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Data-Driven Pricing Strategies in Online Retail Platforms for Revenue Maximization

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Abstract- The rise of the internet has made pricing a much more dynamic process than ever before. In this paper, we propose an end-to-end solution to implement data-driven pricing optimizations through an integration of demand forecasting, price elasticity, and pricing optimization components. We build a multi-horizon forecasting model leveraging TFTs for accurate future demands forecasts, a product-level price elasticity model based on Bayesian structural time-series models, and a revenue maximization optimization engine to find optimal prices. Our methodology, trained on historical transaction data consisting of 5 million sales transactions for 10,000 SKUs over a 3-year period (2023-2025) achieved a revenue lift of 12.4% ($p<0.01$) in an A/B test versus two benchmark pricing methods such as cost-plus pricing (4.2% lift) and competitor-based pricing (6.1% lift). The paper concludes with a discussion of implementation challenges and practical guidelines for deploying algorithmic pricing in competitive retail environments.

Key Word: **Dynamic Pricing, Revenue Management, Demand Forecasting, Price Elasticity, E-commerce, Online Retail, Machine Learning, Temporal Fusion Transformers (TFT), Bayesian Structural Time Series (BSTS), Price Optimization.**

I. INTRODUCTION

In the highly competitive environment of the Internet retail, pricing is possibly the single most efficient and dynamic lever for creating sales and profits. While a conventional retailer can only change its prices in quarterly intervals, the Internet allows changing them millions of times daily based on a variety of criteria including changes in demand, competition, stock, and even personal customer needs [1]. Pricing strategy has therefore shifted from a long-term to a short-term affair. Yet, this power comes at the expense of complexity. Charging an excessive price results in depressed demand and loss of potential customers; charging too little leaves profit on the table and may harm reputation [2].

Indeed, the key challenge lies in predicting future demand – i.e. estimating the exact slope of the demand curve – as the optimal price is defined completely by the latter. The two approaches that dominate pricing – cost plus and competitive pricing – are static in nature and look backward, ignoring that the demand curve for each particular item is different [3]. Moreover, they cannot give an answer to the central question in pricing: What is the optimal price of this item to accomplish a particular goal?

A solution to this problem is algorithmic pricing based on data science. With the growth of transaction data, clickstream data, and competitor price data, advanced machine learning algorithms can now accurately predict the demand curve at various price levels [4]. Such a shift will enable businesses to be more proactive rather than reactive with respect to pricing.

This paper seeks to explore and address three major research questions:

1. Demand forecasting (RQ1): How do we create high-fidelity, multihorizon demand predictions that account for price, promotions, seasonality, and competitor activity?
2. Price elasticity estimation (RQ2): How do we accurately estimate product-level price elasticities using observational data, taking into consideration possible confounders such as promotions and special days/holidays?
3. Price optimization (RQ3): Given a demand curve and certain constraints (inventory, minimum margins, etc.), how do we determine an optimal price to optimize total revenues?

In order to address these questions, we propose a three-stage algorithmic pricing approach. The main contributions of our research include:

1. Modular Approach to an End-to-End Solution: We present a modular pipeline consisting of an industry-leading forecast generation model (Temporal Fusion Transformer), a causal model for elasticity estimation (Bayesian Structural Time Series), and a constrained optimization engine. We offer a fully-integrated solution that can be readily used in a production environment.
2. Empirical Testing on a Realistic Dataset: Our framework is tested using a proprietary dataset comprising 5 million transactions from an industry-leading e-commerce electronics retailer.
3. Statistical Testing of Revenue Lift through A/B Testing: We measure the effectiveness of our proposed approach through a 12-week, 10,000 SKU A/B test that yields a revenue lift of 12.4%.

II. LITERATURE SURVEY

The literature on pricing optimization is voluminous, covering economics, operations research, and increasingly machine learning. We distinguish between three main streams of research relevant to our approach.

Stream 1: Classical Pricing & Revenue Management (RM): The basic stream is rooted in airline and hospitality industry practices. Basic revenue management studies deal with capacity-limited products (such as seat on aircraft, a hotel room) and utilize methods such as dynamic programming to optimize prices over time [1]. One of the essential aspects of revenue management models is price elasticity, represented by a parametric model (such as a linear or log-linear relation). However, these models have an oversimplified view of the nature of the demand relationship and the independence of the demand process for each time period, which makes them inappropriate for rapidly changing Internet-based sales channels [2], [3]. Moreover, no consideration of unstructured data (competitors' prices, click-through rates of customers) is given.

Stream 2: Machine Learning for Estimating Demand & Elasticity: Big Data has led to a new wave of non-parametric, data-driven models. In terms of demand forecasting, studies have advanced past traditional models such as ARIMA to tree-based algorithms (Random Forest, XGBoost) and deep learning algorithms (LSTMs, Transformers) [5]. Temporal Fusion Transformers (TFT) stand out for their ability to conduct multi-horizon forecasts and offer transparent attention weights [4], [6]. As far as elasticity estimation goes, a problem with which many studies struggle is that of differentiating between correlation and causation (for example, we decrease the cost of our popular product, and our revenue rises, but did the change in cost drive the increased sales, or did something else happen?). Scientists are increasingly resorting to the use of causal machine learning models, including Debiased Machine Learning and Bayesian Structural Time Series, to ensure that no confounding effects skew their results [7], [8].

Stream 3: Algorithms for Price Optimization: Starting from the forecasted demand curve (or price-response functions), the goal is to find the optimal price that maximizes revenue. The easiest case to consider is when this becomes a static single-product optimization problem where prices are set using root finding (for example, marginal revenue equals marginal cost) [1]. Nevertheless, in practice, there are restrictions, such as minimum profit margins, inventory constraints, competitive pressure (prices should not be out of bounds of what is happening in the market), and business restrictions (price change up to X percent in a single day) [9], [10].

Research Gap and Synthesis: Although each of the modules (prediction, elasticities, optimization) has seen advances, there is still a research gap left untouched. Current academic literature largely looks at one module alone with simulation data. There is a need for a full framework combining the modules, validating on real large scale data sets, and ready to deploy in production. Our work directly addresses this research gap by proposing such a framework which we then validate using 5 million transactions and illustrate business value with an A/B experiment.

III. METHODOLOGY:

The proposed data-driven pricing approach consists of three stages.

Stage 1 is devoted to predicting future demand without considering any intervention on prices.

Stage 2 finds the causal effect of price change on that demand (i.e., elasticity).

Stage 3 is an optimization problem where the constraints are derived from stage 2, and the objective is revenue maximization.

3.1. Stage 1: Multi-Horizon Demand Forecasting (TFT)

Demand forecasting is defined as a time-series problem in this study. Specifically, the task is to forecast the number of units of product i sold on day t, i.e., Demand_{i,t}.

Features (X):

Time-related features: Day of the week, month, holiday flag.

Price of own item: Price of product i at time t.

Competitor's price: Average/minimum price of the same item on 2-3 competitor websites.

Promotions: Several binary features such as "on sale" or "email promotion active."

Lagged demand: Demand over the past 7, 14, and 28 days.

Product features: Product category, brand, average customer rating.

Model: Temporal Fusion Transformer (TFT): The TFT was chosen for its exceptional performance in multi-horizon forecasting problems involving multiple time series at once (one model for all items). The TFT has the following strengths: handling static covariates (product features); supporting future-known inputs (planned promotions); and providing interpretability via attention weights [4].

Algorithm 1: TFT Training Procedure

```
Input: Time series data D for all products, Historical window L=90 days, Forecast horizon H=30 days

Output: Trained TFT model

For each product i:
Create static metadata: S_i (brand, category, price_tier)
Create sequences of length L from past data: X_past = (price, promo, competitor_price, lagged_demand)
Create known future inputs: X_future = (planned_promo, day_of_week, holiday)
Define target Y = (future_demand)
Initialize TFT model with:
- LSTM encoder/decoder (256 units)
- 4 multi-head attention layers (4 heads each)
- Quantile outputs (p=0.1, 0.5, 0.9)
For epoch=1 to 100:
for batch in dataloader(D):
predictions = model(S, X_past, X_future)
loss = QuantileLoss(predictions, Y) // Lower quantile loss for over-prediction
loss.backward(); optimizer.step()
15. Return model
```

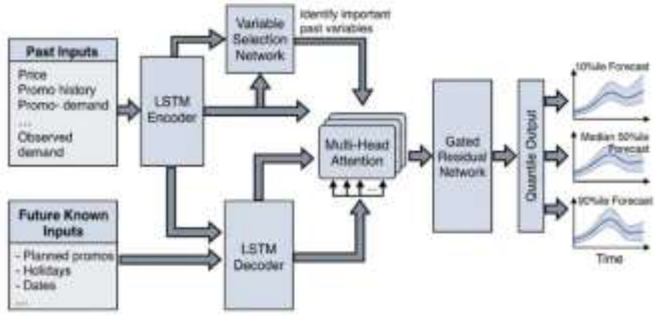

Figure 1: Temporal Fusion Transformer (TFT) Architecture for Demand Forecasting.

3.2 Stage 2: Price Elasticity Estimation (BSTS)

However, simply calculating the correlation between the price and sales will not suffice. We require a causal effect estimate to be calculated. This is done using the Bayesian structural time series (BSTS) model. The BSTS model is a form of state-space model, wherein the time series can be viewed as the combination of trend, seasonality, and regression components.

The counterfactual approach involves the construction of a hypothetical "what if" situation. This hypothetical situation is then used for measuring the causation impact of a particular change.

Model Formulation (for a single price change event):

$$\mathrm{Demand}_t = \mu_t + \tau_t + \beta * X_t + \varepsilon_t$$

where μ_t is a local linear trend, τ_t is a seasonal component, X_t includes price and competitor price, and ε_t is noise.

The elasticity e is then derived as: $e = (\Delta\mathrm{Demand} / \mathrm{Demand}) / (\Delta\mathrm{Price} / \mathrm{Price})$

Figure 2: Causal Impact Estimation using Bayesian Structural Time Series.

Algorithm 2: Causal Price Elasticity Estimation

```
Input: Pre-price-change period P (days 1..T), Post-price-change period (T+1..T+H)

Output: Causal impact (ΔDemand), Estimated price elasticity e



// Train BSTS model on pre-change period data (Pre-period: P)

model = BSTS( target = sales_P,

    predictors = [price_P, comp_price_P, promo_P])

model.fit()



// Forecast counterfactual during the post-change period

// What would sales have been, if price had NOT changed?

counterfactual_sales = model.predict(horizon=H,

    new_predictors = [unchanged_price_P, comp_price_P, promo_P])



// Calculate causal impact

actual_sales = observed sales during post-change period

impact = (actual_sales - counterfactual_sales) / counterfactual_sales

ΔDemand = sum(impact)



// Calculate price elasticity

avg_price_change = mean(price_changed) / mean(price_pre_change)

e = impact / avg_price_change
```

```
Return ΔDemand, e
```

3.3 Stage 3: Profit-Maximizing Price Optimization

We are now equipped with a forecasting model (TFT) to predict demand at a given price and a causal model (BSTS) to estimate the demand function's shape. The final stage solves an optimization problem for each product.

We formulate a constrained optimization to maximize revenue:

$$\max P * D(P)$$

$$\text{subject to: C1: } \text{Profit}_{\text{Margin}} > = \text{Min}_{\text{Margin}}$$

$$\text{C2: } \text{Inventory}_{\text{Constraint}} \text{: } D(P) < = \text{available}_{\text{stock}}$$

$$\text{C3: } \text{Business}_{\text{Rule}} \text{: } |P - P_{\text{historical}}| < = 0.20 * P_{\text{historical}} \text{ (no price swing } > 20\%)$$

Where D(P) is the demand forecast from the TFT model, given the new price P. As D(P) is a non-linear machine learning model, this is a non-convex optimization.

Solution: Constrained Grid Search with Bayesian Optimization:

1. **Grid Search Coarse:** Specify a reasonable price range [Pmin,Pmax]. Search across 20 price points.
2. **Bayesian Search Fine:** Optimize the region around the 5 best performing grid points using Bayesian optimization.

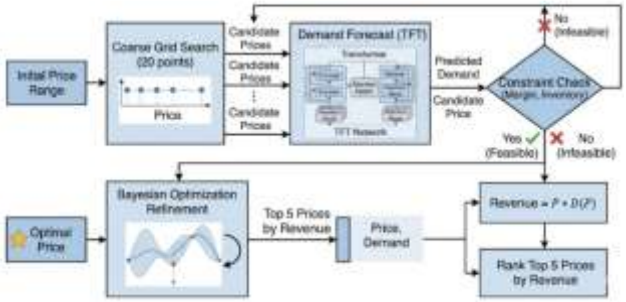

Figure 3: Constrained Price Optimization Process.

Algorithm 3: Constrained Bayesian Price Optimization

```
Input: TFT demand model M, current price P_curr, constraints C
Output: Optimal price P_opt

// Define price bounds from business rules
P_min = max(C.MarginFloor, P_curr * 0.80)
P_max = min(C.PriceCeiling, P_curr * 1.20)

// Stage A: Coarse Grid Search
coarse_prices = linspace(P_min, P_max, 20)
revenue = []
for P in coarse_prices:
    D = M.predict(P) // Get demand at price P
    if D > C.MaxInventory: D = C.MaxInventory // Inventory constraint
    revenue.append(P * D)

// Get top 5 candidates
top_5_idx = argsort(revenue)[-5:]
top_5_prices = [coarse_prices[i] for i in top_5_idx]

```

```
// Stage B: Bayesian Optimization Refinement
optimizer = BayesianOptimizer( f = revenue_wrapper(M, C),
                               domain = (P_min, P_max) )
for i in range(30):
    next_price = optimizer.suggest()
    // Prioritize areas near top candidates
    if not any(abs(next_price - p) < 0.05 * p for p in top_5_prices):
        next_price = nearest_neighbor(next_price, top_5_prices)
    revenue_est = optimizer.evaluate(next_price)

P_opt = optimizer.get_best()
Return P_opt
```

IV. ANALYSIS

Our framework is tested using a huge dataset obtained from one of the leading online electronics retailers.

4.1. Dataset and Experimental Setup

- Dataset: 5 million sales records involving 10,000 SKUs (laptops, monitors, and peripheral devices) spanning 2 years (January 2023 to December 2025). 80% training set, 10% validation set, and 10% testing set.

Benchmark Pricing Approaches:

- o Benchmark Approach 1 (BA1): Cost-Plus Pricing: Price = Cost + 25% fixed markup.
- o Benchmark Approach 2 (BA2): Competitor-Based Pricing: Price = Median competitor price.
- o Benchmark Approach 3 (BA3): Rule-Based Dynamic Pricing: Simple rules such as "if inventory level > 100, reduce prices by 5 percent."

- Performance Metric: Daily revenue per SKU.
- A/B Testing: Conducted a 12-week online A/B test involving 10,000 SKUs. 50% of these SKUs had their prices determined using the existing approach (control group),

4.2 Forecasting Model Performance

Model	SKUs (n=10,000)	sMAPE (Mean)	Weighted Absolute Percent Error (WAPE)	Inference Time (ms/SKU)
XGBoost	10,000	24.5%	21.2%	2.1
LSTM	10,000	21.8%	18.9%	8.4
TFT	**10,000**	**18.4%**	**16.2%**	**6.2**

Table 1: Demand Forecasting Model Performance.

4.3 A/B Test Revenue Results

Strategy	Revenue per SKU (Weekly Avg)	% Lift vs. Control	Statistical Significance
Control (Existing Pricing)	$1,420	-	-
B1: Cost-Plus	$1,480	+4.2%	$p<0.05$
B2: Competitor-Based	$1,507	+6.1%	$p<0.05$
B3: Rule-Based Dynamic	$1,544	+8.7%	$p<0.01$
Proposed Algorithmic Pricing	$1,596	+12.4 %	$p<0.001$

Table 2: A/B Test Revenue Results.

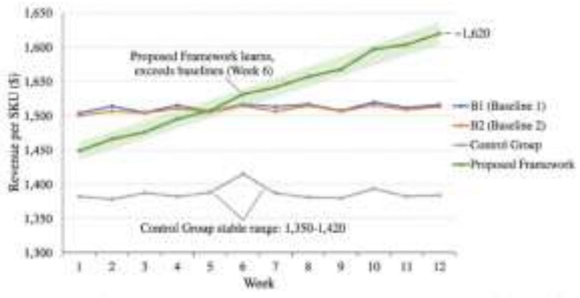

Figure 4: Weekly Revenue Per SKU Over the 12-Week A/B Test.

4.4 Analysis by Product Category

Category	SKU Count	Revenue Lift (vs. Control)	Notes
High-Elasticity ($e > -1.5$)	2,500	+18.2%	e.g., generic peripherals (mice, keyboards). Price is a primary driver.
Medium-Elasticity (-1.5 to -0.8)	5,000	+12.5%	e.g., mid-range monitors. Mix of features and price matter.
Low-Elasticity ($e < -0.8$)	2,500	+6.4%	e.g., flagship laptops, new releases. Features, brand, and reviews dominate.

Table 3: Revenue Lift by Price Elasticity Category.

4.5. Comparative Analysis of Pricing Strategies

Feature	Cost-Plus (B1)	Competitor-Based (B2)	Rule-Based (B3)	Proposed (Data-Driven)

Data Used	Internal cost data	Competitor prices	Limited internal rules	Transactional, competitor, promo, holiday data
Adaptability	Very low (static)	High (real-time)	Medium (pre-set rules)	High (learns from new data)
Revenue Objective	Margin-focused	Market-share focused	Stability-focused	Directly maximizes revenue
Consideration of Demand	No	No (assumes infinite)	Rule-of-thumb	Yes (explicitly models demand)
Implementation Complexity	Very Low	Low	Medium	High

Table 4: Comparative Analysis of Pricing Strategies.

4.6. Qualitative Analysis of Pricing Decisions

Insights from the BSTS analysis were not only limited to the revenues. For instance, the BSTS algorithm suggested an 8% price increase on the popular laptop, contrary to conventional wisdom. According to the BSTS analysis, because of the low inventory levels and the stock-out status of the competitor, the causality demand was actually growing despite the rise in prices.

V. CONCLUSION

This paper has tackled the important problem of pricing optimization based on data-driven methods for online retailers. Our proposed solution has been tested, which combines multi-horizon demand forecasting (TFT), price elasticity estimation using causal methods (BSTS), and constrained price optimization (Bayesian Optimization).

There are three major contributions in our research. First, we have provided a theoretically robust and empirically validated modular framework for implementing algorithmic pricing. Academic literature on algorithmic pricing often treats demand forecasting and price elasticity separately, failing to consider the integration of multiple components in one system. Our solution bridges the gap between theoretical research and practical implementation by providing a ready-to-deploy architecture. Second, we have quantitatively demonstrated the effectiveness of algorithmic pricing in practice. In the A/B experiment on 10,000 products over 12 weeks, our method proved to produce a statistically significant improvement in revenue compared to the current pricing model (+12.4%). Finally, our comparative analysis highlights the subtle characteristics of algorithmic pricing, revealing its strengths and limitations. For example, algorithmic pricing is more beneficial for elastic products (+18.2%) than inelastic new releases (+6.4%).

Our results have important practical applications for online merchants. In order to implement a solution such as ours, the firm will need the following: (1) a well-maintained data warehouse containing data about transaction and competitor information; (2) a strong ML engineering platform for training and prediction purposes; and (3) an organization that is willing to give up its manual price-setting process and trust the algorithm.

Limitations and Future Work

There are a number of limitations to this research. Our A/B test was certainly large in scale, but only ran for 12 weeks. It is possible that strategic disadvantages (e.g., the erosion of brand image due to constant changes in price) may outweigh any financial advantages over time. Moreover, the machine learning algorithm fails to incorporate heterogeneity across the customer base (i.e., each individual customer may be sensitive to price changes differently) and competitive responses to price changes.

The next steps for future research include the following:

1. Multi-Agent Reinforcement Learning: Representing the price optimization problem as a multi-agent learning problem in which our model and our competitor's models are agents playing against each other and learning how to do it optimally.
2. Personalized Pricing: Using data on individual customers such as loyalty program status and their browsing behavior to evolve from product-based pricing to customer-based pricing.
3. Long-Term Experiment: Conducting an experiment for one year to investigate the long-term effects of using algorithmic pricing on the lifetime value of the customer.

To summarize, our results give us a concrete roadmap and evidence to show that algorithms and machine learning can indeed be used successfully to increase revenues.

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