Choosing Dataset:

TMDb movie data

Questions

1. Which genres are most popular from year to year?
   - (What changed between 2015 to 2016)
2. What kinds of properties are associated with movies that have high revenues?
   - or what are the attributes of the movie with high revenues
   - like What properties/attributes does the movies, which have done well at the box office, have?
   - For Instance, Whether the popularity of the movie is dependent on the movie's budget?

In [4]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
%pylab inline
```

```
Populating the interactive namespace from numpy and matplotlib
```

In [5]:

```
# Load Data from a csv file
data = pd.read_csv("tmdb-movies.csv")
```

In [6]:
```
data.head()
```
Out[6]:

	id	imdb_id	popularity	budget	revenue	original_title	cast
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...

5 rows × 21 columns

In [7]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
id                      10866 non-null int64
imdb_id                 10856 non-null object
popularity              10866 non-null float64
budget                  10866 non-null int64
revenue                 10866 non-null int64
original_title          10866 non-null object
cast                    10790 non-null object
homepage                2936 non-null object
director                10822 non-null object
tagline                 8042 non-null object
keywords                9373 non-null object
overview                10862 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
vote_count              10866 non-null int64
vote_average            10866 non-null float64
release_year            10866 non-null int64
budget_adj              10866 non-null float64
revenue_adj             10866 non-null float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

In [8]:

```
# DATA WRANGLING

# cast, homepage, director, tagline, keywords, genres, production_companies co
lumns have less than 10866 values
# so we will inspect these columns

data['homepage'] = data['homepage'].fillna('Homepage Unavailable')
data['cast'] = data['cast'].fillna('Information not available')
data['director'] = data['director'].fillna('Information not available')
data['tagline'] =data['tagline'].fillna('Will Update soon!')
data['keywords'] = data['keywords'].fillna('')
data['overview'] =data['overview'].fillna('Will Update soon!')
data['genres'] = data['genres'].fillna('NA')
data['production_companies'] = data['production_companies'].fillna('')
data['imdb_id'] = data['imdb_id'].fillna('NA')
# print(data['homepage'])
# data['imdb_id'].isnull().values.any()
# data['imdb_id'].isnull().sum()
```

In [9]:
```
# data.info()
data.describe()

# so we can see that there is no revenue and budget for some of the movies

# count_budget = 0
# count_revenue = 0
# for i in range(len(data)):
#     count_budget = (count_budget + 1) if data.loc[i, 'budget'] == 0 else cou
nt_budget
#     count_revenue = (count_revenue + 1) if data.loc[i, 'revenue'] == 0 else
 count_revenue
# print(count_budget, count_revenue)
```

Out[9]:

	id	popularity	budget	revenue	runtime	vote_
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000	10866.0
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863	217.389
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405	575.619
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.0000
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000	17.0000
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000	38.0000
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.00

Posing 1st Question

Which genres are most popular from year to year?

In [10]:
```
# Range of release years
print("From: {} to {}.\n".format(data['release_year'].min(), data['release_yea
r'].max()))
from_1960_to_2015 = range(data['release_year'].min(), data['release_year'].max
() + 1)

genre_column = list(data["genres"])
genre_set = set()
for i in genre_column:
    row = i.split("|")
    for value in row:
        genre_set.add(value)

print(len(genre_set), genre_set)
# total -> 20 genres with one extra 'NA' genre which is substituted in place o
f the genres
# with missing values in the original data
```

```
From: 1960 to 2015.

21 {'Drama', 'Comedy', 'War', 'Horror', 'Animation', 'Western', 'Documentar
y', 'Mystery', 'Foreign', 'Crime', 'Family', 'Adventure', 'Thriller', 'Histor
y', 'NA', 'Music', 'TV Movie', 'Fantasy', 'Action', 'Romance', 'Science Ficti
on'}
```

In [11]:
```
# row by column dataframe of years by genres
years_by_genres = pd.DataFrame(index = from_1960_to_2015, columns = genre_set)
years_by_genres = years_by_genres.fillna(0)
years_by_genres.head()

for i in range(len(data)):
    genres_per_year = data.loc[i, 'genres'].split("|")
    year = data.loc[i, 'release_year']
    for val in genres_per_year:
        years_by_genres.loc[year, val] = years_by_genres.loc[year, val] + 1

years_by_genres.describe()
```

Out[11]:

	Drama	Comedy	War	Horror	Animation	Western	Documenta
count	56.000000	56.000000	56.000000	56.000000	56.000000	56.000000	56.000000
mean	85.017857	67.732143	4.821429	29.232143	12.482143	2.946429	9.285714
std	78.753815	59.957710	4.204358	30.901010	15.142944	2.186069	17.247624
min	13.000000	5.000000	0.000000	1.000000	0.000000	0.000000	0.000000
25%	21.750000	13.000000	2.000000	8.750000	2.000000	1.000000	0.750000
50%	53.000000	52.500000	4.000000	18.000000	4.500000	3.000000	2.000000
75%	110.750000	101.750000	6.250000	29.250000	21.500000	4.000000	6.250000
max	284.000000	198.000000	23.000000	125.000000	50.000000	8.000000	73.000000

8 rows × 21 columns

These statistics clearly show that "Drama" genre is the most watched genre overall until now, followed by "Comedy" genre.

```
- So, the maximum number of movies fall in the category of Drama genre
```

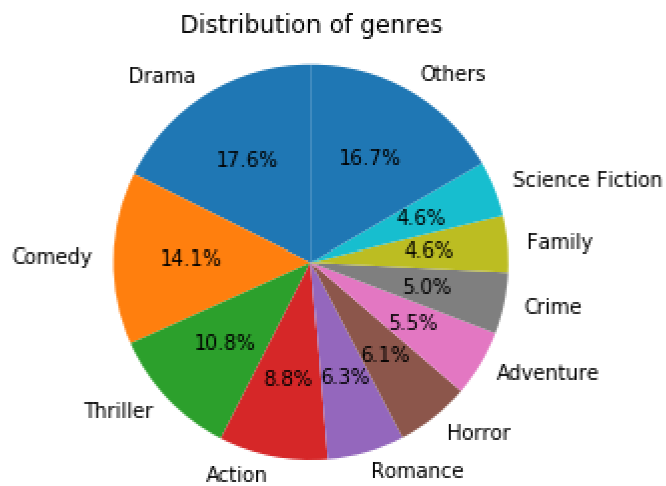
In [17]:

```
# Most popular genres from year to year
year_to_year = pd.Series(np.zeros(len(years_by_genres)), index=from_1960_to_20
15)

# as i could see more than 1 genre having max values so i will individually lo
op through each row
for i in from_1960_to_2015:
    maximum = years_by_genres.max(axis=1).loc[i]
    genre_temp = "| "
    for j in genre_set:
        if maximum == years_by_genres.loc[i, j]:
            genre_temp = genre_temp + j + " | "
    year_to_year.loc[i] = genre_temp

print("Year\t\tPopular Genres\n\n{}".format(year_to_year))

# Pie chart for distribution of genres
genres_total = pd.Series(np.zeros(len(genre_set)), index = genre_set)
for j in genre_set:
    genres_total.loc[j] = years_by_genres[j].sum()

fig, axis = plt.subplots()
# top movies genre per year shown in pi chart
n = 10
distribution = genres_total.sort_values(ascending = False)[0:n]
genre_dist = list(distribution.keys())[0:n]
genre_dist.append("Others")
distribution.set_value("Others", (genres_total.sort_values(ascending=False).va
lues)[n:].sum())
# print(distribution)
axis.pie(distribution, labels = genre_dist, autopct = '%1.1f%%', startangle =
90)
axis.axis('equal')
plt.title("Distribution of genres")
plt.show()
```

Year	Popular Genres
1960	| Drama |
1961	| Drama |
1962	| Drama |
1963	| Drama | Comedy |
1964	| Drama |
1965	| Drama |
1966	| Drama | Comedy |
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 |

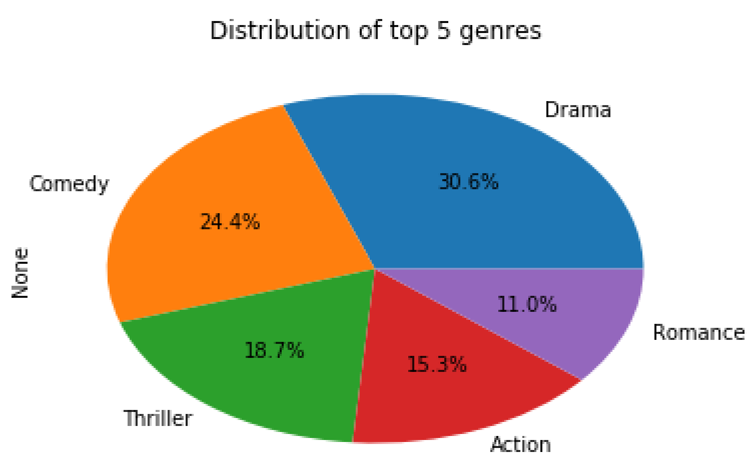
```
2015                | Drama |
dtype: object
```

```
E:\CHITKARA\ML\lib\site-packages\ipykernel\__main__.py:26: FutureWarning: set
_value is deprecated and will be removed in a future release. Please use .at
[] or .iat[] accessors instead
```



In [20]:
```
genres_total.sort_values(ascending=False)[:5].plot(kind="pie",
                                                   autopct = '%1.1f%%',
                                                   title="Distribution of top
 5 genres",
                                                   startangle = 0)
```

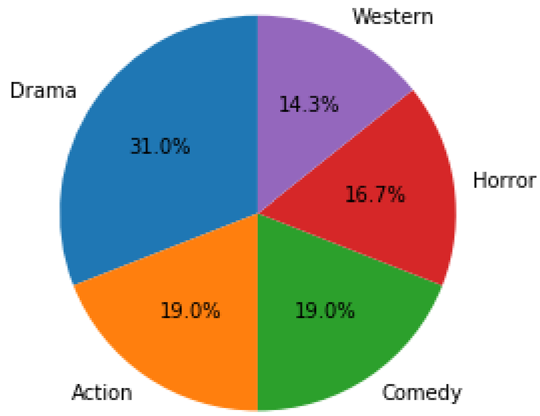
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x62391c14a8>



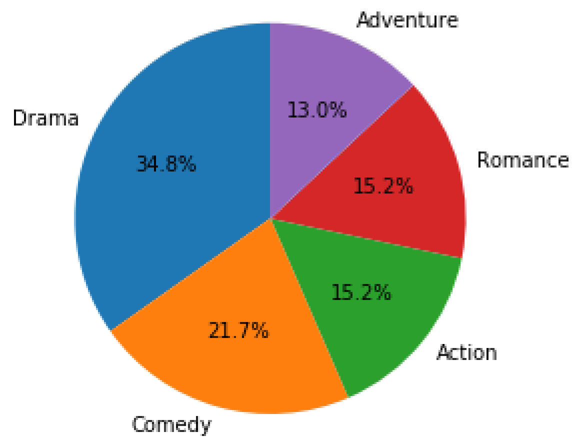
In [21]:

```
# Distribution of Movies per year
for i in from_1960_to_2015:
    fig, axis = plt.subplots()
    # top 5 movies per year shown in pi chart
    n = 5
    distribution = years_by_genres.loc[i, :].sort_values(ascending = False)[0:
n]
    genre_dist = list(distribution.keys())[0:n]
    axis.pie(distribution, labels = genre_dist, autopct = '%1.1f%%', startangl
e = 90)
    axis.axis('equal')
    plt.title("Percentage of movies in each genre in {}".format(i))
    plt.show()
```

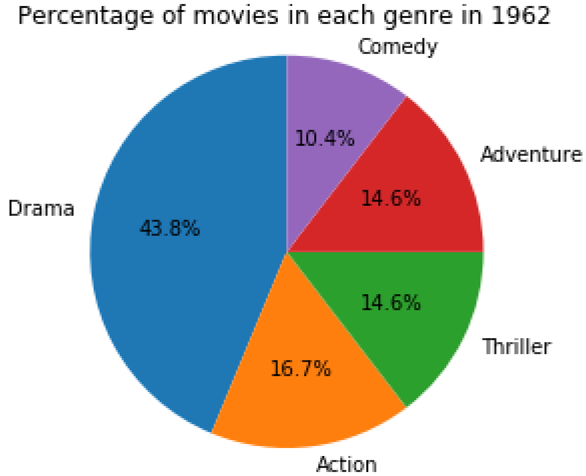
Percentage of movies in each genre in 1960



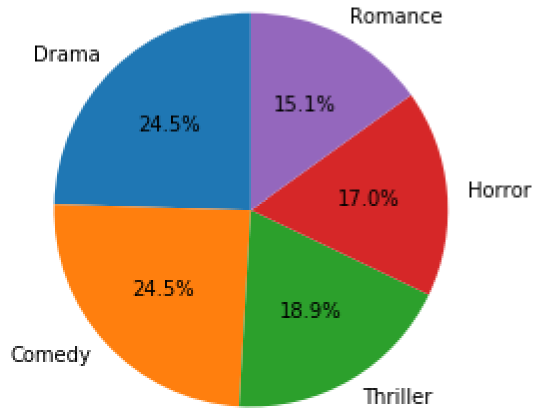
Percentage of movies in each genre in 1961



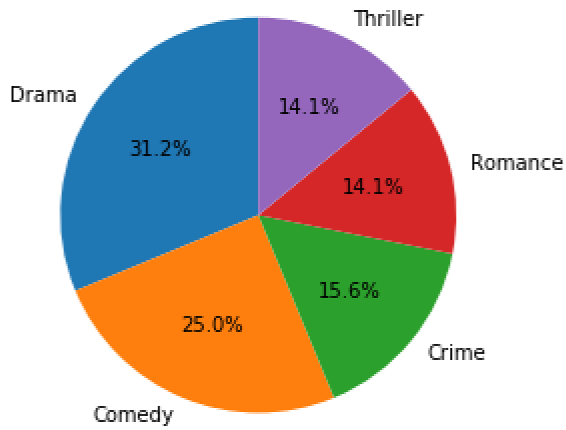
Percentage of movies in each genre in 1962



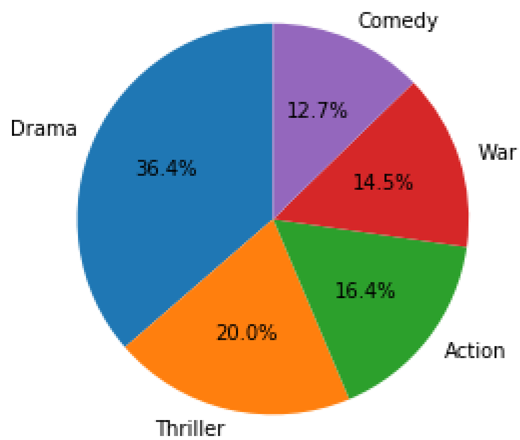
Percentage of movies in each genre in 1963

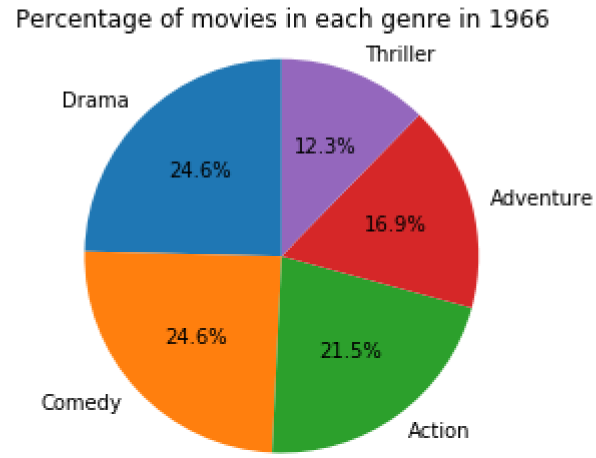


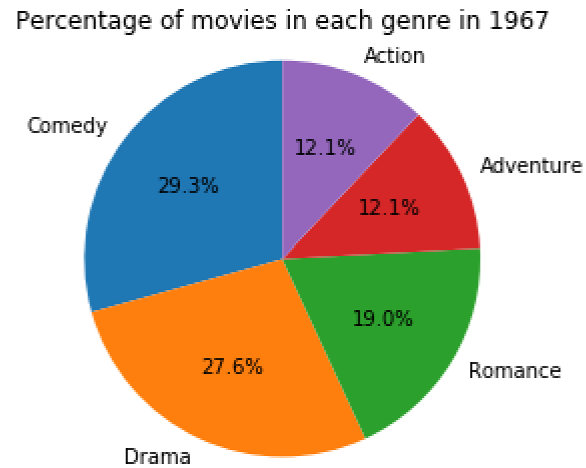
Percentage of movies in each genre in 1964

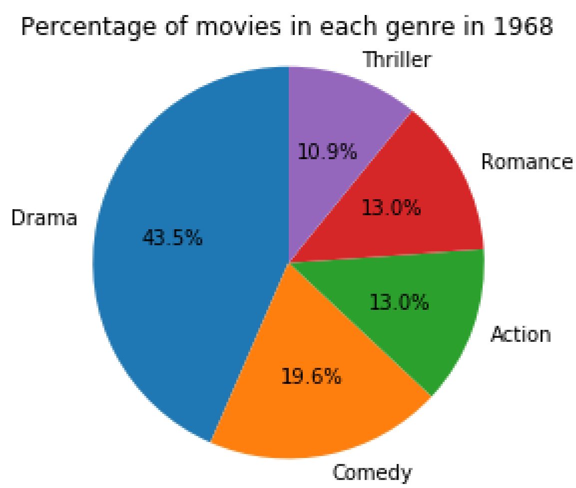


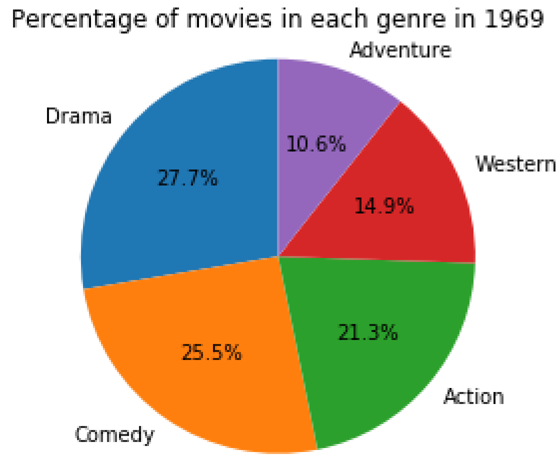
Percentage of movies in each genre in 1965

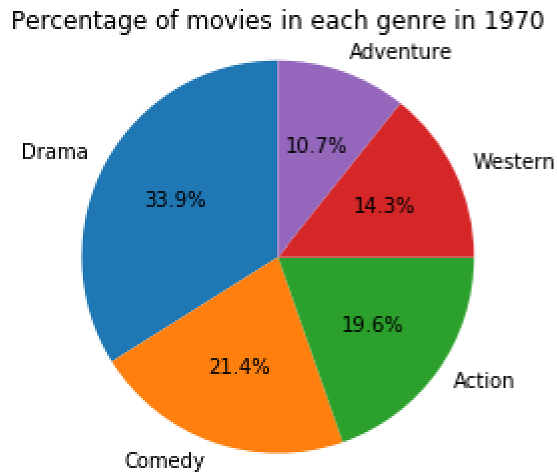


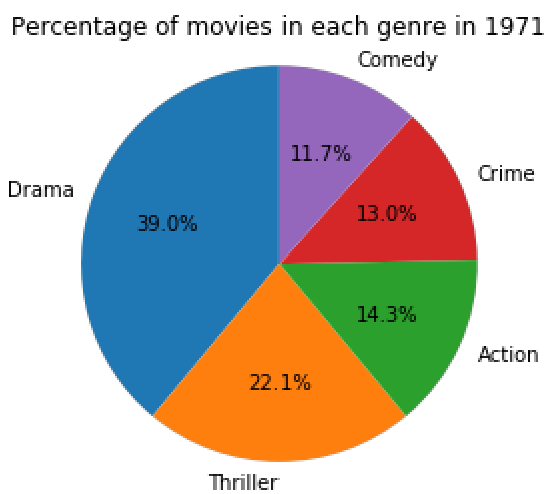

Percentage of movies in each genre in 1966
Thriller
Drama
12.3%
24.6%
Adventure
16.9%
24.6%
21.5%
Comedy
Action


Percentage of movies in each genre in 1967
Action
Comedy
12.1%
Adventure
29.3%
12.1%
19.0%
Romance
27.6%
Drama

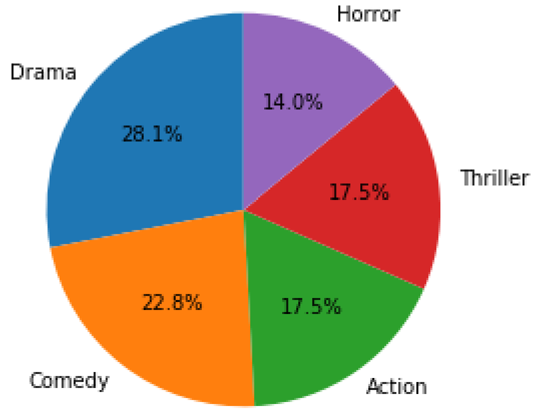

Percentage of movies in each genre in 1968
Thriller
10.9%
Romance
13.0%
Drama
43.5%
13.0%
Action
19.6%
Comedy


Percentage of movies in each genre in 1969
Adventure
Drama
10.6%
Western
27.7%
14.9%
21.3%
25.5%
Action
Comedy

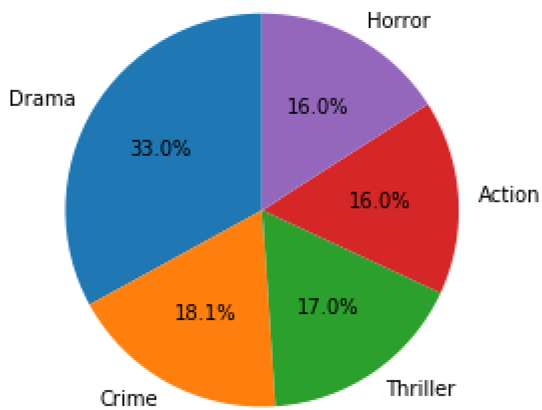

Percentage of movies in each genre in 1970
Adventure
Drama
10.7%
Western
33.9%
14.3%
19.6%
21.4%
Action
Comedy


Percentage of movies in each genre in 1971
Comedy
11.7%
Crime
Drama
13.0%
39.0%
14.3%
Action
22.1%
Thriller

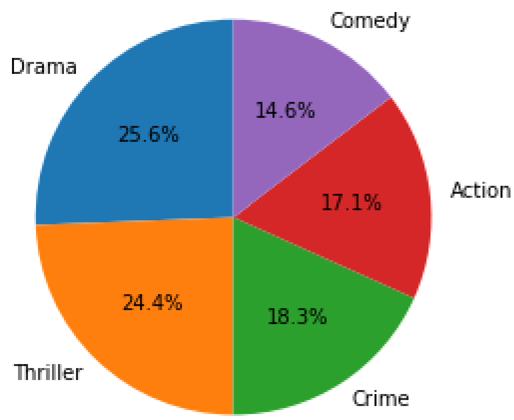
Percentage of movies in each genre in 1972



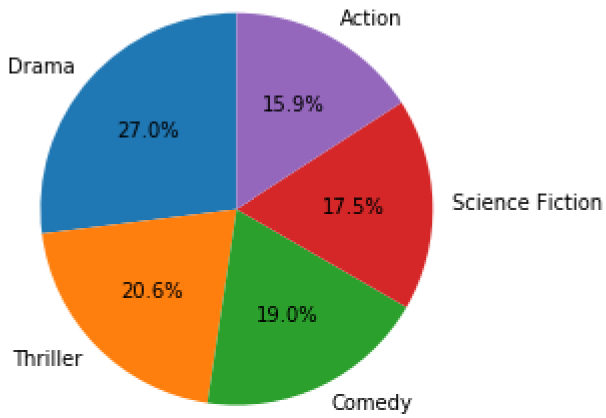
Percentage of movies in each genre in 1973



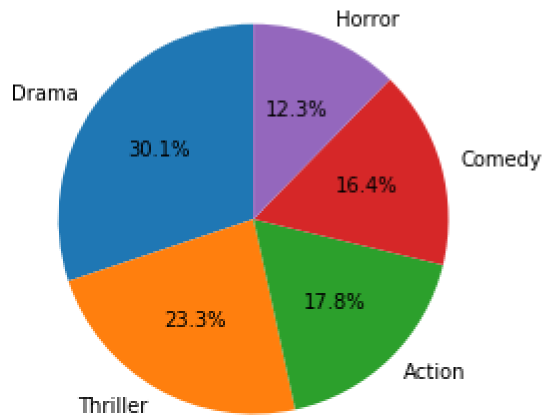
Percentage of movies in each genre in 1974



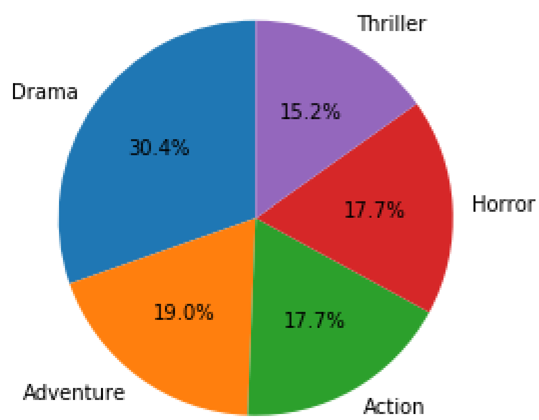
Percentage of movies in each genre in 1975



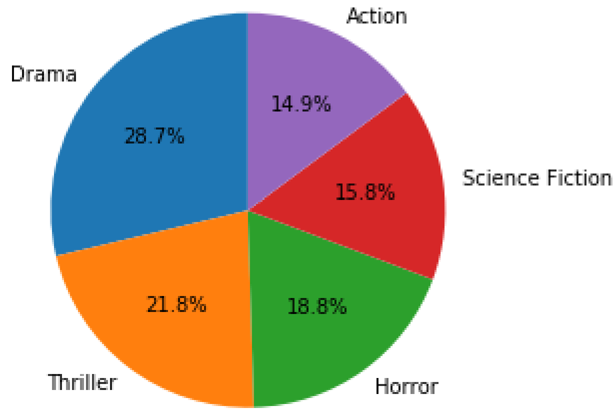
Percentage of movies in each genre in 1976



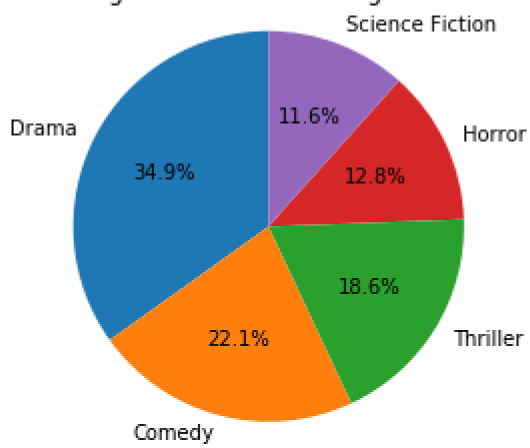
Percentage of movies in each genre in 1977



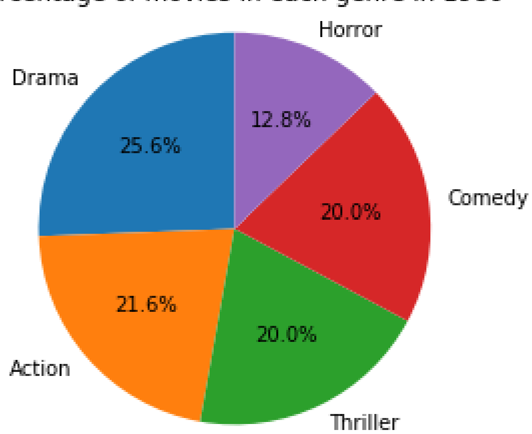
Percentage of movies in each genre in 1978



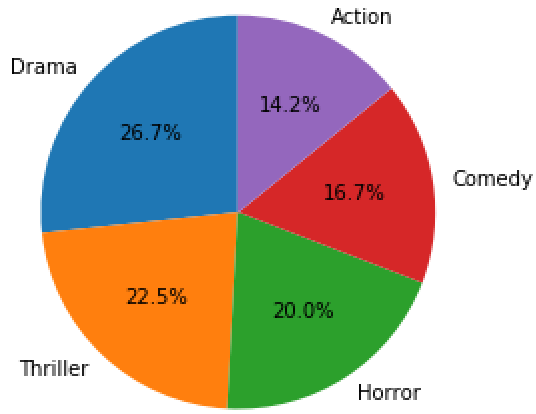
Percentage of movies in each genre in 1979



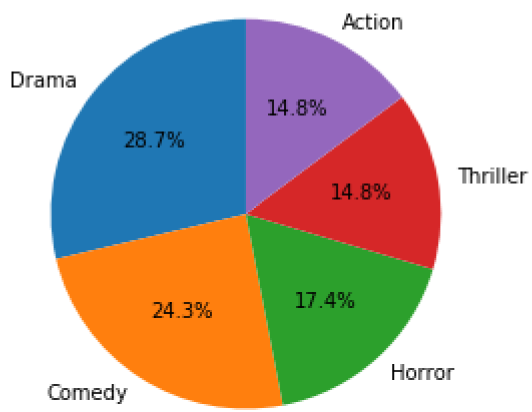
Percentage of movies in each genre in 1980



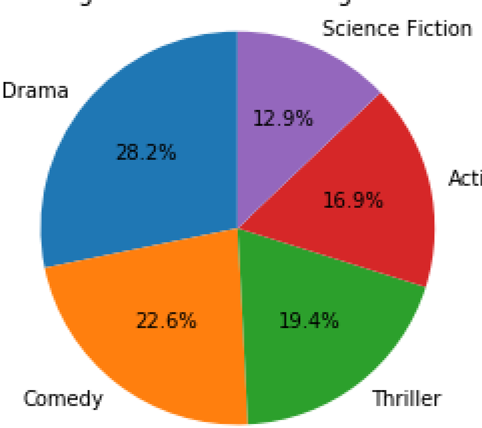
Percentage of movies in each genre in 1981



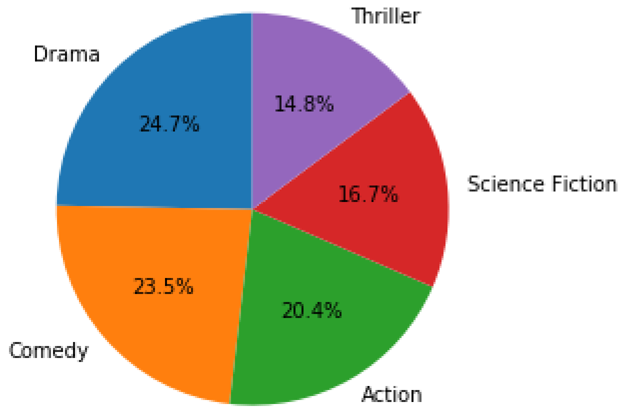
Percentage of movies in each genre in 1982



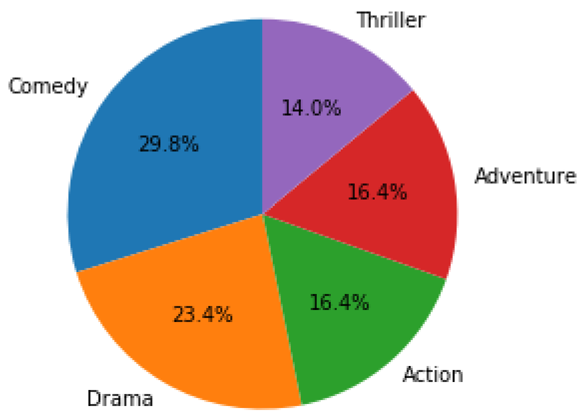
Percentage of movies in each genre in 1983



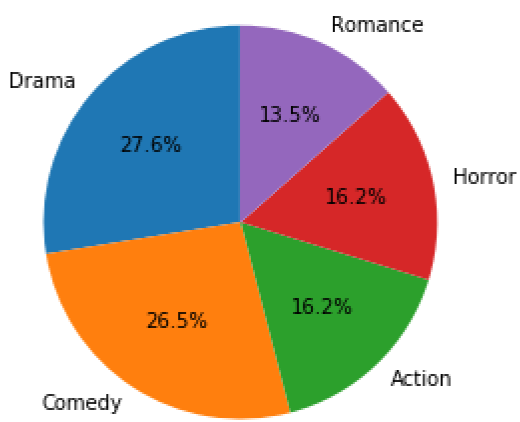
Percentage of movies in each genre in 1984

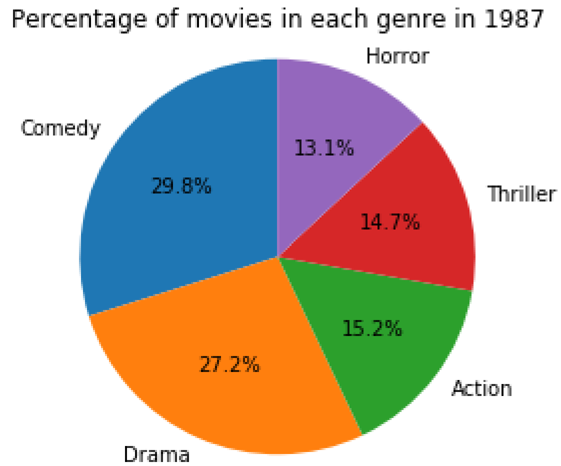


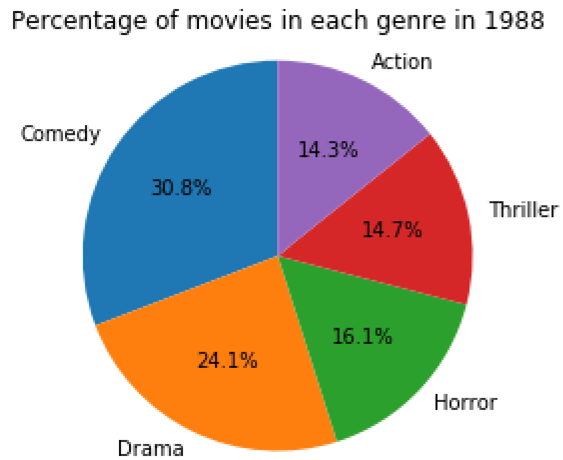
Percentage of movies in each genre in 1985

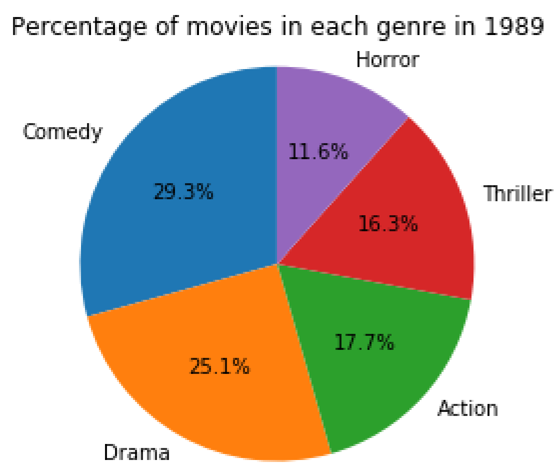


Percentage of movies in each genre in 1986

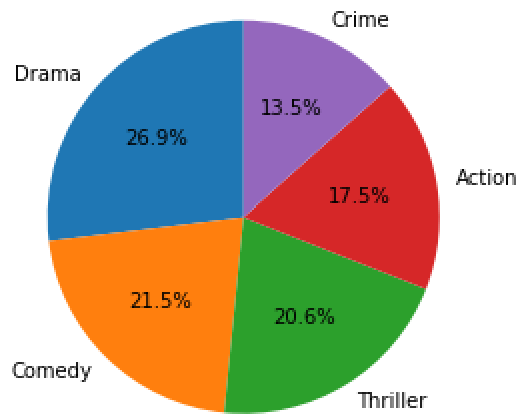



Percentage of movies in each genre in 1987
Horror
Comedy
13.1%
29.8%
Thriller
14.7%
15.2%
27.2%
Action
Drama

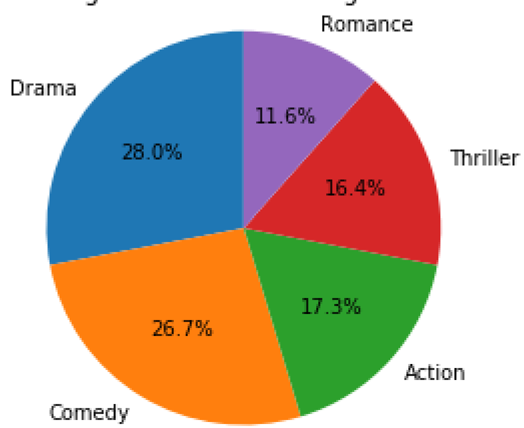

Percentage of movies in each genre in 1988
Action
Comedy
14.3%
30.8%
Thriller
14.7%
16.1%
24.1%
Horror
Drama


Percentage of movies in each genre in 1989
Horror
Comedy
11.6%
29.3%
Thriller
16.3%
17.7%
25.1%
Action
Drama

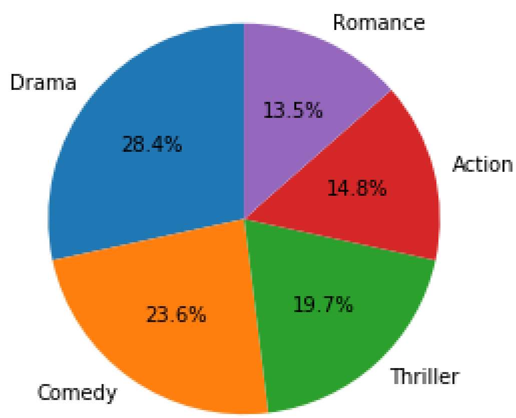
Percentage of movies in each genre in 1990



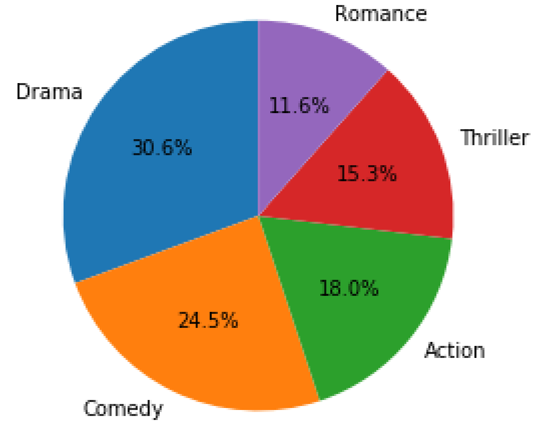
Percentage of movies in each genre in 1991



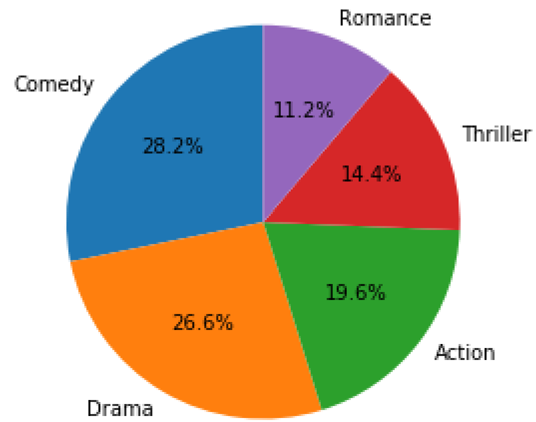
Percentage of movies in each genre in 1992



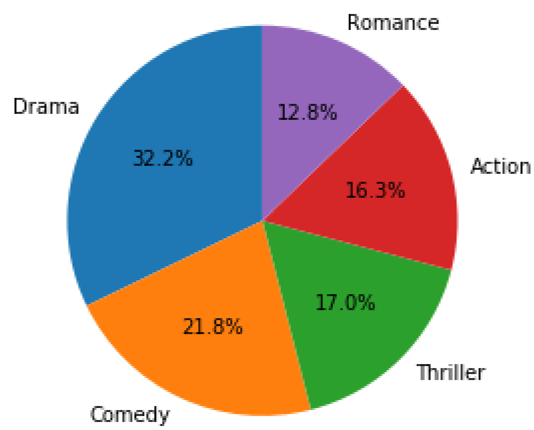
Percentage of movies in each genre in 1993



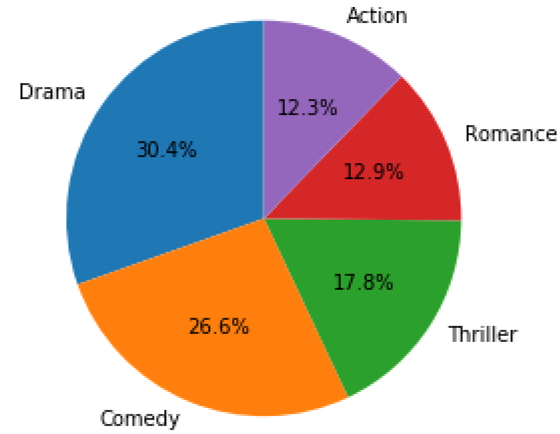
Percentage of movies in each genre in 1994



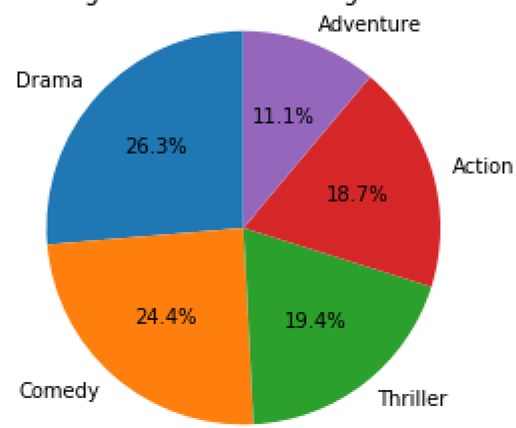
Percentage of movies in each genre in 1995



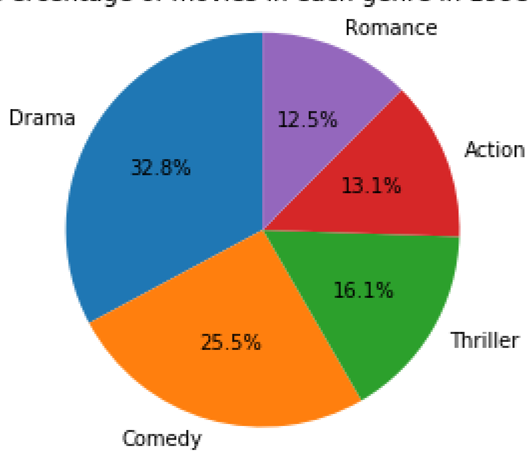
Percentage of movies in each genre in 1996



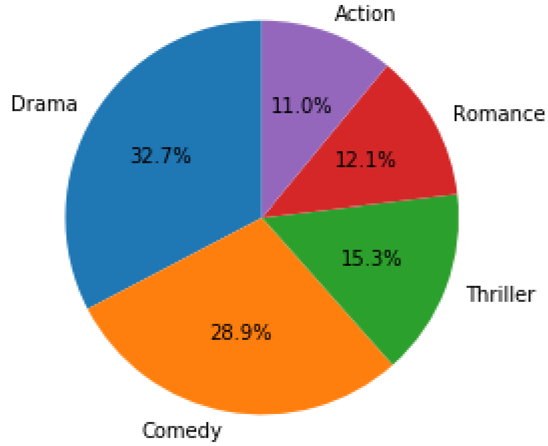
Percentage of movies in each genre in 1997



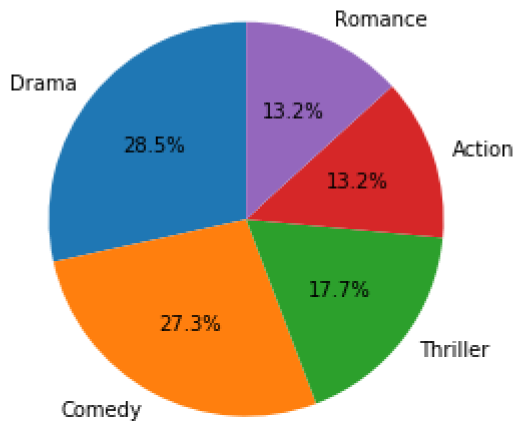
Percentage of movies in each genre in 1998



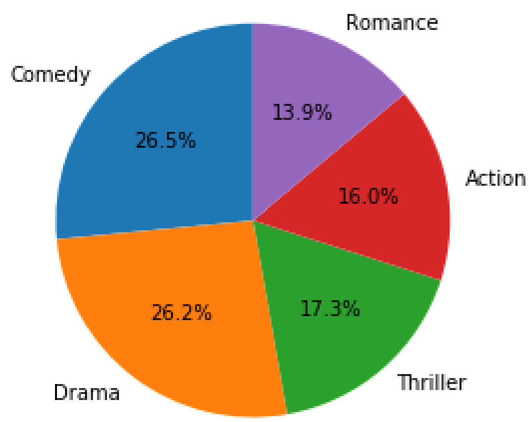
Percentage of movies in each genre in 1999



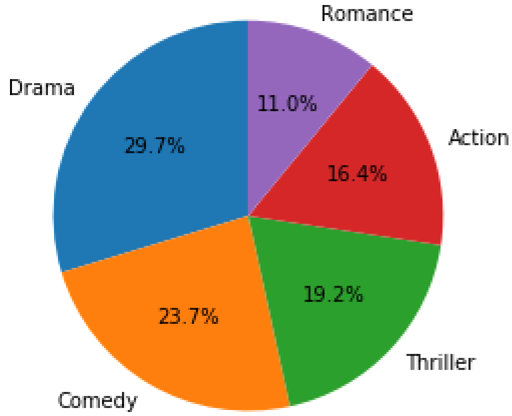
Percentage of movies in each genre in 2000



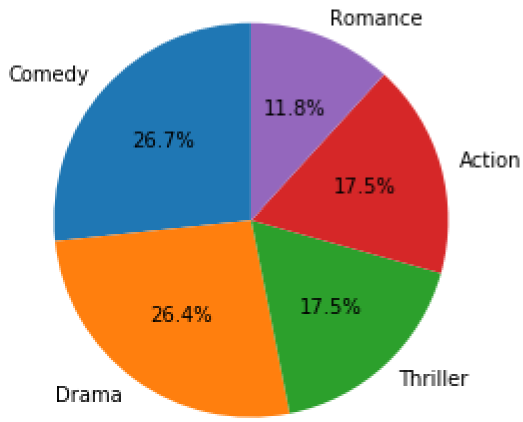
Percentage of movies in each genre in 2001



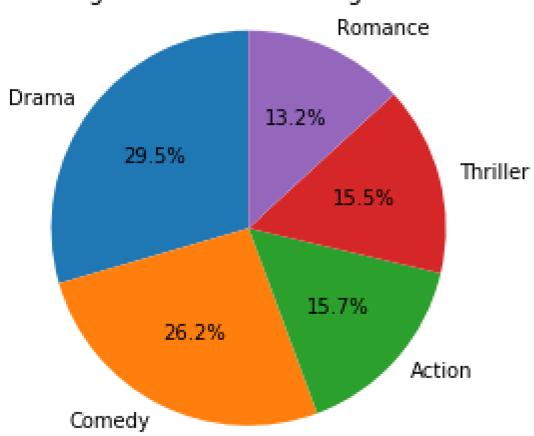
Percentage of movies in each genre in 2002



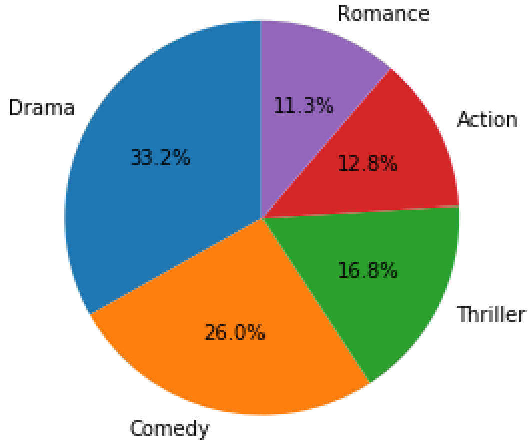
Percentage of movies in each genre in 2003



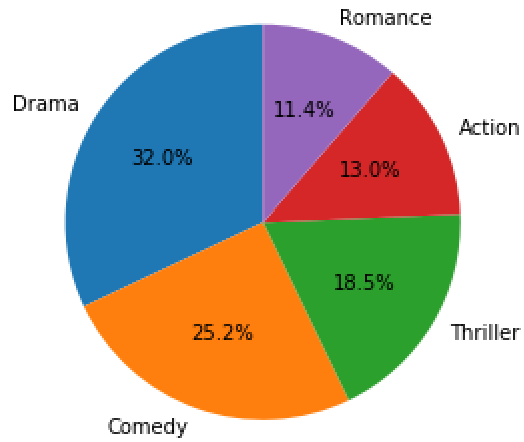
Percentage of movies in each genre in 2004



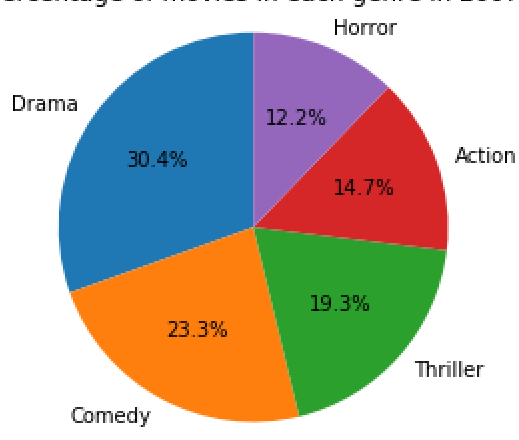
Percentage of movies in each genre in 2005



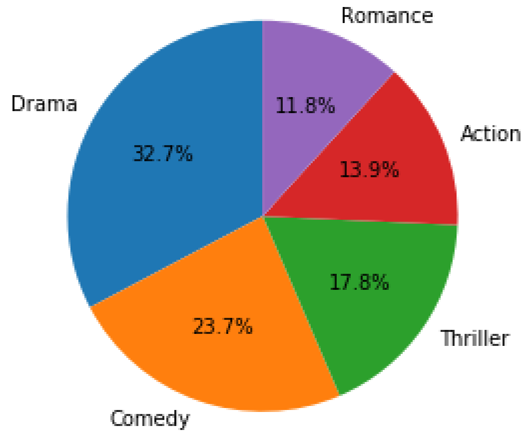
Percentage of movies in each genre in 2006



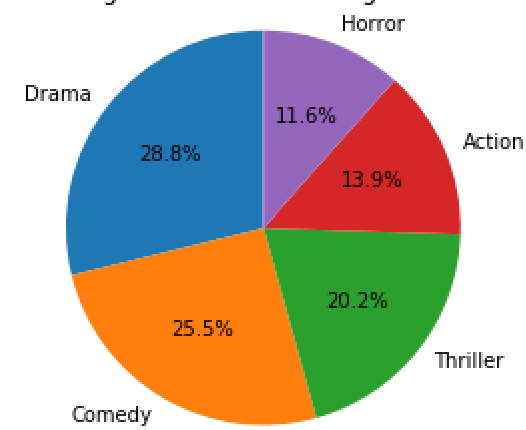
Percentage of movies in each genre in 2007



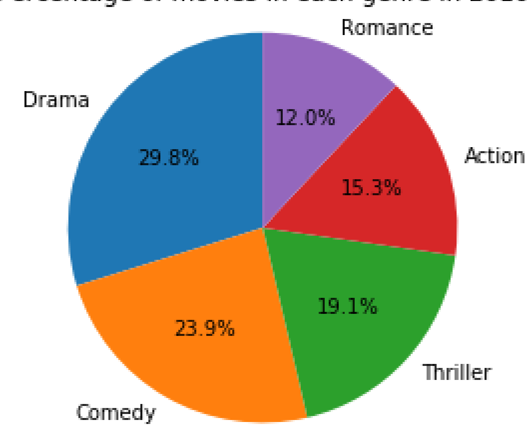
Percentage of movies in each genre in 2008



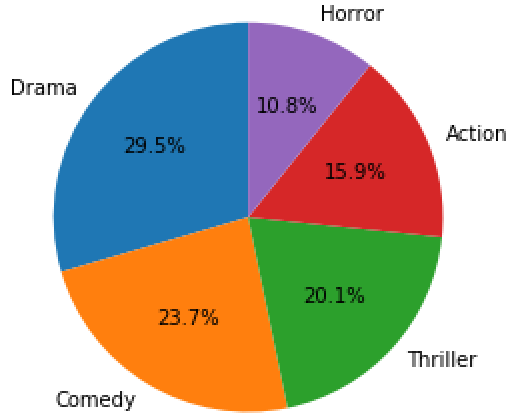
Percentage of movies in each genre in 2009



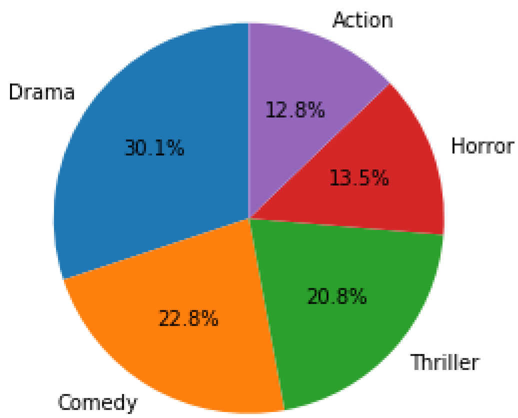
Percentage of movies in each genre in 2010



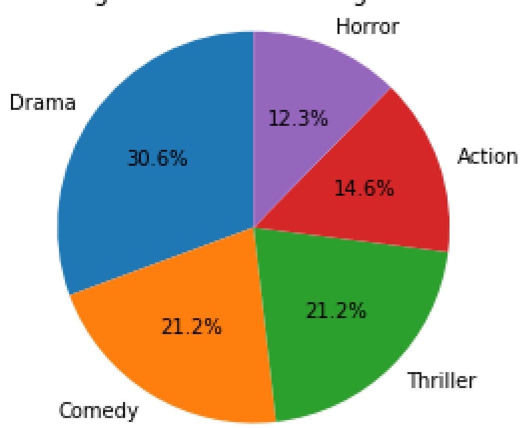
Percentage of movies in each genre in 2011

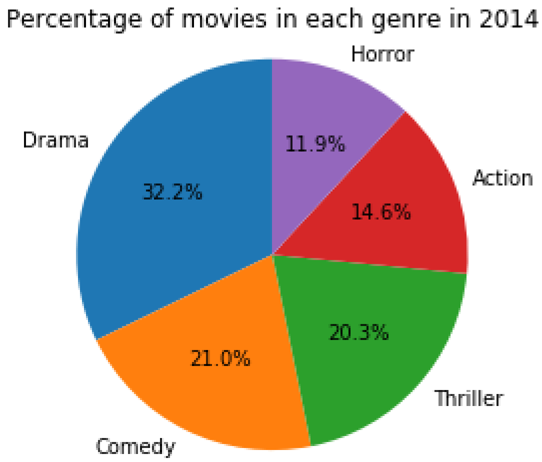


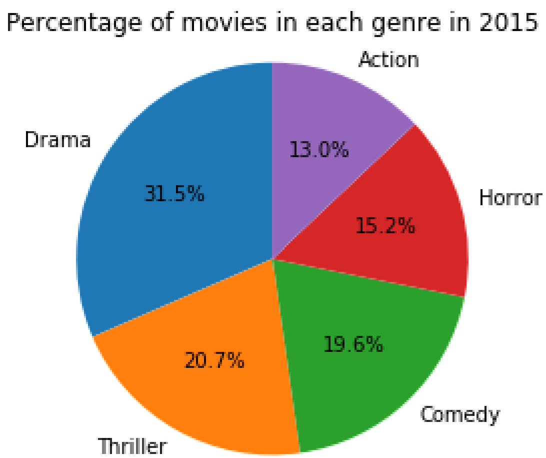
Percentage of movies in each genre in 2012



Percentage of movies in each genre in 2013




Percentage of movies in each genre in 2014
Horror
Drama
11.9%
Action
32.2%
14.6%
20.3%
21.0%
Thriller
Comedy

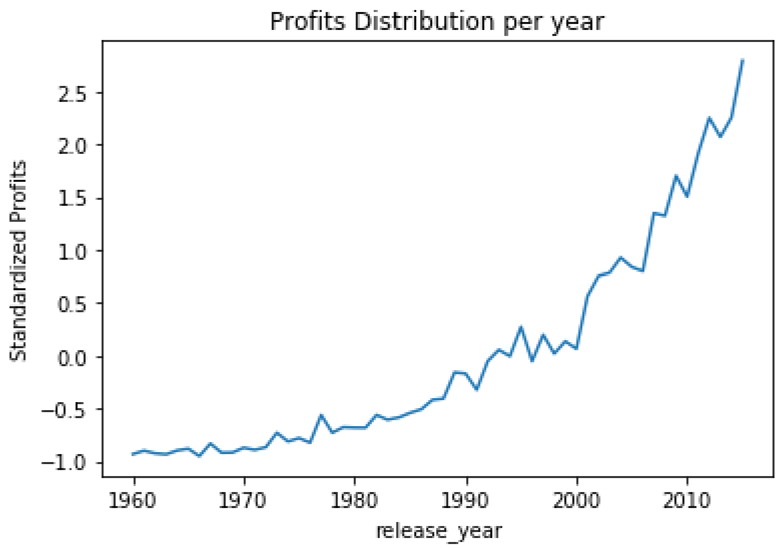

Percentage of movies in each genre in 2015
Action
Drama
13.0%
31.5%
Horror
15.2%
19.6%
20.7%
Comedy
Thriller

In [37]:
```
def standardize(x):
    x_standardized = (x - x.mean()) / x.std(ddof = 0)
    return x_standardized

# standardize popularity
std_pop =  standardize(data['popularity'])

# Exploring profit generated by the movies
profit = data['revenue'].sub(data['budget'], axis=0)

profit_temp = {'id': data['id'],
               'revenue': data['revenue'].values,
               'profits_per_movie': profit.values,
               'release_year': data['release_year'].values,
               'popularity': data['popularity'].values,
               'std_popularity': std_pop.values,
               'budget': data['budget'].values
                #'genres': data['genres'].values
              }

profitable_std_movies = pd.DataFrame(profit_temp)
profitable_std_movies.head()
```

Out[37]:

	budget	id	popularity	profits_per_movie	release_year	revenue	std_popu
0	150000000	135397	32.985763	1363528810	2015	1513528810	32.33483
1	150000000	76341	28.419936	228436354	2015	378436354	27.76963
2	110000000	262500	13.112507	185238201	2015	295238201	12.46433
3	200000000	140607	11.173104	1868178225	2015	2068178225	10.52520
4	190000000	168259	9.335014	1316249360	2015	1506249360	8.687366

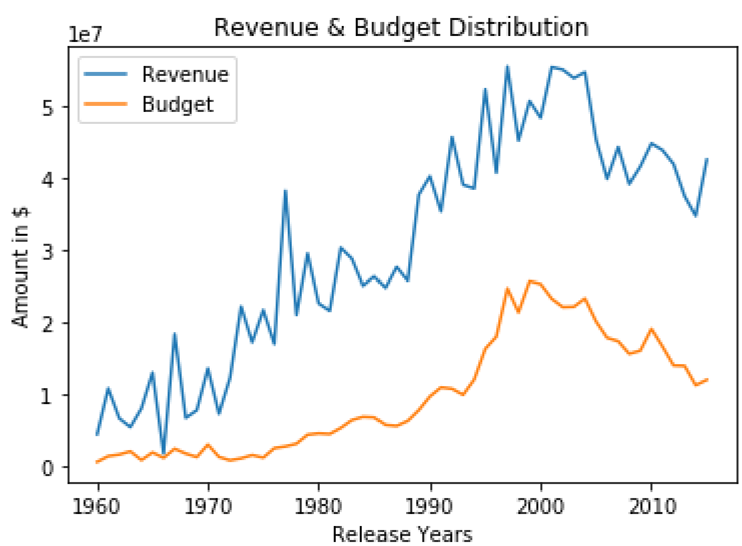
In [67]:
```
def grouping_data(x, column_name):
    return x.groupby(column_name)

# group data by release years
grouped_data_by_years = grouping_data(data, 'release_year')
grouped_profits_by_years = grouping_data(profitable_std_movies, 'release_year'
)

# standardize profits of movies per year
standardize(grouped_profits_by_years.sum()['profits_per_movie']).plot(title="P
rofits Distribution per year")
plt.ylabel("Standardized Profits")
plt.show()
```



We can visualize from the above plot that the profits made by the movie in the 2010-2015 years time period are lot more than the profits made by the movies earlier.

In [74]:
```
# checking whether the revenue collected for each movie is always higher than
 its budget or not
def mean_of_grouped_data(x, column_name):
    return x.mean()[column_name]

per_year_revenue = mean_of_grouped_data(grouped_data_by_years, 'revenue')
per_year_budget = mean_of_grouped_data(grouped_data_by_years, 'budget')

# finding correlation between revenue and budget per year
relation = (np.corrcoef(per_year_revenue, per_year_budget))[0, 1]
print("\nCorrelation between revenue and budget (of the movies per year): {}".
format(relation))

# per_year_revenue.plot(label="Revenue")
# per_year_budget.plot(label="Budget")

plt.plot(from_1960_to_2015, per_year_revenue.values, label="Revenue")
plt.plot(from_1960_to_2015, per_year_budget.values, label="Budget")
plt.ylabel("Amount in $")
plt.xlabel("Release Years")
plt.title("Revenue & Budget Distribution")
plt.legend(loc='upper left')
plt.show()
```

```
Correlation between revenue and budget (of the movies per year): 0.9059874665
884495
```



As the coorelation between revenue and budget (per year) is approx. 0.9. It depicts that both the budget and revenue (variables) are strongly correlated. So, it might be possible that the movie with higher budget also has higher movie revenues. But as the data is not cleaned yet so we cannot assure anything.

We can also see from this plot that the revenue has been mostly higher than the budget of the movie but this does not suggest that the movies will almost always be profitable as in some cases, the revenue and the budget have also not been reported (as discussed earlier). So, it may be a possibility that some of theses movies could have faced losses.

In [48]:
```
# sort the table in descending order according to standardized popularity of t
he movies
profitable_std_movies = profitable_std_movies.sort_values(by='std_popularity',
 axis='index')
profitable_std_movies.head()
```

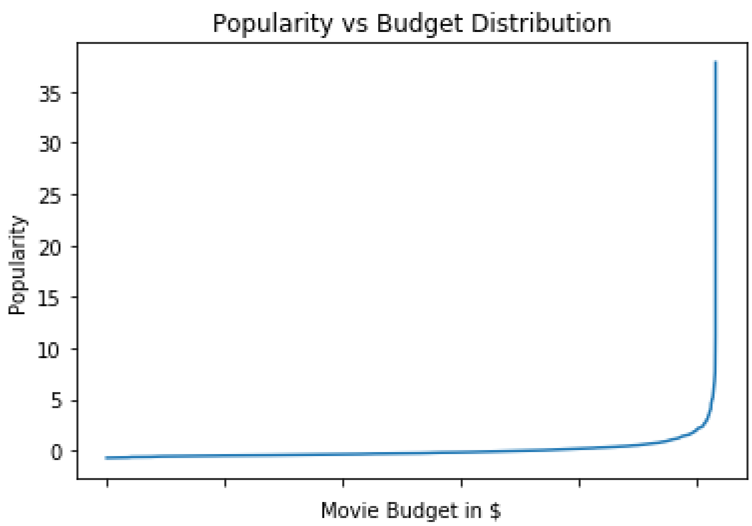
Out[48]:

	budget	id	popularity	profits_per_movie	release_year	revenue	std_popular
6181	0	18729	0.000065	0	1985	0	-0.646286
9977	0	32082	0.000188	0	1971	0	-0.646163
6080	0	174323	0.000620	0	2013	0	-0.645731
6551	0	31329	0.000973	0	2005	0	-0.645378
6961	0	15412	0.001115	0	2006	0	-0.645236

In [63]:

```
def correlation(x, y):
    std_x = standardize(x)
    std_y = standardize(y)
    return (std_x * std_y).mean()

def bool_index(x, column_name):
    return x[column_name].values != 0

index = bool_index(data, 'budget')
popular_vs_budget = correlation(data['budget'].values[index],
                                data['popularity'].values[index])
print(popular_vs_budget)

temp = pd.Series(standardize(profitable_std_movies['popularity'].values[index
]),
                 index=[standardize(profitable_std_movies['budget'].values[ind
ex])])
temp.plot(title="Popularity vs Budget Distribution")
plt.ylabel("Popularity")
plt.xlabel("Movie Budget in $")
plt.show()
```

```
0.479958191675
```

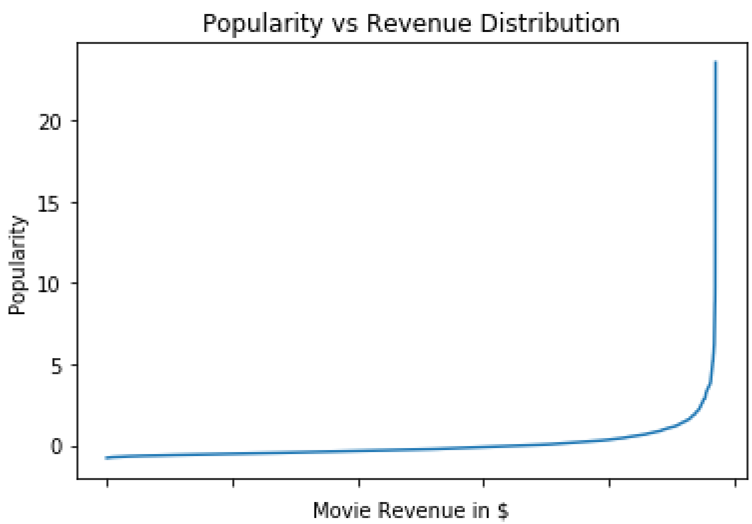


From the above correlation, we can observe that the value 0.48 approx. is positive which depicts a strong relaitonship between budget and popularity of the movie.

Also, the graph shows us the same thing that when the budget (along the x-axis) of the movies increases, the popularity of the also increases. But this graph can be also misleading as the testing values are reduced to half in this case.

In [64]:
```
index = bool_index(profitable_std_movies, 'revenue')

popular_vs_rev = (np.corrcoef((profitable_std_movies['revenue'].values)[index
],
                              (profitable_std_movies['popularity'].values)[ind
ex]))[0, 1]
print(popular_vs_rev)
temp = pd.Series(standardize(profitable_std_movies['popularity'].values[index
]),
                 index=[standardize(profitable_std_movies['revenue'].values[in
dex])])
temp.plot(title="Popularity vs Revenue Distribution")
plt.ylabel("Popularity")
plt.xlabel("Movie Revenue in $")
plt.show()
```

```
0.629315667894
```



So, from the above correlation values 0.63 approx., between variables revenue and std_popularity, we can see that it is close to +1. Hence, we can see that there is a some STRONG relation between revenue and popularity. Because the Correlation value is > 0, which suggests that if one variable increases with certain margin the other will also increase with approx. similar margin as well.

We can say that revenue and popularity are closely and positively correlated.

In [371]:
```
index = bool_index(profitable_std_movies, 'profits_per_movie')

popular_vs_profit = (np.corrcoef((profitable_std_movies['profits_per_movie'].v
alues)[index],
                                 (profitable_std_movies['popularity'].values)[
index])
                    )[0, 1]
print(popular_vs_profit)
```

```
0.615919873113
```

Here, we can see that the variables profits_per_movie and std_popularity are also positively correlated (close to +1) which implies a STRONG relationship between both the variables. So, it may be a possibility that if a movie is more popular it may be more profitable also or vice versa. But not in all cases.

SUMMARY

1. The most popular genre from year to year is DRAMA (with a total of 17.6% drama movies) followed by Comedy (14.1%) as depicted by the plots above.
2. properties/attributes of the movies which are more popular:
   - We could see that some of the values in the budget (column) were 0. So, we did not include those 0 values for finding a similarity in our data. (Data Cleaning)
   - We found the similarity in our data by using Pearson's coefficient.
   - by the correlation value ablove, we can say that the budget of the movies contributes to the popularity of the movie at the box office, but 0.48 value is not a strong evidence to say so. So, it may or may not be the factor in some cases.
   - Similarly, we can also say that the revenue collected and the profit per movie can also be the factors or reasons towards the popularity of the movie as the correlation values for these variables with popularity variable are also positive and above 0.60.
   - We are **tentatively** concluding above points but we don't have any concrete results as the correlation values are positive but not so close to +1.

LIMITATIONS

```
- Incomplete Data: - Missing values, even the lack of a section like budget in this
 case (or a substantial part of the data), could limit its usability.
- Due to lack of data regarding budget (as some fields were 0, thus, having no budg
et at all to analyse) we cannot entirely depend up on the data remaining after data
 cleaning to determine whether the above stated relationship is correct or not.
- Because from the cleaned dataset we arrived at the (budget-popularity, revenue-po
pularity) relationship and since, almost half the dataset was removed dut to the un
availability of budget details, the above stated relationship is partially true.
- So, the lack of budget data also makes our data analysis less reliable.
```

FUTURE PLANS

The report covers only some of the parameters like genres and release_years; revenue & popularity; budget & popularity, etc. There are many more parameters available in the data which can be analysed and expored further.

```
- We can expore the vote count parametre a liitle more and check its relationship w
ith the popularity parameter.
- We can also see whether the cast plays any role in the revenue collection of a mo
vie and the popularity of the movie or even in the vote count.
```