December 2025

Predicting Ad Clickthrough-Rate (CTR)
on real and synthesized ads data

STATS 414: Generative AI

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(1) Problem Overview

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What is the best approach to generate synthetic data to improve CTR classification?

(2) Data Pruning

- **Goal: Reduce computational requirements by narrowing the scope of the problem**
- Original ads dataset: 7 million rows, 35 predictors
- Narrow down to top six task_ids, D1 to D6
- Focus on users who have at least clicked on an ad once

(2) Data Processing

- Converting variables to correct data type
  - pt_d → datetime
- Downcasted numerical data types, reducing memory footprint
- Engineer new count of interest category features
- Remove ID_fields for synthetic data generation
- Remove uninformative features through XGBoost importance analysis

(3) Data Analysis Pre/Post Pruning

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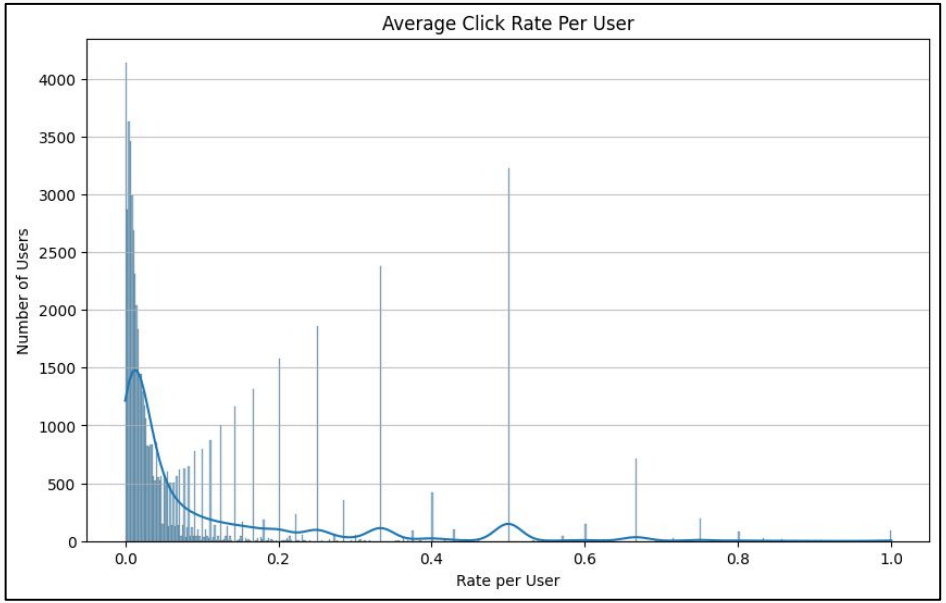

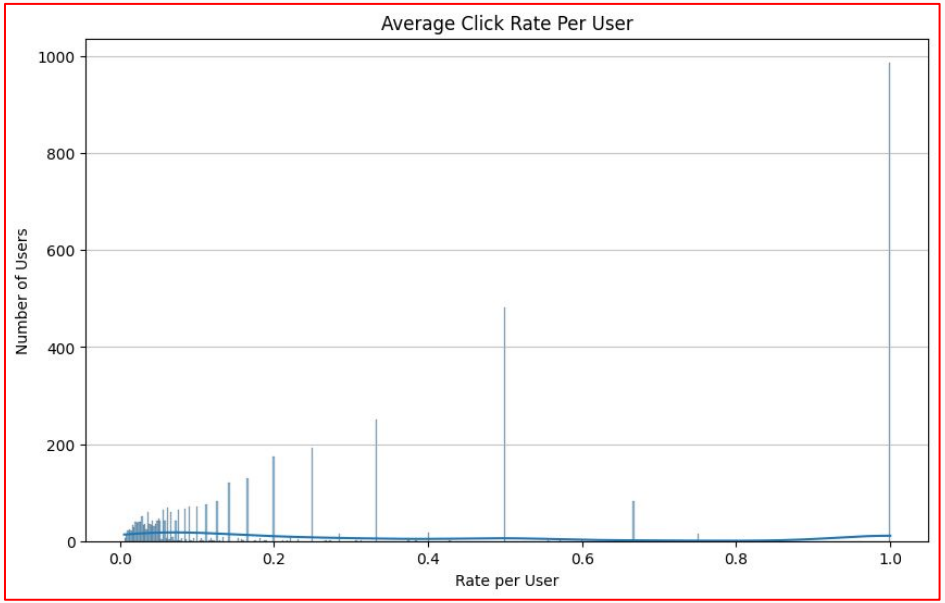

(3) Data Analysis Pre/Post Pruning

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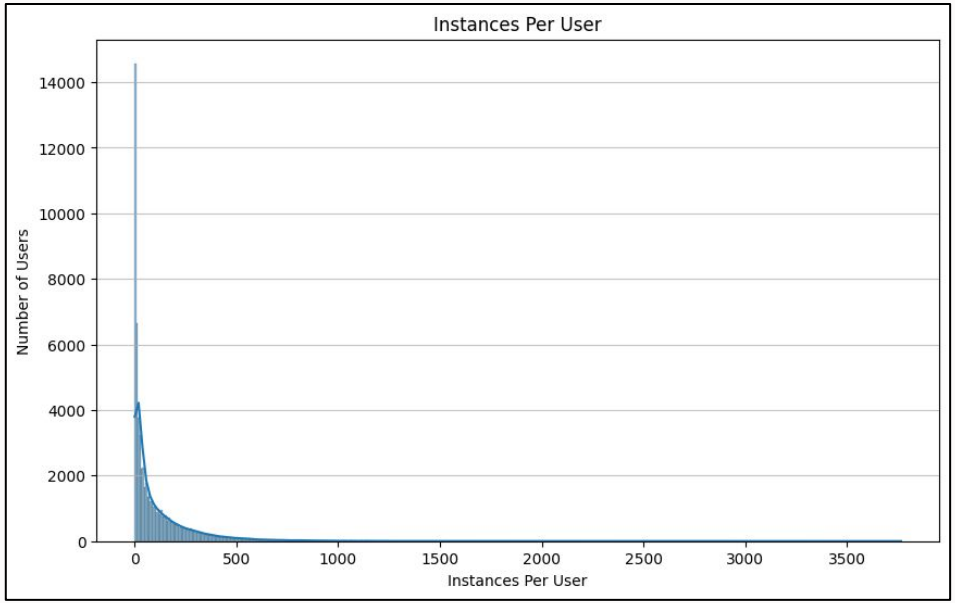

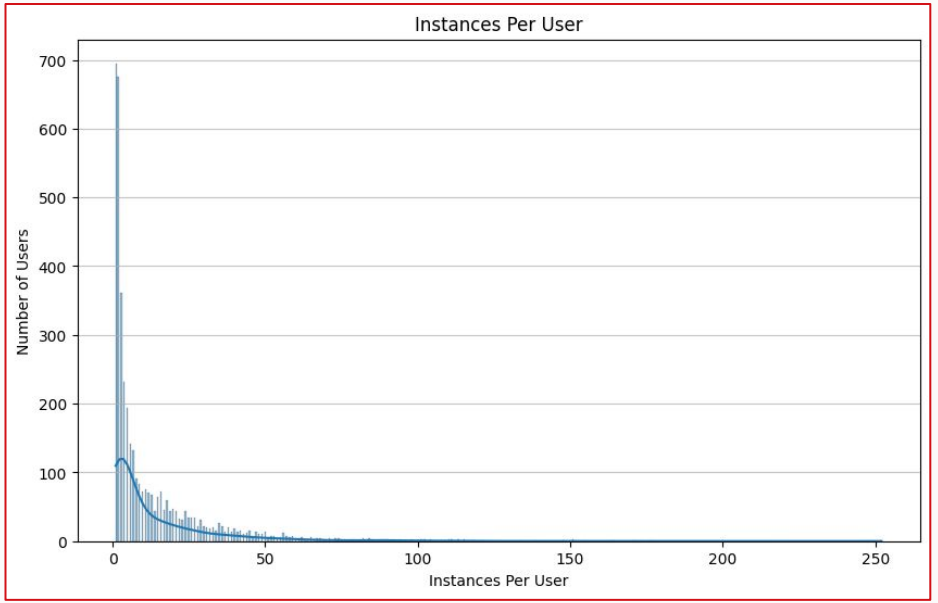

(3) Data Analysis Pre/Post Pruning

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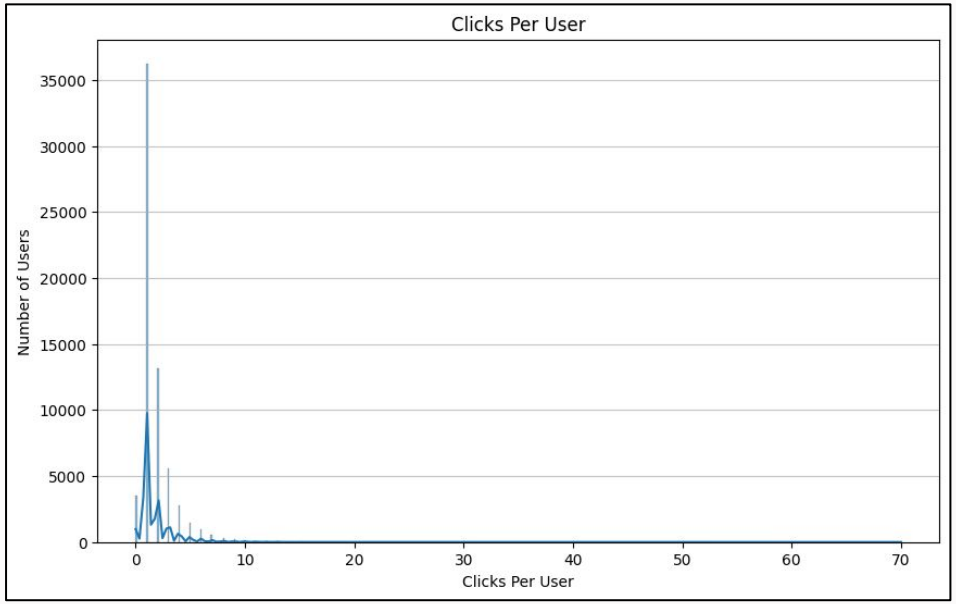

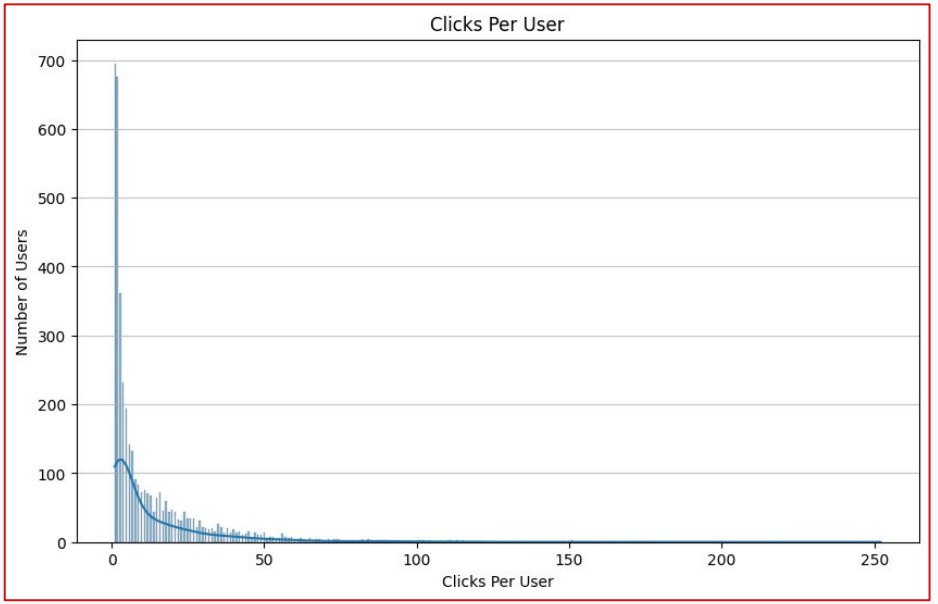

(3.1) Data Analysis Post Pruning

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Dataset	task_id	rows_before	rows_after	ctr_before	ctr_after
1	22100	154812	4628	0.001815	0.060717
2	14584	126367	29359	0.014790	0.063660
3	34382	122094	2724	0.001589	0.071219
4	34975	92381	3880	0.001927	0.045876
5	31941	77470	12677	0.032167	0.196576
6	31996	69691	1555	0.002525	0.113183

Full Dataset CTR: 0.0947 (9.47%)

(4) Synthetic Data Generation: Realtabformer

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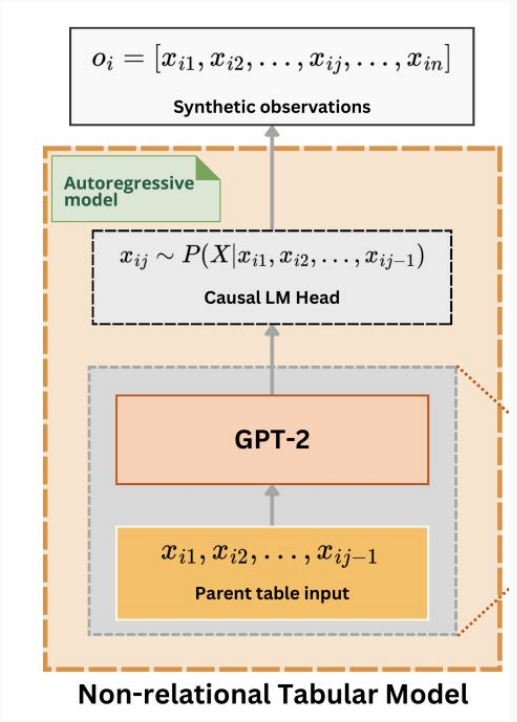
- Realistic Relational and Tabular Transformer
- Uses autoregressive transformer model, ChatGPT-2
- Changed hyperparameters to shorten training process
    - 75 epochs, turned off full sensitivity
- Train a different model for each subset of data D1 - D6 and generate a sample of 10,000 rows



(4) Synthetic Data Generation: CTGAN

- Conditional generative adversarial network
- Uses 2 neural networks, the generator and the critic, to improve the synthetic data
- Learns distributions more accurately due to techniques like conditional generation and oversampling of rare categories
- Train a different model for each subset of data D1 - D6 and generate a sample of 10,000 rows

(5) Problem Overview

How can we develop a framework to evaluate generated synthetic tabular data?

(6) Evaluation: Data Privacy

- Realtabformer already implements regularization to prevent data-copying
  - Uses target masking: artificially introducing missing values
  - Computes a stopping threshold to avoid overfitting using distance to closest record
- Further statistical tests to be evaluate data post-generation
  - DCR using Realtabformer method
  - Membership inference attacks (more comprehensive)

(6) Evaluation: Fidelity

- Conditional generative adversarial network
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- Train a different model for each subset of data D1 - D6 and generate a sample of 10,000 rows

(6) Slide noting high-level synth data evaluation

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- Fidelity Evaluation:
  - Marginal dists can be estimated w/ total variational distance, correlations, and Cramer's V
  - Univariate Measures
    - mean, sd, skewness, etc
    - Chi-squared / total variation distance between empirical distributions
  - Pairwise
    - Numeric-Numeric -> matrix distances on between corr matrices
    - Categorical-Categorical -> Cramer's V
  - Classifier Modeling e.g. RandomForestClassifier modeling whether synthetic or not
    - If close to random guessing, P and Q are similar
  - PRD Precision-Recall on CTGAN and RTF separately
    - Drop to lower dimension space (PCA)
  - How close is the data to the real data?

(6) Fidelity: Graphical Analysis

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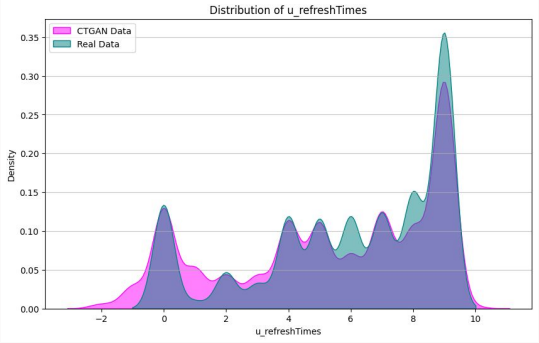

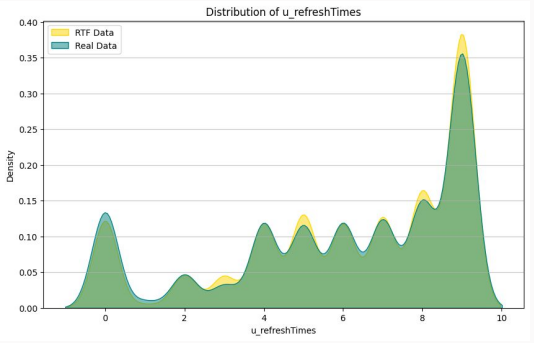

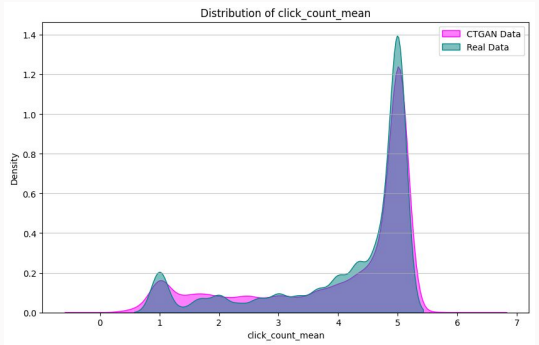

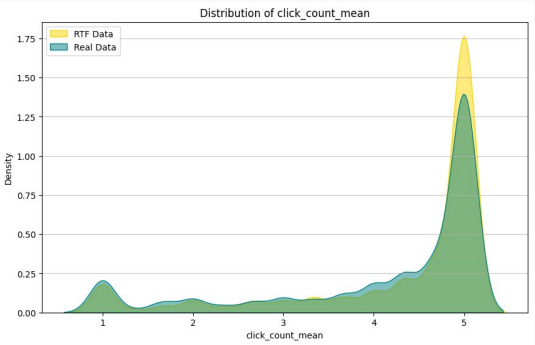

(6) Fidelity: Total Variational Distance and Marginal Cramer's V

Numerical Features: Total Variational Distance

Feature	TVD_CTGAN	TVD_RTF
u_refreshTimes	0.101774	0.032038
u_feedLifeCycle	0.098143	0.014617
u_newsCatIntesrestST_count	0.093361	0.014055
click_count_mean	0.377356	0.087038
close_count_mean	0.037952	0.008097

Categorical Features: Cramer's V

Feature	CramersV CTGAN	CramersV RTF
age	0.101708	0.094325
gender	0.026075	0.034176
city_rank	0.083767	0.086042
device_size	0.350771	0.368568
slot_id	0.464447	0.448289

(6) Fidelity: Absolute Correlation Differences

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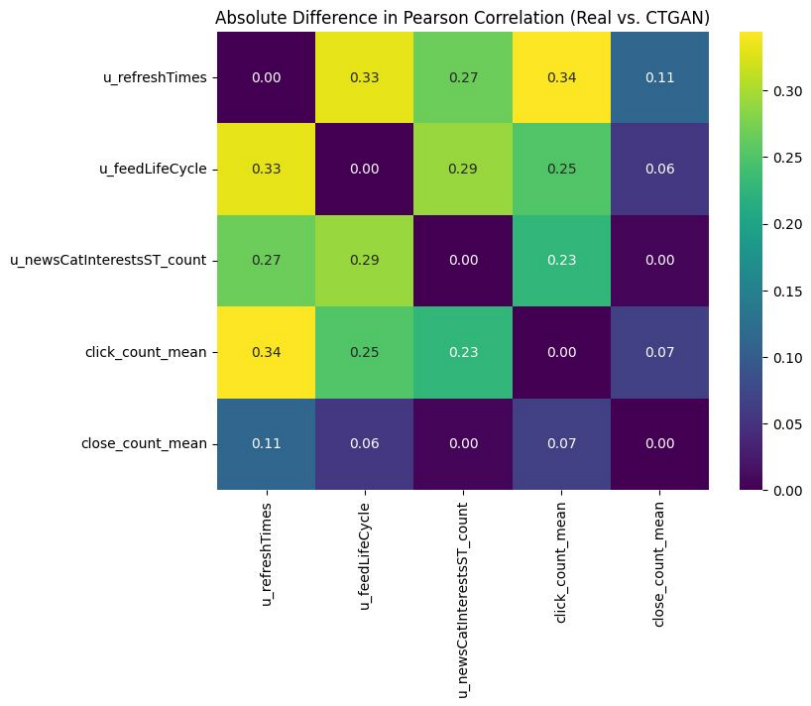

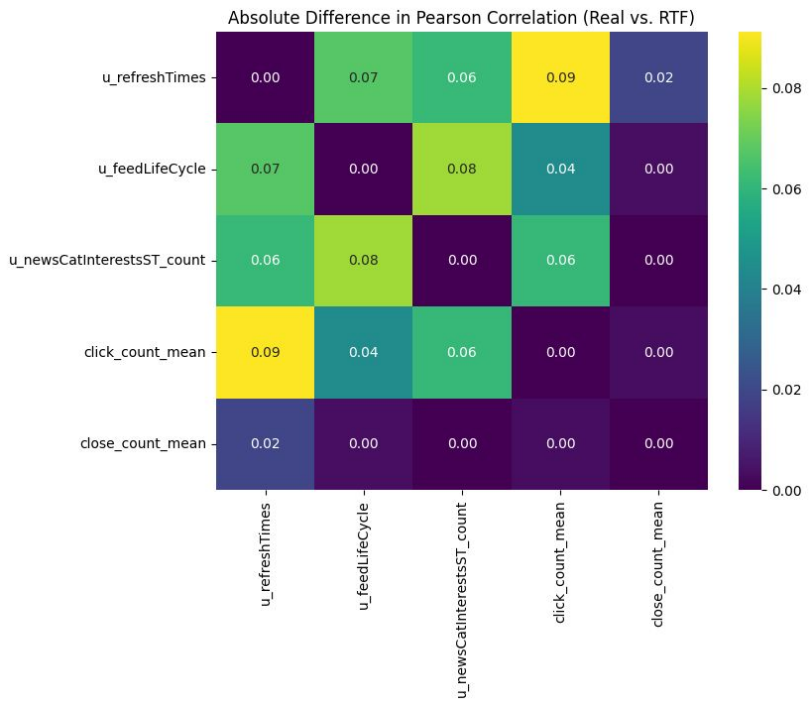

(6) Fidelity: Random Forest Classifier

Detection of Synthetic Data Classification Report

Label	Precision	Recall	F1-Score	Support
0	0.78	0.72	0.75	16447
1	0.88	0.91	0.89	36000

Accuracy Score: 0.85067

Slide noting high-level synth data evaluation

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- Utility Evaluation:
  - Choosing downstream task (already doing, predicting classification 1/0)
    - Test different levels of synthetic data inclusion
    - ALSO, train on synthetic, test on real
  - Model Selection → Taking many models and seeing how introduction of synth data changes optimal model
    - Rank by performance
    - If performance is consistent across different synth data injection levels, **can actually use** synth data for true predictive modeling
  - Utility-interpretability trade off
  - How useful is the data for a task?

(7) Utility: Modeling Pipeline Overview

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- **Goal:** Compare utility of CTGAN vs RealTabFormer synthetic data
- **Two identical pipelines:** Same preprocessing, models, ratios
- **Data:** 54k real (60% train, 20% val, 20% test) + 60k synthetic (D1-D6 per generator)
- **Models:** L1 Logistic Regression and XGBoost
- **Experiments:** Real-only, Synthetic-only, Mixed (0.10×–1.64×)
- **Evaluation:** AUC and PR-AUC (test set)

(7) Logistic Regression Preprocessing

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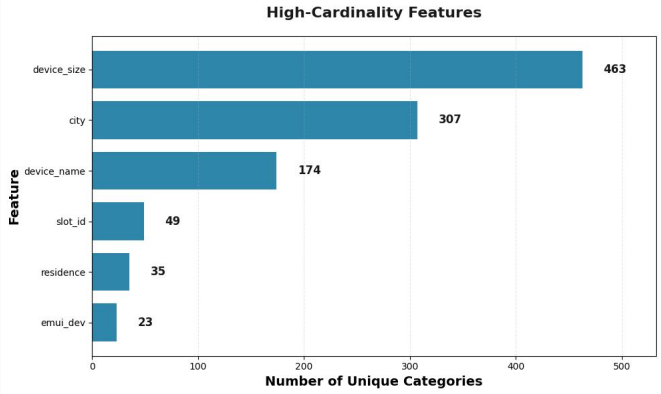
- Numerical features → StandardScaler
- Low-cardinality features → One-Hot Encoding
- High-cardinality features → Target Encoding:
    - Minimum 20 unique values per feature
    - Smoothing (Pulls value toward global mean)
    - Clipping to ±3σ (Prevents any encoded value from going outside a realistic range)



(7) Logistic Regression Results

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Realtabformer

	Synthetic Ratio	Test AUC	PR-AUC
0	0.00× (Real Only)	0.77840	0.40977
1	0.10×	0.77868	0.4093
2	0.36×	0.77883	0.41354 ◀ best
3	0.61×	0.77838	0.40862
4	0.87×	0.77930	0.41112
5	1.13×	0.77887	0.40649
6	1.38×	0.77803	0.40701
7	1.64×	0.77815	0.40349
8	Synthetic Only	0.77033	0.39437

CTGAN

	Synthetic Ratio	Test AUC	PR-AUC
0	0.00× (Real Only)	0.77840	0.40977 ◀ best
1	0.10×	0.77955	0.40593
2	0.36×	0.77793	0.39458
3	0.61×	0.77701	0.38814
4	0.87×	0.77441	0.37847
5	1.13×	0.77190	0.37312
6	1.38×	0.77136	0.37609
7	1.64×	0.77111	0.37339
8	Synthetic Only	0.72978	0.29227

(7) Logistic Regression Interpretation

- City dominates model signal
- Device type & size matter
- Slot ID strongly predictive
- Other features have small effects

Rank	nice_name	coefficient	Odds Ratio
1	city	4.66150	105.794
2	device_size	2.08987	8.084
3	device_name	2.00163	7.401
4	slot_id	1.69733	5.459
5	type=cd_8	0.58251	1.791
6	u_refreshTimes	-0.40471	0.667
7	age_9	0.34999	1.419
8	u_newsCatInterestsST_count	-0.27054	0.763
9	type=6	0.22072	1.247
10	group=3	0.18961	1.209

(7) XGBoost Results

Realtabformer

	Synthetic Ratio	Test AUC	PR-AUC
0	0.00× (Real Only)	0.78092	0.43334
1	0.10×	0.78306	0.43656
2	0.36×	0.78519	0.43858
3	0.61×	0.78573	0.44387
4	0.87×	0.78884	0.44473
5	1.13×	0.79093	0.44294
6	1.38×	0.79288	0.46273 ◀ best
7	1.64×	0.79101	0.44661
8	Synthetic Only	0.78976	0.44515

CTGAN

	Synthetic Ratio	Test AUC	PR-AUC
0	0.00× (Real Only)	0.78092	0.43334
1	0.10×	0.78380	0.43327
2	0.36×	0.78386	0.43234
3	0.61×	0.78367	0.43414
4	0.87×	0.78270	0.43602 ◀ best
5	1.13×	0.78095	0.43285
6	1.38×	0.78160	0.43246
7	1.64×	0.77896	0.42638
8	Synthetic Only	0.72610	0.31395

(7) XGBoost Feature Importance

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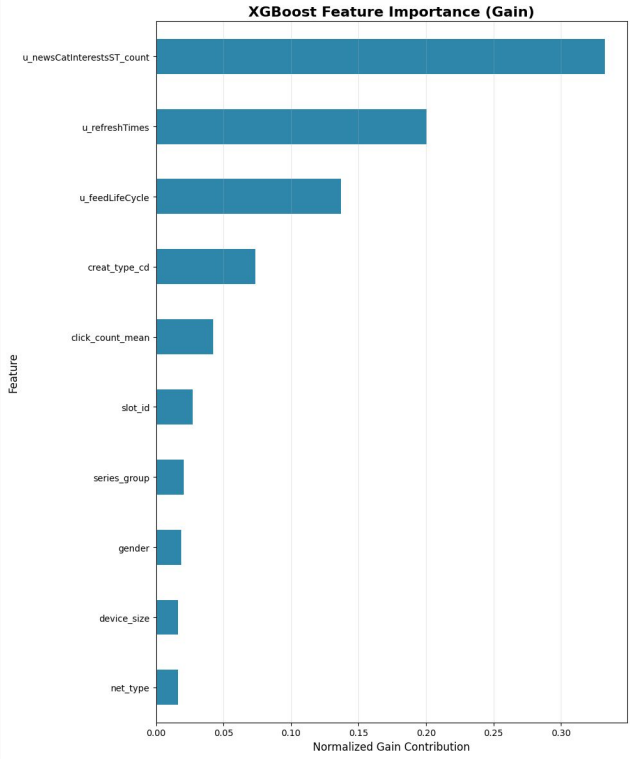
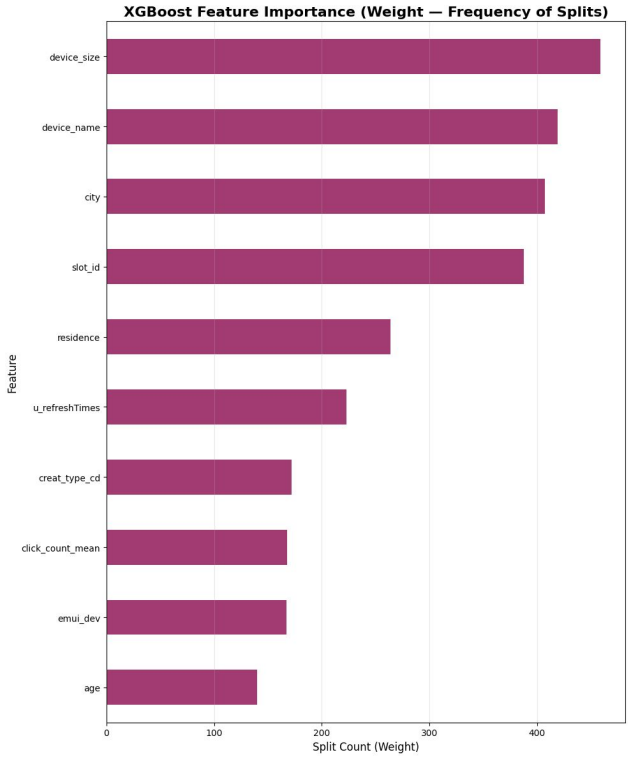


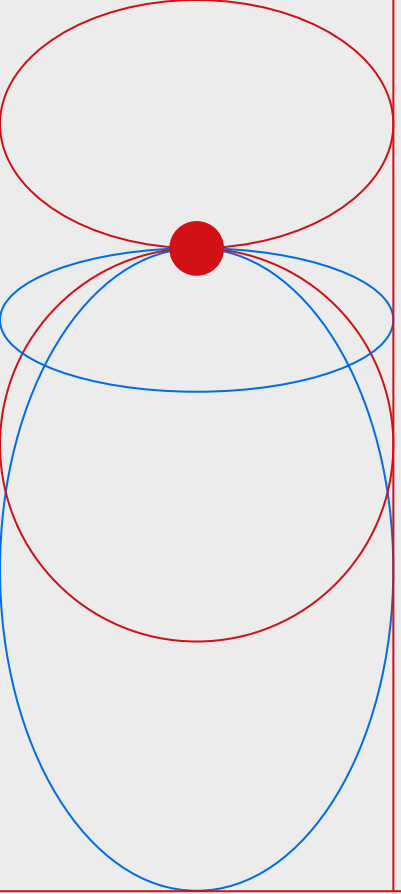


(8) Conclusions

1. Pruning improved CTR signal and reduced computational burden
2. The ideal synthetic-to-real ratios varied by model type
    - Logistic Regression performed best at very low synthetic ratios (0.0×–0.36×) and degraded steadily as synthetic proportion increased.
    - XGBoost performed well even with high synthetic ratios (0.87×–1.38×), showing that more synthetic data can improve a strong nonlinear model
    - REaLTabFormer tolerated higher ratios than CTGAN, which degraded faster
3. Synthetic data marginally improves model's prediction power over random classifier
4. **REaLTabFormer performed best across fidelity and utility**

(8) Limitations/Future Steps

- **Limitations:**
  - Training cost and instability — ReaLTabFormer required long training times and hyperparameters were adjusted to speed up the process
  - Evaluation limited to two synthesizers (CTGAN + RTF)
- **Future work:**
  - Run more comprehensive privacy evaluations
  - Experiment with more recent LLMs
  - Scale synthetic training to full dataset instead of subsets



Thank you