Paper Review: Modeling Long- and Short-Term Temporal Patterns with Deep Neural Networks

Abdullah Mamun

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About this paper

Modeling Long- and Short-Term Temporal Patterns with Deep Neural Networks

Guokun Lai
Carnegie Mellon University
guokun@cs.cmu.edu

Wei-Cheng Chang
Carnegie Mellon University
wchang2@andrew.cmu.edu

Yiming Yang
Carnegie Mellon University
yiming@cs.cmu.edu

Hanxiao Liu
Carnegie Mellon University
hanxiaol@cs.cmu.edu

ABSTRACT

Multivariate time series forecasting is an important machine learning problem across many domains, including predictions of solar plant energy output, electricity consumption, and traffic jam situation. Temporal data arise in these real-world applications often

hazardous events based on historical observations on time series signals. For instance, a better route plan could be devised based on the predicted traffic jam patterns a few hours ahead, and a larger profit could be made with the forecasting of the near-future stock market.

About this paper

- Published by a team of **Carnegie Mellon University** in **ACM SIGRI** conference in 2018
- Cited by **281** as of April 12, 2021
- Main goal is building a **forecasting model** for multi-dimensional time series data.

Time-series problem types in general

- Weather forecasting
- Forecasting by EEG tracing if a patient is having a seizure
- Predicting future daily demands of any product
- Price of stock
- Birth rate at all hospitals in a city
- Corn yield
- Average price of gasoline in a city each day

- *Global properties vs local properties*

Concerns with Time-Series forecasting

- How much data do we have?
- What is the time horizon of predictions that is required?
- Can forecasts be updated frequently over time?
- At what temporal frequency are forecasts required?

Dataset

- Electricity: Energy consumption (kWh) from 321 clients
- Solar: power production of 137 plants
- Exchange rates of 8 foreign countries
- Road occupancy rates of different sensors

Datasets	T	D	L
Traffic	17,544	862	1 hour
Solar-Energy	52,560	137	10 minutes
Electricity	26,304	321	1 hour
Exchange-Rate	7,588	8	1 day

Table 1: Dataset Statistics, where T is length of time series, D is number of variables, L is the sample rate.

LSTNet

- Both Long-term and short-term patterns are important
- Example (solar energy)-
  short-term: cloud-movement effects
  long-term: day vs night, even months or years
- Combination of 2D Convolution and Recurrent networks

LSTNet- Model

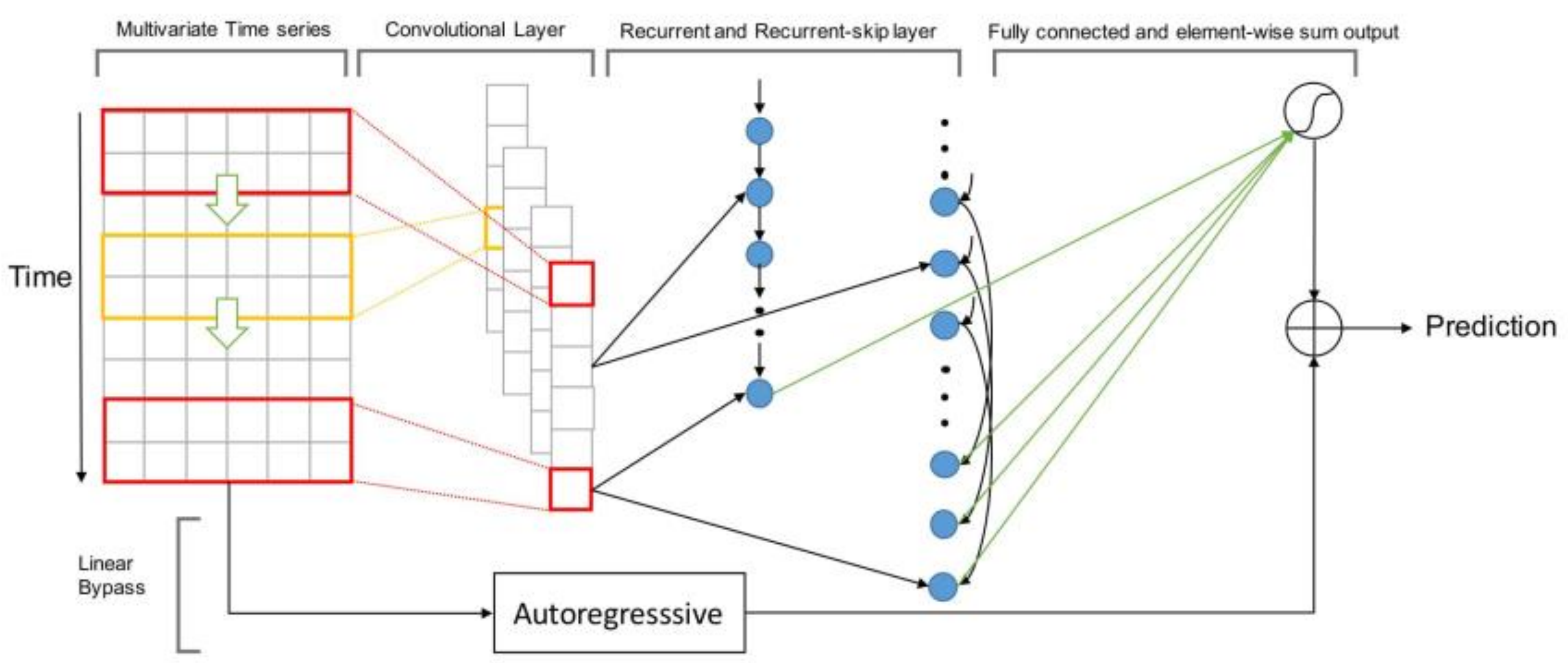
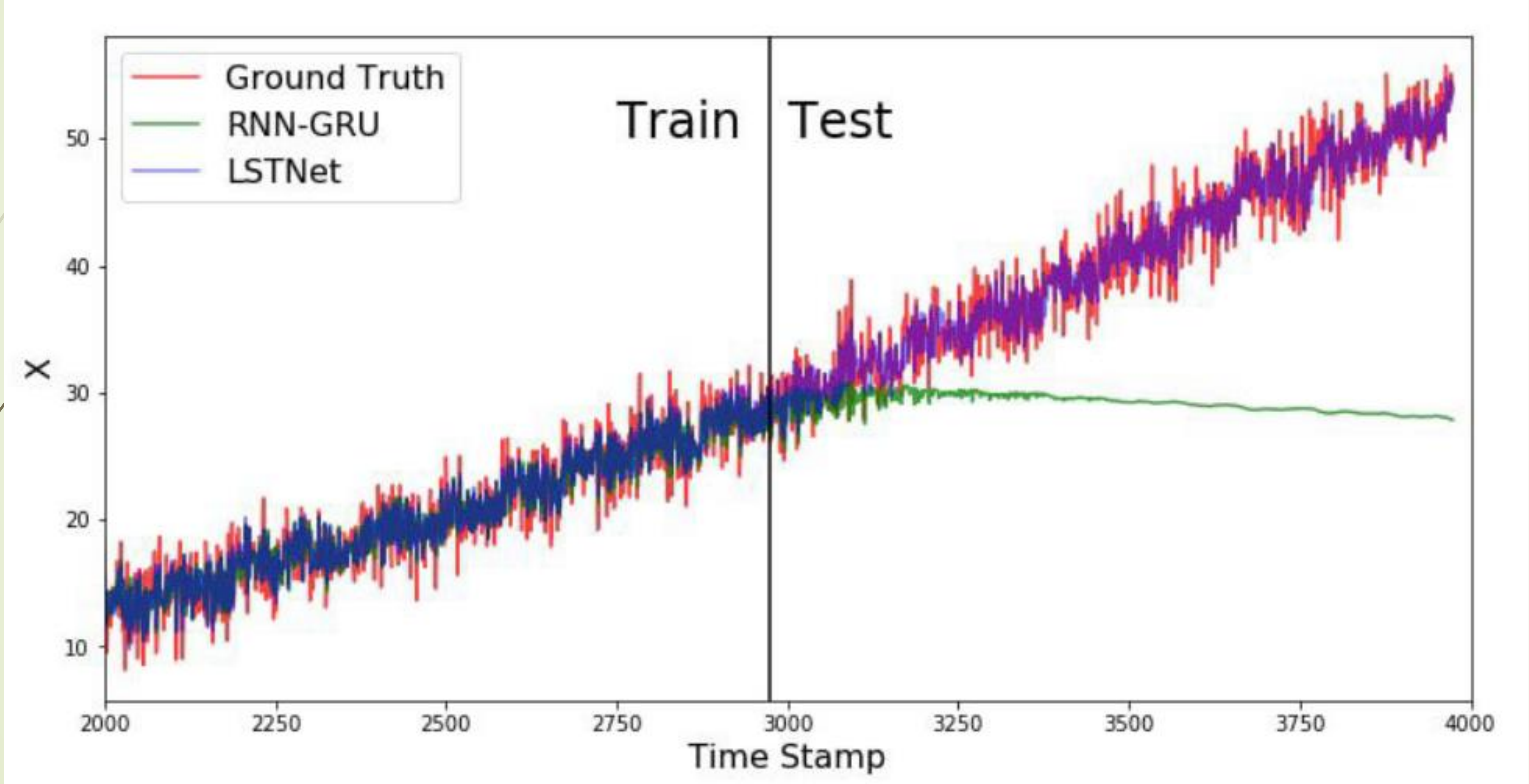


Figure 2: An overview of the Long- and Short-term Time-series network (LSTNet)

Why not traditional RNN models



Ablation Study (study of the importance of individual components)

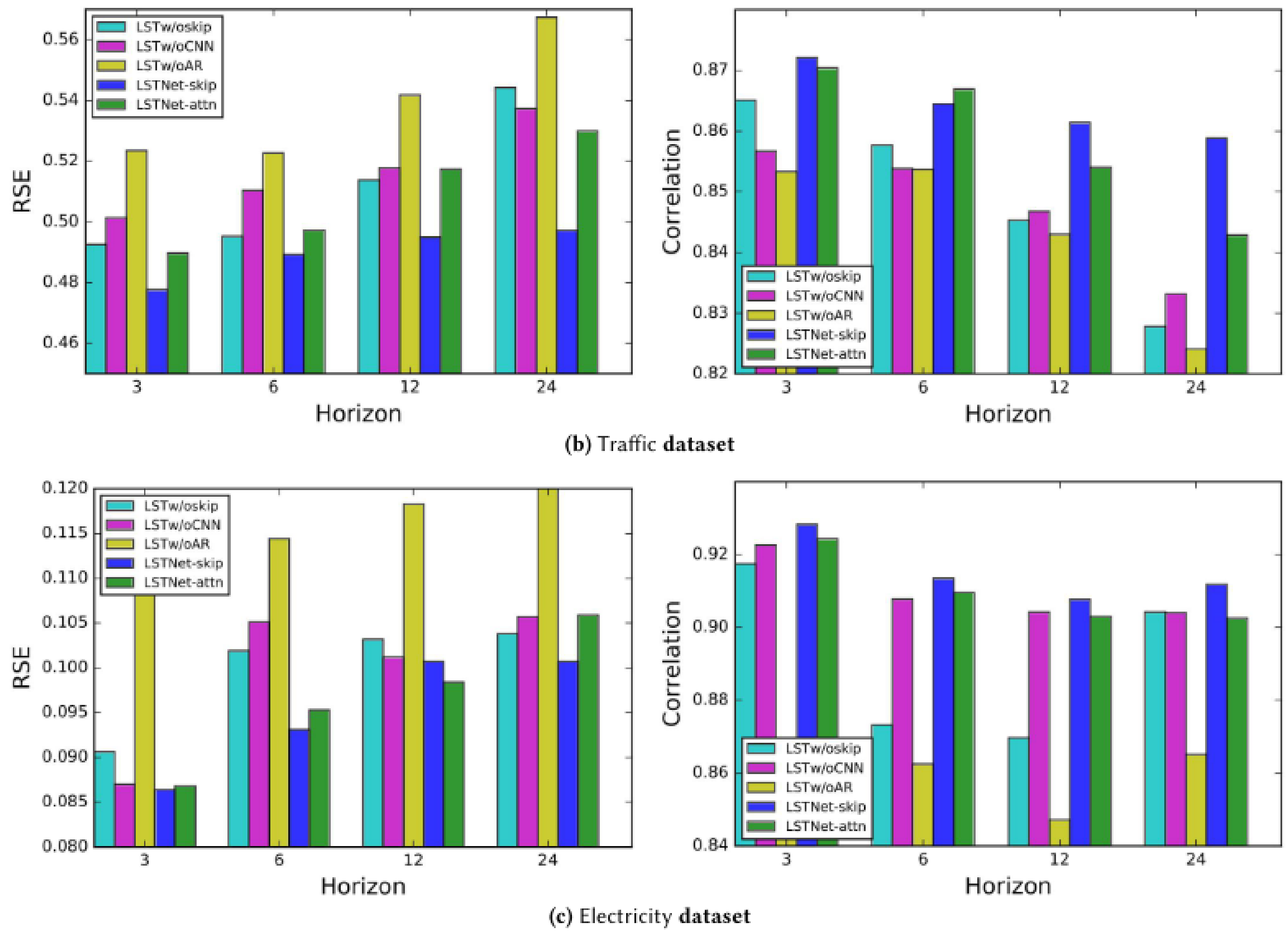


Figure 5: Results of LSTNet in the ablation tests on the Solar-Energy, Traffic and Electricity dataset

Summary

- This method can capture both long-term and short-term patterns
- This method does not scale beyond 1000 features.
- Generally, the autoregressive module is an essential part of the model. Without it the relative error becomes high.
- RNN-GRU model does not respond well to the scale change in the test set.

Thank You!

Contact: abdullahal.mamun1@wsu.edu

Read the paper here
Code is available here