Movie Genre Classification based on Posters

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Introduction

A movie poster goal is to attract potential moviegoers to watch the movie, hence it conveys information regarding the movie. These qualities of a poster raised the assumption that relevant information about a movie's genre can be described in a low-level features of a poster.

Our goal was to achieve a multi-label genre classification to a movie from its poster, using structured features. We aimed to achieve a model which predicts a list of 3 genres.

Multi-Label adaptation

Our adaption of this multi-label is to create a single model for each label (genre) and train a One Vs All binary classifier.

Algorithms

1. Inference - **Loopy Belief Propagation.**
2. Learning - **Gradient Ascent.**

Data and features

We extracted a dataset of 19,000 movies from 2000-2018 that were classified into 8 genres.

We described a poster as a pixel matrix with HSV (Hue, Saturation, Value) dimensions.

We favored HSV representation over RGB (Red, Green, Blue) one because we learnt that RGB is not very correlated within itself, i.e. similar colors might be dimensionally far from each other.

We down scaled, using Gaussian smoothing, the entire dataset to a fixed size of 44 by 30 pixels.

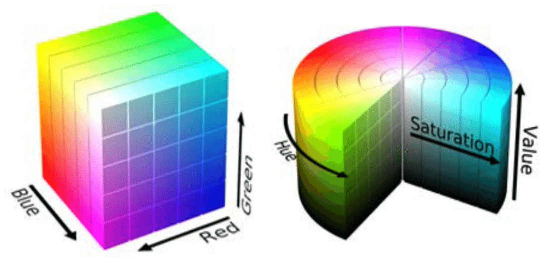


Figure 1. RGB vs. HSV color spaces

The Model

The structured model we used based on splitting the poster into equal-sized non-overlapping blocks. Those blocks will be represented by hidden variables. Each hidden variable is connected to its neighbor blocks (hidden-variables) and can be assigned to a hidden state from a set of hidden states.

Image 1. Basic Model (Horizontal).

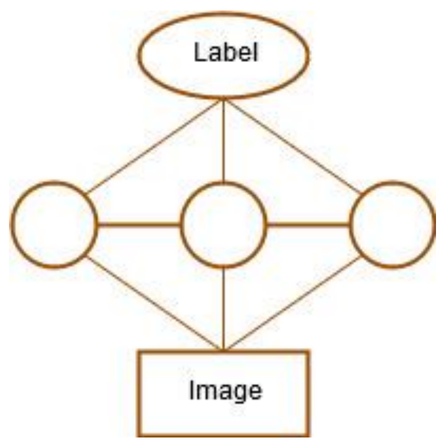


Image 2. Advanced Model.

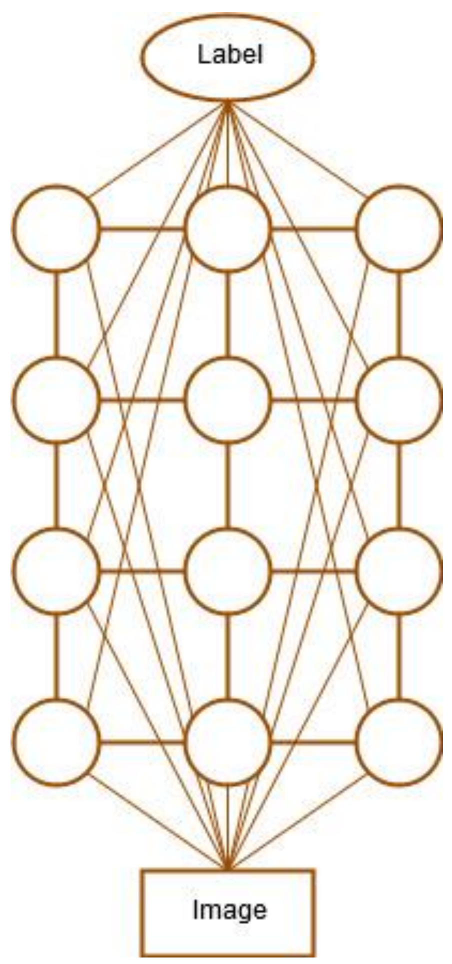
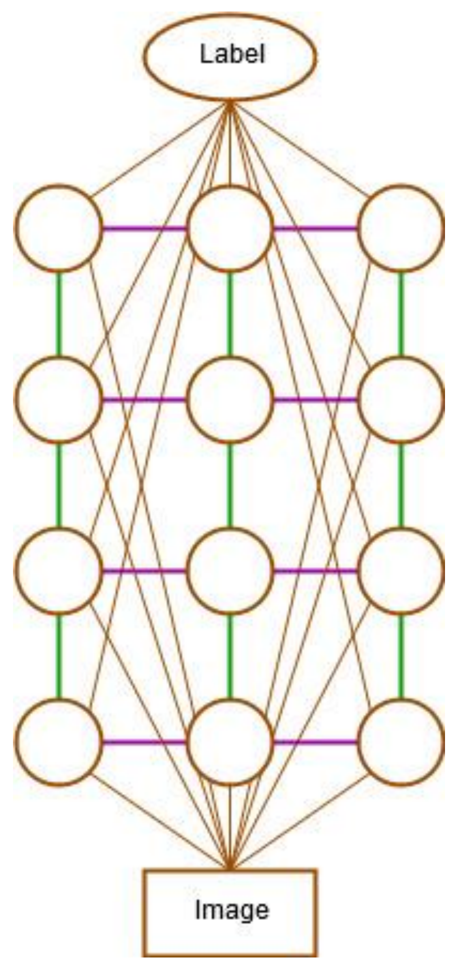


Image 3. Creative Model.



Evaluation Metric

Weighted F1 Score – weighted mean of F1 score of all labels, such that the weights correspond to the number of instances for each label.

$$F_1^{weighted} = \sum_{i=1}^{8} F_1^{C_i} \times |C_i|$$

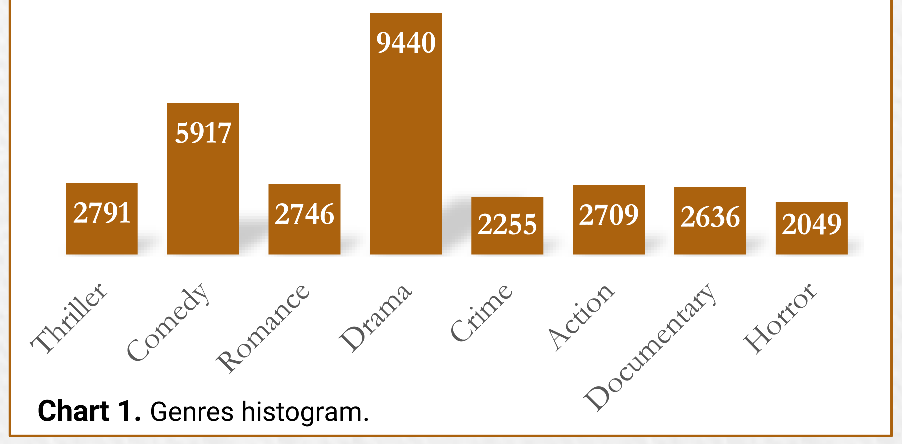


Chart 1. Genres histogram.

Results

Model	F1-Score
Baseline (Naive Bayes)	0.28
Basic (horizontal CRF)	0.35
Advanced (2D CRF)	0.36
Creative (dependencies weighting)	0.37

Table 1. Model Results

Conclusions

Even though there is a slight improvement in F1 Score against our baseline, we conclude that there is no strong benefit to a structured model for this task while using low-level features such as pixel HSV matrix.