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# Comic-Shelf vectors: Convoluting the co-occurrence among comics on the bookshelf

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ABSTRACT

This paper proposed **Comic-Shelf (CS) vectors**, which convolve the co-occurrence of comic titles on the bookshelves ordered by ranking, as a method for modeling sensibilities toward comic titles. By extracting semantic relationships from the orderings based on readers' subjective evaluations and representing them as numerical vectors, we aim to establish a new information representation that reflects user sensibilities. In vector mapping analysis, it was revealed that the comic vectors of titles stored on the same bookshelf were plotted relatively close to one another. Assuming that the affection toward titles included on the same bookshelf is similar, it was inferred that higher vector similarity corresponds to comics that are closer in human affection. Furthermore, it was demonstrated that not only similarities between individual titles but also similarities between bookshelf themes could be visually captured. In a mock recommendation, we investigated whether CS vectors could select titles that aligned with participants' preferences. The results showed that using CS vectors allowed for the selection of comics that better aligned with participants' preferences compared to other methods, demonstrating the effectiveness of the CS vectors.

## 1. Introduction

With the rise of digitization, a vast number of comic titles are now distributed online, making comics a major form of entertainment in contemporary society. Comics have increasingly been adapted into other media such as anime, films, and games, leading to a greater diversity in how people enjoy and engage with these titles. This expansion of titles and the growing opportunities for interaction have diversified the ways in which users encounter and experience comics. Even for the same title, differences in how it is perceived and evaluated can arise depending on the medium through which a user first encountered it or the context in which it was experienced. In this way, when users perceive the same title differently, conventional search and recommendation systems based on standardized information (e.g., genre and author name) may struggle to match users with titles that align with their preferences effectively. Therefore, more flexible recommendation methods that reflect each user's individual sensibility and experience are increasingly needed.

To enable information access based on affection, it is necessary to model users' sensibilities toward comic titles. In the field of music information processing, methods for music retrieval reflecting user sensibilities are proposed by utilizing features derived from playlists, which are the result of users' listening experiences [1–3]. Inspired by this, we consider that it would be possible to acquire a computational representation of relationships between titles if we collect and analyze groups of comic titles organized according to readers' sensibilities. This paper focuses on bookshelves as groups of titles organized based on readers' sensibilities.

A bookshelf contains some lists displaying the owner's favorite comic titles. In digital comic readers like applications on smartphones, favorite comics are in alphabetical order or by read/unread status, though they look like basic bookshelves. This enables users to manage and access titles of interest easily. On the other hand, users can visually express their preferences if they have a function to arrange titles based on subjective evaluation criteria, such as ranking for an arbitrary theme; arranging a bookshelf as their own favorite can be regarded as an active entertainment. Furthermore, in a bookshelf ordered by ranking, titles that are placed close together are likely to have semantic relevance in accordance with the theme of the ranking. This structure, where semantically related items are placed in sequence, is based on a basic idea of word vectorization [4–6].

In this paper, we propose Comic-Shelf (CS) vectors, which convolve the co-occurrence of comic titles on the bookshelves ordered by ranking, as a method for modeling sensibilities toward comic titles. In this paper, we model human affection toward comics using bookshelf data obtained from ComicFaves [7]. Fig. 1 shows an example of a bookshelf

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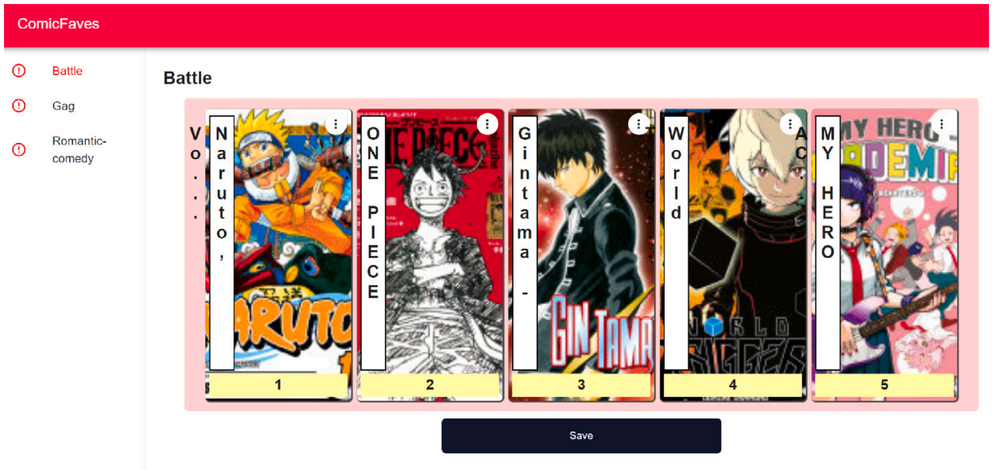



**Fig. 1.** An example of a bookshelf in ComicFaves. Each bookshelf includes five titles, arranged from left to right in a ranking order from 1st to 5th as determined by the bookshelf owner. The images in the figure are captured from Google Books APIs.

created in ComicFaves. Each bookshelf includes five titles, arranged from left to right in ranking order from 1st to 5th as determined by the bookshelf owner reflecting their affections. By extracting semantic relationships from the orderings based on readers' subjective evaluations and representing them as numerical vectors, we aim to establish a new information representation that reflects user sensibilities. Furthermore, we conduct a mock recommendation using the CS vectors and verify the effectiveness of the proposed method. From this perspective, this paper's contribution lies in proposing a mathematical model to capture the co-occurrence of comics in digital bookshelves and the application of the arrangement in the bookshelves to obtain the user's affection toward comic titles.

## 2. Related work

This study involves experiential aspects of entertainment. In this paper, we model users' preferences toward comic titles using bookshelf data, which can be regarded as the result of active entertainment [8]. Other active entertainments include creating music playlists [9] and fan-talking [10,11] through social media. Existing research in entertainment computing explored personal music recommendations using playlists [12] and proposed methods that support visual information acquisition by representing fan-talking in cartoon formats [13]. These studies consistently show that entertainment results serve as valuable information sources reflecting user preferences. This also suggests that bookshelf creation is an active form of entertainment. We examine whether bookshelves created through user enjoyment serve as academically valuable sources of information regarding human affection.

Some computational approaches try to reveal affection toward comics. Imaizumi et al. tried to model comics based on affection; they examined a method to computationally evaluate stories by using appearance rate series that represent the activity tendencies of characters [14]. Other existing studies evaluated comics focusing on the arrangement of panels [15,16], art styles [17,18], and onomatopoeias [19,20]. These studies mainly evaluated individual comic titles based on the content information. However, comic titles often branch out into other media, such as films or anime, and differences in how people are introduced to or experience these titles can lead to significant variations in their evaluations [21]. Accordingly, it is challenging to comparatively evaluate titles against other titles based on the content information of comics. In this paper, we aim to evaluate the relative standing of favorite comics by focusing on their arrangement of order without dealing with content information. This will make it possible to analyze the relationships between comics, e.g., whether the impressions of comics in close proximity on the bookshelf are similar. The analysis could not be realized by conventional evaluation methods.

This paper considers bookshelves as lists of comics, and list structures have been widely studied as an important approach in information processing within the multimedia field. For example, some studies have conceptualized consecutive panels in comics as lists and examined how the characteristics of the panels influence scene perception [22,23]. Additionally, Wang et al. focused on how panel lists visually represent story progression and explored story summarization by converting a film story into a comic style [24]. These studies suggested that visually adjacent items might influence human subjective evaluations of an item. Applying this perspective to bookshelves suggests that comic titles placed next to each other on a bookshelf may share common impressions or affection. Vectors derived by convolving co-occurrence on bookshelves are suggested to be effective for modeling human affection toward comic titles.

## 3. ComicFaves

In this paper, we use bookshelf data obtained from ComicFaves [7]. In ComicFaves, users are able to create their bookshelves according to an arbitrary theme. By accumulating bookshelf data, we are able to construct a dataset that focuses not on content information like Manga109 [25,26] but on how readers perceive comics.

### 3.1. System overview

Fig. 1 shows the user interface of ComicFaves. Users can sort the comics registered on the bookshelf by dragging and dropping the slots to reflect their preferences. Comic titles are registered through a search function that utilizes the Google Books API provided by Google. When a bookshelf is completed, the following information is recorded in the database:

- `shelf_id`: Bookshelf ID
- `user_id`: User ID
- `theme`: Theme of the bookshelf
- `comics`: Array of registered comic information
    - `comic_id`: Comic ID
    - `title`: Title of the comic
    - `author`: Author name
    - `description`: Synopsis
    - `image`: Image URL
    - `rank`: Ranking (based on the user's arrangement)

By aggregating these records, we constructed the bookshelf dataset.

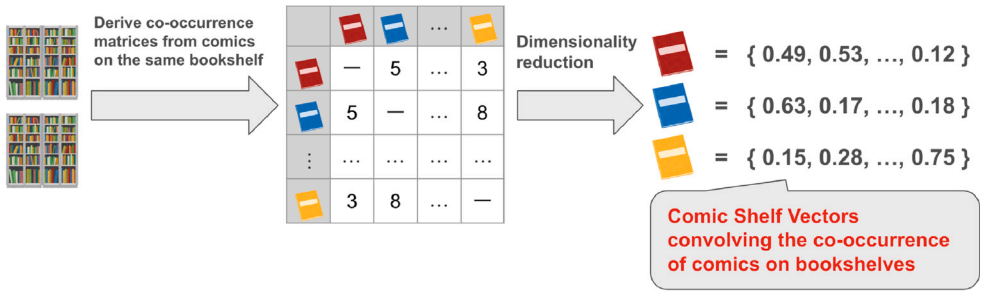



**Fig. 2.** Overview of the modeling method for comics using co-occurrence.

### 3.2. Collected bookshelf dataset

In our preliminary study using ComicFaves, 32 participants each created six themed bookshelves, resulting in 192 bookshelves in total (32 Œ 6) and 960 ranked comic titles. Each bookshelf contained five titles, arranged in order from 1st to 5th. We set the themes as genres and affective keywords. We adopted three genres: "Gag," "Battle" and "Romantic comedy," and three affective keywords: "Thrilling," "Deeply emotional" and "Heartwarming."

By analyzing the rankings of each comic title, we confirmed that focusing on the ranking made it possible to understand how each title was perceived by readers. For example, "Jujutsu Kaisen" appeared in 12 out of 32 participants' Battle bookshelves, but none of them ranked it as their top title. This suggests that while "Jujutsu Kaisen" was widely recognized and selected by many users, it is not necessarily rated as the most outstanding title by any individual. The limitation on the number of titles in each bookshelf may affect the analysis results and the interpretation of relationships between titles. The appropriate settings for ComicFaves, considering efficiency and user-friendliness, will be studied in our future work.

Furthermore, we compared the distribution of registered comic titles for genre themes and for affective keywords. The average number of titles identified in bookshelves for genre themes was 80, while the average in those for affective keywords was 108. We consider that affective keywords result in a wider diversity of selected comic titles because affective keywords might be polysemous and abstract. This result suggested that analyzing bookshelves for affective keywords could potentially be applied to user profiling and recommendation systems based on individual sensibilities. Based on these discussions, we set these trial settings in this paper.

## 4. Proposed idea: Comic-Shelf vector

The proposed method represents affection toward comic titles by vectors convolving the co-occurrence of titles on bookshelves. The vector created by this method is defined as the "Comic-Shelf (CS) vector". Fig. 2 shows the overview of the proposed method. To quantify the co-occurrence, co-occurrence matrices are derived with bookshelf data that records how titles are arranged on bookshelves. The bookshelf data is based on data from ComicFaves. Dimensionality reduction is applied to the co-occurrence matrices to generate vectors for each title.

We derive co-occurrence matrices, which are matrices that either exclude the physical distance between titles or reflect it as a weight. The physical distance between titles on a bookshelf may reflect the preferences of the bookshelf owner, and titles placed closer to each other are likely to reflect more similar preferences of the bookshelf owner. We derive CS vectors from each co-occurrence matrix and conduct the experiment to investigate which better represents affection toward titles: the vectors that reflect physical distance or those that do not. On the bookshelf data from ComicFaves, titles are arranged in order of preference, as indicated by their ranking. We derive a matrix that excludes ranking differences and a weighted matrix reflecting them as weights.

The unweighted co-occurrence matrix is derived using the number of times each pair of titles is included on the same bookshelf. The dimension of this matrix is $N * N$, where $N$ is the total number of unique comic titles in ComicFaves. Each element of the matrix indicates the number of bookshelves in which the titles are included together.

The weighted co-occurrence matrix is derived using the ranking differences of titles included on the same bookshelf. The dimension is also $N * N$, and each element is calculated using the rankings of the titles. The number of bookshelves in which comics $A$ and $B$ are included together is denoted as $K$. The rankings of $A$ and $B$ on bookshelf $k$ are denoted as $rank_k(A)$ and $rank_k(B)$, respectively. The element corresponding to the pair of $A$ and $B$ is calculated as in the following Eq. (1).

$$w(A, B) = \sum_{k=1}^{K} \left(5 - |rank_k(A) - rank_k(B)|\right). \tag{1}$$

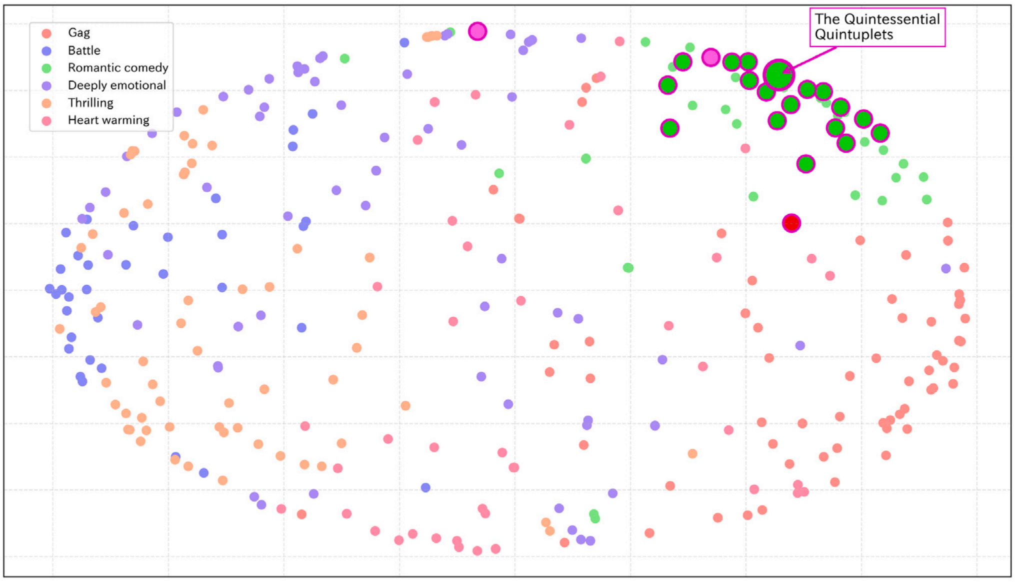
Since each bookshelf in ComicFaves includes five comics in the current version, we set the constant five to ensure positive weights even when the ranking difference is a maximum of four. Additionally, by using a simple constant multiplication of ranking differences, we can reflect bookshelf owners' evaluation order linearly and intuitively in the weights. This function enables us to express relationships between titles more strongly when placed in adjacent rankings and more weakly when their rankings are far apart.

To derive CS vectors for each title, Principal Component Analysis (PCA) [27] is applied to each co-occurrence matrix. During this process, the dimensionality is adjusted so that the cumulative contribution rate of the principal components reaches 0.8, ensuring that important information is preserved while reducing dimensions. This method allows us to quantitatively compare titles based on the distance and direction of their vectors.

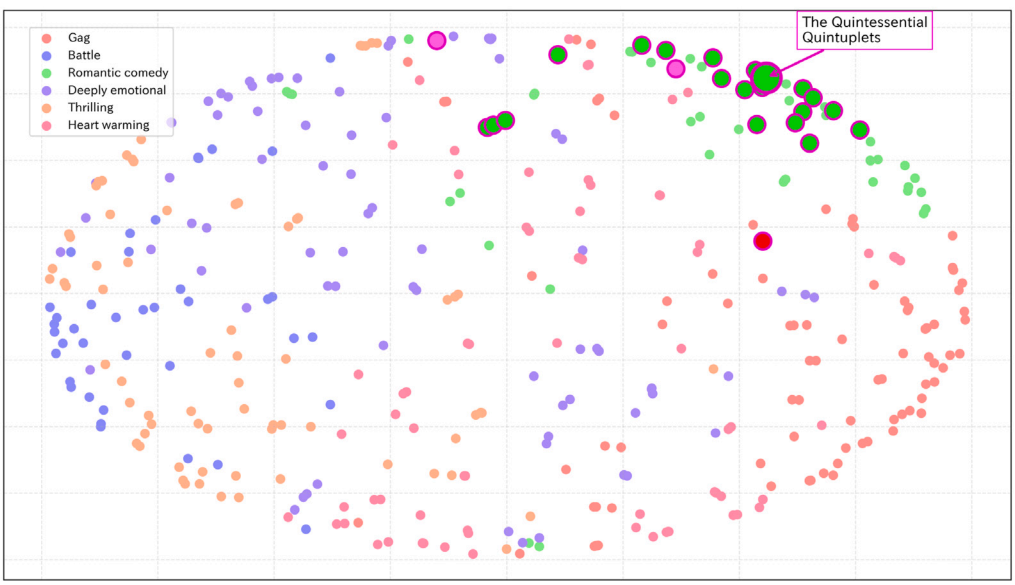
## 5. Vector mapping analysis

We mapped the CS vectors of all titles on the bookshelves in ComicFaves to investigate what features can be extracted. Additionally, we compared vectors that reflect rankings with those that do not to clarify how rankings affect the representation of affection toward comics. Each bookshelf is based on one of the following themes:"Gag", "Battle", "Romantic comedy", "Thrilling", "Deeply emotional" and "Heartwarming". Each bookshelf includes five titles, ranked from 1st to 5th according to the bookshelf owners' preferences. In the mapping analysis, we derived the similarity matrix by evaluating the vector similarity for all pairs of titles and then applied Multidimensional Scaling (MDS) [28] to position the vectors in a two-dimensional space. Then, we can obtain the map, enabling us to understand the overall similarity between vectors visually. We calculated vector similarity using cosine similarity.

Fig. 3 shows the mapping results for CS vectors on the bookshelves in ComicFaves. Fig. 3(a) shows the mapping result for vectors that do not reflect rankings, while Fig. 3(b) shows the one that reflects rankings. Each plot represents a title, and the color of the plot represents




(a) The mapping result for vectors that do not reflect rankings.




(b) The mapping result for vectors that reflect rankings.

**Fig. 3.** The mapping results for the Comic-Shelf vectors on the bookshelves in ComicFaves. Each plot represents a title, and the color of the plot represents the theme of the bookshelf where the title was included. “The Quintessential Quintuplets” and when these titles’ plots are highlighted.

the theme of the bookshelf where the title was included. Although some titles appear in multiple themes, the plot color corresponds to the most frequent theme, which is considered the most relevant. For example, the color of the plot for a title included on two bookshelves for “Battle” and four bookshelves for “Thrilling” is orange, representing “Thrilling.”

In both results, titles on the same bookshelf were plotted relatively close to each other. For example, there were 22 titles included on the same bookshelf as “The Quintessential Quintuplets,” and when these titles’ plots are highlighted, they appear near the plot for “The Quintessential Quintuplets.” Assuming that titles on the same bookshelf reflect similar preferences, higher vector similarity could indicate that the titles themselves are more similar in subjective human affective perception. In addition to individual titles, similarities between themes were also visualized. For instance, “Battle” appeared closer to “Thrilling” and farther from “Romantic comedy”.

Similar results were observed in the overall analysis for both mappings, but differing results were observed in the detailed analysis. We investigated the most similar title for each title’s vector. As a result, 185 out of the 412 titles had different most similar titles depending on whether the vector reflected rankings. For example, a pair of “Re:Zero - Starting Life in Another World -” and “Mouryou Shoujo,” which were the most similar titles when using the unweighted vector, was ranked 33rd in similarity when using the weighted vector.

## 6. Experiment

We conducted a mock recommendation to evaluate whether CS vectors can represent users emotional preferences. If CS vectors appropriately model human affection, comic titles with similar CS vectors may also be perceived as emotionally similar by humans. To verify this

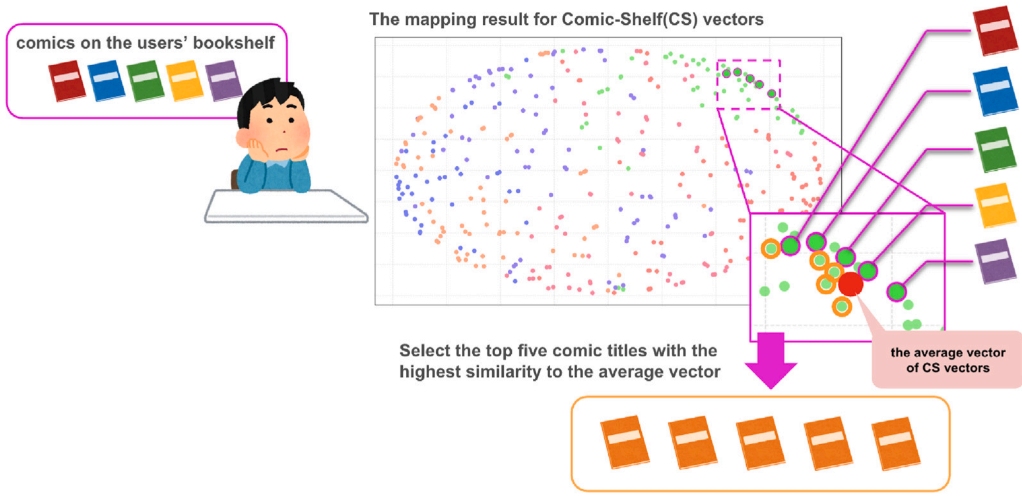



**Fig. 4.** The overview of comic selection using the CS vectors.

hypothesis, we selected comic titles with similar vectors to those on the user's bookshelf, and asked the bookshelf owners to evaluate whether the selected comic titles aligned with their preferences. Based on the evaluation results, we investigated whether CS vectors appropriately reflect human affection as a model. Additionally, we performed a comparative evaluation with existing methods. When applying this approach to actual recommendations, the cold start problem is expected to occur due to insufficient information about new titles. To address this problem, it can be reasonable to take approaches such as deriving temporary vectors based on content similarity [29,30]. This experiment involved 21 participants who created bookshelves in ComicFaves.

The experimental procedure is as follows:

1. Using each bookshelf, select five titles for each method, including the one using CS vectors and the comparative methods.
2. Ask participants to evaluate whether the titles selected in Step 1 comply with their preferences.
3. From the results in Step 2, assess how well each method selects titles that comply with the participants' preferences.

### 6.1. Methods

In Step 1, we used each bookshelf to select five titles for each method, including the one using CS vectors and the comparative methods, which were estimated to be similarly preferred by the participants as the titles on the bookshelf. For the comparative methods, we applied a method using collaborative filtering and another using the summary of comics.

#### 6.1.1. Methods using Comic-Shelf vectors: default and weighted

Fig. 4 shows the overview of comic selection using CS vectors. In the method using the CS vectors, the average vector of comic titles on the bookshelf (bookshelf vector) was applied as information indicating the overall tendency of affection based on those comic titles. We selected the top five comic titles with the highest similarity to the bookshelf vector by comparing them with the vectors of comic titles not included on the bookshelf. CS vectors represent the distributional tendencies of co-occurrence among comic titles, so we use cosine similarity to compute the similarity between vectors. Cosine similarity evaluates similarity based on the angle between vectors, which enables comparison of co-occurrence patterns while normalizing biases caused by differences in frequency.

From the vector mapping results, it was confirmed that the most similar pairs of titles differ between vectors that do not reflect rankings and those that do. To clarify how ranking weights influence the vectors modeling affection toward titles, we conducted selections using both unweighted vectors and weighted vectors. The method using unweighted vectors is defined as "CS vector default," and the method using weighted vectors is defined as "CS vector weighted."

#### 6.1.2. Comparative methods: collaborative filtering and summary of comics

The method using collaborative filtering compares the arrangement of titles in the participant's bookshelf with other bookshelves [31]. Fig. 5 shows the overview of comic selection using collaborative filtering. Bookshelves with similar arrangements of titles are considered to be close to the participant's preferences, and five titles not included on the participant's bookshelf are randomly selected from the top five bookshelves with the highest similarity. Each title only has information about which bookshelf it was included on and its ranking on that bookshelf, but it does not have information about co-occurrence with other titles. This method is defined as "Collaborative based."

Fig. 6 shows the overview of comic selection based on the summary of comics. All summaries were vectorized with BERT in the method using title summaries, and titles estimated to comply closely with the participants' preferences were selected by comparing the summary vectors of titles on the bookshelf with those of other titles. Specifically, we compared the average vector of summary vectors for titles on the bookshelf with the summary vectors of titles not included on the bookshelf, and we selected the top five most similar titles. Since all summaries are in Japanese, we used the Tohoku University version of bert-base-japanese, which is specialized for Japanese data. Vector similarity was calculated using cosine similarity. This method is defined as "BERT based."

### 6.2. Evaluation procedures

In Step 2, participants evaluated whether the titles selected in Step 1 complied with their preferences. Participants evaluated all selected titles they had already read, indicating whether they complied with their preferences by choosing "Yes" or "No." Since each participant created bookshelves for six themes ("Gag," "Battle," "Romantic comedy," "Thrilling," "Deeply emotional" and "Heartwarming"), they evaluated whether the selected titles for each bookshelf complied with their preferences.

From the evaluation results in Step 2, we evaluated how well each method selected titles that complied with the participants' preferences using precision in Step 3. This metric represents the proportion of titles selected by a method that complied with the participants' preferences, ranging from a minimum of 0 to a maximum of 1.

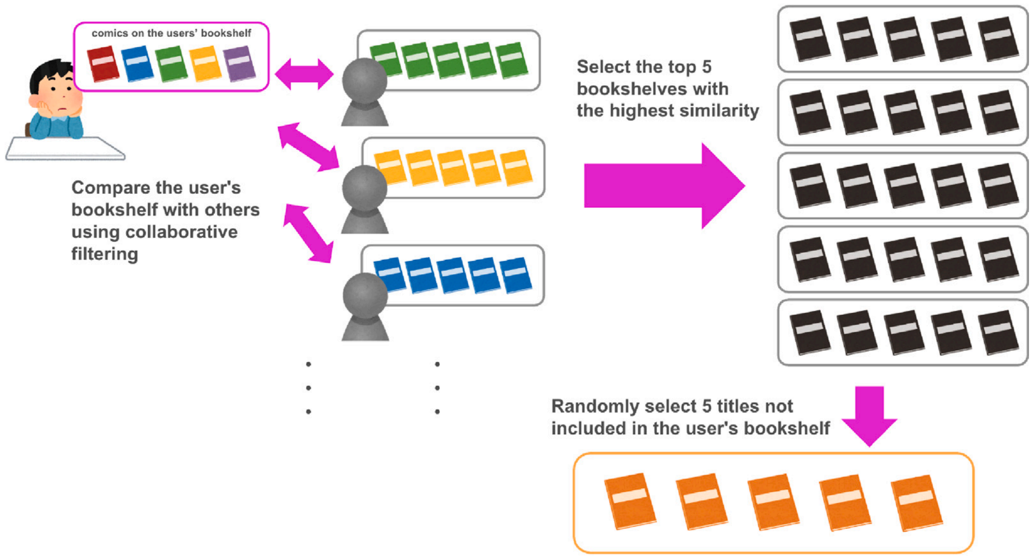



**Fig. 5.** The overview of comic selection using collaborative filtering.

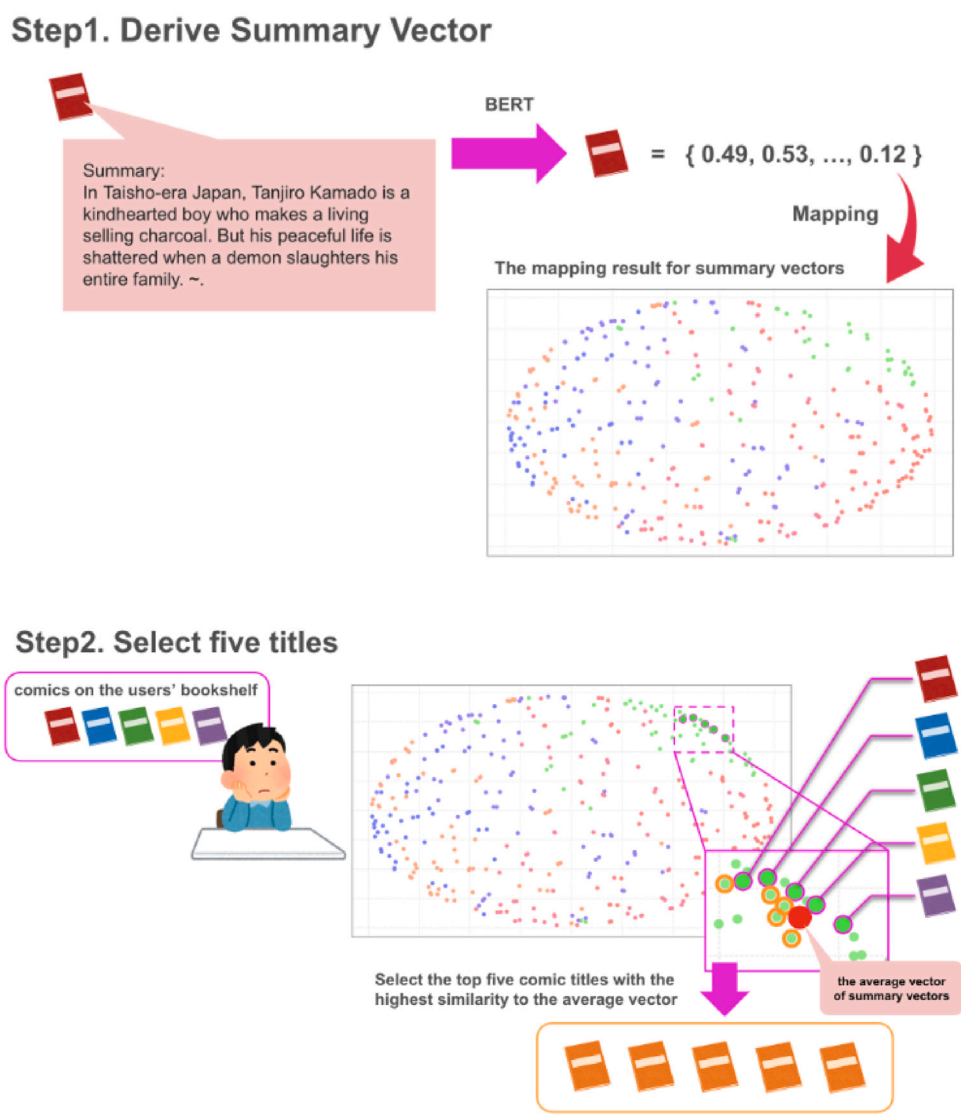



**Fig. 6.** The overview of comic selection based on the summary of comics.

**Table 1**
The result of selecting titles for each participant by each method. Each value represents the precision obtained for each participant by each method.

| Participant ID | CS vector default | CS vector weighted | Collaborative based | BERT based |
|---|---|---|---|---|
| 1 | 0.47 | **0.50** | 0.03 | 0.17 |
| 2 | 0.10 | 0.20 | 0.33 | **0.63** |
| 3 | **0.23** | 0.17 | 0.03 | 0.10 |
| 4 | 0.60 | **0.67** | 0.10 | 0.27 |
| 5 | **0.23** | 0.07 | 0.07 | 0.03 |
| 6 | 0.23 | **0.30** | 0.07 | 0.10 |
| 7 | 0.33 | **0.40** | 0.10 | 0.03 |
| 8 | **0.97** | **0.97** | 0.10 | 0.00 |
| 9 | 0.37 | 0.43 | **0.60** | 0.03 |
| 10 | 0.37 | **0.53** | 0.23 | 0.17 |
| 11 | 0.40 | 0.37 | **0.47** | 0.40 |
| 12 | 0.20 | **0.27** | 0.20 | 0.07 |
| 13 | **0.33** | 0.27 | 0.23 | 0.03 |
| 14 | 0.60 | **0.67** | 0.63 | 0.63 |
| 15 | **0.17** | 0.03 | 0.00 | 0.00 |
| 16 | 0.23 | 0.27 | **0.33** | 0.23 |
| 17 | 0.33 | **0.43** | 0.37 | 0.33 |
| 18 | 0.53 | **0.57** | 0.33 | 0.00 |
| 19 | 0.13 | 0.17 | **0.23** | **0.23** |
| 20 | **0.33** | 0.27 | 0.10 | 0.17 |
| 21 | 0.37 | **0.40** | 0.13 | 0.23 |
| *Average* | 0.36 | **0.38** | 0.22 | 0.18 |

### 6.3. Results and discussions

Table 1 shows how well the titles selected by each method complied with the preferences of each participant. Each value in Table 1 represents the precision obtained for each participant by each method, with the bottom row indicating the average precision across all methods. From Table 1, it can be observed that for 16 out of 21 participants, "CS vector default" and "CS vector weighted" achieved higher precision compared to the comparative methods. As a result, we have found that it is possible to use CS vectors to select titles that better comply with participants' preferences than other methods. Although only previously read titles were evaluated in this experiment, the result suggested that unread titles with vectors similar to those of titles on the bookshelf may also comply with participants' preferences. This suggested the potential usefulness of CS vectors in recommendations. When comparing "CS vector default" and "CS vector weighted," the latter achieved higher precision for 14 participants. As a result, we have found that CS vectors reflecting the rankings model human affection more accurately.

Additionally, considering the possibility that the usefulness of CS vectors for title selection may vary depending on the theme of the bookshelf, we investigated how well each method selected titles that complied with participants' preferences when using bookshelves for each theme. The precision by each method when using bookshelves for each theme was calculated as the average precision obtained for all bookshelves for that theme. Table 2 shows the result. From Table 2, it can be observed that for all themes, "CS vector default" and "CS vector weighted" achieved higher precision compared to the comparative methods, with the highest precision observed when using bookshelves for "Battle." When comparing "CS vector default" and "CS vector weighted," the latter achieved higher or equal precision for all themes. As a result, we have found that regardless of the bookshelf theme, title selection based on vectors reflecting rankings is more effective than other methods.

## 7. Conclusions

This paper proposed CS vectors convolving the co-occurrence of comic titles and quantitatively represented affection toward comics. Additionally, we created both vectors that reflected rankings and those that did not, and investigated which better modeled human affection.

**Table 2**
The results of selecting comics using bookshelves for each theme by each method. Each value represents the precision obtained by each method when using bookshelves for each theme.

| Theme | CS vector default | CS vector weighted | Collaborative based | BERT based |
|---|---|---|---|---|
| Gag | **0.34** | **0.34** | 0.19 | 0.11 |
| Battle | 0.45 | **0.52** | 0.35 | 0.29 |
| Romantic comedy | **0.24** | **0.24** | 0.22 | 0.18 |
| Thrilling | 0.38 | **0.39** | 0.24 | 0.25 |
| Deeply emotional | 0.34 | **0.37** | 0.17 | 0.13 |
| Heartwarming | **0.40** | **0.40** | 0.17 | 0.14 |

The results of the vector mapping showed that titles included on the same bookshelf were plotted relatively close to each other. This suggested that higher vector similarity corresponded to titles closer to subjective human evaluation. Furthermore, we have found that not only title-to-title similarity but also theme-to-theme similarity could be evaluated. In the mock recommendation, we investigated whether titles selected by CS vectors complied with participants' preferences. The results suggested that CS vectors reflecting rankings enabled the selection of titles that better complied with participants' preferences compared to other methods. Additionally, we considered the possibility of identifying unread titles that may comply with their preferences.

In our future work, we will explore the suitability of comic selection using CS vectors and the expansion of their expressive capabilities. We conducted comic selection using CS vectors for each participant in this study, but we did not consider their individual characteristics. Therefore, we will investigate which types of participants' comic selection using CS vectors are effective. Additionally, we will explore whether operations using CS vectors can enable intuitive additions and subtractions of comics [32], such as "comic $X$ is like the sum of comic $A$ and $B$."

We will also examine the utility of the proposed method for other entertainment content. In this study, we modeled affection toward comic titles by treating bookshelves as lists of favorite comic titles. However, listing favorite items is not a concept unique only to bookshelves. Viewing histories on video streaming services such as Netflix [33] and music playlists can also be regarded as similar representations. This suggests that the proposed method can also quantitatively model affection toward other entertainment content. We will investigate whether the proposed method is also useful for other entertainment content. If the proposed method also demonstrates utility for other content, it is estimated that our method lead to a recommendation applicable across different types of entertainment.

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## CRediT authorship contribution statement

**Kodai Imaizumi:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Ryosuke Yamanishi:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Mitsunori Matsushita:** Writing – review & editing, Supervision, Resources, Conceptualization.

## Declaration of competing interest

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

## Data availability

Data will be made available on request.

## References


[1] F. Falcao, D. Mélo, The million playlists songs dataset: a descriptive study over multiple sources of user-curated playlists, in: 16th Brazilian Symposium on Computer Music, 2017, p. 18.

[2] C. Hansen, C. Hansen, L. Maystre, R. Mehrotra, B. Brost, F. Tomasi, M. Lalmas, Contextual and sequential user embeddings for large-scale music recommendation, in: Proceedings of the 14th ACM Conference on Recommender Systems, 2020, pp. 53–62.

[3] K. Benzi, V. Kalofolias, X. Bresson, P. Vandergheynst, Song recommendation with non-negative matrix factorization and graph total variation, in: 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Ieee, 2016, pp. 2439–2443.

[4] T. Mikolov, K. Chen, G. Corrado, J. Dean, Efficient estimation of word representations in vector space, in: 1st International Conference on Learning Representations, ICLR 2013, Scottsdale, Arizona, USA, May 2-4, 2013, Workshop Track Proceedings, 2013.

[5] M. Baroni, G. Dinu, G. Kruszewski, Don't count, predict! a systematic comparison of context-counting vs. context-predicting semantic vectors, in: Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 2014, pp. 238–247.

[6] W. Xu, X. Liu, Y. Gong, Document clustering based on non-negative matrix factorization, in: Proceedings of the 26th Annual International ACM SIGIR Conference on Research and Development in Informaion Retrieval, 2003, pp. 267–273.

[7] K. Imaizumi, R. Yamanishi, M. Matsushita, ComicFaves: organizing shelves for favorite comics based on user's affection, in: Proc. the 2024 Conference on Technologies and Applications of Artificial Intelligence, 2024.

[8] R. Nakatsu, M. Rauterberg, P. Vorderer, A new framework for entertainment computing: from passive to active experience, in: Entertainment Computing - ICEC 2005, 4th International Conference, Sanda, Japan, September 19-21, 2005, Proceedings, Springer, 2005.

[9] B. Brost, R. Mehrotra, T. Jehan, The music streaming sessions dataset, in: Proceedings of the 2019 World Wide Web Conference, WWW 2019, ACM, 2019, pp. 2594–2600.

[10] H.-C. Chang, A new perspective on Twitter hashtag use: Diffusion of innovation theory, Proc. Am. Soc. Inf. Sci. Technol. 47 (1) (2010) 1–4.

[11] X. Wang, F. Wei, X. Liu, M. Zhou, M. Zhang, Topic sentiment analysis in twitter: a graph-based hashtag sentiment classification approach, in: Proceedings of the 20th ACM International Conference on Information and Knowledge Management, 2011, pp. 1031–1040.

[12] K. Tada, R. Yamanishi, S. Kato, Interactive music recommendation system for adapting personal affection: IMRAPA, in: Entertainment Computing-ICEC 2012: 11th International Conference, ICEC 2012, Bremen, Germany, September 26-29, 2012. Proceedings 11, Springer, 2012.

[13] M. Nakamura, Y. Miyazawa, Y. Kidera, T. Moriyama, M. Tamaki, Civo: real-time visualization of social activities by cartoonized twitter, in: Entertainment Computing–ICEC 2011: 10th International Conference, ICEC 2011, Vancouver, Canada, October 5-8, 2011. Proceedings 10, Springer, 2011, pp. 349–353.

[14] K. Imaizumi, R. Yamanishi, Y. Nishihara, T. Ozawa, Estimating groups of featured characters in comics with sequence of characters' appearance, in: Proceedings of the 2021 International Joint Workshop on Multimedia Artworks Analysis and Attractiveness Computing in Multimedia, 2021, pp. 13–18, http://dx.doi.org/10.1145/3463946.3469242.

[15] N. Cohn, Comics, linguistics, and visual language: The past and future of a field, in: Linguistics and the Study of Comics, Springer, 2012, pp. 92–118.

[16] N. Cohn, Navigating comics: An empirical and theoretical approach to strategies of reading comic page layouts, Front. Psychol. 4 (2013) 186, http://dx.doi.org/10.3389/fpsyg.2013.00186.

[17] R. Narita, K. Tsubota, T. Yamasaki, K. Aizawa, Sketch-based manga retrieval using deep features, in: 2017 14th IAPR International Conference on Document Analysis and Recognition, vol. 3, IEEE, 2017, pp. 49–53, http://dx.doi.org/10.1109/ICDAR.2017.291.

[18] T.-N. Le, M.M. Luqman, J.-C. Burie, J.-M. Ogier, Retrieval of comic book images using context relevance information, in: Proceedings of the 1st International Workshop on CoMics ANalysis, Processing and Understanding, 2016.

[19] Y. Nishihara, S. Wu, R. Yamanishi, A method to select comic frames for supporting mimetic onomatopoeia study, in: International Conference on Human-Computer Interaction, Springer, 2022, pp. 348–353.

[20] J. Baek, Y. Matsui, K. Aizawa, COO: Comic onomatopoeia dataset for recognizing arbitrary or truncated texts, in: European Conference on Computer Vision, Springer, 2022, pp. 267–283.

[21] M. Kazuyuki, R. Fuji, Y. Minoru, K. Kenji, Review score estimation based on transfer learning of different media review data, International Journal of Advanced Intelligence (IJAI) 9 (2017).

[22] N. Cohn, R. Taylor, K. Pederson, A picture is worth more words over time: Multimodality and narrative structure across eight decades of American superhero comics, Multimodal Communication 6 (1) (2017).

[23] N. Cohn, Your brain on comics: A cognitive model of visual narrative comprehension, Topics in Cognitive Science 12 (1) (2020) 352–386.

[24] M. Wang, R. Hong, X.-T. Yuan, S. Yan, T.-S. Chua, Movie2comics: Towards a lively video content presentation, IEEE Transactions on Multimedia 14 (3) (2012) 858–870.

[25] T. Ogawa, A. Otsubo, R. Narita, Y. Matsui, T. Yamasaki, K. Aizawa, Object detection for comics using manga109 annotations, 2018, http://dx.doi.org/10.48550/arXiv.1803.08670, arXiv preprint arXiv:1803.08670,

[26] K. Aizawa, A. Fujimoto, A. Otsubo, T. Ogawa, Y. Matsui, K. Tsubota, H. Ikuta, Building a manga dataset "manga109" with annotations for multimedia applications, IEEE Multimedia 27 (2) (2020) 8–18, http://dx.doi.org/10.1109/MMUL.2020.2987895.

[27] A. Maćkiewicz, W. Ratajczak, Principal components analysis (PCA), Computers & Geosciences 19 (3) (1993) 303–342.

[28] M.L. Davison, S.G. Sireci, Multidimensional scaling, in: Handbook of Applied Multivariate Statistics and Mathematical Modeling, Elsevier, 2000, pp. 323–352.

[29] P. Tomeo, I. Fernández-Tobías, I. Cantador, T. Di Noia, Addressing the cold start with positive-only feedback through semantic-based recommendations, International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 25 (Suppl. 2) (2017) 57–78.

[30] S. Wang, H. Ding, Y. Gu, S. Aydore, K. Kalantari, B. Kveton, Language-model prior overcomes cold-start items, 2024, arXiv preprint arXiv:2411.09065.

[31] J.S. Breese, D. Heckerman, C. Kadie, Empirical analysis of predictive algorithms for collaborative filtering, 2013, arXiv preprint arXiv:1301.7363.

[32] Q. Le, T. Mikolov, Distributed representations of sentences and documents, in: International Conference on Machine Learning, PMLR, 2014, pp. 1188–1196.

[33] P. Mathur, A. Arya, A distinctive ensemble approach for unbiased movie recommendations using variants of graph convolution networks, in: Proceedings of the 2024 10th International Conference on Computer Technology Applications, 2024, pp. 286–291.