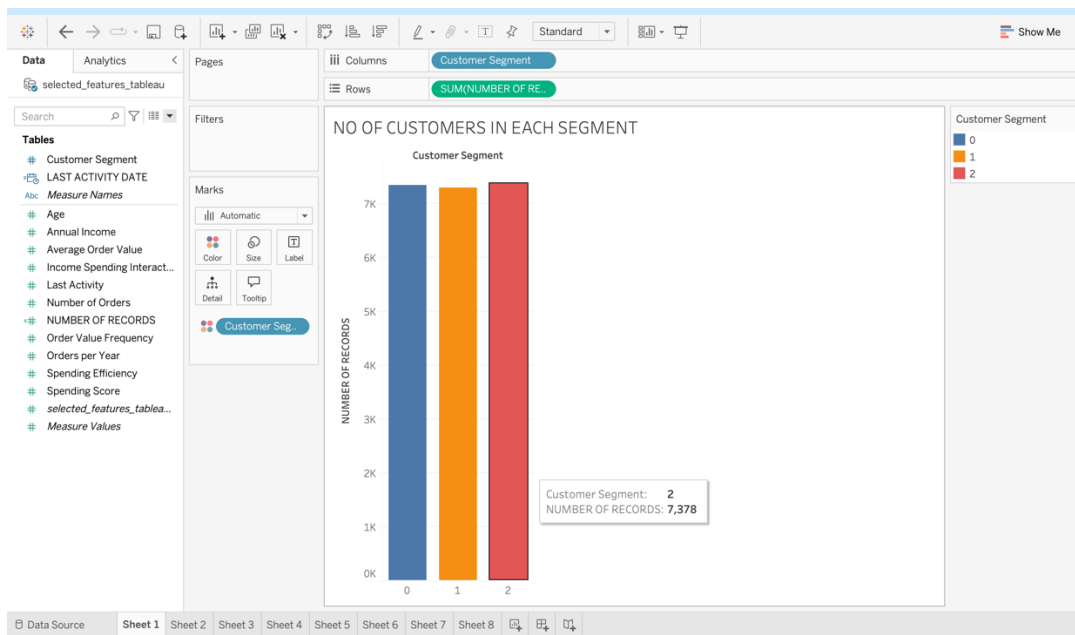


TABLEAU VISUALIZATION USING FEATURES SELECTED FROM RANDOM FOREST SELECTION METHOD

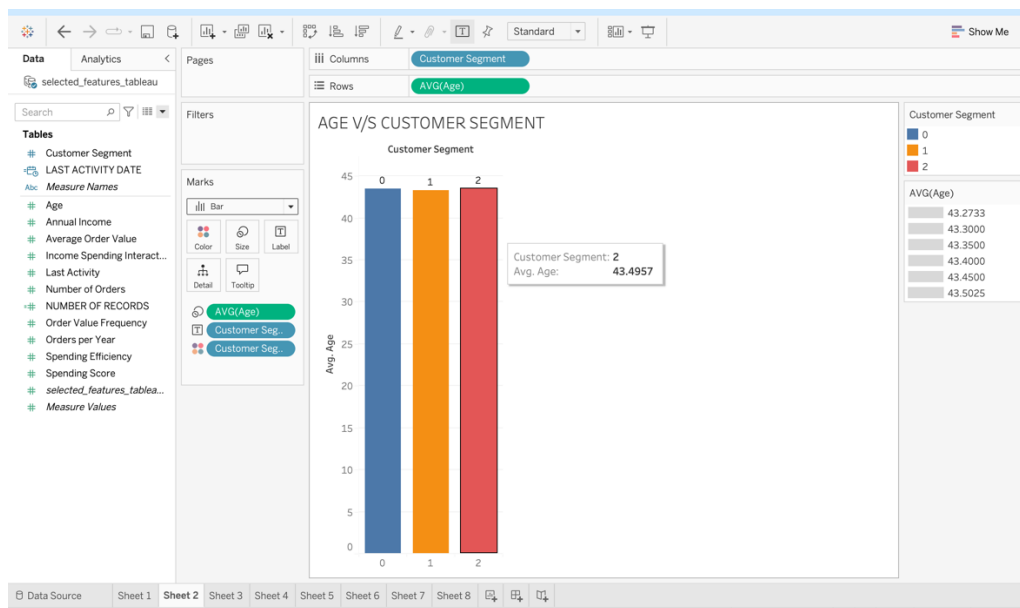
- This will be my ML Model-1.
- I'll convert the dataset with selected features into a csv file, so that it is compatible with Tableau.
- Steps used for converting the dataset into a CSV file is below.

```
jupyter MODEL_BUILDING_RANDOM_FOREST_SELECTION_METHOD Last checkpoint: 11 hours ago (unsaved changes) Logout
File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3 (ipykernel)
In [17]: #CREATING A DATASET WITH THE SELECTED FEATURES FOR VISUALIZATION IN TABLEAU
1 #Combining the selected features and the target variable
2 X_selected = X[top_k_features] #Select the features from the original dataset
3 tableau_data = X_selected.copy()
4 tableau_data['Customer_Segment'] = y #Add the target variable back
5
6
7
In [18]: #EXPORTING THE DATASET INTO A CSV FILE
1 #Export the dataset to a CSV file
2 tableau_data.to_csv('selected_features_tableau.csv', index=False)
3 print("Dataset with selected features saved as 'selected_features_tableau.csv'")
4
5 Dataset with selected features saved as 'selected_features_tableau.csv'.
In [19]: #SAVING IT TO DESKTOP
1 tableau_data.to_csv('Users/sumaiyashad/Desktop/selected_features_tableau.csv', index=False)
2
In [ ]:
```

- The First sheet is about understanding how many customers are there in each segment.

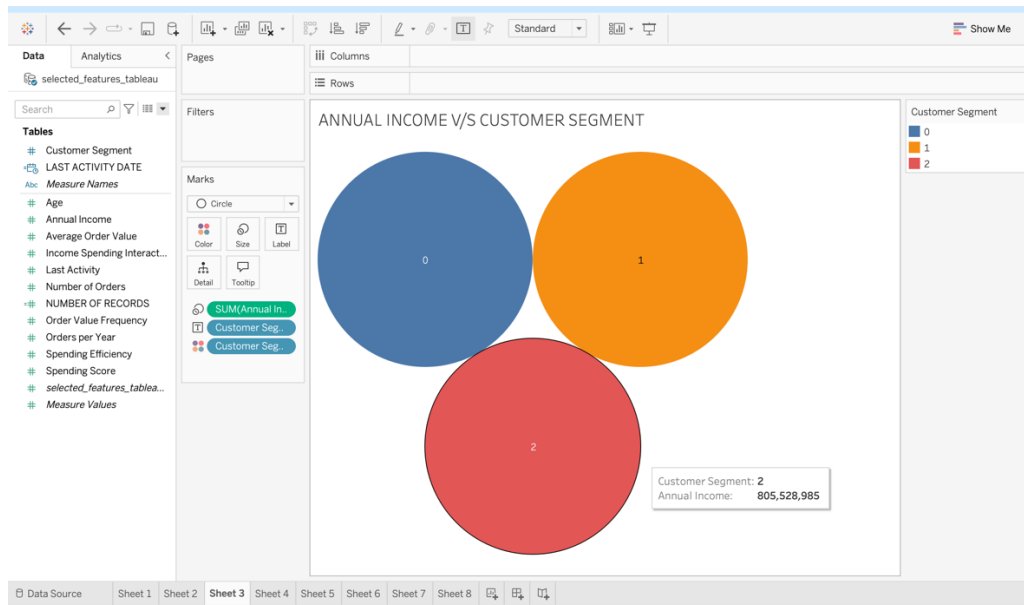


- This visualization shows that segment 2 holds the largest share of customers with over 7k records.
- This segment (2) is significantly larger than the others suggesting that it might represent most common or prevalent customer type in our data set.
- So, segment 2 can be a valuable segment to target for marketing strategies, product recommendations and personalized offers.
- Segments 0 and 1 has fairly evenly distributed customer base which could indicate diverse preferences or behaviors across the customer groups.
- Then I compared Age with Customer Segment.

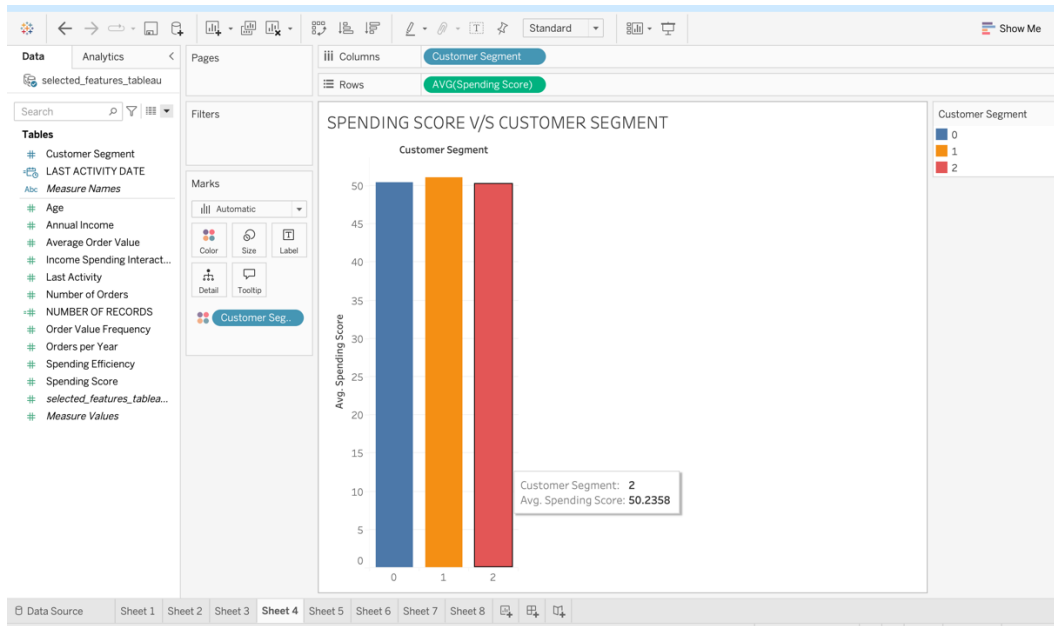


- This shows Segment 0 has an average age of approximately 38 years, Segment 1 has an average age of 40 and Segment 2 has an average age of 43.5.
- This gives us the insight that segment 0 has youngest customers on average, Segment 1 has slightly older customers and Segment 2 has the oldest customers on the average.

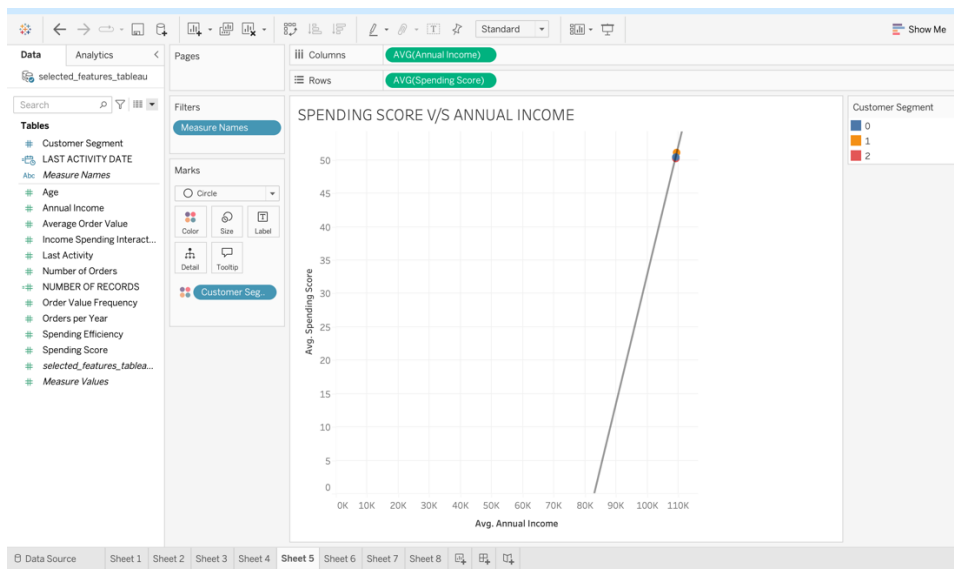
- Now, its Annual Income v/s Customer Segment



- This shows that segment 2 has the largest bubble indicating it has the highest total income.
- Segment 1 has a slightly smaller bubble compared to segment 2 and Segment 0 has the smallest bubble indicating lower total income.
- Spending Score v/s Customer Segment

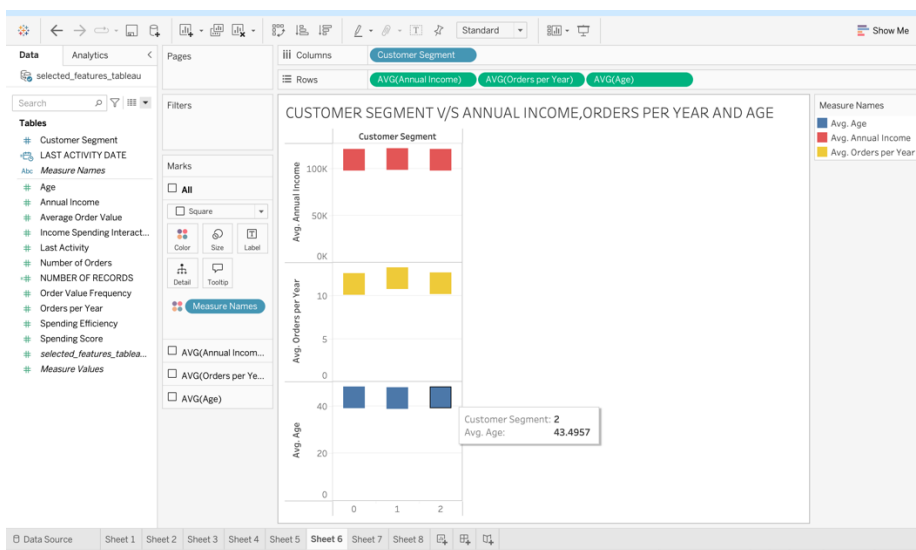


- This shows Segment 2 has the highest spending segment on average with a spending score of 50 indicating that customers in this segment tend to spend more.
- Segment 1 has a lower spending score compared to the other two, suggesting that customers in this segment are more cautious in their spending.
- Spending Score v/s Annual Income



- There is a positive correlation between Annual Income and Spending Score across the customer segments. This insight suggests that customers with higher incomes are more likely to have higher spending scores.
- This could be valuable for segmenting customers based on their income levels and spending behaviors, and it might indicate that income is an important factor in predicting spending behavior.

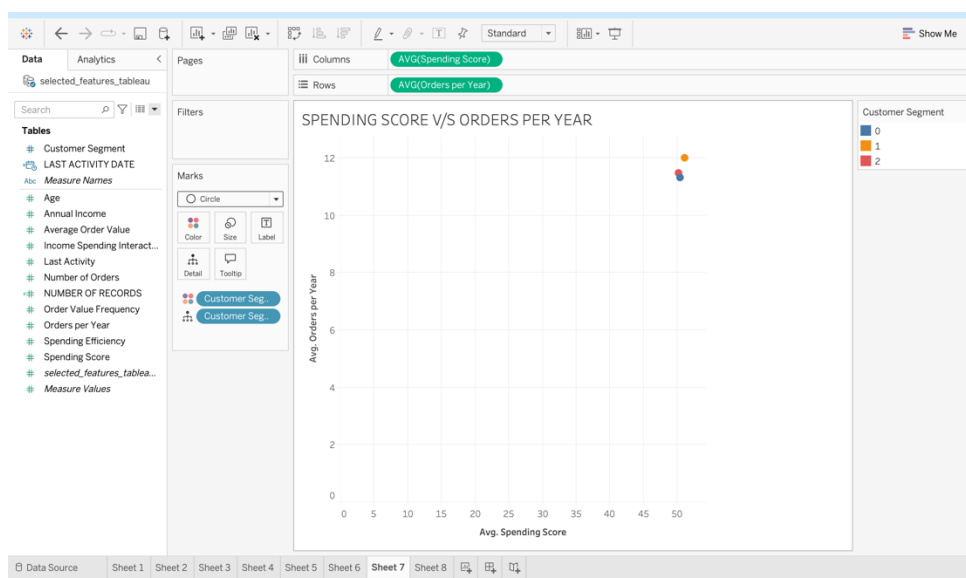
- Customer Segment v/s Annual Income, Orders per year and Age



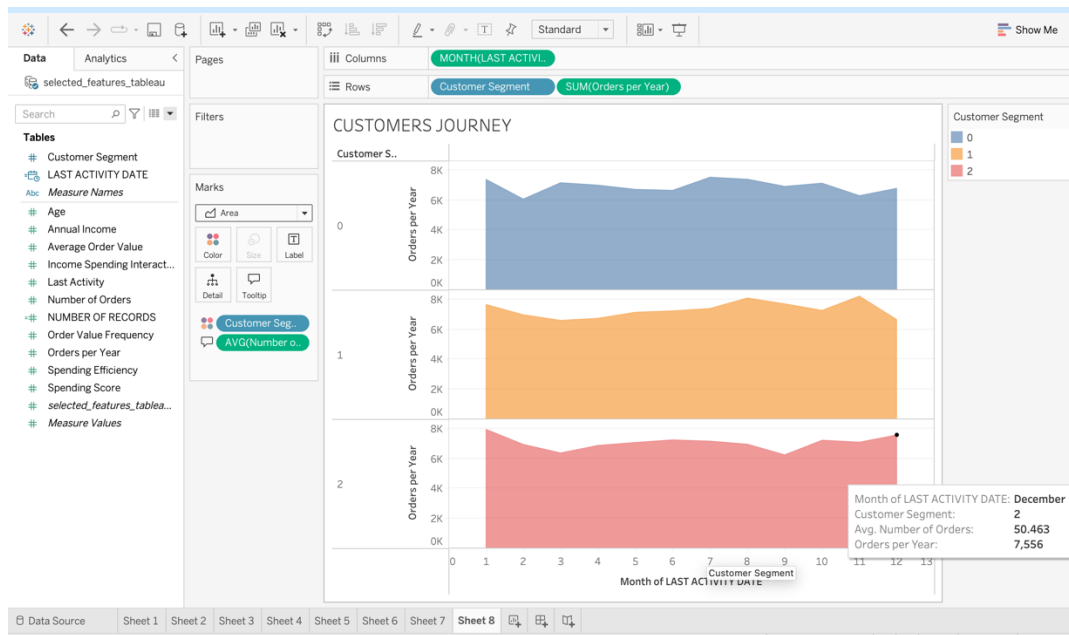
- Segment 2 stands out in both Annual Income and Age, suggesting that this segment may consist of older customers with higher incomes.

- Segment 0 and 1 have similar order frequencies, but segment 2 has significantly higher average income and age, indicating a wealthier and older customer group.
- We can focus on Segment-2 as key segment for high value offers, considering their higher income and Age.
- But based on ordering behavior, segments 0 and 1 might show more potential for increased orders per year.

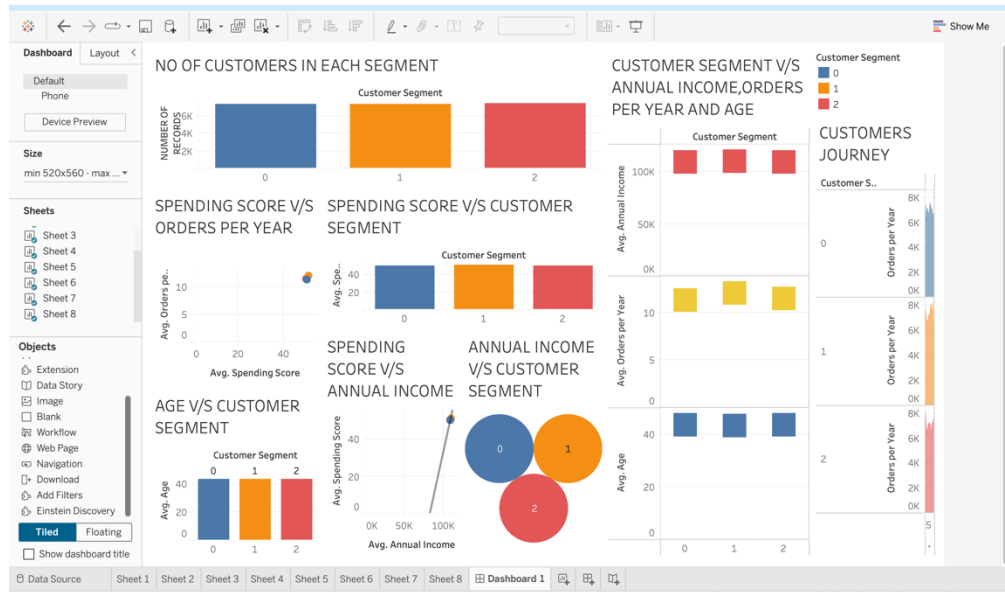
- Spending Score v/s Orders Per year



- The data points appear very sparse, which could mean that the **Avg. Orders per Year** or **Avg. Spending Score** for the **Customer Segments** are very close to each other, or the dataset might not have a sufficient spread in values for these two variables.
- Now we'll see Customers Journey Visualization.



- Customer Segment 0 shows more consistent or stable ordering behavior across months with small fluctuations.
- Customer Segment 1 and Customer Segment 2 show more pronounced fluctuations, suggesting these segments may have seasonal pattern or peaks in certain months.
- Also, it shows that orders per year is slightly higher for all segments around December.
- So, the final dashboard is below



- Segment 2 has the highest annual income and the oldest average age. It also appears to have a slightly lower spending score compared to segment 1 but the high income could suggest they may make higher value purchases. Targeting this segment for premium products or services might be effective.
- While segment 1 has a high spending score, it has a mid-range annual income compared to the other segments. Its orders per year is steady indicating moderate engagement. Segment 1 can be receptive to promotions that encourages repeat purchases or loyalty rewards.
- Segment 0 has the lowest average age and the lowest average income. However, their spending score and orders per year is fairly balanced which could indicate that although they have a low income they engage regularly with the platform. This segment could be ideal for budget friendly products or campaigns that focus on frequency of purchases.