Assignment 3: Ontology Plus Context and Deep Learning Modeling

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Introduction and Problem Statement

The goal of this assignment is to begin to define relationships between different entities or concepts within the movie review documents. The first part of the assignment involved the creation of an ontology for the ten movie reviews of the assigned movie “Angel Has Fallen”. The ontology was used to consider how clusters of the ten documents map to the branches of the ontology and how the other movies in the class corpus could map to the ontology for “Angel Has Fallen”. A final ontology and visualization were created using the Protégé application. The next part of the assignment involved knowledge graph experiments. In these experiments, ontologies were created for the ten movie reviews by algorithms based on the data as opposed to the human-created ontology of the first part of the assignment. The last part of the assignment involved deep learning experiments using the entire class corpus. The deep learning experiments were used for movie review sentiment analysis as well as classification of the movie reviews by movie genre. A total of six experiments were performed using LSTM models, 3 for classification of movie genre and 3 for sentiment analysis.

Literature Review

The word ontology, in the context of natural language processing, is defined as a set of classes, attributes, and relationships that model a specific domain of knowledge (Gruber 2016). Present day examples of ontologies include taxonomies on the web, online product catalogs, and standard terminology for domains. Some of the reasons to develop an ontology include sharing understanding of the structure of information among people or software agents, enabling the reuse of domain knowledge, making domain assumptions explicit, separating domain knowledge from operational knowledge, and analyzing domain knowledge (Noy and McGuinness 2001).

A knowledge graph, like an ontology, also describes entities and their relationships, however ontologies represent the backbone of the formal semantics of a knowledge graph. Ontologies ensure a shared understanding of the data and its meanings, while the knowledge graph puts data into context via linking and semantic metadata (Ontotext 2022). Some current applications of knowledge graphs include question answering systems, such as for chatbots and virtual assistants, recommender systems based on users' preferences and historical interactions, and information retrieval in web-search applications (Chiusano 2022).

LSTM (Long Short-Term Memory) networks are a slightly modified version of RNNs (Recurrent Neural Networks). An RNN is an artificial neural network that uses sequential or time series data to make a prediction but only works well when dealing with short-term dependencies. RNNs cannot recall long-term information to make predictions. An LSTM network, however, is able to selectively remember and forget information that has been given to it, allowing it to utilize long-term information to make predictions. The LSTM network employs a forget gate to remove information from the cell state, an input gate to add information to the cell state, and an output gate to select useful information from the current cell state and show it as an output (Srivastava 2020).

Data

The dataset of movie reviews contains two-hundred documents total consisting of ten movie reviews (five positive and five negative) for twenty different movies in four different movie genres (action, comedy, horror, and sci-fi). For the twenty movies, six are action, five are comedy, four are horror, and five are sci-fi. Each document is defined as a single movie review and contains at least five-hundred words. Some preliminary work was performed to normalize the documents such as, removing punctuation, putting everything in lower case, removing tags, and removing special characters and digits. For the third part of the assignment, stop words were removed from the data and lemmatization was performed. The following is a data dictionary that describes the nine columns of the class-corpus data set.

Table 1. Class-Corpus Data Dictionary

Column Name	Definition
DSI_Title	Student initials, document number, and movie title assigned to the movie review; identical to the Submission File Name
Doc_ID	Unique number assigned to each document row (0 – 199)
Text	The actual text of the movie review
Submission File Name	Student initials, document number, and movie title assigned to the movie review; identical to the DSI_Title
Student Name	Initials associated with each individual student
Genre of Movie	One of four movie genres assigned to the movie: Action, Comedy, Horror, or Sci-Fi
Review Type (pos or neg)	Describes whether the movie review was positive or negative
Movie Title	The title of the movie
Descriptor	Movie genre, movie title, N or P for negative or positive, and Doc_ID

Research Design and Modeling Methods

The first part of the assignment was to create an ontology with the ten movie review documents pertaining to the assigned film, “Angel Has Fallen”. The ontology was developed using Protégé software. The main class in the ontology is called “Movie Thing”, and there are several subclasses related to the movie topics including “Character Job”, “Genre”, “Location”, “Movie”, and “Person”. The “Person” subclass also has several subclasses of people related to the movie including “Actor”, “Character”, “Director”, and “Writer”. The ontology shows relationships of actors and the characters they played, jobs that the characters have in the movie, and relationships between certain characters, among others.

The second part of the assignment was to create a knowledge graph with the ten movie review documents for the assigned film, “Angel Has Fallen”. After performing some data wrangling, including removal of stop words, lemmatization, making words lower case, and removal of empty spaces, a curated vocabulary size was used to create a knowledge graph. Since the full knowledge graph was difficult to read because of the overlapping sources and targets, filters were used to create a list of the top ten sources and targets and a list of the top ten relations or edges. Smaller knowledge graphs were then created using some of the source and targets and edges that were filtered out to make interpretation more straightforward.

The third part of the assignment was to perform sentiment analysis for review type and classification analysis for movie genre using LSTM. Three different experiments were performed for each type of analysis, sentiment and classification of genre, for a total of six experiments, and performance metrics were compared for each experiment. Results were also compared to the results obtained for sentiment analysis and classification of genre with ML models from Assignment 2.

Results, Analysis, and Interpretation

Ontology

The ontology was developed using Protégé software. The main class in the ontology is called “Movie Thing”, and there are several subclasses related to the movie topics including “Character Job”, “Genre”, “Location”, “Movie”, and “Person”. The “Person” subclass also has several subclasses of people related to the movie including “Actor”, “Character”, “Director”, and “Writer”. Relationships were modeled using object properties to show relationships between actor and character, character and character, character and their job in the movie, the movie itself and relevant people, location, and other movies in the series. Figure 1 shows the class and sub-class structure of the ontology, before revealing any entities and their relationships.

Figure 1. Ontology Class Structure

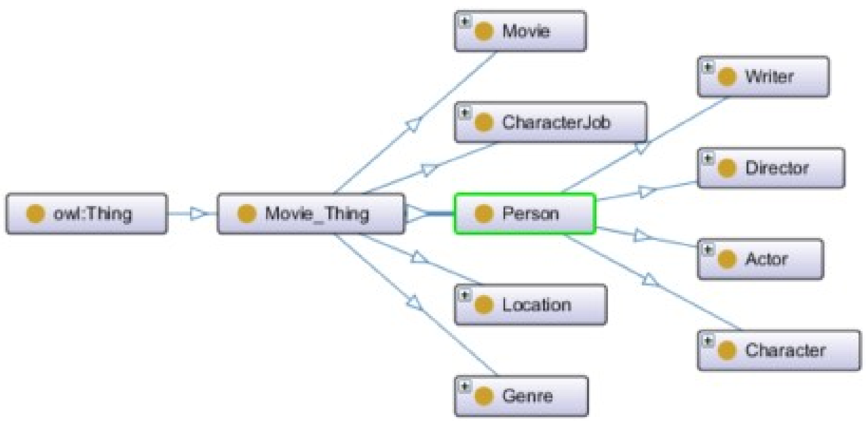
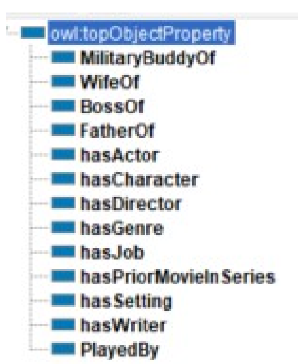


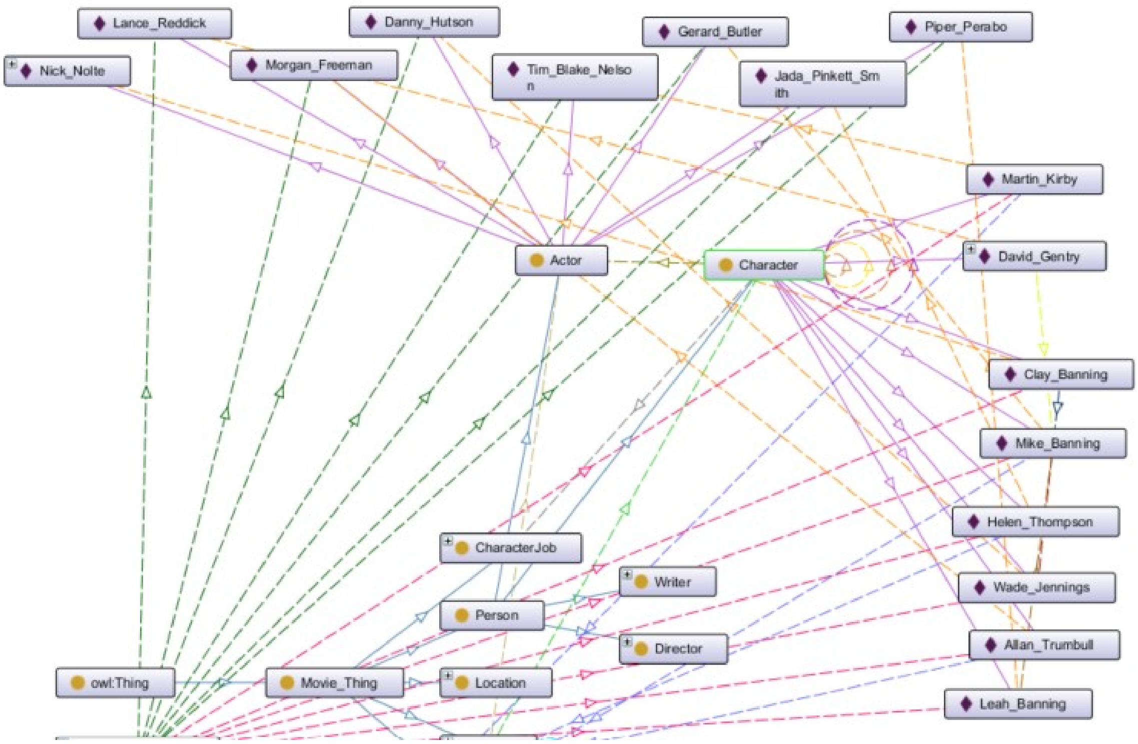
Figure 2 shows the object properties that were used to model relationships between different entities of the ontology.

Figure 2. Object Properties of the Ontology



The largest classes by number of entities and relationships are the character and actor classes. Throughout the movie reviews the same eight characters were mentioned as well as the actors that portrayed them. Certain characters such as Mike Banning and Allan Trumbull were mentioned in movie reviews more often, implying that these characters are more important to the plot of the movie. Figure 3 shows a closer look at the character and actor classes and their entities and relationships.

Figure 3. Character and Actor Classes

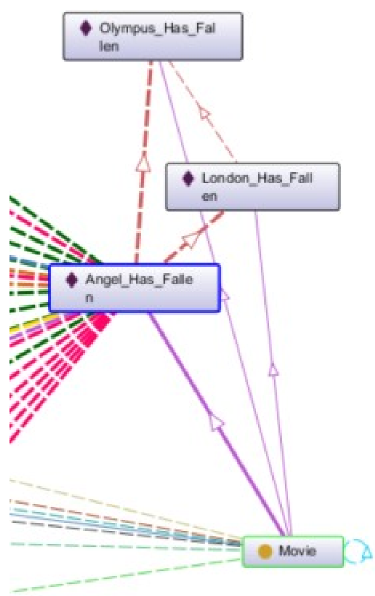


The orange dotted lines show the relationship between the characters and the actors that portrayed them in the film. This is the “PlayedBy” object property. So, from the chart Mike Banning is played by Gerard Butler and Allan Trumbull is played by Morgan Freeman. This is also a possible way to link other movies in the class corpus to the movie presented in this ontology. If different movies contain the same actor, they can be linked together through the shared actor.

Another important aspect of the movie “Angel Has Fallen” that was added to the ontology is reference to movies in the same series that came before. Many of the movie reviews mention the predecessors of “Angel Has Fallen”, namely, “Olympus Has Fallen” and “London

Has Fallen". Figure 4 shows these entities as part of the "Movie" class and how they relate to one another.

Figure 4. Movie Class and Other Movies in the Series



From the ontology, "Olympus Has Fallen" was the first movie in the series, followed by "London Has Fallen", and finally "Angel Has Fallen". This is modeled with the "hasPriorMovieInSeries" object property.

The full visualization of the ontology can be found in the Appendices. In the visualization, other subclasses of the "Movie Thing" class include movie genre, movie director, movie writer, and movie location. Similarly to how different movies from the class corpus could be linked to "Angel Has Fallen" through a shared actor, different movies from the class corpus could also be linked together if they share the same genre, the same writer or director, or the same movie location. Overall, the ontology gives the big picture of the movie "Angel Has Fallen", including key characters and actors, movie genre and setting, jobs of the characters in the movie, relationships between characters in the movie, and writers and director of the movie.

Knowledge Graph Experiments

A knowledge graph was created using the ten movie reviews from the movie “Angel Has Fallen”. The full knowledge graph is difficult to read because of overlapping sources and targets but can be found in the Appendices of this report. In order to narrow down to the most important sources, targets, and edges, two lists were retrieved. One containing the top ten sources and targets for the knowledge graph, and one containing the top ten edges for the knowledge graph. The list output is shown in Table 2.

Table 2. Top Ten Sources/Targets and Edges Lists

Source/Target	Count	Edge	Count
banning	8	fallen	10
angel	8	find	7
olympus	4	kill	4
butler	3	die	4
secret service agent	3	expect	4
drone	2	play	4
tim blake nelson	2	come	4
president	2	include	4
danny hutson	2	want	4
fan	2	suffer	3

The top two sources/targets are “banning” and “angel. The word “banning” refers to the main character in the movie “Mike Banning” but could also refer to the character’s father in the movie “Clay Banning”. This word was chosen as the first filter for the knowledge graph sources/targets. Figure 5 shows the knowledge graph filtered by “banning” for the source/target.

Figure 5. Knowledge Graph Filtered by "Banning" for Source/Target

Some of the results make sense while others are more difficult to interpret. The first result that make sense is "banning has an estranged father". This is mentioned in some of the movie reviews when referring to Mike Banning and his relationship to his father, Clay Banning. In addition "banning" being related to "role" and "win" are related to the role that Banning plays in the movie and that he eventually wins the situation he is in. The remaining relationships to "banning" shown in Figure 5 do not make much sense in the context of the movie reviews.

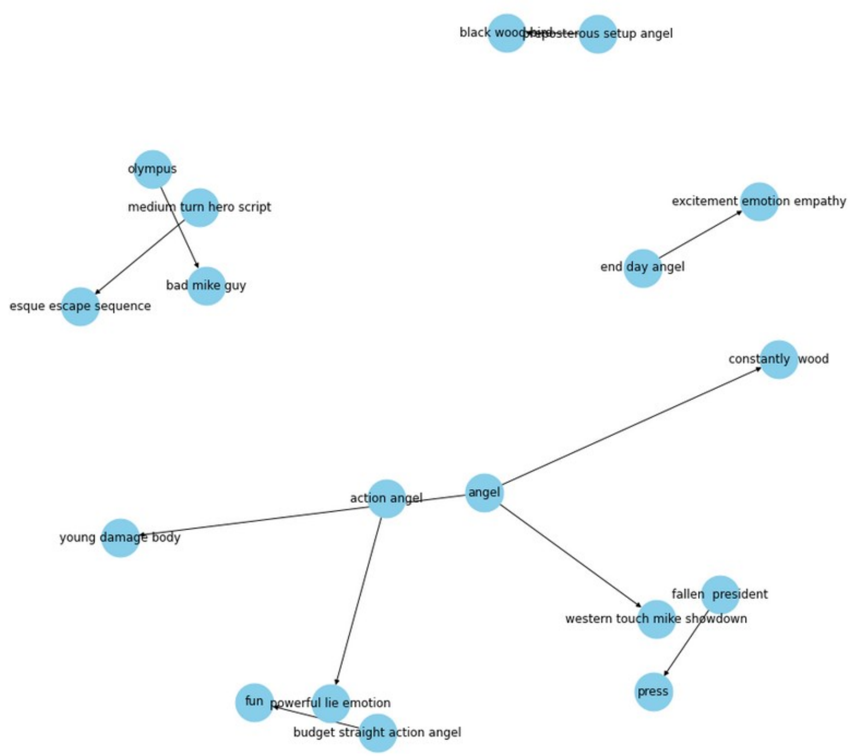
The word "angel", which also had a count of 8 in the top ten source/target list and is also part of the movie title, was used to filter the knowledge graph next. The knowledge graph output is shown in Figure 6.

Figure 6. Knowledge Graph Filtered by "Angel" for Source/Target

Similar to the results of filtering by "banning", some of the relationships make sense and others do not. The relationship "angel is unlikely franchise" make sense because this is referring to the "Angel Has Fallen" franchise as discussed in the movie reviews. The movie is third in a trilogy of movies. Another relationship "angel has american lead figure" also makes sense because it refers to the President of the United States, who is a character in the movie and also an American leader. The other relationships shown in the knowledge graph do not make sense in the context of the movie reviews.

Referring back to Table 2, the top two edges of the knowledge graph are "fallen" and "find". The knowledge graph was first filtered using the edge "fallen", and the results are output in Figure 7.

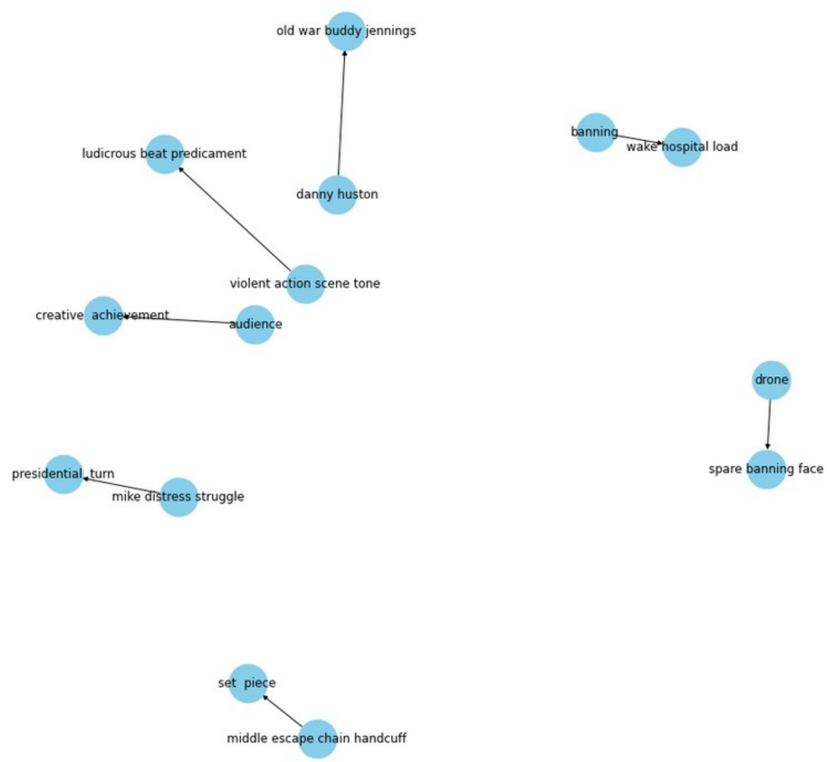
Figure 7. Knowledge Graph Filtered by "Fallen" for Edge



Based on the output shown in Figure 7, not many of the source, edge, target combinations make sense with the edge being "fallen". Some of the sources/targets would make sense with a different edge. For example, "budget straight action angel" and "fun" make sense in the context that the movie review is referring to the action movie "Angel Has Fallen" as fun. In addition, "fallen president" and "press" make sense being related because in the movie an assassination attempt and the President was talked about in the press. The other relationships shown are not readily interpretable.

The word "find" was used to filter the knowledge graph by edge as well. Figure 8 shows the output of this filtered knowledge graph.

Figure 8. Knowledge Graph Filtered by "Find" for Edge



Similar to the results of filtering by "fallen" for the edge, some of these source, edge, target relationships for the edge filter by "find" knowledge graph make sense and others are not easy to interpret. One that makes sense is "audience find creative achievement". This could be referring to the movie as the creative achievement and the audience, or at least the movie reviewer, describing the movie as such. The relationship of "danny hutson" and "old war buddy jennings" makes sense because Mike Banning's military buddy in the movie, Wade Jennings, is played by actor Danny Hutson. Most of the remaining combinations of source, edge, and target do not have any meaning.

Overall, some meaning was able to be extracted from the knowledge graph, especially after filtering for the top ten source/target and edge words. However, most of the source, edge, and target combinations were not able to be interpreted in a meaningful way for the movie and movie reviews.

Deep Learning Experiments

Classification analysis for movie genre and sentiment analysis for movie review type (positive or negative) were performed using LSTM models. The training, test, and validation dataset was split 80%/10%/10%, and a confusion matrix was output for both the train and test data. In addition, a classification report was output for each experiment to compare precision, recall, F1-Score, and accuracy for the test data. For each type of analysis three different experiments were performed, for a total of six experiments. Different experiments were performed by modifying the hidden layers and hidden neurons within the model architecture. The experiments that were performed as well as their loss and accuracy metrics are summarized in Table 3.

Table 3. LSTM Experiment and Loss and Accuracy Metic Summary

Experiment	Model Used	Train Set Loss	Train Set Accuracy	Val Set Loss	Val Set Accuracy	Test Set Loss	Test Set Accuracy
Classification 1	L1 Bidirectional LSTM: 64 hidden neurons with dropout 0.3 L2 Bidirectional LSTM: 32 hidden neurons with dropout 0.3	0.727	0.679	1.867	0.333	1.503	0.333
Classification 2	L1 Bidirectional LSTM: 64 hidden neurons with dropout 0.5 L2 Bidirectional LSTM: 64 hidden neurons with dropout 0.5	1.392	0.371	1.174	0.333	1.258	0.278
Classification 3	L1 Bidirectional LSTM: 128 hidden neurons with dropout 0.3 L2 Bidirectional LSTM: 128 hidden neurons with dropout 0.3	0.117	0.950	0.401	0.889	2.649	0.389
Sentiment 1	L1 Bidirectional LSTM: 64 hidden neurons with dropout 0.3 L2 Bidirectional LSTM: 32 hidden neurons with dropout 0.3	0.720	0.535	0.721	0.444	0.705	0.444
Sentiment 2	L1 Bidirectional LSTM: 64 hidden neurons with dropout 0.5 L2 Bidirectional LSTM: 64 hidden neurons with dropout 0.5	0.368	0.824	1.388	0.333	1.249	0.556
Sentiment 3	L1 Bidirectional LSTM: 128 hidden neurons with dropout 0.3 L2 Bidirectional LSTM: 128 hidden neurons with dropout 0.3	0.489	0.755	2.724	0.444	1.197	0.667

Table 4 shows the output of the classification report that was performed for the test dataset for each experiment. The classification report included the precision, recall, and F1-Score metrics for each genre for the classification of genre experiments and for the sentiment (positive or negative) of each sentiment analysis experiment.

Table 4. Classification Report Output Test Dataset for LSTM Experiments

Experiment	Label	Precision	Recall	F1-Score
Classification 1	Action	1.00	0.25	0.40
	Comedy	1.00	0.20	0.33
	Horror	1.00	0.17	0.29
	Sci-Fi	0.20	1.00	0.33
Classification 2	Action	1.00	0.50	0.67
	Comedy	0.00	0.00	0.00
	Horror	0.00	0.00	0.00
	Sci-Fi	0.19	1.00	0.32
Classification 3	Action	0.00	0.00	0.00
	Comedy	1.00	0.40	0.57
	Horror	1.00	0.33	0.50
	Sci-Fi	0.21	1.00	0.35
Sentiment 1	Negative	0.00	0.00	0.00
	Positive	0.44	1.00	0.62
Sentiment 2	Negative	0.60	0.60	0.60
	Positive	0.50	0.50	0.50
Sentiment 3	Negative	0.62	0.62	0.77
	Positive	1.00	0.25	0.40

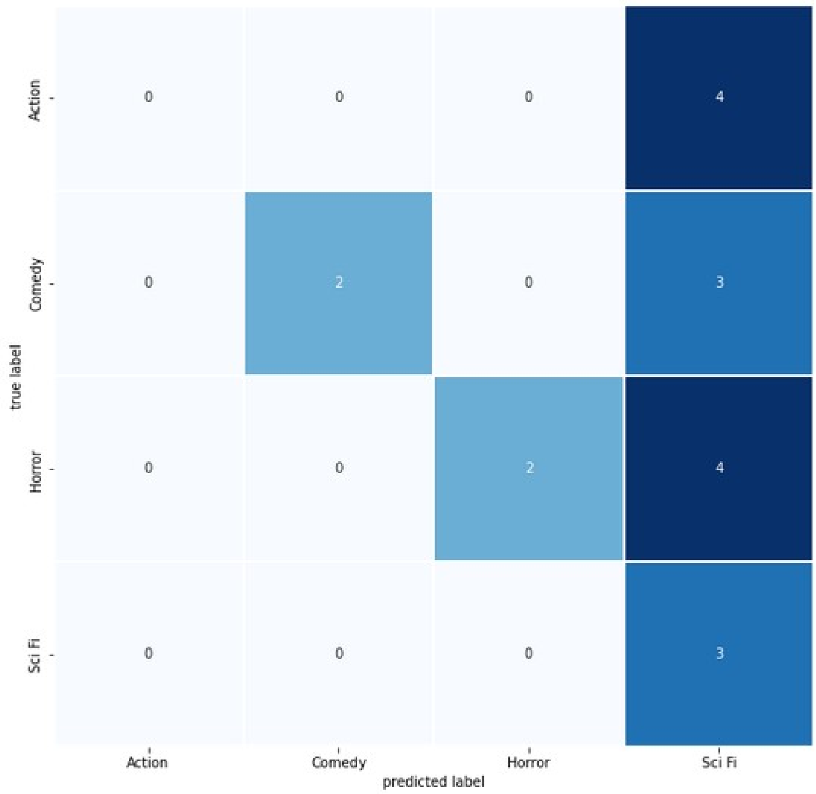
For classification of genre analysis, Classification 1, 2, and 3 were the experiments performed. The first model had two bidirectional LSTM layers, one with 64 neurons and a dropout of 0.3 and one with 32 neurons and a dropout of 0.3. The test set accuracy was very low at 0.333. In addition, the precision and recall scores for each genre were either high for precision and low for recall (Action, Comedy, and Horror) or high for recall and low for precision (Sci-Fi). This means that the model identified very few Action, Comedy, and Horror movies correctly, identified all Sci-Fi movies correctly, and also misidentified all other movies as Sci-Fi as well. The accuracy and loss function curves for the training and validation sets (available in the

Appendices) show diverging lines for both, which indicates overfitting of the model. The training dataset performed pretty well, being able to identify most movie genres. However, it did misidentify some Sci-Fi movies as action and some Action, Comedy, and Horror films as Sci-Fi. Confusion matrices for both the test and training data as well as accuracy and loss function curves are available in the Appendices for all experiments.

In an attempt to improve the model, the second classification experiment was performed with two bidirectional LSTM layers, both with 64 neurons and a dropout of 0.5. This model performed even worse than the first, with a test accuracy of 0.278. Precision score for Action and Recall score for Sci-Fi were both 1.00, but the scores for the remaining genres were 0.00. The test data confusion matrix was similar to that of Classification 1 with most movies being misidentified as Sci-Fi. The training set did not perform well either. It was able to correctly identify most Action and Sci-Fi movies but misidentified most Comedy and Horror films as Sci-Fi. The increased dropout layer seemed to hurt the results rather than improve them.

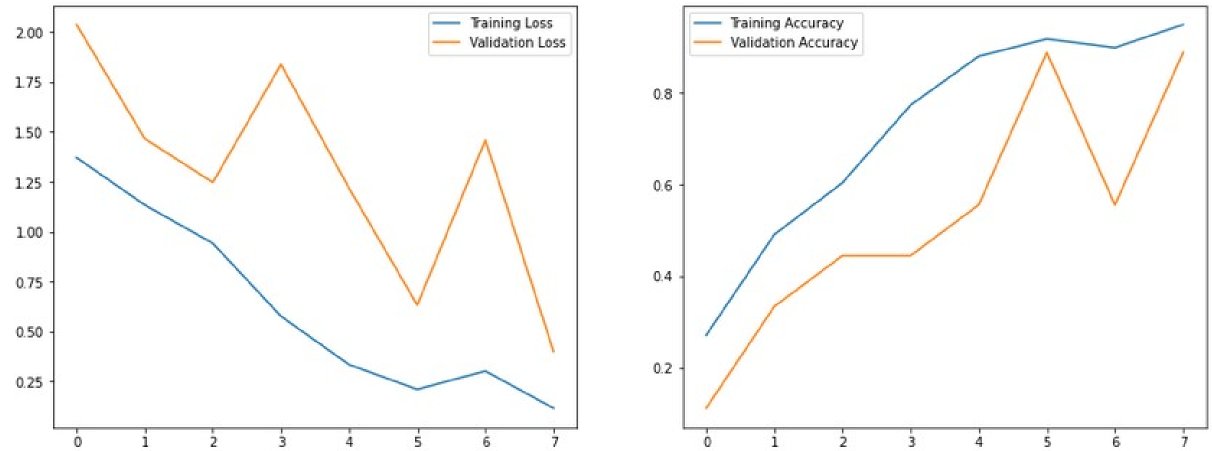
The model that performed the best of the three for classification was the third model, Classification 3. This model had two bidirectional LSTM layers, both with 128 neurons and a dropout of 0.3. The test accuracy was still very low at 0.389, but it did seem that increasing the neurons did slightly improve the model. The test data confusion matrix is shown in Figure 9.

Figure 9. Confusion Matrix for Classification 3 Test Data



From the figure, no Action movies were correctly identified, and very few Comedy and Horror movies were correctly identified. All Sci-Fi movies were correctly identified, but most other movies were incorrectly identified as Sci-Fi also. All of the experiments show that the model leans toward classifying most movies as Sci-Fi even when they are not in that genre. However, the training set performed well for this model with an accuracy of 0.950. Based on the accuracy and loss function curves (Figure 10), the model was in a state of overfitting followed by immediately correcting itself.

Figure 10. Accuracy and Loss Function Curve for Classification 3



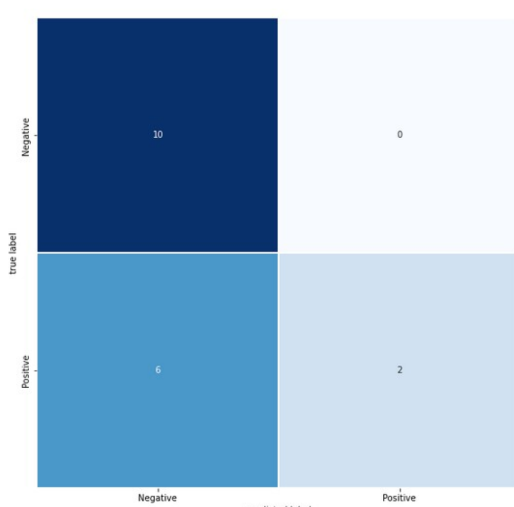
Compared to the classification models in Assignment 2, the ML models performed much better than the LSTM models. The Random Forest model was able to achieve a genre classification accuracy of 0.94. Moving forward, the Random Forest model seems like a much better choice for this classification analysis. Perhaps if there was more data available the LSTM model would have performed better.

For sentiment analysis, Sentiment 1, 2, and 3 were the experiments performed, as summarized in Table 3. The first model had two bidirectional LSTM layers, one with 64 neurons and a dropout of 0.3 and one with 32 neurons and a dropout of 0.3. The test set accuracy was very low at 0.444. In addition, the precision, recall, and F1 scores were all 0.00 for Negative reviews. This means that the model was unable to identify any of the negative reviews correctly; all of the reviews were identified as positive. The accuracy and loss function curves for the training and validation sets (available in the Appendices) show diverging lines for the accuracy and converging lines for the loss. The training dataset performed poorly for the negative reviews as well, identifying most negative reviews as positive. Confusion matrices for both the test and training data as well as accuracy and loss function curves are available in the Appendices for all experiments.

The second sentiment experiment was performed with two bidirectional LSTM layers, both with 64 neurons and a dropout of 0.5. This model performed slightly better than the first, with a test accuracy of 0.556. The performance metrics for the model were about average, with scores of 0.60 for precision, recall and F1 for the Negative reviews and scores of 0.50 for precision, recall and F1 for the Positive reviews. The model was able to correctly identify 6 of 10 Negative reviews and 4 of 8 Positive reviews. The training dataset performed very well for this model, with an accuracy of 0.824. Based on the accuracy and loss function curves for this experiment, the lines for each plot are diverging, indicating an overfitting model. Based on the results, the additional neurons for the second layer and the increased dropout level seemed to help improve the model compared to Sentiment 1.

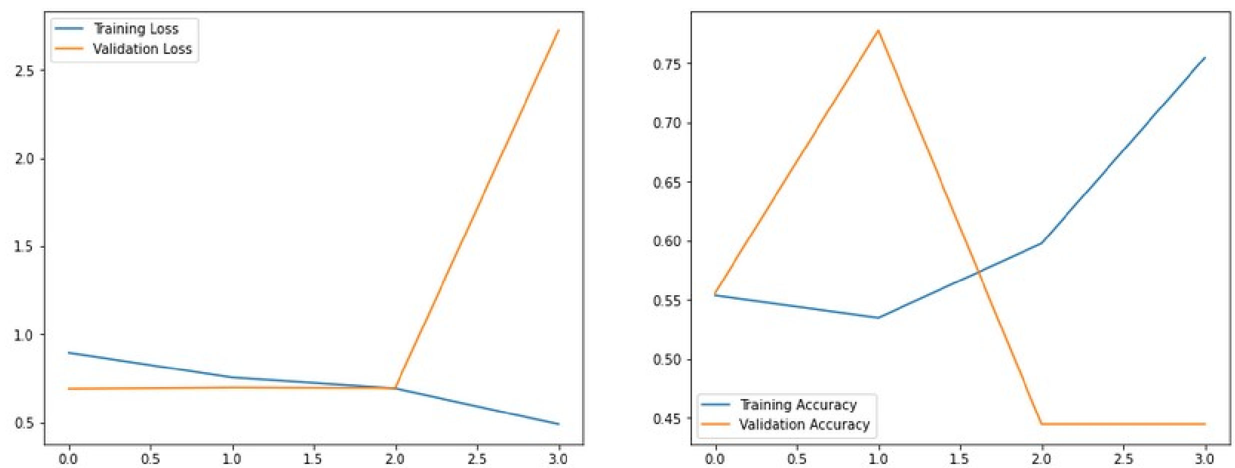
The model with the highest test accuracy of the three for sentiment analysis was the third model, Sentiment 3. This model had two bidirectional LSTM layers, both with 128 neurons and a dropout of 0.3. The test accuracy was somewhat high at 0.667, but the model shifted to predicting more of the Negative reviews correctly than the Positive reviews. The test data confusion matrix is shown in Figure 11.

Figure 11. Confusion Matrix for Sentiment 3 Test Data



From the figure, all Negative reviews were correctly identified but also 6 of 8 Positive reviews were incorrectly identified as negative reviews. The training set did not perform as well for this model as for Sentiment 2, and it also incorrectly identified about 33% of the Positive reviews as Negative reviews. Based on the accuracy and loss function curves (Figure 12), the model was overfitting.

Figure 12. Accuracy and Loss Function Curve for Sentiment 3



Compared to the sentiment analysis models in Assignment 2, the LSTM models performed slightly better than the ML models. The highest accuracy achieved with the ML models was 0.55, while the highest accuracy achieved with the LSTM models was 0.667. Neither the LSTM or ML model experiments performed so far were able to achieve good results for sentiment analysis.

Conclusions

An ontology was developed for the ten reviews for the movie “Angel Has Fallen” using the Protégé application. Through the ontology creation process, the major details of the movie, such as main characters and the actors that portray them, relationships between characters, movie genre, director, writers, and location were all identified and visualized in the ontology. In addition, ways to link all movies in the class corpus were identified, such as linking through genre, director, actors, or film location. Overall, the ontology gives the big picture of the movie “Angel Has Fallen”, including key characters and actors, movie genre and setting, jobs of the characters in the movie, relationships between characters in the movie, and writers and director of the movie. Basic knowledge of the movie was able to be aggregated in this way and can be easily shared.

A knowledge graph was created for the ten movie review for the assigned movie “Angel Has Fallen”. Since the full knowledge graph was difficult to read because of overlapping sources and targets, the most important sources, targets, and edges were narrowed down, and two lists containing the top ten for sources/targets and edges were retrieved. Using these top terms, parts of the knowledge graph were able to be filtered and studied more closely. Overall, some meaning was able to be extracted from the knowledge graph, especially after filtering for the top ten source/target and edge words. However, most of the source, edge, and target combinations were not able to be interpreted in a meaningful way for the movie and movie reviews.

Classification analysis for movie genre and sentiment analysis for movie review type (positive or negative) were performed using LSTM models. For each type of analysis three different experiments were performed, for a total of six experiments. Different experiments were performed by modifying the hidden layers and hidden neurons within the model architecture. For classification analysis, the model that performed the best had two bidirectional LSTM layers, both with 128 neurons and a dropout of 0.3. The test accuracy was still very low at 0.389. All Sci-Fi movies were correctly identified, but most other movies were incorrectly identified as Sci-Fi also. Compared to the classification models in Assignment 2, the ML models performed much better than the LSTM models. The Random Forest model was able to achieve a genre classification accuracy of 0.94. Moving forward, the Random Forest model seems like a much better choice for this classification analysis. Perhaps if there was more data available the LSTM model would have performed better.

For sentiment analysis, the model with the highest test accuracy of the three was the third model, Sentiment 3. This model had two bidirectional LSTM layers, both with 128 neurons and a dropout of 0.3. The test accuracy was somewhat high at 0.667. All Negative reviews were correctly identified but also 6 of 8 Positive reviews were incorrectly identified as negative reviews. Compared to the sentiment analysis models in Assignment 2, the LSTM models performed slightly better than the ML models. The highest accuracy achieved with the ML models was 0.55, while the highest accuracy achieved with the LSTM models was 0.667. Neither the LSTM or ML model experiments performed so far were able to achieve good results for sentiment analysis.

Overall, the LSTM experiments that were performed showed that the model was not able to achieve a good fit for the training and validation set. None of the accuracy and loss function curves showed that the training and validation data were able to stabilize at a similar point. The plots were most divergent lines with evidence of overfitting. Improving the fit of the model could potentially be improved by increasing the number of training examples, but more data is likely needed to achieve this as well.

Directions for Future Work

For future work on the ontology, it would be interesting to start finding relationships between “Angel Has Fallen” entities and entities from other movies in the class corpus. The goal would be to find a way to incorporate all movies from the class corpus into one ontology and perhaps additional movies as well.

For future work with the knowledge graph, improvements could potentially be made by performing other data wrangling methods and adding data to the corpus of documents used for the knowledge graph. Adding data would help the knowledge graph to better identify sources and targets and understand how they relate to each other.

For future work with the deep learning LSTM experiments, many more experiments will have to be performed with modification of even more hyperparameters. Based on the experiments run for this assignment, a good fit for the data is not being achieved. Adding more data and increasing the training dataset might be able to improve the fit of the data and the output of the model for both sentiment analysis and genre classification.

References

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Appendices

Figure A1. Full Ontology for "Angel Has Fallen"

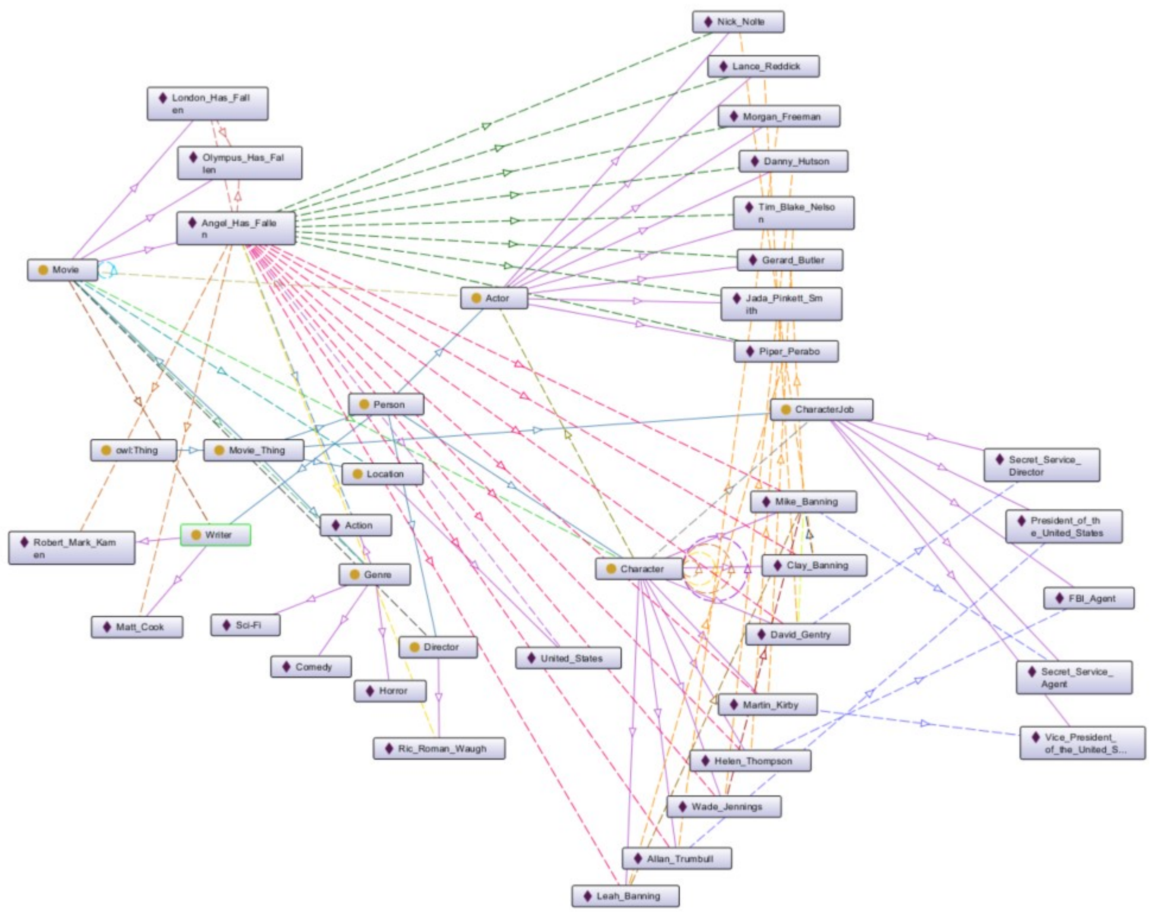

Figure A2. Full Knowledge Graph for "Angel Has Fallen"

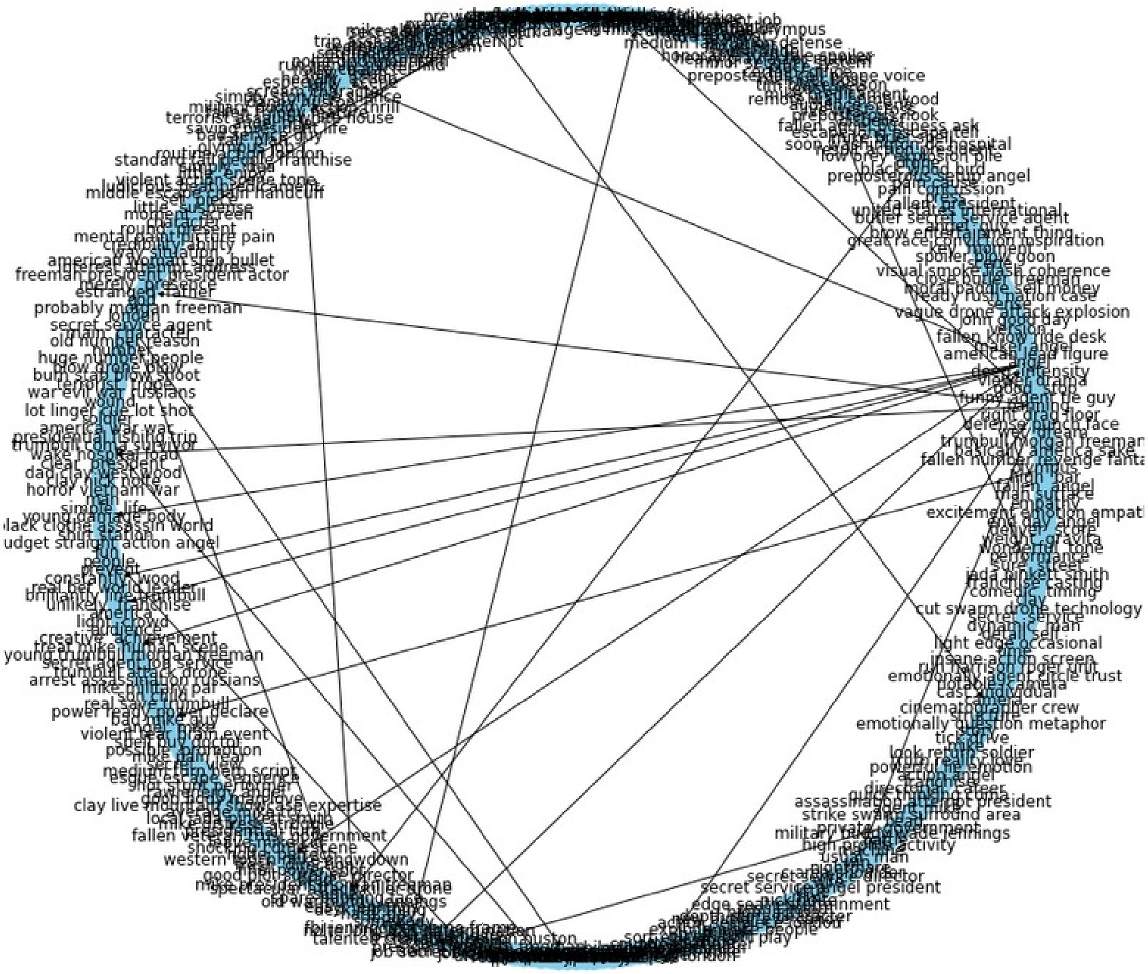

Figure A3. Confusion Matrix for Classification 1 Test Data

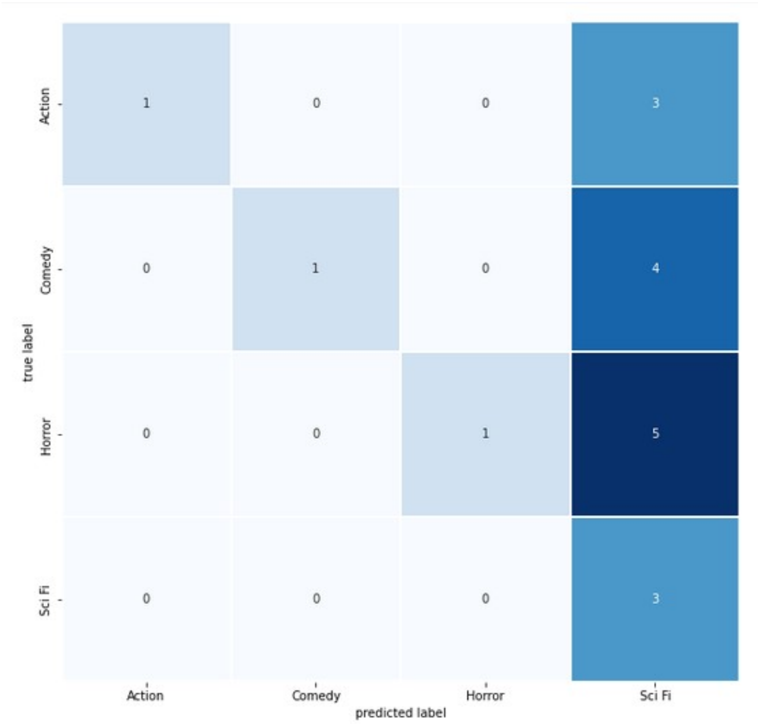

Figure A4. Confusion Matrix for Classification 1 Training Data

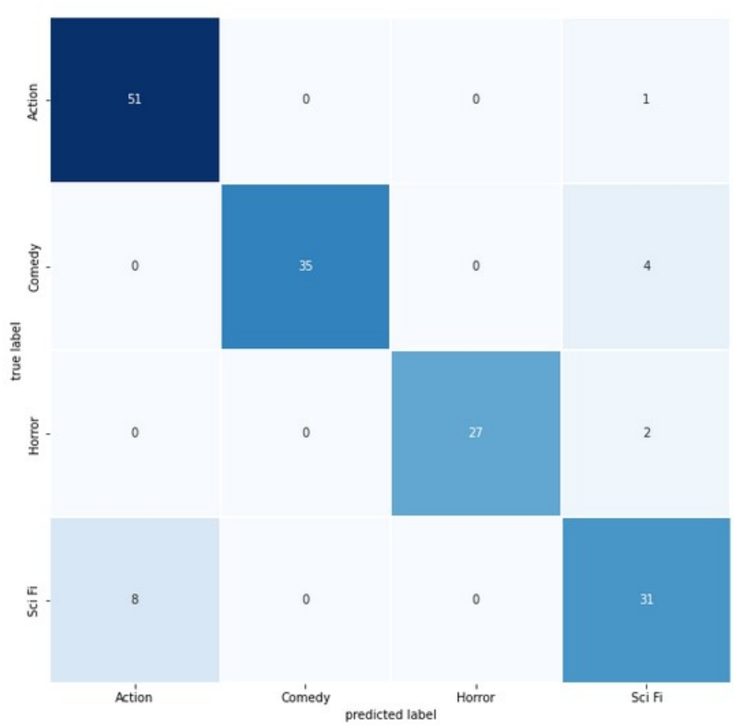

Figure A5. Accuracy and Loss Function Curve for Classification 1

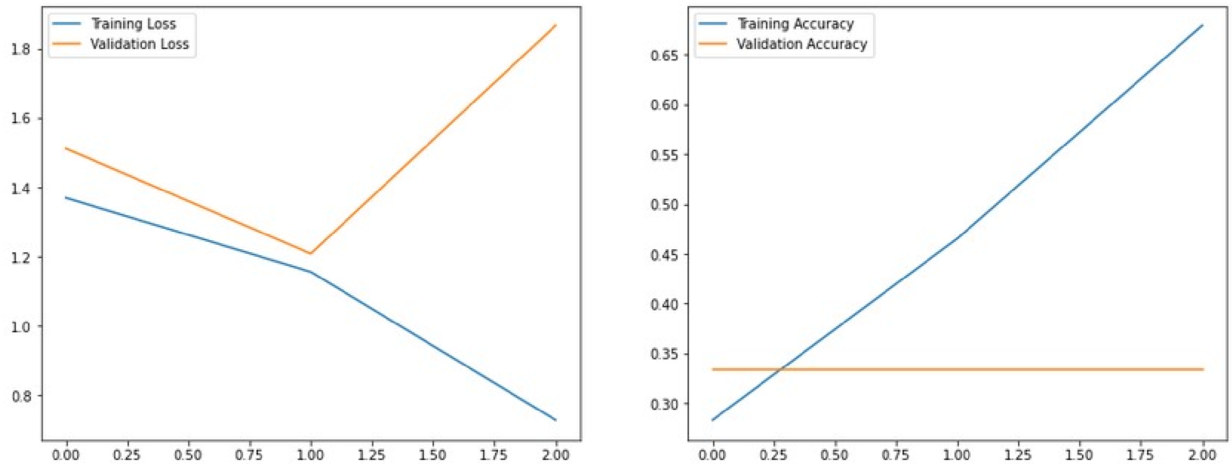

Figure A6. Confusion Matrix for Classification 2 Test Data

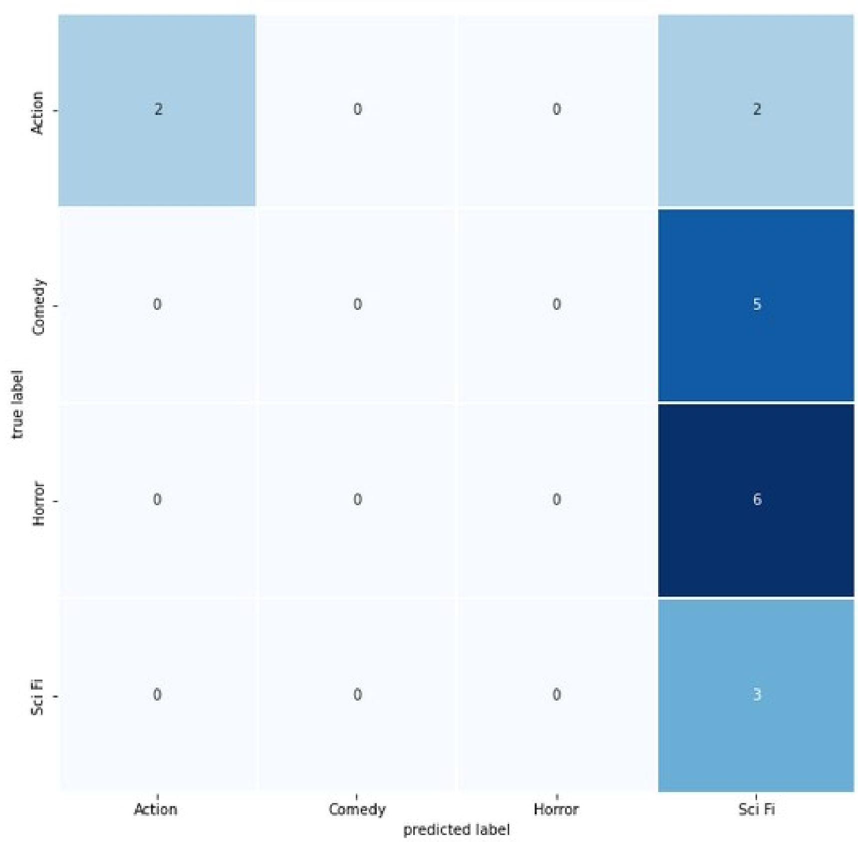

Figure A7. Confusion Matrix for Classification 2 Training Data

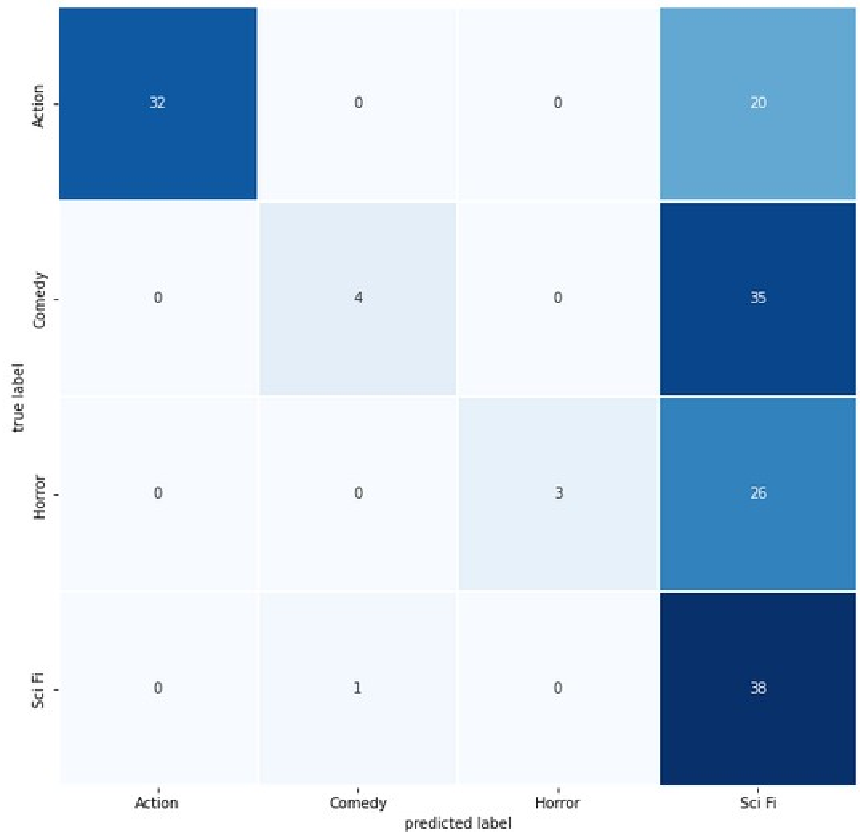

Figure A8. Accuracy and Loss Function Curve for Classification 2

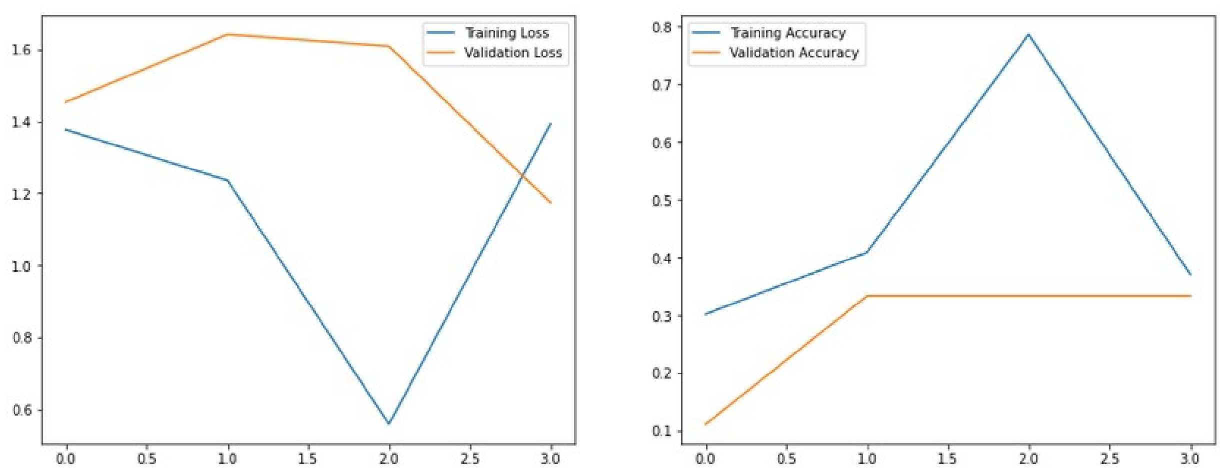

Figure A9. Confusion Matrix for Classification 3 Test Data

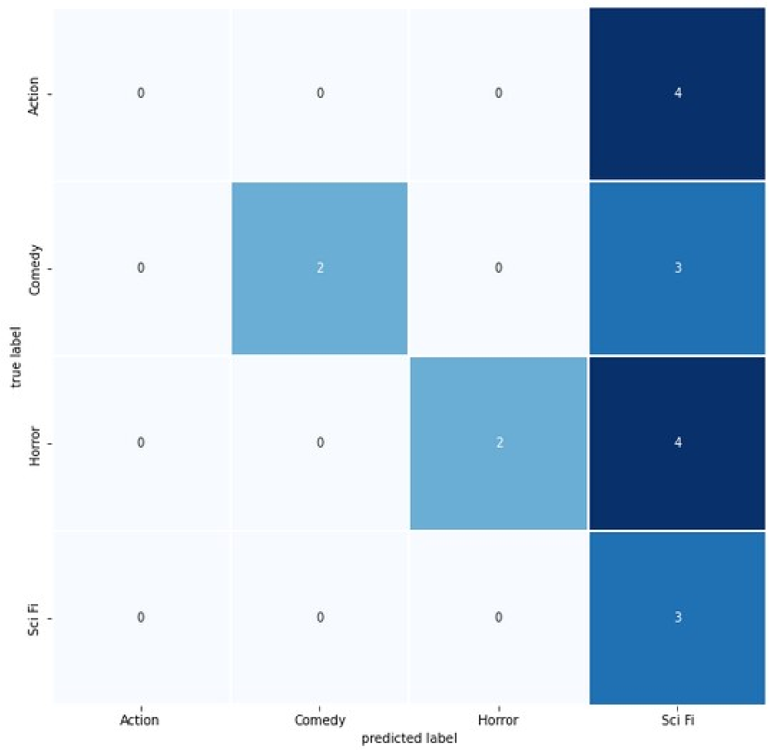

Figure A10. Confusion Matrix for Classification 3 Training Data

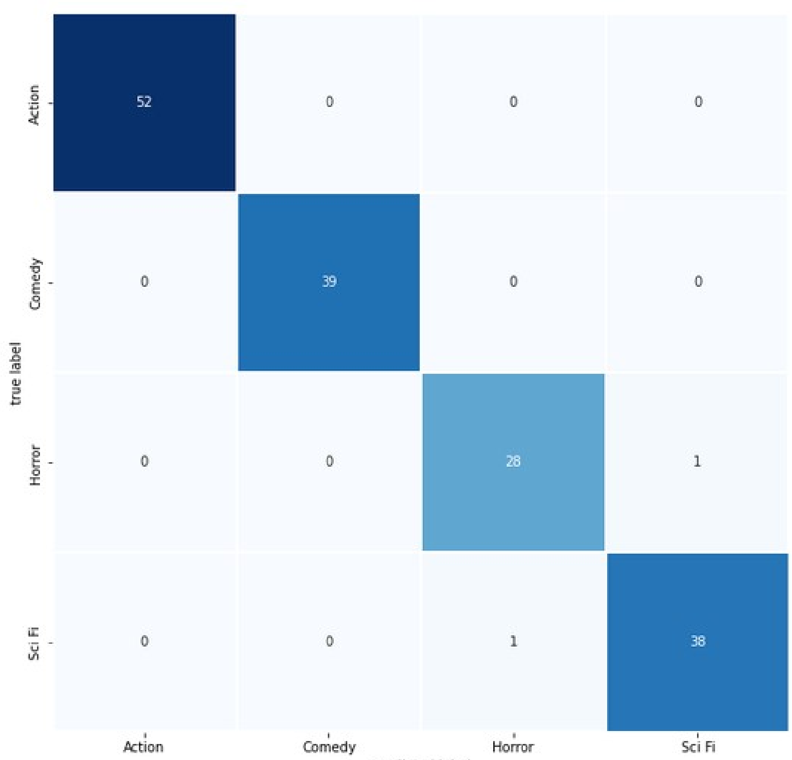

Figure A11. Accuracy and Loss Function Curve for Classification 3

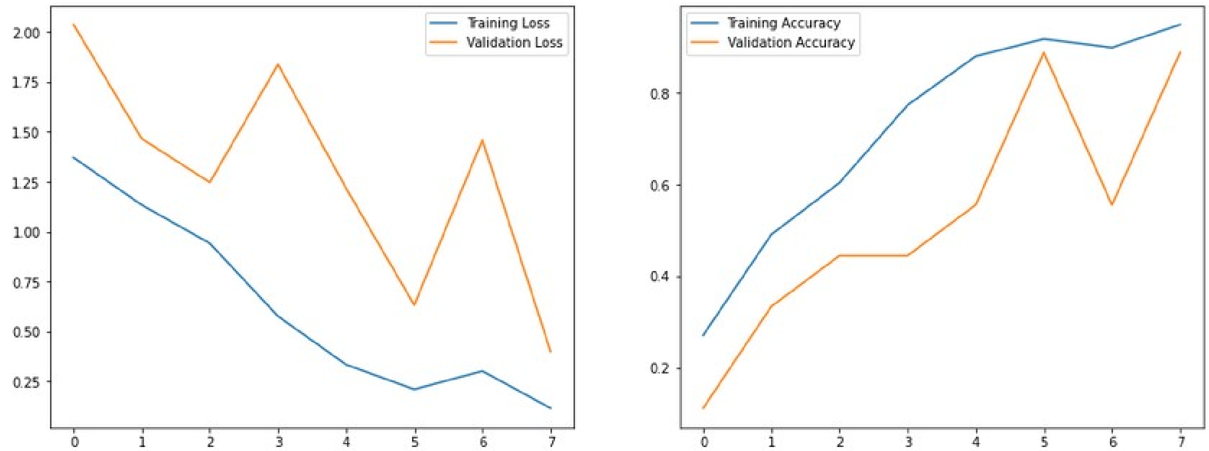

Figure A12. Confusion Matrix for Sentiment 1 Test Data

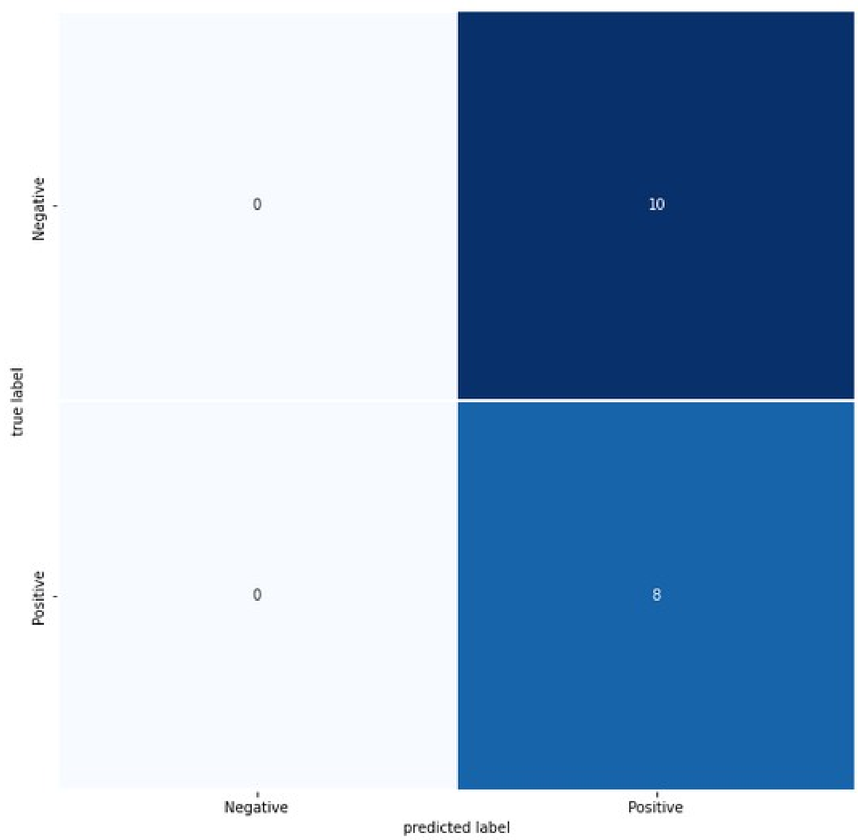

Figure A13. Confusion Matrix for Sentiment 1 Training Data

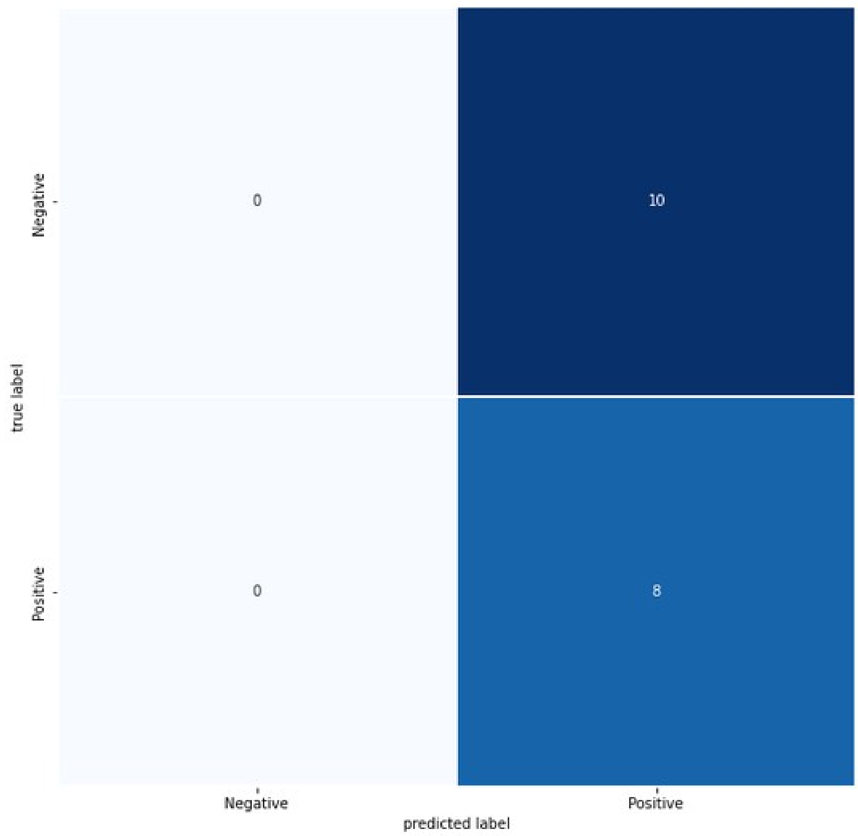

Figure A14. Accuracy and Loss Function Curve for Sentiment 1

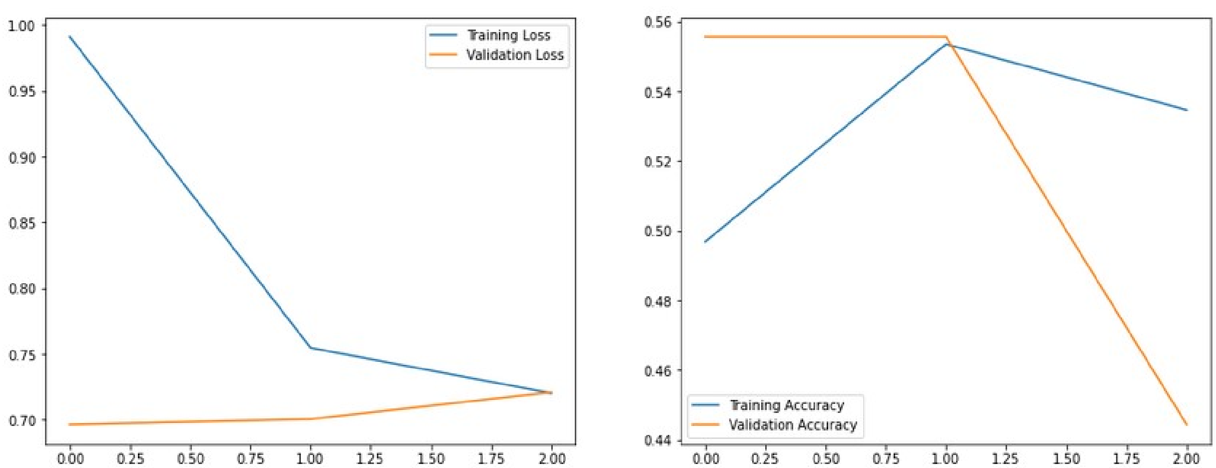

Figure A15. Confusion Matrix for Sentiment 2 Test Data

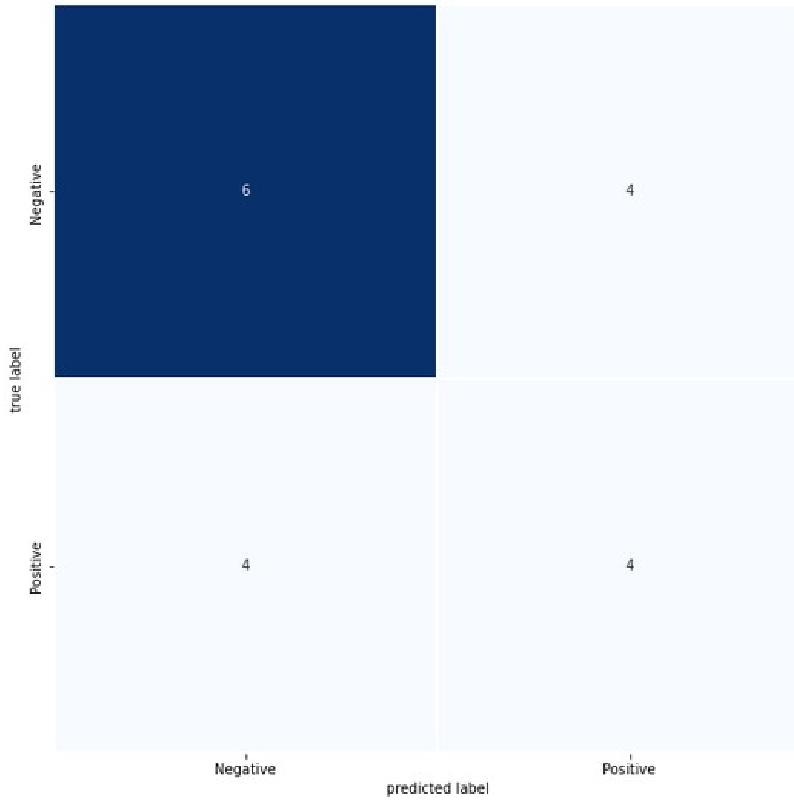

Figure A16. Confusion Matrix for Sentiment 2 Training Data

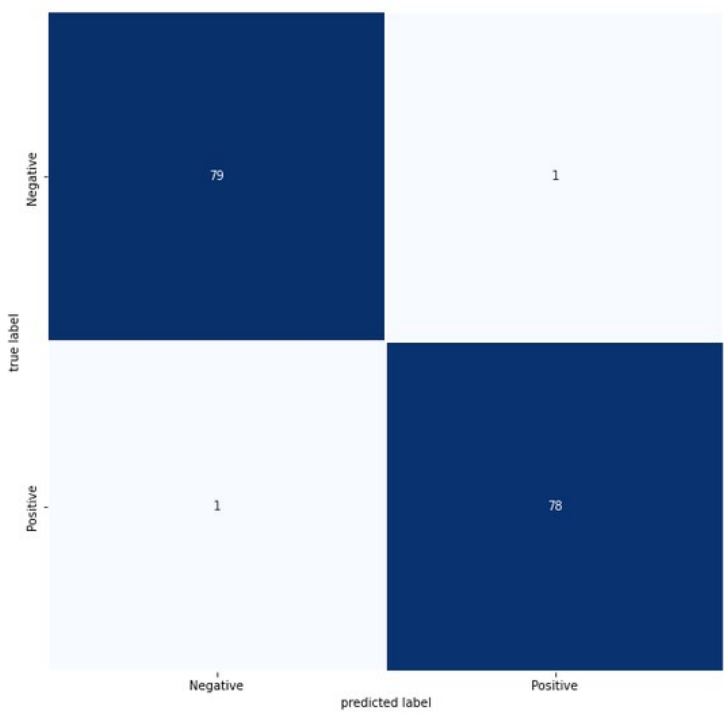

Figure A17. Accuracy and Loss Function Curve for Sentiment 2

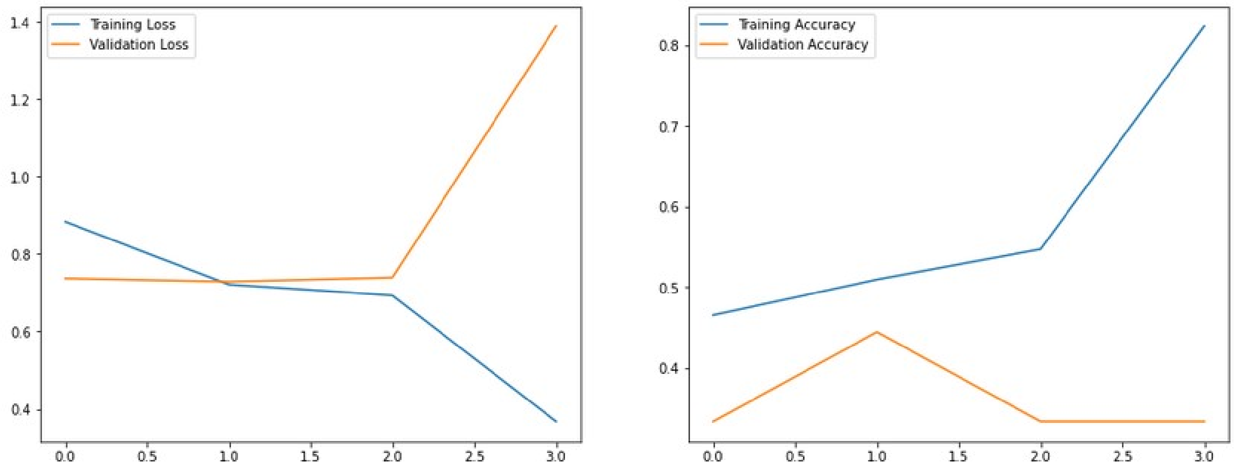

Figure A18. Confusion Matrix for Sentiment 3 Test Data

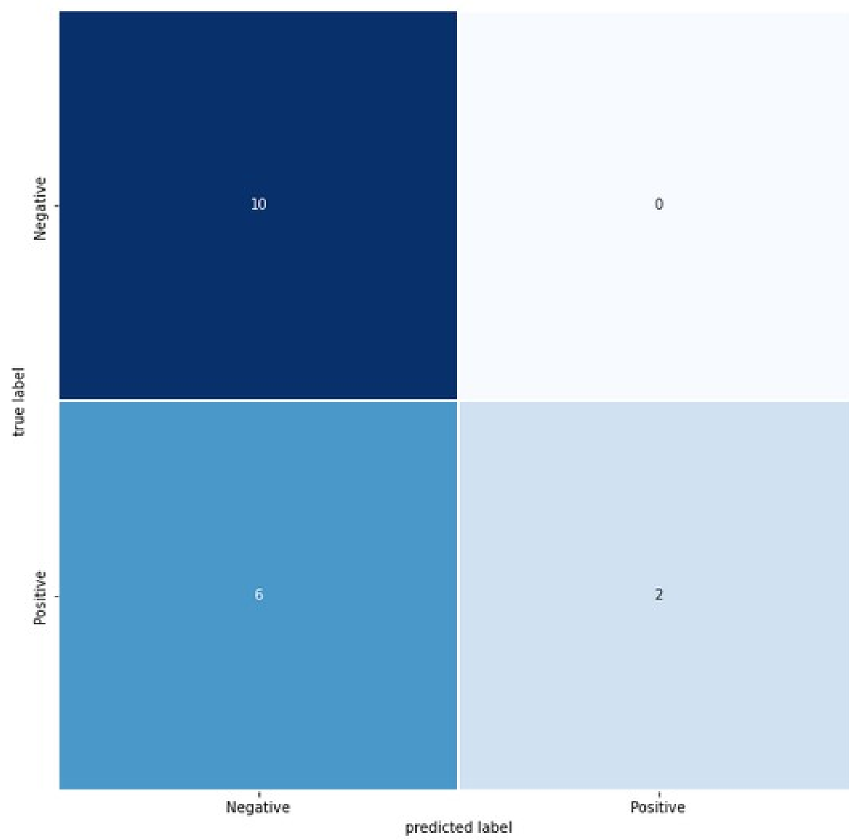

Figure A19. Confusion Matrix for Sentiment 3 Training Data

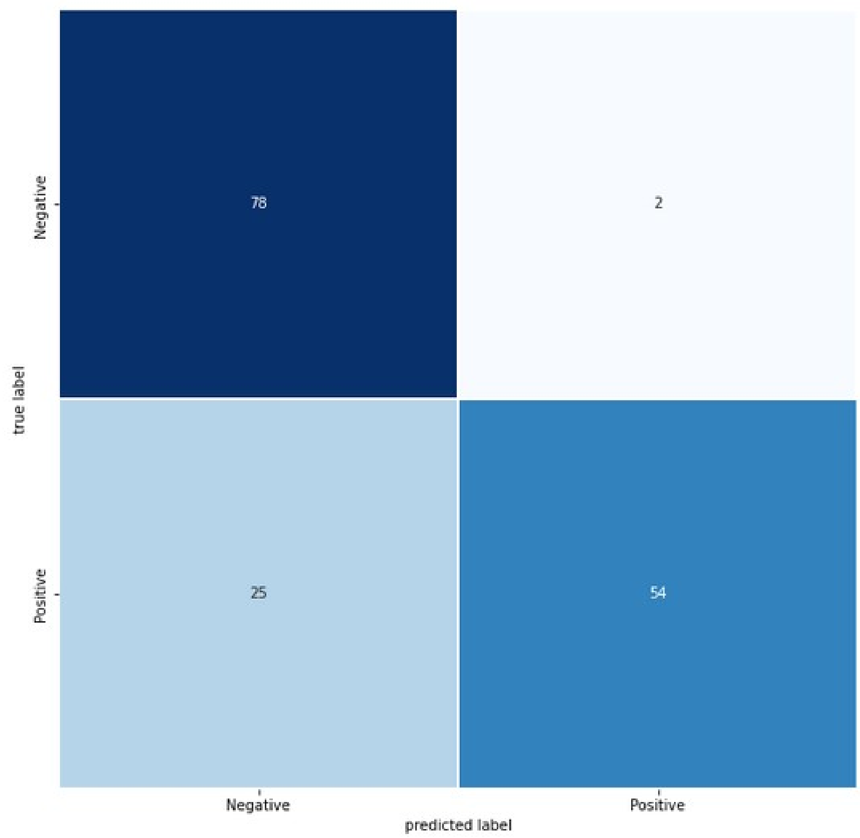

Figure A20. Accuracy and Loss Function Curve for Sentiment 3