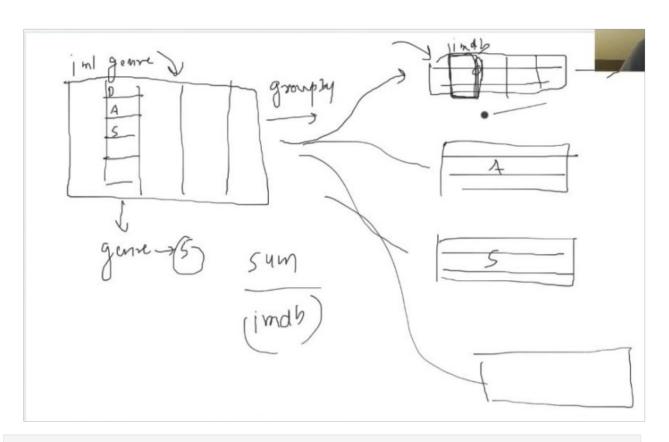
```
import pandas as pd
import numpy as np
movies = pd.read csv('imdb-top-1000.csv')
movies.head(2)
               Series Title Released Year Runtime Genre IMDB Rating
0
  The Shawshank Redemption
                                     1994
                                               142
                                                    Drama
                                                                   9.3
              The Godfather
                                     1972
                                                                   9.2
                                               175 Crime
               Director
                                 Star1
                                        No of Votes
                                                           Gross
Metascore
         Frank Darabont
                           Tim Robbins
                                            2343110
                                                      28341469.0
80.0
1 Francis Ford Coppola Marlon Brando
                                            1620367 134966411.0
100.0
# Groupby - is basically the study of groups
# group by apply hota hai categorical column ke upar (jiska ki value
humesa change karte rahata hai for ex : jenre in our data set)
movies.shape
(1000, 10)
# genre ke basis pe movie ko categorise karna hai suppose sare Drama
type ke movie ko group karna hai then sare crime type ko alag
movies.groupby('Genre') # abhi kuch output nahi dikhega bass pata
chalega ki hum jo operation kye hain usse DataFrameGroupBy object
create ho gya hai
<pandas.core.groupby.generic.DataFrameGroupBy object at</pre>
0x00000290C6ACB8C0>
genres = movies.groupby('Genre')
# Applying builtin aggregation functions on groupby objects
genres.sum()
# yaha pe jo output aa raha hai usme har row me alag alag genre hai
means ki ye table genres ke basis pe groupby ho gya hai and sum
function ko call
# karne se particular column ke sare data add ho gya hai
                                                Series Title ∖
Genre
           The Dark KnightThe Lord of the Rings: The Retu...
Action
```

Adventure Animation Biography Comedy Crime Drama Family Fantasy Film-Noir Horror Mystery Thriller Western	InterstellarBack to the FutureInglourious Bast Sen to Chihiro no kamikakushiThe Lion KingHota Schindler's ListGoodfellasHamiltonThe Intoucha GisaengchungLa vita è bellaModern TimesCity Li The GodfatherThe Godfather: Part II12 Angry Me The Shawshank RedemptionFight ClubForrest Gump E.T. the Extra-TerrestrialWilly Wonka & the Ch Das Cabinet des Dr. CaligariNosferatu The Third ManThe Maltese FalconShadow of a Doubt PsychoAlienThe ThingThe ExorcistNight of the L MementoRear WindowVertigoShutter IslandKahaani Wait Until Dark Il buono, il brutto, il cattivoOnce Upon a Tim	
\	Released_Year	Runtime
Genre		
Action	2008200320102001200219991980197719621954200019	22196
Adventure	2014198520091981196819621959201319751963194819	9656
Animation	2001199419882016201820172008199719952019200920	8166
Biography	1993199020202011200220171995198420182013201320	11970
Comedy	2019199719361931200919641940200120001973196019	17380
Crime	1972197419571994200219991995199120192006199519	13524
Drama	1994199919941975202019981946201420061998198819	36049
Family	19821971	215
Fantasy	19201922	170
Film-Noir	194919411943	312
Horror	19601979198219731968196120171978193320042001	1123
Mystery	200019541958201020121995197219381988201219981997	1429
Thriller	1967	108
Western	1966196819651976	593
Director Genre	IMDB_Rating \	

Action	1367.3	Christopher NolanPeter JacksonChristopher
Nola Adventure	571.5	Christopher NolanRobert ZemeckisQuentin
Tarant Animation	650.3	Hayao MiyazakiRoger AllersIsao
TakahataMa	koto	
Biography KailOliv	698.6	Steven SpielbergMartin ScorseseThomas
Comedy	1224.7	Bong Joon HoRoberto BenigniCharles
ChaplinCha Crime	r 857.8	Francis Ford CoppolaFrancis Ford
CoppolaSid		
Drama ZemeckisMi	2299.7	Frank DarabontDavid FincherRobert
Family	15.6	Steven SpielbergMel
Stuart		
Fantasy Murnau	16.0	Robert WieneF.W.
Film-Noir	23.9	Carol ReedJohn HustonAlfred
Hitchcock	25.5	carot necasonii nastoniiterrea
Horror	87.0	Alfred HitchcockRidley ScottJohn
CarpenterW.	ill 95.7	Christopher NolanAlfred HitcheockAlfred
Mystery Hitchc	95.7	Christopher NolanAlfred HitchcockAlfred
Thriller	7.8	Terence
Young		
Western	33.4	Sergio LeoneSergio LeoneClint
East		
		Star1
No_of_Vote	s \	
Genre		
Action	Christian Ba	leElijah WoodLeonardo DiCaprioElij
72282412 Adventure	Matthew McCo	naugheyMichael J. FoxBrad PittJürg
22576163	TIACCITCW TICCO	naugheyntenaet 3. Toxbraa Tittbarg
Animation 21978630	Daveigh Chase	eRob MinkoffTsutomu TatsumiRyûnosu
Biography	Liam NeesonRo	obert De NiroLin-Manuel MirandaÉri
24006844		
Comedy 27620327	Kang-ho Songl	Roberto BenigniCharles ChaplinChar
Crime	Marlon Brando	oAl PacinoHenry FondaJohn Travolta
33533615	- :	
Drama 61367304	iim KobbinsB	rad PittTom HanksJack NicholsonSur
Family		Henry ThomasGene Wilder
551221		•

Fantasy			Werner KraussMax Schreck
146222			
Film-Noir	0rso	n WellesHum	nphrey BogartTeresa Wright
367215			
Horror	Anthony Perki	nsSigourney	WeaverKurt RussellEll
3742556			
Mystery	Guy PearceJam	es StewartJ	ames StewartLeonardo D
4203004			Andrew Healthan
Thriller			Audrey Hepburn
27733 Western	Clint Eactwoo	duanty Fand	laClint FactwoodClint F
1289665	CLINE Eastwoo	uneilly Folio	laClint EastwoodClint E
1209005			
	Gross	Metascore	
Genre			
Action	3.263226e+10	10499.0	
Adventure	9.496922e+09	5020.0	
	1.463147e+10	6082.0	
	8.276358e+09	6023.0	
,	1.566387e+10	9840.0	
-	8.452632e+09	6706.0	
Drama		19208.0	
_	4.391106e+08	158.0	
	7.827267e+08 1.259105e+08	0.0 287.0	
Horror	1.034649e+09	880.0	
Mystery		633.0	
	1.755074e+07	81.0	
Western	5.822151e+07	313.0	
	2.02230.07	313.0	



genres.min() # minimum value nikal ke de dega and kuch chize
observe kar ssakte hain jaise ki Action me jo sabse purani movie hai
wo 1924 me aayi

thi , action movie ka minimum length 45 hai , advanture movie me sabse kam rating 7.6 hai and so on....

	Series Title	Released Year	Runtime	\
Genre	361163_11666	. Ne teasea_rear	Rancinc	`
Action	300	1924	45	
Adventure	2001: A Space Odyssey		88	
Animation	Ákirá		71	
Biography	12 Years a Slave	e 1928	93	
Comedy	(500) Days of Summe	1921	68	
Crime	12 Angry Mer	1931	80	
Drama	1917	1925	64	
Family	E.T. the Extra-Terrestria		100	
Fantasy	Das Cabinet des Dr. Caligari		76	
Film-Noir	Shadow of a Doubt		100	
Horror	Alier		71	
Mystery	Dark City		96	
Thriller	Wait Until Dark		108	
Western	Il buono, il brutto, il cattivo	1965	132	
	TMDD Dating			
Star1 \ Genre	IMDB_Rating Direc	ctor		

A - 1-1	7.6	A la la 2 a la a	la Charaban	A ' -
Action Khan	7.6	Abnishe	k Chaubey	Aamir
Adventure Khan	7.6	Akira	Kurosawa	Aamir
Animation Molina	7.6	Ad	am Elliot	Adrian
Biography Brody	7.6	А	dam McKay	Adrien
Comedy Khan	7.6	Alejandro G.	Iñárritu	Aamir
Crime Devgn	7.6	Akira	Kurosawa	Ajay
Drama Deol	7.6	А	amir Khan	Abhay
Family Wilder	7.8	M	el Stuart	Gene
Fantasy Schreck	7.9		W. Murnau	Max
Film-Noir Bogart	7.8	Alfred	Hitchcock	Humphrey
Horror Perkins	7.6	Alejandro	Amenábar	Anthony
Mystery Donnadieu	7.6		ex Proyas	Bernard-Pierre
Thriller Hepburn	7.8	Tere	nce Young	Audrey
Western Eastwood	7.8	Clint	Eastwood	Clint
Genre	No_of_Votes	Gross	Metascore	
Action Adventure	25312 29999	3296.0 61001.0	33.0 41.0	
Animation Biography	25229 27254	128985.0 21877.0	61.0 48.0	
Comedy Crime	26337 27712	1305.0 6013.0	45.0 47.0	
Drama Family	25088 178731	3600.0 4000000.0	28.0 67.0	
Fantasy Film-Noir	57428 59556	337574718.0 449191.0	NaN 94.0	
Horror Mystery Thriller Western	27007 33982 27733 65659	89029.0 1035953.0 17550741.0 5321508.0	46.0 52.0 81.0 69.0	
genres.max				

	Series_Title Released_Year	Runtime
Genre		
Action	Yôjinbô 2019	321
Adventure	Zombieland PG	228
Animation	Ôkami kodomo no Ame to Yuki 2020	137
Biography	Zerkalo 2020	209
Comedy	Zindagi Na Milegi Dobara 2020	188
Crime	À bout de souffle 2019	229
Drama	Zwartboek 2020	242
Family	Willy Wonka & the Chocolate Factory 1982	115
Fantasy	Nosferatu 1922	94
Film-Noir	The Third Man 1949	108
Horror	The Thing 2017	122
Mystery	Vertigo 2012	138
Thriller	Wait Until Dark 1967	108
Western	The Outlaw Josey Wales 1976	165
	TMDD Dati's a Discalar Charles	
No_of_Vote Genre	<pre>IMDB_Rating Director Star1 s \</pre>	
Action 2303232	9.0 Zack Snyder Yun-Fat Chow	
Adventure 1512360	8.6 Ömer Faruk Sorak Yves Montand	
Animation 999790	8.6 Yoshifumi Kondô Yôji Matsuda	
Biography 1213505	8.9 Tom McCarthy Éric Toledano	
Comedy	8.6 Zoya Akhtar Ömer Faruk Sorak	
939631 Crime	9.2 Yavuz Turgul Vincent Cassel	
1826188 Drama 2343110	9.3 Çagan Irmak Çetin Tekindor	

Family 372490	7.8	Steven Spielberg	Henry Thomas
Fantasy 88794	8.1	Robert Wiene	Werner Krauss
Film-Noir 158731	8.1	John Huston	Teresa Wright
Horror 787806	8.5	William Friedkin	Sigourney Weaver
Mystery 1129894	8.4	Terry Gilliam	Vidya Balan
Thriller 27733	7.8	Terence Young	Audrey Hepburn
Western 688390	8.8	Sergio Leone	Henry Fonda
000390	Gross	Metascore	
Genre	01033	Tie tubeor e	
Action	936662225.0	98.0	
Adventure	874211619.0	100.0	
Animation	873839108.0	96.0	
Biography	753585104.0	97.0	
Comedy	886752933.0	99.0	
Crime	790482117.0	100.0	
Drama	924558264.0	100.0	
Family	435110554.0	91.0	
Fantasy	445151978.0	NaN	
Film-Noir	123353292.0	97.0	
Horror	298791505.0	97.0	
Mystery	474203697.0	100.0	
Thriller	17550741.0	81.0	
Western	31800000.0	90.0	

genres.mean() # error dega qki bale column ka mean kaise find karega
for that data should be integer

- - - - -

```
TypeError Traceback (most recent call last)
```

File $\sim\anaconda3\Lib\site-packages\pandas\core\groupby\$ groupby.py:1942, in GroupBy._agg_py_fallback(self, how, values, ndim, alt)

1941 try:

-> 1942 res_values = self._grouper.agg_series(ser, alt, preserve_dtype=True)

1943 except Exception as err:

```
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\ops.py:864, in
BaseGrouper.agg series(self, obj, func, preserve dtype)
    862
            preserve dtype = True
--> 864 result = self._aggregate_series_pure_python(obj, func)
    866 npvalues = lib.maybe convert objects(result, try float=False)
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\ops.py:885, in
BaseGrouper. aggregate series pure python(self, obj, func)
    884 for i, group in enumerate(splitter):
            res = func(group)
--> 885
    886
            res = extract result(res)
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\
groupby.py:2454, in GroupBy.mean.<locals>.<lambda>(x)
   2451 else:
            result = self. cython agg general(
   2452
   2453
                "mean",
                alt=lambda x: Series(x,
-> 2454
copy=False).mean(numeric only=numeric only),
                numeric only=numeric only,
   2456
            return result. finalize (self.obj, method="groupby")
   2457
File ~\anaconda3\Lib\site-packages\pandas\core\series.py:6549, in
Series.mean(self, axis, skipna, numeric_only, **kwargs)
   6541 @doc(make doc("mean", ndim=1))
   6542 def mean(
   6543
            self,
   (\ldots)
            **kwargs,
   6547
   6548):
           return NDFrame.mean(self, axis, skipna, numeric only,
-> 6549
**kwargs)
File ~\anaconda3\Lib\site-packages\pandas\core\generic.py:12420, in
NDFrame.mean(self, axis, skipna, numeric only, **kwargs)
  12413 def mean(
  12414
            self.
            axis: Axis | None = 0,
  12415
   (\ldots)
            **kwargs,
  12418
  12419 ) -> Series | float:
            return self. stat function(
> 12420
                "mean", nanops.nanmean, axis, skipna, numeric only,
  12421
**kwarqs
  12422
        )
File ~\anaconda3\Lib\site-packages\pandas\core\generic.py:12377, in
NDFrame. stat function(self, name, func, axis, skipna, numeric only,
**kwarqs)
```

```
12375 validate bool kwarg(skipna, "skipna", none allowed=False)
> 12377 return self. reduce(
  12378
            func, name=name, axis=axis, skipna=skipna,
numeric only=numeric only
  12379 )
File ~\anaconda3\Lib\site-packages\pandas\core\series.py:6457, in
Series. reduce(self, op, name, axis, skipna, numeric only,
filter_type, **kwds)
   6453
            raise TypeError(
   6454
                f"Series.{name} does not allow
{kwd name}={numeric only} "
   6455
                "with non-numeric dtypes."
   6456
-> 6457 return op(delegate, skipna=skipna, **kwds)
File ~\anaconda3\Lib\site-packages\pandas\core\nanops.py:147, in
bottleneck switch. call .<locals>.f(values, axis, skipna, **kwds)
    146 else:
--> 147
            result = alt(values, axis=axis, skipna=skipna, **kwds)
    149 return result
File ~\anaconda3\Lib\site-packages\pandas\core\nanops.py:404, in
datetimelike compat.<locals>.new func(values, axis, skipna, mask,
**kwargs)
    402
            mask = isna(values)
--> 404 result = func(values, axis=axis, skipna=skipna, mask=mask,
**kwaras)
    406 if datetimelike:
File ~\anaconda3\Lib\site-packages\pandas\core\nanops.py:720, in
nanmean(values, axis, skipna, mask)
    719 the sum = values.sum(axis, dtype=dtype sum)
--> 720 the_sum = _ensure_numeric(the_sum)
    722 if axis is not None and getattr(the sum, "ndim", False):
File ~\anaconda3\Lib\site-packages\pandas\core\nanops.py:1701, in
ensure numeric(x)
   1699 if isinstance(x, str):
            # GH#44008, GH#36703 avoid casting e.g. strings to numeric
   1700
-> 1701
            raise TypeError(f"Could not convert string '{x}' to
numeric")
   1702 try:
TypeError: Could not convert string 'The Dark KnightThe Lord of the
Rings: The Return of the KingInceptionThe Lord of the Rings: The
Fellowship of the RingThe Lord of the Rings: The Two TowersThe
MatrixStar Wars: Episode V - The Empire Strikes BackStar
WarsSeppukuShichinin no samuraiGladiatorLéonTerminator 2: Judgment
DayVikram VedhaDangalAvengers: EndgameAvengers: Infinity WarThe Dark
```

Knight RisesOldeuboiRaiders of the Lost ArkAliensStar Wars: Episode VI - Return of the JediUri: The Surgical StrikeK.G.F: Chapter 1Baahubali 2: The ConclusionGangs of WasseypurPaan Singh TomarWarriorV for VendettaBatman BeginsHera PheriLock, Stock and Two Smoking BarrelsAndaz Apna ApnaIndiana Jones and the Last CrusadeDie HardRanSholayYôjinbôSherlock Jr.HaiderLoganRushFord v FerrariMad Max: Fury RoadA WednesdayTaegukgi hwinalrimyeoKill Bill: Vol. 1Jurassic ParkBlade RunnerSanjuroWhite HeatThe GeneralBajrangi BhaijaanBabyBãhubali: The BeginningSerbuan maut 2: BerandalGuardians of the GalaxyBlade Runner 2049The RevenantTropa de Elite 2: O Inimigo Agora é OutroDeadpoolYip ManNefes: Vatan SagolsunTropa de EliteThe AvengersThe Bourne UltimatumCasino RoyaleKill Bill: Vol. 2Mou gaan douPirates of the Caribbean: The Curse of the Black PearlKnockin' on Heaven's DoorThe TerminatorPer un pugno di dollariRio BravoThor: RagnarokStar Wars: Episode VII - The Force AwakensX-Men: Days of Future PastEdge of TomorrowDistrict 9Star TrekLetters from Iwo JimaIron ManYing xiongThe Bourne IdentityThe Blues BrothersDawn of the DeadAguirre, der Zorn GottesThe Wild BunchThe Adventures of Robin HoodThe GentlemenRaaziDunkirkUdta PunjabRoque OneCaptain America: Civil WarAng-ma-reul bo-at-daAjeossiChugyeokjaTakenAvatarApocalyptoHot FuzzSerenityGongdong gyeongbi guyeok JSAThe Count of Monte CristoWo hu cang longThe Boondock SaintsThe GameTombstoneThe FugitiveLat sau san taamDip huet seung hungPredatorEvil Dead IIGhostbustersBadlandsBonnie and ClydeThe Longest DayRed RiverKey LargoScarface: The Shame of the NationDeadpool 2Mission: Impossible - FalloutKingsman: The Secret ServiceCaptain America: The Winter SoldierStar Trek Into DarknessX: First ClassSkyfallLucky Number Slevin3:10 to YumaKung fuThe Bourne SupremacyMan on FireThe Last SamuraiThe Fifth ElementThe Last of the MohicansEmpire of the SunStar Trek II: The Wrath of KhanFirst BloodThe Taking of Pelham One Two ThreeEnter the DragonThe French ConnectionDirty HarryWhere Eagles DareThe Dirty DozenGoldfingerThe Magnificent SevenGuardians of the Galaxy Vol. 2Baby DriverOnly the BraveSicarioHell or High WaterDawn of the Planet of the ApesSerbuan mautEnd of WatchKick-AssCelda 211Sherlock HolmesEastern PromisesHuo Yuan JiaHarry Potter and the Half-Blood Prince300WatchmenLord of WarBatoru rowaiaruMinority ReportDie Hard: With a VengeanceFalling DownLethal WeaponMad Max 2The WarriorsEscape from Alcatraz' to numeric

The above exception was the direct cause of the following exception:

```
2447
                executor.float dtype mapping,
   2448
                engine kwargs,
   2449
                min periods=0,
   2450
   2451 else:
-> 2452
            result = self. cython agg general(
   2453
                "mean",
                alt=lambda x: Series(x,
   2454
copy=False).mean(numeric only=numeric only),
   2455
                numeric only=numeric only,
   2456
            return result.__finalize (self.obj, method="groupby")
   2457
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\
groupby.py:1998, in GroupBy. cython agg general(self, how, alt,
numeric only, min_count, **kwargs)
            result = self. agg py fallback(how, values,
ndim=data.ndim, alt=alt)
   1996
            return result
-> 1998 new_mgr = data.grouped reduce(array func)
   1999 res = self. wrap agged manager(new mgr)
   2000 if how in ["idxmin", "idxmax"]:
File ~\anaconda3\Lib\site-packages\pandas\core\internals\
managers.py:1469, in BlockManager.grouped reduce(self, func)
   1465 if blk.is object:
            # split on object-dtype blocks bc some columns may raise
   1466
            # while others do not.
   1467
   1468
            for sb in blk. split():
-> 1469
                applied = sb.apply(func)
   1470
                result blocks = extend blocks(applied, result blocks)
   1471 else:
File ~\anaconda3\Lib\site-packages\pandas\core\internals\
blocks.py:393, in Block.apply(self, func, **kwargs)
    387 @final
    388 def apply(self, func, **kwargs) -> list[Block]:
    389
    390
            apply the function to my values; return a block if we are
not
    391
            one
    392
            result = func(self.values, **kwarqs)
--> 393
    395
            result = maybe coerce values(result)
    396
            return self. split op result(result)
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\
groupby.py:1995, in
GroupBy._cython_agg_general.<locals>.array func(values)
   1992
            return result
```

1994 assert alt is not None
-> 1995 result = self._agg_py_fallback(how, values, ndim=data.ndim,
alt=alt)
 1996 return result

File ~\anaconda3\Lib\site-packages\pandas\core\groupby\
groupby.py:1946, in GroupBy._agg_py_fallback(self, how, values, ndim,
alt)
 1944 msg = f"agg function failed [how->{how},dtype>{ser.dtype}]"
 1945 # preserve the kind of exception that raised
-> 1946 raise type(err)(msg) from err

res_values = res_values.astype(object, copy=False)

TypeError: agg function failed [how->mean,dtype->object]

1948 if ser.dtype == object:

genres.mean(numeric_only=True) # this is the correct way in new version qki humare pass string data bhi hai

	Runtime	IMDB_Rating	No_of_Votes	Gross
Metascore Genre				
Action	129.046512	7.949419	420246.581395	1.897224e+08
73.419580 Adventure 78.437500	134.111111	7.937500	313557.819444	1.319017e+08
Animation 81.093333	99.585366	7.930488	268032.073171	1.784326e+08
Biography 76.240506	136.022727	7.938636	272805.045455	9.404952e+07
Comedy 78.720000	112.129032	7.901290	178195.658065	1.010572e+08
Crime 77.080460	126.392523	8.016822	313398.271028	7.899656e+07
Drama	124.737024	7.957439	212343.612457	1.225259e+08
79.701245 Family	107.500000	7.800000	275610.500000	2.195553e+08
79.000000 Fantasy	85.000000	8.000000	73111.000000	3.913633e+08
NaN Film-Noir	104.000000	7.966667	122405.000000	4.197018e+07
95.666667 Horror	102.090909	7.909091	340232.363636	9.405902e+07
80.000000 Mystery	119.083333	7.975000	350250.333333	1.047014e+08
79.125000 Thriller 81.000000	108.000000	7.800000	27733.000000	1.755074e+07

```
148.250000
                          8.350000 322416.250000 1.455538e+07
Western
78.250000
             # standard deviation -> same reason
genres.std()
ValueError
                                          Traceback (most recent call
last)
Cell In[56], line 1
----> 1 genres.std()['']
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\
groupby.py:2641, in GroupBy.std(self, ddof, engine, engine kwargs,
numeric only)
   2631
        return np.sgrt(
   2632
                self. numba agg general(
   2633
                    grouped var,
   (\ldots)
            )
   2638
   2639
  2640 else:
-> 2641
            return self. cython agg general(
   2642
                "std".
                alt=lambda x: Series(x, copy=False).std(ddof=ddof),
   2643
                numeric only=numeric only,
   2644
   2645
                ddof=ddof,
   2646
            )
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\
groupby.py:1998, in GroupBy. cython agg general(self, how, alt,
numeric only, min count, **kwargs)
            result = self. agg py fallback(how, values,
   1995
ndim=data.ndim, alt=alt)
   1996
            return result
-> 1998 new mgr = data.grouped reduce(array func)
   1999 res = self. wrap agged manager(new mgr)
   2000 if how in ["idxmin", "idxmax"]:
File ~\anaconda3\Lib\site-packages\pandas\core\internals\
managers.py:1469, in BlockManager.grouped reduce(self, func)
   1465 if blk.is object:
            # split on object-dtype blocks bc some columns may raise
   1466
            # while others do not.
   1467
   1468
            for sb in blk. split():
-> 1469
                applied = sb.apply(func)
   1470
                result blocks = extend blocks(applied, result blocks)
   1471 else:
File ~\anaconda3\Lib\site-packages\pandas\core\internals\
```

```
blocks.py:393, in Block.apply(self, func, **kwargs)
    387 @final
    388 def apply(self, func, **kwargs) -> list[Block]:
    389
    390
            apply the function to my values; return a block if we are
not
    391
            one
    392
            result = func(self.values, **kwarqs)
--> 393
    395
            result = maybe coerce values(result)
    396
            return self. split op result(result)
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\
groupby.py:1973, in
GroupBy. cython agg general.<locals>.array func(values)
   1971 def array func(values: ArrayLike) -> ArrayLike:
   1972
-> 1973
                result = self. grouper. cython operation(
   1974
                    "aggregate",
   1975
                    values,
   1976
                    how,
   1977
                    axis=data.ndim - 1,
   1978
                    min count=min count,
   1979
                    **kwargs,
   1980
                )
            except NotImplementedError:
   1981
                # generally if we have numeric only=False
   1982
   1983
                # and non-applicable functions
   1984
                # try to python agg
   1985
                # TODO: shouldn't min_count matter?
                # TODO: avoid special casing SparseArray here
   1986
                if how in ["any", "all"] and isinstance(values,
   1987
SparseArray):
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\ops.py:831, in
BaseGrouper. cython operation(self, kind, values, how, axis,
min count, **kwargs)
    829 ids, _, _ = self.group_info
    830 ngroups = self.ngroups
--> 831 return cy op.cython operation(
    832
            values=values,
    833
            axis=axis,
    834
            min count=min count,
    835
            comp ids=ids,
    836
            ngroups=ngroups,
    837
            **kwarqs,
    838 )
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\ops.py:550, in
WrappedCythonOp.cython operation(self, values, axis, min count,
```

```
comp ids, ngroups, **kwargs)
    539 if not isinstance(values, np.ndarray):
    540
            # i.e. ExtensionArray
    541
            return values. groupby op(
    542
                how=self.how,
    543
                has dropped na=self.has dropped na,
   (\ldots)
    547
                **kwargs,
    548
--> 550 return self. cython op ndim compat(
    551
            values,
    552
            min count=min count,
    553
            ngroups=ngroups,
            comp ids=comp ids,
    554
    555
            mask=None,
    556
            **kwargs,
    557 )
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\ops.py:344, in
WrappedCythonOp. cython op ndim compat(self, values, min count,
ngroups, comp ids, mask, result mask, **kwargs)
    341
            # otherwise we have OHLC
    342
            return res.T
--> 344 return self. call cython op(
    345
            values,
    346
            min count=min count,
    347
            ngroups=ngroups,
    348
            comp ids=comp ids,
    349
            mask=mask.
    350
            result mask=result mask,
            **kwargs,
    351
    352 )
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\ops.py:402, in
WrappedCythonOp. call cython op(self, values, min count, ngroups,
comp ids, mask, result mask, **kwargs)
    400 out shape = self. get output shape(ngroups, values)
    401 func = self. get cython function(self.kind, self.how,
values.dtype, is numeric)
--> 402 values = self._get cython vals(values)
    403 out dtype = self. get out dtype(values.dtype)
    405 result = maybe fill(np.empty(out shape, dtype=out dtype))
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\ops.py:230, in
WrappedCythonOp. get cython_vals(self, values)
    224 \text{ how} = \text{self.how}
    226 if how in ["median", "std", "sem", "skew"]:
            # median only has a float64 implementation
    227
            # We should only get here with is numeric, as non-numeric
    228
cases
```

```
# should raise in _get_cython_function
   229
           values = ensure float64(values)
--> 230
   232 elif values.dtype.kind in "iu":
           if how in ["var", "mean"] or (
   233
                self.kind == "transform" and self.has_dropped_na
   234
   235
           ):
               # has dropped na check need for
   236
test null group str transformer
               # result may still include NaN, so we have to cast
File pandas\\ libs\\algos common helper.pxi:42, in
pandas. libs.algos.ensure float64()
ValueError: could not convert string to float: 'The Shawshank
Redemption'
genres.std(numeric only=True) # similar as last
            Runtime IMDB Rating No of Votes
                                                        Gross
Metascore
Genre
Action
          28.500706
                        0.304258 432946.814748 2.256724e+08
12.421252
Adventure 33.317320
                        0.229781 301188.347642 1.697543e+08
12.345393
Animation 14.530471
                        0.253221 262173.231571 2.091840e+08
8.813646
Biography
                        0.267140 271284.191372 1.363251e+08
          25.514466
11.028187
                        0.228771 188653.570564 1.946513e+08
Comedy
          22.946213
11.829160
Crime
          27.689231
                        0.335477 373999.730656 1.571191e+08
13.099102
Drama
          27.740490
                        0.267229 305554.162841 2.201164e+08
12.744687
          10,606602
                        0.000000 137008.302816 3.048412e+08
Family
16.970563
                        0.141421 22179.111299 7.606861e+07
          12.727922
Fantasy
NaN
Film-Noir
           4.000000
                        0.152753
                                   54649.083277 7.048472e+07
1.527525
Horror
          13.604812
                        0.311302 234883.508691 9.965017e+07
15.362291
Mystery
          14.475423
                        0.310791 404621.915297 1.567524e+08
18.604435
Thriller
                NaN
                             NaN
                                            NaN
                                                          NaN
NaN
          17.153717
                        0.420317 263489.554280 1.230626e+07
Western
9.032349
```

```
# find the top 3 genres by total earning
movies.groupby('Genre').sum()
                                                 Series Title ∖
Genre
Action
           The Dark KnightThe Lord of the Rings: The Retu...
Adventure
           InterstellarBack to the FutureInglourious Bast...
Animation
           Sen to Chihiro no kamikakushiThe Lion KingHota...
           Schindler's ListGoodfellasHamiltonThe Intoucha...
Biography
           GisaengchungLa vita è bellaModern TimesCity Li...
Comedy
Crime
           The GodfatherThe Godfather: Part II12 Angry Me...
           The Shawshank RedemptionFight ClubForrest Gump...
Drama
           E.T. the Extra-TerrestrialWilly Wonka & the Ch...
Family
Fantasy
                       Das Cabinet des Dr. CaligariNosferatu
Film-Noir
            The Third ManThe Maltese FalconShadow of a Doubt
Horror
           PsychoAlienThe ThingThe ExorcistNight of the L...
Mystery
           MementoRear WindowVertigoShutter IslandKahaani...
Thriller
                                             Wait Until Dark
Western
           Il buono, il brutto, il cattivoOnce Upon a Tim...
                                                Released Year Runtime
Genre
Action
           2008200320102001200219991980197719621954200019...
                                                                 22196
           2014198520091981196819621959201319751963194819...
                                                                  9656
Adventure
Animation
           2001199419882016201820172008199719952019200920...
                                                                  8166
           1993199020202011200220171995198420182013201320...
                                                                 11970
Biography
Comedy
           2019199719361931200919641940200120001973196019...
                                                                 17380
Crime
           1972197419571994200219991995199120192006199519...
                                                                 13524
Drama
           1994199919941975202019981946201420061998198819...
                                                                 36049
Family
                                                     19821971
                                                                   215
Fantasy
                                                     19201922
                                                                   170
Film-Noir
                                                 194919411943
                                                                   312
Horror
                19601979198219731968196120171978193320042001
                                                                  1123
Mystery
            200019541958201020121995197219381988201219981997
                                                                  1429
Thriller
                                                         1967
                                                                   108
Western
                                             1966196819651976
                                                                   593
```

```
IMDB Rating
Director
Genre
                        Christopher NolanPeter JacksonChristopher
Action
                1367.3
Nola...
                        Christopher NolanRobert ZemeckisQuentin
Adventure
                 571.5
Tarant...
Animation
                 650.3
                        Hayao MiyazakiRoger AllersIsao
TakahataMakoto ...
                        Steven SpielbergMartin ScorseseThomas
Biography
                 698.6
KailOliv...
                1224.7
                        Bong Joon HoRoberto BenigniCharles
Comedy
ChaplinChar...
                        Francis Ford CoppolaFrancis Ford
Crime
                 857.8
CoppolaSidney...
                2299.7 Frank DarabontDavid FincherRobert
Drama
ZemeckisMilo...
                  15.6
                                               Steven SpielbergMel
Family
Stuart
Fantasy
                  16.0
                                                  Robert WieneF.W.
Murnau
                  23.9
                                    Carol ReedJohn HustonAlfred
Film-Noir
Hitchcock
Horror
                  87.0
                        Alfred HitchcockRidley ScottJohn
CarpenterWill...
Mystery
                  95.7
                        Christopher NolanAlfred HitchcockAlfred
Hitchc...
Thriller
                   7.8
                                                            Terence
Young
                        Sergio LeoneSergio LeoneClint
Western
                  33.4
East...
                                                       Star1
No of Votes \
Genre
           Christian BaleElijah WoodLeonardo DiCaprioElij...
Action
72282412
Adventure
           Matthew McConaugheyMichael J. FoxBrad PittJürg...
22576163
           Daveigh ChaseRob MinkoffTsutomu TatsumiRyûnosu...
Animation
21978630
Biography
           Liam NeesonRobert De NiroLin-Manuel MirandaÉri...
24006844
           Kang-ho SongRoberto BenigniCharles ChaplinChar...
Comedy
27620327
Crime
           Marlon BrandoAl PacinoHenry FondaJohn Travolta...
```

```
33533615
           Tim RobbinsBrad PittTom HanksJack NicholsonSur...
Drama
61367304
                                     Henry ThomasGene Wilder
Family
551221
Fantasy
                                    Werner KraussMax Schreck
146222
Film-Noir
                    Orson WellesHumphrey BogartTeresa Wright
367215
Horror
           Anthony PerkinsSigourney WeaverKurt RussellEll...
3742556
Mystery
           Guy PearceJames StewartJames StewartLeonardo D...
4203004
                                               Audrey Hepburn
Thriller
27733
           Clint EastwoodHenry FondaClint EastwoodClint E...
Western
1289665
                  Gross
                         Metascore
Genre
Action
           3.263226e+10
                           10499.0
           9.496922e+09
Adventure
                            5020.0
Animation
           1.463147e+10
                            6082.0
           8.276358e+09
                            6023.0
Biography
Comedy
           1.566387e+10
                            9840.0
Crime
           8.452632e+09
                            6706.0
Drama
           3.540997e+10
                           19208.0
Family
           4.391106e+08
                             158.0
Fantasy
           7.827267e+08
                               0.0
Film-Noir
           1.259105e+08
                             287.0
Horror
           1.034649e+09
                             880.0
Mystery
           1.256417e+09
                             633.0
Thriller
           1.755074e+07
                              81.0
Western
           5.822151e+07
                             313.0
# iss dataframe me sare details aa gya but mujhe bass need earning
bale se hai
movies.groupby('Genre').sum()['Gross']
Genre
Action
             3.263226e+10
Adventure
             9.496922e+09
Animation
             1.463147e+10
             8.276358e+09
Biography
             1.566387e+10
Comedy
Crime
             8.452632e+09
Drama
             3.540997e+10
Family
             4.391106e+08
             7.827267e+08
Fantasy
Film-Noir
             1.259105e+08
```

```
1.034649e+09
Horror
Mystery
            1.256417e+09
Thriller
            1.755074e+07
Western
            5.822151e+07
Name: Gross, dtype: float64
# ye abhi index ke basis pe sort hai to isse value ke basis pe sort
kar dete hain taki top earning movies dikh jaye
movies.groupby('Genre').sum()['Gross'].sort values(ascending=False)
Genre
            3.540997e+10
Drama
            3.263226e+10
Action
            1.566387e+10
Comedv
Animation
            1.463147e+10
Adventure
            9.496922e+09
Crime
           8.452632e+09
Biography 8.276358e+09
Mystery
          1.256417e+09
Horror
            1.034649e+09
           7.827267e+08
Fantasy
Family
           4.391106e+08
Film-Noir
            1.259105e+08
            5.822151e+07
Western
Thriller
            1.755074e+07
Name: Gross, dtype: float64
movies.groupby('Genre').sum()
['Gross'].sort values(ascending=False).head(3) # top 3 movie jo ki
maximum revenue generate karta hai box office me
Genre
         3.540997e+10
Drama
Action
         3.263226e+10
         1.566387e+10
Comedy
Name: Gross, dtype: float64
# m2
movies.groupby('Genre')
['Gross'].sum().sort values(ascending=False).head(3) # yaha pahle
column nikale phie sum apply kar dye last method me just opposite
  # kye the 2nd bala method jyada best hai gki time kam lagega hum
kisi specific column pe hi sum apply kar rahe hai but 1st method me
sare column pe sum
#apply karne ke baad required column ko select kar rahe the
Genre
Drama
         3.540997e+10
Action
          3.263226e+10
         1.566387e+10
Comedy
Name: Gross, dtype: float64
```

```
# find the genre with heighest avg IMDB rating
movies.groupby('Genre')['IMDB Rating'].mean()
Genre
Action
            7.949419
Adventure
            7.937500
Animation
            7.930488
Biography
           7.938636
Comedy
            7.901290
            8.016822
Crime
Drama
           7.957439
Family
            7.800000
Fantasy
            8.000000
Film-Noir
            7.966667
Horror
            7.909091
Mystery
            7.975000
Thriller
            7.800000
Western
            8.350000
Name: IMDB Rating, dtype: float64
movies.groupby('Genre')
['IMDB Rating'].mean().sort values(ascending=False).head(1)
Genre
Western
           8.35
Name: IMDB Rating, dtype: float64
#find director with most popularity
movies.groupby('Director') # director ke basis pe group kar lete
hain and then no_of_votes jisko jyada hoga wo popular hoga
<pandas.core.groupby.generic.DataFrameGroupBy object at</pre>
0x00000290C55C7A40>
movies.groupby('Director')["No of Votes"].sum()
Director
Aamir Khan
                        168895
Aaron Sorkin
                         89896
Abdellatif Kechiche
                        138741
Abhishek Chaubey
                         27175
Abhishek Kapoor
                         32628
                        . . .
Zack Snyder
                       1233675
Zaza Urushadze
                         40382
Zova Akhtar
                         99813
Çagan Irmak
                         78925
Ömer Faruk Sorak
                         56960
Name: No of Votes, Length: 548, dtype: int64
```

```
movies.groupby('Director')
["No of Votes"].sum().sort values(ascending=False).head(1)
Director
Christopher Nolan
                     11578345
Name: No of Votes, dtype: int64
#movies.groupby('Genre')['IMDB Rating'].max()
Genre
Action
             9.0
             8.6
Adventure
Animation
             8.6
             8.9
Biography
Comedy
             8.6
Crime
             9.2
Drama
             9.3
Family
             7.8
Fantasy
             8.1
Film-Noir
             8.1
             8.5
Horror
             8.4
Mystery
Thriller
             7.8
Western
             8.8
Name: IMDB Rating, dtype: float64
# find number of movies done by each actor
movies['Star1'].value counts()
Star1
Tom Hanks
                   12
Robert De Niro
                   11
Al Pacino
                   10
Clint Eastwood
                   10
Humphrey Bogart
                    9
Preity Zinta
                    1
Javier Bardem
                    1
Ki-duk Kim
                    1
Vladimir Garin
                    1
Robert Donat
                    1
Name: count, Length: 660, dtype: int64
# but mujhe groupby ke help se karna hai
movies.groupby('Star1')['Series Title'].count() # koi bhi column ko
pakad sakte the bass no of row hi to count karana tha group karane ke
baad
Star1
                        7
Aamir Khan
Aaron Taylor-Johnson
                        1
```

```
Abhay Deol
                        1
Abraham Attah
                        1
Adam Driver
                        1
Zbigniew Zamachowski
                        1
Zooey Deschanel
                        1
                        1
Cetin Tekindor
Éric Toledano
                        1
Omer Faruk Sorak
                        1
Name: Series Title, Length: 660, dtype: int64
# last bale tarike se jo answer aaya tha wo sort tha on the bassis of
index and groupby bale method se jo aaya hai wo sorted hai on the
basis of index
movies.groupby('Star1')
['Series Title'].count().sort values(ascending=False)
Star1
Tom Hanks
                      12
                      11
Robert De Niro
Clint Eastwood
                      10
Al Pacino
                      10
Leonardo DiCaprio
                       9
                      . .
Glen Hansard
                       1
Giuseppe Battiston
                       1
Giulietta Masina
                       1
Gerardo Taracena
                       1
Ömer Faruk Sorak
                       1
Name: Series_Title, Length: 660, dtype: int64
#har question me kuch steps follw kar rahe hain
# step-1 : pahle groupby kar rahe hain kisi specific column pe jaise
ki required hai
# step-2 : and then required column ko nikal rahe hain
# step-3 : phir koi nn koi aggrigate function(min, max, sum etc.) use
kar rahe hain
# GroupBy Attributes and Methods
# find total number of groups -> len
# find items in each group -> size
# first()/last() -> nth item
# get group -> vs filtering
# groups
# describe
# sample
# nunique
# find total number of groups -> len
movies.groupby('Genre')
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at</pre>
0x00000207A42C7890>
len(movies.groupby('Genre'))
14
#m-2
movies['Genre'].nunique()
14
# find items in each group -> size
movies.groupby('Genre').size() # tells ki har group me kitne row
hai (index ke basis pe sort hoga)
Genre
Action
             172
Adventure
              72
Animation
              82
Biography
             88
             155
Comedy
Crime
             107
Drama
             289
Family
               2
Fantasy
               2
Film-Noir
               3
Horror
              11
Mystery
              12
Thriller
               1
Western
               4
dtype: int64
movies['Genre'].value_counts() #(value ke basis pe sort hoga)
Genre
             289
Drama
Action
             172
Comedy
             155
             107
Crime
Biography
              88
              82
Animation
Adventure
              72
              12
Mystery
Horror
              11
Western
               4
               3
Film-Noir
Fantasy
               2
               2
Family
```

Thriller 1

Name: count, dtype: int64

first()/last() -> nth item
genres =movies.groupby('Genre')

genres

<pandas.core.groupby.generic.DataFrameGroupBy object at</pre> 0x0000023A99EA51F0>

genres.fir	st() # har g	genres ki first mo	vies aa jayegi	
Genre		Series_Titl	e Released_Year	Runtime \
Action Adventure Animation Biography Comedy Crime Drama Family Fantasy Film-Noir Horror Mystery Thriller Western	The SI E.T. the Das Cabine	The Dark Knigh Interstella hiro no kamikakush Schindler's Lis Gisaengchun The Godfathe hawshank Redemptio E Extra-Terrestria et des Dr. Caligar The Third Ma Psych Mement Wait Until Dar brutto, il cattiv	r 2014 i 2001 t 1993 g 2019 r 1972 n 1994 l 1982 i 1920 n 1949 o 1960 o 2000 k 1967	152 169 125 195 132 175 142 115 76 104 109 113 108 161
	IMDB_Rating	Direc	tor	Star1 \
Genre Action Adventure Animation Biography Comedy Crime Drama Family Fantasy Film-Noir Horror Mystery Thriller Western	9.0 8.6 8.6 8.9 8.6 9.2 9.3 7.8 8.1 8.5 8.4 7.8	Christopher No Christopher No Hayao Miyaz Steven Spielb Bong Joon Francis Ford Copp Frank Darab Steven Spielb Robert Wi Carol R Alfred Hitchc Christopher No Terence Yo Sergio Le	lan Matthew McCaki Daves erg Lia Ho Kang ola Marlo ont Tin erg Hens ene Werne eed Orso ock Anthony lan Gu	tian Bale Conaughey igh Chase am Neeson g-ho Song on Brando m Robbins ry Thomas er Krauss on Welles y Perkins uy Pearce y Hepburn Eastwood
Genre Action	No_of_Votes 2303232	Gross Meta 534858444.0	score 84.0	

Adventure Animation Biography Comedy Crime Drama Family Fantasy Film-Noir Horror Mystery Thriller Western genres.last()	1512360 651376 1213505 552778 1620367 2343110 372490 57428 158731 604211 1125712 27733 688390 # har	188020017.0 10055859.0 96898818.0 53367844.0 134966411.0 28341469.0 435110554.0 337574718.0 449191.0 32000000.0 25544867.0 17550741.0 6100000.0	74.0 96.0 94.0 96.0 100.0 80.0 91.0 NaN 97.0 97.0 80.0 81.0 90.0	jayega		
J ()				Released	Year	Runtime
\ Genre		30110	3_11110	ne reasea_	_1001	rancine
Action		Escape from A	lcatraz		1979	112
Adventure		Kelly's	Heroes		1970	144
Animation		The Jung	le Book		1967	78
Biography		Midnight	Express		1978	121
Comedy		Breakfast at Ti	ffany's		1961	115
Crime		The 3	9 Steps		1935	86
Drama		L	ifeboat		1944	97
Family Wi	lly Wonka	& the Chocolate	Factory		1971	100
Fantasy		No	sferatu		1922	94
Film-Noir		Shadow of	a Doubt		1943	108
Horror		The	Others		2001	101
Mystery		Lost	Highway		1997	134
Thriller		Wait Unt	il Dark		1967	108
Western		The Outlaw Jose	y Wales		1976	135
IM No_of_Votes	DB_Rating \	Dire	ctor		Star	1

Genre			
Action 121731	7.6	Don Siegel	Clint Eastwood
Adventure	7.6	Brian G. Hutton	Clint Eastwood
45338 Animation	7.6	Wolfgang Reitherman	Phil Harris
166409 Biography	7.6	Alan Parker	Brad Davis
73662 Comedy	7.6	Blake Edwards	Audrey Hepburn
166544 Crime	7.6	Alfred Hitchcock	Robert Donat
51853 Drama	7.6	Alfred Hitchcock	Tallulah Bankhead
26471			
Family 178731	7.8	Mel Stuart	Gene Wilder
Fantasy 88794	7.9	F.W. Murnau	Max Schreck
Film-Noir 59556	7.8	Alfred Hitchcock	Teresa Wright
Horror 337651	7.6	Alejandro Amenábar	Nicole Kidman
Mystery	7.6	David Lynch	Bill Pullman
131101 Thriller	7.8	Terence Young	Audrey Hepburn
27733 Western	7.8	Clint Eastwood	Clint Eastwood
65659			
Genre	Gross	Metascore	
Action Adventure Animation Biography Comedy Crime Drama Family Fantasy Film-Noir Horror Mystery Thriller Western	43000000.0 1378435.0 141843612.0 35000000.0 679874270.0 302787539.0 852142728.0 4000000.0 445151978.0 123353292.0 96522687.0 3796699.0 17550741.0 31800000.0	76.0 50.0 65.0 59.0 76.0 93.0 78.0 67.0 NaN 94.0 74.0 52.0 81.0 69.0	

genres.nth(6) # har group ka 7th movies (qki indexing 0 se) nikal
ke de dega aap observ karenge ki sare group available nahi hai qki jo

```
group
            #available nahi hai usme 7 movie hai hi nahi
                                         Series Title Released Year
Runtime \
16
     Star Wars: Episode V - The Empire Strikes Back
                                                                1980
124
27
                                                                1995
                                                Se7en
127
32
                               It's a Wonderful Life
                                                                1946
130
66
                                               WALL · E
                                                                2008
98
83
                                  The Great Dictator
                                                                1940
125
102
                                           Braveheart
                                                                1995
178
118
                                  North by Northwest
                                                                1959
136
420
                                               Sleuth
                                                                1972
138
724
                                              Get Out
                                                                2017
104
                IMDB Rating
                                           Director
                                                                 Star1 \
         Genre
16
                                    Irvin Kershner
                                                           Mark Hamill
        Action
                         8.7
27
         Crime
                         8.6
                                      David Fincher
                                                       Morgan Freeman
32
         Drama
                         8.6
                                                        James Stewart
                                        Frank Capra
66
     Animation
                         8.4
                                    Andrew Stanton
                                                             Ben Burtt
83
                         8.4
                                    Charles Chaplin
                                                      Charles Chaplin
        Comedy
     Biography
                         8.3
                                         Mel Gibson
                                                            Mel Gibson
102
                                  Alfred Hitchcock
118
     Adventure
                         8.3
                                                            Cary Grant
420
       Mystery
                         8.0
                              Joseph L. Mankiewicz Laurence Olivier
                                                       Daniel Kaluuya
724
                                       Jordan Peele
        Horror
                         7.7
     No_of_Votes
                                Metascore
                         Gross
16
         1159315
                  290475067.0
                                      82.0
27
         1445096
                  100125643.0
                                      65.0
32
          405801
                   82385199.0
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66
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                                      95.0
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102
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118
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                                      98.0
420
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                                      NaN
724
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                                      85.0
# get group -> vs filtering => iske help se kisi particular group ko
dekh sakte hain
genres.get group('Horror')
```

TMDD D	oting \	Series_T	itle Rel	leased_\	⁄ear	Runtime	Genre	
IMDB_R	ating \	Day		7	1060	100	110,000,00	
49		PS	ycho		1960	109	Horror	
8.5				_				
75		Α	lien		1979	117	Horror	
8.4								
271		The TI	ning	1	1982	109	Horror	
8.1								
419		The Exore	cist	1	1973	122	Horror	
8.0								
544 N	ight of th	e Livina I	Dead]	1968	96	Horror	
7.9	J	- J						
707		The Innoce	ents	1	1961	100	Horror	
7.8				_				
724		Get	0ut	7	2017	104	Horror	
7.7		00.0	out		-017	101	1101101	
844		Hallo	ween	1	1978	91	Horror	
7.7		nacco	WCCII	-	1370	91	1101 1 01	
876	Tho	Invisible	Man	1	1933	71	Horror	
7.7	THE	TIIATZIDIG	riaii	_	1933	/ 1	1101101	
932			Caur	-	2004	102	Harrar	
			Saw	4	2004	103	Horror	
7.6		Th. 0+1		-	0001	101	110,000,00	
948		The Otl	ners	4	2001	101	Horror	
7.6								
	n	irector		Star	r1 N	lo_of_Vote	c	Gross
Metasc		110001		Jean	I	10_01_V0CC	3	01033
49	Alfred Hi	tchcock	Anthony	y Perkir		60421	1 3200	00000.0
97.0	Attreu III	CCIICOCK	Anthony	y reikti	15	00421	1 3200	.0000.0
	D; dl o	Coo++ (Ci aou no		- m	70700	6 7000	20000 0
75	ктате	y Scott S	Sigourne	ey weave	31	78780	0 /890	0.0000
89.0	1.h. C.		1/	L D	. 7	27127	1 1070	2222
271	John Ca	rpenter	Kurt	t Russel	LL	37127	1 13/8	32838.0
57.0						2.222		
419	William F	riedkin	Eller	n Bursty	/n	36239	3 23296	06145.0
81.0	_	_	_	_			_	
544	George A.	Romero	Dua	ane Jone	es	11655	7 8	39029.0
89.0								
707	Jack	Clayton	Debo	orah Ker	rr	2700	7 261	L6000.0
88.0								
724	Jorda	n Peele	Daniel	l Kaluuy	/a	49285	1 17604	10665.0
85.0								
844	John Ca	rpenter I	Donald F	Pleasend	ce	23310	6 4700	0.0000
87.0								
876	Jame	s Whale	Clau	ude Rair	าร	3068	3 29879	91505.0
87.0								
932	Ja	mes Wan	Ca	ary Elwe	es	37902	0 5600	0369.0
46.0				•				
	lejandro A	menábar	Nicol	le Kidma	an	33765	1 9652	22687.0
74.0						23.33	3 00.	
, 410								

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genres.get group('Fantasy')
                     Series Title Released Year
                                                             Genre \
                                                  Runtime
321
     Das Cabinet des Dr. Caligari
                                            1920
                                                       76
                                                           Fantasy
568
                        Nosferatu
                                            1922
                                                       94
                                                           Fantasy
     IMDB Rating
                      Director
                                         Star1
                                                No of Votes
Gross \
             8.1
                  Robert Wiene
                               Werner Krauss
321
                                                      57428
337574718.0
568
             7.9
                   F.W. Murnau
                                  Max Schreck
                                                      88794
445151978.0
     Metascore
321
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568
           NaN
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321
     Das Cabinet des Dr. Caligari
                                            1920
                                                       76
                                                           Fantasy
568
                        Nosferatu
                                            1922
                                                       94
                                                           Fantasy
     IMDB Rating
                      Director
                                         Star1
                                                No of Votes
Gross \
321
             8.1
                  Robert Wiene Werner Krauss
                                                      57428
337574718.0
568
             7.9
                   F.W. Murnau
                                  Max Schreck
                                                      88794
445151978.0
     Metascore
321
           NaN
568
           NaN
# groups
genres.groups
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ke sare index jaise Action categories me kon kon se index ke movies
hain
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# describe
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          Runtime
/
            count
                                     std
                                            min
                                                     25%
                                                            50%
                                                                    75%
                         mean
max
Genre
```

Action 372.0 129.046512 28.500706 45.0 110.75 127.5 143.25 321.0 Adventure 72.0 134.111111 33.317320 88.0 109.00 127.0 149.00 228.0 Animation 82.0 99.585366 14.530471 71.0 90.00 99.5 106.75 137.0 Biography 209.0 155.0 112.129032 22.946213 68.0 96.00 129.0 146.25 209.0 Comedy 155.0 112.129032 22.946213 68.0 96.00 106.0 124.50 188.0 Crime 107.0 126.392523 27.689231 80.0 106.50 122.0 141.50 229.0 Drama 289.0 124.737024 27.740490 64.0 105.00 121.0 137.00 242.0 Family 2.0 107.500000 10.606602 100.0 103.75 107.5 111.25 115.0 Family 2.0 85.000000 12.727922 76.0 80.50 85.0 89.50 94.0 Fitm-Noir 3.0 104.000000 4.000000 100.0 102.00 104.0 106.00 108.0 Horror 11.0 102.090909 13.604812 71.0 98.00 103.0 109.00 122.0 Mysterry 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Fhrilter 1.0 108.000000 77.153717 132.0 134.25 148.0 108.0 Western 4.0 148.250000 17.153717 132.0 134.25 148.0 162.00 188.0 Mysterry 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Fhrilter 1.0 108.000000 77.153717 132.0 134.25 148.0 162.00 108.0 Mysterry 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Fhrilter 1.0 108.000000 77.55777 132.0 134.25 148.0 162.00 108.0 Mysterry 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Fhrilter 1.0 108.000000 77.5578 80.00 108.0 108											
Adventure 72.0 134.11111 33.317320 88.0 109.00 127.0 149.00 228.0 Animation 82.0 99.585366 14.530471 71.0 90.00 99.5 106.75 137.0 81.00 125.0 136.022727 25.514466 93.0 120.00 129.0 146.25 209.0 Comedy 15.0 112.129032 22.946213 68.0 96.00 106.0 124.50 188.0 Crime 107.0 126.392523 27.689231 80.0 106.50 122.0 141.50 229.0 Drama 289.0 124.737024 27.740490 64.0 105.00 121.0 137.00 242.0 Family 2.0 107.500000 10.606602 100.0 103.75 107.5 111.25 115.0 Family 2.0 85.000000 12.727922 76.0 80.50 85.0 89.50 94.0 Film-Noir 3.0 104.000000 4.000000 100.0 102.00 104.0 106.00 108.0 Horror 11.0 102.090909 13.604812 71.0 98.00 103.0 109.00 122.0 Mystery 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Thrilter 1.0 108.000000 NaN 108.0 108.00 108.0 Horror 4.0 148.250000 17.153717 132.0 134.25 148.0 162.00 Western 4.0 148.250000 17.153717 132.0 134.25 148.0 162.00 165.0 Metascore Count Metascore Count Metascore Count Metascore Count Metascore Scouth Sc		172.0	129	.046512	28.	500	706	45.0	110.75	127.5	143.25
Animation 82.0 99.585366 14.530471 71.0 90.00 99.5 106.75 137.0 137.0 136.0 136.022727 25.514466 93.0 120.00 129.0 146.25 209.0 200.0 155.0 112.129032 22.946213 68.0 96.00 106.0 124.50 188.0 107.0 126.392523 27.689231 80.0 106.50 122.0 141.50 229.0 120		72.0	134	. 111111	33.	3173	320	88.0	109.00	127.0	149.00
137.0 Biography Biolography Biologra		92.0	00	E0E266	11	E 2 0 .	471	71 0	00 00	00 5	106 75
209.0 'Comedy 155.0 112.129032 22.946213 68.0 96.00 106.0 124.50 188.0 Crime 107.0 126.392523 27.689231 80.0 106.50 122.0 141.50 229.0 Drama 289.0 124.737024 27.740490 64.0 105.00 121.0 137.00 242.0 Family 2.0 107.500000 10.606602 100.0 103.75 107.5 111.25 115.0 Fantasy 2.0 85.000000 12.727922 76.0 80.50 85.0 89.50 94.0 Film-Noir 3.0 104.000000 4.000000 100.0 102.00 104.0 106.00 108.0 Horror 11.0 102.090909 13.604812 71.0 98.00 103.0 109.00 122.0 Mystery 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Thriller 1.0 108.000000 NaN 108.0 108.00 108.0 108.00 Horson 4.0 148.250000 17.153717 132.0 134.25 148.0 162.00 165.0 Mestern 4.0 148.250000 17.153717 132.0 134.25 148.0 162.00 165.0 Moreover \text{Count mean 75\% max count Genre } Gross Metascore \text{Count mean 75\% max count Genre } Action 172.0 7.949419 2.674437e+08 936662225.0 143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.937500 1.998070e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0		82.0	99	. 383300	14.	2304	1 /1	71.0	90.00	99.5	100.75
Comedy 188.0 155.0 112.129032 22.946213 68.0 96.00 106.0 124.50 188.0 107.0 126.392523 27.689231 80.0 106.50 122.0 141.50 229.0 Drama 289.0 124.737024 27.740490 64.0 105.00 121.0 137.00 242.0 Tamily 2.0 107.500000 10.606602 100.0 103.75 107.5 111.25 115.0 Tamtasy 2.0 85.000000 12.727922 76.0 80.50 85.0 89.50 94.0 Till 3.0 104.000000 4.000000 100.0 102.00 104.0 106.00 94.0 Till 102.090909 13.604812 71.0 98.00 103.0 109.00 122.0 Mystery 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Thriller 1.0 108.00000 NaN 108.0 108.0 108.0 108.0 <t< td=""><td></td><td>88.0</td><td>136</td><td>.022727</td><td>25.</td><td>514</td><td>466</td><td>93.0</td><td>120.00</td><td>129.0</td><td>146.25</td></t<>		88.0	136	.022727	25.	514	466	93.0	120.00	129.0	146.25
188.0		155.0	112	. 129032	22.	9462	213	68.0	96.00	106.0	124.50
229.0	188.0										
Drama 289.0 124.737024 27.740490 64.0 105.00 121.0 137.00 124.0 137.00 124.0 137.00 125.00 1		107.0	126	. 392523	27.	6892	231	80.0	106.50	122.0	141.50
Family	Drama	289.0	124	.737024	27.	7404	490	64.0	105.00	121.0	137.00
115.0 Fantasy 2.0 85.000000 12.727922 76.0 80.50 85.0 89.50 94.0 Film-Noir 3.0 104.000000 4.000000 100.0 102.00 104.0 106.00 108.0 Horror 11.0 102.090909 13.604812 71.0 98.00 103.0 109.00 122.0 Mystery 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Thriller 1.0 108.000000 NaN 108.0 108.00 108.0 108.0 western 4.0 148.250000 17.153717 132.0 134.25 148.0 162.00 165.0		2.0	107	500000	10	6066	502	100 0	103 75	107 5	111 25
94.0 Film-Noir 3.0 104.000000 4.000000 100.0 102.00 104.0 106.00 108.0 Horror 11.0 102.090909 13.604812 71.0 98.00 103.0 109.00 122.0 Mystery 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Thriller 1.0 108.000000 NaN 108.0 108.00 108.0 108.00 108.0		2.0	107	. 500000	10.	0000	JUZ	100.0	105.75	107.5	111.23
Film-Noir 108.0 Horror 11.0 102.090909 13.604812 71.0 98.00 103.0 109.00 122.0 Mystery 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Thrilter 1.0 108.000000 NaN 108.0 108.00 108.0 108.00 108.0 Western 4.0 148.250000 17.153717 132.0 134.25 148.0 162.00 165.0 IMDB_Rating Gross Metascore count mean 75% max count Genre Action 172.0 7.949419 2.674437e+08 936662225.0 143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0		2.0	85	. 000000	12.	7279	922	76.0	80.50	85.0	89.50
Horror 11.0 102.090909 13.604812 71.0 98.00 103.0 109.00 122.0 Mystery 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Thriller 1.0 108.000000 NaN 108.0 108.00 108.0 108.00 108.		3.0	104	. 000000	4.	0000	900	100.0	102.00	104.0	106.00
122.0 Mystery 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 Thriller 1.0 108.000000 NaN 108.0 108.00 108.0 108.00 108.0 Western 4.0 148.250000 17.153717 132.0 134.25 148.0 162.00 165.0 IMDB_Rating Gross Metascore count mean 75% max count Genre Action 172.0 7.949419 2.674437e+08 936662225.0 143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0		11.0	100					71.0	00.00	100.0	100.00
Mystery 138.0 12.0 119.083333 14.475423 96.0 110.75 117.5 130.25 138.0 1.0 108.000000 NaN 108.0 108.00 108.0 108.00 Western 4.0 148.250000 17.153717 132.0 134.25 148.0 162.00 Metascore Count mean 6ross max Count mean 75% max Action 172.0 7.949419 2.674437e+08 936662225.0 143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama <td></td> <td>11.0</td> <td>102</td> <td>. 090909</td> <td>13.</td> <td>6048</td> <td>312</td> <td>/1.0</td> <td>98.00</td> <td>103.0</td> <td>109.00</td>		11.0	102	. 090909	13.	6048	312	/1.0	98.00	103.0	109.00
Thriller 1.0 108.000000 NaN 108.0 108.00 108.0 108.00 Western 4.0 148.250000 17.153717 132.0 134.25 148.0 162.00 IMDB_Rating Gross Metascore count mean 75% max Count Genre Action 172.0 7.949419 2.674437e+08 936662225.0 143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0	Mystery	12.0	119	. 083333	14.	4754	423	96.0	110.75	117.5	130.25
108.0 Western		1 0	108	000000		ı	NaN	108 0	108 00	108 0	108 00
IMDB_Rating Gross Metascore count mean 75% max Count Genre Action 172.0 7.949419 2.674437e+08 936662225.0 143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0			100	. 000000			vaiv	100.0	100.00		100.00
IMDB_Rating Gross Metascore \		4.0	148	. 250000	17.	153	717	132.0	134.25	148.0	162.00
Metascore count mean 75% max count Genre Action 172.0 7.949419 2.674437e+08 936662225.0 143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0	105.0										
count mean 75% max Count Genre Action 172.0 7.949419 2.674437e+08 936662225.0 143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0	Metascore		ing			• •		Gro	SS		
Genre Action 172.0 7.949419 2.674437e+08 936662225.0 143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0	rictascore	•	unt	mea	n.			7.	5%	max	
Action 172.0 7.949419 2.674437e+08 936662225.0 143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0											
143.0 Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0	Genre				•	• •					
Adventure 72.0 7.937500 1.998070e+08 874211619.0 64.0 Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0		17	2.0	7.949419	9.		2.6	74437e+	08 936	662225.0	
Animation 82.0 7.930488 2.520612e+08 873839108.0 75.0 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0		7	2.0	7.93750	Э.		1.9	98070e+	08 874	211619.0	
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Biography 88.0 7.938636 9.829924e+07 753585104.0 79.0 Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0		8	∠.⊍	7.930488	σ.		2.5	∠⊍012e+	ud 8/3	0.80168	
Comedy 155.0 7.901290 8.107809e+07 886752933.0 125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0	Biography	8	8.0	7.93863	6.		9.8	29924e+	07 753	585104.0	
125.0 Crime 107.0 8.016822 7.102163e+07 790482117.0 87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0		15	5.0	7.901290	9 .		8.1	07809e+	07 886	752933.0	
87.0 Drama 289.0 7.957439 1.164461e+08 924558264.0	125.0										
Drama 289.0 7.957439 1.164461e+08 924558264.0		10	7.0	8.016822	2.		7.1	02163e+	07 790	482117.0	
241.0	Drama	28	9.0	7.957439	9.		1.1	64461e+	08 924	558264.0	
	241.0										

Family 2.0	2.0	7.800000		3.27332	9e+08	435110	554.0
Fantasy 0.0	2.0	8.000000		4.18257	7e+08	445151	978.0
Film-Noir 3.0	3.0	7.966667		6.27306	8e+07	123353	292.0
Horror	11.0	7.909091		1.36281	7e+08	298791	505.0
11.0 Mystery	12.0	7.975000		1.31094	9e+08	474203	697.0
8.0 Thriller	1.0	7.800000		1.75507	4e+07	17550741.0	
1.0 Western	4.0	8.350000		1.920000e+07		31800000.0	
4.0							
Genre	mean	std	min	25%	50%	75%	max
Action Adventure Animation Biography Comedy Crime Drama Family Fantasy Film-Noir Horror Mystery Thriller Western	73.419580 78.437500 81.093333 76.240506 78.720000 77.080460 79.701245 79.000000 NaN 95.666667 80.000000 79.125000 81.000000 78.250000	12.421252 12.345393 8.813646 11.028187 11.829160 13.099102 12.744687 16.970563 NaN 1.527525 15.362291 18.604435 NaN 9.032349	33.0 41.0 61.0 48.0 45.0 47.0 28.0 67.0 NaN 94.0 46.0 52.0 81.0 69.0	65.00 69.75 75.00 70.50 72.00 69.50 72.00 73.00 NaN 95.00 77.50 65.25 81.00 72.75	74.0 80.5 82.0 76.0 79.0 77.0 82.0 79.0 NaN 96.0 87.0 77.0	82.00 87.25 87.50 84.50 88.00 87.00 89.00 85.00 NaN 96.50 88.50 98.50 81.00	98.0 100.0 96.0 97.0 99.0 100.0 100.0 91.0 NaN 97.0 97.0 100.0 81.0 90.0
[14 rows x 40 columns]							
# sample							

sample
genres.sample() # har geners ka koi ek random movies dikha dega

	Series_Title Re	leased_Year	Runtime
Genre \			
702	Bonnie and Clyde	1967	111
Action	•		
458	The Wizard of Oz	1939	102
Adventure			
358	Persepolis	2007	96
Animation	•		
622	American Gangster	2007	157
Biography	J		
481	The Artist	2011	100
Comedy			

222		Prisoners	2013	153
Crime 988 Close	Encoun	ters of the Third Kind	1977	138
Drama				
688 Family	E.T.	the Extra-Terrestrial	1982	115
568		Nosferatu	1922	94
Fantasy		T. M. 1	1041	100 511
456 Noir		The Maltese Falcon	1941	100 Film-
844		Halloween	1978	91
Horror		M	2000	110
69 Mystery		Memento	2000	113
700		Wait Until Dark	1967	108
Thriller	huana	:1 houte :1 cotting	1066	161
12 Il Western	buono,	il brutto, il cattivo	1966	161
		D: .	C. 1	N 6 1/ 1
/ TWDR	Rating	Director	Star1	No_of_Votes
702	7.8	Arthur Penn	Warren Beatty	102415
458	8.0	Victor Fleming	George Cukor	371379
358	8.0	Vincent Paronnaud	Marjane Satrapi	88656
622	7.8	Ridley Scott	Denzel Washington	392449
481	7.9	Michel Hazanavicius	Jean Dujardin	230624
222	8.1	Denis Villeneuve	Hugh Jackman	601149
988	7.6	Steven Spielberg	Richard Dreyfuss	184966
688	7.8	Steven Spielberg	Henry Thomas	372490
568	7.9	F.W. Murnau	Max Schreck	88794
456	8.0	John Huston	Humphrey Bogart	148928
844	7.7	John Carpenter	Donald Pleasence	233106
69	8.4	Christopher Nolan	Guy Pearce	1125712
700	7.8	Terence Young	Audrey Hepburn	27733
12	8.8	Sergio Leone	Clint Eastwood	688390
	Gross	Metascore		

```
702
     909838190.0
                       86.0
458
       2076020.0
                       92.0
358
       4445756.0
                       90.0
622
    130164645.0
                       76.0
481
     44671682.0
                       89.0
222
      61002302.0
                       70.0
988 132088635.0
                       90.0
688 435110554.0
                       91.0
568 445151978.0
                        NaN
456
       2108060.0
                       96.0
844
      47000000.0
                       87.0
69
      25544867.0
                       80.0
700
      17550741.0
                       81.0
12
       6100000.0
                       90.0
genres.sample(2) # abb do do random movies dikhega abhi error islye
aa raha hai gki
_ _ _ _ _
ValueError
                                          Traceback (most recent call
last)
Cell In[48], line 1
----> 1 genres.sample(2)
File ~\anaconda3\Lib\site-packages\pandas\core\groupby\
groupby.py:5780, in GroupBy.sample(self, n, frac, replace, weights,
random_state)
   5777
                assert frac is not None
                sample size = round(frac * group size)
   5778
-> 5780
            grp sample = sample.sample(
                group size,
   5781
                size=sample size,
   5782
   5783
                replace=replace,
                weights=None if weights is None else
   5784
weights arr[grp indices],
   5785
                random state=random state,
   5786
            sampled indices.append(grp indices[grp sample])
   5787
   5789 sampled indices = np.concatenate(sampled indices)
File ~\anaconda3\Lib\site-packages\pandas\core\sample.py:152, in
sample(obj len, size, replace, weights, random state)
    149
            else:
    150
                raise ValueError("Invalid weights: weights sum to
zero")
--> 152 return random state.choice(obj len, size=size,
replace=replace, p=weights).astype(
    153
            np.intp, copy=False
    154 )
```

File numpy\\random\\mtrand.pyx:1001, in
numpy.random.mtrand.RandomState.choice()

ValueError: Cannot take a larger sample than population when 'replace=False'

genres.sample(2,replace=True) # abb jisme ek hi row hai wo repeate ho
jayega

6	Series_Title	Released_Year	Runtime	
Genre \ 774	3:10 to Yuma	2007	122	
Action	5.20			
144	Warrior	2011	140	
Action	_			
884	The Peanut Butter Falcon	2019	97	
Adventure				
329	The Martian	2015	144	
Adventure	_, ,,			
43	The Lion King	1994	88	
Animation		2012	101	
740	Wreck-It Ralph	2012	101	
Animation	F4.V. 1	1004	107	
657	Ed Wood	1994	127	
Biography	C'ada a 11 M	2005	144	
373	Cinderella Man	2005	144	
Biography		2010	120	
463	Knives Out	2019	130	
Comedy	The Down le Dans of Caire	1005	0.2	
835	The Purple Rose of Cairo	1985	82	
Comedy	Dayz n the Head	1001	110	
669	Boyz n the Hood	1991	112	
Crime	The Cilence of the Lambe	1001	110	
28	The Silence of the Lambs	1991	118	
Crime 443	La Strada	1054	100	
Drama	La Straua	1954	108	
73	The Chining	1980	146	
Drama	The Shining	1900	140	
	Wonka & the Chocolate Factory	1971	100	
Family	worka & the chocotate ractory	19/1	100	
688	E.T. the Extra-Terrestrial	1982	115	
Family	L.I. the Extra-Terrestriat	1902	113	
568	Nosferatu	1922	94	
Fantasy	Nosieratu	1922	34	
568	Nosferatu	1922	94	
Fantasy	Nosteratu	1922	34	
309	The Third Man	1949	104	Fil
Noir	THE THILL HAIL	1949	104	110
INOTI				

456		The Maltese F	alcon 19	41	100 I	-ilm-
Noir 844		Hall	oween 19	78	91	
Horror 544	N	ight of the Living	Dead 19	68	96	
Horror 145		Shutter I	sland 20	10	138	
Mystery 81		Rear W	indow 19	54	112	
Mystery 700		Wait Until	Dark 19	67	108	
Thriller 700		Wait Until	Dark 19	67	108	
Thriller 115	Per	qualche dollaro i	n più 19	65	132	
Western 691		The Outlaw Josey	Wales 19	76	135	
Western						
IMDB_Ra ² 774 144 884 329 43 740 657 373 463 835 669 28 443 73 698 688 568 568 568 568 309 456 844 544 145 81 700 700 115 691	7.7 8.7 8.6 8.5 7.8 8.9 7.8 8.4 7.9 8.4 7.9 8.7 7.9 8.4 7.9 8.7 7.9 8.4 7.9 8.3 7.8 8.3 7.9 8.3 8.3 8.3 8.3 8.3 8.3 8.3 8.3 8.3 8.3	Director James Mangold Gavin O'Connor Tyler Nilson Ridley Scott Roger Allers Rich Moore Tim Burton Ron Howard Rian Johnson Woody Allen John Singleton Jonathan Demme Federico Fellini Stanley Kubrick Mel Stuart Steven Spielberg F.W. Murnau F.W. Murnau Carol Reed John Huston John Carpenter George A. Romero Martin Scorsese Alfred Hitchcock Terence Young Terence Young Sergio Leone Clint Eastwood	Russell Crow Tom Hard Michael Schwart Matt Damo Rob Minkof John C. Reill Johnny Dep Russell Crow Daniel Crai Mia Farro Cuba Gooding Jr Jodie Foste Anthony Quin Jack Nicholso Gene Wilde Henry Thoma Max Schrec Max Schrec Orson Welle Humphrey Bogar Donald Pleasenc Duane Jone Leonardo DiCapri James Stewar Audrey Hepbur Audrey Hepbur Clint Eastwoo Clint Eastwoo	e - y z n f y p e g w . r 1 n n r s k k s t e s o 1 t n n d	_Votes 288797 435950 66346 760094 942045 380195 164937 176153 454203 47102 126082 270197 58314 898237 178733 372490 88794 88794 158733 148928 233106 116557 129894 444074 27733 27773 27773 27773 232777 65659	7 9 5 4 5 7 1 1 3 2 2 7 4 4 4 4 4 4 4 4 3 3 3 3 4 4 4 4 4 4 4

774 144 884	Gross 53606916.0 13657115.0 13122642.0	Metascore 76.0 71.0 70.0							
329 43	228433663.0 422783777.0	80.0 88.0							
740	189422889.0	72.0							
657	5887457.0	70.0							
373	61649911.0	69.0							
463	165359751.0	82.0							
835	10631333.0	75.0							
669	57504069.0	76.0							
28 443	130742922.0 101832153.0	85.0 NaN							
73	44017374.0	66.0							
698	4000000.0	67.0							
688	435110554.0	91.0							
568	445151978.0	NaN							
568	445151978.0	NaN							
309	449191.0	97.0							
456	2108060.0	96.0							
844	47000000.0	87.0							
544	89029.0	89.0							
145 81	128012934.0 36764313.0	63.0 100.0							
700	17550741.0	81.0							
700	17550741.0	81.0							
115	15000000.0	74.0							
691	31800000.0	69.0							
	vece punique()	# box 2000	c ===	kitno	uniaua	data	ho:	action	h = 7 =

genres.nunique() # har genres me kitna unique data hai action bale
movies me released_year me 61 unique value hai matlab ki bahut ssare
movies

#aaise honge jo ki same year me release

hua hoga

	Series_Title	Released_Year	Runtime	<pre>IMDB_Rating</pre>	Director
Star1 \ Genre	_	_		_	
Action	172	61	78	15	123
121	1,1	01	, 0	10	123
Adventure	72	49	58	10	59
59					
Animation	82	35	41	11	51
77					
Biography	88	44	56	13	76
72					
Comedy	155	72	70	11	113
133					

Crime	106	56	65	14	86
85					
Drama	289	83	95	14	211
250					
Family	2	2	2	1	2
2					
Fantasy	2	2	2	2	2
2					
Film-Noir	3	3	3	3	3
3					
Horror	11	11	10	8	10
11					
Mystery	12	11	10	8	10
11					
Thriller	1	1	1	1	1
1					
Western	4	4	4	4	2
2					

	No of Votes	Gross	Metascore
Genre		0.000	
Action	172	172	50
Adventure	72	72	33
Animation	82	82	29
Biography	88	88	40
Comedy	155	155	44
Crime	107	107	39
Drama	288	287	52
Family	2	2	2
Fantasy	2	2	0
Film-Noir	3	3	3
Horror	11	11	9
Mystery	12	12	7
Thriller	1	1	1
Western	4	4	4

agg method
passing dict
genres.sum()

Series_Title \

Genre Action The Dark KnightThe Lord of the Rings: The Retu... Adventure InterstellarBack to the FutureInglourious Bast... Sen to Chihiro no kamikakushiThe Lion KingHota... Animation Biography Schindler's ListGoodfellasHamiltonThe Intoucha... GisaengchungLa vita è bellaModern TimesCity Li... Comedy Crime The GodfatherThe Godfather: Part II12 Angry Me... The Shawshank RedemptionFight ClubForrest Gump... Drama E.T. the Extra-TerrestrialWilly Wonka & the Ch... Family

Fantasy Film-Noir Horror Mystery Thriller Western	Das Cabinet des Dr. CaligariNosferatu The Third ManThe Maltese FalconShadow of a Doubt PsychoAlienThe ThingThe ExorcistNight of the L MementoRear WindowVertigoShutter IslandKahaani Wait Until Dark Il buono, il brutto, il cattivoOnce Upon a Tim	
\ Genre	Released_Year	Runtime
Action	2008200320102001200219991980197719621954200019	22196
Adventure	2014198520091981196819621959201319751963194819	9656
Animation	2001199419882016201820172008199719952019200920	8166
Biography	1993199020202011200220171995198420182013201320	11970
Comedy	2019199719361931200919641940200120001973196019	17380
Crime	1972197419571994200219991995199120192006199519	13524
Drama	1994199919941975202019981946201420061998198819	36049
Family	19821971	215
Fantasy	19201922	170
Film-Noir	194919411943	312
Horror	19601979198219731968196120171978193320042001	1123
Mystery	200019541958201020121995197219381988201219981997	1429
Thriller	1967	108
Western	1966196819651976	593
Director Genre	IMDB_Rating \	
Action	1367.3 Christopher NolanPeter JacksonChristo	pher
Nola Adventure	571.5 Christopher NolanRobert ZemeckisQuent	in
Tarant Animation	650.3 Hayao MiyazakiRoger AllersIsao	
TakahataMa Biography	koto 698.6 Steven SpielbergMartin ScorseseThomas	

KailOliv		
Comedy	1224.7	Bong Joon HoRoberto BenigniCharles
ChaplinCha	r	3
Crime	857.8	Francis Ford CoppolaFrancis Ford
CoppolaSid		Frank DarabontDavid FincherRobert
Drama ZemeckisMi	2299.7	Frank DarabontDavid FincherRobert
Family	15.6	Steven SpielbergMel
Stuart	15.0	Steven Spie Coergnee
Fantasy	16.0	Robert WieneF.W.
Murnau		
Film-Noir	23.9	Carol ReedJohn HustonAlfred
Hitchcock	07.0	Alford Hitabasal Didlay Coattlaba
Horror CarpenterW	87.0	Alfred HitchcockRidley ScottJohn
Mystery	95.7	Christopher NolanAlfred HitchcockAlfred
Hitchc	33.7	em 13 topher No talliter ea militaries enter ea
Thriller	7.8	Terence
Young		
Western	33.4	Sergio LeoneSergio LeoneClint
East		
		Star1
No of Vote	s \	Start
Genre	,	
Action	Christian Ba	leElijah WoodLeonardo DiCaprioElij
72282412 Adventure	Matthay McCo	naugheyMichael J. FoxBrad PittJürg
22576163	Macthew McCo	Haugheymichaet J. Toxbrad FittSurg
Animation	Daveigh Chas	eRob MinkoffTsutomu TatsumiRyûnosu
21978630		•
Biography	Liam NeesonR	obert De NiroLin-Manuel MirandaÉri
24006844		
Comedy	Kang-ho Song	Roberto BenigniCharles ChaplinChar
27620327 Crime	Marlon Brand	oAl PacinoHenry FondaJohn Travolta
33533615	riai con brand	oat racinonemy rondasomi fravotta
Drama	Tim RobbinsB	rad PittTom HanksJack NicholsonSur
61367304		
Family		Henry ThomasGene Wilder
551221		
Fantasy		Werner KraussMax Schreck
146222 Film-Noir	Orc	on WellesHumphrey BogartTeresa Wright
367215	013	on wettesnumpiney bogartreresa wright
Horror	Anthony Perk	insSigourney WeaverKurt RussellEll
3742556	,	
Mystery	Guy PearceJa	mes StewartJames StewartLeonardo D

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4203004
                                              Audrey Hepburn
Thriller
27733
           Clint EastwoodHenry FondaClint EastwoodClint E...
Western
1289665
                  Gross Metascore
Genre
           3.263226e+10
Action
                           10499.0
Adventure
           9.496922e+09
                            5020.0
Animation
           1.463147e+10
                            6082.0
           8.276358e+09
                            6023.0
Biography
Comedy
           1.566387e+10
                            9840.0
Crime
           8.452632e+09
                            6706.0
Drama
           3.540997e+10
                           19208.0
Family
           4.391106e+08
                             158.0
           7.827267e+08
                               0.0
Fantasy
Film-Noir
           1.259105e+08
                             287.0
           1.034649e+09
                             880.0
Horror
                             633.0
Mystery
           1.256417e+09
Thriller
           1.755074e+07
                              81.0
Western 5.822151e+07
                             313.0
# agg method
# passing dict
# yadi aap particular column ke upar koi particular aggrigate function
apply karna chahate ho to usse ek dictionary me pass kar do
genres.agg(
    {
        'Runtime': 'mean',
        'IMDB Rating': 'mean',
        'No of Votes': 'sum',
        'Gross':'sum',
        'Metascore': 'min'
    }
)
              Runtime IMDB Rating No of Votes
                                                       Gross
Metascore
Genre
Action
           129.046512
                          7.949419
                                       72282412 3.263226e+10
33.0
Adventure 134.111111
                          7.937500
                                       22576163 9.496922e+09
41.0
           99.585366
                                       21978630 1.463147e+10
Animation
                          7.930488
61.0
Biography 136.022727
                          7.938636
                                       24006844 8.276358e+09
48.0
Comedy
           112.129032
                          7.901290
                                       27620327 1.566387e+10
```

45.0				
Crime	126.392523	8.016822	33533615	8.452632e+09
47.0				
Drama	124.737024	7.957439	61367304	3.540997e+10
28.0				
Family	107.500000	7.800000	551221	4.391106e+08
67.0				
Fantasy	85.000000	8.000000	146222	7.827267e+08
NaN				
Film-Noir	104.000000	7.966667	367215	1.259105e+08
94.0				
Horror	102.090909	7.909091	3742556	1.034649e+09
46.0				
Mystery	119.083333	7.975000	4203004	1.256417e+09
52.0				
Thriller	108.000000	7.800000	27733	1.755074e+07
81.0				
Western	148.250000	8.350000	1289665	5.822151e+07
69.0				

passing list

suppose har numerical column ke lye [min, max & mean] nikalna chahate hain

genres[['Runtime','IMDB_Rating','No_of_Votes','Gross','Metascore']].ag
g(['min','max','mean']) # jis bhi column pe muiliple functions apply
karna hai usse ek list me pass kar do

#and jo functions apply karna hai usse bhi ek list

me pass kar do

-	Runtime			<pre>IMDB_Rating</pre>		
No_of_Votes						
	min	max	mean	min	max	mean
min						
Genre						
	4.5	201	100 046510	7.0		7 040410
Action	45	321	129.046512	7.6	9.0	7.949419
25312						
Adventure	88	228	134.111111	7.6	8.6	7.937500
29999						
Animation	71	137	99.585366	7.6	8.6	7.930488
25229						
Biography	93	209	136.022727	7.6	8.9	7.938636
27254						
Comedy	68	188	112.129032	7.6	8.6	7.901290
26337						
Crime	80	229	126.392523	7.6	9.2	8.016822
27712						
Drama	64	242	124.737024	7.6	9.3	7.957439
25088						
Family	100	115	107.500000	7.8	7.8	7.800000

178731						
Fantasy 57428	76	94	85.000000	7.9	8.1	8.000000
Film-Noir	100	108	104.000000	7.8	8.1	7.966667
59556	200		101100000	7.10	0.1	, 130000,
Horror	71	122	102.090909	7.6	8.5	7.909091
27007	06	120	110 002222	7.6	0 4	7 075000
Mystery 33982	96	138	119.083333	7.0	8.4	7.975000
Thriller	108	108	108.000000	7.8	7.8	7.800000
27733						
Western	132	165	148.250000	7.8	8.8	8.350000
65659						
				Gross		
\						
	max		mean	min		max
mean Genre						
Genre						
Action	2303232	420	246.581395	3296.0	9366	62225.0
1.897224e+0						
Adventure	1512360	313	557.819444	61001.0	8/42	11619.0
1.319017e+0	999790	268	032.073171	128985.0	8738	39108.0
1.784326e+		200	0321073171	12030310	0,50	3310010
Biography		272	805.045455	21877.0	7535	85104.0
9.404952e+0		170	105 650065	1205.0	0067	F2022 0
Comedy 1.010572e+0	939631 ຄຂ	1/8	195.658065	1305.0	8807	52933.0
Crime	1826188	313	398.271028	6013.0	7904	82117.0
7.899656e+0						
Drama	2343110	212	343.612457	3600.0	9245	58264.0
1.225259e+0 Family	372490	275	610.500000	4000000.0	4351	10554 O
2.195553e+		213	010.500000	4000000.0	7331	10334.0
Fantasy	88794	73	111.000000	337574718.0	4451	51978.0
3.913633e+0		100	405 000000	440101 0	1222	52202 0
Film-Noir 4.197018e+	158731	122	405.000000	449191.0	1233	53292.0
Horror	787806	340	232.363636	89029.0	2987	91505.0
9.405902e+0				23020	_,,	
Mystery		350	250.333333	1035953.0	4742	03697.0
1.047014e+0		2.7	722 000000	17550741 0	175	E0741 0
Thriller 1.755074e+0	27733	21	733.000000	17550741.0	1/5	50741.0
Western	688390	322	416.250000	5321508.0	318	00000.0
1.455538e+0				-		
	Mo+2555					
	Metascore					

```
min
                                  mean
                        max
Genre
Action
               33.0
                       98.0
                             73.419580
Adventure
               41.0
                      100.0
                             78.437500
Animation
               61.0
                       96.0
                             81.093333
               48.0
                       97.0
                             76.240506
Biography
               45.0
                       99.0
Comedy
                             78.720000
Crime
               47.0
                      100.0
                             77.080460
                      100.0
Drama
               28.0
                             79.701245
Family
               67.0
                       91.0
                             79.000000
Fantasy
                NaN
                        NaN
                                   NaN
Film-Noir
               94.0
                       97.0
                             95.666667
               46.0
                       97.0
Horror
                             80.000000
Mystery
               52.0
                      100.0 79.125000
Thriller
               81.0
                       81.0
                             81.000000
               69.0
                       90.0 78.250000
Western
# adding both syntax
genres.agg(
    {
        'Runtime':['mean','min'],
        'IMDB Rating': 'mean',
        'No_of_Votes':['sum','max'],
        'Gross':'sum',
        'Metascore':'min'
    }
)
# abb sirf runtime me min and min value and no of votes me sum and max
value dikhega
                            IMDB Rating No of Votes
              Runtime
Gross
                 mean
                        min
                                   mean
                                                 sum
                                                          max
sum
Genre
                                            72282412
Action
           129.046512
                         45
                               7.949419
                                                      2303232
3.263226e+10
           134.111111
                         88
                               7.937500
                                            22576163
                                                      1512360
Adventure
9.496922e+09
Animation
            99.585366
                         71
                               7.930488
                                            21978630
                                                       999790
1.463147e+10
Biography
           136.022727
                         93
                               7.938636
                                            24006844 1213505
8.276358e+09
Comedy
           112.129032
                         68
                               7.901290
                                            27620327
                                                       939631
1.566387e+10
           126.392523
Crime
                         80
                               8.016822
                                            33533615
                                                      1826188
8.452632e+09
           124.737024
Drama
                         64
                               7.957439
                                            61367304 2343110
3.540997e+10
```

Family	107.500000	100	7.800000	551221	372490
4.391106e+	-08				
Fantasy	85.000000	76	8.000000	146222	88794
7.827267e+	-08				
Film-Noir	104.000000	100	7.966667	367215	158731
1.259105e+	-08				
Horror	102.090909	71	7.909091	3742556	787806
1.034649e+	-09				
Mystery	119.083333	96	7.975000	4203004	1129894
1.256417e+	-09				
Thriller	108.000000	108	7.800000	27733	27733
1.755074e+	-07				
Western	148.250000	132	8.350000	1289665	688390
5.822151e+	-07				
	Metascore min				
Genre					
A - 4	22.0				

	Metascore
	min
Genre	
Action	33.0
Adventure	41.0
Animation	61.0
Biography	48.0
Comedy	45.0
Crime	47.0
Drama	28.0
Family	67.0
Fantasy	NaN
Film-Noir	94.0
Horror	46.0
Mystery	52.0
Thriller	81.0
Western	69.0

looping on groups genres

<pandas.core.groupby.generic.DataFrameGroupBy object at
0x000001E5E9F2CA10>

for group,data in genres: # group basically sare group ko specify
karega and data uss group ke sare data ko
 print(type(group),type(data))

```
<class 'str'> <class 'pandas.core.frame.DataFrame'>
```

```
<class 'str'> <class 'pandas.core.frame.DataFrame'>
for group, data in genres:
    print(data)
                  # har group ke data ko print kar dega jab hum data
ko print karayenge
                                           Series Title Released Year
Runtime \
                                                                 2008
2
                                        The Dark Knight
152
         The Lord of the Rings: The Return of the King
                                                                 2003
5
201
                                                                 2010
                                              Inception
8
148
10
     The Lord of the Rings: The Fellowship of the Ring
                                                                 2001
178
13
                 The Lord of the Rings: The Two Towers
                                                                 2002
179
. .
. . .
968
                                           Falling Down
                                                                 1993
113
979
                                          Lethal Weapon
                                                                 1987
109
982
                                              Mad Max 2
                                                                 1981
96
983
                                           The Warriors
                                                                 1979
92
985
                                   Escape from Alcatraz
                                                                 1979
112
             IMDB Rating
                                    Director
                                                          Star1
      Genre
No of Votes
     Action
                     9.0
                          Christopher Nolan Christian Bale
2303232
                     8.9
     Action
                              Peter Jackson
                                                    Elijah Wood
1642758
     Action
                          Christopher Nolan Leonardo DiCaprio
                     8.8
2067042
                     8.8
                              Peter Jackson
                                                    Elijah Wood
     Action
1661481
13
     Action
                     8.7
                              Peter Jackson
                                                    Elijah Wood
1485555
```

968	Action	7.6	Joel Schum	acher	Michae	l Doug	las
1716 979	40 Action	7.6	Richard D	onner	M	el Gib	son
2368	94						
982 1665	Action 88	7.6	George M	iller	Mo	el Gib	son
	Action	7.6	Walter	Hill	Mic	hael B	eck
	Action	7.6	Don S	iegel	Clint	Eastw	ood
1217	31						
2 5 8 10 13 968 979 982 983 985	Gross 534858444.0 377845905.0 292576195.0 315544750.0 342551365.0 40903593.0 65207127.0 12465371.0 22490039.0 43000000.0	Metascore 84.0 94.0 74.0 92.0 87.0 56.0 68.0 77.0 65.0 76.0					
	10WS X 10 CO	_	es_Title Re	leased_Y	ear Ru	ntime	Genre
\ 21		Inte	rstellar	2	014	169	Adventure
47		Back to th	e Future	1	.985	116	Adventure
93	In	glourious	Basterds	2	009	153	Adventure
110			Das Boot	1	.981	149	Adventure
114	200	1: A Space	0dyssey	1	.968	149	Adventure
957	Fear and Loa	thing in L	as Vegas	1	.998	118	Adventure
964			Dead Man	1	.995	121	Adventure
966		А	pollo 13		PG	140	Adventure
984		The Mupp	et Movie	1	.979	95	Adventure
991		Kelly'	s Heroes	1	.970	144	Adventure

	IMDB_Rating	Director	Star1	No_of_Votes
21	8.6	Christopher Nolan	Matthew McConaughey	1512360
47	8.5	Robert Zemeckis	Michael J. Fox	1058081
93	8.3	Quentin Tarantino	Brad Pitt	1267869
110	8.3	Wolfgang Petersen	Jürgen Prochnow	231855
114	8.3	Stanley Kubrick	Keir Dullea	603517
957	7.6	Terry Gilliam	Johnny Depp	259753
964	7.6	Jim Jarmusch	Johnny Depp	90442
966	7.6	Ron Howard	Tom Hanks	269197
984	7.6	James Frawley	Jim Henson	32802
991	7.6	Brian G. Hutton	Clint Eastwood	45338
21 47 93 110 114 957 964 966 984 991	Gross 188020017.0 210609762.0 120540719.0 11487676.0 56954992.0 10680275.0 1037847.0 173837933.0 76657000.0 1378435.0	50.0		
	rows x 10 col		le Released_Year Run	time
Genr 23	Sen to C	hihiro no kamikakush	ni 2001	125
43	ation	The Lion Kir	ng 1994	88
46	ation	Hotaru no hak	ka 1988	89
56	ation	Kimi no na wa	a. 2016	106
Anim 58	ation Spider-Man:	Into the Spider-Vers	se 2018	117

Anim	ation			
	ation			
 956		Mulan	1998	88
	ation	Mulan	1990	00
971	- 4	Omohide poro poro	1991	118
976	ation	The Little Mermaid	1989	83
986	ation	Watership Down	1978	91
992	ation ation	The Jungle Book	1967	78
Antille	ation			
No. o	<pre>IMDB_Rating f Votes \</pre>	Director	Star1	
23	8.6	Hayao Miyazaki	Daveigh Chase	651376
43	8.5	Roger Allers	Rob Minkoff	942045
46	8.5	Isao Takahata	Tsutomu Tatsumi	235231
56	8.4	Makoto Shinkai	Ryûnosuke Kamiki	194838
58	8.4	Bob Persichetti	Peter Ramsey	375110
956	7.6	Tony Bancroft	Barry Cook	256906
971	7.6	Isao Takahata	Miki Imai	27071
976	7.6	Ron Clements	John Musker	237696
986	7.6	Martin Rosen	John Hubley	33656
992	7.6	Wolfgang Reitherman	Phil Harris	166409
23 43	Gross 10055859.0 422783777.0	Metascore 96.0 88.0		
46 56 58	150734678.0 5017246.0 190241310.0	94.0 79.0 87.0		
956 971 976 986	120620254.0 453243.0 111543479.0 232841485.0	71.0 90.0 88.0 64.0		

992	141843612.0	65.0				
	rows x 10 columns] Series_Title	Released_Year Run	time	Genre	IMDB_Rating	
7	Schindler's List	1993	195	Biography	8.9	
15	Goodfellas	1990	146	Biography	8.7	
18	Hamilton	2020	160	Biography	8.6	
35	The Intouchables	2011	112	Biography	8.5	
38	The Pianist	2002	150	Biography	8.5	
923	La Vie En Rose	2007	140	Biography	7.6	
940	Finding Neverland	2004	106	Biography	7.6	
949	Blow	2001	124	Biography	7.6	
952	The Hurricane	1999	146	Biography	7.6	
987	Midnight Express	1978	121	Biography	7.6	
	Director	Star1	No_	_of_Votes	Gross	
Meta 7	score Steven Spielberg	Liam Neeson		1213505	96898818.0	
94.6 15) Martin Scorsese	Robert De Niro		1020727	46836394.0	
90.6 18) Thomas Kail	Lin-Manuel Miranda		55291	440984783.0	
90.6 35) Olivier Nakache	Éric Toledano		760360	13182281.0	
57.6 38) Roman Polanski	Adrien Brody		729603	32572577.0	
85.6						
923	Olivier Dahan	Marion Cotillard		82781	10301706.0	
66.6 940		Johnny Depp		198677	51680613.0	
67.6 949				240714	52990775.0	
52.6)	Johnny Depp				
952 74.6	Norman Jewison)	Denzel Washington		91557	50668906.0	

987 AT 59.0	lan Parker	Brad Davis	73662	35000000.0
[88 rows x]	10 columns]	Ser:	ies_Title Relea	ased_Year
Runtime \ 19 132		Gisa	aengchung	2019
26 116		La vita	a è bella	1997
51 87		Mode	ern Times	1936
52 87		Cit	ty Lights	1931
64 170			3 Idiots	2009
977 The Nak 85	ked Gun: From	the Files of Poli	ce Squad!	1988
978 93	Pl	anes, Trains & Au		1987
989 112			g Goodbye	1973
994 87		A Hard Day	J	1964
995 115		Breakfast at ⁻	liffany's	1961
Genre No of Votes	<pre>IMDB_Rating \</pre>	Director	Sta	<u>^1</u>
19 Comedy 552778	8.6	Bong Joon Ho	Kang-ho Sor	ng
26 Comedy 623629	8.6	Roberto Benigni		
51 Comedy 217881	8.5	•	•	
52 Comedy 167839	8.5	Charles Chaplin	•	
64 Comedy 344445	8.4	Rajkumar Hirani	Aamir Kha	an
	7.6	 David Zucker	Leslie Nielse	
977 Comedy 152871 978 Comedy	7.6 7.6	John Hughes		
124773 989 Comedy 26337	7.6	Robert Altman	Elliott Gou	
_000,				

994	Comedy		7.6	Richard	Lester	John	Lennon		
4035	Comedy		7.6	Plako	Edwards	Audrey H	onhurn		
1665	-		7.0	blake	Euwarus	Audiey n	ервитп		
1005	44								
	G	ross	Metascore	1					
19	533678		96.0						
26	575982		59.6						
51	1632		96.6						
52		81.0	99.6						
64	65329	08.0	67.6)					
977	787561	77.0	76.0)					
978	495302	80.0	72.0						
989	9590		87.6						
994	137800		96.6						
995	6798742	70.0	76.0)					
[155		101							
[122	rows x		_	o Doloo	and Vann	Duntino	Conro		
TMDB	Pating	\ Se	ries_iii	e ketea	seu_rear	Runtime	Genre		
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	_Rating	The	Godfathe	ır	1972	175	Crime		
9.2		1116	dourache	. I	1972	175	CITIIIC		
3	The Go	dfathe	r: Part I	T	1974	202	Crime		
9.0	1.1.0 00	a . a cc		. -	257.	202	0. 10		
4		12	Angry Me	en	1957	96	Crime		
9.0			0 ,						
6		Pu	lp Fictio	n	1994	154	Crime		
8.9									
22		Cida	de de Dei	IS	2002	130	Crime		
8.6									
				•					
050			unny Came	٠.	1007	100	Crimo		
958		Г	unny Game	25	1997	108	Crime		
7.6 960			Sleeper	· c	1996	147	Crime		
7.6			3 teepei	3	1990	147	CITIIIE		
974	The God	father	: Part II	T	1990	162	Crime		
7.6				. -	2550	202	0. 10		
980		Bl	ood Simpl	.e	1984	99	Crime		
7.6			•						
999		Th	e 39 Step	S	1935	86	Crime		
7.6									
		_						_	
NA . I		D	irector		Star1	No_of_Vot	es	Gross	
_	score	Гd	C1-	M 1	Danada	16202	C7 124	066411 0	
100.		LOLG	Coppola	Mar.ron	Brando	16203	0/ 134	966411.0	
3		Ford	Coppola	٨٦	Pacino	11299	52 57	300000.0	
90.0		1010	соррота	AL	I actilo	11299	JZ J1.	0.0000.0	
50.0									

4 96.0	Sidney	y Lumet	Henry F	onda	689845	430	60000.0	
6	Quentin Ta	rantino	John Trav	olta	1826188	1079	28762.0	
94.0 22 79.0	Fernando Me	irelles	Kátia	Lund	699256	750	63397.0	
958 69.0	Michael	Haneke	Susanne Lo	thar	65058	2173	45863.0	
960	Barry Le	evinson	Robert De	Niro	186734	491	0.0000	
49.0 974 60.0	Francis Ford (Coppola	Al Pa	cino	359809	666	66062.0	
980	Joe	el Coen	Ethan	Coen	87745	21	50000.0	
82.0 999 93.0	Alfred Hit	tchcock	Robert D	onat	51853	3027	87539.0	
[107	rows x 10 colu	umns1						
0 9 11 17 20		Ser awshank F For the Cuck	ries_Title Redemption Fight Club rrest Gump Roo's Nest rai Pottru	_	Year Run 1994 1999 1994 1975 2020	time 142 139 142 133 153	Genre Drama Drama Drama Drama	\
990 993 996 997 998	Fron		la testa Blowup Giant Eternity Lifeboat		 1971 1966 1956 1953 1944	157 111 201 118 97	Drama Drama Drama Drama Drama	
	IMDB_Rating		Direc	tor	S	tar1		
No_of 0 23431	f_Votes \ 9.3	F	rank Darab	ont	Tim Rob	bins		
9	8.8		David Finc	her	Brad	Pitt		
18547 11 18092	8.8	Ro	bert Zemec	kis	Tom H	lanks		
17	8.7		Milos For	man J	ack Nicho	lson		
91808 20 54995	8.6		Sudha Kong	ara	Su	riya		
990 30144	7.6		Sergio Le	one	Rod Ste	iger		

7.6 Michelangelo Antonioni David Hemmings
56513 996 7.6 George Stevens Elizabeth Taylor
34075 997 7.6 Fred Zinnemann Burt Lancaster
43374 998 7.6 Alfred Hitchcock Tallulah Bankhead
26471
Gross Metascore
0 28341469.0 80.0 9 37030102.0 66.0
11 330252182.0 82.0
17 112000000.0 83.0 20 556832648.0 NaN
 990 696690.0 77.0
993 632532802.0 82.0
996 195217415.0 84.0 997 30500000.0 85.0
998 852142728.0 78.0
[289 rows x 10 columns]
<pre>Genre \</pre>
688 E.T. the Extra-Terrestrial 1982 115 Family
698 Willy Wonka & the Chocolate Factory 1971 100 Family
IMDB_Rating Director Star1 No_of_Votes
Gross \ 688 7.8 Steven Spielberg Henry Thomas 372490
435110554.0 698 7.8 Mel Stuart Gene Wilder 178731
4000000.0
Metascore 688 91.0 698 67.0
Series_Title Released_Year Runtime Genre \ 321 Das Cabinet des Dr. Caligari 1920 76 Fantasy
Nosferatu 1922 94 Fantasy
IMDB_Rating Director Star1 No_of_Votes
Gross \ 321 8.1 Robert Wiene Werner Krauss 57428
337574718.0
568 7.9 F.W. Murnau Max Schreck 88794 445151978.0

	M .					
321	Metascore NaN					
568	NaN					
	Series_Title Release	d_Year	Runtime	G	enre IM	DB_Rating
309	The Third Man	1949	104	Film-	Noir	8.1
309	THE THIT HAH	1949	104	I T CIII-	INOTI	0.1
456	The Maltese Falcon	1941	100	Film-	Noir	8.0
712	Shadow of a Doubt	1943	108	Film-	Noir	7.8
	Director	Star1	No of '	Votes	Gr	OSS
Meta	score	Start	110_01_	VULES	OI (J33
309		Welles	1.	58731	44919	1.0
97.0		Donout	1	40020	210006	0 0
456 96.0	John Huston Humphrey	Bogart	1.	48928	210806	J. U
		Wright	!	59556	12335329	2.0
94.0		3				
T.110.0	Series_Title R	eleased_	_Year R	untime	Genre	
1MDB _.	_Rating \ Psycho		1960	109	Horror	
8.5	rsycho		1900	109	1101101	
75	Alien		1979	117	Horror	
8.4	TI TI		1000	100		
271 8.1	The Thing		1982	109	Horror	
419	The Exorcist		1973	122	Horror	
8.0	,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,					
544	Night of the Living Dead		1968	96	Horror	
7.9 707	The Innocents		1961	100	Horror	
7.8	The Innocents		1901	100	1101101	
724	Get Out		2017	104	Horror	
7.7			1070	0.1		
844	Halloween		1978	91	Horror	
876	The Invisible Man		1933	71	Horror	
7.7						
932	Saw		2004	103	Horror	
7.6 948	The Others		2001	101	Horror	
7.6	The others		2001	101	1101101	
		_				_
Mo+a	Director	Sta	ar1 No_	of_Vote	S	Gross
49	score Alfred Hitchcock Antho	ny Perk:	ins	60421	1 3200	0000.0
97.0		,				

75	Ridley Scott	Sigourney Weaver	7	787806	78900000.0		
89.0 271	John Carpenter	Kurt Russell	. 3	371271	13782838.0		
57.0	William Eminaldi	Ellan Dunatum	_	062202	222006145 0		
419 81.0	William Friedkin	Ellen Burstyr		362393	232906145.0		
544	George A. Romero	Duane Jones	. 1	16557	89029.0		
89.0 707	Jack Clayton	Deborah Kerr		27007	2616000.0		
88.0	·						
724 85.0	Jordan Peele	Daniel Kaluuya	1 4	192851	176040665.0		
844	John Carpenter	Donald Pleasence	. 2	233106	47000000.0		
87.0		Clauda Daina		20002	200701505 0		
876 87.0	James Whale	Claude Rains		30683	298791505.0		
932	James Wan	Cary Elwes	3	379020	56000369.0		
46.0 948 <i>A</i>	Alejandro Amenábar	Nicole Kidmar	, 3	37651	96522687.0		
74.0	_			757051			
69 81 119 145 220 393 420 714 829 899 959 961	Series_Title R Memento Rear Window Vertigo Shutter Island Kahaani Twelve Monkeys Sleuth The Lady Vanishes Spoorloos El cuerpo Dark City Lost Highway		112 My 128 My 138 My 122 My 129 My 138 My 96 My 107 My 112 My 100 My 134 My	Genre vstery vstery vstery vstery vstery vstery vstery vstery vstery vstery vstery	IMDB_Rating 8.4 8.3 8.2 8.1 8.0 7.8 7.7 7.6 7.6		
Gross	Directo	r	Sta	ırl No	_of_Votes		
69	Christopher Nola	n	Guy Pear	ce	1125712		
255448 81	Alfred Hitchcoc	k Jan	nes Stewa	irt	444074		
367643 119	Alfred Hitchcoc	k Jan	nes Stewa	ırt	364368		
145	3200000.0 145 Martin Scorsese Leonardo DiCaprio 1129894 128012934.0						
220 103595	Sujoy Ghos	h \	'idya Bal	.an	57806		
393 571414	Terry Gillia	m Br	uce Will	.is	578443		
	Joseph L. Mankiewic	z Laurer	ice Olivi	.er	44748		

714 Alfr 474203697.0	ed Hitcho	cock	Margar	et Lock	wood	4	7400
829 Ge	eorge Slui	izer Berna	rd-Piern	re Donna	dieu	3	3982
367916835.0 899	Oriol Pa	aulo	Jo	se Coro	nado	5	7549
140340673.0 959	Alex Pro	oyas	F	Rufus Se	well	18	7927
14378331.0 961	David Ly	/nch	E	Bill Pul	lman	13	1101
3796699.0							
Metascor 69 80. 81 100. 119 100. 145 63. 220 Na 393 74. 420 Na 714 98. 829 Na 829 Na 899 Na 959 66. 961 52. Serie 700 Wait Unt	0 0 0 0 N 0 N 0 N 0 es_Title F	Released_Ye 19			Genre riller	IMDB_	Rating \ 7.8
Dir	ector	Sta	rl No_d	of_Votes		Gross	Metascore
700 Terence	Young Au	udrey Hepbu	rn	27733	17550	741.0	81.0
C		Series_T	itle Rel	Leased_Y	ear Ru	ntime	
Genre \ 12 Il buono	o, il brut	to, il cat	tivo	1	966	161	Western
48 Once	Upon a Ti	ime in the	West	1	968	165	Western
115 Per	qualche	dollaro in	più	1	965	132	Western
691	The Outl	law Josey W	ales	1	976	135	Western
<pre>IMDB_Rat Gross \</pre>	ing	Director		Star	1 No_c	f_Vote	S
12 6100000.0	8.8 Se	ergio Leone	Clint	Eastwoo	d	68839	0
	8.5 Se	ergio Leone	Her	nry Fond	a	30284	4
	8.3 Se	ergio Leone	Clint	Eastwoo	d	23277	2

```
691
            7.8 Clint Eastwood Clint Eastwood
                                                         65659
31800000.0
     Metascore
12
          90.0
48
          80.0
115
          74.0
          69.0
691
for group, data in genres:
    print(group)
                                   #har group ko print kar dega
Action
Adventure
Animation
Biography
Comedy
Crime
Drama
Family
Fantasy
Film-Noir
Horror
Mystery
Thriller
Western
# find the heighest rated movie of each genre
for group, data in genres:
    print(data['IMDB Rating'].max()) # ye har genre ke maxm
imdb rating ko nikal ke dega
9.0
8.6
8.6
8.9
8.6
9.2
9.3
7.8
8.1
8.1
8.5
8.4
7.8
8.8
for group, data in genres:
    print(data[data['IMDB Rating'] == data['IMDB Rating'].max()] )
```

```
Series_Title Released_Year Runtime Genre IMDB_Rating \
2 The Dark Knight 2008 152 Action 9.0
         Director Starl No of Votes Gross
Metascore
2 Christopher Nolan Christian Bale 2303232 534858444.0
   Series Title Released Year Runtime Genre IMDB Rating \
21 Interstellar 2014 169 Adventure 8.6
          Director Starl No of Votes
Gross \
21 Christopher Nolan Matthew McConaughey 1512360 188020017.0
   Metascore
21
   74.0
                Series_Title Released_Year Runtime Genre \
23 Sen to Chihiro no kamikakushi 2001 125 Animation
   IMDB_Rating Director Star1 No_of_Votes
Gross \ 23 8.6 Hayao Miyazaki Daveigh Chase 651376
10055859.0
   Metascore
23
     96.0
     Series_Title Released_Year Runtime Genre IMDB_Rating \
7 Schindler's List 1993 195 Biography 8.9
        Director Starl No of Votes
                                         Gross Metascore
7 Steven Spielberg Liam Neeson 1213505 96898818.0 94.0
     Series_Title Released_Year Runtime Genre IMDB_Rating \
     Gisaengchung 2019 132 Comedy 8.6 vita è bella 1997 116 Comedy 8.6
26 La vita è bella
                            116 Comedy
Director Star1 No_of_Votes Gross
Metascore
19 Bong Joon Ho Kang-ho Song 552778 53367844.0
96.0
26 Roberto Benigni Roberto Benigni 623629 57598247.0
59.0
   Series_Title Released_Year Runtime Genre IMDB_Rating \
1 The Godfather 1972 175 Crime 9.2
           Director Starl No of Votes Gross
Metascore
1 Francis Ford Coppola Marlon Brando 1620367 134966411.0
100.0
         Series Title Released Year Runtime Genre IMDB Rating
```

0 T	he Shawshank Redemption	1994	142 Drama	9.3
	Director St rank Darabont Tim Robb	arl No_of_Votes oins 2343110 Series_Title Rele	28341469.0	ascore 80.0 Lme
Genro	E.T. the Extr	a-Terrestrial	1982	115
Fami 698 Fami	Willy Wonka & the Choc	olate Factory	1971 1	L00
C		irector St	ar1 No_of_Votes	5
	7.8 Steven Sp	ielberg Henry Tho	omas 372496)
698	10554.0 7.8 Mel 000.0	Stuart Gene Wil	lder 178731	Ī
688 698	67.0			
321	Series Das Cabinet des Dr. Ca	_Title Released_Ye lligari 19		Genre \ ntasy
321	s \	tor Star1 ene Werner Krauss	No_of_Votes 57428	
321	Metascore NaN Series_Title Released ctor \	_Year Runtime	Genre IMDB_Ra	ating
309	The Third Man l Reed	1949 104 Fi	ilm-Noir	8.1
S	Starl No_of_Vo Orson Welles 158 eries_Title Released_Ye ctor \		97.0	
49		109 Horro	or 8.5	Alfred
	Star1 No of	Votes Gross	Metascore	
	Anthony Perkins	04211 32000000.0	97.0	\
69 81 I	Memento 20 Rear Window 19	00 113 Myste 54 112 Myste	ery 8.4	
	Director	Starl No_of_\		5

```
Metascore
69 Christopher Nolan Guy Pearce 1125712 25544867.0
80.0
    Alfred Hitchcock James Stewart 444074 36764313.0
81
100.0
       Series_Title Released_Year Runtime Genre
                                                   IMDB Rating \
700 Wait Until Dark
                            1967
                                     108 Thriller
                           Starl No of Votes
         Director
                                             Gross Metascore
700 Terence Young Audrey Hepburn
                                       27733 17550741.0
                                                              81.0
                     Series Title Released Year Runtime
                                                          Genre \
12 Il buono, il brutto, il cattivo
                                          1966
                                                    161 Western
   IMDB Rating
                   Director
                                     Star1 No of Votes
                                                            Gross
12
           8.8 Sergio Leone Clint Eastwood 688390 6100000.0
   Metascore
12 90.0
# aache se dekhne ke lye
df = pd.DataFrame(columns=movies.columns)
df
                         # ek empty dataframe bana lye like movies
dataframe
Empty DataFrame
Columns: [Series Title, Released_Year, Runtime, Genre, IMDB_Rating,
Director, Star1, No of Votes, Gross, Metascore]
Index: []
df = pd.DataFrame(columns=movies.columns)
for group, data in genres:
   df= pd.concat([df,data[data['IMDB Rating'] ==
data['IMDB Rating'].max()]])
df
C:\Users\jayra\AppData\Local\Temp\ipykernel 23732\1685166070.py:5:
FutureWarning: The behavior of DataFrame concatenation with empty or
all-NA entries is deprecated. In a future version, this will no longer
exclude empty or all-NA columns when determining the result dtypes. To
retain the old behavior, exclude the relevant entries before the
concat operation.
 df= pd.concat([df,data[data['IMDB Rating'] ==
data['IMDB Rating'].max()]])
```

Conro		Series_Title	Released_	Year	Runtime	
Genre \ 2		The Dark Knight		2008	152	
Action 21		Interstellar		2014	169	
Adventure						
23 Animation	Sen to C	hihiro no kamikakushi		2001	125	
7 Biography		Schindler's List		1993	195	
Biography 19		Gisaengchung		2019	132	
Comedy 26		La vita è bella		1997	116	
Comedy						
1 Crime		The Godfather		1972	175	
0	The	Shawshank Redemption		1994	142	
Drama 688	E.T.	the Extra-Terrestrial		1982	115	
Family 698 Willy	Wonka &	the Chocolate Factory		1971	100	
Family		•				
321 Fantasy	Das Cab	inet des Dr. Caligari		1920	76	
309		The Third Man		1949	104	Film-
Noir 49		Psycho		1960	109	
Horror 69		Memento		2000	113	
Mystery						
81 Mystery		Rear Window		1954	112	
700		Wait Until Dark		1967	108	
Thriller 12 I	l buono,	il brutto, il cattivo		1966	161	
Western	·	·				
	Rating	Director		9	Star1	
No_of_Vote 2	s \ 9.0	Christopher Nolan	Chris	tian	Bale	
2303232		·				
21 1512360	8.6	Christopher Nolan I	Matthew Mc	Conau	ugney	
23 651376	8.6	Hayao Miyazaki	Dave	eigh (Chase	
7	8.9	Steven Spielberg	Li	.am Ne	eeson	
1213505 19	8.6	Bong Joon Ho	Kan	ıa-ho	Song	
552778		<u> </u>			_	
26	8.6	Roberto Benigni	Robert	o Ber	nigni	

```
623629
                                                Marlon Brando
             9.2 Francis Ford Coppola
1
1620367
             9.3
                         Frank Darabont
                                                  Tim Robbins
2343110
688
             7.8
                       Steven Spielberg
                                                 Henry Thomas
372490
698
             7.8
                             Mel Stuart
                                                  Gene Wilder
178731
             8.1
                           Robert Wiene
                                                Werner Krauss
321
57428
                                                 Orson Welles
309
             8.1
                             Carol Reed
158731
             8.5
                       Alfred Hitchcock
                                              Anthony Perkins
49
604211
             8.4
                      Christopher Nolan
                                                   Guy Pearce
69
1125712
             8.4
                       Alfred Hitchcock
                                                James Stewart
81
444074
700
             7.8
                                               Audrey Hepburn
                          Terence Young
27733
             8.8
                           Sergio Leone
                                               Clint Eastwood
12
688390
           Gross
                  Metascore
2
     534858444.0
                        84.0
21
     188020017.0
                        74.0
23
      10055859.0
                        96.0
7
      96898818.0
                        94.0
19
      53367844.0
                        96.0
                        59.0
26
      57598247.0
1
     134966411.0
                       100.0
0
      28341469.0
                        80.0
688
     435110554.0
                        91.0
698
       4000000.0
                        67.0
321
     337574718.0
                         NaN
309
        449191.0
                        97.0
49
      32000000.0
                        97.0
69
      25544867.0
                        80.0
81
      36764313.0
                       100.0
700
      17550741.0
                        81.0
12
       6100000.0
                        90.0
df = pd.DataFrame(columns=movies.columns)
for group, data in genres:
    # Filter for the highest IMDB rating in the current group
    highest rating row = data[data['IMDB Rating'] ==
data['IMDB_Rating'].max()]
    # Use pd.concat to append the highest rating row to df
    df = pd.concat([df, highest rating row])
```

C:\Users\jayra\AppData\Local\Temp\ipykernel_23732\492345485.py:6: FutureWarning: The behavior of DataFrame concatenation with empty or all-NA entries is deprecated. In a future version, this will no longer exclude empty or all-NA columns when determining the result dtypes. To retain the old behavior, exclude the relevant entries before the concat operation.

df = pd.concat([df, highest_rating_row])

	Series_Title	Released_Year	Runtime	
Genre \ 2	The Dark Knight	2008	152	
Action	The Dark Kinght	2000	132	
21	Interstellar	2014	169	
Adventure				
23	Sen to Chihiro no kamikakushi	2001	125	
Animation 7	Schindler's List	1993	195	
Biography	Jeninater 3 List	1995	193	
19	Gisaengchung	2019	132	
Comedy				
26	La vita è bella	1997	116	
Comedy 1	The Godfather	1972	175	
Crime	The Godrather	1972	1/5	
0	The Shawshank Redemption	1994	142	
Drama				
688	E.T. the Extra-Terrestrial	1982	115	
Family	. Wanta C the Charaleta Fastani	1071	100	
698 Willy Family	y Wonka & the Chocolate Factory	1971	100	
321	Das Cabinet des Dr. Caligari	1920	76	
Fantasy			. •	
309	The Third Man	1949	104	Film-
Noir	2	1000	100	
49 Horror	Psycho	1960	109	
69	Memento	2000	113	
Mystery	Hemented	2000	113	
81	Rear Window	1954	112	
Mystery				
700	Wait Until Dark	1967	108	
Thriller 12	[l buono, il brutto, il cattivo	1966	161	
Western	te baono, it bracto, it cattivo	1900	101	
	_Rating Director	9	Star1	
No_of_Vote	es \			

```
69 25544867.0 80.0
81 36764313.0 100.0
700 17550741.0 81.0
12 6100000.0 90.0
```

```
# split (apply) combine Strategy
# apply -> builtin function
```

genres.apply(min)

C:\Users\jayra\AppData\Local\Temp\ipykernel_23732\1443917609.py:1: FutureWarning: The provided callable <built-in function min> is currently using np.minimum.reduce. In a future version of pandas, the provided callable will be used directly. To keep current behavior pass the string np.minimum.reduce instead.

genres.apply(min)

C:\Users\jayra\AppData\Local\Temp\ipykernel_23732\1443917609.py:1: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to silence this warning.

genres.apply(min)

	Series_Title	Released_Year	Runtime
Genre \ Genre		_	
Action Action	300	1924	45
Adventure Adventure	2001: A Space Odyssey	1925	88
Animation Animation	Akira	1940	71
Biography Biography	12 Years a Slave	1928	93
Comedy Comedy	(500) Days of Summer	1921	68
Crime Crime	12 Angry Men	1931	80
Drama Drama	1917	1925	64
Family Family	E.T. the Extra-Terrestrial	1971	100
Fantasy Fantasy	Das Cabinet des Dr. Caligari	1920	76

Film-Noir		Shadow of a Doubt	1941 100
Film-Noir Horror		Alien	1933 71
Horror Mystery		Dark City	1938 96
Mystery Thriller		Wait Until Dark	1967 108
Thriller Western Western	Il buono, il	brutto, il cattivo	1965 132
Star1 \ Genre	IMDB_Rating	Director	
Action	7.6	Abhishek Chaubey	Aamir
Khan Adventure	7.6	Akira Kurosawa	Aamir
Khan Animation	7.6	Adam Elliot	Adrian
Molina Biography	7.6	Adam McKay	Adrien
Brody Comedy Khan	7.6	Alejandro G. Iñárritu	Aamir
Crime Devgn	7.6	Akira Kurosawa	Ajay
Drama Deol	7.6	Aamir Khan	Abhay
Family Wilder	7.8	Mel Stuart	Gene
Fantasy	7.9	F.W. Murnau	Max
Schreck Film-Noir	7.8	Alfred Hitchcock	Humphrey
Bogart Horror Perkins	7.6	Alejandro Amenábar	Anthony
Mystery Donnadieu	7.6	Alex Proyas	Bernard-Pierre
Thriller	7.8	Terence Young	Audrey
Hepburn Western Eastwood	7.8	Clint Eastwood	Clint
Comm	No_of_Votes	Gross Metascore	
Genre Action Adventure Animation Biography	25312 29999 25229 27254	3296.0 NaM 61001.0 NaM 128985.0 NaM 21877.0 NaM	I I

```
Comedy
                 26337
                              1305.0
                                             NaN
Crime
                 27712
                              6013.0
                                             NaN
Drama
                 25088
                              3600.0
                                             NaN
Family
                178731
                           4000000.0
                                            67.0
Fantasy
                 57428
                         337574718.0
                                             NaN
Film-Noir
                 59556
                            449191.0
                                            94.0
                                            46.0
Horror
                 27007
                             89029.0
Mystery
                 33982
                           1035953.0
                                            NaN
Thriller
                 27733
                          17550741.0
                                            81.0
Western
                 65659
                           5321508.0
                                            69.0
# find number of movies starting with A for each group
def foo(group):
    print(group)
    return group
genres.apply(foo)
                                            Series Title Released Year
Runtime \
2
                                                                   2008
                                        The Dark Knight
152
         The Lord of the Rings: The Return of the King
                                                                   2003
201
8
                                               Inception
                                                                   2010
148
10
     The Lord of the Rings: The Fellowship of the Ring
                                                                   2001
178
13
                 The Lord of the Rings: The Two Towers
                                                                   2002
179
. .
. . .
                                            Falling Down
                                                                   1993
968
113
979
                                           Lethal Weapon
                                                                   1987
109
982
                                               Mad Max 2
                                                                   1981
96
                                            The Warriors
                                                                   1979
983
92
985
                                   Escape from Alcatraz
                                                                   1979
112
             IMDB Rating
                                    Director
                                                           Star1
      Genre
No of Votes
                     9.0
                           Christopher Nolan
                                                  Christian Bale
     Action
2303232
     Action
                     8.9
                               Peter Jackson
                                                     Elijah Wood
1642758
```

8 Action	8.8 C	hristopher No	lan Leona	rdo DiCap	rio
2067042 10 Action	8.8	Peter Jack	son	Elijah W	ood
1661481 13 Action	8.7	Peter Jack	son	Elijah W	ood
1485555	0.,				
968 Action 171640	7.6	Joel Schumac	ner Mic	hael Doug	las
979 Action 236894	7.6	Richard Don	ner	Mel Gib	son
982 Action 166588	7.6	George Mil	ler	Mel Gib	son
983 Action 93878	7.6	Walter H	ill I	Michael B	eck
985 Action 121731	7.6	Don Sie	gel Cl	int Eastw	ood
Gross Me 2 534858444.0 5 377845905.0 8 292576195.0 10 315544750.0 13 342551365.0 968 40903593.0 979 65207127.0 982 12465371.0 983 22490039.0 985 43000000.0	etascore 84.0 94.0 74.0 92.0 87.0 56.0 68.0 77.0 65.0 76.0				
\		es_Title Relea	ased_Year	Runtime	Genre
21	Inte	rstellar	2014	169	Adventure
47 Bao	ck to th	e Future	1985	116	Adventure
93 Inglo	ourious	Basterds	2009	153	Adventure
110		Das Boot	1981	149	Adventure
114 2001:	A Space	0dyssey	1968	149	Adventure
957 Fear and Loath:	ing in L	as Vegas	1998	118	Adventure
964		Dead Man	1995	121	Adventure

986	984 The Muppet Movie 1979 95 Adventure
MDB_Rating Director Starl No_of_Votes	· ·
IMDB_Rating	001
21 8.6 Christopher Nolan Matthew McConaughey 1512360 47 8.5 Robert Zemeckis Michael J. Fox 1058081 93 8.3 Quentin Tarantino Brad Pitt 1267869 110 8.3 Wolfgang Petersen Jürgen Prochnow 231855 114 8.3 Stanley Kubrick Keir Dullea 603517	Serious 1970 144 Adventure
21	
93 8.3 Quentin Tarantino Brad Pitt 1267869 110 8.3 Wolfgang Petersen Jürgen Prochnow 231855 114 8.3 Stanley Kubrick Keir Dullea 603517 957 7.6 Terry Gilliam Johnny Depp 259753 964 7.6 Jim Jarmusch Johnny Depp 90442 966 7.6 Ron Howard Tom Hanks 269197 984 7.6 James Frawley Jim Henson 32802 991 7.6 Brian G. Hutton Clint Eastwood 45338 Gross Metascore 21 188020017.0 74.0 47 210609762.0 87.0 93 120540719.0 69.0 110 11487676.0 86.0 114 56954992.0 84.0 957 10680275.0 41.0 966 173837933.0 77.0 984 76657000.0 74.0 991 1378435.0 50.0 [72 rows x 10 columns] Series_Title Released_Year Runtime Genre \ 23 Sen to Chihiro no kamikakushi 2001 125	
110 8.3 Wolfgang Petersen Jürgen Prochnow 231855 114 8.3 Stanley Kubrick Keir Dullea 603517 957 7.6 Terry Gilliam Johnny Depp 259753 964 7.6 Jim Jarmusch Johnny Depp 90442 966 7.6 Ron Howard Tom Hanks 269197 984 7.6 James Frawley Jim Henson 32802 991 7.6 Brian G. Hutton Clint Eastwood 45338 Gross Metascore 21 188020017.0 74.0 47 210609762.0 87.0 93 120540719.0 69.0 110 11487676.0 86.0 114 56954992.0 84.0 957 10680275.0 41.0 964 1037847.0 62.0 966 173837933.0 77.0 984 76657000.0 74.0 991 1378435.0 50.0 [72 rows x 10 columns] Series_Title Released_Year Runtime Genre \ 23 Sen to Chihiro no kamikakushi 2001 125	47 8.5 Robert Zemeckis Michael J. Fox 1058081
114 8.3 Stanley Kubrick Keir Dullea 603517 957 7.6 Terry Gilliam Johnny Depp 259753 964 7.6 Jim Jarmusch Johnny Depp 90442 966 7.6 Ron Howard Tom Hanks 269197 984 7.6 James Frawley Jim Henson 32802 991 7.6 Brian G. Hutton Clint Eastwood 45338 Gross Metascore 21 188020017.0 74.0 47 210609762.0 87.0 93 120540719.0 69.0 110 11487676.0 86.0 114 56954992.0 84.0 957 10680275.0 41.0 964 1037847.0 62.0 966 173837933.0 77.0 984 76657000.0 74.0 991 1378435.0 50.0 [72 rows x 10 columns] Series_Title Released_Year Runtime Genre \ 23 Sen to Chihiro no kamikakushi 2001 125	93 8.3 Quentin Tarantino Brad Pitt 1267869
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984 7.6 James Frawley Jim Henson 32802 991 7.6 Brian G. Hutton Clint Eastwood 45338 Gross Metascore 1 188020017.0 74.0 47 210609762.0 87.0 93 120540719.0 69.0 110 11487676.0 86.0 114 56954992.0 84.0 957 10680275.0 41.0 964 1037847.0 62.0 966 173837933.0 77.0 984 76657000.0 74.0 991 1378435.0 50.0 [72 rows x 10 columns] Series_Title Released_Year Runtime Genre \ 23 Sen to Chihiro no kamikakushi 2001 125	964 7.6 Jim Jarmusch Johnny Depp 90442
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21 188020017.0 74.0	991 7.6 Brian G. Hutton Clint Eastwood 45338
A a diament diament	21 188020017.0

43		The Lion King	1994	88
Anım 46	ation	Hotaru no haka	1988	89
_	ation	notaru no naka	1900	09
56	a c z o n	Kimi no na wa.	2016	106
	ation			
58		Into the Spider-Verse	2018	117
	ation			
		• • • • • • • • • • • • • • • • • • • •		
956		Mulan	1998	88
	ation			
971	-4:	Omohide poro poro	1991	118
976	ation	The Little Mermaid	1989	83
	ation	THE LITTEE HET MAIN	1303	03
986		Watership Down	1978	91
	ation	The level a Deale	1007	70
992 Anim	ation	The Jungle Book	1967	78
VIITIII	acion			
	<pre>IMDB_Rating</pre>	Director	Star1	
	f_Votes \	Havaa Missaalii	Davisiah Chass	651276
23	8.6	Hayao Miyazaki	Daveigh Chase	651376
43	8.5	Roger Allers	Rob Minkoff	942045
46	8.5	Isao Takahata	Tsutomu Tatsumi	235231
56	8.4	Makoto Shinkai	Ryûnosuke Kamiki	194838
Ε0	0.4	Bob Persichetti	Datas Daması	275110
58	8.4	BOD PERSICHETTI	Peter Ramsey	375110
956	7.6	Tony Bancroft	Barry Cook	256906
971	7.6	Isao Takahata	Miki Imai	27071
976	7.6	Ron Clements	John Musker	237696
986	7.6	Martin Rosen	John Hubley	33656
992	7.6	Wolfgang Reitherman	Phil Harris	166409
	Gross	Metascore		
23 43	10055859.0 422783777.0	96.0 88.0		
46	150734678.0	94.0		
		3 3		

56 58	5017246.0 190241310.0	79.0 87.0			
956 971 976 986 992	120620254.0 453243.0 111543479.0 232841485.0 141843612.0	71.0 90.0 88.0 64.0 65.0			
[82	rows x 10 columns]				
	= -	Released_Year	Runtime	Genre	<pre>IMDB_Rating</pre>
7	Schindler's List	1993	195	Biography	8.9
15	Goodfellas	1990	146	Biography	8.7
18	Hamilton	2020	160	Biography	8.6
35	The Intouchables	2011	112	Biography	8.5
38	The Pianist	2002	150	Biography	8.5
923	La Vie En Rose	2007	140	Biography	7.6
940	Finding Neverland	2004	106	Biography	7.6
949	Blow	2001	124	Biography	7.6
952	The Hurricane	1999	146	Biography	7.6
987	Midnight Express	1978	121	Biography	7.6
	Director	C+	an I Na	of Votos	Cross
Meta	Director score	31	ari NO_	of_Votes	Gross
7 94.0	Steven Spielberg	Liam Nee	son	1213505	96898818.0
15 90.0	Martin Scorsese	Robert De N	liro	1020727	46836394.0
18	Thomas Kail	Lin-Manuel Mira	nda	55291 4	140984783.0
90.0 35	Olivier Nakache	Éric Toled	ano	760360	13182281.0
57.0 38 85.0	Roman Polanski	Adrien Br	ody	729603	32572577.0
923	Olivier Dahan	Marion Cotill	ard	82781	10301706.0

66.0 940 Ma	rc Forster	Johnny Donn	198677	51680613.0
67.0	ic roistei	Johnny Depp	190077	51000013.0
949	Ted Demme	Johnny Depp	240714	52990775.0
52.0 952 Norm	an Jewison	Denzel Washington	91557	50668906.0
74.0	an sewison	Delizee Washington	31337	30000300.0
	lan Parker	Brad Davis	73662	35000000.0
59.0				
[88 rows x	10 columns]	_		
Runtime \		Ser	ies_Title Rele	eased_Year
19		Gis	aengchung	2019
132		1	- > 1 - 11 -	1007
26 116		La Vit	a è bella	1997
51		Mod	ern Times	1936
87 52		Ci	ty Lights	1931
87		CI	ty Lights	1931
64			3 Idiots	2009
170				
977 The Na 85	ked Gun: From	the Files of Poli	ce Squad!	1988
978	Р	lanes, Trains & Au	tomobiles	1987
93		T b - 1		1072
989 112		ine Lon	g Goodbye	1973
994		A Hard Da	y's Night	1964
87 995		Breakfast at	Tiffany's	1961
115		Dieakiast at	TITIONY 5	1901
Conro	TMDD Dating	Director	C+-	n 1
Genre No of Votes		Director	Sta	31 T
$19\overline{C}$ omedy		Bong Joon Ho	Kang-ho So	ong
552778 26 Comedy	8.6	Roberto Benigni	Roberto Benig	nni
623629	0.0	Nobel to benight	MODEL TO DELLE	JII I
51 Comedy	8.5	Charles Chaplin	Charles Chapl	lin
217881 52 Comedy	8.5	Charles Chaplin	Charles Chapl	lin
167839			•	
64 Comedy 344445	8.4	Rajkumar Hirani	Aamir Kh	nan

977	Comedy	7.6	David	Zucker	Leslie N	iolcon
15287		7.0	Daviu	Zuckei	restre M	Tersen
	Comedy	7.6	John	Hughes	Steve	Martin
12477 989	Comedy	7.6	Robert	Altman	Elliott	Gould
26337	7					
994 4035	Comedy	7.6	Richard	Lester	John	Lennon
	Comedy	7.6	Blake	Edwards	Audrey H	epburn
16654	44					
	Gross N	Metascore				
19	53367844.0	96.0				
26 51	57598247.0 163245.0	59.0 96.0				
52	19181.0	99.0				
64	6532908.0	67.0				
 977	78756177.0	76.0				
978	49530280.0	72.0				
989	959000.0	87.0				
994 995	13780024.0 679874270.0	96.0 76.0				
[1EE	nove v 10 col.	ımp a 1				
[133	rows x 10 colu Sei		e Relea	sed_Year	Runtime	Genre
_	_Rating $ackslash$	_		_		.
1 9.2	Ine	Godfathe	Γ	1972	175	Crime
3	The Godfather	r: Part I	I	1974	202	Crime
9.0 4	12	Angry Me	n	1957	96	Crime
9.0	12	Aligi y He	1	1957	90	CLTINE
6	Pul	lp Fictio	n	1994	154	Crime
8.9 22	Cidad	de de Deu:	S	2002	130	Crime
8.6	0_00					GG
			•			
958	Fu	unny Game	S	1997	108	Crime
7.6		C1		1000	1 47	C
960 7.6		Sleeper	S	1996	147	Crime
974	The Godfather:	: Part II	I	1990	162	Crime
7.6 980	D1,	ood Simple	3	1984	99	Crime
7.6	BU	σου στιιρι	5	1904	99	CLTINE
999	The	e 39 Step	S	1935	86	Crime

7.6				
	Director	Star1	No_of_Votes	Gross
	core Francis Ford Coppola	Marlon Brando	1620367	134966411.0
	Francis Ford Coppola	Al Pacino	1129952	57300000.0
90.0	Sidney Lumet	Henry Fonda	689845	4360000.0
96.0	Quentin Tarantino	John Travolta	1826188	107928762.0
94.0	Fernando Meirelles	Kátia Lund	699256	7563397.0
79.0 				
958 69.0	Michael Haneke	Susanne Lothar	65058	217345863.0
960 49.0	Barry Levinson	Robert De Niro	186734	49100000.0
	rancis Ford Coppola	Al Pacino	359809	66666062.0
980	Joel Coen	Ethan Coen	87745	2150000.0
82.0 999 93.0	Alfred Hitchcock	Robert Donat	51853	302787539.0
[107 r	rows x 10 columns]			
0 9 11 17 0 20	The Shawshank F One Flew Over the Cu	Fight Club orrest Gump	nsed_Year Run 1994 1999 1994 1975 2020	time Genre 142 Drama 139 Drama 142 Drama 133 Drama 153 Drama
990 993 996 997 998		iù la testa Blowup Giant to Eternity Lifeboat	1971 1966 1956 1953 1944	157 Drama 111 Drama 201 Drama 118 Drama 97 Drama
	MDB_Rating	Director	S	tar1
No_of_ 0	9.3	Frank Darabont	Tim Rob	bins
234311 9	8.8	David Fincher	Brad	Pitt
185474 11	8.8	Robert Zemeckis	Tom H	anks
180922 17	8.7	Milos Forman	Jack Nicho	lson

918088				
20	8.6	Sudha Kongara	Suriy	a
54995				
• •				
000	7.6	Corgio Loono	Dod Ctoigo	r
990 30144	7.0	Sergio Leone	Rod Steige	
993	7.6	Michelangelo Antonioni	David Hemming	ς
56513	, 10	The cange to Amedia on a	Davia Hemming	J
996	7.6	George Stevens	Elizabeth Taylo	r
34075				
997	7.6	Fred Zinnemann	Burt Lancaste	r
43374	7.0	A1.6	Tallulah Dauluhaa	ال ا
998 26471	7.6	Altred Hitchcock	Tallulah Bankhea	a
204/1				
	Gross	Metascore		
0 2834	11469.0	80.0		
9 3703	30102.0	66.0		
	52182.0	82.0		
	0.0000	83.0		
20 55683	32648.0	NaN		
990 69	96690.0	77.0		
	32802.0	82.0		
	17415.0	84.0		
	0.0000	85.0		
998 85214	12728.0	78.0		
[200	10	1		
[289 rows	X 10 CO	_	Released Year Ru	ntime
Genre \		Series_litte	neteaseu_rear nu	пстше
688	E.T	. the Extra-Terrestrial	1982	115
Family				
698 Willy	/ Wonka	& the Chocolate Factory	1971	100
Family				
TMDD	Datina	Divoctor	Ctow1 No of Vo	4
Gross \	_Rating	Director	Star1 No_of_Vo	tes
688	7.8	Steven Spielberg Henry	y Thomas 372	490
435110554		steven spicisery nem	, 1110mas 372	130
698	7.8	Mel Stuart Gen	e Wilder 178	731
4000000.0				
Metas				
688 698	91.0 67.0			
090	07.0	Series Title Release	ed Year Runtime	Genre \
321 Das (Cabinet	des Dr. Caligari	—	Fantasy
568		Nosferatu		Fantasy
				-

Gross	<pre>IMDB_Rating Director s \</pre>	Star1 No_of_Votes
321		rner Krauss 57428
568		lax Schreck 88794
	51978.0	iax Sem cer 60754
7731.	31370.0	
321	Metascore NaN	
568	NaN	
	Series Title Released Ye	ear Runtime Genre IMDB Rating
\		
309	The Third Man 19	949 104 Film-Noir 8.1
456	The Maltese Falcon 19	941 100 Film-Noir 8.0
712	Shadow of a Doubt 19	943 108 Film-Noir 7.8
,	onadon or a boast	710 100 11011 11011 710
		carl No_of_Votes Gross
	score	
309	Carol Reed Orson Wel	les 158731 449191.0
97.0		140000 0100000 0
456	John Huston Humphrey Bog	gart 148928 2108060.0
96.0		-h+ F0FFC 1222F2202 0
	Alfred Hitchcock Teresa Wri	ght 59556 123353292.0
94.0	Series Title Relea	ased Year Runtime Genre
TMDR	Rating \	ised_rear Kuittille delite
49	Nating (Psycho	1960 109 Horror
8.5	1 3 y cm	1300 103 1101101
75	Alien	1979 117 Horror
8.4		
271	The Thing	1982 109 Horror
8.1	_	
419	The Exorcist	1973 122 Horror
8.0		
544	Night of the Living Dead	1968 96 Horror
7.9	_, _	
707	The Innocents	1961 100 Horror
7.8	Ca+ 0+	2017 104 Henren
724	Get Out	2017 104 Horror
7.7 844	Halloween	1070 01 Harrar
7.7	пастомеен	1978 91 Horror
876	The Invisible Man	1933 71 Horror
7.7	THE THETSIBLE HAIT	1333 /1 1101101
932	Saw	2004 103 Horror
7.6		

948 7.6	The 01	thers	2001	101	Horror	
	Director	Sta	ar1 No_	of_Votes	Gross	
Metaso 49 97.0	core Alfred Hitchcock	Anthony Perk	ins	604211	32000000.0	
75 89.0	Ridley Scott	Sigourney Wear	ver	787806	78900000.0	
271 57.0	John Carpenter	Kurt Russ	ell	371271	13782838.0	
419 81.0	William Friedkin	Ellen Burs	tyn	362393	232906145.0	
544 89.0	George A. Romero	Duane Joi	nes	116557	89029.0	
707 88.0	Jack Clayton	Deborah Ko	err	27007	2616000.0	
724 85.0	Jordan Peele	Daniel Kalu	uya	492851	176040665.0	
844 87.0	John Carpenter	Donald Please	nce	233106	47000000.0	
876 87.0	James Whale	Claude Ra	ins	30683	298791505.0	
932 46.0	James Wan	Cary Elv	wes	379020	56000369.0	
	Alejandro Amenábar	Nicole Kid	man	337651	96522687.0	
69 81 119 145 220 393 420	Series_Title Re Memento Rear Window Vertigo Shutter Island Kahaani Twelve Monkeys Sleuth The Lady Vanishes Spoorloos El cuerpo Dark City Lost Highway	eleased_Year 2000 1954 1958 2010 2012 1995 1972 1938 1988 2012 1998 1997	Runtime 113 112 128 138 122 129 138 96 107 112 100 134	Mystery Mystery	- 8.4 8.4 8.3 8.2 8.1 8.0 7.8 7.7 7.6 7.6	
Gross	Directo	r		Star1 N	o_of_Votes	
69 255448	Christopher Nolar	า	Guy P	earce	1125712	
81 367643	Alfred Hitchcock	Κ .	James St	ewart	444074	
119 320000	Alfred Hitchcock	Κ .	James St	ewart	364368	
145	Martin Scorses	e Leona	ardo DiC	aprio	1129894	

128012934.0 220 Sujoy Ghosh Vidya Balan 57806 1035953.0 393 Terry Gilliam Bruce Willis 578443 57141459.0 420 Joseph L. Mankiewicz Laurence Olivier 44748 4081254.0 714 Alfred Hitchcock Margaret Lockwood 47400 474203697.0 829 George Sluizer Bernard-Pierre Donnadieu 33982 367916835.0 899 Oriol Paulo Jose Coronado 57549 140340673.0 959 Alex Proyas Rufus Sewell 187927 14378331.0 961 David Lynch Bill Pullman 131101 3796699.0 Metascore 69 80.0 81 100.0 119 100.0 145 63.0 220 NaN 393 74.0 420 NaN 714 98.0 829 NaN 959 66.0 961 52.0 Series_Title Released_Year Runtime Genre IMDB_Rating \ 700 Wait Until Dark 1967 108 Thriller 7.8 Director Starl No_of_Votes Gross Metascore 700 Terence Young Audrey Hepburn 27733 17550741.0 81.0 Series_Title Released_Year Runtime Genre \ 12 Il buono, il brutto, il cattivo 1966 161 Western 48 Once Upon a Time in the West 1968 165 Western 115 Per qualche dollaro in più 1965 132 Western 691 The Outlaw Josey Wales 1976 135 Western						
1035953.0 393				5.3	5700	
393	-	Sujoy Ghosh	\	/idya Balan	5/80	06
420 Joseph L. Mankiewicz Laurence Olivier 44748 4081254.0 714 Alfred Hitchcock Margaret Lockwood 47400 474203697.0 829 George Sluizer Bernard-Pierre Donnadieu 33982 367916835.0 899 Oriol Paulo Jose Coronado 57549 140340673.0 959 Alex Proyas Rufus Sewell 187927 14378331.0 961 David Lynch Bill Pullman 131101 3796699.0 Metascore 69 80.0 81 100.0 119 100.0 145 63.0 220 NaN 393 74.0 420 NaN 393 74.0 420 NaN 794 98.0 829 NaN 899 Series Title Released Year Runtime Genre IMDB_Rating \ Town Wait Until Dark 1967 108 Thriller 7.8 Director Starl No_of_Votes Gross Metascore 700 Terence Young Audrey Hepburn 27733 17550741.0 81.0 Series_Title Released_Year Runtime Genre \ 12 Il buono, il brutto, il cattivo 1966 161 Western 48 Once Upon a Time in the West 1968 165 Western 115 Per qualche dollaro in più 1965 132 Western 691 The Outlaw Josey Wales 1976 135 Western	393	Terry Gilliam	Ві	ruce Willis	57844	.3
714 Alfred Hitchcock Margaret Lockwood 47400 474203697.0 829 George Sluizer Bernard-Pierre Donnadieu 33982 367916835.0 899 Oriol Paulo Jose Coronado 57549 140340673.0 959 Alex Proyas Rufus Sewell 187927 14378331.0 961 David Lynch Bill Pullman 131101 3796699.0 Metascore 69 80.0 81 100.0 119 100.0 145 63.0 220 NaN 393 74.0 420 NaN 714 98.0 829 NaN 899 NaN 899 NaN 899 NaN 899 Series_Title Released_Year Runtime Genre IMDB_Rating \ 700 Wait Until Dark 1967 108 Thriller 7.8 Director Starl No_of_Votes Gross Metascore 700 Terence Young Audrey Hepburn 27733 17550741.0 81.0 Series_Title Released_Year Runtime Genre III buono, il brutto, il cattivo 1966 161 Western 48 Once Upon a Time in the West 1968 165 Western 115 Per qualche dollaro in più 1965 132 Western 691 The Outlaw Josey Wales 1976 135 Western	420 Joseph	L. Mankiewicz	Laurer	nce Olivier	4474	.8
829	714 Al1	fred Hitchcock	Margare	et Lockwood	4740	0
899	829 (George Sluizer	Bernard-Pierre	e Donnadieu	3398	2
959	899	Oriol Paulo	Jos	se Coronado	5754	.9
961		Alex Proyas	Rı	ufus Sewell	18792	.7
Metascore 69		David Lynch	D-	ill Dullman	12110	1
69 80.0 81 100.0 119 100.0 145 63.0 220 NaN 393 74.0 420 NaN 714 98.0 829 NaN 899 NaN 899 NaN 959 66.0 961 52.0 Series_Title Released_Year Runtime Genre IMDB_Rating \ 700 Wait Until Dark 1967 108 Thriller 7.8 Director Starl No_of_Votes Gross Metascore 700 Terence Young Audrey Hepburn 27733 17550741.0 81.0 Series_Title Released_Year Runtime Genre \ 12 Il buono, il brutto, il cattivo 1966 161 Western 48 Once Upon a Time in the West 1968 165 Western 115 Per qualche dollaro in più 1965 132 Western 691 The Outlaw Josey Wales 1976 135 Western		David Lynch	0.	ice rucciiian	13110	1
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Series_Title Released_Year Runtime Genre \ 12 Il buono, il brutto, il cattivo	Di	irector	Star1 No_o	f_Votes	Gross Me	tascore
Genre \ 12 Il buono, il brutto, il cattivo 1966 161 Western 48 Once Upon a Time in the West 1968 165 Western 115 Per qualche dollaro in più 1965 132 Western 691 The Outlaw Josey Wales 1976 135 Western	700 Terence	Young Audrey	/ Hepburn	27733 1755	0741.0	81.0
12 Il buono, il brutto, il cattivo 1966 161 Western 48 Once Upon a Time in the West 1968 165 Western 115 Per qualche dollaro in più 1965 132 Western 691 The Outlaw Josey Wales 1976 135 Western		Se	eries_Title Rele	eased_Year R	untime	
Per qualche dollaro in più 1965 132 Western The Outlaw Josey Wales 1976 135 Western	-	no, il brutto,	il cattivo	1966	161 We	stern
691 The Outlaw Josey Wales 1976 135 Western	48 Once	upon a Time i	n the West	1968	165 We	stern
·	115 Pe	er qualche doll	aro in più	1965	132 We	stern
IMDB_Rating Director Star1 No_of_Votes	691	The Outlaw J	losey Wales	1976	135 We	stern
	IMDB_Ra	ating Di	rector	Starl No_	of_Votes	

Gross \				
12	8.8	Sergio Leone	Clint Eastwood	688390
6100000.0				
48	8.5	Sergio Leone	Henry Fonda	302844
5321508.0				
115	8.3	Sergio Leone	Clint Eastwood	232772
15000000.0				
691	7.8	Clint Eastwood	Clint Eastwood	65659
31800000.0				
Metaso	core			
12	90.0			
	30.0			
115	74.0			
691	59.0			

C:\Users\jayra\AppData\Local\Temp\ipykernel_23732\2904676014.py:1: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to silence this warning.

genres.apply(foo)

												Se	rie	s Ti	tle
Released_ Genre	_Year	\												_	
Action 2008	2										The	e D	ark	Kni	ght
2000	5		The I	_ord	lof	the	Rings	:	The	Re	turr	1 0	f t	he K	ing
2003	8												In	cept	ion
2010															
2001	10	The	Lord	of	the	Ring	gs: The	Э	Fel	low	ship	0	f t	he R	ing
2001	13				The	Lord	d of th	ne	Ri	ngs	: Th	ne	Two	Tow	ers
2002															
 Thriller	700										Wai	+	llnt	il Da	ark
1967	700										···aı		011 C	100	31 K
Western	12					IJ	buond	Э,	il	br	utto),	il	catt	ivo
1966	40						0			_	- ·			l 1.1	
1968	48						0nce	U	pon	а	IIME	2 1	n t	ne w	est
1300	115						Pei	r	qua	lch	e do	าไ	aro	in	oiù
1965															
	691								The	0u	tlaw	v J	ose	y Wa	les

```
1976
               Runtime
                            Genre
                                   IMDB Rating
                                                           Director \
Genre
                                                  Christopher Nolan
         2
Action
                   152
                           Action
                                            9.0
         5
                   201
                           Action
                                            8.9
                                                      Peter Jackson
         8
                   148
                           Action
                                            8.8
                                                  Christopher Nolan
         10
                   178
                           Action
                                            8.8
                                                      Peter Jackson
                                                      Peter Jackson
         13
                   179
                                            8.7
                           Action
Thriller 700
                   108
                        Thriller
                                            7.8
                                                      Terence Young
Western
         12
                          Western
                                            8.8
                   161
                                                       Sergio Leone
         48
                   165
                          Western
                                            8.5
                                                       Sergio Leone
         115
                   132
                          Western
                                            8.3
                                                       Sergio Leone
         691
                   135
                          Western
                                            7.8
                                                     Clint Eastwood
                            Starl No of Votes
                                                        Gross Metascore
Genre
Action
         2
                  Christian Bale
                                        2303232
                                                  534858444.0
                                                                     84.0
         5
                                                                     94.0
                     Elijah Wood
                                        1642758
                                                 377845905.0
         8
                                                                     74.0
               Leonardo DiCaprio
                                        2067042
                                                  292576195.0
                                        1661481
         10
                     Elijah Wood
                                                                     92.0
                                                  315544750.0
         13
                     Elijah Wood
                                        1485555
                                                  342551365.0
                                                                     87.0
                  Audrey Hepburn
Thriller 700
                                                   17550741.0
                                          27733
                                                                     81.0
                  Clint Eastwood
Western
         12
                                         688390
                                                    6100000.0
                                                                     90.0
                                                                     80.0
         48
                     Henry Fonda
                                         302844
                                                    5321508.0
                  Clint Eastwood
                                                                     74.0
         115
                                         232772
                                                   15000000.0
         691
                  Clint Eastwood
                                          65659
                                                   31800000.0
                                                                     69.0
[1000 \text{ rows } \times 10 \text{ columns}]
def foo(group):
    print(group['Series_Title'].str.startswith('A')) # ek boolean
series milega
    return group
genres.apply(foo)
2
       False
5
       False
8
       False
10
       False
13
       False
968
       False
979
       False
982
       False
983
       False
985
       False
```

```
Name: Series_Title, Length: 172, dtype: bool
21
       False
47
       False
93
       False
110
       False
114
       False
       . . .
957
       False
964
       False
966
        True
984
       False
       False
991
Name: Series Title, Length: 72, dtype: bool
23
       False
43
       False
46
       False
56
       False
58
       False
956
       False
971
       False
976
       False
986
       False
       False
992
Name: Series_Title, Length: 82, dtype: bool
       False
7
15
       False
18
       False
35
       False
38
       False
923
       False
940
       False
949
       False
       False
952
987
       False
Name: Series Title, Length: 88, dtype: bool
19
       False
26
       False
51
       False
52
       False
64
       False
977
       False
978
       False
989
       False
994
        True
995
       False
Name: Series Title, Length: 155, dtype: bool
```

```
1
       False
3
       False
4
       False
6
       False
22
       False
       . . .
958
       False
960
       False
974
       False
980
       False
999
       False
Name: Series_Title, Length: 107, dtype: bool
       False
0
9
       False
11
       False
17
       False
20
       False
       . . .
990
       False
993
       False
996
       False
997
       False
998
       False
Name: Series_Title, Length: 289, dtype: bool
688
       False
698
       False
Name: Series_Title, dtype: bool
321
       False
568
       False
Name: Series_Title, dtype: bool
309
       False
456
       False
       False
712
Name: Series Title, dtype: bool
       False
49
75
        True
271
       False
419
       False
544
       False
707
       False
724
       False
844
       False
876
       False
932
       False
948
       False
Name: Series_Title, dtype: bool
69
       False
81
       False
119
       False
```

```
145
       False
       False
220
393
       False
420
       False
714
       False
829
       False
899
       False
959
       False
961
       False
Name: Series Title, dtype: bool
700
       False
Name: Series Title, dtype: bool
12
       False
48
       False
115
       False
691
       False
Name: Series Title, dtype: bool
C:\Users\jayra\AppData\Local\Temp\ipykernel 23732\2904676014.py:1:
DeprecationWarning: DataFrameGroupBy.apply operated on the grouping
columns. This behavior is deprecated, and in a future version of
pandas the grouping columns will be excluded from the operation.
Either pass `include_groups=False` to exclude the groupings or
explicitly select the grouping columns after groupby to silence this
warning.
  genres.apply(foo)
                                                    Series Title
Released Year \
Genre
Action
         2
                                                 The Dark Knight
2008
         5
                  The Lord of the Rings: The Return of the King
2003
         8
                                                       Inception
2010
              The Lord of the Rings: The Fellowship of the Ring
         10
2001
```

The Lord of the Rings: The Two Towers

Il buono, il brutto, il cattivo

Once Upon a Time in the West

Per qualche dollaro in più

Wait Until Dark

13

48

115

2002

1967

1966

1968

Thriller 700

Western 12

1965	601			-	0 11 1		
1976	691			The	Outlaw Josey	Wales	
		Runtime	Genre	IMDB Rating	Dir	ector \	
Genre		Runcinc	deme	THOB_Nating	DII	(
Action	2 5 8 10 13	152 201 148 178 179	Action Action Action Action Action	9.0 8.9 8.8 8.8	Christopher Peter Ja Christopher Peter Ja Peter Ja	ckson Nolan ckson	
 Thriller	700	108	 Thriller	7.8	Terence	Young	
Western	12 48 115 691	161 165 132 135	Western Western Western Western	8.8 8.5 8.3 7.8	Sergio Sergio Sergio Clint Eas	Leone Leone Leone	
			Star1	No_of_Votes	Gross	Metascore	
Genre Action	2 5 8 10 13	El: Leonardo El:	tian Bale ijah Wood DiCaprio ijah Wood ijah Wood	2303232 1642758 2067042 1661481 1485555	534858444.0 377845905.0 292576195.0 315544750.0 342551365.0	84.0 94.0 74.0 92.0 87.0	
Thriller Western	700 12 48 115 691	Clint He Clint	y Hepburn Eastwood rry Fonda Eastwood Eastwood	27733 688390 302844 232772 65659	17550741.0 6100000.0 5321508.0 15000000.0 31800000.0	81.0 90.0 80.0 74.0 69.0	
[1000 rov	ws x	10 column:	s]				
<pre>def foo(group): return (group['Series_Title'].str.startswith('A')).sum() # ek boolean series milega</pre>							
genres.apply(foo)							
C:\Users\jayra\AppData\Local\Temp\ipykernel_23732\2904676014.py:1: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to silence this warning. genres.apply(foo)							

```
Genre
             10
Action
Adventure
              2
              2
Animation
Biography
              9
Comedy
             14
Crime
              4
Drama
             21
Family
              0
Fantasy
              0
Film-Noir
              0
Horror
              1
Mystery
              0
Thriller
              0
Western
              0
dtype: int64
# find ranking of each movie in the group according to IMDB score
def rank movie(group):
    group['genre rank']= group['IMDB Rating'].rank(ascending=False)
    return group
genres.apply(rank movie)
C:\Users\jayra\AppData\Local\Temp\ipykernel 23732\2409710219.py:1:
DeprecationWarning: DataFrameGroupBy.apply operated on the grouping
columns. This behavior is deprecated, and in a future version of
pandas the grouping columns will be excluded from the operation.
Either pass `include_groups=False` to exclude the groupings or
explicitly select the grouping columns after groupby to silence this
warning.
  genres.apply(rank movie)
                                                    Series Title
Released Year \
Genre
Action
                                                 The Dark Knight
         2
2008
         5
                  The Lord of the Rings: The Return of the King
2003
         8
                                                       Inception
2010
              The Lord of the Rings: The Fellowship of the Ring
         10
2001
                          The Lord of the Rings: The Two Towers
         13
2002
Thriller 700
                                                 Wait Until Dark
```

1967 Western	12			Il buono, il	brutto, il cattivo	o
1966	48			Once Upon	a Time in the Wes	t
1968	115			Per qua	lche dollaro in pi	ù
1965	691			The	Outlaw Josey Wales	5
1976						
Genre		Runtime	Genre	<pre>IMDB_Rating</pre>	Directo	r \
Action	2 5 8 10 13	152 201 148 178 179	Action Action Action Action Action	9.0 8.9 8.8 8.7	Christopher Nolar Peter Jackson Christopher Nolar Peter Jackson Peter Jackson	า า า
Thriller Western	700 12 48 115 691	161 165 132	hriller Western Western Western Western	7.8 8.8 8.5 8.3 7.8	Terence Young Sergio Leong Sergio Leong Sergio Leong Clint Eastwood	e e e
Metascore Genre	e \		Star1	No_of_Votes	Gross	
Action	2	Christi	an Bale	2303232	534858444.0	84.0
	5	Elij	ah Wood	1642758	377845905.0	94.0
	8	Leonardo D	iCaprio	2067042	292576195.0	74.0
	10	Elij	ah Wood	1661481	315544750.0	92.0
	13	Elij	ah Wood	1485555	342551365.0	87.0
Thriller	700	Audrey	Hepburn	27733	17550741.0	81.0
Western	12	Clint E	astwood	688390	6100000.0	90.0
	48	Henr	y Fonda	302844	5321508.0	80.0
	115	Clint E	astwood	232772	15000000.0	74.0
	691	Clint E	astwood	65659	31800000.0	69.0

```
genre rank
Genre
Action
          2
                         1.0
          5
                         2.0
          8
                         3.5
          10
                         3.5
          13
                         6.0
Thriller 700
                         1.0
Western
          12
                         1.0
          48
                         2.0
          115
                         3.0
          691
                         4.0
[1000 \text{ rows } \times 11 \text{ columns}]
# find normalized IMDB rating group wise
```

```
X normalized = (X – X minimum)

(X maximum – X minimum)
```

```
def normal(group):
    group['norm_rating'] = (group['IMDB_Rating'] -
group['IMDB_Rating'].min())/(group['IMDB_Rating'].max() -
group['IMDB_Rating'].min())
    return group

genres.apply(normal)

C:\Users\jayra\AppData\Local\Temp\ipykernel_23732\2582220829.py:5:
DeprecationWarning: DataFrameGroupBy.apply operated on the grouping
columns. This behavior is deprecated, and in a future version of
pandas the grouping columns will be excluded from the operation.
Either pass `include_groups=False` to exclude the groupings or
explicitly select the grouping columns after groupby to silence this
```

```
warning.
  genres.apply(normal)
                                                     Series Title
Released Year \
Genre
Action
         2
                                                  The Dark Knight
2008
         5
                  The Lord of the Rings: The Return of the King
2003
         8
                                                        Inception
2010
         10
              The Lord of the Rings: The Fellowship of the Ring
2001
         13
                           The Lord of the Rings: The Two Towers
2002
. . .
Thriller 700
                                                  Wait Until Dark
1967
Western
         12
                                 Il buono, il brutto, il cattivo
1966
         48
                                    Once Upon a Time in the West
1968
         115
                                      Per qualche dollaro in più
1965
         691
                                           The Outlaw Josey Wales
1976
              Runtime
                           Genre
                                  IMDB Rating
                                                         Director \
Genre
Action
         2
                   152
                          Action
                                           9.0
                                                Christopher Nolan
         5
                                                    Peter Jackson
                   201
                          Action
                                           8.9
         8
                   148
                          Action
                                           8.8
                                                Christopher Nolan
                   178
                                                    Peter Jackson
         10
                          Action
                                           8.8
                                                    Peter Jackson
         13
                   179
                          Action
                                           8.7
Thriller 700
                        Thriller
                                           7.8
                                                    Terence Young
                   108
Western
         12
                   161
                         Western
                                           8.8
                                                     Sergio Leone
         48
                   165
                         Western
                                           8.5
                                                     Sergio Leone
         115
                   132
                         Western
                                           8.3
                                                     Sergio Leone
         691
                   135
                                           7.8
                                                   Clint Eastwood
                         Western
                           Starl No of Votes
                                                      Gross
Metascore \
Genre
                 Christian Bale
                                      2303232 534858444.0
                                                                   84.0
Action 2
```

	5	Elijah Wood	1642758	377845905.0	94.0
	8 Led	onardo DiCaprio	2067042	292576195.0	74.0
	10	Elijah Wood	1661481	315544750.0	92.0
	13	Elijah Wood	1485555	342551365.0	87.0
Thriller	700	Audrey Hepburn	27733	17550741.0	81.0
Western	12	Clint Eastwood	688390	6100000.0	90.0
	48	Henry Fonda	302844	5321508.0	80.0
	115	Clint Eastwood	232772	15000000.0	74.0
	691	Clint Eastwood	65659	31800000.0	69.0
	no	rm rating			
Genre		_			
Action	2	1.000000			
	5 8	0.928571 0.857143			
	10	0.857143			
	13	0.785714			
 Thriller	700	 NaN			
Western	12	1.000000			
	48	0.700000			
	115 691	0.500000 0.000000			
	091	0.00000			
[1000 rov	ws x 11 o	columns]			
		tiple cols			
duo = mov	vies.grou	upby(['Director','S	tar1'])		
<pre><pandas.c 0x00000023<="" pre=""></pandas.c></pre>		upby.generic.DataFr 10>	ameGroupBy	object at	
#size					
duo.size	()				
Director		Star1			
Aamir Kha		Amole Gupte	1		
Aaron Soi		Eddie Redmayne che Léa Seydoux	1 1		
Abac c ca c	LI KCCIII	che Lea Seydoux	±		

```
Shahid Kapoor
Abhishek Chaubey
                                       1
Abhishek Kapoor
                     Amit Sadh
                                       1
Zaza Urushadze
                     Lembit Ulfsak
                                       1
Zoya Akhtar
                     Hrithik Roshan
                                       1
                     Vijay Varma
                                       1
                     Cetin Tekindor
                                       1
Cagan Irmak
Ömer Faruk Sorak
                     Cem Yilmaz
                                       1
Length: 898, dtype: int64
#get group
duo.get group(('Aamir Khan','Amole Gupte'))
        Series Title Released Year Runtime
                                             Genre IMDB Rating
Director \
65 Taare Zameen Par
                              2007
                                        165
                                             Drama
                                                            8.4 Aamir
Khan
                                  Gross
          Star1
                 No of Votes
                                         Metascore
  Amole Gupte
                      168895
                              1223869.0
                                               NaN
# # find the most earning actor->director combo
duo['Gross'].sum() # abhi sare actor director ka earning ek sath aa
jayega
Director
                     Star1
                     Amole Gupte
Aamir Khan
                                         1223869.0
Aaron Sorkin
                     Eddie Redmayne
                                       853090410.0
Abdellatif Kechiche Léa Seydoux
                                         2199675.0
Abhishek Chaubey
                     Shahid Kapoor
                                       218428303.0
                     Amit Sadh
Abhishek Kapoor
                                         1122527.0
                                          . . .
                     Lembit Ulfsak
Zaza Urushadze
                                          144501.0
Zoya Akhtar
                     Hrithik Roshan
                                         3108485.0
                     Vijay Varma
                                         5566534.0
                     Cetin Tekindor
Cagan Irmak
                                       461855363.0
Ömer Faruk Sorak
                     Cem Yilmaz
                                       196206077.0
Name: Gross, Length: 898, dtype: float64
duo['Gross'].sum().sort values(ascending=True)
Director
                      Star1
Anders Thomas Jensen
                      Ulrich Thomsen
                                         1.305000e+03
Thomas Jahn
                      Til Schweiger
                                         3.296000e+03
Jaco Van Dormael
                      Jared Leto
                                         3.600000e+03
Shane Meadows
                      Paddy Considine
                                         6.013000e+03
                      Won Bin
Jeong-beom Lee
                                         6.460000e+03
Werner Herzog
                      Klaus Kinski
                                         1.124605e+09
Christopher Nolan
                      Christian Bale
                                         1.242940e+09
Billy Wilder
                      William Holden
                                         1.286779e+09
```

```
Joe Russo
                                         2.205039e+09
Anthony Russo
                      Toshirô Mifune
Akira Kurosawa
                                         2.999877e+09
Name: Gross, Length: 898, dtype: float64
duo['Gross'].sum().sort values(ascending=True).head(1)
Director
                      Star1
Anders Thomas Jensen Ulrich Thomsen 1305.0
Name: Gross, dtype: float64
# find the best(in-terms of metascore(avg)) actor -> genre combo
movies.groupby(['Star1','Genre'])['Metascore'].mean()
Star1
                      Genre
Aamir Khan
                      Action
                                    NaN
                      Adventure
                                   84.0
                      Comedy
                                   67.0
Aaron Taylor-Johnson
                      Action
                                   66.0
Abhay Deol
                                    NaN
                      Drama
Zbigniew Zamachowski Comedy
                                   88.0
Zooey Deschanel
                      Comedy
                                   76.0
Çetin Tekindor
                      Drama
                                    NaN
Éric Toledano
                      Biography
                                   57.0
Ömer Faruk Sorak
                      Comedy
                                    NaN
Name: Metascore, Length: 829, dtype: float64
movies.groupby(['Star1','Genre'])['Metascore'].mean().reset index()
reset index karne se dataframe ban jayega
                    Star1
                               Genre
                                      Metascore
0
               Aamir Khan
                              Action
                                            NaN
1
               Aamir Khan Adventure
                                            84.0
                                            67.0
2
               Aamir Khan
                              Comedy
3
     Aaron Taylor-Johnson
                              Action
                                            66.0
4
               Abhay Deol
                               Drama
                                            NaN
824
     Zbigniew Zamachowski
                                            88.0
                              Comedy
825
          Zooey Deschanel
                              Comedy
                                            76.0
826
           Cetin Tekindor
                               Drama
                                            NaN
            Éric Toledano Biography
827
                                            57.0
         Ömer Faruk Sorak
828
                              Comedy
                                            NaN
[829 rows x 3 columns]
movies.groupby(['Star1','Genre'])
['Metascore'].mean().reset index().sort values('Metascore',ascending=F
alse).head(1)
              Star1
                     Genre Metascore
230 Ellar Coltrane
                     Drama
                                100.0
```

agg on multiple groupby duo[['Runtime','IMDB_Rating','No_of_Votes','Gross','Metascore']].agg(['min','max','mean']) Runtime IMDB Rating / min max mean min max mean Star1 Director Amole Gupte 165.0 8.4 Aamir Khan 165 165 8.4 8.4 Aaron Sorkin Eddie Redmayne 129 129 129.0 7.8 7.8 7.8 Abdellatif Kechiche Léa Seydoux 180 180 180.0 7.7 7.7 7.7 7.8 Abhishek Chaubey Shahid Kapoor 148 148 148.0 7.8 7.8 Amit Sadh 7.7 Abhishek Kapoor 130 130 130.0 7.7 7.7 Lembit Ulfsak Zaza Urushadze 87 87 87.0 8.2 8.2 8.2 Zoya Akhtar Hrithik Roshan 155 155 155.0 8.1 8.1 8.1 8.0 Vijay Varma 154 154 154.0 8.0 8.0 8.3 Cagan Irmak Çetin Tekindor 112 112 112.0 8.3 8.3 Ömer Faruk Sorak Cem Yilmaz 127 127 127.0 8.0 8.0 8.0 No of Votes Gross \ min max mean min Star1 Director Aamir Khan Amole Gupte 168895 168895 168895.0 1223869.0 Aaron Sorkin Eddie Redmayne 89896 89896 89896.0 853090410.0 Abdellatif Kechiche Léa Seydoux 138741 138741.0 138741 2199675.0 Abhishek Chaubey Shahid Kapoor 27175 27175 27175.0 218428303.0 Abhishek Kapoor Amit Sadh 32628 32628 32628.0 1122527.0

Zaza Urushadze 144501.0	Lembit Ulfsak	40382	40382	40382.0	
Zoya Akhtar 3108485.0	Hrithik Roshan	67927	67927	67927.0	
	Vijay Varma	31886	31886	31886.0	
5566534.0 Çagan Irmak 461855363.0	Çetin Tekindor	78925	78925	78925.0	
Ömer Faruk Sorak 196206077.0	Cem Yilmaz	56960	56960	56960.0	
				Meta	ascore
\		max		mean	min
max		iliux	!	ilicari	111,211
Director	Star1				
Aamir Khan NaN	Amole Gupte	1223869.0	12238	69.0	NaN
Aaron Sorkin 77.0	Eddie Redmayne	853090410.0	8530904	10.0	77.0
Abdellatif Kechiche 89.0	Léa Seydoux	2199675.0	21996	75.0	89.0
Abhishek Chaubey NaN	Shahid Kapoor	218428303.0	2184283	03.0	NaN
Abhishek Kapoor 40.0	Amit Sadh	1122527.0	11225	27.0	40.0
Zaza Urushadze	Lembit Ulfsak	144501.0	1445	01.0	73.0
73.0 Zoya Akhtar	Hrithik Roshan	3108485.0	31084	85.0	NaN
NaN	Vijay Varma	5566534.0	55665	34.0	65.0
65.0 Çagan Irmak NaN	Çetin Tekindor	461855363.0	4618553	63.0	NaN
Ömer Faruk Sorak NaN	Cem Yilmaz	196206077.0	1962060	77.0	NaN
		mean			
Director Aamir Khan	Star1 Amole Gupte	NaN			
Aaron Sorkin	Eddie Redmayne	77.0			
Abdellatif Kechiche Abhishek Chaubey	Léa Seydoux Shahid Kapoor	89.0 NaN			
Abhishek Kapoor	Amit Sadh	40.0			

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Zaza Urushadze Lembit Ulfsak 73.0
Zoya Akhtar Hrithik Roshan NaN
Vijay Varma 65.0
Cagan Irmak Çetin Tekindor NaN
Ömer Faruk Sorak Cem Yilmaz NaN
[898 rows x 15 columns]
```

EXERCISE

```
ipl = pd.read_csv('deliveries.csv')
ipl
        match id inning
                                  batting team
bowling team \
               1
                           Sunrisers Hyderabad
                                                 Royal Challengers
Bangalore
                           Sunrisers Hyderabad
                                                 Royal Challengers
               1
Bangalore
               1
                           Sunrisers Hyderabad
                                                 Royal Challengers
Bangalore
                           Sunrisers Hyderabad
                                                 Royal Challengers
               1
Bangalore
                                                 Royal Challengers
                           Sunrisers Hyderabad
Bangalore
. . .
           11415
                           Chennai Super Kings
                                                               Mumbai
179073
Indians
                           Chennai Super Kings
                                                               Mumbai
179074
           11415
Indians
179075
           11415
                           Chennai Super Kings
                                                               Mumbai
Indians
179076
           11415
                           Chennai Super Kings
                                                               Mumbai
Indians
179077
           11415
                           Chennai Super Kings
                                                               Mumbai
Indians
                       batsman non striker
                                                 bowler
              ball
        over
is_super_over
                    DA Warner
                                  S Dhawan
                                               TS Mills
0
                 1
0
1
                 2
                    DA Warner
                                  S Dhawan
                                               TS Mills
           1
0
   . . .
2
                 3
                    DA Warner
                                  S Dhawan
                                               TS Mills
0
3
                 4
                    DA Warner
                                  S Dhawan
                                               TS Mills
0
4
                    DA Warner
                                  S Dhawan
                                               TS Mills
           1
                 5
```

0						
		•				
179073 0	20	2 RA	Jadeja	SR Watson	SL Malinga	
179074	20	3 SR	Watson	RA Jadeja	SL Malinga	
0 179075 0	20	4 SR	Watson	RA Jadeja	SL Malinga	
179076	20	5 SN	Thakur	RA Jadeja	SL Malinga	
0 179077 0	20	6 SN	Thakur	RA Jadeja	SL Malinga	
	bye_runs	legb	ye_runs	noball_runs	penalty_runs	batsman_runs
0	0		0	0	6	0
1	0		0	0	6	0
2	0		Θ	0	6) 4
3	0		0	0	(0
4	Θ		0	0	6	0
179073	0		0	0) 1
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179075	0		0	0	6	
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179077	0		0	0	0	0
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ipl	.shap	e						
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	match	_id	inning	bat	tting_team		bow	ling_team
ove	r \							
0		1	1	Sunrisers	Hyderabad	Royal Challer	igers	Bangalore
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2		1	1	Sunrisers	нуцегарац	Royal Challer	igers	Bangatore
3		1	1	Sunrisers	Hydorahad	Royal Challer	narc	Rangalore
1			1	Juili 15el 5	ilyuel abau	Royal Challer	iger 5	ballyature
4		1	1	Sunrisers	Hyderabad	Royal Challer	nars	Rangalore
1		_	_	Julii 13Cl 3	Try de l'abad	Royal Charles	igers	Dangatore
_								
	ball	b	atsman no	on_striker	bowler	is_super_over	•	bye_runs
\								_
0	1	DA	Warner	S Dhawan	TS Mills	()	0
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2	3	DΑ	Warner	S Dhawan	15 MILLS	0	,	0
3	4	DΔ	Warner	S Dhawan	TS Mills	()	0
,		אט	warner	5 Dilawan	15 111 (3		,	O .
4	5	DA	Warner	S Dhawan	TS Mills	0)	0
	legby	e_ru	ns noba	ll_runs pe	enalty_runs	batsman_runs	ext	ra_runs \
0			0	0	0	0		0
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2
             0
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3
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4
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                                          0
                player dismissed dismissal kind fielder
   total runs
0
                             NaN
                                             NaN
                                                      NaN
1
            0
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2
            4
                             NaN
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                                                      NaN
3
            0
                             NaN
                                             NaN
                                                      NaN
4
            2
                             NaN
                                             NaN
                                                      NaN
[5 rows x 21 columns]
# find the top 10 batsman in terms of run scored
# har batsman ne jitne ball kheli hai usko grouped kar lo
ipl.groupby('batsman')
<pandas.core.groupby.generic.DataFrameGroupBy object at</pre>
0x0000023AA3FC7AA0>
ipl.groupby('batsman')['batsman_runs'].sum() # har group ke batsman
ka run sum ho jayega abhi index ke according sort hai value ke
according kar lo
batsman
A Ashish Reddy
                    280
A Chandila
                      4
                     53
A Chopra
A Choudhary
                     25
A Dananjaya
                      4
YV Takawale
                    192
Yashpal Singh
                     47
                      3
Younis Khan
Yuvraj Singh
                   2765
Z Khan
                    117
Name: batsman_runs, Length: 516, dtype: int64
ipl.groupby('batsman')
['batsman runs'].sum().sort values(ascending=False)
batsman
V Kohli
                5434
SK Raina
                5415
RG Sharma
                4914
DA Warner
                4741
S Dhawan
                4632
IC Pandey
                   0
J Denly
                   0
```

```
P Raj
                  0
Sunny Gupta
                  0
L Ablish
Name: batsman runs, Length: 516, dtype: int64
ipl.groupby('batsman')
['batsman runs'].sum().sort values(ascending=False).head(10)
batsman
                  5434
V Kohli
SK Raina
                  5415
RG Sharma
                  4914
DA Warner
                  4741
S Dhawan
                  4632
CH Gayle
                  4560
MS Dhoni
                  4477
RV Uthappa
                  4446
AB de Villiers
                  4428
G Gambhir
                  4223
Name: batsman runs, dtype: int64
# find the batsman with max no of sixes
ipl['batsman runs'] == 6 # ek boolean series mil jayega
0
          False
1
          False
2
          False
3
          False
4
          False
179073
          False
179074
          False
179075
          False
179076
          False
179077
          False
Name: batsman_runs, Length: 179078, dtype: bool
six = ipl[ipl['batsman runs'] == 6]
                                        # sare ball ka details mil
six
jayega jaha pe ki six laga hai
        match id inning
                                 batting team
bowling_team
               1
                          Sunrisers Hyderabad Royal Challengers
10
Bangalore
47
               1
                          Sunrisers Hyderabad Royal Challengers
Bangalore
75
               1
                          Sunrisers Hyderabad Royal Challengers
Bangalore
89
                       1 Sunrisers Hyderabad Royal Challengers
               1
Bangalore
```

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91 Bangalor	1		1	Sunrise	rs Hyae	erabad	Royal	Challer	igers
ballyatul	C								
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178987	11415		2	Chennai	Super	Kinas			Mumbai
Indians						J -			
179048	11415		2	Chennai	Super	Kings			Mumbai
Indians									
179061	11415		2	Chennai	Super	Kings			Mumbai
Indians	11415		_	CI '	•	17.			NA 1 :
179062	11415		2	Chennai	Super	Kings			Mumbai
Indians 179063	11415		2	Chennai	Supor	Kinac			Mumbai
Indians	11413		2	Cileilliai	Super	KIIIYS			riulibat
Illutalis									
	over ba	11	k	oatsman	non s	striker		bowler	
is_super	_over \				_				
10	_ 2	4	DA	Warner	S	Dhawan	A Ch	oudhary	
0									
47	8	4 MC	Her	nriques	S	Dhawan		TM Head	
0	10	2 1/		C	MC II.	•	A CI-		
75 0	13	2 Yu	vraj	Singh	MC Her	nriques	A Ch	oudhary	
89	15	3 Yu	vrai	Singh	MC Har	nriques	ς	Aravind	
0	13	<i>3</i> 10	viaj	Jiligii	ric rici	II Iques	3	Alavilla	
91	15	5 MC	Her	riques	Yuvra	j Singh	S	Aravind	
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178987	6	4	SR	Watson	Sł	<pre>K Raina</pre>	SL	Malinga	
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179048 0	16	1	D.	J Bravo	SK	Watson	SL	Malinga	
179061	18	2	SR	Watson	D.	J Bravo	KH	Pandya	
0	10	۷	511	Wacson	D.	Diavo	IXI	Tanaya	
179062	18	3	SR	Watson	D.	J Bravo	KH	Pandya	
0								,	
179063	18	4	SR	Watson	D.	J Bravo	KH	Pandya	
Θ									
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6					-		-		
75		0			9	(0		0
6									
89		0			9		0		0

6					
91		0	0	0	0
6					
178987		0	0	0	Θ
6					
179048		0	0	0	0
6					
179061		0	0	0	0
6					
179062		0	0	0	0
6					
179063		0	0	0	0
6					
	ovtra runc	total runs	nlaver	diemiesed	diemiceal kind
fielder	extra_runs	total_runs	prayer	_arsiiirssea	dismissal_kind
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75	0	6		NaN	NaN
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89	0	6		NaN	NaN
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91	0	6		NaN	NaN
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178987	0	6		NaN	NaN
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179048	0	6		NaN	NaN
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179061	0	6		NaN	NaN
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179062	0	6		NaN	NaN
NaN					
179063	0	6		NaN	NaN
NaN					

[8170 rows x 21 columns]

six.groupby('batsman')# batsman ke basis pe group kar diye and abb
kisi bhi column ko extract karo suppose batsman colum ko hi pakarte
hain

<pandas.core.groupby.generic.DataFrameGroupBy object at $0 \times 0000023AA3B3BBC0>$

```
six.groupby('batsman')['batsman'] # abb iski count nikal lo
<pandas.core.groupby.generic.SeriesGroupBy object at</pre>
0x0000023A9CFF9B80>
six.groupby('batsman')['batsman'].count() # abb sort kar lo
batsman
A Ashish Reddy
                    15
A Choudhary
                     1
A Flintoff
                     2
A Hales
                     6
                     5
A Mishra
Y Venugopal Rao
                    37
YK Pathan
                   161
YV Takawale
                     3
Yuvraj Singh
                   149
                     2
Z Khan
Name: batsman, Length: 336, dtype: int64
six.groupby('batsman')['batsman'].count().sort values(ascending=False)
batsman
CH Gayle
                  327
AB de Villiers
                  214
MS Dhoni
                  207
SK Raina
                  195
RG Sharma
                  194
CK Langeveldt
                    1
JDS Neesham
                    1
SK Trivedi
                    1
D Shorey
                    1
MN van Wyk
                    1
Name: batsman, Length: 336, dtype: int64
six.groupby('batsman')
['batsman'].count().sort values(ascending=False).head(1)
batsman
CH Gayle
            327
Name: batsman, dtype: int64
# find batsman with most number of 4's and 6's in last 5 overs
# hume unn sare ball ki need hi nahi hai jo ki 1 se 15 over tak feka
qva hai
temp=ipl[ipl['over']>15]
temp
```

	atch_id	ir	nning	k	oatting _.	_team			
bowling_te	1		1	Sunrise	s Hyde	rabad	Royal	. Challe	ngers
Bangalore 94	1		1	Sunrise	rs Hyde	rabad	Royal	. Challe	ngers
Bangalore 95	1		1	Sunrise	rs Hvde	rabad	Roval	. Challe	ngers
Bangalore 96	1			Sunrise	_		_	. Challe	
Bangalore					J		•		
97 Bangalore	1		1	Sunrise	rs Hyde	rabad	Royal	. Challe	ngers
179073 Indians	11415		2	Chennai	Super I	Kings			Mumbai
179074	11415		2	Chennai	Super I	Kings			Mumbai
Indians 179075	11415		2	Chennai	Super I	Kings			Mumbai
Indians 179076	11415		2	Chennai	Super	Kings			Mumbai
Indians 179077	11415			Chennai	·	_			Mumbai
Indians	11413			CHCIIIIGI	Super	Rings			Hambai
	ver ba	11	h	atsman	non c	triker		bowler	
				acsilian	11011_3	CITKEI		DOWLEI	
93	over \ 16	1		riques	Yuvraj		YS	Chahal	
			MC Hen	riques	- Yuvraj	Singh			
93 0 94 0	16 16	1 2	MC Hen	riques riques	- Yuvraj Yuvraj	Singh Singh	YS	Chahal Chahal	
93 0 94 0 95	16	1	MC Hen	riques	- Yuvraj Yuvraj	Singh	YS	Chahal	
93 0 94 0 95 0 96	16 16	1 2	MC Hen MC Hen Yuvraj	riques riques	- Yuvraj Yuvraj	Singh Singh Hooda	YS YS	Chahal Chahal	
93 0 94 0 95 0 96 0 97	16 16 16	1 2 3	MC Hen MC Hen Yuvraj	riques riques Singh	Yuvraj Yuvraj DJ Yuvraj	Singh Singh Hooda	YS YS YS	Chahal Chahal Chahal	
93 — — 0 94 0 95 0 96	16 16 16 16	1 2 3 4	MC Hen MC Hen Yuvraj	riques riques Singh Hooda	Yuvraj Yuvraj DJ Yuvraj	Singh Singh Hooda Singh	YS YS YS	Chahal Chahal Chahal Chahal	
93 0 94 0 95 0 96 0 97	16 16 16 16 16	1 2 3 4 5	MC Hen MC Hen Yuvraj DJ Yuvraj	riques riques Singh Hooda Singh	Yuvraj Yuvraj DJ Yuvraj DJ	Singh Singh Hooda Singh Hooda	YS YS YS	Chahal Chahal Chahal Chahal	
93 0 94 0 95 0 96 0 97 0 179073	16 16 16 16 16 	1 2 3 4 5	MC Hen MC Hen Yuvraj DJ Yuvraj	riques riques Singh Hooda Singh Jadeja	Yuvraj Yuvraj Yuvraj Yuvraj DJ SR N	Singh Singh Hooda Singh Hooda 	YS YS YS SL N	Chahal Chahal Chahal Chahal Alinga	
93 — — 93 — 94 94 95 96 97 9 97 9 97 9 97 9 97 9 97 9 97	16 16 16 16 16 	1 2 3 4 5 2 3	MC Hen MC Hen Yuvraj DJ Yuvraj RA SR	riques riques Singh Hooda Singh Jadeja Watson	Yuvraj Yuvraj DJ Yuvraj DJ SR N	Singh Singh Hooda Singh Hooda Watson Jadeja	YS YS YS SL N	Chahal Chahal Chahal Chahal Malinga Malinga	
93 0 94 0 95 0 96 0 97 0 179073 0 179074 0 179075 0	16 16 16 16 16 20 20 20	1 2 3 4 5 2 3 4	MC Hen MC Hen Yuvraj DJ Yuvraj RA SR SR	riques riques Singh Hooda Singh Jadeja Watson Watson	Yuvraj Yuvraj Yuvraj DJ SR N RA .	Singh Singh Hooda Singh Hooda Watson Jadeja Jadeja	YS YS YS SL M SL M	Chahal Chahal Chahal Chahal Malinga Malinga	
93 0 94 0 95 0 96 0 97 0 179073 0 179074 0 179075	16 16 16 16 16 	1 2 3 4 5 2 3	MC Hen MC Hen Yuvraj DJ Yuvraj RA SR SR	riques riques Singh Hooda Singh Jadeja Watson	Yuvraj Yuvraj Yuvraj DJ SR N RA .	Singh Singh Hooda Singh Hooda Watson Jadeja	YS YS YS SL M SL M	Chahal Chahal Chahal Chahal Malinga Malinga	
93 0 94 0 95 0 96 0 97 0 179073 0 179074 0 179075 0 179076	16 16 16 16 16 20 20 20	1 2 3 4 5 2 3 4	MC Hen MC Hen Yuvraj DJ Yuvraj RA SR SR SN	riques riques Singh Hooda Singh Jadeja Watson Watson	Yuvraj Yuvraj DJ Yuvraj DJ SR N RA . RA .	Singh Singh Hooda Singh Hooda Watson Jadeja Jadeja	YS YS YS SL N SL N SL N	Chahal Chahal Chahal Chahal Malinga Malinga	

		bye_runs	legbye_runs	noball_runs	penalty_runs	
batsman_ 93	_runs	0	0	0	0	
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96 1		0	0	0	0	
97 1		0	0	0	0	
179073 1		0	0	0	0	
179074 2		Θ	Θ	0	0	
179075 1		0	0	0	0	
179076 2		0	0	0	0	
179077 0		0	0	0	0	
fielder	extra	a_runs to	cal_runs pla	ayer_dismissed	dismissal_kind	
93 NaN		Θ	0	NaN	NaN	
94 Sachin B	Baby	0	Θ	MC Henriques	caught	
95 NaN		0	1	NaN	NaN	
96 NaN		Θ	1	NaN	NaN	
97 NaN		0	1	NaN	NaN	
179073 NaN		0	1	NaN	NaN	
179074 NaN 179075		0	2 1	NaN SR Watson	NaN run out	KH
Pandya 179076		0	2	NaN	NaN	KΠ
NaN 179077		0	0	SN Thakur	lbw	
NaN		•		Jii Hailai	COW	

```
[40400 rows x 21 columns]
temp[(temp['batsman runs'] ==4) | (temp['batsman runs'] ==6)]
        match id inning
                                  batting team
bowling team \
                           Sunrisers Hyderabad
                                                Royal Challengers
101
Bangalore
105
               1
                           Sunrisers Hyderabad
                                                Royal Challengers
Bangalore
109
               1
                           Sunrisers Hyderabad
                                                 Royal Challengers
Bangalore
                           Sunrisers Hyderabad
                                                 Royal Challengers
114
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                           Sunrisers Hyderabad
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Bangalore
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179052
           11415
                           Chennai Super Kings
                                                              Mumbai
Indians
179061
           11415
                        2
                           Chennai Super Kings
                                                              Mumbai
Indians
179062
           11415
                        2
                           Chennai Super Kings
                                                              Mumbai
Indians
                           Chennai Super Kings
                                                              Mumbai
179063
           11415
Indians
179071
           11415
                           Chennai Super Kings
                                                              Mumbai
Indians
                                    non striker
                                                       bowler
              ball
                          batsman
        over
is super over
                                                     TS Mills
                 3
                    Yuvraj Singh
                                       DJ Hooda
101
          17
0
105
          18
                 1
                         DJ Hooda
                                   Yuvraj Singh A Choudhary
0
109
          18
                 5
                    Yuvraj Singh
                                       DJ Hooda A Choudhary
114
                    Yuvraj Singh
                                                     TS Mills
          19
                                       DJ Hooda
0
115
          19
                 3 Yuvraj Singh
                                       DJ Hooda
                                                     TS Mills
0
. . .
179052
                        SR Watson
                                       DJ Bravo
                                                   SL Malinga
          16
                        SR Watson
                                                    KH Pandya
179061
          18
                 2
                                       DJ Bravo
179062
          18
                 3
                        SR Watson
                                       DJ Bravo
                                                    KH Pandya
```

179063	18	4	SR	Watson	[OJ Bravo	KH Pandya	Э
0 179071	19	6	RA	Jadeia	SI	R Watson	JJ Bumral	า
9				,				
		bye_rui	ns lea	nhve run	s nol	nall runs	penalty_r	ıns
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101			0		0	0		0
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6			U		U	U		U
109			0		0	Θ		0
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114			0		0	0		0
4 115			0		0	Θ		0
6			•		•	J		J
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179063
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[7592 rows x 21 columns]
temp.groupby('batsman')
['batsman'].count().sort values(ascending=False).head(1).index[0]
'MS Dhoni'
# find V Kohli's record against all teams
temp = ipl[ipl['batsman'] == 'V Kohli']
temp
        match id inning
                                          batting team
bowling team
             1
                          Royal Challengers Bangalore
                                                              Mumbai
2590
              12
Indians
2591
              12
                          Royal Challengers Bangalore
                                                              Mumbai
Indians
              12
                          Royal Challengers Bangalore
2593
                                                              Mumbai
Indians
2594
              12
                          Royal Challengers Bangalore
                                                              Mumbai
Indians
2597
                          Royal Challengers Bangalore
                                                              Mumbai
              12
Indians
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                          Royal Challengers Bangalore
177522
           11345
                                                        Sunrisers
Hyderabad
177523
           11345
                          Royal Challengers Bangalore
                                                        Sunrisers
Hyderabad
                          Royal Challengers Bangalore
177524
           11345
                       2
                                                        Sunrisers
Hyderabad
177525
                          Royal Challengers Bangalore
           11345
                                                        Sunrisers
Hyderabad
177527
           11345
                          Royal Challengers Bangalore
                                                        Sunrisers
Hyderabad
              ball
                    batsman
                                 non striker
                                                        bowler
        over
is super_over
                 2
                    V Kohli
                                                   TG Southee
2590
                                    CH Gayle
0
2591
                 3
                    V Kohli
                                    CH Gayle
                                                   TG Southee
2593
                 5
                    V Kohli
                                    CH Gayle
                                                   TG Southee
0
```

2594	1	6	٧	Kohli			CH Gayle		TG So	outhee	
0 2597	2	1	V	Kohli			CH Gayle	Harbh	naian	Singh	
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177522	1	7	٧	Kohli	AB	de	Villiers		В	Kumar	
0 177523	2	1	V	Kohli	ΔR	de	Villiers		K	Ahmed	
0											
177524 0	2	2	٧	Kohli	AB	de	Villiers		K	Ahmed	
177525 0	2	3	٧	Kohli	AB	de	Villiers		K	Ahmed	
177527 0	2	5	V	Kohli	AB	de	Villiers		K	Ahmed	
h a d a s		. –	าร	legby	e_rı	ıns	noball_r	uns p	penal	ty_runs	
batsman_ 2590	_runs	\	0			0		0		0	
0			^			•		0		0	
2591 1			0			0		0		0	
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0			U			U		U		U	
		• (
177522			0			0		0		0	
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6											
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177527			0			0		0		0	
0											
61.7.1	extra	_runs	to	otal_ru	ns	pla	ayer_dismi	ssed o	dismi	ssal_kind	
fielder 2590		1			1			NaN		NaN	
NaN											
2591 NaN		0			1			NaN		NaN	
2593		0			0			NaN		NaN	

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NaN
2594
                              1
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177522
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177525
                                               NaN
NaN
                                           V Kohli
177527
                              0
                                                            caught WP
Saha
[4211 rows x 21 columns]
temp.groupby('bowling team')['batsman runs'].sum()
bowling team
                            749
Chennai Super Kings
Deccan Chargers
                            306
Delhi Capitals
                             66
Delhi Daredevils
                            763
                            283
Gujarat Lions
Kings XI Punjab
                            636
Kochi Tuskers Kerala
                             50
Kolkata Knight Riders
                            675
Mumbai Indians
                            628
Pune Warriors
                            128
Rajasthan Royals
                            370
Rising Pune Supergiant
                             83
Rising Pune Supergiants
                            188
Sunrisers Hyderabad
                            509
Name: batsman runs, dtype: int64
temp.groupby('bowling team')['batsman runs'].sum().reset index()
                              batsman_runs
               bowling team
0
        Chennai Super Kings
                                        749
            Deccan Chargers
                                        306
1
2
             Delhi Capitals
                                         66
3
           Delhi Daredevils
                                        763
4
              Gujarat Lions
                                        283
5
                                        636
            Kings XI Punjab
6
       Kochi Tuskers Kerala
                                         50
7
      Kolkata Knight Riders
                                        675
```

```
8
             Mumbai Indians
                                       628
9
              Pune Warriors
                                       128
10
           Rajasthan Royals
                                       370
     Rising Pune Supergiant
11
                                        83
12
    Rising Pune Supergiants
                                       188
        Sunrisers Hyderabad
                                       509
# Create a function that can return the highest score of any batsman
ipl
        match id inning
                                  batting team
bowling team \
                                                Royal Challengers
               1
                           Sunrisers Hyderabad
Bangalore
                          Sunrisers Hyderabad
                                                Royal Challengers
               1
Bangalore
                          Sunrisers Hyderabad
                                                Royal Challengers
               1
Bangalore
                          Sunrisers Hyderabad
                                                Royal Challengers
               1
Bangalore
                           Sunrisers Hyderabad
                                                Royal Challengers
               1
Bangalore
179073
           11415
                           Chennai Super Kings
                                                              Mumbai
Indians
           11415
                          Chennai Super Kings
179074
                                                              Mumbai
Indians
179075
           11415
                          Chennai Super Kings
                                                              Mumbai
Indians
179076
           11415
                           Chennai Super Kings
                                                              Mumbai
Indians
179077
           11415
                          Chennai Super Kings
                                                              Mumbai
Indians
              ball
                      batsman non striker
                                                bowler
        over
is super over
                    DA Warner
                                  S Dhawan
                                              TS Mills
0
0
                                              TS Mills
1
                 2
                    DA Warner
                                  S Dhawan
0
2
                 3
                    DA Warner
                                  S Dhawan
                                              TS Mills
0
3
                    DA Warner
                                  S Dhawan
                                              TS Mills
0
4
                 5
                    DA Warner
                                  S Dhawan
                                              TS Mills
0
          20
                    RA Jadeja
                                 SR Watson
                                            SL Malinga
179073
```

0 179074	20	3 S	SR Watson	RA Jadeja	SL Malinga	
0 179075	20	4 S	SR Watson	RA Jadeja	SL Malinga	
0 179076	20		SN Thakur	RA Jadeja	SL Malinga	
0				_		
179077 0	20	6 S	SN Thakur	RA Jadeja	SL Malinga	
	bye_runs	leg	bye_runs	noball_runs	penalty_run	s batsman_runs
0	0		0	- 0	_	0 0
1	0		0	0		0 0
2	0		0	0	(9 4
3	0		0	0		0
4	0		0	0		0
179073	Θ		0	Θ	(0 1
179074	Θ		0	Θ	(0 2
179075	0		0	0	(9 1
179076	0		0	0	(0 2
179077	0		0	0	(0 0
fielder	extra_run	ıs t	otal_runs	player_disr	missed dismis	sal_kind
0 NaN		0	0		NaN	NaN
1		0	0		NaN	NaN
NaN 2		0	4		NaN	NaN
NaN 3		0	Θ		NaN	NaN
NaN						
4 NaN		2	2		NaN	NaN
179073		0	1		NaN	NaN

```
NaN
179074
                              2
                                               NaN
                                                              NaN
NaN
179075
                                        SR Watson
                                                          run out
                                                                   KH
Pandya
179076
                              2
                                               NaN
                                                              NaN
NaN
179077
                              0
                                        SN Thakur
                                                              lbw
NaN
[179078 rows x 21 columns]
temp= ipl[ipl['batsman'] =='V Kohli']
temp.groupby('match id')
['batsman runs'].sum().sort values(ascending=False).head(1).values[0]
113
def highest(batsman):
    temp = ipl[ipl['batsman'] == batsman]
    return temp.groupby('match id')
['batsman runs'].sum().sort values(ascending=False).head(1).values[0]
highest('MS Dhoni')
89
highest('DA Warner')
126
import matplotlib.pyplot as plt
                 Series Title Released Year
                                              Runtime
                                                         Genre
IMDB Rating
     The Shawshank Redemption
                                        1994
                                                   142
                                                         Drama
9.3
1
                The Godfather
                                        1972
                                                   175
                                                         Crime
9.2
2
              The Dark Knight
                                        2008
                                                   152
                                                        Action
9.0
       The Godfather: Part II
3
                                                   202
                                        1974
                                                         Crime
9.0
4
                 12 Angry Men
                                        1957
                                                    96
                                                         Crime
9.0
. .
       Breakfast at Tiffany's
                                                        Comedy
995
                                        1961
                                                   115
7.6
```

996	Gi	ant	1956	201	Dra	ma
7.6 997	From Here to Eternity		1953	118	Dra	ma
7.6 998	Lifeboat		1944	97 Drama		
7.6 999 7.6	The 39 Steps		1935	86 Crime		me
	Director		Star1	No_of_Vo	tes	Gross
0	Frank Darabont	Ti	m Robbins	2343	3110	28341469.0
1	Francis Ford Coppola	Marl	on Brando	1620	367	134966411.0
2	Christopher Nolan	Chris	tian Bale	2303	3232	534858444.0
3	Francis Ford Coppola		Al Pacino	1129	952	57300000.0
4	Sidney Lumet		enry Fonda	689845		4360000.0
995	Blake Edwards	Audre	y Hepburn	166	5544	679874270.0
996	George Stevens	Elizabe	th Taylor	34	1075	195217415.0
997	Fred Zinnemann	Burt	Lancaster	43	374	30500000.0
998	Alfred Hitchcock	Tallulah	Bankhead	26	6471	852142728.0
999	Alfred Hitchcock	Rob	ert Donat	51	853	302787539.0
0 1 2 3 4 995 996 997 998 999	Metascore 80.0 100.0 84.0 90.0 96.0 76.0 84.0 85.0 78.0 93.0 0 rows x 10 columns]					