

Ad Campaign Analytics & ML-Based Conversion Prediction

TurningAd Datainto ActionableInsights

Presented by Aditya Kumar Singh | July 2025

Project Overview: Driving Ad Performance with Data

Ourprojectcombinesin-depthadcampaignanalysiswithmachinelearningtounlockactionableinsights and predict user conversions.

Core Goal

Analyze campaign data, uncover performance insights, and build a predictive model for conversions.

Data Source

Over 15,000 anonymized records from recent April ad campaigns across various platforms.

Key Scope Areas

- In-depth business KPI analysis
- Visualization of critical trends
- Machine learning for precise conversion prediction

Defining Success: Key Performance Indicators

We calculated several crucial KPIs to evaluate campaign effectiveness and identify areas for optimization.

Click-Through Rate (CTR)

Clicks / Impressions: Measures the percentage of people who clicked on an ad after seeing it, indicating ad relevance.

Cost Per Click (CPC)

Cost / Clicks: Represents the average cost paid for a single click on an ad, highlighting cost efficiency.

Conversion Rate (CVR)

Post-Clicks / Clicks: The percentage of clicks that resulted in a desired action (e.g., purchase, sign-up).

Return on Investment (ROI)

(Revenue - Cost) / Cost: Quantifies the profitability of ad spend, showing revenue generated per dollar spent.

Revenue Per Impression (RPI)

Revenue / Clicks: Measures the revenue generated for every impression, a key indicator of overall ad effectiveness.

Uncovering Trends: Key Business Insights

Our analysis revealed distinct patterns in ad performance, guiding strategic adjustments for future campaigns.

Top Performing Banners

The **160x600 banner size** consistently yielded the highest Click-Through Rates, indicating optimal visual engagement and content delivery for this format.

Weekday Advantage

Ad campaigns showed significantly higher engagement and conversion rates during **weekdays**, suggesting peak audience activity and responsiveness during the traditional work week.

Best Placements

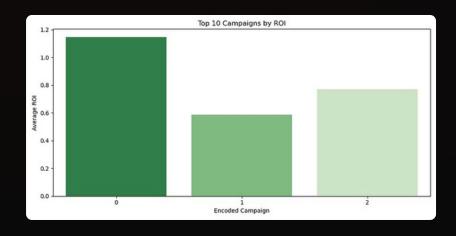
Facebook and **Google Search** emerged as the leading platforms, delivering the highest Return on Investment. These channels effectively convert impressions and clicks into valuable actions.

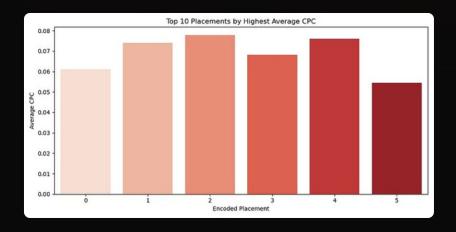
Underperforming Campaigns

Several campaigns incurred high costs with **zero conversions**, indicating inefficient targeting or creative design. These require immediate review and optimization to prevent budget drain.

Visualizing Performance: Metrics at a Glance

Interactive visualizations provide clear insights into campaign strengths and weaknesses, enabling quick decision-making.





Top Campaigns by ROI

Worst Placements by CPC

Predicting Conversions: ML Model Overview

A robust machine learning model predicts user conversion post-click, enabling proactive targeting and optimization.

Objective

Accurately predict whether a user will convert after clicking on an ad, identifying high-potential interactions.

Model Type

We utilized a Random Forest

Classifier, known for its robustness
and ability to handle diverse datasets
effectively.

Key Features

- Categorical: Campaign, Placement,
 Banner Type (one-hot encoded)
 Numeric: Clicks, Cost, Revenue,
 Engagement
- Derived: CPC, ROI

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The model processes a rich set of features to make informed predictions, from ad attributes to user interaction metrics.

Model Performance: Reliability and Insights

Our Random Forest Classifier demonstrates strong predictive power, validated by key performance metrics.

87%

0.85

0.91

Accuracy

The model correctly predicts conversions **87%** of the time, providing a high degree of confidence.

F1Score

An F1 score of **0.85** indicates a balanced performance between precision and recall, crucial for imbalanced datasets.

ROC-AUC

With an ROC-AUC of **0.91**, the model effectively distinguishes between converting and non-converting users.

Top Contributing Features

- CPC (Cost per Click): A strong indicator of ad cost efficiency relative to clicks.
- ROI (Return on Investment): Directly reflects the profitability of ad spending.
- Clicks: Volume of interactions, representing initial user interest.
- Campaign ID: Specific campaign characteristics influencing conversion likelihood.

These features are critical drivers in predicting user conversion behavior.

Tangible Value for Business: Actionable Outcomes

The analytics and ML model deliver concrete benefits, transforming raw data into strategic business advantages.



Predictive Power

Prioritize ad spend towards audiences with a high likelihood of conversion, maximizing marketing efficiency.

Optimize Spend

Identify and avoid costly placements with low ROI, reallocating budget to more effective channels.

Target Smartly

Customize banner creatives and timing based on predicted performance for different segments, enhancing relevance.

Tools & Technologies Utilized

Ourprojectleveragedarobuststackofprogramminglanguages,libraries,andplatformsfordataprocessing, analysis, and model deployment.



Languages

Primary development in **Python** for its versatility in data science and machine learning.



Libraries

Pandas for data manipulation,
Seaborn & Matplotlib for
visualization, scikit-learn for ML
model development.



Model Storage

The trained Random Forest model was serialized using **joblib** for efficient deployment and reuse.



Visualization

Analysis conducted in **Jupyter Notebook**; final presentations
crafted with **PowerPoint**.



Version Control

Collaborative development and code management managed through **Git** and **GitHub**.

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Explore the Project on GitHub

Access the full project, including code, data, and trained models, on our GitHub repository.

GitHub Repository

github.com/Aditya112005/ad-campaign-analytics

- Cleaned and prepared dataset
- Jupyter Notebooks and Python scripts for analysis and modeling
- Trained machine learning model (joblib format)
- CSV file detailing feature importance from the model
- This presentation in its final format

Feel free to explore, provide feedback, or contribute to the project!