Homework 2 - Predict Future Sales

For all parts below, answer all parts as shown in the Google document for Homework 2. Be sure to include both code that justifies your answer as well as text to answer the questions. Show runtime results for each cell. We also ask that code be commented to make it easier to follow.

Part 1 - Data Cleaning and Merging

In [ ]:
```
# TODO: code for data cleaning and merging
```

Write your answer here

In [308]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [309]:
```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, cal
l drive.mount("/content/gdrive", force_remount=True).
```

In [310]:
```
cd '/content/gdrive/My Drive/519/HW2'
```

```
/content/gdrive/My Drive/519/HW2
```

In [311]:
```
# Load data
items=pd.read_csv("items.csv")
shops=pd.read_csv("shops.csv")
item_categories=pd.read_csv("item_categories.csv")
train=pd.read_csv("sales_train.csv")
test=pd.read_csv("test.csv")
```

In [312]:
```
train.head()
```

Out[312]:

	date	date_block_num	shop_id	item_id	item_price	item_cnt_day
0	02.01.2013	0	59	22154	999.00	1.0
1	03.01.2013	0	25	2552	899.00	1.0
2	05.01.2013	0	25	2552	899.00	-1.0
3	06.01.2013	0	25	2554	1709.05	1.0
4	15.01.2013	0	25	2555	1099.00	1.0

In [313]:
```
# drop duplicates
subset = ['date','date_block_num','shop_id','item_id','item_cnt_day']
print(train.duplicated(subset=subset).value_counts())
train.drop_duplicates(subset=subset, inplace=True)
print("shape of train:",train.shape)
```

```
False    2935825
True          24
dtype: int64
shape of train: (2935825, 6)
```

In [314]:
```python
# merge data
train= pd.merge(train,items,on='item_id',how='left')
train= pd.merge(train,item_categories,on='item_category_id',how='left')
train= pd.merge(train,shops,on='shop_id',how='left')
train.head()
```

Out[314]:

	date	date_block_num	shop_id	item_id	item_price	item_cnt_day	item_name	item_cat
0	02.01.2013	0	59	22154	999.00	1.0	ЯВЛЕНИЕ 2012 (BD)	
1	03.01.2013	0	25	2552	899.00	1.0	DEEP PURPLE The House Of Blue Light LP	
2	05.01.2013	0	25	2552	899.00	-1.0	DEEP PURPLE The House Of Blue Light LP	
3	06.01.2013	0	25	2554	1709.05	1.0	DEEP PURPLE Who Do You Think We Are LP	
4	15.01.2013	0	25	2555	1099.00	1.0	DEEP PURPLE 30 Very Best Of 2CD (Фирм.)	

In [315]:
```python
perc =[.20, .40, .60, .80,.95,.999]

with pd.option_context('float_format', '{:.2f}'.format):
  print(train.describe(percentiles = perc).item_price)
```

```
count   2935825.00
mean        890.86
std        1729.81
min          -1.00
20%         199.00
40%         349.00
50%         399.00
60%         599.00
80%        1199.00
95%        2690.00
99.9%     23990.00
max      307980.00
Name: item_price, dtype: float64
```

In [316]:
```python
train['item_price'].sort_values().tail(5)
```

Out[316]:
```
2931356     42990.0
2327138     49782.0
1488125     50999.0
885130      59200.0
1163150    307980.0
Name: item_price, dtype: float64
```

item_price:

1. Take the max price value as an outlier.
2. min item_price = -1, replace it with median.

In [317]:
```python
# replace median for price= -1
train[train['item_price']==-1]
```

Out[317]:

	date	date_block_num	shop_id	item_id	item_price	item_cnt_day	item_name	ite
484675	15.05.2013	4	32	2973	-1.0	1.0	DmC Devil May Cry [PS3, русские субтитры]	

In [318]:
```python
price_check = train[(train['item_id']==2973) & (train['shop_id']==32)] # filte
r
price_check = price_check[price_check['item_price'] > 0 ]                # ge
t all records for price>0
train.loc[train['item_price']==-1,'item_price']= price_check['item_price'].med
ian()  # replace with median
```

In [319]:
```
# delete outliers of item_price
train = train.loc[train['item_price']<100000]

with pd.option_context('float_format', '{:.2f}'.format):
  print(train.describe(percentiles = perc).item_price)
```

```
count   2935824.00
mean        890.75
std        1720.50
min           0.07
20%         199.00
40%         349.00
50%         399.00
60%         599.00
80%        1199.00
95%        2690.00
99.9%     23990.00
max       59200.00
Name: item_price, dtype: float64
```

In [320]:
```
# delete refund items
train = train.loc[train['item_cnt_day']>0]

with pd.option_context('float_format', '{:.2f}'.format):
  print(train.describe(percentiles = perc).item_cnt_day)
```

```
count   2928468.00
mean          1.25
std           2.62
min           1.00
20%           1.00
40%           1.00
50%           1.00
60%           1.00
80%           1.00
95%           2.00
99.9%        22.00
max        2169.00
Name: item_cnt_day, dtype: float64
```

In [321]:
```
#check null values
null_values = train.isnull().values.any()
null_values
```

Out[321]:
```
False
```

In [49]:
```
train.head()
```

Out[49]:

	date	date_block_num	shop_id	item_id	item_price	item_cnt_day	item_name	item_cat
0	02.01.2013	0	59	22154	999.00	1.0	ЯВЛЕНИЕ 2012 (BD)	
1	03.01.2013	0	25	2552	899.00	1.0	DEEP PURPLE The House Of Blue Light LP	
3	06.01.2013	0	25	2554	1709.05	1.0	DEEP PURPLE Who Do You Think We Are LP	
4	15.01.2013	0	25	2555	1099.00	1.0	DEEP PURPLE 30 Very Best Of 2CD (Фирм.)	
5	10.01.2013	0	25	2564	349.00	1.0	DEEP PURPLE Perihelion: Live In Concert DVD (К...	

Part 2 - Time Series Analysis

In [ ]:
```
# TODO: code for time series analysis
```

Write your answer here

In [322]:
```
import datetime

train["date"] = pd.to_datetime(train["date"]).dt.strftime('%d/%m/%Y')
train.head()
```

Out[322]:

	date	date_block_num	shop_id	item_id	item_price	item_cnt_day	item_name	item_cat
0	01/02/2013	0	59	22154	999.00	1.0	ЯВЛЕНИЕ 2012 (BD)	
1	01/03/2013	0	25	2552	899.00	1.0	DEEP PURPLE The House Of Blue Light LP	
3	01/06/2013	0	25	2554	1709.05	1.0	DEEP PURPLE Who Do You Think We Are LP	
4	15/01/2013	0	25	2555	1099.00	1.0	DEEP PURPLE 30 Very Best Of 2CD (Фирм.)	
5	01/10/2013	0	25	2564	349.00	1.0	DEEP PURPLE Perihelion: Live In Concert DVD (К...	

In [323]:

```python
# insert 'weekday', 'month', 'year' column
train.insert(1,"weekday",pd.to_datetime(train["date"]).dt.strftime('%A'))

month = []
for date in train['date'].values:
  d,m,y = date.split("/")
  month.append(m)

train.insert(2,"month",month)

train['year'] = (train['date_block_num'] // 12 ) + 2013
train.head()
```

Out[323]:

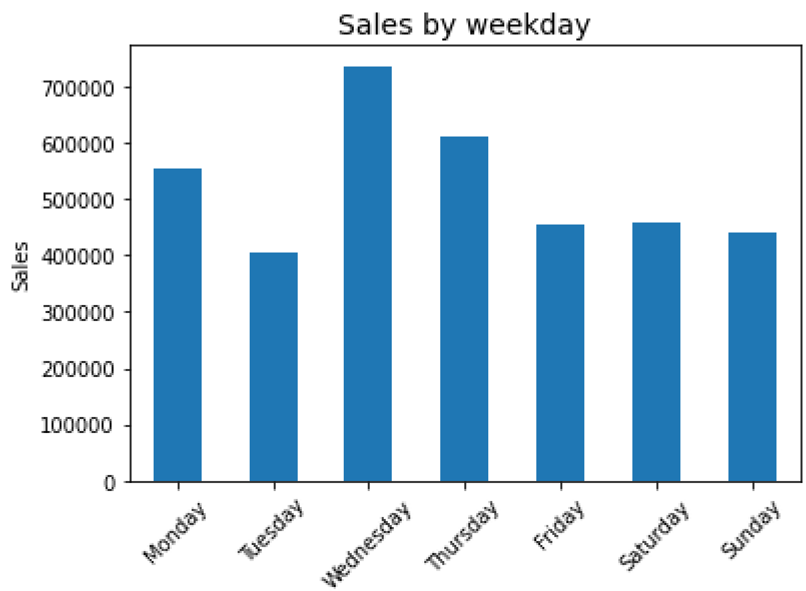
	date	weekday	month	date_block_num	shop_id	item_id	item_price	item_cnt_day
0	01/02/2013	Wednesday	02	0	59	22154	999.00	1.0
1	01/03/2013	Thursday	03	0	25	2552	899.00	1.0
3	01/06/2013	Sunday	06	0	25	2554	1709.05	1.0
4	15/01/2013	Tuesday	01	0	25	2555	1099.00	1.0
5	01/10/2013	Thursday	10	0	25	2564	349.00	1.0

In [324]:
```
# add 'revenue' column
train['revenue'] = train.item_price * train.item_cnt_day
train.head()
```

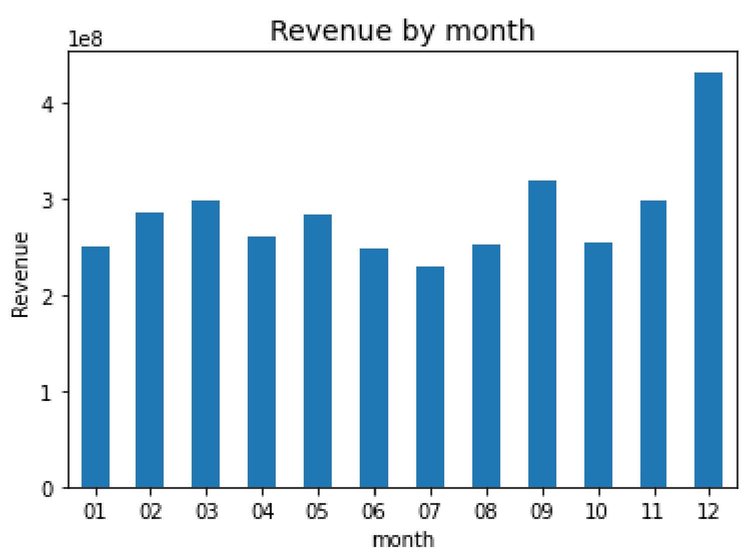
Out[324]:

	date	weekday	month	date_block_num	shop_id	item_id	item_price	item_cnt_day
0	01/02/2013	Wednesday	02	0	59	22154	999.00	1.0
1	01/03/2013	Thursday	03	0	25	2552	899.00	1.0
3	01/06/2013	Sunday	06	0	25	2554	1709.05	1.0
4	15/01/2013	Tuesday	01	0	25	2555	1099.00	1.0
5	01/10/2013	Thursday	10	0	25	2564	349.00	1.0

In [325]:
```
days = [ 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
mons = [ '01', '02', '03', '04', '05', '06', '07', '08', '09', '10', '11', '12']

weekday_sale=train.groupby('weekday')['item_cnt_day'].sum()
weekday_sale.index=days
weekday_sale.plot(kind='bar')
plt.title("Sales by weekday", size=14)
plt.xticks(rotation=45)
plt.ylabel('Sales')
plt.show()
```

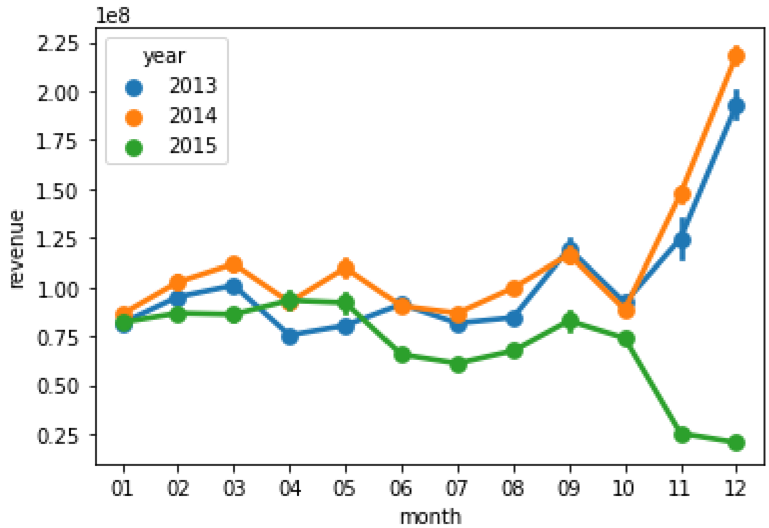


In [326]:
```
train.groupby('month')['revenue'].sum().plot(kind='bar')
plt.title("Revenue by month", size=14)
plt.xticks(rotation=0)
plt.ylabel('Revenue')
plt.show()
```



In [327]:
```
sns.pointplot(x='month', y='revenue', hue='year', data=train, estimator=np.sum
)
```

Out[327]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f803e2aab70>
```



In [328]:
```
print("total counts in 2013:",train[train['year']==2013].shape)
print("total counts in 2014:",train[train['year']==2014].shape)
print("total counts in 2015:",train[train['year']==2015].shape)
```

```
total counts in 2013: (1264481, 14)
total counts in 2014: (1053199, 14)
total counts in 2015: (610788, 14)
```

Explain:

1. For weekdays, items are sold more on weekends, and less on workdays. People tend to shop when they are resting at home.
2. For months, monthly revenue are higher in the 4th season, especially in December. Maybe because there are more holidays like Christmas so that there are more discounts.
3. We can see that records in 2015 is extremly less than those in 2013 and 2014, and that's why the revenue in 2015 sharply decreased.

Part 3 - More Time Series Analysis

In [ ]:
```
# TODO: code for time series analysis
```

Write your answer here

In [58]:
```
pip install googletrans
```

```
Requirement already satisfied: googletrans in /usr/local/lib/python3.6/dist-p
ackages (3.0.0)
Requirement already satisfied: httpx==0.13.3 in /usr/local/lib/python3.6/dist
-packages (from googletrans) (0.13.3)
Requirement already satisfied: sniffio in /usr/local/lib/python3.6/dist-packa
ges (from httpx==0.13.3->googletrans) (1.1.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.6/dist-packa
ges (from httpx==0.13.3->googletrans) (2020.6.20)
Requirement already satisfied: idna==2.* in /usr/local/lib/python3.6/dist-pac
kages (from httpx==0.13.3->googletrans) (2.10)
Requirement already satisfied: httpcore==0.9.* in /usr/local/lib/python3.6/di
st-packages (from httpx==0.13.3->googletrans) (0.9.1)
Requirement already satisfied: chardet==3.* in /usr/local/lib/python3.6/dist-
packages (from httpx==0.13.3->googletrans) (3.0.4)
Requirement already satisfied: hstspreload in /usr/local/lib/python3.6/dist-p
ackages (from httpx==0.13.3->googletrans) (2020.9.23)
Requirement already satisfied: rfc3986<2,>=1.3 in /usr/local/lib/python3.6/di
st-packages (from httpx==0.13.3->googletrans) (1.4.0)
Requirement already satisfied: contextvars>=2.1; python_version < "3.7" in /u
sr/local/lib/python3.6/dist-packages (from sniffio->httpx==0.13.3->googletran
s) (2.4)
Requirement already satisfied: h2==3.* in /usr/local/lib/python3.6/dist-packa
ges (from httpcore==0.9.*->httpx==0.13.3->googletrans) (3.2.0)
Requirement already satisfied: h11<0.10,>=0.8 in /usr/local/lib/python3.6/dis
t-packages (from httpcore==0.9.*->httpx==0.13.3->googletrans) (0.9.0)
Requirement already satisfied: immutables>=0.9 in /usr/local/lib/python3.6/di
st-packages (from contextvars>=2.1; python_version < "3.7"->sniffio->httpx==
0.13.3->googletrans) (0.14)
Requirement already satisfied: hpack<4,>=3.0 in /usr/local/lib/python3.6/dist
-packages (from h2==3.*->httpcore==0.9.*->httpx==0.13.3->googletrans) (3.0.0)
Requirement already satisfied: hyperframe<6,>=5.2.0 in /usr/local/lib/python
3.6/dist-packages (from h2==3.*->httpcore==0.9.*->httpx==0.13.3->googletrans)
(5.2.0)
```

In [329]:
```
from googletrans import Translator

translator = Translator()
item_categories['item_category_name'] = item_categories['item_category_name'].
apply(translator.translate, src='ru', dest='en').apply(getattr, args=('text'
,))
item_categories.head()
```

Out[329]:

	item_category_name	item_category_id
0	PC - Headsets / Headphones	0
1	Accessories - PS2	1
2	Accessories - PS3	2
3	Accessories - PS4	3
4	Accessories - PSP	4

In [330]:
```
# replace with the translated column
train.drop(['item_category_name'],axis=1,inplace=True)
train= pd.merge(train,item_categories,on='item_category_id',how='left')
train.head()
```

Out[330]:

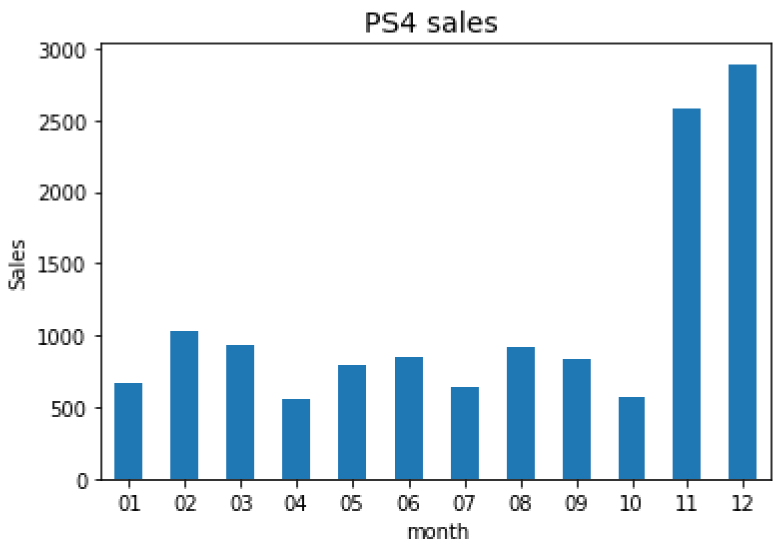
	date	weekday	month	date_block_num	shop_id	item_id	item_price	item_cnt_day
0	01/02/2013	Wednesday	02	0	59	22154	999.00	1.0
1	01/03/2013	Thursday	03	0	25	2552	899.00	1.0
2	01/06/2013	Sunday	06	0	25	2554	1709.05	1.0
3	15/01/2013	Tuesday	01	0	25	2555	1099.00	1.0
4	01/10/2013	Thursday	10	0	25	2564	349.00	1.0

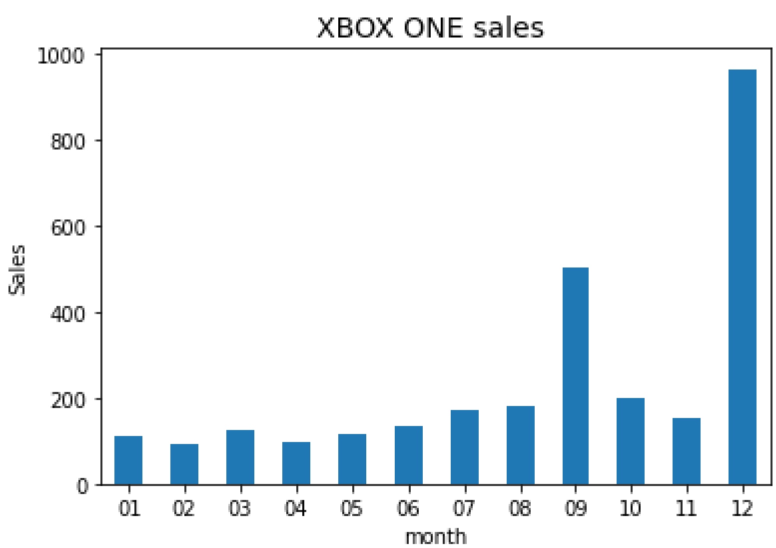
In [331]:
```
train1 = copy.deepcopy(train)
```

Interested Category: Game consoles

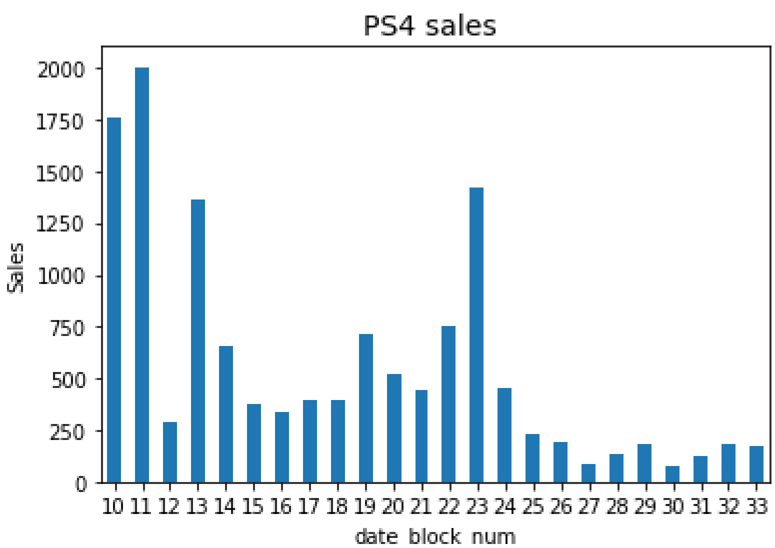
In [332]:

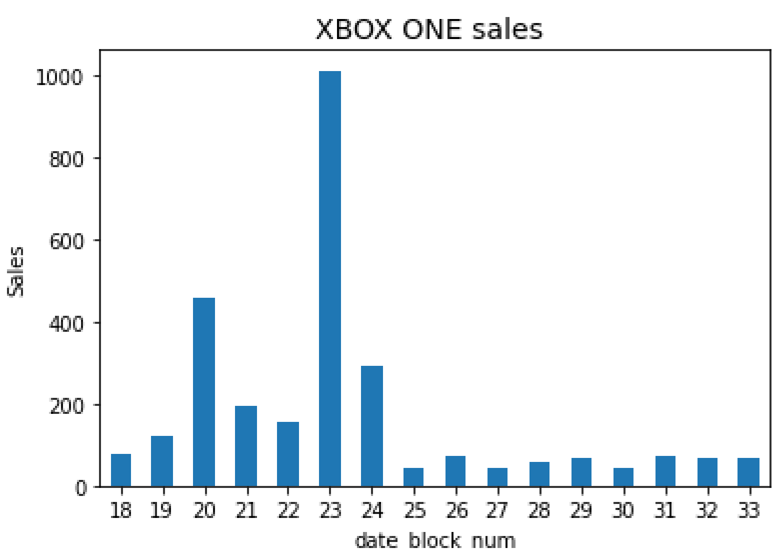
```
PS4 = train.loc[train['item_category_name']=='Game consoles - PS4']
PS4.groupby('month')['item_cnt_day'].sum().reindex(mons).plot(kind='bar')

plt.title("PS4 sales ", size=14)
plt.xticks(rotation=0)
plt.ylabel('Sales')
plt.show()

Xbox1 = train.loc[train['item_category_name']=='Game consoles - XBOX ONE']
Xbox1.groupby('month')['item_cnt_day'].sum().reindex(mons).plot(kind='bar')

plt.title("XBOX ONE sales ", size=14)
plt.xticks(rotation=0)
plt.ylabel('Sales')
plt.show()
```





In [333]:
```
PS4 = train.loc[train['item_category_name']=='Game consoles - PS4']
PS4.groupby('date_block_num')['item_cnt_day'].sum().plot(kind='bar')

plt.title("PS4 sales ", size=14)
plt.xticks(rotation=0)
plt.ylabel('Sales')
plt.show()

Xbox1 = train.loc[train['item_category_name']=='Game consoles - XBOX ONE']
Xbox1.groupby('date_block_num')['item_cnt_day'].sum().plot(kind='bar')

plt.title("XBOX ONE sales ", size=14)
plt.xticks(rotation=0)
plt.ylabel('Sales')
plt.show()
```





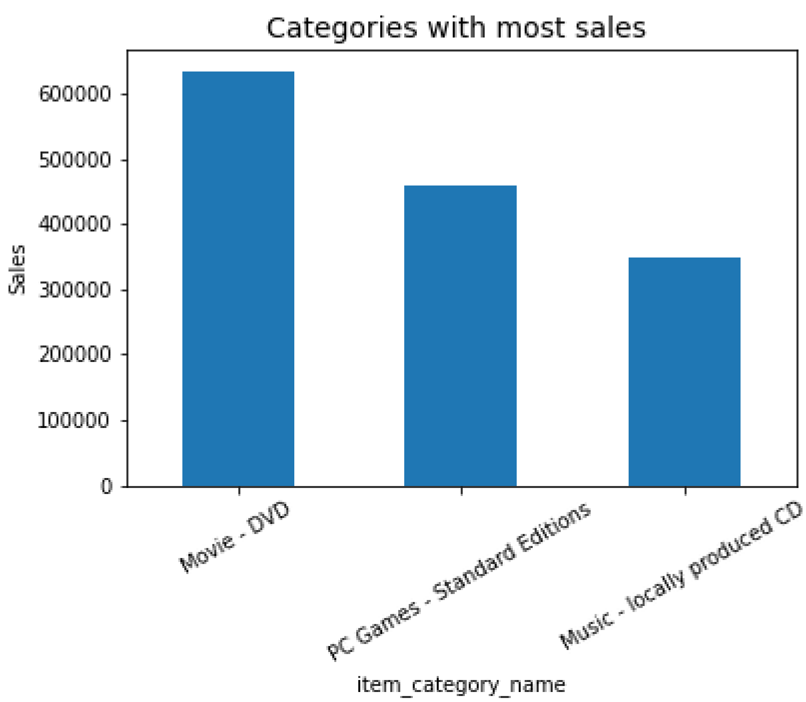
> During 2013-2015, Sony and Microsoft released their newest game consoles:

- PS4 was released in 2013.10
- Xbox One was released in 2014.9

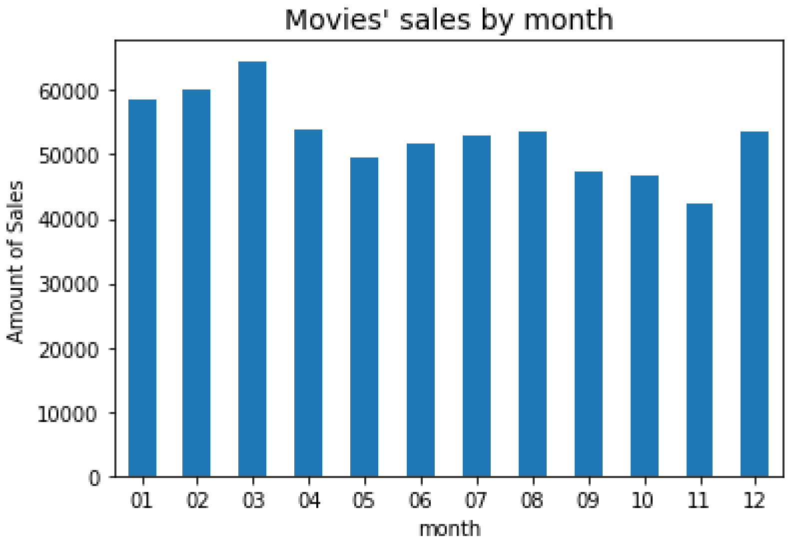
From the plot we can see that here are indeed sales peaks during during this time.
Also we can see the Chirstmas brings sales peak.

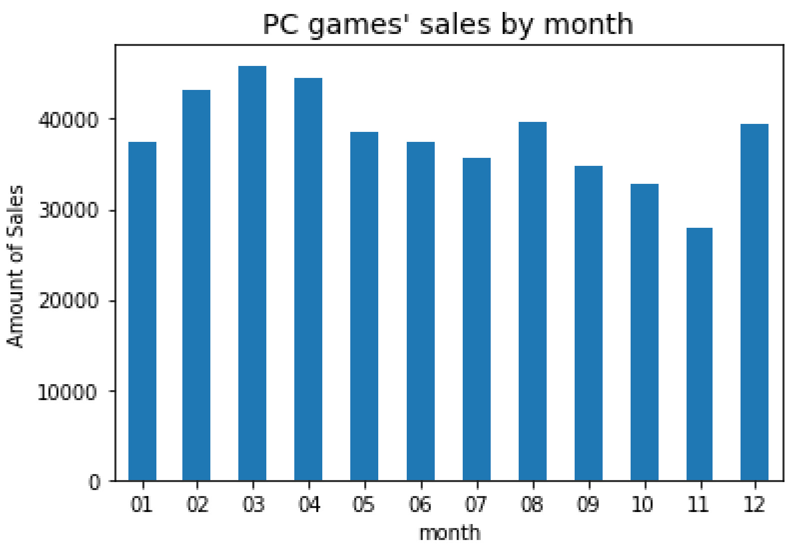
Item categories with most sales

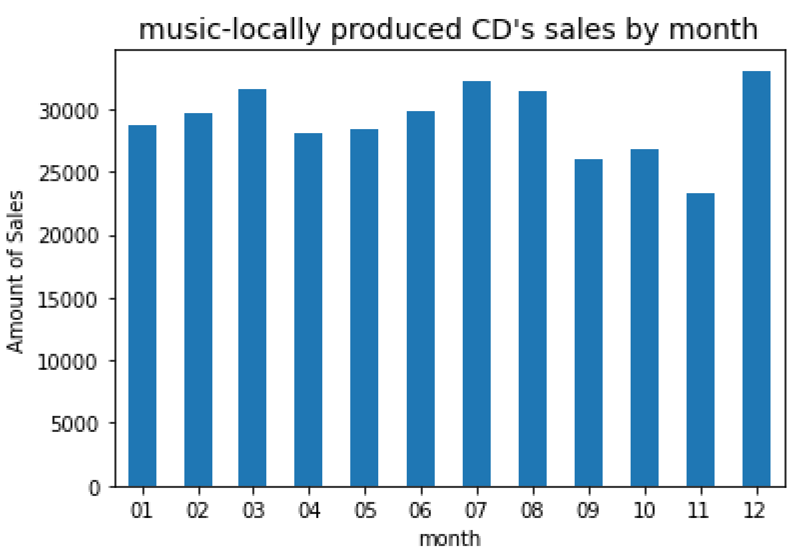
In [334]:
```
train.groupby('item_category_name')['item_cnt_day'].sum().nlargest(3).plot(kin
d='bar')

plt.title("Categories with most sales ", size=14)
plt.xticks(rotation=30)
plt.ylabel('Sales')
plt.show()
```



In [335]:
```
movie = train.loc[train['item_category_name']=='Movie - DVD']
movie.groupby('month')['item_cnt_day'].sum().reindex(mons).plot(kind='bar')


plt.title("Movies' sales by month", size=14)
plt.xticks(rotation=0)
plt.ylabel('Amount of Sales')
plt.show()

PCgames = train.loc[train['item_category_name']=='PC Games - Standard Edition
s']
PCgames.groupby('month')['item_cnt_day'].sum().reindex(mons).plot(kind='bar')


plt.title("PC games' sales by month", size=14)
plt.xticks(rotation=0)
plt.ylabel('Amount of Sales')
plt.show()

music = train.loc[train['item_category_name']=='Music - locally produced CD']
music.groupby('month')['item_cnt_day'].sum().reindex(mons).plot(kind='bar')

plt.title("music-locally produced CD's sales by month", size=14)
plt.xticks(rotation=0)
plt.ylabel('Amount of Sales')
plt.show()
```


Movies' sales by month
Amount of Sales
0
10000
20000
30000
40000
50000
60000
01 02 03 04 05 06 07 08 09 10 11 12
month

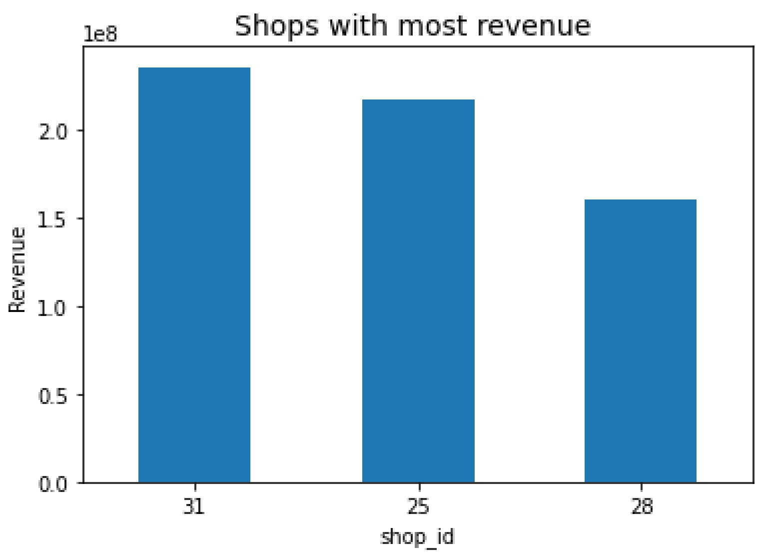

PC games' sales by month
Amount of Sales
0
10000
20000
30000
40000
01 02 03 04 05 06 07 08 09 10 11 12
month


music-locally produced CD's sales by month
Amount of Sales
0
5000
10000
15000
20000
25000
30000
01 02 03 04 05 06 07 08 09 10 11 12
month

Item categories with most sales are: Movie(DVD), PCgames(standard editions), Music(loccally produced CD)
All of them have roughly even distribution over the 12 months. So they are not affected much by the holidays.

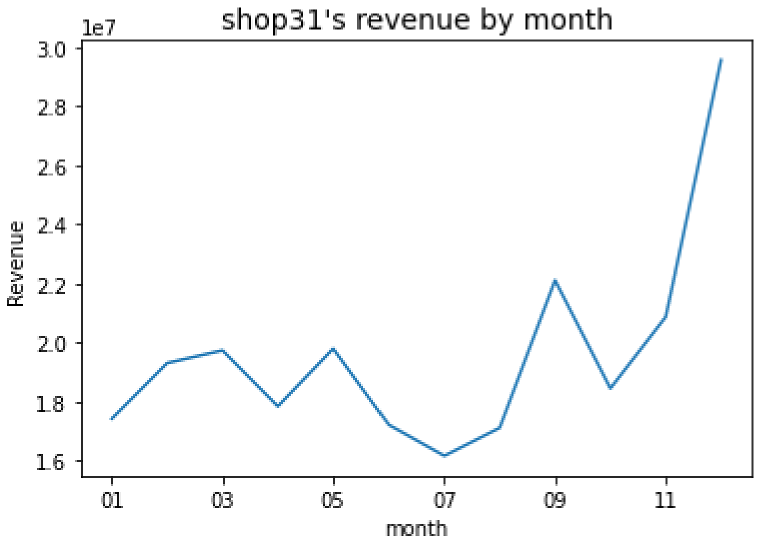
Shops with most revenue are: shop #31, #25, #28

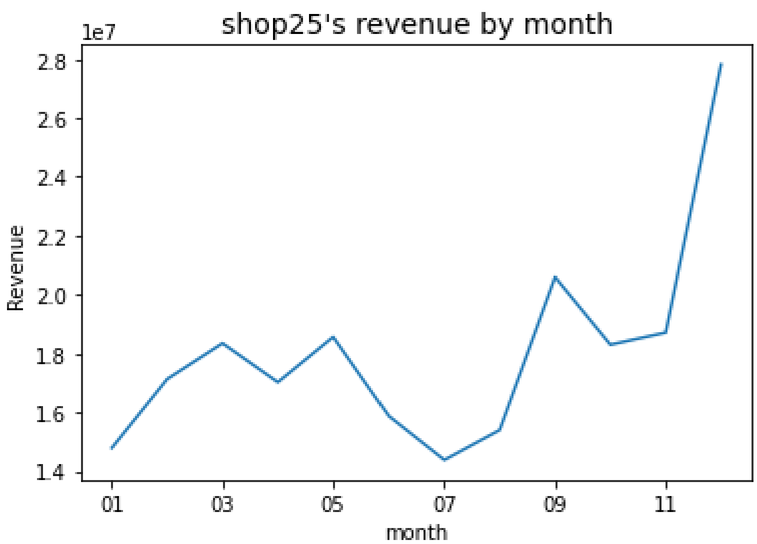
In [336]:
```
train.groupby('shop_id')['revenue'].sum().nlargest(3).plot(kind='bar')

plt.title("Shops with most revenue ", size=14)
plt.xticks(rotation=0)
plt.ylabel('Revenue')
plt.show()
```

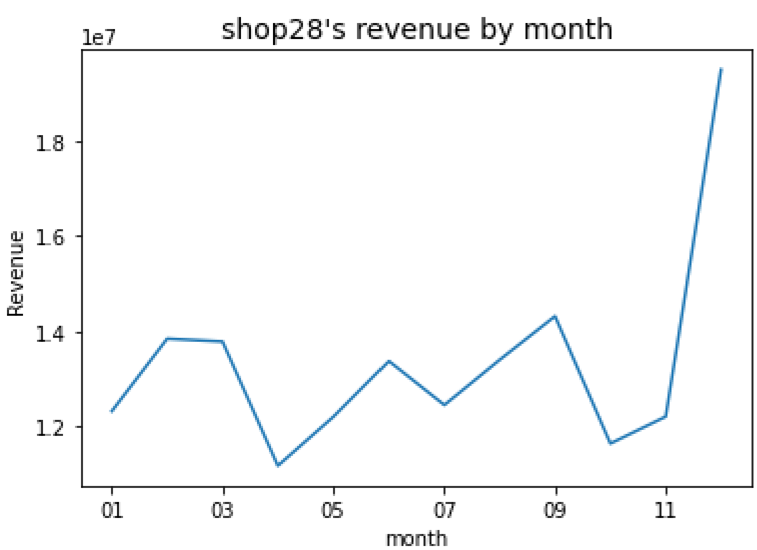


In [337]:

```
fig = plt.figure()

#plt.subplot(1,3,1)
shop31 = train.loc[train['shop_id']==31]
shop31.groupby('month')['revenue'].sum().reindex(mons).plot()

plt.title("shop31's revenue by month", size=14)
plt.xticks(rotation=0)
plt.ylabel('Revenue')
plt.show()

#plt.subplot(1,3, 2)
shop25 = train.loc[train['shop_id']==25]
shop25.groupby('month')['revenue'].sum().reindex(mons).plot()

plt.title("shop25's revenue by month", size=14)
plt.xticks(rotation=0)
plt.ylabel('Revenue')
plt.show()

#plt.subplot(1,3,3)
shop28 = train.loc[train['shop_id']==28]
shop28.groupby('month')['revenue'].sum().reindex(mons).plot()

plt.title("shop28's revenue by month", size=14)
plt.xticks(rotation=0)
plt.ylabel('Revenue')
plt.show()
```


shop31's revenue by month
1e7
3.0
2.8
2.6
2.4
2.2
2.0
1.8
1.6
Revenue
01
03
05
07
09
11
month


shop25's revenue by month
1e7
2.8
2.6
2.4
2.2
2.0
1.8
1.6
1.4
Revenue
01
03
05
07
09
11
month


shop28's revenue by month
1e7
1.8
1.6
1.4
1.2
Revenue
01
03
05
07
09
11
month

The highest revenue are around 2.5-3+e7 in December, while the lowset revenue are around 1.2+e7. The revenue raised a lot in December because of the Christmas, but other time are evenly distributed.

Part 4 - Analyze Price Change

In [338]:
```
# drop shops & items not in test data
test_shops = test.shop_id.unique()
test_items = test.item_id.unique()
train = train[train.shop_id.isin(test_shops)]
train = train[train.item_id.isin(test_items)]
train2 = copy.deepcopy(train)

print('train:', train.shape)
```

```
train: (1221488, 14)
```

In [215]:
```
last_price=train.groupby(['date_block_num','shop_id','item_id'])[['item_price'
]].mean().reset_index().rename(columns={'item_price':'last_price'})
last_price.date_block_num=last_price.date_block_num+1
train01=train.merge(last_price,on=['shop_id','item_id','date_block_num'])
```

In [71]:

```
train01.head()
```

Out[71]:

	date	weekday	month	date_block_num	shop_id	item_id	item_price	item_cnt_day
0	02/02/2013	Saturday	02	1	50	3851	899.0	1.0
1	14/02/2013	Thursday	02	1	50	3851	899.0	1.0
2	27/02/2013	Wednesday	02	1	50	3851	899.0	1.0
3	02/07/2013	Thursday	07	1	50	3871	2499.0	1.0
4	02/11/2013	Monday	11	1	50	3871	2499.0	1.0

In [212]:

```
train1 = copy.deepcopy(train)
```

In [216]:

```
train01['price_change']=train01['item_price']/train01['last_price']-1
train01.head(2)
```

Out[216]:

	date	weekday	month	date_block_num	shop_id	item_id	item_price	item_cnt_day
0	04/06/2013	Saturday	06	3	25	8093	1399.0	1.0
1	04/04/2013	Thursday	04	3	25	8093	1399.0	1.0

In [217]:

```
train01=train01.dropna()
```

In [218]:
```
price_change=train01.groupby(['date_block_num','shop_id','item_id'])[['price_c
hange']].mean().reset_index()
price_change.head()
```

Out[218]:

	date_block_num	shop_id	item_id	price_change
0	3	2	482	0.000000
1	3	2	1916	0.000000
2	3	2	2252	0.000000
3	3	2	2308	-0.078524
4	3	2	2678	0.000000

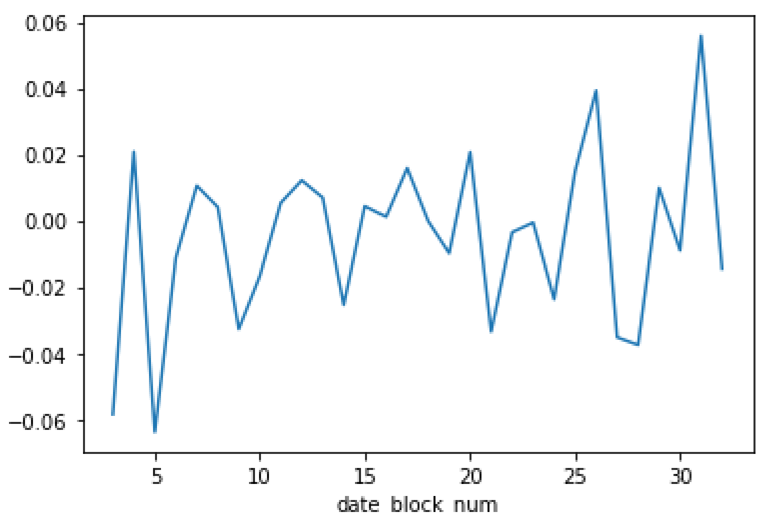
In [219]:
```
sale_num=train01.groupby(['date_block_num','shop_id','item_id'])[['item_cnt_da
y']].sum().reset_index()
```

Assume that the price change will affect the sales in a month's time:

In [220]:
```
# for i in range(1,13):
sale_num.date_block_num=sale_num.date_block_num-1
merge_df=price_change.merge(sale_num,on=['date_block_num','shop_id','item_id'
])
corr=merge_df.groupby('date_block_num').apply(lambda x:x[['price_change','item
_cnt_day']].corr().iloc[0,1])
```

In [221]:
```
corr.plot()
```

Out[221]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7fff640160>



We can see that, the next month's sales do not have linear relations with the price change. Thus the price change does not affect sales much.

Plots for the items that have the most price change:

In [222]:
```
item_check = train1
item_check['date'] =pd.to_datetime(item_check.date)
item_check['price_change']=0

def groupfunc(group):
    if group['shop_id'].count()>1: # only for those have multiple sale records
        group.sort_values(['date'],inplace=True)
        initial_price = group['item_price'].head(1)
        group['price_change'] = group['item_price'].apply(lambda x:x-initial_p
rice)
    return group

%prun item_check = item_check.groupby(['shop_id','item_id']).apply(groupfunc)
```

In [223]:
```
check0 = copy.deepcopy(item_check)
item_check = item_check.sort_values(by=['price_change'])

with pd.option_context('float_format', '{:.2f}'.format):
  print(item_check.describe(percentiles = perc).price_change)
```

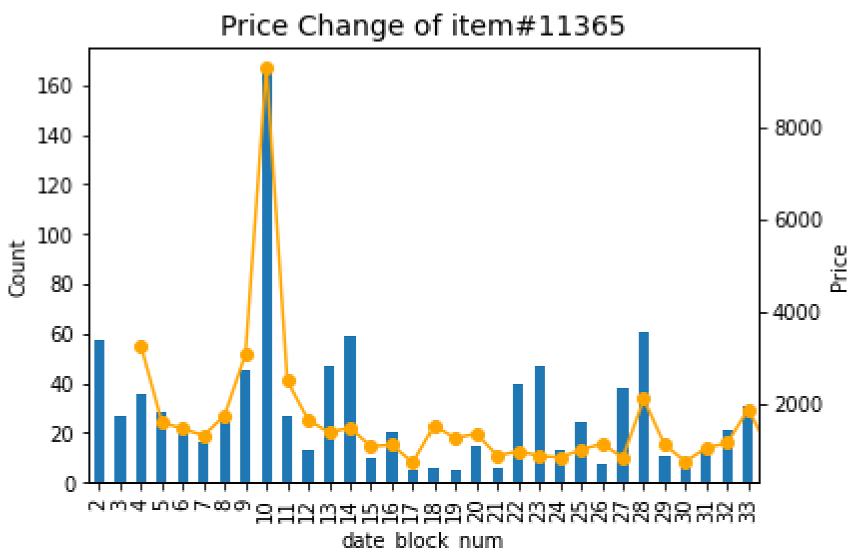
```
count   527979.00
mean       -68.13
std        576.62
min     -10098.00
20%          0.00
40%          0.00
50%          0.00
60%          0.00
80%          0.00
95%        391.00
99.9%     2363.37
max      57470.00
Name: price_change, dtype: float64
```

In [224]:
```
price_decrese_max = item_check.tail(2)
price_decrese_max
```

Out[224]:

shop_id	item_id		date	weekday	month	date_block_num	shop_id	item_id	item_pric
24	**17717**	**234145**	2014-07-29	Tuesday	07	18	24	17717	16790.(
12	**11365**	**66854**	2013-09-17	Tuesday	09	8	12	11365	59200.(

In [225]:
```
item2 = item_check[(item_check['item_id']==11365) & (item_check['shop_id']==12
)]

ax1 = item2.groupby('date_block_num')['item_price'].mean().plot(secondary_y=Tr
ue,marker = 'o',color='orange')
ax2 = item2.groupby('date_block_num')['item_cnt_day'].sum().plot(kind='bar')

ax2.set_title("Price Change of item#11365", size=14)
ax1.set_ylabel("Price")
ax2.set_ylabel('Count')
plt.show()
```



Item with the most price change does not have strong relation to its sales.

Part 5 - Analyze Item Release Time

In [ ]:
```
# TODO: code to analyze time since item is released
```

Write your answer here

In [339]:
```
subet_date = train[['date','shop_id','item_id']]
df = subet_date.groupby(['item_id','shop_id']).min().reset_index().rename(colu
mns={"date":"date_min_same"})
df_merge = pd.merge(df,df,on='item_id')
df.head()
```

Out[339]:

	item_id	shop_id	date_min_same
0	30	2	03/01/2013
1	30	3	03/08/2013
2	30	4	03/02/2013
3	30	5	03/03/2013
4	30	6	01/06/2015

In [340]:
```
df_other_shop = df_merge[df_merge['shop_id_x']!=df_merge['shop_id_y']]
df_other_shop = df_other_shop[['item_id','shop_id_x','date_min_same_y']]
df_date_other = df_other_shop.groupby(['item_id','shop_id_x']).min().reset_ind
ex()
df_date_other.columns =['item_id','shop_id','date_min_other']
df_release_date = pd.merge(df,df_date_other, on = ['item_id','shop_id'],how =
'left')
df_release_date
```

Out[340]:

	item_id	shop_id	date_min_same	date_min_other
0	30	2	03/01/2013	01/02/2014
1	30	3	03/08/2013	01/02/2014
2	30	4	03/02/2013	01/02/2014
3	30	5	03/03/2013	01/02/2014
4	30	6	01/06/2015	01/02/2014
...	...	...	...	...
111399	22167	53	10/04/2013	01/02/2014
111400	22167	56	05/01/2014	01/02/2014
111401	22167	57	01/10/2014	01/02/2014
111402	22167	58	03/03/2014	01/02/2014
111403	22167	59	12/03/2013	01/02/2014

111404 rows × 4 columns

In [342]:
```
days_diff = pd.merge(train,df_release_date,on=['item_id','shop_id']).dropna()
days_diff.head()
```

Out[342]:

	date	weekday	month	date_block_num	shop_id	item_id	item_price	item_cnt_day
0	01/02/2013	Wednesday	02	0	59	22154	999.0	1.0
1	01/03/2013	Thursday	03	0	25	2574	399.0	2.0
2	01/05/2013	Saturday	05	0	25	2574	399.0	1.0
3	01/07/2013	Monday	07	0	25	2574	399.0	1.0
4	01/08/2013	Tuesday	08	0	25	2574	399.0	2.0

In [ ]:
```
days_diff['date'] =pd.to_datetime(days_diff.date)
days_diff['date_min_same'] =pd.to_datetime(days_diff.date_min_same)
days_diff['date_min_other'] =pd.to_datetime(days_diff.date_min_other)
days_diff['days_selfshop'] = days_diff['date'] - days_diff['date_min_same']
days_diff['days_othershop'] = days_diff['date'] - days_diff['date_min_other']
```

In [345]:
```
days_diff.tail()
```

Out[345]:

	date	weekday	month	date_block_num	shop_id	item_id	item_price	item_cnt_day	i
1221483	2015-10-22	Thursday	10	33	25	7327	349.0	1.0	
1221484	2015-10-24	Saturday	10	33	25	7315	399.0	1.0	
1221485	2015-10-31	Saturday	10	33	25	7409	299.0	1.0	
1221486	2015-10-09	Friday	09	33	25	7409	299.0	1.0	
1221487	2015-10-10	Saturday	10	33	25	7409	299.0	1.0	

In [346]:
```
diff = days_diff[['item_cnt_day','days_selfshop','days_othershop']]
diff['days_selfshop'] = diff['days_selfshop'].dt.days
diff['days_othershop'] = diff['days_othershop'].dt.days
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:2: SettingWithCo
pyWarning:
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/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy

/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:3: SettingWithCo
pyWarning:
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/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports u
ntil
```

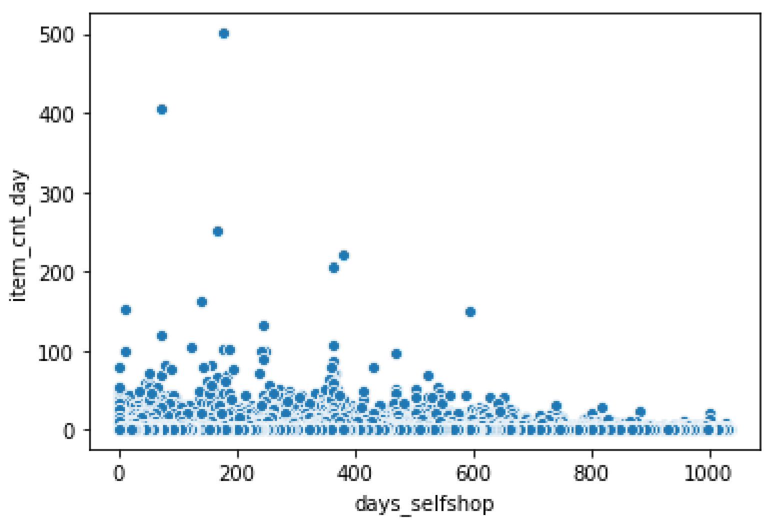
In [356]:
```
diff = diff[(diff['days_selfshop']>0) & (diff['days_othershop']>0)]
diff.tail(10)
```

Out[356]:

	item_cnt_day	days_selfshop	days_othershop
1221471	10.0	2	3
1221472	3.0	3	4
1221473	2.0	4	5
1221474	4.0	5	6
1221475	1.0	6	7
1221476	4.0	7	8
1221477	1.0	8	9
1221483	1.0	4	20
1221485	1.0	22	30
1221487	1.0	1	9

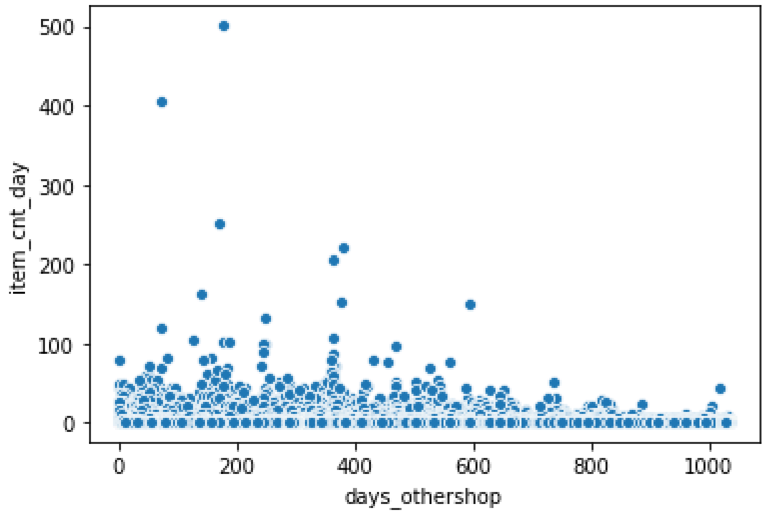
In [355]:
```
sns.scatterplot(x='days_selfshop', y='item_cnt_day', data=diff)
```

Out[355]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7ff9bea898>



In [358]:
```
sns.scatterplot(x='days_othershop', y='item_cnt_day', data=diff)
```

Out[358]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7ff9c3e668>



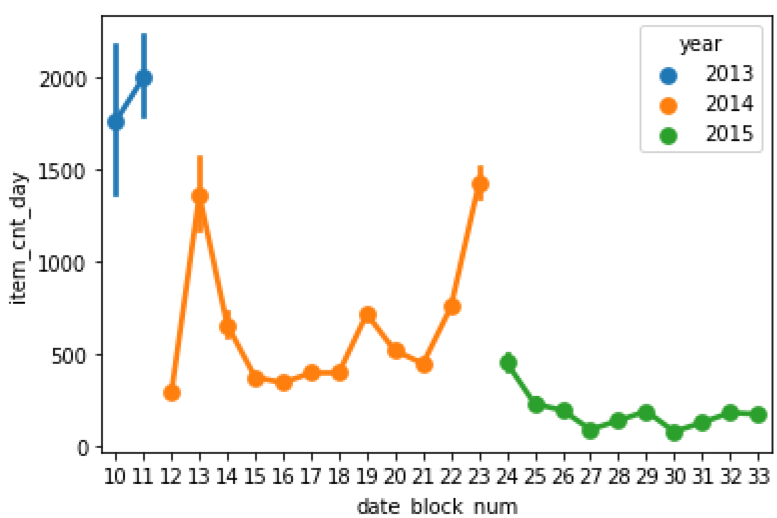
There is no strong relation betwen the days period and item counts.

Part 6 - Interesting Plot

In [ ]:
```
# TODO: code to generate the plot here.
```

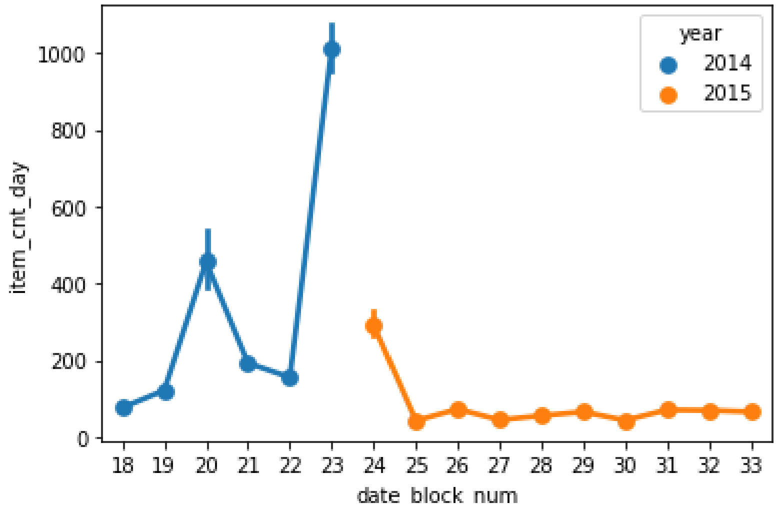
In [359]:
```
sns.pointplot(x='date_block_num', y='item_cnt_day', hue='year', data=PS4,estim
ator=np.sum)
```

Out[359]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7ff9c24668>



In [360]:
```
sns.pointplot(x='date_block_num', y='item_cnt_day', hue='year', data=Xbox1,est
imator=np.sum)
```

Out[360]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7ff9c687f0>



Both PS4 and Xbox have a low amount sales after their released time, while only got higher on holidays. Thus for game consoles, the good sales record may not last very long.

In [361]:
```
item_categories['item_category_type'] = item_categories['item_category_name'].
str.split('-').map(lambda x: x[0])
item_categories['item_category_sub_type'] = item_categories['item_category_nam
e'].str.split('-').map(lambda x: x[1].strip() if len(x) > 1 else x[0].strip())
item_categories.head()
```

Out[361]:

	item_category_name	item_category_id	item_category_type	item_category_sub_type
0	PC - Headsets / Headphones	0	PC	Headsets / Headphones
1	Accessories - PS2	1	Accessories	PS2
2	Accessories - PS3	2	Accessories	PS3
3	Accessories - PS4	3	Accessories	PS4
4	Accessories - PSP	4	Accessories	PSP

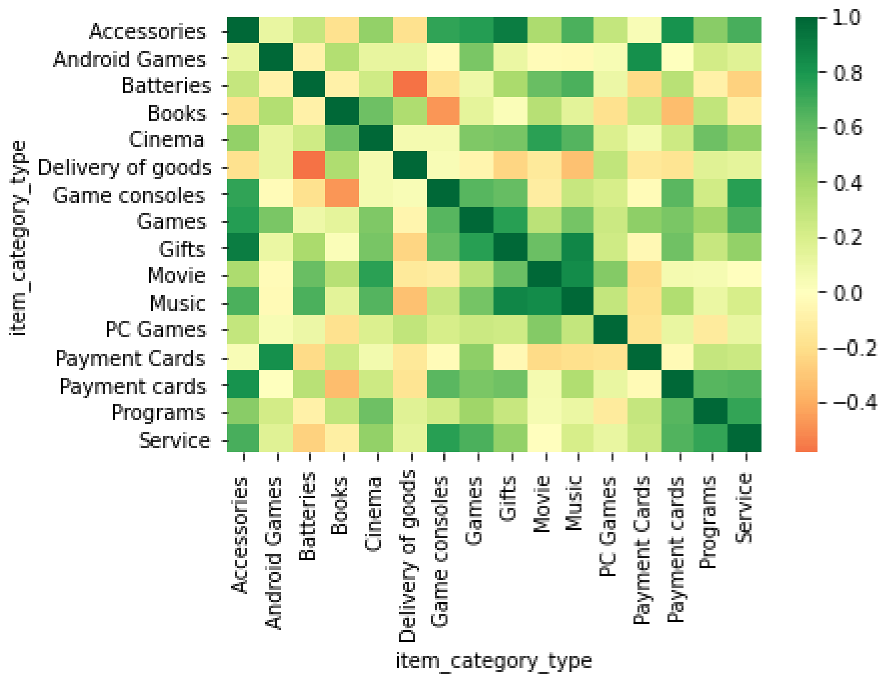
In [362]:
```
train= pd.merge(train,item_categories,on='item_category_id',how='left')
train.head()
```

Out[362]:

	date	weekday	month	date_block_num	shop_id	item_id	item_price	item_cnt_day
0	01/02/2013	Wednesday	02	0	59	22154	999.0	1.0
1	01/03/2013	Thursday	03	0	25	2574	399.0	2.0
2	01/05/2013	Saturday	05	0	25	2574	399.0	1.0
3	01/07/2013	Monday	07	0	25	2574	399.0	1.0
4	01/08/2013	Tuesday	08	0	25	2574	399.0	2.0

In [363]:
```
# Exploring data by category
cat_items = train.groupby(['month', 'item_category_type'])[['item_cnt_day']].s
um().reset_index()

cat_pivot = cat_items.pivot(index='month', columns='item_category_type', value
s='item_cnt_day').fillna(0)

# Draw heatmap
corr = cat_pivot.corr()
sns.heatmap(corr, center=0, cmap='RdYlGn')
```

Out[363]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7ff9cc0f60>



- From the heat map we can see taht movies, music, PC games, cinema are all positively correlated. They could all be considered as ways of entertainment.
- Another interesting finding is that I assume that PC game will have high relation with Andorid games. But they are not. Since they are all belong to game category, this seems a little strange.
  Maybe it's because the target platform of these two(PC and Android phones) are different.People are likely to play different kinds of games on these two platforms.

Part 7 - Prediction Model

In [98]:
```
from sklearn.preprocessing import LabelEncoder
from itertools import product
from xgboost import XGBRegressor
from xgboost import plot_importance
```

In [365]:
```
# Load data
items=pd.read_csv("items.csv")
shops=pd.read_csv("shops.csv")
item_categories=pd.read_csv("item_categories.csv")
train=pd.read_csv("sales_train.csv")
test=pd.read_csv("test.csv")
```

In [366]:
```
train = train[(train.item_price < 100000 )& (train.item_price > 0)& (train.ite
m_cnt_day < 1000)]
train.loc[train.item_cnt_day < 1, "item_cnt_day"] = 0
```

In [ ]:
```
translator = Translator()
item_categories['item_category_name'] = item_categories['item_category_name'].
apply(translator.translate, src='ru', dest='en').apply(getattr, args=('text'
,))
```

In [368]:
```
#possess the shop data

train.loc[train.shop_id == 0, 'shop_id'] = 57
test.loc[test.shop_id == 0, 'shop_id'] = 57

train.loc[train.shop_id == 1, 'shop_id'] = 58
test.loc[test.shop_id == 1, 'shop_id'] = 58

train.loc[train.shop_id == 10, 'shop_id'] = 11
test.loc[test.shop_id == 10, 'shop_id'] = 11
```

In [369]:
```
shops["city"] = shops.shop_name.str.split(" ").map( lambda x: x[0] )
shops["category"] = shops.shop_name.str.split(" ").map( lambda x: x[1] )
shops.head()
```

Out[369]:

	shop_name	shop_id	city	category
0	!Якутск Орджоникидзе, 56 фран	0	!Якутск	Орджоникидзе,
1	!Якутск ТЦ "Центральный" фран	1	!Якутск	ТЦ
2	Адыгея ТЦ "Мега"	2	Адыгея	ТЦ
3	Балашиха ТРК "Октябрь-Киномир"	3	Балашиха	ТРК
4	Волжский ТЦ "Волга Молл"	4	Волжский	ТЦ

In [370]:
```
#Encoding the shop cats so that they can be presented as numbers.
shops["shop_category"] = LabelEncoder().fit_transform( shops.category )
shops["shop_city"] = LabelEncoder().fit_transform( shops.city )

shops = shops[["shop_id", "shop_category", "shop_city"]]
shops.head()
```

Out[370]:

	shop_id	shop_category	shop_city
0	0	4	0
1	1	9	0
2	2	9	1
3	3	7	2
4	4	9	3

In [372]:
```
# process the item_cat data

item_categories['item_category_type'] = item_categories['item_category_name'].
str.split('-').map(lambda x: x[0])
item_categories['item_category_sub_type'] = item_categories['item_category_nam
e'].str.split('-').map(lambda x: x[1].strip() if len(x) > 1 else x[0].strip())
item_categories.head()
```

Out[372]:

	item_category_name	item_category_id	item_category_type	item_category_sub_type
0	PC - Headsets / Headphones	0	PC	Headsets / Headphones
1	Accessories - PS2	1	Accessories	PS2
2	Accessories - PS3	2	Accessories	PS3
3	Accessories - PS4	3	Accessories	PS4
4	Accessories - PSP	4	Accessories	PSP

In [373]:
```
item_categories['item_category_type_code'] = LabelEncoder().fit_transform(item
_categories['item_category_type'])
item_categories['item_category_sub_type_code'] = LabelEncoder().fit_transform(
item_categories['item_category_sub_type'])
item_categories = item_categories[['item_category_id','item_category_type_cod
e','item_category_sub_type_code']]
item_categories.head()
```

Out[373]:

	item_category_id	item_category_type_code	item_category_sub_type_code
0	0	15	34
1	1	0	43
2	2	0	44
3	3	0	45
4	4	0	47

In [374]:
```
matrix = []
#train=train1
cols = ['date_block_num','shop_id','item_id']
for i in range(34):
    sales = train[train.date_block_num==i]
    matrix.append(np.array(list(product([i], sales.shop_id.unique(), sales.ite
m_id.unique())), dtype='int16'))
```

In [375]:
```
matrix = pd.DataFrame(np.vstack(matrix), columns=cols)
matrix['date_block_num'] = matrix['date_block_num'].astype(np.int8)

matrix.sort_values(cols,inplace=True)
```

In [376]:
```
group = train.groupby(['date_block_num','shop_id','item_id']).agg({'item_cnt_d
ay': ['sum']})
group.columns = ['item_cnt_month']
group.reset_index(inplace=True)

matrix = pd.merge(matrix, group, on=cols, how='left')
matrix['item_cnt_month'] = (matrix['item_cnt_month']
                                .fillna(0)
                                .clip(0,20)
                                .astype(np.float16))
```

In [377]:
```
matrix.head()
```

Out[377]:

	date_block_num	shop_id	item_id	item_cnt_month
0	0	2	19	0.0
1	0	2	27	1.0
2	0	2	28	0.0
3	0	2	29	0.0
4	0	2	32	0.0

In [378]:
```
# predict date should be the 34th month
test['date_block_num'] = 34
```

In [379]:
```
matrix = pd.concat([matrix, test], ignore_index=True, sort=False, keys=cols)
matrix.fillna(0, inplace=True) # 34 month
```

In [380]:
```
matrix = pd.merge(matrix, shops, on=['shop_id'], how='left')
matrix = pd.merge(matrix, items, on=['item_id'], how='left')
matrix = pd.merge(matrix, item_categories, on=['item_category_id'], how='left'
)
```

In [381]:
```
matrix.drop(['item_name'], axis=1, inplace=True)
matrix.drop(['ID'], axis=1, inplace=True)
```

In [382]:
```
matrix.head()
```

Out[382]:

	date_block_num	shop_id	item_id	item_cnt_month	shop_category	shop_city	item_category_
0	0	2	19	0.0	9	1	
1	0	2	27	1.0	9	1	
2	0	2	28	0.0	9	1	
3	0	2	29	0.0	9	1	
4	0	2	32	0.0	9	1	

In [383]:
```
#prepare the model
data = matrix
X_train = data[data.date_block_num < 33].drop(['item_cnt_month'], axis=1)
Y_train = data[data.date_block_num < 33]['item_cnt_month']
X_valid = data[data.date_block_num == 33].drop(['item_cnt_month'], axis=1)
Y_valid = data[data.date_block_num == 33]['item_cnt_month']
X_test = data[data.date_block_num == 34].drop(['item_cnt_month'], axis=1)
```

In [38]:

```
model = XGBRegressor(
    max_depth=8,
    n_estimators=1000,
    min_child_weight=300,
    colsample_bytree=0.8,
    subsample=0.8,
    eta=0.3,
    seed=42)

model.fit(
    X_train,
    Y_train,
    eval_metric="rmse",
    eval_set=[(X_train, Y_train), (X_valid, Y_valid)],
    verbose=True,
    early_stopping_rounds = 1)
```

```
[23:07:25] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linea
r is now deprecated in favor of reg:squarederror.
[0]	validation_0-rmse:1.63887	validation_1-rmse:1.22084
Multiple eval metrics have been passed: 'validation_1-rmse' will be used for
early stopping.

Will train until validation_1-rmse hasn't improved in 1 rounds.
[1]	validation_0-rmse:1.6187	validation_1-rmse:1.20904
[2]	validation_0-rmse:1.59478	validation_1-rmse:1.19135
[3]	validation_0-rmse:1.57197	validation_1-rmse:1.17862
[4]	validation_0-rmse:1.55073	validation_1-rmse:1.16683
[5]	validation_0-rmse:1.52659	validation_1-rmse:1.15394
[6]	validation_0-rmse:1.50818	validation_1-rmse:1.14717
[7]	validation_0-rmse:1.49196	validation_1-rmse:1.13847
[8]	validation_0-rmse:1.47927	validation_1-rmse:1.13106
[9]	validation_0-rmse:1.47032	validation_1-rmse:1.1255
[10]	validation_0-rmse:1.46451	validation_1-rmse:1.12241
[11]	validation_0-rmse:1.45633	validation_1-rmse:1.1175
[12]	validation_0-rmse:1.44745	validation_1-rmse:1.1146
[13]	validation_0-rmse:1.44079	validation_1-rmse:1.11198
[14]	validation_0-rmse:1.43487	validation_1-rmse:1.10858
[15]	validation_0-rmse:1.42938	validation_1-rmse:1.1059
[16]	validation_0-rmse:1.42366	validation_1-rmse:1.10271
[17]	validation_0-rmse:1.41833	validation_1-rmse:1.10069
[18]	validation_0-rmse:1.4142	validation_1-rmse:1.09906
[19]	validation_0-rmse:1.40993	validation_1-rmse:1.09737
[20]	validation_0-rmse:1.40317	validation_1-rmse:1.09527
[21]	validation_0-rmse:1.399	validation_1-rmse:1.0937
[22]	validation_0-rmse:1.39201	validation_1-rmse:1.091
[23]	validation_0-rmse:1.38744	validation_1-rmse:1.09029
[24]	validation_0-rmse:1.38448	validation_1-rmse:1.08832
[25]	validation_0-rmse:1.3823	validation_1-rmse:1.08735
[26]	validation_0-rmse:1.37944	validation_1-rmse:1.08533
[27]	validation_0-rmse:1.37755	validation_1-rmse:1.08446
[28]	validation_0-rmse:1.37346	validation_1-rmse:1.0819
[29]	validation_0-rmse:1.37029	validation_1-rmse:1.08108
[30]	validation_0-rmse:1.36791	validation_1-rmse:1.07965
[31]	validation_0-rmse:1.36573	validation_1-rmse:1.07827
[32]	validation_0-rmse:1.36244	validation_1-rmse:1.07709
[33]	validation_0-rmse:1.36104	validation_1-rmse:1.07659
[34]	validation_0-rmse:1.35659	validation_1-rmse:1.07553
[35]	validation_0-rmse:1.35334	validation_1-rmse:1.07427
[36]	validation_0-rmse:1.35195	validation_1-rmse:1.07328
[37]	validation_0-rmse:1.35026	validation_1-rmse:1.07288
[38]	validation_0-rmse:1.34789	validation_1-rmse:1.07211
[39]	validation_0-rmse:1.34585	validation_1-rmse:1.07084
[40]	validation_0-rmse:1.34514	validation_1-rmse:1.07006
[41]	validation_0-rmse:1.34353	validation_1-rmse:1.06913
[42]	validation_0-rmse:1.34287	validation_1-rmse:1.06868
[43]	validation_0-rmse:1.33875	validation_1-rmse:1.06853
[44]	validation_0-rmse:1.33678	validation_1-rmse:1.06794
[45]	validation_0-rmse:1.33472	validation_1-rmse:1.06641
[46]	validation_0-rmse:1.33206	validation_1-rmse:1.06549
[47]	validation_0-rmse:1.33109	validation_1-rmse:1.06523
[48]	validation_0-rmse:1.33028	validation_1-rmse:1.0651
[49]	validation_0-rmse:1.32709	validation_1-rmse:1.06475
[50]	validation_0-rmse:1.32593	validation_1-rmse:1.06442
```

```
[51]	validation_0-rmse:1.32427	validation_1-rmse:1.06328
[52]	validation_0-rmse:1.32281	validation_1-rmse:1.06278
[53]	validation_0-rmse:1.32207	validation_1-rmse:1.0621
[54]	validation_0-rmse:1.3207	validation_1-rmse:1.06205
[55]	validation_0-rmse:1.31976	validation_1-rmse:1.06155
[56]	validation_0-rmse:1.31859	validation_1-rmse:1.06079
[57]	validation_0-rmse:1.31692	validation_1-rmse:1.06021
[58]	validation_0-rmse:1.31495	validation_1-rmse:1.06028
Stopping. Best iteration:
[57]	validation_0-rmse:1.31692	validation_1-rmse:1.06021
```

Out[38]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=0.8, eta=0.3, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0,
             max_depth=8, min_child_weight=300, missing=None, n_estimators=10
00,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=42,
             silent=None, subsample=0.8, verbosity=1)
```

In [39]:

```
Y_pred = model.predict(X_valid).clip(0, 20)
Y_test = model.predict(X_test).clip(0, 20)

submission = pd.DataFrame({
    "ID": test.index,
    "item_cnt_month": Y_test
})
submission.to_csv('submission.csv', index=False)
```

I use the XGBRegressor model to do the prediction, and has rmse=1.06.

Part 8 - Final Result

Report the rank, score, number of entries, for your highest rank. Include a snapshot of your best score on the leaderboard as confirmation. Be sure to provide a link to your Kaggle profile. Make sure to include a screenshot of your ranking. Make sure your profile includes your face and affiliation with SBU.

Kaggle Link: [https://www.kaggle.com/haruka03 (https://www.kaggle.com/haruka03)](https://www.kaggle.com/haruka03)

Highest Rank: 4977

Score: 1.09659

Number of entries: 1

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4974	Valery	1.09635	5	2y
4975	onchiri	1.09647	18	4mo
4976	TBelinic	1.09654	1	3y
4977	haruka03	1.09659	1	3m

Your First Entry ↑

Welcome to the leaderboard!

4978	moto_gochi	1.09728	1	12d
4979	YotaCat	1.09774	5	2y

1 submissions for haruka03 Sort by Most recent

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Submission and Description	Public Score	Use for Final Score
submission.csv 4 minutes ago by yaoli add submission details	1.09659	☐

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