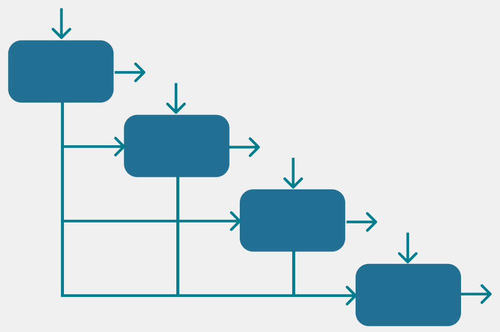
Attention LSTM

Evaluation of Time Series Forecasting Performance: a Comparison With LSTM and SARIMA

ALSTM



Main Features

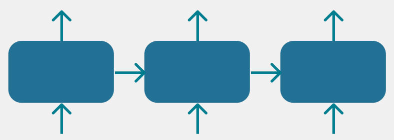
Direct communication between time steps

Hypothesis:

Better forecasting performace

Learn longer patterns in time series

LSTM



Features

Distant time steps can not communicate directly

Problems

Computationally heavy to learn long patterns

SARIMA

AR

AutoRegressive:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t.$$

MA

Moving Average:

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

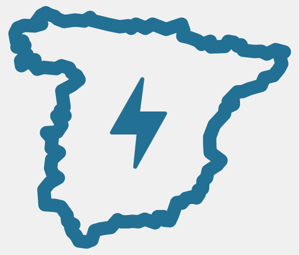
Seasonal: Accounts for ciclicity of time series

Integrated: Differentiation makes time series stationary

Training Strategies

ALSTM & LSTM:	Training	Validation	Test
SARIMA:	Training		Test

Dataset & Context



Daily frequency, 2015 to 2018

Electricity Data

Spanish electricity grid load

Weather Data

Spain's 5 biggest cities

Min, max and average temperature

Precipitation (rain and snow)

Main Task:

Forecast following day/month grid load

Following Day Prediction RMSE

ALSTM:	0,2106	± 0,0059
LSTM:	0,2110	± 0,0013
LSTM:	0,1802	

Following Month Prediction

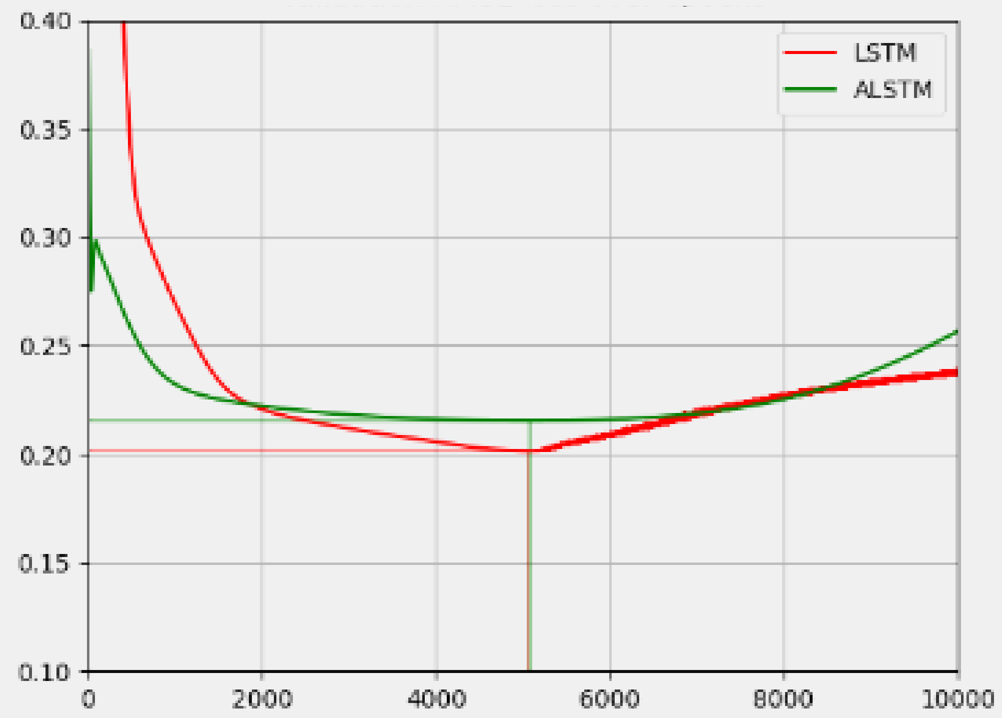
RMSE

ALSTM:	0,218	± 0,028
LSTM:	0,216	± 0,024
SARIMA:	0,195	± 0,025

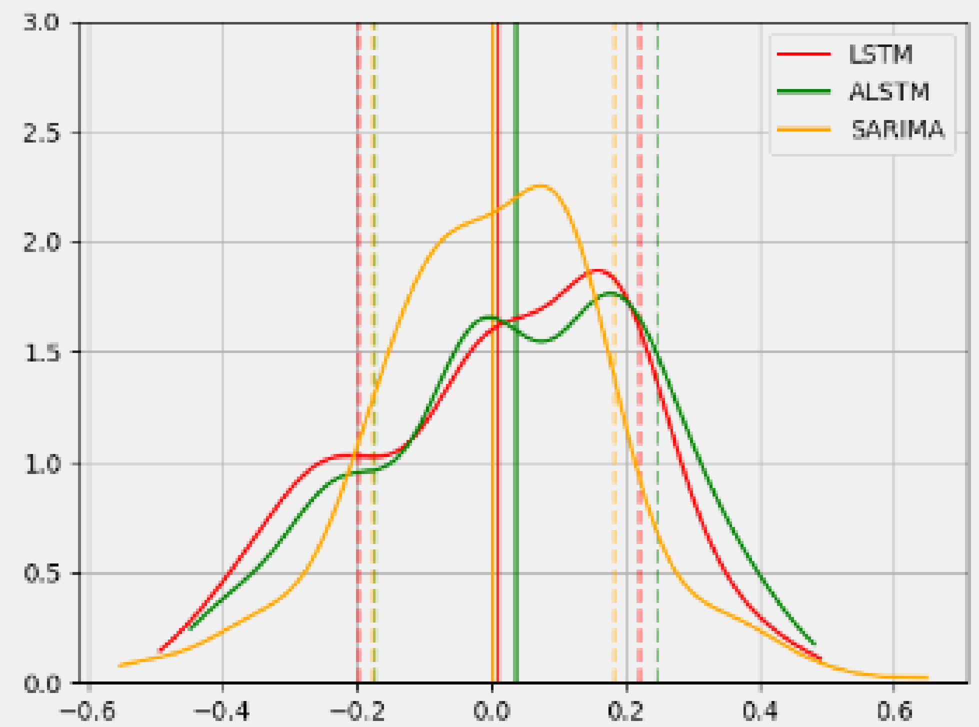
1st order diff. RMSE

ALSTM:	0,226	± 0,028
LSTM:	0,250	± 0,026
SARIMA:	0,249	± 0,026

Validation RMSE over Epochs



Following Day Forecast Error Distribution



	MEAN	STD
ALSTM:	-0,023	0,210
LSTM:	-0,023	0,209
SARIMA:	-0,003	0,180