**Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM)**

Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are types of neural networks designed for sequential data. However, standard RNNs suffer from vanishing gradient issues, which LSTMs address through specialized gating mechanisms.

**Dataset and Preprocessing:**

The dataset consists of sequential data for time series prediction. The preprocessing steps included:

* **Normalization**: Scaling input values to a range of [0,1] for stable training.
* **Sequence Generation**: Creating input-output pairs for training the models.
* **Data Splitting**: Dividing into training (80%), validation (10%), and test (10%) sets.

**Model Architectures**

1. **Baseline RNN Model**

A simple RNN model with essential layers for sequence learning.

**Architecture:**

* Input: Time series sequences
* RNN Layer: Single RNN layer with 50 units
* Dense Layer: Fully connected layer with ReLU activation
* Output Layer: Linear activation for regression tasks

**Training Performance:**

* Epochs: 20
* Batch Size: 32
* Final Validation Loss: ~0.045

1. **Optimized LSTM Model:**

Using hyperparameter tuning, the model was improved by optimizing:

* Number of LSTM units: 50, 100
* Dropout Rate: 0.2-0.5
* Optimizer: Adam, RMSprop

**Best Hyperparameters Selected:**

* LSTM Units: 100
* Dropout: 0.3
* Learning Rate: 0.001

**Final Training Performance:**

* Epochs: 20
* Batch Size: 32
* Final Validation Loss: ~0.032
* Test Loss: ~0.029

**Evaluation and Comparison:**

The performance of the baseline RNN and optimized LSTM models was compared using loss trends.

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| **Model** | **Test Loss** |
| Baseline RNN | 0.045 |
| Optimized LSTM | 0.029 |

Validation loss trends showed a steady improvement, with the optimized LSTM outperforming the baseline RNN.

**Conclusion:**

This study demonstrated how hyperparameter tuning enhances RNN/LSTM performance in time series prediction tasks. The optimized LSTM achieved better accuracy by adjusting the number of units, dropout, and optimizer settings.

**Future Enhancements:**

* Increasing training epochs with a learning rate scheduler.
* Experimenting with bidirectional LSTMs for improved performance.
* Applying attention mechanisms for better sequential context understanding.

**Findings and Work Log Summary**

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| **Phase** | **Work Done** | **Duration** | **Difficulty Level (1-10)** |
| Loading Dataset | Load and preprocess dataset (normalization, sequence generation) | 15 mins | 4 |
| RNN Implementation | Define RNN architecture with recurrent and dense layers | 50 mins | 6 |
| Model Compilation | Compile the RNN with optimizer, loss, and metrics | 15 mins | 3 |
| Model Training | Train the RNN on the dataset for multiple epochs | 55 mins | 7 |
| Model Evaluation | Evaluate the RNN model using loss on the test set | 10 mins | 5 |
| LSTM Implementation | Define LSTM architecture with optimized hyperparameters | 35 mins | 7 |
| Model Compilation | Compile the LSTM with optimizer, loss, and metrics | 5 mins | 3 |
| Model Training | Train the LSTM on the dataset for multiple epochs | 50 mins | 8 |
| Model Evaluation | Evaluate the LSTM model using loss on the test set | 10 mins | 5 |
| Results Comparison | Compare RNN and LSTM performance | 7 mins | 4 |