Advanced Time Series

Lecture 3: Forecasting II

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What we've learned so far

Basic elements:

- basic encoder-decoder design
- probabilistic forecasting
- mentioned some extensions: AR → attention

Today

More advanced blocks:

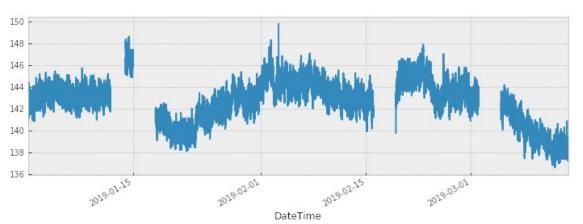
- AR and attention in details
- various example architectures

AR block implementation

Time series scales

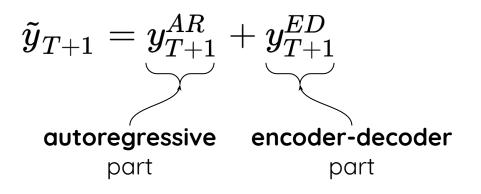
For **non-stationary** time series, **scale** may possess a problem: non-linear elements of deep learning models do not scale. **Variability** may be, in contrast, **nearly**

constant.



Time series scales

Linear elements, in contrast, are **resilient** to scale changes. We may want to add a **direct AR component**:



$$y_{T+1}^{AR} = \sum_{k=0}^{k=h} W_k y_{T-k} + b$$

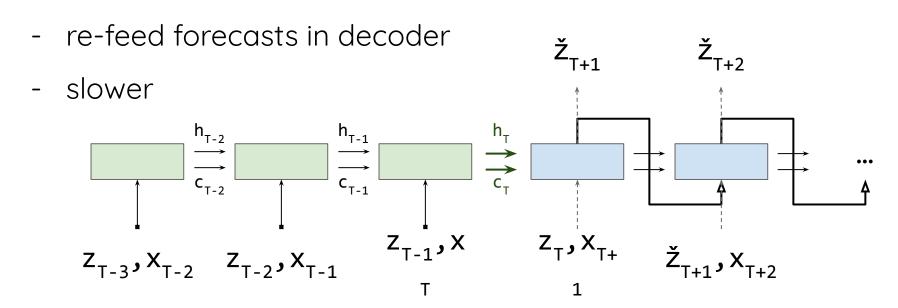
AR component

Direct AR component:

- handles changing (non-seasonal!) scale
- works nicely with other elements, objective functions and training procedures (it's just a dense layer after all)

Shared weights

Design technicalities:



LSTM recap

- input: (N, L, H_{in}) (batch_first==True)
- output: (N, L, H_{out})
- h: (n_layers, N, H_{out})
- c: (n_layers, N, H_{out})

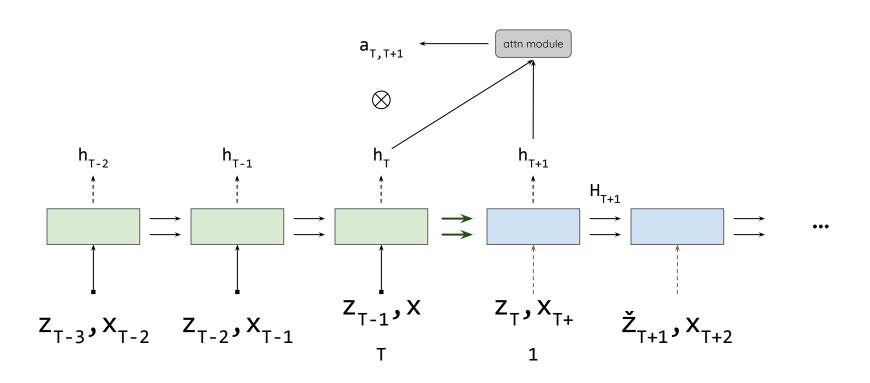
For power consumption (grid-level): $H_{in} = 1$

Temporal attention

Motivation

- last hidden state of the encoder may be not enough to encode the history properly
- some specific moments in history may be more important than others
- we want some mechanism able to look at those moments

Idea



Idea

- hidden state H_{T+1} is a combination of h_{T+1} and a weighted sum of $(..., h_{T-3}, h_{T-2}, h_{T-1}, h_{T})$: $F(h_{T+1}; a_{k,T+1}, h_{k})$
- weights (**attention** scores) are some proper functions of \mathbf{h}_k and \mathbf{h}_{T+1} : $\mathbf{A}(\mathbf{h}_k, \mathbf{h}_{T+1})$
- this is basically a version of soft alignment, known in NLP

Neural Machine Translation By Jointly Learning To Align And

Translate

Implementation

- power consumption dataset (for simplicity)
- GRU, not LSTM single hidden vector
- F is a simple feedforward nets and A scalar product
- have to iterate manually in GRU (need all intermediate hidden states),
 hence will use GRUCell

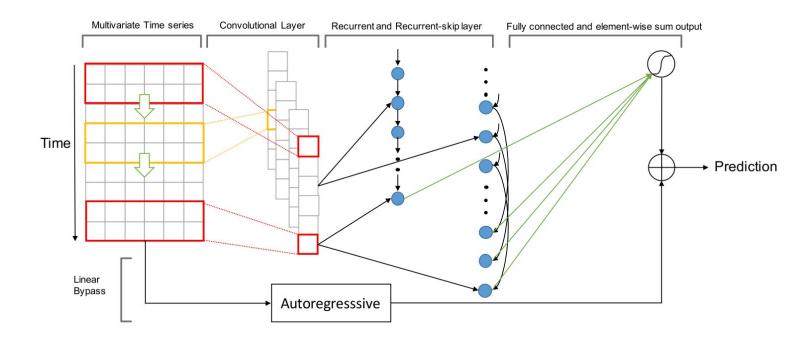
LSTNet & others: all the blocks

Setup:

- multivariate time series
- global + local patterns
- Conv + Recurrent + skip connections + AR loop

Modeling Long- and Short-Term Temporal Patterns with

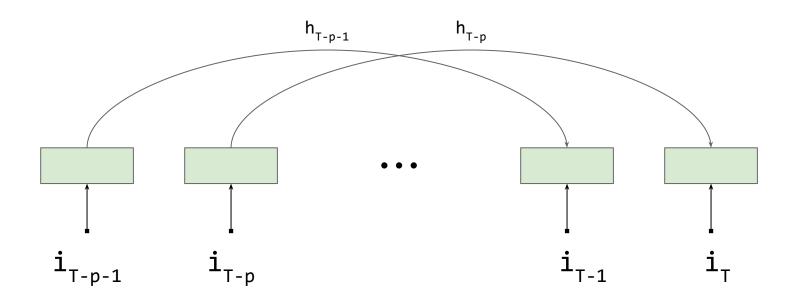
Deep Neural Networks



Features:

- **convolutions** look natural for multivariate t.s.: capture short range dependencies between variables
- recurrent layer (GRU) captures long range dependencies
- recurrent skip-connections: capture seasonality (longer range)

LSTNet: recurrent-skip



Features:

- **temporal attention**(instead of rec. skip): no need to specify lag time
- AR bypass: discussed earlier
- available in GluonTS

LSTM-MSNet

Setup:

- input data: similar to DeepAR
- explicit handling of seasonality
- slicing: similar to W1 encoder-decoder

LSTM-MSNet: Leveraging Forecasts on Sets of Related

<u>Time Series with Multiple Seasonal Patterns</u>

DeepGLO

Setup:

- high-dimensional t. s.
- **no normalization**: handled by initialization
- temporal CNN

Think Globally, Act Locally: A Deep Neural Network

Approach to High-Dimensional Time Series Forecasting

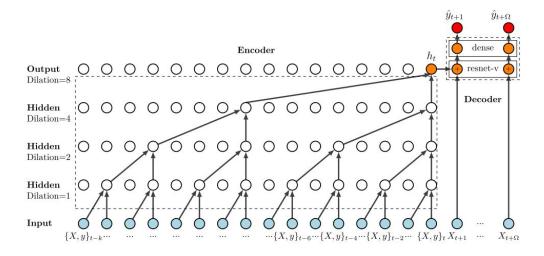
Other

Shape and Time Distortion Loss for Training Deep Time Series
Forecasting Models

<u>Probabilistic Forecasting with Temporal Convolutional Neural</u> <u>Network</u>

Other

<u>Probabilistic Forecasting with Temporal Convolutional Neural</u> <u>Network</u>



Next time

- N-BEATS
- transformer architecture
- convolutions in details
- setting up the classification problem

HW 2

A Multi-Horizon Quantile Recurrent Forecaster

https://arxiv.org/abs/1711.11053

Paper implementation:

- deadline is June 10 24:00
- see instructions in Google Classroom

questions?