

EDS THEORY ACTIVITY NO-1

NAME- SAMRUDDHI DEEPAK PHULARI

ROLL NO – CS4-34

PRN NO – 202401040129

DATASET – MOVIELENS LATEST DATASET

	A	B	C	D	E	
1	userId	movieId	tag	timestamp		
2	2	60756	funny	1.45E+09		
3	2	60756	Highly quo	1.45E+09		
4	2	60756	will ferrell	1.45E+09		
5	2	89774	Boxing sto	1.45E+09		
6	2	89774	MMA	1.45E+09		
7	2	89774	Tom Hardy	1.45E+09		
8	2	106782	drugs	1.45E+09		
9	2	106782	Leonardo	1.45E+09		
10	2	106782	Martin Sc	1.45E+09		
11	7	48516	way too lo	1.17E+09		
12	18	431	Al Pacino	1.46E+09		
13	18	431	gangster	1.46E+09		
14	18	431	mafia	1.46E+09		
15	18	1221	Al Pacino	1.46E+09		
16	18	1221	Mafia	1.46E+09		
17	18	5995	holocaust	1.46E+09		
18	18	5995	true story	1.46E+09		
19	18	44665	twist endir	1.46E+09		
20	18	52604	Anthony H	1.46E+09		
21	18	52604	courtroom	1.46E+09		
22	18	52604	twist endir	1.46E+09		
23	18	88094	britpop	1.46E+09		
24	18	88094	indie recor	1.46E+09		
25	18	88094	music	1.46E+09		
26	18	144210	dumpster c	1.46E+09		

7	18	144210	Sustainable	1.46E+09		
8	21	1569	romantic c	1.42E+09		
9	21	1569	wedding	1.42E+09		
0	21	118985	painter	1.42E+09		
1	21	119141	bloody	1.42E+09		
2	49	109487	black hole	1.49E+09		
3	49	109487	sci-fi	1.49E+09		
4	49	109487	time-trave	1.49E+09		
5	62	2	fantasy	1.53E+09		
6	62	2	magic boa	1.53E+09		
7	62	2	Robin Willi	1.53E+09		
8	62	110	beautiful s	1.53E+09		
9	62	110	epic	1.53E+09		
0	62	110	historical	1.53E+09		
1	62	110	inspiration	1.53E+09		
2	62	110	Medieval	1.53E+09		
3	62	110	mel gibson	1.53E+09		
4	62	110	Oscar (Bes	1.53E+09		
5	62	110	revenge	1.53E+09		
6	62	110	sword figh	1.53E+09		
7	62	410	black com	1.53E+09		
8	62	410	Christina R	1.53E+09		
9	62	410	Christophe	1.53E+09		
0	62	410	dark come	1.53E+09		
1	62	410	family	1.53E+09		
2	62	410	gothic	1.53E+09		

76	260	action	1.44E+09	
76	260	sci-fi	1.44E+09	
103	260	EPIC	1.43E+09	
103	260	great soun	1.43E+09	
103	296	good dialo	1.43E+09	
103	296	great soun	1.43E+09	
103	296	non-linear	1.43E+09	
106	4896	Everything	1.47E+09	
106	106489	adventure	1.47E+09	
112	260	classic sci-	1.44E+09	
112	260	engrossing	1.44E+09	
112	260	EPIC	1.44E+09	
119	260	classic	1.44E+09	
119	260	Nerd	1.44E+09	
119	101142	animation	1.44E+09	
119	101142	funny	1.44E+09	
119	101142	stone age	1.44E+09	
119	115149	action	1.44E+09	
119	115149	killer	1.44E+09	
119	115149	widows/w	1.44E+09	
119	115617	animation	1.44E+09	
119	115617	kids	1.44E+09	
119	115617	robots	1.44E+09	
119	120635	action	1.44E+09	
119	120635	murder	1.44E+09	
119	120635	police	1.44E+09	

Files

Analyze your files with code written by Gemini

Upload

sample_data

tags.csv

```
import pandas as pd
df=pd.read_csv('/content/tags.csv')
print(df)
```

	userId	movieId	tag	timestamp
0	2	60756	funny	1445714994
1	2	60756	Highly quotable	1445714996
2	2	60756	will ferrell	1445714992
3	2	89774	Boxing story	1445715207
4	2	89774	MMA	1445715200
...
3678	606	7382	for katie	1171234019
3679	606	7936	austere	1173392334
3680	610	3265	gun fu	1493843984
3681	610	3265	heroic bloodshed	1493843978
3682	610	168248	Heroic Bloodshed	1493844270

[3683 rows x 4 columns]

```
sum_id=df['userId'].sum()
print(sum_id)
```

1587923

```
[14] 2. # Find total number of rows (tags) in the dataset.#
print(len(df))
```

3683

```
[15] 3.# Find the total number of unique users.#
print(df['userId'].nunique())
```

58

```
[16] 4.#Find the total number of unique movies.#
print(df['movieId'].nunique())
```

1572

```
[18] 5.# Find the total number of unique tags.#
print(df['tag'].nunique())
```

1589

```
6.# Find the most common tag used.#
print(df['tag'].value_counts().idxmax())
```

In Netflix queue

```
[19] 7.#Find the least common tag#
least_common_tag = df['tag'].value_counts().idxmin()
print(least_common_tag)
```

Heroic Bloodshed

```
[20] 8.#Find how many tags contain the word "funny".#  
      funny_tags_count = df['tag'].str.contains('funny', case=False).sum()  
      print(funny_tags_count)
```

⇒ 28

```
▶ 9.#Find the number of tags created each year.#  
df['year'] = df['timestamp'].dt.year  
tag_counts_by_year = df.groupby('year').size()  
print(tag_counts_by_year)
```

⇒

year	
2006	1533
2007	46
2008	9
2009	166
2010	133
2011	13
2012	47
2013	10
2014	7
2015	191
2016	355
2017	329
2018	844

dtype: int64

```
✓ [24] 10.#Find the average number of tags per user.#  
ls      average_tags_per_user = df.groupby('userId').size().mean()  
        print(average_tags_per_user)
```

⇒ 63.5

```
✓ [25] 11.#Find the user who assigned the most tags.#  
ls      user_with_most_tags = df['userId'].value_counts().idxmax()  
        print(user_with_most_tags)
```

⇒ 474

```
✓ [26] 12.#Find the movie that received the most tags.#  
ls      movie_with_most_tags = df['movieId'].value_counts().idxmax()  
        print(movie_with_most_tags)
```

⇒ 296

```
✓ [27] 13.#Find the earliest tagging time.#  
ls      earliest_tagging_time = df['timestamp'].min()  
        print(earliest_tagging_time)
```

⇒ 2006-01-13 19:09:12

✓
0s [28] 14.# Find the latest tagging time.#
latest_tagging_time = df['timestamp'].max()
print(latest_tagging_time)

↗ 2018-09-16 11:50:03

✓
0s [29] 15.# Find users who tagged more than 1000 movies.#
users_with_more_than_1000_movies = df.groupby('userId').filter(lambda x: len(x) > 1000)
print(users_with_more_than_1000_movies)

↗

	userId	movieId	tag	timestamp	year
981	474	1	pixar	2006-01-14 02:47:05	2006
982	474	2	game	2006-01-16 01:39:12	2006
983	474	5	pregnancy	2006-01-16 01:11:43	2006
984	474	5	remake	2006-01-16 01:11:43	2006
985	474	7	remake	2006-01-16 01:40:42	2006
...
2483	474	40819	Johnny Cash	2006-01-14 01:03:15	2006
2484	474	41566	C.S. Lewis	2006-01-13 19:46:57	2006
2485	474	41997	In Netflix queue	2006-01-13 19:13:23	2006
2486	474	42002	In Netflix queue	2006-01-14 01:29:10	2006
2487	474	42740	In Netflix queue	2006-02-01 14:30:37	2006

[1507 rows x 5 columns]

✓
0s 16.# Find tags used by more than 10 users.#
tags_used_by_more_than_10_users = df.groupby('tag').filter(lambda x: len(x) > 10)
print(tags_used_by_more_than_10_users)

↗

	userId	movieId	tag	timestamp	year
0	2	60756	funny	2015-10-24 19:29:54	2015
17	18	44665	twist ending	2016-03-02 19:51:23	2016
20	18	52604	twist ending	2016-03-10 22:58:02	2016
23	18	88094	music	2016-03-08 13:43:29	2016
31	49	109487	sci-fi	2017-04-25 04:08:52	2017
...
3659	599	2959	quirky	2017-06-26 06:01:58	2017
3665	599	2959	surreal	2017-06-26 06:01:40	2017
3667	599	2959	thought-provoking	2017-06-26 06:01:41	2017
3669	599	2959	twist ending	2017-06-26 06:01:28	2017
3673	606	1357	music	2007-04-16 23:16:33	2007

[855 rows x 5 columns]

```
[31] 17.#Find the number of different tags assigned to each movie.#
tags_per_movie = df.groupby('movieId')['tag'].nunique()
print(tags_per_movie)
```

```
movieId
1      2
2      4
3      2
5      2
7      1
..
183611 3
184471 3
187593 3
187595 2
193565 4
Name: tag, Length: 1572, dtype: int64
```

```
18.#Find the average time difference between two tags.#
time_diff = df['timestamp'].sort_values().diff().mean()
print(time_diff)
```

```
1 days 06:10:14.679793590
```

```
✓ [33] 19.# Find movies that were tagged in 2015.#
0s movies_in_2015 = df[df['timestamp'].dt.year == 2015]['movieId'].unique()
print(movies_in_2015)
```

```
[ 60756  89774 106782    260    296 101142 115149 115617 120635  4878
 7147   7361  97938 126548   6711  71494  90769  96084 118784 127172
 5952  98809 112552  80834    356    527   1625   1721   2329   2571
 3949   5989   8533  55765  58295  69122  69481  72998  79132  80489
 80906  89745  90439  92259  95067  95441  97304  99114 104218 104841
105504]
```

```
✓ 20.# List all tags containing "Al Pacino".#
0s al_pacino_tags = df[df['tag'].str.contains('Al Pacino', case=False)]['tag'].unique()
print(al_pacino_tags)
```

```
['Al Pacino']
```