Sri Lanka Institute of Information Technology

# Deep Learning for Time Series Forecasting using MLP & LSTM

Deep Learning

Assignment 2


**Submitted by:**

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## 1. Introduction

Time series forecasting is the technique of analysing time series data the use of data and models to make predictions and make strategic decisions. This is now not continually a correct prediction, and the probability of predictions can range greatly, when dealing with variables that differ extensively between time collection information and elements past our control.

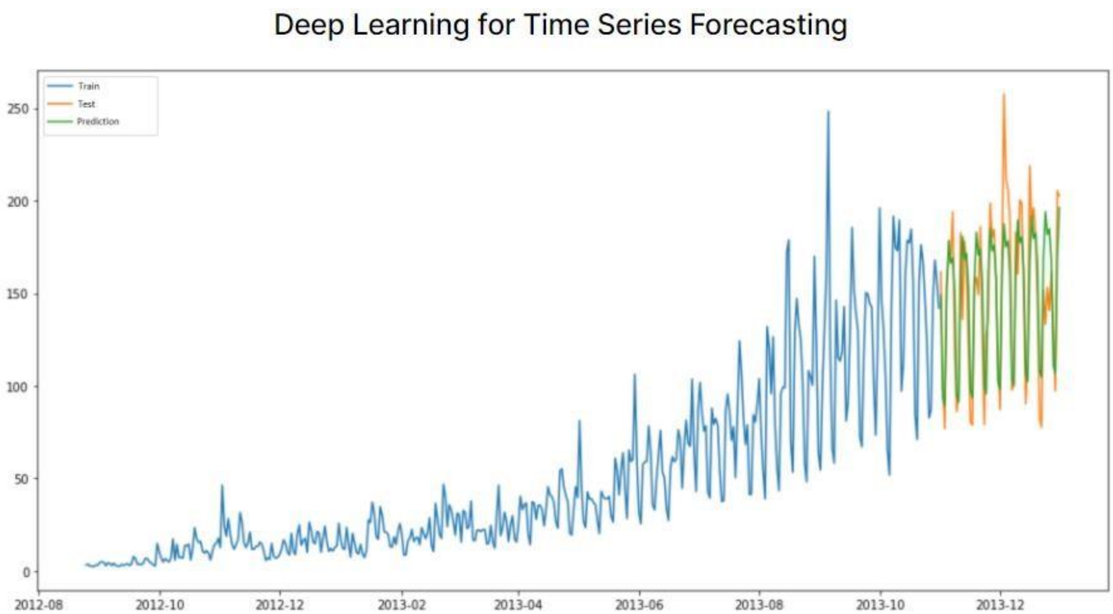
However, predict information about which consequences are extra or much less probable than different feasible outcomes. The extra facts we have, the greater correct the predictions can be. While prediction and "forecast" commonly imply the equal thing, the distinction can be seen. In some industries, a forecast may also relate to records at a future time, whilst a forecast typically relates to future data. Series forecasting is frequently used in conjunction with time collection analysis. Time series evaluation includes developing models to recognize the most important dates and causes. The evaluation can explain "why" the results you see. The prediction then takes the subsequent step as to what must appear with this expertise and predictable extrapolations for the future.

Time series prediction occurs when scientific predictions primarily based on historic facts with stamps are made. This consists of constructing models primarily based on historic evaluation and the usage of them for future observations and strategic decisions. An essential distinction in prognosis is that a future result is now not available at all at some stage in labour and can solely be assessed via cautious evaluation and scientific history. Of course, the unpredictable and the unknown have limits. Time series prediction is no longer fool proof, appropriate or beneficial in all situations. Because there are no without a doubt express regulation on whether or no longer to use predictions, analysts and datasets want to apprehend the boundaries of evaluation and what their models can support. Not all models fit all datasets or reply all questions.

Data teams should use time collection forecasts when they apprehend the wants of the enterprise and have the proper statistics and forecasting skills to reply the demand. A top forecast works with clean, synchronized records and can discover actual traits and patterns in historic data. Analysts can distinguish between random fluctuations or outliers and separate actual data from seasonal fluctuations.

## 2. <u>Methodology</u>

**What is the Time series forecasting?**




Time series forecasting is an essential region of deep learning that is regularly neglected.

It is vital due to the fact there are so many prediction issues that contain a time component. These troubles are disregarded due to the fact it is this time factor that makes time series problems more tough to handle.

The intention of this notebook is to advance and evaluate specific procedures to time-series problems.

The reason of this article is to display a way in which time collection data can be effectively encoded into smaller sizes for use in non-time series models. Here we will come a time series of 12 (12 months) with a single cost and use it in a deep gaining knowledge of MLP model as a substitute of the use of time series in an LSTM model, which may be the traditional approach.

**Predict future sales**

Predict the whole income of every product and keep for the following month. By fixing this quiz, you can observe and enhance your know-how in the discipline of data science.

Historical data on every day income are available. The venture is to predict the whole quantity of objects bought in a pattern in every store. Please be aware that the list of shops and merchandise adjustments barely each month.

## 3. Dataset Description

Dataset Link: https://www.kaggle.com/c/competitive-data-science-predict-future-sales

You are furnished with day-by-day historic income data. The assignment is to forecast the whole quantity of merchandise bought in each save for the check set. Note that the listing of retail outlets and merchandise barely modifications each month. Creating a robust model that can deal with such conditions is section of the challenge.

**File descriptions**

- sales_train.csv - the training set. Daily historical data from January 2013 to October 2015.
- test.csv - the test set. You need to forecast the sales for these shops and products for November 2015.
- sample_submission.csv - a sample submission file in the correct format.
- items.csv - supplemental information about the items/products.
- item_categories.csv - supplemental information about the items categories.
- shops.csv- supplemental information about the shops.

**Data fields**

- ID - an Id that represents a (Shop, Item) tuple within the test set
- shop_id - unique identifier of a shop
- item_id - unique identifier of a product
- item_category_id - unique identifier of item category
- item_cnt_day - number of products sold. You are predicting a monthly amount of this measure
- item_price - current price of an item
- date - date in format dd/mm/yyyy
- date_block_num - a consecutive month number, used for convenience. January 2013 is 0, February 2013 is 1..., October 2015 is 33
- item_name - name of item
- shop_name - name of shop
- item_category_name - name of item category

This dataset is permitted to be used for any purpose, including commercial use.

# 4. Implementation

1. Dependencies

```python
import os, warnings, random
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
import tensorflow as tf
import tensorflow.keras.layers as L
from tensorflow.keras import optimizers, Sequential, Model

# Set seeds to make the experiment more reproducible.
def seed_everything(seed=0):
    random.seed(seed)
    np.random.seed(seed)
    tf.random.set_seed(seed)
    os.environ['PYTHONHASHSEED'] = str(seed)
    os.environ['TF_DETERMINISTIC_OPS'] = '1'

seed = 0
seed_everything(seed)
warnings.filterwarnings('ignore')
pd.set_option('display.float_format', lambda x: '%.2f' % x)
```

2. Loading Data

```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```python
test = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/DL /competitive-data-science-predict-future-sales/test.csv', dtype={'ID': 'int32', 'shop_id': 'int32',
                                                   'item_id': 'int32'})
item_categories = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/DL /competitive-data-science-predict-future-sales/item_categories.csv',
                              dtype={'item_category_name': 'str', 'item_category_id': 'int32'})
items = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/DL /competitive-data-science-predict-future-sales/items.csv', dtype={'item_name': 'str', 'item_id': 'int32',
                                                 'item_category_id': 'int32'})
shops = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/DL /competitive-data-science-predict-future-sales/shops.csv', dtype={'shop_name': 'str', 'shop_id': 'int32'})
sales = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/DL /competitive-data-science-predict-future-sales/sales_train.csv', parse_dates=['date'],
                    dtype={'date': 'str', 'date_block_num': 'int32', 'shop_id': 'int32',
                      'item_id': 'int32', 'item_price': 'float32', 'item_cnt_day': 'int32'})
```

3. Join Datasets

```python
train = sales.join(items, on='item_id', rsuffix='_').join(shops, on='shop_id', rsuffix='_').join(item_categories, on='item_category_id', rsuffix='_').drop(['item_id_', 'shop_id_', 'item_category
```

4. Let's look at the raw data

```python
print(f'Train rows: {train.shape[0]}')
print(f'Train columns: {train.shape[1]}')

display(train.head().T)
display(train.describe())
```

```
Train rows: 2935849
Train columns: 10
```

| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| **date** | 2013-02-01 00:00:00 | 2013-03-01 00:00:00 | 2013-05-01 00:00:00 | 2013-06-01 00:00:00 | 2013-01-15 00:00:00 |
| **date_block_num** | 0 | 0 | 0 | 0 | 0 |
| **shop_id** | 59 | 25 | 25 | 25 | 25 |
| **item_id** | 22154 | 2552 | 2552 | 2554 | 2555 |
| **item_price** | 999.00 | 899.00 | 899.00 | 1709.05 | 1099.00 |
| **item_cnt_day** | 1 | 1 | -1 | 1 | 1 |
| **item_name** | ЯВЛЕНИЕ 2012 (BD) | DEEP PURPLE The House Of Blue Light LP | DEEP PURPLE The House Of Blue Light LP | DEEP PURPLE Who Do You Think We Are LP | DEEP PURPLE 30 Very Best Of 2CD (Фирм.) |
| **item_category_id** | 37 | 58 | 58 | 58 | 56 |
| **shop_name** | Ярославль ТЦ "Альтаир" | Москва ТРК "Атриум" | Москва ТРК "Атриум" | Москва ТРК "Атриум" | Москва ТРК "Атриум" |
| **item_category_name** | Кино - Blu-Ray | Музыка - Винил | Музыка - Винил | Музыка - Винил | Музыка - CD фирменного производства |

| | date_block_num | shop_id | item_id | item_price | item_cnt_day | item_category_id |
|---|---|---|---|---|---|---|
| **count** | 2935849.00 | 2935849.00 | 2935849.00 | 2935849.00 | 2935849.00 | 2935849.00 |
| **mean** | 14.57 | 33.00 | 10197.23 | 890.62 | 1.24 | 40.00 |
| **std** | 9.42 | 16.23 | 6324.30 | 1726.44 | 2.62 | 17.10 |
| **min** | 0.00 | 0.00 | 0.00 | -1.00 | -22.00 | 0.00 |
| **25%** | 7.00 | 22.00 | 4476.00 | 249.00 | 1.00 | 28.00 |
| **50%** | 14.00 | 31.00 | 9343.00 | 399.00 | 1.00 | 40.00 |
| **75%** | 23.00 | 47.00 | 15684.00 | 999.00 | 1.00 | 55.00 |
| **max** | 33.00 | 59.00 | 22169.00 | 307980.00 | 2169.00 | 83.00 |

5. Time period of the dataset

```
print(f"Min date from train set: {train['date'].min().date()}")
print(f"Max date from train set: {train['date'].max().date()}")
```

```
Min date from train set: 2013-01-01
Max date from train set: 2015-12-10
```

```
test_shop_ids = test['shop_id'].unique()
test_item_ids = test['item_id'].unique()
# Only shops that exist in test set.
train = train[train['shop_id'].isin(test_shop_ids)]
# Only items that exist in test set.
train = train[train['item_id'].isin(test_item_ids)]
```

6. Data pre-processing

```
train_monthly = train[['date', 'date_block_num', 'shop_id', 'item_id', 'item_cnt_day']]
train_monthly = train_monthly.sort_values('date').groupby(['date_block_num', 'shop_id', 'item_id'], as_index=False)
train_monthly = train_monthly.agg({'item_cnt_day':['sum']})
train_monthly.columns = ['date_block_num', 'shop_id', 'item_id', 'item_cnt']
train_monthly = train_monthly.query('item_cnt >= 0 and item_cnt <= 20')
# Label
train_monthly['item_cnt_month'] = train_monthly.sort_values('date_block_num').groupby(['shop_id', 'item_id'])['item_cnt'].shift(-1)

display(train_monthly.head(10).T)
display(train_monthly.describe().T)
```

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| **date_block_num** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **shop_id** | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 | 2.00 |
| **item_id** | 33.00 | 482.00 | 491.00 | 839.00 | 1007.00 | 1010.00 | 1023.00 | 1204.00 | 1224.00 | 1247.00 |
| **item_cnt** | 1.00 | 1.00 | 1.00 | 1.00 | 3.00 | 1.00 | 2.00 | 1.00 | 1.00 | 1.00 |
| **item_cnt_month** | 2.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | nan | nan | nan |

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **date_block_num** | 593829.00 | 20.18 | 9.14 | 0.00 | 13.00 | 22.00 | 28.00 | 33.00 |
| **shop_id** | 593829.00 | 32.07 | 16.90 | 2.00 | 19.00 | 31.00 | 47.00 | 59.00 |
| **item_id** | 593829.00 | 10015.02 | 6181.82 | 30.00 | 4418.00 | 9171.00 | 15334.00 | 22167.00 |
| **item_cnt** | 593829.00 | 2.10 | 2.31 | 0.00 | 1.00 | 1.00 | 2.00 | 20.00 |
| **item_cnt_month** | 482536.00 | 2.07 | 2.17 | 0.00 | 1.00 | 1.00 | 2.00 | 20.00 |

7. Time Series processing

```
monthly_series = train_monthly.pivot_table(index=['shop_id', 'item_id'], columns='date_block_num',values='item_cnt', fill_value=0).reset_index()
monthly_series.head()
```

| date_block_num | shop_id | item_id | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2 | 30 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | 2 | 31 | 0 | 4 | 1 | 1 | 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 | 1 |
| **2** | 2 | 32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 2 | 2 | 0 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| **3** | 2 | 33 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 |
| **4** | 2 | 53 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 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 |

Currently we have one series (33 months) for each unique pair of “shop_id” and “item_id”, but probably would be better to have multiple smaller series of each unique pair, so we are generating multiple series of size 12 (one year) for each unique pair

```
first_month = 20
last_month = 33
serie_size = 12
data_series = []

for index, row in monthly_series.iterrows():
    for month1 in range((last_month - (first_month + serie_size)) + 1):
        serie = [row['shop_id'], row['item_id']]
        for month2 in range(serie_size + 1):
            serie.append(row[month1 + first_month + month2])
        data_series.append(serie)

columns = ['shop_id', 'item_id']
[columns.append(i) for i in range(serie_size)]
columns.append('label')

data_series = pd.DataFrame(data_series, columns=columns)
data_series.head()
```

| | shop_id | item_id | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | label |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | 2 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **2** | 2 | 31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **3** | 2 | 31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| **4** | 2 | 32 | 2 | 2 | 0 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |

8. Dropping Identifier columns as we don't need them anymore

```
data_series = data_series.drop(['item_id', 'shop_id'], axis=1)
```

9. Train and Validation Sets

```
labels = data_series['label']
data_series.drop('label', axis=1, inplace=True)
train, valid, Y_train, Y_valid = train_test_split(data_series, labels.values, test_size=0.10, random_state=0)
```

```
print("Train set", train.shape)
print("Validation set", valid.shape)
train.head()
```

```
Train set (200327, 12)
Validation set (22259, 12)
```

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **207604** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **45150** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **143433** | 0 | 0 | 4 | 2 | 1 | 2 | 2 | 1 | 0 | 0 | 0 | 1 |
| **202144** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **136088** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 |

10. Reshape Data [Time-series shape (data points, time-steps, features)]

```
X_train = train.values.reshape((train.shape[0], train.shape[1], 1))
X_valid = valid.values.reshape((valid.shape[0], valid.shape[1], 1))

print("Train set reshaped", X_train.shape)
print("Validation set reshaped", X_valid.shape)
```

```
Train set reshaped (200327, 12, 1)
Validation set reshaped (22259, 12, 1)
```

11. Regular LSTM Model

```
serie_size =  X_train.shape[1] # 12
n_features =  X_train.shape[2] # 1

epochs = 20
batch = 128
lr = 0.0001

lstm_model = Sequential()
lstm_model.add(L.LSTM(10, input_shape=(serie_size, n_features), return_sequences=True))
lstm_model.add(L.LSTM(6, activation='relu', return_sequences=True))
lstm_model.add(L.LSTM(1, activation='relu'))
lstm_model.add(L.Dense(10, kernel_initializer='glorot_normal', activation='relu'))
lstm_model.add(L.Dense(10, kernel_initializer='glorot_normal', activation='relu'))
lstm_model.add(L.Dense(1))
lstm_model.summary()

adam = optimizers.Adam(lr)
lstm_model.compile(loss='mse', optimizer=adam)
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 12, 10)            480
_________________________________________________________________
lstm_1 (LSTM)                (None, 12, 6)             408
_________________________________________________________________
lstm_2 (LSTM)                (None, 1)                 32
_________________________________________________________________
dense (Dense)                (None, 10)                20
_________________________________________________________________
dense_1 (Dense)              (None, 10)                110
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 11
=================================================================
Total params: 1,061
Trainable params: 1,061
Non-trainable params: 0
_________________________________________________________________
```

```
lstm_history = lstm_model.fit(X_train, Y_train,
                              validation_data=(X_valid, Y_valid),
                              batch_size=batch,
                              epochs=epochs,
                              verbose=2)
```

```
Epoch 1/20
1566/1566 - 22s - loss: 1.5067 - val_loss: 1.3122
Epoch 2/20
1566/1566 - 18s - loss: 1.3280 - val_loss: 1.2557
Epoch 3/20
1566/1566 - 18s - loss: 1.2744 - val_loss: 1.2236
Epoch 4/20
1566/1566 - 18s - loss: 1.2339 - val_loss: 1.1950
Epoch 5/20
1566/1566 - 18s - loss: 1.2026 - val_loss: 1.1723
Epoch 6/20
1566/1566 - 18s - loss: 1.1754 - val_loss: 1.1573
Epoch 7/20
1566/1566 - 18s - loss: 1.1700 - val_loss: 1.1529
Epoch 8/20
1566/1566 - 18s - loss: 1.1677 - val_loss: 1.1511
Epoch 9/20
1566/1566 - 18s - loss: 1.1664 - val_loss: 1.1484
Epoch 10/20
1566/1566 - 18s - loss: 1.1652 - val_loss: 1.1484
Epoch 11/20
1566/1566 - 18s - loss: 1.1642 - val_loss: 1.1489
Epoch 12/20
1566/1566 - 18s - loss: 1.1637 - val_loss: 1.1464
Epoch 13/20
1566/1566 - 18s - loss: 1.1629 - val_loss: 1.1453
Epoch 14/20
1566/1566 - 18s - loss: 1.1624 - val_loss: 1.1446
Epoch 15/20
1566/1566 - 18s - loss: 1.1616 - val_loss: 1.1444
Epoch 16/20
1566/1566 - 18s - loss: 1.1616 - val_loss: 1.1459
Epoch 17/20
1566/1566 - 18s - loss: 1.1610 - val_loss: 1.1430
Epoch 18/20
1566/1566 - 18s - loss: 1.1604 - val_loss: 1.1421
Epoch 19/20
1566/1566 - 18s - loss: 1.1604 - val_loss: 1.1458
Epoch 20/20
1566/1566 - 18s - loss: 1.1603 - val_loss: 1.1410
```

## 12. LSTM Autoencoder

```
encoder_decoder = Sequential()
encoder_decoder.add(L.LSTM(serie_size, activation='relu', input_shape=(serie_size, n_features), return_sequences=True))
encoder_decoder.add(L.LSTM(6, activation='relu', return_sequences=True))
encoder_decoder.add(L.LSTM(1, activation='relu'))
encoder_decoder.add(L.RepeatVector(serie_size))
encoder_decoder.add(L.LSTM(serie_size, activation='relu', return_sequences=True))
encoder_decoder.add(L.LSTM(6, activation='relu', return_sequences=True))
encoder_decoder.add(L.TimeDistributed(L.Dense(1)))
encoder_decoder.summary()

adam = optimizers.Adam(lr)
encoder_decoder.compile(loss='mse', optimizer=adam)
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_8 (LSTM)                (None, 12, 12)            672
_________________________________________________________________
lstm_9 (LSTM)                (None, 12, 6)             456
_________________________________________________________________
lstm_10 (LSTM)               (None, 1)                 32
_________________________________________________________________
repeat_vector_1 (RepeatVecto (None, 12, 1)             0
_________________________________________________________________
lstm_11 (LSTM)               (None, 12, 12)            672
_________________________________________________________________
lstm_12 (LSTM)               (None, 12, 6)             456
_________________________________________________________________
time_distributed_1 (TimeDist (None, 12, 1)             7
=================================================================
Total params: 2,295
Trainable params: 2,295
Non-trainable params: 0
_________________________________________________________________
```

```
encoder_decoder_history = encoder_decoder.fit(X_train, X_train,
                                              batch_size=batch,
                                              epochs=epochs,
                                              verbose=2)
```

```
Epoch 1/20
1566/1566 - 34s - loss: 1.6350
Epoch 2/20
1566/1566 - 29s - loss: 1.2388
Epoch 3/20
1566/1566 - 29s - loss: 1.1044
Epoch 4/20
1566/1566 - 29s - loss: 1.0701
Epoch 5/20
1566/1566 - 29s - loss: 1.0494
Epoch 6/20
1566/1566 - 29s - loss: 1.0377
Epoch 7/20
1566/1566 - 29s - loss: 1.0321
Epoch 8/20
1566/1566 - 29s - loss: 1.0235
Epoch 9/20
1566/1566 - 29s - loss: 1.0134
Epoch 10/20
1566/1566 - 29s - loss: 1.0002
Epoch 11/20
1566/1566 - 29s - loss: 0.9849
Epoch 12/20
1566/1566 - 29s - loss: 0.9707
Epoch 13/20
1566/1566 - 29s - loss: 0.9671
Epoch 14/20
1566/1566 - 29s - loss: 0.9761
Epoch 15/20
1566/1566 - 29s - loss: 0.9629
Epoch 16/20
1566/1566 - 29s - loss: 0.9706
Epoch 17/20
1566/1566 - 28s - loss: 0.9445
Epoch 18/20
1566/1566 - 29s - loss: 0.9326
Epoch 19/20
1566/1566 - 29s - loss: 0.9253
Epoch 20/20
1566/1566 - 29s - loss: 0.9327
```

```
rpt_vector_layer = Model(inputs=encoder_decoder.inputs, outputs=encoder_decoder.layers[3].output)
time_dist_layer = Model(inputs=encoder_decoder.inputs, outputs=encoder_decoder.layers[5].output)
encoder_decoder.layers
```

```
[<keras.layers.recurrent_v2.LSTM at 0x7f2c59c92b90>,
 <keras.layers.recurrent_v2.LSTM at 0x7f2c597b9d50>,
 <keras.layers.recurrent_v2.LSTM at 0x7f2c568ad550>,
 <keras.layers.core.RepeatVector at 0x7f2c5adff310>,
 <keras.layers.recurrent_v2.LSTM at 0x7f2c5aecb910>,
 <keras.layers.recurrent_v2.LSTM at 0x7f2c5aeaf950>,
 <keras.layers.wrappers.TimeDistributed at 0x7f2c5adfbad0>]
```

13. LSTM – This is just a regular LSTM, a layer that can receive sequence data and learn based on it nothing much to talk about
14. Repeat Vector Layer

```
rpt_vector_layer_output = rpt_vector_layer.predict(X_train[:1])
print('Repeat vector output shape', rpt_vector_layer_output.shape)
print('Repeat vector output sample')
print(rpt_vector_layer_output[0])
```

```
Repeat vector output shape (1, 12, 1)
Repeat vector output sample
[[0.04086111]
 [0.04086111]
 [0.04086111]
 [0.04086111]
 [0.04086111]
 [0.04086111]
 [0.04086111]
 [0.04086111]
 [0.04086111]
 [0.04086111]
 [0.04086111]
 [0.04086111]]
```

15. Time Distributed Layer

```
time_dist_layer_output = time_dist_layer.predict(X_train[:1])
print('Time distributed output shape', time_dist_layer_output.shape)
print('Time distributed output sample')
print(time_dist_layer_output[0])
```

```
Time distributed output shape (1, 12, 6)
Time distributed output sample
[[0.00000000e+00 0.00000000e+00 2.94537116e-02 0.00000000e+00
  0.00000000e+00 8.18665028e-02]
 [0.00000000e+00 1.97241805e-03 2.10141242e-02 2.69282726e-03
  0.00000000e+00 6.13531172e-02]
 [0.00000000e+00 7.52239721e-03 1.43331224e-02 1.05716754e-02
  0.00000000e+00 4.35485244e-02]
 [0.00000000e+00 1.57864634e-02 9.29334480e-03 2.25895494e-02
  0.00000000e+00 2.95862462e-02]
 [0.00000000e+00 2.64813378e-02 5.65298367e-03 3.71751934e-02
  0.00000000e+00 1.88286118e-02]
 [0.00000000e+00 3.90007496e-02 3.17051704e-03 5.16946651e-02
  0.00000000e+00 1.08537497e-02]
 [0.00000000e+00 5.35230786e-02 1.60688115e-03 6.28760457e-02
  0.00000000e+00 5.41194109e-03]
 [0.00000000e+00 6.85746968e-02 7.15526054e-04 6.78812340e-02
  0.00000000e+00 2.16754153e-03]
 [1.45982262e-02 7.98508003e-02 2.71278812e-04 6.48648813e-02
  0.00000000e+00 6.24831708e-04]
 [4.93545271e-02 7.95824453e-02 8.50855504e-05 5.47706857e-02
  0.00000000e+00 1.10372705e-04]
 [1.09804645e-01 7.74990842e-02 2.16115222e-05 4.00958583e-02
  0.00000000e+00 9.49478726e-06]
 [2.04627350e-01 7.55009949e-02 4.42350301e-06 2.44729351e-02
  0.00000000e+00 2.85907845e-07]]
```

16. Defining the encoding model –

    What we want is to encode the whole series into a single value, so we need the output from the layer with a single neuron (In this case it's the third LSTM layer). We will take only the encoding part of the model and define it as a new one.

```
encoder = Model(inputs=encoder_decoder.inputs, outputs=encoder_decoder.layers[2].output)
```

17. Now let's encode the train and validation time series

```
train_encoded = encoder.predict(X_train)
validation_encoded = encoder.predict(X_valid)
print('Encoded time-series shape', train_encoded.shape)
print('Encoded time-series sample', train_encoded[0])
```

```
Encoded time-series shape (200327, 1)
Encoded time-series sample [0.04086111]
```

18. Add new encoded features to the train and validation sets

```
train['encoded'] = train_encoded
train['label'] = Y_train

valid['encoded'] = validation_encoded
valid['label'] = Y_valid

train.head(10)
```

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | encoded | label |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **207604** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.04 | 0 |
| **45150** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.04 | 0 |
| **143433** | 0 | 0 | 4 | 2 | 1 | 2 | 2 | 1 | 0 | 0 | 0 | 1 | 0.65 | 1 |
| **202144** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.04 | 0 |
| **136088** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0.05 | 1 |
| **121675** | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0.10 | 0 |
| **185281** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.04 | 1 |
| **70087** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 1 | 3 | 0.88 | 0 |
| **105249** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.04 | 0 |
| **183257** | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 1 | 0 | 0 | 0 | 1 | 0.45 | 0 |

19. MLP with LSTM encoded feature

    For the MLP model we are only using the current month "item_count" and the encoded time-series feature from our LSTM encoder model, the idea is that we won't need the whole series because we already have a column that represents the whole series into a single value

```python
last_month = serie_size - 1
Y_train_encoded = train['label']
train.drop('label', axis=1, inplace=True)
X_train_encoded = train[[last_month, 'encoded']]

Y_valid_encoded = valid['label']
valid.drop('label', axis=1, inplace=True)
X_valid_encoded = valid[[last_month, 'encoded']]

print("Train set", X_train_encoded.shape)
print("Validation set", X_valid_encoded.shape)
```

```
Train set (200327, 2)
Validation set (22259, 2)
```

```python
X_train_encoded.head()
```

| | 11 | encoded |
|---|---|---|
| **207604** | 0 | 0.04 |
| **45150** | 0 | 0.04 |
| **143433** | 1 | 0.65 |
| **202144** | 0 | 0.04 |
| **136088** | 0 | 0.05 |

```python
mlp_model = Sequential()
mlp_model.add(L.Dense(10, kernel_initializer='glorot_normal', activation='relu', input_dim=X_train_encoded.shape[1]))
mlp_model.add(L.Dense(10, kernel_initializer='glorot_normal', activation='relu'))
mlp_model.add(L.Dense(1))
mlp_model.summary()

adam = optimizers.Adam(lr)
mlp_model.compile(loss='mse', optimizer=adam)
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_5 (Dense)              (None, 10)                30
_________________________________________________________________
dense_6 (Dense)              (None, 10)                110
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 11
=================================================================
Total params: 151
Trainable params: 151
Non-trainable params: 0
_________________________________________________________________
```

```python
mlp_history = mlp_model.fit(X_train_encoded.values, Y_train_encoded.values, epochs=epochs, batch_size=batch, validation_data=(X_valid_encoded, Y_valid_encoded), verbose=2)
```

```
Epoch 1/20
1566/1566 - 2s - loss: 1.3476 - val_loss: 1.2150
Epoch 2/20
1566/1566 - 1s - loss: 1.2412 - val_loss: 1.1982
Epoch 3/20
1566/1566 - 1s - loss: 1.2324 - val_loss: 1.1938
Epoch 4/20
1566/1566 - 1s - loss: 1.2287 - val_loss: 1.1926
Epoch 5/20
1566/1566 - 1s - loss: 1.2263 - val_loss: 1.1912
Epoch 6/20
1566/1566 - 1s - loss: 1.2244 - val_loss: 1.1884
Epoch 7/20
1566/1566 - 1s - loss: 1.2225 - val_loss: 1.1876
Epoch 8/20
1566/1566 - 1s - loss: 1.2210 - val_loss: 1.1873
Epoch 9/20
1566/1566 - 1s - loss: 1.2201 - val_loss: 1.1855
Epoch 10/20
1566/1566 - 1s - loss: 1.2187 - val_loss: 1.1840
Epoch 11/20
1566/1566 - 1s - loss: 1.2176 - val_loss: 1.1844
Epoch 12/20
1566/1566 - 1s - loss: 1.2169 - val_loss: 1.1825
Epoch 13/20
1566/1566 - 1s - loss: 1.2162 - val_loss: 1.1821
Epoch 14/20
1566/1566 - 1s - loss: 1.2153 - val_loss: 1.1816
Epoch 15/20
1566/1566 - 1s - loss: 1.2144 - val_loss: 1.1813
Epoch 16/20
1566/1566 - 1s - loss: 1.2136 - val_loss: 1.1804
Epoch 17/20
1566/1566 - 1s - loss: 1.2130 - val_loss: 1.1809
Epoch 18/20
1566/1566 - 1s - loss: 1.2122 - val_loss: 1.1784
Epoch 19/20
1566/1566 - 1s - loss: 1.2115 - val_loss: 1.1809
Epoch 20/20
1566/1566 - 1s - loss: 1.2110 - val_loss: 1.1769
```

20. Comparing Models

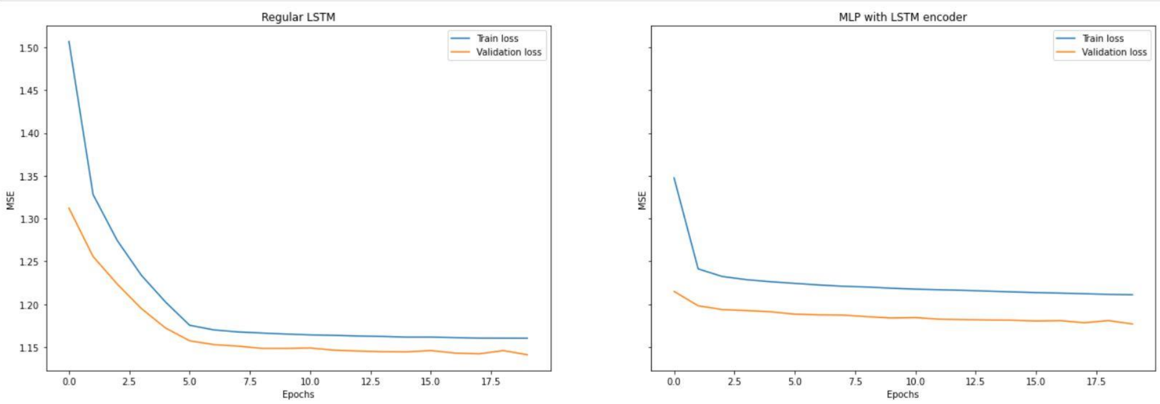
    As you can see, we tried to build both models with a similar topology (type/number of layers and neurons), so it could make more sense to compare them. The results are close, also they may change a bit depending on the random initialization of the networks weights, so we would say they are very similar in terms of performance.

```
fig, (ax1, ax2) = plt.subplots(1, 2, sharey=True,figsize=(22,7))

ax1.plot(lstm_history.history['loss'], label='Train loss')
ax1.plot(lstm_history.history['val_loss'], label='Validation loss')
ax1.legend(loc='best')
ax1.set_title('Regular LSTM')
ax1.set_xlabel('Epochs')
ax1.set_ylabel('MSE')

ax2.plot(mlp_history.history['loss'], label='Train loss')
ax2.plot(mlp_history.history['val_loss'], label='Validation loss')
ax2.legend(loc='best')
ax2.set_title('MLP with LSTM encoder')
ax2.set_xlabel('Epochs')
ax2.set_ylabel('MSE')

plt.show()
```




21. Regular LSTM on train and validation

```
lstm_train_pred = lstm_model.predict(X_train)
lstm_val_pred = lstm_model.predict(X_valid)
print('Train rmse:', np.sqrt(mean_squared_error(Y_train, lstm_train_pred)))
print('Validation rmse:', np.sqrt(mean_squared_error(Y_valid, lstm_val_pred)))
```

```
Train rmse: 1.0764664296356412
Validation rmse: 1.0681904215881908
```

22. MLP with LSTM encoder on train and validation

```
mlp_train_pred2 = mlp_model.predict(X_train_encoded.values)
mlp_val_pred2 = mlp_model.predict(X_valid_encoded.values)
print('Train rmse:', np.sqrt(mean_squared_error(Y_train_encoded, mlp_train_pred2)))
print('Validation rmse:', np.sqrt(mean_squared_error(Y_valid_encoded, mlp_val_pred2)))
```

```
Train rmse: 1.1001068362419109
Validation rmse: 1.0848680365287242
```

23. Build Test Set

```
latest_records = monthly_series.drop_duplicates(subset=['shop_id', 'item_id'])
X_test = pd.merge(test, latest_records, on=['shop_id', 'item_id'], how='left', suffixes=['', '_'])
X_test.fillna(0, inplace=True)
X_test.drop(['ID', 'item_id', 'shop_id'], axis=1, inplace=True)
X_test.head()
```

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 1.00 | 2.00 | 2.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 | 3.00 | 1.00 | 0.00 |
| **1** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 3.00 | 2.00 | 0.00 | 1.00 | 3.00 | 1.00 |
| **3** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 |
| **4** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

24. Regular LSTM model test predictions

For the regular LSTM model, we just need the last 12 months, because that's our series input size.

```
X_test = X_test[[(i + (34 - serie_size)) for i in range(serie_size)]]
X_test.head()
```

| | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1.00 | 2.00 | 2.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 | 3.00 | 1.00 | 0.00 |
| **1** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 3.00 | 2.00 | 0.00 | 1.00 | 3.00 | 1.00 |
| **3** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 |
| **4** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

25. Reshape data [Time-series shape (data points, time-steps, features)]

```
X_test_reshaped = X_test.values.reshape((X_test.shape[0], X_test.shape[1], 1))
print(X_test_reshaped.shape)
```

```
(214200, 12, 1)
```

26. Making predictions

```
lstm_test_pred = lstm_model.predict(X_test_reshaped)
```

27. MLP with LSTM encoded feature test predictions.

For the MLP model with the encoded features we are only using the current month "item_count" and the encoded time-series feature from our LSTM encoder model.

Encoding the time-series

```
test_encoded = encoder.predict(X_test_reshaped)
```

28. Add encoded features to the test set

```
X_test['encoded'] = test_encoded
X_test.head()
```

| | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | encoded |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1.00 | 2.00 | 2.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 | 3.00 | 1.00 | 0.00 | 0.65 |
| **1** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 |
| **2** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 3.00 | 2.00 | 0.00 | 1.00 | 3.00 | 1.00 | 1.06 |
| **3** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.04 |
| **4** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 |

```
X_test_encoded = X_test[[33, 'encoded']]
print("Train set", X_test_encoded.shape)
X_test_encoded.head()
```

```
Train set (214200, 2)
```

| | 33 | encoded |
|---|---|---|
| **0** | 0.00 | 0.65 |
| **1** | 0.00 | 0.04 |
| **2** | 1.00 | 1.06 |
| **3** | 0.00 | 0.04 |
| **4** | 0.00 | 0.04 |

29. Making predictions

```
mlp_test_pred = mlp_model.predict(X_test_encoded)
```

30. Predictions from the regular LSTM model

```
lstm_prediction = pd.DataFrame(test['ID'], columns=['ID'])
lstm_prediction['item_cnt_month'] = lstm_test_pred.clip(0., 20.)
lstm_prediction.to_csv('lstm_submission.csv', index=False)
lstm_prediction.head(10)
```

| | ID | item_cnt_month |
|---|---|---|
| **0** | 0 | 0.55 |
| **1** | 1 | 0.49 |
| **2** | 2 | 0.85 |
| **3** | 3 | 0.17 |
| **4** | 4 | 0.49 |
| **5** | 5 | 0.44 |
| **6** | 6 | 0.98 |
| **7** | 7 | 0.17 |
| **8** | 8 | 1.22 |
| **9** | 9 | 0.49 |

31. Predictions from the MLP model with LSTM encoded feature.

```
mlp_prediction = pd.DataFrame(test['ID'], columns=['ID'])
mlp_prediction['item_cnt_month'] = mlp_test_pred.clip(0., 20.)
mlp_prediction.to_csv('mlp_submission.csv', index=False)
mlp_prediction.head(10)
```

| | ID | item_cnt_month |
|---|---|---|
| 0 | 0 | 0.23 |
| 1 | 1 | 0.39 |
| 2 | 2 | 0.71 |
| 3 | 3 | 0.39 |
| 4 | 4 | 0.39 |
| 5 | 5 | 0.58 |
| 6 | 6 | 0.91 |
| 7 | 7 | 0.21 |
| 8 | 8 | 0.72 |
| 9 | 9 | 0.39 |

## 5. Results

As you can see, we tried to build both models with a similar topology (type/number of layers and neurons), so it could make more sense to compare them. The results are close, also they may change a bit depending on the random initialization of the networks weights, so we would say they are very similar in terms of performance.

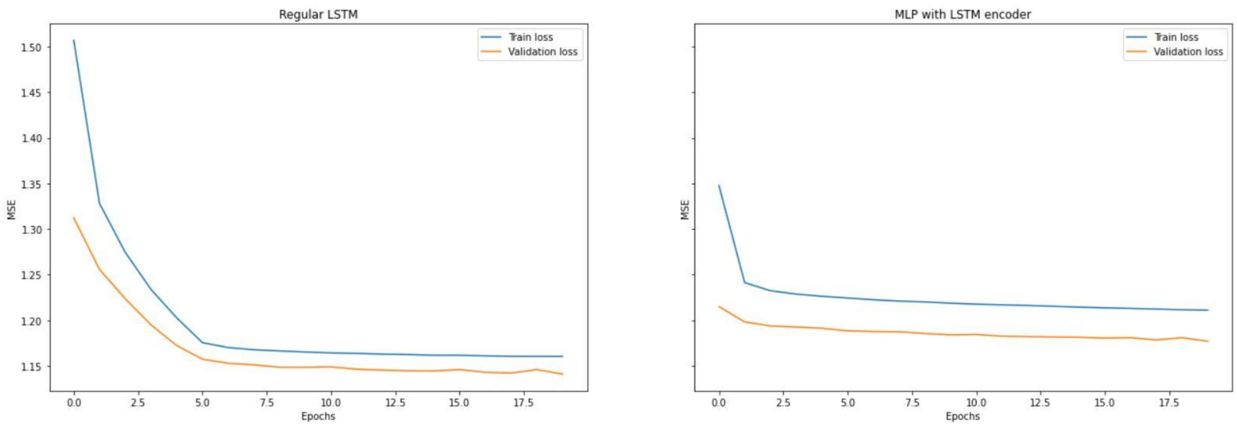
```
fig, (ax1, ax2) = plt.subplots(1, 2, sharey=True,figsize=(22,7))

ax1.plot(lstm_history.history['loss'], label='Train loss')
ax1.plot(lstm_history.history['val_loss'], label='Validation loss')
ax1.legend(loc='best')
ax1.set_title('Regular LSTM')
ax1.set_xlabel('Epochs')
ax1.set_ylabel('MSE')

ax2.plot(mlp_history.history['loss'], label='Train loss')
ax2.plot(mlp_history.history['val_loss'], label='Validation loss')
ax2.legend(loc='best')
ax2.set_title('MLP with LSTM encoder')
ax2.set_xlabel('Epochs')
ax2.set_ylabel('MSE')

plt.show()
```

The best algorithm is Multiplayer perception Model or MLP model for Time series forecasting because the minimum validation rmse in this model.



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