國立高雄科技大學
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語言模型及循環神經網路

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https://github.com/chiayisu/Natural-Language-Processing

Agenda

- 語言模型
- 計算圖
- 循環神經網路 (RNN)
- 反向傳播及損失函數
- 演算法複雜度及句子的長度
- Text Generation Example
- 語言模型的評估
- RNN Example

語言模型

語言模型介紹

- 根據前一個語詞預測下一個語詞

- 他有很多 _____

錢

書籍

房子

- And many words

語言模型：公式定義

- 假設我們有一個序列 $x^1 \ldots x^t$ ，x^{t+1} 的計算方法如下：
- $p(x^{t+1} | x^t, \ldots, x^1)$
- x^{t+1}為所有單詞中其中一個語詞
- 下一個語詞所會出現的機率的運算稱語言模型。

語言模型

- 語言模型也可以用來產生一段文字的機率
- 假設我們要產生一段文字 $x^1 \ldots x^T$ ，其計算方式如下
- $p(x^1, \ldots, x^T) = \mathrm{p}(x^1) * \mathrm{p}(x^2|x^1) * \cdots * \mathrm{p}(x^T|x^{T-1}, \ldots, x^1)$

$$= \boxed{\prod_{t=1}^{T} \mathrm{p}(x^t|x^{t-1}, \ldots, x^1)}$$

Language model is everywhere and every day.

face
- facebook
- facebook login
- facebook sign up
- facebook messenger
- facebook app
- face shield
- facebook stock
- facebook video downloader
- facetime
- facebook logo

goog
- google
- google translate
- google maps
- google classroom
- google news
- google scholar
- google docs
- google images
- google mail
- google play

amaz
- amazon prime video
- amazon prime
- amazon
- amazing talker
- amazon taiwan
- amazon stock
- amazon us
- amazon jobs
- amazon india
- amazon kindle

How to learn a language model?

- N-gram (Pre-Deep Learning)
- RNN
- LSTM
- Seq2Seq
- GPT
- BERT
- …

N-gram 語言模型的問題

- 以投資方面，他有很多 _____
- Sparsity (4-grams)
  - $\frac{C(\text{有很多\_\_\_})}{c(\text{有很多})}$
  - Numerator : add smoothing term
  - Denominator : Back off
  - This problem gets worse when n is increased.
- Storage
  - Needs to store all the counts

N-gram 語言模型的實例：路透社語料庫

- Today the ___
- Probability Distribution
  - company 0.153
  - bank 0.153
  - price 0.077
  - italian 0.039
  - emirate 0.039
- Have a sparsity problem.
- https://nlpforhackers.io/language-models

Tri-Gram 語言模型：文本生成

- Today the ___

- Probability Distribution
  - company 0.153
  - bank 0.153
  - price 0.077
  - italian 0.039
  - emirate 0.039

Tri-Gram 語言模型：文本生成

- Today $\boxed{\text{the price}}$___
- Probability Distribution
  - $\boxed{\text{of 0.308}}$
  - for 0.050
  - it 0.046
  - to 0.046
  - is 0.031
- …

Tri-Gram 語言模型：文本生成

- today the price of gold per ton , while production of shoe lasts and shoe industry , the bank intervened just after it considered and rejected an imf demand to rebuild depleted european stocks , sept 30 end primary 76 cts a share .
- 文法上有些地方合理有些不合理，但是句子間的關聯性不大
- n越大，語言模型表現越好
- 然而，n越大，越難找到相對應的語詞，每個語詞的機率也越小 (Sparsity Problem)

Neural Language Model : Fixed-window

- ~~as the proctor started the clock~~ the students opened their ___

output distribution

$$\hat{\boldsymbol{y}} = \mathrm{softmax}(\boldsymbol{U}\boldsymbol{h} + \boldsymbol{b}_2) \in \mathbb{R}^{|V|}$$

hidden layer

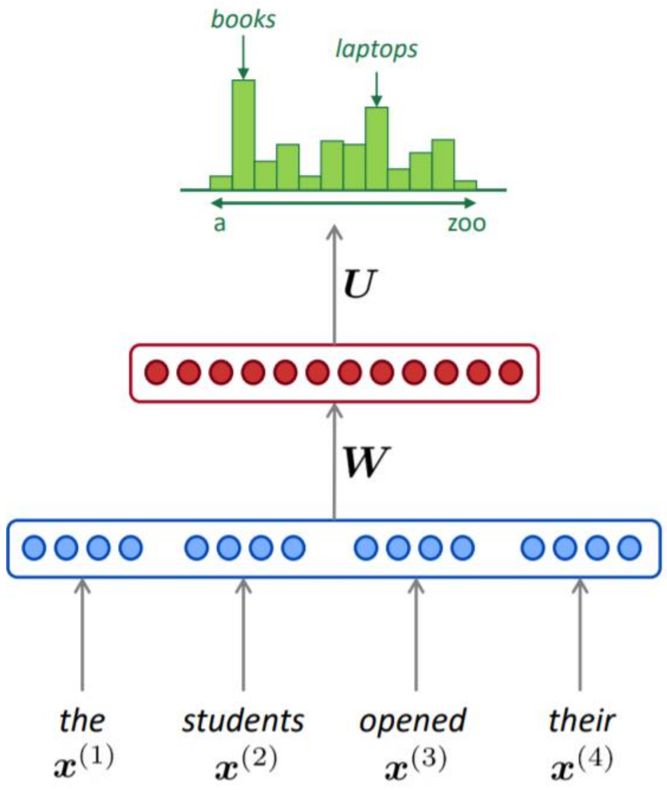
$$\boldsymbol{h} = f(\boldsymbol{W}\boldsymbol{e} + \boldsymbol{b}_1)$$

concatenated word embeddings

$$\boldsymbol{e} = [\boldsymbol{e}^{(1)}; \boldsymbol{e}^{(2)}; \boldsymbol{e}^{(3)}; \boldsymbol{e}^{(4)}]$$

words / one-hot vectors

$$\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \boldsymbol{x}^{(3)}, \boldsymbol{x}^{(4)}$$



固定視窗大小語言模型的好處及壞處

- 好處
  - 解決了 N-Gram 模型的問題
- 壞處
  - 視窗太小資訊量可能不足
  - 當視窗大小增加權重大小也會增加
  - 視窗大小永遠不夠大
  - 每個輸入都有不同的權重

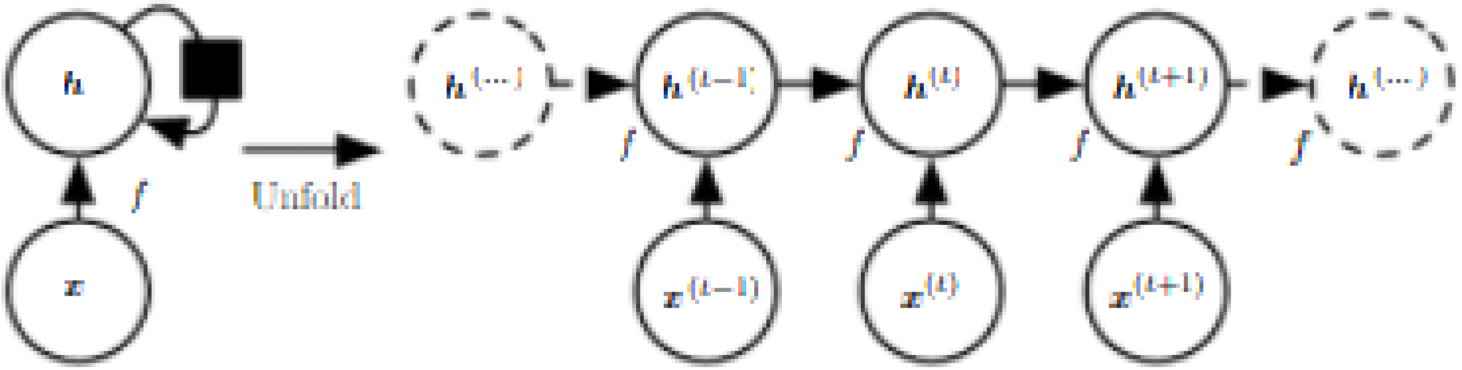
w x

$$\begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

- 因此：我們需要一個網路來處理任意長度的句子

計算圖

循環圖及展開圖

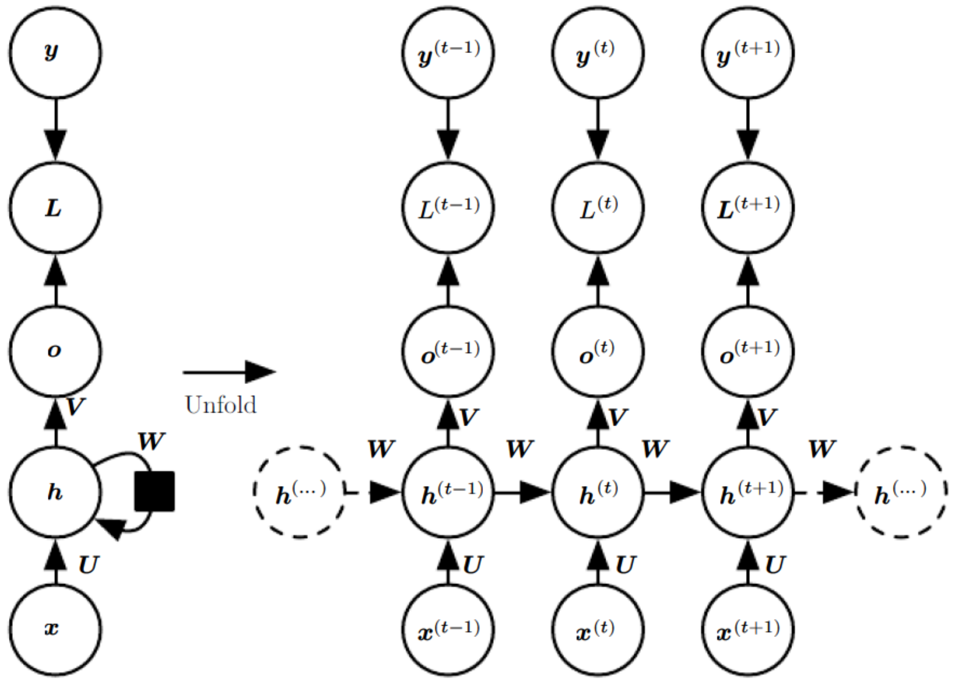


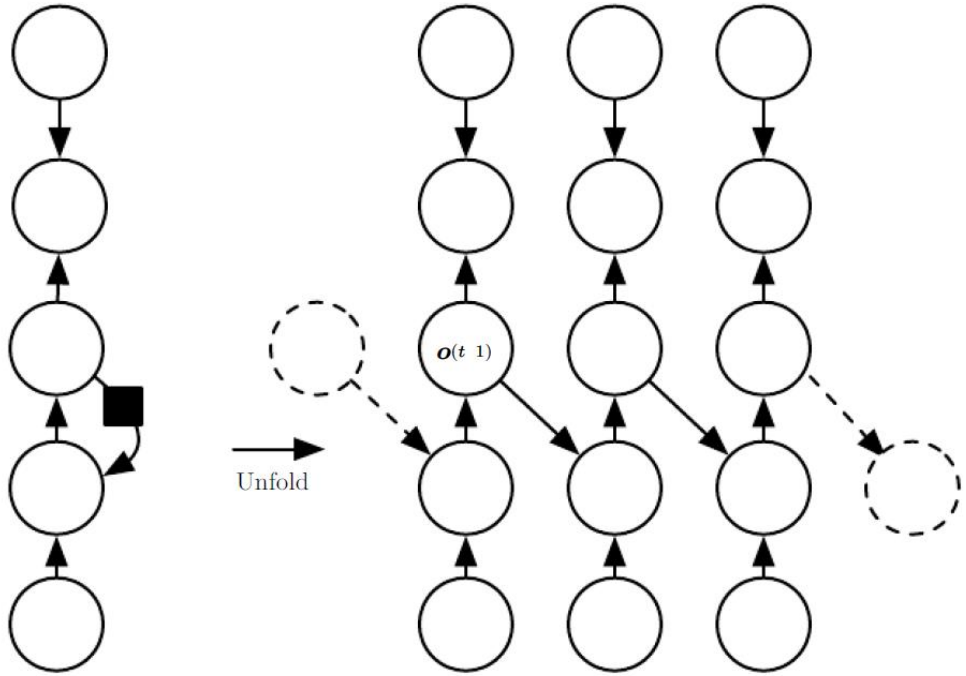
循環圖與展開圖的比較

- 循環圖
  - 簡潔
- 展開圖
  - 較明確
  - 能夠清楚的展示前向及反向傳播的資訊

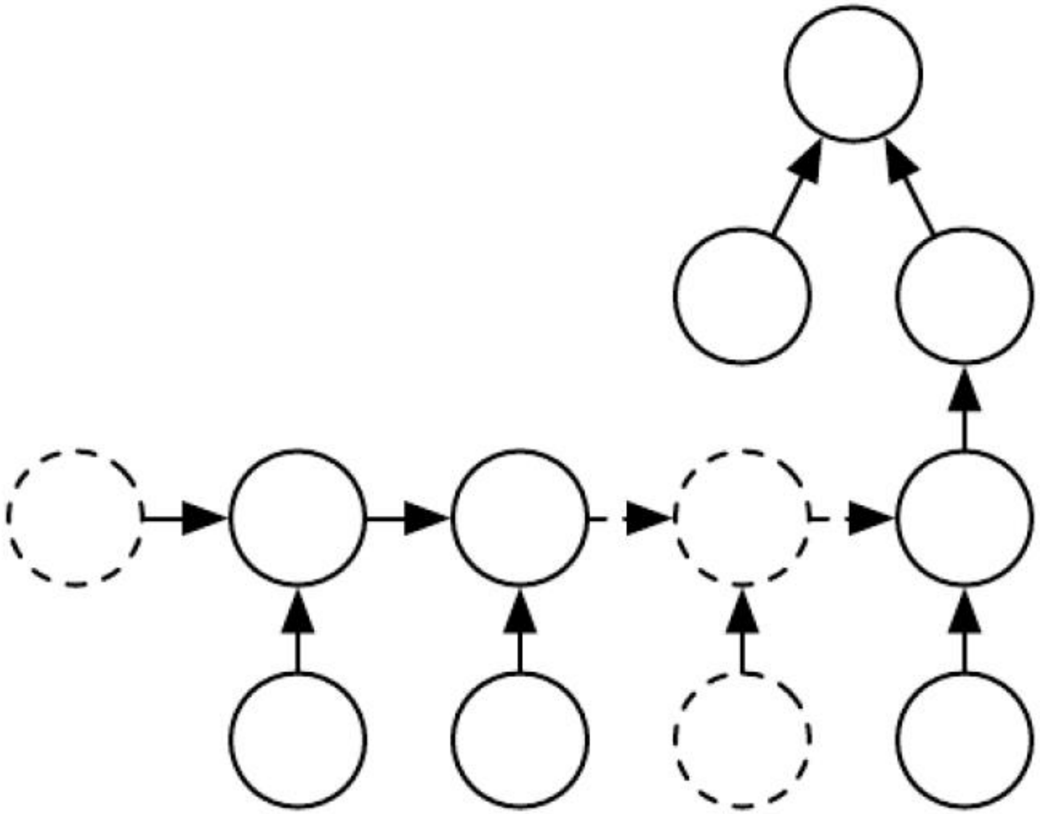
循環神經網路 (RNN)

RNN Design Patterns





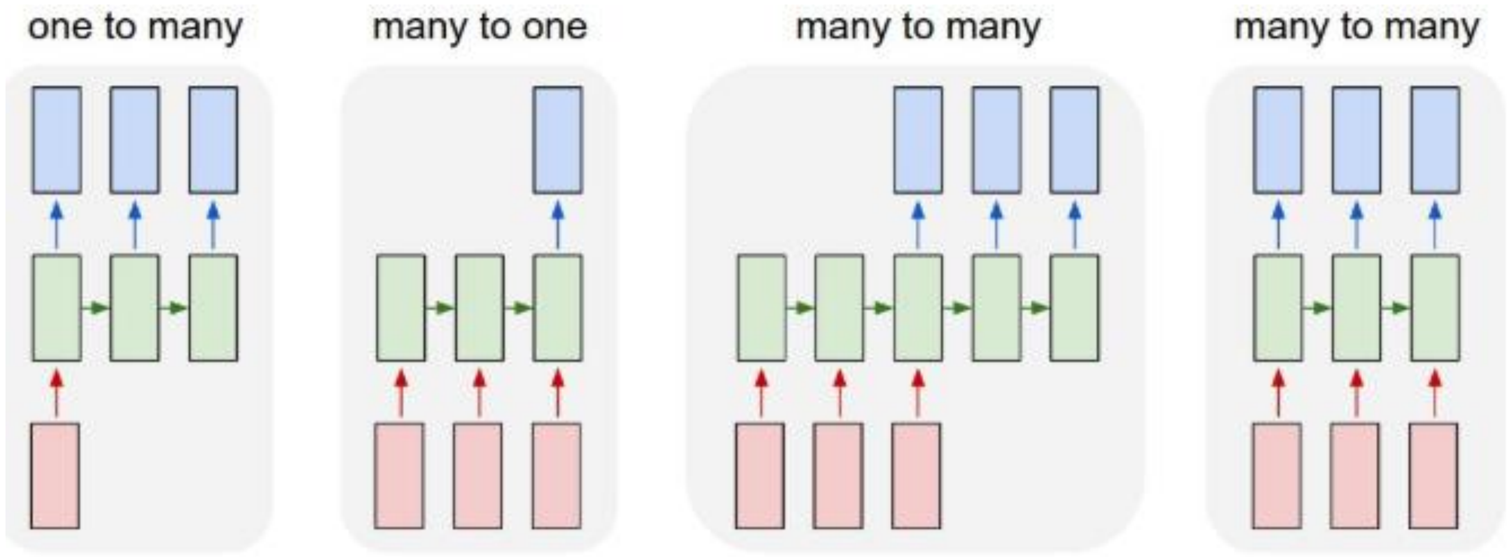
RNN Design Patterns



RNN Overview

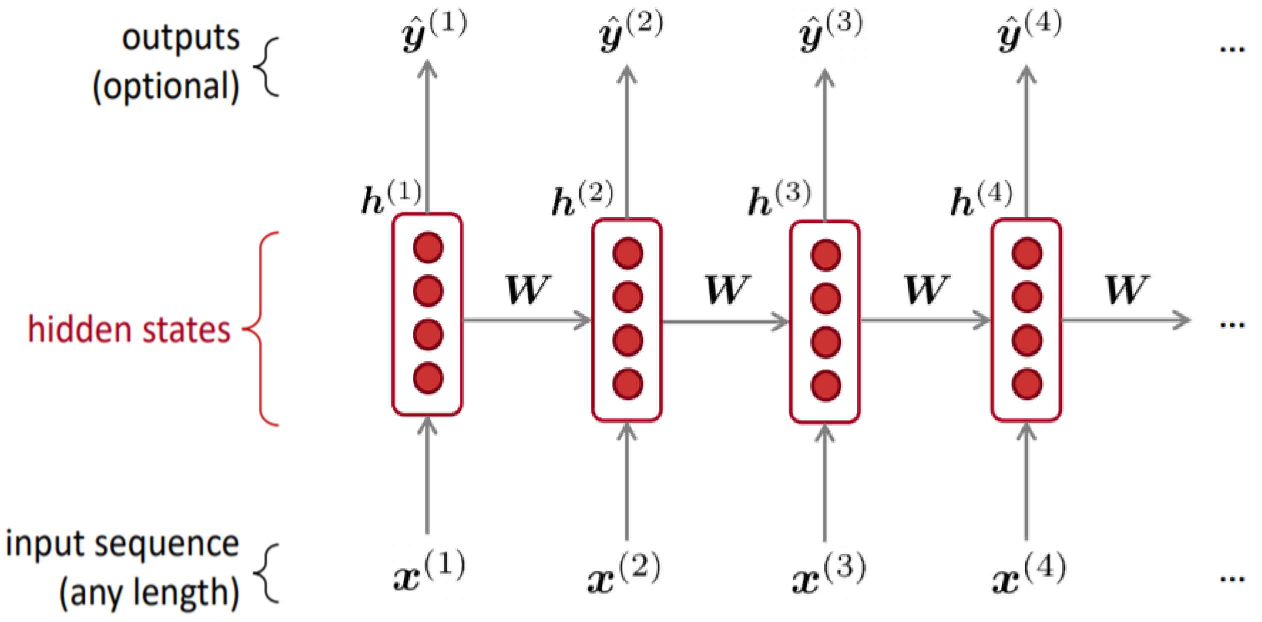
- (1) Image Captioning (2) Sentiment Analysis (3) Machine Translation (4) Video Classification

(1) (2) (3) (4)



循環神經網路(RNN)

- W通常會重複使用
- 隱含層的計算會採用之前的資訊以及目前所輸入的資訊
- 輸入的句子可以是任意長度
- RNN不一定每個輸入都要有輸出



Detail of RNNLM

output distribution

$\hat{\boldsymbol{y}}^{(t)} = \mathrm{softmax}\left(\boldsymbol{U}\boldsymbol{h}^{(t)} + \boldsymbol{b}_2\right) \in \mathbb{R}^{|V|}$

hidden states

$\boldsymbol{h}^{(t)} = \sigma\left(\boldsymbol{W}_h\boldsymbol{h}^{(t-1)} + \boldsymbol{W}_e\boldsymbol{e}^{(t)} + \boldsymbol{b}_1\right)$

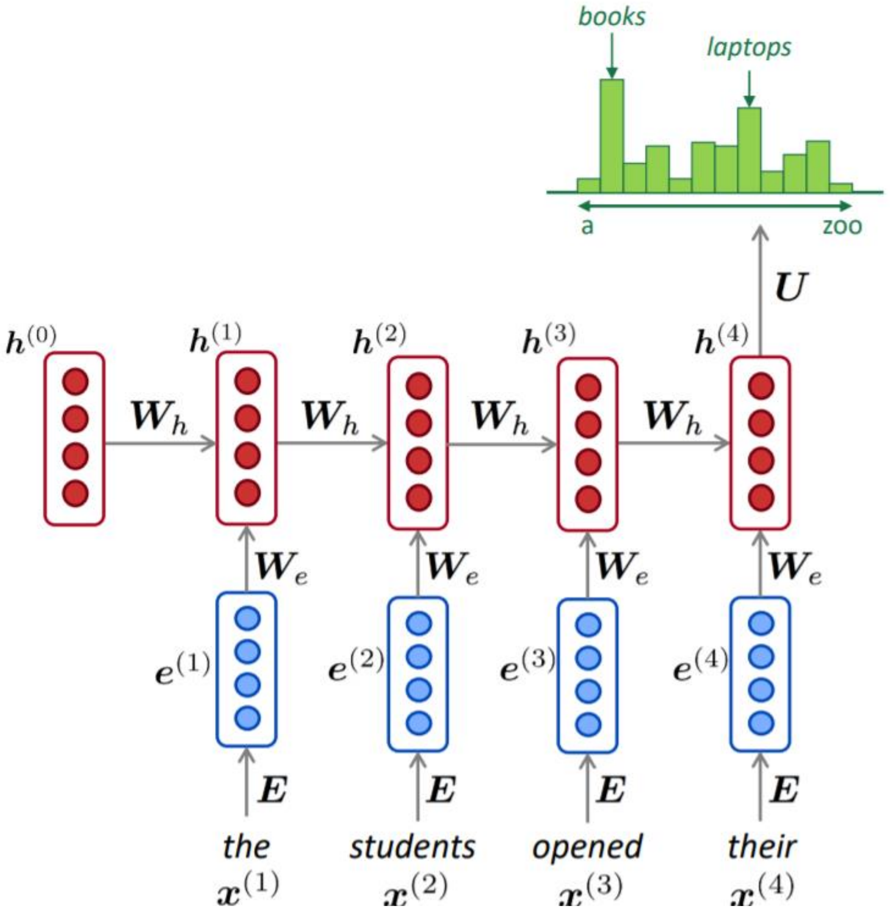
$\boldsymbol{h}^{(0)}$ is the initial hidden state

word embeddings

$\boldsymbol{e}^{(t)} = \boldsymbol{E}\boldsymbol{x}^{(t)}$

words / one-hot vectors

$\boldsymbol{x}^{(t)} \in \mathbb{R}^{|V|}$



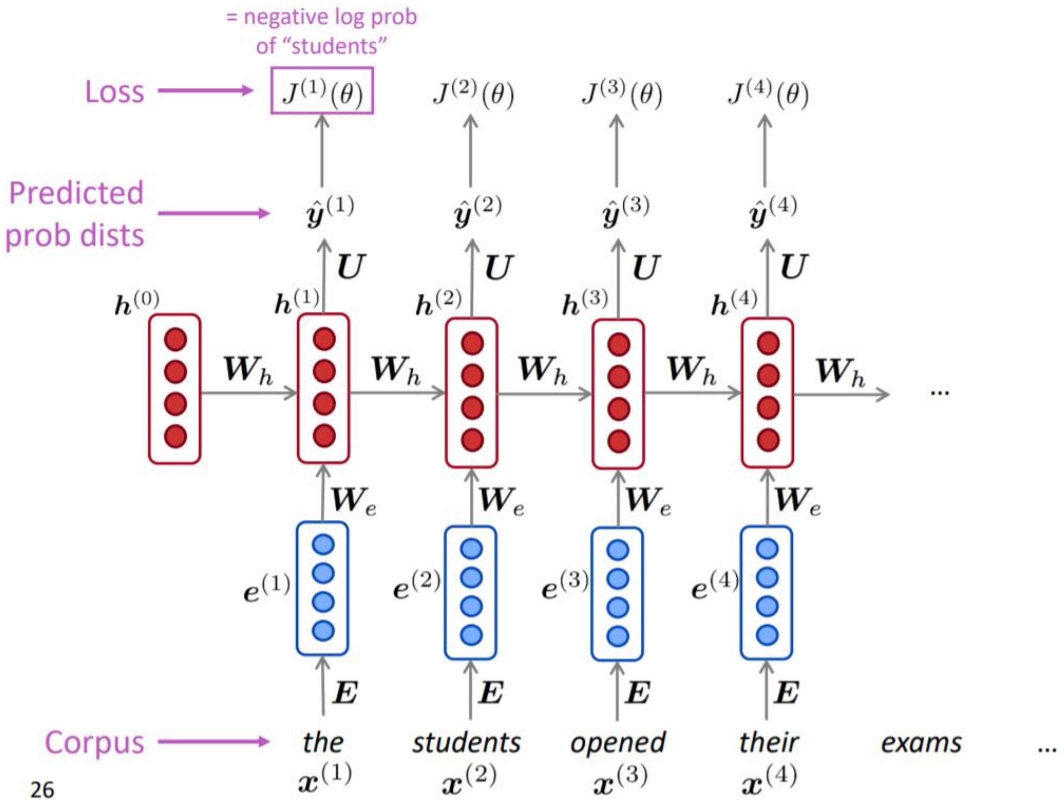
RNNLM: 好處及壞處

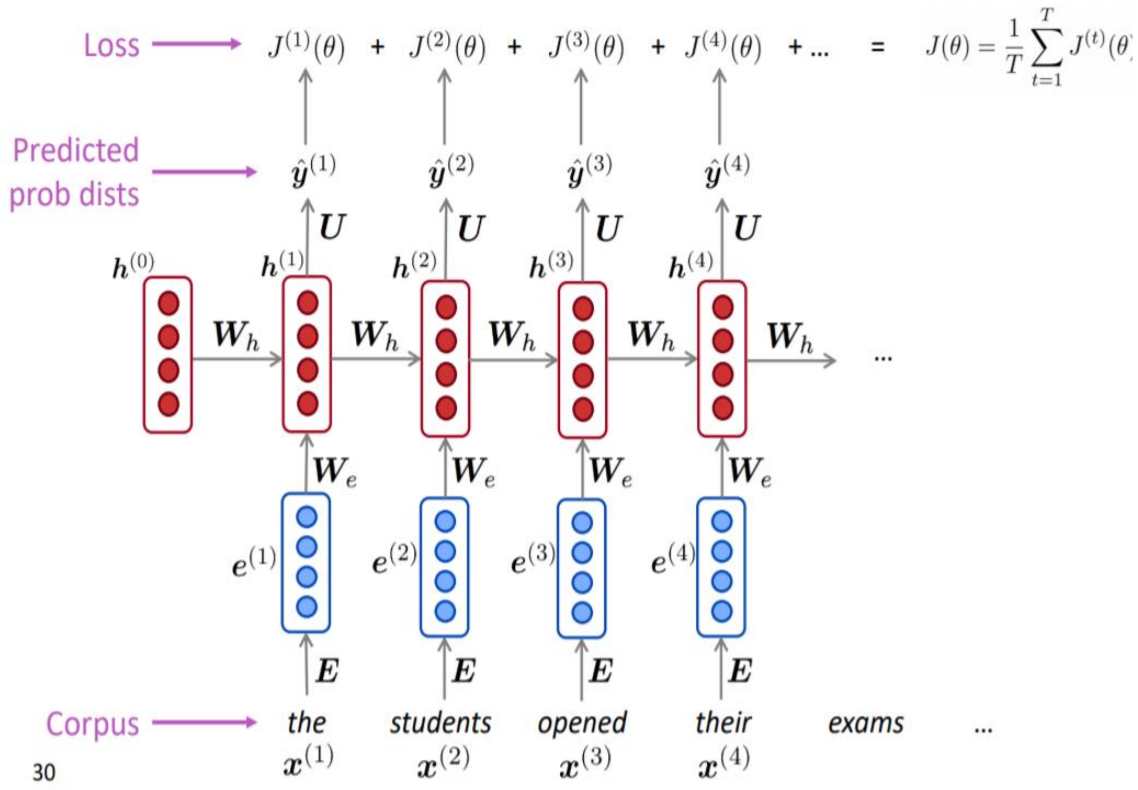
- 好處:
  - 可以處理任何長度的輸入
  - 理論上可以運用到歷史資訊
  - 當輸入增加時，模型的大小不會跟著增加
  - 因為每個權重的輸入都相同，所以每個輸入的處理過程都相同
- 壞處
  - 運算速度較慢
  - 實際上無法有效運用歷史資訊 (梯度消失、爆炸)

RNNLM : Training

- 將語詞序列輸入到RNN；計算出每一個時序的機率分布
- 計算損失值
- 將損失值取平均

RNNLM : Training



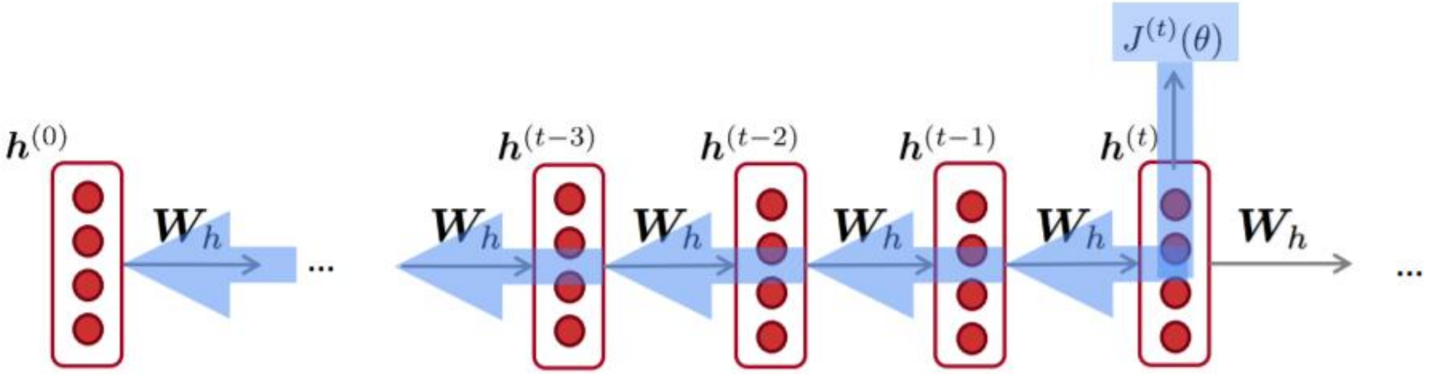


RNNLM : Training

- 利用整個文本來計算梯度非常消耗資源
- 因此，通常我們採用小Batch的句子或文本來計算梯度

反向傳播及損失函數

RNN : 反向傳播



- $\frac{\partial J^{(t)}}{\partial W_h} = \sum_{i=1}^{t} \boxed{\frac{\partial J^{(t)}}{\partial W_h|_i}}$

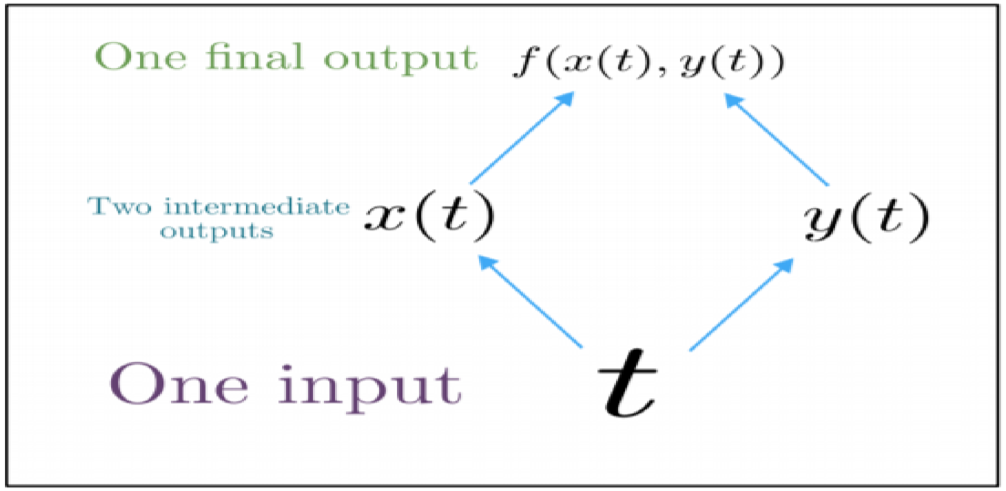
How to Calculate?

- This is called "backpropagation through time"

Backpropagation : Multivariable Chain Rule

- Given a multivariable function $f(x, y)$, and two single variable functions $x(t)$ and $y(t)$, here's what the multivariable chain rule says:

$$\underbrace{\frac{d}{dt} f(x(t), y(t))}_{\text{Derivative of composition function}} = \frac{\partial f}{\partial x}\frac{dx}{dt} + \frac{\partial f}{\partial y}\frac{dy}{dt}$$



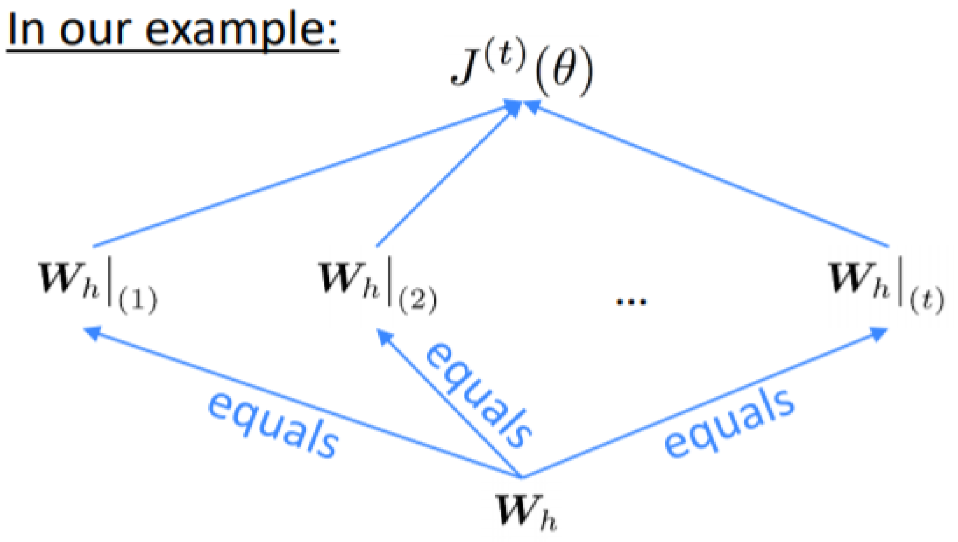
- https://web.stanford.edu/class/archive/cs/cs224n/cs224n.1194/slides/cs224n-2019-lecture06-rnnlm.pdf

Backpropagation : RNN

- $\frac{\partial J^{(t)}}{W_h} = \sum_{i=1}^{t} \frac{\partial J^{(t)}}{\partial W_h|_i} * \boxed{\frac{\partial W_h|_i}{\partial W_h}}$

- $\frac{dx}{dx} = ?$

- Timestep is from t to 1.



- https://web.stanford.edu/class/archive/cs/cs224n/cs224n.1194/slides/cs224n-2019-lecture06-rnnlm.pdf

RNN : 損失函數

- 損失函數的選擇會根據不同的任務而不同
- 如果我們任務是輸出一個機率分布
  - Cross-Entropy Loss
- 如果我們的任務為預測下一個語詞
  - 目標將會是最大化Log-Likelihood 或是最小化負的Log-Likelihood

演算法複雜度及句子的長度

如何決定序列的長度?

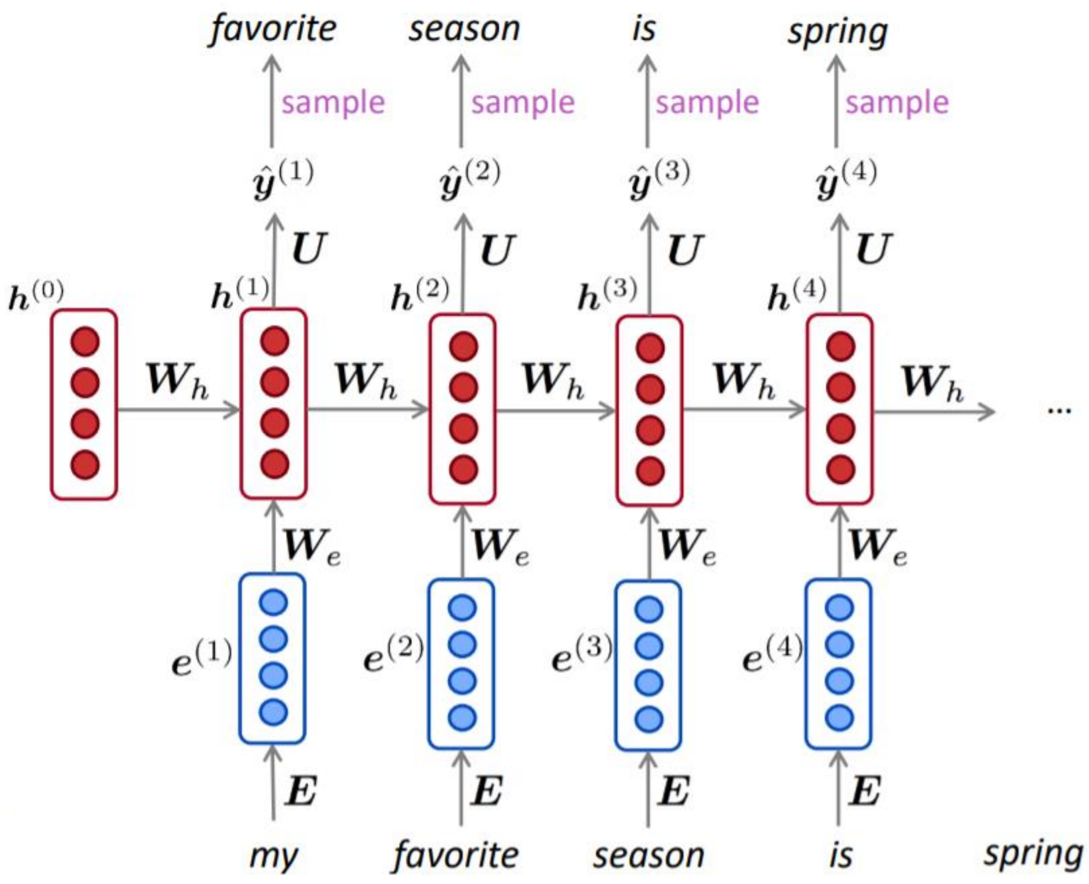
- 在文本中加一個特殊符號，當輸出此特殊符號就停止輸出 (Schmidhuer, 2012)
- 加一個Bernoulli的模型判斷是否繼續輸出 (better and more general)
- 加一個而外的輸出來預測輸出序列長度 (Goodfellow, 2014d)

RNN：演算法複雜度

- Forward Propagation Runtime (cannot be parallelized)
  - $O(\tau)$
- Forward Propagation Memory Cost
  - $O(\tau)$
- Backward Propagation Runtime
  - $O(\tau)$
- Parameter Complexity
  - O(1)

Text Generation Example

RNNLM : Text Generation



RNNLM trained on Harry Potter

- Have the characteristic's name but still difficult to read. It has run-on sentences.

"Sorry," Harry shouted, panicking—"I'll leave those brooms in London, are they?"

"No idea," said Nearly Headless Nick, casting low close by Cedric, carrying the last bit of treacle Charms, from Harry's shoulder, and to answer him the common room perched upon it, four arms held a shining knob from when the spider hadn't felt it seemed. He reached the teams too.

- https://medium.com/deep-writing/harry-potter-written-by-artificial-intelligence-8a9431803da6

RNNLM trained on Recipes

- Challenging task.
- Still fluent but nonsensical

```
     Title: CHOCOLATE RANCH BARBECUE
Categories: Game, Casseroles, Cookies, Cookies
     Yield: 6 Servings

     2 tb Parmesan cheese -- chopped
     1 c  Coconut milk
     3    Eggs, beaten

  Place each pasta over layers of lumps. Shape mixture into the moderate oven and simmer
  until firm. Serve hot in bodied fresh, mustard, orange and cheese.

  Combine the cheese and salt together the dough in a large skillet; add the ingredients
  and stir in the chocolate and pepper.
```

- https://gist.github.com/nylki/1efbaa36635956d35bcc

RNNLM trained on Paint Color Name

- character lever RNNLM
- Trained by using RGB

- https://aiweirdness.com/post/160776374467/new-paint-colors-invented-by-neural-network

語言模型的評估

困惑度 (Perplexity)

- 用來評估語言模型
- 困惑度越低越佳
- 困惑度公式如下

$$perplexity = \prod_{t=1}^{T}\left(\frac{1}{P(x^{(t+1)}|x^{t}\dots x^{1})}\right)^{1/T}$$

$$= exp\left(\frac{1}{T}\sum_{t=1}^{T} -\log \hat{y}_{x_{t+1}}^{(t)}\right) = \exp(J(\theta))$$

RNNs have greatly improved perplexity

Model	Perplexity
Interpolated Kneser-Ney 5-gram (Chelba et al., 2013)	67.6
RNN-1024 + MaxEnt 9-gram (Chelba et al., 2013)	51.3
RNN-2048 + BlackOut sampling (Ji et al., 2015)	68.3
Sparse Non-negative Matrix factorization (Shazeer et al., 2015)	52.9
LSTM-2048 (Jozefowicz et al., 2016)	43.7
2-layer LSTM-8192 (Jozefowicz et al., 2016)	30
Ours small (LSTM-2048)	43.9
Ours large (2-layer LSTM-2048)	39.8

- https://research.fb.com/building-an-efficient-neural-language-model-over-a-billion-words/

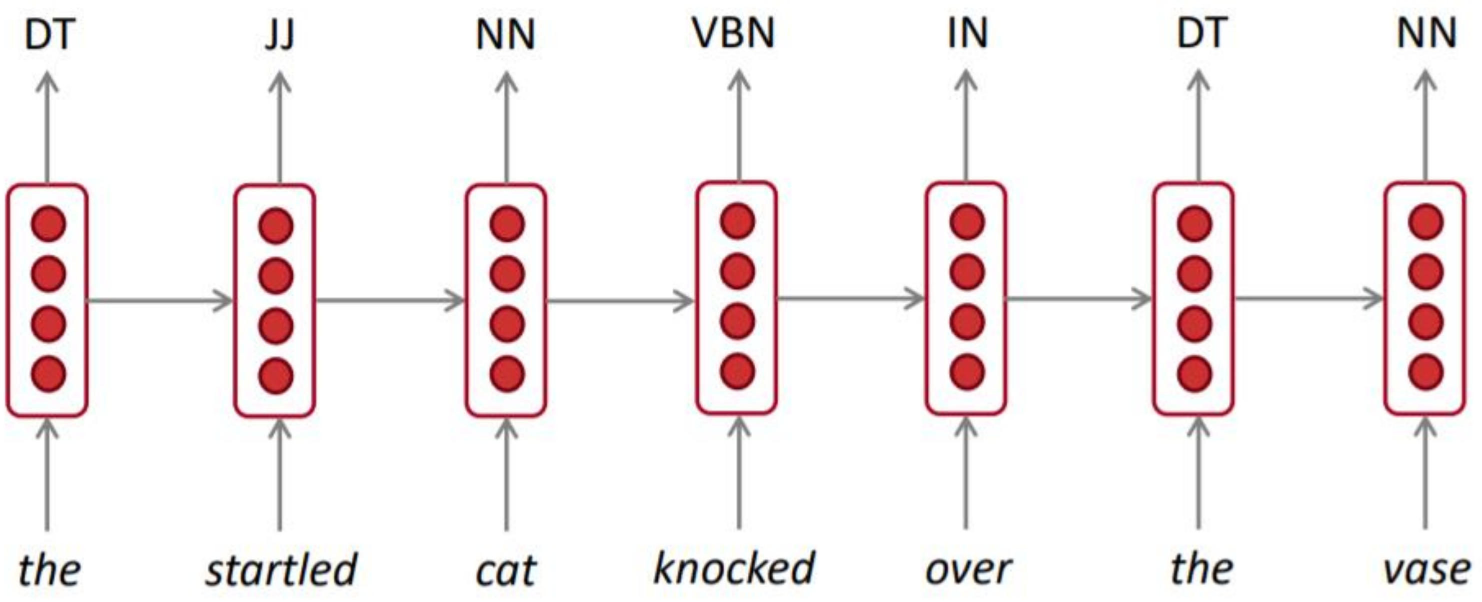
RNN Example

Why is Language Model important?

- Language Model is a benchmark task so it can help us understand how well the computer understands human language.
- Language Model is involved in many NLP tasks. E.g.
  - Predictive Typing
  - Speech Recognition
  - Handwriting Recognition
  - Spelling/Grammar Correction
  - Authorship Identification
  - Machine Translation
  - Summarization
  - Dialogue

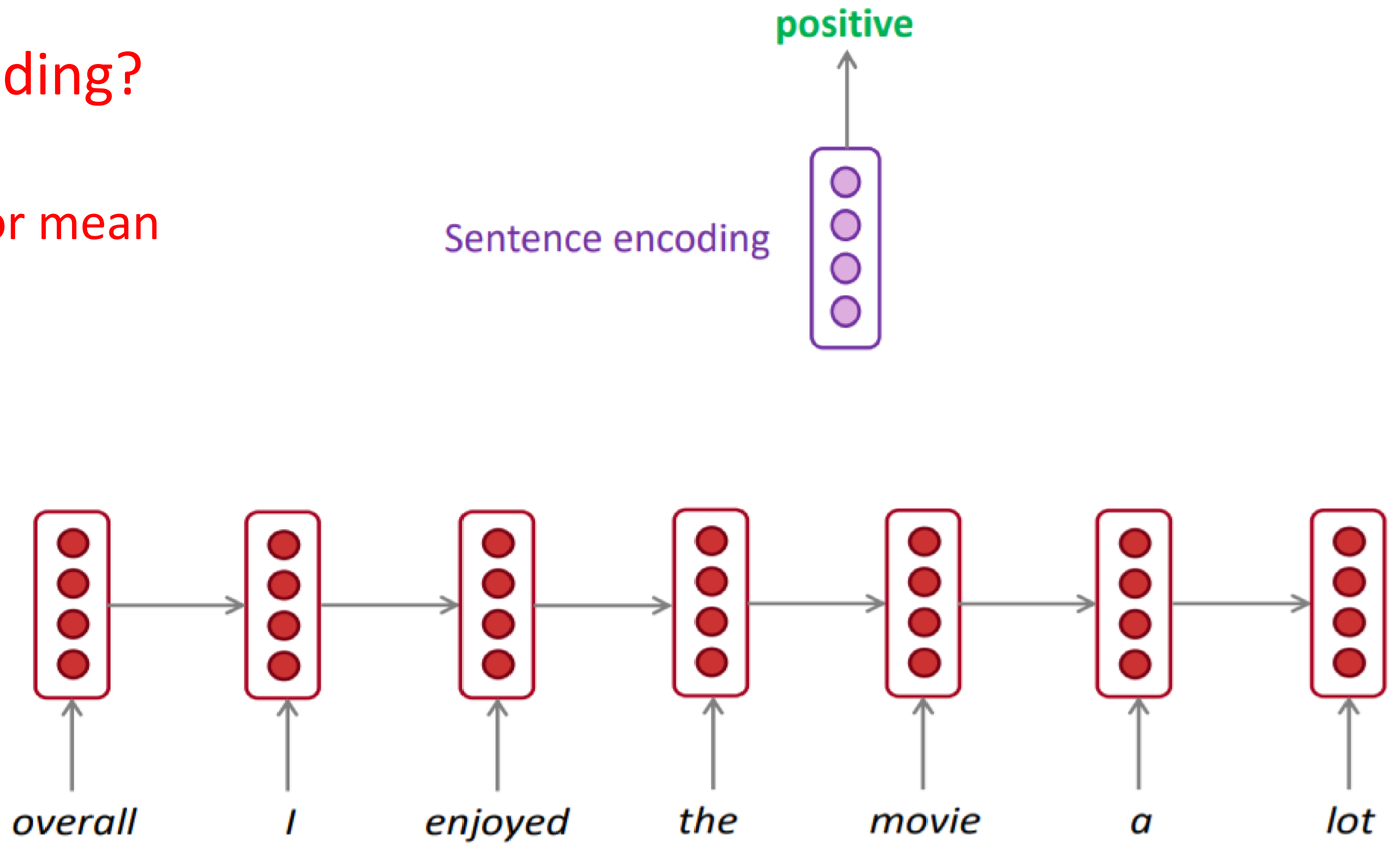
RNN for Tagging

- E.g. Part-of-Speech, Name Entity Recognition



RNN for Sentence Classification

- e.g. Sentiment Classification
- How to choose encoding?
  - Final Hidden State
  - Element-wise max or mean



RNN for Text Generation

- Speech Recognition, Machine Translation etc.

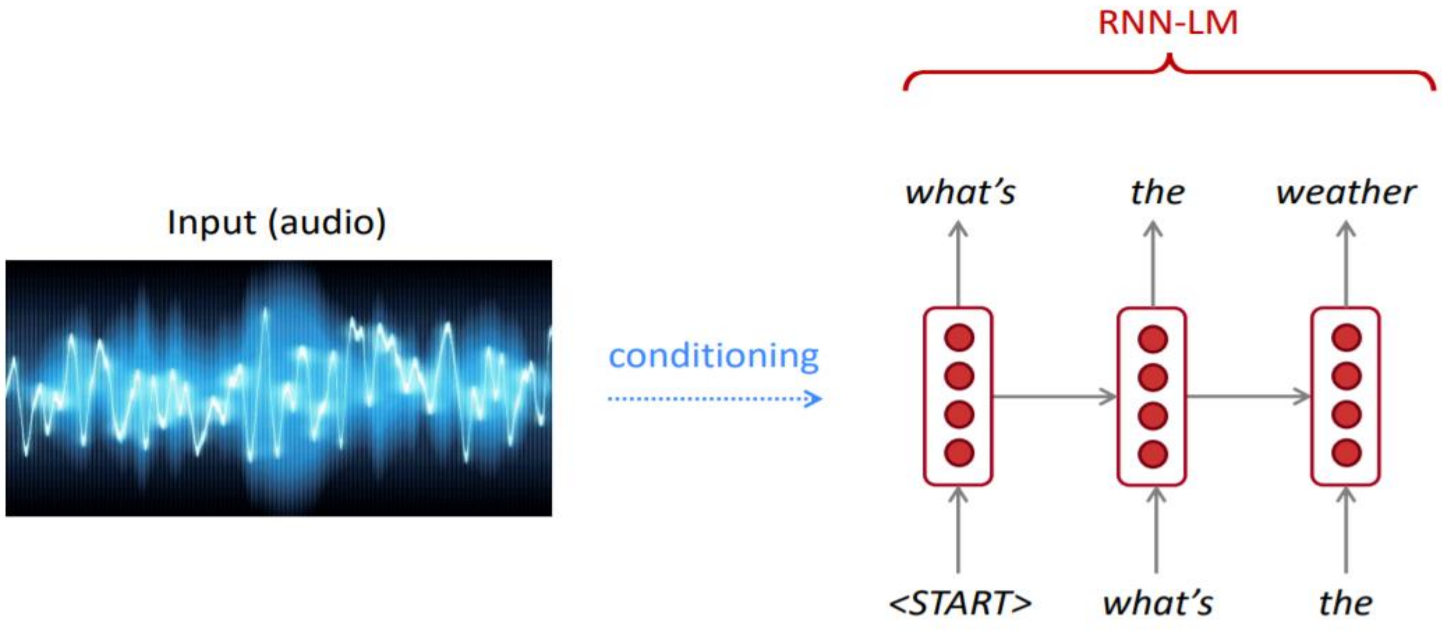


Image Captioning

- The task of describing image by using natural language.

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

"boy is doing backflip on wakeboard."

Fun Examples

```
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''www.e-complete''.

'''See also''': [[List of ethical consent processing]]

== See also ==
*[[Iender dome of the ED]]
*[[Anti-autism]]

===[[Religion|Religion]]===
*[[French Writings]]
*[[Maria]]
*[[Revelation]]
*[[Mount Agamul]]

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* [http://www.biblegateway.nih.gov/entrepre/ Website of the World Festival. The labour of India

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* [http://www.romanology.com/ Constitution of the Netherlands and Hispanic Competition for Bila
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For $\bigoplus_{n=1,\ldots,m}$ where $\mathcal{L}_{m_\bullet} = 0$, hence we can find a closed subset $\mathcal{H}$ in $\mathcal{H}$ and any sets $\mathcal{F}$ on X, U is a closed immersion of S, then $U \to T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \mathrm{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \to V$. Consider the maps M along the set of points Sch_{fppf} and $U \to U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ??. Hence we obtain a scheme S and any open subset $W \subset U$ in $Sh(G)$ such that $\mathrm{Spec}(R') \to S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S. We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \to \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\mathrm{GL}_{S'}(x'/S'')$ and we win. $\square$

To prove study we see that $\mathcal{F}|_U$ is a covering of $\mathcal{X}'$, and $\mathcal{T}_i$ is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and $\mathcal{F}_p$ exists and let $\mathcal{F}_i$ be a presheaf of $\mathcal{O}_X$-modules on $\mathcal{C}$ as a $\mathcal{F}$-module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\mathrm{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1}\mathcal{F})$$

is a unique morphism of algebraic stacks. Note that

$$\mathrm{Arrows} = (Sch/S)^{opp}_{fppf}, (Sch/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \longrightarrow (U, \mathrm{Spec}(A))$$

is an open subset of X. Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S.

Proof. See discussion of sheaves of sets. $\square$

The result for prove any open covering follows from the less of Example ??. It may replace S by $X_{spaces,\acute{e}tale}$ which gives an open subspace of X and T equal to S_{Zar}, see Descent, Lemma ??. Namely, by Lemma ?? we see that R is geometrically regular over S.

References

- 斎藤康毅, Deep Learning 2: 用Python進行自然語言處理的基礎理論實作.
- Manning et al., CS224n Natural Language Processing with Deep Learning, Stanford University.
- Goodfellow et al., Deep Learning Books, Online Version