Analysing MegaMart Acquisition Target Data

This is a deep dive analysis presented to senior management at MegaMart management. MegaMart is planning to acquire another retailer to expand its market share. The company has provided MegaMart with several tables relating to thier customers and sales. After this analysis, the management at MegaMart should be able to decide whether to acquire this company or not.

Key Objectives

- Read in data from provided csv files.
- Explore the data.
- Feature engineering (add / remove columns).
- Perform different Analyses.

In [ ]:
```
import pandas as pd
import numpy as np
```

1- Read in data from provided csv files

The data files are provided in the data directory. we have two files to work with:

- project_transactions.csv
- product.csv

In [ ]:
```
# import the transaction.csv file
transactions = pd.read_csv("data/project_transactions.csv")
transactions.head()
```

Out[ ]:

	household_key	BASKET_ID	DAY	PRODUCT_ID	QUANTITY	SALES_VALUE	STORE_ID	RETAIL_DISC	WEEK_NO	COUPON_DISC	COUF
0	1364	26984896261	1	842930	1	2.19	31742	0.00	1	0.0	
1	1364	26984896261	1	897044	1	2.99	31742	-0.40	1	0.0	
2	1364	26984896261	1	920955	1	3.09	31742	0.00	1	0.0	
3	1364	26984896261	1	937406	1	2.50	31742	-0.99	1	0.0	
4	1364	26984896261	1	981760	1	0.60	31742	-0.79	1	0.0	

2- Explore the data

In [ ]:
```
# exploring data types and memory usage
transactions.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2146311 entries, 0 to 2146310
Data columns (total 11 columns):
 #   Column             Dtype  
---  ------             -----  
 0   household_key      int64  
 1   BASKET_ID          int64  
 2   DAY                int64  
 3   PRODUCT_ID         int64  
 4   QUANTITY           int64  
 5   SALES_VALUE        float64
 6   STORE_ID           int64  
 7   RETAIL_DISC        float64
 8   WEEK_NO            int64  
 9   COUPON_DISC        float64
 10  COUPON_MATCH_DISC  float64
dtypes: float64(4), int64(7)
memory usage: 180.1 MB
```

the memory usage is 180 MB, thats alot of memory. there are many columns of int64 and float64 datatypes we have to take a closer look to see if they can changed to smallest appropriate datatype.

In [ ]:
```
transactions.describe().round()
```

Out[ ]:

	household_key	BASKET_ID	DAY	PRODUCT_ID	QUANTITY	SALES_VALUE	STORE_ID	RETAIL_DISC	WEEK_NO	COUPON_DI
count	2146311.0	2.146311e+06	2146311.0	2146311.0	2146311.0	2146311.0	2146311.0	2146311.0	2146311.0	214631
mean	1056.0	3.404897e+10	390.0	2884715.0	101.0	3.0	3268.0	-1.0	56.0	-
std	605.0	4.723748e+09	190.0	3831949.0	1152.0	4.0	9122.0	1.0	27.0	
min	1.0	2.698490e+10	1.0	25671.0	0.0	0.0	1.0	-130.0	1.0	-5
25%	548.0	3.040798e+10	229.0	917231.0	1.0	1.0	330.0	-1.0	33.0	
50%	1042.0	3.281176e+10	392.0	1027960.0	1.0	2.0	372.0	0.0	57.0	
75%	1581.0	4.012804e+10	555.0	1132771.0	1.0	3.0	422.0	0.0	80.0	
max	2099.0	4.230536e+10	711.0	18316298.0	89638.0	840.0	34280.0	4.0	102.0	

Downcast numeric data.

we can downcast the following:

- household_key to int32
- DAY to int16
- PRODUCT_ID to int32
- QUANTITY to int32
- STORE_ID to int32
- WEEK_NO to int8

recall that:

- 8-bits = -128 to 127
- 16-bits = -32,768 to 32,767
- 32-bits = -2,147,483,648 to 2,147,483,647
- 64-bits = -9,223,372,036,854,775,808 to 9,223,372,036,854,775,807

In [ ]:
```
transactions = transactions.astype(
    {"household_key": "int32",
     "DAY" : "int16",
     "PRODUCT_ID":"int32",
     "QUANTITY":"int32",
     "STORE_ID":"int32",
     "WEEK_NO":"int8"
     })
```

In [ ]:
```
#lets see the memory usage now
transactions.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2146311 entries, 0 to 2146310
Data columns (total 11 columns):
 #   Column             Dtype
---  ------             -----
 0   household_key      int32
 1   BASKET_ID          int64
 2   DAY                int16
 3   PRODUCT_ID         int32
 4   QUANTITY           int32
 5   SALES_VALUE        float64
 6   STORE_ID           int32
 7   RETAIL_DISC        float64
 8   WEEK_NO            int8
 9   COUPON_DISC        float64
 10  COUPON_MATCH_DISC  float64
dtypes: float64(4), int16(1), int32(4), int64(1), int8(1)
memory usage: 120.8 MB
```

Great, that's almost 33% less memory usage.

In [ ]:
```
# check for null values
transactions.isna().sum()
```

Out[ ]:
```
household_key        0
BASKET_ID            0
DAY                  0
PRODUCT_ID           0
QUANTITY             0
SALES_VALUE          0
STORE_ID             0
RETAIL_DISC          0
WEEK_NO              0
COUPON_DISC          0
COUPON_MATCH_DISC    0
dtype: int64
```

In [ ]:
```python
# Calculate unique households in dataset with nunique (describe could also be used)
transactions["household_key"].nunique()
```
Out[ ]:
```
2099
```
In [ ]:
```python
# Calculate unique product_ids in dataset with nunique
transactions["PRODUCT_ID"].nunique()
```
Out[ ]:
```
84138
```

3- Feature engineering (add / remove columns)

In [ ]:
```python
# no need to split discoun into three different columns (RETAIL_DISC, COUPON_DISC, and COUPON_MATCH_DISCOUNT)
# We can just add them up as a total discount

transactions["total_discount"] = transactions["RETAIL_DISC"] + transactions["COUPON_DISC"] + transactions["COUP
```
In [ ]:
```python
# now lets rid of COUPON_DISC, COUPON_MATCH_DISC, and RETAIL_DISC since we have the total value
transactions = transactions.drop(["COUPON_DISC", "COUPON_MATCH_DISC","RETAIL_DISC"], axis=1)
```
In [ ]:
```python
transactions.describe()
```
Out[ ]:

	household_key	BASKET_ID	DAY	PRODUCT_ID	QUANTITY	SALES_VALUE	STORE_ID	WEEK_NO	total_discount
count	2.146311e+06	2.146311e+06	2.146311e+06	2.146311e+06	2.146311e+06	2.146311e+06	2.146311e+06	2.146311e+06	2.146311e+06
mean	1.056232e+03	3.404897e+10	3.895059e+02	2.884715e+06	1.009703e+02	3.105908e+00	3.267939e+03	5.632742e+01	-5.519609e-01
std	6.050059e+02	4.723748e+09	1.900530e+02	3.831949e+06	1.152364e+03	4.186300e+00	9.122392e+03	2.715024e+01	1.260272e+00
min	1.000000e+00	2.698490e+10	1.000000e+00	2.567100e+04	0.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00	-1.300200e+02
25%	5.480000e+02	3.040798e+10	2.290000e+02	9.172310e+05	1.000000e+00	1.290000e+00	3.300000e+02	3.300000e+01	-6.900000e-01
50%	1.042000e+03	3.281176e+10	3.920000e+02	1.027960e+06	1.000000e+00	2.000000e+00	3.720000e+02	5.700000e+01	-5.000000e-02
75%	1.581000e+03	4.012804e+10	5.550000e+02	1.132771e+06	1.000000e+00	3.490000e+00	4.220000e+02	8.000000e+01	0.000000e+00
max	2.099000e+03	4.230536e+10	7.110000e+02	1.831630e+07	8.963800e+04	8.400000e+02	3.428000e+04	1.020000e+02	3.990000e+00

In [ ]:
```python
#for some reason the total discount column have positive and negative values
#we can count how many positive and negative values are there.
print(str(transactions["total_discount"].loc[transactions["total_discount"] > 0].count())+" positive values")
print(str(transactions["total_discount"].loc[transactions["total_discount"] < 0].count())+" negative values")
```
```
32 positive values
1084950 negative values
```
It is clear that the majority of values are negative and it makes sence as they represent discount values. We can just change every negative values to be positive by multiplying by -1.

In [ ]:
```python
transactions["total_discount"] = transactions["total_discount"].apply(lambda x: -x if x < 0 else x)
```
In [ ]:
```python
# now we check again to see how many positive values are there
print(str(transactions["total_discount"].loc[transactions["total_discount"] > 0].count())+" positive values")
print(str(transactions["total_discount"].loc[transactions["total_discount"] < 0].count())+" negative values")
```
```
1084982 positive values
0 negative values
```
Great, we have no negative values.

In [ ]:
```python
#now lets add another column to calculat the percentage discount
transactions["discount_pct"] = transactions["total_discount"]/transactions["SALES_VALUE"]
```
In [ ]:
```python
transactions.head()
```
Out[ ]:

	household_key	BASKET_ID	DAY	PRODUCT_ID	QUANTITY	SALES_VALUE	STORE_ID	WEEK_NO	total_discount	discount_pct
0	1364	26984896261	1	842930	1	2.19	31742	1	0.00	0.000000
1	1364	26984896261	1	897044	1	2.99	31742	1	0.40	0.133779
2	1364	26984896261	1	920955	1	3.09	31742	1	0.00	0.000000
3	1364	26984896261	1	937406	1	2.50	31742	1	0.99	0.396000
4	1364	26984896261	1	981760	1	0.60	31742	1	0.79	1.316667

Notice the inf value in the 5th row in the discount_pct column This happened because of the division above We can solve this problem by capping the values to equal at most 1 (you can't get more than 100% discount right?)

In [ ]:
```python
transactions["discount_pct"] = transactions["discount_pct"].apply(lambda x: x if x < 1 else 1)
```
In [ ]:
```python
#lets check again.
```

```
transactions.head()
```

Out[ ]:

	household_key	BASKET_ID	DAY	PRODUCT_ID	QUANTITY	SALES_VALUE	STORE_ID	WEEK_NO	total_discount	discount_pct
0	1364	26984896261	1	842930	1	2.19	31742	1	0.00	0.000000
1	1364	26984896261	1	897044	1	2.99	31742	1	0.40	0.133779
2	1364	26984896261	1	920955	1	3.09	31742	1	0.00	0.000000
3	1364	26984896261	1	937406	1	2.50	31742	1	0.99	0.396000
4	1364	26984896261	1	981760	1	0.60	31742	1	0.79	1.000000

4- Perform different analyses

Overall Statistics

- The total sales (sum of `SALES_VALUE`),
- Total discount (sum of `total_discount`)
- Overall percentage discount (sum of total_discount / sum of sales value)
- Avg discount percentage
- Total quantity sold (sum of `QUANTITY`).
- Max quantity sold in a single row. Inspect the row as well. Does this have a high discount percentage?
- Total sales value per basket (sum of sales value / nunique basket_id).
- Total sales value per household (sum of sales value / nunique household_key).

In [ ]:
```
# The total sales
transactions["SALES_VALUE"].sum().round(2)
```

Out[ ]:
```
6666243.5
```

In [ ]:
```
# Total discount
transactions["total_discount"].sum().round(2)
```

Out[ ]:
```
1184696.9
```

In [ ]:
```
# Overall percentage discount
(transactions["total_discount"].sum()/transactions["SALES_VALUE"].sum()).round(4)
```

Out[ ]:
```
0.1777
```

In [ ]:
```
# Avg discount percentage
transactions["discount_pct"].mean()
```

Out[ ]:
```
0.21213963866213095
```

In [ ]:
```
#Total quantity sold
transactions["QUANTITY"].sum()
```

Out[ ]:
```
216713611
```

In [ ]:
```
#Max quantity sold
transactions["QUANTITY"].max()
```

Out[ ]:
```
89638
```

In [ ]:
```
#The max quantity sold has discount percentage lower that avg discount.
transactions.loc[transactions["QUANTITY"].argmax()]
```

Out[ ]:
```
household_key     6.300000e+02
BASKET_ID         3.474915e+10
DAY               5.030000e+02
PRODUCT_ID        6.534178e+06
QUANTITY          8.963800e+04
SALES_VALUE       2.500000e+02
STORE_ID          3.840000e+02
WEEK_NO           7.300000e+01
total_discount    1.345000e+01
discount_pct      5.380000e-02
Name: 1442095, dtype: float64
```

In [ ]:
```
# Sales value per basket
transactions["SALES_VALUE"].sum()/transactions["BASKET_ID"].nunique()
```

Out[ ]:
```
28.61797938516092
```

In [ ]:
```
#Sales value per household
transactions["SALES_VALUE"].sum()/transactions["household_key"].nunique()
```

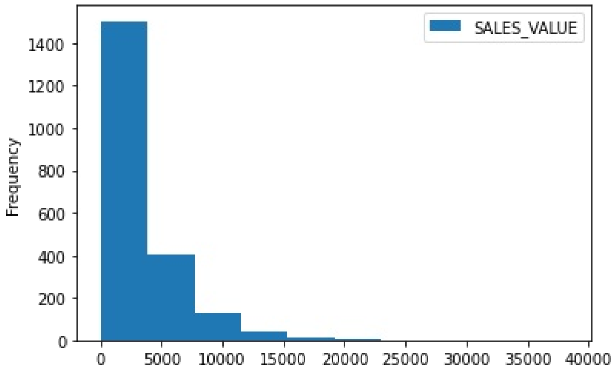
Out[ ]:
```
3175.9140066698424
```

Household Analysis

- Plot the distribution of total sales value purchased at the household level.
- What were the top 10 households by sales value?
- What were the top 10 households by quantity purchased?
- Plot the total sales value for our top 10 households by value, ordered from highest to lowest.

In [ ]:
```
#Plot the distribution of total sales value purchased at the household level.
transactions.groupby("household_key").agg({'SALES_VALUE':'sum'}).plot.hist()
```

Out[ ]: <AxesSubplot:ylabel='Frequency'>



In [ ]:
```
# store top 10 households by total value and quantity
top10_value = (transactions.groupby("household_key").agg({'SALES_VALUE': 'sum'})
 .sort_values("SALES_VALUE", ascending=False).iloc[:10])

top10_quant = (transactions.groupby("household_key").agg({"QUANTITY": "sum"})
 .sort_values("QUANTITY", ascending=False).iloc[:10])
```

In [ ]:
```
top10_value
```

Out[ ]:

household_key	SALES_VALUE
1023	38319.79
1609	27859.68
1453	21661.29
1430	20352.99
718	19299.86
707	19194.42
1653	19153.75
1111	18894.72
982	18790.34
400	18494.14

In [ ]:
```
top10_quant
```

Out[ ]:

household_key	QUANTITY
1023	4479917
755	3141769
1609	2146715
13	1863829
1430	1741892
1527	1734632
1762	1669880
707	1640193
1029	1496204
1314	1492863

In [ ]:
```
# we can use multiple aggregation to create both in a single table an option
# this here is just to use to compare to chart
```

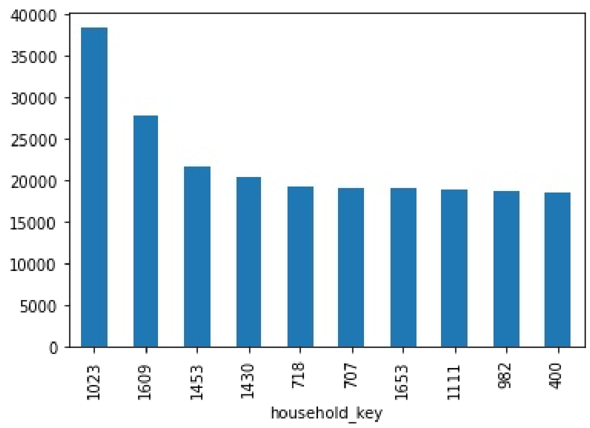
```
(transactions.groupby("household_key").agg({'SALES_VALUE': 'sum','QUANTITY': 'sum'})
 .sort_values("SALES_VALUE", ascending=False).loc[:, "SALES_VALUE"].describe()
)
```

Out[ ]:
```
count     2099.000000
mean      3175.914007
std       3287.043772
min          8.170000
25%        971.035000
50%       2145.710000
75%       4295.395000
max      38319.790000
Name: SALES_VALUE, dtype: float64
```

In [ ]:
```
# top 10 households by sales value plotted with a bar plot

top10_value["SALES_VALUE"].plot.bar()
```

Out[ ]:
```
<AxesSubplot:xlabel='household_key'>
```



Product Analysis

- Which products had the most sales by sales_value? Plot a horizontal bar chart.
- Did the top selling items have a higher than average discount rate?
- Look up the names of the top 10 products by sales in the `products.csv` dataset.
- What was the name most common `PRODUCT_ID` among rows with the households in our top 10 households by sales value?
- Look up the product name of the item that had the highest quantity sold in a single row.

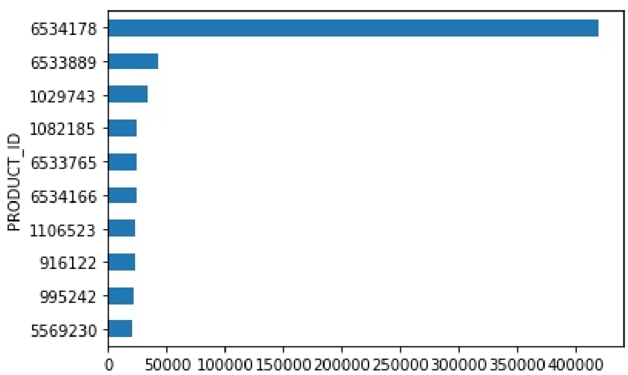
In [ ]:
```
# Create top 10 products by sales df
# group by PRODUCT_ID and sum sales value by product
# Sort in descending order and grab top 10 rows

top10_products = (transactions
                  .groupby(["PRODUCT_ID"])
                  .agg({"SALES_VALUE": "sum"})
                  .sort_values("SALES_VALUE", ascending=False)
                  .iloc[:10]
)
```

In [ ]:
```
# plot top 10 products by sale value

top10_products["SALES_VALUE"].sort_values().plot.barh()
```

Out[ ]:
```
<AxesSubplot:ylabel='PRODUCT_ID'>
```



In [ ]:
```
# Calculate the total discount for top 10 products
# Divide that by sales value for top 10 products

((transactions
 .query("PRODUCT_ID in @top10_products.index")
 .loc[: ,"total_discount"]
```

```
 .sum())
/(transactions
 .query("PRODUCT_ID in @top10_products.index")
 .loc[: ,"SALES_VALUE"]
  .sum())
)
```

Out[ ]: 0.10331343713193793

In [ ]:
```
# read in products data

products = pd.read_csv("data/product.csv")

products.head()
```

Out[ ]:

	PRODUCT_ID	MANUFACTURER	DEPARTMENT	BRAND	COMMODITY_DESC	SUB_COMMODITY_DESC	CURR_SIZE_OF_PRODUCT
0	25671	2	GROCERY	National	FRZN ICE	ICE - CRUSHED/CUBED	22 LB
1	26081	2	MISC. TRANS.	National	NO COMMODITY DESCRIPTION	NO SUBCOMMODITY DESCRIPTION	
2	26093	69	PASTRY	Private	BREAD	BREAD:ITALIAN/FRENCH	
3	26190	69	GROCERY	Private	FRUIT - SHELF STABLE	APPLE SAUCE	50 OZ
4	26355	69	GROCERY	Private	COOKIES/CONES	SPECIALTY COOKIES	14 OZ

In [ ]:
```
# Look up top 10 products for households in top10_value table
# Use query to reference index of top10_value to filter to relevant households
# Use value counts to get counts by product_id (this will be order in descending order)
# Then grab the top 10 products with iloc and extract the index to get product numbers

top_hh_products = (transactions
                   .query("household_key in @top10_value.index")
                   .loc[:, "PRODUCT_ID"]
                   .value_counts()
                   .iloc[:10]
                   .index)
```

In [ ]:
```
# Filter product table to products from prior cell
products.query("PRODUCT_ID in @top_hh_products")
```

Out[ ]:

	PRODUCT_ID	MANUFACTURER	DEPARTMENT	BRAND	COMMODITY_DESC	SUB_COMMODITY_DESC	CURR_SIZE_OF_PRODUCT
10630	860776	2	PRODUCE	National	VEGETABLES - ALL OTHERS	CUCUMBERS	36 CT
20973	951590	910	GROCERY	National	BAKED BREAD/BUNS/ROLLS	MAINSTREAM WHITE BREAD	20 OZ
24250	981760	69	GROCERY	Private	EGGS	EGGS - X-LARGE	1 DZ
29657	1029743	69	GROCERY	Private	FLUID MILK PRODUCTS	FLUID MILK WHITE ONLY	1 GA
35576	1082185	2	PRODUCE	National	TROPICAL FRUIT	BANANAS	40 LB
38262	1106523	69	GROCERY	Private	FLUID MILK PRODUCTS	FLUID MILK WHITE ONLY	1 GA
40600	1127831	5937	PRODUCE	National	BERRIES	STRAWBERRIES	16 OZ
57181	6533889	69	MISC SALES TRAN	Private	COUPON/MISC ITEMS	GASOLINE-REG UNLEADED	
57221	6534178	69	KIOSK-GAS	Private	COUPON/MISC ITEMS	GASOLINE-REG UNLEADED	
68952	9677202	69	GROCERY	Private	PAPER TOWELS	PAPER TOWELS & HOLDERS	

In [ ]:
```
# Product with highest quantity in a single row

products.query("PRODUCT_ID == 6534178")
```

Out[ ]:

	PRODUCT_ID	MANUFACTURER	DEPARTMENT	BRAND	COMMODITY_DESC	SUB_COMMODITY_DESC	CURR_SIZE_OF_PRODUCT
57221	6534178	69	KIOSK-GAS	Private	COUPON/MISC ITEMS	GASOLINE-REG UNLEADED	

In [ ]:
```
# Look up 10 product names for all customers (from first cell)

products.query("PRODUCT_ID in @top10_products.index")
```

Out[ ]:

	PRODUCT_ID	MANUFACTURER	DEPARTMENT	BRAND	COMMODITY_DESC	SUB_COMMODITY_DESC	CURR_SIZE_OF_PRODUCT
16863	916122	4314	MEAT	National	CHICKEN	CHICKEN BREAST BONELESS	
25754	995242	69	GROCERY	Private	FLUID MILK PRODUCTS	FLUID MILK WHITE ONLY	
29657	1029743	69	GROCERY	Private	FLUID MILK PRODUCTS	FLUID MILK WHITE ONLY	1 GA
35576	1082185	2	PRODUCE	National	TROPICAL FRUIT	BANANAS	40 LB
38262	1106523	69	GROCERY	Private	FLUID MILK PRODUCTS	FLUID MILK WHITE ONLY	1 GA
53097	5569230	1208	GROCERY	National	SOFT DRINKS	SOFT DRINKS 12/18&15PK CAN CAR	12 OZ
57171	6533765	69	KIOSK-GAS	Private	FUEL	GASOLINE-REG UNLEADED	
57181	6533889	69	MISC SALES TRAN	Private	COUPON/MISC ITEMS	GASOLINE-REG UNLEADED	
57216	6534166	69	MISC SALES TRAN	Private	COUPON/MISC ITEMS	GASOLINE-REG UNLEADED	
57221	6534178	69	KIOSK-GAS	Private	COUPON/MISC ITEMS	GASOLINE-REG UNLEADED	

In [ ]:

```
# Use the following snippet to create a Date Column then drop. Then drop the `Day` and `Week_no` columns.

transactions = (transactions
                .assign(date =
                        (pd.to_datetime("2016", format='%Y')
                        + pd.to_timedelta(transactions["DAY"].sub(1).astype(str) + " days"))
                       )
                .drop(["DAY"], axis=1)
               )
```

In [ ]:

```
transactions.head()
```

Out[ ]:

	household_key	BASKET_ID	PRODUCT_ID	QUANTITY	SALES_VALUE	STORE_ID	WEEK_NO	total_discount	discount_pct	date
0	1364	26984896261	842930	1	2.19	31742	1	0.00	0.000000	2016-01-01
1	1364	26984896261	897044	1	2.99	31742	1	0.40	0.133779	2016-01-01
2	1364	26984896261	920955	1	3.09	31742	1	0.00	0.000000	2016-01-01
3	1364	26984896261	937406	1	2.50	31742	1	0.99	0.396000	2016-01-01
4	1364	26984896261	981760	1	0.60	31742	1	0.79	1.000000	2016-01-01

TIME BASED ANALYSIS

- Plot the sum of sales by month. Are sales growing over time?
- Plot the same series after filtering down to dates April 2016 and October 2017.
- Plot the sum of sales 2016 vs the 2017 sales.
- Plot total sales by day of week.

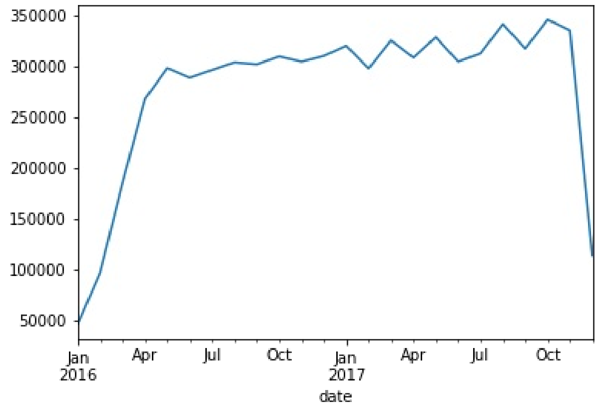
In [ ]:

```
# Set a date index, graby the sales column, and calculate a monthly sum using resampling.
# Then build the default line plot

(transactions.set_index("date")
 .loc[:, "SALES_VALUE"]
 .resample("M")
 .sum()
 .plot())
```

Out[ ]:

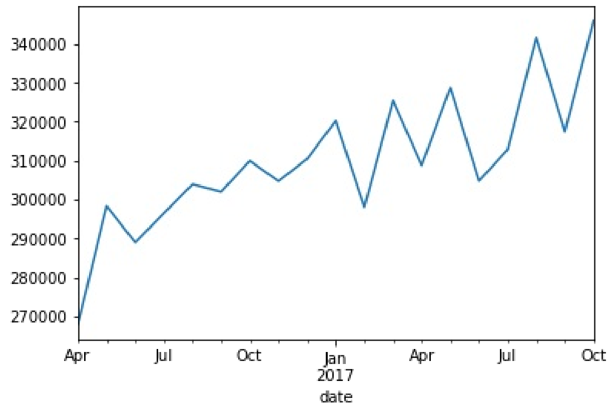
```
<AxesSubplot:xlabel='date'>
```



In [ ]:

```
# Filter above plot to specified date range with row slice in .loc
(transactions
 .set_index("date")
 .loc["2016-04":"2017-10", "SALES_VALUE"]
 .resample("M")
 .sum()
 .plot())
```

Out[ ]: <AxesSubplot:xlabel='date'>

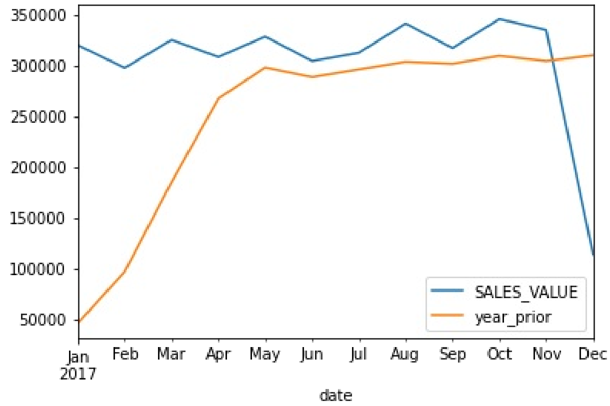


In [ ]:

```
# After resampling monthly sales, create a year_prior column with assign
# This column is our monthly sales shifted forward a year (12 rows/months)

(transactions
 .set_index("date")
 .loc[:, ["SALES_VALUE"]]
 .resample("M")
 .sum()
 .assign(year_prior = lambda x: x["SALES_VALUE"].shift(12))
 .loc["2017"]
 .plot())
```

Out[ ]: <AxesSubplot:xlabel='date'>

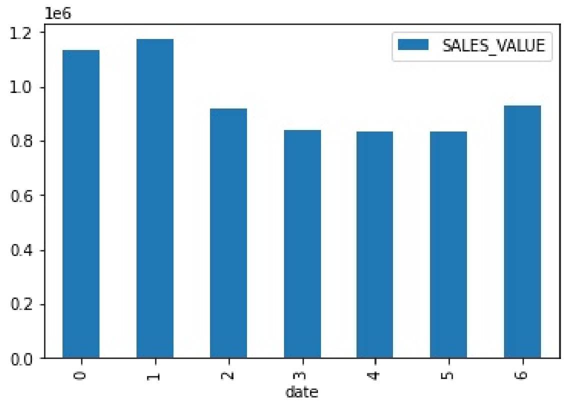


In [ ]:

```
# Group transactions by dayofweek, then calculate sum and plot a bar chart
(transactions
 .groupby(transactions["date"].dt.dayofweek)
 .agg({"SALES_VALUE": "sum"})
 .plot.bar()
)
```

Out[ ]:

```
<AxesSubplot:xlabel='date'>
```



DEMOGRAPHICS

- Read in the `hh_demographic.csv` file.
- Group the transactions table by household_id, and calculate the sum of SALES VALUE by household.
- Join the demographics DataFrame to the transactions table. Since we're interested in analyzing the demographic data we have.
- Plot the sum of sales by age_desc and income_desc.
- Create a pivot table of the mean household sales by `AGE_DESC` and `HH_COMP_DESC`.

In [ ]:

```
# Specify columns to include
dem_cols = ["AGE_DESC", "INCOME_DESC", "household_key", "HH_COMP_DESC"]

# Convert the object columns here to category dtype
dem_dtypes = {"AGE_DESC": "category", "INCOME_DESC": "category", "HH_COMP_DESC":"category"}

demographics = pd.read_csv('data/hh_demographic.csv',
                          usecols=dem_cols,
                          dtype=dem_dtypes
                          )
```

In [ ]:

```
demographics.head()
```

Out[ ]:

	AGE_DESC	INCOME_DESC	HH_COMP_DESC	household_key
0	65+	35-49K	2 Adults No Kids	1
1	45-54	50-74K	2 Adults No Kids	7
2	25-34	25-34K	2 Adults Kids	8
3	25-34	75-99K	2 Adults Kids	13
4	45-54	50-74K	Single Female	16

In [ ]:

```
demographics.info(memory_usage="deep")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 801 entries, 0 to 800
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   AGE_DESC       801 non-null    category
 1   INCOME_DESC    801 non-null    category
 2   HH_COMP_DESC   801 non-null    category
 3   household_key  801 non-null    int64
dtypes: category(3), int64(1)
memory usage: 10.9 KB
```

In [ ]:

```
# Create total sales by household dataframe

household_sales = (transactions
                   .groupby("household_key")
                   .agg({"SALES_VALUE": "sum"})
                  )

household_sales
```

Out[ ]:

	SALES_VALUE
household_key	
1	4330.16
2	1954.34
3	2653.21
4	1200.11
5	779.06
...	...
2095	3790.49
2096	1301.65
2097	8823.83
2098	682.46
2099	691.30

2099 rows × 1 columns

In [ ]:

```
# Join household sales and demographics table on household_key (inner since we're interested in both sets)

household_sales_demo = (household_sales.merge(demographics,
                             how="inner",
                             left_on='household_key',
                             right_on="household_key",
                             )
                       )
```

In [ ]:

```
household_sales_demo.info(memory_usage="deep")
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 668 entries, 0 to 667
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   household_key  668 non-null    int64
 1   SALES_VALUE    668 non-null    float64
 2   AGE_DESC       668 non-null    category
 3   INCOME_DESC    668 non-null    category
 4   HH_COMP_DESC   668 non-null    category
dtypes: category(3), float64(1), int64(1)
memory usage: 19.8 KB
```

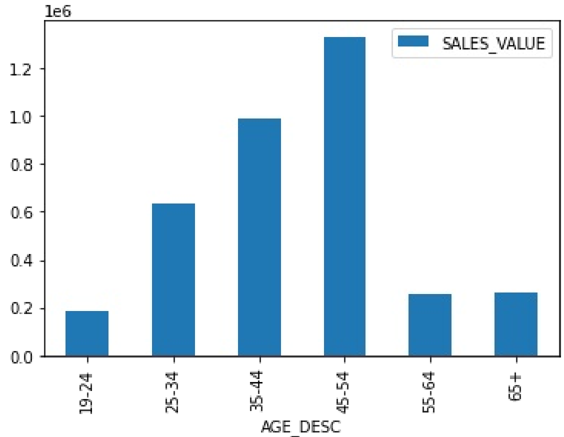
In [ ]:

```
# Calculate sum of sales by age group

(household_sales_demo
.groupby(["AGE_DESC"])
.agg({"SALES_VALUE": "sum"})
```

```
.plot.bar()
)
```

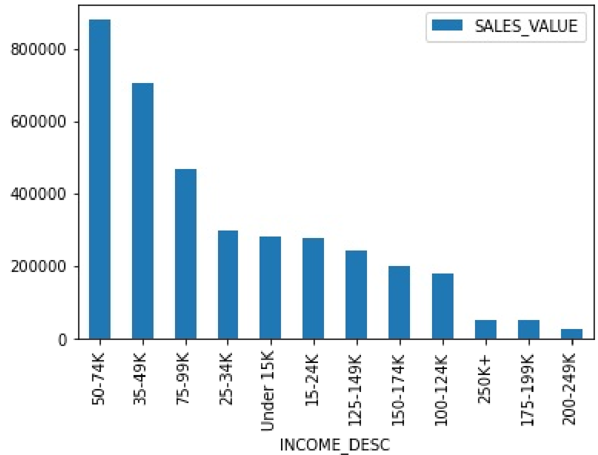
Out[ ]: <AxesSubplot:xlabel='AGE_DESC'>



In [ ]:
```
# Calculate sum of sales by income, ordered by magnitude

(household_sales_demo.groupby(["INCOME_DESC"])
.agg({"SALES_VALUE": "sum"})
.sort_values("SALES_VALUE", ascending=False)
.plot.bar())
```

Out[ ]: <AxesSubplot:xlabel='INCOME_DESC'>



In [ ]:
```
# Calculate mean household spend by Age Description and HH Composition
# Format with a heatmap across all cells

(household_sales_demo.pivot_table(index="AGE_DESC",
                 columns="HH_COMP_DESC",
                 values="SALES_VALUE",
                 aggfunc="mean",
                 margins=True)
 .style.background_gradient(cmap="RdYlGn", axis=None)
)
```

Out[ ]:

HH_COMP_DESC	1 Adult Kids	2 Adults Kids	2 Adults No Kids	Single Female	Single Male	Unknown	All
AGE_DESC							
19-24	7268.796667	5428.945000	4020.800000	4576.095556	3216.835000	4911.275000	4692.077692
25-34	5512.196875	5753.973514	5638.515833	4807.440588	4909.522381	7356.270000	5435.517521
35-44	6297.737778	6691.772264	6260.412444	6015.192069	4844.192000	4227.691818	6090.556728
45-54	6632.569167	6610.484490	5839.527027	4549.365405	4636.637083	4843.995682	5534.879958
55-64	3064.870000	4695.655000	5752.413684	4816.148462	3922.546250	7973.750000	5168.924200
65+	4040.810000	5536.866667	4614.108571	4059.699412	3871.556000	2879.290000	4340.936500
All	6032.802143	6280.069103	5599.857756	4895.928361	4544.646750	4936.127778	5468.398743

PRODUCT DEMOGRAPHICS

- Read in the product csv file.
- Only read in product_id and department from product (consider converting columns).

- Join the product DataFrame to transactions and demographics tables, performing an inner join when joining both tables.
- Pivot the fully joined dataframe by AGE_DESC and DEPARTMENT, calculating the sum of sales.

In [ ]:
```
# specify columns to use
product_cols = ["PRODUCT_ID", "DEPARTMENT"]

# specify datatypes for each column
product_dtypes = {"PRODUCT_ID": "Int32", "DEPARTMENT": "category"}

product = pd.read_csv('data/product.csv',
                      usecols=product_cols,
                      dtype=product_dtypes)
```

In [ ]:
```
product.dtypes
```

Out[ ]:
```
PRODUCT_ID       Int32
DEPARTMENT    category
dtype: object
```

In [ ]:
```
# Join all three tables together with an inner join
# Join product on product_id (only shared column)
trans_demo_dept = (transactions
                   .merge(demographics,
                          how="inner",
                          left_on='household_key',
                          right_on="household_key",)
                   .merge(product,
                          how="inner",
                          left_on="PRODUCT_ID",
                          right_on="PRODUCT_ID")

             )
```

In [ ]:
```
# much smaller than our original, uncoverted transactions df!
trans_demo_dept.info(memory_usage="deep")
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1161575 entries, 0 to 1161574
Data columns (total 14 columns):
 #   Column          Non-Null Count    Dtype
---  ------          --------------    -----
 0   household_key   1161575 non-null  int32
 1   BASKET_ID       1161575 non-null  int64
 2   PRODUCT_ID      1161575 non-null  int32
 3   QUANTITY        1161575 non-null  int32
 4   SALES_VALUE     1161575 non-null  float64
 5   STORE_ID        1161575 non-null  int32
 6   WEEK_NO         1161575 non-null  int8
 7   total_discount  1161575 non-null  float64
 8   discount_pct    1161575 non-null  float64
 9   date            1161575 non-null  datetime64[ns]
 10  AGE_DESC        1161575 non-null  category
 11  INCOME_DESC     1161575 non-null  category
 12  HH_COMP_DESC    1161575 non-null  category
 13  DEPARTMENT      1161575 non-null  category
dtypes: category(4), datetime64[ns](1), float64(3), int32(4), int64(1), int8(1)
memory usage: 76.4 MB
```

In [ ]:
```
# Where does our youngest demographic rank near the top in sales?

(trans_demo_dept.pivot_table(index="DEPARTMENT",
                             columns="AGE_DESC",
                             values="SALES_VALUE",
                             aggfunc="sum")
 .style.background_gradient(cmap="RdYlGn", axis=1))
```

Out[ ]:

AGE_DESC	19-24	25-34	35-44	45-54	55-64	65+
DEPARTMENT						
	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
AUTOMOTIVE	11.640000	21.250000	72.580000	55.920000	0.000000	16.370000
CHARITABLE CONT	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
CHEF SHOPPE	81.300000	134.160000	348.530000	418.240000	80.860000	149.240000
CNTRL/STORE SUP	2.000000	0.000000	1.000000	9.950000	2.000000	0.100000
COSMETICS	698.630000	2273.030000	4362.020000	5187.570000	986.260000	600.900000
COUP/STR & MFG	7.490000	48.420000	121.200000	154.550000	40.680000	20.490000
DAIRY DELI	3.800000	3.850000	7.390000	16.750000	3.140000	1.940000
DELI	4043.300000	18181.940000	34577.290000	44334.220000	9850.540000	10462.330000
DELI/SNACK BAR	0.000000	0.000000	6.980000	1.560000	0.000000	3.310000
DRUG GM	25297.430000	85298.050000	126480.340000	177007.130000	29220.930000	32759.760000
ELECT &PLUMBING	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
FLORAL	776.990000	2355.570000	5246.600000	6835.690000	1112.690000	1160.220000
FROZEN GROCERY	1.640000	53.050000	108.960000	84.500000	54.220000	20.190000
GARDEN CENTER	41.980000	380.110000	701.830000	1487.900000	248.070000	441.810000
GM MERCH EXP	0.000000	0.000000	17.760000	30.370000	12.050000	2.950000
GRO BAKERY	0.000000	0.000000	0.000000	2.180000	0.000000	0.000000
GROCERY	99008.270000	327926.160000	490616.030000	667162.980000	127082.010000	129117.270000
HBC	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
HOUSEWARES	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
KIOSK-GAS	8465.180000	50817.910000	92614.660000	96858.440000	16329.770000	17853.990000
MEAT	11957.340000	37162.660000	61003.950000	87407.670000	20001.910000	17514.190000
MEAT-PCKGD	10453.130000	30029.690000	46499.110000	59855.460000	11891.430000	10413.650000
MEAT-WHSE	0.000000	0.000000	1.000000	4.000000	1.000000	0.000000
MISC SALES TRAN	2031.730000	8200.660000	9976.190000	23617.850000	7762.980000	2657.760000
MISC. TRANS.	73.520000	757.370000	1334.700000	859.080000	688.730000	142.630000
NUTRITION	1146.400000	11067.450000	15941.860000	16366.510000	2504.010000	3114.280000
PASTRY	2386.730000	8161.420000	13706.810000	19534.790000	3601.860000	5162.800000
PHARMACY SUPPLY	0.000000	5.970000	3.980000	1.990000	0.000000	0.000000
PHOTO	4.980000	5.190000	6.980000	2.490000	0.000000	1.990000
PORK	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
POSTAL CENTER	0.000000	0.000000	0.000000	5.960000	1.000000	0.330000
PROD-WHS SALES	0.000000	0.000000	2.520000	5.000000	0.000000	0.000000
PRODUCE	10170.590000	41706.460000	67779.890000	96442.730000	21326.150000	23295.780000
RESTAURANT	1.390000	389.040000	234.110000	540.310000	33.900000	30.650000
RX	0.000000	0.000000	26.880000	26.780000	0.000000	10.990000
SALAD BAR	1330.150000	2050.060000	3631.810000	4770.150000	925.770000	1677.880000
SEAFOOD	461.180000	2080.940000	3101.910000	5551.320000	1363.950000	1341.450000
SEAFOOD-PCKGD	1500.270000	4189.130000	6346.770000	10079.840000	2975.970000	2206.100000
SPIRITS	2983.750000	2474.460000	1491.370000	3218.340000	263.180000	141.640000
TOYS	0.000000	0.000000	0.000000	1.490000	0.000000	0.000000
TRAVEL & LEISUR	50.220000	173.560000	283.190000	431.480000	81.150000	133.200000
VIDEO	0.000000	7.990000	13.990000	0.000000	0.000000	0.000000
VIDEO RENTAL	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

EXPORT

Export your pivot table to an excel file.

In [ ]:

```
# Call to_excel on pivot table above - note the formatting gets passed to excel too!

(trans_demo_dept.pivot_table(index="DEPARTMENT",
                             columns="AGE_DESC",
                             values="SALES_VALUE",
                             aggfunc="sum")
```

```
 .style.background_gradient(cmap="RdYlGn", axis=1)
 .to_excel("demographic_category_sales.xlsx", sheet_name="sales_pivot")
)
```

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