October 2025

Analysis and Predictive Modeling *on ads and user data*

STATS 414: Generative AI

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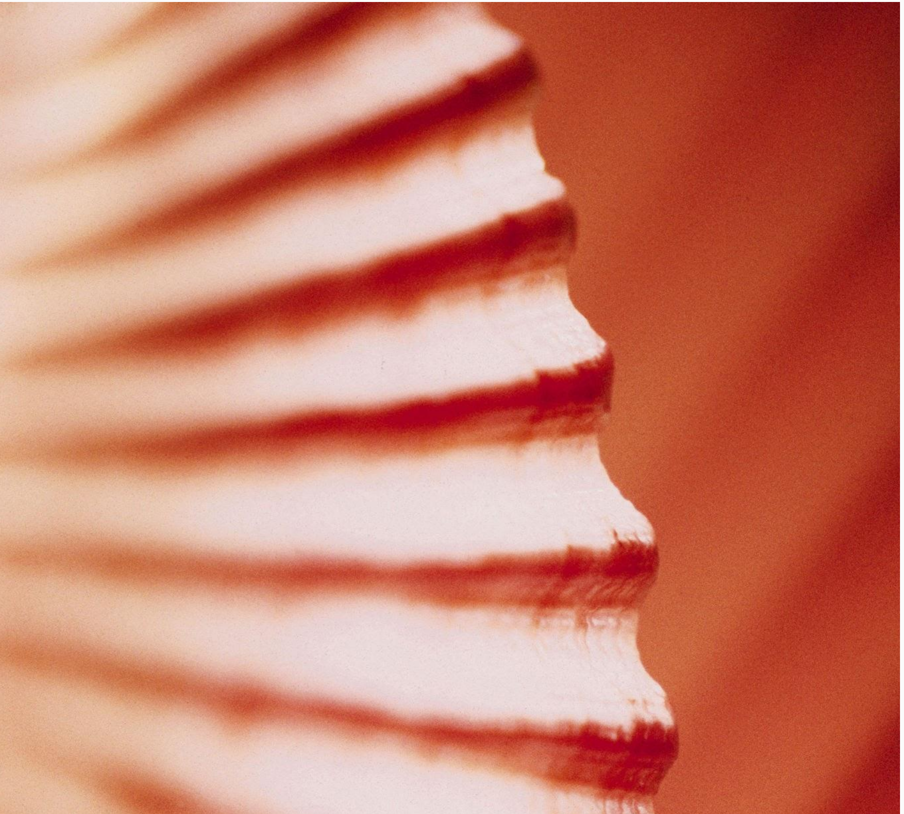
Agenda

October 2025



01 Problem Overview

02 Data Processing

03 Exploratory Data Analysis

04 Logistic Regression

05 Feature Selection with LASSO

06 XGBoost

07 Conclusions

01 Problem Overview

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Given information such as user gender, user engagement on news feeds, and ad placement ID, **can we predict whether an ad will be clicked**?

02 Data Processing

October 2025

- Ads Dataset: 7 million rows, 35 predictors
- Change variable pt_d (time stamp) to date time format
- Standardize variables
- One hot encoded variables like age and gender as categorical
- Checked for missing values
- Engineered new features such as count of unique ads clicked and count of unique ads closed

03 Exploratory Data Analysis

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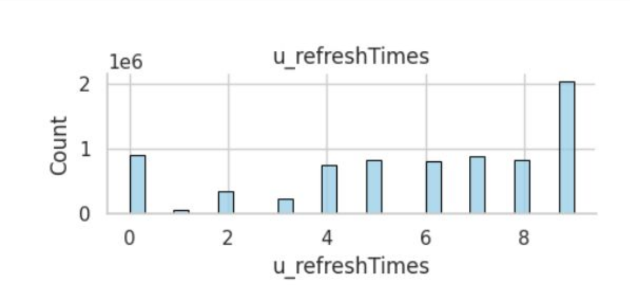
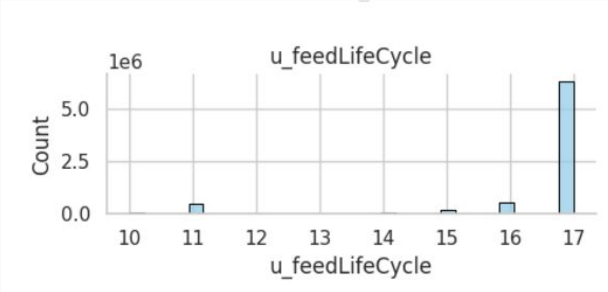
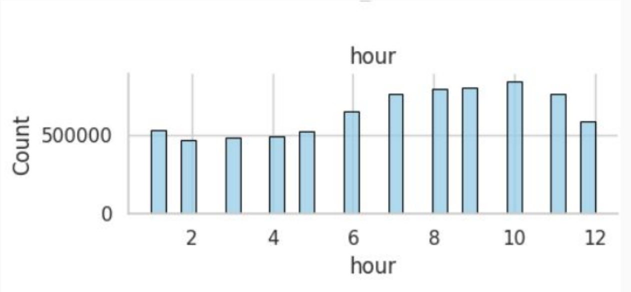
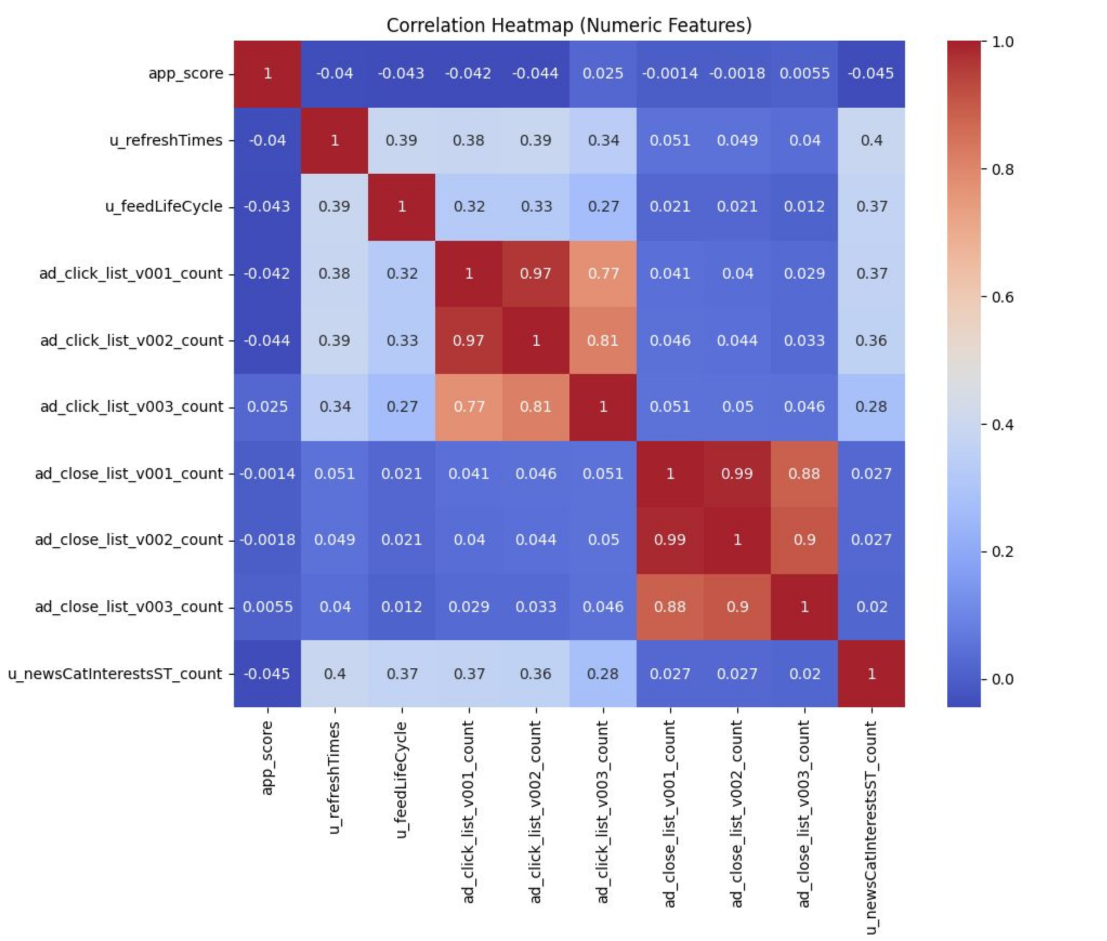






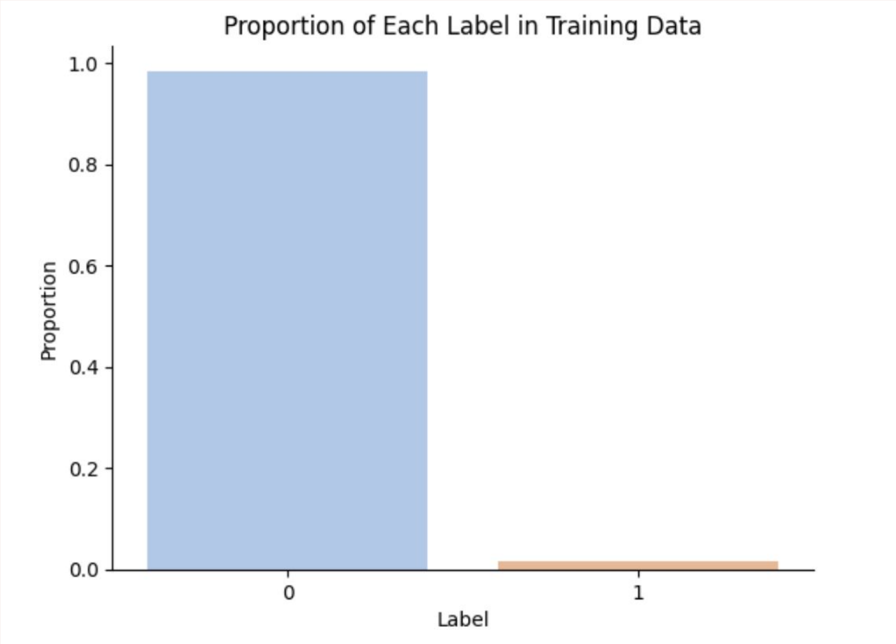
03 Exploratory Data Analysis

October 2025



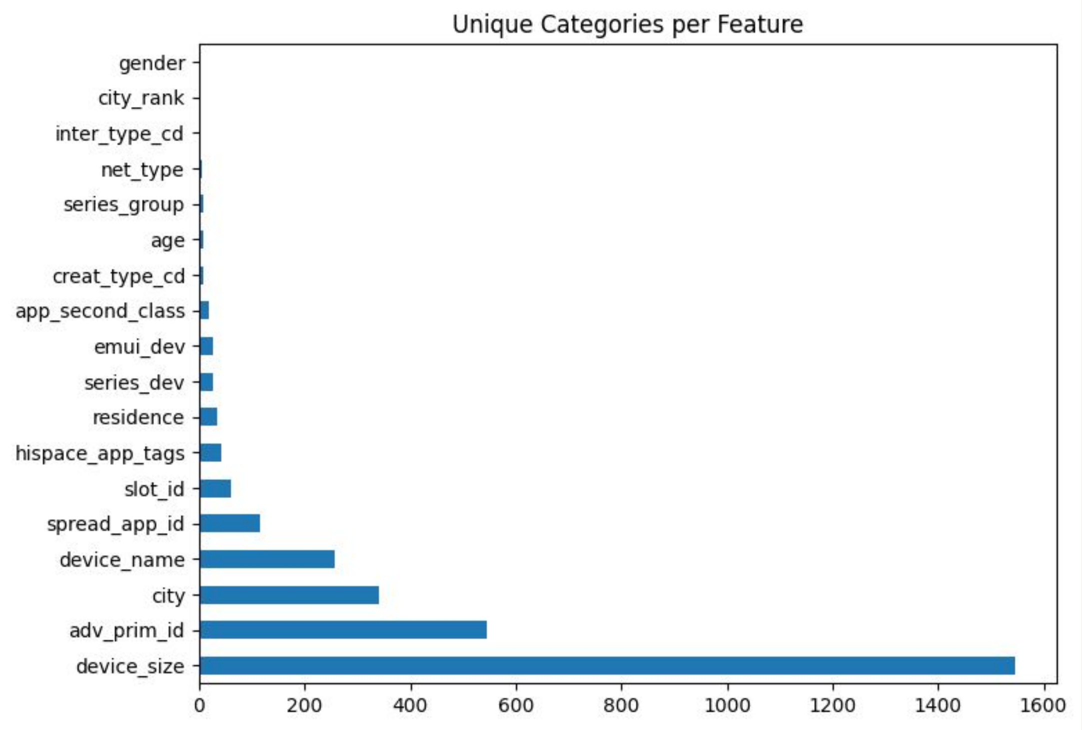
03 Exploratory Data Analysis

- Severely imbalanced dataset (1: ad clicked, 0: ad not clicked)
- Methods to deal with imbalance:
  - Undersampling from the majority class
  - Synthetic Minority Oversampling Technique for Nominal and Continuous (SMOTE-NC)
  - Adjusting model parameters



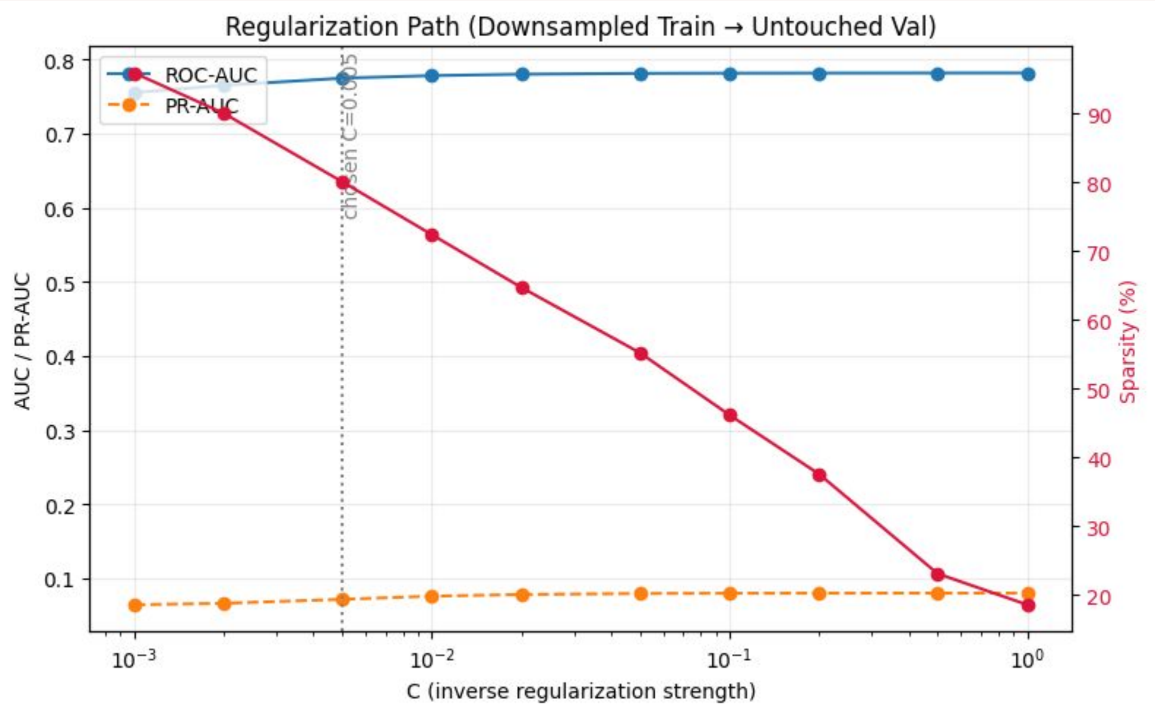
(5) Logistic Regression Pre-Processing

- Removed device_size, adv_prim_id, city, device_name
- Downsampled training data (6.1M to 200K) to balance classes



05 Feature Selection by LASSO

- C = 0.005
- 221 Coefficients Total
- 44 Nonzero after Lasso
- 80% Sparsity



(5) Evaluation Metrics

Across Threshold Metrics

- ROC-AUC: 0.77
- PR-AUC : 0.07

Ranks true clicks above non-clicks 77% of the time

Averages a precision of 7% across all recall levels

Confusion Matrix at Optimal Threshold of 0.80

	Pred 0	Pred 1
Actual 0	1473911	37366
Actual 1	18628	5199

- Precision: 0.12
- Recall: 0.22
- F1 Score: 0.16

(5) Logistic Regression Predictors

Top Positive Predictors

	feature	coef	odds_ratio
47	slot_id_46	1.017	2.77
59	slot_id_58	0.650	1.92
115	spread_app_id_197	0.610	1.84
66	slot_id_65	0.513	1.67
14	slot_id_13	0.458	1.58
29	slot_id_28	0.444	1.56
39	slot_id_38	0.385	1.47
36	slot_id_35	0.384	1.47
63	slot_id_62	0.327	1.39
193	app_second_class_18	0.246	1.28

Top Negative Predictors

	feature	coef	odds_ratio
217	net_type_4	-0.099	0.91
51	slot_id_50	-0.104	0.90
10	inter_type_cd_3	-0.109	0.90
60	slot_id_59	-0.132	0.88
31	slot_id_30	-0.186	0.83
0	u_feedLifeCycle	-0.234	0.79
1	u_refreshTimes	-0.530	0.59
214	creat_type_cd_10	-0.810	0.44
70	slot_id_69	-1.052	0.35
17	slot_id_16	-1.413	0.24

(5) Logistic Regression: Adding SMOTENC

- Experimented with an alternate way to deal with data imbalance
- SMOTENC to deal with both our numerical and categorical features
- Pipeline:
    - **Undersampling** so that majority to minority class has a ratio of 2:1
    - **SMOTENC** so that the end dataset has equal samples from ad clicked and ad not clicked
- Didn't result in significant model improvement

(5) Evaluation Metrics

Threshold Metrics: 0.5 & Optimal 0.824

- ROC-AUC: 0.7810 — Ranks true clicks above non-clicks 78% of the time
- PR-AUC : 0.0782 — Averages a precision of 7.8% across all recall levels

Confusion Matrix at Optimal Threshold of 0.824

	Pred 0	**Pred 1**
Actual 0	1471247	40030
Actual 1	18404	5423

- Precision: 0.119
- Recall: 0.228
- F1 Score: 0.1566

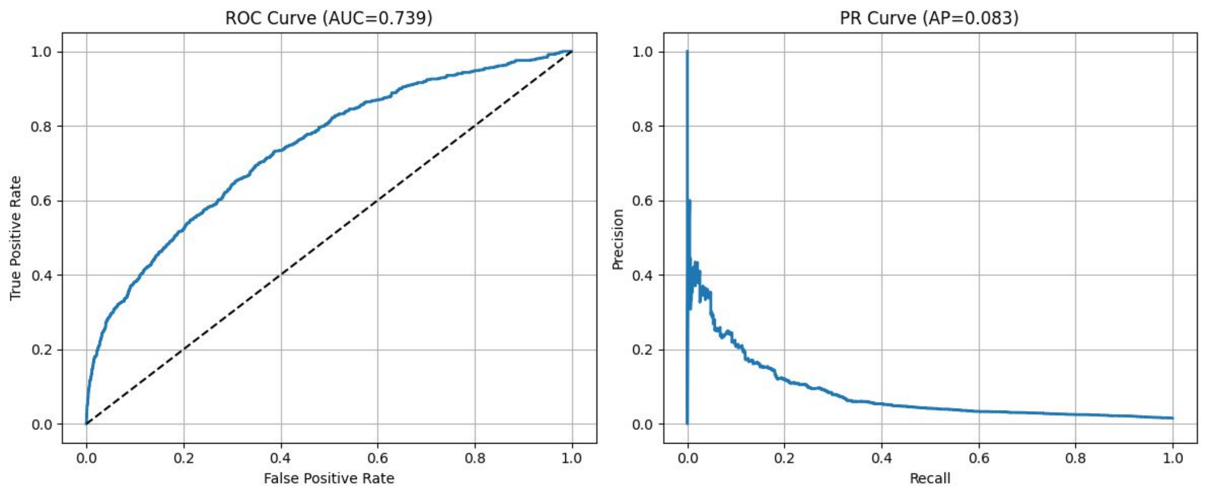
(6) XG Boost Pre-Processing

- Parsed **pt_d** as datetime and sorted by time
- List-like features converted to count features (e.g. ad_click_list_v001_count)
    - **Aggregated into**: click_count_mean, close_count_mean
- Standardized numeric features before applying SMOTENC
- Sampled 200,000 rows
    - Performed undersampling (5:1) on training set
    - 80/20 train/test split

Stage	**Total Rows**	**Class 0**	**Class 1**	**Ratio**
Original	200k	196,896	3,104	63:1
Train	160k	157,517	2,483	63:1
Test	40k	39,379	621	63:1
After Undersampling	14,898	12,415	2,483	5:1
After SMOTENC	24,830	12,415	12,415	1:1

(6) XG Boost with scale_pos_weight

- **scale_pos_weight**: 63.4
- **Model hyperparameters**:
  - n_estimators=400
  - max_depth=4
  - gamma=1.0
  - colsample_bytree=0.7
  - early_stopping=50
- **Had threshold** = 0.5
  - **Optimal threshold**: 0.988



(6) Evaluation Metrics

Threshold Metrics: 0.5 & Optimal 0.988

- ROC-AUC: 0.7388 — Ranks true clicks above non-clicks 74% of the time
- PR-AUC : 0.0830 — Averages a precision of 8% across all recall levels

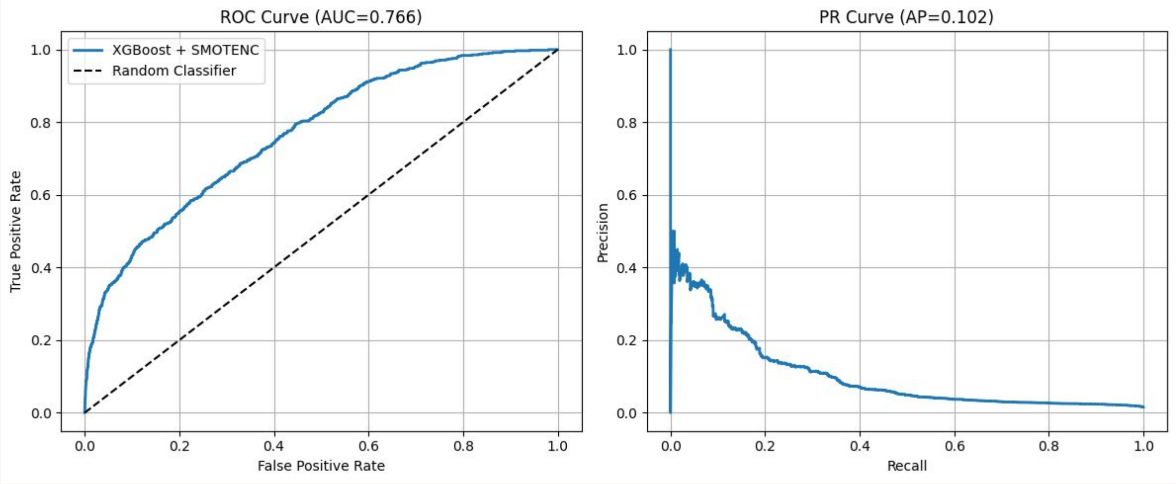
Confusion Matrix at Optimal Threshold of 0.988

	Pred 0	**Pred 1**
Actual 0	38738	641
Actual 1	511	110

- Precision: 0.1465
- Recall: 0.1771
- F1 Score: 0.1603

(6) XG Boost: Adding SMOTENC

- Applied SMOTENC to rebalance training to 1:1
- Removed scale_pos_weight
- **Model hyperparameters**:
  - n_estimators=400
  - max_depth=4
  - gamma=2.5
  - colsample_bytree=0.7
  - early_stopping=30
- **Had threshold** = 0.5
  - **Optimal threshold**: 0.826



(6) Evaluation Metrics

Threshold Metrics: 0.5 & Optimal 0.826

- ROC-AUC: 0.7659
- PR-AUC : 0.1021

Ranks true clicks above non-clicks 77% of the time

Averages a precision of 10% across all recall levels

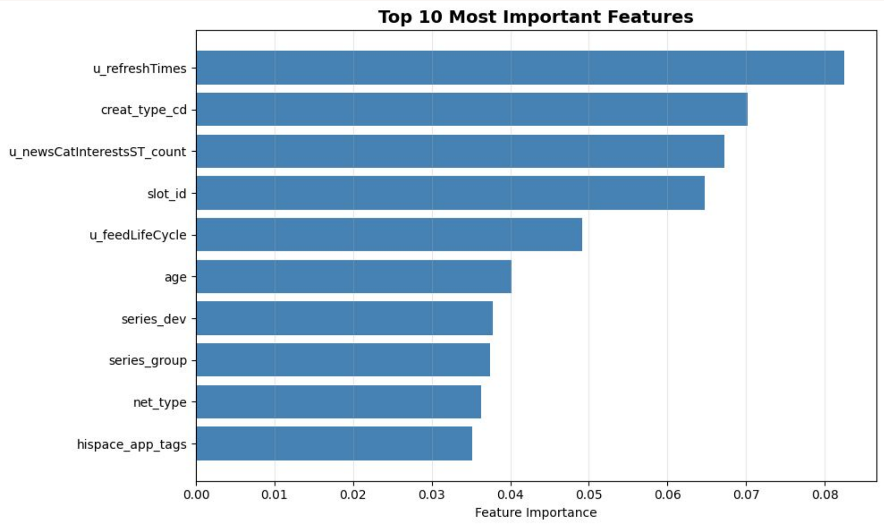
Confusion Matrix at Optimal Threshold of 0.826

	Pred 0	**Pred 1**
Actual 0	38932	447
Actual 1	511	110

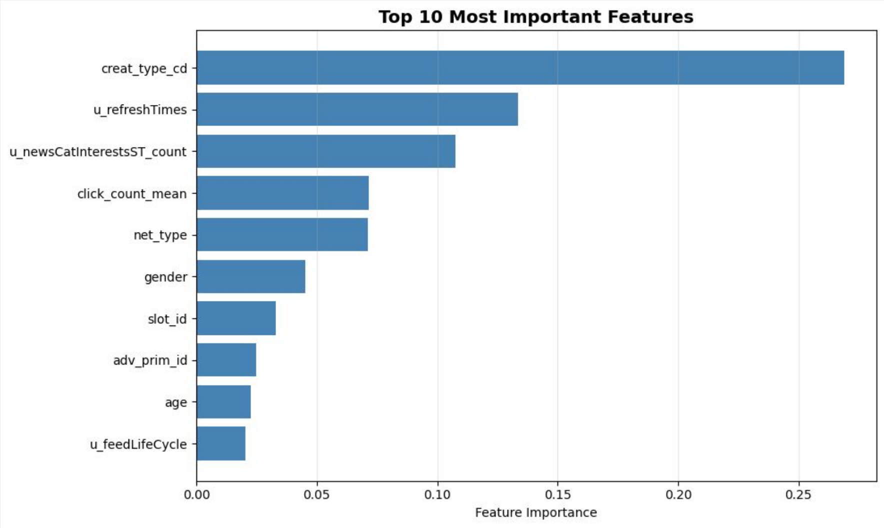
- Precision: 0.1975
- Recall: 0.1771
- F1 Score: 0.1868

(6) Feature Importance

Top Features: Simple XG Boost



Top Features: SMOTENC XG Boost



Engagement/activity, creative type, short term interest seem to be the top features in both models

Model Comparison

	F1 Score@0.5	ROC-AUC	PR-AUC
Random Classifier	0.03	0.5	0.02
Logistic Regression - undersampling	0.07	0.77	0.07
Logistic Regression - undersampling & SMOTENC	0.07	0.78	0.08
XGBoost - undersampling	0.05	0.74	0.08

(7) Conclusions

- Overall models perform better than the random classifier, which can reveal important insights for marketing companies about which factors get users to click
  - Ad placement and user engagement matter significantly whether a user clicks on an add
  - Content-type matching matters
- Limitations:
  - Imbalanced data leads to many false positives and low precision
  - Very marginal improvement in using SMOTENC
- Future work:
  - Fine-tuning hyperparameters
  - Further domain understanding about the variables and their meaning
  - Using the Feeds Dataset for a more feature-rich dataset
  - Utilizing cloud computing for model training and analysis

Thank you