Movie Poster Genre Prediction

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Context

Context

Nature of the problem:
Multi-label Classification

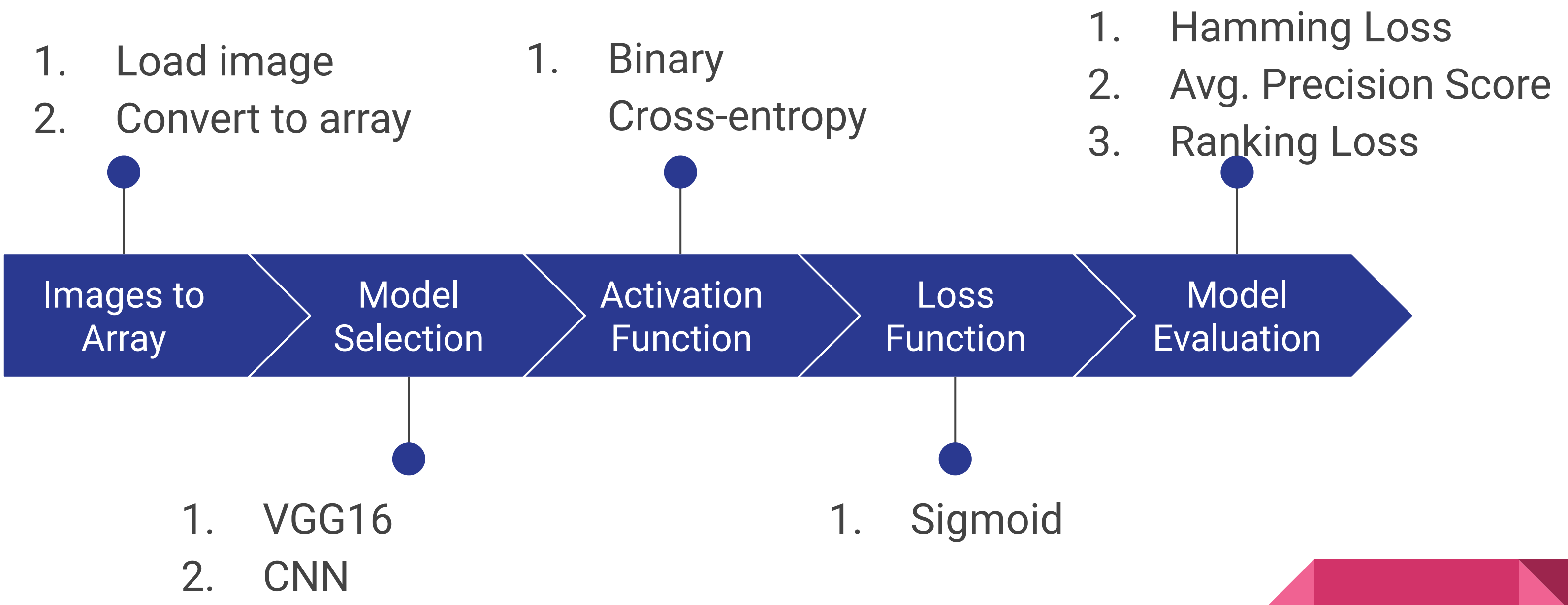
Problem Statement:
Are we able to predict the labelled set of unseen posters through analysing training instances with a known labelled set?

Dataset:
Labelled genre movie poster dataset with respective images from *Wei-Ta Chu and Hung-Jui Guo*

Total of 25 genres *(-2)* with 552 permutations *(193 unique)*

Implementation

Process



1. Load image
2. Convert to array
Images to Array
Model Selection
1. VGG16
2. CNN
1. Binary Cross-entropy
Activation Function
Loss Function
1. Sigmoid
1. Hamming Loss
2. Avg. Precision Score
3. Ranking Loss
Model Evaluation

Breaking It Down - Preprocessing

Images to Array:

1. Load & resize image

2. Convert loaded images in PIL format into a *Numpy* array

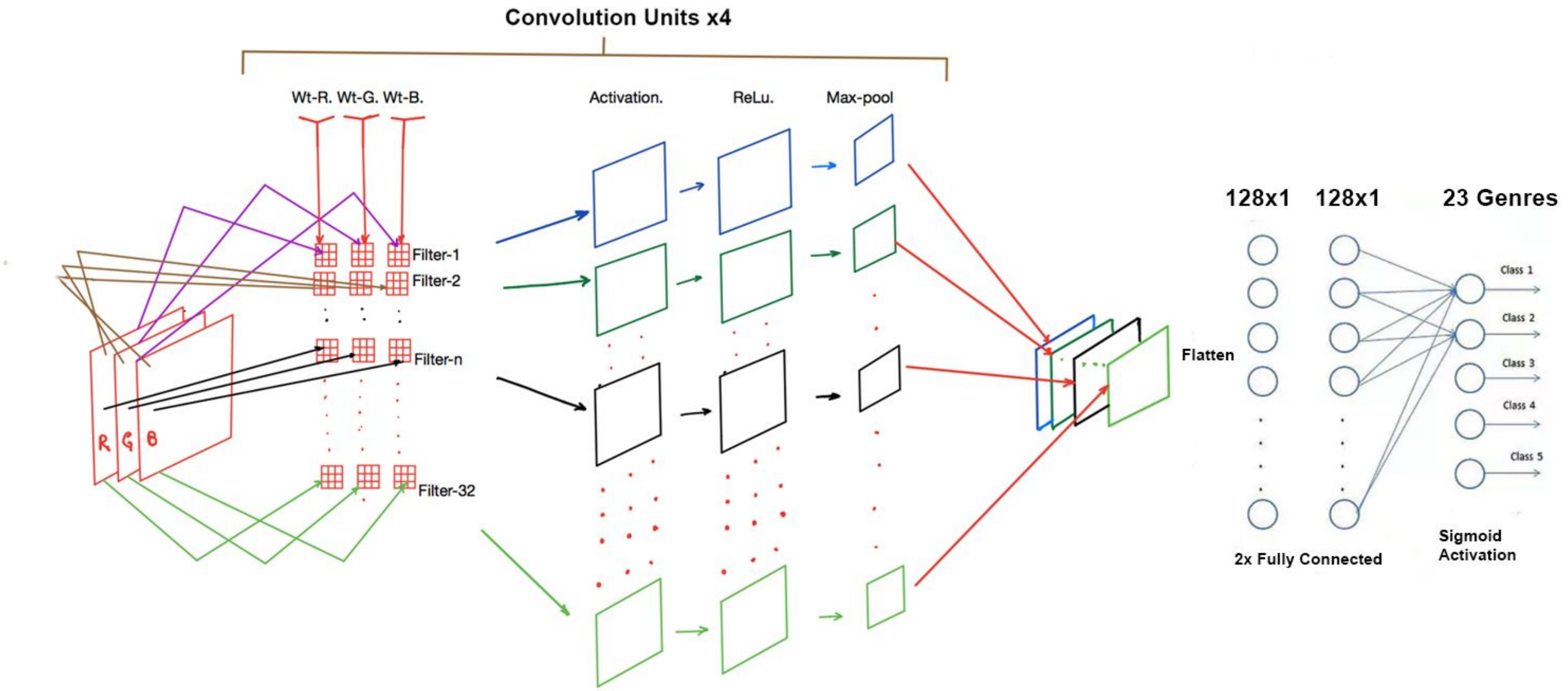
3. Divide by colour range for each channel

Setting up X and y:

X - Images converted to arrays

y - MHE labelled dataset *(Label vector)*

Breaking It Down - CNN Architecture

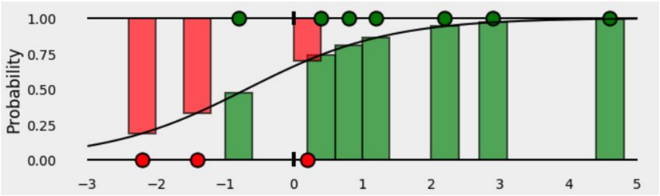


Breaking It Down - Activation & Loss Functions

Loss Function:

Binary Cross-entropy Loss

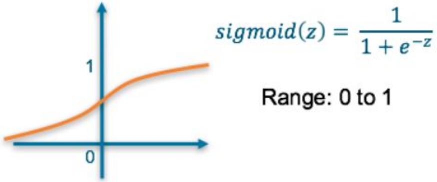
The loss computed for every CNN output vector component is not affected by other component values, it tries to decide for each class whether the example belongs to that class or not



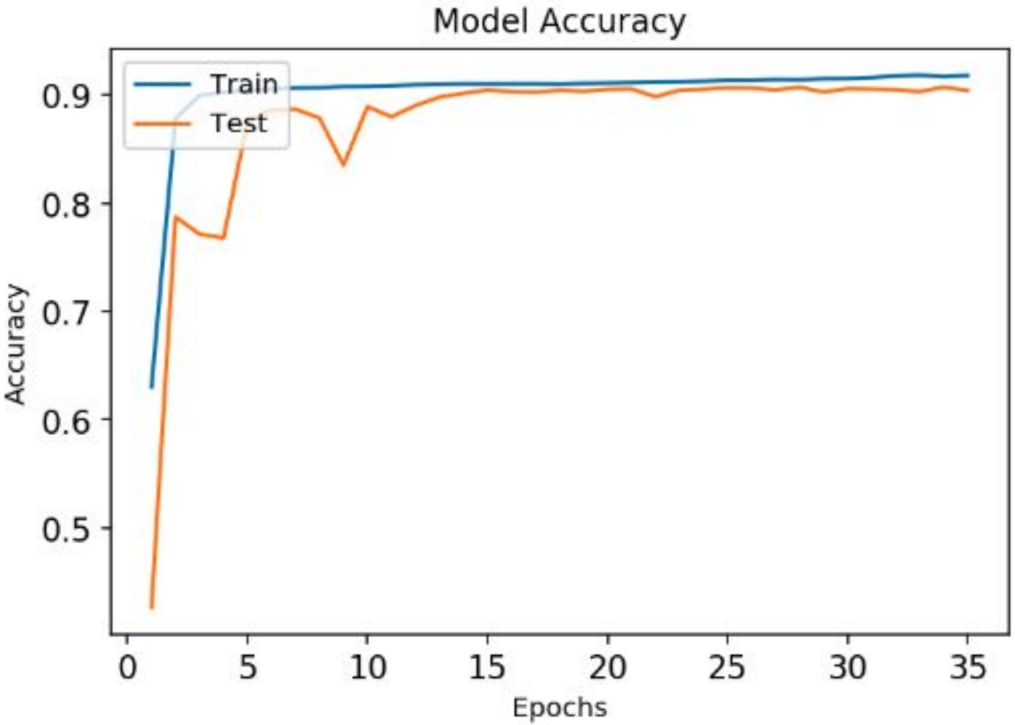
Activation Function:

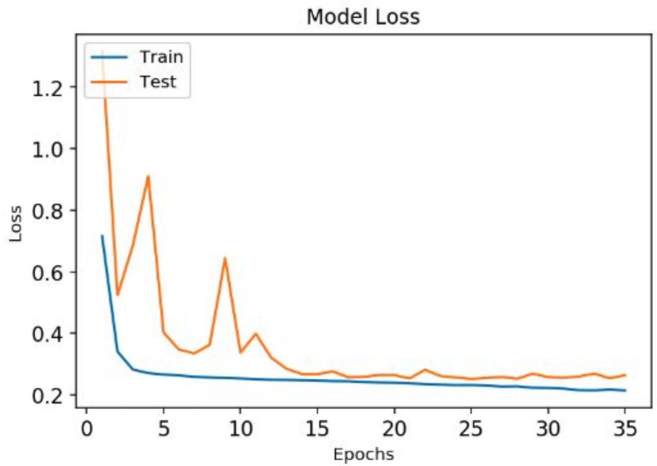
Sigmoid

This allows the model to output a number between 0 and 1 for each label independently. This number indicates the probability that the corresponding attribute is present in the image



Model Accuracy - 0.87



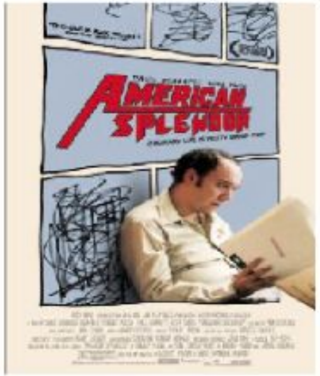



```
Mean Training Accuracy:  0.902
Mean Testing Accuracy:  0.873
Mean Training Loss:  0.257
Mean Testing Loss:  0.361
```

Samples of Model Predictions on Test Images

Genre Predictions:
Drama (0.704)
Comedy (0.372)
Romance (0.259)
Crime (0.134)

Movie Title: American Splendor
Actual Genres: Biography | Comedy | Drama



Genre Predictions:
Drama (0.536)
Thriller (0.271)
Action (0.233)
Crime (0.224)

Movie Title: Answers To Nothing
Actual: Drama | Mystery | Romance

Genre Predictions:
Action (0.581)
Thriller (0.357)
Drama (0.289)
Sci-Fi (0.224)

Movie Title: Inspector Gadget
Actual: Action | Adventure | Comedy

Genre Predictions:
Horror (0.379)
Drama (0.272)
Thriller (0.268)
Documentary (0.243)

Movie Title: Quaruntine
Actual: Horror | Thriller

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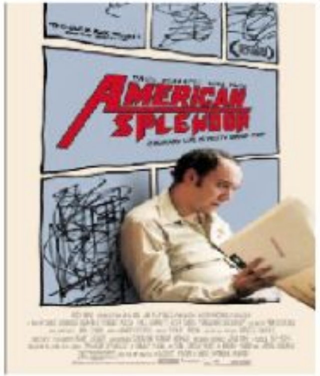

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Samples of Model Predictions on Unseen

```
Genre Predictions:
Drama (0.616)
Action (0.437)
Crime (0.406)
Thriller (0.297)
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Fast & Furious: Hobbs & Shaw
Actual: Action | Adventure


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Genre Predictions:
Drama (0.663)
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The Voyage of Doctor Dolittle
Actual: Adventure | Comedy | Family


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Genre Predictions:
Drama (0.473)
Thriller (0.249)
Horror (0.242)
Action (0.151)
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Star Wars: The Rise of Skywalker
Actual: Action | Adventure | Fantasy


```
Genre Predictions:
Drama (0.733)
Thriller (0.34)
Crime (0.21)
Mystery (0.175)
```

Halloween Kills
Actual: Horror | Thriller

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Evaluation

Metrics for Model Evaluation

1) Hamming Loss

The fraction of misclassified labels

7/10

2) Avg. Precision

Averages the entire ranking of model predictions

0.19

3) Ranking Loss

The expectation of the mis-rank rate over all possible pairs of labels

2/10

Conclusions

Challenges & Limitations

- The main challenge in multi-label classification is data imbalance
  - Collecting more poster data for under-represented genres will not solve this issue
- Subjective movie labelling by IMDb sources & varied posters for release
- Limited packages to deal with multi-label classification problems i.e *iterative stratification for splitting data effectively, one-error loss etc.*

Learnings

- Transfer learning proved to be of little value in this multi-label problem. A **ConvNet was our model of choice in achieving a high model accuracy** as compared to VGG16
- The activtaion and loss functions, **Sigmoid & Binary Cross-entropy** respectively were crucial in pushing the model's predictions in the right direction. In my experimenting on Colab, I tried numerous combinations like Softmax and Categorical Cross-entropy which achieved maximum accuracy score of 0.6
- Having a **small batch-size of 32** as compared to 64 or 128 also improved model scores
- After 50 or more epochs, there was little progress in decrease in loss
- The main multi-label classification evaluation metrics are **Hamming Loss, Ranking Loss, One-erro**r (which there was no functions for), hence, to produce more angles on final evaluation, I have chosen **Average Precision** as another metric
- **Hamming Loss score of 7/10** indicates that for every 10 classifications, we only have 3 correct. So on average, 1 out of 3 movies are predicted rightly (assuming every movie has 3 genres)
- **Average Precision** looks at the entire rankings predicted across the 23 genres. And having **a score of close to 20%** across 552 permutations of genres, proves to be rather encoruaging
- **Ranking Loss** looks at how the expectation of the mis-rank rate over all possible pairs of labels, which had a **mis-rank rate of 0.2** for possible pairs. Which is good, but has it's limitations since some movies 1 genre, or 3.

Moving Forward

Next Steps

- Conduct SMOTE to severely under/over sample the majority/minority class to create a large number of distinct training sets to increase performance
- Employ iterative stratification of train and test
- Further explore interpretability of the ConvNet
- Deepen understanding of inner workings of the ConvNet

References

Credits to...

- *IMDb*, "Movie Database"
- *Wei-Ta Chu and Hung-Jui Guo*, "Movie Genre Classification based on Poster Images with Deep Neural Networks," Proceedings of International Workshop on Multimodal Understanding of Social, Affective and Subjective Attributes, pp. 39-45, 2017. (in conjunction with ACM Multimedia 2017)
- *Pulkit Sharma*, "Your First Multi-label Image Classficiation"
- *Piotr Szymanski and Tomasz Kajdanowicz*, "A Network Perspective on Stratification of Multi-Label Data"
- *Rafał Grodzicki, Jacek Mańdziuk, and Lipo Wang*, "Improved Multilabel Classification with Neural Networks"
- *Xi-Zhu Wu, Zhi-Hua Zhou*, "A Unified View of Multi-Label Performance Measures"
- *Victor Lavrenko*, "Evaluation 12: mean average precision"
- *Peltarion* "Modeling View"
- *Apil Tamang*, CNN Image
- *Daniel Godoy*, Binary Cross-entropy Image

Thank you.