Advertisement Data Prediction

Leon Zhang, Ishan Miglani, Qing Shen, Keya Keya

Online Advertisement for Mobile Apps

- Meetsocial, overseas marketing service for Chinese business
- Small-to-medium enterprises, mobile apps
- Advertising strategy advisory based on historical data on previous ads
- A model outputs predicted clicks/installs with features of ad
- Features: spend, channel, os, device, targeting people.
- Goal: cut down unnecessary spend on ads



Action, Prediction, & Decision-Making

- The Action Optimizing advertising settings (targeting ages,genders, budget) for SME campaigns.
- The Prediction: Forecasting clicks, installs, and purchases based on campaign settings.
- **The Decision:** Data-backed recommendations to maximize chosen target metric (e.g., maximize clicks within budget constraints).

Data Source

Table 1: 320000 rows with many NAN values, product info, methods, spend, clicks/installs of ad

ad_id	campaig	n_id	adgrou	p_id o	calendar_date	ucompany_id	product_id				product	t_name		product_category
15738995501	1573899	5501	157389	995501 2	2022-01-02	66703	tile.connect.onet.onnect.pairs.matching.game.free.puzzle			Tile Con	nect - Tile I			
15738995501	1573899	5501	157389	995501 2	2022-01-03	66703	tile.connect.onet.onnect.pairs.matching.game.free.puzzle		Tile Connect - Tile Match Game					
15712434228	1571243	4228	157124	434228 2	2022-01-05	32227	com.sevenpirates.idlejp							
campaign_c	bjective	ch	nannel	gende	r os_type	ad_networ	k_type	device	spend	impressions	clicks	installs	purchase	purchase_value
		G	oogle		ANDROID	SEARCH		TABLET	0	2	0	0	0	0
		G	oogle		ANDROID	SEARCH_P	ARTNERS	MOBILE	0	2	0	0	0	0
		G	oogle		ANDROID	YOUTUBE_	WATCH	MOBILE	30.2455	1874	37	0	0	0

Data Source

Table 2: 30000 rows intersecting table 1 with "ad_id", providing more information about different ad groups - (targeting age, gender, campaign_objective, etc.)

ad_id	channel	product_id	product_name	product_category	ad_first_dt	ad_last_dt
15712434228	Google	com.sevenpirates.idl	銇勩亼銉硷紒鏀剧疆鎴~ +		2022/1/4	2022/2/16
15738995501	Google	tile.connect.onet.on	Tile Connect - Tile Match Game		2022/1/1	2022/2/8
15745148062	Google	com.meet.andr	Hurrah		2022/1/4	2022/1/4

ucompany_id	campaign_objective	targeting_age	targeting_genders	os_type
32227	APP_INSTALLS	24-65	male	ANDROID
66703	APP_INSTALLS	18-65		ANDROID
16727	APP_INSTALLS	18-65		ANDROID

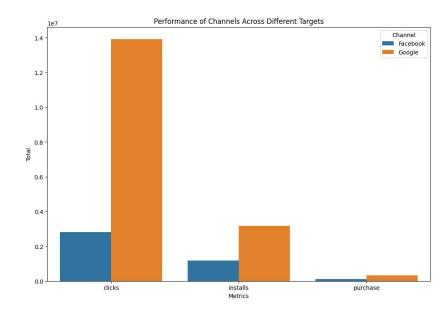
EDA and Feature Engineering

- Huge target variance and skewed distribution
- Merged two tables by their corresponding "ad_id"
- Scraped ratings out of 5, number of ratings and number of reviews
- Built 2 different scrapers for Google Play store and IOS store
- Also scraped categorical information about the apps whether they are games or productivity apps (eg. categories PUZZLE, CASUAL, SINGLE PLAYER, STYLIZED, OFFLINE, ROLE PLAYING, BOARD, ABSTRACT STRATEGY, ETC.)

spend	impressions	clicks	installs	purchase	irchase_vali	PUZZLE	CASUAL	NGLE PLAYE	STYLIZED	OFFLINE	OLE PLAYIN	BOARD	RACT STRA
68.9997	4762	73	23	0	0	0	0	0	0	0	0	0	0
30.5187	1722	33	11	0	0	0	0	0	0	0	0	0	0
0.3825	63	3	6	0	0	0	0	0	1	0	0	0	0

Data Preprocessing

- Handling Missing values
- Remove rows with null values
- Create dummy values for categorical features
- Left with ~27K rows and 59 features
- Addressing Skewness: Log Transformations
- Feature Scaling: StandardScaler



Modeling Overview

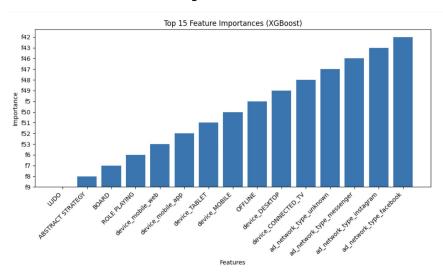
Model Tested	RMSE	R ²		
Linear Regression (Baseline)	1.770	0.478		
Random Forest	0.818	0.889		
SVR	1.516	0.617		
XGBoost	0.778	0.899 188%		
Decision Tree Regression	1.064	0.812		
Ensemble Model (RF + XGBoost)	0.799	0.894		

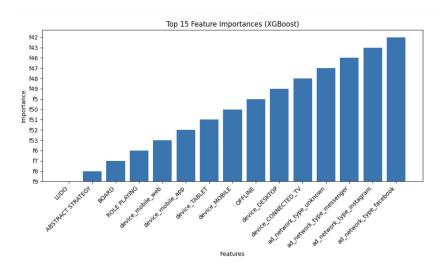
XGBoost Regression Model

Targets	RMSE	R ²
Clicks	0.778	0.899
Installs	0.775	0.860
Purchase	0.756	0.896
Click/Impression (CTR)	0.869	0.738
Impressions	0.903	0.916

Similar to Clicks, our other targets performed better in XGBoost compared to the other models we tested.

Feature Importance

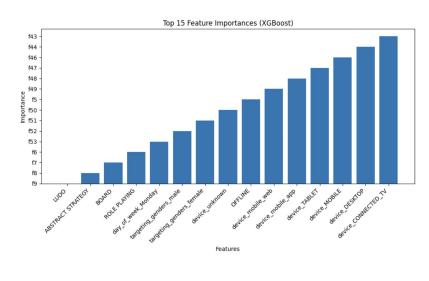


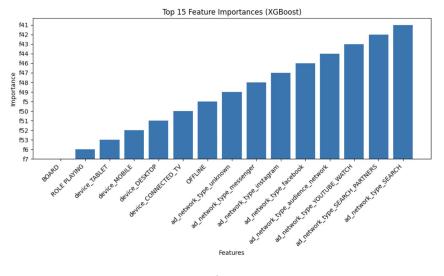


Clicks

Installs

Feature Importance





Impressions

Purchase

Deployment Plan

Integration with Business Systems: The model will be integrated into existing business systems through APIs, allowing it to access real-time data and provide on-the-fly predictions. This integration ensures that the model's insights are directly usable in the decision-making process.

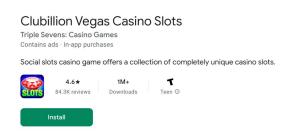
Cloud Deployment: To handle scalability and ensure accessibility, the model will be deployed on a cloud platform. This approach provides the necessary computational resources and allows for easy scaling as data volume and user base grow.

User Interface: A user-friendly dashboard will be developed to display the model's predictions and insights. This dashboard will allow business users to interact with the model's outputs easily, customize inputs, and visualize data in an understandable format.

Embedding the model in real business scenarios

We generated the 23,040 different combinations by multiplying the number of possible choices for each spend level.

Total Combinations=(Number of Age Combinations)×(Number of Campaign Objectives)×(Number of Channel Google Options)×(Number of OS Type iOS Options)×(Number of Ad Network Types per Channel Google Option)× (Number of Device Types)×(Number of Gender Combinations)





Data range: 01-12-2022 to 31-12-2022

Category: Casino Rating: 4.6255

Num_comments: 12842

Num-rating: 84247

Model's strategy v.s. Human's strategy

With a single ad budget of \$2 a day, based on the same budget, the updated ad strategy is expected to result in a 41.9% lift in the number of clicks.

Settings	New Strategy	Previous Strategy
target_age	13-26	45-65
channel	Facebook	Google, Facebook
os_type	Andriod	Andriod
campaign_objective	CONVERSIONS	APP_INSTALLS
ad_network_type	audience_network	All
device	CONNECTED_TV	mobile_app
targeting_genders	female	female,male

spend	predicted_clicks	previous_clicks
2	2.173	1.531
4	2.208	1.676
6	2.251	1.974

Way Forward

Data Collection: Advertiser's Side

- Ad Creative Data:
 - Types and styles of images and videos.
 - Tone and content of text descriptions.
- Advertiser Profile Data:
 - Company size and industry type.
 - Advertising budget levels.
 - Brand reputation metrics.

Data Collection: User Side on the Platform

- User Behavioral Data:
 - Whether a user clicked on an ad link.
 - Duration of ad viewing by the user.
 - Duration of user's stay on the landing page post-click.
 - User interactions with content

Further we can do:

- Richer User Profiles
- Improved Segmentation
- Contextual Relevance
- Competitor Data Analysis

Way Forward

Model evaluation with experts

 Although the model can generate the best advertising strategies, whether these strategies are applicable in real scenarios and whether the recommended parameters are usable still require human evaluation.

Improvements in Predictive Modeling

- Advanced Predictive Models: more complex models like neural networks or transformers
- Hybrid Models: Combine different types of models, such as machine learning models with rule-based systems

Enhancements in Deployment

Dynamic Feedback
Mechanisms: Instead of
exhausting all possible
combinations in a
predictive model, integrate
deep reinforcement
learning to add dynamic
feedback mechanisms