数据分析要求

一、数据摘要和可视化

- 数据摘要

1. 标称属性，给出每个可能取值的频数

2. 数值属性，给出5数概括及缺失值的个数

- 数据可视化

使用直方图、盒图等检查数据分布及离群点

二、数据缺失的处理

- 观察数据集中缺失数据，分析其缺失的原因。分别使用下列四种策略对缺失值进行处理:

1. 将缺失部分剔除

2. 用最高频率值来填补缺失值

3. 通过属性的相关关系来填补缺失值

4. 通过数据对象之间的相似性来填补缺失值

注意：在处理后完成，要对比新旧数据集的差异。

In [ ]:

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

columns = ['movieId', 'title', 'genres']
movies = pd.read_csv('/kaggle/input/movielens-10m-dataset-latest-version/ml-10M100K/movies.dat'
movies.head(5)
```

Out[ ]:

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

In [ ]:

```
movies['genres'] = movies['genres'].apply(lambda x: x.split('|'))
movies['year'] = movies['title'].apply(lambda x: int(x[-5:-1]) if x[-5:-1].isdigit() else -1
movies['title'] = movies['title'].apply(lambda s: s[:-7] if s[-5:-1].isdigit() else s)
movies.head(5)
```

Out[ ]:

	movieId	title	genres	year
0	1	Toy Story	[Adventure, Animation, Children, Comedy, Fantasy]	1995
1	2	Jumanji	[Adventure, Children, Fantasy]	1995
2	3	Grumpier Old Men	[Comedy, Romance]	1995
3	4	Waiting to Exhale	[Comedy, Drama, Romance]	1995
4	5	Father of the Bride Part II	[Comedy]	1995

In [ ]:

```
columns = ['userId','movieId', 'rating', 'timestamp']
ratings = pd.read_csv('/kaggle/input/movielens-10m-dataset-latest-version/ml-10M100K/ratings.da
ratings['timestamp'] = pd.to_datetime(ratings['timestamp'], unit='s').dt.year
ratings.head()
```

Out[ ]:

	userId	movieId	rating	timestamp
0	1	122	5.0	1996
1	1	185	5.0	1996
2	1	231	5.0	1996
3	1	292	5.0	1996
4	1	316	5.0	1996

1. Data Details -- Movies dataset & Ratings dataset

Nominal Attributes

`genres` - the genres of the movies

In [ ]:

```
movies_genres = movies['genres']
exploded_movies_genres = movies_genres.explode('genres')
count_movies_genres  = exploded_movies_genres.value_counts()
count_movies_genres
```

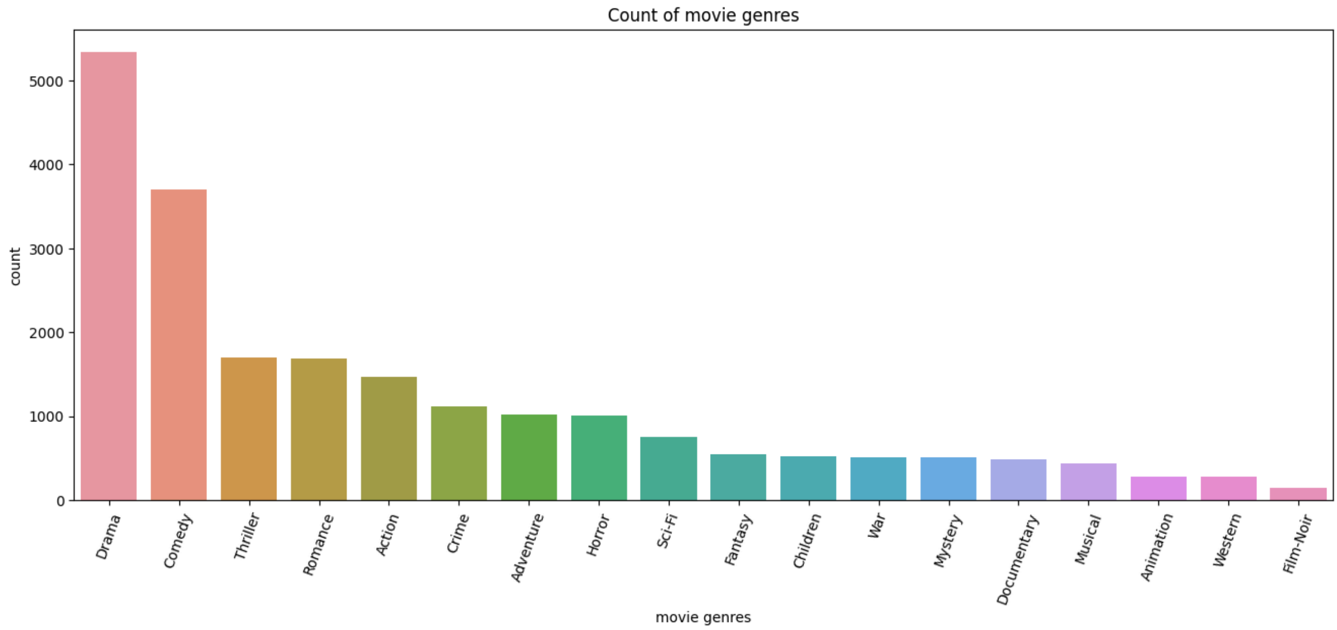
Out[ ]:

```
genres
Drama                 5339
Comedy                3703
Thriller              1706
Romance               1685
Action                1473
Crime                 1118
Adventure             1025
Horror                1013
Sci-Fi                 754
Fantasy                543
Children               528
War                    511
Mystery                509
Documentary            482
Musical                436
Animation              286
Western                275
Film-Noir              148
IMAX                    29
(no genres listed)       1
Name: count, dtype: int64
```

经过分析，认为IMax类别、no genres listed 属于异常数据，在value_count后删去处理

In [ ]:

```
count_movies_genres_process = count_movies_genres[:-2]
plt.figure(figsize=(16,6))
sns.barplot(y=count_movies_genres_process.values, x=count_movies_genres_process.index)
plt.title("Count of movie genres")
plt.xlabel("movie genres")
plt.xticks(rotation=70)
plt.ylabel("count")
plt.show()
```



Numeric Attributes

`rating` - rating of the movie

`year` - year of the movie

`timestamp` - timestamp of the rating

In [ ]:

```
numeric_movie_data = pd.DataFrame(movies, columns=['year'])
numeric_movie_describe = numeric_movie_data.describe()
numeric_movie_describe.loc[['mean', '25%', '50%', '75%', 'max']].astype(int)
```

Out[ ]:

	year
mean	1986
25%	1979
50%	1994
75%	2001
max	2008

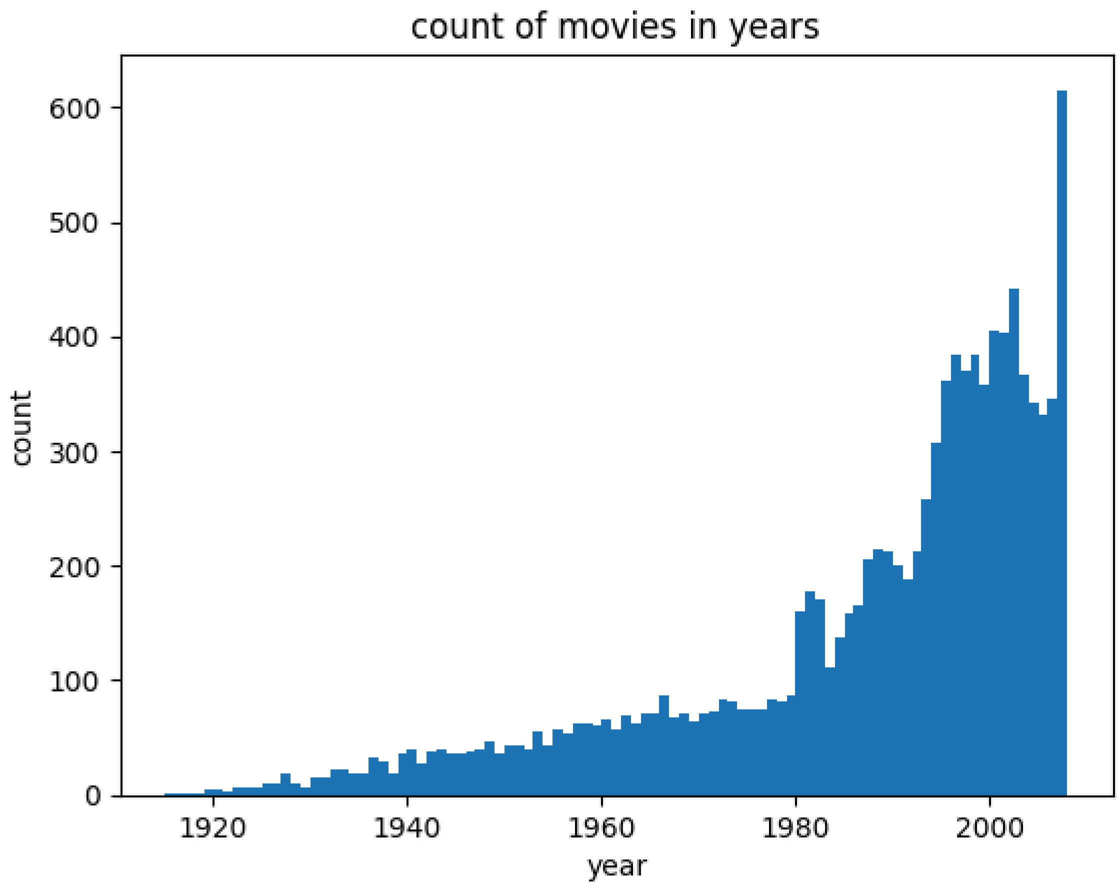
In [ ]:

```
bin_size = numeric_movie_data.max() - numeric_movie_data.min()
plt.hist(numeric_movie_data,bin_size[0])
plt.xlabel('year')
plt.ylabel("count")
plt.title("count of movies in years")
```

```
/tmp/ipykernel_33/851313466.py:2: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
  plt.hist(numeric_movie_data,bin_size[0])
```

Out[ ]:

```
Text(0.5, 1.0, 'count of movies in years')
```



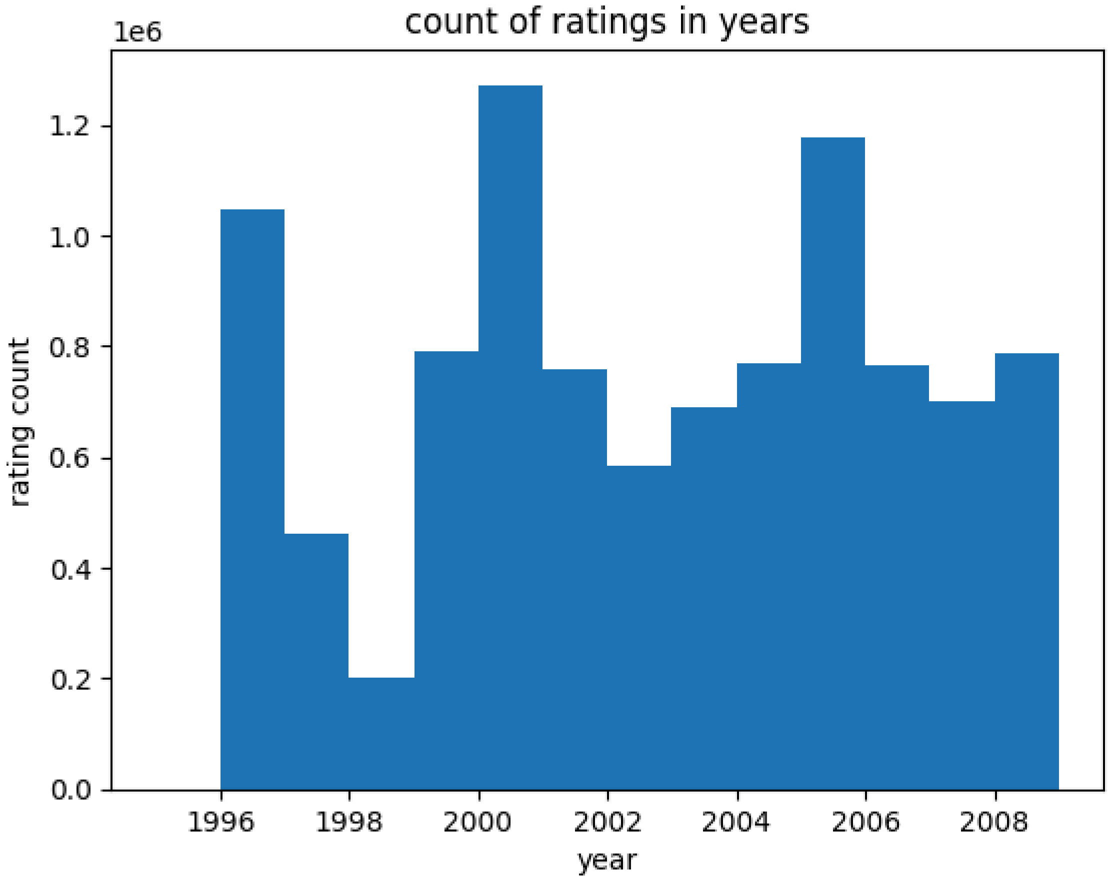
In [ ]:
```
numeric_rating_data = pd.DataFrame(ratings, columns=['rating','timestamp'])
numeric_rating_describe = numeric_rating_data.describe()
numeric_rating_describe.loc[['mean', '25%', '50%', '75%', 'max']]
```

Out[ ]:

	rating	timestamp
mean	3.512422	2002.199779
25%	3.000000	2000.000000
50%	4.000000	2002.000000
75%	4.000000	2005.000000
max	5.000000	2009.000000

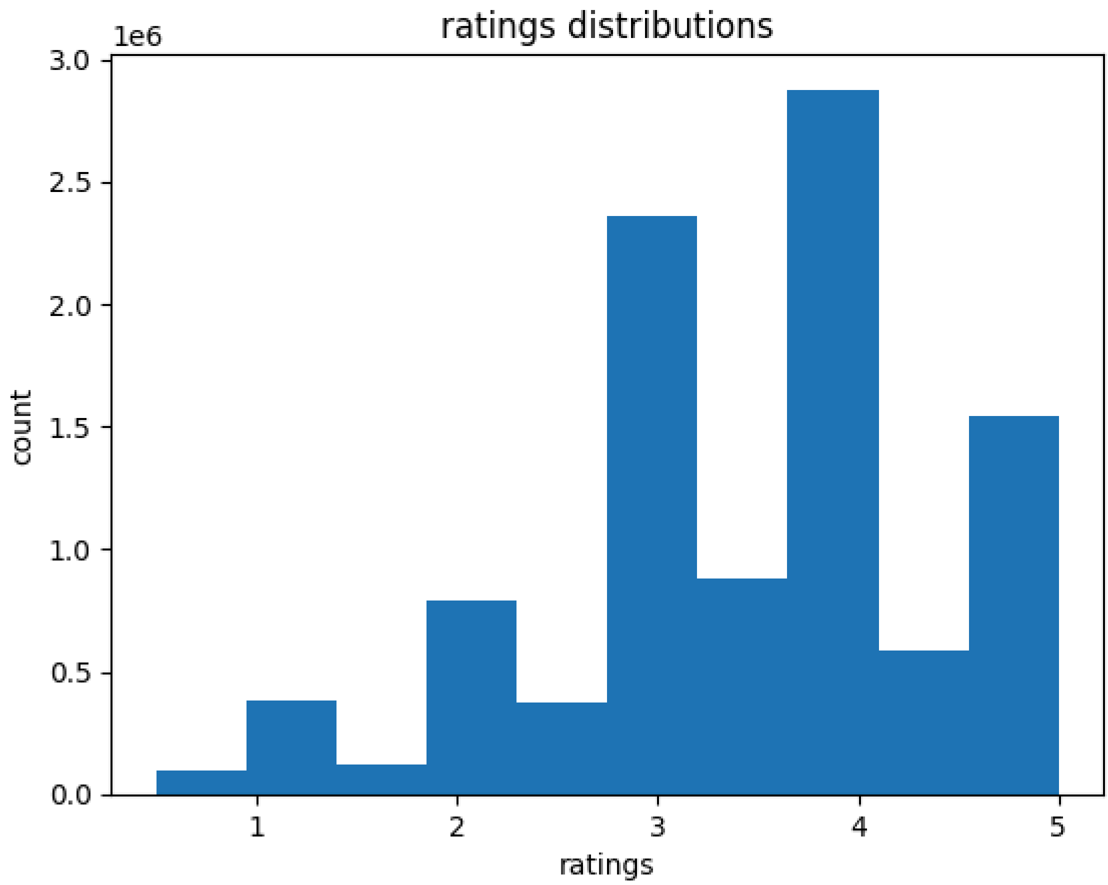
In [ ]:
```
bin_size = numeric_rating_data['timestamp'].max() - numeric_rating_data['timestamp'].min()
plt.hist(numeric_rating_data['timestamp'],bin_size)
plt.xlabel('year')
plt.ylabel("rating count")
plt.title("count of ratings in years")
```

Out[ ]:
```
Text(0.5, 1.0, 'count of ratings in years')
```



In [ ]:
```
plt.hist(numeric_rating_data['rating'])
plt.xlabel('ratings')
plt.ylabel("count")
plt.title("ratings distributions")
```

Out[ ]:
```
Text(0.5, 1.0, 'ratings distributions')
```



2. Dealing With NaN

NaN Analysis

以primary_language列为例，其的缺乏可能是由于目录下并非某一种编程语言，可能是图书分享等文件形式，因此这一列为缺失状态，对结果的影响并不大，下面依据多种方法处理这一列的缺失数据。

1. 将缺失部分剔除

2. 用最高频率值来填补缺失值

3. 通过属性的相关关系来填补缺失值

4.通过数据对象之间的相似性来填补缺失值

经过统计，无空缺值，无需填充

In [ ]:

```
movies_NaN_counts = movies.isna().sum()
print('movies_NaN_counts:\n',movies_NaN_counts)
ratings_NaN_counts = ratings.isna().sum()
ratings_NaN_counts
print('ratings_NaN_counts:\n',ratings_NaN_counts)
```

```
movies_NaN_counts:
 movieId    0
title      0
genres     0
year       0
dtype: int64
ratings_NaN_counts:
 userId       0
movieId      0
rating       0
timestamp    0
dtype: int64
```