Genre Prediction for TV Series

Zübeyir Bodur
Computer Engineering
Bilkent University
Ankara, Turkey
zubeyir.bodur@ug.bilkent.edu.tr

Alperen Öziş
Computer Engineering
Bilkent University
Ankara, Turkey
alperen.ozis@ug.bilkent.edu.tr

***Abstract*—We aim to examine the performance of neural networks designed for multi-label classification task, by training them with a dataset of different context, tuning the hyperparameters accordingly. In our case, the multi-label classification task is predicting the genres of TV series, by using a neural network designed for predicting the genres of movies. The dataset consists of 6803 posters of TV series, which classifies those posters in different genres in multi-hot encoded format. The model consists of 7 layers, where first 4 of them are convolutional neural networks, followed by fully connected neural networks. It uses Adam optimizer, categorical cross-entropy loss and inverted dropout as well. By tuning the learning rate and shrink ratios of the posters, we will train the model and gather our results.**

***Index Terms*—neural networks, classification, computer vision, genre prediction, model**

I. Introduction

Our mind can work both non-deterministic and deterministic, therefore we can easily make predictions with or without having enough prior knowledge on what we are predicting. Computers, on the other hand, can not make such decisions that easily. Depending on the application, they will need a set of data, large or small, to make such predictions. Some of the applications have scarce data, therefore methods that require less data were developed, such as conjoint data analysis. For example, using this method, we can predict the rank of another computer by using the rankings of computers ranked by a customer, who ranked as less as 16 computers [1]. This is because we have several features about those computers, such as the processing power, memory size, other than their name or brand.

Multi-label classification, however, is a task where large amount of data can be found. For example, in order to classify set of images of animals, we can easily find hundreds of thousands of images of cats, dogs, or any specific animal image. However, only data we have in this problem is the image of an animal itself. Therefore, in addition to ease of finding data on this task, the models being developed also require large data, a model that was trained with only hundreds of movie posters would be unsuccessful, as there would be a lot of bias and error due to data scarcity, and trained model would be less random. For solving multi-label classification and other problems that require data, there have been various methods developed. Using Neural Networks (NN) have become a common practice as of 2022.

Genre prediction is also a multi-label classification task. So far, There have been various methods developed, in which using NNs become common. However, it is still questionable that a genre predictor that is developed for one domain can be applied to another domain. In this paper, we aim to answer this question by using a NN that was developed for genre prediction of movies, and by training and testing this model with a dataset of TV series, and discuss the results.

II. Related Literature

One of the earliest works for classifying a dataset for genre prediction was developed by Z. Rasheed and M. Shaah in 2002 [2]. The data to be classified was trailers of movies. Using features such as average shot length and visual disturbence in the scenes, they were able to classify movies into action and non-action. Then, they did further classification into non-action movies, and were able to subclass those non-action movies into horror, comedy and drama or other as well, by looking at the distribution of light in those trailers [2].

Later, in 2014, M. Ivasic-Kos, M. Pobar and L. Mikec tried to classify images of movie posters into genres [3]. They examined the low-level features of those posters, such as edges and colors to classify posters into 6 different genres, using a dataset of 1,500 movie posters. Later, in 2015, M. Ivasic-Kos, M. Pobar, and I. Ipsic tried this on 6,000 posters, but they used algorithms such as K-Nearest Neighbours (KNN), Random K-Labelsets (RAKEL), and Naïve Bayes. This way, they were able to transform multi-label classes into multiple single-label classifications [4].

First approach that used neural networks (NN) was introduced by S. Kjartansson and A. Ashavsky [5]. In their paper, they discuss genre classification of books. They used a dataset of 19,000 books which were classified into 10 genres. In addition to the covers of the books, they also had another dataset for titles of the images, since they also used these to predict the book's genre. As their approach, they used numerous methods and tested each of those methods, namely Fully Connected Networks (FCN), Convolutional Pool Networks, SqueezeNet, VGG-16 and 5 more methods.

In 2017, an interesting paper, written by W. Chu and H, Guo, objects detected in a movie poster were also considered by using YOLO object detection in the NN, which was trained with IMDb movie dataset [6]. However, the accuracy of the model were as low as 19 %.

Currently, there are plenty of open source repositories in GitHub and datasets in Kaggle, where genre classification problem is attempted to be solved [7]. One of them was Nirman Dave, who tried to mimic a mini-VGG styled network using 7 layers. The results were promising, however, within their hyperparameters, the model achieved 51 % accuracy in their predictions [8].

III. Approach

The approach we will be using for predicting the genres of TV series from their posters is to use Nirman Dave's model [8], which was previously designed for movies.

A. Architecture

The model consists of 4 convolution layers, followed by 3 fully connected layers. The layers were sequentially placed as follows:

$$ConvLayer1(size = 3x3, filters = 32) \rightarrow$$
$$Max - Pool(size = 2x2) \rightarrow$$

$$ConvLayer2(size = 3x3, filters = 32) \rightarrow$$
$$Max - Pool(size = 2x2) \rightarrow$$

$$ConvLayer3(size = 3x3, filters = 32) \rightarrow$$
$$Max - Pool(size = 2x2) \rightarrow$$

$$ConvLayer4(size = 3x3, filters = 64) \rightarrow$$
$$Max - Pool(size = 2x2) \rightarrow$$

$$FullyConnectedLayer(size = 64) \rightarrow$$
$$Dropout(probability = 0.5) \rightarrow$$

$$FullyConnectedLayer(size = 32) \rightarrow$$
$$Dropout(probability = 0.5) \rightarrow$$

$$FullyConnectedLayer(size = num\_classes)$$

The activation function used for the first 6 layers are the Rectified Linear Unit function (ReLU) in Equation 1 to introduce non-linearity in the network. Functions such as sigmoid, tanh were not preferred as they may cause the gradient of the loss function to vanish.

$$f(x) = \begin{cases} 0 & x < 0 \\ x & x \geq 0 \end{cases} \tag{1}$$

The last layer uses a soft-max activation, so that output is a $num\_classes$ dimensional vector, where each number, $P_i(I)$, in the closed interval [0,1], which denotes the probability if a TV series whose poster $I_{m,n}$ is given belongs to $genre_i$. The $num\_classes$), and what those classes (genres) are selected in consideration of the exploratory analysis of the dataset in section IV-B.

Since we are using the soft-max function to compute the possibility, the output will sort the genres according to their likelihoods of having a genre as its main genre. Therefore, due to this reduction from multi-label classification to single-label classification, we will choose our genres so that those chosen genres have minimum co-occurrence in section IV-A.

B. Optimization

Optimizers, or solvers, in neural networks help us learn the model weights using different algorithms. For this project, we will not change the solver that was used in the previous model [8], which is a well-known stochastic optimization called Adam [9].

The reason for not changing the optimizer is that Dave uses this optimizer as it works well on data with noisy gradients, like poster image data. In addition, it is a common practice to use Adam for large problems, like image classification.

Adam optimizer is defined as follows. At epoch t the first and second raw moment (m_t and v_t) of the gradient (dx) and gradient squared (dx^2) of the loss functions are computed. Then, the biased estimators of those moments are computed with respect to the current epoch. Then the model weights w_t is updated with respect to the given learning rate (η). To prevent the division by zero, a non-zero number (ϵ) is used [10], [11]:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) dx \tag{2}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) dx^2 \tag{3}$$

$$\hat{m_t} = \frac{m_t}{1 - \beta_1^t} \tag{4}$$

$$\hat{v_t} = \frac{v_t}{1 - \beta_2^t} \tag{5}$$

$$w_t = w_{t-1} - \eta \frac{\hat{m_t}}{\sqrt{\hat{v_t} + \epsilon}} \tag{6}$$

C. Loss Function

Loss is a summation of errors for each data point made by training and validation set. The idea is minimize this loss function. Since the problem is still an multi-label classification problem, we did not change the loss function in the previous model, namely Categorical Cross-entropy Loss (CC Loss), since genres in TV series are still multi-hot encoded vectors, that is a TV show can have more than one genre [9].

CC Loss measures the average number of bits needed to identify an event drawn from a set [9]. In this case, this event is the correct set of genres for a given TV series poster, and the bits are genres for which a given poster is predicted. CC Loss is defined by:

$$CCLoss = -\sum_{i=1}^{num\_classes} x_i \cdot log_2(\hat{x_i}) \tag{7}$$

where $\hat{x}$ is a $num\_classes$ dimensional vector of predicted probabilities, and x is the vector of ground truth values, where $\forall \hat{x_i} \in [0, 1]; \forall x_i \in \{0, 1\}$ [12].

D. Regularization

Regularization is a process of reducing overfitting in the neural network. In this project, we will keep using Inverted Dropout method from the model we are using.

Inverted Dropout method drops-out randomly chosen units in a neural network at a probability $p : dropout\_rate$. By dropping randomly selected units, interdependent learning among the neurons and overfitting can be reduced [13]. For this project, we will keep using the same dropout rate $p = 0.5$ and will not use Inverted Dropout on the test set.

E. Hyperparameters

The model obviously has several hyperparameters. However, in this project, we will fix the following:

- Dropout rate, $p = 0.5$
- Number of layers, 7.
- Activation functions. ReLU is a stable activation function. Other activation functions such as LeakyReLU or Parametric ReLU could be used, however, they may introduce more parameters to be tuned or may not improve the accuracy significantly.
- Batch size, fixed at 32.
- Number of epochs, fixed at 20.
- Decay rates for exponential moving averages of m and v, namely β_1 and β_2. Fixed at $\beta_1 = 0.9$, $\beta_2 = 0.999$
- Epsilon, fixed at $\epsilon = 10^{-8}$.

The following hyperparameters will be tuned:

a) Learning Rate (η): Learning rate is the η value in the Adam optimizer discussed in III-B. The original paper which introduces Adam optimizer recommends the default value of learning rate to be $\eta = 10^{-3}$ [9]. We will tune the learning rate for the values in the set $[5 \cdot 10^{-4}, 10^{-4}, 5 \cdot 10^{-5}]$, while Dave's model tunes for the values in the set $[10^{-3}, 10^{-4}, 10^{-5}, 10^{-6}, 10^{-7}]$ [9].

b) Input image size: Originally, the model aims to see if the CNN can pick up on granular details on images that are less shrunk, meaning the model will always be trained on shrunken images [9]. In this project, our dataset have varying input sizes, ranging from 300x200 to 2000x4000. So, we have resized the images to the size 182x268, then we have trained the in the following shrinking rates: [37, 44, 51].

TABLE I
SHRUNKEN IMAGE SIZES

Shrink Ratio (%)	Size (pixels)
37	67 x 99
44	80 x 118
51	93 x 137

IV. EXPERIMENT

As the purpose of the project suggests, we are using a dataset of TV series, which includes their genres and posters.

A. Dataset

We were not able to find a ready-to-use dataset that contained TV series posters together with their genres. So we decided to create our own dataset using IMDb database [14] and a Python library which allows us to fetch data from IMDb. We joined some of the tables in the database and selected unique ids of the TV series with the following constraints:

- is a TV Show
- released after 1950
- has at least 1000 votes cast

Then using these ids and the IMDbPY library [15] we retrieved genres and poster image URLs of the TV series. and then finally we have downloaded the poster images. The dataset with which we are going to train the model consists of 6803 images of posters of TV series. We have a csv file which has a row for every movie containing the $uniqueId$ and the $genres$ related to that series. And then in a folder we have our poster images who are named with with their ids. As explained in III-A, we have resized the images while preprocessing the data.

B. Exploratory Data Analysis

In this step, we have examined our dataset to find the best choices of classes to pick for predictions. The goal is to find the choices where the co-occurrence of these genres are minimized. First, we have plotted the number of TV shows for each genre in Fig. 3. By looking at this plot we can observe that almost half of the TV shows are Drama or Comedy, therefore, we did not choose these two as our target genres.

Next, we have plotted the heat map of co-occurrence of each genre. Here, we can observe that there are genres that co-occur with each other and genres that do not co-occur with each other. However, in order to get a large data size, we also needed to pick the genres with large number of TV shows. Therefore, starting from the left hand side of the plot in Fig. 3, we have added the genres that co-occur the least with the current list of target genres. To do this, we have also plotted 26 plots for showing how much of a genre co-occur with other genres in percents. The genres chosen had the plots in Fig. 2-4. By examining all these 3 types of plots, we have decided to choose Romance, Action, Horror, Documentary, and Reality-TV shows as our target genres. With this step, we were able to add one more class to our list of target genres compared to the previous model.

V. RESULTS

For the training step, the data set was split into 3 folds, training data, 60 %, validation data, 30 % and test data, 10 %.

A. Training and Validation Results

In Fig. 5-13, the training and validation accuracies are plotted. We can observe that, for the configuration where the learning rate is 0.0005 and the shrink ratio is 44 %, it have achieved the best validation accuracy of 37.8 % and training accuracy of 38 % at epoch 10. Since we have saved the models so that the best epoch is saved, instead of the last epoch, we will use this configuration for the predictions.

B. Sample Predictions

In figures 1 and 2 are some of the sample predictions we obtained using the best model we trained. Given an image of a poster, it predicts the probabilities of categories.

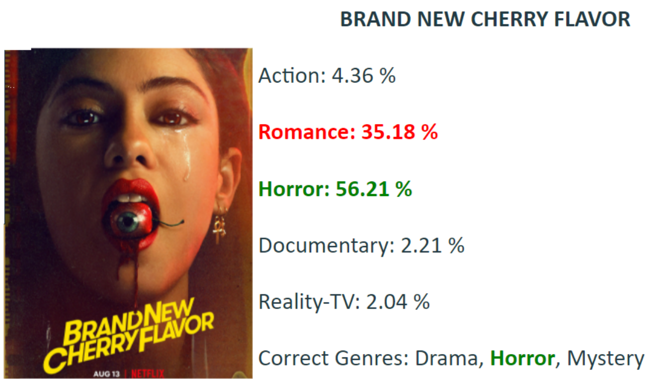


Fig. 1. Sample Prediction 1

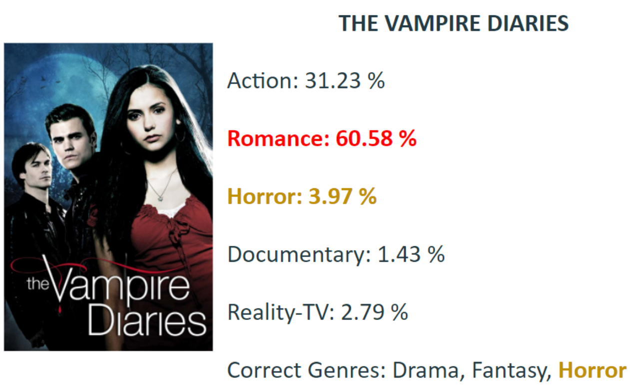


Fig. 2. Sample Prediction 2

C. Conclusion

This project is a good example of why all image classification tasks are the same. In fact, genre prediction tasks is rather challenging. Despite all the work done in exploratory data analysis stage, where we have found the genre set with minimum co-occurrence, the accuracy was lower than the original model's. However, it should be noted that the size of the training set was 5 times smaller than the original model, as we are using these models on a smaller and filtered data set. What's more, with a data set 5 times smaller, our model was able to get approximately 78 % performance of the original model.

One more reason why this task does not have accuracies as high as a handwritten digit recognition could be that the relation between a TV Show poster, or a movie poster is not as strong as other classification tasks. In addition, it is a challenging task for even humans; one might think that the TV Show Breaking Bad can have Horror as it's main genre, if they had no knowledge of the show.

References

[1] S. Dayanık, ”Traditional Conjoint (or Trade-off) Analysis and Market Simulation”, pp. 1-10, Mar. 15, 2022. [Online]. [Accessed Mar. 23, 2022].
[2] Rasheed, Zeeshan & Shah, Mubarak. (2002). Movie Genre Classification By Exploiting Audio-Visual Features Of Previews. 2. 10.1109/ICPR.2002.1048494.
[3] Ivašić-Kos, Marina & Pobar, Miran & Mikec, Luka. (2014). Movie posters classification into genres based on low-level features. 1198-1203. 10.1109/MIPRO.2014.6859750.
[4] Ivašić-Kos, Marina & Pobar, Miran & Ipsic, Ivo. (2015). Automatic Movie Posters Classification into Genres. Advances in Intelligent Systems and Computing. 311. 319-328. 10.1007/978-3-319-09879-1_32.
[5] Kjartansson, Sigtryggur & Ashavsky, Alexander. (2017). Can you Judge a Book by its Cover? Retrieved from http://cs231n.stanford.edu/reports/2017/pdfs/814.pdf
[6] Chu, Wei-Ta & Guo, Hung-Jui. (2017). Movie Genre Classification based on Poster Images with Deep Neural Networks. 39-45. 10.1145/3132515.3132516.
[7] J. Zhou, “Genre classification on movie posters,” www.linkedin.com. https://www.linkedin.com/pulse/genre-classification-movie-posters-jianda-zhou/ [Accessed 27-Mar-2022]
[8] N. Dave, “Movie Genre Prediction,” GitHub. [Online]. Available: https://github.com/nddave/Movie-Genre-Prediction [Accessed 27-Mar-2022]
[9] N. Dave, “Movie Genre Prediction,” GitHub. [Online]. Available: https://github.com/nddave/Movie-Genre-Prediction/blob/master/paper/predicting-movie-genres-paper.pdf [Accessed 27-Mar-2022]
[10] D. Kingma and J. Lei Ba, “Adam: A Method For Stochastic Optimization,” ICLR 2015. [Online]. Available: https://arxiv.org/pdf/1412.6980.pdf. [Accessed: 27-Mar-2022].
[11] Vitaly Bushaev. “Adam, Latest Trends in Deep Learning Optimization.” Towards Data Science, Towards Data Science, 22 Oct. 2018, [Online]. Available: towardsdatascience.com/adam-latest-trends-in-deep-learning-optimization-6be9a291375c.[Accessed: 27-Mar-2022].
[12] “Categorical Crossentropy Loss Function.” [Online]. Available: peltarion.com/knowledge-center/documentation/modeling-view/build-an-ai-model/loss-functions/categorical-crossentropy. [Accessed: 27-Mar-2022].
[13] N. Srivastava, G. Hinton, A. Krizhevsky, and R. Salakhutdinov, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting,” Journal of Machine Learning Research, vol. 15, pp. 1929–1958, 2014, Accessed: Aug. 11, 2020. [Online]. Available: https://jmlr.org/papers/volume15/srivastava14a.old/srivastava14a.pdf/ [Accessed: 27-Mar-2022].
[14] ”Tables From IMDB Database”. [Online]. Available: https://datasets.imdbws.com/ [Accessed: 27-Mar-2022].
[15] “Cinemagoer (previously known as imdbpy).” [Online]. Available: https://cinemagoer.github.io/. [Accessed: 27-Mar-2022].

Appendix

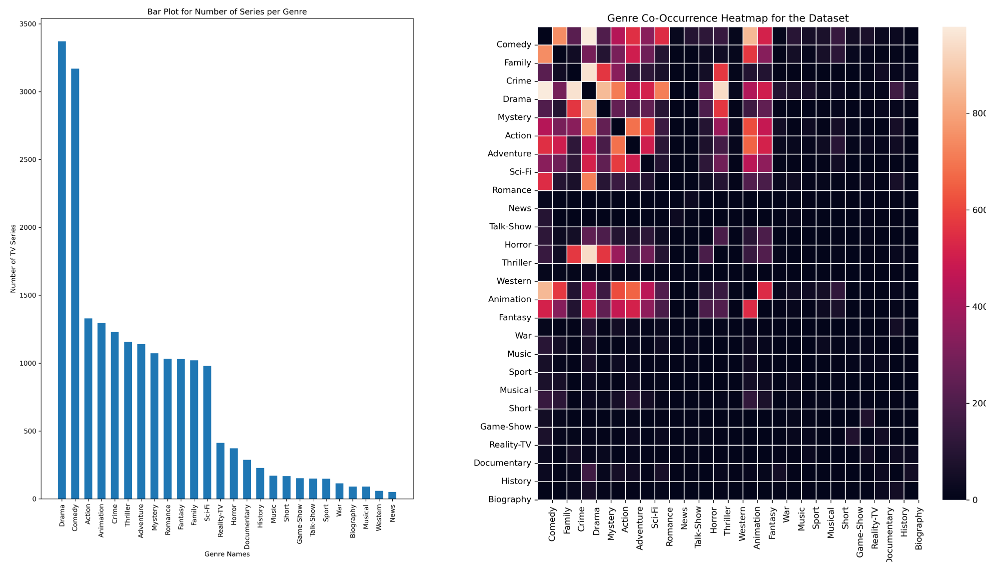


Fig. 3. Bar plot of the dataset that shows the frequency of each genre (left), and the co-occurrence heat-map of the dataset (right)

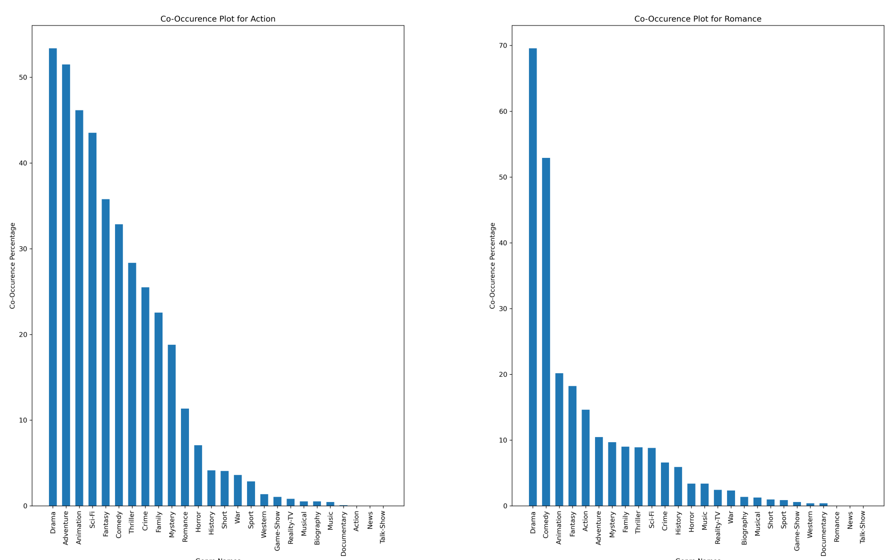


Fig. 4. Bar plot of the co-occurrence of Action (left) and Romance (right) genres with respect to the rest of the genres

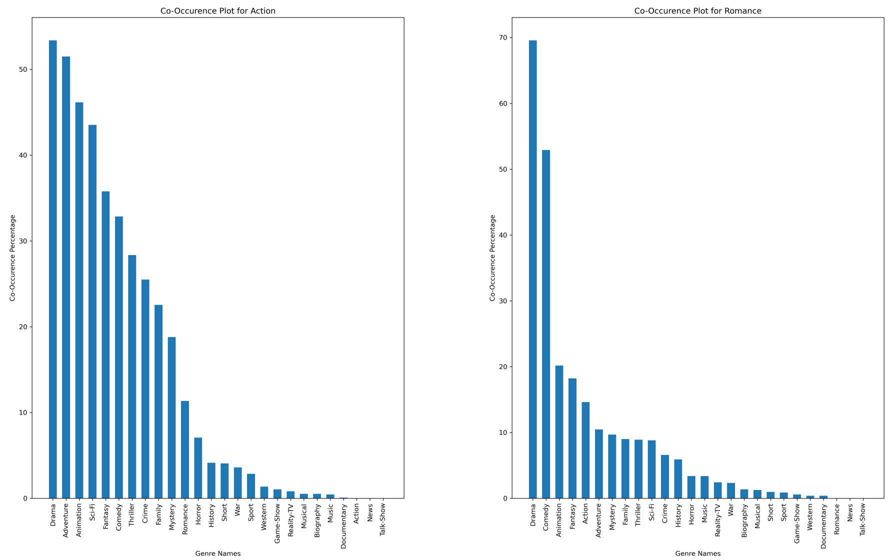


Fig. 5. Bar plot of the co-occurrence of Documentary (left) and Horror (right) genres with respect to the rest of the genres

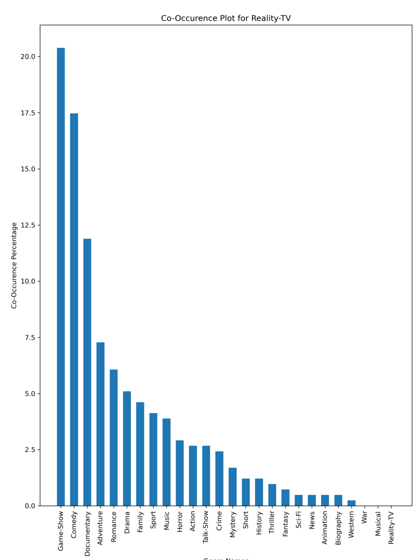


Fig. 6. Bar plot of the co-occurrence of Documentary genre with respect to the rest of the genres

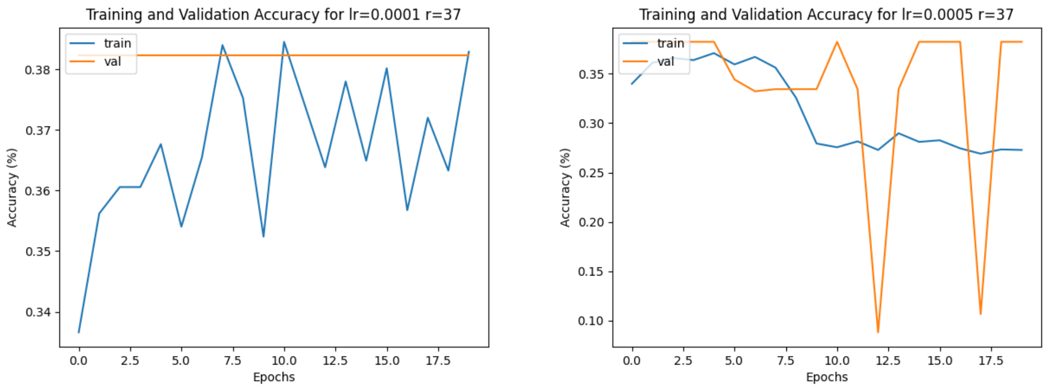


Fig. 7. Training and validation accuracies for the given settings, where the learning rate and the shrink ratio is (0.0001, 37 %) (left) and (0.0005, 37 %) (right)

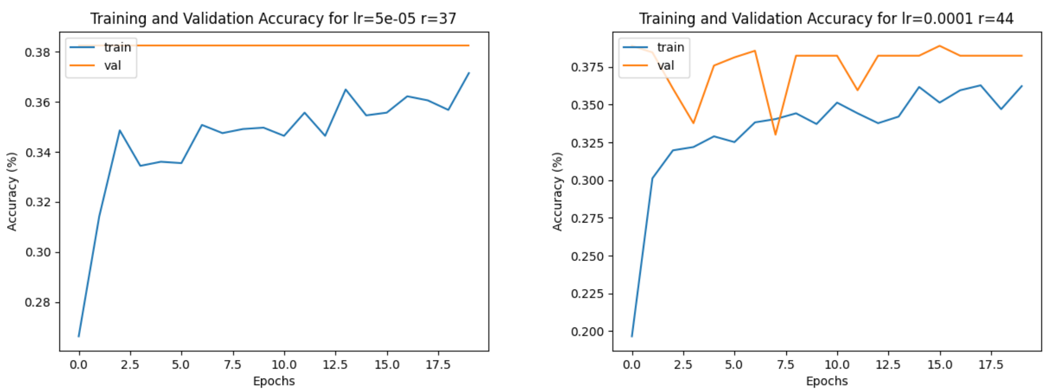


Fig. 8. Training and validation accuracies for the given settings, where the learning rate and the shrink ratio is (0.00005, 37 %) (left) and (0.0001, 44 %) (right)

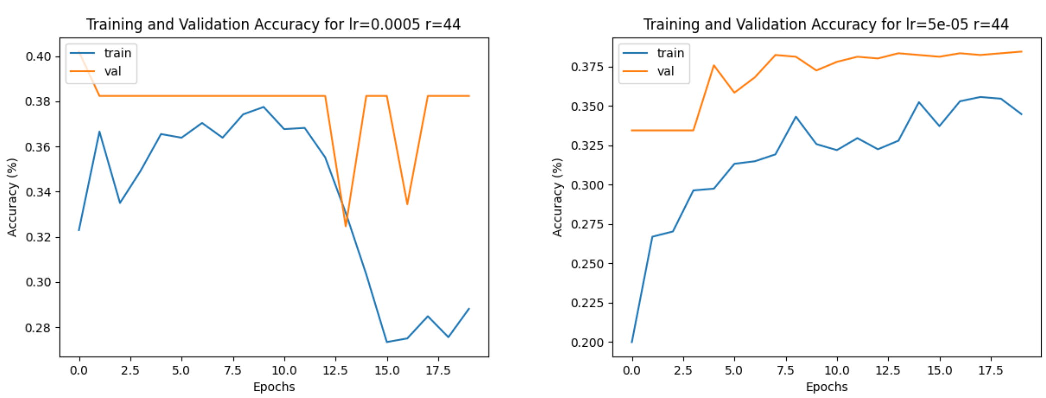
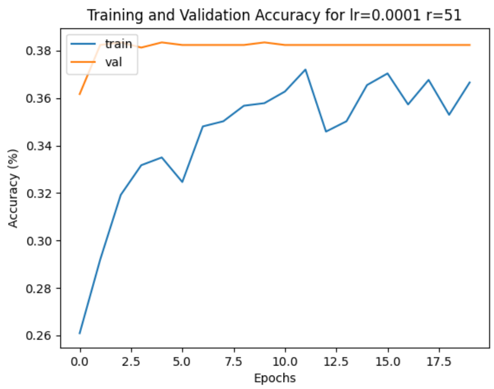


Fig. 9. Training and validation accuracies for the given settings, where the learning rate and the shrink ratio is (0.0005, 44 %) (left) and (0.00005, 44 %) (right)



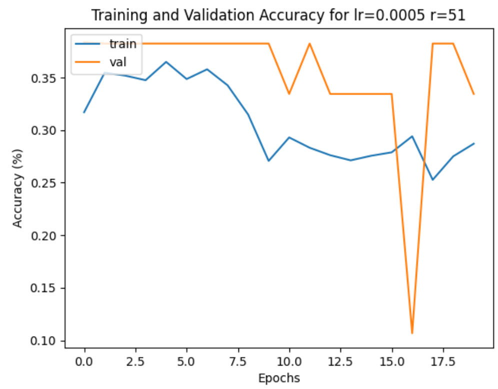


Fig. 10. Training and validation accuracies for the given settings, where the learning rate and the shrink ratio is (0.0001, 51 %) (left) and (0.0005, 51 %) (right)

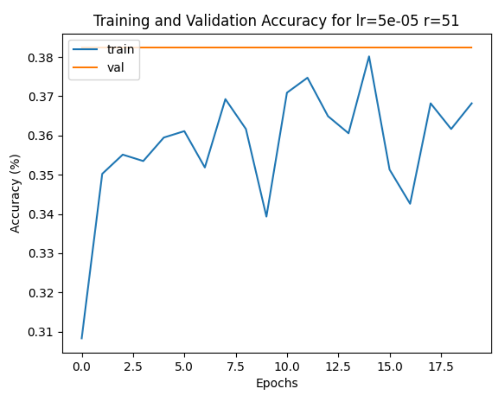


Fig. 11. Training and validation accuracies for the given setting, where the learning rate and the shrink ratio is (0.00005, 51 %)