Data Collection: I have extracted the movies which had either the highest grossing on box office or were the lowest.

Movies Extracted:

Avatar (2009)
Avengers: Endgame (2019)
Avengers: Infinity War (2018)
Conan the Barbarian (2011)
Disaster Movie (2008)
Dragonball Evolution (2009)
Fantastic Beasts: The Crimes of Grindelwald (2018)
Frozen (I) (2013)
Furious 7 (2015)
Gods of Egypt (2016)
Green Zone (2010)
Incredibles 2 (2018)
Jurassic World (2015)
Ram Gopal Varma Ki Aag (2007)
Star Wars: Episode VII - The Force Awakens (2015)
The Adventures of Pluto Nash (2002)
The Lion King (2019)
Thugs of Hindostan (2018)
Timeline (2003)
Titanic (1997)

Snapshot of Data:

	Movie_Title	Rating	Review_Title	Reviews
0	Avengers: Endgame (2019)	[No rating, 10/10, 7/10, No rating, 6/10, 8/10...	[Plot holes and other blockbuster weaknesses, ...	[Much like I did for Infinity War, I was caugh...
1	Avatar (2009)	[9/10, 6/10, No rating, 7/10, 8/10, 9/10, No r...	[Gorgeous and 100% otherworldly--but the story...	[As of today, there are 2675 reviews for "Avat...
2	Titanic (1997)	[9/10, 8/10, 10/10, No rating, 5/10, 9/10, 9/1...	[My review is this film's 2400th....so what mo...	["Titanic" won a bazillion Oscars and is consi...
3	Star Wars: Episode VII - The Force Awakens (2015)	[10/10, 9/10, No rating, 5/10, 8/10, 7/10, No ...	[A slightly more adult Star Wars that shows Lu...	[I have never been a huge fan of the Star Wars...
4	Avengers: Infinity War (2018)	[9/10, 9/10, No rating, 9/10, No rating, 10/10...	[Extravagant clash of the titans, The Marvel p...	[Have found myself liking or loving a lot of M...

Keyword Extraction: For Keyword extraction I have used Keybert package. So for each movie the code has generated 5 keywords for low diversity score and 5 keywords for a high diversity score based on cosine similarity between candidates and the documents. The assumption made is that the most similar candidates to the document are good keywords or phrases. I have also added generated bi-grams and tri-grams for both diversity scores.

Maximal Marginal Relevance – This is used for diversifying the result as written above. It tries to minimize redundancy and maximize diversity of results in text summarization.

	Movie	Ngrams	Low_diversity	gh_dive ty
0	Avatar (2009)	(1, 1)	[(blockbuster, 0.4033), (avatar, 0.3443), (ju	[(blockbuster, 0.4033), (element, -0.0719), (average, 0.121), (blatantly, -0.0071), (enraptured, 0.1273)]
1	Avatar (2009)	(1, 2)	[(reviews avatar, 0.5623), (jurassic park, 0.	[(reviews avatar, 0.5623), (create facsimiles, -0.1042), (visit theater, 0.256), (spy betray, -0.0667), (unreservedly, 0.0
3	Avatar (2009)	(2, 2)	[(reviews avatar, 0.5623), (jurassic park, 0.	[(reviews avatar, 0.5623), (create facsimiles, -0.1042), (visit theater, 0.256), (spy betray, -0.0667), (population differ
4	Avengers: Endgame (2019)	(1, 1)	[(avengers, 0.3995), (summary, 0.3408), (s	[(avengers, 0.3995), (celluloid, -0.13), (comprehensively, 0.2181), (plotting, 0.2678), (average, 0.055)]
5	Avengers: Endgame (2019)	(1, 2)	[(summaries avengers, 0.5462), (infinity w	[(summaries avengers, 0.5462), (celluloid, -0.13), (criticisms treating, 0.1658), (values charts, 0.136), (defining corne
7	Avengers: Endgame (2019)	(2, 2)	[(summaries avengers, 0.5462), (infinity w	[(summaries avengers, 0.5462), (underplayed organic, 0.0259), (values charts, 0.136), (possibly hoped, 0.1053), (clo
8	Avengers: Infinity War (2018)	(1, 1)	[(marvel, 0.561), (reviews, 0.3316), (ultror	[(marvel, 0.561), (excel, -0.0611), (saddened, 0.0472), (risks, 0.0617), (antiseptic, 0.0535)]

Keeping a low score will give keywords which have similar cosine similaries hence a low diversity.

A high score will give keywords which have very different cosine scores hence a high diversity.

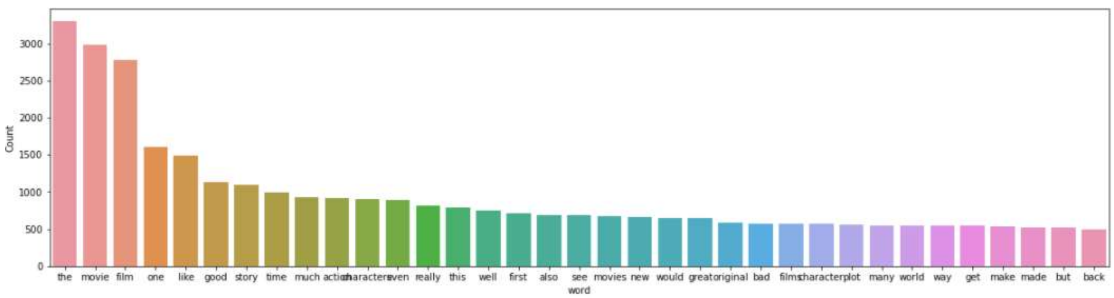
Sentiment Analysis:

	neg	neu	pos	compound
0	0.104	0.663	0.234	1.0000
1	0.127	0.593	0.280	1.0000
2	0.152	0.591	0.257	1.0000
3	0.182	0.601	0.217	0.9999
4	0.232	0.559	0.210	-1.0000
5	0.184	0.597	0.219	1.0000
6	0.124	0.624	0.252	1.0000
7	0.099	0.600	0.301	1.0000
8	0.168	0.613	0.220	1.0000
9	0.160	0.589	0.251	1.0000
10	0.184	0.620	0.197	0.9985
11	0.108	0.594	0.298	1.0000
12	0.120	0.622	0.257	1.0000
13	0.182	0.604	0.213	0.9997
14	0.152	0.583	0.265	1.0000
15	0.155	0.591	0.254	1.0000
16	0.115	0.609	0.275	1.0000
17	0.149	0.598	0.253	1.0000
18	0.165	0.627	0.208	1.0000
19	0.133	0.583	0.284	1.0000

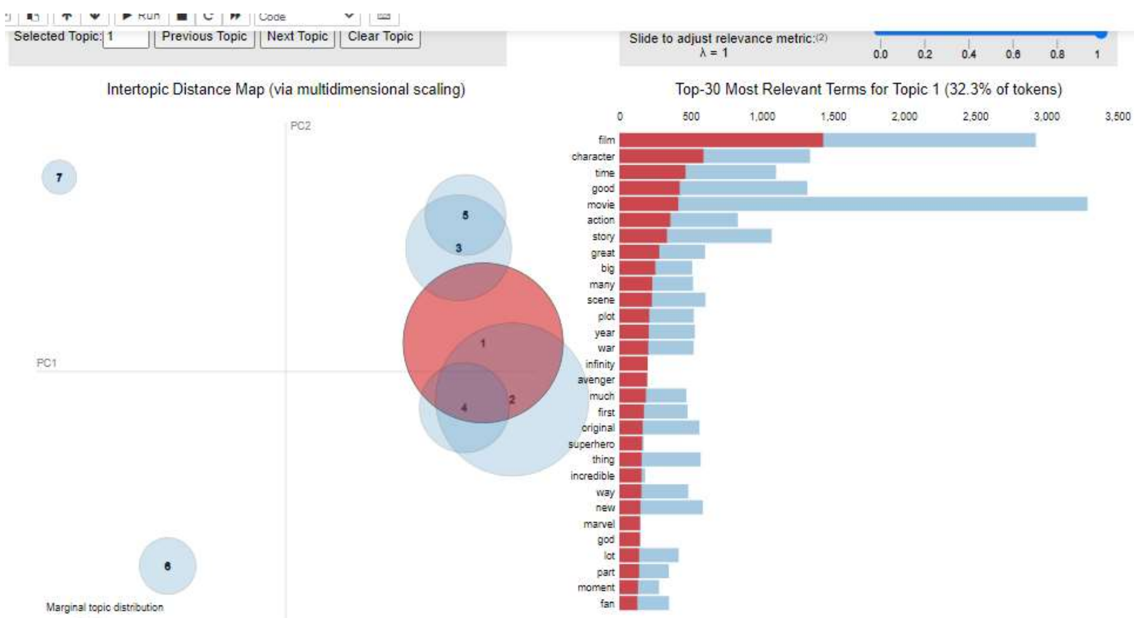
From the sentiment scores we can the overall sentiment is mostly neutral, followed by positive and then negative.

LDA

Firstly I have checked the most occurring words:



From LDA we have made 7 topics:



As we can see Topic 1, 4, 2 have lot of common words.

Topic 1 &3 and 3 & 5 has overlaps.

Topic 6 and 7 are very different and has no overlaps from any other.

Topics 1, 4, 2 - These topics mostly surround around superhero action movies which are really good. Most occurring terms for these are: action, war, superhero, good, great.

Topics 3 and 5: They center on good fantasy movies. These have most occurring terms like: fantasy, prequel, good and great.

Topic 6 and 7: These topics are usually for dramas like Titanic and some action movies which were not so okay.

Associated Keywords for top 10 Keywords:

Keywords: The associated keywords are taken from Keywordtools.io

Keyword	**Associated Keyword**
blockbuster	blockbuster movie, blockbuster meaning in hindi, blockbuster vs netflix, blockbuster action movies
avengers	avengers endgame, avengers infinity war, avengers wallpaper, avengers series
overrated	overrated meaning, overrated meaning in hindi, overrated movies,
comedies	comedy action, comedy acchi acchi, comedy app, comedy actor
disney	disney+ hotstar, disneyland, disney+ hotstar plans, c disneynow, disneyland c
dragonball	dragon ball z, dragon ball af, dragon ball all movies, dragon ball anime
grindlewald	grindelwald in harry potter, grindelwald movie, grindelwald vs dumbledore
inconsistencies	inconsistency hindi meaning, consistency hobgoblin little minds, inconsistencies-plaza,
obnoxiousness	obnoxiousness meaning, obnoxiousness meaning in hindi,

	obnoxiousness synonym, is obnoxiousness a word, obnoxious blog

References:

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