sales_predictions_Supervised_LSTM

June 10, 2022

1 Sales Predictions using Time Series Data

- https://www.kaggle.com/competitions/competitive-data-science-predict-future-sales/data

1.1 Overview of Problem

"You are provided with daily historical sales data. The task is to forecast the total amount of products sold in every shop for the test set. Note that the list of shops and products slightly changes every month. Creating a robust model that can handle such situations is part of the challenge." *(src: competition page)*

1.2 Imports

[1]:
```
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
import seaborn as sns

from keras.callbacks import EarlyStopping
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Flatten
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
```

1.3 Load Data

- The data provided from the Kaggle competition was edited and saved
- This notebook will load the updated file and continue from there

[2]:
```
# Load the data
```

[2]:
```
dfSales = pd.read_csv("dfShopItemsFull.csv")
```

1.4 Quick Stats on the data

dfSales.info()

There are not any null values, but the instructions mention that there are holes in data for stores and items within some months. I am going to transform the data into a dataframe with item and store as the key and the sums for each month in the columns.

[4]:
```
dfSales.head()
```

[4]:

	date_block_num	shop_id	item_id	item_cnt_month
0	0	0	32	6.0
1	0	0	33	3.0
2	0	0	35	1.0
3	0	0	43	1.0
4	0	0	51	2.0

Much of the text of the data is in Russian. This is not really relevant because we do not need to look at item descriptions and category names. We can work with just IDs. I don't see any need to load the item and shops files unless I want to include item descriptions in my report.

1.5 Supervised Learning

1.5.1 LSTM Artificial Neural Network with Linear Activation

- The Long Short Term Memory Neural Network is a good option for time sequence data
- To use this model we needed to align a lookback so that the model is trained using the data for the next time period as the result from the current
- In a single variable time series problem, we can just look at the next record
- In our problem we have a combination of items and stores so we need to have a lookback offset of items * stores
- Some models will look forward by more than one timeslot, but due to computational and time restrictions we looked ahead by a single month
- Similarly, we restricted our model to 2 LSTM layers and 1 dense layer
- Results would have been improved with a deeper model but time constraints necessitated a simple model

Scale the Data

- The data must be scaled to use an LSTM Neural Network

[5]:
```
#training_labels = dfSales['item_cnt_month']
```

[9]:
```
scaler = MinMaxScaler(feature_range=(0, 1))
dfScaled = pd.DataFrame(scaler.
 ↪fit_transform(dfSales[['date_block_num','shop_id','item_id','item_cnt_month']]),
                                          columns=␣
 ↪['date_block_num','shop_id','item_id','item_cnt_month'])
```

[10]:
```
dfScaled
```

[10]:

	date_block_num	shop_id	item_id	item_cnt_month
0	0.0	0.000000	0.001443	0.022152
1	0.0	0.000000	0.001489	0.019778
2	0.0	0.000000	0.001579	0.018196
3	0.0	0.000000	0.001940	0.018196
4	0.0	0.000000	0.002301	0.018987
…	…	…	…	…
44443435	1.0	0.610169	0.574361	0.017405
44443436	1.0	0.610169	0.590554	0.017405
44443437	1.0	0.610169	0.757680	0.017405
44443438	1.0	0.610169	0.814651	0.017405
44443439	1.0	0.610169	0.718345	0.017405

[44443440 rows x 4 columns]

[11]:
```
# The orginal dataframe takes 1.3 GB of memory
# I am going to remove the original dataset due to memory constraints
del dfSales
```

Test and Train Data Split

[ ]:
```
# Break the dataset into test and training
# traning with everything except the last month and test with that
```

[8]:
```
last_month_size = dfScaled[dfScaled['date_block_num'].astype(int)==1].shape[0]
```

[46]:
```
#X_test = dfScaled.iloc[-last_month_size:]
```

[48]:
```
#X_train = dfScaled.iloc[:-last_month_size]
```

[50]:
```
#y_train = training_labels[:-last_month_size]
```

[51]:
```
#y_test = training_labels[-last_month_size:]
```

Model

- We tested a few different model configurations
- Some of them either took too long to train or resulted in too high loss
- For the purposes of brevity, we are only showing one model in this notebook

[12]:
```
last_month_size = dfScaled[dfScaled['date_block_num'].astype(int)==1].shape[0]
```

[13]:
```
trainx = np.array(dfScaled.iloc[:-last_month_size,:].reset_index().
 ↪drop(['index'],axis=1))
trainy = dfScaled.iloc[last_month_size:,:]['item_cnt_month'].reset_index().
 ↪drop(['index'],axis=1)
```

[14]:
```
trainy
```

[14]:
```
           item_cnt_month
0                0.025316
1                0.019778
2                0.028481
3                0.017405
4                0.019778
…                   …
43136275         0.017405
43136276         0.017405
43136277         0.017405
43136278         0.017405
43136279         0.017405

[43136280 rows x 1 columns]
```

[15]:
```
trainx
```

[15]:
```
array([[0.        , 0.        , 0.00144346, 0.0221519 ],
       [0.        , 0.        , 0.00148857, 0.01977848],
       [0.        , 0.        , 0.00157878, 0.0181962 ],
       …,
       [0.96969697, 0.61016949, 0.75767964, 0.01740506],
       [0.96969697, 0.61016949, 0.81465109, 0.01740506],
       [0.96969697, 0.61016949, 0.71834544, 0.01740506]])
```

[16]:
```
trainx = np.reshape(trainx, (trainx.shape[0], 1, 4))
#testx = np.reshape(testx, (testx.shape[0], 1, 4))
```

[17]:
```
trainx.shape
```

[17]:
```
(43136280, 1, 4)
```

[18]:
```
# create and fit the LSTM network

model = Sequential()
model.add(LSTM(256, return_sequences = True, input_shape = (trainx.shape[1],␣
 ↪4)))
model.add(LSTM(128,input_shape = (trainx.shape[1], 2)))
#model.add(Flatten())
model.add(Dense(1))
model.compile(loss = 'mean_squared_error', optimizer = 'adam')
```

```
2022-06-08 14:01:36.441899: I
tensorflow/core/common_runtime/process_util.cc:146] Creating new thread pool
with default inter op setting: 2. Tune using inter_op_parallelism_threads for
```

best performance.

[19]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 1, 256)            267264
_________________________________________________________________
lstm_1 (LSTM)                (None, 128)               197120
_________________________________________________________________
dense (Dense)                (None, 1)                 129
=================================================================
Total params: 464,513
Trainable params: 464,513
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```
call_backs = [EarlyStopping(monitor='loss', patience=3, verbose=1)]
history = model.fit(trainx, trainy, epochs = 20, batch_size = 60, verbose =␣
 ↪True, shuffle = False,  callbacks = call_backs)
model.save_weights('LSTMBasic1.h5')
# This will run a day. Hopefully it comes up with something useful
```

```
2022-06-08 14:02:00.366077: I
tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:185] None of the MLIR
Optimization Passes are enabled (registered 2)

Epoch 1/20
170849/718938 [======>…] - ETA: 1:05:10 - loss: 7.9538e-07
```

[22]:
```
# This finished but I lost connection and didn't see the verbose output
history.epoch
# Look up how to get the loss for each epoch
```

[22]:
```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
```

[ ]:
```
# Predict using training data to see how accurate it is for training
y_hat = model.predict(trainx)
```

[29]:
```
y_hat
```

[29]:
```
array([[0.04450752],
       [0.03698179],
       [0.03183561],
       …,
       [0.01730757],
```

```
       [0.01730722],
       [0.01730787]], dtype=float32)
```

[31]:
```
# I messed up but I dont want to restart the kernel. I should have scaled the item_cnt_month on its own
dfYhat = dfScaled.iloc[:-last_month_size,:].reset_index().drop(['index'],axis=1)
```

[35]:
```
dfYhat['item_cnt_month'] =y_hat
```

[36]:
```
dfYhat
```

[36]:

	date_block_num	shop_id	item_id	item_cnt_month
0	0.000000	0.000000	0.001443	0.044508
1	0.000000	0.000000	0.001489	0.036982
2	0.000000	0.000000	0.001579	0.031836
3	0.000000	0.000000	0.001940	0.031828
4	0.000000	0.000000	0.002301	0.034396
…	…	…	…	…
43136275	0.969697	0.610169	0.574361	0.017309
43136276	0.969697	0.610169	0.590554	0.017309
43136277	0.969697	0.610169	0.757680	0.017308
43136278	0.969697	0.610169	0.814651	0.017307
43136279	0.969697	0.610169	0.718345	0.017308

[43136280 rows x 4 columns]

[38]:
```
dfScaled.iloc[:-last_month_size,:]
```

[38]:

	date_block_num	shop_id	item_id	item_cnt_month
0	0.000000	0.000000	0.001443	0.022152
1	0.000000	0.000000	0.001489	0.019778
2	0.000000	0.000000	0.001579	0.018196
3	0.000000	0.000000	0.001940	0.018196
4	0.000000	0.000000	0.002301	0.018987
…	…	…	…	…
43136275	0.969697	0.610169	0.574361	0.017405
43136276	0.969697	0.610169	0.590554	0.017405
43136277	0.969697	0.610169	0.757680	0.017405
43136278	0.969697	0.610169	0.814651	0.017405
43136279	0.969697	0.610169	0.718345	0.017405

[43136280 rows x 4 columns]

[43]:
```
# We need to unscale the data so we can see it in the original scale
yhat_unscaled = scaler.inverse_transform(dfYhat)[:, 3]
```

[45]:
```
yhat_unscaled.shape
```

[45]:
```
(43136280,)
```

[47]:
```
trainy
```

[47]:
```
           item_cnt_month
0                0.025316
1                0.019778
2                0.028481
3                0.017405
4                0.019778
…                   …
43136275         0.017405
43136276         0.017405
43136277         0.017405
43136278         0.017405
43136279         0.017405

[43136280 rows x 1 columns]
```

[48]:
```
# Calculate RMSE of unscaled data
# The result is fair, but not greet
# We need to see what else good for the domain
mean_squared_error(trainy, yhat_unscaled)
```

[48]:
```
1.257088408350787
```

[51]:
```
# Calculate RMSE of scaled data
# This seems good for an RMSE on the training data
mean_squared_error(dfScaled.iloc[:-last_month_size,3], y_hat)
```

[51]:
```
8.372294129050908e-07
```

[52]:
```
dfScaled.iloc[-last_month_size:,:]
```

[52]:
```
           date_block_num   shop_id   item_id  item_cnt_month
43136280             1.0  0.000000  0.001443        0.017405
43136281             1.0  0.000000  0.001489        0.017405
43136282             1.0  0.000000  0.001579        0.017405
43136283             1.0  0.000000  0.001940        0.017405
43136284             1.0  0.000000  0.002301        0.017405
…                    …         …         …               …
44443435             1.0  0.610169  0.574361        0.017405
44443436             1.0  0.610169  0.590554        0.017405
44443437             1.0  0.610169  0.757680        0.017405
44443438             1.0  0.610169  0.814651        0.017405
44443439             1.0  0.610169  0.718345        0.017405
```

```
[1307160 rows x 4 columns]
```

[54]:
```
# Predict using the last month and submit to Kaggle Competition
testx = np.array(dfScaled.iloc[-last_month_size:,:].reset_index().
 ↪drop(['index'],axis=1))
testx = np.reshape(testx, (testx.shape[0], 1, 4))
predict34 = model.predict(testx)
```

[55]:
```
predict34
```

[55]:
```
array([[0.01742227],
       [0.01742227],
       [0.01742228],
       …,
       [0.01732376],
       [0.01732335],
       [0.01732411]], dtype=float32)
```

[56]:
```
dfYhatTest = dfScaled.iloc[-last_month_size:,:].reset_index().
 ↪drop(['index'],axis=1)
```

[57]:
```
dfYhatTest['item_cnt_month'] =predict34
```

[86]:
```
predict34_unscaled = scaler.inverse_transform(dfYhatTest)
```

[87]:
```
predict34_unscaled
```

[87]:
```
array([[ 3.30000000e+01,  0.00000000e+00,  3.20000000e+01,
         2.17446089e-02],
       [ 3.30000000e+01,  0.00000000e+00,  3.30000000e+01,
         2.17516720e-02],
       [ 3.30000000e+01,  0.00000000e+00,  3.50000000e+01,
         2.17634439e-02],
       …,
       [ 3.30000000e+01,  3.60000000e+01,  1.67970000e+04,
        -1.02769315e-01],
       [ 3.30000000e+01,  3.60000000e+01,  1.80600000e+04,
        -1.03284925e-01],
       [ 3.30000000e+01,  3.60000000e+01,  1.59250000e+04,
        -1.02326691e-01]])
```

[125]:
```
dfPredict34 = pd.DataFrame(data=predict34_unscaled,␣
 ↪columns=['date_block_num','shop_id','item_id','item_cnt_month'])
```

[126]:
```
dfPredict34['date_block_num'] = np.around(dfPredict34['date_block_num'])
dfPredict34['shop_id'] = np.around(dfPredict34['shop_id'])
dfPredict34['item_id'] = np.around(dfPredict34['item_id'])
```

```
dfPredict34 = dfPredict34.astype({'date_block_num':int,'shop_id':int,'item_id':
 ↪int})
```

[127]:
```
# Check for duplicates
dfPredict34[dfPredict34.duplicated(subset=['shop_id','item_id'])]
# This might be a rounding issue
# Looks good now that I rounded before casting to int
# I was getting an error that I could merge dataframes on a non-unique multi␣
 ↪index.
# The code in the above block fixed that issue
```

[127]:
```
Empty DataFrame
Columns: [date_block_num, shop_id, item_id, item_cnt_month]
Index: []
```

[134]:
```
# I am going to merge with test so I want to make shop_id and item_id the␣
 ↪indices
dfPredict34.set_index(['shop_id','item_id'],inplace=True)
```

[120]:
```
dfTest = pd.read_csv("../input/future-sales/test.csv")
```

[121]:
```
dfTest[dfTest.duplicated(subset=['shop_id','item_id'])]
# This df looks good on duplicated
```

[121]:
```
Empty DataFrame
Columns: [ID, shop_id, item_id]
Index: []
```

[129]:
```
dfTest.set_index(['shop_id','item_id'],inplace=True)
```

[130]:
```
dfTest
```

[130]:
```
                     ID
shop_id item_id
5       5037          0
        5320          1
        5233          2
        5232          3
        5268          4
…                     …
45      18454    214195
        16188    214196
        15757    214197
        19648    214198
        969      214199
```

```
[214200 rows x 1 columns]
```

[135]:
```
dfTest['item_cnt_month'] = dfPredict34['item_cnt_month']
```

[136]:
```
dfPredict34
```

[136]:
```
                 date_block_num  item_cnt_month
shop_id item_id
0       32                   33        0.021745
        33                   33        0.021752
        35                   33        0.021763
        43                   33        0.021813
        51                   33        0.021858
…                           …              …
36      12733                33       -0.100158
        13092                33       -0.100438
        16797                33       -0.102769
        18060                33       -0.103285
        15925                33       -0.102327

[1307160 rows x 2 columns]
```

[141]:
```
dfTest[dfTest['item_cnt_month'].isnull()]
# It looks like there are new iteams that are not in training
# and I will need to impute values

# This leads back to an issue that was missed during exploratory data analysis␣
 ↪(EDA)
# I created a dataframe with every item and shop listed for each month IF the␣
 ↪item was in the tranining data
# I did not use the items.csv for anything
# The test data had items that were not in the training data at all
# I will discuss this more in the analysis and results section
```

[141]:
```
                     ID  item_cnt_month
shop_id item_id
5       5320          1             NaN
        5268          4             NaN
        5826         45             NaN
        3731         54             NaN
        3538         64             NaN
…                   …              …
45      15033    214130             NaN
        7572     214150             NaN
        9030     214154             NaN
        1867     214161             NaN
        12470    214173             NaN
```

```
[15414 rows x 2 columns]
```

[142]:
```
dfTest.reset_index(inplace=True)
dfPredict34.reset_index(inplace=True)
```

[153]:
```
missing_items = dfTest[dfTest['item_cnt_month'].isnull()]['item_id'].unique()
```

[157]:
```
dfPredict34[dfPredict34['item_id'].isin(missing_items)]
```

[157]:
```
Empty DataFrame
Columns: [shop_id, item_id, date_block_num, item_cnt_month]
Index: []
```

[158]:
```
# Manual inspection shows that several missing items are similar to the next␣
 ↪item id over
# This is not always true but will use it for initial impute
# In many cases, it is the same game but on different platform
# A better impute would check the text string then compare with statistical␣
 ↪trends of the platform
# Is PS4 or Xbox more popular?
```

[158]:
```
367
```

[185]:
```
i = 0
for index,row in dfTest[dfTest['item_cnt_month'].isnull()].iterrows():
    item_id = row['item_id'].astype(int)
    # Try add one
    query_impute =␣
 ↪dfPredict34['item_cnt_month'][(dfPredict34['item_id']==item_id +1 ) &␣
 ↪(dfPredict34['shop_id']==row['shop_id'])]
    if query_impute.shape[0] == 0: # Try  remove 1
        query_impute =␣
 ↪dfPredict34['item_cnt_month'][(dfPredict34['item_id']==item_id - 1 ) &␣
 ↪(dfPredict34['shop_id']==row['shop_id'])]
    dfTest.loc[index,'item_cnt_month'] = float(query_impute)
```

[186]:
```
# Check for NaNs now
dfTest[dfTest['item_cnt_month'].isnull()]
```

[186]:
```
Empty DataFrame
Columns: [shop_id, item_id, ID, item_cnt_month]
Index: []
```

[187]:
```
max(dfTest['item_cnt_month'])
```

[187]:
```
30.731201887130737
```

[62]:
```
min(dfTest['item_cnt_month'])
```

[62]:
```
-0.338518440723418
```

[188]:
```
dfTest.shape
```

[188]:
```
(214200, 4)
```

[189]:
```
dfTest
```

[189]:

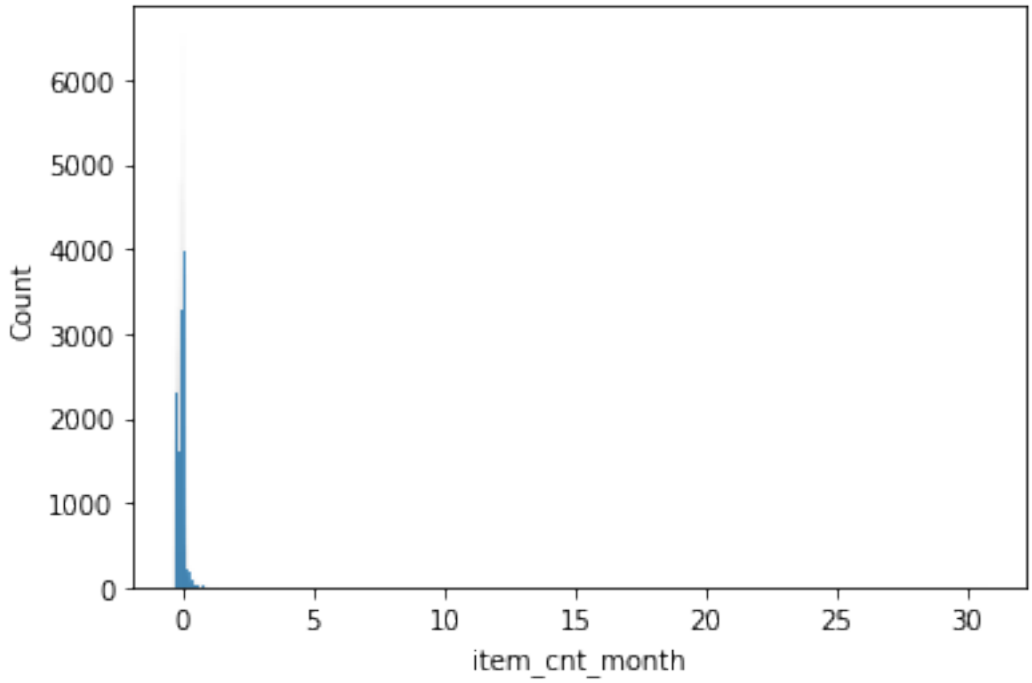
	shop_id	item_id	ID	item_cnt_month
0	5	5037	0	0.039118
1	5	5320	1	0.033375
2	5	5233	2	0.145055
3	5	5232	3	0.039855
4	5	5268	4	0.033375
…	…	…	…	…
214195	45	18454	214195	-0.071913
214196	45	16188	214196	-0.178715
214197	45	15757	214197	-0.177975
214198	45	19648	214198	-0.183713
214199	45	969	214199	-0.145012

[214200 rows x 4 columns]

[193]:
```
# Save CSV
dfTest[['ID','item_cnt_month']].to_csv("sample_submission.csv",index=False)
```

[190]:
```
sns.histplot(dfTest['item_cnt_month'])
```

[190]:
```
<AxesSubplot:xlabel='item_cnt_month', ylabel='Count'>
```



1.6 Analysis and Results

- The Kaggle Score for test data is 1.18078
  - I assume that is RMSE on test data which is similar to what I had on train
  - This puts me in the mid place on the leaderboard
- What went well
  - The general idea of the LSTM model showed promise for this problem
  - The scaled RMSE on the training data was very low
  - The training time over this very large model using a notebook with 30 GB of RAM and 8 cores was approximately 1 day
- What can be improved
  - A deeper network would improve performance
  - Using more epochs could improve performance. We limited our model to 20 epochs and used an early stop to cut that off if loss didn't improve in 3 epochs
  - The biggest issue is with feature value clustering and imputing values
  - We could improve the model by using unsupervised techniques to cluster items and shops
  - The items include categories that have some value but we need additional clustering
  - The item clusters are things such as Games - Xbox, Accessories - Xbox, Games - PS4 and various book, music, and video categories
  - These could help with imputing missing values in the test and training data
  - An issue with this type of data is that many of these items come out on a certain date, have a spike, then fade
  - To properly trend items we need to track trends on a few axis
  - Some of this could include natural language proceessing.
  - For example, if we have data on the sales for the release month of 2 different Call of

Duty games and we have new Call of Duty game in the test data, we can assume it will have similar results
  - In another example, if the release date of a game on Xbox was in November but was in December for PS4, we could use the Xbox data, scaled by platform popularity to estimate the value for the PS4 version.

1.7 References

- https://www.tutorialspoint.com/time_series/time_series_lstm_model.htm
- https://machinelearningmastery.com/time-series-prediction-lstm-recurrent-neural-networks-python-keras/
- https://stackoverflow.com/questions/41233635/meaning-of-inter-op-parallelism-threads-and-intra-op-parallelism-threads