Objetive: Our goal is to find how quantity of each item in each province, changes from each month and year. During milestone 1, we try to finish all the preprocessing steps and draw necessary graphs for insights. We will try to build the model and make predictions in milestone 2 and later stages.

```
#Import Files
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving item.csv to item.csv
Saving train.csv to train.csv
```

```
#Read data
import pandas as pd
import numpy as np
df_item = pd.read_csv('item.csv')
df_train = pd.read_csv('train.csv')
print(df_item)
print(df_train)
```

```
     item_id brand_id  brandfamily_id  package_id info_id
0          1  [6, 14]               1           1     BHS
1          6  [6, 19]               2           1     BHM
2         54  [6, 14]               1           1     BHS
3         15  [6, 19]               2           1     BHM
4        108     [19]               3           1     MQB
..       ...      ...             ...         ...     ...
113       78   [6, 8]               4           4    BZMN
114        5     [11]               5           1     HGO
115       83     [19]               3           1     MQB
116       87     [19]               3           2     MQB
117       12     [19]               3           4     MQB

[118 rows x 5 columns]
          datetime  order_id  user_id  item_id  province_id  city_id  quantity
0       2017-01-02      8806      404        1            2       19  8.298021
1       2017-01-02     22552      404        1            2       19  8.298021
2       2017-01-02       494      489        6            1        0  0.376088
3       2017-01-02     62721       28       54            2       19  1.488643
4       2017-01-02     24790      231       15            0       10  0.748268
...            ...       ...      ...      ...          ...      ...       ...
145190  2020-12-29     72305      390       18            0       10  0.733838
145191  2020-12-30     55224      321       27            1        3  0.792584
145192  2020-12-31     75987      326      105            0        4  0.009584
145193  2020-12-31     27911      326      105            0        4  0.015935
145194  2020-12-31     55625      326       75            0        4  0.069767

[145195 rows x 7 columns]
```

We find that our two tales have a common column called id, we need to combine them in order to continue the analysis.

```
#Data integrity
df_wine = pd.merge(df_item,df_train, on = 'item_id')
df_wine
```

	item_id	brand_id	brandfamily_id	package_id	info_id	datetime	order_id
0	1	[6, 14]	1	1	BHS	2017-01-02	8806
1	1	[6, 14]	1	1	BHS	2017-01-02	22552
2	1	[6, 14]	1	1	BHS	2017-01-06	54066
3	1	[6, 14]	1	1	BHS	2017-01-07	67828
4	1	[6, 14]	1	1	BHS	2017-01-10	4205
...	...	...	...	...	...	...	...
145190	12	[19]	3	4	MQB	2020-09-21	52082
145191	12	[19]	3	4	MQB	2020-09-26	11453

The join result get a table with 145195 rows and 11 columns, which is good

```
#Explode composite values
from ast import literal_eval
df_wine['brand_id'] = df_wine['brand_id'].astype(str)
df_wine['brand_id'] = df_wine['brand_id'].apply(literal_eval)
df_wine = df_wine.explode('brand_id')
df_wine
```

	item_id	brand_id	brandfamily_id	package_id	info_id	datetime	order_id
0	1	6	1	1	BHS	2017-01-02	8806
						2017-01-	

We find that brand_id has composite items(it is a list), wh need to change its types to numeric. Explode the lists to get more rows(217723)

```
#Data Cleaning

#Check Data Type
df_wine.dtypes
```

```
item_id            int64
brand_id          object
brandfamily_id     int64
package_id         int64
info_id           object
datetime          object
order_id           int64
user_id            int64
province_id        int64
city_id            int64
quantity         float64
dtype: object
```

We check the types find that some types are unclear, they are object which are hard to handle

```
from datetime import datetime
#Convert types
df_wine['brand_id'] = df_wine['brand_id'].astype(int)
df_wine['info_id'] = df_wine['info_id'].astype('category')
df_wine['datetime'] = pd.to_datetime(df_wine['datetime'], format='%Y-%m-%d')
df_wine.dtypes
```

```
item_id                    int64
brand_id                   int64
brandfamily_id             int64
package_id                 int64
info_id                 category
datetime          datetime64[ns]
order_id                   int64
user_id                    int64
province_id                int64
city_id                    int64
quantity                 float64
dtype: object
```

```
# Convert string id to numeric
df_wine['info_id'] = df_wine['info_id'].cat.codes
```

```
df_wine['info_id'] = df_wine['info_id'].astype(int)
df_wine.dtypes
```

```
df_wine.dtypes
```

```
item_id                    int64
brand_id                   int64
brandfamily_id             int64
package_id                 int64
info_id                    int64
datetime          datetime64[ns]
order_id                   int64
user_id                    int64
province_id                int64
city_id                    int64
quantity                 float64
dtype: object
```

We try to make sure every id is int. Convert brand_id to int. Cast info_id into category then convert into int. Convert the datetime from object to datetime object.

```
#Cleaning NA values

df_wine.dropna(axis = 0, how = "any")
df_wine
```

	item_id	brand_id	brandfamily_id	package_id	info_id	datetime	order_id
0	1	6	1	1	3	2017-01-02	8806
0	1	14	1	1	3	2017-01-02	8806
1	1	6	1	1	3	2017-01-02	22552
1	1	14	1	1	3	2017-01-02	22552
2	1	6	1	1	3	2017-01-06	54066
...	...	...	...	...	...	...	...
145190	12	19	3	4	11	2020-09-21	52082
145191	12	19	3	4	11	2020-09-26	11453

We check NA thourgh all rows and columns. We fine that there is no missing values at all, which means the table is good itself.

```
#Check negative values


print("The unusual values for item id:",df_wine[ df_wine.iloc[: , 0] < 0 ])
```

```
print("The unusual values for brand id:",df_wine[ df_wine.iloc[: , 1] < 0 ])
print("The unusual values for brandfamily id:",df_wine[ df_wine.iloc[: , 2] < 0 ])
print("The unusual values for package id:",df_wine[ df_wine.iloc[: , 3] < 0 ])
print("The unusual values for order id:",df_wine[ df_wine.iloc[: , 6] < 0 ])
print("The unusual values for user id:",df_wine[ df_wine.iloc[: , 7] < 0 ])
print("The unusual values for province id:",df_wine[ df_wine.iloc[: , 8] < 0 ])
print("The unusual values for city id:",df_wine[ df_wine.iloc[: , 9] < 0 ])
print("The unusual values for quantity :",df_wine[ df_wine.iloc[: , 10] < 0 ])
```

```
The unusual values for item id: Empty DataFrame
Columns: [item_id, brand_id, brandfamily_id, package_id, info_id, datetime, order_id,
Index: []
The unusual values for brand id: Empty DataFrame
Columns: [item_id, brand_id, brandfamily_id, package_id, info_id, datetime, order_id,
Index: []
The unusual values for brandfamily id: Empty DataFrame
Columns: [item_id, brand_id, brandfamily_id, package_id, info_id, datetime, order_id,
Index: []
The unusual values for package id: Empty DataFrame
Columns: [item_id, brand_id, brandfamily_id, package_id, info_id, datetime, order_id,
Index: []
The unusual values for order id: Empty DataFrame
Columns: [item_id, brand_id, brandfamily_id, package_id, info_id, datetime, order_id,
Index: []
The unusual values for user id: Empty DataFrame
Columns: [item_id, brand_id, brandfamily_id, package_id, info_id, datetime, order_id,
Index: []
The unusual values for province id: Empty DataFrame
Columns: [item_id, brand_id, brandfamily_id, package_id, info_id, datetime, order_id,
Index: []
The unusual values for city id: Empty DataFrame
Columns: [item_id, brand_id, brandfamily_id, package_id, info_id, datetime, order_id,
Index: []
The unusual values for quantity : Empty DataFrame
Columns: [item_id, brand_id, brandfamily_id, package_id, info_id, datetime, order_id,
Index: []
```

We check whether there are negative values in every id columns and also quantity columns(not alllowed, should be removed as they are unusual values). The good news is that there is no negative values through those columns.

```
#split date
df_wine.insert(0, 'month',  df_wine['datetime'].dt.month)
df_wine.insert(0, 'year',  df_wine['datetime'].dt.year)
df_wine.insert(0, 'date', pd.to_datetime(df_wine[['year', 'month']].assign(DAY=1)))
df_wine = df_wine.drop('datetime', axis=1)
df_wine = df_wine.drop('year', axis=1)
df_wine = df_wine.drop('month', axis=1)
df_wine
```

	date	item_id	brand_id	brandfamily_id	package_id	info_id	order_id	u:
0	2017-01-01	1	6	1	1	3	8806	
0	2017-01-01	1	14	1	1	3	8806	
1	2017-01-01	1	6	1	1	3	22552	
1	2017-01-01	1	14	1	1	3	22552	
2	2017-01-01	1	6	1	1	3	54066	
...	...	...	...	...	...	...	...	
145190	2020-09-01	12	19	3	4	11	52082	

We split the date into year and month, and combine agian, as our target is to predict through year and month(day is not important)

```
from sklearn.preprocessing import StandardScaler
from sklearn import preprocessing
print(df_wine.iloc[:,1:10])
data_scaled = pd.DataFrame(preprocessing.scale(df_wine.iloc[:,1:10]),columns = df_wine.ilo
df_array = np.array(df_wine.iloc[:,1:10])
X_std = StandardScaler().fit_transform(df_array)
from sklearn.decomposition import PCA
pca = PCA(n_components = 4)
principalComponents = pca.fit_transform(X_std)
print("PCA Variance",pca.explained_variance_)
print("PCA Variance",pca.explained_variance_ratio_)
print("Cumulative PCA Variance",np.cumsum(pca.explained_variance_ratio_))
principalDf = pd.DataFrame(data = principalComponents)
principalDf
result = pd.DataFrame(pca.components_,columns=data_scaled.columns)
print(result.abs().max(axis=1))
result.abs()
```

```
        item_id  brand_id  brandfamily_id  ...  user_id  province_id  city_id
0             1         6               1  ...      404            2       19
0             1        14               1  ...      404            2       19
1             1         6               1  ...      404            2       19
1             1        14               1  ...      404            2       19
2             1         6               1  ...      395            0       10
...         ...       ...             ...  ...      ...          ...      ...
145190       12        19               3  ...       18            0       10
145191       12        19               3  ...      450            0       10
145192       12        19               3  ...      262            0       10
145193       12        19               3  ...      248            0       10
145194       12        19               3  ...       24            0       10

[217723 rows x 9 columns]
PCA Variance [2.195108   1.41419053 1.14127356 1.01680283]
PCA Variance [0.24389977 0.15713156 0.12680759 0.11297757]
Cumulative PCA Variance [0.24389977 0.40103133 0.52783892 0.64081649]
0    0.491384
1    0.537006
2    0.565828
3    0.775233
dtype: float64
      item id  brand id  brandfamily id  package id   info id  order id   user id  pr
```

We know province_id, brandfamily_id, brand_id, item_id are most important features from PCA . As our main target is to predict each item in each province through each month and year, we will try to remove unnecessary columns.

```
#dimension reduction
df_wine = df_wine.drop([ 'package_id', 'info_id', 'order_id', 'user_id', 'city_id'], axis=
df_wine
```

	date	item_id	brand_id	brandfamily_id	province_id	quantity
0	2017-01-01	1	6	1	2	8.298021
0	2017-01-01	1	14	1	2	8.298021
1	2017-01-01	1	6	1	2	8.298021
1	2017-01-01	1	14	1	2	8.298021
2	2017-01-01	1	6	1	0	0.377183
...	...	...	...	...	...	...
145190	2020-09-01	12	19	3	0	3.643725
145191	2020-09-01	12	19	3	0	1.457490
145192	2020-09-01	12	19	3	0	2.914980
145193	2020-09-01	12	19	3	0	1.457490
145194	2020-09-01	12	19	3	0	0.728745

217723 rows × 6 columns

We remove the columns 'package_id', 'info_id', 'order_id', 'user_id', 'city_id' from the tables. They are insensitive to analysis and also not our anylysis focus in the prediction.

```
df_wine = df_wine.groupby(['date', 'province_id', 'item_id','brand_id','brandfamily_id'])[
df_wine
```

	date	province_id	item_id	brand_id	brandfamily_id	quantity
0	2017-01-01	0	1	6	1	421.313155
1	2017-01-01	0	1	14	1	421.313155
2	2017-01-01	0	2	11	5	5.654450
3	2017-01-01	0	15	6	2	117.478060
4	2017-01-01	0	15	19	2	117.478060
...	...	...	...	...	...	...
8579	2020-12-01	2	109	6	2	46.565716
8580	2020-12-01	2	109	19	2	46.565716
8581	2020-12-01	2	110	13	9	128.102211
8582	2020-12-01	2	111	6	2	23.734884
8583	2020-12-01	2	111	19	2	23.734884

8584 rows × 6 columns

We aggregate the quantity through all remaning columns to get how each item in each province varies through each month and year.

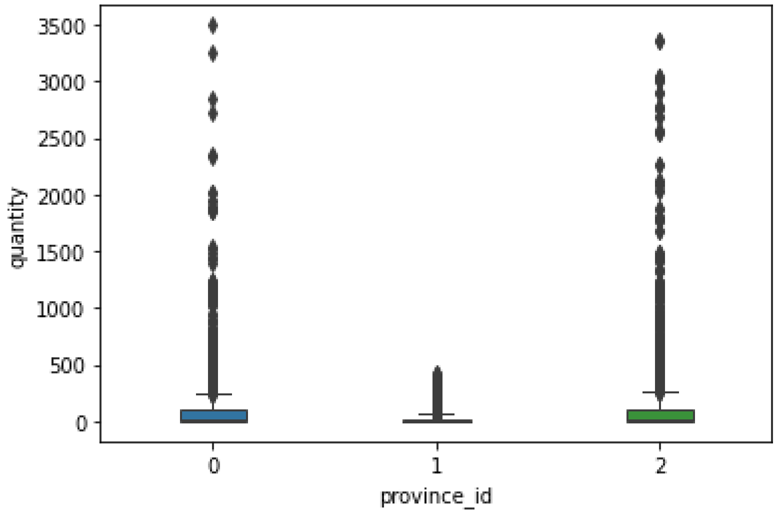
```
import seaborn as sns
```

```
#Visulize Outliers
sns.scatterplot(x='date', y='quantity', data=df_wine)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdd4479ea50>
```

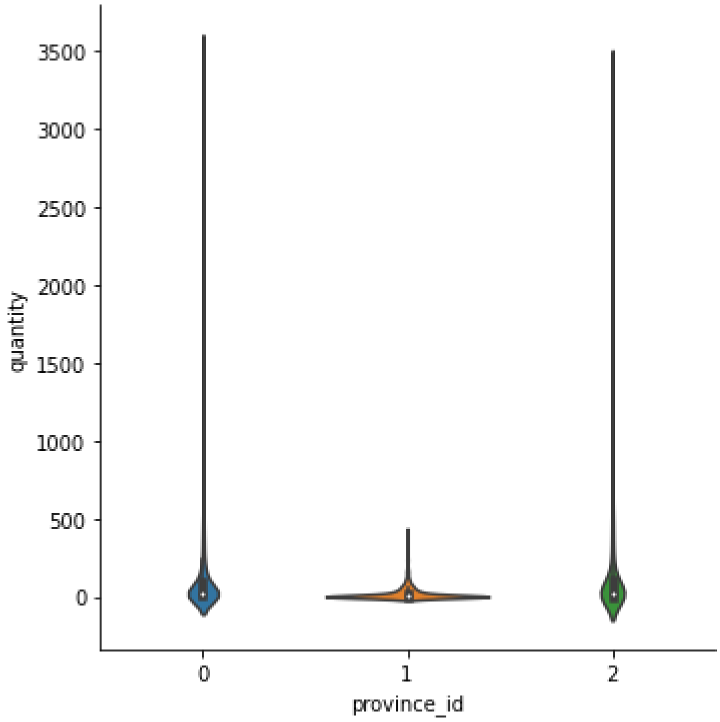

```
sns.boxplot(x = 'province_id', y='quantity', data=df_wine , width = 0.3, linewidth = 1)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdd447212d0>
```




```
# Violin plots
sns.catplot(x = 'province_id', y='quantity', data=df_wine, kind="violin")
```

```
<seaborn.axisgrid.FacetGrid at 0x7fdd446ac050>
```



Obviouslly the graphs look not normal and has a lot of outliers and one side, we need to handle them immediatelly

```
Q1 = df_wine['quantity'].quantile(0.25)
Q3 = df_wine['quantity'].quantile(0.75)
IQR = Q3 - Q1
index = df_wine[(df_wine['quantity'] < (Q1 - 1.5 * IQR)) |(df_wine['quantity'] > (Q3 + 1.5
```

```
index = df_wine[(df_wine['quantity'] < (Q1 - 1.5 * IQR)) |(df_wine['quantity'] > (Q3 + 1.5
df_wine.drop(index, inplace=True)
df_wine
```

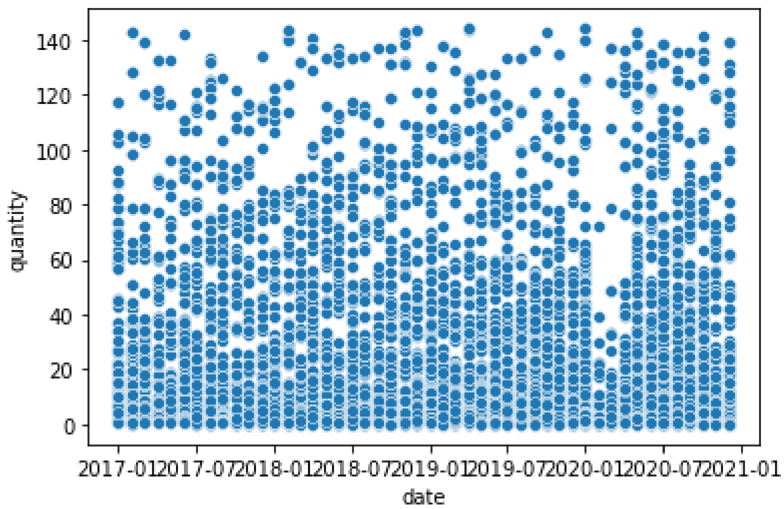
	date	province_id	item_id	brand_id	brandfamily_id	quantity
2	2017-01-01	0	2	11	5	5.654450
3	2017-01-01	0	15	6	2	117.478060
4	2017-01-01	0	15	19	2	117.478060
5	2017-01-01	0	18	19	3	57.459522
6	2017-01-01	0	19	11	5	43.250291
...	...	...	...	...	...	...
8579	2020-12-01	2	109	6	2	46.565716
8580	2020-12-01	2	109	19	2	46.565716
8581	2020-12-01	2	110	13	9	128.102211
8582	2020-12-01	2	111	6	2	23.734884
8583	2020-12-01	2	111	19	2	23.734884

7451 rows × 6 columns

Through outliers drop we remove around 1100 rows through the IQR rule. We then check through visulization agian.

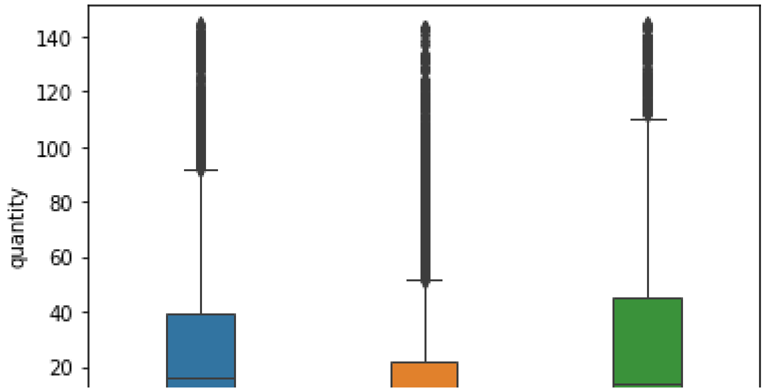
```
sns.scatterplot(x='date', y='quantity', data=df_wine)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fdd44619ed0>



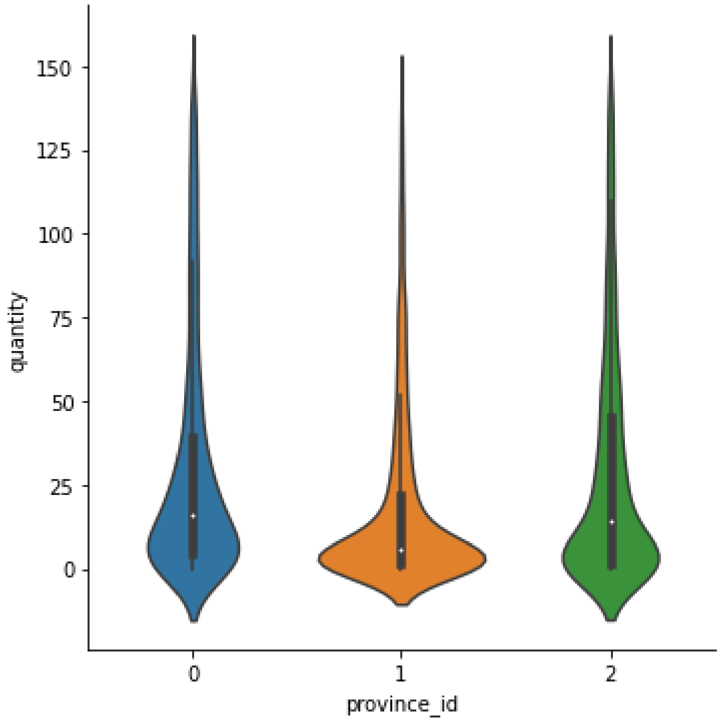

```
sns.boxplot(x = 'province_id', y='quantity', data=df_wine , width = 0.3, linewidth = 1)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdd44629690>
```




```
sns.catplot(x = 'province_id', y='quantity', data=df_wine, kind="violin")
```

```
<seaborn.axisgrid.FacetGrid at 0x7fdd446a7a10>
```

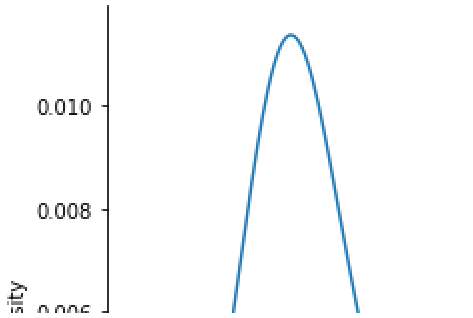


We still get some quantities whcih are large. However, the overall perfomence is much better. There are much fewer values beyond.

```
#Data Visulization

sns.displot(df_wine, x='quantity', kind = 'kde',bw_adjust = 5)
```

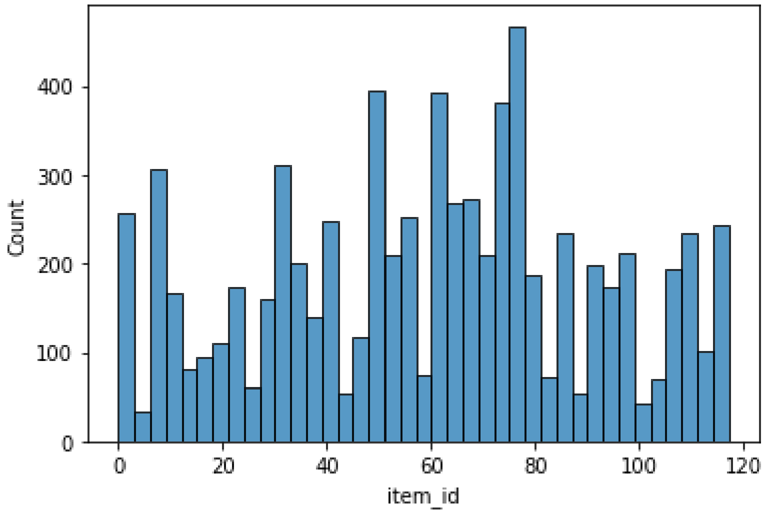
```
<seaborn.axisgrid.FacetGrid at 0x7fdd4445eb50>
```



From density plot of quantity, we see that most quantity are small and near 0, only a small part are large

```
sns.histplot(df_wine, x='item_id', binwidth = 3, bins=df_wine['item_id'].nunique())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdd4441e490>
```



We plot the histgrams through id and find there is huge difference between each item.

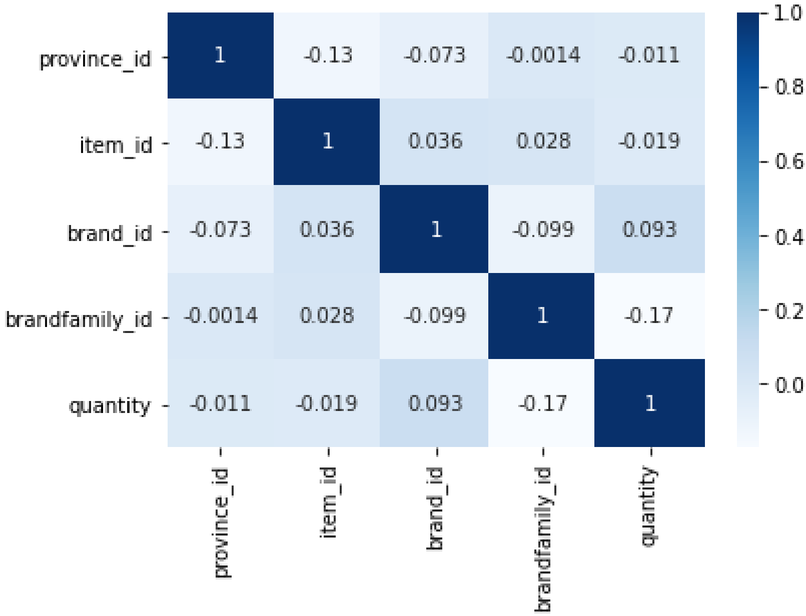
```
sns.catplot(x='province_id', y='quantity', kind="bar", data=df_wine)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fdd443873d0>
```

Use bar chart we find that province 0 has most quantities, follwed by province 2. Province 1 has least quantity.

```
sns.heatmap(df_wine.corr(), annot=True, cmap="Blues")
```

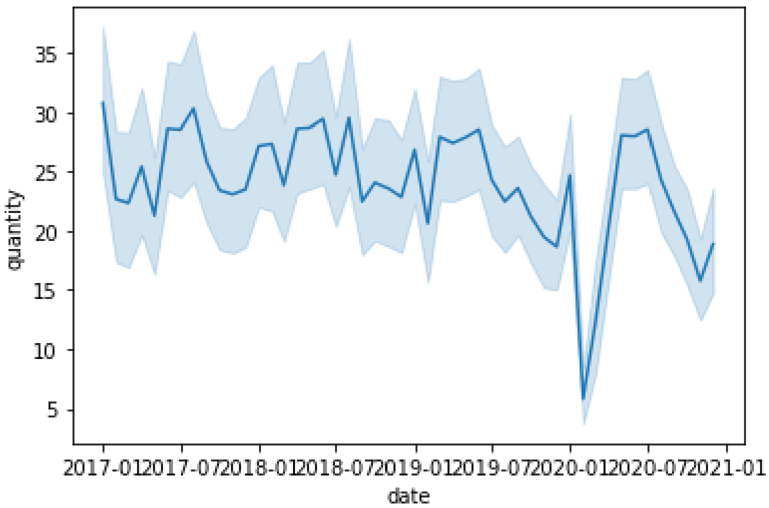
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdd440cfe10>
```



From the heatmap, we find that there is not much direct relationship between each predictor(and also quantity). We can say they are almost indenpendent with each other.

```
sns.lineplot(data = df_wine, x='date', y='quantity')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdd43f2d050>
```



We have a sense of how overall quantity varies with month and year. It drops sharplly at

```
from google.colab import drive
drive.mount('drive')
#df_wine.to_csv('My Drive/Colab Notebooks/IE7275/Project/wine.csv')
df_wine.to_csv('/content/drive/MyDrive/Colab Notebooks/IE7275/Project/wine.csv')
```

```
Drive already mounted at drive; to attempt to forcibly remount, call drive.mount("dri
```

Save the new table to google drive and download in convenience of future use.