Individual Contribution

Name of Student: Md Tajrianul Islam

Islam.mdta@northeastern.edu

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Submitted to –Eugenia Bastos

MPS Analytics, College of Professional Studies, Northeastern University

Capstone Group Presentation and Write up_Individual Contribution

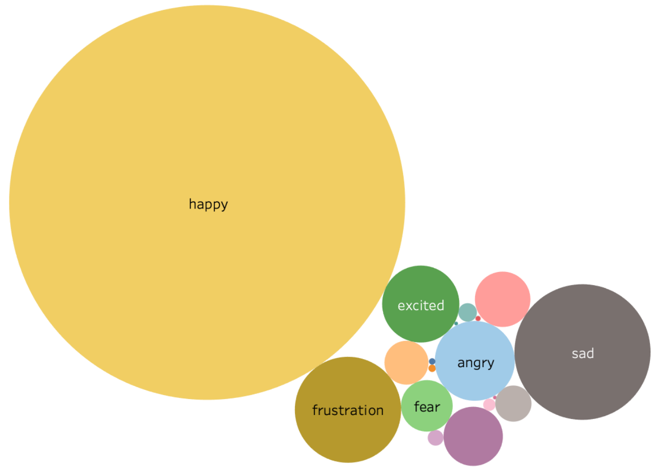
**Introduction**

I had the chance of leading the group to complete this capstone project. Other than planning the project timeline and setting up individual deliverables, I am also a very effective person when it comes to designing research processes, doing necessary literature review and domain research. So, we all started with our EDA with the given dataset. A major role for me was to explain the sponsor deliverable and make clear ideas about our goals to my group mates. After group discussions we decided to make our target variable emotional engagement. Then my major role was to preprocess the data to make it ready for my group members to build the models on it. After the models and validations were ready I went through the codes to ensure we are on track to meet our project goals. After the codes were ready, I went ahead and prepared for the project write up and presentation along with the help of another group member.

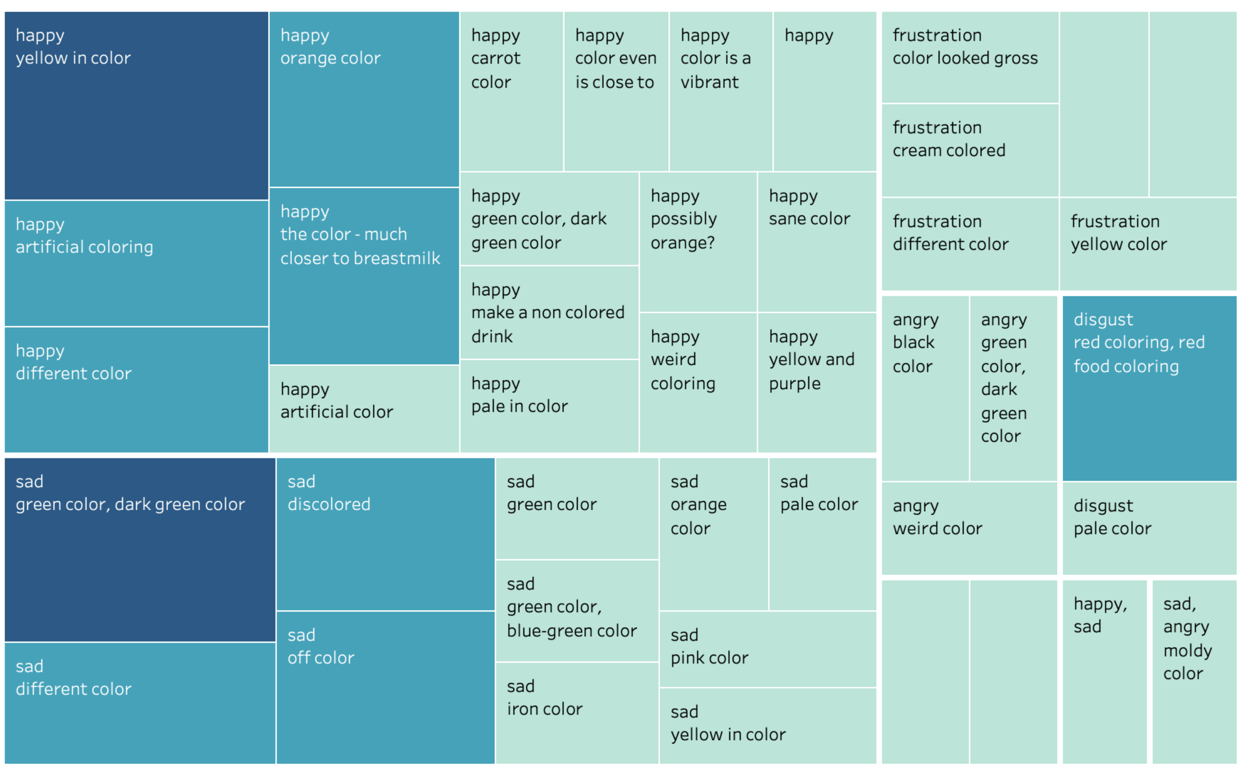
To make sure everyone in the group is working to their strengths, we did some group exercise to ensure we as a group are on the same page about our roles and our expectations from the project. We all participated in EDA because that brought different perspectives about the existing dataset. I used Tableau to create EDA, then for data preprocessing I used Rstudio. We also used lucidspark for project kickoff meetings.

**Data Analysis**

We start with the EDA, then process the data, build the model and validate it. Our sponsor has provided us with a dataset that contains 15,365 rows of reviews of baby products from different pharmaceutical companies, calculated emotional engagement with PathosAI, and whether the consumer will recommend the product or not. The dataset also holds information about the date the reviews were made, what was the driver behind the sale with Ad recalls, when color and taste of the products were mentioned in the reviews, and different stages of their customer journey.




The first thing we try to look at is what are the different emotions that has been registered in our data. What we see is the majority of the reviews are positive reviews, which is quite expected given the fact that they are all baby products.



I also wanted to see if a specific color, taste or shape have to do with the overall positivity or negativity of the product review.  What we see is yellow and orange is often associated with happy feelings whereas green or dark green is associated with sadness. This resembles the color theory that we have learned in branding.

| Manufacturer (group) | Recommend/Not Recommend (group) Avg. Emotional Engagement Null | Not Recommended | Recommend.. |
|---|---|---|---|
| A2 | 1.98 | | |
| Abbott | 1.39 | 0.17 | 1.61 |
| All Other | 1.54 | 0.49 | 2.26 |
| Danone | 1.28 | 1.56 | 1.68 |
| Friesland Campina | -0.54 | | |
| Hain Celestial | 1.25 | 0.20 | 1.48 |
| Hero Group | 2.84 | | |
| Nestle | 1.54 | 1.39 | 1.74 |
| Nutricia | 1.77 | | |
| Plum Baby | 1.30 | -0.15 | 1.05 |
| RB Health | 1.43 | 0.21 | 1.58 |

After that we also look into how the average emotional engagement may vary a lot depending on whether a consumer recommends the product or not. One thing to notice is some of the brands have only null values for their recommendation column.

To start the analysis, I want to transform the data and make it ready to run the model. Although, for the final project I did it in a different way, where I manually encoded some specific columns for them to be used in supervised learning. To prepare the data for that, I uploaded the data, checked for spelling mistakes, null values were identified and removed, and finally data types for each of the columns were formatted. The Emotion column was divided into three categories: positive (containing one or two positive emotions), negative (containing one or two negative emotions), and unclear (containing both positive or negative). Values were classified based on that. Next, Emotional Engagement was transformed into a numerical variable.

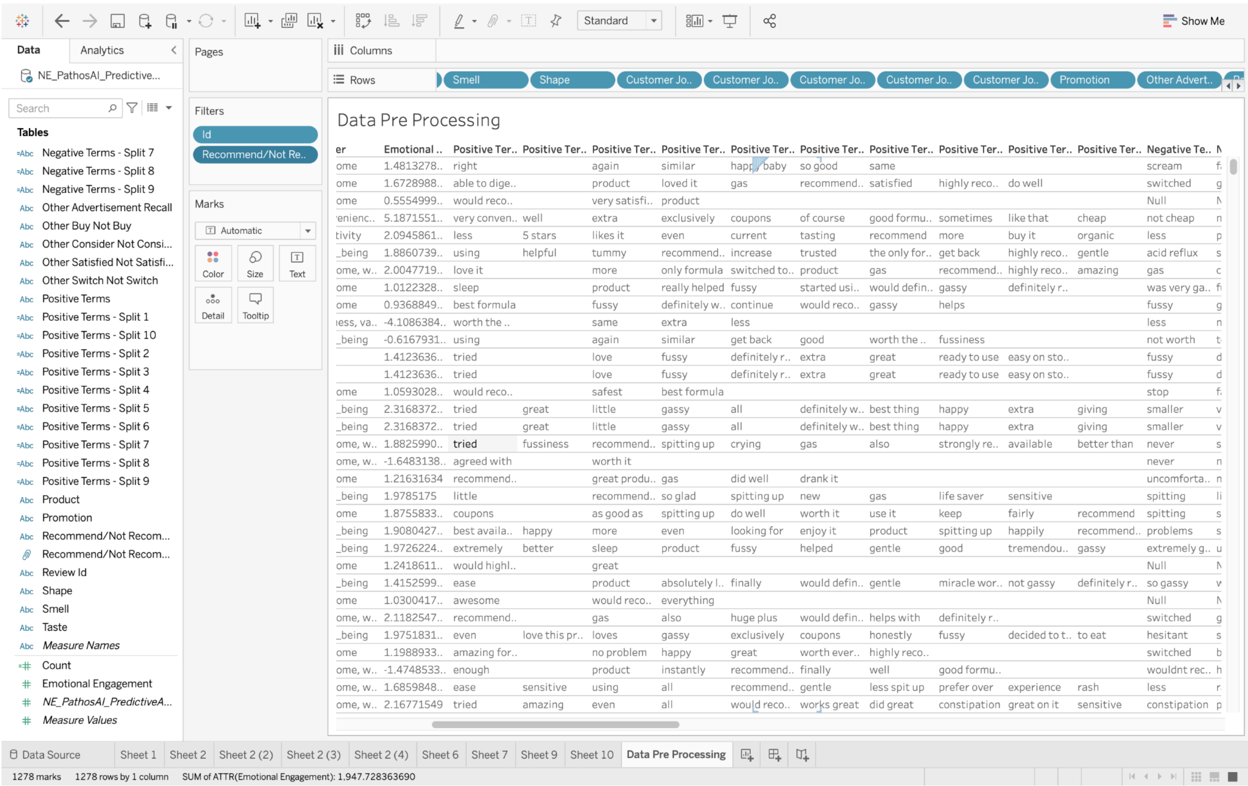
```
library(tidyverse)
# assign each emotion a number. Negative is -5:-1 positive is 1-4
Capstone <- Capstone %>%
  mutate(Emotion_Value = if_else(Emotion == "disgust", -5,
                                 if_else(Emotion %in% "angry", -4,
                                 if_else(Emotion %in% "fear", -2,
                                         if_else(Emotion %in% "sad", -1,
                                                 if_else(Emotion == "frustration", -3,
                                                         if_else(Emotion %in% "happy", 2,
          if_else(Emotion %in% "excited", 4,
          if_else(Emotion %in% "surprised", 3,0)))))))))
table(Capstone$Emotion_Value)

plot(Capstone$Date, Capstone$Emotion_Value)
sum(!is.na(Capstone$`recommend/not recommend`))
#1278 non-na's

table(Capstone$`recommend/not recommend`)

#create field for positive and neg. recommendations
Capstone$NotRecommended <-  str_detect(Capstone$`recommend/not recommend`,
                                       "avoid|cannot|not|never|wouldnt")
table(Capstone$NotRecommended)
Capstone$Recommended <- str_detect(Capstone$`recommend/not recommend`,
                                   "recommend|appreciated|positive|preferred")
table(Capstone$Recommended)
```

But on the other hand, for my own research proposal I wanted to have a different target variable. which is whether the reviewer will ultimately recommend the product or not. For that also we have to follow the similar procedure of getting rid of the null values.




## Conclusion

For the capstone project, we have applied multiple linear regression and support vector machines to predict the emotional engagement. An emotionally engaged customer is three times more likely to recommend, re-purchase and they are also less likely to be price sensitive. Also as a group we concluded that SVM is a better model to predict emotional engagement. As a group leader and a team member I think I have made a fair amount of contribution. I definitely think our project timeline could have been more organized. Also, we have a couple of member leaving the course early and not being able to join due to some personal issue, that may have slowed down our progress a little. Also, I could have been more involved in making models, but as group we decided to work on our strengths.