\mathbb{C}_\beta)$ by deleting the 3rd and 5th columns which corresponded to c_c and c_e.

With these fitted matrices, we were able to measure inverse similarities between the story models by using Frobenius distance. Suppose that $\mathcal{M}(\mathbb{C}_\alpha) \in \mathbb{R}^{M\times K}$ is reduced into $\mathcal{M}'(\mathbb{C}_\alpha) \in \mathbb{R}^{M'\times K'}$ in accordance with $\mathcal{M}(\mathbb{C}_\beta) \in \mathbb{R}^{M'\times K'}$. When a similarity between $\mathcal{M}(\mathbb{C}_\alpha)$ and $\mathcal{M}(\mathbb{C}_\beta)$ was notated as $\mathcal{S}^{PM}(\mathcal{M}(\mathbb{C}_\alpha), \mathcal{M}(\mathbb{C}_\beta))$, which can be defined as:

$$\mathcal{S}^{PM}(\mathcal{M}(\mathbb{C}_\alpha), \mathcal{M}(\mathbb{C}_\beta)) = \frac{1}{\left\|\mathcal{M}'(\mathbb{C}_\alpha) - \mathcal{M}(\mathbb{C}_\beta)\right\|_F}, \tag{40}$$

where $\left\|\mathcal{M}'(\mathbb{C}_\alpha) - \mathcal{M}(\mathbb{C}_\beta)\right\|_F$ indicates a Frobenius distance between $\mathcal{M}'(\mathbb{C}_\alpha)$ and $\mathcal{M}(\mathbb{C}_\beta)$.

4.1.2. Shape of affective fluctuation function

In the previous section, we reduced the sizes of bigger story matrices to smaller ones to compare them with each other, since it is hard to presume the existence of nonexistent characters or affective events. However, the AFFs are functions which indicate the changes in the tensions according to the progression of the stories. It enabled the modification of domains of the AFFs and approximate nonexistent or unobserved values of them by using the interpolation methods.

First, since the number of segments within the narrative works was different from each other, the domains of AFFs also varied and needed to be uniform. In this study, we transformed the domain of the AFFs into a range $(0, 1]$ en bloc. For example, when a narrative work $\mathbb{C}_\alpha$ had L segments, its AFF $\mathcal{F}_\alpha(l)$ could be transformed as:

$$\widehat{\mathcal{F}}_\alpha(x_l) = \mathcal{F}_\alpha(l),\ x_l = \frac{l}{L}, \tag{41}$$

where $\widehat{\mathcal{F}}_\alpha(x_l)$ indicates a transformation of $\mathcal{F}_\alpha(l)$.

Based on this unification of the domains, we could modify the AFFs from a discrete function to a continuous function using the interpolation methods. We used the polynomial interpolation which is well-known to transform AFFs. When $\widetilde{\mathcal{F}}_\alpha(x)$ is a continuous form of $\mathcal{F}_\alpha(l)$, it can be formulated as:

$$\widetilde{\mathcal{F}}_\alpha(x) = \sum_{l=0}^{L-1} k_l x^l,\ x \in (0, 1], \tag{42}$$

where k_l indicates a coefficient for a lth term of $\widetilde{\mathcal{F}}_\alpha(x)$. Also, for $x_l \in (0, 1]$ which is in accordance with $s_{\alpha,l}$, we are able to notate $\widetilde{\mathcal{F}}_\alpha(x)$ with a system of linear equations as:

$$\begin{bmatrix} x_1^{L-1} & x_1^{L-2} & \cdots & x_1 & 1 \\ x_2^{L-1} & x_2^{L-2} & \cdots & x_2 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{L-1}^{L-1} & x_{L-1}^{L-2} & \cdots & x_{L-1} & 1 \\ x_L^{L-1} & x_L^{L-2} & \cdots & x_L & 1 \end{bmatrix} \begin{bmatrix} k_{L-1} \\ k_{L-2} \\ \vdots \\ k_2 \\ k_1 \end{bmatrix} = \begin{bmatrix} \widehat{\mathcal{F}}_\alpha(x_1) \\ \widehat{\mathcal{F}}_\alpha(x_2) \\ \vdots \\ \widehat{\mathcal{F}}_\alpha(x_{L-1}) \\ \widehat{\mathcal{F}}_\alpha(x_L) \end{bmatrix}. \tag{43}$$

Then, we approximated the coefficients k_l based on the Lagrange Interpolating Polynomial which is also a well-known method [32]. Finally, $\widetilde{\mathcal{F}}_\alpha(x)$ is approximated as:

$$\widetilde{\mathcal{F}}_\alpha(x) = \sum_{l=1}^{L} \left\{ \prod_{\substack{k\in[1,L] \\ l\neq k}} \frac{x_l - x_k}{x - x_k} \right\} \times \widehat{\mathcal{F}}_\alpha(x_l). \tag{44}$$

To compare the shapes of the AFFs with each other through $\widetilde{\mathcal{F}}_\alpha(x)$, we composed Affective Fluctuation Vectors (AFVs), and calculated similarities among the AFVs. An AFV for $\mathbb{C}_\alpha$ is notated as $\overrightarrow{\mathcal{F}_\alpha}$. For composing $\overrightarrow{\mathcal{F}_\alpha}$, we collected samples from $\widetilde{\mathcal{F}}_\alpha(x)$ in regular intervals of $1/\mathcal{I}$. It can be formulated as:

$$\overrightarrow{\mathcal{F}_\alpha} = \left\langle \widetilde{\mathcal{F}}_\alpha\left(\frac{1}{\mathcal{I}}\right), \widetilde{\mathcal{F}}_\alpha\left(\frac{2}{\mathcal{I}}\right), \ldots, \widetilde{\mathcal{F}}_\alpha(1) \right\rangle. \tag{45}$$

Furthermore, when we compare $\mathbb{C}_\alpha$ and $\mathbb{C}_\beta$, we can determine $\mathcal{I}$ as:

$$\mathcal{I} = \begin{cases} \max\left\{L_\alpha, L_\beta\right\}, & \text{if (LMC of } \mathbb{C}_\alpha \text{ and } \mathbb{C}_\beta) \\ & \geq 0.5 \times L_\alpha \times L_\beta \\ \text{LMC of } \mathbb{C}_\alpha \text{ and } \mathbb{C}_\beta, & \text{otherwise,} \end{cases} \tag{46}$$

where LMC indicates the least common multiple and L_α indicates the number of segments in $\mathbb{C}_\alpha$.

Based on the AFVs, we applied various similarity metrics to compare the shapes of the AFFs which indicated the changes in the tension levels. In this preliminary study, we used the Euclidean distance to estimate inverse similarities among them. When $\mathcal{S}^{AFF}(\mathcal{F}_\alpha(l), \mathcal{F}_\beta(l))$ means a similarity between $\mathcal{F}_\alpha(l)$ and $\mathcal{F}_\beta(l)$, it can be conducted as

$$\mathcal{S}^{AFF}(\mathcal{F}_\alpha(l), \mathcal{F}_\beta(l)) = \frac{1}{\left\| \overrightarrow{\mathcal{F}_\alpha} - \overrightarrow{\mathcal{F}_\beta} \right\|_2}, \tag{47}$$

where $\left\| \overrightarrow{\mathcal{F}_\alpha} - \overrightarrow{\mathcal{F}_\beta} \right\|_2$ denotes an euclidean distance between $\overrightarrow{\mathcal{F}_\alpha}$ and $\overrightarrow{\mathcal{F}_\beta}$.

Finally, to estimate the story-based similarities among the narrative works, we combined the two similarity metrics by using the linear combination. It is formulated as:

$$\mathcal{S}(\mathbb{C}_\alpha, \mathbb{C}_\beta) = w_\mathcal{S} \times \mathcal{S}^{PM}(\mathcal{M}(\mathbb{C}_\alpha), \mathcal{M}(\mathbb{C}_\beta)) + (1 - w_\mathcal{S}) \times \mathcal{S}^{AFF}(\mathcal{F}_\alpha(l), \mathcal{F}_\beta(l)), \tag{48}$$

where $w_\mathcal{S} \in [0, 1]$ is a weighting factor for combining the two similarity metrics. A value of $w_\mathcal{S}$ is determined by the performance evaluation which is depicted in Section 5.

4.2. Story-based collaborative filtering

To recommend narrative works with the story-based similarity measurement, we applied it to the conventional item clustering-based CF methods (ICCF) [33,34]. An algorithm for a recommendation can be procedurally represented as follows.

1. Cluster narrative works with the story-based similarity measurement.
2. Estimate the preference of the users for narrative works by using composed clusters as neighborhood groups.
3. Compose Top-N list of narrative works to recommend for users.

First, the narrative works were clustered based on the story-based similarities proposed in Section 4.1 by using the k-NN (Nearest Neighborhood) algorithm which is well-known; we maximized the total summation of the similarities within each cluster. Additionally, to build the cluster model, we had to determine the number of clusters.

In order to determine the number of clusters, we modified the Fukuyama–Sugeno index [35,36] which is widely used in fuzzy-clustering. It is formulated as:

$$FS_k = \sum_{\forall \mathbb{C}_\alpha} \sum_{\forall \mathcal{G}_i} \mu_{\mathcal{G}_i}(\mathbb{C}_\alpha)^k \times \left(\mathcal{S}(\mathbb{C}_\alpha, C_i) - \mu\right), \tag{49}$$

$$\mu_{\mathcal{G}_i}(\mathbb{C}_\alpha) = \sum_{\substack{\forall \mathbb{C}_\beta \in \mathcal{G}_i \\ \mathbb{C}_\alpha \neq \mathbb{C}_\beta}} \mathcal{S}(\mathbb{C}_\alpha, \mathbb{C}_\beta) \times \frac{1}{|\mathcal{G}_i|}, \tag{50}$$

$$\mu = \sum_{\forall C_i} \sum_{\substack{\forall C_j \\ C_i \neq C_j}} \mathcal{S}(C_i, C_j) \times \frac{2}{I(I-1)}, \tag{51}$$

where $\mathcal{G}_i$ indicates an ith cluster, I denotes the number of clusters in a current cluster model, C_i is a center of the ith cluster, $\mathcal{G}_i$, μ means an average of similarities among the centers, $\mu_{\mathcal{G}_i}(\mathbb{C}_\alpha)$ is a membership degree of $\mathbb{C}_\alpha$ for $\mathcal{G}_i$, $|\mathcal{G}_i|$ indicates the number of narrative works included in $\mathcal{G}_i$, and k is an user-defined parameter which is a positive integer. In this regard, a first term of Eq. (49) indicated a compactness of each cluster, a second term was in accordance with an adjacency among the clusters, and finally FS_k was the Fukuyama–Sugeno index for the current cluster model. The better the quality of a cluster model of the narrative works is, the lower a value of FS_k for the model is. Therefore, we determined the number of clusters as a number which makes FS_k minimize.

Secondly, the users' preferences for the narrative works were estimated by a weighted average of the ratings which were placed for neighborhoods of the narrative works. It can be formulated as:

$$p_{u_i,\mathbb{C}_\alpha} = \sum_{\forall \mathbb{C}_\beta \in \mathcal{G}_i} H\left(u_i, \mathbb{C}_\beta\right) \times r_{u_i,\mathbb{C}_\beta} \times \mathcal{S}(\mathbb{C}_\alpha, \mathbb{C}_\beta),\ \mathbb{C}_\alpha \in \mathcal{G}_i, \tag{52}$$

$$H\left(u_i, \mathbb{C}_\beta\right) = \begin{cases} 1, & \text{if } r_{u_i,\mathbb{C}_\beta} \neq \varnothing \\ 0, & \text{otherwise,} \end{cases} \tag{53}$$

where $p_{u_i,\mathbb{C}_\alpha}$ indicates an estimated preference of u_i for $\mathbb{C}_\alpha$, $r_{u_i,\mathbb{C}_\beta}$ means a rating for $\mathbb{C}_\beta$ given by u_i, and $H\left(u_i, \mathbb{C}_\beta\right)$ denotes an indicator function to check an existence of $r_{u_i,\mathbb{C}_\beta}$. Finally, we provided top-N narrative works to the users which received the highest values for the estimated preferences.

As demonstrated in the recommendation procedures, we were able to provide the narrative works for users fully-independent from formats, media, domains, and physical characteristics of the narrative works based on the affective character network, the story model built upon it, and the story-based similarity measurement.

5. Evaluation and discussion

In this study, we conducted an evaluation with five experiments: three of them were for verifying the affective character network and the others were to assure the story-based recommendation. For composing the affective character network, we focused on detecting the communities on the character networks, estimating the affective relationships among the characters, and detecting the affective event occurred within the narrative works. In the case of the story-based recommender system, we concentrated on the story-based similarity measurement and performance of the recommendation method.

Common to all of the conducted experiments, it was hard to compose comparison groups, since a research area of this study was challenging and unprecedented. Also for the same reason, it was difficult to find any benchmark dataset or massive dataset. Furthermore, there was not any ground truth to analyze the stories of the narrative works, since understanding the stories was quite intuitive with the subjective criteria. It made it difficult to build objective criteria to evaluate the proposed models and methods.

Therefore, we conducted human evaluations by user surveys. For the user survey, we composed a dataset of narrative works with 10 movies which were evenly distributed on various genres. Also, we made a user group composed of 25 people who were faculty members and students of the Chung-Ang University. Based on the dataset and user group, we collected data for the evaluation which are described in following sections. Table 2 is a list of the titles and publication years of the narrative works included within the dataset. In the remaining sections, we depict the methods and results of the experiments and discuss them.

5.1. Verifying the affective character network

In this section, we focused on verifying the efficiency of the affective character network and the reliability of the method for composing it. As the first step for extracting the social information from the character network, we evaluated the reliability of the community detection which is described in Section 3.1.3, since the other parts were slightly modified from the already verified methods introduced in our previous works (e.g., composing the character network with the co-occurrences of the characters [10], extracting the centralities and roles of the characters [10], and segmenting the narrative works with the occurrences of characters [11,18]).

Secondly, for composing the affective character network, we evaluated how reliable the method was with estimating the affective relationships among the characters; the method is depicted in Section 3.2.1. It was important, since this method determined the edges of the affective character network.

Furthermore, with regard to building the story model, we verified the accuracy of the method for detecting the affective events; this method is described in Section 3.2.2. The affective events were a foundation of modeling and comparing the stories in the proposed methodology. Also, since it was difficult to determine the ground truth for problems we had tried to solve, we compared the results of the proposed method with the user survey.

5.1.1. Accuracy of community detection

To determine $w_{\mathbb{Q}}$ and evaluate the community detection method, we measured the accuracy of the community detection in regular intervals; $\Delta w_{\mathbb{Q}} = 0.05$. We used only precision for measuring the accuracy, since the recall which is ordinarily used together had a conflict with the precision. The reason was that the characters were unconditionally included in only one community in the proposed method.

In addition, we could not use standard assessment metrics for the community detection methods, since they are inadequate for this study. The standard metrics focus on how perfectly the detected groups match with the actual communities. However, as displayed in Figs. 4 and 5, groups of the main and minor characters are quite distinct, which are meaningful for analyzing the stories. In here, our primary concern is whether the proposed method can trace temporal changes in the characters' communities. We recognize that the precision also does not accord with this requirement. Moreover, measuring accuracies of the proposed method segment by segment is excessively labor-intensive. As a preliminary and challenging research, development of the assessment metrics will be the top priority for our future studies.

To conduct experiment, we had made users watch an arbitrary narrative work and build communities of characters in an arbitrary segment. Then, we compared users' responses with the results of the proposed method. We assigned three users for $\mathbb{C}_1$, $\mathbb{C}_2$, $\mathbb{C}_8$, $\mathbb{C}_9$, and $\mathbb{C}_{10}$ and two users for the others, since former ones have more complicated stories (i.e., stories which are twisted or rapidly developed) than the others. Also, to verify how accurately the proposed method could detect dynamic changes in the communities, we selected segments, which located around turning points, as experimental subjects. The subjects were evenly chosen from the front and the rear of the climaxes. An accuracy measurement for the proposed method can be formulated as:

$$p^{\mathcal{G}}(w_{\mathbb{Q}}) = \sum_{\forall u_j} \sum_{\forall c_i \in C_\alpha^{Main}} \frac{\mathcal{T}(c_i, s_{\alpha,l})}{|C_\alpha^{Main}|} \times \frac{1}{|U|}, \tag{54}$$

$$\mathcal{T}(c_i, s_{\alpha,l}) = \begin{cases} 1, & \text{if } G(s_{\alpha,l})_i = G(s_{\alpha,l})_i^{u_j} \\ 0, & \text{otherwise,} \end{cases} \tag{55}$$

where u_j is a jth respondent of our user-survey, $\mathbb{C}_\alpha$ is a target narrative work, $s_{\alpha,l}$ is a target segment, $G(s_{\alpha,l})_i$ indicate a community including c_i on $s_{\alpha,l}$, $G(s_{\alpha,l})_i^{u_j}$ means a community including c_i on $s_{\alpha,l}$ which thought by u_j, $\mathcal{T}(c_i, s_{\alpha,l})$ is an indicator function to compare $G(s_{\alpha,l})_i$ with $G(s_{\alpha,l})_i^{u_j}$, $|U|$ is the number of respondents, and $p^{\mathcal{G}}(w_{\mathbb{Q}})$ denotes a precision of the proposed method on a certain weighting value, $w_{\mathbb{Q}}$. In this regard, a result for evaluating the proposed community detection method is plotted in Fig. 11.

As displayed in Fig. 11, $p^{\mathcal{G}}(w_{\mathbb{Q}})$ had the highest value on $w_{\mathbb{Q}} = 0.80$. It did not exhibit a big gap compared to the peripheral values. However, it demonstrated a meaningful gap with an average value of $p^{\mathcal{G}}(w_{\mathbb{Q}})$. This result verified that our hypothesis was reasonable, which is introduced in Section 3.1.3: we should have considered the internal connectivities among the characters more than their external connectivities, since most of the characters were connected to each other and the peripheral ones of the protagonists or their opponents.

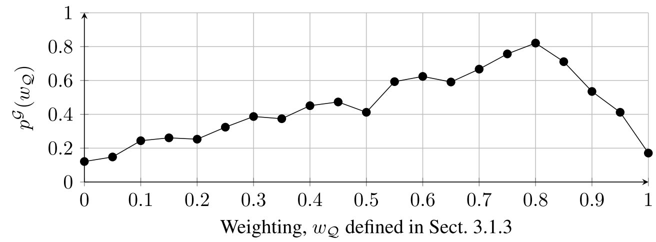


Fig. 11. Determining weighting value, $w_{\mathbb{Q}}$ based on accuracies of the proposed community detection method.

Table 3
Results of the experiment for evaluating affective relationship estimation.

Metric	MAE^I	MAE^F
Value	0.14	0.20

5.1.2. Reliability of the affective relationship estimation

To evaluate the reliability of the proposed method for estimating affective relationships, we applied the differences between the automatically estimated affective relationships and the manually annotated ones by the respondents. We used the Mean Absolute Error (MAE) which is well-known and widely used for measuring differences.

To conduct the experiment, we had made users watch an arbitrary narrative work and annotate the affective relationships among the characters in an arbitrary segment. Then, we compared users' responses with the results of the proposed method. We assigned three users for the narrative works from $\mathbb{C}_3$ to $\mathbb{C}_7$, which are the romance or drama films, and two users for the others, since they have more emotionally sensitive stories than the others. As different from the former experiment, we selected segments that have low degrees of the affective fluctuation, to evaluate how minutely the proposed method was able to extract the emotional relationships. The MAEs for the two kinds of affective relationships in the proposed method (i.e., the emotional state and the affective fluctuation) can be calculated as:

$$MAE^I = \sum_{\forall u_j} \sum_{\substack{\forall c_i, c_j \in C_\alpha^{Main} \\ c_i \neq c_j}} \frac{\left\| I(s_{\alpha,l})_{i,j} - I(s_{\alpha,l})_{i,j}^{u_j} \right\|_2}{|C_\alpha^{Main}|} \times \frac{1}{|U|}, \tag{56}$$

$$MAE^F = \sum_{\forall u_j} \sum_{\substack{\forall c_i, c_j \in C_\alpha^{Main} \\ c_i \neq c_j}} \frac{\left\| F(s_{\alpha,l})_{i,j} - F(s_{\alpha,l})_{i,j}^{u_j} \right\|_2}{|C_\alpha^{Main}|} \times \frac{1}{|U|}, \tag{57}$$

where $I(s_{\alpha,l})_{i,j}$ and $F(s_{\alpha,l})_{i,j}$ are automatically estimated emotional states and the degrees of affective fluctuation of c_i for c_j, respectively, $I(s_{\alpha,l})_{i,j}^{u_j}$ and $F(s_{\alpha,l})_{i,j}^{u_j}$ indicate $I(s_{\alpha,l})_{i,j}$ and $F(s_{\alpha,l})_{i,j}$ which are estimated by a respondent, u_j, respectively, and MAE^I and MAE^F are the average differences for the emotional states and the degrees of affective fluctuation, respectively. In this regard, an experimental result for the proposed method of estimating the affective relationships is displayed in Table 3.

As displayed, both of the MAE^I and MAE^F had quite low values. In addition, the ranges and standard deviations (S.D.) of the MAE^I and MAE^F had low values; range and S.D. of MAE^I were 0.61 and 0.44, receptively, and the MAE^I were 0.72 and 0.50, respectively. These findings indicated that the proposed method had not only high reliability, but also stable performance. However, we could not compare it with other existing methods since there were not any previous methods which have the same or similar purpose. The comparison of the reliability of the affective relationship estimation will be one of our future studies.

5.1.3. Efficiency of the affective event detection

Evaluating the efficiency of the proposed method to detect the affective events in the narrative works was conducted by two metrics: the precision and recall. The precision is used for measuring how accurately affective events were detected, and the recall indicates how many affective events are found when considering all of the affective events. In order to combine these two metrics, we applied the F-measure which is well-known and widely-used. Also, since the recall is important as much as the precision, we set β (a coefficient of F-measure) as 1 which means that we have considered both of them equally. It can be formulated as:

$$p^E = \sum_{\forall u_j} \frac{\left|E_\alpha \cap E_\alpha^{u_j}\right|}{|E_\alpha|} \times \frac{1}{|U|},\ r^E = \sum_{\forall u_j} \frac{\left|E_\alpha \cap E_\alpha^{u_j}\right|}{\left|E_\alpha^{u_j}\right|} \times \frac{1}{|U|}, \tag{58}$$

$$F_1^E = 2 \cdot \frac{p^E \times r^E}{p^E + r^E}, \tag{59}$$

where E_α is a set of the affective events detected by the proposed method, $E_\alpha^{u_j}$ indicates a set of affective event detected by u_j, p^E and r^E which are the precision and recall of the proposed method, respectively, for detecting the affective events, and F_1^E denotes a F_1-measure of the proposed method. The F_1-measure for the turning points or the major affective events were calculated in the same way. In this regard, an experimental result for the proposed method of detecting the affective events is shown in Table 4.

Table 4 demonstrates that the proposed method for detecting the affective events had reliable accuracy on both sides: the precision and recall. Though, the proposed method showed low recall (0.67) for detecting the turning points on romance movies. This result means that the proposed method was not elaborate enough to reflect delicate emotional states and the changes among the characters. Also, the proposed method exhibited better performance for the turning points than for the major affective events, primarily on the recall. This result might indicate that there were semantically meaningful events which were not affectively intense. In future studies, we will attempt to represent the semantics of the dialogues and actions from the characters into the proposed story model and the character network.

5.2. Verifying story-based recommendation

To verify the efficiency of the story-based recommendation method, we focused on the (i) accuracy of the story-based similarity measurement described in Section 4.1 and (ii) performance of the story-based recommendation method depicted in Section 4.2. Obviously, the performance of the recommendation was dependent on the accuracy of the similarities among the narrative works. However, we compared the results of these two experiments to display whether the similarities of the stories and users' preferences for the narrative works were related to each other. Additionally, our experiments were conducted with a limited scale, since choosing the data sources and collecting the data for this study required a substantial amount of effort.

5.2.1. Reliability of the story-based similarity measurement

To evaluate the reliability of the story-based similarity measurement and decide $w_{\mathcal{S}}$, we measured the difference between the similarities estimated by the proposed measurement and the similarities assumed by the respondents of the user survey in regular intervals; $\Delta w_{\mathcal{S}} = 0.05$. To conduct the experiment, we had made users watch two arbitrary narrative works from our dataset, and annotate how similar the two narrative works were. An average difference of similarities is calculated by using MAE as:

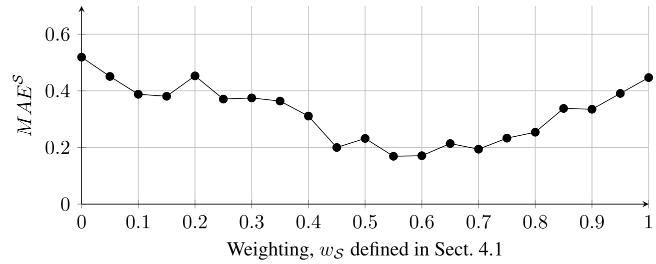


Fig. 12. Determining weighting value, $w_{\mathcal{S}}$ based on accuracies of the proposed similarity measurement.

$$MAE^{\mathcal{S}} = \sum_{\forall u_j} \sum_{\substack{\forall \mathbb{C}_\alpha, \mathbb{C}_\beta \\ \mathbb{C}_\alpha \neq \mathbb{C}_\beta}} \left\| \mathcal{S}(\mathbb{C}_\alpha, \mathbb{C}_\beta) - \mathcal{S}(\mathbb{C}_\alpha, \mathbb{C}_\beta)^{u_j} \right\|_2 \times \frac{1}{|U|}, \tag{60}$$

where $\mathcal{S}(\mathbb{C}_\alpha, \mathbb{C}_\beta)$ and $\mathcal{S}(\mathbb{C}_\alpha, \mathbb{C}_\beta)^{u_j}$ are respectively similarities between the $\mathbb{C}_\alpha$ and $\mathbb{C}_\beta$ estimated by the proposed method and u_j and $MAE^{\mathcal{S}}$ indicates an average difference for the story-based similarity measurement. In this regard, a result of the evaluation for the similarity measurement is plotted in Fig. 12. Also, the similarities which were automatically estimated and collected from the user survey are provided in Table 5.

As displayed in Fig. 12, $MAE^{\mathcal{S}}$ had the lowest value on the $w_{\mathcal{S}} = 0.55$. The location of the optimal $w_{\mathcal{S}}$ which was approximately 0.50 in the cognition of human beings for the stories with changes in the tensions and flows of the affective events are similarly important. However, there was no significant gap between the lowest and the highest $MAE^{\mathcal{S}}$ values, when excluding both extremes. For this result, we presumed that there were other features that determined the similarities among the narrative works. We will attempt to assume and verify other unconsidered features with more varied and larger datasets in our future studies.

Table 5 demonstrates the differences between the automatically and manually estimated similarities for each narrative work, respectively, on the optimal $w_{\mathcal{S}}$. On each cell of the table, upper values were the automatically estimated values and the others were manually inserted from the respondents. Generally, the proposed similarity measurement demonstrated acceptable performance. Nevertheless, similar to Section 5.1.3, the proposed method displayed a weak point for romance movies. It may be because of a similar reason to the previous experiment.

5.2.2. Performance of the story-based recommender system

The method for performance evaluation of the story-based recommender system was similar to the method presented in Section 5.2.1. It was just modified from the estimated similarities to the predicted preferences. Thus, we compared the predicted preferences with the ratings from the respondents by using MAE. It can be formulated as:

$$MAE^{p} = \sum_{\forall u_j} \sum_{\forall \mathbb{C}_\alpha \in \mathbb{C}} \left\| p_{u_j,\mathbb{C}_\alpha} - r_{u_j,\mathbb{C}_\alpha} \right\|_2 \times \frac{1}{|\mathbb{C}|} \times \frac{1}{|U|}, \tag{61}$$

where $\mathbb{C}$ is a set of narrative works in our dataset, $|\mathbb{C}|$ indicates the number of narrative works in our dataset, and MAE^p denotes an average difference between the predicted preferences and the ratings. In this experiment, the ranges of the ratings and the preferences are [0, 1], and the ratings were the input as discrete values included in a set, {0.2, 0.4, 0.6, 0.8, 1.0}. In this regard, a result of

Table 4
Results of the experiment for evaluating affective event detection; p^M, r^M, and F_1^M are precision, recall, and F_1-measure for detecting the major affective events, respectively, and it is same for the metrics for the turning points: p^T, r^T, and F_1^T.

Metric	p^E	r^E	F_1^E	p^M	r^M	F_1^M	p^T	r^T	F_1^T
Value	0.88	0.81	0.85	0.87	0.79	0.83	0.95	0.97	0.98

Table 5
Results of the experiment for the story-based on similarity measurement with the optimal $w_{\mathcal{S}}$; on each cell, an upper value was automatically estimated and the other one was inserted by the respondents of the user-survey.

	$\mathbb{C}_1$	$\mathbb{C}_2$	$\mathbb{C}_3$	$\mathbb{C}_4$	$\mathbb{C}_5$	$\mathbb{C}_6$	$\mathbb{C}_7$	$\mathbb{C}_8$	$\mathbb{C}_9$	$\mathbb{C}_{10}$
$\mathbb{C}_1$	1.00 1.00	0.23 0.10	0.41 0.37	0.18 0.25	0.14 0.30	0.74 0.59	0.89 0.71	0.77 0.61	0.41 0.66	0.41 0.71
$\mathbb{C}_2$	0.23 0.10	1.00 1.00	0.21 0.01	0.13 0.07	0.19 0.06	0.24 0.30	0.20 0.12	0.44 0.59	0.27 0.60	0.30 0.63
$\mathbb{C}_3$	0.41 0.37	0.21 0.01	1.00 1.00	0.41 0.89	0.66 0.98	0.11 0.00	0.24 0.09	0.31 0.14	0.04 0.17	0.09 0.10
$\mathbb{C}_4$	0.18 0.25	0.13 0.07	0.41 0.89	1.00 1.00	0.48 0.80	0.21 0.07	0.34 0.19	0.15 0.01	0.10 0.31	0.17 0.13
$\mathbb{C}_5$	0.14 0.30	0.19 0.06	0.66 0.98	0.48 0.80	1.00 1.00	0.20 0.11	0.13 0.21	0.35 0.00	0.20 0.03	0.10 0.04
$\mathbb{C}_6$	0.74 0.59	0.24 0.30	0.11 0.00	0.21 0.07	0.20 0.11	1.00 1.00	0.67 0.84	0.45 0.11	0.51 0.39	0.18 0.10
$\mathbb{C}_7$	0.89 0.71	0.20 0.12	0.24 0.09	0.34 0.19	0.13 0.21	0.67 0.84	1.00 1.00	0.31 0.11	0.56 0.21	0.24 0.17
$\mathbb{C}_8$	0.77 0.61	0.44 0.59	0.31 0.14	0.15 0.01	0.35 0.00	0.45 0.11	0.31 0.11	1.00 1.00	0.47 0.48	0.11 0.30
$\mathbb{C}_9$	0.41 0.66	0.27 0.60	0.04 0.17	0.10 0.31	0.20 0.03	0.51 0.39	0.56 0.21	0.47 0.48	1.00 1.00	0.24 0.10
$\mathbb{C}_{10}$	0.41 0.71	0.30 0.63	0.09 0.10	0.17 0.13	0.10 0.04	0.18 0.10	0.24 0.17	0.11 0.30	0.24 0.10	1.00 1.00

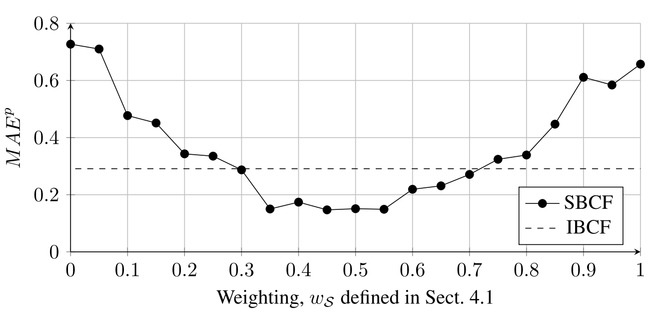


Fig. 13. Performance of the proposed recommendation method and IBCF according to the weighting value, $w_{\mathcal{S}}$; SBCF (Story-Based Collaborative Filtering) which indicates the proposed method and IBCF refers to item-based collaborative filtering.

the evaluation for the story-based recommender system is plotted in Fig. 13.

As displayed in Fig. 13, we compared the proposed recommendation method with one of the conventional CF methods, the IBCF (Item-Based Collaborative Filtering). With most of the values of $w_{\mathcal{S}}$ excluding both of the extremes, the proposed recommendation method displayed better performance (i.e., lower MAE^p values) than the IBCF. Also, it demonstrated that the MAE^p had the lowest value on $w_{\mathcal{S}} = 0.45$ which is nearby the optimal $w_{\mathcal{S}} = 0.55$. This finding indicates that the similarities among the narrative works and the preferences of the users were highly correlated. Although we could not conduct the experiment with an adequate sized comparison group because of an absence of existing methods, we have deduced another method to demonstrate the utility of the story-based recommender system.

To show how correlated the similarities of the stories and the preferences of users are, we used Pearson correlation coefficient between $MAE^{\mathcal{S}}$ and MAE^p. The correlation coefficient was 0.75, which indicate that the reliability of the story-based similarity and the performance of story-based recommender system were positively correlated. Moreover, it directly displays the efficiency of the story-based similarity and indirectly proves the reliability of the proposed story model.

6. Related work

With an overflowing amount of the narrative works distributed on the WWW, various studies have been conducted to effectively provide the narrative works for users. The number of previous studies for content providing systems (e.g., retrieval, recommendation, curation, etc.) demonstrates that many attempts have been made to analyze the contents of the narrative works. Most of these studies have stopped at analyzing cursory factors of the narrative works. A few studies have extracted affective features which stimulate users' emotional states; however, they have not been able to connect them such that they represent the substantial matters (i.e., mainly the stories) of an overall narrative work. This circumstance commonly happens with content providing systems which are based on content analysis methods.

Since it is hard to find previous computational models for the stories which can be applied and used in real applications, we compare the proposed model and methods with existing content analysis approaches with affective features, physical features, and social network analysis methods, respectively.

6.1. Affective content analysis

Various studies have been conducted on affective content analysis and affective recommender systems [3]. Most of them are for narrative works which is one of the most affective items. Nevertheless, they focused on the affective reactions of the users rather than the affective features of the narrative works. Their methods, which indirectly connect to the contents of narrative works, are acceptable to avoid dependencies on media, formats and domains. Though, they cannot elicit the stories that the narrative works attempt to deliver.

These methods can be categorized into two groups: (i) classifying the affective features with the affective reactions [4,5,7] and (ii) adopting CF methods that are widely used within most of user-intimated domains [17,6]. The classification based methods are founded on the premise of a generality of human beings' emotions. They exhibited good performance, and made the problem simpler than the others. However, they are inappropriate for personalized services. On the other hand, CF-based methods have the inherent limitations of data sparsity and scalability. Additionally, to represent the emotional states of the users, they apply two types of emotional models: categorical and circumflex. Although the categorical models are simple and intuitive, they do not effectively represent the degrees of emotional states.

Two previous studies [4,5] are representative approaches that are based on classifying the users by using their affective reactions. Chênes et al. [4] proposed a highlight detection method for movies. They collected users' physiological reactions while watching movies. By checking the physiological reactions, they chose candidates for the highlights based on the dynamic changes of the reactions. They insisted that the more the users reacted to a segment of the movies, the more possibly it contained highlights. Kierkels et al. [5] suggested indexing and retrieval methods. First, they measured the physiological reactions of the users (e.g., electrocardiogram (ECG), galvanic skin response (GSR), etc.), when the users watched segments of the movies. The users' physiological reactions were transformed into vectors on a 2-dimensional circumflex model (Arousal–Valence model) by using a linear combination [37]. The vectors were annotated on the segments of movies. Finally, the retrieval was conducted by transforming the emotional words within the queries into vectors on the circumflex model and then matching them with the annotations for the segments. Since these methods were using the users' physiological reactions, they are more independent from the domains than other methods that are based on physical features. However, it is hard to apply to personalized services, because they assume the generality of human beings' emotions.

Different from the previous studies, Xu et al. [7] proposed an affective content analysis method which provides not only the types of emotional states, but also the intensities of the emotional states. It does so using the Arousal–Valence model to represent emotions. They categorized the emotional states of the users on the circumflex model by using a fuzzy clustering algorithm. By using conditional random fields (CRFs), they discovered relationships between the sequential physical features (visual and audio) of the videos and the emotional responses of the users. This study was meaningful in that the emotional intensities were based on both visual and audio features. However, the users' personal characteristics for their expected emotional reactions were difficult to reflect, since the authors built a single model for all of the users. Additionally, the physical features they used were not enough to reflect the stories of the narrative works, which increases the dependency for a particular media.

To solve the issue related to semantic gaps, Benini et al. [17,6] proposed an inventive affective content analysis method with connotative features. They suggested that the connotative features were an intermediate layer between the physical features and the semantics. The connotative features were extracted from the audiovisual characteristics of the narrative works. Then, they were described with the assumption that similar users will react similarly for similar connotative features. It is similar to the basic assumption of the CF methods. Furthermore, they proposed an affective recommender system with connotative features by predicting the latent connotative features within the scenes of the movies with a Support Vector Regression (SVR). It was a meaningful study in terms of utilizing a contribution of the structural narratology into computational analysis of the narrative works. Though, one limitation is that it cannot elicit the temporal dynamics of the stories.

Other studies have attempted a separate approach by affectively analyzing the content with meta-data. Ahn et al. [38,39] proposed a concept of cultural meta-data to annotate the narrative works, which contain information about the plots, genres, similarities of the moods, and more. Also, they suggested methods to semi-automatically generate the meta-data. The cultural meta-data is an efficient tool that can represent the semantics of the stories with low costs. However, it is not fully automated since it requires raw data from human beings such as reviews.

6.2. Content analysis with physical features

In image and audio processing areas, various studies on content analysis have been conducted traditionally (e.g., computational aesthetics) [15,16]. Also, many studies have extended their analysis methods into the content providing services like recommender systems. However, these methods have a crucial limitation: the gap between the low level physical features and high level semantics. Instead of reducing the gap with domain knowledge, they used a strategy to avoid the limitation by applying machine learning, data mining, and more.

Using initial conceptual suggestions from the computational aesthetics field, exponents introduced the semantic gap and conceptual methodologies to solve it [15,16]. Also, they recommended methods to elicit high level semantics like the narratives from the physical features (e.g., discovering scenes within videos by using physical similarities among shots). Based on this method, they semantically indexed and classified the scenes.

Two previous studies [13,14] are examples of segmenting the narrative works for movies. Hanjalic et al. [13] segmented the movies by using similarities among the shots. It was based on an assumption that the visual features within a single scene are consistent. This segmentation method can be described as: (i) finding two shots which have high similarity, (ii) checking shots between the two shots whether there is any shot which has higher similarity than the two shots, and (iii) if there is not, determining an existence of the scene between the two shots. Although their method demonstrated good performance, the spatial backgrounds can dramatically change even in a single scene and sometimes distinct scenes are continuously proceeded within the same spatial background; moreover, some movies have only one spatial background (e.g., The Man from Earth (2007), 7 años (2016), etc.). In the another study, Chasanis et al. [14] segmented the movies with the bag of visual words model which is a modification of the bag of words model in the image processing area. Their method is much more delicate and exhibits better performance than the former one, by applying a similar approach with text segmentation. However, it also has the same limitation as the former one [13], since they are based upon only visual features which are highly sensitive to the spatial backgrounds of the stories.

In a case of content analysis with audio features, Yang et al. [12] proposed a method to detect events in movies. First, they found non-silence segments in the movies based on the energy of the audio signal. Potential candidates for changing points were estimated by distances between non-silence segments. It is similar to our segmentation method which uses non-characters-occurred areas and distances among the areas. Though, this method is subordinated to physical characteristics of the media.

Furthermore, a few studies have tried content analysis with both visual and audio features. As a representative example, Li et al. [40] proposed a novel content analysis method for videos, called audiovisual tempo analysis, by introducing the existing video abstraction methods. They analyzed the tempos of audio and visual signals in both long and short terms. The visual tempo was measured by three features: camera motion, object motion, and motion variance. The motion variance indicates a complexity of the object motions. In addition, the audio tempo was estimated by two features: short term energy and frequency of onset. The frequency of onset indicates the frequencies of each note. Based on these features, they segmented the videos into several sub-stories by using the temporal dynamics of the features in the long and short terms.

Some studies applying event-based media processing were conducted with a the similar purpose [41]. These methods detect the meaningful events of multimedia from audio–visual features. The features include not only static features like Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF), but also spatio-temporal features like Spatio-Temporal Interest Points (STIP). However, these methods have not been applied to the narrative works, but instead have been used for detecting terrorism or crime incidents.

Nevertheless, most of these methodologies do not avoid the inherent limitation of the gap between the low level physical features and high level semantics. To improve this problem, Benini et al. proposed novel methods based on connotative features that users might naturally recognize but difficult to be extracted by computational methods [17,6]. As introduced in Section 6.1, they used the connotative features as the intermediate layer between the physical and semantic layers. Although it is enough to analyze a single shot or scene in the videos, it is not enough to analyze the stories that are temporally dynamic.

As also depicted in Section 6.1, Xu et al. [7] conducted a study which extracted the affective characteristics of the videos from the physical features. By applying CRFs, they discovered the latent relationships between the physical features and the semantics. Nevertheless, the results of their analysis did not extend to areas of the stories.

These studies were conducted on various media, including comic books [42,43]. Yu et al. [43] introduced various physical features extracted from characters in the comics, and suggested a method for retrieving the characters based on multiple features. Similarly, Le et al. [42] represented the comics with multilayer graphs by using Region Adjacency Graphs (RAGs). By mining the subgraphs of the RAGs and comparing the subgraphs, they conducted the comic retrieval. Although their studies are interesting approaches, they did not result in a physical analysis of the narrative works.

6.3. Content analysis with social network

To model and analyze stories and stories of narrative works, various studies have been conducted with social network analysis (e.g., RoleNet [20], CharNet [8], CoCharNet [10,11,18], etc.). These studies are commonly based on the social networks between the characters which are referred to as the character network. The use of the character networks is not dependent on any particular media, format, and domain. However, most of the existing studies for SNA-based content analysis have been conducted limitedly within particular media and data sources. They measured the intensities of the social relationships between the characters by using frequencies of co-occurrences and dialogues of the characters.

Limiting the definitions of the social relationships not only make the character networks media-dependent, but also reduce the accuracies of the character networks. CharNet [8] uses the scripts of the movies as a data source. Nevertheless, the scripts keep changing during the process of movie production. It is difficult to obtain final versions of the scripts that match the movies. On other hand, CoCharNet [10] is based on the co-occurrences of the characters. Although it is based on the final versions of movies, face recognition of the characters involves many errors. Errors often arise when the characters are not human beings and when actors/actresses modify their appearance according to the flow of stories (e.g., although in the 'Star Wars' series, Anakin Skywalker and Darth Vader look different, they are a single character).

To solve this problem, a few studies have proposed methods that use multiple data sources. Nevertheless, it is not a fundamental solution. Zhang et al. [44] combined two data sources, scripts and videos, that are mainly used to analyze movies. They composed two character networks based on the co-occurrences of the characters' faces and transacted dialogues among the characters, respectively. By matching these graphs, they constructed the character networks more accurately than previous studies have. Also, Sang and Xu [45] suggested a method that improved the robustness of the aforementioned method [44]. Moreover, Sang et al. [46] compared the sensitivities of the data extracted from the scripts and video. These studies supplement the problems of the co-occurrence based character networks which are caused by incorrect facial recognition. However, they still have the limitation that the disclosed scripts and videos (especially in the movies) do not exactly match, since the scripts are continuously edited during the production of movies.

As a partial solution, we defined the character networks more generally. The character networks are just a representation of the social relationships among the characters. Nevertheless, the character network only partially represents the external shapes of the stories. The social relationships among the characters are not the stories; they are the outcomes of the flows of the stories. The plot or story line is a sequence of events which are described in the narrative works and logically related to each other. The consideration of only the social relationships does not fully represent the events between the characters.

To address this limitation, Tran et al. [11,18] proposed a method to segment the narrative works. In addition, they suggested a concept referred to as the dynamic character network [19]. It addresses many issues by considering the dynamicity of the narrative works. The dynamics of the character network demonstrates the growths of the social relationships among the characters. In this article, we applied it to analyze the changes in the communities of characters. However, it is still a social representation of the stories. It does not quite reflect the events that occurred in the stories which can change the tension levels. To elicit the tensions, we applied the characters' emotional information.

Jung et al. [9] attempted to annotate the emotional states of characters on the character network. However, they could not reflect the dynamic changes of the affective relationships among the characters, since they only considered the emotional states of the characters on average across an overall narrative work. Similarly, Cipresso and Pietro [47] conducted an experiment to build an affective social network between characters. They extracted directional affective relationships among the characters by using psychometrics. Though, they also considered all of the affective relationships across the movies, which limited how much they reflected the progressions of events or plots in the movies. They measured the emotional intensities between the characters based on user surveys, which limits the possibility that the model will be used for practical applications. To solve these limitations, we combined two approaches, the dynamic and affective character networks.

A few studies suggested segmentation and summarization methods for the narrative works by applying the character networks [48,49,18]. Liang et al. [48] proposed a method to segment the movies by matching the scenes to the scripts for the movies. To match them, they used the bag of words model and Hidden Markov Model (HMM). They modeled the occurrences of the characters as vectors on each scene and each shot. Then, they applied HMM which had the occurrence vectors in the scenes as hidden states, and the vectors of the shots as observations. Although it is a fresh and interesting approach, it ignores the differences between the scripts and the movies. Based on a similar segmentation method, Sang et al. [49] suggested a summarization method. By representing the occurrences of characters within each scene as a vector, they clustered the scenes with similarities among these vectors. Finally, they decomposed the movies into sub-stories by detecting points that the clusters were materially altered. This method demonstrated meaningful performance. However, they found it difficult to semantically refer to sub-stories, since the story is a sequence of events described in the narrative works. The occurrences of characters are too implicit of a data source to discover the events. In the case of the Marvel Cinematic Universe (MCU), 'Nicholas Joseph "Nick" Fury' is a character that scarcely appears in the MCU movies. Although this character has only a few scenes, he requires the stories of the narrative works within the MCU to be connected to each other.

7. Conclusion and future work

In this study, we proposed the affective character network and the methods for utilizing it for story-based content analysis and recommender systems based on understanding the stories of the narrative works (e.g., movies, novels, comics, etc.). With this goal, we focused on three purposes: (i) eliciting, (ii) modeling, and (iii) utilizing the stories.

We evaluated the efficiencies of the proposed methods with a group of real narrative works. The experimental results demonstrated that the proposed methods are reliable and the hypothesized assumptions are reasonable. However, a purpose of this evaluation was to identify the probability of automatically analyzing the stories and not demonstrating outstanding performance, since this is preliminary and challenging research. As we mentioned, a story is a spontaneously generated 'data structure' which is manufactured, analyzed, and consumed by human beings to exchange knowledge and information.

Nevertheless, the proposed methodology has following limitations: (i) problems with considering focalization [50,51], (ii) difficulties with addressing a gap between *Discourse* and *Historie* [52], and (iii) the absence of experiments with large-scale datasets. The limitations are described in detail below.

1. Focalization: In the narrative works, when authors just imply many parts within the whole stories to emphasize the salient parts, it is referred to as focalization. The focalization makes the character networks, which are built on only the expressed parts, difficult to match with what the authors intend and the users understand.
2. Gap between *Discourse* and *Historie*: This gap refers to when the represented story lines are different from the original story lines in the narrative worlds. The authors twist the time axes of the narrative works with their artistic techniques (e.g., ellipsis, flashback, repetition, summarization, changes in perspective, etc.) in the same manner as the previous one. This approach makes it difficult for the computer to realize whole narrative worlds because it cannot detect the twisted parts.
3. Scale of Dataset: This limitation is more of a physical reason than former limitation. Even if we automatically process the narrative works, validating the generated data and correcting errors have to be conducted manually which is extremely time-consuming and labor-intensive work.

To deal with the limitations, we suggest the following future research directions: (i) modeling stories with multiple layers, (ii) detecting transitions of time and perspectives, and (iii) improving the methods to compose the character networks. The directions are depicted in detail below.

1. Multi-layered story model: We only focused on the stories as a sequence of events. However, other physical features (e.g., lighting, arrangement of colors, background music, etc.) are also designed by the authors to emphasize their intention. We expect that these features inform on the context in the manner that authors intended such as where and what the authors do. It can be conducted by the multi-layered story model including the layers of events, connotative features, physical features, and more.
2. Detecting time of the narrative world: An order of the events are described in the narrative works; however, the order in which the events actually occurred and when the events are introduced in the narrative worlds are different from each other. To approximate the understanding of the people in the stories, we should recover the twisted time lines of the stories. We anticipate that the characters' emotional states at the starting and ending points of the segments are clues for how to rearrange the segments.
3. Building character networks: The character networks are the foundation of our studies. We have enhanced the accuracies and reliabilities of the methods to build the character networks. Though, it is still not fully automated and limited to a few media and formats. In addition, it is not sensitive enough to reflect slight changes in the characters' emotional states, as demonstrated in the experimental results. Therefore, contributions from the image and audio processing areas are required to construct sufficient and reliable datasets.

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O-Joun Lee is in combined M.S./Ph.D. course in School of Computer Engineering at Chung-Ang University, Korea. He received the B.Eng. in Software Science from Dankook University in 2015. His research topics are recommendation system on digital content by using sequential pattern mining, incremental clustering, and social network analysis.

Jason J. Jung is an Associate Professor in Chung-Ang University, Korea, since September 2014. Before joining CAU, he was an Assistant Professor in Yeungnam University, Korea since 2007. Also, He was a postdoctoral researcher in INRIA Rhone-Alpes, France in 2006, and a visiting scientist in Fraunhofer Institute (FIRST) in Berlin, Germany in 2004. He received the B.Eng. in Computer Science and Mechanical Engineering from Inha University in 1999. He received M.S. and Ph.D. degrees in Computer and Information Engineering from Inha University in 2002 and 2005, respectively. His research topics are knowledge engineering on social networks by using many types of AI methodologies, e.g., data mining, machine learning, and logical reasoning. Recently, he have been working on intelligent schemes to understand various social dynamics in large scale social media (e.g., Twitter and Flickr).