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DL-Ops

Assignment 2- RNN, LSTM

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Problem Statement:

Question 1:

You have been provided a DATASET, which contains pairs of the words (x,y) i.e. akhbaar अख़बार in which the first word is a Latin word(words we usually type while chatting with friends in WhatsApp) and the second word is its corresponding word in native script. Your main goal is to train a seq2seq model which takes as input the romanized string and produces the corresponding word in native script.
For Example, Jabki yah Jainon se km hai. ⇒ जबकि यह जनै ो ं सेकम है। [75]

a) Build a seq2seq model which contains the following layers - [20]
(i) input layer for character embeddings
(ii) one encoder which sequentially encodes the input character sequence (Latin)
(iii) one decoder which takes the last state of the encoder as an input and produces one character output at a time (native).
Please note that the dimension of input character embeddings, the hidden state of encoders and decoders, the cell(RNN and LSTM), and the number of layers in the encoder and decoder should be passed as an argument.
(Note:- For Reference you may refer to this Blog, but the implementation must be in PyTorch only.)
b) Now train your model using the standard train, test, and val data provided in the dataset. Try below mentioned hyperparameters and draw the correlation table along with the plot (loss/accuracy VS. hyperparameter) for both RNN and LSTM. [20]
(i) Input embedding size: 16, 64
(ii) number of encoder layers: 1,3
(iii) number of decoder layers: 1,3
(iv) hidden layer size: 16,64
c) Based on the above parts please try to answer the following- [10]
(i) Does RNN takes less time to converge than LSTM? Reason to support your answer.
(ii) Does dropout leads to better performance? Proof to support your answer.
(iii) Using a smaller size in hidden layer does not give good results? Proof to support your answer.
d) Now add an attention network to your LSTM seq2seq model and train your model along with the hyperparameter tuning. (you can use single or multiple attention layers) [25]
(i) Plot the accuracy/loss.
(ii) Report the test accuracy.
(iii) Does the attention-based model performs better than the LSTM? Proof to support your answer.

Question 2:

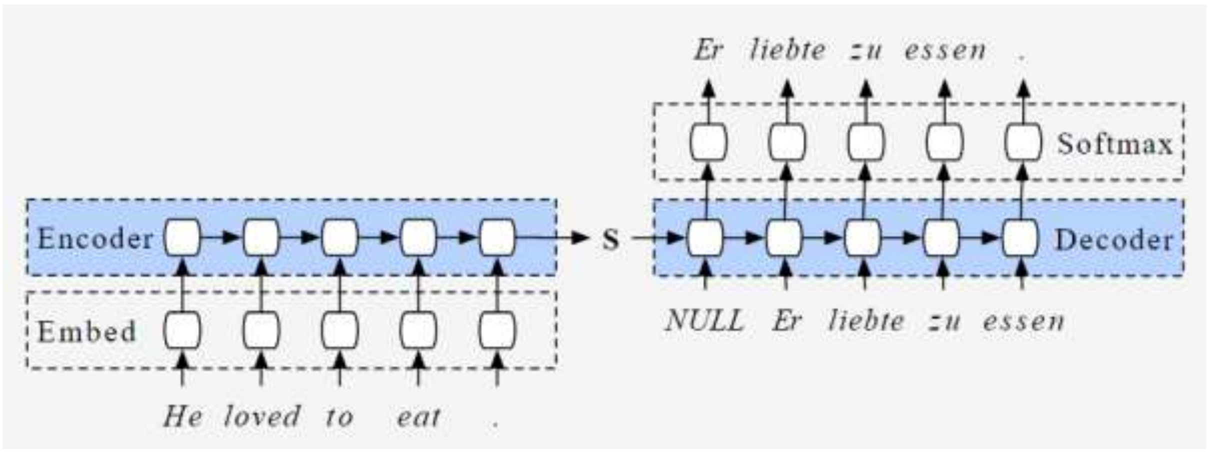
The dataset you have been given is Individual household electric power consumption dataset. [25]
(i)Split the dataset into train and test (80:20) and do the basic preprocessing. [10]
(ii) Use LSTM to predict the global active power while keeping all other important features and predict it for the testing days by training the model and plot the real global active power and predicted global active power for the testing days and comparing the results. [8]
(iii) Now split the dataset in train and test (70:30) and predict the global active power for the testing days and compare the results with part (ii). [7]

Solution of Question 1:

Sequence to Sequence (often abbreviated to seq2seq) models is a special class of Recurrent Neural Network architectures that we typically use (but not restricted) to solve complex Language problems like Machine Translation, Question Answering, creating Chatbots, Text Summarization, etc. In this question, we have to use a Seq2Seq model to transliterate text written in a Romanised script into the native script (Hindi – Devnagari).

Encoder-Decoder Architecture:

The most common architecture used to build Seq2Seq models is Encoder-Decoder architecture



The encoder and decoder components of the Seq2Seq model are typically implemented using LSTM or GRU models. The encoder reads the input sequence and produces internal state vectors or a context vector, which summarize the input information and aid the decoder in generating accurate predictions. The encoder LSTM calculates hidden state vectors (h_i) and cell state vectors (c_i) at each time step, using an input sequence element (Xi), previous hidden and cell state vectors, and a formula that updates the internal state vectors.

During training, we discard the outputs of the encoder and only retain the internal states to generate the context vector. The LSTM reads the input sequence one character at a time, and if the input is a sequence of length 't', the LSTM reads it in 't' time steps.

The decoder uses the context vector to generate the output sequence, one character at a time. The LSTM in the decoder also maintains hidden state vectors (h) and cell state vectors (c) at each time step. The output sequence element at each time step (Yi) is a probability distribution over the entire vocabulary, generated by applying a softmax activation function to the output of the decoder LSTM cell. This output sequence element is a vector of size "vocab_size" representing the probability distribution of the next native script character .

Encoder :

- Both encoder and the decoder are LSTM models (or sometimes GRU models)
- Encoder reads the input sequence and summarizes the information in something called the **internal state vectors** or **context vector** (in case of LSTM these are called the hidden state and cell state vectors). We discard the outputs of the encoder and only

preserve the internal states. This context vector aims to encapsulate the information for all input elements in order to help the decoder make accurate predictions.

- The hidden states *h_i* are computed using the formula:

$$h_t = f(W^{(hh)} h_{t-1} + W^{(hx)} x_t)$$

Decoder :

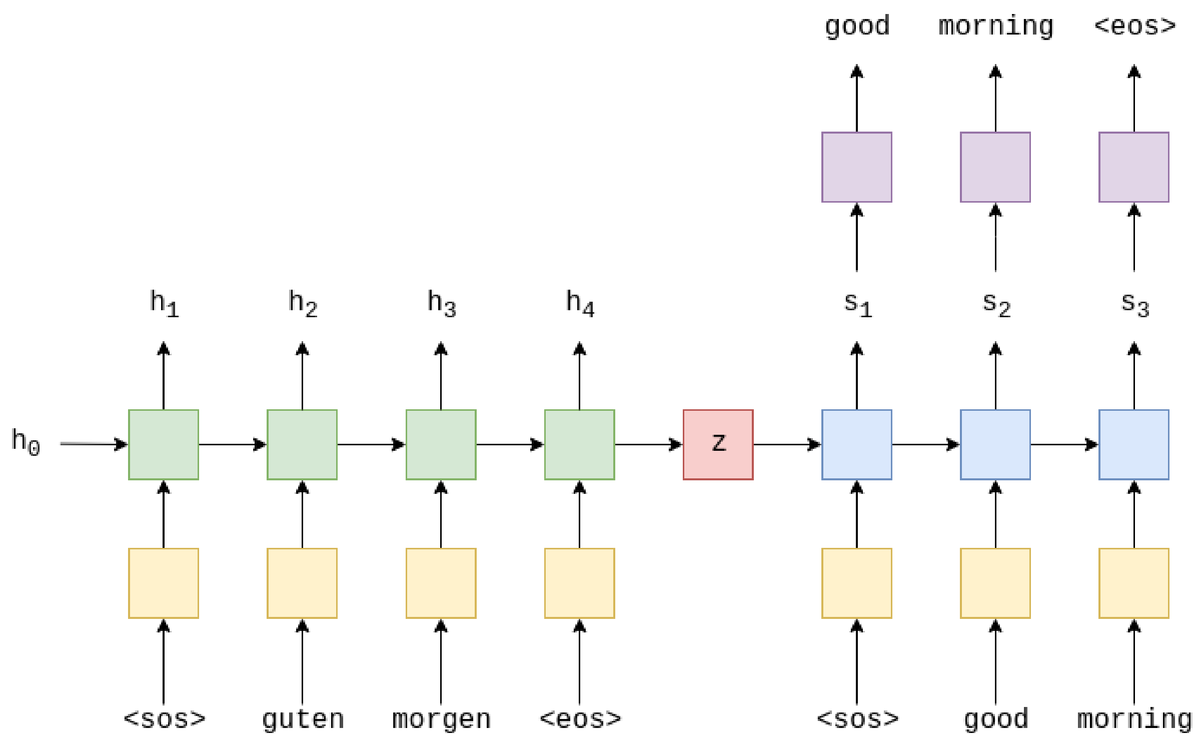
- The decoder is an LSTM whose initial states are initialized to the final states of the Encoder LSTM, i.e. the context vector of the encoder's final cell is input to the first cell of the decoder network. Using these initial states, the decoder starts generating the output sequence, and these outputs are also taken into consideration for future outputs.
- A stack of several LSTM units where each predicts an output y_t at a time step t.
- Each recurrent unit accepts a hidden state from the previous unit and produces and output as well as its own hidden state.
- Any hidden state *h_i* is computed using the formula:

$$h_t = f(W^{(hh)} h_{t-1})$$

- The output *y_t* at time step *t* is computed using the formula:

$$y_t = softmax(W^S h_t)$$

- The outputs are calculated using the hidden state at the current time step together with the respective weight W(S). Softmax is used to create a probability vector which will help to determine the final output (e.g. word in the question-answering problem).



Given Dataset: Dakshina Dataset

The Dakshina dataset is a collection of text in both Latin and native scripts for 12 South Asian languages. For each language, the dataset includes a large collection of native script Wikipedia text, a romanization lexicon which consists of words in the native script with attested romanizations, and some full sentence parallel data in both a native script of the language and the basic Latin alphabet.

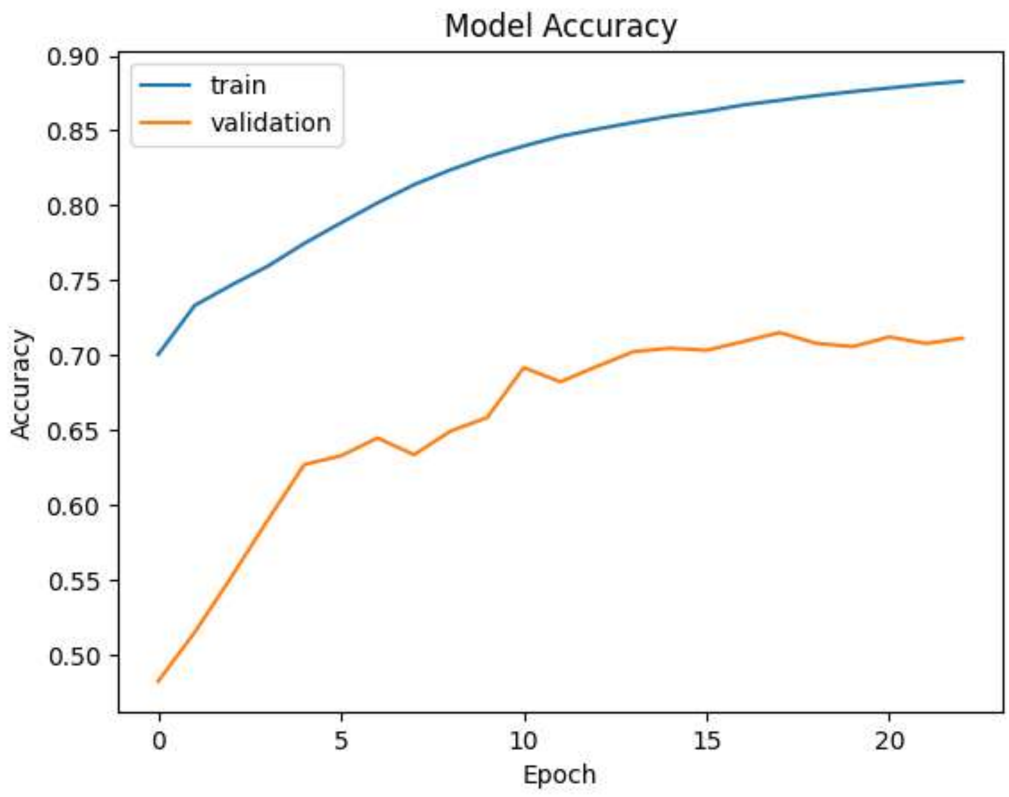
Dataset URL: https://github.com/google-research-datasets/dakshina

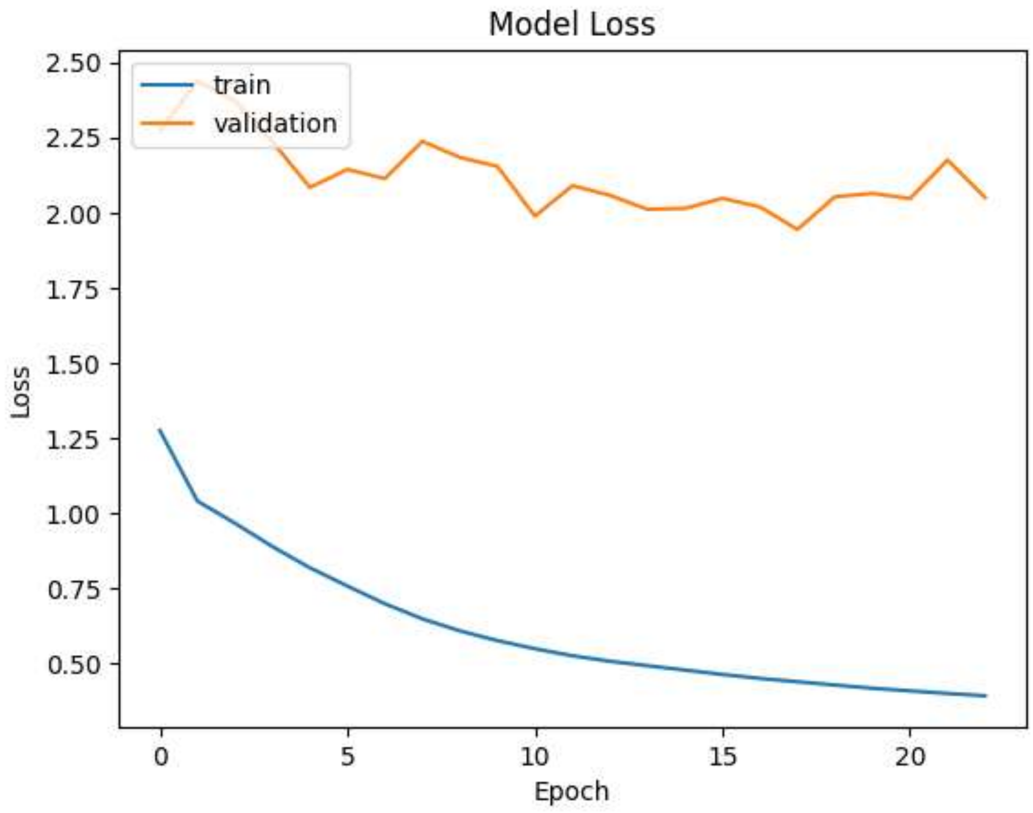
There are 12 languages represented in the dataset: Bangla (`bn`), Gujarati (`gu`), Hindi (`hi`), Kannada (`kn`), Malayalam (`ml`), Marathi (`mr`), Punjabi (`pa`), Sindhi (`sd`), Sinhala (`si`), Tamil (`ta`), Telugu (`te`) and Urdu (`ur`).
All data is derived from Wikipedia text. Each language has its own directory, in which there are three subdirectories:

In current problem, only Hindi will be used

Question 1. (a)

Model Training:





Test accuracy: 0.694876372814178

Question 1. (b)

Hyper Parameter Tuning Results:

hp_sr_no	cell_type	latentDim	hidden	numEncoders	numDecoders	loss	accuracy
1	LSTM	256	256	1	1	2.49975	0.7147046
2	LSTM	256	256	1	3	2.75975	0.6713313
3	LSTM	256	256	3	1	2.606636	0.7063083
4	LSTM	256	256	3	3	2.508584	0.6749741
5	LSTM	256	64	1	1	2.310676	0.6800385
6	LSTM	256	64	1	3	2.207703	0.6965645
7	LSTM	256	64	3	1	2.338297	0.7058937
8	LSTM	256	64	3	3	2.395483	0.6698208
9	**LSTM**	**256**	**16**	**1**	**1**	**1.907725**	**0.7253369**
10	LSTM	256	16	1	3	2.405247	0.6676884
11	LSTM	256	16	3	1	2.475985	0.695365
12	LSTM	256	16	3	3	2.674471	0.6634977
13	LSTM	64	256	1	1	2.599865	0.6579742
14	LSTM	64	256	1	3	2.835968	0.6011994
15	LSTM	64	256	3	1	2.402174	0.6987117
16	LSTM	64	256	3	3	2.405754	0.6789723
17	LSTM	64	64	1	1	2.523144	0.6383829
18	LSTM	64	64	1	3	2.447909	0.6409892
19	LSTM	64	64	3	1	2.173887	0.7212202
20	LSTM	64	64	3	3	2.649691	0.6713461
21	LSTM	64	16	1	1	2.03449	0.6999704
22	LSTM	64	16	1	3	2.759135	0.5996742
23	LSTM	64	16	3	1	2.159513	0.6959425
24	LSTM	64	16	3	3	2.271587	0.6132534
25	LSTM	16	256	1	1	2.44103	0.653354
26	LSTM	16	256	1	3	2.194506	0.646794
27	LSTM	16	256	3	1	2.390213	0.675981
28	LSTM	16	256	3	3	2.698914	0.6109433
29	LSTM	16	64	1	1	1.947442	0.6836073
30	LSTM	16	64	1	3	2.676237	0.5025618
31	LSTM	16	64	3	1	1.925528	0.6066045
32	LSTM	16	64	3	3	2.297896	0.495602
33	LSTM	16	16	1	1	1.561581	0.6278395
34	LSTM	16	16	1	3	2.243077	0.5084999
35	LSTM	16	16	3	1	1.600244	0.5978528
36	LSTM	16	16	3	3	1.827661	0.5747224
37	RNN	256	256	1	1	2.885987	0.6096106
38	RNN	256	256	1	3	2.945172	0.5924478
39	RNN	256	256	3	1	2.868594	0.6002073
40	RNN	256	256	3	3	3.09671	0.6046202
41	RNN	256	64	1	1	2.864011	0.5886569
42	RNN	256	64	1	3	2.951321	0.5976307
43	RNN	256	64	3	1	2.891716	0.6164519

Best Result Found:

Cell type	Lstm
Latent dim	256
Hidden dim	16
Num encoders	1
Num decoders	1
Loss	1.9077255
Accuracy	0.7253369

c) Based on the above parts please try to answer the following- [10]

(i) Does RNN takes less time to converge than LSTM? Reason to support your answer.

Yes

RNNs are simpler than LSTMs and have a smaller number of parameters, which can make them faster to train and converge. RNNs also have a simpler gating mechanism that can be less prone to overfitting. However, RNNs can suffer from the vanishing gradient problem, where gradients can become very small and cause the network to have difficulty learning long-term dependencies.

LSTMs, on the other hand, have a more complex architecture with more parameters and a more sophisticated gating mechanism. LSTMs are designed to address the vanishing gradient problem by using a set of gates to selectively forget or remember information from previous time steps. While this can improve the network's ability to learn long-term dependencies, it can also make LSTMs slower to converge and more prone to overfitting.

In general, the choice between RNNs and LSTMs depends on the specific problem and dataset being used. While RNNs can be faster to train and converge, LSTMs may be more effective at learning long-term dependencies and avoiding overfitting.

(ii) Does dropout leads to better performance? Proof to support your answer.

Yes.

Dropout is a regularization technique commonly used in deep learning to prevent overfitting. Dropout randomly drops out a proportion of the neurons in a neural network during training, forcing the remaining neurons to learn more robust representations. This can help the network generalize better to new data and improve performance on the test set.

There have been several studies that have shown that dropout can lead to better performance. For example, in a 2014 paper titled "Dropout: A Simple Way to Prevent Neural Networks from Overfitting", the authors conducted experiments on several benchmark datasets and showed that dropout improved performance on all of them. Another study from 2017 titled "Dropout Improves Recurrent Neural Networks for Handwriting Recognition" showed that dropout can improve performance on sequence prediction tasks, such as handwriting recognition.

Moreover, dropout has become a widely used technique in deep learning and is included in many state-of-the-art models. For example, dropout is used in the popular ResNet and Inception architectures for image classification, as well as in the LSTM-based models for sequence prediction.

In summary, there is empirical evidence to support that dropout can lead to better performance in deep learning models. However, the extent of the improvement and the optimal dropout rate may depend on the specific dataset and problem being addressed, and may require some experimentation to determine the best hyperparameters for the model.

(iii) Using a smaller size in hidden layer does not give good results? Proof to support your answer.

Not always.

Increasing the size of the hidden layer in a neural network can improve its performance by increasing its capacity to learn complex patterns in the data, but can also increase the risk of overfitting. Using a smaller size in the hidden layer can reduce the capacity of the model and prevent overfitting, but may not be able to capture complex patterns as well. The choice of the hidden layer size depends on the complexity of the problem and amount of training data available, and may require experimentation to find the optimal hyperparameters.

Solution of Question 2:

Time series prediction is one application of LSTM (Long Short-Term Memory), which are a type of recurrent neural network (RNN) that is well-suited to sequence data such as time series. Here are the steps to implement time series prediction using LSTM:

1. Data Preparation: The first step is to prepare your time series data by splitting it into training and test sets, normalizing the data, and formatting it into a suitable shape for the LSTM model. This often involves transforming the time series data into a supervised learning problem by framing the data as input-output pairs.

2. Model Architecture: The next step is to define the LSTM model architecture, which typically involves specifying the number of LSTM layers, the number of hidden units per layer, the activation functions, and the dropout rate. You can also experiment with different architectures to find the best one for your data.

3. Model Training: Once the model architecture is defined, you can train the LSTM model using the training set. During training, the model updates its weights and biases to minimize the prediction error. You can use a variety of loss functions and optimization algorithms to train the model.

4. Model Evaluation: After training, you can evaluate the performance of the LSTM model using the test set. Common metrics for evaluating time series prediction models include mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R-squared).

5. Prediction: Once the model is trained and evaluated, you can use it to make predictions on new, unseen data. This involves feeding the input data to the model and obtaining the predicted output.

Overall, time series prediction using LSTM is a complex process that requires careful data preparation, model architecture design, and training and evaluation. However, it can be a powerful tool for making accurate predictions on time series data.

Given Dataset:

Dataset Name: Individual household electric power consumption Data Set

Data Set Characteristics:	Multivariate, Time-Series	**Number of Instances:**	2075259	**Area:**	Physical
Attribute Characteristics:	Real	**Number of Attributes:**	9	**Missing Values?**	Yes

Data Set Information:

This archive contains 2075259 measurements gathered in a house located in Sceaux (7km of Paris, France) between December 2006 and November 2010 (47 months).
Notes:
1.(global_active_power*1000/60 - sub_metering_1 - sub_metering_2 - sub_metering_3) represents the active energy consumed every minute (in watt hour) in the household by electrical equipment not measured in sub-meterings 1, 2 and 3.

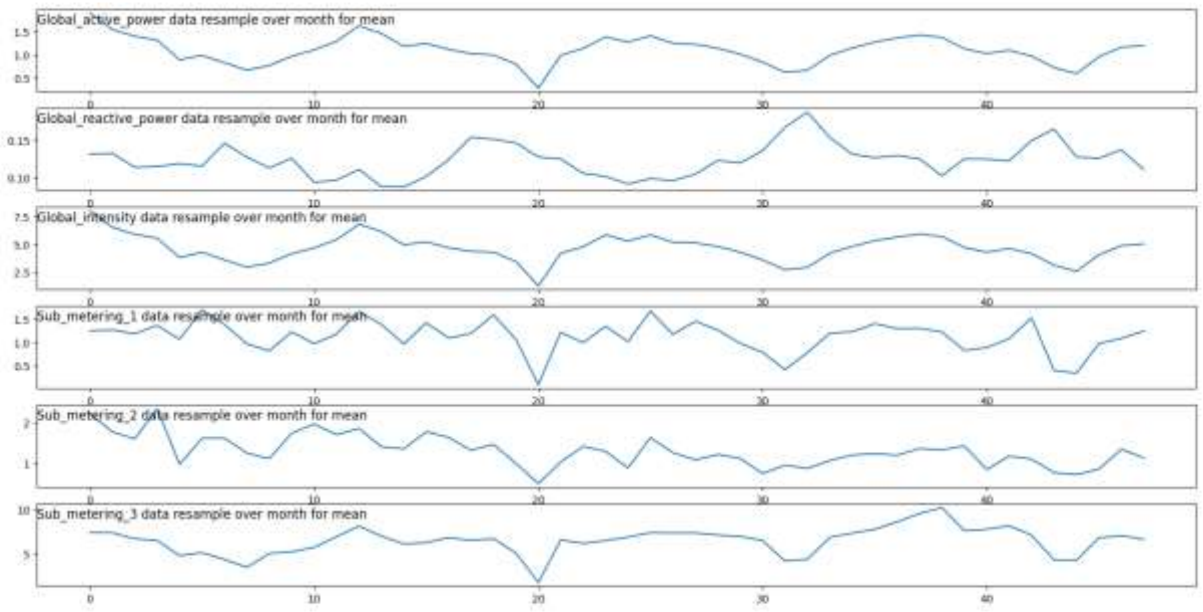
2.The dataset contains some missing values in the measurements (nearly 1,25% of the rows). All calendar timestamps are present in the dataset but for some timestamps, the measurement values are missing: a missing value is represented by the absence of value between two consecutive semi-colon attribute separators. For instance, the dataset shows missing values on April 28, 2007.

Attribute Information:

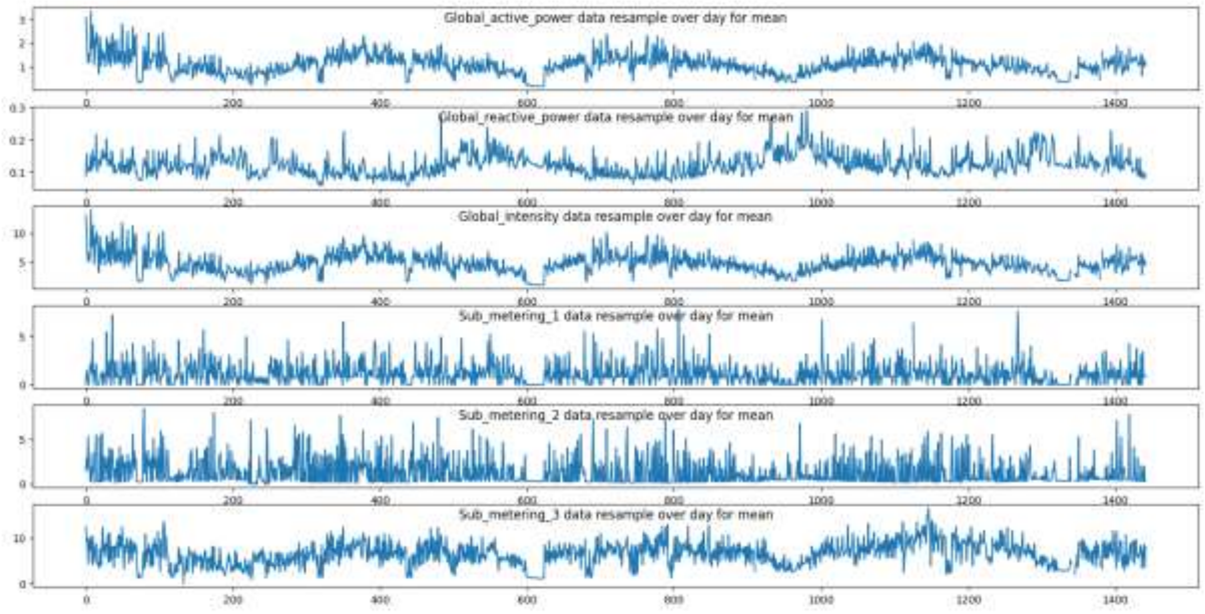
1.date: Date in format dd/mm/yyyy
2.time: time in format hh:mm:ss
3.global_active_power: household global minute-averaged active power (in kilowatt)
4.global_reactive_power: household global minute-averaged reactive power (in kilowatt)
5.voltage: minute-averaged voltage (in volt)
6.global_intensity: household global minute-averaged current intensity (in ampere)
7.sub_metering_1: energy sub-metering No. 1 (in watt-hour of active energy). It corresponds to the kitchen, containing mainly a dishwasher, an oven and a microwave (hot plates are not electric but gas powered).
8.sub_metering_2: energy sub-metering No. 2 (in watt-hour of active energy). It corresponds to the laundry room, containing a washing-machine, a tumble-drier, a refrigerator and a light.
9.sub_metering_3: energy sub-metering No. 3 (in watt-hour of active energy). It corresponds to an electric water-heater and an air-conditioner.

Data Exploration:

Monthly Mean of different parameters:



Daily Mean of different parameters:



Data Pre-processing:

MinMaxScaler is a data normalization technique used in machine learning to transform the data in a way that the values are between 0 and 1. This technique is commonly used to rescale numerical data, especially in deep learning models. The MinMaxScaler is used to transform the data so that it is in the range of [0, 1] using the following formula:

X_scaled = (X - X_min) / (X_max - X_min)

where X is the original data, X_min and X_max are the minimum and maximum values in the data set, and X_scaled is the normalized data.

The main purpose of using the MinMaxScaler is to scale the data to the same range to avoid any feature dominating over the other. For example, if we have two features, one having a range of [0, 1] and another having a range of [0, 100], then the second feature may dominate the first feature, causing the model to perform poorly.

Model Architecture

```
LSTMModel(
  (lstm): LSTM(7, 100, batch_first=True)
  (dropout): Dropout(p=0.1, inplace=False)
  (fc): Linear(in_features=100, out_features=1, bias=True)
)
```

Hyper Parameters for LSTM:

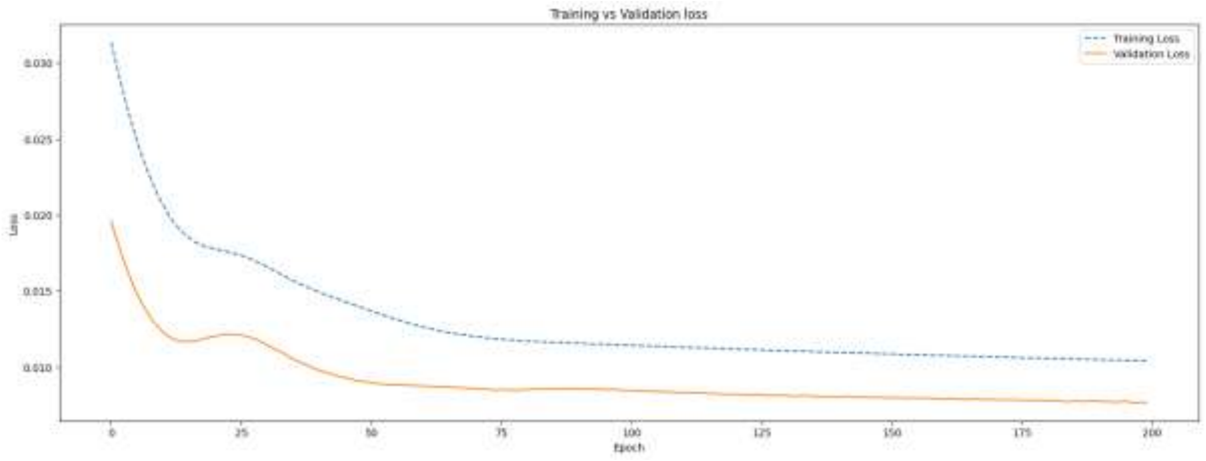
- *In Dimension : 7*
- *Out Dimension : 100*
- *Loss Function: MSE Loss*
- *Optimiser: Adam*
- *Learning Rate: 0.0001*
- *Drop Out : 0.1*
- *Number of epochs: 200*

Model with 80-20 Training

Log:

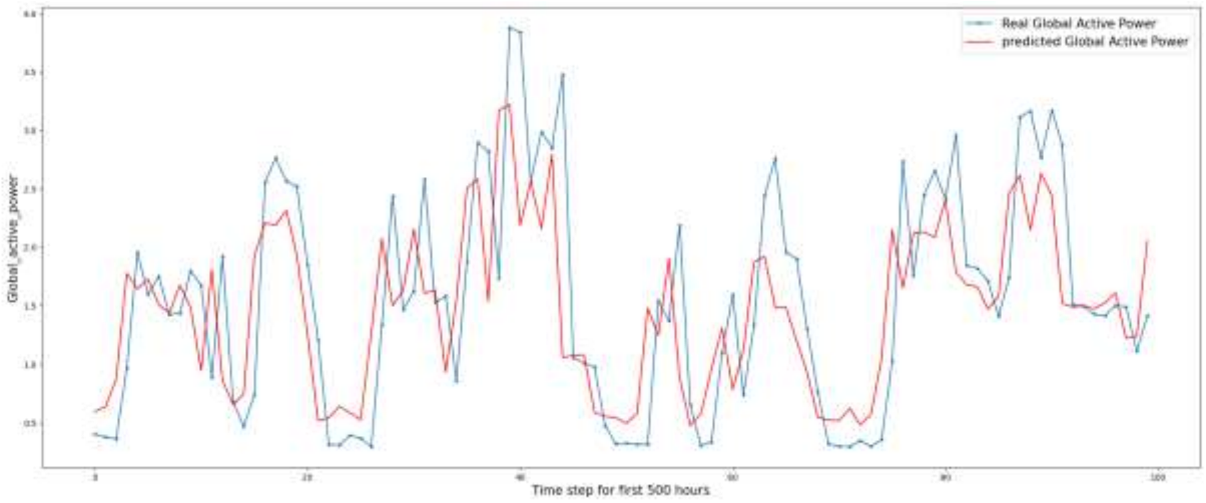
```
Epoch 10, Train Loss: 0.031362, Test Loss: 0.019585
Epoch 20, Train Loss: 0.020634, Test Loss: 0.012282
Epoch 30, Train Loss: 0.017757, Test Loss: 0.012019
Epoch 40, Train Loss: 0.016601, Test Loss: 0.011427
Epoch 50, Train Loss: 0.014911, Test Loss: 0.009778
Epoch 60, Train Loss: 0.013675, Test Loss: 0.008931
Epoch 70, Train Loss: 0.012630, Test Loss: 0.008755
Epoch 80, Train Loss: 0.012001, Test Loss: 0.008560
Epoch 90, Train Loss: 0.011679, Test Loss: 0.008519
Epoch 100, Train Loss: 0.011559, Test Loss: 0.008572
Epoch 110, Train Loss: 0.011439, Test Loss: 0.008451
Epoch 120, Train Loss: 0.011289, Test Loss: 0.008316
Epoch 130, Train Loss: 0.011172, Test Loss: 0.008199
Epoch 140, Train Loss: 0.011060, Test Loss: 0.008128
Epoch 150, Train Loss: 0.010961, Test Loss: 0.008041
Epoch 160, Train Loss: 0.010868, Test Loss: 0.007978
Epoch 170, Train Loss: 0.010758, Test Loss: 0.007887
Epoch 180, Train Loss: 0.010666, Test Loss: 0.007830
Epoch 190, Train Loss: 0.010566, Test Loss: 0.007794
Epoch 200, Train Loss: 0.010473, Test Loss: 0.007740
```

Training vs Validation Loss

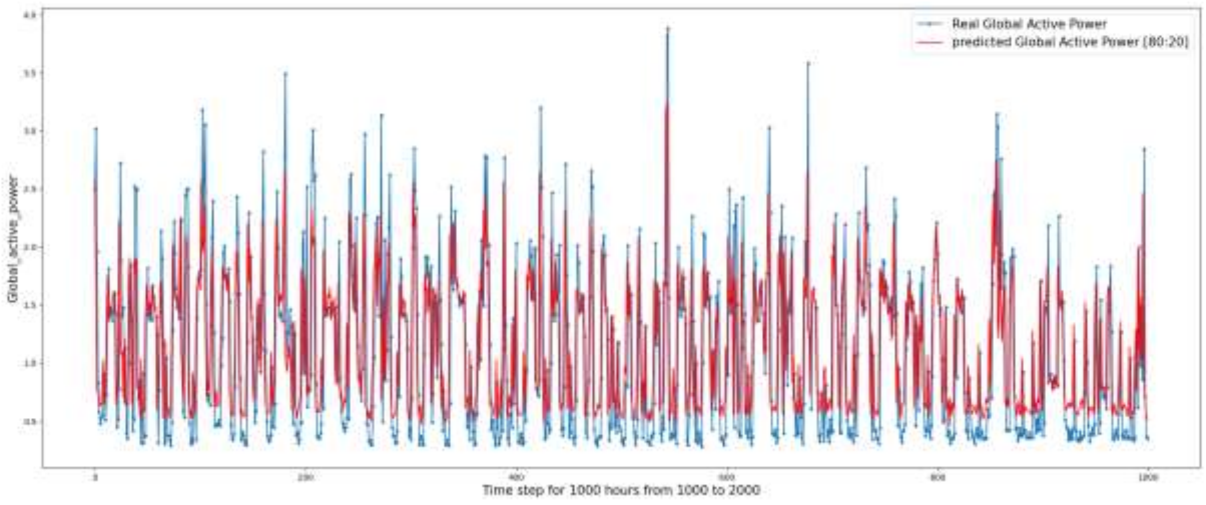


Test RMSE: **0.565**

Time step for first 100 hours



Time step for 1000 hours from 1000 to 2000

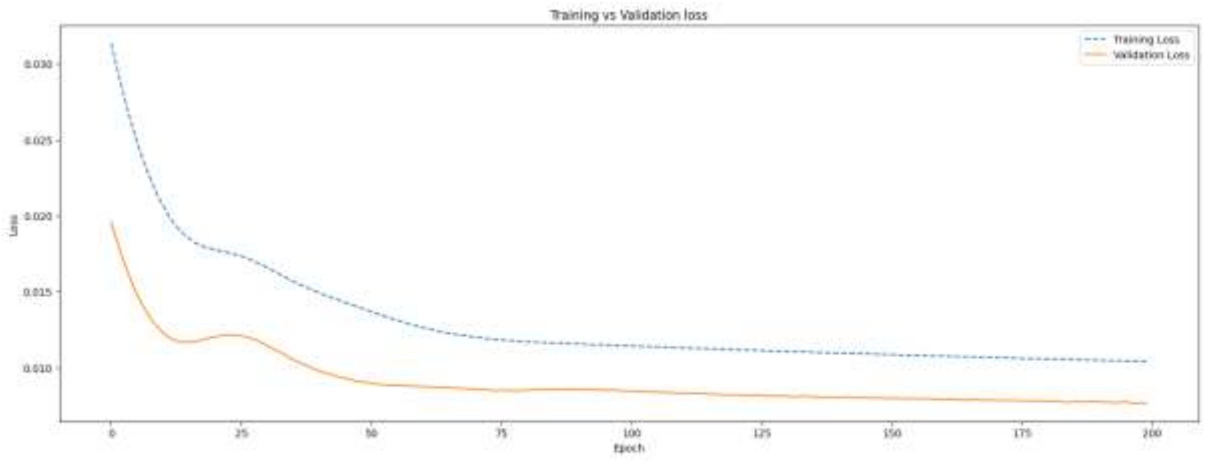


Data Split 70-30:

Model Training Log:

```
Epoch 10, Train Loss: 0.032408, Test Loss: 0.026220
Epoch 20, Train Loss: 0.019658, Test Loss: 0.014716
Epoch 30, Train Loss: 0.017375, Test Loss: 0.013495
Epoch 40, Train Loss: 0.016209, Test Loss: 0.012465
Epoch 50, Train Loss: 0.014673, Test Loss: 0.011144
Epoch 60, Train Loss: 0.013643, Test Loss: 0.010372
Epoch 70, Train Loss: 0.012667, Test Loss: 0.009834
Epoch 80, Train Loss: 0.012007, Test Loss: 0.009468
Epoch 90, Train Loss: 0.011619, Test Loss: 0.009249
Epoch 100, Train Loss: 0.011380, Test Loss: 0.009247
Epoch 110, Train Loss: 0.011268, Test Loss: 0.009224
Epoch 120, Train Loss: 0.011161, Test Loss: 0.009143
Epoch 130, Train Loss: 0.011042, Test Loss: 0.009115
Epoch 140, Train Loss: 0.010937, Test Loss: 0.008970
Epoch 150, Train Loss: 0.010825, Test Loss: 0.008929
Epoch 160, Train Loss: 0.010749, Test Loss: 0.008843
Epoch 170, Train Loss: 0.010617, Test Loss: 0.008838
Epoch 180, Train Loss: 0.010557, Test Loss: 0.008749
Epoch 190, Train Loss: 0.010485, Test Loss: 0.008721
Epoch 200, Train Loss: 0.010394, Test Loss: 0.008659
```

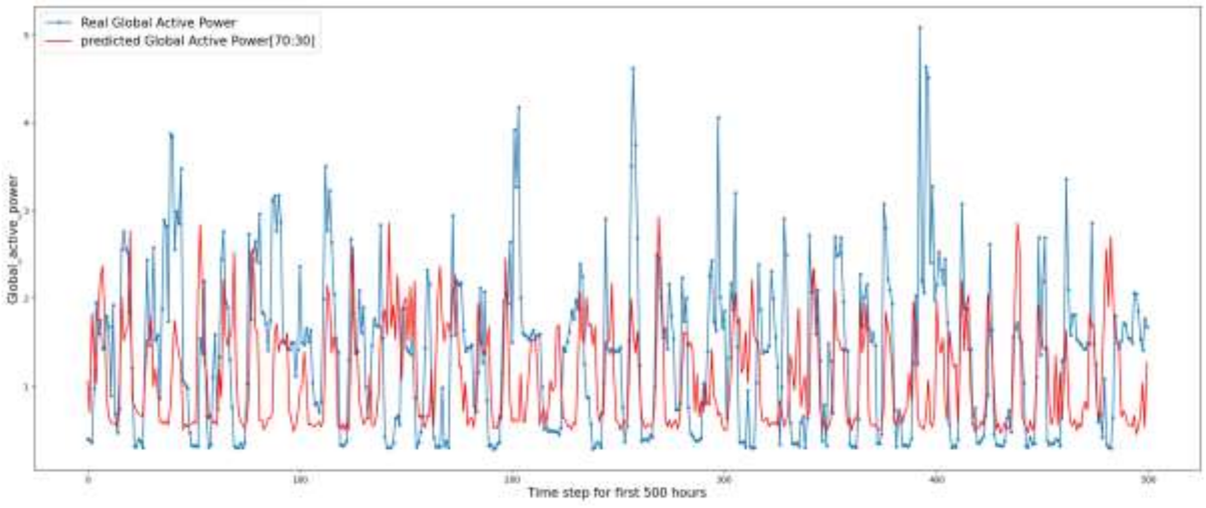
Training vs Validation Loss:



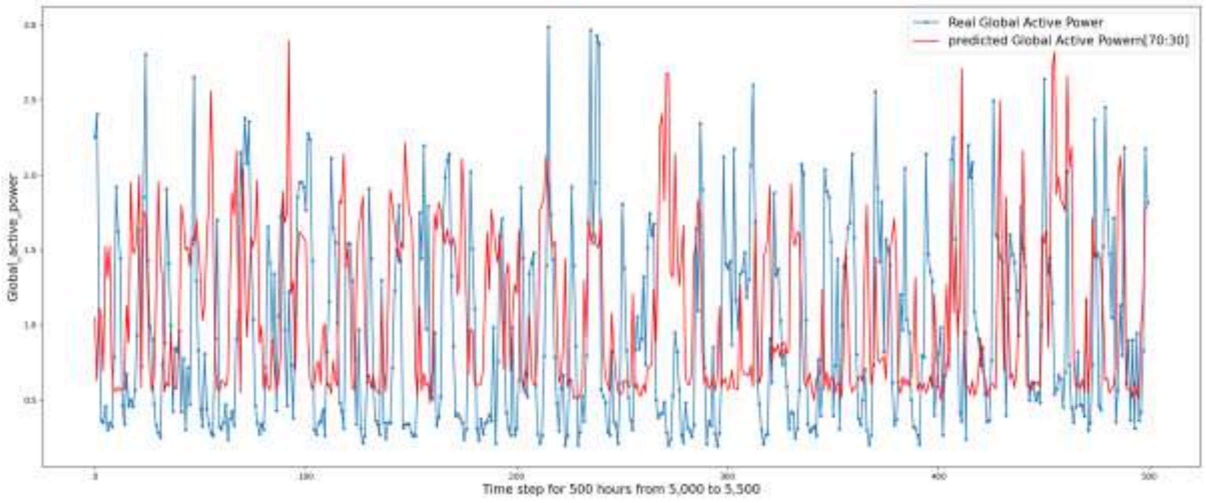
Test RMSE: 0.598

Predictions:

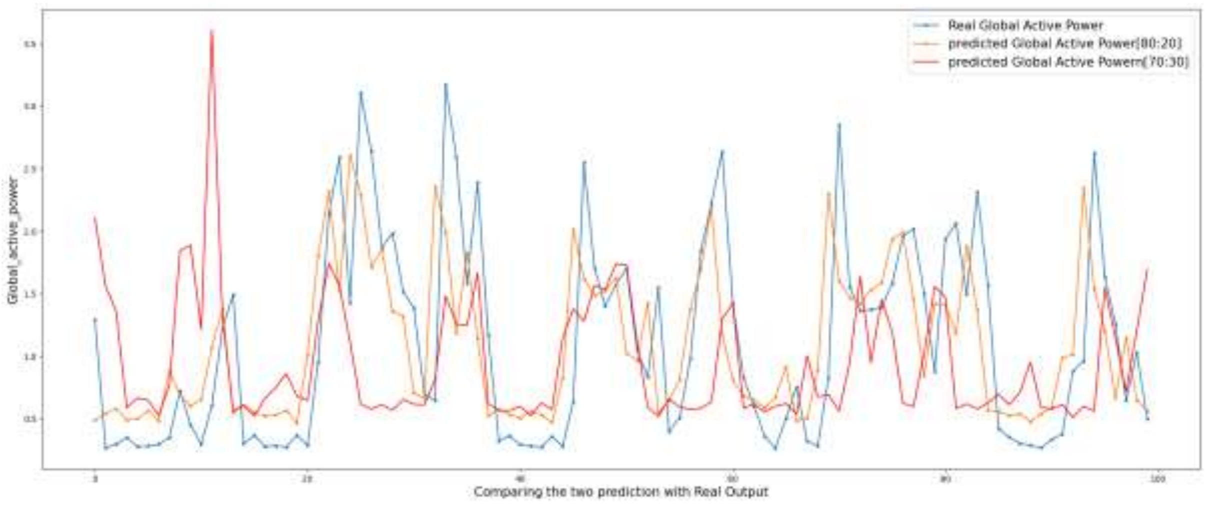
Real Global Active Power [70:30] for first 500 hours



Real Global Active Power [70:30] for 500 hours from 5,000 to 5,500



Comparison



Conclusion:

80:20 splits MSE error is lower than the same of 70:30 split. Model 80:20 performs better as it gets more exposer to training data.