Training and Inference

```
In [50]: import numpy as np
         import pandas as pd
         import seaborn as sns
         import matplotlib as mpl
         import matplotlib.pyplot as plt
         import math
         from sklearn.metrics import mean squared error
         from sklearn.preprocessing import MinMaxScaler
         import tensorflow as tf
         from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import LSTM, Dense
In [51]: # Check if GPU is available
         print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
         print("GPU devices:", tf.config.list_physical_devices('GPU'))
         # Enable memory growth to prevent TensorFlow from allocating all GPU memory
         gpus = tf.config.list physical devices('GPU')
         if gpus:
             try:
                 for qpu in qpus:
                     tf.config.experimental.set memory growth(gpu, True)
                 print(f"GPU is available and will be used")
             except RuntimeError as e:
                 print(e)
        Num GPUs Available: 1
        GPU devices: [PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
        GPU is available and will be used
In [52]: import os
         os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
         import logging
         logging.getLogger('tensorflow').setLevel(logging.ERROR)
```

```
import warnings
warnings.filterwarnings('ignore')
```

Import data

```
In [53]: TRAIN_EPOCHS = 100
         NUM_FEATURES = 1 # univariate time series, SINR or PHR or dlBler
         TIME_STEP = 100 # Number of past time steps to use
         BATCH_SIZE = 16 # it works for time series
         INPUT_WIDTH = 64
         LABEL WIDTH = 64
         PREDICTION_STEPS = 64 # prediction steps into the future
In [54]: df_raw = pd.read_csv('data_one_feat_sinr_clean.csv', header=None)
         plt.figure(figsize=(10, 1))
         plot_features = df_raw[0][1:500]
         plt.plot(range(len(plot_features)), plot_features)
         plt.show()
                                 100
                                                   200
                                                                     300
                                                                                       400
                                                                                                          500
In [55]: df = df_raw.copy()
         df = df[1:] # full data
         print(df.shape)
         print(df.head())
```

```
(1717, 1)
        1 - 2.0
        2 - 2.5
        3 1.5
        4 - 2.0
        5 - 4.5
In [56]: # Scale the data to the range [0, 1]
         scaler = MinMaxScaler(feature range=(0, 1))
         scaled_data = scaler.fit_transform(df.values)
         # Define the function to create the dataset
         def create_dataset(dataset, time_step=1):
             dataX, dataY = [], []
             for i in range(len(dataset) - time step - 1):
                 a = dataset[i:(i + time_step), 0]
                 dataX.append(a)
                 dataY.append(dataset[i + time step, 0])
             return np.array(dataX), np.array(dataY)
         # Split the data into training and testing sets
         training size = int(len(scaled data) * 0.80)
         test size = len(scaled data) - training size
         train_data, test_data = scaled_data[0:training_size, :], scaled_data[training_size:len(scaled_data), :]
         # Create the datasets for training and testing
         X train, y train = create dataset(train data, TIME STEP)
         X test, y test = create dataset(test data, TIME STEP)
         print(X_train.shape, y_train.shape)
         # Reshape the input to be [samples, time steps, features] which is required for LSTM
         X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
         X test = X test.reshape(X test.shape[0], X test.shape[1], 1)
         print(X_train.shape, y_train.shape)
         print(scaled data.shape)
        (1272, 100) (1272,)
        (1272, 100, 1) (1272,)
        (1717, 1)
```

```
In [57]: import tensorflow as tf
         from tensorflow.keras import mixed precision
         # GPU Configuration
         print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
         gpus = tf.config.list_physical_devices('GPU')
         if gpus:
             try:
                 for gpu in gpus:
                     tf.config.experimental.set_memory_growth(gpu, True)
                 # Enable mixed precision for faster training
                 policy = mixed precision.Policy('mixed float16')
                 mixed precision.set global policy(policy)
                 print("GPU enabled with mixed precision")
             except RuntimeError as e:
                 print(e)
         # Increase batch size for GPU
         BATCH SIZE = 64
         # Create optimized datasets
         train dataset = tf.data.Dataset.from tensor slices((X train, y train))
         train dataset = train dataset.cache().shuffle(10000).batch(BATCH SIZE).prefetch(tf.data.AUTOTUNE)
         # Build model (same as before)
         model = Sequential(name='LSTM model')
         model.add(LSTM(100, return sequences=True, input shape=(TIME STEP, NUM FEATURES)))
         model.add(LSTM(50, return_sequences=False))
         model.add(Dense(25))
         model.add(Dense(1, dtype='float32')) # Output layer uses float32 for mixed precision
         model.compile(optimizer='adam', loss='mean squared error')
         # Train with dataset
         history = model.fit(train_dataset,
                             epochs=TRAIN_EPOCHS,
                             verbose=1)
```

Num GPUs Available: 1 GPU enabled with mixed precision Epoch 1/100 20/20 — **- 2s** 11ms/step - loss: 0.0515 Epoch 2/100 20/20 -**0s** 10ms/step - loss: 0.0061 Epoch 3/100 20/20 -**0s** 10ms/step - loss: 0.0038 Epoch 4/100 20/20 -**0s** 10ms/step - loss: 0.0039 Epoch 5/100 20/20 -**0s** 10ms/step - loss: 0.0032 Epoch 6/100 20/20 -**0s** 10ms/step - loss: 0.0028 Epoch 7/100 20/20 -**0s** 10ms/step - loss: 0.0024 Epoch 8/100 20/20 -**0s** 10ms/step - loss: 0.0028 Epoch 9/100 20/20 -**0s** 10ms/step - loss: 0.0021 Epoch 10/100 20/20 -**0s** 10ms/step - loss: 0.0025 Epoch 11/100 20/20 — **0s** 10ms/step - loss: 0.0018 Epoch 12/100 20/20 — **0s** 10ms/step - loss: 0.0028 Epoch 13/100 **0s** 10ms/step - loss: 0.0017 20/20 -Epoch 14/100 20/20 — **0s** 11ms/step - loss: 0.0030 Epoch 15/100 20/20 -**0s** 11ms/step - loss: 0.0019 Epoch 16/100 20/20 -**0s** 10ms/step - loss: 0.0022 Epoch 17/100 20/20 -**0s** 10ms/step - loss: 0.0016 Epoch 18/100 20/20 -**0s** 10ms/step - loss: 0.0018 Epoch 19/100 20/20 -**0s** 11ms/step - loss: 0.0019 Epoch 20/100 20/20 -**0s** 11ms/step - loss: 0.0020 Epoch 21/100

20/20		05	10ms/step - lo)SS:	0.0018
	22/100		201137 3 600		010010
20/20		0s	10ms/step - lo	oss:	0.0015
Epoch	23/100				
		0s	10ms/step - lo	oss:	0.0019
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	25/100	US	10ms/step - Lo	055:	0.0024
•	23/ 100	05	10ms/sten - 10	255!	0.0012
	26/100		10m3/ 5 cop - co		0.0012
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•	27/100				
		0s	10ms/step - lo	oss:	0.0012
•	28/100	0 -	10		0.0015
	29/100	US	10ms/step - Lo	055:	0.0015
		05	11ms/step - lo	255!	0.0014
	30/100		11m3/3 cop - co		0.001
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•	31/100				
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	26 /100	0s	10ms/step – lo	oss:	0.0016
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Epoch	49/100				
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20/20	54/100	0s	10ms/step -	loss:	0.0021
-	55/100	0s	10ms/step -	loss:	0.0012
•	56/100	0s	10ms/step -	loss:	0.0016
-	57/100	0 s	10ms/step -	loss:	0.0016
Epoch	58/100		·		
Epoch	59/100		·		
Epoch	60/100		•		
	61/100	0s	10ms/step -	loss:	0.0014
	62/100	0s	10ms/step -	loss:	0.0012
20/20	63/100	0s	10ms/step -	loss:	8.8327e-04
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cpoch	64/100				

20/20 -		0s	10ms/step -	loss:	0.0011
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20/20 -		0s	10ms/step -	loss:	9.4867e-04
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20/20 -		0s	11ms/step -	loss:	0.0013
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	72/100	0s	10ms/step -	loss:	0.0014
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20/20 -		0s	11ms/step -	loss:	0.0016
Epoch					
	75 /400	0s	11ms/step -	loss:	0.0017
Epoch 7		0.0	10mc/c+on	10001	0 0012
Epoch 7		05	10ms/step -	1055.	0.0013
•	7 0 7 1 0 0	0s	10ms/step -	loss:	0.0016
Epoch					
		0s	10ms/step -	loss:	0.0010
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	70 /100	0s	10ms/step -	loss:	0.0011
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Epoch 8					
		0s	10ms/step -	loss:	0.0017
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Epoch 8		-	10m3/ 3 ccp	.0551	J. 5557 C 04
		0s	10ms/step -	loss:	0.0014
Epoch 8					
20/20 -		0s	10ms/step -	loss:	0.0016

```
Epoch 86/100
                          - 0s 10ms/step - loss: 0.0018
20/20 -
Epoch 87/100
                           0s 10ms/step - loss: 0.0011
20/20 —
Epoch 88/100
20/20 -
                           0s 10ms/step - loss: 0.0011
Epoch 89/100
20/20 -
                           0s 10ms/step - loss: 0.0012
Epoch 90/100
                           0s 10ms/step - loss: 0.0013
20/20 —
Epoch 91/100
20/20 -
                           0s 10ms/step - loss: 0.0011
Epoch 92/100
                           0s 10ms/step - loss: 0.0010
20/20 -
Epoch 93/100
20/20 —
                          - 0s 10ms/step - loss: 0.0013
Epoch 94/100
                           0s 10ms/step - loss: 7.7659e-04
20/20 -
Epoch 95/100
20/20 —
                           0s 10ms/step - loss: 0.0011
Epoch 96/100
                           0s 10ms/step - loss: 8.3333e-04
20/20 -
Epoch 97/100
20/20 —
                           0s 10ms/step - loss: 0.0014
Epoch 98/100
                           0s 10ms/step - loss: 8.1514e-04
20/20 -
Epoch 99/100
20/20 -
                           0s 10ms/step - loss: 8.1351e-04
Epoch 100/100
20/20 —
                          - 0s 10ms/step - loss: 0.0011
```

In [58]: model.summary()

Model: "LSTM_model"

Layer (type)	Output Shape	Param #
lstm_6 (LSTM)	(None, 100, 100)	40,800
lstm_7 (LSTM)	(None, 50)	30,200
dense_6 (Dense)	(None, 25)	1,275
dense_7 (Dense)	(None, 1)	26

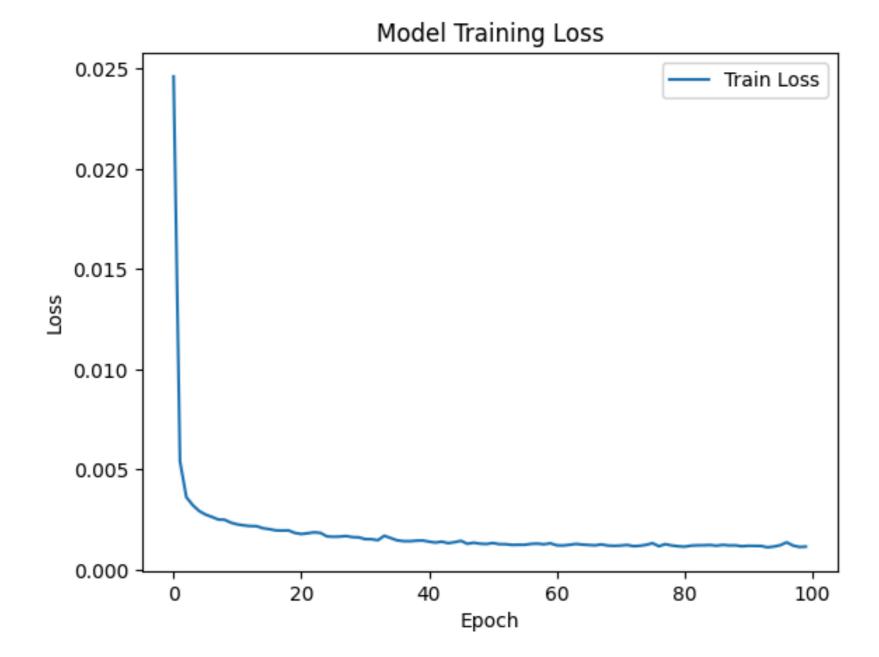
Total params: 216,909 (847.31 KB)

Trainable params: 72,301 (282.43 KB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 144,608 (564.89 KB)

```
In [59]: # Plot the training loss
    plt.plot(history.history['loss'], label='Train Loss')
    plt.title('Model Training Loss')
    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend()
    plt.show()
```



```
In [60]: # Convert history.history (dict) to DataFrame
history_df = pd.DataFrame(history.history)

# Save to CSV
history_df.to_csv("training_history.csv", index=False)

In [61]: # Reload history
loaded_history = pd.read_csv("training_history.csv")

In [62]: model.save("lstm_trained.keras")
```

Inference

```
In [63]: model = tf.keras.models.load model('./lstm trained.keras')
In [64]: # Make predictions
         train predict = model.predict(X train, verbose=0)
         test_predict = model.predict(X_test, verbose=0)
         # Transform back to original form (if your data was scaled)
         train predict = scaler.inverse transform(train predict)
         test predict = scaler.inverse transform(test predict)
         y_train_inv = scaler.inverse_transform(y_train.reshape(-1, 1))
         y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1))
         # Calculate RMSE
         train_rmse = math.sqrt(mean_squared_error(y_train_inv, train_predict))
         test rmse = math.sgrt(mean squared error(y test inv, test predict))
         print(f'Train RMSE: {train rmse}')
         print(f'Test RMSE: {test rmse}')
         # Plot the results
         # Shift train predictions for plotting
         train predict plot = np.empty like(scaled data)
         train_predict_plot[:, :] = np.nan
         train_predict_plot[TIME_STEP:len(train_predict) + TIME_STEP, :] = train_predict
         # Shift test predictions for plotting
         test predict plot = np.empty like(scaled data)
         test predict plot[:, :] = np.nan
         test_predict_plot[len(train_predict) + (TIME_STEP * 2) + 1:len(scaled_data) - 1, :] = test_predict
         # Plot baseline and predictions
         plt.figure(figsize=(14, 8))
         plt.plot(scaler.inverse transform(scaled data), label='Original Data')
         plt.plot(train predict plot, label='Train Prediction')
         plt.plot(test_predict_plot, label='Test Prediction')
         plt.legend()
         plt.show()
```

Train RMSE: 1.1997010250692295 Test RMSE: 1.466150489210406

