Dynamic Pricing For Sports Event Tickets

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Abstract

The objective of this paper is to create a dynamic pricing model that could achieve revenue improvement for a National Football League (NFL) team. The motivation is the increased willingness for sports franchises to adopt data analytics as a tool to support their pricing decisions. Demand for sports events is varying in nature due to different factors (i.e., opponent, weather, star players). We examined single-game ticket data from both primary and secondary markets and evaluated several demand forecasting models. Next, we implemented the optimization model to determine ideal prices that maximize revenue. Finally, we built an interactive dashboard that visualizes the model result to provide a clear picture for franchise decision-makers.

Introduction

Dynamic pricing allows the sports team to make the optimal pricing strategy for event tickets and act upon the constantly changing market conditions to increase attendance and maximize profits with each customer, eventually boosting sales and competitiveness. The most common methods are cost-based, competitors-based, and demand-based, and the price optimization in this study is aligned with demand. To predict customer purchasing behavior at specific dates before games, we deploy machine learning tools to evaluate external factors like weather, traffic and internal factors directly related to past sales and team performance to generate demand prediction. The final goal is to sell the price-segmented tickets to interested customers at specific times in the primary market with articulated prices, which can compete with secondary market price fluctuation and gain revenue opportunities.

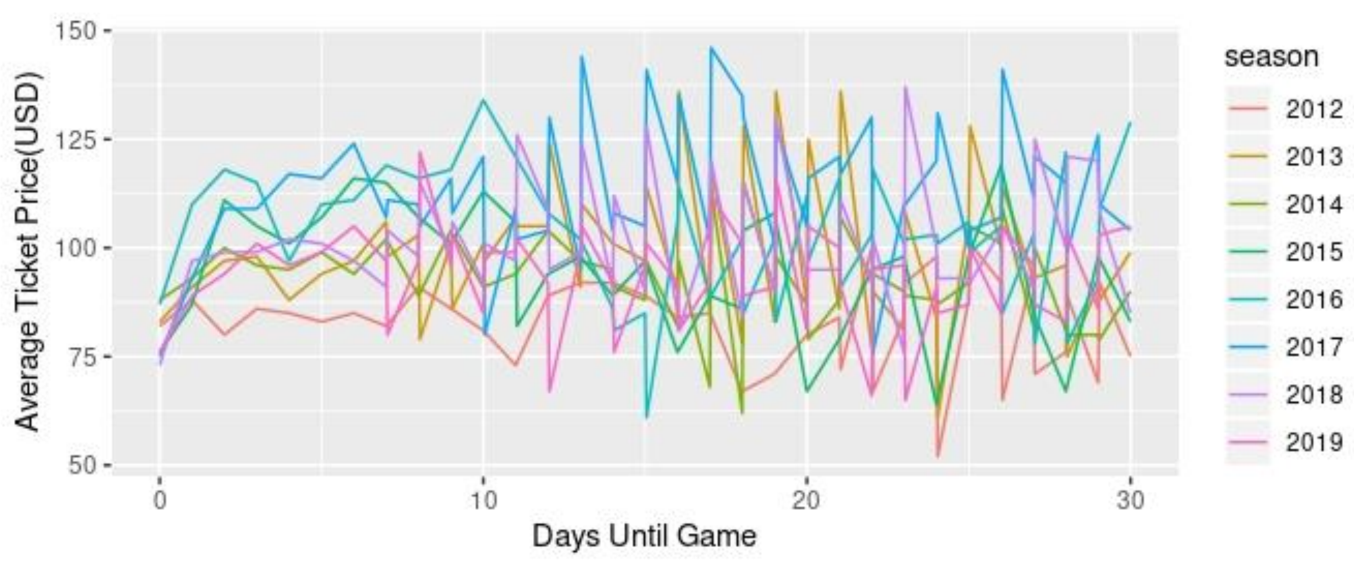


Figure 1. Indianapolis Colts Average Ticket Price vs. Days Until Games

Research questions:

- ➢ How well do popular machine learning models perform at ticket demand forecast?
- ➢ How much does our pricing optimization increase revenues of the past games?

Literature Review

Author	Summary	Methodology
Strnad et al. (2015)	Predict soccer match attendance by comparing numerous NN models	3-layer MLP, 3-layer TLFN, 3-layer Elman RNN, 2-layer RBFN
Kemper et al. (2016)	Applied mathematical theory of dynamic pricing with empirical methods	Monte Carlo, Linear Regression, Logistic Regression
Shapiro et al. (2012)	Examine factors influencing ticket price for MLB team in both primary and secondary market	Compare the results of 1) 2SLS using season ticket and secondary market price as input variable and 2) OLS model excluding those variables
Diehl et al. (2015)	Investigate elasticity of demand in the secondary market for NFL ticket and how elasticity varies across different seat types	General Linear Model, includes NFL Fan Cost Index (FCI) for concessions

Table 1. Literature review summary

The novelty of this study is that we compared and contrasted all the machine learning methods used previously, and adopted Random Forest to deliver the most accurate result.

Methodology

Data

Ticket sales transaction on the primary and secondary markets was retrieved from 2012 to 2019 (unsold inventory data missing from 2012 to 2016).

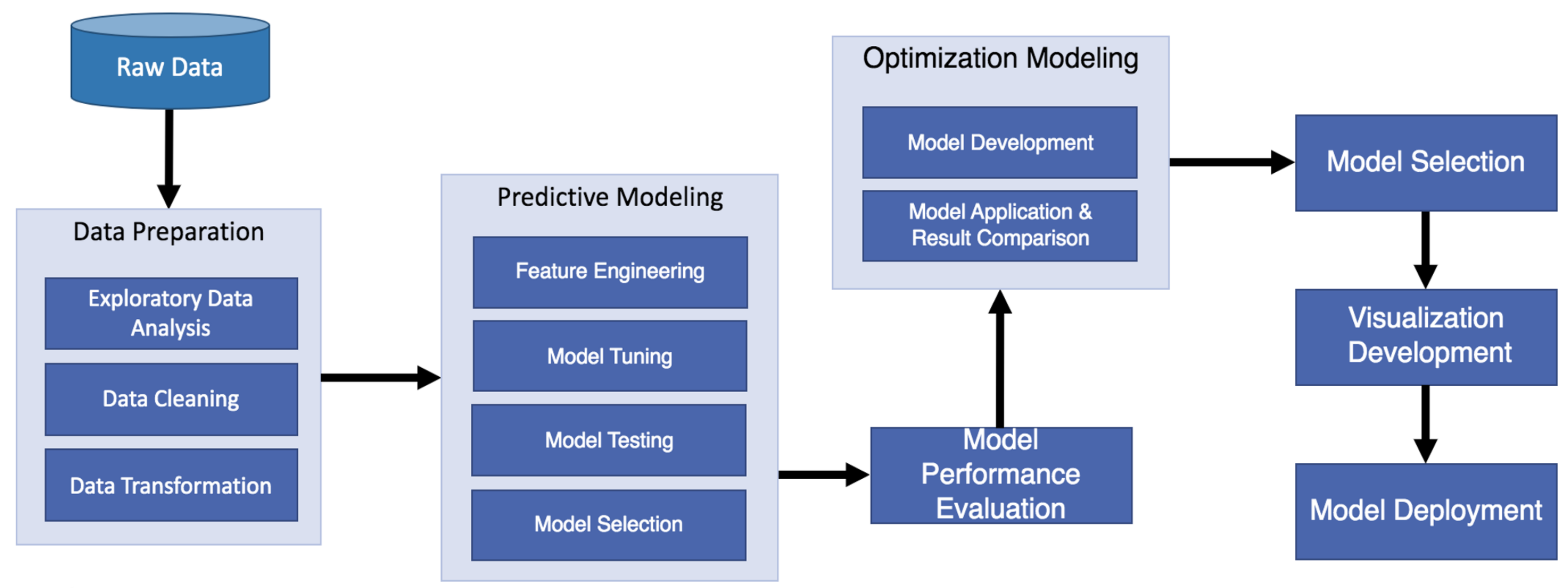


Figure 2. Study Design

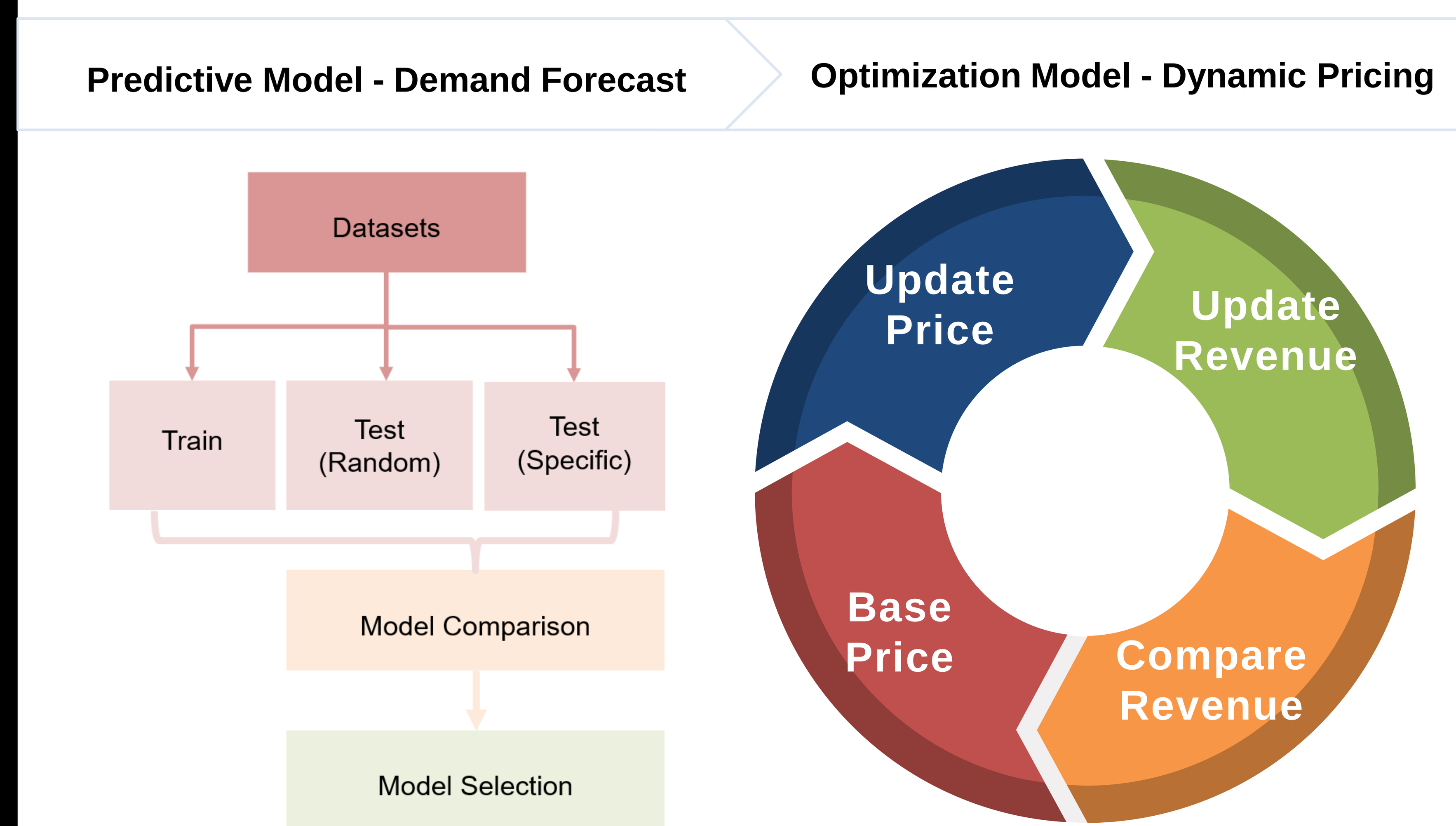
Model Design and Selection

The Random Forest Algorithm was used to build a predictive model to learn the demand of the market under different circumstances.

Given $P(ticket\ sold \mid time, price, others)$ that was provided by the predictive model, we would have the expected revenue as:

$$E(Revenue) = P(\text{ticket sold} \mid factors) * Price$$

Therefore, we could use a recurring method to optimize the price for every ticket to reach a maximum expected revenue.



Model Evaluation / Statistical & Business Performance Measures

The predictive models were evaluated on overall accuracy and AUC statistical performance measures because what we needed from the predictive model was the predicted probability instead of the predicted outcome. Therefore, AUC would be a more reasonable indicator comparing to other metrics like accuracy. The business performance measure we considered is the expected revenue generated from the model.

Results

The AUC was used as model evaluation metric in this binary classification problem.

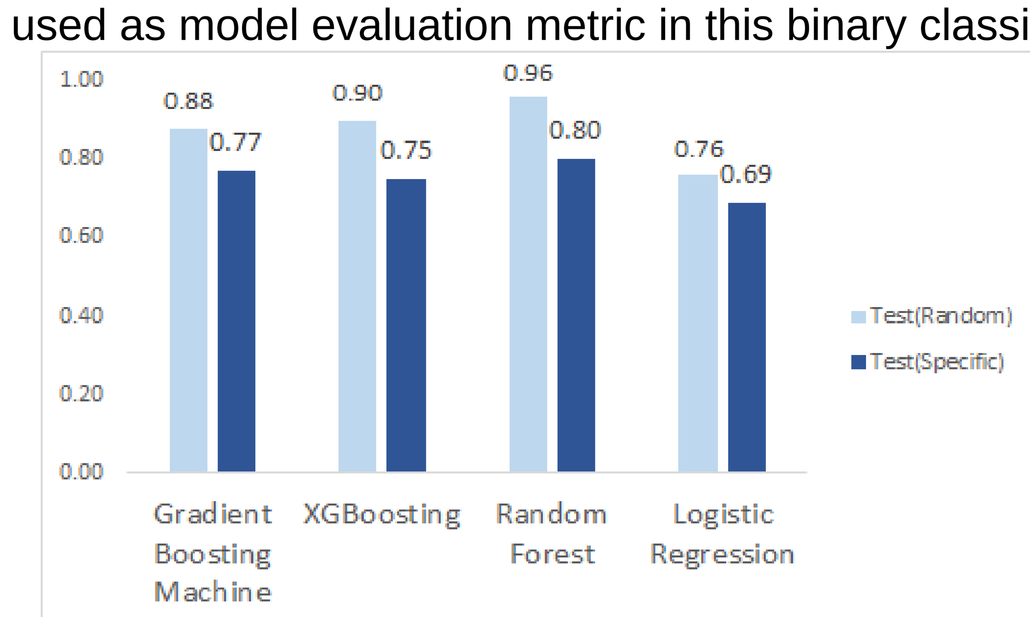


Figure 3. Model Evaluation

We attempted to maximize revenue by increasing sales in the low-price, high-potential-demand sections and adjusting price in low-demand high-price sections, 6 sections are selected for pricing optimization stimulation and revenue comparison. The lower 1.5 IQR to maximum was used as recommended price range.

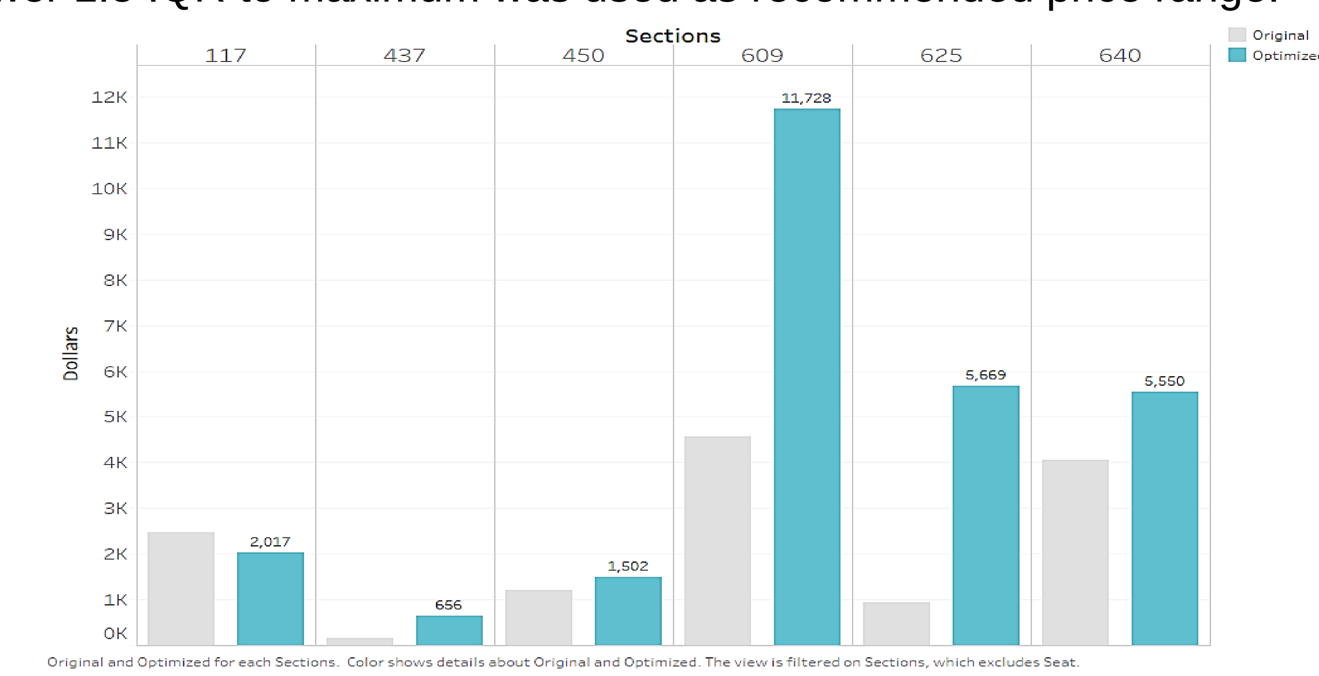


Figure 4. Original and Optimized Revenue Comparison

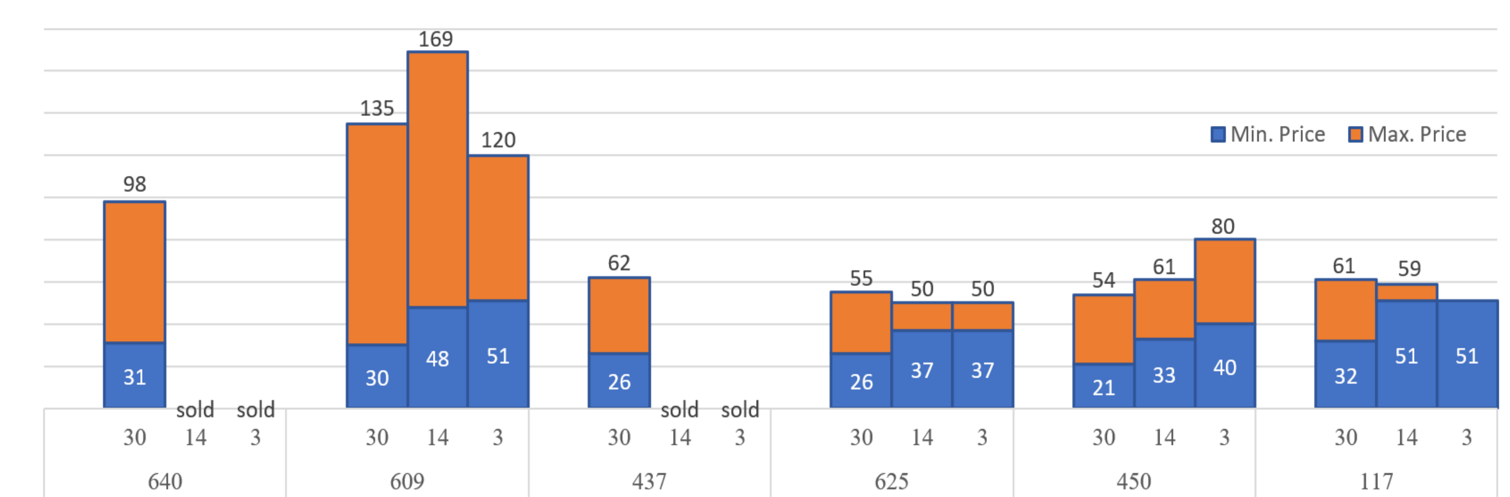


Figure 5. Recommended Price Range over the 30-days, 14-days, 3-days Time Points

Conclusions

The sports ticket market could have a giant potential increase in profit with the introduction of dynamic pricing to the market. A properly designed optimization method could bring enormous benefits to both the teams and the society.

A gradient ascent method based on an accurate predictive model could be an efficient approach to optimize the price of sport event tickets dynamically. The demonstration using the approach proves that this approach could bring huge revenue increase when applying to cheaper tickets.

Acknowledgements

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