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DSC630-T301

Course Project--Final Write-Up

Overview:

Intro:

In August of 2021 Disney introduced a new ticketing scheme to the Disneyland Resort in response to their new reservation system in place due to Coronavirus restrictions. Their reservation system works by selecting a date in which you want to visit and reserving such date to ensure your entry in line with capacity limits. The new ticketing scheme introduced by Disney is known as Magic Key Pass which replaced their old Annual Pass program.

When purchasing expensive Dream Key passes, die-hard Disneyland fans were under the impression they would be let into Disneyland/California Adventure every day of the year. They were highly disappointed when they found out they were unable to do so due to lack of reservations available to either park. Many blamed not being able to reserve a date on Disney's lack of preparation and over-selling/promoting a program they were not able to accommodate. Could upset magic key holders be avoided if Disney had used predictive analysis to determine how to promote their new ticketing scheme in a way that everyone (key holders and day ticket purchasers) would benefit from it?

For this project I focused on Disney's overall revenue for the years before, during, and after covid to have a largescale image of how their revenue was impacted. In addition to the overall revenue trends this project includes predictive models focusing on reviews left by Disney guests throughout various parks. The need to add this second dataset comes from the limited data provided by Disney as a whole. Additionally, to determine future monetary trends of a company it is best to step back and focus on how the consumers/guests are reacting to the experiences the company provides.

In the initial dataset containing revenue the following variables were used to determine factors that might affect Disney's revenue:

- Revenue
- Cost of goods sold
- Gross profit
- General and administrative expense
- Operating expense total

The dataset containing guest reviews relied heavily on the following variables:

- Rating
- Review_Text
- Branch
- Sentiment

These variables allowed for predictive models to be tested and ran to determine which method would be best to implement to get a greater number of positive reviews. The overall goal will be to see which park (location) received the most positive reviews and how that might fall in line with the assumption that the Magic Key program hurt Disney's California park's revenue.

Executive Summary:

Reviews are a beneficial way for a company like Disney to try and predict how future guests will feel in similar situations. Predicting what reviews are classed as "negative" will help Disney change such flaws to better the guest experience. If most negative reviews contain key words, the connect to the Magic Key program then it can be assumed there is a correlation between negative reviews and negative revenue.

Because guests enter the parks every day and leave countless reviews daily it is hard to upkeep these predictive models with changing times, to have more meaningful results the models need to constantly run as the data changes. Another major issue that arises with reviews left by guests is this idea that when people have a positive experience (anywhere for the matter) they are less inclined to leave a positive review versus when an experience is bad, and a negative review is given. The constantly changing data and lack of variety in reviews can prove to be an issue yet this did not seem to be the case throughout the project.

Based on the predictive models used on the reviews, Logistic Regression, multinomial Naive Bayes classifier and Decision Tree Classifier the accuracies were quite low, falling below 50% What these predictive models' accuracy numbers tell us is that these models need more data to predict whether a review is positive or negative. As we cannot fully trust these models, I looked deeper in which park (by location) received the better (positive) reviews.

Of course, California proved to be the reigning park (versus Disney Paris and Disney Hong Kong) which led me to the conclusion that no matter how many changes Disney makes the positive revenue will always be there. Disney might see a small hiccup in revenue as they implement these changes and will probably be hit by negative reviews but at the end of the day when a big company like Disney makes changes it is ultimately for the greater (company and guests) good.

Technical Report:

Background of the problem:

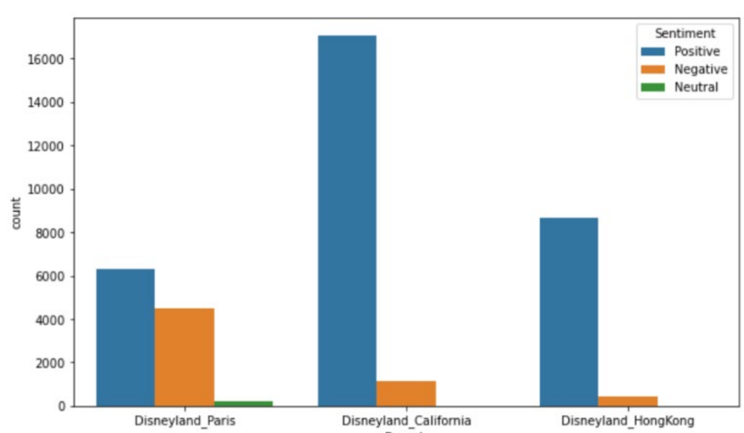
As mentioned in the beginning of this report, my project's focus is to determine whether Disney implementing their new Magic Key program in replacement of their Annual Pass hurt their revenue. After the yearlong closure due to COVID-19 Disney saw a decline in revenue and there were a lot of factors that played a role in such decline. To determine if new trends that Disney executes throughout the year in terms of ticketing schemes hurts the company (monetary wise) I implemented prediction models to help filter through guest reviews. Guest reviews are the most reliable source as to how the public is reacting to changing prices and ticket availability.

Methods:

Using the initial dataset which contained Disney revenue per quarter starting from 2018 to 2021, this dataset was crucial in determining when Disney's revenue was at its lowest and at its peak, I conducted simple. A correlation matrix was done to determine the correlation between revenue and other variables such as: Cost of goods sold, Gross profit, General and administrative expense, and Operating expense total. This matrix allowed me to see what other factors might have impacted the loss of Disney revenue (if I was to assume the Magic Key program was not a factor). Additionally, on this dataset I ran an observation count to discover revenue ($) value trends. The calculations on the initial dataset were a good starting point for determining what might have been the cause for a loss in Disney revenue but more data was necessary, thus I resorted to Disney guest review data as what consumers opinion on a company is crucial to their succession/failure.

The second dataset I decided to work on included reviews on Disney parks (California, Hong Kong, and Paris) this dataset was important to work with as I relied heavily on guest's opinions of the park and made the connection that happier guests lead to a revenue increase. To do such assumption, I ran three models on my data: Logistic Regression, multinomial Naive Bayes classifier and Decision Tree Classifier. The predictive models gave back low accuracies, which will be discussed later in this report, the model with the highest accuracy was multinomial Naive Bayes classifier.

After running the models on my dataset, I created more readable (versus numbers) sentiment value to be able to create graphs like the following to get a greater idea of how reviews are split (positive/negative) throughout the parks.



Results:

After using TextBlob to find the sentiment polarity of the ratings in the dataset I ran three models on my data frame. The first model, Logistic Regression, resulted in a 40% accuracy in determining whether a review is positive or negative. This comes from the TextBlob implemented earlier that can distinguish keywords and categorize them as ‘good’ or ‘bad.’ As an initial model a 40% accuracy is not very good. It is not ideal to have a predictive model the incorrectly assigns reviews as positive/negative more than half the time it is ran.

The second model gave only slightly better results with 50% accuracy through a multinomial Naive Bayes classifier. The 50% accuracy is not the best yet can also be worse, but we do not want to rely on a model who only half the time correctly predicts values. At this point in the project, I blamed the lack of performance for the initial models on only using a small (100 values) snippet of my whole (40,000+ values) dataset values (the reasoning behind this is explained in the conclusion).

After the initial two model I decided a third would not hurt my chances in finding a better accuracy, for my final model I used a Decision Tree Classifier. To my surprise this model gave a worse accuracy to the two previous models and resulted in a 20% accuracy. I believe the reason for this low accuracy is having only split into one decision tree based on ratings and reviews. This model was clearly not a good choice but interesting when compared to the ‘best’ model.

Focusing on the best model I had, with 50% accuracy, the multinomial Naive Bayes classifier and the worst, with 20% accuracy, the Decision Tree Classifier I noticed that my NB classifier mostly considered reviews with a rating of 5 whereas the Decision Tree classifier had a more variety of ratings, 4’s and 5’s. considering both models took in the same dataset values it is quite interesting to see that the lowest accuracy was working the best. To build on this a stronger model such as random tree could be implemented and assumed to have better results/accuracies.

Discussion/conclusion:

Because my dataset was so big when I was running my models my computer would crash and I decided to run each model on the top (first not necessarily top in terms of highest rating/sentiment) 100 inputs. Only using 100 inputs allowed my models to quickly run on the dataset but this might have also been the cause to such low accuracies. If I had a more capable machine, I would have potentially had better accuracies thus a better predictive model method.

This idea that a better machine brings in better accuracies is important as we assume big corporations like Disney can plug and chug a lot of data in seconds. Having the capacity to do so will benefit the Disney Company as a whole. If my results were able to predict positive results on a small scale it is only a wonder what Disney can do with such information.

In the end I concluded that the Magic Key program may have negatively impacted Disney to a minuscule extent. I say minuscule because no reviews mentioned the Magic Key program, so if any guests were unhappy with the new ticketing scheme there was not a strong hatred to go to the lengths of complaining about it. Because the program is new, I also ran a check on the mention of annual pass in guest reviews and less than 1% of reviews mentioned the annual pass. Guests are not unhappy with Disney’s new ticketing schemes, it almost seems like Disney is set, they have guests so enthralled by other factors that new programs are just accepted. Disney can skyrocket their company by implementing these predictive methods and take guest's complaints/suggestions and use for the company greater good thus increasing their revenue drastically for years to come.

Acknowledgments:

A lot of the coding done to accomplish this project was made possible by a concurrent class I was taking this semester in Bellevue: DSC 550. The book, "Machine Learning with Python Cookbook" provided helpful tutorials on how to implement models into the dataset I was using. Along with "Machine Learning with Python Cookbook" I used previous assignments to help guide me throughout the entire process.

Another helpful website that provided me with insight alongside was Scikit-Learn which provided helpful tutorials and model breakdown to further my understanding of predictive models. Dataset information was made possible by Kaggle which included a deeper explanation of what each variable meant per dataset as well as what could potentially be calculated with the given variables.

References:

Book:

Albon, Chris. Machine Learning with Python Cookbook. O'reilly, 2020.

Datasets:

2022, https://craft.co/the-walt-disney/metrics.

"Disneyland Reviews". Kaggle.Com, 2022, https://www.kaggle.com/arushchillar/disneyland-reviews?select=DisneylandReviews.csv.

Website:

“Scikit-Learn: Machine Learning In Python — Scikit-Learn 1.0.2 Documentation". Scikit-Learn.Org,

2022, https://scikit-learn.org/stable/index.html.