In [159]:

import pandas as pd import numpy as np import matplotlib.pyplot as plt

## Import the three datasets

In [96]:

```
movies = pd.read_csv(r'movies.dat', sep = "::", names = ['MovieID', 'Title', 'Genres'], engine='python')
```

# help(pd.read\_csv) engine : {'c', 'python'}, optional Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

In [97]:

movies.head()

Genres	Title	MovieID	
Animation Children's Come dy	Toy Story (1995)	1	0
Adventure Children's Fantas y	Jumanji (1995)	2	1
Comedy Romance	Grumpier Old Men (1995)	3	2
Comedy Drama	Waiting to Exhale (1995)	4	3
Comedy	Father of the Bride Part II (1995)	5	4

In [98]:

```
ratings = pd.read_csv(r'ratings.dat', sep = "::", names = ['UserID','MovieID', 'Rating', 'Timestamp'],
engine='python')
```

In [99]:

ratings.head()

Out[99]:

UserID MovieID Rating Timestamp

0	1	1193	5	978300760
1	1	661	3	978302109
2	1	914	3	978301968
3	1	3408	4	978300275
4	1	2355	5	978824291

In [100]:

```
users = pd.read_csv(r'users.dat', sep = "::", names = ['UserID', 'Gender', 'Age', 'Occupation', 'Zip-Code'],
engine='python')
users.head()
```

#### Out[100]:

	UserID	Gender	Age	Occupation	Zip-Code
0	1	F	1	10	48067
1	2	M	56	16	70072
2	3	M	25	15	55117
3	4	M	45	7	02460
4	5	M	25	20	55455



Out[101]:

((3883, 3), (6040, 5), (1000209, 4))

# Create a new dataset [Master\_Data] with the following columns MovieID Title UserID Age Gender Occupation Rating. (Hint: (i) Merge two tables at a time. (ii) Merge the tables using two primary keys MovieID & UserId)

In [102]:

```
movie_ratings = pd.merge(movies, ratings, on = "MovieID")
display (movie_ratings.head())
display (movie_ratings.shape)
```

	MovieID	Title	Genres	UserID	Rating	Timestamp
0	1	Toy Story (1995)	Animation Chi ldren's Comed y	1	5	978824268

1	1	Toy Story (1995)	Animation Chi  dren's Comed   y	6	4	978237008
2	1	Toy Story (1995)	Animation Chi ldren's Comed y	8	4	978233496
3	1	Toy Story (1995)	Animation Chi ldren's Comed y	9	5	978225952
4	1	Toy Story (1995)	Animation Chi ldren's Comed y	10	5	978226474

(1000209, 6)

In [103]:

users.head()

## Out[103]:

Zip-Code	Occupation	Age	Gender	UserID	
48067	10	1	F	1	0
70072	16	56	M	2	1
55117	15	25	M	3	2
02460	7	45	M	4	3
55455	20	25	M	5	4

data = pd.merge(movie\_ratings, users, on = "UserID")

display (data.head())
display (data.shape)

	MovieI D	Title	Genres	UserID	Rating	Timesta mp	Gender	Age	Occupa tion	Zip- Code
0	1	Toy Story (1995)	Animati on Child ren's Co medy	1	5	9788242 68	F	1	10	48067
1	48	Pocahon tas (1995)	Animati on Child ren's Mu sical Ro mance	1	5	9788243 51	F	1	10	48067
2	150	Apollo 13 (1995)	Drama	1	5	9783017 77	F	1	10	48067
3	260	Star Wars: Episode IV - A New Hope (1977)	Action  Adventu re Fanta sy Sci-Fi	1	4	9783007 60	F	1	10	48067
4	527	Schindle r's List (1993)	Drama  War	1	5	9788241 95	F	1	10	48067

(1000209, 10)

Explore the datasets using visual representations (graphs or tables), also include your comments on the following:

1. User Age Distribution

In [106]:

import matplotlib.pyplot as plt from matplotlib.style import use %matplotlib inline

# Visualize age distribution of users
users.Age.plot.hist(bins=50)
plt.style.use('ggplot')
plt.title('User Age Distribution')
plt.xlabel('Age')
plt.show()

# User rating of the movie "Toy Story" - access the MovieID column & check where MovieID=1 mean of Ratio

In [107]:

```
#extract movie data for movie toy story
df_ts = data[data['MovieID'] == 1]
#View toy story first five records
df_ts.head()
#display (df_ts.shape)-(2077, 10)
```

Out[107]:

	MovieI D	Title	Genres	UserID	Rating	Timesta mp	Gender	Age	Occupa tion	Zip- Code
0	1	Toy Story (1995)	Animati on Child ren's Co medy	1	5	9788242 68	F	1	10	48067
53	1	Toy Story (1995)	Animati on Child ren's Co medy	6	4	9782370 08	F	50	9	55117
124	1	Toy Story (1995)	Animati on Child ren's Co medy	8	4	9782334 96	M	25	12	11413
263	1	Toy Story (1995)	Animati on Child ren's Co medy	9	5	9782259 52	M	25	17	61614
369	1	Toy Story (1995)	Animati on Child ren's Co	10	5	9782264 74	F	35	1	95370

	In [108]
lf_ts[ <mark>'Rating</mark> '].mean()	
	Out[108]
1.146846413095811	
	In [109]
data.Rating[data['MovieID'] == 1].mean()	
	Out[109]
4.146846413095811	
Top 25 movies by viewership rating	
	In [110]

#### #explore movie data for viewership by movie title

```
data_count = data['Title'].value_counts()
data_count[0:25]
```

#### Out[110]:

3428
(1977) 2991
trikes Back (1980) 2990
e Jedi (1983) 2883
2672
2653
2649
2590
2583
2578
2538
2514
2513
2459
2443
2369
2318
2304
2288
2278
2269
Menace (1999) 2250
2241
2227
2223

In [111]:

	Rating
Title	
\$1,000,000 Duck (1971)	3.027027
'Night Mother (1986)	3.371429
'Til There Was You (1997)	2.692308
'burbs, The (1989)	2.910891
And Justice for All (1979)	3.713568

In [112]:

```
titlewise_mean.sort_values('Rating',ascending=False).head(25)
top_25 = titlewise_mean.sort_values('Rating',ascending=False).head(25)
top_25
```

#### Out[112]:

Rating	
	Title
5.000000	Ulysses (Ulisse) (1954)
5.000000	Lured (1947)
5.000000	Follow the Bitch (1998)

Bittersweet Motel (2000)	5.000000
Song of Freedom (1936)	5.000000
One Little Indian (1973)	5.000000
Smashing Time (1967)	5.000000
Schlafes Bruder (Brother of Sleep) (1995)	5.000000
Gate of Heavenly Peace, The (1995)	5.000000
Baby, The (1973)	5.000000
I Am Cuba (Soy Cuba/Ya Kuba) (1964)	4.800000
Lamerica (1994)	4.750000
Apple, The (Sib) (1998)	4.666667
Sanjuro (1962)	4.608696
Seven Samurai (The Magnificent Seven) (Shichinin no samurai) (1954)	4.560510
Shawshank Redemption, The (1994)	4.554558
Godfather, The (1972)	4.524966
Close Shave, A (1995)	4.520548
Usual Suspects, The (1995)	4.517106
Schindler's List (1993)	4.510417
Wrong Trousers, The (1993)	4.507937
Dry Cleaning (Nettoyage ♦ sec) (1997)	4.500000
Inheritors, The (Die Siebtelbauern) (1998)	4.500000
Mamma Roma (1962)	4.500000
Bells, The (1926)	4.500000

Find the ratings for all the movies reviewed by for a particular user of

In [113]:

```
#View user records where UserID=2696
df_user = data[data['UserID'] == 2696]
df_user.head()
#display (df_ts.shape) #(2077, 10)
```

Out[113]:

	MovieI D	Title	Genres	UserID	Rating	Timesta mp	Gender	Age	Occupa tion	Zip- Code
991035	350	Client, The (1994)	Drama  Mystery  Thriller	2696	3	9733088 86	M	25	7	24210
991036	800	Lone Star (1996)	Drama  Mystery	2696	5	9733088 42	M	25	7	24210
991037	1092	Basic Instinct (1992)	Mystery  Thriller	2696	4	9733088 86	M	25	7	24210
991038	1097	E.T. the Extra- Terrestri al (1982)	Children 's Drama  Fantasy  Sci-Fi	2696	3	9733086 90	M	25	7	24210
991039	1258	Shining, The (1980)	Horror	2696	4	9733087 10	M	25	7	24210

Feature Engineering: Use column genres:	
1. Find out all the unique genres (Hint: split the	
making a list and then process the data to find categories of genres)	out only the unique
	In [114]:
#df_genres = data['Genres'] #df_split = df_genres.split("\")	
#df_genres	
	In [115].
	In [115]:
data.Genres.head()	

Out[115]: Animation|Children's|Comedy 0 Animation|Children's|Musical|Romance 1 2 Drama 3 Action|Adventure|Fantasy|Sci-Fi 4 Drama|War Name: Genres, dtype: object In [116]: data.Genres = data.Genres.str.split("|") data.Genres[:3] Out[116]: 0 [Animation, Children's, Comedy] 1 [Animation, Children's, Musical, Romance] 2 [Drama] Name: Genres, dtype: object In [117]: data.shape Out[117]: (1000209, 10)

data5k = data[:5000]data5k

Out[138]:

	MovieI D	Title	Genres	UserID	Rating	Timesta mp	Gender	Age	Occupa tion	Zip- Code
0	1	Toy Story (1995)	[Animat ion, Children 's, Comedy ]	1	5	9788242 68	F	1	10	48067
1	48	Pocahon tas (1995)	[Animat ion, Children 's, Musical, Romanc e]	1	5	9788243 51	F	1	10	48067
2	150	Apollo 13 (1995)	[Drama]	1	5	9783017 77	F	1	10	48067
3	260	Star Wars: Episode IV - A New Hope (1977)	[Action, Adventu re, Fantasy, Sci-Fi]	1	4	9783007 60	F	1	10	48067
4	527	Schindle r's List (1993)	[Drama, War]	1	5	9788241 95	F	1	10	48067
5	531	Secret Garden, The (1993)	[Childre n's, Drama]	1	4	9783021 49	F	1	10	48067
6	588	Aladdin (1992)	[Animat ion,	1	4	9788242 68	F	1	10	48067

Children	
's, Comedy	
, Musical]	

7	594	Snow White and the Seven Dwarfs (1937)	[Animat ion, Children 's, Musical]	1	4	9783022 68	F	1	10	48067
8	595	Beauty and the Beast (1991)	[Animat ion, Children 's, Musical]	1	5	9788242 68	F	1	10	48067
9	608	Fargo (1996)	[Crime, Drama, Thriller]	1	4	9783013 98	F	1	10	48067
10	661	James and the Giant Peach (1996)	[Animat ion, Children 's, Musical]	1	3	9783021 09	F	1	10	48067
11	720	Wallace & Gromit: The Best of Aardma n Animati o	[Animat ion]	1	3	9783007 60	F	1	10	48067
12	745	Close Shave, A (1995)	[Animat ion, Comedy , Thriller]	1	3	9788242 68	F	1	10	48067
13	783	Hunchb ack of Notre Dame, The (1996)	[Animat ion, Children 's, Musical]	1	4	9788242 91	F	1	10	48067
14	914	My Fair Lady (1964)	[Musical , Romanc e]	1	3	9783019 68	F	1	10	48067
15	919	Wizard of Oz, The (1939)	[Advent ure, Children 's, Drama, Musical]	1	4	9783013 68	F	1	10	48067

16	938	Gigi (1958)	[Musical	1	4	9783017 52	F	1	10	48067
17	1022	Cinderel la (1950)	[Animat ion, Children 's, Musical]	1	5	9783000 55	F	1	10	48067
18	1028	Mary Poppins (1964)	[Childre n's, Comedy , Musical]	1	5	9783017 77	F	1	10	48067
19	1029	Dumbo (1941)	[Animat ion, Children 's, Musical]	1	5	9783022 05	F	1	10	48067
20	1035	Sound of Music, The (1965)	[Musical	1	5	9783017 53	F	1	10	48067
21	1097	E.T. the Extra- Terrestri al (1982)	[Childre n's, Drama, Fantasy, Sci-Fi]	1	4	9783019 53	F	1	10	48067
22	1193	One Flew Over the Cuckoo' s Nest (1975)	[Drama]	1	5	9783007 60	F	1	10	48067
23	1197	Princess Bride, The (1987)	[Action, Adventu re, Comedy , Romanc e]	1	3	9783022 68	F	1	10	48067
24	1207	To Kill a Mockin gbird (1962)	[Drama]	1	4	9783007 19	F	1	10	48067
25	1246	Dead Poets Society (1989)	[Drama]	1	4	9783020 91	F	1	10	48067
26	1270	Back to the Future	[Comed y, Sci-	1	5	9783000 55	F	1	10	48067

(1985)	Fi]
--------	-----

27	1287	Ben-Hur (1959)	[Action, Adventu re, Drama]	1	5	9783020 39	F	1	10	48067
28	1545	Ponette (1996)	[Drama]	1	4	9788241 39	F	1	10	48067
29	1566	Hercules (1997)	[Advent ure, Animati on, Children 's, Comedy , Mus	1	4	9788243 30	F	1	10	48067
•••										
4970	2499	God Said 'Ha!' (1998)	[Comed y]	78	5	9785710 83	F	45	1	98029
4971	2539	Analyze This (1999)	[Comed y]	78	1	9785713 71	F	45	1	98029
4972	2596	SLC Punk! (1998)	[Comed y, Drama]	78	4	9785708 73	F	45	1	98029
4973	2599	Election (1999)	[Comed y]	78	5	9785706 48	F	45	1	98029
4974	2622	Midsum mer Night's Dream, A (1999)	[Comed y, Fantasy]	78	3	9785713 71	F	45	1	98029
4975	2671	Notting Hill (1999)	[Comed y, Romanc e]	78	3	9785712 81	F	45	1	98029
4976	2690	Ideal Husband , An (1999)	[Comed y]	78	3	9785709 74	F	45	1	98029
4977	2759	Dick (1999)	[Comed y]	78	3	9785712 81	F	45	1	98029
4978	2858	America n Beauty	[Comed y, Drama]	78	5	9785706 48	F	45	1	98029

(1999)

4979	2971	All That Jazz (1979)	[Musical	78	5	9778116 65	F	45	1	98029
4980	2997	Being John Malkovi ch (1999)	[Comed y]	78	2	9785706 48	F	45	1	98029
4981	3052	Dogma (1999)	[Comed y]	78	4	9785707 67	F	45	1	98029
4982	3060	Commit ments, The (1991)	[Comed y, Drama]	78	4	9785709 74	F	45	1	98029
4983	3072	Moonstr uck (1987)	[Comed y]	78	3	9778111 62	F	45	1	98029
4984	3114	Toy Story 2 (1999)	[Animat ion, Children 's, Comedy	78	4	9785706 48	F	45	1	98029
4985	3159	Fantasia 2000 (1999)	[Animat ion, Children 's, Musical]	78	4	9785703 74	F	45	1	98029
4986	3174	Man on the Moon (1999)	[Comed y, Drama]	78	3	9785709 74	F	45	1	98029
4987	3175	Galaxy Quest (1999)	[Advent ure, Comedy , Sci-Fi]	78	4	9785710 83	F	45	1	98029
4988	3178	Hurrican e, The (1999)	[Drama]	78	4	9785708 73	F	45	1	98029
4989	3247	Sister Act (1992)	[Comed y, Crime]	78	4	9785713 71	F	45	1	98029
4990	3253	Wayne's World (1992)	[Comed y]	78	3	9785711 75	F	45	1	98029
4991	3255	League	[Comed	78	5	9785708	F	45	1	98029

		of Their Own, A (1992)	y, Drama]			73				
4992	3282	Differen t for Girls (1996)	[Comed y]	78	4	9785711 75	F	45	1	98029
4993	3358	Defendi ng Your Life (1991)	[Comed y, Romanc e]	78	4	9785708 73	F	45	1	98029
4994	3545	Cabaret (1972)	[Musical , War]	78	5	9785703 74	F	45	1	98029
4995	3549	Guys and Dolls (1955)	[Musical	78	4	9778116 66	F	45	1	98029
4996	3599	Anchors Aweigh (1945)	[Comed y, Musical]	78	3	9778116 66	F	45	1	98029
4997	3600	Blue Hawaii (1961)	[Comed y, Musical]	78	3	9778119 82	F	45	1	98029
4998	3606	On the Town (1949)	[Musical	78	5	9778116 66	F	45	1	98029
4999	3614	Honeym oon in Vegas (1992)	[Comed y, Romanc e]	78	3	9785712 81	F	45	1	98029

 $5000 \text{ rows} \times 10 \text{ columns}$ 

In [139]:

```
x = []
for rn in range(len(data5k)):
  x = x + data5k.Genres[rn]
```

data5k.Genres

0	[Animation, Children's, Comedy]
1	[Animation, Children's, Musical, Romance]
2	[Drama]
3	[Action, Adventure, Fantasy, Sci-Fi]
4	[Drama, War]
5	[Children's, Drama]
6	[Animation, Children's, Comedy, Musical]
7	[Animation, Children's, Musical]
8	[Animation, Children's, Musical]
9	[Crime, Drama, Thriller]
10	[Animation, Children's, Musical]
11	[Animation]
12	[Animation, Comedy, Thriller]
13	[Animation, Children's, Musical]
14	[Musical, Romance]
15	[Adventure, Children's, Drama, Musical]
16	[Musical]
17	[Animation, Children's, Musical]
18	[Children's, Comedy, Musical]
19	[Animation, Children's, Musical]
20	[Musical]
21	[Children's, Drama, Fantasy, Sci-Fi]
22	[Drama]
23	[Action, Adventure, Comedy, Romance]
24	[Drama]
25	[Drama]
26	[Comedy, Sci-Fi]
27	[Action, Adventure, Drama]
28	[Drama]
29	[Adventure, Animation, Children's, Comedy, Mus
4970	[Comedy]
4971	[Comedy]
4972	[Comedy, Drama]
4973	[Comedy]
4974	[Comedy, Fantasy]
4975	[Comedy, Romance]
4976	[Comedy]
4977	[Comedy]
4978	[Comedy, Drama]
4979	[Musical]
4980	[Comedy]
4981	[Comedy]
4982	[Comedy, Drama]
4983	[Comedy]
4984	[Animation, Children's, Comedy]

4985	[Animation, Children's, Musical]	
4986	[Comedy, Drama]	
4987	[Adventure, Comedy, Sci-Fi]	
4988	[Drama]	
4989	[Comedy, Crime]	
4990	[Comedy]	
4991	[Comedy, Drama]	
4992	[Comedy]	
4993	[Comedy, Romance]	
4994	[Musical, War]	
4995	[Musical]	
4996	[Comedy, Musical]	
4997	[Comedy, Musical]	
4998	[Musical]	
4999	[Comedy, Romance]	
Name: Genre	es, Length: 5000, dtype: object	
		In [140]:
unique_genre	res = list(set(x))	
print (unique	e_genres)	
	ama', 'Adventure', 'Horror', 'Mystery', 'Documenta	
"Children's",	, 'Fantasy', 'Romance', 'Action', 'War', 'Film-Noir', '	Musical', 'Thriller']

1. Create a separate column for each genre category with a one-hot encoding (1 and 0) whether or not the movie belongs to that genre.

In [141]:

unique\_genres = pd.Series(unique\_genres)

In [142]:

```
df = pd.DataFrame()
for row in data5k.Genres:
    a = unique_genres.isin(row)
    df = df.append(a,ignore_index = True)
df[:5]
```

Out[142]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0
2	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0
4	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0

In [143]:

df.columns = unique\_genres
df.head()

	Cri me	Dr am a	Ad ven tur e	Ho rro r	My ster y	me	We ster n	Ani ma tio n	Co me dy	Sci- Fi	Chi ldr en' s	Fa nta sy	Ro ma nce	Act ion	Wa r	Fil m- Noi r	Mu sica l	Th rill er
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0
2	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0
4	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0

In [144]:

data5k.head()

### Out[144]:

	MovieI D	Title	Genres	UserID	Rating	Timesta mp	Gender	Age	Occupa tion	Zip- Code
0	1	Toy Story (1995)	[Animat ion, Children 's, Comedy ]	1	5	9788242 68	F	1	10	48067
1	48	Pocahon tas (1995)	[Animat ion, Children 's, Musical, Romanc e]	1	5	9788243 51	F	1	10	48067

2	150	Apollo 13 (1995)	[Drama]	1	5	9783017 77	F	1	10	48067
3	260	Star Wars: Episode IV - A New Hope (1977)	[Action, Adventu re, Fantasy, Sci-Fi]	1	4	9783007 60	F	1	10	48067
4	527	Schindle r's List (1993)	[Drama, War]	1	5	9788241 95	F	1	10	48067

In [147]:

#data5k = pd.concat((data5k, df), axis = 1)
data5k = pd.concat((data5k.Title, df), axis = 1)
data5k.head()

Out[147]:

	Tit le	Cri me	Dr am a	Ad ven tur e	Ho rro r	My ste ry	Do cu me nta ry	We ste rn	An im ati on	Co me dy	Sci -Fi	Ch ild ren 's	Fa nta sy	Ro ma nce	Act ion	Wa r	Fil m- Noi r	Mu sic al	Th rill er
0	To y Sto ry (19 95)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	Poc aho nta s (19 95)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0
2	Ap oll	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

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1. Determine the features affecting the ratings of any particular movie.

In [160]:

#correlation - best #hypothesis testing import seaborn as sns %matplotlib inline

In [161]:

```
corr = data5k.corr()
sns.heatmap(corr, xticklabels=corr.columns.values, yticklabels=corr.columns.values, annot = True,
annot_kws={'size':10})
                                                                                                         Out[161]:
<matplotlib.axes._subplots.AxesSubplot at 0x7ff48622b6d8>
                                                                                                          In [175]:
# create a Python list of feature names
feature_cols=['Age','Occupation']
# use the list to select a subset of the original DataFrame
X=data[feature_cols]
# select a Series from the DataFrame
y=data.Rating
  1. Develop an appropriate model to predict the movie ratings
                                                                                                          In [180]:
from sklearn.model_selection import train_test_split
# split into training and testing sets
X_train,X_test,y_train,y_test=train_test_split(X,y,random_state=1)
# import model
from sklearn.linear_model import LinearRegression
# instantiate
linreg=LinearRegression()
# fit the model to the training data (learn the coefficients)
linreg.fit(X_train,y_train)
```

```
# make predictions on the testing set
y_pred=linreg.predict(X_test)
from sklearn.metrics import mean_squared_error
# compute the RMSE of our predictions
print(np.sqrt(mean_squared_error(y_test,y_pred)))
```

#### 1.1153284258531615

In [ ]: