EDA_retail

March 29, 2018

```
In [1]: import pandas as pd
        import os
        from datetime import datetime
        import matplotlib.pyplot as plt
        import numpy as np
        from itertools import product
        import gc
        from tqdm import tqdm_notebook
        from itertools import product
        import sklearn
        import scipy.sparse
        import lightgbm as lgb
        from sklearn.linear_model import LinearRegression
        from sklearn.metrics import r2_score
```

```
In [2]: DATA_FOLDER = '~/.kaggle/competitions/competitive-data-science-final-project/'

        transactions    = pd.read_csv(os.path.join(DATA_FOLDER, 'sales_train.csv'))
        items           = pd.read_csv(os.path.join(DATA_FOLDER, 'items.csv'))
        item_categories = pd.read_csv(os.path.join(DATA_FOLDER, 'item_categories.csv'))
        shops           = pd.read_csv(os.path.join(DATA_FOLDER, 'shops.csv'))
        test            = pd.read_csv(os.path.join(DATA_FOLDER, 'test.csv'))
```

Having loaded the data, let's examine it

```
In [4]: transactions.describe(include = 'all')
```

```
Out[4]:               date  date_block_num       shop_id       item_id    item_price  \
        count      2935849    2.935849e+06  2.935849e+06  2.935849e+06  2.935849e+06
        unique        1034             NaN           NaN           NaN           NaN
        top     28.12.2013             NaN           NaN           NaN           NaN
        freq          9434             NaN           NaN           NaN           NaN
        mean           NaN    1.456991e+01  3.300173e+01  1.019723e+04  8.908532e+02
        std            NaN    9.422988e+00  1.622697e+01  6.324297e+03  1.729800e+03
        min            NaN    0.000000e+00  0.000000e+00  0.000000e+00 -1.000000e+00
        25%            NaN    7.000000e+00  2.200000e+01  4.476000e+03  2.490000e+02
        50%            NaN    1.400000e+01  3.100000e+01  9.343000e+03  3.990000e+02
        75%            NaN    2.300000e+01  4.700000e+01  1.568400e+04  9.990000e+02
```

```
max           NaN    3.300000e+01  5.900000e+01  2.216900e+04  3.079800e+05

        item_cnt_day
count   2.935849e+06
unique           NaN
top              NaN
freq             NaN
mean    1.242641e+00
std     2.618834e+00
min    -2.200000e+01
25%     1.000000e+00
50%     1.000000e+00
75%     1.000000e+00
max     2.169000e+03
```

There are some high price values that will need to be examined.

In [6]:
```
transactions.dtypes
```

Out[6]:
```
date                 object
date_block_num        int64
shop_id               int64
item_id               int64
item_price          float64
item_cnt_day        float64
dtype: object
```

In [7]:
```
items.describe(include = 'all')
```

Out[7]:
```
                                             item_name      item_id  \
count                                            22170  22170.00000
unique                                           22170          NaN
top         T1 Track Car Single          NaN
freq                                                 1          NaN
mean                                               NaN  11084.50000
std                                                NaN   6400.07207
min                                                NaN      0.00000
25%                                                NaN   5542.25000
50%                                                NaN  11084.50000
75%                                                NaN  16626.75000
max                                                NaN  22169.00000

        item_category_id
count       22170.000000
unique               NaN
top                  NaN
freq                 NaN
mean           46.290753
std            15.941486
```

```
min              0.000000
25%             37.000000
50%             40.000000
75%             58.000000
max             83.000000
```

In [8]: shops.describe(include = 'all')

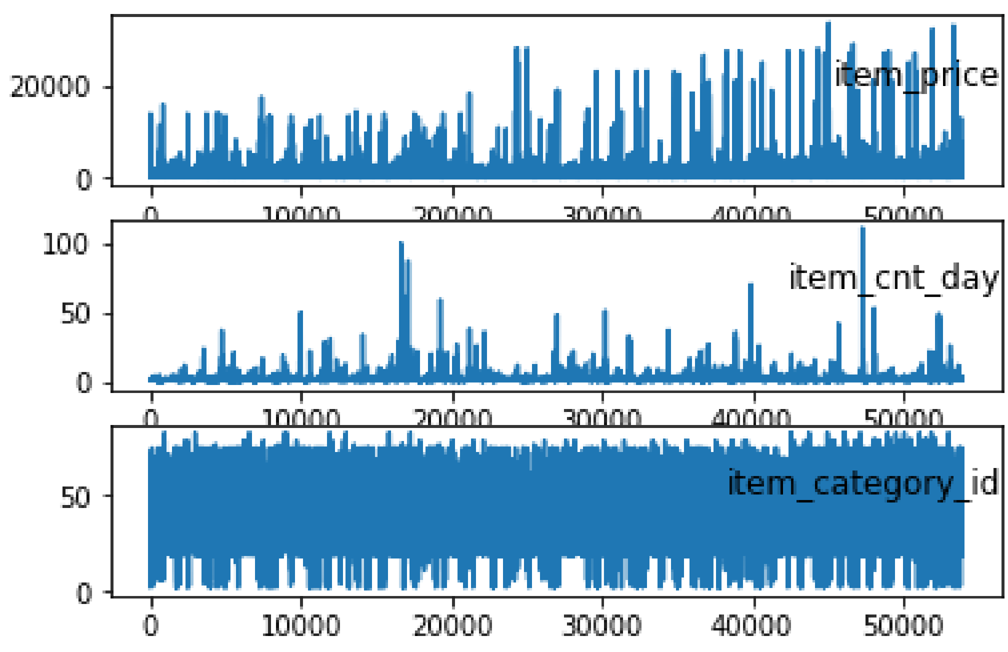
```
Out[8]:                                              shop_name    shop_id  \
count                                                      60  60.000000
unique                                                     60        NaN
top     ______________ ____ "_______...        NaN
freq                                                        1        NaN
mean                                                      NaN  29.500000
std                                                       NaN  17.464249
min                                                       NaN   0.000000
25%                                                       NaN  14.750000
50%                                                       NaN  29.500000
75%                                                       NaN  44.250000
max                                                       NaN  59.000000

        shop_city
count   60.000000
unique        NaN
top           NaN
freq          NaN
mean    16.333333
std      8.150422
min      1.000000
25%     10.750000
50%     15.000000
75%     22.000000
max     32.000000
```

In [9]: item_categories.describe(include = 'all')

```
Out[9]:          item_category_name  item_category_id
count                          84         84.000000
unique                         84               NaN
top       -                    NaN
freq                            1               NaN
mean                          NaN         41.500000
std                           NaN         24.392622
min                           NaN          0.000000
25%                           NaN         20.750000
50%                           NaN         41.500000
75%                           NaN         62.250000
max                           NaN         83.000000
```

Here is the summary of what we have: shop id, item id and date block are needed to arrange the date. Additional usable fields from across several files are: item count, item price, shop city, shop name, shop city, item name, item category, item category id That's it. This is not a feature rich data set. Let's try to combine transactions and items and see what kind of data we have for a specified shop, just as an example:

```
In [11]: select_store = 26
         data_df = transactions.loc[(transactions['shop_id'] == select_store)]
         data_df = pd.merge(data_df, items, how = 'left', on = ['item_id'])

                  #PLOT SELECTED COLUMNS FOR THE SELECTED STORE
         values = data_df.values
         to_plot = [4, 5,7]
         i=1
         plt.figure()
         for item in to_plot:
             plt.subplot(len(to_plot), 1, i)
             plt.plot(values[:, item])
             #plt.yticks([])
             plt.title(data_df.columns[item], y=0.5, loc='right')
             i += 1
         plt.show()


         data_df.head()
```



Out[11]:

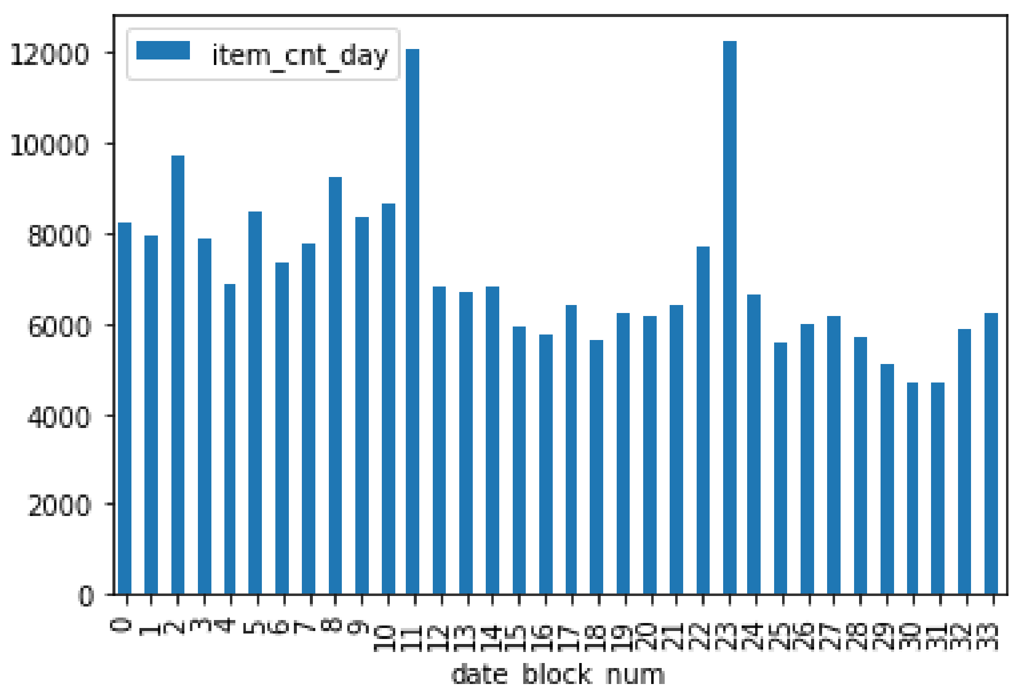
```
         date  date_block_num  shop_id  item_id  item_price  item_cnt_day  \
0  19.01.2013               0       26    12691       449.0           1.0
1  13.01.2013               0       26    12714       149.0           1.0
2  06.01.2013               0       26    12718       299.0           1.0
3  21.01.2013               0       26    12719       149.0           1.0
4  30.01.2013               0       26    13370       299.0           1.0

                                        item_name  item_category_id
0    .  (/ ) (2DVD)                     40
1                                      ()               40
2                                         "" (BD)               37
3                                               8                40
4  ....1: 8 (.3...                     49
```

it would be also interesting to look at the behavior of stores as time series. I already know from prior EDA that stores 12 and 9 are causing the model to deteriorate massively. let's see if we find the cause. I will plot total item count by month for selected stores, including the problematic ones.

In [13]:

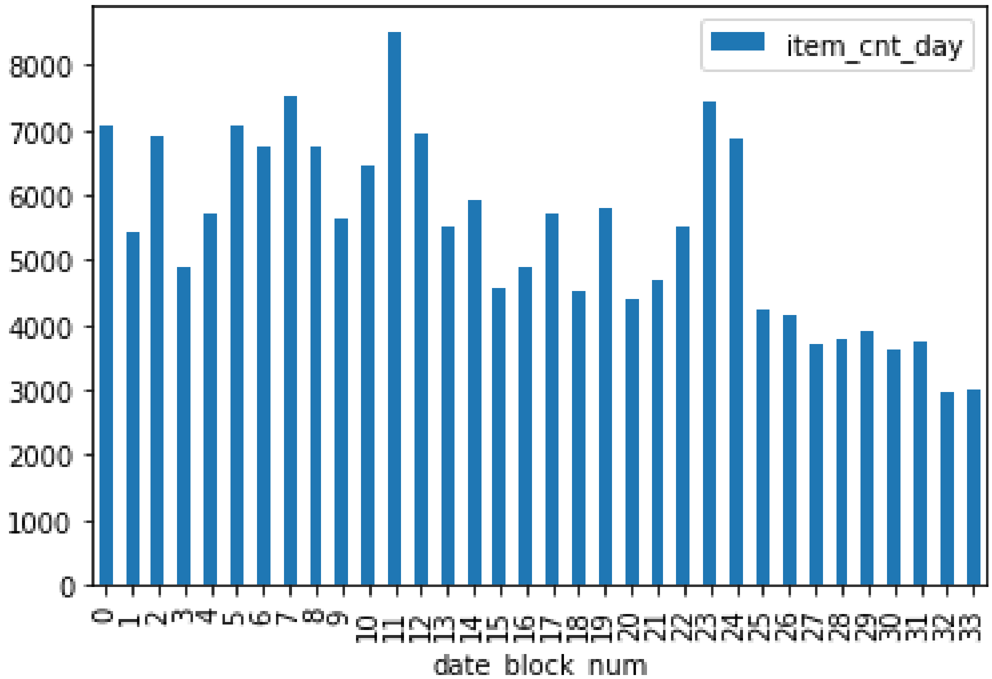
```python
temp = transactions.groupby(['shop_id','date_block_num'], as_index = False).sum()

#Plot store 25 = normal
temp_rev = temp[temp['shop_id'] == 25][['date_block_num','item_cnt_day']]
temp_rev.set_index('date_block_num',inplace = True)
temp_rev.plot(kind = 'bar')
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x10e999f90>



```
In [14]: #another normal store 28
         temp_rev = temp[temp['shop_id'] == 28][['date_block_num','item_cnt_day']]
         temp_rev.set_index('date_block_num',inplace = True)
         temp_rev.plot(kind = 'bar')
```

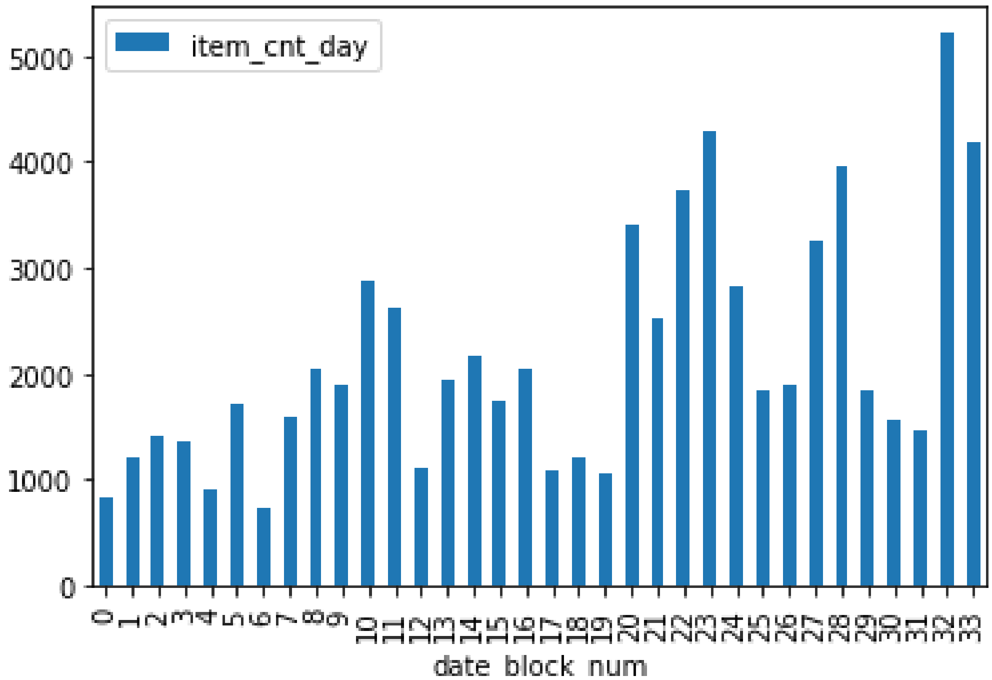
```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x10f031290>
```



This is actually quite typical for this data set. there is a down time trend, and spikes in December. I have to predict November, so the seasonal spike is less of a concern. Let's look now at the stores that are not behaving well

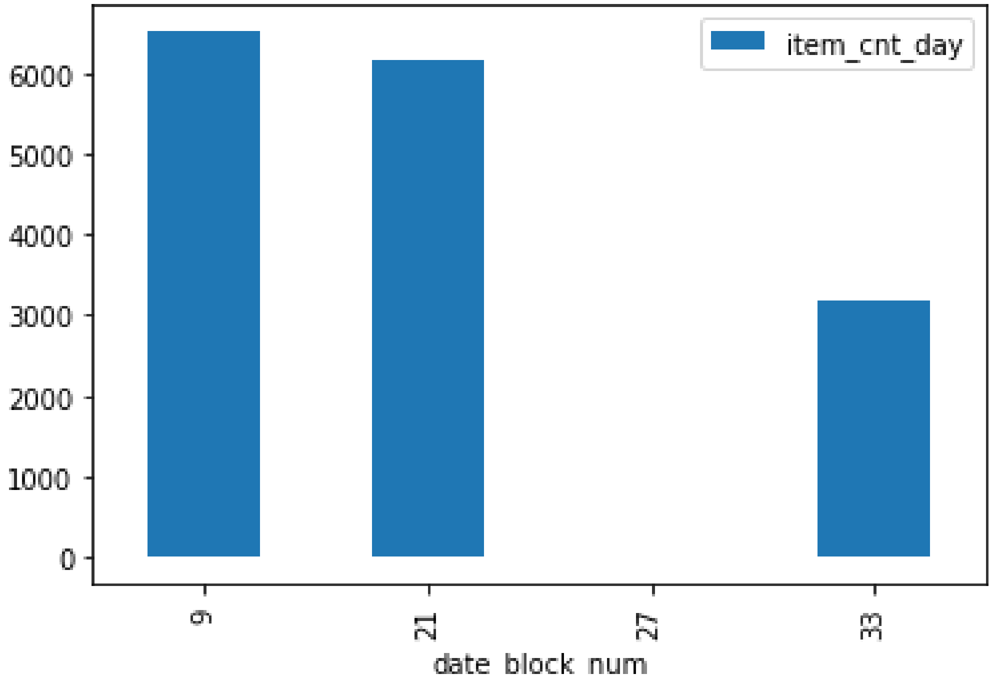
```
In [16]:     #store 12 first:
         temp_rev = temp[temp['shop_id'] == 12][['date_block_num','item_cnt_day']]
         temp_rev.set_index('date_block_num',inplace = True)
         temp_rev.plot(kind = 'bar')
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x11243f3d0>
```




```
In [17]: #and this is store 9
         temp_rev = temp[temp['shop_id'] == 9][['date_block_num','item_cnt_day']]
         temp_rev.set_index('date_block_num',inplace = True)
         temp_rev.plot(kind = 'bar')
```

```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x10e3b9850>
```



Both stores 12 and 9 reveal very atypical patterns. I have already run the model without any data set exclusions and uploaded the prediction just to test the waters; fixing the problems associated with these 2 is highly likely to improve the results significantly. To the point: exclusion of just shop12 from the dataset resulted in the R2 improvement from 0.253/0.316 to 0.575/0.670 on the validation set for linear regression and light gbm, respectively.

Now let's take a look whether there are outliers in the last month as suggested by store 12 data; in this case I am looking for large values in target (this is month 33) that would not have correspondingly large values in previous months. Here we are:

```
In [24]: sales = transactions

         def downcast_dtypes(df):
             '''
                 Changes column types in the dataframe:

                         `float64` type to `float32`
                         `int64`   type to `int32`
             '''

             # Select columns to downcast
             float_cols = [c for c in df if df[c].dtype == "float64"]
             int_cols =   [c for c in df if df[c].dtype == "int64"]

             # Downcast
             df[float_cols] = df[float_cols].astype(np.float32)
```

```
    df[int_cols]   = df[int_cols].astype(np.int32)

    return df

# Create "grid" with columns
index_cols = ['shop_id', 'item_id', 'date_block_num']

# For every month we create a grid from all shops/items combinations from that month
grid = []
for block_num in sales['date_block_num'].unique():
    cur_shops = sales.loc[sales['date_block_num'] == block_num, 'shop_id'].unique()
    cur_items = sales.loc[sales['date_block_num'] == block_num, 'item_id'].unique()
    grid.append(np.array(list(product(*[cur_shops, cur_items, [block_num]])),dtype='i

# Turn the grid into a dataframe
grid = pd.DataFrame(np.vstack(grid), columns = index_cols,dtype=np.int32)

# Groupby data to get shop-item-month aggregates
gb = sales.groupby(index_cols,as_index=False).agg({'item_cnt_day':{'target':'sum'}})

# Fix column names
gb.columns = [col[0] if col[-1]=='' else col[-1] for col in gb.columns.values]

# Join it to the grid
all_data = pd.merge(grid, gb, how='left', on=index_cols).fillna(0)

all_data = downcast_dtypes(all_data)
del grid, gb
gc.collect();


#now create lags


# List of columns that we will use to create lags
cols_to_rename = list(all_data.columns.difference(index_cols))

shift_range = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]

for month_shift in tqdm_notebook(shift_range):
    train_shift = all_data[index_cols + cols_to_rename].copy()

    train_shift['date_block_num'] = train_shift['date_block_num'] + month_shift

    foo = lambda x: '{}_lag_{}'.format(x, month_shift) if x in cols_to_rename else x
    train_shift = train_shift.rename(columns=foo)

    all_data = pd.merge(all_data, train_shift, on=index_cols, how='left').fillna(0)
```

```
        del train_shift

/Applications/anaconda3/envs/tensorflow/lib/python2.7/site-packages/pandas/core/groupby.py:429
  return super(DataFrameGroupBy, self).aggregate(arg, *args, **kwargs)


HBox(children=(IntProgress(value=0, max=12), HTML(value=u'')))
```

```
In [27]: temp_alone_all = all_data[(all_data['date_block_num'].isin([31,32,33])) & (all_data['
                                  & (all_data['target_lag_1'] <= 5) & (all_data['target_lag_2'] <
                                     (all_data['target_lag_3'] <= 5)]

         temp_alone_all.head()
```

Out[27]:

	shop_id	item_id	date_block_num	target	target_lag_1	\
10242580	42	11354	31	72.0	0.0	
10350097	59	6507	31	102.0	2.0	
10457876	42	3351	32	136.0	0.0	
10508726	25	3351	32	146.0	0.0	
10630596	12	15067	32	73.0	0.0	

	target_lag_2	target_lag_3	target_lag_4	target_lag_5	\
10242580	0.0	0.0	0.0	0.0	
10350097	1.0	3.0	5.0	0.0	
10457876	0.0	0.0	0.0	0.0	
10508726	0.0	0.0	0.0	0.0	
10630596	0.0	0.0	0.0	0.0	

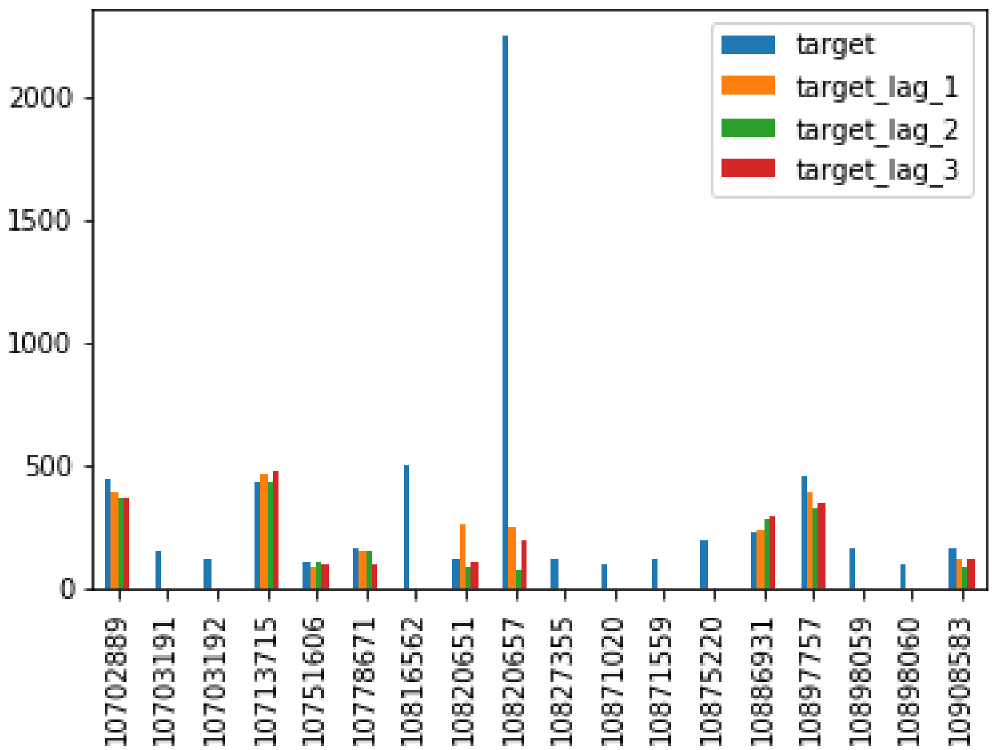
	target_lag_6	target_lag_7	target_lag_8	target_lag_9	\
10242580	0.0	0.0	0.0	0.0	
10350097	0.0	0.0	0.0	0.0	
10457876	0.0	0.0	0.0	0.0	
10508726	0.0	0.0	0.0	0.0	
10630596	0.0	0.0	0.0	0.0	

	target_lag_10	target_lag_11	target_lag_12
10242580	0.0	0.0	0.0
10350097	0.0	0.0	0.0
10457876	0.0	0.0	0.0
10508726	0.0	0.0	0.0
10630596	0.0	0.0	0.0

As expected, these values include stores 12 and 9. I have checked product descriptions for these one-time spikes, and while most of them belong to computer games (apparently just came out) which makes sense, there are several other data points which suggest that these are not repeatable transactions. I will make an adjustment for these as I tune up the model. I addition, store 12 has the following outlier:

```
In [28]: temp_large = all_data[(all_data['date_block_num']== 33) & (all_data['target'] > 100)]
         temp_large[['target', 'target_lag_1', 'target_lag_2', 'target_lag_3']].plot(kind =  'l
```

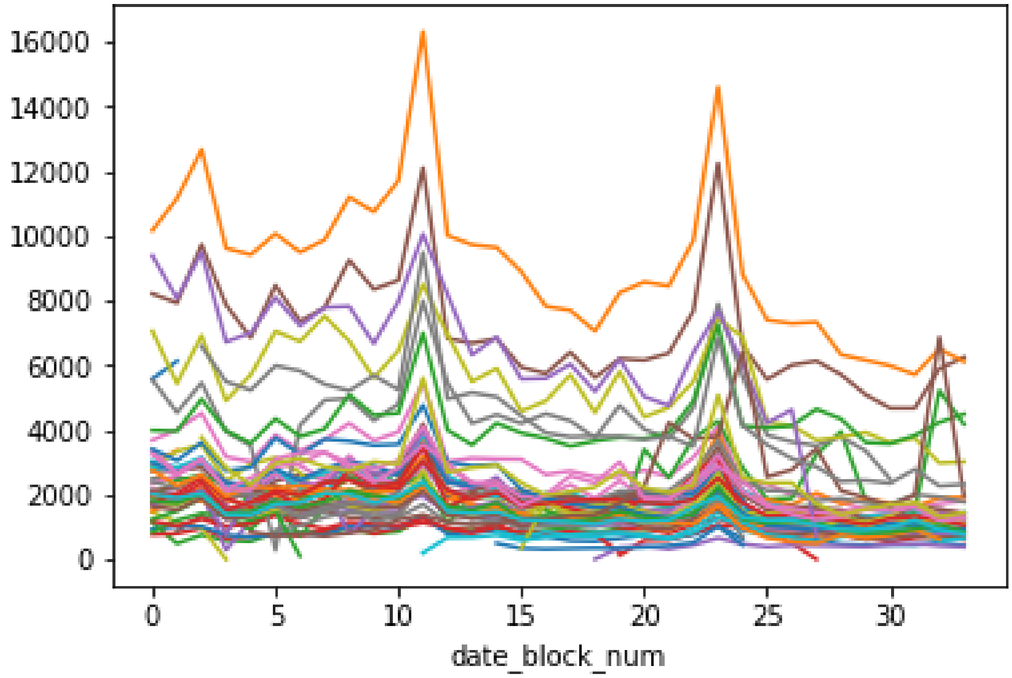
```
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x1124d2650>
```



Looking at this, it's pretty clear that the value should be clipped, or perhaps better normalized. I think it's the culprit in the form of item 11373 in store 12 at time 33 only which is delivery by mail. I will replace it with a normalized value and manipulate the individual valuein the submission set.

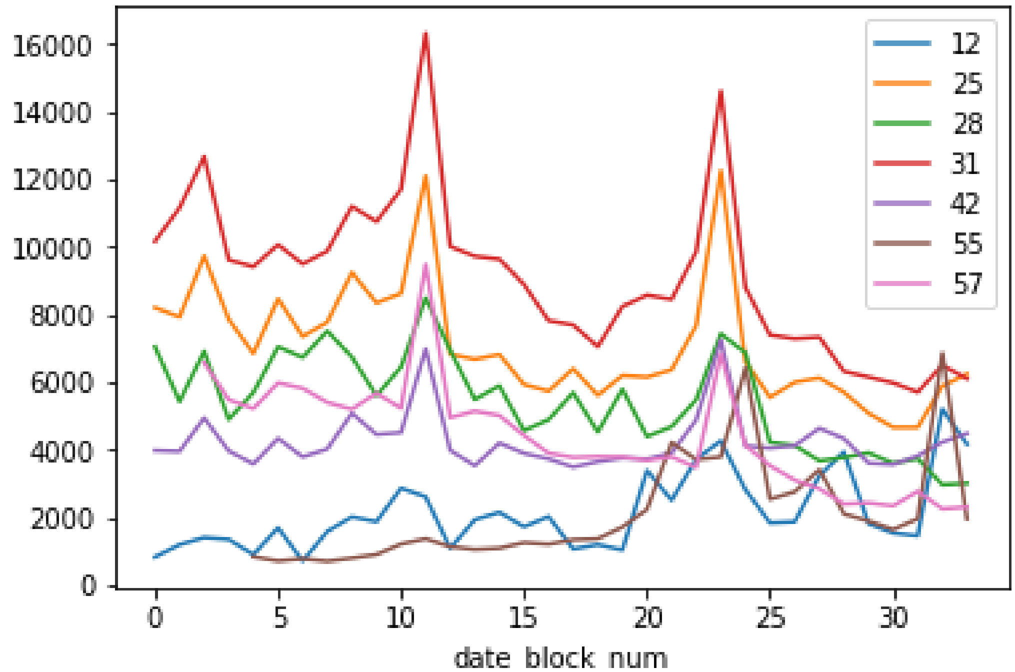
```
In [29]: transactions.groupby(['date_block_num', 'shop_id']).sum()['item_cnt_day'].unstack().pl
```

```
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1c533d10>
```



While the above is not the cleanest graph, it's actually very informative. Again, thinking of the outliers: I see spikes in the penultimate and last months that shouldn't be there. Remember: the spikes in previous years are December, and the data stops in October. Let's examine this a little closer:

```
In [37]: temp = transactions.groupby(['date_block_num', 'shop_id']).sum()['item_cnt_day'].unsta
         temp = temp.T
         temp = temp[temp[32] > 2000]
         temp = temp.T
         temp.plot().legend()

Out[37]: <matplotlib.legend.Legend at 0x111bcf710>
```



There you go. As a minimum, same store 12 is messing things up here, but perhaps store 25 deserves some attention. And definitely store 55, which is actually another problem child I have encountered. I will take care of the outliers and things should be in good shape.