

Udacity_proj2

April 5, 2019

```
In [20]: # Use this cell to set up import statements for all of the packages that you
#        plan to use.

# Remember to include a 'magic word' so that your visualizations are plotted
# inline with the notebook. See this page for more:
# http://ipython.readthedocs.io/en/stable/interactive/magics.html
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
%matplotlib inline
```

Investigating the shape of Data.

```
In [21]: # Load your data and print out a few lines. Perform operations to inspect data
#        types and look for instances of missing or possibly errant data.
df = pd.read_csv('tmdb-movies.csv')
df.head
```

```
Out[21]: <bound method NDFrame.head of
```

				id	imdb_id	popularity	budget	revenue
0	135397	tt0369610	32.985763	150000000	1513528810			
1	76341	tt1392190	28.419936	150000000	378436354			
2	262500	tt2908446	13.112507	110000000	295238201			
3	140607	tt2488496	11.173104	200000000	2068178225			
4	168259	tt2820852	9.335014	190000000	1506249360			
5	281957	tt1663202	9.110700	135000000	532950503			
6	87101	tt1340138	8.654359	155000000	440603537			
7	286217	tt3659388	7.667400	108000000	595380321			
8	211672	tt2293640	7.404165	74000000	1156730962			
9	150540	tt2096673	6.326804	175000000	853708609			
10	206647	tt2379713	6.200282	245000000	880674609			
11	76757	tt1617661	6.189369	176000003	183987723			
12	264660	tt0470752	6.118847	15000000	36869414			
13	257344	tt2120120	5.984995	88000000	243637091			
14	99861	tt2395427	5.944927	280000000	1405035767			
15	273248	tt3460252	5.898400	44000000	155760117			
16	260346	tt2446042	5.749758	48000000	325771424			
17	102899	tt0478970	5.573184	130000000	518602163			

18	150689	tt1661199	5.556818	95000000	542351353
19	131634	tt1951266	5.476958	160000000	650523427
20	158852	tt1964418	5.462138	190000000	209035668
21	307081	tt1798684	5.337064	30000000	91709827
22	254128	tt2126355	4.907832	110000000	470490832
23	216015	tt2322441	4.710402	40000000	569651467
24	318846	tt1596363	4.648046	28000000	133346506
25	177677	tt2381249	4.566713	150000000	682330139
26	214756	tt2637276	4.564549	68000000	215863606
27	207703	tt2802144	4.503789	81000000	403802136
28	314365	tt1895587	4.062293	20000000	88346473
29	294254	tt4046784	3.968891	61000000	311256926
...
10836	38720	tt0061170	0.239435	0	0
10837	19728	tt0060177	0.291704	0	0
10838	22383	tt0060862	0.151845	0	0
10839	13353	tt0060550	0.276133	0	0
10840	34388	tt0060437	0.102530	0	0
10841	42701	tt0062262	0.264925	75000	0
10842	36540	tt0061199	0.253437	0	0
10843	29710	tt0060588	0.252399	0	0
10844	23728	tt0059557	0.236098	0	0
10845	5065	tt0059014	0.230873	0	0
10846	17102	tt0059127	0.212716	0	0
10847	28763	tt0060548	0.034555	0	0
10848	2161	tt0060397	0.207257	5115000	12000000
10849	28270	tt0060445	0.206537	0	0
10850	26268	tt0060490	0.202473	0	0
10851	15347	tt0060182	0.342791	0	0
10852	37301	tt0060165	0.227220	0	0
10853	15598	tt0060086	0.163592	0	0
10854	31602	tt0060232	0.146402	0	0
10855	13343	tt0059221	0.141026	700000	0
10856	20277	tt0061135	0.140934	0	0
10857	5921	tt0060748	0.131378	0	0
10858	31918	tt0060921	0.317824	0	0
10859	20620	tt0060955	0.089072	0	0
10860	5060	tt0060214	0.087034	0	0
10861	21	tt0060371	0.080598	0	0
10862	20379	tt0060472	0.065543	0	0
10863	39768	tt0060161	0.065141	0	0
10864	21449	tt0061177	0.064317	0	0
10865	22293	tt0060666	0.035919	19000	0

0	original_title \
1	Jurassic World
2	Mad Max: Fury Road
	Insurgent

3	Star Wars: The Force Awakens
4	Furious 7
5	The Revenant
6	Terminator Genisys
7	The Martian
8	Minions
9	Inside Out
10	Spectre
11	Jupiter Ascending
12	Ex Machina
13	Pixels
14	Avengers: Age of Ultron
15	The Hateful Eight
16	Taken 3
17	Ant-Man
18	Cinderella
19	The Hunger Games: Mockingjay - Part 2
20	Tomorrowland
21	Southpaw
22	San Andreas
23	Fifty Shades of Grey
24	The Big Short
25	Mission: Impossible - Rogue Nation
26	Ted 2
27	Kingsman: The Secret Service
28	Spotlight
29	Maze Runner: The Scorch Trials
...	...
10836	Walk Don't Run
10837	The Blue Max
10838	The Professionals
10839	It's the Great Pumpkin, Charlie Brown
10840	Funeral in Berlin
10841	The Shooting
10842	Winnie the Pooh and the Honey Tree
10843	Khartoum
10844	Our Man Flint
10845	Carry On Cowboy
10846	Dracula: Prince of Darkness
10847	Island of Terror
10848	Fantastic Voyage
10849	Gambit
10850	Harper
10851	Born Free
10852	A Big Hand for the Little Lady
10853	Alfie
10854	The Chase
10855	The Ghost & Mr. Chicken

10856 The Ugly Dachshund
 10857 Nevada Smith
 10858 The Russians Are Coming, The Russians Are Coming
 10859 Seconds
 10860 Carry On Screaming!
 10861 The Endless Summer
 10862 Grand Prix
 10863 Beregis Avtomobilya
 10864 What's Up, Tiger Lily?
 10865 Manos: The Hands of Fate

cast \

0 Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
 1 Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
 2 Shailene Woodley|Theo James|Kate Winslet|Ansel...
 3 Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
 4 Vin Diesel|Paul Walker|Jason Statham|Michelle ...
 5 Leonardo DiCaprio|Tom Hardy|Will Poulter|Domhn...
 6 Arnold Schwarzenegger|Jason Clarke|Emilia Clar...
 7 Matt Damon|Jessica Chastain|Kristen Wiig|Jeff ...
 8 Sandra Bullock|Jon Hamm|Michael Keaton|Allison...
 9 Amy Poehler|Phyllis Smith|Richard Kind|Bill Ha...
 10 Daniel Craig|Christoph Waltz|LÃa Seydoux|Ralp...
 11 Mila Kunis|Channing Tatum|Sean Bean|Eddie Redm...
 12 Domhnall Gleeson|Alicia Vikander|Oscar Isaac|S...
 13 Adam Sandler|Michelle Monaghan|Peter Dinklage|...
 14 Robert Downey Jr.|Chris Hemsworth|Mark Ruffalo...
 15 Samuel L. Jackson|Kurt Russell|Jennifer Jason ...
 16 Liam Neeson|Forest Whitaker|Maggie Grace|Famke...
 17 Paul Rudd|Michael Douglas|Evangeline Lilly|Cor...
 18 Lily James|Cate Blanchett|Richard Madden|Helen...
 19 Jennifer Lawrence|Josh Hutcherson|Liam Hemswor...
 20 Britt Robertson|George Clooney|Raffey Cassidy|...
 21 Jake Gyllenhaal|Rachel McAdams|Forest Whitaker...
 22 Dwayne Johnson|Alexandra Daddario|Carla Gugino...
 23 Dakota Johnson|Jamie Dornan|Jennifer Ehle|Eloi...
 24 Christian Bale|Steve Carell|Ryan Gosling|Brad ...
 25 Tom Cruise|Jeremy Renner|Simon Pegg|Rebecca Fe...
 26 Mark Wahlberg|Seth MacFarlane|Amanda Seyfried|...
 27 Taron Egerton|Colin Firth|Samuel L. Jackson|Mi...
 28 Mark Ruffalo|Michael Keaton|Rachel McAdams|Lie...
 29 Dylan O'Brien|Kaya Scodelario|Thomas Brodie-Sa...

 10836 Cary Grant|Samantha Eggar|Jim Hutton|John Stan...
 10837 George Peppard|James Mason|Ursula Andress|Jere...
 10838 Burt Lancaster|Lee Marvin|Robert Ryan|Woody St...
 10839 Christopher Shea|Sally Dryer|Kathy Steinberg|A...
 10840 Michael Caine|Paul Hubschmid|Oskar Homolka|Eva...

10841 Will Hutchins|Millie Perkins|Jack Nicholson|Wa...
 10842 Sterling Holloway|Junius Matthews|Sebastian Ca...
 10843 Charlton Heston|Laurence Olivier|Richard Johns...
 10844 James Coburn|Lee J. Cobb|Gila Golan|Edward Mul...
 10845 Sid James|Jim Dale|Angela Douglas|Kenneth Will...
 10846 Christopher Lee|Barbara Shelley|Andrew Keir|Fr...
 10847 Peter Cushing|Edward Judd|Carole Gray|Eddie By...
 10848 Stephen Boyd|Raquel Welch|Edmond O'Brien|Donal...
 10849 Michael Caine|Shirley MacLaine|Herbert Lom|Joh...
 10850 Paul Newman|Lauren Bacall|Julie Harris|Arthur ...
 10851 Virginia McKenna|Bill Travers|Geoffrey Keen|Pe...
 10852 Henry Fonda|Joanne Woodward|Jason Robards|Paul...
 10853 Michael Caine|Shelley Winters|Millicent Martin...
 10854 Marlon Brando|Jane Fonda|Robert Redford|E.G. M...
 10855 Don Knotts|Joan Staley|Liam Redmond|Dick Sarge...
 10856 Dean Jones|Suzanne Pleshette|Charles Ruggles|K...
 10857 Steve McQueen|Karl Malden|Brian Keith|Arthur K...
 10858 Carl Reiner|Eva Marie Saint|Alan Arkin|Brian K...
 10859 Rock Hudson|Salome Jens|John Randolph|Will Gee...
 10860 Kenneth Williams|Jim Dale|Harry H. Corbett|Joa...
 10861 Michael Hynson|Robert August|Lord 'Tally Ho' B...
 10862 James Garner|Eva Marie Saint|Yves Montand|Tosh...
 10863 Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...
 10864 Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...
 10865 Harold P. Warren|Tom Neyman|John Reynolds|Dian...

homepage \
 0 <http://www.jurassicworld.com/>
 1 <http://www.madmaxmovie.com/>
 2 <http://www.thedivergentseries.movie/#insurgent>
 3 <http://www.starwars.com/films/star-wars-episod...>
 4 <http://www.furious7.com/>
 5 <http://www.foxmovies.com/movies/the-revenant>
 6 <http://www.terminatormovie.com/>
 7 <http://www.foxmovies.com/movies/the-martian>
 8 <http://www.minionsmovie.com/>
 9 <http://movies.disney.com/inside-out>
 10 <http://www.sonypictures.com/movies/spectre/>
 11 <http://www.jupiterascending.com>
 12 <http://exmachina-movie.com/>
 13 <http://www.pixels-movie.com/>
 14 http://marvel.com/movies/movie/193/avengers_ag...
 15 <http://thehatefuleight.com/>
 16 <http://www.taken3movie.com/>
 17 <http://marvel.com/movies/movie/180/ant-man>
 18 NaN
 19 <http://www.thehungergames.movie/>
 20 <http://movies.disney.com/tomorrowland>

21		NaN
22		http://www.sanandreamovie.com/
23	https://www.facebook.com/fiftyshadesofgreymovie	
24		http://www.thebigshortmovie.com/
25		http://www.missionimpossible.com
26		NaN
27		http://www.kingsmanmovie.com/
28		http://www.spotlightthefilm.com
29		http://mazerunnermovies.com
...		...
10836		NaN
10837		NaN
10838		NaN
10839		NaN
10840		NaN
10841		NaN
10842		NaN
10843		NaN
10844		NaN
10845		NaN
10846		NaN
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10850		NaN
10851		NaN
10852		NaN
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10855		NaN
10856		NaN
10857		NaN
10858		NaN
10859		NaN
10860		NaN
10861		NaN
10862		NaN
10863		NaN
10864		NaN
10865		NaN

	director \
0	Colin Trevorrow
1	George Miller
2	Robert Schwentke
3	J.J. Abrams
4	James Wan
5	Alejandro González Iñárritu

6	Alan Taylor
7	Ridley Scott
8	Kyle Balda Pierre Coffin
9	Pete Docter
10	Sam Mendes
11	Lana Wachowski Lilly Wachowski
12	Alex Garland
13	Chris Columbus
14	Joss Whedon
15	Quentin Tarantino
16	Olivier Megaton
17	Peyton Reed
18	Kenneth Branagh
19	Francis Lawrence
20	Brad Bird
21	Antoine Fuqua
22	Brad Peyton
23	Sam Taylor-Johnson
24	Adam McKay
25	Christopher McQuarrie
26	Seth MacFarlane
27	Matthew Vaughn
28	Tom McCarthy
29	Wes Ball
...	...
10836	Charles Walters
10837	John Guillermin
10838	Richard Brooks
10839	Bill Melendez
10840	Guy Hamilton
10841	Monte Hellman
10842	Wolfgang Reitherman
10843	Basil Dearden Eliot Elisofon
10844	Daniel Mann
10845	Gerald Thomas
10846	Terence Fisher
10847	Terence Fisher
10848	Richard Fleischer
10849	Ronald Neame
10850	Jack Smight
10851	James Hill
10852	Fielder Cook
10853	Lewis Gilbert
10854	Arthur Penn
10855	Alan Rafkin
10856	Norman Tokar
10857	Henry Hathaway
10858	Norman Jewison

10859	John Frankenheimer
10860	Gerald Thomas
10861	Bruce Brown
10862	John Frankenheimer
10863	Eldar Ryazanov
10864	Woody Allen
10865	Harold P. Warren

	tagline	...
0	The park is open.	...
1	What a Lovely Day.	...
2	One Choice Can Destroy You	...
3	Every generation has a story.	...
4	Vengeance Hits Home	...
5	(n. One who has returned, as if from the dead.)	...
6	Reset the future	...
7	Bring Him Home	...
8	Before Gru, they had a history of bad bosses	...
9	Meet the little voices inside your head.	...
10	A Plan No One Escapes	...
11	Expand your universe.	...
12	There is nothing more human than the will to s...	...
13	Game On.	...
14	A New Age Has Come.	...
15	No one comes up here without a damn good reason.	...
16	It Ends Here	...
17	Heroes Don't Get Any Bigger	...
18	Midnight is just the beginning.	...
19	The fire will burn forever.	...
20	Imagine a world where nothing is impossible.	...
21	Believe in Hope.	...
22	A rescue pilot survived an earthquake, this is...	...
23	Are you curious?	...
24	This is a true story.	...
25	Desperate Times. Desperate Measures.	...
26	Ted is Coming, Again.	...
27	Manners maketh man.	...
28	Break the story. Break the silence.	...
29	The Maze Was Just the Beginning.	...
...
10836	Run, don't walk to see Walk, Don't Run.	...
10837	There was no quiet on the Western Front!	...
10838	Rough, tough and ready.	...
10839	Every year he rises from the pumpkin patch...	...
10840	NaN	...
10841	Suspenseful desert pursuit in the "High Noon"	...
10842	NaN	...
10843	Where the Nile divides, the great Cinerama adv...	...

10844	The ORIGINAL man of mystery!	...
10845	How the west was lost!	...
10846	DEAD for Ten Years DRACULA, Prince of Darkness...	...
10847	How could they stop the devouring death...that...	...
10848	A Fantastic and Spectacular Voyage... Through
10849	Shirley MacLaine raises Michael Caine!	...
10850	Harper takes a case - and the payoff is murder.	...
10851	From The Pages Of The Beloved Best Seller... A...	...
10852	All the action you can take...all the adventur...	...
10853	Is any man an Alfie? Ask any girl!	...
10854	The chase is on!	...
10855	G-G-GUARANTEED! YOU'LL BE SCARED UNTIL YOU LAU...	...
10856	A HAPPY HONEYMOON GOES TO THE DOGS!...When a G...	...
10857	Some called him savage- and some called him sa...	...
10858	IT'S A PLOT! ...to make the world die laughing!!	...
10859	NaN	...
10860	Carry On Screaming with the Hilarious CARRY ON...	...
10861	NaN	...
10862	Cinerama sweeps YOU into a drama of speed and
10863	NaN	...
10864	WOODY ALLEN STRIKES BACK!	...
10865	It's Shocking! It's Beyond Your Imagination!	...

		overview runtime \
0	Twenty-two years after the events of Jurassic ...	124
1	An apocalyptic story set in the furthest reach...	120
2	Beatrice Prior must confront her inner demons ...	119
3	Thirty years after defeating the Galactic Empi...	136
4	Deckard Shaw seeks revenge against Dominic Tor...	137
5	In the 1820s, a frontiersman, Hugh Glass, sets...	156
6	The year is 2029. John Connor, leader of the r...	125
7	During a manned mission to Mars, Astronaut Mar...	141
8	Minions Stuart, Kevin and Bob are recruited by...	91
9	Growing up can be a bumpy road, and it's no ex...	94
10	A cryptic message from Bondâs past sends him...	148
11	In a universe where human genetic material is ...	124
12	Caleb, a 26 year old coder at the world's larg...	108
13	Video game experts are recruited by the milita...	105
14	When Tony Stark tries to jumpstart a dormant p...	141
15	Bounty hunters seek shelter from a raging bliz...	167
16	Ex-government operative Bryan Mills finds his ...	109
17	Armed with the astonishing ability to shrink i...	115
18	When her father unexpectedly passes away, youn...	112
19	With the nation of Panem in a full scale war, ...	136
20	Bound by a shared destiny, a bright, optimisti...	130
21	Billy "The Great" Hope, the reigning junior mi...	123
22	In the aftermath of a massive earthquake in Ca...	114
23	When college senior Anastasia Steele steps in ...	125

24	The men who made millions from a global econom...	130
25	Ethan and team take on their most impossible m...	131
26	Newlywed couple Ted and Tami-Lynn want to have...	115
27	The story of a super-secret spy organization t...	130
28	The true story of how The Boston Globe uncover...	128
29	Thomas and his fellow Gladers face their great...	132
...
10836	British industrialist Sir William Rutland - "B...	114
10837	A young pilot in the German air force of 1918,...	156
10838	The Professionals is a 1966 American Western f...	117
10839	This classic "Peanuts" tale focuses on the thu...	25
10840	Colonel Stok, a Soviet intelligence officer re...	102
10841	A hired gun seeks to enact revenge on a group ...	82
10842	Christopher Robin's bear attempts to raid a be...	25
10843	English General Charles George Gordon, a devou...	134
10844	When scientists use eco-terrorism to impose th...	108
10845	Stodge City is in the grip of the Rumpo Kid an...	93
10846	Whilst vacationing in the Carpathian Mountain,...	90
10847	A small island community is overrun with creep...	89
10848	The science of miniaturization has been unlock...	100
10849	Harry Dean (Michael Caine) has a perfect plan ...	109
10850	Harper is a cynical private eye in the best tr...	121
10851	Born Free (1966) is an Open Road Films Ltd./Co...	95
10852	A naive traveler in Laredo gets involved in a ...	95
10853	The film tells the story of a young man who le...	114
10854	Most everyone in town thinks that Sheriff Cald...	135
10855	Luther Heggs aspires to being a reporter for h...	90
10856	The Garrisons (Dean Jones and Suzanne Pleshett...	93
10857	Nevada Smith is the young son of an Indian mot...	128
10858	Without hostile intent, a Soviet sub runs agro...	126
10859	A secret organisation offers wealthy people a ...	100
10860	The sinister Dr Watt has an evil scheme going...	87
10861	The Endless Summer, by Bruce Brown, is one of ...	95
10862	Grand Prix driver Pete Aron is fired by his te...	176
10863	An insurance agent who moonlights as a carthie...	94
10864	In comic Woody Allen's film debut, he took the...	80
10865	A family gets lost on the road and stumbles up...	74

	genres \
0	Action Adventure Science Fiction Thriller
1	Action Adventure Science Fiction Thriller
2	Adventure Science Fiction Thriller
3	Action Adventure Science Fiction Fantasy
4	Action Crime Thriller
5	Western Drama Adventure Thriller
6	Science Fiction Action Thriller Adventure
7	Drama Adventure Science Fiction
8	Family Animation Adventure Comedy

9	Comedy Animation Family
10	Action Adventure Crime
11	Science Fiction Fantasy Action Adventure
12	Drama Science Fiction
13	Action Comedy Science Fiction
14	Action Adventure Science Fiction
15	Crime Drama Mystery Western
16	Crime Action Thriller
17	Science Fiction Action Adventure
18	Romance Fantasy Family Drama
19	War Adventure Science Fiction
20	Action Family Science Fiction Adventure Mystery
21	Action Drama
22	Action Drama Thriller
23	Drama Romance
24	Comedy Drama
25	Action
26	Comedy
27	Crime Comedy Action Adventure
28	Drama Thriller History
29	Action Science Fiction Thriller
...	...
10836	Comedy Romance
10837	War Action Adventure Drama
10838	Action Adventure Western
10839	Family Animation
10840	Thriller
10841	Western
10842	Animation Family
10843	Adventure Drama War History Action
10844	Adventure Comedy Fantasy Science Fiction
10845	Comedy Western
10846	Horror
10847	Science Fiction Horror
10848	Adventure Science Fiction
10849	Action Comedy Crime
10850	Action Drama Thriller Crime Mystery
10851	Adventure Drama Action Family Foreign
10852	Western
10853	Comedy Drama Romance
10854	Thriller Drama Crime
10855	Comedy Family Mystery Romance
10856	Comedy Drama Family
10857	Action Western
10858	Comedy War
10859	Mystery Science Fiction Thriller Drama
10860	Comedy
10861	Documentary

10862	Action Adventure Drama
10863	Mystery Comedy
10864	Action Comedy
10865	Horror

	production_companies	release_date	\
0	Universal Studios Amblin Entertainment Legenda...	6/9/15	
1	Village Roadshow Pictures Kennedy Miller Produ...	5/13/15	
2	Summit Entertainment Mandeville Films Red Wago...	3/18/15	
3	Lucasfilm Truenorth Productions Bad Robot	12/15/15	
4	Universal Pictures Original Film Media Rights ...	4/1/15	
5	Regency Enterprises Appian Way CatchPlay Anony...	12/25/15	
6	Paramount Pictures Skydance Productions	6/23/15	
7	Twentieth Century Fox Film Corporation Scott F...	9/30/15	
8	Universal Pictures Illumination Entertainment	6/17/15	
9	Walt Disney Pictures Pixar Animation Studios W...	6/9/15	
10	Columbia Pictures Danjaq B24	10/26/15	
11	Village Roadshow Pictures Dune Entertainment A...	2/4/15	
12	DNA Films Universal Pictures International (UP...	1/21/15	
13	Columbia Pictures Happy Madison Productions	7/16/15	
14	Marvel Studios Prime Focus Revolution Sun Studios	4/22/15	
15	Double Feature Films The Weinstein Company Fil...	12/25/15	
16	Twentieth Century Fox Film Corporation M6 Film...	1/1/15	
17	Marvel Studios	7/14/15	
18	Walt Disney Pictures Genre Films Beagle Pug Fi...	3/12/15	
19	Studio Babelsberg StudioCanal Lionsgate Walt D...	11/18/15	
20	Walt Disney Pictures Babieka A113	5/19/15	
21	Escape Artists Riche-Ludwig Productions	6/15/15	
22	New Line Cinema Village Roadshow Pictures Warn...	5/27/15	
23	Focus Features Trigger Street Productions Mich...	2/11/15	
24	Paramount Pictures Plan B Entertainment Regenc...	12/11/15	
25	Paramount Pictures Skydance Productions China ...	7/23/15	
26	Universal Pictures Media Rights Capital Fuzzy ...	6/25/15	
27	Twentieth Century Fox Film Corporation Marv Fi...	1/24/15	
28	Participant Media Open Road Films Anonymous Co...	11/6/15	
29	Gotham Group Temple Hill Entertainment TSG Ent...	9/9/15	
...	
10836	Columbia Pictures Corporation	1/1/66	
10837	Twentieth Century Fox Film Corporation	6/21/66	
10838	Columbia Pictures	11/1/66	
10839	Warner Bros. Home Video	10/27/66	
10840	Lowndes Productions Limited	12/22/66	
10841	Proteus Films	10/23/66	
10842	NaN	1/1/66	
10843	Julian Blaustein Productions Ltd.	6/9/66	
10844	20th Century Fox	1/16/66	
10845	Peter Rogers Productions	3/1/66	
10846	Seven Arts Productions Hammer Film Productions	1/9/66	

10847	Planet Film Productions Protelco	6/20/66
10848	Twentieth Century Fox Film Corporation	8/24/66
10849	Universal Pictures	12/16/66
10850	Warner Bros.	2/23/66
10851	High Road	6/22/66
10852	Eden Productions Inc.	5/31/66
10853	NaN	3/29/66
10854	Horizon Pictures Columbia Pictures Corporation	2/17/66
10855	Universal Pictures	1/20/66
10856	Walt Disney Pictures	2/16/66
10857	Paramount Pictures Solar Productions Embassy P...	6/10/66
10858	The Mirisch Corporation	5/25/66
10859	Gibraltar Productions Joel Productions John Fr...	10/5/66
10860	Peter Rogers Productions Anglo-Amalgamated Fil...	5/20/66
10861	Bruce Brown Films	6/15/66
10862	Cherokee Productions Joel Productions Douglas ...	12/21/66
10863	Mosfilm	1/1/66
10864	Benedict Pictures Corp.	11/2/66
10865	Norm-Iris	11/15/66

	vote_count	vote_average	release_year	budget_adj	revenue_adj
0	5562	6.5	2015	1.379999e+08	1.392446e+09
1	6185	7.1	2015	1.379999e+08	3.481613e+08
2	2480	6.3	2015	1.012000e+08	2.716190e+08
3	5292	7.5	2015	1.839999e+08	1.902723e+09
4	2947	7.3	2015	1.747999e+08	1.385749e+09
5	3929	7.2	2015	1.241999e+08	4.903142e+08
6	2598	5.8	2015	1.425999e+08	4.053551e+08
7	4572	7.6	2015	9.935996e+07	5.477497e+08
8	2893	6.5	2015	6.807997e+07	1.064192e+09
9	3935	8.0	2015	1.609999e+08	7.854116e+08
10	3254	6.2	2015	2.253999e+08	8.102203e+08
11	1937	5.2	2015	1.619199e+08	1.692686e+08
12	2854	7.6	2015	1.379999e+07	3.391985e+07
13	1575	5.8	2015	8.095996e+07	2.241460e+08
14	4304	7.4	2015	2.575999e+08	1.292632e+09
15	2389	7.4	2015	4.047998e+07	1.432992e+08
16	1578	6.1	2015	4.415998e+07	2.997096e+08
17	3779	7.0	2015	1.195999e+08	4.771138e+08
18	1495	6.8	2015	8.739996e+07	4.989630e+08
19	2380	6.5	2015	1.471999e+08	5.984813e+08
20	1899	6.2	2015	1.747999e+08	1.923127e+08
21	1386	7.3	2015	2.759999e+07	8.437300e+07
22	2060	6.1	2015	1.012000e+08	4.328514e+08
23	1865	5.3	2015	3.679998e+07	5.240791e+08
24	1545	7.3	2015	2.575999e+07	1.226787e+08
25	2349	7.1	2015	1.379999e+08	6.277435e+08
26	1666	6.3	2015	6.255997e+07	1.985944e+08

27	3833	7.6	2015	7.451997e+07	3.714978e+08
28	1559	7.8	2015	1.839999e+07	8.127872e+07
29	1849	6.4	2015	5.611998e+07	2.863562e+08
...
10836	11	5.8	1966	0.000000e+00	0.000000e+00
10837	12	5.5	1966	0.000000e+00	0.000000e+00
10838	21	6.0	1966	0.000000e+00	0.000000e+00
10839	49	7.2	1966	0.000000e+00	0.000000e+00
10840	13	5.7	1966	0.000000e+00	0.000000e+00
10841	12	5.5	1966	5.038511e+05	0.000000e+00
10842	12	7.9	1966	0.000000e+00	0.000000e+00
10843	12	5.8	1966	0.000000e+00	0.000000e+00
10844	13	5.6	1966	0.000000e+00	0.000000e+00
10845	15	5.9	1966	0.000000e+00	0.000000e+00
10846	16	5.7	1966	0.000000e+00	0.000000e+00
10847	13	5.3	1966	0.000000e+00	0.000000e+00
10848	42	6.7	1966	3.436265e+07	8.061618e+07
10849	14	6.1	1966	0.000000e+00	0.000000e+00
10850	14	6.0	1966	0.000000e+00	0.000000e+00
10851	15	6.6	1966	0.000000e+00	0.000000e+00
10852	11	6.0	1966	0.000000e+00	0.000000e+00
10853	26	6.2	1966	0.000000e+00	0.000000e+00
10854	17	6.0	1966	0.000000e+00	0.000000e+00
10855	14	6.1	1966	4.702610e+06	0.000000e+00
10856	14	5.7	1966	0.000000e+00	0.000000e+00
10857	10	5.9	1966	0.000000e+00	0.000000e+00
10858	11	5.5	1966	0.000000e+00	0.000000e+00
10859	22	6.6	1966	0.000000e+00	0.000000e+00
10860	13	7.0	1966	0.000000e+00	0.000000e+00
10861	11	7.4	1966	0.000000e+00	0.000000e+00
10862	20	5.7	1966	0.000000e+00	0.000000e+00
10863	11	6.5	1966	0.000000e+00	0.000000e+00
10864	22	5.4	1966	0.000000e+00	0.000000e+00
10865	15	1.5	1966	1.276423e+05	0.000000e+00

[10866 rows x 21 columns]>

In [22]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
id                10866 non-null int64
imdb_id           10856 non-null object
popularity        10866 non-null float64
budget            10866 non-null int64
revenue           10866 non-null int64
original_title    10866 non-null object
```

```

cast                10790 non-null object
homepage            2936 non-null object
director            10822 non-null object
tagline             8042 non-null object
keywords            9373 non-null object
overview            10862 non-null object
runtime             10866 non-null int64
genres              10843 non-null object
production_companies 9836 non-null object
release_date        10866 non-null object
vote_count          10866 non-null int64
vote_average        10866 non-null float64
release_year        10866 non-null int64
budget_adj          10866 non-null float64
revenue_adj         10866 non-null float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB

```

```

In [23]: # to check the number of rows and coloumn
df.tail()

```

```

Out[23]:
      id  imdb_id  popularity  budget  revenue  \
10861   21  tt0060371    0.080598      0      0
10862 20379  tt0060472    0.065543      0      0
10863 39768  tt0060161    0.065141      0      0
10864 21449  tt0061177    0.064317      0      0
10865 22293  tt0060666    0.035919  19000      0

```

```

      original_title  \
10861   The Endless Summer
10862      Grand Prix
10863  Beregis Avtomobilya
10864  What's Up, Tiger Lily?
10865  Manos: The Hands of Fate

```

```

      cast homepage  \
10861  Michael Hynson|Robert August|Lord 'Tally Ho' B...  NaN
10862  James Garner|Eva Marie Saint|Yves Montand|Tosh...  NaN
10863  Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...  NaN
10864  Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...  NaN
10865  Harold P. Warren|Tom Neyman|John Reynolds|Dian...  NaN

```

```

      director  tagline  \
10861  Bruce Brown  NaN
10862  John Frankenheimer  Cinerama sweeps YOU into a drama of speed and ...
10863  Eldar Ryazanov  NaN
10864  Woody Allen  WOODY ALLEN STRIKES BACK!

```

```

10865      Harold P. Warren      It's Shocking! It's Beyond Your Imagination!

...                                              overview runtime \
10861      ...      The Endless Summer, by Bruce Brown, is one of ...      95
10862      ...      Grand Prix driver Pete Aron is fired by his te...      176
10863      ...      An insurance agent who moonlights as a carthie...      94
10864      ...      In comic Woody Allen's film debut, he took the...      80
10865      ...      A family gets lost on the road and stumbles up...      74

                                genres \
10861                                Documentary
10862      Action|Adventure|Drama
10863                                Mystery|Comedy
10864                                Action|Comedy
10865                                Horror

                                production_companies release_date \
10861                                Bruce Brown Films      6/15/66
10862      Cherokee Productions|Joel Productions|Douglas ...      12/21/66
10863                                Mosfilm      1/1/66
10864                                Benedict Pictures Corp.      11/2/66
10865                                Norm-Iris      11/15/66

      vote_count  vote_average  release_year      budget_adj  revenue_adj
10861           11           7.4           1966      0.000000           0.0
10862           20           5.7           1966      0.000000           0.0
10863           11           6.5           1966      0.000000           0.0
10864           22           5.4           1966      0.000000           0.0
10865           15           1.5           1966  127642.279154           0.0

```

[5 rows x 21 columns]

```

In [24]: # statistic values for this data
df.describe()

```

```

Out[24]:
      count      id      popularity      budget      revenue      runtime \
count  10866.000000  10866.000000  1.086600e+04  1.086600e+04  10866.000000
mean    66064.177434    0.646441  1.462570e+07  3.982332e+07   102.070863
std     92130.136561    1.000185  3.091321e+07  1.170035e+08   31.381405
min         5.000000    0.000065  0.000000e+00  0.000000e+00    0.000000
25%    10596.250000    0.207583  0.000000e+00  0.000000e+00   90.000000
50%    20669.000000    0.383856  0.000000e+00  0.000000e+00   99.000000
75%    75610.000000    0.713817  1.500000e+07  2.400000e+07  111.000000
max    417859.000000   32.985763  4.250000e+08  2.781506e+09  900.000000

      vote_count  vote_average  release_year      budget_adj  revenue_adj
count  10866.000000  10866.000000  10866.000000  1.086600e+04  1.086600e+04
mean    217.389748    5.974922   2001.322658  1.755104e+07  5.136436e+07

```


std	575.619058	0.935142	12.812941	3.430616e+07	1.446325e+08
min	10.000000	1.500000	1960.000000	0.000000e+00	0.000000e+00
25%	17.000000	5.400000	1995.000000	0.000000e+00	0.000000e+00
50%	38.000000	6.000000	2006.000000	0.000000e+00	0.000000e+00
75%	145.750000	6.600000	2011.000000	2.085325e+07	3.369710e+07
max	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

```
In [25]: # check the rows and columns of this dataset
df.shape
```

```
Out[25]: (10866, 21)
```

```
In [26]: # check each columns number of unique values
df.nunique()
```

```
Out[26]: id                10865
imdb_id                  10855
popularity               10814
budget                   557
revenue                  4702
original_title          10571
cast                    10719
homepage                 2896
director                 5067
tagline                  7997
keywords                 8804
overview                10847
runtime                  247
genres                   2039
production_companies     7445
release_date             5909
vote_count               1289
vote_average              72
release_year              56
budget_adj               2614
revenue_adj              4840
dtype: int64
```

```
In [27]: df.isnull().sum()
```

```
Out[27]: id                0
imdb_id                  10
popularity               0
budget                   0
revenue                  0
original_title           0
cast                     76
homepage                 7930
director                 44
```

tagline	2824
keywords	1493
overview	4
runtime	0
genres	23
production_companies	1030
release_date	0
vote_count	0
vote_average	0
release_year	0
budget_adj	0
revenue_adj	0
dtype: int64	

Data cleaning process by filling null values with mean and also drop duplicate data

```
In [28]: # drop unuseful columns
df.drop(['id', 'imdb_id', 'homepage', 'overview'], axis=1, inplace=True) # do not forget i

df.fillna(df.mean(), inplace = True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 17 columns):
popularity          10866 non-null float64
budget              10866 non-null int64
revenue             10866 non-null int64
original_title      10866 non-null object
cast                10790 non-null object
director            10822 non-null object
tagline             8042 non-null object
keywords            9373 non-null object
runtime             10866 non-null int64
genres              10843 non-null object
production_companies 9836 non-null object
release_date        10866 non-null object
vote_count          10866 non-null int64
vote_average        10866 non-null float64
release_year        10866 non-null int64
budget_adj          10866 non-null float64
revenue_adj         10866 non-null float64
dtypes: float64(4), int64(5), object(8)
memory usage: 1.4+ MB
```

```
In [29]: # calculate sum of null value for each coloumn
df.isnull().sum()
```

```

Out[29]: popularity          0
        budget              0
        revenue             0
        original_title      0
        cast                76
        director            44
        tagline             2824
        keywords            1493
        runtime             0
        genres              23
        production_companies 1030
        release_date        0
        vote_count          0
        vote_average        0
        release_year        0
        budget_adj          0
        revenue_adj         0
        dtype: int64

```

```

In [30]: # Drop null values for each column containing null values
        df.dropna(inplace = True)
        df.info()

```

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 7032 entries, 0 to 10865
Data columns (total 17 columns):
popularity          7032 non-null float64
budget              7032 non-null int64
revenue             7032 non-null int64
original_title      7032 non-null object
cast                7032 non-null object
director            7032 non-null object
tagline             7032 non-null object
keywords            7032 non-null object
runtime             7032 non-null int64
genres              7032 non-null object
production_companies 7032 non-null object
release_date        7032 non-null object
vote_count          7032 non-null int64
vote_average        7032 non-null float64
release_year        7032 non-null int64
budget_adj          7032 non-null float64
revenue_adj         7032 non-null float64
dtypes: float64(4), int64(5), object(8)
memory usage: 988.9+ KB

```

```

In [31]: # to replace all the zero value in column with mean value.
        df['popularity']=df['popularity'].replace(0,df['popularity'].mean())

```

```
df['revenue']=df['revenue'].replace(0,df['revenue'].mean())
df['runtime']=df['runtime'].replace(0,df['runtime'].mean())
df['budget_adj']=df['budget_adj'].replace(0,df['budget_adj'].mean())
df['revenue_adj']=df['revenue_adj'].replace(0,df['revenue_adj'].mean())
```

```
In [32]: df.describe()
```

```
Out[32]:
```

	popularity	budget	revenue	runtime	vote_count \
count	7032.000000	7.032000e+03	7.032000e+03	7032.000000	7032.000000
mean	0.829463	2.084426e+07	8.339878e+07	104.882895	312.684300
std	1.180185	3.602117e+07	1.330625e+08	23.704753	693.182087
min	0.000188	0.000000e+00	2.000000e+00	4.000000	10.000000
25%	0.278573	0.000000e+00	2.824752e+07	92.000000	24.000000
50%	0.506241	5.000000e+06	5.931630e+07	101.000000	73.000000
75%	0.956217	2.600000e+07	5.931630e+07	114.000000	263.000000
max	32.985763	4.250000e+08	2.781506e+09	705.000000	9767.000000

	vote_average	release_year	budget_adj	revenue_adj
count	7032.000000	7032.000000	7.032000e+03	7.032000e+03
mean	6.013239	1999.383817	3.484685e+07	1.074617e+08
std	0.876516	13.468216	3.492787e+07	1.631156e+08
min	1.500000	1960.000000	9.693980e-01	2.861934e+00
25%	5.500000	1992.000000	2.037761e+07	3.923478e+07
50%	6.100000	2003.000000	2.500950e+07	7.643072e+07
75%	6.600000	2010.000000	3.463336e+07	7.643072e+07
max	8.400000	2015.000000	4.250000e+08	2.827124e+09

```
In [33]: # calculate sum of all duplicated value
df.duplicated().sum()
```

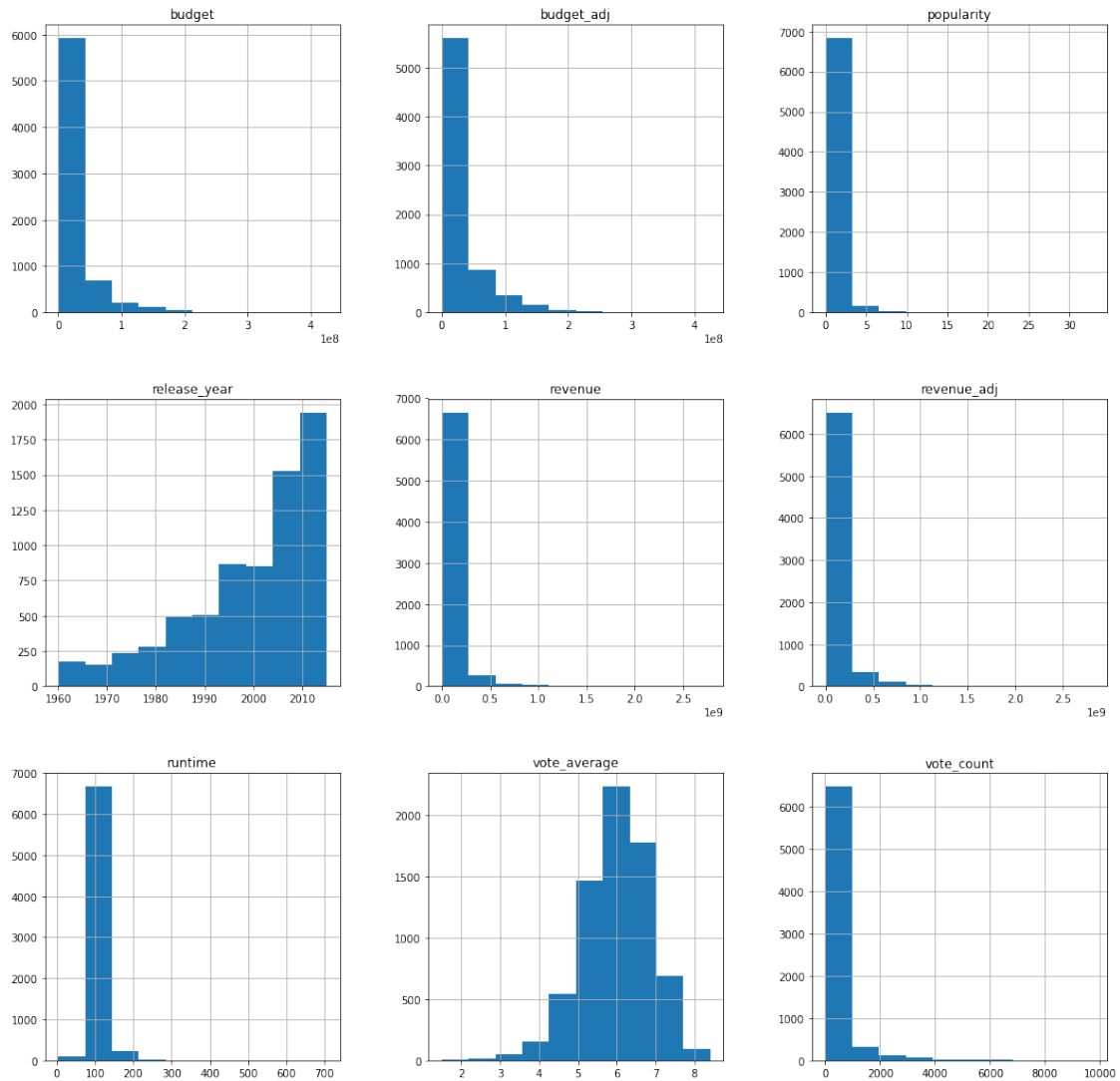
```
Out[33]: 1
```

```
In [34]: # Drop duplicate value
df.drop_duplicates(inplace=True)
```

```
In [35]: # calculate sum of all duplicated value
df.duplicated().sum()
```

```
Out[35]: 0
```

```
In [36]: # visulize each variables
df.hist(figsize=(18,18));
```



Exploration with Visuals and Conclusions

The questions about this dataset:

- 1) Does higher budget mean higher popularity ?
- 2) Do the runtime affect the vote count and popularity?
- 3) Is Higher popularity means higher profits ?
- 4) What are the Features Associate with Top 10 Revenue Movies ?

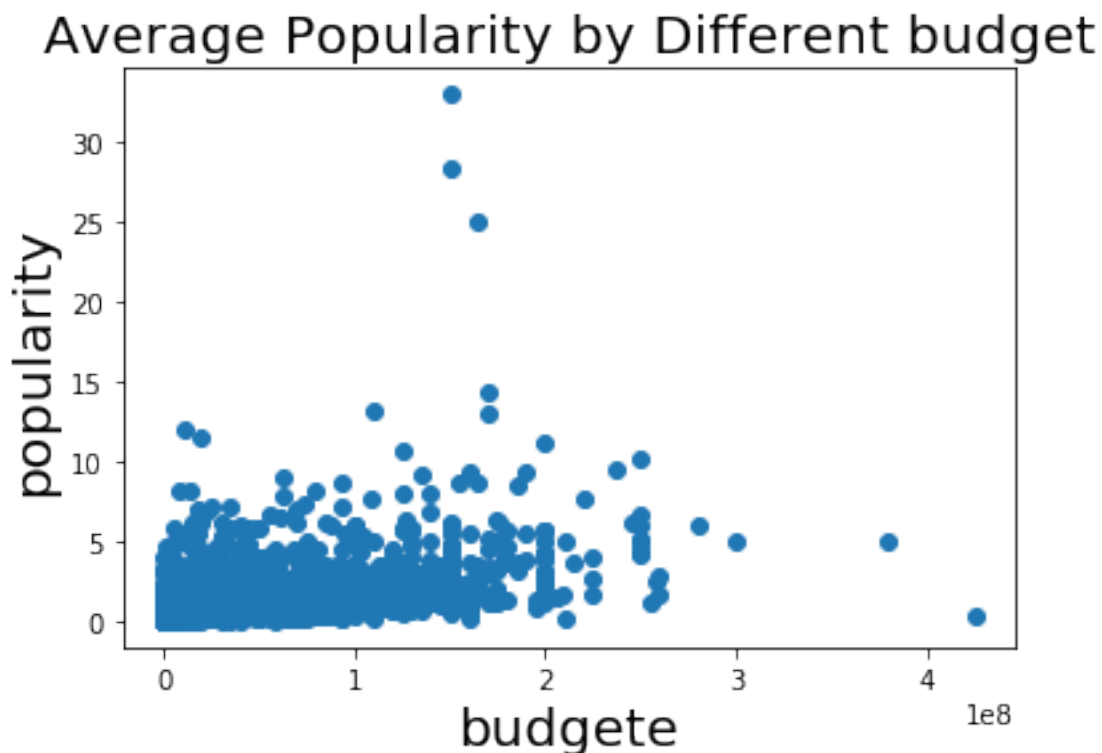
EVALUATING QUESTION 1

- 1) Does higher budget mean higher popularity ?

```
In [37]: # plot the relation between budget and popularity
x = df['budget']
y = df['popularity']

plt.scatter(x,y)
plt.title('Average Popularity by Different budget',fontsize=20)
plt.xlabel('budgete',fontsize=20)
plt.ylabel('popularity',fontsize=20)

Out[37]: Text(0,0.5,'popularity')
```



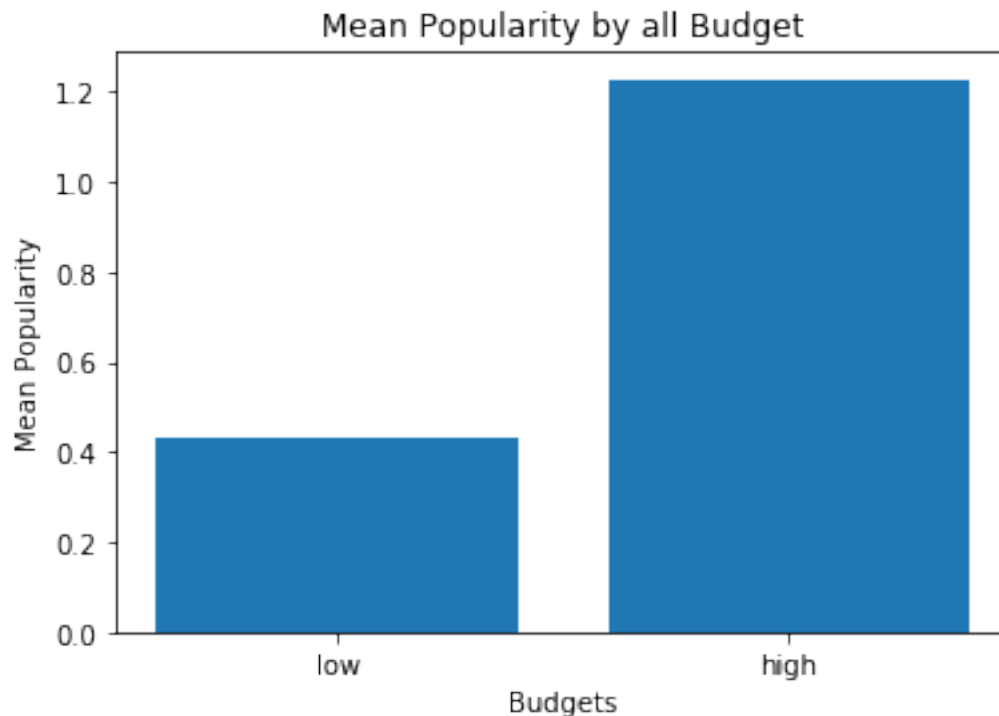
As per the above scatter plot its very difficult to observe strong relationship between popularity and budget. So we use other method to observe the relationship between them. In this method we divide data set in to two group on the basis of median.

```
In [38]: # divide the budget into two groups : lesser_cost and more_cost.
med = df['budget'].median()
lesser_cost = df.query('budget < {}'.format(med))
more_cost = df.query('budget >= {}'.format(med))

In [39]: # check lesser cost and more cost mean values
mean_low_budget = lesser_cost['popularity'].mean()
mean_high_budget = more_cost['popularity'].mean()
```

```
In [40]: # create a bar chart with the values we get above
locations = [1,2]
heights = [mean_low_budget , mean_high_budget]
labels=['low','high']
plt.bar(locations, heights, tick_label = labels)
plt.title('Mean Popularity by all Budget')
plt.xlabel('Budgets')
plt.ylabel('Mean Popularity')
```

```
Out[40]: Text(0,0.5,'Mean Popularity')
```



```
In [41]: increase_percentage = (mean_high_budget - mean_low_budget) / mean_high_budget * 100
increase_percentage
```

```
Out[41]: 64.898675962706122
```

Answer for question 1

From the above bar plot we conclude that higher budget movie gains higher popularity. Higher budget movie have Mean popularity more than twice than the Mean popularity of lower budget movie.

EVALUATING QUESTION 2

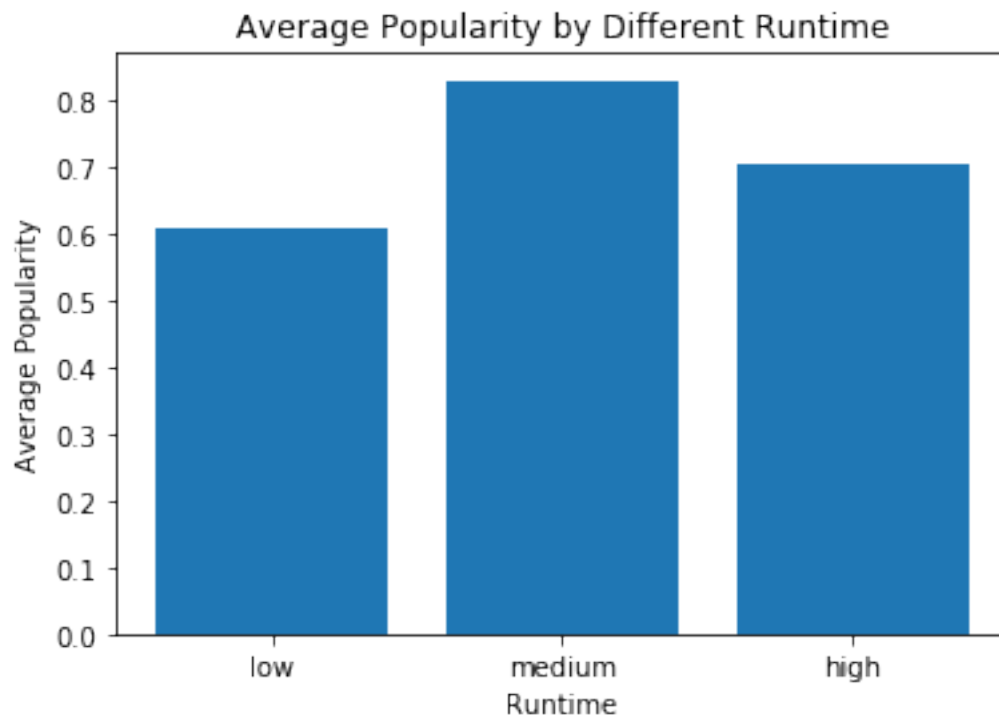
2) Do the runtime affect the vote count and popularity?

```
In [42]: # There 3 groups with query(). <60 min: lowest , 60 min <= <= - 120 min: medium ,
lowest = df.query('runtime < {}'.format(100))
med = df.query('runtime < {}'.format(200))
highest = df.query('runtime > {}'.format(200))
```

```
In [43]: # check mean popularity of different movie lengths
mean_of_lowest = lowest['popularity'].mean()
mean_of_med = med['popularity'].mean()
mean_of_highest = highest['popularity'].mean()
```

```
In [44]: locations = [1,2,3]
heights = [mean_of_lowest, mean_of_med, mean_of_highest]
labels=['low','medium','high']
plt.bar(locations, heights, tick_label = labels)
plt.title('Average Popularity by Different Runtime')
plt.xlabel('Runtime')
plt.ylabel('Average Popularity')
```

```
Out[44]: Text(0,0.5,'Average Popularity')
```



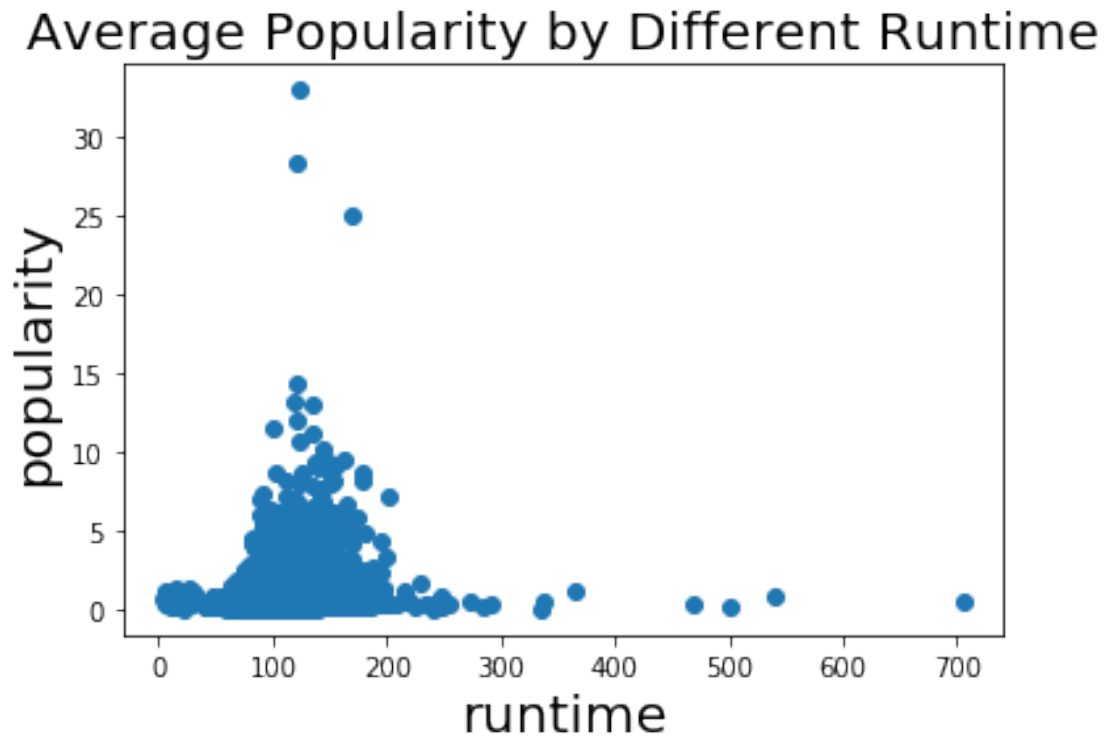
```
In [45]: # scatter plot between runtime and popularity
x = df['runtime']
y = df['popularity']
```



```
plt.scatter(x,y)

plt.title('Average Popularity by Different Runtime',fontsize=20)
plt.xlabel('runtime',fontsize=20)
plt.ylabel('popularity',fontsize=20)
```

Out[45]: Text(0,0.5,'popularity')



ANSWER FOR QUESTION 2

From the above two plots, we can simply say that If the movies are within 200 minutes, it will be more popular. Once the movies run over 200 minutes, it's hard for them to gain high popularity

EVALUATING QUESTION 3

3) Is Higher popularity means higher profits ?

```
In [49]: # calculation for the mean of popularity
mean = df['popularity'].median()
lowest_popularity = df.query('popularity < {}'.format(mean))
more_popularity = df.query('popularity >= {}'.format(mean))
```

```
In [50]: # create a new column called profit.
df['profit'] = df['revenue'] - df['budget']
```

```
In [51]: # average net profit for low_popularity and high_popularity
mean_profit_of_low = lowest_popularity['profit'].mean()
```

```
mean_profit_of_high = more_popularity['profit'].mean()
df.head()
```

```
Out[51]:
```

	popularity	budget	revenue	original_title
0	32.985763	150000000	1.513529e+09	Jurassic World
1	28.419936	150000000	3.784364e+08	Mad Max: Fury Road
2	13.112507	110000000	2.952382e+08	Insurgent
3	11.173104	200000000	2.068178e+09	Star Wars: The Force Awakens
4	9.335014	190000000	1.506249e+09	Furious 7

	cast	director
0	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi...	Colin Trevorrow
1	Tom Hardy Charlize Theron Hugh Keays-Byrne Nic...	George Miller
2	Shailene Woodley Theo James Kate Winslet Ansel...	Robert Schwentke
3	Harrison Ford Mark Hamill Carrie Fisher Adam D...	J.J. Abrams
4	Vin Diesel Paul Walker Jason Statham Michelle ...	James Wan

	tagline
0	The park is open.
1	What a Lovely Day.
2	One Choice Can Destroy You
3	Every generation has a story.
4	Vengeance Hits Home

	keywords	runtime
0	monster dna tyrannosaurus rex velociraptor island	124.0
1	future chase post-apocalyptic dystopia australia	120.0
2	based on novel revolution dystopia sequel dyst...	119.0
3	android spaceship jedi space opera 3d	136.0
4	car race speed revenge suspense car	137.0

	genres
0	Action Adventure Science Fiction Thriller
1	Action Adventure Science Fiction Thriller
2	Adventure Science Fiction Thriller
3	Action Adventure Science Fiction Fantasy
4	Action Crime Thriller

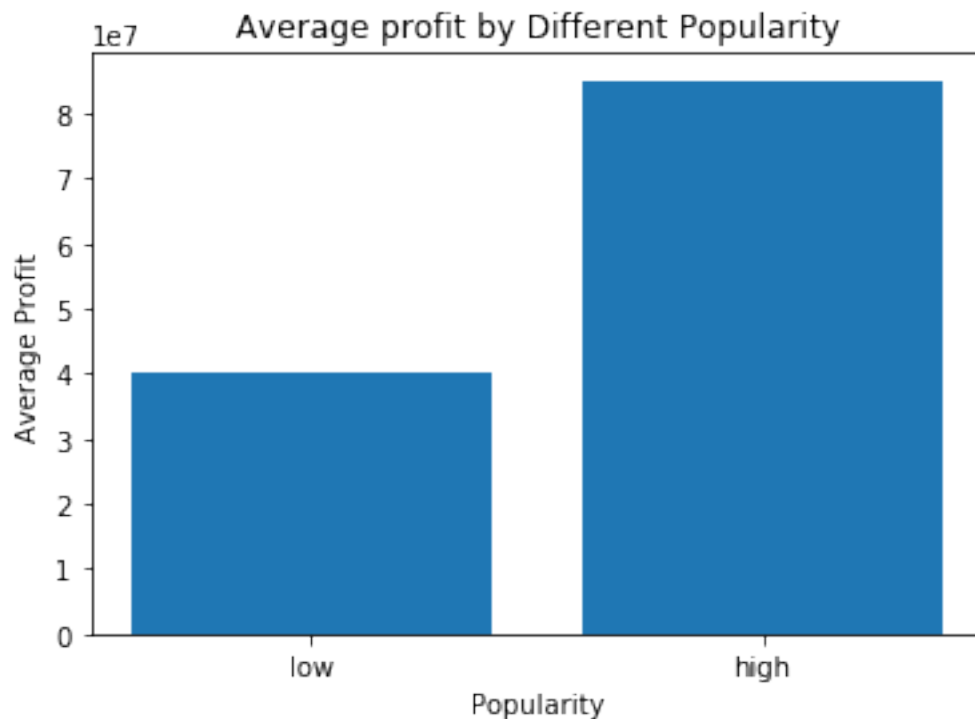
	production_companies	release_date	vote_count
0	Universal Studios Amblin Entertainment Legenda...	6/9/15	5562
1	Village Roadshow Pictures Kennedy Miller Produ...	5/13/15	6185
2	Summit Entertainment Mandeville Films Red Wago...	3/18/15	2480
3	Lucasfilm Truenorth Productions Bad Robot	12/15/15	5292
4	Universal Pictures Original Film Media Rights ...	4/1/15	2947

	vote_average	release_year	budget_adj	revenue_adj	profit
0	6.5	2015	1.379999e+08	1.392446e+09	1.363529e+09
1	7.1	2015	1.379999e+08	3.481613e+08	2.284364e+08

2	6.3	2015	1.012000e+08	2.716190e+08	1.852382e+08
3	7.5	2015	1.839999e+08	1.902723e+09	1.868178e+09
4	7.3	2015	1.747999e+08	1.385749e+09	1.316249e+09

```
In [52]: # create a bar chart with the values we get above
locations = [1,2]
heights = [mean_profit_of_low, mean_profit_of_high]
labels=['low','high']
plt.bar(locations, heights, tick_label = labels)
plt.title('Average profit by Different Popularity')
plt.xlabel('Popularity')
plt.ylabel('Average Profit')
```

```
Out[52]: Text(0,0.5,'Average Profit')
```



ANSWER FOR QUESTION 3

From the above graph we observe that higher popularity leads to more Average profit.

EVALUATING QUESTION 4

4) What are the Features Associate with Top 10 Revenue Movies ?

```
In [53]: top10_revenue = df.nlargest(10,'revenue')
top10_revenue.hist(figsize=(20,20))
```

```
Out[53]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f94e9f7c6d8>,
<matplotlib.axes._subplots.AxesSubplot object at 0x7f94ea0a7320>],
```

```

<matplotlib.axes._subplots.AxesSubplot object at 0x7f94ea0d8908>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x7f94ea0aae80>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f94ea0959e8>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f94ea095b38>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x7f94ea10f2b0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f94ea078da0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f94e9ff80f0>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x7f94eae61d68>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f94e9f94ef0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f94eae3b38>]], dtype=object

```



ANSWER FOR QUESTION 4

From the above plot we conclude that Runtime ranges from 100 mins to 200 mins. The released year are between 1995 to 2015 leads to top 10 revenue movies.

1 CONCLUSION

- 1) Higher budget movie gains higher popularity. Higher budget movie have Mean popularity more than twice than the Mean popularity of lower budget movie.
- 2) If the movies are within 200 minutes, it will be more popular. Once the movies run over 200 minutes, it's hard for them to gain high popularity.
- 3) Higher popularity leads to more Average profit.
- 4) Runtime ranges from 100 mins to 200 mins. The released year are between 1995 to 2015 leads to top 10 revenue movies.

2 LIMITATIONS

- 1) There are plenty of missing data and many zeros which effect the data analysis process.
- 2) Its very difficult to know how the measurement should be done for coloumn like vote_counts and popularity.
- 3) For movies outside the country currency is not indicated. So its also effect the data analysis process.

3 REFERENCE

- 1) I mainly watch instructor video to know the data analysis process after watching video i follow the same steps.
- 2) I have also paid account of Data Camp. So i also refer some steps from there.

In []: