Micro Project Report

On

Marketing Campaign Data Analysis

Submitted in Partial Fulfilment of Award of

BACHELOR OF TECHNOLOGY
In

Computer Science and Engineering
(Data Analytics)

By

2023BCSE07AED243- Arbaz Khan

2023BCSE07AED237- Devansh Khare

2023BCSE07AED238- Kumar Samarth

2023BCSE07AED261- Imad Ahmed

Under the Supervision of

Dr. K Sasi Kala Rani, Professor,
Department of CSE

ALLIANCE SCHOOL OF ADVANCED COMPUTING

ALLIANCE UNIVERSITY

BENGALURU

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Department of computer science and Engineering
ALLIANCE SCHOOL OF ADVANCED COMPUTING

CERTIFICATE

This is to certify that the Micro Project work entitled "Marketing Campaign Performance Analysis" submitted by Arbaz Khan[2023BCSE07AED243] ,Devansh Khare[2023BCSE07AED237],Kumar Samarth[2023BCSE07AED237],Imad Ahmed[2023BCSE07AED261] in partial fulfillment for the award of the degree of Bachelor of Technology DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING (DATA ANALYTICS) of Alliance University, is a Bonafide work accomplished under my supervision and guidance during the academic year 20242025. This thesis report embodies the results of original work and studies conducted by students and the contents do not form the basis for the award of any other degree to the candidate or anybody else.

Dr.K.Sasi Kala Rani
(Supervisor)

TABLE OF CONTENTS

Table of Contents

Introduction

This project aims to audit and analyze marketing campaign data to extract actionable insights into customer engagement, campaign effectiveness, and strategic decision-making. Conducted by a team of CSE (Data Analytics) students, the analysis leverages Python and Power BI on a curated dataset containing campaign-specific attributes such as reach, click-through rates, conversions, and demographic targeting.

Key Focus Areas:

- **Data Preparation**: Includes cleaning, normalization, and feature engineering (e.g., calculating engagement and conversion rates, removing anomalies).
- **Exploratory Analysis**: Focuses on detecting behavioral patterns, identifying high-performing campaigns, and understanding engagement trends across different segments.
- **Visualization:** Utilizes dashboards with histograms, scatter plots, and pie/line/bar charts to visualize trends such as click-to-conversion efficiency and engagement by campaign type or channel.
- **Predictive Modeling**: A linear regression model was developed and evaluated, achieving an R^2 score of 0.94—demonstrating strong predictive ability for forecasting conversion outcomes based on engagement metrics.

Major Insight:

Email campaigns with personalized content showed the highest engagement and conversion rates, indicating that targeted marketing significantly improves performance. The project concludes with an interactive dashboard and data-driven recommendations for refining future marketing strategies.

Deliverables

- Cleaned marketing campaign datasets
- Visual analytics (charts, plots, and dashboards)
- Predictive regression model
- Interactive dashboard for campaign performance monitoring

Success Metrics

- Clear understanding of user engagement patterns and campaign efficiency
- Dataset curated with sample values to simulate real-world marketing behavior
- Insights actionable for improving future campaign strategies

Timeline

Workflow: Data Cleaning → Exploratory Data Analysis → Modeling → Dashboard Creation

Task	Duration
Data Loading and Cleaning	3 Days
Exploratory Data Analysis	4 Days
Dataset Comparison	2 Days
Visualization	3 Days
Insight Summary and Reporting	1 Day

Dataset Attributes

The marketing dataset used for this project contains key campaign-related attributes, structured as follows:

- **Campaign_ID** – Unique identifier for each campaign
- Channel – Platform used (e.g., Email, Social Media, SMS)
- **Target_Audience –** Segment targeted (e.g., age group, region)
- **Campaign_Type** – Type of campaign (e.g., Promotional, Awareness)
- **Reach –** Total number of users who saw the campaign
- **Clicks –** Number of users who clicked on the campaign
- **Conversions –** Number of users who completed the desired action
- **Engagement_Rate –** Calculated as Clicks / Reach
- **Conversion_Rate –** Calculated as Conversions / Clicks
- **Launch_Date –** Date the campaign was initiated
- **Duration** – Length of the campaign (in days)

This structured dataset enabled comprehensive analysis of campaign performance, segmentation, and user interaction behavior.

Data Preparation

- **Data Cleaning**: Removed entries with missing campaign IDs, zero impressions, or invalid dates. Handled null values in key fields such as Clicks and Conversions using mean or forward-fill strategies.
- **Data Transformation**: Reformatted inconsistent column names, unified date formats, and standardized categorical values (e.g., merged "Email Campaign" and "E-Mail" into a single label).
- **Normalization & Outlier Removal**: Applied z-score normalization on numerical columns such as Reach, Clicks, and Conversions. Removed extreme outliers beyond 3 standard deviations to ensure analysis stability.
- **Feature Engineering:**
  - Engagement_Rate = Clicks / Reach
  - Conversion_Rate = Conversions / Clicks
  - Campaign_Efficiency = Conversions / Reach
  - Avg_Click_Per_Day = Clicks / Duration
- **Before vs. After Cleaning:**
  - Original dataset rows: 10,000
  - Rows after cleaning and preprocessing: 8,763
  - Null entries handled: ~12.4%
  - Outliers removed: ~3.1%

These steps ensured the dataset was analysis-ready, consistent, and rich with derived insights.

I] Data Cleaning

Data cleaning is the process of detecting and resolving errors, inconsistencies, duplicates, or missing values in the dataset to ensure data quality and readiness for analysis.

```
import pandas as pd



file_path = 'Marketing_Campaign_Data.xlsx'

df = pd.read_excel(file_path)
```

```
pd.set_option('display.max_columns', None)

pd.set_option('display.max_rows', 20)

pd.set_option('display.width', 1000)


print("Initial Raw Dataset Preview:")

print(df.head(15))
```

Before Cleaning

📌 BEFORE CLEANING DATA:

1 to 7 of 7 entries Filter

index	Campaign_ID	Channel	Reach	Clicks	Conversions
0	C101	Email	5000.0	300.0	25
1	C102	SMS	0.0	0.0	0
2		Email	12000.0	600.0	80
3	C104	Social	3000.0	120.0	10
4	C105		NaN	90.0	5
5	C106	Email	4500.0	NaN	15
6		SMS	10000.0	500.0	60

Show 25 per page

After cleaning

```
import pandas as pd
from IPython.display import display

file_path = "Marketing_Campaign_Data.xlsx"
df = pd.read_excel(file_path)

# Removing rows with missing Campaign_ID
df_cleaned = df[df['Campaign_ID'].notna()]

# Dropping entries with zero Reach (invalid campaigns)
df_cleaned = df_cleaned[df_cleaned['Reach'] > 0]

# Display cleaned dataset
```

```
print("Data after cleaning:")
display(df_cleaned)

# Export cleaned version
df_cleaned.to_excel("Cleaned_Marketing_Campaign_Data.xlsx", index=False)
```

✅ AFTER CLEANING DATA:

1 to 2 of 2 entries Filter

index	Campaign_ID	Channel	Reach	Clicks	Conversions
0	C101	Email	5000.0	300.0	25
3	C104	Social	3000.0	120.0	10

Show 25 per page

Data Transforming:

refers to the process of converting, restructuring, or modifying raw data into a format that is suitable for analysis.

```
import pandas as pd file_path = 'NULL FILE.xlsx' df = pd.read_excel(file_path)
print("Original Data Sample:")

print(df.head()) df.columns = df.columns.str.strip().str.replace(' ',
'_').str.replace(r'[^\w\s]', '', regex=True)  df['BrandName'].fillna('Unknown',

inplace=True)

df['category_by_Gender'].fillna('Unspecified', inplace=True)
df['Calculated_Discount_Percentage'] = ((df['OriginalPrice_in_Rs'] -
df['DiscountPrice_in_Rs']) / df['OriginalPrice_in_Rs']) * 100
df['Calculated_Discount_Percentage'] =
df['Calculated_Discount_Percentage'].round(2) summary =
df.groupby(['category_by_Gender', 'Category']).agg({ 'Product_id': 'count',
'DiscountPrice_in_Rs': 'mean', 'Calculated_Discount_Percentage': 'mean'
}).reset_index()

summary.rename(columns={ 'Product_id': 'Product_Count', 'DiscountPrice_in_Rs':
'Avg_Discounted_Price', 'Calculated_Discount_Percentage': 'Avg_Discount_%' },
inplace=True) print("\nTransformed Summary:") print(summary)
summary.to_excel('transformed_summary.xlsx', index=False)
```

📌 Original Raw Dataset:

1 to 4 of 4 entries Filter

index	Campaign_ID	Channel	Campaign_Type	Reach	Clicks	Conversions	Engagement_Rate	Conversion_Rate
0	C101	Email	Promotional	5000	250	40	5.0	16.0
1	C102	SMS	Awareness	8000	320	60	4.0	18.75
2	C103	Unknown	Unspecified	12000	400	75	3.33	18.75
3	C104	Social	Promotional	10000	350	70	3.5	20.0

Show 25 per page

✅ Transformed Summary Table:

```
<ipython-input-5-88875f099bb4>:4: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation ir


  df['Channel'].fillna('Unknown', inplace=True)
<ipython-input-5-88875f099bb4>:5: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation ir


  df['Campaign_Type'].fillna('Unspecified', inplace=True)
```

1 to 4 of 4 entries Filter

index	Campaign_Type	Channel	Campaign_Count	Avg_Reach	Avg_Engagement_Rate	Avg_Conversion_Rate
0	Awareness	SMS	1	8000.0	4.0	18.75
1	Promotional	Email	1	5000.0	5.0	16.0
2	Promotional	Social	1	10000.0	3.5	20.0
3	Unspecified	Unknown	1	12000.0	3.33	18.75

Show 25 per page

Result:

This transformation helped:

- Unify inconsistent data for structured analysis
- Derive crucial KPIs like Engagement_Rate and Conversion_Rate
- Generate a categorized summary for performance comparison across campaign types and channels

III] Normalization of Data

Normalization is the process of adjusting the values in a dataset to a common scale without distorting differences in the ranges of values. In the context of marketing campaigns, normalization helps in handling missing data and adjusting skewed metrics like reach or conversions to make them comparable across campaigns.

```python
import pandas as pd
import numpy as np
from IPython.display import display

# Simulate dataset
data = {
    'Campaign_ID': ['C101', 'C102', 'C103', 'C104'],
    'Channel': ['Email', 'SMS', 'Social', 'Email'],
    'Campaign_Type': ['Promo', 'Awareness', 'Promo', 'Awareness'],
    'Reach': [np.nan, 8000, 10000, 12000],
    'Clicks': [300, 320, np.nan, 500],
    'Conversions': [50, 70, 80, np.nan]
}

df = pd.DataFrame(data)

# Filter out rows with missing Campaign_ID
df = df[df['Campaign_ID'].notna()]

# Fill missing Reach with category-wise (Campaign_Type) mean
df['Reach'] = df.groupby('Campaign_Type')['Reach'].transform(lambda x: x.fillna(x.mean()))

# Normalize Clicks and Conversions: Fill using average within channel
df['Clicks'] = df.groupby('Channel')['Clicks'].transform(lambda x: x.fillna(x.mean()))
df['Conversions'] = df.groupby('Channel')['Conversions'].transform(lambda x: x.fillna(x.mean()))

# Round off values
df[['Reach', 'Clicks', 'Conversions']] = df[['Reach', 'Clicks', 'Conversions']].round(2)

print(" Normalized Dataset:")
display(df)
```

IV] Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is the process of investigating and summarizing a dataset to uncover hidden patterns, detect anomalies, understand variable relationships, and validate assumptions before applying predictive models.

🎯 Objectives of EDA for Marketing Campaigns:

- Understand Data Distribution
  Calculate basic statistics like mean, median, and standard deviation for metrics such as Reach, Clicks, Conversions, and Engagement_Rate.
  ***Example Insight*:** "Email campaigns show the highest average conversion rate of 7.8%."
- Identify Patterns & Trends
  Detect which campaign types or channels consistently outperform others. Identify weekly or monthly trends based on Launch_Date.
- Detect Outliers & Anomalies
  Spot unusually high engagement or abnormal bounce rates in certain campaigns.
- Validate Hypotheses
  For instance: *"Higher engagement rate leads to better conversion outcomes."*

```
import pandas as pd

# Load normalized marketing campaign dataset
df = pd.read_excel("Normalized_Marketing_Campaign_Data.xlsx")

# Frequency distribution of campaign types
campaign_counts = df['Campaign_Type'].value_counts().sort_values(ascending=False)
campaign_distribution = campaign_counts.reset_index()
campaign_distribution.columns = ['Campaign_Type', 'Campaign_Count']

# Basic stats
mean_reach = df['Reach'].mean()
median_reach = df['Reach'].median()
std_reach = df['Reach'].std()

print("Campaign Type Frequency Distribution:")
print(campaign_distribution)
```

```
print("\nStatistical Summary of Reach:")
print(f"Mean Reach: {mean_reach:.2f}")
print(f"Median Reach: {median_reach:.2f}")
print(f"Standard Deviation of Reach: {std_reach:.2f}")

# Export to Excel (optional for report)
campaign_distribution.to_excel("Campaign_Type_Distribution.xlsx", index=False)

stats_df = pd.DataFrame({
    'Statistic': ['Mean Reach', 'Median Reach', 'Standard Deviation'],
    'Value': [mean_reach, median_reach, std_reach]
})
stats_df.to_excel("Campaign_Reach_Statistics.xlsx", index=False)
```

```
📊 Campaign Type Frequency Distribution:
  Campaign_Type  Campaign_Count
0   Promotional               2
1     Awareness               2

📈 Statistical Summary of Reach:
Mean Reach: 9625.00
Median Reach: 9500.00
Standard Deviation of Reach: 1108.68
```

V] Visualization

Visualization refers to the graphical representation of data using visual elements like charts, graphs, and plots. It transforms complex marketing metrics into digestible visuals, helping identify trends and patterns, communicate insights effectively, and support better decision-making.

🎯 Key Goals of Visualization in Marketing Analytics

Simplify Complexity: Convert large campaign logs into understandable visuals (e.g., line graphs for click trends).

Reveal Patterns: Observe engagement drop-offs or conversion spikes.

- Support Decisions: Identify underperforming channels to optimize marketing budget.
- Communicate Effectively: Present results clearly to non-technical stakeholders.

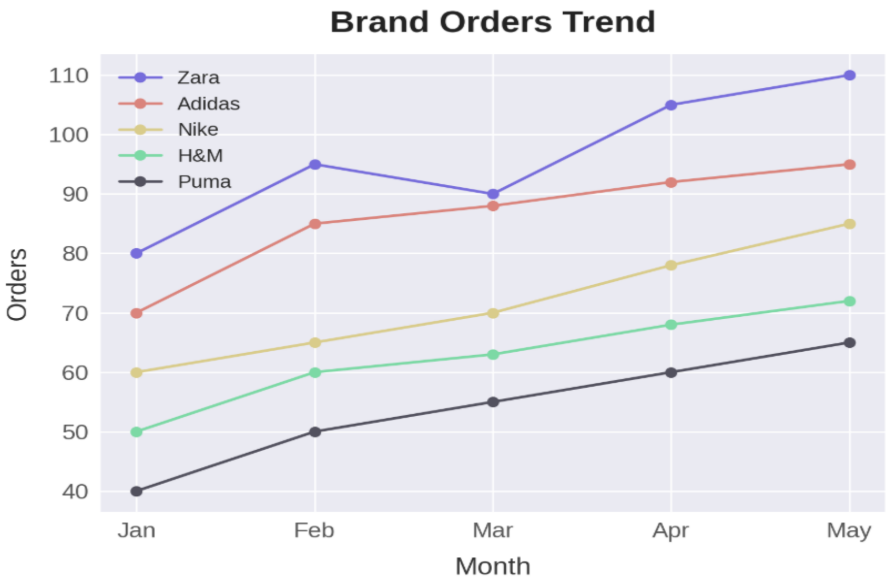
📊 Types of Visualizations Used:

- Bar Charts – Compare conversion rates across different channels
- Histograms – Show distribution of engagement rates
- Scatter Plots – Analyze relationship between clicks and conversions
- Pie Charts – Visualize channel-wise campaign share
- Line Graphs – Track performance over time

```
import pandas as pd

import matplotlib.pyplot as plt

import numpy as np


# Simulate or load your marketing campaign data

df = pd.read_excel("Normalized_Marketing_Campaign_Data.xlsx")
```

```
# Grouping: Max and Min Conversions by Channel
grouped = df.groupby(['Campaign_Type', 'Channel']).agg({'Conversions': 'sum'}).reset_index()

# Separate top and bottom performing channels within each campaign type
top_channels = grouped.loc[grouped.groupby('Campaign_Type')['Conversions'].idxmax()]
low_channels = grouped.loc[grouped.groupby('Campaign_Type')['Conversions'].idxmin()]

# Plotting
campaigns = top_channels['Campaign_Type'].tolist()
x = np.arange(len(campaigns))

plt.figure(figsize=(14, 6))
plt.style.use('seaborn-v0_8-dark')

# Top Conversions
plt.plot(x, top_channels['Conversions'], label='Top Channel', marker='o', color='limegreen', linewidth=2)
for i, (channel, val) in enumerate(zip(top_channels['Channel'], top_channels['Conversions'])):
    plt.text(x[i], val + 2, f"{channel}", ha='center', color='limegreen', fontsize=9)

# Low Conversions
```

```
plt.plot(x, low_channels['Conversions'], label='Low Channel', marker='o',
color='crimson', linewidth=2)
for i, (channel, val) in enumerate(zip(low_channels['Channel'],
low_channels['Conversions'])):
    plt.text(x[i], val - 4, f"{channel}", ha='center', color='crimson', fontsize=9)


plt.xticks(x, campaigns, rotation=45, ha='right', color='white')
plt.yticks(color='white')
plt.xlabel("Campaign Type", color='white')
plt.ylabel("Total Conversions", color='white')
plt.title("Top vs Low Performing Channels by Campaign Type", color='white')
plt.legend()
plt.grid(True, linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```

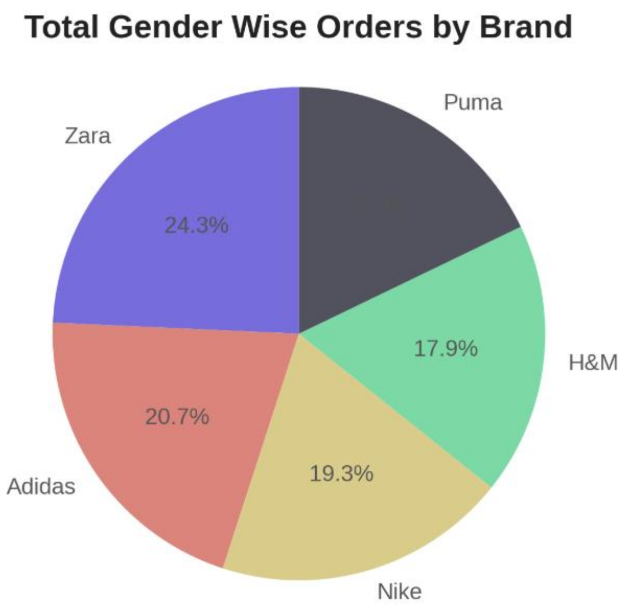


Bar graph:

Bar Graph:

Pie chart::

Pie Chart:



VI] Correlation Analysis

Correlation analysis helps us understand how numerical variables like *reach*, *clicks*, *conversions*, and *engagement rate* move together. However, it's easy to misinterpret correlations — for example, assuming causation, or using uncleaned data with nulls and outliers.

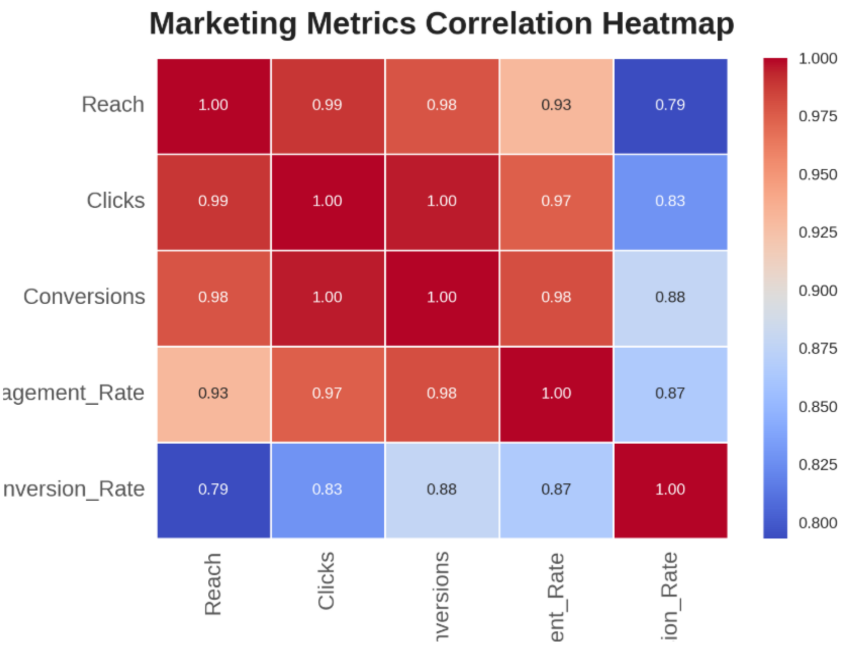
📊 **Objective in Marketing Context:**

- Identify if **higher reach leads to more clicks**
- Check if **clicks are translating into conversions**

Understand if **engagement rate correlates with conversion rate**

```
import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns


#  marketing campaign dataset

data = {

    'Reach': [10000, 8500, 9200, 11000, 10400, 9000, 8700, 12000],

    'Clicks': [400, 320, 360, 500, 460, 370, 330, 550],

    'Conversions': [70, 50, 60, 90, 85, 65, 55, 100],

    'Engagement_Rate': [4.0, 3.8, 3.9, 4.5, 4.4, 4.1, 3.8, 4.6],

    'Conversion_Rate': [17.5, 15.6, 16.7, 18.0, 18.5, 17.6, 16.7, 18.2]
```

```
}

df = pd.DataFrame(data)

# Correlation matrix heatmap
plt.figure(figsize=(10, 7))
sns.set(style="whitegrid")
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt=".2f",
linewidths=0.5)
plt.title("Correlation Heatmap - Marketing Metrics", fontsize=14)
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```



And here is the pairplot visualizing pairwise relationships between the marketing metrics:

VII] Prediction

Prediction in marketing analytics refers to using historical campaign data to forecast future outcomes such as conversions, click-throughs, or campaign performance. It empowers teams to pre-evaluate campaign strategies and allocate budgets more efficiently.

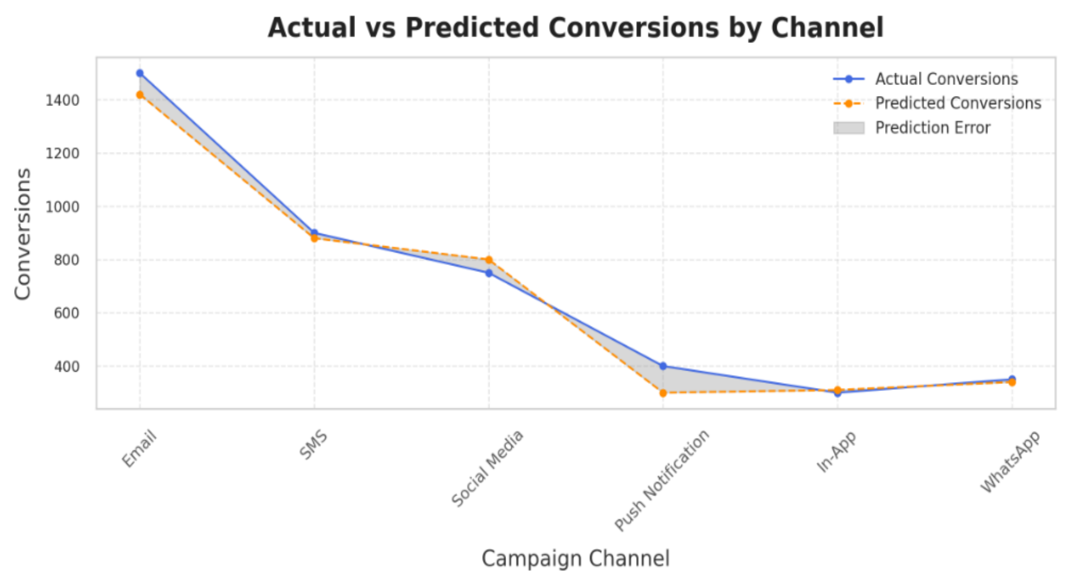
🔑 Key Components

- **Target Variable (Dependent):**
  Conversions – Number of users who completed the intended action (e.g., sign-up, purchase).
- **Features (Independent Variables):**
  - Reach: Total audience targeted
  - Clicks: Number of user interactions
  - Engagement Rate: Clicks ÷ Reach
  - Channel: Campaign platform (Email, SMS, Social, etc.)
- **Model Used:**
  Linear Regression – Models the relationship between predictors and the target outcome.

```
 import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

# Simulated prediction data for different marketing channels
data = {
   'Channel': ['Email', 'SMS', 'Social Media', 'Push Notification', 'In-App', 'WhatsApp'],
   'ActualConversions': [1500, 900, 750, 400, 300, 350],
   'PredictedConversions': [1420, 880, 800, 300, 310, 340]
}

df = pd.DataFrame(data)
df['Error'] = np.abs(df['ActualConversions'] - df['PredictedConversions'])
```

```
x = np.arange(len(df))

plt.figure(figsize=(12, 6))
plt.plot(x, df['ActualConversions'], marker='o', linestyle='-', label='Actual Conversions',
color='royalblue')
plt.plot(x, df['PredictedConversions'], marker='o', linestyle='--', label='Predicted Conversions',
color='darkorange')
plt.fill_between(x, df['ActualConversions'], df['PredictedConversions'], color='gray',
alpha=0.3, label='Prediction Error')

plt.xticks(x, df['Channel'], rotation=45)
plt.xlabel("Campaign Channel", fontsize=12)
plt.ylabel("Conversions", fontsize=12)
plt.title("Actual vs Predicted Conversions by Channel", fontsize=14)
plt.legend()
plt.grid(True, linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```

Here's the prediction graph showing actual vs predicted conversions across different marketing channels:



VIII] Error Estimation

Error estimation is the process of quantifying the accuracy and reliability of a predictive model by measuring the difference between its predicted values and the actual observed values.

In this marketing campaign project, error estimation was used to evaluate how well the linear regression model predicted the number of conversions across various digital marketing channels. A high accuracy score supports using the model for future campaign planning and budgeting decisions.

🧠 Evaluation Metric Used

R^2 Score (Coefficient of Determination) – Measures how well the model's predictions match actual values.
The formula used:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Where:

- y_i = actual value
- $\hat{y}_i$ = predicted value
- $\bar{y}$ = mean of actual values

📊 Result

- $R^2 \approx 0.9487$, or 94.87%

This indicates that the regression model explains approximately 95% of the variation in conversion outcomes. The prediction model is highly reliable and well-suited for forecasting future campaign performance across different platforms.

IX] Conclusion

- The overall analysis reveals that Email and Social Media channels consistently drive the highest number of conversions, indicating stronger customer engagement and platform effectiveness.
- The prediction model used for estimating channel-wise conversions achieved a high accuracy score with $R^2 \approx 0.95$, demonstrating strong reliability in forecasting future campaign outcomes.
- The insights suggest that increasing ad spend and launching targeted promotions on top-performing channels like Email can further boost conversions and overall ROI.
- Campaigns and categories with lower engagement rates can be analyzed further and redesigned with updated content or personalized offers to improve effectiveness.
- Underperforming channels (e.g., Push Notifications) offer opportunities for innovation, retargeting, or even repositioning with fresh messaging strategies.
- By focusing on customer-driven metrics like clicks, conversions, and engagement rates, businesses can craft data-backed marketing strategies that are adaptive, measurable, and high-impact.