Data Visualization Report

🟦 Introduction

Since its debut in the early '90s, *Power Rangers* has evolved through numerous seasons, each with unique characters and narratives. With such a long-running franchise, fans often debate which seasons were the most successful and which characters had the greatest impact. This project investigates two main questions: **How has the show's popularity changed over time?** and **Which characters were the most prominent across seasons?**

To answer these, we analyzed two datasets - `power_rangers_seasons.csv` and `power_rangers_episodes.csv`. Our approach combines season-level metrics like episode count, air dates, and producers with character-level analysis based on episode descriptions and IMDb ratings. Through visualization and text analysis, we aimed to uncover how structural choices and character appearances shaped audience reception and engagement throughout the franchise's history.

Question 1: What Factors Influence a Season's Popularity and How Does Season Duration Impact Audience Reception?

Introduction

The Power Rangers franchise has not only entertained audiences for decades but has also evolved in its storytelling and production style. In this analysis, we aim to delve deeper into what determines a season's popularity beyond simple IMDb ratings. Specifically, we examine whether certain factors—such as the number of episodes, the role of different producers, and the overall duration of a season—have a measurable impact on audience reception. By understanding these relationships, we can gain insights into how production choices may affect viewer engagement over the long run.

To tackle this question, we use the `power_rangers_seasons.csv` dataset, which contains season-level information including:

- `season_title`, `season_num`
- `number_of_episodes`
- `air_date_first_ep` and `air_date_last_ep`
- `producer`
- `IMDB_rating`

These variables provide a structured view of each season, allowing us to analyze the correlation between season length/duration and its overall rating.

Approach

Our strategy involves several key steps:

1. **Data Processing:**
   - Convert date columns (e.g., `air_date_first_ep` and `air_date_last_ep`) into datetime objects.
   - Calculate the season duration (in days) as the difference between the first and last air dates.
   - Categorize seasons based on duration, if necessary (e.g., short, medium, long).
2. **Visualization Techniques:**
   To answer our question effectively, we use a combination of visualizations:
   - **Bar Charts:** To compare the average IMDb ratings across different producers. This chart helps in revealing which producers consistently have better-received seasons.
   - **Scatter Plots with Regression Lines:** To explore the correlation between the number of episodes (or season duration) and IMDb ratings, highlighting whether longer seasons tend to score higher or lower.
   - **Boxplots:** To display the distribution of ratings across various season duration categories. Boxplots are instrumental in detecting outliers and understanding variability.
   - **Time Series Plots:** To observe how ratings have trended over time, thus providing context on changing audience preferences and production quality over the years.
3. **Data Aggregation:**
   We aggregate key variables (e.g., mean ratings per producer, total votes, and season duration) to examine trends and potential correlations between these factors and audience reception.

Analysis

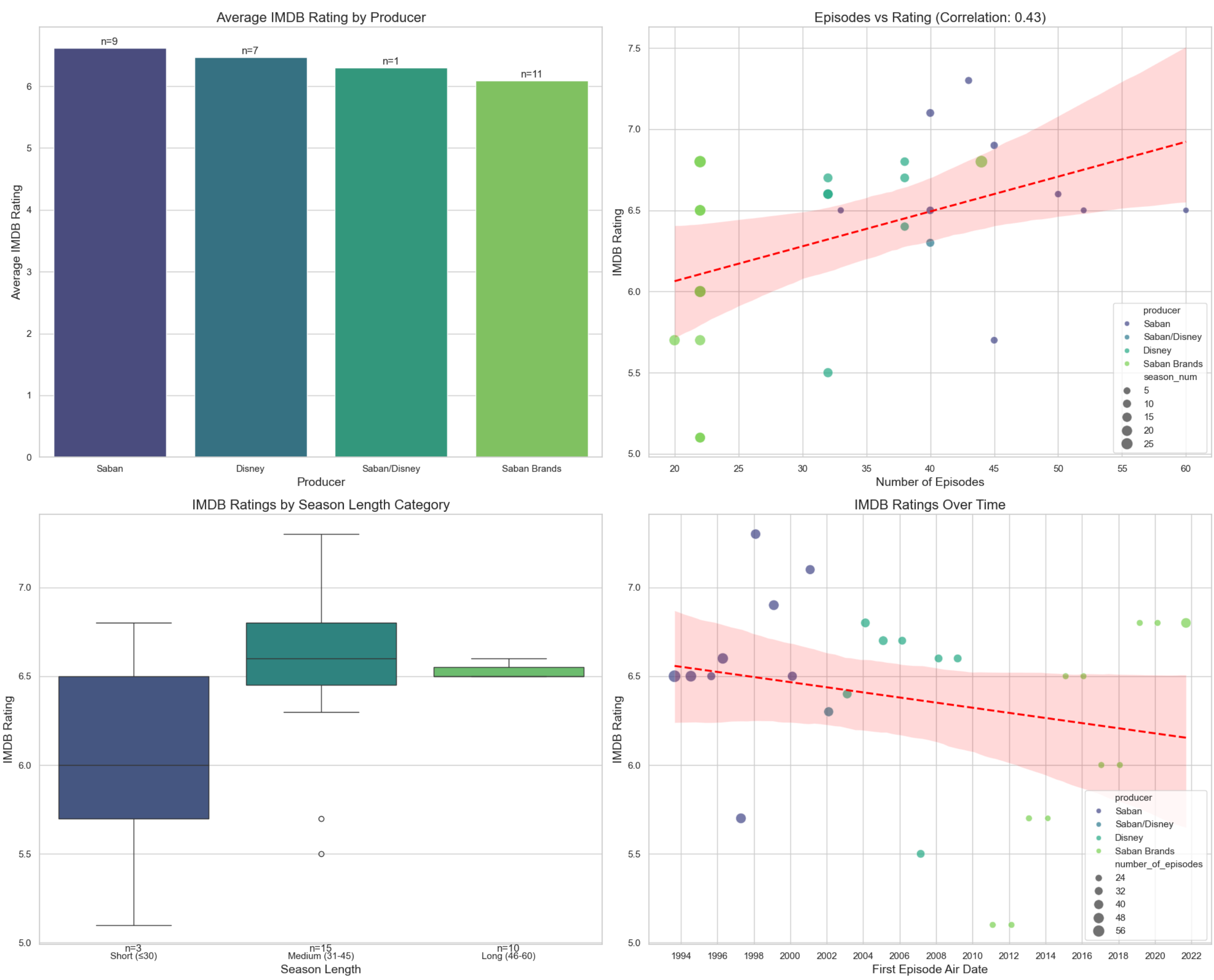
Below are code examples that illustrate our analysis.

Code Block 1: Analyzing Key Popularity Factors

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.dates as mdates

# Assume seasons_df is the DataFrame loaded from power_rangers_seasons.csv
# Preprocess dates and compute season duration in days
seasons_df['air_date_first_ep'] =
```

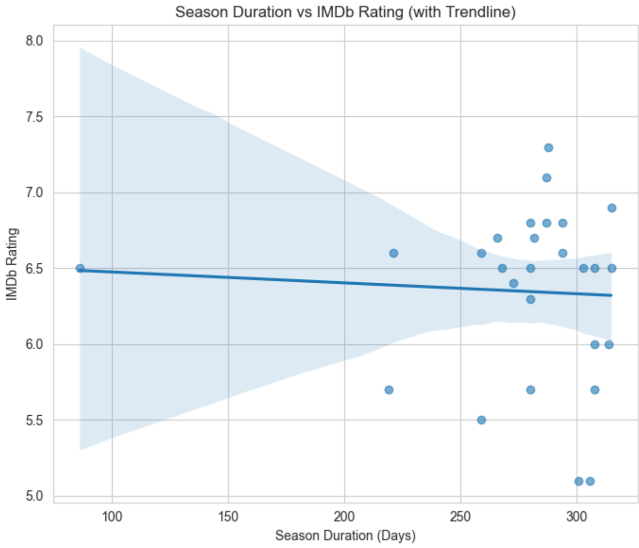
```
pd.to_datetime(seasons_df['air_date_first_ep'])
seasons_df['air_date_last_ep'] =
pd.to_datetime(seasons_df['air_date_last_ep'])
seasons_df['season_duration'] = (seasons_df['air_date_last_ep'] -
seasons_df['air_date_first_ep']).dt.days

# Set up the visualization style
sns.set(style="whitegrid")
fig, axes = plt.subplots(2, 2, figsize=(20, 16))

# 1. Average IMDb Rating by Producer
producer_ratings = seasons_df.groupby('producer')
['IMDB_rating'].mean().sort_values(ascending=False)
producer_counts = seasons_df.groupby('producer').size()
sns.barplot(x=producer_ratings.index, y=producer_ratings.values,
ax=axes[0, 0], palette='viridis')
axes[0, 0].set_title('Average IMDb Rating by Producer')
axes[0, 0].set_xlabel('Producer')
axes[0, 0].set_ylabel('Average IMDb Rating')
for i, v in enumerate(producer_ratings.values):
    axes[0, 0].text(i, v + 0.05, f"n=
{producer_counts[producer_ratings.index[i]]}", ha='center')

# 2. Number of Episodes vs. IMDb Rating
sns.scatterplot(data=seasons_df, x='number_of_episodes', y='IMDB_rating',
hue='producer',
                size='season_num', sizes=(50, 200), alpha=0.7, ax=axes[0,
1], palette='viridis')
sns.regplot(data=seasons_df, x='number_of_episodes', y='IMDB_rating',
scatter=False, ax=axes[0, 1],
            color='red', line_kws={"linestyle": "--"})
corr = seasons_df['number_of_episodes'].corr(seasons_df['IMDB_rating'])
axes[0, 1].set_title(f'Number of Episodes vs. IMDb Rating (Corr:
{corr:.2f})')
axes[0, 1].set_xlabel('Number of Episodes')
axes[0, 1].set_ylabel('IMDb Rating')

# 3. IMDb Ratings by Season Duration Category (Assuming the category
exists)
sns.boxplot(data=seasons_df, x='season_length_category', y='IMDB_rating',
ax=axes[1, 0], palette='viridis')
axes[1, 0].set_title('IMDb Ratings by Season Length Category')
axes[1, 0].set_xlabel('Season Length Category')
axes[1, 0].set_ylabel('IMDb Rating')
for i, category in
enumerate(seasons_df['season_length_category'].unique()):
    count = len(seasons_df[seasons_df['season_length_category'] ==
category])
    axes[1, 0].text(i, seasons_df['IMDB_rating'].min() - 0.15, f"n=
```

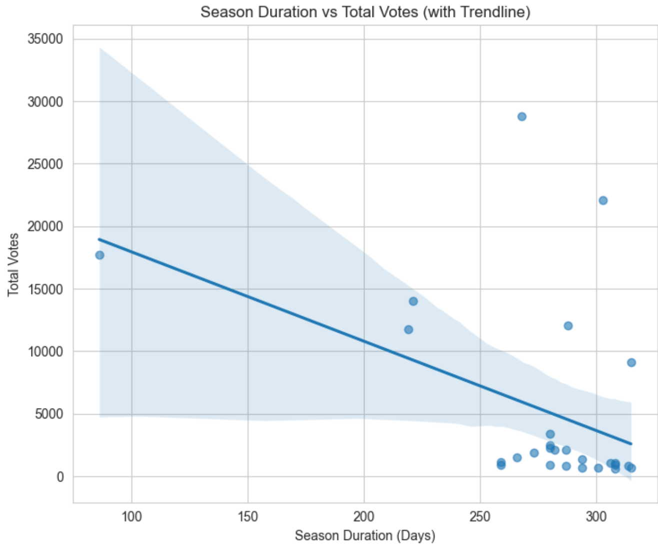
```
{count}", ha='center')

# 4. IMDb Ratings Over Time
sns.scatterplot(data=seasons_df, x='air_date_first_ep', y='IMDB_rating',
hue='producer',
                size='number_of_episodes', sizes=(50, 200), alpha=0.7,
ax=axes[1, 1], palette='viridis')
sns.regplot(data=seasons_df,
x=mdates.date2num(seasons_df['air_date_first_ep']), y='IMDB_rating',
            scatter=False, ax=axes[1, 1], color='red', line_kws=
{"linestyle": "--"})
years = mdates.YearLocator(2)
years_fmt = mdates.DateFormatter('%Y')
axes[1, 1].xaxis.set_major_locator(years)
axes[1, 1].xaxis.set_major_formatter(years_fmt)
axes[1, 1].set_title('IMDb Ratings Over Time')
axes[1, 1].set_xlabel('First Episode Air Date')
axes[1, 1].set_ylabel('IMDb Rating')

plt.tight_layout()
plt.show()
```



Code Block 2: Season duration's affect on viewer engagement

```
# Set seaborn style
sns.set_style("whitegrid")

# Create subplots
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# # Scatter plot: Season Duration vs IMDb Rating
# sns.scatterplot(data=seasons_df, x="season_duration", y="IMDB_rating",
ax=axes[0])
# axes[0].set_title("Season Duration vs IMDb Rating")
# axes[0].set_xlabel("Season Duration (Days)")
# axes[0].set_ylabel("IMDb Rating")

# # Scatter plot: Season Duration vs Total Votes
# sns.scatterplot(data=seasons_df, x="season_duration",
y="total_votes_season", ax=axes[1])
# axes[1].set_title("Season Duration vs Total Votes")
# axes[1].set_xlabel("Season Duration (Days)")
# axes[1].set_ylabel("Total Votes")

# Scatter plot with trendline: Season Duration vs IMDb Rating
sns.regplot(data=seasons_df, x="season_duration", y="IMDB_rating",
ax=axes[0], scatter_kws={"alpha": 0.6})
axes[0].set_title("Season Duration vs IMDb Rating (with Trendline)")
axes[0].set_xlabel("Season Duration (Days)")
axes[0].set_ylabel("IMDb Rating")

# Scatter plot with trendline: Season Duration vs Total Votes
sns.regplot(data=seasons_df, x="season_duration", y="total_votes_season",
ax=axes[1], scatter_kws={"alpha": 0.6})
axes[1].set_title("Season Duration vs Total Votes (with Trendline)")
axes[1].set_xlabel("Season Duration (Days)")
axes[1].set_ylabel("Total Votes")

# Show the plots
plt.tight_layout()
plt.show()
```





Discussion

The analysis of season popularity and duration reveals several key insights into the Power Rangers franchise:

- **Producer Influence:**
  The bar chart reveals only small variations in average IMDb rating across producers. Thus, producer identity by itself may not be a definitive factor in determining season popularity.
- **Number of Episodes and Viewer Engagement:**
  Although the number of episodes does not significantly alter the season's quality (as measured by IMDb ratings), it appears to affect engagement. Longer seasons tend to receive fewer votes, which suggests that viewer fatigue or decreased motivation to rate might be at play.
- **Season Duration:**
  The scatter plots comparing season duration with both IMDb ratings and total votes show that the length of a season has little impact on its quality. However, longer seasons are associated with lower viewer engagement, potentially due to audience fatigue even when the narrative remains strong.
- **Temporal Trends:**
  The time series visualization of IMDb ratings indicates that viewer reception has evolved over the franchise's lifespan. This trend may reflect shifts in production quality, changes in viewer demographics, or broader industry trends, offering valuable context about how earlier seasons compare with more recent ones.
- **Key Conclusion:**
  Season duration itself does not impact the show's quality (i.e., IMDb ratings remain relatively steady regardless of length), but viewers appear less engaged with longer seasons, as evidenced by lower total votes. This distinction is crucial for producers and showrunners who wish to maintain a loyal fanbase while balancing narrative pacing.

In summary, the structure and timing of a season—specifically its duration and release schedule—emerge as key determinants of audience engagement and sustained popularity in the Power Rangers franchise, even if they do not substantially affect perceived quality.

Question 2: Which characters were the most prominent across seasons?

Introduction

The Power Rangers franchise is often discussed online with passionate fan takes - claims like “Tommy carries the franchise” or “Rita drove the engagement” frequently appear in fan forums and videos. We wanted to explore whether these assumptions hold up under data scrutiny. Specifically, we asked: **Which characters appear most frequently throughout the series?** And more importantly, **do these characters appear in highly rated episodes?**

To answer this, we used the `power_rangers_episodes.csv` dataset. This file contains episode-level data including descriptions (`desc`), IMDb ratings, total votes, and air dates. We used `desc` for character extraction and combined it with rating information to assess audience reception.

Approach

We applied basic **text analysis** to the `desc` field to identify character names mentioned in each episode. We then calculated:

- **Total number of mentions** for each character across all episodes (to see who appears the most).
- **Most mentioned character per season**, to highlight changing popularity over time.
- **Average IMDb rating** of the episodes each character appeared in (to gauge quality).

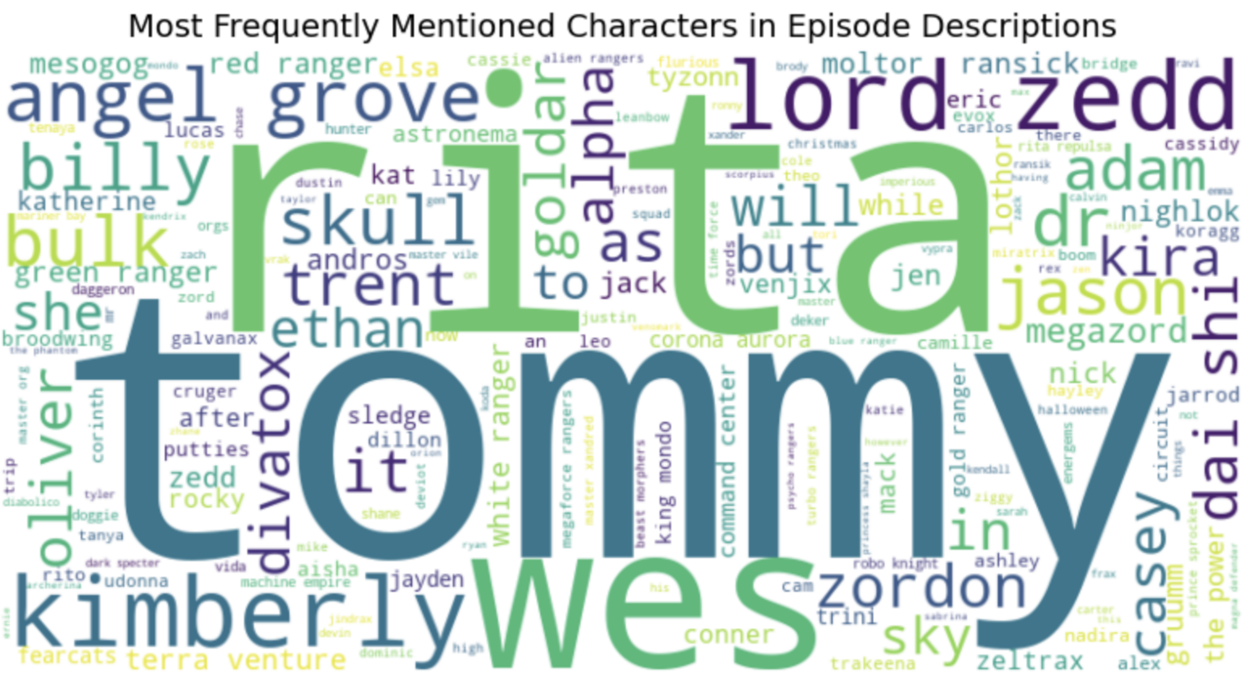
To visualize our findings, we used:

1. **Word Cloud** (for character mentions): Helps emphasize character prominence by frequency. Larger words = more mentions.
2. **Table of Top Mentioned Character in Each Season**: Provides a quick overview of which character stood out most per season, offering season-specific insight into character focus.
3. **Bar Chart** (Top 10 characters by average IMDb rating): Useful for comparing quality scores visually.

Analysis

Code Block 1: Word cloud of mentioned characters

```
from wordcloud import WordCloud
from collections import Counter
import re, nltk
nltk.download("stopwords")

# Extract capitalized words (likely names) from episode descriptions
word_counter = Counter()
for desc in episodes_df["desc"].dropna():
    words = re.findall(r'\b[A-Z][a-z]+(?:\s[A-Z][a-z]+)?\b', desc)
    word_counter.update(w.lower() for w in words)

# Remove non-character words and generate word cloud
non_chars = {"the", "power rangers", "ranger", "meanwhile"}
char_freq = {w: c for w, c in word_counter.items() if w not in non_chars}
WordCloud(width=800,
height=400).generate_from_frequencies(char_freq).to_image()
```



Code Block 2: Top mentioned character in each season

```
# Get top mentioned character per season
season_top_chars = []

for season, group in episodes_df.groupby("season_title"):
    word_counter = Counter()
    for desc in group["desc"].dropna():
        words = re.findall(r'\b[A-Z][a-z]+(?:\s[A-Z][a-z]+)?\b', desc)
        filtered = [w for w in words if w not in ["The", "Power Rangers",
"The Rangers", "Meanwhile", "He", "They", "When", "With"]]
```

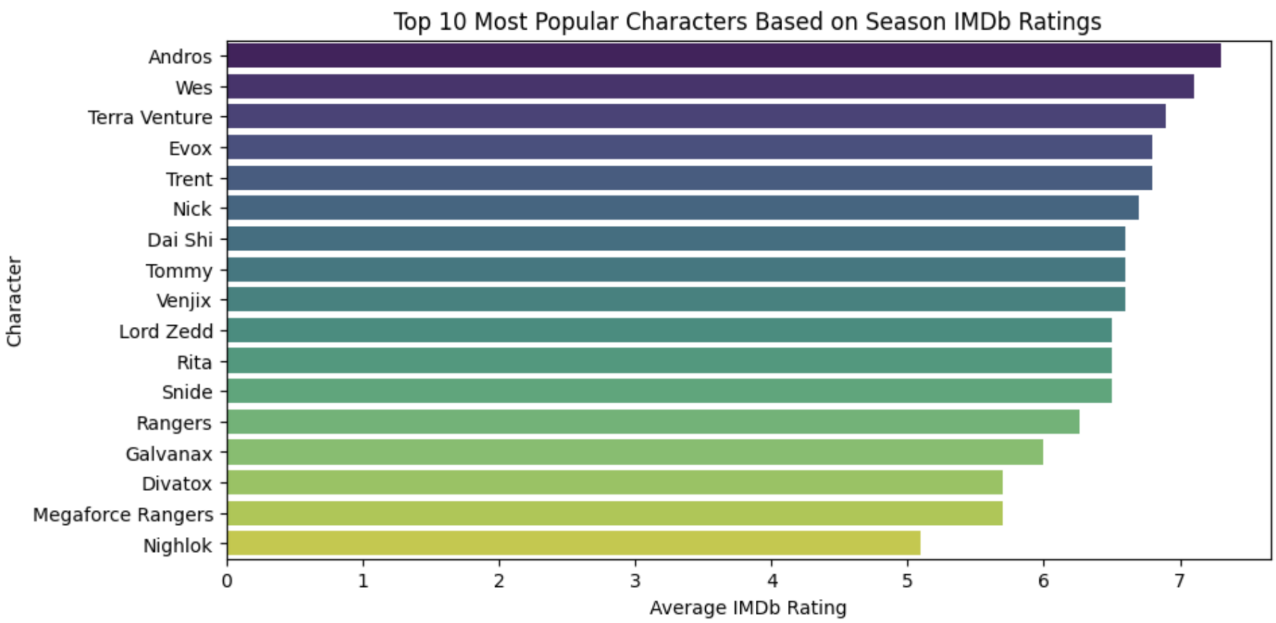
```
            word_counter.update(filtered)
        if word_counter:
            top_char = word_counter.most_common(1)[0][0]
            season_top_chars.append((season, top_char))

season_char_df = pd.DataFrame(season_top_chars, columns=["season", "Most 
Common Character"])
```

	Season	Most Common Character
0	Beast Morphers (Season 1)	Rangers
1	Beast Morphers (Season 2)	Evox
2	Dino Charge	Rangers
3	Dino Super Charge	Snide
4	Dino Thunder	Trent
5	In Space	Andros
6	Jungle Fury	Dai Shi
7	Lightspeed Rescue	Rangers
8	Lost Galaxy	Terra Venture
9	Megaforce	Megaforce Rangers
10	Mighty Morphin (Season 1)	Rita
11	Mighty Morphin (Season 2)	Lord Zedd
12	Mighty Morphin (Season 3)	Rita
13	Mystic Force	Nick
14	Ninja Steel	Galvanax
15	Ninja Storm	Rangers
16	Operation Overdrive	Rangers
17	R.P.M.	Venjix
18	S.P.D.	Rangers
19	Samurai	Nighlok
20	Super Megaforce	Rangers
21	Super Ninja Steel	Rangers

22	Super Samurai	Nighlok
23	Time Force	Wes
24	Turbo	Divatox
25	Wild Force	Rangers
26	Zeo	Tommy

Code Block 3: Top popular characters based on IMDB rating

```
# Merge most common characters with season IMDb ratings
merged_df = seasons_df.merge(season_char_df, on="season_title")
character_ratings = merged_df.groupby("Most Common Character")
["IMDB_rating"].mean().reset_index()

# Bar chart: Top characters by average IMDb rating
sns.barplot(data=character_ratings.sort_values("IMDB_rating",
ascending=False).head(10),
            x="Average IMDb Rating", y="Character", palette="viridis")
plt.title("Top 10 Most Popular Characters Based on Season IMDb Ratings")
plt.show()
```



Discussion

The **word cloud** highlights frequently mentioned characters such as **Tommy**, **Rita**, and **Wes**, reflecting their strong presence in the *Power Rangers* universe. Notably, **Tommy** appears in around **4–5 seasons**, far more than most other characters, which explains his prominence in overall mentions. His recurring role across multiple eras has made him a foundational figure in the franchise's legacy.

When looking at the **most mentioned character per season**, however, the data shows a different focus. Generic mentions like **"Rangers"** dominate many seasons, especially those with strong ensemble casts. But unique names such as **Andros** (*In Space*), **Wes** (*Time Force*), and **Evox** (*Beast Morphers*) indicate seasons where individual characters were more central to the narrative. The **IMDb rating-based character chart** reveals yet another angle. Characters like **Andros**, **Wes**, and **Terra Venture** are associated with the **highest-rated seasons**, despite not being the most frequently mentioned. This implies that critical acclaim is more closely tied to compelling storytelling and character arcs than to mere frequency of appearance.

In summary, while **Tommy's** recurring presence across multiple seasons solidifies his iconic status—earning him the reputation as the *"carrier"* of the franchise - other characters make a lasting impact through **strong, single-season arcs** that resonate with audiences and critics alike. These insights highlight that while **visibility and nostalgia fuel popularity**, it is **compelling storytelling and character depth** that often lead to **critical acclaim**.

🟩 Conclusion

Our findings reveal that while season length and number of episodes have minimal impact on average IMDb ratings, they significantly influence viewer engagement—longer seasons tend to receive fewer votes, possibly due to fatigue. Additionally, the franchise's popularity has fluctuated over time, reflecting broader changes in production and audience expectations. When it comes to characters, **Tommy Oliver's** frequent appearances across multiple eras confirm his status as a franchise icon. However, the most highly rated seasons often centered on **less frequent but narratively strong characters**, like **Andros** or **Wes**, showing that **quality character arcs can rival legacy when it comes to impact**.

Overall, both structural factors and character prominence contribute to how each season is received, offering a data-driven lens on what has made certain *Power Rangers* seasons and characters resonate more than others.