# Milestone_2_SUBMIT

April 12, 2017

## 1 CS 109B Advanced Topics in Data Science, Final Project, Milestone 2

### 1.1 Group 9 - Steve Robbins, Chad Tsang, and Ted Heuer

**Harvard University Spring 2017 Due Date:** Wednesday, April 12th, 2017 at 11:59pm

### 1.2 Milestone 2: Assembling training data, due Wednesday, April 12, 2017

We are aware that you have little time this week, due to the midterm. So this milestone is a bit easier to achieve than the others. The goal for this week is to prepare the data for the modeling phase of the project. You should end up with a typical data setup of training data X and data labels Y.

The exact form of X and Y depends on the ideas you had previously. In general though Y should involve the genre of a movie, and X the features you want to include to predict the genre. Remember from the lecture that more features does not necessarily equal better prediction performance. Use your application knowledge and the insight you gathered from your genre pair analysis and additional EDA to design Y. Do you want to include all genres? Are there genres that you assume to be easier to separate than others? Are there genres that could be grouped together? There is no one right answer here. We are looking for your insight, so be sure to describe your decision process in your notebook.

In preparation for the deep learning part we strongly encourage you to have two sets of training data X, one with the metadata and one with the movie posters. Make sure to have a common key, like the movie ID, to be able to link the two sets together. Also be mindful of the data rate when you obtain the posters. Time your requests and choose which poster resolution you need. In most cases w500 should be sufficient, and probably a lower resolution will be fine.

The notebook to submit this week should at least include:

- Discussion about the imbalanced nature of the data and how you want to address it
- Description of your data
- What does your choice of Y look like?
- Which features do you choose for X and why?
- How do you sample your data, how many samples, and why?

*Important*: You do not need to upload the data itself to Canvas.

### 1.3 Solution

For this project, to date we have extracted the raw data of 20 years of movies (1997 to 2016) from TMDB which have received over 25 votes. The information extracted and derived is described

below, organized by source and anticipated usage. *Note that if time permits, we may elect to include additional features from alternative sources to potentially attempt to improve classification performance.*

**Metadata Extracted from TMDB (*No Anticipated Predictive Value - Not included in the models*)** - TMDB_Genres: The original set of TMDB genres associated to this movie. As the response value is derived from this set, this will not be used as a predictor. - TMDB_Id: The unique TMDB identifier, used for reference and data acquisition, without any anticipated predictive capability. - IMDB_Id: The unique IMDB identifier, used for reference and data acquisition, without any anticipated predictive capability. - Original_Title: The original title of the movie, used for display purposes.

**Metadata Extracted from TMDB (*Anticipated Predictive Value - Included in the models*)** - Belongs_to_collection: Indicator of whether the movie is part of a collection, trilogy, and so forth. - Budget: The budget of the movie, which is envisioned to have predictive value. - Original_Language: The original language of the movie, likely to have predictive strength if the dataset included more "Foreign" samples. - Overview: The short, narrative plot summary, which could have predictive capability when reduced and NLP applied. - Popularity: The popularity rating of the movie on TMDB, which may have predictive capability. - Poster_Path: The remote poster filename, when combined with the base path and image size can be used to retrieve the poster image from TMDB. This is also used as a key to the local copy of the poster image. - Production_Companies: The production company(-ies) which released the movie; which is expected to have predictive value. - Release_Date_Month: The month of release of the movie. As movies of similar genres may be released during certain times of the year (such as Action in the Summer month) may have predictive strength. - Release_Date_Year: The year of release of the movie. As genres ebb/flow over the years may have predictive strength when denormalized from the Release Date into year. - Revenue: The revenue the movie produced in release. - Runtime: The runtime in minutes of the movie. It is expected certain abnormal runtimes may inform the genre, such as long runtimes perhaps indicating a dramatic movie, and shorter being correlated to comedy or animation. - Title: The title of the movie, generally in English, both for display purposes and if the length of the title tends to correlate to certain genres. - Vote_Average: The user contributed rating of the movie. - Vote_Count: The number of user votes for the movie.

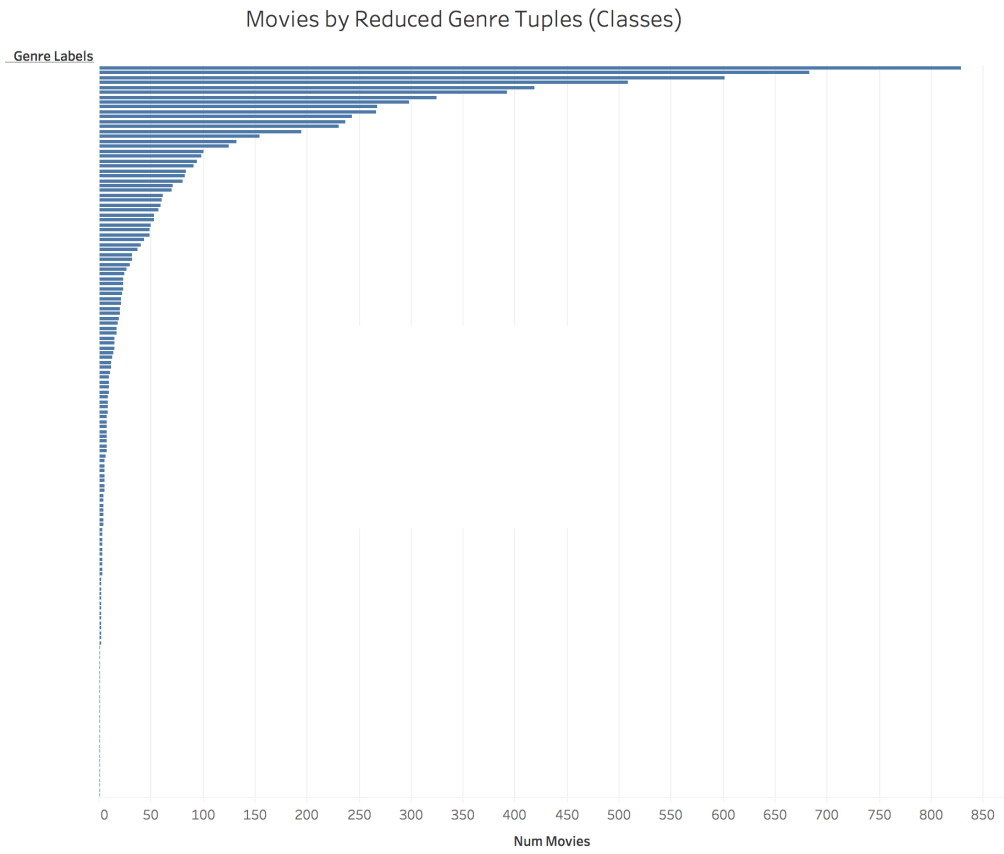
**Poster Images:**

- The locally cached jpg images of the TMDB-identified poster (which may be different from the IMDB version) with size "w500", stored by filename from "Poster Path" in the TMDB attribute.

**Derived Data:** - Reduced_Genre: The reduced/simplified class to which we have elected to map the movie, namely the response category to be elaborated next. - Movie Poster Principal Components : The poster images will be converted to greyscale from color then have dimensionality reduction performed via PCA then images mapped to the 90% variance explained PCA components as predictors. - Overview Text Bag of Words Principal Components: The overview narrative description will be converted to a vector of the corpus then have dimensionality reduction performed via PCA with the overview mapped to the 90% variance explained PCA components as predictors.

**Choice of Response Value:**

The desired response variable is a reflection of the genre of the movie. Unfortunately, the data as obtained from TMDB has one to four different genres assigned to each movie. Concatenating the genres together without modification would result in a very significant number of classes (thousands of potential classes), more than would be practical given the quantity of data available




and the time constraints of the project. As such, we have explored a few techniques to reduce the number of genres suitable for this project.

Our first approach reduced the movies by the first genre listed, which resulted in twenty classes. This reduction seemed a bit simplistic, so we chose to examine the genre correlations and apply heuristics to the data. The infrequent genres were manually mapped to more common where it made intuitive sense, and correlations of the genres were examined to effectively creating a reduced number of classes, 149. The resultant classes do include the general categories and specifics, such as "Action" and "Crime/Action", but every movie is uniquely mapped to a single class of genre tuples. Approximately 107 of the 149 classes (72%) have very low frequencies (8% of the data) can be categorized as "Other".

As such, we have created a synthetic response variable/class derived from the existing genre data and heuristics, denoted "Reduce_genre" above.

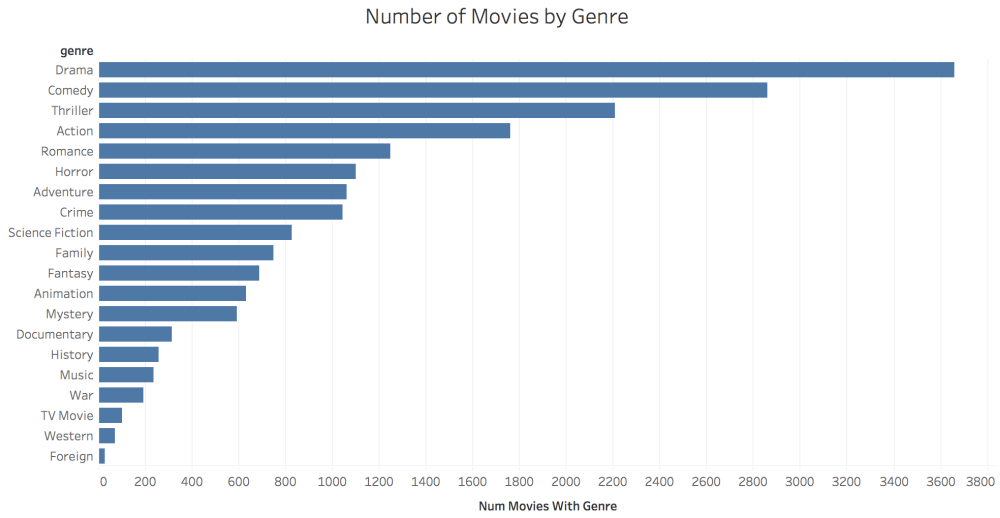
**Imbalanced nature of the data**

Unfortunately, even with this normalization the response classes are highly imbalanced, resulting in 23 of the 149 reduced classes representing over 80% of the total 8,060 movies extracted, with the drama class in particular dominating with 829 (10.2%) of the 8060 movies.

This would further be exacerbated by reduction to a single TMDB genre, with 3658 (45.3%) observations having drama as a listed genre.

**Sampling, Sampling Technique and Sample Size**

We intend on addressing the class imbalance using two techniques, namely categorizing all of the extremely low frequency classes into an "Other" category as explained above, and employing




stratified sampling with class weights.

There are a number of sampling techniques that were considered. The simplest approach is a random sample, however due to the imbalanced nature of the data would likely focus on the few dominant classes disregarding the minority classes. We have considered oversampling the data which would repeatedly sample the minority classes to equalize class imbalance, undersampling which would effectively ignore some data in the majority classes, synthetic data generation which was dismissed as it would be intuitively difficult to generate, and stratified sampling with class weights.

Stratified sampling preserves the class structure when performing sampling, by sampling a number of observations relative to the overall class proportion from the distinct classes, namely with the assigned genres forming the strata. As such, any sample of the data will maintain the relative class frequencies present in the original, complete dataset. Additionally, the class proportions (weights) are known from the overall dataset (and honored in the sample) and thus can be used to adjust for the imbalance of the classes with machine learning algorithms.

Sample size will be chosen to be as large as computationally tractable for the purpose; for example during development we may find it convenient to work with a representative subset of the data, the generation of the PCA rotation matrix can be resource intensive, and cross-validation techniques rely upon sampling.

---

*Supporting Code and Analysis Below*

### 1.3.1 Install Packages

```
In [1]: #!pip install IMDbPY
        #(only supported in Python 2)
        # Documentation for IMDb library:
                # http://imdbpy.sourceforge.net/support.html#documentation
                # http://imdbpy.sourceforge.net/docs/README.package.txt

In [2]: #!pip install tmdbsimple
        # Documentation for TMDb library
                # https://github.com/celiao/tmdbsimple/
                # (good resource) https://developers.themoviedb.org/3/discover/movi

In [3]: from IPython.display import Image
        import urllib

        from imdb import IMDb
        import tmdbsimple as tmdb
        tmdb.API_KEY = 'c5d41f08e55fca6e9f5fc0b6d1735540'

In [4]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        %matplotlib inline

        import matplotlib.cm as cmx
        import matplotlib.colors as colors
        from pandas.tools.plotting import scatter_matrix
```

### 1.3.2 TMDb Genres

```
In [5]: num_genres = len(tmdb.Genres().list()['genres'])

        idx = range(0, num_genres)
        cols = ['genre_id', 'genre']

        tmdb_genre_df = pd.DataFrame(index=idx, columns=cols)

In [6]: for i in range(0, num_genres):
            tmdb_genre_df['genre_id'][i] = tmdb.Genres().list()['genres'][i].values
            tmdb_genre_df['genre'][i] = tmdb.Genres().list()['genres'][i].values()

In [7]: foreign_df = pd.DataFrame([[10769, 'Foreign']], columns=cols) #add Foreign

        tmdb_genre_df = tmdb_genre_df.append(foreign_df, ignore_index=True)

In [8]: tmdb_genre_df

Out[8]:    genre_id            genre
        0        28           Action
```

```
1         12        Adventure
2         16        Animation
3         35           Comedy
4         80            Crime
5         99      Documentary
6         18            Drama
7      10751           Family
8         14          Fantasy
9         36          History
10        27           Horror
11     10402            Music
12      9648          Mystery
13     10749          Romance
14       878  Science Fiction
15     10770         TV Movie
16        53         Thriller
17     10752              War
18        37          Western
19     10769          Foreign
```

### 1.3.3 Get Genre Listings for Large Sample of Movies

```
In [9]: discover = tmdb.Discover()

In [10]: def movie_genres_list(year, min_votes):

             movies_in_year = discover.movie(primary_release_year=year, vote_count_
             max_page = (movies_in_year['total_pages'] - 1)
             movies_per_page = 20 #always 20 entries per page

             idx = range(0, max_page * movies_per_page)
             cols = ['movie_id', 'num_genres', 'id_1', 'id_2', 'id_3', 'id_4', 'id_
                     'id_6', 'id_7', 'id_8', 'id_9', 'id_10', 'id_11']

             movies_genres_table = pd.DataFrame(index=idx, columns=cols)

             for i in range(0, max_page):
                 movies_page = discover.movie(page=(i+1), primary_release_year=year

                 for j in range(0, movies_per_page):
                     genre_list = movies_page['results'][j]['genre_ids']
                     row_num = i * movies_per_page + j
                     movies_genres_table.iloc[row_num, 0] = movies_page['results']|
                     movies_genres_table.iloc[row_num, 1] = len(genre_list)

                     for k in range(0, len(genre_list)):
                         movies_genres_table.loc[row_num][k+2] = genre_list[k]
```

```
            return movies_genres_table
```

```
In [11]: min_votes=25
```

**Converted Section BELOW to MARKDOWN (from here)** movies_2016 = movie_genres_list(year=2016, min_votes=min_votes)
movies_2015 = movie_genres_list(year=2015, min_votes=min_votes)
movies_2014 = movie_genres_list(year=2014, min_votes=min_votes)
movies_2013 = movie_genres_list(year=2013, min_votes=min_votes)
movies_2012 = movie_genres_list(year=2012, min_votes=min_votes)
movies_2011 = movie_genres_list(year=2011, min_votes=min_votes)
movies_2010 = movie_genres_list(year=2010, min_votes=min_votes)
movies_2009 = movie_genres_list(year=2009, min_votes=min_votes)
movies_2008 = movie_genres_list(year=2008, min_votes=min_votes)
movies_2007 = movie_genres_list(year=2007, min_votes=min_votes)
movies_2006 = movie_genres_list(year=2006, min_votes=min_votes)
movies_2005 = movie_genres_list(year=2005, min_votes=min_votes)
movies_2004 = movie_genres_list(year=2004, min_votes=min_votes)
movies_2003 = movie_genres_list(year=2003, min_votes=min_votes)
movies_2002 = movie_genres_list(year=2002, min_votes=min_votes)
movies_2001 = movie_genres_list(year=2001, min_votes=min_votes)
movies_2000 = movie_genres_list(year=2000, min_votes=min_votes)
movies_1999 = movie_genres_list(year=1999, min_votes=min_votes)
movies_1998 = movie_genres_list(year=1998, min_votes=min_votes)
movies_1997 = movie_genres_list(year=1997, min_votes=min_votes)
movies_genres_raw_TMDb = pd.concat([movies_2016, movies_2015, movies_2014, movies_2013, movies_2012, movies_2011, movies_2010, movies_2009, movies_2008, movies_2007, movies_2006, movies_2005, movies_2004, movies_2003, movies_2002, movies_2001, movies_2000, movies_1999, movies_1998, movies_1997])
movies_genres_raw_TMDb.iloc[:10, :]
movies_genres_raw_TMDb.shape

### 1.3.4 Write and Read Raw TMDb Genres File Locally

movies_genres_raw_TMDb = movies_genres_raw_TMDb.fillna(0) movies_genres_raw_TMDb.iloc[:10, :]
movies_genres_raw_TMDb.to_csv('movies_genres_raw_TMDb', index=False)

**Converted Section ABOVE to MARKDOWN (to here)**

```
In [12]: movies_genres_table = pd.read_csv('movies_genres_raw_TMDb.csv')
         print movies_genres_table.shape
         movies_genres_table.iloc[:10, :]
```

```
(8060, 13)
```

Out[12]:

| | movie_id | num_genres | id_1 | id_2 | id_3 | id_4 | id_5 | id_6 | id_7 | id_8 | id_9 | id_10 | id_11 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 293660 | 4 | 28 | 12 | 35 | 10749 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 297761 | 4 | 28 | 80 | 14 | 878 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 209112 | 3 | 28 | 12 | 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 271110 | 3 | 12 | 28 | 878 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 329865 | 4 | 53 | 18 | 878 | 9648 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 284052 | 4 | 28 | 12 | 14 | 878 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 246655 | 4 | 28 | 12 | 14 | 878 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 269149 | 4 | 16 | 12 | 10751 | 35 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 259316 | 3 | 12 | 28 | 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 330459 | 4 | 28 | 18 | 878 | 10752 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

In [ ]:

### 1.3.5 Create Table Showing How Genres Relate to Eachother

In [13]:
```
def create_genre_pairs(tmdb_genre_df, movies_genres_table):

    idx = tmdb_genre_df['genre_id']
    cols = tmdb_genre_df['genre_id']

    genre_pairs_table = pd.DataFrame(index=idx, columns=cols)
    genre_pairs_table = genre_pairs_table.fillna(0)

    total_movies = len(movies_genres_table)

    for row_num in range(0, total_movies):

        num_genres = movies_genres_table.iloc[row_num, 1]

        for i in range(0, num_genres):

            for j in range(0, num_genres):

                x = movies_genres_table.iloc[row_num, i+2]
                y = movies_genres_table.iloc[row_num, j+2]
```

```
                        genre_pairs_table.loc[x, y] = genre_pairs_table.loc[x, y]

    genre_pairs_table_names = genre_pairs_table.copy()

    new_idx = tmdb_genre_df['genre']
    new_cols = tmdb_genre_df['genre']

    genre_pairs_table_names.columns = new_cols
    genre_pairs_table_names = genre_pairs_table_names.set_index(new_idx)

    return genre_pairs_table_names
```

In [14]:
```
genre_pairs = create_genre_pairs(tmdb_genre_df, movies_genres_table)
```

In [15]:
```
genre_pairs
```

Out[15]:

| genre | Action | Adventure | Animation | Comedy | Crime | Documentary |
|---|---|---|---|---|---|---|
| genre | | | | | | |
| Action | 1760 | 590 | 150 | 371 | 438 | 7 |
| Adventure | 590 | 1060 | 236 | 317 | 67 | 7 |
| Animation | 150 | 236 | 632 | 224 | 9 | 5 |
| Comedy | 371 | 317 | 224 | 2858 | 250 | 20 |
| Crime | 438 | 67 | 9 | 250 | 1042 | 9 |
| Documentary | 7 | 7 | 5 | 20 | 9 | 314 |
| Drama | 534 | 251 | 63 | 938 | 596 | 24 |
| Family | 90 | 298 | 365 | 410 | 7 | 11 |
| Fantasy | 232 | 305 | 166 | 224 | 15 | 1 |
| History | 78 | 42 | 1 | 16 | 15 | 13 |
| Horror | 166 | 47 | 13 | 140 | 63 | 3 |
| Music | 8 | 9 | 19 | 109 | 10 | 36 |
| Mystery | 92 | 41 | 15 | 52 | 174 | 1 |
| Romance | 87 | 75 | 26 | 690 | 54 | 0 |
| Science Fiction | 421 | 250 | 121 | 144 | 23 | 1 |
| TV Movie | 7 | 20 | 8 | 40 | 5 | 2 |
| Thriller | 784 | 227 | 24 | 173 | 635 | 4 |
| War | 65 | 27 | 1 | 9 | 6 | 8 |
| Western | 26 | 22 | 3 | 17 | 9 | 0 |
| Foreign | 5 | 2 | 1 | 6 | 1 | 3 |

| genre | Drama | Family | Fantasy | History | Horror | Music | Mystery |
|---|---|---|---|---|---|---|---|
| genre | | | | | | | |
| Action | 534 | 90 | 232 | 78 | 166 | 8 | 92 |
| Adventure | 251 | 298 | 305 | 42 | 47 | 9 | 41 |
| Animation | 63 | 365 | 166 | 1 | 13 | 19 | 15 |
| Comedy | 938 | 410 | 224 | 16 | 140 | 109 | 52 |
| Crime | 596 | 7 | 15 | 15 | 63 | 10 | 174 |
| Documentary | 24 | 11 | 1 | 13 | 3 | 36 | 1 |
| Drama | 3658 | 134 | 186 | 222 | 206 | 130 | 288 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Family | 134 | 747 | 210 | 2 | 3 | 34 | 10 |
| Fantasy | 186 | 210 | 687 | 3 | 87 | 13 | 53 |
| History | 222 | 2 | 3 | 258 | 3 | 2 | 4 |
| Horror | 206 | 3 | 87 | 3 | 1101 | 5 | 187 |
| Music | 130 | 34 | 13 | 2 | 5 | 236 | 4 |
| Mystery | 288 | 10 | 53 | 4 | 187 | 4 | 593 |
| Romance | 841 | 70 | 93 | 29 | 21 | 60 | 39 |
| Science Fiction | 171 | 75 | 156 | 1 | 177 | 6 | 71 |
| TV Movie | 47 | 45 | 18 | 5 | 12 | 12 | 6 |
| Thriller | 969 | 11 | 110 | 36 | 645 | 5 | 421 |
| War | 148 | 0 | 3 | 67 | 2 | 3 | 5 |
| Western | 29 | 2 | 3 | 1 | 10 | 0 | 2 |
| Foreign | 17 | 2 | 0 | 2 | 3 | 1 | 2 |

| genre | Romance | Science Fiction | TV Movie | Thriller | War | Weste |
|---|---|---|---|---|---|---|
| genre | | | | | | |
| Action | 87 | 421 | 7 | 784 | 65 | 2 |
| Adventure | 75 | 250 | 20 | 227 | 27 | 2 |
| Animation | 26 | 121 | 8 | 24 | 1 | |
| Comedy | 690 | 144 | 40 | 173 | 9 | 1 |
| Crime | 54 | 23 | 5 | 635 | 6 | |
| Documentary | 0 | 1 | 2 | 4 | 8 | |
| Drama | 841 | 171 | 47 | 969 | 148 | 2 |
| Family | 70 | 75 | 45 | 11 | 0 | |
| Fantasy | 93 | 156 | 18 | 110 | 3 | |
| History | 29 | 1 | 5 | 36 | 67 | |
| Horror | 21 | 177 | 12 | 645 | 2 | 1 |
| Music | 60 | 6 | 12 | 5 | 3 | |
| Mystery | 39 | 71 | 6 | 421 | 5 | |
| Romance | 1247 | 46 | 13 | 103 | 24 | |
| Science Fiction | 46 | 824 | 14 | 320 | 5 | |
| TV Movie | 13 | 14 | 102 | 11 | 0 | |
| Thriller | 103 | 320 | 11 | 2206 | 37 | 1 |
| War | 24 | 5 | 0 | 37 | 191 | |
| Western | 6 | 3 | 0 | 17 | 2 | 7 |
| Foreign | 8 | 1 | 0 | 4 | 0 | |

| genre | Foreign |
|---|---|
| genre | |
| Action | 5 |
| Adventure | 2 |
| Animation | 1 |
| Comedy | 6 |
| Crime | 1 |
| Documentary | 3 |
| Drama | 17 |
| Family | 2 |
| Fantasy | 0 |

```
History                2
Horror                 3
Music                  1
Mystery                2
Romance                8
Science Fiction        1
TV Movie               0
Thriller               4
War                    0
Western                0
Foreign               25
```

### 1.3.6 Total Number of Genre Listings for All Movies

In [16]:
```
def get_genre_totals(tmdb_genre_df, genre_pairs):

    idx = tmdb_genre_df['genre']
    cols = ['num_movies_with_genre']

    genre_totals = pd.DataFrame(index=idx, columns=cols)

    for i in range(0, len(genre_totals)):
        genre_totals.iloc[i,0] = genre_pairs.ix[tmdb_genre_df['genre'][i],

    return genre_totals
```

In [17]:
```
genre_totals = get_genre_totals(tmdb_genre_df, genre_pairs)
genre_totals.to_csv('genre_totals.csv', index=True)
genre_totals
```

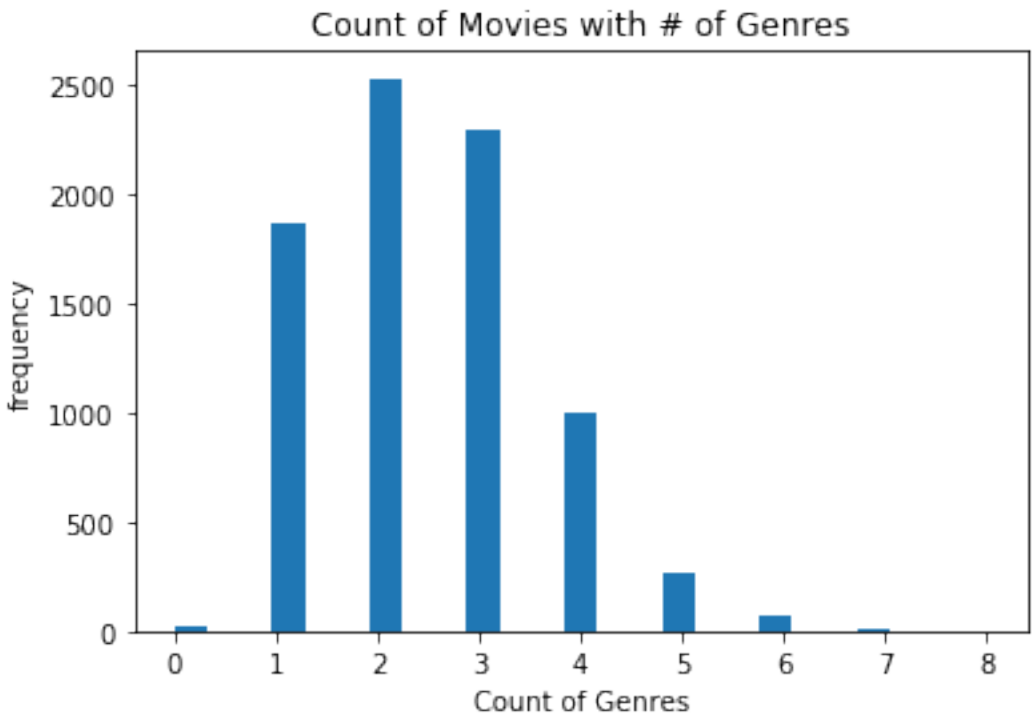
Out[17]:

| genre | num_movies_with_genre |
|---|---|
| Action | 1760 |
| Adventure | 1060 |
| Animation | 632 |
| Comedy | 2858 |
| Crime | 1042 |
| Documentary | 314 |
| Drama | 3658 |
| Family | 747 |
| Fantasy | 687 |
| History | 258 |
| Horror | 1101 |
| Music | 236 |
| Mystery | 593 |
| Romance | 1247 |
| Science Fiction | 824 |
| TV Movie | 102 |

```
Thriller                          2206
War                                191
Western                             70
Foreign                             25
```

```
In [18]: plt.hist(movies_genres_table['num_genres'].values,
              25)
         plt.title('Count of Movies with # of Genres')
         plt.xlabel('Count of Genres')
         plt.ylabel('frequency')
```

```
Out[18]: <matplotlib.text.Text at 0x11583ca90>
```




*Check that Genre Totals Match*

```
In [19]: sum(genre_totals.iloc[:, 0])
```

```
Out[19]: 19611
```

```
In [20]: sum(movies_genres_table.loc[:,'num_genres'])
```

```
Out[20]: 19611
```

### 1.3.7 Create Heat Map of Genre Relationships

In [21]:
```
def norm_genre_pairs(tmdb_genre_df, genre_pairs, genre_totals):

    new_idx = tmdb_genre_df['genre']
    new_cols = tmdb_genre_df['genre']

    #set the same x/y axis genre to 0
    genre_pairs_plot = genre_pairs.copy()

    for idx in new_idx:
        genre_pairs_plot.set_value(idx, idx, 0)

    norm_genre_pairs_plot = genre_pairs_plot.copy()

    for j in range(0, len(genre_totals)):
        for i in range(0, len(genre_totals)):
            norm_genre_pairs_plot.iloc[i, j] = float(genre_pairs_plot.iloc

    return norm_genre_pairs_plot
```

In [22]:
```
norm_genre_pairs_plot = norm_genre_pairs(tmdb_genre_df, genre_pairs, genre
norm_genre_pairs_plot
```

Out[22]:

| genre | Action | Adventure | Animation | Comedy | Crime |
|---|---|---|---|---|---|
| genre | | | | | |
| Action | 0.000000 | 0.556604 | 0.237342 | 0.129811 | 0.420345 |
| Adventure | 0.335227 | 0.000000 | 0.373418 | 0.110917 | 0.064299 |
| Animation | 0.085227 | 0.222642 | 0.000000 | 0.078376 | 0.008637 |
| Comedy | 0.210795 | 0.299057 | 0.354430 | 0.000000 | 0.239923 |
| Crime | 0.248864 | 0.063208 | 0.014241 | 0.087474 | 0.000000 |
| Documentary | 0.003977 | 0.006604 | 0.007911 | 0.006998 | 0.008637 |
| Drama | 0.303409 | 0.236792 | 0.099684 | 0.328202 | 0.571977 |
| Family | 0.051136 | 0.281132 | 0.577532 | 0.143457 | 0.006718 |
| Fantasy | 0.131818 | 0.287736 | 0.262658 | 0.078376 | 0.014395 |
| History | 0.044318 | 0.039623 | 0.001582 | 0.005598 | 0.014395 |
| Horror | 0.094318 | 0.044340 | 0.020570 | 0.048985 | 0.060461 |
| Music | 0.004545 | 0.008491 | 0.030063 | 0.038139 | 0.009597 |
| Mystery | 0.052273 | 0.038679 | 0.023734 | 0.018195 | 0.166987 |
| Romance | 0.049432 | 0.070755 | 0.041139 | 0.241428 | 0.051823 |
| Science Fiction | 0.239205 | 0.235849 | 0.191456 | 0.050385 | 0.022073 |
| TV Movie | 0.003977 | 0.018868 | 0.012658 | 0.013996 | 0.004798 |
| Thriller | 0.445455 | 0.214151 | 0.037975 | 0.060532 | 0.609405 |
| War | 0.036932 | 0.025472 | 0.001582 | 0.003149 | 0.005758 |
| Western | 0.014773 | 0.020755 | 0.004747 | 0.005948 | 0.008637 |
| Foreign | 0.002841 | 0.001887 | 0.001582 | 0.002099 | 0.000960 |

| genre | Documentary | Drama | Family | Fantasy | History |
|---|---|---|---|---|---|
| genre | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Action | 0.022293 | 0.145981 | 0.120482 | 0.337700 | 0.302326 |
| Adventure | 0.022293 | 0.068617 | 0.398929 | 0.443959 | 0.162791 |
| Animation | 0.015924 | 0.017223 | 0.488621 | 0.241630 | 0.003876 |
| Comedy | 0.063694 | 0.256424 | 0.548862 | 0.326055 | 0.062016 |
| Crime | 0.028662 | 0.162931 | 0.009371 | 0.021834 | 0.058140 |
| Documentary | 0.000000 | 0.006561 | 0.014726 | 0.001456 | 0.050388 |
| Drama | 0.076433 | 0.000000 | 0.179384 | 0.270742 | 0.860465 |
| Family | 0.035032 | 0.036632 | 0.000000 | 0.305677 | 0.007752 |
| Fantasy | 0.003185 | 0.050847 | 0.281124 | 0.000000 | 0.011628 |
| History | 0.041401 | 0.060689 | 0.002677 | 0.004367 | 0.000000 |
| Horror | 0.009554 | 0.056315 | 0.004016 | 0.126638 | 0.011628 |
| Music | 0.114650 | 0.035539 | 0.045515 | 0.018923 | 0.007752 |
| Mystery | 0.003185 | 0.078732 | 0.013387 | 0.077147 | 0.015504 |
| Romance | 0.000000 | 0.229907 | 0.093708 | 0.135371 | 0.112403 |
| Science Fiction | 0.003185 | 0.046747 | 0.100402 | 0.227074 | 0.003876 |
| TV Movie | 0.006369 | 0.012849 | 0.060241 | 0.026201 | 0.019380 |
| Thriller | 0.012739 | 0.264899 | 0.014726 | 0.160116 | 0.139535 |
| War | 0.025478 | 0.040459 | 0.000000 | 0.004367 | 0.259690 |
| Western | 0.000000 | 0.007928 | 0.002677 | 0.004367 | 0.003876 |
| Foreign | 0.009554 | 0.004647 | 0.002677 | 0.000000 | 0.007752 |

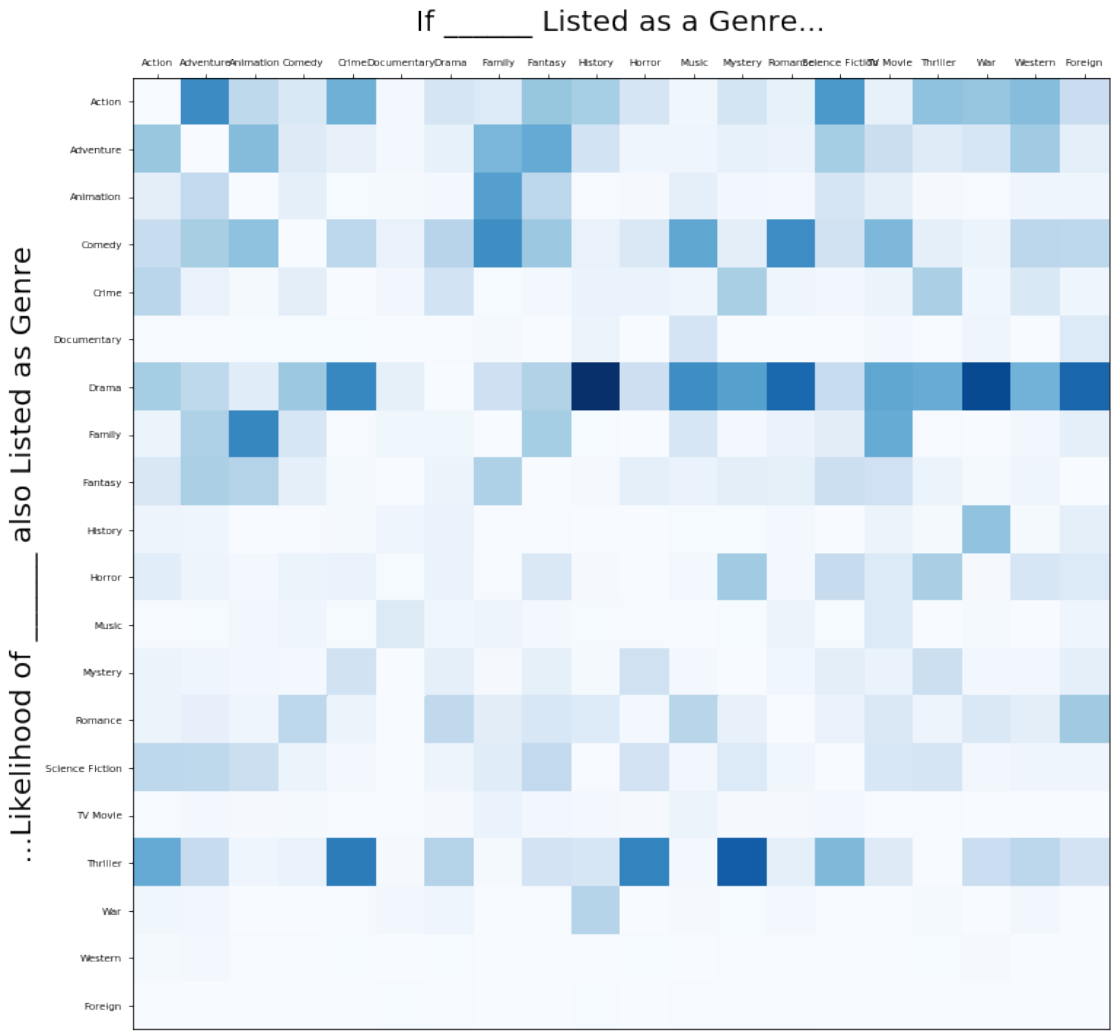
| genre | Horror | Music | Mystery | Romance | Science Fiction |
|---|---|---|---|---|---|
| genre | | | | | |
| Action | 0.150772 | 0.033898 | 0.155143 | 0.069767 | 0.510922 |
| Adventure | 0.042688 | 0.038136 | 0.069140 | 0.060144 | 0.303398 |
| Animation | 0.011807 | 0.080508 | 0.025295 | 0.020850 | 0.146845 |
| Comedy | 0.127157 | 0.461864 | 0.087690 | 0.553328 | 0.174757 |
| Crime | 0.057221 | 0.042373 | 0.293423 | 0.043304 | 0.027913 |
| Documentary | 0.002725 | 0.152542 | 0.001686 | 0.000000 | 0.001214 |
| Drama | 0.187103 | 0.550847 | 0.485666 | 0.674419 | 0.207524 |
| Family | 0.002725 | 0.144068 | 0.016863 | 0.056135 | 0.091019 |
| Fantasy | 0.079019 | 0.055085 | 0.089376 | 0.074579 | 0.189320 |
| History | 0.002725 | 0.008475 | 0.006745 | 0.023256 | 0.001214 |
| Horror | 0.000000 | 0.021186 | 0.315346 | 0.016840 | 0.214806 |
| Music | 0.004541 | 0.000000 | 0.006745 | 0.048115 | 0.007282 |
| Mystery | 0.169846 | 0.016949 | 0.000000 | 0.031275 | 0.086165 |
| Romance | 0.019074 | 0.254237 | 0.065767 | 0.000000 | 0.055825 |
| Science Fiction | 0.160763 | 0.025424 | 0.119730 | 0.036889 | 0.000000 |
| TV Movie | 0.010899 | 0.050847 | 0.010118 | 0.010425 | 0.016990 |
| Thriller | 0.585831 | 0.021186 | 0.709949 | 0.082598 | 0.388350 |
| War | 0.001817 | 0.012712 | 0.008432 | 0.019246 | 0.006068 |
| Western | 0.009083 | 0.000000 | 0.003373 | 0.004812 | 0.003641 |
| Foreign | 0.002725 | 0.004237 | 0.003373 | 0.006415 | 0.001214 |

| genre | TV Movie | Thriller | War | Western | Foreign |
|---|---|---|---|---|---|
| genre | | | | | |
| Action | 0.068627 | 0.355394 | 0.340314 | 0.371429 | 0.20 |
| Adventure | 0.196078 | 0.102901 | 0.141361 | 0.314286 | 0.08 |

```
Animation          0.078431  0.010879  0.005236  0.042857     0.04
Comedy             0.392157  0.078422  0.047120  0.242857     0.24
Crime              0.049020  0.287851  0.031414  0.128571     0.04
Documentary        0.019608  0.001813  0.041885  0.000000     0.12
Drama              0.460784  0.439257  0.774869  0.414286     0.68
Family             0.441176  0.004986  0.000000  0.028571     0.08
Fantasy            0.176471  0.049864  0.015707  0.042857     0.00
History            0.049020  0.016319  0.350785  0.014286     0.08
Horror             0.117647  0.292384  0.010471  0.142857     0.12
Music              0.117647  0.002267  0.015707  0.000000     0.04
Mystery            0.058824  0.190843  0.026178  0.028571     0.08
Romance            0.127451  0.046691  0.125654  0.085714     0.32
Science Fiction    0.137255  0.145059  0.026178  0.042857     0.04
TV Movie           0.000000  0.004986  0.000000  0.000000     0.00
Thriller           0.107843  0.000000  0.193717  0.242857     0.16
War                0.000000  0.016772  0.000000  0.028571     0.00
Western            0.000000  0.007706  0.010471  0.000000     0.00
Foreign            0.000000  0.001813  0.000000  0.000000     0.00
```

In [23]:
```
def plot_heat_map(tmdb_genre_df, norm_genre_pairs_plot):

    new_idx = tmdb_genre_df['genre']
    new_cols = tmdb_genre_df['genre']

    data = norm_genre_pairs_plot
    fig, ax = plt.subplots(figsize = (12,12))
    heatmap = ax.pcolor(data, cmap=plt.cm.Blues)
    ax.set_xticks(np.arange(data.shape[0])+0.5, minor = False)
    ax.set_yticks(np.arange(data.shape[1])+0.5, minor = False)

    ax.invert_yaxis()
    ax.xaxis.tick_top()
    ax.set_xticklabels(new_idx, minor=False, fontsize=7)
    ax.set_yticklabels(new_cols, minor=False, fontsize=7)

    plt.ylabel('...Likelihood of ______ also Listed as Genre', fontsize=20
    plt.title('If ______ Listed as a Genre...',
              horizontalalignment='center',
              fontsize=20,
              y = 1.04)

    plt.show()
```

In [24]:
```
plot_heat_map(tmdb_genre_df, norm_genre_pairs_plot)
```




### 1.3.8 Reducing Genres

```
In [25]: def genre_reducer(movies_genres_table, genre_id_table, genre_id_to_change,

             genre_id_table = genre_id_table[genre_id_table.genre_id != genre_id_to

             num_rows = movies_genres_table.shape[0]

             for row in range(0, num_rows):

                 # pull out number of genres and genre id list
                 num_ids = movies_genres_table.iloc[row, 1]
                 id_list = movies_genres_table.iloc[row][2:(2 + num_ids)]

                 # change genre ids
```

```
                for i in range(0, num_ids):
                    if id_list[i] == genre_id_to_change:
                        id_list[i] = new_genre_id

                new_id_list = list(set(id_list)) # remove duplicates
                new_num_ids = len(new_id_list) # get new number of genres

                # change movies genres table to reflect new genre ids
                movies_genres_table.iloc[row, 1] = new_num_ids
                movies_genres_table.iloc[row][2:(2 + new_num_ids)] = new_id_list
                movies_genres_table.iloc[row][(2 + new_num_ids):] = 0

            return genre_id_table, movies_genres_table
```

```
In [26]: # tmdb_genre_df
```

```
In [27]: # movies_genres_table.iloc[:10,:]
```

```
In [28]: genre_id_table = tmdb_genre_df.copy()
         movies_genres = movies_genres_table.copy()
```

```
In [29]: # change all "adventure" to "action"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl
```

```
In [30]: # change all "sci fi" to "action"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl
```

```
In [31]: # change all "war" to "drama"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl
```

```
In [32]: # change all "western" to "drama"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl
```

```
In [33]: # change all "mystery" to "thriller"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl
```

```
In [34]: # change all "horror" to "thriller"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl
```

```
In [35]: # change all "history" to "drama"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl
```

```
In [36]: # change all "tv movie" to "drama"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl
```

```
In [37]: # change all "foreign" to "drama"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl
```

```
In [38]: # change all "fantasy" to "action"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl
```

```
In [39]: # change all "music" to "drama"
         genre_id_table, movies_genres = genre_reducer(movies_genres, genre_id_tabl

In [40]: ### ADD/REMOVE GENRE CHANGES HERE

In [ ]:

In [41]: movies_genres.iloc[:10,:]
```

Out[41]:

| | movie_id | num_genres | id_1 | id_2 | id_3 | id_4 | id_5 | id_6 | id_7 | id_8 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 293660 | 3 | 35 | 28 | 10749 | 0 | 0 | 0 | 0 | 0 |
| 1 | 297761 | 2 | 80 | 28 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 209112 | 1 | 28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 271110 | 1 | 28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 329865 | 3 | 18 | 28 | 53 | 0 | 0 | 0 | 0 | 0 |
| 5 | 284052 | 1 | 28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 246655 | 1 | 28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 269149 | 4 | 16 | 35 | 28 | 10751 | 0 | 0 | 0 | 0 |
| 8 | 259316 | 1 | 28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 330459 | 2 | 18 | 28 | 0 | 0 | 0 | 0 | 0 | 0 |

| | id_9 | id_10 | id_11 |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 |

```
In [42]: genre_id_table
```

Out[42]:

| | genre_id | genre |
|---|---|---|
| 0 | 28 | Action |
| 2 | 16 | Animation |
| 3 | 35 | Comedy |
| 4 | 80 | Crime |
| 5 | 99 | Documentary |
| 6 | 18 | Drama |
| 7 | 10751 | Family |
| 13 | 10749 | Romance |
| 16 | 53 | Thriller |

```
In [43]: genre_id_table = genre_id_table.reset_index(drop=True)
         genre_id_table
```

Out[43]:

| | genre_id | genre |
|---|---|---|
| 0 | 28 | Action |
| 1 | 16 | Animation |
| 2 | 35 | Comedy |
| 3 | 80 | Crime |
| 4 | 99 | Documentary |
| 5 | 18 | Drama |
| 6 | 10751 | Family |
| 7 | 10749 | Romance |
| 8 | 53 | Thriller |

### 1.3.9 Table and Heat Map of Reduced Genre Relationships

In [44]:
```
genre_pairs_revised = create_genre_pairs(genre_id_table, movies_genres)
genre_pairs_revised
```

Out[44]:

| genre | Action | Animation | Comedy | Crime | Documentary | Drama | Family |
|---|---|---|---|---|---|---|---|
| genre | | | | | | | |
| Action | 2815 | 408 | 744 | 455 | 14 | 976 | 419 |
| Animation | 408 | 632 | 224 | 9 | 5 | 91 | 365 |
| Comedy | 744 | 224 | 2858 | 250 | 20 | 1039 | 410 |
| Crime | 455 | 9 | 250 | 1042 | 9 | 605 | 7 |
| Documentary | 14 | 5 | 20 | 9 | 314 | 75 | 11 |
| Drama | 976 | 91 | 1039 | 605 | 75 | 3927 | 185 |
| Family | 419 | 365 | 410 | 7 | 11 | 185 | 747 |
| Romance | 226 | 26 | 690 | 54 | 0 | 866 | 70 |
| Thriller | 1228 | 45 | 312 | 689 | 8 | 1162 | 22 |

| genre | Romance | Thriller |
|---|---|---|
| genre | | |
| Action | 226 | 1228 |
| Animation | 26 | 45 |
| Comedy | 690 | 312 |
| Crime | 54 | 689 |
| Documentary | 0 | 8 |
| Drama | 866 | 1162 |
| Family | 70 | 22 |
| Romance | 1247 | 141 |
| Thriller | 141 | 2787 |

In [45]:
```
genre_totals = get_genre_totals(genre_id_table, genre_pairs_revised)
genre_totals
```

Out[45]:

| genre | num_movies_with_genre |
|---|---|
| Action | 2815 |
| Animation | 632 |
| Comedy | 2858 |
| Crime | 1042 |

```
Documentary                   314
Drama                        3927
Family                        747
Romance                      1247
Thriller                     2787
```

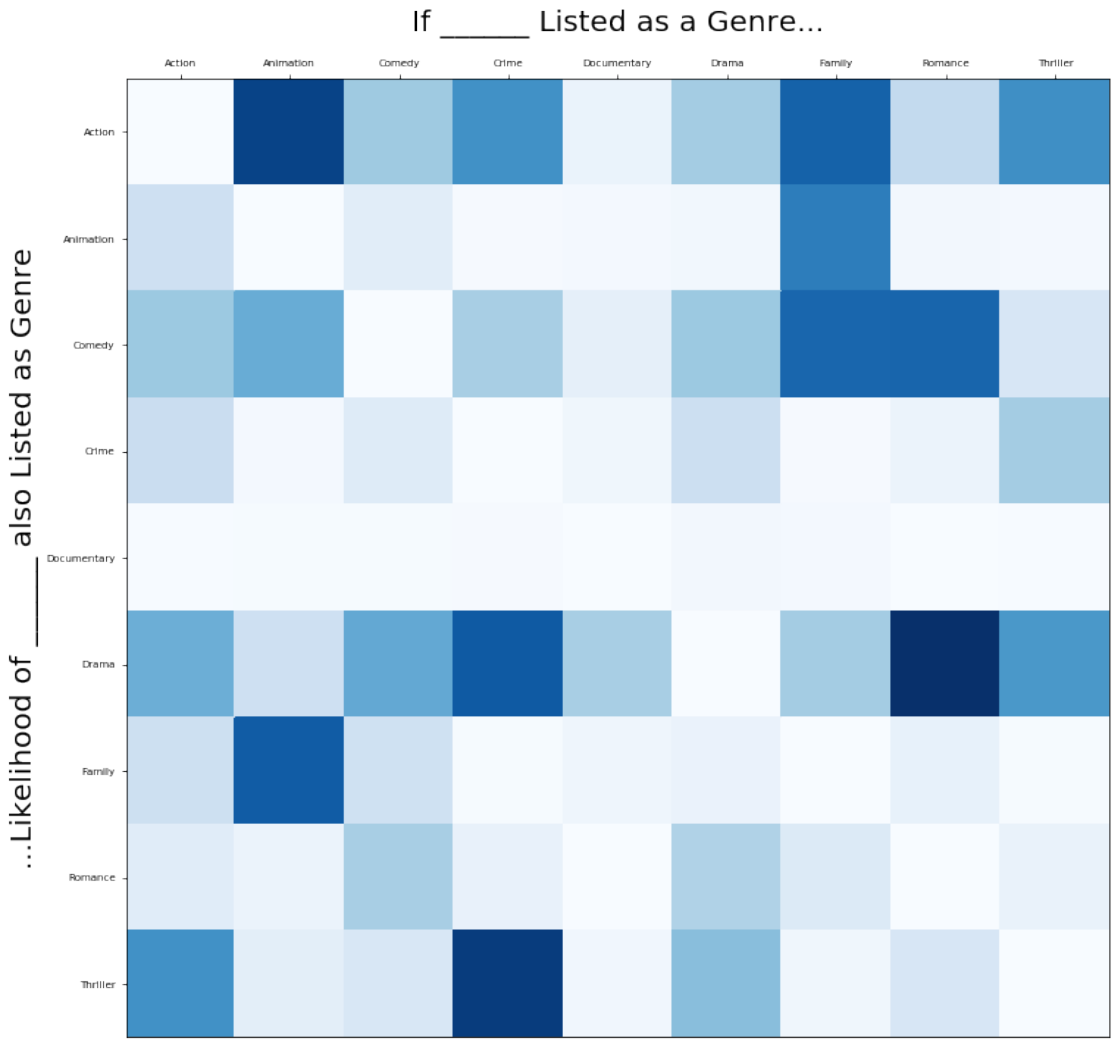
In [46]:
```
norm_genre_pairs_revised = norm_genre_pairs(genre_id_table, genre_pairs_re
norm_genre_pairs_revised
```

Out[46]:

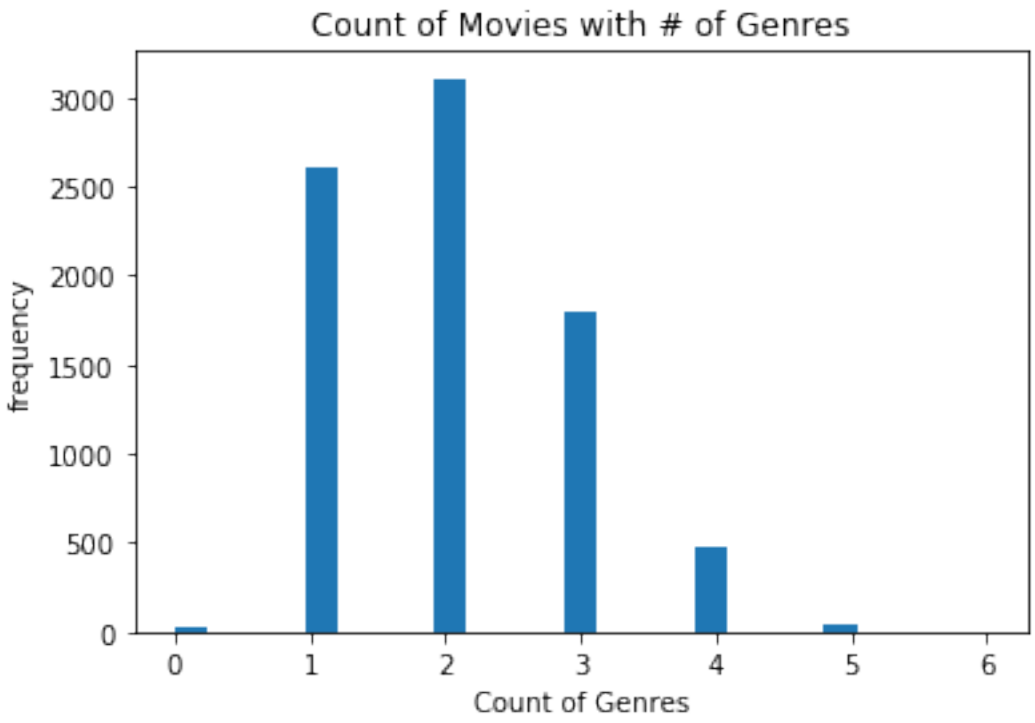
| genre | Action | Animation | Comedy | Crime | Documentary | Dram |
|---|---|---|---|---|---|---|
| genre | | | | | | |
| Action | 0.000000 | 0.645570 | 0.260322 | 0.436660 | 0.044586 | 0.24853 |
| Animation | 0.144938 | 0.000000 | 0.078376 | 0.008637 | 0.015924 | 0.02317 |
| Comedy | 0.264298 | 0.354430 | 0.000000 | 0.239923 | 0.063694 | 0.26457 |
| Crime | 0.161634 | 0.014241 | 0.087474 | 0.000000 | 0.028662 | 0.15406 |
| Documentary | 0.004973 | 0.007911 | 0.006998 | 0.008637 | 0.000000 | 0.01909 |
| Drama | 0.346714 | 0.143987 | 0.363541 | 0.580614 | 0.238854 | 0.00000 |
| Family | 0.148845 | 0.577532 | 0.143457 | 0.006718 | 0.035032 | 0.04711 |
| Romance | 0.080284 | 0.041139 | 0.241428 | 0.051823 | 0.000000 | 0.22052 |
| Thriller | 0.436234 | 0.071203 | 0.109167 | 0.661228 | 0.025478 | 0.29590 |

| genre | Family | Romance | Thriller |
|---|---|---|---|
| genre | | | |
| Action | 0.560910 | 0.181235 | 0.440617 |
| Animation | 0.488621 | 0.020850 | 0.016146 |
| Comedy | 0.548862 | 0.553328 | 0.111948 |
| Crime | 0.009371 | 0.043304 | 0.247219 |
| Documentary | 0.014726 | 0.000000 | 0.002870 |
| Drama | 0.247657 | 0.694467 | 0.416936 |
| Family | 0.000000 | 0.056135 | 0.007894 |
| Romance | 0.093708 | 0.000000 | 0.050592 |
| Thriller | 0.029451 | 0.113071 | 0.000000 |

In [47]:
```
plot_heat_map(genre_id_table, norm_genre_pairs_revised)
```




```
In [48]: plt.hist(movies_genres['num_genres'].values,
               25)
         plt.title('Count of Movies with # of Genres')
         plt.xlabel('Count of Genres')
         plt.ylabel('frequency')

Out[48]: <matplotlib.text.Text at 0x117ed12d0>
```




### 1.3.10 Get Unique Genre Combos

```
In [49]: np_empty = np.empty((len(movies_genres),2))
         np_empty[:] = np.nan

In [50]: genres_list_df = pd.DataFrame(np_empty, columns=['movie_id', 'genres_list'
         genres_list_df.shape

Out[50]: (8060, 2)

In [51]: genres_list_df = genres_list_df.astype(object)

In [52]: genres_as_list = list()

         for i in range(0, len(movies_genres)):
             num_genres = movies_genres.iloc[i, 1]
             genres_list = list(movies_genres.iloc[i, 2:(2 + num_genres)])
             genres_list.sort()
             genres_as_list.append(genres_list)

             genres_list_df.iloc[i, 0] = movies_genres.iloc[i, 0]
             genres_list_df.iloc[i, 1] = genres_list

         unique_genres_list = [list(x) for x in set(tuple(x) for x in genres_as_lis
```

```
In [53]: genres_list_df.iloc[:25, :]
```

Out[53]:

| | movie_id | genres_list |
|---|---|---|
| 0 | 293660 | [28, 35, 10749] |
| 1 | 297761 | [28, 80] |
| 2 | 209112 | [28] |
| 3 | 271110 | [28] |
| 4 | 329865 | [18, 28, 53] |
| 5 | 284052 | [28] |
| 6 | 246655 | [28] |
| 7 | 269149 | [16, 28, 35, 10751] |
| 8 | 259316 | [28] |
| 9 | 330459 | [18, 28] |
| 10 | 127380 | [16, 28, 35, 10751] |
| 11 | 328111 | [16, 28, 35, 10751] |
| 12 | 313369 | [18, 35, 10749] |
| 13 | 274870 | [18, 28, 10749] |
| 14 | 278927 | [18, 28] |
| 15 | 291805 | [28, 35, 53, 80] |
| 16 | 277834 | [16, 28, 35, 10751] |
| 17 | 47933 | [28] |
| 18 | 188927 | [28, 53] |
| 19 | 258489 | [28] |
| 20 | 324668 | [28, 53] |
| 21 | 283366 | [18, 28] |
| 22 | 333371 | [28] |
| 23 | 324786 | [18] |
| 24 | 333484 | [18, 28] |

```
In [54]: unique_genres_df = pd.DataFrame(columns=['genre_labels', 'num_movies'])

         unique_genres_df.loc[:, 'genre_labels'] = unique_genres_list
         unique_genres_df.loc[:, 'num_movies'] = 0

In [55]: for i in range(0, len(unique_genres_df)):
             unique_genres_df.iloc[i, 1] = genres_as_list.count(unique_genres_df.il

In [56]: unique_genres_df
         unique_genres_df.to_csv('unique_genre_tuple_frequencies_TMDb.csv', index=F
         print unique_genres_df.shape

(149, 2)


In [57]: unique_genres_sorted = unique_genres_df.sort_values('num_movies', ascendin
         unique_genres_sorted.iloc[:30, :]
```

Out[57]:

| | genre_labels | num_movies |
|---|---|---|
| 0 | [18] | 829 |

```
1                   [35]         683
2                   [53]         601
3               [28, 53]         508
4               [18, 35]         419
5               [18, 53]         392
6            [18, 10749]         324
7        [18, 35, 10749]         298
8                   [28]         267
9               [18, 28]         266
10         [18, 53, 80]         243
11          [35, 10749]         237
12         [18, 28, 53]         230
13                  [99]         194
14              [28, 35]         154
15         [28, 53, 80]         132
16     [18, 28, 53, 80]         125
17              [16, 28]         100
18  [16, 28, 35, 10751]          98
19              [18, 80]          94
20      [16, 28, 10751]          91
21              [35, 53]          83
22           [16, 10751]          82
23              [53, 80]          80
24      [28, 35, 10751]          71
25         [28, 35, 53]          70
26              [18, 99]          61
27           [35, 10751]          60
28         [18, 28, 35]          59
29      [18, 28, 10749]          57
```

```
In [58]: len(unique_genres_sorted)
```

```
Out[58]: 149
```

```
In [59]: sum(unique_genres_sorted.iloc[:, 1])  # check we have all the movies
```

```
Out[59]: 8060
```

```
In [ ]:
```

### 1.3.11 Reduce Number of Genre Pairs

```
In [60]: cutoff_threshold_pct = 0.01
         cutoff_threshold_num = int(cutoff_threshold_pct * sum(unique_genres_sorted
         cutoff_row = 0

         for i in range(0, len(unique_genres_sorted)):
             if unique_genres_sorted.iloc[i, 1] > cutoff_threshold_num:
                 cutoff_row = cutoff_row + 1
```

```
In [61]: cutoff_threshold_num

Out[61]: 80

In [62]: cutoff_row

Out[62]: 23

In [63]: sum(unique_genres_sorted.iloc[cutoff_row:, 1])

Out[63]: 1610

In [64]: selected_genre_pairs = unique_genres_sorted.iloc[:cutoff_row, :]
         selected_genre_pairs = selected_genre_pairs.reset_index(drop=True)
         selected_genre_pairs
```

Out[64]:

| | genre_labels | num_movies |
|---|---|---|
| 0 | [18] | 829 |
| 1 | [35] | 683 |
| 2 | [53] | 601 |
| 3 | [28, 53] | 508 |
| 4 | [18, 35] | 419 |
| 5 | [18, 53] | 392 |
| 6 | [18, 10749] | 324 |
| 7 | [18, 35, 10749] | 298 |
| 8 | [28] | 267 |
| 9 | [18, 28] | 266 |
| 10 | [18, 53, 80] | 243 |
| 11 | [35, 10749] | 237 |
| 12 | [18, 28, 53] | 230 |
| 13 | [99] | 194 |
| 14 | [28, 35] | 154 |
| 15 | [28, 53, 80] | 132 |
| 16 | [18, 28, 53, 80] | 125 |
| 17 | [16, 28] | 100 |
| 18 | [16, 28, 35, 10751] | 98 |
| 19 | [18, 80] | 94 |
| 20 | [16, 28, 10751] | 91 |
| 21 | [35, 53] | 83 |
| 22 | [16, 10751] | 82 |

### 1.3.12 Revised Overall Dataset to Reflect Reduced Genre Pairs

```
In [65]: row_ref = 0

         y_labels = genres_list_df.copy()

         for i in range(0, len(genres_list_df)):
```

```
            for j in range(0, len(selected_genre_pairs)):

                if (genres_list_df.iloc[i, 1] == selected_genre_pairs.iloc[j, 0]):

                    y_labels.iloc[row_ref, :] = genres_list_df.iloc[i, :]
                    row_ref = row_ref + 1

        y_labels = y_labels.iloc[:row_ref, :]
```

In [66]:
```
y_labels.iloc[:25, :]
```

Out[66]:

| | movie_id | genres_list |
|---|---|---|
| 0 | 209112 | [28] |
| 1 | 271110 | [28] |
| 2 | 329865 | [18, 28, 53] |
| 3 | 284052 | [28] |
| 4 | 246655 | [28] |
| 5 | 269149 | [16, 28, 35, 10751] |
| 6 | 259316 | [28] |
| 7 | 330459 | [18, 28] |
| 8 | 127380 | [16, 28, 35, 10751] |
| 9 | 328111 | [16, 28, 35, 10751] |
| 10 | 313369 | [18, 35, 10749] |
| 11 | 278927 | [18, 28] |
| 12 | 277834 | [16, 28, 35, 10751] |
| 13 | 47933 | [28] |
| 14 | 188927 | [28, 53] |
| 15 | 258489 | [28] |
| 16 | 324668 | [28, 53] |
| 17 | 283366 | [18, 28] |
| 18 | 333371 | [28] |
| 19 | 324786 | [18] |
| 20 | 333484 | [18, 28] |
| 21 | 68735 | [28] |
| 22 | 121856 | [28] |
| 23 | 43074 | [18, 28, 53] |
| 24 | 207932 | [53] |

In [67]:
```
len(y_labels)
```

Out[67]: 6450

In [68]:
```
sum(selected_genre_pairs.iloc[:, 1])
```

Out[68]: 6450

In [69]:
```
y_labels.to_csv('y_labels.csv', index=False)
```

In [70]:
```
y_labels_check = pd.read_csv('y_labels.csv')
y_labels_check.iloc[:25, :]
```

Out[70]:

| | movie_id | genres_list |
|---|---|---|
| 0 | 209112 | [28] |
| 1 | 271110 | [28] |
| 2 | 329865 | [18, 28, 53] |
| 3 | 284052 | [28] |
| 4 | 246655 | [28] |
| 5 | 269149 | [16, 28, 35, 10751] |
| 6 | 259316 | [28] |
| 7 | 330459 | [18, 28] |
| 8 | 127380 | [16, 28, 35, 10751] |
| 9 | 328111 | [16, 28, 35, 10751] |
| 10 | 313369 | [18, 35, 10749] |
| 11 | 278927 | [18, 28] |
| 12 | 277834 | [16, 28, 35, 10751] |
| 13 | 47933 | [28] |
| 14 | 188927 | [28, 53] |
| 15 | 258489 | [28] |
| 16 | 324668 | [28, 53] |
| 17 | 283366 | [18, 28] |
| 18 | 333371 | [28] |
| 19 | 324786 | [18] |
| 20 | 333484 | [18, 28] |
| 21 | 68735 | [28] |
| 22 | 121856 | [28] |
| 23 | 43074 | [18, 28, 53] |
| 24 | 207932 | [53] |

### 1.3.13 Stratified Sampler Function

In [71]:
```
def stratified_sampler(dataset, observations):
    # Performs a stratified sample on the dataset and returns the number o
    # requested.
    #
    # Parameters:
    #    dataset:  The dataframe to sample, observing class relationships.
    #    observations:  The number of total target observations across all
    #
    # Returns:
    #    A pandas dataframe sampled from the dataset maintaining class rel
    class_weights = dataset.groupby("genres_list").agg(['count'])/len(data
    class_sample_counts = class_weights * observations
    sampled = pd.DataFrame()
    for class_to_sample in class_sample_counts.iterrows():
        class_name = class_to_sample[0]
        desired_class_observations = class_to_sample[1][0]
        sampled_obs = dataset[dataset["genres_list"]==class_name].sample(i
        sampled = sampled.append(sampled_obs, ignore_index=True)
    return sampled
```

```
In [72]: temp = stratified_sampler(y_labels_check, 1000)
         print(len(temp))
```

```
988
```

```
In [73]: temp.iloc[:25, :]
```

Out[73]:

| | movie_id | genres_list |
|---|---|---|
| 0 | 228165 | [16, 10751] |
| 1 | 51162 | [16, 10751] |
| 2 | 13934 | [16, 10751] |
| 3 | 14836 | [16, 10751] |
| 4 | 16418 | [16, 10751] |
| 5 | 11802 | [16, 10751] |
| 6 | 15601 | [16, 10751] |
| 7 | 81003 | [16, 10751] |
| 8 | 19595 | [16, 10751] |
| 9 | 13459 | [16, 10751] |
| 10 | 73723 | [16, 10751] |
| 11 | 10800 | [16, 10751] |
| 12 | 9016 | [16, 28, 10751] |
| 13 | 297270 | [16, 28, 10751] |
| 14 | 21683 | [16, 28, 10751] |
| 15 | 251768 | [16, 28, 10751] |
| 16 | 140870 | [16, 28, 10751] |
| 17 | 8965 | [16, 28, 10751] |
| 18 | 14317 | [16, 28, 10751] |
| 19 | 109445 | [16, 28, 10751] |
| 20 | 7450 | [16, 28, 10751] |
| 21 | 13179 | [16, 28, 10751] |
| 22 | 342917 | [16, 28, 10751] |
| 23 | 139649 | [16, 28, 10751] |
| 24 | 223706 | [16, 28, 10751] |

*Check Sampler Function*

```
In [74]: class_weights_all = y_labels_check.groupby("genres_list").agg(['count'])/l
         class_weights_sample = temp.groupby("genres_list").agg(['count'])/len(temp
```

```
In [75]: x = class_weights_all.iloc[:, 0]
         y = class_weights_sample.iloc[:, 0]
         z = pd.DataFrame([x.round(4)*100, y.round(4)*100, x.round(4)*100 - y.round
         z = z.transpose()
         z.columns = ['all_pct_genre', 'samp_pct_genre', 'delta_pct']
         z
```

Out[75]:

| genres_list | all_pct_genre | samp_pct_genre | delta_pct |
|---|---|---|---|

| | | | |
|---|---|---|---|
| [16, 10751] | 1.27 | 1.21 | 0.06 |
| [16, 28, 10751] | 1.41 | 1.42 | −0.01 |
| [16, 28, 35, 10751] | 1.52 | 1.52 | 0.00 |
| [16, 28] | 1.55 | 1.52 | 0.03 |
| [18, 10749] | 5.02 | 5.06 | −0.04 |
| [18, 28, 53, 80] | 1.94 | 1.92 | 0.02 |
| [18, 28, 53] | 3.57 | 3.54 | 0.03 |
| [18, 28] | 4.12 | 4.15 | −0.03 |
| [18, 35, 10749] | 4.62 | 4.66 | −0.04 |
| [18, 35] | 6.50 | 6.48 | 0.02 |
| [18, 53, 80] | 3.77 | 3.74 | 0.03 |
| [18, 53] | 6.08 | 6.07 | 0.01 |
| [18, 80] | 1.46 | 1.42 | 0.04 |
| [18] | 12.85 | 12.96 | −0.11 |
| [28, 35] | 2.39 | 2.33 | 0.06 |
| [28, 53, 80] | 2.05 | 2.02 | 0.03 |
| [28, 53] | 7.88 | 7.89 | −0.01 |
| [28] | 4.14 | 4.15 | −0.01 |
| [35, 10749] | 3.67 | 3.64 | 0.03 |
| [35, 53] | 1.29 | 1.21 | 0.08 |
| [35] | 10.59 | 10.63 | −0.04 |
| [53] | 9.32 | 9.41 | −0.09 |
| [99] | 3.01 | 3.04 | −0.03 |