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Machine Learning for Anime Recommendation System Using K-Means Clustering

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ABSTRACT

The increasing popularity of Japanese-origin animation industries or so-called "anime" attracts more interest from already-known fans and ordinary people who are just interested in watching. However, many viewers need advice in the form of recommendations for their preferred anime. This research aims to help viewers by developing a system that could provide some recommendations for several anime series related to the current series watched by the viewers. On the other side, this research could provide a reference to other researchers, especially those whose research focuses on Machine Learning, Artificial Intelligence, and Japanese Animation culture. In this paper, the K-Means Clustering method is used to build the clustering model based on the data series, and the Elbow Method is used to determine the appropriate number of clusters. The result of this research indicates that the system can provide several titles of anime series related to the initial title of the anime series entered by the user at each iteration.

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1. INTRODUCTION

Anime is a branch of animation originating from Japan. The global popularity and accessibility of anime through streaming platforms, conventions, merchandise, and fan communities have contributed to the growth of anime fandom worldwide. Viewers from different countries and cultural backgrounds have embraced anime as a form of entertainment, art, and cultural exchange, leading to a diverse and vibrant anime community that transcends geographical boundaries. The ability to connect with fellow fans, participate in discussions, attend events, and engage with anime content online has enriched the anime-watching experience for viewers around the world, allowing them to share their love for anime and discover new series and genres. With its broad range of themes and genres that attract audiences from various age groups, anime has gained considerable popularity in recent decades. According to the World Population Review website (Anime Popularity by Country 2024, n.d.), interest in anime in 2024, based on the Google search term, is very high among people in China, followed by Egypt and Yemen. The same website reports that Japan has the highest percentage of its population watching anime (75.87%), followed by the United States (71.86%). The development of streaming services at the beginning of the 21st century made anime more accessible and enjoyable for audiences worldwide.

Anime preferences are shaped by a multitude of factors, including genre, art style, narrative complexity, character development, themes, cultural context, personal experiences, social influences, production studios, voice acting, sound design, critical reception, personal values, psychological factors, gender representation, and global accessibility. The tastes and preferences of viewers are very subjective and can differ greatly depending on personal interests, hobbies, and emotional ties to the anime's stories and characters. By comprehending the various forces that shape their preferences, we can appreciate the richness and complexity of anime as a medium that speaks to viewers on a personal, emotional, and cultural level.

Given the immense diversity of anime content and the personal nature of viewer preferences, recommendation systems have become essential tools for helping fans discover new anime that aligns with their interests. These systems assist viewers in navigating the vast array of genres and styles, enhancing their overall viewing experience and deepening their engagement with the medium. In recent years, there has been a significant focus on utilizing deep learning in recommender systems (Zheng, 2019). Deep learning approaches have demonstrated the potential to improve recommendation systems' efficiency and accuracy by efficiently handling massive volumes of data and generating customized recommendations. Furthermore, real-time AI-enabled recommendations for farm management systems have been successfully provided by machine learning algorithms in the agricultural sector (Liakos et al., 2018).

The growing popularity and diversity of anime have made it challenging for viewers to navigate the vast array of available content, which is why effective recommendation systems are essential for enhancing the anime viewing experience. Anime recommendation systems provide significant value by helping users discover shows that align with their preferences, saving them time and increasing satisfaction with the content they watch. In practical terms, such systems can lead to increased user engagement and platform retention, which are important metrics for streaming services and other anime-related platforms. Scientifically, recommendation systems for anime also contribute to advancements in AI and machine learning by allowing researchers to test and refine algorithms in a dynamic and culturally relevant field.

Various studies have proposed innovative approaches to recommendation systems, such as using sentiment analysis and machine learning for chatbot-based recommendations (Hsu & Liao, 2022), integrating sentiment analysis with XGBRS frameworks for drug recommendations (Paliwal et al., 2022), and employing machine learning for weather-specific crop recommendations (Pachade & Sharma, 2022). These examples illustrate how AI and machine learning can create sophisticated recommendation systems tailored to specific fields. The integration of these technologies enables recommendation systems to offer precise, personalized suggestions that enhance decision-making across industries.

In the context of anime, building an effective recommendation system requires consideration of methodologies and algorithms proposed in the literature. Collaborative filtering, a prominent method, identifies taste-based user groups to make personalized recommendations (Hu et al., 2008). This technique leverages user preferences and behaviors, allowing the system to suggest anime that aligns with individual interests, thus increasing satisfaction and engagement. Additionally, content-based filtering algorithms, which recommend anime based on the shows' attributes and characteristics, cater to specific viewer preferences (Jain et al., 2023). Such systems are vital for helping viewers discover content tailored to their tastes and enhancing their overall viewing experience.

Anime recommendation systems specifically developed with collaborative filtering enhance user satisfaction by providing tailored suggestions based on individual ratings and interactions with anime (Girsang et al., 2020). These technologies are not only crucial for improving the user experience but also highlight the potential impact of optimized recommendation systems on user engagement. Furthermore, research into recommendation algorithms for anime has shown that such systems can save users time and improve their experience by suggesting relevant content (Meng, 2023). Moving forward, a multidisciplinary approach combining collaborative filtering, content-based strategies, and machine learning algorithms will be critical to advancing anime recommendation systems. Employing methods such as the Elbow Method and K-Means Clustering for determining ideal clusters can further improve the accuracy and effectiveness of recommendations, ultimately meeting the evolving needs of anime viewers and supporting innovation in recommendation system design.

2. LITERATURE REVIEW

2.1. Anime and its preferences

Anime is a dynamic and multifaceted form of entertainment that continues to captivate audiences globally. Its rich storytelling, diverse genres, and visual artistry have solidified its position as a cultural phenomenon with a lasting impact on popular culture. The impact of anime on society is profound, influencing not only entertainment but also fashion, technology, and even tourism. The global appeal of anime has led to the establishment of dedicated fan communities, conventions, and streaming platforms. Anime functions as a medium for Japanese cultural diplomacy, meaning that Japan spreads its cultural influence abroad through food, entertainment, language, and other things that are integrated into the anime itself (Alani, 2022). In recent years, anime has gained mainstream recognition with the success of films such as "Your Name" and "Demon Slayer: Mugen Train," breaking box office records and garnering critical acclaim. The accessibility of streaming services has further contributed to the popularity of anime, allowing viewers worldwide to enjoy a vast library of titles. Therefore, to provide a comprehensive overview of anime, it is essential to consider its cultural significance, historical development, genres, impact on society, and global reach.

Anime preferences are a complex and multifaceted aspect of individual taste that can be influenced by a myriad of factors. One of the primary determinants of anime preferences is genre. Anime encompasses a wide range of genres, including but not limited to action, adventure, romance, comedy, fantasy, science fiction, horror, and slice of life. Although the classification of the genre can vary among users due to the differences in opinion toward the genre itself, study research was conducted by Cho et al. (2020) to define the classification of the genre of anime based on nine constituent factors that define the genre classification of anime, namely audience, setting, mood, character, plot, subjects, association with other works, feature, and production. Each genre appeals to different audiences based on their interests, emotions, and experiences, and even gender differences. For example, viewers who enjoy high-intensity action sequences and intricate fight scenes may gravitate towards action or shounen anime like "Naruto" or "Attack on Titan," while those who prefer heartwarming stories about friendship and personal growth may prefer slice-of-life anime such as "Clannad" or "March Comes in Like a Lion." The reception and critical acclaim of an anime can also influence viewers' preferences, as positive reviews, awards, and word-of-mouth recommendations can pique interest and draw attention to a particular series. Anime that receive widespread acclaim for their storytelling, animation quality, character development, and thematic depth are more likely to attract viewers who value these aspects in their anime-watching experience. Conversely, negative reviews or controversies surrounding an anime may deter viewers from engaging with it, shaping their preferences based on external perceptions and critiques.

In the context of recommendation systems, the incorporation of advanced algorithms and technologies is crucial for enhancing performance and accuracy. For instance, the ToxTrac software has been developed for tracking organisms, offering fast and robust tracking capabilities (Rodriguez et al., 2018). This software's advantages, such as high processing speed and robustness against false positives, make it a valuable tool for analyzing user behavior and preferences in anime recommendation systems. Additionally, algorithm development for precision feeding in dairy cattle demonstrates the potential of algorithms to influence outcomes in various domains, including animal-related fields (Souza et al., 2022). By leveraging algorithms to optimize feeding strategies, platforms can enhance user experiences and outcomes in anime recommendation systems.

2.2. Recommendation system methods

The use of artificial intelligence models has been massively used in various commodities in recent decades, this is the impact of intensive research on AI algorithms in conjunction with developments in hardware such as processors, GPU power, and hard disks. If we take several examples in the biomedical field, there is the application of AI to detect anomalies and automate determining the location of anomalies in the hippocampus area in people affected by Alzheimer's (Furqon et al., 2023; Islam et al., 2023), then in the textile field, there is AI to detect defects in iron and defects in wood (Akhyar, Furqon, et al., 2022; Akhyar, Novamizanti, et al., 2022). There are many direct and indirect applications humans use in everyday life, such as recommendation systems which we will discuss in this paper. Recommendation systems are part of artificial intelligence algorithms which have the ability to filter information and provide personalized suggestions for online information, products, or services based on data user preferences and behavior (Roy & Dutta, 2022).

In the realm of anime recommendation systems, machine-learning algorithms play a crucial role in enhancing the accuracy and efficiency of suggestions (Choudhary et al., 2023). By utilizing advanced algorithms, these systems can analyze vast amounts of user data to predict preferences and recommend anime that are likely to be well-received. Moreover, the incorporation of Hierarchical Latent Tree Analysis (HLTA) has been proposed to identify taste-based user groups, further refining the recommendation process (Hu et al., 2008). This approach enables the system to group users with similar tastes together, allowing for more targeted and effective recommendations.

One innovative recommendation engine, RikoNet, has introduced a novel approach to anime recommendations through its AniReco system (Soni et al., 2021). By adopting a content-based filtering strategy, AniReco focuses on analyzing the content of anime to make personalized suggestions to users. This method enhances the user experience by providing tailored recommendations that align with individual preferences. Similarly, the AniReco system proposed in another study emphasizes the importance of reflecting users' potential preferences in recommending animation works and related content (Ota et al., 2017). By considering user preferences and potential interests, such systems can enhance the relevance and quality of recommendations. Recommendation systems can be described based on type as in Figure 1.

The Content-Based Filtering (CBF) approach involves extracting attributes related to items liked by users, such as genre, category, or other features, and generating recommendations based on the similarity of attributes between items that have been liked and those that would be recommended. In contrast, Collaborative Filtering (CF) uses information from a group of users to discover patterns of similarity in preferences and predict items that other users might like based on those similarities. CF, via memory-based filtering, is divided into two types: user-based CF, which considers the similarity between users, and item-based CF, which considers the similarity between items. CF, via model-based filtering, employs a complex algorithm based on selected features. A hybrid approach, on the other hand, combines elements from both CBF and CF to improve the quality of

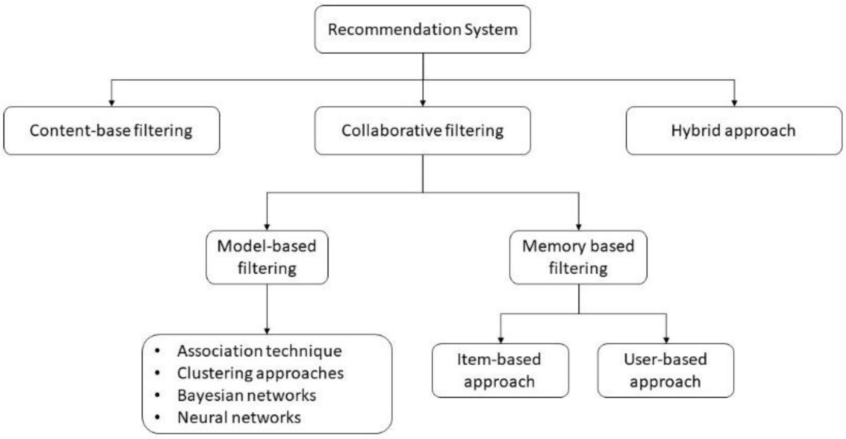

Figure 1. Types of recommendation system

recommendations. This may include using CBF as an initial filter to generate a list of relevant items, followed by applying CF to enhance the accuracy and personalization of recommendations (Roy & Dutta, 2022). In this research, we use the K-Means Algorithm, a model-based filtering technique within the clustering approaches, due to its effectiveness in grouping similar items and users into clusters. The K-Means algorithm enables us to categorize anime titles into distinct clusters based on shared features, which helps to reveal hidden patterns in viewer preferences. By assigning new users or items to these clusters, we can provide more accurate recommendations based on the groupings that best match their preferences. This approach is particularly useful for large datasets, where K-Means can handle high-dimensional data and optimize the clustering process, making it suitable for improving the scalability and efficiency of anime recommendation systems.

2.3. K-Means Algorithm

K-Means is one of the most popular algorithms for clustering data. The basic idea of this algorithm involves initially placing the centroids (central points of clusters) randomly or using a specific initialization method (such as K-Means++ for better performance). The algorithm then iteratively relocates each centroid to the mean location of the data points assigned to its cluster and reassigns data points to the cluster whose centroid is closest. This process continues until the assignments of points to clusters no longer change significantly or until a maximum number of iterations is reached, indicating that the algorithm has converged to a stable set of clusters. The goal of K-Means is not to reduce the distance between data points and their centroids to zero; instead, the objective is to minimize the within-cluster variation. This is measured by the within-cluster sum of squares (WCSS) or inertia—the sum of squared distances between each data point and the centroid of the cluster it belongs to. A lower WCSS value indicates more compact clusters, with each point being closer to its respective centroid. (Jin & Han, 2010). The K-Means algorithm divides a set of N samples X into K disjoint cluster C, where each cluster is represented by the mean μ_i of the samples in the cluster. Mathematically, this algorithm aims to select centroids that minimize the inertia, or within-cluster sum-of-squares criterion, which can be expressed as:

$$\sum_{i=0}^{n} \min_{\mu_j \in C} \left(\left\| x_i - \mu_j \right\|^2 \right) \quad (1)$$

Where K is the number of clusters, Ci is the i-th cluster, x represents a data point in cluster Ci and μ_i is the centroid of cluster Ci. Inertia is a metric that evaluates the compactness of clusters in a dataset. It measures the degree to which points within a cluster are close to each other and their cluster's centroid. Essentially, it quantifies the tightness of the clusters formed by algorithms like k-means. A lower inertia value indicates that the points in each cluster are closer to one another and to the center of the cluster, signifying that the clusters are more internally coherent or well-defined, unfortunately it suffers from various drawbacks, Inertia as a metric for evaluating K-Means clustering has several drawbacks: (a) inertia assumes that clusters are convex and isotropic, meaning that it does not perform well with elongated clusters or irregularly shaped manifolds; (b) inertia is not a normalized metric, so although lower values are preferable and zero is ideal, this measure can be misleading in high-dimensional spaces due to inflated Euclidean distances (an effect of the "curse of dimensionality"). To mitigate this issue, it is often beneficial to apply dimensionality reduction techniques, such as Principal Component Analysis (PCA) (Maćkiewicz & Ratajczak, 1993), before K-Means clustering, as this can reduce the dimensionality of the data, improve clustering accuracy, and accelerate calculations. Several unexpected K-Means cluster results in real cases can be seen in Figure 2.

3. RESEARCH METHODOLOGY

The dataset used in this research is entitled "Anime DataSet 2022". This dataset is a list of more than 18,000 anime series and movies aired from 1907 until the end of 2022 (Anime DataSet 2022, n.d.). Some new upcoming series of anime that will be aired in the first quarter of 2023 are included in the data as well. The list was obtained through web-scrapping from "Anime Planet", one of the largest anime and manga database websites,

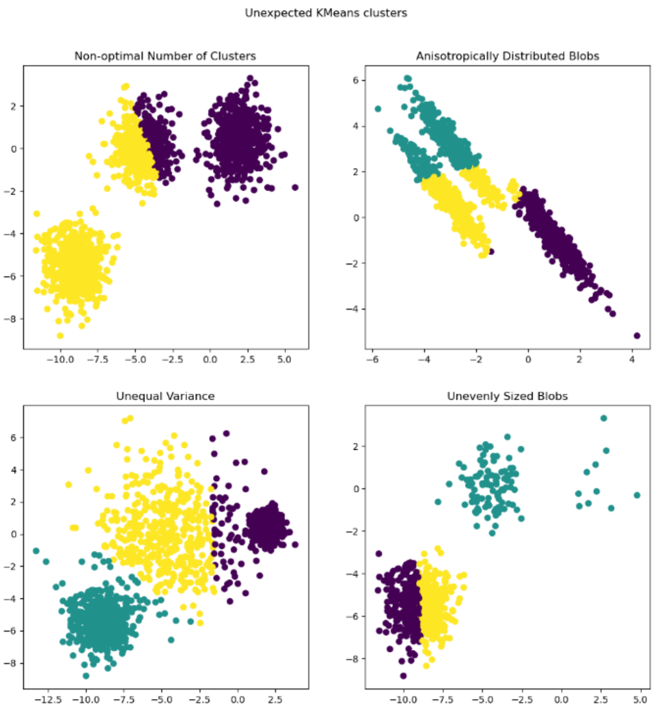

Figure 2. Unexpected K-Means clusters in real case

and summarized in .csv form. The dataset is openly accessible on Kaggle. There are 17 classes inside the dataset, namely Rank, Name, Japanese Name, Type, Episodes, Sudio, Release Season, Tags, Rating, Release Year, End Year, Description, Content Warning, Related Manga, Related Anime, Voice Actor, and Staff. Out of 17 classes, two classes were used as the indicators for the model namely Tags and Content Warning, and Name class is used as the input. At the end, the model will display the list of anime recommendations related to the input (Name class) based on the similar values in Tags and Content Warning classes and will be sorted based on Rank class.

Methods used to model the recommendation system are by using the K-means clustering. The model was designed using Python programming language through the sklearn library to perform the K-means clustering calculations. To determine the number of groups or clusters (k) that will be used, the Elbow method will be applied to identify the appropriate number of clusters (k) before starting to cluster the data. Model testing will be performed at the end of the process.

Before building the model, data needs to be pre-processed in advance. To perform the .csv data pre-processing, the Pandas library is used. Other libraries used in this research are nltk and string to remove the numbers and punctuation as well as change the uppercase letters into lowercase letters on Name class, and to perform advanced calculation, math, and numpy libraries were used in this research. To visualize the data, matplotlib and seaborn libraries were used. The recommendation model program is shown in Figure 3.

4. RESULTS AND DISCUSSIONS

4.1. Data Pre-processing

The first process is doing the data pre-processing. In this step, the number of null values for each variable is shown using the pandas library (Figure 2). Since this research only uses three out of 17 classes, therefore only Name, Tags, and Content Warning (written as Content_Warning in the .csv data) will be focused on. The result found that there are no null values found in the Name class. However, null values exist for both Tags and Content Warning classes. For the Name class, the pre-processing was done by removing the numbers and punctuation as well as changing any uppercase letters into lowercase letters so that the result can be viewed in Figure 4. For both Tags and Content Warning classes, the pre-processing was done by identifying each value by comma and double comma separation respectively. Additionally, the null value in the Content Warning class is classified as Safe and therefore the word “Safe” is being filled out at null columns and the null value in Tags is dropped or in other words, the column without value in Tags class will not be used. The result of pre-processed Tags and Content Warning values are displayed in Figure 5 and Figure 6.

4.2. Model building

Before creating a clustering model, the first thing to do is to determine the appropriate number of clusters for the model. Therefore, the Elbow method is used for training to determine the number of clusters for the classification model. The graph result is shown in Figure 7.

According to the result, with a maximum of 100 clusters, the elbow point is estimated at around 20 Clusters. Therefore, the list of anime in the dataset will be clustered into 20 different groups based on the Tags and Content Warning classes. Additionally, a dictionary was created as shown in Figure 1.

```python
database = {
    "Sean":{
        "df":[],
        "Recommendation":[],
        "Query":[],
        "n":0,
        "Cluster":{},
        "Iteration":0
    },
    "Elvin":{
        "df":[],
        "Recommendation":[],
        "Query":[],
        "n":0,
        "Cluster":{},
        "Iteration":0
    }

}


def recommendation_system(Name,show = 10):
    Input_User = input("Input your film: ").lower()
    temp = []
    database[Name]["Query"].append(Input_User)
    result = df[df["Name"].str.contains(Input_User)]["Cluster"].to_numpy()
    database[Name]["n"] = database[Name]["n"] + result.shape[0]
    unique_values, counts = np.unique(result, return_counts=True)
    for value, count in zip(unique_values, counts):
        print(f"{value}: {count}")
        try:
            database[Name]['Cluster'][value] += count
        except:
            database[Name]['Cluster'][value] = 0
            database[Name]['Cluster'][value] += count
    database[Name]['Cluster'] = dict(sorted(database[Name]['Cluster'].items(), key=lambda item: item[1], reverse=True))
    database[Name]["Iteration"] += 1
    for value, i in database[Name]['Cluster'].items():
        temp.append(df[df["Cluster"] == value])
    database[Name]["Recommendation"].append(pd.concat(temp).sort_values(['Rank',"Rating"]).head(show))
```

Figure 3. Anime recommendation system model

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18495 entries, 0 to 18494
Data columns (total 17 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Rank              18495 non-null  int64  
 1   Name              18495 non-null  object 
 2   Japanese_name     7938 non-null   object 
 3   Type              18495 non-null  object 
 4   Episodes          9501 non-null   float64
 5   Studio            12018 non-null  object 
 6   Release_season    4116 non-null   object 
 7   Tags              18095 non-null  object 
 8   Rating            15364 non-null  float64
 9   Release_year      18112 non-null  float64
 10  End_year          2854 non-null   float64
 11  Description       18491 non-null  object 
 12  Content_Warning   1840 non-null   object 
 13  Related_Mange     7627 non-null   object 
 14  Related_anime     10063 non-null  object 
 15  Voice_actors      15309 non-null  object 
 16  staff             13005 non-null  object 
dtypes: float64(4), int64(1), object(12)
memory usage: 2.4+ MB
```

Figure 4. Check for null values

```
Stopword :  {'between', 'some', 'our', 'it', 'under', 'will', 'hadn', 'other', "didn't", "weren't", 'ourselves', 'by', 'yours',
'was', 'me', 'them', 'why', 're', 'couldn', 'ours', 'or', 'at', "needn't", 'herself', 'mightn', 'shouldn', "don't", 'in', 'whe
n', 'down', 'her', 'about', 'out', 'won', 'each', 'shan', "shan't", 'nor', 'with', "doesn't", 'no', 'not', 'only', 'we', 'shoul
d', 'before', "you'd", 'until', 'she', "you're", 'aren', 'am', 'what', 'as', 'he', 'just', 'more', "mightn't", "shouldn't", 'ai
n', "wasn't", 'yourselves', 'weren', 'my', "that'll", 'wasn', 'don', 'again', 'can', 'been', 'm', "it's", 'doesn', 'are', 'bot
h', 'were', 'its', 'himself', "mustn't", 'his', 'themselves', 'who', "wouldn't", 'didn', 'below', 'these', 'for', 'this', "yo
u've", 'than', 've', 'which', 'yourself', 'during', 'i', 'to', 'o', "couldn't", 's', 'any', 'once', "isn't", 'of', 'hasn', 'ha
s', 'the', 'above', "aren't", 'then', 'all', 'be', 'you', 'those', "she's", 'while', 'after', 'that', 'they', 'few', 'had', 'l
l', 'isn', 'now', 'on', 'if', 'so', 'your', 'did', 'having', 'wouldn', 'and', 'their', 'very', 'here', 'same', 't', 'hers', 'hi
m', 'myself', 'through', 'up', 'y', 'mustn', 'against', 'over', 'from', 'there', 'into', 'do', 'haven', 'too', 'how', 'where',
'own', 'needn', 'is', 'a', 'but', 'off', 'does', 'itself', 'being', "you'll", 'ma', 'an', "won't", 'd', "hadn't", 'because', "h
aven't", 'theirs', 'doing', "should've", "hasn't", 'have', 'most', 'whom', 'such', 'further'}
punctuation :  {'?', '[', '>', '"', '/', ']', '=', ')', '+', '`', '-', '{', '$', '}', ',', '\\', '<', '(', '!', '~', '&', ':',
'#', '%', "'", '^', ';', '.', '|', '*', '_', '@'}
```

Figure 5. Pre-processing result for name class

```
0        Action, Adventure, Fantasy, Shounen, Demons, H...
1        Drama, Fantasy, Romance, Shoujo, Animal Transf...
2        Fantasy, Ancient China, Chinese Animation, Cul...
3        Action, Adventure, Drama, Fantasy, Mystery, Sh...
4        Action, Fantasy, Horror, Shounen, Dark Fantasy...
                                ...
18490    Action, Ancient China, Chinese Animation, Hist...
18491                                   Chinese Animation
18492    Chinese Animation, Family Friendly, Short Epis...
18493    Chinese Animation, Family Friendly, Short Epis...
18494                         Comedy, Slice of Life, Dogs
Name: Tags, Length: 18095, dtype: object
```

Figure 6. “Tags” pre-processing result

```
0                                        Explicit Violence
1        Emotional Abuse,, Mature Themes,, Physical Abu...
2                                                     Safe
3        Animal Abuse,, Mature Themes,, Violence,, Dome...
4                           Cannibalism,, Explicit Violence
                                ...
18490                                                 Safe
18491                                                 Safe
18492                                                 Safe
18493                                                 Safe
18494                                                 Safe
Name: Content_Warning, Length: 18095, dtype: object
```

Figure 7. “Content Warning” pre-processing result

This dictionary will be used to store the username and preferred anime by inputting the English title of the anime for each iteration, and a list of anime recommendations for each iteration. Inside the dictionary, there are two usernames being input, which are “Sean” and “Elvin”. Out of these two usernames, only the username “Sean” will become the subject of the program testing process.

4.3. Model testing

The first username being tested is “Sean”. During the initial iteration, the English title of the anime being inputted is “Demon Slayer”. It turns out that during the initial iteration, the other animes matched with Demon Slayer are grouped in cluster numbers 8, 14, and 18 (Figure 8). Animes within those clusters are most likely similar to Demon Slayer. Those animes have “Action” Tags and “Violence” Content Warning except “Attack on Titan the Final Season Part II” which didn’t have the “Violence” Content Warning. The result of the initial phase is shown in Figure 8. Then, the username “Sean” updated the input as a result of choosing one of the recommendations shown during the initial iteration phase. The second English title of the anime being inputted is “Attack on Titan”. As shown in Figure 9, 10, 11, and 12, now the list of anime recommendations is changing to those that are grouped in cluster numbers 0, 1, 3, 5, 8 14, 15, and 18. Indicates that the second preferred anime has another Tags value outside “Action” or another Content Warning value aside from “Violence” which is related to other animes grouped in other clusters.

5. CONCLUSIONS

The increasing popularity of anime accompanied by technological advances and the emergence of various streaming service platforms can certainly attract more audiences to enjoy them. Both new audiences who do not have insight into anime culture and old audiences who are fans of anime culture can now watch via various available streaming media. Moreover, implementing a recommendation system can help lay audiences provide recommendations for other anime that have similar themes to the current preferred anime. From an academic point of view, the existence of studies on this recommendation system can be a basis for researchers who have similar interests so that it can be developed further.

However, there are some limitations found in this study. First, this study only makes a list of recommendations based on similar Tags and Content Warning values with the input while neglecting other attributes. Related to the program, users need to input the English name of the anime in general (like “Demon Slayer” but not “Demon Slayer the movie”, etc.) or else the result will be displayed the same for every iteration. Finally, the method used to determine the appropriate number of clusters needed (Elbow method) might be not the best for this case since it is supposed to show the elbow graph (joint lines with clear angle), not the curve.

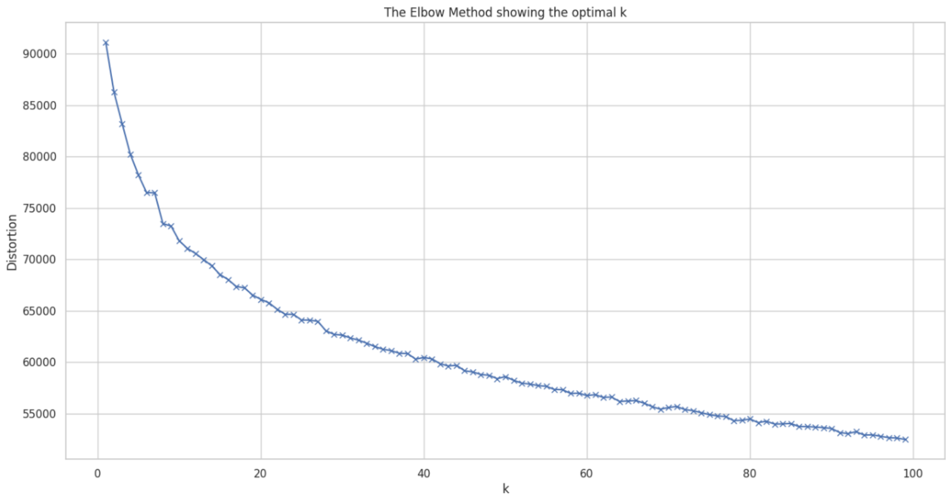

Figure 8. Elbow method result

```
Input your film: demon slayer
8: 1
14: 2
18: 1
```

Figure 9. Initial iteration-related clusters for username "Sean"

	Rank	Name	Japanese_name	Type	Episodes	Studio	Release_season	Tags	Rating	Release_year	End_year	Description
0	1	demon slayer kimetsu no yaiba entertainment...	Kimetsu no Yaiba: Yuukaku-hen	TV	NaN	ufotable	Fall	Action, Adventure, Fantasy, Shounen, Demons, H...	4.60	2021.0	NaN	'Tanjiro and his friends accompany the Hashira...
1	2	fruits basket the final season	Fruits Basket the Final	TV	13.0	TMS Entertainment	Spring	Drama, Fantasy, Romance, Shoujo, Animal Transf...	4.60	2021.0	NaN	'The final arc of Fruits Basket.'
3	4	fullmetal alchemist brotherhood	Hagane no Renkinjutsushi: Full Metal Alchemist	TV	64.0	Bones	Spring	Action, Adventure, Drama, Fantasy, Mystery, Sh...	4.58	2009.0	2010.0	"The foundation of alchemy is based on the law...
4	5	attack on titan rd season part ii	Shingeki no Kyojin Season 3: Part II	TV	10.0	WIT Studio	Spring	Action, Fantasy, Horror, Shounen, Dark Fantasy...	4.57	2019.0	NaN	'The battle to retake Wall Maria begins now! W...
5	6	jujutsu kaisen	NaN	TV	24.0	MAPPA	Fall	Action, Horror, Shounen, Curse, Exorcists, Mon...	4.56	2020.0	2021.0	'Although Yuji Itadori looks like your average...
6	7	attack on titan the final season part ii	Shingeki no Kyojin The Final Season: Part II	TV	NaN	MAPPA	Winter	Action, Drama, Fantasy, Horror, Shounen, Dark ...	4.56	2022.0	NaN	'Continuation of\xa0Attack on Titan The Final ...
7	8	attack on titan the final season	Shingeki no Kyojin The Final Season	TV	16.0	MAPPA	Winter	Action, Drama, Fantasy, Horror, Shounen, Dark ...	4.55	2020.0	2021.0	"It's been four years since the Scout Regiment...
8	9	demon slayer kimetsu no yaiba movie mugen t...	Kimetsu no Yaiba Movie: Mugen Ressha-hen	Movie	NaN	ufotable	NaN	Action, Drama, Fantasy, Shounen, Demons, Histo...	4.54	2020.0	NaN	'Tanjirou\xa0and the group have completed thei...
12	13	demon slayer kimetsu no yaiba	Kimetsu no Yaiba	TV	26.0	ufotable	Spring	Action, Adventure, Comedy, Drama, Fantasy, Sho...	4.51	2019.0	NaN	'Bloodthirsty demons lurk in the woods, and no...
13	14	hunter x hunter	NaN	TV	148.0	MADHOUSE	Fall	Action, Adventure, Drama, Fantasy, Shounen, Mo...	4.51	2011.0	2014.0	'Drawn to the mystique of the unknown, Hunters...

Figure 10. Initial iteration recommendation result for username "Sean"

```
Input your film: attack on titan
0: 2
1: 3
3: 2
5: 1
8: 6
14: 2
15: 1
18: 6
```

Figure 11. Iteration 1 related clusters for username “Sean”

	Rank	Name	Japanese_name	Type	Episodes	Studio	Release_season	Tags	Rating	Release_year	End_year	Description
0	1	demon slayer kimetsu no yaiba entertainment...	Kimetsu no Yaiba: Yuukaku-hen	TV	NaN	ufotable	Fall	Action, Adventure, Fantasy, Shounen, Demons, H...	4.60	2021.0	NaN	'Tanjiro and his friends accompany the Hashira...
1	2	fruits basket the final season	Fruits Basket the Final	TV	13.0	TMS Entertainment	Spring	Drama, Fantasy, Romance, Shoujo, Animal Transf...	4.60	2021.0	NaN	'The final arc of Fruits Basket.'
3	4	fullmetal alchemist brotherhood	Hagane no Renkinjutsushi: Full Metal Alchemist	TV	64.0	Bones	Spring	Action, Adventure, Drama, Fantasy, Mystery, Sh...	4.58	2009.0	2010.0	"The foundation of alchemy is based on the law...
4	5	attack on titan rd season part ii	Shingeki no Kyojin Season 3: Part II	TV	10.0	WIT Studio	Spring	Action, Fantasy, Horror, Shounen, Dark Fantasy...	4.57	2019.0	NaN	'The battle to retake Wall Maria begins now! W...
5	6	jujutsu kaisen	NaN	TV	24.0	MAPPA	Fall	Action, Horror, Shounen, Curse, Exorcists, Mon...	4.56	2020.0	2021.0	'Although Yuji Itadori looks like your average...
6	7	attack on titan the final season part ii	Shingeki no Kyojin The Final Season: Part II	TV	NaN	MAPPA	Winter	Action, Drama, Fantasy, Horror, Shounen, Dark ...	4.56	2022.0	NaN	'Continuation ofxa0Attack on Titan The Final ...
7	8	attack on titan the final season	Shingeki no Kyojin The Final Season	TV	16.0	MAPPA	Winter	Action, Drama, Fantasy, Horror, Shounen, Dark ...	4.55	2020.0	2021.0	"It's been four years since the Scout Regiment...
8	9	demon slayer kimetsu no yaiba movie mugen t...	Kimetsu no Yaiba Movie: Mugen Ressha-hen	Movie	NaN	ufotable	NaN	Action, Drama, Fantasy, Shounen, Demons, Histo...	4.54	2020.0	NaN	'Tanjirou\xa0and the group have completed thei...
9	10	haikyuu karasuno high school vs shiratorizaw...	Haikyuu!! Karasuno Koukou vs Shiratorizawa Ga...	TV	10.0	Production I.G	Fall	Shounen, Sports, Animeism, School Club, School...	4.53	2016.0	NaN	'Picking up where the second season ended, the...
10	11	your name	Kimi no Na wa.	Movie	NaN	CoMix Wave Films	NaN	Drama, Romance, Body Swapping, Gender Bender, ...	4.51	2016.0	NaN	'Mitsuha and Taki are two total strangers livi...

Figure 12. Iteration 1 recommendation result for username “Sean”

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