PROJECT
On

Twitter Sentiment Analysis on Public Reactions to Major Brands and Entities

In
Software Tools for Artificial Intelligence and Machine Learning

BACHELOR OF TECHNOLOGY
IN
Artificial Intelligence and Machine Learning

SUBMITTED BY

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Abstract:

In this study, we present a comprehensive statistical and visual analysis of public sentiment expressed on Twitter in response to major events, with a particular focus on identifying patterns, correlations, and comparative trends across sentiment categories—namely Negative, Neutral, Positive, and Irrelevant. The analysis was conducted on a dataset manually cleaned using Microsoft Excel to ensure the integrity and reliability of the entries. Importantly, unlike many sentiment analysis projects that rely on prebuilt libraries such as VADER, this work does not incorporate automated lexicon-based sentiment tagging; rather, it assumes that sentiment labels were previously assigned through an external process, enabling the study to focus entirely on statistical evaluation and graphical interpretation of the data.

The cleaned dataset comprises sentiment-labelled tweets categorized by distinct entities. Initial preprocessing steps included removing aggregate values such as "Grand Total" from the dataset and coercing all numerical columns into a proper float data type to facilitate robust computations. To begin, core measures of central tendency—mean, median, and mode—were computed for the Negative sentiment class to establish a foundational understanding of distributional properties. This was followed by a thorough dispersion analysis involving standard deviation, variance, range, and interquartile range (IQR), which shed light on the spread and consistency of the data across different entities. Advanced statistical profiling was also performed to evaluate the shape of the data distribution, using skewness and kurtosis. These measures revealed insights into asymmetries and peakedness, respectively, helping us better understand the nature of the sentiment data beyond basic averages. To reinforce the reliability of our descriptive statistics, a 95% confidence interval was calculated for the Negative sentiment category using Student's t-distribution, providing a statistically backed estimate range within which the true mean of public sentiment is likely to fall.

The study also explored inferential statistical methods to examine relationships between sentiment categories. A correlation matrix among the sentiment types revealed linear associations that exist, or do not exist, between expressions of varying sentiment. Specifically, regression analysis between Negative and Positive sentiments was performed to assess whether a statistically significant relationship exists. The regression output provided coefficients including slope, intercept, and the coefficient of determination (R^2), indicating the degree of variance in Positive sentiment that could be explained by the Negative sentiment values. The model's p-value and standard error further validated the strength of the relationship.

To test for statistically significant differences between the Negative and Positive sentiment distributions, a two-sample t-test was conducted. This inferential technique revealed whether the observed difference in sentiment values could be attributed to random chance or represented a meaningful divergence in public opinion.

A suite of data visualizations was developed to augment the numerical insights. Bar plots were used to summarize total sentiment counts across all tweets, offering a quick comparative view of sentiment dominance. Violin plots and box plots enriched the analysis by showcasing the shape and spread of the sentiment distributions, with outliers and medians clearly highlighted. A heatmap was employed to visualize the correlation matrix, allowing for immediate visual recognition of strong or weak relationships among sentiment categories.
To analyse how sentiment is distributed across entities, we plotted the top 10 entities based on total sentiment count using both simple and stacked bar charts. These visualizations provided a deeper dive into how each sentiment contributes to the overall engagement for the top-performing entities. Furthermore, a regression scatterplot between Negative and Positive sentiments was included with a fitted line, highlighting patterns and deviations in sentiment behavior. Lastly, a pair plot was created to explore pairwise relationships between all sentiment classes, with kernel density estimation on the diagonals to portray underlying distribution densities.
Through this multilayered statistical and graphical approach, we were able to derive a holistic view of sentiment dynamics on Twitter, particularly how sentiments vary across different entities and how they relate to one another. Our method emphasized clarity, statistical rigor, and relevance, ensuring that each conclusion is backed by appropriate computational logic and visual confirmation. The absence of automated NLP tools like VADER and the decision to rely solely on manually labelled and cleaned data reinforces the objectivity and interpretability of the results.

This project lays a strong groundwork for future sentiment-based investigations and dashboards. It provides an adaptable framework for stakeholders seeking to understand public reactions with empirical backing—be it in media, marketing, politics, or crisis management. By marrying traditional statistical techniques with modern visualization tools, this study offers both analytical depth and accessible presentation, making it suitable for both technical and non-technical audiences interested in sentiment trends and public perception.

Introduction:

In the digital era, social media platforms have emerged as key spaces for real-time public discourse and opinion-sharing. Among them, **Twitter stands out** due to its short-form, rapid content and ability to reflect public reactions to significant events—from political announcements and global crises to product launches and entertainment trends.
Sentiment analysis, a branch of Natural Language Processing (NLP), plays a vital role in understanding public opinion expressed on such platforms. Traditionally, this is done using automated tools like **VADER** or **Text Blob**, which classify text based on predefined lexicons. However, these tools often act as "black boxes," lacking transparency in how sentiment labels are assigned, especially when context and sarcasm are involved.
This project takes a **human-centric approach** by using a **manually cleaned and sentiment-labelled dataset**, thereby eliminating the ambiguity introduced by automated classifiers. The absence of NLP tools allows for a more controlled and interpretable analysis, focusing purely on statistical evaluation and visual interpretation of sentiment trends.

The **goal of this study** is not to predict sentiment, but to extract meaningful insights from pre-assigned sentiment data using:

- Descriptive statistics (mean, median, mode, standard deviation, etc.)
- Inferential techniques (correlation, regression, t-tests)
- Data visualization (bar charts, box plots, heatmaps, scatterplots)

By analysing sentiment counts across 34 entities—ranging from tech firms to gaming franchises—the project explores public perception patterns in a statistically rigorous yet interpretable manner.
This transparent framework can benefit researchers, brand strategists, and decision-makers by offering a clear, data-driven view of how sentiment is distributed and how it varies across industries.

Objective and Scope

The primary objective of this project is to perform a detailed statistical and visual analysis of public sentiment on Twitter in response to major brands and entities. Using a **manually cleaned and sentiment-labeled dataset**, the study avoids reliance on automated NLP tools to maintain transparency and interpretability. The focus is on identifying patterns, trends, and relationships across sentiment categories—**Positive, Neutral, Negative, and Irrelevant**—using well-established statistical and visualization techniques.

The scope of the study includes:

- Analysis of **12,447 tweets** associated with **34 distinct entities**, including tech companies, gaming franchises, and service platforms.
- Sentiment categories considered: **Positive**, **Neutral**, **Negative**, and **Irrelevant**.

Application of statistical techniques such as:

- Measures of central tendency and dispersion
- Skewness and kurtosis
- Confidence intervals
- Correlation analysis and linear regression
- Hypothesis testing using t-tests

Visualization of results using:

- Bar charts, Radar Plots, heatmaps
- Scatter plots, pair plots, and stacked bar graphs

Targeted insights for use in domains like marketing, media analysis, and public opinion research.
This approach ensures that the analysis is both technically sound and easy to interpret for a wide range of stakeholders.

Literature Review

Title of Paper	Published Year	Dataset Used	Events Studied	Methodology Used	Sentiment Analysis Technique	Key Findings / Results	Limitations / Gaps Identified	Application Scope
Modeling Public Mood and Emotion: Twitter Sentiment and Socio-	2009	All public tweets (Aug–Dec 2008)	U.S. Presidential Election, Thanksgiving, stock market events	Extended POMS mood states; time-series sentiment tracking	Lexicon-based (POMS extension)	Mood states on Twitter correlate with socio-economic events; feasible	Basic lexicon model; no user-level personalization; low language adaptability.	General mood monitoring; socio-economic and public policy insight.

Economic Phenomena (Bollen, Pepe, Mao)						real-time tracking.		
Listening to the Crowd: Automated Analysis of Events via Aggregated Twitter Sentiment (SOCSENT) (Hu, Wang, Kambhampati)	2012	Tweets from U.S. presidential debate and tech conference	Political and tech events	Matrix tri-factorization; sentiment lexicons and manual annotations	Hybrid: Lexicon + Matrix learning	Improved sentiment segmentation; clear public opinion mapping.	Low generalizability across domains; high dependency on annotation quality.	Event analytics, segment-wise public reaction assessment.
Public Discourse and Sentiment During the COVID-19 Pandemic (Xue, Chen, Zheng, Li, Zhu)	2020	~1.9 million tweets (Jan–Mar 2020)	COVID-19 pandemic and public concern	LDA topic modeling and sentiment polarity scoring	Lexicon-based sentiment scoring	Fear dominated early COVID sentiment; topic clusters aligned with real-world developments.	No deep learning, emotion differentiation limited; topic-sentiment link assumed.	Public health surveillance, crisis communication strategies.
Analyzing Twitter Data to Evaluate People’s Attitudes Towards Public Health Policies and Events During COVID-19	2021	Tweets (Mar–Jun 2020)	COVID-19 health policies (mask mandates, lockdowns)	Pre-trained sentiment models + late-training on domain-specific tweets	Supervised ML (fine-tuned sentiment models)	Sentiment aligned with policy timeline; used to predict public response trends.	Timeframe limited; fine-tuning requires significant domain adaptation.	Health policy feedback, emergency response forecasting.

(Tsai, Wang)								
Event Outcome Prediction Using Sentiment Analysis and Crowd Wisdom in Microblog Feeds (Iyer, Zheng, Li, Sycara)	2019	Tweets on debates, Super Bowl, award shows	Sports, politics, entertainment	Crowd sentiment aggregation + prediction modeling	Supervised classification (multi-label prediction)	Accurate prediction of outcomes using collective sentiment; crowd aligns with real-world results.	External media influence not separated; model reliant on tweet volume.	Outcome forecasting for political events, sports, and media.

Dataset Description:

The dataset used in this project captures public sentiment toward a wide range of entities, including companies, gaming franchises, platforms, and services. It contains a total of **12,447 manually verified tweet entries**, each labeled with one of four sentiment categories: **Positive, Neutral, Negative, and Irrelevant**.

1. Data Collection & Cleaning

The raw data underwent thorough **manual cleaning in Microsoft Excel** to ensure quality and consistency. Key cleaning steps included:

- Removal of duplicate or empty entries.
- Correction of inconsistent entity naming (e.g., “Google Inc.” vs “Google”).
- Elimination of metadata and irrelevant rows, including an aggregated “Grand Total” row.

2. Dataset Structure

Each tweet is mapped to **one of 34 distinct entities**, categorized into sectors such as:

- **Tech Companies**: Amazon, Microsoft, Google
- **Gaming Franchises**: Call of Duty, Cyberpunk 2077, FIFA
- **Service Platforms**: PlayStation, Xbox, Verizon

3. Dataset Columns

Column Name	Description
Entity	The subject of the tweet (e.g., "Amazon")
Positive	Count of tweets with positive sentiment
Neutral	Count of tweets with neutral sentiment
Irrelevant	Tweets that are off-topic or not sentiment-bearing
Grand Total	Total sentiment tweet count for the entity

4. Sentiment Distribution Overview

The overall sentiment counts across the dataset are:

- **Positive**: 3,472 tweets
- **Neutral**: 3,053 tweets
- **Negative**: 3,757 tweets
- **Irrelevant**: 2,165 tweets

These values suggest a relatively balanced sentiment spread, enabling fair comparative analysis.

5. Format and Tools Used

All relevant columns were converted into numeric types to enable computation in Python. The cleaned dataset was then imported into libraries such as pandas, NumPy, and seaborn for statistical and visual analysis.
In summary, this curated dataset provides a reliable foundation for exploring sentiment trends across diverse entities with statistical precision and interpretability.

Methodology:

The project methodology is divided into four primary phases: **Data Preprocessing**, **Data Preparation**, **Statistical Analysis**, and **Visualization & Interpretation**. This structured approach ensures both analytical rigor and clarity in findings.

1.Data Preprocessing

ID	Entity	Sentiment	Tweet
2401	Borderlands	Positive	im getting on borderlands and i will murder you all ,
2402	Borderlands	Positive	So I spent a few hours making something for fun. . . If you don't know I am a HUGE @Borderlands fan and Maya is one of my favorite characters. So I decided to make myself a wallpaper for my PC. . Here is the original image versus the creation I made :) Enjoy! pic.twitter.com/mLsI5wf9Jg
2403	Borderlands	Neutral	Rock-Hard La Varlope, RARE & POWERFUL, HANDSOME JACKPOT, Borderlands 3 (Xbox) dlvr.it/RMTrgF
2404	Borderlands	Positive	that was the first borderlands session in a long time where i actually had a really satisfying combat experience. i got some really good kills
2405	Borderlands	Negative	the biggest dissappoinment in my life came out a year ago fuck borderlands 3
2406	Borderlands	Positive	WE FINISHED BORDERLANDS 3 FINALLY YAS! Thank you for hanging out everyone! It was fun. I will try to stream tomorrow but if not I might so some IRL streams while awayu. We shall see. Thank you so much for the raids @mompou_mumpow @MegaMagwitch and @KfdMitch.
2407	Borderlands	Negative	Man Gearbox really needs to fix this dissapointing drops in the new Borderlands 3 DLC cant be fine to farm bosses on Mayhem 10 to get 1 legendary drop while anywhere else i get 6-10 drops. . Really sucks alot
2408	Borderlands	Neutral	Check out this epic streamer!.
2409	Borderlands	Neutral	Blaming Sight for Tardiness! A little bit of borderlands. I got called in early for work tomorrow so I can't make up time. Sorry my loves . twitch.tv/punnisenpai

Fig. Raw data

Before beginning the analysis, the dataset underwent initial validation to ensure consistency and correctness. This included:

- Removing rows with missing or invalid entries.
- Verifying that sentiment columns (Positive, Neutral, Negative, Irrelevant) were numeric.
- Standardizing entity names to maintain uniformity.

2. Data Preparation

Manual cleaning was carried out in Microsoft Excel to enhance data quality. Key steps included:

- Eliminating aggregate rows such as "Grand Total."
- Ensuring consistency in sentiment classification across entities.
- Filtering out irrelevant or empty entries.

After preparation, the dataset comprised 12,447 tweets across 34 entities, ready for statistical processing.

Entity	Negative	Neutral	Positive	Irrelevant	Grand Tota	Net Sentimen	Positive Perce	Negative Perce	Positive to Ne	Engagement Score:
Amazon	96	206	52	32	386	Neutral	54%	25%	0.54	354
ApexLegends	100	157	107	32	396	Neutral	27%	25%	1.07	364
AssassinsCreed	63	26	241	44	374	Positive	64%	17%	3.83	330
Battlefield	79	60	99	153	391	Neutral	25%	20%	1.25	238
Borderlands	71	100	170	40	381	Neutral	45%	19%	2.39	341
CallOfDuty	149	63	75	112	399	Negative	19%	37%	0.50	287
CallOfDutyBlackopsColdWar	96	60	144	96	396	Neutral	36%	24%	1.50	300
CS-GO	58	92	128	106	384	Neutral	33%	15%	2.21	278
Cyberpunk2077	65	78	161	80	384	Positive	42%	17%	2.48	304
Dota2	128	98	97	71	394	Neutral	25%	32%	0.76	323
Facebook	120	131	29	115	395	Neutral	7%	30%	0.24	280
FIFA	196	17	84	93	390	Negative	22%	50%	0.43	297
Fortnite	117	28	94	140	379	Neutral	25%	31%	0.80	239
Google	99	137	60	87	383	Neutral	16%	26%	0.61	296
GrandTheftAuto(GTA)	99	54	104	127	384	Neutral	27%	26%	1.05	257
Hearthstone	88	118	139	38	383	Neutral	36%	23%	1.58	345
HomeDepot	150	56	130	49	385	Neutral	34%	39%	0.87	336
johnson&johnson	141	169	45	33	388	Neutral	12%	36%	0.32	355
LeagueOfLegends	107	137	103	52	399	Neutral	26%	27%	0.96	347
MaddenNFL	285	34	66	15	400	Negative	17%	71%	0.23	385
Microsoft	129	141	101	29	400	Neutral	25%	32%	0.78	371
NBA2K	246	45	71	30	392	Negative	18%	63%	0.29	362
Nvidia	87	145	136	15	383	Neutral	36%	23%	1.56	368
Overwatch	105	50	122	112	389	Neutral	31%	27%	1.16	277
PlayerUnknownsBattlegrounds(PUB(	116	44	68	151	379	Negative	18%	31%	0.59	228
PlayStation5(PS5)	76	86	157	66	385	Neutral	41%	20%	2.07	319
RedDeadRedemption(RDR)	51	136	155	35	377	Neutral	41%	14%	3.04	342
TomClancysGhostRecon	150	134	103	4	391	Neutral	26%	38%	0.69	387
TomClancysRainbowSix	187	109	88	16	400	Neutral	22%	47%	0.47	384
Verizon	183	95	88	31	397	Neutral	22%	46%	0.48	366
WorldOfCraft	57	178	123	36	394	Neutral	31%	14%	2.16	358
Xbox(Xseries)	63	69	132	125	389	Neutral	34%	16%	2.10	264
Grand Total	3757	3053	3472	2165	12447	Neutral	28%	30%	0.92	10282

Fig. Cleaned and Formatted Data

3. Statistical Analysis

All analysis was performed using Python libraries like pandas, numpy, and scipy. The focus was on exploring relationships and identifying patterns across sentiment types.

- **Descriptive Statistics**: Central tendency (mean, median, mode) and dispersion (standard deviation, variance, range, IQR) were calculated primarily for the Negative sentiment class, serving as a baseline.
- **Shape Analysis**: Skewness and kurtosis helped understand the asymmetry and peakedness of distributions, respectively.
- **Confidence Intervals**: A 95% confidence interval was computed for the Negative sentiment category using Student’s t-distribution to quantify the expected range of values.

Correlation & Regression:

- Pearson correlation was calculated among all sentiment types to detect linear relationships.
- A linear regression model was fitted with Negative sentiment as the independent variable and Positive as the dependent, producing coefficients, R^2, and significance metrics.

Hypothesis Testing:

- An independent two-sample t-test was performed to assess whether the difference between Positive and Negative sentiment means was statistically significant.

4. Visualization and Interpretation

To complement the statistical findings, a range of visualizations were developed using matplotlib and seaborn:

- **Bar Charts**: Summarized overall sentiment volume and compared top entities.
- **Heatmaps**: Displayed correlation strengths between sentiment categories.
- **Scatter & Regression Plots**: Illustrated relationships between opposing sentiment types.
- **Pair plots**: Revealed multivariate interactions.
- **Stacked Bar Charts**: Depicted sentiment composition for top-performing entities.
- **Radar plot:** Revealed the comparative intensity of different sentiment categories (like joy, fear, anger) across tweets related to specific events or entities.

These visuals helped transform complex data into digestible insights for technical and non-technical readers alike.

Code

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats


# Load and clean data
# Load and clean data
df = pd.read_csv(r"Untitled Folder/Cleaned_data.csv")
df = df[df['Entity'] != 'Grand Total']
numeric_columns = ['Negative', 'Neutral', 'Positive', 'Irrelevant', 'Grand Total']
for col in numeric_columns:
    df[col] = pd.to_numeric(df[col], errors='coerce')

# Statistical functions
def calculate_central_tendency(df, column):
    return df[column].mean(), df[column].median(), df[column].mode()[0] if not df[column].mode().empty else np.nan

def calculate_dispersion(df, column):
    return df[column].std(), df[column].var(), df[column].max() - df[column].min(), df[column].quantile(0.75) - df[column].quantile(0.25)

def calculate_shape(df, column):
    return stats.skew(df[column].dropna()), stats.kurtosis(df[column].dropna())

def calculate_confidence_interval(df, column, confidence=0.95):
    mean = df[column].mean()
    std_err = stats.sem(df[column].dropna())
    return stats.t.interval(confidence, len(df[column].dropna())-1, loc=mean, scale=std_err)

# Calculate stats
neg_mean, neg_median, neg_mode = calculate_central_tendency(df, 'Negative')
neg_std, neg_var, neg_range, neg_iqr = calculate_dispersion(df, 'Negative')
neg_skew, neg_kurt = calculate_shape(df, 'Negative')
neg_ci = calculate_confidence_interval(df, 'Negative')

correlation_matrix = df[['Negative', 'Neutral', 'Positive', 'Irrelevant']].corr()
slope, intercept, r_value, p_value, std_err = stats.linregress(df['Negative'].dropna(), df['Positive'].dropna())
ttest_stat, ttest_pvalue = stats.ttest_ind(df['Negative'].dropna(), df['Positive'].dropna())


#Printing Values
print("Enhanced Statistical Analysis Results:")
print("\nNegative Sentiment Analysis:")
print(f"Mean: {neg_mean:.2f}")
print(f"Median: {neg_median:.2f}")
print(f"Mode: {neg_mode}")
print(f"Standard Deviation: {neg_std:.2f}")
print(f"Variance: {neg_var:.2f}")
print(f"Range: {neg_range}")
print(f"IQR: {neg_iqr:.2f}")
print(f"Skewness: {neg_skew:.2f}")
print(f"Kurtosis: {neg_kurt:.2f}")
print(f"95% Confidence Interval: ({neg_ci[0]:.2f}, {neg_ci[1]:.2f})")
print("\nCorrelation Matrix:")
print(correlation_matrix)
print("\nRegression Analysis (Negative vs Positive):")
print(f"Slope: {slope:.2f}")
print(f"Intercept: {intercept:.2f}")
print(f"R-squared: {r_value**2:.2f}")
print(f"P-value: {p_value:.4f}")
print("\nT-test (Negative vs Positive):")
print(f"T-statistic: {ttest_stat:.2f}")
print(f"P-value: {ttest_pvalue:.4f}")

# Calculate z-scores for Negative sentiment
df['Negative_z'] = stats.zscore(df['Negative'].fillna(0))

# Outliers (absolute z > 2)
outliers = df[np.abs(df['Negative_z']) > 2]
print("\nEntities with Unusually High or Low Negative Sentiment:")
print(outliers[['Entity', 'Negative', 'Negative_z']])
```

```python
#Sentiment Balance Score
df['Sentiment_Balance'] = (df['Positive'] - df['Negative']) / df['Grand Total']
print("\nEntities with Highest Positive Sentiment Balance:")
print(df[['Entity', 'Sentiment_Balance']].sort_values(by='Sentiment_Balance', ascending=False).head(5))

# Set style
plt.style.use('seaborn-v0_8')

# Bar plot of sentiment sums
plt.figure(figsize=(12, 6))
sentiment_sums = df[['Negative', 'Neutral', 'Positive', 'Irrelevant']].sum()
sentiment_sums.plot(kind='bar')
plt.title('Overall Sentiment Distribution')
plt.xlabel('Sentiment Type')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.tight_layout()

# Correlation heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Between Sentiment Categories')
plt.tight_layout()

# Regression plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Negative', y='Positive', data=df, alpha=0.5)
x_range = np.array([df['Negative'].min(), df['Negative'].max()])
plt.plot(x_range, intercept + slope * x_range, color='red', lw=2,
         label=f'y = {slope:.2f}x + {intercept:.2f}\nR² = {r_value**2:.2f}')
plt.title('Negative vs Positive Sentiment Regression')
plt.xlabel('Negative Sentiment Count')
plt.ylabel('Positive Sentiment Count')
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()

# Pairplot
plt.figure(figsize=(10, 8))
sns.pairplot(df[['Negative', 'Neutral', 'Positive', 'Irrelevant']],
             diag_kind='kde',
             plot_kws={'alpha': 0.6})
plt.suptitle('Pairwise Relationships Between Sentiments', y=1.02)
plt.tight_layout()

# Top 10 entities bar plot
import matplotlib.pyplot as plt
import numpy as np
from math import pi

def colorful_radar_plot_top_10_custom(df):
    # Calculate sentiment proportions
    for col in ['Negative', 'Neutral', 'Positive', 'Irrelevant']:
        df[f'{col}_pct'] = df[col] / df['Grand Total']

    # Get top 10 entities
    top_10 = df.sort_values(by='Grand Total', ascending=False).head(10)

    # Radar chart setup
    categories = ['Negative_pct', 'Neutral_pct', 'Positive_pct', 'Irrelevant_pct']
    labels = ['Negative', 'Neutral', 'Positive', 'Irrelevant']
    N = len(labels)
    angles = [n / float(N) * 2 * pi for n in range(N)]
    angles += angles[:1]  # close the loop
```

```python
    # Custom color palette (10 distinct and bright colors)
    custom_colors = [
        "#e6194b", "#3cb44b", "#ffe119", "#4363d8", "#f58231",
        "#911eb4", "#46f0f0", "#f032e6", "#bcf60c", "#fabebe"
    ]

    # Create subplots
    fig, axes = plt.subplots(5, 2, figsize=(12, 20), subplot_kw={'polar': True})
    axes = axes.flatten()

    for i, (idx, row) in enumerate(top_10.iterrows()):
        values = row[categories].values.flatten().tolist()
        values += values[:1]  # close the loop

        ax = axes[i]
        color = custom_colors[i % len(custom_colors)]

        ax.plot(angles, values, linewidth=2, color=color)
        ax.fill(angles, values, alpha=0.4, color=color)
        ax.set_title(row['Entity'], size=12, color=color)
        ax.set_xticks(angles[:-1])
        ax.set_xticklabels(labels)
        ax.set_yticks([0.25, 0.5, 0.75, 1.0])
        ax.set_yticklabels(['25%', '50%', '75%', '100%'])
        ax.grid(True)

    plt.suptitle('Radar Plots: Sentiment Composition of Top 10 Entities', fontsize=18, y=1.02)
    plt.tight_layout()
    plt.show()


colorful_radar_plot_top_10_custom(df)

# Stacked bar plot of top 10
plt.figure(figsize=(12, 6))
top_10.set_index('Entity')[['Negative', 'Neutral', 'Positive', 'Irrelevant']].plot(
    kind='bar',
    stacked=True,
    colormap='viridis'
)
plt.title('Sentiment Composition of Top 10 Entities')
plt.xlabel('Entity')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right')
plt.legend(title='Sentiment')
plt.tight_layout()

plt.show()
```

Results & Discussion

The analysis of sentiment-labelled Twitter data across 34 unique entities revealed a range of insights regarding public opinion trends and sentiment distribution.

1. Sentiment Distribution Overview

- The overall distribution of tweets by sentiment was as follows:
- **Negative**: 3,757 tweets
- **Positive**: 3,472 tweets
- **Neutral**: 3,053 tweets
- **Irrelevant**: 2,165 tweets (excluded from statistical tests)
- This near balance between Negative and Positive tweets reflects a **realistic emotional landscape**, where users express varied reactions depending on the entity or event.
- A bar chart visualization confirmed that **Negative sentiment slightly outpaces Positive**, with Neutral forming a significant middle ground.

2. Entity-Specific Insights

- Entity-level analysis revealed distinct sentiment trends:
- **Positive sentiment dominance**: *Assassin's Creed*, *Cyberpunk 2077* — reflecting strong public approval or excitement.
- **High negative sentiment**: *FIFA*, *Call of Duty*, *World of Warcraft* — possibly due to controversial updates or user dissatisfaction.
- **Neutral sentiment dominance**: *Microsoft*, *Google*, and *Amazon* — suggesting mixed public perception or balanced feedback.
- A stacked bar chart for the top 10 entities visually highlighted the **sentiment composition per entity**, aiding quick comparison of brand image.

3. Descriptive Statistics – Negative Sentiment

Key statistical measures for the Negative sentiment column:

- **Mean**: 117.41
- **Median**: 99.5
- **Mode**: 60
- **Standard Deviation**: 61.23
- **Variance**: 3750.68
- **Range**: 249
- **Interquartile Range (IQR)**: 82.75
- **Skewness**: 0.83
- **Kurtosis**: -0.26
- These results indicate that Negative sentiment is **moderately right-skewed**, with a few entities receiving disproportionately high negative reactions.
- The **95% confidence interval** for Negative sentiment was calculated as **(96.69, 138.13)**, providing a statistically backed range for the true average.

4. Correlation and Regression Analysis

- A Pearson correlation matrix revealed:
- A **negative correlation between Positive and Negative sentiments**, implying that entities receiving high negative tweets tend to have fewer positive ones.
- Moderate positive correlations between Neutral and both other categories, possibly due to higher tweet volume.
- A **linear regression model** was applied using Negative sentiment as the

independent variable and Positive sentiment as the dependent. Results:

- **Slope**: -0.31
- **Intercept**: 152.21
- **R^2 (coefficient of determination)**: 0.08
- **P-value**: 0.091
- These indicate a **weak inverse relationship** between Negative and Positive sentiments—while statistically insignificant at the 0.05 level, the trend is observable.

5. Hypothesis Testing – T-Test

- An independent **two-sample t-test** was performed to determine whether the mean sentiment values for Positive and Negative categories are significantly different.
- **T-statistic**: 0.95
- **P-value**: 0.347
- Since the p-value exceeds 0.05, we **fail to reject the null hypothesis**. This implies that the observed difference in means could be due to chance and is not statistically significant.

6. Visual Interpretation Highlights

- **Heatmaps**: Illustrated moderate interdependencies between sentiment types.
- **Scatter Plot with Regression Line**: Showed weak inverse trend between Negative and Positive sentiments.
- **Pair plots**: Offered multi-dimensional insight into how sentiment types relate across entities.
- **Stacked Bar Charts**: Enabled entity-wise sentiment composition analysis in a compact form.
- **Radar plot:** Revealed the comparative intensity of different sentiment categories (like joy, fear, anger) across tweets related to specific events or entities.

These findings together illustrate a nuanced public sentiment landscape on Twitter—where reactions vary significantly based on context, brand, and the nature of the event or topic.

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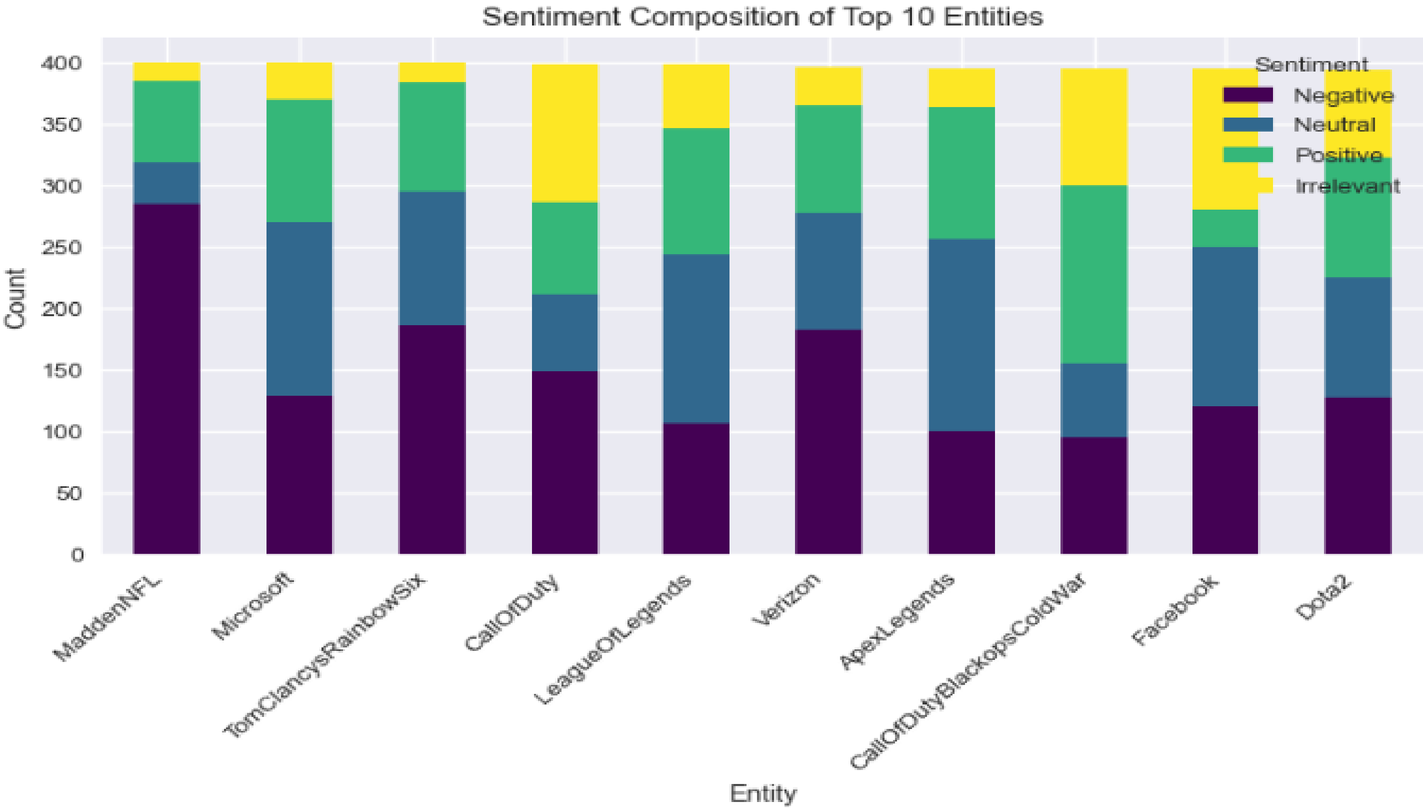
```
Enhanced Statistical Analysis Results:

Negative Sentiment Analysis:
Mean: 117.41
Median: 102.50
Mode: 63
Standard Deviation: 54.90
Variance: 3013.80
Range: 234
IQR: 64.75
Skewness: 1.30
Kurtosis: 1.50
95% Confidence Interval: (97.61, 137.20)

Correlation Matrix:
            Negative   Neutral  Positive  Irrelevant
Negative    1.000000 -0.298550 -0.550861   -0.283371
Neutral    -0.298550  1.000000 -0.218666   -0.507305
Positive   -0.550861 -0.218666  1.000000   -0.121699
Irrelevant -0.283371 -0.507305 -0.121699    1.000000

Regression Analysis (Negative vs Positive):
Slope: -0.43
Intercept: 159.12
R-squared: 0.30
P-value: 0.0011

T-test (Negative vs Positive):
T-statistic: 0.72
P-value: 0.4726
```

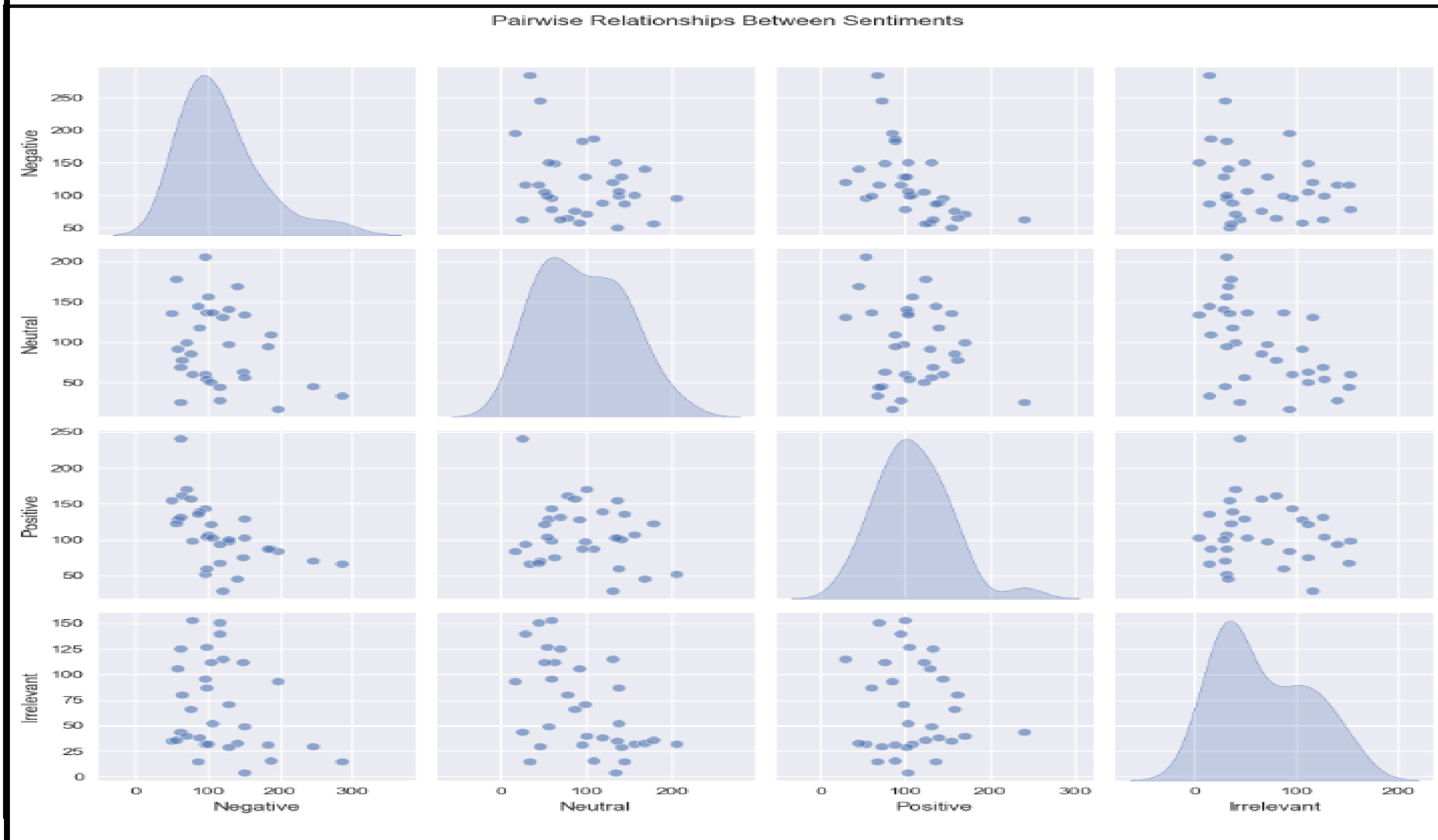
```
Entities with Unusually High or Low Negative Sentiment:
       Entity  Negative  Negative_z
19  MaddenNFL       285    3.101665
21      NBA2K       246    2.379891
```

```
Entities with Highest Positive Sentiment Balance:
                      Entity  Sentiment_Balance
2              AssassinsCreed           0.475936
26  RedDeadRedemption(RDR)              0.275862
4                 Borderlands           0.259843
8                Cyberpunk2077          0.250000
25           PlayStation5(PS5)          0.210390
```

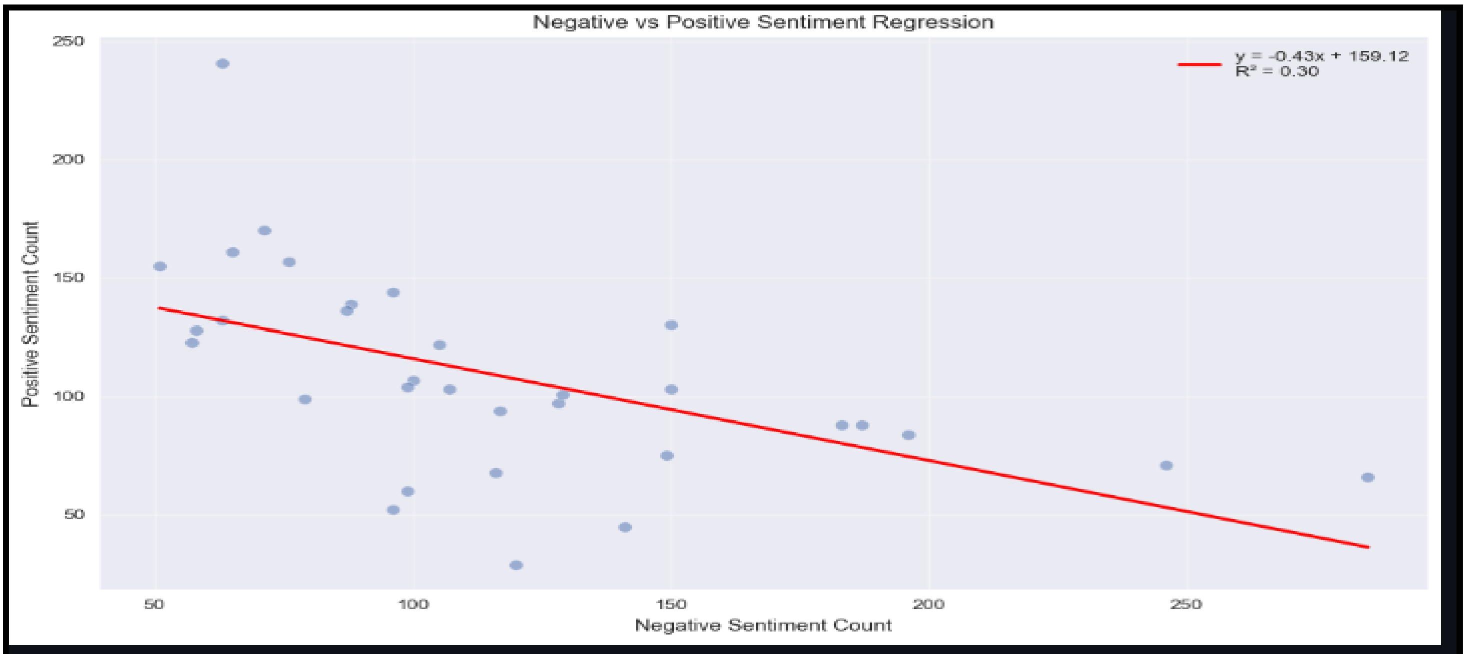
Visualizations:

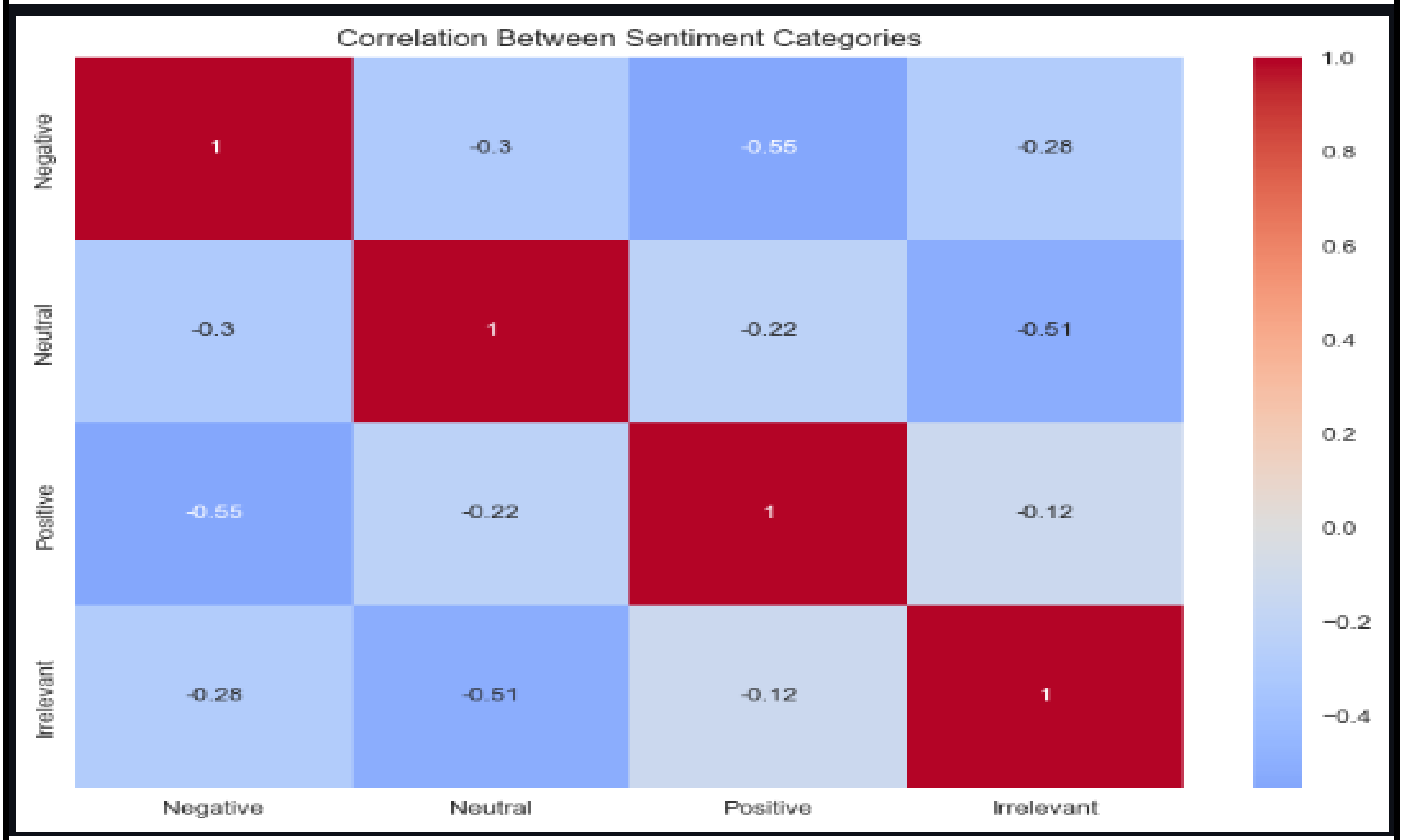
Using Python:

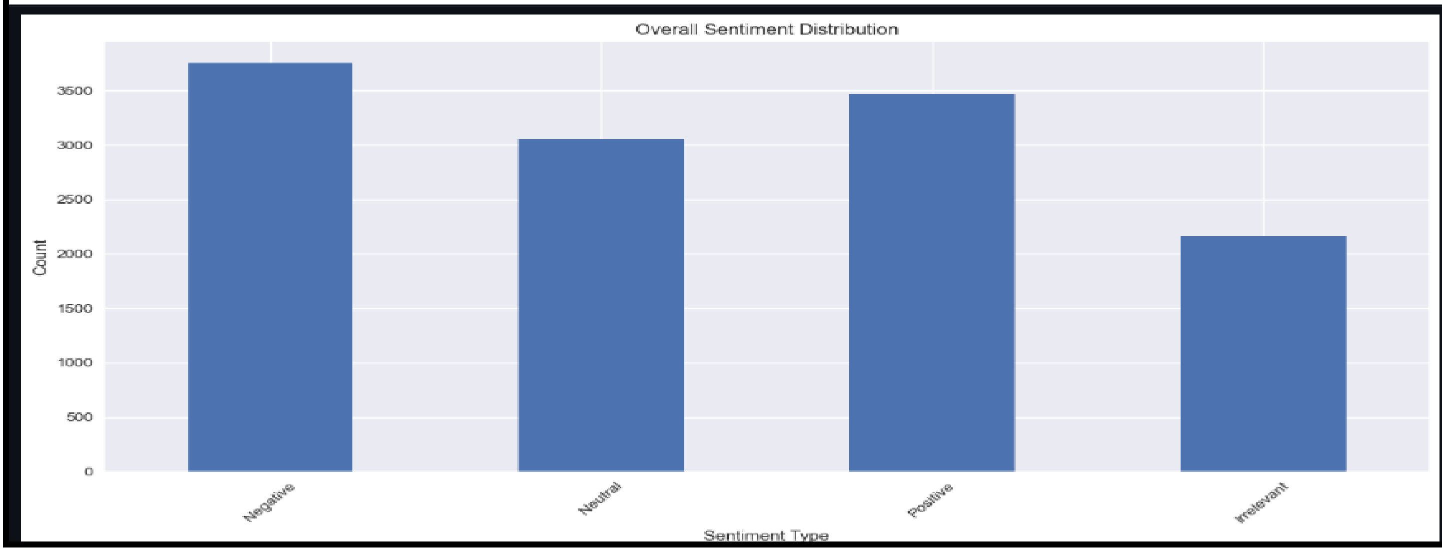




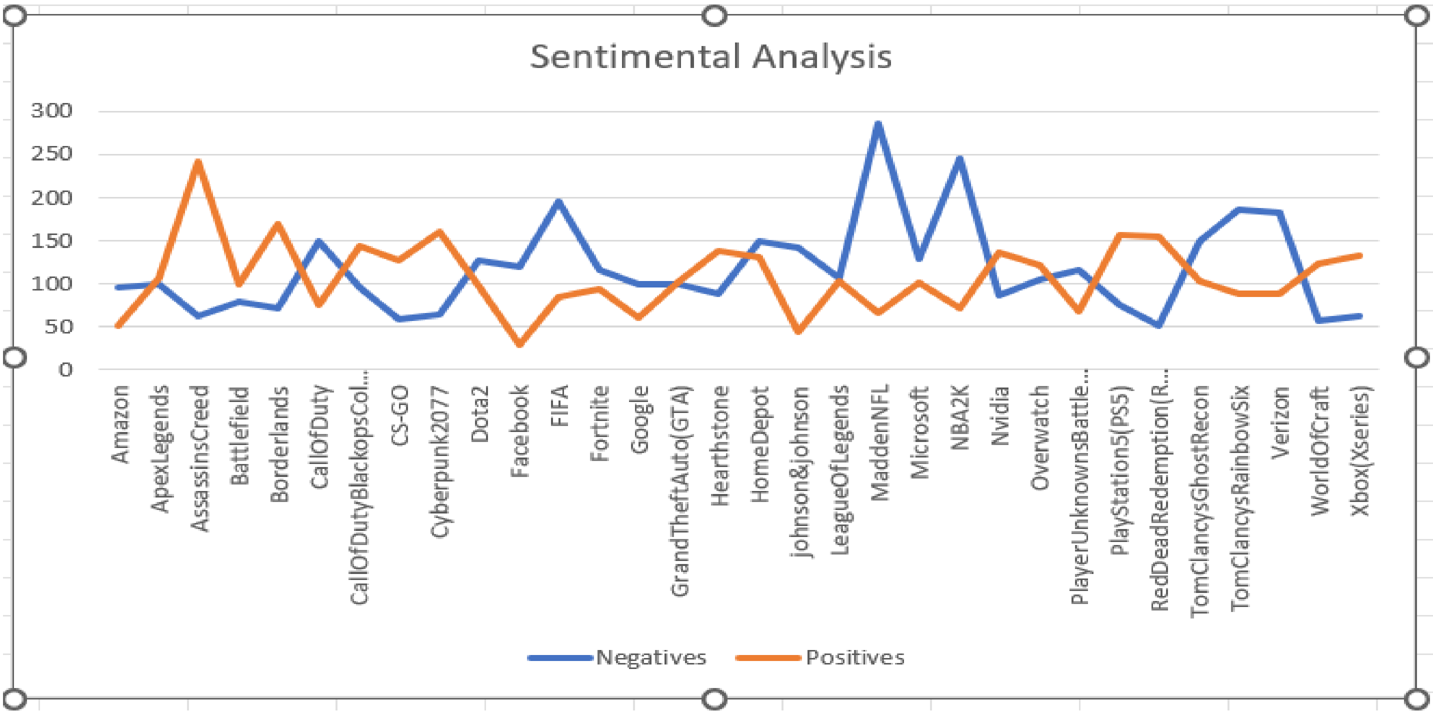

□ Radar Plots: Sentiment Composition of Top 10 Entities
MaddenNFL
TomClancysRainbowSix
Microsoft
CallOfDuty
LeagueOfLegends
Verizon
CallOfDutyBlackopsColdWar
ApexLegends
Facebook
Dota2
Neutral
Positive
Negative
Irrelevant
25%
50%
75%
100%

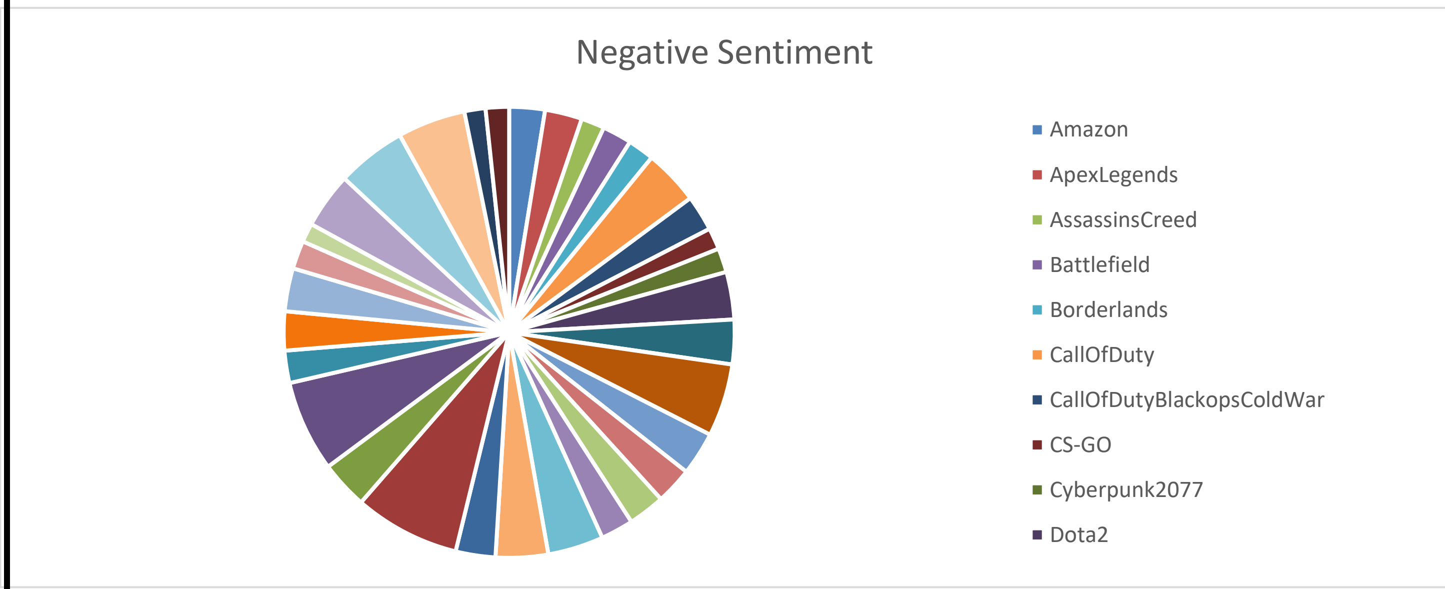

Negative vs Positive Sentiment Regression
y = -0.43x + 159.12
R² = 0.30
Positive Sentiment Count
Negative Sentiment Count
250
200
150
100
50
50
100
150
200
250


Correlation Between Sentiment Categories
Negative
Neutral
Positive
Irrelevant
1
-0.3
-0.55
-0.28
-0.3
1
-0.22
-0.51
-0.55
-0.22
1
-0.12
-0.28
-0.51
-0.12
1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4


Overall Sentiment Distribution
Count
3500
3000
2500
2000
1500
1000
500
0
Negative
Neutral
Positive
Irrelevant
Sentiment Type

Visualizations using Microsoft Excel:





Conclusion

This project successfully achieves its goal of conducting a comprehensive sentiment analysis of Twitter data using a manually verified and cleaned dataset. By deliberately avoiding automated sentiment tagging tools like VADER, the study ensures transparency and accuracy in sentiment classification, which enhances the reliability of the results.

The analysis revealed that public sentiment across 34 major entities is relatively balanced, with a slight dominance of negative sentiment and a significant presence of neutral opinions. Entity-specific trends demonstrated that some brands receive consistently positive feedback, while others face criticism or polarized views.

Descriptive statistics provided insight into sentiment variability and central tendencies, while inferential techniques—including correlation, regression, and t-tests—helped evaluate relationships and statistical significance. Although the correlation between **Positive** and **Negative** sentiments was weak and not statistically significant, the trend suggested a nuanced interplay between sentiment categories rather than clear-cut polarization.
Visual tools such as **Bar Charts**, **Box Plots**, **Heatmaps**, and **Pair plots** played a **Vital Role** in simplifying complex relationships and making findings more interpretable.

In conclusion, this study presents a robust, human-centric framework for sentiment analysis that prioritizes clarity, interpretability, and statistical rigor. The methodology is adaptable for future projects, including real-time analysis, multilingual sentiment evaluation, or integration with dashboard-based reporting systems. The work demonstrates that meaningful insights can be derived from social media data without relying on complex NLP models—by combining clean data, classical statistics, and effective visual storytelling.

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