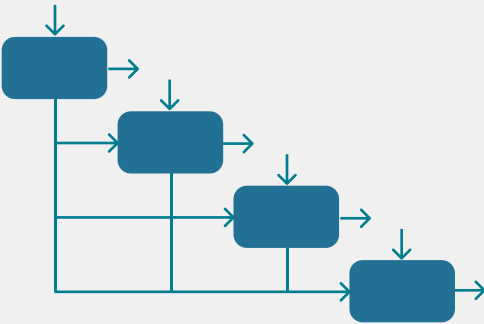


# Attention LSTM

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

### ALSTM



#### Main Features

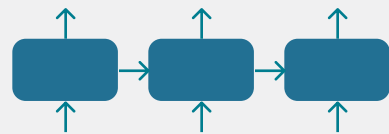
Direct communication between time steps

#### Hypothesis:

Better forecasting performance

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:

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

Seasonal:

Accounts for ciclicity of time series

Integrated:

Differentiation makes time series stationary

#### MA

Moving Average:

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

## Training Strategies

ALSTM & LSTM:

Training

Validation

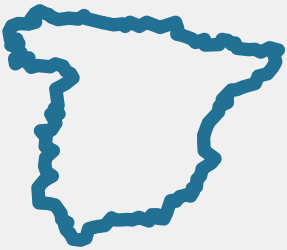
Test

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