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"Puck Pricing": Dynamic Hockey Ticket Price Optimization

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ABSTRACT

Dynamic pricing is a real-time strategy where corporations adjust prices "on the fly" in response to changing market demand. The hospitality industry has widely adopted this strategy to maximize expected revenue by raising prices in the summer or weekends when demand for hotel rooms is at a premium. In recent years, the sports industry has started to catch on to this trend. As the strategies revolutionized baseball ticketing, more hockey teams have started to experiment dynamic pricing. The purpose of this paper is to explore the methodology of applying dynamic pricing to hockey ticketing arena.

INTRODUCTION

Business Question

Anyone who has ever purchased tickets online may have noticed that ticket prices often vary based on exogenous factors such as team popularity and ticket availability. As game day approaches, ticket demand varies resulting in "dynamic" ticket prices – prices that change daily and sometimes even hourly. However, these price fluctuations do not necessarily represent an "optimal" price (where optimality is defined as prices that generate maximum revenue) due the following fact:

- The dynamic ticket prices make no assumptions about price elasticity; If a ticket is sold at $X this does not mean that the optimal price is indeed $X? The optimal price may be higher or lower depending on how sensitive the consumer is to that price point.

The question we ask in this paper is: what are the dynamic factors that influence hockey ticket prices and what is the optimal price on any given day?

Why Hockey?

Dynamic pricing is a popular topic in sports, particular in baseball which has started to vastly discount tickets due to factors like inclement weather. The baseball industry has, arguably, a greater opportunity for dynamic pricing since it plays more games in larger venues than hockey. It is also an outdoor sport and therefore attendance is more contingent on weather – a very clear dynamic pricing factor.

However, although the hockey industry has less opportunity to alter prices than the baseball industry, they charge more for their tickets and, with an estimated $3.3B in North American revenue (according to Business Insider), have a considerable amount of money on the table. Additionally, since the hockey industry has just recently started to consider dynamic pricing, the primary predictors of price are still being investigated with a larger opportunity to discover insights and drive value through the organization. According to a report by Temple University, *The Importance of Sports Analytics, Both In The Game and Off the Field*, 97% of baseball teams employ analytics professionals, while only 23% of hockey teams do, which is the lowest percentage of any of the four major sports in North America.

Hockey also faces a unique challenge in that it sells in areas of the country that do not traditionally play hockey – Arizona, Florida, California, etc., and dynamic pricing can play a key factor in driving revenues and attendance. Although it has been adopted by a large percentage of teams in other sports, dynamic pricing is just taking hold in hockey and will likely have an increasing impact on the business of hockey in coming years.

MODELING DATA

Price optimization studies how demand varies in relation to price and derives an optimal price from the relationship. In order to develop this type of model, demand and pricing data were gathered from

SeatGeek.com, a one-stop search platform that polls the secondary ticket marketplace[1]. The data gathered included resale ticket listing counts and average prices of 67 games for a major Midwest hockey team in the 2014 – 2015 season against 29 opponents. The data was pulled daily over a span of 5 weeks. A few key assumptions were made with this data:

- The secondary market is a much truer representation of demand than the primary market. The secondary price can drop below face value if the demand for a particular game is low and can exceed face value if the demand is high. Additionally, the secondary price has the ability to naturally react to dynamic factors. For example, if multiple tickets still remain the day before an event the prices can drastically drop in a last ditch attempt to generate revenue. In fact, the assumption we make is that the secondary market price is in fact the dynamic price
- The gathered listing count data is tantamount to ticket supply not demand. The actual demand (quantity sold) for any particular date is equal to the sum of the new ticket listing count and the change in listings from the prior date, as seen in the below equation:

$$Demand_t = Listing\ Count_{t-1} - Listing\ Count_t + Listing\ Count_{New}$$

  In order to retain clean data, records were removed if the listing count was larger than the prior date ($Listing\ Count_t$ > $Listing\ Count_{t-1}$) and the new ticket listings could not be approximated

- Gathered ticket prices are the average ticket prices for all seats sold across the stadium. Thus, this paper assumes there is no section or seat variation in response to exogenous factors
- Only individual ticket sales were considered, thus season ticket sales are not discussed or analyzed in this paper

In addition to ticket data, Table 1 lists the covariate data studied in the model.

Model Input Data	
Seasonal/Time Factors	• Days Until Game • Time of Game (Early Afternoon, Evening, Night) • Day of Game (Sunday – Saturday) • Special Holiday Games (New Years, Thanksgiving) • Current Month (at time of pricing data pull) • Current Week (at time of pricing data pull)
Opponent Factors	• Number of Stanley Cup Wins • Previous Season Total Points • Previous Season Playoff Indicator • Star Player on Team Indicator • Franchise Value
Stadium Factors	• Home Team Soft Drink Price
Social Factors	• Opponent Facebook Fans • Opponent Twitter Fans • Twitter Counts for Posts with the teams name as a hashtag

Table 1. List of candidate factors that may influence hockey resale ticket price

[1] The secondary ticket marketplace, or the “resale” market, includes websites in which fans can sell their tickets either above or below face value depending on the demand of the ticket.

THEORY

Pricing strategies often require a holistic approach due to the varying business constraints as well as the multitude of methods in deriving an optimal price. For the purposes of this paper, a three phase approach was developed to model dynamic resale ticket pricing.

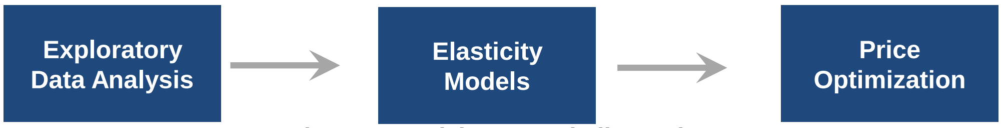


Figure 1. Model Approach Illustration

EXPLORATORY DATA ANALYSIS

The first phase analyzed the correlations between the input factors and average price/demand. The purpose of this phase was two-fold:

- To understand the dynamic nature of resale ticket prices
- To explore the factors that influence resale ticket prices so that they can be controlled for in the price elasticity models

ELASTICITY MODELS

The second phase determined how sensitive fans are to hockey ticket prices. Elasticity measures the estimated quantity change due to the estimated price change as follows:

$$Elasticity = \frac{\%\ Change\ Quantity}{\%\ Change\ Price}$$

In order to approximate elasticity, a Hierarchical Bayesian model was built at the opponent level. Hierarchical Bayesian models were chosen due to the low sample size available for each game. Since the sample size is low, Bayesian models will “shrink” the estimates towards the overall average, thus producing more reliable estimates. These models followed the following equation form:

$$Ln(Quantity) = Elasticity * \ Ln(Price) + \mu_1 * Var_1 + \ \mu_2 * Var_2 \ + \ ... + \ \mu_n * Var_n$$

$Where:$
$Var_i = Input\ variables\ as\ mentioned\ in\ Table\ 1\ such\ as\ “Number\ of\ tweets”$
$u_i = Coefficient\ for\ Var_i$
$n = Number\ of\ statistically\ significant\ predictive\ input\ variables$

In order to produce reasonable estimates, positive elasticity estimates were truncated to zero. This was supported by research done by Emory Sports Marketing Analytics that suggests the Midwest team for which the data was pulled is among a set of hockey teams that are relatively insensitive to price. Accordingly, the price elasticity would be closer to zero and demand would remain relatively constant regardless of price.

PRICE OPTIMIZATION

After modeling elasticity, time based input variables such as prior date ticket price were incorporated into a price optimization algorithm. Table 2 outlines the non-linear program used in this problem.

Maximize Daily Revenue

$$= \sum_{i=1}^{Games} New\ Price_i \times \ New\ Quantity_i \quad (1)$$

Subject To:

$$\sum_{i=1}^{Games} (Elasticity_i \ \times \%\ Price\ Change_i) \times Old\ Quantity_i + \ Old\ Quantity_i - \ New\ Quantity_i \ = 0 \quad (2)$$

$$\sum_{i=1}^{Games} Abs(\%\ Price\ Change_i) \leq 10\% \quad (3)$$

$$\sum_{i=1}^{Games} New\ Quantity_i \leq Remaining\ Tickets_i \quad (4)$$

Table 2. Price Optimization Formulation

$Where$:
$Old\ Price_i = Yesterdays\ seat\ geek\ price\ for\ Game_i$
$Old\ Quantity_i = Yesterdays\ seat\ geek\ quantity\ sold\ for\ Game_i$
$New\ Price_i = New\ optimized\ price\ for\ Game_i$
$New\ Quantity_i = New\ estimated\ quantity\ sold\ for\ Game_i$
$Remaining\ Tickets_i = Remaining\ supply\ of\ tickets\ (listing\ count)\ for\ Game_i$
$Elasticity_i = Elasticity\ for\ Game_i\ (based\ on\ the\ opponent)$
$\%\ Price\ Change_i = \%\ price\ change\ for\ Game_i = \dfrac{New\ Price_i - \ Old\ Price_i}{Old\ Price_i}$

In the above formulation, the new price is a free variable whose value is determined through the optimization. Equation (1) is the objective function which attempts to maximize revenue defined as the new price multiplied by the estimated quantity sold based on the new price. Equations (2) through (4) are constraint functions:

- Equation (2) estimates the new quantity based on the classic elasticity equation relating % price change to % quantity change
- Equation (3) ensures that the total price change in any given ticket cannot be farther than 10% from the original price. This constraint tempers any drastic changes to produce reasonable prices
- Equation (4) constrains the estimated quantity to be less or equal to the available resale ticket supply

RESULTS

EDA and Elasticity Results

A thorough EDA identified the top factors that affected price/quantity for each opponent. As shown in Figure 2, the overall trends over time ("Days Until Game") suggested that the sales quantity decreased while the average price increased slightly approaching game day.

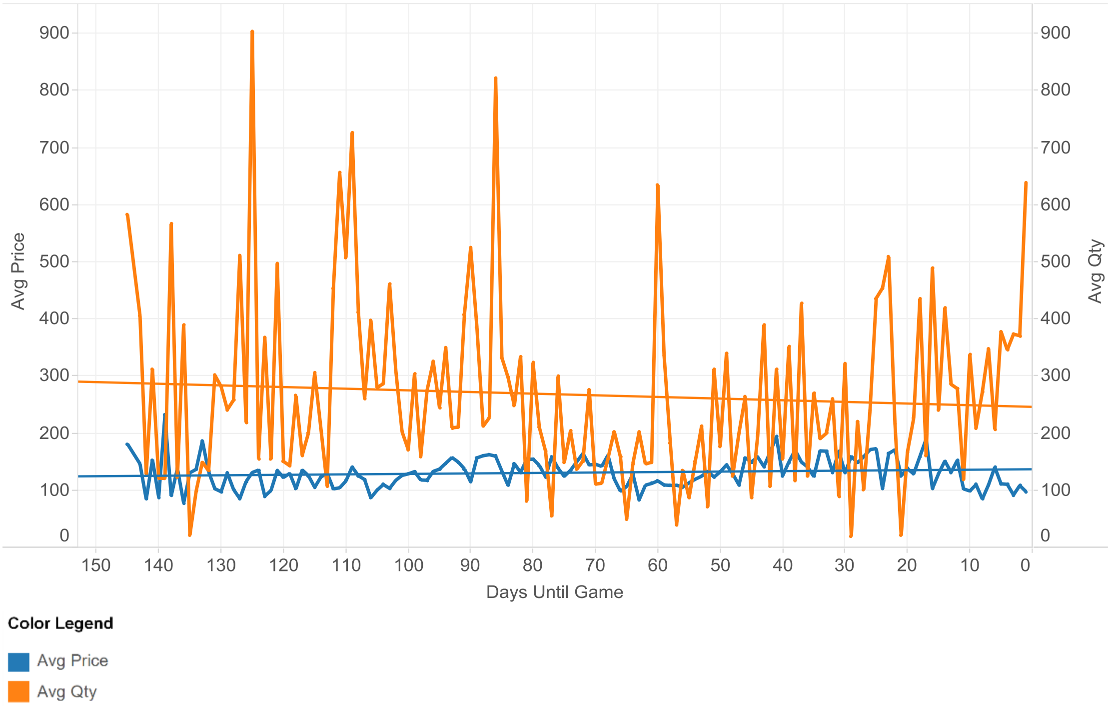
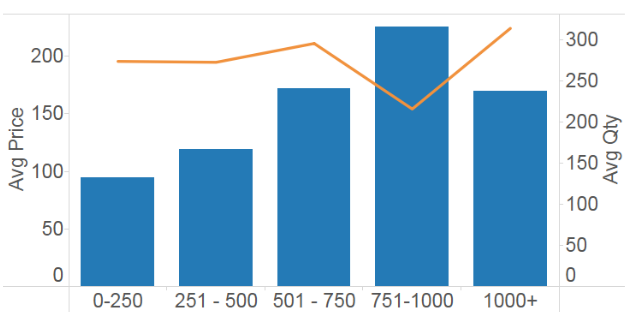
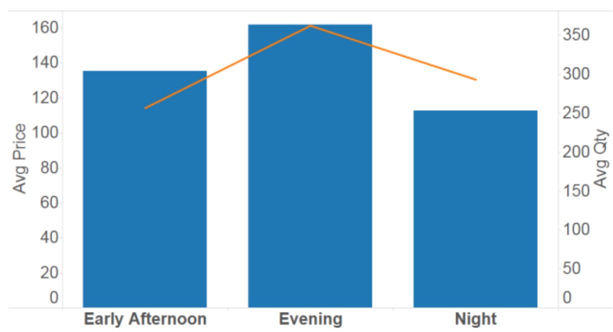


Figure 2. Average Resale Ticket Price vs. Quantity Sold Over Days Until Game

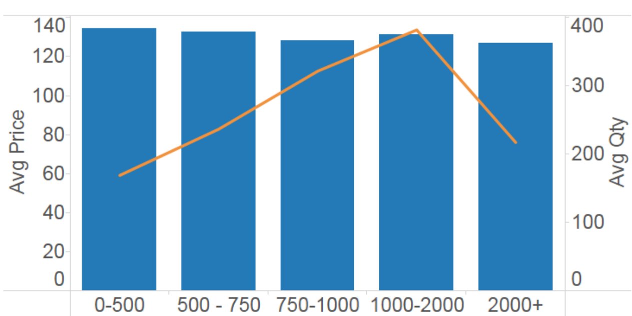
Along with the overall time trends, the EDA showed strong relationships in each of the variable categories. The following graphs show the top variables shown to have a relationship with price and quantity.



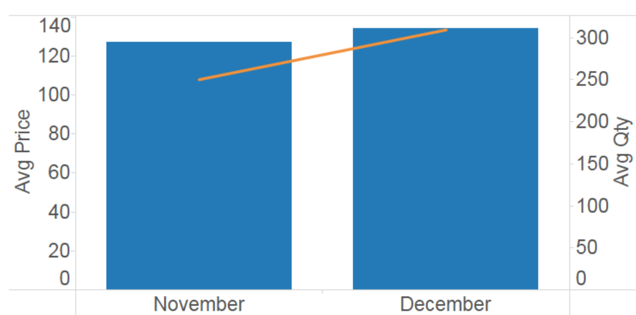
Franchise Value



Time of Game



Number of Tweets



Month of Day in Ticket Sales

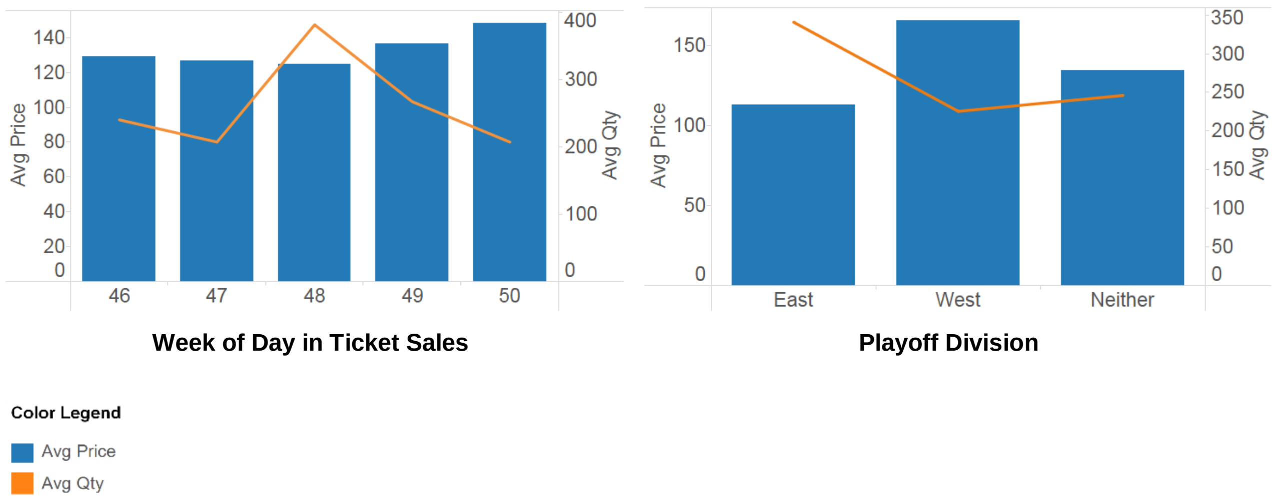


Figure 3. EDA Results

As shown in Figure 3, the covariate data was found to have strong linear and non-linear relationships to price and quantity sold. However, many of these relationships served as proxies for the opponent. Thus, when the price elasticity was modeled at the opponent level these relationships were "washed" out and captured by the random intercept. Figure 4 shows the fixed variables that were significant in the elasticity models (log of price was used as a random variable):

Solutions for Fixed Effects					
Variables	**Parameter Estimate**	**Std. Error**	**DF**	**T Value**	**P Value**
Intercept	13.1795	2.5044	26	5.26	<.0001
Franchise Value	0.2024	0.06416	929	3.15	0.0017
Time of Game Night Indicator	0.6816	0.1900	929	3.59	0.0004
Time of Game Early Afternoon Indicator	0.8488	0.3120	929	2.72	0.0066
Number of Tweets	-0.00021	0.000055	929	-3.80	0.0002
Month of Day in Ticket Sales	2.1628	0.2429	929	8.90	<.0001
Week of Day in Ticket Sales	-0.7166	0.09171	929	-7.81	<.0001
Days Until Game	-0.00741	0.002167	929	-3.42	0.0006
Playoff – West Division – Indicator	0.6253	0.2606	929	2.40	0.0166
Playoff – East Division – Indicator	1.0880	0.1709	929	6.37	<.0001
Playoff – Final – Indicator	1.2197	0.7717	929	1.58	0.1143

Figure 4. Significant Price Elasticity Factors

Price Optimization Results

The opponent elasticity was then used in an optimization algorithm to derive an optimal price per game. The average price change was $10.17 for daily incremental expected revenue of $109K for tickets in the secondary market. Figure 5 displays the optimization results by division opponents.

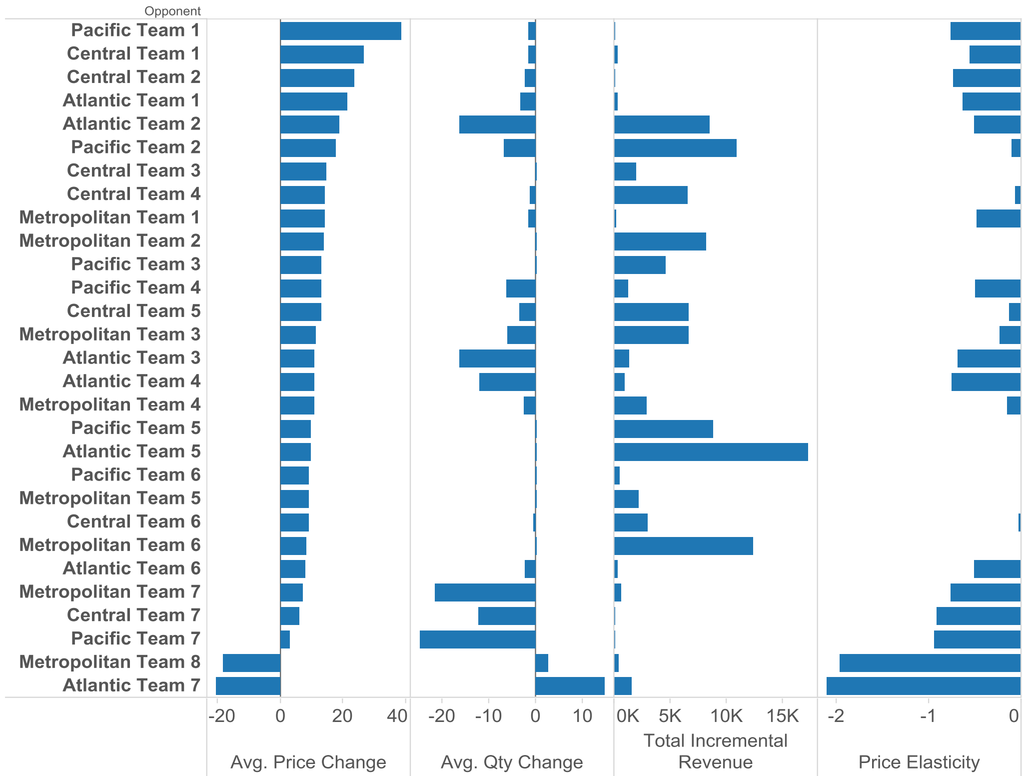


Figure 5. Optimization Results by Division Opponents

The optimization results show that although the quantity decreased due to an increase in price, the price increase is large enough to still generate positive incremental revenue. This suggests that the previous prices were priced below the optimal revenue point. It is also interesting to note that the majority of the optimal prices were bounded by the ±10% constraint on maximum price changes. This suggests that most prices were not only priced below the optimal revenue point but that they were drastically under this point.

In order to better analyze how far below the optimal point the current sales were, an efficient frontier was developed. Optimizations were run to determine the optimal revenue at varying volumes and plotted to determine the shape of the frontier. Figure 6 displays this graph which clearly shows that the current baseline sales are priced well below an optimal point.

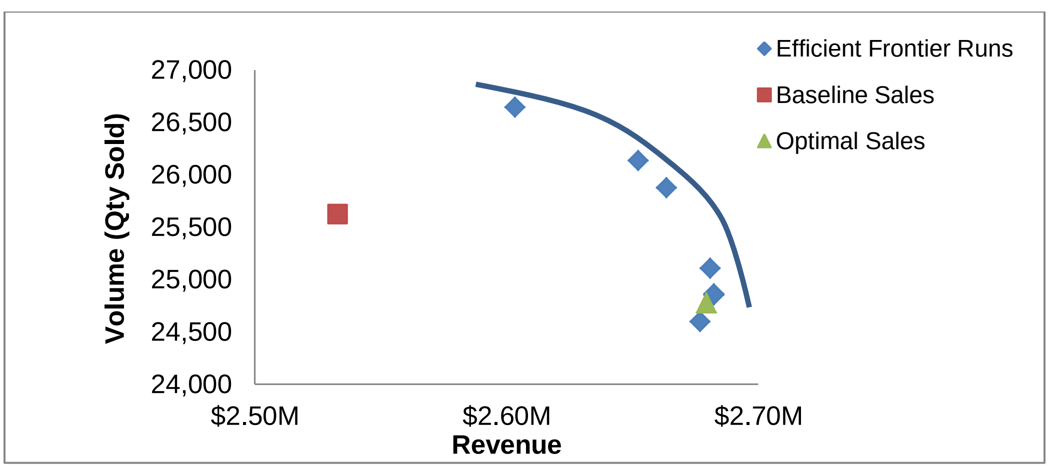


Figure 6: Efficient Frontier

CONCLUSION

This paper highlighted the key drivers of dynamic ticket prices for a hockey team and discussed the methodology to optimize prices using elasticity. It was found that the largest drivers of dynamic ticket prices were days until game, time of game, daily home team tweet count, opponent previous season playoff status, opponent franchise value and the current month/week.

After using these factors to determine the price elasticity, an optimization was performed to arrive at an optimal resale ticket price. Many of the optimal prices were bounded by the constraint that tempered price changes to ±10% of the original price. The model suggested that with an average price change of $10.17, the secondary ticket market could generate $109K of incremental revenue. This finding of price increase was supported by the fact that the secondary tickets were priced below the optimal resale price point.

It should be noted that the expected revenue is based on a single day's worth of incremental revenue in the resale market at the time of this analysis. Future considerations can be made to simulate the benefits over time as game day approaches. Furthermore, since the data was collected at a stadium level, section level insights were impossible to discern. In reality, certain sections may have different price sensitivities and/or be closer to the optimal revenue point resulting in marginal incremental revenue.

To implement the use of dynamic pricing, hockey teams may also choose to begin by using a tiered system instead of dynamically pricing each individual ticket. Tickets would have 1 of 3 possible prices, depending on the tier of the game. For example, Saturday night rivalry games would have a value of "High," and front row tickets might cost $200 for all "High" games. On the other hand, Wednesday afternoon games would have a value of "Medium," and front row tickets might cost $100 for all "Medium" games. Using a tiered system could provide fans with increased transparency into dynamic pricing methods. While hockey teams may use dynamic pricing as a way to increase revenue, special consideration should also be given to the possibility of not varying ticket prices at the cost of alienating their core fan base. Ultimately, analytics has the potential to play an integral role in hockey but, as with any business, should be applied in the overall context of sound business objectives.

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