CNIT484 - Transformer Team Project

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Project Introduction

For our final data science project, our group decided to focus on the applications of machine learning and large language models in the finance field. We wanted to focus our efforts on using these models to gain insights from pre-existing investment data that could be used by someone aiming to gain knowledge about the stock market, or even as a tool that could help smart investing. Machine learning models can be a useful way of automating data science techniques, especially when using datasets that contain thousands or even hundreds of thousands of rows. Our project is a case study of how such models could be used in future applications of data in a number of fields, not just limited to finance. Of course, our model is less developed and technical than one such as ChatGPT or other large language models, but, in theory, further development and continuation of the project could see similar results at a higher success level.

Our creative process for the project began with the selection of a dataset. We chose a Yahoo Finance dataset containing information about mutual funds and ETFs in the United States. Containing over 25,000 rows of data, each instance of data contained the name, date, and opening, high, low, and closing data for each ETF or mutual fund. We chose this dataset because of its detailed contents as well as monitoring of the same funds over time, which in theory would help our model identify patterns with regard to market success and chronological time. Following the identification of the dataset, the data was prepared and loaded into our transformer-based model. The model was then instantiated and ran, the results of which were evaluated through the use of a loss function. The full code as well as a breakdown of each of its parts is detailed below.

Data Selection and Preparation

Data Selection

The initial dataset comprised ETF (Exchange-Traded Fund) prices obtained from Kaggle, ensuring a rich dataset amenable to time-series analysis and forecasting.

Data Preparation

The data preparation phase involved several steps to refine and transform the raw data into a structured format suitable for input into our Transformer-based model. These steps were as follows:

- Data Importing and Initial Assessment:

  The ETF prices were imported into a pandas DataFrame. An initial assessment of the dataset was conducted to understand the data types and identify any immediate cleaning requirements.

- Column Renaming and Type Conversion:

  The columns were renamed for consistency and ease of understanding ("fund_symbol" to "fund", "price_date" to "date", and "adj_close" to "adjClose").

  The date column was converted to datetime objects to facilitate time-series manipulation.

```
[1] %autosave 60
    import pandas as pd

    Autosaving every 60 seconds

    df = pd.read_csv("ETF prices.csv")

[3] # show column names
    df.columns

    Index(['fund_symbol', 'price_date', 'open', 'high', 'low', 'close',
           'adj_close', 'volume'],
          dtype='object')

[4] # convert date
    df['price_date'] = pd.to_datetime(df['price_date'])

[5] # change column name
    df = df.rename(columns = {"fund_symbol": "fund", "price_date": "date", "adj_close": "adjClose"})

    # Convert numeric columns to float (if necessary)
    numeric_cols = df.select_dtypes(include=['number']).columns

    # Round numeric columns to two decimals
    df[numeric_cols] = df[numeric_cols].round(2)

[6] # show column types
    df.dtypes

    fund                object
    date        datetime64[ns]
    open               float64
    high               float64
    low                float64
    close              float64
    adjClose           float64
    volume               int64
    dtype: object
```

Figure 1: Read file and converted column types

- Rounding Numeric Values:

  All numeric columns were rounded to two decimal places to maintain consistency and avoid any potential floating-point arithmetic issues during calculations.

- Data Filtering:

  The dataset was filtered to focus on specific ETFs of interest, identified as 'AAA' and 'SPY'. This was done to narrow down the analysis to relevant subsets of the data.

```
[8] dfTest = df.copy()
    df = df[df['fund'] == 'AAA'][['open', 'high', 'low', 'close', 'adjClose']]
    dfTest = dfTest[dfTest['fund'] == 'SPY'][['open', 'high', 'low', 'close', 'adjClose']]
```

```
print(df)
print(dfTest)
```

```
      open   high    low  close  adjClose
0    25.10  25.12  25.07  25.07     24.85
1    25.06  25.07  25.05  25.07     24.85
2    25.04  25.05  25.02  25.03     24.81
3    25.01  25.06  25.01  25.02     24.80
4    25.02  25.03  25.01  25.01     24.79
..     ...    ...    ...    ...       ...
305  25.04  25.04  25.02  25.03     25.03
306  25.03  25.04  25.02  25.02     25.02
307  25.04  25.04  25.02  25.02     25.02
308  25.02  25.03  25.02  25.03     25.03
309  25.04  25.04  25.04  25.04     25.04

[310 rows x 5 columns]
           open    high     low   close  adjClose
3262244   43.97   43.97   43.75   43.94     25.80
3262245   43.97   44.25   43.97   44.25     25.98
3262246   44.22   44.38   44.12   44.34     26.04
3262247   44.41   44.84   44.38   44.81     26.31
3262248   44.97   45.09   44.47   45.00     26.42
...         ...     ...     ...     ...       ...
3269502  467.22  469.10  464.45  468.19    468.19
3269503  466.06  469.57  465.19  469.44    469.44
3269504  462.34  463.90  457.77  458.97    458.97
3269505  464.07  466.56  461.73  464.60    464.60
3269506  462.00  464.03  455.30  455.56    455.56

[7263 rows x 5 columns]
```

Figure 2: Created test data frame and filtered rows

- Feature Engineering:

  A new feature, mean, was calculated as the mean of selected numeric columns (open, high, low, close, and adjClose) to condense the dataset and provide a singular feature representing average daily price.

- Data Structure Modification:

  The DataFrame was then restructured to include only the mean column, reflecting the new feature created for the analysis.

Data Integration: For the Transformer model to comprehend and process the data effectively, integration of the feature set was paramount. The following actions were implemented:

- Conversion to Float:

Numeric data was converted to float type to ensure compatibility with the PyTorch tensor operations used within the model.

- Dataset Copying for Testing:

  A copy of the dataset was created for testing purposes to validate the model's performance on unseen data.

```
[10] df['mean'] = df.mean(axis=1)
     df = df[['mean']]

     dfTest['mean'] = dfTest.mean(axis=1)
     dfTest = dfTest[['mean']]
```

```
[11] print(df)
     print(dfTest)
```

```
           mean
     0    25.042
     1    25.020
     2    24.990
     3    24.980
     4    24.972
     ..      ...
     305  25.032
     306  25.026
     307  25.028
     308  25.026
     309  25.040

     [310 rows x 1 columns]
                 mean
     3262244   40.286
     3262245   40.484
     3262246   40.620
     3262247   40.950
     3262248   41.190
     ...          ...
     3269502  467.430
     3269503  467.940
     3269504  460.390
     3269505  464.312
     3269506  458.490

     [7263 rows x 1 columns]
```

Figure 3: Calculated row average and printed results

Model Selection and Creation

```python
import torch
import torch.nn as nn
import torch.nn.init as init
import math
import torch.optim as optim
import matplotlib.pyplot as plt
from torchtext import data
```

Figure 4: Imported libraries

Selection Rationale

For this project, we aimed to develop a robust model capable of handling sequence data, emphasizing learning long-range dependencies within our dataset of ETF prices. Given the sequential nature of financial time series data, where past events can influence future trends, a model that effectively captures such dependencies is crucial.

The transformer model, introduced in "Attention is All You Need" by Vaswani et al., revolutionized sequence modeling through self-attention mechanisms. This architecture allows for parallel processing of sequences and focuses on the most relevant parts of the input data, making it highly suitable for our time series forecasting task. Unlike recurrent neural networks (RNNs) and their variants (LSTM and GRU), transformers do not process data sequentially, eliminating potential bottlenecks and enabling more efficient training on large datasets.

Model Architecture

Our transformer model is structured as follows:

Transformer Encoder Layers: We utilized a series of transformer encoder layers, which are the building blocks of the model. Each encoder layer comprises two sub-layers: a multi-head self-attention mechanism and a position-wise fully connected feed-forward network. Layer normalization and dropout are also employed within each sub-layer to enhance training stability and prevent overfitting.

```python
# Defined transformer model
# ======================================================================
class TransformerModel(nn.Module):
    def __init__(self, input_dim, d_model, nhead, num_encoder_layers, dropout=0.1):
        super(TransformerModel, self).__init__()
        self.encoder_layer = nn.TransformerEncoderLayer(d_model=d_model, nhead=nhead, dropout=dropout)
        self.transformer_encoder = nn.TransformerEncoder(self.encoder_layer, num_layers=num_encoder_layers)
        self.transformer_encoder.embed_dim = d_model  # Set the embed_dim attribute
        self.fc = nn.Linear(d_model, 1)  # Adjusted linear layer input dimension

    def forward(self, src, src_mask=None):
        src = self.transformer_encoder(src, src_mask)
        src = src.mean(dim=1)  # Aggregate sequence to a single vector along the sequence dimension
        src = self.fc(src)
        return src.squeeze(-1)  # Squeeze to remove the extra dimension
```

Figure 5: Defined the transformer model

Positional Encoding: Since the transformer lacks any recurrence mechanisms, positional encodings are added to the input embeddings at the bottom of the encoder stack to inject some information about the relative or absolute position of the tokens in the sequence.

Linear Transformation: The output of the transformer encoder is passed through a linear layer, which projects the d-dimensional encoder output to a scalar value representing the predicted price, ensuring our model's output matches our target variable's nature.

Initialization and Regularization: Weights of the model are initialized using Xavier uniform initialization, which is a common practice for deep learning models to help in converging faster and more effectively during training. Regularization techniques like dropout are used to prevent the model from overfitting on the training data.

```python
# Initialized weights, implemented positional encoding, and incorporated masking
# ==================================================================================
class TransformerEncoderLayer(nn.Module):
    def __init__(self, d_model, nhead, dim_feedforward=2048, dropout=0.1):
        super(TransformerEncoderLayer, self).__init__()
        self.self_attn = nn.MultiheadAttention(d_model, nhead)
        self.linear1 = nn.Linear(d_model, dim_feedforward)
        self.dropout = nn.Dropout(dropout)
        self.linear2 = nn.Linear(dim_feedforward, d_model)
        self.norm1 = nn.LayerNorm(d_model)
        self.norm2 = nn.LayerNorm(d_model)
        self.dropout1 = nn.Dropout(dropout)
        self.dropout2 = nn.Dropout(dropout)

    def forward(self, src, src_mask=None):
        src2 = self.self_attn(src, src, src, attn_mask=src_mask)[0]
        src = src + self.dropout1(src2)
        src = self.norm1(src)
        src2 = self.linear2(self.dropout(F.relu(self.linear1(src))))
        src = src + self.dropout2(src2)
        src = self.norm2(src)
        return src

class PositionalEncoding(nn.Module):
    def __init__(self, d_model, max_len=5000):
        super(PositionalEncoding, self).__init__()
        self.dropout = nn.Dropout(p=0.1)

        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len, dtype=torch.float).unsqueeze(1)
        div_term = torch.exp(torch.arange(0, d_model, 2).float() * (-math.log(10000.0) / d_model))
        pe[:, 0::2] = torch.sin(position * div_term)
        pe[:, 1::2] = torch.cos(position * div_term)
        pe = pe.unsqueeze(0).transpose(0, 1)
        self.register_buffer('pe', pe)

    def forward(self, x):
        x = x + self.pe[:x.size(0), :]
        return self.dropout(x)

def init_weights(module):
    if isinstance(module, (nn.Linear, nn.Conv2d)):
        init.xavier_uniform_(module.weight.data)
        if module.bias is not None:
            module.bias.data.fill_(0.01)
```

Figure 6: Initialized weights, implemented positional encoding, and incorporated masking

```python
# Ran the model
# ======================================================================
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)
num_epochs = 20 # Number of training epochs

# training the model
# ===================
print("\nTraining the model...")
for epoch in range(num_epochs):
    model.train()
    running_loss = 0.0

    for batch in train_iterator:
        optimizer.zero_grad()
        input_sequence = batch.text.float()  # Convert input data to float type if needed
        target_sequence = batch.label.float()  # Convert target data to float type if needed

        output = model(input_sequence)
        loss = criterion(output, target_sequence)
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    avg_loss = running_loss / len(train_iterator)
    epochs.append(epoch+1)
    avg_losses.append(avg_loss)
    print(f'Epoch [{epoch+1}/{num_epochs}], Avg Loss: {avg_loss:.4f}')

print('Finished Training\n')
```

Figure 7: Ran the model

```python
# Tokenize data, built vocabulary, created batches, and created input and target sequences.
# ==========================================================================================
epochs = []
avg_losses = []

TEXT = data.Field(tokenize=lambda x: x, use_vocab=True, batch_first=True)
LABEL = data.Field(sequential=False, use_vocab=False, dtype=torch.float)

class CustomDataset(data.Dataset):
    def __init__(self, df, text_field, label_field):
        fields = [('text', text_field), ('label', label_field)]
        examples = []
        for i, row in df.iterrows():
            text = [str(val) for val in row.values]
            label = row['mean']
            examples.append(data.Example.fromlist([text, label], fields))
        super().__init__(examples, fields)

train_data = CustomDataset(df, TEXT, LABEL) # Create dataset instances
test_data = CustomDataset(df, TEXT, LABEL)

TEXT.build_vocab(train_data)  # Build vocabulary

BATCH_SIZE = 1
train_iterator, test_iterator = data.BucketIterator.splits(
    (train_data, test_data),
    batch_size=BATCH_SIZE,
    sort_key=lambda x: len(x.text),
    shuffle=True
)

for batch in train_iterator:
    input_sequence = batch.text  # Input sequence tensor
    target_sequence = batch.label  # Target sequence tensor
```

Figure 8: Tokenized data, built vocabulary, created batches, and created input and target

Implementation Details

The transformer model was implemented using PyTorch's neural network module (torch.nn).

The key parameters for our model were:

- **Input dimension (input_dim):** Set to 1, as the input feature is the average price.
- **Model dimension (d_model):** Also set to 1, matching our input dimension, which simplifies the architecture while focusing on learning the crucial temporal relationships.
- **The number of heads (nhead):** Set to 1 due to the single-dimensional nature of our input and model dimensions.
- **Number of encoder layers (num_encoder_layers):** Chosen as 3 to allow the model to learn complex patterns without becoming overly complex, which could lead to overfitting given our dataset's size.
- **Dropout rate (dropout):** Configured at 0.1 to moderate the effect of dropout regularization, balancing between model complexity and training speed.

```
# Initated an instance of the model
# ======================================================================
input_dim = 1  # Dimension of input features (mean)
d_model = 1  # Hidden dimension of the transformer model
nhead = 1  # Number of attention heads
num_encoder_layers = 3  # Number of transformer encoder layers
dropout = 0.1  # Dropout rate for transformer layers
max_len = 10000  # Adjust based on the maximum sequence length in your data

model = TransformerModel(input_dim, d_model, nhead, num_encoder_layers, dropout)
model.apply(init_weights)

encoder_layer = TransformerEncoderLayer(d_model, nhead)
positional_encoder = PositionalEncoding(d_model, max_len)
model.encoder = nn.Sequential(encoder_layer, positional_encoder)
```

Figure 9: Instantiated the model

This configuration establishes a lightweight yet powerful model suited for our predictive task, ensuring efficient training and inference, and robustness to overfitting, given the limited size of the ETF dataset.

```
Training the model...
Epoch [1/20], Avg Loss: 602.0486
Epoch [2/20], Avg Loss: 545.5426
Epoch [3/20], Avg Loss: 476.1661
Epoch [4/20], Avg Loss: 399.3801
Epoch [5/20], Avg Loss: 320.9098
Epoch [6/20], Avg Loss: 245.9135
Epoch [7/20], Avg Loss: 178.5441
Epoch [8/20], Avg Loss: 121.7028
Epoch [9/20], Avg Loss: 76.9305
Epoch [10/20], Avg Loss: 44.3781
Epoch [11/20], Avg Loss: 22.8910
Epoch [12/20], Avg Loss: 10.3019
Epoch [13/20], Avg Loss: 3.9337
Epoch [14/20], Avg Loss: 1.2368
Epoch [15/20], Avg Loss: 0.3114
Epoch [16/20], Avg Loss: 0.0626
Epoch [17/20], Avg Loss: 0.0119
Epoch [18/20], Avg Loss: 0.0043
Epoch [19/20], Avg Loss: 0.0034
Epoch [20/20], Avg Loss: 0.0034
Finished Training
```

Figure 10: Epoch training results

Model Testing and Evaluation

To begin with, the evaluation of a model's performance is key in efforts to further comprehend the performance levels. Within this project, we delved into the change of behavior in the training loss along with epochs. The analysis permitted a profound evolution of the model performance over time.

```python
# Plotting
plt.plot(epochs, avg_losses, label='Average Loss')
plt.xlabel('Epoch')
plt.ylabel('Average Loss')
plt.title('Training Loss')
plt.legend()
plt.show()
```

Figure 11: Plotted testing results in

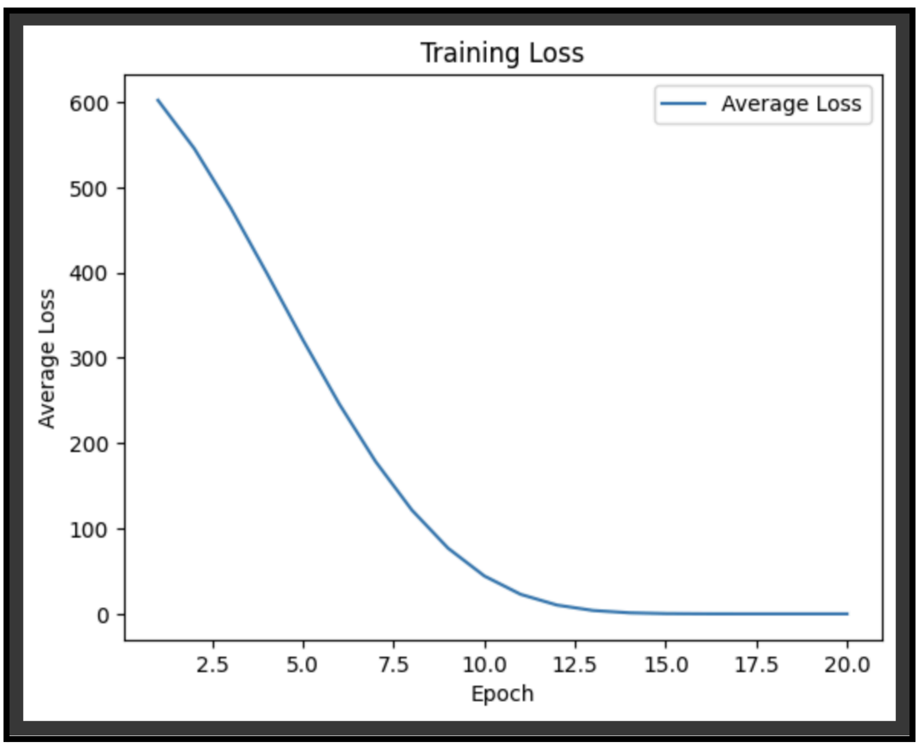


Figure 12: Training plot

Training Loss Evolution: Firstly, the model was plotted under the name of "Training Loss" in which the epochs were gauges based upon the average loss. As presented in Figure 12, during the early stages of training, the model exhibited an average loss of 600.

- This appears to be the highest average loss throughout the entire testing evolution portraying the fact that the model was struggling to capture the underlying patterns within the training data. However, as training progressed, a significant transition occurred as shown in the Figure.
- The training loss steadily decreased, reaching a range between 0-100 by the 20th epoch. Overall, this dramatic reduction in the training loss suggests that the model gradually improved its ability to minimize errors and better fit the training data.

```
# Evaluate the model on the test set
# ====================================================================
test_data = CustomDataset(dfTest, TEXT, LABEL)
test_iterator = data.BucketIterator(test_data, batch_size=BATCH_SIZE, shuffle=False)


# Evaluate on test data
model.eval()
total_loss = 0.0
predictions = []
ground_truths = []

with torch.no_grad():
  for batch in test_iterator:
    input_sequence = batch.text.float()
    target_sequence = batch.label.float()

    output = model(input_sequence)
    loss = criterion(output, target_sequence)
    total_loss += loss.item()

    predictions.append(output.squeeze(0).tolist())  # Collect predictions
    ground_truths.extend(target_sequence.tolist())  # Collect ground truth values
```

Figure 13: Ran model on the test dataset

Epoch Progression:

- To evaluate the model, the training loss must be acquired to analyze the progression of the epochs. Though the model required approximately 2.5 epochs towards the beginning, it learned to stabilize and exhibit discernible learning patterns displaying a notable shift across the epochs.
- By the 10th-12th epoch, the model's performance had stabilized, indicating that it had converged to a state where further training yielded minimal improvements. This convergence suggests that the model had reached a point of optimization, where additional epochs would not significantly enhance its performance on the training data.

Model Testing:

- Hence with the training being complete, the model was tested on a separate dataset to assess its generalization capabilities.

```
avg_test_loss = total_loss / len(test_iterator)
print(f'\nTest Loss: {avg_test_loss:.4f}')
```

Figure 14: Calculated testing loss

```
Test Loss: 22509.3808
```

Figure 15: Testing loss results

- The test results revealed a test loss of 22509.3808, indicating that the model's performance on unseen data was not as optimal as expected. This discrepancy between training and testing performance underscores the importance of evaluating models on datasets.

References

Model was built with the help of ChatGPT

Leone, S. (2021, December 11). *US funds dataset from Yahoo Finance*. Kaggle. https://www.kaggle.com/datasets/stefanoleone992/mutual-funds-and-etfs/data

Lstm_vs_transformer/lstm_vs__transformer.ipynb at main · maym5/LSTM_VS_TRANSFORMER. GitHub. (n.d.). https://github.com/maym5/lstm_vs_transformer/blob/main/lstm_vs__transformer.ipynb

May, M. (2023, June 24). *Transformers vs. LSTM for stock price time series prediction*. Medium. https://medium.com/@mskmay66/transformers-vs-lstm-for-stock-price-time-series-prediction-3a26fcc1a782

```
!pip install torchtext==0.6.0
```

Prepare ETF data for transformer

```
%autosave 60
import pandas as pd
```

```
Autosaving every 60 seconds
```

```
df = pd.read_csv("ETF prices.csv")
```

```
# show column names
df.columns
```

```
Index(['fund_symbol', 'price_date', 'open', 'high', 'low', 'close',
       'adj_close', 'volume'],
      dtype='object')
```

```
# convert date
df['price_date'] = pd.to_datetime(df['price_date'])
```

```
# change column name
df = df.rename(columns = {"fund_symbol": "fund", "price_date": "date", "adj_close": "adjClose"})

# Convert numeric columns to float (if necessary)
numeric_cols = df.select_dtypes(include=['number']).columns

# Round numeric columns to two decimals
df[numeric_cols] = df[numeric_cols].round(2)
```

```
# show column types
df.dtypes
```

```
fund                object
date        datetime64[ns]
open               float64
high               float64
low                float64
close              float64
adjClose           float64
volume               int64
dtype: object
```

```
print(df)
```

```
        fund       date   open   high    low  close  adjClose  volume
0        AAA 2020-09-09  25.10  25.12  25.07  25.07     24.85   17300
1        AAA 2020-09-10  25.06  25.07  25.05  25.07     24.85   23500
2        AAA 2020-09-11  25.04  25.05  25.02  25.03     24.81   33400
3        AAA 2020-09-14  25.01  25.06  25.01  25.02     24.80   13100
4        AAA 2020-09-15  25.02  25.03  25.01  25.01     24.79   12100
...      ...        ...    ...    ...    ...    ...       ...     ...
3866025  ZSL 2021-11-23  26.81  27.21  26.30  26.35     26.35  190900
3866026  ZSL 2021-11-24  26.79  26.96  26.57  26.69     26.69  109000
3866027  ZSL 2021-11-26  26.67  28.14  26.67  27.72     27.72  205500
3866028  ZSL 2021-11-29  27.89  28.56  27.80  28.27     28.27  411900
3866029  ZSL 2021-11-30  28.15  28.73  25.91  28.49     28.49  219400

[3866030 rows x 8 columns]
```

```
dfTest = df.copy()
df = df[df['fund'] == 'AAA'][['open', 'high', 'low', 'close', 'adjClose']]
dfTest = dfTest[dfTest['fund'] == 'SPY'][['open', 'high', 'low', 'close', 'adjClose']]
```

```
print(df)
print(dfTest)
```

```
    open   high    low  close  adjClose
0  25.10  25.12  25.07  25.07     24.85
1  25.06  25.07  25.05  25.07     24.85
2  25.04  25.05  25.02  25.03     24.81
```

```
3    25.01  25.06  25.01  25.02     24.80
4    25.02  25.03  25.01  25.01     24.79
..     ...    ...    ...    ...       ...
305  25.04  25.04  25.02  25.03     25.03
306  25.03  25.04  25.02  25.02     25.02
307  25.04  25.04  25.02  25.02     25.02
308  25.02  25.03  25.02  25.03     25.03
309  25.04  25.04  25.04  25.04     25.04

[310 rows x 5 columns]
           open    high     low   close  adjClose
3262244   43.97   43.97   43.75   43.94     25.80
3262245   43.97   44.25   43.97   44.25     25.98
3262246   44.22   44.38   44.12   44.34     26.04
3262247   44.41   44.84   44.38   44.81     26.31
3262248   44.97   45.09   44.47   45.00     26.42
...         ...     ...     ...     ...       ...
3269502  467.22  469.10  464.45  468.19    468.19
3269503  466.06  469.57  465.19  469.44    469.44
3269504  462.34  463.90  457.77  458.97    458.97
3269505  464.07  466.56  461.73  464.60    464.60
3269506  462.00  464.03  455.30  455.56    455.56

[7263 rows x 5 columns]
```

```
df['mean'] = df.mean(axis=1)
df = df[['mean']]

dfTest['mean'] = dfTest.mean(axis=1)
dfTest = dfTest[['mean']]


print(df)
print(dfTest)
```

```
       mean
0    25.042
1    25.020
2    24.990
3    24.980
4    24.972
..      ...
305  25.032
306  25.026
307  25.028
308  25.026
309  25.040

[310 rows x 1 columns]
            mean
3262244   40.286
3262245   40.484
3262246   40.620
3262247   40.950
3262248   41.190
...          ...
3269502  467.430
3269503  467.940
3269504  460.390
3269505  464.312
3269506  458.490

[7263 rows x 1 columns]
```

```
import torch
import torch.nn as nn
import torch.nn.init as init
import math
import torch.optim as optim
import matplotlib.pyplot as plt
from torchtext import data
```

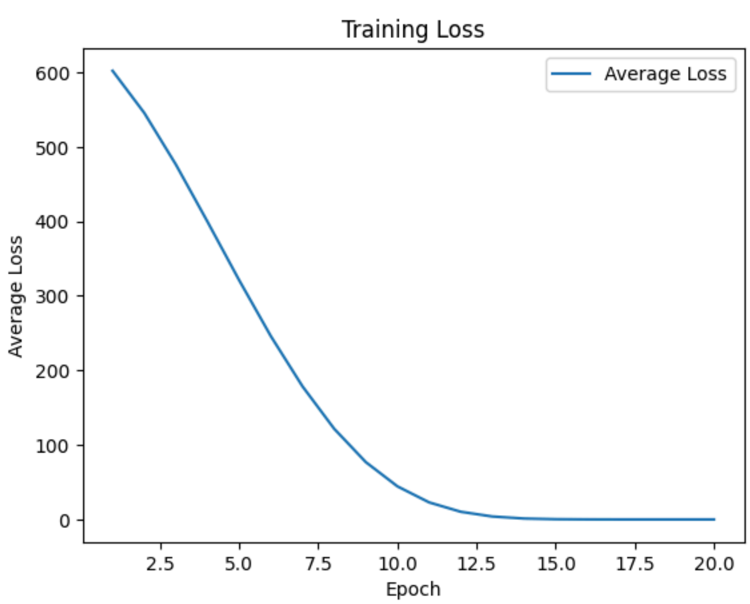
```
# Defined transformer model
# ======================================================================
class TransformerModel(nn.Module):
    def __init__(self, input_dim, d_model, nhead, num_encoder_layers, dropout=0.1):
        super(TransformerModel, self).__init__()
        self.encoder_layer = nn.TransformerEncoderLayer(d_model=d_model, nhead=nhead, dropout=dropout)
        self.transformer_encoder = nn.TransformerEncoder(self.encoder_layer, num_layers=num_encoder_layers)
        self.transformer_encoder.embed_dim = d_model  # Set the embed_dim attribute
```

```
        self.fc = nn.Linear(d_model, 1)  # Adjusted linear layer input dimension

    def forward(self, src, src_mask=None):
        src = self.transformer_encoder(src, src_mask)
        src = src.mean(dim=1)  # Aggregate sequence to a single vector along the sequence dimension
        src = self.fc(src)
        return src.squeeze(-1)  # Squeeze to remove the extra dimension


# Initialized weights, implemented positional encoding, and incorporated masking
# ==================================================================================
class TransformerEncoderLayer(nn.Module):
    def __init__(self, d_model, nhead, dim_feedforward=2048, dropout=0.1):
        super(TransformerEncoderLayer, self).__init__()
        self.self_attn = nn.MultiheadAttention(d_model, nhead)
        self.linear1 = nn.Linear(d_model, dim_feedforward)
        self.dropout = nn.Dropout(dropout)
        self.linear2 = nn.Linear(dim_feedforward, d_model)
        self.norm1 = nn.LayerNorm(d_model)
        self.norm2 = nn.LayerNorm(d_model)
        self.dropout1 = nn.Dropout(dropout)
        self.dropout2 = nn.Dropout(dropout)

    def forward(self, src, src_mask=None):
        src2 = self.self_attn(src, src, src, attn_mask=src_mask)[0]
        src = src + self.dropout1(src2)
        src = self.norm1(src)
        src2 = self.linear2(self.dropout(F.relu(self.linear1(src))))
        src = src + self.dropout2(src2)
        src = self.norm2(src)
        return src

class PositionalEncoding(nn.Module):
    def __init__(self, d_model, max_len=5000):
        super(PositionalEncoding, self).__init__()
        self.dropout = nn.Dropout(p=0.1)

        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len, dtype=torch.float).unsqueeze(1)
        div_term = torch.exp(torch.arange(0, d_model, 2).float() * (-math.log(10000.0) / d_model))
        pe[:, 0::2] = torch.sin(position * div_term)
        pe[:, 1::2] = torch.cos(position * div_term)
        pe = pe.unsqueeze(0).transpose(0, 1)
        self.register_buffer('pe', pe)

    def forward(self, x):
        x = x + self.pe[:x.size(0), :]
        return self.dropout(x)

def init_weights(module):
    if isinstance(module, (nn.Linear, nn.Conv2d)):
        init.xavier_uniform_(module.weight.data)
        if module.bias is not None:
            module.bias.data.fill_(0.01)


# Tokenize data, built vocabulary, created batches, and created input and target sequences.
# ==========================================================================================
epochs = []
avg_losses = []

TEXT = data.Field(tokenize=lambda x: x, use_vocab=True, batch_first=True)
LABEL = data.Field(sequential=False, use_vocab=False, dtype=torch.float)

class CustomDataset(data.Dataset):
    def __init__(self, df, text_field, label_field):
        fields = [('text', text_field), ('label', label_field)]
        examples = []
        for i, row in df.iterrows():
            text = [str(val) for val in row.values]
            label = row['mean']
            examples.append(data.Example.fromlist([text, label], fields))
        super().__init__(examples, fields)

train_data = CustomDataset(df, TEXT, LABEL) # Create dataset instances
test_data = CustomDataset(df, TEXT, LABEL)

TEXT.build_vocab(train_data)  # Build vocabulary
```

```
TEXT.build_vocab(train_data)  # Build vocabulary

BATCH_SIZE = 1
train_iterator, test_iterator = data.BucketIterator.splits(
    (train_data, test_data),
    batch_size=BATCH_SIZE,
    sort_key=lambda x: len(x.text),
    shuffle=True
)

for batch in train_iterator:
    input_sequence = batch.text  # Input sequence tensor
    target_sequence = batch.label  # Target sequence tensor


# Initated an instance of the model
# ======================================================================
input_dim = 1  # Dimension of input features (mean)
d_model = 1  # Hidden dimension of the transformer model
nhead = 1  # Number of attention heads
num_encoder_layers = 3  # Number of transformer encoder layers
dropout = 0.1  # Dropout rate for transformer layers
max_len = 10000  # Adjust based on the maximum sequence length in your data

model = TransformerModel(input_dim, d_model, nhead, num_encoder_layers, dropout)
model.apply(init_weights)

encoder_layer = TransformerEncoderLayer(d_model, nhead)
positional_encoder = PositionalEncoding(d_model, max_len)
model.encoder = nn.Sequential(encoder_layer, positional_encoder)


# Ran the model
# ======================================================================
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)
num_epochs = 20 # Number of training epochs

# training the model
# ===================
print("\nTraining the model...")
for epoch in range(num_epochs):
    model.train()
    running_loss = 0.0

    for batch in train_iterator:
        optimizer.zero_grad()
        input_sequence = batch.text.float()  # Convert input data to float type if needed
        target_sequence = batch.label.float()  # Convert target data to float type if needed

        output = model(input_sequence)
        loss = criterion(output, target_sequence)
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    avg_loss = running_loss / len(train_iterator)
    epochs.append(epoch+1)
    avg_losses.append(avg_loss)
    print(f'Epoch [{epoch+1}/{num_epochs}], Avg Loss: {avg_loss:.4f}')

print('Finished Training\n')

# Plotting
plt.plot(epochs, avg_losses, label='Average Loss')
plt.xlabel('Epoch')
plt.ylabel('Average Loss')
plt.title('Training Loss')
plt.legend()
plt.show()


# Evaluate the model on the test set
# =====================================================================
test_data = CustomDataset(dfTest, TEXT, LABEL)
test_iterator = data.BucketIterator(test_data, batch_size=BATCH_SIZE, shuffle=False)
```

```
# Evaluate on test data
model.eval()
total_loss = 0.0
predictions = []
ground_truths = []

with torch.no_grad():
  for batch in test_iterator:
    input_sequence = batch.text.float()
    target_sequence = batch.label.float()

    output = model(input_sequence)
    loss = criterion(output, target_sequence)
    total_loss += loss.item()

    predictions.append(output.squeeze(0).tolist())  # Collect predictions
    ground_truths.extend(target_sequence.tolist())  # Collect ground truth values

avg_test_loss = total_loss / len(test_iterator)
print(f'\nTest Loss: {avg_test_loss:.4f}')
```

```
/usr/local/lib/python3.10/dist-packages/torch/nn/modules/transformer.py:286: UserWarning: enable_nested_tensor is True, but
  warnings.warn(f"enable_nested_tensor is True, but self.use_nested_tensor is False because {why_not_sparsity_fast_path}")
/usr/local/lib/python3.10/dist-packages/torch/nn/modules/loss.py:535: UserWarning: Using a target size (torch.Size([1])) tha
  return F.mse_loss(input, target, reduction=self.reduction)

Training the model...
Epoch [1/20], Avg Loss: 602.0486
Epoch [2/20], Avg Loss: 545.5426
Epoch [3/20], Avg Loss: 476.1661
Epoch [4/20], Avg Loss: 399.3801
Epoch [5/20], Avg Loss: 320.9098
Epoch [6/20], Avg Loss: 245.9135
Epoch [7/20], Avg Loss: 178.5441
Epoch [8/20], Avg Loss: 121.7028
Epoch [9/20], Avg Loss: 76.9305
Epoch [10/20], Avg Loss: 44.3781
Epoch [11/20], Avg Loss: 22.8910
Epoch [12/20], Avg Loss: 10.3019
Epoch [13/20], Avg Loss: 3.9337
Epoch [14/20], Avg Loss: 1.2368
Epoch [15/20], Avg Loss: 0.3114
Epoch [16/20], Avg Loss: 0.0626
Epoch [17/20], Avg Loss: 0.0119
Epoch [18/20], Avg Loss: 0.0043
Epoch [19/20], Avg Loss: 0.0034
Epoch [20/20], Avg Loss: 0.0034
Finished Training
```




```
Test Loss: 22509.3808
```