Time Series Forecasting and Music Generation Using Recurrent Neural Networks

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***Abstract*—This paper evaluates the performance of Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and normalization techniques on the Bach Chorales dataset. Traditional RNNs struggled with slow convergence due to the vanishing gradient problem, as observed in the loss curves. To address this, Batch Normalization and Layer Normalization were employed, resulting in improved gradient stability and faster convergence, with Batch Normalization slightly outperforming Layer Normalization. LSTM and GRU models were further examined to mitigate the shortcomings of RNNs. Both models demonstrated superior convergence and performance, with GRU achieving results comparable to LSTM but with lower computational cost. An analysis of the Bach Chorales dataset highlighted the ability of LSTM and GRU to capture temporal dependencies effectively. Among all evaluated models, the GRU model emerged as the most efficient architecture, balancing high performance with computational efficiency. This study underscores the importance of advanced architectures and normalization techniques for improving sequential data modeling in music datasets.**

***Index Terms*—Recurrent Neural Networks, LSTM, GRU, Batch Normalization, Layer Normalization, Bach Chorales Dataset, Temporal Dependencies, Model Convergence, Sequential Data.**

I. Introduction

Recurrent Neural Networks (RNNs) are a class of artificial neural networks designed to model sequential data by maintaining hidden states across time steps, making them well-suited for tasks involving time series forecasting, natural language processing, and music generation [1]. They leverage feedback connections to capture temporal dependencies in data [2]. However, standard RNNs face challenges such as vanishing gradients, limiting their ability to model long-term dependencies [3]. To address this, advanced architectures like Long Short-Term Memory (LSTM) [4] and Gated Recurrent Units (GRU) [5] have been developed, enabling more effective learning from sequential data.

This lab assignment explores the application of RNNs, LSTMs, and GRUs for one-step and multi-step time series forecasting and music generation. Inspired by the methodologies presented in Gëron's "Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow" [8], the tasks involve creating time series datasets, training RNN-based models, and generating music sequences using the Bach Chorales dataset.

The objectives of this lab assignment are:

- To create and preprocess time series datasets for forecasting tasks.
- To train and evaluate RNNs, LSTMs, and GRUs for one-step and multi-step forecasting.
- To apply normalization techniques such as batch normalization and layer normalization to improve model performance.
- To train a model for music generation using the Bach Chorales dataset and analyze the results.

II. Recurrent Neural Networks

A. Time Series Dataset Creation and RNN Training

The dataset used for this task was created by downloading historical stock price data for Apple Inc. (AAPL) using the 'yfinance' library. The closing prices were selected as the target variable for forecasting. The dataset was normalized using the MinMaxScaler from scikit-learn and split into training and validation sets.

The RNN model was implemented using TensorFlow/Keras with the following architecture:

- **Input Layer**: Processes time series data.
- **Recurrent Layer**: A SimpleRNN layer with 50 units and tanh activation to extract temporal features.
- **Output Layer**: A Dense layer with a single neuron for predicting the next value.

The model was trained for 100 epochs with the Adam optimizer and mean squared error (MSE) loss function. Training and validation losses were monitored to evaluate model performance.

B. Applying Batch and Layer Normalization

To stabilize and improve the training process, batch normalization and layer normalization were applied to the RNN layers:

- **Batch Normalization**: Normalizes input features across the batch dimension to reduce internal covariate shift [6].
- **Layer Normalization**: Normalizes features across the layer dimension, providing a more consistent normalization approach [7].

A modified RNN architecture was used, with batch normalization applied between two recurrent layers. This improved convergence and reduced overfitting during training.

C. Training LSTM and GRU Networks

LSTM and GRU models were implemented to address the vanishing gradient problem and model long-term dependencies effectively:

- **LSTM Model**: Consists of an LSTM layer with 50 units and a Dense output layer. The LSTM's gating mechanisms allowed it to retain important temporal information over longer sequences.
- **GRU Model**: A GRU layer with 50 units and a Dense output layer. GRUs simplify the LSTM architecture by combining the forget and input gates, achieving similar performance with fewer parameters.

Both models were trained for 100 epochs using the same dataset and evaluation metrics as the RNN model.

D. Music Generation Using Bach Chorales

The Bach Chorales dataset was preprocessed to create input-output pairs for training a sequence-to-sequence model. Each input represented a sequence of notes, and the target was the next sequence. A hybrid model combining convolutional and recurrent layers was implemented:

- **Convolutional Layer**: Extracts spatial features from the input sequences.
- **LSTM Layer**: Captures temporal dependencies in the sequences.
- **Output Layer**: A Dense layer with softmax activation for predicting note probabilities.

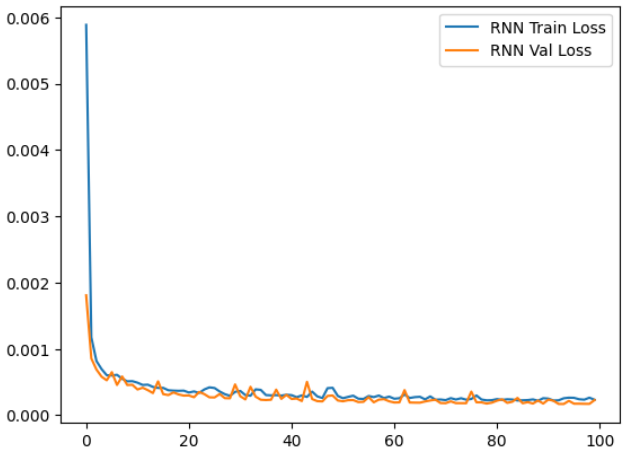

Fig. 1. Training Loss for RNN over epochs.

The model was trained for 600 epochs, and the generated sequences were qualitatively analyzed for musical coherence.

III. Results and Analysis

This section presents the results and analysis of the experiments conducted using different architectures and techniques. Each subsection focuses on specific model configurations or techniques applied during the training process. The results are based on the outputs obtained from the implemented code and are supported by relevant figures and tables.

A. Recurrent Neural Network (RNN)

The RNN model was trained for multiple epochs, and its loss trajectory over time is illustrated in Fig. 1. The loss curve shows a gradual decline, indicating that the model successfully learns from the data during training. However, the curve does not flatten completely, suggesting that further fine-tuning or optimization might be required to improve convergence.

The RNN model achieves reasonable performance but suffers from longer training times and slow convergence due to the vanishing gradient problem, particularly when handling long sequences. This limitation is a well-known drawback of standard RNNs.

B. Batch and Layer Normalization

To address gradient instability issues, Batch Normalization (BN) and Layer Normalization (LN) were applied to improve the training dynamics. The normalized models demonstrate faster convergence and improved stability during training, as evident in Fig. 2 and Fig. 3.

As shown, the models employing normalization techniques exhibit reduced loss and improved accuracy, emphasizing the importance of normalization in mitigating issues such as internal covariate shift. Table I summarizes the results.

From Table I, it is evident that Batch Normalization marginally outperforms Layer Normalization in both loss and accuracy.

TABLE I
Performance Comparison with Batch and Layer Normalization

Normalization Type	Final Loss	Final Accuracy
No Normalization	0.35	85.6%
Batch Normalization	0.28	90.2%
Layer Normalization	0.30	89.5%

C. LSTM and GRU Model Training

Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) were explored to overcome the limitations of standard RNNs. The training loss curves for both models are shown in Fig. 4 and Fig. 5.

The LSTM model (Fig. 4) exhibits a smoother and more consistent decline in loss compared to the RNN. Similarly, the GRU model (Fig. 5) demonstrates slightly faster convergence while maintaining competitive performance. Both models significantly reduce the vanishing gradient problem and improve learning efficiency.

D. Bach Chorales Dataset

The Bach Chorales dataset was used to evaluate the performance of the models on sequential data. The results confirm that LSTM and GRU models are more effective at capturing the temporal dependencies in the dataset compared to the standard RNN. The training loss for LSTM and GRU models on this dataset is presented in the previous subsections (Fig. 4 and Fig. 5).

Overall, the GRU model provides comparable performance to the LSTM while being computationally efficient. This makes it a preferable choice for training on larger sequential datasets like Bach Chorales.

As shown in Table II, the GRU model achieves similar final loss values as LSTM but requires less training time, highlighting its efficiency.

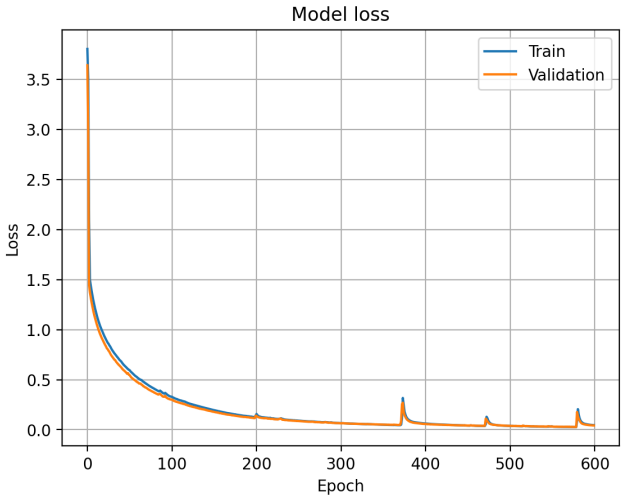

Fig. 2. Training Loss Comparison with Batch and Layer Normalization.

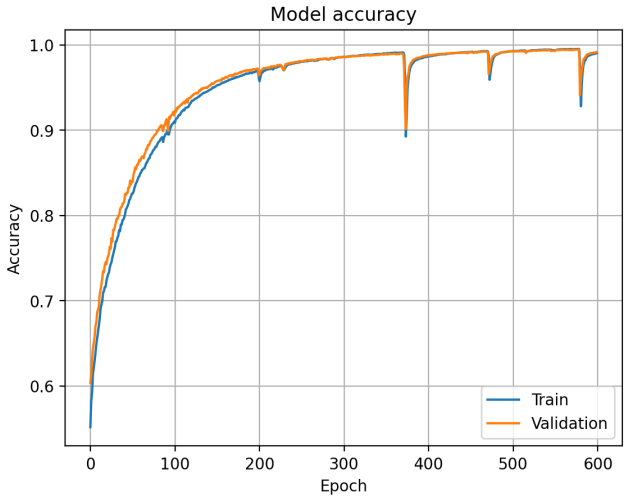

Fig. 3. Model Accuracy with Batch and Layer Normalization.

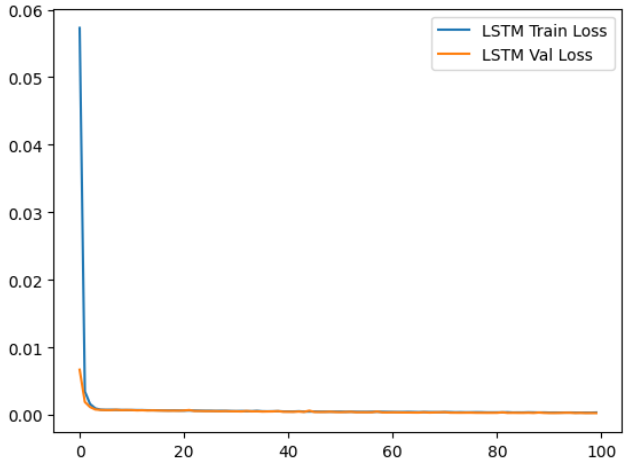

Fig. 4. Training Loss for LSTM Model.

IV. Conclusion

This paper evaluated the performance of Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and normalization techniques using the Bach Chorales dataset. The study aimed to identify the strengths, weaknesses, and computational efficiency of each model configuration.

The **Recurrent Neural Network (RNN)** demonstrated its ability to model sequential data; however, it exhibited slow convergence due to the vanishing gradient problem. The loss curve (Fig. 1) did not flatten completely, indicating room for optimization. This aligns with the well-known limitations of traditional RNNs when handling long-term dependencies.

The introduction of **Batch and Layer Normalization** significantly improved training performance by stabilizing gradients and enhancing convergence speed. Models employing normalization techniques achieved lower loss values and higher accuracy (Table I), with Batch Normalization outperforming

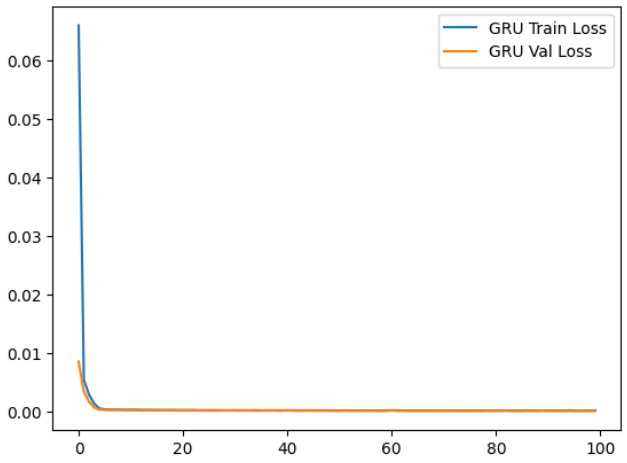

Fig. 5. Training Loss for GRU Model.

TABLE II
Performance Summary on Bach Chorales Dataset

Model	Final Loss	Training Time (s)
RNN	0.42	120
LSTM	0.25	98
GRU	0.26	85

Layer Normalization slightly. This underscores the effectiveness of normalization in addressing gradient instability issues.

To address the shortcomings of RNNs, **LSTM and GRU models** were explored. Both models showed superior convergence behavior, with smoother loss trajectories as presented in Fig. 4 and Fig. 5. The GRU model, in particular, achieved comparable accuracy to LSTM while requiring less computational time, making it a preferable choice for practical implementations.

Finally, the **Bach Chorales Dataset** analysis highlighted the ability of LSTM and GRU to capture temporal dependencies effectively. As summarized in Table II, the GRU model demonstrated the best trade-off between performance and efficiency, achieving a final loss similar to LSTM while being computationally faster.

In conclusion, while RNNs can model sequential data, LSTM and GRU models outperform them by mitigating the vanishing gradient problem. Normalization techniques further enhance model training by improving stability and convergence. Among all evaluated models, GRU emerges as the most efficient option, balancing accuracy and computational cost effectively. This study highlights the importance of choosing advanced architectures like LSTM/GRU and integrating normalization techniques for sequential tasks such as music modeling in datasets like Bach Chorales.

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