

NBC Rating War: The Office vs. Parks and Recreation

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CSCI 403 Final Project

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What is interesting about these datasets?

The two datasets used in this project are “The Office Dataset” and “Parks and Recreation Episode Data”. The first dataset concerns the NBC sitcom The Office [1], which aired 201 episodes over nine seasons from 2005 to 2013. The second dataset contains data on the 2009–2015 sitcom Parks and Recreation, which aired 126 episodes and has been compared stylistically to The Office. Though the datasets were published by different users to Kaggle and the data were sourced from different locations, the data are presented in comma-separated values format with columns using the same naming scheme [1] [2]. Each dataset consists of two tables: one containing episode and season numbers, titles, writers, directors, air dates, and viewer numbers and one containing IMDb ratings, vote counts, and episode synopses. There was one exception: production codes were only present in the dataset for The Office. Both datasets were released into the public domain.

Where was the data obtained?

The data was obtained by different users on Kaggle.

1. B. Cruise, [Parks and Recreation Dataset](#), Kaggle.com
2. N. Prabhavalkar, [The Office Dataset](#), Kaggle.com.

License restrictions

Both data sets are [CC0: Public Domain](#). The following is quoted from creativecommons.org: ”The person who associated a work with this deed has dedicated the work to the public domain by waiving all of his or her rights to the work worldwide under copyright law, including all related and neighboring rights, to the extent allowed by law. You can copy, modify, distribute and perform the work, even for commercial purposes, all without asking permission.”

Significant attributes as loaded into the database

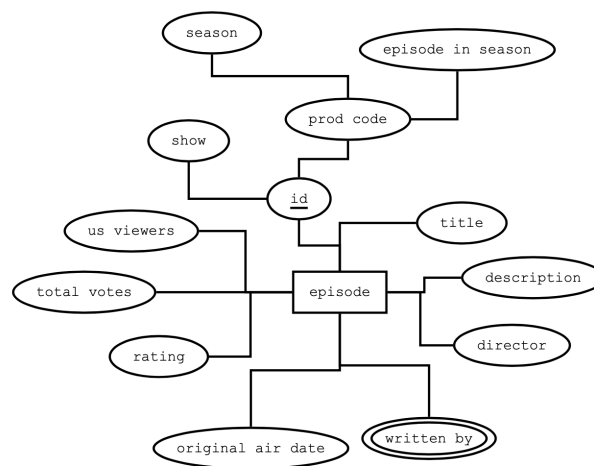


Figure 1: ER diagram

Analysis of our datasets

Functional dependencies:

episode_id -> season, episode_in_season, episode_overall, title, director, writer,
↔ air_date, us_viewers, rating, total_votes, description

episode_overall, show -> episode_id

show, season, episode_in_season -> episode_overall

season, episode_in_season -> prod_code

Our dataset is normalized to BCNF which you can see by the fact the only functional dependency we have has the superkey of the relation as the functional determiner.

Data loading

The attached Python program uses transactions to ensure no data is added anywhere if a single table has errors. Every individual operation is committed only if all table(s) are able to be modified appropriately.

Data Cleaning Operations we Performed

The two tables in each dataset contained several duplicate columns, namely season and episode numbers, title, and air date. We determined that an episode can be uniquely identified by its season and episode number, so data were loaded with a uniqueness constraint on those columns in both tables. One may expect an episode title to be unique within a series, but this turned out not to be the case for Parks and Recreation: both S2.E16 and S6.E17 are titled “Galentine’s Day”. Due to the limitations of the tool used to load the data files into the database, we loaded the raw data into tables with columns with one-to-one correspondence. To perform data manipulations, the data were inserted into new tables with new formatting using INSERT INTO ... SELECT statements. These new tables contained the episode_id column, which was set to the primary key, and converted viewer counts from a float to an int. In the raw data, the writers column is a multi-valued attribute. To normalize the dataset, a third table was created containing episode_writer pairs. This was accomplished using the PostgreSQL function regexp_split_to_table() by pattern matching the word “and” and ampersands. These cleaning operations result in a database that has no duplicate nor orphaned rating entries. No data is duplicated between tables. Episodes can be added as long as they have a season and episode number provided.

Data growth estimate over the next 10 years

Current sizes:

The Office dataset = 52.49 kB

Parks and Recreation dataset = 37.64 kB

Growth:

The datasets will likely not grow over time as both the Office and Parks and Recreation finished making new episodes.

SQL Security concerns

Permissions:

To ensure no unneeded access occurred to the data, we only granted permission to our group members who we trust. Permissions were granted for each group member for each table created

and based on group permissions given by the professors, only the trusted group members had access to read, write, and query this database.

SQL Injection:

We used /copy to load the dataset so there was no danger of SQL injection because the command only loads data and will not execute any SQL statements. Only our team members are in the project schema group role, preventing unnecessary access to our data.

Interesting queries done with our data

1. What are the most common words used in the episode descriptions for 'The Office' and 'Parks and Recreation'?"

```
SELECT word, COUNT(*) AS word_count FROM (
  SELECT regexp_split_to_table(description, E'\\s+') AS word
  FROM episode
  WHERE description IS NOT NULL
) AS words
WHERE word NOT IN ('the', 'and', 'is', 'in', 'of', 'it', 'to', 'a', 'for',
  ↳ 'with', 'on', 'as', 'at', 'by', 'an', 'from', 'but', 'or', 'was',
  ↳ 'were', 'are', 'you', 'we', 'they', 'he', 'she', 'it', 'that', 'this',
  ↳ 'his', 'her', 'its', 'their', 'our', 'be', 'have', 'has', 'do', 'did',
  ↳ 'does', 'not', 'what', 'when', 'where', 'how', 'why', 'who', 'which',
  ↳ 'there', 'then', 'if', 'else', 'for', 'while', 'when', 'about', 'into',
  ↳ 'out', 'up', 'down', 'over', 'under', 'between', 'through', 'after',
  ↳ 'before', 'during', 'with', 'without', 'within', 'among', 'between')
GROUP BY word
ORDER BY word_count DESC
LIMIT 20;
```

word	word_count
Michael	137
Leslie	110
Andy	101
Dwight	89
tries	81
Jim	78
Meanwhile,	73
office	67
new	61
Pam	60
Ron	52
Tom	49
gets	45
Ben	45
Dunder	41
get	38
Chris	31
Ann	30
party	30
find	27

- What are the top five contributing writers across both shows in terms of total episodes written, and what are their average ratings and viewership for the episodes they wrote for each show?

```

SELECT
    ew.name,
    COUNT(*) AS total_episodes_written,
    COUNT(CASE WHEN ew.episode_show = 'The Office' THEN 1 END) AS office_episodes,
    ROUND(AVG(CASE WHEN ew.episode_show = 'The Office' THEN e.rating END), 3) AS
        ⇨ office_avg_rating,
    ROUND(AVG(CASE WHEN ew.episode_show = 'The Office' THEN e.us_viewers END), 3) AS
        ⇨ office_avg_views,
    COUNT(CASE WHEN ew.episode_show = 'Parks and Recreation' THEN 1 END) AS
        ⇨ parks_episodes,
    ROUND(AVG(CASE WHEN ew.episode_show = 'Parks and Recreation' THEN e.rating END),
        ⇨ 3) AS parks_avg_rating,
    ROUND(AVG(CASE WHEN ew.episode_show = 'Parks and Recreation' THEN e.us_viewers
        ⇨ END), 3) AS parks_avg_views
FROM
    episode_writer ew
JOIN
    episode e ON ew.episode_show = e.show
              AND ew.episode_season = e.season
              AND ew.episode_episode_in_season = e.episode_in_season
GROUP BY
    ew.name
ORDER BY
    total_episodes_written DESC
LIMIT 5

```

name	total_episodes_written	office_episodes	office_avg_rating	office_avg_views	parks_episodes	parks_avg_rating	parks_avg_views
Michael Schur	31	12	8.480	8350000.000	19	8.517	3997368.421
Mindy Kaling	23	23	8.432	7862173.913	0		
Paul Lieberstein	21	21	8.243	9014761.905	0		
Alan Yang	16	0			16	8.194	3845000.000
Lee Eisenberg	16	16	8.333	8380000.000	0		

- For those who directed both shows, which show outperformed the other for the episodes they directed?

```

WITH DirectorStats AS (
    SELECT
        director,
        show,
        COUNT(DISTINCT description) AS total_episodes,
        AVG(rating) AS average_rating
    FROM
        episode
    WHERE
        director IN (
            SELECT DISTINCT director
            FROM episode
            GROUP BY director
            HAVING COUNT(DISTINCT show) > 1
        )
    GROUP BY
        director, show
)
SELECT

```

```

ds.director,
SUM(ds.total_episodes) AS total_episodes,
SUM(CASE WHEN ds.show = 'Parks and Recreation' THEN ds.total_episodes ELSE 0
↪ END) AS parks_episodes,
AVG(CASE WHEN ds.show = 'Parks and Recreation' THEN ds.average_rating END) AS
↪ parks_avg_rating,
SUM(CASE WHEN ds.show = 'The Office' THEN ds.total_episodes ELSE 0 END) AS
↪ office_episodes,
AVG(CASE WHEN ds.show = 'The Office' THEN ds.average_rating END) AS
↪ office_avg_rating,
CASE WHEN MAX(CASE WHEN ds.show = 'Parks and Recreation' THEN ds.average_rating
↪ END) >
        MAX(CASE WHEN ds.show = 'The Office' THEN ds.average_rating END)
        THEN 'Parks and Recreation'
        ELSE 'The Office'
END AS higherRated_show
FROM
DirectorStats ds
GROUP BY
ds.director
ORDER BY
total_episodes DESC;

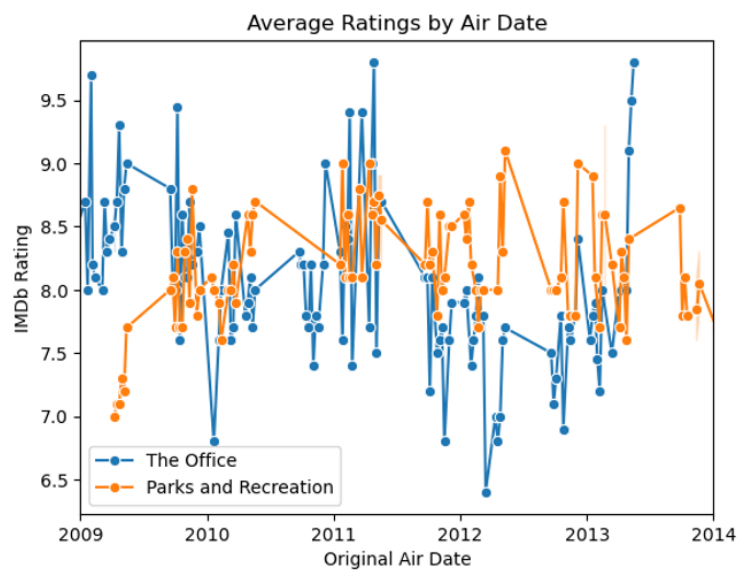
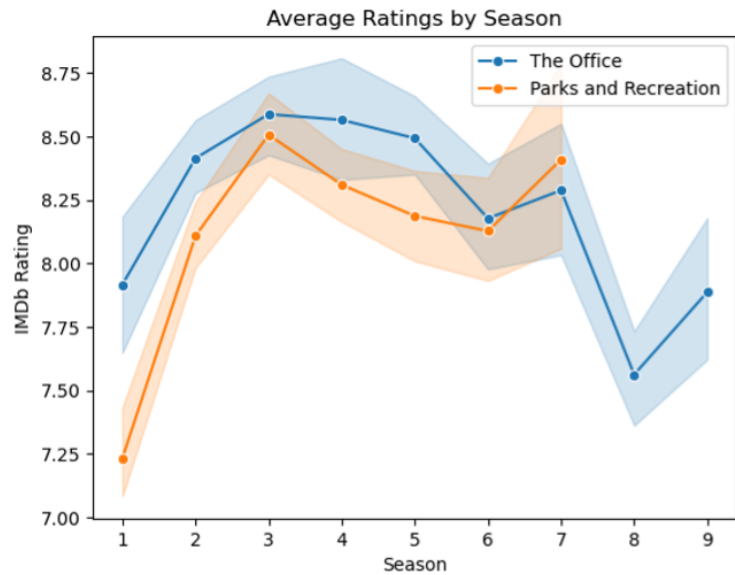
```

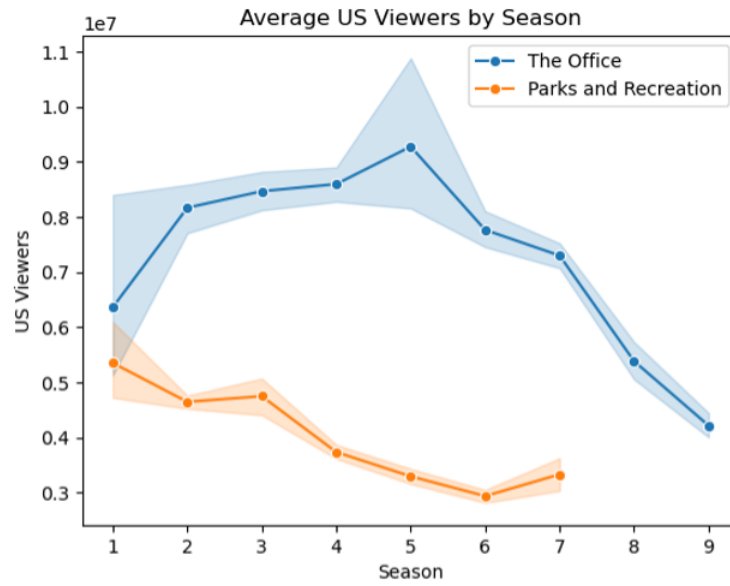
director	total_episodes	parks_episodes	parks_avg_rating	office_episodes	office_avg_rating	higherRated_show
Dean Holland	29	27	8.366666666666667	2	8.100000000000000	Parks and Recreation
Randall Einhorn	18	5	8.440000000000000	13	8.223076923076923	Parks and Recreation
Greg Daniels	17	3	8.066666666666667	14	8.464285714285714	The Office
Ken Whittingham	17	8	8.050000000000000	9	8.333333333333333	The Office
Paul Feig	16	1	8.000000000000000	15	8.446666666666667	The Office
Jeffrey Blitz	12	1	7.100000000000000	11	8.181818181818181	The Office
Ken Kwapis	11	1	7.600000000000000	10	8.400000000000000	The Office
David Rogers	11	1	8.100000000000000	10	8.050000000000000	Parks and Recreation
Troy Miller	10	7	8.200000000000000	3	7.833333333333333	Parks and Recreation
Charles McDougall	10	2	8.000000000000000	8	8.362500000000000	The Office
Matt Sohn	9	1	8.200000000000000	8	7.937500000000000	Parks and Recreation
Craig Zisk	7	5	8.500000000000000	2	8.550000000000000	The Office
Tucker Gates	5	2	8.600000000000000	3	8.400000000000000	Parks and Recreation
Seth Gordon	4	2	7.600000000000000	2	8.250000000000000	The Office
Alex Hardcastle	3	2	8.150000000000000	1	7.400000000000000	Parks and Recreation
(15 rows)						

What performance improvements did you make to your schema?

yes

Visualizing the Data





Technical challenges in obtaining, manipulating, and loading the dataset(s)

When loading our data, we douns