TMDb

July 8, 2018

1 Project: Exploring the Movie Database (TMDB)

1.1 Table of contents

Introduction

I like action, animation, fantasy, and science fiction movies (not necessarily in that order!). For a personal project I would have liked the know what are the most popular movies in these categories. Do other people like these categories as well? Do these movies make money?

But that would be a personal project. I have refrained from these questions in the current project. Instead I have followed the standard procedure of wrangling and exploring a given dataset. Along the way I have asked questions based upon the features of the dataset.

1. What are the most popular movies of all time?
2. What are the features associated with these movies?
3. Who are the most popular directors?
4. How is the revenue distribution?
5. What are the top-grossing movies of all time?
6. Who are the directors of top-grossing movies?
7. Is popularity related to revenue?
8. Who are the most productive directors?
9. What's the yearly movie production rate?
10. Which genres have been popular over the years?

In the following, I first describe the data wrangling phase where I load the data into a dataframe, and then assess and clean. Then I describe my explorations of the dataset. I have explored *popularity, revenue, their interelation, directors, years,* and* genres.* Along the way I also find the answers to the questions posed above.

1.1.1 Libraries

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        % matplotlib inline
```

```python
import seaborn as sns
sns.set()
```

Wrangle

1.1.2 Gather

In [2]:
```python
dataset = pd.read_csv('tmdb-movies.csv');
dataset.head()
```

Out[2]:
```
       id    imdb_id  popularity     budget     revenue  \
0  135397  tt0369610   32.985763  150000000  1513528810
1   76341  tt1392190   28.419936  150000000   378436354
2  262500  tt2908446   13.112507  110000000   295238201
3  140607  tt2488496   11.173104  200000000  2068178225
4  168259  tt2820852    9.335014  190000000  1506249360

                 original_title  \
0                Jurassic World
1            Mad Max: Fury Road
2                     Insurgent
3  Star Wars: The Force Awakens
4                     Furious 7

                                                cast  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...

                                            homepage          director  \
0                      http://www.jurassicworld.com/   Colin Trevorrow
1                        http://www.madmaxmovie.com/     George Miller
2     http://www.thedivergentseries.movie/#insurgent  Robert Schwentke
3  http://www.starwars.com/films/star-wars-episod...       J.J. Abrams
4                           http://www.furious7.com/         James Wan

                         tagline      ...        \
0             The park is open.      ...
1            What a Lovely Day.      ...
2       One Choice Can Destroy You      ...
3  Every generation has a story.      ...
4              Vengeance Hits Home      ...

                                            overview runtime  \
0  Twenty-two years after the events of Jurassic ...     124
1  An apocalyptic story set in the furthest reach...     120
```

```
2  Beatrice Prior must confront her inner demons ...     119
3  Thirty years after defeating the Galactic Empi...     136
4  Deckard Shaw seeks revenge against Dominic Tor...     137

                                      genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         Adventure|Science Fiction|Thriller
3   Action|Adventure|Science Fiction|Fantasy
4                      Action|Crime|Thriller

                                production_companies release_date vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15       5562
1  Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15       6185
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15       2480
3          Lucasfilm|Truenorth Productions|Bad Robot     12/15/15       5292
4  Universal Pictures|Original Film|Media Rights ...       4/1/15       2947

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08
3           7.5          2015  1.839999e+08  1.902723e+09
4           7.3          2015  1.747999e+08  1.385749e+09

[5 rows x 21 columns]
```

We see that there are 21 features associated with each entry. The questions I am interested in primarily concerns the popularity and box-office performance of a movie. In this respect, some of the features like 'id', 'imdb_id', and 'homepage' are irrelevant. In the next phases of the wrangling procedure I shall consider modifying the dataframe to our need.

1.1.3 Assess

Because a number of features could not be displayed abobe, let's first generate a list of the features in the dataset. This information will be helpful in deciding which features to keep.

```
In [3]: dataset.columns
```

```
Out[3]: Index(['id', 'imdb_id', 'popularity', 'budget', 'revenue', 'original_title',
               'cast', 'homepage', 'director', 'tagline', 'keywords', 'overview',
               'runtime', 'genres', 'production_companies', 'release_date',
               'vote_count', 'vote_average', 'release_year', 'budget_adj',
               'revenue_adj'],
              dtype='object')
```

We can safely drop 'id', 'imdb_id', 'budget', 'revenue', and 'homepage' features: 'id' , 'imdb_id', and 'homepage' should have any relevance to the popularity and revenue of a movie, and raw 'budget' and 'revenue' are unnecessary as their adjusted values are also given in the final columns. It may be argued that the tagline, keywords, and overview matters for the popularity and revenue of a movie. However, this information may be redundant when the genres are specified or just too difficult to use. In the following, I have therefore decided to drop these features as well. Because the popularity score is already given, I shall not need 'vote_count' and 'vote_average'.

```
In [4]: list_drop = ['id', 'imdb_id', 'budget', 'revenue', 'homepage', 'tagline', 'overview', 'v
        dataset.drop(list_drop, axis=1, inplace=True)
        dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 11 columns):
popularity              10866 non-null float64
original_title          10866 non-null object
cast                    10790 non-null object
director                10822 non-null object
runtime                 10866 non-null int64
genres                  10843 non-null object
production_companies    9836 non-null object
release_date            10866 non-null object
release_year            10866 non-null int64
budget_adj              10866 non-null float64
revenue_adj             10866 non-null float64
dtypes: float64(3), int64(2), object(6)
memory usage: 933.9+ KB
```

1.1.4 Clean

Time to clean data! We see that come entries for cast are missing. Let's have a look at some of these movies.

Cast

```
In [5]: dataset[dataset.cast.isnull()].head()
```

```
Out[5]:      popularity                             original_title cast  \
        371    0.422901                          Sanjay's Super Team  NaN
        441    0.220751  Winter on Fire: Ukraine's Fight for Freedom  NaN
        465    0.201696                                  Bitter Lake  NaN
        536    0.122543                                A Faster Horse  NaN
        538    0.114264                           The Mask You Live In  NaN

                        director  runtime       genres  \
        371         Sanjay Patel        7    Animation
        441     Evgeny Afineevsky       98  Documentary
        465          Adam Curtis      135  Documentary
        536           David Gelb       90  Documentary
```

```
538  Jennifer Siebel Newsom       88  Documentary

                                    production_companies release_date  \
371                              Pixar Animation Studios     11/25/15
441  Passion Pictures|Campbell Grobman Films|Afinee...      10/9/15
465                                                  BBC      1/24/15
536                                                  NaN      10/8/15
538                                                  NaN       1/1/15

     release_year  budget_adj  revenue_adj
371          2015         0.0          0.0
441          2015         0.0          0.0
465          2015         0.0          0.0
536          2015         0.0          0.0
538          2015         0.0          0.0
```

```
In [6]: dataset[dataset.cast.isnull()].shape
```

```
Out[6]: (76, 11)
```

We see that adjusted budget and revenue seem to be missing as well. (They cannot be zero!) Moreover, there are just 76 such items out of 10754, less than one percent. I therefore drop these entries in the following.

```
In [7]: dataset = dataset[pd.notnull(dataset['cast'])]
        dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10790 entries, 0 to 10865
Data columns (total 11 columns):
popularity              10790 non-null float64
original_title          10790 non-null object
cast                    10790 non-null object
director                10752 non-null object
runtime                 10790 non-null int64
genres                  10768 non-null object
production_companies    9800 non-null object
release_date            10790 non-null object
release_year            10790 non-null int64
budget_adj              10790 non-null float64
revenue_adj             10790 non-null float64
dtypes: float64(3), int64(2), object(6)
memory usage: 1011.6+ KB
```

Director The next missing field is 'director'. Let's have a look at the missing entries.

```
In [8]: dataset[dataset.director.isnull()].head()
```

```
Out[8]:       popularity                        original_title  \
        532     0.126594        Iliza Shlesinger: Freezing Hot
        548     0.108072            Sense8: Creating the World
        556     0.100910                        With This Ring
        1032    0.291253  Marvel Studios: Assembling a Universe
        1054    0.269468                    Unlocking Sherlock

                                                          cast director  runtime  \
        532                                       Iliza Shlesinger      NaN       71
        548   Tuppence Middleton|Bae Doona |Brian J. Smith|A...      NaN       25
        556   Regina Hall|Jill Scott|Eve|Brooklyn Sudano|Dei...      NaN      105
        1032  Robert Downey Jr.|Chris Hemsworth|Chris Evans|...      NaN       43
        1054  Benedict Cumberbatch|Martin Freeman|Steven Mof...      NaN       60

                                 genres  \
        532                      Comedy
        548   Documentary|Science Fiction
        556              Comedy|Romance
        1032        TV Movie|Documentary
        1054        TV Movie|Documentary

                                  production_companies release_date  release_year  \
        532                      New Wave Entertainment      1/23/15          2015
        548                                     Netflix      8/10/15          2015
        556   Lifetime Television|Sony Pictures Television      1/24/15          2015
        1032                   Marvel Studios|ABC Studios      3/18/14          2014
        1054                                        NaN      1/19/14          2014

              budget_adj  revenue_adj
        532          0.0          0.0
        548          0.0          0.0
        556          0.0          0.0
        1032         0.0          0.0
        1054         0.0          0.0
```

```
In [9]: dataset[dataset.director.isnull()].shape
```

```
Out[9]: (38, 11)
```

Budget and revenue are missing for these ones as well. There are just 38 of them. I shall remove them too.

```
In [10]: dataset = dataset[pd.notnull(dataset['director'])]
         dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10752 entries, 0 to 10865
Data columns (total 11 columns):
popularity              10752 non-null float64
```

```
original_title          10752 non-null object
cast                    10752 non-null object
director                10752 non-null object
runtime                 10752 non-null int64
genres                  10732 non-null object
production_companies    9780 non-null object
release_date            10752 non-null object
release_year            10752 non-null int64
budget_adj              10752 non-null float64
revenue_adj             10752 non-null float64
dtypes: float64(3), int64(2), object(6)
memory usage: 1008.0+ KB
```

Genre Some genre entries are missing.

In [11]:
```
dataset[dataset.genres.isnull()].head()
```

Out[11]:
```
      popularity                          original_title  \
424     0.244648                          Belli di papÃă
997     0.330431    Star Wars Rebels: Spark of Rebellion
1712    0.302095                       Prayers for Bobby
1897    0.020701  Jonas Brothers: The Concert Experience
2370    0.081892                         Freshman Father

                                                   cast  \
424   Diego Abatantuono|Matilde Gioli|Andrea Pisani|...
997   Freddie Prinze Jr.|Vanessa Marshall|Steve Blum...
1712  Ryan Kelley|Sigourney Weaver|Henry Czerny|Dan ...
1897  Nick Jonas|Joe Jonas|Kevin Jonas|John Lloyd Ta...
2370  Britt Irvin|Merrilyn Gann|Barbara Tyson|Anthon...

                      director  runtime genres        production_companies  \
424               Guido Chiesa      100    NaN                         NaN
997   Steward Lee|Steven G. Lee       44    NaN                         NaN
1712           Russell Mulcahy       88    NaN  Daniel Sladek Entertainment
1897           Bruce Hendricks       76    NaN                         NaN
2370             Michael Scott        0    NaN                         NaN

     release_date  release_year  budget_adj  revenue_adj
424      10/29/15          2015         0.0          0.0
997       10/3/14          2014         0.0          0.0
1712      2/27/09          2009         0.0          0.0
1897      2/27/09          2009         0.0          0.0
2370       6/5/10          2010         0.0          0.0
```

In [12]:
```
dataset[dataset.genres.isnull()].shape
```

Out[12]: (20, 11)

And these too have missing budget and revenue and are few in numbers. Drop them!

```
In [13]: dataset = dataset[pd.notnull(dataset['genres'])]
         dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10732 entries, 0 to 10865
Data columns (total 11 columns):
popularity              10732 non-null float64
original_title          10732 non-null object
cast                    10732 non-null object
director                10732 non-null object
runtime                 10732 non-null int64
genres                  10732 non-null object
production_companies    9773 non-null object
release_date            10732 non-null object
release_year            10732 non-null int64
budget_adj              10732 non-null float64
revenue_adj             10732 non-null float64
dtypes: float64(3), int64(2), object(6)
memory usage: 1006.1+ KB
```

Production company Curiously a significant muber of movies have their production company missing. Let's take a look.

```
In [14]: dataset[dataset.production_companies.isnull()].head()
```

```
Out[14]:      popularity               original_title  \
         228    0.584363            Racing Extinction
         259    0.476341           Crown for Christmas
         295    0.417191          12 Gifts of Christmas
         298    0.370258  The Girl in the Photographs
         328    0.367617                  Advantageous

                                                           cast        director  \
         228  Elon Musk|Jane Goodall|Louie Psihoyos|Leilani ...  Louie Psihoyos
         259  Danica McKellar|Rupert Penry-Jones|Ellie Botte...       Alex Zamm
         295  Katrina Law|Donna Mills|Aaron O'Connell|Melani...  Peter Sullivan
         298  Kal Penn|Claudia Lee|Kenny Wormald|Toby Heming...      Nick Simon
         328  Jacqueline Kim|James Urbaniak|Freya Adams|Ken ...  Jennifer Phang

              runtime                        genres production_companies release_date  \
         228       90         Adventure|Documentary                  NaN      1/24/15
         259       84                      TV Movie                  NaN     11/27/15
         295       84               Family|TV Movie                  NaN     11/26/15
         298       95          Crime|Horror|Thriller                  NaN      9/14/15
         328       92  Science Fiction|Drama|Family                  NaN      6/23/15
```

```
     release_year  budget_adj  revenue_adj
228          2015         0.0          0.0
259          2015         0.0          0.0
295          2015         0.0          0.0
298          2015         0.0          0.0
328          2015         0.0          0.0
```

```
In [15]: dataset[dataset.production_companies.isnull()].shape
```

```
Out[15]: (959, 11)
```

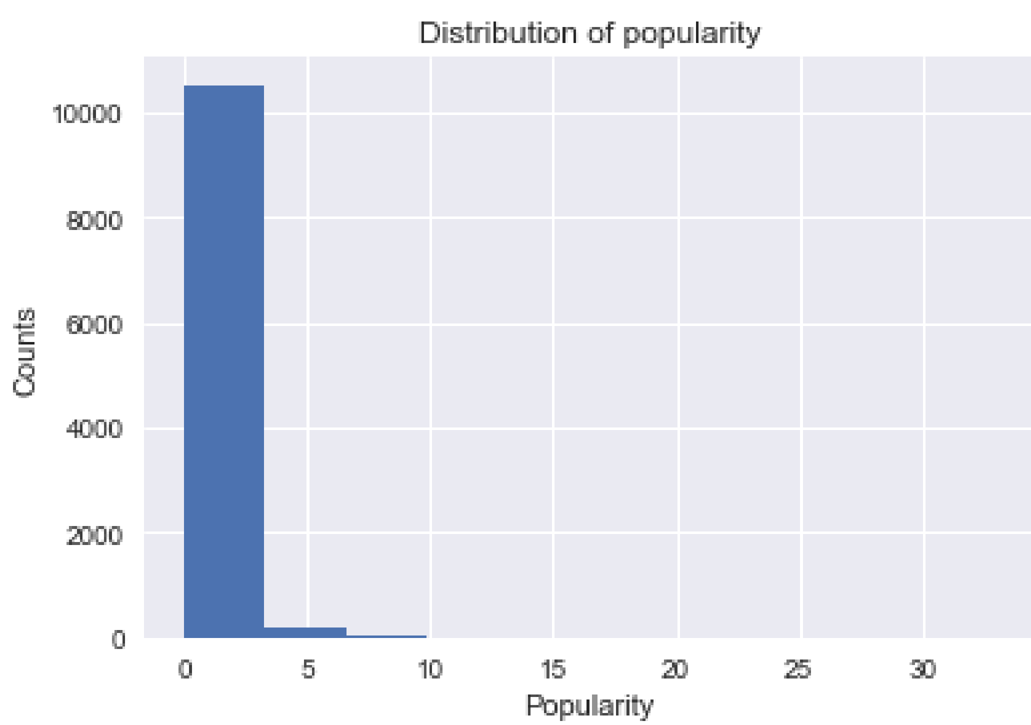
While the budget and revenue information are missing for these ones as well, they are quite large in number. I shall keep them for now. I shall disregard them while exploring revenue.

Exploratory data analysis

1.1.5 1. Popularity

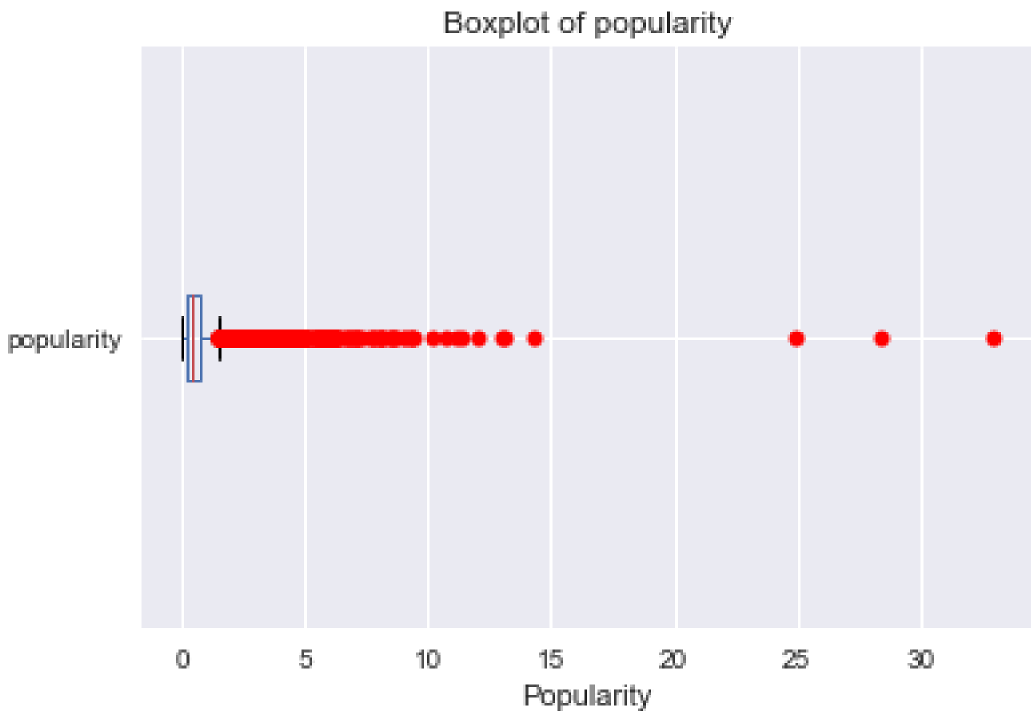
Let's start with popularity. Because it is a float, we start with histogram analysis. Our goal here is to see the distribution of popularity across movies.

```
In [16]: dataset.popularity.hist()
         plt.xlabel('Popularity')
         plt.ylabel('Counts')
         plt.title('Distribution of popularity');
```



It seems like there are a outlies which have skewed the distribution. To confirm this I use boxplot in the following with the "definite" outliers marked red.

In [17]:
```
dataset.popularity.plot(kind='box', vert=False, sym='r')
plt.xlabel('Popularity')
plt.title('Boxplot of popularity');
```



This confirms my suspicion about outliers. The outliers are the most popular movies in the database. For the time-being I am interested in the distribution of *typical* popularity values. To identify the typical points in shall use the five-point summary.

In [18]:
```
dataset.popularity.describe()
```

Out[18]:
```
count    10732.000000
mean         0.652609
std          1.004757
min          0.000188
25%          0.210766
50%          0.387136
75%          0.720621
max         32.985763
Name: popularity, dtype: float64
```

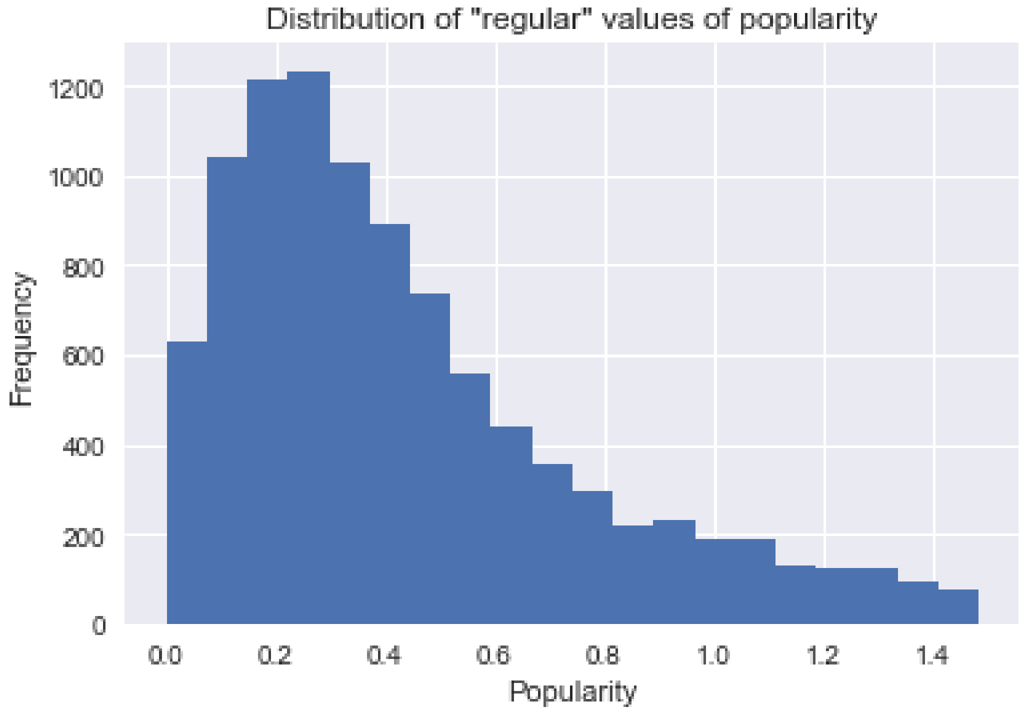
Regular We shall now determine inner fences in boxplot to select the typical (regular) values.

In [19]:
```
# Quartiles and fences
q1_pop = dataset.popularity.describe()['25%']
q3_pop = dataset.popularity.describe()['75%']
iqr_pop = q3_pop - q1_pop
fence_low_pop = q1_pop - 1.5 * iqr_pop
fence_high_pop = q3_pop + 1.5 * iqr_pop

# Regular and outlier samples
dataset_pop_reg = dataset.query('popularity > {} and popularity < {}'.format(fence_low_
dataset_pop_out = dataset.query('popularity < {} or popularity > {}'.format(fence_low_p
dataset_pop_reg.shape
```

Out[19]: (9796, 11)

We now plot the histogram of typical values of popularity.

In [20]:
```
dataset_pop_reg.popularity.plot.hist(bins=20)
plt.xlabel('Popularity')
plt.title('Distribution of "regular" values of popularity');
```



We see that the typical value of popularity as around 0.3. It is however heavily skewed to the right, meaning that more than half of the movies have popularity greater than this. To get more exact figures we generate the statistics.

In [21]:
```
dataset_pop_reg.popularity.describe()
```

```
Out[21]: count    9796.000000
         mean        0.438906
         std         0.325973
         min         0.000188
         25%         0.198252
         50%         0.351092
         75%         0.595587
         max         1.483329
         Name: popularity, dtype: float64
```

Top 10! What are the top ten movies in terms of popularity? This relates to our first few questions. In the following we shall explore features associated with the most popular movies in the list.

```
In [22]: dataset.sort_values(by='popularity', ascending=False).head(10)
```

```
Out[22]:       popularity                           original_title  \
         0      32.985763                           Jurassic World
         1      28.419936                       Mad Max: Fury Road
         629    24.949134                             Interstellar
         630    14.311205                  Guardians of the Galaxy
         2      13.112507                                Insurgent
         631    12.971027      Captain America: The Winter Soldier
         1329   12.037933                                Star Wars
         632    11.422751                                John Wick
         3      11.173104             Star Wars: The Force Awakens
         633    10.739009    The Hunger Games: Mockingjay - Part 1

                                                          cast  \
         0     Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
         1     Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
         629   Matthew McConaughey|Jessica Chastain|Anne Hath...
         630   Chris Pratt|Zoe Saldana|Dave Bautista|Vin Dies...
         2     Shailene Woodley|Theo James|Kate Winslet|Ansel...
         631   Chris Evans|Scarlett Johansson|Sebastian Stan|...
         1329  Mark Hamill|Harrison Ford|Carrie Fisher|Peter ...
         632   Keanu Reeves|Michael Nyqvist|Alfie Allen|Wille...
         3     Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
         633   Jennifer Lawrence|Josh Hutcherson|Liam Hemswor...

                                  director  runtime  \
         0               Colin Trevorrow      124
         1                 George Miller      120
         629           Christopher Nolan      169
         630                  James Gunn      121
         2             Robert Schwentke      119
         631      Joe Russo|Anthony Russo      136
         1329               George Lucas      121
```

```
632   Chad Stahelski|David Leitch      101
3                      J.J. Abrams      136
633                Francis Lawrence      123

                                          genres  \
0     Action|Adventure|Science Fiction|Thriller
1     Action|Adventure|Science Fiction|Thriller
629             Adventure|Drama|Science Fiction
630            Action|Science Fiction|Adventure
2          Adventure|Science Fiction|Thriller
631            Action|Adventure|Science Fiction
1329           Adventure|Action|Science Fiction
632                             Action|Thriller
3      Action|Adventure|Science Fiction|Fantasy
633         Science Fiction|Adventure|Thriller

                                   production_companies release_date  \
0     Universal Studios|Amblin Entertainment|Legenda...       6/9/15
1     Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15
629   Paramount Pictures|Legendary Pictures|Warner B...      11/5/14
630   Marvel Studios|Moving Picture Company (MPC)|Bu...      7/30/14
2     Summit Entertainment|Mandeville Films|Red Wago...      3/18/15
631                                      Marvel Studios      3/20/14
1329   Lucasfilm|Twentieth Century Fox Film Corporation      3/20/77
632   Thunder Road Pictures|Warner Bros.|87Eleven|De...     10/22/14
3             Lucasfilm|Truenorth Productions|Bad Robot     12/15/15
633                              Lionsgate|Color Force     11/18/14

      release_year    budget_adj   revenue_adj
0             2015  1.379999e+08  1.392446e+09
1             2015  1.379999e+08  3.481613e+08
629           2014  1.519800e+08  5.726906e+08
630           2014  1.565855e+08  7.122911e+08
2             2015  1.012000e+08  2.716190e+08
631           2014  1.565855e+08  6.583651e+08
1329          1977  3.957559e+07  2.789712e+09
632           2014  1.842182e+07  7.252661e+07
3             2015  1.839999e+08  1.902723e+09
633           2014  1.151364e+08  6.927528e+08
```

The list definitely makes sense (although I was somewhat surprised by the entry john Wick!). This also answer to the first question: **What are the most popular movies of all time?** In the following we explore the numerical features of these movies to answer our second question: **What are the features associated with these movies?**

```
In [23]: dataset.sort_values(by='popularity', ascending=False).head(10).describe()
```

```
Out[23]:        popularity     runtime  release_year    budget_adj   revenue_adj
        count   10.000000   10.000000     10.000000  1.000000e+01  1.000000e+01
```

mean	17.212237	127.000000	2010.700000	1.199485e+08	9.413288e+08
std	8.274145	17.676098	11.851395	5.334061e+07	8.452280e+08
min	10.739009	101.000000	1977.000000	1.842182e+07	7.252661e+07
25%	11.576547	120.250000	2014.000000	1.046841e+08	4.042936e+08
50%	13.041767	122.000000	2014.000000	1.379999e+08	6.755589e+08
75%	22.289652	133.000000	2015.000000	1.554341e+08	1.222407e+09
max	32.985763	169.000000	2015.000000	1.839999e+08	2.789712e+09

These are the numerical characteristics of the top ten popular movies. Their runtime seems to a slightly high compared to other movies. All of them are pretty recent with the exception of Star Wars (not surprisingly). They all are high-budget movies the minimum being around 10 million USD and the median being around 140 million USD. All them earned more than 70 million USD the highest one reaching almost 2.8 billion USD (Star Wars!).

Popular movie directors **Who are the most popular movie directors?** (Third question.) There is no unique way to answer this, at least in terms of ranking. I could just choose the directors of most popular movies and rank them according to the movies. But this will be injustcie to directors who have many movies which are popular. In the following I have considered 100 most popular movies and counted the directors. Quentin Tanation and Christopher Nolan come on top, each delivering 5 among the 100 most popular movies.

```
In [24]: dataset.sort_values(by='popularity', ascending=False).head(100).director.value_counts()
```

```
Out[24]: Quentin Tarantino    5
         Christopher Nolan    5
         David Yates          4
         Peter Jackson        4
         Chris Columbus       3
         Francis Lawrence     3
         Gore Verbinski       2
         James Cameron        2
         David Fincher        2
         Jon Favreau          2
         Name: director, dtype: int64
```

1.1.6 2. Revenue

In our discussions on popularity, we saw that popular movies tend to make good money too. In this part we shall explore the distribution of revenue across the movies in the database. But first, lt us remember that there are many zero entries in the field. Let us first see how many of them are there.

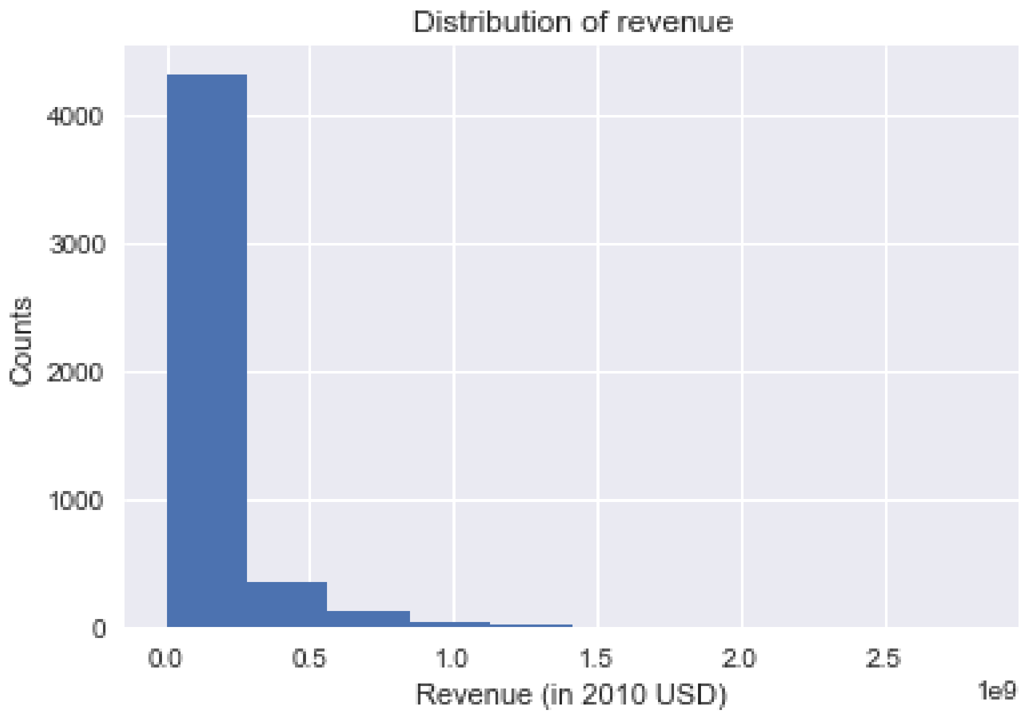
```
In [25]: dataset.query('revenue_adj == 0').shape
```

```
Out[25]: (5888, 11)
```

There's a lot of zeros! Nevertheless, we still have more than 4000 movies with information on revenue. We create a dataframe for the latter movies and explore.

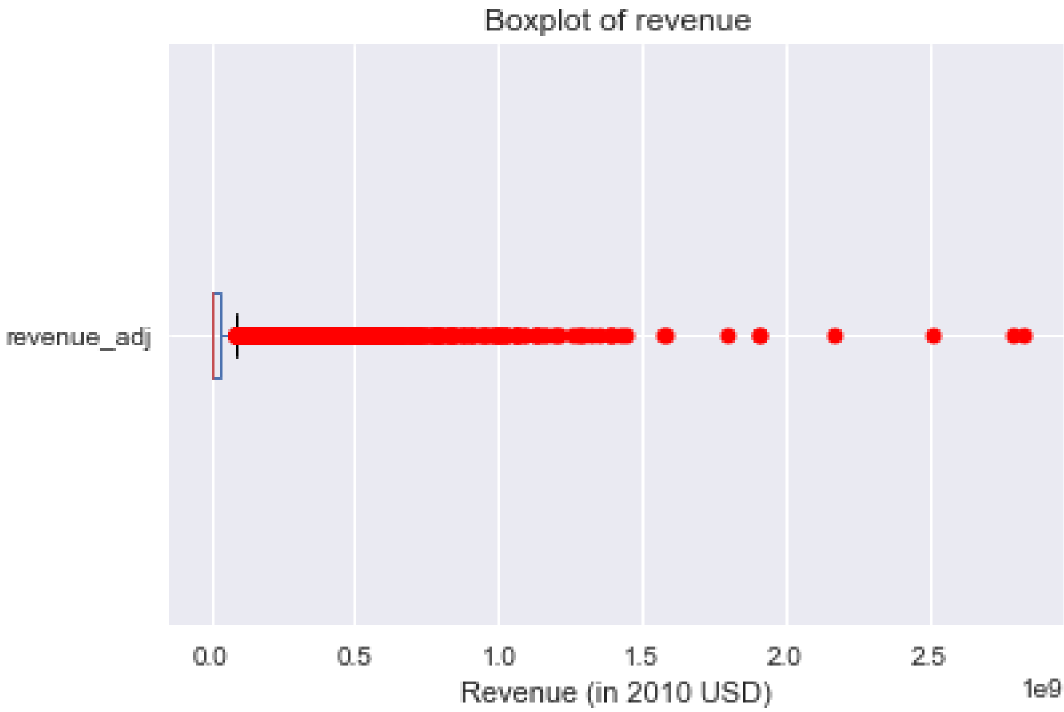
Revenue proper

```
In [26]: dataset_rev = dataset.query('revenue_adj > 0')
         dataset_rev.revenue_adj.hist()
         plt.xlabel('Revenue (in 2010 USD)')
         plt.ylabel('Counts')
         plt.title('Distribution of revenue');
```



We see that here too the distribution is affected by the presence of outliers. To get a visual sense, we use boxplot as before.

```
In [27]: dataset.revenue_adj.plot.box(vert=False, sym='r')
         plt.xlabel('Revenue (in 2010 USD)')
         plt.title('Boxplot of revenue');
```



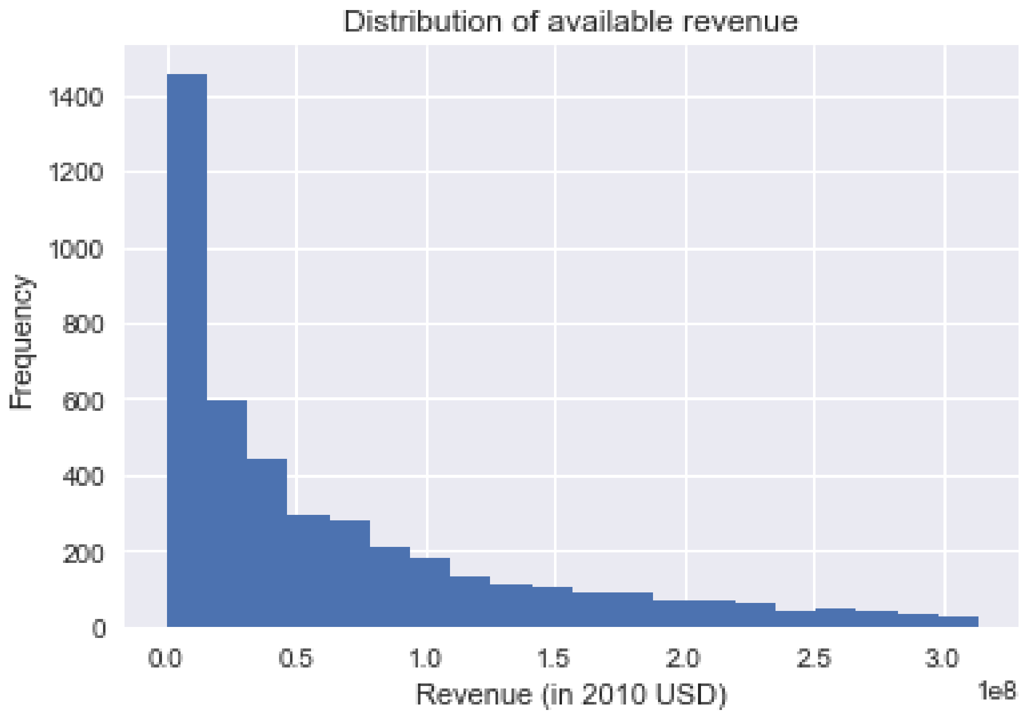
So there are many outliers. To get a distribution for the regular entries, I use the parameters of boxplot to separate the outliers. This is the same procedure as was the case with popularity.

In [28]:
```
# quartiles
q1_rev = dataset_rev.revenue_adj.describe()['25%']
q3_rev = dataset_rev.revenue_adj.describe()['75%']

# interquartile range
iqr_rev = q3_rev - q1_rev

# fences
fence_low_rev  = q1_rev - 1.5 * iqr_rev
fence_high_rev = q3_rev + 1.5 * iqr_rev

# Regular and outlier samples
dataset_rev_reg = dataset_rev.query('revenue_adj > {} and revenue_adj < {}'.format(fenc
dataset_rev_out = dataset_rev.query('revenue_adj < {} or revenue_adj > {}'.format(fence

# shape of the regular dataset
dataset_rev_reg.shape
```

Out[28]: (4373, 11)

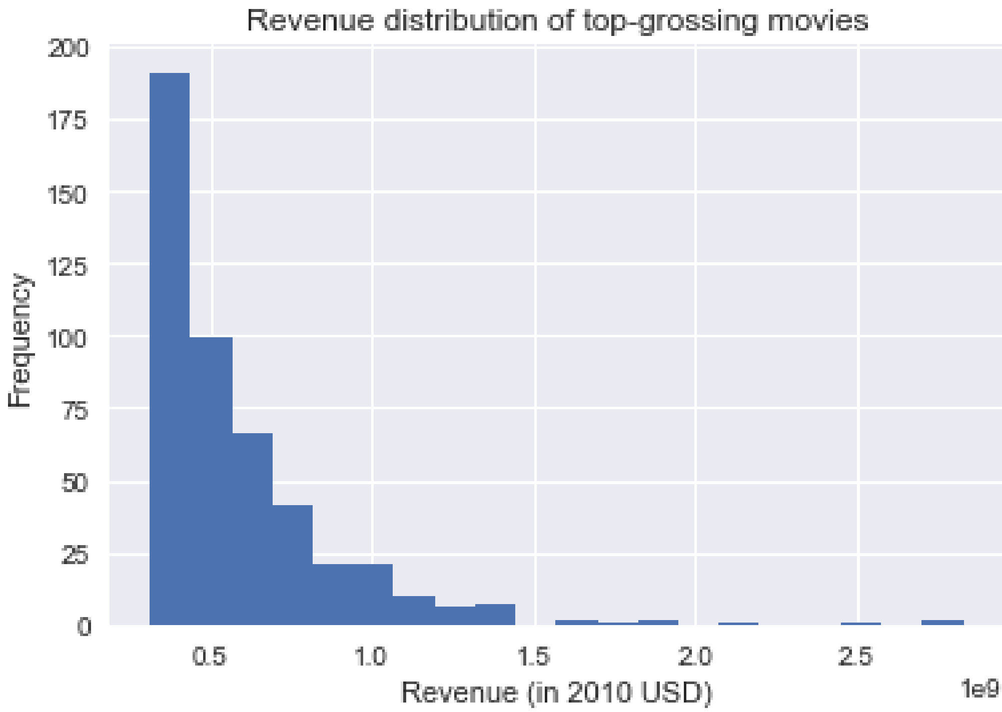
In [29]:
```
dataset_rev_reg = dataset_rev.query('revenue_adj > {} and revenue_adj < {}'.format(fenc
dataset_rev_reg.revenue_adj.plot.hist(bins=20)
```

```
plt.xlabel('Revenue (in 2010 USD)')
plt.title('Distribution of available revenue');
```



We see that unlike popularity histogram, there is no peak in the revenue distribution. It's more skewed. This also answers our fourth question: **How is the revenue distribution?** From the above distribution I wondered if the same is true for the top-grossing movies (outliers).

```
In [30]: dataset_rev_out = dataset_rev.query('revenue_adj < {} or revenue_adj > {}'.format(fence
         dataset_rev_out.revenue_adj.plot.hist(bins=20)
         plt.xlabel('Revenue (in 2010 USD)')
         plt.title('Revenue distribution of top-grossing movies');
```



Yes, the revenue distribution of the top-grossing movies is no different from the rest. But **what are these top-grossing movies?** (Our fifth question.) I give the list of top ten movies in terms of revenue and their characteristics.

Top ten!

```
In [31]: dataset.sort_values(by='revenue_adj', ascending=False).head(10)
```

```
Out[31]:        popularity                      original_title  \
         1386     9.432768                              Avatar
         1329    12.037933                           Star Wars
         5231     4.355219                             Titanic
         10594    2.010733                         The Exorcist
         9806     2.563191                                Jaws
         3       11.173104         Star Wars: The Force Awakens
         8889     2.900556           E.T. the Extra-Terrestrial
         8094     1.136610                             The Net
         10110    2.631987      One Hundred and One Dalmatians
         4361     7.637767                         The Avengers

                                                        cast  \
         1386   Sam Worthington|Zoe Saldana|Sigourney Weaver|S...
         1329   Mark Hamill|Harrison Ford|Carrie Fisher|Peter ...
         5231   Kate Winslet|Leonardo DiCaprio|Frances Fisher|...
         10594  Linda Blair|Max von Sydow|Ellen Burstyn|Jason ...
```

```
9806   Roy Scheider|Robert Shaw|Richard Dreyfuss|Lorr...
3      Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
8889   Henry Thomas|Drew Barrymore|Robert MacNaughton...
8094   Sandra Bullock|Jeremy Northam|Dennis Miller|We...
10110  Rod Taylor|J. Pat O'Malley|Betty Lou Gerson|Ma...
4361   Robert Downey Jr.|Chris Evans|Mark Ruffalo|Chr...

                                             director  runtime  \
1386                                    James Cameron      162
1329                                     George Lucas      121
5231                                    James Cameron      194
10594                                 William Friedkin      122
9806                                 Steven Spielberg      124
3                                          J.J. Abrams      136
8889                                 Steven Spielberg      115
8094                                    Irwin Winkler      114
10110  Clyde Geronimi|Hamilton Luske|Wolfgang Reitherman       79
4361                                       Joss Whedon      143

                                      genres  \
1386   Action|Adventure|Fantasy|Science Fiction
1329           Adventure|Action|Science Fiction
5231                     Drama|Romance|Thriller
10594                     Drama|Horror|Thriller
9806                  Horror|Thriller|Adventure
3      Action|Adventure|Science Fiction|Fantasy
8889   Science Fiction|Adventure|Family|Fantasy
8094        Crime|Drama|Mystery|Thriller|Action
10110         Adventure|Animation|Comedy|Family
4361           Science Fiction|Action|Adventure

                                    production_companies release_date  \
1386   Ingenious Film Partners|Twentieth Century Fox ...     12/10/09
1329    Lucasfilm|Twentieth Century Fox Film Corporation      3/20/77
5231   Paramount Pictures|Twentieth Century Fox Film ...     11/18/97
10594                     Warner Bros.|Hoya Productions     12/26/73
9806         Universal Pictures|Zanuck/Brown Productions      6/18/75
3              Lucasfilm|Truenorth Productions|Bad Robot     12/15/15
8889             Universal Pictures|Amblin Entertainment       4/3/82
8094                                   Columbia Pictures      7/28/95
10110                            Walt Disney Productions      1/25/61
4361                                      Marvel Studios      4/25/12

       release_year    budget_adj   revenue_adj
1386           2009  2.408869e+08  2.827124e+09
1329           1977  3.957559e+07  2.789712e+09
5231           1997  2.716921e+08  2.506406e+09
10594          1973  3.928928e+07  2.167325e+09
```

```
9806             1975  2.836275e+07  1.907006e+09
3                2015  1.839999e+08  1.902723e+09
8889             1982  2.372625e+07  1.791694e+09
8094             1995  3.148127e+07  1.583050e+09
10110            1961  2.917944e+07  1.574815e+09
4361             2012  2.089437e+08  1.443191e+09
```

```
In [32]: dataset.sort_values(by='revenue_adj', ascending=False).head(50).describe()
```

```
Out[32]:        popularity     runtime  release_year    budget_adj   revenue_adj
         count   50.000000   50.000000     50.000000  5.000000e+01  5.000000e+01
         mean     5.594902  136.560000   1997.700000  1.392524e+08  1.317835e+09
         std      4.761581   28.385941     16.044899  8.145784e+07  4.451266e+08
         min      0.760503   78.000000   1961.000000  2.372625e+07  9.658933e+08
         25%      2.758491  121.250000   1985.500000  7.110709e+07  1.033247e+09
         50%      4.950633  136.000000   2002.500000  1.392025e+08  1.145192e+09
         75%      6.684794  153.500000   2011.000000  1.886158e+08  1.388085e+09
         max     32.985763  201.000000   2015.000000  3.683713e+08  2.827124e+09
```

Highest grossing movie directors **Who directs these movies?** (Our sixth question) Following the procedure for popularity we have the following list.

```
In [33]: dataset.sort_values(by='revenue_adj', ascending=False).head(100).director.value_counts(
```

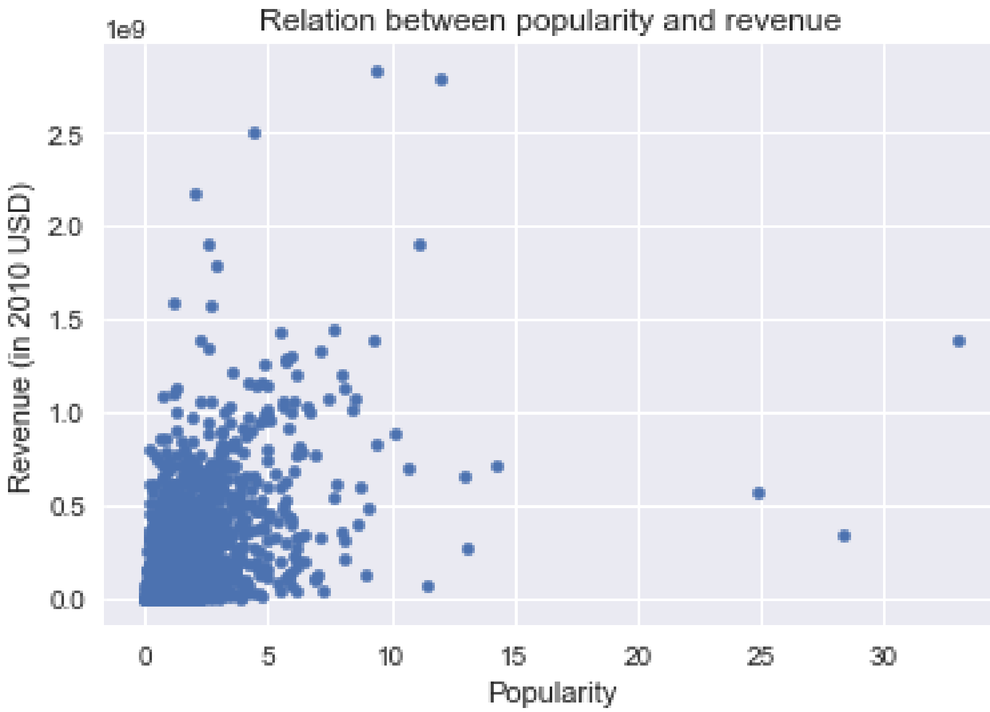
```
Out[33]: Steven Spielberg     7
         Peter Jackson        6
         Michael Bay          4
         George Lucas         4
         David Yates          4
         Christopher Nolan    3
         Sam Raimi            3
         James Cameron        3
         Gore Verbinski       3
         Chris Columbus       3
         Name: director, dtype: int64
```

Definitely not the same as before!

1.1.7 3. Popularity versus Revenue

We saw that the most popular and most revenue generating movies need not overlap. Here we want see if these is any correlation. This is our seventh question:** Is popularity related to revenue?** (It should be positive.)

```
In [34]: dataset_rev.plot(kind='scatter', x='popularity', y='revenue_adj');
         plt.xlabel('Popularity')
         plt.ylabel('Revenue (in 2010 USD)')
         plt.title('Relation between popularity and revenue');
```



As the scatter plot portrays, there is definitely a positive correlation. The outliers have made the correlation a difficilt to see. Also, there is a lot of spread. In the following, we ask a related question: How strong is the correlation among the outliers? If a movie is an outlier in popularity, what are the chances it will be an outlier in revenue, and vice versa?

```
In [35]: # sets of popular and revenue outliers
         set_pop_out =  set(dataset_pop_out.original_title)
         set_rev_out =  set(dataset_rev_out.original_title)
         print('Popular outlier = {} and Revenue outlier = {}'
               .format(len(set_pop_out), len(set_rev_out)))
```

```
Popular outlier = 928 and Revenue outlier = 469
```

```
In [36]: # intersect of sets of popular and revenue outliers
         print('Intersect: {}'.format(len(set_pop_out.intersection(set_rev_out))))
```

```
Intersect: 330
```

A popular outlier has less than fift percent chance (331/930) of being a revenue outlier whereas a revenue outlier has more than fifty percent (331/470) chance of being a popular outlier.

1.1.8 4. Directors

Let's explore the data on directors. (It's a categorical feature compared to the numerical features above.) **Who are the most productive directors?** (Eighth question.)

In [37]:
```
dataset.director.value_counts()[:10]
```

Out[37]:
```
Woody Allen          45
Clint Eastwood       34
Steven Spielberg     29
Martin Scorsese      28
Ridley Scott         23
Ron Howard           22
Steven Soderbergh    22
Joel Schumacher      21
Brian De Palma       20
Barry Levinson       19
Name: director, dtype: int64
```

Not surprisingly, Woody Allen (45) comes at top followed by Clint Eastwood (34) and Steven Spielberg (20). Spielberg is closely followed by Martin Scorses (28). I wondered how many movies does a director generally make?

In [38]:
```
dataset.director.value_counts().describe()
```

Out[38]:
```
count    5018.000000
mean        2.138701
std         2.529060
min         1.000000
25%         1.000000
50%         1.000000
75%         2.000000
max        45.000000
Name: director, dtype: float64
```

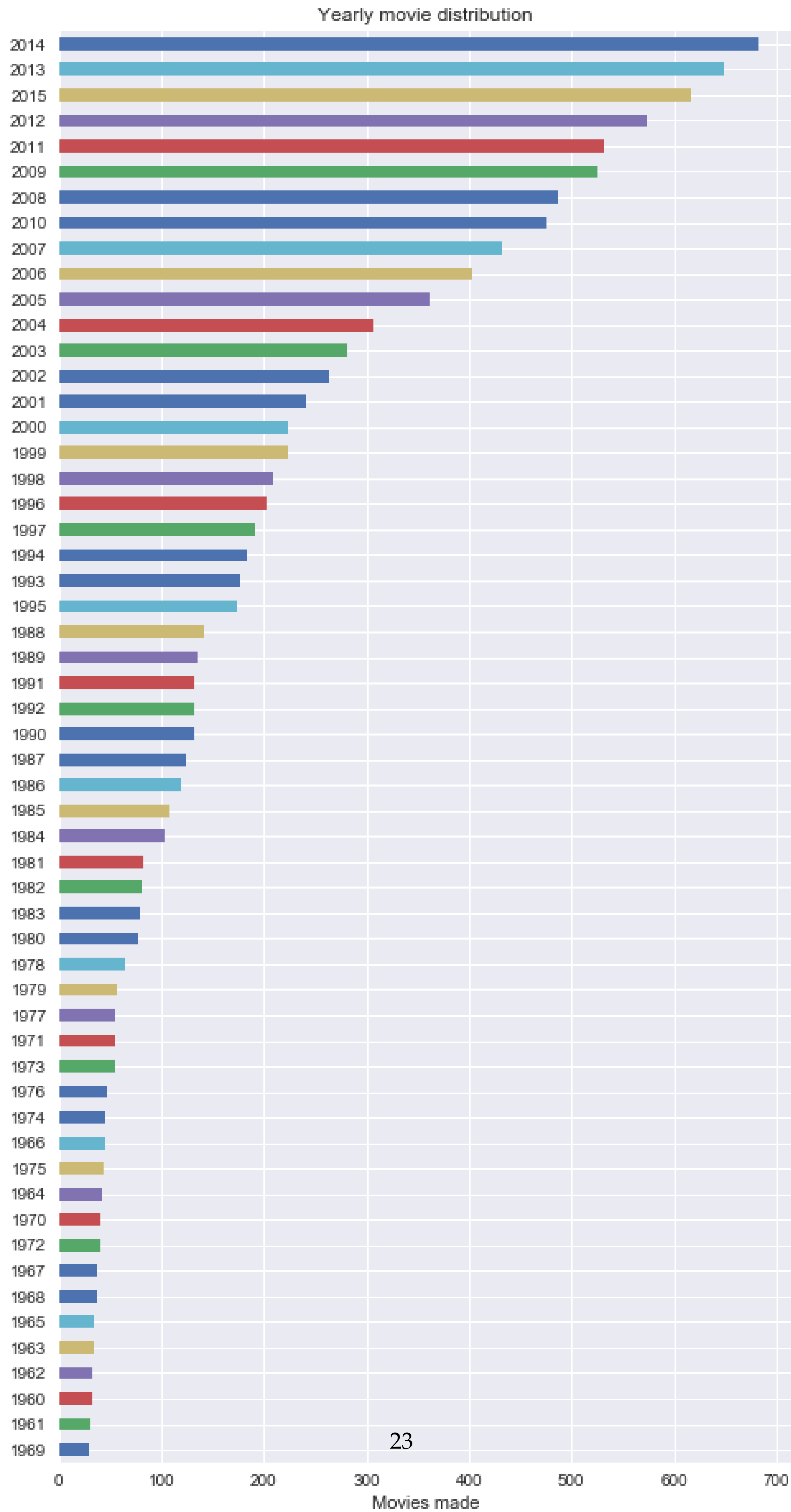
It seems that a director typically makes just one movie!

1.1.9 5. Year

** What's the yearly movie production rate? ** (Question 9.) This is best displayed graphically.

In [39]:
```
# select the year column
year = dataset.release_year

# value counts
year_counts = year.value_counts()

# reverse the value counts series to have the maximum on top
year_counts_rev = year_counts.reindex(year_counts.index[::-1])
```

In [40]:
```
year_counts_rev.plot.barh(figsize=(8, 16))
plt.xlabel('Movies made')
plt.title('Yearly movie distribution');
```


Yearly movie distribution
2014
2013
2015
2012
2011
2009
2008
2010
2007
2006
2005
2004
2003
2002
2001
2000
1999
1998
1996
1997
1994
1993
1995
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1985
1984
1981
1982
1983
1980
1978
1979
1977
1971
1973
1976
1974
1966
1975
1964
1970
1972
1967
1968
1965
1963
1962
1960
1961
1969
0
100
200
300
400
500
600
700
Movies made

So the number movies per year is increasing steadily, though not always monotonically. For example, 2010 had less number of movies made than in year 2009 and 2008. Similarly, 2015 had less movies than 2013 and 2014.

1.1.10 6. Genre

Finally, we address the last question: **Which genres are most popular from year to year?**

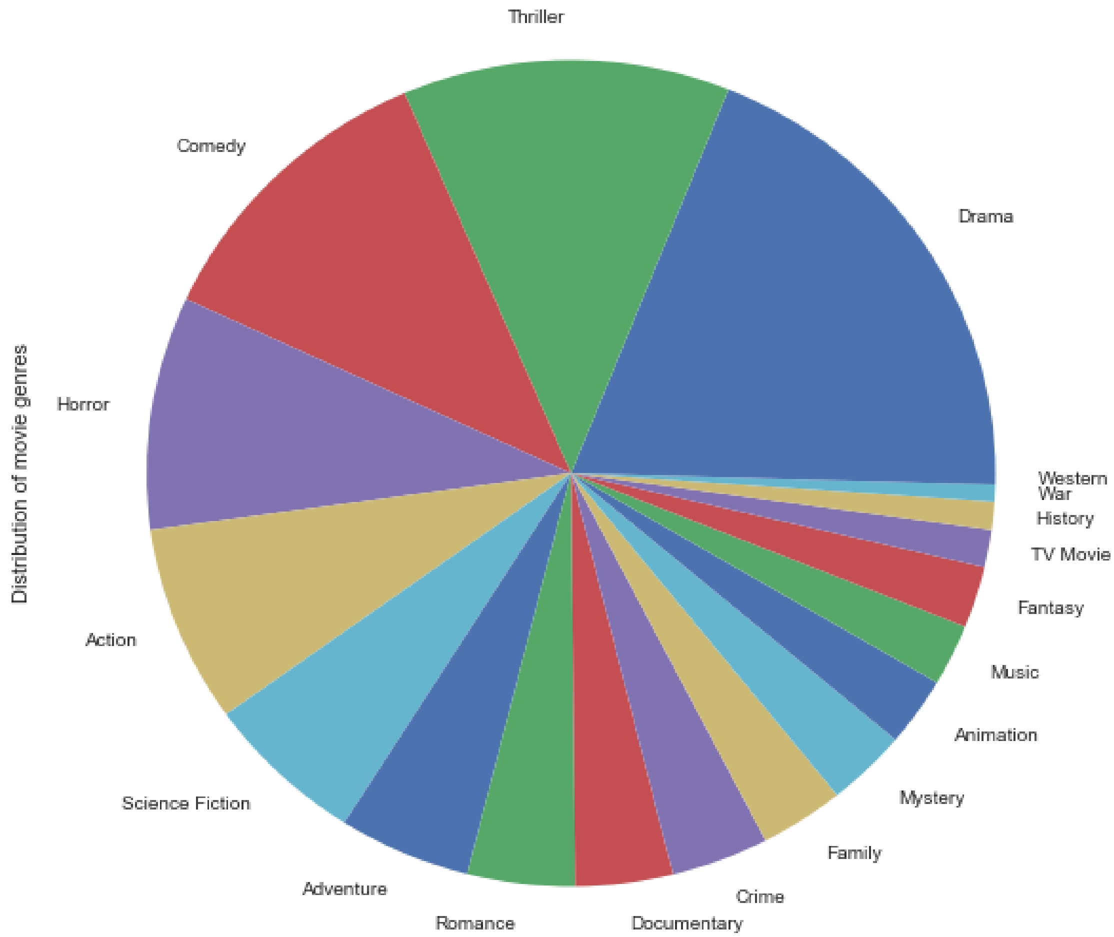
In [41]:
```
# earliest and latest years of record
earliest = int(dataset.release_year.describe()['min'])
latest = int(dataset.release_year.describe()['max'])

# For each year, collect the genres and find out
# the frequncy distribution
pop_gen = {}
for year in np.arange(earliest, latest+1):
    # collect the genre strings of a year as a series
    genres_year = dataset.query('release_year == {}'.format(year))['genres']
    genres = []
    # split and store genre strings in 'genres' list
    for genre in genres_year:
        genres.append(str(genre).split('|'))

    # make a flat list from 'genres' list
    # so that we can determine frequencies
    flat_list = [item for sublist in genres for item in sublist]
    # make the flat list into a pandas series
    # so that we can use the pd.value_counts() function
    genres = pd.Series(flat_list)
    pop_gen[str(year)] = genres.value_counts().idxmax()

# print the most popular genres per year
pop_gen
```

Out[41]:
```
{'1960': 'Drama',
 '1961': 'Drama',
 '1962': 'Drama',
 '1963': 'Comedy',
 '1964': 'Drama',
 '1965': 'Drama',
 '1966': 'Drama',
 '1967': 'Comedy',
 '1968': 'Drama',
 '1969': 'Drama',
 '1970': 'Drama',
 '1971': 'Drama',
```

```
'1972': 'Drama',
'1973': 'Drama',
'1974': 'Drama',
'1975': 'Drama',
'1976': 'Drama',
'1977': 'Drama',
'1978': 'Drama',
'1979': 'Drama',
'1980': 'Drama',
'1981': 'Drama',
'1982': 'Drama',
'1983': 'Drama',
'1984': 'Drama',
'1985': 'Comedy',
'1986': 'Drama',
'1987': 'Comedy',
'1988': 'Comedy',
'1989': 'Comedy',
'1990': 'Drama',
'1991': 'Drama',
'1992': 'Drama',
'1993': 'Drama',
'1994': 'Comedy',
'1995': 'Drama',
'1996': 'Drama',
'1997': 'Drama',
'1998': 'Drama',
'1999': 'Drama',
'2000': 'Drama',
'2001': 'Comedy',
'2002': 'Drama',
'2003': 'Comedy',
'2004': 'Drama',
'2005': 'Drama',
'2006': 'Drama',
'2007': 'Drama',
'2008': 'Drama',
'2009': 'Drama',
'2010': 'Drama',
'2011': 'Drama',
'2012': 'Drama',
'2013': 'Drama',
'2014': 'Drama',
'2015': 'Drama'}
```

Drama first! Comedy second. And none else! This is al the more surprising from to the fact that thriller is the most common genre after drama, and not comedy, as we below.

```
In [42]: pd.Series(flat_list).value_counts().plot(kind='pie', figsize=(10,10), label='Distributi
```



Conclusions

In the above analysis I have explored popularity, revenue, their relation, directors, years, and genres in the movie database (TMDB). The prime characteristic of the database is the presence of outlier. In popularity, for example, we saw that a handful of movies reached a score as high as 10 whereas more than 3 out of 4 had a score below 1.

Revenue had a lot of missing values. Of the movies that did have the data, we saw that here too the presence of outliers was prominent. In fact, the distribution seemed exponential, not even having a peak anywhere. In a sense, there is no typical value of revenue.

Next we considered the relation between popularity and revenue with mulple metrics. They are definitely positively correlated on the average, although there is a lot of spread. I compared most popular movies with highet-grossing movies. A popular outlier has less than fift percent chance (331/930) of being a revenue outlier whereas a revenue outlier has more than fifty percent (331/470) chance of being a popular outlier. I also looked at the directors of these movies. While there is a definite overlap there were some interesting mossions in each. Quentin Tarantino came out in top as a popular movie make, but he was not among the top ten revenue generators. Steven

Spielberg came out in top as a revenue generator, but he was not among the top ten popular directors (in my interpretaion, of course!).

Just for fun, I also looked at the prolificity of directors. Woody Allen (45) came in top followed by Clint Eastwood (34) and Steven Spielberg (20). Spielberg is closely followed by Martin Scorses (28).

More an more movies are being made over the years. The progression, however, is not strctly monotonic. For example, 2010 had less number of movies made than in year 2009 and 2008. Similarly, 2015 had less movies than 2013 and 2014.

Let me end the report with a curious observation about genres. I looked at the most popular genre in a year. Drama came first and comedy second. And none else ever made in the list! This is all the more surprising becase comedy is not the second most frequent genre over all; it is thriller. Yet, while comedy came out to be most popular genere many times, thriller never showed up. Something to be investigated soon.

1.1.11 Limitations

Any data-science investigation is limited by the quality of the dataset and the analysis. The current investigation is no exception. The dataset for the current investigation has entries for years 1960 to 2015. We could not make any concrete comments about movies made before or afterwards.

The revenue was not list for almost half of the movies. So the statistics mentioned in relation to revenue, while representative, may not be robust. This is especially true for the outliers for which we may have missed some top-grossing movies.

While the popularity metric made sense in terms of the movies that we know to be popular, its definition was missing in the description of the dataset. While it must be a reasonable function of the various features of a movie, we cannot be sure that it did not favor some types of movies over others.

On the analysis side, I was not able to explore all the features involved in the dataset and their dependency. Given time, it would have been interesting to explore, for example, the influence of cast and directors on popularity, the popularity of different genres, or if a particular genre is getting more and more popular, among others.