Movie Reviews Under Review

Part 2: Clustering and Classification

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MSDS 453: Natural Language Processing

Introduction

Continuing the process to compare and classify movies based on their reviews, it is necessary to perform three tasks: clustering, classification, and topic modeling. Each of these methods aims to group documents in a way that identifies similarities between them, forming the basis for personalized recommendations that have become so characteristic of services around the globe, from Netflix to Spotify. Performing accurate classification is key to understanding the meaning of documents. For each goal - clustering, classification, and topic modeling - alternative approaches will be evaluated to determine which is most apt at differentiating between documents and identifying uniting themes.

The Data

The data set for this project is the class corpus data set, compiled of ten reviews for each student in the class. The "trained data" was a 80% split of the corpus data frame, excluding the Genre of Movie (target variable). These texts were processed with a clean method to normalize, tokenize, lemmatize, stem documents and remove stopwords, then recombine the tokens to create a string per document. If train and test data were not needed, the data was processed as mentioned above directly from the corpus data frame, without dropping the target variable.

Research Design and Methods

Part 1: Clustering

For data clustering, the texts were run through a KMeans model trained on the training set of documents after processing as described above. Three models were created, one for each of 3, 4, and 5 clusters. After training these on the training data set, the models were used to predict clusters for both the training and test data sets. The silhouette score and cluster placements were saved for each of these trials, and the cluster distribution based on genre was printed. Additionally, the document titles in the testing model (3, 4, or 5 clusters) with the highest silhouette score were printed and used as the basis for refinement of the model.

Part 2: Classification

For the classification portion, the training and testing data will be used and transformed based on a TF-IDF vector fit to the training data. Then, four tests will be performed: naive bayes, SVM, and pre-trained BERT classification with both binary and multi-models. These models will be trained on the training data, and then will predict classifications for the testing data based on

movie genre. However, the BERT binary classification will be based on the sentiment of the documents rather than movie genre.

For the BERT classification models, the classification accuracy will be determined for the raw text, the cleaned raw text (with smart double/single quotes and long dashes, and non-ASCII characters removed), and the final text (cleaned as described in the data section). Then, accuracy measures and confusion matrices will be made for each to determine the best classification model. After determining the best model, measures will be considered on how to adjust the model for improvement.

Part 3: Topic Modeling

Topic modeling will include latent semantic analysis and latent dirichlet allocation. The text, processed in the clean method as described in the data section, will be modeled in LSA and LDA in tokenized format. Heatmaps will be made for each of these models to analyze the topic similarity, and the matrix similarities will be analyzed as well. Each model will be created with five topics each consisting of 10 words.

The Results

Clustering

The 3, 4, and 5 cluster runs of the training data had a silhouette score of .515, .533, and .454, respectively. The testing data's cluster runs had silhouette scores of .355, .489, and .523, respectively. Since the testing cluster with five documents had the highest silhouette score, the composition of its clusters were analyzed to adjust the model. The clusters had reasonably grouped distinctions, with a cluster for some of the more thoughtful, mind-mending action movies like Inception grouped with similarly intense Sci-Fi movies like Equilibrium. However, one issue with the clusters was that they were very uneven. For example, the third cluster had about 14 movies, whereas the first had 5 and the fourth had only 3. Additionally, though the cluster number was 5, there were only 4 groups made. To fix this, the embedding size for the Doc2Vec input vectors to run the KMeans tests was increased from 200 to 300. It seems the higher number of characteristic features in the Doc2Vec vector was able to better differentiate the documents, reducing the document numbers for clusters 1, 3, and 4 to 7, 11, and 5, respectively.

Classification

The Naive Bayes test had an accuracy score of .78, with 7 false positives in the confusion matrix. The SVM test had an accuracy score of 1.0 with a false positive rate of 0. The binary

classification model for sentiment classification had an accuracy of .5625 for each of the raw, raw cleaned, and final processed text. The multi-class classification BERT model had an accuracy of .1875 for the raw and raw cleaned text, and an accuracy of .375 for the full processed text. Based on the evidence, the BERT models were less apt at performing multi-class classification relative to the Native Bayes and SVM. Given that the Naive Bayes and SVM tests were only performed for movie genre, there is not a comparison to the BERT model for binary classification. However, between the naive bayes and SVM models, the SVM test performed the best in predicting genre, with a rate of 100% accuracy. This would be the chosen model for production and implementation based on its performance.

Given that the next best model was Naive Bayes, this model was chosen for improvement attempts. Instead of using maximum features of 5000 for the TF-IDF vector, the limit was set to 4000. This did slightly increase model performance by increasing the Naive Bayes accuracy score to .84 and reducing the false positive number to 5 documents.

Topic Modeling

The LSA model's five topics had the following words with its highest coefficients: movie, toxic, holmes, squad, and movie. The LDA model's first five words were: movie, movie, first, movie, movie. Additionally, manual observation of the LSA models' 10 words resulted in some ability to recognize a topic. For example, the "toxic" cluster centered around The Toxic Avenger characters and themes, as well as some action and superhero callouts. The "Squad" cluster was a more action-forward cluster, with Suicide Squad appearing as the main theme, with several character or actor-specific terms. LDA, in contrast, did not have as much differentiation; each cluster was a mix of loosely related specifics like "Taken" and very general film terms like "story" and "character." It is clear that based on this process, the LSA was more successful in forming some sort of topic, though it was still not a clear segmentation of the data.

In an attempt to improve these models, the number of topics was increased from 5 to 10. Though the first five topics for LSA were relatively unchanged, the added topics were fairly clustered, differentiated to the point that, for some, specific movies could even be picked out as defining the topic. More importantly, for those with shared movies, their similarities were clear, such as the shared superhero theme of The Toxic Avenger and Suicide Squad. For LDA, the topic specificity did improve, as there seemed to be less disparate themes within each topic. An example is the first topic, which had words centering around the Liam Neeson action movie.

However, each topic still did have several more general words like “scene,” “though,” and “since.” A recommended improvement for this LDA model would be to remove words that are commonly fillers, like “though” and “since,” or words with a very low TF-IDF score.

Conclusions

For each of clustering, classification, and topic modeling, there were models that stood out as the best to use and others that had specific improvement areas. The clustering approach was best completed by the KMeans models with a higher number of clusters, though general performance on testing data was still unsatisfactory. Changing the embedding dimensions of the Doc2Vec vector did slightly improve the performance of this model when the cluster count was held constant.

For classification, SVM stood out as the best multi-class classification model. Naive Bayes was not unsatisfactory, as the BERT binary and multi-class classification models were, but Naive Bayes was still clearly worse than SVM. However, decreasing the value for maximum features on the TF-IDF vector did help to improve the performance of the Naive Bayes model, bringing it to a usable accuracy.

Finally, the LSA approach to topic modeling stood out relative to LDA as having more defining topics and more unique words in its chosen ten. Increasing the number of topics increased performance for both models, though there could be a performance drop-off with too many topics.

Appendix

1. Classification Confusion Matrix Naive Bayes, post-adjustment

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[[8 0 0 0]
[0 8 0 0]
[0 0 7 0]
[0 0 5 4]]
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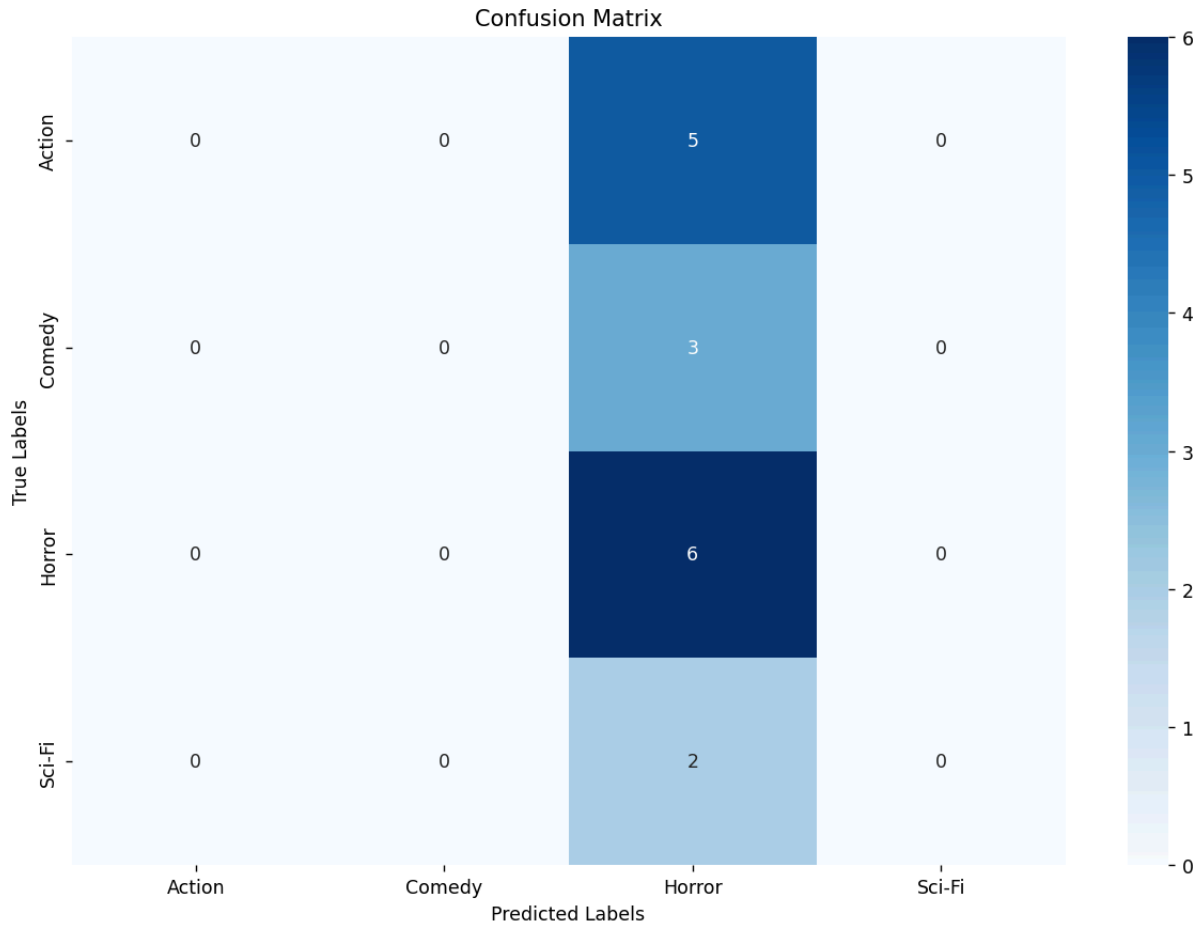
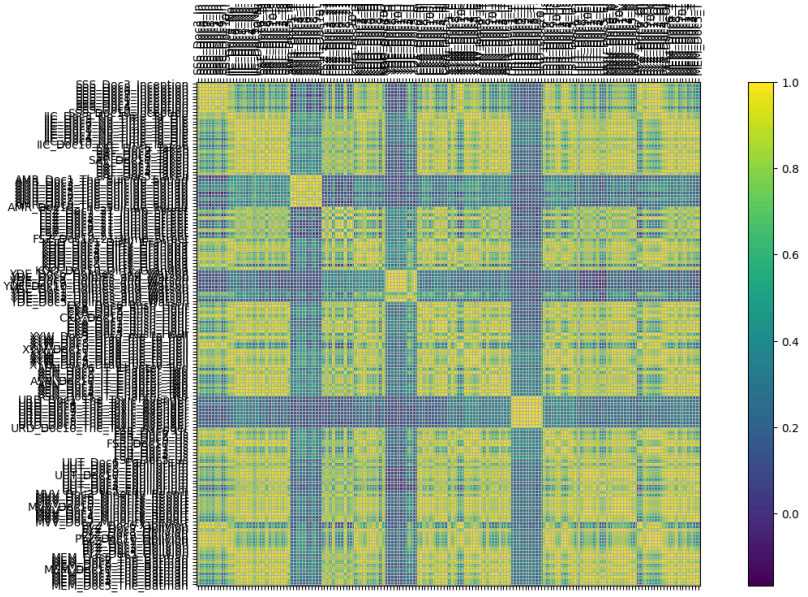
2. BERT Multi-class Classification Confusion Matrix



3. LSA Model, 5 topics of 10 words each



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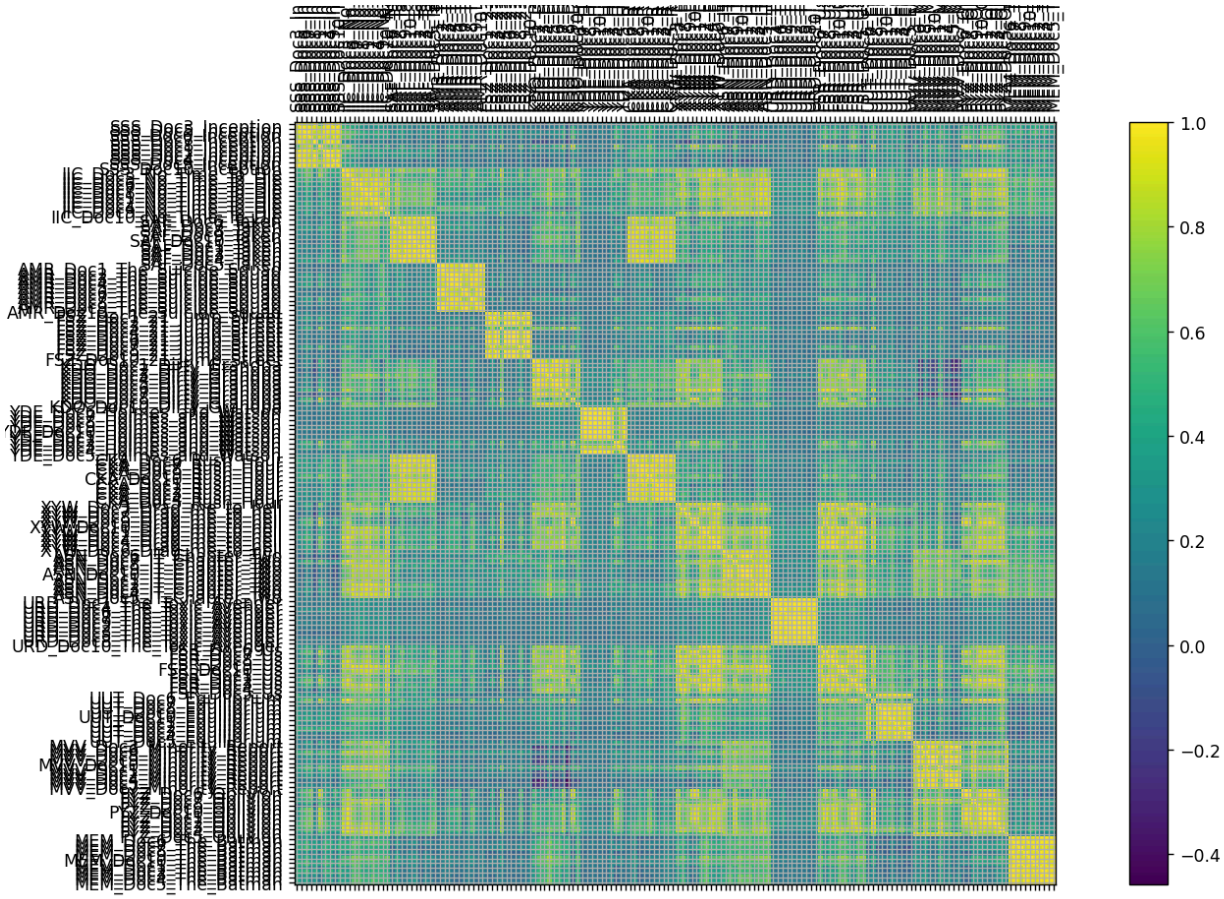

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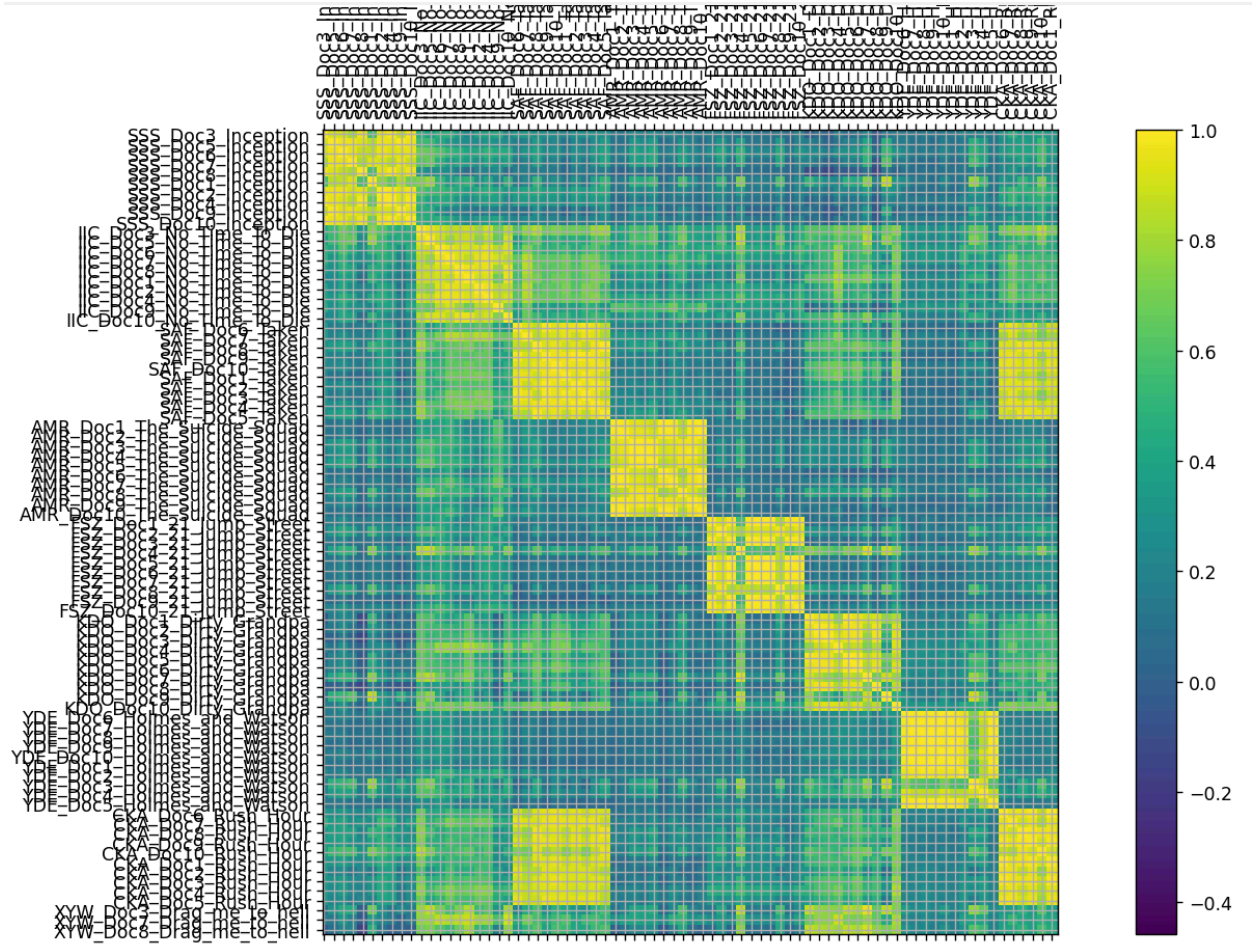
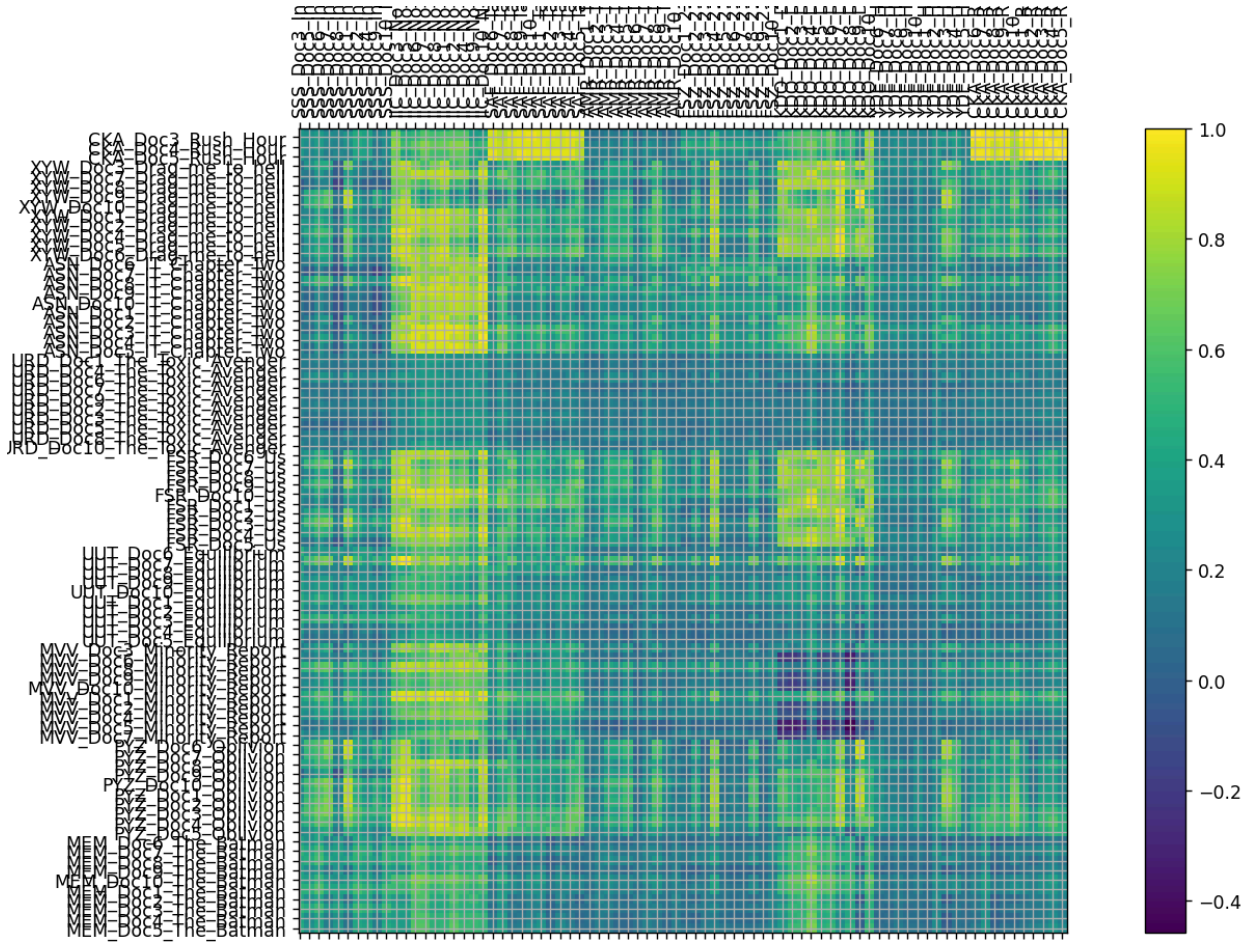
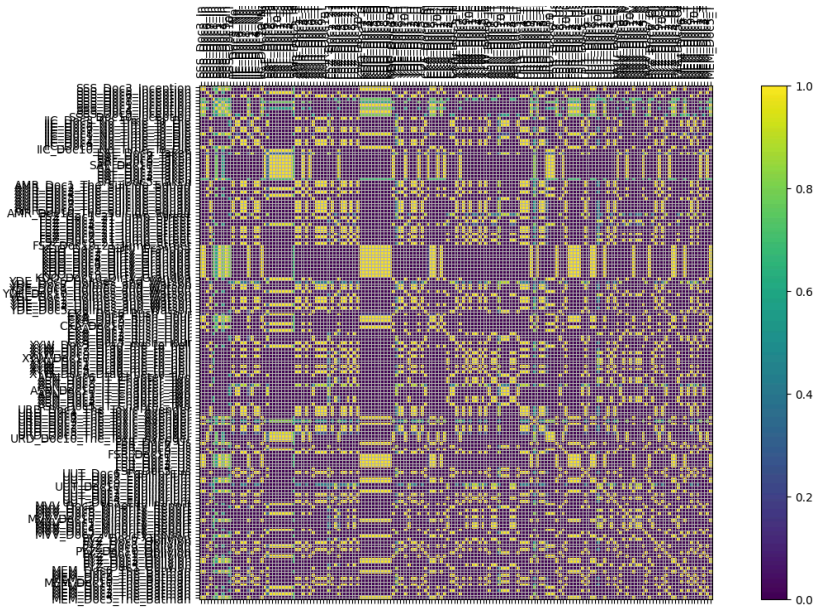




5. LDA Model, 5 topics of 10 words each



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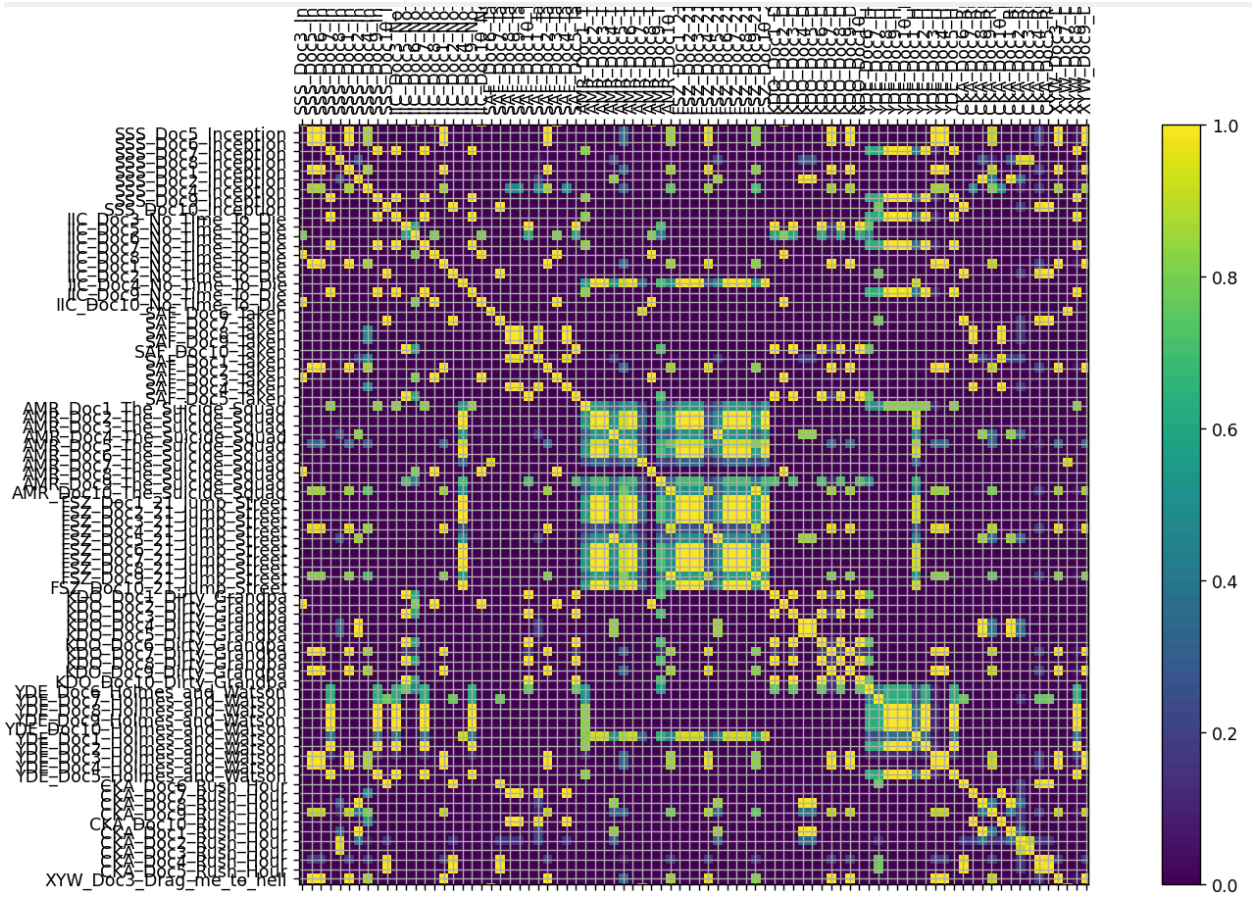
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SSS_Doc7_Inception
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SSS_Doc4_Inception
SSS_Doc3_Inception
SSS_Doc10_Inception
IIC_Doc2_No_Time_To_Die
IIC_Doc3_No_Time_To_Die
IIC_Doc7_No_Time_To_Die
IIC_Doc6_No_Time_To_Die
IIC_Doc1_No_Time_To_Die
IIC_Doc5_No_Time_To_Die
IIC_Doc4_No_Time_To_Die
IIC_Doc9_No_Time_To_Die
IIC_Doc10_No_Time_To_Die
SAF_Doc6_Taken
SAF_Doc7_Taken
SAF_Doc8_Taken
SAF_Doc9_Taken
SAF_Doc10_Taken
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SAF_Doc2_Taken
SAF_Doc5_Taken
SAF_Doc4_Taken
SAF_Doc3_Taken
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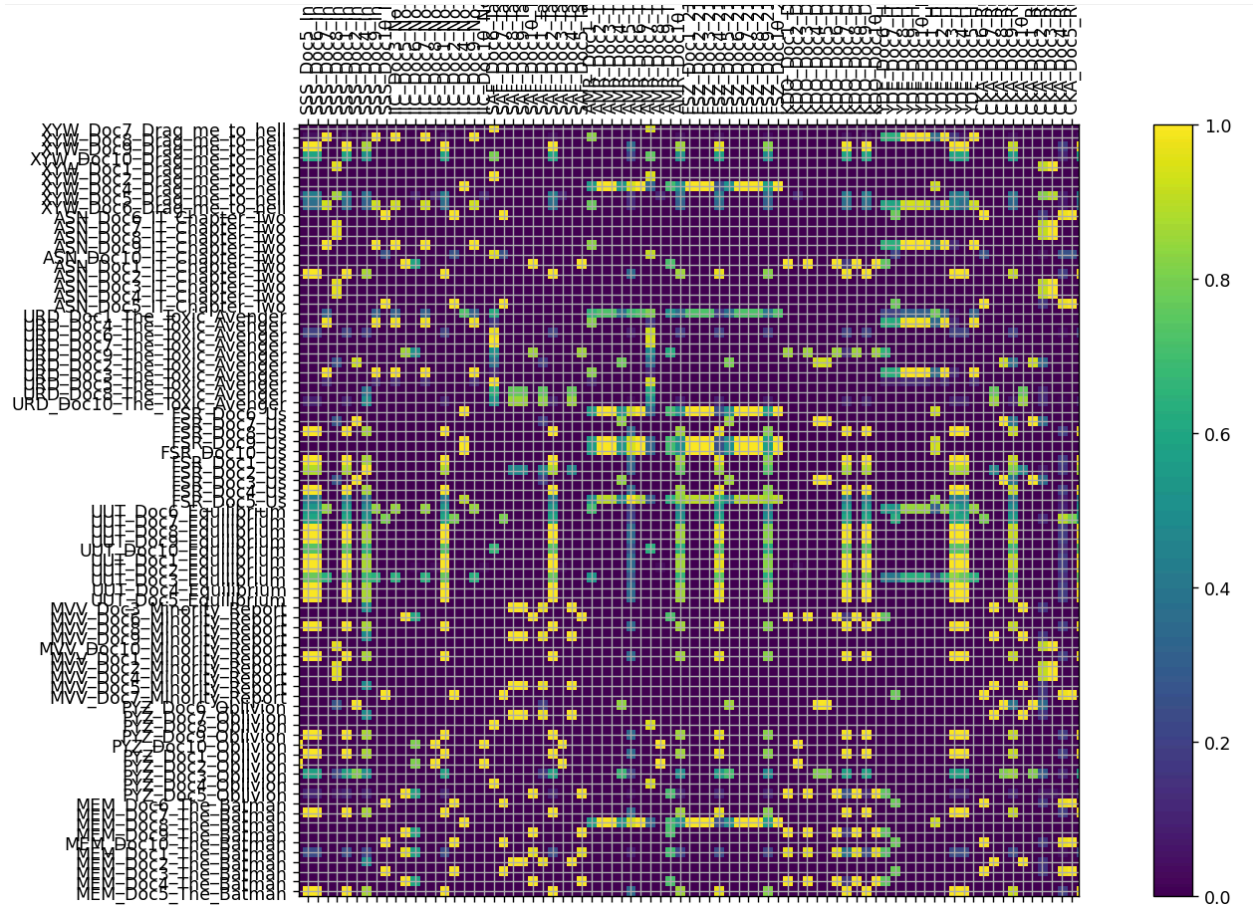
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