In [1]:
```python
import pandas as pd

from datetime import datetime
# Display figures inline in Jupyter notebook
import matplotlib.pyplot as plt
import seaborn as sn
# Use seaborn style defaults and set the default figure size
sn.set(rc={'figure.figsize':(11, 4)})
```

In [2]:
```python
# !pip install mlxtend
from mlxtend.frequent_patterns import apriori, association_rules
```

Reading the data files

In [3]:
```python
events=pd.read_csv('events.csv')
```

In [4]:
```python
events.head(5)
```

Out[4]:

	timestamp	visitorid	event	itemid	transactionid
0	1433221332117	257597	view	355908	NaN
1	1433224214164	992329	view	248676	NaN
2	1433221999827	111016	view	318965	NaN
3	1433221955914	483717	view	253185	NaN
4	1433221337106	951259	view	367447	NaN

In [5]:
```python
category_tree=pd.read_csv('category_tree.csv')
```

In [6]:
```python
category_tree.head(5)
```

Out[6]:

	categoryid	parentid
0	1016	213.0
1	809	169.0
2	570	9.0
3	1691	885.0
4	536	1691.0

In [7]:
```python
category_tree.shape
```

Out[7]: (1669, 2)

In [8]:
```python
category_tree.parentid.nunique()
```

Out[8]: 362

In [9]:
```python
item_prop=pd.read_csv('item_properties_part1.csv')
item_prop2=pd.read_csv('item_properties_part2.csv')
```

In [10]:
```python
item_props=pd.concat([item_prop,item_prop2],ignore_index=True)
```

In [11]:
```python
item_props.head(5)
```

Out[11]:

	timestamp	itemid	property	value
0	1435460400000	460429	categoryid	1338
1	1441508400000	206783	888	1116713 960601 n277.200
2	1439089200000	395014	400	n552.000 639502 n720.000 424566
3	1431226800000	59481	790	n15360.000
4	1431831600000	156781	917	828513

In [12]:
```python
item_props.dtypes
```

Out[12]:
```
timestamp     int64
itemid        int64
property     object
value        object
dtype: object
```

In [13]:
```python
item_props=item_props.sort_values(by='timestamp')
```

Change timestamp to date-time format i tried to convert it directly but it gave me DateTime in the future so i divided the value by 1000 before converting it to be reasonable. maybe it's wrong but I did this just to be readable

In [14]:
```python
item_props['timestamp']=item_props['timestamp'].apply( lambda x: datetime.fromtimestamp(x/1000))
```

In [15]:
```python
item_props.shape
```

Out[15]: (20275902, 4)

In [16]:
```python
item_props.itemid.nunique()
```

Out[16]: 417053

In [17]:
```python
item_props
```

Out[17]:

	timestamp	itemid	property	value
5903679	2015-05-10 05:00:00	317951	790	n32880.000
5668945	2015-05-10 05:00:00	422842	480	1133979
11314219	2015-05-10 05:00:00	310185	776	103591
15170322	2015-05-10 05:00:00	110973	112	679677
15170323	2015-05-10 05:00:00	179597	available	0
...	...	...	...	...
9472989	2015-09-13 05:00:00	364708	928	769062
9473006	2015-09-13 05:00:00	231604	888	561561 1055803 447378 n12.000 1135780 1284577 ...
2199697	2015-09-13 05:00:00	161357	888	12762 16970 145048 237874 1229126 784581 12977...
9472887	2015-09-13 05:00:00	267142	available	0
20275901	2015-09-13 05:00:00	275768	888	888666 n10800.000 746840 1318567

20275902 rows × 4 columns

Exploring properties of items over time

In [18]:
```python
item_props=item_props.set_index('timestamp')
```

In [19]:
```python
item_props=item_props.sort_values(by=['timestamp', 'itemid','property', 'value'])
```

In [20]:
```python
item_props
```

Out[20]:

timestamp	itemid	property	value
2015-05-10 05:00:00	0	159	519769
2015-05-10 05:00:00	0	283	66094 372274 478989
2015-05-10 05:00:00	0	6	1152934 1238769
2015-05-10 05:00:00	0	678	372274
2015-05-10 05:00:00	0	790	n91200.000
...	...	...	...
2015-09-13 05:00:00	466864	790	n111840.000
2015-09-13 05:00:00	466864	813	1148082 353870 1262739
2015-09-13 05:00:00	466864	888	1262739 205682 1050016 1154859
2015-09-13 05:00:00	466864	available	0
2015-09-13 05:00:00	466865	888	150169 780351 820477 437265 951705 103274 1154...

20275902 rows × 3 columns

Most frequently changed properties

from the below code we find properties **888,790,available,categoryid,451** the most frequently changed properties

In [21]:
```python
# item_props[item_props.duplicated(['itemid','property'])].property.value_counts()
```

In [22]:
```python
sn.barplot(x=item_props.property.value_counts().index[0:10], y=item_props.property.value_counts()[0:10])
```

Out[22]: <AxesSubplot:ylabel='property'>

get the changed items over time

In [23]:
```python
changed_items=item_props[item_props.duplicated(['itemid','property'])]
changed_items
```

Out[23]:

timestamp	itemid	property	value
2015-05-17 05:00:00	0	6	1152934 1238769
2015-05-17 05:00:00	1	790	n5760.000
2015-05-17 05:00:00	1	888	172646
2015-05-17 05:00:00	1	available	0
2015-05-17 05:00:00	3	283	138228 150169 1182824 327918 261419
...	...	...	...
2015-09-13 05:00:00	466864	790	n111840.000
2015-09-13 05:00:00	466864	813	1148082 353870 1262739
2015-09-13 05:00:00	466864	888	1262739 205682 1050016 1154859
2015-09-13 05:00:00	466864	available	0
2015-09-13 05:00:00	466865	888	150169 780351 820477 437265 951705 103274 1154...

8272088 rows × 3 columns

listing the items that have different category over time

In [24]:
```python
changed_items[changed_items['property']=='categoryid']
```

Out[24]:

timestamp	itemid	property	value
2015-05-17 05:00:00	25	categoryid	1509
2015-05-17 05:00:00	94	categoryid	1147
2015-05-17 05:00:00	130	categoryid	1277
2015-05-17 05:00:00	149	categoryid	1120
2015-05-17 05:00:00	168	categoryid	1006
...	...	...	...
2015-09-13 05:00:00	466738	categoryid	1617
2015-09-13 05:00:00	466767	categoryid	1114
2015-09-13 05:00:00	466768	categoryid	1244
2015-09-13 05:00:00	466783	categoryid	1114
2015-09-13 05:00:00	466829	categoryid	438

371161 rows × 3 columns

let's check frist item **393623** and property **categoryid**

In [25]:
```python
# item_props[(item_props['itemid']==369722) &(item_props['property']=='categoryid')]['value']
```

In [26]:
```python
item_props[(item_props['itemid']==393623) &(item_props['property']=='categoryid')]['value'].astype(int).plot(gr
```

Out[26]: <AxesSubplot:xlabel='timestamp'>

the changes in items avaiablibty over time

In [27]:
```python
changed_items[changed_items['property']=='available']
```

Out[27]:

timestamp	itemid	property	value
2015-05-17 05:00:00	1	available	0
2015-05-17 05:00:00	6	available	1
2015-05-17 05:00:00	15	available	1
2015-05-17 05:00:00	16	available	0
2015-05-17 05:00:00	19	available	1
...	...	...	...
2015-09-13 05:00:00	466848	available	1
2015-09-13 05:00:00	466853	available	0
2015-09-13 05:00:00	466858	available	1
2015-09-13 05:00:00	466861	available	0
2015-09-13 05:00:00	466864	available	0

1086586 rows × 3 columns

checck avaiablibty of item 267142 and 379701 over time

In [28]:
```python
item_props[(item_props['itemid']==267142) &(item_props['property']=='available')]['value'].astype(int).plot(gri
```

Out[28]: <AxesSubplot:xlabel='timestamp'>

In [29]:
```python
item_props[(item_props['itemid']==379701) &(item_props['property']=='available')]['value'].astype(int).plot(gri
```

Out[29]: <AxesSubplot:xlabel='timestamp'>

In [30]:
```python
# item_props[(item_props['itemid']==267142) &(item_props['property']=='available')]['value']
```

item 267142 almost not available most of time it was available only once at 2015-08-02 05:00:00 in contrast to item 379701 which was avaiable most of time

Num of unique properties per item

In [31]:
```python
propertiesperitem=item_props.groupby(['itemid'])['property'].nunique()
```

In [32]:
```python
propertiesperitem=propertiesperitem.to_frame( name="nuniqueproperty")
```

In [33]:
```python
propertiesperitem
```

Out[33]:

itemid	nuniqueproperty
0	28
1	35
2	24
3	29
4	25
...	...
466862	31
466863	23
466864	28
466865	27
466866	42

417053 rows × 1 columns

from the below output we find that the averaage number of properties per item amlost **28** and max is **59** and min **12**

In [34]:
```python
propertiesperitem.describe()
```

Out[34]:

	nuniqueproperty
count	417053.000000
mean	28.782466
std	7.409326
min	12.000000
25%	24.000000
50%	27.000000
75%	31.000000
max	59.000000

In [35]:
```python
# item_props.groupby(['itemid','property'])['value'].nunique().to_frame(name='numofchanges').sort_values(by='nu
```

Properties that are constant over time

In [36]:
```python
valuesperproperty=item_props.groupby(['itemid','property'],as_index=False).agg({'value':{'count','nunique'}})
```

In [37]:
```python
# valuesperproperty=valuesperproperty.reset_index()
```

In [38]:
```python
valuesperproperty.columns = ["itemid","property","value_nunique","value_count"]
```

In [39]:
```python
valuesperproperty[(valuesperproperty['value_nunique']==1)&(valuesperproperty['value_count']>1)]
```

Out[39]:

itemid	property	value_nunique	value_count

Validating resullt by explore example of returned rows

- we can see rom the below output /graph that the value is the same over time

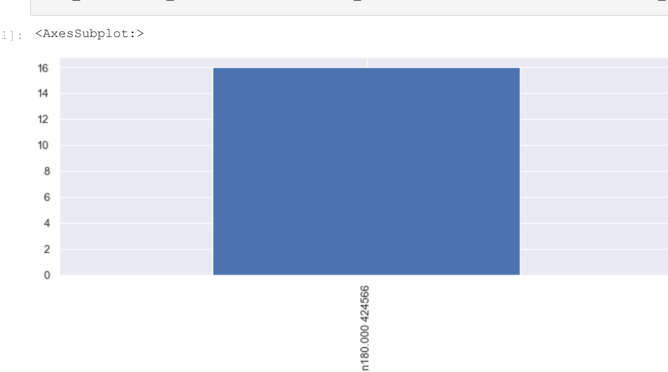
In [40]:
```python
item_props[(item_props.itemid==40)&(item_props.property=='810')]
```

Out[40]:

timestamp	itemid	property	value
2015-05-24 05:00:00	40	810	n180.000 424566
2015-05-31 05:00:00	40	810	n180.000 424566
2015-06-07 05:00:00	40	810	n180.000 424566
2015-06-14 05:00:00	40	810	n180.000 424566
2015-06-28 05:00:00	40	810	n180.000 424566
2015-07-05 05:00:00	40	810	n180.000 424566
2015-07-12 05:00:00	40	810	n180.000 424566
2015-07-19 05:00:00	40	810	n180.000 424566
2015-07-26 05:00:00	40	810	n180.000 424566
2015-08-02 05:00:00	40	810	n180.000 424566
2015-08-09 05:00:00	40	810	n180.000 424566
2015-08-16 05:00:00	40	810	n180.000 424566
2015-08-23 05:00:00	40	810	n180.000 424566
2015-08-30 05:00:00	40	810	n180.000 424566
2015-09-06 05:00:00	40	810	n180.000 424566
2015-09-13 05:00:00	40	810	n180.000 424566

In [41]:
```python
item_props[(item_props.itemid==40)&(item_props.property=='810')]['value'].value_counts().plot.bar(stacked=True)
```

Out[41]: <AxesSubplot:>



- from the below code we can find that there are **1104** unique property that are constant over time for some items
- also we see that the count for some property is the same of the number of unquie items so i think this properties may be the meta data about every item like **descibtion or registerdate** because every item have it
- the top of this properties are **764,159,790,364 and 283**

In [42]:
```python
valuesperproperty.property.nunique()
```

Out[42]: 1104

In [43]:
```python
valuesperproperty.property.value_counts()
```

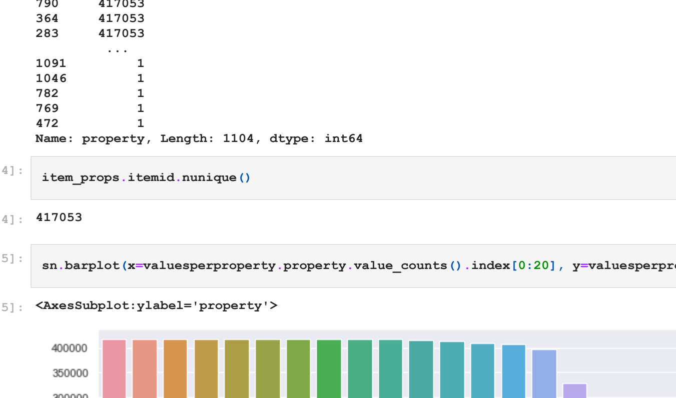
Out[43]:
```
764     417053
159     417053
790     417053
364     417053
283     417053
         ...
1091         1
1046         1
782          1
769          1
472          1
Name: property, Length: 1104, dtype: int64
```

In [44]:
```python
item_props.itemid.nunique()
```

Out[44]: 417053

In [45]:
```python
sn.barplot(x=valuesperproperty.property.value_counts().index[0:20], y=valuesperproperty.property.value_counts()
```

Out[45]: <AxesSubplot:ylabel='property'>



Snapshot merge

check the dublicated snapshot we have 7497165 dublicated rows of 20275902 which will reduce the data size by 40% after droping it

In [46]:
```python
item_props[item_props.duplicated(['itemid','property','value'])]
```

Out[46]:

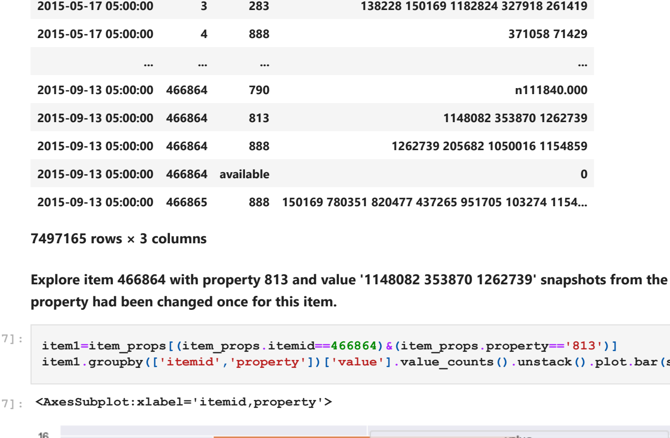
timestamp	itemid	property	value
2015-05-17 05:00:00	0	6	1152934 1238769
2015-05-17 05:00:00	1	790	n5760.000
2015-05-17 05:00:00	1	888	172646
2015-05-17 05:00:00	3	283	138228 150169 1182824 327918 261419
2015-05-17 05:00:00	4	888	371058 71429
...	...	...	...
2015-09-13 05:00:00	466864	790	n111840.000
2015-09-13 05:00:00	466864	813	1148082 353870 1262739
2015-09-13 05:00:00	466864	888	1262739 205682 1050016 1154859
2015-09-13 05:00:00	466864	available	0
2015-09-13 05:00:00	466865	888	150169 780351 820477 437265 951705 103274 1154...

7497165 rows × 3 columns

Explore item 466864 with property 813 and value '1148082 353870 1262739' snapshots from the below graph we note that this property had been changed once for this item.

In [47]:
```python
item1=item_props[(item_props.itemid==466864)&(item_props.property=='813')]
item1.groupby(['itemid','property'])['value'].value_counts().unstack().plot.bar(stacked=True)
```

Out[47]: <AxesSubplot:xlabel='itemid,property'>



let's drop the duplicates with consider keeping the last snapshot

In [48]:
```python
item_props_merged=item_props.drop_duplicates(subset=['itemid','property','value'], keep='last')
```

In [49]:
```python
item_props_merged.shape
```

Out[49]: (12778737, 3)

Checking some items before and after snapshots merge

Before Merge

In [50]:
```python
item_props[(item_props.itemid==91477)&(item_props.property=='888')]
```

Out[50]:

timestamp	itemid	property	value
2015-05-10 05:00:00	91477	888	215907 409406
2015-05-17 05:00:00	91477	888	215907 409406
2015-05-24 05:00:00	91477	888	215907 409406
2015-05-31 05:00:00	91477	888	215907 409406
2015-06-07 05:00:00	91477	888	215907 409406
2015-06-14 05:00:00	91477	888	215907 409406
2015-06-28 05:00:00	91477	888	215907 409406
2015-07-05 05:00:00	91477	888	215907 409406
2015-07-12 05:00:00	91477	888	215907 409406
2015-07-19 05:00:00	91477	888	215907 409406
2015-07-26 05:00:00	91477	888	215907 409406
2015-08-02 05:00:00	91477	888	215907 409406
2015-08-09 05:00:00	91477	888	215907 409406
2015-08-16 05:00:00	91477	888	215907 409406
2015-08-23 05:00:00	91477	888	215907 409406
2015-08-30 05:00:00	91477	888	215907 409406
2015-09-06 05:00:00	91477	888	215907 409406 726612 999696
2015-09-13 05:00:00	91477	888	215907 409406 726612 999696

After merge

In [51]:
```python
item_props_merged[(item_props_merged.itemid==91477)&(item_props_merged.property=='888')]
```

Out[51]:

timestamp	itemid	property	value
2015-08-30 05:00:00	91477	888	215907 409406
2015-09-13 05:00:00	91477	888	215907 409406 726612 999696

Before merge

In [52]:
```python
item_props[(item_props.itemid==89439)&(item_props.property=='888')]
```

Out[52]:

timestamp	itemid	property	value
2015-05-10 05:00:00	89439	888	390539 n24.000
2015-05-17 05:00:00	89439	888	390539 n24.000
2015-05-24 05:00:00	89439	888	390539 n24.000 1252796
2015-05-31 05:00:00	89439	888	390539 n24.000 1252796
2015-06-07 05:00:00	89439	888	390539 n24.000 1252796
2015-06-14 05:00:00	89439	888	390539 n24.000 1252796
2015-06-28 05:00:00	89439	888	390539 n24.000 1252796
2015-07-05 05:00:00	89439	888	390539 n24.000 1252796
2015-07-12 05:00:00	89439	888	390539 n24.000 1252796
2015-07-19 05:00:00	89439	888	390539 n24.000 1252796
2015-07-26 05:00:00	89439	888	390539 n24.000 1252796
2015-08-02 05:00:00	89439	888	390539 n24.000 1252796
2015-08-09 05:00:00	89439	888	390539 n24.000 1252796
2015-08-16 05:00:00	89439	888	390539 n24.000 1252796
2015-08-23 05:00:00	89439	888	390539 n24.000 1252796
2015-08-30 05:00:00	89439	888	390539 n24.000 1252796
2015-09-06 05:00:00	89439	888	390539 n24.000 1252796
2015-09-13 05:00:00	89439	888	390539 n24.000 1252796

In [53]:
```python
item_props_merged[(item_props_merged.itemid==89439)&(item_props_merged.property=='888')]
```

Out[53]:

timestamp	itemid	property	value
2015-05-17 05:00:00	89439	888	390539 n24.000
2015-09-13 05:00:00	89439	888	390539 n24.000 1252796

Exploring events data

- **we have 2756101 row in event data and 5 columns**
- **1407580 unique vistior**
- **235061 unique items**
- **3 types of events view,addtocart and transaction**
- **for the below graph the most occured event is view by precentage 96% events. then addtocart and the lowest is transaction with precentang 0.8%**

In [54]:
```python
events
```

Out[54]:

	timestamp	visitorid	event	itemid	transactionid
0	1433221332117	257597	view	355908	NaN
1	1433224214164	992329	view	248676	NaN
2	1433221999827	111016	view	318965	NaN
3	1433221955914	483717	view	253185	NaN
4	1433221337106	951259	view	367447	NaN
...	...	...	...	...	...
2756096	1438398785939	591435	view	261427	NaN
2756097	1438399813142	762376	view	115946	NaN
2756098	1438397820527	1251746	view	78144	NaN
2756099	1438398530703	1184451	view	283392	NaN
2756100	1438400163914	199536	view	152913	NaN

2756101 rows × 5 columns

Change timestamp to date-time format i tried to convert it directly but it gave me DateTime in the future so i divided the value by 1000 before converting it to be reasonable. maybe it's wrong but I did this just to be readable

In [55]:
```python
events['timestamp']=events['timestamp'].apply( lambda x: datetime.fromtimestamp(x/1000))
```

In [56]:
```python
events=events.set_index('timestamp')
events=events.sort_values(by='timestamp')
```

In [57]:
```python
events.visitorid.nunique()
```

Out[57]: 1407580

In [58]:
```python
events.itemid.nunique()
```

Out[58]: 235061

In [59]:
```python
events.event.describe()
```

Out[59]:
```
count     2756101
unique          3
top          view
freq      2664312
Name: event, dtype: object
```

In [60]:
```python
events.event.value_counts().plot.bar(stacked=True)
```

Out[60]: <AxesSubplot:>

Validating each row that has event type transaction have already transaction-id

In [61]:
```
events[(events.event=='transaction')&(events.transactionid.isna())]
```

Out[61]:

	visitorid	event	itemid	transactionid
timestamp				

In [62]:
```
events[events.event=='transaction']
```

Out[62]:

timestamp	visitorid	event	itemid	transactionid
2015-05-03 05:27:21.391	869008	transaction	40685	9765.0
2015-05-03 05:35:01.772	345781	transaction	438400	1016.0
2015-05-03 06:01:47.591	586756	transaction	440917	10942.0
2015-05-03 06:07:38.961	435495	transaction	175893	6173.0
2015-05-03 06:31:14.903	266417	transaction	445106	12546.0
...	...	...	...	...
2015-09-18 04:08:16.512	152963	transaction	12504	5772.0
2015-09-18 04:08:16.512	152963	transaction	72462	5772.0
2015-09-18 04:08:16.528	152963	transaction	380196	5772.0
2015-09-18 04:38:18.098	152963	transaction	362697	5670.0
2015-09-18 04:43:12.017	152963	transaction	21970	8904.0

22457 rows × 4 columns

Transcations per visitor

- number of visitors who are purchasing is 11719
- the visitor who has more transactions is 1150086 he has 559
- the avg number of transcation per vistor is ~2 and min is 1 and max is 559

In [63]:
```
events[events.event=='transaction']['visitorid'].nunique()
```

Out[63]: 11719

In [64]:
```
transpervistior=events[events.event=='transaction'].groupby('visitorid').agg({'transactionid':'count'})
transpervistior.columns=['totalnumtrans']
```

In [65]:
```
transpervistior=transpervistior.sort_values(by='totalnumtrans',ascending=False)
```

In [66]:
```
transpervistior
```

Out[66]:

visitorid	totalnumtrans
1150086	559
152963	349
530559	286
684514	189
861299	188
...	...
535433	1
535446	1
535618	1
535623	1
1407398	1

11719 rows × 1 columns

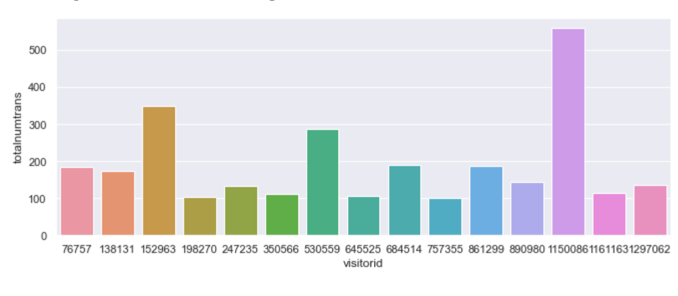
In [67]:
```
transpervistior.describe()
```

Out[67]:

	totalnumtrans
count	11719.000000
mean	1.916290
std	8.850529
min	1.000000
25%	1.000000
50%	1.000000
75%	1.000000
max	559.000000

In [68]:
```
sn.barplot(x=transpervistior.index[0:15], y=transpervistior.totalnumtrans[0:15] )
```

Out[68]: <AxesSubplot:xlabel='visitorid', ylabel='totalnumtrans'>



Items per transaction

- max number of items per transcation is 31 and min is 1 and avg is almost also 1
- total number of items Purchased is highest in half of the months

In [69]:
```
itemspertrans=events.reset_index().groupby('transactionid',as_index=False).agg({'timestamp':lambda x:max(x),'it
itemspertrans.columns=['transactionid','timestamp','unique_items','totalnumitems']
itemspertrans=itemspertrans.sort_values(by='totalnumitems',ascending=False)
```

In [70]:
```
itemspertrans
```

Out[70]:

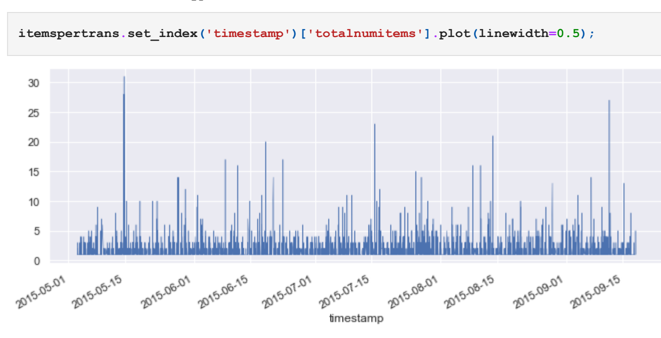
	transactionid	timestamp	unique_items	totalnumitems
7063	7063.0	2015-05-14 20:05:25.163	[238209, 262699, 108096, 447818, 265775, 25614...	31
765	765.0	2015-05-14 18:40:13.848	[262699, 447818, 108096, 256146, 265775, 13059...	28
8351	8351.0	2015-09-11 17:04:05.760	[277183, 412333, 4067, 86691, 256146, 380971, ...	27
2753	2753.0	2015-07-15 19:03:17.204	[100898, 220513, 402816, 439963, 12836, 151471...	23
6993	6993.0	2015-08-13 21:37:26.043	[238993, 339032, 260036, 20918, 283492, 107175...	21
...	...	...	...	...
6418	6418.0	2015-06-01 01:53:27.795	[25071]	1
6419	6419.0	2015-05-27 21:58:47.900	[95598]	1
6420	6420.0	2015-08-05 23:13:36.626	[67719]	1
6421	6421.0	2015-05-17 02:59:13.897	[280946]	1
17671	17671.0	2015-06-20 03:57:21.755	[5470]	1

17672 rows × 4 columns

In [71]:
```
itemspertrans.totalnumitems.describe()
```

Out[71]:
```
count    17672.000000
mean         1.270767
std          0.974793
min          1.000000
25%          1.000000
50%          1.000000
75%          1.000000
max         31.000000
Name: totalnumitems, dtype: float64
```

In [72]:
```
itemspertrans.set_index('timestamp')['totalnumitems'].plot(linewidth=0.5);
```



Most Purchased items

- top pruchased item 461686 found in 133 transcation

In [73]:
```
trasactions=events[events.event=='transaction']
```

In [74]:
```
trasactions
```

Out[74]:

timestamp	visitorid	event	itemid	transactionid
2015-05-03 05:27:21.391	869008	transaction	40685	9765.0
2015-05-03 05:35:01.772	345781	transaction	438400	1016.0
2015-05-03 06:01:47.591	586756	transaction	440917	10942.0
2015-05-03 06:07:38.961	435495	transaction	175893	6173.0
2015-05-03 06:31:14.903	266417	transaction	445106	12546.0
...	...	...	...	...
2015-09-18 04:08:16.512	152963	transaction	12504	5772.0
2015-09-18 04:08:16.512	152963	transaction	72462	5772.0
2015-09-18 04:08:16.528	152963	transaction	380196	5772.0
2015-09-18 04:38:18.098	152963	transaction	362697	5670.0
2015-09-18 04:43:12.017	152963	transaction	21970	8904.0

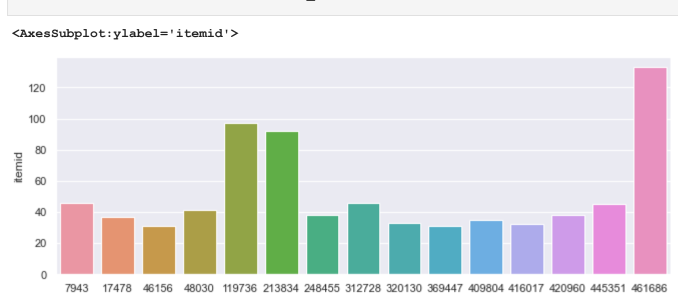
22457 rows × 4 columns

In [75]:
```
trasactions['itemid'].value_counts()
```

Out[75]:
```
461686    133
119736     97
213834     92
7943       46
312728     46
         ... 
376944      1
279944      1
386126      1
313722      1
72462       1
Name: itemid, Length: 12025, dtype: int64
```

In [76]:
```
sn.barplot(x=trasactions.itemid.value_counts().index[0:15], y=trasactions.itemid.value_counts()[0:15] )
```

Out[76]: <AxesSubplot:ylabel='itemid'>



Add to cart Events

- almost 2.5% of events is add to cart type
- highest addtocart item 461686 found in 306 transcation which also highest purchased makesense
- the below figure have similar distribution to the above one of the purchased items because each item before being transaction it was addtocart

In [77]:
```
addtocart=events[events.event=='addtocart']
addtocart
```

Out[77]:

timestamp	visitorid	event	itemid	transactionid
2015-05-03 05:00:04.384	693516	addtocart	297662	NaN
2015-05-03 05:00:29.427	693516	addtocart	297662	NaN
2015-05-03 05:01:25.008	979664	addtocart	338222	NaN
2015-05-03 05:04:00.603	260113	addtocart	125751	NaN
2015-05-03 05:10:02.006	319455	addtocart	342530	NaN
...	...	...	...	...
2015-09-18 04:41:42.108	152963	addtocart	21970	NaN
2015-09-18 04:45:20.572	1108521	addtocart	134455	NaN
2015-09-18 04:45:22.842	1108521	addtocart	134455	NaN
2015-09-18 04:50:49.803	572446	addtocart	187465	NaN
2015-09-18 04:50:49.834	572446	addtocart	187465	NaN

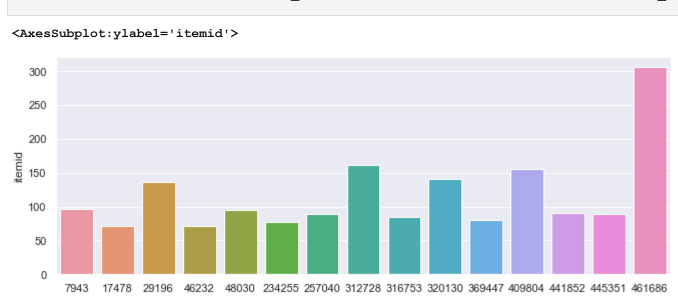
69332 rows × 4 columns

In [78]:
```
addtocart['itemid'].value_counts()
```

Out[78]:
```
461686    306
312728    162
409804    156
320130    141
29196     136
         ... 
409983      1
418099      1
32622       1
374135      1
38381       1
Name: itemid, Length: 23903, dtype: int64
```

In [79]:
```
sn.barplot(x=addtocart.itemid.value_counts().index[0:15], y=addtocart.itemid.value_counts()[0:15] )
```

Out[79]: <AxesSubplot:ylabel='itemid'>



Machine Learning applications

- Cross-selling using assoication rules
- Demand Forecasting for items or forcasting weekly sales using time series algorithms
- Customer Segmation using kmean cluster and RFM
- item category classifcation

In [80]:
```
transcationevents=events.dropna()
transcationevents
```

Out[80]:

timestamp	visitorid	event	itemid	transactionid
2015-05-03 05:27:21.391	869008	transaction	40685	9765.0
2015-05-03 05:35:01.772	345781	transaction	438400	1016.0
2015-05-03 06:01:47.591	586756	transaction	440917	10942.0
2015-05-03 06:07:38.961	435495	transaction	175893	6173.0
2015-05-03 06:31:14.903	266417	transaction	445106	12546.0
...	...	...	...	...
2015-09-18 04:08:16.512	152963	transaction	12504	5772.0
2015-09-18 04:08:16.512	152963	transaction	72462	5772.0
2015-09-18 04:08:16.528	152963	transaction	380196	5772.0
2015-09-18 04:38:18.098	152963	transaction	362697	5670.0
2015-09-18 04:43:12.017	152963	transaction	21970	8904.0

22457 rows × 4 columns

Associaciton Rule Learning

The association rules method is to present these correlations in the best way through rules, if there are significant correlations between the items that occur simultaneously and frequently, and if there are significant correlations. In other words, it is a rule-based machine learning technique used to find patterns in data.

```
- Apriori Algorithm -
```

It is a basket analysis method and is used to reveal product associations.

Support(X, Y) = Freq(X, Y) / N

There are 3 very simple formulas. The 1st is the Support value. It expresses the probability of X and Y occurring together. It is the frequency of X and Y appearing together divided by N.

Confidence(X, Y) = Freq(X, Y) / Freq(X)

It expresses the probability of purchasing product Y when product X is purchased. The frequency at which X and Y appear together divided by the frequency at which X appears.

Lift = Support(X, Y) / (Support(x) * Support (Y))

When X is purchased, the probability of buying Y increases by a multiple of lift. The probability of X and Y appearing together is the product of the probabilities of X and Y appearing separately. It states an expression such as how many times the probability of buying another product increases when we buy a product.

Our aim is to suggest products to users in the product purchasing process by applying association analysis to the online retail II dataset.

Build Transaction Dataset

In [81]:
```
# We need to create below structure:

# Rows represents transactions (transcation, shopping cart etc.), columns represents items
# We simulate as binary that which transaction  contains which items
# If the item is in the transcation, the intersection cell will be "1". If is not, it will be "0"

# Description   Item1      Item2    Item3
# trans
# trans1          0          1         0
# trans2          1          0         1
# trans3          0          0         0
# trans4          1          0         0
# trans5          0          0         1
```

Extract Quantity of Item per transcation

In [82]:
```
transcationevents.reset_index().groupby(['transactionid','itemid']).agg({"timestamp": "count"}).rename(columns=
```

Out[82]:

transactionid	itemid	Quantity
2212.0	325772	4
3011.0	259147	3
12363.0	275354	3
15607.0	294438	3
4904.0	255725	3
...	...	...
5898.0	176162	1
5897.0	142756	1
5896.0	230911	1
5895.0	90453	1
17671.0	5470	1

22323 rows × 1 columns

Check first item from event data will find 4 rows form same item

In [83]:
```
events[(events.transactionid==2212.0)&(events.itemid==325772)]
```

Out[83]:

timestamp	visitorid	event	itemid	transactionid
2015-07-06 01:19:04.506	852251	transaction	325772	2212.0
2015-07-06 01:21:59.771	852251	transaction	325772	2212.0
2015-07-06 01:22:39.353	852251	transaction	325772	2212.0
2015-07-06 01:36:56.639	852251	transaction	325772	2212.0

In [84]:
```
items = list(transcationevents.itemid.unique())
grouped = transcationevents.groupby('transactionid')
transaction_level_df = grouped.aggregate(lambda x: tuple(x)).reset_index()[['transactionid','itemid']]
```

In [85]:
```
transaction_level_df
```

Out[85]:

	transactionid	itemid
0	0.0	(425758,)
1	1.0	(454430,)
2	2.0	(151855,)
3	3.0	(85842,)
4	4.0	(224184,)
...	...	...
17667	17667.0	(433567,)
17668	17668.0	(212289,)
17669	17669.0	(132418, 260256)
17670	17670.0	(461686,)
17671	17671.0	(5470,)

17672 rows × 2 columns

In [86]:
```
# transaction_dict = {item:0 for item in items}
# output_dict = dict()
# temp = dict()
# for rec in transaction_level_df.to_dict('records'):
#     transactionid = rec['transactionid']
#     items_list = rec['itemid']
#     transaction_dict = {item:0 for item in items}
#     transaction_dict.update({item:1 for item in items if item in items_list})
#     temp.update({transactionid:transaction_dict})

# new = [v for k,v in temp.items()]
# tranasction_df = pd.DataFrame(new)
# del(tranasction_df[tranasction_df.columns[0]])
```

In [87]:
```
def create_transaction_item_df(df):
    return df.reset_index().groupby(['transactionid','itemid']).agg({"timestamp": "count"}).rename(columns={'ti
```

In [88]:
```
gr_tran_itm_df=create_transaction_item_df(transcationevents)
```

In [89]:
```
df=gr_tran_itm_df.copy()
```

In [90]:
```
df.columns=[ col[1] for col in df.columns]
```

In [91]:
```
df=df[list(trasactions.itemid.value_counts().index[0:1000])]
```

In [92]:
```
df.head()
```

Out[92]:

transactionid	461686	119736	213834	7943	312728	445351	48030	248455	420960	17478	...	372941	254290	79956	416530	35278
0.0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
1.0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
2.0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
3.0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0
4.0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0

5 rows × 1000 columns

In [93]:
```
gr_tran_itm_df.shape
```

Out[93]: (17672, 12025)

In [94]:
```
# 3. Possibilities of All Possible Item Combinations

# Support(X, Y) = Freq(X, Y) / N
# There are 3 very simple formulas. The 1st is the Support value. It expresses the probability of
# X and Y occurring together. It is the frequency of X and Y appearing together divided by N.

# Confidence(X, Y) = Freq(X, Y) / Freq(X)
# It expresses the probability of purchasing item Y when item X is purchased.
# The frequency at which X and Y appear together divided by the frequency at which X appears.

# Lift = Support(X, Y) / (Support(x) * Support (Y))
# When X is purchased, the probability of buying Y increases by a multiple of lift.
# The probability of X and Y appearing together is the item of the probabilities
# of X and Y appearing separately.
# It states an expression such as how many times the probability of buying another item
# increases when we buy a item.
```

In [95]:
```
frequent_itemsets = apriori(df, min_support=0.001, use_colnames=True)

frequent_itemsets.sort_values("support", ascending=False).head()
```

Out[95]:

	support	itemsets
0	0.007526	(461686)
1	0.005432	(119736)
2	0.005206	(213834)
3	0.002603	(7943)
4	0.002603	(312728)

In [96]:
```
# By inserting the support values we found with Apriori into the association_rules function,
# we find some other statistical data such as cofidance and lift.
rules = association_rules(frequent_itemsets, metric="support", min_threshold=0.001)

rules.sort_values("support", ascending=False).head()
```

Out[96]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(213834)	(445351)	0.005206	0.002546	0.002207	0.423913	166.475362	0.002194	1.731429
1	(445351)	(213834)	0.002546	0.005206	0.002207	0.866667	166.475362	0.002194	7.460955

According to this table, the probability of 213834 item and product numbered 445351 appearing together is 0.002207. The probability of being bought together is 0.423913. The increase in the probability of buying these two products together is 166.475362

Forcasting weekly sales

In [97]:
```
transcationevents["Week"]=transcationevents.index.isocalendar().week
transcationevents["Month"]=transcationevents.index.month
```

```
D:\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
D:\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
```

In [98]:
```
# weekly_transcations=transcationevents.groupby(['Week','Month'],as_index=False).agg({"transactionid":'count'})
```

In [99]:
```
weekly_transcations=transcationevents.reset_index().groupby(['Week','Month'],as_index=False).agg({"transactioni
```

In [100…
```
# transcationevents.resample('W').mean().
```

In [101…
```
weekly_transcations.columns=['Week','Month','Num_trans','timestamp']

weekly_transcations
```

Out[101…

	Week	Month	Num_trans	timestamp
0	18	5	68	2015-05-03 23:54:04.483
1	19	5	1111	2015-05-10 23:36:29.779
2	20	5	1208	2015-05-17 23:59:19.929
3	21	5	1067	2015-05-24 23:45:36.022
4	22	5	1140	2015-05-31 23:39:50.544
5	23	6	1178	2015-06-07 23:57:48.138
6	24	6	969	2015-06-14 23:45:02.327
7	25	6	1316	2015-06-21 23:49:10.247
8	26	6	1218	2015-06-28 23:48:26.851
9	27	6	357	2015-06-30 23:59:35.698
10	27	7	719	2015-07-05 23:58:29.938
11	28	7	1313	2015-07-12 23:58:06.851
12	29	7	1264	2015-07-19 23:57:42.354
13	30	7	1351	2015-07-26 23:54:07.386
14	31	7	1160	2015-07-31 23:57:59.529
15	31	8	182	2015-08-02 23:36:27.528
16	32	8	1083	2015-08-09 23:59:52.106
17	33	8	912	2015-08-16 23:50:29.168
18	34	8	1158	2015-08-23 23:53:08.737
19	35	8	1114	2015-08-30 23:25:06.702
20	36	8	172	2015-08-31 23:58:13.909
21	36	9	763	2015-09-06 23:49:45.572
22	37	9	1112	2015-09-13 23:25:35.302
23	38	9	522	2015-09-18 04:43:12.017

In [102…
```
weekly_transcations=weekly_transcations.set_index('timestamp').resample('W').mean()
```

In [103…
```
weekly_transcations
```

Out[103…

timestamp	Week	Month	Num_trans
2015-05-03	18.0	5.0	68.0
2015-05-10	19.0	5.0	1111.0
2015-05-17	20.0	5.0	1208.0
2015-05-24	21.0	5.0	1067.0
2015-05-31	22.0	5.0	1140.0
2015-06-07	23.0	6.0	1178.0
2015-06-14	24.0	6.0	969.0
2015-06-21	25.0	6.0	1316.0
2015-06-28	26.0	6.0	1218.0
2015-07-05	27.0	6.5	538.0
2015-07-12	28.0	7.0	1313.0
2015-07-19	29.0	7.0	1264.0
2015-07-26	30.0	7.0	1351.0
2015-08-02	31.0	7.5	671.0
2015-08-09	32.0	8.0	1083.0
2015-08-16	33.0	8.0	912.0
2015-08-23	34.0	8.0	1158.0
2015-08-30	35.0	8.0	1114.0
2015-09-06	36.0	8.5	467.5
2015-09-13	37.0	9.0	1112.0
2015-09-20	38.0	9.0	522.0

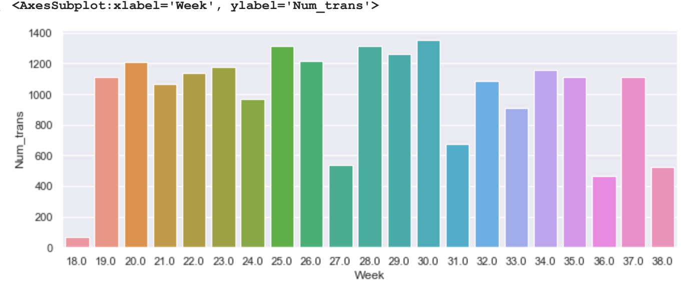
Visual weekly Sales time series

In [104…
```
weekly_transcations.groupby('Week').agg({'Num_trans':'sum'}).plot()
```

Out[104… <AxesSubplot:xlabel='Week'>

In [105…
```
sn.barplot(x=weekly_transcations['Week'], y=weekly_transcations['Num_trans'] )
```

Out[105… <AxesSubplot:xlabel='Week', ylabel='Num_trans'>



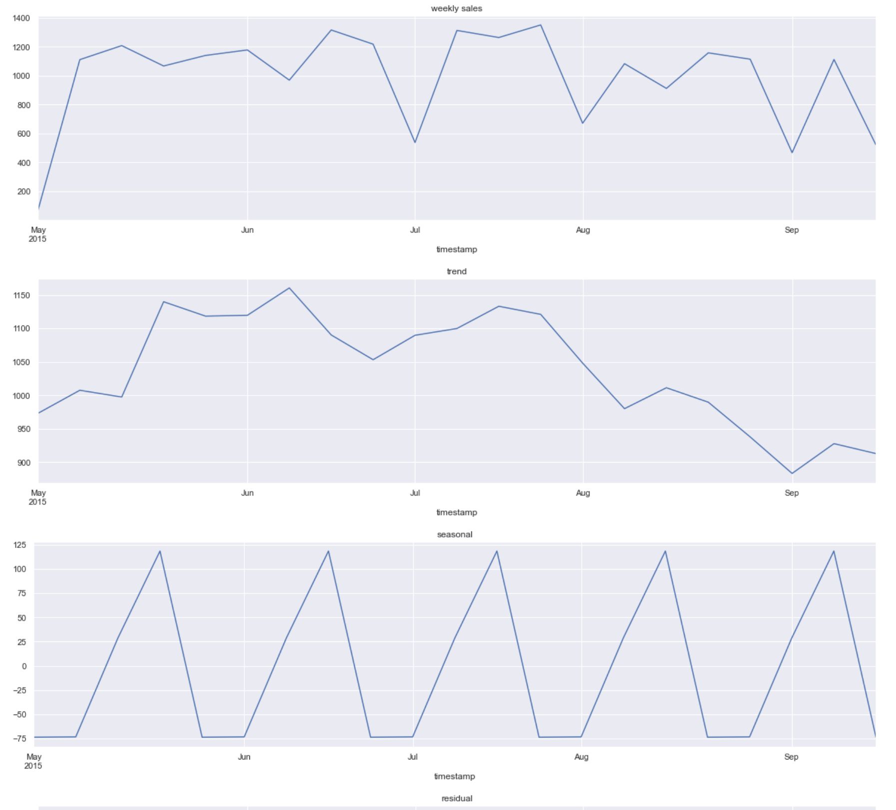
Decomposing

Seasonal Decompose gives the decomposition of the time series into its estimated trend component, estimated seasonal component, and estimated residual. We can also plot the original data to look at what components of the data influence its true value the most.

In [106…
```
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [107…
```
# weekly_transcations.sort_index(inplace=True)
```

In [108…
```
multi_plot = seasonal_decompose(weekly_transcations['Num_trans'], model = 'add', extrapolate_trend='freq', peri

plt.figure(figsize=(20,5))
multi_plot.observed.plot(title = 'weekly sales')

plt.figure(figsize=(20,5))
multi_plot.trend.plot(title = 'trend')

plt.figure(figsize=(20,5))
multi_plot.seasonal.plot(title = 'seasonal')

plt.figure(figsize=(20,5))
multi_plot.resid.plot(title = 'residual');
```



Forecasting using ARIMA Model

In [109…
```python
import statsmodels.api as sm
from math import sqrt
```

In [110…
```python
weekly_transcations
```

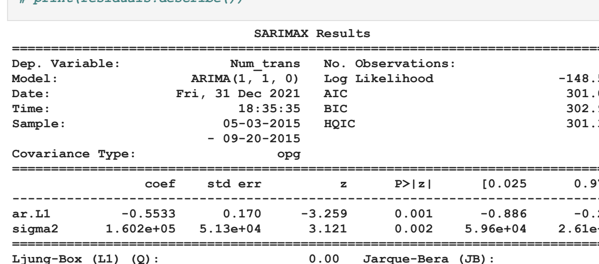
Out[110…

timestamp	Week	Month	Num_trans
2015-05-03	18.0	5.0	68.0
2015-05-10	19.0	5.0	1111.0
2015-05-17	20.0	5.0	1208.0
2015-05-24	21.0	5.0	1067.0
2015-05-31	22.0	5.0	1140.0
2015-06-07	23.0	6.0	1178.0
2015-06-14	24.0	6.0	969.0
2015-06-21	25.0	6.0	1316.0
2015-06-28	26.0	6.0	1218.0
2015-07-05	27.0	6.5	538.0
2015-07-12	28.0	7.0	1313.0
2015-07-19	29.0	7.0	1264.0
2015-07-26	30.0	7.0	1351.0
2015-08-02	31.0	7.5	671.0
2015-08-09	32.0	8.0	1083.0
2015-08-16	33.0	8.0	912.0
2015-08-23	34.0	8.0	1158.0
2015-08-30	35.0	8.0	1114.0
2015-09-06	36.0	8.5	467.5
2015-09-13	37.0	9.0	1112.0
2015-09-20	38.0	9.0	522.0

We will fit an ARIMA model to the entire weekly_transcations dataset and review the residual errors. First, we fit an ARIMA(1,1,0) model. This sets the lag value to 1 for autoregression, uses a difference order of 1 to make the time series stationary, and uses a moving average model of 0.

In [111…
```python
# fit model
model =sm.tsa.ARIMA(weekly_transcations['Num_trans'], order=(1,1,0))
model_fit = model.fit()
# summary of fit model
print(model_fit.summary())
# line plot of residuals
residuals = pd.DataFrame(model_fit.resid)
residuals.plot()
plt.show()
# # density plot of residuals
# residuals.plot(kind='kde')
# plt.show()
# # summary stats of residuals
# print(residuals.describe())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:              Num_trans   No. Observations:                   21
Model:                 ARIMA(1, 1, 0)   Log Likelihood                -148.503
Date:                Fri, 31 Dec 2021   AIC                            301.006
Time:                        18:35:35   BIC                            302.998
Sample:                    05-03-2015   HQIC                           301.395
                         - 09-20-2015
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.5533      0.170     -3.259      0.001      -0.886      -0.221
sigma2      1.602e+05   5.13e+04      3.121      0.002    5.96e+04    2.61e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                 0.09
Prob(Q):                              0.95   Prob(JB):                         0.96
Heteroskedasticity (H):               0.45   Skew:                            -0.16
Prob(H) (two-sided):                  0.32   Kurtosis:                         3.07
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```



Split data to train and test and get RMSE

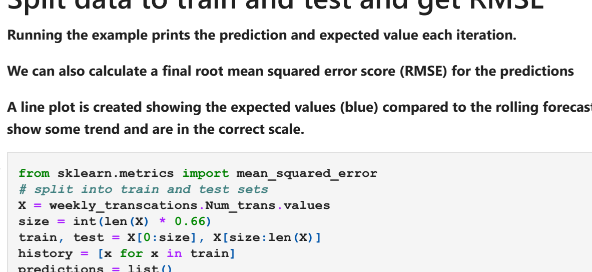
Running the example prints the prediction and expected value each iteration.

We can also calculate a final root mean squared error score (RMSE) for the predictions

A line plot is created showing the expected values (blue) compared to the rolling forecast predictions (red). We can see the values show some trend and are in the correct scale.

In [112…
```python
from sklearn.metrics import mean_squared_error
# split into train and test sets
X = weekly_transcations.Num_trans.values
size = int(len(X) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in train]
predictions = list()
# walk-forward validation
for t in range(len(test)):
        model = sm.tsa.ARIMA(history, order=(1,1,0))
        model_fit = model.fit()
        output = model_fit.forecast()
        yhat = output[0]
        predictions.append(yhat)
        obs = test[t]
        history.append(obs)
        print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts
rmse = sqrt(mean_squared_error(test, predictions))
print('Test RMSE: %.3f' % rmse)
# plot forecasts against actual outcomes
plt.plot(test)
plt.plot(predictions, color='red')
plt.show()
```

```
predicted=1322.549499, expected=671.000000
predicted=912.161919, expected=1083.000000
predicted=912.998484, expected=912.000000
predicted=983.248073, expected=1158.000000
predicted=1051.624078, expected=1114.000000
predicted=1132.876437, expected=467.500000
predicted=733.593378, expected=1112.000000
predicted=790.378490, expected=522.000000
Test RMSE: 378.496
```



In [113…
```python
!nbmerge "revision-Task.ipynb" "Customer segmentation.ipynb"  >all_.ipynb
```

Customer Segmentation with RFM & K-Means

In [114…
```python
import pandas as pd

from datetime import datetime

# Display figures inline in Jupyter notebook
import matplotlib.pyplot as plt
import seaborn as sn
# Use seaborn style defaults and set the default figure size
sn.set(rc={'figure.figsize':(11, 4)})
import warnings
warnings.filterwarnings('ignore')
```

In [115…
```python
events=pd.read_csv('events.csv')
```

Data Perpartion

In [116…
```python
events['timestamp']=events['timestamp'].apply( lambda x: datetime.fromtimestamp(x/1000))
```

In [117…
```python
events
```

Out[117…

	timestamp	visitorid	event	itemid	transactionid
0	2015-06-02 07:02:12.117	257597	view	355908	NaN
1	2015-06-02 07:50:14.164	992329	view	248676	NaN
2	2015-06-02 07:13:19.827	111016	view	318965	NaN
3	2015-06-02 07:12:35.914	483717	view	253185	NaN
4	2015-06-02 07:02:17.106	951259	view	367447	NaN
...	...	...	...	...	...
2756096	2015-08-01 05:13:05.939	591435	view	261427	NaN
2756097	2015-08-01 05:30:13.142	762376	view	115946	NaN
2756098	2015-08-01 04:57:00.527	1251746	view	78144	NaN
2756099	2015-08-01 05:08:50.703	1184451	view	283392	NaN
2756100	2015-08-01 05:36:03.914	199536	view	152913	NaN

2756101 rows × 5 columns

In [118…
```python
events.dtypes
```

Out[118…
```
timestamp        datetime64[ns]
visitorid                 int64
event                    object
itemid                    int64
transactionid           float64
dtype: object
```

In [119…
```python
df=events.copy()
```

In [120…
```python
df.isnull().sum()
```

Out[120…
```
timestamp              0
visitorid              0
event                  0
itemid                 0
transactionid    2733644
dtype: int64
```

In [121…
```python
df.dropna(inplace = True)
df.isnull().sum()
```

Out[121…
```
timestamp        0
visitorid        0
event            0
itemid           0
transactionid    0
dtype: int64
```

In [122…
```python
df.shape
```

Out[122…
```
(22457, 5)
```

In [123…
```python
df.describe([0.05,0.01,0.25,0.50,0.75,0.80,0.90,0.95,0.99]).T
```

Out[123…

	count	mean	std	min	1%	5%	25%	50%	75%	80%	90%	
visitorid	22457.0	700481.127488	403657.194682	172.0	17676.00	76757.0	346597.0	712121.0	1062424.0	1133097.0	1245921.4	132
itemid	22457.0	236566.088614	134810.094990	15.0	4582.68	23221.8	120114.0	238804.0	352115.0	374962.0	422905.0	44
transactionid	22457.0	8826.497796	5098.996290	0.0	181.56	887.8	4411.0	8813.0	13224.0	14104.8	15880.4	1

In [124…
```python
max(df.timestamp)
```

Out[124…
```
Timestamp('2015-09-18 04:43:12.017000')
```

Recency, Frequency & Monetary value calculation

we'll calculate is the three key factors of RFM Analysis (recency, frequency, and monetary).
Recency: How recently customers made their purchase.
Frequency: For simplicity, we'll count the number of times each customer made a purchase.
Monetary: How much money they spent in total.
We are going to calculate these three key factors by grouping them by customers and taking "2015/09/18" as our reference end date since this is the last transaction date listed in our dataset.

In [125…
```python
# Recency   = Overall latest invoice date - individual customer's last invoice date
# Frequency = count of invoice no. of transaction(s)
# Monetary = Sum of Total amount for each cutomer

# Set 2015/09/18 as the overall last transcation date. This is to calculate recency in days.
```

In [126…
```python
df
```

Out[126…

	timestamp	visitorid	event	itemid	transactionid
130	2015-06-02 07:17:56.276	599528	transaction	356475	4000.0
304	2015-06-01 23:18:20.981	121688	transaction	15335	11117.0
418	2015-06-01 23:25:15.008	552148	transaction	81345	5444.0
814	2015-06-01 18:38:56.375	102019	transaction	150318	13556.0
843	2015-06-01 18:01:58.180	189384	transaction	310791	7244.0
...	...	...	...	...	...
2755294	2015-07-31 23:12:56.570	1050575	transaction	31640	8354.0
2755349	2015-07-31 23:57:58.779	861299	transaction	456602	3643.0
2755508	2015-07-31 17:48:50.123	855941	transaction	235771	4385.0
2755603	2015-07-31 17:12:40.300	548772	transaction	29167	13872.0
2755607	2015-07-31 18:09:49.163	1051054	transaction	312728	17579.0

22457 rows × 5 columns

In [127…
```python
#Recency Metric
import datetime as dt
today_date = dt.datetime(2021,12,30)
temp_df = (today_date - df.groupby("visitorid").agg({"timestamp":"max"}))
temp_df.rename(columns={"timestamp": "Recency"}, inplace = True)
recency_df = temp_df["Recency"].apply(lambda x: x.days)
# Frequency Metric
temp_df = df.groupby(["visitorid","transactionid"]).agg({"transactionid":"count"})
freq_df = temp_df.groupby("visitorid").agg({"transactionid":"count"})
freq_df.rename(columns={"transactionid": "Frequency"}, inplace = True)

# Monetary Metric
## it should be  item price but i dont have this  feild on data

monetary_df = df.groupby("visitorid").agg({"itemid":"sum"})
monetary_df.rename(columns = {"itemid": "Monetary"}, inplace = True)
rfm = pd.concat([recency_df, freq_df, monetary_df],  axis=1)
```

In [128…
```python
df = rfm
df["RecencyScore"] = pd.qcut(df['Recency'], 5, labels = [5, 4, 3, 2, 1])
df["FrequencyScore"] = pd.qcut(df['Frequency'].rank(method = "first"), 5, labels = [1,2,3,4,5])
df["MonetaryScore"] = pd.qcut(df['Monetary'], 5, labels = [1,2,3,4,5])
df["RFM_SCORE"] = df['RecencyScore'].astype(str) + df['FrequencyScore'].astype(str) + df['MonetaryScore'].astyp
seg_map = {
        r'[1-2][1-2]': 'Hibernating',
        r'[1-2][3-4]': 'At Risk',
        r'[1-2]5': 'Can\'t Loose',
        r'3[1-2]': 'About to Sleep',
        r'33': 'Need Attention',
        r'[3-4][4-5]': 'Loyal Customers',
        r'41': 'Promising',
        r'51': 'New Customers',
        r'[4-5][2-3]': 'Potential Loyalists',
        r'5[4-5]': 'Champions'
}

df['Segment'] = df['RecencyScore'].astype(str) + rfm['FrequencyScore'].astype(str)
df['Segment'] = df['Segment'].replace(seg_map, regex=True)
df.head()
```

Out[128…

visitorid	Recency	Frequency	Monetary	RecencyScore	FrequencyScore	MonetaryScore	RFM_SCORE	Segment
172	2328	1	475556	4	1	5	415	Promising
186	2331	1	49029	4	1	1	411	Promising
264	2305	1	621784	5	1	5	515	New Customers
419	2345	1	19278	4	1	1	411	Promising
539	2388	1	94371	2	1	1	211	Hibernating

In [129…
```python
rfm = df.loc[:,"Recency":"Monetary"]
```

In [130…
```python
df.groupby("visitorid").agg({"Segment": "sum"}).head()
```

Out[130…

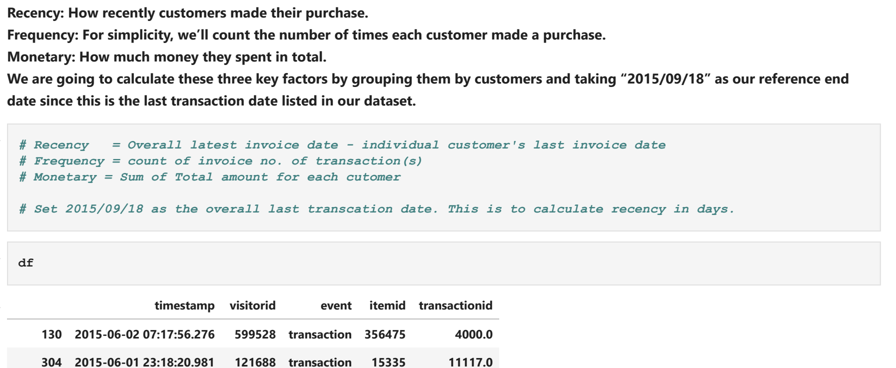
visitorid	Segment
172	Promising
186	Promising
264	New Customers
419	Promising
539	Hibernating

Explore the RFM values

once we have every visitor's individual recency, frequency, and monetary value calculated, we'd like to see the distribution graph to understand the data better.

In [131…
```python
fig, ax = plt.subplots(1, 3, figsize=(16, 8))

# Recency distribution plot
sn.histplot(rfm['Recency'], kde=True, ax=ax[0])

# Frequency distribution plot
sn.histplot(rfm.query('Frequency < 1000')['Frequency'], kde=True, ax=ax[1])

# Monetary distribution plot
sn.histplot(rfm.query('Monetary < 10000')['Monetary'], kde=True, ax=ax[2])
```

Out[131…
```
<AxesSubplot:xlabel='Monetary', ylabel='Count'>
```



In [132…
```python
df
```

Out[132…

visitorid	Recency	Frequency	Monetary	RecencyScore	FrequencyScore	MonetaryScore	RFM_SCORE	Segment
172	2328	1	475556	4	1	5	415	Promising
186	2331	1	49029	4	1	1	411	Promising
264	2305	1	621784	5	1	5	515	New Customers
419	2345	1	19278	4	1	1	411	Promising
539	2388	1	94371	2	1	1	211	Hibernating
...	...	...	...	...	...	...	...	...
1406787	2403	1	336832	2	5	3	253	Can't Loose
1406981	2416	1	436004	1	5	4	154	Can't Loose
1407070	2421	1	215596	1	5	2	152	Can't Loose
1407110	2338	1	360922	4	5	4	454	Loyal Customers
1407398	2367	1	218917	3	5	2	352	Loyal Customers

11719 rows × 8 columns

Clustering with the K-Means Algorithm

In [133…
```python
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler
```

In [134…
```python
#scale
sc = MinMaxScaler((0,1))
df = sc.fit_transform(rfm)

#Kmeans
kmeans = KMeans(n_clusters = 10)
k_fit = kmeans.fit(df)
```

In [135…
```python
k_fit.n_clusters
```

Out[135…
```
10
```

In [136…
```python
k_fit.cluster_centers_
```

Out[136…
```
array([[9.55339194e-01, 3.31159983e-04, 2.72321896e-03],
       [3.43601204e-01, 5.49583794e-04, 3.04244433e-03],
       [6.51485534e-01, 6.29632685e-04, 3.03805874e-03],
       [7.41322452e-02, 1.19005743e-03, 3.85068126e-03],
       [8.59395075e-01, 6.73053231e-04, 3.05262279e-03],
       [5.46085792e-01, 4.71346464e-04, 2.99596562e-03],
       [2.09620519e-01, 6.10620864e-04, 3.13547835e-03],
       [7.58668053e-01, 1.07667747e-03, 3.64626006e-03],
       [4.46163173e-01, 7.71365635e-04, 3.48275891e-03],
       [2.97906602e-01, 4.01197605e-01, 4.48952552e-01]])
```

In [137…
```python
k_fit.labels_
```

Out[137…
```
array([6, 6, 3, ..., 0, 1, 5])
```

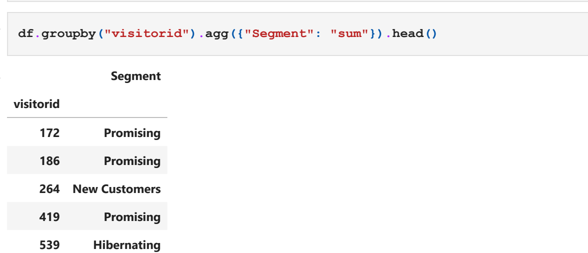
In [138…
```python
df[0:5]
```

Out[138…
```
array([[2.46376812e-01, 0.00000000e+00, 3.74502469e-03],
       [2.68115942e-01, 0.00000000e+00, 3.85928972e-04],
       [7.97101449e-02, 0.00000000e+00, 4.89663724e-03],
       [3.69565217e-01, 0.00000000e+00, 1.51626204e-04],
       [6.81159420e-01, 0.00000000e+00, 7.43018014e-04]])
```

Determining the Optimum Number of Clusters

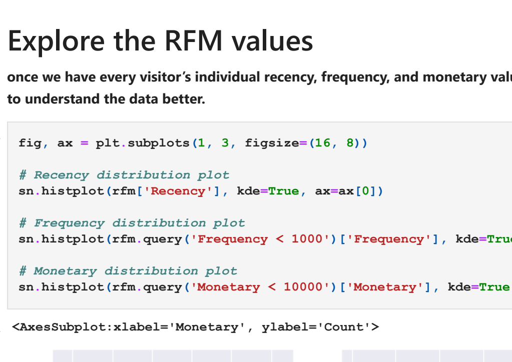
In [139…
```python
kmeans = KMeans(n_clusters = 2)
k_fit = kmeans.fit(df)
ssd = []

K = range(1,30)

for k in K:
    kmeans = KMeans(n_clusters = k).fit(df)
    ssd.append(kmeans.inertia_)

plt.plot(K, ssd, "bx-")
plt.xlabel("Distance Residual Sums Versus Different k Values")
plt.title("Elbow method for Optimum number of clusters")
```

Out[139…
```
Text(0.5, 1.0, 'Elbow method for Optimum number of clusters')
```



In [140…
```python
# !pip install yellowbrick
```

In [141…
```python
from yellowbrick.cluster import KElbowVisualizer
kmeans = KMeans()
visu = KElbowVisualizer(kmeans, k = (2,20))
visu.fit(df)
visu.poof();
```



In [142…
```python
kmeans = KMeans(n_clusters = 6).fit(df)
cluster = kmeans.labels_
pd.DataFrame({"VistiorID": rfm.index, "cluster": cluster})
```

Out[142…

	VistiorID	cluster
0	172	5
1	186	5
2	264	2
3	419	0
4	539	4
...	...	...
11714	1406787	1
11715	1406981	3
11716	1407070	3
11717	1407110	5
11718	1407398	4

11719 rows × 2 columns