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Instacart Customer Behavior Analysis and Recommender Design

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Import required packages:

In [1]:

```
#!pip install squarify
import os
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import font_manager as fm
from  matplotlib import cm
import matplotlib as mpl
import numpy as np
import squarify
from sklearn.metrics.pairwise import cosine_similarity
#% matplotlib inline
plt.style.use('ggplot')
```

Import data:

In [2]:

```
path = os.path.join(os.getcwd(),"data")
table_name = []
table_dic = {}

for file in os.listdir(path):
    filename = file.split('.')[0]
    table_name.append(filename)
    table_dic[filename] = pd.read_csv(os.path.join(path, file))

print(table_name)
print(table_dic.keys())
```

```
['products', 'orders', 'order_products__train', 'departments', 'aisl
es', 'order_products__prior']
dict_keys(['products', 'orders', 'order_products__train', 'departmen
ts', 'aisles', 'order_products__prior'])
```

In [3]:

```
Products = table_dic['products']
Orders = table_dic['orders']
Departments = table_dic['departments']
Aisles = table_dic['aisles']
Order_products_train = table_dic['order_products__train']
Order_products_prior = table_dic['order_products__prior']
```

Part 1. Explore the data frame and data relationship

1. Explore the data frame of each table

(1) Products

49K+ rows

- **product_id:** product identifier (Primary Key)
- **product_name:** name of the product
- **aisle_id:** aisle identifier (Foreign Key)
- **department_id:** department identifier (Foreign Key)

In [4]:

```
Products.head()
```

Out[4]:

	product_id	product_name	aisle_id	department_id
0	1	Chocolate Sandwich Cookies	61	19
1	2	All-Seasons Salt	104	13
2	3	Robust Golden Unsweetened Oolong Tea	94	7
3	4	Smart Ones Classic Favorites Mini Rigatoni Wit...	38	1
4	5	Green Chile Anytime Sauce	5	13

In [5]:

```
# Explore the primary key of this table

print(len(Products))
p = set(Products["product_id"])
print(len(p))
```

```
49688
49688
```

(2) Orders

3M+ rows

- **order_id:** order identifier (Primary Key)
- **user_id:** user/customer identifier (Foreign Key)
- **eval_set:** which evaluation set this order belongs in (see SET described below)
- **order_number:** the order sequence number for this user (1 = first, n = nth)
- **order_dow:** the day of the week the order was placed on
- **order_hour_of_day:** the hour of the day the order was placed on
- **days_since_prior:** days since the last order, capped at 30 (with NAs for order_number = 1)

In [6]:

```
Orders.head()
```

Out[6]:

	order_id	user_id	eval_set	order_number	order_dow	order_hour_of_day	days_since_prior_
0	2539329	1	prior	1	2	8	
1	2398795	1	prior	2	3	7	
2	473747	1	prior	3	3	12	
3	2254736	1	prior	4	4	7	
4	431534	1	prior	5	4	15	

In [7]:

```
# Explore the primary key of this table

print(len(Orders))
p = set(Orders["order_id"])
print(len(p))
```

```
3421083
3421083
```

(3) Departments

21 rows

- **department_id:** department identifier (Primary Key)
- **department:** the name of the department

In [8]:

```
Departments.head()
```

Out[8]:

	department_id	department
0	1	frozen
1	2	other
2	3	bakery
3	4	produce
4	5	alcohol

In [9]:

```
# Explore the primary key of this table

print(len(Departments))
p = set(Departments["department_id"])
print(len(p))
```

```
21
21
```

(4) Aisles

134 rows

- **aisle_id:** aisle identifier
- **aisle:** the name of the aisle

In [10]:

```
Aisles.head()
```

Out[10]:

	aisle_id	aisle
0	1	prepared soups salads
1	2	specialty cheeses
2	3	energy granola bars
3	4	instant foods
4	5	marinades meat preparation

In [11]:

```
# Explore the primary key of this table

print(len(Aisles))
p = set(Aisles["aisle_id"])
print(len(p))
```

```
134
134
```

(5) Order_products_train

1M+ rows

- **order_id:** Order identifier (Primary Key 1, Foreign Key 1)
- **product_id:** Product identifier (Primary Key 1, Foreign Key 1)
- **add_to_cart_order:** Order in which each product was added to cart
- **reordered:** 1 if this product has been ordered by this user in the past, 0 otherwise

In [12]:

```
Order_products_train.head()
```

Out[12]:

	order_id	product_id	add_to_cart_order	reordered
0	1	49302	1	1
1	1	11109	2	1
2	1	10246	3	0
3	1	49683	4	0
4	1	43633	5	1

In [13]:

```
# Explore the primary key of this table

print(len(Order_products_train))
p = Order_products_train[["order_id","product_id"]]
p_new = p.drop_duplicates()
print(len(p_new))
```

```
1384617
1384617
```

(6) Order_products_prior

32M+ rows

- **order_id:** Order identifier (Primary Key 1, Foreign Key 1)
- **product_id:** Product identifier (Primary Key 1, Foreign Key 1)
- **add_to_cart_order:** Order in which each product was added to cart
- **reordered:** 1 if this product has been ordered by this user in the past, 0 otherwise

In [14]:

```
Order_products_prior.head()
```

Out[14]:

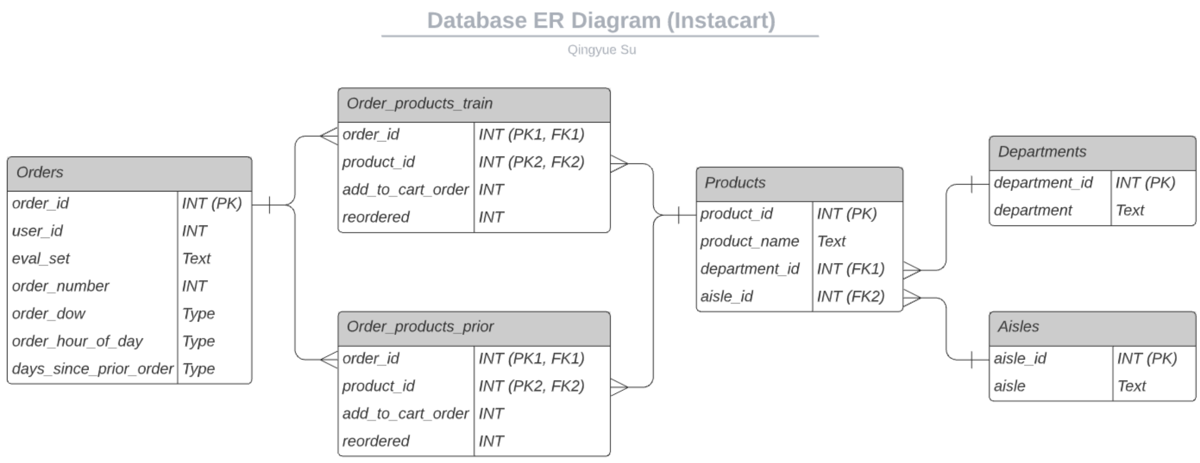
	order_id	product_id	add_to_cart_order	reordered
0	2	33120	1	1
1	2	28985	2	1
2	2	9327	3	0
3	2	45918	4	1
4	2	30035	5	0

In [15]:

```
# Explore the primary key of this table

print(len(Order_products_prior))
p = Order_products_prior[["order_id","product_id"]]
p_new = p.drop_duplicates()
print(len(p_new))
```

```
32434489
32434489
```

2. Draw an E-R diagram



Part 2. Explanatory data analysis (EDA) of customer data

- How many orders the dataset has? How to divide the train and test orders?
- How many unique users we have? How to divide the train and test users?
- How many orders each user created? What's the most common total number of orders one user created?
- What day of week do the users purchase?
- What time of day do the users purchase?
- How often do the users purchase?
- How many products do people purchase in an order? What's the most common total number of products in one order?
- How many transaction and unique products is in this dataset?
- How the products distribute in different department?
- What are the product that people purchase the most?
- What are the aisles where people purchase the most?
- What are the departments where people purchase the most?

1. How many orders the dataset has? How to divide the train and test orders?

order_id: order identifier

In [16]:

```
p = set(Orders["order_id"])
print(len(p))
```

```
3421083
```

eval_set: which evaluation set this order belongs in (see SET described below)

In [17]:

```
p = set(Orders["eval_set"])
print(p)
```

```
{'test', 'prior', 'train'}
```

- **prior**: orders prior to that users most recent order (~3.2m orders)
- **train**: training data supplied to participants (~131k orders)
- **test**: test data reserved for machine learning competitions (~75k orders)

In [18]:

```
Orders.groupby(["eval_set"])[['order_id']].nunique()
# Orders['order_id'].groupby(Orders["eval_set"]).count()
```

Out[18]:

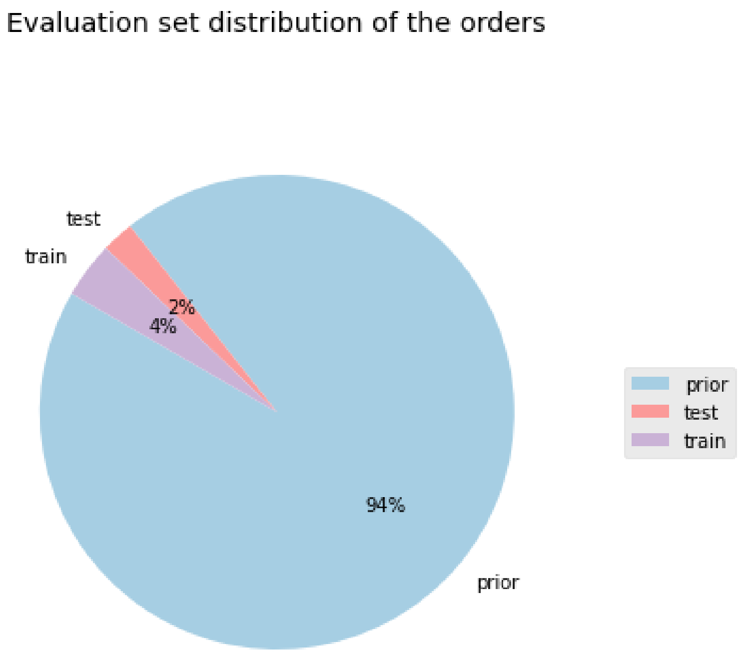
	order_id
eval_set	
prior	3214874
test	75000
train	131209

Outcome:

- there are 3,421,083 orders in total.
- there are 3,214,874 orders that are prior.
- there are 131,209 orders that are in train set.
- there are 75,000 orders that are in test set.

In [19]:

```
# Pie chart, where the slices will be ordered and plotted counter-clockwise:
labels = ['prior', 'test', 'train']
sizes = [3214874, 75000, 131209]
explode = (0, 0.1, 0.1)  # only "explode" the 2nd slice (i.e. 'Hogs')

fig, axes = plt.subplots(figsize=(9,6),ncols=2) # Set the graph location and siz
e
ax1, ax2 = axes.ravel()

colors = cm.Paired(np.arange(len(sizes))/len(sizes)) # colormaps: Paired, autum
n, rainbow, gray,spring,Darks
patches, texts, autotexts = ax1.pie(sizes, labels=labels, autopct='%1.0f%%',
        shadow=False, startangle=150, colors=colors)

ax1.axis('equal')

# Set the size of characters
proptease = fm.FontProperties()
proptease.set_size('medium')
# font size include: ‘xx-small’,x-small’,'small’,'medium’,‘large’,‘x-large’,‘xx-
large’ or number, e.g. '12'
plt.setp(autotexts, fontproperties=proptease)
plt.setp(texts, fontproperties=proptease)

ax1.set_title('Evaluation set distribution of the orders', loc='center')

# ax2 only shows the legend
ax2.axis('off')
ax2.legend(patches, labels, loc='center left')

plt.tight_layout()
#plt.savefig('Demo_project_set_legend_good.jpg')
plt.show()
```



2. How many unique users we have? How to divide the train and test users?

user_id: customer identifier

In [20]:

```
p = set(Orders["user_id"])
print(len(p))
```

```
206209
```

In [21]:

```
Orders.groupby(["eval_set"])[['user_id']].nunique()
#Orders['order_id'].groupby(Orders["eval_set"]).count()
```

Out[21]:

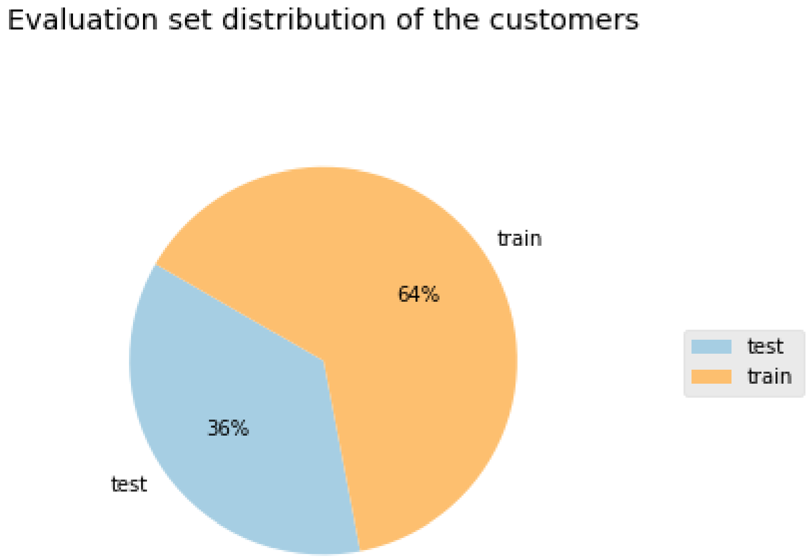
	user_id
eval_set	
prior	206209
test	75000
train	131209

Outcome:

- there are 206209 unique customer in total.
- there are 131209 customers in the train set.
- there are 75000 customers in the test set.

In [22]:

```
# Pie chart, where the slices will be ordered and plotted counter-clockwise:
labels = ['test', 'train']
sizes = [75000, 131209]
explode = (0.1, 0.1)  # only "explode" the 2nd slice (i.e. 'Hogs')

fig, axes = plt.subplots(figsize=(8,5),ncols=2) # Set the graph location and siz
e
ax1, ax2 = axes.ravel()

colors = cm.Paired(np.arange(len(sizes))/len(sizes)) # colormaps: Paired, autum
n, rainbow, gray,spring,Darks
patches, texts, autotexts = ax1.pie(sizes, labels=labels, autopct='%1.0f%%',
        shadow=False, startangle=150, colors=colors)

ax1.axis('equal')

# Set the size of characters
proptease = fm.FontProperties()
proptease.set_size('medium')
# font size include: ‘xx-small’,x-small’,'small’,'medium’,‘large’,‘x-large’,‘xx-
large’ or number, e.g. '12'
plt.setp(autotexts, fontproperties=proptease)
plt.setp(texts, fontproperties=proptease)

ax1.set_title('Evaluation set distribution of the customers', loc='center')

# ax2 only shows the legend
ax2.axis('off')
ax2.legend(patches, labels, loc='center left')

plt.tight_layout()
#plt.savefig('Demo_project_set_legend_good.jpg')
plt.show()
```



3. How many orders each user created? What's the most common total number of orders one user created?

In [23]:

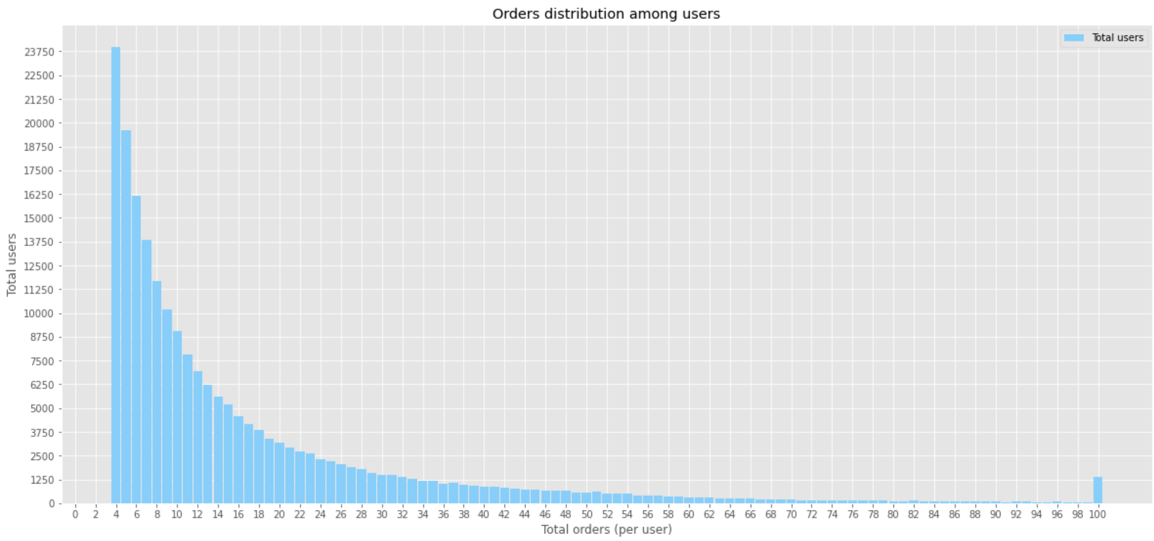
```
# Step1: Calculate the total amount of orders per user

order_per_user = Orders.groupby(["user_id"])[['order_number']].nunique()

order_per_user_new = pd.DataFrame(order_per_user) # transfer to the dataframe
order_per_user_new.reset_index(inplace=True)

# Step2: Calculate the total users buying the same total orders

total_order_user = order_per_user_new.groupby(["order_number"])[['user_id']].nun
ique()

total_order_user_new = pd.DataFrame(total_order_user) # transfer to the datafram
e
total_order_user_new.reset_index(inplace=True)

# Step3: Sort the values

total_order_user_new2 = total_order_user_new.sort_values(by=['order_number'],asc
ending=True,na_position='first')
total_order_user_new2.head()
```

Out[23]:

	order_number	user_id
0	4	23986
1	5	19590
2	6	16165
3	7	13850
4	8	11700

In [24]:

```
plt.figure(figsize=(20, 9))
plt.subplot(1, 1, 1)

#N = 97
values = total_order_user_new2["user_id"]
index = total_order_user_new2["order_number"]

width = 0.9

p2 = plt.bar(index, values, width, label="Total users", color="#87CEFA")

plt.xlabel('Total orders (per user)')
plt.ylabel('Total users')

plt.title('Orders distribution among users')

plt.xticks(np.arange(0, 102, 2))
plt.yticks(np.arange(0, 25000, 1250))

plt.legend(loc="upper right")
plt.show()
```



Outcome:

- The amount of orders for each customers are between 4 to 100.
- Majority of people had purchased 4 to 10 times.

4. What day of week do the users purchase?

order_dow: the day of the week the order was placed on

In [25]:

```
p = set(Orders["order_dow"])
print(p)
```

```
{0, 1, 2, 3, 4, 5, 6}
```

In [26]:

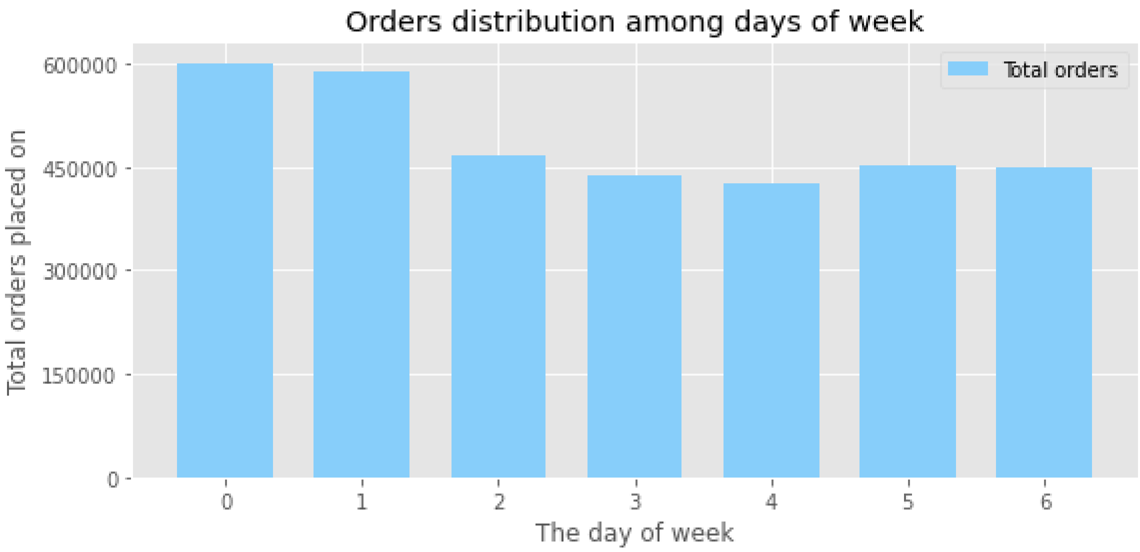
```
order_per_weekday = Orders.groupby(["order_dow"])[['order_id']].nunique()
order_per_weekday

order_per_weekday_new = pd.DataFrame(order_per_weekday) # transfer to the datafr
ame
order_per_weekday_new.reset_index(inplace=True)
order_per_weekday_new
```

Out[26]:

	order_dow	order_id
0	0	600905
1	1	587478
2	2	467260
3	3	436972
4	4	426339
5	5	453368
6	6	448761

In [27]:

```
plt.figure(figsize=(9, 4))

plt.subplot(1, 1, 1)

#N = 7
values = order_per_weekday_new["order_id"]
index = order_per_weekday_new["order_dow"]

width = 0.7

p2 = plt.bar(index, values, width, label="Total orders", color="#87CEFA")

plt.xlabel('The day of week')
plt.ylabel('Total orders placed on')

plt.title('Orders distribution among days of week')

plt.xticks(np.arange(0, 7, 1))
plt.yticks(np.arange(0, 740000, 150000))

plt.legend(loc="upper right")

plt.show()
```



Outcome:

- 0 (Sun) and 1 (Mon) has the most orders in a week
- 4 (Thur) has the least orders.

5. What time of day do the users purchase?

order_hour_of_day: the hour of the day the order was placed on

In [28]:

```
p = set(Orders["order_hour_of_day"])
print(p)
```

```
{0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 1
9, 20, 21, 22, 23}
```

In [29]:

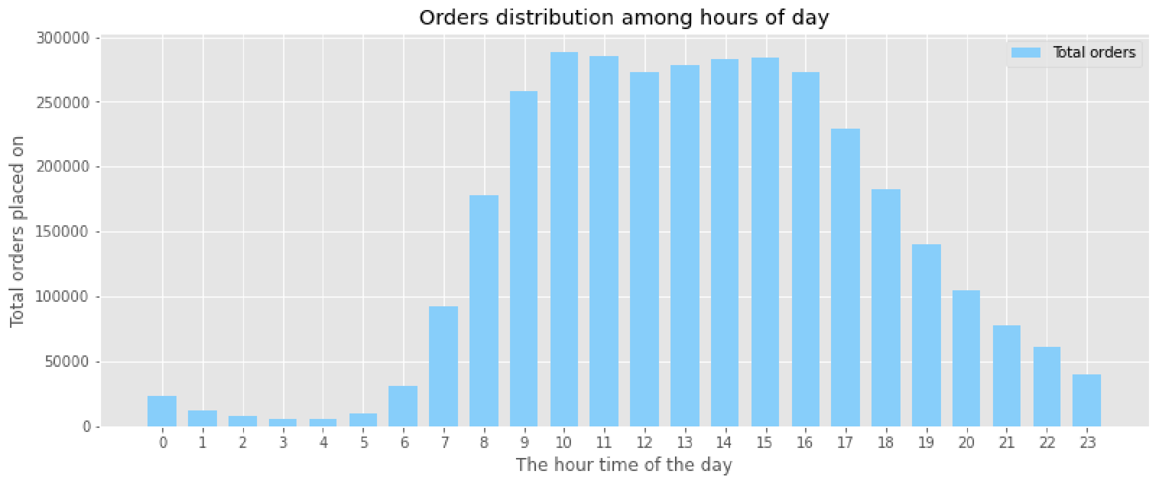
```
# What time of day do people purchase?

Order_per_hour_of_day = Orders.groupby(["order_hour_of_day"])[['order_id']].nuni
que()
Order_per_hour_of_day


Order_per_hour_of_day_new = pd.DataFrame(Order_per_hour_of_day) # transfer to th
e dataframe
Order_per_hour_of_day_new.reset_index(inplace=True)
Order_per_hour_of_day_new.head()
```

Out[29]:

	order_hour_of_day	order_id
0	0	22758
1	1	12398
2	2	7539
3	3	5474
4	4	5527

In [30]:

```
plt.figure(figsize=(13, 5))

plt.subplot(1, 1, 1)

#N = 7
values = Order_per_hour_of_day_new["order_id"]
index = Order_per_hour_of_day_new["order_hour_of_day"]

width = 0.7

p2 = plt.bar(index, values, width, label="Total orders", color="#87CEFA")

plt.xlabel('The hour time of the day')
plt.ylabel('Total orders placed on')

plt.title('Orders distribution among hours of day')

plt.xticks(np.arange(0, 24, 1))
#plt.yticks(np.arange(0, 740000, 150000))

plt.legend(loc="upper right")

plt.show()
```



Outcome:

- Looks like people like to order between 8am to 6pm.

6. How often do the users purchase?

days_since_prior_order: days since the last order, capped at 30 (with NAs for order_number = 1)

In [31]:

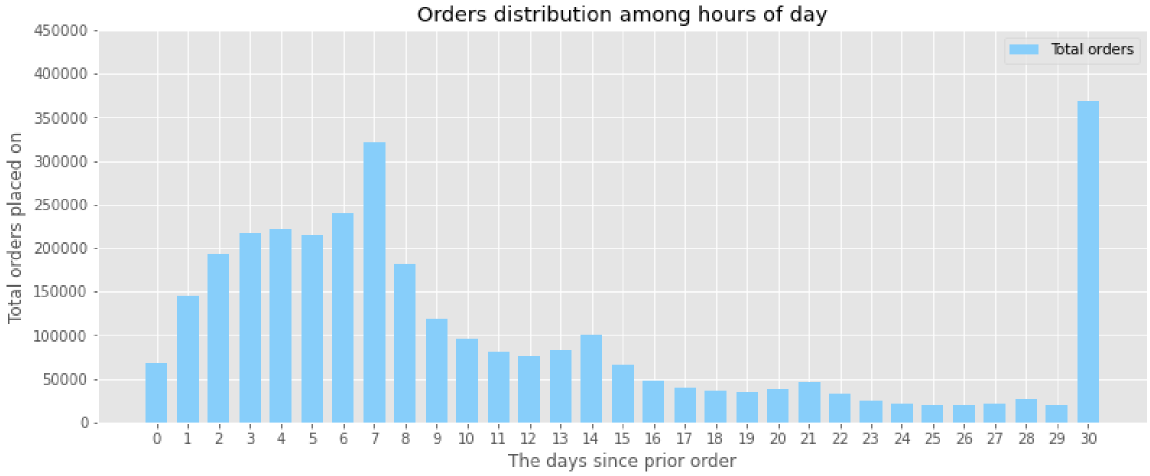
```
# transfer the type
prior_order_new = Orders[["days_since_prior_order","order_id"]].dropna() # need
 to drop NA
prior_order_new["days_since_prior_order"]=prior_order_new["days_since_prior_orde
r"].astype(int) # day => integer
#prior_order_new.head()

# group the data
Order_per_days_since_prior = prior_order_new.groupby(["days_since_prior_order"])
[['order_id']].nunique()

Order_per_days_since_prior_new = pd.DataFrame(Order_per_days_since_prior) # tran
sfer to the dataframe
Order_per_days_since_prior_new.reset_index(inplace=True)
Order_per_days_since_prior_new.head()
```

Out[31]:

	days_since_prior_order	order_id
0	0	67755
1	1	145247
2	2	193206
3	3	217005
4	4	221696

In [32]:

```
plt.figure(figsize=(13, 5))

plt.subplot(1, 1, 1)

#N = 7
values = Order_per_days_since_prior_new["order_id"]
index = Order_per_days_since_prior_new["days_since_prior_order"]

width = 0.7

p2 = plt.bar(index, values, width, label="Total orders", color="#87CEFA")

plt.xlabel('The days since prior order')
plt.ylabel('Total orders placed on')

plt.title('Orders distribution among hours of day')

plt.xticks(np.arange(0, 31, 1))
plt.yticks(np.arange(0, 480000, 50000))

plt.legend(loc="upper right")

plt.show()
```



Outcome:

- Looks like majority people order once a week, between 0 to 7.
- And there are people who order once more than 30 days.

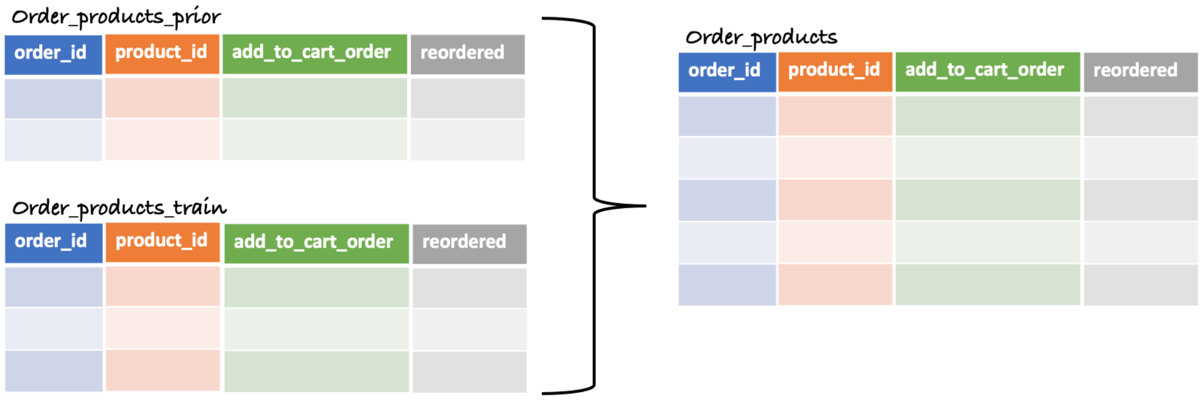
7. How many products do people purchase in an order? What's the most common total number of products in one order?

In [33]:

```python
# Concatenation of both tables.
Order_products = pd.concat([Order_products_prior, Order_products_train])
Order_products.head()
```

Out[33]:

	order_id	product_id	add_to_cart_order	reordered
0	2	33120	1	1
1	2	28985	2	1
2	2	9327	3	0
3	2	45918	4	1
4	2	30035	5	0



Order_products = pd.concat([Order_products_prior, Order_products_train])

Append rows of DataFrames

In [34]:

```
Products_per_order = Order_products.groupby(["order_id"])[['product_id']].nuniqu
e()
#Products_per_order.head()
Products_per_order_new = pd.DataFrame(Products_per_order) # transfer to the data
frame
Products_per_order_new.reset_index(inplace=True)
#Products_per_order_new.head()

#Products_per_order_new
Sum_order_per_sum_products = Products_per_order_new.groupby(["product_id"])[['or
der_id']].nunique()
#Products_per_order.head()
Sum_order_per_sum_products_new = pd.DataFrame(Sum_order_per_sum_products) # tran
sfer to the dataframe
Sum_order_per_sum_products_new.reset_index(inplace=True)
Sum_order_per_sum_products_new.head()
```

Out[34]:

	product_id	order_id
0	1	163593
1	2	194361
2	3	215060
3	4	230299
4	5	237225

In [35]:

```
plt.figure(figsize=(13, 6))

plt.subplot(1, 1, 1)

#N = 7
values = Sum_order_per_sum_products_new["order_id"]
index = Sum_order_per_sum_products_new["product_id"]

width = 0.5

p2 = plt.bar(index, values, width, label="Total orders", color="#87CEFA")

plt.xlabel('Total number of products per order')
plt.ylabel('Total orders placed on')

plt.title('Orders distribution among total products per order')

plt.xticks(np.arange(0, 141, 5))
#plt.yticks(np.arange(0, 480000, 50000))

plt.legend(loc="upper right")

plt.show()
```

Outcome:

- People mostly purchase 4 items per order.
- Majority of people like to purchase between 3 to 8 items per order.

8. How many transaction and unique products is in this dataset?

In [36]:

```
print(Order_products.shape[0])
print(len(Order_products.order_id.unique()))
print(len(Order_products.product_id.unique()))
```

```
33819106
3346083
49685
```

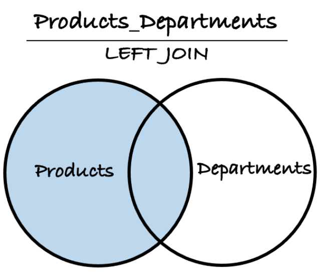
9. How the products distribute in different department?

In [37]:

```
# Merging tables together.

# Step 1
Products_Departments = pd.merge(Products, Departments, how='left', on=['departme
nt_id', 'department_id'])
Products_Departments.head()
```

Out[37]:

	product_id	product_name	aisle_id	department_id	department
0	1	Chocolate Sandwich Cookies	61	19	snacks
1	2	All-Seasons Salt	104	13	pantry
2	3	Robust Golden Unsweetened Oolong Tea	94	7	beverages
3	4	Smart Ones Classic Favorites Mini Rigatoni Wit...	38	1	frozen
4	5	Green Chile Anytime Sauce	5	13	pantry

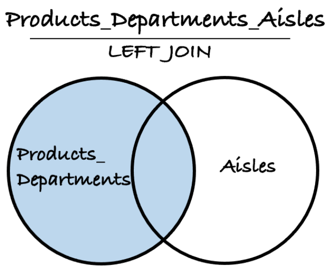


In [38]:

```
# Step 2
Products_Departments_Aisles = pd.merge(Products_Departments, Aisles, how='left',
on=['aisle_id', 'aisle_id'])
Products_Departments_Aisles.head()
```

Out[38]:

	product_id	product_name	aisle_id	department_id	department	aisle
0	1	Chocolate Sandwich Cookies	61	19	snacks	cookies cakes
1	2	All-Seasons Salt	104	13	pantry	spices seasonings
2	3	Robust Golden Unsweetened Oolong Tea	94	7	beverages	tea
3	4	Smart Ones Classic Favorites Mini Rigatoni Wit...	38	1	frozen	frozen meals
4	5	Green Chile Anytime Sauce	5	13	pantry	marinades meat preparation



In [39]:

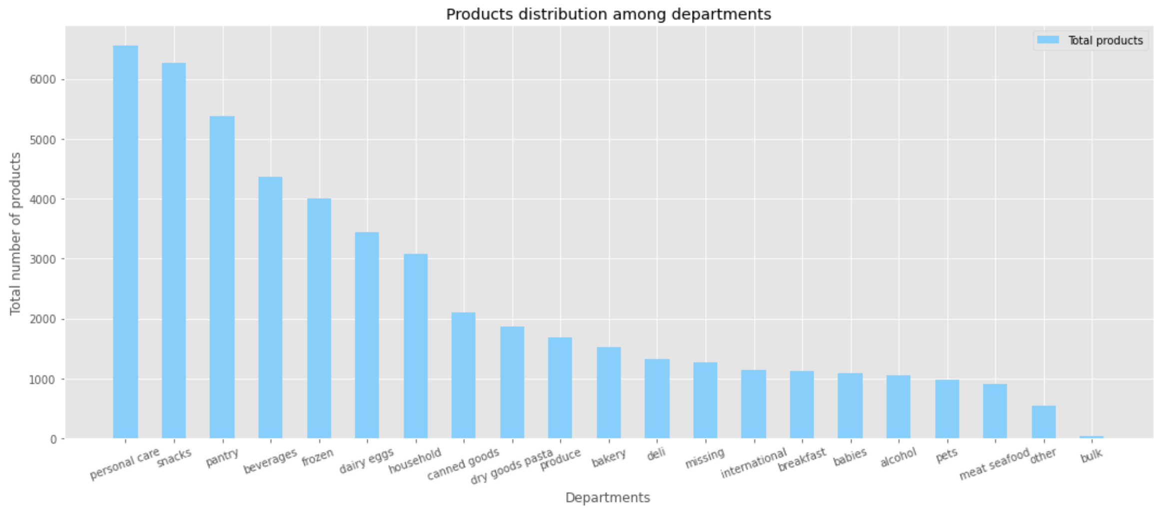
```
Sum_product_per_department = Products_Departments_Aisles.groupby(["department"])
[['product_id']].nunique()
#Products_per_order.head()
Sum_product_per_department_new = pd.DataFrame(Sum_product_per_department) # tran
sfer to the dataframe
Sum_product_per_department_new.reset_index(inplace=True)
Sum_product_per_department_new_2= Sum_product_per_department_new.sort_values(by=
'product_id', ascending=False)
Sum_product_per_department_new_2.head()
```

Out[39]:

	department	product_id
17	personal care	6563
20	snacks	6264
16	pantry	5371
3	beverages	4365
10	frozen	4007

In [40]:

```
plt.figure(figsize=(18, 7))

plt.subplot(1, 1, 1)

#N = 7
values = Sum_product_per_department_new_2["product_id"]

index = Sum_product_per_department_new_2["department"]

width = 0.5

p2 = plt.bar(index, values, width, label="Total products", color="#87CEFA")

plt.xlabel('Departments')
plt.ylabel('Total number of products')

plt.title('Products distribution among departments')

plt.xticks(rotation=20)
#plt.yticks(np.arange(0, 480000, 50000))

plt.legend(loc="upper right")

plt.show()
```



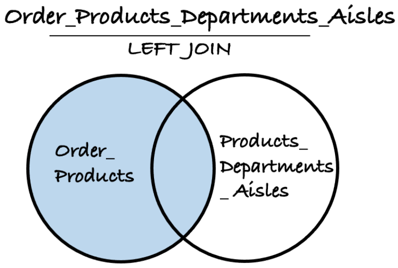
10. What are the product that people purchase the most?

In [41]:

```
# Merging Products_Departments_Aisles and Order_products.

Order_Products_Departments_Aisles = pd.merge(Order_products, Products_Department
s_Aisles, how='left', on=['product_id', 'product_id'])
Order_Products_Departments_Aisles.head()
```

Out[41]:

	order_id	product_id	add_to_cart_order	reordered	product_name	aisle_id	department_id
0	2	33120	1	1	Organic Egg Whites	86	16
1	2	28985	2	1	Michigan Organic Kale	83	4
2	2	9327	3	0	Garlic Powder	104	13
3	2	45918	4	1	Coconut Butter	19	13
4	2	30035	5	0	Natural Sweetener	17	13



In [42]:

```
# Find out the top 15 products people purchased the most.

Sum_order_per_product_name = Order_Products_Departments_Aisles.groupby(["product
_name"])[['order_id']].count()

Sum_order_per_product_name_new = pd.DataFrame(Sum_order_per_product_name) # tran
sfer to the dataframe
Sum_order_per_product_name_new.reset_index(inplace=True)
Sum_order_per_product_name_new_2= Sum_order_per_product_name_new.sort_values(by=
'order_id', ascending=False)

Sum_order_per_product_name_new_2.columns = ['product_name', 'total_order_number'
]
Sum_order_per_product_name_new_2.head(15)
```

Out[42]:

	product_name	total_order_number
3677	Banana	491291
3472	Bag of Organic Bananas	394930
31923	Organic Strawberries	275577
28843	Organic Baby Spinach	251705
30300	Organic Hass Avocado	220877
28807	Organic Avocado	184224
22415	Large Lemon	160792
42908	Strawberries	149445
23422	Limes	146660
32481	Organic Whole Milk	142813
31366	Organic Raspberries	142603
32568	Organic Yellow Onion	117716
30003	Organic Garlic	113936
32608	Organic Zucchini	109412
29011	Organic Blueberries	105026

Outcome:

- The top 15 items that people purchase the most are above.
- Most of them are organic fruits/veggies. All of them are fruits/veggies.

11. What are the aisles where people purchase the most?

In [43]:

```
# Finding top 15 aisles.

Sum_order_per_aisle = Order_Products_Departments_Aisles.groupby(["aisle"])[['ord
er_id']].count()

Sum_order_per_aisle_new = pd.DataFrame(Sum_order_per_aisle) # transfer to the da
taframe
Sum_order_per_aisle_new.reset_index(inplace=True)
Sum_order_per_aisle_new_2= Sum_order_per_aisle_new.sort_values(by='order_id', as
cending=False)

Sum_order_per_aisle_new_2.columns = ['aisle', 'total_order_number']
Sum_order_per_aisle_new_2.head(15)
```

Out[43]:

	aisle	total_order_number
50	fresh fruits	3792661
53	fresh vegetables	3568630
98	packaged vegetables fruits	1843806
133	yogurt	1507583
93	packaged cheese	1021462
83	milk	923659
131	water seltzer sparkling water	878150
25	chips pretzels	753739
119	soy lactosefree	664493
11	bread	608469
110	refrigerated	599109
62	frozen produce	545107
71	ice cream ice	521101
32	crackers	478430
42	energy granola bars	473835

12. What are the departments where people purchase the most?

In [44]:

```python
# Finding top 15 departments.
Sum_order_per_department = Order_Products_Departments_Aisles.groupby(["departmen
t"])[['order_id']].count()

Sum_order_per_department_new = pd.DataFrame(Sum_order_per_department) # transfer
to the dataframe
Sum_order_per_department_new.reset_index(inplace=True)
Sum_order_per_department_new_2= Sum_order_per_department_new.sort_values(by='ord
er_id', ascending=False)

Sum_order_per_department_new_2.columns = ['aisle', 'total_order_number']
Sum_order_per_department_new_2.head(15)
```

Out[44]:

	aisle	total_order_number
19	produce	9888378
7	dairy eggs	5631067
20	snacks	3006412
3	beverages	2804175
10	frozen	2336858
16	pantry	1956819
2	bakery	1225181
6	canned goods	1114857
8	deli	1095540
9	dry goods pasta	905340
11	household	774652
13	meat seafood	739238
4	breakfast	739069
17	personal care	468693
1	babies	438743

Part 3. Recommender design and model evaluation

1. Recommender design

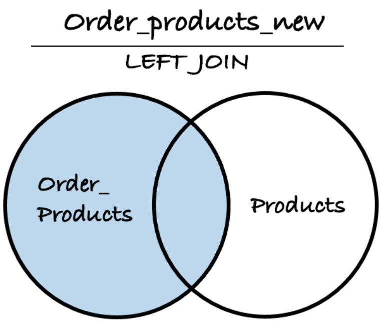
(1) Data Preprocessing

In [45]:

```
Order_products_new = pd.merge(Order_products, Products, how='left', on=['product
_id', 'product_id'])
Order_products_new.head()
```

Out[45]:

	order_id	product_id	add_to_cart_order	reordered	product_name	aisle_id	department_id
0	2	33120	1	1	Organic Egg Whites	86	16
1	2	28985	2	1	Michigan Organic Kale	83	4
2	2	9327	3	0	Garlic Powder	104	13
3	2	45918	4	1	Coconut Butter	19	13
4	2	30035	5	0	Natural Sweetener	17	13

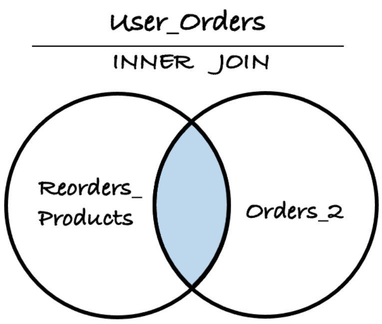


In [46]:

```
# get the list of orders that have been reordered before
Reorders_Products = Order_products_new[Order_products_new['reordered'] == 1]

# get the order_id and user_id information
Orders_2 = Orders[['order_id', 'user_id']]

# merge to get user_id and product_id
User_Orders = Reorders_Products.merge(Orders_2, on='order_id') # inner join
User_Orders.head()
```

Out[46]:

	order_id	product_id	add_to_cart_order	reordered	product_name	aisle_id	department_id
0	2	33120	1	1	Organic Egg Whites	86	16
1	2	28985	2	1	Michigan Organic Kale	83	4
2	2	45918	4	1	Coconut Butter	19	13
3	2	17794	6	1	Carrots	83	4
4	2	40141	7	1	Original Unflavored Gelatine Mix	105	13



In [47]:

```
# filtering out the high volumn products that user reordered more than once
User_Orders['high_volume'] = (User_Orders['product_id'].value_counts().sort_valu
es(ascending=False)>1)
High_Volume = User_Orders[User_Orders['high_volume'] == True]

High_Volume.head()
```

Out[47]:

	order_id	product_id	add_to_cart_order	reordered	product_name	aisle_id	department_id
1	2	28985	2	1	Michigan Organic Kale	83	4
2	2	45918	4	1	Coconut Butter	19	13
3	2	17794	6	1	Carrots	83	4
4	2	40141	7	1	Original Unflavored Gelatine Mix	105	13
5	2	1819	8	1	All Natural No Stir Creamy Almond Butter	88	13

In [48]:

```
# get a matrix of different high volume items that particular user purchased
High_Volume_Users = High_Volume.groupby(['user_id', 'product_name']).size().sort
_values(ascending=False).unstack().fillna(0)

High_Volume_Users.head()
```

Out[48]:

product_name	0% Fat Blueberry Greek Yogurt	0% Fat Free Organic Milk	0% Fat Organic Greek Vanilla Yogurt	0% Greek Strained Yogurt	0% Greek Yogurt Black Cherry on the Bottom	0% Greek, Blueberry on the Bottom Yogurt	0% Milkfat Greek Yogurt Honey	1 % Lowfat Milk	A Ma I
user_id									
27	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
66	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
90	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
150	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 9314 columns

In [49]:

```
# merge to get user_id and product_id
Order_products_new_2 = Order_products_new.merge(Orders, on='order_id',how="left"
) # inner join
Order_products_new_2.head()
```

Out[49]:

	order_id	product_id	add_to_cart_order	reordered	product_name	aisle_id	department_id
0	2	33120	1	1	Organic Egg Whites	86	16
1	2	28985	2	1	Michigan Organic Kale	83	4
2	2	9327	3	0	Garlic Powder	104	13
3	2	45918	4	1	Coconut Butter	19	13
4	2	30035	5	0	Natural Sweetener	17	13

In [50]:

```
# calculate similarity between each user
Cosine_Dists = pd.DataFrame(cosine_similarity(High_Volume_Users),index=High_Volu
me_Users.index, columns=High_Volume_Users.index)
Cosine_Dists.head()
```

Out[50]:

user_id	27	66	90	150	155	206	208	214	222	382	...	205908	205943	205970	20!
user_id															
27	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.176777	
66	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.000000	
90	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.000000	
150	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.000000	
155	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.000000	

5 rows × 6869 columns

In [51]:

```
High_Volume_Products = High_Volume.groupby(['product_name', 'user_id']).size().s
ort_values(ascending=False).unstack().fillna(0)
High_Volume_Products.head()
```

Out[51]:

user_id	27	66	90	150	155	206	208	214	222	382	...	205908	205943	20597(
product_name														
0% Fat Blueberry Greek Yogurt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.(
0% Fat Free Organic Milk	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.(
0% Fat Organic Greek Vanilla Yogurt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.(
0% Greek Strained Yogurt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.(
0% Greek Yogurt Black Cherry on the Bottom	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.(

5 rows × 6869 columns

(2) Recommender Model (Function)

In [62]:

```
def Recommender_System(user_id):

    '''
    enter user_id and return a list of 5 recommendations.
    '''
    High_Volume_Users = High_Volume.groupby(['user_id', 'product_name']).size().
sort_values(ascending=False).unstack().fillna(0)
    Cosine_Dists = pd.DataFrame(cosine_similarity(High_Volume_Users),index=High_
Volume_Users.index, columns=High_Volume_Users.index)

    recommendations = pd.Series(np.dot(High_Volume_Products.values,Cosine_Dists[
user_id]), index=High_Volume_Products.index)
    recommendations_1 = recommendations.sort_values(ascending=False)

    return recommendations_1.head()
```

In [63]:

```
# recommendation for customer id 382.
Recommender_System(382)
```

Out[63]:

```
product_name
Sparkling Natural Mineral Water    15.226952
Organic 1% Low Fat Milk             6.845234
Macaroni & Cheese                   6.668021
Banana                              4.265109
Bag of Organic Bananas              4.056538
dtype: float64
```

2. Model evaluation

(1) Basic exploration of the model

In [64]:

```
recommendations = Recommender_System(382)
recommendations_list = recommendations.index.tolist()

#recommendations_list
set(recommendations_list)
```

Out[64]:

```
{'Bag of Organic Bananas',
 'Banana',
 'Macaroni & Cheese',
 'Organic 1% Low Fat Milk',
 'Sparkling Natural Mineral Water'}
```

In [65]:

```
user=382

top_20_itmes = Order_products_new_2[Order_products_new_2.user_id == user].produc
t_name.value_counts().head(20)
top_20_items_list = top_20_itmes.index.tolist()

#top_20_items_list
set(top_20_items_list)
```

Out[65]:

```
{'Arancita Rossa',
 'Chocolate Milk 1% Milkfat',
 'Flax Plus Raisin Bran Cereal',
 'Florida Orange Juice With Calcium & Vitamin D',
 'Lean Protein & Fiber Bar Chocolate Almond Brownie',
 'Low Fat 1% Milk',
 'Macaroni & Cheese',
 'Natural Classic Pork Breakfast Sausage',
 'Naturals Savory Turkey Breakfast Sausage',
 'Organic 1% Low Fat Milk',
 'Organic American Cheese Singles',
 'Organic Large Brown Grade AA Cage Free Eggs',
 'Organic Spelt Pretzels',
 'Organic Strawberries',
 'Organic Whole Grain Wheat English Muffins',
 'Red Lentil Dahl Soup',
 'Sparkling Natural Mineral Water',
 'Sparkling Orange Juice & Prickly Pear Beverage',
 'Total 0% Nonfat Plain Greek Yogurt',
 'Vanilla Almond Breeze'}
```

In [66]:

```
set(recommendations_list) & set(top_20_items_list)
```

Out[66]:

```
{'Macaroni & Cheese',
 'Organic 1% Low Fat Milk',
 'Sparkling Natural Mineral Water'}
```

In [72]:

```
(len(set(recommendations_list) & set(top_20_items_list)))/5
```

Out[72]:

```
0.6
```

(2) Define a metric for model evaluation

In this project, since I want to find a ratio to measure whethter the items I recommend are the items the users would order for another time, I decide to use the recall ratio as the evaluation metric, which means the percentage of the items the customer had purchased are actually from the recommender.

The function is shown below.

$$Recall = \frac{tp}{tp + fn}$$

(3) Model evaluation function

In [70]:

```
# filter 1000 users for calculation
#  because the dataframe is too large
users = High_Volume.user_id.unique().tolist()
# calculate recall for the :1000 users
def how_match():
    res = []
    for user in sorted(users)[:1000]:
        recommendations = Recommender_System(user)
        top_20_itmes = Order_products_new_2[Order_products_new_2.user_id == user
].product_name.value_counts().head(20)

        recommendations_list = recommendations.index.tolist()
        top_20_items_list = top_20_itmes.index.tolist()

        res.append((len(set(recommendations_list) & set(top_20_items_list)))/5)
    return np.mean(res)
```

In [71]:

```
# get metric for the :1000 users
how_match()
```

Out[71]:

```
0.5296000000000001
```

In [ ]:

```

```

In [ ]:

```

```