STAT W5243: Applied Data Science - Project 1: Korean Drama Analysis

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Link to Github: https://github.com/My990813/Applied-Data-Science-Project-One

Introduction and Data

The global popularity of Korean dramas (K-dramas) has grown significantly in recent years, presenting an opportunity to analyze the factors contributing to their success and audience reception. Our study examines a comprehensive dataset of K-dramas from 2015 to 2023, integrating information from multiple sources to understand the relationships between production characteristics, viewer ratings, and commercial success. The project began with team members proposing different datasets, with the Korean Drama dataset (proposed by Mengyan Li) ultimately being selected due to its complexity, data quality challenges, and interpretability potential. We began with the Korean Drama from 2015-2023 with Actors & Reviews by Chanon Charuchinda - Kaggle dataset, originally compiled by data expert Chanon Charuchinda through web scraping from MyDramaList.com.

With that dataset as our starting point, we worked with five distinct but related datasets:

1. **Korean Dramas from 2015-2023** (1,752 records, 17 columns):

- Source: Chanon Charuchinda on Kaggle
- Contains comprehensive drama information including:
    - Basic metadata (ID, name, release year)
    - Production details (director, screenwriter)
    - Broadcast information (episodes, duration, air dates, network)
    - Content details (rating, synopsis)
    - Performance metrics (website ranking, popularity ranking)
- Raw data location: korean_drama.csv

2. **Top Korean Drama List (~1500)**

- Source: Top Korean Drama List (~1500) by Noor Rizki - Kaggle
- Similar to Dataset 1 but has a larger number of dramas (1500)
- Raw data location: kdrama_list.csv

3. **Top 100 Korean Dramas (2023)**

- Source: Top 100 KDrama 2023 by Gianina-Maria Petrascu - Kaggle
- Similar to Dataset 1 but has more detailed information on the best dramas in 2023 only
- Raw data location: top_100_kdrama.csv

We merged datasets 1-3 to get a dataset with... [finish this]

4. **Movie Industry Sales Revenue in South Korea (2014-2023)**

- Source: Movie Industry Sales Revenue in South Korea 2014-2023 by ID831717 - Statista
- Contains revenue data for the Korean film industry from 2014 to 2023, which we used to
- Raw data location: statistic_id831717_movie-industry-sales-revenue-in-south-korea-2014-2023.xlsx

5. **Reviews for Korean Dramas from 2015-2023 (Dataset 1)**

- Source: Korean Drama from 2015-2023 with Actors & Reviews by Chanon Charuchinda - Kaggle
- Same as Dataset 1 but with review data
- Raw data location: reviews.csv

In our project, we looked at Korean Drama information data and review data for Korean Drama from 2015 to 2023. In the beginning of the project, each of us brought the data we are interested in to the meeting and voted for the best data. Mengyan Li brought this Korean Drama Data because of her interest in Korean drama. In the end of the meeting, Korean Drama Data got the highest vote because of its complexity and interpretability. The data is from Kaggle. https://www.kaggle.com/datasets/chanoncharuchinda/korean-drama-2015-23-actor-and-reviewmydramalist?select=reviews.csv It was made by Chanon

Charuchinda, a data expert, for educational purpose.

As explained by Chanon Charuchinda, the data was taken from https://mydramalist.com/shows/top_korean_dramas?page=1 through web scraping. Chanon Charuchinda shared four csv data in Kaggle. After discussion, we chose two csv data—korean_drama.csv which included 1752 Korean drama's information and review.csv which included 10625 reviews given to the drama from users on the website. We chose these two because the other two csv did not contain any numerical data.

There are 10 columns in review.csv including user ID, drama name, Score for Story, Score for acting, Score for music, Score for rewatch value, Overall Score, Review, Number of episode that the reviewer watched, and Number of people on the website that find this comment helpful.

Research Objectives

Our analysis focused on three key relationships:

1. the connection between popularity, ranking and viewer ratings
2. the relationship between popularity and textual review sentiment (using NLP methods)
3. the correlation between drama popularity and industry revenue

Methodology

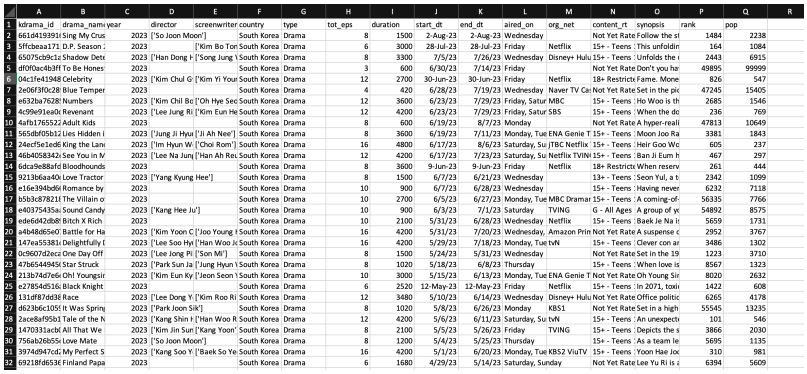
Initial Data Collection

Because of interest in Korean drama, we searched Korean drama on Kaggle and found the files. The data was taken from https://mydramalist.com/shows/top_korean_dramas?page=1 through web scraping by Chanon Charuchinda–a data expert on Kaggle. The data is structured data with data quality problem such as date format, missing value, and outliers. The date contains mismatched date. Some are month-date-year but some are date-month-year. There are many missing values and outliers. For example, in the `pop` column in korean_drama.csv, there are many 99999 which are different from other Popularity Ranking

values and are obviously outliers. And for missing values: there are many missing values in the categorical variable for example director name. And we cannot use KNN or other imputation methods for it.

Our study focus is popularity of Korean dramas. Many variables may contribute to the popularity such as the length of drama, music, and acting. Thus we focus on what score the users give to the dramas in many different sectors–music, story, acting, etc. And we also look at the correlation between different variables such as rank and popularity. We used multiple statistical methods such as t-test, linear regression to approach this problem and found meaningful results.

Data Cleaning



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	kdrama_id	drama_nam	year	director	screenwriter	country	type	tot_eps	duration	start_dt	end_dt	aired_on	org_net	content_rt	synopsis	rank	pop	
2	661d419391	Sing My Crus	2023	['So Joon Moon']		South Korea	Drama	8	1500	2-Aug-23	2-Aug-23	Wednesday		Not Yet Rate	Follow the st	1484	2238	
3	5ffcbeaa171	D.P. Season :	2023		['Kim Bo Ton	South Korea	Drama	6	3000	28-Jul-23	28-Jul-23	Friday	Netflix	15+ - Teens	This unfoldin	164	1084	
4	65075cb9c1a	Shadow Dete	2023	['Han Dong H	['Song Jung \	South Korea	Drama	8	3300	7/5/23	7/26/23	Wednesday	Disney+ Hulu	15+ - Teens	Unfolds the t	2443	6915	
5	df0f0ac4b3ff	To Be Hones	2023			South Korea	Drama	3	600	6/30/23	7/14/23	Friday		Not Yet Rate	Don't you ha	49895	99999	
6	04c1fe41948	Celebrity	2023	['Kim Chul G	['Kim Yi Youn	South Korea	Drama	12	2700	30-Jun-23	30-Jun-23	Friday	Netflix	18+ Restricte	Fame. Mone	826	547	
7	2e06f3f0c28	Blue Temper	2023			South Korea	Drama	4	420	6/28/23	7/19/23	Wednesday	Naver TV Ca	Not Yet Rate	Set in the pic	47245	15405	
8	e632ba7628	Numbers	2023	['Kim Chil Ba	['Oh Hye Seo	South Korea	Drama	12	3600	6/23/23	7/29/23	Friday, Satur	MBC	15+ - Teens	Ho Woo is th	2685	1546	
9	4c99e91ea0	Revenant	2023	['Lee Jung Ri	['Kim Eun He	South Korea	Drama	12	4200	6/23/23	7/29/23	Friday, Satur	SBS	15+ - Teens	When the do	236	769	
10	4afb176552	Adult Kids	2023			South Korea	Drama	8	600	6/19/23	8/7/23	Monday		Not Yet Rate	A hyper-reali	47813	10649	
11	565dbf05b12	Lies Hidden i	2023	['Jung Ji Hyu	['Ji Ah Nee']	South Korea	Drama	8	3600	6/19/23	7/11/23	Monday, Tue	ENA Genie T	15+ - Teens	Moon Joo Ra	3381	1843	
12	24ecf5e1ed8	King the Lan	2023	['Im Hyun W	['Choi Rom']	South Korea	Drama	16	4800	6/17/23	8/6/23	Saturday, Su	JTBC Netflix	15+ - Teens	Heir Goo Wo	605	237	
13	46b4058342	See You in M	2023	['Lee Na Jung	['Han Ah Reu	South Korea	Drama	12	4200	6/17/23	7/23/23	Saturday, Su	Netflix TVIN	15+ - Teens	Ban Ji Eum h	467	297	
14	6dca9e88afd	Bloodhounds	2023			South Korea	Drama	8	3600	9-Jun-23	9-Jun-23	Friday	Netflix	18+ Restricte	When reserv	261	444	
15	9213b6aa40	Love Tractor	2023	['Yang Kyung Hee']		South Korea	Drama	8	1500	6/7/23	6/21/23	Wednesday		13+ - Teens	Seon Yul, a t	2342	1099	
16	e16e394bd6	Romance by	2023			South Korea	Drama	10	900	6/7/23	6/28/23	Wednesday		15+ - Teens	Having neve	6232	7118	
17	b5b3c87821	The Villain o	2023			South Korea	Drama	10	2700	6/5/23	6/27/23	Monday, Tue	MBC Dramar	15+ - Teens	A coming-of-	56335	7766	
18	e40375435a	Sound Candy	2023	['Kang Hee Ju']		South Korea	Drama	10	900	6/3/23	7/1/23	Saturday	TVING	G - All Ages	A group of yo	54892	8575	
19	ede6d42db8	Bitch X Rich	2023			South Korea	Drama	10	2100	5/31/23	6/28/23	Wednesday	Netflix	15+ - Teens	Baek Je Na is	5659	1731	
20	a4b486b5e0	Battle for Ha	2023	['Kim Yoon C	['Joo Young I	South Korea	Drama	16	4200	5/31/23	7/20/23	Wednesday,	Amazon Prin	Not Yet Rate	A suspense d	2952	3767	
21	147ea5538 1	Delightfully I	2023	['Lee Soo Hy	['Han Woo Jc	South Korea	Drama	16	4200	5/29/23	7/18/23	Monday, Tue	tvN	15+ - Teens	Clever con ar	3486	1302	
22	0c9607d2ec	One Day Off	2023	['Lee Jong Pi	['Son Mi']	South Korea	Drama	8	1500	5/24/23	5/31/23	Wednesday		Not Yet Rate	Set in the 19	1223	3710	
23	47b6544945	Star Struck	2023	['Park Sun Ja	['Jung Hyun \	South Korea	Drama	8	1020	5/18/23	6/8/23	Thursday		15+ - Teens	When love is	8567	1323	
24	213b74d7e6	Oh! Youngsir	2023	['Kim Eun Ky	['Jeon Seon \	South Korea	Drama	10	3000	5/15/23	6/13/23	Monday, Tue	ENA Genie T	Not Yet Rate	Oh Young Sir	8020	2632	
25	e27854d516	Black Knight	2023			South Korea	Drama	6	2520	12-May-23	12-May-23	Friday	Netflix	15+ - Teens	In 2071, toxi	1422	608	
26	131df87dd3	Race	2023	['Lee Dong Y	['Kim Roo Ri	South Korea	Drama	12	3480	5/10/23	6/14/23	Wednesday	Disney+ Hulu	Not Yet Rate	Office politic	6265	4178	
27	d623b6c105	It Was Spring	2023	['Park Joon Sik']		South Korea	Drama	8	1020	5/8/23	6/26/23	Monday	KBS1	Not Yet Rate	Set in a high	55545	13235	
28	2ace8af95b1	Tale of the N	2023	['Kang Shin I	['Han Woo R	South Korea	Drama	12	4200	5/6/23	6/11/23	Saturday, Su	tvN	15+ - Teens	An unexpecte	101	546	
29	1470331acb	All That We	2023	['Kim Jin Sur	['Kang Yoon'	South Korea	Drama	8	2100	5/5/23	5/26/23	Friday	TVING	15+ - Teens	Depicts the s	3866	2030	
30	756ab26b55	Love Mate	2023	['So Joon Moon']		South Korea	Drama	8	1200	5/4/23	5/25/23	Thursday		15+ - Teens	As a team le	5695	1135	
31	3974d947cd	My Perfect S	2023	['Kang Soo Y	['Baek So Ye	South Korea	Drama	16	4200	5/1/23	6/20/23	Monday, Tue	KBS2 ViuTV	15+ - Teens	Yoon Hae Jo	310	981	
32	69218fd653	Finland Papa	2023			South Korea	Drama	6	1680	4/29/23	5/14/23	Saturday, Sunday		Not Yet Rate	Lee Yu Ri is a	6394	5609	

	A	B	C	D	E	F	G	H	I	J	K
1	user_id	title	story_score	acting_cast_	music_score	rewatch_valu	overall_score	review_text	ep_watched	n_helpful	
2	c8ffdab3f2a3	Sing My Crus	9	9	10	9	9	the Best Son	8 of 8 episod	23	
3	c8ffdab3f2a3	Happy Merry	5	7	9	4	6.5	I'm Happy ar	8 of 8 episod	31	
4	c8ffdab3f2a3	Duty After Sc	4	9	3	1	4	This PART 2	4 of 4 episod	121	
5	c8ffdab3f2a3	Our Dating S	9	9.5	9	9	9	I want to pla	8 of 8 episod	79	
6	c8ffdab3f2a3	The Director	7.5	8.5	7	6	7	Half-Cooked,	10 of 10 epis	66	
7	c8ffdab3f2a3	Unlock My B	9	9.5	7	8	8.5	Satisfying se	12 of 12 epis	26	
8	c8ffdab3f2a3	Roommates	8	9	9	9	9	MATES of Pc	8 of 8 episod	72	
9	c8ffdab3f2a3	The Golden S	8	9	6	8	8	RUSTED SPO	16 of 16 epis	37	
10	c8ffdab3f2a3	Big Mouth	8.5	10	8	8.5	8.5	RUSHED END	16 of 16 epis	101	
11	c8ffdab3f2a3	Blueming	8	9.5	7	7	8.5	FULLY BLOO	11 of 11 epis	76	
12	c8ffdab3f2a3	Grid	6.5	9	5	6	6.5	AFTER EVER	10 of 10 epis	52	
13	c8ffdab3f2a3	Semantic Err	7	9.5	9	9.5	9	Illogically ad	8 of 8 episod	172	
14	c8ffdab3f2a3	Twenty-Five	9	10	9	7	9	BUT SERIOU	16 of 16 epis	212	
15	c8ffdab3f2a3	All of Us Are	6	7.5	5	5	6.5	You need to	12 of 12 epis	263	
16	c8ffdab3f2a3	Ghost Doctor	9	9.5	6	6	8.5	It started out	16 of 16 epis	50	
17	c8ffdab3f2a3	Bad and Craz	9	9	8	7	8	CRAZY GOOI	12 of 12 epis	54	
18	c8ffdab3f2a3	Happiness	7.5	9	6	8.5	8	WARNING, T	12 of 12 epis	69	
19	c8ffdab3f2a3	My Sweet De	7	8.5	5.5	6	7	TOO SHORT!	8 of 8 episod	49	
20	c8ffdab3f2a3	Dali and the	8	9	7.5	7.5	8	WE NEED M	16 of 16 epis	46	
21	c8ffdab3f2a3	Lovers of the	7	7.5	8	4	6.5	Charming bu	16 of 16 epis	55	
22	c8ffdab3f2a3	Wish You: Yo	7.5	7.5	9	7	8	I WANT MOI	8 of 8 episod	56	
23	c8ffdab3f2a3	The School N	9	9	6.5	8	8	NETFLIX, GIV	6 of 6 episod	47	
24	c8ffdab3f2a3	Where Your	8.5	9.5	9.5	9	9	MORE MORE	8 of 8 episod	41	
25	c8ffdab3f2a3	Itaewon Clas	7.5	9.5	6	6	8	Is SEO-JOON	16 of 16 epis	46	
26	01b015525e8	Sing My Crus	8.5	9	10	10	9	Second Winc	8 of 8 episod	37	
27	01b015525e8	Star Struck	8	8.5	7.5	6.5	7.5	More like a g	8 of 8 episod	24	
28	01b015525e8	Happy Merry	6	7	7.5	3.5	6	They got the	8 of 8 episod	25	
29	01b015525e8	The Eighth S	10	10	10	10	10	Blooming lik	10 of 10 epis	12	
30	01b015525e8	Individual Cir	9	9.5	8	8.5	8	Why did the	8 of 8 episod	4	
31	01b015525e8	The Director	6.5	7.5	7.5	5	6.5	Just . . . Bad.	10 of 10 epis	8	
32	01b015525e8	Happy Ending	8	9	9	8	8	An Empty Sp	8 of 8 episod	3	
33	01b015525e8	Summer Stri	7.5	8.5	8.5	6	7.5	Tumbling do	12 of 12 epis	17	
34	01b015525e8	Roommates	8	8.5	8	9	8.5	Throwback t	8 of 8 episod	51	

The above are the two tables we started for the data cleaning process. The following are our approaches:

In the first step, we focused on **removing outliers**, particularly in the popularity ('pop') and overall score columns, as these would serve as dependent variables in our linear regression analyses. Using boxplot visualization with interquartile range calculations, we identified and removed data points that fell outside the upper and lower limits. This process resulted in the removal of 609 outlier entries, significantly improving the data's statistical validity.

The second step **addressed inconsistencies in date formatting** across the dataset. We encountered various date formats, with some entries following a month-date-year format while others used date-month-year. Using Python's `datetime` library, we standardized all dates to a consistent year-month-day format. During this process, we made the decision to exclude entries that contained only month and year information, as these incomplete date entries could potentially skew our temporal analysis.

The third step involved **handling missing values** in the dataset. Our analysis revealed that the majority of missing data occurred in three main categories: director names, screenwriter names, and network information. While our initial plan was to complete these missing entries through web scraping from various drama databases, time constraints of our two-week project deadline made this approach impractical. We did end up writing a script for web scraping using Selenium and BeautifulSoup (can be found under scripts/scrape_mydramalist.py), but due to rate limiting, we were unable to scrape all the necessary data in time. Theoretically with more time, we could have scraped all the missing data and filled in the missing values. Instead, we opted to replace missing categorical values with "Others" as a placeholder and removed entries with missing numerical values to maintain data integrity for our quantitative analyses.

Data Merging

Merging the Korean Drama Datasets (Datasets 1-3)

To combine the three Korean drama datasets spanning 2015-2023, since we noticed that all the datasets have the drama names (with different column names), we decided to merge the datasets using that column.

First, datasets 1 (1,752 dramas) and 2 (1,647 dramas) were merged using an outer join on the title column, resulting in 2,302 unique entries. Missing values in overlapping columns were filled using corresponding values from the other dataset, with special handling for episode counts that required string parsing.

Second, we incorporated dataset 3 (100 top dramas from 2023) using another outer join on common columns plus the title field, expanding the final dataset to 2,402 entries. Duplicate entries were removed by keeping only the first occurrence when grouping by title and year. The merged dataset preserved the most complete information from each dataset while standardizing formats and handling overlapping data fields systematically.

The following is the final merged and cleaned Korean Dramas dataset, spanning 3 other datasets:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	title	year	kdrama_id	director	screenwriter	tot_eps	duration	start_dt	end_dt	aired_on	org_net	content_rt	synopsis	rank	pop	music_score	story_score	acting_cast_	rewatch_val	overall_scor	n_helpful
2	The Family Is	2015	9170c31a02(	['Joo Dong M	['Kim Shin Hy	20	3600	1/3/15	3/15/15	Saturday, Su	SBS	15+ - Teens	A grandma h	7995	4289	6	7.8	8.2	6	8	6
3	The Lover	2015	2dc531911b(	['Kim Tae Eu	['Kim Min Se	12	3000	4/2/15	6/25/15	Thursday	Mnet	18+ Restricte	The series ta	5486	527	7.7	8.5	9	8	8.7	15
4	Love of Eve	2015	832b2dcd1a(	['Lee Gye Jo(	Others	120	2400	5/18/15	10/30/15	Monday, Tue	MBC	15+ - Teens	Three wome	54646	12387	1	3	3	1	3	1
5	Love on a Ro	2015	5eda227cf63	['Choi Ji Yeor	['Choi Min Ki	101	2100	4/6/15	8/21/15	Monday, Tue	KBS2	15+ - Teens	A drama abo	8341	7469	5	5.4	5.1	3	5.1	5
6	Kill Me, Heal	2015	e8c09f0f7d0	['Kim Jin Ma	['Jin Soo Wa	20	3720	1/7/15	3/12/15	Wednesday,	MBC	15+ - Teens	A traumatic	232	29	8.8	8.5	9	8	8.7	59
7	Delicious Lov	2015	a38a585a6c(	Others	Others	3	1800	11/5/15	11/10/15	Monday, Tue	Naver TV Cas	Not Yet Rate	A teen roma	9163	4826	5.2	2.8	3.8	1	3.5	3
8	Love Detectiv	2015	fff500c6bfe7	Others	Others	10	600	11/11/15	11/20/15	Monday, Tue	Naver TV Cas	Not Yet Rate	Sherlock K is	8964	4942	3.5	3.5	7	1	4	2
9	The Time We	2015	12208c74d6!	['Jo Soo Wor	['Jung Do Yo(	16	3840	6/27/15	8/16/15	Saturday, Su	SBS	15+ - Teens	Choi Won is	5880	670	6.4	7	7.6	4.3	7.2	12
10	The Dearest	2015	729e5a41ac:	['Choi Chang	['Seo Hyun Jo	116	2100	12/7/15	5/20/16	Monday, Tue	MBC	15+ - Teens	An upbeat fa	53280	11354	3	4.2	5	1	3.5	1
11	The Eccentric	2015	cc11a722be3	['Lee Duk Gu	['Yoo Nam K	12	4500	8/17/15	9/22/15	Monday, Tue	KBS2	Not Yet Rate	Oh In Yeong	7125	2769	7.8	7.3	7.8	6.2	7.9	3
12	Awl	2015	b5446cda98	['Kim Seok Y(	['Kim Soo Jin	12	3900	10/24/15	11/29/15	Saturday, Su	jTBC	15+ - Teens	Soo In has a	3410	3958	5.6	6.6	7.4	5.8	7.1	7
13	Bubblegum	2015	f8ecb7e2038	['Kim Byung	['Lee Mi Na']	16	3600	10/26/15	12/15/15	Monday, Tue	tvN	15+ - Teens	Park Ri Hwar	7163	996	7	7.5	8.8	6.1	7.3	12
14	Noble, My Lo	2015	e2328f79d0(	['Kim Yang H	Others	20	900	8/23/15	9/16/15	Monday, Tue	Naver TV Cas	13+ - Teens	Kang Hoon is	5090	310	6.4	6.7	7.5	6.5	7.4	14
15	My Mother Is	2015	65e26535bd:	['Ko Heung S	['Lee Geun Y	136	2400	6/22/15	12/31/15	Monday, We	SBS	15+ - Teens	Gyeong Sook	44090	14364	10	10	10	10	10	0
16	Love Cells Se	2015	3bef90625c1	Others	Others	12	600	9/14/15	10/1/15	Monday, Tue	Naver TV Cas	13+ - Teens	In this bitter-	8646	3225	6	4.6	7.8	3.9	5.9	2
17	Flower of the	2015	62df2045415	['Kim Min Sh	['Park Hyun J	50	3900	3/14/15	8/30/15	Saturday, Su	MBC	15+ - Teens	South Korear	6954	4493	1	4	4.5	1	4	2
18	Six Flying Dra	2015	61790e3827(	['Shin Kyung	['Kim Young	50	3600	10/5/15	3/22/16	Monday, Tue	SBS	15+ - Teens	A fictional, h	162	531	9.7	9.8	9.9	8.9	9.8	27
19	Missing Noir	2015	64309e69d8(	['Lee Seung '	['Lee Yoo Jin	10	4200	3/28/15	5/30/15	Saturday	OCN	15+ - Teens	Gil Su Hyeon	1040	1413	9	8.3	9.2	6.9	8.7	12
20	Jumping Girl	2015	5ef07c61a4d	Others	Others	15	600	4/27/15	4/28/15	Monday, Tue	Daum Kakao	15+ - Teens	Follows the l	9145	3662	6.5	6.4	7.6	6.8	6.8	3
21	My Beautiful	2015	e265f560507	['Kim Chul G(	['Yoo Sung Y(	16	3600	6/20/15	8/9/15	Saturday, Su	OCN	15+ - Teens	Kim Do Hyun	2542	1538	8.9	8.8	8.9	7.1	8.7	9
22	Shine or Go (	2015	45af025f19d	['Song Hyung	['Kim Sun Mi	24	3900	1/19/15	4/7/15	Monday, Tue	MBC	15+ - Teens	Wang So, a (	3958	1632	8	7.3	8.6	5.1	7.8	11
23	Missing Kore	2015	0f989ec2490	['Min Doo Sh	Others	6	600	11/3/15	11/12/15	Tuesday, We	Naver TV Cas	Not Yet Rate	ÃúMissing K	8905	4337	3.9	6.4	7.1	3.4	6.4	1
24	She Was Pre	2015	1985f18b5a1	['Jeong Dae '	['Jo Sung He(	16	3600	9/16/15	11/11/15	Wednesday,	MBC	15+ - Teens	As a young g	1933	32	7.9	7.6	8.6	6	7.8	36
25	She Is 200 Ye	2015	ffaec6267d9	Others	Others	5	600	10/27/15	10/27/15	Others	Naver TV Cas	Not Yet Rate	200-year-old	8782	2678	6	6.1	6.1	4.2	6.4	3
26	Warm and C	2015	81c8f1d83d7	['Park Hong I	['Hong Jung I	16	3600	5/13/15	7/2/15	Wednesday,	MBC	15+ - Teens	A man and a	5707	635	8.2	7.6	8.9	7.1	8.5	14
27	Girl of 0AM	2015	634519fd3e7	Others	Others	8	900	5/4/15	5/14/15	Others	MBC every1	Not Yet Rate	Gong Ji Dan,	7755	2845	7.4	7	8.1	5.5	7.6	3
28	Girls' Love St	2015	8a5f7bb42f2	Others	Others	50	540	6/16/15	8/15/15	Wednesday	Daum Kakao	Not Yet Rate	Four women	52369	8459	5	4.8	6.2	5.2	5.5	3
29	Assembly	2015	56f7a1b9c72	['Hwang In H	['Jung Hyun I	20	3720	7/15/15	9/17/15	Wednesday,	KBS2	Not Yet Rate	Jin Sang Pil i	4927	5731	8.5	9.8	9.5	9	9.5	6
30	We Broke Up	2015	dce6fe763f2	Others	['Jeon Seon '	10	900	6/29/15	7/17/15	Monday, We	Naver TV Cas	Not Yet Rate	Ji Won Yeon	6979	1712	8.5	7.3	8.2	7.1	8.1	4
31	Splendid Poli	2015	75c1221d1d(	['Kim Sang H	['Kim Yi Your	50	3600	4/13/15	9/29/15	Monday, Tue	MBC	15+ - Teens	Princess Jung	4965	3091	7.1	6.9	7.4	4.7	7.2	6
32	Spy	2015	14fb3da5d0(	['Park Hyun S	['Han Sang W	16	3000	1/9/15	3/6/15	Friday	KBS2	Not Yet Rate	Hye Rim is a	7174	2132	6.7	6.3	8.2	4.4	6.9	5
33	To Be Contin	2015	05be099411(	Others	Others	12	900	8/18/15	9/3/15	Thursday	MBC every1	G - All Ages	This web dra	5890	911	8.8	6.6	7.6	7.2	7.6	3
34	Late Night R	2015	1ede9e8879	['Hwang In R	Others	20	1800	7/4/15	9/5/15	Saturday	SBS	Not Yet Rate	A late night	3327	3914	8.9	9.4	9.4	9.3	9.4	6
35	Sweet, Savag	2015	53d882ba89(	['Kang Dae S	['Son Geun Ji	16	3780	11/18/15	1/14/16	Wednesday,	MBC	15+ - Teens	At home, Tae	7123	4165	5.2	6.8	7.5	4.5	6.8	4

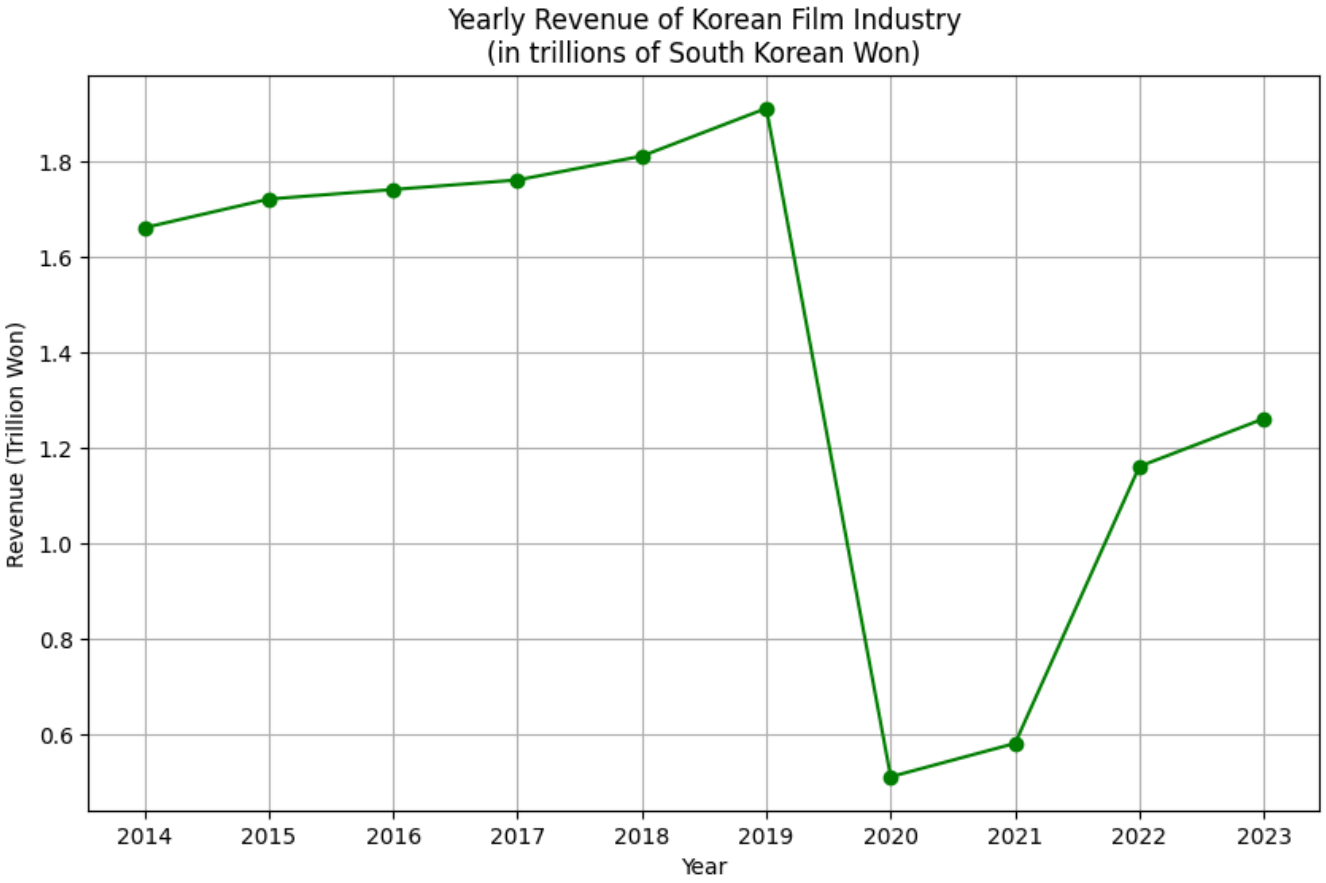
Merging the (Merged) Korean Drama Dataset with Review Data (Datasets 5)

For merging the merged Korean Drama Dataset with the Review dataset (Dataset 5), we similarly merged the two tables on their respective drama title columns, and then dropped any rows where numerical values were missing. This resulted in a final dataset of 11,776 rows with 32 columns.

Merging the (Merged) Korean Drama Dataset with Yearly Revenue Data (Datasets 4)

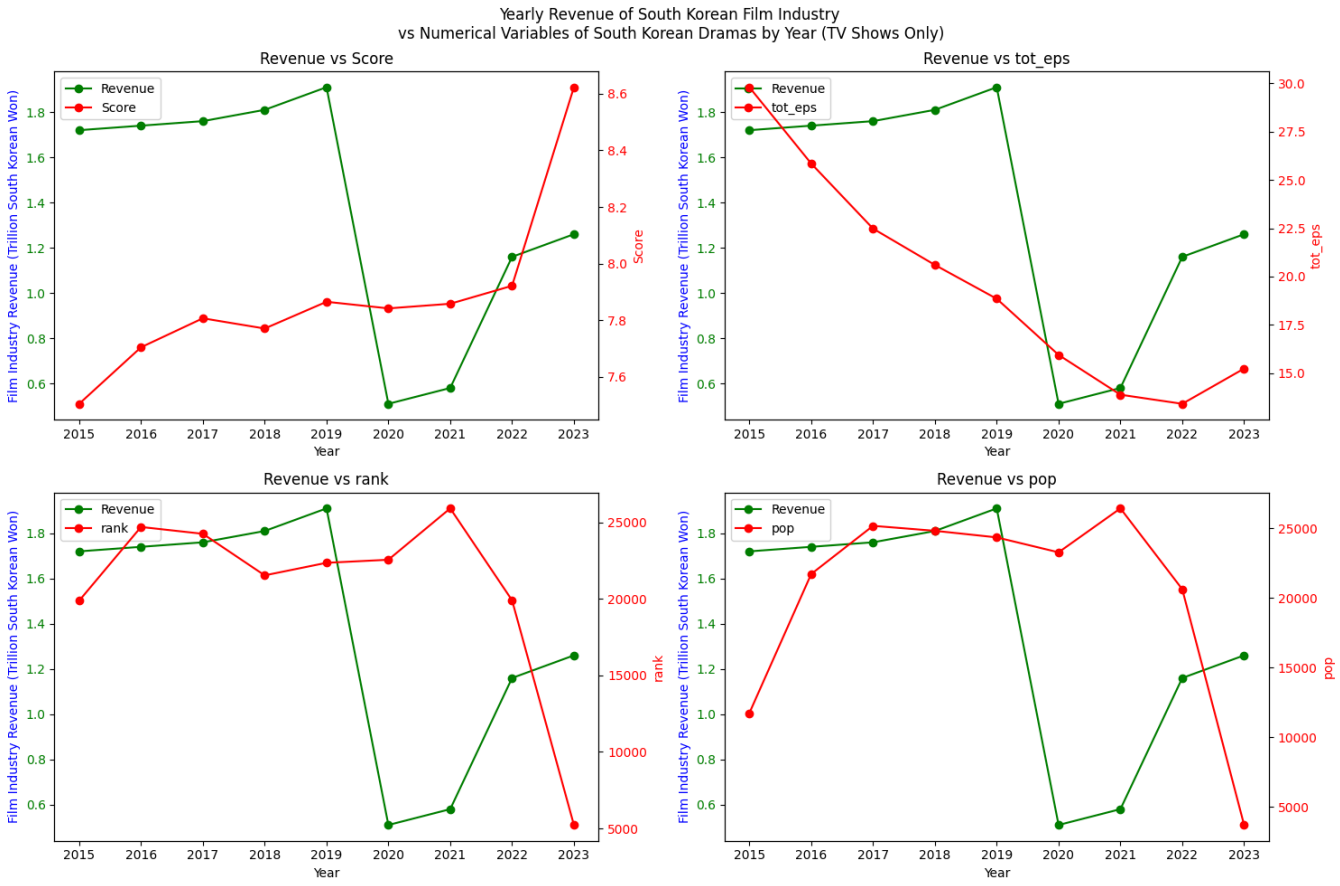
Since this merging process is a little bit different from the previous two merges, we will explain it in detail.

Just to demonstrate, the revenue data is yearly:



Note that this revenue variable is for the entire South Korean film industry, not just dramas. However, Korean dramas do indeed contribute a significant portion of South Korea's economic output, including revenue from exports and employment. This analysis is still useful to see how the drama industry is doing relative to the rest of the film industry.

Furthermore, we merge the revenue data with the drama data by year. To do so, we grouped the drama data by year and then merged the revenue data with the drama data by year. With our resulting dataset, we can compare the trends of revenue by year alongside the other numerical variables:



We also generated a correlation heatmap of the revenue data with the other numerical variables:

Here are some notable findings from the line plots and correlation matrix above:

- Pre-Pandemic Trends (2015-2019)
  - `revenue` of the South Korean Film Industry showed steady growth from 2015 to 2019, while scores gradually improved
  - `tot_eps` (total episodes) was decreasing steadily, suggesting a trend toward shorter series formats while maintaining higher revenue
  - `pop` (popularity) and `rank` maintained relatively stable patterns, indicating consistent audience engagement

- Pandemic Impact (2020)
    - `revenue` dropped sharply in 2020, falling to about 0.5 trillion won from 1.9 trillion won in 2019
    - Surprisingly, `score` remained stable during this period, suggesting that while the industry's financial performance suffered, content quality was maintained. Or that during the pandemic, shows that were filmed prior were being released. Or that the audience was more forgiving during the pandemic.
    - `tot_eps` continued its downward trend, possibly accelerated by production challenges during the pandemic
- Post-Pandemic Recovery (2021-2023)
    - `revenue` shows a gradual recovery pattern but hasn't returned to pre-pandemic levels
    - `score` reached its highest point (8.6) in 2023, showing significant improvement
    - `pop` and `rank` show volatile patterns during the recovery period

Other Notable Findings:

- The strong negative correlation between `year` and `tot_eps` (total number of episodes) (-0.95) suggests a clear industry shift toward shorter formats—whether due to the pandemic or other factors
- The positive correlation between `tot_eps` and `revenue` (0.68) implies that longer series historically generated more revenue, though this trend might be changing
- The relatively weak correlation between `revenue` and `popularity/rank` (-0.062/-0.00023) suggests that commercial success isn't necessarily tied to traditional popularity metrics

Exploratory Data Analysis

Below is the summary statistics of variables: We can see the mean for `music_score`, `story_score`, `acting_cast_score`, `rewatch_value_score`, and `overall_score` are very close to the median compared to other variables. Although they are close, the data itself is still skewed. The standard deviation of the popularity ranking is the highest, meaning there is a lot of variation in the data.

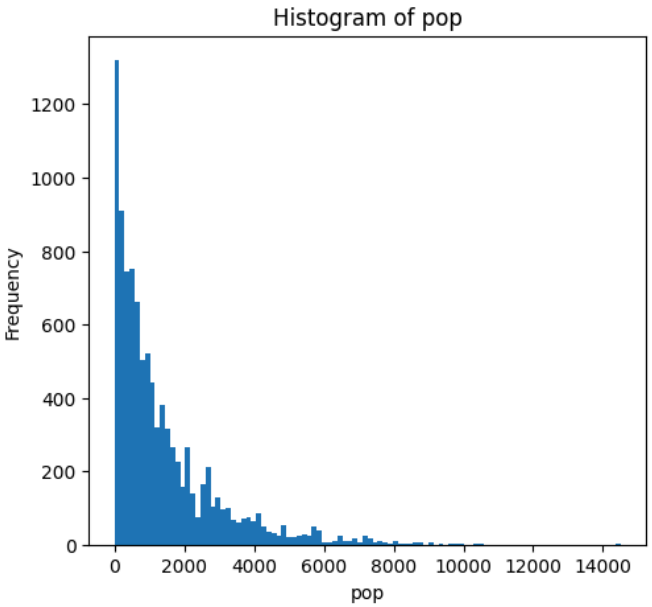
	year	tot_eps	duration	rank	pop	story_score	acting_cast_sc
count	9823	9823	9823	9823	9823	9823	98
mean	2019.11	18.7209	3020.11	3196.22	1401.66	7.56179	8.500
std	2.29225	17.0432	1333.96	2816.44	1547.09	2.18148	1.68
min	2015	1	52	8	1	1	
25%	2017	12	1980	985	331	6.5	
50%	2019	16	3600	2506	875	8	
75%	2021	16	4200	5090	1893.5	9	
max	2023	150	6000	56186	14507	10	

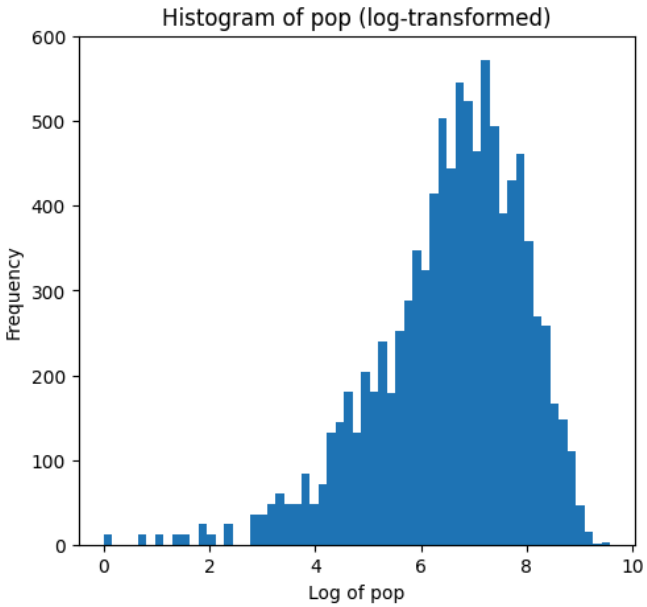
Definition of each variable (column header):

- `year` : Year of the drama (2015-2023)
- `tot_eps` : Total number of episodes
- `duration` : Duration of each episode
- `rank` : Ranking of the drama (lower is more popular)
- `pop` : Popularity ranking of the drama (lower is more popular)
- `story_score` : User-submitted score for story (from reviews)
- `acting_cast_score` : User-submitted score for acting cast (from reviews)
- `music_score` : User-submitted score for music (from reviews)
- `rewatch_value_score` : User-submitted score for rewatch value (from reviews)
- `overall_score` : User-submitted overall score (from reviews)
- `n_helpful` : Number of people that found review helpful (from reviews)

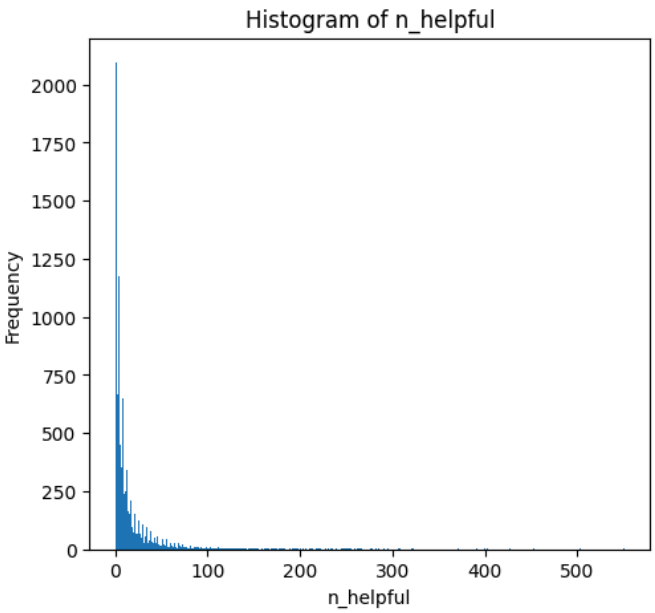
Distribution of Numerical Variables (and Log Transformed)

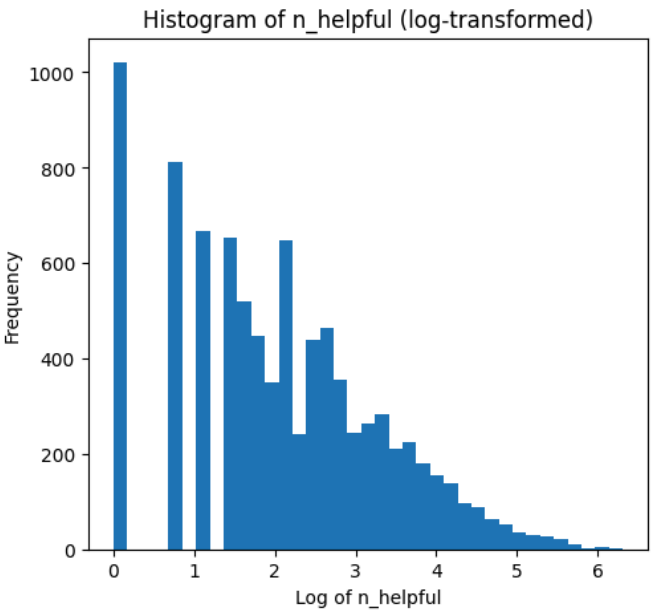
To study the distribution of numerical variables, we first plotted the histograms of all numeric variables, along with log transformations of those distributions as done in class. Below are the histograms of greatest interest, but all the distributions can be found in our final_report.ipynb Jupyter notebook.



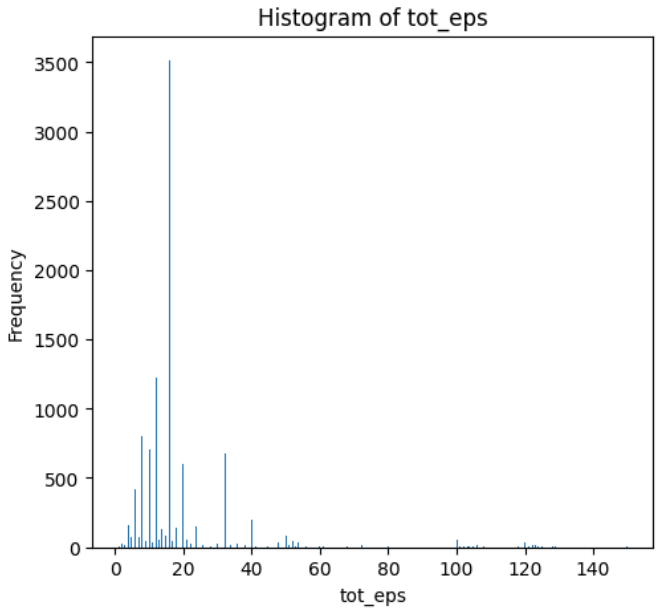


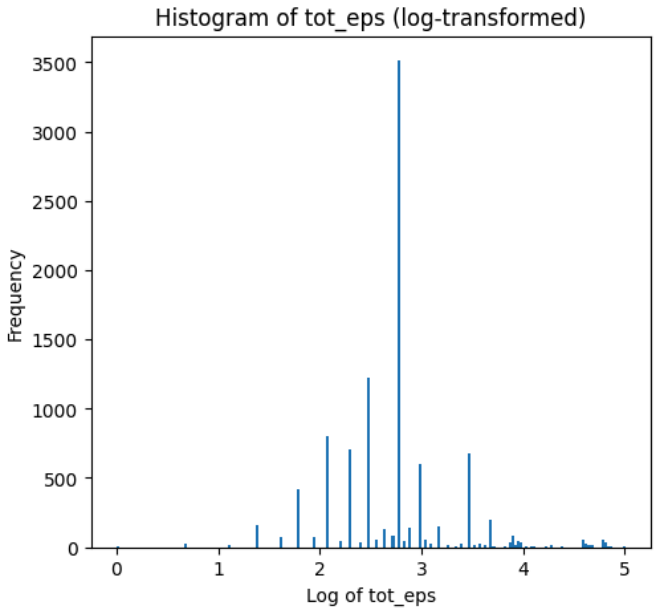
- `pop` (popularity ranking) remains heavily right-skewed, with most dramas having low popularity scores (<2000) and a few outliers reaching 12000+. As we saw in class, a log transformation makes the distribution more normal, suggesting a multiplicative effect in popularity growth



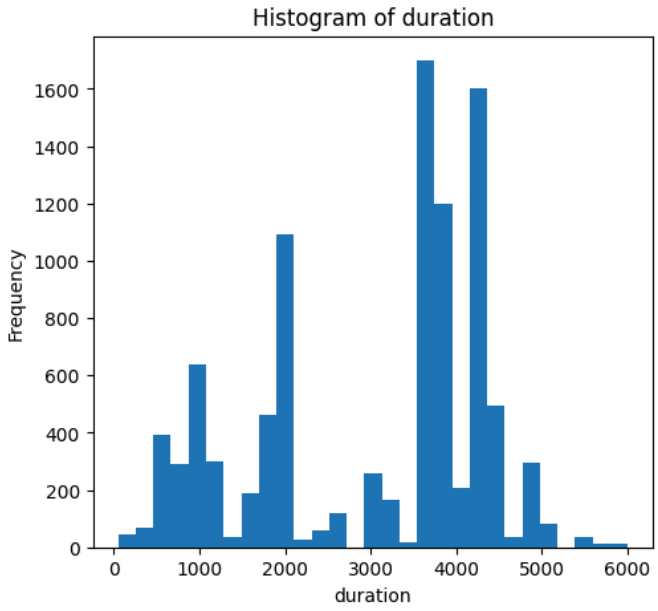


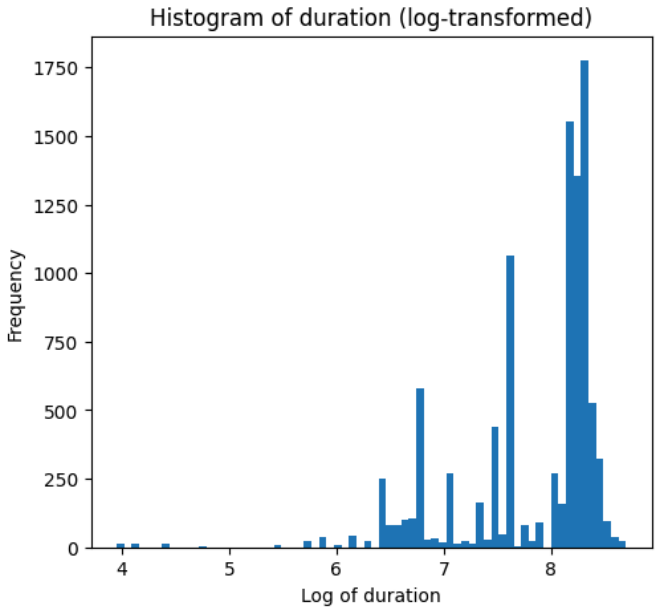
- `n_helpful` shows an extreme right skew, with most reviews getting few helpful votes and a rapid drop-off



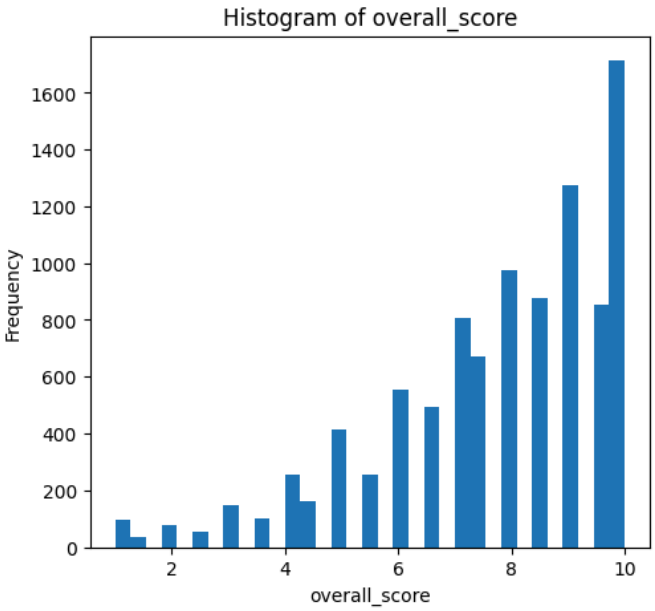


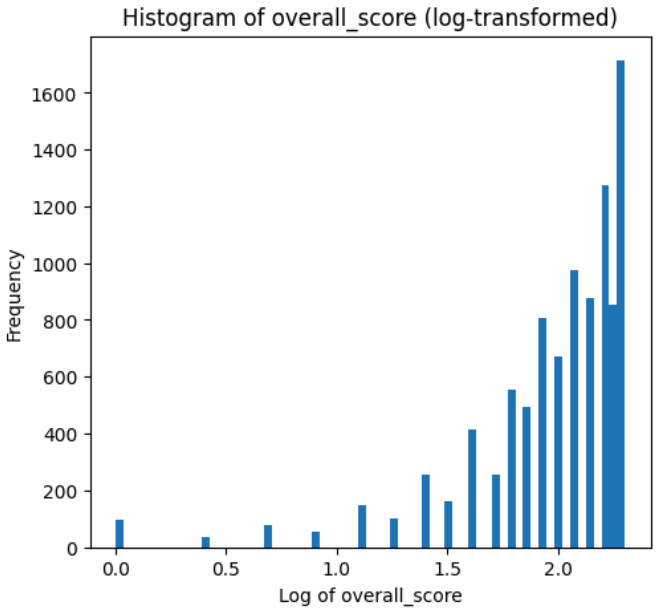
- `tot_eps` shows distinct clustering around certain episode counts (16, 32, or 50 episode dramas across multiple seasons), reflecting common show format lengths



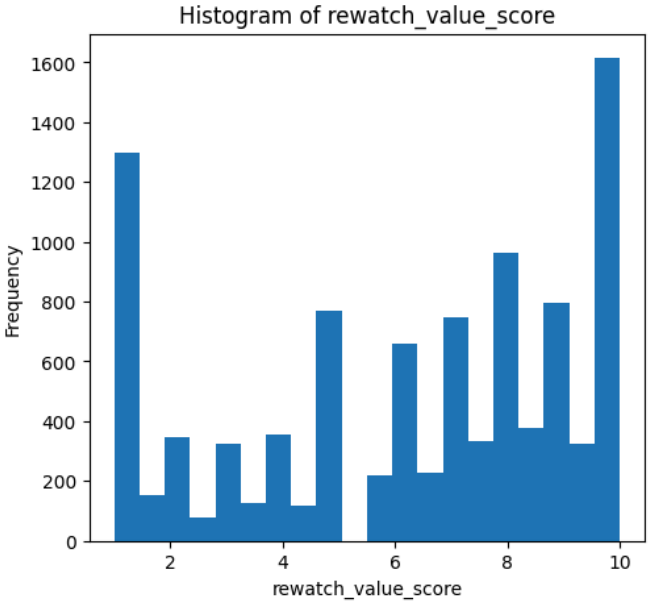


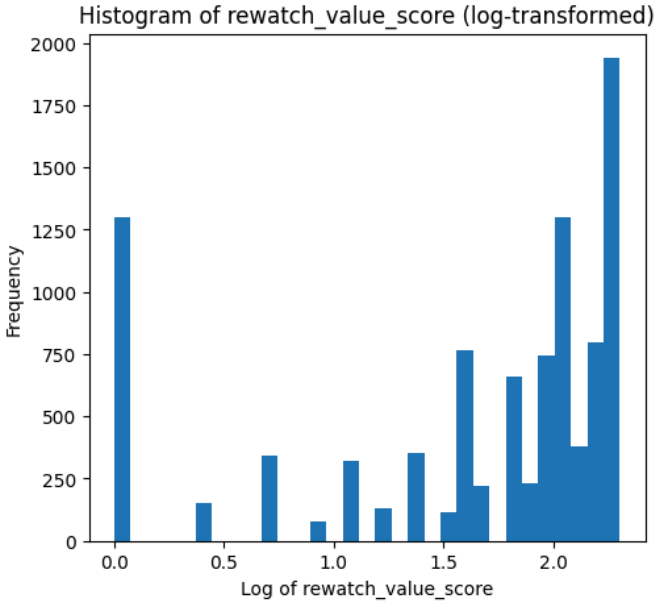
`duration` also exhibits multiple distinct peaks, likely corresponding to standard episode lengths for different drama formats





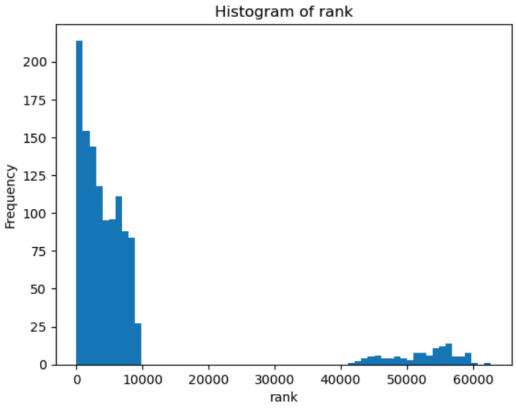
- Most score related columns: `story_score`, `acting_cast_score`, `music_score`, `overall_score` are left-skewed, meaning that most viewers gave high scores to most dramas, while a few have very low score (e.g. 1-2). As we saw in class, a log transformation of left-skewed data does not make the distribution more normal but in fact skews it more to the left.
- Only `overall_score` is shown above for brevity, but once again, all the distributions can be found in final_report.ipynb

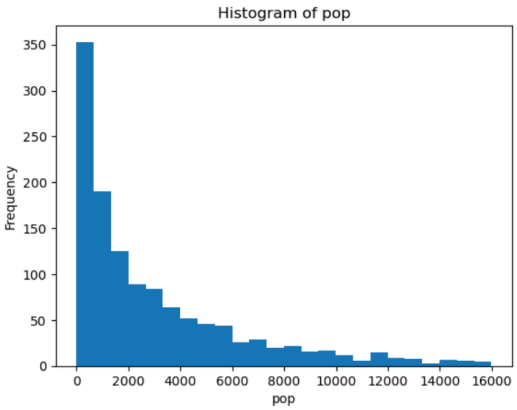




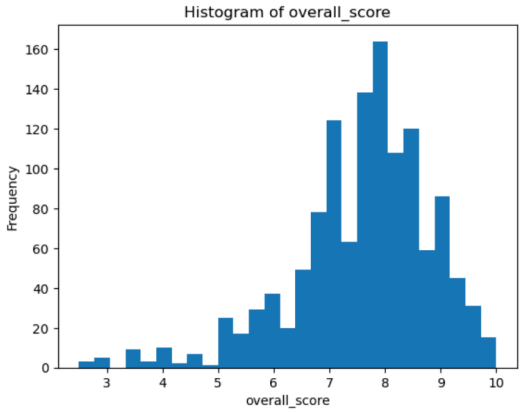
- The only potential exception is `rewatch_value_score`, which is bi-modal with a slight left skew, suggesting that most dramas fall into two categories: those that

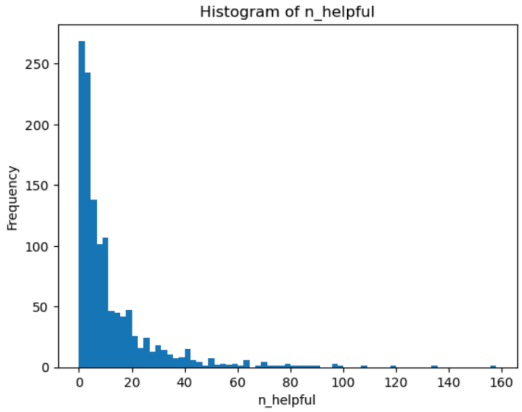
are highly rewatchable (9-10) and likely one-time watches (1-2)





- `rank` and `pop` (popularity ranking) are also right skewed. Since higher number in ranking means lower popularity, most drama ranked high in the ranking and only a few have low popularity.

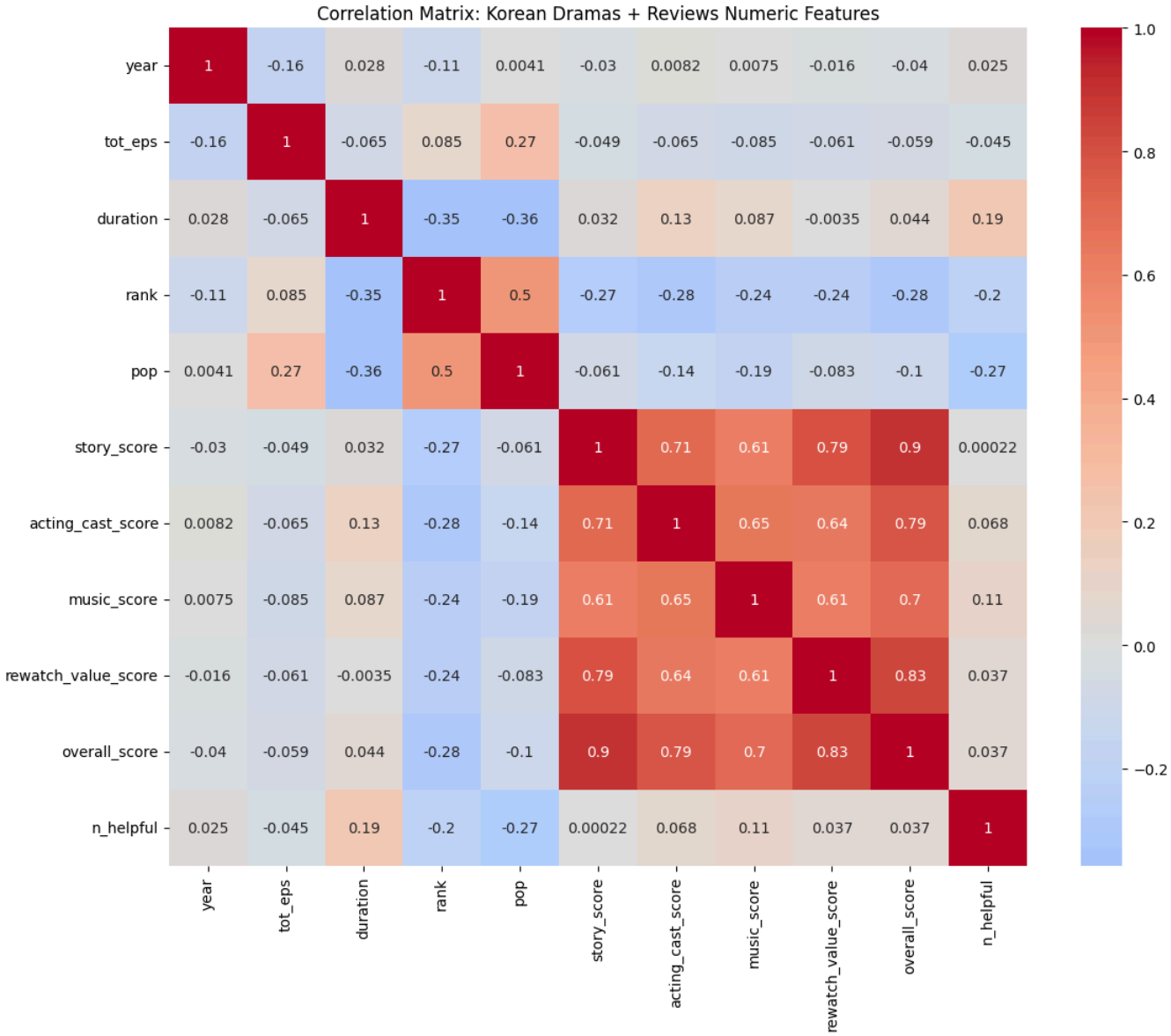




- `overall_score` is left skewed, meaning most audience gave high scores to the drama overall. The data for the `n_helpful` (number of people that found review helpful) is right skewed, meaning the review are very personalized so that not so many people hold same opinion.

Correlation Heatmap and Plots of Numerical Variables

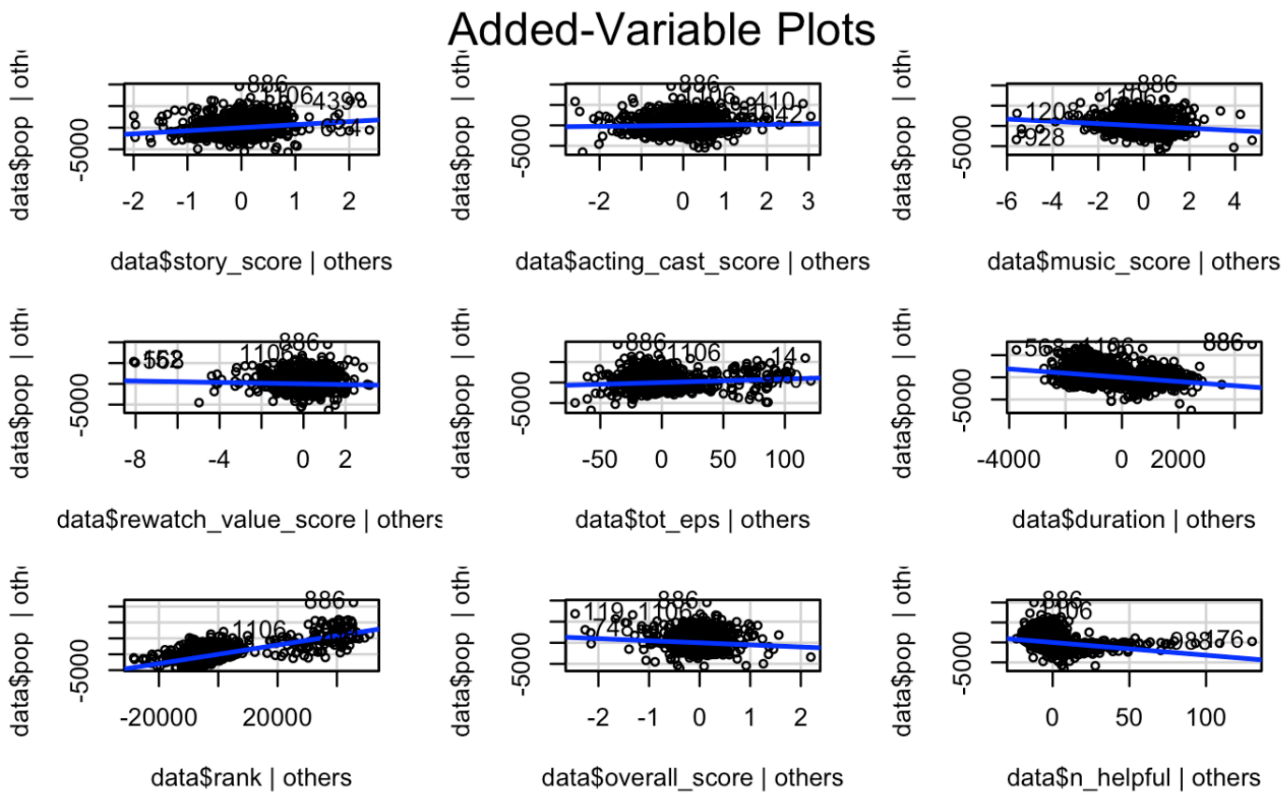
Below is the correlation heatmap of all numerical values and some notable findings:



- `overall_score` has very strong **positive correlations** with `story_score` (0.9), `rewatch_value_score` (0.83), `acting_cast_score` (0.79), and `music_score` (0.7)—which is to be expected, people who enjoy the story, acting, and music are more likely to enjoy the drama overall
- `pop` has a **moderate positive correlation** with `rank` (0.5), suggesting that more popular dramas might not always have the best rankings
- `duration` has **negative correlations** with `rank` (-0.40) and `pop` (-0.38)
- `year` exhibits very weak correlations with most variables, suggesting quality and sentiment metrics aren't strongly tied to when the drama was released

Digging deeper into individual variable correlations, we can see that `pop` (popularity) and `rank` are highly correlated. And `music_score`, `story_score`, `acting_cast_score`,

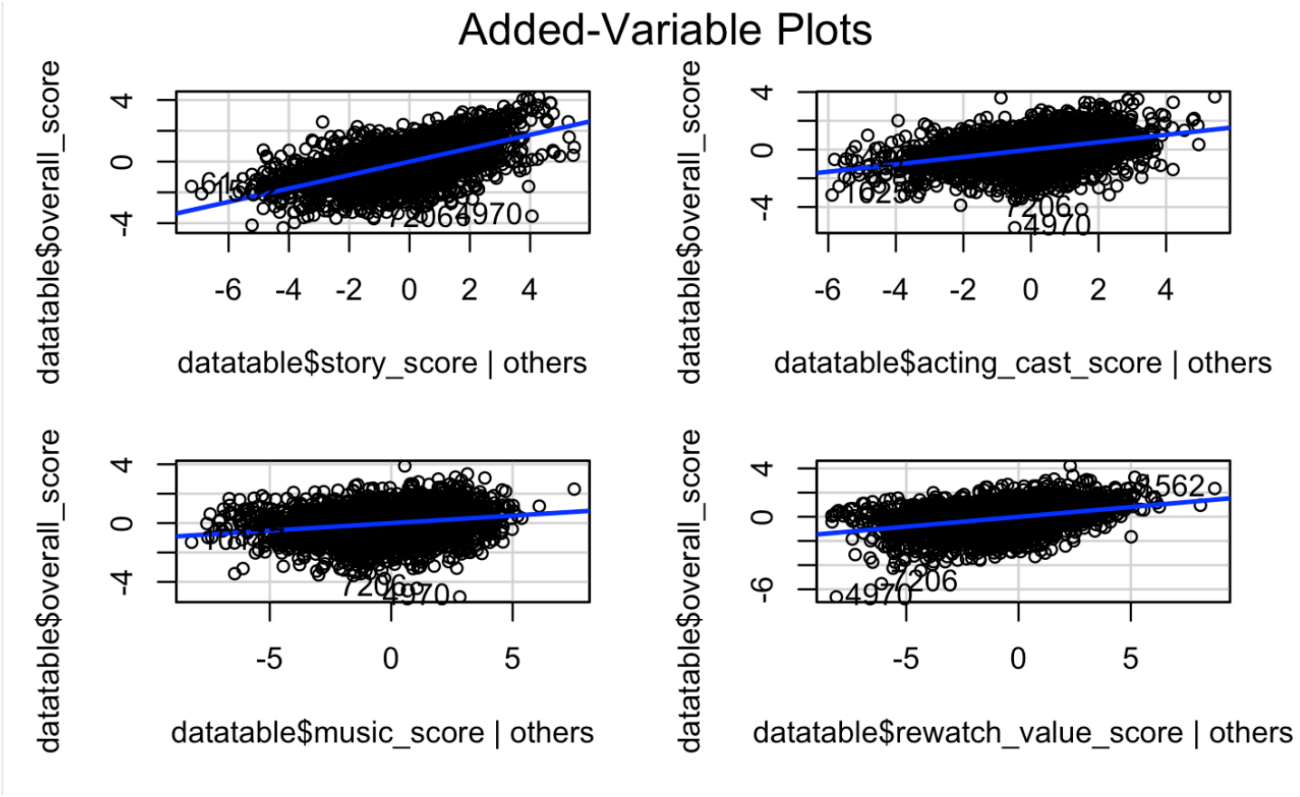
`rewatch_value_score`, and `overall_score` are highly correlated:



Linear Regression Analysis

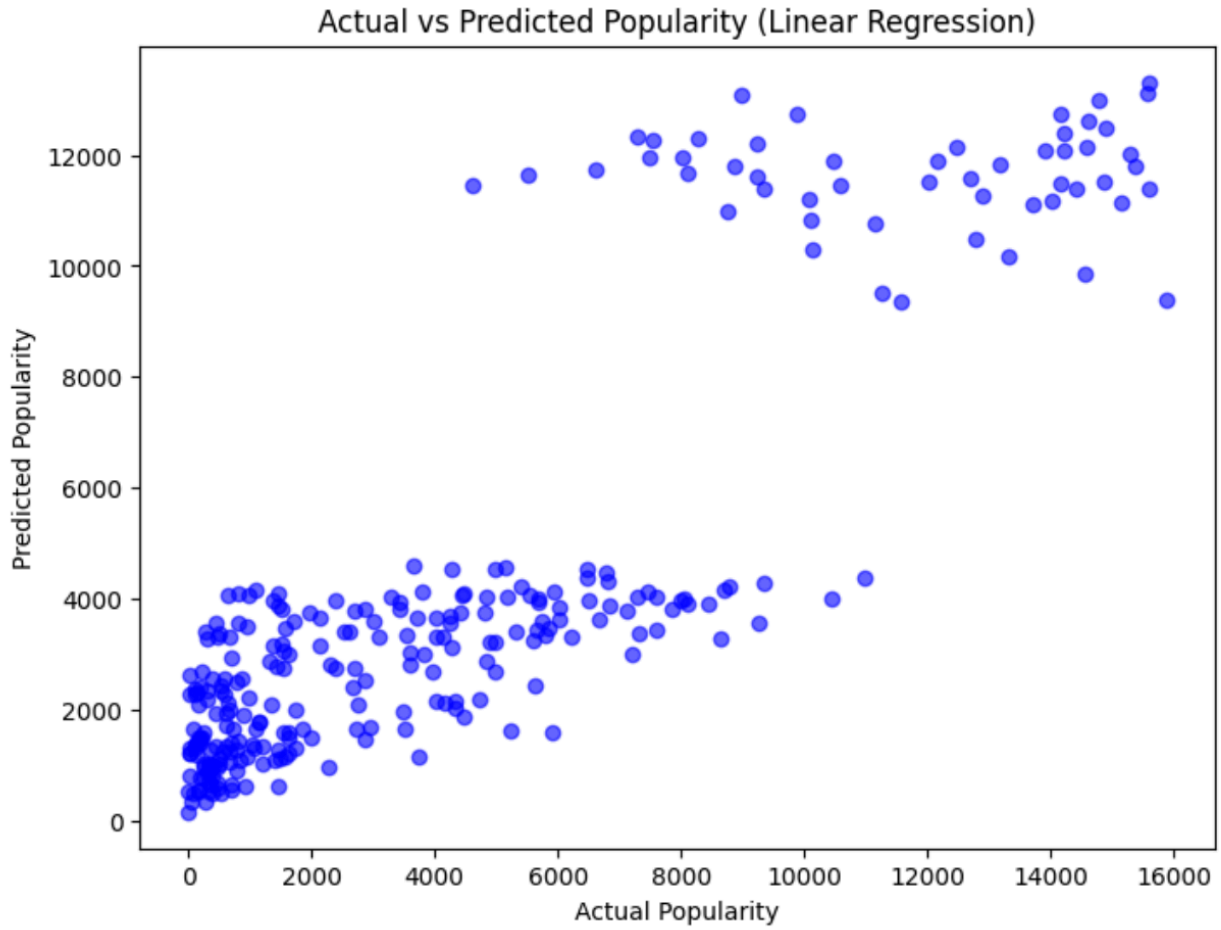
Same thing happened when we look at the linear regression plot. We can see that there is a positive relationship between `pop` (popularity rank) and `rank`. We also found that there is a negative relationship between `duration` and `pop`, meaning longer drama has higher popularity. Interesting thing to see is that there is a negative relationship between `n_helpful` (number of people found the review helpful) and `pop`, meaning when there is more people sharing same opinion, the drama is more popular.

By looking at the drama information and the review separately, we did the following EDA and analysis:



This is the linear regression analysis between the `overall_score` and `story_score`, `acting_cast_score`, `music_score`, and `rewatch_value_score`. We can see that these are all positive relationship, meaning the `story_score`, `acting_cast_score`, `music_score`, and `rewatch_value_score` all have a positive impact on the `overall_score`.

By looking at the drama information without the impact of review, we found the following thing:



This is a simple linear regression without standardization and normalization.

Comparison: Without standardization and normalization and with standardization and normalization:

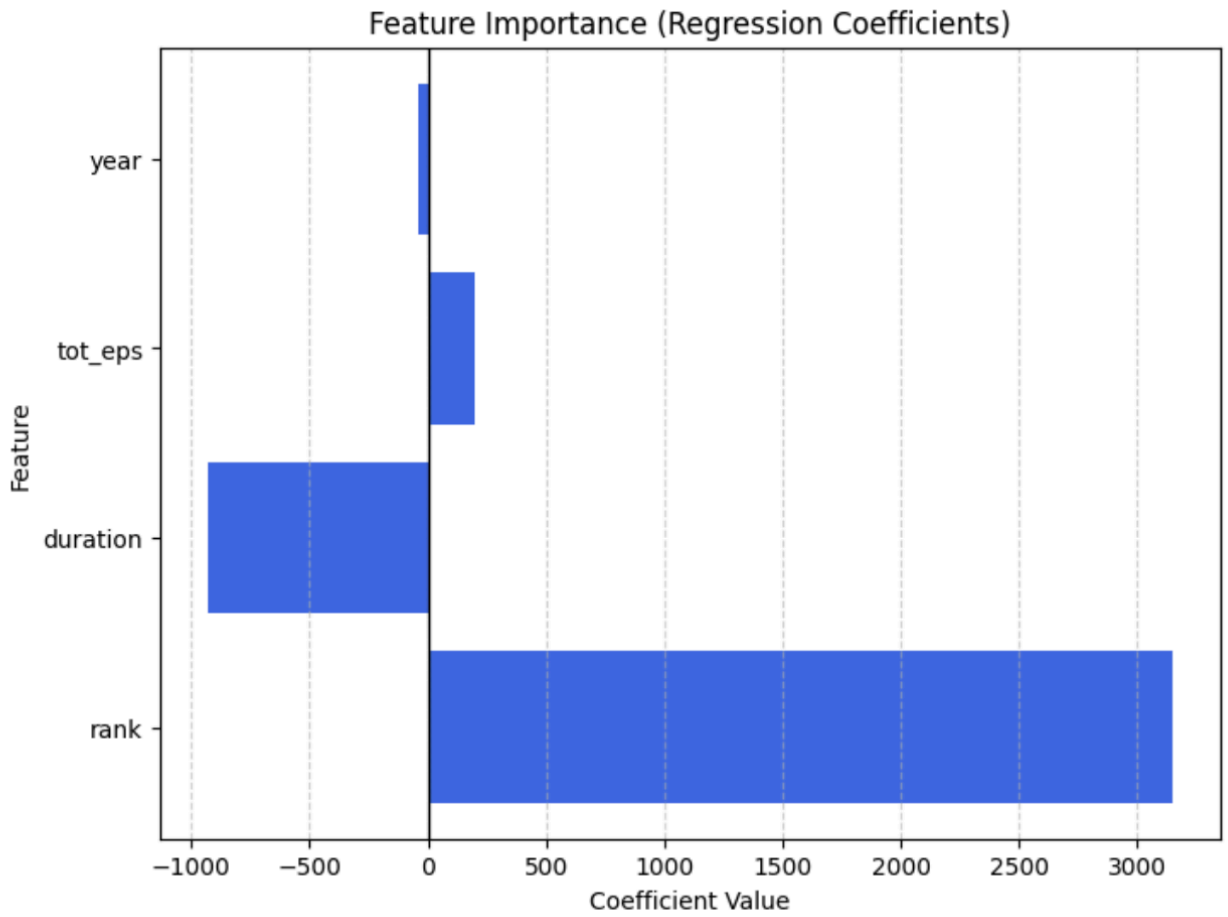
Feature	Coefficient
`year`	-16
`tot_eps`	7
`duration`	-0.6
`rank`	0.2

Feature	Coefficient
`year`	-38

Feature	Coefficient
`tot_eps`	195
`duration`	-929
`rank`	3146

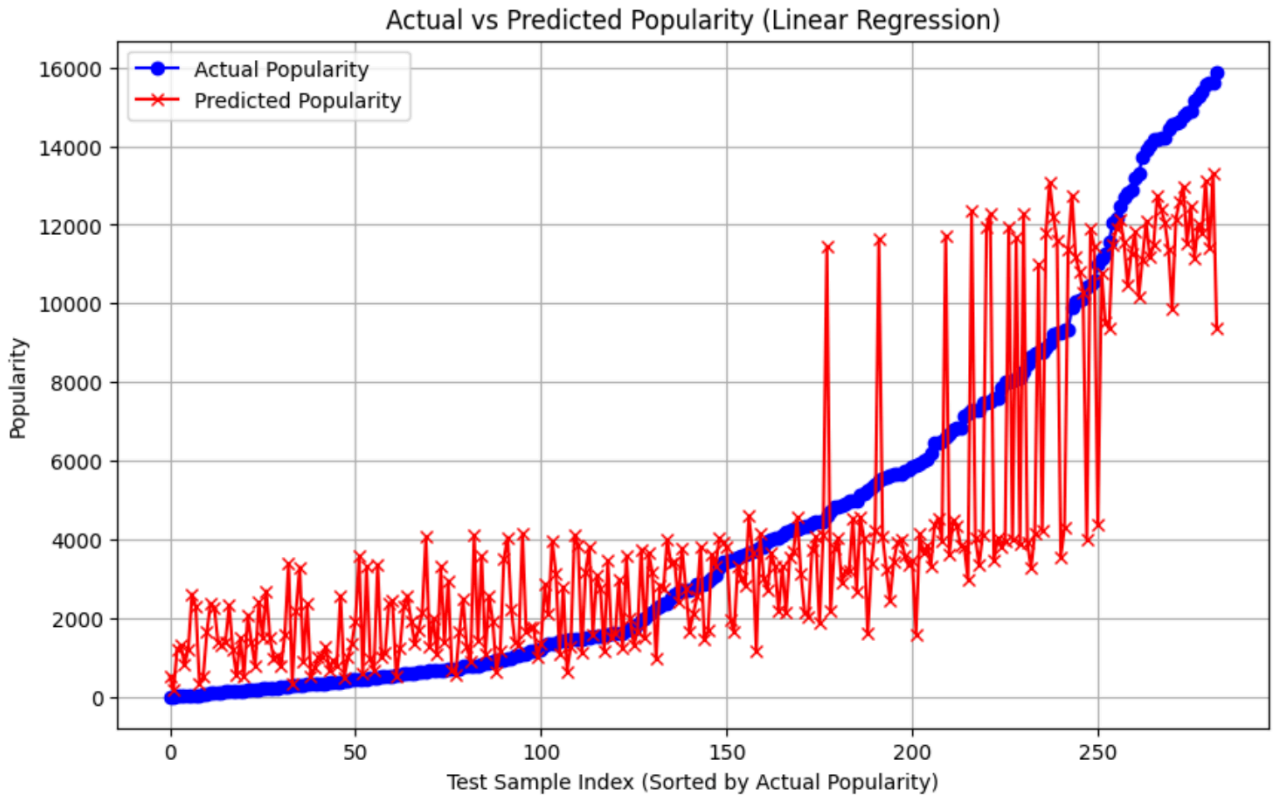
This is with standardization and normalization.

`rank` was already strongly correlated with `pop`, but because it had a larger scale originally, it may have had a smaller coefficient in the unstandardized model. After standardization, its impact is clearer, leading to a larger coefficient, indicating that it has the strongest influence in predicting popularity.



From the bar chart, `rank` has the strongest positive impact, suggesting that higher-ranked dramas are significantly more popular. `duration`, on the other hand, has a substantial negative effect, indicating that dramas aired for a longer period tend to be less popular,

possibly due to audiences losing interest over time. `tot_eps` has a smaller but still positive influence, implying that dramas with more episodes may attract greater engagement. Finally, the `year` of release has the least impact, showing that a drama's release year is not a major factor in determining its popularity.



The actual vs. predicted popularity of K-dramas can tell us some insights about the model fit.

The blue line represents the actual popularity values, sorted in increasing order. The red crosses represent the predicted popularity values from the linear regression model.

The predicted values roughly follow the increasing trend of actual popularity, indicating that the model is capturing some underlying patterns.

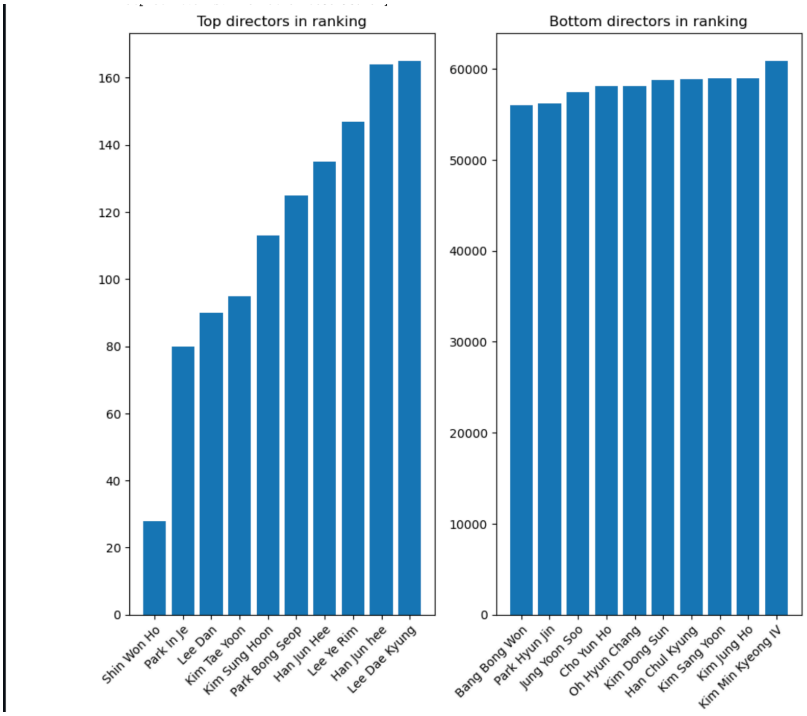
There is significant scatter in the predicted values, especially in the higher popularity range. This suggests that the model struggles to accurately predict very popular dramas. The linear regression model seems to perform better for less popular dramas (left side of the graph), where the red points are closer to the blue line. The variance increases significantly as popularity rises.

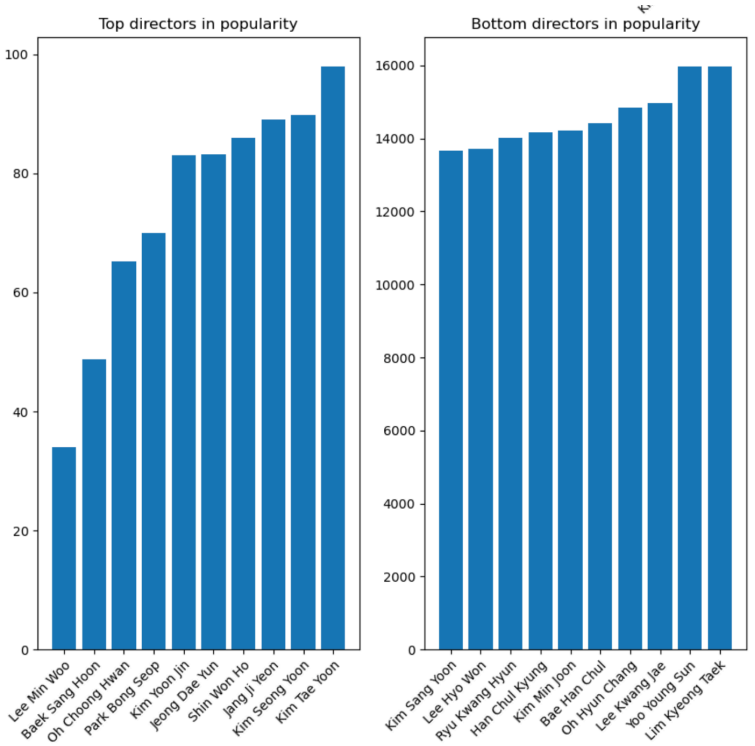
	T statistics	p value
Year	-0.03	0.98
Total number of episodes	0.30	0.76
Duration of each episode	2.65	0.01
rank	-0.79	0.43

T-test on Standardized Variables

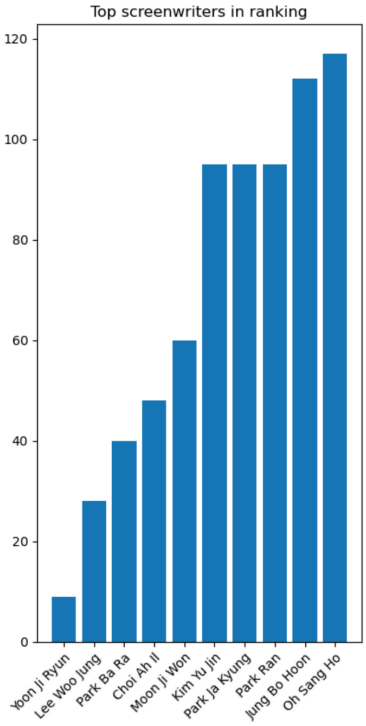
In this T-test on standardized variables, the null hypothesis (H_0) states that there is no significant difference in the mean values of each feature between the training and test sets. The results indicate that most features, including `year`, `tot_eps` (total number of episodes), and `rank`, are well-balanced between the training and test sets, as their high p-values suggest no significant difference in their distributions. However, `duration` stands out with a statistically significant p-value (0.008), implying a potential distribution shift between the two sets. This suggests that the model might face inconsistencies when predicting dramas with extreme duration values, possibly affecting overall performance.

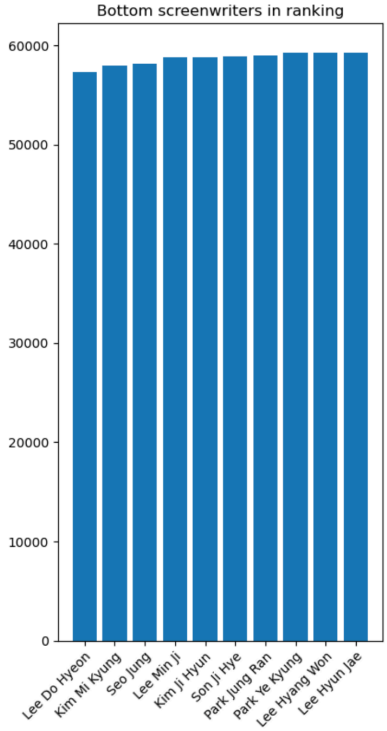
Besides, we also did analysis on the directors and screenwriters of Korean drama:

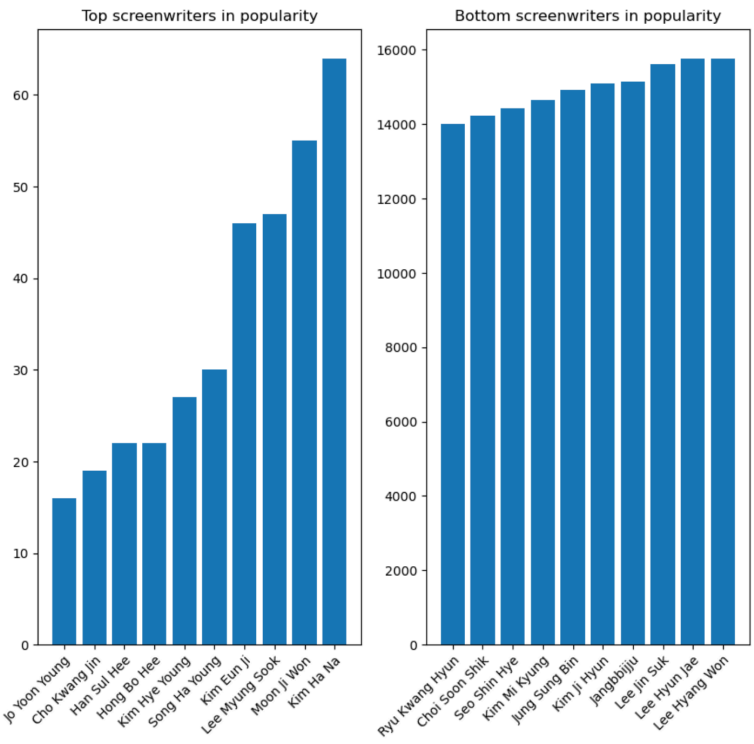



Top directors in popularity
Lee Min Woo
Baek Sang Hoon
Oh Choong Hwan
Park Bong Seop
Kim Yoon Jin
Jeong Dae Yun
Shin Won Ho
Jang Ji Yeon
Kim Seong Yoon
Kim Tae Yoon

Bottom directors in popularity
Kim Sang Yoon
Lee Hyo Won
Ryu Kwang Hyun
Han Chul Kyung
Kim Min Joon
Bae Han Chul
Oh Hyun Chang
Lee Kwang Jae
Yoo Young Sun
Lim Kyeong Taek


Top screenwriters in ranking
Yoon Ji Ryun
Lee Woo Jung
Park Ba Ra
Choi Ah Il
Moon Ji Won
Kim Yu Jin
Park Ja Kyung
Park Ran
Jung Bo Hoon
Oh Sang Ho

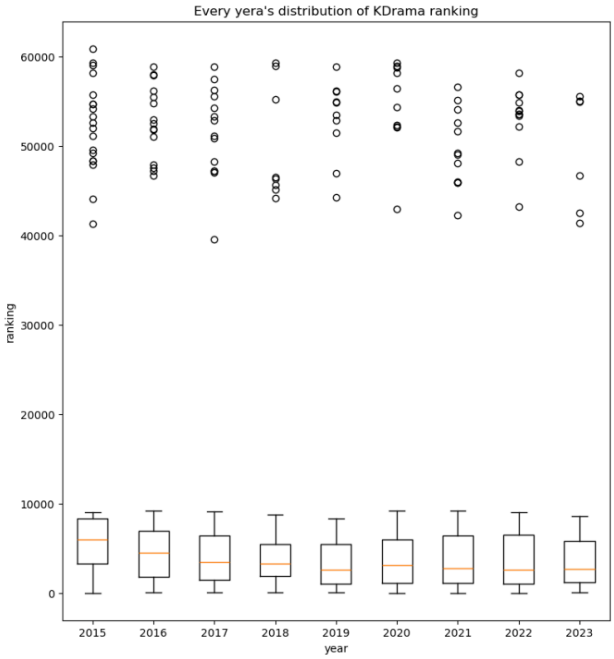

Bottom screenwriters in ranking
Lee Do Hyeon
Kim Mi Kyung
Seo Jung
Lee Min Ji
Kim Ji Hyun
Son Ji Hye
Park Jung Ran
Park Ye Kyung
Lee Hyang Won
Lee Hyun Jae

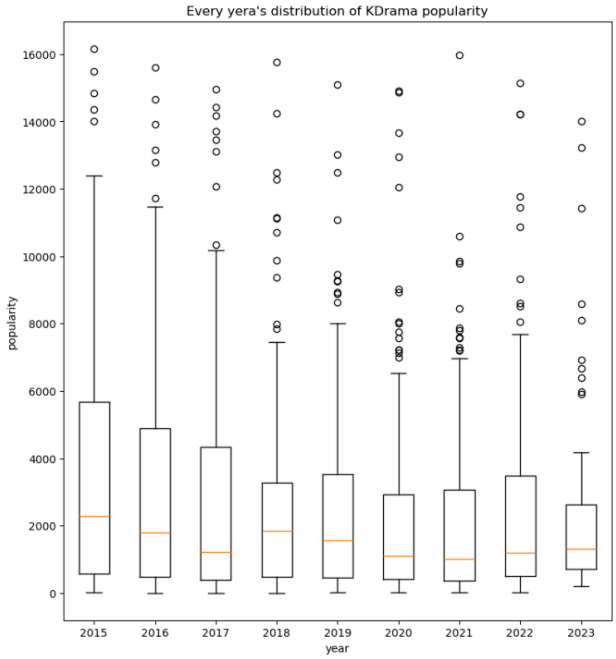


The top 10 and bottom 10 directors/screenwriters with respect to Korean Drama ranking and popularity are shown in the above charts. Besides, we also did some analysis based on time difference:

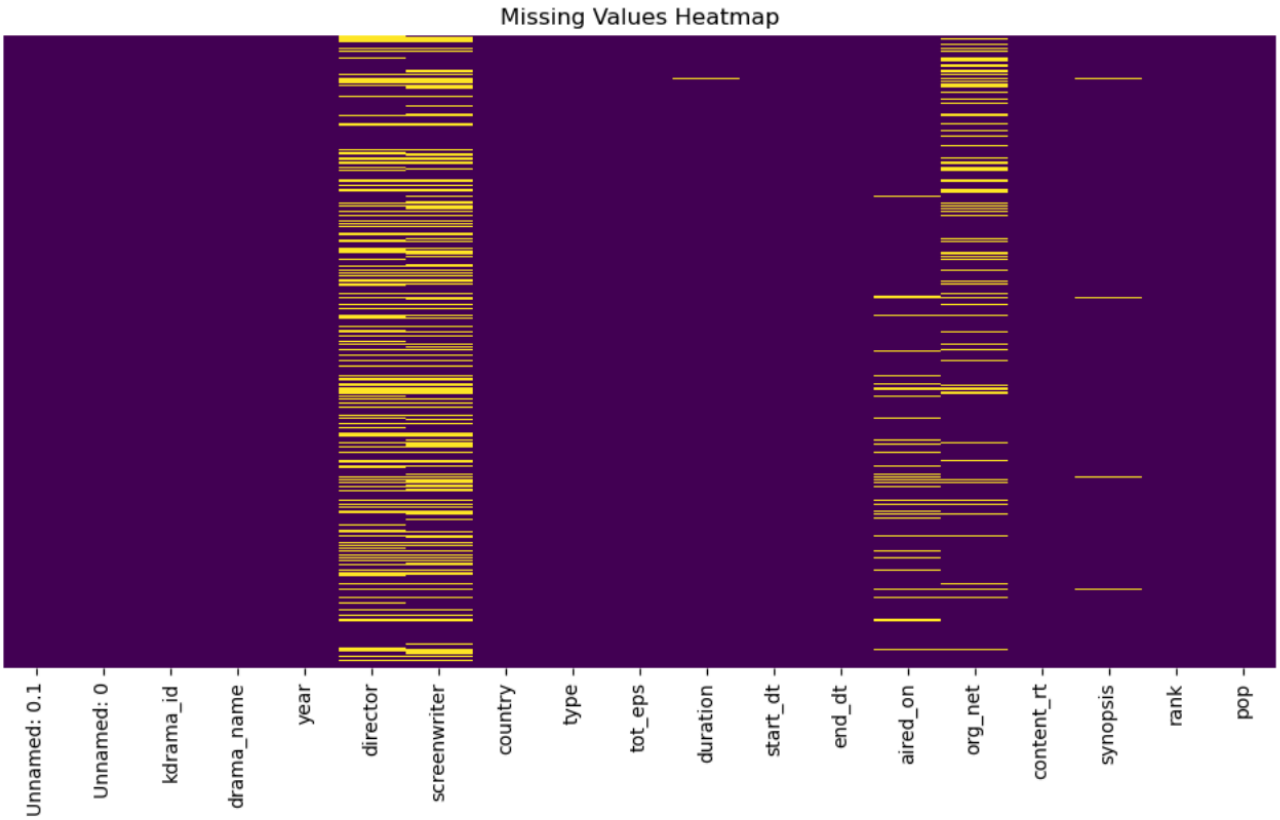
```
             rank
year
2015  13557.000000
2016  10953.423077
2017   9029.570248
2018   6431.562500
2019   6738.812030
2020   7210.656250
2021   7429.543478
2022   7217.151316
2023   7251.461538
```

```
             pop
year
2015  3986.105769
2016  3304.057692
2017  3019.719008
2018  2681.273438
2019  2635.781955
2020  2410.546875
2021  2207.514493
2022  2455.144737
2023  2518.200000
```





From the boxplots, we can see Korean Drama ranking increased from 2015 to 2018, and there was a slightly decreasing trend after 2019, which is also supported by the trend of mean ranking each year. There was an apparent increase in the overall popularity of Korean Drama (since lower number indicates higher popularity).



From the missing value heatmap, we can see most missing values are the name of directors and screenwriters, and Network that it aired on.

Feature Engineering

Variance and Box-Cox Transformation

Below are the feature engineering we did:

```python
from sklearn.feature_selection import VarianceThreshold
# First, let's check the variance of the numerical features.
num_features = Data.select_dtypes(include=[np.number]).columns
variance = Data[num_features].var()
print("Variance of numerical features:")
print(variance)
# We choose a threshold. Here, we set a threshold of 0.01.
vt = VarianceThreshold(threshold=0.01)
X_num = Data[num_features].fillna(0)  # temporarily fill missing values for variance calculation
vt.fit(X_num)
features_to_keep = X_num.columns[vt.get_support()]

print("\nNumerical features to keep (variance above threshold):")
print(list(features_to_keep))
```

```
Variance of numerical features:
tot_eps                7.146182e+02
duration               2.071882e+06
rank                   2.103369e+08
pop                    1.128234e+07
music_score            2.265932e+00
story_score            1.748072e+00
acting_cast_score      1.297782e+00
rewatch_value_score    3.432114e+00
overall_score          1.566452e+00
n_helpful              2.621988e+02
dtype: float64

Numerical features to keep (variance above threshold):
['tot_eps', 'duration', 'rank', 'pop', 'music_score', 'story_score', 'acting_cast_score', 'rewatch_value_score',
'overall_score', 'n_helpful']
```

First, we checked the variance of all numerical features and we set a threshold of 0.01. After calculation, no features has zero or near zero variance, thus our features are all good.

```
from scipy.stats import boxcox
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# Numerical Data Transformations
num_cols = Data.select_dtypes(include=[np.number]).columns

# For Box-Cox transformation, the data must be positive.
for col in ['tot_eps', 'duration', 'rank', 'pop', 'music_score', 'story_score', 'acting_cast_score', 'rewatch_val
    if col in Data.columns:
        # Check for non-positive values and shift if necessary
        min_val = Data[col].min()
        if min_val <= 0:
            Data[col] = Data[col] + abs(min_val) + 1
        transformed, lam = boxcox(Data[col])
        Data[col + '_boxcox'] = transformed
        print(f"Applied Box-Cox transformation on {col} (lambda: {lam:.4f}).")
        # Optionally, drop or retain the original column

# Standardize numerical features
scaler = StandardScaler()
Data[num_cols] = scaler.fit_transform(Data[num_cols])

# Normalize (MinMax scaling)
minmax = MinMaxScaler()
Data[num_cols] = minmax.fit_transform(Data[num_cols])

# Categorical Data Transformations
cat_cols = Data.select_dtypes(include=["object"]).columns
print("\nCategorical columns before encoding:", list(cat_cols))


# One-hot encoding for categorical variables
df_encoded = pd.get_dummies(Data, columns=cat_cols, drop_first=True)

print("\nShape after one-hot encoding:", df_encoded.shape)
```

```
Applied Box-Cox transformation on tot_eps (lambda: -0.2501).
Applied Box-Cox transformation on duration (lambda: 0.7327).
Applied Box-Cox transformation on rank (lambda: 0.0761).
Applied Box-Cox transformation on pop (lambda: 0.2159).
Applied Box-Cox transformation on music_score (lambda: 2.5040).
Applied Box-Cox transformation on story_score (lambda: 2.2960).
Applied Box-Cox transformation on acting_cast_score (lambda: 3.7727).
Applied Box-Cox transformation on rewatch_value_score (lambda: 1.4414).
Applied Box-Cox transformation on overall_score (lambda: 2.5676).
Applied Box-Cox transformation on n_helpful (lambda: -0.0933).

Categorical columns before encoding: ['title', 'kdrama_id', 'director', 'screenwriter', 'start_dt', 'end_dt', 'aire
d_on', 'org_net', 'content_rt', 'synopsis']

Shape after one-hot encoding: (1248, 6997)
```

Next, we performed feature transformation. First, it is unnecessary to normalize the 5 score attributes since they are already with the range [0, 10]. It is sufficient to divide them by 10. Then, we performed box-cox transformation to the rest 5 numerical attributes to reduce their skewness. These 5 numerical attributes require rescaling, since their ranges are diverse. The Number of people-finding-this-comment-helpful (n_helpful) is applied normalization instead of standardization because it is skewed to 0. Since Rank and Popularity are both ranking-variables, they are applied the reversive function f(x)=1-x after normalization. Total number of episodes (tot_eps) and Duration of single episode in second (duration) are applied normalization instead of standardization due to their limited value sets.
Not all categorical variables are encoded. For example, year is not encoded since it is useful

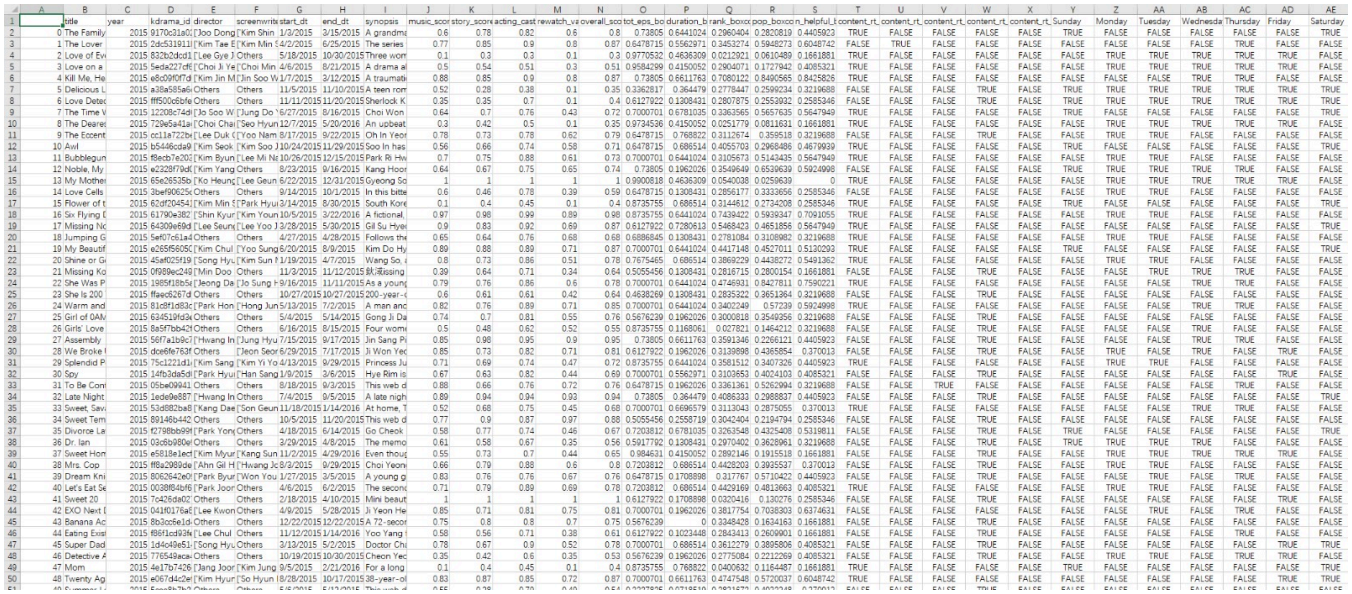
as the index for time series analysis; attributes like directors and screenwriters are impractical to encode directly, as this will produce hundreds of new variables. The only variables we applied one-hot encoding to are Content Rating (content_rt) and Aired-on Date (aired_on) because their types are limited. Content Rating was simply one-hot encoded. For Aired-on Date, since a show can be aired on several days of week, we created 7 new variables for each day of week, so each entry can have multiple True values among the 7.
The following is the refined version of feature engineering:

In [7]:

```
from scipy.stats import boxcox
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# Numerical Data Transformations
# Divide the scores by 10
Data[['music_score', 'story_score', 'acting_cast_score', 'rewatch_value_score', 'overall_score']] /= 10

# For Box-Cox transformation, the data must be positive.
num_cols = ['tot_eps', 'duration', 'rank', 'pop', 'n_helpful']
for col in num_cols:
    if col in Data.columns:
        # Check for non-positive values and shift if necessary
        min_val = Data[col].min()
        if min_val <= 0:
            Data[col] = Data[col] + abs(min_val) + 1
        transformed, lam = boxcox(Data[col])
        Data[col + '_boxcox'] = transformed
        print(f"Applied Box-Cox transformation on {col} (lambda: {lam:.4f}).")

# Normalize (MinMax scaling)
num_cols2 = ['tot_eps_boxcox', 'duration_boxcox', 'n_helpful_boxcox']
minmax = MinMaxScaler()
Data[num_cols2] = minmax.fit_transform(Data[num_cols2])

# Normalize with reversing
num_cols3 = ['rank_boxcox', 'pop_boxcox']
minmax = MinMaxScaler()
Data[num_cols3] = 1 - minmax.fit_transform(Data[num_cols3])

# Categorical Data Transformations
cat_cols = ['content_rt']
print("\nCategorical columns before encoding:", list(cat_cols))

# One-hot encoding for categorical variables
df_encoded = pd.get_dummies(Data, columns=cat_cols, drop_first=True)

# One-hot encoding aired_on
import re
df_encoded['aired_on'] = df_encoded['aired_on'].apply(lambda x: re.split(r",[ \n]*", x))
days = ['Sunday', 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday']
one_hot = {day: [] for day in days}
for aired_days in df_encoded['aired_on']:
    for day in days:
        one_hot[day].append(day in aired_days)
one_hot_df = pd.DataFrame(one_hot)
df_encoded = pd.concat([df_encoded, one_hot_df], axis=1)
df_encoded.drop(['aired_on'], axis=1, inplace=True)

# Optionally, drop or retain the original column
df_encoded.drop(num_cols, axis=1, inplace=True)
print("\nShape after one-hot encoding:", df_encoded.shape)
```

```
Applied Box-Cox transformation on tot_eps (lambda: -0.2501).
Applied Box-Cox transformation on duration (lambda: 0.7327).
Applied Box-Cox transformation on rank (lambda: 0.0761).
Applied Box-Cox transformation on pop (lambda: 0.2159).
Applied Box-Cox transformation on n_helpful (lambda: -0.0933).

Categorical columns before encoding: ['content_rt']

Shape after one-hot encoding: (1248, 30)
```

Below is the final cleaned data after feature engineering:



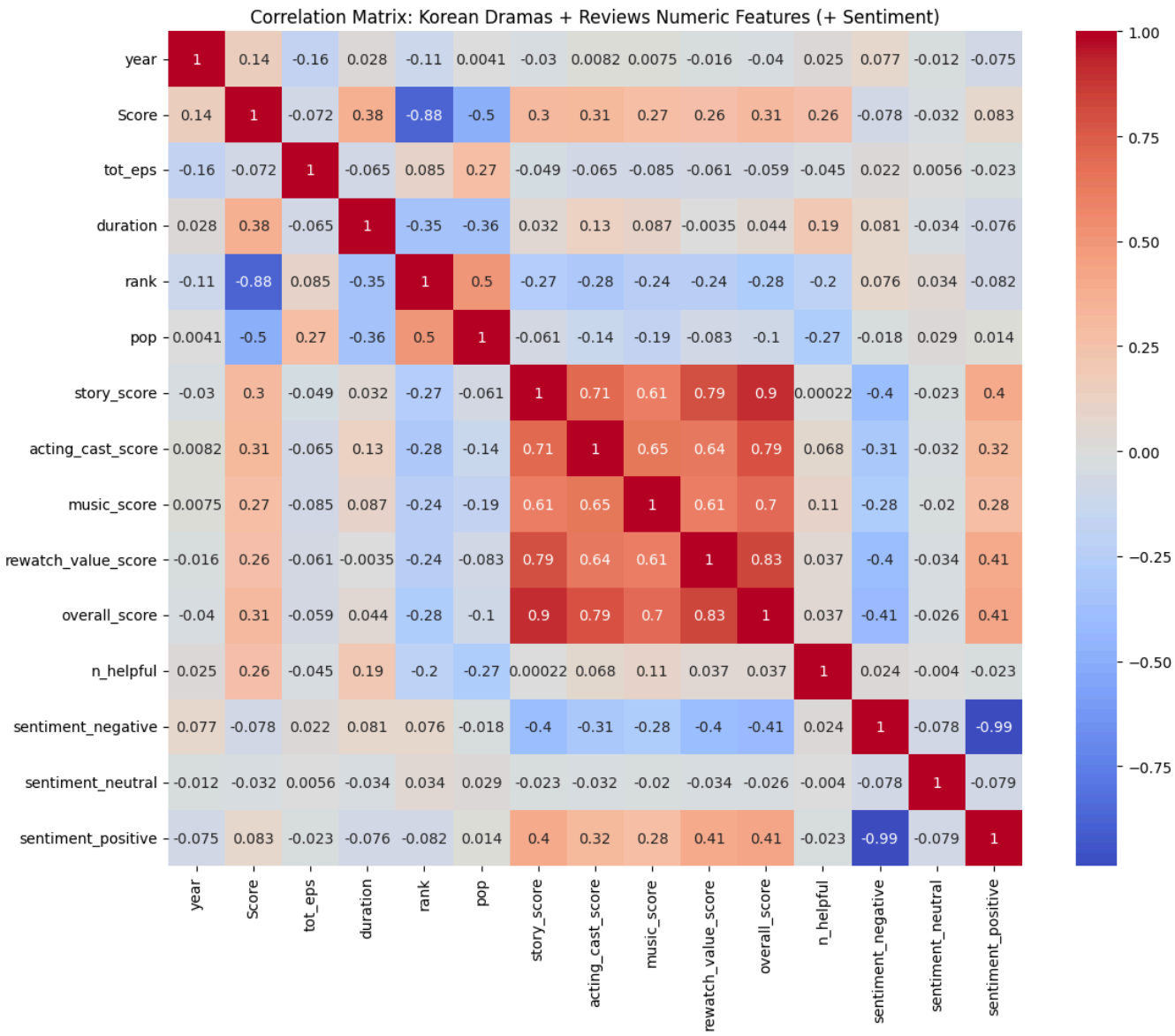
	title	year	kdrama_id	director	screenwrite	start_dt	end_dt	synopsis	music_scor	story_scor	acting_cast	rewatch_va	overall_sco	tot_eps_bo	duration_b	rank_boxc	pop_boxco	n_helpful_l	content_rt_	content_rt_	content_rt_	content_rt_	content_rt_	Sunday	Monday	Tuesday	Wednesda	Thursday	Friday	Saturday
2	0 The Family	2015	9170c31a0	Joo Dong	Kim Shin	1/3/2015	3/15/2015	A grandma	0.6	0.78	0.82	0.6	0.8	0.73805	0.6441024	0.2960404	0.2820819	0.4405923	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
3	1 The Lover	2015	2dc531911	Kim Tae E	Kim Min S	4/2/2015	6/25/2015	The series	0.77	0.85	0.9	0.8	0.87	0.6478715	0.5562971	0.3453274	0.5948273	0.6048742	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
4	2 Love of Sv	2015	522b2dcd1	Lee Gye J	Others	5/18/2015	10/30/2015	Three wom	0.1	0.3	0.3	0.1	0.3	0.9770532	0.4636309	0.0212902	0.0610489	0.1661881	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE
5	3 Love on a	2015	5eda227cf	Choi Ji Ye	Choi Min	4/6/2015	8/21/2015	A drama al	0.5	0.54	0.51	0.3	0.51	0.9584299	0.4150052	0.2904071	0.1727942	0.4085321	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE
6	4 Kill Me, Hel	2015	e8c09f0f7d	Kim Jin M	Jin Soo W	1/7/2015	3/12/2015	A traumati	0.88	0.85	0.9	0.8	0.87	0.73805	0.6611763	0.7080122	0.8490565	0.8425826	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE
7	5 Delicious L	2015	a38a585a6	Others	Others	11/5/2015	11/10/2015	A teen rom	0.52	0.28	0.38	0.1	0.35	0.3362817	0.364479	0.2778447	0.2599234	0.3219688	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
8	6 Love Detec	2015	ff9500e6bfe	Others	Others	11/11/2015	11/20/2015	Sherlock K	0.35	0.35	0.7	0.1	0.4	0.6127922	0.1308431	0.2807875	0.2553932	0.2585346	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
9	7 The Time V	2015	12208c74d	Jo Soo W	Jung Do Y	6/27/2015	8/16/2015	Choi Won	0.64	0.7	0.76	0.43	0.72	0.7000701	0.6781035	0.3263565	0.5657635	0.5647949	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
10	8 The Dearer	2015	729e5a41a	Choi Chai	Seo Hyun	12/7/2015	5/20/2016	An upbeat	0.3	0.42	0.5	0.1	0.25	0.9734596	0.4150052	0.0251779	0.0811631	0.1661881	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE	FALSE
11	9 The Eccent	2015	cc11a722b	Lee Duk C	Yoo Nam	8/17/2015	9/22/2015	Oh In Yeor	0.78	0.73	0.78	0.62	0.79	0.6478715	0.768822	0.3112674	0.359518	0.3219688	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
12	10 Awl	2015	b5446cda9	Kim Seok	Kim Soo J	10/24/2015	11/29/2015	Soo In has	0.56	0.66	0.74	0.58	0.71	0.6478715	0.686514	0.4055703	0.2968486	0.4679939	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
13	11 Bubblegun	2015	f8ecb7e20	Kim Byun	Lee Mi Na	10/26/2015	12/15/2015	Park Ri Hw	0.7	0.75	0.88	0.61	0.73	0.7000701	0.6441024	0.3105673	0.5143435	0.5647949	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
14	12 Noble, My	2015	e2228f79d	Kim Yang	Others	8/23/2015	9/16/2015	Kang Hoon	0.64	0.67	0.75	0.65	0.74	0.73805	0.1962026	0.3549649	0.6539639	0.5924998	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE
15	13 My Mother	2015	65e26535b	Ko Heung	Lee Geun	6/22/2015	12/31/2015	Gyeong So	1	1	1	1	1	0.9900818	0.4636309	0.0540038	0.0259639	0	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE
16	14 Love Cells	2015	3bef90625	Others	Others	9/14/2015	10/1/2015	In this bitte	0.6	0.46	0.78	0.39	0.59	0.6478715	0.1308431	0.2856177	0.3333656	0.2585346	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
17	15 Flower of t	2015	62df20454	Kim Min S	Park Hyui	3/14/2015	8/30/2015	South Kore	0.1	0.4	0.45	0.1	0.4	0.8735755	0.686514	0.3144812	0.2734208	0.2585346	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
18	16 Six Flying D	2015	61790e382	Shin Kyur	Kim Youn	10/5/2015	3/22/2016	A fictional,	0.97	0.98	0.99	0.89	0.98	0.8735755	0.6441024	0.7439422	0.5939347	0.7091055	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
19	17 Missing Nc	2015	64309e69d	Lee Seung	Lee Yoo J	3/28/2015	5/30/2015	Gil Su Hyeo	0.9	0.83	0.92	0.69	0.87	0.6127922	0.7280613	0.5468423	0.4651856	0.5647949	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
20	18 Jumping G	2015	5ef07c61a	Others	Others	4/27/2015	4/28/2015	Follows the	0.65	0.64	0.76	0.68	0.68	0.6886845	0.1308431	0.2781084	0.3108982	0.3219688	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
21	19 My Beautif	2015	e265f5605	Kim Chul	Yoo Sung	6/20/2015	8/9/2015	Kim Do Hy	0.89	0.88	0.89	0.71	0.87	0.7000701	0.6441024	0.4417148	0.4527011	0.5130293	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
22	20 Shine or Gi	2015	45af025f19	Song Hyu	Kim Sun N	1/19/2015	4/7/2015	Wang So, (	0.8	0.73	0.86	0.51	0.78	0.7675465	0.686514	0.3869229	0.4438272	0.5491362	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
23	21 Missing Ko	2015	0f989ec249	Min Doo	Others	11/3/2015	11/12/2015	秋天missing	0.39	0.64	0.71	0.34	0.64	0.5055456	0.1308431	0.2816715	0.2800154	0.1661881	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	FALSE	FALSE
24	22 She Was P	2015	1985f18b5	Jeong Da	Jo Sung H	9/16/2015	11/11/2015	As a young	0.79	0.76	0.86	0.6	0.78	0.7000701	0.6441024	0.4746931	0.8427811	0.7590221	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE
25	23 She Is 200	2015	ffaed6287d	Others	Others	10/27/2015	10/27/2015	200-year-c	0.6	0.61	0.61	0.42	0.64	0.4638269	0.1308431	0.2835222	0.3651384	0.2219688	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
26	24 Warm and	2015	81c8f1d83	Park Hon	Hong Jun	5/13/2015	7/2/2015	A man and	0.82	0.76	0.89	0.71	0.85	0.7000701	0.6441024	0.3402249	0.57239	0.5924998	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
27	25 Girl of 9AM	2015	634519fd3	Others	Others	5/4/2015	5/14/2015	Gong Ji Da	0.74	0.7	0.81	0.55	0.76	0.5676239	0.1962026	0.3000818	0.3549356	0.3219688	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
28	26 Girls' Love	2015	8a5f7bb42	Others	Others	6/16/2015	8/15/2015	Four wom	0.5	0.48	0.62	0.52	0.55	0.8735755	0.1168061	0.027821	0.1464212	0.3219688	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
29	27 Assembly	2015	56f7a1b9c	Hwang In	Jung Hyu	7/15/2015	9/17/2015	Jin Sang Pi	0.85	0.98	0.95	0.9	0.95	0.73805	0.6611763	0.3591346	0.2266121	0.4405923	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
30	28 We Broke I	2015	dce6fe763	Others	Jeon Seor	6/29/2015	7/17/2015	Ji Won Yec	0.85	0.73	0.82	0.71	0.81	0.6127922	0.1962026	0.3139898	0.4365854	0.370013	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
31	29 Splendid P	2015	75c1221d1	Kim Sang	Kim Yi Yo	4/13/2015	9/29/2015	Princess Ju	0.71	0.69	0.74	0.47	0.72	0.8735755	0.6441024	0.3581512	0.3407326	0.4405923	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
32	30 Spy	2015	14fb3da5d	Park Hyui	Han Sang	1/9/2015	3/6/2015	Hye Rim is	0.67	0.63	0.82	0.44	0.69	0.7000701	0.5562971	0.3103653	0.4024103	0.4085321	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
33	31 To Be Cont	2015	05be09941	Others	Others	8/18/2015	9/3/2015	This web d	0.88	0.66	0.76	0.72	0.76	0.6478715	0.1962026	0.3361361	0.5262994	0.3219688	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
34	32 Late Night	2015	1ede9e887	Hwang In	Others	7/4/2015	9/5/2015	A late nigh	0.89	0.94	0.94	0.93	0.94	0.73805	0.364479	0.4086333	0.2988837	0.4405923	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
35	33 Sweet, Savi	2015	53d882ba8	Kang Dae	Son Geun	11/18/2015	1/14/2016	At home, T	0.52	0.68	0.75	0.45	0.68	0.7000701	0.6696579	0.3113043	0.2875055	0.370013	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
36	34 Sweet Tem	2015	89146b442	Others	Others	10/5/2015	11/20/2015	This web d	0.77	0.9	0.87	0.97	0.88	0.5055456	0.2558719	0.3042404	0.2194794	0.2585346	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
37	35 Divorce La	2015	f2798bbb99	Park Yong	Others	4/18/2015	6/14/2015	Go Cheok	0.58	0.77	0.74	0.46	0.67	0.7203812	0.6781035	0.3263548	0.4325408	0.5319811	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE
38	36 Dr. Ian	2015	03c6b980e	Others	Others	3/29/2015	4/8/2015	The memo	0.61	0.58	0.67	0.35	0.56	0.5917792	0.1308431	0.2970402	0.3628961	0.3219688	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE
39	37 Sweet Hon	2015	e5818e1ec	Kim Myur	Kang Sun	11/2/2015	4/29/2016	Even thoug	0.55	0.73	0.7	0.44	0.65	0.984631	0.4150052	0.2892146	0.1915518	0.1661881	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE
40	38 Mrs. Cop	2015	ff8a2989de	Ahn Gil H	Hwang Jo	8/3/2015	9/29/2015	Choi Yeon	0.66	0.79	0.88	0.6	0.8	0.7203812	0.686514	0.4428203	0.3935537	0.370013	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
41	39 Dream Kni	2015	8062642e0	Park Byur	Won You	1/27/2015	3/5/2015	A young g	0.83	0.76	0.76	0.67	0.76	0.6478715	0.1708898	0.217767	0.5710422	0.4405923	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
42	40 Let's Eat Se	2015	0038f84bf6	Park Joor	Others	4/6/2015	6/2/2015	The secon	0.71	0.79	0.89	0.69	0.78	0.7203812	0.686514	0.4429169	0.4812663	0.4085321	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
43	41 Sweet 20	2015	7c426da02	Others	Others	2/18/2015	4/10/2015	Mini beaut	1	1	1	1	1	0.6127922	0.1708898	0.0320416	0.130276	0.2585346	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
44	42 EXO Next D	2015	041f0176a6	Lee Kwon	Others	4/9/2015	5/28/2015	Ji Yeon He	0.85	0.71	0.81	0.75	0.81	0.7000701	0.1962026	0.3817754	0.7038303	0.6374631	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
45	43 Banana Ac	2015	8b3cc5e1d	Others	Others	12/22/2015	12/22/2015	A 72-secor	0.75	0.8	0.8	0.7	0.75	0.5676239	0	0.3348428	0.1634163	0.1661881	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
46	44 Eating Exsl	2015	8861cd93f	Lee Chul	Others	11/12/2015	1/14/2016	Yoo Yang	0.58	0.56	0.71	0.38	0.61	0.6127922	0.1023448	0.2843413	0.2609901	0.1661881	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
47	45 Super Dad	2015	1d4c49e51	Song Hyu	Others	3/13/2015	5/2/2015	Doctor Chi	0.78	0.67	0.9	0.52	0.78	0.7000701	0.686514	0.4612279	0.3895806	0.4085321	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE
48	46 Detective A	2015	776549aca	Others	Others	10/19/2015	10/30/2015	Cheon Yec	0.35	0.42	0.6	0.35	0.53	0.5676239	0.1962026	0.2775084	0.2212269	0.4085321	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE	FALSE
49	47 Mom	2015	4e17b7426	Jang Joor	Kim Jung	9/5/2015	2/21/2016	For a long	0.1	0.4	0.45	0.1	0.4	0.8735755	0.768822	0.0400632	0.1164487	0.1661881	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
50	48 Twenty Ag	2015	e067d4c2e	Kim Hyun	So Hyun	8/28/2015	10/17/2015	38-year-ol	0.83	0.87	0.85	0.72	0.87	0.7000701	0.6611763	0.4747548	0.5720037	0.6048742	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE

ML-based Sentiment Analysis

Since we have access to the full text of the reviews, we decided to analyze the emotional valence of user reviews. To do so, we implemented machine learning-based sentiment analysis using a pre-trained DistilBERT model (we chose the lxyuan/distilbert-base-multilingual-cased-sentiments-student variant due to its performance on benchmark datasets). The model was deployed using the Hugging Face `transformers` library and configured to run on the optimal available hardware (MPS for Apple Silicon, CUDA for NVIDIA GPUs, or CPU as fallback). Reviews were processed in batches of 100 to optimize computational efficiency while managing memory usage.

The analysis revealed a relatively balanced distribution between positive (4,891) and negative (4,871) reviews, with only 61 classified as neutral. This sentiment data was merged with our existing features to provide additional context for understanding viewer reception patterns and their relationship with drama characteristics like episode length, acting scores, and overall popularity.

Below is the correlation matrix of the sentiment analysis with notable findings:



- Strong negative correlation (-0.99) between `sentiment_negative` and `sentiment_positive`, which is expected as they are opposing measures
- Positive sentiment shows moderate positive correlations with `story_score` (0.4), `rewatch_value_score` (0.41), and `overall_score` (0.41)—suggesting that better-rated dramas tend to generate more positive sentiment in reviews. This also demonstrates that the sentiment analysis is working as intended; the text of the reviews is being analyzed correctly.
- `sentiment_neutral` shows very weak correlations across the board, suggesting neutral reviews don't strongly relate to any other metrics

Key Findings

Our comprehensive analysis of **Korean drama data from 2015-2023** revealed several significant patterns across multiple dimensions of the industry. Through statistical analysis of features and audience reception, we identified clear trends in viewing preferences and content evolution.

Statistical Validity: The statistical analysis demonstrated **meaningful variance** across all examined features, validating their inclusion in our study. Numerical variables consistently showed asymmetrical distributions, necessitating careful statistical analysis through **Box-Cox transformations and standardization**.

Audience Reception Analysis: Our sentiment analysis pipeline, using the **DistilBERT model**, revealed fascinating insights into viewer behavior and preferences. Review scores demonstrated a pronounced left-skewed distribution, with the majority of dramas receiving **ratings between 8-10**. The analysis uncovered an almost perfect split between **positive (4,891)** and **negative (4,871)** reviews, with remarkably few neutral sentiments (61 reviews). This polarization suggests that K-dramas tend to elicit **strong emotional responses** from viewers, with **robust correlations between positive sentiment and high scores** across story quality (0.4), rewatch value (0.41), and overall rating (0.41).

Audience Reception Analysis (Reviews): Content format preferences emerged as a crucial factor in drama success. Our analysis revealed that dramas with **fewer than 20 episodes** consistently achieved higher popularity rankings, indicating a clear audience preference for more concise storytelling formats. This finding was reinforced by the **negative correlation (-0.38)** between episode duration and popularity ranking. The **bi-modal distribution of rewatch value scores** further suggested that dramas tend to fall into two distinct categories: highly rewatchable content (scoring 9-10) or single-viewing experiences (scoring 1-2). Similarly, since there is a negative relationship between overall score/rewatch value score/ music score and popularity ranking and there is a positive relationship between story score/ acting cast score and popularity ranking, it's likely that most of the audience enjoys a Korean drama because of its story and acting cast, but higher level of music or rewatch value means less popularity. In other words, most audience may not like a Korean drama due to its music or rewatch value.

Challenges and Future Recommendations

Our research encountered several significant challenges that inform our recommendations for future studies. **Data quality** presented persistent challenges, particularly regarding missing information for directors and screenwriters, inconsistent date formatting across sources, and varying levels of completeness in our multiple data sources. These issues required substantial preprocessing and standardization efforts.

Technical limitations also impacted our research scope. Web scraping restrictions from MyDramaList's anti-bot protections constrained our ability to gather additional historical data. Resource constraints affected our processing of large-scale sentiment analysis, and memory management became crucial when handling high-dimensional feature spaces after categorical encoding.

Looking forward, we recommend several key areas for future research enhancement. First, implementing **advanced web scraping** techniques using rotating proxies and user agents would enable more comprehensive data collection. We also suggest developing automated data validation and standardization pipelines to improve data quality consistency. Establishing direct partnerships with data providers for **API access** would significantly enhance data reliability and completeness.

Additionally, incorporating production **budget data**, international **viewing statistics**, and **marketing spend** information would provide a more complete picture of drama success factors. These enhancements, combined with robust cross-validation methods and ensemble prediction approaches, would significantly advance our understanding of the Korean drama industry's evolution and success factors. Going even further, given the abundance of text data in our dataset, implementation of **topic modeling** on review text and synopses could uncover deeper thematic trends.

Contribution:

- **Mengyan Li (ml4779)**: Finding the data, Data Cleaning(fixing date format, remove outliers, merge datasets, drop/change to others for missing values),

EDA(summary statistics, linear regression for the merged data and review.csv,correlation heatmap, missing value heatmap, histrogram for numerical variables), feature engineering(filter out zero/near-zero variance features, Box-Cox transformation, standardization/normalization, one-hot encoding), Report drafting

- **Zishun Shen (zs2695)**: EDA(tentatively approach to visualize the dataset, top and bottom ranking of the directors and screenwriters through popularity rank and rank, ranking through year boxplot), feature engineering (one-hot encoding)
- **Zhisheng Yang (zy2675)**: Data Cleaning(tentatively approach to drop missing values), EDA and feature engneering(linear regression visualization and standardize/normalize data, t test, feature importance bar chart, The actual vs. predicted popularity of K-dramas)
- **Shayan Chowdhury (sc4040)**: report drafting and editing, web scraping script, combining popularity/ranking and revenue over the year, ML-based sentiment analysis of reviews using HuggingFace transformers and DistilBERT (feature engineering), merging of multiple kdramas datasets, merging of kdramas + revenue dataset