Фреймворк PyTorch для разработки искусственных нейронных сетей

Урок 5. Рекурентные сети для обработки последовательностей

Практическое задание

- Обучить GRU, LSTM для предсказания временного ряда на примере https://www.kaggle.com/c/favorita-grocery-sales-forecasting (https://www.kaggle.com/c/favorita-grocery-sales-forecasting) (для каждого типа продуктов)

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В [ ]:

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В [ ]:
```
import numpy
import matplotlib.pyplot as plt
import pandas as pd
import math
from keras.models import Sequential
from keras.layers import Dense,Dropout
from keras.layers import LSTM
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
```

В [1]:
```
import os, sys
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# PATH_DATA = '/content/drive/lesson5/data/'
PATH_DATA = '.\\data\\'
print(PATH_DATA)
```

```
.\data\
```

В [ ]:
```
%%time

train = pd.read_csv(PATH_DATA + "train.csv", sep=",")
print(train.shape)
# train = train.set_index('id')
train.head(3)
```

В [ ]:
```
train.info()
```

В [3]:
```
# функция для оптимизации использования памяти
def reduce_memory(df):
    """Снижает размерности строк"""

    float_cols = df.select_dtypes(include=['float']).columns
    int_cols = df.select_dtypes(include=['int64']).columns

    df[float_cols] = df[float_cols].astype('float32')
    df[int_cols] = df[int_cols].astype('int32')

    return df
```

В [4]:
```
reduce_memory(train)
train.info()
```

В [ ]:
```
train_dt = train[['date', 'store_nbr', 'unit_sales']]
train_dt.info()
# train_dt.info(memory_usage='deep')
train_dt.head(3)
```

В [ ]:
```
%%time

train_dt.to_csv(PATH_DATA + 'train_dt.csv', index=False)
```

В [ ]:
```
# del (train_dt)
# del(train)

# Освобождаем память
import gc
gc.collect()
gc.collect() # два раза подряд, для надёжности
```

В [2]:
```
%%time

train_dt = pd.read_csv(PATH_DATA + "train_dt.csv", sep=",")
print(train_dt.shape)
train_dt.info()
train_dt.head(3)
```

```
(125497040, 3)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 125497040 entries, 0 to 125497039
Data columns (total 3 columns):
 #   Column      Dtype  
---  ------      -----  
 0   date        object 
 1   store_nbr   int64  
 2   unit_sales  float64
dtypes: float64(1), int64(1), object(1)
memory usage: 2.8+ GB
Wall time: 33.2 s
```

Out[2]:

	date	store_nbr	unit_sales
0	2013-01-01	25	7.0
1	2013-01-01	25	1.0
2	2013-01-01	25	2.0

Data processing

Subseting, join and aggregating data

В [6]:
```
stores = pd.read_csv(PATH_DATA + "stores.csv")
```

В [9]:
```
%%time

t=train_dt.groupby(['store_nbr','date'], as_index=False).agg({"unit_sales": "sum"})
train = pd.merge(t, stores, how='left', on=['store_nbr'])
mask=train['state']=='Pichincha'
train=train.loc[mask]
train=train.groupby(['date'], as_index=False).agg({"unit_sales": "sum"})
```

```
Wall time: 125 ms
```

Sales for Pichincha state (train data)

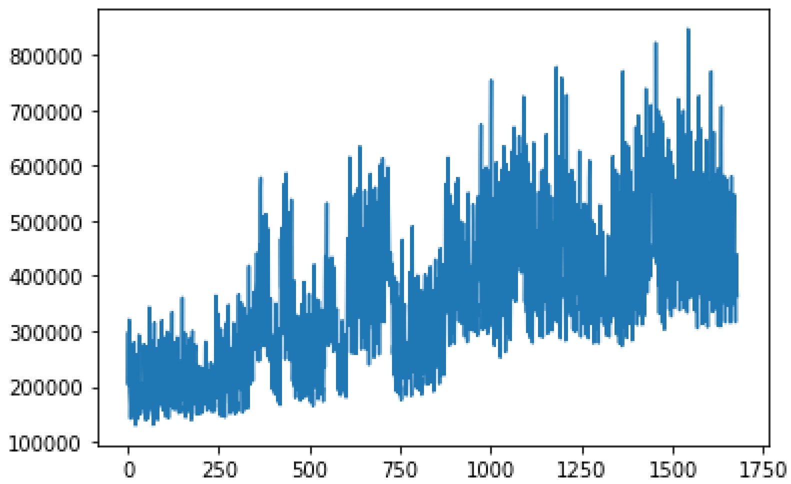
В [23]:
```
print(train.shape)
train.info()
train.tail(12)
```

```
(1679, 2)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1679 entries, 0 to 1678
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   date        1679 non-null   object 
 1   unit_sales  1679 non-null   float32
dtypes: float32(1), object(1)
memory usage: 32.8+ KB
```

Out[23]:

	date	unit_sales
1667	2017-08-04	425713.15625
1668	2017-08-05	500614.56250
1669	2017-08-06	547592.12500
1670	2017-08-07	396073.43750
1671	2017-08-08	347288.25000
1672	2017-08-09	367813.87500
1673	2017-08-10	315940.31250
1674	2017-08-11	406504.40625
1675	2017-08-12	389945.59375
1676	2017-08-13	438714.53125
1677	2017-08-14	377126.43750
1678	2017-08-15	363382.59375

В [24]:
```
import matplotlib.pyplot as plt

plt.plot(train['unit_sales'])
plt.show()
```



There is a trend over time especially for the 2015 year, by 2015 and 2016 the slope gets lower and loses trend. It’s easy to recognize how the sales increasing over the last quarters.

В [25]:
```
# Сохраняем результат в файл
train.to_csv(PATH_DATA + 'train_data.csv', index=False)
```

Загрузка подготовленных данных

В [5]:
```
train = pd.read_csv(PATH_DATA + "train_data.csv", sep=",")
print(train.shape)
train.info()
train.head(3)
```

```
(1679, 2)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1679 entries, 0 to 1678
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   date        1679 non-null   object 
 1   unit_sales  1679 non-null   float64
dtypes: float64(1), object(1)
memory usage: 26.4+ KB
```

Out[5]:

	date	unit_sales
0	2013-01-02	295729.00
1	2013-01-03	203589.56
2	2013-01-04	203090.77

Разделение выборки для обучающих и тестовых данных

В [6]:
```
train_size = int(len(train) * 0.75)
test_size = len(train) - train_size

print(train_size,test_size, len(train))
```

```
1259 420 1679
```

В [7]:
```
train1= train[0:train_size]
test =  train[train_size:len(train)]
print(len(train1), len(test))
```

```
1259 420
```

В [8]:
```
train1=train1.set_index("date")
test=test.set_index("date")
train=train.set_index("date")
train1=train1.values
test=test.values
train=train.values
```

Determine the number of previous time steps to use as input variables to predict the next time period. In this case (look_back) determinated to 1

В [9]:
```
def create_dataset(dataset, look_back=1):
    dataX, dataY = [], []
    for i in range(len(dataset)-look_back-1):
        a = dataset[i:(i+look_back), 0]
        dataX.append(a)
        dataY.append(dataset[i + look_back, 0])
    return numpy.array(dataX), numpy.array(dataY)
```

В [11]:
```
# import numpy

look_back = 1
trainX, trainY = create_dataset(train1, look_back)
testX, testY = create_dataset(test, look_back)
```

В [19]:
```
trainX.shape, trainY.shape
```

Out[19]:
```
((1257, 1), (1257,))
```

Multilayer Perceptron model
A simple network with 1 input (look_back) , 1 hidden layer with 8 neurons and one (1) output layer.

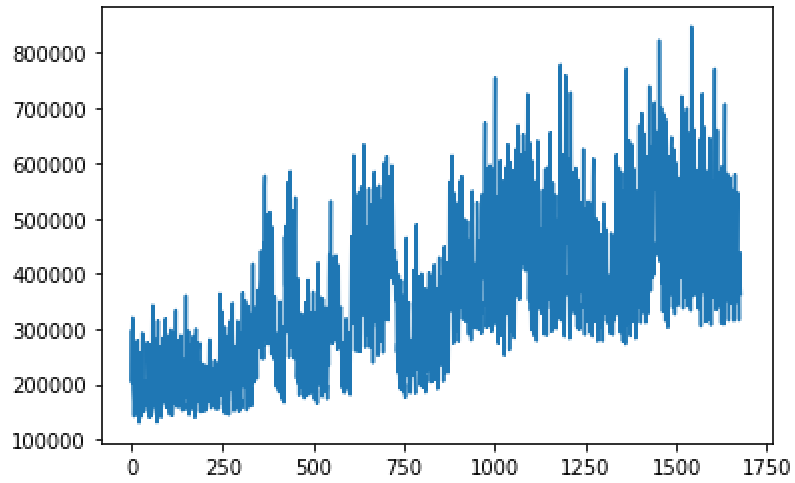
В [14]:
```
model = Sequential()
model.add(Dense(8, input_dim=look_back, activation='relu'))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
model.fit(trainX, trainY, epochs=200, batch_size=2, verbose=2)
```

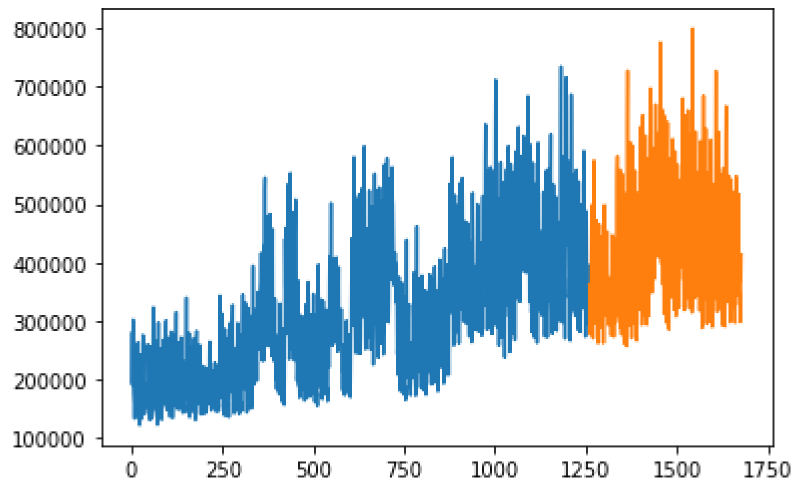
```
Epoch 67/200
629/629 - 2s - loss: 7554625536.0000 - 2s/epoch - 2ms/step
Epoch 68/200
629/629 - 2s - loss: 7545674752.0000 - 2s/epoch - 2ms/step
Epoch 69/200
629/629 - 2s - loss: 7530616832.0000 - 2s/epoch - 2ms/step
Epoch 70/200
629/629 - 2s - loss: 7553161728.0000 - 2s/epoch - 2ms/step
Epoch 71/200
629/629 - 2s - loss: 7506878464.0000 - 2s/epoch - 2ms/step
Epoch 72/200
629/629 - 1s - loss: 7539394048.0000 - 1s/epoch - 2ms/step
Epoch 73/200
629/629 - 2s - loss: 7538317312.0000 - 2s/epoch - 2ms/step
Epoch 74/200
629/629 - 2s - loss: 7543454720.0000 - 2s/epoch - 2ms/step
Epoch 75/200
629/629 - 2s - loss: 7526384640.0000 - 2s/epoch - 2ms/step
Epoch 76/200
629/629 - 1s - loss: 7545986560.0000 - 1s/epoch - 2ms/step
```

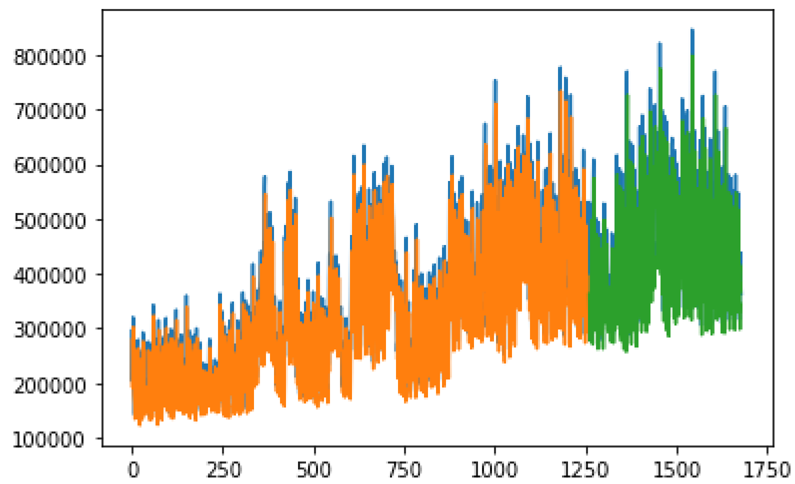
В [16]:
```
trainScore = model.evaluate(trainX, trainY, verbose=0)
print('Train Score: %.2f MSE (%.2f RMSE)' % (trainScore, math.sqrt(trainScore)))
testScore = model.evaluate(testX, testY, verbose=0)
print('Test Score: %.2f MSE (%.2f RMSE)' % (testScore, math.sqrt(testScore)))
```

```
Train Score: 7544227328.00 MSE (86857.51 RMSE)
Test Score: 13193974784.00 MSE (114865.03 RMSE)
```

В [17]:
```
trainPredict = model.predict(trainX)
testPredict = model.predict(testX)

trainPredictPlot = numpy.empty_like(train)
trainPredictPlot[:, :] = numpy.nan
trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict

testPredictPlot = numpy.empty_like(train)
testPredictPlot[:, :] = numpy.nan
testPredictPlot[len(trainPredict)+(look_back*2)+1:len(train)-1, :] = testPredict

plt.plot(train)
plt.show()
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.show()
plt.plot(train)
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.show()
```







The average error in the training data is 86.857 units and the averrage in the test data is 114.865 units sold per day

сеть: LSTM слои+Conv1D +Dense слой.

В [ ]:
```
callback = EarlyStopping(monitor='val_mae', patience=2)

model = Sequential()

model.add(LSTM(64, input_shape = (inputs.shape[1], inputs.shape[2]), return_sequences="True"))
model.add(LSTM(64, return_sequences="True")) # <None, 3,32>
model.add(Conv1D(64, 3, activation="linear")) #(None,3,64)
#model.add(Conv1D(64, 1, activation="linear"))
model.add(Flatten())                          # (None, 3*64)
model.add(Dense(3, activation="linear"))      # (None,3)

model.add(Dense(1, activation="linear"))

model.compile(loss="mse", optimizer="adam", metrics=['mae'])

history = model.fit(
    dataset_train,
    epochs=epochs,
    validation_data=dataset_val,
    callbacks=[callback, tensorboard_callback])


plt.plot(history.history['mae'][1:],
         label='Средняя абсолютная ошибка на обучающем наборе')
plt.plot(history.history['val_mae'][1:],
         label='Средняя абсолютная ошибка на проверочном наборе')
plt.ylabel('Средняя ошибка')
plt.legend()
plt.show()
```

В [ ]:

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Все параметры класса RNN
Приведём список всех параметров класса RNN в фреймворке PyTorch:
nn.RNN
… (input_size, hidden_size, num_layers=1, nonlinearity='tanh', bias=True, … batch_first=False, dropout=0, bidirectional=False) [doc]

Отметим не упомянутый ранее параметр dropout. По умолчанию он равен нулю. При ненулевом значении, после каждого слоя (num_layers > 1), кроме последнего, вставляется слой dropout, который с вероятностью dropout случайно "отключает" (делает нулевыми) часть элементов тензоров на выходах каждой ячейке.

Установка параметра bias в значение False ликвидирует вектор смещения после перемножения матриц.

В [ ]:
```
https://qudata.com/ml/ru/NN_RNN_Torch.html - ML: Рекуррентные сети на PyTorch
```