A Dynamic Ticket Pricing Solution for an NFL Team

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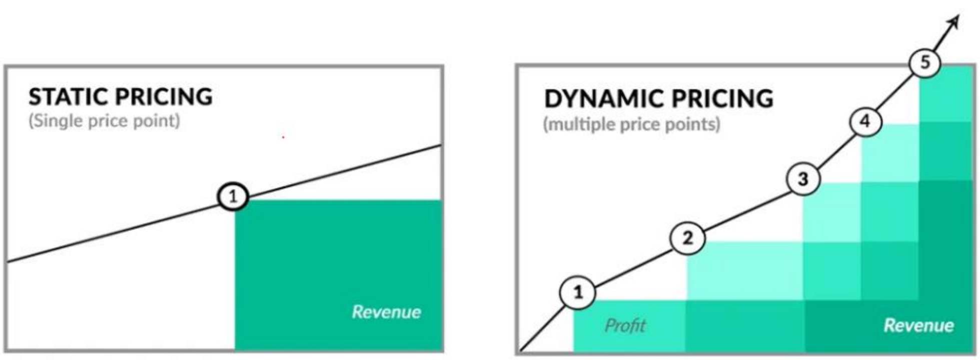
ABSTRACT

We are developing a dynamic ticket pricing model in collaboration with a National Football League (NFL) team. Our model was developed using real-time inventory data, data from internal and third party (e.g. Stubhub.com, Ticketexchange.com, Ticketmaster.com, etc.) ticket sales transactions and opponent demographics. Since ticket sales are one of the key revenue generators for professional sports teams, being able to maximize this revenue using intelligent data-driven models that are operationally feasible in real-time is key for the partner. We discuss what we found to be state-of-the-art in this area, our model proto-typing journey, and what worked best for us that lead to reliable cross-validated model performance, but also timely dynamic predictions. We believe anyone interested in pricing, recommendations systems, or professional sports will find our insights valuable to their work.

Keywords: sports analytics, dynamic pricing, recommendations system

INTRODUCTION

Dynamic pricing is varying price for something based on market conditions and is typically practiced by charging a higher price when demand is higher for the product or service ("Dynamic Pricing: Definition of Dynamic Pricing by Lexico", n.d.). This is demonstrated visually in the graphic below ("Static v dynamic pricing", 2018). Instead of capturing only one price and a portion of the demand curve, businesses can increase the proportion of the demand curve they are capturing and increase their total revenue by attracting customers with varying price sensitivities.



Dynamic pricing has only recently been made widespread in the NFL, so best practices have not yet emerged, and processes have not yet been standardized. The NFL was slow to adopt this practice as opposed to other professional sports leagues (Kaplan, 2015). It was introduced before the 2014 season and after one year, only half the teams in the NFL were participating ("NFL teams that using variable or dynamic ticket pricing", 2015). A major reason so few teams were practicing dynamic pricing was because consumers don't like it when the fact that different consumers have paid different amounts is made visible in some way. Since team are limited geographically in terms of who will buy tickets to their events, they rely heavily on loyal customers and are weary of making them angry. This practice can however dramatically increase revenues for the team, sometimes by multiple millions of dollars, which is why more teams are moving towards the practice now and potentially sacrificing the number of attendees for more revenue. There's also an idea that the sports ticket market will adjust over time just as the travel industry has. Over time, fans will watch ticket prices more closely and won't buy unless the price matches their willingness to pay (Campbell, 2019)

In the ticket market, customers have the option to purchase tickets from either the primary or secondary markets. The primary market is where customers will purchase tickets directly from the team. In the primary market, customers can feel safer about the transaction and know that their team is the entity making money off of the sale. However, according to our NFL partner, over time this trend of well-feelings has decreased in importance for ticket purchasers because practices increasing the credibility of tickets in the secondary market have improved. The secondary market includes resell websites such as StubHub and SeatGeek. Sellers in the secondary market have been able to achieve an advantage on price while the NFL teams have had to stick to their internal pricing restrictions. When teams dynamically price, they can take some of the sales away from the secondary market and bring the revenue back to their own teams.

We are working to build a model that will help the pricing team determine the optimal price for each ticket based on different market conditions. By modeling this process, we can help the pricing team reduce the number of decisions that are currently being made manually, and of course increase revenues from ticket sales. Each season, the pricing team releases a certain number of tickets for each game in April, then releases more tickets as the game approaches. They must decide how many tickets to release at each time period, and at what price for every category of seat. If the tickets are underpriced, tickets disappear very rapidly. If they hold on to too many tickets for the week leading up to the game when sales are affected by weather, injuries, and the teams' record, they end up going unsold ("The 2 Types of Ticket Pricing: Variable & Dynamic", 2017). There are all kinds of combinations of decisions and consequences as the season goes on and we hope to alleviate some of the pressure and pain that comes with all of these decisions.

The remainder of the paper includes a literature review on previous dynamic pricing models, an overview of the data, our proposed methodology, tested models, results, and conclusions. Our conclusion will include future research directions and implications of the study.

LITERATURE REVIEW

Yet another reason dynamic pricing has been scarce in the NFL is that there are a few companies that have developed proprietary algorithms that won't publish their findings to gain clients. That means our team relied primarily on literature from other sports and events to learn how dynamic pricing models have been built in the past.

Bouchet, Troilo, and Walkup (2016) interviewed employees and leaders of multiple professional sports leagues with the purpose of investigating leaders' perceptions of their organizations dynamic pricing practices versus their actual practices. While there is a high perception that their organizations use dynamic pricing, the actual number that use it is much lower. Many teams left pricing to a third party and very few of the teams updated their prices daily. The author mentions that the difference between these professional sports organizations and the travel industry where dynamic pricing is much more common is the lack of information that the travel industry has and the lack of secondary markets. This implies that dynamic pricing in the long run should be even more effective for revenue maximization in sports. Sahin (2019) who built an adaptive neurofuzzy inference system (ANFIS) model and calculated a price multiplier parameter which was optimized to maximize total revenue. This model however required extensive time based information about the pricing strategy used.

Lots of information has been published pertaining to dynamic pricing in Major League Baseball (MLB) which can be explained at least in part by the fact that dynamic pricing was successful in the MLB long before it was even permitted in the NFL. Shapiro and Drayer (2013) wanted to investigate how the factors that influence dynamically priced tickets in the primary market differ from the significant factors that influence ticket prices in the secondary market. They built two regression models for the primary market and two models for the secondary market. While many variables were significant in both markets, each market did have unique significant variables that were not present in the other market's model. Xu, Fader, and Veeraraghavan (2016) built a comprehensive, three stage regression model to optimize one MLB team's revenue from their single-game ticket sales. The model first forecasted game demand, then ticket quantity choice, and finally seat section choice for consumers. They fed this model into an expected revenue forecast model. One important finding from this study was that demand modeling are price flexibility are found to be more important than the frequency of price updates when dynamically pricing. This finding is important because it seems as though companies use the frequency of price updates as a heuristic for success when it is in fact not the most important in improving overall revenue.

Another paper about the soccer team Bayern Munich published by Kemper and Breuer (2016) was of great interest to our team. Bayern Munich has some of the highest attendance of European football clubs, but some of the lowest ticket prices. Kemper and Breuer thought they were charging below customers' willingness to pay. They pointed out that purely the existence of a secondary ticket market is evidence that tickets are inefficiently priced in the primary market and thus the secondary market holds valuable information when deciding how to price tickets. They developed 8 different demand functions based on the type of seats in the stadium and used a Monte Carlo simulation to show expected revenues and demonstrate that the dynamic model results in higher revenues than their current model.

Out of the studies found about football, one by Arslan, Tereyagoglu, and Yilmaz (2019) looked at the NFLto contrast all teams that were dynamically pricing with those who were not. Teams who were dynamically pricing sold about 3% more tickets than those who were not and they attributed it to the fact that dynamic pricing was quality-signaling to price sensitive customers. Their approach involved using a difference in differences with propensity score weighting approach. They concluded that dynamic pricing has a more positive impact for towns with lower income levels, towns with higher income diversity, and for less attractive games. This analysis however did not take place at the revenue level. The other research we found related to football was published by Arslan, Easley, Wang, and Yilmaz (2019). The team worked alongside a university football team to build models based on two very different customer segments. They built a multinomial logit and mixed-multinomial logit model to find the optimal price for each segment, then modeled customer utility to determine who would purchase tickets at each price. They used these two models to optimize revenue. Their models however were not easily interpretable. One applicable finding from their study is that customers were less likely to choose a seat in a given section as its inventory got smaller past a certain point.

As for other kinds of events and general findings about dynamic pricing, Patel (2018) developed measures to track prices over time and compare companies within an industry. They tried to find the point at which ticket volume was too concentrated. They stated that dynamic pricing models can have bias and underestimate or underestimate the effect of dynamic events such as a player becoming injured. The model they propose sets a baseline price for tickets, then measures the quality of inventory on a given day based on the number of tickets sold, and at determines what price should be charged comparative to the baseline price. Bauer and Reiss (2019) looked at Pearl Jam concerts across three years at the same venue in Chicago and mentioned that if enough differentiated price points are not set for an event or within a section, tickets will still be resold on the secondary market individually at their true market value. Finally, Fonseca (2017) discusses a general linear demand curve methodology for dynamic pricing, but offers insight about how price optimization is based on customers' characteristics whereas dynamic pricing is based on market conditions in a given moment.

	Study	Summary	Methodology
All Sports	Bouchet, Troilo, & Walkup (2016)	Perceptions versus actual dynamic pricing practices in leagues	Interviews and surveys of employees and leaders
	Sahin (2019)	Optimizing sporting event pricing based on game, time, and inventory-related factors	Adaptive neurofuzzy inference system (ANFIS) model with a price multiplier parameter
MLB	Shapiro & Drayer (2013)	How the factors that influence dynamic primary market prices differ from the secondary market factors	2 regression models for the primary market and 2 regression models for the secondary market
	Jiaqi Xu, Fader, & Veeraraghavan (2016)	How one MLB team can optimize revenue from their single-game tickets	Comprehensive demand regression model of game demand, ticket quantity, and seat section
Soccer	Kemper & Breuer (2016)	How the European soccer team with the highest attendance could raise their revenues significantly	Bernoulli model of dynamic pricing and Monte Carlo simulation for revenue
Football	Arslan, Easley, Wang, & Yilmaz (2019)	Helping college football team find optimal pricing strategy to maximize revenue over 2 distinct segments	2 price models in multinomial logit then customer utility model to predict purchase at each price
	Arslan, Tereyagoglu, & Yilmaz (2019)	Evaluating success metrics of NFL teams that dynamically price vs. those who do not	Difference in differences with propensity score weighting for tickets sold and revenue
Other Events and General Methods	Fonseca (2017)	Describes a general framework to maximize profits in R	Linear demand model based on historical demand
	Patel (2018)	Developing measures for price tracking over time and find at what point ticket volume is concentrated	Regression model that adjusts some baseline price based on quality of remaining inventory
	Bauer & Reiss (2019)	Analyzing dynamic pricing by observing 3 Pearl Jam concerts at the same venue in different years	Calculated lost revenue by subtracting average secondary market price from primary price

DATA

The confidential data was provided by the NFL partner. Each table is summarized below.

Table 1: Table 'Secondary' provided by NFL Team

Variable	Description
Event_name	Identifier for each game. Prior to 2018, game date was the indicator, after then the opponent was the indicator
Section_name	Section in Stadium
Row_name	Row in Section. An N indicates infill seats (folding chairs, non-permanent). A W indicates wheelchair accessible.
Event_date	Date of Event
Seat_num	First seat in the block of seats
Num_seats	Number of seats in transaction
Last_seat	Last seat in the block of seats
Orig_purchase_price	Primary Market price per ticket for each seat in transaction
Add_datetime	Date of transaction, for example if the activity_name is TE Posting this indicates when the tickets were posted.
TE_posting_price	Price of posting on secondary market
TE_purchase_price	Price of purchase on secondary market
Sales_channel	Indicates whether transaction occurred on stubhub, TM Exchange, etc. Note: Prior to 2018, data for channels outside of TM Exchange were not available.
Activity_name	Transaction activity type (ticket posted, resale, cancelled, etc.)
Season_year	Season of Event. Note: season runs from August to February, so a game in January of 2018 would be a part of the 2017 season.
Acct_id	Account ID of original seatholder
Assoc_acct_id	Account ID of purchaser

Table 2: Table 'Primary' provided by NFL Team

Variable	Description
SaleDate	Date of Sale
TicketingAccountId	Account Number of purchaser. -1 indicates a purchaser without an account at time of purchase.
Eventcode	Identifier for each game. Prior to 2018, game date was the indicator, after then the opponent was the indicator
Eventdesc	Describes the game
SectionName	Section in Stadium
RowName	Row in Section. An N indicates infill seats (folding chairs, non-permanent). A W indicates wheelchair accessible.
FirstSeat	First seat in the block of seats
LastSeat	Last seat in the block of seats
TotalRevenue	Revenue for entire transaction
PurchasePrice	Purchase price of each ticket in transaction
QtySeat	Number of seats in transaction
EventDate	Date of Event
Season	Season of Event. Note: season runs from August to February, so a game in January of 2018 would be a part of the 2017 season.

Table 3: Table ‘Opp’ provided by NFL Team

Variable	Description
Season	Season of Event. Note: season runs from August to February, so a game in January of 2018 would be a part of the 2017 season.
Opponent	Team playing against the NFL Team
Team	Opposition Team
VisitingTeam	Opponent team
OppWin	Rate of opponent wins
NFL TeamWin	Rate of NFL Team wins
RoadAttendance	Fan attendance rate
FacebookFans	Number of Facebook fans
Distance	How far is the team’s location from Indiana
Home Opener	Flag indicating home opened
Temp at Kick	Temperature at kickoff
Rain/Snow	Flag indicating rain or snow
NFL Team Out of Contention	Flag indicating NFL Team no longer having a chance to win
LastVisitYears	Years since last visit
OppScoredLY	Points scored when the team visited last time
OppDefGivenLY	Points scored by our team during last visit
OppPlayoff(Prev Bin)	Did opposition make it to playoff
Top25Jersey(Ordinal)	How many players in opposing team in top 5 NFL players
OffMVP(Interval)	When was the last offensive MVP of the opponent team
DefMVP(Interval)	When was the last defensive MVP of the opponent team
OddsFeb	Betting odds
Division	Which division is the game; it is a 1/0 flag
GAindyL10	This should be the win: loss ratio in last 10 games but it is not that case. It is difficult to interpret this variable

Table 4: Table ‘Unsold Inventory’ provided by NFL Team

Variable	Description
Event_name	Identifier for each game. Prior to 2018, game date was the indicator, after then the opponent was the indicator
Team	Team playing against the NFL Team
Time of Game	Time of the match
Event_date	Date of the match
Seat Type	Price varies by the seat type; contains seat-type information.
RowClass	There are 3 row classes (‘Manifest”, “ADA” and “infill”)
Num_seats	Numbers of seats unsold in that rowclass
Section_name	Section in Stadium
Row_name	Row in Section. An N indicates infill seats (folding chairs, non-permanent). A W indicates wheelchair accessible.
Seat_num	First seat in the block of seats
Last_seat	Last seat in the block of seats
Price_code	Price code
Price Code	Price code
Block_full_price	Difficult to interpret the column
Class_name	Ticket is unsold in which class

METHODOLOGY

Solution 1 – Revenue maximation model

The objective of the dynamic pricing model is to increase revenue. Following is the method to achieve the optimization-

Quantities of ticket sold is a function of price and other factors. These other factors would include team features, opponent features and external factors such as weather condition at kickoff. For example, if we lower the price it is logical that the quantity sold would be higher. This would lead to decrease in value created of the game and will drive down the willingness to pay of the user. Decrease in willingness to pay would thereby impact revenue.

Besides price the other factors that impact price are external condition, opponent team, team situation, player injuries etc.

Quantity of tickets sold = A1*Price +A2*Opponent team +A3*Temperature + A4*Playoff_run + A5*Facebook_Fans + A6*Days from Game + A7*Tickets already sold + Constant

We feature engineered variables that could have an impact on the ticket price. Variable significance will be obtained using the historical data. The co-efficient of the equation will change based on the seat type. Once we have the equation of the quantity of tickets sold, we would then move onto using a solver to identify the maximum price for which the Revenue = Price * Quantity equation maximizes. This can be done by either differentiation or by solving the quadratic equation

We will receive the Volume as a function of price from above equation. We can tweak the price from a minimum range to maximum threshold to get the maximum revenue for the NFL Team. This would generate the curve which would solve the optimization problem.

Cross Validation- We plan to use 7-fold cross validation because the data is present from 2012-2019. We will use every year in the test set and other years in the train set. For example- 2012-2019 would train set and 2019 could be a test set. The Train:Test ratio of the data would be 85:15. RMSE would be the metric for model evaluation

Solution 2 – Pricing tool

Another way the team can recover maximum revenue is to bridge the price gap between the primary and secondary markets.

Our solution is to provide a matrix of days left to the game, and volume of tickets sold, with each cell populated with a ratio by which when a base price is multiplied, would give the price that could be set in order to recover as much as the secondary market.

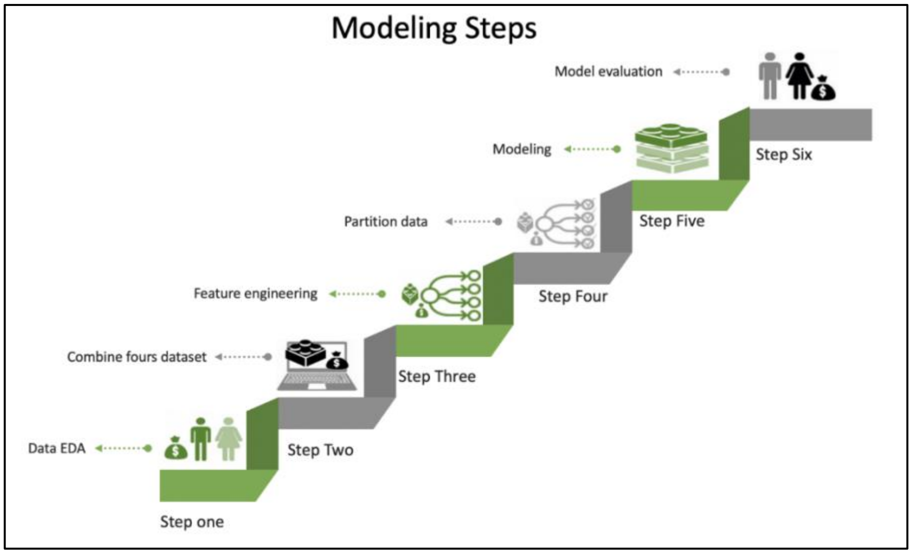
This solution can be split into two phases.

1) Calculating ratios and building the matrix
2) The baseline (initial) price calculation

Data Preparation and Modeling process-

Data Preparations process-

Modeling steps-



MODELS

SOLUTION 1: Revenue Optimization Model

Step 1: Identifying price drivers

We developed a Random Forest model to calculate the significance of various features on price. We observed that the secondary and primary markets had varying feature significances

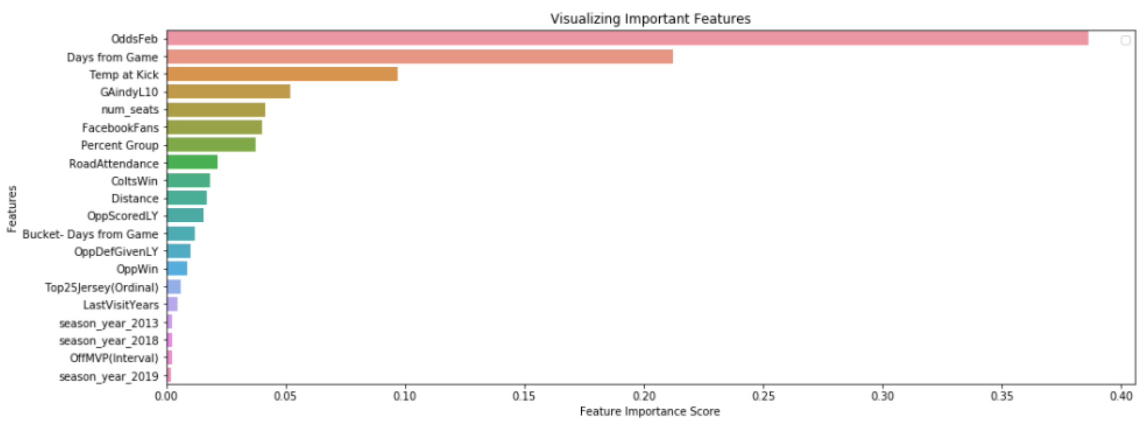


Fig: Secondary market feature importance

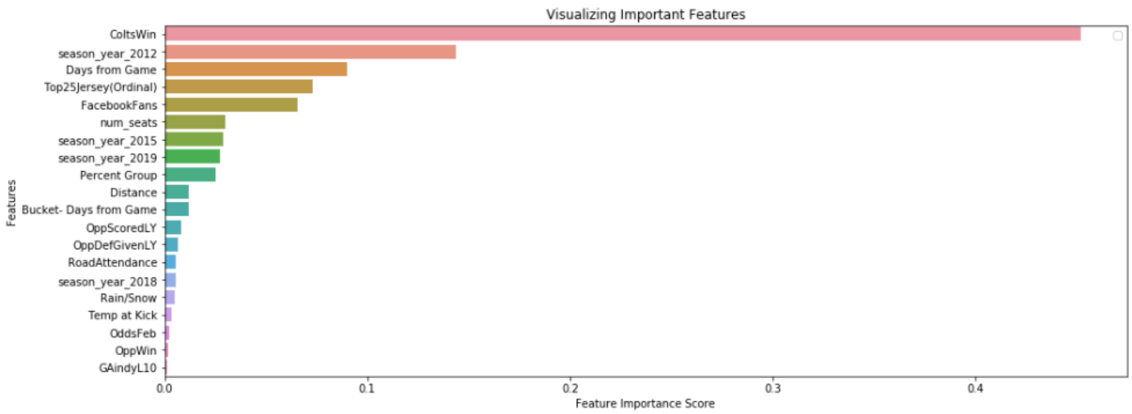


Fig: Primary market feature importance

Step 2: Creating a demand model:

We used several ML algorithms to model the equation of demand as a function of price and other factors, such as team in contention, temperature at kickoff, opponent features and internal team features.

We observed extremely low accuracies for daily and weekly predictions, so then tried creating buckets of days to the game. 8 buckets were created so as to equally proportion the % volume of sales into the 8 buckets.

Time Interval	Model	R_2	Price Coefficient	Effect on price
Daily	Linear	0.05	+	Price doesn’t decrease with increase in Quantity
Weekly	Linear	0.25	+	
Bi-Weekly	Linear	0.45	(-0.005)	Optimal Price shoots to very high number
Bi-Weekly	Random Forest	0.90 Overfit	-	
8 Intervals	Linear	0.35	-	

Table: Model evaluation - performance metrics summary

Step 3: Revenue Optimization

Our final step would have been to find the optimal price that maximizes revenue for the different sections and days to game, but unfortunately, we observed extremely low R_2 values for our machine learning models for the demand equation. Our hypothesis from the price driver model, is that our NFL team's fans have displayed slightly price indifferent tendencies, and not having data about the fans is just depriving our model of some key variables. Given that the co-efficient for price from the demand models are either positive which would indicate that even with an increase in price, quantity just increases. Other models gave extremely small and negative coefficients for price such as -0.005 – such small negative coefficients only lead to absurdly high predicted values of price like $15k for a ticket.

SOLUTION 2: Pricing decision support tool

Step 1: Initial ratio calculator

We observed the secondary market price fluctuation across time and number of tickets sold. The price in the secondary market was compared with that of the primary market initial price. The fluctuations in the secondary market are captured in terms of ratio. Ratio in the tables are Secondary market price divided by Primary initial base price.

Secondary market ratio table- This suggests that the Secondary market starts with a very high initial price and then lowers it down based on the demand. If we use the same logic in the secondary market It will lead to $125k increase in revenue *(10% of the primary market revenue).*

Initial Price = 94	% Volume occupied									
Time Groups	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
>90 days	1.6	1.7	1.5	1.4	1.4	1.4	2.9	2.2	NA	NA
60-90 days	1.3	1.6	1.7	1.5	1.4	1.4	1.3	1.4	1.7	NA
40-60 days	1.1	1.2	1.4	1.6	1.5	1.4	1.4	1.4	1.5	NA
25-40 days	0.7	0.9	1.1	1.4	1.5	1.3	1.3	1.4	1.2	0.9
15-25 days	0.5	0.7	0.9	1.1	1.5	1.5	1.3	1.3	1.2	1.1
5-15 days	NA	0.6	0.7	0.8	0.9	1.3	1.4	1.3	1.2	1.2
1-5 days	NA	1.7	0.5	0.6	0.6	0.7	1.0	1.2	1.2	1.1
<1 days	NA	NA	NA	1.4	1.3	1.1	0.6	0.5	0.8	1.0

Primary market ratio table- There is no fluctuation in the price based on the demand.

Initial Price = 94	% Volume occupied									
Time Groups	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
>90 days	1.0	1.0	1.0	1.2	1.2	1.0	0.8	1.2	1.2	NA
60-90 days	0.9	1.0	1.1	1.0	1.1	1.2	1.2	1.2	1.1	NA
40-60 days	0.9	0.9	0.9	1.0	1.1	1.1	1.1	1.0	0.9	1.3
25-40 days	0.9	0.9	1.0	1.0	1.0	1.0	1.0	1.1	1.1	1.3
15-25 days	0.9	0.8	0.9	1.0	1.1	1.1	1.0	0.9	0.9	1.4
5-15 days	NA	1.0	1.0	1.0	1.1	1.1	1.1	1.1	1.0	1.1
1-5 days	NA	NA	0.9	1.0	1.0	1.0	1.1	1.1	1.1	1.0
<1 days	NA	NA	NA	NA	0.6	0.8	1.0	1.0	1.0	1.0

Primary market quantity sold- Majority of the quantity sold in primary market are higher than 90 days.

Initial Price = 94	% Volume occupied									
Time Groups	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
>90 days	1024	304	107	69	43	12	0	0	0	0
60-90 days	101	177	174	57	19	22	14	0	0	0
40-60 days	12	165	116	108	82	30	9	0	0	0
25-40 days	1	97	73	99	141	82	30	1	0	0
15-25 days	0	14	111	65	100	95	77	17	0	0
5-15 days	0	4	41	108	115	152	196	141	46	0
1-5 days	0	0	4	36	68	97	257	412	305	49
<1 days	0	0	0	0	0	1	5	47	227	762

In order to use the secondary market grid, the initial price of each game is to be identified

Step 2: Initial pricing for 2020 Games

We used Random forest model to price the Initial price for 2020 games. This is also done with the perspective that the more popular games should have a higher price. The model gave more than 90% accuracy for historical time period. With this knowledge, our NFL partners can correctly price their ticket, so fans are drawn towards buying from primary channels. Once we have the baseline price we used the multiplier from the secondary data. The strategy os to keep the price higher in the beginning and then reduce it bases on the demand. This has been the strategy of the secondary market which is not followed in the primary segment. The ratio used is in between 1.3x-1.6x based on the historical data. *(results are pasted below)*

RESULTS

To help the NFL team, we have calculated the price that they should set of their seats in price code "D" for the 2020 season, in order to bridge the revenue gap between primary and secondary markets; The results are as follows:

2020 Opponent	Predicted Initial Price based on Historical Primary Market data (Price Code = D)	Suggested Initial Price based on Previous Secondary Market Data (1.3x to 1.6x)
Titans	$143	$180 to $220
Texans	$150	$190 to $230
Jaguars	$145	$190 to $230
Packers	$165	$210 to $250
Vikings	$150	$190 to $230
Ravens	$137	$180 to $220
Jets	$148	$190 to $230
Bengals	$144	$190 to $230

On implementing solution 2 on the Primary data for 2019, we would have received a 10% ($125,000) increase in revenue by setting the suggested price.

CONCLUSIONS

Our study explores two solutions to optimize revenue with dynamic pricing for an NFL team. While one approach focusses on revenue maximization, the other explores bridging the revenue gap between the primary and secondary markets and suggesting primary prices based on historical secondary market data.

Both of the proposed models may have some limitations. Adding consideration of customers buying patterns and other characteristics might enhance the applicability of the dynamic pricing model. Additionally, considering consumer resale effects and cannibalization within sections will improve the model performance

Dynamic pricing provides marketers full visibility into the pricing schedule for the upcoming months of sales. Customers may choose to wait for a lower price but risk their preferred seat or all tickets for these highly anticipated games selling out. It rewards customers who are willing to pay more with first access to a limited supply of tickets and to the best seats available, as opposed to creating a frenzy to purchase the best available seats the moment they go on sale.

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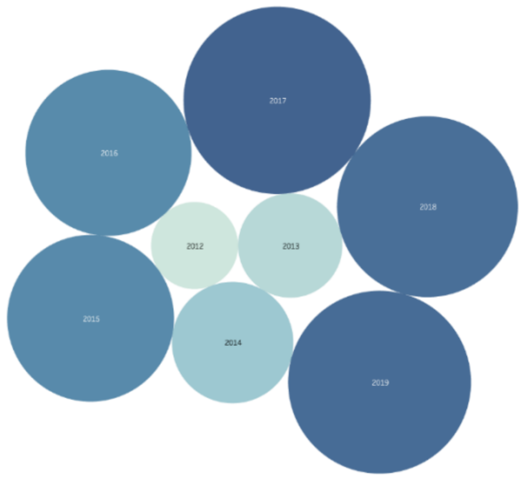
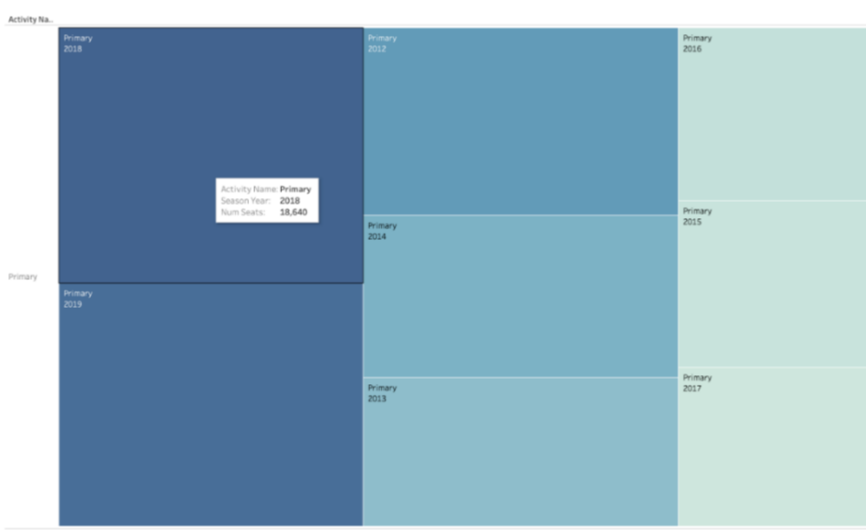
APPENDIX

EDA results

Ticket sold across years comparison



Sales from Primary channel is increasing year over year- The number of tickets sold by primary channel is increasing over the years.



Total Number of Unsold inventory- Number of unsold inventory is very low in 2019 is lower than 2018

Year of Event Date		
2017	2018	2019
23,643	60,712	41,602

Number of seats vacant by Month and year- 2018 September to November had the highest number of vacant seats