CLICK-THROUGH RATE PREDICTION CAPSTONE By Amanda Ahn



01

CONTEXT

Online advertising revenue equates to more than hundreds of billions of dollars for companies. An average of 60-80% of companies' revenue in the U.S. comes from advertisements.



02

MOTIVE

As a society that continues to modernize and digitalize, online advertisements, as source of revenue, will only increase. Accurately predicting CTR can help increase total company profits by modifying select features of advertisements to increase click rate, which increases likelihood of customers buying the product.



03

PROBLEM STATEMENT

The goal of this project is to identify the significant features of advertisements to improve in order to boost CTR by increasing the base model by at least 5% through the use of machine learning techniques.

NUMBER OF RECORDS:

40,428,967 rows & 24 columns

COLUMN NAMES:

id, click, hour, C1, banner_pos, site_id, site_domain, site_category, app_id, app_domain, app_category, deivce_id, device_model, device_type, device_conn_type, C14, C15, C16, C17, C18, C19, C20, C21.

DATA TYPES:

DATA

Source: Kaggle, Avazu CTR

Prediction Dataset

- Floats
- Integers
- objects/strings

DATA CLEANING:

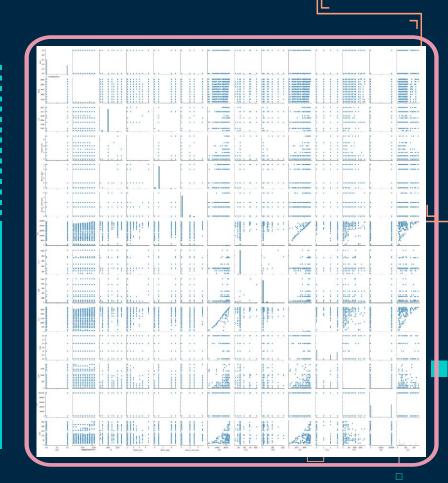
No null or duplicate values

EXPLORATORY DATA ANALYSIS

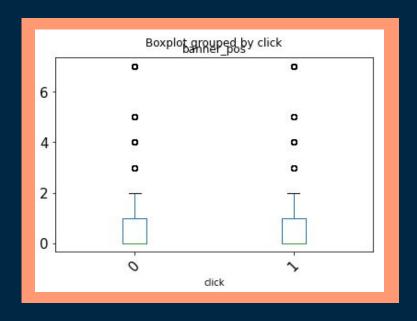
Seaborn pairplot for visualization of each feature with each other

Feature C14 and C17 have positive correlation with each other

Keep these features in mind



FEATURE EXPLORATION



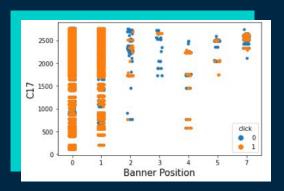
Boxplot of click vs banner_pos columns

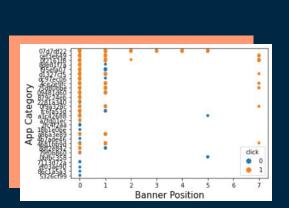
- Self hypothesized important features
- Background in UI/UX \rightarrow advertisement position on app/site is very important
- No deducible conclusion from boxplot

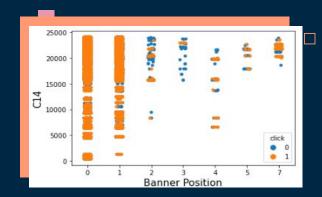
STRIP-PLOTS

Specific comparison plots of suspected important individual features

No deducible conclusions again \rightarrow move to modeling









MODELING PROCESS

Choose first model: Logistic Regression

most basic model to assess how it performs

2ND & 3RD MODELS

Use RandomOverSampler to balance data → had way more values for non-click data group than click data group Refit all models to new datasets and determine best one

PARAMETRIC TUNING



2nd Model: Random Forest need greater accuracy than LR Model

3rd Model: Gradient Boosting since RF Model > LR Model, use Gradient instead of Decision Tree MODIFY DATA & REFIT MODELS

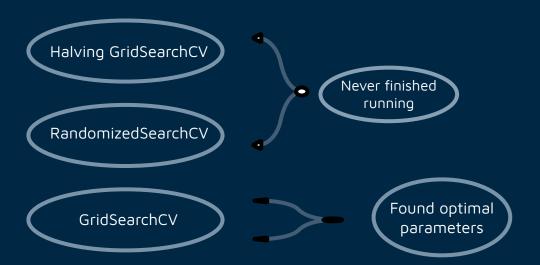
Best model: Random Forest

Hyperparameter tuning using GridSearchCV to find optimal parameters





HYPERPARAMETER TUNING

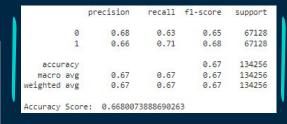


BEST MODEL

3

		precision	recall	f1-score	support
	0	0.58	0.64	0.61	67128
	1	0.60	0.53	0.56	67128
accur	acy			0.59	134256
macro	avg	0.59	0.59	0.59	134256
weighted	avg	0.59	0.59	0.59	134256
Accuracy	Scor	e: 0.588115	242521749	5	

LOGISTIC REGRESSION



RANDOM FOREST

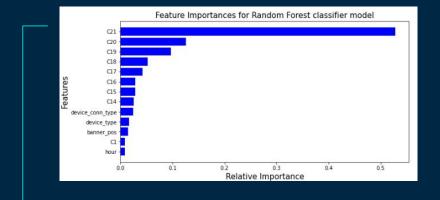


2

80%0	precision	recall	f1-score	support
0	0.64	0.57	0.60	67128
1	0.61	0.67	0.64	67128
accuracy			0.62	134256
macro avg	0.62	0.62	0.62	134256
weighted avg	0.62	0.62	0.62	134256
0.62242283398	87975			

GRADIENT BOOSTING

FEATURE IMPORTANCE



	Features	Importance scores	
0	hour	0.008086	
1	C1	0.008771	
2	banner_pos	0.014281	
3	device_type	0.016927	
4	device_conn_type	0.024372	
5	C14	0.025311	
6	C15	0.028052	
7	C16	0.028483	
8	C17	0.042065	
9	C18	0.052380	
10	C19	0.097249	
11	C20	0.125926	
12	C21	0.528097	

FEATURE C21

CONCLUSION



Best Model: Random Forest Model with balanced data and best hyperparameters using GridSearchCV.

Accuracy score: 0.67 ROC-AUC score: 0.72

Stakeholders: Marketing, advertising, design directors

Unfortunate that feature C21 is hidden by Avazu, but nonetheless, when trying to improve click through rate for advertisements, companies should focus on feature C21



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THANKS

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