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UofSC Athletics Practicum Project
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UNIVERSITY OF South Carolina

Problem Statement

Using both Gamecock athletics ticketing data and resale ticketing data, identify and explore undervalued football seats (sections, rows, seat number) by opponent, conference, and game time.

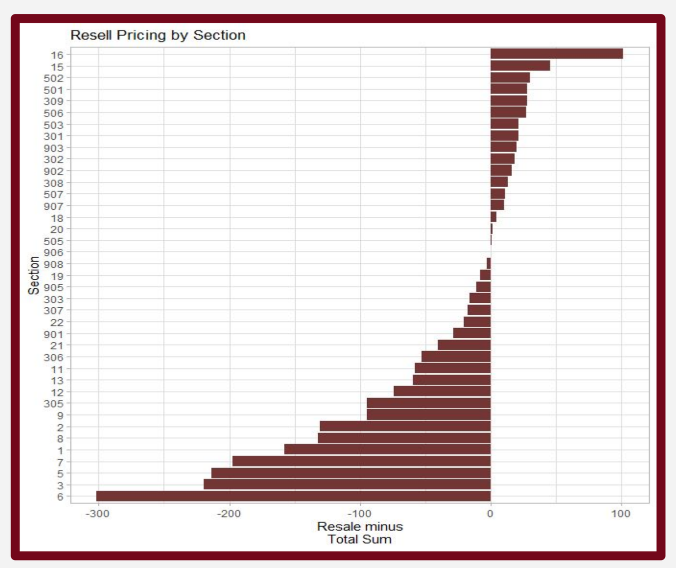
Background

Our project is based off of records from 3 seasons (2021-2023) of home football games. Each record represents a ticket that was resold on the secondary market (Ticketmaster).

The original dataset consisted of 111,844 rows, which covered 103 sections of the stadium. Among other things, our cleaning process included removing the SC state game (because it was rescheduled), assuring that all event names were distinct, and removing the box seat sections (3 sections).

After cleaning, we ended up with a dataset of 86,304 records broken down by 25 variables. The data included 100 sections of the stadium, and covered 20 games across 16 different opponents.

Preliminary Findings



We are able to see that the most undervalued sections are 15 & 16, with section 16 selling up to $100 above retail price. On the contrary, we can see that generally the most overvalued sections are sections 1 - 9.

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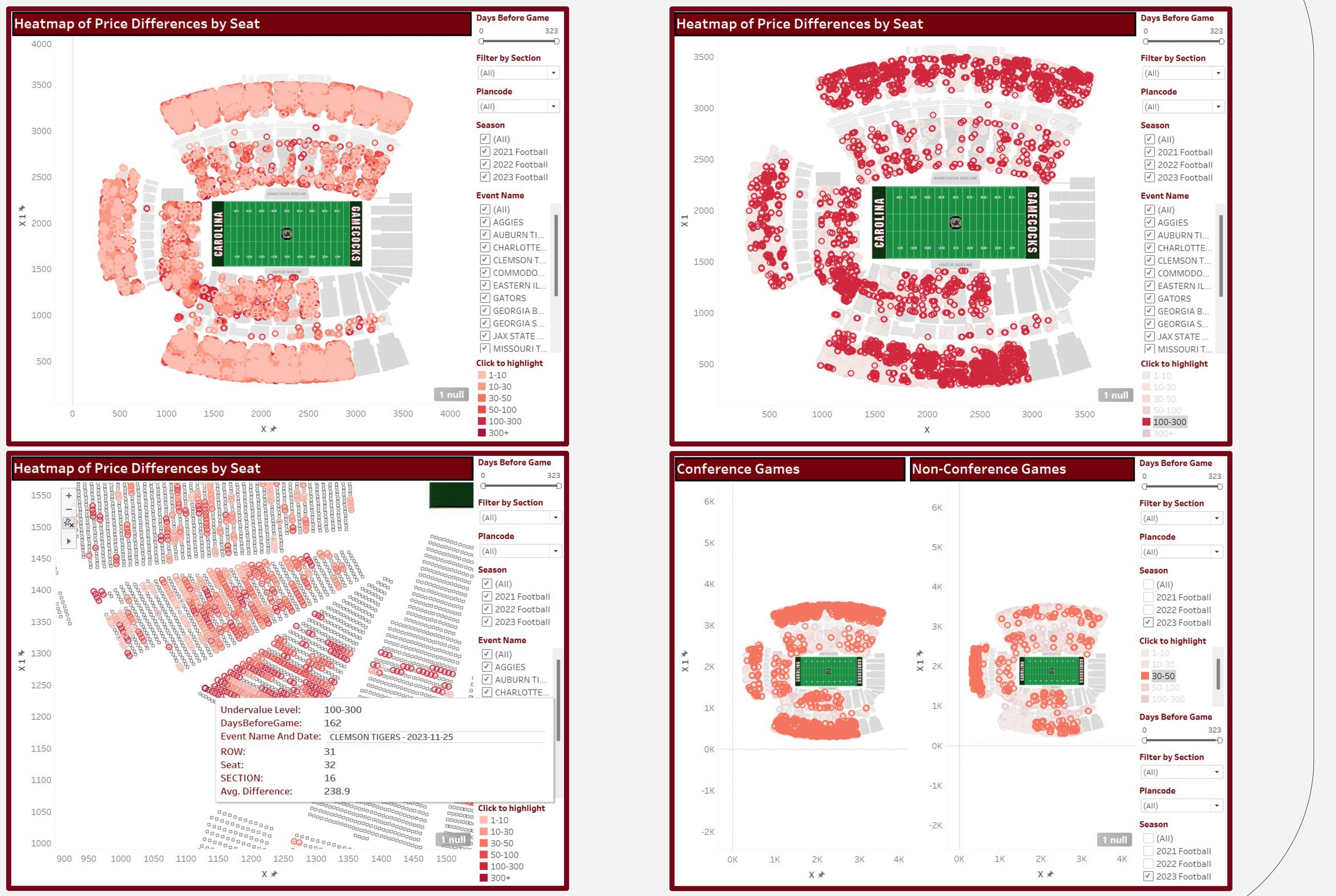
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
SECTION.F11    -69.804      4.258 -16.395  < 2e-16 ***
SECTION.F12    -83.453      4.217 -19.789  < 2e-16 ***
SECTION.F13    -68.992      4.237 -16.282  < 2e-16 ***
SECTION.F14    -28.796      5.133  -5.610 2.03e-08 ***
SECTION.F15     37.555      4.204   8.934  < 2e-16 ***
SECTION.F16     64.794      6.882   9.415  < 2e-16 ***
SECTION.F18     -2.735      5.650  -0.484 0.628329
SECTION.F19    -16.594      4.738  -3.502 0.000462 ***
SECTION.F2    -139.182      3.790 -36.720  < 2e-16 ***
SECTION.F20     -8.715      4.255  -2.048 0.040531 *
SECTION.F21    -50.521      3.851 -13.118  < 2e-16 ***
SECTION.F22    -32.692      4.076  -8.020 1.07e-15 ***
SECTION.F3    -225.916      3.336 -67.722  < 2e-16 ***
SECTION.F301     1.453      2.649   0.548 0.583469
SECTION.F302    -3.403      2.667  -1.276 0.202036
SECTION.F303   -32.484      2.578 -12.602  < 2e-16 ***
SECTION.F304   -34.750      2.771 -12.543  < 2e-16 ***
SECTION.F305  -105.139      3.103 -33.880  < 2e-16 ***
SECTION.F306   -66.000      2.918 -22.615  < 2e-16 ***
SECTION.F307   -31.332      2.633 -11.898  < 2e-16 ***
SECTION.F308    -1.372      2.489  -0.551 0.581553
SECTION.F309     7.241      3.086   2.347 0.018942 *
Residual standard error: 142.8 on 74174 degrees of freedom
Multiple R-squared:  0.3916,	Adjusted R-squared:  0.3911
F-statistic: 757.9 on 63 and 74174 DF,  p-value: < 2.2e-16
```

This is our first multiple regression model showcasing coefficient values for each section, excluding sections 100 and 400 (due to high donation amounts.) Our first model made up for 39% of the variability in price difference, giving us an idea of what our visualizations should look like.

Visualizations

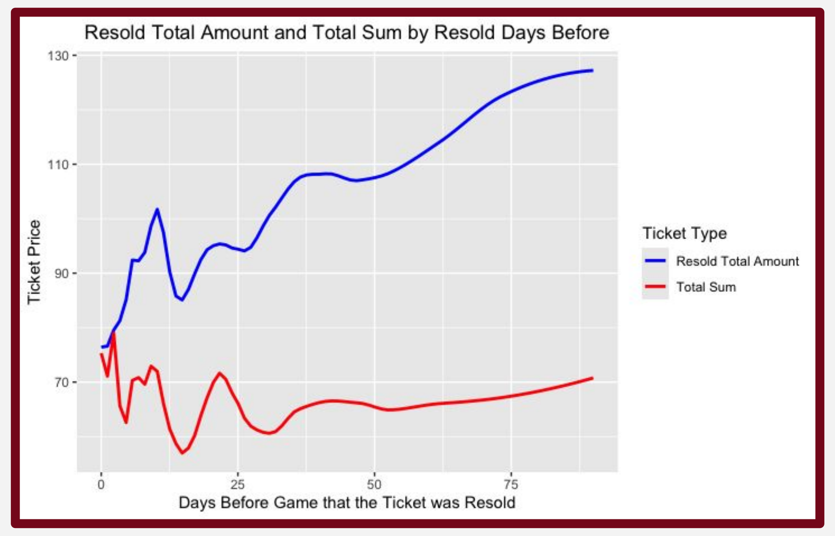


These visualizations provide an easy and effective way of viewing the overall distribution of undervalued seats across various sections of Williams Brice Stadium. Each of the circles on any one of the visuals represent a seat that has been bought on the retail market (from USC) and resold on the secondary market (Ticketmaster).

The darker the red color, the higher the difference between retail and resell prices.
On the right hand side of the visuals, we have the ability to filter by certain criteria such as: How many days before the game the ticket was bought, section, season, opponent, and undervalue level ($1-10, $10-30, $30-50, $50-100, $100-300, $300+).

Analytics

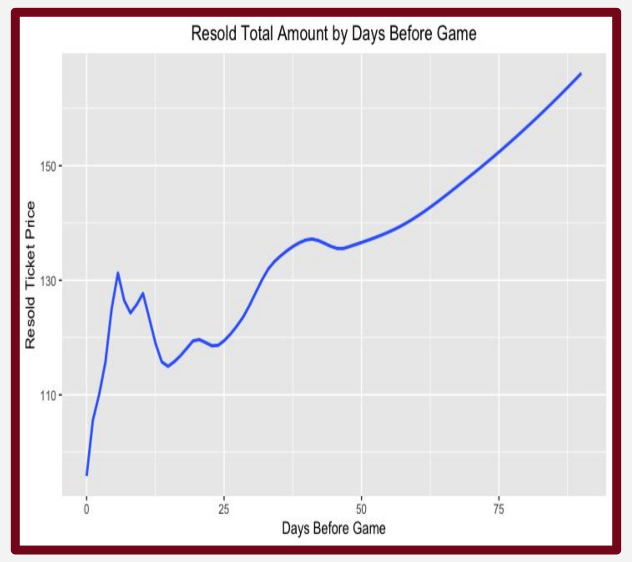
After presenting our findings to the the athletic department, they suggested we analyze price differences by days before an event that a ticket was purchased. This gives them an idea of price fluctuations as a ticket approaches game time. We settled on constraining days before an event to 90. This was our first step in exploring the value of dynamic pricing. implementing a dynamic pricing model.



These visuals are based on excluding season ticket holder prices and original ticket prices greater than $1000.

Dynamic Pricing

As a final step in our project, we wanted to see whether dynamic pricing would be a good idea for Gamecock Athletics when it comes to football. We analyzed the resale data, which already followed a dynamic pricing model. In this analysis we looked at how the price of tickets on the secondary market changed as purchases approached gameday.



This plot showcases the trend of ticket prices as the days before games increase. We see a reversal in the trend for resold ticket prices around 12 days out, which could be explained by the fact that the game time is announced 12 days before the event.

As a final step, we created 3 models to predict ticket price based on various factors. Of the 3, we wanted to showcase the most concise model, the coefficients of which are seen below. This model was able to capture 84% of the variation in price.

```
Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
resold_days_before        0.495770   0.007835   63.27   <2e-16 ***
CLUB club seat          203.590411   3.322553   61.27   <2e-16 ***
CLUB not a club seat    136.628016   0.536974  254.44   <2e-16 ***
CONFERENCE SEC           38.898963   0.632206   61.53   <2e-16 ***
ClemsonGame not clemson -97.773516   0.748884 -130.56   <2e-16 ***
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 44.73 on 38354 degrees of freedom
Multiple R-squared:  0.8392,	Adjusted R-squared:  0.8391
F-statistic: 4.002e+04 on 5 and 38354 DF,  p-value: < 2.2e-16
```

Results & Future Work

Using our finalized model, we were able to predict new values of ticket prices among non season ticket holders. We found that as a result of not dynamically pricing these tickets, USC Athletics missed out on $2,478,683 over the past 3 seasons. With this information, we recommend that the department should implement a dynamic pricing model.

Our client asked us to research instances that impacted ticket demand, which include the state fair weekends, parents' weekends, and homecoming. Another area of continuation would be identifying if differences within sections impact value, such as to what extent a seat being next to the aisle would impact the seats overall value.