Retina_ai

March 6, 2018

1 Section 1 - Data Gathering

Given this table: create table page_table(visitor_id int, visit_date date, page_name varchar(100))
1.1 How would you look at 10 sample rows in this table?
SELECT visitor_id, visit_date, page_name
FROM page_table
LIMIT 10;
1.2 How would you look at visitors who saw the 'home page' or the 'checkout page'?
SELECT DISTINCT visitor_id
FROM page_table
WHERE page_name in ('home page', 'checkout page');
1.3 Get a list of 100 visitors who saw the most pages
SELECT visitor_id, COUNT(DISTINCT page_name)
FROM page_table
GROUP BY visitor_id
ORDER BY COUNT(DISTINCT page_name) DESC
LIMIT 100;

2 SECTION 2 - DATA PROCESSING / ANALYSIS

```
In [1]: # Let's download and unzip the files
        !rm *csv *zip*
        !wget https://s3.amazonaws.com/retina-public-datasets/data-scientist-assignment/weekly_s
        !unzip -o weekly_sales.zip
```

```
--2018-03-07 00:56:15--  https://s3.amazonaws.com/retina-public-datasets/data-scientist-assignme
Resolving s3.amazonaws.com (s3.amazonaws.com)... 54.231.82.250
Connecting to s3.amazonaws.com (s3.amazonaws.com)|54.231.82.250|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 872049 (852K) [application/zip]
Saving to: weekly_sales.zip

weekly_sales.zip    100%[===================>] 851.61K   772KB/s    in 1.1s

2018-03-07 00:56:16 (772 KB/s) - weekly_sales.zip saved [872049/872049]

Archive:  weekly_sales.zip
```

```
inflating: sales_week_starting_2012-10-01.csv
inflating: __MACOSX/._sales_week_starting_2012-10-01.csv
inflating: sales_week_starting_2012-10-08.csv
inflating: __MACOSX/._sales_week_starting_2012-10-08.csv
inflating: sales_week_starting_2012-10-15.csv
inflating: __MACOSX/._sales_week_starting_2012-10-15.csv
inflating: sales_week_starting_2012-10-22.csv
inflating: __MACOSX/._sales_week_starting_2012-10-22.csv
inflating: sales_week_starting_2012-10-29.csv
inflating: __MACOSX/._sales_week_starting_2012-10-29.csv
inflating: sales_week_starting_2012-11-05.csv
inflating: __MACOSX/._sales_week_starting_2012-11-05.csv
inflating: sales_week_starting_2012-11-12.csv
inflating: __MACOSX/._sales_week_starting_2012-11-12.csv
inflating: sales_week_starting_2012-11-19.csv
inflating: __MACOSX/._sales_week_starting_2012-11-19.csv
inflating: sales_week_starting_2012-11-26.csv
inflating: __MACOSX/._sales_week_starting_2012-11-26.csv
inflating: sales_week_starting_2012-12-03.csv
inflating: __MACOSX/._sales_week_starting_2012-12-03.csv
inflating: sales_week_starting_2012-12-10.csv
inflating: __MACOSX/._sales_week_starting_2012-12-10.csv
inflating: sales_week_starting_2012-12-17.csv
inflating: __MACOSX/._sales_week_starting_2012-12-17.csv
inflating: sales_week_starting_2012-12-24.csv
inflating: __MACOSX/._sales_week_starting_2012-12-24.csv
inflating: sales_week_starting_2012-12-31.csv
inflating: __MACOSX/._sales_week_starting_2012-12-31.csv
inflating: sales_week_starting_2013-01-07.csv
inflating: __MACOSX/._sales_week_starting_2013-01-07.csv
inflating: sales_week_starting_2013-01-14.csv
inflating: __MACOSX/._sales_week_starting_2013-01-14.csv
inflating: sales_week_starting_2013-01-21.csv
inflating: __MACOSX/._sales_week_starting_2013-01-21.csv
inflating: sales_week_starting_2013-01-28.csv
inflating: __MACOSX/._sales_week_starting_2013-01-28.csv
inflating: sales_week_starting_2013-02-04.csv
inflating: __MACOSX/._sales_week_starting_2013-02-04.csv
inflating: sales_week_starting_2013-02-11.csv
inflating: __MACOSX/._sales_week_starting_2013-02-11.csv
inflating: sales_week_starting_2013-02-18.csv
inflating: __MACOSX/._sales_week_starting_2013-02-18.csv
inflating: sales_week_starting_2013-02-25.csv
inflating: __MACOSX/._sales_week_starting_2013-02-25.csv
inflating: sales_week_starting_2013-03-04.csv
inflating: __MACOSX/._sales_week_starting_2013-03-04.csv
inflating: sales_week_starting_2013-03-11.csv
inflating: __MACOSX/._sales_week_starting_2013-03-11.csv
```

```
inflating: sales_week_starting_2013-03-18.csv
inflating: __MACOSX/._sales_week_starting_2013-03-18.csv
inflating: sales_week_starting_2013-03-25.csv
inflating: __MACOSX/._sales_week_starting_2013-03-25.csv
inflating: sales_week_starting_2013-04-01.csv
inflating: __MACOSX/._sales_week_starting_2013-04-01.csv
inflating: sales_week_starting_2013-04-08.csv
inflating: __MACOSX/._sales_week_starting_2013-04-08.csv
inflating: sales_week_starting_2013-04-15.csv
inflating: __MACOSX/._sales_week_starting_2013-04-15.csv
inflating: sales_week_starting_2013-04-22.csv
inflating: __MACOSX/._sales_week_starting_2013-04-22.csv
inflating: sales_week_starting_2013-04-29.csv
inflating: __MACOSX/._sales_week_starting_2013-04-29.csv
inflating: sales_week_starting_2013-05-06.csv
inflating: __MACOSX/._sales_week_starting_2013-05-06.csv
inflating: sales_week_starting_2013-05-13.csv
inflating: __MACOSX/._sales_week_starting_2013-05-13.csv
inflating: sales_week_starting_2013-05-20.csv
inflating: __MACOSX/._sales_week_starting_2013-05-20.csv
inflating: sales_week_starting_2013-05-27.csv
inflating: __MACOSX/._sales_week_starting_2013-05-27.csv
inflating: sales_week_starting_2013-06-03.csv
inflating: __MACOSX/._sales_week_starting_2013-06-03.csv
inflating: sales_week_starting_2013-06-10.csv
inflating: __MACOSX/._sales_week_starting_2013-06-10.csv
inflating: sales_week_starting_2013-06-17.csv
inflating: __MACOSX/._sales_week_starting_2013-06-17.csv
inflating: sales_week_starting_2013-06-24.csv
inflating: __MACOSX/._sales_week_starting_2013-06-24.csv
inflating: sales_week_starting_2013-07-01.csv
inflating: __MACOSX/._sales_week_starting_2013-07-01.csv
inflating: sales_week_starting_2013-07-08.csv
inflating: __MACOSX/._sales_week_starting_2013-07-08.csv
inflating: sales_week_starting_2013-07-15.csv
inflating: __MACOSX/._sales_week_starting_2013-07-15.csv
inflating: sales_week_starting_2013-07-22.csv
inflating: __MACOSX/._sales_week_starting_2013-07-22.csv
inflating: sales_week_starting_2013-07-29.csv
inflating: __MACOSX/._sales_week_starting_2013-07-29.csv
inflating: sales_week_starting_2013-08-05.csv
inflating: __MACOSX/._sales_week_starting_2013-08-05.csv
inflating: sales_week_starting_2013-08-12.csv
inflating: __MACOSX/._sales_week_starting_2013-08-12.csv
inflating: sales_week_starting_2013-08-19.csv
inflating: __MACOSX/._sales_week_starting_2013-08-19.csv
inflating: sales_week_starting_2013-08-26.csv
inflating: __MACOSX/._sales_week_starting_2013-08-26.csv
```

```
  inflating: sales_week_starting_2013-09-02.csv
  inflating: __MACOSX/._sales_week_starting_2013-09-02.csv
  inflating: sales_week_starting_2013-09-09.csv
  inflating: __MACOSX/._sales_week_starting_2013-09-09.csv
```

```
In [2]: # Take a peek at one of the csv files
        !head sales_week_starting_2012-10-01.csv
```

```
sale_time,purchaser_gender
2012-10-01 01:42:22,female
2012-10-01 02:24:53,female
2012-10-01 02:25:40,female
2012-10-01 02:30:42,female
2012-10-01 02:51:32,male
2012-10-01 03:03:00,female
2012-10-01 03:09:10,female
2012-10-01 03:09:40,male
2012-10-01 03:16:08,female
```

```
In [3]: '''
        Try to read the files and create a big dataframe for them
        '''
        import glob
        import pandas as pd

        # get data file names
        allFiles = glob.glob("sales*.csv")
        frame = pd.DataFrame()
        list_ = []
        for file_ in sorted(allFiles):
            #print(file_)
            df = pd.read_csv(file_,index_col="sale_time", header=0, parse_dates=[0])
            #print(df.count())
            list_.append(df)
        frame = pd.concat(list_)
        print(frame.count())
```

```
purchaser_gender    204329
dtype: int64
```

```
In [4]: # Look at the first few rows
        frame.head()
```

```
Out[4]:                     purchaser_gender
        sale_time
        2012-10-01 01:42:22           female
```

```
2012-10-01 02:24:53          female
2012-10-01 02:25:40          female
2012-10-01 02:30:42          female
2012-10-01 02:51:32            male
```

In [5]:
```
# Look at the last few rows to make sure the dates look correct
frame.tail()
```

Out[5]:
```
                    purchaser_gender
sale_time
2013-09-15 23:30:51          female
2013-09-15 23:42:02          female
2013-09-15 23:43:24            male
2013-09-15 23:43:32            male
2013-09-15 23:48:47            male
```

In [6]:
```
frame.describe()
```

Out[6]:
```
       purchaser_gender
count            204329
unique                2
top              female
freq             107740
```

In [7]:
```
# Check for null values
frame.isna().any()
```

Out[7]:
```
purchaser_gender    False
dtype: bool
```

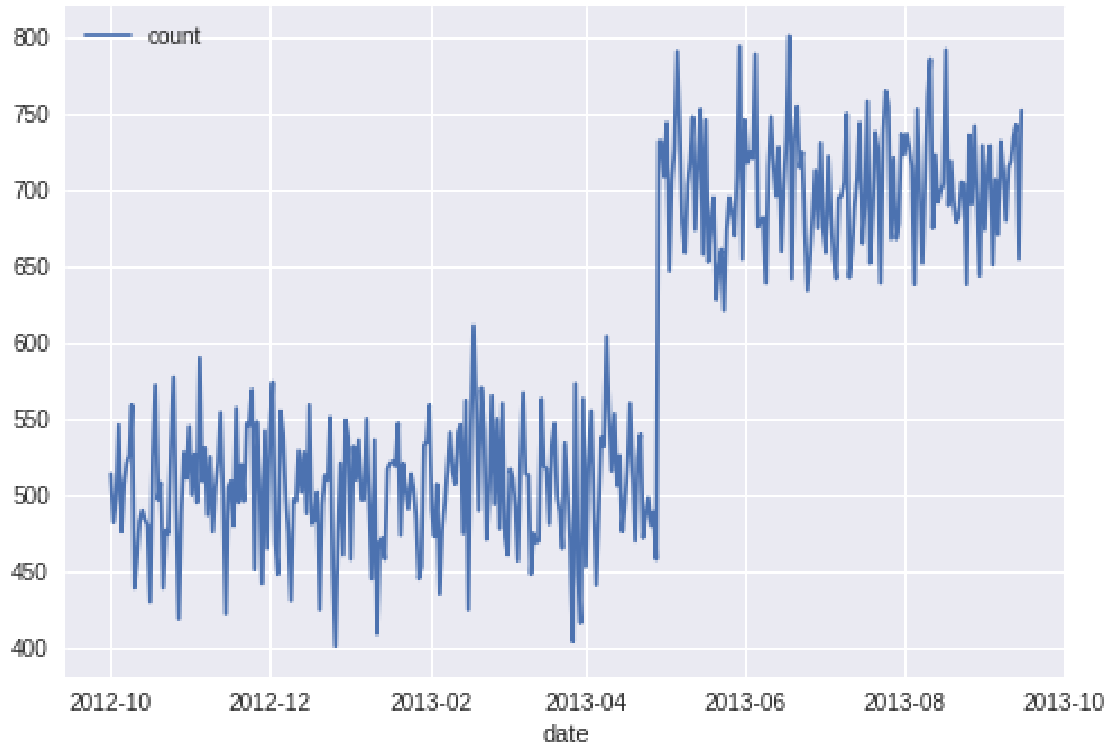
In [8]:
```
# Create date column to be used for the next question
df = frame.copy()
df['date'] = df.index.date
df.head()
```

Out[8]:
```
                    purchaser_gender        date
sale_time
2012-10-01 01:42:22          female  2012-10-01
2012-10-01 02:24:53          female  2012-10-01
2012-10-01 02:25:40          female  2012-10-01
2012-10-01 02:30:42          female  2012-10-01
2012-10-01 02:51:32            male  2012-10-01
```

2.0.1 2.1 Plot the number of daily sales for all 50 weeks

In [9]:
```
daily = df.groupby('date').count()
daily.columns = ['count']
daily.plot()
```

Out[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8400447f60>
```



2.0.2 2.2 It looks like there has been a sudden change in daily sales. On what date was that sudden change?

It looks like some time in 2013-05 has a sudden change/increase in daily sales. Let's dive into details of the data between 2013/04/15 and 2013/05/15 to find the exact date when it happened

```
In [10]: from datetime import datetime
         def to_date(s):
           return datetime.strptime(s, '%Y%m%d').date()

         daily[(daily.index >  to_date('20130415')) & (daily.index <  to_date('20130515'))]
```

```
Out[10]:             count
         date
         2013-04-16    494
         2013-04-17    518
         2013-04-18    560
         2013-04-19    516
         2013-04-20    470
         2013-04-21    524
         2013-04-22    540
         2013-04-23    472
         2013-04-24    487
```

```
2013-04-25    498
2013-04-26    480
2013-04-27    489
2013-04-28    458
2013-04-29    732
2013-04-30    732
2013-05-01    709
2013-05-02    744
2013-05-03    647
2013-05-04    707
2013-05-05    728
2013-05-06    791
2013-05-07    743
2013-05-08    679
2013-05-09    659
2013-05-10    703
2013-05-11    719
2013-05-12    748
2013-05-13    674
2013-05-14    719
```

The data shows that 2013-04-29 was when the sudden increase in sales happened!

2.0.3 2.3 Is the change in daily sales at the date you selected statistically significant? If so, what is the p-value? How would you describe this statistical significance to a non-technical individual?

In a two-sample t-test, the null hypothesis is that the means of both groups are the same. I will run this to test the hypothesis:

```
In [11]: # Create 2 datasets: before and after change
         before_change = daily[daily.index < to_date('20130429')]
         after_change = daily[daily.index >= to_date('20130429')]
         print(before_change.describe() )
         print(after_change.describe() )
```

```
            count
count  210.000000
mean   504.400000
std     40.001579
min    401.000000
25%    477.000000
50%    504.500000
75%    533.750000
max    611.000000
            count
count  140.000000
mean   702.892857
std     39.324640
```

```
min      621.000000
25%      674.000000
50%      704.500000
75%      731.250000
max      801.000000
```

In [12]:
```
'''
Run 2-sample t-test to compare the 2 datasets
'''
import scipy.stats as stats
stats.ttest_ind(a= before_change,
                b= after_change,
                equal_var=False)    # Assume samples have equal variance?
```

Out[12]:
```
Ttest_indResult(statistic=array([-45.94353319]), pvalue=array([3.48724685e-138]))
```

p-value is significant low (3.48724685e-138 ~ 0) so we can reject null hypothesis that the means of the both groups are the same. In other words, the change in daily sales is statistically significant.

An explanation of statistical significance to non-technical individual: statistical significance is a concept used to provide justification for accepting or rejecting a given hypothesis; it means that hypothesis being tested is unlikely to have arisen randomly (by chance)

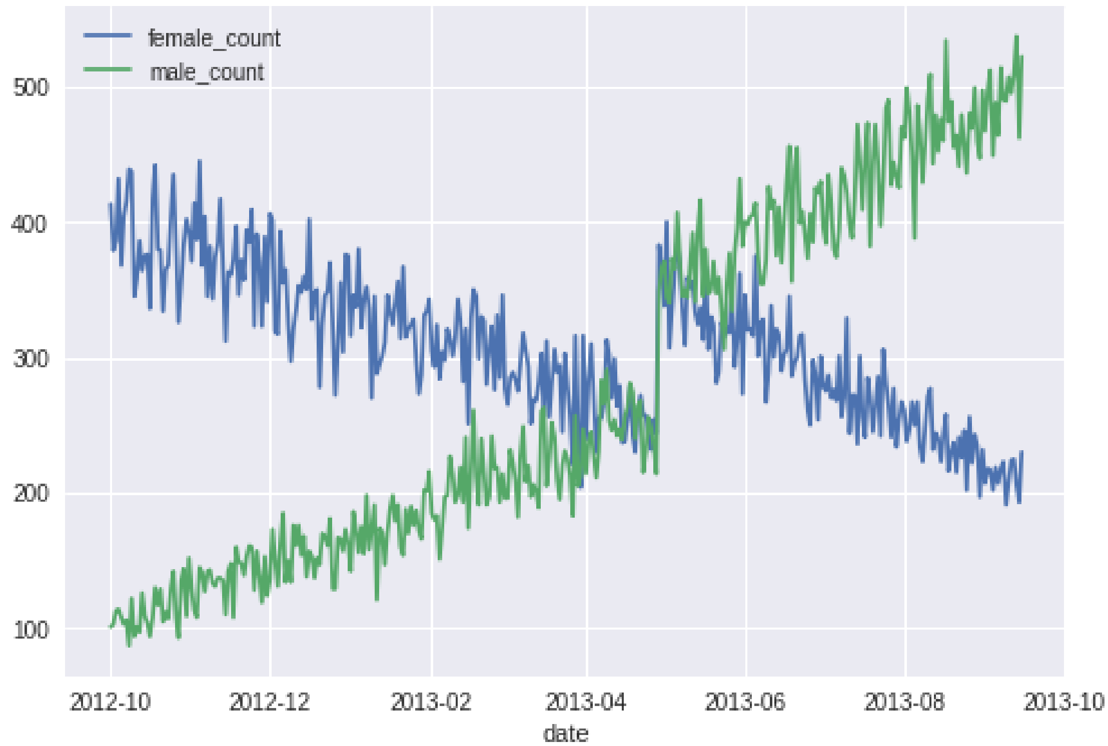
2.0.4 2.4 - Does the data suggest that the change in daily sales is due to a shift in the proportion of male-vs-female customers? Please use plots to support your answer (a rigorous statistical analysis is not necessary).

In [13]:
```
female_df = df[df.purchaser_gender == 'female'].groupby('date').count()
female_df.columns = ['female_count']
male_df = df[df.purchaser_gender == 'male'].groupby('date').count()
male_df.columns = ['male_count']

female_df.head()
```

Out[13]:
```
            female_count
date
2012-10-01           413
2012-10-02           379
2012-10-03           386
2012-10-04           432
2012-10-05           368
```

In [14]:
```
female_df.join(male_df).plot()
```

Out[14]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8401355ef0>
```



The plot is showing that the change in daily sales is due to a shift in the proportion of male-vs-female customers. Specifically, male customers started to be much less than females have purchased (male:female = 1:4) back in 2012 but gradually increased since then and finally surpassed around May/2013 and continued to move upward while female purchasers continued to go down. ### 2.5 - Assume a given day is divided into four dayparts: night (12:00AM - 6:00AM), morning (6:00AM to 12:00PM), afternoon (12:00PM to 6:00PM) and evening (6:00PM - 12:00AM). What is the percentage of sales in each daypart over all 50 weeks?

In [0]:
```
def to_time(s):
  return datetime.strptime(s, '%I:%M%p').time()

def time2daypart(t):
  if to_time('12:00AM') <= t <= to_time('6:00AM'):
    return 'night'
  elif (to_time('6:00AM') < t <= to_time('12:00PM')):
    return 'morning'
  elif (to_time('12:00PM') < t <= to_time('6:00PM')):
    return 'afternoon'
  else:
    return 'evening'

df2 = frame.copy()
df2['time'] = df2.index.time
df2['dayparts'] = df2['time'].map(time2daypart)
```

```
In [16]: # Find the percentage of sales for each daypart over all 50 weeks
         df2.groupby('dayparts').count()['time'] * 100./ len(df2)
```

```
Out[16]: dayparts
         afternoon    39.412418
         evening      20.857049
         morning      30.770473
         night         8.960060
         Name: time, dtype: float64
```

3 SECTION 3 - MACHINE LEARNING (QUALITATIVE ANALYSIS)

3.0.1 3.1 - Describe how you would go about evaluating this data and how you would build a product recommendation engine. Do NOT actually build the recommendation engine, rather just describe how you would build it.

To evaluate this data, let's load the data and see what it looks like

```
In [17]: # Let's download the csv
         !wget https://s3.amazonaws.com/retina-public-datasets/data-scientist-assignment/ml/Samp
```

```
--2018-03-07 00:56:40--  https://s3.amazonaws.com/retina-public-datasets/data-scientist-assignme
Resolving s3.amazonaws.com (s3.amazonaws.com)... 52.216.224.67
Connecting to s3.amazonaws.com (s3.amazonaws.com)|52.216.224.67|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 17747953 (17M) [application/x-www-form-urlencoded]
Saving to: SampleData_FlowerShop_Transactions_Table.csv

SampleData_FlowerSh 100%[===================>]  16.92M  4.51MB/s    in 3.9s

2018-03-07 00:56:45 (4.30 MB/s) - SampleData_FlowerShop_Transactions_Table.csv saved [17747953/1
```

```
In [0]: #Load csv to dataframe
        df = pd.read_csv('SampleData_FlowerShop_Transactions_Table.csv',header=0 )#,index_col="s
```

```
In [19]: # High-level look at statistics to see if there is anything unusual
         df.describe()
```

```
Out[19]:          customer_id  transaction_id  total_sale_amount_usd  cost_of_sale  \
         count  385013.000000    3.850130e+05           3.850130e+05  3.850130e+05
         mean     4997.230969    9.452573e+05           8.134100e+03  2.571442e+03
         std      2889.498474    2.778214e+05           1.070741e+05  4.083110e+04
         min         1.000000    4.640300e+05          -3.312632e+04 -1.382760e+04
         25%      2495.000000    7.045830e+05           1.900000e+00  6.000000e-01
         50%      4995.000000    9.450410e+05           4.011000e+01  1.180000e+01
         75%      7502.000000    1.185831e+06           6.526300e+02  2.064000e+02
         max     10000.000000    1.426667e+06           6.915119e+06  3.104436e+06
```

```
         sku_quantity
count  385013.000000
mean      161.375003
std      1632.450990
min         1.000000
25%         1.000000
50%         2.000000
75%        16.000000
max    169934.000000
```

In [20]:
```
df.count()
```

Out[20]:
```
customer_id             385013
transaction_id          385013
product_type            385013
vendor                  385013
total_sale_amount_usd   385013
cost_of_sale            385013
sku_quantity            385013
dtype: int64
```

In [21]:
```
# Calculate adjusted_sale = total_sale_amount_usd - cost_of_sale
df['adjusted_sale'] = df['total_sale_amount_usd'] - df['cost_of_sale']
df.head()
```

Out[21]:
```
   customer_id  transaction_id product_type      vendor  \
0         7639          464030  DOZEN ROSES  Supplier B
1         7615          464032  DOZEN ROSES  Supplier B
2         5654          464036    ANTHURIUM  Supplier B
3         8069          464038    DAFFODILS      OTHERS
4         9243          464040    ANTHURIUM  Supplier B

   total_sale_amount_usd  cost_of_sale  sku_quantity  adjusted_sale
0                 321.32         190.4             9         130.92
1                  77.60          21.4             3          56.20
2                 484.55         214.2             1         270.35
3                   7.52           0.4             1           7.12
4                  48.36          29.0             3          19.36
```

In [22]:
```
# Let's look at time series of the adjusted sales using plot
df2 = df.pivot(index='transaction_id', columns='product_type', values='adjusted_sale')
df2.describe()
```

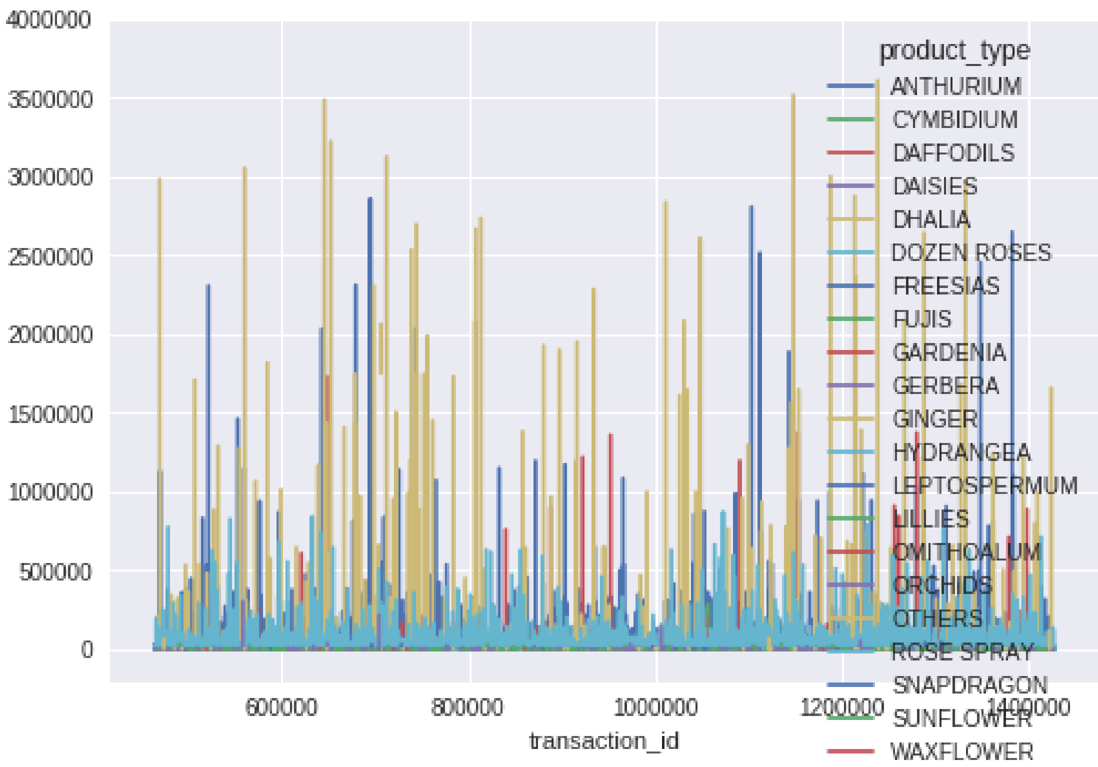
Out[22]:
```
product_type     ANTHURIUM      CYMBIDIUM     DAFFODILS        DAISIES  \
count         1.181260e+05    4610.000000  3.176100e+04   20081.000000
mean          4.521224e+03    9261.519857  3.858235e+03    2084.028296
std           4.394599e+04   43488.043686  4.453052e+04    9807.751171
min          -8.898050e+03    -397.220000 -7.678570e+03   -1489.680000
```

```
25%           1.980000e+00      3.482500  9.000000e-01      4.150000
50%           4.354500e+01     43.185000  5.810000e+00    135.180000
75%           5.708800e+02    723.067500  4.665000e+01    791.690000
max           3.615955e+06 488554.820000  1.730167e+06 261566.990000

product_type        DHALIA   DOZEN ROSES      FREESIAS         FUJIS  \
count         3.747100e+04  1.152790e+05   8464.000000   5617.000000
mean          2.573064e+04  3.299564e+03    510.654080    269.129502
std           2.001170e+05  2.387491e+04   3994.117313    819.513376
min          -1.929872e+04 -5.741180e+03   -495.070000     -8.620000
25%           8.400000e-01  2.080000e+00      0.320000      1.120000
50%           2.023000e+01  4.923000e+01      2.810000     16.600000
75%           9.175150e+02  5.497400e+02     28.350000    121.060000
max           3.810683e+06  1.128854e+06  78043.280000  11149.210000

product_type      GARDENIA       GERBERA          ...      HYDRANGEA  \
count          1261.000000    403.000000          ...     775.000000
mean            331.026154    376.205757          ...     379.439561
std            1568.896804   1651.443427          ...    2339.113480
min           -1226.310000    -55.770000          ...    -925.130000
25%              1.210000      0.060000           ...       0.295000
50%             15.700000      0.370000           ...       3.100000
75%            129.550000      2.580000           ...      17.655000
max          36802.360000  14580.930000           ...   31384.980000

product_type  LEPTOSPERMUM       LILLIES    OMITHOALUM        ORCHIDS  \
count          1735.000000  18408.000000    981.000000    9382.000000
mean            480.105787    332.903976   1675.320102    2513.483650
std            2377.470156   1962.988306   8091.073420   19921.512874
min            -215.280000   -169.030000   -439.010000   -2156.420000
25%              1.255000      0.190000      0.180000       0.620000
50%             10.730000      1.390000      1.330000      11.265000
75%            134.265000     13.670000      5.710000     156.427500
max          25134.300000  33137.470000  64192.420000  401416.530000

product_type          OTHERS    ROSE SPRAY    SNAPDRAGON     SUNFLOWER  \
count            4523.000000   1327.000000   2108.000000   1431.000000
mean             1782.699076   2753.438561    116.693515   2903.424801
std             12961.426435   8164.274643    392.799219  11922.816356
min             -2680.930000   -261.980000    -43.560000   -453.440000
25%                 0.030000     10.965000      0.735000      2.190000
50%                 2.780000    233.270000      8.870000     57.590000
75%                77.425000   1006.330000     64.277500    615.915000
max            181429.810000  58611.130000   4352.700000  95219.280000

product_type     WAXFLOWER
count          1258.000000
mean            803.631892
```

```
std          5705.824025
min            -1.700000
25%             0.030000
50%             0.925000
75%            17.937500
max         88167.490000

[8 rows x 21 columns]
```

In [23]:
```
df2.plot()
```

Out[23]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f840032b080>
```



The plot shows that Dhalia is the most profitable item, next is Anthurium. Let's double-check with the data

In [24]:
```
# total sales of products, sor
import numpy as np
df.groupby('product_type').agg({'adjusted_sale':np.sum}).sort_values('adjusted_sale', a
```

Out[24]:
```
              adjusted_sale
product_type
DHALIA         9.641530e+08
ANTHURIUM      5.340741e+08
```

```
DOZEN ROSES    3.803705e+08
DAFFODILS      1.225414e+08
CYMBIDIUM      4.269561e+07
DAISIES        4.184937e+07
ORCHIDS        2.358150e+07
OTHERS         8.063148e+06
LILLIES        6.128096e+06
FREESIAS       4.322176e+06
SUNFLOWER      4.154801e+06
ROSE SPRAY     3.653813e+06
OMITHOALUM     1.643489e+06
FUJIS          1.511700e+06
WAXFLOWER      1.010969e+06
LEPTOSPERMUM   8.329835e+05
GARDENIA       4.174240e+05
HYDRANGEA      2.940657e+05
SNAPDRAGON     2.459899e+05
GERBERA        1.516109e+05
GINGER         6.900000e-01
```

Indeed, the 3 top sellers are Dhalia, Anthurium and Dozen Roses. Ginger is the bottom of the list which is barely profitable

Now let's look from vendor's perspective:

```
In [25]: df.groupby('vendor').agg({'adjusted_sale':np.sum}).sort_values('adjusted_sale', ascendi
```

```
Out[25]:              adjusted_sale
         vendor
         Supplier B   1.286240e+09
         Supplier A   5.847566e+08
         Supplier C   2.189188e+08
         Supplier D   3.627076e+07
         OTHERS       1.550933e+07
```

Supplier B is definitely the one that is most profitable.

From customer's perspective: Here are the top 5:

```
In [26]: df.groupby('customer_id').agg({'adjusted_sale':np.sum}).sort_values('adjusted_sale', as
```

```
Out[26]:              adjusted_sale
         customer_id
         210             4332172.39
         2979            4288797.70
         2665            4187782.15
         2716            4048931.97
         2380            3974081.14
```

Build a product recommendation engine I would use filtering to build product recommendation engine. The 2 approaches include:

- Content-based: A popular, recommended product has similar attributes to what the user views or likes. In this case, I try to find look alike items (in this case, flowers) and recommend them. Information/features of flowers can be color, stem length, family (bulb, orchid, etc.), fragrance, pedal length, pedal width, season, etc. Based on these information we can find look-alike (related) of these flowers. We simply use these look-alikes to recommend for the original choice of flowers.

- Collaborative (user-based): Other users, who like the same products the user views or likes, also liked a recommended product. The recommendation engine can rely on likes and desires of other users in order to compute a similarity index between users and recommend items to them accordingly. For example, user A and user B both rate highly Dhalia and Lillies. B also likes Cymbidium and Daffodils so these can also be recommended to A. To implement this, we build User/Item matrix where each cell has the rating of what users have on particular items/flowers. To measure similarity, we can use cosine similarity or correlations between vectors of users/items.

I can also combine both filtering types in order to build a more prosperous and sophisticated recommendation engine to enrich user experience.

4 SECTION 4 - VISUALIZATION & BASIC DATA MANIPULATION

```
In [27]: !wget https://s3.amazonaws.com/retina-public-datasets/data-scientist-assignment/org/org
```

```
--2018-03-07 00:57:05--  https://s3.amazonaws.com/retina-public-datasets/data-scientist-assignme
Resolving s3.amazonaws.com (s3.amazonaws.com)... 52.216.82.235
Connecting to s3.amazonaws.com (s3.amazonaws.com)|52.216.82.235|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 4416 (4.3K) [text/csv]
Saving to: org_data.csv

org_data.csv        100%[===================>]   4.31K  --.-KB/s    in 0s

2018-03-07 00:57:06 (124 MB/s) - org_data.csv saved [4416/4416]
```

```
In [28]: import pandas as pd
         import numpy as np
         df = pd.read_csv('org_data.csv',header=0, dtype={'employee_id': np.int, 'manager_employ
         df.head()
```

```
Out[28]:    employee_id  manager_employee_id     employee_name
         0       310675            750317498    Elisha Bentley
         1      1201346            666716720    Tomas Atkinson
         2      1227778      100001000000000     Kianna Benson
         3      1602606           1018684196  Scarlett Stanley
         4      2901687            750317498     Danica Clarke
```

4.0.1 4.1 - Who is the head of this organization?

To answer this question, we want to query on managers who are not employees:

```
In [29]: df[~df.manager_employee_id.isin(df.employee_id)]
```

```
Out[29]:     employee_id  manager_employee_id    employee_name
         92    828754905            872485186  Giancarlo Avila
```

4.0.2 4.2 - What is the average and median manager to employee ratio?

```
In [30]: df2 = df[['manager_employee_id', 'employee_id']].groupby('manager_employee_id').count()
         df2.rename(columns = {'employee_id': 'employee_count'}, inplace=True)
         df2.mean()
```

```
Out[30]: employee_count    3.527778
         dtype: float64
```

```
In [31]: df2.median()
```

```
Out[31]: employee_count    2.0
         dtype: float64
```

1 manager has average of 3.53 employees and median of 2 employees

4.0.3 4.3 - What is the maximum depth of the organization?

```
In [32]: max_depth = 0
         def findMaxDepth(df, manager_id, current_depth):
             employees = df[df.manager_employee_id == manager_id].employee_id
             emp_max_depth = []
             if (employees.empty):
                 return current_depth
             for employee in employees:
                 #print(employee, current_depth + 1)
                 emp_max_depth += [findMaxDepth(df, employee, current_depth + 1)]
             #print(emp_max_depth)
             return max(emp_max_depth)

         findMaxDepth(df, 872485186, 0)
```

```
Out[32]: 6
```

4.0.4 4.4 - Draw a visual plot of the organizational chart.

```
In [33]: #!apt-get install graphviz -y
         !pip install pydot
```

```
Requirement already satisfied: pydot in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: pyparsing>=2.1.4 in /usr/local/lib/python3.6/dist-packages (from
```

```
In [34]: from IPython.display import Image
         import pydot

         graph = pydot.Dot(graph_type='graph')

         # Use df to create edges
         for _, row in df.iterrows():
           edge = pydot.Edge(row['manager_employee_id'], row['employee_id'])
           graph.add_edge(edge)


         Image(graph.create_png(), width=5000)
```

Out[34]: