Eye_Tracking_Example

May 19, 2021

1 *FOR HERSHEY ONLY*

2 Eye Tracking Overview

Subjects wore eye-tracking goggles while they shopped, and the data tells us: - a row for every "glance" the eyeball made - attributes about the product (color/price/type) that the eyeball glanced at - the spatial x,y,z coordinates of the glance - the timing of the glance, which is used to determine whether it was a **fixation** or not

OBJECTIVE: Predict the likelihood of a glance to be a fixation. What factors matter? The goal is insights. This model is intended to yield insights, which may help product placement, packaging, and pricing decisions.

Imports and directory setup

[17]:
```
# imports
from pathlib import Path
import os
import numpy as np
import pandas as pd
import pickle
import datarobot as dr
import datetime

# display options for notebooks only
```

```
pd.set_option('display.max_columns', 500)
pd.set_option('display.max_rows', 199)
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))

# set path directories
curr_dir = Path(os.getcwd())
data_dir = Path(curr_dir.parents[0] / 'data/')
artifacts_dir = Path(curr_dir.parents[0] / 'artifacts/')
```

```
<IPython.core.display.HTML object>
```

Helper Functions These functions will be used later, throughout this notebook. Simply run this cell so that the functions exist later.

[18]:
```
# This function reduces the memory footprint of a dataframe
# Makes things run faster
def reduce_mem_usage(df, verbose=True):
    import numpy as np

    numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
    start_mem = df.memory_usage().sum() / 1024**2
    for col in df.columns:
        col_type = df[col].dtypes
        if col_type in numerics:
            c_min = df[col].min()
            c_max = df[col].max()
            if str(col_type)[:3] == 'int':
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(np.int8).
↪max:
                    df[col] = df[col].astype(np.int8)
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinfo(np.
↪int16).max:
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.
↪int32).max:
                    df[col] = df[col].astype(np.int32)
                elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.
↪int64).max:
                    df[col] = df[col].astype(np.int64)
            else:
                if c_min > np.finfo(np.float16).min and c_max < np.finfo(np.
↪float16).max:
                    df[col] = df[col].astype(np.float16)
                elif c_min > np.finfo(np.float32).min and c_max < np.finfo(np.
↪float32).max:
```

```
                    df[col] = df[col].astype(np.float32)
                else:
                    df[col] = df[col].astype(np.float64)
    end_mem = df.memory_usage().sum() / 1024**2
    if verbose:
        print('Mem. usage decreased to {:5.2f} MB ({:.1f}% reduction)'.
↪format(end_mem, 100 * (start_mem - end_mem) / start_mem))
    return df
```

2.0.1 Importing Data

[19]:
```
ORIGINAL_DATA_FILENAME = 'DR Merged Fixation-Dwell-Purchase.csv'  # original␣
↪data
TARGET_VARIABLE_NAME   = 'Fixation' # what are we predicting?
OUTPUT_DATA_FILENAME = 'fixation_training.csv.gz' # (optional) do you want to␣
↪export the training data as a file?
```

[20]:
```
indata = pd.read_csv(Path(data_dir) / ORIGINAL_DATA_FILENAME)
indata = reduce_mem_usage(indata)
```

```
Mem. usage decreased to 29.94 MB (56.8% reduction)
```

[21]:
```
cleandata = indata[['Respondent ID','Product Code','Aisle','Avg Z', 'Avg␣
↪Y','Avg X','Price','Color','Strikezone',
                    'Categorized Group','Brand','Overarching Category␣
↪Exp','WMT','Fixation'
                   ]].copy()
cleandata['Price'] = np.round(cleandata['Price'], 2)
cleandata.Fixation.replace(('Yes', 'No'), (1, 0), inplace=True)
cleandata.Strikezone.replace(('Strikezone', 'No'), ('Yes', 'No'), inplace=True)
cleandata['Color'] = cleandata['Color'].str.replace('/','_')
cleandata['Color'].fillna('Missing', inplace=True)

# Would we need to scale the coordinates to the same system?
# assuming no, but here is where you would want to do that
# from sklearn.preprocessing import MinMaxScaler

cleandata.head(6)
```

[21]:

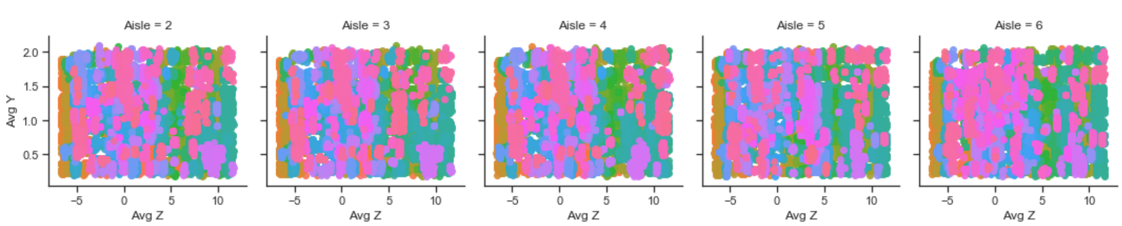
	Respondent ID	Product Code	Aisle	Avg Z	Avg Y	Avg X	Price	\
0	1005	1	2	2.9375	1.741211	-7.925781	9.617188	
1	3597	1	2	2.9375	1.741211	-7.925781	9.617188	
2	4049	1	2	2.9375	1.741211	-7.925781	9.617188	
3	4057	1	2	3.0000	1.939453	-7.914062	9.617188	
4	4108	1	2	2.9375	1.741211	-7.925781	9.617188	
5	4309	1	2	2.9375	1.741211	-7.925781	9.617188	

```
  Color Strikezone Categorized Group  Brand Overarching Category Exp  \
0  Gold         No     PREMIUM POUCH  Lindt                  PREMIUM
1  Gold         No     PREMIUM POUCH  Lindt                  PREMIUM
2  Gold         No     PREMIUM POUCH  Lindt                  PREMIUM
3  Gold         No     PREMIUM POUCH  Lindt                  PREMIUM
4  Gold         No     PREMIUM POUCH  Lindt                  PREMIUM
5  Gold         No     PREMIUM POUCH  Lindt                  PREMIUM

                           WMT  Fixation
0  LINDOR ASST 15.3OZ XL POUCH         0
1  LINDOR ASST 15.3OZ XL POUCH         0
2  LINDOR ASST 15.3OZ XL POUCH         0
3  LINDOR ASST 15.3OZ XL POUCH         1
4  LINDOR ASST 15.3OZ XL POUCH         0
5  LINDOR ASST 15.3OZ XL POUCH         0
```

Plot the points for each glance If we plot all of the data on a scatter plot, and color every single product differently, then in theory we should be able to visualize the product layout.

[22]:
```python
# library & dataset
import seaborn as sns
import matplotlib.pyplot as plt
sns.set(style="ticks")
sns.set_palette("bright")  #https://chrisalbon.com/python/data_visualization/
 ↪seaborn_color_palettes/

g = sns.FacetGrid(cleandata[cleandata['Product Code']<9999], col="Aisle",␣
 ↪hue="Product Code")
g.map(plt.scatter, "Avg Z", "Avg Y", alpha=.9)

# only the Lindt brand
#g = sns.FacetGrid(cleandata[cleandata['Brand']<'Lindt'], col="Aisle",␣
 ↪hue="Product Code")
#g.map(plt.scatter, "Avg Z", "Avg Y", alpha=.9)
```

[22]: <seaborn.axisgrid.FacetGrid at 0x12339ea10>

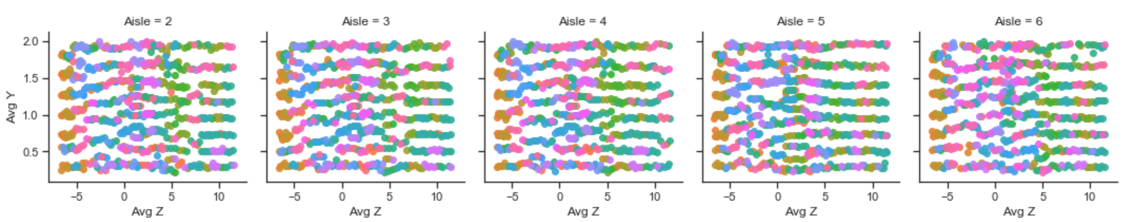


That's so ugly and difficult to see, because there is a point for every single glance from the eyeball. Let's find a center point for every product in every aisle, and only plot a single point.

Average the glances for each product to find the "center" Instead of plotting every point, let's calculate the center for each product. Then we can reduce the dataset to 1 row for every Aisle-Product combination. This might make it easier to visualize, as well as help us with some feature engineering.

[23]:
```
# there was an error with the coords where Fixation=No
# technically this fix only works if 100% of Product-Aisles have a =Yes record
# only a small handful donot, so this will suffice for a first draft
only_fixation = cleandata[cleandata['Fixation']==1].copy()

pointdata = only_fixation[['Aisle','Product Code','Avg Z','Avg Y','Avg X']].
 ↪groupby(['Aisle','Product Code'], as_index=False)['Avg Z','Avg Y','Avg X'].
 ↪agg('mean')

g = sns.FacetGrid(pointdata, col="Aisle", hue="Product Code")
g.map(plt.scatter, "Avg Z", "Avg Y", alpha=.9)
```

[23]: <seaborn.axisgrid.FacetGrid at 0x128221ad0>



That's a little better! ________________________________

Now, we can refer to the locations as the singular point. While we're at it, let's also rename the coordinates to x,y because it's easier to think about it that way.

NOTE: all x,y coords for each Aisle-Product combination are now the same.

[24]:
```
cleandata.set_index(['Aisle','Product Code'])
pointdata.set_index(['Aisle','Product Code'])
cleanpointdata = pd.merge(cleandata.drop(columns=['Avg Z','Avg Y','Avg␣
 ↪X']),pointdata, on=['Aisle','Product Code']).copy()
cleanpointdata.drop(columns=['Strikezone','Fixation','Respondent ID'],␣
 ↪inplace=True)
cleanpointdata.drop_duplicates(inplace=True)
cleanpointdata.rename(columns={'Avg Z': 'x', 'Avg Y': 'y', 'Avg X': 'z'},␣
 ↪inplace=True)
```

```
cleanpointdata = cleanpointdata.reset_index(drop=True)
```

[25]:
```
cleanpointdata.head(7)
```

[25]:
```
   Product Code  Aisle     Price  Color Categorized Group  Brand  \
0             1      2  9.617188   Gold     PREMIUM POUCH  Lindt
1             1      3  9.617188   Gold     PREMIUM POUCH  Lindt
2             1      4  9.617188   Gold     PREMIUM POUCH  Lindt
3             1      5  9.617188   Gold     PREMIUM POUCH  Lindt
4             1      6  9.617188   Gold     PREMIUM POUCH  Lindt
5            10      2  2.779297  Brown       PREMIUM BAR  Lindt
6            10      3  2.779297  Brown       PREMIUM BAR  Lindt

  Overarching Category Exp                                    WMT         x  \
0                  PREMIUM              LINDOR ASST 15.3OZ XL POUCH  3.023438
1                  PREMIUM              LINDOR ASST 15.3OZ XL POUCH  3.029297
2                  PREMIUM              LINDOR ASST 15.3OZ XL POUCH  3.042969
3                  PREMIUM              LINDOR ASST 15.3OZ XL POUCH  3.406250
4                  PREMIUM              LINDOR ASST 15.3OZ XL POUCH  2.189453
5                  PREMIUM  LINDT EXCELLENCE 95% DARK CHOCOLATE BAR  1.977539
6                  PREMIUM  LINDT EXCELLENCE 95% DARK CHOCOLATE BAR  1.924805

          y         z
0  1.930664 -7.914062
1  1.928711 -7.914062
2  1.934570 -7.914062
3  1.692383 -7.925781
4  1.693359 -7.910156
5  1.234375 -7.929688
6  1.227539 -7.859375
```

[26]:
```
cleanpointdata.to_csv(Path(data_dir) / 'clean_point_data.csv', index=False)
```

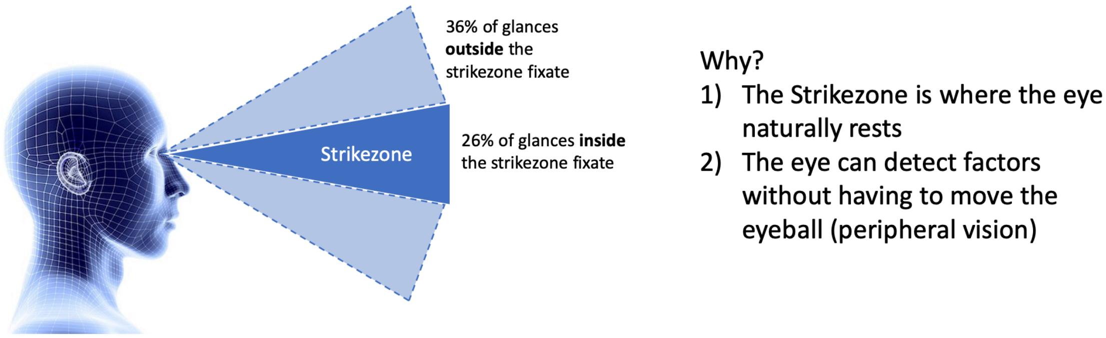
2.0.2 Reviewing the "Strikezone"

[10]:
```
cleandata.groupby(['Strikezone']).agg({'Fixation': ['mean','count']})
```

[10]:
```
            Fixation
                mean   count
Strikezone
No          0.363653   58520
Yes         0.265293  100817
```

This is interesting, that *Fixation is more likely to occur OUTSIDE of the Strikezone*, rather than inside of it. This is backward from what our intuition says.

Then, what is the advantage of the strikezone? Well, the number of glances seems to be concentrated inside the Strikezone.



Ths is because the human eye rests in this range. So, in one sense, the glances *outside* the strike zone are of higher quality because there is a purpose for the eyeball to leave it's comfort zone. Consider the possibility that *the human detects the object* ***before*** *moving eyeball out of the strikezone.* In other words, peripheral vision. Does this imply that these eye-tracking studies may be missing data which could be useful? More importantly, how can we measure data that the eyeball is not actually looking at yet?

Our best option is to **give our data peripheral vision, as well**. Instead of learning that the color Yellow is good for fixating, perhaps we consider if it's just the color yellow, or the fact that yellow is next to other colors that make it stand out. Or put differntly - is it the price that makes someone fixate? Or is it the price in relation to the price adjacent to it.

You may be thinking - can we build a model to predict the *number* of fixations, instead of the the probability of a glance to be a fixation? One could argue that we shouldn't care about the fixation:glance ratio, but instead just care about the pure volume of fixations that a product receives. This is a good point. We will also use this approach as well, and compare the insights.

2.0.3 Accounting for Adjacency with Feature Engineering

Earlier, we estimated the location of each product by averaging the x,y,z coordinates for each Aisle-Product combination. Now, we can use spatial functions to extract adjacency information.

For each product, query neighbors within a specified distance `r`. The hyperparameters `r` is tricky to tune, because there is no implied unit like inches or centimeters to work with. However with some trial and error we arrived at several buffers of varying distances: - `closest`: some do not even have neighbors, some have 1 or 2 - `close`: most have at least 3 or 4 neighbors, some have 10 - `far`: everyone has many neighbors, an average of 10-20 neighbors - `section`: a very large section which contains around 50 neighbors each

[11]:
```python
from scipy.spatial import cKDTree
```

[12]:
```python
def list_magic(df, newcol, nearlist, itemlist):

    closest_items = []
    for i, neighbors_list in enumerate(nearlist):
        remapped = []
        for row_index in neighbors_list:
```

```python
            if i != row_index:
                remapped.append(itemlist[row_index])
        closest_items.append(remapped)

    df[newcol] = pd.Series(closest_items, index=df.index)

    return df

def find_neighbors(df):
    aisles = list(df['Aisle'].unique())

    counter = 1
    for a in aisles:

        result = df[df.Aisle==a].copy()
        mytree = cKDTree(result[['x', 'y', 'z']].values, leafsize=50)

        closest = mytree.query_ball_tree(mytree, r=0.25, p=1, eps=0)
        close = mytree.query_ball_tree(mytree, r=0.5, p=1, eps=0)
        far = mytree.query_ball_tree(mytree, r=0.8, p=1, eps=0)
        section = mytree.query_ball_tree(mytree, r=1, p=1, eps=0)

        prods = result['Product Code'].tolist()
        colors = result['Color'].tolist()
        prices = result['Price'].tolist()
        groups = result['Categorized Group'].tolist()

        result = list_magic(result, 'closest_colors', closest, colors)
        result = list_magic(result, 'close_colors', close, colors)
        result = list_magic(result, 'far_colors', far, colors)
        result = list_magic(result, 'section_colors', section, colors)

        result = list_magic(result, 'closest_prices', closest, prices)
        result = list_magic(result, 'close_prices', close, prices)
        result = list_magic(result, 'far_prices', far, prices)
        result = list_magic(result, 'section_prices', section, prices)

        result = list_magic(result, 'closest_groups', closest, groups)
        result = list_magic(result, 'close_groups', close, groups)
        result = list_magic(result, 'far_groups', far, groups)
        result = list_magic(result, 'section_groups', section, groups)

        if counter == 1:
            final = result.copy()
        else:
            final = final.append(result)
```

```
        counter += 1

    return final
```

[13]:
```
merged_with_neighbors = find_neighbors(cleanpointdata)
merged_with_neighbors.drop(columns=['x','y','z','Color','Price','Categorized␣
↪Group','Brand','Overarching Category Exp','WMT'], inplace=True)
mergedpointdata = pd.merge(cleanpointdata,merged_with_neighbors,␣
↪on=['Aisle','Product Code'])
```

[15]:
```
mergedpointdata.sample(n=2)
```

[15]: 82938

Now let's create some additional variables which compares the item to the surrounding items: * `rng_of_prices_{vicinity}` this is the ratio of price to surrounding items in the vicinity * `ratio_price_to_min_{vicinity}` this is the product price divided by the minimum price in the vicinity * `ratio_price_to_max_{vicinity}` this is the product price divided by the minimum price in the vicinity * `ratio_price_to_avg_{vicinity}` this is the product price divided by the minimum price in the vicinity * `is_higest_{vicinity}` and `is_lowest_{vicinity}` this is a binary flag for if the product is the most expensive or most cheap in the vicinity

[18]:
```
expanded_prices = mergedpointdata.copy()
for l in ['closest','close','far','section']:

    expanded_prices['__max_of_prices_' + l] = expanded_prices[l + '_prices'].
↪apply(lambda row: np.nan if len(row) <= 2 else max(row))
    expanded_prices['__min_of_prices_' + l] = expanded_prices[l + '_prices'].
↪apply(lambda row: np.nan if len(row) <= 2 else min(row))
    expanded_prices['__avg_of_prices_' + l] = expanded_prices[l + '_prices'].
↪apply(lambda row: np.nan if len(row) <= 2 else np.median(row))

    expanded_prices['rng_of_prices_' + l] = expanded_prices['__max_of_prices_'␣
↪+ l] - expanded_prices['__min_of_prices_' + l]
    expanded_prices['ratio_price_to_min_' + l] = expanded_prices['Price'] /␣
↪expanded_prices['__min_of_prices_' + l]
    expanded_prices['ratio_price_to_avg_' + l] = expanded_prices['Price'] /␣
↪expanded_prices['__avg_of_prices_' + l]
    expanded_prices['ratio_price_to_max_' + l] = expanded_prices['Price'] /␣
↪expanded_prices['__max_of_prices_' + l]

    expanded_prices['is_highest_' + l] = (expanded_prices['Price'] >=␣
↪expanded_prices['__max_of_prices_' + l]).astype(int)
    expanded_prices['is_lowest_' + l] = (expanded_prices['Price'] <=␣
↪expanded_prices['__min_of_prices_' + l]).astype(int)
```

```
    expanded_prices = expanded_prices.loc[:,~expanded_prices.columns.str.
 ↪startswith('__')]
```

[19]:
```
expanded_prices.
 ↪drop(columns=['closest_prices','close_prices','far_prices','section_prices','closest_groups
                                                    ␣
 ↪,'far_colors','section_colors','x','y','z','Price','Color','Categorized␣
 ↪Group','Brand','Overarching Category Exp','WMT'], inplace=True)
expanded_prices.sample(n=2)
```

[19]:
```
    Product Code  Aisle  rng_of_prices_closest  ratio_price_to_min_closest  \
89           116      3                    NaN                         NaN
96           117      5               3.740234                         1.0

    ratio_price_to_avg_closest  ratio_price_to_max_closest  \
89                         NaN                         NaN
96                         1.0                    0.374592

    is_highest_closest  is_lowest_closest  rng_of_prices_close  \
89                   0                  0             3.740234
96                   0                  1             4.439453

    ratio_price_to_min_close  ratio_price_to_avg_close  \
89                       1.0                  0.751638
96                       1.0                  0.903150

    ratio_price_to_max_close  is_highest_close  is_lowest_close  \
89                  0.374592                 0                1
96                  0.335380                 0                1

    rng_of_prices_far  ratio_price_to_min_far  ratio_price_to_avg_far  \
89           5.300781                1.333721                 0.90315
96           5.558594                1.333721                 0.90315

    ratio_price_to_max_far  is_highest_far  is_lowest_far  \
89                0.320929               0              0
96                0.309498               0              0

    rng_of_prices_section  ratio_price_to_min_section  \
89               7.296875                    1.333721
96               7.960938                    1.333721

    ratio_price_to_avg_section  ratio_price_to_max_section  \
89                    0.751638                    0.249565
96                    0.903150                    0.232374
```

```
    is_highest_section  is_lowest_section
89                   0                  0
96                   0                  0
```

Next, we can calculate the distance to the nearest items of the same color: - `dist_to_same_color` - distance to the nearest color from all of the other products

[20]:
```
def closest_color(df):
    aisles = list(df['Aisle'].unique())
    counter=1

    for a in aisles:

        single_aisle = df[df.Aisle==a].copy().reset_index(drop=True)

        color_list = list(single_aisle['Color'].unique())

        single_aisle_tree = cKDTree(single_aisle[['x', 'y', 'z']].values,␣
↪leafsize=5)

        for color in color_list:
            #print(color)
            single_color = single_aisle[single_aisle.Color==color].copy()
            if single_color.size == 0:
                continue

            single_color_tree = cKDTree(single_color[['x', 'y', 'z']].values,␣
↪leafsize=5)

            dists = single_aisle_tree.sparse_distance_matrix(single_color_tree,␣
↪max_distance=9999, p=1).todense()

            dists[dists<=0] = 99999
            mindists = dists.min(axis=1)
            df_mindists = pd.DataFrame(mindists)
            colname = 'dist2color_' + color
            df_mindists.columns=[colname]

            single_aisle = pd.concat([single_aisle, df_mindists], axis=1)

            single_aisle.reset_index(drop=True).set_index(['Product␣
↪Code','Aisle'])

        if counter==1:
            final = single_aisle.copy()
```

```
        else:
            final = final.append(single_aisle, sort=False)
        counter+=1

    return final
```

[21]:
```
expanded_colors = closest_color(cleanpointdata)
expanded_colors.drop(columns=['x','y','z','Price','Categorized␣
↪Group','Brand','Overarching Category Exp','WMT'], inplace=True)

# collapse distance matrix to closest to SAME color
mask = expanded_colors['Color'].values == expanded_colors.columns[3:].str.
↪extract('_(.*)$').values
expanded_colors['dist_to_same_color'] = expanded_colors.iloc[:,3:].where(mask.
↪T).bfill(1).iloc[:,0]
dist_to_color = expanded_colors[['Product Code','Aisle','dist_to_same_color']]
dist_to_color.head(2)
```

[21]:

	Product Code	Aisle	dist_to_same_color
0	1	2	0.186523
1	10	2	0.324219

Next, lets create counter columns for each color in the vicinity of the product, and then calculate the ratio of the vicinity which is the same color. The final column's we'll keep are: - `dominant_color_{vicinity}` - the single most dominant color in the vicinity. With ties, we do alphabetically (this could probably be done better in the future) - `color_vs_dominant_{vicinity}` - we create a categorical variable by concatenating the color and the dominant color. This not done because we think it'll help the model, but because this could provide some good insights. - `same_color_ratio_{vicinity}` - This is a percentage of the vicinity that is the same color as the product

[22]:
```
from collections import Counter

vicinitydata = mergedpointdata[['Product␣
↪Code','Aisle','Color','closest_colors','close_colors','far_colors','section_colors']].
↪copy()
list_of_vicinities =␣
↪['closest_colors','close_colors','far_colors','section_colors']

colors = vicinitydata['Color'].unique().tolist()

# outer loop through all of the vicinities
for v in list_of_vicinities:
    drop_later_list = []
```

```
    # find the most common
    vicinitydata['dominant_color_' + v.split("_")[0]] = vicinitydata[v].
↪apply(lambda x: Counter(", ".join(x).split(", ")).most_common(1)[0][0])

    # lists into strings
    vicinitydata[v] = vicinitydata[v].apply(', '.join)
    vicinitydata['dominant_color_' + v.split("_")[0]] =␣
↪vicinitydata['dominant_color_' + v.split("_")[0]].apply(''.join)

    # count items in string (used to be a list)
    vicinitydata['item_count_' + v.split("_")[0]] = vicinitydata[v].str.split().
↪str.len()

    # identify combination of color vs the dominant color   COLOR|DOMINANT
    vicinitydata['color_vs_dominant_' + v.split("_")[0]] =␣
↪vicinitydata['Color'].astype(str) + "|" + vicinitydata['dominant_color_' + v.
↪split("_")[0]].astype(str)

    # loop through all colors and calculate the same color ratio
    for c in colors:
        temp = v.split("_")[0] + '__' + c
        drop_later_list.append(temp)
        vicinitydata[temp] = vicinitydata[v].str.count(c)
        mask = vicinitydata['Color'].values == vicinitydata.columns[1:].str.
↪extract('__(.*)$').values
        vicinitydata['same_color_' + v.split("_")[0]] = vicinitydata.iloc[:,1:].
↪where(mask.T).bfill(1).iloc[:,0]

        drop_later_list.append('same_color_' + v.split("_")[0])
    drop_later_list.append('item_count_' + v.split("_")[0])

    vicinitydata['same_color_ratio_' + v.split("_")[0]] =␣
↪vicinitydata['same_color_' + v.split("_")[0]] / (vicinitydata['item_count_'␣
↪+ v.split("_")[0]] + 1e-6)

    vicinitydata.drop(columns=drop_later_list, inplace=True)
vicinitydata.drop(columns=list_of_vicinities + ['Color'], inplace=True)

vicinitydata.head(2)
```

[22]:

```
   Product Code  Aisle dominant_color_closest color_vs_dominant_closest  \
0             1      2                   Gold                 Gold|Gold
1             1      3                   Gold                 Gold|Gold

   same_color_ratio_closest dominant_color_close color_vs_dominant_close  \
0                  0.333333                  Red                Gold|Red
```

```
1                  0.400000                 Red               Gold|Red

   same_color_ratio_close dominant_color_far color_vs_dominant_far  \
0                0.250000              Black            Gold|Black
1                0.166667              Brown            Gold|Brown

   same_color_ratio_far dominant_color_section color_vs_dominant_section  \
0              0.111111                  Black                Gold|Black
1              0.103448                    Tan                  Gold|Tan

   same_color_ratio_section
0                  0.071429
1                  0.069767
```

Merging and Exporting Next, we merge the datasets together before exporting it to a .csv file.

[23]:
```
merged_colors = pd.merge(mergedpointdata,dist_to_color, on=['Aisle','Product␣
 ↪Code'])
merged_colors_prices = pd.merge(merged_colors, expanded_prices,␣
 ↪on=['Aisle','Product Code'])
merged_colors_prices_vicinity = pd.merge(merged_colors_prices, vicinitydata,␣
 ↪on=['Aisle','Product Code'])
```

[24]:
```
merged_colors_prices_vicinity.head(3)
```

[24]:
```
   Product Code  Aisle     Price Color Categorized Group  Brand  \
0             1      2  9.617188  Gold     PREMIUM POUCH  Lindt
1             1      3  9.617188  Gold     PREMIUM POUCH  Lindt
2             1      4  9.617188  Gold     PREMIUM POUCH  Lindt

  Overarching Category Exp                      WMT         x         y  \
0                  PREMIUM  LINDOR ASST 15.3OZ XL POUCH  3.023438  1.930664
1                  PREMIUM  LINDOR ASST 15.3OZ XL POUCH  3.029297  1.928711
2                  PREMIUM  LINDOR ASST 15.3OZ XL POUCH  3.042969  1.934570

          z                closest_colors  \
0 -7.914062             [Gold, Tan, Green]
1 -7.914062  [Red, Gold, Gold, Tan, Green]
2 -7.914062             [Gold, Tan, Green]

                                       close_colors  \
0  [Red, Red, Gold, Gold, Red, Brown, Tan, Blue, …
1  [Red, Red, Gold, Gold, Red, Brown, Tan, Blue, …
2  [Red, Red, Gold, Gold, Red, Brown, Yellow, Tan…
```

```
                                         far_colors  \
0  [Red, Red, Yellow, Tan, Orange, Gold, Gold, Re…
1  [Brown, Red, Red, Yellow, Tan, Orange, Gold, G…
2  [Brown, Red, Red, Yellow, Tan, Orange, Gold, G…

                                     section_colors  \
0  [Yellow, Brown, Red, Red, Yellow, Tan, Tan, Ta…
1  [Yellow, Brown, Red, Red, Yellow, Tan, Tan, Ta…
2  [Yellow, Brown, Red, Red, Yellow, Tan, Tan, Ta…

                                     closest_prices  \
0                [5.94140625, 1.6796875, 1.6796875]
1  [9.9765625, 5.94140625, 3.98046875, 1.6796875,…
2                [5.94140625, 1.6796875, 1.6796875]

                                       close_prices  \
0  [9.9765625, 1.6396484375, 5.94140625, 3.980468…
1  [9.9765625, 1.6396484375, 5.94140625, 3.980468…
2  [9.9765625, 1.6396484375, 5.94140625, 3.980468…

                                         far_prices  \
0  [9.9765625, 1.6396484375, 2.240234375, 1.63964…
1  [5.98046875, 9.9765625, 1.6396484375, 2.240234…
2  [5.98046875, 9.9765625, 1.6396484375, 2.240234…

                                     section_prices  \
0  [5.98046875, 5.98046875, 9.9765625, 1.63964843…
1  [5.98046875, 5.98046875, 9.9765625, 1.63964843…
2  [5.98046875, 5.98046875, 9.9765625, 1.63964843…

                                     closest_groups  \
0          [PREMIUM POUCH, OTG XL BAR, OTG XL BAR]
1  [PREMIUM POUCH, PREMIUM POUCH, PREMIUM POUCH, …
2          [PREMIUM POUCH, OTG XL BAR, OTG XL BAR]

                                       close_groups  \
0  [PREMIUM POUCH, OTG XL BAR, PREMIUM POUCH, PRE…
1  [PREMIUM POUCH, OTG XL BAR, PREMIUM POUCH, PRE…
2  [PREMIUM POUCH, OTG XL BAR, PREMIUM POUCH, PRE…

                                         far_groups  \
0  [PREMIUM POUCH, OTG XL BAR, OTG GIANT BAR, OTG…
1  [PREMIUM POUCH, PREMIUM POUCH, OTG XL BAR, OTG…
2  [PREMIUM POUCH, PREMIUM POUCH, OTG XL BAR, OTG…

                                     section_groups  dist_to_same_color  \
0  [PREMIUM POUCH, PREMIUM POUCH, PREMIUM POUCH, …            0.186523
```

```
1  [PREMIUM POUCH, PREMIUM POUCH, PREMIUM POUCH, …           0.132812
2  [PREMIUM POUCH, PREMIUM POUCH, PREMIUM POUCH, …           0.155273

   rng_of_prices_closest  ratio_price_to_min_closest  \
0               4.261719                    5.725581
1               8.296875                    5.725581
2               4.261719                    5.725581

   ratio_price_to_avg_closest  ratio_price_to_max_closest  is_highest_closest  \
0                    5.725581                    1.618672                   1
1                    2.416094                    0.963978                   0
2                    5.725581                    1.618672                   1

   is_lowest_closest  rng_of_prices_close  ratio_price_to_min_close  \
0                  0             8.476562                  6.411458
1                  0             8.476562                  6.411458
2                  0             8.476562                  6.411458

   ratio_price_to_avg_close  ratio_price_to_max_close  is_highest_close  \
0                  3.398206                  0.963978                 0
1                  3.398206                  0.963978                 0
2                  5.725581                  0.963978                 0

   is_lowest_close  rng_of_prices_far  ratio_price_to_min_far  \
0                0           8.976562                9.617188
1                0           8.976562                9.617188
2                0           8.976562                9.617188

   ratio_price_to_avg_far  ratio_price_to_max_far  is_highest_far  \
0                4.292938                0.963978               0
1                3.460295                0.963978               0
2                3.460295                0.963978               0

   is_lowest_far  rng_of_prices_section  ratio_price_to_min_section  \
0              0               9.476562                    9.617188
1              0               9.476562                    9.617188
2              0               9.476562                    9.617188

   ratio_price_to_avg_section  ratio_price_to_max_section  is_highest_section  \
0                    3.460295                    0.917972                   0
1                    3.460295                    0.917972                   0
2                    3.460295                    0.917972                   0

   is_lowest_section dominant_color_closest color_vs_dominant_closest  \
0                  0                   Gold                 Gold|Gold
1                  0                   Gold                 Gold|Gold
2                  0                   Gold                 Gold|Gold
```

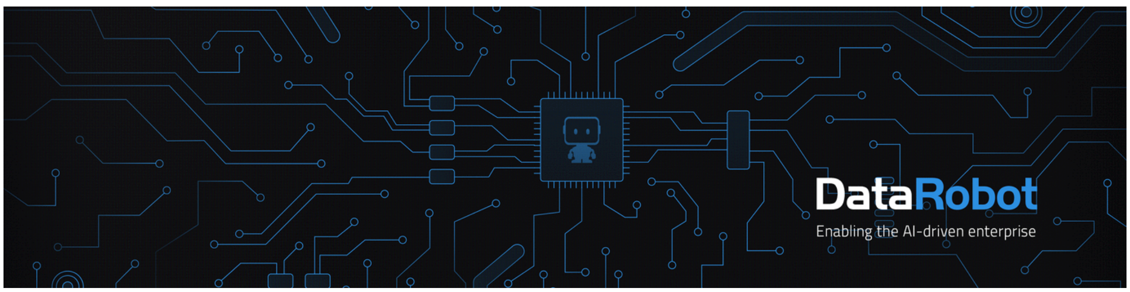
```
   same_color_ratio_closest dominant_color_close color_vs_dominant_close  \
0                  0.333333                  Red                Gold|Red
1                  0.400000                  Red                Gold|Red
2                  0.333333                  Red                Gold|Red

   same_color_ratio_close dominant_color_far color_vs_dominant_far  \
0                0.250000              Black            Gold|Black
1                0.166667              Brown            Gold|Brown
2                0.166667              Brown            Gold|Brown

   same_color_ratio_far dominant_color_section color_vs_dominant_section  \
0              0.111111                  Black                Gold|Black
1              0.103448                    Tan                  Gold|Tan
2              0.103448                    Tan                  Gold|Tan

   same_color_ratio_section
0                  0.071429
1                  0.069767
2                  0.071429
```

[36]:

```
original_keep_cols = ['Respondent ID','Product␣
↪Code','Aisle','Strikezone','Categorized Group','Brand','Overarching Category␣
↪Exp','WMT','Fixation']
new_feats_drop_cols = ['x','y','z','Color','Categorized␣
↪Group','WMT','Brand','Overarching Category Exp',
                      ␣
↪'closest_colors','close_colors','far_colors','section_colors',
                     ␣
↪'closest_prices','close_prices','far_prices','section_prices',
                     ␣
↪'closest_groups','close_groups','far_groups','section_groups']

join_keys=['Aisle','Product Code']

outdata = pd.merge(cleandata[original_keep_cols],␣
↪merged_colors_prices_vicinity[merged_colors_prices_vicinity.columns.
↪difference(new_feats_drop_cols)]
                   , on=join_keys)

outdata[outdata.columns.difference(join_keys)].to_csv(Path(data_dir /␣
↪'training_data_for_likelihood.csv'), header=True, index=False)
```

```python
consolidated = pd.DataFrame(outdata[outdata.columns.difference(['Respondent ID','Product Code'])].pivot_table(values='Fixation', index=[c for c in outdata.columns if c not in ['Respondent ID','Product Code','Fixation']], aggfunc=['sum','count']))
consolidated.columns = ["_".join((j,k)) for j,k in consolidated.columns]
consolidated = consolidated.reset_index()

consolidated.to_csv(Path(data_dir / 'training_data_for_counts.csv'), header=True, index=False)
```

Two files are now created for modeling: - `training_data_for_likelihood.csv` - each row represents a glance - `training_data_for_counts.csv` - each row represents a product-aisle combination, glances and fixations are a sum



Predictive Modeling

Now that we've added features to each glance that describes the vicinity of the product, we can build a predictive model to see what features prove to be correlated with `Fixation`.

Here is a brief look at the dataset:

[38]:
```python
outdata[outdata.columns.difference(join_keys)].sample(n=5)
```

[38]:
```
                 Brand Categorized Group  Fixation Overarching Category Exp  \
19344          Hershey        CPC SS MED         0               CANDY DISH
61847        Milky Way        CPC SS MED         0               CANDY DISH
115787  Russell Stover    SUGAR FREE PEG         1               SUGAR FREE
24589           Kisses         CPC PARTY         0               CANDY DISH
76952             Dove         CPC SHARE         0               CANDY DISH

           Price  Respondent ID Strikezone  \
19344   2.779297            642         No
61847   2.779297           3250        Yes
115787  1.870117           3813        Yes
24589   9.976562            497         No
76952   3.980469            771        Yes

                                         WMT color_vs_dominant_close  \
19344             HERSHEY MC SNK SIZE MED BAG             Brown|Brown
61847              MILKY WAY FUN SIZE MED BAG             Brown|Brown
115787                    RSL STVR PBC SF PEG             White|White
24589   Kisses - Milk Chocolate with Almonds            Brown|Orange
```

76952	DOVE DC SSLT CRML PROMISES	White|Black

	color_vs_dominant_closest	color_vs_dominant_far	\
19344	Brown|Brown	Brown|Green	
61847	Brown|Black	Brown|Brown	
115787	White|White	White|White	
24589	Brown|	Brown|Brown	
76952	White|White	White|White	

	color_vs_dominant_section	dist_to_same_color	dominant_color_close	\
19344	Brown|Silver	0.230469	Brown	
61847	Brown|Brown	0.264160	Brown	
115787	White|White	0.162109	White	
24589	Brown|Brown	0.351562	Orange	
76952	White|White	0.208008	Black	

	dominant_color_closest	dominant_color_far	dominant_color_section	\
19344	Brown	Green	Silver	
61847	Black	Brown	Brown	
115787	White	White	White	
24589		Brown	Brown	
76952	White	White	White	

	is_highest_close	is_highest_closest	is_highest_far	\
19344	0	0	0	
61847	0	0	0	
115787	0	0	0	
24589	1	0	1	
76952	0	0	0	

	is_highest_section	is_lowest_close	is_lowest_closest	is_lowest_far	\
19344	0	0	0	0	
61847	0	1	0	1	
115787	0	1	0	0	
24589	1	0	0	0	
76952	0	0	0	0	

	is_lowest_section	ratio_price_to_avg_close	\
19344	0	0.571945	
61847	1	0.798541	
115787	0	0.376376	
24589	0	1.307732	
76952	0	1.432186	

	ratio_price_to_avg_closest	ratio_price_to_avg_far	\
19344	NaN	0.860339	
61847	NaN	0.932503	

```
115787                     NaN              0.375932
24589                      NaN              1.889053
76952                      1.0              1.432186

        ratio_price_to_avg_section  ratio_price_to_max_close  \
19344                     0.860339                  0.569656
61847                     0.798541                  0.569656
115787                    0.376376                  0.318106
24589                     1.889053                  1.000000
76952                     1.432186                  0.570229

        ratio_price_to_max_closest  ratio_price_to_max_far  \
19344                          NaN                0.569656
61847                          NaN                0.526257
115787                         NaN                0.193983
24589                          NaN                1.000000
76952                     0.570229                0.398982

        ratio_price_to_max_section  ratio_price_to_min_close  \
19344                     0.526257                  1.167350
61847                     0.199411                  1.000000
115787                    0.188188                  1.000000
24589                     1.000000                  1.889053
76952                     0.365757                  3.980469

        ratio_price_to_min_closest  ratio_price_to_min_far  \
19344                          NaN                1.167350
61847                          NaN                1.000000
115787                         NaN                1.050466
24589                          NaN                2.866442
76952                     1.432186                3.980469

        ratio_price_to_min_section  rng_of_prices_close  \
19344                     1.167350             2.498047
61847                     1.000000             2.099609
115787                    1.050466             4.008789
24589                     3.778107             4.695312
76952                     3.980469             5.980469

        rng_of_prices_closest  rng_of_prices_far  rng_of_prices_section  \
19344                     NaN           2.498047               2.900391
61847                     NaN           2.501953              11.158203
115787                    NaN           7.860352               8.157227
24589                     NaN           6.496094               7.335938
76952                4.201172           8.976562               9.882812

        same_color_ratio_close  same_color_ratio_closest  \
```

19344	0.400000	0.999999
61847	0.454545	0.000000
115787	0.666667	1.000000
24589	0.250000	0.000000
76952	0.285714	0.666666

	same_color_ratio_far	same_color_ratio_section
19344	0.142857	0.125000
61847	0.375000	0.324324
115787	0.500000	0.368421
24589	0.428571	0.450000
76952	0.285714	0.295082

For the predictive modeling step, the dataset was uploaded to DataRobot Autopilot. We made sure to use Group Partitioning on `Respondent ID`, in order to prevent the model from overfitting on specific indivuals who may have biases towards specific products.

Variables such as `WMT` are very specific to the exact product description, and we want to force the model to learn on trends that generalize well across other products as well.

We also want to pay attention to the variable `Brand` as this may carry with it the context of the colors and price which we'd rather force the model to learn on its own.

For this reason, we build 3 exploratory models: * With all variables * Removing WMT variable * Removing WMT and Brand variables

To simplify the insights, we stick with only the `far` and `close` visual ranges as well.

For predicting whether a glance would be a Fixation or not, the best model was an open source python model called `Balanced Random Forest Classifier`. The AUC was 0.72 for training, cross-vadidation, and holdout.

First, we examine the feature importance of the model, and note that `Strikezone` appears as the top variable. This isn't surprising, but recall our earlier insight about why glances *outside* the strikezone are more likely to fixate.

2.0.4 Predicting Fixation Counts vs Predicting Likelihood

We may not care to build a model that predicts likelihood of a glance to fixate. Hypothetically if we knew a certain combination of features yielded a 99% chance to fixate, but that only happened only once in a blue moon, wouldn't we rather have the product in an area that yields a higher volume of fixations even if it was a low likelihood? Hence, we'll continue with building a regression model to predict `Sum of Fixation`

2.0.5 A note about interpretation (be careful!)

When we first build a model, we use a lot of different variables which may be describing the same thing. For instance, each product has a minimum surrounding price, a maximum surrounding price, and an average surrounding price.

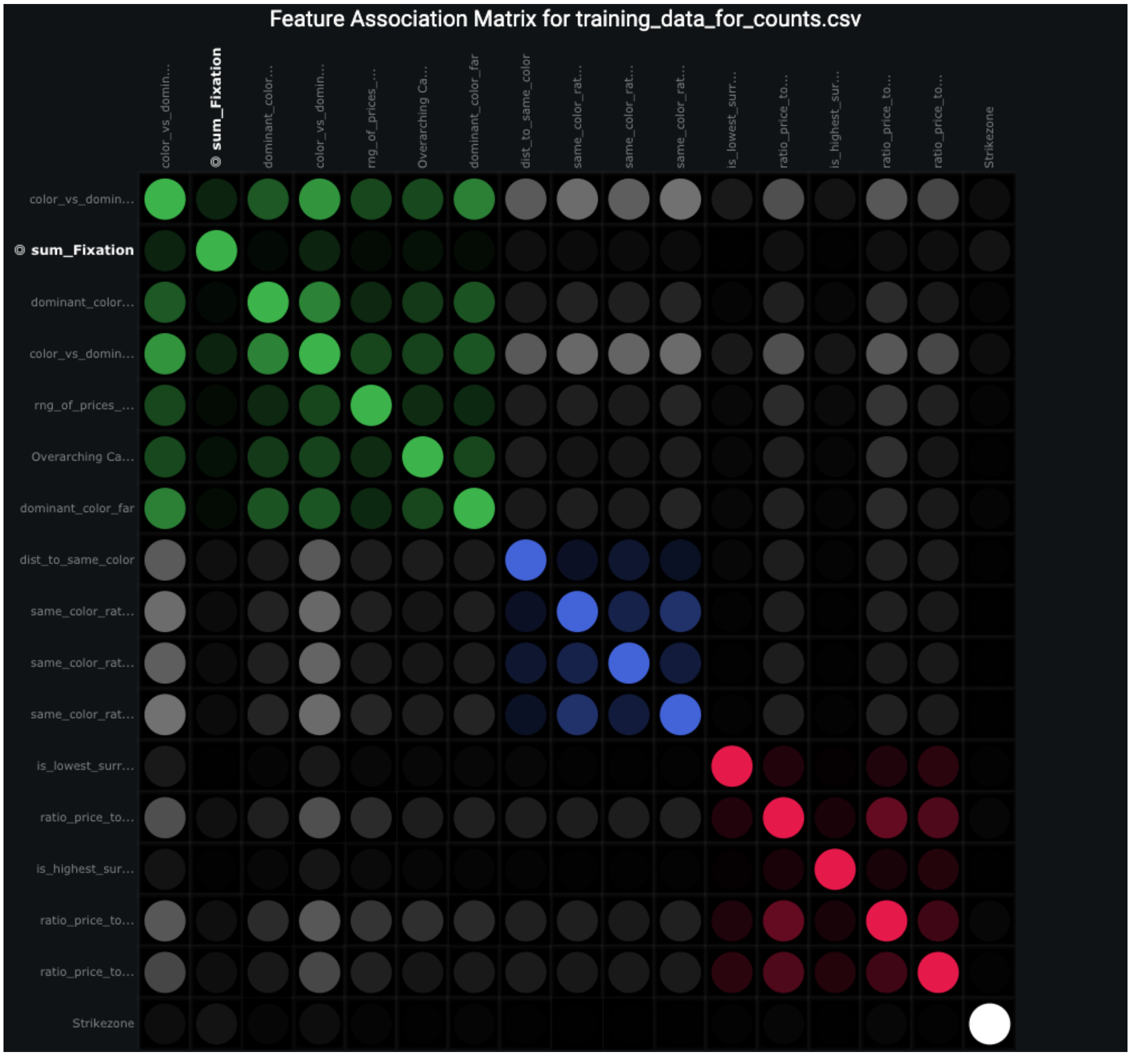
It is tempting to use the Partial Dependence Plot in the Feature Effects section of DataRobot in order to explain the effect. However, it is critical that we remember how Partial Dependence works. Recall that **Partial Dependence assumes that the features are not correlated with each other**.

The assumption of independence is the biggest issue with PD plots. For the computation of the PDP at a certain `minimum surrounding price` (e.g. \$5.00), we average over the marginal distribution of `average surrounding price`, which might include a `average surroundong price` below \$5.00, which is not only unrealistic, but impossible in in the extremes. One solution to this problem is Accumulated Local Effect plots or short ALE plots that work with the conditional instead of the marginal distribution. At this time (Q1 2020), DataRobot does not produce ALE plots.

Also, heterogeneous effects might be hidden because PD plots only show the average marginal effects. Suppose that for chocolate, the data points have a positive association with the prediction – the larger the feature value the larger the prediction – and candy has a negative association – the smaller the feature value the larger the prediction. The PD curve could be a horizontal line, since the effects of both halves of the dataset (candy vs chocolate) could cancel each other out. You then conclude that the feature has no effect on the prediction.

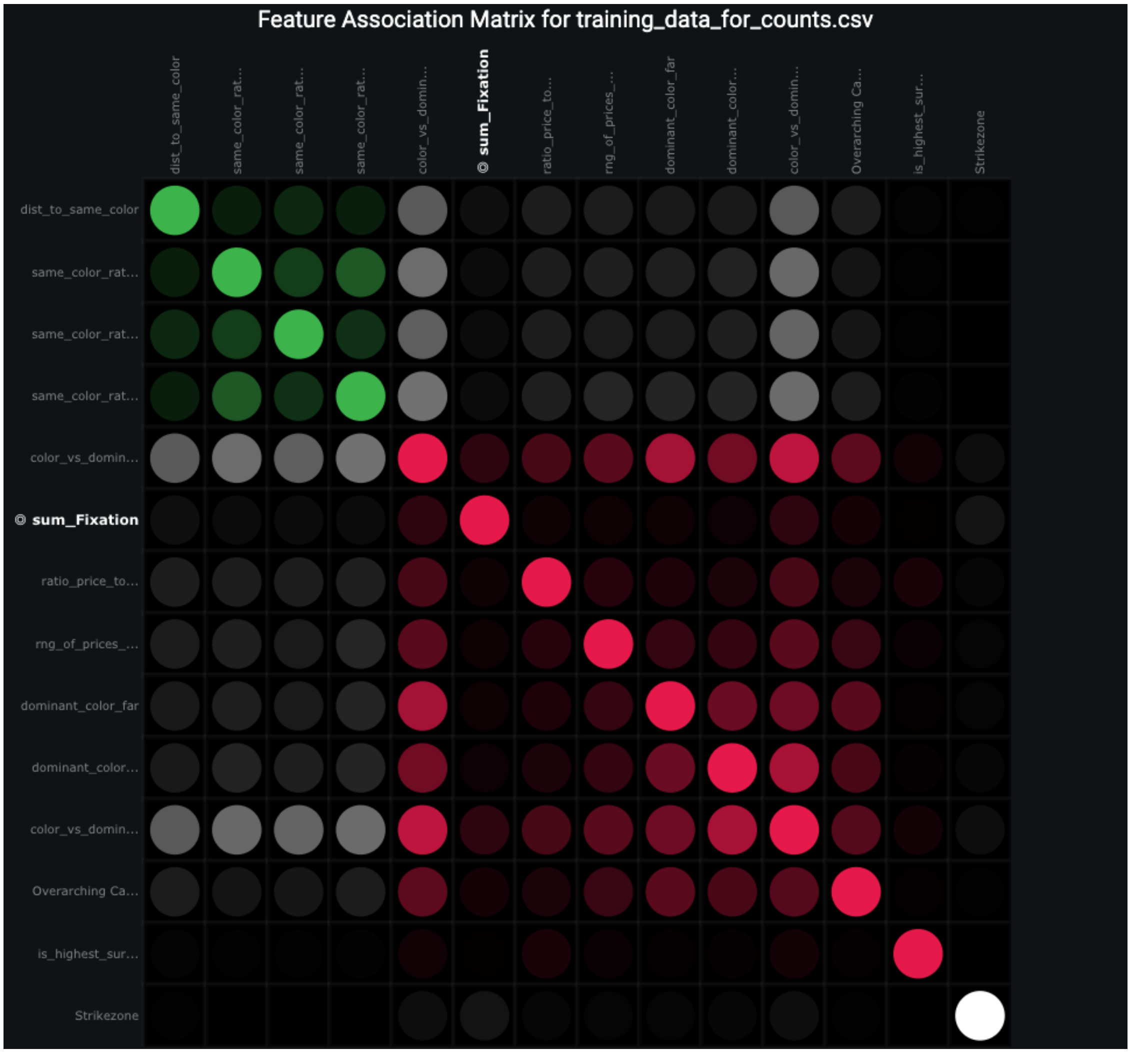
Before we proceed, we will iterate the model building process by removing correlated variables. This means that instead of min, max, and avg, we will end up using just 1. Many iterations are helpful to achieve the best model possible while still removing one of the three.

Initially, we started with many variables and utilized the correlation plots within DataRobot:

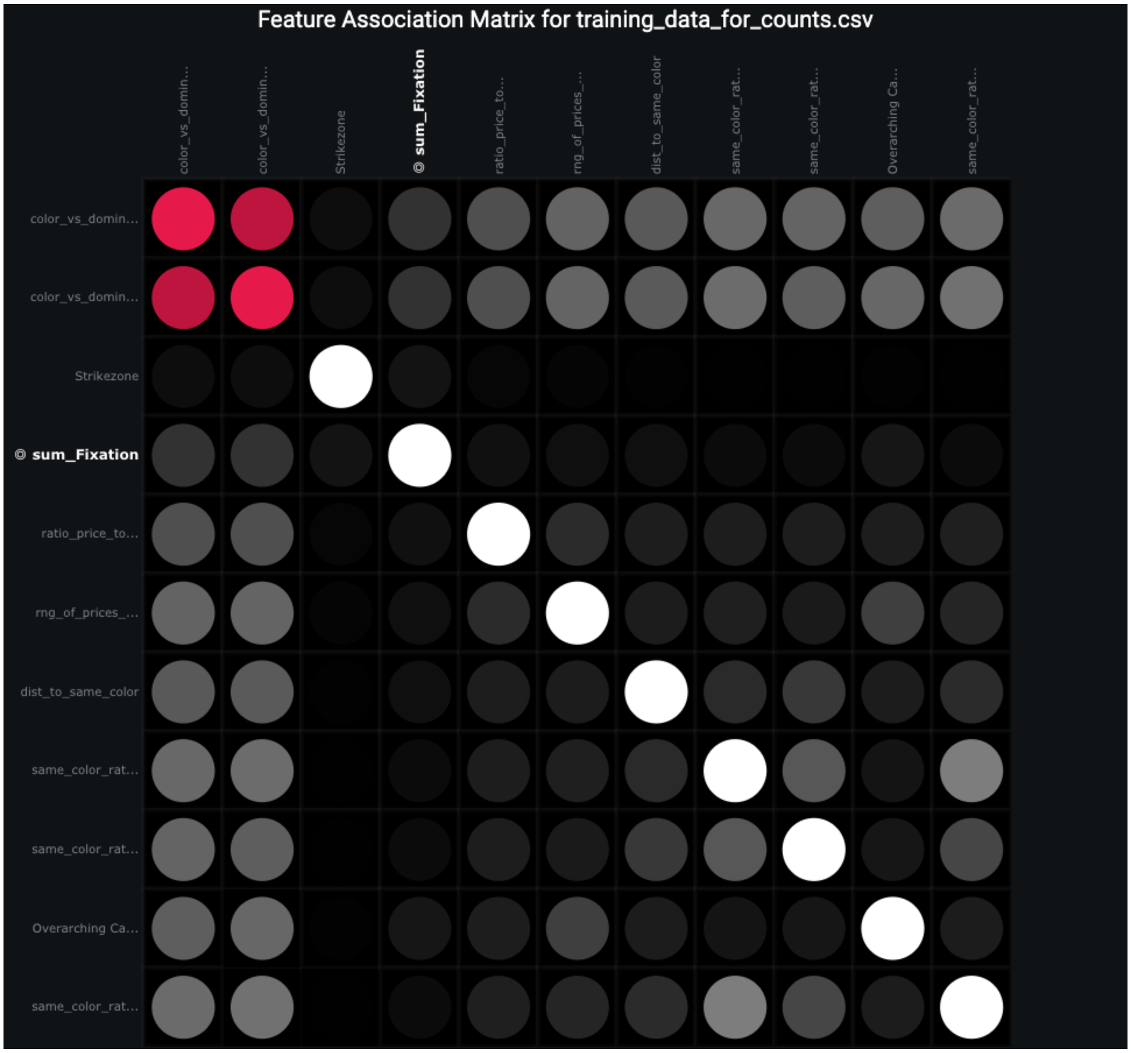


The colors illustrate a cluster. The goal is to make decisions about variable removal, to eliminate the clusters and retain the best model performance possible.

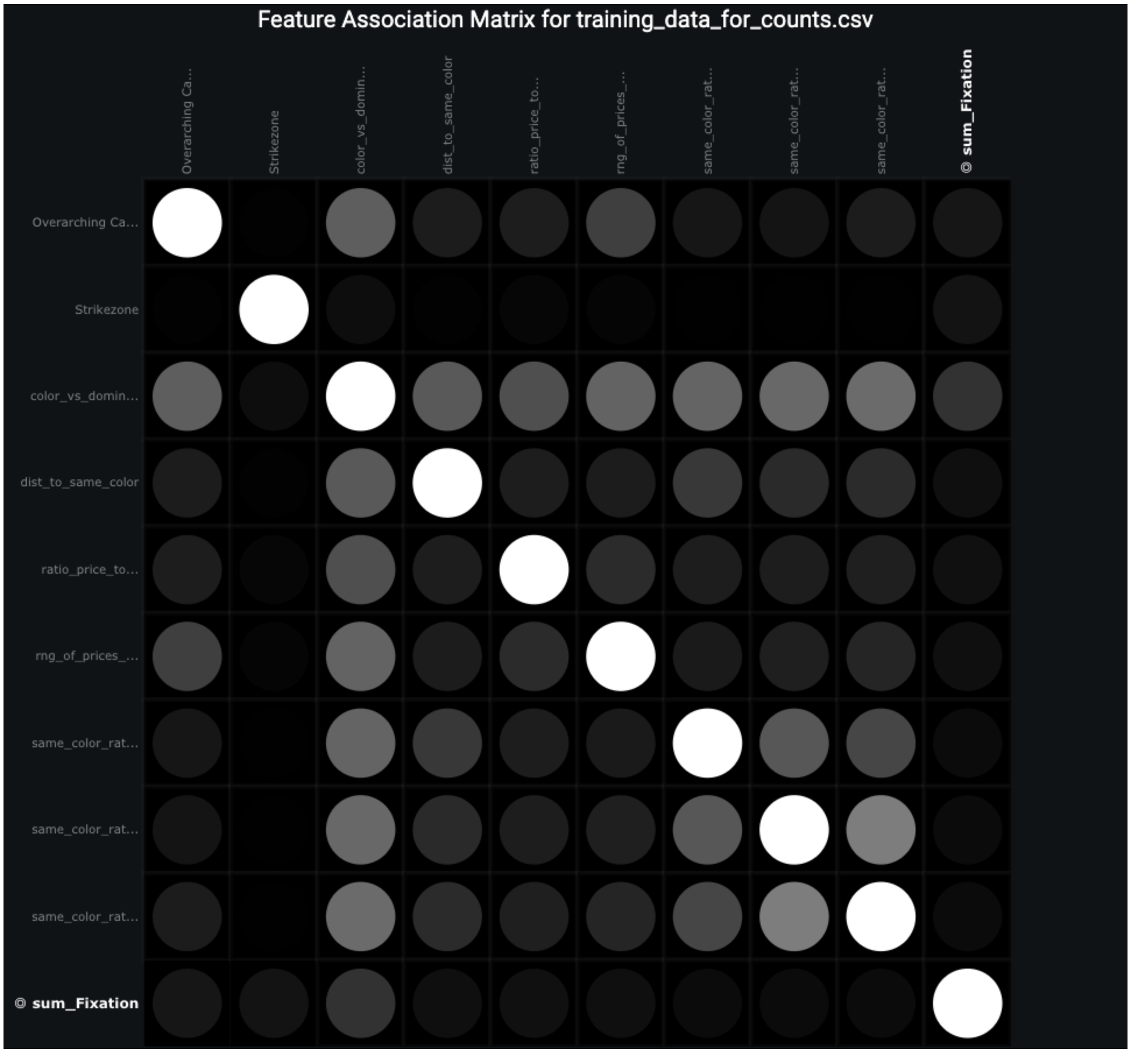
The next sequence illustrates the progressive iterations and how we eliminated correlated clusters.



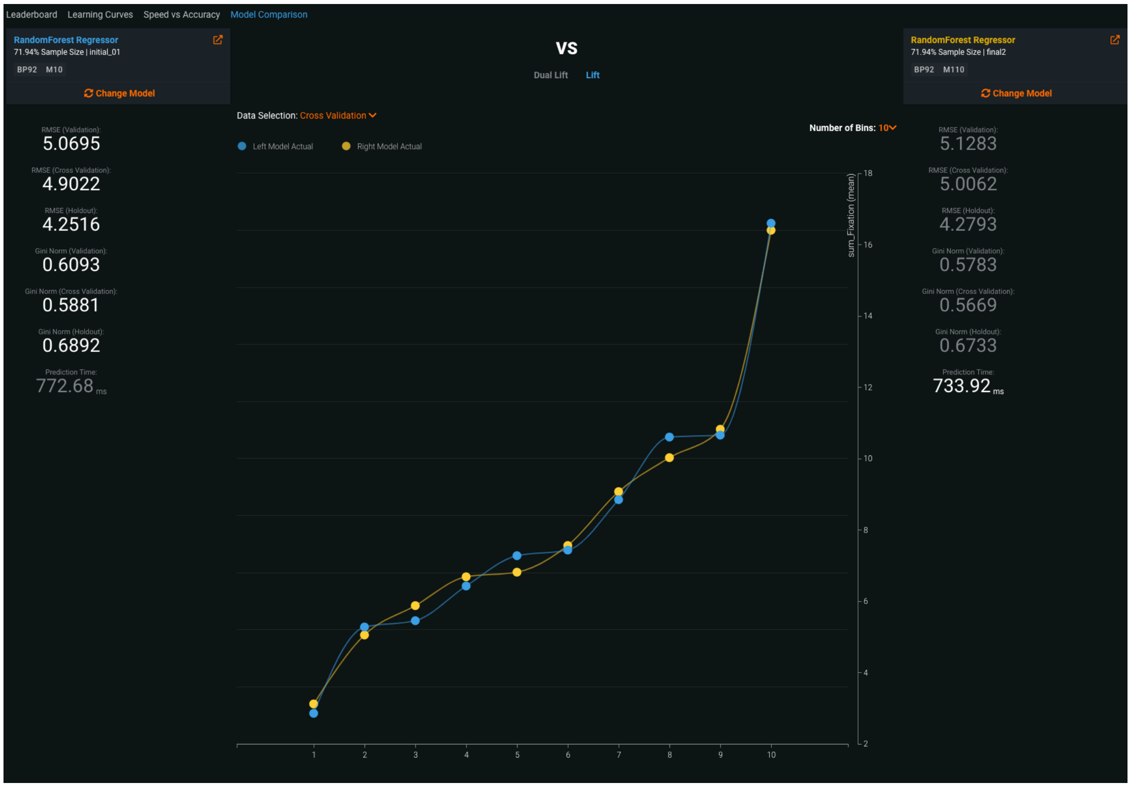
Feature Association Matrix for training_data_for_counts.csv
dist_to_same_color
same_color_rat...
same_color_rat...
same_color_rat...
color_vs_domin...
sum_Fixation
ratio_price_to...
rng_of_prices_...
dominant_color_far
dominant_color...
color_vs_domin...
Overarching Ca...
is_highest_sur...
Strikezone



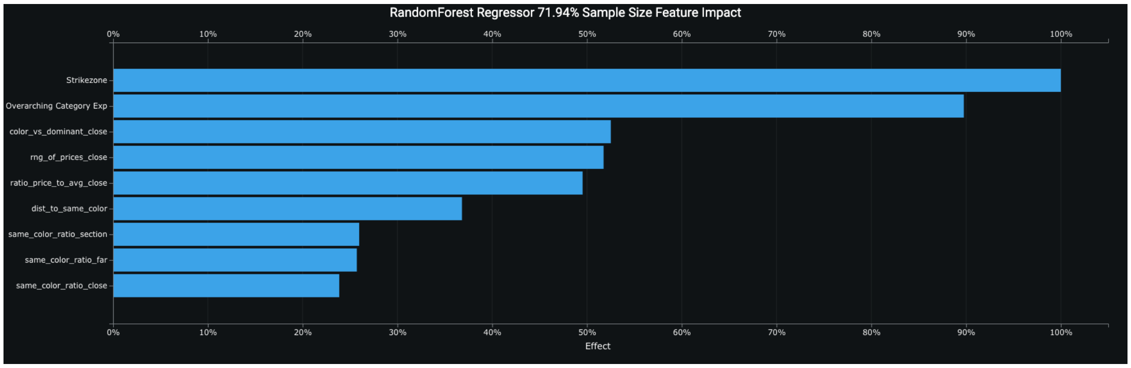
Finally, we arrive at our goal:



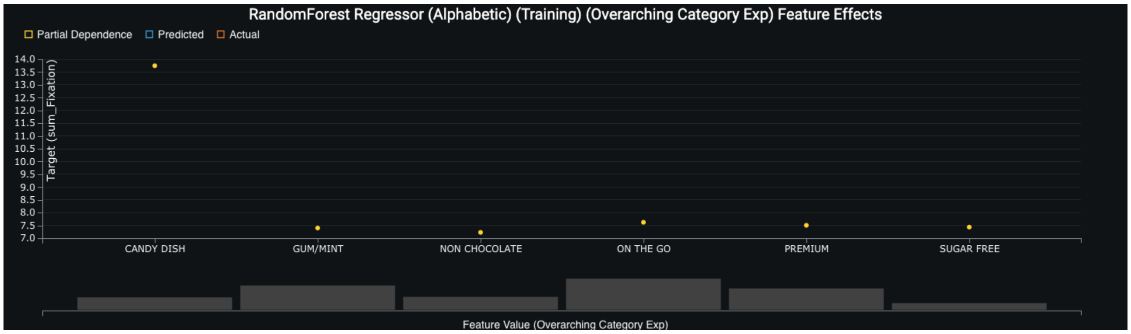
Model Evaluation Did we have to sacrifice much predictive performance while removing correlated variables? In this case, no. Using the Model Comparison tab in DataRobot, we note that the performance is similar.

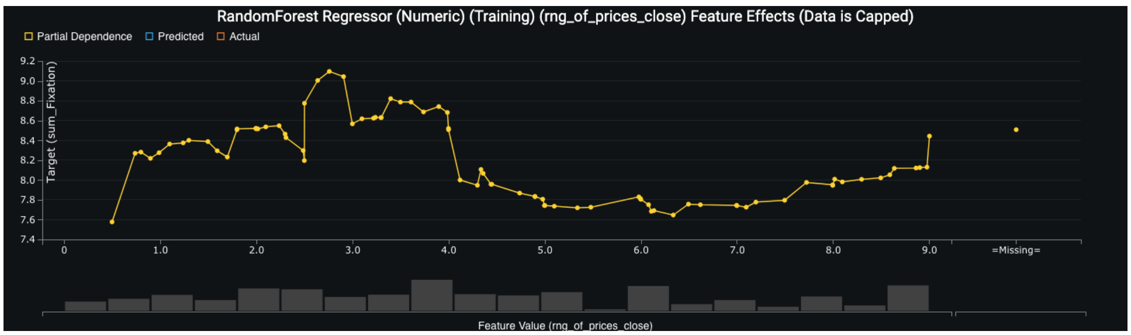


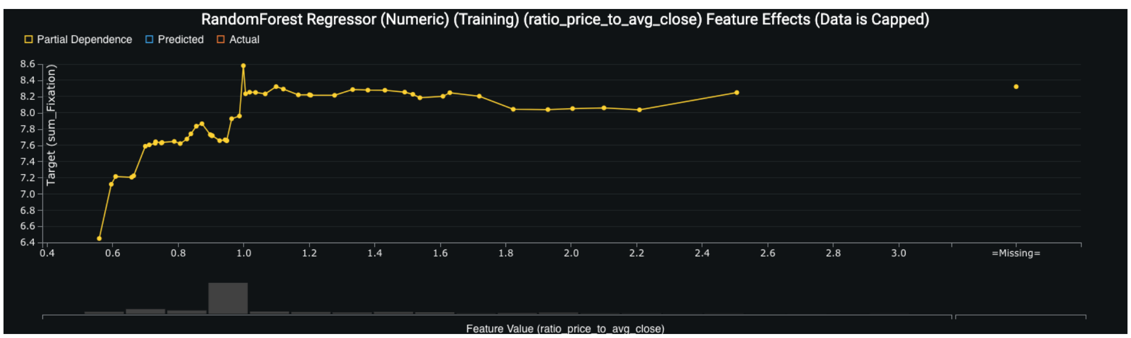
Feature Impact So with our new simplified model, these are the most impactful features to the model.

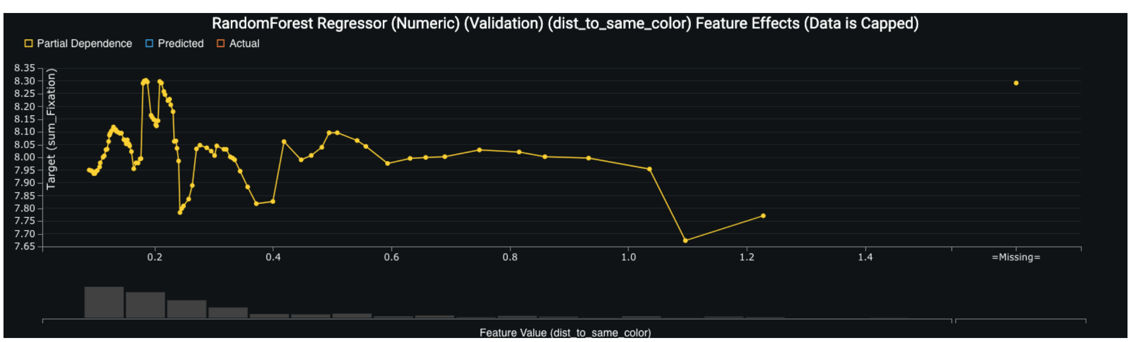


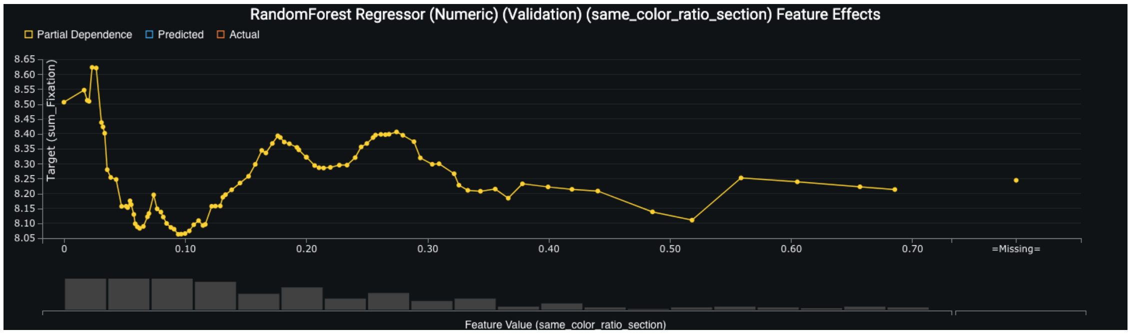
Feature Effects Now let's dig into the feature effects to see if we can gain any insights.

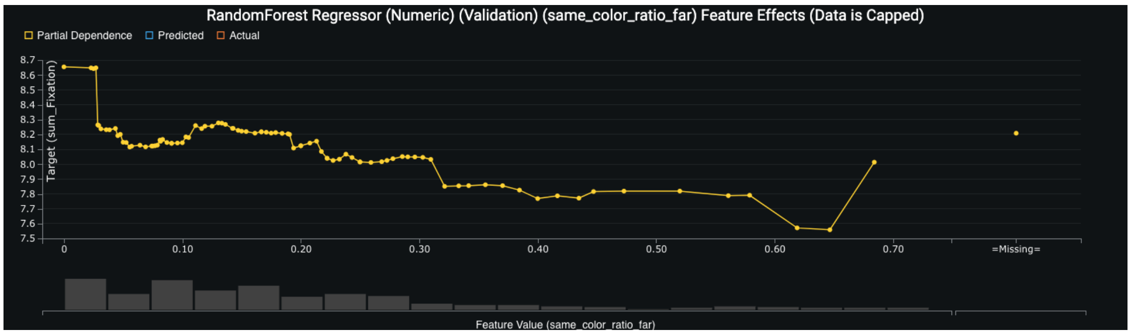

RandomForest Regressor (Alphabetic) (Training) (Overarching Category Exp) Feature Effects
Partial Dependence
Predicted
Actual
Target (sum_Fixation)
14.0
13.5
13.0
12.5
12.0
11.5
11.0
10.5
10.0
9.5
9.0
8.5
8.0
7.5
7.0
CANDY DISH
GUM/MINT
NON CHOCOLATE
ON THE GO
PREMIUM
SUGAR FREE
Feature Value (Overarching Category Exp)

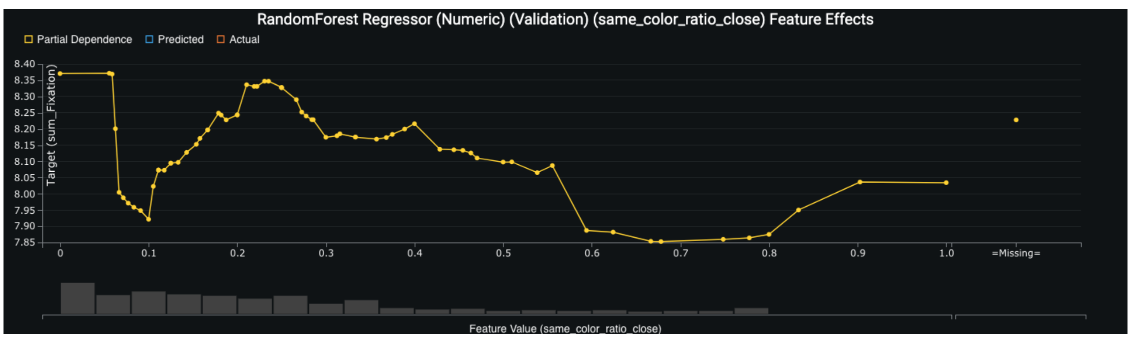

RandomForest Regressor (Numeric) (Training) (rng_of_prices_close) Feature Effects (Data is Capped)
Partial Dependence
Predicted
Actual
Target (sum_Fixation)
9.2
9.0
8.8
8.6
8.4
8.2
8.0
7.8
7.6
7.4
0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
=Missing=
Feature Value (rng_of_prices_close)


RandomForest Regressor (Numeric) (Training) (ratio_price_to_avg_close) Feature Effects (Data is Capped)
Partial Dependence
Predicted
Actual
Target (sum_Fixation)
8.6
8.4
8.2
8.0
7.8
7.6
7.4
7.2
7.0
6.8
6.6
6.4
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1.8
2.0
2.2
2.4
2.6
2.8
3.0
=Missing=
Feature Value (ratio_price_to_avg_close)


RandomForest Regressor (Numeric) (Validation) (dist_to_same_color) Feature Effects (Data is Capped)
Partial Dependence
Predicted
Actual
Target (sum_Fixation)
8.35
8.30
8.25
8.20
8.15
8.10
8.05
8.00
7.95
7.90
7.85
7.80
7.75
7.70
7.65
0.2
0.4
0.6
0.8
1.0
1.2
1.4
=Missing=
Feature Value (dist_to_same_color)


RandomForest Regressor (Numeric) (Validation) (same_color_ratio_section) Feature Effects
Partial Dependence
Predicted
Actual
Target (sum_Fixation)
8.65
8.60
8.55
8.50
8.45
8.40
8.35
8.30
8.25
8.20
8.15
8.10
8.05
0
0.10
0.20
0.30
0.40
0.50
0.60
0.70
=Missing=
Feature Value (same_color_ratio_section)


RandomForest Regressor (Numeric) (Validation) (same_color_ratio_far) Feature Effects (Data is Capped)
Partial Dependence
Predicted
Actual
Target (sum_Fixation)
8.7
8.6
8.5
8.4
8.3
8.2
8.1
8.0
7.9
7.8
7.7
7.6
7.5
0
0.10
0.20
0.30
0.40
0.50
0.60
0.70
=Missing=
Feature Value (same_color_ratio_far)


RandomForest Regressor (Numeric) (Validation) (same_color_ratio_close) Feature Effects
Partial Dependence
Predicted
Actual
Target (sum_Fixation)
8.40
8.35
8.30
8.25
8.20
8.15
8.10
8.05
8.00
7.95
7.90
7.85
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
=Missing=
Feature Value (same_color_ratio_close)

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```
# This code was useful for exporting csv files for every aisle
"""
for aisle, df_aisle in merged.groupby('Aisle'):
    a = str(df_aisle['Aisle'].min())
    filename = 'dataset_for_aisle_' + a + '.csv'
    df_aisle.rename(columns={'Avg Z': 'x', 'Avg Y': 'y'}, inplace=True)
    df_aisle.to_csv(Path(data_dir) / filename, index=False)
"""
```