COMP5046
Natural Language Processing

Lecture 13: Content Review and Exam Guide

Semester 1, 2020
School of Computer Science
The University of Sydney, Australia

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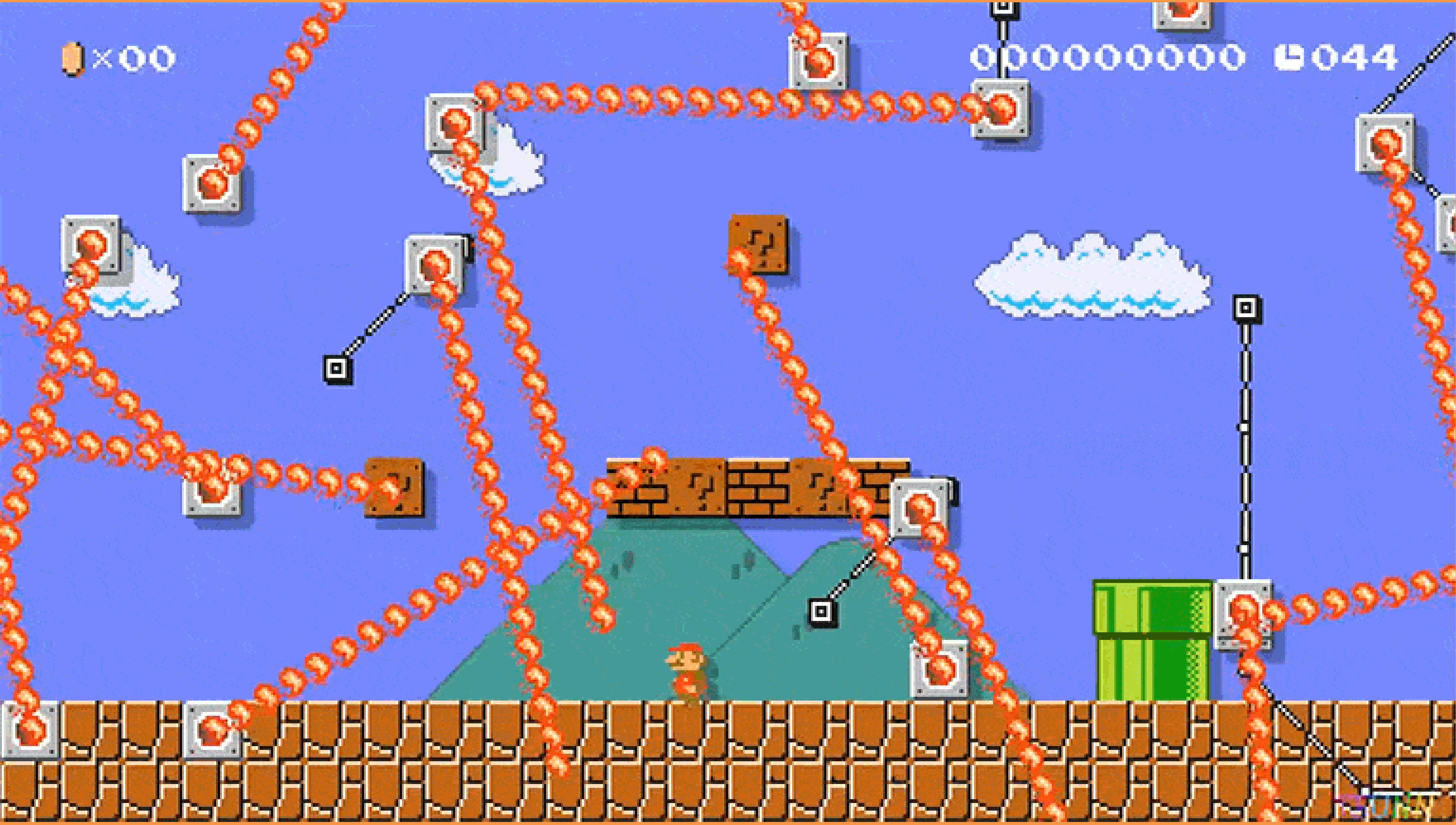
0 LECTURE PLAN

Lecture 13: Content Review and Exam Guide

1. Overview
2. Learning Content Summary
3. Final Exam Guide

Your Journey…!



You are a survivor!!

COMP5046 Natural Language Processing

Survey (5 mins)

Have your say! ☺

If you are reading this outside of the lecture, please do this now!

- *Unit of Study Evaluation survey at:*

https://student-surveys.sydney.edu.au/students/

- *Your answers are completely anonymous*
- *Please write specific comments*
- *I personally read every single comment*

1 COMP5046 Natural Language Processing

What we learned in this course!

- Week 1: Introduction to Natural Language Processing (NLP)
- Week 2: Word Embeddings (Word Vector for Meaning)
- Week 3: Word Classification with Machine Learning I
- Week 4: Word Classification with Machine Learning II

NLP and Machine Learning

- Week 5: Language Fundamental
- Week 6: Part of Speech Tagging
- Week 7: Dependency Parsing
- Week 8: Language Model

NLP Techniques

- Week 9: Information Extraction: Named Entity Recognition
- Week 10: Advanced NLP: Attention and Reading Comprehension
- Week 11: Advanced NLP: Transformer and Machine Translation
- Week 12: Advanced NLP: Graph Neural Network with NLP

Advanced Topic

- Week 13: Future of NLP and Exam Review

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Advanced Topic

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2 Lecture Summary

2 Lecture Summary

Lecture 1 Summary

Word Representation with WordNet

- Use e.g. WordNet, a thesaurus containing lists of synonym sets and hypernyms (“is a” relationships).
- Problems with resources like WordNet

Representing words as discrete symbols

- One-hot vector ☺

  motel = [0 0 0 0 0 0 0 0 0 0 **1** 0 0 0 0]
  hotel = [0 0 0 0 0 0 0 **1** 0 0 0 0 0 0 0]

In web search, if user searches for “**Seattle motel**”, we would like to match documents containing “**Seattle hotel**”

- Problems with words as discrete symbols

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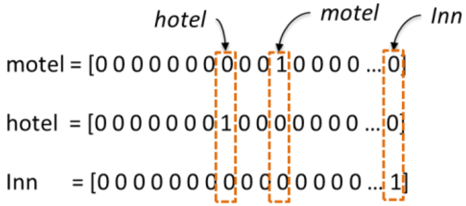
Lecture Summary

Lecture 1 Summary

Count based Word representation

Important to know: how each techniques works / pros and cons

- ***One-hot encoding***



- ***Bag of Words***

[1, 1, 1, 1, 2, 2, 2, 1, 1, 3]

a	are	been	day	have	how	nice	see	to	you
1	1	1	1	2	2	2	1	1	3

- ***Term Frequency-Inverse Document Frequency***

TF is a count of how many times a word occurs in a given document (= bag of words)

IDF is the number of times a word occurs in a corpus of documents

$$w_{i,j}=tf_{i,j}\times\log\left(\frac{N}{df_{i}}\right)$$

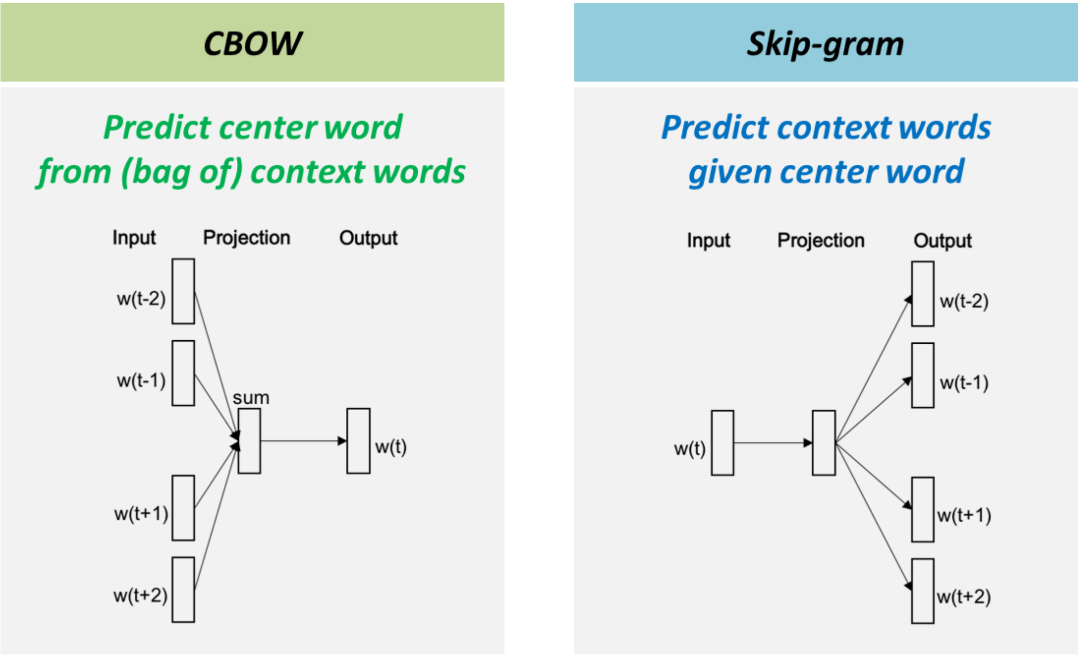
2 Lecture Summary

Lecture 2 Summary

Prediction-based Word Representation

Important to know: how each techniques works / pros and cons

- ***Word2Vec (CBOW, Skip-Gram)***



CBOW	**Skip-gram**
Predict center word from (bag of) context words	*Predict context words given center word*

Key parameter for training methods: window size, negative samples

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Lecture Summary

Lecture 2 Summary

Prediction-based Word Representation

Important to know: how each techniques works / pros and cons

- ***FastText with n-gram embedding***

- ***Glove***

  “Methods like skip-gram may do better on the analogy ask, but they poorly utilize the statistics of the corpus since they train on separate local context windows instead of on global co-occurrence counts.”

Lecture Summary

Lecture 3 Summary

Word Embedding Evaluation

- Intrinsic Evaluation
- Extrinsic Evaluation

Type	How to work / Benefit
Intrinsic	Evaluation on a specific/intermediate subtask
	• Fast to compute • Helps to understand that system • Not clear if really helpful unless correlation to real task is established
Extrinsic	Evaluation on a real task
	• Can take a long time to compute accuracy • Unclear if the subsystem is the problem or its interaction or other subsystems

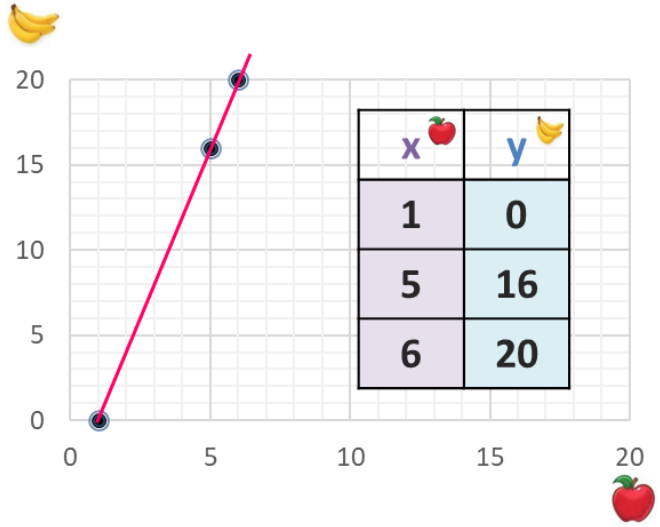
2 Lecture Summary

Lecture 3 Summary

Deep Learning for Natural Language Processing

- Perceptron and Neural Network (NN)
- Multilayer Perceptron

Input: x=number of apple given by Lisa
Output: y=number of banana received by Lisa
Parameters: Need to be estimated



x	y
1	0
5	16
6	20

Model $y = \overset{weight}{W} x + \overset{bias}{b}$

*How can we find the parameters, **w** and **b**?*

2 Lecture Summary

Lecture 3 Summary

Deep Learning for Natural Language Processing

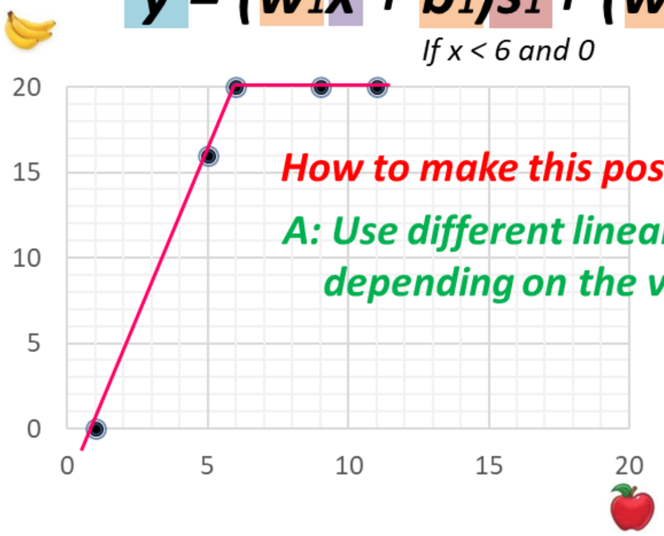
- Perceptron and Neural Network (NN)
- Multilayer Perceptron

Nonlinear Neural Network

Data

x	y
1	0
5	16
6	20
9	20
11	20

$$y = (\overset{\text{weight}}{w_1}x + \overset{\text{bias}}{b_1})\underset{\text{If } x < 6 \text{ and } 0}{s_1} + (\overset{\text{weight}}{w_2}x + \overset{\text{bias}}{b_2})\underset{\text{If } x >= 6 \text{ and } 0}{s_2}$$



How to make this possible?

A: Use different linear functions depending on the value of x

2

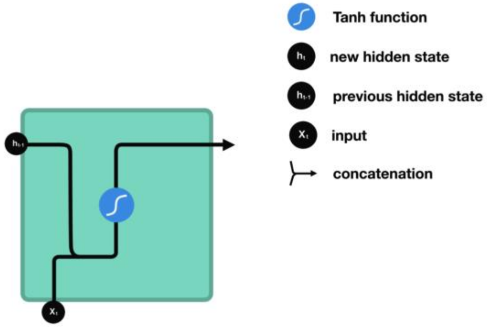
Lecture Summary

Lecture 4 Summary

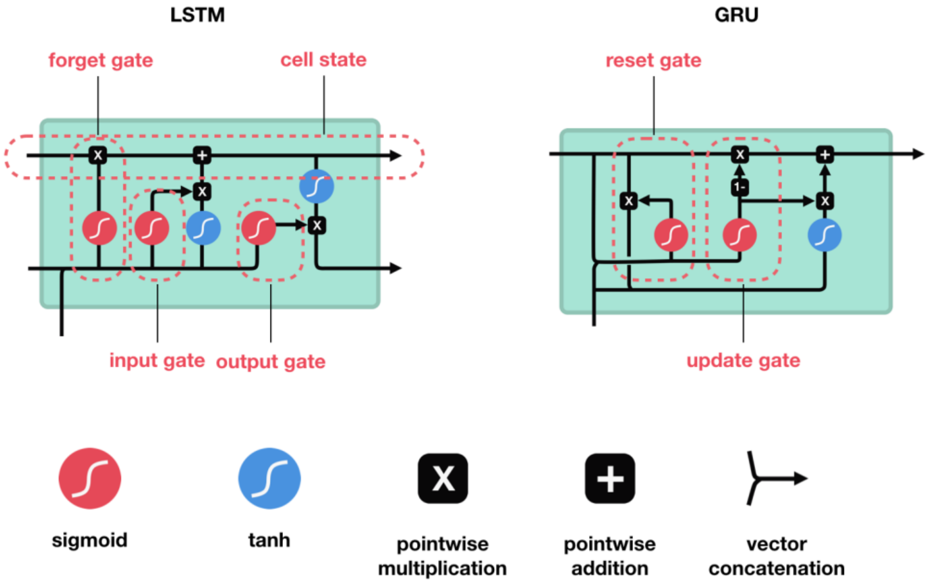
Seq2Seq Learning

Seq2Seq Deep Learning

1. RNN (Recurrent Neural Network)
2. LSTM (Long Short-Term Memory)
3. GRU (Gated Recurrent Unit)



$$\underbrace{\boxed{h_t}}_{\text{New hidden state}} = \underbrace{\boxed{f_W}}_{\text{A function with parameters } W}(\overbrace{\boxed{h_{t-1}}}^{\text{Previous state}}, \overbrace{\boxed{x_t}}^{\text{input}})$$



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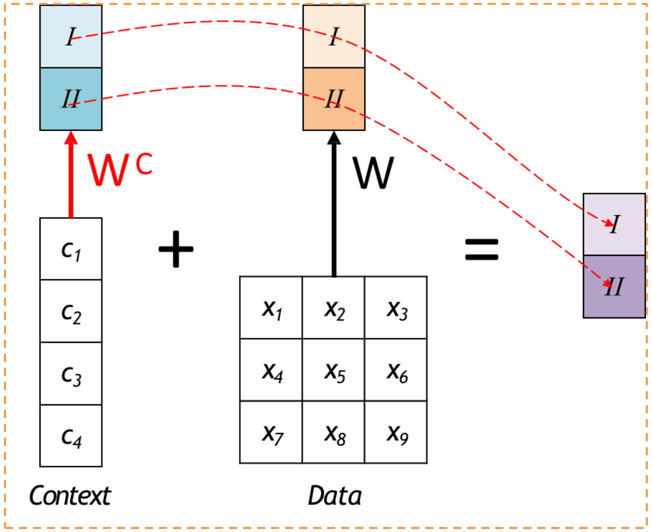

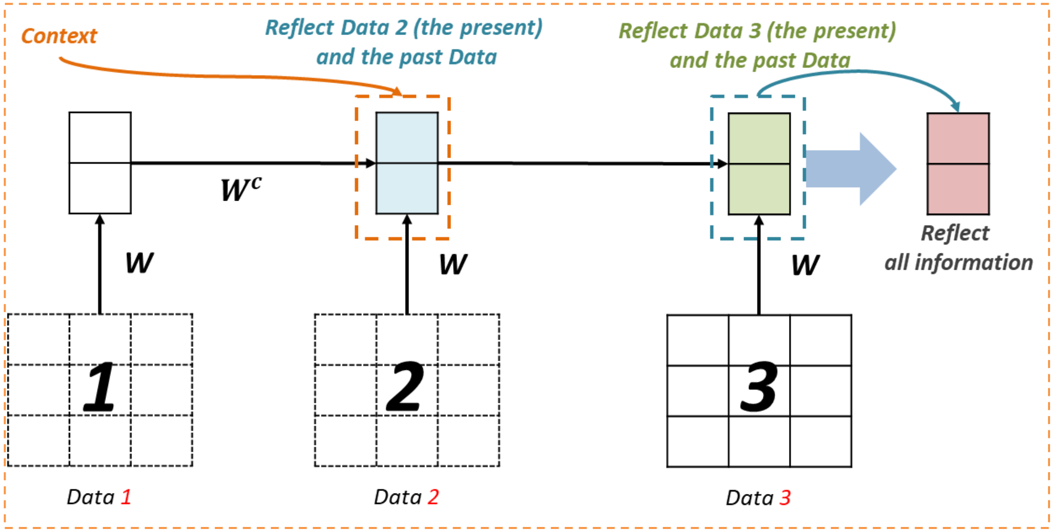

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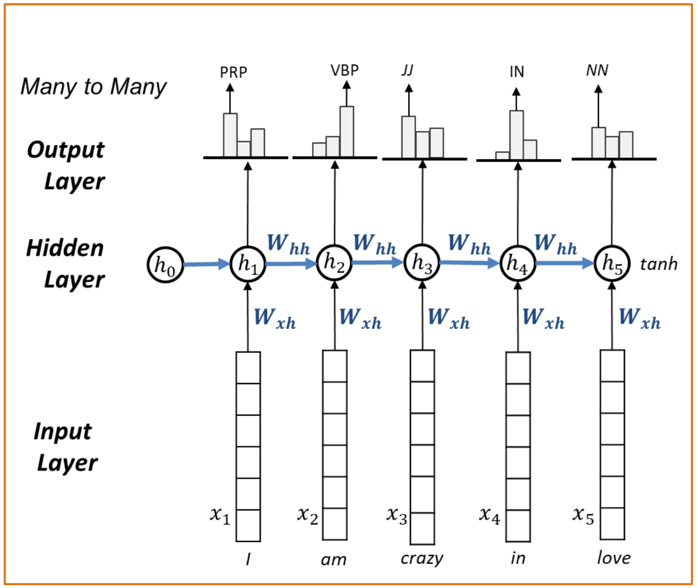

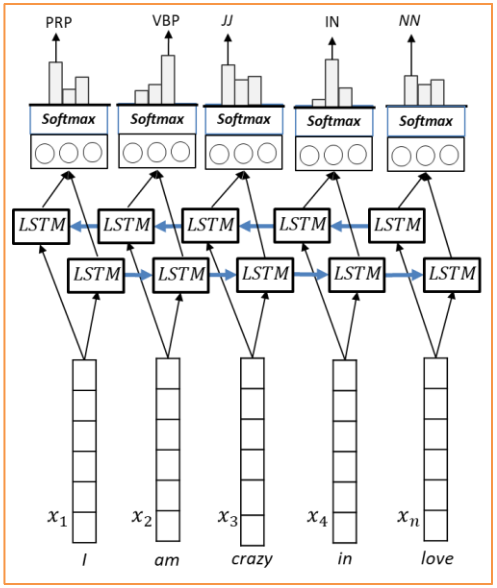

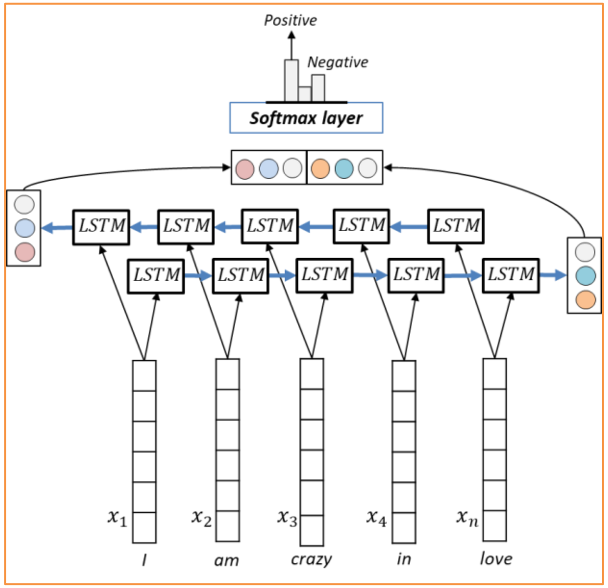

2 Lecture Summary

Lecture 4 Summary

Seq2Seq Learning

Seq2Seq Deep Learning

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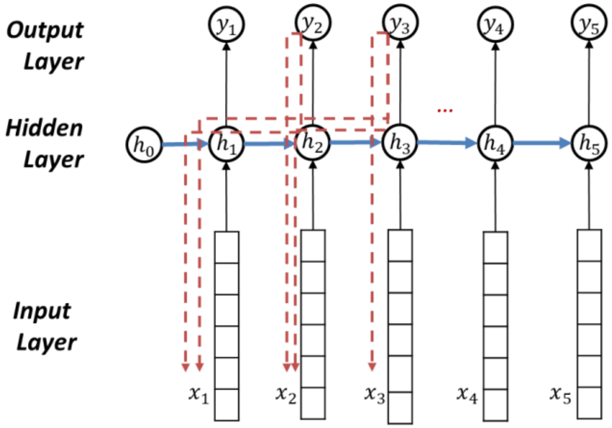
Backpropagation through time

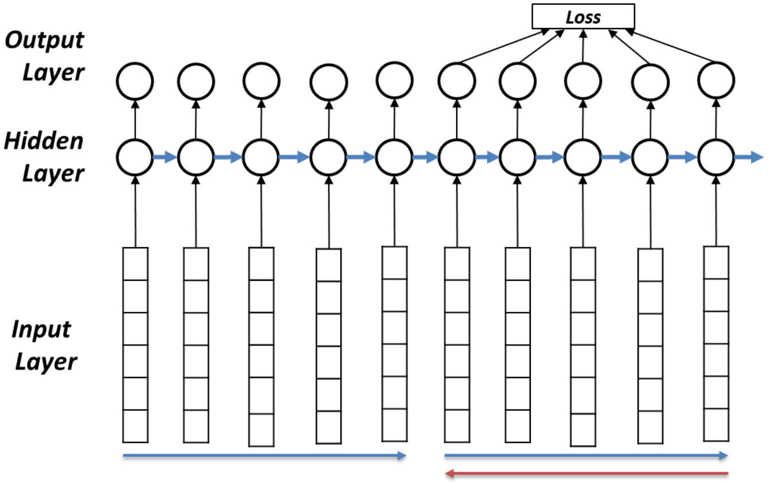


What about ***very long sequence?***

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

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

Truncated Backpropagation through time



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

Lecture Summary

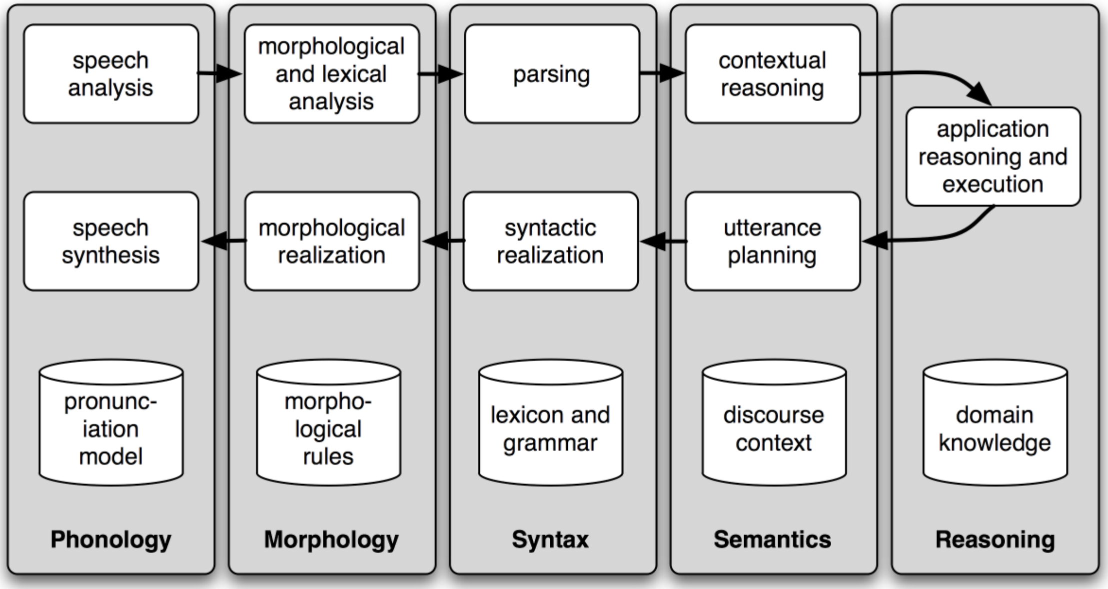
Lecture 5 Summary

Language Fundamental

1. Phonology, Morphology, Syntax, Semantics, Pragmatics

Text Preprocessing

1. Tokenization
2. Cleaning and Normalisation
3. Stemming and Lemmatisation
4. Stopword
5. Regular Expression



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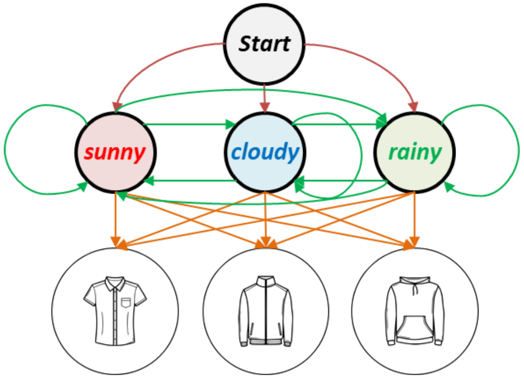
Lecture Summary

Lecture 6 Summary

1. Part-of-Speech Tagging
2. Baseline Approaches
    1. Rule-based Model
    2. Look-up Table Model
    3. N-Gram Model
3. Probabilistic Approaches
    1. Hidden Markov Model
    2. Conditional Random Field
4. Deep Learning Approaches



*Predicting the **weather (hidden variable)** based on the type of **clothes that someone wears (observed)***

Initial

Rainy	0.6
Cloudy	0.3
Sunny	0.1

Transitions

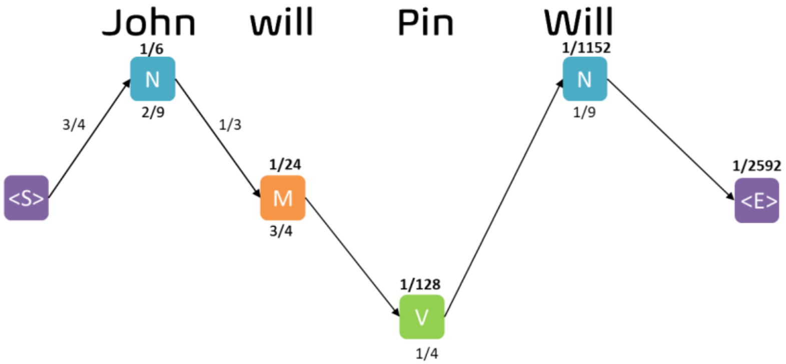
		Tomorrow		
		Rainy	Cloudy	Sunny
Today	Rainy	0.6	0.3	0.1
	Cloudy	0.4	0.3	0.3
	Sunny	0.1	0.4	0.5

Emissions

	Shirts	Jacket	Hoodies
Rainy	0.8	0.19	0.01
Cloudy	0.5	0.4	0.1
Sunny	0.01	0.2	0.79

	N	V	M
Emma	4/9	0	0
John	2/9	0	0
Will	1/9	0	3/4
Pin	2/9	1/4	0
Can	0	0	1/4
Meet	0	2/4	0
Pat	0	1/4	0

	N	V	M	<E>
<S>	3/4	0	1/4	0
N	1/9	1/9	3/9	4/9
V	4/4	0	0	0
M	1/4	3/4	0	0



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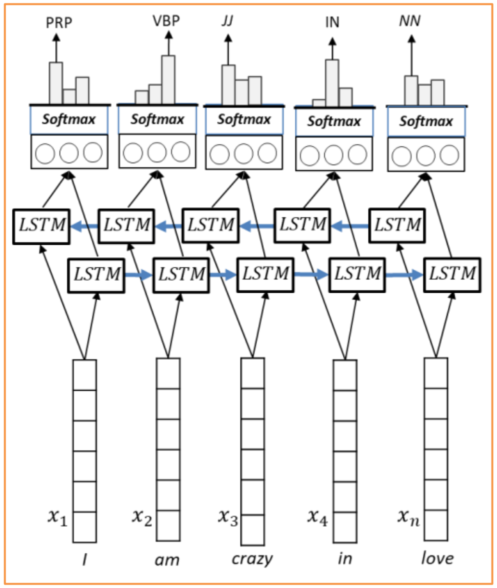
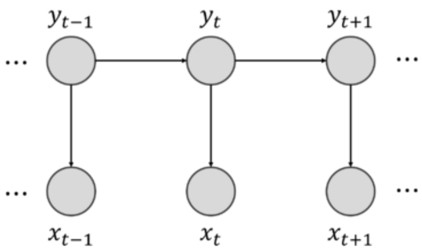
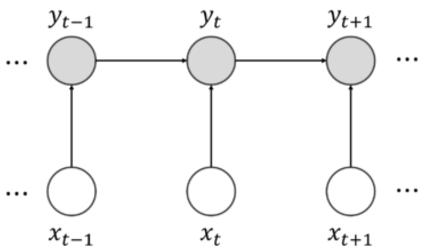


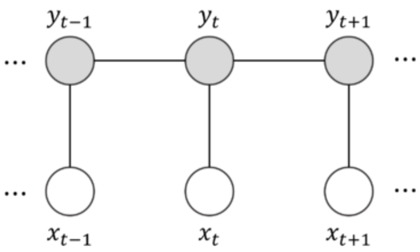
HMM



MEMM



CRF



2 Lecture Summary

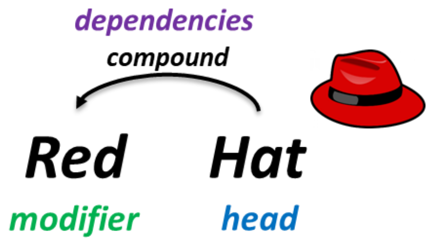
Lecture 7 Summary

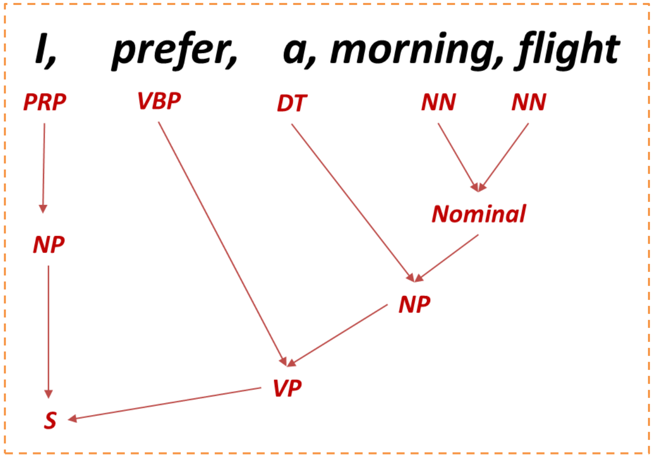
Linguistic Structure

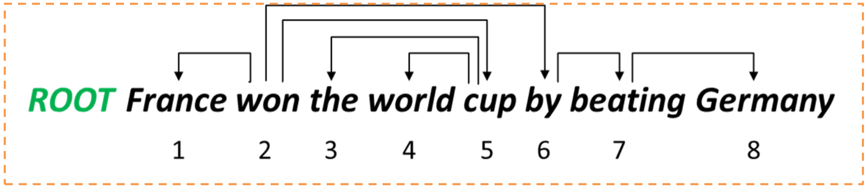
Dependency Structure

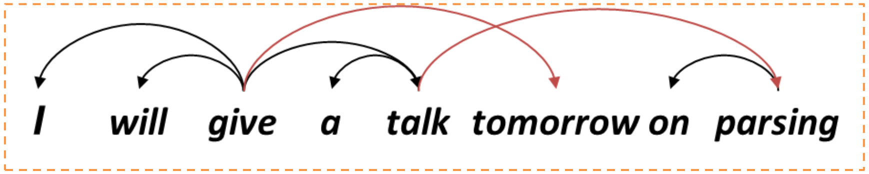
Dependency Parsing Algorithms

1. Transition-based Dependency Parsing
2. Deep Learning-based Dependency Parsing









2 Lecture Summary

Lecture 7 Summary

Linguistic Structure

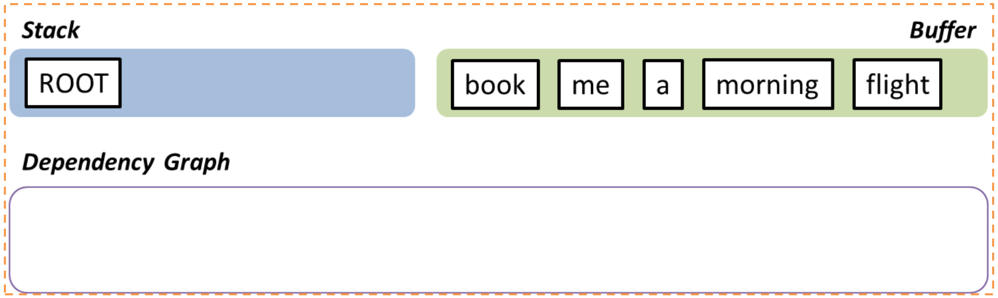
Dependency Structure

Dependency Parsing Algorithms

1. Transition-based Dependency Parsing
2. Deep Learning-based Dependency Parsing

Graph-based Dependency Parsing

Transaction-based Dependency Parsing



Stack

Buffer

ROOT

book me a morning flight

Dependency Graph

How to choose next action?

***Unlabeled Attachment Score**

***Labeled Attachment Score**

2

Lecture Summary

Lecture 8 Summary

Language Model

Traditional Language Model

Neural Language Model

Natural Language Generation

Other NLG Approaches

Language Model and NLG Evaluation

$$\mathbf{P(An,\ adorable,\ little,\ boy,\ is,\ spreading,\ smiles)}$$
$$= P(An) \times P(adorable|An) \times P(little|An\ adorable) \times P(boy|An\ adorable\ little) \times P(is|An\ adorable\ little\ boy) \times P(spreading|An\ adorable\ little\ boy\ is) \times P(smiles|An\ adorable\ little\ boy\ is\ spreading)$$

Trained Corpus

An adorable little boy is ....

....

.... *An adorable little boy is*

....

....

An adorable little boy laughed

....

....

....

- ***Count-based***
- ***N-gram Language Models***

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Lecture Summary

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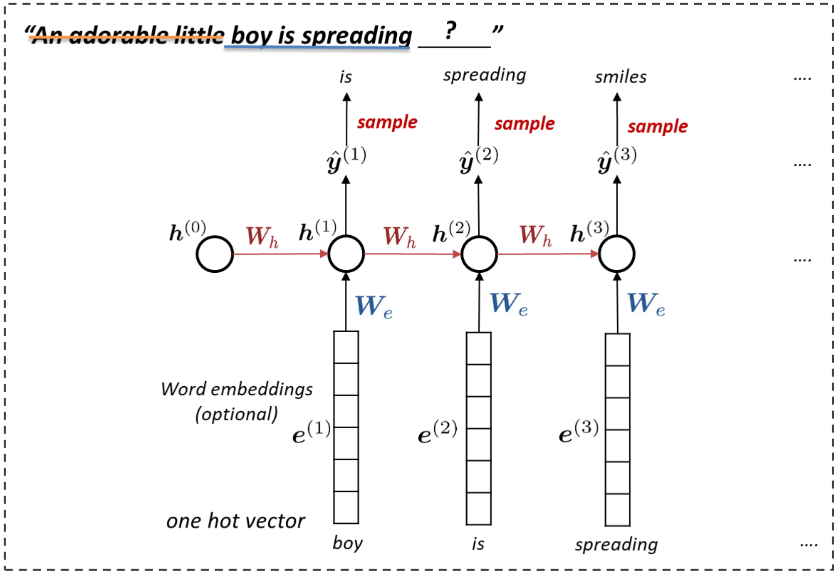

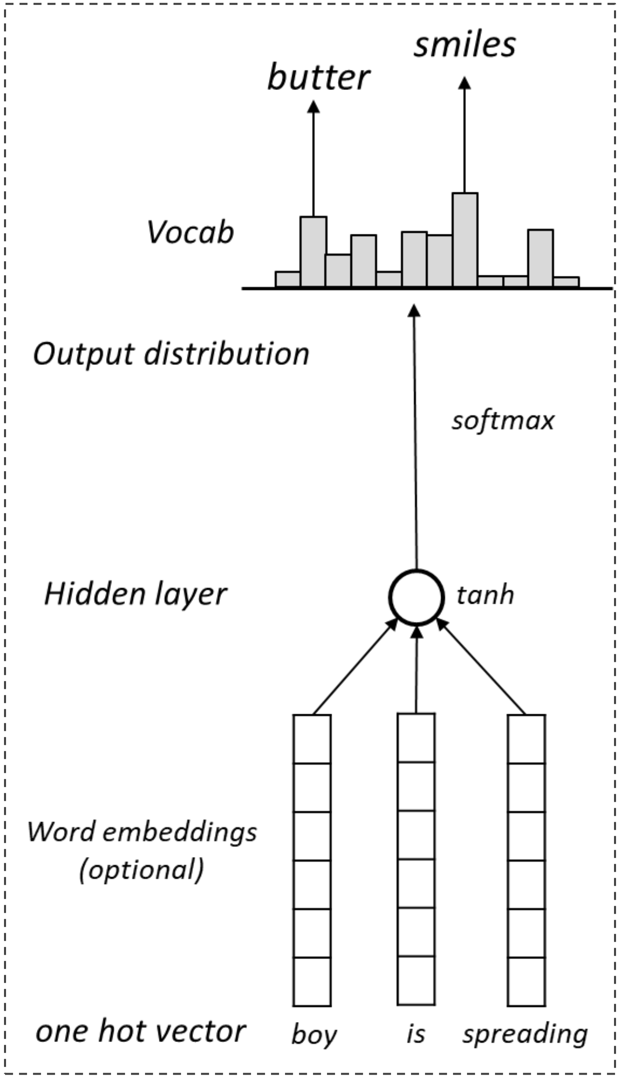

Lecture Summary

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Language Model
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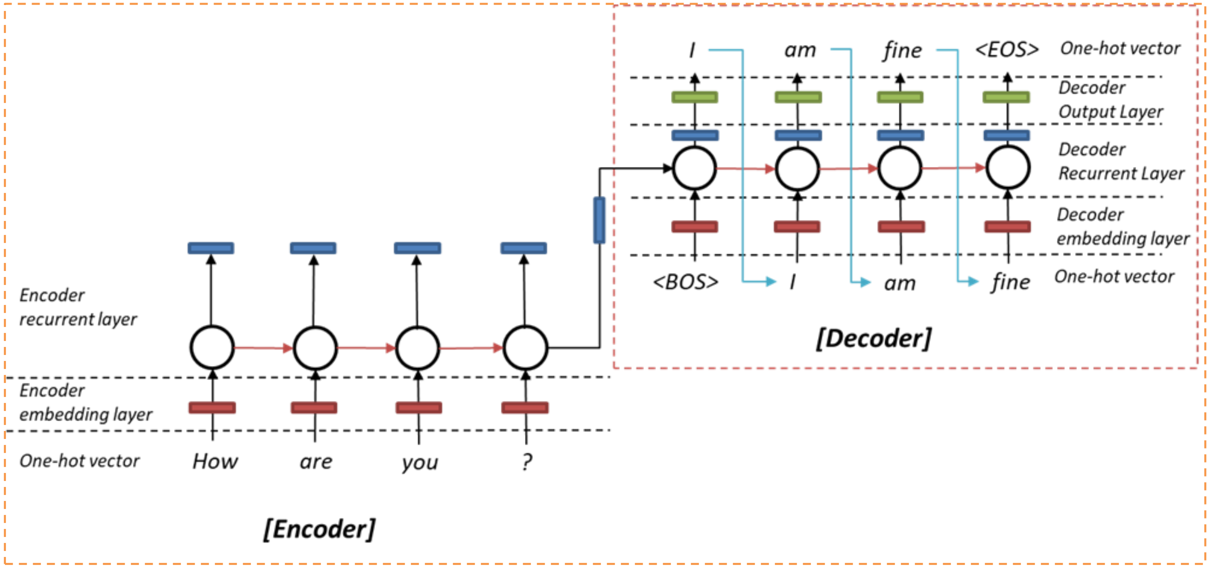

Decoding Algorithm
1: Greedy Decoding
2: Beam Search

2

Lecture Summary

Lecture 8 Summary

Language Model
Traditional Language Model
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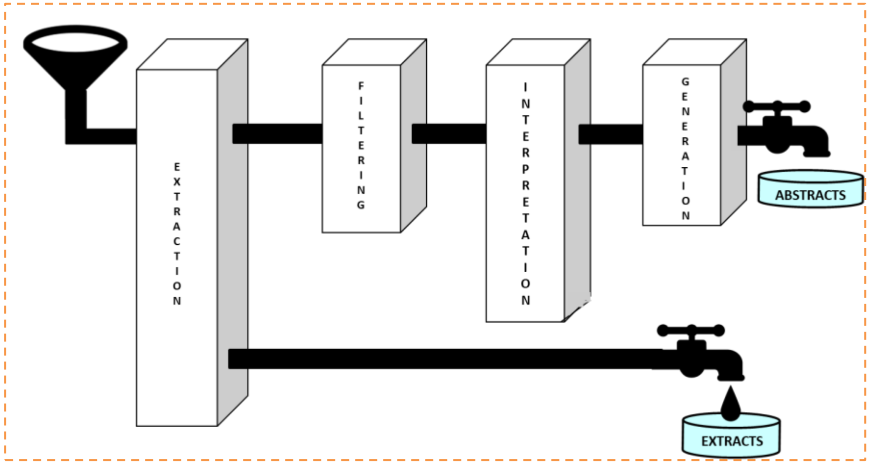
Other NLG Approaches
Language Model and NLG Evaluation

“Flights from *ORIGIN* to *DEST* on *DEPT_DATE* *DEPT_TIME*. Just one moment please”



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Lecture Summary

Lecture 8 Summary

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Perplexity

$$\text{perplexity} = \prod_{t=1}^{T} \left(\frac{1}{P_{\text{LM}}(\boldsymbol{x}^{(t+1)} \mid \boldsymbol{x}^{(t)}, \ldots, \boldsymbol{x}^{(1)})} \right)^{1/T\,1/T}$$

So, Lower Perplexity is better!

2

Lecture Summary

Lecture 9 Summary

Information Extraction

Named Entity Recognition (NER)

1. Traditional NER
2. Sequence Model for NER
3. NER Evaluation

Coreference Resolution

1. Mention-pair
2. Mention Ranking model
3. Coreference Evaluation

Rule-based NER

1. *Determining **which person holds what office in what organization***
2. *Determining **where an organization is located***

Unigram	Mr.	Scott	Morrison	flew	to	Beijing
Lowercase unigram	mr.	scott	morrison	flew	to	beijing
POS tag	nnp	nnp	nnp	vbd	to	nnp
length	3	5	4	4	2	7
In first-name gazetteer	no	yes	no	no	no	no
In location gazetteer	no	no	no	no	no	yes
3-letter suffix	Mr.	ott	son	lew	-	ing
2-letter suffix	r.	tt	on	ew	to	ng
1-letter suffix	.	t	n	w	o	g
Tag predictions	O	B-per	I-per	O	O	B-loc

2 Lecture Summary

Lecture 9 Summary

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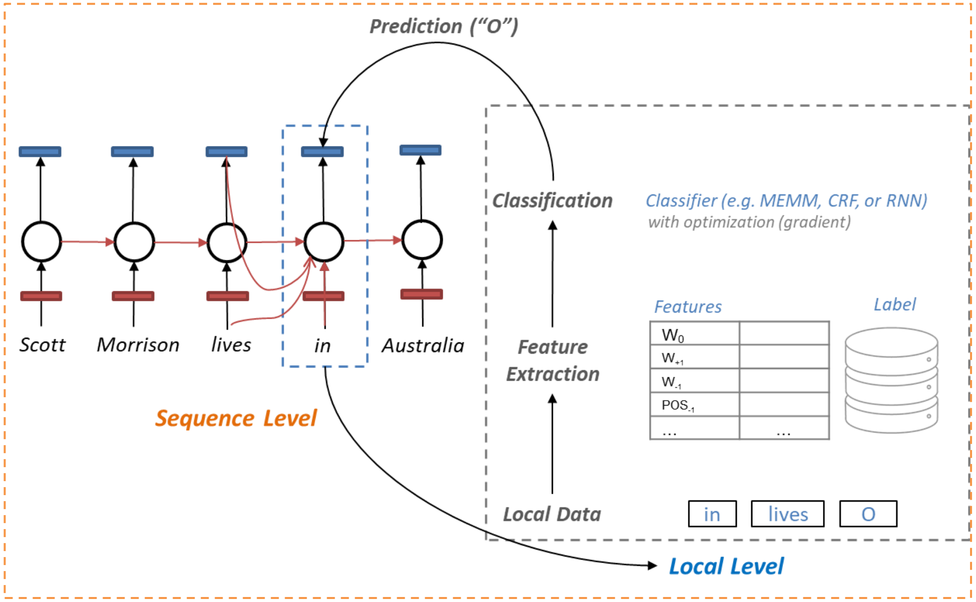
	Josiah	tells	Caren	John	Smith	is	a	student
IO encoding	PER	O	PER	PER	PER	O	O	O
IOB encoding	B-PER	O	B-PER	B-PER	I-PER	O	O	O



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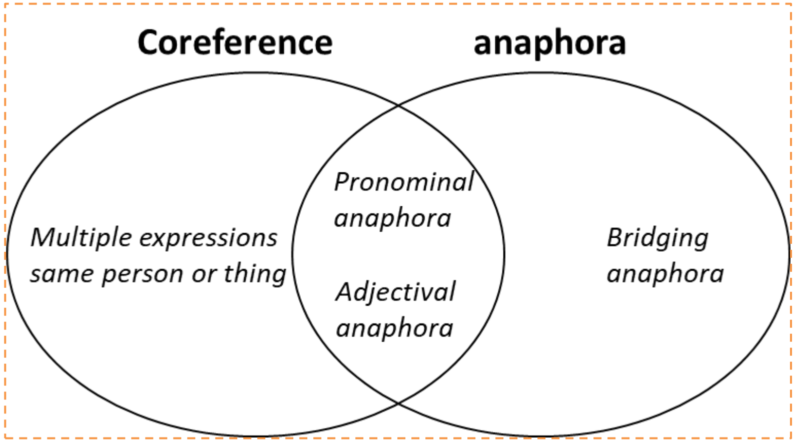

Ivanka was happy that Donald said he considered nominating her because she is very good with numbers

Ivanka

Donald

he

her

she

Gold cluster 1

Gold cluster 2

2 Lecture Summary

Lecture 9 Summary

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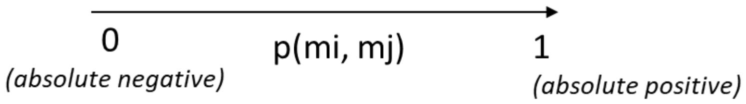

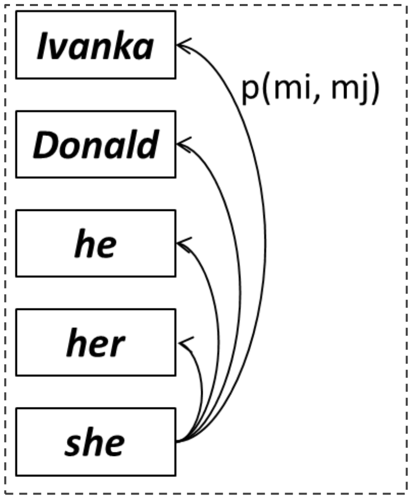

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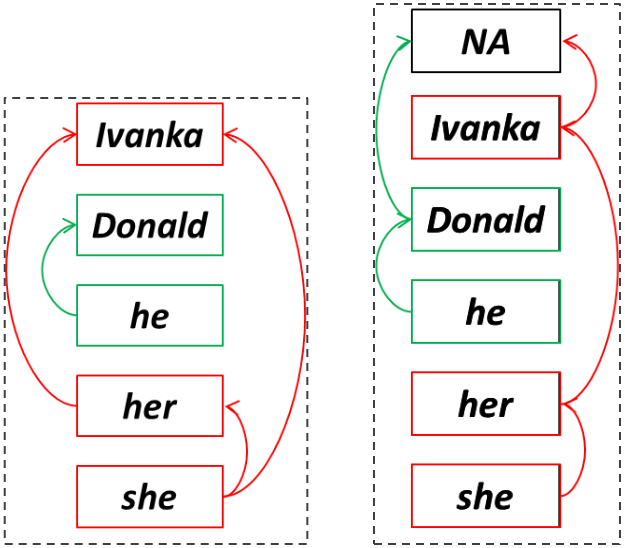

$$J = -\sum_{i=2}^{N} \sum_{j=1}^{i} y_{ij} \underline{\log p(m_j, m_i)}$$

Coreferent mentions pairs should get high probability, others should get low probability

Iterate through mentions

Iterate through candidate antecedents (previously occurring mentions)

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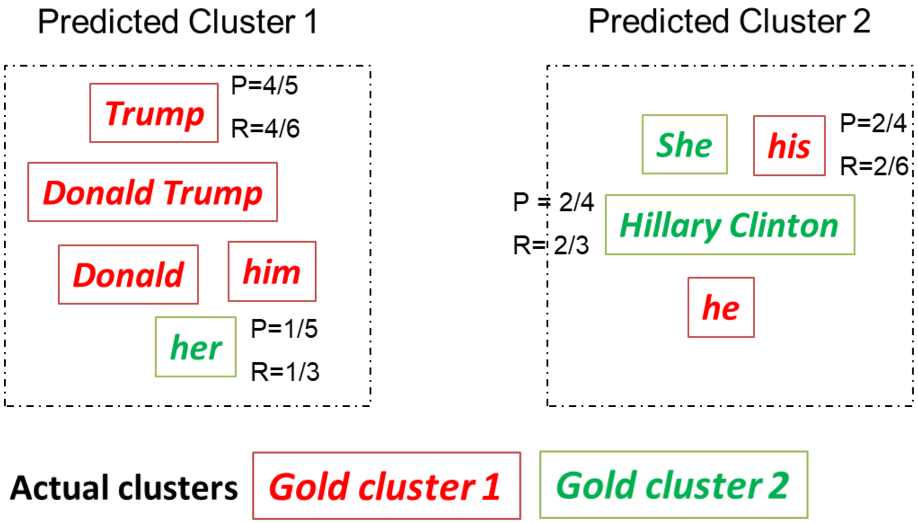
2. Mention Ranking model
3. Coreference Evaluation



Predicted Cluster 1

Trump P=4/5 R=4/6

Donald Trump

Donald

him

her P=1/5 R=1/3

Predicted Cluster 2

She

his P=2/4 R=2/6

P = 2/4 R= 2/3 Hillary Clinton

he

Actual clusters **Gold cluster 1** **Gold cluster 2**

2

Lecture Summary

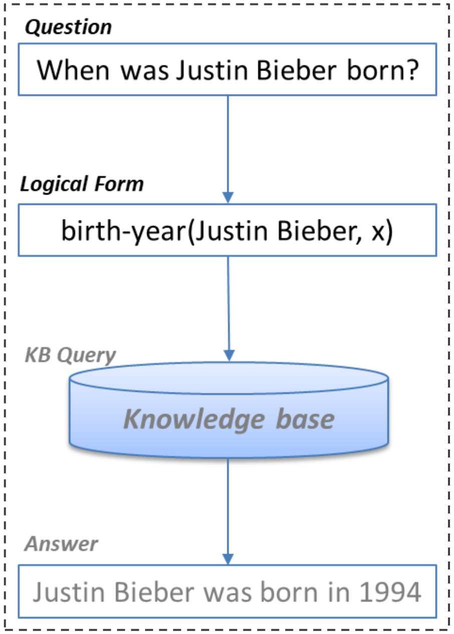
Lecture 10 Summary

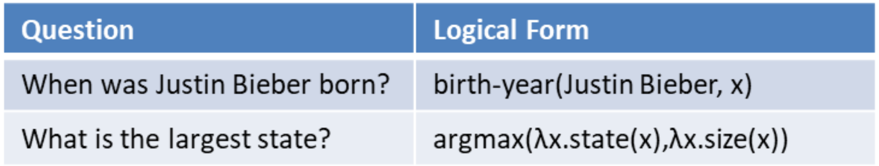
Question Answering

Knowledge-based Question Answering

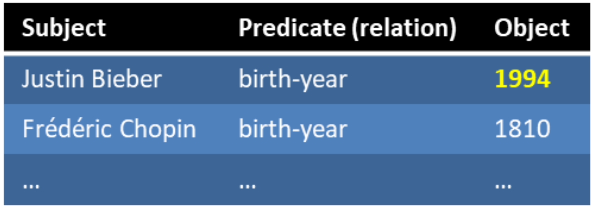
IR-based Question Answering and Reading Comprehension

Additional: Visual Question Answering





Question	Logical Form
When was Justin Bieber born?	birth-year(Justin Bieber, x)
What is the largest state?	argmax(λx.state(x),λx.size(x))



Subject	Predicate (relation)	Object
Justin Bieber	birth-year	1994
Frédéric Chopin	birth-year	1810
…	…	…

Lecture Summary

Lecture 10 Summary

Question Answering

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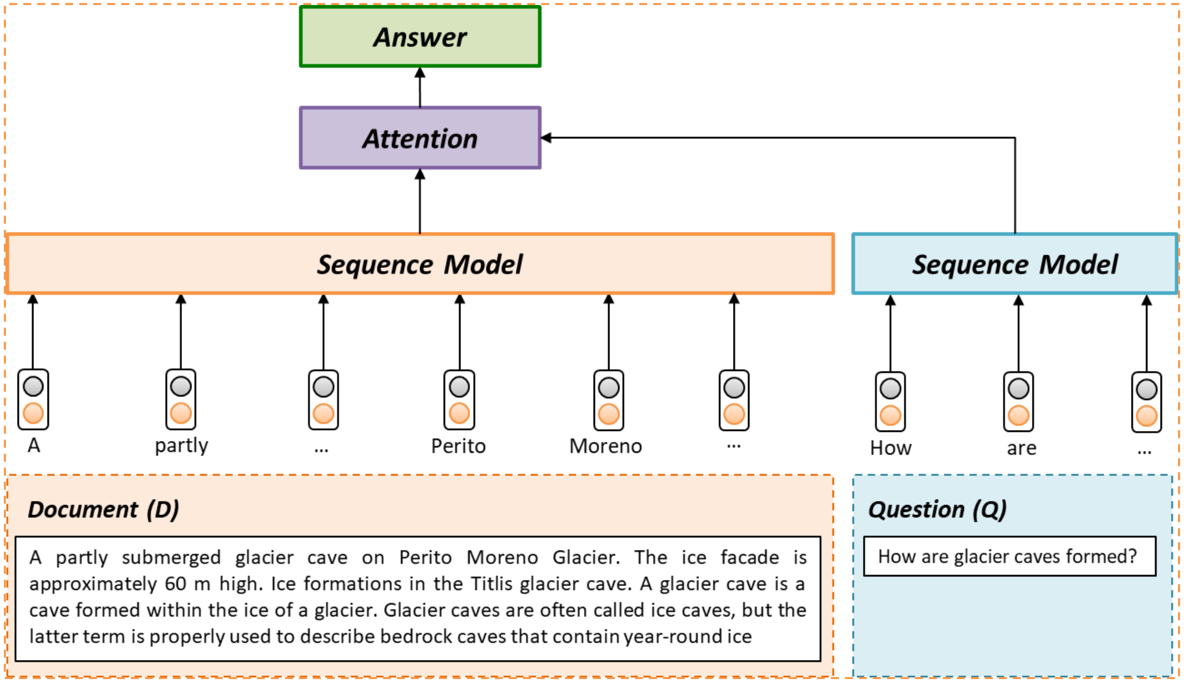
IR-based Question Answering and Reading Comprehension

Additional: Visual Question Answering



A partly submerged glacier cave on Perito Moreno Glacier. The ice facade is approximately 60 m high. Ice formations in the Titlis glacier cave. A glacier cave is a cave formed within the ice of a glacier. Glacier caves are often called ice caves, but the latter term is properly used to describe bedrock caves that contain year-round ice

How are glacier caves formed?

Lecture Summary

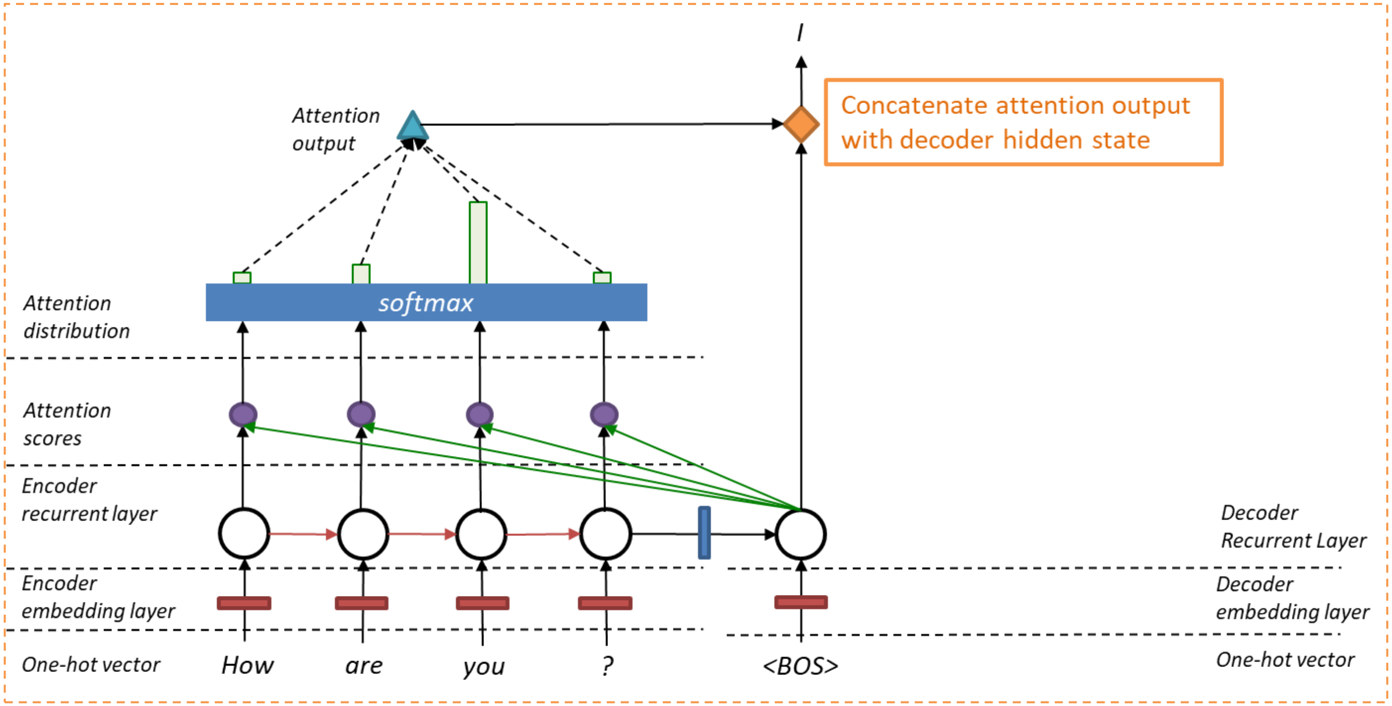
Lecture 10 Summary

Question Answering

Knowledge-based Question Answering

IR-based Question Answering and Reading Comprehension

Additional: Visual Question Answering



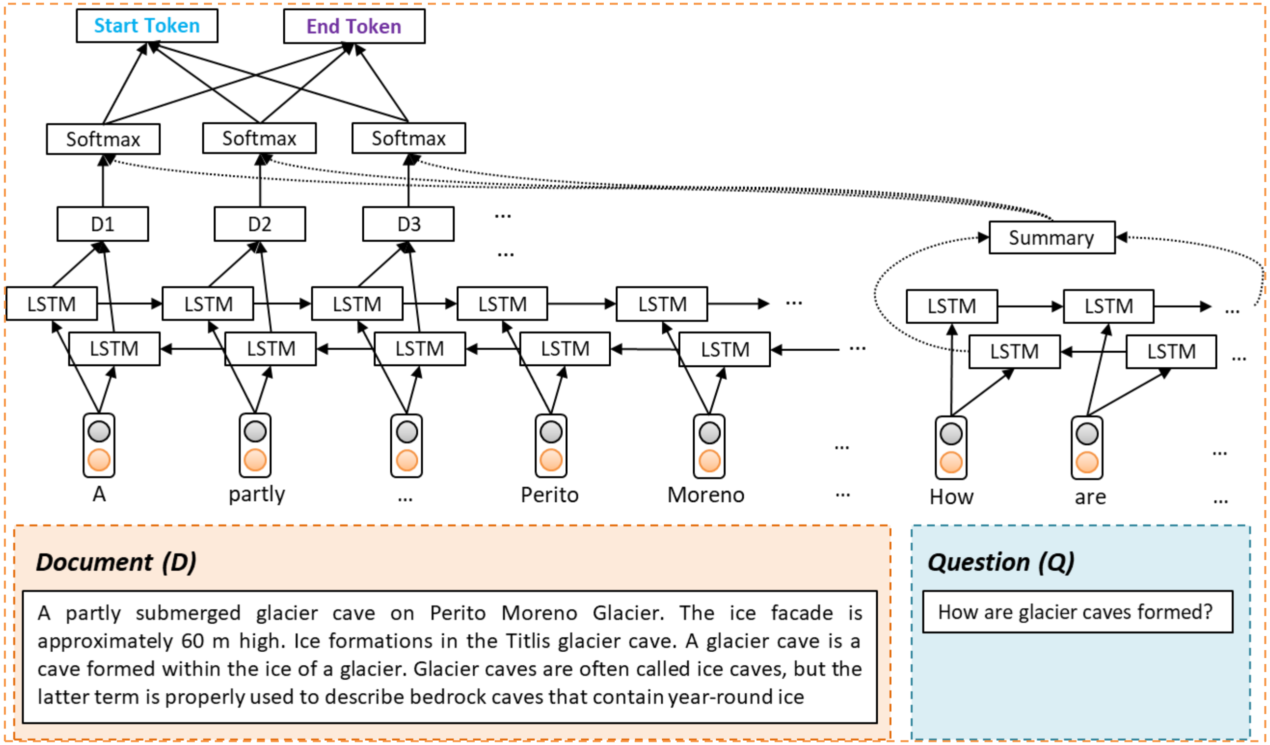
Lecture 10 Summary

Question Answering

Knowledge-based Question Answering

IR-based Question Answering and Reading Comprehension

Additional: Visual Question Answering



Document (D)

A partly submerged glacier cave on Perito Moreno Glacier. The ice facade is approximately 60 m high. Ice formations in the Titlis glacier cave. A glacier cave is a cave formed within the ice of a glacier. Glacier caves are often called ice caves, but the latter term is properly used to describe bedrock caves that contain year-round ice

Question (Q)

How are glacier caves formed?

2

Lecture Summary

Lecture 10 Summary

Question Answering

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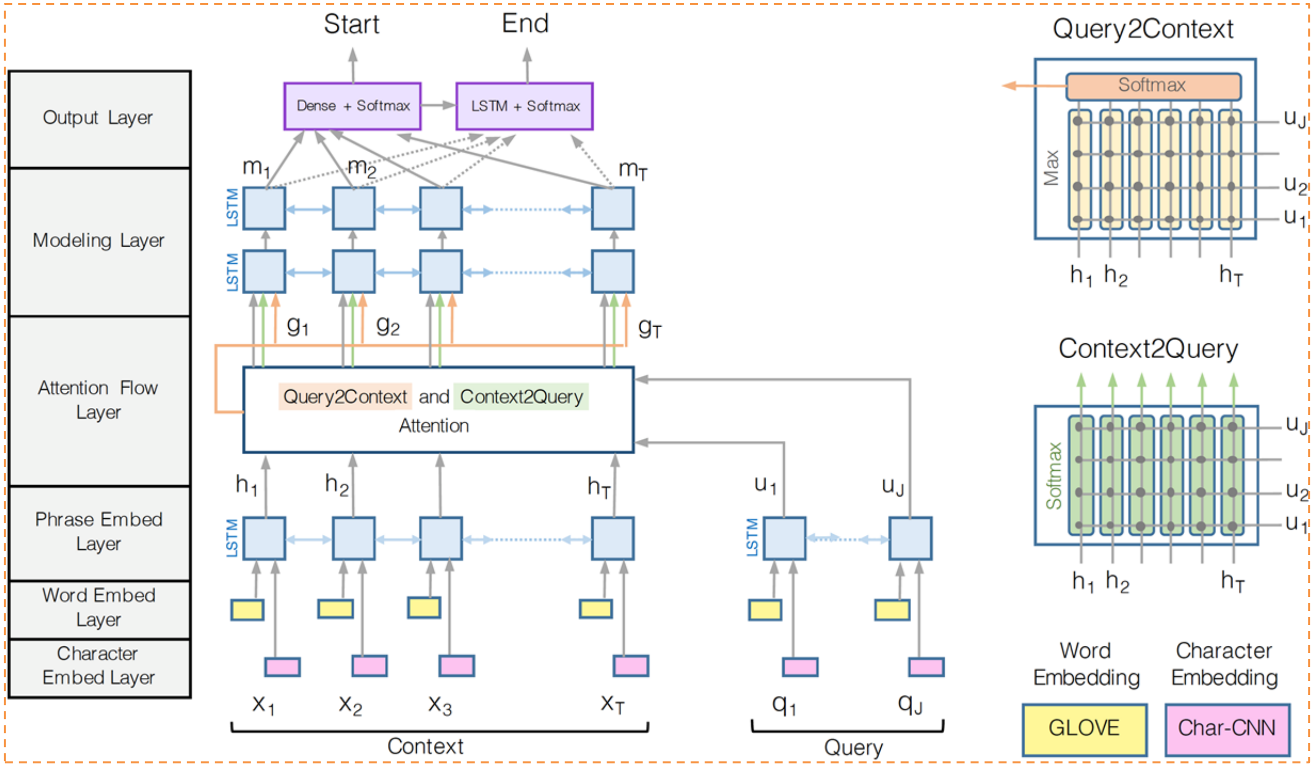
Additional: Visual Question Answering



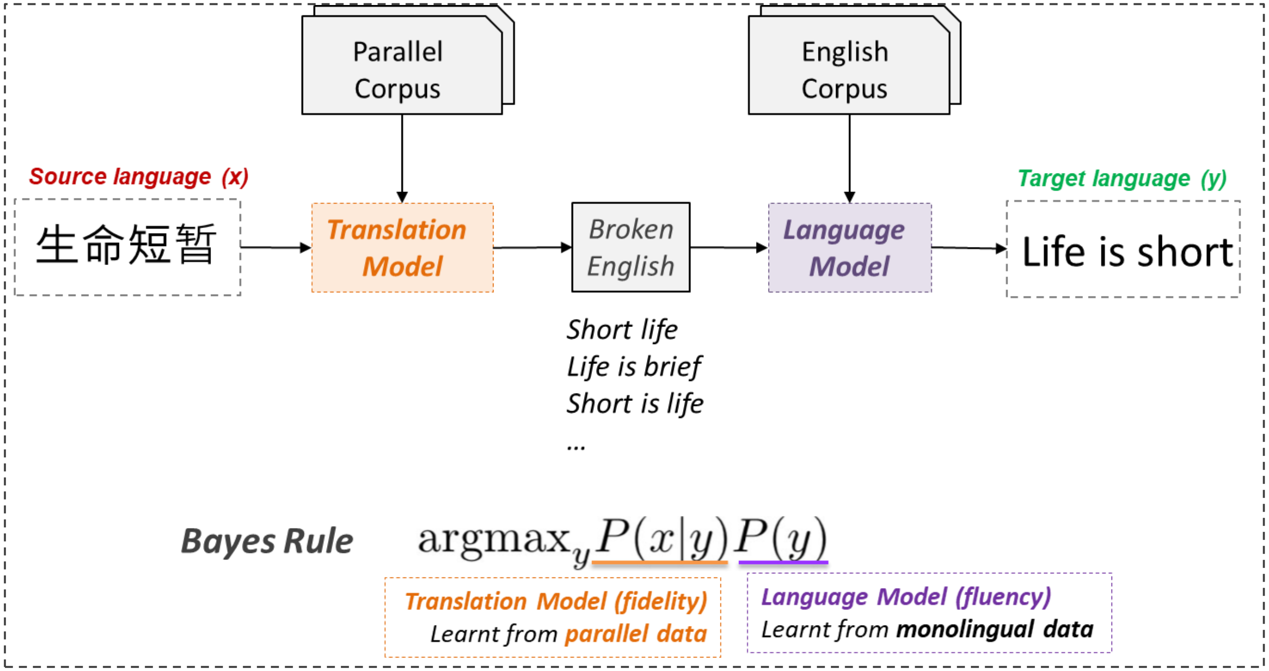
Lecture Summary

Lecture 11 Summary

Machine Translation

- Statistical Machine Translation
- Neural Machine Translation
- Attention and Transformer for MT

The Rise of the Pre-trained Model



$$\text{argmax}_y \underline{P(x|y)}\,\underline{P(y)}$$

Translation Model (fidelity) Learnt from *parallel data*

Language Model (fluency) Learnt from **monolingual data**

Lecture Summary

Lecture 11 Summary

Machine Translation

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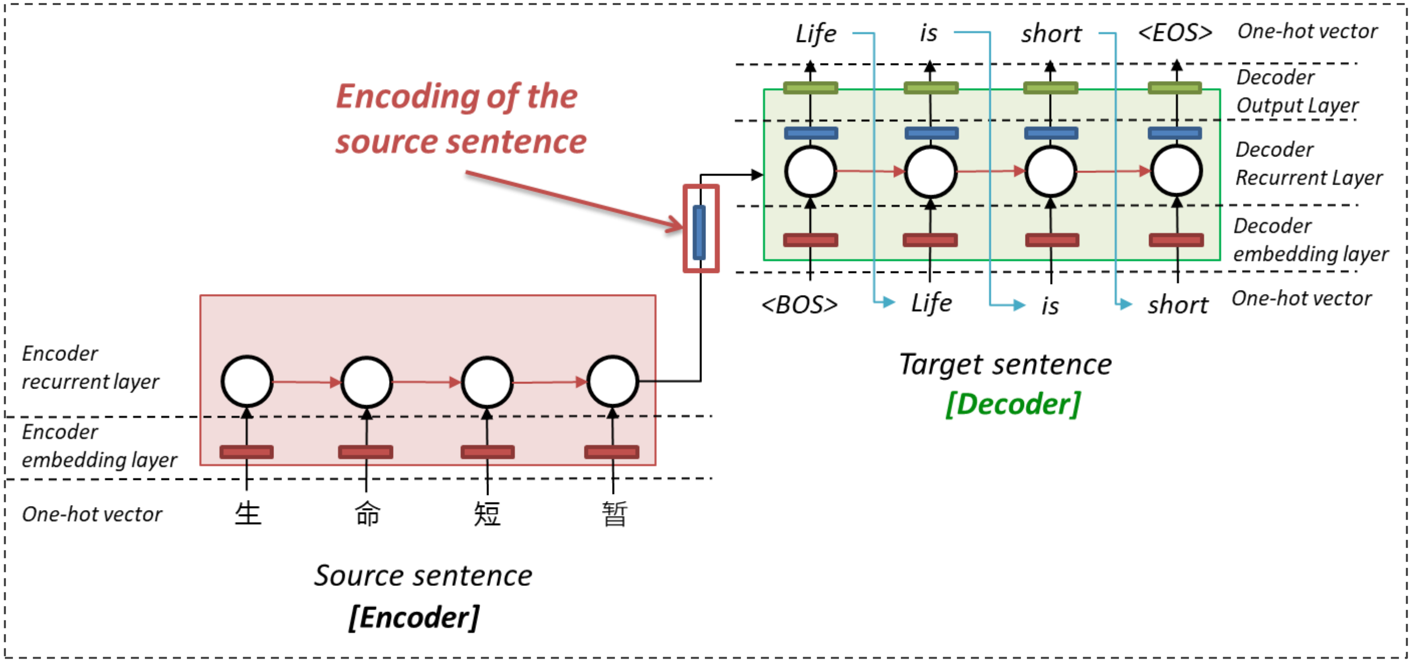
The Rise of the Pre-trained Model



2 Lecture Summary

Lecture 11 Summary

Machine Translation

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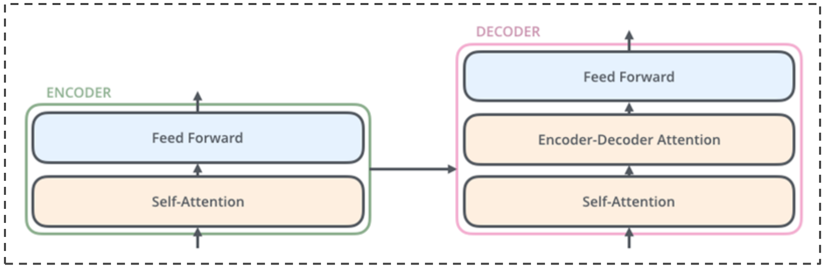
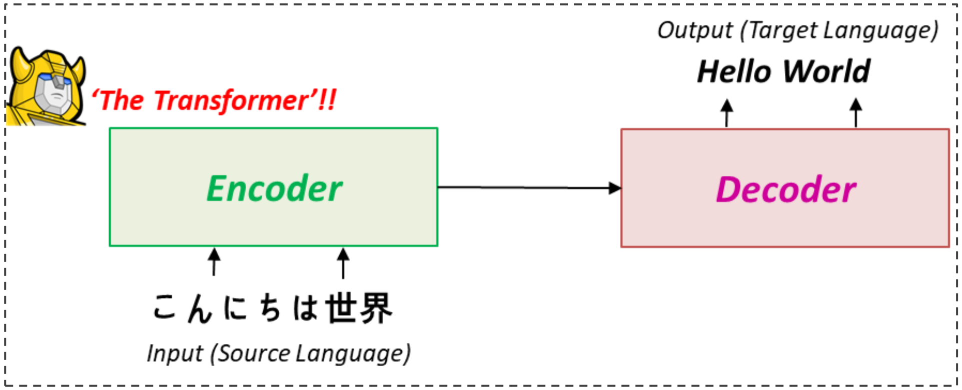
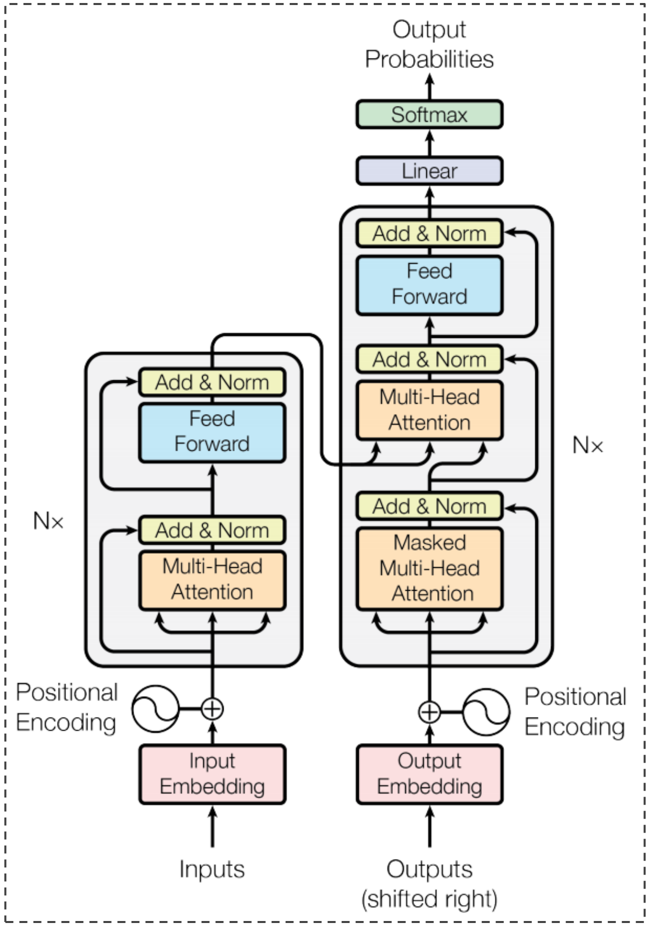
The Rise of the Pre-trained Model







2 Lecture Summary

Lecture 11 Summary

Machine Translation

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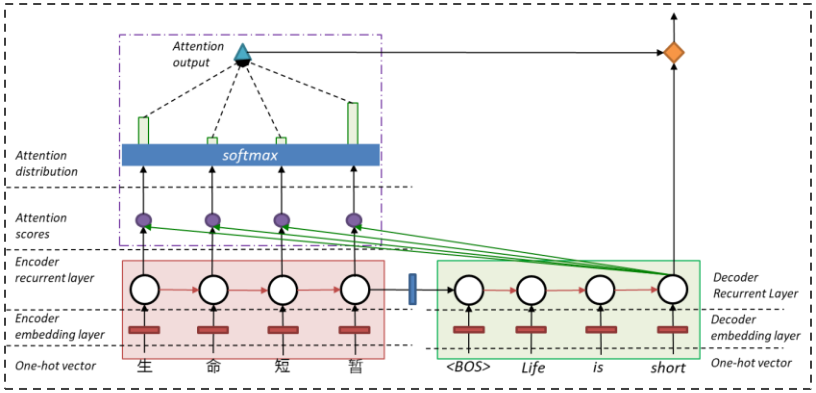
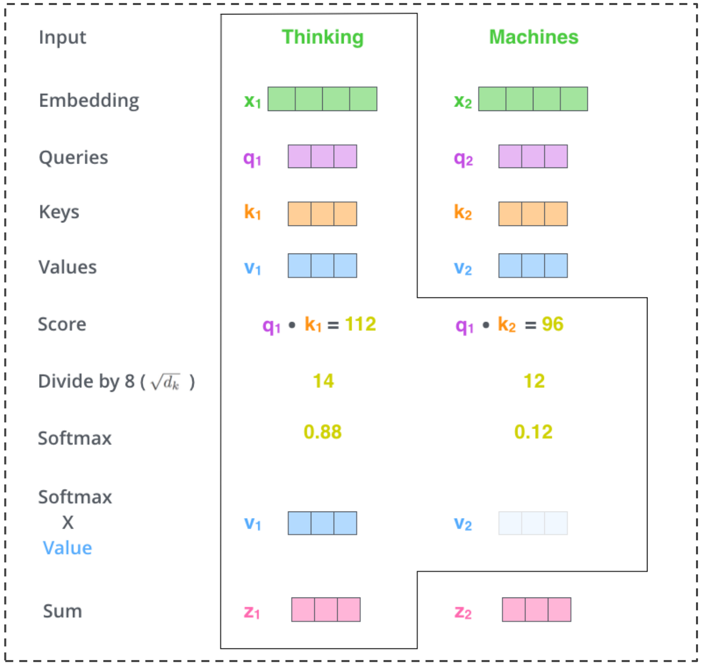
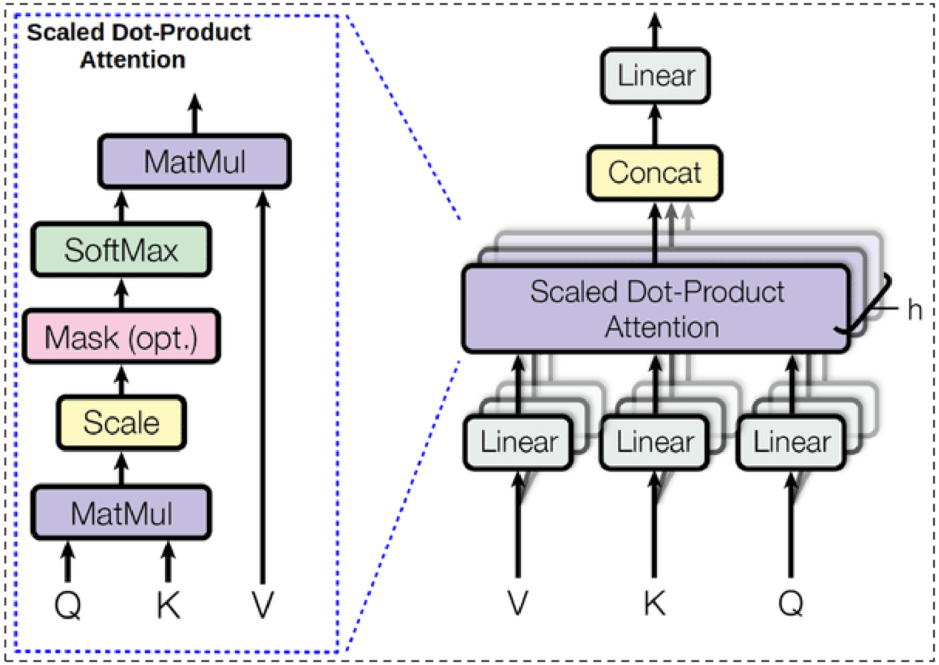




Input	Thinking	Machines
Embedding	x_1	x_2
Queries	q_1	q_2
Keys	k_1	k_2
Values	v_1	v_2
Score	$q_1 \cdot k_1 = 112$	$q_1 \cdot k_2 = 96$
Divide by 8 ($\sqrt{d_k}$)	14	12
Softmax	0.88	0.12
Softmax X Value	v_1	v_2
Sum	z_1	z_2



2

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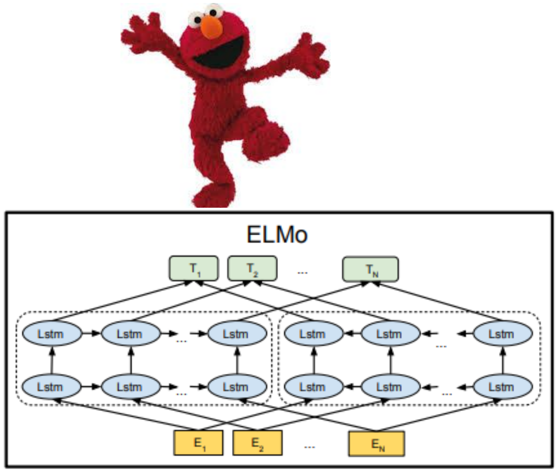
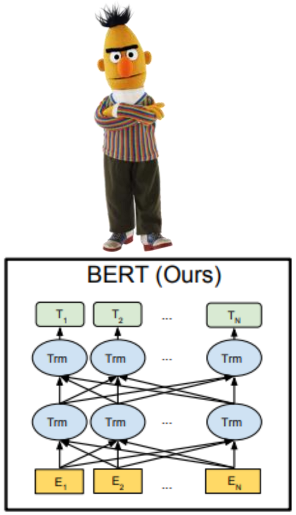
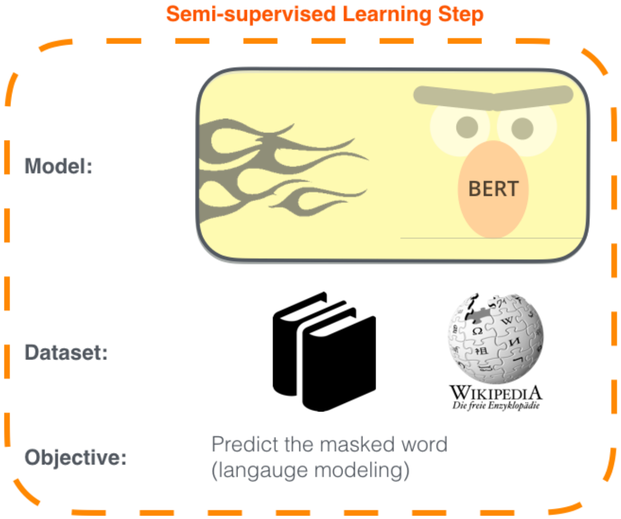


(Peters et al, 2018)



(Devlin et al, 2018)

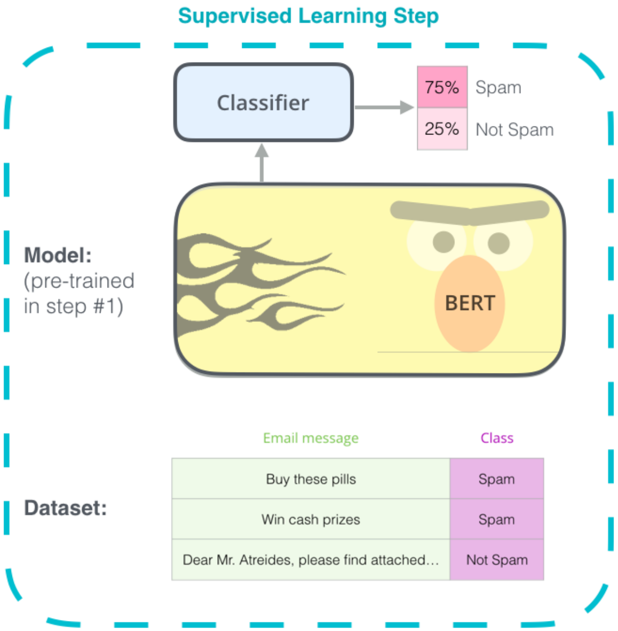


Semi-supervised Learning Step

Model:

Dataset:

Objective: Predict the masked word (langauge modeling)



Supervised Learning Step

Model: (pre-trained in step #1)

Dataset:

Email message	Class
Buy these pills	Spam
Win cash prizes	Spam
Dear Mr. Atreides, please find attached…	Not Spam

2

Lecture Summary

Lecture 12 Summary

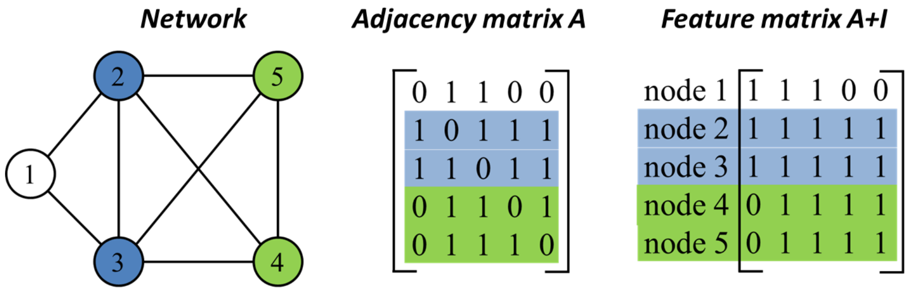
Graph and Natural Language Processing

Graph Neural Networks

Graph Neural Networks – Task-based

Graph Neural Networks and NLP Application

- Text Classification
- Document Timestamping
- Text to image generation

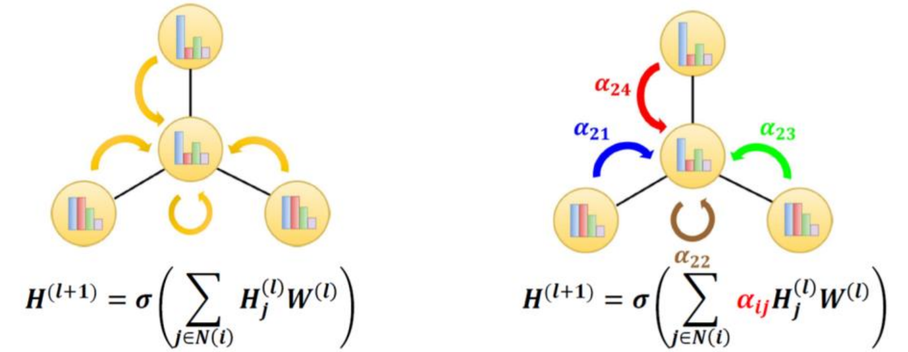


$$A = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 \end{bmatrix}$$

$$A+I = \begin{array}{c|ccccc} \text{node 1} & 1 & 1 & 1 & 0 & 0 \\ \text{node 2} & 1 & 1 & 1 & 1 & 1 \\ \text{node 3} & 1 & 1 & 1 & 1 & 1 \\ \text{node 4} & 0 & 1 & 1 & 1 & 1 \\ \text{node 5} & 0 & 1 & 1 & 1 & 1 \end{array}$$

Vanilla GCN updates information of neighbor atoms **with same importance**.

Attention mechanism enables it to update nodes **with different importance**



$$H^{(l+1)} = \sigma\left(\sum_{j \in N(i)} H_j^{(l)} W^{(l)}\right)$$

$$H^{(l+1)} = \sigma\left(\sum_{j \in N(i)} \alpha_{ij} H_j^{(l)} W^{(l)}\right)$$

2 Lecture Summary

Lecture 12 Summary

Graph and Natural Language Processing

Graph Neural Networks

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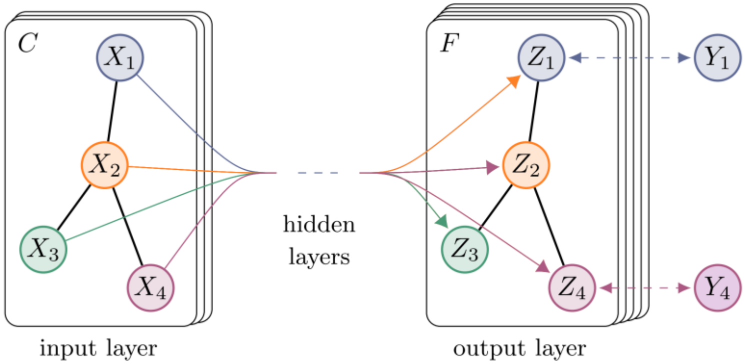

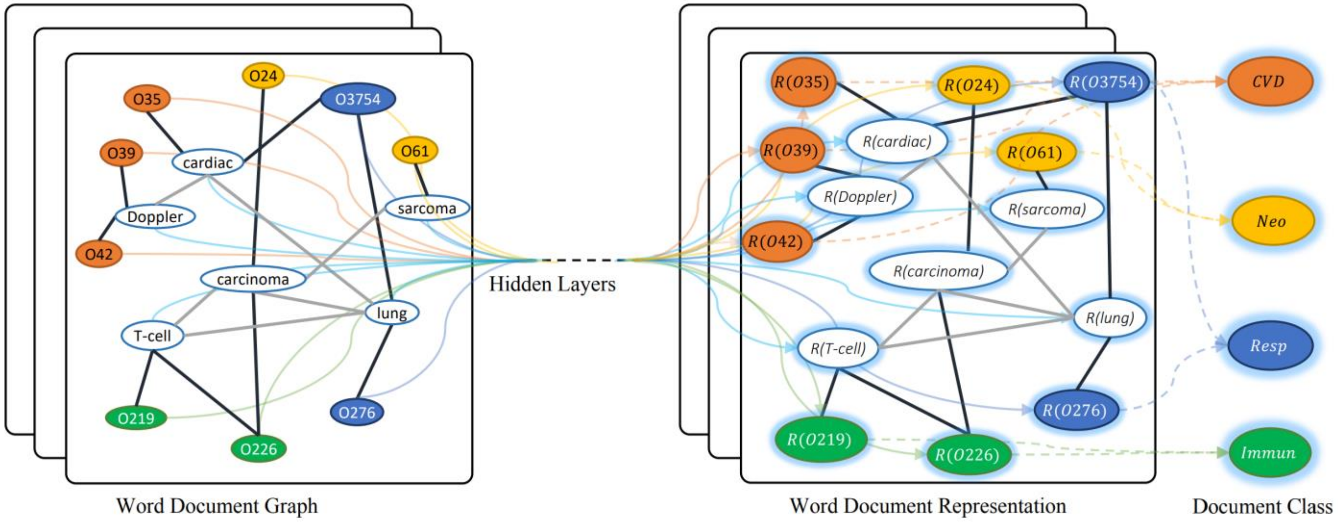

3 Exam Guide

Assessment Update

[Original Assessment Plan]

Assessment	Weight	Due	Length
Lab exercises	10%	Multiple weeks (By Monday 6pm or Tuesday 6pm)	n/a
Assignment 1	20%	Week 8	n/a
Assignment 2	20%	Week 14	n/a
Final exam	50%	Formal Exam Period	2 hours

To pass UoS, achieve at least 40% (20 out of 50)

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[Updated Assessment Plan]

Assessment	Weight	Due	Length
Lab exercises	10%	**Multiple weeks (All by Tuesday 6pm)**	n/a
Assignment 1	20%	Week 8	n/a
Assignment 2	30%	Week 14	n/a
Oral Quiz – Case Study (5Qs interview style)	15%	1 day after the formal exam period via Zoom [the exact date will be announced soon]	10 mins
Take-home Exam (Open Book)	25%	Formal exam period	1 hours

To pass UoS, achieve at least 40% (24 out of 60)

To pass UoS, achieve at least 40% (16 out of 40)

Sample Q would be demonstrated in Week 13.

3 Exam Guide

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3 Exam Guide

Final Exam (40%) – Take-home (25%) and Oral (15%)

Take home exam (25%) - Canvas

1:00PM Saturday 20 June 2020 **Check your personal exam timetable at Sydney Student*

Canvas Exam Site

- The canvas exam site is different that the Canvas site we use during the semester for teaching
- It is called Final exam for COMP5046
- The Exams office will give you access to the exam site
- The recommended browsers for Canvas: Chrome and Firefox, not Internet Explorer or others

Exam Conditions

- ***1 hour***, Online exam (+10 minutes reading time)
- ***Open book*** examination, Unsupervised (Un-proctored)
- ***Complete ALL questions*** in the space provided on the exam paper
- **Eight (8) questions (total 25 marks)** = **five (5) 2 marks questions** + **three (3) 5 marks questions**

Exam Guide

Final Exam (40%) – Take-home (25%) and Oral (15%)

Oral exam (15%) - Zoom

21-23 June 2020 **The oral exam timetable will be shared on 31st of May*

Exam Conditions

- ***10mins***, Zoom-based Interview.
- ***Oral Interview Style***

Before the Oral Exam:

- *Your candidate timetable will tell you when your oral examination is scheduled to begin (The oral exam timetable will be shared on 31st of May)*
- *You will be asked to arrive earlier than the scheduled time for your examination. For all candidates, this will be no later than 10 minutes prior to their examination start time. These arrangements are to ensure the quality of the internet connection.*
- *When you arrive at the room, you will be asked to show your student ID (card)*
- *You will be asked to stand by in the waiting room.*

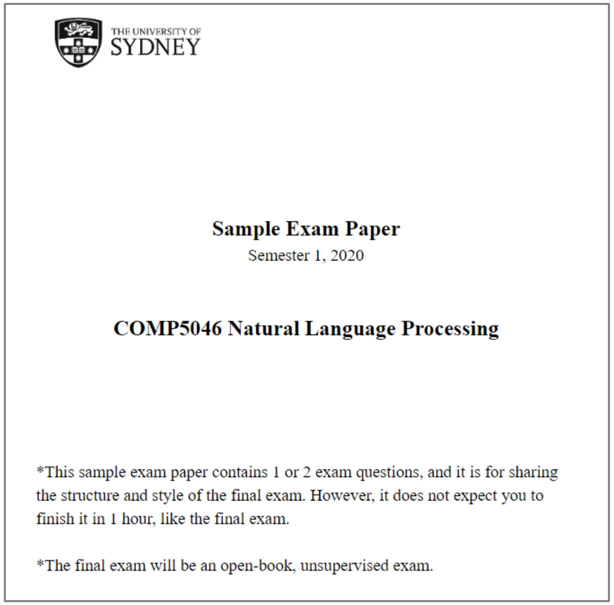
3 Exam Guide

Final Exam Preview! (All available in Canvas)

Let’s Have a Look at this Together!

Sample Online Exam – Question and Answer

Sample Oral Exam – Interview



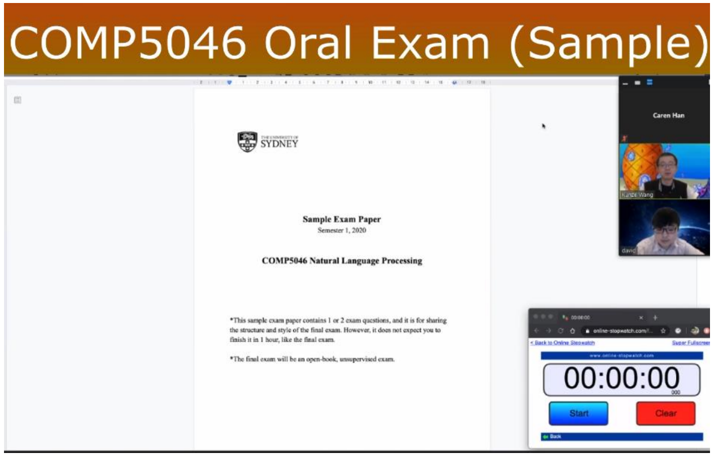
THE UNIVERSITY OF SYDNEY

Sample Exam Paper
Semester 1, 2020

COMP5046 Natural Language Processing

*This sample exam paper contains 1 or 2 exam questions, and it is for sharing the structure and style of the final exam. However, it does not expect you to finish it in 1 hour, like the final exam.

*The final exam will be an open-book, unsupervised exam.



COMP5046 Oral Exam (Sample)

3

Exam Guide

Reminder! Suggestion!

The questions are not easily googlalable.
Your answer will be checked by the plagiarism checking software.

Well organized and be quick
Allocate time according to the marks for each question

3

Exam Guide

Students in different time zones

- Important for international students who could not come to Australia and exchange students who had to return to their country.
- If you are in a different time zone and the exam is too early/too late for you, you can apply for Special Consideration to have special arrangements for the exam:

https://www.sydney.edu.au/students/special-consideration.html#time-zone

All Good! Thanks for following and surviving

GOOD LUCK in YOUR FINAL EXAM