Lecture Notes on

Pattern Recognition

Module 09(D): Recurrent Neural Network (RNN)

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Road map

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Recurrent Neural Network

- Why RNN?
- RNN
- RNN Example

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Application: Booking System

- Slot Filling

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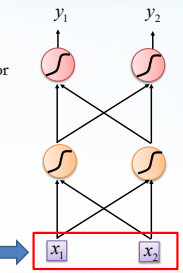
Application: Booking System

- Solving slot filling by FFN?
  - Input:
    - Word represented as a vector



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One Hot Encoding

- The vector is lexicon size.
- Each dimension corresponds to a word in the lexicon
- The dimension for the word is 1, and others are 0

lexicon = {apple, bag, cat, dog, elephant}

apple = [1 0 0 0 0]
bag = [0 1 0 0 0]
cat = [0 0 1 0 0]
dog = [0 0 0 1 0]
elephant = [0 0 0 0 1]

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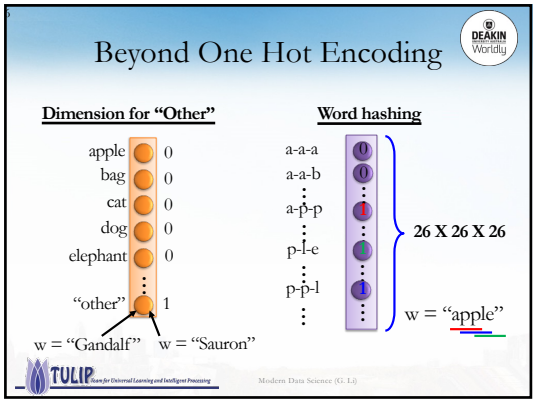
Beyond One Hot Encoding



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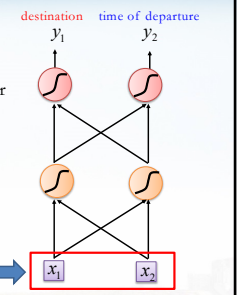
Application: Booking System

- Solving slot filling by FFN?
  - Input:
    - Word represented as a vector
  - Output:
    - Probability distribution that the input word belonging to the slots



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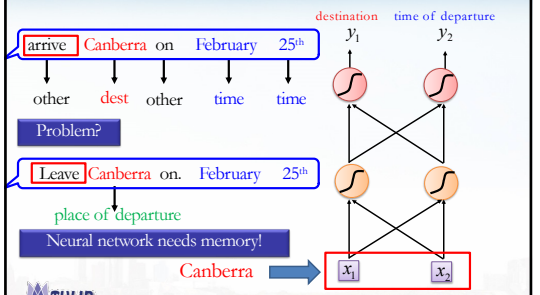
Example Application



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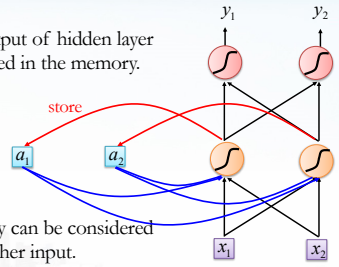
Recurrent Neural Network (RNN)

The output of hidden layer are stored in the memory.



Memory can be considered as another input.

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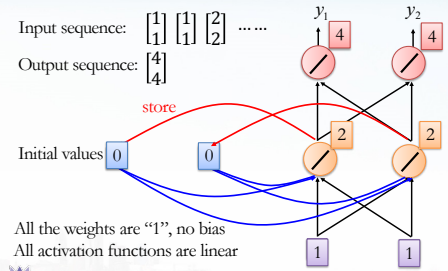
Example

Input sequence: $\begin{bmatrix}1\\1\end{bmatrix}\begin{bmatrix}1\\1\end{bmatrix}\begin{bmatrix}2\\2\end{bmatrix}\cdots\cdots$

Output sequence: $\begin{bmatrix}4\\4\end{bmatrix}$



All the weights are "1", no bias
All activation functions are linear

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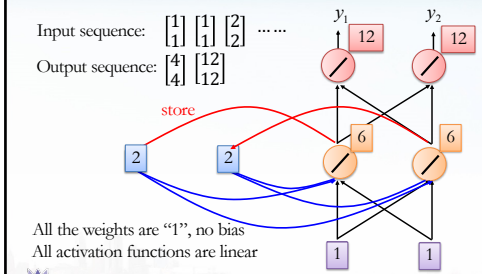
Example

Input sequence: $\begin{bmatrix}1\\1\end{bmatrix}\begin{bmatrix}1\\1\end{bmatrix}\begin{bmatrix}2\\2\end{bmatrix}\cdots\cdots$

Output sequence: $\begin{bmatrix}4\\4\end{bmatrix}\begin{bmatrix}12\\12\end{bmatrix}$



All the weights are "1", no bias
All activation functions are linear

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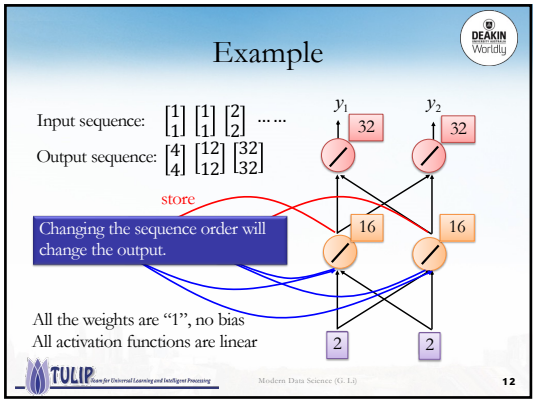

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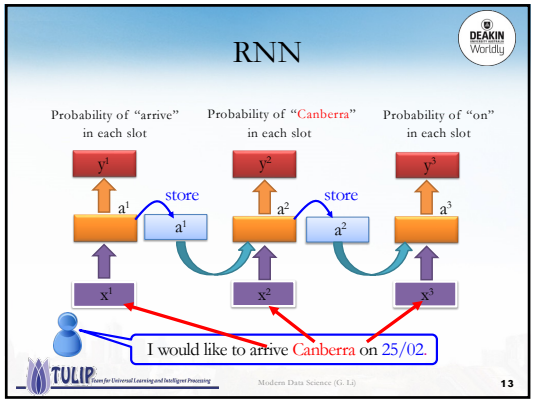

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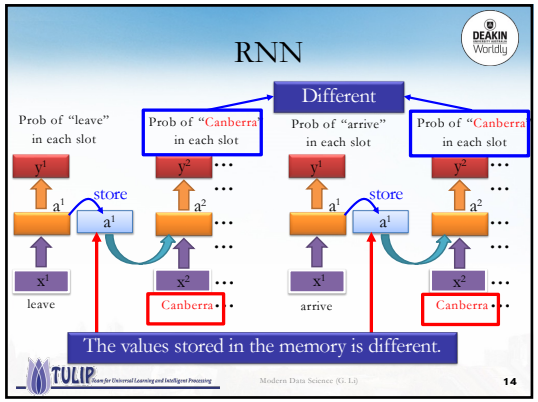

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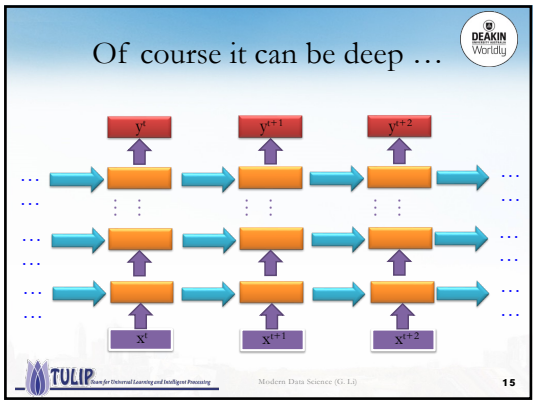

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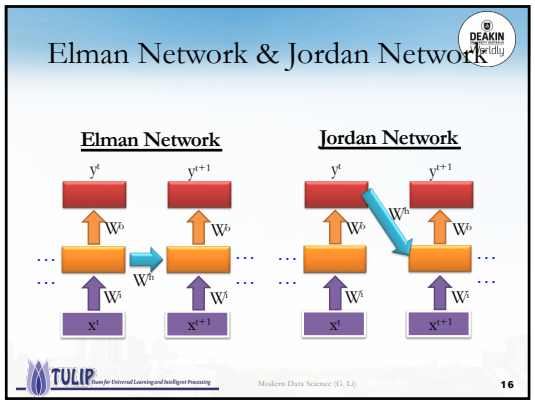

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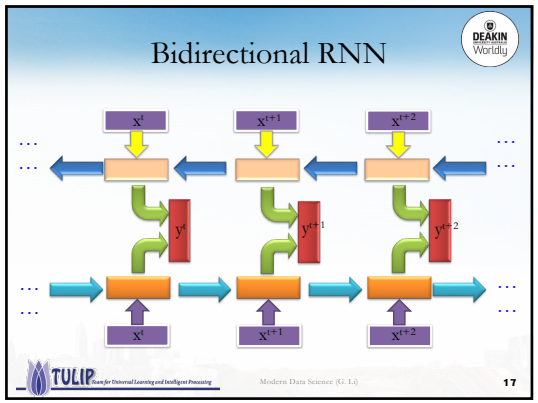

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LSTM

- Why LSTM?
- LSTM
- LSTM and FFN

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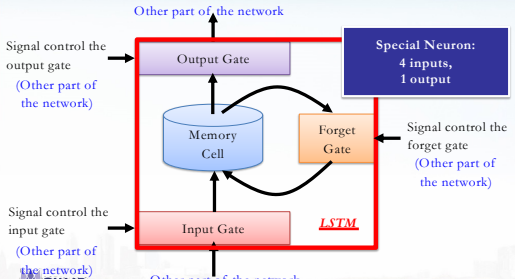
Long Short-Term Memory (LSTM)



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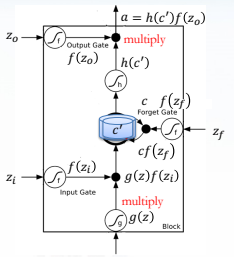
Long Short-Term Memory (LSTM)



Activation function f is usually a sigmoid function

- Between 0 and 1
- Mimic open and close gate

$$c' = g(z)f(z_i) + cf(z_f)$$

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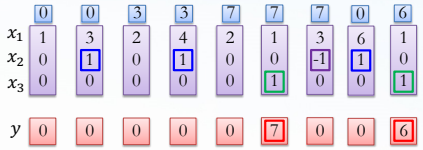
LSTM - Example



When $x_2 = 1$, add the numbers of x_1 into the memory

When $x_2 = -1$, reset the memory

When $x_3 = 1$, output the number in the memory.

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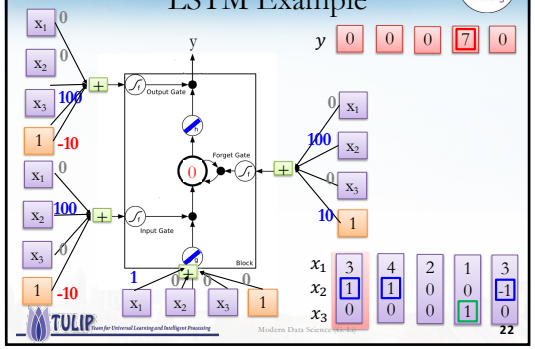
LSTM Example



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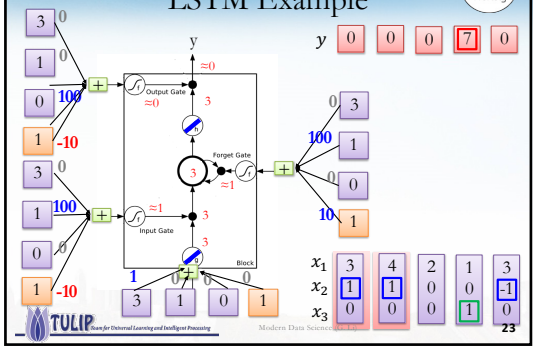
LSTM Example



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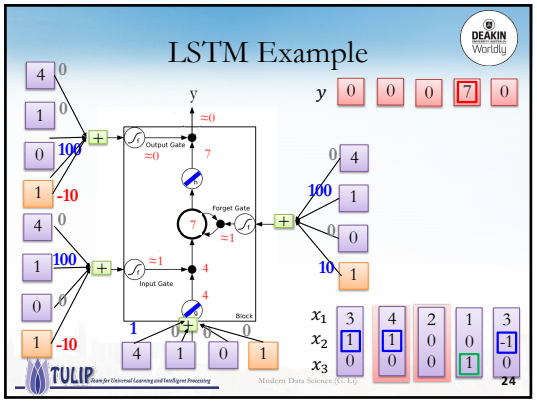

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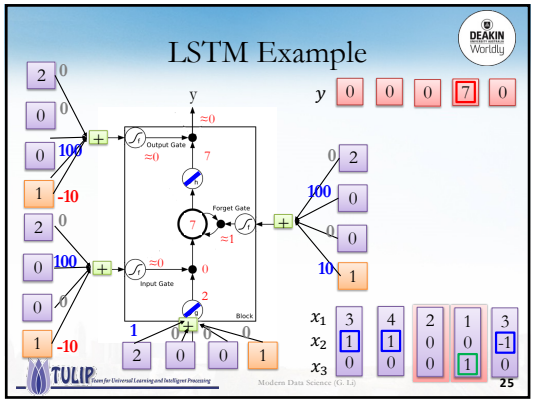

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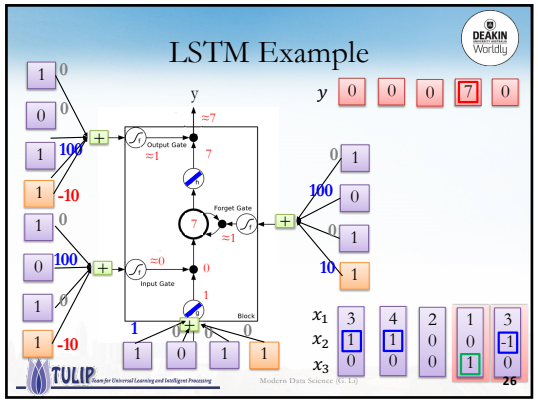

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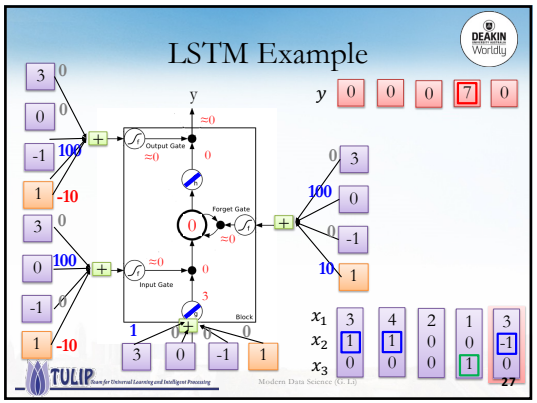

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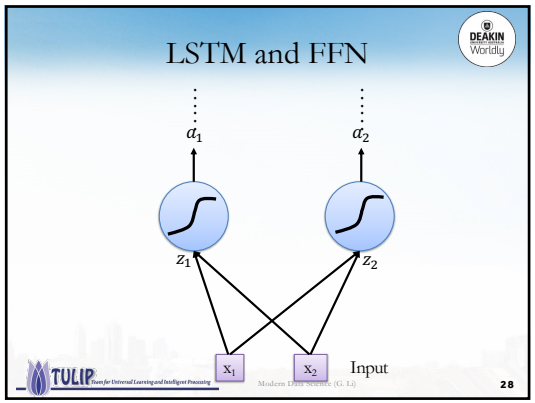

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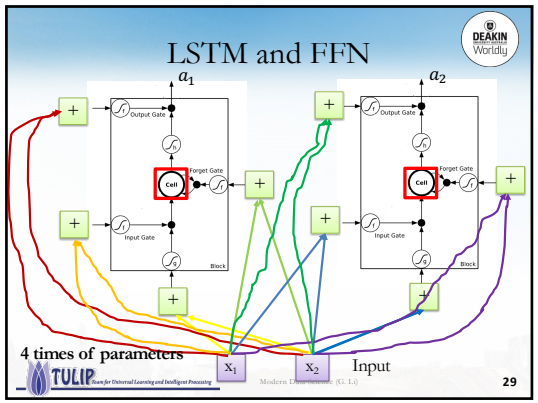

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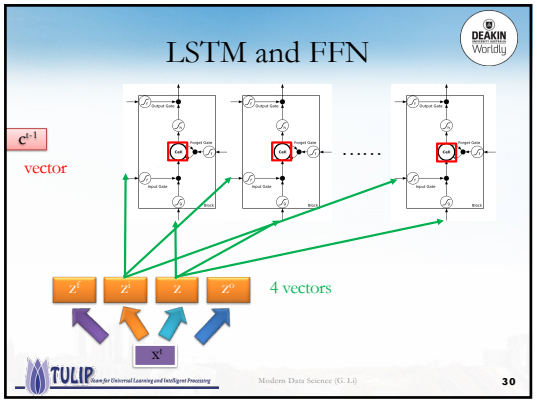

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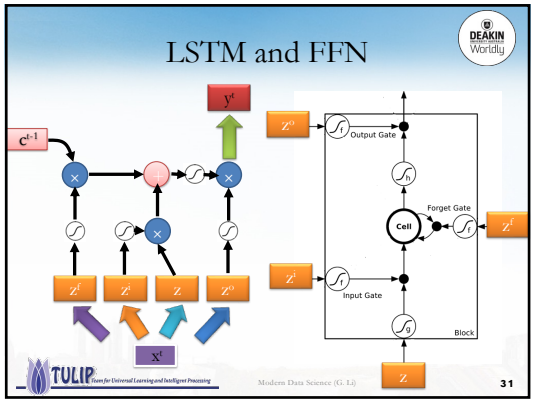

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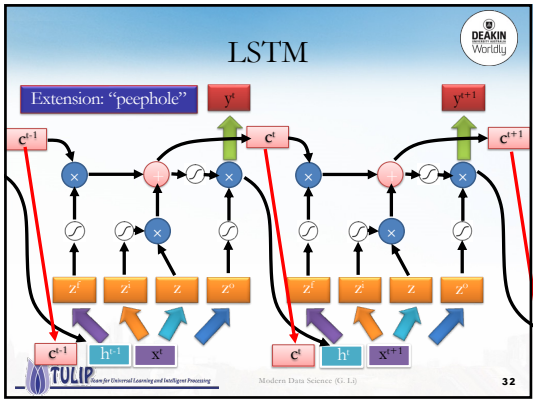

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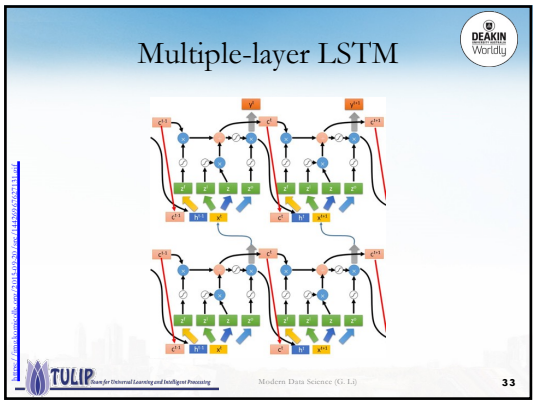

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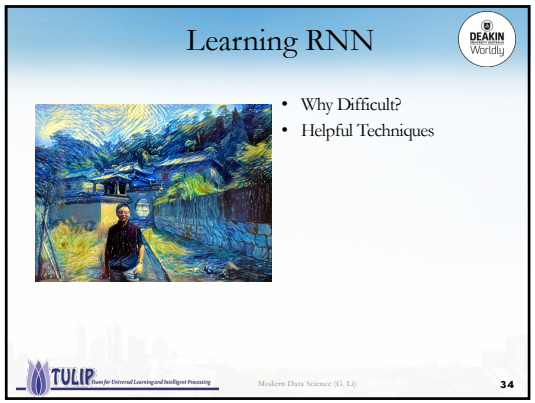

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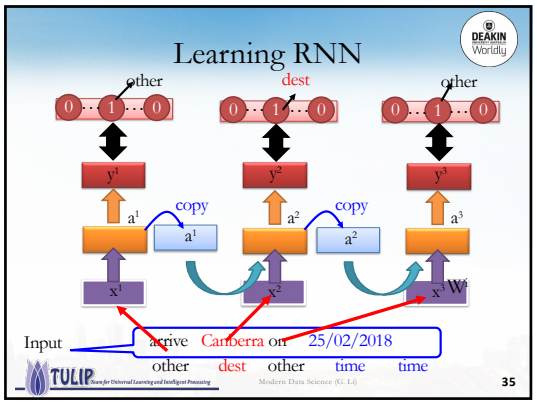

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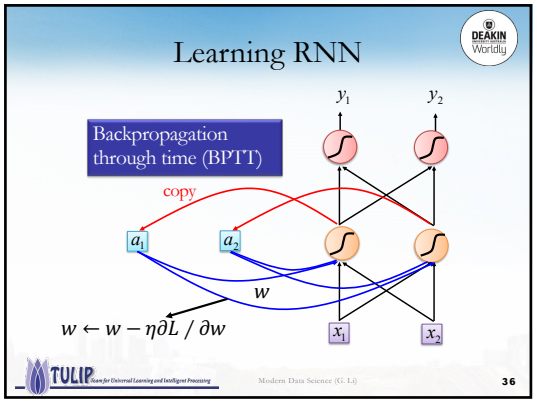
Learning RNN



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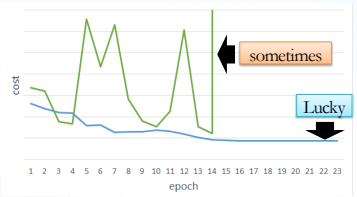
Learning RNN

- RNN-based network is not always easy to learn

Real experiments on Language modeling



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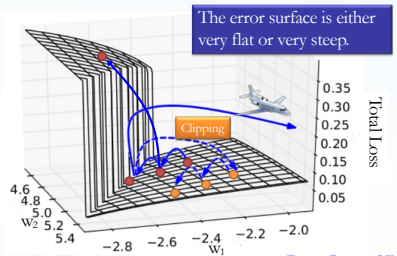
Learning RNN



[Razvan Pascanu, ICML'13]

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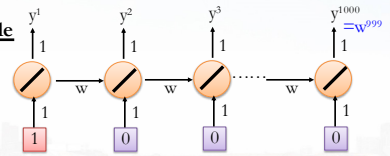
Why Difficult?

$w = 1 \Rightarrow y^{1000} = 1$
$w = 1.01 \Rightarrow y^{1000} \approx 20000$
Large $\partial L/\partial w$ → Small Learning rate?

$w = 0.99 \Rightarrow y^{1000} \approx 0$
$w = 0.01 \Rightarrow y^{1000} \approx 0$
small $\partial L/\partial w$ → Large Learning rate?

Toy Example



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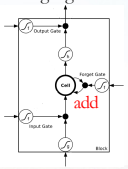
Helpful Techniques

- Long Short-term Memory (LSTM)
  - Can deal with gradient vanishing (not gradient explode)
  - Memory and input are **added**
    - The influence never disappears unless forget gate is closed

No Gradient vanishing
(If forget gate is opened.)



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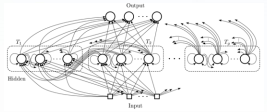
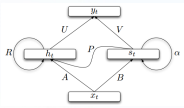
Helpful Techniques

Clockwise RNN



[Jan Koutnik, JMLR'14]

Structurally Constrained Recurrent Network (SCRN)



[Tomas Mikolov, ICLR'15]

Vanilla RNN Initialized with Identity matrix + ReLU activation function
[Quoc V. Le, arXiv'15]
- Outperform or be comparable with LSTM in 4 different tasks

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RNN/LSTM Applications

- Applications
- Attention-based Model
- Visual Question Answering

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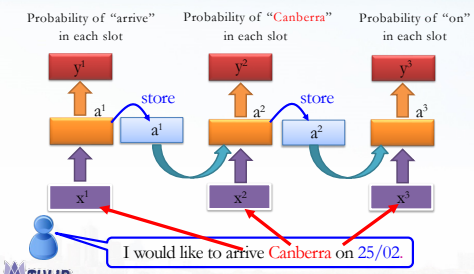
Applications: Many to Many



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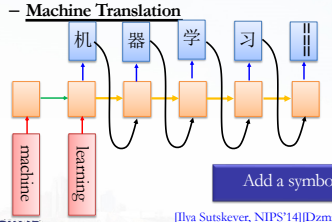
Many to Many (No Limitation)

- Both input and output are both sequences ***with different lengths.***
  → ***Sequence to sequence learning***
  – **Machine Translation**



[Ilya Sutskever, NIPS'14][Dzmitry Bahdanau, arXiv'15]

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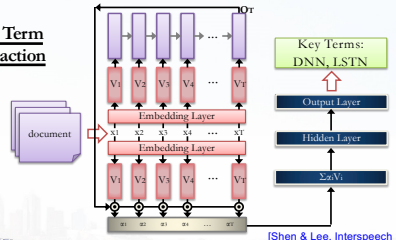
Applications: Many to One

- Input is a vector sequence, but output is only one vector

Key Term Extraction



[Shen & Lee, Interspeech 16]

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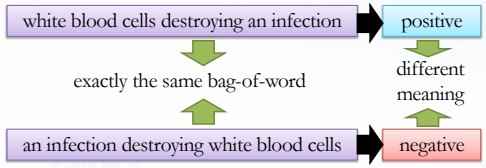
Sequence-to-sequence Auto-encoder - Text

- To understand the meaning of a word sequence, the order of the words can not be ignored.



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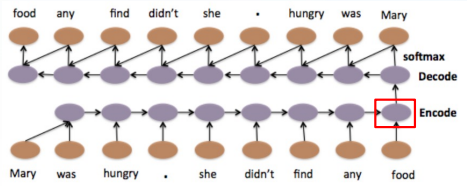
Sequence-to-sequence Auto-encoder - Text



- Li, Jiwei, Minh-Thang Luong, and Dan Jurafsky. "A hierarchical neural autoencoder for paragraphs and documents." *arXiv preprint arXiv:1506.01057*(2015).

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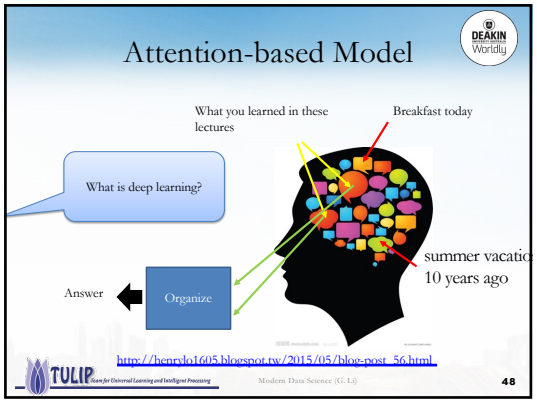

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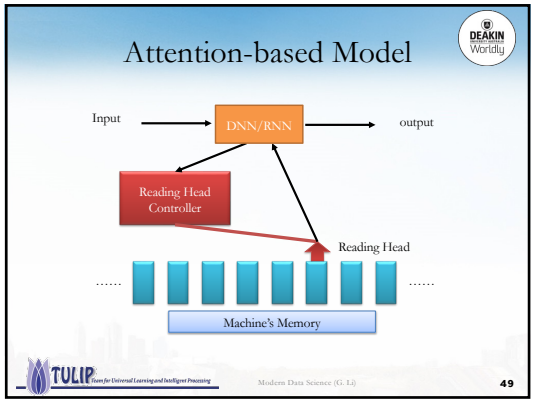

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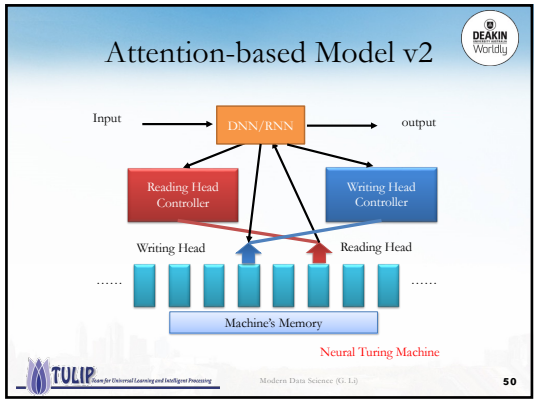

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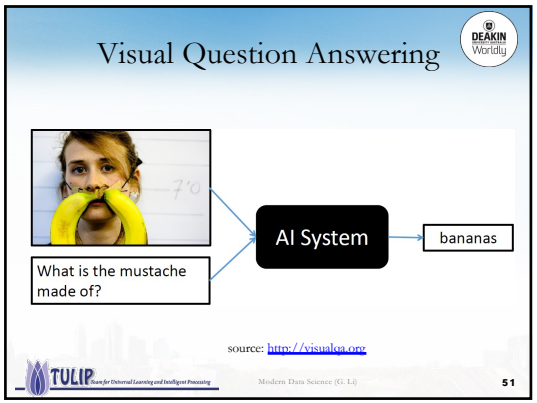

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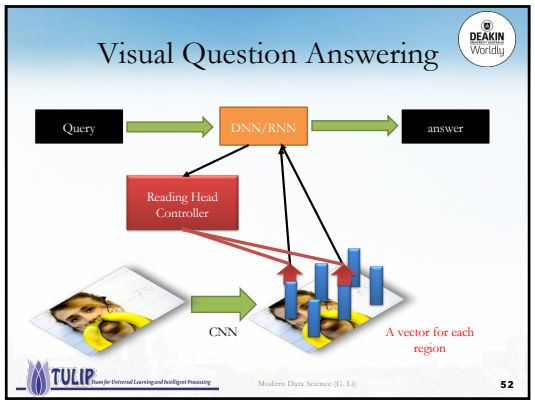

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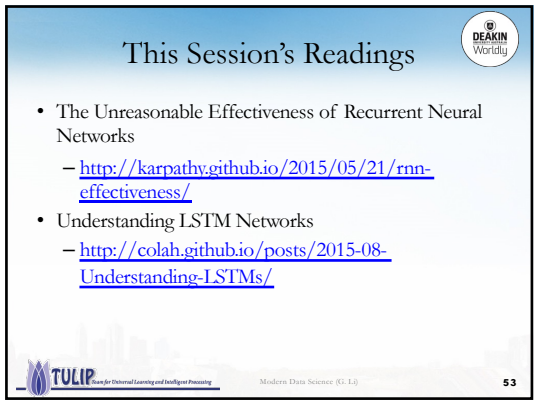

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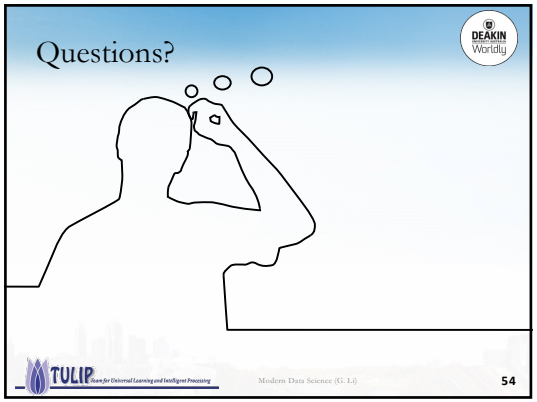

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