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Analysis Hybrid Metrics for Emotion Detection (Case Study: Gaming Context)

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Abstract

The rising popularity of online gaming has positioned Steam as a leading platform for accessing diverse games. Beyond gameplay, Steam enables users to submit reviews, offering valuable data for analyzing emotional tone and classifying feedback as positive or negative. This study analyzed 8,000 reviews from Steam across four games: *The Sims 4*, *Counter-Strike 2*, *FIFA 23*, and *Dead by Daylight*. Plutchik's emotion theory, with its eight basic emotions served as the foundation for classification, utilizing the NRC Lexicon as an emotional dictionary. A hybrid algorithm combining cosine similarity (70%) and Euclidean distance (30%) with a threshold mechanism was employed to label emotions. Reviews exceeding the threshold received specific emotion labels, while others were classified as "unknown." Positive reviews, associated with joy, trust, fear, and surprise, were predominant for *The Sims 4*. Conversely, *Counter-Strike 2*, *FIFA 23*, and *Dead by Daylight* garnered largely negative reviews, highlighting the utility of emotional analysis in evaluating user feedback.

A. Introduction

Gaming is a cultural phenomenon deeply embedded in the lives of millions. While often regarded as entertainment, it has also become a focus of psychological research. Game psychology, an interdisciplinary field, explores the psychological processes and behaviors triggered by gameplay. Plass et al. define game psychology as studying how game features influence player engagement and cognitive development [1]. Games can evoke many emotions, such as excitement and frustration. Positive emotions are known to enhance learning, whereas negative emotions can hinder it [2], [3].

During gameplay, players experience emotions like sadness and joy, form attachments, and recall personal memories [4]. These emotional responses are influenced by game quality (design, mechanics, team size) [5], [6] and genre [7], [8]. Players share their emotional experiences through reviews [9], providing valuable feedback for developers to improve game design.

Recently, the trend in sentiment analysis research has investigated emotion detection within review contexts, particularly in game community platforms or social media. Guzsvinecz and Szűcs [10] identified genre-specific emotional patterns, while Yu et al. [11] combined LDA topic modeling and BERT to analyze esports reviews on Steam. Parvin and Hoque [12] proposed an ensemble-based ML approach to classify six primary emotions from Bengali text, achieving an F1 score of 62.39%. Wardani et al. [13] used the Plutchik model and cosine similarity to detect alter ego accounts on Twitter. Building on these studies, we investigate emotion detection across various game genres.

This research proposes a novel hybrid similarity method to improve the detection of player emotions in Steam reviews. We gathered reviews from various titles and genres on the Steam Community website. Then, we analyzed reviews across various genres, detecting them based on Robert Plutchik's eight primary emotions [14] (joy, trust, fear, surprise, sadness, disgust, anger, and anticipation). Our findings will provide valuable insights for game developers to enhance player retention strategies and long-term profitability.

B. Research Method

This study employs a hybrid method combining Cosine Similarity and Euclidean approaches, as explained in the introduction section. The process begins with data collection, data cleaning, emotion classification of reviews, and sentiment score calculation, as illustrated in **Error! Reference source not found.**.

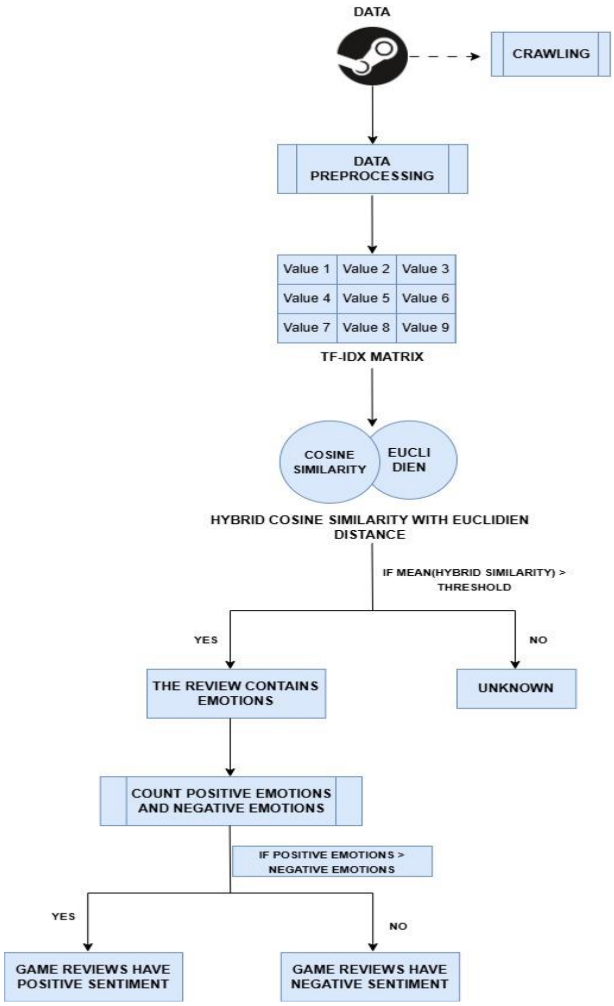

Figure 1. System Design

1. *Data*

The data utilized in this study is derived from reviews of games such as EA Sports FIFA 23[15], Counter-Strike 2 [16] The Sims 4 [17], and Dead by Daylight [18] on the Steam Community platform. A total of 2,000 reviews were collected for each game, resulting in an aggregate of 8,000 reviews employed in this research. The collected reviews are not exclusively in English, as some are in other foreign languages; thus, they will be translated into English during the preprocessing phase.

To extract data from Steam, the BeautifulSoup library [19] in Python was utilized. While this library is capable of parsing HTML and XML data, it is not suitable for dynamic websites. Therefore, HTML parsing combined with Selenium automation was employed to address this limitation. To collect data from Steam, the researcher utilized the URLs of the target web pages. The results of the crawling process were stored in a .csv file.

2. *Data Preprocessing*

Data preprocessing is the initial stage of data management, aimed at preparing review data for analysis by cleaning it to ensure its usability. This process involves several steps, including case folding, tokenization, stopword removal, and stemming. However, prior to these preprocessing stages, the data must first be translated, as some reviews are not in English. To perform the translation, the

Python library *googletrans* [20] was utilized. Reviews that are not in English are identified and translated from their original language into English during this step.

The initial stage is case folding, a process that converts uppercase letters to lowercase to standardize the format of review data, ensuring uniformity and facilitating subsequent processing steps. Following case folding, the text is divided into smaller units, or tokens, in a process known as tokenization. However, the resulting tokens often contain many common words, such as *for*, *like*, and *to*, which do not contribute meaningful value. These common words are removed during the stopword removal stage. Even after stopwords are eliminated, some words may still contain affixes. To remove these affixes, the stemming process is applied [13].

Table 1. Overview Data Preprocessing

Review	Result
Great way to lose all confidence you had in yourself and the confidence in your team, whilst being called a Noob in more languages then you will understand, and be laughed at because you still run default skins.	['great', 'way', 'lose', 'confid', 'confid', 'team', 'whilst', 'call', 'noob', 'languag', 'understand', 'laugh', 'still', 'run', 'default', 'skin']

3. TF-IDX Matrix

Prior to executing the hybrid algorithm phase, the preprocessing stage includes assigning weights to the documents using Term Frequency-Inverse Document Frequency (TF-IDF). The process begins by determining the frequency of words in the reviews corresponding to each emotion lexicon, based on Plutchik's model of eight basic emotions: anger, fear, joy, sadness, disgust, surprise, trust, and anticipation [13]. To determine the emotion associated with each word, the NRC Lexicon [21] is employed as the emotional reference. Subsequently, the frequency for each emotion is normalized by dividing it by the total number of words in the lexicon, as described in Equation 1 for Term Frequency [22]. This step produces the word occurrence values for each emotion category, forming the basis for further analysis.

$$TF\ (t_k, d_j) = f\ (t_k, d_j)$$

Information:
TF = Number of review period frequencies
f = Number of emotion occurrence frequencies
dj = Document –j
tk = Term –k

The second stage involves reducing the weight of each word obtained in the previous step if its frequency of occurrence is high across all emotion lexicons. This is achieved using the second formula, Inverse Document Frequency (IDF) [22]. Once the Term Frequency (TF) and IDF values have been determined, the next step is to calculate their product. The resulting values are then transformed into vectors using the *TfidfVectorizer* library in Python [23].

$$IDF(t_k) = log\, \frac{N}{df(t)}$$

Information:
IDF = Weight term
N = Total number of emotion dictionaries
df = Number of word occurrences

4. *Hybrid Cosine Similarity with Euclidien Distance*

This study employs a hybrid algorithm combining cosine similarity and Euclidean distance. The initial step involves calculating the similarity between two documents using cosine similarity. The previously obtained TF-IDF vectors serve as the input for this distance calculation, which is conducted using Formula **Error! Reference source not found.** [13].

$$similarity = \frac{\mathrm{x}\,.\,\mathrm{y}}{||x||\,.\,||y||}$$

Information:
similarity = Similarities of two vector
x = vector 1
y = vector 2

The second calculation utilizes Euclidean Distance [24]. This method is similar to cosine similarity but computes the distance between the two document vectors by taking the square root of the sum of squared differences. The smaller the distance between the vectors, the higher the similarity. Conversely, a larger distance indicates lower similarity.

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

Information:
d = Distance
x1 = Latitude Coordinate 1
x2 = Latitude Coordinate 2
y1 = Longitude Coordinate 1
y2 = Longitude Coordinate 2

The results of the Cosine Similarity and Euclidean Distance calculations are then combined. The weighting scheme applied is 70%:30%, where 70% of the cosine similarity result and 30% of the Euclidean distance result are used. These weighted values are summed to produce a hybrid score between the two algorithms. A threshold is applied to assign labels: if the hybrid score exceeds the threshold, the review is labeled with one of Plutchik's emotions. Otherwise, the system assigns the label "unknown."

The next step involves determining whether the game's reviews are classified as positive or negative based on the identified emotions. According to Plutchik's theory, emotions are divided into eight categories, which are further classified into positive and negative emotions. Positive emotions include joy, fear, surprise, and trust, while negative emotions consist of sadness, anger, anticipation, and disgust [23]. Using the previously identified emotions, the total number of occurrences for each emotion across all reviews is calculated. These totals are then summed based on their classification as positive or negative emotions using Formula **Error! Reference source not found.** [24]. If the total for positive emotions exceeds that of negative emotions, the game's reviews are classified as positive. Conversely, if the total for negative emotions is greater, the reviews are classified as negative.

$$a + b = b + a$$

Information:
a = numeric A
b = numeric B

C. Result and Analysis

The results of this study are categorized into three parts: the emotional outcome of each review, the total number of emotions across all reviews, and the final outcome indicating whether the game received positive or negative reviews. The following are the findings of the conducted research:

1. The Emotional of Each Review

The review data is divided into individual words, with each word assigned an emotion, resulting in a single review potentially containing multiple emotions. However, some reviews consist solely of emojis, causing the system to interpret them as symbols and assign an "unknown" label, as they are considered to lack identifiable emotions.

Table 2. Overview the emotional outcome of each review

No	Review	Result
1	To those who got it for free: Download mods instead of buying cashgrab dlcs.,,,,,,,	fear, disgust
2	HEADS UP FOR POTENTIAL BUYERS - The base game will be FREE TO PLAY from Oct 18th. :)	fear,disgust, trust
3	Sims 4 is a lot of fun but the exorbitant prices on the DLC are just too much. The DLC really adds a lot to the game so not having it hurts.	fear, joy, sadness, disgust, anticipation
4	88% off is a damn good price for what it's offering. I recommend it highly. Only downside is... DLC being worth A$ 608.30 with discounts... EA... are you serious. Edit after almost exactly 3 years; Never imagined to see EA of all companies make this game free. I feel really bad for those who spent full price for this.	anger, fear, joy, sadness, disgust, surprise, trust, anticipation
5	I love The Sims. I love The Sims 4. Here's why I don't recommend it. -Still launches through Origin. Buying on Steam just adds another layer of DRM. -If you previously purchased through Origin, you will need to redownload any DLC, even if you already had it installed -Your DLC carries over, the base game does not, which means you'll have to purchase the base game again. -Your DLC doesn't 'unlock' through Steam's store, if you purchased it on	fear, joy, disgust, trust, anticipation

	Origin (because of course it doesn't) This is probably the worst Steam integration I've ever seen. Don't buy it here if you already own it, just use "add non-Steam game to library". It's almost identical and $20 cheaper.

As previously explained, a single review may contain more than one emotion (**Table 2**). This phenomenon arises due to the presence of bias in the data, where a single word can be associated with multiple emotions, leading to a single review reflecting multiple emotional states.

2. The Total Number of Emotions Across All Review

The study utilized four games, each yielding distinct results. The analysis of the total emotions identified in the reviews for each game is presented as follows:

A.) The Sims 4

The Sims 4 is a simulation game developed by Electronic Arts. It was released in 2014 and is available on multiple platforms, including Windows, macOS, PlayStation, and others [25]. Numerous players have provided reviews of the game, which can serve as valuable data for this research.

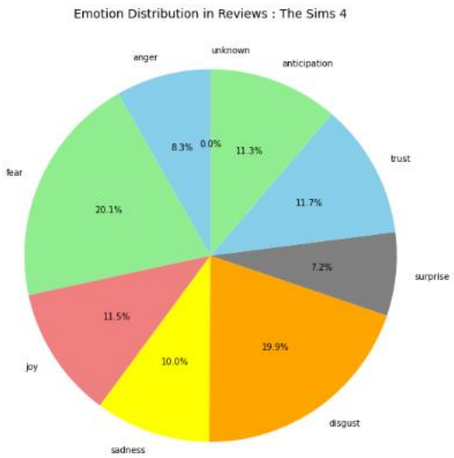

Figure 1. Distribution emotion graph from The Sims 4 review

Figure 1 illustrates the total distribution of the eight Plutchik emotions identified in *The Sims 4* reviews. The highest percentage is attributed to **fear**, accounting for 20.1%. Fear is an emotion that arises from uncertainty regarding unmet expectations [21]. Based on the analysis of 2,000 data, the majority of players expressed that the game is excessively expensive while offering features that are not significantly better than those in *The Sims 4*.

The second highest percentage of emotions is disgust, at 19.9%. Disgust is an emotion characterized by rejection or aversion to something unfavorable [26]. In *The Sims 4*, many players purchased the game with the expectation of accessing comprehensive features. However, they reported feeling bored and encountering numerous unresolved bugs, which led to disappointment and a reluctance to continue playing.

Table 3. Total all emotions from The Sims 4

Emotions	Total
Anger	816

Fear	1992
Joy	1134
Sadness	988
Disgust	1969
Surprise	716
Trust	1155
Anticipation	1115
Unknown	1

B.) Counter-Strike 2

Counter-Strike 2 is an action game featuring two teams: the first team represents the terrorists, while the second team represents the counter-terrorists. Similar to *The Sims 4*, this game is available on multiple platforms [27]. On Steam, numerous player reviews are available and can be utilized as data, with the results presented as follows:

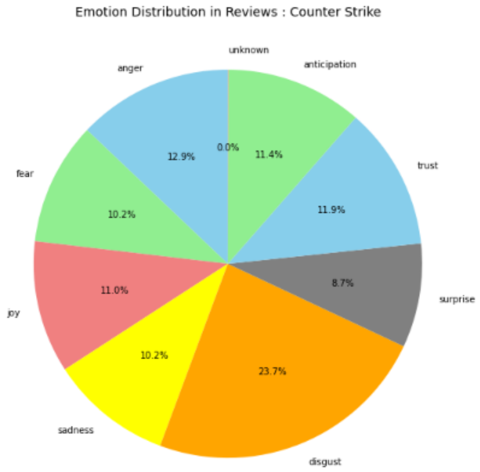

Figure 2. Distribution emotion graph from Counter-Strike 2 review

Figure 2 presents a graph displaying the total distribution of the eight Plutchik emotions in reviews of the game *Counter-Strike 2*. The highest percentage among all emotions is disgust, accounting for 23.7%. As previously explained, disgust is characterized by a sense of rejection toward something unfavorable [26]. Many players expressed frustration about encountering opponents suspected of being hackers during matches, leading to feelings of discomfort and disappointment.

The second highest percentage is anger, at 12.9%. Anger is an emotion that arises when an individual is unable to manage their feelings due to perceived offenses [21], [26]. Based on the analysis, many players experienced this emotion due to encountering problematic opponents, such as suspected hackers or players engaging in discriminatory behavior. Additionally, frequent server crashes further fueled frustration and anger among a significant portion of players.

Table 4. Total all emotions from Counter-Strike 2

Emotions	**Total**
Anger	1081
Fear	857

Joy	923
Sadness	852
Disgust	1983
Surprise	726
Trust	996
Anticipation	954
Unknown	3

C.) EA Sports FIFA 23

EA Sports FIFA 23 is a company that develops sports games such as football, Formula **Error! Reference source not found.**, basketball, and other similar sports genres. These games are available on both PC and gaming consoles [28]. In this study, the author utilized data from *FIFA 23*, and the results are as follows:

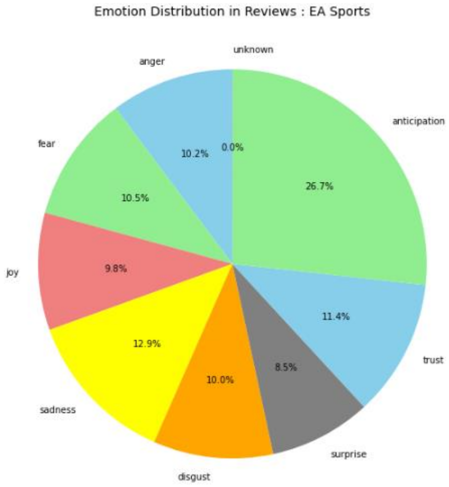

Figure 3. Distribution emotion graph from EA Sports FIFA 23 review

Figure 3 illustrates the distribution of emotions in EA Sports games based on player reviews, with the largest percentage being anticipation at 26.7%. Anticipation is an emotion that arises when an individual forms expectations about something [26]. Players' expectations for this version of the game were that it would surpass the previous one. However, reviews revealed that graphical quality and minor details showed no significant improvements, and server crashes occurred occasionally.

The second highest percentage is sadness, at 12.9%. The sadness stems from the profound disappointment experienced by players [26]. Many players felt that the game's quality did not justify its high price. Most of them purchased the game out of loyalty to their favorite football clubs. However, the outcomes often failed to meet their expectations, leading to feelings of disappointment and reluctance.

Table 5. Total all emotions from FIFA 23

Emotions	Total
Anger	767
Fear	787
Joy	730

Sadness	965
Disgust	746
Surprise	635
Trust	854
Anticipation	2000
Unknown	1

D.) Dead by Daylight

Dead by Daylight is a horror game that supports multiplayer gameplay, where players can assume the roles of either killers or survivors. This game is highly popular on Steam and ranks as the number-one title in the horror genre [29]. The following are the results of the emotional distribution based on player reviews:

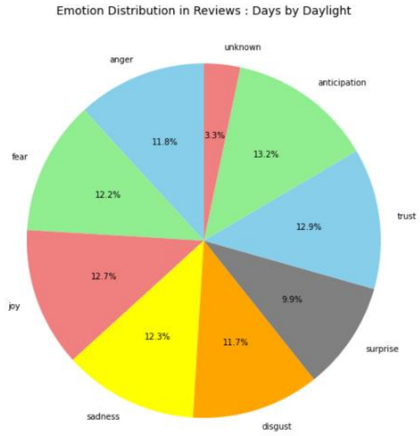

Figure 4. Distribution emotion graph from Dead by Daylight review

Figure 4 illustrates the distribution of emotions in player reviews of *Dead by Daylight*, with the largest percentage attributed to anticipation. Many players are fans of horror or thriller films, which leads to high expectations for this game. While the game successfully delivers a suspenseful horror narrative, several technical issues remain, such as hosts frequently disconnecting and players going AFK (away from keyboard) during matches. These problems often leave other players feeling disadvantaged.

Trust is the second most prevalent emotion, accounting for 12.9%. Trust reflects a player's confidence in the game [26]. Despite its technical shortcomings, the majority of players continue to enjoy the game due to its engaging storyline and impressive animations, prompting them to keep playing and even recommend it to their friends. Unlike the emotional distributions observed in the three previously analyzed games, this game has a higher percentage of unknown emotions, at 3.3%.

Table 6. Total all emotions from Dead by Daylight

Emotions	Total
Anger	1142
Fear	1183
Joy	1229
Sadness	1187
Disgust	1129

Surprise	958
Trust	1243
Anticipation	1279
Unknown	321

3. Positive Reviews or Negative Reviews

Section 2 explains that the eight emotions defined by Plutchik can be categorized into positive emotions (joy, trust, surprise, and fear) and negative emotions (sadness, disgust, anger, and anticipation). The system not only displays the graphical distribution of these emotions but also calculates the total for each category, both positive and negative emotions.

A.) The Sims 4

Table 3 presents the total emotions based on Plutchik's theory for reviews of *The Sims 4*. The eight emotions are divided into two categories to determine whether the game has predominantly positive or negative reviews. The calculations for each category are as follows:

Positive : joy + trust + surprise + fear
: 1134 + 1155 + 716 + 1992 = 4997
Negative : sadness + disgust + anger + anticipation
: 988 + 1969 +816 + 1115 = 4888

The calculations above indicate that the total positive emotions amount to 4,197, while the total negative emotions reach 4,888. Based on these results, *The Sims 4* has predominantly positive reviews from players.

B.) Counter-Strike 2

The results of the total distribution of the eight Plutchik emotions in *Counter-Strike 2* reviews are presented in **Table 4.** To determine whether the game has predominantly positive or negative reviews, the calculations for both categories are as follows:

Positive : joy + trust + surprise + fear
: 923 + 996 + 726 + 857 = 3502
Negative : sadness + disgust + anger + anticipation
: 852 + 1983 + 1081 + 954 = 4870

The calculations above reveal that the total for the positive category is 3,502, while the negative category amounts to 4,870. Based on these results, it can be concluded that *Counter-Strike 2* has predominantly negative reviews.

C.) EA Sports FIFA 23

Table 5 presents the total distribution of all eight Plutchik emotions for *FIFA 23* reviews. From these results, we can determine whether the game has predominantly positive or negative reviews. The calculations for each category are as follows:

Positive : joy + trust + surprise + fear
: 730 + 854 + 635 + 787 = 3006
Negative : sadness + disgust + anger + anticipation

: 965 + 746 + 767 + 2000 = 4478

The positive category has a total of 3,006, while the negative category has a total of 4,478. Based on these results, it can be concluded that *FIFA 23* has predominantly negative reviews from players.

D.) Dead by Daylight

The results of the total Plutchik emotions for *Dead by Daylight* reviews are presented in **Table 6.** The following are the calculations for both categories:

Positive : joy + trust + surprise + fear
: 1229 + 1243 + 958 + 1183 = 4613
Negative : sadness + disgust + anger + anticipation
: 1187 + 1129 + 1142 + 1279 = 4737

The calculations above show that the positive review category totals 4,613, while the negative review category totals 4,737. Based on these results, it can be concluded that the reviews for this game are predominantly negative.

D. Conclusion

This study utilizes reviews from four games: *The Sims 4*, *Counter-Strike 2*, *EA Sports (FIFA)*, and *Dead by Daylight*. The methodology employed is a hybrid algorithm combining cosine similarity and Euclidean distance, while the emotional framework used is Plutchik's theory of emotions. The study analyzes three key outcomes: the emotional content of each review, the Plutchik emotion distribution for each review, and the classification of reviews as positive or negative based on player feedback.

A single review may contain more than one emotion, as a single word can be categorized under multiple emotions. Reviews that do not express any emotions or consist solely of emojis are labeled as "unknown" by the system.

The distribution of the eight Plutchik emotions in each review is displayed in a graph with percentages. From this graph, it is possible to identify which emotion has the highest percentage. The largest percentage of emotions for each of the four games is as follows: for *The Sims 4*, the highest percentage is fear; for *Counter-Strike 2*, it is disgust; and for both *FIFA* and *Dead by Daylight*, the highest percentage is anticipation.

The eight emotions based on Plutchik's theory can be divided into positive and negative categories. The positive emotions include joy, trust, surprise, and fear, while the negative emotions include anger, sadness, disgust, and anticipation. From the emotion distribution, the author calculated the total number of each of the eight Plutchik emotions and then summed them based on their respective categories. The results show that only *The Sims 4* received predominantly positive reviews compared to the other three games.

For future research, it is recommended to classify each word under only one emotion. Additionally, other text similarity algorithms, such as Manhattan distance, Minkowski distance, and similar methods, can be used to cluster game reviews.

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