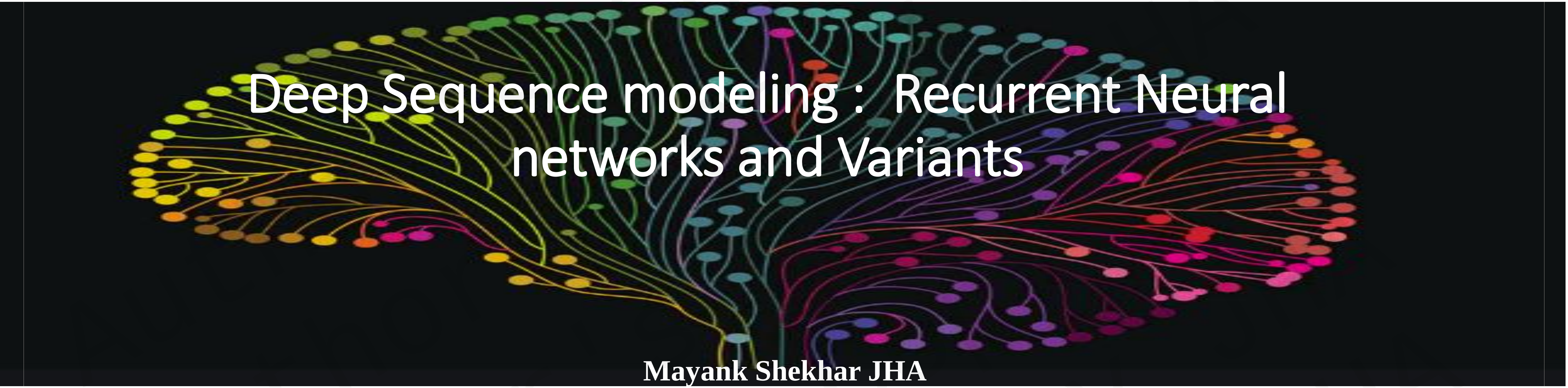

Deep Sequence modeling : Recurrent Neural networks and Variants

Mayank Shekhar JHA

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(Maitre de Conférences)

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Sequence Modelling

Recurrent Neural Networks

Long Short Term Memory (LSTMs)

Application: Prognostics and Deep Learning

Sequence Modelling

Motivations
Challenges
Some ideas
Design

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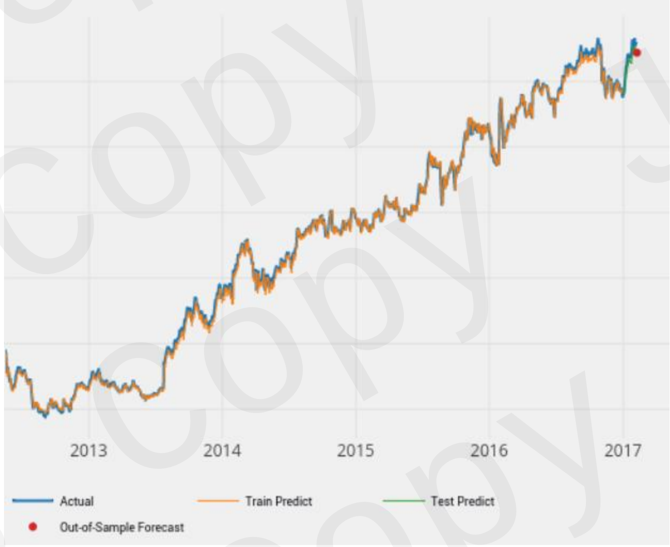
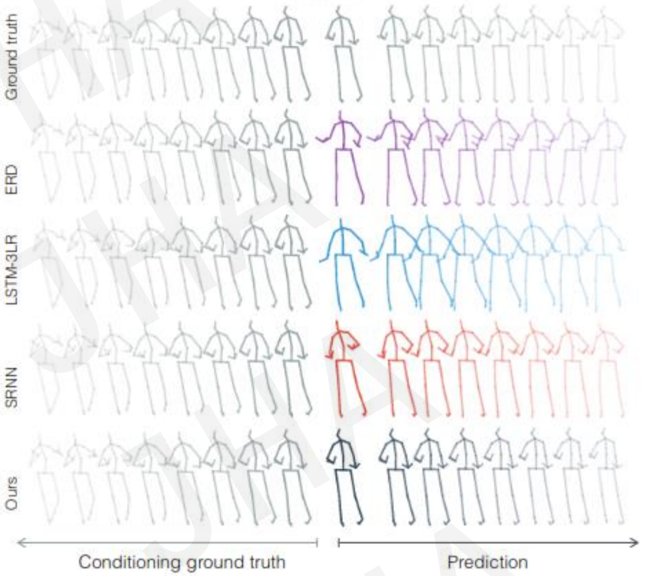
Sequence modelling : Motivations

- Sequential data:
  - time series forecasting,
  - motion prediction (human, self driving cars)
  - sensor data: machine health monitoring/prediction
  - text processing/prediction
  - machine translation



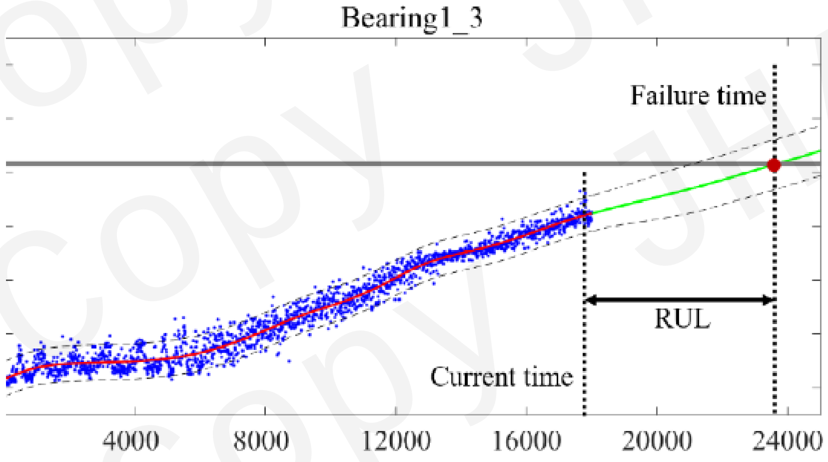
Financial market prediction (Dixon et al.)



Human Motion Prediction

Martinez et al., 2016

*I am from London but I live in Paris and I speak fluent **English.***



Component Failure Prediction
(Yoo et al., 2018)

Sequence modelling : Motivations > Challenges

- Inputs data
  - Variable lengths
  - spatially + temporally dependent
  - ordered
  - output data different length than input (machine translation)

Sequence modelling : Motivations >Challenges > Some ideas

1. Fixed window
   - cannot model long term dependencies
2. Use whole sequence as counts (I occurs 3 times)
   - no learning of order (what followed by what?)
3. Large window length input
   - each has separate parameter
   - learning will not transfer at other places in the sequence.

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One hot coding

[00100101000101011000011….] ➡ ???

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Sequence modelling : Motivations >Challenges > Some ideas

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- Feed forward NN, not designed to:
  - handle variable data lengths
  - parameter sharing (correlation, temporal dependency…)
  - track long term dependency + order

- CovNets:
  - can share parameters across time but remain shallow.

Sequence modelling : Motivations >Challenges > Some ideas > Design

- Variable length inputs
- Learn long term dependencies
- Learn the order in data
- Share parameters across sequence
- Make predictions (long term) efficiently.

Recurrent Neural Networks

RNNs: Structure

- Recurrence of states. Ex. a dynamical system
- Recursive computation ➔ Computational graph

$$s_t = f(s_{t-1}, w)$$

$$\cdots \xrightarrow{f} s_{t-1} \xrightarrow{f} s_t \xrightarrow{f} s_{t+1} \xrightarrow{f} s_{t+2}$$

$$\begin{aligned} s_3 &= f(s_2, w) \\ &= f(f(s_1, w), w) \end{aligned}$$

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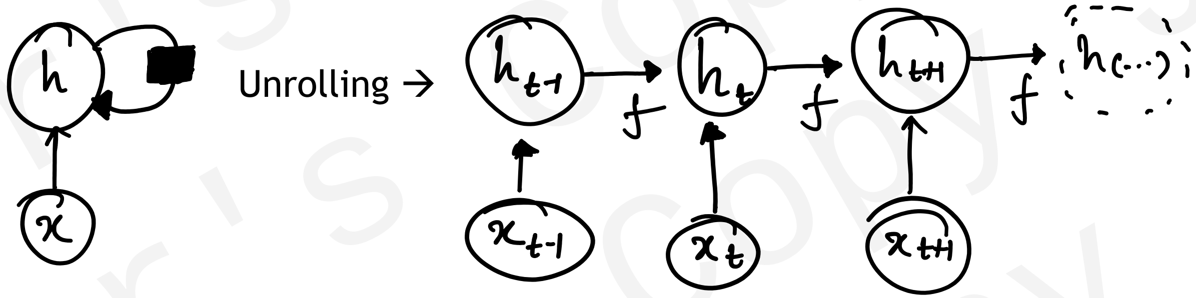
  New state contains information about history.

$$s_t = f(s_{t-1}, w)$$

Rewritten

$$h_t = f(h_{t-1}, x_t, w)$$

RNNs : Output of node fed back into the hidden nodes (recurrent, cyclic structure)



- Captures dependency in input data.
- Same weights at each time step : some weight sharing.

$$h_t = f(h_{t-1}, x_t)$$
$$= \sigma(W^h h_{t-1} + W^x x_{t-1})$$

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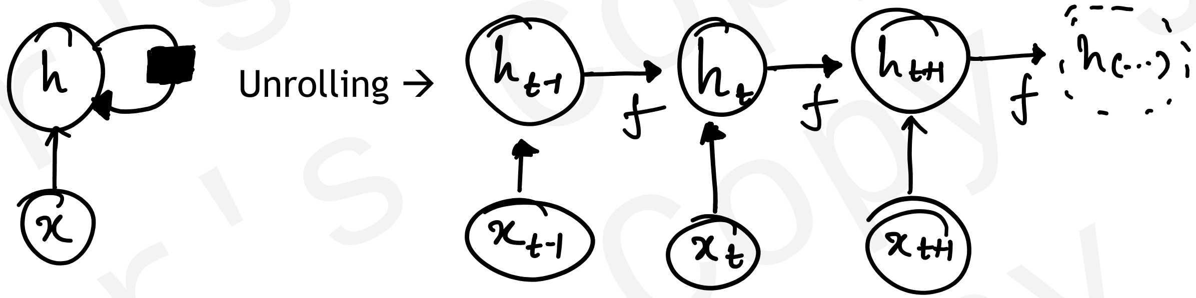

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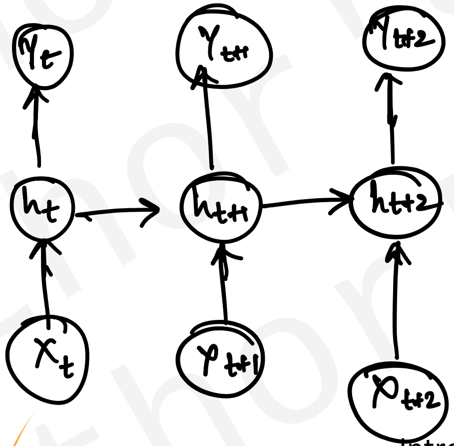

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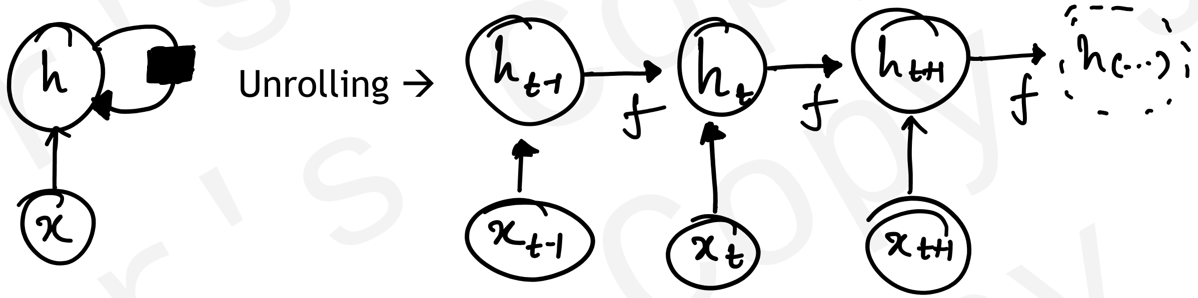

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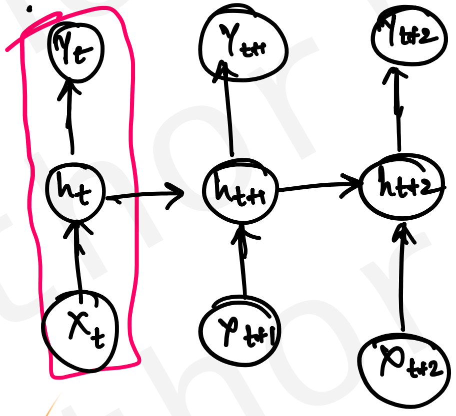

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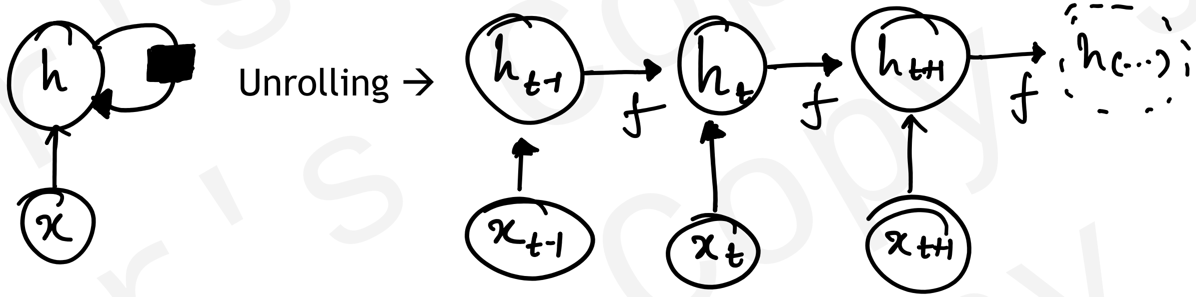

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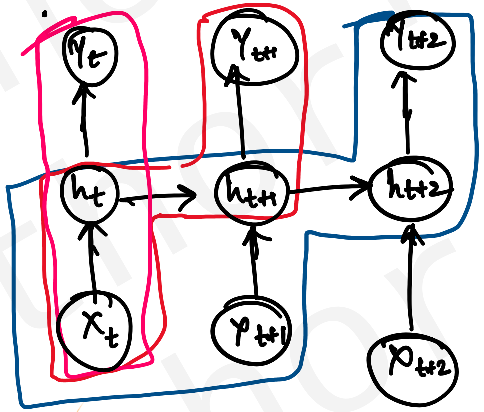

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- Depending upon application:
  - h needs to be rich,
  - capture all historical trends {cyclicity, seasonality, trend, fluctuations, global/local}

- Advantage:
  - learnt model has same size (regardless of input size)
  - possible to use same transition function f

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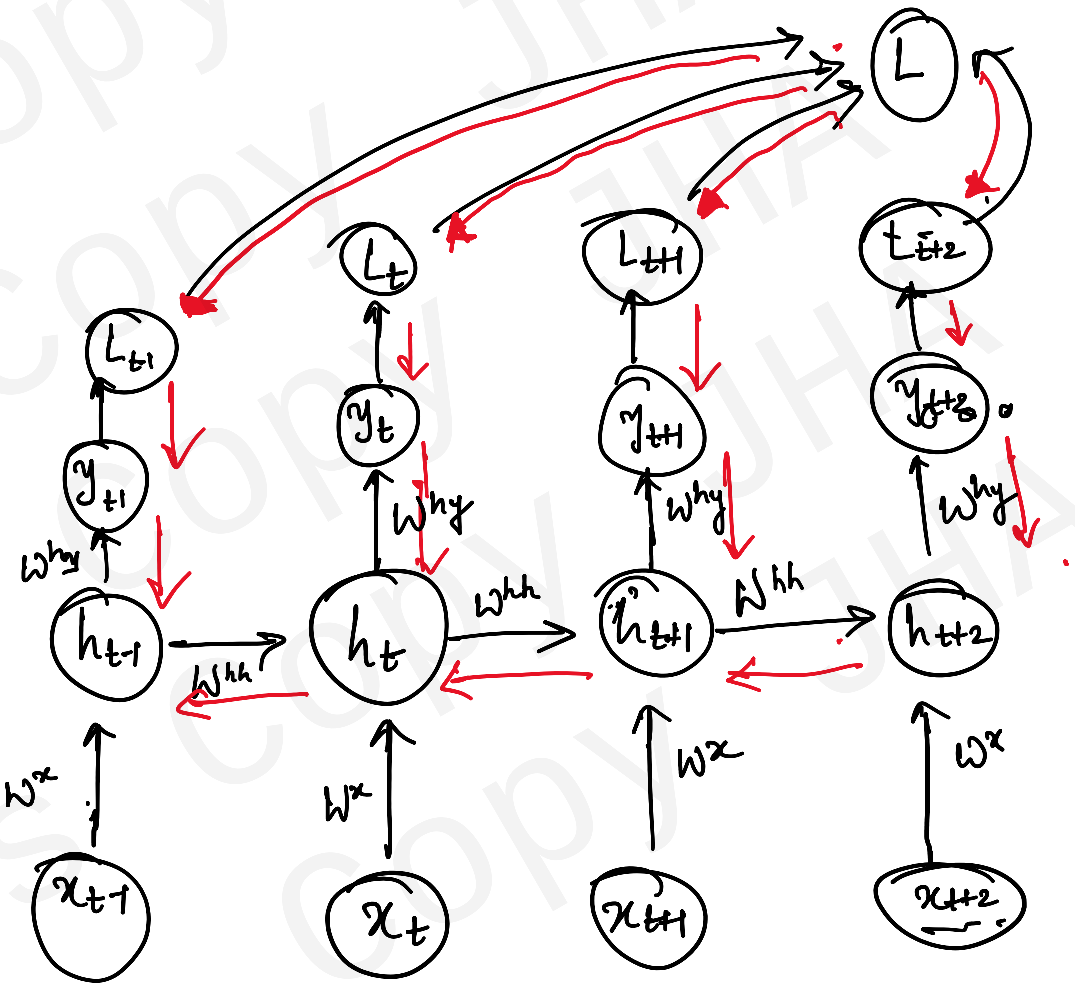
  - possible to use same transition function *f*

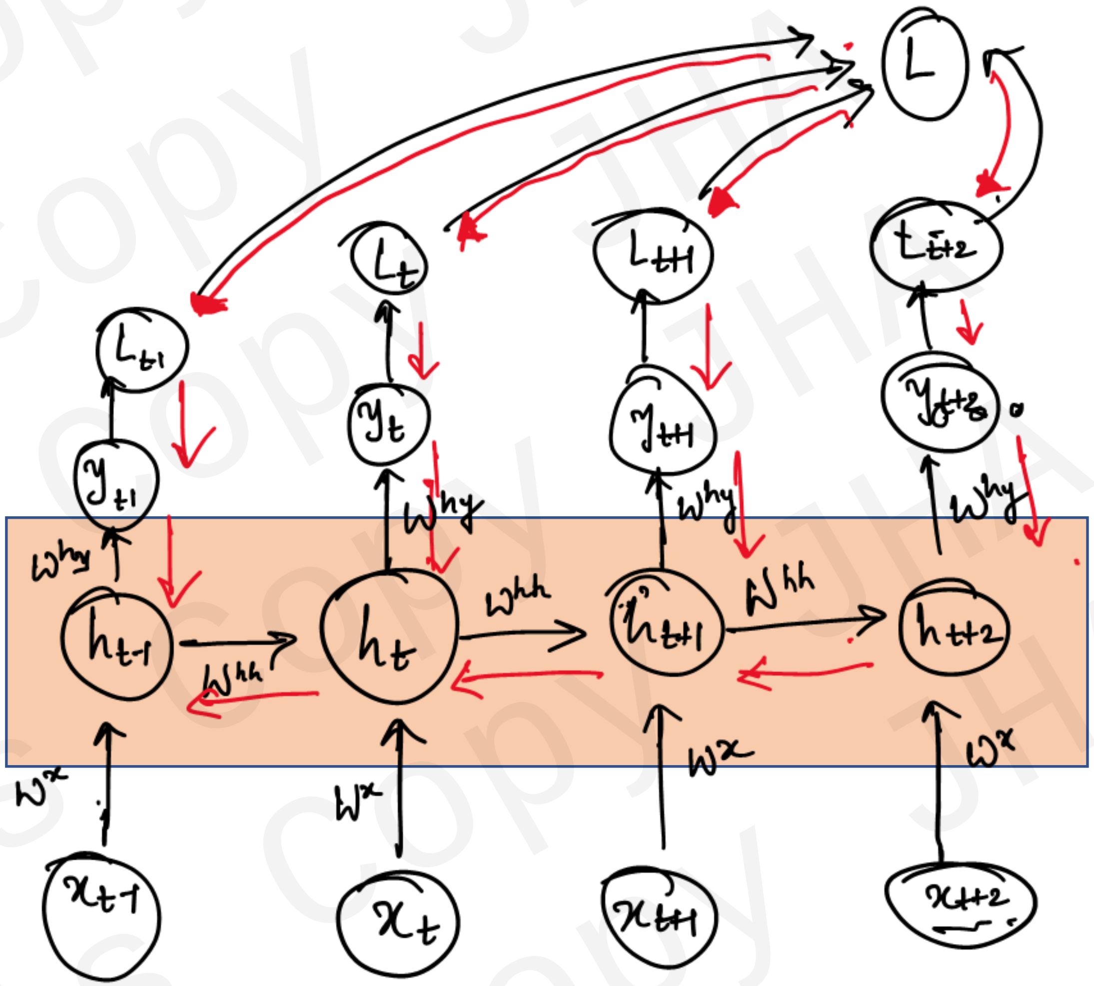
- Learning → Back-propagation through time (BPTT)
  - errors calculated/back-propagated over time = BP over unrolled network
  - gradients calculated in time.
  - Training slower than MLP:
    - repeated multiplication of weights in sequence length
    - repeated product of derivative of activation function.



Challenges:

Vanishing gradients: Many values <<1

- activation gradient products
- small weights
- negligible gradient ➔ negligible learning.



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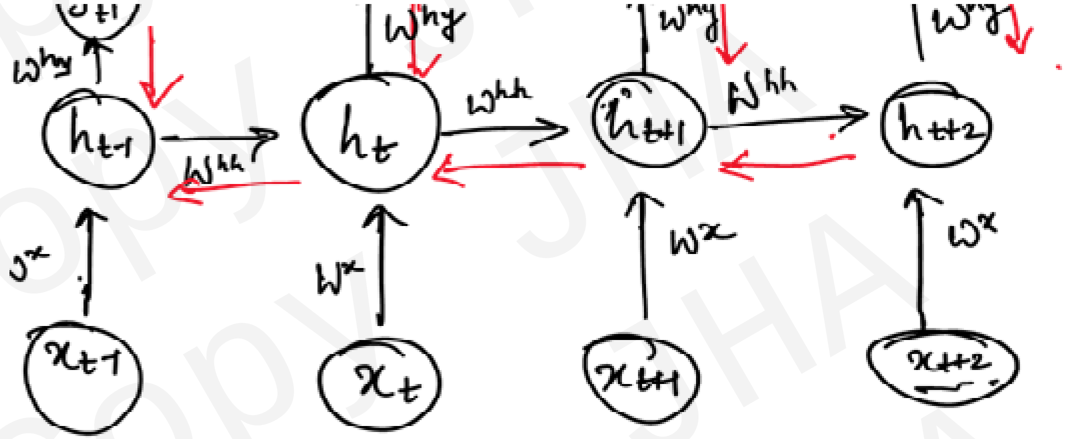

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Long range Learning:

- hidden units modify with new information
- vanishing gradient problem ➔ new information not preserved over long ranges.
    - time series forecasting: seasonality etc.

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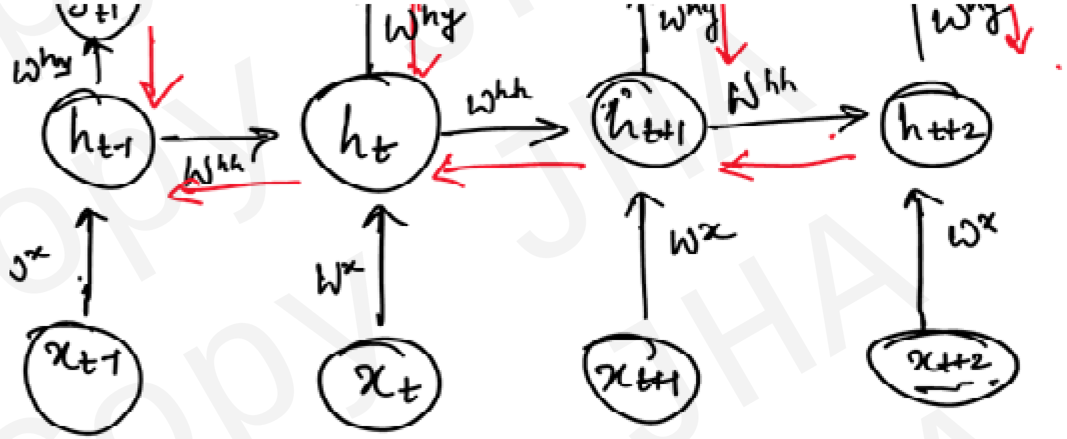

Long range Learning:

- hidden units modify with new information
- vanishing gradient problem ➔ new information not preserved over long ranges.
  - time series forecasting: seasonality etc.
  - machine translation: relation of first word to context
  - prognostics: prediction of state of health at long time range

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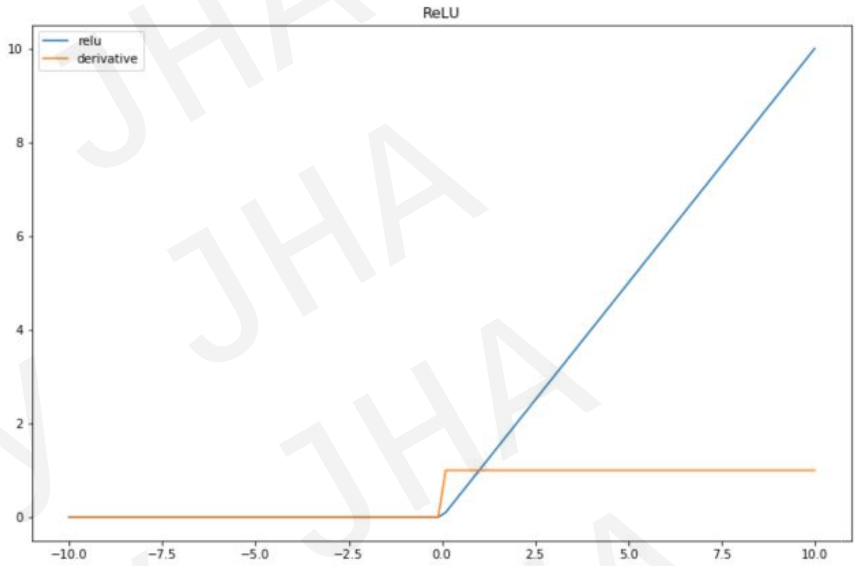
Prediction Drift:

- next step prediction ➔ recurrence of *h* learnt
- long range prediction → recurrence of *h* over multiple steps
- error cumulation over multiple time steps

Solution:

- Efficient parameter initialization
- Non-saturating activation functions: ReLU, Leaky ReLu…
- Gradient clipping



- Gated Cells:
  - "control" the information flow
  - allow more useful information, forget non-useful information…
  - track information through many time steps to filter out the useless ones.

Long Short Term Memory (LSTMs)

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LSTMs (Hochreiter & Schmidhuber 1997)

Gated RNNs: let selective information through

$$h_t = f(h_{t-1}, x_t)$$
$$= \sigma(W^h h_{t-1} + W^x x_{t-1})$$

cleverly designed

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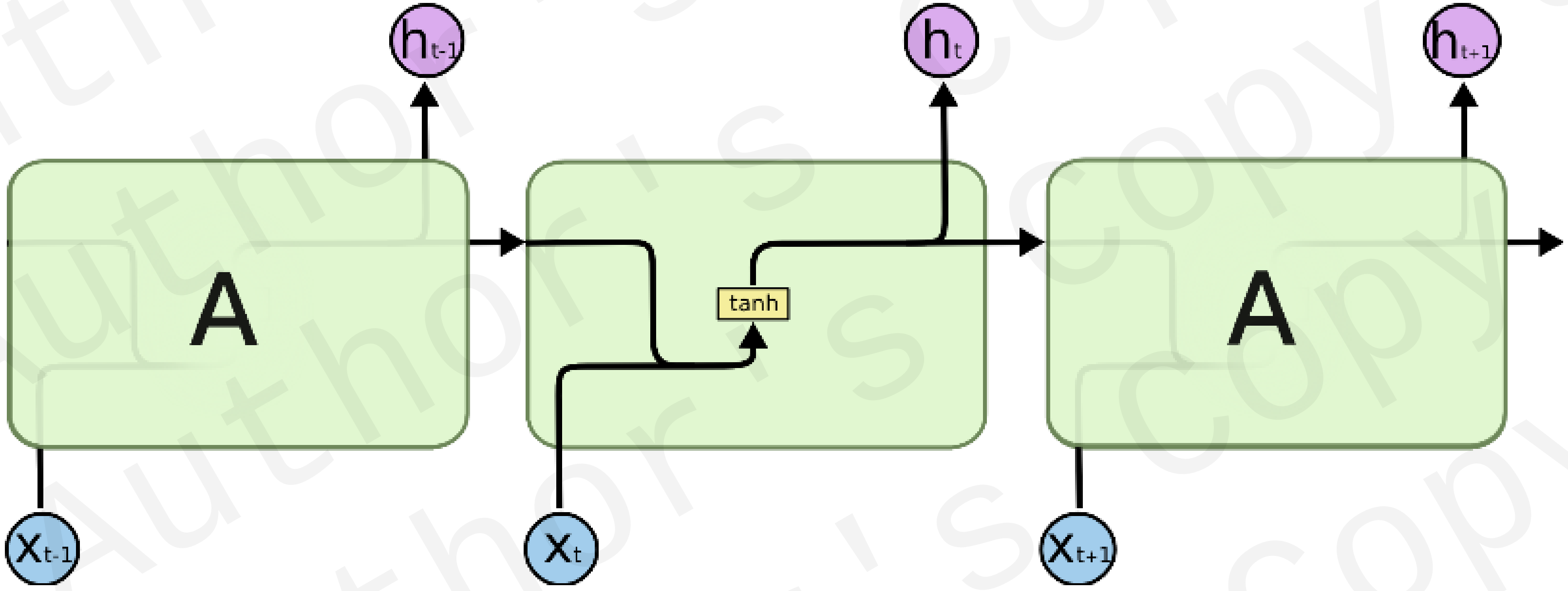

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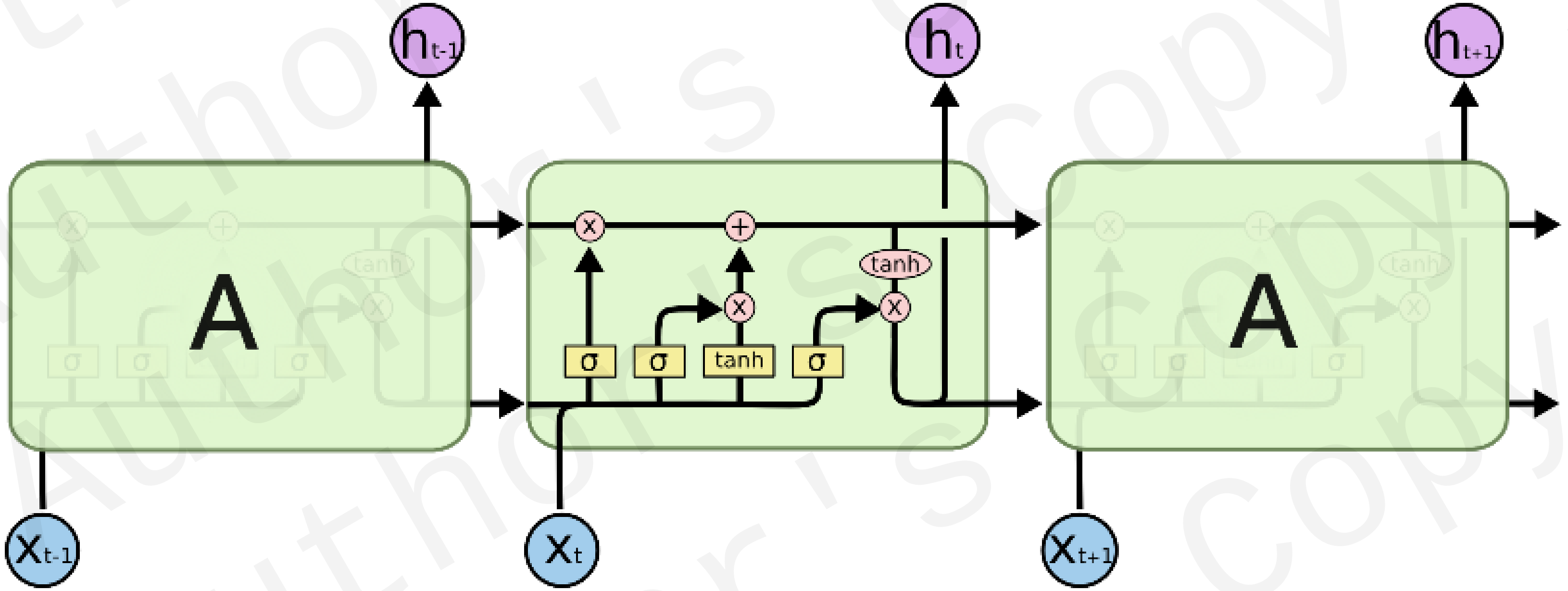

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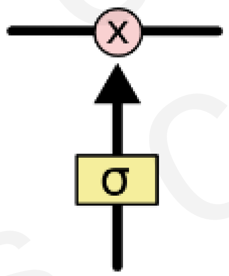
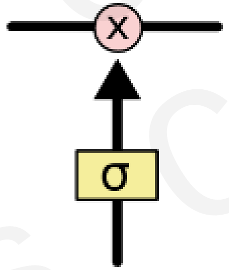


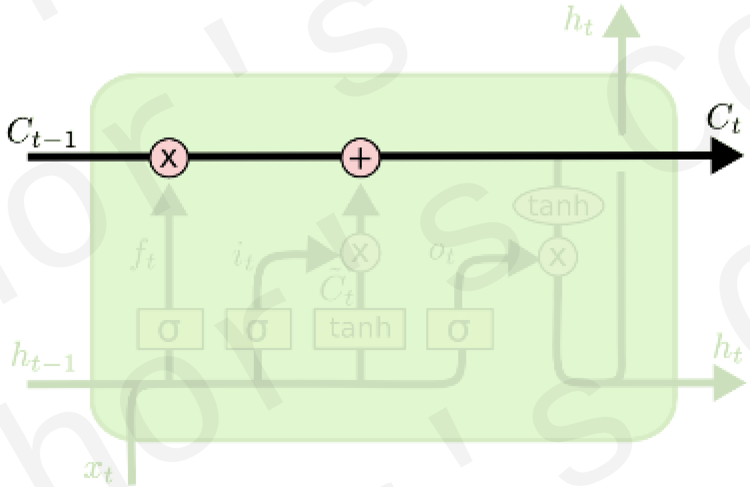
LSTMs (Hochreiter & Schmidhuber 1997)

Cell state: let selective information through

Gates:



Cell state : Information highway.



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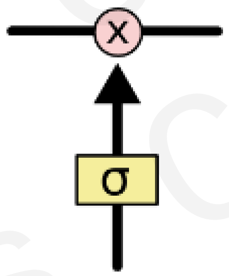
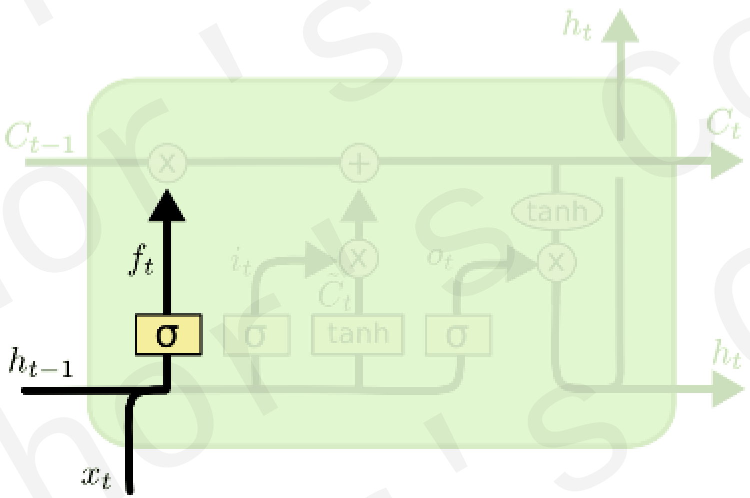


Cell state : Information highway.

1. Forget:



$$f_t = \sigma(W^f[h_{t-1}, x_t] + b_f)$$

LSTMs (Hochreiter & Schmidhuber 1997)

Cell state: let selective information through

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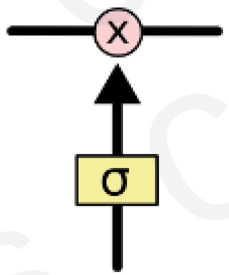
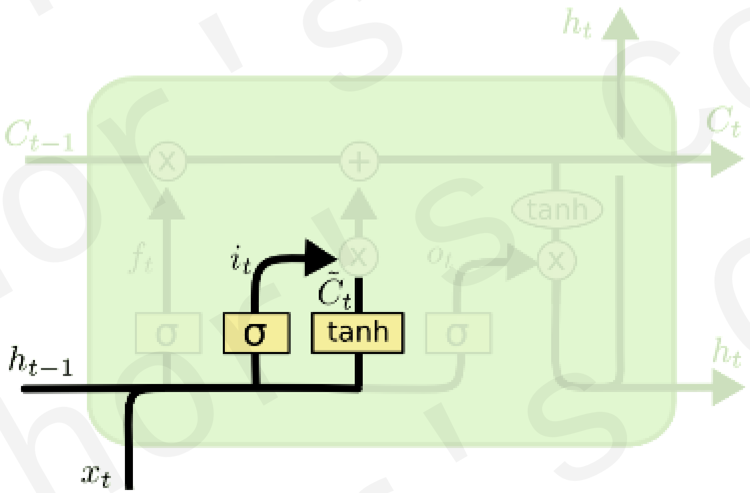


Cell state : Information highway.

1. What to Forget:

2. what to Store:



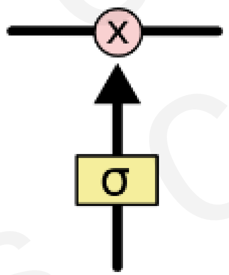
$$i_t = \sigma(W^i[h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W^C[h_{t-1}, x_t] + b_C)$$

LSTMs (Hochreiter & Schmidhuber 1997)

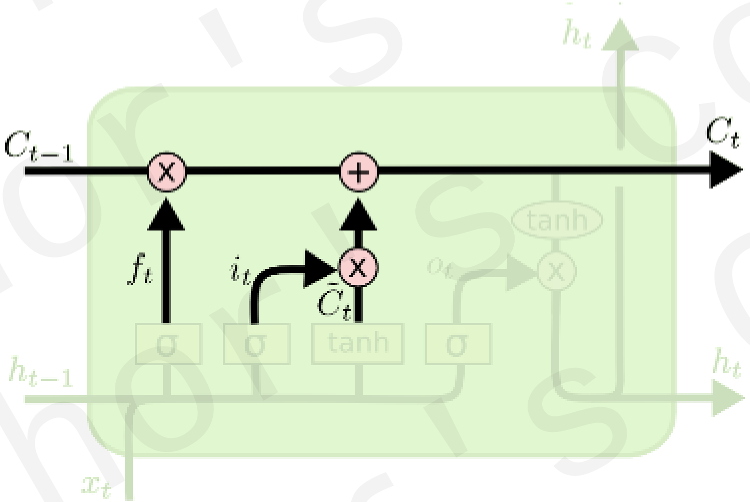
Cell state: let selective information through

Gates:



Cell state : Information highway.

1. What to Forget:
2. what to Store:
3. Update old cell state:



$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

LSTMs (Hochreiter & Schmidhuber 1997)

Cell state: let selective information through

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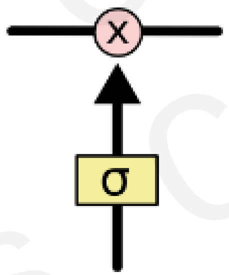
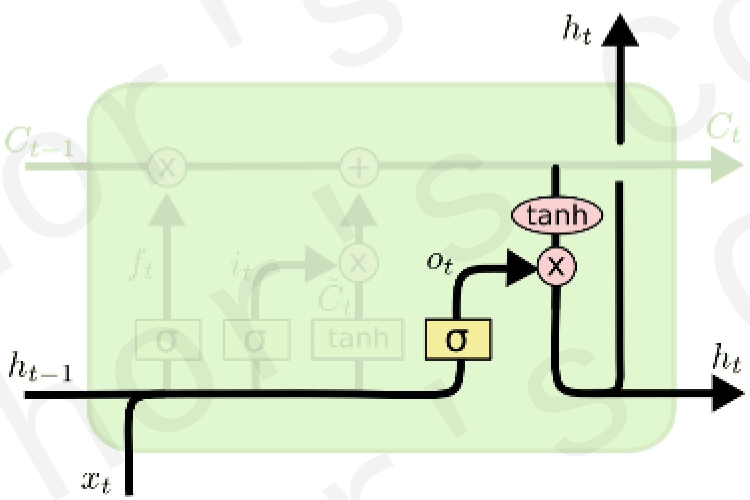


Cell state : Information highway.

1. What to Forget:
2. What to Store:
3. Update old cell state:
4. Generate output:



$$o_t = \sigma(W^o[h_{t-1}, x_t] + b_o)$$

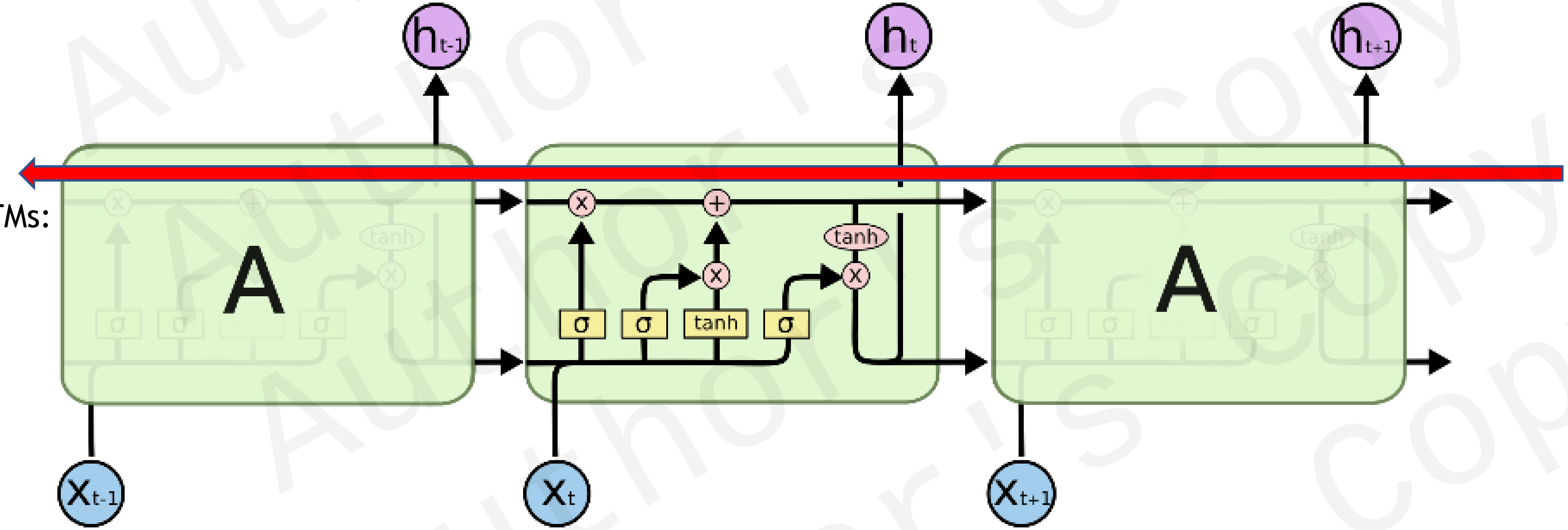
$$h_t = o_t \odot \tanh(C_t)$$

LSTMs (Hochreiter & Schmidhuber 1997)

Gated RNNs: let selective information through

Backpropagation: Uninterrupted gradient flow
Learning:
Faster than RNNs,
Long range dependency conserved..

LSTMs:



$$f_t = \sigma(W^f[C_{t-1}, h_{t-1}, x_t] + b_f)$$

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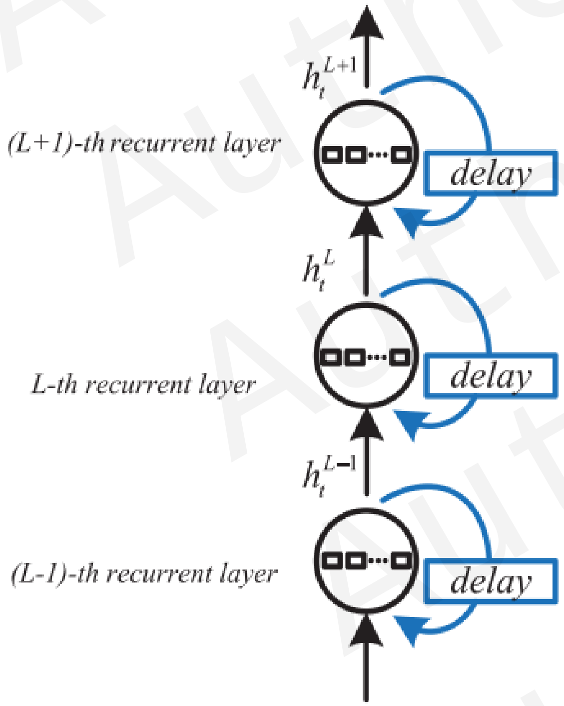
$$o_t = \sigma(W^o[C_{t-1}, h_{t-1}, x_t] + b_o)$$

LSTM Variants:

- Peephole connections
- Gated Recurrent Units (GRUs) (Cho et al. 2014)
- etc.

Deep (Stacked) LSTMs (Fernández, Graves, & Schmidhuber,2007):



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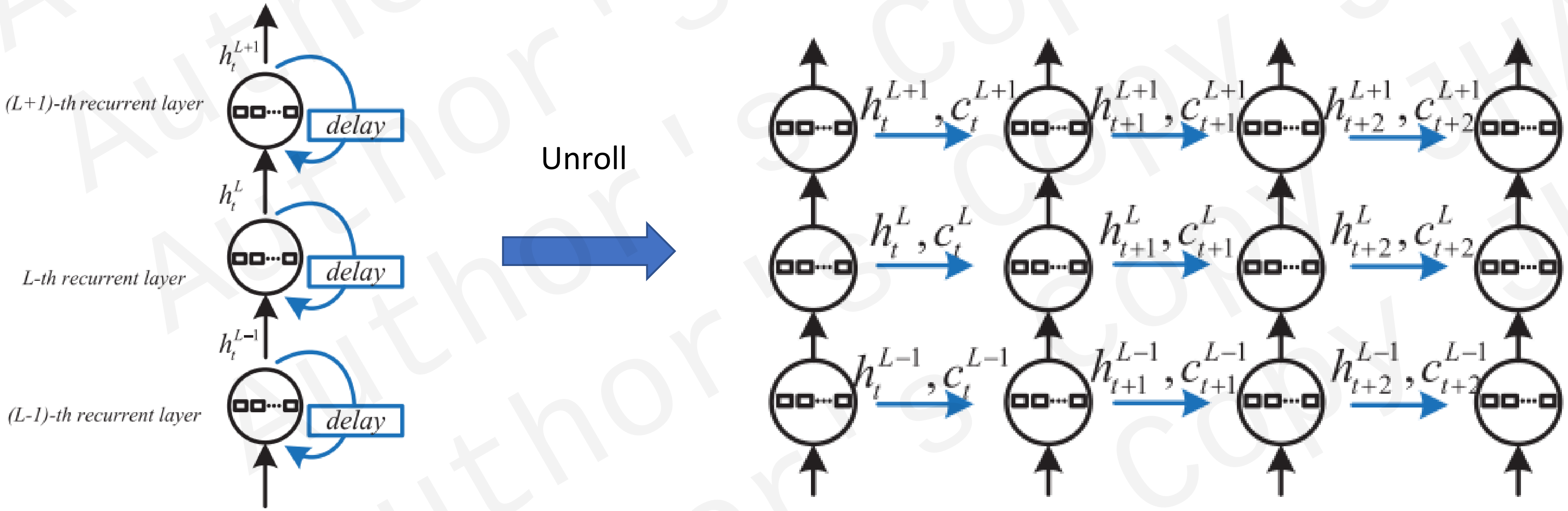


Image credits: Fernández, Graves, & Schmidhuber,2007

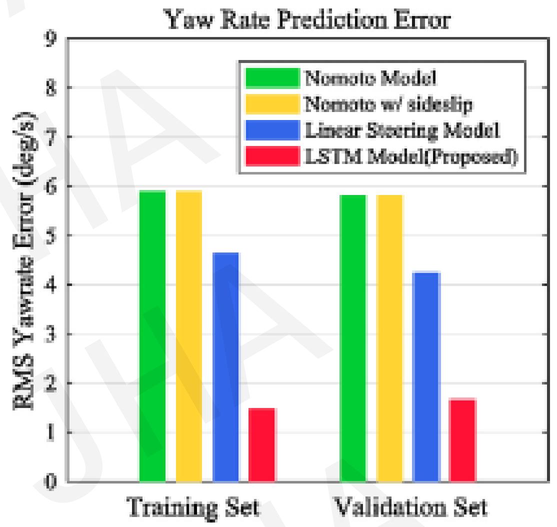
Deep LSTMs

- Advantages over RNNs:
  - Learn long term dependencies easily.
  - Avoid vanishing gradient problem through easy information flow.

- Replaced RNNs for Identification of Non-linear systems (dynamical systems).
  - Benchmarking performance LSTM > RNN > MLP > CNN (different datasets/ factors)

(A Richard et al. 2019)

Deep LSTMs



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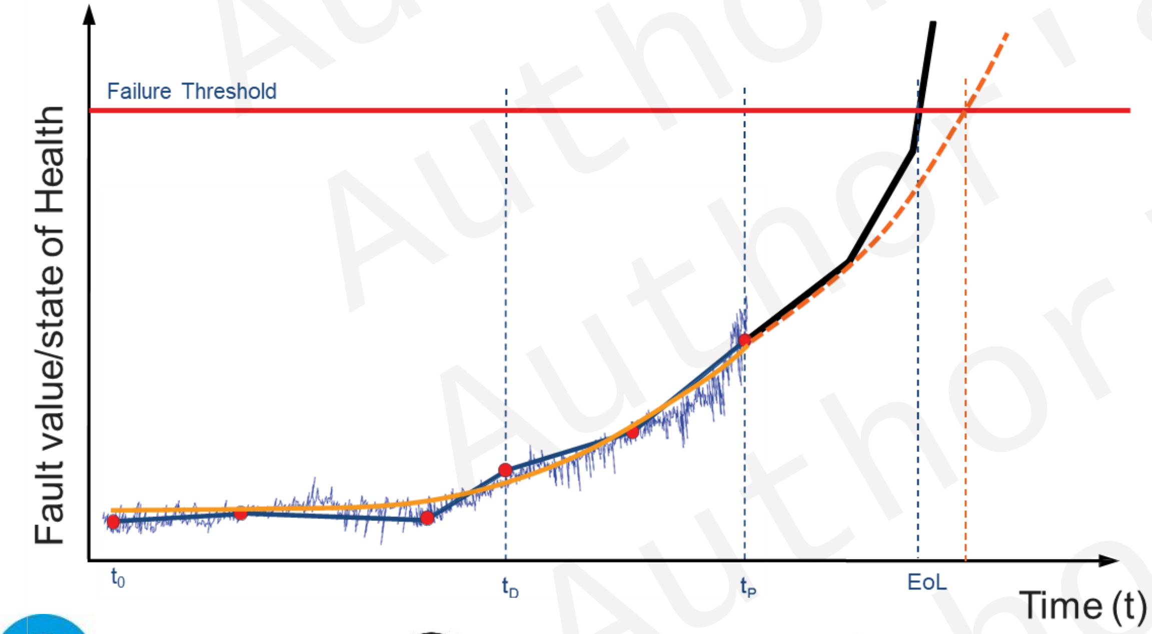
  - Dynamic Model identification using Deep-LSTM : complex coupled non-linear effects Unmanned surface Vehicles (Woo et al, 2018) etc.
  - Learning Inverse dynamics for Robot control (Liu et al. 2019)
- Forecasting non-linear, non-stationary time series data : Short–long horizon.
- Limitations:
  - Deep LSTMs very long to train : 1000 sequence data → 1000 gradients to calculate!
  - Incoming New data → Perturbs the existing learning.

- Is this state of the art? → NO! surpassed by Attention-based mechanisms (2015) for LSTM (efficient learning, long range predictions,…)

Application:
Prognostics and Deep Learning

System degradation

- Machines (dynamical systems) degrade with:
  - time
  - operational load cycles
  - operational conditions etc.



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Prognostics

- Prognostics:
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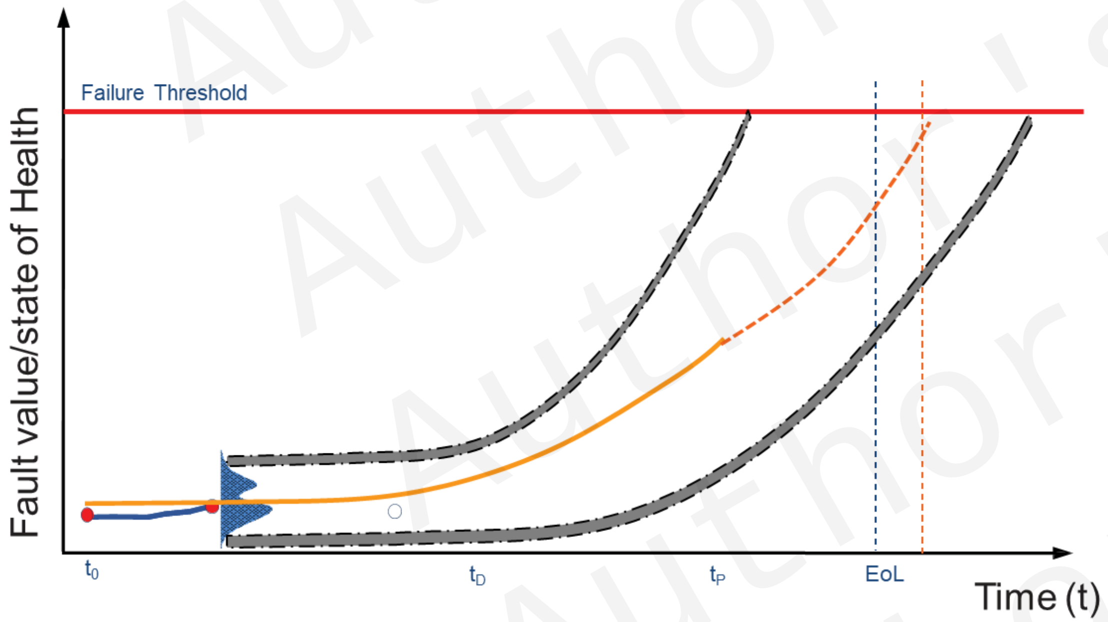

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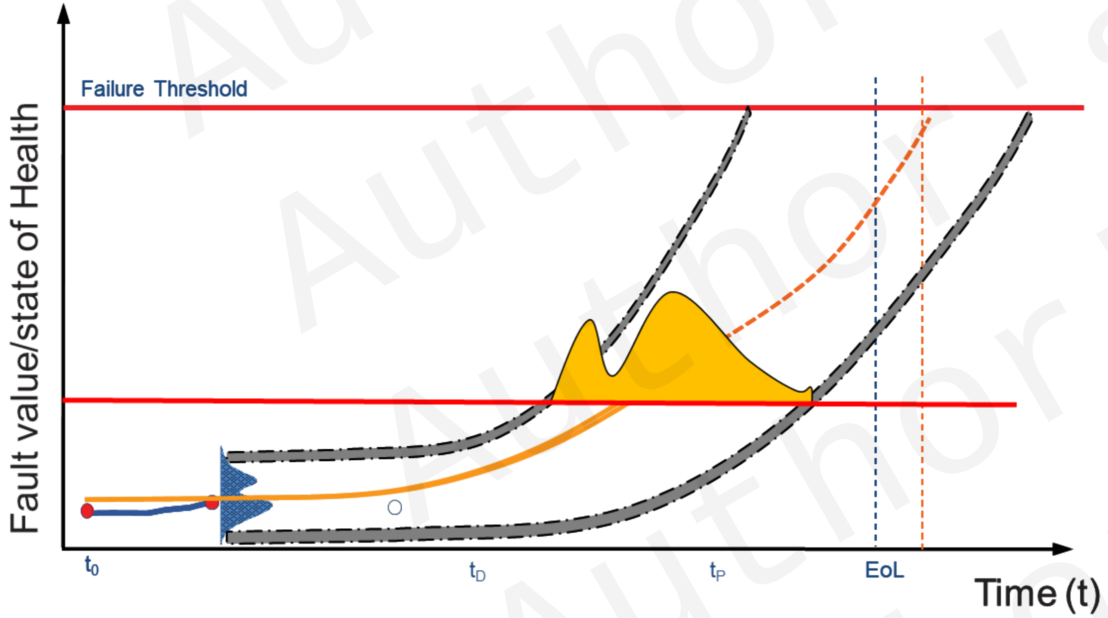

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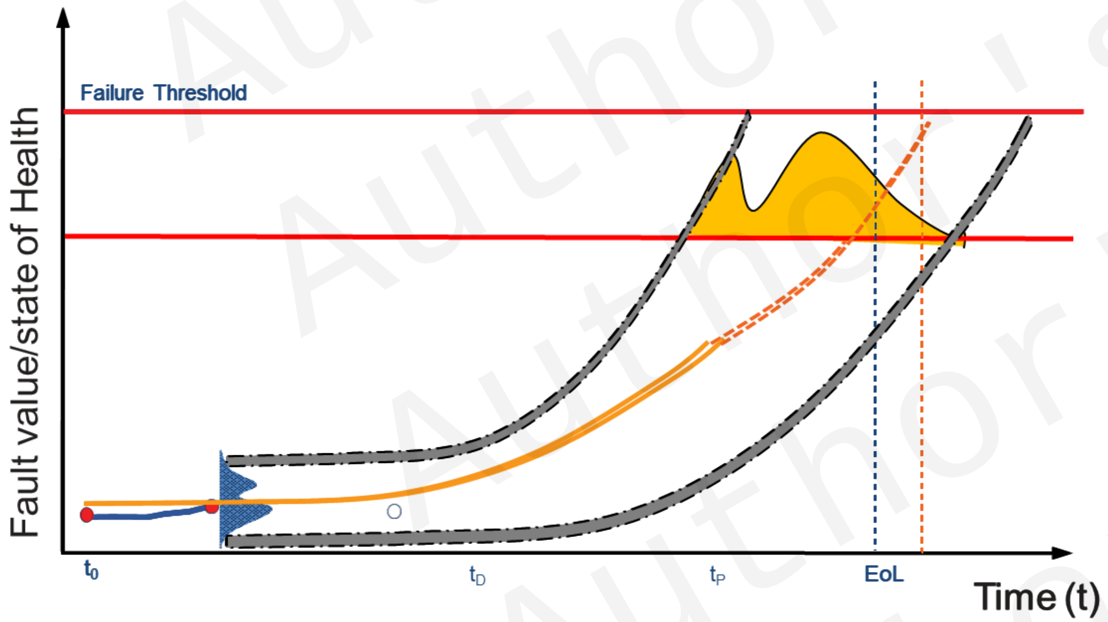

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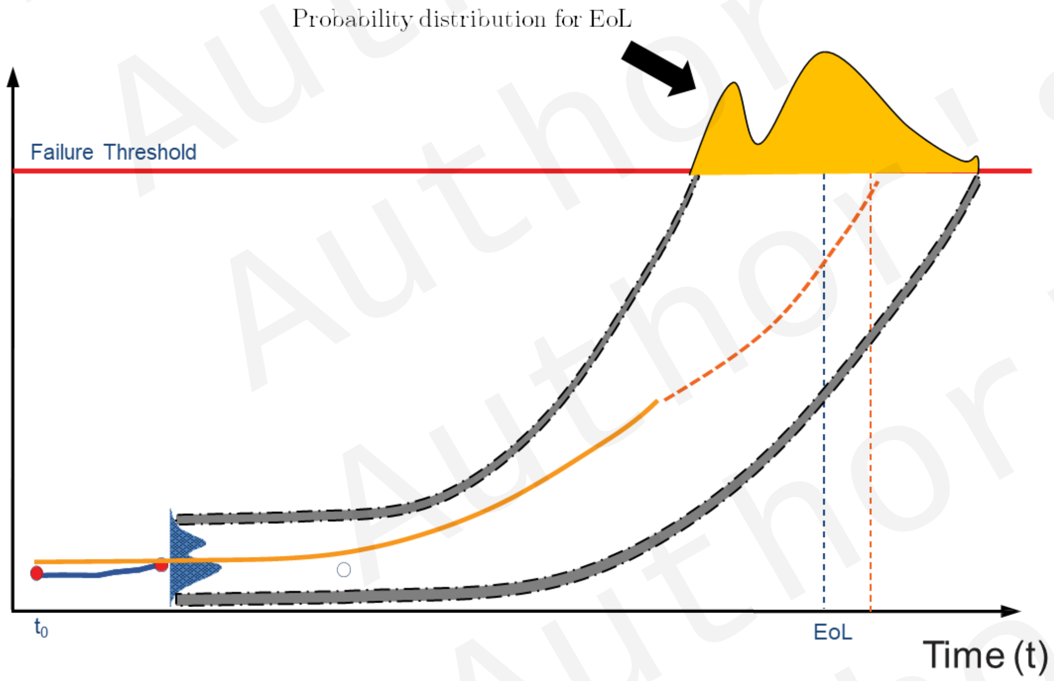
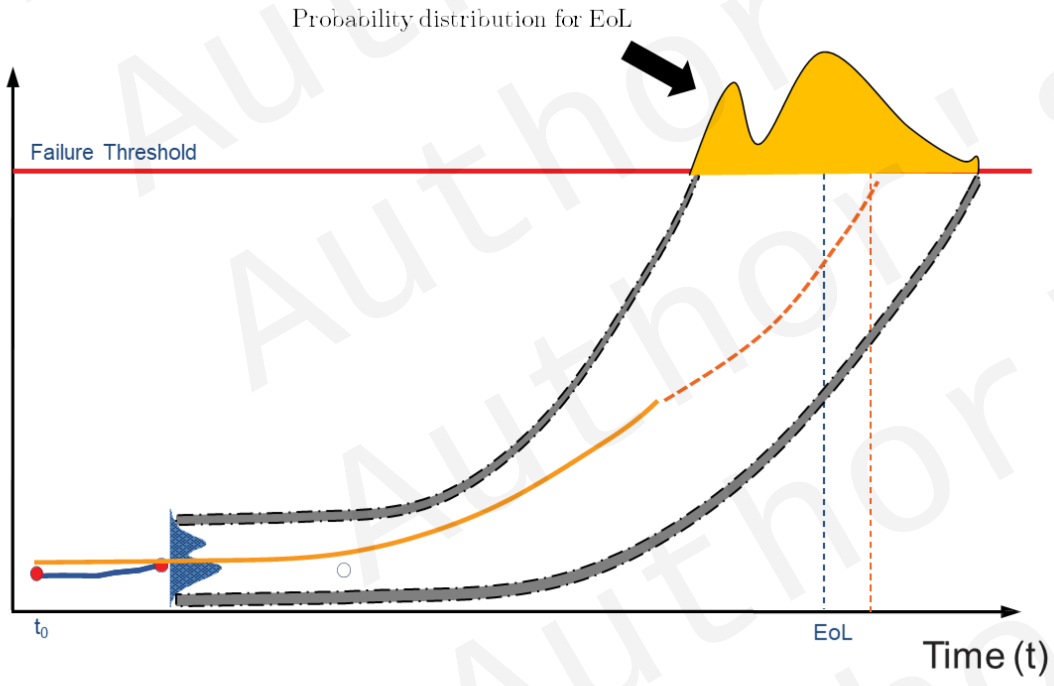
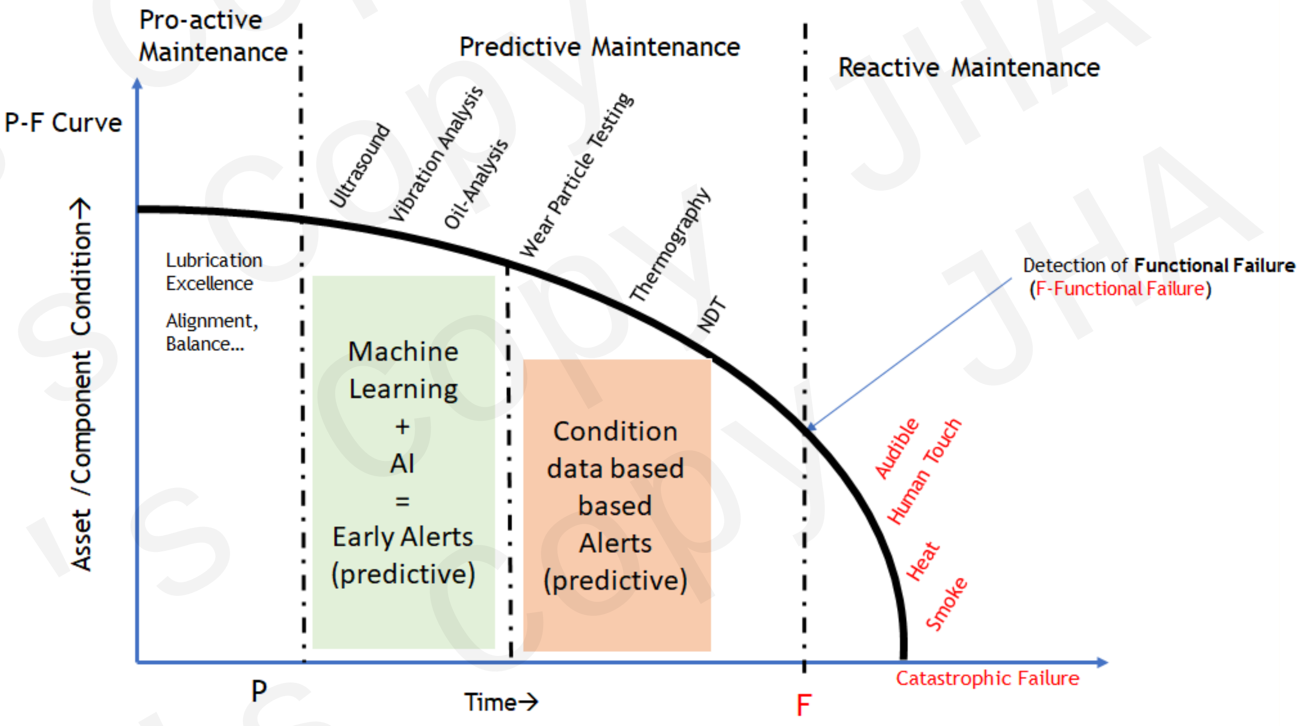


JHA Mayank , Email: mayank-shekhar.jha [at] univ-lorraine.fr

Prognostics

- Prognostics:
  - Estimate (state of health) → identification of degradation model.
  - Prediction of future health + **Remaining Useful Life (RUL)**
  - Evaluate: Decision “when failure occurs ???” “what maintenance strategy”





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Degradation Data

- Degradation:
  - unknown, non-linear varying dynamics
  - sensor data: non-stationary process → trend, seasonality, cyclic etc.
  - depends on qualitative+ quantitative factors.

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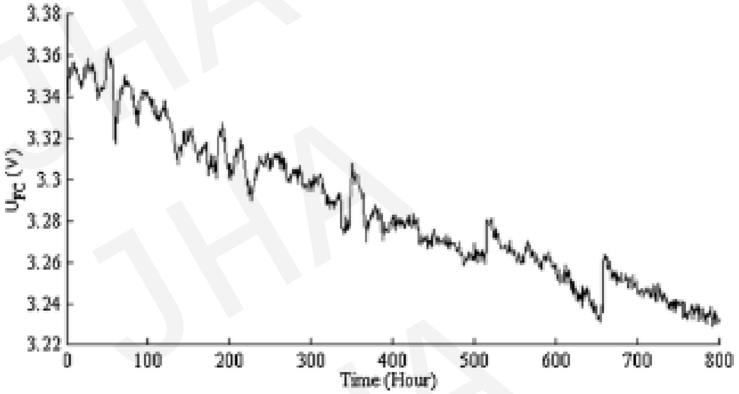

PEM Fuel Cell degradation (Jha et al. 2016)

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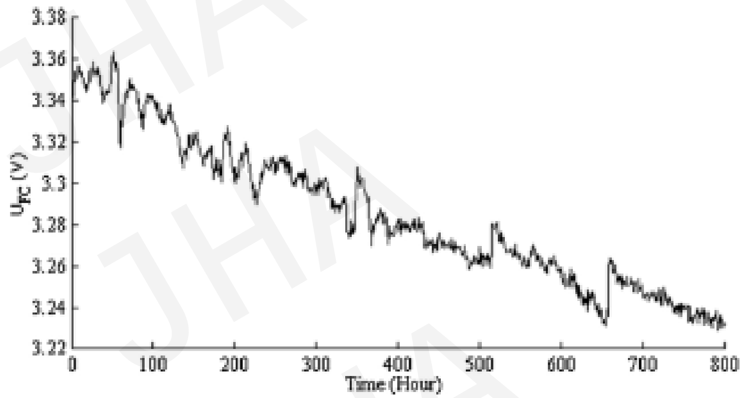

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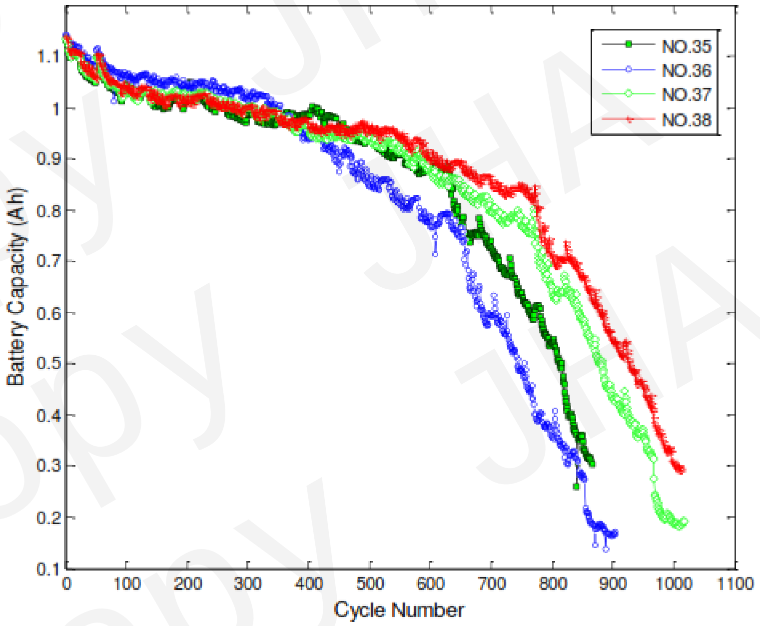
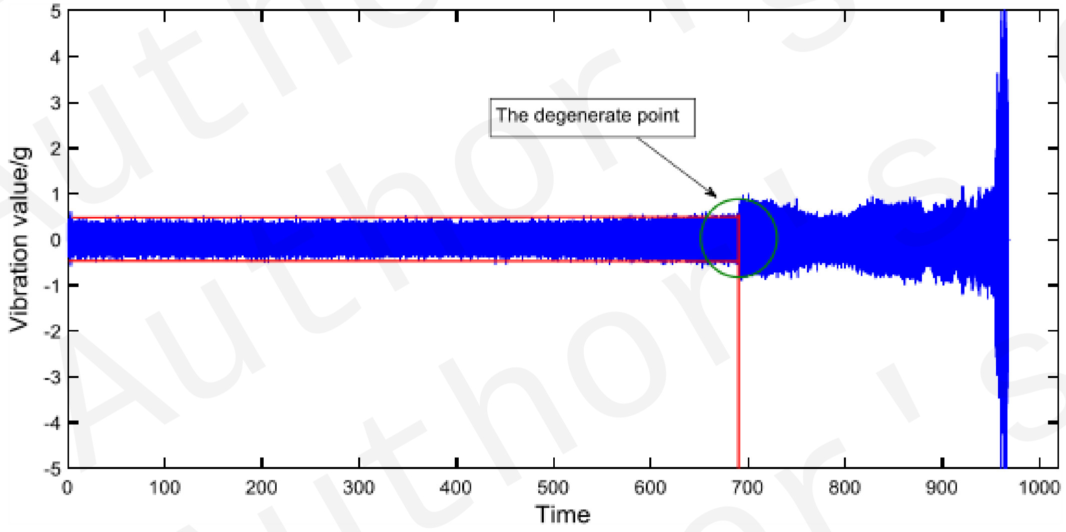


Lithium-ion battery degradation,
Center for Advanced Life Cycle Engineering (CALCE)
in University of Maryland (He W., Williard N., Osterman M., & Pecht M., 2011)



Roller bearing degradation (PRONOSTIA platform)

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- Degradation:
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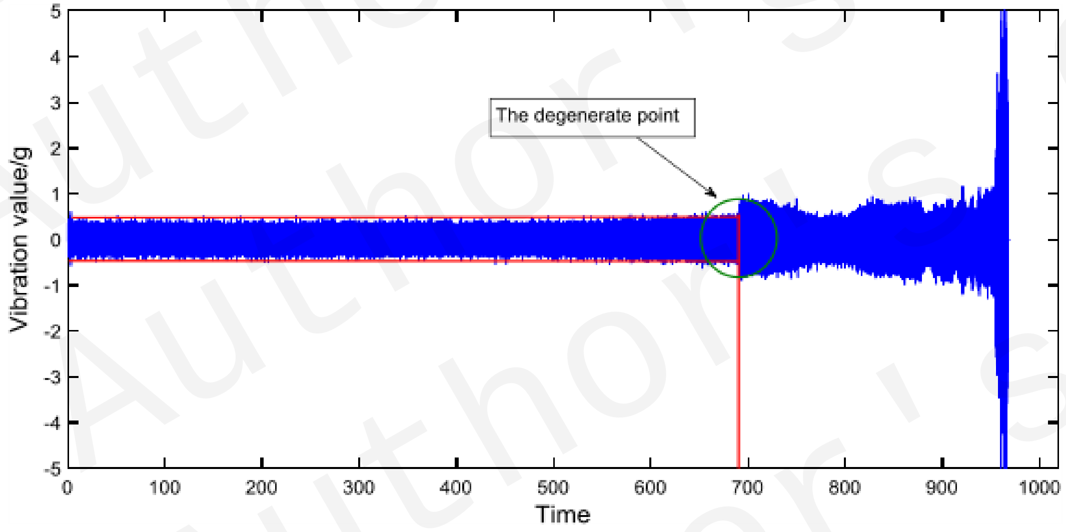
- Raw degradation data → Hidden features / representation:
    - Spatially varying
    - Temporally varying
    - Multimodal characteristics



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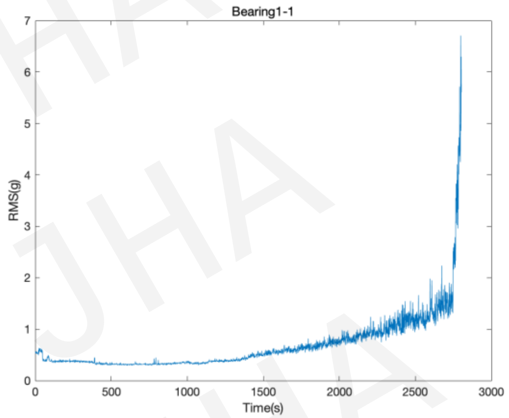

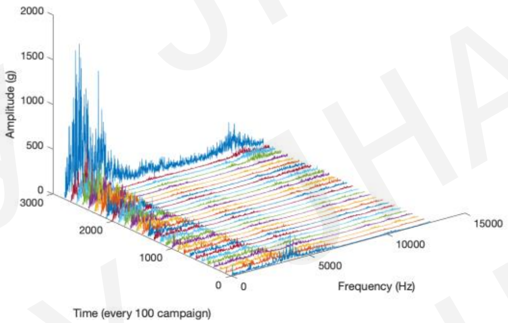

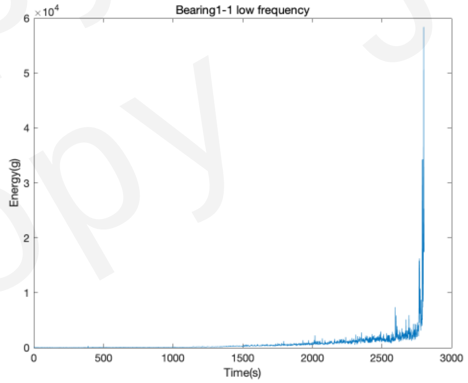

Photo: Report of Jha

Degradation Data

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Deep LSTMs

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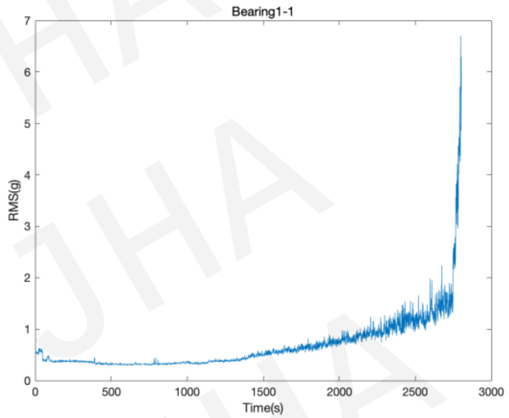
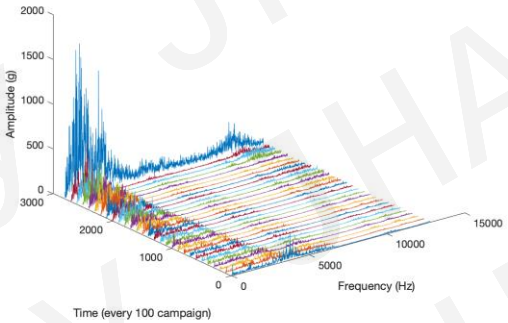
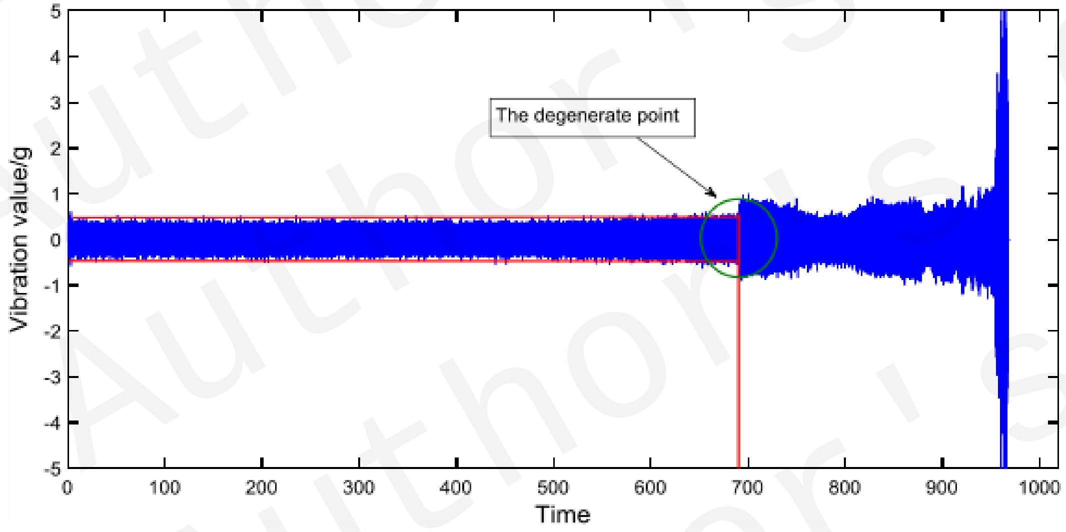
CNNs







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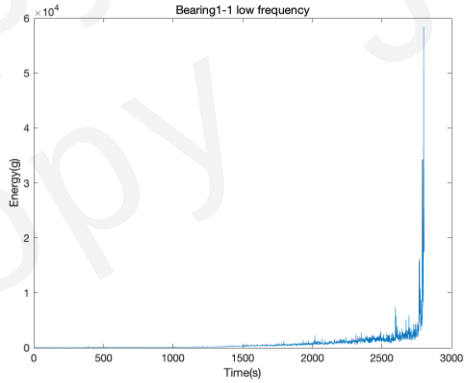
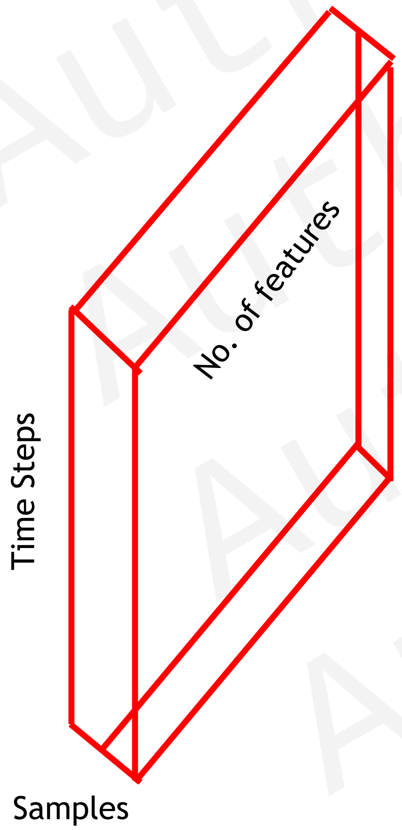


Photo: Report of Jha

Deep LSTMs for Prognostics

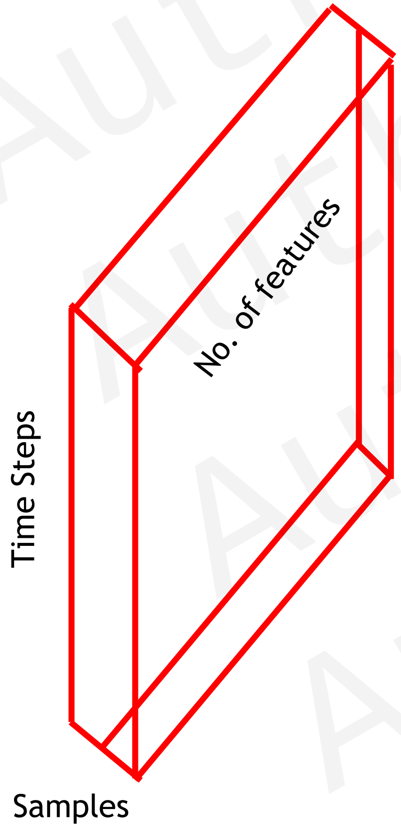
Basic Architecture



3D- Input

Deep LSTMs for RUL prediction

Basic Architecture



3D- Input

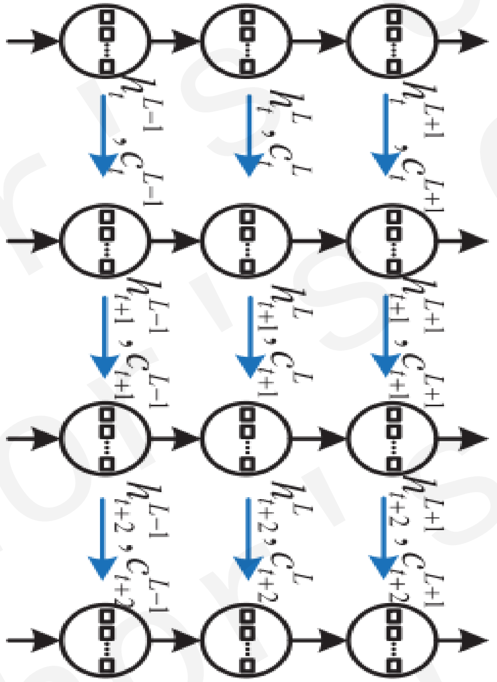
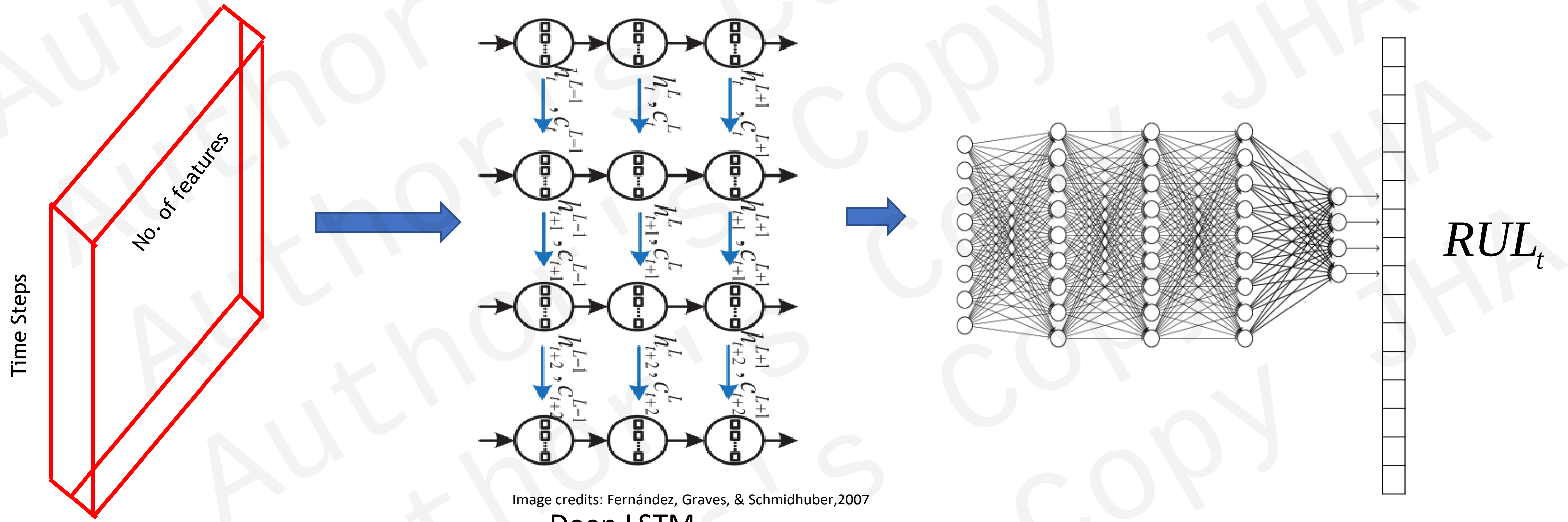


Image credits: Fernández, Graves, & Schmidhuber,2007

Deep LSTM
+ dropout schemes

Deep LSTMs for RUL prediction

Basic Architecture: LSTMs: Temporal features + FNNs: Map features in RULs



Samples

3D- Input

Image credits: Fernández, Graves, & Schmidhuber,2007

Deep LSTM
+ dropout schemes

Fully connected Layer

Target Vector

Deep LSTMs for RUL prediction

- Degradation data➔ Time Series sequence ➔ segmented into sliding windows.
- Each sliding window is assigned a target RUL value [Zeng et al, 2017]

$X = [X_1, X_2, \ldots, X_t, \ldots X_{T-1}]$ to estimate RUL_{T-1}

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Many variants exist!

$[X_t, X_{t-1}, \ldots, X_{t-d+1}], \epsilon \mathbb{R}^d$

$[\mathrm{RUL}_{t+L}, \mathrm{RUL}_{t+L+1}, \ldots, \mathrm{RUL}_n]$

Training tuples:

$([X_t, X_{t-1}, \ldots, X_{t-d+1}], \mathrm{RUL}_{t+L})$

$\widehat{\mathrm{RUL}_{t+L}} = \phi(X_t, X_{t-1}, \ldots, X_{t-d+1})$

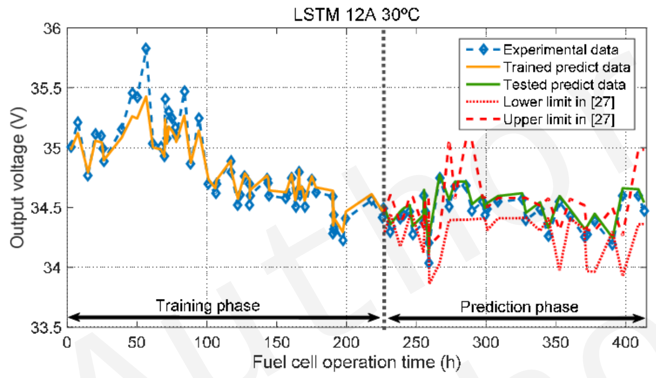
Loss Calculation : Error based cost function

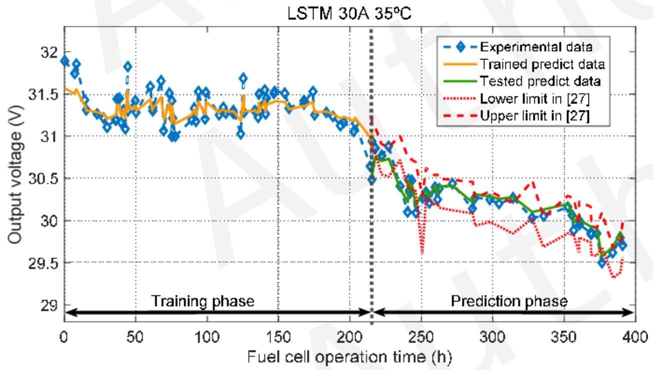
$$J = \sum_t \|(RUL_{est}^t - RUL_{calc}^t\|^2$$

Some issues:

- Independent Windows → to assure assumption of i.i.d
- Dependent windows → claim more realistic.

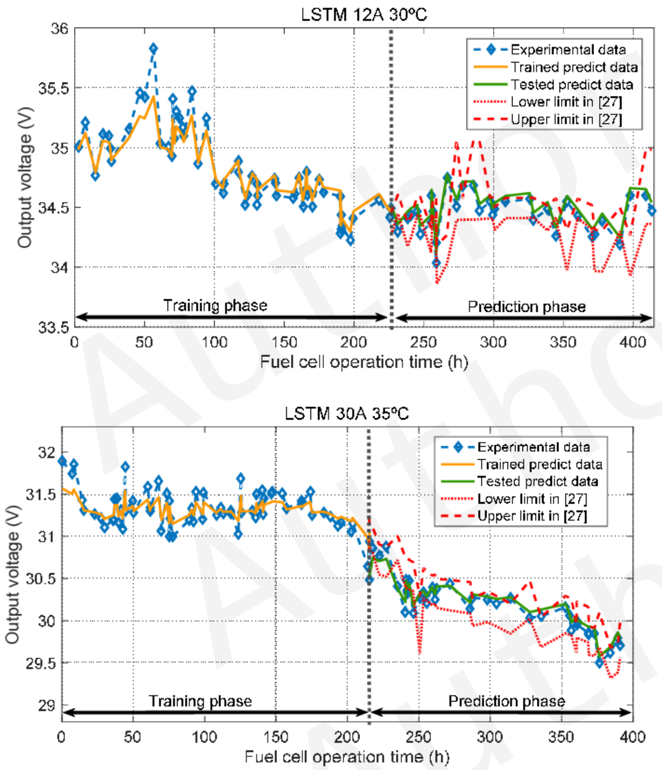
Some applications:





PEM Fuel Cell degradation

Some applications:



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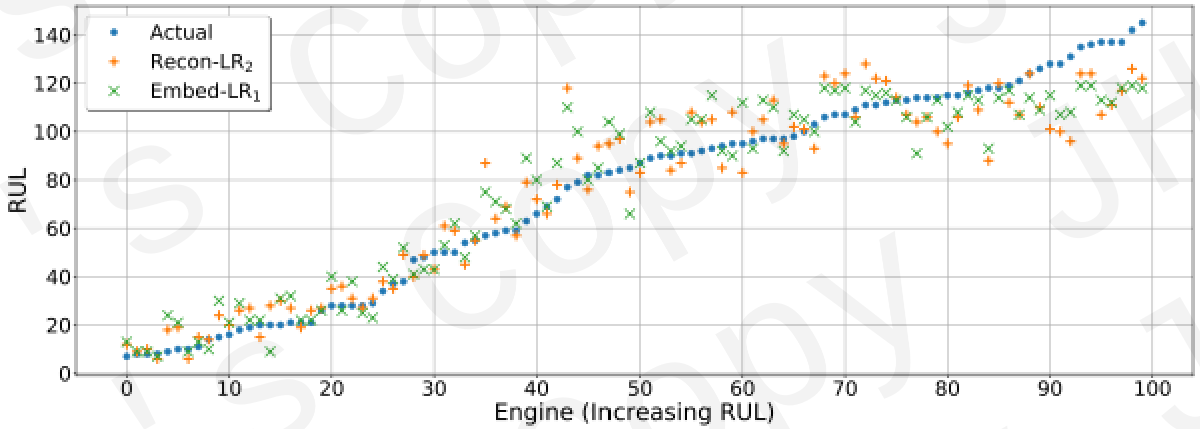
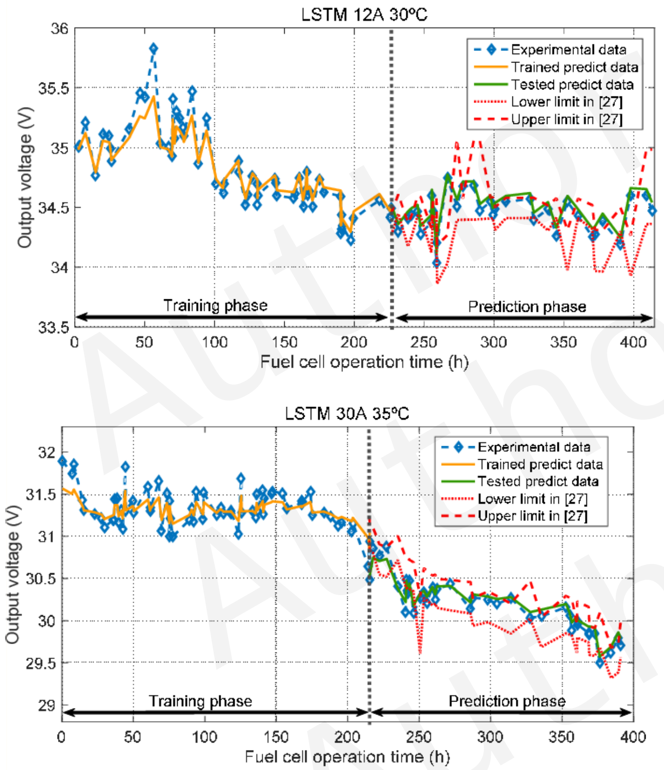


[Gugulothu et al 2017]

Some applications:



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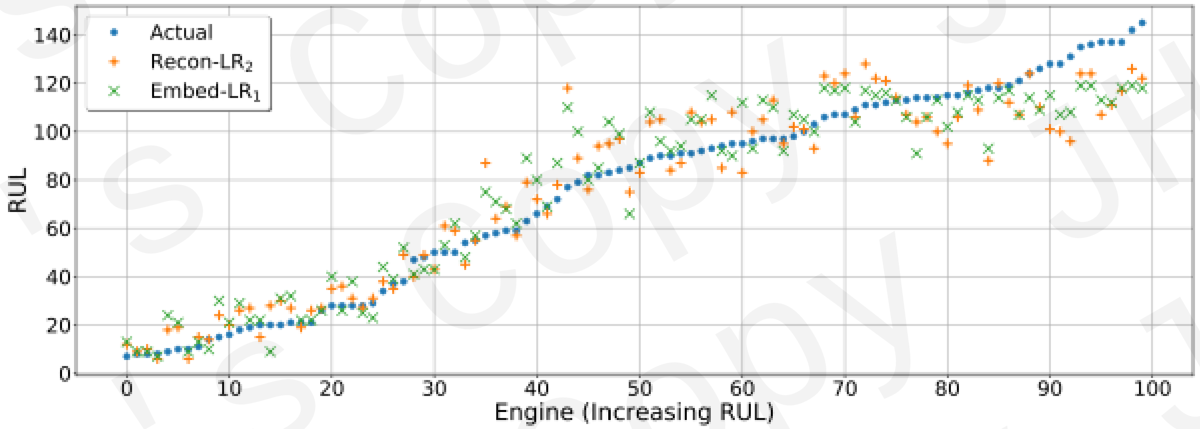
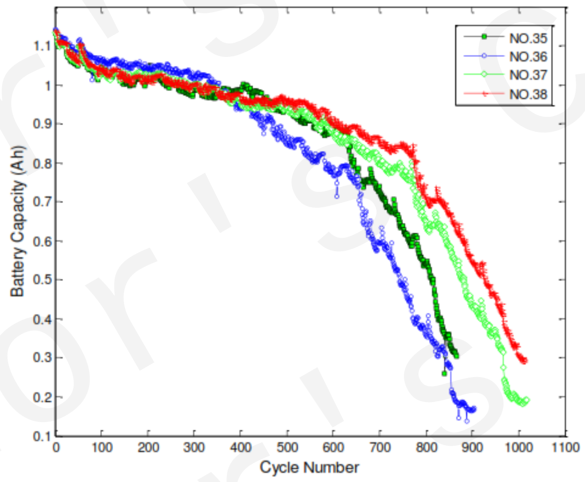


[Gugulothu et al 2017]

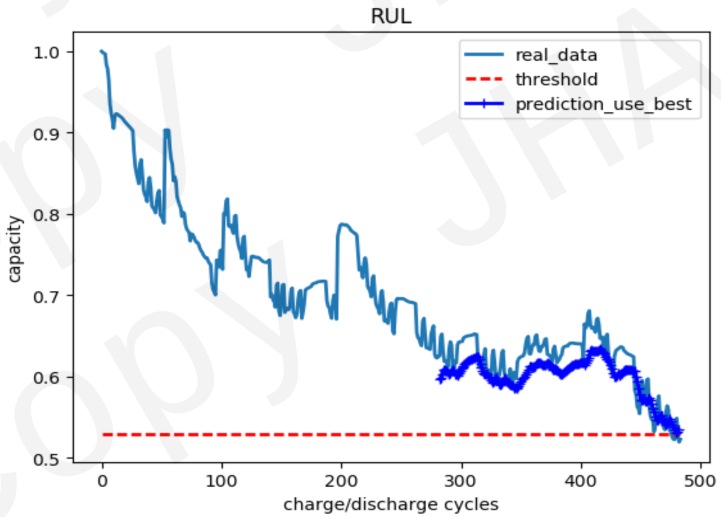
Engine prognostics (NASA) : CMAPSS
'Commercial Modular Aero-Propulsion System Simulation'
[Zhang et al, 2017]

- unknown non-linear dynamics,
- non-stationary (multi modal degradation,
- multiple modes of degradation)



Lithium-ion battery RUL prediction

(He W., Williard N., OstermanM., & Pecht M., 2011)



CNNs for Prognostics

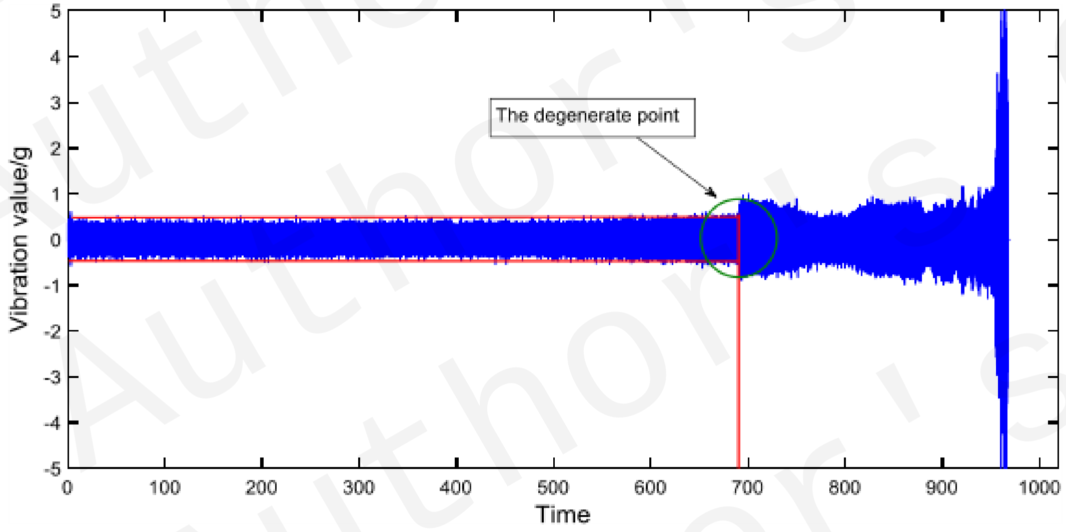
- LSTMs: good sequence learning

but good input sequence needs to be provided!!

- Feature extraction needs domain knowledge.
- Labelled data → difficult !

- CNNs → Hidden features / representation of sequence:
  - Spatially varying
  - Temporally varying
  - Multimodal characteristics

CNNs



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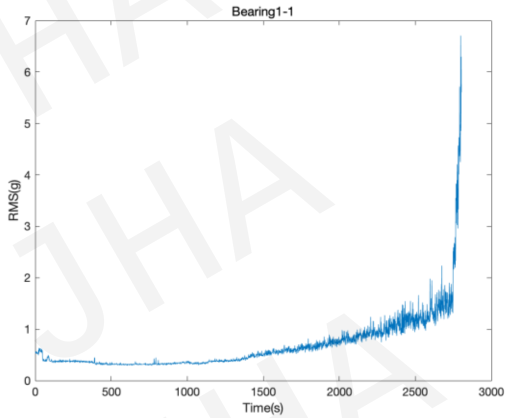

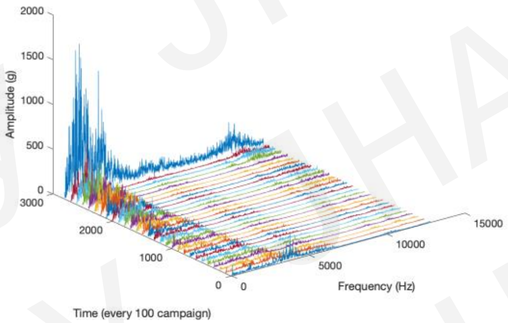

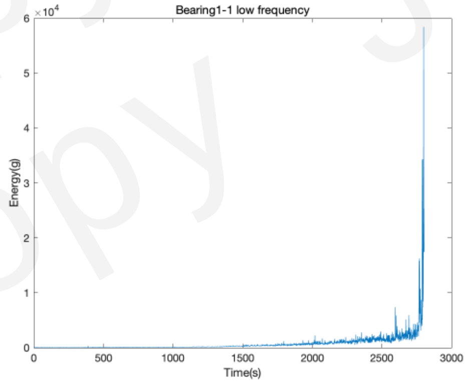

Photo: Report of Jha

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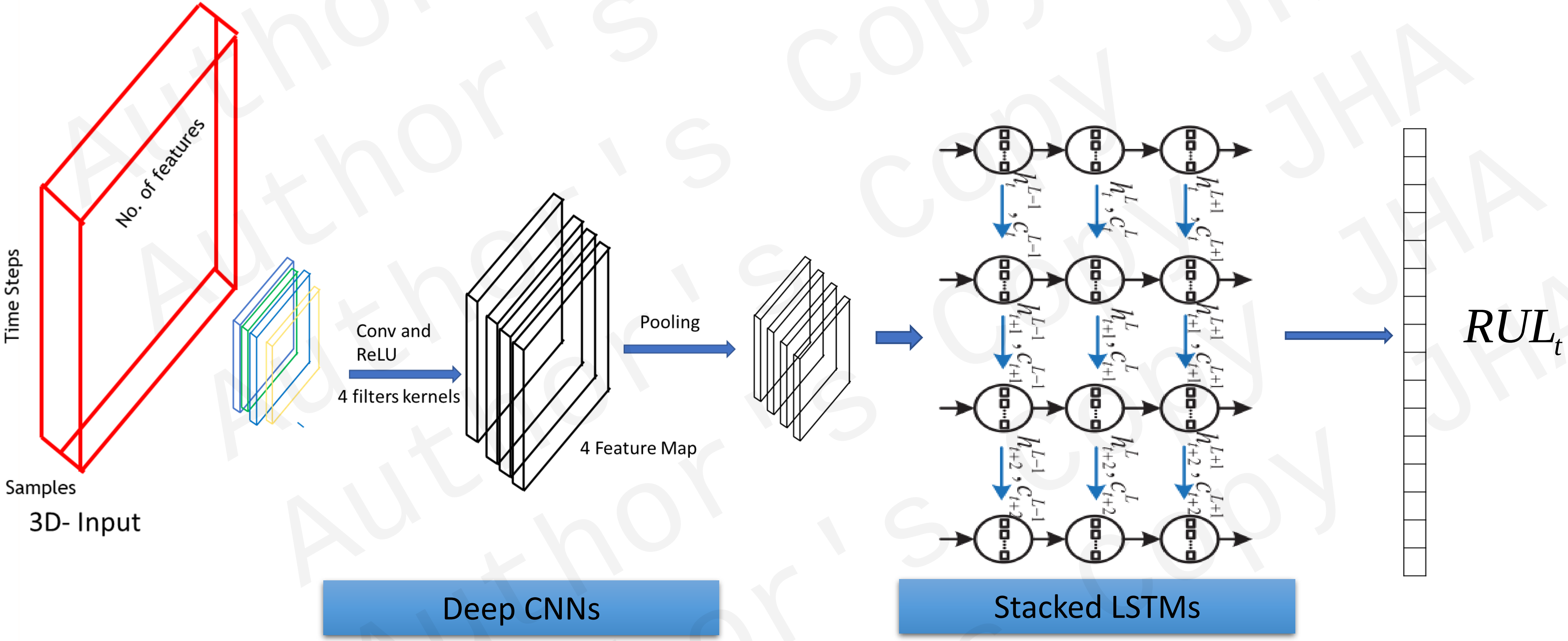
CNNs for Prognostics

- CNNs → Traditionally, 2D-3D structured data for face/object recognition
- Prognostics → 3D structured topology for sequence data



CNNs for Prognostics

- Automatically learn feature representation, hidden multimodal distributions

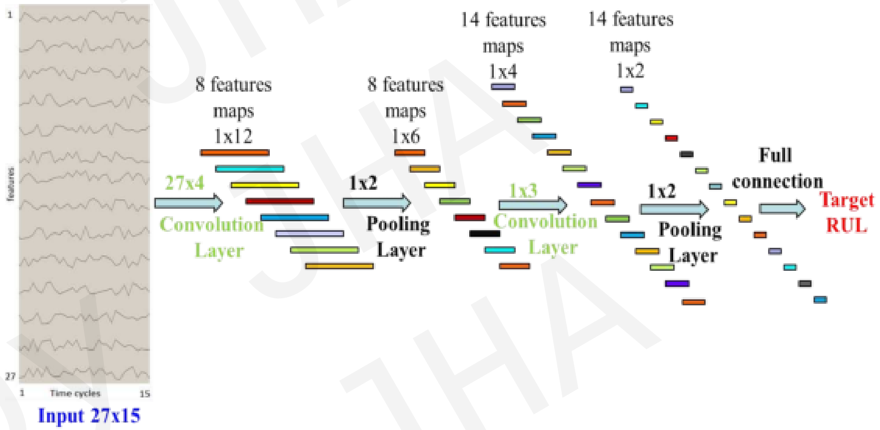
[Liu et al., 2017] [Jing et al., 2017] [Li et al., 2018]

&

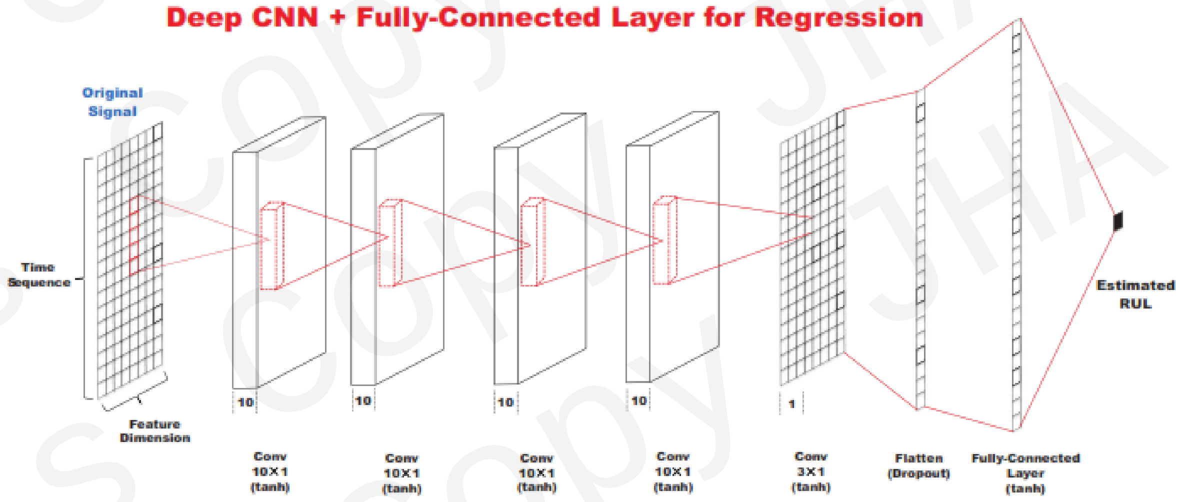
- Efficient learning with multi-variate sequential (time series) data.

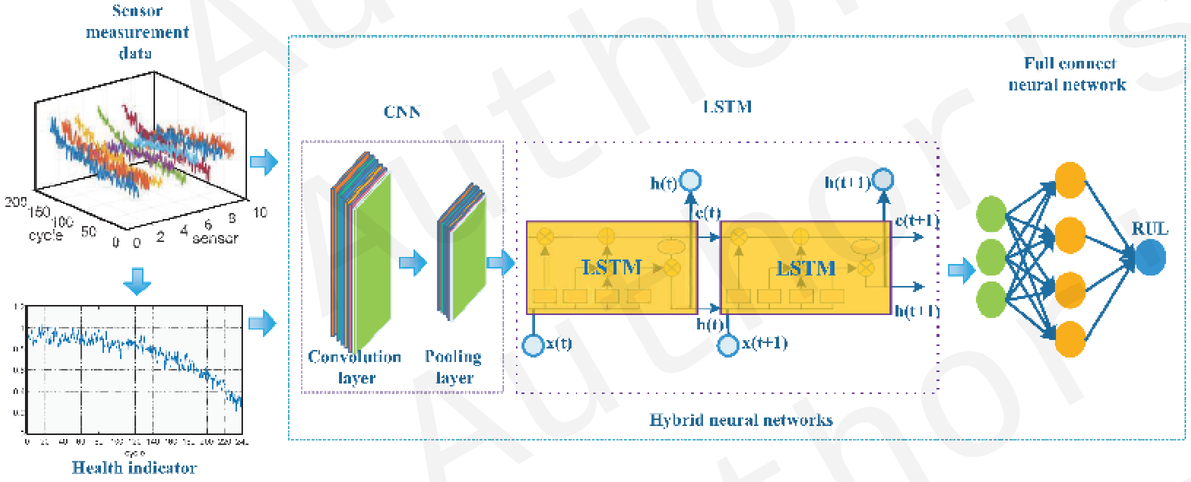
[Babu et al., 2016]

- Hybrid structure



[Babu et al., 2016]





[Liu et al., 2017]

[Kong et al. 2019]

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