What Can We Learn From Movie Colors?

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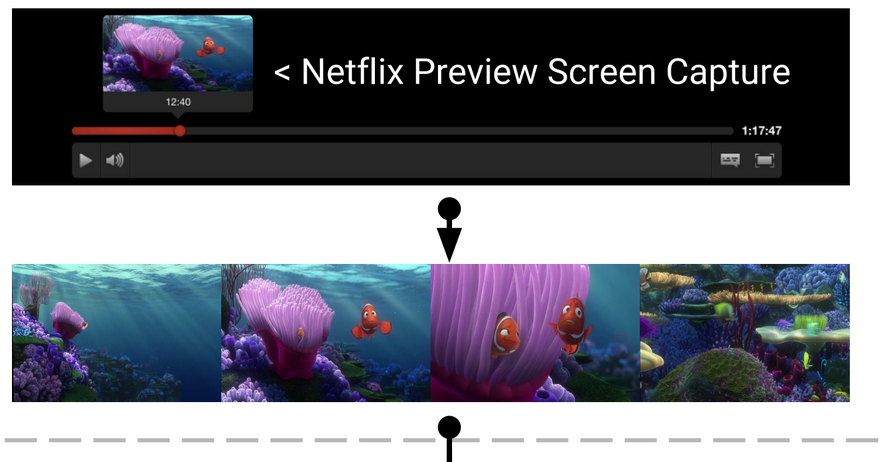
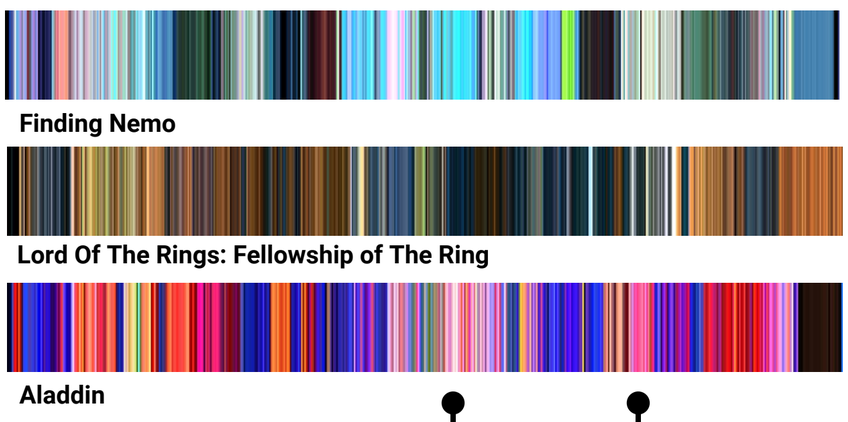
Data Collection:



Feature Extraction:

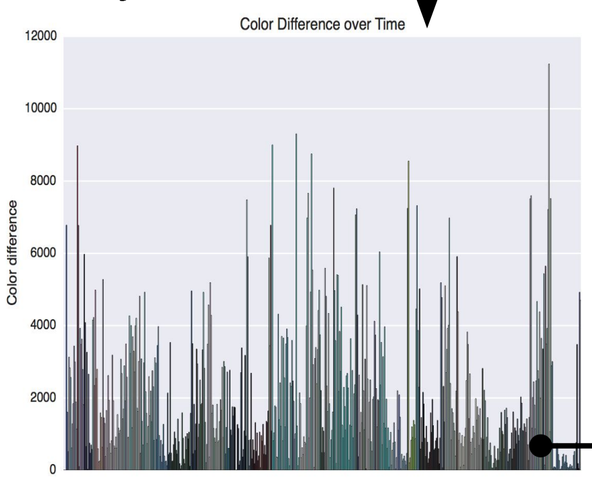
Mean Pixel Colors Per Frame

Color Barcode

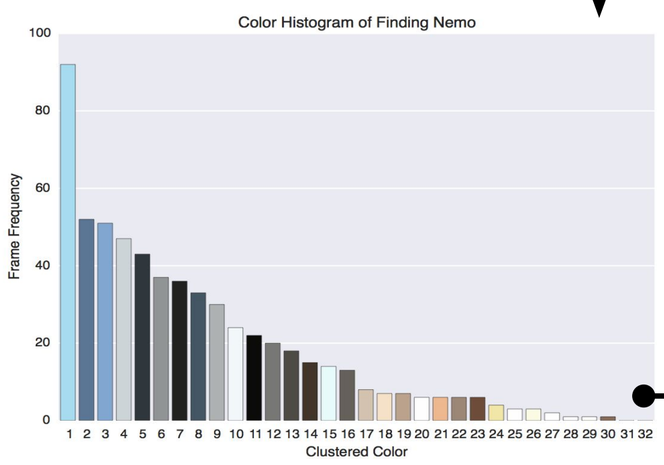


Processing

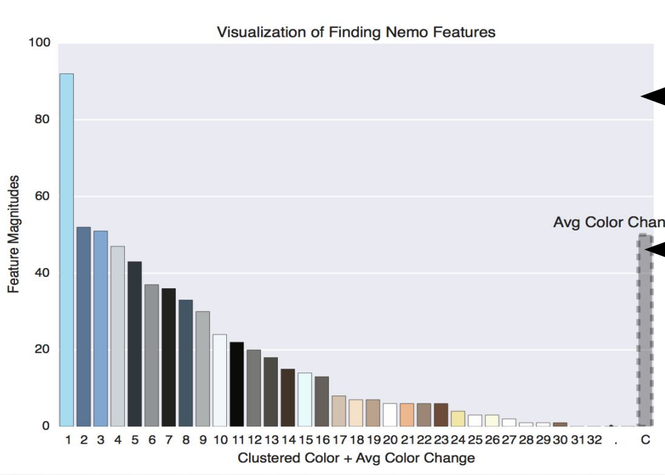
Color Dynamics



Clustered Color Histogram



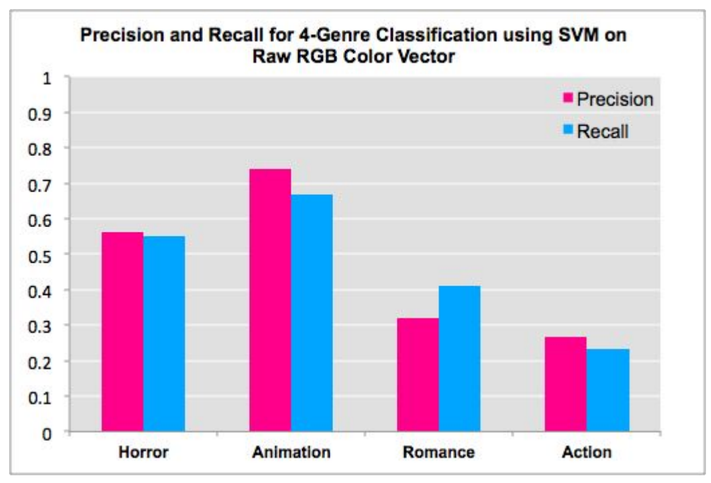
Color Hist. + Avg Color Change



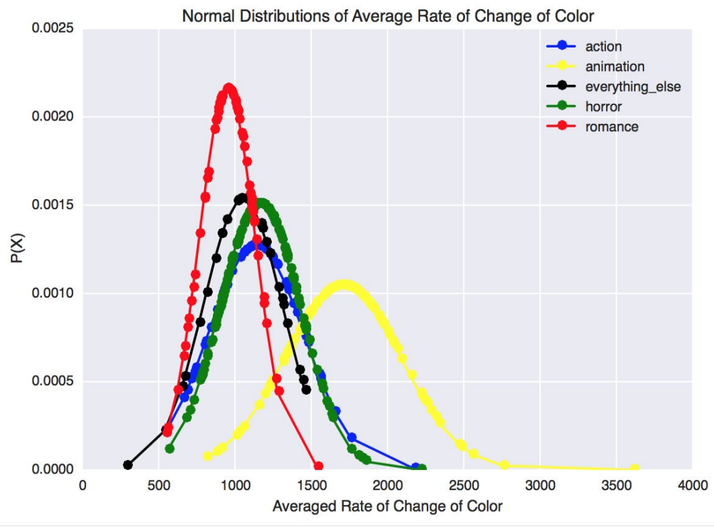
Summary:

- We applied **Supervised Learning** to create a **movie genre classifier.**
- Our raw data was Netflix preview screen captures at 10 second intervals using our own Java based automation script for ~450 movies across the four genres.
- Our final **feature** was **X** = **{256 color cluster histogram, avg. color change}**.
- Our genre **classes** were **Y** = **{Action, Animation, Horror, Romance}**.
- We attempted **Multinomial Naive Bayes** and **1-v-all SVM** to predict the genres of a film based on its color features.
- We also attempted **Unsupervised Learning K-Means Clustering** algorithm on our movies to observe patterns across movies.

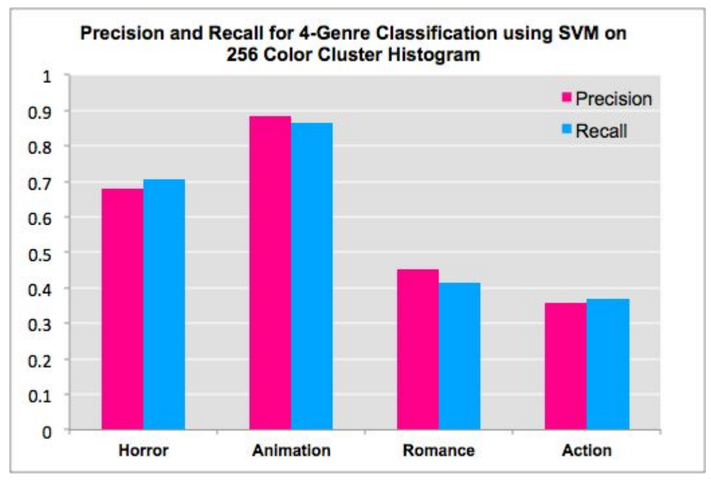
- To construct a basic feature vector from the preview frame captures we stored the mean pixel value as an RGB color barcode.
- We chose mean color as opposed to other statistical measures because the netflix preview window pixels are already downsampled mean colors of the full frame.
- We applied Naive Bayes and SVM for 10 trials and 10 fold cross validation.
- **Results:** Our initial results were not very promising with action movie classification accuracy at 25% (random classifier accuracy).



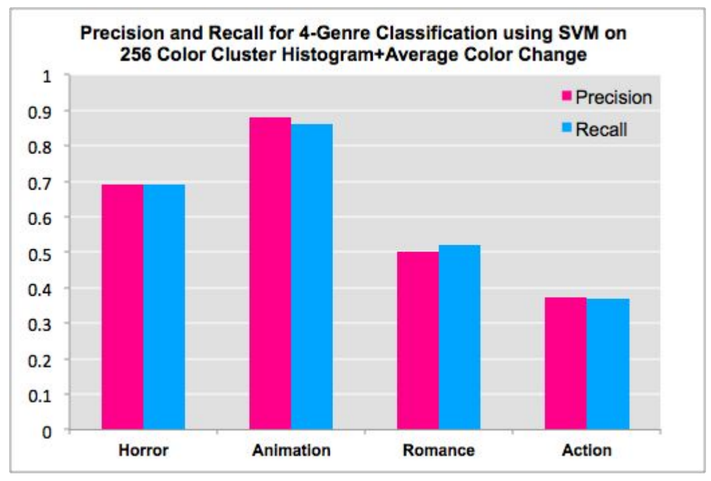
- Color dynamics comes from the intuition that action movies will transition faster and romance movies perhaps slower.
- We first converted the RGB values to CIELUV format, so that we can find the euclidean color distance between each frame. This allows us to track the change of color per frame.
- **Results:** We show how the normalized distribution of averaged rate of change of color across the different genres do reveal some insights in the data.



- We needed to represent the RGB values of the same frame together in the feature vector and dissociate frame-time as the “dimension” since it varies based on sampling.
- We ran **K-Means** to cluster all the movies into [32, 64, 128, 256] colors to determine what our base color palette for all movies.
- We applied Naive Bayes and SVM on the color histogram feature for 10 trials and 10 fold cross validation.
- **Results:** Accuracy across genres improved drastically. SVM gave better results.



- Finally, we decided to combine both the color histogram and average color change into a single feature vector.
- We applied Naive Bayes and SVM on the feature vector for 10 trials and 10 fold cross validation.
- **Results:** The classification accuracy for Romance movies improved significantly from ~40% to ~50% with color dynamics information. Other movies genres were unaffected. SVM gave better results.



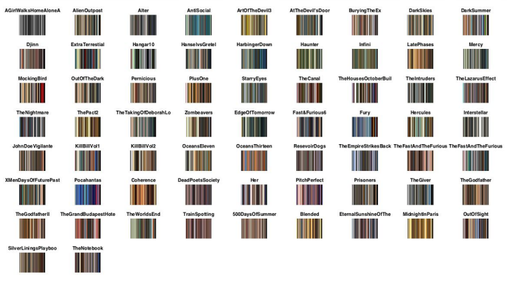
Conclusion:

- We classified animated movies based on color information with **88% accuracy** (recall and precision) with SVM on color histogram and dynamics.
- For non-animated films, horror movies movies have distinctive color histograms and romance movies have distinctive color dynamics.
- Horror and Romance classification accuracies were **69%** and **51%**.

Future Work:

- We tried unsupervised learning (K = 7 means clustering) on the “color barcodes” of movies with limited success. It will be interesting to try again with the improved color histogram+dynamics vector.
- A larger corpus of movie data and better quality data (full frames, higher sampling rate) may improve accuracy.

Cluster 1



Cluster 2