Paper Title:
Distributed deep learning for big data time series analysis

Paper Link:
https://link.springer.com/chapter/10.1007/978-3-031-15063-0_31

1 Summary

1.1 Motivation

To tackle the formidable task of large-scale traffic flow prediction, it confronts three significant challenges First, it requires lots of computation when the prediction must be performed in large scale Second, achieving good accuracy of time series prediction is challenging for most traditional machine learning algorithms. Third, the amount of training data is so big that is very difficult to train on a single machine.

1.2 Contribution

The proposed big data time series analysis system solves all the above problems using distributed deep learning. The experimental results show that the system can predict the traffic flow in large scale at accuracy levels that are much higher than that of traditional machine learning models. The entire traffic flow prediction system runs on Apache Spark big data framework, which allows the prediction to be performed on large scale. A Temporal Convolutional Networks (TCN) model is proposed and applied to achieve high accuracy of traffic flow prediction. The model trained on a huge amount of training data using a distributed deep learning framework namely BigDL.

1.3 Methodology

The proposed TCN model consists of an architecture of 3 temporal blocks. Each temporal block consists of two 1D Causal Convolutional layers and alternately Normalization, Dropout, and ReLU as activation layers. The deep learning model was trained using a distributed approach, where the entire dataset underwent preprocessing on the Apache Spark platform for formatting and data cleansing. Subsequently, Orca and RayOnSpark libraries were employed to establish a distributed environment. The data was introduced into this distributed environment and converted into the standard time series data format using the Chronos library. The data was partitioned into equal segments and distributed across machines, following the data parallelism approach. The deep learning model was deployed to all machines within the distributed clusters, and each machine conducted training on its assigned data segments. Model weights were updated through forward-backward propagation. The evaluation and analysis of model errors on the test dataset followed a similar distributed process. The Chronos library facilitated the reloading of the model from the trained weights for testing and evaluation.

1.4 Conclusion

The temporal Convolutional Networks deep learning model achieved very high performance compared to with traditional machine learning model.

2 Limitations

2.1 First Limitation

Real-time Predictions - The first limitation is the real-time applicability of traffic flow predictions. While the system excels at large-scale predictions, real-time scenarios pose challenges due to dynamic data changes. Further research is essential to enhance real-time capabilities.

2.2 Second Limitation

Data Security - The paper acknowledges the importance but lacks specific insights into protective measures. Clarification and robust security strategies are needed. Addressing these limitations is vital for real-world applications.

3 Synthesis

The paper's innovative approach to large-scale traffic flow prediction using distributed deep learning opens doors to a range of applications and future research prospects. It has the potential to transform traffic management, congestion prediction, and the development of smart cities, while also driving progress in machine learning methodologies.