# Strategic Pricing Architecture & Predictive Modeling for Collegiate Athletics: A Five-Year Optimization Framework

## 1. Executive Strategic Overview

The collegiate athletic landscape is currently navigating a period of unprecedented economic volatility and opportunity. Athletic departments are no longer merely administrative bodies; they are sophisticated enterprise entities that must balance the mission of student-athlete development with the rigors of financial sustainability. In this context, ticket pricing—traditionally an art governed by historical precedent and intuition—must evolve into a science governed by predictive analytics and algorithmic optimization.

This report serves as a comprehensive blueprint for the University of Toledo Athletic Department to transition from static, cost-plus pricing models to a dynamic, value-based pricing architecture. The mandate is clear: to develop a machine learning framework capable of predicting the "actual average ticket price" (intrinsic market value) before administrative markups, and subsequently, to engineer a five-year pricing trajectory that targets a specific terminal value while adhering to inflationary and retention constraints.

The challenge is multi-dimensional. Unlike professional sports franchises, which operate with a profit-maximization mandate, collegiate pricing is complicated by the "Town and Gown" dynamic, where community engagement is as critical as revenue generation. Furthermore, the pricing structure is bifurcated into the "Base Price" (the transactional cost of the seat) and the "Markup" (the philanthropic priority seating contribution, or Rocket Fund donation). Disentangling these components to reveal the true market elasticity of the seat itself requires a sophisticated decomposition methodology.

Our analysis leverages the provided data schema—a rich tapestry of fields including season\_code, price\_type, pr\_level, and item\_code—to construct a dual-engine model. The first engine, utilizing Gradient Boosted Decision Trees (XGBoost), will isolate the baseline willingness-to-pay (WTP) for every seat in the Glass Bowl and Savage Arena. The second engine, a constrained optimization solver, will chart the optimal path from current pricing to the Year 5 target, ensuring that the 3% annual inflationary floor is met without triggering mass churn among loyal season ticket holders.

This report is structured to guide the Data Science and Ticket Sales teams through every phase of this transformation, from data forensics and feature engineering to algorithmic selection and strategic implementation. By adopting this rigorous approach, the department can expect not only to hit its 5-year revenue targets but to do so while enhancing fan satisfaction through transparent, value-aligned pricing.

## 2. The Data Ecosystem: Forensics and Schema Analysis

The foundation of any high-fidelity pricing model is the integrity and granularity of its input data. The provided text file 1 reveals a complex, albeit fragmented, ticketing taxonomy that reflects years of evolving business rules, promotional strategies, and donor classifications. To build a predictive model capable of isolating the "actual average ticket price," we must first semantically map these fields to economic variables.

### 2.1 Deconstructing the Temporal Identifiers: season\_code and event\_code

The field season\_code (e.g., "BB26", "FB23", "VB24") serves as the primary temporal anchor for the dataset. In a predictive modeling context, this cannot be treated merely as a categorical label or a simple bucket for aggregation. It must be decomposed into sequential time-series features that capture the trajectory of the program. "FB23" (Football 2023) and "BB24" (Basketball 2024) represent distinct demand cycles influenced by the team's performance in the preceding season.

#### 2.1.1 The Momentum Variable

Predictive models for sports ticketing are heavily dependent on "program momentum." A season following a Mid-American Conference (MAC) Championship—such as Toledo's recent football successes—carries a "championship premium" latent variable that significantly alters the price elasticity of demand. If we simply treat "FB23" as a category, the model loses this context.

* **Strategic Implication:** The model must transform season\_code into continuous variables such as Seasons\_Since\_Championship and Winning\_Percentage\_Lag1 (the winning percentage of the previous season).2
* **Data Enrichment:** We must join external performance data to the season\_code. For example, linking "FB24" to the previous year's 11-3 record creates a signal that justifies a higher starting base price than a season following a 6-6 record.

#### 2.1.2 The Micro-Economy of event\_code

The event\_code (e.g., "MB01", "WB05", "F01") represents specific games or events. In the context of the MAC, not all events are created equal. The variation in demand between a Saturday afternoon homecoming game and a Tuesday night "MACtion" game in November is drastic.

* **Granularity:** "MB01" might be a non-conference basketball game against a lower-tier opponent, while "MB08" could be the rivalry game against Bowling Green (The Battle of I-75).3 Treating these as equivalent data points in an "average price" calculation would skew the results.
* **Feature Engineering:** The model must utilize event\_code to pull external metadata. This includes the Opponent's NET Ranking (for basketball), Opponent FPI (for football), and critically, the Day of Week. Research indicates that mid-week games, while valuable for television revenue, often suffer from lower intrinsic ticket demand due to the inconvenience for working families.4 The model must account for this by applying a negative weight to Tuesday/Wednesday event\_codes.

### 2.2 The Inventory Hierarchy: item\_code and pr\_level

The item\_code (e.g., "FLEX", "MBS", "F01CHB") and pr\_level (e.g., "Club", "Rocket Fund - Zone A", "General Admission") are the critical determinants of the base price.

#### 2.2.1 Decoding pr\_level for Valuation

The pr\_level field is the Rosetta Stone for understanding the "Markup" vs. "Base Price" dilemma. The presence of explicitly named tiers like "Rocket Fund - Zone A" through "Zone C" and "Club" confirms a priority seating model where the *effective price* paid by the consumer is a composite of the ticket cost and the required donation.

* **Segmentation Strategy:** The model must separate rows based on pr\_level before training. A "Suite" data point (e.g., Inner Suite $37,800) operates on a completely different demand curve than "Women's General Admission" ($110). Lumping these together to find a single "average" would result in a meaningless metric.
* **Target Encoding:** Instead of generic one-hot encoding, we will use Target Encoding for pr\_level. We replace the categorical level with the historical average yield of that section. This preserves the ordinal nature of seat quality (e.g., Courtside > Lower Reserved > Upper Reserved) and helps the tree-based model understand the hierarchy of value immediately.5

**Table 1: Strategic Mapping of pr\_level to Economic Value Tiers**

| **pr\_level Category** | **Examples from Dataset** | **Economic Characteristic** | **Modeling Strategy** |
| --- | --- | --- | --- |
| **Luxury / Premium** | "Inner Suite (505-510)", "Loge", "Club" | Highly Inelastic Demand. Status-driven. | Model as separate cluster. Price sensitivity is low; focus on amenity value. |
| **Donor Priority** | "Rocket Fund - Zone A", "Rocket Fund - Zone B" | Composite Good (Ticket + Donation). | Decompose Total Price. Model Base Price elasticity separately from Donation elasticity. |
| **Standard Reserved** | "Lower Reserved", "Sideline A", "West Reserved" | Elastic Demand. Value-driven. | Core training set for "Market Price" prediction. High volume data. |
| **Economy / Entry** | "General Admission", "Bleachers", "Upper Reserved" | Highly Elastic. Price-sensitive. | Focus on volume maximization. "Loss leader" strategy potential. |

#### 2.2.2 The item\_code Nuance

The item\_code often differentiates between full season packages ("MBS" - Men's Basketball Season) and single items ("MB01"). The user request asks for "price per season... and then price per game."

* **Linkage:** We must create a relational map where the sum of the predicted prices for individual event\_codes (e.g., MB01...MB15) is compared against the predicted price for the bundled item\_code (MBS).
* **The Discount Arbitrage:** Typically, a season ticket (item\_code = MBS) is priced at a discount relative to the sum of single games to incentivize the upfront capital commitment. The model must learn this "bundling discount" factor (typically 20-30%) and apply it when generating the 5-year plan for season tickets.6

### 2.3 The Transactional Context: price\_type

The price\_type field is highly granular, containing over 200 unique values in the dataset.1 Analyzing this field is crucial for filtering out "noise" transactions that do not reflect true market value.

#### 2.3.1 The "Grogan" Factor

Multiple price types reference "Grogan" (e.g., "Transfer Full Price - Grogan", "Season F/S - Grogan"). Research confirms this refers to the **Joe Grogan Room**, a premium hospitality area in Savage Arena available to donors at the Gold level ($600+).7

* **Bundled Utility:** Transactions labeled "Grogan" represent a bundled product (Ticket + Hospitality + Status). The model must not conflate "Grogan" prices with standard "Lower Reserved" prices, even if the view of the court is similar. The "Grogan" tag adds a *hospitality premium* that must be isolated.
* **Flagging Methodology:** We will create a binary feature Is\_Hospitality derived from price\_type. If the string contains "Grogan" or "Club", the value is 1. This allows the algorithm to learn the specific dollar value attributed to the hospitality component.

#### 2.3.2 Filtering Internal and Discounted Codes

Price types such as "Transfer", "Comp", "Faculty/Staff" (F/S), and "Student Guest" represent subsidized or internal pricing mechanisms.

* **Exclusion Logic:** For the purpose of predicting the *optimal market price* to charge the general public, these rows should be excluded from the training set or weighted significantly lower. Training a pricing model on "$40 Faculty/Staff" tickets 8 when the public price is $100 would artificially depress the predicted optimal price.
* **The "Full Price" Standard:** The "Full Price" and "Day of Full Price" codes represent the purest signal of unconstrained consumer willingness to pay. These transactions will form the "Gold Standard" training subset.

## 3. Disentangling Price vs. Markup: The "Decomposition" Methodology

The user explicitly requests a model to "predict the actual average ticket price... before the markup." In the context of collegiate athletics, "markup" is a nuanced term that principally refers to the **Priority Seat Contribution (PSC)**—the mandatory donation required to purchase the ticket.9

### 3.1 The Structural Components of Price

Toledo's pricing architecture 8 confirms a tiered model where the total cost to the fan is the sum of two distinct financial instruments:

$$P\_{Total} = P\_{Base} + D\_{Required} + F\_{Fees}$$

1. **Base Price ($P\_{Base}$):** The face value of the ticket. This is the transactional revenue recognized immediately by the ticket office. It is often kept artificially low to maintain the appearance of affordability.
2. **Markup / Donation ($D\_{Required}$):** The "Rocket Fund" contribution required to access specific zones (e.g., Zone A, Zone B). This is philanthropic revenue, often tax-deductible (historically 80%, though tax laws have evolved) 12, and accrues to the athletic development arm.
3. **Fees ($F\_{Fees}$):** Ancillary facility fees or processing charges.

### 3.2 The "Intrinsic Value" Problem

The core challenge is that the $P\_{Base}$ often does not reflect the true economic value of the seat. For example, a Zone A seat might have a $P\_{Base}$ of $240, identical to a Zone B seat, but Zone A requires a $600 donation while Zone B requires $300.

* *The Fan's Perspective:* The fan does not care about the accounting split; they care about the **Total Cost of Ownership (TCO)**. They are paying $840 for Zone A and $540 for Zone B.
* *The Model's Objective:* To predict the "actual average ticket price before markup," we are essentially trying to model $P\_{Base}$. However, if we simply train a model on historical $P\_{Base}$, we will just learn the university's past administrative decisions (which were likely static), not the *market's* valuation.

### 3.3 The Analytical Solution: The "Effective Price" Method

To truly answer the user's need for an *optimized* base price, we must first model the **Total Willingness to Pay (WTP)** for the seat, and then subtract the fixed donation component.

Step 1: Construct the Total Effective Price ($P\_{Eff}$)

For every historical transaction in the dataset, we calculate the effective price paid by the consumer.

$$P\_{Eff} = \text{Paid\\_Amount} + \text{Imputed\\_Donation}$$

We derive Imputed\_Donation by mapping the pr\_level to the historical Rocket Fund brochure data.11

* If pr\_level == "Rocket Fund - Zone A", Imputed\_Donation = $600.
* If pr\_level == "General Admission", Imputed\_Donation = $0.

Step 2: Train the ML Model on $P\_{Eff}$

We train our machine learning model (XGBoost) to predict $P\_{Eff}$ based on seat quality, opponent, date, and team performance. This gives us the True Market Value of the seat location.

Step 3: Derive the Optimal Base Price ($P\_{Opt\\_Base}$)

Once the model predicts the True Market Value ($P\_{True}$), we calculate the optimal base price for the 5-year plan by subtracting the planned donation levels.

$$P\_{Opt\\_Base} = P\_{True} - D\_{Planned}$$

This approach ensures that the "Base Price" we recommend is not just a random number, but a residual value derived from the market's total valuation of the experience, accounting for the "markup" (donation) that the department intends to charge.

## 4. Machine Learning Model Selection & Architecture

The task of predicting ticket prices based on tabular data (CSV fields) with a mix of categorical and numerical features requires a specific class of algorithms. While Deep Learning (Neural Networks) generates buzz, **Gradient Boosted Decision Trees (GBDT)** are widely considered the state-of-the-art for structured tabular data problems of this nature.

### 4.1 Recommendation: XGBoost (Extreme Gradient Boosting)

After reviewing the research snippets regarding comparative model performance 13, we definitively recommend **XGBoost** over LSTM or Linear Regression for this specific application.

#### 4.1.1 Why XGBoost?

1. **Tabular Supremacy:** Ticket sales data is structured—rows of transactions with defined columns. Research consistently shows that for datasets with fewer than 10 million rows (typical for university ticketing databases), tree-based ensembles like XGBoost outperform Deep Learning models in both accuracy and training speed.13
2. **Handling Categorical Nuance:** The dataset is heavy on categoricals (event\_code, price\_type, item\_code). XGBoost can handle these efficiently, especially when paired with techniques like target encoding, without exploding the dimensionality of the data as One-Hot Encoding would for high-cardinality fields.
3. **Interpretability via Feature Importance:** It is crucial for the Ticket Office to understand *why* the model predicts a price. XGBoost provides "Feature Importance" scores (Gain/Cover), allowing us to report specific insights: "Section 104 is priced high primarily because of the pr\_level=Club factor, but the model suggests a discount for Tuesday games because the Day\_of\_Week feature has a strong negative weight." This explainability is critical for stakeholder buy-in, which is often lost in "black box" Neural Networks.16
4. **Handling Sparsity and Missing Data:** Ticket sales data is often sparse (e.g., premium price types might not exist for every game). XGBoost has built-in mechanisms to handle missing values (sparsity-aware split finding).17

### 4.2 Alternative Models Considered and Rejected

* **Linear Regression (OLS):** While interpretable, OLS fails to capture the non-linear relationships in ticketing. Demand does not drop linearly with price; it often "cliffs" at psychological thresholds (e.g., crossing $100). OLS cannot model these distinct regimes effectively.
* **LSTM / RNN:** These are excellent for pure time-series forecasting (e.g., stock prices). However, ticket pricing is not a pure time series. A football game in 2024 against Bowling Green is more similar to a game in 2022 against Bowling Green than it is to the game *last week* against a generic opponent. The sequential dependency is weak compared to the *structural* dependency (opponent quality, seat location). Using LSTM would be overfitting and data-inefficient.18

### 4.3 Model Architecture and Feature Engineering Pipeline

The success of the XGBoost model depends on the quality of the input features. We propose the following feature engineering pipeline:

**Table 2: Feature Engineering Specification**

| **Feature Name** | **Type** | **Derived From** | **Transformation Logic** | **Rationale** |
| --- | --- | --- | --- | --- |
| Season\_Momentum | Continuous | season\_code | Calculate Winning\_Pct\_Lag1 (Last season's win %) and Seasons\_Since\_Championship. | Captures the "hype" factor driving demand. |
| Opponent\_Tier | Categorical | event\_code | Map opponent names to tiers: 1 (Rival/P5), 2 (MAC Top), 3 (MAC Bottom), 4 (FCS). | Not all games are equal; creates demand variance. |
| Is\_Rivalry | Binary | event\_code | 1 if opponent is BGSU or NIU; 0 otherwise. | Specifically targets the high-demand rivalry premiums.3 |
| Day\_Condition | Categorical | event\_code | Weekend (Sat/Sun) vs. Weekday (Mon-Fri). | Critical for analyzing the negative impact of "MACtion" mid-week games.4 |
| Seat\_Value\_Index | Ordinal | pr\_level | Rank order zones (1=Bleacher to 10=Suite). | Provides the model with the hierarchy of physical inventory. |
| Donation\_Load | Continuous | pr\_level | The $ amount of donation required for this zone. | Allows model to understand the *total* cost burden on the fan. |
| Inflation\_Index | Continuous | External | CPI value for the transaction year.19 | Normalizes historical prices to current dollars. |

## 5. The 5-Year Strategic Optimization Engine

Once the XGBoost model provides the "True Market Value" (the baseline), we must project this forward. The user requires a **5-Year Plan** with a target price at Year 5, subject to a 3% inflation floor. This transitions the problem from *prediction* to *constrained optimization*.

### 5.1 Defining the Objective Function

We assume the strategic goal is to **Maximize Total Revenue** over the 5-year period while hitting the target price. If we simply raise prices linearly to hit the target, we might overshoot demand elasticity in Year 2 or 3, causing a collapse in attendance that creates a "dead stadium" atmosphere, hurting long-term brand value.

**Objective:** Maximize $R\_{total} = \sum\_{t=1}^{5} (P\_t \times D(P\_t))$

Where:

* $P\_t$ is the price in Year $t$.
* $D(P\_t)$ is the Demand function (estimated via the Price Elasticity derived from the XGBoost model).

### 5.2 The Constraints

1. **Terminal Constraint:** $P\_5 = P\_{target}$ (The user's specific goal, e.g., reaching a $300 base price for Zone A).
2. **Inflation Floor Constraint:** $P\_t \ge P\_{t-1} \times 1.03$ (Prices must rise by *at least* 3% annually to cover rising operational costs).
3. **Churn Ceiling (The "Shock" Limit):** $P\_t \le P\_{t-1} \times 1.15$. Research suggests that price hikes exceeding 15% in a single year trigger a "shock" response, leading to mass non-renewal (churn).20 This constraint smooths the trajectory.
4. **Monotonicity:** $P\_t \ge P\_{t-1}$ (Prices should never decrease in this specific 5-year growth plan).

### 5.3 The Solver: Sequential Least Squares Programming (SLSQP)

We recommend using the scipy.optimize.minimize function in Python with the **SLSQP** method. This algorithm is specifically designed to handle complex non-linear optimization problems with both equality constraints (Target Price) and inequality constraints (Inflation Floor, Churn Ceiling).22

Mathematical Formulation for the Solver:

Let $x = [P\_1, P\_2, P\_3, P\_4, P\_5]$ be the vector of prices for the 5 years.

Minimize: Negative Revenue (standard optimization practice)

$$f(x) = - \sum\_{t=1}^{5} (x\_t \times \text{Predicted\\_Sales}(x\_t))$$

**Subject to:**

1. $x\_5 - P\_{target} = 0$ (Equality Constraint)
2. $x\_t - 1.03 \times x\_{t-1} \ge 0$ for $t=2..5$ (Inequality Constraint - Inflation)
3. $1.15 \times x\_{t-1} - x\_t \ge 0$ for $t=2..5$ (Inequality Constraint - Churn Cap)

This mathematical rigor ensures that the "5-year plan" is not just a spreadsheet exercise, but a chemically balanced trajectory that extracts maximum value without breaking the bond with the fan base.

## 6. Granularity Level 1: Season Ticket Pricing Strategy

The "Season Ticket" is the lifeblood of the athletic department's financial stability. The data provided includes extensive reference to season packages (item\_code = "MBS", "FBP") and their renewal structures.

### 6.1 Retention Modeling and Churn

For season tickets, the primary metric is **Renewal Rate**. The 5-year plan must account for the fact that every price increase carries a probability of churn.

* **The "Lock-In" Effect:** Recent industry trends, such as those seen at Northern Illinois (a MAC peer), involve "locking in" prices for multi-year commitments.24
* **Strategy:** The model should incorporate a **Retention Decay Function**. If the price increases by 3%, retention might stay at 95%. If it increases by 10%, retention might drop to 88%.
* **Variable Pricing Tiers:** The "Inner Suite" ($37,800) represents a B2B (Business-to-Business) relationship. These clients are less sensitive to price but highly sensitive to *value* (networking, amenities). The 5-year plan for Suites should focus on "Value-Add" inflation (adding parking passes, exclusive access) to justify the 3% hike, rather than just raising the price. Conversely, the "Women's General Admission" ($110) is a B2C (Business-to-Consumer) volume play. The 5-year plan here should be conservative, perhaps freezing the price for Years 1-3 to build the base, then applying a step-increase in Year 4.

## 7. Granularity Level 2: Single Game Dynamic Pricing

The user request specifically asks for "price per game per seat per sport." While the 5-year plan governs season tickets, the single-game inventory requires a **Dynamic Pricing** approach.

### 7.1 The "MACtion" Paradox

The Mid-American Conference is unique due to its television contract which shifts games to Tuesday and Wednesday nights in November ("MACtion").4

* **Pricing Implication:** These games offer high national TV exposure but suffer from low in-person attendance due to the inconvenience.
* **Model Adjustment:** The XGBoost model will likely predict a significantly lower *intrinsic value* for event\_codes corresponding to Tuesday nights.
* **Strategy:** The pricing model should not apply the 5-year increases uniformly. We recommend a **Variable Pricing Tier**:
  + **Tier 1 (Saturday Rivalry/Homecoming):** Premium Pricing. Apply a 20-30% markup over the base.
  + **Tier 2 (Saturday Standard):** Base Pricing.
  + **Tier 3 (MACtion/Mid-Week):** Discount Pricing. These games should be priced near the floor to maximize volume (attendance), which drives ancillary revenue (concessions, parking) and looks better on TV.25

### 7.2 The Rivalry Premium

The data confirms that games against Bowling Green (BGSU) and Northern Illinois (NIU) are statistical outliers in terms of demand.3

* **Actionable Insight:** The optimization model should automatically flag these event\_codes. For the 5-year plan, we can aggressively forecast price increases for these specific matchups at a rate higher than inflation (e.g., 5-7%), as the emotional WTP for a rivalry game is highly inelastic.

## 8. External Factors & Market Context

Toledo, Ohio operates in a specific economic and climatological reality that the model must respect.

### 8.1 Weather and Attendance

The "Glass Bowl" is an outdoor stadium. November in Toledo averages highs of 50°F and lows of 34°F.27

* **Impact:** Demand degrades linearly as temperature drops. The model must include Forecasted\_Temperature (using historical averages for the 5-year plan) as a feature.
* **Strategic Response:** For late-season games, the pricing strategy should pivot from "Revenue Maximization" to "Yield Management"—lowering prices to ensure bodies in seats, or bundling tickets with warm-weather merchandise (e.g., "The Beanie Bundle").

### 8.2 Economic Constraints

Lucas County economic indicators 28 suggest a price-sensitive local population. The "Women's General Admission" price of $110 is an accessible entry point that must be protected. Aggressive price hikes in the "Economy" tiers could price out the local community, damaging the "Team Toledo" brand equity.29

## 9. Technical Implementation Roadmap

To operationalize this research, the Data Science team should follow this execution path:

### Phase 1: Data Pipeline Construction (Weeks 1-4)

* Ingest the CSV file corresponding to.1
* Execute the "Decomposition Methodology" to strip donations from base prices.
* Enrich data with external weather 27 and rivalry 30 datasets.

### Phase 2: Model Training (Weeks 5-8)

* Train the XGBoost Regressor to predict Base\_Price\_Yield.
* Validate using Time-Series Cross-Validation (train on 2019-2023, test on 2024).
* Extract Price Elasticity coefficients for each pr\_level.

### Phase 3: The 5-Year Solver (Weeks 9-10)

* Implement the scipy.optimize.minimize routine.
* Define the Revenue\_Function using the elasticity curves from Phase 2.
* Set the constraints: $P\_5 = P\_{Target}$, $Inflation = 3\%$.
* Run the solver to generate the optimal price vector $[P\_1, P\_2, P\_3, P\_4, P\_5]$.

### Phase 4: Deployment & Dashboarding (Week 11+)

* Deploy the model into a dashboard for the Ticket Sales department.
* Allow sales reps to see the "Recommended Price" vs. "Floor Price" for every seat.

## 10. Conclusion

The transition to an AI-driven, optimized pricing model represents a significant leap in maturity for the University of Toledo Athletic Department. By moving away from "gut feel" pricing to a stochastic model that respects the distinct economics of the "Rocket Fund" donation versus the "Base Ticket," the department can unlock latent revenue without alienating its loyal fan base.

The proposed **XGBoost + Constrained Optimization** framework provides the necessary mathematical rigor to value inventory correctly. It accounts for the nuance of the "Grogan" hospitality experience, the "MACtion" attendance challenges, and the inelastic demand of the "Inner Suite" clientele. By adhering to the 5-year optimization trajectory, Toledo Athletics can confidently navigate the inflationary environment, ensuring that the target price is reached not by accident, but by design.

**Recommendation:** We advise an immediate pilot of this model for the upcoming Football renewal cycle, specifically targeting the "Lower Reserved" and "Rocket Fund Zone" segments where price elasticity is most stable and data volume is highest. This will serve as the proof-of-concept for the broader 5-year rollout.

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