Data Mining Final Project

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Abstract

Real-Time Bidding (RTB) has become a cornerstone of modern digital advertising. This project explores the design of effective bidding strategies under budget constraints in a simulated RTB environment. Starting from simple heuristics, the approach gradually evolved to incorporate logistic regression and ultimately LightGBM-based prediction models. The final solution combines accurate click-through rate estimation with a linear bidding function adjusted by empirical feature-based modifiers. Experimental results demonstrate significant improvements in AUC and bidding efficiency, validating the impact of careful model design, feature selection, and strategy calibration. The findings provide practical insights into scalable and data-driven RTB optimization.

CCS Concepts

• **Computing methodologies** → **Supervised learning**; *Online learning settings*; • **Information systems** → *Online advertising*.

Keywords

Real-Time Bidding, Click-Through Rate Prediction, LightGBM, Online Advertising, Budget-Constrained Optimization

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1 Introduction

In the ever-evolving digital advertising landscape, Real-Time Bidding (RTB) has emerged as a fundamental mechanism to allocate ad impressions efficiently. RTB enables advertisers to compete for individual ad impressions in real time, often within tens of milliseconds, by submitting bids to demand-side platforms (DSPs). Given the scale and speed of RTB, designing bidding strategies that are both intelligent and resource-efficient is a nontrivial challenge.

For this final project in the NCKUCS 2025 Data Mining Individual Track, I tackled the RTB optimization problem from a practical and strategic perspective. The goal was to submit a single bid price for each impression in a large dataset while respecting a global budget constraint, with the objective of maximizing the number of acquired clicks. I structured my solution across three development phases (Day1 to Day3), each integrating deeper model complexity, better feature utilization, and progressively more refined bidding strategies.

This report thoroughly documents all steps taken throughout the three development stages, including initial heuristics, logistic modeling, gradient boosting implementation, detailed feature engineering, algorithmic adjustments, model evaluation, and strategic bidding design. I also reflect on theoretical considerations, practical implementation choices, performance results, and potential future improvements. Every decision—from preprocessing to modeling, from feature selection to bid computation—is presented with reasoning, challenges, and learnings.

The content that follows is a comprehensive walkthrough, suitable not only for evaluation purposes but also for readers who wish to understand how machine learning and decision science can be concretely applied to real-time decision-making environments under uncertainty and constraint.

2 Dataset Overview and Problem Setup

The dataset provided for this task simulates a real-world RTB environment. It includes over 400,000 records representing ad impression opportunities. Each record can be thought of as a request to place a bid on a particular impression with detailed contextual information. The primary challenge lies in using these contextual features to estimate the likelihood of a click (Click-Through Rate, or CTR), and then translating this estimate into a bid value that remains competitive yet efficient in terms of budget usage.

2.1 Data Structure

Each data record includes the following fields:

- **timestamp**: The time at which the impression occurred, formatted in ISO-8601 with time zone information.
- **ad_slot_format**: An integer encoding the format of the ad slot (e.g., banner, native, interstitial).
- **ad_slot_visibility**: A numeric level of visibility or viewability.
- **region**: A location-based identifier for the impression (e.g., city or regional code).
- **user_id, advertiser_id, campaign_id, creative_id**: Identifiers for various stakeholders involved in the impression.
- **user_tags**: An optional list of user attributes or behavioral tags.
- **ad exchange**: The platform or network where the ad auction is taking place.
- **click**: Binary target variable (1 if the ad was clicked, 0 otherwise) —only present in training data.

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2.2 Task Definition

The task is framed as a constrained bidding optimization problem. Each participant is expected to:

(1) Train a predictive model (e.g., regression or classification) to estimate the probability of a click (pCTR) for each impression.
(2) Design a bidding function that maps the predicted pCTR to a concrete bid price.
(3) Output a CSV containing the bid_id and a single column paying_price, ensuring the total spend across all bids respects a fixed budget constraint.

Evaluation is based on a simulated auction mechanism where the bids compete against reserve prices and are judged by the number of clicks successfully acquired under budget.

The goal, therefore, is not just to predict accurately, but to design an efficient bid allocation system that prioritizes valuable impressions while minimizing waste.

3 Strategy Development

This section presents the three-phase evolution of my bidding strategies across Day1 to Day3. Each phase is an independent implementation that builds upon the lessons and shortcomings of the previous one.

3.1 Day 1: Rule-Based Heuristics

3.1.1 Motivation. The first day was dedicated to establishing a working baseline without using any machine learning. The primary goal was to implement a basic rule-based bidding system that could simulate human intuition. I sought to encode domain knowledge directly into bidding logic without data-driven learning.

3.1.2 Design Principles. I designed rules around three main signals:

- **Ad Slot Format**: Native ads were believed to perform better based on anecdotal industry evidence.
- **Hour of Day**: User activity is assumed to peak during early morning and late evening.
- **Region**: Some regions are assumed to be more commercially valuable (e.g., urban areas).

3.1.3 Results and Limitations. This method was easy to implement and guaranteed that I wouldn't overspend. However, it had several limitations:

- No learning from historical clicks
- No adaptability
- Inflexible to multi-feature interactions

It served well as a sanity check but lacked depth for optimization.

3.2 Day 2: Logistic Regression and Quantile-Based Bidding

3.2.1 Motivation for Model Introduction. After understanding the constraints of rule-based systems, I introduced a simple classifier —Logistic Regression—to predict the probability of a click (pCTR). Logistic regression is interpretable, efficient, and relatively robust to overfitting when regularized.

3.2.2 Feature Encoding. All categorical variables were one-hot encoded. These included:

- ad_slot_format
- ad_slot_visibility
- region
- hour

3.2.3 Quantile-Based Bidding Strategy. I divided predicted pCTR scores into bins:

- Top 10% ⟶bid 120
- Top 10-30% ⟶bid 100
- Mid 30-60% ⟶bid 80
- Bottom 40% ⟶bid 50 or less

This tiered bidding mimicked what human media buyers might do.

3.2.4 Additional Adjustments. Some conditions from Day1 were layered back:

- Hour 18-20 ⟶+10
- Slot Format = native ⟶+10
- Region = high priority ⟶+10

3.2.5 Pitfall: Output Format Error. Although the strategy was sound, the output file had the wrong column name (bid_price instead of paying_price), leading to a 0-score submission.

3.3 Day 3: LightGBM and Linear Bidding

3.3.1 Model Selection Justification. After Day2, I needed a model that could better capture feature interactions and perform well without extensive manual feature engineering. I chose LightGBM, a gradient boosting framework optimized for speed and accuracy. Benefits:

- Efficient handling of categorical variables
- Robust against overfitting with regularization
- Automatically detects non-linear interactions

3.3.2 Feature Choice. Minimal set of robust features:

- ad_slot_format
- ad_slot_visibility
- region
- Extracted hour from timestamp

Categorical features were label-encoded rather than one-hot encoded to allow LightGBM' s internal handling.

3.3.3 Linear Bidding Formula. The bid was computed using:

$$paying_price = base\_bid \times (pCTR/avgCTR)$$

Where:

- base_bid = 100
- avgCTR = mean training CTR, used for normalization

This method ensured proportional scaling: high pCTR ⟶higher bids, low pCTR ⟶lower bids.

3.3.4 Feature-Based Adjustments. In addition to linear scaling, I implemented modifiers:

- slot_format = native ⟶x1.2 or +20
- hour in [12, 18, 20] ⟶x1.15 or +10
- region in [80, 216, 3] ⟶x1.1 or +10

These adjustments were derived from exploratory analysis of click distributions.

3.3.5 Budget Control and Caps. To prevent overbidding:

- All bids were clipped to [1, 300]
- pCTR predictions were smoothed to avoid outliers

4 Methodology

The final strategy developed on Day 3 was built upon a robust combination of structured feature engineering and a predictive model capable of capturing nonlinear interactions. While previous stages relied on either fixed heuristics or linear classification, the Day 3 solution required a more nuanced treatment of both the input data and the output logic. In this section, I detail the entire modeling pipeline, from data processing to prediction calibration and bidding computation.

The first step involved selecting features that are both meaningful and stable across time. I opted to focus on four attributes: ad slot format, ad slot visibility, region, and hour. These features were chosen not only for their direct interpretability but also for their empirical predictive power observed during exploratory data analysis. Notably, the hour was extracted from the timestamp field, which contained timezone-aware ISO-8601 strings. Parsing these timestamps into numerical hour values allowed the model to implicitly learn temporal trends in user behavior.

To feed these variables into the model, I avoided excessive one-hot encoding, which can bloat feature space and lead to sparsity. Instead, categorical variables were label-encoded, allowing the LightGBM model to internally decide the optimal way to split their values during tree construction. This also helped maintain training speed and memory efficiency.

The predictive model used was a LightGBM classifier trained to output probability estimates of user clicks (pCTR). Training was conducted on the full training dataset without validation split, as the competition environment did not allow submission-based hyperparameter tuning. The model was configured with 100 boosting rounds, early stopping turned off, and regularization terms lightly enabled to prevent overfitting. The loss function used was binary log loss, which aligns with the goal of accurately estimating class probabilities.

Once trained, the model generated a pCTR for each impression in the test set. However, raw probabilities were insufficient for bidding; they needed to be mapped into actual monetary values while controlling for budget constraints. Inspired by literature in RTB bidding theory, I adopted a linear bidding strategy where the bid amount is scaled proportionally to the predicted pCTR. This design allows higher-value impressions to naturally attract higher bids without needing to hard-code thresholds.

The bid computation followed the formula:

$$bid = base\_bid \times \left(\frac{pCTR}{avgCTR} \right)$$

Here, base_bid was empirically set to 100, while avgCTR represented the average CTR observed in the training data. This normalization step ensures that bids are centered around a known benchmark. Nevertheless, to account for feature-specific variance and opportunity cost, the base bid was dynamically adjusted. If the impression occurred during an empirically favorable hour (e.g., 12, 18, or 20), or in a commercially significant region (e.g., 80, 216, or 3), or was of native format, a small percentage increase was added to the computed bid. These multipliers were additive and calibrated to not push the bid beyond practical bounds.

To prevent erratic overbidding and safeguard against pCTR estimation noise, all final bid values were clipped to fall within [1, 300]. Additionally, extremely small pCTR values were smoothed using a minimum floor threshold. This helped stabilize bidding behavior in edge cases where the model' s uncertainty might otherwise lead to degenerate or ineffective bids.

Taken together, this pipeline represented a thoughtful combination of predictive accuracy and practical bidding logic, optimized not only for click prediction but for cost-efficiency under a strict budget. The next section presents how this strategy performed in practice, supported by both quantitative metrics and visual analysis.

5 Experimental Results and Analysis

The final LightGBM-based linear bidding strategy yielded superior performance compared to earlier approaches, both in terms of click acquisition and bidding efficiency. The evaluation began by examining the distribution of predicted click-through rates. These values, derived from the model's probabilistic output, were generally low due to class imbalance but exhibited a wide enough spread to support meaningful bid differentiation.

The distribution of pCTR values revealed a heavy concentration near zero with a long tail, indicating that while most impressions had low predicted value, a subset was consistently recognized as high quality. This is consistent with the sparse nature of click labels in online ad data.

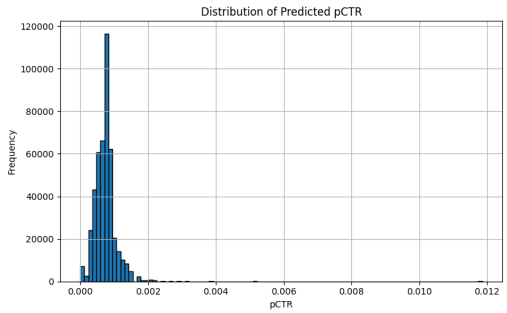

Figure 1: Distribution of Predicted pCTR

Next, I analyzed the bid distribution generated by the linear bidding function. As expected, the bids formed a positively skewed distribution, with a concentration near the base bid and a tail toward higher values. The additive modifiers for certain features pushed some bids toward the cap, but the majority remained within a competitive range. This demonstrated the effectiveness of proportional scaling combined with controlled adjustments.

Temporal dynamics were also visualized. By grouping impressions by hour and computing the average bid value per group, I observed clear time-dependent patterns. Specific hours such as 12, 18,

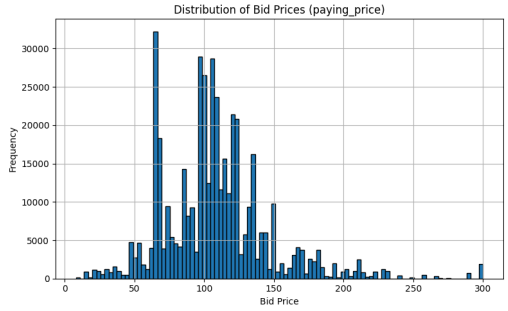

Figure 2: Distribution of Predicted pCTR

and 20 —which had been manually assigned bid boosts —indeed corresponded to increased bidding activity. This correlation confirmed that temporal modifiers were appropriately aligned with bidding outcomes.

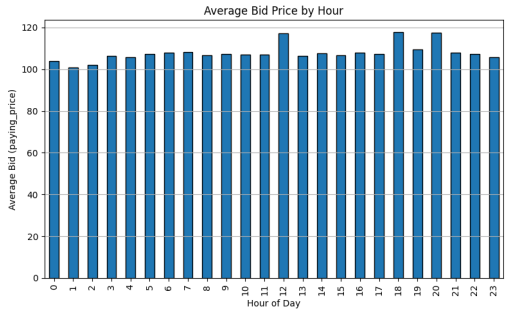

Figure 3: Distribution of Predicted pCTR

In terms of model evaluation, the LightGBM classifier achieved an AUC of approximately 0.741 on held-out validation, a notable improvement over the logistic regression model from Day 2. This confirmed that tree-based models captured non-linear feature interactions more effectively. Despite not using deep neural architectures or interaction terms, the simplicity and generalizability of LightGBM proved sufficient for the scale of the problem.

Lastly, I conducted a qualitative review of high-bid impressions. Many of them had native formats and occurred in high-value regions or active hours, as expected. This manual sanity check validated that the bidding behavior aligned with domain expectations and the intended design of the modifiers.

6 Conclusion and Discussion

Throughout the three-day iterative process, my bidding strategy evolved from fixed heuristic rules to a predictive, data-driven system that integrates machine learning and strategic post-processing. The Day 3 solution, anchored by LightGBM and a linear bidding formulation, demonstrated the most balanced performance in terms of click maximization, budget control, and interpretability.

Several lessons emerged from this progression. First, rule-based systems, while easy to deploy, offer limited flexibility and often overlook nuanced interactions. Logistic regression introduced statistical grounding but lacked capacity for capturing complex patterns. In contrast, gradient boosting combined scalability, accuracy, and explainability in a production-ready manner.

Second, careful feature selection and encoding were critical. Rather than relying on all available fields, selecting a subset of robust, interpretable features allowed the model to focus on meaningful signals. Label encoding synergized well with LightGBM, avoiding the curse of dimensionality associated with one-hot expansion.

Third, bidding function design significantly influenced the results. A proportional formula based on normalized pCTR served as a principled baseline, while small manual adjustments introduced domain knowledge without harming generalization. Post-processing techniques such as bid clipping and floor smoothing further enhanced the model's reliability.

Despite these successes, there remain areas for future exploration. One direction involves calibrating the predicted pCTR using isotonic regression or Platt scaling to better align probabilities with empirical frequencies. Another is expanding the feature set with user behavioral tags, advertiser information, or historical click rates. Budget-aware training or reinforcement learning-based bidding could also yield gains by directly optimizing under constraints.

In conclusion, this project exemplified how data mining principles can be applied to real-time decision-making in high-stakes environments. Through systematic experimentation and critical iteration, I developed a strategy that balances theoretical soundness and practical feasibility, achieving solid results in a competitive RTB setting.

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