In this notebook, we will try and explore the basic information about the dataset given. The relational set of files describing customers' orders over time.

Objective:

The goal of the competition is to predict which products will be in a user's next order. The dataset is anonymized and contains a sample of over 3 million grocery orders from more than 200,000 Instacart users.

For each user, 4 and 100 of their orders are given, with the sequence of products purchased in each order

Let us start by importing the necessary modules.

In [14]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings(action='ignore')
color = sns.color_palette()

from sklearn.feature_selection import RFE, f_regression
from sklearn.linear_model import (LinearRegression, Ridge, Lasso)
from sklearn.preprocessing import MinMaxScaler
from sklearn.ensemble import RandomForestRegressor
```

Let us list out the files that are present.

In [15]:
```
order_products_train_df = pd.read_csv("C:/Users/Deepv/Desktop/instacart/order_products__train.csv")

order_products_prior_df = pd.read_csv("C:/Users/Deepv/Desktop/instacart/order_products__prior.csv")

orders_df = pd.read_csv("C:/Users/Deepv/Desktop/instacart/orders.csv")

products_df = pd.read_csv("C:/Users/Deepv/Desktop/instacart/products.csv")

aisles_df = pd.read_csv("C:/Users/Deepv/Desktop/aisles.csv")
```

```
departments_df = pd.read_csv("C:/Users/Deepv/Desktop/departments.csv")
```

In [16]:

```
orders_df.head()
```

Out[16]:

	order_id	user_id	eval_set	order_number	order_dow	order_hour_of_day	days_since_prior_order
0	2539329	1	prior	1	2	8	NaN
1	2398795	1	prior	2	3	7	15.0
2	473747	1	prior	3	3	12	21.0
3	2254736	1	prior	4	4	7	29.0
4	431534	1	prior	5	4	15	28.0

In [17]:

```
order_products_prior_df.head()
```

Out[17]:

	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 [18]:

```
order_products_train_df.head()
```

Out[18]:

	order_id	product_id	add_to_cart_order	reordered
0	1	49302	1	1
1	1	11109	2	1
2	1	10246	3	0

	order_id	product_id	add_to_cart_order	reordered
3	1	49683	4	0
4	1	43633	5	1

As we could see, orders.csv has all the information about the given order id like the user who has purchased the order, when was it purchased, days since prior order and so on.

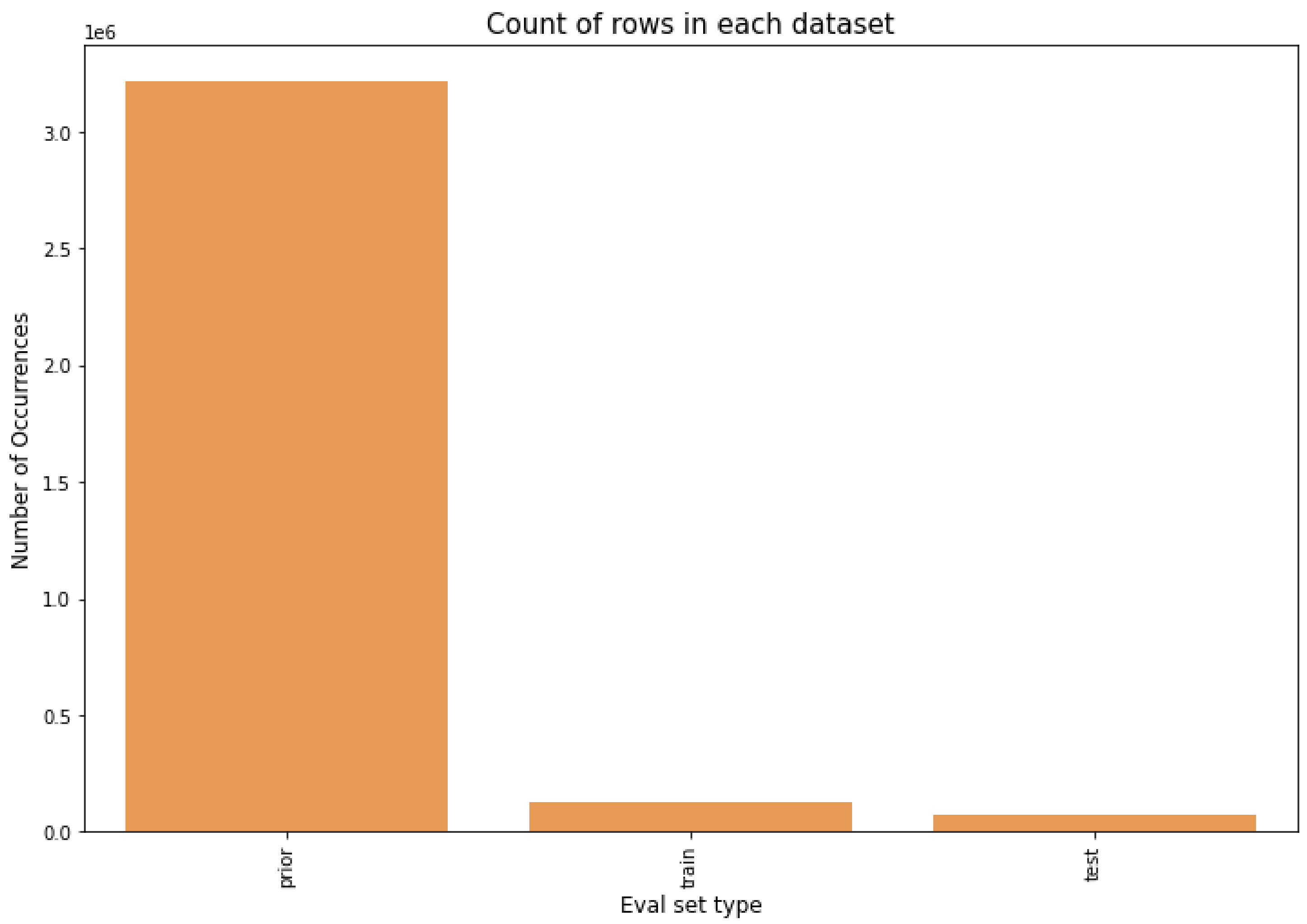
The columns present in order_products_train and order_products_prior are same. Then what is the difference between these files.?

As mentioned earlier, in this dataset, 4 to 100 orders of a customer are given (we will look at this later) and we need to predict the products that will be re-ordered. So the last order of the user has been taken out and divided into train and test sets. All the prior order informations of the customer are present in order_products_prior file. We can also note that there is a column in orders.csv file called eval_set which tells us as to which of the three datasets (prior, train or test) the given row goes to.

Order_products*csv file has more detailed information about the products that been bought in the given order along with the re-ordered status.

Let us first get the count of rows in each of the three sets.

In [19]:
```
cnt_srs = orders_df.eval_set.value_counts()

plt.figure(figsize=(12,8))
sns.barplot(cnt_srs.index, cnt_srs.values, alpha=0.8, color=color[1])
plt.ylabel('Number of Occurrences', fontsize=12)
plt.xlabel('Eval set type', fontsize=12)
plt.title('Count of rows in each dataset', fontsize=15)
plt.xticks(rotation='vertical')
plt.show()
```



In [20]:
```
def get_unique_count(x):
    return len(np.unique(x))

cnt_srs = orders_df.groupby("eval_set")["user_id"].aggregate(get_unique_count)
cnt_srs
```

Out[20]:
```
eval_set
prior    206209
```

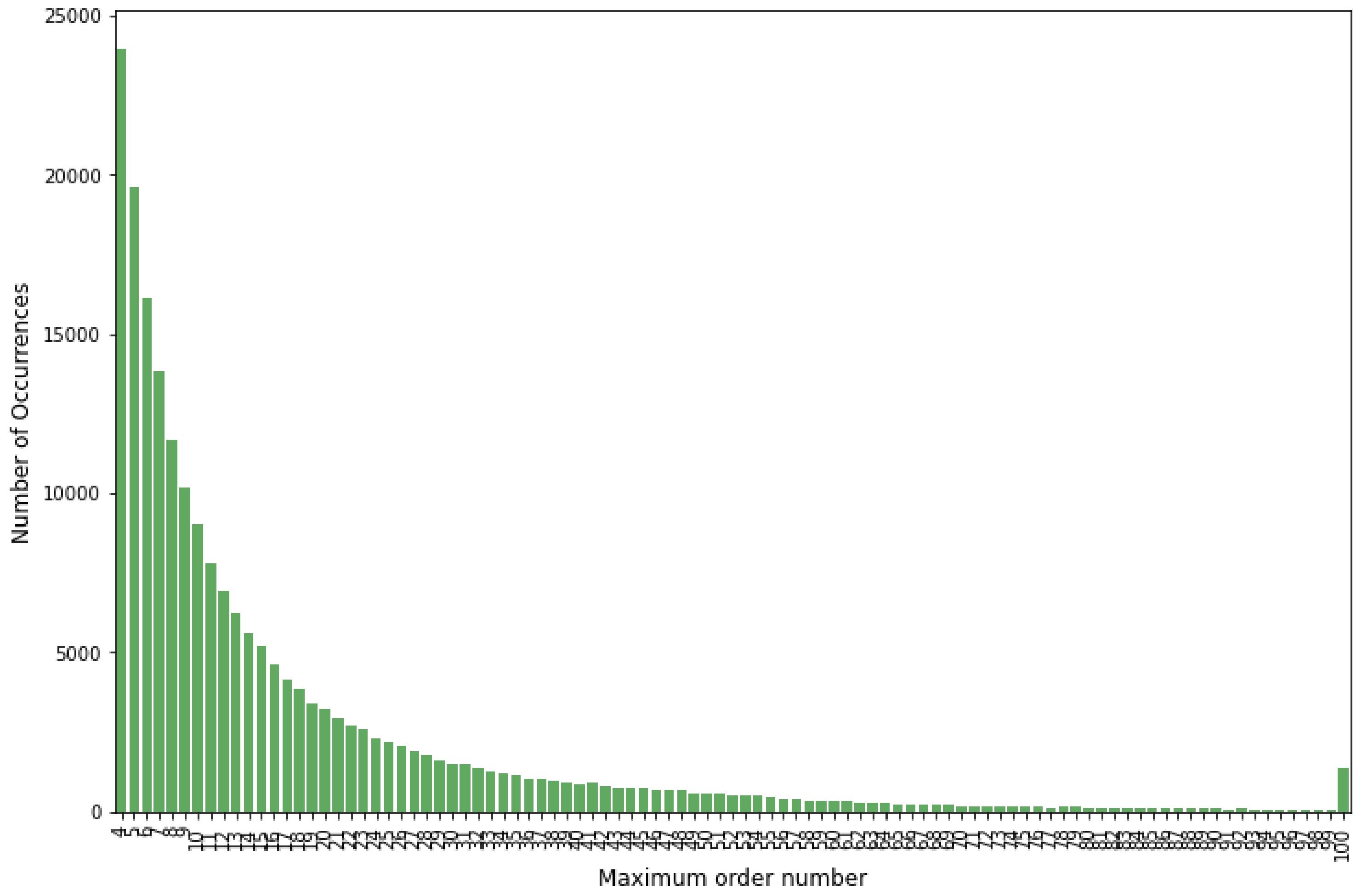
```
test      75000
train    131209
Name: user_id, dtype: int64
```

So there are 206,209 customers in total. Out of which, the last purchase of 131,209 customers are given as train set and we need to predict for the rest 75,000 customers.

Now let us validate the claim that 4 to 100 orders of a customer are given.

In [21]:

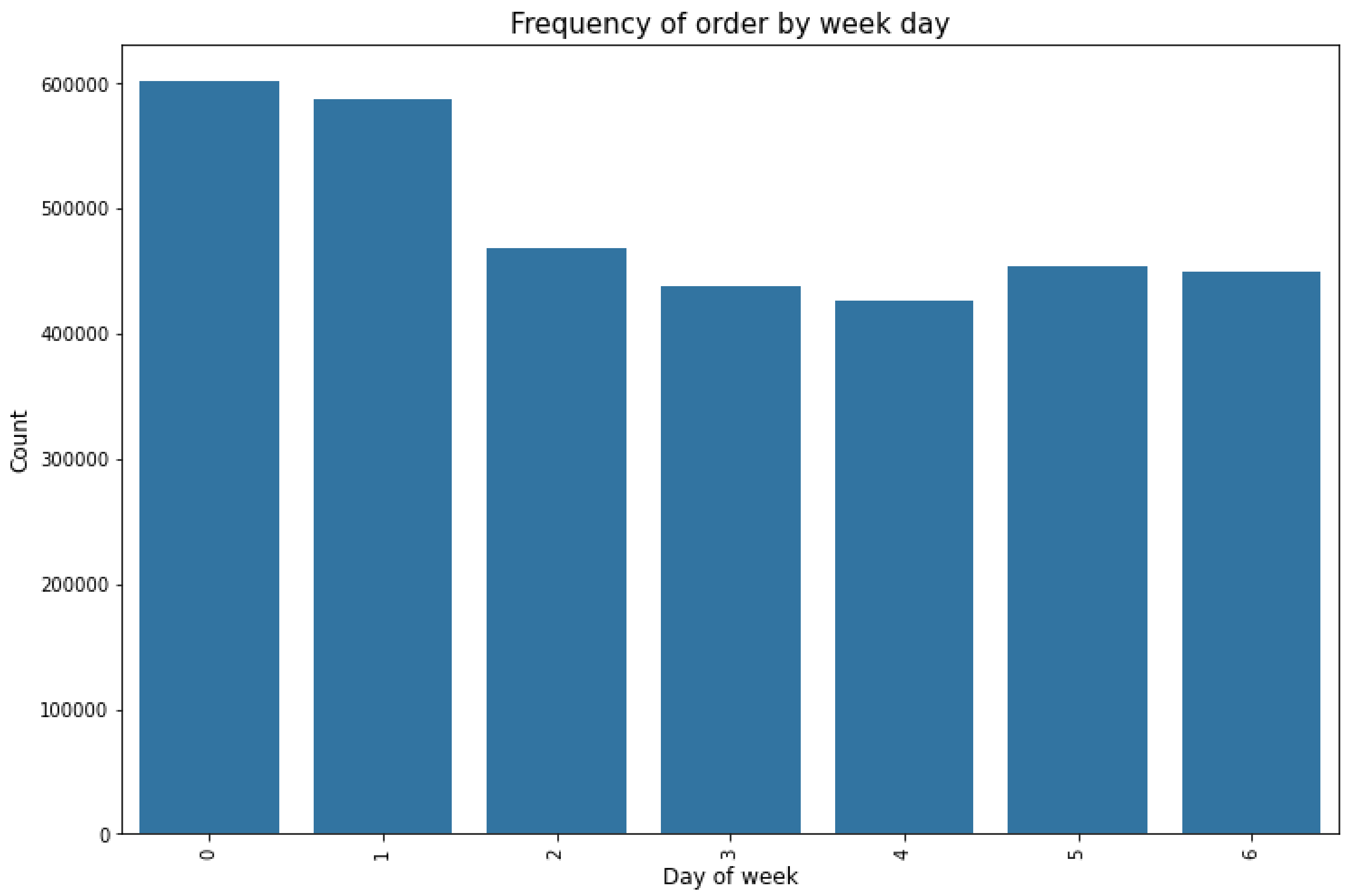
```
cnt_srs = orders_df.groupby("user_id")["order_number"].aggregate(np.max).reset_index()
cnt_srs = cnt_srs.order_number.value_counts()

plt.figure(figsize=(12,8))
sns.barplot(cnt_srs.index, cnt_srs.values, alpha=0.8, color=color[2])
plt.ylabel('Number of Occurrences', fontsize=12)
plt.xlabel('Maximum order number', fontsize=12)
plt.xticks(rotation='vertical')
plt.show()
```



So there are no orders less than 4 and is max capped at 100 as given in the data page.

Now let us see how the ordering habit changes with day of week.

In [22]:
```
plt.figure(figsize=(12,8))
sns.countplot(x="order_dow", data=orders_df, color=color[0])
plt.ylabel('Count', fontsize=12)
plt.xlabel('Day of week', fontsize=12)
plt.xticks(rotation='vertical')
plt.title("Frequency of order by week day", fontsize=15)
plt.show()
```

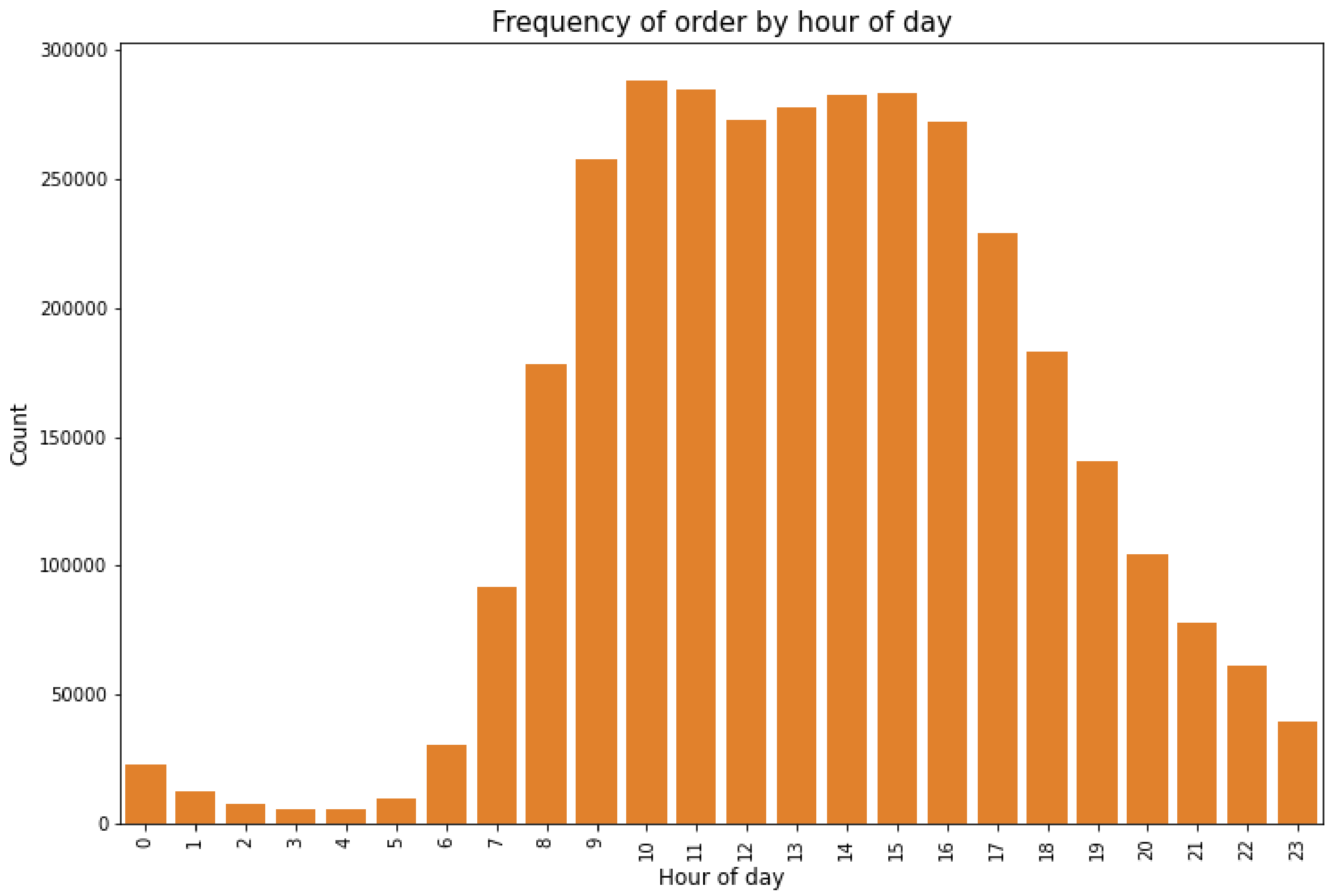


Seems like 0 and 1 is Saturday and Sunday when the orders are high and low during Wednesday.

Now we shall see how the distribution is with respect to time of the day.

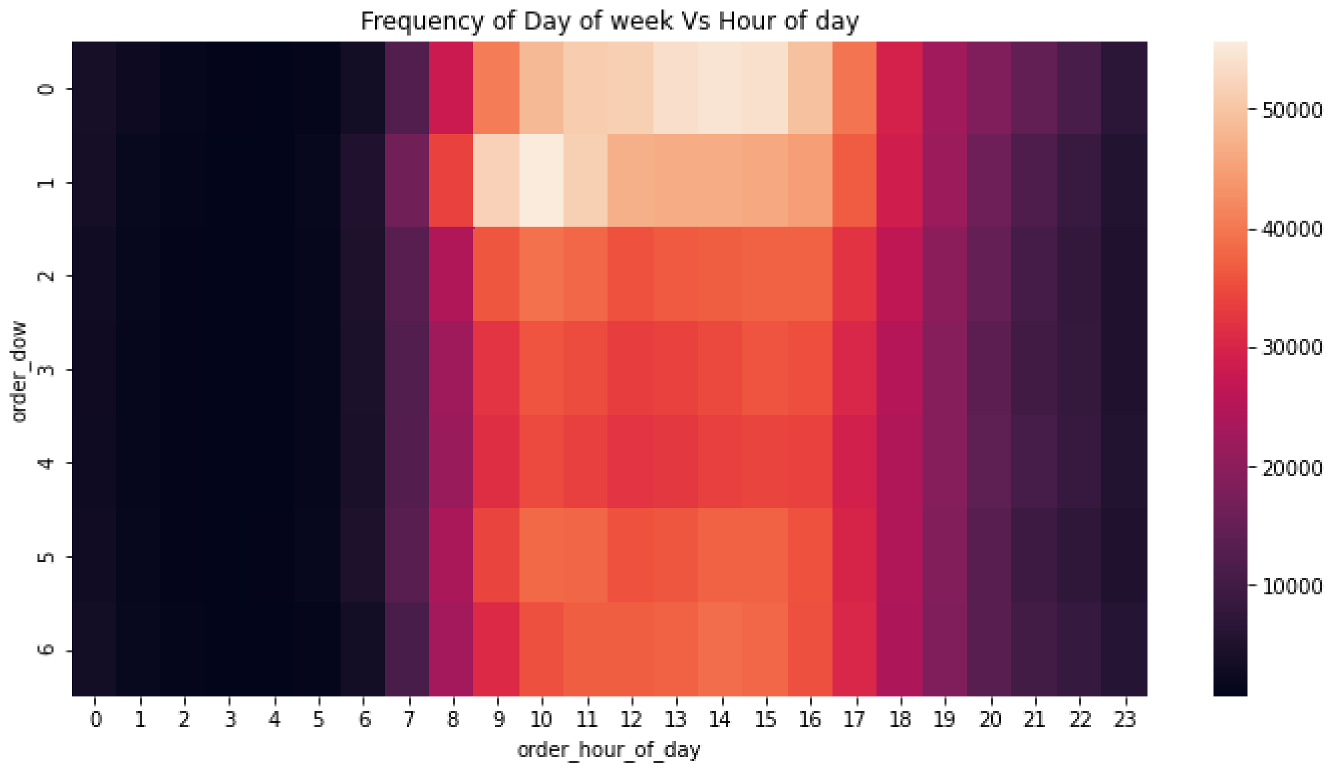
In [23]:
```
plt.figure(figsize=(12,8))
sns.countplot(x="order_hour_of_day", data=orders_df, color=color[1])
```

```
plt.ylabel('Count', fontsize=12)
plt.xlabel('Hour of day', fontsize=12)
plt.xticks(rotation='vertical')
plt.title("Frequency of order by hour of day", fontsize=15)
plt.show()
```



So majority of the orders are made during day time. Now let us combine the day of week and hour of day to see the distribution.

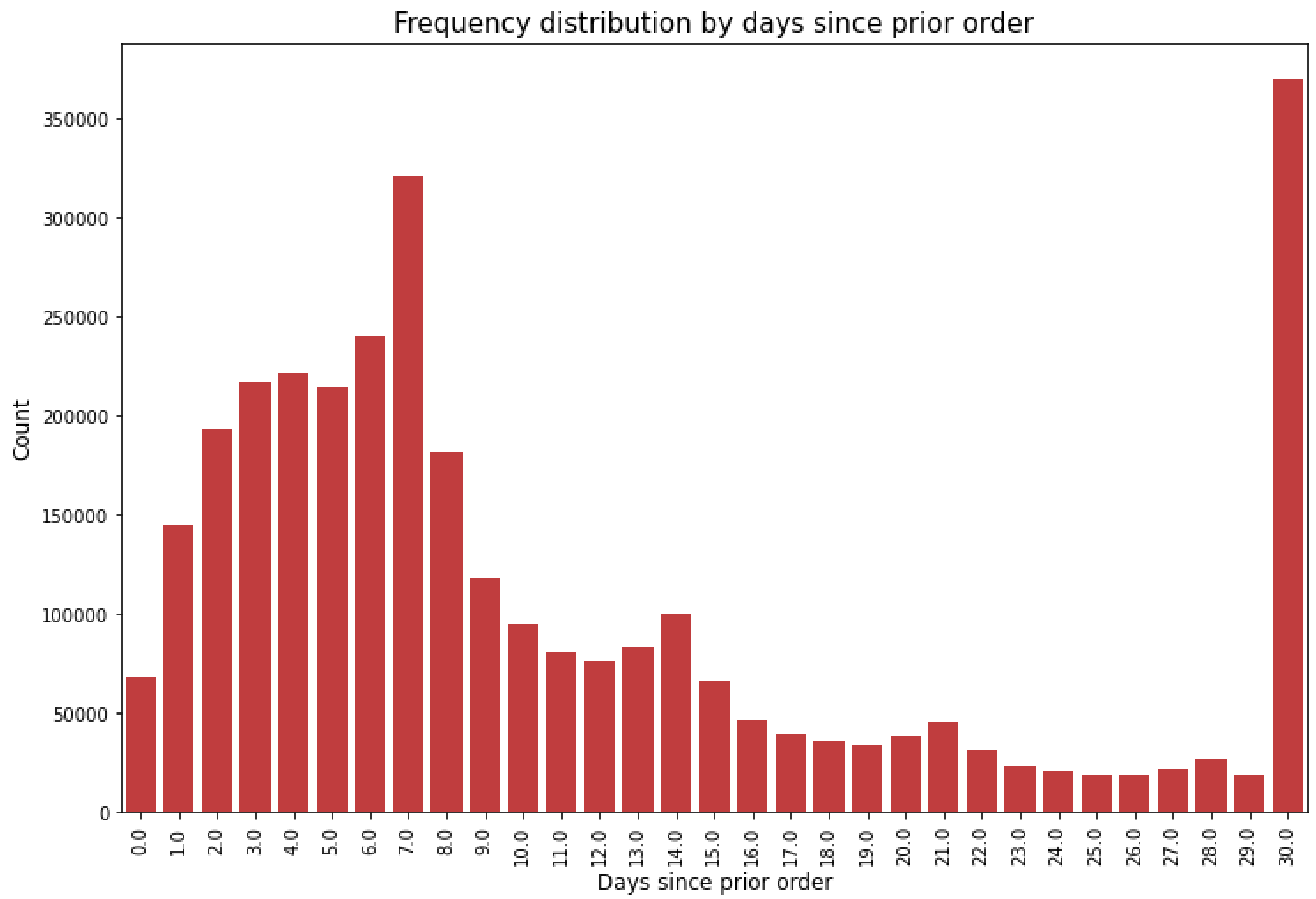
In [25]:
```
grouped_df = orders_df.groupby(["order_dow", "order_hour_of_day"])["order_number"].aggregate("count").reset_index()
grouped_df = grouped_df.pivot('order_dow', 'order_hour_of_day', 'order_number')

plt.figure(figsize=(12,6))
sns.heatmap(grouped_df)
plt.title("Frequency of Day of week Vs Hour of day")
plt.show()
```



Seems Satuday evenings and Sunday mornings are the prime time for orders.

Now let us check the time interval between the orders.

In [27]:
```
plt.figure(figsize=(12,8))
sns.countplot(x="days_since_prior_order", data=orders_df, color=color[3])
plt.ylabel('Count', fontsize=12)
plt.xlabel('Days since prior order', fontsize=12)
plt.xticks(rotation='vertical')
plt.title("Frequency distribution by days since prior order", fontsize=15)
plt.show()
```



Looks like customers order once in every week (check the peak at 7 days) or once in a month (peak at 30 days). We could also see smaller peaks at 14, 21 and 28 days (weekly intervals).

Since our objective is to figure out the re-orders, let us check out the re-order percentage in prior set and train set.

In [28]:
```
# percentage of re-orders in prior set #
order_products_prior_df.reordered.sum() / order_products_prior_df.shape[0]
```

Out[28]:
```
0.5896974667922161
```

In [29]:
```
# percentage of re-orders in train set #
order_products_train_df.reordered.sum() / order_products_train_df.shape[0]
```

Out[29]:
```
0.5985944127509629
```

On an average, about 59% of the products in an order are re-ordered products.

No re-ordered products:

Now that we have seen 59% of the products are re-ordered, there will also be situations when none of the products are re-ordered. Let us check that now.

In [33]:
```
grouped_df = order_products_prior_df.groupby("order_id")["reordered"].aggregate("sum").reset_index()
grouped_df["reordered"].loc[grouped_df["reordered"]>1] = 1
grouped_df.reordered.value_counts() / grouped_df.shape[0]
```

Out[33]:
```
1    0.879151
0    0.120849
Name: reordered, dtype: float64
```

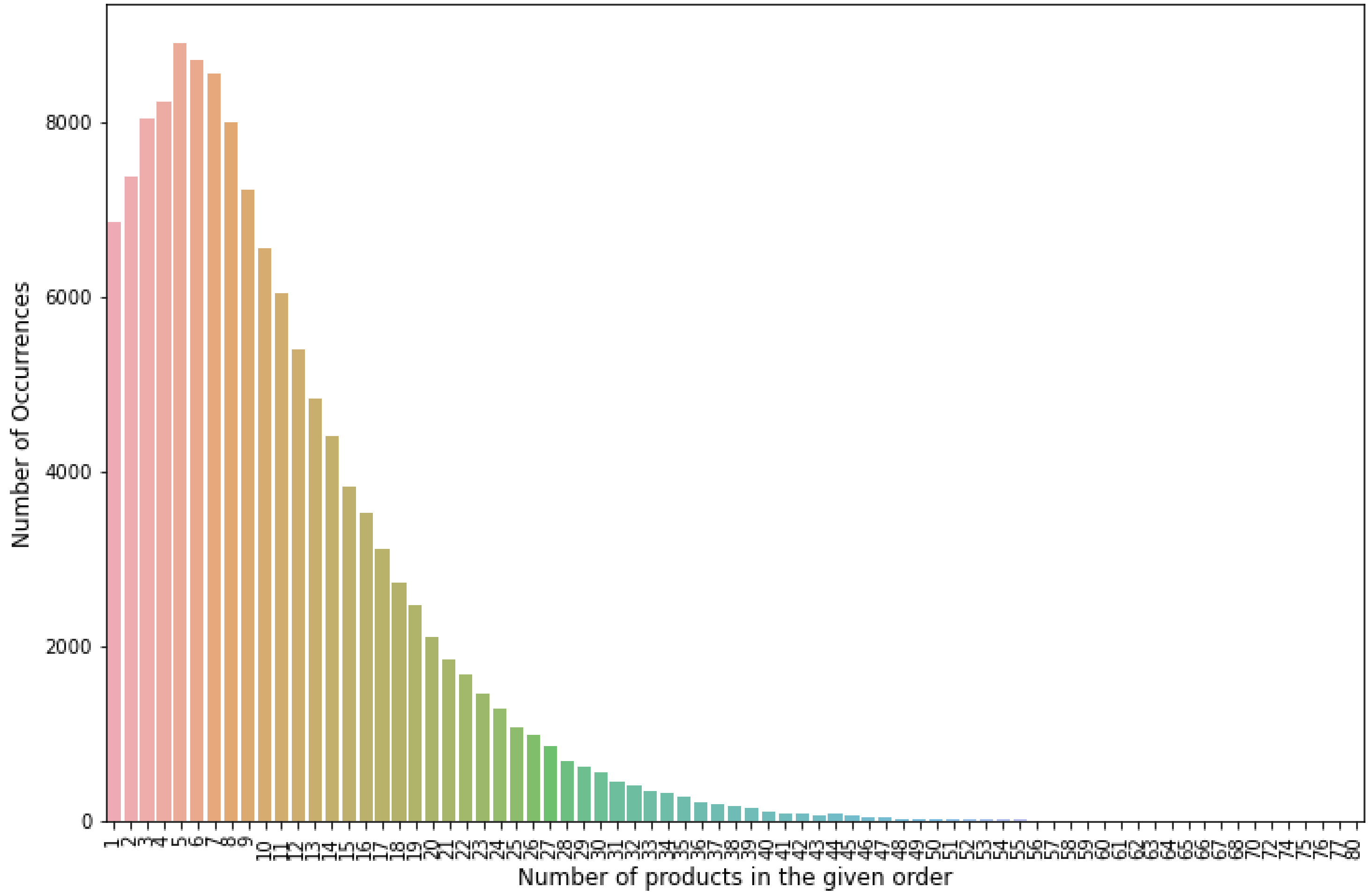
In [34]:
```
grouped_df = order_products_train_df.groupby("order_id")["reordered"].aggregate("sum").reset_index()
grouped_df["reordered"].loc[grouped_df["reordered"]>1] = 1
grouped_df.reordered.value_counts() / grouped_df.shape[0]
```

Out[34]:
```
1    0.93444
0    0.06556
Name: reordered, dtype: float64
```

About 12% of the orders in prior set has no re-ordered items while in the train set it is 6.5%.

Now let us see the number of products bought in each order.

In [35]:
```
grouped_df = order_products_train_df.groupby("order_id")["add_to_cart_order"].aggregate("max").reset_index()
cnt_srs = grouped_df.add_to_cart_order.value_counts()

plt.figure(figsize=(12,8))
sns.barplot(cnt_srs.index, cnt_srs.values, alpha=0.8)
plt.ylabel('Number of Occurrences', fontsize=12)
plt.xlabel('Number of products in the given order', fontsize=12)
plt.xticks(rotation='vertical')
plt.show()
```



A right tailed distribution with the maximum value at 5.!

Before we explore the product details, let us look at the other three files as well.

In [36]:
```
products_df.head()
```

Out[36]:

	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 [37]:
```
aisles_df.head()
```

Out[37]:

	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 [38]:
```
departments_df.head()
```

Out[38]:

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

	department_id	department
4	5	alcohol

Now let us merge these product details with the order_prior details.

In [39]:
```
order_products_prior_df = pd.merge(order_products_prior_df, products_df, on='product_id', how='left')
order_products_prior_df = pd.merge(order_products_prior_df, aisles_df, on='aisle_id', how='left')
order_products_prior_df = pd.merge(order_products_prior_df, departments_df, on='department_id', how='left')
order_products_prior_df.head()
```

Out[39]:

	order_id	product_id	add_to_cart_order	reordered	product_name	aisle_id	department_id	aisle	department
0	2	33120	1	1	Organic Egg Whites	86	16	eggs	dairy eggs
1	2	28985	2	1	Michigan Organic Kale	83	4	fresh vegetables	produce
2	2	9327	3	0	Garlic Powder	104	13	spices seasonings	pantry
3	2	45918	4	1	Coconut Butter	19	13	oils vinegars	pantry
4	2	30035	5	0	Natural Sweetener	17	13	baking ingredients	pantry

In [40]:
```
cnt_srs = order_products_prior_df['product_name'].value_counts().reset_index().head(20)
cnt_srs.columns = ['product_name', 'frequency_count']
cnt_srs
```

Out[40]:

	product_name	frequency_count
0	Banana	472565
1	Bag of Organic Bananas	379450
2	Organic Strawberries	264683
3	Organic Baby Spinach	241921
4	Organic Hass Avocado	213584
5	Organic Avocado	176815
6	Large Lemon	152657

	product_name	frequency_count
7	Strawberries	142951
8	Limes	140627
9	Organic Whole Milk	137905
10	Organic Raspberries	137057
11	Organic Yellow Onion	113426
12	Organic Garlic	109778
13	Organic Zucchini	104823
14	Organic Blueberries	100060
15	Cucumber Kirby	97315
16	Organic Fuji Apple	89632
17	Organic Lemon	87746
18	Apple Honeycrisp Organic	85020
19	Organic Grape Tomatoes	84255

In [ ]:

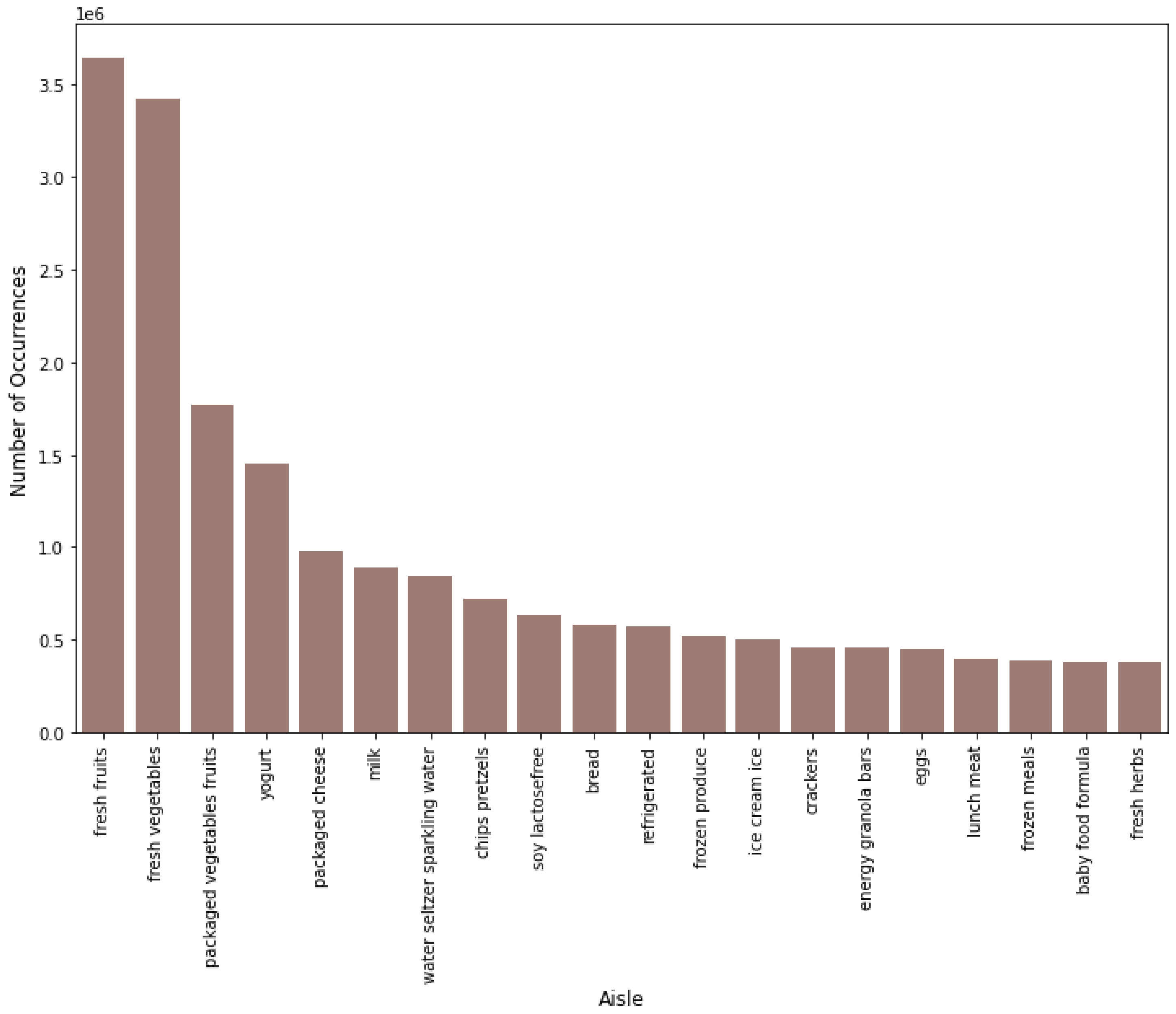
```
```

In [ ]:

```
Wow. Most of them are organic products.! Also majority of them are fruits.

Now let us look at the important aisles.
```

In [41]:

```
cnt_srs = order_products_prior_df['aisle'].value_counts().head(20)
plt.figure(figsize=(12,8))
sns.barplot(cnt_srs.index, cnt_srs.values, alpha=0.8, color=color[5])
plt.ylabel('Number of Occurrences', fontsize=12)
plt.xlabel('Aisle', fontsize=12)
plt.xticks(rotation='vertical')
plt.show()
```

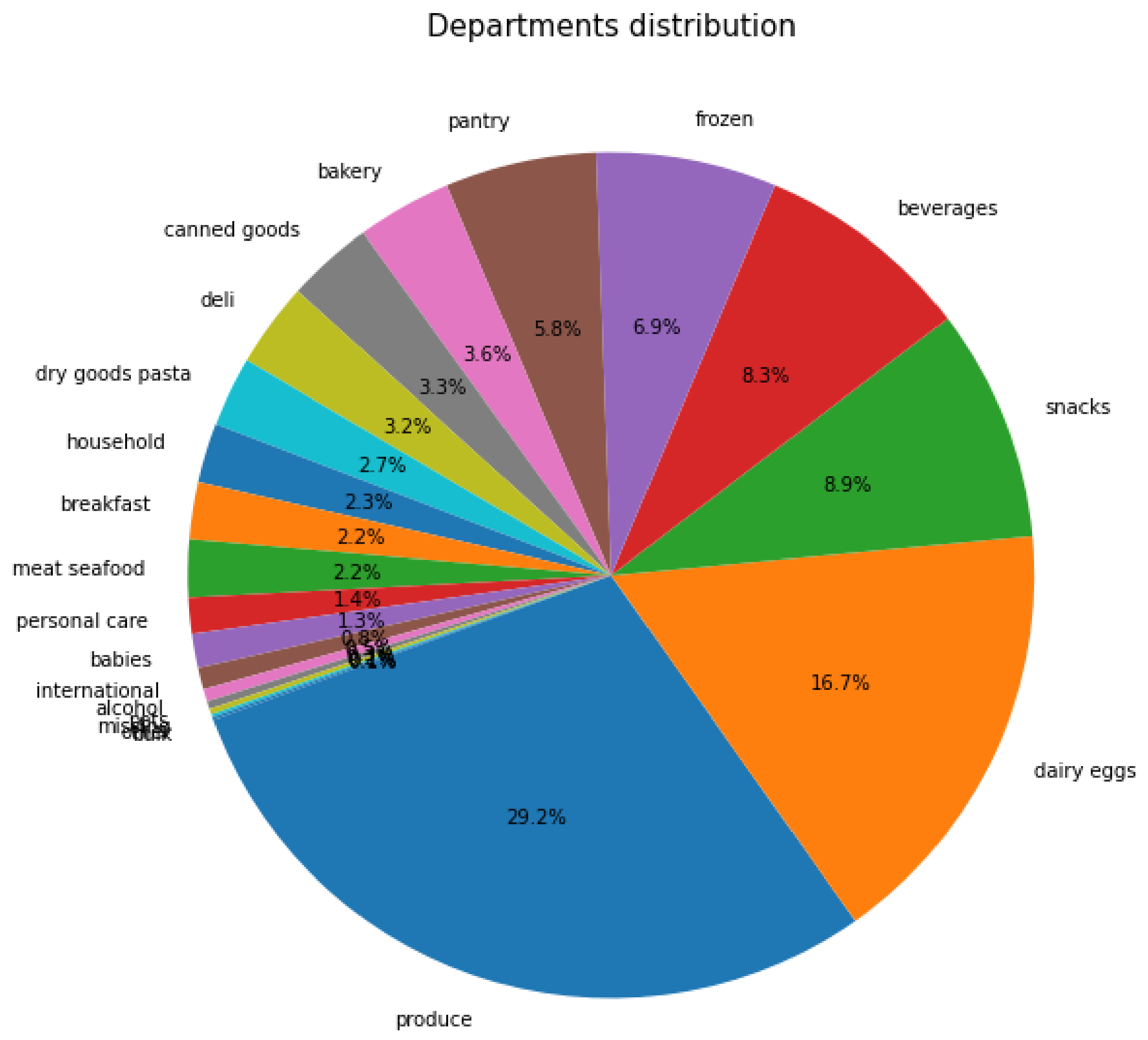


The top two aisles are fresh fruits and fresh vegetables.!

Department Distribution:

Let us now check the department wise distribution.

In [42]:
```
plt.figure(figsize=(10,10))
temp_series = order_products_prior_df['department'].value_counts()
labels = (np.array(temp_series.index))
sizes = (np.array((temp_series / temp_series.sum())*100))
plt.pie(sizes, labels=labels,
        autopct='%1.1f%%', startangle=200)
plt.title("Departments distribution", fontsize=15)
plt.show()
```

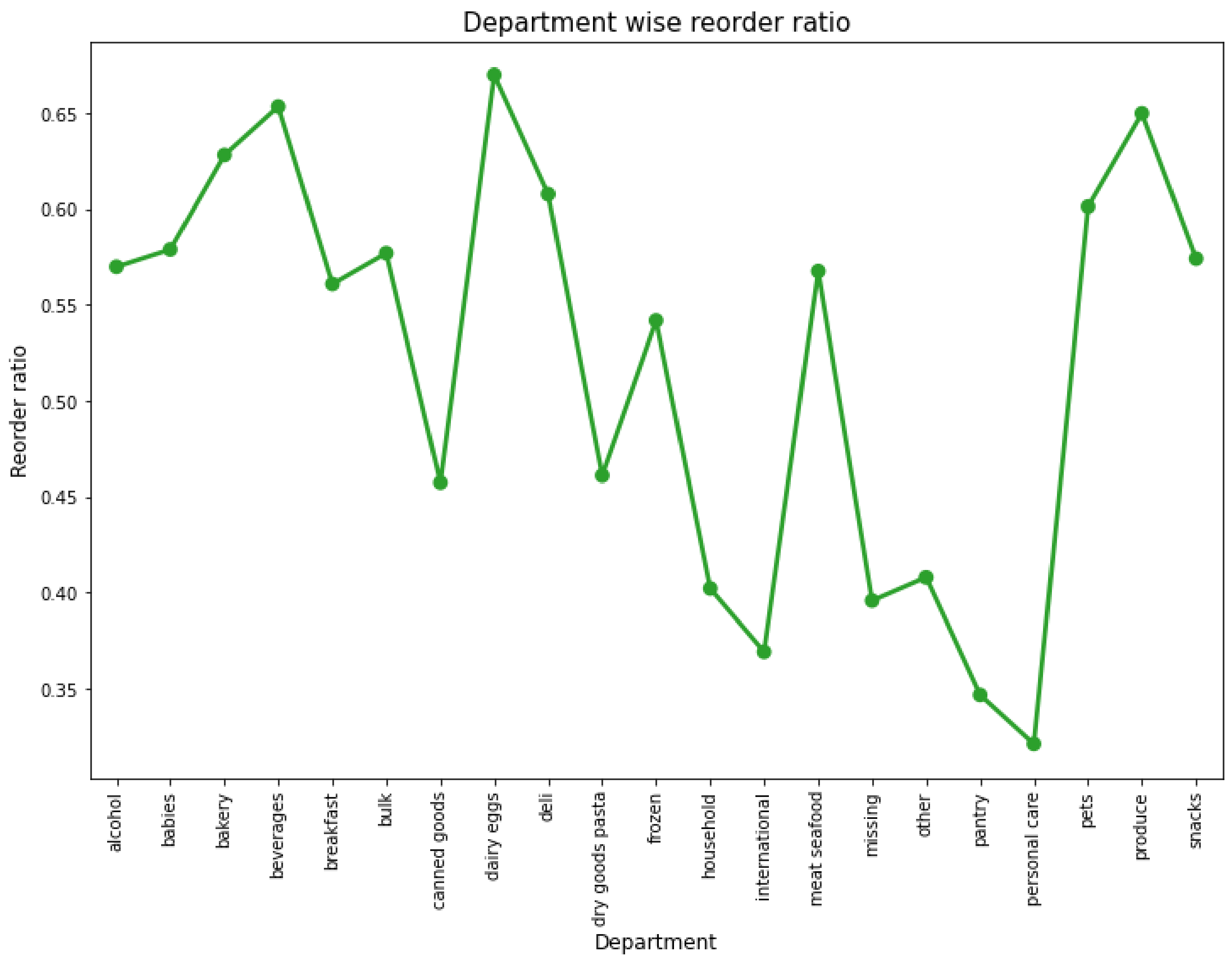


Produce is the largest department. Now let us check the reordered percentage of each department.

Department wise reorder ratio:

In [43]:

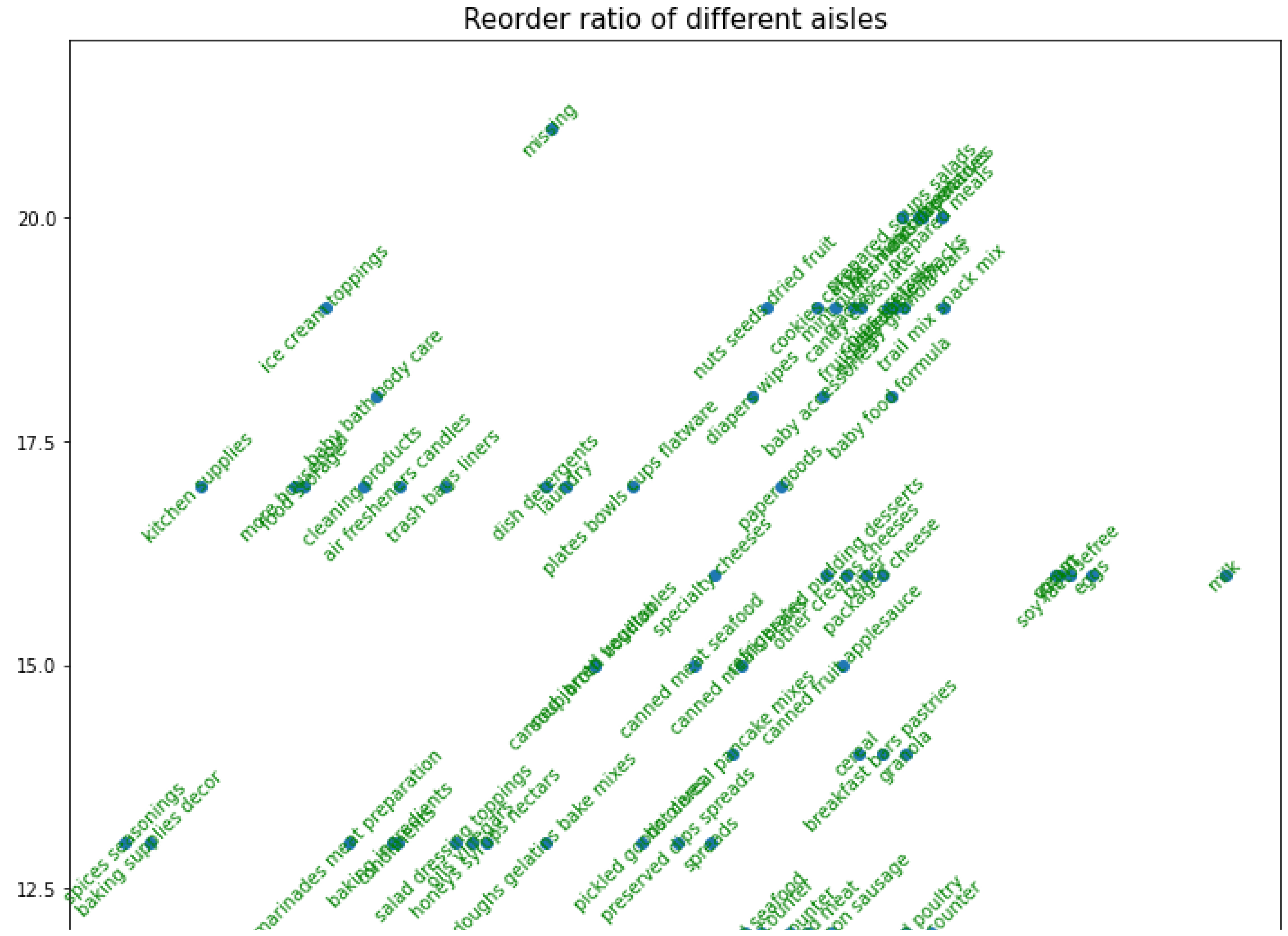
```
grouped_df = order_products_prior_df.groupby(["department"])["reordered"].aggregate("mean").reset_index()

plt.figure(figsize=(12,8))
sns.pointplot(grouped_df['department'].values, grouped_df['reordered'].values, alpha=0.8, color=color[2])
plt.ylabel('Reorder ratio', fontsize=12)
plt.xlabel('Department', fontsize=12)
plt.title("Department wise reorder ratio", fontsize=15)
plt.xticks(rotation='vertical')
plt.show()
```

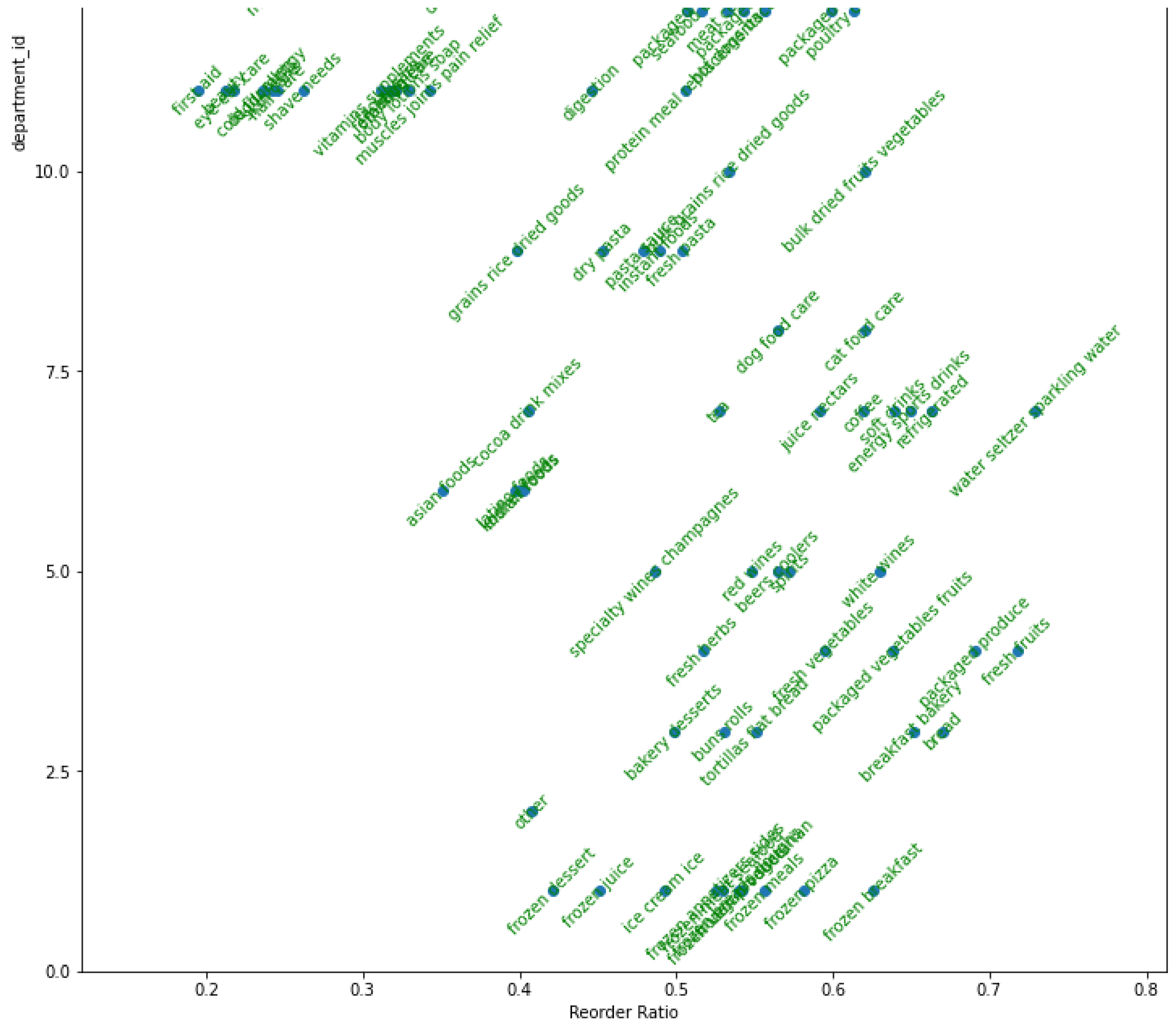


Personal care has lowest reorder ratio and dairy eggs have highest reorder ratio.

Aisle - Reorder ratio:

In [44]:
```
grouped_df = order_products_prior_df.groupby(["department_id", "aisle"])["reordered"].aggregate("mean").reset_index(
fig, ax = plt.subplots(figsize=(12,20))
ax.scatter(grouped_df.reordered.values, grouped_df.department_id.values)
for i, txt in enumerate(grouped_df.aisle.values):
    ax.annotate(txt, (grouped_df.reordered.values[i], grouped_df.department_id.values[i]), rotation=45, ha='center',
plt.xlabel('Reorder Ratio')
plt.ylabel('department_id')
plt.title("Reorder ratio of different aisles", fontsize=15)
plt.show()
```

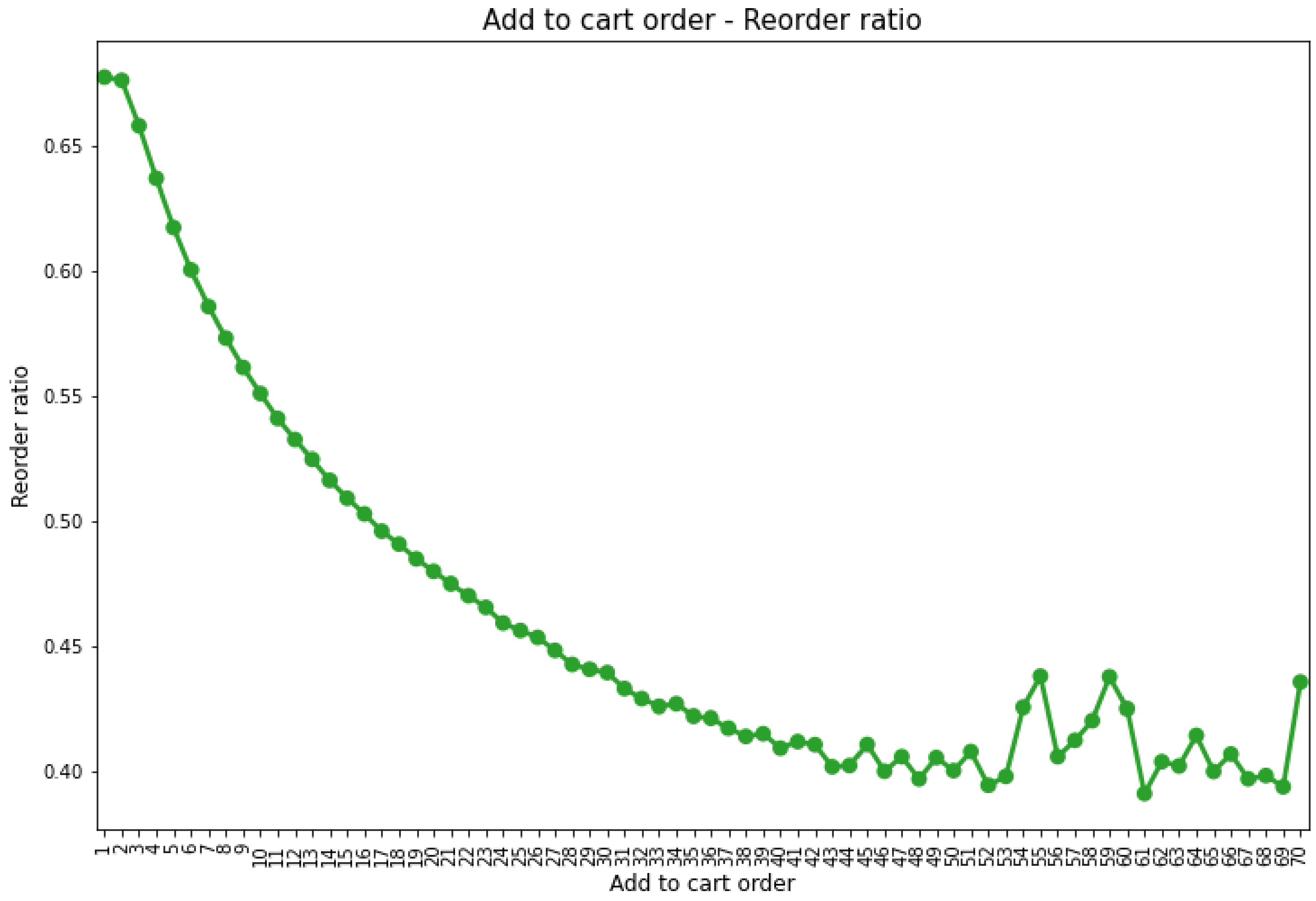




Add to Cart - Reorder ratio:

Let us now explore the relationship between how order of adding the product to the cart affects the reorder ratio.

In [46]:
```
order_products_prior_df["add_to_cart_order_mod"] = order_products_prior_df["add_to_cart_order"].copy()
order_products_prior_df["add_to_cart_order_mod"].loc[order_products_prior_df["add_to_cart_order_mod"]>70] = 70
grouped_df = order_products_prior_df.groupby(["add_to_cart_order_mod"])["reordered"].aggregate("mean").reset_index()

plt.figure(figsize=(12,8))
sns.pointplot(grouped_df['add_to_cart_order_mod'].values, grouped_df['reordered'].values, alpha=0.8, color=color[2])
plt.ylabel('Reorder ratio', fontsize=12)
plt.xlabel('Add to cart order', fontsize=12)
plt.title("Add to cart order - Reorder ratio", fontsize=15)
plt.xticks(rotation='vertical')
plt.show()
```



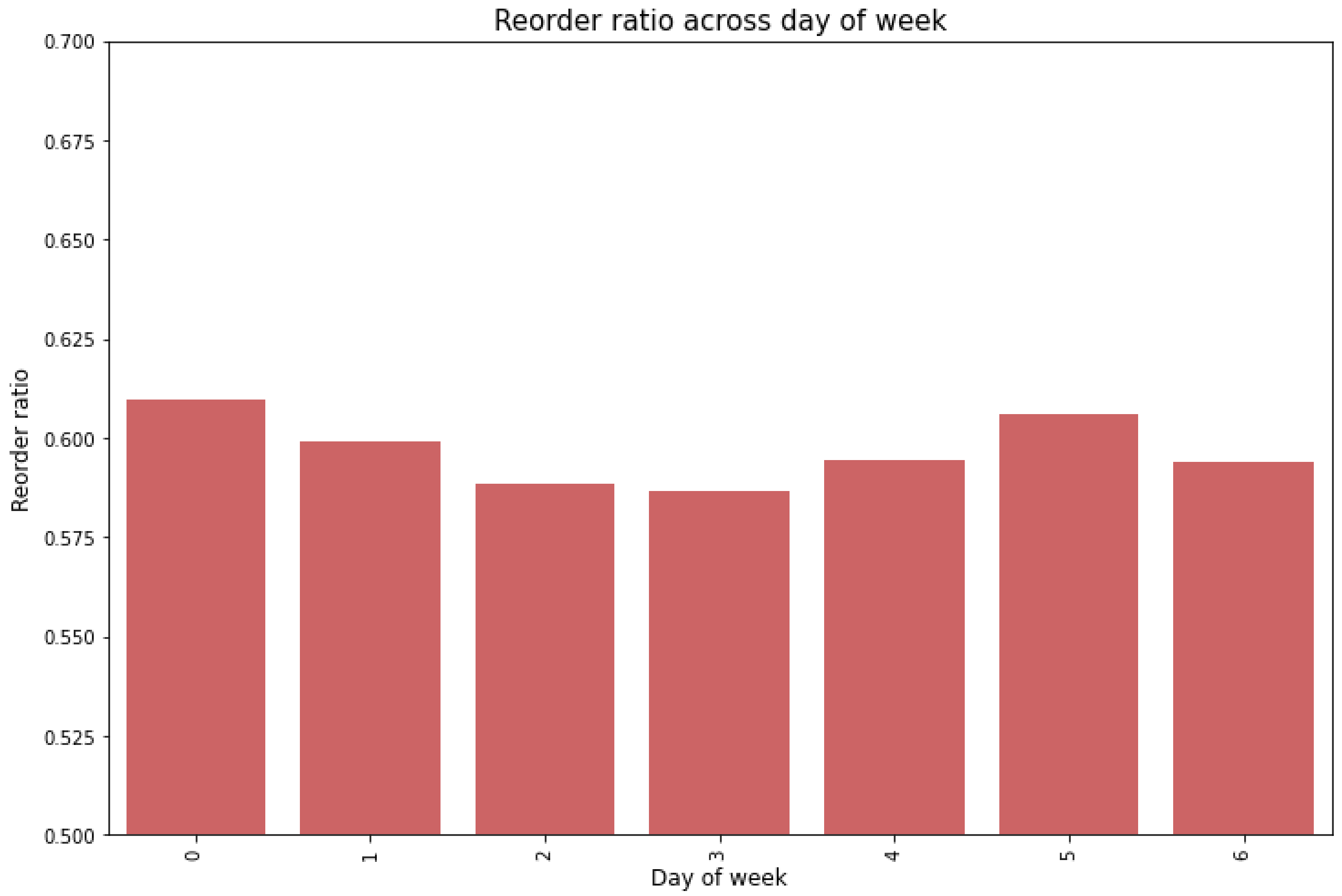
In [ ]:

```
Looks like the products that are added to the cart initially are more likely to be reordered again compared to the or

Reorder ratio by Time based variables:
```

In [47]:

```
order_products_train_df = pd.merge(order_products_train_df, orders_df, on='order_id', how='left')
grouped_df = order_products_train_df.groupby(["order_dow"])["reordered"].aggregate("mean").reset_index()
```

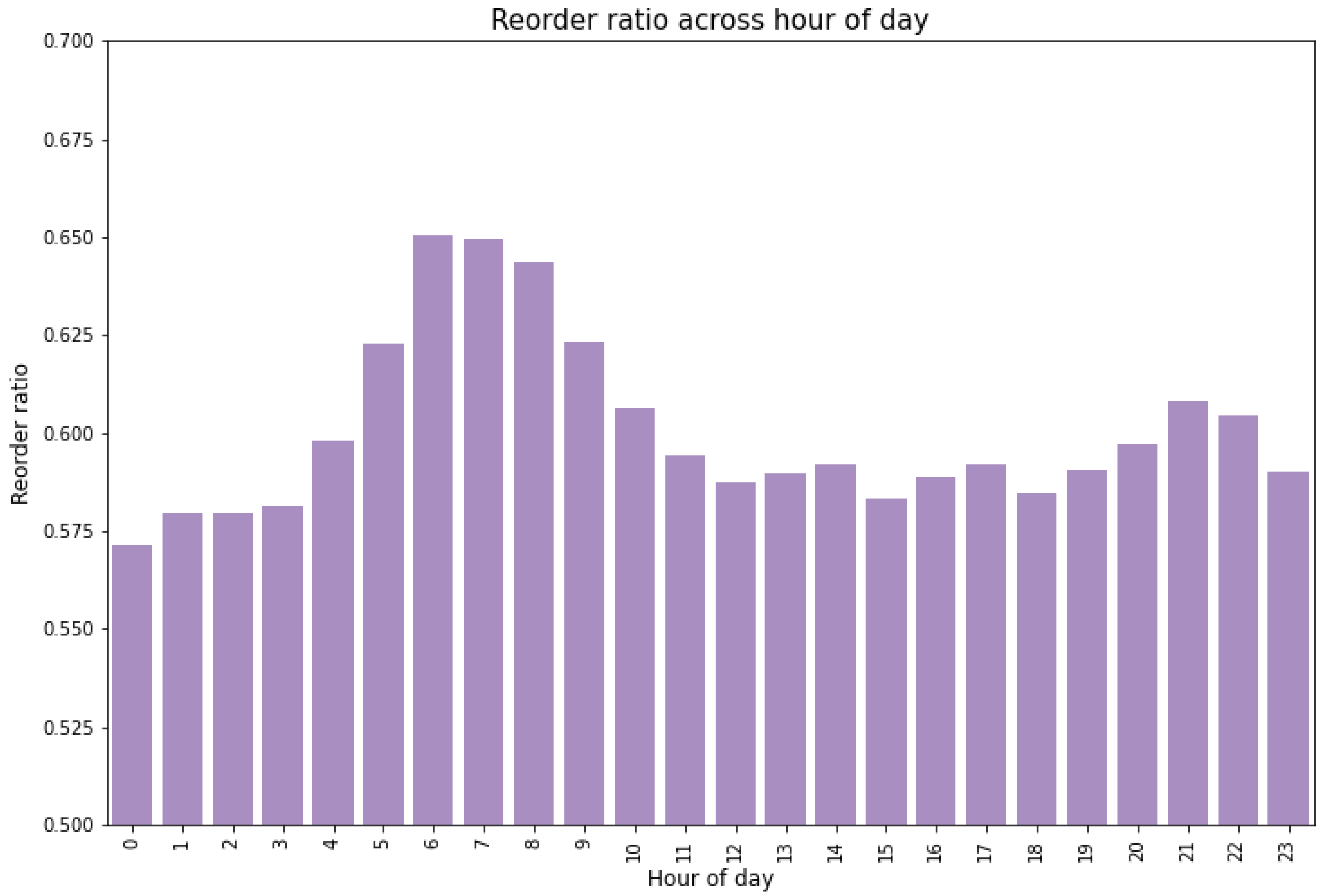
```
plt.figure(figsize=(12,8))
sns.barplot(grouped_df['order_dow'].values, grouped_df['reordered'].values, alpha=0.8, color=color[3])
plt.ylabel('Reorder ratio', fontsize=12)
plt.xlabel('Day of week', fontsize=12)
plt.title("Reorder ratio across day of week", fontsize=15)
plt.xticks(rotation='vertical')
plt.ylim(0.5, 0.7)
plt.show()
```



seems like 0 and 1 is Saturday and Sunday when the reorders are high and low during Wednesday

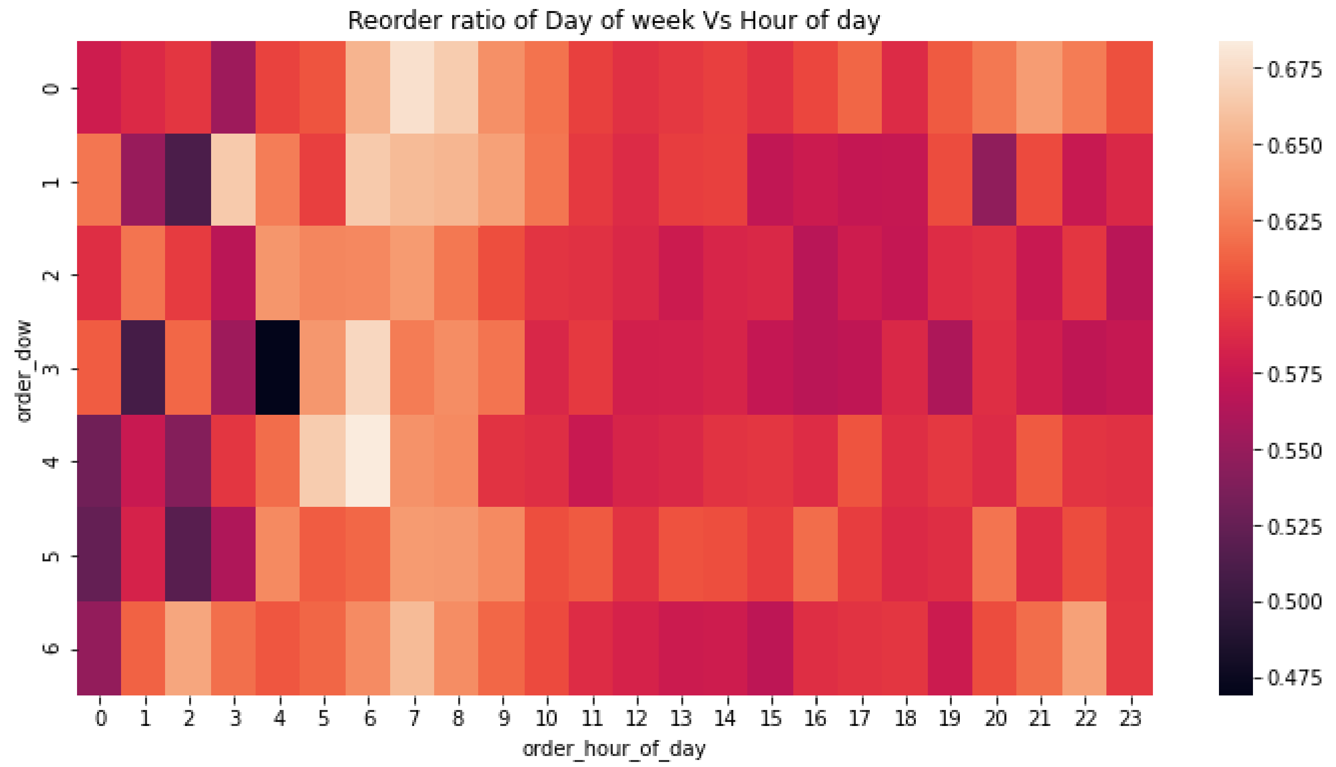
In [48]:

```
grouped_df = order_products_train_df.groupby(["order_hour_of_day"])["reordered"].aggregate("mean").reset_index()

plt.figure(figsize=(12,8))
sns.barplot(grouped_df['order_hour_of_day'].values, grouped_df['reordered'].values, alpha=0.8, color=color[4])
plt.ylabel('Reorder ratio', fontsize=12)
plt.xlabel('Hour of day', fontsize=12)
plt.title("Reorder ratio across hour of day", fontsize=15)
plt.xticks(rotation='vertical')
plt.ylim(0.5, 0.7)
plt.show()
```



In [49]:

```
grouped_df = order_products_train_df.groupby(["order_dow", "order_hour_of_day"])["reordered"].aggregate("mean").reset
grouped_df = grouped_df.pivot('order_dow', 'order_hour_of_day', 'reordered')

plt.figure(figsize=(12,6))
sns.heatmap(grouped_df)
plt.title("Reorder ratio of Day of week Vs Hour of day")
plt.show()
```



Looks like reorder ratios are quite high during the early mornings compared to later half of the day.

THANK YOU!!

BY - DEEPAK VISHWAKARMA

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In [ ]:
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