DEEP LEARNING APPROACHES FOR PREDICTIVE MAINTENANCE

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MOTIVATION

- **Preventive maintenance:**
  - *Taking the necessary actions to prevent failure of equipment from occurring before it happens*
- Traditional Approaches to PM
  - Time-based maintenance
  - Usage-based maintenance
- **PM in the age of Big data**
  - Predictive Maintenance
  - Prescriptive Maintenance
- **Why PM?**
  - Less disruption in operation
  - Improved life expectancy of equipment
  - Improved efficiency etc

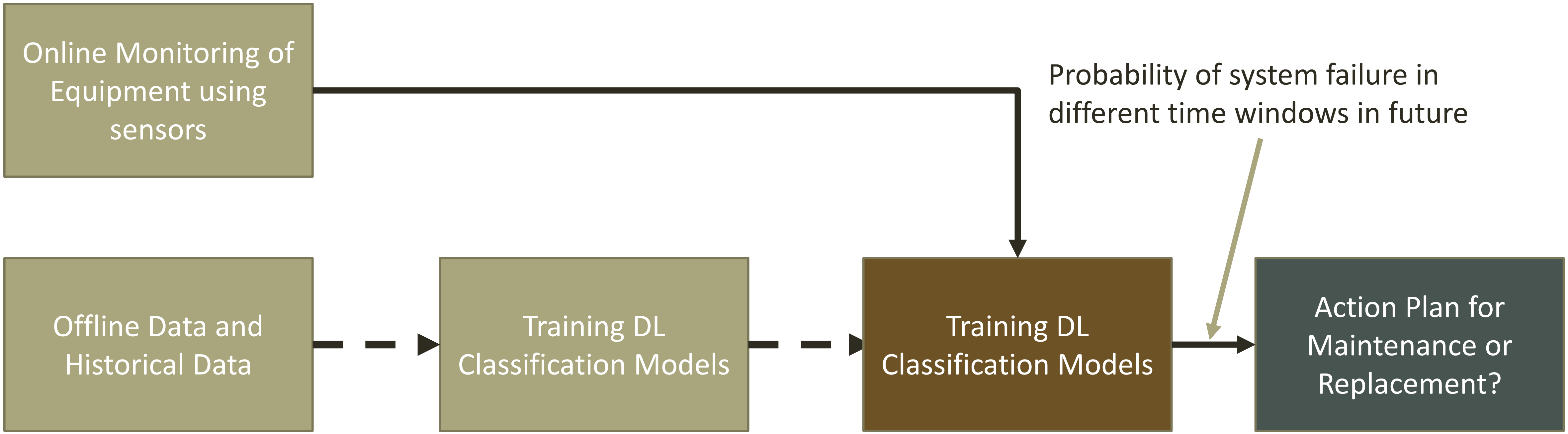
PROBLEM STATEMENT

- **Preventive maintenance:**
  - Predict the failure of the equipment and time horizon (Prognostic modelling)
    - Use of data to build models for failure
  - Action based on prognostic prediction (Maintenance Optimization)
    - Provide decisions for a maintenance schedule, and related decisions for preventing failure

Dynamic Prognostic and Maintenance Optimization from Data?

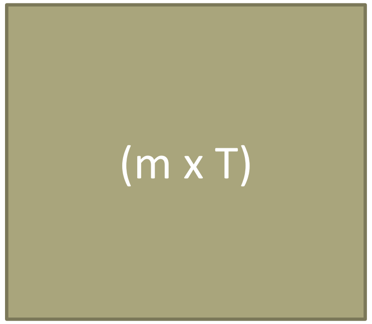
PROBLEM STATEMENT

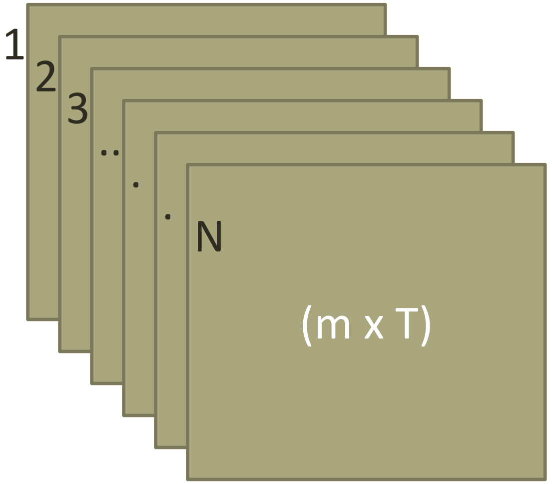
Dynamic Prognostic and Maintenance Optimization from Data



PROBLEM STATEMENT

N components monitored using *m* sensors for Time instants *T*

$\mathbf{X}_i =$ 



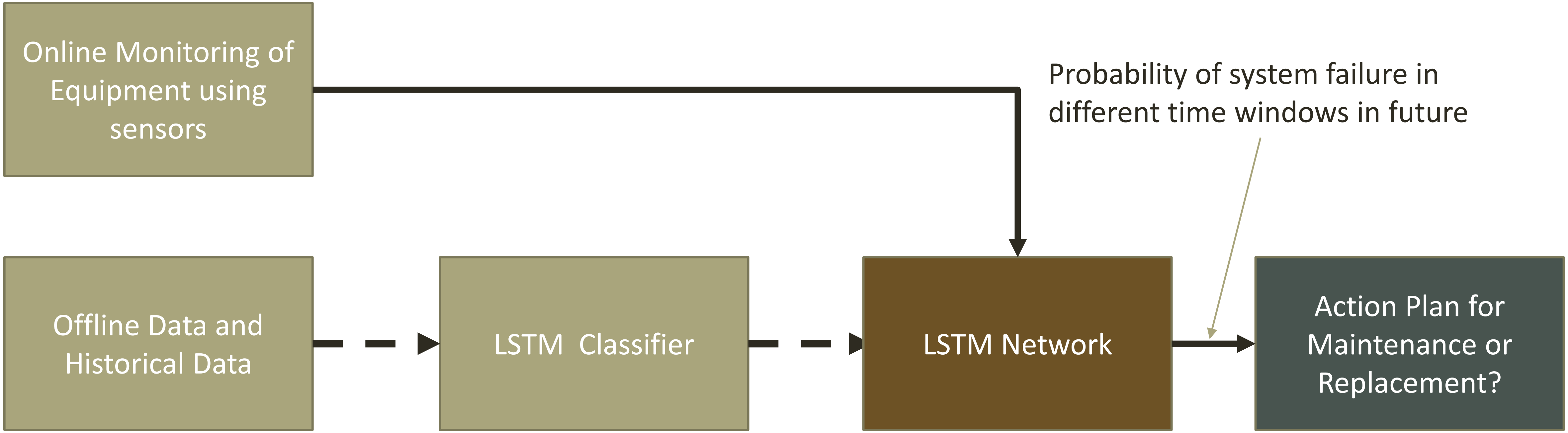
True Residual/remaining useful lifetime (RUL) belongs to?

[1]Nguyen and Medjaher, *Reliability Engineering and System Safety 188 (2019)*

PROBLEM STATEMENT

Dynamic Prognostic and Maintenance Optimization from Data[1]

1. Predict the system residual useful lifetime (RUL)
2. Action Plan or decisions



[1]Nguyen and Medjaher, *Reliability Engineering and System Safety 188 (2019)*

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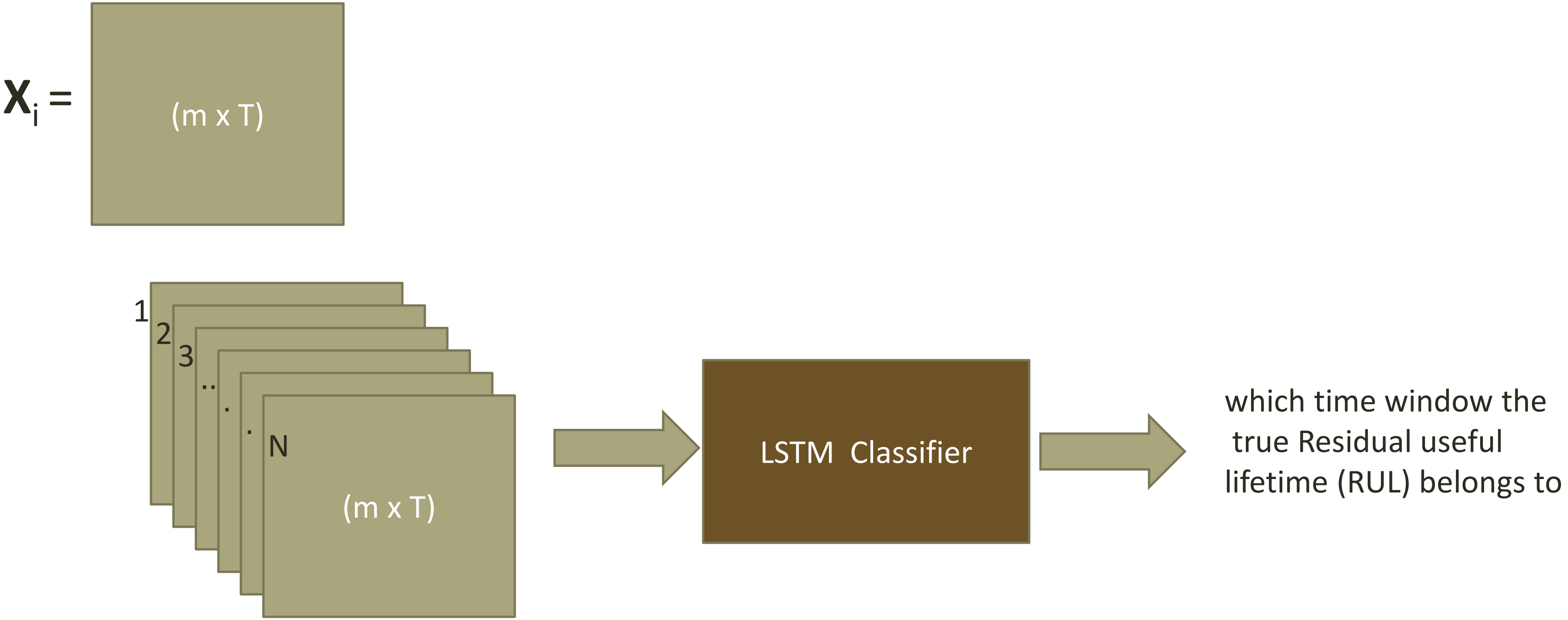

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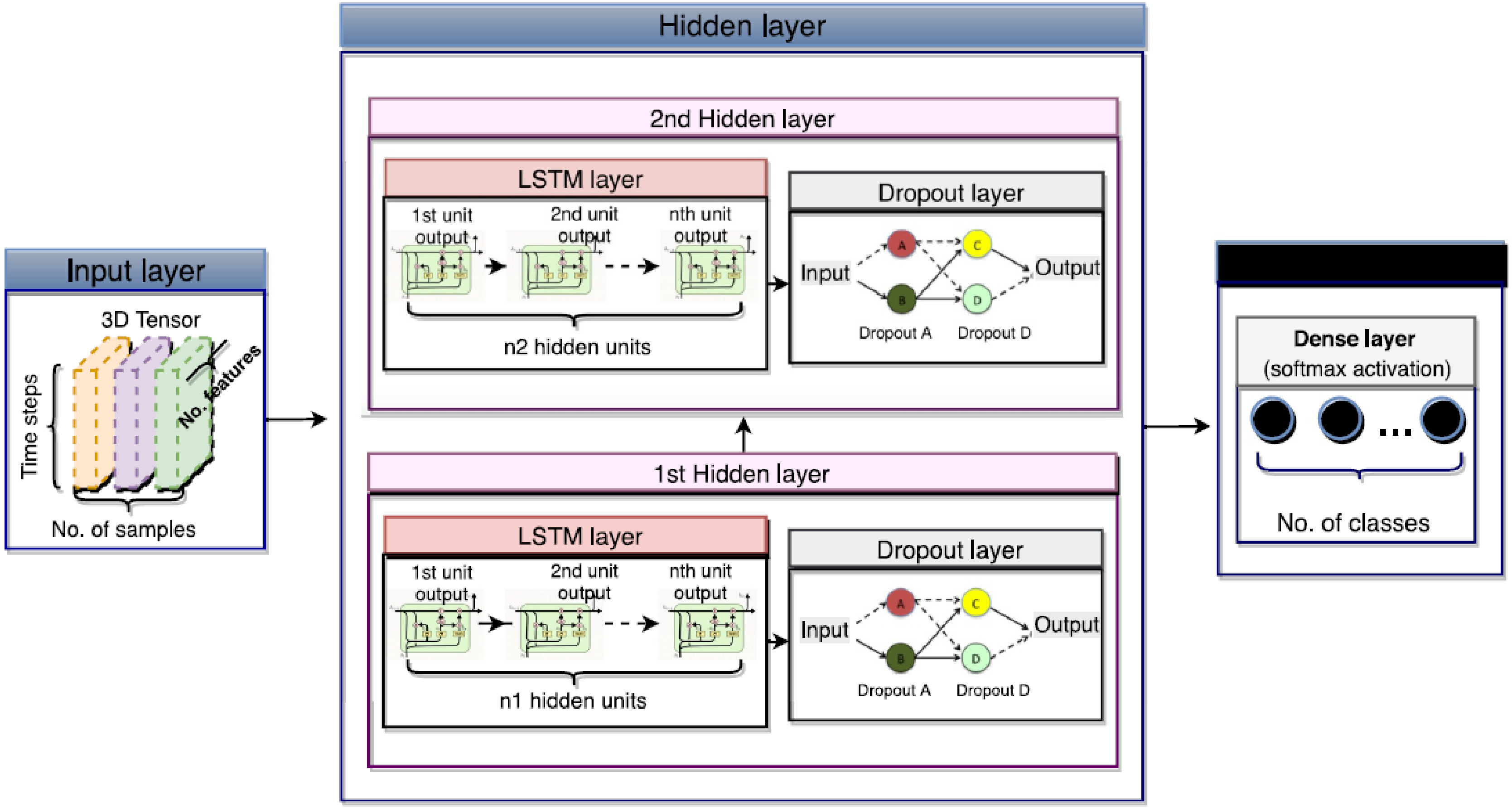


[1]Nguyen and Medjaher, *Reliability Engineering and System Safety 188 (2019)*

PROBLEM STATEMENT

N components monitored using *m* sensors for Time instants *T*

LABELS of Data

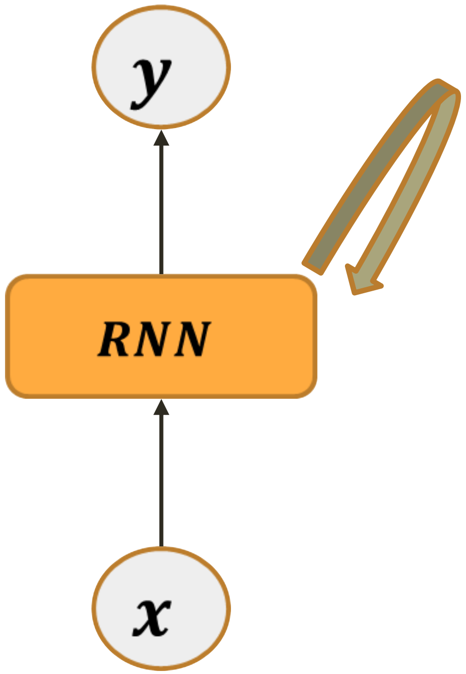
- Class 0: Deg0: RUL > w_1 — Normal
- Class 1: Deg1: w_0 < RUL < w_1 — Degradation
- Class 2: Deg2: RUL < w_0 — Failure

[1]Nguyen and Medjaher, *Reliability Engineering and System Safety 188 (2019)*

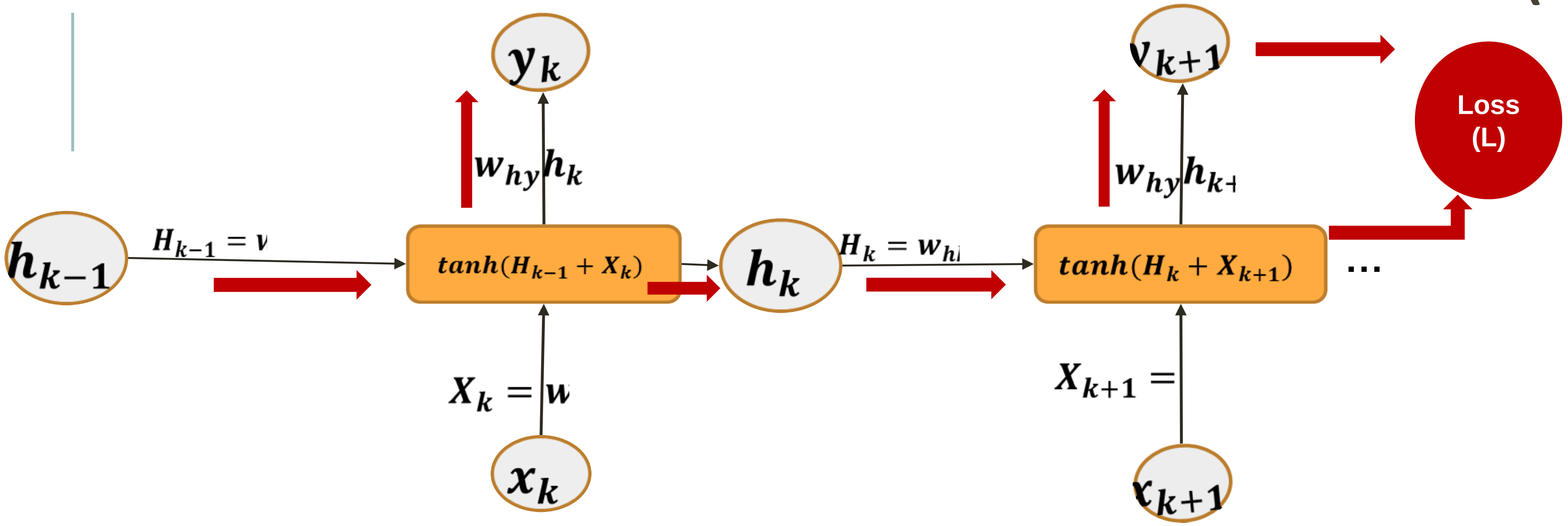
RECURRRENT NEURAL NETWORKS (RNN)

- Text data is considered as Sequence data where a sequence of inputs leading to sequence of outputs where one text influences the neighbor texts in the sequence.
- RNN models the sequence data

Pictorial representation of RNN (A simplified graph):



BACKPROPAGATION THROUGH TIME (BTT)



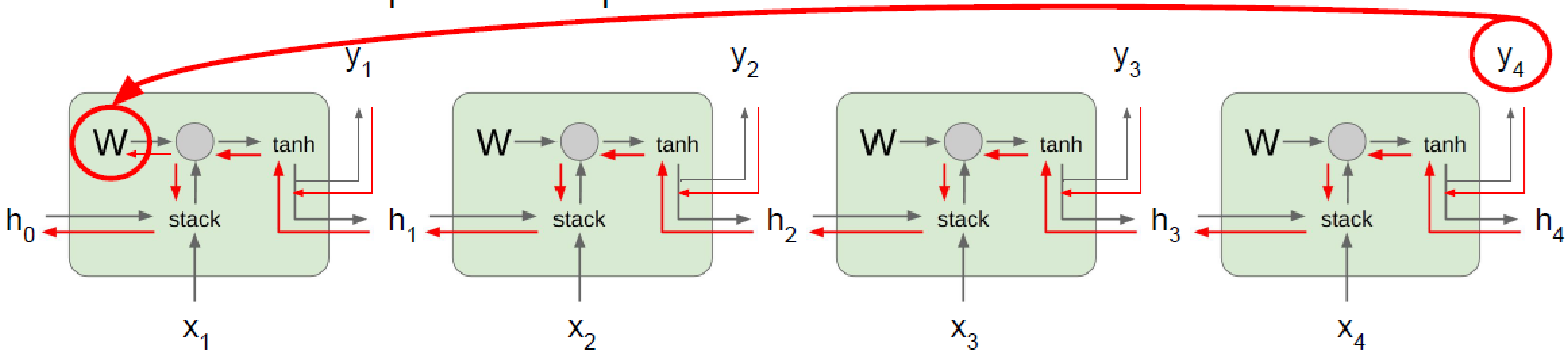
- $\frac{\partial h_{k+1}}{\partial h_k} = tanh'(H_k + X_{k+1})w_{hh}$
- $\frac{\partial h_{k+1}}{\partial x_{k+1}} = tanh'(H_k + X_{k+1})w_{hx}$
- $\frac{\partial L_{k+1}}{\partial w_{hh}} = \frac{\partial L_{k+1}}{\partial y_{k+1}} \frac{\partial y_{k+1}}{\partial h_{k+1}} \frac{\partial h_{k+1}}{\partial h_k} \frac{\partial h_k}{\partial h_{k-1}} \frac{\partial h_{k-1}}{\partial w_{hh}}$
- $\frac{\partial L_{k+1}}{\partial w_{hx}} = \frac{\partial L_{k+1}}{\partial y_{k+1}} \frac{\partial y_{k+1}}{\partial h_{k+1}} \frac{\partial h_{k+1}}{\partial w_{hx}}$
- $\frac{\partial L}{\partial w_{hh}} = \sum \frac{\partial L_k}{\partial w_{hh}}, \ \frac{\partial L}{\partial w_{hx}} = \sum \frac{\partial L_k}{\partial w_{hx}}$

BACKPROPAGATION THROUGH TIME (BTT)

Vanilla RNN Gradient Flow

Gradients over multiple time steps:

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013



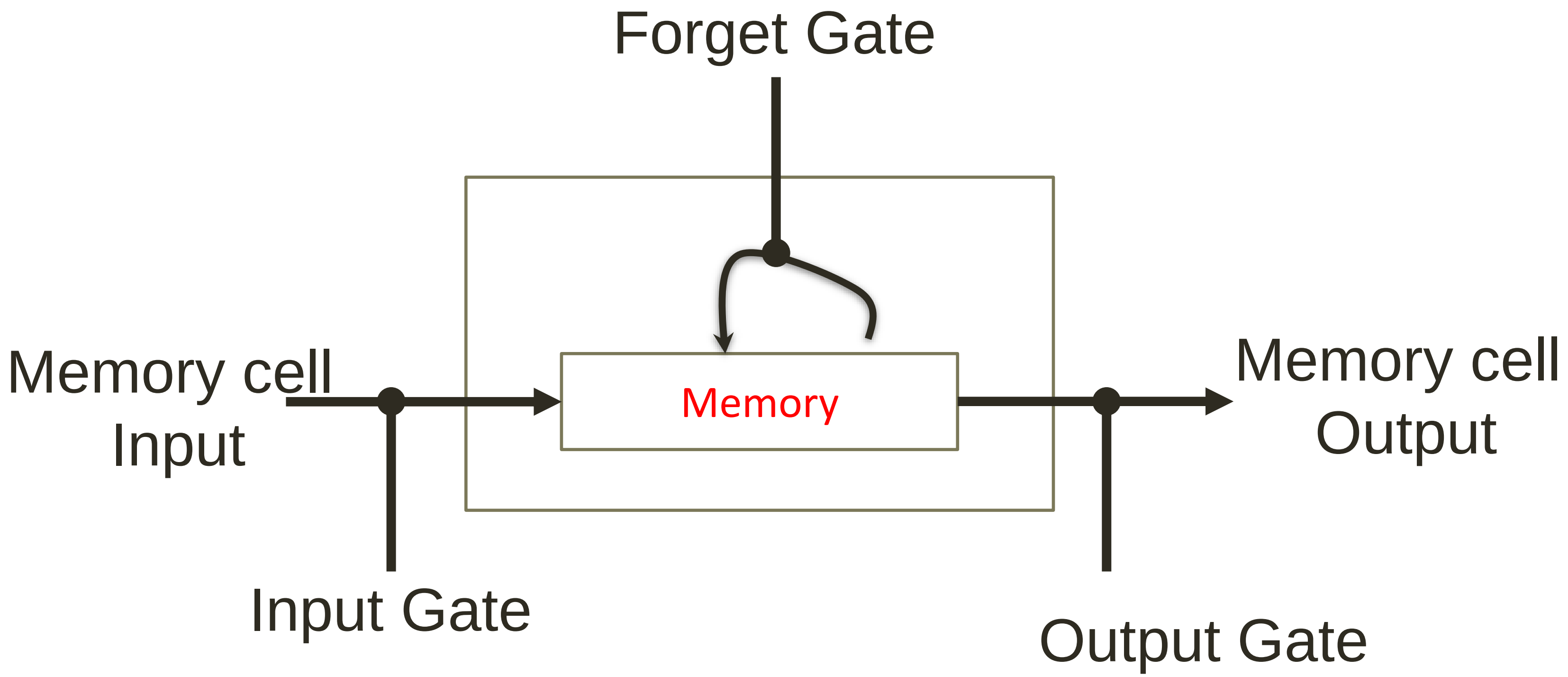
$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W} \qquad \boxed{\frac{\partial h_t}{\partial h_{t-1}} = tanh'(W_{hh}h_{t-1} + W_{xh}x_t)W_{hh}}$$

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T}\frac{\partial h_t}{\partial h_{t-1}} \cdots \frac{\partial h_1}{\partial W} = \frac{\partial L_T}{\partial h_T}\left(\prod_{t=2}^{T} \boxed{\frac{\partial h_t}{\partial h_{t-1}}}\right)\frac{\partial h_1}{\partial W}$$

Source:C231n, Stanford University, Fei Fei Li et al.

LONG SHORT-TERM MEMORY NETWORKS

A class of RNN: Handles Vanishing Gradient Problem



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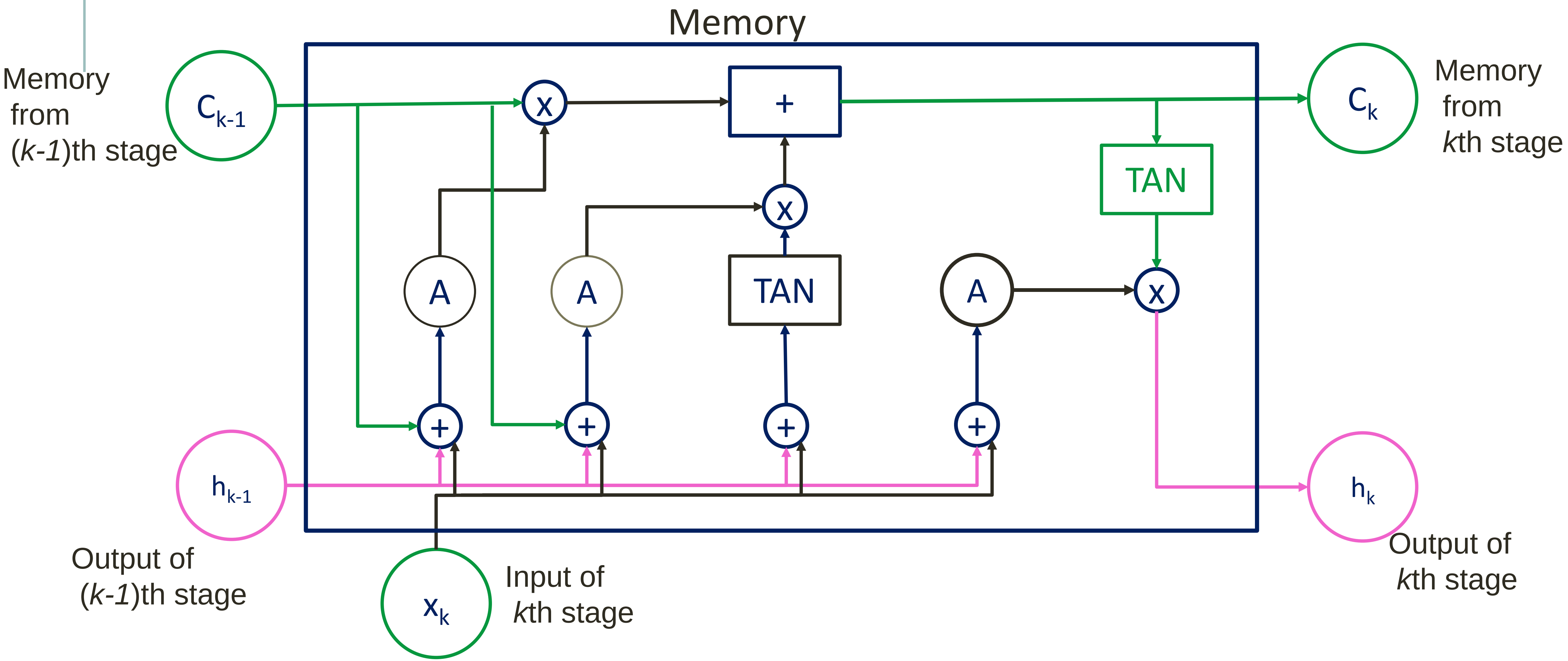
LONG SHORT-TERM MEMORY NETWORKS



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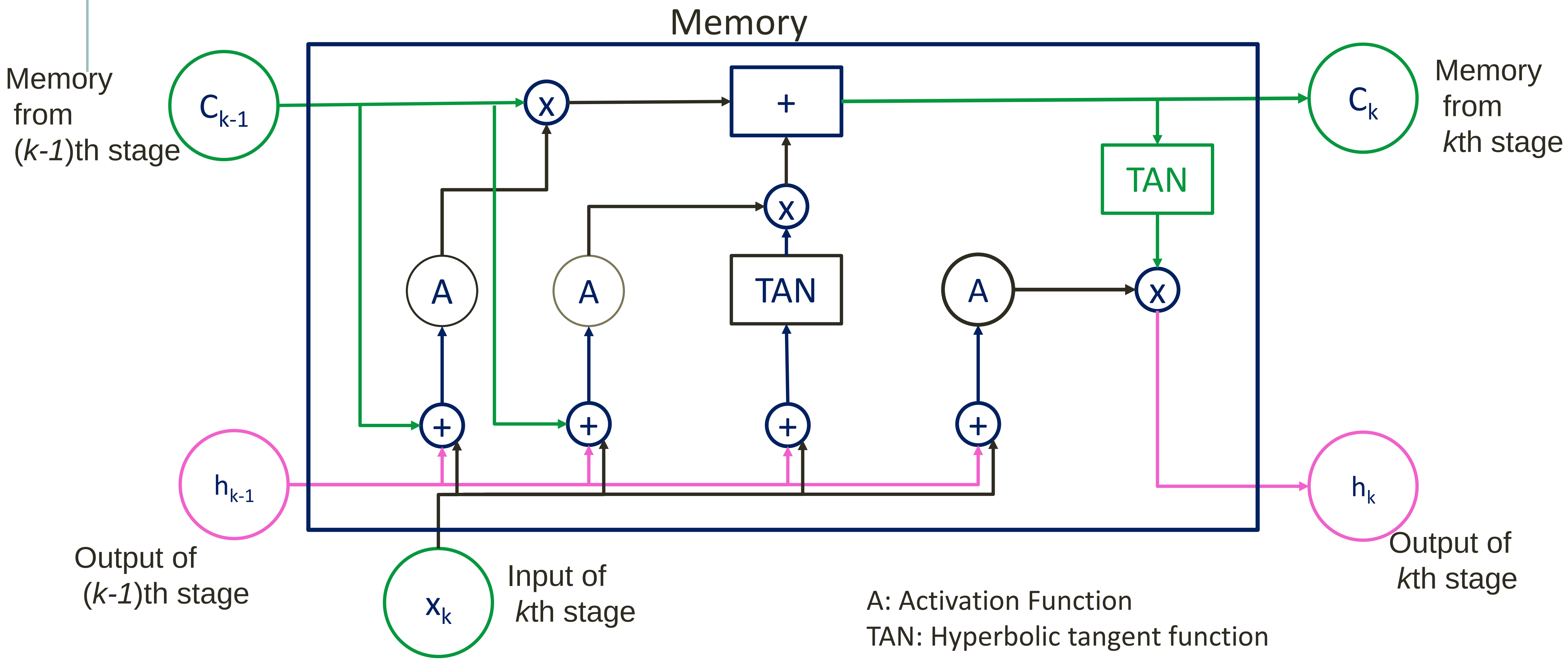
LONG SHORT-TERM MEMORY NETWORKS



A: Activation Function
TAN: Hyperbolic tangent function
X: Element-wise multiplication
+: Element-wise addition/concatenation

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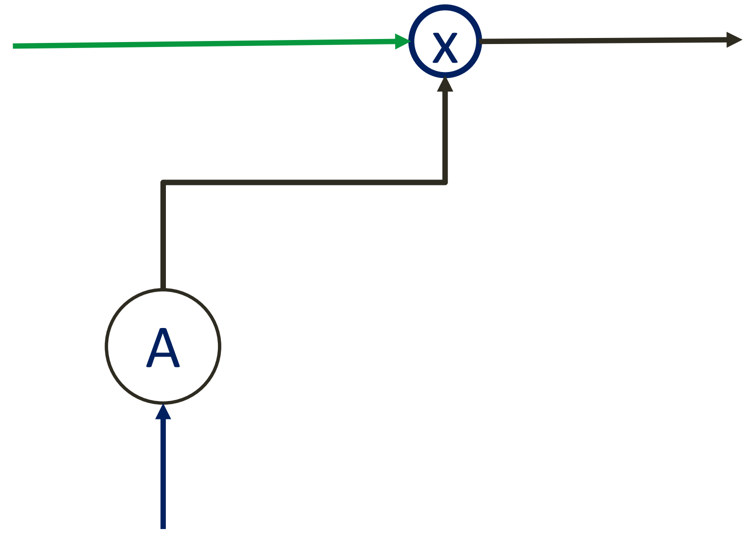
LONG SHORT-TERM MEMORY NETWORKS

Gates



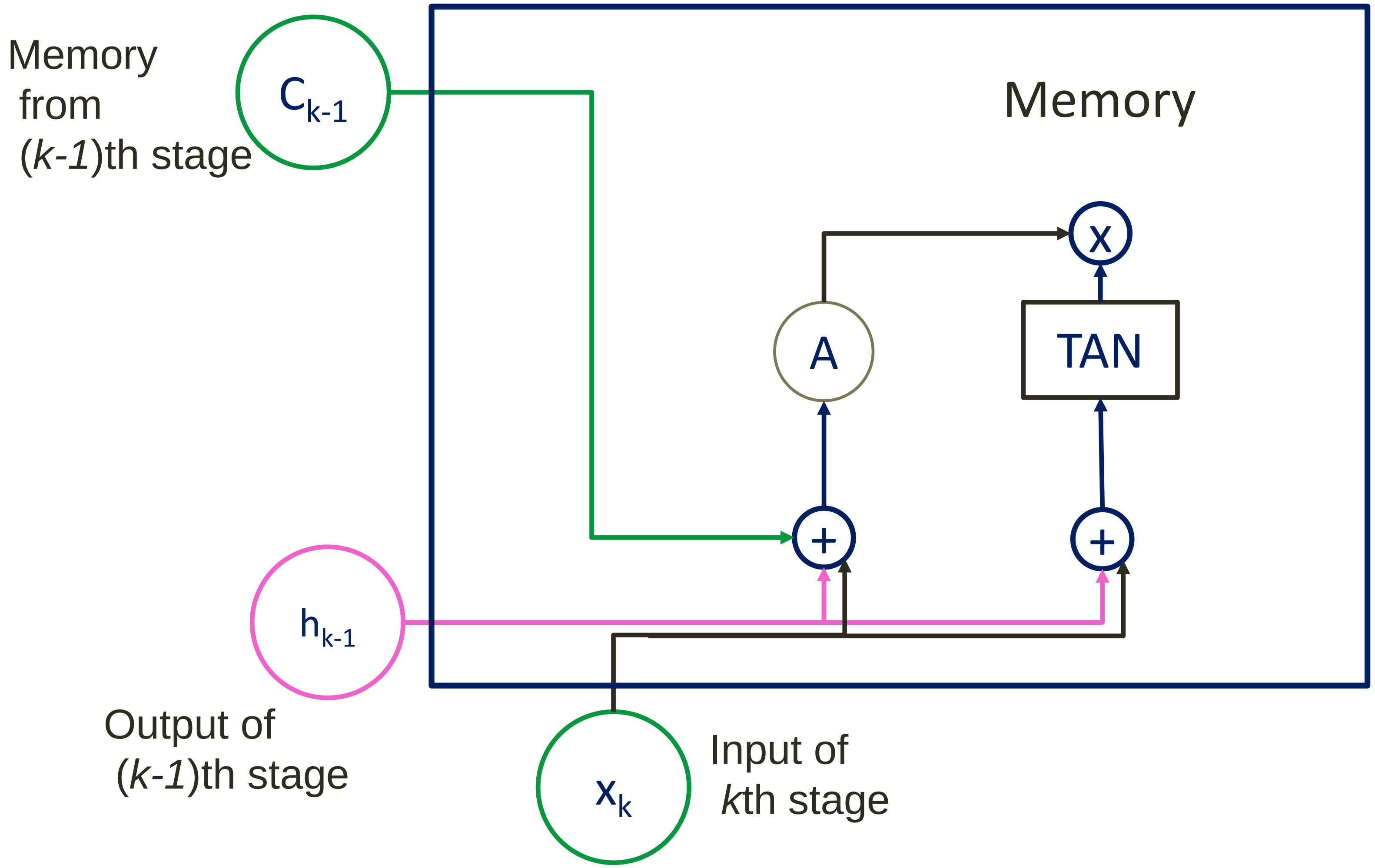
Gates: A Followed by x

Gates: Role in Controlling information passing to or from memory

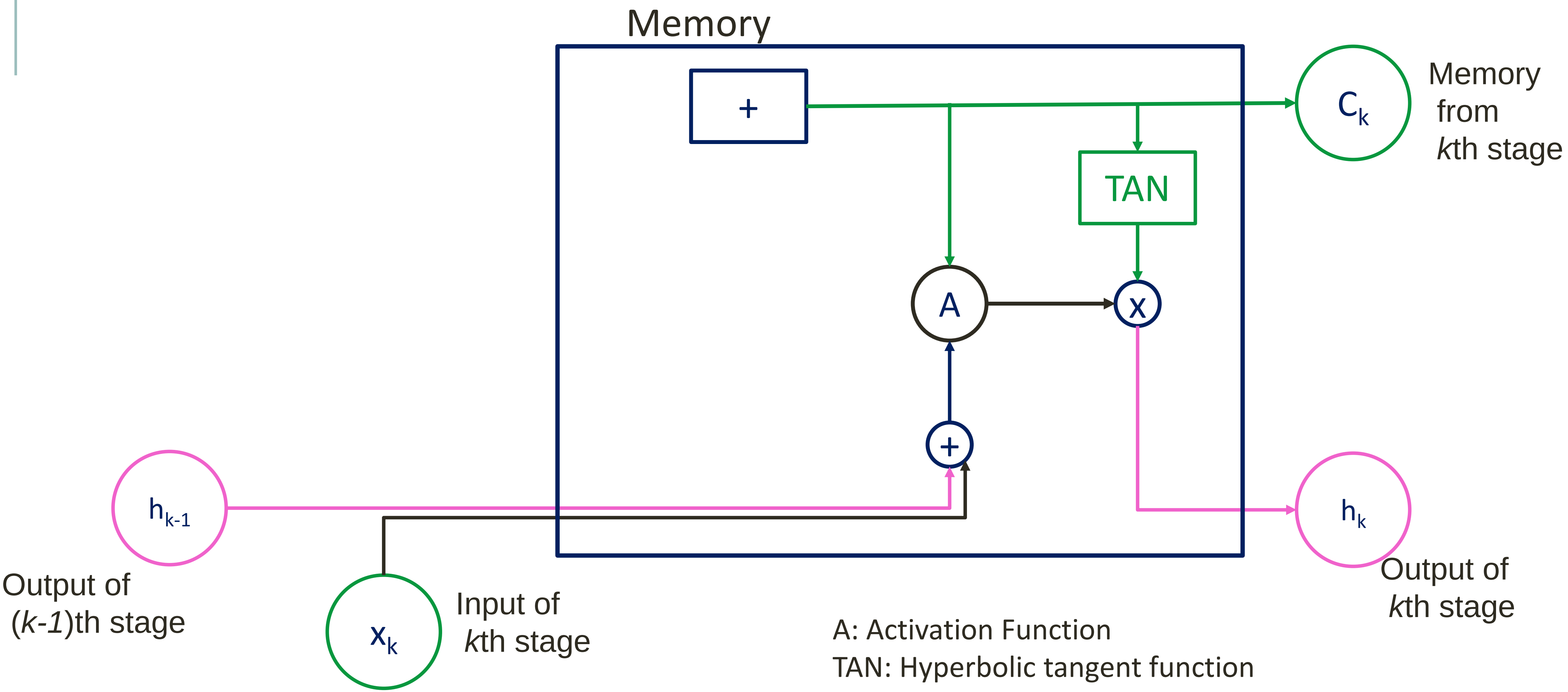
A Activation Function layer (Typically, Sigmoid function)

x Pointwise multiplication operation

LONG SHORT-TERM MEMORY NETWORKS INPUT GATES



LONG SHORT-TERM MEMORY NETWORKS
OUTPUT GATES



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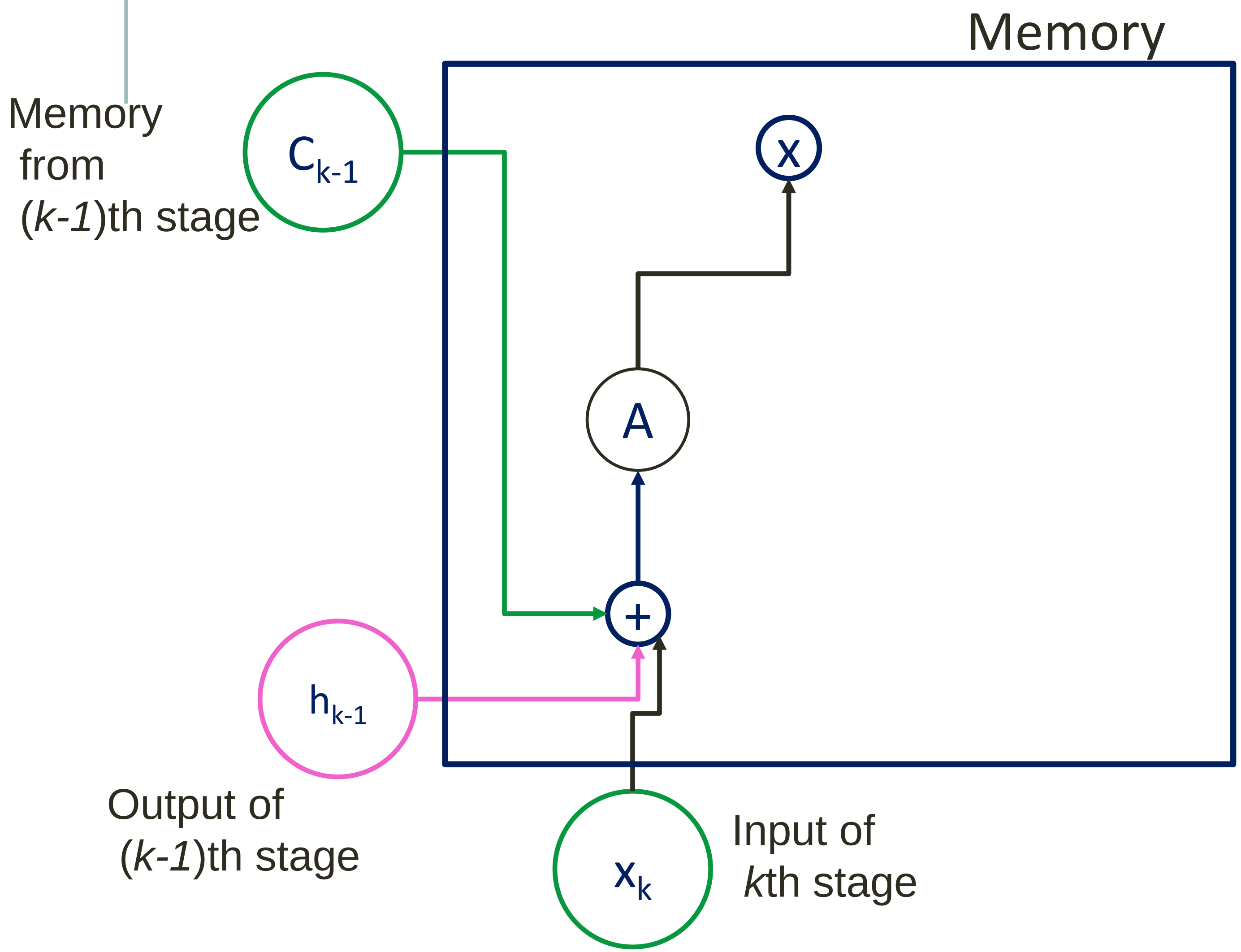
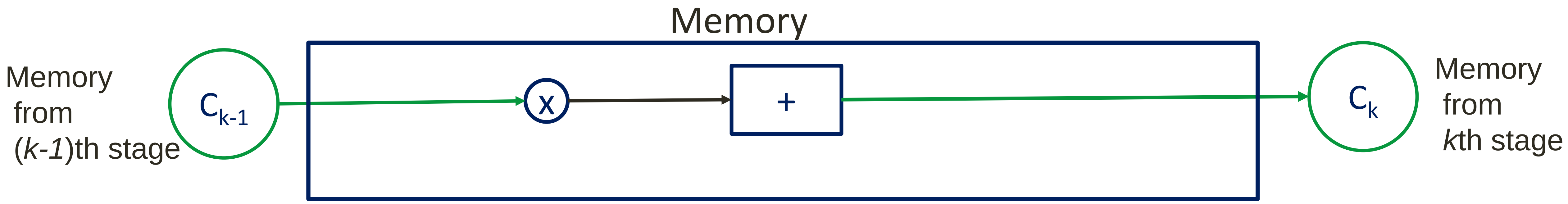
LONG SHORT-TERM MEMORY NETWORKS
FORGET GATE



[1]Nguyen and Medjaher, *Reliability Engineering and System Safety 188 (2019)*

LONG SHORT-TERM MEMORY NETWORKS CELL STATE VECTOR



Update: By forgetting old memory using forget gate and the addition of new memory using the input gate

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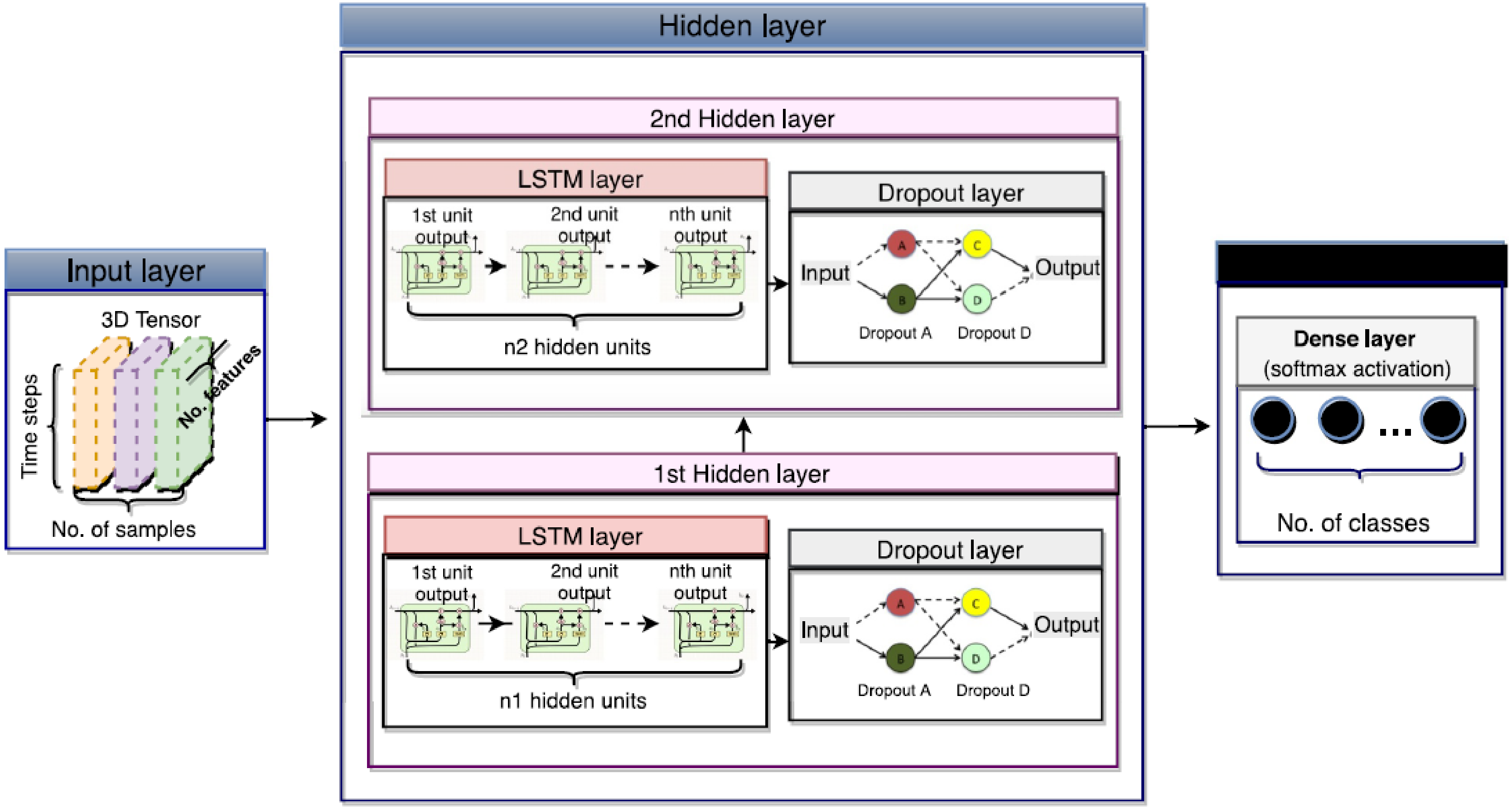

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EXPERIMENTS: TURBOFAN ENGINE DEGRADATION SIMULATION

Data set:

- Normal to degradation condition of the engine
- Degradation times
- Operation mode of engine
- 21 Characteristics of Engine

4 subsets:

- FD001: Single Operating Condition, One fault type
- FD002: Six Operating Conditions, One fault type
- FD003: Single Operating Condition, Two fault types
- FD004: Six Operating Conditions, Two fault types

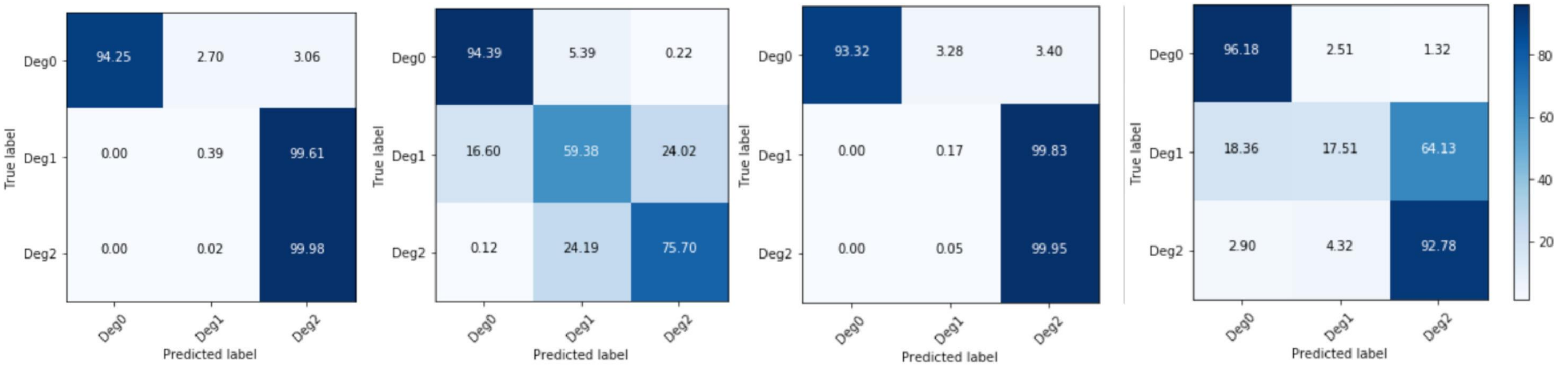
EXPERIMENTS: TURBOFAN ENGINE DEGRADATION SIMULATION

Results: w_o =10 and w_1=20,

LABELS of Data

- Class 0: Deg0: RUL > w_1
- Class 1: Deg1: w_0 < RUL <w_1
- Class 2: Deg 2: RUL < w_0

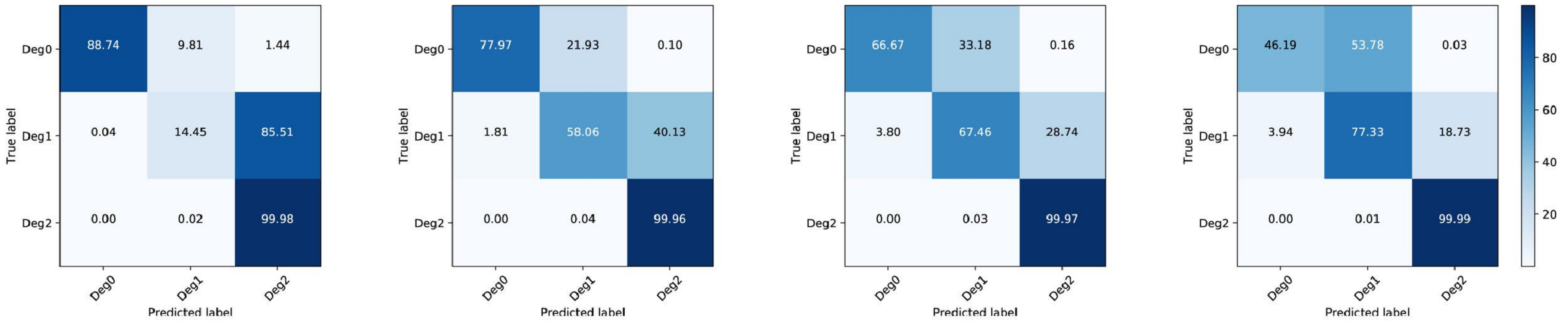
EXPERIMENTS: TURBOFAN ENGINE DEGRADATION SIMULATION



(a) FD001 (b) FD002 (c) FD003 (d) FD004

EXPERIMENTS: TURBOFAN ENGINE DEGRADATION SIMULATION:

Effect of Time Window on FD001



(a) $w_0 = 10,\ w_1 = 30$ (b) $w_0 = 10, w_1 = 50$ (c) $w_0 = 10,\ w_1 = 70$ (d) $w_0 = 10,\ w_1 = 90$

CONCLUSIONS

- Predictive Maintenance is an important aspect of the Industry
- PM problems can be formulated as a 3-class problem to predict the remaining useful time as a variable of interest
- Time-series modeling using RNN and its variants are ideal DL models for this kind of problem
- LSTM can be used to avoid vanishing gradient problems
- Case study using TurboFAN Engine degradation