Grocery Shopping Behavior By Time of Day

MIDS-INFO-W200 Summey 2017 Section 2
Project 2: Data Analysis
Presented: August 17th, 2017
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The Purpose:

The purpose of this project is to conduct a preliminary analysis of open datasets from Instacart and dunnhumby to investigate the potential effects of time on consumer behavior with the goal of determining optimal times and content for in-app and out-of-app advertising with respect to healthy versus unhealthy foods.

The Focus:

Our hypothesis is that that during meal times people would be more likely to buy more since they may be hungrier and that later in the day, people may have less self control and thus purchase more unhealthy items. Based on our hypothesis, our project will focus on the following questions in order to examine our hypothesis and determine optimal times for advertising and the content of the advertisements:

- What are the peak hours for Instacart users and dunnhumby grocery store customers?
- When are unhealthy and healthy foods more common so that ads can target those preferences?
- How can advertisers take advantage of preferences for specific categories throughout the day?
- Does quantity of items in the cart differ throughout the day?
    - How do people shop during peak hours?
    - If people order at meal times, how much more likely are they to order more quantities of food?
- How often do people order again on Instacart?
    - Does a smaller number of days since prior order lead to less items on average in a user's cart?
- Overall, can online and offline purchase patterns be comparable and inform strategic advertising?
- What are potential next steps for additional research?

The Context:

Instacart[1] is a grocery delivery service that began in 2012 and currently operates nationwide in more than 30 states. With a plan to serve 80% of American households by 2018, they have started their expansion into 100 new cities earlier this year, many of which are outside major metropolitan areas. Earlier this year, they shared an anonymized dataset contains a sample of over 3 million grocery orders from more than 200,000 Instacart users.

[1] "About Us." *Instacart*. LinkedIn, https://www.linkedin.com/company-beta/2732417/ 14 August 2017

dunnhumby[2] is the world's leading Customer Data Science company with offices throughout Europe, Asia, Africa, and the Americas and works with companies including Tesco, Monoprix, Raley's, Whole Foods, Coca-Cola, P&G, and PepsiCo. Through their Source Files platform, we have attained their Complete Journey dataset that contains household level transactions over two years from a group of 2,500 households who are frequent shoppers at a retailer.

The Source:
- *Original Dataset: "The Instacart Online Grocery Shopping Dataset 2017", Accessed from https://www.instacart.com/datasets/grocery-shopping-2017 on July 30,2017*
- *Original Dataset: "The Complete Journey", Accessed from https://www.dunnhumby.com/sourcefiles on August 7,2017*

The Raw Data Files:
Our raw data files were in .csv format made up of more than 3.4 million rows of data, separated in 6 different files.

Instacart

DATASET	DESCRIPTION	# FILES
aisles.csv	Aisle IDs and aisle names	1
departments.csv	Department IDs and department names	1
order_products_prior.csv & order_products_train.csv[3]	Order IDs, product IDs, add to cart order (order in which each product was added to cart) and reordered status (1 if this product has been ordered by this user in the past, 0 otherwise)	2
orders.csv	Order IDs, user IDs, day of the week, hour of the day, order number and days since prior order (capped at 30 with NAs when order number = 1)	1
products.csv	Product IDs, product names, aisle IDs and department IDs	1

[2] "About Us." *dunnhumby*. LinkedIn, https://www.linkedin.com/company-beta/6608/ 14 August 2017
[3] Order_products_prior.csv holds data on orders made prior to the user's most recent order (~ 3.2 million orders). Order_products_train.csv holds data on training data supplied by Instacart (~ 131,000 orders).

Dunnhumby

DATASET	DESCRIPTION	# FILES
product.csv	Product IDs, manufacturer, department, brand, commodity description, sub-commodity description, current size of product	1
transaction_data.csv	Household keys, basket IDs, product IDs, quantity, sales value, store IDs, retail price discrepancy, transaction time, week number	1

We will be focusing on the following columns for each dataset:

- Instacart: aisle names, order ids, add to cart order, reordered status, user ids, hour of the day, days since prior order and product names
- Dunnhumby: household keys, commodity description, quantity and transaction time

The Reconciliation:

We used a random sample of 100 user_ids from the 33.8 million row Instacart Online Grocery Shopping Dataset, and combined data from the aisle.csv, department.csv, orders.csv, order_products__prior.csv, order_products__train.csv and products.csv. This generated a dataset that had 14,353 observations.

From the dunnhumby source files, we used their Complete Journey dataset that consisted of household level transactions over two years from a group of 2,500 households with over 2.5 million observations over 102 weeks.The product dataset, consisting of descriptor information about the product and the transaction_dataset, which encompassed information about the product's transaction, were merged by product_id and filtered so that relevant departments were left in the dataset[4]. The first 26 weeks were taken in the Complete Journey dataset in order to reduce the sample size to a manageable amount. The Complete Journey dataset was also randomly sampled for 100 household_keys. This generated a dataset that had 18,552 observations.

User_id and household_key were used as the main ID to randomly sample on since we wanted to see the variation among users as opposed to a random sample of all the orders in both datasets.

Observed Inconsistencies:

We observed a few data inconsistencies with our datasets (both raw and sampling):

[4] The following categories were excluded: Automotive, Charitable, Control/Store Supplies, cosmetics, coupons, drugs, floral, electrical and plumbing, housewares, garden center, gasoline, miscellaneous transactions, pharmacy supply, photography, toys, travel and leisure, video, video rentals, and restaurants.

With the Instacart data, there were 22 orders that had blank values and were dropped from the data set. Additionally, we were unable to definitively identify the days of the week associated with the orders. In our datasets, the days of the week were numbered sequentially and there was no explicit delineation of which number corresponded with which day of the week, let alone which month the data was selected from. While this would prevent some further analysis and conclusions, the investigating team decided to move forward and consider time of day as the primary dimension of analysis.

In the dunnhumby set, two product identification numbers were included that did not have an associated record in the product_id.csv. Consequently, we filtered these products out. Further as a result of blank departments within the data for certain products, 3 household_keys were dropped from the dunnhumby dataset during the cleaning. Our final dataset thus became 97 household_keys.

Finally, as a function of our sampling protocol, each dataset was "missing orders" from different hours of the day. For dunnhumby, there were no orders made at hours 0, 3 and 4am. For Instacart, no orders were made at 4am. This is an element of our sample due to our sampling with random selection. We will move forward with our analysis with these caveats in mind.

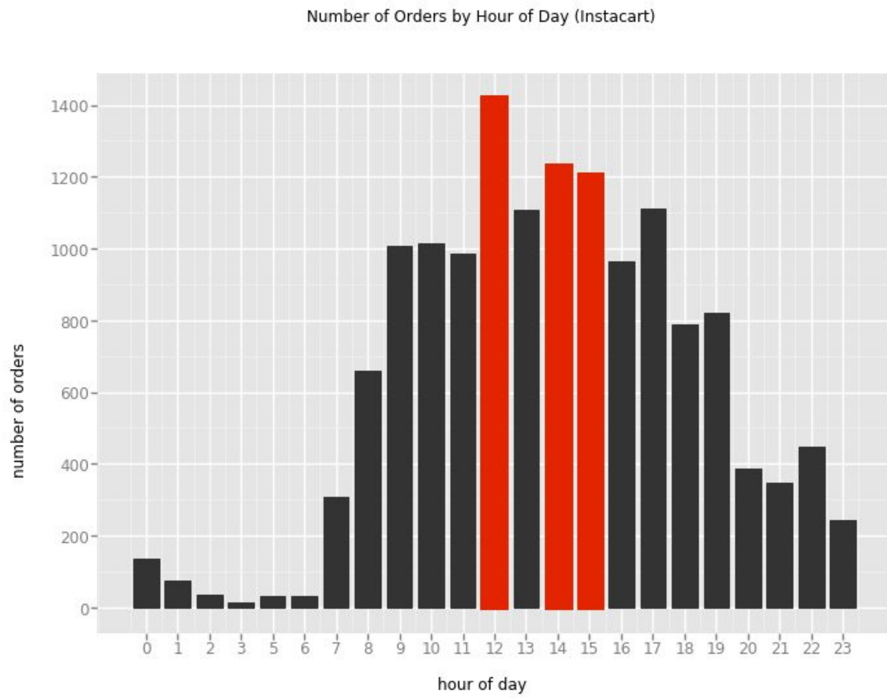
Grouping for Analyses:

To run analyses on the composition of the orders, we decided to add two more columns to our datasets based on the product's aisle names in Instacart and commodity descriptions (comm_desc) in dunnhumby: healthy and foodgroup. For the "healthy" column, we labeled aisles/comm_desc as "healthy" and "unhealthy," leaving ambiguous aisles like "refrigerated" and neutral aisles like "oils vinegars" unlabeled. For the "foodgroup" column, we labeled aisles/comm_desc by referencing USDA's National Nutrient Database for Standard Reference Release 28[5] with 2 additional categories for aisles for non-food items and "other." Some related categories were combined for simplicity.

[5] US Department of Agriculture, Agricultural Research Service, Nutrient Data Laboratory. USDA National Nutrient Database for Standard Reference, Release 28 (Slightly revised). Version Current: May 2016. Internet: http://www.ars.usda.gov/ba/bhnrc/ndl

The Instacart (Online) Story:

<u>What are the peak hours for ordering among **Instacart** users?</u>

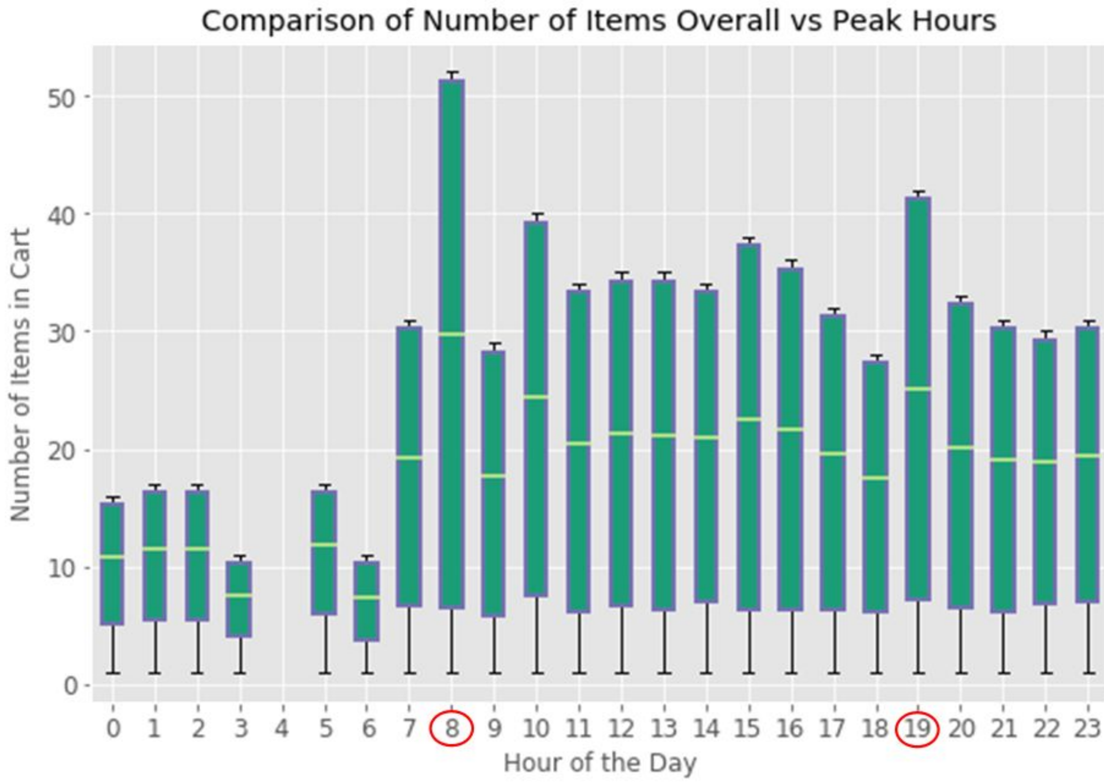


Peak hours: 12pm, 2pm and 3pm

The greatest number of orders were placed during the hours of 12pm, 2pm and 3pm which suggest potentially optimal times for advertisement. As digital advertisers want to maximize the audience that sees the ads that they produce, it follows that the peak-hours, in this case 12pm, 2pm and 3pm, would provide the greatest potential audience, assuming there is no volume-based advertising pricing.

<u>How does average cart size differ throughout the day?</u>

To begin our analysis, we first looked at the peak hours specified in the prior section, namely 12pm, 2pm and 3pm. To accurately compare the shopping behavior of users during peak hours to behavior during regular hours, we created a function, calc_boxplot_val, to calculate the median, max, min and range of each hour of the day. Below is the resulting boxplot.



Contrary to what we had expected, the median number of items in cart were above the overall median,but not the highest during peak hours. Rather, the hours when shoppers had the most number of items in their cart was at 8am and 7pm. Given these results, 8am and 7pm may be good times for promotional discounts on new products, as their is a higher willingness to buy more items than average.

To further explore cart size in relation to hour of day even more, we divided the dataset into separate 6-hour periods and added another ‘time_of_day’ label to each order. Orders made from 0-6am were labeled “Early Morning”, 6am-12pm were labeled “Morning”, 12pm-6pm were labeled “Early Afternoon” and 6pm-12am were labeled “Evening.”

time_of_day	average number of items in cart
Early Afternoon	10.41
Early Morning	8.59
Evening	11.52
Morning	10.44

Above chart shows the time period of the day with the average number of items ordered in a customer’s cart

From there, we obtained the average cart order by time_of_day. Average cart sizes made in the evening, that is between 6pm-12am, are observed as higher than average cart sizes during other hours of the day by approximately one to three items. Based on these results, we would suggest curtailing advertising campaigns during the early morning as people are buying less items on average and increasing during evenings when people are buying more.

If people order at meal times, how much more likely are they to order more quantities of food?

Diving deeper into smaller time ranges of the day, we looked standard mealtime hours. Orders made from 7-9am were labeled "Breakfast," those made between 12-1pm were labeled "Lunch", and those made between 5-7pm were labeled "Dinner." Hours outside of those ranges were labeled "Reg." This is a general analysis of the time periods and future research could include respondents including the time of their specific meals, which would aid in the specific analysis of these time periods, as, for example, in the most extreme case, individuals who work a night shift would have a very different breakfast time than those who work traditional business hours.

	average number of items in cart
meal_time_of_day	
Breakfast	9.68
Dinner	11.10
Lunch	10.35
Reg	10.66

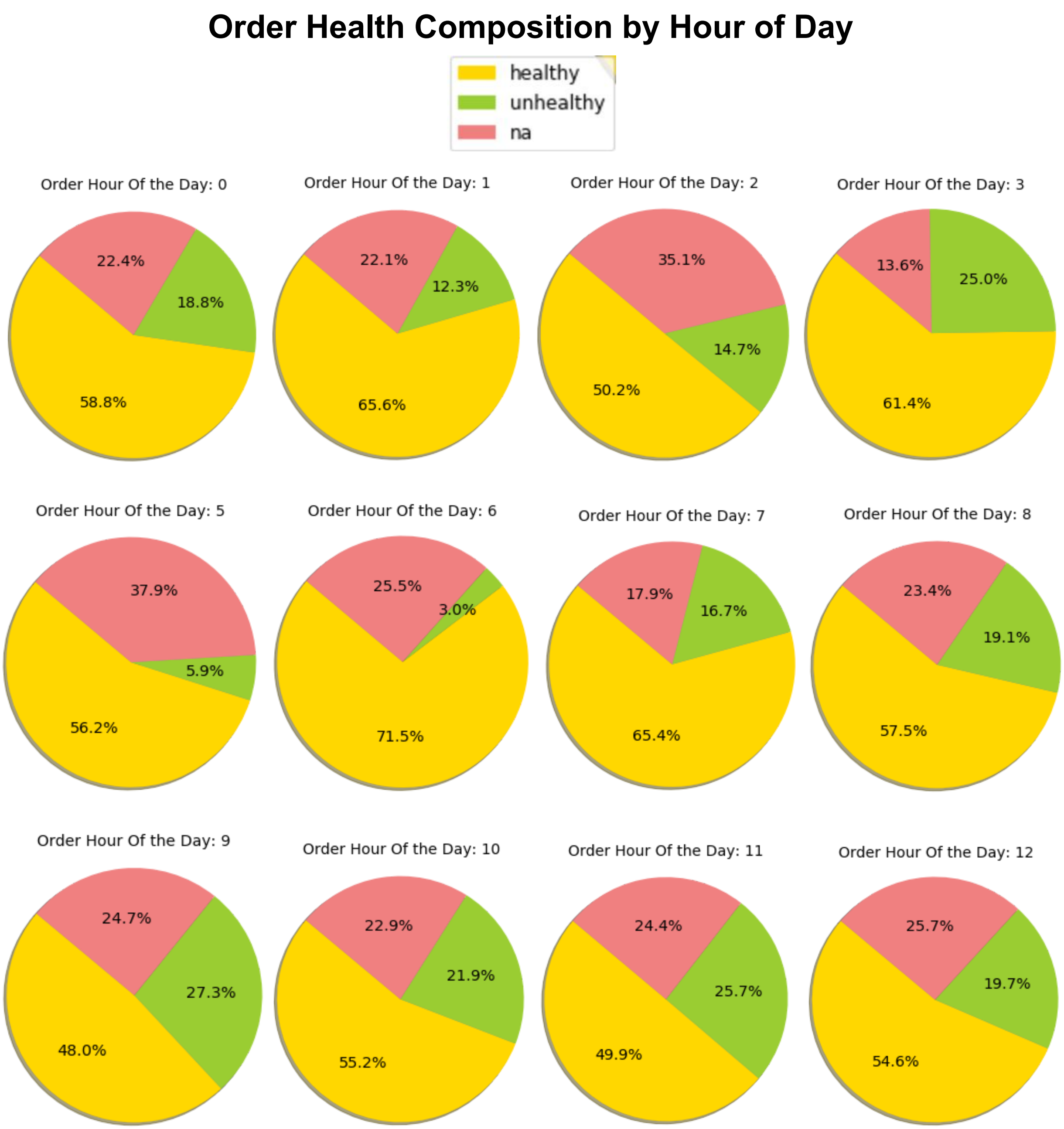
Above chart shows the meal period of the day with the average number of items ordered in a customer's cart

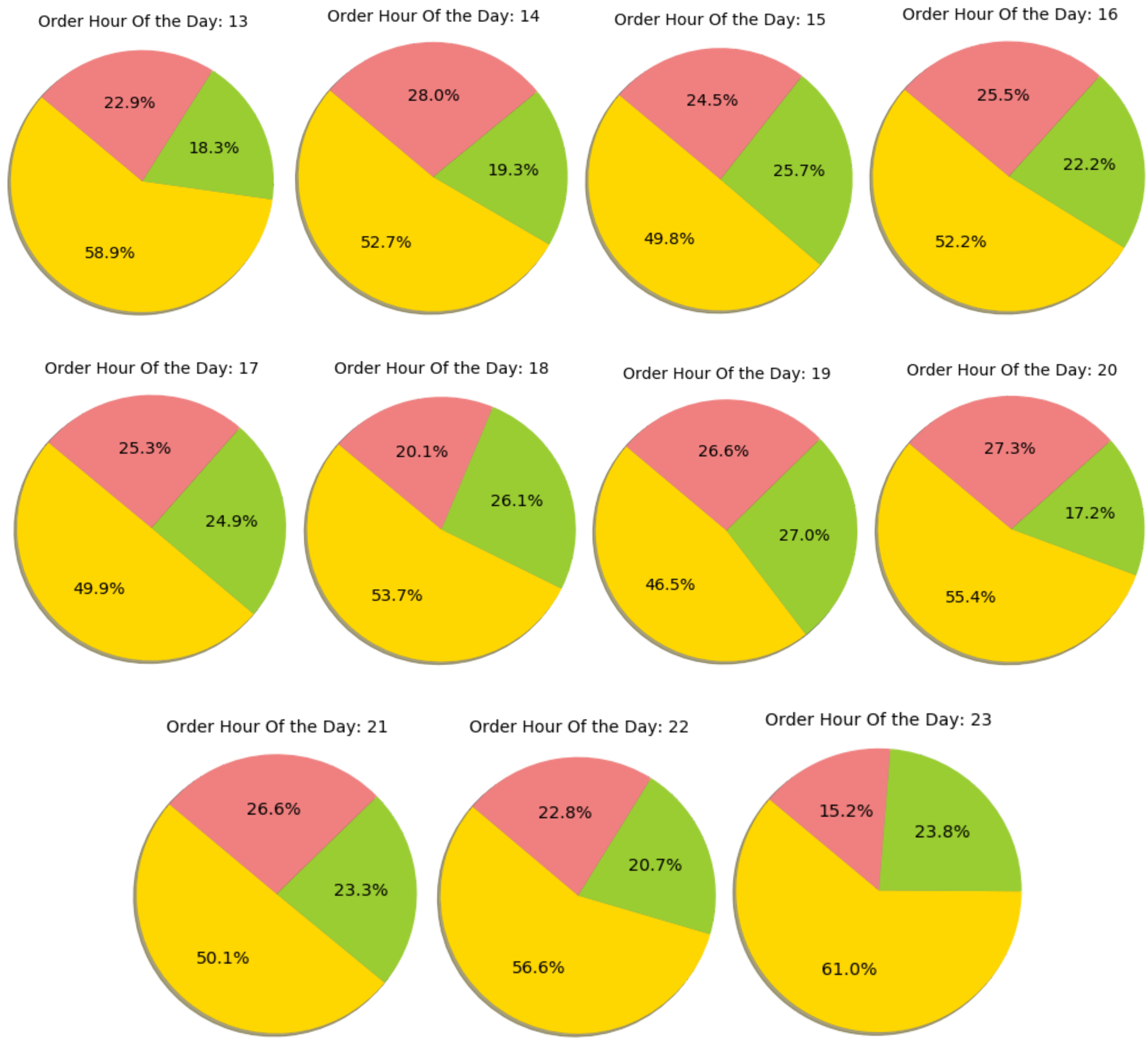
After sectioning out the standard mealtime hours, we obtained the average cart order by meal_time_of_day. We observe that average cart sizes seem to be higher during dinner hours, but not too radically different, thus passing a sanity check. The implications for these data are that there is a higher willingness to add items to one's cart during dinner and perhaps more advertisements could further increase this number. Alternatively, the other datapoints (Breakfast, Lunch, and Reg) could indicate that there is greater opportunity for individuals to add more items in their order. To be able to definitively make a conclusion, more information about everything from prices, to time spent on computers would need to be included in this analysis.

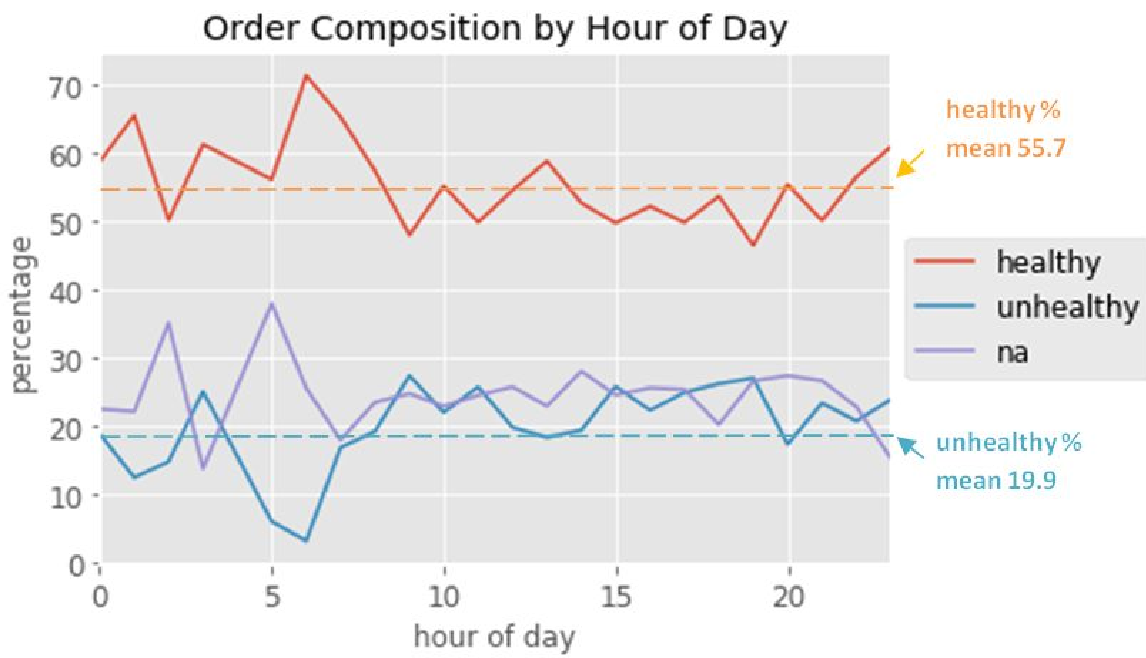
Do percentage of healthy items in the cart differ throughout the day?

To answer this question, we added the two additional columns of "healthy" and "foodgroup" and took a slice of the Instacart_data dataset with order_id, order_hour_of_day, and one of the two newly added columns. Then we ran two functions, add_health_count and add_food_group for each order id in the dataset.

- Add_health_count first calculated the number of order items labeled as "healthy", "unhealthy" or "na". The function then divided these numbers by the total order size to obtain the final percentage for each label.
- Add_food_group first calculated the number of order items labeled according to the 11 food group categories and divided these numbers by the total order size to obtain the final percentage of the order composed of the respective categories.




Order Hour Of the Day: 13
22.9%
18.3%
58.9%
Order Hour Of the Day: 14
28.0%
19.3%
52.7%
Order Hour Of the Day: 15
24.5%
25.7%
49.8%
Order Hour Of the Day: 16
25.5%
22.2%
52.2%
Order Hour Of the Day: 17
25.3%
24.9%
49.9%
Order Hour Of the Day: 18
20.1%
26.1%
53.7%
Order Hour Of the Day: 19
26.6%
27.0%
46.5%
Order Hour Of the Day: 20
27.3%
17.2%
55.4%
Order Hour Of the Day: 21
26.6%
23.3%
50.1%
Order Hour Of the Day: 22
22.8%
20.7%
56.6%
Order Hour Of the Day: 23
15.2%
23.8%
61.0%



From the charts above, we can see that there is a general trend of predominantly healthier orders for the Instacart data with percentages ranging from 46.5%- 71.5%. The largest imbalance in healthy and unhealthy ratios in an order occurs at 1am, 5am and 6am.

Upon a closer look, however, it appears that the number of user_ids ordering at this time are less than 10 and the results should thus be taken with discretion.

order_hour_of_day	Number of unique household keys
0	9
1	6
3	2
5	3
6	6

This data informs us that advertising campaigns may scale back during the early morning hours, as there are less users shopping on the app, and may not present the greatest return on advertising spend (ROAS).

Top 10 Healthy and Unhealthy Average Percentages by Hour of the Day

*Below chart shows the hours of the day with the highest percentage of **healthy** items in the cart:*

order_hour_of_day	Order Healthy %	Order Unhealthy %	Order NA %
6	71.46%	3.03%	25.51%
1	65.60%	12.35%	22.05%
7	65.39%	16.74%	17.87%
3	61.36%	25.00%	13.64%
23	61.01%	23.82%	15.17%
13	58.88%	18.26%	22.87%
0	58.82%	18.77%	22.41%
8	57.46%	19.13%	23.40%
22	56.59%	20.65%	22.76%
5	56.18%	5.88%	37.93%

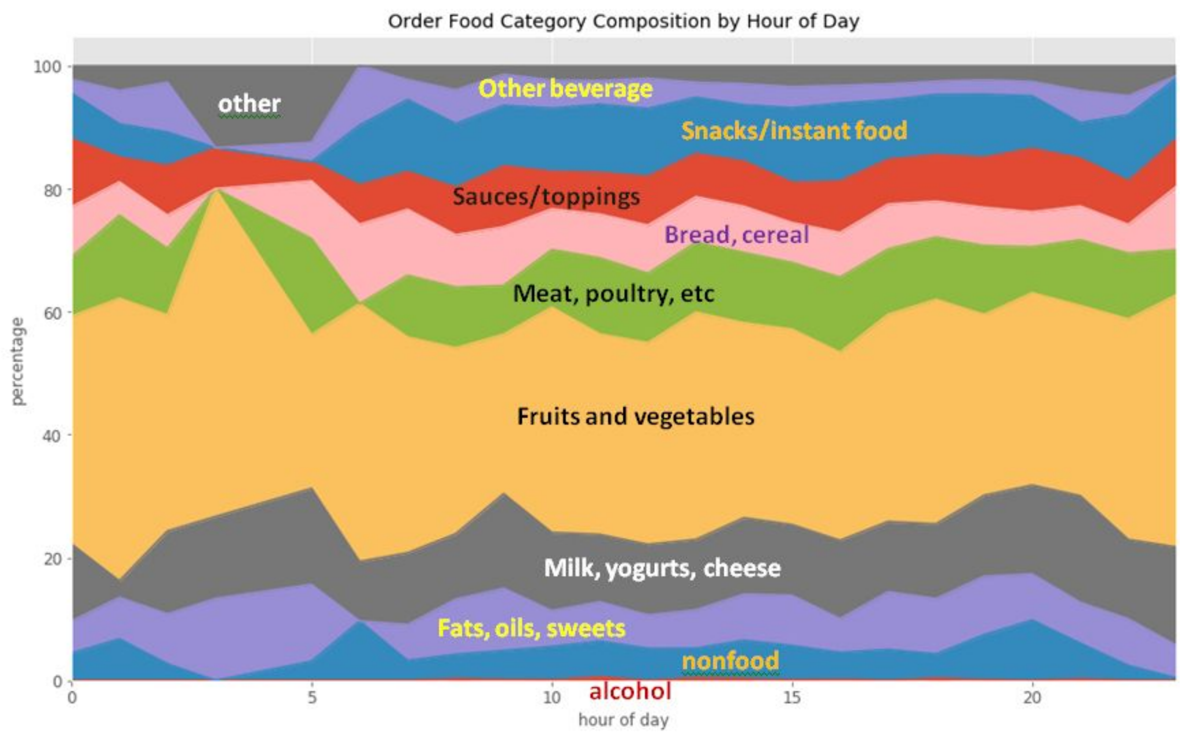
*Below chart shows the hours of the day with the highest percentage of **unhealthy** items in the cart:*

order_hour_of_day	Order Healthy %	Order Unhealthy %	Order NA %
9	48.01%	27.31%	24.68%
19	46.49%	26.96%	26.55%
18	53.72%	26.14%	20.14%
15	49.78%	25.74%	24.48%
11	49.89%	25.67%	24.44%
3	61.36%	25.00%	13.64%
17	48.85%	24.85%	25.29%
23	61.01%	23.82%	15.17%
21	50.13%	23.29%	26.57%
16	52.24%	22.24%	25.52%

Based upon these data, we observe that time of day does not play a significant role in the determination of healthy versus unhealthy food ordered. However, by removing the hours of day with sample sizes below 10, there appears to be a trend for the 3-7pm hour period. Orders that were purchased between these hours were around 2% higher than the average unhealthy percentage of orders overall. Thus, this might present an optimal time to display unhealthy-food advertisements.

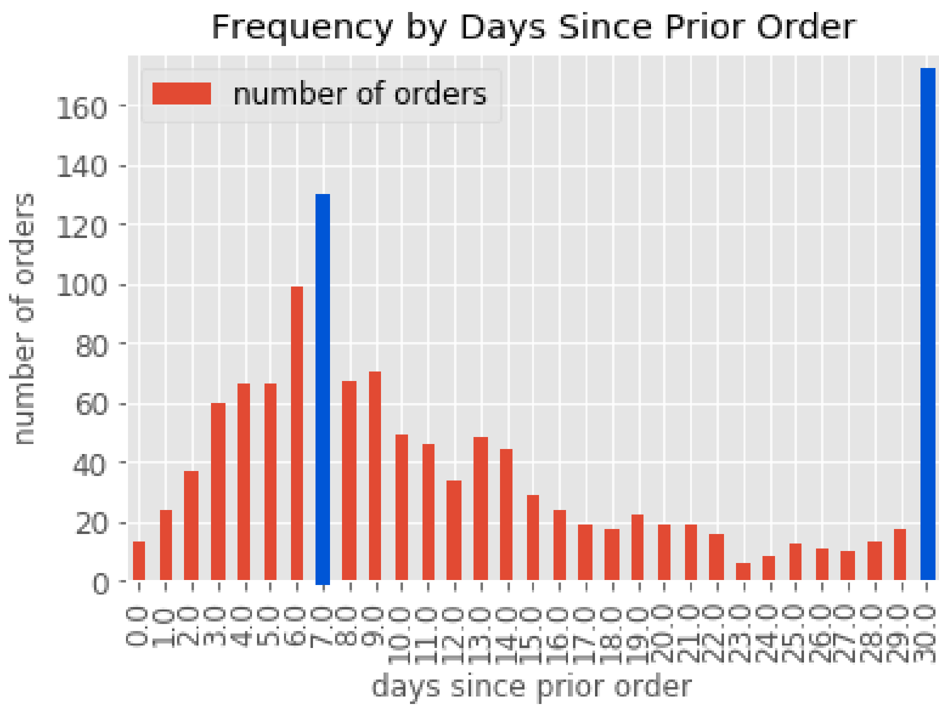
Given that the average healthy percentage for all orders is around 55%, health-conscious advertisements may be suitable throughout the day for Instacart users in this dataset.

Does percentage of specific categories vary throughout the day?



Generally speaking, Instacart shoppers are quite healthy with at least 30%-53% of their orders being made up of fruits and vegetables. This percentage slightly dips at 5am, 9am, and 7pm but stays above 25%. Additional insights into the demographics and dietary preferences of Instacart users would be essential in better determining suitable ad content but this above chart suggests that Instacart shoppers may be more engaged with health-conscious ads.

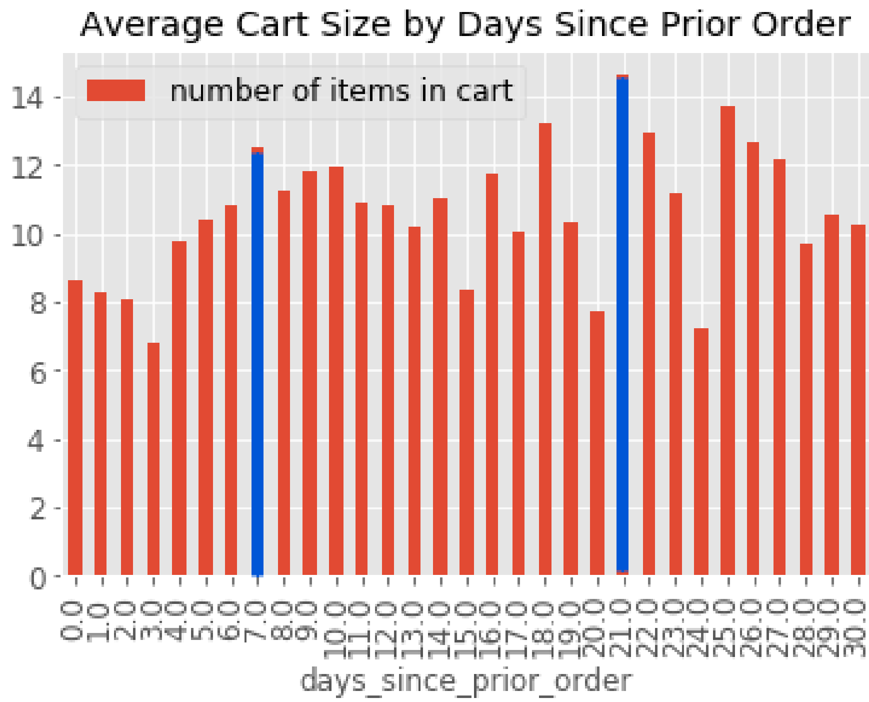
<u>How often do people order again on Instacart?</u>



We observe that people often order again on Instacart 6-7 or 30 days after their last order. There are a number of potential reasons for these data. For example, Instacart could be sending out promotions or advertisements to encourage the re-engagement of the user with the service around the week and month mark, following a purchase. Alternatively, a natural pattern of individuals purchasing products weekly or monthly as a part of routine could explain the high amount of 6-7 and 30 day orders. However, due to the extreme number of 30 day orders, particularly relative to the quantity of orders in the preceding handful of days, we might intuit that 30 days is a catch-all value for all the following orders that are greater than 30 days out. The data and documentation did not specify this and we would seek to explore this further in future research.

Future advertising campaigns could be explored around the one week mark as there appears to be a high-willingness to engage with the platform. This raises the potential for additional marketing of add-on products that could increase the average order size and contribute to more units purchased.

Does a smaller number of days since prior order lead to less items on average in a user's cart?

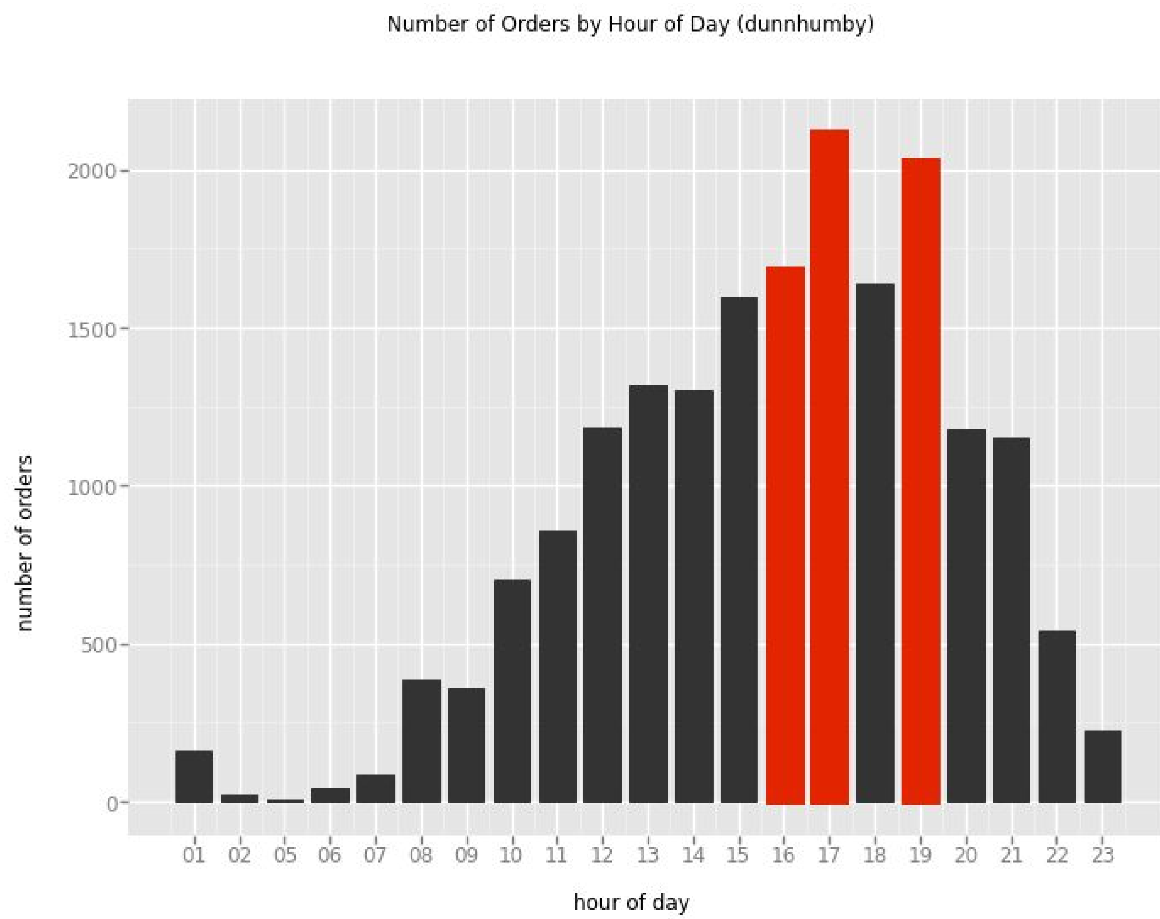


Within the first 7-day period, we observe that average cart size peaks at the 7th day mark with orders of around 12 items in a customer's cart. Beyond the 7-day period, cart size varies but seems to reach a higher average when people reorder after 21 days.

Based on these results, we see that individuals consistently purchase larger orders between 4 and 14 days, and that, interestingly, exactly three weeks following the prior order, customers have the largest purchase carts. This, again, could indicate willingness to purchase more goods, or could be reflective of other variables that would need to be investigated further.

The dunnhumby (Offline) Story:

<u>What are the peak hours for ordering among **dunnhumby** respondents?</u>



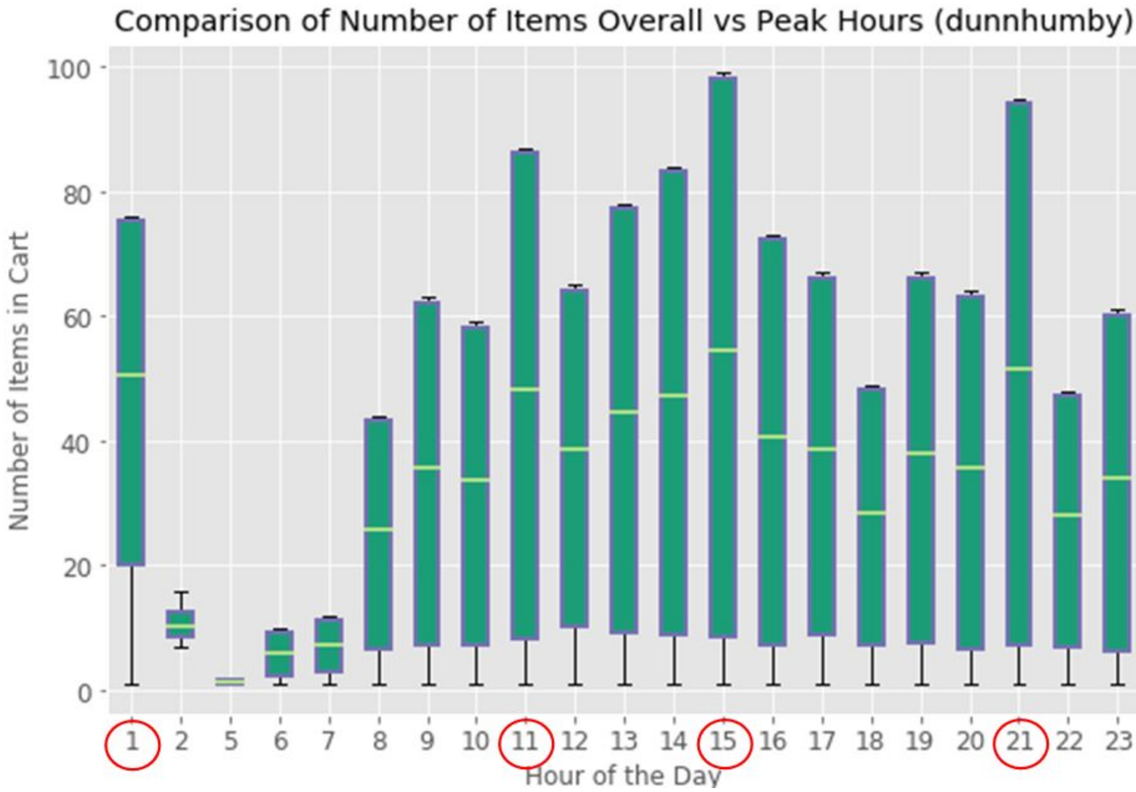
Peak hours: 4pm, 5pm, 7pm

Compared to the hours in Instacart the peak hours were much later. This could be because Dunnhumby is based on in-person visits to the grocery store, as compared to Instacart, which is all done through Instacart website or mobile application. It follows that more individuals purchase groceries in-person later in the day, after work, as opposed to online where a user could surreptitiously shop from his or her workplace during the workday. Because this data, similar to the Instacart data, corresponds with the waking hours of normal individuals, this passes a sanity check.

With respect to advertising, this could indicate that digital advertisements that are displayed during the workday could prompt in-person shopping at grocery stores - as a friendly reminder to visit the grocery store after work. This discrepancy in peak hours suggests that the two populations could be very different with respect to their grocery shopping behaviors.

Does average cart size differ throughout the day?

We start again, by looking at the peak hours in comparison to other hours.



Similar to the results from Instacart, it appears that users do not have more items in their cart at peak hours compared to regular hours. Instead, the hours with the highest median number of items in the cart appears to be 1am, 3pm and 9pm. Though the results from 1am should be understood with caution as the sample size is less than 10, 3pm and 9pm (both with sample sizes of more than 45) are potentially optimal times for new product advertisements given the higher willingness to purchase more items.

time_of_day	average number of items in cart
Early Afternoon	10.91
Early Morning	10.43
Evening	9.84
Morning	10.38

Above chart shows the time period of the day with the average number of items ordered in a customer's cart

From these data, we observe that there is very little variation between Early Afternoon, Early Morning and Morning in the average number of items in cart at in-person grocery stores. However, there is a slight dip in item amount in the Evening from 6pm-12am, which may suggest a less advantageous timing for ads.

If people shop at meal times, how much more likely are they to order more quantities of food?

meal_time_of_day	average number of items in cart
Breakfast	9.19
Dinner	9.96
Lunch	12.29
Reg	10.56

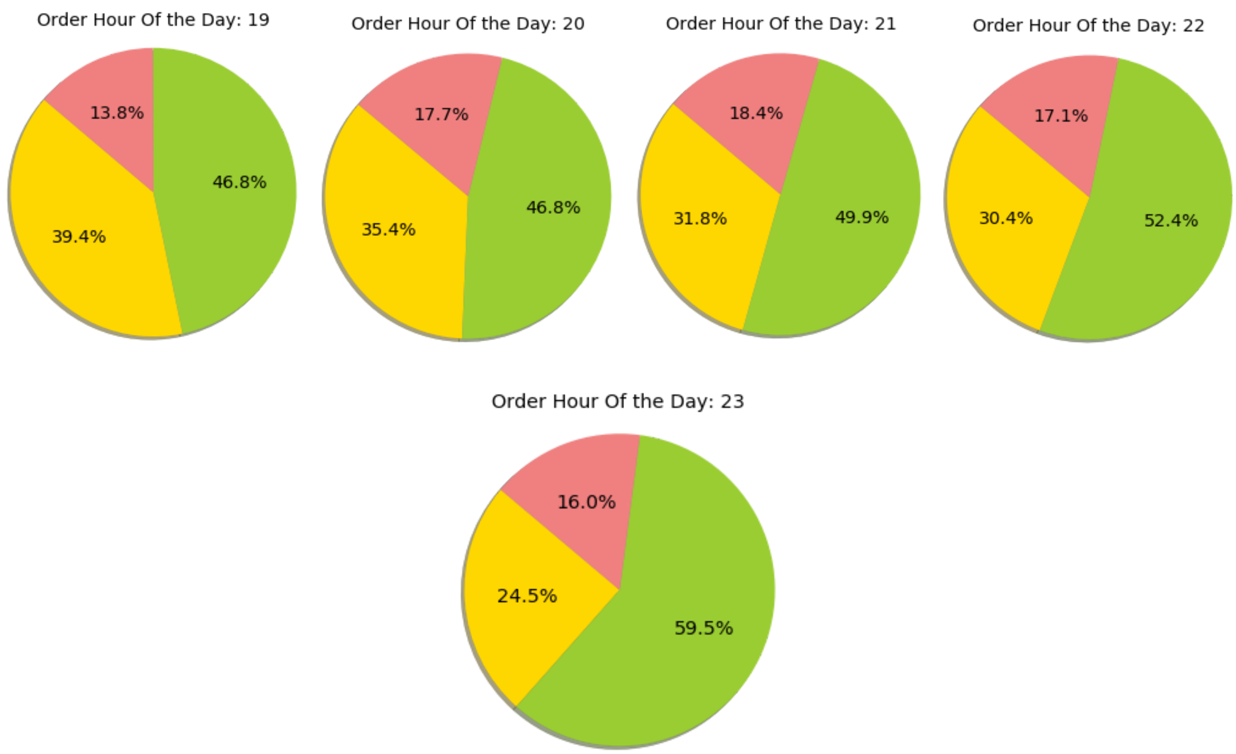
Above chart shows the meal period of the day with the average number of items ordered in a customer's cart

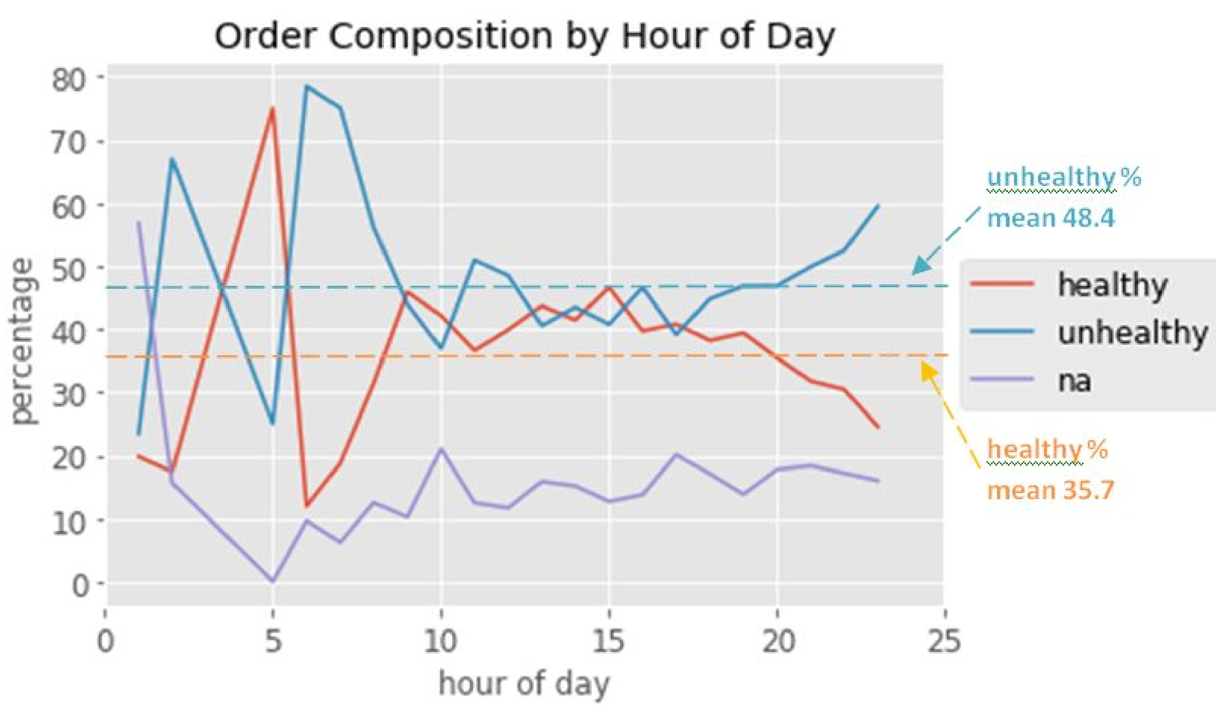
Interestingly, relative to the previous analysis with respect to time, we observe that there is a greater number of items in the cart on average during lunch hours, particularly compared with purchases made during breakfast or dinner times. The potential here is that people may be shopping during their lunch break from work or generally hungrier after hours of working. With more information on location of the grocery stores and proximity to people's work locations, advertisers may find an opportunity to engage those that are walking through grocery stores to pass time rather than necessity.

Do percentage of healthy items in the cart differ throughout the day?

Just as we did for the Instacart dataset, we added the additional columns "healthy" and "foodgroup" to dunnhumby and ran the two functions add_health_count and add_food_category to better understand the order composition of dunnhumby client shoppers.

Order Health Composition by Hour of Day





Compared to the Instacart dataset, there is a greater proportion of unhealthy food in the dunnhumby dataset. A potential reasoning is the increased opportunities for people to be exposed to the placement of unhealthy food options as they walk around the grocery store or wait in line. Product placement plays a greater role in selection of food items in physical grocery stores where people shop for themselves.

Taking a closer look at the percentage breakdowns by hour of day, advertisers may consider unhealthier content specifically at hours 2am, 6am, 8am, 11am and 9-11pm. Healthier ads may be more successful at 9am, 10am, and 1-2pm.

Top 10 Healthy and Unhealthy Average Percentages by Hour of the Day

*Below chart shows the hours of the day with the highest percentage of **healthy** items in the cart:*

order_hour_of_day	Order Healthy %	Order Unhealthy %	Order NA %
5	75.00%	25.00%	0%
15	46.59%	40.74%	12.67%
9	45.87%	43.93%	10.20%
13	43.63%	40.53%	15.84%
10	42.11%	36.91%	20.98%
14	41.43%	43.44%	15.13%
17	40.77%	39.12%	20.10%
12	39.88%	48.48%	11.64%
16	39.70%	46.57%	13.74%
19	39.38%	46.80%	13.82%

*Below chart shows the hours of the day with the highest percentage of **unhealthy** items in the cart:*

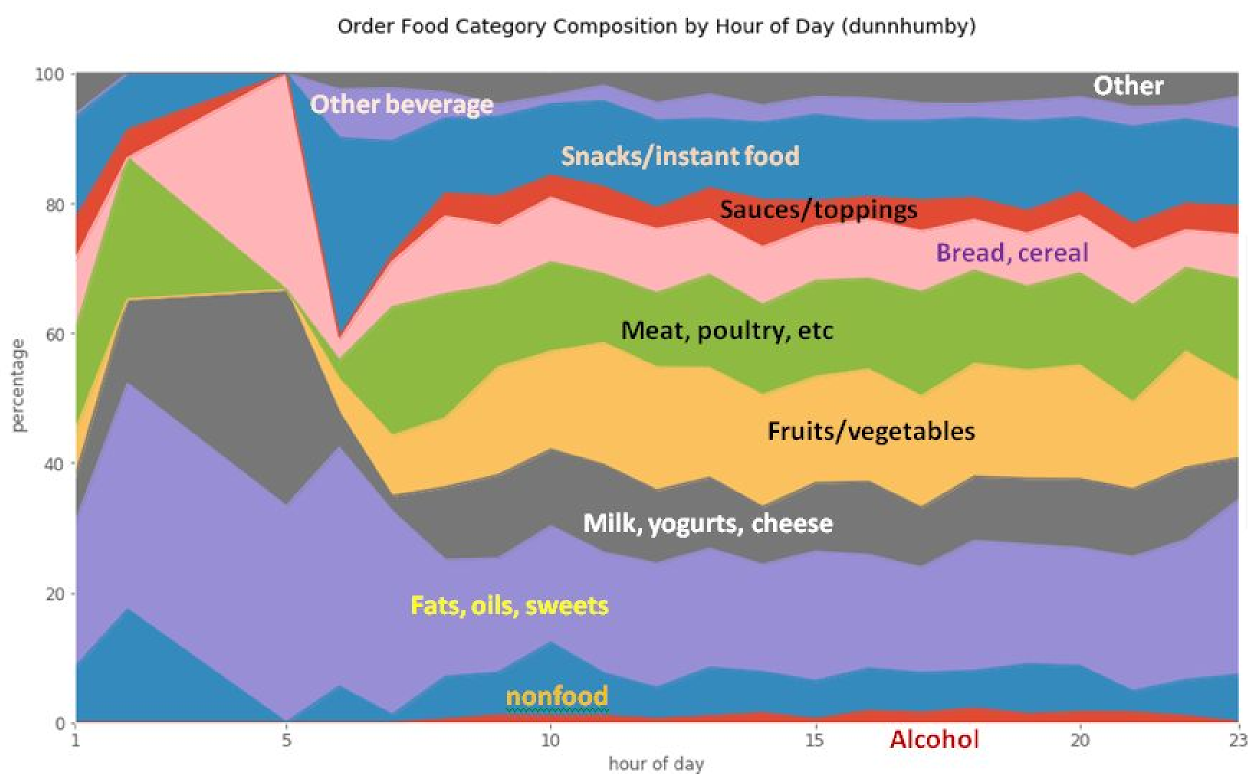
order_hour_of_day	Order Healthy %	Order Unhealthy %	Order NA %
6	11.92%	78.46%	9.62%
7	18.75%	75.03%	6.22%
2	17.41%	66.96%	15.63%
23	24.54%	59.48%	15.98%
8	31.41%	56.10%	12.50%
22	30.44%	52.43%	17.13%
11	36.59%	50.93%	12.48%
21	31.76%	49.88%	18.36%
12	39.88%	48.48%	11.64%
20	35.44%	46.84%	17.72%

Looking at these two charts, it appears that dunnhumby shoppers shop healthier between 9am-7pm. From 8-11pm, the percentage of unhealthy items in the cart increases. It's important to note that when looking at the first few hours of the charts, rows with percentages above 65% should be understood with discretion as the sample size of household keys made during those hours (namely 2, 5, 6, and 7) are less than 10.

The earliest hours have significant variation, and could be because of the smaller sample set.

order_hour_of_day	Number of unique household keys
2	2
5	1
6	9
7	8

Does percentage of specific categories vary throughout the day?



According to the graph above, it seems like order composition after 7am stays mostly within the same range for all categories. From 0-7am, however, there is a higher percentage of items in the ‘fats,oils,sweets,’ ‘milk,yogurts,cheese’ and ‘bread,cereal’ categories. Again, this great discrepancy may be due to the smaller sample size of household keys during those hours.

Overall, while the Instacart dataset saw average percentages between 5-13% for items categorized as fats,oils,sweets, the dunnhumby sample average percentages ranged from 17-36% throughout the day.

How often do people repeat shop at grocery stores?

To calculate the frequency at which dunnhumby shoppers visited the store again, we used the WEEK_NO column of the dataset. We applied the function, find_reorder_frequency, which averaged the differences between every week value recorded under a unique household_key. We then added this list of values as a new column ‘weeks_since_prior’ to a slice of the dunnhumby_data.

	weeks_since_prior
count	97.0
mean	1.7
std	1.0
min	0.0
25%	1.1
50%	1.6
75%	2.1
max	6.0

From the dunnhumby dataset it looks like people frequently shop at physical grocery shops with a visit every 1.7 weeks on average. This makes sense since people typically need to purchase their weekly groceries and thus follow similar shopping behaviors. In previous consumer behavior studies done by Target, it was found that people frequently go back to the same place to repurchase common items. “Left to its own devices, the brain will try to make almost any repeated behavior into a habit, because habits allow our minds to conserve effort.” [6]

Conclusion:

Instacart is a web/app grocery delivery service, while dunnhumby captures data from physical grocery stores. Through our data analysis and exploration, we have observed that both data sets and populations would not be good analogues for comparison, as the purchasing patterns

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[6] DUHIGG, CHARLES. “How Companies Learn Your Secrets.” *The New York Times*, The New York Times, 18 Feb. 2012, www.nytimes.com/2012/02/19/magazine/shopping-habits.html.

for both groups are significantly different. Though not comparable, the analyses on both datasets have shed light on potentially optimal times for advertisers and type of content that may resonate with shoppers within the online and offline settings.

According to our analyses, the optimal advertising time for increased customers views for online/in-app ads would be from 12pm to 3pm, while for in-store customers it would be 4pm to 7pm. In contrast to our expectations, the peak hours did not have higher average items per cart, so for advertising to get customers to buy more items, then the ideal advertisement would be different. With regards to advertisements to get customers to buy more items, it would appear that promoting new products to Instacart customers may be most effective at 8AM and 7PM when there is a higher willingness to purchase more items. For in-store customers, the ads would be most effective around noon lunch hour, where customers are predisposed to buying more items as well or more specifically on average around 11 AM, 3PM and 9PM.

With regards to type of foods, Instacart customers purchase a higher percentage of healthy foods per order compared to in-store customers. Thus, it would be wise to tailor advertisements that highlight healthier food options for Instacart users that adhere to their preferences. For in-store customers in the dunnhumby dataset, unhealthy food advertisements would be more effective since there is a greater percentage of unhealthy items purchased. This is especially true for the hours early morning/morning 2AM, 6AM to 8AM, and 9AM to 11AM and evening hours 9PM to 11PM.

For future research, we suggest additional data to further test out these results, as there are additional factors not evident in our data that impact the observations and conclusions we have drawn. These include the impact of pricing, promotions for products, existing advertising campaigns, locations and user demographics. Further research must include these data to facilitate the analysis and derivation of conclusions and their implications and impact on online marketing and ROAS calculations.

Furthermore, for Instacart, we would be interested in investigating user patterns in relation to abandoned carts: while the data we analyzed were completed orders, there could potentially be significant marketing dollars spent on abandoned or zombie carts online.

Snapshot Views

Instacart					
Hours	Many people on website and app	People buying the more items	Less users- may not present greatest ROAS	Suggest healthy content	Test unhealthy content
0		x	--		
1			--		
2			--		
3					
4					
5			--		
6			--		
7				x	
8		x		x	
9				x	
10				x	
11				x	
12	x			x	
13				x	
14	x			x	
15	x			x	x
16				x	x
17		x		x	x
18		x		x	x
19		x		x	x
20		x		x	
21		x		x	
22		x		x	
23		x			

Dunnhumby					
Hours	More people in store	People buying the more items	Less users- may not present greatest ROAS	Suggest healthy content	Test unhealthy content
0			--		
1		x			
2					X
3					
4	X				
5	X				
6					X
7	X				
8					X
9				X	
10				X	
11		X			X
12		X			
13		X		X	
14				X	
15		X		X	
16					
17					
18			--		
19			--		
20			--		
21		X	--		X
22			--		X
23			--		X