ONLINE AD CLICK PREDICTOR FOR deliveroo

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Executive Summary

OBJECTIVE

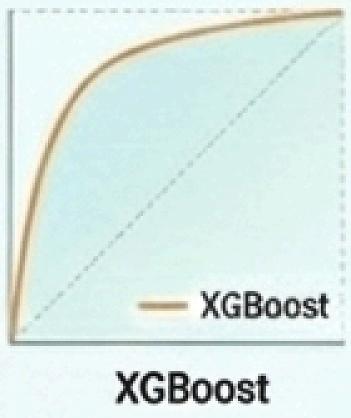
Predict which users will click Deliveroo ads and translate insights into actionable targeting and budget decisions.

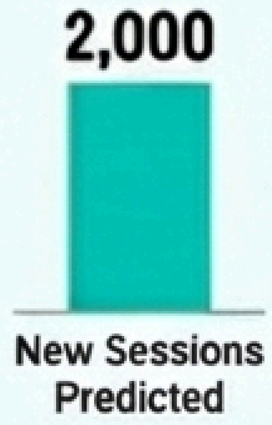
WHAT WE DID

- Explored session-level data to identify key conversion drivers (channel, timing, prior behaviour).
- Built and compared multiple classification models; selected the best-performing model for scoring new users.
- Created customer segments (clustering) to support audience strategy beyond "one-size-fits-all" targeting.

KEY RESULT

XGBoost delivered the strongest performance (Highest AUC = 0.985) and was used to generate click predictions for the 2,000 new sessions.





BUSINESS IMPACT

Prioritize spend on higher-converting channels (Facebook), optimize targeting by time and user history, and use model scores to focus campaigns on high-intent sessions.

Budget Optimization

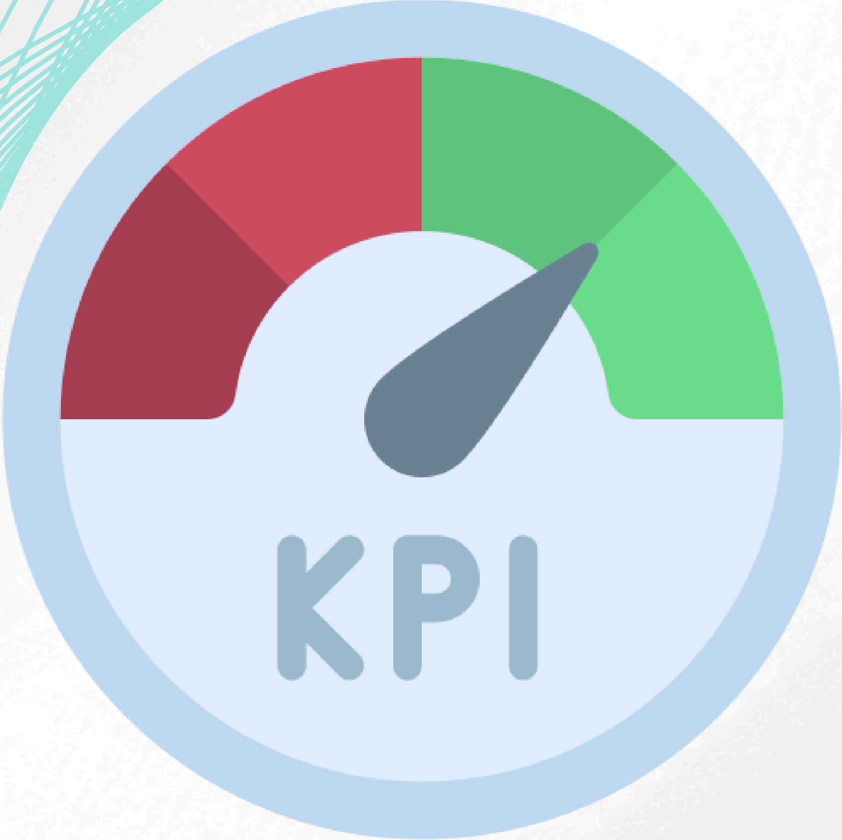
High-Intent Focus

Summary Presentation

Project outline and agenda

Aim of the project

The **aim** of this project was to find the best model which could predict the click (conversion) for Deliveroo’s ad campaign, as well as create an iterative dashboard to enlight the most useful KPIs to assist managerial decisions.



Project outline and agenda

Data

The dataset tracks user sessions and behavioral metadata, including:

User Geography & Demographics:

- **Region**: Specific French territories (e.g., North France, South France, Alsace and East France).
- **Social Network**: The platform where the user saw the ad campaign

Temporal Context:

- **Weekday**
- **Daytime**

Behavioral Metrics:

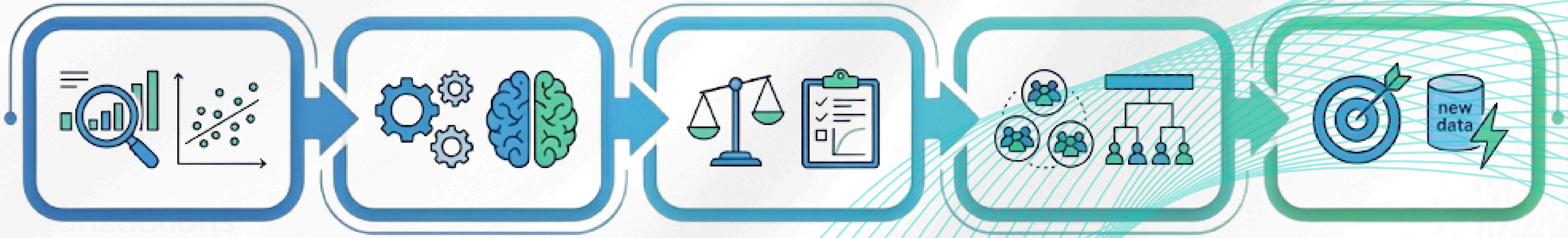
- **Time_On_Previous_Website**: Engagement duration before arriving at the current page.
- **Number_of_Previous_Orders**: A measure of user loyalty and historical "stickiness."
- **Restaurant_Type**: The category of food the user is interested in (Sushi, Burger, Groceries, Kebab, French).

Technical Metadata:

- **Carrier**: The user's internet service provider (Free, Bouygues, Orange, SFR), which can serve as a proxy for connection quality or socioeconomic status.

Project outline and agenda

Methods



EXPLORATORY DATA ANALYSIS (EDA)

Correlation Studies
Identify Key Drivers

MODELING PHASE

K-Nearest Neighbors (KNN)
Logistic Regression (AIC/BIC, LASSO)
Decision Trees
Random Forests
XGBoost

EVALUATION

AUC-ROC Metrics
Confusion Matrices

UNSUPERVISED LEARNING (SEGMENTATION)

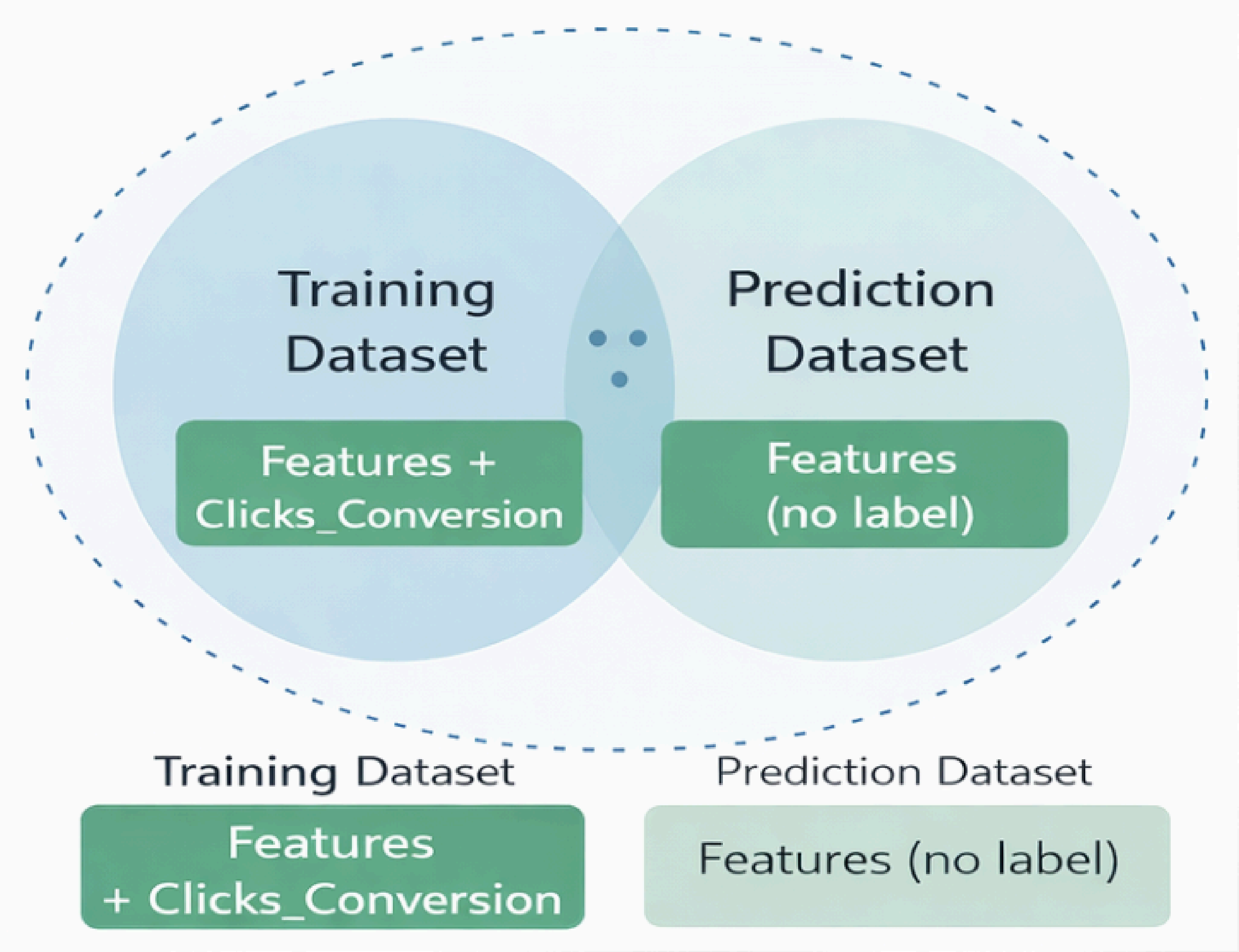
K-means
Hierarchical Clustering
Consumer Profiles

FINAL VALIDATION & PREDICTION

Validate Best Model
Actionable Click Predictions on New Data

Data Description

Overview



- Session level dataset capturing user context, channel, and prior behaviour
- Objective: Predict **Clicks_Conversion**
  - (0 = no click, 1 = click)
  - **Class imbalance**: 85.1% click
- Two Files:
  - **Training set**: features + labels (18,000)
  - **Prediction set**: same features, no labels (2,000)

one row = one user session/visit

Data Description

Feature Landscape

User Context

- **Region** - Region in France (6 categories)
- **Weekday** - Day of the week (7 categories)
- **Daytime** - Time of day (0-1)

Acquisition Channel

- **Social_Network** - which social network was the user referred from (3 categories)

Offer Context

- **Restaurant_Type** - e.g. Burger (4 categories)

Connectivity Proxy

- **Carrier** - (4 categories)

Behavioural History

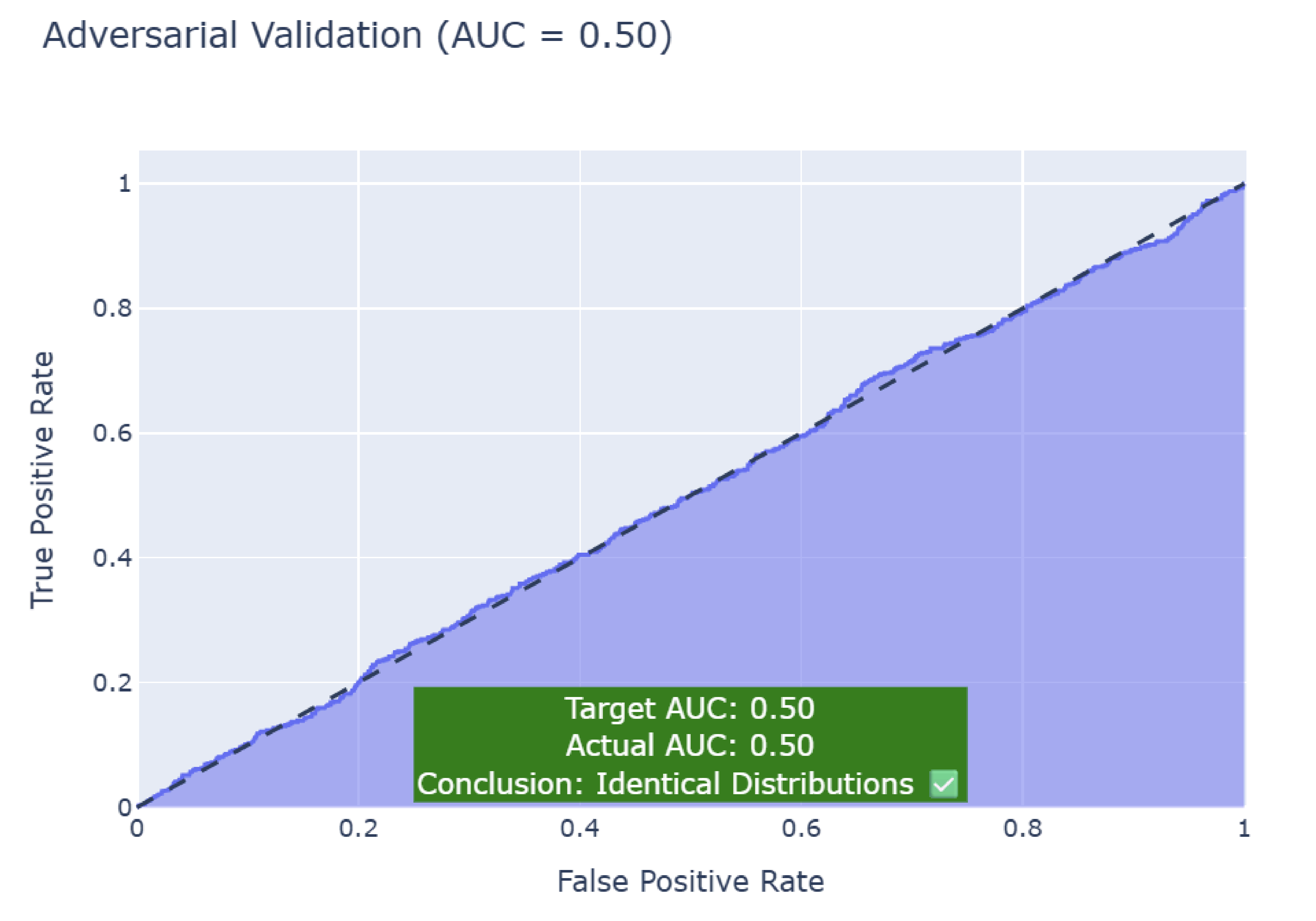
- **Number_of_Previous_Orders** - How many order has the user placed before (range 0-11)
- **Time_on_Previous_Website** - Length of time in seconds a user spent on the previous website (range 5-18,000 avg. 900)

Mix of categorical + numerical features → pre-processing required

Data Description

Training data vs Prediction Data

Feature	Test Used	p-value	Conclusion
Region	Freq Check	1.000	✅ Stable
Daytime	KS Test	0.902	✅ Stable
Carrier	Freq Check	1.000	✅ Stable
Time_On_Previous_Website	KS Test	0.677	✅ Stable
Weekday	Freq Check	1.000	✅ Stable
Social_Network	Freq Check	1.000	✅ Stable
Number_of_Previous_Orders	KS Test	0.997	✅ Stable
Restaurant_Type	Freq Check	1.000	✅ Stable

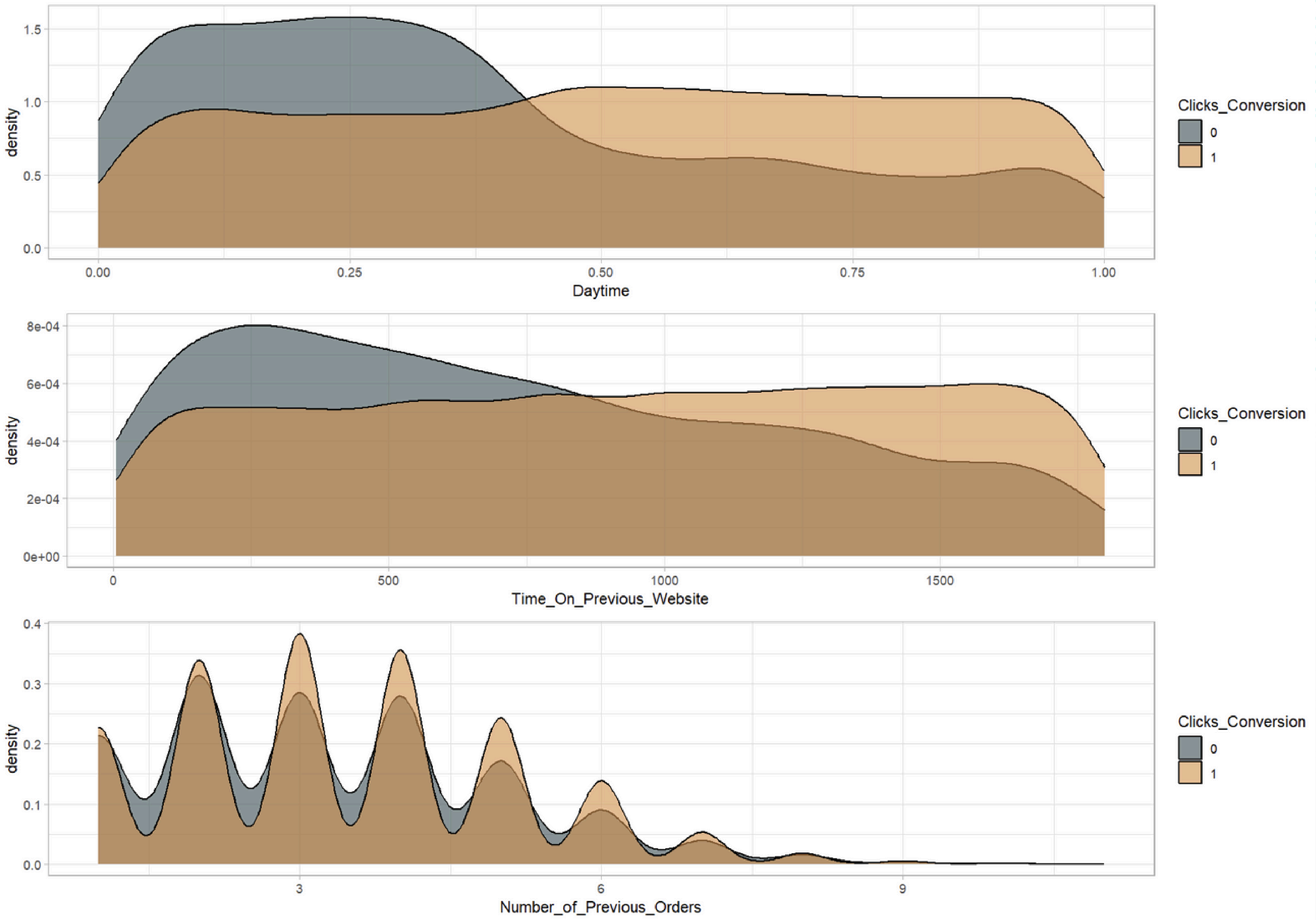


Data Description

Conversion patterns across numerical features

- **Daytime** shows non-converters peaking early, while converters are more spread and relatively higher later
- **Time on Previous Website** exhibits a clear right shift for converters, suggesting stronger browsing intent.
- **Number of Previous Orders** shows a softer but interpretable signal, with converters slightly skewed toward higher repeat orders.

Overall, these patterns indicate that numerical variables contribute relevant behavioral signal for modeling.

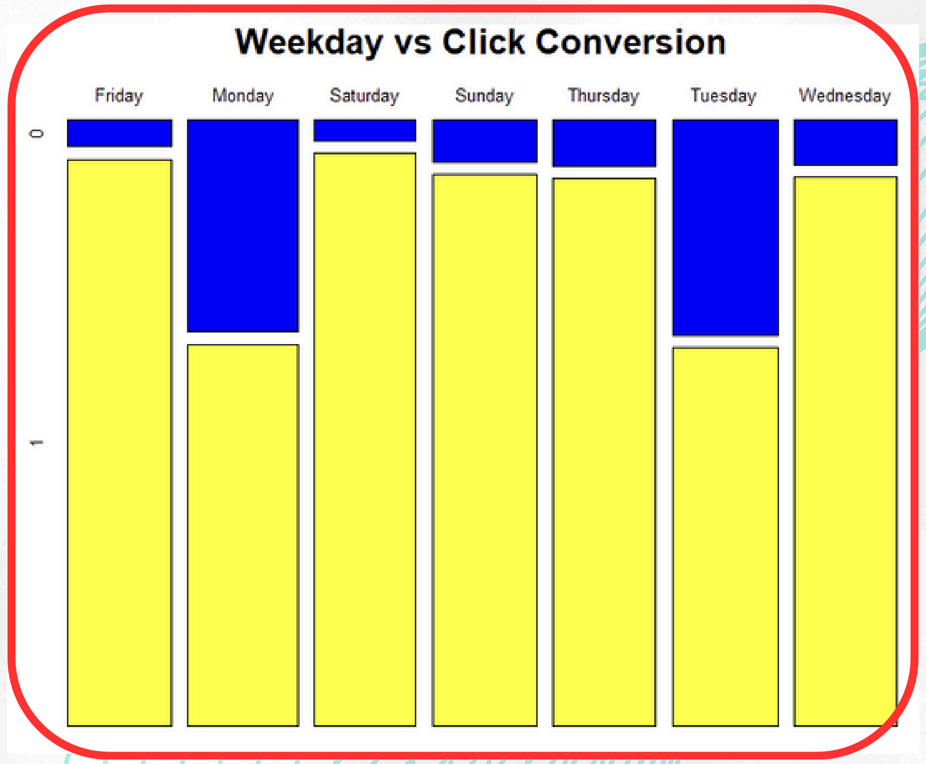


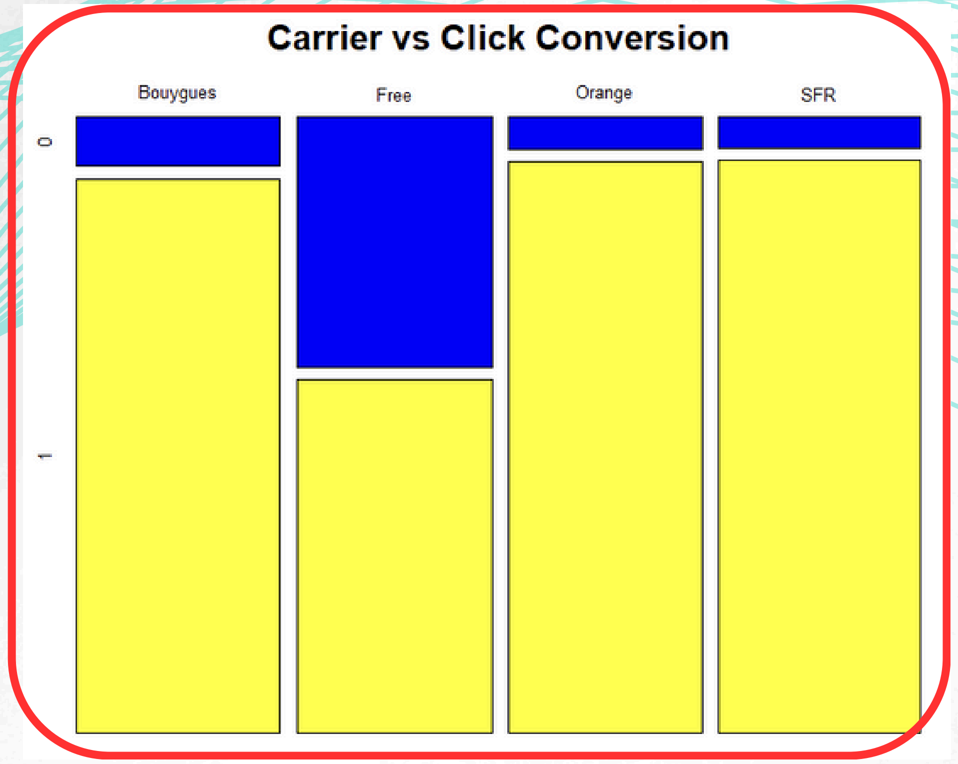
Data Description

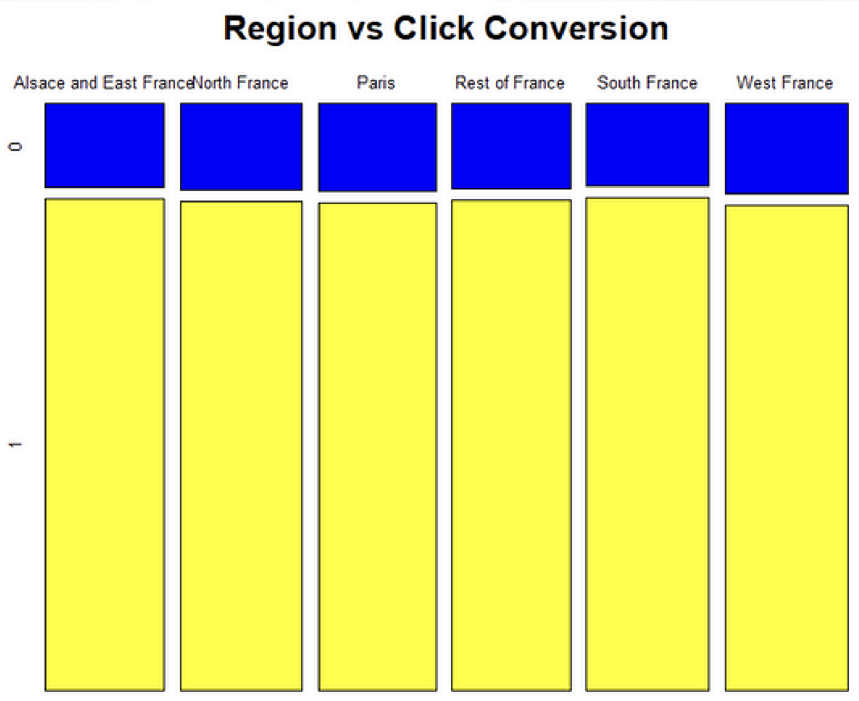
Conversion patterns across categorcial features

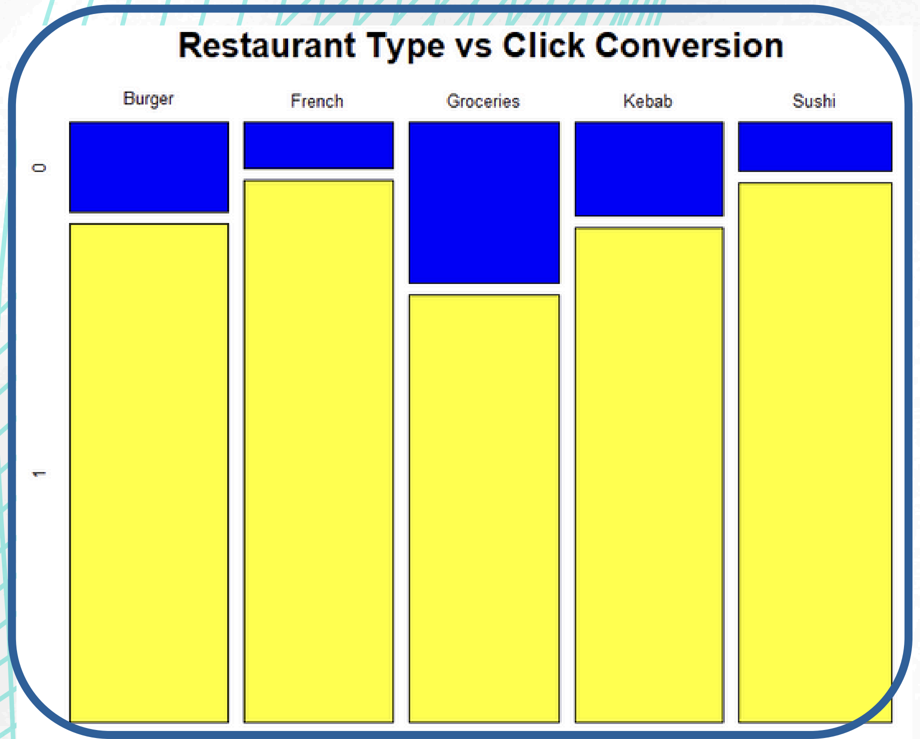
- **Weekday** and **Carrier** show strong separation and high predictive value.
- **Social Network** and **Restaurant Type** show moderate but informative effects
- **Region** shows minimal signal.

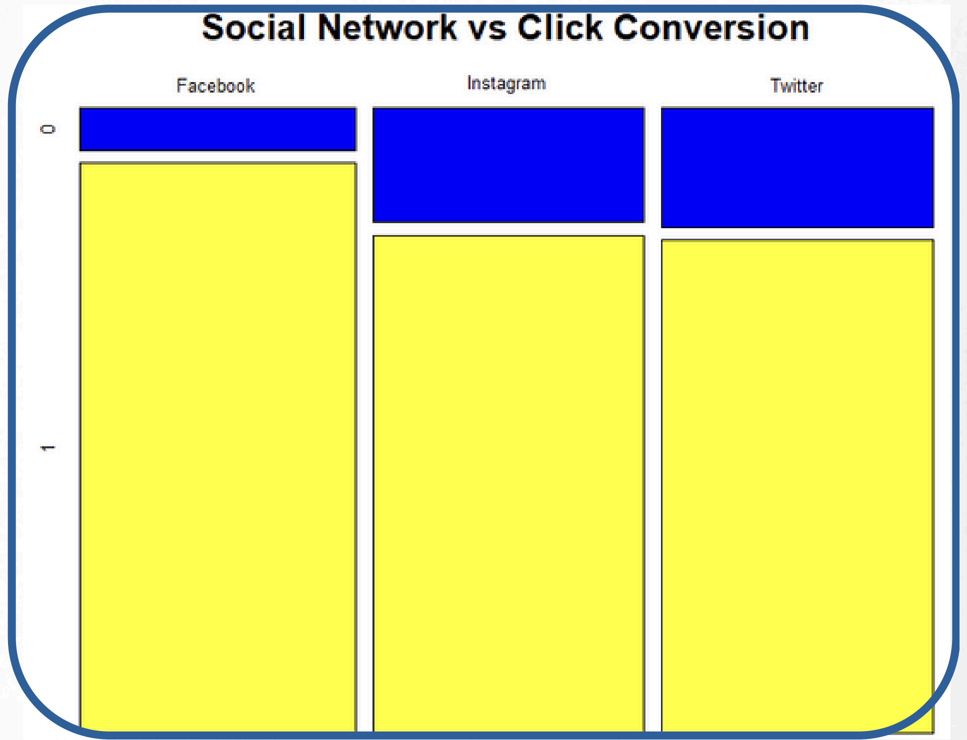
Overall, supports retaining these categorical features with penalization for weaker effects.











Methods Description

Modeling approach

GOAL (BUSINESS & ML)

Objective: Predict Clicks_Conversion (0/1) for each user session → "Who will click?"

Output: Binary prediction used for targeted marketing and budget allocation.

So, it's better to use discriminative models, rather than generative.

WHICH APPROACH FITS OUR DATA

Features are mixed-type: categorical + numeric, implying tree-based ensembles to be good choice.

Click behavior is driven by interactions (e.g., platform × time × region), so we tested both interpretable and non-linear models.

MODEL WORKFLOW

- **Data cleaning**: NA checks + convert categorical variables to factors.
- **Split**: 70% train / 30% (fixed seed).
- **Validation**: 10-fold CV where relevant.
- **Evaluation**: ROC–AUC, due to class imbalance.
- **Key idea**: start baselines, then move to ensembles to capture complex patterns.

Methods Description

Baseline models: KNN & Decision Tree

K-Nearest Neighbors (KNN)

Predicts a session based on the behavior of most similar past sessions (“neighbors”).

How we trained it:

- 10-fold cross-validation
- Tuned k from 1 to 50
- Selected best k by CV performance

Pros / Cons for our task:

✅ Simple baseline; captures “similar users behave similarly”

❌ Can struggle with many categorical levels / sparse encodings; sensitive to feature scaling and distance definition

Decision Tree

Learns “if–then” rules, easy to explain as marketing segments

How we trained it:

- Trained on full feature set
- Performed cross-validation for tree size
- Pruned to the optimal size to reduce overfitting

Pros / Cons for our task:

✅ Very interpretable; good for explaining drivers and building simple targeting rules

❌ Single trees can be unstable and miss subtle patterns → performance typically below ensembles

Methods Description

Classical models: Logistic, LASSO

Logistic Regression AIC / BIC

Outputs a click probability; good performance for binary classification task.

How we trained it:

- Tuned a classification threshold by scanning 0.01→0.98
- Picked the threshold that best balanced Accuracy + Sensitivity + Specificity

Pros / Cons for our task:

✅ Interpretable effects; stable; easy to communicate (“feature increases/decreases click odds”); helps to control overfitting

❌ Mostly linear; limited at capturing complex interactions unless engineered manually

Lasso

Logistic regression with feature selection (shrinks weak signals toward zero).

How we trained it:

- Similar to logistic regression
- Performed cross-validation for lambda choice

Pros / Cons for our task:

✅ Helps when many dummy variables add noise; improves generalization

❌ Still mainly linear; can miss interaction effects that matter in click behavior

Methods Description

Ensemble models: Random Forest & Gradient Boosting

Random Forest

Averages many trees → captures non-linearities and interactions with better stability.

How we trained it:

- 500 trees
- Used OOB error as built-in validation signal
- Computed feature importance

Pros / Cons for our task:

✅ Robust to weird feature shapes; good interaction capture

❌ Less transparent than logistic / single tree; heavier compute

Gradient Boosting

builds trees sequentially, where each new tree focuses on correcting the previous errors.

How we trained it:

- 100 trees
- Maximum depth 3
- Computed feature importance

Pros / Cons for our task:

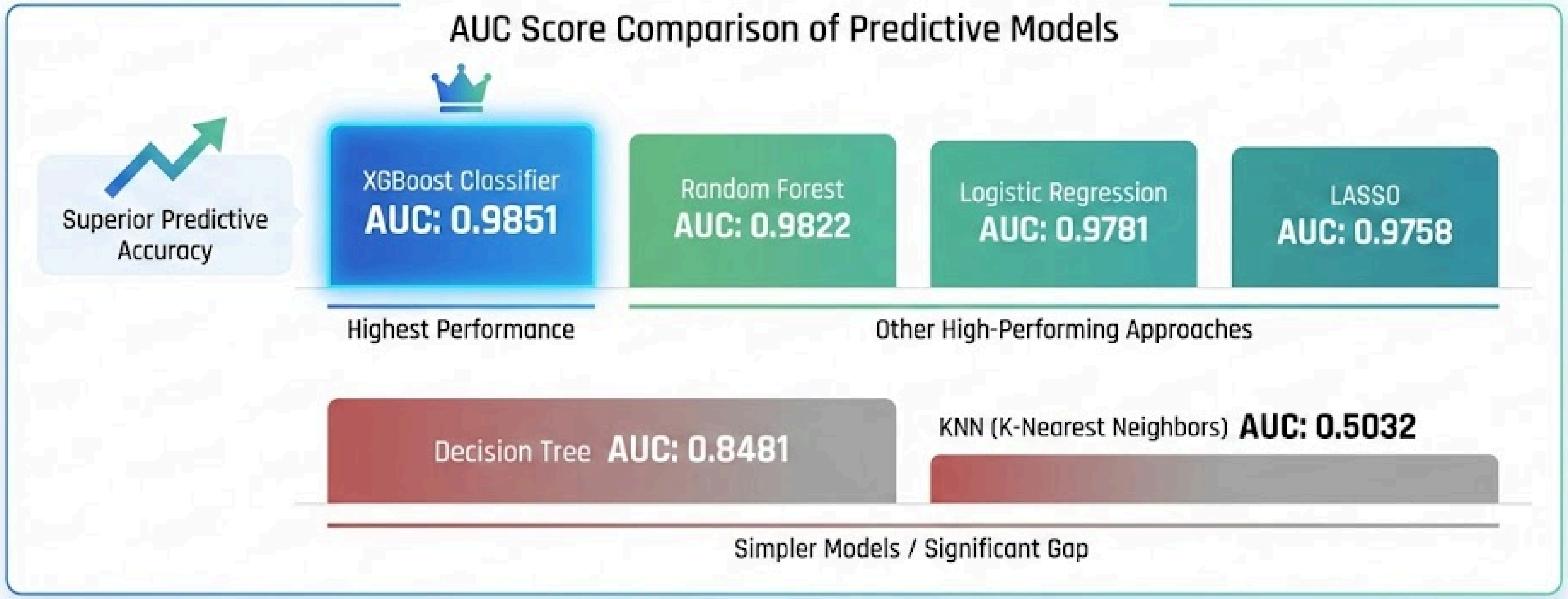
✅ Best at learning subtle interaction effects

❌ More complex; needs careful control of overfitting

Results

Outputs

The Best Model is **XGBoost**, but Others Show Strong Performance



Based on a comprehensive comparison, the XGBoost classifier achieved the highest AUC score of 0.9851. While XGBoost led, Random Forest (0.9822), Logistic Regression (0.9781), and LASSO (0.9758) also demonstrated strong predictive capabilities. In contrast, the Decision Tree and KNN models showed substantially lower performance.

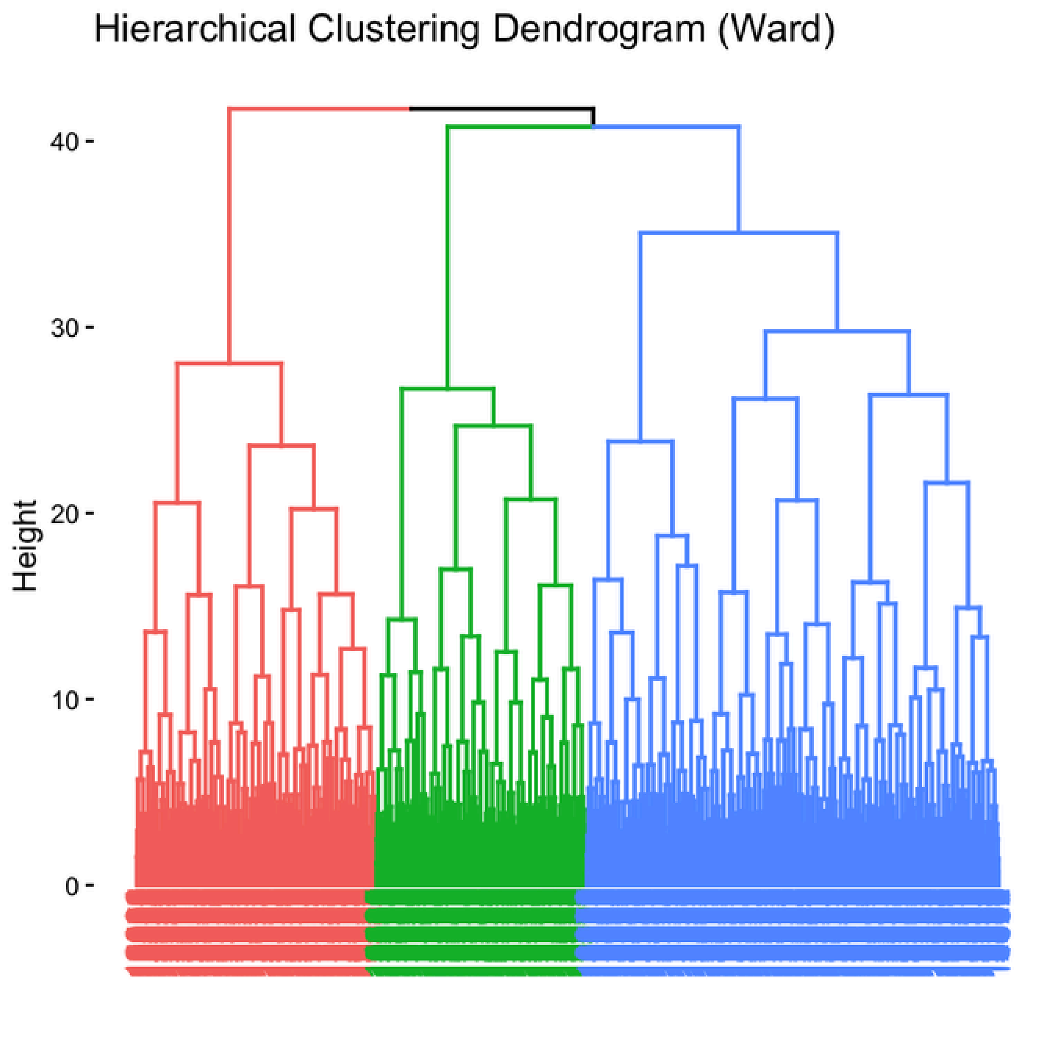
Results

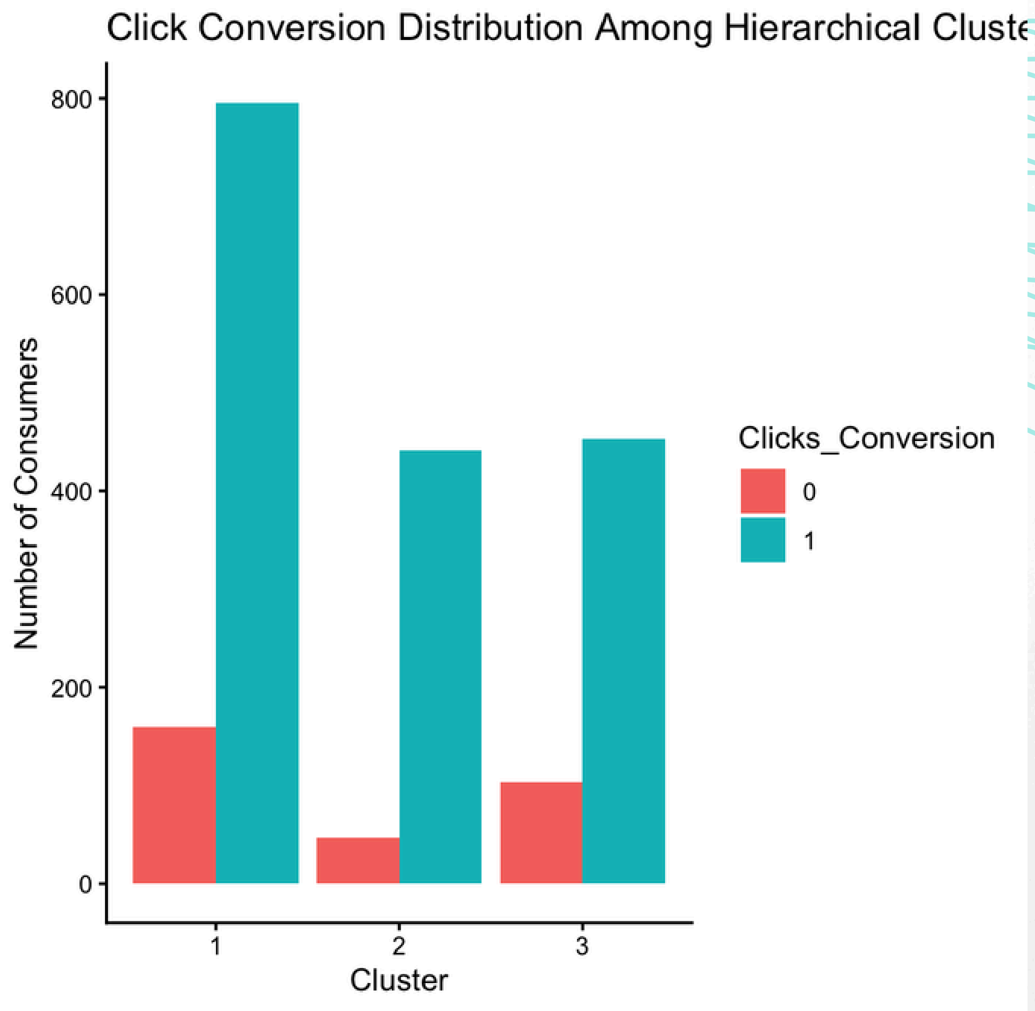
Outputs

To uncover hidden patterns within the Deliveroo dataset, we employed agglomerative hierarchical clustering using Ward's method to minimize within-cluster variance.

By analyzing the resulting dendrogram, we identified distinct customer segments based on their demographic profiles and ordering behaviors, such as average order value and frequency.

This unsupervised learning approach allowed us to move beyond simple demographics, revealing multi-dimensional groups, ranging from high-value loyalists to price-sensitive occasional users





Results

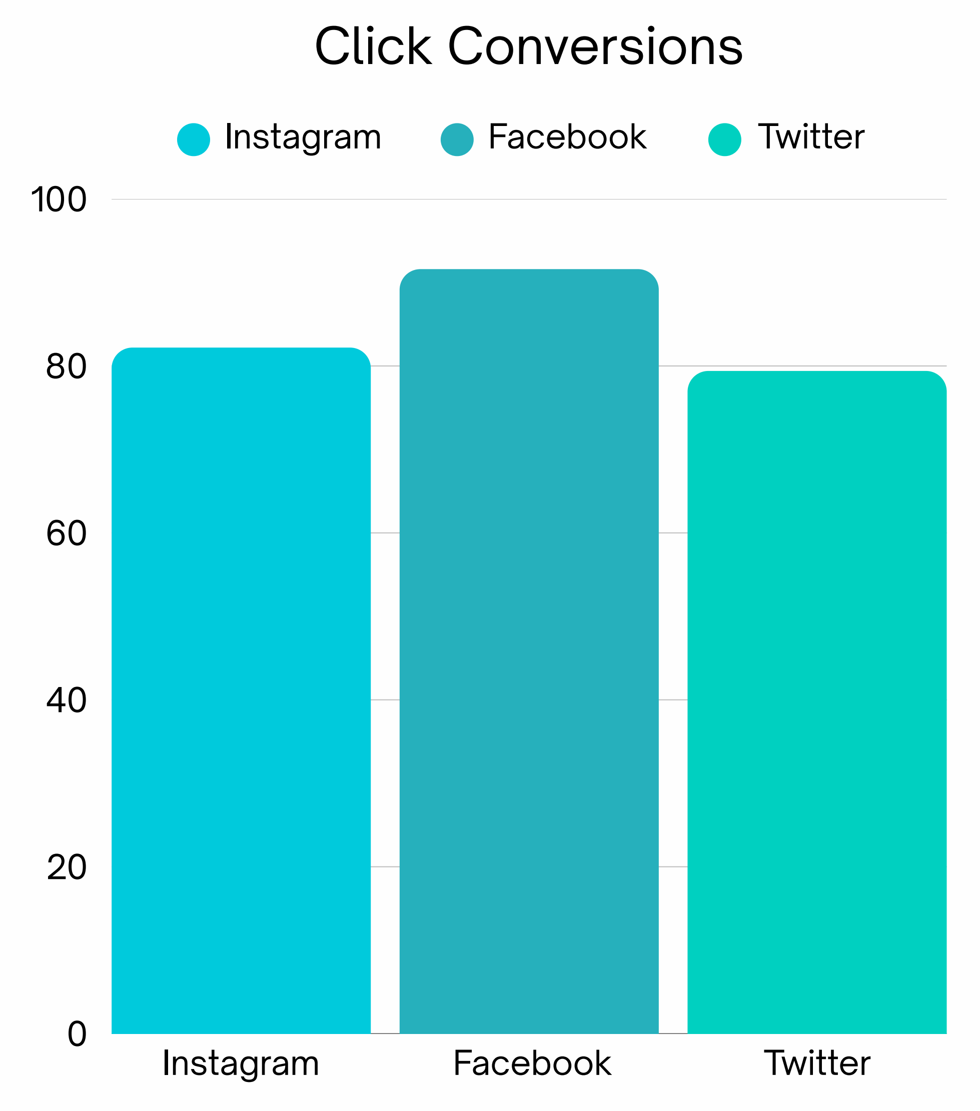
Outputs

To validate the best model’s performance on unseen data, we apply our XGBoost classifier to unseen data.

Utilizing a one-hot encoded feature matrix, the model processed thousands of new observations to achieve a predicted click rate of 88.7%, identifying 1,599 potential conversions against 204 non-clicks.

We can conclude and confirm that the model has a robust ability to distinguish high-intent consumers, offering a data-driven foundation for optimizing future advertising spend and maximizing campaign engagement.

Implications and Recommendations



Platform Optimisation

Facebook is clearly outperforming other channels Twitter is the weakest, which makes it a candidate for budget reduction or targeting reviews

Recommended Action:
Consider reallocating the budget from Twitter to Facebook & Instagram

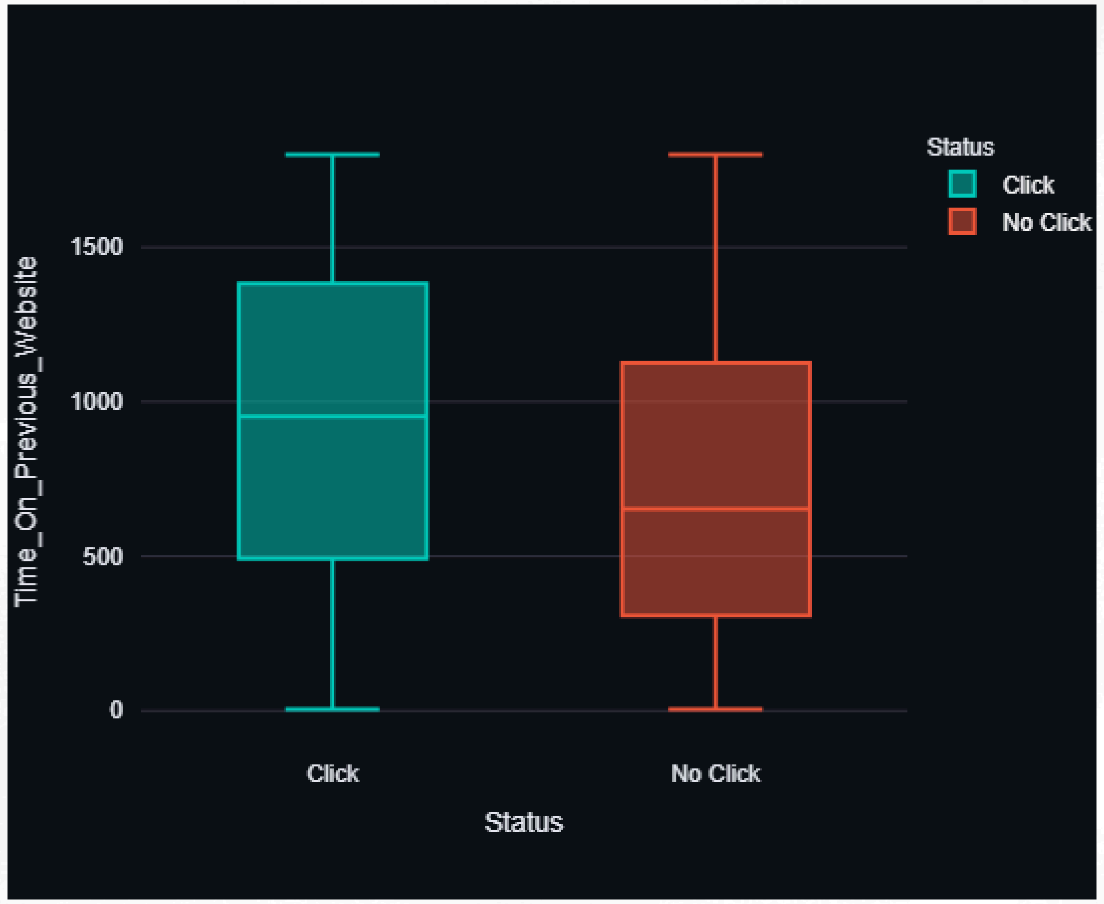
CARRIER TARGETTING KPI AND INSIGHT

CARRIER	CONVERSION RATE
SFR	94.48%
ORANGE	94.33%
BOUYGUES	91.12%
FREE	57.33%

- 37 percentage points lower conversion rate of FREE
- Likely due to price sensitivity or younger / lower income users
- For the same spend, Free is delivering ~40% fewer conversions than other carriers
- Recommended Action: Decision to be made if Deliveroo wants to either exclude Free carrier completely or create specialized creative for them

Implications and Recommendations

TIME ON PREVIOUS WEBSITE IMPACT

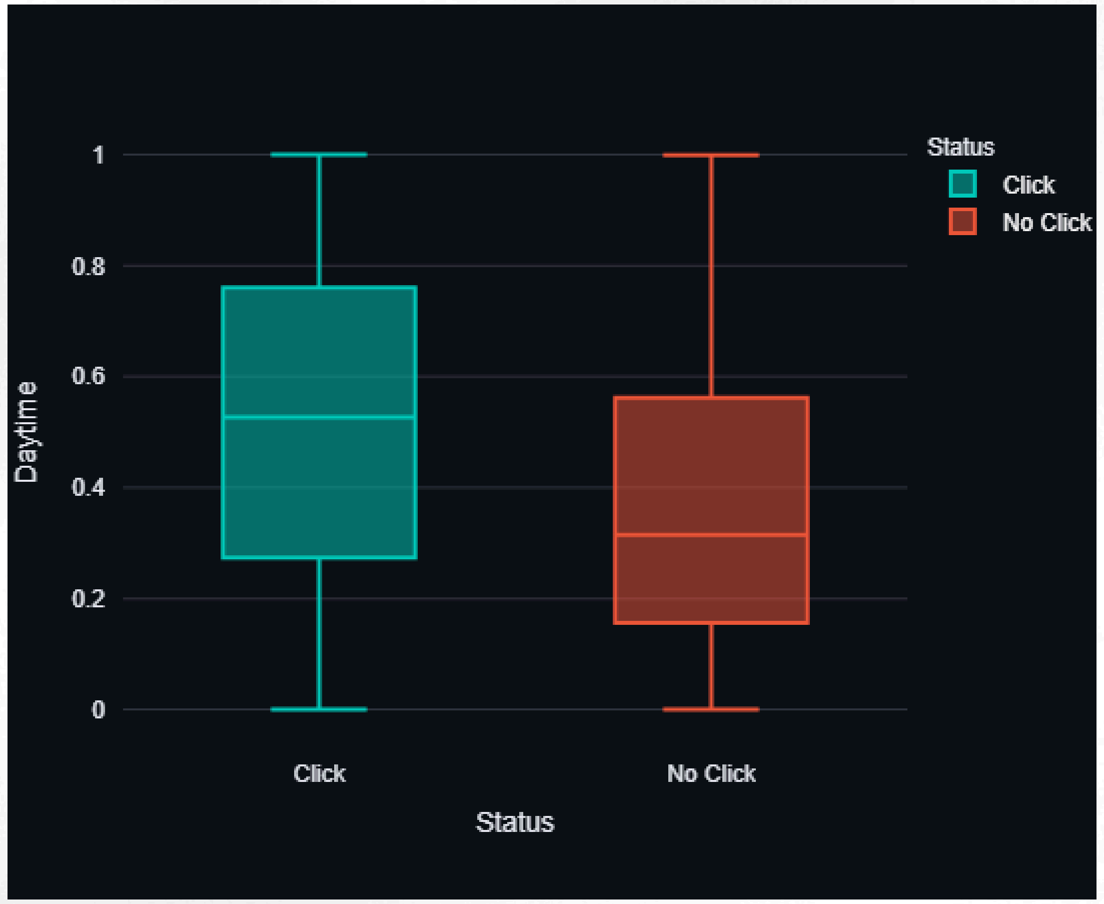


As we can see converters spend ~16 minutes browsing vs ~11 minutes for non-converters (950s vs 650s median)
Longer browsing time = stronger purchase intent and higher conversion probability

Recommended Actions:

- Increase bids for users with 10+ minute engagement history
- Prioritize retargeting for high-engagement segments (12+ min)
- Reduce spend on low-engagement users (<5 min) or use for awareness only

TIME OF DAY IMPACT

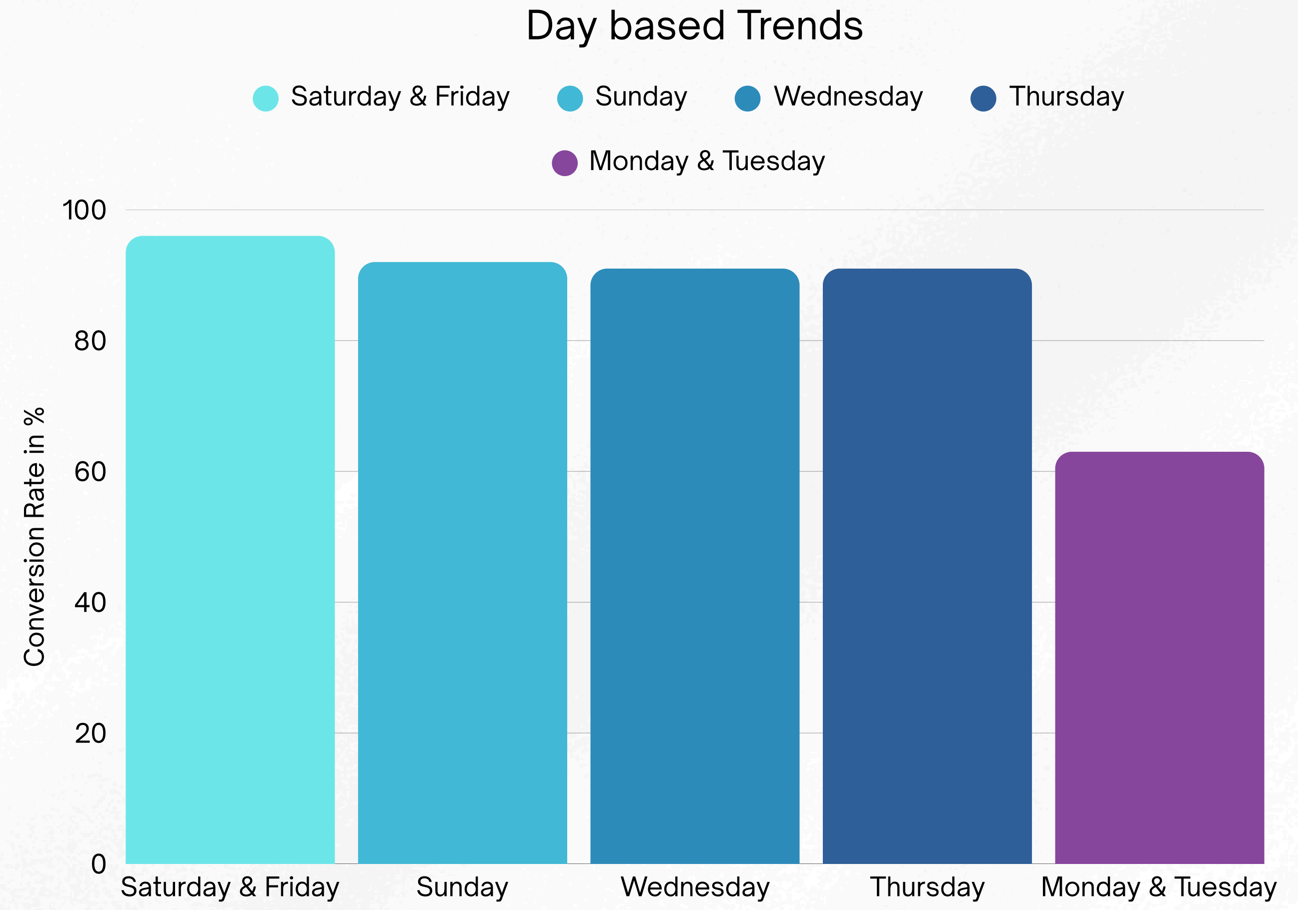


Converters cluster around lunch/dinner hours (median: 12:30 vs 7:40 for non-converters)
Peak conversion windows: 11.00-14.00 (lunch), 18.00-19.00 (dinner)

Recommended Actions:

- Increase ad spend during peak meal windows
- Reduce morning budget (6 AM - 10 AM)
- Lunch creative: "Quick delivery" messaging
- Dinner creative: Family meals and premium options

Implications and Recommendations



We observe a 30+ percentage point difference between the best and worst days

Recommended Actions -

Take the best performing metrics and run ads only on them, for example -

- On Monday/Tuesday, run ads only on Facebook (highest CTR) in the Evening slots(77% CTR) and target loyal customers only
- This will cut the Mon/Tue budget and maintain 90% of the clicks !

Customer Segment Conversion Funnel

Target: New Customer Click → Conversion Rate > 80%

PREVIOUS ORDERS	CONVERSION RATE
0 (COMPLETELY NEW)	78.79
3-4 (MID TIER)	85-86%
6 (LOYAL)	87% CTR

Recommendation - Focus on First-to-Second Order Conversion

- **+4.1 percentage point CTR jump from first to second order**
- **Launch targeted "rescue campaigns" for users who ordered once but haven't returned within 14 days (15-20% discount + free delivery)**

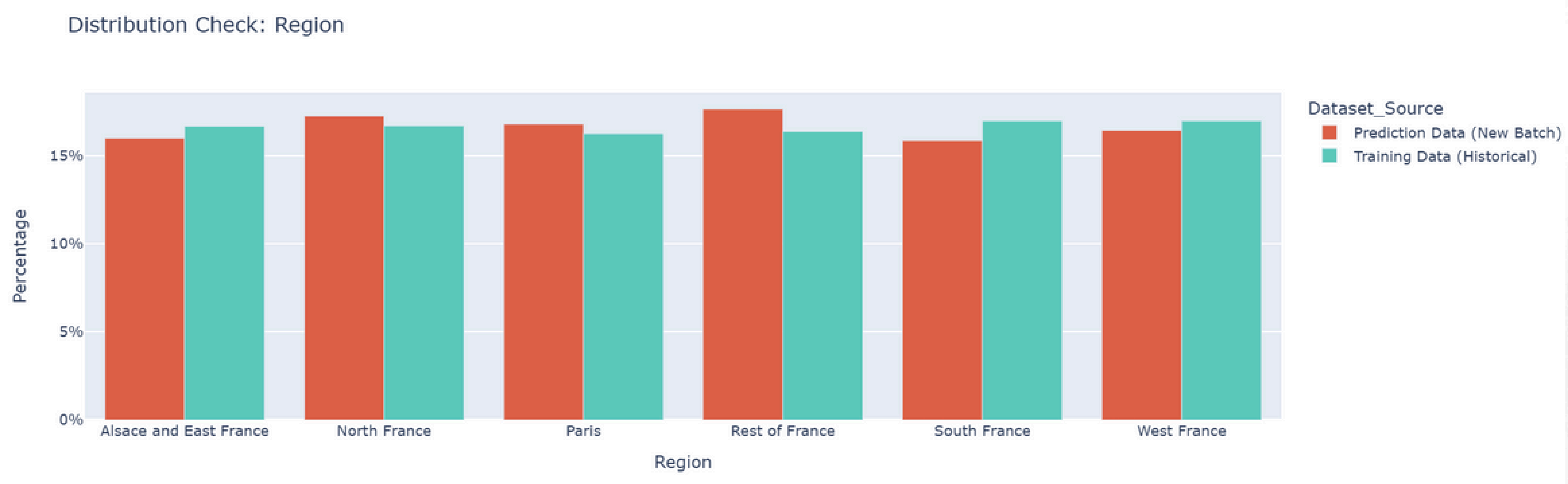
The company could also Segment Ad Channels by Customer Lifecycle

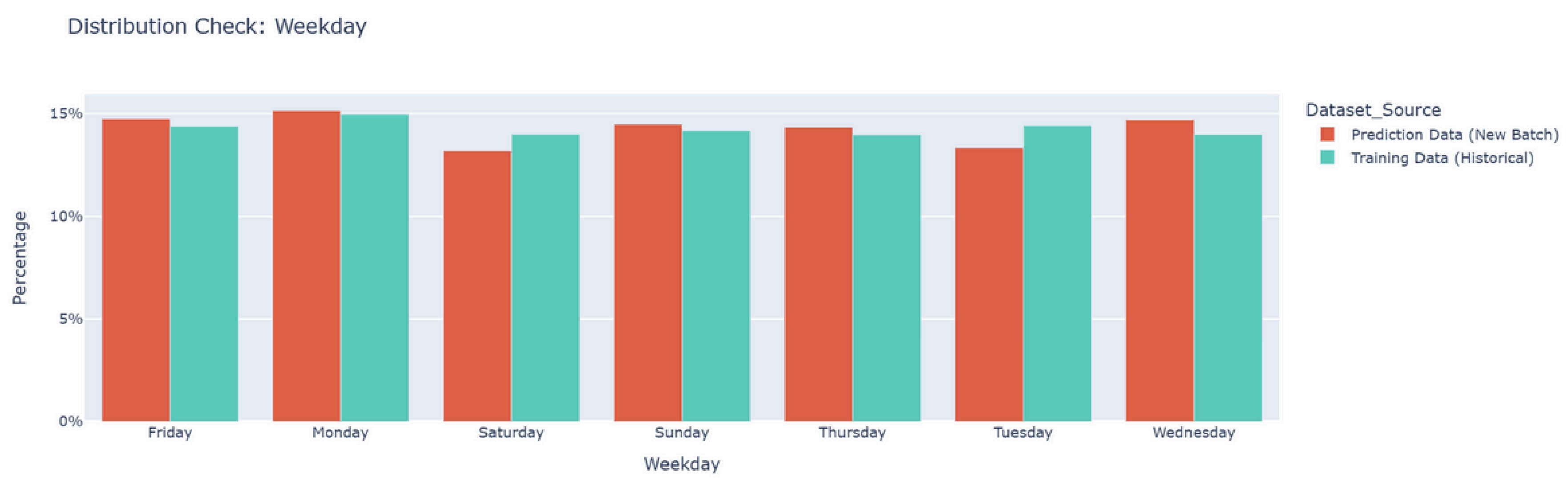
- **New customers: Instagram performs best (89.9% CTR)**
- **Loyal customers (3+ orders): Facebook dominates (96.4% CTR)**
- **Recommendation: Shift loyal customer budgets from Instagram to Facebook; save Instagram for acquisition**

Thank you

Appendix

Training vs Predict Data





Appendix

Training vs Predict Data