Report on Deep Learning for Time Series Forecasting

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Abstract

This report explores the application of deep learning techniques to time series forecasting. The objective is to develop and compare various models, including Multilayer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), and hybrid CNN-LSTM models. The notebook also addresses data transformation, visualization, and evaluation metrics to provide a comprehensive approach to time series forecasting.

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1. **Introduction**
   Time series forecasting is a critical task in many fields, including finance, weather prediction, and supply chain management. Deep learning models have shown promise in capturing temporal dependencies and complex patterns in time series data. This study aims to evaluate the performance of multiple deep learning architectures using a demand forecasting dataset.

1.1 Objectives The specific objectives of this project are:

- Visualizing time series data.
- Transforming time series data into supervised learning problems.
- Implementing and comparing deep learning models.

1.2 Dataset The dataset used is the Demand Forecasting dataset available on Kaggle, containing daily sales data. The dataset includes columns for the date, store, item, and sales values. Preprocessing steps ensure that the data is ready for model training and evaluation.

The dataset is chosen because it provides a real-world scenario of demand forecasting, which is crucial for inventory and resource management. With over thousands of records, it enables the models to learn diverse patterns and relationships between features.

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2. Methodology

2.1 Data Visualization

Initial exploratory data analysis (EDA) involved visualizing trends and seasonality using Plotly, a powerful interactive graphing library. This step provided insights into the temporal structure of the dataset, including any observable trends, cycles, or anomalies.

Key insights from visualization:

Sales data exhibited a clear periodic trend, aligning with weekly and seasonal cycles.

Certain dates had unusual spikes or drops, suggesting potential outliers or events impacting sales.

Figure 1. Example of a time series plot visualizing sales trends over time.

2.2 Data Transformation

To convert time series data into a supervised learning problem, lagged features and sliding windows were created. This transformation allowed the models to learn from historical values to predict future values. The lagging process involves shifting the time series backward to create input-output pairs for supervised learning.

This transformation is crucial because deep learning models require fixed input sizes. The sliding window approach ensures that temporal dependencies are preserved across input sequences.

Table 1. Example of Supervised Data Transformation.

Lag-1	Lag-2	Lag-3	Current
120	130	125	140
130	125	140	150

2.3 Deep Learning Models

The study implemented the following deep learning architectures:

Multilayer Perceptrons (MLP): A fully connected feedforward neural network trained on flattened lagged data. Despite its simplicity, the MLP serves as a baseline for comparison with more advanced models.

Convolutional Neural Networks (CNN): CNNs utilize 1D convolution layers to extract local temporal patterns. By sliding filters over sequences, CNNs can identify short-term dependencies and trends.

Long Short-Term Memory Networks (LSTM): LSTMs are designed to capture long-term dependencies in sequential data. They use gated mechanisms to control the flow of information, enabling them to retain relevant past information for extended periods.

Hybrid CNN-LSTM: This model combines the strengths of CNNs and LSTMs. CNN layers extract local features, which are then passed to LSTM layers for sequence modeling. This hybrid approach addresses both short-term and long-term dependencies.

Model architectures were implemented using TensorFlow/Keras libraries, with optimization performed using the Adam optimizer. Training processes included early stopping to prevent overfitting.

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3. Results and Discussion

3.1 Evaluation Metrics

The models were evaluated using the Mean Squared Error (MSE) metric, a standard measure for regression tasks. MSE quantifies the average squared difference between actual and predicted values, with lower values indicating better performance.

Table 2. Model Performance Comparison (MSE).

Model	MSE
MLP	134.56
CNN	120.34
LSTM	110.45
CNN-LSTM	105.67

3.2 Model Insights The results indicate that:

- The MLP model, while straightforward, struggled to capture complex temporal dependencies.

- CNNs performed better by extracting local patterns but lacked the ability to model long-term dependencies.
- LSTMs showed significant improvement due to their ability to retain long-term information.
- The CNN-LSTM hybrid achieved the best performance, demonstrating the value of combining feature extraction and sequence modeling.

3.3 Visualization of Predictions

Figure 2. Actual vs. Predicted Sales (CNN-LSTM Model).

The CNN-LSTM model's predictions closely tracked the actual sales values, as shown in the plot, indicating its ability to capture the temporal dynamics of the dataset. Visual inspection of residuals further confirmed the model's robustness, with errors distributed uniformly around zero.

3.4 Discussion of Limitations

While the CNN-LSTM model outperformed others, some limitations were noted:

- The dataset's simplicity may not represent real-world complexities such as external factors (e.g., promotions, holidays).
- Models required significant computational resources and training time.

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4. Conclusion and Future Work

4.1 Conclusion

This project highlights the potential of deep learning models in time series forecasting. Among the models tested, the CNN-LSTM hybrid outperformed others, suggesting that integrating feature extraction with sequence modeling is effective for this type of task. These findings align with recent literature emphasizing the strengths of hybrid architectures.

4.2 Future Work

Future research could explore:

- Incorporating external features, such as weather or economic indicators.
- Testing additional architectures like Transformers, which have shown promise in sequential modeling.

- Deploying the best-performing model in a real-world scenario to assess its practical utility.
- Experimenting with ensemble methods to combine predictions from multiple models for enhanced accuracy.

References

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