ANIME LIVE-ACTION ADAPTATIONS: DECIPHERING SUCCESS FACTORS

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Context

The genre of Japanese animated series, more commonly known as anime, has become an international pop culture phenomenon. It has spawned large communities of both international and Japanese fans, creating an industry worth billions of dollars. A market analysis by GrandViewReport (2023) valued anime's market share at $28.61 billion USD and predicted it to continue growing explosively. Anime's rapid rise in popularity has elicited numerous responses from the global entertainment industry. Netflix, for example, has reportedly begun adding more anime titles to its catalogue after more than half of users in 2022 watched anime at least once (Peters, 2022). Sony Entertainment recently acquired Crunchyroll, arguably the U.S.' biggest streaming service specializing in anime (Brzeski, 2022).

In the steady and continuous rise in popularity of anime, one of the emerging responses from the Western world is the live-action adaptation of popular anime. Anime live-action adaptation refers to the process of converting the Japanese animated series into live-action films/movies and TV shows. This live-action trend has faced much backlash from its audience, often receiving criticism for the lack of fidelity to the source material, controversial casting, and overall poor quality of the adaptation. A quick search of "anime live adaptation" on YouTube will display video discussions on the topic, with hit videos such as "Why live-action Anime Will Never Work" by Nasu and "Why I hate live-action Anime Adaptations" by The Cosmonaut Variety Hour. A CNBC article by Mitra (2019) recommended that Hollywood completely stay away from anime live-action adaptations.

Although live-action adaptations have an overall terrible reputation, some recent adaptations have seen massive success. In particular, One Piece stands out as a breakthrough. To date, it is the only mainstream live-action adaptation to have achieved massive success. Other live-action adaptations of similarly popular anime such as Bleach and Death Note have been flopped despite also having a large pre-existing fanbase like One Piece. One Piece's breakthrough success (and other successful adaptations) leads to a few questions regarding live-action adaptations: How did One Piece succeed where so many other adaptations have failed? What factors separate well-received adaptations from flops? With the use of various computational methods, namely, latent dirichlet allocation, term frequency-based analysis, and sentiment analysis, the project aims to answer the following questions regarding anime live-action adaptations:

1. Based on the reviews and reactions to live-action adaptations, what are the main factors influencing the success or failure of anime live-action adaptations?
2. What are the most common sentiments or themes mentioned in reviews and discussions of anime live-action adaptations?
3. Based on the analysis, how can filmmakers and studios make better decisions when adapting anime into live-action formats?

Methods

This project answers the aforementioned research questions by analyzing the reactions to selected live-action anime adaptations. To be specific, the reactions used in this project can be classified into two categories: reviews from dedicated review aggregator websites and comments from YouTube videos discussing the adaptations. Reviews will always focus on evaluating the corresponding adaptation, and they are more likely to come from the "movie-goer" audience who may not be as concerned with the source material. YouTube comments, on the other hand, are better described as just reactions since they may not always evaluate the adaptation. They are shorter pieces of text that discuss the adaptation without evaluating it. Since these two types of text entities are quite different, they are categorized into two and will serve as one layer of comparison in this study.

The reviews used in this study were collected from Rotten Tomatoes and IMDB. These two were chosen because they hold the largest number of reviews among all review aggregator websites. User reviews were used. Critic reviews were excluded due to difficulties in collecting enough data points. The YouTube comments were collected from the official trailers of the adaptation and review or discussion videos about the adaptation.

This project analyzed the reactions from 6 live-action anime adaptations. Namely, these are Alice in Borderland, One Piece, Cowboy Bebop, Bleach, Death Note, and Dragonball: Evolution. The selection of adaptations was performed on the basis of text entity count and balancing successful vs unsuccessful adaptations. The adaptations with the most amount of reviews and discussions were favored in order to reach a significant number of text entities. To facilitate comparison, the roster of adaptations was deliberately arranged to have 2 successful adaptations, 2 neutral/mixed adaptations, and 2 unsuccessful adaptations. Of the 6 adaptations, Alice in Borderland, One Piece were chosen as the successful adaptations. Bleach and Cowboy Bebop were chosen as the mixed adaptations. Death Note and Dragonball: Evolution were chosen to be the unsuccessful adaptations.

In total, the text entities collected amounted to 55,358, with 19,267 reviews and 36,091 reactions.

Textual Corpora

This project utilized Python to extract text entities and perform computational methods. The following is a breakdown of the modules and code used:

I. Pandas

Pandas is a popular data manipulation and analysis library for Python. It can perform numerous actions related to data such as creating data structures, reading tables, transforming data, and more. For this project, Pandas was used primarily for 2 things: to store outputs in DataFrames to be used elsewhere in the project, and to read data from Excel and CSV files.

II. Selenium

Selenium is an automation tool that allows for programmatically automated web browser interaction through Python with the use of Selenium's WebDriver. In this project, Selenium was the package used to extract text entities from IMDB and Rotten Tomatoes. In order to successfully collate reviews from the websites (IMDB and Rotten Tomatoes), a chrome WebDriver was used to skim through all the user-inputted reviews on the aforementioned websites. For the IMDB web scraper, in order to access, and then store all the user reviews into a DataFrame, the WebDriver makes use of the click() function in order to load all the reviews before storing them (since only a certain number of user reviews can be displayed during the initial loading of the website). As for the Rotten Tomatoes web scraper, the website contains a "next page" button which, after a certain amount of reviews, goes to the next set of reviews. Again, using the WebDriver click() function, the web scraper can store all the reviews on the current page before moving on to the next page until all the user reviews have been successfully accessed and stored.

For the actual extraction and searching of web elements, Selenium was also used. Its find_element(By.CLASS_NAME).text() function was used to single out and extract the review text. The find_element() function was also used to find the "next page" button.

For rotten tomatoes, reviews were identified and extracted using the class "audience-review-row" as the search key. This review entity signifies one review, containing the review_body, username, rating, and other pieces of information. To extract the details from the review entity, more specific class identifiers such as "audience-reviews__review" for the review body and "audience-reviews__name" for the username were used.

For IMDB, the class of "review-container" was used as the search key for review entities. To obtain the review text, the "textContent" attribute of reviews identified by the "text show-more__control" was extracted from the review container.

III. YouTube API

The YouTube API allows developers to extract public data from YouTube. Through YouTube's API and Google's API Discovery Service, python can interact with YouTube's API. In this project, YouTube's API was used to extract video response data in the form of a nested dictionary from YouTube videos. Comment contents were extracted from their respective snippets and page tokens were used to navigate through different comment pages.

Data Cleaning and Preprocessing

To ensure the proper function of computational methods used in this project, particularly for term frequency-based analysis and topic modeling, the textual corpora should not be fed in as it is but processed and cleaned as required by the computational methods.

I. Language Detection

The critic site reviews and Youtube comments have a collection of English and non-English text entries. Limiting the text to only one language, in this case English, would ensure more consistent and interpretable results.

Langdetect is a port of Google's language-detection library from Java to Python. The detect function of the library identifies the language which the text has the highest probability of being. Entries detected to be non-English were then dropped from the corpora.

II. Regular Expression Cleaning

The IMDB reviews in particular have unwanted text extracted alongside the actual review entries in the form of the IMDB website attaching a rating and a prompt to rate the helpfulness of the review to the entry.

A function which specified a regular expression pattern to match the unwanted text and replace it with an empty string was created to solve this issue.

III. Lemmatization

A spaCy library was added to load a pre-trained English language model, en_core_web_sm, in order to facilitate the lemmatization process. This English language model was created with a spaCy natural language processing pipeline to lemmatize input text.

IV. Stop Word Removal

Stop words are commonly used words in the language which contribute little to generating insights when processing a textual corpus. The Natural Language Toolkit was used to download a list of English stop words which were then removed from the corpus.

V. Gensim Preprocessing

Gensim is a Python package commonly used in natural language processing. The package contains a simple_preprocess() function which can complete standard text preprocessing tasks like converting text to lowercase, removing punctuation, splitting text into individual words, and other procedures to facilitate the tokenization, normalization, and cleaning of a text.

While some of these processes have already been completed by previous functions, Gensim text preprocessing was implemented both as a final step and a layer of redundancy to ensure that text is properly processed for use in computational methods.

VI. Bigram and Trigram Models

The English language contains many phrases and compound words which just do not carry the same meaning when split into their individual components. A relevant example for this project would be the phrase “live-action.” As such, Gensim’s Phrases model was used in order to generate bigrams and trigrams which could be important in generating insights from computational analysis.

The bigrams and trigrams were generated based on their minimum count from their instances in the documents and according to a specified threshold which dictates how easily a collection of words could be identified as a bigram or trigram.

Computational Analysis

I. Sentiment Analysis

Sentiment Analysis is a technique used to evaluate the emotional tone of a text by assigning a numerical score that reflects its sentiment. In this project, the Natural Language Toolkit package's VADER Lexicon and SentimentIntensityAnalyzer were used to perform the sentiment analysis.

The VADER (Valence Aware Dictionary and sEntiment Reasoner) lexicon is specifically attuned to sentiments expressed in social media. It outputs 4 numerical values, negative, neutral, positive, and compound scores. The negative, neutral, and nositive scores collectively form a set of values that sum up to 1, each score describing the magnitude of a certain sentiment and its proportion in the statement. The compound score can best be described as a "normalized, weighted composite score" ranging from 1 (positive sentiment) to -1(negative sentiment). For this project, the compound score is particularly important as it captures the overall sentiment of a statement in a single value.

In terms of implementation, sentiment analysis was executed by passing a dataframe containing the text entities through a function. In this function, sentiment scores for each piece of text are calculated with nltk's sentiment analyzer and subsequently appended to an output dataframe. To further process this data, it is run through another function that uses the describe() function to create another output data frame containing statistical measures of the sentiment scores.

II. Term Frequency-Based Analysis

The Term Frequency-Based Analysis investigates the significance of certain terms or words based on how often they appear within a document. In this project's case, the analysis showcases both the frequency of terms per live-action adaptation and combined as well (i.e. the frequency of terms for the reviews and comments from all anime live-action adaptations). This is done with the use of SciKit Learn's CountVectorizer which basically does the counting per appearance of each word in a particular text or document. To start, after importing CountVectorizer, a function was made that takes in 2 parameters, words_list and medium. The word_list refers to the actual preprocessed data (Anime Live-Action Adaptations) which will be run through the CountVectorizer. Using the stop_words built-in stop words list ('english'), the CountVectorizer does not add into the count uninformative words (e.g., the, and, is, etc.). Aside from this, the CountVectorizer also makes use of the max_feature parameter to only get the top n elements of the term frequency-based list, in the project's case, it is 2000. The array of words are then passed onto a Pandas DataFrame to be saved as an Excel file which has 2 columns: (1) term and (2) frequency. This is arranged by frequency in descending order.

Apart from the regular term frequency-based analysis, this project also utilizes TF-IDF (Term Frequency - Inverse Document Frequency) to find words most relevant to each document. Like its regular variant, the main factor in determining salient words is a term's frequency in a document. However, TF-IDF also considers the ratio of documents that contain a specific term. Terms in a document that also appear in all or numerous documents are considered insignificant to that unique document, resulting in a lower score/relevance for that term/document combination.

Gensim's TfidfModel class was used to apply TF-IDF to the existing term frequency setup. Before passing the text to the term frequency code, gensim's TfidfModel first identifies all words that pass the TF-IDF threshold set in the code. Afterward, these words are moved from the text, now ready to be passed through the term frequency function.

III. Topic Modeling

Topic Modeling is a way to extract common themes from a textual corpus, which could be helpful in identifying which themes or topics are similar between different corpora. Latent Dirichlet Allocation, the chosen topic modeling method used for this project, assumes that each document is a collection of different topics, and that each word could be identified to at least one topic.

In order to generate LDA models, the preprocessed text should be used to create an id2word dictionary and a corpus which maps each word (according to its unique ID) to its frequency in the document. This was done by feeding the preprocessed text into the gensim.corpora Dictionary which initializes the id to word mappings and collects corpus statistics. The dictionary was then used to generate a term document frequency matrix in a bag-of-words format, as is required by the LDA model. The matrix was then passed into a TF-IDF model to remove low-value words from the corpus based on a specific threshold. The threshold set for the critic sites like Rotten Tomatoes and IMDB were set to 0.05 due to the more coherent structure of the text entries from these websites while it was set to 0.21 for Youtube as the comments from the videos tend to have less of a focus on topic and words used. The threshold for the combined critic site corpus was raised to 0.07 as it incorporates entries from two different mediums.

Once the required inputs are generated, it is ready to pass them onto the Gensim LDA model, but the resulting model would be unoptimized, as it would use default settings which were not fit specifically for the input corpora. The settings in question would be the topic count and the alpha and beta parameters. The topic count would dictate how many topics the LDA model would generate using the given corpora. A value too high or too low would make it difficult to extract insights from the model. The alpha and beta parameters could be seen as concentration parameters for the dirichlet distribution used in the model. To put it simply, the alpha parameter dictates the likelihood of a document containing a mixture of topics, while the beta parameter dictates the likelihood of a topic containing a mixture of words.

LDA models were iterated over a topic range of 5 to 15, alpha parameters of 0.01, 0.31, 0.61, symmetric, and asymmetric, and beta parameters similar to the alpha parameters bar the asymmetric value. A coherence score based on the topics produced for each collection of parameters was generated with the Gensim CoherenceModel and then placed in a dataframe. This process was completed for all 6 live-action adaptation corpora for each of the 4 mediums (Rotten Tomatoes, IMDB, Youtube, and Rotten Tomatoes + IMDB), with each adaptation being generateds 200 LDA models. The most suitable set of parameters was realized by finding which set was most frequent while still having a coherence score within 10% of the maximum value. Finally, the parameters used were as follows: a topic count of 10, an asymmetric alpha parameter, and a beta parameter of 0.61

Once all the LDA models were generated according to the aforementioned parameters, they were ready for interpretation. However, to streamline comparison among the numerous

LDA models, the .diff() function provided by Gensim for LDA models was used to get the Jaccard similarities between each pair of topics inferred by two models. The function returns a matrix of distances between each topic and a matrix of annotations which contains the similar and different tokens within each topic. These matrices are then plotted on a heatmap using matplotlib. These plots help visualize what different entities say about the same subject.

Results and Analysis:

I. Sentiment Analysis

To summarize the results of the sentiment analysis, boxplots illustrating the distribution of data among the different categories were used. Please see Figure 1 for boxplot diagrams describing every category.

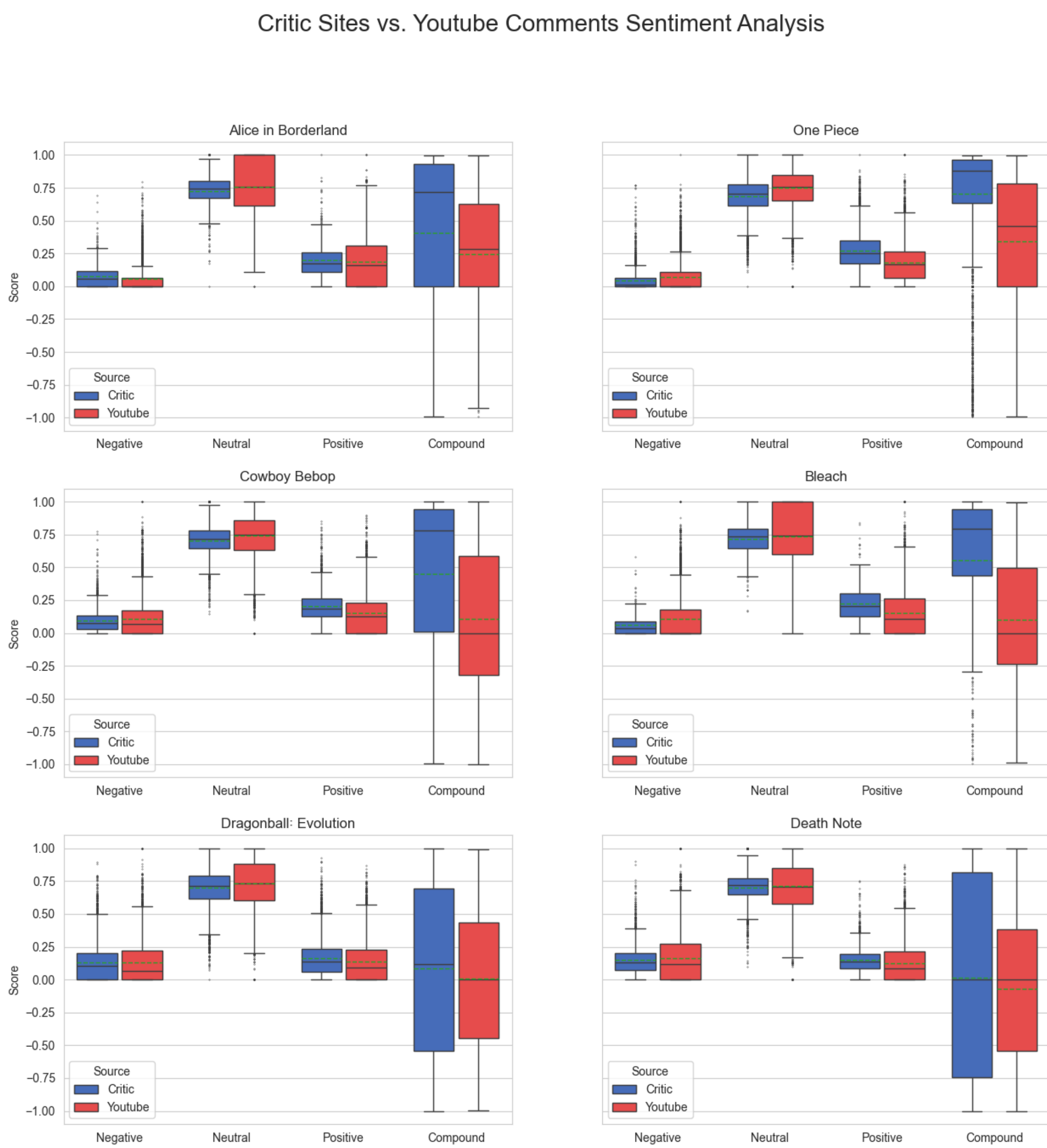

Figure 1. The sentiments of each live-action adaptation for critic site reviews and Youtube comments visualized using box plots.

Figure 1's boxplots are divided by title, and then further divided by data sources (blue critic website reviews and red for YouTube comments). The diagrams are arranged by title popularity. As the successful adaptations, One Piece and Alice in Borderland are beside each other at the top of the figure. Cowboy Bebop and Bleach follow in the next row as the neutral adaptations. The unsuccessful adaptations take the last row. As displayed in the figure, the average reaction to any adaptation is mostly neutral. Even for successful animes, the neutral sentiment takes about two-thirds of the average statement's overall score. The rest of the statement's sentiment is spread between positive and negative, with variations depending on the anime.

One important feature revealed by the boxplot is that there are always numerous outliers. This is true regardless of the success and overall sentiment of the adaptation. Bad adaptations have a non-insignificant number of positive sentiments, and even the most successful adaptations like One Piece have a number of negative statements. This illustrates that opinions about an adaptation are always mixed to some extent, although there will definitely be clear trends.

One important pattern displayed by the figure is that reactions' sentiments generally correlate with the rating and observed popularity of an adaptation. Please see Figure 2 and 3 for a compound score comparison between the different titles.

Figure 2. The compound sentiment score for each adaptation taken from critic site reviews.

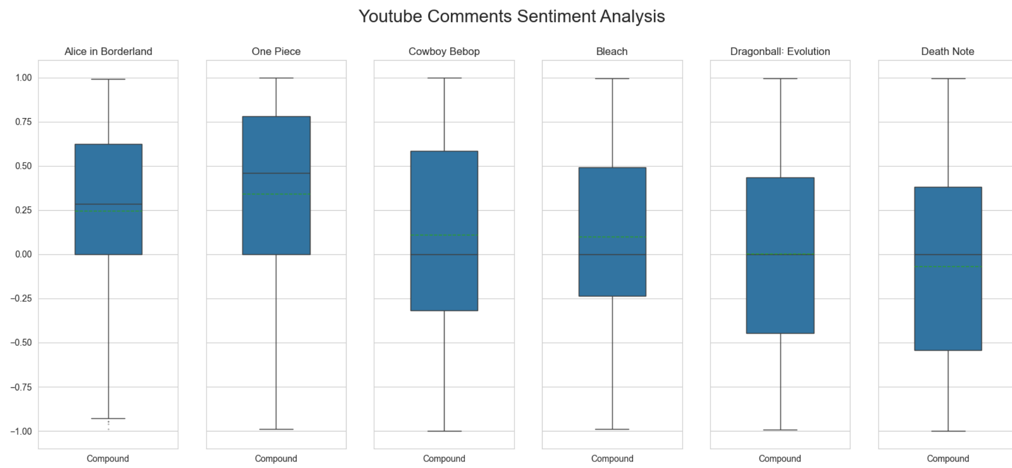

Figure 3. The compound sentiment score for each adaptation taken from Youtube comments.

The compound score summarizes a statement's overall sentiment into one value. Statements with compound scores above 0.5 are considered positive, while statements with scores below -0.5 are considered negative. Those with scores between 0.5 and -0.5 are considered neutral. As displayed in the boxplots above, the distributions of successful/neutral anime are evidently more skewed towards 1. In Figure 2, which describes the critic sites data set, the correlation between sentiment and success of adaptations is most evident in the distributions of the negative adaptations. Their boxplots are much more spread out, and their mean lines lie closer to 0 compared to the rest of the adaptations. This means that they typically have much more negative sentiment in their statements. The positive and neutral adaptations also display box plots correlated with their rating, but in the critic_sites these distributions don't correlate uniformly with their corresponding adaptation's rating (i.e. Bleach has better sentiment than Alice in Borderland despite having lower ratings and perceived popularity.).

Figure 3 also displays similar patterns, but in less magnitude and with more uniformity. From left to right, the compound scores neatly correlate with the categorization of the titles. Good adaptations have higher scores than neutral adaptations, and neutral adaptations have higher scores than bad adaptations. However, the difference between the average sentiments between different titles is much lower. Most of the boxplots tend towards 0, indicating that the average sentiment score is far more neutral in YouTube comments. Please see Figure 4 for a direct comparison between the compound scores of critic_sites reviews and YouTube comments.

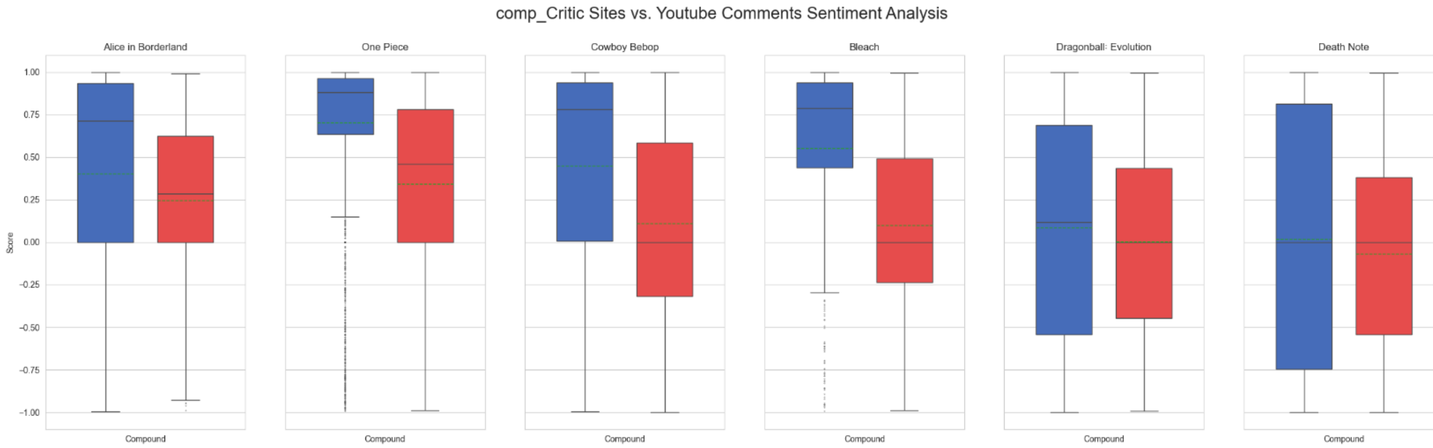

Figure 4. A comparison between the compound sentiment scores of critic site reviews and youtube comments for each live-action adaptation.

Figure 4 displays a side-by-side comparison between the compound scores of data from critic sites vs data from YouTube. Critic site data is displayed in blue, while YouTube is displayed in red. In this figure, it is especially noticeable that critic site sentiments are more polarizing. Red box plots always tend towards the middle and are always around the same size (indicating lower standard deviation). Blue boxplots, on the other hand, are varied and reflect the success of an adaptation in greater magnitude. This illustrates that reviews are generally more evaluative than comments. As expected, comments may not always contain significant information or reflect the author's sentiment. Some comments may just be short, relatively meaningless statements. Nevertheless, both comments and reviews reflect the success/popularity of an adaptation to varying extents.

II. Term Frequency-Based Analysis

The results of the Term Frequency-Based Analysis (both the individual and the combined TFBA for the Anime Live-Action Adaptations), show that the mode of adaptation (i.e. a series or a movie) matters and has a significant contribution to the overall success of an adaptation. Note that the diagrams under the Term-Frequency-Based analysis are those that have yet to consider how important each term is on a specific adaptation relative to other adaptations. With that, going to a more specific set of visualizations (i.e. the Term Frequency-Based Analysis per adaptation) from YouTube comments and review websites respectively.

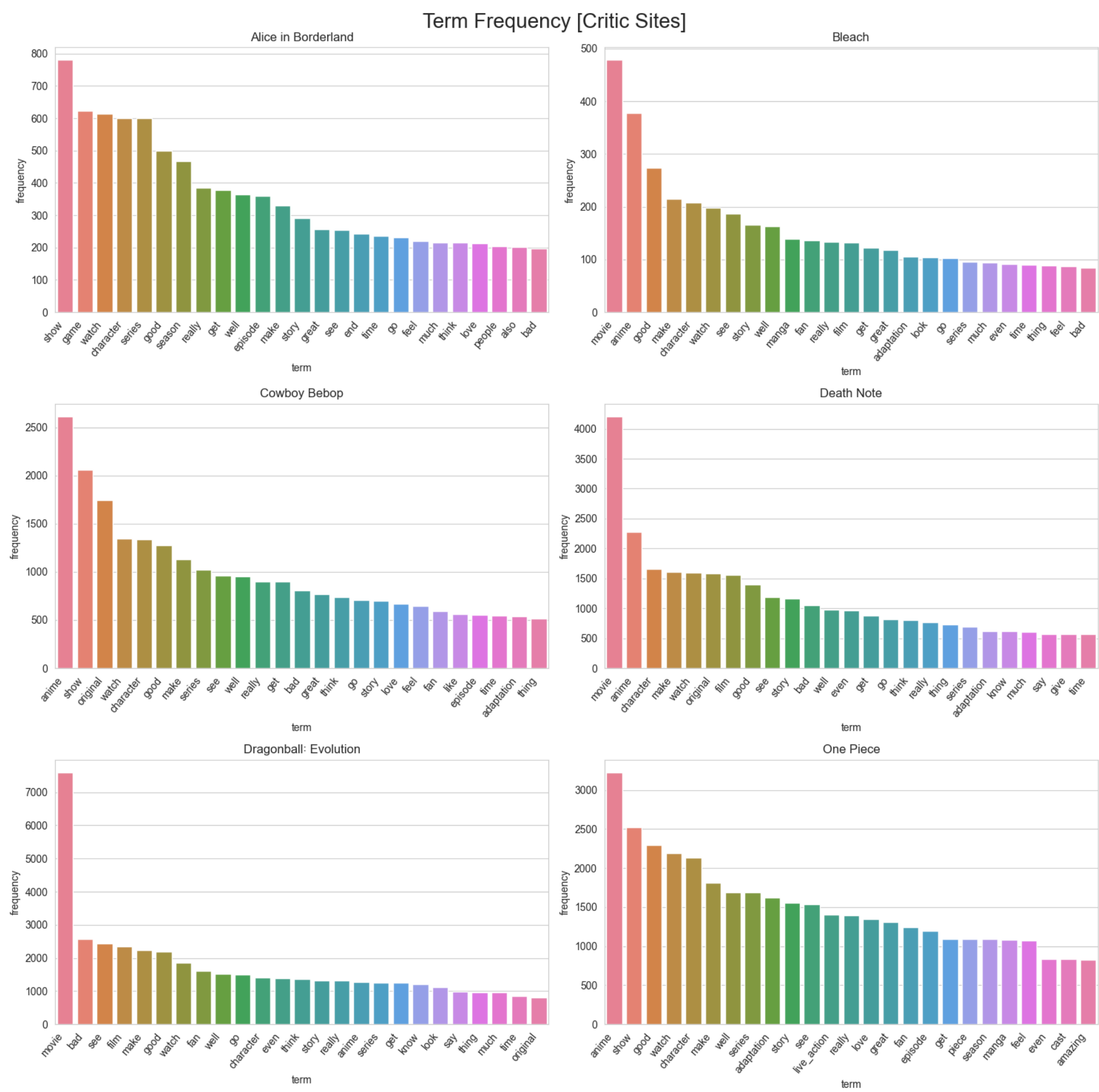

Figure 5. Term frequency bar graphs for critic site reviews

Looking at the Dragonball: Evolution and Death Note bar plot in Figure 5–both of which fall under the category of ‘bad’ adaptations–it can be seen that the most frequent term for both is ‘movie’ which points to the fact that both are adaptations that opted to convert their anime counterparts into a film/movie rather than a series. Consequently, when looking at the adaptations we classified as successes (One Piece and Alice in Borderland), one of their most frequent terms is ‘show’ aligning with their respective mode of adaptation. The same also applies to the remaining two adaptations. Therefore, the adaptation approach–whether it is a series or a movie–significantly matters for the consumers of these adaptations as exhibited in the collection of term frequency bar plots in Figure 5.

TF-IDF-Applied TF-BA

Applying TF-IDF or Term Frequency-Inverse Document Frequency to the anime live-action adaptations allows for new insights to take form. Please see Figures 6 and 7 for the term frequency bar plots, this time with terms passing the TF-IDF threshold removed.

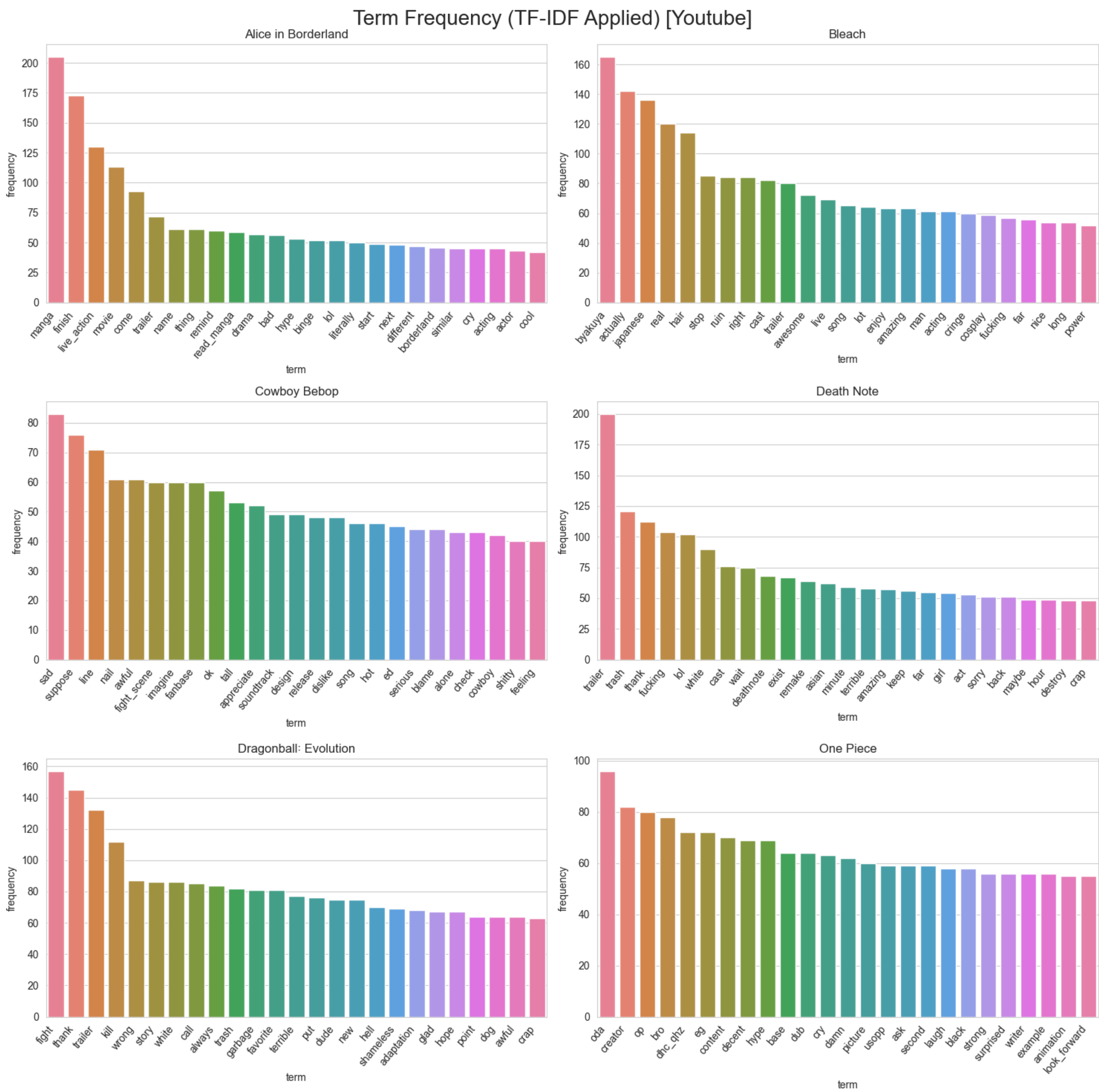

Figure 6. Term Frequency (TF-IDF applied) from YouTube comments.

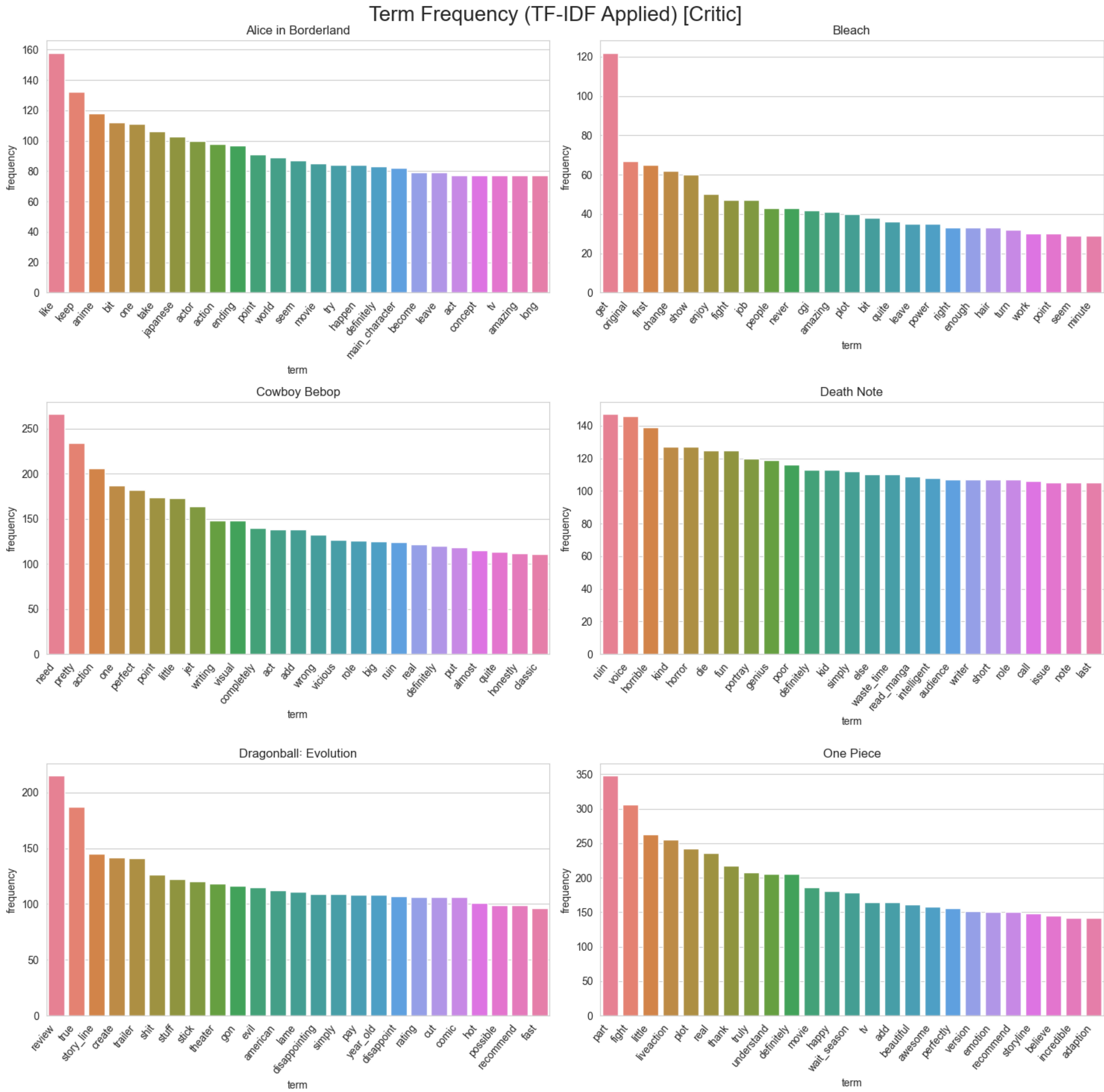

Figure 7. Term Frequency (TF-IDF Applied) visualization from critic site reviews.

Figure 6 is a barplot of the TF-IDF applied term-frequency from YouTube, while Figure 7 is for critic site reviews. In these figures, disproportionately present terms like good, bad, or character have been removed. Only the top 25 terms significant to the specific title are shown.

Although terms have been filtered to only show those relevant to the title, many terms are simply adjectives or insults likely used to praise or attack the adaptation. Apart from these, however, the terms provide some insights and common themes into the factors being discussed in live-action adaptations:

1. **Music and Voice**

Bleach: song
Cowboy Bebop: soundtrack
Death Note: voice
One Piece: dub

Music seems to be one element that is discussed across multiple titles, especially in the YouTube comments. In Figure 6's Bleach and Cowboy Bebop, the term "song" appears in each title's top 15 terms. "Soundtrack" also appears in Figure 6's Cowboy Bebop. Among casual viewers, it seems that song and music are a somewhat common point of discussion.

Voice also seems to be another important audio element that users discuss across titles. "Dub" is mentioned in Figure 6's One Piece, while "Voice" is directly mentioned in Figure 7's Death Note. Collectively, music and voice make up the audio elements that are somewhat evident in the term frequency. They don't appear too often, but they appear in multiple documents.

2. **Visuals and design translation**

Bleach: hair, cosplay
Cowboy Bebop: tall, design, visual

Another salient point seems to be the visual design of the adaptation, especially for certain adaptations like Bleach and Cowboy Bebop. In Figure 6's Bleach, the terms "hair" and "cosplay" are among the top 25 terms. "Hair" appears again in Figure 7's Bleach, showing that it is a common concern amongst people discussing Bleach. Bleach characters have quite distinctive hair, so it seems that the design translation of hair from anime to live-action concerns viewers and fans of the anime.

Figure 6's Cowboy Bebop contains the terms "tall" and "design". "Visual" is directly mentioned among Cowboy Bebop reviews, as displayed in Figure 7's Cowboy Bebop. In this case, the discussion may focus more on the background and environment design rather than character design. Cowboy Bebop was originally set in a neo-noir space design, so discussions may have centered around whether the theme of the previous environment was properly captured in the adaptation. Character design could also have been discussed, since "tall" also appeared.

Visuals, both in terms of characters and background, seem to be of importance when the source material contains distinctive themes that may not always be captured in the adaptation.

3. Action

Alice: action

Bleach: fight

Bebop: action

Dragonball: fight

One Piece: fight

Action seems to be a particularly important aspect given that the anime counterparts of the adaptations all intertwine with the action genre. This means that while action may not be the main genre for all the adaptations, action still exists within said adaptations.

Starting with the negative reactions as seen in the YouTube comments for Dragonball: Evolution found in Figure 6, aside from the negative terms used, "fight" is also a salient term for the aforementioned adaptation. Looking at Figure 7, "fight" is also a common frequent term between Bleach and One Piece. All three of these adaptations have anime counterparts well-known for their numerous, high-quality action sequences. A more specific term in Figure 6, that is, "fight_scene," was also shown to be one of Cowboy Bebop's salient terms. Alice in Borderland and Cowboy Bebop, as seen in Figure 7, share the frequent term "action" in their respective bar plots. All these entail that the translation of certain fight scenes or even the action aspect in general, is what consumers also consider when it comes to anime live-action adaptations.

4. Plot

One Piece: oda, author, writer

Alice in Borderland: manga, read_manga

For the anime live-action adaptations that were deemed successful in this project (Alice in Borderland and One Piece), the producers seem to take into proper consideration their respective source material (anime and manga) which contributed to the overall success of each. To support this, as shown in Figure 6, the frequent terms for One Piece are "oda," the creator of One Piece, "author," and "writer." Additionally, it can also be seen that "manga" and "read_manga" are frequent terms in YouTube comments for Alice in Borderland. It is apparent–for consumers–in these successful adaptations that the anime is appropriately reproduced and converted to live-action based on their respective original content, that is, manga.

5. Casting

Death Note: white, cast

DragonBall: white

Casting has become a controversial topic for Death Note and Dragonball: Evolution live-action adaptation. Referring to Figure 7, Death Note had the terms "white" and "cast" as its salient terms. "White" is also amongst the top terms in Dragonball: Evolution's YouTube comments. Keep in mind that both of these adaptations are under the classification of 'bad' for this project. With that being said, appropriate casting was not taken into consideration in both adaptations as shown with the negative reactions from YouTube user comments. This subsequently contributed to the adaptation's overall unfavorableness towards consumers.

III. Topic Modeling

Visualizations of the LDA models give us similar insights as the term frequency-based analysis with the added detail of being able to see which terms are associated to a certain topic, as well as the size of a given topic within a certain document.

The LDA models are visualized using the interactive pyLDAvis interface. Figures 8.1 and 8.2 show examples of the LDA model for YouTube comments and critic site reviews about the One Piece live-action adaptation, respectively. It could be seen that the largest topic for both models reflects the general sentiment about the adaptation. For One Piece, the dominant terms present in topic 1 are mostly positive words, such as good, love, great, enjoy, and amazing, among others.

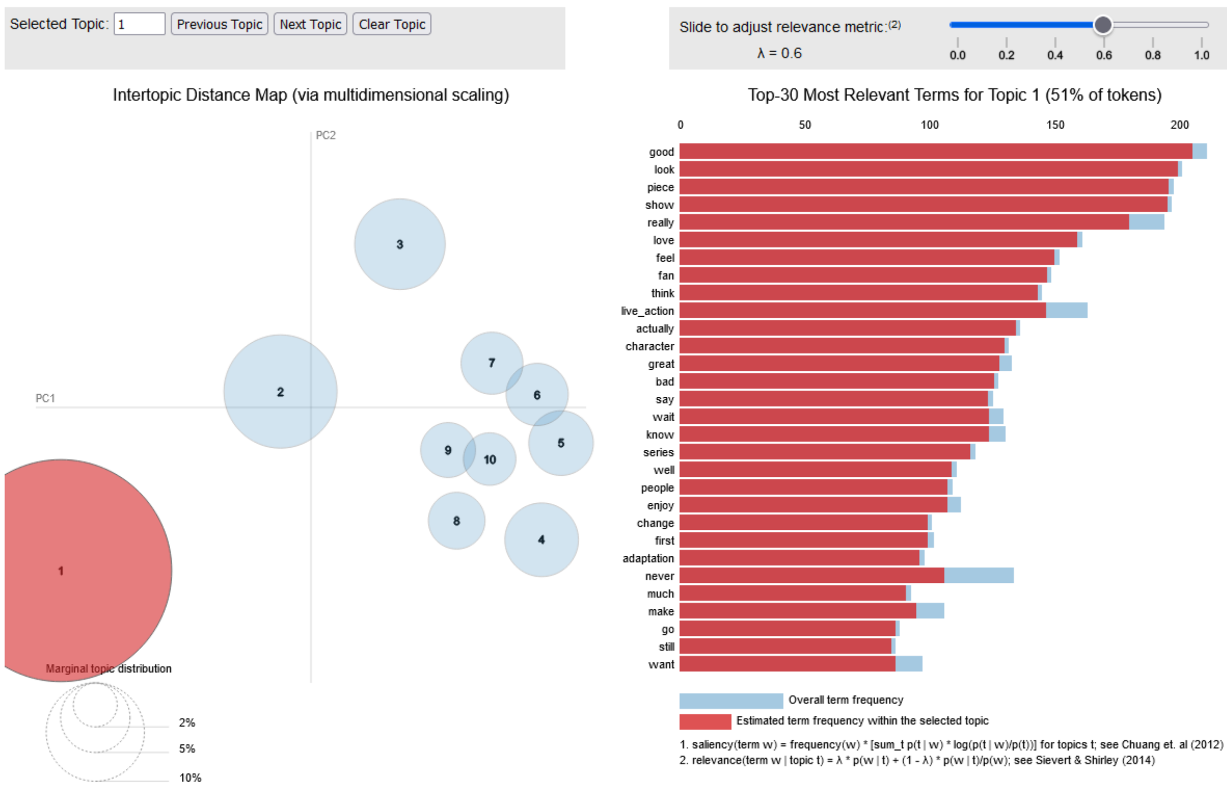

Figure 8.1. An LDA Visualization of YouTube comments about the One Piece adaptation.

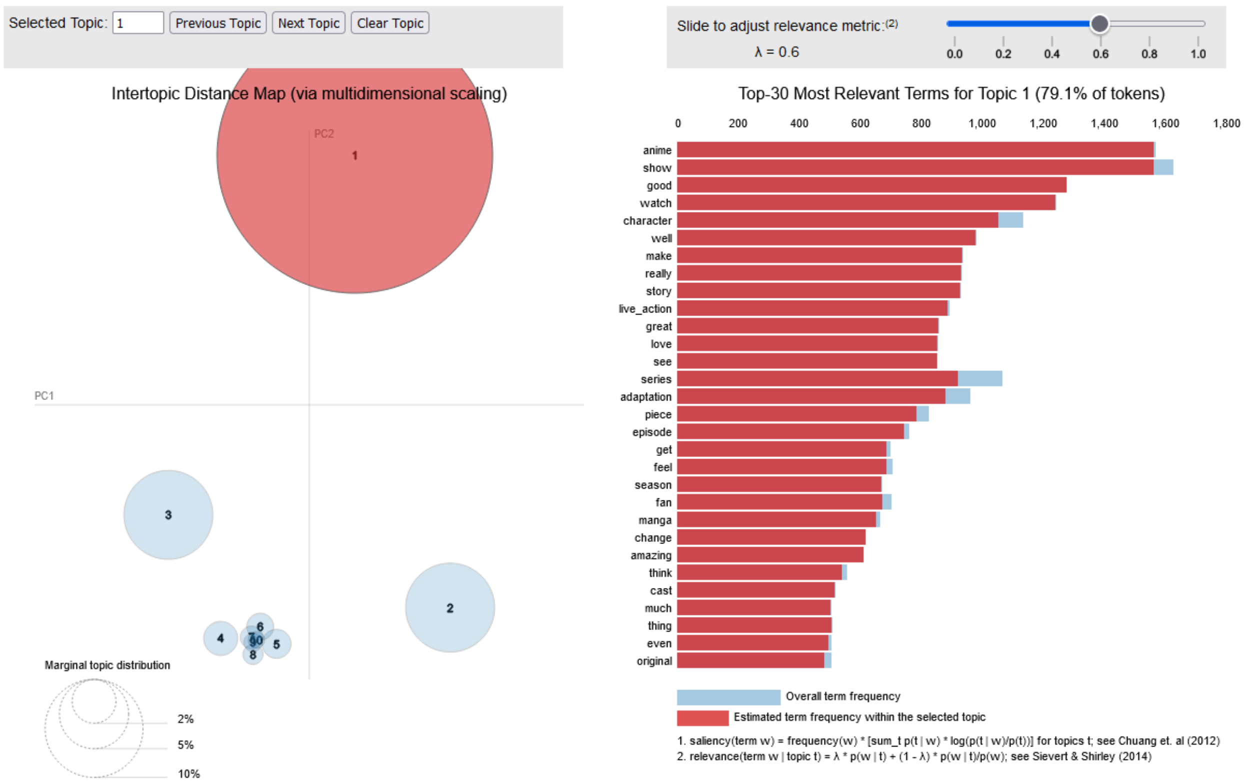

Figure 8.2. An LDA Visualization of critic site reviews about the One Piece adaptation.

Taking a look at the largest topic for other adaptations show similar insights. Figure 9 shows the general sentiments for a mixed adaptation and bad adaptation in Cowboy Bebop and Dragonball: Evolution, respectively. It could be noted that for a mixed adaptation, the adjectives "good" and "bad" are among the most frequent terms, with good being more frequent than bad, but the inverse is true for a bad adaptation, wherein "bad" is now more frequent than "good."

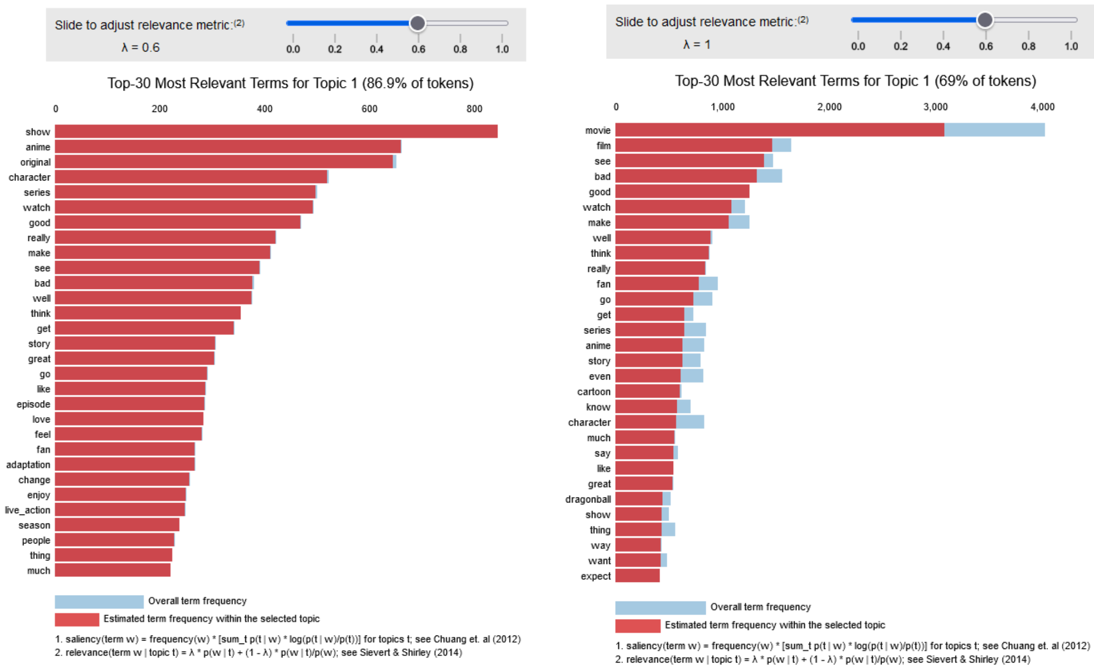

Figure 9. The most relevant terms for topic 2 of critic reviews for the Cowboy Bebop (left) and Dragonball: Evolution (right) live-action adaptation.

This trend follows for the topic models for the other live-action adaptations, for both comments and reviews, but have chosen not to be shown as figures 8 and 9 are representative of the results for these adaptations due to their similarities.

A closer look at the other topics show interesting insights other than the initial thoughts and general sentiments about the adaptation. Figure 10 shows us the most relevant terms for topic 2 of the models for the critic site reviews of the Death Note and One Piece live-action adaptations. Words and phrases such as story, series, original, adaptation, capture essence, authenticity, and faithfully, provide an insight that a significant contributor to the success of an adaptation lies in how well it holds the integrity of the source material.

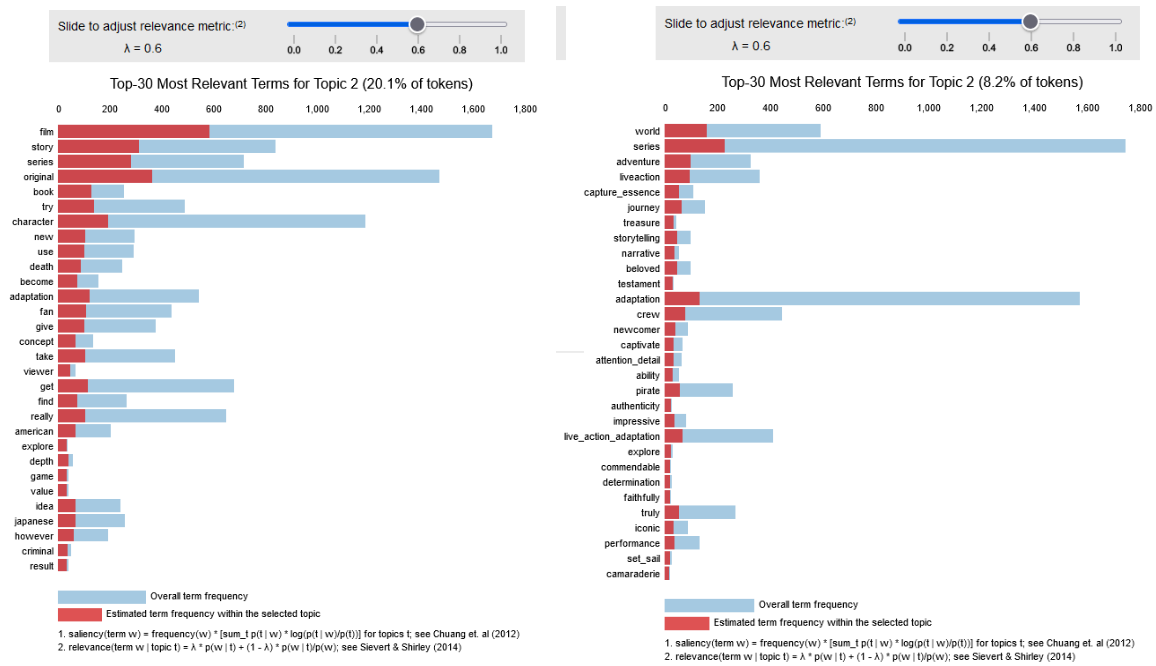

Figure 10. The most relevant terms for topic 2 of critic reviews for the Death Note (left) and One Piece (right) live-action adaptation.

An interesting similarity between the Cowboy Bebop, Death Note, and Dragonball: Evolution adaptations is the presence of the word American among dominant topics. The word is sometimes accompanied by Western, Japanese culture, offensive, wash, take, and version, which may allude to the fact that a negative factor shared between these three adaptations is the excessive Americanization of these originally Japanese works, which might rub longtime fans in the wrong way.

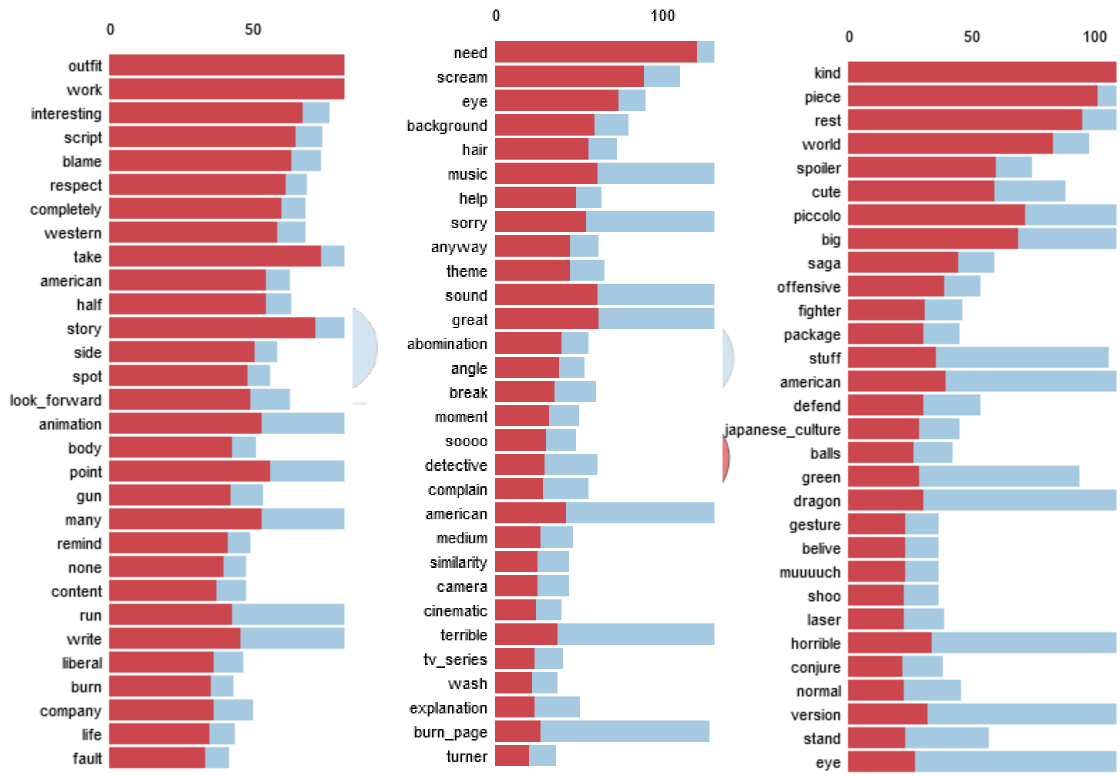

Figure 11. The most relevant terms for certain topics of YouTube comments for the Cowboy Bebop (left), Death Note (middle), and Dragonball: Evolution (right) adaptations.

LDA Model Comparison

To facilitate and streamline the comparison of different LDA models, the Jaccard similarities of the topics of different LDA models were plotted on a heatmap. As could be seen in Figure 10, however, there is not much use in generating a Jaccard distance heatmap for every LDA model combination, particularly in the case of comments and reviews. This heatmap visualization between the two different types of text entries confirms what was realized in the sentiment analysis wherein reviews have more substantial content and are more evaluative in nature. As such, it would be better to stick to comparing LDA models of reviews as these entries are more focused on evaluating the live-action adaptation.

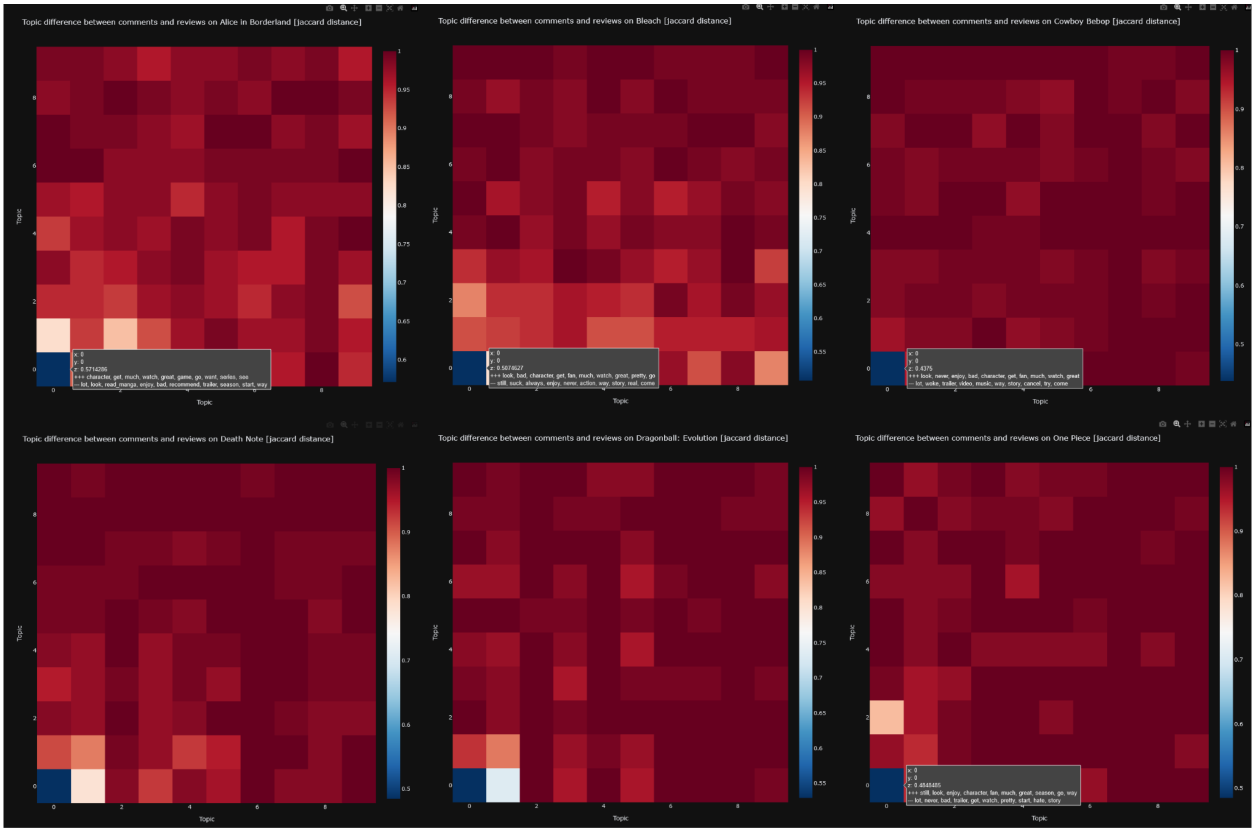

Figure 12. Heatmaps for the topic difference between critic site reviews and Youtube comments for each individual live-action adaptation.

Examples of more insightful comparisons may include comparing what the different critic sites, IMDB and Rotten Tomatoes, say about the same title. Figures 12.1 and 12.2 show that shared factors between successful adaptations may lie in the characters, casting, and visuals, as noted by the intersecting tokens. The different tokens might be modifiers to the intersections, showing that fans want something that was realistically portrayed and interpreted in a live-action adaptation.

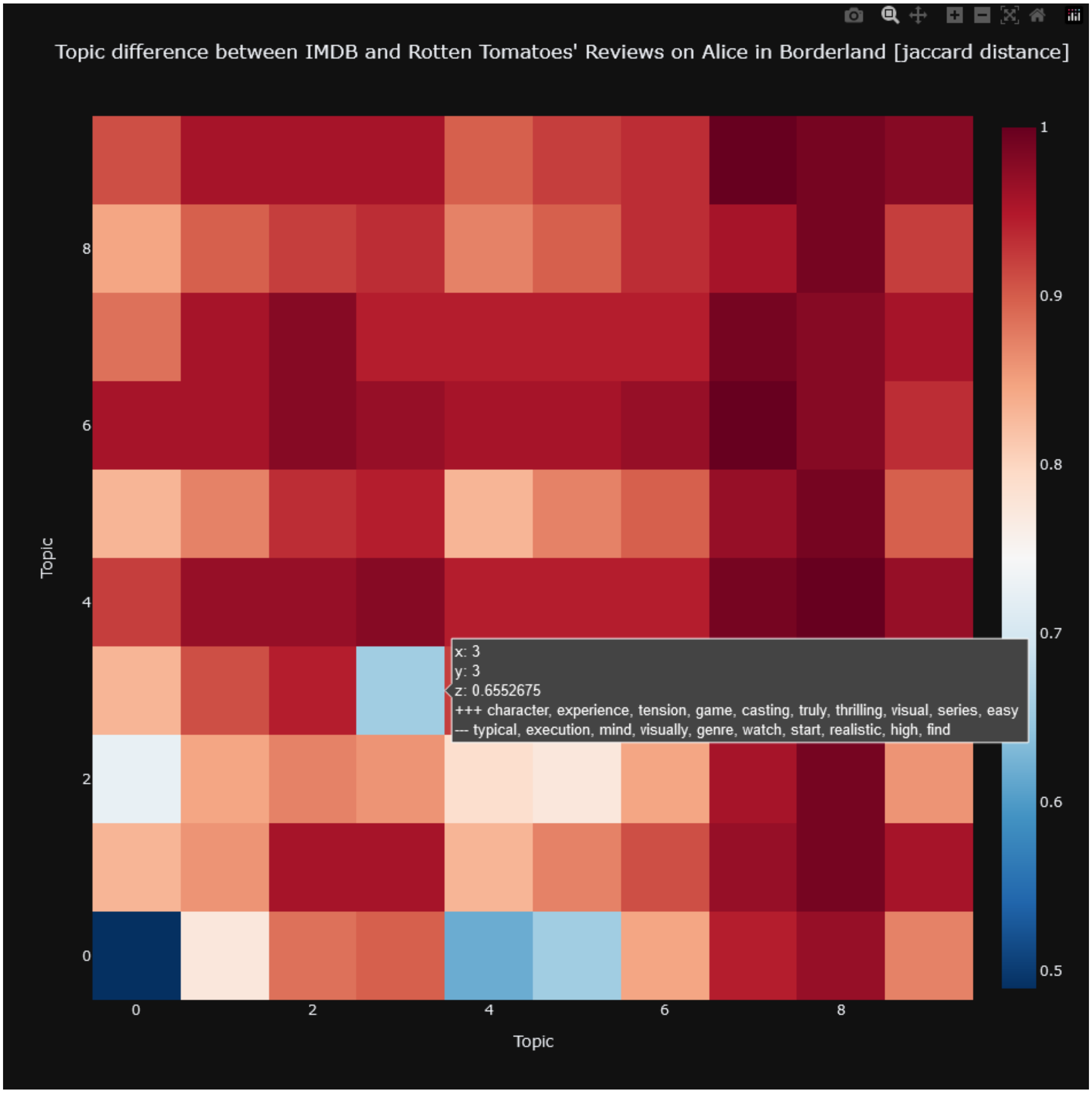

Figure 13.1. Heatmaps for the topic difference between IMDB and Rotten Tomatoes' reviews on Alice in Borderland.

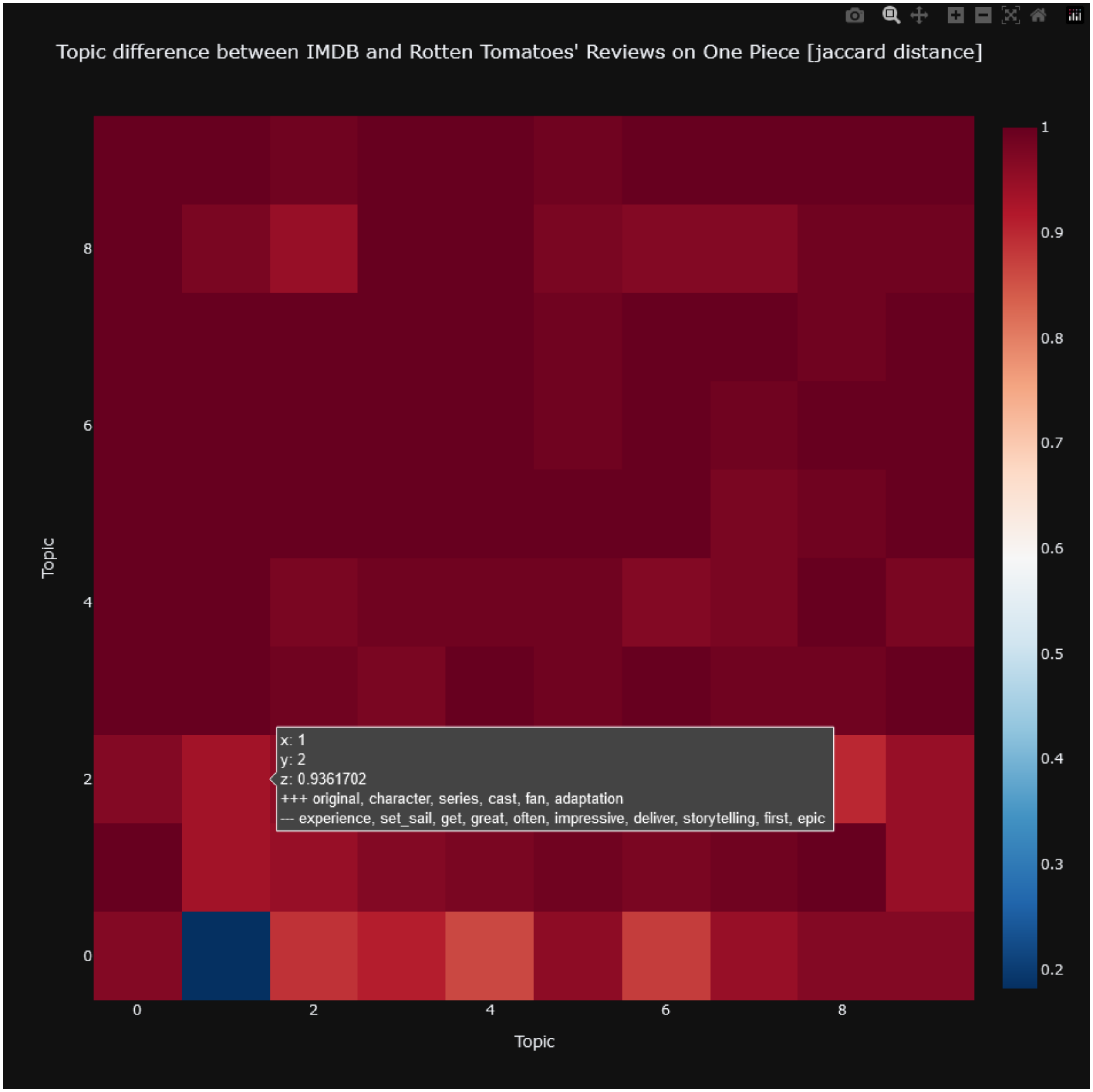

Figure 13.2. Heatmaps for the topic difference between IMDB and Rotten Tomatoes' reviews on One Piece.

Figures 13.1 and 13.2 show critic site differences in adaptations with mixed reviews. The similar topics from these LDA models may describe the factors that are holding these adaptations back from success or are the good qualities that just about salvage them from failure. In the same topic for Bleach and Cowboy Bebop are the words bad and character, which may be saying that the live-action needs to improve on characterization along with action and great, which might be a redeeming factor for the adaptation. The words casting and music are also present, signifying the importance of these elements in a good adaptation.

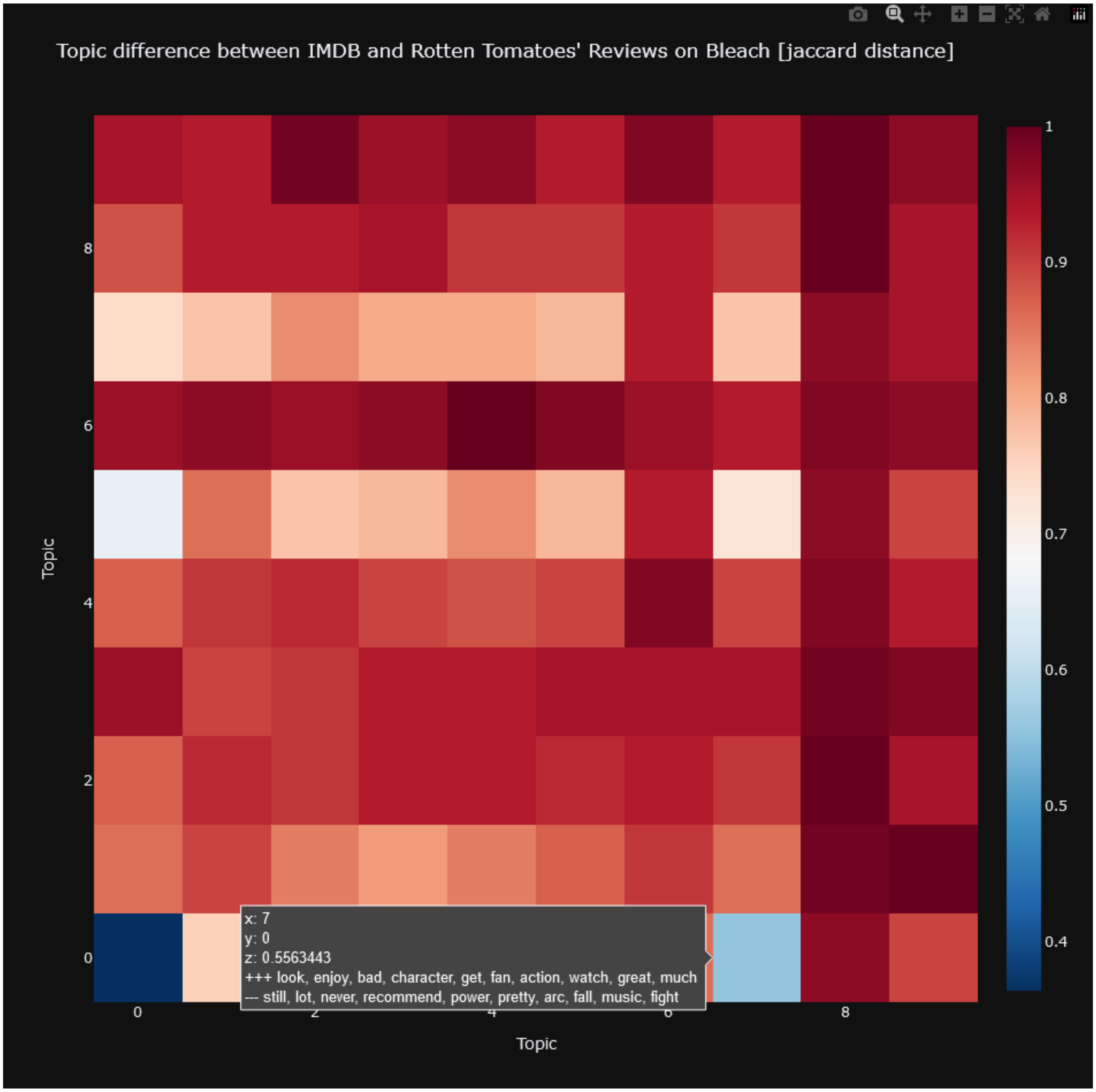

Figure 14.1. Heatmaps for the topic difference between IMDB and Rotten Tomatoes' reviews on Bleach.

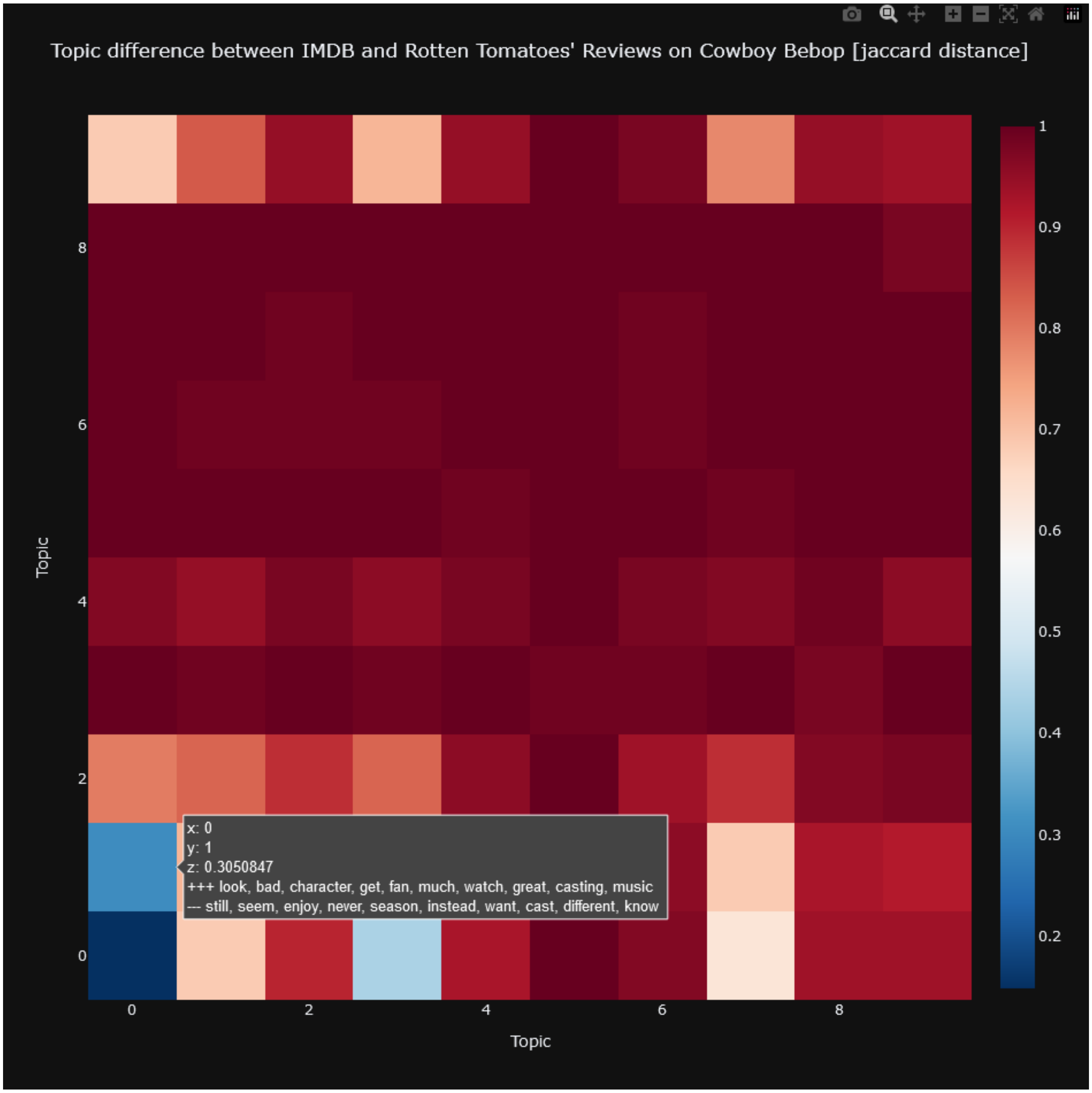

Figure 14.2. Heatmaps for the topic difference between IMDB and Rotten Tomatoes' reviews on Cowboy Bebop.

Figures 14.1 and 14.2 show the critic site differences on badly-received adaptations like Death Note and Dragonball: Evolution. The dominant problems for the Death Note adaptation seem to be about the bad characterization and infidelity from the source material. Dragonball: Evolution, on the other hand, seems to suffer from bad action sequences, which is incredibly problematic for a Dragonball title.

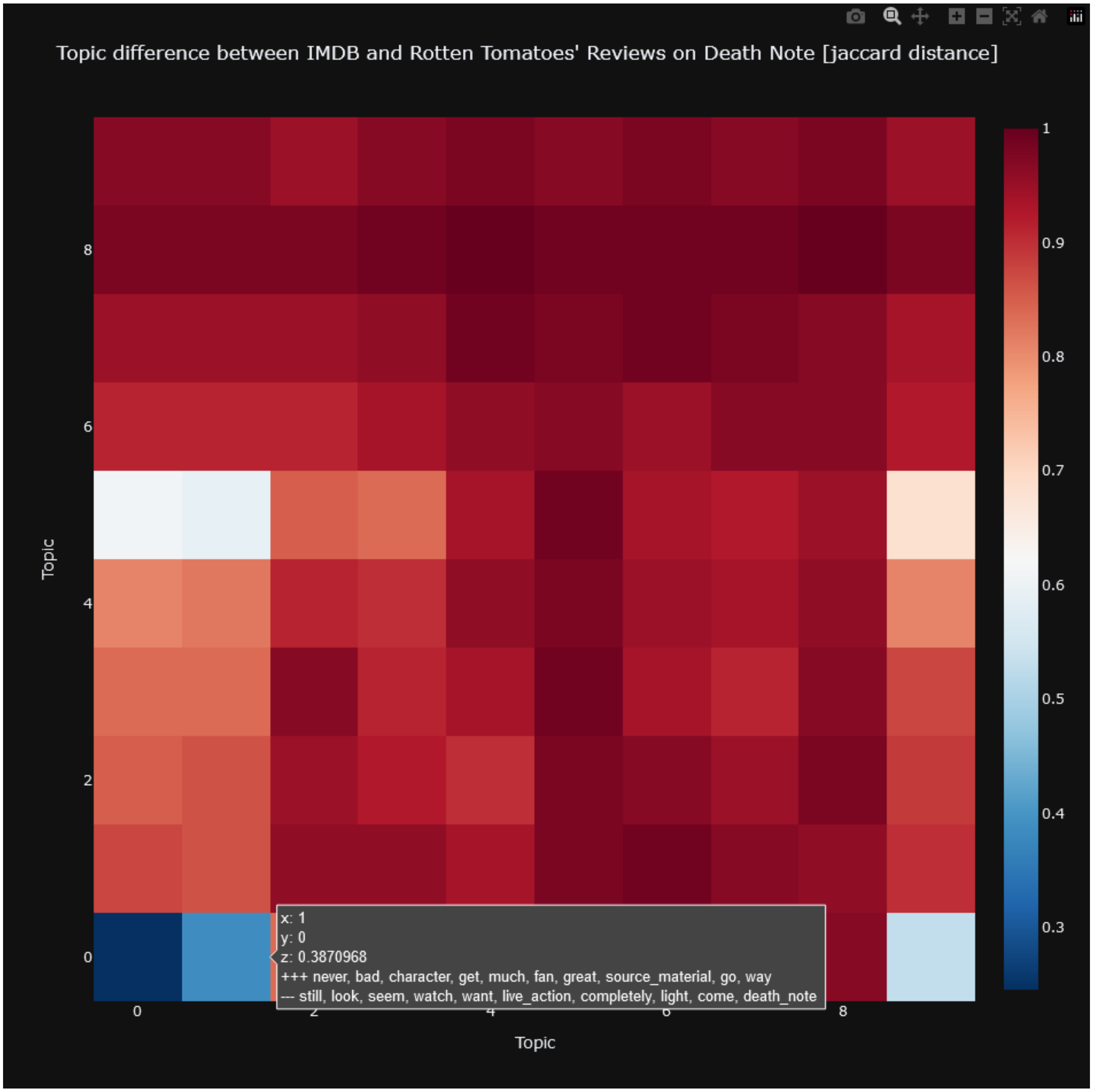

Figure 15.1. Heatmaps for the topic difference between IMDB and Rotten Tomatoes' reviews on Death Note.

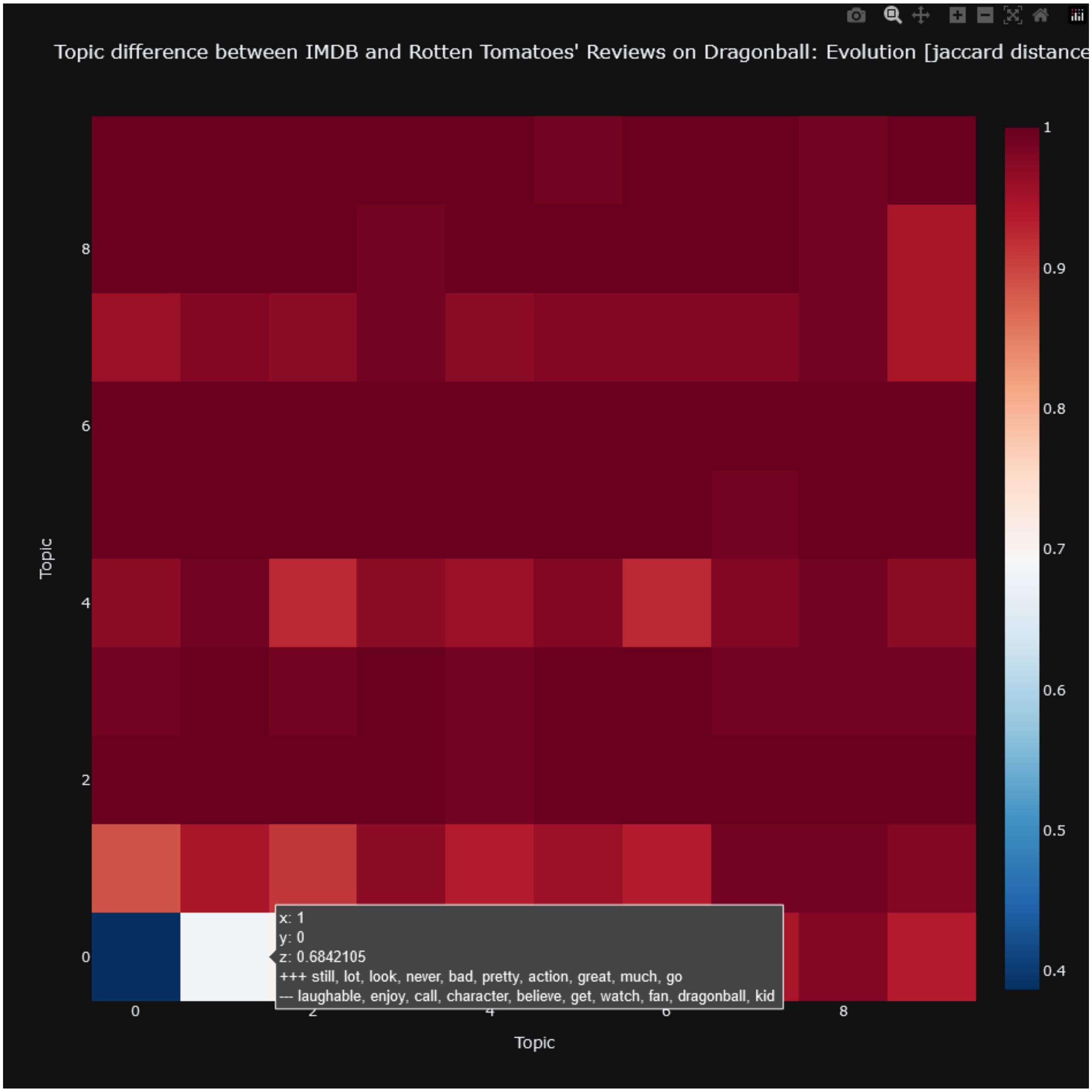

Figure 15.2. Heatmaps for the topic difference between IMDB and Rotten Tomatoes' reviews on Dragonball: Evolution.

The recurring tokens from LDA similarities revolve around two main themes: the elements of the adaptation such as evidenced by tokens like characters, casting, visuals, action sequences, and music, and how well translated the original work is into a live-action given by tokens such as original, adaptation, and source material. The most relevant disjunctive tokens which seem to be modifiers for the intersecting tokens are realistic and believe, which shows how despite wanting the adaptation to be faithful to the source material, its translation into live-action should still be realistic and believable lest it become unsettling to watch.

Social Analysis

I. Nostalgia and Attachment

One of the definitive findings of this project is that the fidelity of an adaptation to its source material is an important factor in an adaptation's success. The source material is always a major topic in discussions of live-action anime adaptations. In particular, the casting of characters seems to be a very prevalent topic.

One way of explaining the emphasis people seem to place on the source material is by considering the emotional background behind a person's perspective on a certain anime. Fans of the source material viewed it long before watching the adaptation. When these fans encounter the adaptation created years later, they are not just watching a new film but also revisiting their memories and perceptions of the past. A key factor to consider here is that people typically associate the past with longing and pleasure. This is known as nostalgia. People do not remember the past exactly as it was. Instead, they paint the past in broad strokes, often viewing it as a vaguely warm and positive experience. Our memory skewed positively (Johnson, 2022). That is why fans feel particularly offended and displeased when an adaptation disrespects the source material; an inaccurate adaptation not only distorts the source material's plot but also collides with the positive memories and nostalgia people hold of the source material.

Another emotional factor to consider is attachment. In this case, attachment refers to a feeling of emotional connection that fans develop towards the characters, world, and themes of the source material. Over time, as fans engage with an anime series, they develop a sense of belonging and emotional resonance with the story and its characters. This is especially true of characters. It can be easy to feel as if characters of stories relevant to a person's childhood grew up alongside them. Hence, adaptations that change or vandalize characters or other aspects of the source material can be difficult for fans to digest emotionally. Fans would feel as if their friend was being misinterpreted, or something they loved was arbitrarily changed.

II. Transportation Theory and Immersion

Transportation Theory or Narrative Transportation is a concept in psychology that explores the idea of people immersing themselves in a narrative to the point of becoming less aware of reality during their viewing of the narrative (Guldenpfennig, 2022). It states that people experience a state of “transportation” when they become engrossed in a narrative. In this state, they empathize with the characters and invest themselves in the events of the narrative.

Viewing adaptations from the lens of Transportation Theory could help explain some of the common problems people have with live-action adaptations. To be able to fully immerse oneself in a narrative, its elements must always preserve the narrative. If something is out of place, then it could break a person’s immersion and disconnect them from the narrative. For fans of the source material, breaking away from the narrative could happen simply because of obvious differences between the adaptation and their memories of the source material. When they see that a character or specific element is different from how they remember, they can no longer fully immerse themselves in the narrative. For individuals indifferent to the source material, breaking immersion could happen due to poorly translated elements of the film. Anime has a very distinct style from Western media. They typically have overblown fight scenes and ridiculous character designs. The plot, settings, and other elements of anime are also stylistically different. Translating these unique elements into films or series risks distorting the immersive qualities of the source material. The elements in the source material all work together to create a unique narrative. If even one of those elements is translated poorly, then it will seem out of place and potentially distort a narrative. This could partially explain why the film elements (plot, fight scenes, characters, designs, etc.) and their fidelity to the source material are common issues. Many adaptations seem to suffer from this problem; concrete examples include Bleach’s hair problem or Dragonball: Evolution’s comparatively lackluster fight scenes.

Conclusion and Discussion

Based on the reactions and reviews to 6 of the largest anime live-action adaptations, the main factors that decide an adaptation's success can be divided into 2 categories. Firstly, factors related to an adaptation's fidelity to its source material seem to be very important. Are the action scenes translated well? Has this character's essence and personality been preserved? Does the actor casted for this role actually fit? Does the overall design and theme match the source material? Casting, visual design, audio design, action, and story all play an important role simply in the way they relate to the source material. The nostalgia and attachment people have towards the source material are strong emotional drivers that affect their evaluation of an adaptation.

Secondly, elements of film themselves seem to play an important role regardless of their connection to the source material. Does this character look good or does he look out of place and ugly? Is the CGI used to make the action scenes well-made? Is the adaptation's soundtrack nice to listen to? Is the story engaging? These elements do not have anything to do with the source material, but they nevertheless play a large role in determining the success of their adaptations. If the source material's narrative is not fully preserved and translated well, then it can break the immersion of the adaptation.

With these factors in mind, this project presents a few recommendations for filmmakers and the filmmaking industry.

1. **Mode Consideration.** Condensing anime (especially those with an already long and deep story and plot) into a single film is not recommended as it can cause the loss of certain plot points and scenes as compensation for the shorter runtime. Producers should thoroughly assess whether a movie or a series is an apt choice for their adaptation, especially considering the depth of the source material and the limited runtime of movies.
2. **Fidelity vs Reinterpretation.** In general, it is better to follow the source material. Changing too many things or completely vandalizing certain characters will only serve to anger fans and disrupt the narrative. Creative reinterpretation should be considered carefully, with respect towards the source material's essence and meaning. To aid in the translation of anime to live-action, it is recommended to take input from the original author especially if reinterpretation is being considered.

3. **Aesthetics.** Animes have wacky and overblown designs. These need to be translated carefully into live-action. If designs do not preserve the theme and essence of the source material, then fans will not be pleased. If designs look visually unappealing, then it will affect the entire adaptation.
4. **Film Elements.** Adaptations should not neglect film elements just because they have a pre-existing fanbase coming from the source material. If the film elements are done poorly, then the adaptation will be unsuccessful no matter how big the source material is. Hence, filmmakers should treat live-action adaptations with the same rigor that they treat every other film. They should thoroughly understand and consider the music, action, plot, characters, and designs.
5. **Casting.** Proper evaluation for casting is a must when it comes to translating anime into live-action. People tend to become attached to characters. Careless casting will aggravate fans with emotional attachments towards characters. This was revealed in Figure 6 where the terms "white" and "cast" (TF-IDF) were shown to be frequent terms in user reactions on Death Note, an adaptation that the project classified as a 'bad' adaptation, indicating that inappropriate casting became a factor of the overall negative reactions to Death Note. This also holds true for Dragonball: Evolution where "white" is also a salient term.

Recommendations

To further improve upon this project, a more diverse and representative sample of live-action adaptations is recommended. Having a bigger sample size would provide a more holistic and nuanced understanding of the factors that influence the success or failure of live-action adaptation.

A more comprehensive textual corpora is also recommended, such as one that incorporates actual critic reviews, even with a small sample size, for analyses that consider both the perspectives of the layman and expert.

Incorporating user engagement metrics such as rating scores are also recommended to have a bigger depth of analysis in understanding both the qualitative and quantitative measures of live-action adaptations.

Limitations

The small sample size of adaptations in the project means that findings may not be completely applicable to all live-action adaptations. Factors influencing an adaptation's success or failure may vary greatly across different adaptations.

The extraction and creation of the textual corpora may be improved upon. The dataset for Youtube comments, in particular, would greatly benefit from a feature from the Youtube API that allows the extraction of most-liked comments in order to filter out insubstantial and low-insight comments from the dataset. Google's language-detection library also poses a slight problem in filtering the dataset to include only English entries as it would sometimes incorrectly identify an entry's language and thus mark English entries for removal from the dataset.

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