main

March 22, 2020

1 Project Introduction

This is a comprehensive data science project for the Final of WISERCLUB 2019-2020. The project is about **Business Analytics** and **Data Mining**. It consists of three parts: Part 1: Explorative Data Analysis Part 2: Data Preprocessing Part 3: Model Training and Prediction Each part has seversal problems. We have got two csv files, named *data.csv* and *holiday.csv*, derived from a new retail specialty coffee operator. The task is to use data and models to find hidden information.

1.1 Packages used in the project

pandas, numpy, matplotlib, scipy, math, datetime, sklearn, xgboost, imblearn

1.2 Methods used in the project

Aggregate Functions (groupby in Pandas), Hypothesis Testing (T test, F test), String Format, Lambda Expression, Adaboost, Random Forest, Cross Validation, Xgboost, GridSearchCV, Oversampling

Now, let's begin the exploration in the ocean of data. Since the project is very informative, you can use the contents of Jupyter Notebook to help you locate and read for convenience.

2 Part 1: Explorative Data Analysis

1. Find the time span of the order data.
2. Find the number of orders each day. a. Boss: we need to design two different strategies for sales in workdays and sales in weekends. True or False? Explain.
3. Find the number of users.
4. Find ten commodities with the highest sales and draw graphs with x-axis the commodity name and y-axis the # of orders.
5. Find the discount rate of each order and concat it onto the original dataset with column name *discount_rate*.You may use *pay_money*, *coffeestore_share_money*, *commodity_origin_money* and *commodity_income*.
6. Find the average discount of each week. One week should consist of Sunday to Saturday.

7. Find the *Retention Rate* of any five days. It is the ratio of users purchasing again on the next day. For example, if you want to compute the *Retention Rate* on 2019-02-10, then you need to find users who bought goods on 02-09 and 02-10.

8. Find the *Week Retention Rate* of any day, which means finding users buying at that day and buying again within the next seven days.

9. Find the *Week Retention Rate* of any day for *new users* , which means finding users buying at that day *for the first time* and buying again within the next seven days.

10. Find the *Retention Rate WITHIN* one week of new users. You could choose any week you want, but it must consist of Sunday to Saturday. You need to find users buying the first product and buying again within that week.

11. Find "Active Users" (which means the number of orders of one user is greater equal to 5).

12. Write the table you get in 11 as a csv file with filename *ActiveUser.csv*.

13. Provide a description of the number of orders for each active user (# of ActiveUser, mean, range, std, variance,skewness and kurtosis).

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams['font.family'] = 'SimHei'
```

In [2]:
```
Data = pd.read_csv("data.csv", encoding = "UTF-8")
Data.head()
```

Out[2]:
```
   Unnamed: 0  Unnamed: 0.1          dt     phone_no  member_id  \
0           0             0  2019-01-25  13901387938      14442
1           1             1  2019-01-27  13901387938      14442
2           2             2  2019-01-23  13901387938      14442
3           3             3  2019-02-01  13901387938      14442
4           4             4  2019-01-27  13901387938      14442

  commodity_code commodity_name  commodity_origin_money  coupon_id  \
0          SP025                                   27.0     7045.0
1          SP209        NFC                        24.0        NaN
2          SP025                                   27.0     5589.0
3          SP025                                   27.0     6604.0
4          SP010                               27.0     6947.0

   coupon_money one_category_name two_category_name  commodity_income  \
0         19.44                                                  7.56
1          0.00                                                0.00
2         22.14                                                  4.86
3         19.44                                                  7.56
4         14.04                                                  12.96
```

```
   pay_money  coffeestore_share_money
0       7.56                      0.0
1       0.00                      0.0
2       4.86                      0.0
3       7.56                      0.0
4      12.96                      0.0
```

```
In [3]: Holiday = pd.read_csv("holiday.csv", encoding = "UTF-8")
        Holiday.head()
```

```
Out[3]:            dt  month  weekday  week_of_year  type  last_type  \
        0  2017-10-09     10        1            41     0          0
        1  2017-10-10     10        2            41     0          0
        2  2017-10-11     10        3            41     0          0
        3  2017-10-12     10        4            41     0          0
        4  2017-10-13     10        5            41     0          0

           holiday_distance  holiday_code
        0               -82             0
        1               -81             0
        2               -80             0
        3               -79             0
        4               -78             0
```

2.1 Problem 1Find the time span of the order data.

Method 1: groupby

```
In [4]: Data.groupby('dt')[['dt']].count().head(1)
```

```
Out[4]:                dt
        dt
        2019-01-20  69859
```

```
In [5]: Data.groupby('dt')[['dt']].count().tail(1)
```

```
Out[5]:                dt
        dt
        2019-03-01  53279
```

Method 2: loop

```
In [6]: print('The time span of the order data:',Data['dt'].min(),'to', Data['dt'].max())
```

```
The time span of the order data: 2019-01-20 to 2019-03-01
```

2.2 Problem 2Find the number of orders each day.

In [7]:
```
dt_sales = Data.groupby('dt')[['member_id']].count()
dt_sales.columns = ['daily_orders']
print('The number of orders each day:')
dt_sales
```

The number of orders each day:

Out[7]:

dt	daily_orders
2019-01-20	69859
2019-01-21	117686
2019-01-22	118409
2019-01-23	126331
2019-01-24	125764
2019-01-25	122092
2019-01-26	77779
2019-01-27	66399
2019-01-28	106025
2019-01-29	104704
2019-01-30	101047
2019-01-31	97701
2019-02-01	87458
2019-02-02	64267
2019-02-03	43106
2019-02-04	7113
2019-02-05	8516
2019-02-06	7769
2019-02-07	7655
2019-02-08	7822
2019-02-09	8452
2019-02-10	8241
2019-02-11	40365
2019-02-12	43334
2019-02-13	50789
2019-02-14	49092
2019-02-15	49836
2019-02-16	29672
2019-02-17	25179
2019-02-18	52260
2019-02-19	51624
2019-02-20	53121
2019-02-21	51817
2019-02-22	53685
2019-02-23	31964
2019-02-24	27414
2019-02-25	53969

```
2019-02-26          50018
2019-02-27          48970
2019-02-28          51272
2019-03-01          53279
```

2.2.1 Problem 2-aBoss: we need to design two different strategies for sales in workdays and sales in weekends.

Answer: True. As you can see from the data above, the orders in workdays are much greater than orders in weekends. Thus, different strategies for sales should be designed. Here are the relevant descriptive statistics and hypothesis testings.

1. Separate weekdays and weekends

```
In [8]: Holiday =  Holiday[(Holiday['dt'] > '2019-01-19') & (Holiday['dt'] < '2019-03-02')] #
        Holiday.head()
```

```
Out[8]:              dt  month  weekday  week_of_year  type  last_type  \
        468  2019-01-20      1        7             3     1          0
        469  2019-01-21      1        1             4     0          0
        470  2019-01-22      1        2             4     0          0
        471  2019-01-23      1        3             4     0          0
        472  2019-01-24      1        4             4     0          0

             holiday_distance  holiday_code
        468               -15             0
        469               -14             0
        470               -13             0
        471               -12             0
        472               -11             0
```

```
In [9]: orders = Data.groupby('dt')[['dt']].count()
        orders.columns = ['daily_orders']

        holiday_weekday = Holiday['weekday']
        holiday_weekday = holiday_weekday.to_frame()
        holiday_weekday.index = Holiday['dt']
        holiday_weekday.columns = ['weekday']

        orders_day = pd.concat([orders, holiday_weekday], axis = 1)
        orders_day.head()
```

```
Out[9]:             daily_orders  weekday
        dt
        2019-01-20         69859        7
        2019-01-21        117686        1
        2019-01-22        118409        2
        2019-01-23        126331        3
        2019-01-24        125764        4
```

```
In [10]: orders_weekday = orders_day[orders_day['weekday'] < 6]
         orders_weekend = orders_day[orders_day['weekday'] > 5]
```

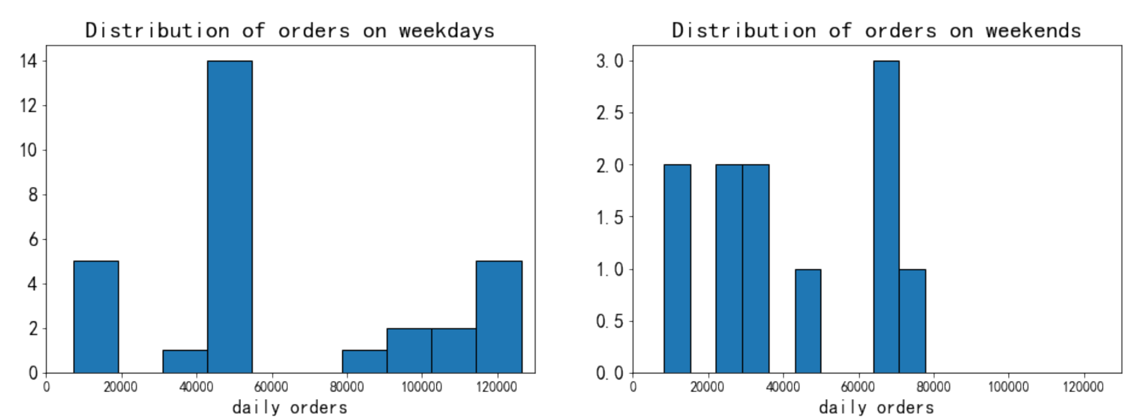
2. Descriptive statistics of weekdays and weekends

```
In [11]: desc_weekday = orders_weekday['daily_orders'].to_frame().describe()
         desc_weekday.columns = ['daily_orders_weekday']
         desc_weekend = orders_weekend['daily_orders'].to_frame().describe()
         desc_weekend.columns = ['daily_orders_weekend']
         pd.concat([desc_weekday, desc_weekend], axis = 1)
```

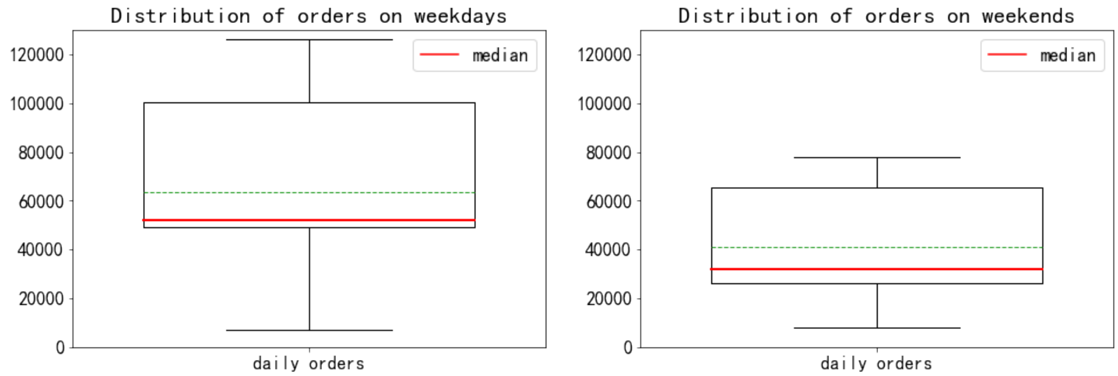
Out[11]:

	daily_orders_weekday	daily_orders_weekend
count	30.000000	11.000000
mean	63317.433333	41121.090909
std	38163.933323	24806.559328
min	7113.000000	8241.000000
25%	49000.500000	26296.500000
50%	52038.500000	31964.000000
75%	100210.500000	65333.000000
max	126331.000000	77779.000000

```
In [12]: plt.figure(figsize = (16,5))
         plt.subplot(1,2,1)
         plt.hist(orders_weekday['daily_orders'], edgecolor='black')
         plt.title('Distribution of orders on weekdays', fontsize = 20)
         plt.xticks(fontsize = 12)
         plt.yticks(fontsize = 16)
         plt.xlabel('daily orders', fontsize = 16)
         plt.xlim(0, 130000)
         plt.subplot(1,2,2)
         plt.hist(orders_weekend['daily_orders'], edgecolor='black')
         plt.title('Distribution of orders on weekends', fontsize = 20)
         plt.xticks(fontsize = 12)
         plt.yticks(fontsize = 16)
         plt.xlabel('daily orders', fontsize = 16)
         plt.xlim(0, 130000)
         plt.show()
```



```
In [13]: import matplotlib.lines as mlines

         plt.figure(figsize = (16,5))
         plt.subplot(1,2,1)
         plt.boxplot(orders_weekday['daily_orders'], widths = 0.7, labels = ['daily orders'],
                     meanline = True, showmeans = True, medianprops = {'color': 'red', 'linewid
         plt.title('Distribution of orders on weekdays', fontsize = 20)
         plt.ylim(0, 130000)
         plt.xticks(fontsize = 16)
         plt.yticks(fontsize = 16)
         median_line = mlines.Line2D([], [], color = 'red', label = 'median')
         plt.legend(handles=[median_line], fontsize=16)

         plt.subplot(1,2,2)
         plt.boxplot(orders_weekend['daily_orders'], widths = 0.7, labels = ['daily orders'],
                     meanline = True, showmeans = True, medianprops = {'color': 'red', 'linewid
         plt.title('Distribution of orders on weekends', fontsize = 20)
         plt.ylim(0, 130000)
         plt.xticks(fontsize = 16)
         plt.yticks(fontsize = 16)
         plt.legend(handles=[median_line], fontsize = 16)
         plt.show()
```



3. Test whether var(orders_weekday) = var(orders_weekend)

```
In [14]: orders_weekday_mean = orders_weekday['daily_orders'].mean()
         orders_weekend_mean = orders_weekend['daily_orders'].mean()
         orders_weekday_var = orders_weekday['daily_orders'].var()
         orders_weekend_var = orders_weekend['daily_orders'].var()

         n1 = len(orders_weekday)
         n2 = len(orders_weekend)
```

Method 1: F Test

```
In [15]: from scipy.stats import f

         def ftest(n1, n2, var1, var2):
             '''
                 F test
             '''
             F = var1 / var2
             p_value = 2 * min(f.sf(F, n1-1, n2-1), 1 - f.sf(F, n1-1, n2-1))
             print('F =',round(F, 6))
             print('critical_region:','F <',round(f.isf(0.975, 29, 10),6),'or','F >',round(f.i
             if p_value < 0.05:    # at the 5% signicance level
                 print('p-value=',round(p_value, 6))
                 print('Reject the hypothesis orders_weekday_var = orders_weekend_var.')
                 print('Thus, orders_weekday_mean is not equal to orders_weekend_mean at 5% co
             else:
                 print('p-value=',round(p_value, 6))
                 print('Accept the hypothesis orders_weekder_var = orders_weekend_var.')
                 print('Thus, orders_weekday_mean = orders_weekend_mean at 5% confidence level

         ftest(n1, n2, orders_weekday_var, orders_weekend_var)
```

```
F = 2.366863
critical_region: F < 0.39548 or F > 3.318587
p-value= 0.152171
Accept the hypothesis orders_weekder_var = orders_weekend_var.
Thus, orders_weekday_mean = orders_weekend_mean at 5% confidence level.
```

Method 2: Levene Test

```
In [16]: from scipy import stats
         '''
         Levene test: Homogeneity test of variances
         '''
         leveneTestRes = stats.levene(orders_weekday['daily_orders'], orders_weekend['daily_ord
         print('w-value=%6.4f, p-value=%6.4f' %leveneTestRes)
```

```
w-value=0.8195, p-value=0.3709
```

4. Test whether mean(orders_weekday) = mean(orders_weekend) Method 1: Self-defining Two Sample T Test Function

```
In [17]: # two sample t test with equal variance, one-sided
         from scipy.stats import t

         def ttest(n1, n2, mean1, mean2, var1, var2):
```

```
    '''
        two sample T test with equal unknown variance, one-sided
    '''
    sp2 = ((n1-1)*var1 + (n2-1)*var2)/(n1+n2-2) # sp2 = 1240813903.8532245
    T = (orders_weekday_mean - orders_weekend_mean) / ((sp2/n1+sp2/n2) ** 0.5)  # T
    p_value = t.sf(T, n1+n2-2)
    print('T =',round(T, 6))
    print('critical_region:','T >',round(t.isf(0.05, n1+n2-2),6))
    if p_value < 0.05:    # at the 5% signicance level
        print('p-value=',round(p_value ,6))
        print('Reject the hypothesis orders_weekday_mean = orders_weekend_mean.')
        print('Thus, orders_weekday_mean > orders_weekend_mean at 5% confidence level
    else:
        print('p-value=',round(p_value ,6))
        print('Accept the hypothesis orders_weekday_mean = orders_weekend_mean.')
        print('Thus, orders_weekday_mean = orders_weekend_mean at 5% confidence level

ttest(n1, n2, orders_weekday_mean, orders_weekend_mean, orders_weekday_var, orders_we
```

```
T = 1.787694
critical_region: T > 1.684875
p-value= 0.040799
Reject the hypothesis orders_weekday_mean = orders_weekend_mean.
Thus, orders_weekday_mean > orders_weekend_mean at 5% confidence level.
```

Method 2: Two Sample T Test by using 'from scipy import stats'

```
In [18]: # two-sided, 5% confidence level
         tTestRes = stats.stats.ttest_ind(orders_weekday['daily_orders'], orders_weekend['dail
         print('T-statistic=%6.4f, p-value=%6.4f' %tTestRes)
```

```
T-statistic=1.7877, p-value=0.0816
```

Though we cannot reject the hyphothesis that sales in workdays and sales in weekends are different at 5% confidence level for two-sided test, **we can reject it at 5% confidence level for one-sided test**. Thus, the sales in weekdays are higher than sales in weekends.

From the histograms and boxplots above, it is noted that the number of some daily orders are below 20000 both on weekdays and weekends. Looking up the corresponding dates in the calendar according to the specific data we get in Problem 2, we find that the dates with orders below 20000 is during the Spring Festival of 2019.

```
In [19]: slice_orders_day = orders_day[orders_day['daily_orders'] < 20000]
         slice_orders_day
```

```
Out[19]:             daily_orders  weekday
         dt
         2019-02-04          7113        1
```

```
2019-02-05          8516        2
2019-02-06          7769        3
2019-02-07          7655        4
2019-02-08          7822        5
2019-02-09          8452        6
2019-02-10          8241        7
```

From the table above, it can be considered that there is no difference between the number of orders on weekdays and weekends during the Spring Festival. This is a special case. However, after dropping the data during the Spring Festival, as you can see from the table and boxplots below, it is obvious that the difference between the number of orders on weekdays and weekends is significant.

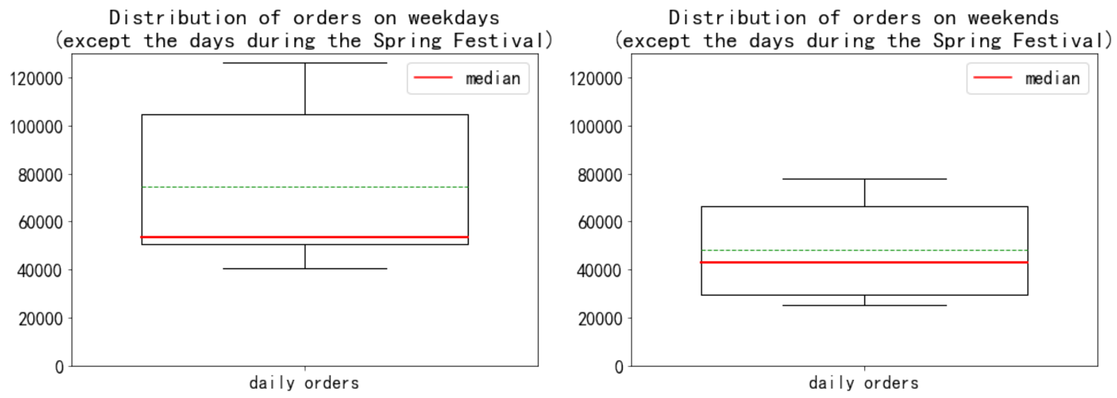
In [20]:
```
slice_orders_weekday = orders_weekday[orders_weekday['daily_orders'] > 20000]
slice_orders_weekend = orders_weekend[orders_weekend['daily_orders'] > 20000]
desc_slice_weekday = slice_orders_weekday['daily_orders'].to_frame().describe()
desc_slice_weekday.columns = ['daily_orders_weekday']
desc_slice_weekend = slice_orders_weekend['daily_orders'].to_frame().describe()
desc_slice_weekend.columns = ['daily_orders_weekend']
pd.concat([desc_slice_weekday, desc_slice_weekend], axis = 1)
```

Out[20]:

	daily_orders_weekday	daily_orders_weekend
count	25.000000	9.000000
mean	74425.920000	48404.333333
std	31442.615071	20999.623199
min	40365.000000	25179.000000
25%	50789.000000	29672.000000
50%	53279.000000	43106.000000
75%	104704.000000	66399.000000
max	126331.000000	77779.000000

In [21]:
```
import matplotlib.lines as mlines

plt.figure(figsize = (16,5))
plt.subplot(1,2,1)
plt.boxplot(slice_orders_weekday['daily_orders'], widths = 0.7, labels = ['daily orde
            meanline = True, showmeans = True, medianprops = {'color': 'red', 'linewi
plt.title('Distribution of orders on weekdays\n(except the days during the Spring Fes
plt.ylim(0, 130000)
plt.xticks(fontsize = 16)
plt.yticks(fontsize = 16)
median_line = mlines.Line2D([], [], color = 'red', label = 'median')
plt.legend(handles=[median_line], fontsize=16)

plt.subplot(1,2,2)
plt.boxplot(slice_orders_weekend['daily_orders'], widths = 0.7, labels = ['daily orde
            meanline = True, showmeans = True, medianprops = {'color': 'red', 'linewi
plt.title('Distribution of orders on weekends\n(except the days during the Spring Fes
plt.ylim(0, 130000)
```

```
plt.xticks(fontsize = 16)
plt.yticks(fontsize = 16)
plt.legend(handles=[median_line], fontsize = 16)
plt.show()
```



We can also do the hypothesis testings to verify our conclusion.

```
In [22]: n3 = len(slice_orders_weekday)
         n4 = len(slice_orders_weekend)
         slice_orders_weekday_mean = slice_orders_weekday['daily_orders'].mean()
         slice_orders_weekend_mean = slice_orders_weekend['daily_orders'].mean()
         slice_orders_weekday_var = slice_orders_weekday['daily_orders'].var()
         slice_orders_weekend_var = slice_orders_weekend['daily_orders'].var()

         print('(Except the days during the Spring Festival)')
         ftest(n3, n4, slice_orders_weekday_var, slice_orders_weekend_var)
```

```
(Except the days during the Spring Festival)
F = 2.24189
critical_region: F < 0.39548 or F > 3.318587
p-value= 0.237908
Accept the hypothesis orders_weekder_var = orders_weekend_var.
Thus, orders_weekday_mean = orders_weekend_mean at 5% confidence level.
```

```
In [23]: # two sample t test with equal variance, one-sided
         print('(Except the days during the Spring Festival)')
         ttest(n3, n4, slice_orders_weekday_mean, slice_orders_weekend_mean, slice_orders_weeke
```

```
(Except the days during the Spring Festival)
T = 1.956517
critical_region: T > 1.693889
p-value= 0.029589
Reject the hypothesis orders_weekday_mean = orders_weekend_mean.
Thus, orders_weekday_mean > orders_weekend_mean at 5% confidence level.
```

2.3 Problem 3Find the number of users.

```
In [24]: user_num = len(Data.groupby('member_id')[['member_id']].count())
         print('The number of users is', user_num)
```

```
The number of users is 466886
```

2.4 Problem 4Find ten commodities with the highest sales.

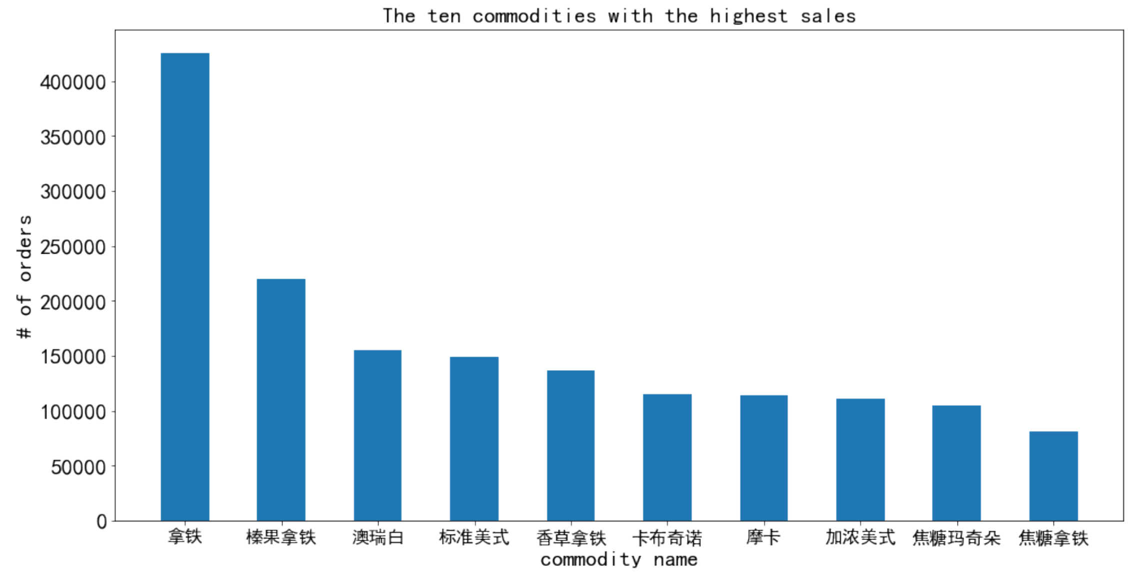
Draw graphs with x-axis the commodity name and y-axis the # of orders.

```
In [25]: commodities = Data.groupby('commodity_name')[['commodity_name']].count()
         commodities.columns = ['orders']
         top10_commodities = commodities.sort_values(by = ['orders'], ascending = False).head(
         print('The ten commodities with the highest sales:')
         top10_commodities
```

```
The ten commodities with the highest sales:
```

```
Out[25]:                 orders
         commodity_name
                           425514
                         219627
                           155506
                         148666
                         136841
                         115475
                           113754
                         110526
                        105081
                          81120
```

```
In [26]: # top10_commodities.reset_index()
         top10_commodities.insert(0, 'commodity_name', top10_commodities.index)
         list_names = top10_commodities.commodity_name.tolist()
         list_sales = top10_commodities.orders.tolist()
         plt.figure(figsize = (16, 8))
         plt.bar(list_names, height = list_sales, width = 0.5)
         plt.title('The ten commodities with the highest sales', fontsize = 20)
         plt.xticks(fontsize = 16)
         plt.yticks(fontsize = 20)
         plt.xlabel('commodity name', fontsize = 20)
         plt.ylabel('# of orders', fontsize = 20)
         plt.show()
```



2.5 Problem 5Find the discount rate of each order and concat it onto the original dataset with column name *discount_rate*.

In [27]:
```
discount_rate = Data.commodity_income / Data.commodity_origin_money # Series
discount_rate = discount_rate.to_frame()
discount_rate.columns=['discount_rate']
Data = pd.concat([Data, discount_rate], axis = 1)
Data.head()
```

Out[27]:
```
   Unnamed: 0  Unnamed: 0.1          dt     phone_no  member_id  \
0           0             0  2019-01-25  13901387938      14442
1           1             1  2019-01-27  13901387938      14442
2           2             2  2019-01-23  13901387938      14442
3           3             3  2019-02-01  13901387938      14442
4           4             4  2019-01-27  13901387938      14442

  commodity_code commodity_name  commodity_origin_money  coupon_id  \
0          SP025                                   27.0     7045.0
1          SP209         NFC                       24.0        NaN
2          SP025                                   27.0     5589.0
3          SP025                                   27.0     6604.0
4          SP010                                 27.0     6947.0

   coupon_money one_category_name two_category_name  commodity_income  \
0         19.44                                                  7.56
1          0.00                                                0.00
2         22.14                                                  4.86
3         19.44                                                  7.56
```

```
4         14.04                                              12.96

   pay_money  coffeestore_share_money  discount_rate
0       7.56                      0.0           0.28
1       0.00                      0.0           0.00
2       4.86                      0.0           0.18
3       7.56                      0.0           0.28
4      12.96                      0.0           0.48
```

2.6 Problem 6Find the average discount of each week. (One week should consist of Sunday to Saturday.)

In [28]:
```
# find which seven days could be combined into one week
holiday_day = Holiday.groupby(['week_of_year'])[['week_of_year']].count()
holiday_day.columns = ['days']
holiday_day
```

Out[28]:
```
              days
week_of_year
3                1
4                7
5                7
6                7
7                7
8                7
9                5
```

In [29]:
```
holiday_week_of_year = Holiday['week_of_year']
holiday_week_of_year = holiday_week_of_year.to_frame()
holiday_week_of_year.index = Holiday['dt']
holiday_week_of_year.columns = ['week_of_year']

discount_rate_sum = Data.groupby('dt')[['discount_rate']].sum()
discount_rate_sum.columns = ['discount_rate_sum']

discount = pd.concat([dt_sales, discount_rate_sum, holiday_week_of_year], axis = 1)
discount.head()
```

Out[29]:
```
            daily_orders  discount_rate_sum  week_of_year
dt
2019-01-20         69859       25703.825175             3
2019-01-21        117686       44597.227917             4
2019-01-22        118409       44737.627817             4
2019-01-23        126331       47913.169124             4
2019-01-24        125764       48211.078974             4
```

In [30]:
```
average_discount = discount.groupby('week_of_year')['daily_orders', 'discount_rate_sum
average_discount = average_discount[(average_discount.index > 3) & (average_discount.i
# Note: One week should consist of 7 days
```

```
discount_rate_weekly = average_discount.discount_rate_sum / average_discount.daily_ord
discount_rate_weekly = discount_rate_weekly.to_frame()
discount_rate_weekly.columns=['discount_rate_weekly']
average_discount = pd.concat([average_discount, discount_rate_weekly], axis = 1)
average_discount.rename(columns = {"daily_orders": "weekly_orders"}, inplace = True)
average_discount
```

Out[30]:

week_of_year	weekly_orders	discount_rate_sum	discount_rate_weekly
4	754460	286698.672087	0.380005
5	604308	241709.679206	0.399978
6	55568	19649.704967	0.353615
7	288267	135698.193614	0.470738
8	321885	149798.599166	0.465379

In [31]:

```
print('The average discount of each week:')
average_discount.drop(['weekly_orders','discount_rate_sum'], axis = 1, inplace = True)
average_discount
```

```
The average discount of each week:
```

Out[31]:

week_of_year	discount_rate_weekly
4	0.380005
5	0.399978
6	0.353615
7	0.470738
8	0.465379

2.7 Problem 7Find the *Retention Rate* of any five days. It is the ratio of users purchasing again on the next day.

Here are three methods. Method 1 is easy to figure out but it is tedious. Method 2 is an improvement on Method 1. Method 3 is is an improvement on Method 2. It is recommended and more useful.

Method 1: Compute Retention Rate of given five days directly

In [32]:

```
# The conditions of the slice will change with the specific dates
# We use the example 2019-01-21 to 2019-01-25
slice_0120a =  Data[Data['dt'] < '2019-01-21']                                    # 2019
slice_0121a =  Data[(Data['dt'] > '2019-01-20') & (Data['dt'] < '2019-01-22')] # 2019
slice_0122a =  Data[(Data['dt'] > '2019-01-21') & (Data['dt'] < '2019-01-23')] # 2019
slice_0123a =  Data[(Data['dt'] > '2019-01-22') & (Data['dt'] < '2019-01-24')] # 2019
slice_0124a =  Data[(Data['dt'] > '2019-01-23') & (Data['dt'] < '2019-01-25')] # 2019
slice_0125a =  Data[(Data['dt'] > '2019-01-24') & (Data['dt'] < '2019-01-26')] # 2019

slice_0120 = slice_0120a.drop_duplicates(subset = ['member_id'], keep = 'first', inpla
slice_0121 = slice_0121a.drop_duplicates(subset = ['member_id'], keep = 'first', inpla
```

```
    slice_0122 = slice_0122a.drop_duplicates(subset = ['member_id'], keep = 'first', inpla
    slice_0123 = slice_0123a.drop_duplicates(subset = ['member_id'], keep = 'first', inpla
    slice_0124 = slice_0124a.drop_duplicates(subset = ['member_id'], keep = 'first', inpla
    slice_0125 = slice_0125a.drop_duplicates(subset = ['member_id'], keep = 'first', inpla

    print('The retention rate of 2019-01-21 to 2019-01-25:',
          round(len(slice_0120['member_id'].loc[slice_0120['member_id'].isin(slice_0121['m
          round(len(slice_0121['member_id'].loc[slice_0121['member_id'].isin(slice_0122['m
          round(len(slice_0122['member_id'].loc[slice_0122['member_id'].isin(slice_0123['m
          round(len(slice_0123['member_id'].loc[slice_0123['member_id'].isin(slice_0124['m
          round(len(slice_0124['member_id'].loc[slice_0124['member_id'].isin(slice_0125['m
```

```
The retention rate of 2019-01-21 to 2019-01-25: 0.1523 0.2463 0.2353 0.2278 0.221
```

Method 2: Compute Retention Rate of given five days by using loop and 'format'

```
In [33]: slice_dt_all = [] # slice Data by dt(date)
         slice_dt_uni = [] # drop duplicates about users of slice_dt_all
         num_user_buy = [] # number of users purchasing on that day
         num_user_buy_again = [] # number of users purchasing again on the next day
         retention_rate = [] # the ratio of users purchasing again on the next day

         for j in range(6):
             # The conditions of the slice will change with the specific dates
             # We use the example 2019-01-21 to 2019-01-25
             slice_dt_all.append(Data[(Data['dt'] > '2019-01-{}'.format(j+19)) & (Data['dt'] <
             slice_dt_uni.append(slice_dt_all[j].drop_duplicates(subset = ['member_id'], keep =
             num_user_buy.append(len(slice_dt_uni[j]))
             if j > 0:
                 user_buy_again = slice_dt_uni[j-1].member_id.loc[slice_dt_uni[j-1].member_id.i
                 num_user_buy_again.append(len(user_buy_again))
                 if num_user_buy[j-1] == 0:
                     print('There are no users purchasing again on the next day!'
                           'Thus, the retention rate of this day cannot be computed!')
                     break
                 retention_rate.append(round(num_user_buy_again[j-1] / num_user_buy[j-1], 4))

         print('The retention rate of 2019-01-21 to 2019-01-25:', ', '.join(str(i) for i in ret
```

```
The retention rate of 2019-01-21 to 2019-01-25: 0.1523, 0.2463, 0.2353, 0.2278, 0.221
```

Method 3: Compute Retention Rate of any five days by using loop and 'import datetime'

```
In [34]: import datetime

         slice_dt_all = [] # slice Data by dt(date)
         slice_dt_uni = [] # drop duplicates about users of slice_dt_all
```

```python
num_user_buy = [] # number of users purchasing on that day
num_user_buy_again = [] # number of users purchasing again on the next day
retention_rate = [] # the ratio of users purchasing again on the next day

first_dt = input('Please enter the first day that you want to compute the retention ra
date = datetime.datetime.strptime(first_dt, '%Y-%m-%d')

if date <= datetime.datetime(2019, 1, 20, 0, 0) or date > datetime.datetime(2019, 2, 
    last_date = date + datetime.timedelta(days=4)
    last_dt = last_date.strftime("%Y-%m-%d")
    print('The retention rate of {} to {}'.format(first_dt, last_dt),
          'cannot be computed! Some dates are not in the time span!')
else:
    for j in range(6):
        date1 = date - datetime.timedelta(days=2)
        date2 = date
        dt1 =  date1.strftime("%Y-%m-%d")
        dt2 =  date2.strftime("%Y-%m-%d")
        slice_dt_all.append(Data[(Data['dt'] > dt1) & (Data['dt'] < dt2)])
        slice_dt_uni.append(slice_dt_all[j].drop_duplicates(subset = ['member_id'], ke
        num_user_buy.append(len(slice_dt_uni[j])) # number of users buying on one day
        if j > 0:
            user_buy_again = slice_dt_uni[j-1].member_id.loc[slice_dt_uni[j-1].member_
            num_user_buy_again.append(len(user_buy_again)) # number of users buying a
            if num_user_buy[j-1] == 0:
                print('There are no users purchasing on the day before that day!'
                      'Thus, the retention rate of this day cannot be computed!')
                break
            else:
                retention_rate.append(round(num_user_buy_again[j-1] / num_user_buy[j-
        date = date + datetime.timedelta(days=1)

    last_date = date - datetime.timedelta(days=2)
    last_dt = last_date.strftime("%Y-%m-%d")
    if num_user_buy[j-1] == 0:
        pass
    else:
        print('The retention rate of {} to {}:'.format(first_dt, last_dt), ', '.join(
```

```
Please enter the first day that you want to compute the retention rate (from 2019-01-21 to 201
The retention rate of 2019-01-21 to 2019-01-25: 0.1523, 0.2463, 0.2353, 0.2278, 0.221
```

2.8 Problem 8Find the *Week Retention Rate* of any day, which means finding users buying at that day and buying again within the next seven days.

Method 1: Compute Week Retention Rate of the given day directly

```
In [35]: slice_0121_0127a = Data[(Data['dt'] > '2019-01-20') & (Data['dt'] < '2019-01-28')] # 
         slice_0121_0127 = slice_0121_0127a.drop_duplicates(subset = ['member_id'], keep = 'fi

         print('The week retention rate of 2019-01-20:',
               round(len(slice_0120['member_id'].loc[slice_0120['member_id'].isin(slice_0121_0
```

```
The week retention rate of 2019-01-20: 0.5108
```

Method 2: Compute Week Retention Rate of any day by using 'import datetime'

```
In [36]: import datetime

         slice_dt_all = [] # slice Data by dt(date)
         slice_dt_uni = [] # drop duplicates about users of slice_dt_all

         dt = input('Please enter the day that you want to compute the week retention rate (fro
         date = datetime.datetime.strptime(dt, '%Y-%m-%d')

         if date < datetime.datetime(2019, 1, 20, 0, 0) or date > datetime.datetime(2019, 2, 2
             print('The week retention rate of {}'.format(dt), 'cannot be computed! Some dates 
         else:
             # slice of that day
             date1 = date - datetime.timedelta(days=1)
             date2 = date + datetime.timedelta(days=1)
             dt1 =  date1.strftime("%Y-%m-%d")
             dt2 =  date2.strftime("%Y-%m-%d")
             slice_dt_all.append(Data[(Data['dt'] > dt1) & (Data['dt'] < dt2)])
             slice_dt_uni.append(slice_dt_all[0].drop_duplicates(subset = ['member_id'], keep 
             num_user_buy = len(slice_dt_uni[0]) # number of users buying at that day

             # slice of the next seven days
             date3 = date
             date4 = date + datetime.timedelta(days=8)
             dt3 =  date3.strftime("%Y-%m-%d")
             dt4 =  date4.strftime("%Y-%m-%d")
             slice_dt_all.append(Data[(Data['dt'] > dt3) & (Data['dt'] < dt4)])
             slice_dt_uni.append(slice_dt_all[1].drop_duplicates(subset = ['member_id'], keep 
             user_buy_again = slice_dt_uni[0].member_id.loc[slice_dt_uni[0].member_id.isin(slic
             num_user_buy_again = len(user_buy_again) # number of users buying again within th
             if num_user_buy == 0:
                 print('There are no users buying at that day!'
                       'Thus, the week retention rate of this day cannot be computed!')
             else:
                 retention_rate = round(num_user_buy_again / num_user_buy, 4)
                 print('The week retention rate of {}:'.format(dt), retention_rate)
```

```
Please enter the day that you want to compute the week retention rate (from 2019-01-20 to 2019-
The week retention rate of 2019-01-20: 0.5108
```

2.9 Problem 9Find the *Week Retention Rate* of any day for *new users*, which means finding users buying at that day *for the first time* and buying again within the next seven days.

Method 1: Compute Week Retention Rate of the given day for new users directly

```
In [37]: slice_0122_0128a = Data[(Data['dt'] > '2019-01-21') & (Data['dt'] < '2019-01-29')] # 
         slice_0122_0128 = slice_0122_0128a.drop_duplicates(subset = ['member_id'], keep = 'fi

         new_user = slice_0121[-slice_0121['member_id'].isin(slice_0120['member_id'])] # len(n
         new_user_buy_again = new_user['member_id'].loc[new_user['member_id'].isin(slice_0122_

         week_retention_rate_new_user = round(len(new_user_buy_again) / len(new_user), 4)
         print('The week retention rate of 2019-01-21 for new users:', week_retention_rate_new_
```

```
The week retention rate of 2019-01-21 for new users: 0.6026
```

Method 2: Compute Week Retention Rate of any day for new users by using 'import datetime'

```
In [38]: import datetime

         slice_dt_all = [] # slice Data by dt(date)
         slice_dt_uni = [] # drop duplicates about users of slice_dt_all

         print('Please enter the day that you want to compute the week retention rate for new u
         dt = input()
         date = datetime.datetime.strptime(dt, '%Y-%m-%d')

         if date < datetime.datetime(2019, 1, 20, 0, 0) or date > datetime.datetime(2019, 2, 2
             print('The week retention rate of {} for new users'.format(dt),
                   'cannot be computed! Some dates are not in the time span!')
         else:
             # slice of that day
             date1 = date - datetime.timedelta(days=1)
             date2 = date + datetime.timedelta(days=1)
             dt1 =  date1.strftime("%Y-%m-%d")
             dt2 =  date2.strftime("%Y-%m-%d")
             slice_dt_all.append(Data[(Data['dt'] > dt1) & (Data['dt'] < dt2)])
             slice_dt_uni.append(slice_dt_all[0].drop_duplicates(subset = ['member_id'], keep =

             # slice of the next seven days
             date3 = date
             date4 = date + datetime.timedelta(days=8)
             dt3 =  date3.strftime("%Y-%m-%d")
             dt4 =  date4.strftime("%Y-%m-%d")
             slice_dt_all.append(Data[(Data['dt'] > dt3) & (Data['dt'] < dt4)])
             slice_dt_uni.append(slice_dt_all[1].drop_duplicates(subset = ['member_id'], keep =
```

```
# slice of old users
slice_dt_all.append(Data[Data['dt'] < dt3])
slice_dt_uni.append(slice_dt_all[2].drop_duplicates(subset = ['member_id'], keep =

new_user = slice_dt_uni[0][-slice_dt_uni[0].member_id.isin(slice_dt_uni[2].member_
new_user_buy_again = new_user.member_id.loc[new_user.member_id.isin(slice_dt_uni[
if len(new_user) == 0:
    print('There are no new users buying at that day!'
          'Thus, the week retention rate of this day for new users cannot be compu
else:
    week_retention_rate_new_user = round(len(new_user_buy_again) / len(new_user),
    print('The week retention rate of {} for new users:'.format(dt), week_retenti
```

```
Please enter the day that you want to compute the week retention rate for new users (from 2019-
2019-01-21
The week retention rate of 2019-01-21 for new users: 0.6026
```

2.10 Problem 10Find the *Retention Rate WITHIN* one week of new users.

Method 1: Compute the Retention Rate WITHIN one given week of new users step by step

In [39]:
```
# slice_0121_0127a = Data[(Data['dt'] > '2019-01-20') & (Data['dt'] < '2019-01-28')]
# slice_0121_0127 = slice_0121_0127a.drop_duplicates(subset = ['member_id'], keep = '
# new user in 2019-01-21 to 2019-01-27
new_user = slice_0121_0127[-slice_0121_0127['member_id'].isin(slice_0120['member_id']]

slice_0121_0127_mem_dt_order = slice_0121_0127a.groupby(['member_id','dt'])['member_i
slice_0121_0127_mem_dt_order = slice_0121_0127_mem_dt_order.to_frame()
slice_0121_0127_mem_dt_order.columns = [['orders']]
slice_0121_0127_mem_dt_order.head()
```

Out[39]:

member_id	dt	orders
1520	2019-01-22	2
	2019-01-25	2
1525	2019-01-21	2
	2019-01-25	1
1533	2019-01-22	3

In [40]:
```
slice_0121_0127_mem_dt_order = slice_0121_0127_mem_dt_order.reset_index()
slice_0121_0127_mem_dt_order.index.names = ['num']
slice_0121_0127_mem_dt_order.columns = ['member_id','dt','orders']
slice_0121_0127_mem_dt_order.head()
```

Out[40]:

num	member_id	dt	orders
0	1520	2019-01-22	2

```
1         1520  2019-01-25      2
2         1525  2019-01-21      2
3         1525  2019-01-25      1
4         1533  2019-01-22      3
```

```
In [41]: slice_0121_0127_mem_dt = slice_0121_0127_mem_dt_order.groupby('member_id')[['dt']].cou
         slice_0121_0127_mem_dt = slice_0121_0127_mem_dt[slice_0121_0127_mem_dt['dt'] == True]
         # slice_0121_0127_mem_dt.insert(0, 'member_id', slice_0121_0127_mem_dt.index)
         slice_0121_0127_mem_dt = slice_0121_0127_mem_dt.reset_index()
         slice_0121_0127_mem_dt.index.names = ['num']
         slice_0121_0127_mem_dt.head()
```

```
Out[41]:      member_id   dt
         num
         0         1520  True
         1         1525  True
         2         1557  True
         3         1575  True
         4         1613  True
```

```
In [42]: new_user_buy_again = new_user['member_id'].loc[new_user['member_id'].isin(slice_0121_(

         retention_rate_within_one_week = round(len(new_user_buy_again) / len(new_user), 4) # 
         print('The retention rate within 2019-01-21 to 2019-01-27 of new users:', retention_ra
```

```
The retention rate within 2019-01-21 to 2019-01-27 of new users: 0.3058
```

Method 2: Compute the Retention Rate WITHIN any week of new users by using 'import datetime'

```
In [43]: import datetime

         def retention_rate_within_one_week_of_new_users(dt):
             slice_dt_all = []
             slice_dt_uni = []
             date = datetime.datetime.strptime(dt, '%Y-%m-%d')
             # slice of one week
             date1 = date - datetime.timedelta(days=1)
             date2 = date + datetime.timedelta(days=7)
             dt1 =  date1.strftime("%Y-%m-%d")
             dt2 =  date2.strftime("%Y-%m-%d")
             slice_dt_all.append(Data[(Data['dt'] > dt1) & (Data['dt'] < dt2)])
             slice_dt_uni.append(slice_dt_all[0].drop_duplicates(subset = ['member_id'], keep =

             # slice of old users
             date3 = date
             dt3 =  date3.strftime("%Y-%m-%d")
             slice_dt_all.append(Data[Data['dt'] < dt3])
```

```
        slice_dt_uni.append(slice_dt_all[1].drop_duplicates(subset = ['member_id'], keep =

        # new users in this week
        new_user = slice_dt_uni[0][-slice_dt_uni[0].member_id.isin(slice_dt_uni[1].member_

        slice_week_mem_dt_order = slice_dt_all[0].groupby(['member_id','dt'])['member_id']
        slice_week_mem_dt_order = slice_week_mem_dt_order.to_frame()
        slice_week_mem_dt_order.columns = [['orders']]

        slice_week_mem_dt_order = slice_week_mem_dt_order.reset_index()
        slice_week_mem_dt_order.index.names = ['num']
        slice_week_mem_dt_order.columns = ['member_id','dt','orders']

        slice_week_mem_dt = slice_week_mem_dt_order.groupby('member_id')[['dt']].count()>
        slice_week_mem_dt = slice_week_mem_dt[slice_week_mem_dt['dt'] == True]
        slice_week_mem_dt = slice_week_mem_dt.reset_index()
        slice_week_mem_dt.index.names = ['num']

        new_user_buy_again = new_user['member_id'].loc[new_user['member_id'].isin(slice_we
        if len(new_user) == 0:
            print('There are no new users buying this week!'
                  ' Thus, the retention rate within this week of new users cannot be compu
            return
        retention_rate_within_one_week = round(len(new_user_buy_again) / len(new_user), 4
        date4 = date + datetime.timedelta(days=6)
        dt4 =  date4.strftime("%Y-%m-%d")
        print('The retention rate within {} to {} of new users:'.format(dt, dt4), retentio
```

In [44]:
```
slice_Holiday = Holiday[(Holiday['dt'] > '2019-01-19') & (Holiday['dt'] < '2019-03-02
slice_Holiday = slice_Holiday[['dt','weekday', 'week_of_year']]

pd.pivot_table(slice_Holiday, index = 'week_of_year', columns = 'weekday', aggfunc =
```

Out[44]:
```
                       dt                                                    \
weekday                 1           2           3           4           5
week_of_year
3                       0           0           0           0           0
4              2019-01-21  2019-01-22  2019-01-23  2019-01-24  2019-01-25
5              2019-01-28  2019-01-29  2019-01-30  2019-01-31  2019-02-01
6              2019-02-04  2019-02-05  2019-02-06  2019-02-07  2019-02-08
7              2019-02-11  2019-02-12  2019-02-13  2019-02-14  2019-02-15
8              2019-02-18  2019-02-19  2019-02-20  2019-02-21  2019-02-22
9              2019-02-25  2019-02-26  2019-02-27  2019-02-28  2019-03-01


weekday                 6           7
week_of_year
3                       0  2019-01-20
```

```
4              2019-01-26  2019-01-27
5              2019-02-02  2019-02-03
6              2019-02-09  2019-02-10
7              2019-02-16  2019-02-17
8              2019-02-23  2019-02-24
9                       0           0
```

```
In [45]: week_num = input('Please enter the week of year (from 4 to 8): ')
         week_num = eval(week_num)

         if type(week_num) == int:
             if week_num < 4 or week_num > 8:
                 print('The retention rate within this week of new users cannot be computed! So
             else:
                 dt = '2019-01-21'
                 for j in range(4, 9):
                     if week_num == j:
                         retention_rate_within_one_week_of_new_users(dt)
                         break
                     else:
                         date = datetime.datetime.strptime(dt, '%Y-%m-%d')
                         date = date + datetime.timedelta(days=7)
                         dt =  date.strftime("%Y-%m-%d")
                         j += 1
         else:
             print('Please enter the correct digit format!')
```

```
Please enter the week of year (from 4 to 8): 4
The retention rate within 2019-01-21 to 2019-01-27 of new users: 0.3058
```

Note: The retention rate within the 7^{th} week (2019-02-11 to 2019-02-17) or 8^{th} week (2019-02-18 to 2019-02-24) of 2019 of new users cannot be computed since there are no new users that week.

2.11 Problem 11Find "Active Users" (which means the number of orders of one user is greater equal to 5).

```
In [46]: all_users_Data = Data.groupby(['member_id'])['commodity_code'].count()
         active_users_Data = all_users_Data[all_users_Data >= 5]
         active_users_index = active_users_Data.index
         active_users = Data.loc[Data['member_id'].isin(active_users_index)] # contain duplica
```

2.12 Problem 12Write the table you get in 11 as a csv file with filename *ActiveUser.csv*.

```
In [47]: active_users.to_csv('ActiveUser.csv')
```

2.13 Problem 13Provide a description of the number of orders for each active user (# of ActiveUser, mean, range, std, variance, skewness and kurtosis).

In [48]:
```
# # The number of ActiveUser is 166308
# len(active_users.drop_duplicates(subset = ['member_id'], keep = 'first', inplace = 
#
# from numpy import mean,ptp,var,std
# print(mean(active_user_order), ptp(active_user_order), var(active_user_order), std(
```

In [49]:
```
active_user_order = active_users.groupby('member_id')[['commodity_name']].count()
active_user_order.columns = ['orders']
active_user_order.head()
```

Out[49]:

member_id	orders
1525	7
1533	12
1557	50
1574	24
1575	139

In [50]:
```
active_user_order.describe()
```

Out[50]:

	orders
count	166308.000000
mean	10.418188
std	7.599244
min	5.000000
25%	6.000000
50%	8.000000
75%	12.000000
max	585.000000

In [51]:
```
print('# of ActiveUser:',int(active_user_order.count()))
print('mean:', round(float(active_user_order.mean()), 6))
print('range:', int(active_user_order.max()-active_user_order.min()))
print('std:', round(float(active_user_order.std()), 6))
print('variance:', round(float(active_user_order.var()), 6))
print('skewness:', round(float(active_user_order.skew()), 6))
print('kurtosis:', round(float(active_user_order.kurt()), 6))
```

```
# of ActiveUser: 166308
mean: 10.418188
range: 580
std: 7.599244
variance: 57.748512
skewness: 6.542469
kurtosis: 241.357987
```

3 Part 2: Data Preprocessing

1. Remove the first column of the data in *data.csv* , because it is just a copy of index.
2. Boss: To implement Collaborative Filtering in recommendation systems, we need a user-item table to show the number of orders for each user and each item. Try to construct *user-item* table. An example of user-item pair: (Phone_No,)
3. Boss: Life is not like a Markov Chain, which means everyone's past behavior is correlated with his present one.
   And that is why we could exploit past purchase behavior to predict their future buying trends. Try to construct a dataset to show this past purchasing behavior trend. For convenience, several instructions are proposed as follows a. Two days correspond to one dimension. b. The last two days of the time span of the data should be the *future* , which means it corresponds to the *target* field for the
   following data mining models. c. The length of each user vector must be maximized. d. The dataset should be a DataFrame in Pandas, so you could customize the columns as you wish. For example, if the time span is from 2019-02-01 to 2019-02-10, then there are 10 days altogether. So each user corresponds to
   a 5-dimensional vector, with 4 features and 1 target dimension. The vector [4, 0, 0, 0, 1] means this user bought one good
   between 02-09 and 02-10, and four goods between 02-01 and 02-02. Additionally, the length of each user vector MUST BE 5
   because of the rule c.

3.1 Problem 1Remove the first column of the data in data.csv, because it is just a copy of index.

In [52]:
```
# Data.columns
Data.drop(['Unnamed: 0'], axis = 1, inplace = True)
Data.head()
```

Out[52]:
```
   Unnamed: 0.1          dt     phone_no  member_id commodity_code  \
0             0  2019-01-25  13901387938      14442          SP025
1             1  2019-01-27  13901387938      14442          SP209
2             2  2019-01-23  13901387938      14442          SP025
3             3  2019-02-01  13901387938      14442          SP025
4             4  2019-01-27  13901387938      14442          SP010

  commodity_name  commodity_origin_money  coupon_id  coupon_money  \
0                                   27.0     7045.0         19.44
1       NFC                         24.0        NaN          0.00
2                                   27.0     5589.0         22.14
3                                   27.0     6604.0         19.44
4                                 27.0     6947.0         14.04

  one_category_name two_category_name  commodity_income  pay_money  \
0                                                  7.56       7.56
1                                                0.00       0.00
```

```
2                                          4.86       4.86
3                                          7.56       7.56
4                                          12.96      12.96

   coffeestore_share_money  discount_rate
0                      0.0           0.28
1                      0.0           0.00
2                      0.0           0.18
3                      0.0           0.28
4                      0.0           0.48
```

3.2 Problem 2

Boss: To implement Collaborative Filtering in recommendation systems, we need a user-item table to show the number of orders for each user and each item. Try to construct *user-item* table. An example of user-item pair: (Phone_No,)

In [53]:
```python
slice_user_item = Data[['Unnamed: 0.1', 'phone_no', 'commodity_name']]
# slice_user_item.rename(columns={'Unnamed: 0.1': 'orders'}, inplace = True)
slice_user_item.columns = ['orders', 'phone_no', 'commodity_name']

user_item_table = pd.pivot_table(slice_user_item, index = 'phone_no', columns = 'comm
                                 aggfunc = len, fill_value = 0)
```

In [54]:
```python
user_item_table.head() # len(user_item_table)=466886
```

Out[54]:
```
                orders                                                    \
commodity_name NFC NFC NFC NFC NFC 330ml
phone_no
51379898             0        0           0        0             0          0
57047978             0        0           0        0             0          0
61120518             0        0           0        0             0          0
62288158             0        0           0        0             1          0
64618166             0        0           0        0             0          0

                                         ...                              \
commodity_name     ...
phone_no                                 ...
51379898          0    0       0      0  ...       0       0    0      0    0
57047978          0    0       0      0  ...       0       0    0      0    0
61120518          0    0       0      0  ...       0       0    0      0    0
62288158          0    0       0      0  ...       0       0    0      0    0
64618166          0    0       0      0  ...       0       0    0      0    0


commodity_name
phone_no
51379898            0     0          0     0      0
57047978            0     0          0     0      0
```

```
61120518              0      0           0      0       0
62288158              0      0           0      0       0
64618166              0      0           0      0       0

[5 rows x 73 columns]
```

3.3 Problem 3

Boss: Life is not like a Markov Chain, which means everyone's past behavior is correlated with his present one. And that is why we could exploit past purchase behavior to predict their future buying trends. Try to construct a dataset to show this past purchasing behavior trend.

```
In [55]: import math
         print('The length of each user vector:', math.floor(len(orders)/2)) # len(order) = 41
```

```
The length of each user vector: 20
```

```
In [56]: slice_0121_0301 = Data[Data['dt'] > '2019-01-20']
         slice_user_date = slice_0121_0301[['Unnamed: 0.1', 'phone_no', 'dt']]
         # slice_user_date.rename(columns={'Unnamed: 0.1': 'orders'}, inplace = True)
         slice_user_date.columns = ['orders', 'phone_no', 'dt']
         slice_user_date.head()
```

```
Out[56]:    orders     phone_no          dt
         0       0  13901387938  2019-01-25
         1       1  13901387938  2019-01-27
         2       2  13901387938  2019-01-23
         3       3  13901387938  2019-02-01
         4       4  13901387938  2019-01-27
```

The following function is used to make two days correspond to one dimension.

```
In [57]: import datetime

         def determine_period(dt):
             dt = datetime.datetime.strptime(dt, '%Y-%m-%d')
             j = 1
             period = -1
             first_day = datetime.datetime(2019, 1, 20, 0, 0)
             last_day = datetime.datetime(2019, 3, 1, 0, 0)
             if dt <= first_day or dt > last_day:
                 return period
             while (first_day + datetime.timedelta(days=(2*j-1))) < last_day:
                 period_day_1 = first_day + datetime.timedelta(days=(2*j-1))
                 period_day_2 = first_day + datetime.timedelta(days=(2*j))
                 if (dt == period_day_1) or (dt == period_day_2):
                     period = j
                     break
```

```
                else:
                    j += 1

            return period
```

```
In [58]: dim = slice_user_date.dt.apply(lambda x: determine_period(x))
         dim = dim.to_frame()
         dim.columns=['period']
         slice_user_date = pd.concat([slice_user_date, dim], axis = 1)
         slice_user_date.drop(['dt'], axis = 1, inplace = True)
         slice_user_date.head()
```

```
Out[58]:    orders     phone_no  period
         0       0  13901387938       3
         1       1  13901387938       4
         2       2  13901387938       2
         3       3  13901387938       6
         4       4  13901387938       4
```

```
In [59]: user_date_table = pd.pivot_table(slice_user_date, index = 'phone_no', columns = 'peri
         user_date_table.head()
```

```
Out[59]:          orders
         period        1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16 17 18 19 20
         phone_no
         51379898      0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
         62288158      0  0  0  0  1  0  0  0  0  0  1  0  1  0  0  1  1  0  0  1
         65310185      1  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0
         67443044      0  0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
         67469370      1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
```

4 Part 3: Model Training and Prediction

Boss: For the target field, 1 means he purchased in the future and 0 means he did not. Then you could use traditional classification algorithms to predict the future behaviors of all users.

1. Transform the data you got from the last section into an array in Numpy.
2. Split the data into features X and targets Y.
3. Use *Adaboost*, *Random Forest* in Sklearn to construct the model for prediction with 3-fold cross validation
   a. (Optional) Use *Xgboost*. b. Boss: Please do not use *Naive-Bayes* or *Support Vector Machine* in this project. True or False? Explain.
4. Tune your model and report the best metrics you could get for your model and the corresponding confusion matrix and model name. At least Adaboost and Random Forest should be used for tuning. Here are some suggestions.
   a. Try to do oversampling or undersampling. This is an imbalanced classification problem.

b. Change the parameters of each model (e.g. *scale_pos_weight* in *Xgboost* and probability threshold), more information could
be found in the Official Documentations. c. Accuracy is not suitable to be an evaluation metric in this case. Use F1-measure. d. Try to not record the # of orders for each user. Record whether he bought the goods instead, 1 if he bought and 0 otherwise. e. Try to record the active-user feature. Many users did not only buy one cup of drink during two days, so whether one user is
active should be taken into consideration. f. Try to split the data with respect to Workdays and Weekends and train two different models. If that is the best choice, then
you should report two metrics, one for Workdays Model and the other one for Weekends Model.

5. After tuning, try to explain why your model works better.

4.1 Problem 1Transform the data you got from the last section into an array in Numpy.

```
In [60]: dataset = np.array(user_date_table) # user_date_table.values
```

4.2 Problem 2Split the data into features X and targets Y.

```
In [61]: X, Y = dataset[:,0:19], dataset[:,19]

In [62]: X

Out[62]: array([[0, 0, 0, ..., 0, 0, 0],
                [0, 0, 0, ..., 1, 0, 0],
                [1, 0, 0, ..., 0, 0, 0],
                ...,
                [0, 5, 0, ..., 0, 0, 0],
                [0, 0, 1, ..., 0, 0, 0],
                [0, 0, 1, ..., 0, 0, 0]], dtype=int64)

In [63]: Y

Out[63]: array([0, 1, 0, ..., 3, 0, 0], dtype=int64)
```

Boss: For the target field, 1 means he purchased in the future and 0 means he did not. Then you could use traditional classification algorithms to predict the future behaviors of all users.

```
In [64]: y = Y
         y[y > 0] = 1
         y

Out[64]: array([0, 1, 0, ..., 1, 0, 0], dtype=int64)
```

4.3 Problem 3Use Adaboost, Random Forest in Sklearn to construct the model for prediction with 3-fold cross validation.

```
In [65]: from sklearn.model_selection import train_test_split

         X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 42) # test_s
```

Adaboost

```
In [66]: from sklearn.metrics import classification_report
         from sklearn.ensemble import AdaBoostClassifier
         from sklearn.model_selection import cross_val_score

         AdaBoost_clf = AdaBoostClassifier(n_estimators = 10)    # default # of weak classifie
         AdaBoost_clf.fit(X_train, y_train)
         y_prediction = AdaBoost_clf.predict(X_test)
         print('Train score: {:.3f}'.format(AdaBoost_clf.score(X_train, y_train)))
         print('Test score: {:.3f}'.format(AdaBoost_clf.score(X_test, y_test)))
         print(classification_report(y_test, y_prediction))
```

```
Train score: 0.888
Test score: 0.887
              precision    recall  f1-score   support

           0       0.90      0.98      0.94     99407
           1       0.62      0.25      0.35     14217

    accuracy                           0.89    113624
   macro avg       0.76      0.61      0.65    113624
weighted avg       0.87      0.89      0.86    113624
```

```
In [67]: # 3-fold cross validation
         acc_scores = cross_val_score(AdaBoost_clf, X_train, y_train, cv = 3) # model, raw_dat
         print(acc_scores) # accuracy
```

```
[0.88711892 0.88814863 0.88802542]
```

Random Forest

```
In [68]: from sklearn.ensemble import RandomForestClassifier

         random_forest_clf = RandomForestClassifier()
         random_forest_clf.fit(X_train, y_train)
         y_prediction = random_forest_clf.predict(X_test)
         print('Train score: {:.3f}'.format(random_forest_clf.score(X_train, y_train)))
         print('Test score: {:.3f}'.format(random_forest_clf.score(X_test, y_test)))
         print(classification_report(y_test, y_prediction))
```

```
Train score: 0.952
Test score: 0.879
              precision    recall  f1-score   support

           0       0.90      0.97      0.93     99407
```

```
           1       0.54      0.24      0.33     14217

    accuracy                           0.88    113624
   macro avg       0.72      0.60      0.63    113624
weighted avg       0.85      0.88      0.86    113624
```

```
In [69]: # 3-fold cross validation
         acc_scores = cross_val_score(random_forest_clf, X_train, y_train, cv = 3) # model, ra
         print(acc_scores) # accuracy
```

```
[0.87932127 0.87910125 0.88008695]
```

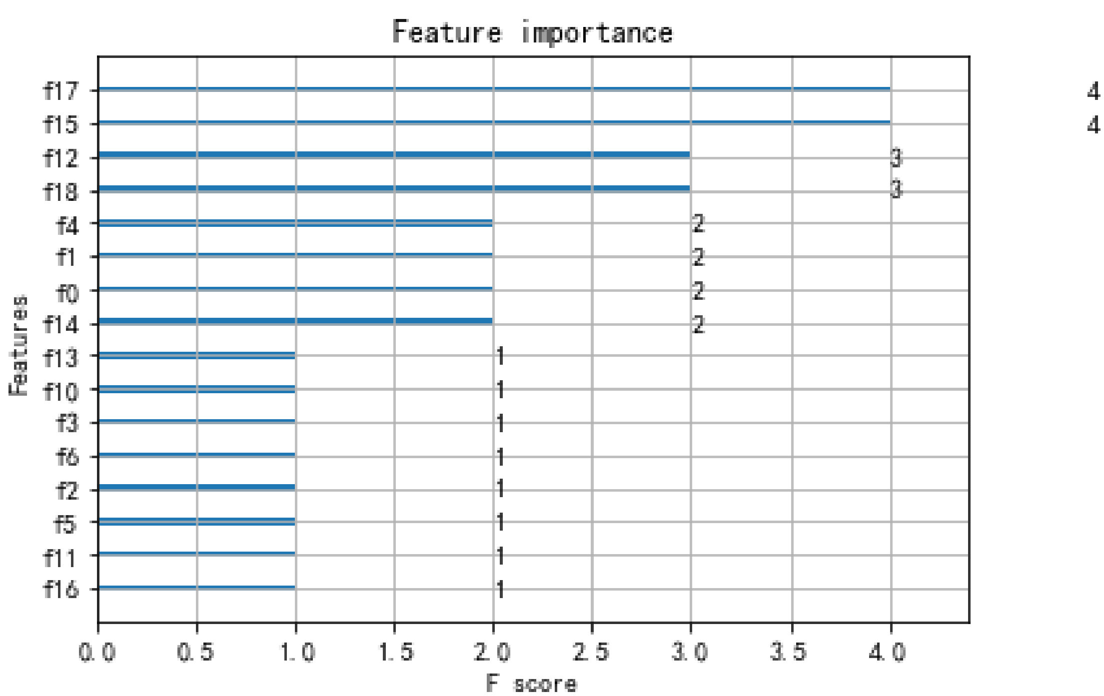
4.3.1 Problem 3-aXgboost

```
In [70]: import xgboost as xgb
         from xgboost import XGBClassifier
         from sklearn.metrics import accuracy_score
         from sklearn import metrics

         dtrain = xgb.DMatrix(X_train, label = y_train)
         dtest = xgb.DMatrix(X_test, label = y_test)

         params={'booster':'gbtree', 'max_depth': 2, 'eta': 1,  #  Booster parameters:  max_de
                 'objective': 'binary:logistic', # objective [ default=reg:linear], logistic r
                 'eval_metric': 'auc', # The evaluation index needed to verify the data, auc:
                                       #'nthread': 4, # of CPU threads
                 'lambda': 0, # [default=0], L2 regular penalty coefficient, the larger the pa
                              # alpha [default=0], L1 regular penalty coefficient, can make t
                 'subsample': 1, # subsample [default=1], random sampling of training samples
                 'colsample_bytree': 1, # colsample_bytree [default=1], the proportion of rand
                 'min_child_weight': 2,  # min_child_weight [default=1], max_delta_step [defau
                 'seed': 0} # seed [default=0]

         num_round = 10
         bst1 = xgb.train(params, dtrain, num_round)

         train_pred = bst1.predict(dtrain)
         train_prediction = (train_pred >= 0.5)*1 # let 0.5 be the threshold

         y_pred = bst1.predict(dtest)
         y_prediction = (y_pred >= 0.5)*1 # let 0.5 be the threshold


         print('Train accuracy: {:.3f}'.format(accuracy_score(y_train, train_prediction)))
         print('Test accuracy: {:.3f}\n'.format(accuracy_score(y_test, y_prediction)))
```

```
print(classification_report(y_test, y_prediction))

confusion_matrix = pd.DataFrame(metrics.confusion_matrix(y_test, y_prediction))
confusion_matrix.columns = ['not buy [0]', 'buy [1]']
confusion_matrix.index = ['predict not buy [0]', 'predict buy [1]']
print('confusion matrix:\n ', confusion_matrix)
```

```
Train accuracy: 0.888
Test accuracy: 0.888

              precision    recall  f1-score   support

           0       0.90      0.98      0.94     99407
           1       0.64      0.24      0.35     14217

    accuracy                           0.89    113624
   macro avg       0.77      0.61      0.64    113624
weighted avg       0.87      0.89      0.87    113624

confusion matrix:
                       not buy [0]  buy [1]
predict not buy [0]        97437     1970
predict buy [1]            10773     3444
```

In [71]:
```
from xgboost import plot_importance # display importance of feature
plot_importance(bst1)
plt.show()
```



```
In [72]: bst2 = XGBClassifier(max_depth = 2, n_estimators = num_round, silent = True, objective
         bst2.fit(X_train, y_train)

         train_prediction = bst2.predict(X_train)
         y_prediction = bst2.predict(X_test)

         print('Train accuracy: {:.3f}'.format(accuracy_score(y_train, train_prediction)))
         print('Test accuracy: {:.3f}\n'.format(accuracy_score(y_test, y_prediction)))
         print(classification_report(y_test, y_prediction))

         confusion_matrix = pd.DataFrame(metrics.confusion_matrix(y_test, y_prediction))
         confusion_matrix.columns = ['not buy [0]', 'buy [1]']
         confusion_matrix.index = ['predict not buy [0]', 'predict buy [1]']
         print('confusion matrix:\n ', confusion_matrix)

         # 3-fold cross validation
         acc_scores = cross_val_score(bst2, X_train, y_train, cv = 3)
         print('\n3-fold cross validation:')
         print(acc_scores)
```

```
Train accuracy: 0.888
Test accuracy: 0.887

              precision    recall  f1-score   support

           0       0.89      0.99      0.94     99407
           1       0.70      0.17      0.27     14217

    accuracy                           0.89    113624
   macro avg       0.80      0.58      0.61    113624
weighted avg       0.87      0.89      0.86    113624

confusion matrix:
                       not buy [0]  buy [1]
predict not buy [0]        98358     1049
predict buy [1]            11795     2422

3-fold cross validation:
[0.88766458 0.88846547 0.88833345]
```

4.3.2 Problem 3-b

Boss: We could, but we do not use Naive Bayes or Support Vector Machine in this project.

Answer: True. Reasons are as follows.

Why do we not use Naive Bayes in this project? Because Naive Bayes model assumes that attributes are independent from each other, this assumption is often not valid in practical applications. When the correlation between attributes is large, the result of classification is not good. In this project, whether the users will purchased in the future is correlated with their past behaviors. Meanwhile, we need to know the prior probability, which usually depends on the assumption.

Why do we not use Support Vector Machine in this project? If we use linear SVM, the data of users' purchasing behavior may be linearly indivisible. If we use kernel trick, it may be overfitting. Moreover, finding the best model requires us to test different combinations of kernel functions and model parameters. When the sample data is very large, the process of training is very time-consuming, which will also consume a lot of memory.

4.4 Problem 4Tune your model and report the best metrics you could get for your model and the corresponding confusion matrix and model name. At least Adaboost and Random Forest should be used for tuning.

d. Try to not record the # of orders for each user. Record whether he bought the goods instead, 1 if he bought and 0 otherwise.

```
In [73]: dataset = np.array(user_date_table)
         X, Y = dataset[:,0:19], dataset[:,19]
         X[X > 0] = 1
         y = Y
         y[y > 0] = 1

         X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 42) # test_s
```

a. Try to do oversampling or undersampling. This is an imbalanced classification problem.

4.4.1 To be continued...

```
In [74]: from imblearn.over_sampling import SMOTE
         from imblearn.under_sampling import ClusterCentroids

         X_resampled_over, y_resampled_over = SMOTE().fit_sample(X_train, y_train)

         X_resampled_under, y_resampled_under = ClusterCentroids().fit_sample(X_train, y_train)
```

Adaboost

```
In [76]: from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
         from sklearn.metrics import f1_score

         # default_model = AdaBoostClassifier(base_estimator = None, n_estimators = 50, learni
         # learning rate: if too large, it is easy to miss the optimal value; if too small, th
         # algorithms = 'SAMME.R' or 'SAMME'

         AdaBoost_clf = AdaBoostClassifier()
         param_test = {'n_estimators': list(range(20, 71))}
         clf = GridSearchCV(AdaBoost_clf, param_grid = param_test, scoring = 'f1', cv = 3)
```

```
        clf.fit(X_train, y_train)
        y_preds = clf.predict(X_test)
        test_f1 = f1_score(y_test, y_preds)

        print('f1 scoce: {:.3f}'.format(test_f1))
        print('confusion matrix:\n', metrics.confusion_matrix(y_test, y_preds))
        print('The best f1 score: {:.3f}'.format(clf.best_score_))
        print('The best measure', clf.best_estimator_)  # get the classification model for th
```

```
f1 scoce: 0.337
confusion matrix:
 [[97601  1806]
 [10970  3247]]
The best f1 score: 0.347
The best measure AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None, learning_rate=1.(
                   n_estimators=21, random_state=None)
```

Random Forest

```
In [77]: from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
         from sklearn.metrics import f1_score

         # default model
         # n_estimators = 10, criterion='gini', max_depth = None, min_samples_split = 2, min_s
         # max_features = 'auto', max_leaf_nodes = None, min_impurity_decrease = 0.0, min_impu
         # bootstrap = True, oob_score = False, n_jobs = 1, random_state = None, verbose = 0,

         random_forest_clf = RandomForestClassifier()
         param_test = {'n_estimators': list(range(5, 16))}
         clf = GridSearchCV(random_forest_clf, param_grid = param_test, scoring = 'f1', cv = 3)
         clf.fit(X_train, y_train)
         y_preds = clf.predict(X_test)
         test_f1 = f1_score(y_test, y_preds)

         print('f1 scoce: {:.3f}'.format(test_f1))
         print('confusion matrix:\n', metrics.confusion_matrix(y_test, y_preds))
         print('The best f1 score: {:.3f}'.format(clf.best_score_))
         print('The best measure', clf.best_estimator_)  # get the classification model for th
```

```
f1 scoce: 0.333
confusion matrix:
 [[96645  2762]
 [10823  3394]]
The best f1 score: 0.333
The best measure RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
```

```
                         min_samples_leaf=1, min_samples_split=2,
                         min_weight_fraction_leaf=0.0, n_estimators=13,
                         n_jobs=None, oob_score=False, random_state=None,
                         verbose=0, warm_start=False)
```

Xgboost

```
In [78]: from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
         from sklearn.metrics import f1_score

         # params = {'max_depth': 2, 'eta': 0.1, 'silent': 1, 'objective': 'binary:logistic' }
         bst = XGBClassifier(max_depth = 2, learning_rate = 0.1, silent = True, objective = 'b
         param_test = {'n_estimators': list(range(100, 141, 1))}
         clf = GridSearchCV(estimator = bst, param_grid = param_test, scoring = 'f1', cv = 3)
         clf.fit(X_train, y_train)
         y_preds = clf.predict(X_test)
         test_f1 = f1_score(y_test, y_preds)

         print('f1 scoce: {:.3f}'.format(test_f1))
         print('confusion matrix:\n', metrics.confusion_matrix(y_test, y_preds))
         print('The best f1 score: {:.3f}'.format(clf.best_score_))
         print('The best measure', clf.best_estimator_)  # get the classification model for th
```

```
f1 scoce: 0.336
confusion matrix:
 [[97667  1740]
 [11000  3217]]
The best f1 score: 0.341
The best measure XGBClassifier(base_score=0.5, booster=None, colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints=None,
              learning_rate=0.1, max_delta_step=0, max_depth=2,
              min_child_weight=1, missing=nan, monotone_constraints=None,
              n_estimators=137, n_jobs=0, num_parallel_tree=1,
              objective='binary:logistic', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=1, silent=True, subsample=1,
              tree_method=None, validate_parameters=False, verbosity=None)
```

e. Try to record the active-user feature. Many users did not only buy one cup of drink during two days, so whether one user is active should be taken into consideration.

```
In [79]: user_date_table_temp = pd.DataFrame(np.array(user_date_table), index = user_date_tabl
         user_date_table_temp.head()
```

```
Out[79]:           1  2  3  4  5  6  7  8  9  10  11  12  13  14  15  16  17  18  19  \
         phone_no
         51379898  0  0  0  1  0  0  0  0  0   0   0   0   0   0   0   0   0   0   0
```

```
62288158  0  0  0  0  1  0  0  0  0   0   1   0   1   0   0   1   1   0   0
65310185  1  0  0  0  0  0  0  0  0   0   0   0   0   0   1   0   0   0   0
67443044  0  0  1  0  0  0  0  0  0   0   0   0   0   0   0   0   0   0   0
67469370  1  0  0  0  0  0  0  0  0   0   0   0   0   0   0   0   0   0   0

          20
phone_no
51379898   0
62288158   1
65310185   0
67443044   0
67469370   0
```

In [80]:
```python
active_state = user_date_table_temp.index.isin(active_users['phone_no']) # array of T
active_state = active_state.astype(int) # array of 1 and 0
active_state = pd.DataFrame(active_state, index = user_date_table.index, columns = ['a

user_date_active_table = pd.concat([active_state, user_date_table_temp], axis = 1)
user_date_active_table.head()
```

Out[80]:
```
          active-user  1  2  3  4  5  6  7  8  9 ...  11  12  13  14  15  16  \
phone_no                                         ...
51379898            0  0  0  0  1  0  0  0  0  0 ...   0   0   0   0   0   0
62288158            1  0  0  0  0  1  0  0  0  0 ...   1   0   1   0   0   1
65310185            0  1  0  0  0  0  0  0  0  0 ...   0   0   0   0   1   0
67443044            0  0  0  1  0  0  0  0  0  0 ...   0   0   0   0   0   0
67469370            0  1  0  0  0  0  0  0  0  0 ...   0   0   0   0   0   0

          17  18  19  20
phone_no
51379898   0   0   0   0
62288158   1   0   0   1
65310185   0   0   0   0
67443044   0   0   0   0
67469370   0   0   0   0

[5 rows x 21 columns]
```

In [81]:
```python
dataset_new = np.array(user_date_active_table)
```

In [82]:
```python
X, Y = dataset_new[:,0:20], dataset_new[:,20]
```

In [83]:
```python
y = Y
X[X > 0] = 1
y[y > 0] = 1
```

In [84]:
```python
X
```

Out[84]:
```
array([[0, 0, 0, ..., 0, 0, 0],
       [1, 0, 0, ..., 1, 0, 0],
```

```
        [0, 1, 0, ..., 0, 0, 0],
        ...,
        [1, 0, 1, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0]], dtype=int64)
```

```
In [85]: y
```

```
Out[85]: array([0, 1, 0, ..., 1, 0, 0], dtype=int64)
```

4.4.2 To be continued...

f. Split the data with respect to Weekdays and Weekends and train two different models.

4.4.3 To be continued...

4.5 Problem 5After tuning, try to explain why your model works better.

Hint: For every case you try in Problem 4, please record the result and the trend. Does the model behave better or worse? The performances will show you the hidden information of the data and you could use business intuition to explain the phenomenons. That is the answer of Problem 5.

4.5.1 To be continued...

Indeed, tuning models is the most difficult problem of this project and it is very time-consuming since there are many cases for us to consider. Frankly speaking, I am not very familiar with some models and I still have a long way to go.