Can Injector Location Predict Treatment Success?

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Introduction

The beauty industry estimated global value is 571 billion US dollars in 2023 with an expected growth rate annually is 3.8% (Statista, 2023) and is a highly competitive landscape for keeping the top product positions as well as for new innovative products. Part of this massive product landscape is the use of botulinum toxin for aesthetic appeal – better known as Botox – which is an injectable treatment for different areas of the face like frown lines, crow's feet, etc. Botox is made by Allergan/Abbvie who see annual sales of about 3.5 billion US dollars for aesthetic indications and 3.5 billion US dollars for therapeutic indications. For the aesthetic space, it could be very lucrative for a company to develop a competitive product to Botox and attempt to get part of their market share for an injectable toxin treatment. Data presented for Milestone 4 will focus on the aesthetic indication of frown lines with a toxin drug product.

This project will investigate the relationship between the location of an aesthetic injector and subject results after receiving a new toxin injected into the glabella region. Data from two studies that were conducted across the United States and Canada will be analyzed. By better understanding which locations had better outcomes, we can then use this information to help create predictions for other locations. These predictions can then help sales teams target existing and new areas in hopes of having an aesthetic practice carry this new product. Such information could be very useful and impactful to generate new accounts and revenue for this new drug product.

Two studies were conducted to assess change from baseline in frown lines at key study timepoints after receiving an injection of study drug in the glabella region as well as consumer interest in receiving Botox treatment will be the two main data sources. The study data details physician evaluations of subjects over time after an injection of botulinum toxin while the Google Trends data details what locations people are looking to get treated with a toxin.

Valuable information can be obtained by evaluating and analyzing these two data sources. Since my company is interested in getting new customers to try our new drug product, data mining techniques can be employed to shed light on features of existing practices that use our product as well as how to add new clients by investigating the following questions:

1. What is the relationship of location to ratings? Do some locations have better performance than others?
2. To predict which locations have the best outcomes, where location can be at the practice level or metro area level and best outcome is defined as having an effect at Week 24.

Initially, I was also interested in understanding if areas where people have a higher interest in being treated have better outcomes. However, this analysis ended up being more complex and I dropped it for this current effort.

<u>Organized and detailed summary of Milestones 1- 3</u>

In order to address my two analytical questions, I began by prepping each data source for analysis with the goal of merging all data into a single dataset for analysis. All analyses were conducted in Jupyter Notebook. As stated in milestone 1, logistic regression will be used to address these research questions.

The first data source details the evaluation of subjects' frown lines on 4-point scale of Severe (3), Moderate (2), Mild (1) or None (0) over a 36-week period. Subjects have a baseline measurement, then receive a treatment (drug or placebo) and evaluated every 4 weeks up to 36 weeks. Post-baseline measurements are then re-coded to treatment success (1=Yes and 2=No) defined as a None/Mild rating for Yes or Moderate/Severe for No. These data were collected at different locations throughout the United States and Canada during 2018 and 2019.

The second data source from Google Trends shows people who are interested in getting treated for different metro-areas in the United States and Canada from 2019 through 2022. Interested in treatment is defined by the trend score (a scaled score on a range of 0 to 100 based on a topic's proportion to all searches on all topics).

A third data source was introduced to merge the Google Trends metro level data to the injector practice location. This data was not used in analysis.

The results of the exploratory data analysis show that for demographics, there are more females than males in these two studies as well as most subjects are Caucasian and tend to be between the ages of 40 to 60 years of age. These studies were not stratified for these demographics and all subjects met the age requirements to participate in these studies. The wrinkle scale data shows that overall, the placebo and drug groups move in opposite directions on the scale which is expected if the drug is efficacious (Figure 1). Likewise, the rating scales are similarly distributed between the two studies which are done in different locations of the United States and Canada (Figure 2). Further examination of the severity data shows that across visits, severity increases overall, likewise, one can determine that as the study visits increase, the study population is decreasing as subjects leave the studies (Figure 3 and Figure 4). When split by treatment, the severity ratings show that the subjects who received drug perform better on the severity scale though treatment does wear off. When looking at the data by location, severity ratings show similar differences for placebo versus drug. In terms of site differences, one can see that for each treatment group – there are differences between the locations (Figure 5 and Figure 6). For the Google Trends data, Figure 7 shows customer interest by each metro area.

Figure 1.

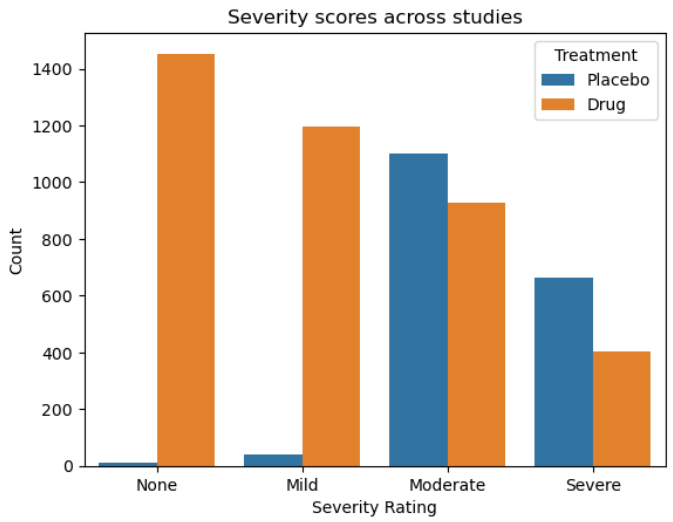


Figure 2.

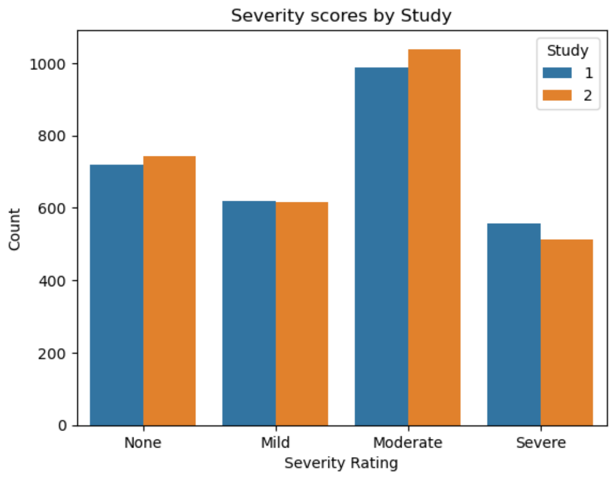


Figure 3.

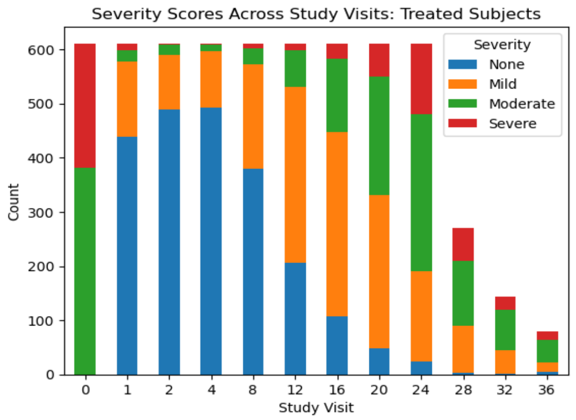


Figure 4.

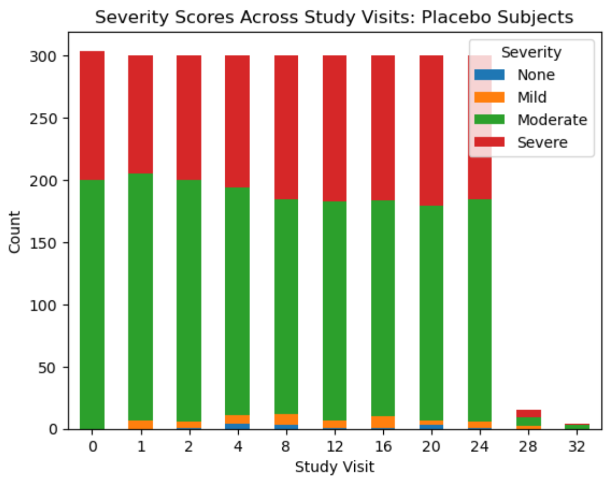


Figure 5.

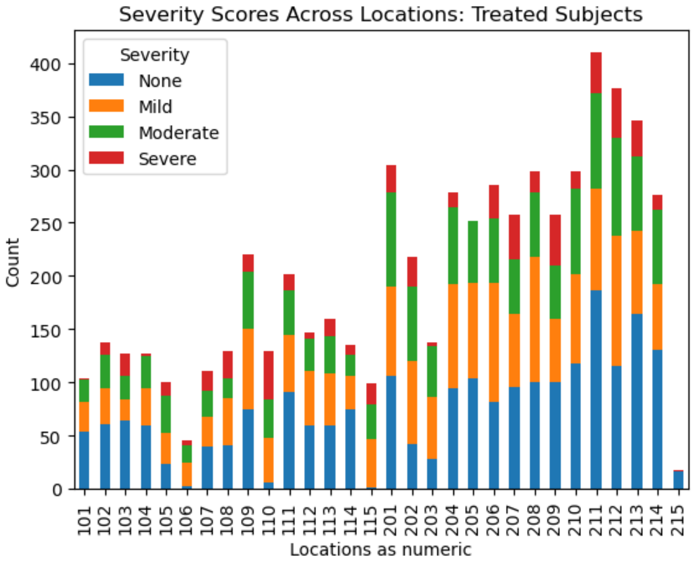


Figure 6.

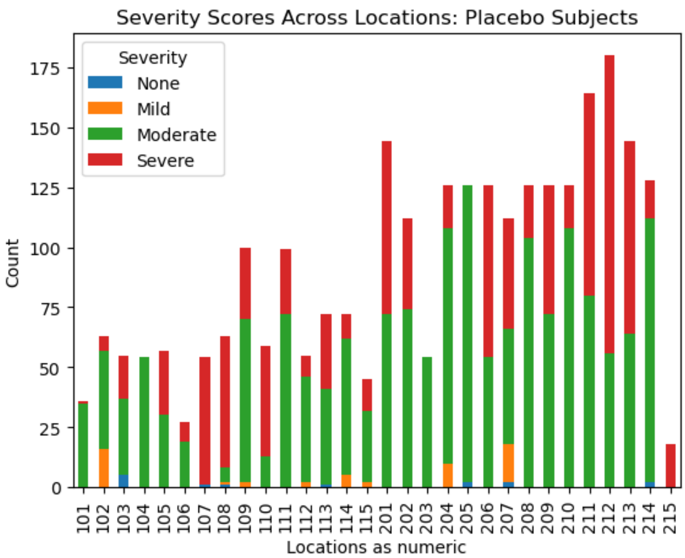
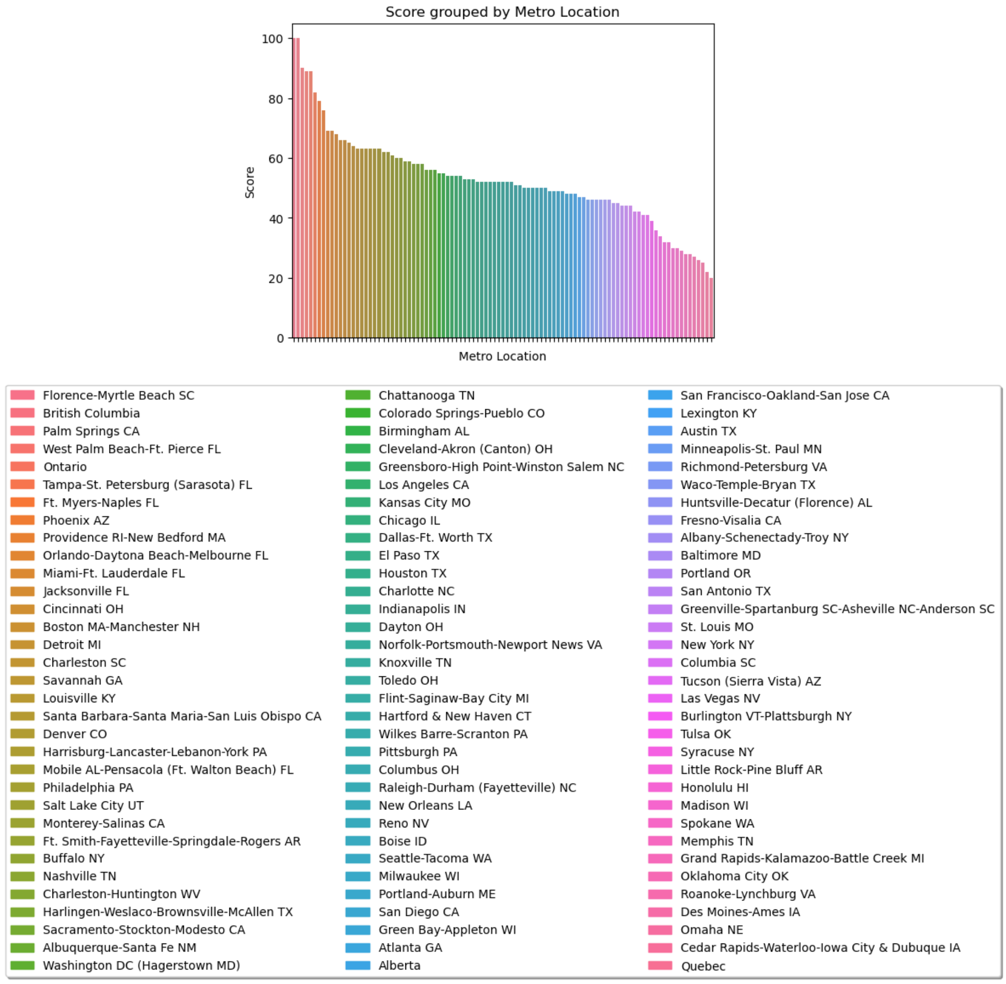


Figure 7.



After exploratory data analysis was complete, I focused on creating the final, merged dataset (two versions for the two locations). Steps taken were to create a composite variable to represent the target if a subject had a successful response at Week 24. Since each subject had up to 36 weeks of data (a row for each timepoint), I reduced the data down to a single row per subject by creating a composite score of their experience on the drug up to Week 24. Likewise, I developed a method to merge the Google Trends data. For this step, I used the third data source to act as a bridge between the study data and the Google Trends data. Also, I created grouping variables for Age, as well as the Google Trends data by creating a categorical variable for High, Medium and Low scores of customer interest in treatment. Columns that would not be used in the modeling were dropped as well as checking to confirm there was no missing data or duplicate rows. At this stage, two final data frame were created, one with region and the other with injector location. Once I had split the data frame for the different ways of analyzing location, I then dummied all categorical variables while keeping in mind to drop one level of each variable to avoid multicollinearity. The final step for Milestone 2 was to create a target and features data frame for each of the two models that I developed.

In order to prepare the data for modeling, the resulting target and features datasets were each divided into train and test datasets. Logistic regression modeling was conducted with three methods for training and test datasets. The three methods are: 1) logistic regression on the datasets with all features 2) logistic regression on the datasets using features reduction by calculating the chi-square for each dummied feature and dropping features that did not meet the threshold of greater than 0.2. and 3) using hyper-parameterization on the feature reduced datasets in from Step 2 to determine the best parameters and running a logistic regression using the best resulting parameters. Table 1 details the results of these analyses with each column named for which method was used for the logistic regression model. The best model run was the dataset where features were reduced, and hyper-parameterization was used to determine the best parameters for the logistic regression. Method 3 has an R-squared value of 0.69 for the injector location and an accuracy score of 0.65 while for metro region, the R-squared value was slightly higher at 0.71 and an accuracy score of 0.65.

Table 1. Results summarized from logistic regression model

Model 1 (by SITE)	Method 1	Method 2	Method 3
R-squared	0.69	0.71	**0.69**
Accuracy	0.60	0.60	**0.65**

Model 2 (by REGION)	Method 1	Method 2	Method 3
R-squared	0.69	**0.71**	**0.71**
Accuracy	0.67	**0.65**	**0.65**

Conclusion:

The results of this analysis show that it is possible to predict which location has the best outcomes by injector location as well as by metro area with a 65% accuracy. The data supporting this analysis is robust however, I think there could be additional work done prior to deploying this model. Specifically, I was interested in coding location and metro areas in order to create a ‘similarity score’ between different cities in order to potentially expand the generalizability of predictions. Likewise, I think it would be interesting to investigate using another classification method for modeling and see if the resulting accuracy score improved. Also, though I did not present an interpretation of the logistic regression coefficients, I think it is an important aspect that needs to be included. Prior to making any recommendations, I would have these steps included. Also, it would be good to view the methodology for creating a ‘similarity score’ with another colleague to get their input and feedback. The results that are presented in this paper are a good starting point, however, additional analyses should be conducted in order to put forth the best model possible.

Reference

Beauty & Personal Care - Worldwide (Accessed 2023, June 3). Statista website.
https://www.statista.com/outlook/cmo/beauty-personal-care/worldwide