Milestone 5

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Introduction

This project uses the challenge of predicting movie genres as a way to compare different types of models used in Machine Learning. We compare several "traditional" models such as Random Forests and Support Vector Classifiers, as well as a variety of Convolutional Neural Networks trained on images of the movie posters.

Methods

Data Collection and Feature Extraction

Our data sources were two online databases, TMDb and IMDb. We regarded TMDb as our main source, relying on its labels and poster image data; significantly, we determined that the TMDb database id was sufficiently randomly distributed that we could use its last digit to divide our data consistently into training and test cohorts. [Our intent was to reserve the last few digits (7, 8, and 9) for a final "never-before-seen" assessment of our optimal model; as we never reached the point of having a model worth that test, those movies remain "in the vault."]

Because querying these databases is rate-limited, and because we wanted to protect ourselves from last-minute discoveries that we needed "just one more" column, we downloaded as much as we could at the beginning of the project. Among the fields we retrieved were the IMDb Id (allowing joins between the two data sources), to retrieve the cast and crew, producer information, plot summary, keywords, budget, revenue, release date, runtime, original language, and image data for the poster.

Some fields required further processing in order to fit the needs of the models. For example, we explored breaking out the `release_date` into three *categorical* predictors: one for the month of release (e.g. to capture summer action films), one for the year mod 4, and one for the year converted into a presidential term. We broke out the latter two because there is a 4-year economic cycle and we thought that they would capture the idea that different genres may have been popular during different times – but not in a way that is modeled by "time moves forward." This seemed like an approach that might bear fruit because so many cultural and economic developments in the US are related to the presidential terms. These turned out not to be very useful and we abandoned them in later stages.

It would be prohibitive to do a separate binary encoding of all of the actors and directors, so we took a simpler approach to try and model some people's "affinity" for certain genres. Within each genre, we counted the number of films in the training set for each actor and director, which we called their "genre affinity score". We discarded those below a threshold of 10 (chosen based on visual inspection). Finally, for each movie-genre combination, we took the sum of the (surviving) actor-genre (or director-genre) affinity scores for all actors (or directors) in that film. We called that the movie's cast-genre-affinity score, and used it as a predictor.

Previous research (see https://link.springer.com/chapter/10.1007/978-3-319-23989-7_8) has shown that bag-of-word models are highly predictive for categorizing IMDb movies. Thus, to examine this finding ourselves, we built additional features by extracting bag-of-word features from IMDb's movie overviews (the synopsis of a given movie), using the Natural Language Toolkit (NTLK) package. We removed punctuation and stopwords using the 50 corpora and lexical resources provided by the NTLK package. We also treated the genre labels themselves as stopwords, to avoid biasing the results. We took the 50 most frequent keywords and created binary indicator columns for each. Visual inspection affirms our belief that some keywords appear more in certain genres than others. For example, “love” appears more often in Romance overviews, while “fight” appears more in Action and Sci-Fi films.

In popular culture, we see that posters with dark, mysterious imagery often correspond with Sci-Fi and horror films, while vibrant, more simple imagery follows animation. We thought it would be interesting to explore whether colors in movie posters are predictive for genre. For use with traditional models, we converted images to HSV and extracted the five most common values for each channel, although we only used the single most common hue in our actual model development.

For our CNN models, we resized the poster images to a consistent and manageable size of 48X48, and we augmented the image data by creating a second version of each image, reflected left to right. For optimal memory performance within Keras, we stored these data as pickled numpy arrays.

We modeled the genres as a family of independent binary outcomes (for example, a romantic comedy would have “True”/“1” for the `genre_romance` and `genre_comedy` columns) for the following reasons: 1) This allows us to use the Hamming loss to better assess partially-correct predictions, and the Macro-F1 score for evaluating our models. 2) It eliminates the risk of creating a hand-curated list of hybrid genres that will fail to predict some new fusion film that might occur in the future. 3) It allows us to use our “genre affinity” approach. 4) As various genres have different base rates of occurrence, none of which are particularly large, by modeling each genre separately we can mostly ignore the difference between genres’ base rates, and rely on separate class weights for each constituent model. We can then build an ensemble model which uses the best model for each genre. The best models for each movie genre might use different classification algorithms (Logistic Regression, Random Forest, SVC) and different sets of predictors.

Traditional Models

For each movie genre, we created classification models using the following algorithms:

Dummy Models (most frequent, stratified) – Since we have highly unbalanced classes, the simplest model always predicts `0`. It will have no false positives and no true positives. This will be hard to beat in terms of classification “accuracy”, but is fairly useless. Other metrics that consider both specificity and precision, such as the F1 score, will be more useful. The stratified model predicts each outcome randomly in proportion to its base rate; this has an F1-Score equal to the base rate and is a practical baseline.

Logistic Regression (LR) – We created several variations on Logistic Regression models for each genre. We do not expect these to be particularly effective, but they are quick to evaluate, accommodate class weights, and also provide a simple baseline.

Random Forest - For this kind of classification problem, in which many different features are not directly comparable (how does the presence of Alfred Hitchcock scale against runtime?) and interactions are complicated, random forests are potentially quite powerful, although the tuning/training time is expensive. We allowed the tuner to run over a variety of hyperparameters.

Support Vector Classifier (SVC) - Because of the heterogeneous nature of our features, we expect the response to vary among small scale localities of our feature space. We therefore used a Radial Basis Function (RBF) kernel with coarse tuning of the Cost (C) and Gamma SVM hyperparameters. Needless to say, these are also quite expensive to train.

Ensemble model - Once we had evaluated the above models, the ensemble model was built by taking the prediction, for each genre, of the model that had the highest F-score on the *training* data.

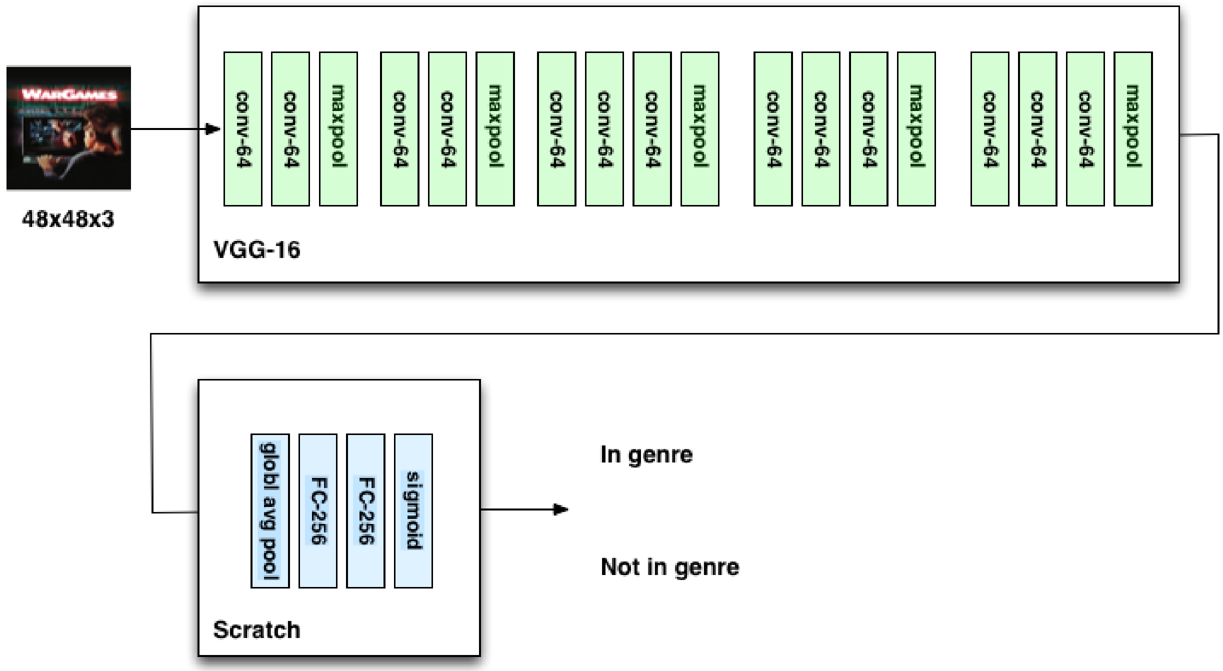
In training our models, we grouped our predictors into four groups:

- **Base 3** TMDb data for `budget`, `runtime`, and `revenue`.
- **Hue** The most frequently occurring hue in the poster image, and the count of pixels which are that hue.
- **Genre Affinity** The set of genre affinity scores as defined above.
- **Overview** Bag-of-words encoding of the 50 most frequent words in the TMDb `overview` field.

Details can be found in Milestone 3.

Convolutional Neural Networks (CNN) and Keras

For the deep learning portion of the project, we construct an initial “base” model with fairly “neutral” settings. Our intent is to perturb each hyperparameter in turn to assess its impact on the results. Our base model starts with VGG16, a publicly available, pre-trained Convolutional Neural Network (CNN), which lets us leverage its image feature extraction capabilities, particularly the generic image features (color blobs, line edges, etc) encoded in its earlier layers.



The VGG16 portion of our base model consists of the VGG16 network with its weights frozen and the `include_top` parameter set to `False`; this omits its last three layers since we’re not classifying the sort of natural images in the ImageNet. Instead, we added a 2-D global average pooling layer, two (2) 256-node FC layers using ReLU activation, and a sigmoid (binary) classifier, since we’re performing binary classification for each movie genre.

We created a custom objective (loss) function to explicitly maximize our F-Score. We chose not to use Keras’s binary cross-entropy objective function, due to the imbalanced nature of our data and since we’re trying to maximize FScore. As part of our assessment, we determined that using our custom loss function resulted in higher test F-scores than using Keras’s function.

For the custom layers appended to VGG16, weights were initialized using `he_normal`, the `Adam()` optimizer with default settings was used, and L1 regularization with $\lambda = 10^{-5}$ was applied to the second FC layer. Processing all images (21,000) in one batch during training was deemed impractical due to computing resource constraints, we chose a batch size of 256. We decided on 10 epochs since we felt this would provide sufficient model training to compare each model.

As described above, our image data was resampled to 48x48; one benefit of using VGG16 is that it worked “out of box” with our resized images. We note that Resnet and InceptionV3 wouldn’t work with the lower resolution images.

While our primary focus was to improve the performance of the VGG16-based model, we created and evaluated a “from Scratch” model separately to compare it with our base model. This model consisted of the following flow: conv2D -> Maxpool -> flatten -> Dense (activation = relu) -> Dense (activation = sigmoid)" with hyper-parameters configured as closely as possible to our base model, to facilitate comparison.

Once we had established a baseline using our initial model, we investigated how model hyperparameters might affect performance by evaluating model performance as we iterate over a range of values for each hyperparameter in turn. Our comparison tool was a small-multuple plot showing the train and test F-Score over the 10 epochs for each combination of genre and hyperparameter value. (For details, please see our Milestone 4 deliverable.) The hyperparameters varied were:

Number of Nodes in the FC Layers - We varied the number of nodes in our custom FC layers as follows: (FC1, FC2) - (256,4) (256,64) (256,256) (1024,64) (1024,256) (4096,4096). We noticed that models with fewer nodes in the FC1/FC2 layers typically, but not always, underperformed.

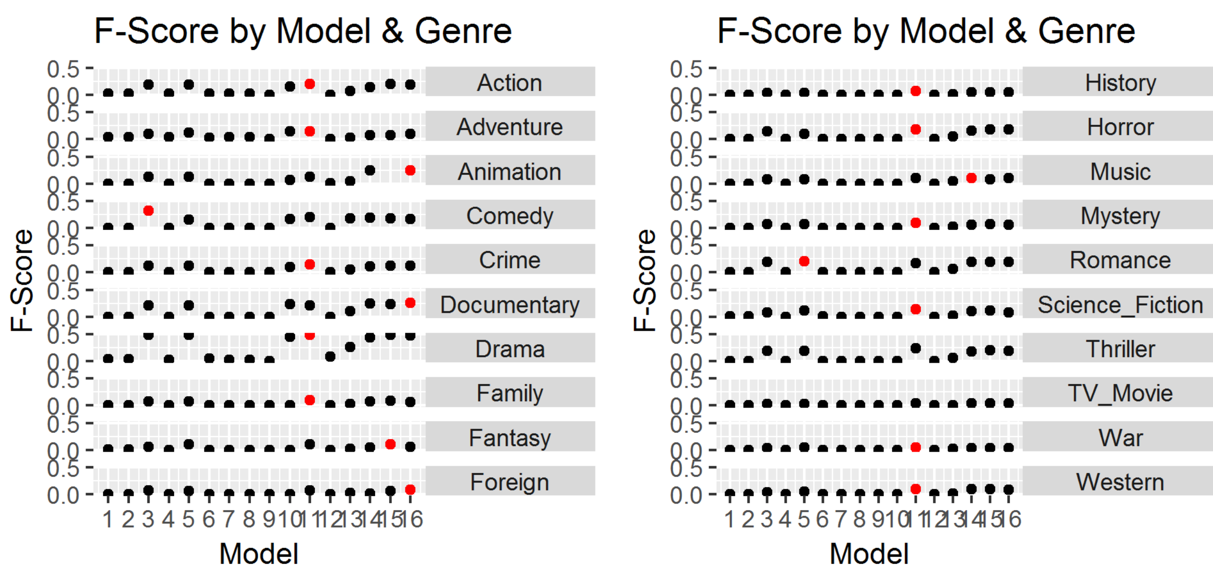
Regularization - Regularization is used to counteract overfitting, so we experimented with both L1 and L2 regularization, varying λ by factors of 10. Predictably, setting λ too high, (10^{-4} for L1 and 10^{-2} for L2) results in a low and flat F-Score plot, but setting it too low (such as 10^{-6}) allows overfitting.

Learning rate - We experimented with two dynamic learning rate approaches: tuning functions: 1) A "Learning Rate Decay" function that decayed after the first 5 epochs and 2) a "reduce learning rate on plateau" function (RLROP) that used validation loss as feedback to dynamically update the learning rate. The general idea is that learning rate should decrease over epoch runs since the model should be converging. We observed that RLROP performed significantly better than "Learning Rate Decay", although we note that RLROP, uniquely in our experiments, introduces a dependency on the test data and we should have re-validated those results on a separate test set.

Retraining - Movie poster images have many of the same low-level features as natural images, but their higher-level structure is somewhat different. We considered that allowing the final 2 or 3 layers of VGG-16 to be retrained while keeping the lower layers frozen would account for this.

Results

We compare our F-Score on the test cohort for every model and every genre. The best-performing model for each genre is highlighted in red:



Models: **1.** LogReg using 3 base predictors only; **2.** LogReg unbalanced w/3 predictors; **3.** LogReg unbalanced w/3 predictors and base_rate_cutoff; **4.** LogReg unbalanced w/Hue; **5.** LogReg unbalanced w/Hue and base_rate_cutoff; **6.** LogReg w/affinity and overview_features; **7.** LogReg w/affinity predictors; **8.** LogReg w/Hue; **9.** Most Frequent (Dummy); **10.** RandomForest; **11.** RandomForest optimizing for Fscore; **12.** RandomForest w/H; **13.** Stratified (Dummy); **14.** SVC; **15.** SVC optimizing for Fscore; **16.** SVC w/Hue

In most genres, the Random Forest optimized for F-Score (11) did the best; on almost all of the others one of the SVC variants was the best. In general, those two families of models outperformed the Logistic Regression by a notable amount, but `Romance` and `Comedy` show that occasionally even a Logistic Regression model can outperform more sophisticated models.

By combining the "best of genre" models, we arrived at our ensemble model. Its confusion matrix was:

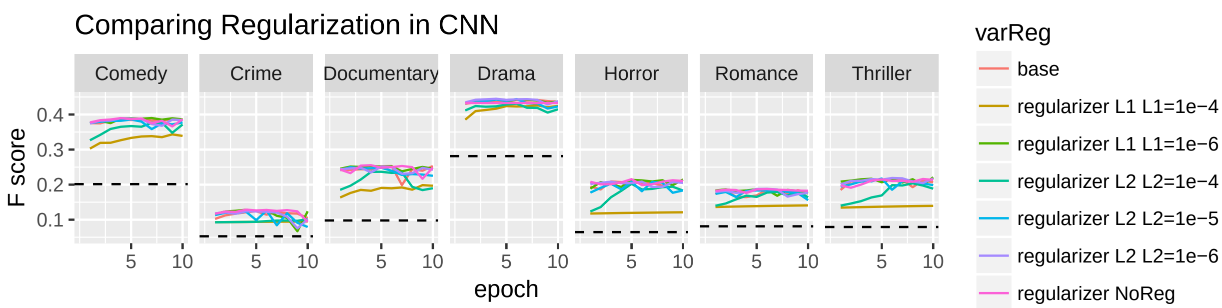
```
        predicted_1 predicted_0
true_1     12,376      18,026
true_0    114,829     379,989
```

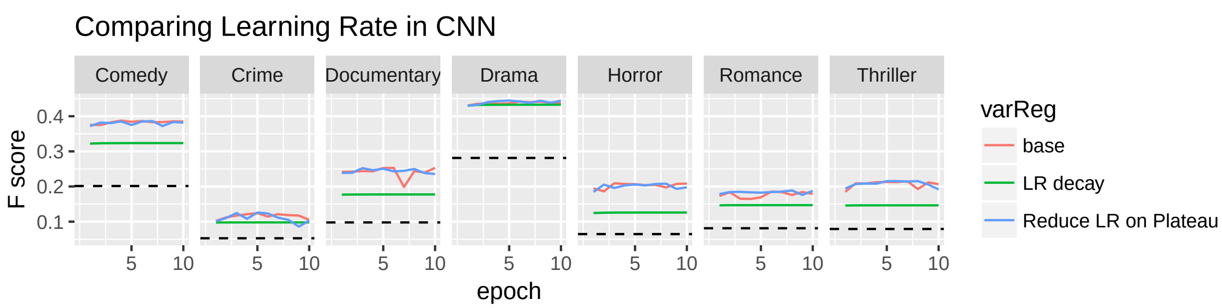
and its Macro-F1 score is 0.574.

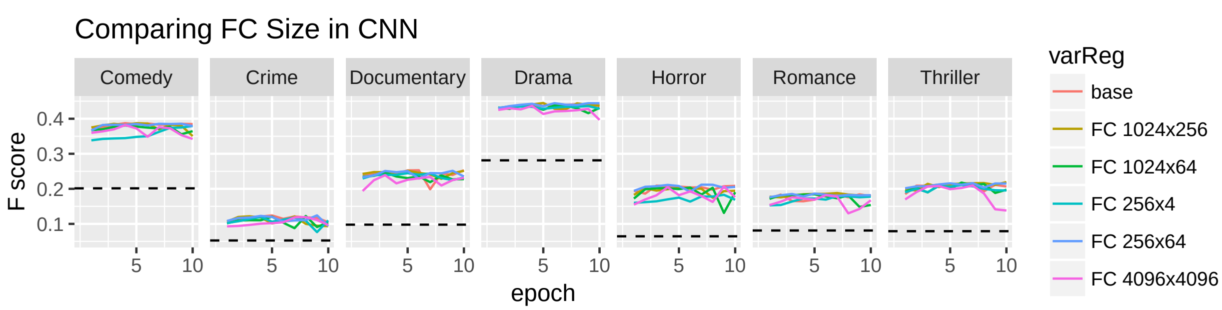
CNNs

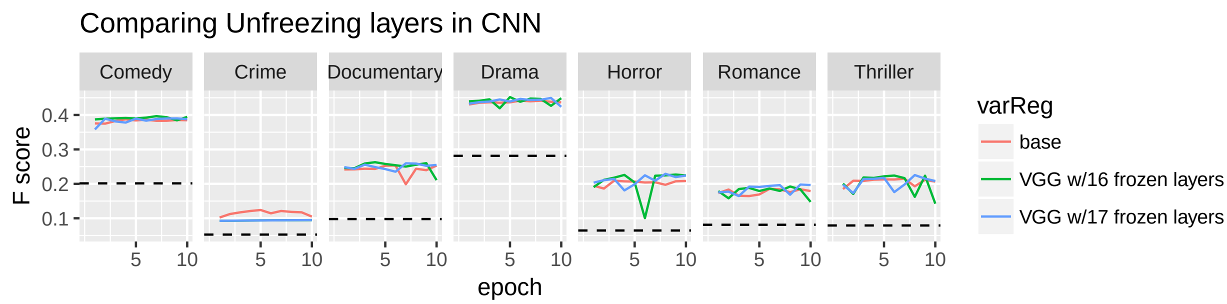
Our CNNs were trained on those movies with ids ending in 0, and tested on those with ids ending in 2. There were approximately 21,000 movies in each cohort, and their base rates for each genre were approximately equal.

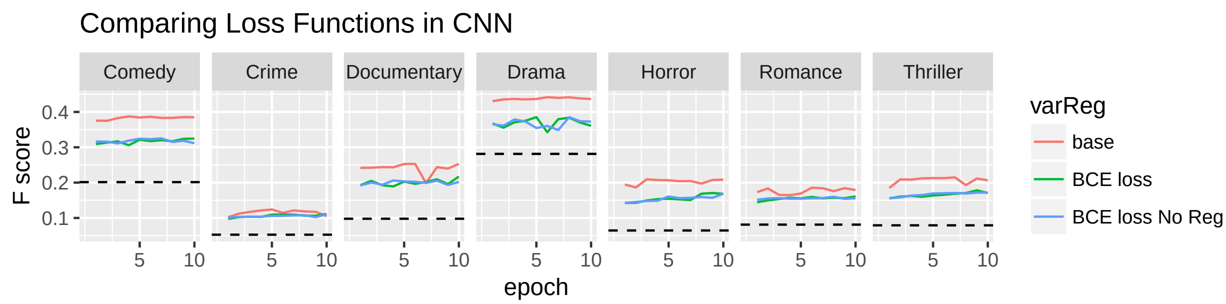
We examine the F-Score computed on the test data over ten epochs. Each chart compares several variants to the "base" model. The dashed line shows the base rate, which is also the theoretical F-Score of a stratified dummy model. We omit those genres with baserates under 5% because their models often fail to predict *any* positive outcomes, and thus their F-Score is undefined.











Discussion

Regularization We find that $\lambda_2 \approx 10^{-6}$ scores the best, although $\lambda_1 \approx 10^{-6}$ shows a nice gentle improvement over several epochs.

Learning Rate LR decay clearly loses in this case, while RLROP sometimes outperforms a flat learning rate.

FC Size The largest network, 4096x4096, is often the worst performer (presumably because it facilitates overfitting on the training set despite some amount of L1 regularization.) While the specifics vary from genre to genre, the 1024x256 and 256x64 models offer the right balance between having enough free parameters to produce a sufficiently rich model, without having so many as to allow overfitting.

Unfreezing VGG Layers The partially unfrozen layers seem to outperform the base model in general. This is not too surprising, since we increase the number of parameters simply by unfreezing, but they do not tend to overfit, implying that the retraining does update the pretrained model to optimize for high-level features found on movie posters.

Loss Function Our choice to start off with the F-Score-based loss function shows a clear benefit here.

Conclusion

Our best performing CNN model came close to, but did not outperform, the best models created earlier with more traditional Machine Learning methods such as SVCs and Random Forests. In all cases, however, time limitations prevented us from optimally tuning our models, so it is hard to tell which would have prevailed. The F-Score-based objective function had a larger effect than any of the other hyperparameters that we varied. It is also worth emphasizing that the "traditional" models used movie metadata while our CNN model used only image data. We expect that a model that merged the CNN and meta-data features would surpass both.

We trained several dozen models and assessed their performance. We learned that there is no single best tool, even when looking at subsets of the same problem with the same data set. Ensemble models allow the strengths of each model to offset the weaknesses of others.