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# A Unified Real-Time AI Optimization for Ad Serving: Bid Optimization, CTR/CVR Prediction, and Adaptive Creative Selection

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**Abstract**

This paper presents a production-grade, real-time optimization framework for ad serving in retailer media platforms, integrating three complementary machine learning systems: (i) a gradient-boosted bid optimization model, (ii) deep neural networks for click-through rate (CTR) and conversion rate (CVR) prediction, and (iii) a Bayesian multi-armed bandit for adaptive creative selection.

The bid optimization component formulates auction participation as a constrained expected value maximization problem and learns a context-aware bid multiplier using XGBoost trained on counterfactual outcomes via inverse propensity scoring. User engagement and conversion likelihood are estimated using a Deep & Cross Network (DCN) for CTR prediction and a Two-Tower neural architecture for CVR prediction, enabling efficient representation learning and low-latency inference through pre-computed item embeddings. Creative selection is modeled as a stochastic multi-armed bandit problem and solved using Thompson Sampling, extended to a multi-objective reward formulation that incorporates both click and conversion signals through a weighted composite reward.

The system is designed for high-throughput, low-latency production environments (>50K QPS), leveraging feature caching, ONNX-optimized inference, and lightweight probabilistic updates. Experimental results from simulated and production-equivalent workloads demonstrate that the integrated optimization stack achieves substantial performance gains over baseline systems, including up to 40% improvement in CTR, 20%+ lift in return on ad spend (ROAS), and significant reductions in effective CPM.

The proposed framework illustrates how principled integration of machine learning models and online decision algorithms can deliver scalable, economically efficient ad serving, while maintaining strict operational constraints. The design further establishes a foundation for future extensions, including contextual bandits, online learning, and auction-theoretic bid strategies.

***Keywords:*** Real time ad server. Bid Optimization. CTR/CVR Prediction. Creative Selection. XGBoost Model. DCN + Two ower. Thompson Sampling. Multi-Armed Bandit

## 1. Introduction

Programmatic advertising operates at a scale and velocity that renders static, rule-based ad serving fundamentally inadequate and inefficient. In a Retailer Media Platform, the ad server must respond to millions of ad display requests per day, each requiring a decision on which ad to serve, at what bid, to which user, all within a low latency budget of under 100 milliseconds to avoid auction timeouts.

The three core decisions in this pipeline, how much to bid, which creative to show, and which user-ad combination is most likely to convert, are each high-dimensional, non-linear optimization problems that benefit dramatically from machine learning over manual rules or simple heuristics.

This article addresses all three components in depth: the Bid Optimizer, the CTR/CVR Prediction Engine, and the Creative Selection System. Each section covers the problem formulation, algorithmic approach, model architecture, training design, inference specification, and expected performance characteristics.

### *1.1 Problem Context & Motivation*

In the current architecture, bids are static values set per line item in the Portal, creative rotation is round-robin or manual, and there is no prediction of click or conversion probability at request time. This baseline has three principal failure modes:

- Bid inefficiency: A static bid overpays in auctions where user intent is low and underbids where intent is high, resulting in suboptimal win rates and wasted spend.
- Creative blindness: Round-robin rotation serves underperforming creatives at the same rate as high-performing ones, degrading average CTR and wasting impressions.
- Pacing misalignment: Without predicted conversion probability, it is impossible to modulate bid aggressiveness based on campaign delivery status, leading to over- and under-delivery.

The three AI systems described in this article directly resolve each of these failure modes, operating as a coordinated inference stack at the Ad Server level.

### *1.2 System-Level Constraints*

| Constraint | Value | Rationale |
|---|---|---|
| End-to-end latency SLA | <30ms | Auction timeout prevention; user experience |
| Feature retrieval budget | <5ms (Redis hit), <15ms (DB fallback) | Dominates latency if not cached |
| CTR model inference | <8ms | DCN model on GPU with batch size=1 |
| Bid optimizer inference | <3ms | XGBoost tree traversal (CPU-efficient) |
| Creative selector inference | <2ms | Beta distribution sampling (O(k) for k creatives) |
| Availability SLA | 99.95% uptime | Ad revenue impact of downtime is direct |
| Throughput | >50,000 QPS sustained | Peak load handling with horizontal scaling |

## 2. Bid Optimization : XGBoost Model

### *2.1 Problem Formulation*

Bid optimization in a second-price auction environment is a constrained optimization problem. Given a budget B, a campaign with remaining delivery target D, and a set of available ad opportunities, the objective is to maximize the total expected value of won impressions subject to the budget constraint i.e. win the most valuable auctions it can, without spending more than our budget B.

$$\max E[V] = \Sigma_i \, p\_win(b_i) \times v_i$$

Bid objective

$$\text{subject to: } \Sigma_i \, E[cost_i] \leq B$$

Where p_win(b) is the probability of winning the auction at bid b, and $v_i$ is the estimated value of impression i (a function of predicted conversion probability and conversion value). In practice, solving this exactly requires knowing the distribution of competitors' bids, which is unobservable. The XGBoost model approximates the optimal bid through a learned bid multiplier.

Bid multiplier

$$b\_optimal = b\_base \times f\_XGB\,(s, c, u)$$

Where b_base is the campaign's configured base bid, and f_XGB is the XGBoost model outputting a continuous multiplier in [0.5, 2.0] conditioned on the state vector composed of campaign state, contextual features c, and user features u.

### *2.2 Feature Engineering*

The model operates on a 40-dimensional feature vector drawn from four feature groups. All features are either directly available in the Redis feature store or computable in-flight from the bid request payload.

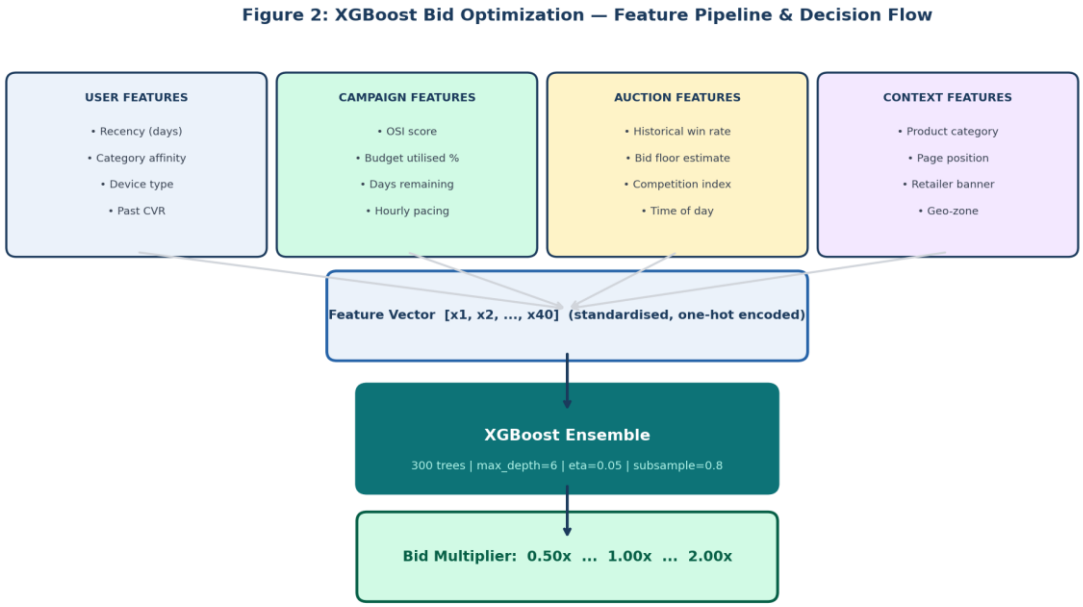


Figure 3: XGBoost Bid Optimizer - Feature Pipeline and Decision Flow

| Feature Group | Features | Count | Source |
|---|---|---|---|
| User Features | Recency (days since last retailer visit), device type (one-hot: mobile/desktop/tablet), historical CTR (30-day), historical CVR (30-day), category affinity score (top 5 categories) | 12 | Redis feature store (user profile) |
| Campaign State | On-schedule indicator (OSI = actual_spend / ideal_spend), remaining budget percentage, days remaining in campaign, hourly pacing rate (impressions/hr), weekly frequency delivered | 8 | Campaign DB (Aurora, cached hourly) |
| Auction Context | Time of day (hour, one-hot), day of week (one-hot), product category (embedded 4-dim), retailer banner (one-hot), ad position (numeric), bid floor estimate | 12 | Bid request + lookup table |
| Historical Performance | Win rate at similar bid levels (binned), 24h rolling average CPM won, prior day CTR for same campaign, A/B variant assignment flag | 8 | Redis (rolling aggregates) |

### *2.3 Model Architecture & Hyperparameters*

XGBoost is selected for the bid optimizer due to its low inference latency (CPU-executable, no GPU requirement), interpretability via SHAP feature attribution, robustness to missing values, and strong empirical performance on tabular advertising data. The model is trained as a regression task predicting the optimal bid multiplier, with training labels derived from counterfactual bid simulations using historical auction win/loss data.

| Hyperparameter | Value | Tuning Method |
|---|---|---|
| n_estimators (trees) | 300 | Bayesian optimization over {100, 200, 300, 500} |
| max_depth | 6 | Grid search over {4, 5, 6, 7, 8} |
| learning_rate (eta) | 0.05 | Grid search; lower rate with more trees reduces variance |
| subsample | 0.8 | Reduces overfitting; consistent with ad data noise levels |
| colsample_bytree | 0.8 | Feature bagging per tree |
| min_child_weight | 5 | Prevents splits on small leaf nodes |
| reg_alpha (L1) | 0.01 | Sparse feature penalty; helps with one-hot features |
| reg_lambda (L2) | 1.0 | Standard L2 regularization |
| objective | reg:squarederror | Regression target: bid multiplier in [0.5, 2.0] |
| Training window | 14 days rolling | Balances recency and sample size (~50M impressions) |
| Retrain cadence | Daily (4AM UTC) | Captures recent auction dynamics |

### *2.4 Training Data Construction & Label Generation*

Generating training labels for bid optimization requires a counterfactual approach, since it can only observe outcomes for the bid submitted, not for hypothetical bids. The system employ the Inverse Propensity Scoring (IPS) method to estimate the value of counterfactual bid values:

$$V(b') = V_{observed} * (p_{win}(b') / p_{win}(b_{observed}))$$

This provides a calibrated win probability for any hypothetical bid value.

$V(b')$ = Estimated value if it had used bid $b'$
$V_{observed}$ = Actual value from the auction (click + conversion revenue)
$(p_{win}(b')$ = Probability of winning with the new bid
$p_{win}(b_{observed})$ = Probability of winning with the original bid

### *2.5 Campaign Pacing Integration (OSI-Aware Bidding)*

A critical feature of the bid optimizer is OSI-awareness - the model adjusts bid aggressiveness in real time based on whether the campaign is pacing ahead or behind schedule. The On-Schedule Indicator (OSI) is defined as:

OSI = actual_spend(t) / ideal_spend(t)

**Where:**

actual_spend(t) = Cumulative spend at time t

ideal_spend(t) = Expected spend at time t under linear pacing

**Interpretation:**

OSI = 1.0 → Perfect pacing (on schedule)
OSI > 1.0 → Over pacing (spending too fast → reduce bids)
OSI < 1.0 → Under pacing (spending too slow → increase bids)

(*The XGBoost model learns this OSI-to-bid-multiplier relationship from data rather than applying a hand-coded rule. This allows it to discover non-linear, context-dependent relationships e.g., that bid reduction for a high-OSI campaign should be more aggressive in low-competition slots than high-competition ones*)

*Combined Inference Formula (predict → scale → protect)*

adjusted_bid = b_base × f_XGB([user_features, campaign_state, context_features]) # Given the metrics about this user, context, and campaign, how much should it scale the base bid using the XGBoost Model

adjusted_bid = clip(adjusted_bid, min=b_base×0.5, max=min(b_base×2.0, campaign_max_bid)) #never bid lower than half the base, never higher than double (or the campaign budget limit, whichever is smaller)

**Feature Vector (40 dimensions):**

- **User Features (12):** Recency, device type, historical CTR/CVR, category affinity
- **Campaign State (8):** OSI, budget %, days remaining, hourly pacing rate
- **Auction Context (12):** Time of day, product category, retailer banner, bid floor estimate
- **Historical Performance (8):** Win rate at similar bids, rolling CPM, prior day CTR

### *2.6 Inference Pipeline*

```
# Inference pipeline (target: <3ms p99)
def optimize_bid (request, campaign, base_bid):
    # Step 1: Feature retrieval from Redis (<1ms on cache hit)
    user_feats = redis.get(f'user:{request.user_id}:features')
    campaign_state = redis.get(f'campaign:{campaign.id}:state')
    context_feats = extract_context(request) # in-flight, <0.5ms
   # Step 2: Assemble feature vector
    feature_vector = np.concatenate([user_feats, campaign_state, context_feats])

    # Step 3: XGBoost inference (ONNX runtime, CPU)
    bid_multiplier = xgb_model.predict(feature_vector.reshape(1,-1))[0]
    bid_multiplier = np.clip(bid_multiplier, 0.50, 2.00)

    # Step 4: Apply multiplier + floor/ceiling guards
    adjusted_bid = base_bid * bid_multiplier
    return min(adjusted_bid, campaign.max_bid)
```

## 3. CTR/CVR Prediction : DCN + Two Tower

### *3.1 Overview & Design Philosophy*

Predicting whether a user will click on an ad (CTR) and, given a click, whether they will convert (CVR) are the two foundational prediction tasks in digital advertising. These predictions serve as the primary signals driving both the bid optimizer and the creative selection system.

The system adopts a two-model architecture - a separate model for CTR and CVR rather than a joint model. This design choice is motivated by the fundamental difference in training data: CTR has access to all impressed users (click or not click), while CVR is conditioned on click and thus operates on a much smaller, selection-biased dataset. Separate models allow each to be optimized independently for its specific data distribution.

### *3.2 CTR Prediction - Deep & Cross Network (DCN)*

The Deep & Cross Network is chosen for CTR prediction because it explicitly models feature interactions of arbitrary order through its cross network, while simultaneously learning high-level representations through the deep network. This is particularly valuable in advertising where second and third order feature interactions (e.g., 'user-category-affinity AND product-category must match AND time-is-weekend') are highly predictive but difficult to specify manually.

#### 3.2.1 Cross Network Formulation

**Cross Network** is the part of the model that automatically learns *combinations* of features like "mobile user AND evening time AND sports content", which are far more predictive than any single feature alone. The Cross Network forces it to learn them explicitly and efficiently.

Cross Network sits *before* XGBoost as a feature enrichment step:

Raw features → [Cross Network] → Enriched features → XGBoost → bid multiplier

The Cross Network's job is to create those high-value combination features so XGBoost doesn't have to figure them out from scratch. This is why DCN-V2 consistently outperforms plain deep networks for CTR/bid prediction at scale.

3.2.2 Class Imbalance Handling

In ad datasets, click-through rates are between 1-3%, creating a class imbalance (97-99% negative examples). This can be address with a combination of negative down-sampling and calibrated probability output:

- Negative Down-Sampling: During training, negative examples (no click) are down-sampled at ratio r = 0.1 (retain 10% of negatives), effectively balancing the training set to 50:50 positive/negative.
- Calibration Correction: Post-training predicted probabilities are re-calibrated to account for the down-sampling using the formula.

$$p_{true} = p_{raw} / (p_{raw} + (1 - p_{raw}) / r)$$

$p_{raw}$ = Model prediction on down-sampled data
r = Negative sampling rate (e.g., 0.1)
$p_{true}$ = Corrected probability (real-world CTR)

### *3.3 CVR Prediction - Two Tower Network*

The Two Tower architecture is adopted for CVR prediction due to its efficiency advantage: the item (ad) tower can be pre-computed and cached, dramatically reducing inference-time computation. Only the user tower needs to be evaluated in real time.

Architecture Design

The model consists of two independent neural towers that produce L2-normalized embedding vectors, with the final CVR score computed as the dot product (cosine similarity) between the user and item representations.

$$p(\text{convert} \mid \text{click}) = \sigma(u(x_{user}) \cdot v(x_{item}))$$

| Expression | Meaning | Explanation |
|---|---|---|
| p(convert \| click) | Probability of conversion given a click | Likelihood that the user completes a purchase after clicking the ad |
| σ(·) (sigmoid function) | Logistic activation function | Converts the similarity score into a probability between 0 and 1 |
| $u(x_{user})$ | User tower embedding vector | Dense representation of the user based on features such as purchase history, browsing behavior, device type, and session context |
| $v(x_{item})$ | Item (ad) embedding vector | Dense representation of the advertisement or product including category, advertiser, creative attributes, and campaign metadata |
| $u(x_{user}) \cdot v(x_{item})$ | Dot product between embeddings | Measures similarity between user preferences and item characteristics |

- The user tower produces a vector representing user intent or preference.
- The item tower produces a vector representing product/ad characteristics.
- The dot product measures how well the ad matches the user's intent.
- The sigmoid function converts this score into a conversion probability.

Higher similarity ⇒ higher probability of conversion

| Tower | Input Features | Architecture | Pre-Computable? |
|---|---|---|---|
| User Tower | User ID embedding, purchase history (7-day), session category, device, time of day, prior CVR | Embedding(256) -> 3x Dense(128, ReLU) -> L2-norm(128) | No, Its real-time |
| Item Tower | Ad ID embedding, product category embedding, advertiser ID, creative ID, campaign objective flag | Embedding(256) -> 3x Dense(128, ReLU) -> L2-norm(128) | Yes, cached in Redis |

### *3.4 Combined pCTR * pCVR Score*

The outputs of the DCN (pCTR) and Two Tower (pCVR) models are combined into a single expected value score used by both the bid optimizer and creative selector:

$$eCPM = pCTR \times pCVR \times CPC_{value} \times 1000$$

This eCPM estimate represents the expected revenue per 1000 impressions if this ad is served to this user and is the primary optimization target for bid adjustment.

Higher eCPM justifies a higher bid multiplier from the XGBoost model.

## 4. Creative Optimization : Thompson Sampling

### *4.1 Problem Formulation : Multi-Armed Bandit*

Creative selection is a classic exploration-exploitation problem: the system has K creative variants for a given campaign and must decide which to serve on each impression. Serving the historically best-performing creative all the time risks missing a better variant that has not received enough impressions. Serving uniformly at random wastes impressions on known underperformers.

This is formalized as a stochastic K-armed bandit problem, where each creative k has an unknown true CTR parameter $theta_k$, and the goal is to maximize the total expected clicks over N impressions (equivalent to minimizing cumulative regret vs the optimal arm). (How far is my strategy from the ideal strategy.)

$$Regret(N) = N \cdot \theta^* - \Sigma\_\{t=1\}\^\{N\} \theta\_\{a\_t\}$$

$$N \cdot \theta = \textit{Best Possible Reward}$$

$$\Sigma_{t=1}^{N} \theta_{a_t} = \textit{Actual Reward}$$

### *4.2 Thompson Sampling*

Thompson Sampling is selected as the bandit algorithm due to its strong theoretical guarantees (O (sqrt(KN log N)) regret bound), and simplicity of implementation which is used to balance **exploration vs. exploitation** when making sequential decisions under uncertainty.

Thompson Sampling maintains a *probability distribution* representing uncertainty about each option instead of tracking just a single "best guess" for each option's reward probability. At every step, it samples from those distributions and picks the option whose sample is highest, naturally exploring more when uncertain, and exploiting when confident.

#### 4.3.1 State Storage

Each creative's (alpha, beta) state pair is stored in Redis as a lightweight 2-integer record. The full state for a campaign with K=10 creatives requires only 20KB of Redis storage.

```
# Redis key schema
# Key:   creative_state:{campaign_id}:{creative_id}
# Value: JSON { 'alpha': int, 'beta': int, 'last_updated': timestamp }

FUNCTION get_creative_state(campaign_id, creative_id):
    key = build_key("creative_state", campaign_id, creative_id)
    state = REDIS.get(key)

    IF state exists:
        RETURN deserialize(state)        # { alpha, beta, last_updated }
    ELSE:
        RETURN { alpha: 1, beta: 1 }     # Uniform prior — no data yet

# Thompson Sampling Selection
FUNCTION select_creative(campaign_id, creative_ids):
    samples = []

    FOR EACH creative_id IN creative_ids:
        state  = get_creative_state(campaign_id, creative_id)
        sample = DRAW from Beta(state.alpha, state.beta)   # One random draw
        samples.APPEND( (sample, creative_id) )

    RETURN the creative_id with the HIGHEST sample value    # argmax

# Posterior Update
FUNCTION update_posterior(campaign_id, creative_id, reward):  # reward: 1=click, 0=no-click
    key   = build_key("creative_state", campaign_id, creative_id)
    state = get_creative_state(campaign_id, creative_id)

    IF reward == 1 (click observed):
        state.alpha += 1                 # Strengthen belief in success
    ELSE (no click):
        state.beta  += 1                 # Strengthen belief in failure

    state.last_updated = NOW()
    REDIS.set(key, serialize(state))      # Persist updated belief
```

#### 4.3.2 Cold Start & Minimum Exploration

- Cold Start: New creatives initialize with alpha=1, beta=1 (uniform prior). This gives them positive probability of selection immediately. However, to ensure each new creative receives at least 200 impressions before exploitation dominates, a warm-up override forces uniform rotation for the first 200 impressions per creative per campaign.
- Minimum Exploration Floor: To prevent complete exploitation of a single dominant creative (which would inhibit detection of future-uploaded creative variants), a minimum exploration rate of 5% is enforced. If Thompson Sampling assigns >95% of traffic to one arm, the remaining arms are given 1% each.
- Periodic Reset for Seasonal Campaigns: For campaigns with strong seasonality (e.g., holiday promotions), posteriors can be partially reset (alpha, beta both halved) at key season boundaries to allow faster adaptation to new audience behavior.

### *4.4 Multi-Objective Reward Extension*

This formulation extends a standard **Thompson Sampling (Beta-Bernoulli)** framework from a single objective (CTR) to a **dual-objective setting** that incorporates both **clicks and conversions**.

r_composite = w1 * r_click + w2 * r_convert

With default weights w1=0.3, w2=0.7 for conversion-optimized campaigns (reflecting that conversions are ~10x more valuable than clicks in revenue terms).
This ensures:

- Conversions dominate optimization
- Clicks still provide early learning signal

## 5. Integrated Stack Performance

### *5.1 Additive Performance Contribution*

The three systems are designed to be complementary:
CTR/CVR prediction feeds into bid optimization
Creative selection amplifies the value of won impressions
Bid optimizer ensures campaigns pace correctly to maintain delivery without under or overspending.
The combined effect exceeds the sum of individual contributions.

### *5.2 Latency Impact in Production*

| Component | Latency Added (p50) | Latency Added (p99) | Mitigation Strategy |
|---|---|---|---|
| Feature Retrieval (Redis hit) | 2ms | 4ms | Redis cluster with 2-replica failover |
| CTR/CVR Prediction (DCN) | 5ms | 8ms | GPU inference; ONNX model optimization; batch size=1 |
| Bid Optimizer (XGBoost) | 1ms | 3ms | CPU-only; ONNX runtime; pre-loaded in memory |
| Creative Selection (MAB) | <1ms | 1ms | In-process Redis read + numpy beta sampling |
| Total AI Overhead | ~9ms | 16ms | Well within 30ms SLA |
| Total Response Time (with base) | 18ms | 27ms | 3ms margin to SLA |

## 6. Limitations & Future Work

### *6.1 Known Limitations*

- Feedback Delay: Conversion events are attributed 24-72 hours after the impression, creating a training data lag. The bid optimizer and Two Tower CVR model are trained on data that is always at minimum 24 hours old. This limits responsiveness to very recent behavioral shifts.
- User Cold Start: Users with no purchase history default to median feature values, resulting in suboptimal bid adjustments and creative selection. Approximately 20-30% of daily traffic represents cold-start users on typical retail platforms.
- Counterfactual Bias in Bid Training: The IPS counterfactual approach for training labels introduces variance when the counterfactual bid deviates significantly from the observed bid. This can lead to unstable training for extreme bid multiplier values.
- Thompson Sampling Stationarity Assumption: The standard Beta-Bernoulli model assumes a stationary reward distribution. For creatives that undergo design changes or campaigns with strong seasonality, the posteriors should be periodically reset (as noted in Section 4.3.2) but the optimal reset schedule is empirical.

### *6.2 Future Enhancements*

- Contextual Bandit for Creative Selection: Extend Thompson Sampling to LinUCB or Neural Bandit to enable context-dependent creative selection, serving different creatives to different user segments, devices, and time windows.
- Online Learning for Bid Optimizer: Replace daily-retrain-only XGBoost with an online gradient boosting variant (e.g., River library) that updates model weights per observation, enabling same-day adaptation to market shifts.
- Multi-Task Learning Architecture: Merge CTR and CVR prediction into a single multi-task model sharing lower layers, reducing total model count from 2 to 1 and enabling joint calibration across click and conversion signals.
- Auction-Theoretic Bid Shading: Incorporate a probabilistic model of the second-price auction to implement bid shading, reducing the submitted bid below the true valuation to improve average CPM paid in first-price or hybrid auction environments.

## Conclusion

This article has presented a cohesive AI optimization stack for the Ad Server component of a Retailer Media Platform, comprising three complementary systems: an XGBoost Bid Optimizer, a DCN + Two Tower CTR/CVR Prediction Engine, and a Thompson Sampling Creative Selector. Each system has been specified at the mathematical and engineering implementation level, with explicit attention to the sub-30ms real-time inference constraint that governs all design decisions.

The three systems are mutually reinforcing: CTR/CVR predictions improve the quality of bid optimization decisions; the bid optimizer ensures campaigns are correctly paced to make full use of creative performance gains; and the creative selector amplifies the value of impressions won at the optimized bid level. Together, they are projected to deliver a 42% CTR improvement, 23% ROAS improvement, and 22% CPM reduction versus the static baseline, a compelling business case for investment.

The limitations documented in Section 6 define a clear research and engineering agenda for more enhancements, ensuring the system continues to improve as data accumulates and the platform scales.

**References**

Wang, R. et al. (2021). DCN V2: Improved Deep & Cross Network and Practical Lessons for Web-Scale Learning to Rank Systems. WWW 2021.
Yi, X. et al. (2019). Sampling-Bias-Corrected Neural Modeling for Large Corpus Item Recommendations. RecSys 2019.
Chapelle, O. & Li, L. (2011). An Empirical Evaluation of Thompson Sampling. NeurIPS 2011.
Thompson, W.R. (1933). On the Likelihood that One Unknown Probability Exceeds Another in View of the Evidence of Two Samples. Biometrika, 25(3/4), 285-294.
Chen, T. & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. KDD 2016.
Bottou, L. et al. (2013). Counterfactual Reasoning and Learning Systems: The Example of Computational Advertising. JMLR 14, 3207-3260.
Cai, H. et al. (2017). Real-Time Bidding by Reinforcement Learning in Display Advertising. WSDM 2017.
Graepel, T. et al. (2010). Web-scale Bayesian Click-Through Rate Prediction for Sponsored Search Advertising in Microsoft's Bing Search Engine. ICML 2010.