Clustering Customers & Predicting Purchasing Behavior with Instacart Data

Team 24: Marion Cassim, Nicole Flowerhill, Eugene Huang, Dongwon Jang, Pruek Vanna-iampikul

Introduction

The emergence of COVID-19 and its subsequent impact on consumer behavior created a shockwave through the global retail industry, creating winners of those who prioritized digital and omnichannel funnels, and losers of those that prioritized a physical retail footprint.

To succeed in this new environment, the use of data analytics is necessary to better understand customers while ensuring that they have the right product mix, sufficient inventory, and appropriate levels of staffing to guarantee an experience that will help generate customer loyalty.

Problem Definition

This project seeks to determine the possibility of segmenting grocery customers based on the items that they purchase and repurchase, the order that they purchase items, the length of time between purchases, and the time and day that a customer makes a purchase. We also seek to predict whether a customer will repurchase an item or similar items in the future.

Data Collection, Data Cleaning, Preprocessing, and Feature Engineering

We used Instacart's Online Grocery Shopping Dataset from 2017. It contains anonymized data of over 3 million orders from over 200,000 users, covering between 4 and 100 orders per user. The dataset has order information, product information, department and aisle information per product, the order in which products were added to cart and whether the product was ordered by a user previously.

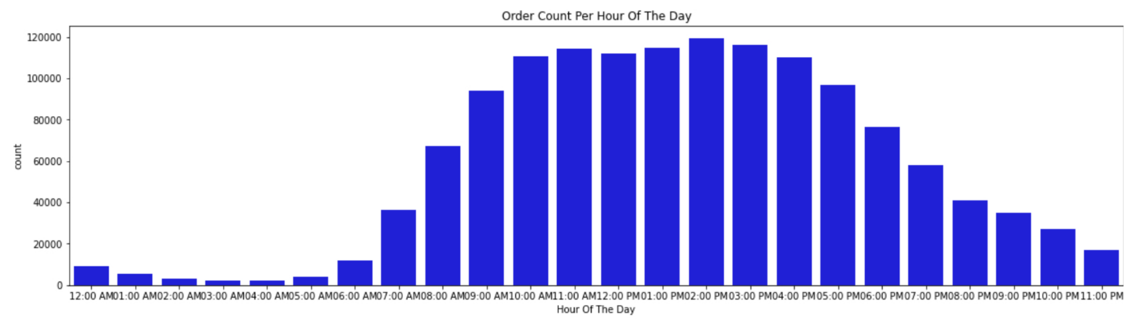
A thorough review of the dataset revealed that the data provided by Instacart was quite clean and there was not any missing information or items that did not make sense. We joined several csv files containing order information, product information, department and aisle information per product to create a holistic dataset to use in our model. Given the dataset size and limitations of our personal computers, we used a subset of the data that contained the items ordered in the last order of a sequence of orders by Instacart customers. This dataset contained 1,384,617 data points and 16 variables.

To prepare the dataset for model building, we conducted feature engineering by creating and modifying several variables. We changed the order day of week, which was a range of integers from 0 to 6, to Saturday through Friday respectively. We also changed the order hour of day, which was a range of integers from 0 to 23, to a 12HR datetime format that included whether the order was placed in the AM or PM. Based on further review, we decided to create a new variable, order_part_of_day, to bin the hours the order was placed into higher level categories. This reduced the number of levels for time of day from 24 to 7.

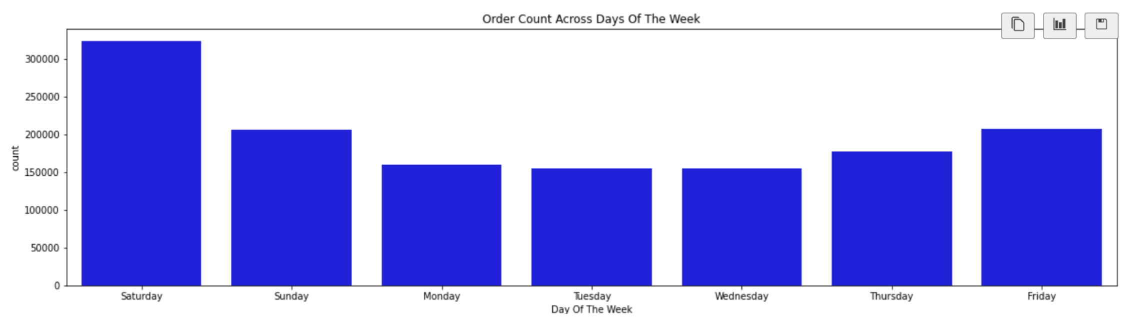
Exploratory Data Analysis

Through EDA using python's matplot library, we were able to observe several key points in terms of user's orders and date & time of order.

Analyzing the hour of day allowed us to conclude that most orders were placed between 10am to 3pm (Figure 1), with highest counts of orders on Saturday and Sunday (Figure 2)

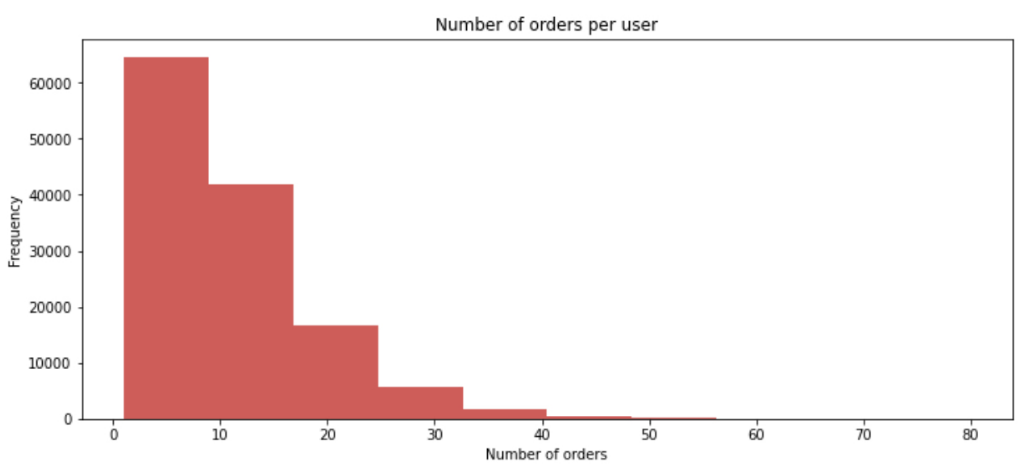


(Figure 1: Count of Orders per Hour of the Day)



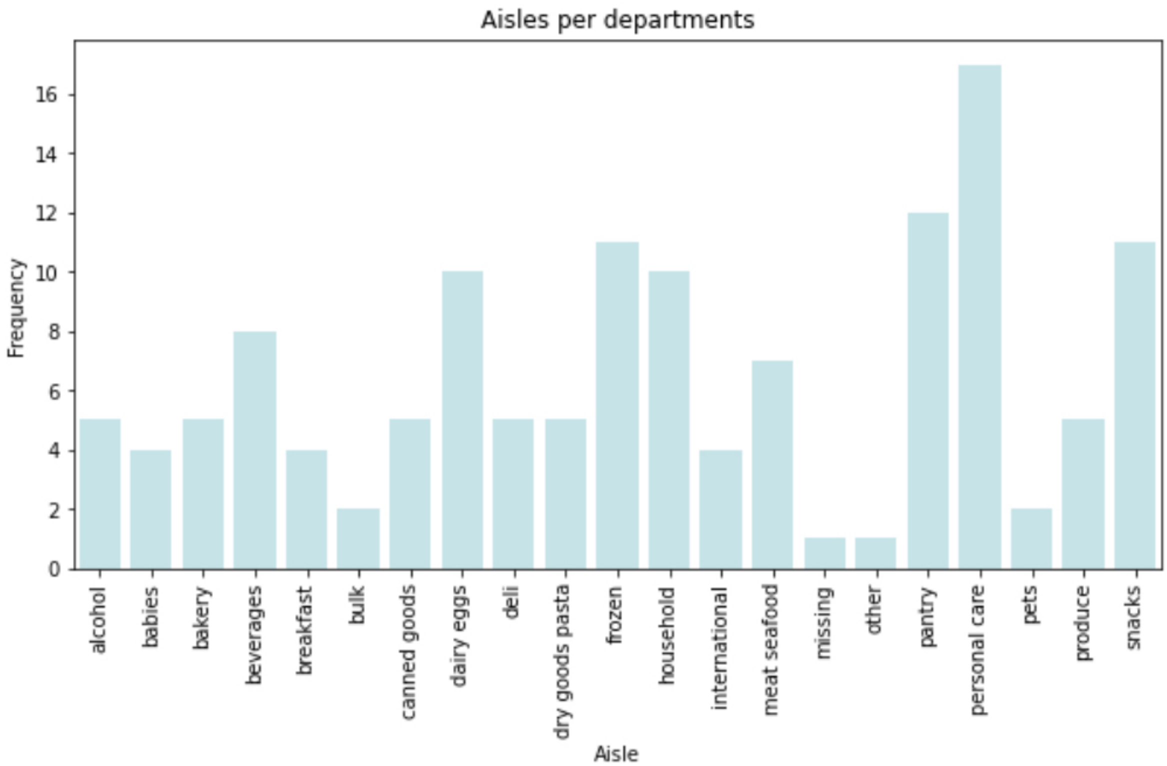
(Figure 2: Count of Orders Across Day of the Week)

In comparing the number of orders for each user, we can see that our sample dataset has users ordering between 3-10 orders (Figure 3).

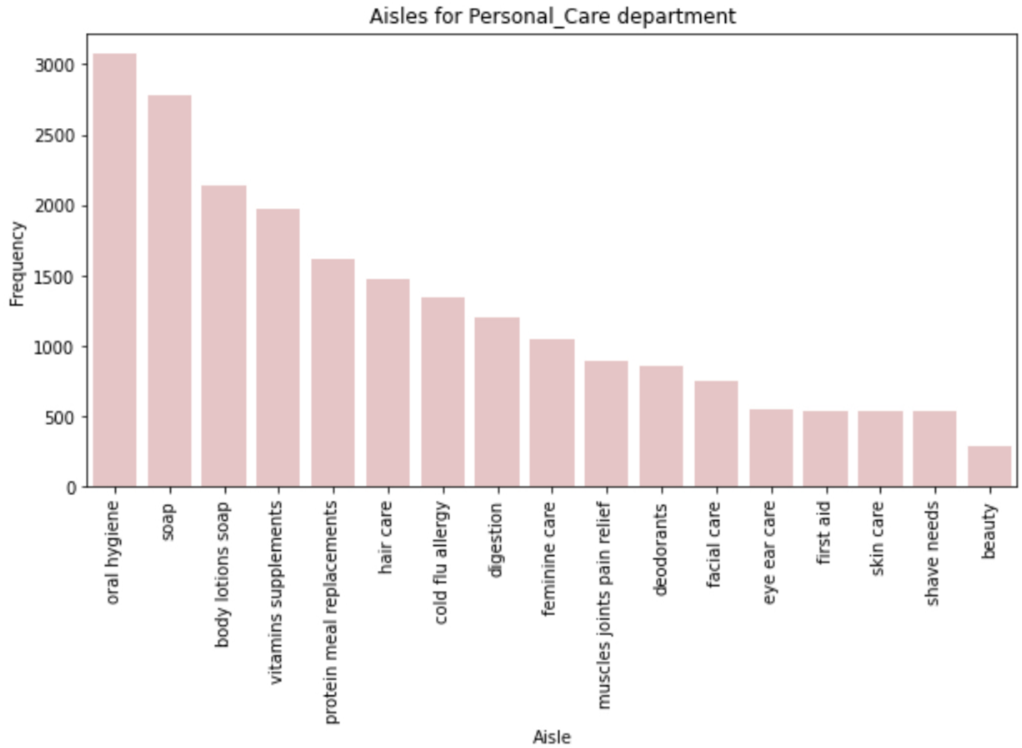


(Figure 3: Number of Orders per User)

Looking into the possible types of orders that a user can make, we see that products are categorized into different departments, each with their own number of aisles (Figure 4). The department with the biggest number of aisles is the "personal care" department, which we further analyzed in Figure 5 in order to see the different possible products.

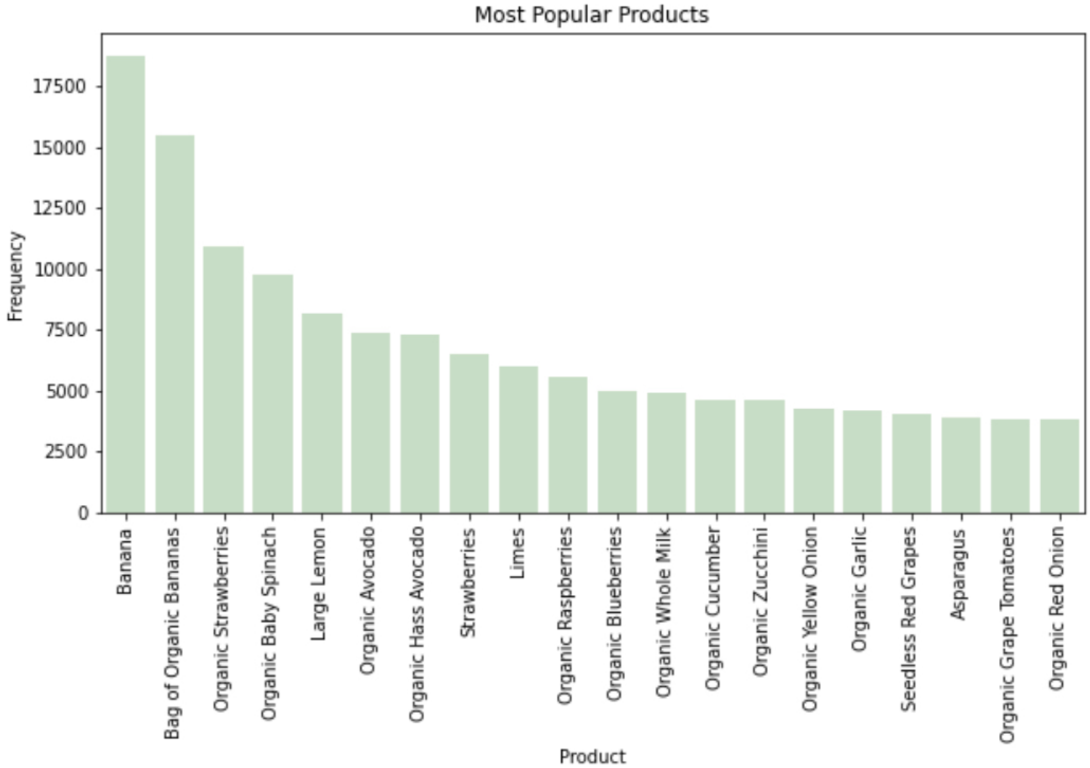


(Figure 4: Number of Aisles per Department)



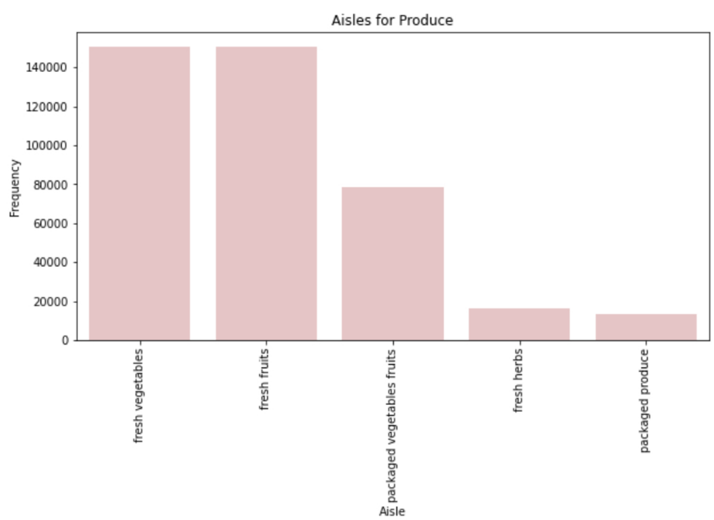
(Figure 5: Number of Aisles for "Personal Care" Department)

Although the "personal care" department had the highest number of aisles, we realized that its quantity of aisles may or may not not correlate with the purchase quantity from this department. To analyze further, we created an analysis of the most popular products purchased (Figure 6) comparing the amount of times a product was purchased. We concluded no significant relationship between department aisle quantity and amount of products purchased after observing that the most popular products purchased were not of the "personal care" department. Since there is a large quantity of unique products, we have limited our Figure 6 graph to the top 20 most purchased products.



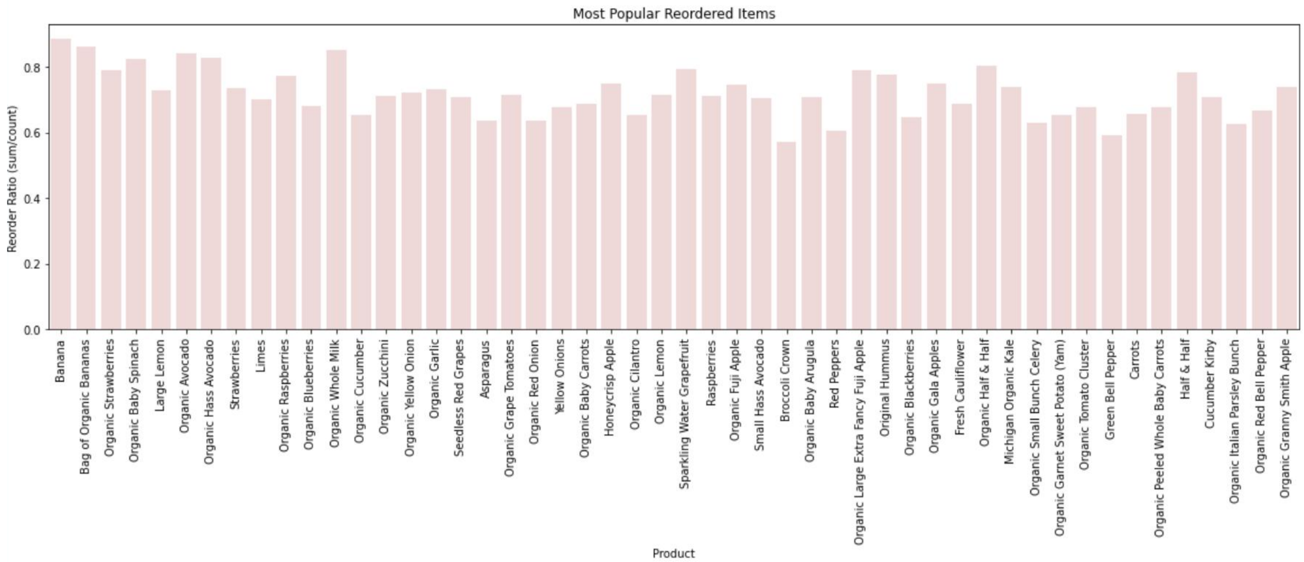
(Figure 6: Top 20 Most Popular Products)

We notice that the highest frequency of products ordered are fresh produce, belonging to the "produce department," and observe in Figure 7 that only 5 aisles belong to this department (compared to the "personal care" department's 17 aisles).



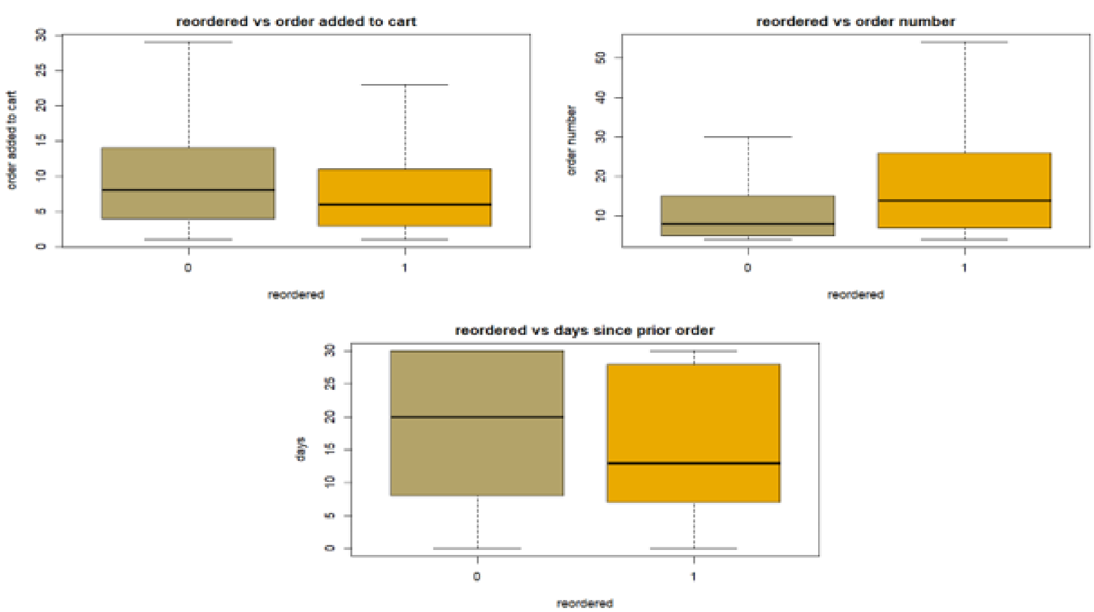
(Figure 7: Aisles for "Produce" Department)

One of the most important pieces of our EDA includes the analysis of reordered items in our sampled dataset to find how many times a customer has re-ordered the same product. A product reorder ratio metric was created using the sum of each product divided by how many times that product was re-ordered, and a graph was created to show the top 50 products with the highest reorder ratio (excluding products that have not been reordered at all). The results are parallel with previous findings in acknowledging that “produce” products are the ones most frequently reordered by customers.



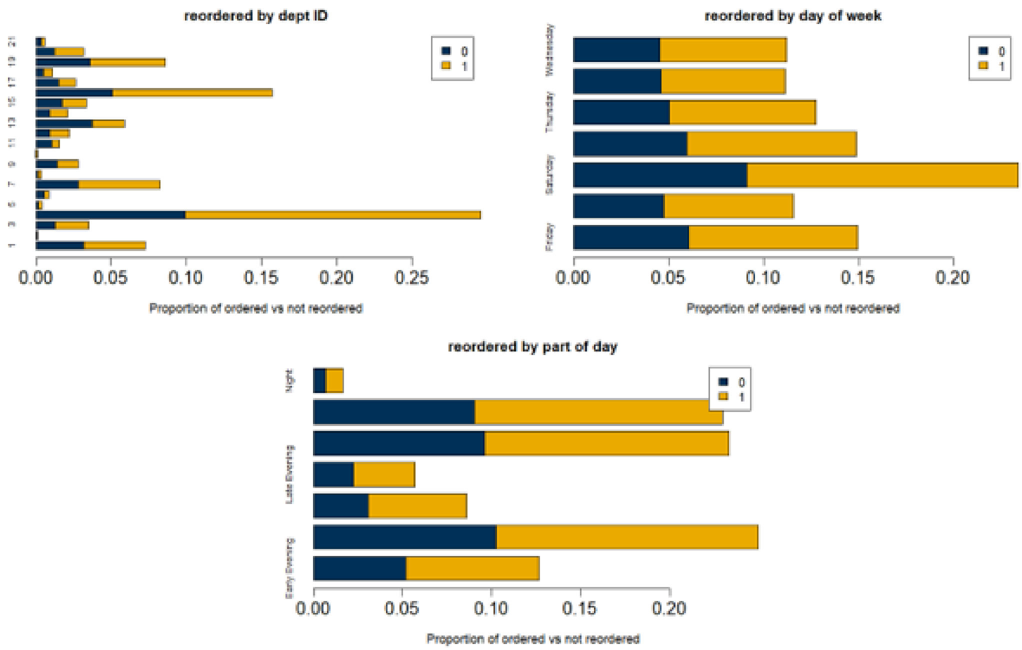
(Figure 8: Top 50 Most Popular Reordered Items)

We also conducted further EDA in R comparing our predictors with the response variable of whether a product was reordered or not. Based on the boxplots in Figure 9, we can see that there appears to be a significant difference between the number of days since the previous order made by a customer and whether a product was reordered or not, where items associated with a lower number of days since the prior order were reordered while those associated with a higher of number of days since the prior order were not reordered.



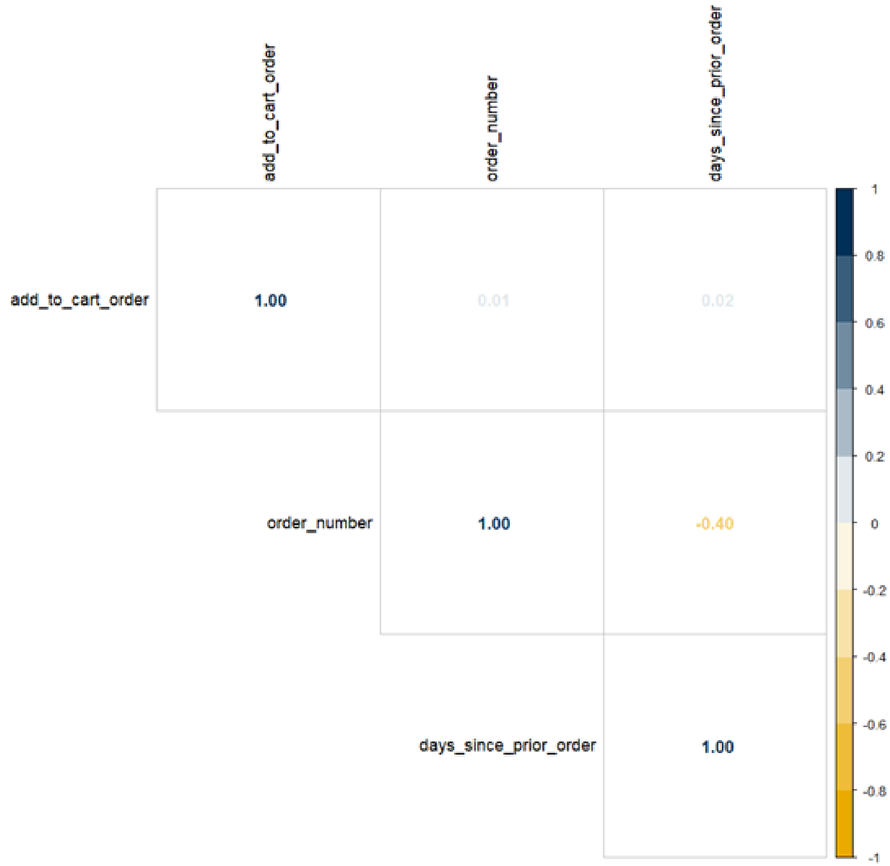
(Figure 9: Comparison of Numerical Features with Reordered Response Variable)

We can also see that items associated with customers who placed a higher number of orders were more likely to be reordered. Items that were ordered to a customer's cart earlier in the add to cart sequence were more likely to be reordered compared to those that were added later in the sequence.



(Figure 10: Comparison of Categorical Features with Reordered Response Variable)

Based on the bar plots in Figure 10, there does not appear to be much of a difference in the proportion of products that were reordered versus those that were not when viewed by the part of day the order was made and the day of the week the order was made. There appears to be a significant difference in the proportion of products that were reordered versus those that were not when viewing them by the department the products belonged to.



(Figure 11: Correlation Plot of Numerical Predictors)

Based on the correlation plot in Figure 11, we can see that there is a low negative correlation between the number of orders placed by a customer and the days since the customer's prior order (-0.40). There is a negligible correlation between the other numerical predictors.

Methods

Initial Dataset

The dataset that we used for our model contained 1,384,617 data points, 7 predictors and 1 response variable. The features are listed below in Figure 12:

FEATURE	DESCRIPTION	TYPE
reordered	1 if this product has been ordered by this user in the past, 0 otherwise	RESPONSE
add_to_cart_order	order in which each product was added to cart	NUMERICAL
aisle_id	aisle identifier	CATEGORICAL
order_number	number of orders made by customer	NUMERICAL
order_dow	the day of the week the order was placed on	CATEGORICAL
days_since_prior_o	days since the last order, capped at 30	NUMERICAL
part_of_day	the part of day an order was made	CATEGORICAL

(Figure 12: Features of Initial Dataset)

We randomly split the dataset into training and test sets using a 70%/30% split respectively. The training set contains 580,177 data points that are classified as reordered, accounting for approximately 59.9% of the training set. The test set contains 248,647 data points that are classified as reordered, accounting for approximately 59.9% of the test set.

Feature Selection

We built an initial logistic regression model in R with all the features as a foundation to conduct feature selection from. VIF analysis of the initial model results produced an error, indicating that there was perfect correlation between two or more of the predictors in the model. Subsequent analysis of the relationships between the categorical predictors using Cramer V produced the following results:

Feature 1	Feature 2	Cramer V
REORDERED	ASILE	0.2346
REORDERED	DEPT	0.1972
REORDERED	DOW	0.01686
REORDERED	POD	0.03348
AISLE	DEPT	1
AISLE	DOW	0.03246
AISLE	POD	0.02552
DEPT	DOW	0.02462
DEPT	POD	0.0165
ORDER	POD	0.02475

(Figure 13: Cramer V Analysis of Categorical Variables)

The range of values that Cramer V can produce is between 0 and 1, where 0 indicates that there is no association between two variables and 1 indicates that there is perfect association between two variables. Based on our analysis results in Figure 13, we can see that there is perfect collinearity between the aisle_id and department_id predictors.

We conducted forward-backward stepwise regression for feature selection, and it confirmed the multicollinearity issue by removing all levels associated with the department_id predictor, thus effectively eliminating the predictor from the model.. A subsequent VIF analysis of the reduced logistic regression model generated from stepwise regression indicated that multicollinearity was no longer an issue:

```
                           GVIF  Df GVIF^(1/(2*Df))
order_number           1.144415   1        1.069774
aisle_id               1.041450 133        1.000153
add_to_cart_order      1.033005   1        1.016369
days_since_prior_order 1.131455   1        1.063699
part_of_day            1.011866   6        1.000984
order_dow              1.017353   6        1.001435

VIF Threshold: 10
```

(Figure 14: VIF results from Logistic Regression Model after Stepwise Regression)

Logistic Regression (Supervised Method)

We used the supervised learning method of logistic regression to predict whether a customer would reorder a product (0 means will not reorder, 1 means will reorder), which could potentially be used to make future product recommendations based on their previous orders [Peng], [Huang].

The coefficients of the logistic regression model selected by stepwise regression are as follows:

```
Call:
glm(formula = reordered ~ order_number + aisle_id + add_to_cart_order + 
    days_since_prior_order + part_of_day + order_dow, family = "binomial", 
    data = train)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-3.0874  -1.1447   0.6475   0.9758   2.6966  

Coefficients:
                         Estimate Std. Error  z value Pr(>|z|)    
(Intercept)              0.325082   0.046886    6.933 4.11e-12 ***
order_number             0.567756   0.003217  176.472  < 2e-16 ***
aisle_id2               -0.318752   0.061403   -5.191 2.09e-07 ***
aisle_id3                0.070729   0.050126    1.411 0.158238    
aisle_id4               -0.190791   0.052532   -3.632 0.000281 ***
aisle_id5               -1.170807   0.069144  -16.933  < 2e-16 ***
aisle_id6               -0.836972   0.076702  -10.912  < 2e-16 ***
aisle_id7               -0.174872   0.079839   -2.190 0.028502 *  
aisle_id8               -0.375426   0.079120   -4.745 2.09e-06 ***
aisle_id9               -0.183567   0.052706   -3.483 0.000496 ***
aisle_id10              -1.763326   0.156486  -11.268  < 2e-16 ***
aisle_id11              -1.779032   0.096843  -18.370  < 2e-16 ***
aisle_id12              -0.073094   0.077854   -0.939 0.347801    
aisle_id13               0.210591   0.061262    3.438 0.000587 ***
aisle_id14               0.375164   0.058868    6.373 1.85e-10 ***
aisle_id15              -0.108585   0.094973   -1.143 0.252902    
aisle_id16              -0.171635   0.050275   -3.414 0.000640 ***
aisle_id17              -1.159949   0.051954  -22.326  < 2e-16 ***
aisle_id18               0.078039   0.106349    0.734 0.463070    
aisle_id19              -0.883532   0.052681  -16.771  < 2e-16 ***
aisle_id20              -0.887852   0.065898  -13.473  < 2e-16 ***
```

aisle_id21	0.114418	0.047878	2.390	0.016857	*
aisle_id22	-1.287405	0.086034	-14.964	< 2e-16	***
aisle_id23	0.073822	0.055337	1.334	0.182187	
aisle_id24	0.654368	0.046794	13.984	< 2e-16	***
aisle_id25	-0.951140	0.068153	-13.956	< 2e-16	***
aisle_id26	0.099553	0.054009	1.843	0.065291	.
aisle_id27	0.109992	0.075908	1.449	0.147336	
aisle_id28	-0.075424	0.084667	-0.891	0.373018	
aisle_id29	-0.886079	0.067284	-13.169	< 2e-16	***
aisle_id30	-0.536682	0.062738	-8.554	< 2e-16	***
aisle_id31	0.285873	0.049310	5.797	6.73e-09	***
aisle_id32	0.547969	0.051907	10.557	< 2e-16	***
aisle_id33	-0.947927	0.113867	-8.325	< 2e-16	***
aisle_id34	-0.056845	0.063111	-0.901	0.367739	
aisle_id35	0.271308	0.058477	4.640	3.49e-06	***
aisle_id36	0.105716	0.052363	2.019	0.043496	*
aisle_id37	-0.378636	0.049108	-7.710	1.25e-14	***
aisle_id38	0.201735	0.049854	4.047	5.20e-05	***
aisle_id39	-0.219464	0.090274	-2.431	0.015054	*
aisle_id40	-0.011632	0.078335	-0.148	0.881959	
aisle_id41	0.328003	0.067048	4.892	9.98e-07	***
aisle_id42	0.139849	0.059016	2.370	0.017803	*
aisle_id43	-0.073260	0.058090	-1.261	0.207259	
aisle_id44	-1.270671	0.125584	-10.118	< 2e-16	***
aisle_id45	-0.081248	0.051931	-1.565	0.117691	
aisle_id46	0.100385	0.094806	1.059	0.289672	
aisle_id47	-1.312295	0.076744	-17.100	< 2e-16	***
aisle_id48	0.173688	0.064517	2.692	0.007100	**
aisle_id49	0.274002	0.057457	4.769	1.85e-06	***
aisle_id50	0.127285	0.055724	2.284	0.022361	*
aisle_id51	-0.219887	0.057839	-3.802	0.000144	***
aisle_id52	0.325971	0.053177	6.130	8.79e-10	***
aisle_id53	0.410638	0.052131	7.877	3.35e-15	***
aisle_id54	-0.099685	0.051241	-1.945	0.051726	.
aisle_id55	-1.202671	0.125627	-9.573	< 2e-16	***
aisle_id56	-0.493218	0.088696	-5.561	2.69e-08	***
aisle_id57	0.047416	0.061937	0.766	0.443944	
aisle_id58	-0.122809	0.079130	-1.552	0.120663	
aisle_id59	-0.052414	0.051663	-1.015	0.310323	
aisle_id60	-0.875274	0.079424	-11.020	< 2e-16	***
aisle_id61	0.011872	0.052672	0.225	0.821676	
aisle_id62	0.393894	0.093252	4.224	2.40e-05	***
aisle_id63	-0.609277	0.056572	-10.770	< 2e-16	***
aisle_id64	0.238150	0.059384	4.010	6.06e-05	***
aisle_id65	-0.380813	0.077279	-4.928	8.32e-07	***
aisle_id66	-0.913542	0.055918	-16.337	< 2e-16	***
aisle_id67	0.206312	0.050672	4.072	4.67e-05	***
aisle_id68	-0.236691	0.110758	-2.137	0.032597	*
aisle_id69	-0.427876	0.050476	-8.477	< 2e-16	***
aisle_id70	-0.584737	0.087176	-6.708	1.98e-11	***
aisle_id71	-0.018748	0.076196	-0.246	0.805642	
aisle_id72	-0.995029	0.053507	-18.596	< 2e-16	***
aisle_id73	-0.815301	0.107924	-7.554	4.21e-14	***
aisle_id74	-0.730289	0.061932	-11.792	< 2e-16	***
aisle_id75	-0.429492	0.058894	-7.293	3.04e-13	***

aisle_id75	-0.429492	0.058894	-7.293	3.04e-13	***
aisle_id76	-0.305621	0.103563	-2.951	0.003167	**
aisle_id77	0.284110	0.050483	5.628	1.82e-08	***
aisle_id78	0.063067	0.049628	1.271	0.203797	
aisle_id79	0.172254	0.054505	3.160	0.001576	**
aisle_id80	-1.301176	0.106820	-12.181	< 2e-16	***
aisle_id81	-0.419476	0.051334	-8.172	3.05e-16	***
aisle_id82	-0.260444	0.155532	-1.675	0.094026	.
aisle_id83	0.137659	0.046697	2.948	0.003199	**
aisle_id84	0.913489	0.049164	18.580	< 2e-16	***
aisle_id85	-1.319876	0.069246	-19.061	< 2e-16	***
aisle_id86	0.628557	0.050187	12.524	< 2e-16	***
aisle_id87	-1.437724	0.105702	-13.602	< 2e-16	***
aisle_id88	-0.361909	0.051564	-7.019	2.24e-12	***
aisle_id89	-0.934466	0.060369	-15.479	< 2e-16	***
aisle_id90	-0.518846	0.088660	-5.852	4.85e-09	***
aisle_id91	0.435828	0.049084	8.879	< 2e-16	***
aisle_id92	-0.135465	0.051234	-2.644	0.008191	**
aisle_id93	0.307043	0.053225	5.769	7.99e-09	***
aisle_id94	-0.298602	0.053031	-5.631	1.80e-08	***
aisle_id95	-0.229043	0.063656	-3.598	0.000321	***
aisle_id96	0.148864	0.050221	2.964	0.003035	**
aisle_id97	-1.993271	0.110760	-17.996	< 2e-16	***
aisle_id98	0.067879	0.050827	1.336	0.181711	
aisle_id99	-0.005581	0.060741	-0.092	0.926787	
aisle_id100	-0.955861	0.054403	-17.570	< 2e-16	***
aisle_id101	-0.979518	0.092840	-10.551	< 2e-16	***
aisle_id102	-1.367189	0.164143	-8.329	< 2e-16	***
aisle_id103	-1.155524	0.130898	-8.828	< 2e-16	***
aisle_id104	-2.041161	0.058157	-35.098	< 2e-16	***
aisle_id105	-0.549944	0.058992	-9.322	< 2e-16	***
aisle_id106	0.043862	0.051297	0.855	0.392521	
aisle_id107	0.134516	0.048398	2.779	0.005447	**
aisle_id108	0.074840	0.051354	1.457	0.145023	
aisle_id109	-1.523855	0.131970	-11.547	< 2e-16	***
aisle_id110	-0.407754	0.058504	-6.970	3.18e-12	***
aisle_id111	-0.689812	0.072953	-9.456	< 2e-16	***
aisle_id112	0.428970	0.049356	8.691	< 2e-16	***
aisle_id113	-0.372915	0.155717	-2.395	0.016628	*
aisle_id114	-1.105892	0.058073	-19.043	< 2e-16	***
aisle_id115	0.662884	0.048503	13.667	< 2e-16	***
aisle_id116	-0.032910	0.049177	-0.669	0.503350	
aisle_id117	-0.255519	0.051430	-4.968	6.76e-07	***
aisle_id118	-1.754733	0.140724	-12.469	< 2e-16	***
aisle_id119	-0.426370	0.093886	-4.541	5.59e-06	***
aisle_id120	0.447355	0.047614	9.395	< 2e-16	***
aisle_id121	0.075613	0.050306	1.503	0.132821	
aisle_id122	-0.143841	0.064238	-2.239	0.025144	*
aisle_id123	0.321342	0.047165	6.813	9.55e-12	***
aisle_id124	-0.137105	0.091789	-1.494	0.135253	
aisle_id125	0.191090	0.082161	2.326	0.020028	*
aisle_id126	-1.059739	0.094425	-11.223	< 2e-16	***
aisle_id127	-0.841177	0.073301	-11.476	< 2e-16	***
aisle_id128	-0.034810	0.053805	-0.647	0.517649	
aisle_id129	-0.033245	0.053408	-0.622	0.533631	
aisle_id130	-0.287333	0.055878	-5.142	2.72e-07	***
aisle_id131	-0.324768	0.051901	-6.257	3.91e-10	***

```
aisle_id132                 -1.745145   0.191059   -9.134  < 2e-16 ***
aisle_id133                 -0.951173   0.097726   -9.733  < 2e-16 ***
aisle_id134                 -0.247564   0.123985   -1.997 0.045855 *
add_to_cart_order           -0.290281   0.002285 -127.011  < 2e-16 ***
days_since_prior_order      -0.158617   0.002387  -66.460  < 2e-16 ***
part_of_dayEarly_Afternoon   0.015740   0.007623    2.065 0.038948 *
part_of_dayEarly_Morning     0.152960   0.009939   15.390  < 2e-16 ***
part_of_dayLate Evening      0.031618   0.011212    2.820 0.004802 **
part_of_dayLate_Afternoon    0.001455   0.007699    0.189 0.850090
part_of_dayLate_Morning      0.060377   0.007754    7.786 6.90e-15 ***
part_of_dayNight            -0.009286   0.018220   -0.510 0.610300
order_dowMonday              0.016228   0.008650    1.876 0.060637 .
order_dowSaturday            0.057876   0.007357    7.866 3.65e-15 ***
order_dowSunday              0.072383   0.008115    8.920  < 2e-16 ***
order_dowThursday           -0.002392   0.008481   -0.282 0.777943
order_dowTuesday            -0.014690   0.008754   -1.678 0.093333 .
order_dowWednesday          -0.022869   0.008762   -2.610 0.009053 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1305706  on 969231  degrees of freedom
Residual deviance: 1173431  on 969083  degrees of freedom
AIC: 1173729

Number of Fisher Scoring iterations: 4
                aisle_id3                 aisle_id12                 aisle_id15                 aisle_id18
                        4                         13                         16                         19
               aisle_id23                 aisle_id26                 aisle_id27                 aisle_id28
                       24                         27                         28                         29
               aisle_id34                 aisle_id40                 aisle_id43                 aisle_id45
                       35                         41                         44                         46
               aisle_id46                 aisle_id54                 aisle_id57                 aisle_id58
                       47                         55                         58                         59
               aisle_id59                 aisle_id61                 aisle_id71                 aisle_id78
                       60                         62                         72                         79
               aisle_id82                 aisle_id98                 aisle_id99                aisle_id106
                       83                         99                        100                        107
              aisle_id108                aisle_id116                aisle_id121                aisle_id124
                      109                        117                        122                        125
              aisle_id128                aisle_id129  part_of_dayLate_Afternoon           part_of_dayNight
                      129                        130                        141                        143
          order_dowMonday          order_dowThursday           order_dowTuesday
                      144                        147                        148

 Variables not selected by forward-backward stepwise: department_id2 department_id3 department_id4 department_id5
department_id6 department_id7 department_id8 department_id9 department_id10 department_id11 department_id12
department_id13 department_id14 department_id15 department_id16 department_id17 department_id18 department_id19
department_id20 department_id21
```

(Figure 15: Logistic Regression Model Results Following Stepwise Regression)

As we can see from the results above, all the numerical predictors, and many levels of the categorical predictors, have a statistically significant relationship with the reordered response variable at the 99.999% significance level.

When checking the p-value for the overall model, we have a value of zero, indicating that the overall model is statistically significant and has explanatory power.

Results and Discussion

Prediction Results

			TRUE CLASS	
			NEGATIVE	POSITIVE
			NOT REORDERED	REORDERED
PREDICTED CLASS	NEGATIVE	NOT REORDERED CLASSIFICATION	**True Negative (TN)** Product is predicted to not be reordered and is truly not reordered	**False Negative (FN)** Product is predicted to not be reordered, but is reordered
	POSITIVE	REORDERED CLASSIFICATION	**False Positive (FP)** Product is predicted to be reordered, but is not reordered	**True Positive (TP)** Product is predicted to be reordered and is truly reordered

	NOT REORDERED	REORDERED
NOT REORDERED CLASSIFICATION	70,648	40,983
REORDERED CLASSIFICATION	96,090	207,664

(Figure 16: Confusion Matrix of Prediction Results and Interpretation Guide)

When evaluating prediction model results, we can use accuracy, precision, sensitivity, and specificity ratios:

Accuracy is the ratio of correctly labeled data points compared to the entire set of data points and is represented by the following equation:

$$\frac{TP+TN}{TP+FP+FN+TN}$$

Precision is the ratio of data points that were correctly labeled as positive compared to the entire set of data points that were labeled as positive and is represented by the following equation:

$$\frac{TP}{TP+FP}$$

Sensitivity is the ratio of data points that were correctly labeled as positive compared to the entire set of data points that are truly positive and is represented by the following equation:

$$\frac{TP}{TP + FN}$$

Specificity is the ratio of data points that were correctly labeled as negative compared to the entire set of data points that are truly negative. Specificity is represented by the following equation:

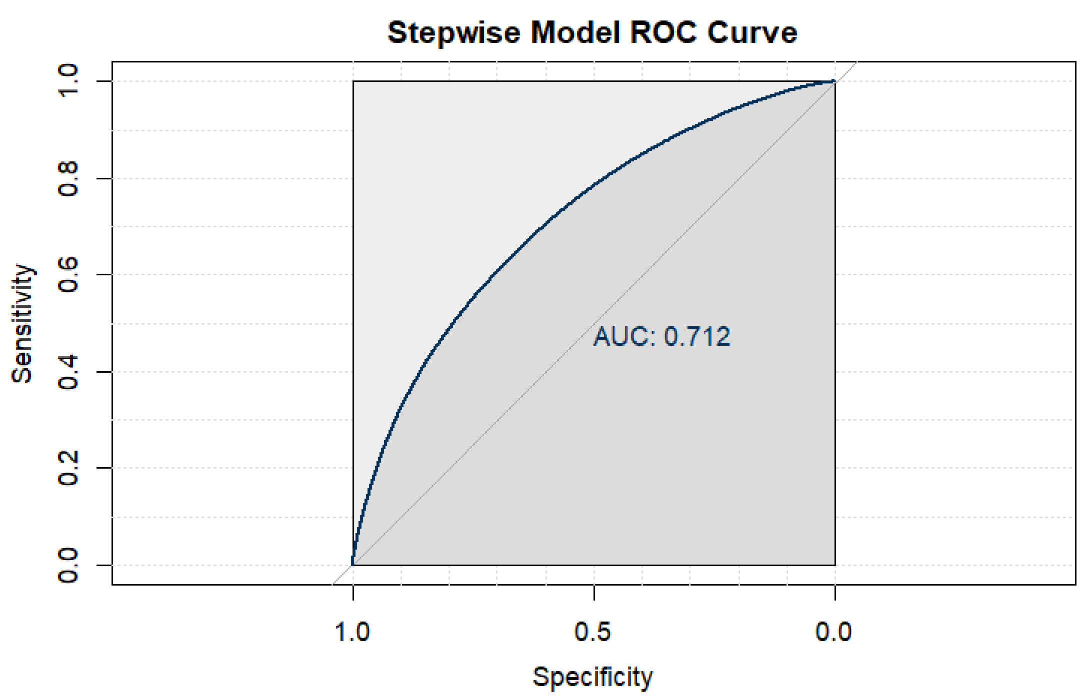
$$\frac{TN}{TN + FP}$$

Our model's accuracy, precision, sensitivity, and specificity scores are as follows:

MODEL TYPE	ACCURACY	PRECISION	SENSITIVITY	SPECIFICITY
STEPWISE	0.6700097	0.6836585	0.8351760	0.4237067

(Figure 17: Model Results)

Precision and sensitivity are the two most important metrics for our model, as we want to know if a customer will reorder an item or not. Our logistic regression model predicts 83 out of 100 reorders and 68 out of 100 reorder predictions were correct.

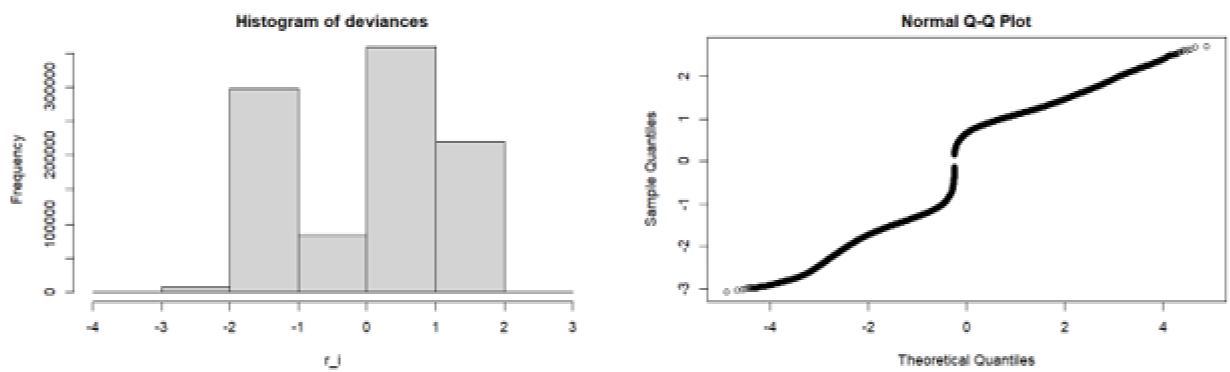


(Figure 18: ROC-AUC Curve)

An ROC curve is a graphical interpretation of how capable our model is at distinguishing between products that were reordered versus products that weren't reordered. The AUC score is a summary of the curve with a score between 1 and 0, with 1 representing perfect separation between two classes. Our model accomplished an AUC score of 0.712, which is significantly better than the 0.5 score of a random classifier.

Goodness-of-Fit

As deviance residuals are the equivalent to the residuals in standard linear regression, one of the things we want to check is normality to see if the model is a good fit for the data. We used a histogram and QQ plot of the deviance residuals to check for normality:



(Figure 19: Histogram and QQ Plot of Residuals)

Basedon the histogram and QQ plot of the deviance residuals, there appears to be a significant departure of normality. This is confirmed by a deviance test for goodness-of-fit using deviance residuals, where we achieve a p-value of 0, indicating that the model is not a good fit for the data.

We can try to improve the model fit by adding interaction terms, transforming predictors, and identifying and removing outliers. Sometimes it may also be the case where the logit function may not fit the data and we can try other s-shape functions, such as probit or complementary log-log.

<u>Methods: Next Step - Unsupervised:</u>

Since the purchase information will only contain the product information, we plan on combining and engineering new features out of existing information to provide a more meaningful product prediction.

For our unsupervised method, we are planning to use clustering to segment customers, where data points that have similar features are grouped [Kashwan]. We plan to use the elbow method and distortion score to determine the best number of clusters. To evaluate cluster separation, we will use TSNE plots.

Our study can cluster based on the features mentioned in the problem definition. We will apply the k-means algorithm, a time-efficient method which starts with an initial k amount of clusters, finds centroids of the clusters, and reiterates until convergence [Kashwan], [Huang]. The results of k-means can initialize a Gaussian Mixture Model, a soft clustering method with the additional parameter covariance to cluster the model more flexibly [Cikovic]. GMM is computationally expensive and may take issue with high-dimensional data, so it may require preprocessing for dimensionality reduction [Cikovic].

Conclusion:

We collected the data from Instacart's Online Grocery Shopping Dataset from 2017 and performed the data cleaning by checking for any missing information. Next, we combined all the data into a single table and explored the data analysis to understand the statistics of the dataset in order to perform feature selection for our prediction model. For our prediction model, we built a supervised model using logistic regression to predict the reordering of certain products. We selected certain features by using Cramer V to find the best correlation between each feature and the response, and the correlation among pairs of features. The most impactful features were selected and those with high correlation with the already selected features were omitted. Our logistic regression model proved to be successful with an AUC score of 0.712, which is a significant improvement over the 0.5 score of a random classifier. From here, as our final task, we plan to further reinforce our reorder prediction model using an unsupervised method of customer segmentation.

Gantt Chart:

https://github.com/instakartproject/cs7641/blob/main/CS7641_Fall2022_Group24_GanttChart.xlsx

Updated Contribution table:

TASK TITLE	TASK OWNER
Midterm Proposal	All
Introduction & Background	EH
EDA Methods	MC, EH
Method Results & Discussion	NF, MC, DJ, PV, EH
Next Steps	NF, MC, DJ, PV
Conclusion	DJ, PV, NF
GitHub Page	EH

Citations:

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Dataset:

"The Instacart Online Grocery Shopping Dataset 2017", Accessed from https://www.instacart.com/datasets/grocery-shopping-2017 on <date>