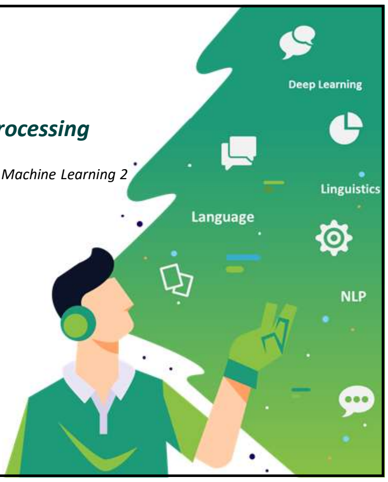
COMP5046

Natural Language Processing

Lecture 4: Word Classification and Machine Learning 2



Dr. Caren Han

Semester 1, 2021
School of Computer Science,
University of Sydney

1

0 LECTURE PLAN

Lecture 4: Word Classification and Machine Learning 2

1. **Machine Learning and NLP: Finish**
2. Seq2Seq Learning
3. Seq2Seq Deep Learning
   1. RNN (Recurrent Neural Network)
   2. LSTM (Long Short-Term Memory)
   3. GRU (Gated Recurrent Unit)
4. Data Transformation for Deep Learning NLP
5. Next Week Preview
   - Natural Language Processing Stack

…. And some interesting notice in the end of the lecture!

2

1 Machine Learning and NLP

The purpose of Natural Language Processing: Overview

Application

Understanding		*Searching*
Sentiment Analysis, *Topic Classification*, *Topic Modelling*, ….	*Dialog*, *Translation*	*Search*, ….

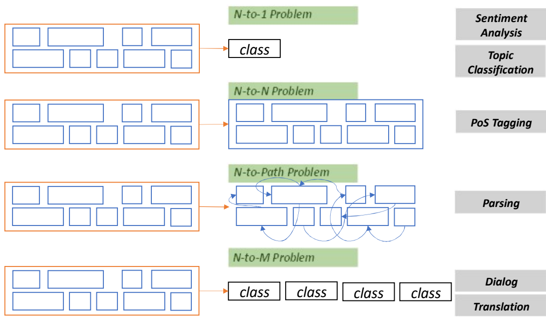
NLP Stack

Entity Extraction	When Sebastian Thrun …	When Sebastian Thrun PERSON started at Google ORG in 2007 DATE
Parsing	Claudia sat on a stool	
PoS Tagging	She sells seashells	[she/PRP] [sells/VBZ] [seashells/NNS]
Stemming	Drinking, Drank, Drunk	Drink
Tokenisation	How is the weather today	[How] [is] [the] [weather] [today]

3

1 Machine Learning and NLP

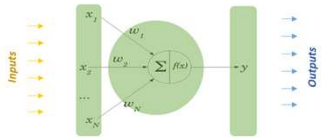
Problem Abstraction



4

1 Machine Learning and NLP

Prediction

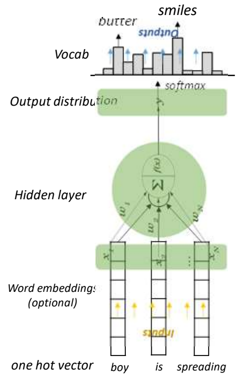


x_i	Inputs	**Features** words (indices or vectors!), context windows, sentences, documents, etc.
y_i	Outputs (labels)	**What we try to predict/classify** • E.g. word meaning, sentiment, name entity

5

1 Machine Learning and NLP

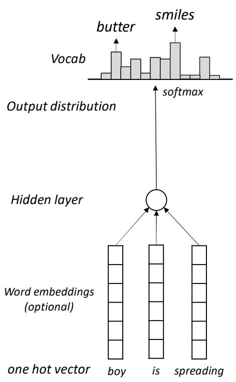
Prediction



6

1 Machine Learning and NLP

Prediction



What if we consider this as a __sequential input__? Let's add the concept 'time'

7

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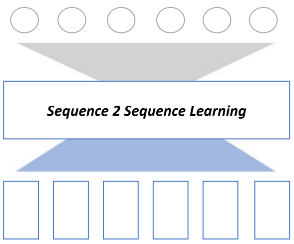
8

2 Sequence 2 Sequence Learning

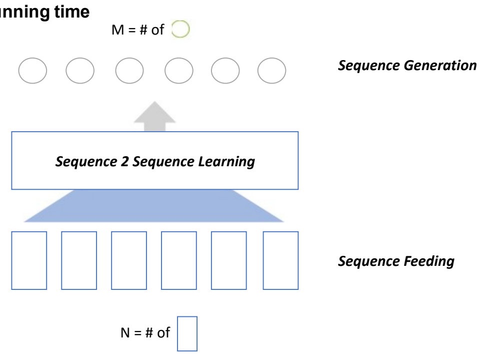
Illustration



9

2 Sequence 2 Sequence Learning

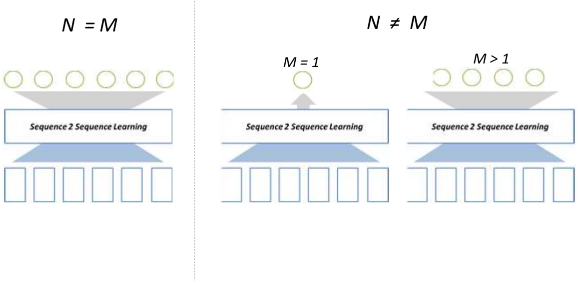
Running time



10

2 Sequence 2 Sequence Learning

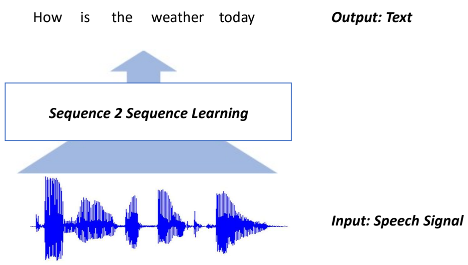
Sequence 2 Sequence Learning



11

2 Sequence 2 Sequence Learning

Seq2Seq – Speech Recognition



12

2 Sequence 2 Sequence Learning

Seq2Seq – Movie Frame Labelling

Swing Swing Hit Bat_Broken

Output: Scene Labels

Sequence 2 Sequence Learning

Input: Video Frame

13

2 Sequence 2 Sequence Learning

Seq2Seq – PoS Tagging

ADV VERB DET NOUN NOUN

Output: Part of Speech

Sequence 2 Sequence Learning

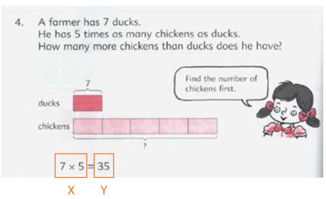
How is the weather today

Input: Text

14

2 Sequence 2 Sequence Learning

Seq2Seq – Arithmetic Calculation



15

2 Sequence 2 Sequence Learning

Seq2Seq – Arithmetic Calculation

3 5

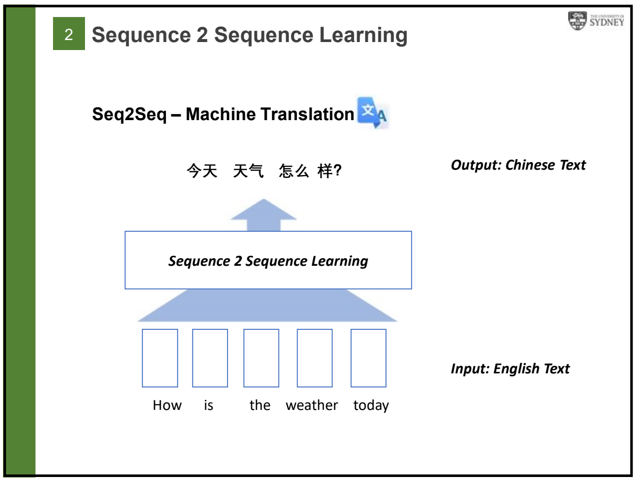
Output: Numbers

Sequence 2 Sequence Learning

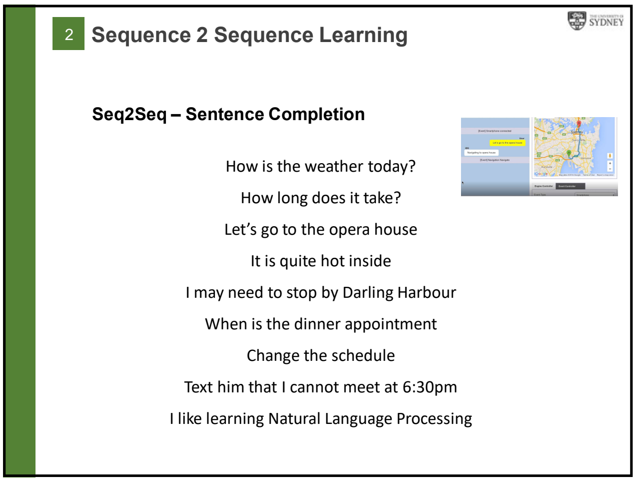
Input: Math Expression

7 x 5

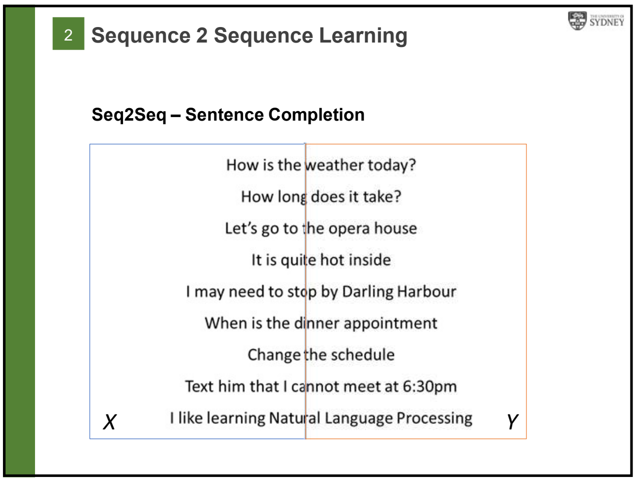
16


2
Sequence 2 Sequence Learning
Seq2Seq – Machine Translation
今天 天气 怎么 样?
Output: Chinese Text
Sequence 2 Sequence Learning
Input: English Text
How
is
the
weather
today

17


2
Sequence 2 Sequence Learning
Seq2Seq – Sentence Completion
How is the weather today?
How long does it take?
Let's go to the opera house
It is quite hot inside
I may need to stop by Darling Harbour
When is the dinner appointment
Change the schedule
Text him that I cannot meet at 6:30pm
I like learning Natural Language Processing

18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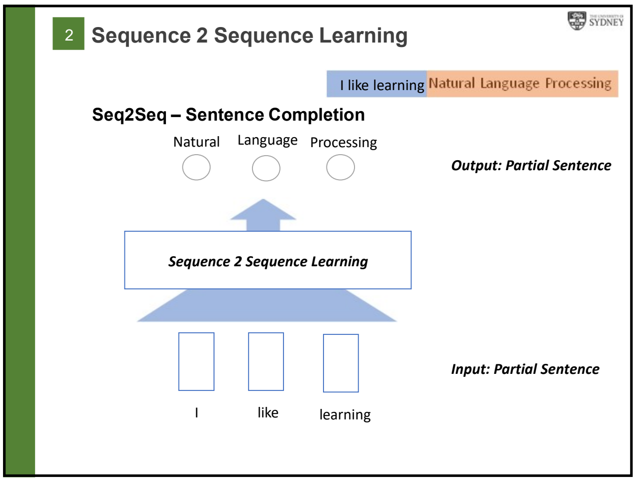
When is the dinner appointment
Change the schedule
Text him that I cannot meet at 6:30pm
I like learning Natural Language Processing
X
Y

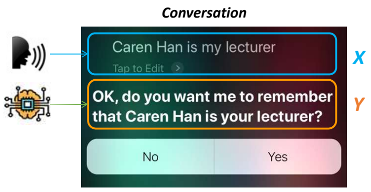
19


2
Sequence 2 Sequence Learning
I like learning Natural Language Processing
Seq2Seq – Sentence Completion
Natural
Language
Processing
Output: Partial Sentence
Sequence 2 Sequence Learning
Input: Partial Sentence
I
like
learning

20

2 Sequence 2 Sequence Learning

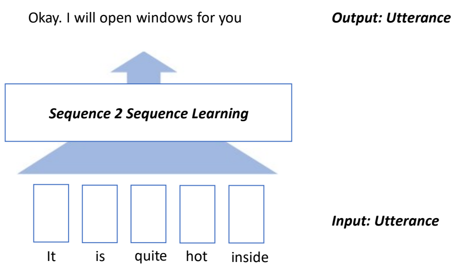
Seq2Seq – Conversation Modelling



21

2 Sequence 2 Sequence Learning

Seq2Seq – Conversation Modelling



22

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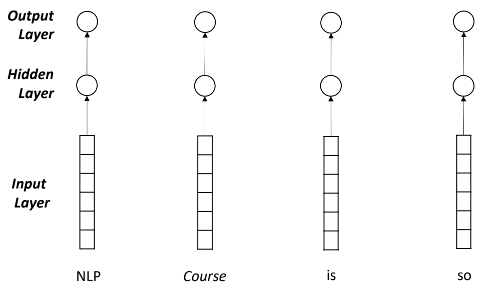
23

3 Seq2Seq with Deep Learning

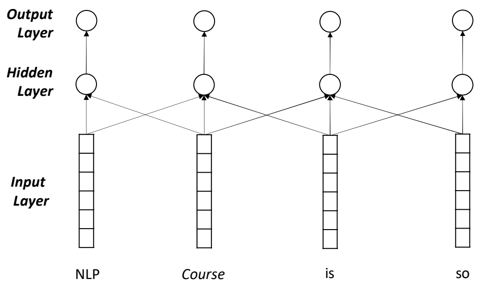
Prediction



24

3 Seq2Seq with Deep Learning

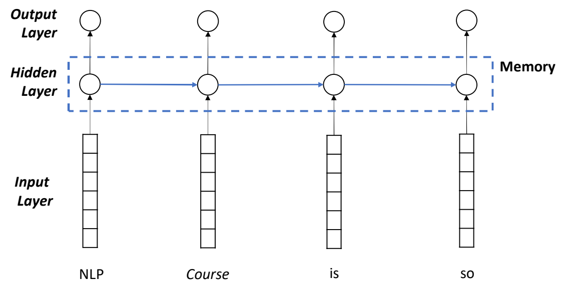
Prediction + Convolution Idea



25

3 Seq2Seq with Deep Learning

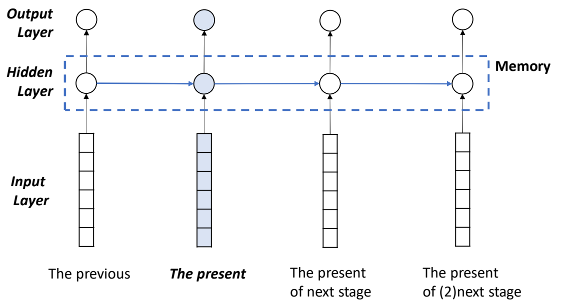
Prediction + Memory = Sequence Modelling



26

3 Seq2Seq with Deep Learning

Prediction + Memory = Sequence Modelling

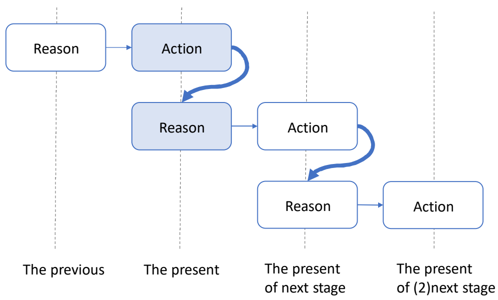


27

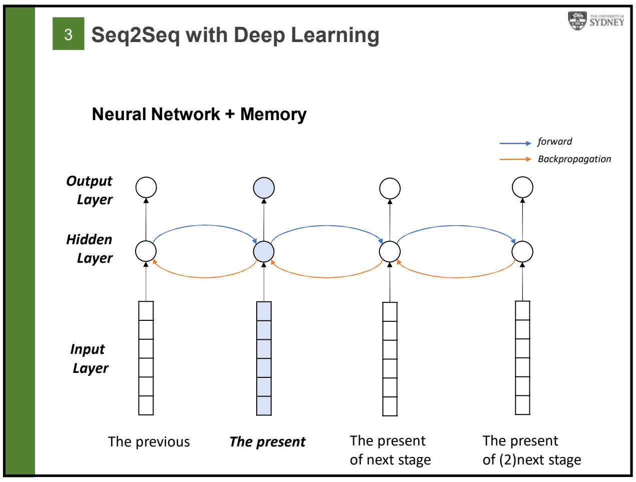
3 Seq2Seq with Deep Learning

Neural Network + Memory

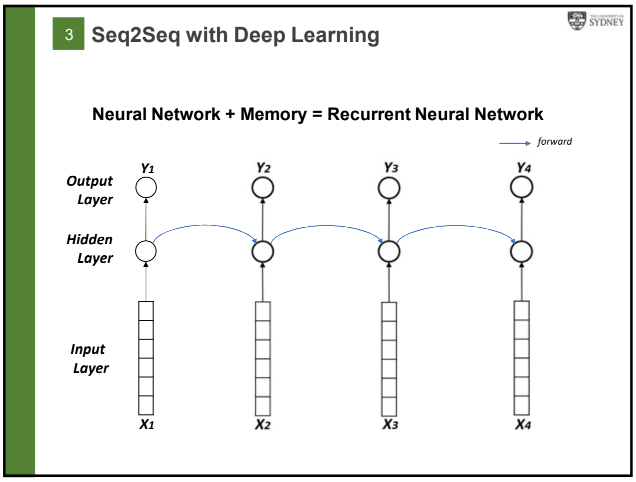
Memory is vital to experiences, it is the retention of information over time for the purpose of influencing future action



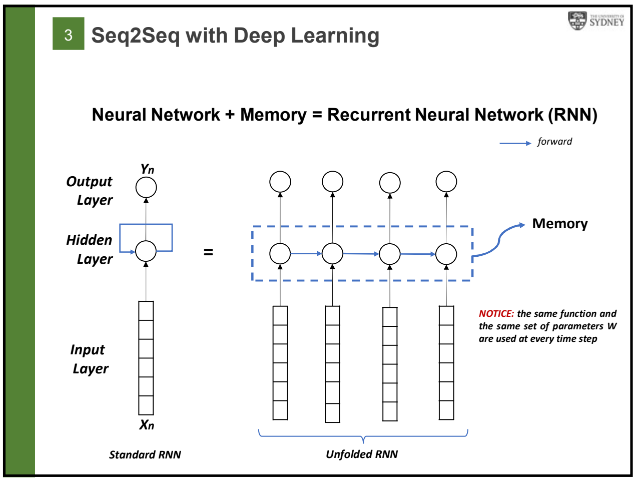
28


3
Seq2Seq with Deep Learning
SYDNEY
Neural Network + Memory
forward
Backpropagation
Output Layer
Hidden Layer
Input Layer
The previous
The present
The present of next stage
The present of (2)next stage

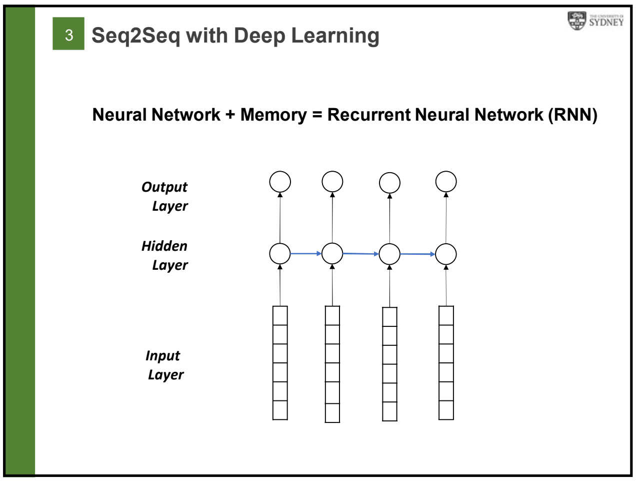
29


3
Seq2Seq with Deep Learning
SYDNEY
Neural Network + Memory = Recurrent Neural Network
forward
Output Layer
Hidden Layer
Input Layer
Y1
Y2
Y3
Y4
X1
X2
X3
X4

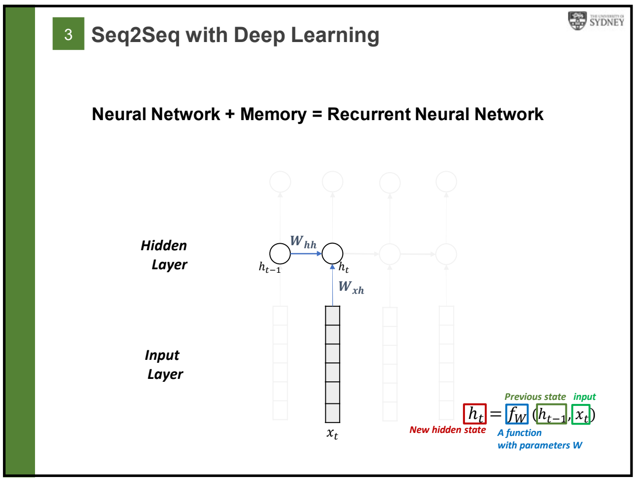
30


3
Seq2Seq with Deep Learning
SYDNEY
Neural Network + Memory = Recurrent Neural Network (RNN)
forward
Output Layer
Hidden Layer
Input Layer
Yn
Xn
=
Memory
NOTICE: the same function and the same set of parameters W are used at every time step
Standard RNN
Unfolded RNN

31

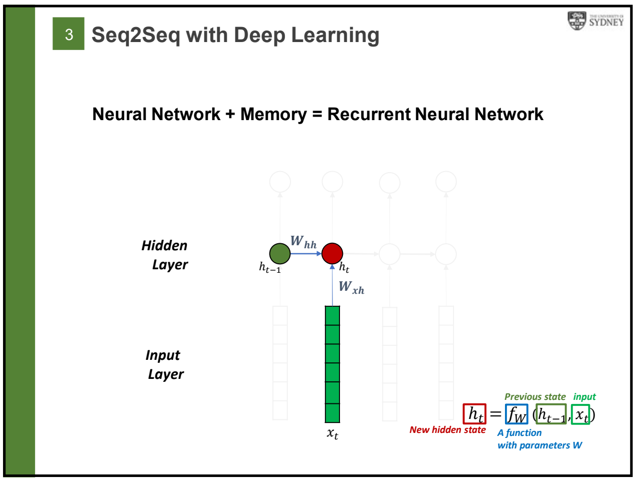

3
Seq2Seq with Deep Learning
SYDNEY
Neural Network + Memory = Recurrent Neural Network (RNN)
Output Layer
Hidden Layer
Input Layer

32



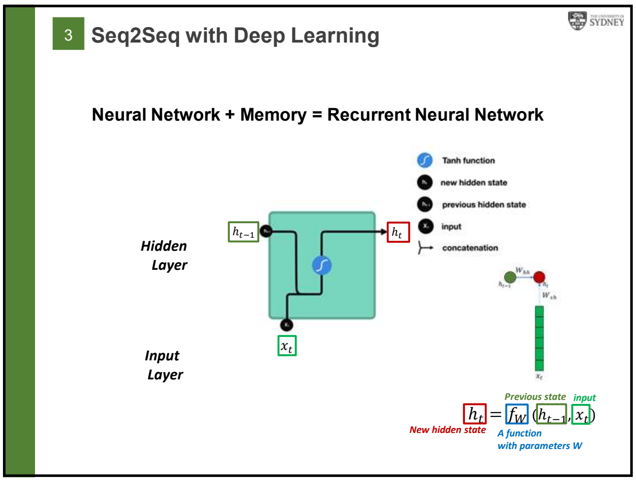
3 Seq2Seq with Deep Learning
Neural Network + Memory = Recurrent Neural Network
Hidden Layer
Input Layer
W_{hh}
h_{t-1}
h_t
W_{xh}
x_t
Previous state
input
$h_t = f_W(h_{t-1}, x_t)$
New hidden state
A function with parameters W

33



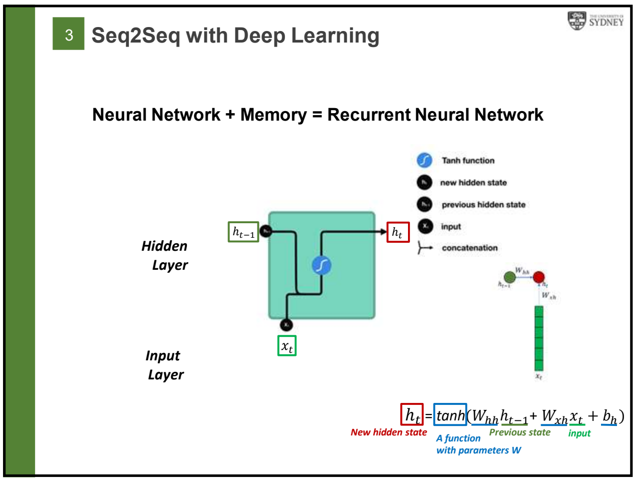
3 Seq2Seq with Deep Learning
Neural Network + Memory = Recurrent Neural Network
Hidden Layer
Input Layer
W_{hh}
h_{t-1}
h_t
W_{xh}
x_t
Previous state
input
$h_t = f_W(h_{t-1}, x_t)$
New hidden state
A function with parameters W

34



3 Seq2Seq with Deep Learning
Neural Network + Memory = Recurrent Neural Network
Tanh function
new hidden state
previous hidden state
input
concatenation
Hidden Layer
Input Layer
h_{t-1}
h_t
x_t
Previous state
input
$h_t = f_W(h_{t-1}, x_t)$
New hidden state
A function with parameters W

35

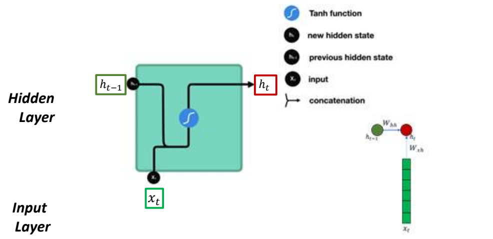


3 Seq2Seq with Deep Learning
Neural Network + Memory = Recurrent Neural Network
Tanh function
new hidden state
previous hidden state
input
concatenation
Hidden Layer
Input Layer
h_{t-1}
h_t
x_t
$h_t = tanh(W_{hh} h_{t-1} + W_{xh} x_t + b_h)$
New hidden state
A function with parameters W
Previous state
input

36

3 Seq2Seq with Deep Learning

Neural Network + Memory = Recurrent Neural Network



$$\boxed{h_t} = \boxed{tanh}(W_{hh} h_{t-1} + W_{xh} x_t + b_h)$$

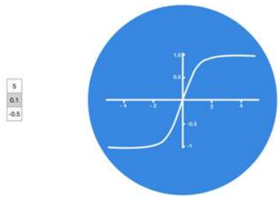
New hidden state · *A function with parameters W* · *Previous state* · *input*

37

3 Seq2Seq with Deep Learning

Tanh activation

The tanh activation is used to help regulate the values flowing through the network. The tanh function squishes values to always be between -1 and 1.

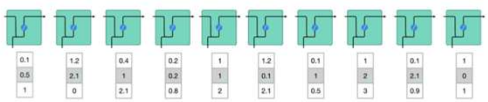


38

3 Seq2Seq with Deep Learning

Neural Network + Memory = Recurrent Neural Network

With Sequence Input

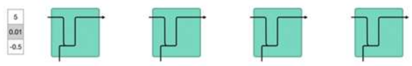


39

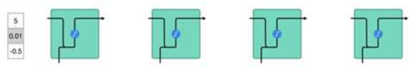
3 Seq2Seq with Deep Learning

Neural Network + Memory = Recurrent Neural Network

Q: Why do we need tanh function?



Vector Transformations without tanh



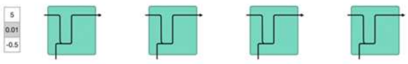
Vector Transformations with tanh

40

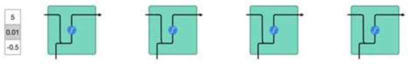
3 Seq2Seq with Deep Learning

Neural Network + Memory = Recurrent Neural Network

Q: Why do we need tanh function?



Vector Transformations without tanh



Vector Transformations with tanh

41

3 Seq2Seq with Deep Learning

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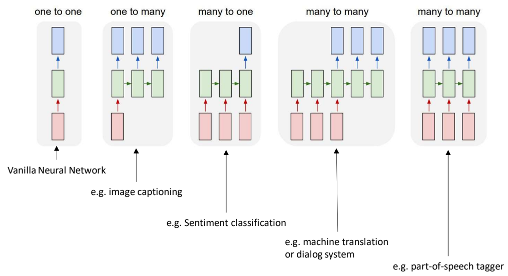
Neural Network + Memory = Recurrent Neural Network

Several Variants of RNN



42

3 Seq2Seq with Deep Learning

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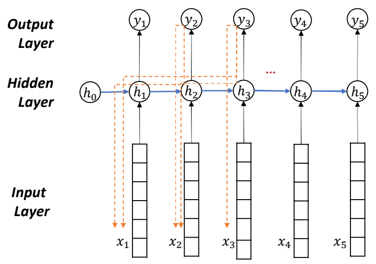
Neural Network + Memory = Recurrent Neural Network

Backpropagation through time



What about ***very long sequence?***

Use ***Truncate Backpropagation*** *through time*

- *Similar as* ***standard backpropagation*** *on unrolled network*
- *Similar as* ***training very deep networks*** *with tied parameters*

43

3 Seq2Seq with Deep Learning

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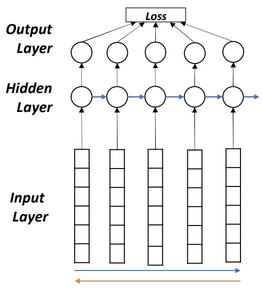
Neural Network + Memory = Recurrent Neural Network

Truncated Backpropagation through time



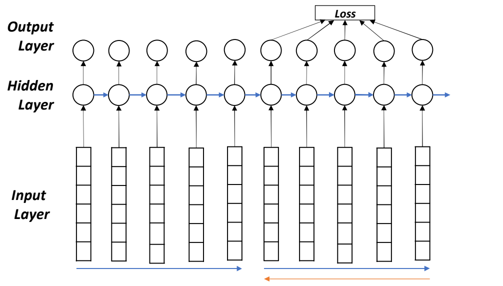
Run forward and backward through chunks of the sequence instead of whole sequence

44

3 Seq2Seq with Deep Learning

Neural Network + Memory = Recurrent Neural Network

Truncated Backpropagation through time



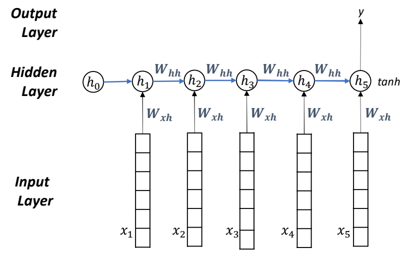
Carry hidden states forward in time forever, but only backpropagate for some smaller number of steps

45

3 Seq2Seq with Deep Learning

Neural Network + Memory = Recurrent Neural Network

Many to 1

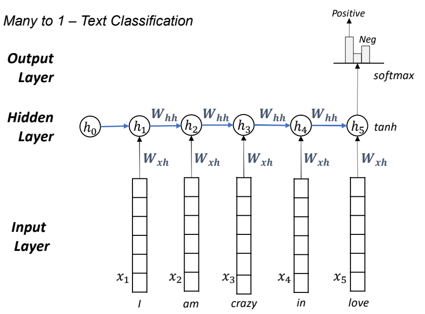


46

3 Seq2Seq with Deep Learning

Neural Network + Memory = Recurrent Neural Network

Many to 1 – Text Classification

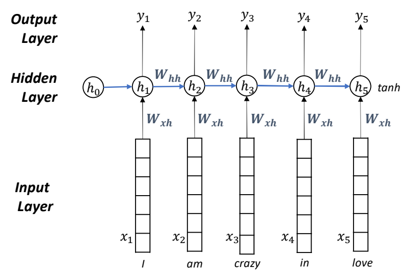


47

3 Seq2Seq with Deep Learning

Neural Network + Memory = Recurrent Neural Network

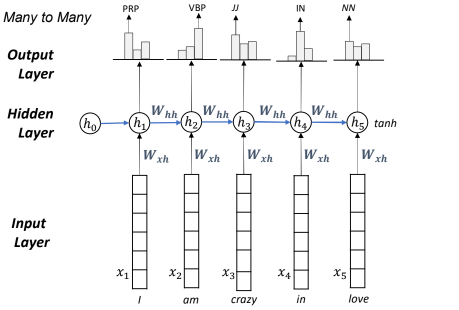
Many to Many



48

3 Seq2Seq with Deep Learning

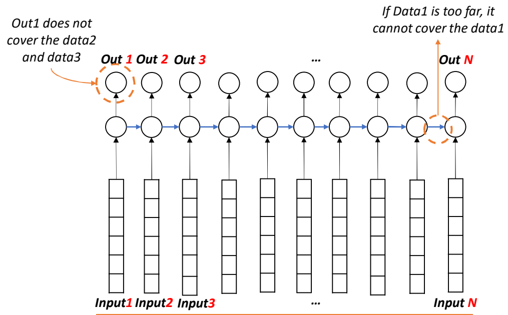
Neural Network + Memory = Recurrent Neural Network



49

3 Seq2Seq with Deep Learning

Limitation of Vanilla RNN

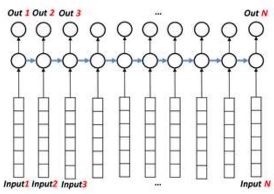


The Problem of Learning Long-Range Dependencies

50

3 Seq2Seq with Deep Learning

Limitation of Vanilla RNN

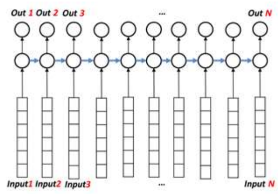


"I grew up in Italy … (5 more sentences)… My grandma's house was very cosy and… (5 more sentences)… I speak fluent ____"

51

3 Seq2Seq with Deep Learning

Limitation of Vanilla RNN



$$\left\|\frac{\partial h_i}{\partial h_{i-1}}\right\|_2 < 1$$

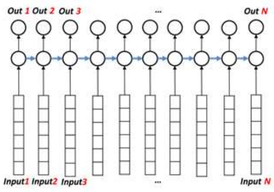
Limitation1: Vanishing Gradient Issue

During back-propagation and calculating gradients, it tends to get smaller and smaller as we keep on moving backward in the Network. This means that the neurons in the Earlier layers learn very slowly as compared to the neurons in the later layers in the Hierarchy.

52

3 Seq2Seq with Deep Learning

Limitation of Vanilla RNN



$$\left\| \frac{\partial h_i}{\partial h_{i-1}} \right\|_2 > 1$$

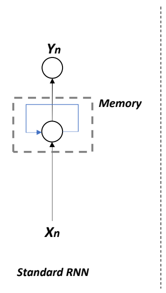
Limitation2: Exploding Gradient

In RNN, error gradients can accumulate during an update and result in very large gradients. These in turn result in large updates to the network weights, and an unstable network. At an extreme, the values of weights can become so large as to overflow and result in NaN weight values that can no longer be updated.

53

3 Seq2Seq with Deep Learning

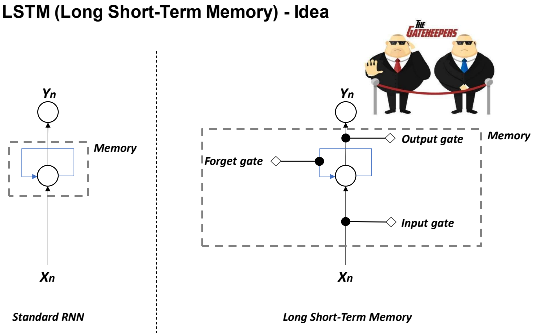
LSTM (Long Short-Term Memory) - Idea



54

3 Seq2Seq with Deep Learning

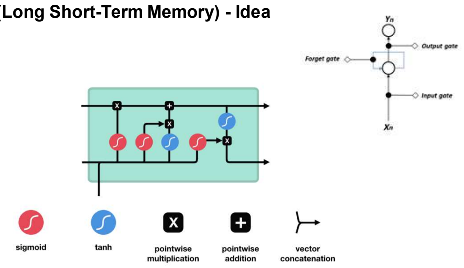
LSTM (Long Short-Term Memory) - Idea



55

3 Seq2Seq with Deep Learning

LSTM (Long Short-Term Memory) - Idea



- 4 times more parameters than RNN
- Mitigates **vanishing gradient** problem through **gating**
- Widely used and was SOTA in many sequence learning problems

State-Of-The-Art

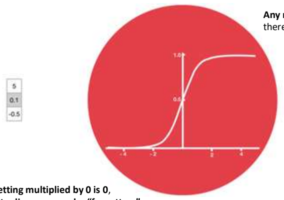
56

3 Seq2Seq with Deep Learning

Sigmoid activation

A sigmoid activation is similar to the tanh activation. Instead of squishing values between -1 and 1, it squishes values between 0 and 1.

Any number multiplied by 1 is the same value therefore that value stays **the same or is "kept."**

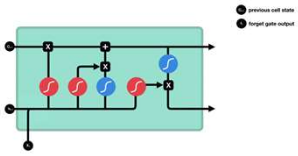


Any number getting multiplied by 0 is 0, causing **values to disappears or be "forgotten."**

57

3 Seq2Seq with Deep Learning

LSTM (Long Short-Term Memory) – Forget Gate



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

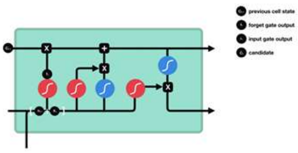
Decides what information should be thrown away or kept

Information from the **previous hidden state** and information from the **current input** is passed through the sigmoid function. Values come out between 0 and 1. The closer to 0 means to forget, and the closer to 1 means to keep.

58

3 Seq2Seq with Deep Learning

LSTM (Long Short-Term Memory) – Input Gate



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

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

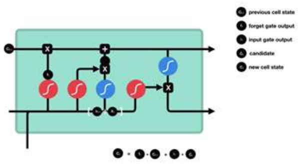
1. *Pass the previous hidden state and current input into a sigmoid function*
2. *Pass the hidden state and current input into the tanh function to squish values between -1 and 1 to help regulate the network*
3. *Multiply the tanh output with the sigmoid output*

**sigmoid output will decide which information is important to keep from the tanh output*

59

3 Seq2Seq with Deep Learning

LSTM (Long Short-Term Memory) – Cell States



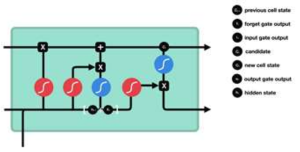
$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$

- *the cell state gets pointwise multiplied by the forget vector*
- *take the output from the input gate and do a pointwise addition which updates the cell state to new values that the neural network finds relevant*
- *That gives us our new cell state*

60

3 Seq2Seq with Deep Learning

LSTM (Long Short-Term Memory) – Output Gate



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

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

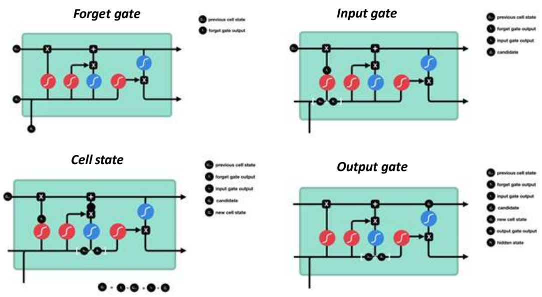
decides what the next hidden state should be.

- pass the previous hidden state and the current input into a sigmoid function
- pass the newly modified cell state to the tanh function
- multiply the tanh output with the sigmoid output to decide what information the hidden state should carry

61

3 Seq2Seq with Deep Learning

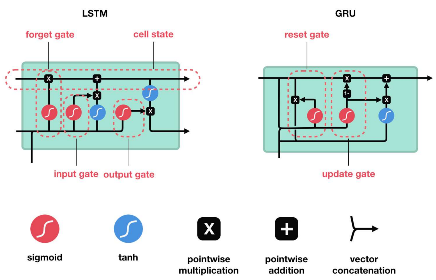
LSTM (Long Short-Term Memory) - Overall



62

3 Seq2Seq with Deep Learning

Gated Recurrent Unit

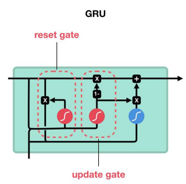


63

3 Seq2Seq with Deep Learning

Gated Recurrent Unit

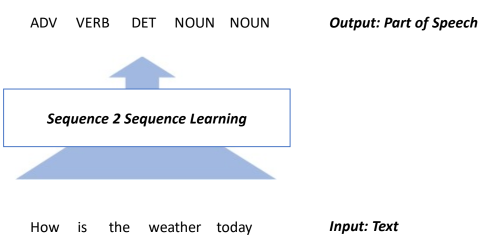
- GRU first computes an **update gate** based on **current input word vector** and **hidden state**
- Compute reset gate similarly but with different weights
  - If reset gate unit is ~0, then this ignores previous memory and only stores the new word information
- Final memory at time step combines current and previous time steps



64

3 Seq2Seq Modelling

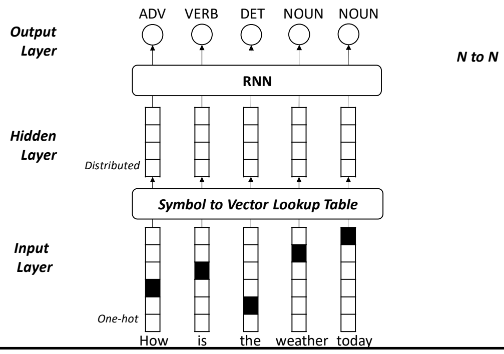
Seq2Seq – PoS tagger



65

3 Seq2Seq Modelling

Sequence Modelling for POS Tagging



66

0 LECTURE PLAN

Lecture 4: Word Classification and Machine Learning 2

1. Machine Learning and NLP: Finish
2. Seq2Seq Learning
3. Seq2Seq Deep Learning
   1. RNN (Recurrent Neural Network)
   2. LSTM (Long Short-Term Memory)
   3. GRU (Gated Recurrent Unit)
4. **Data Transformation for Deep Learning NLP**
5. Next Week Preview
   - Natural Language Processing Stack

67

4 Data Transformation for Deep Learning NLP

ImageNet: Image Classification

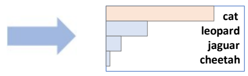
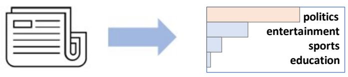


Image Pixel

68

4 Data Transformation for Deep Learning NLP

Topic Classification



News Articles

69

4 Data Transformation for Deep Learning NLP

Visual Question Answering

70

4 Data Transformation for Deep Learning NLP

Visual Question Answering

What color of the shirt does he wear

Submit

Predicted top-5 answers with confidence:

orange	99.999%
yellow	0.001%
orange and white	0.000%
yellow and orange	0.000%
orange and black	0.000%

71

4 Data Transformation for Deep Learning NLP

Visual Question Answering

Where is he sitting

Submit

Predicted top-5 answers with confidence:

couch	71.669%
chair	21.119%
sofa	2.730%
living room	1.376%
room	1.276%

72

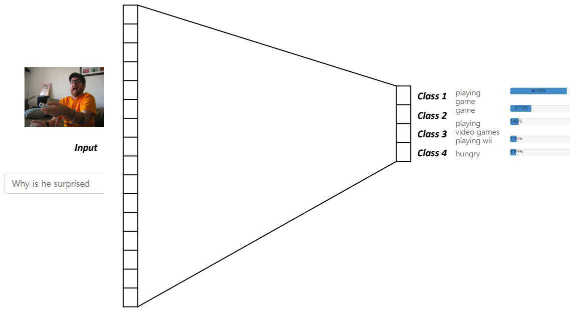
4 Data Transformation for Deep Learning NLP

Visual Question Answering

73

4 Data Transformation for Deep Learning NLP

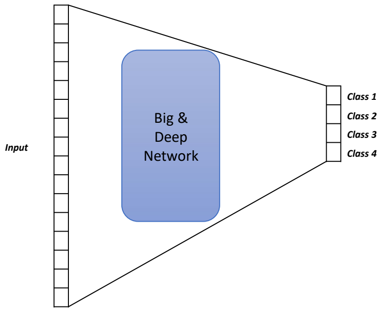
Classification Formulation



74

4 Data Transformation for Deep Learning NLP

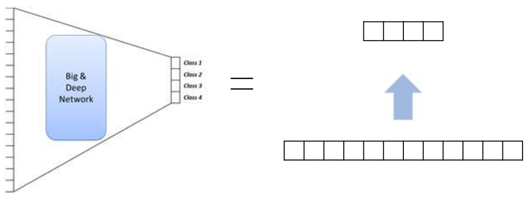
Classification Formulation



75

4 Data Transformation for Deep Learning NLP

Classification



76

4 Data Transformation for Deep Learning NLP

Graphical Notation for Data

Data X

10
2
8
2
15
3
5
1
5

=

Data X

10	2	8
2	15	3
5	1	5

77

4 Data Transformation for Deep Learning NLP

V to 1

10
2
8
2
15
3
5
1
5

=

10	2	8
2	15	3
5	1	5

→ ?

78

4 Data Transformation for Deep Learning NLP

V to 1 – Simple Method

center one

10	2	8
2	15	3
5	1	5

→ 15

median

10	2	8
2	15	3
5	1	5

→ 5

average

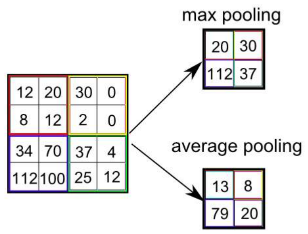
10	2	8
2	15	3
5	1	5

→ 5.6

79

4 Data Transformation for Deep Learning NLP

V to 1 – Simple Method



80

4 Data Transformation for Deep Learning NLP

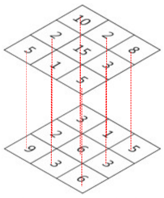
V to 1 – Weighted Method

Weighted Sum

10	2	8		3	1	5		
2	15	3		2	6	3	→	253
5	1	5		9	3	6		
Value				Weight				

Weighted Average

10	2	8		3/9	1/9	5/9		
2	15	3		2/9	6/9	3/9	→	6.65
5	1	5		9/9	3/9	6/9		
Value				Weight				



Element-wise multiplication

81

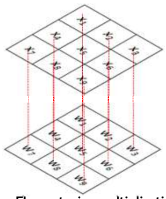
4 Data Transformation for Deep Learning NLP

V to 1 – General Form

Weighted Sum

x_1	x_2	x_3		w_1	w_2	w_3		
x_4	x_5	x_6		w_4	w_5	w_6	→	~
x_7	x_8	x_9		w_7	w_8	w_9		

$$v = x_1 * w_1 + x_2 * w_2 + \cdots + x_9 * w_9$$



Element-wise multiplication

82

4 Data Transformation for Deep Learning NLP

V to 1 – Linear Algebra

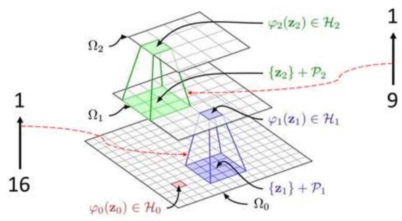
[1 x 9] matrix X [9x1] matrix = [1x1] matrix

$$\begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 & x_6 & x_7 & x_8 & x_9 \end{bmatrix} \times \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \\ w_6 \\ w_7 \\ w_8 \\ w_9 \end{bmatrix} = \sum_i^9 x_i * w_i$$

83

4 Data Transformation for Deep Learning NLP

Convolution Neural Network (1)



(a) Hierarchy of Image Feature Maps

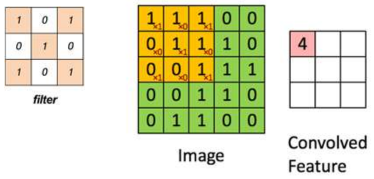
Data Abstraction

Mairal et al., Convolutional Kernel Networks, 2014

84

4 Data Transformation for Deep Learning NLP

Convolution Neural Network (2)

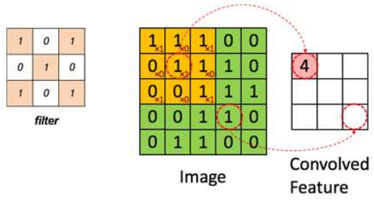


Mairal et al., Convolutional Kernel Networks, 2014

85

4 Data Transformation for Deep Learning NLP

Convolution Neural Network (2)

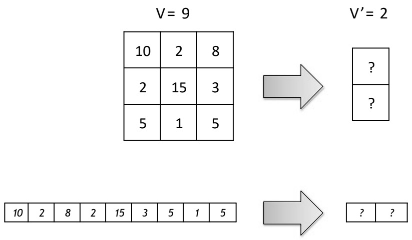


Mairal et al., Convolutional Kernel Networks, 2014

86

4 Data Transformation for Deep Learning NLP

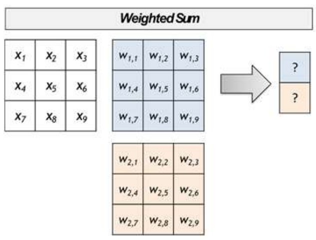
V to V'



87

4 Data Transformation for Deep Learning NLP

V to V' – generalized method

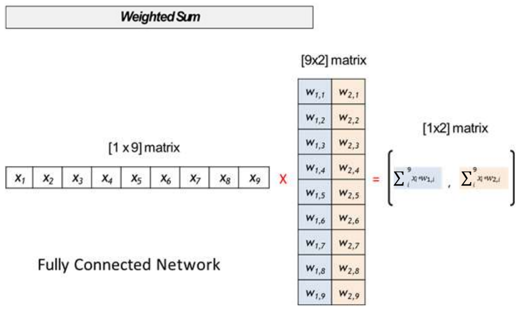


$$\begin{bmatrix} v_1 = x_1 * w_{1,1} + x_2 * w_{1,1} + \cdots + x_9 * w_{1,9} \\ v_2 = x_1 * w_{2,1} + x_2 * w_{2,1} + \cdots + x_9 * w_{2,9} \end{bmatrix}$$

88

4 **Data Transformation for Deep Learning NLP**

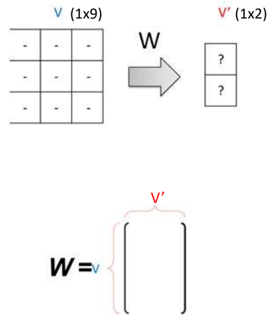
V to V' – generalized method



89

4 **Data Transformation for Deep Learning NLP**

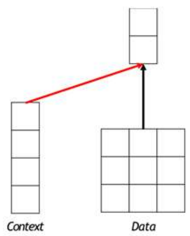
V to V' – Projection Notation



90

4 **Data Transformation for Deep Learning NLP**

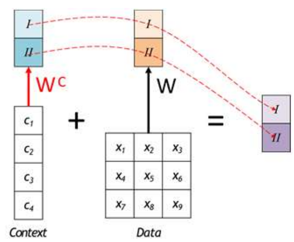
V to V' – Projection with Context (1)



91

4 **Data Transformation for Deep Learning NLP**

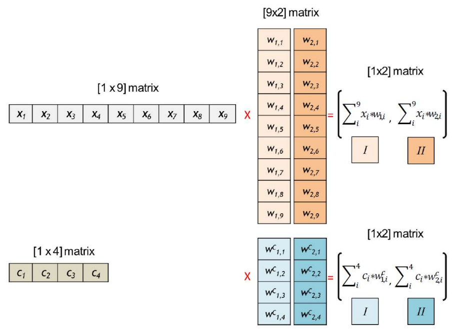
V to V' – Projection with Context (2)



92

4 Data Transformation for Deep Learning NLP

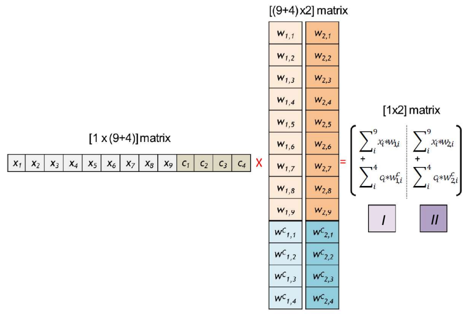
V to V' with Context - Linear Algebra



93

4 Data Transformation for Deep Learning NLP

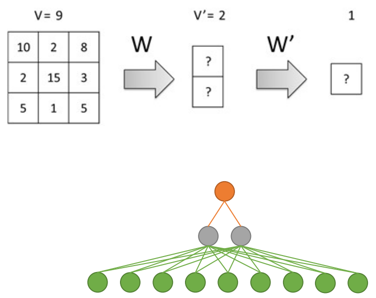
V to V' with Context - Linear Algebra (Simplified)



94

4 Data Transformation for Deep Learning NLP

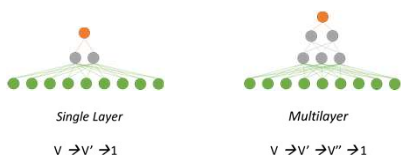
V → V' → 1



95

4 Data Transformation for Deep Learning NLP

V → V' → 1



96

4 Data Transformation for Deep Learning NLP

Seq2Seq Encoding

Single Item Summarisation

V → W → V'

-	-	-
-	-	-
-	-	-

?
?

Multiple Item Summarisation

?

97

4 Data Transformation for Deep Learning NLP

Multiple Item Summarisation

Data 1

10	2	8
2	15	3
5	1	5

Data 2

13	4	8
4	5	2
1	45	31

Data 3

6	3	4
1	7	1
3	4	0

→ *V*

?	?	?
?	?	?
?	?	?

→ *V'*

?
?

→ *1*

?

98

4 Data Transformation for Deep Learning NLP

Vs to V'

(10+ 13+ 6)/3 (8+8+4)/3

10	2	8
2	15	3
5	1	5

13	4	8
4	5	2
1	45	31

6	3	4
1	7	1
3	4	0

→

9.6	?	6.6
?	?	?
?	?	?

Element-wise Average

99

4 Data Transformation for Deep Learning NLP

Vs to V'

10	2	8
2	15	3
5	1	5

13	4	8
4	5	2
1	45	31

6	3	4
1	7	1
3	4	0

x $w^1 = 0.2$ x $w^2 = 0.4$ x $w^3 = 0.4$ *Element-wise multiplication*

2	0.4	1.6
0.4	3	0.6
1	0.2	1.0

\+

5.2	1.6	3.2
1.6	2	0.8
0.4	18	12.4

\+

2.4	1.2	1.6
0.4	2.8	0.4
1.2	1.6	0

→

9.6	3.2	6.4
2.4	7.8	1.8
2.6	19.8	13.4

Element-wise summation

100

4 **Data Transformation for Deep Learning NLP**

Temporal Summarisation

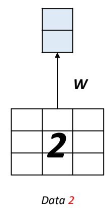
Context

How to include Temporal information?

101

4 **Data Transformation for Deep Learning NLP**

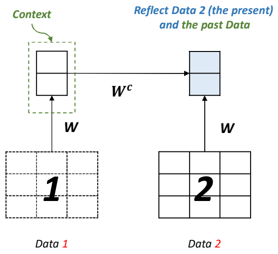
Vs → V's → V'



102

4 **Data Transformation for Deep Learning NLP**

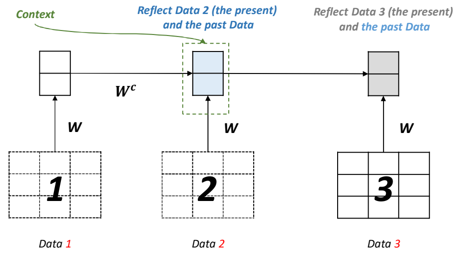
Vs → V's → V'



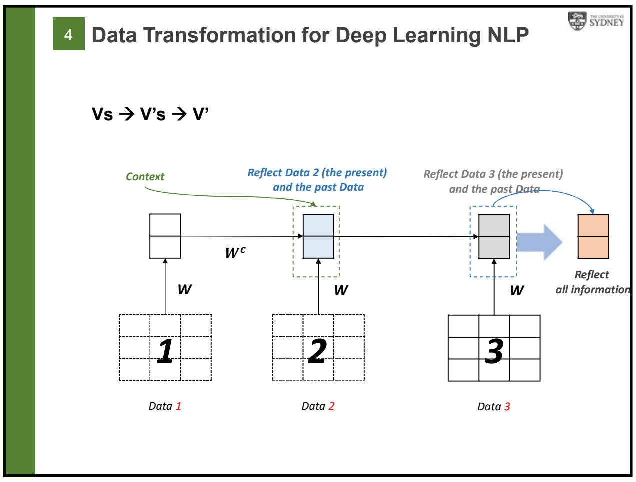
103

4 **Data Transformation for Deep Learning NLP**

Vs → V's → V'



104



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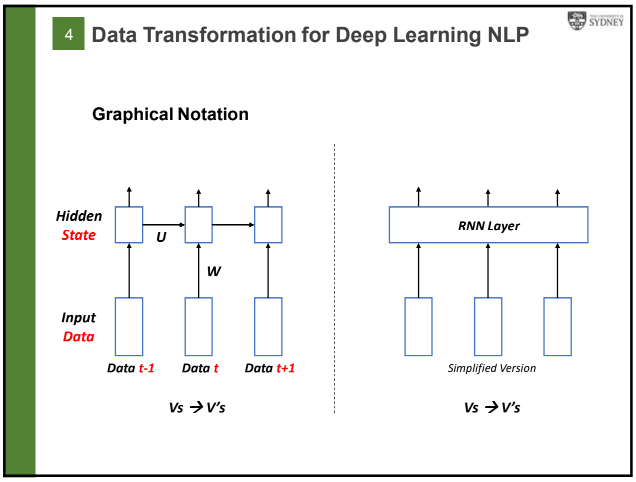
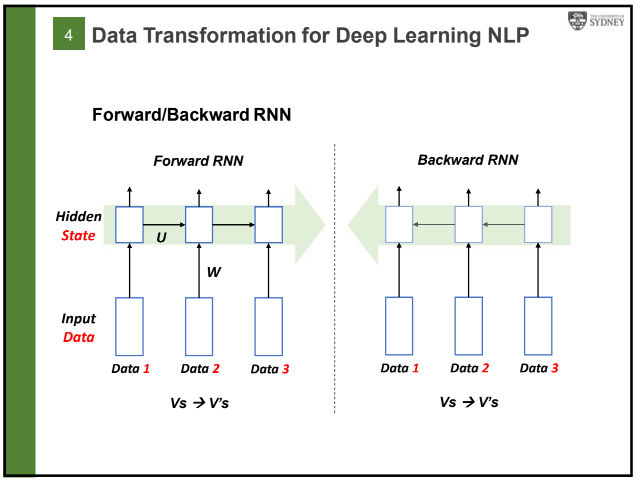
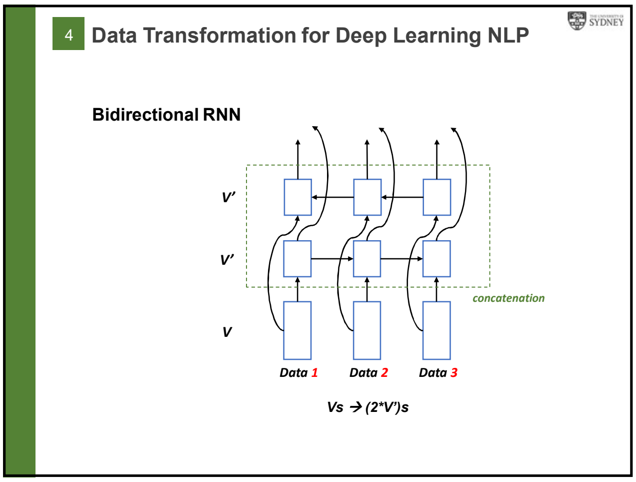


106



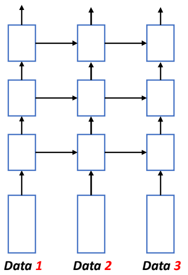
107



108

4 Data Transformation for Deep Learning NLP

Stacking RNN

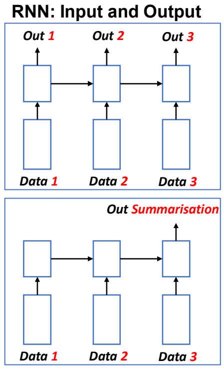


Vs → V's

109

4 Data Transformation for Deep Learning NLP

RNN: Input and Output



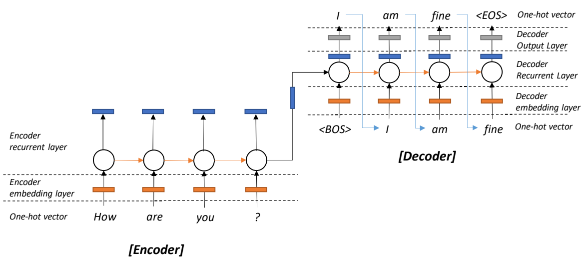
- ✓ *Vs → V's*
- ✓ *Len(Vs) → Len(V's)*

- ✓ *Vs → 1*

110

4 Data Transformation for Deep Learning NLP

Seq2Seq Encoding and Decoding- Dialog System



111

0 LECTURE PLAN

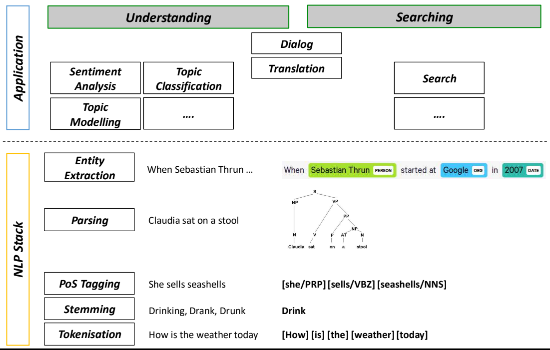
Lecture 4: Word Classification and Machine Learning 2

1. Machine Learning and NLP: Finish
2. Seq2Seq Learning
3. Seq2Seq Deep Learning
   1. RNN (Recurrent Neural Network)
   2. LSTM (Long Short-Term Memory)
   3. GRU (Gated Recurrent Unit)
4. Data Transformation for Deep Learning NLP
5. **Next Week Preview**
   - Natural Language Processing Stack

112

5 Next Week Preview

The purpose of Natural Language Processing: Overview



113

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Figure Reference

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114