# Multi-Label Movie Genre Classification

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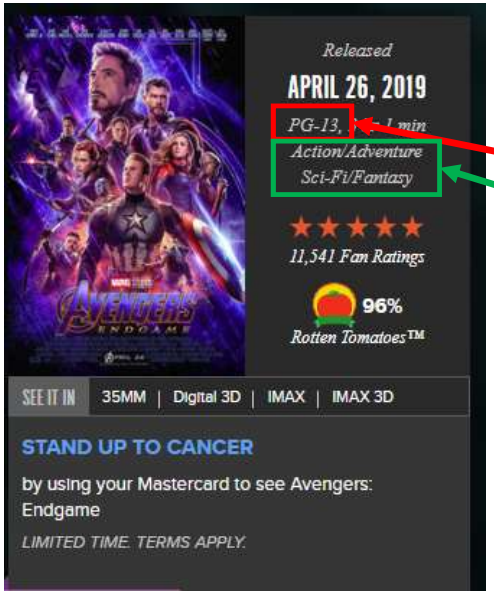
Springboard

Data Science Intensive Capstone Project

October 1, 2018 Cohort

# Types of Classification Tasks




## Binary Classification

- Spam
- Not spam

Binary Classification:
Only 2 choices

## Multiclass Classification

- Dog
- Cat
- Horse
- Fish
- Bird
- ...

Multi-class Classification:
Each observation is assigned to one and only one class

## Multi-label Classification

- Dog
- Cat
- Horse
- Fish
- Bird
- ...

Multi-label Classification:
Each observation can be classified into multiple classes

# Multi-Label Classification - Applications

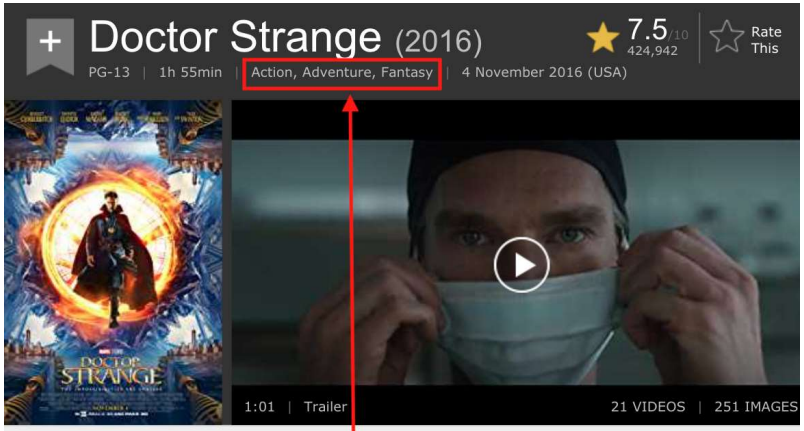
Multi-Label Classification for Image/Scene Categorization



Horror: 0.02%
Romance: 0.02%
Adventure: 99.96%
Documentary: 0.0%

- Multi-Label Classification of Genres based on movie Posters

Multi-Label Classification of Movie Genre using Plot




While on a journey of physical and spiritual healing, a brilliant neurosurgeon is drawn into the world of the mystic arts.

# Prediction Problem

- Given the plot of the movie, what are the genres they fall into?

- Total of 27 Possible Genres
- Movies are classified anywhere from 1 to 12 genres

# Who might care?

Online Streaming Companies






Movie Review Websites

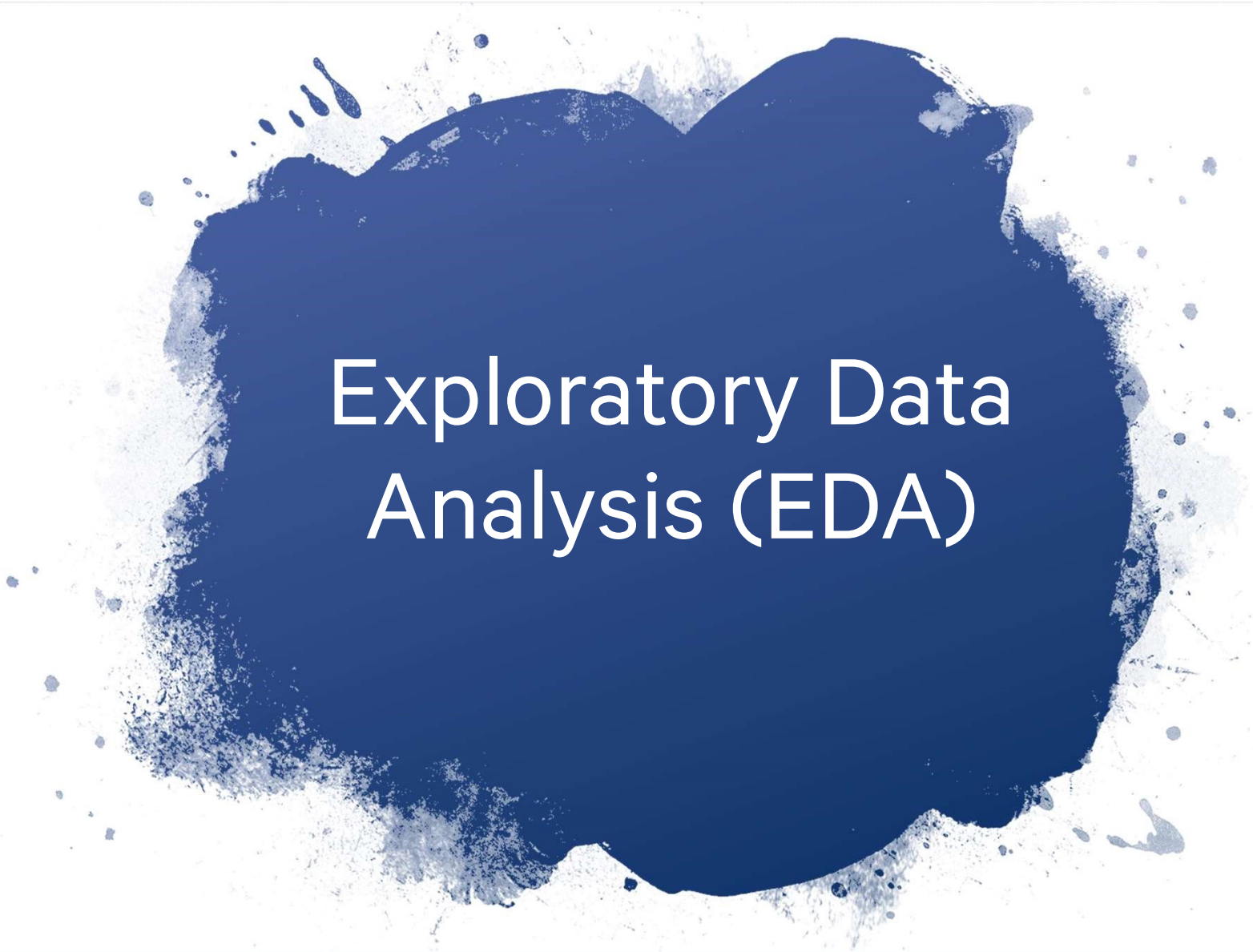



# Data Overview

- Data set obtained from IMDB
- Column Description
  - Movie Title
  - Movie Plot
  - Plot Language
  - 27 Movie Genres

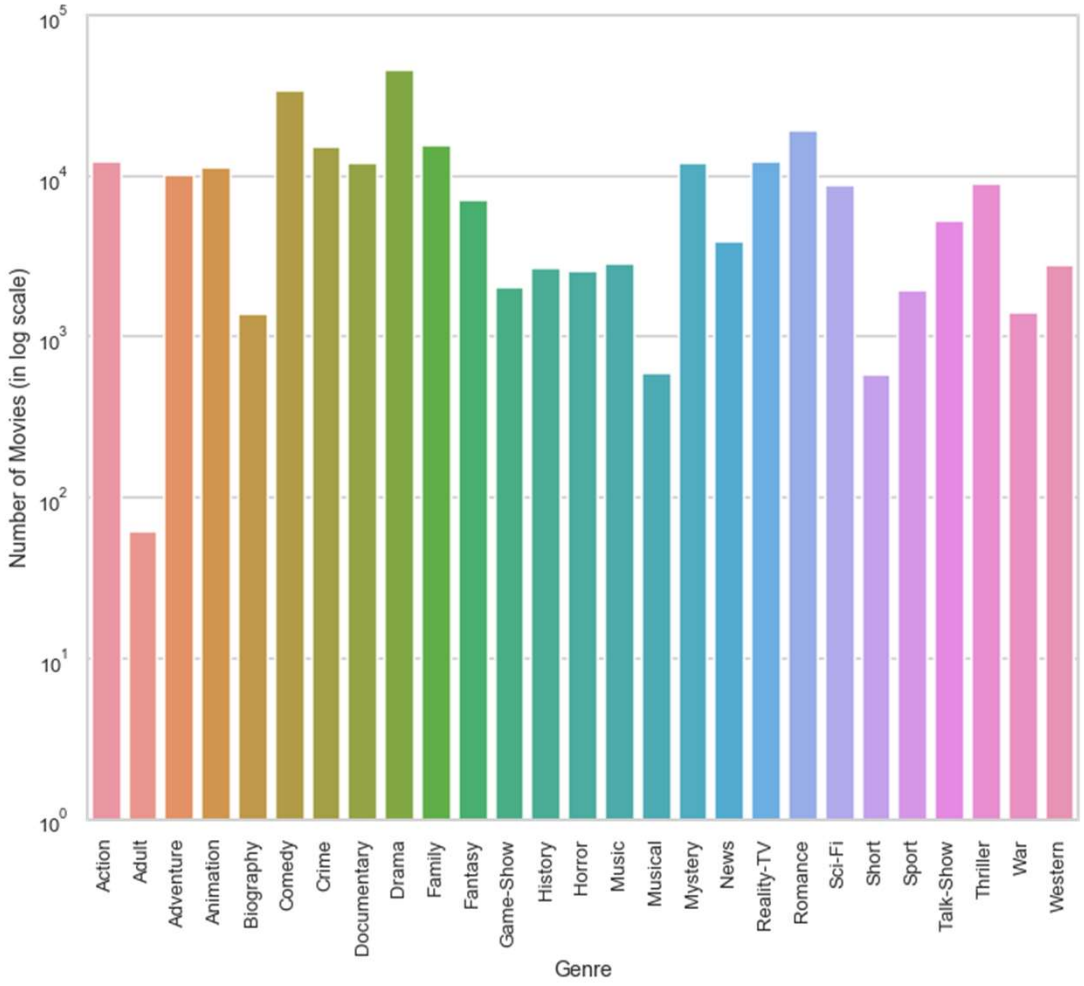
| | title | plot | Action | Adult | Adventure | Animation | ... | Sport | Talk-Show | Thriller | War | Western | plot_lang |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | "#7DaysLater" (2013) | dayslater interactive comedy series feature en... | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | en |
| 1 | "#BlackLove" (2015) {Crash the Party (#1.9)} | week leave workshops women consider idea ladie... | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | en |

2 rows × 30 columns


Exploratory Data
Analysis (EDA)

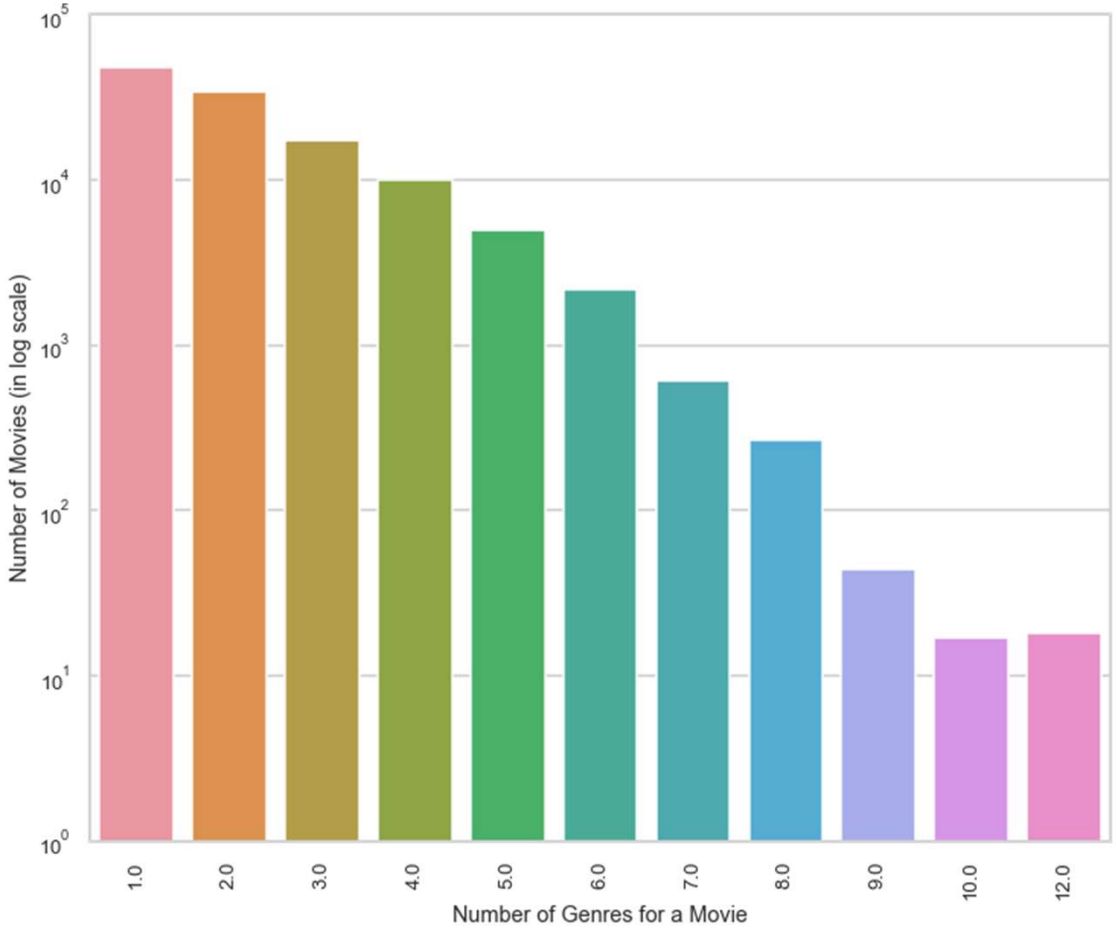
# Number of Movies per Genre

- Highest Genre Movies = Drama (45891) followed by Comedy (33870)
- Lowest Genre Movies = Adult (61)



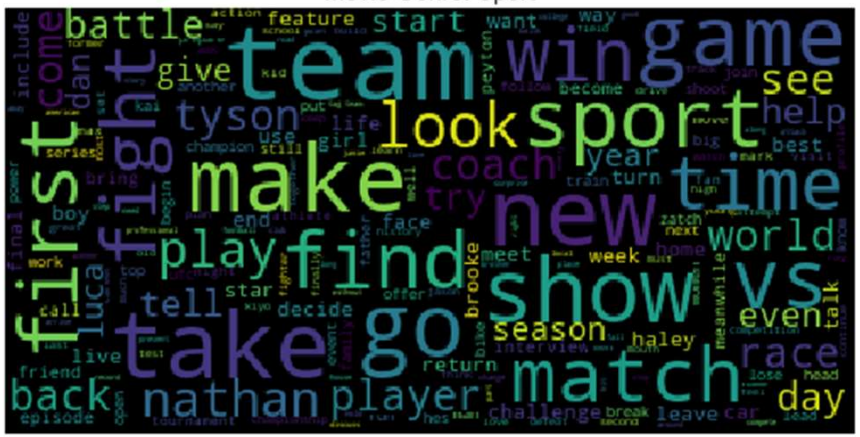
# Number of Genres per Movie

- Average of 2.1 genres per movie
- 18 movies are classified using 12 genres!



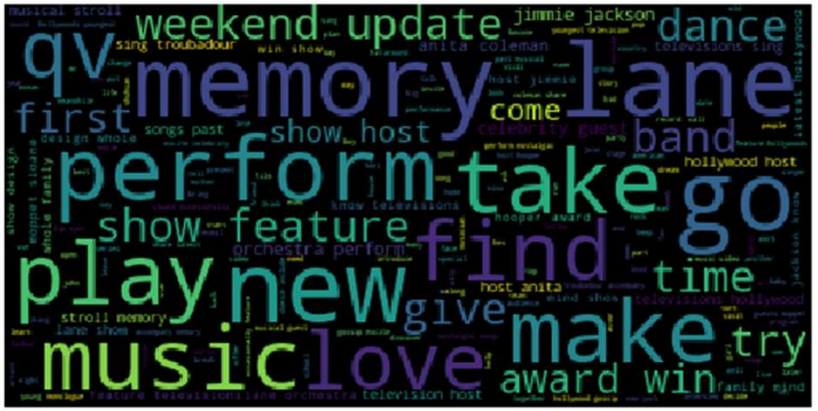
# Word Cloud plots – [Sports, Music]

Movie Genre: Sport




Relevant words – ‘team, vs, sport, first, match, player, race’

Movie Genre: Music




Relevant words – ‘memory, lane, perform, play, love, award, show’

# Word Cloud plots – [Biography, War]

Movie Genre: Biography

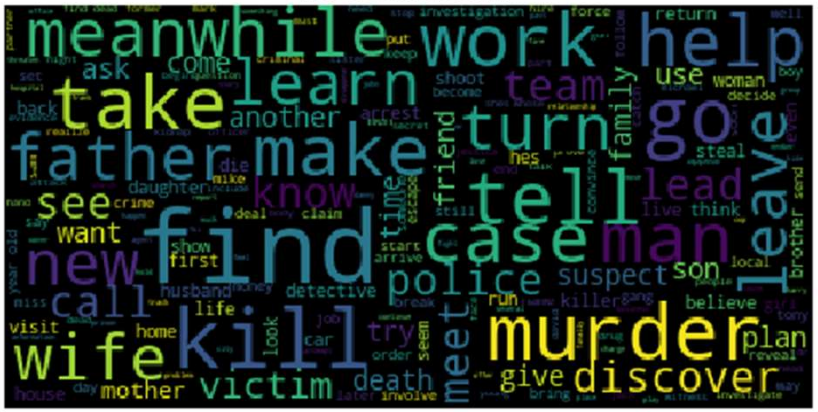

Relevant words – ‘life, career, world, story, interview’

Movie Genre: War


Relevant words – ‘german, order, plan, kill, mission, american’

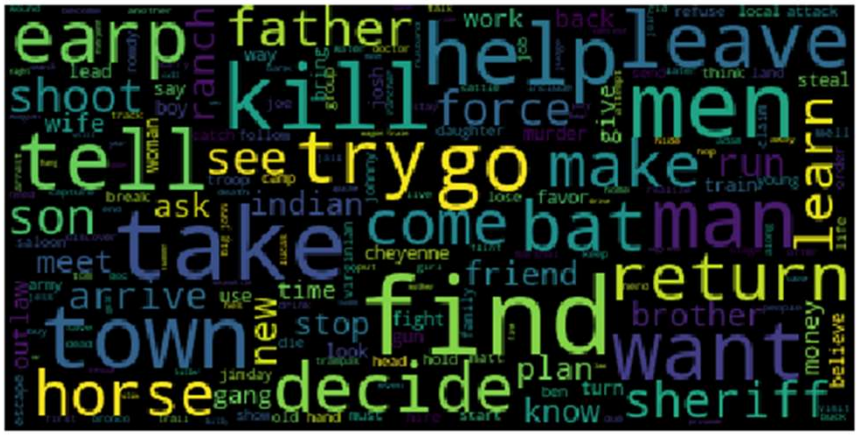
# Word Cloud plots – [Crime, Western]

Movie Genre: Crime




Relevant words – ‘kill, murder, case, police, victim’

Movie Genre: Western




Relevant words – ‘horse, sheriff, town, kill, Indian, gang’

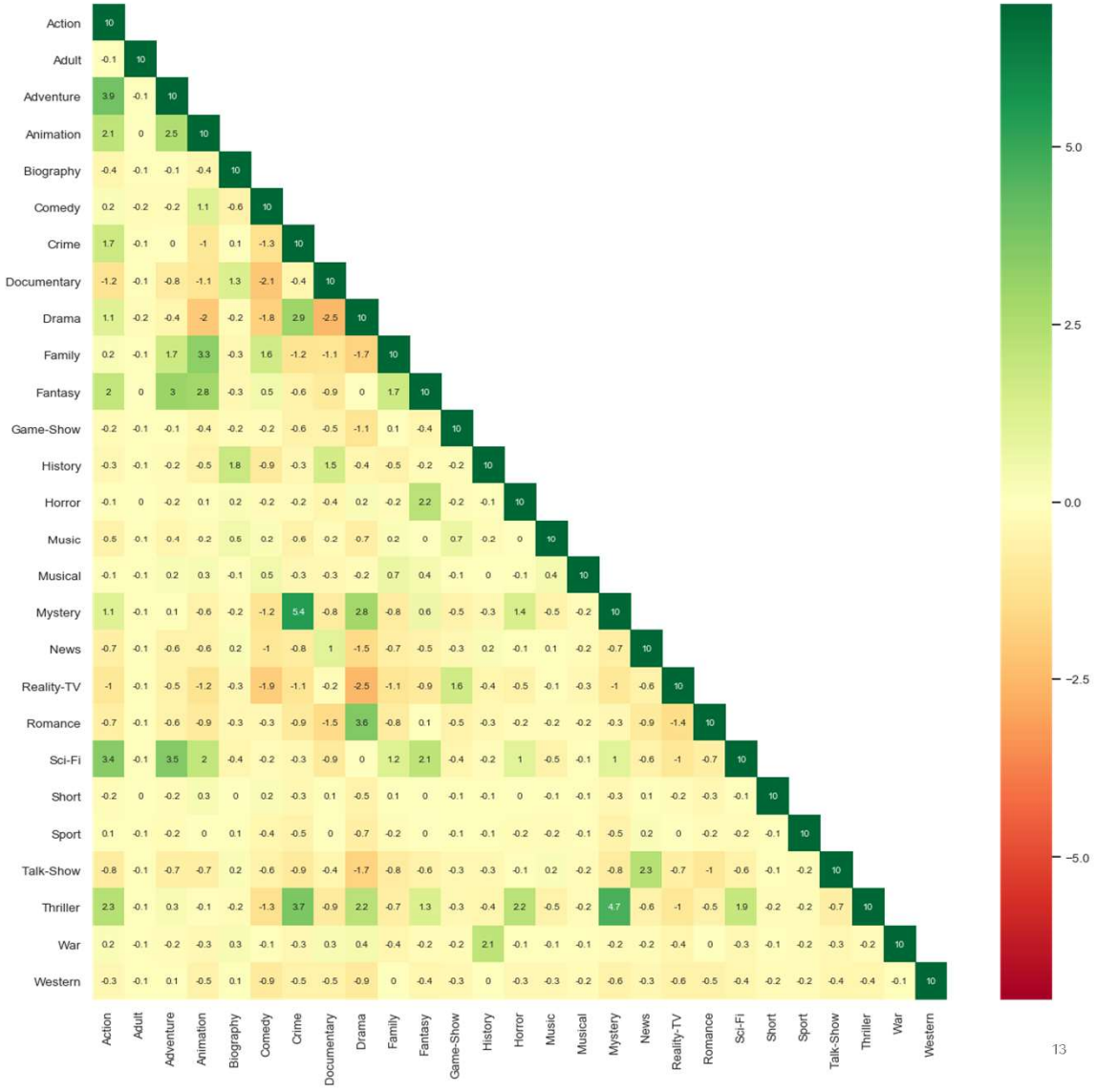
# Correlation Analysis - Heatmap

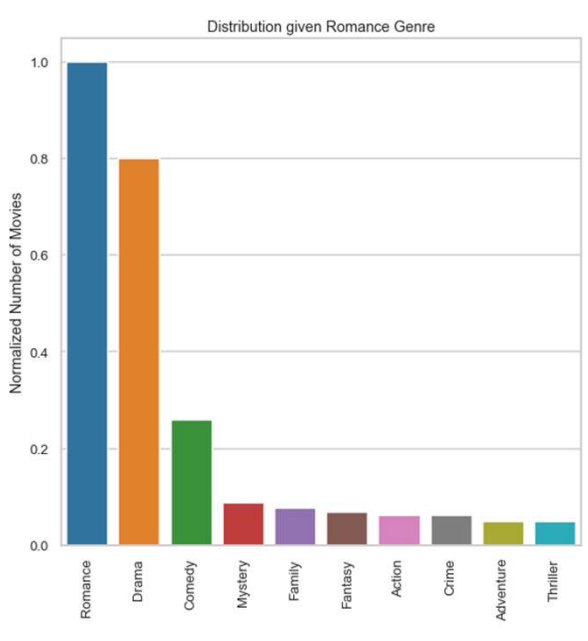
Genres with strong positive correlation

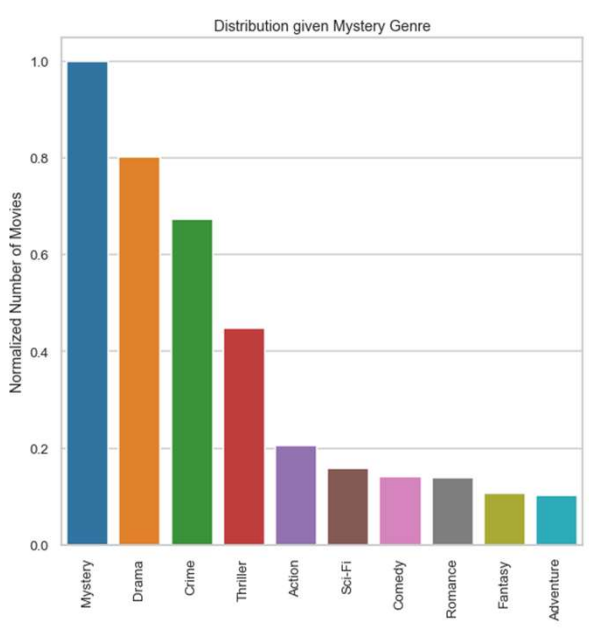
- Action, Adventure, Fantasy & Sci-Fi
- Animation, Fantasy & Family
- Crime, Thriller, Mystery & Drama
- Drama & Romance
- Game-Show & Reality-TV
- War & History

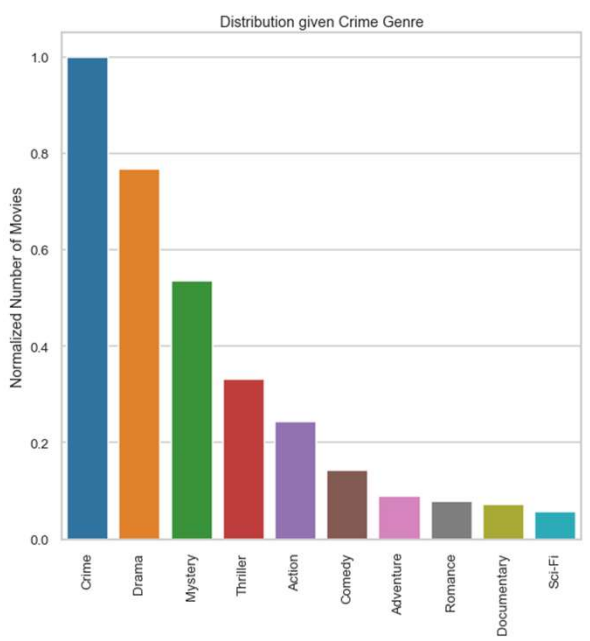
Genres with strong negative correlation

- Animation & Drama
- Comedy & Documentary



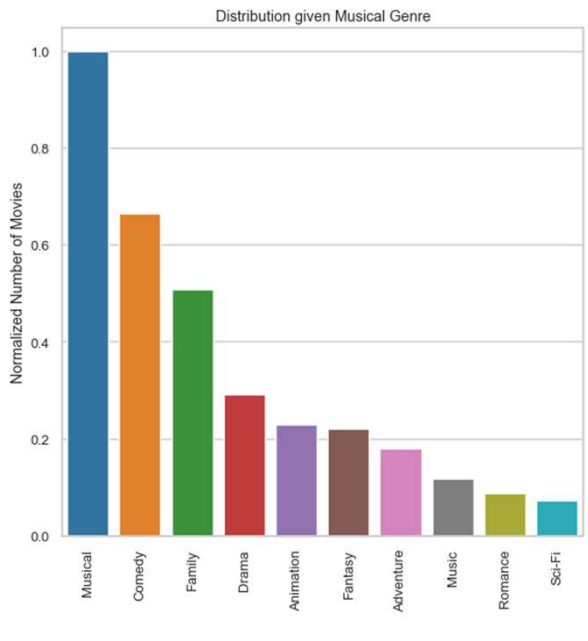


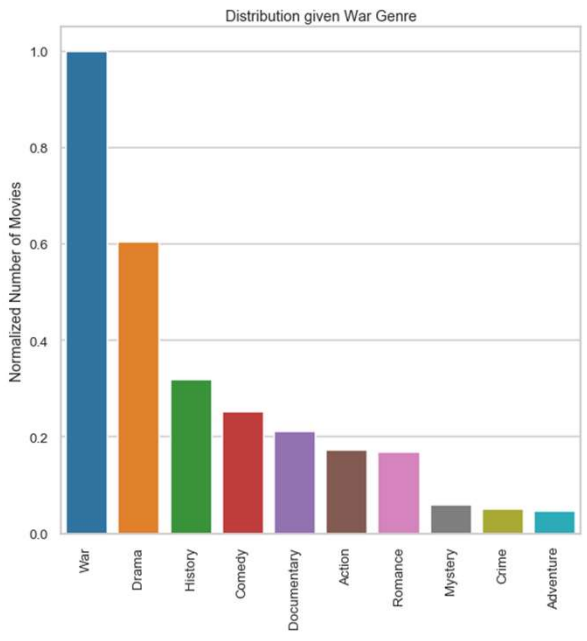



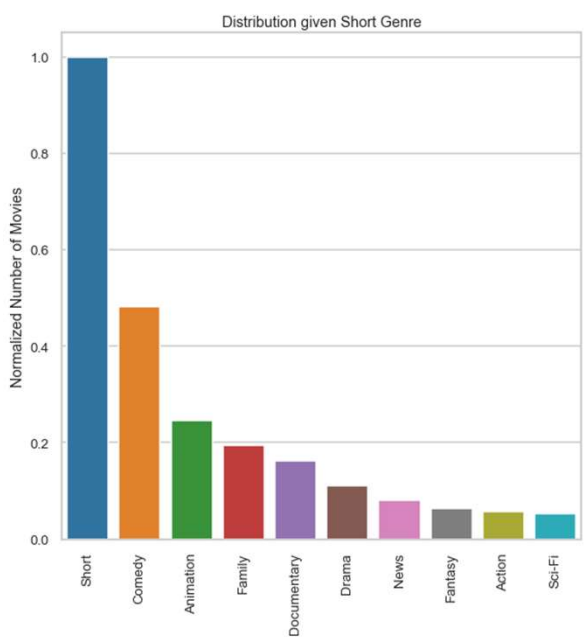




# Multi-Genre Distribution Plots

80% of the Crime, Mystery & Romance movies are also categorized as Drama

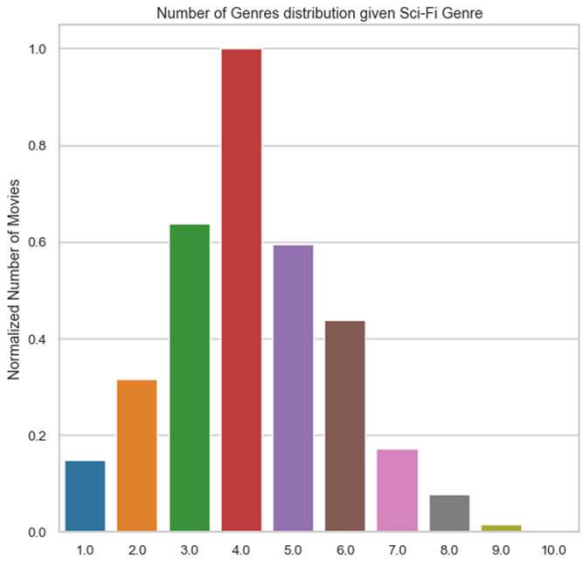


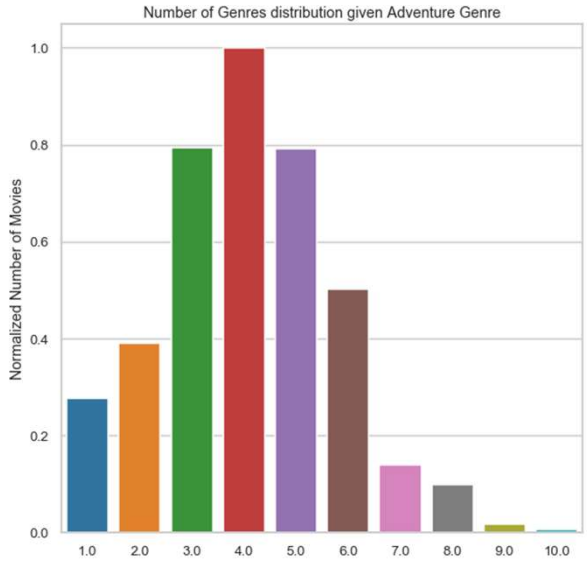



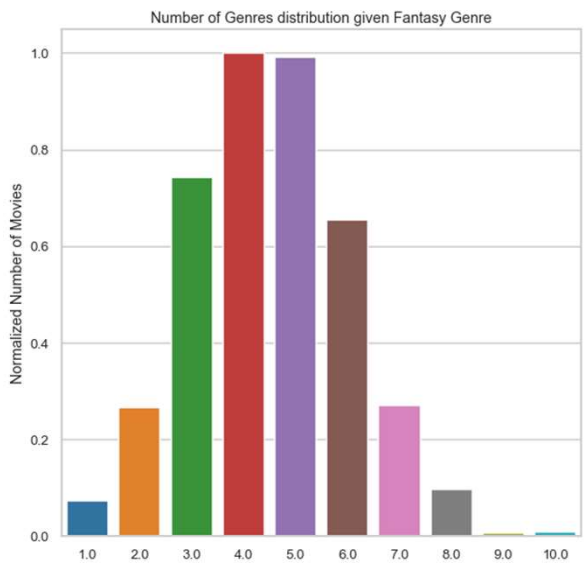




# Multi-Genre Distribution Plots

65% of Musical movies are Comedy, 60% of War movies are Drama, Half of Short movies are Comedies

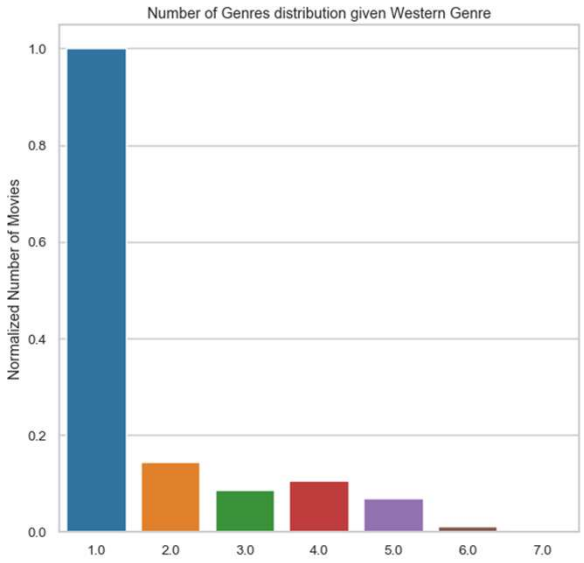


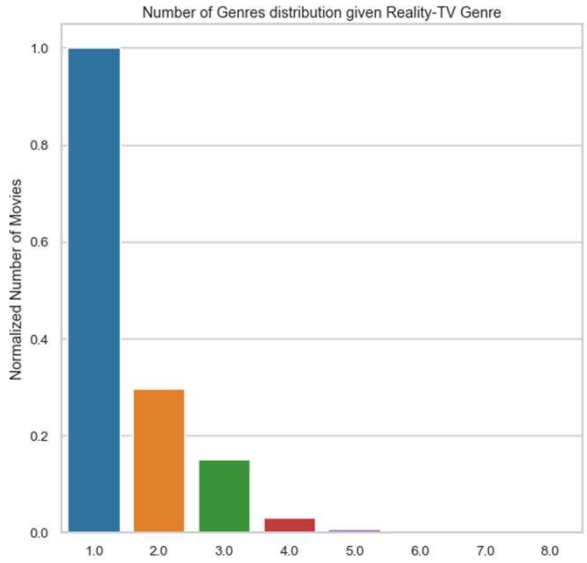



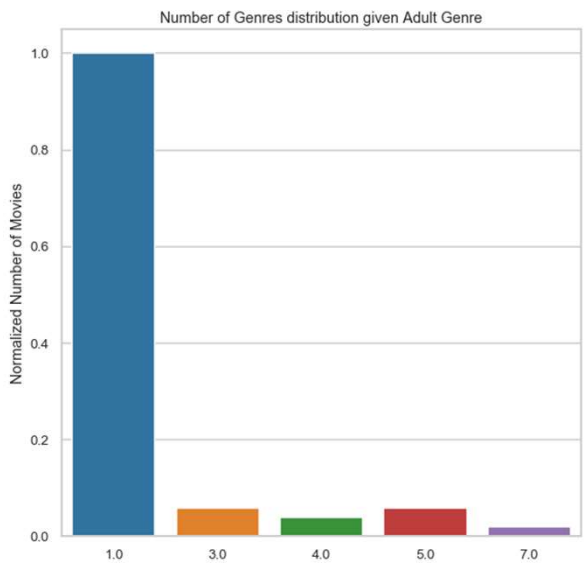




# Number of Genres for [Sci-Fi, Adventure, Fantasy]

Adventure, Fantasy, Sci-Fi have 3 to 6 categories




# Number of Genres for [Adult, Reality-TV, Western]

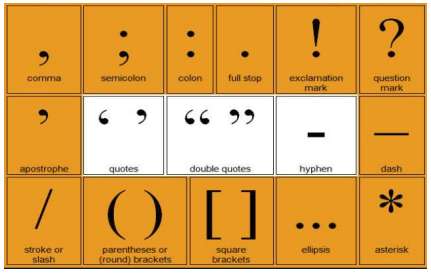
Adult, Reality-TV, Western are typically categorized to a single genre

```
print(remove_tags('<html><h2>Learning NLP</h2></html>'))
print(remove_tags(' <a>Movie-Plot</a>'))
```

executed in 3ms, finished 15:08:11 2019-04-28

```
Learning NLP
Movie-Plot
```

Remove HTML Tags




Remove Punctuations

áàâäãå ÁÀÂÄÃÅ çÇ
éèêë ÉÈÊË íìîï ÍÌÎÏ
ñÑ óòôöõ ÓÒÔÖÕ
úùûü ÚÙÛÜ ÿŸ

Convert accented characters to ASCII

```
def keep_alpha(sentence):
    alpha_sentence = re.sub('[^a-z A-Z]+', ' ', sentence)
    return alpha_sentence
```

Keep only alphabetic strings

# Text Preprocessing

| Sample text with Stop Words | Without Stop Words |
|---|---|
| GeeksforGeeks – A Computer Science Portal for Geeks | GeeksforGeeks , Computer Science, Portal ,Geeks |
| Can listening be exhausting? | Listening, Exhausting |
| I like reading, so I read | Like, Reading, read |

Stop words removal

| | original_word | lemmatized_word |
|---|---|---|
| 0 | trouble | trouble |
| 1 | troubling | trouble |
| 2 | troubled | trouble |
| 3 | troubles | trouble |

| | original_word | lemmatized_word |
|---|---|---|
| 0 | goose | goose |
| 1 | geese | goose |

Lemmatization

| Raw | Lowercased |
|---|---|
| Canada<br>CanadA<br>CANADA | canada |

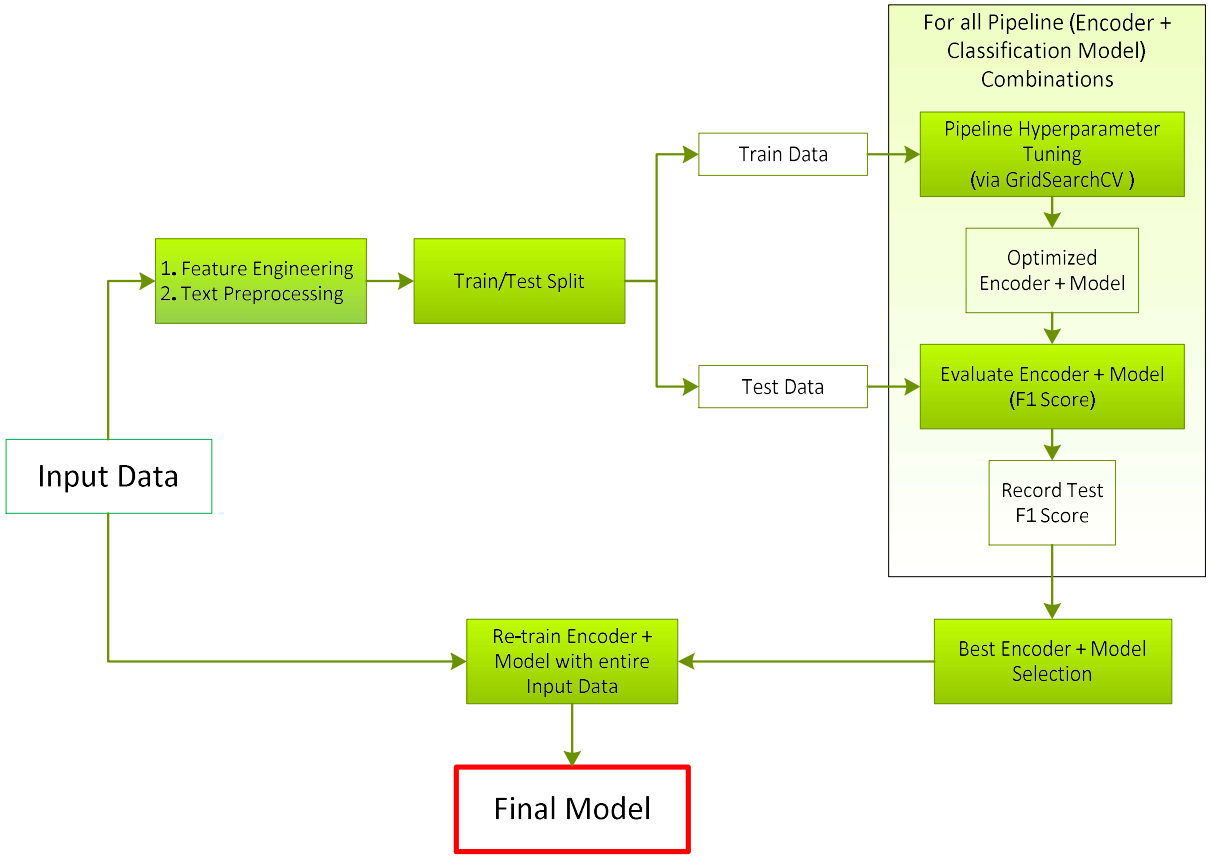
Lower casing all the words

# Text Preprocessing


Modeling

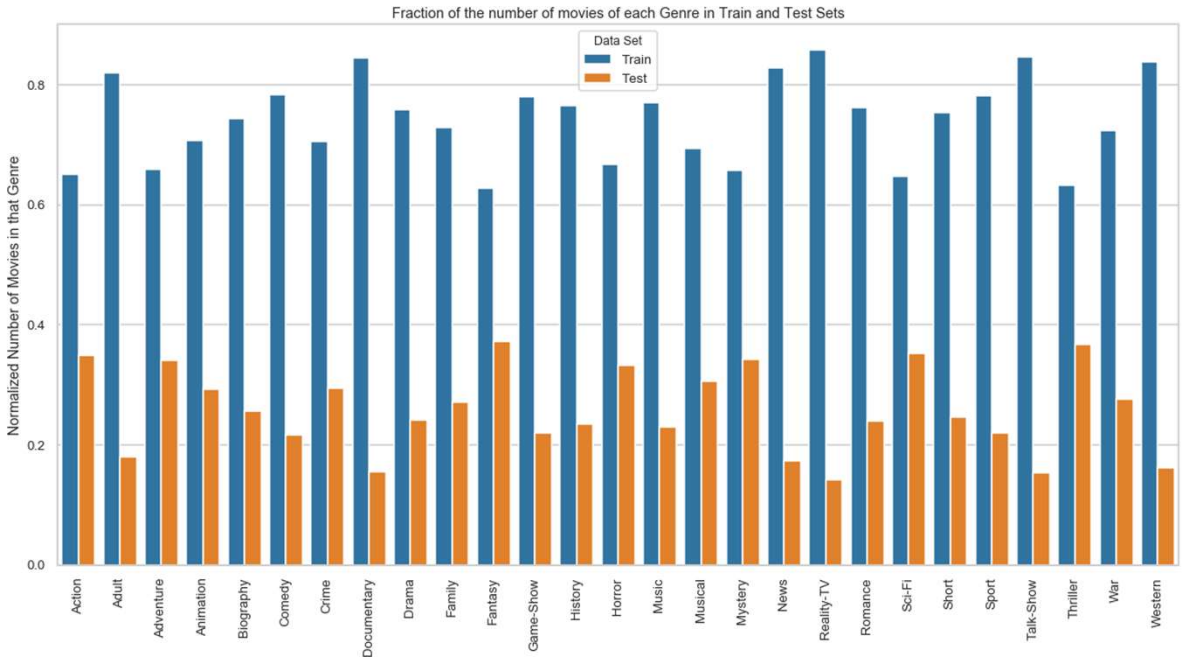
# Modeling Overview

- Type: Supervised Learning
- Classification (Multi-label) Problem with 27 labels
- Pipeline consists of
  - Encoder
  - Classification Model



# Train/Test Split

- Imbalanced Data with genre occurrences ranging from 61 (Adult) to 45891 (Drama)
- Train/Test split such that
  - At least 60% of the samples in the training set
  - At least 15% of the samples in the test set



For each Genre

$$\text{Precision (Action)} = \frac{\text{Number of movies 'correctly' identified as Action Genre}}{\text{Total number of movies that have been identified as Action Genre}}$$

$$\text{Recall (Action)} = \frac{\text{Number of movies 'correctly' identified as Action Genre}}{\text{Total number of Action Genre movies in the data set}}$$

$$\text{F1 score (Action)} = \frac{2 * \text{Precision(Action)} * \text{Recall(Acation)}}{\text{Precision(Action)} + \text{Recall(Action)}}$$

Overall F1 Score = Weighted Average of individual Genre F1 Score

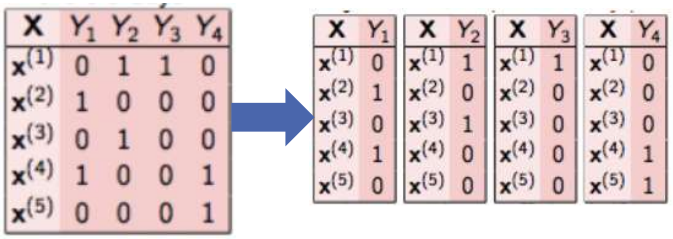
# Evaluation Metric – Overall F1 Score

| | |
|---|---|
| Multi-Label Algorithm | • Binary Relevance<br>• Label Powerset<br>• Label Powerset with Clustering |
| Text Encoder | • Count Vectorizer<br>• TF-IDF<br>• Sentence Embedding |
| Classifiers | • Logistic Regression, Linear SVC, Naïve Bayes<br>• Cosine Similarity<br>• Neural Networks |

Multi-Label Algorithm + Text Encoder + Classifiers

### Binary Relevance

- Treat each label as a separate single class Classification
- 27 Genres ➔ 27 Binary Classifiers



| X | $Y_1$ | $Y_2$ | $Y_3$ | $Y_4$ |
|---|---|---|---|---|
| $x^{(1)}$ | 0 | 1 | 1 | 0 |
| $x^{(2)}$ | 1 | 0 | 0 | 0 |
| $x^{(3)}$ | 0 | 1 | 0 | 0 |
| $x^{(4)}$ | 1 | 0 | 0 | 1 |
| $x^{(5)}$ | 0 | 0 | 0 | 1 |

| X | $Y_1$ |
|---|---|
| $x^{(1)}$ | 0 |
| $x^{(2)}$ | 1 |
| $x^{(3)}$ | 0 |
| $x^{(4)}$ | 1 |
| $x^{(5)}$ | 0 |

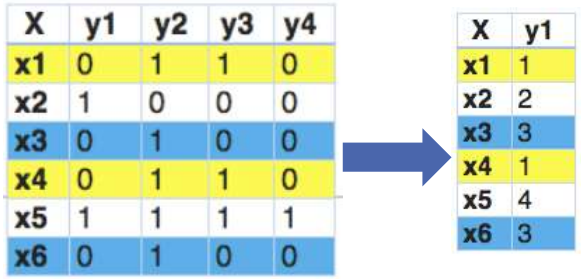
| X | $Y_2$ |
|---|---|
| $x^{(1)}$ | 1 |
| $x^{(2)}$ | 0 |
| $x^{(3)}$ | 1 |
| $x^{(4)}$ | 0 |
| $x^{(5)}$ | 0 |

| X | $Y_3$ |
|---|---|
| $x^{(1)}$ | 1 |
| $x^{(2)}$ | 0 |
| $x^{(3)}$ | 0 |
| $x^{(4)}$ | 0 |
| $x^{(5)}$ | 0 |

| X | $Y_4$ |
|---|---|
| $x^{(1)}$ | 0 |
| $x^{(2)}$ | 0 |
| $x^{(3)}$ | 0 |
| $x^{(4)}$ | 1 |
| $x^{(5)}$ | 1 |

### Label Powerset

- Treat each of the unique genre combinations found in the training data as a possible class
- 1505 Unique genre combinations ➔ Multi-class classification with 1505 classes



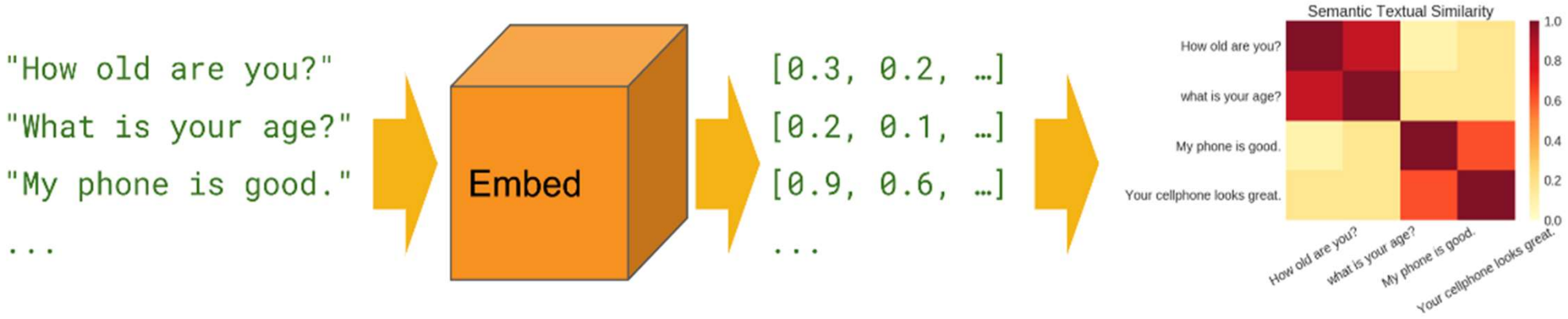
| X | y1 | y2 | y3 | y4 |
|---|---|---|---|---|
| x1 | 0 | 1 | 1 | 0 |
| x2 | 1 | 0 | 0 | 0 |
| x3 | 0 | 1 | 0 | 0 |
| x4 | 0 | 1 | 1 | 0 |
| x5 | 1 | 1 | 1 | 1 |
| x6 | 0 | 1 | 0 | 0 |

| X | y1 |
|---|---|
| x1 | 1 |
| x2 | 2 |
| x3 | 3 |
| x4 | 1 |
| x5 | 4 |
| x6 | 3 |

### Label Powerset with Clustering

- Reduce the number of genre combinations by clustering (from 1505 to 75)

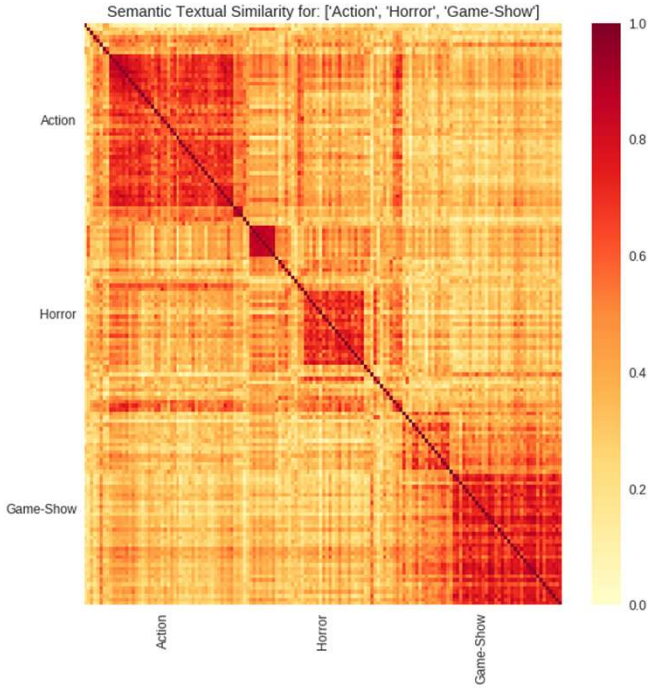
# Multi-Label Classification Algorithms

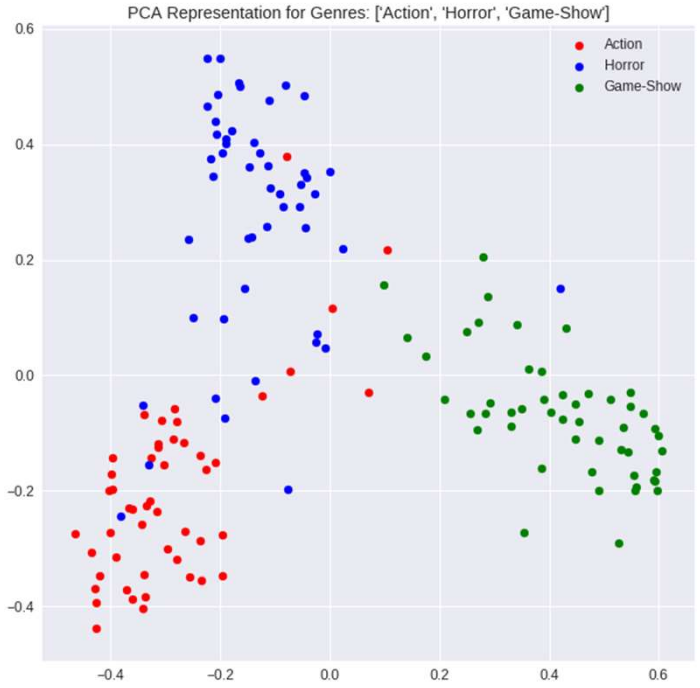



## Text Encoder – Sentence Embedding

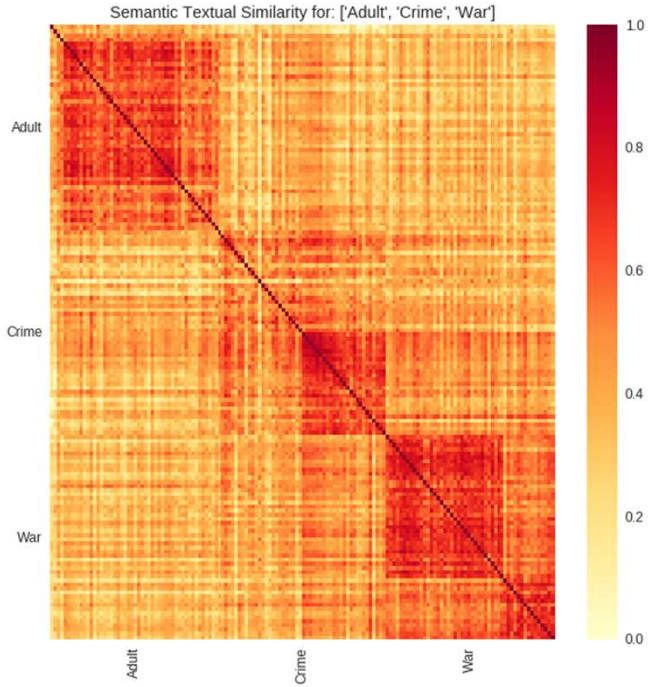
- Google Universal Sentence Encoder (USE) converts input sentence to 512 dimension numeric vectors
- Preserves the semantic meaning of the sentence

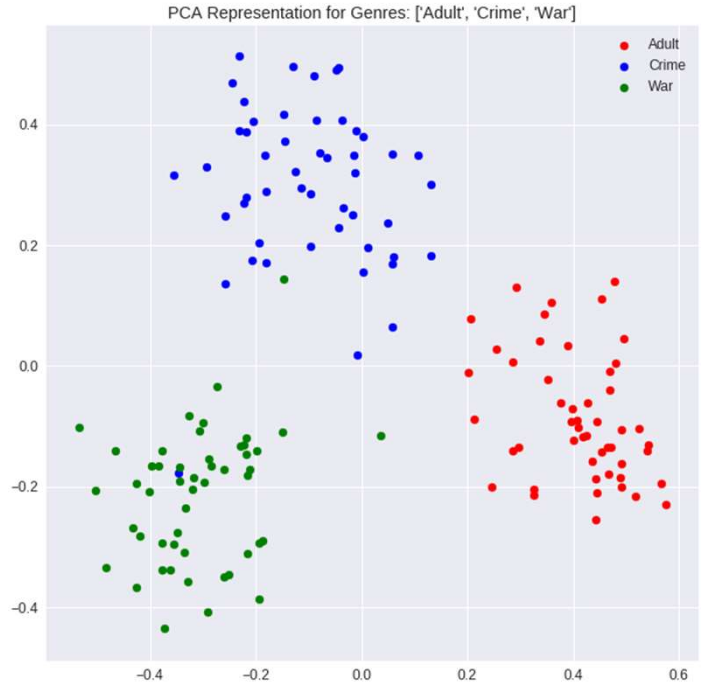
# Sentence Embedding – [Action, Horror, Game-Show]



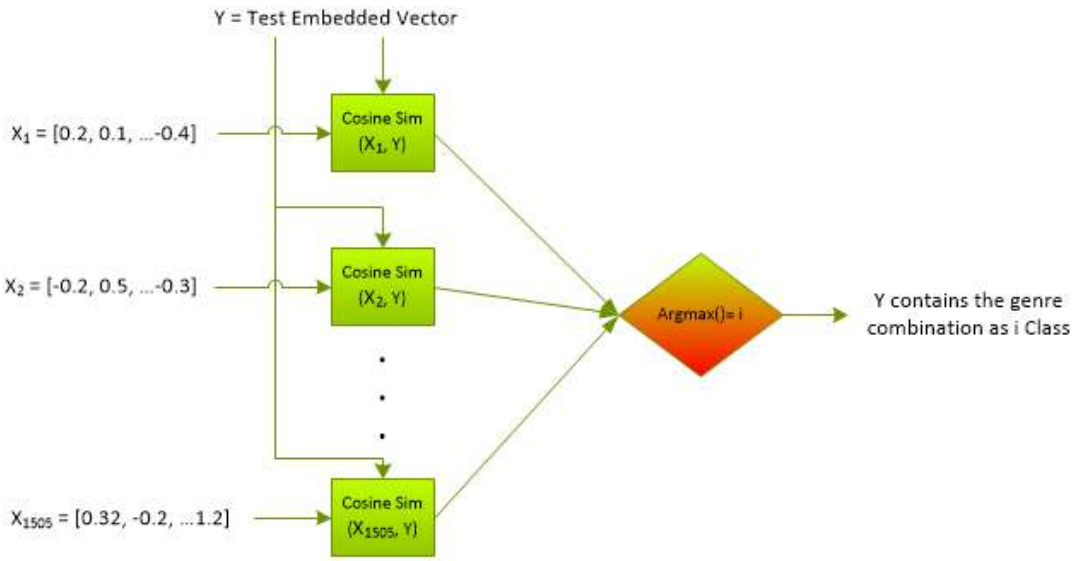
# Sentence Embedding – [Adult, Crime, War]



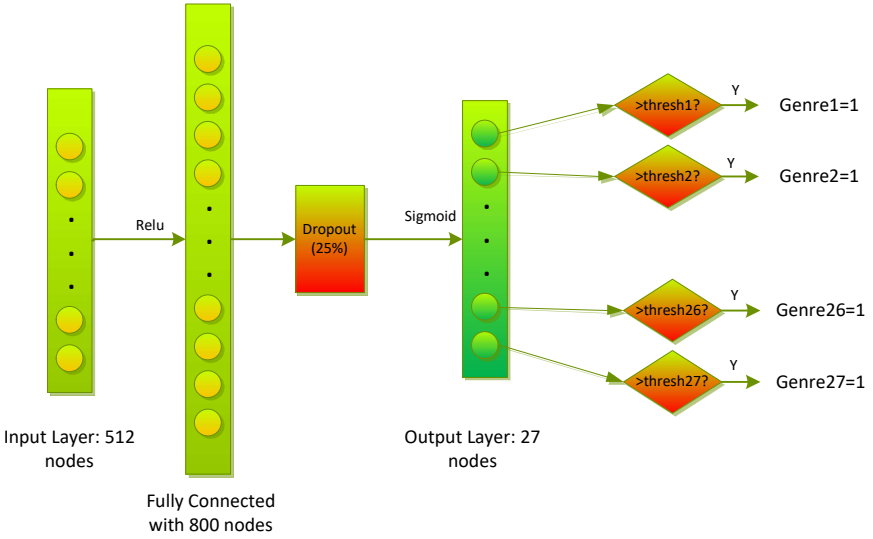



# Classification Models – Cosine Similarity

- Sentence Embedding of similar genres cluster together
- Cosine Similarity $(\vec{x}, \vec{y}) =$
- $$\frac{\vec{x}\cdot\vec{y}}{||\vec{x}||\ ||\vec{y}||} = \frac{\sum_{i=1}^{512} x_i y_i}{\sqrt{\sum_{i=1}^{512} x_i^2}\sqrt{\sum_{i=1}^{512} y_i^2}}$$

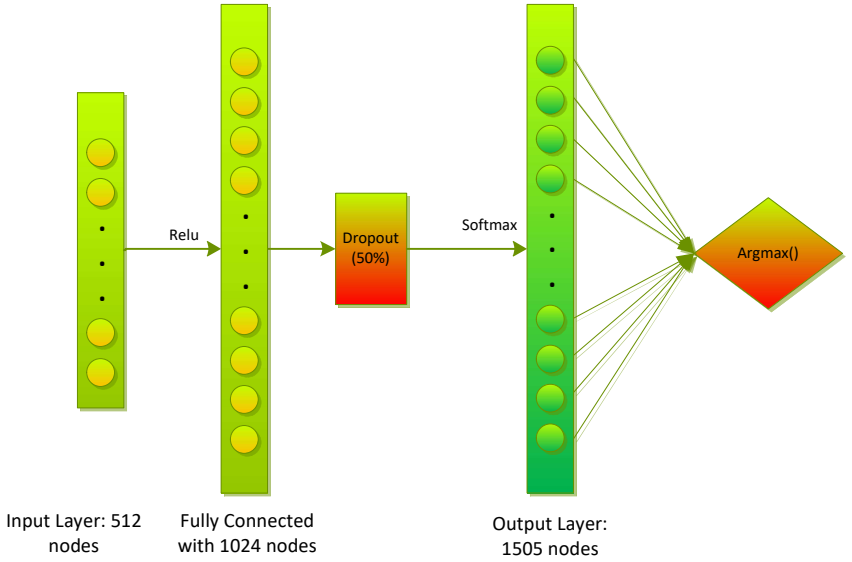


# Classification Models – Neural Network




## Using Binary Relevance

- Each Genre predicted separately ➔ Output Layer = 27 Neurons
- Use sigmoid Activation Function




## Using Label Powerset

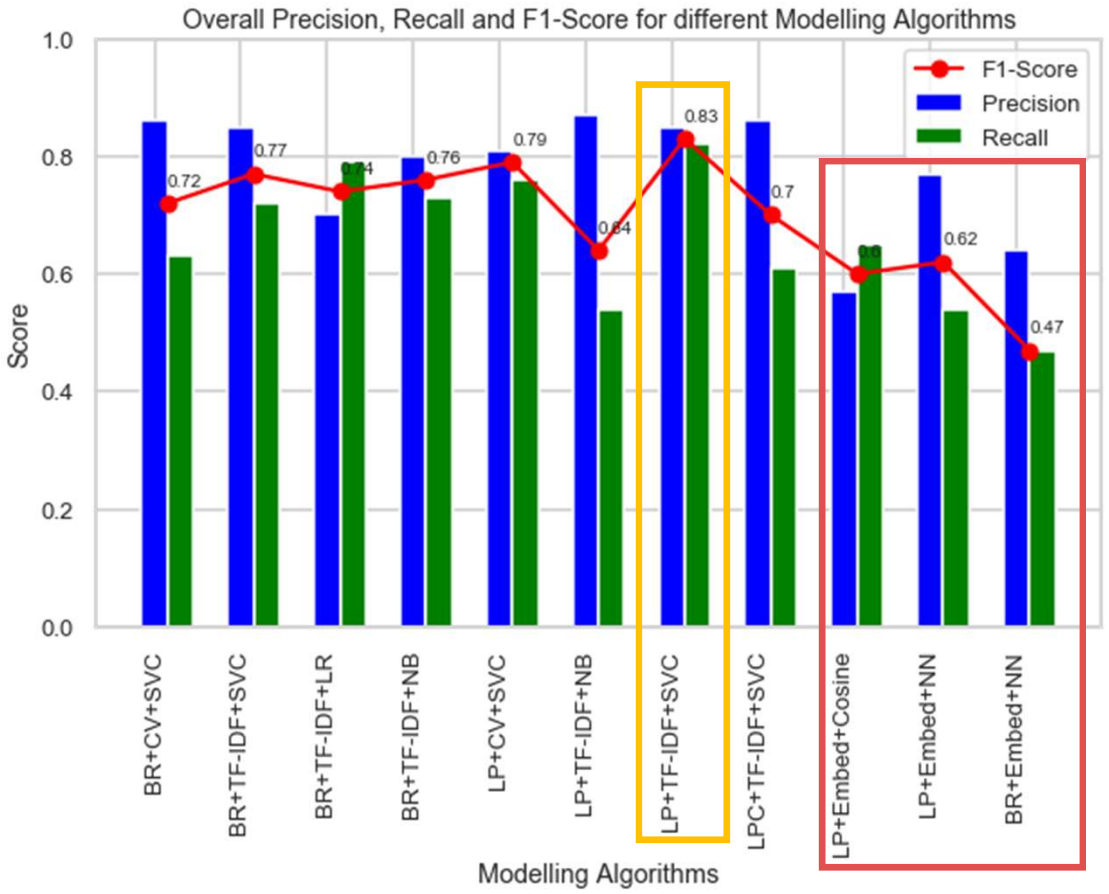
- Output Layer = 1505 Neurons
- Use softmax Activation Function since a single class is predicted

# Result Summary

- Best predicting Model: Label Powerset + TF-IDF + Linear SVC (Overall F1-Score = 0.83)
- Models using Sentence Embedding performance is worse compared to other Vectorizers and ML models

BR: Binary Relevance
LP: Label Powerset
LPC: Label Powerset with Clustering
CV: Count Vectorizer
Embed: Sentence Embedding via USE

SVC: Linear Support Vector Classifier
LR: Logistic Regression
NB: Naïve Bayes
Cosine: Cosine Similarity
NN: Neural Networks



# Label Powerset + TF-IDF + Linear SVC

- Hyperparameters
  - TF-IDF
    - Ngram = (1, 2)
    - Min_df = 2
    - Max_df = 0.5
  - LinearSVC
    - C = 10
- Overall F1-score = 0.83
- Poorest performing Genre = Adult
  - F1-score = 0.32, but only 11 samples

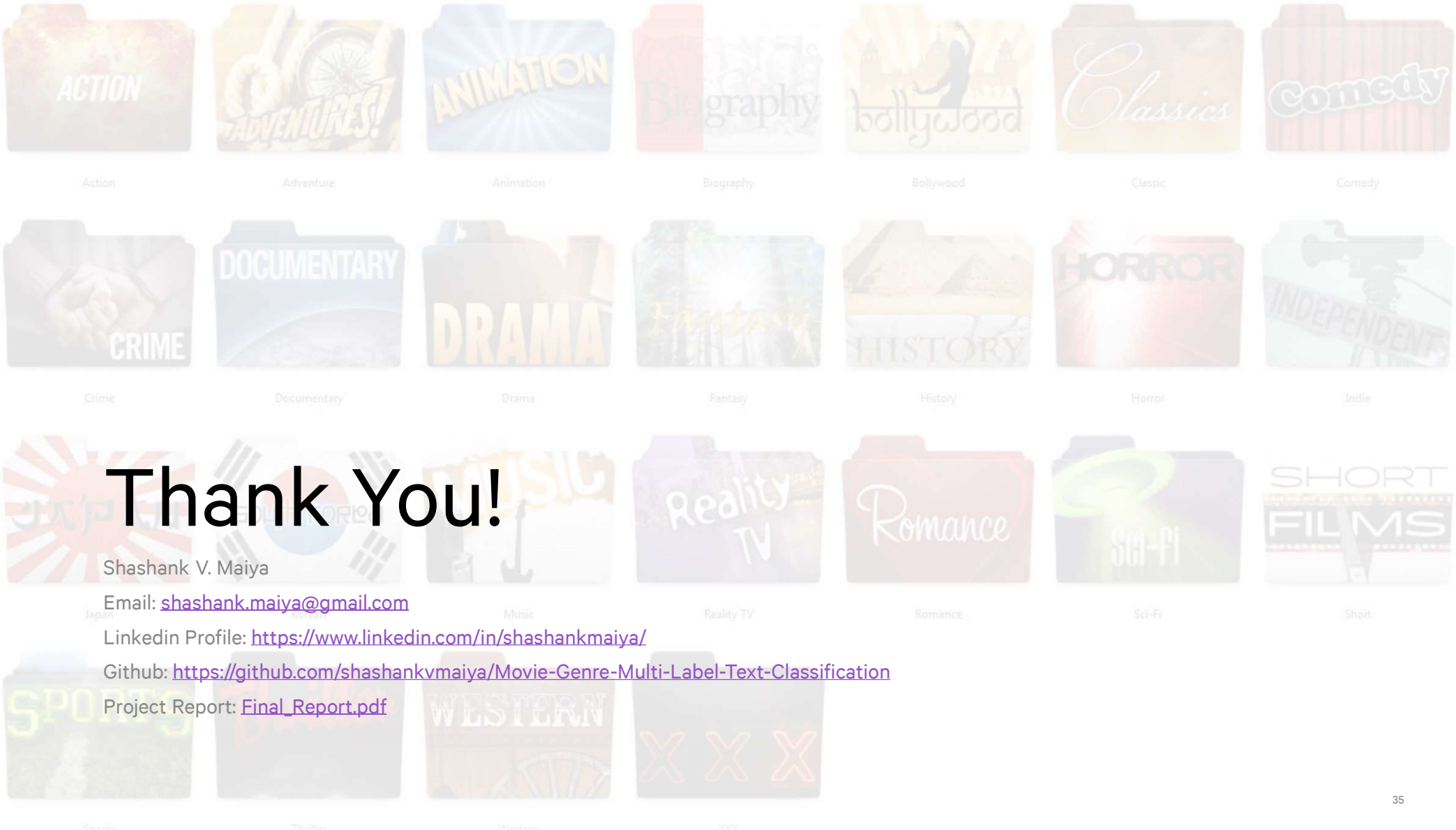
| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Action | 0.87 | 0.82 | 0.84 | 4321.0 |
| Adult | 0.38 | 0.27 | 0.32 | 11.0 |
| Adventure | 0.85 | 0.80 | 0.82 | 3496.0 |
| Animation | 0.86 | 0.84 | 0.85 | 3333.0 |
| Biography | 0.54 | 0.43 | 0.48 | 354.0 |
| Comedy | 0.87 | 0.84 | 0.85 | 7320.0 |
| Crime | 0.86 | 0.86 | 0.86 | 4453.0 |
| Documentary | 0.72 | 0.73 | 0.73 | 1863.0 |
| Drama | 0.91 | 0.87 | 0.89 | 11067.0 |
| Family | 0.82 | 0.84 | 0.83 | 4173.0 |
| Fantasy | 0.86 | 0.78 | 0.81 | 2643.0 |
| Game-Show | 0.79 | 0.90 | 0.85 | 450.0 |
| History | 0.64 | 0.65 | 0.65 | 623.0 |
| Horror | 0.75 | 0.60 | 0.67 | 854.0 |
| Music | 0.76 | 0.80 | 0.78 | 654.0 |
| Musical | 0.75 | 0.65 | 0.70 | 182.0 |
| Mystery | 0.85 | 0.80 | 0.82 | 4114.0 |
| News | 0.76 | 0.80 | 0.78 | 681.0 |
| Reality-TV | 0.80 | 0.78 | 0.79 | 1748.0 |
| Romance | 0.87 | 0.86 | 0.87 | 4581.0 |
| Sci-Fi | 0.88 | 0.80 | 0.84 | 3055.0 |
| Short | 0.53 | 0.40 | 0.46 | 142.0 |
| Sport | 0.75 | 0.78 | 0.76 | 426.0 |
| Talk-Show | 0.77 | 0.86 | 0.81 | 809.0 |
| Thriller | 0.84 | 0.73 | 0.78 | 3254.0 |
| War | 0.74 | 0.71 | 0.72 | 388.0 |
| Western | 0.68 | 0.85 | 0.75 | 445.0 |
| Avg/Total | 0.85 | 0.82 | 0.83 | 65440.0 |

# Conclusions

- Out of the 11 models considered, the best predicting model uses TF-IDF Vectorizer, Linear Support Vector Classifier and Label Powerset approach to achieve an overall F1-score of 0.83
- Sentence Embedding doesn't provide any benefit
- EDA specific Observations
  - Drama and Comedy the most popular Genre
  - On an average, a movie is classified into 2 genres (and a maximum of 12 genres)
  - Few strongly correlated genres include – a) Crime, Mystery & Thriller, b) Drama & Romance
  - 80% of Crime, Mystery and Thriller movies are also categorized as Drama

# Limitations and Ideas

- Improving Sentence Embedding
  - Sentence embedding doesn't require the sentence lemmatization, or stop word removal, or in fact any of the text preprocessing steps. Use the original text before preprocessing to obtain sentence embedding




# Thank You!

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Github: https://github.com/shashankvmaiya/Movie-Genre-Multi-Label-Text-Classification

Project Report: Final_Report.pdf