Natural Language Processing

Deep Learning for Text Classification

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Outline

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1. Processing natural language data
2. Recurrent neural networks
3. Sentiment analysis as classification
4. Case study: sentiment of IMDB movie reviews

Processing Language Data

Representation of Words

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- Traditionally: one-hot, tf-idf, …
  - Sparse

0 0 0 …... 0 1 0 0 … 0

Size = vocabulary size ^{2}
(e.g., ~30000^2)

- Recently: word embedding
  - Dense

0.04 0.05 …

Size = a user-defined smaller size X vocabulary size
(e.g., ~300 X 30000)

Advantages

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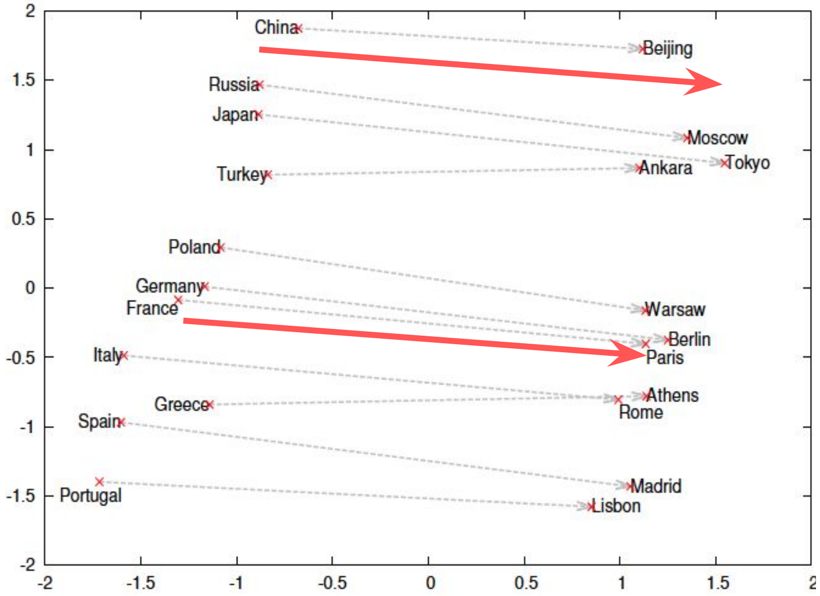
- Not exclusive to deep learning
- Reduced feature size
- Vector arithmetics:
  - “Paris”- “France” + “China” = ?
- Similarity: cosine distance



[Source: Mikolov et al, NIPS’13]

Usage

- Major deep learning toolkits have it conveniently built in!
- Keras (& tensorflow)
  - `keras.layers.Embedding(vocab_size, embedding_size)`
- Input: sequence of word ID
- Output: sequence of word embeddings
- You must create a dictionary & decide its size

Design Challenges (I)

- Size of vocabulary
- Add special words in dictionary: <pad>, <sos>, <eos>, <unk>
- Tokenize and stemming: pros and cons

  Pros: reduce size, group words with similar meanings

  “read”, “reader”, “reading” -> “read”

  Cons: ambiguity, special cases

  “U.S.”, “White House”, “ / and - ”,

Design Challenges (II)

- Length: usually cropped to e.g. 100 words
- Noisy:
  - special invisible symbols → heuristic processing
  - repeated symbols → spaces, !!!!.....,
  - Emoji
  - URLs
- Characters vs. words?

Recurrent Neural Networks (RNN)

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Recurrent Neural Network: Basics

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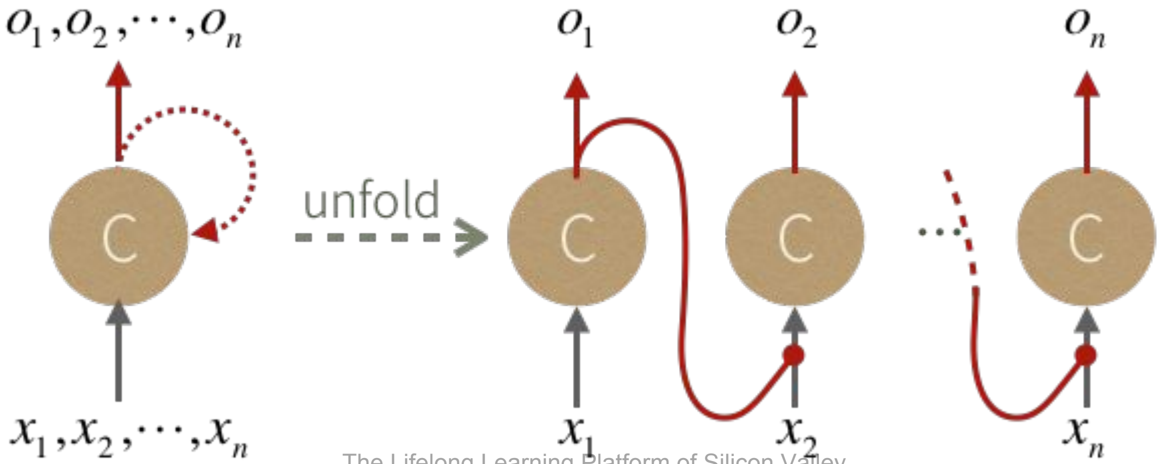
- The same cell *C* is used recurrently (repeatedly)
- A memory (state) is kept in *C* that carries information



RNN Applications

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Almost any **sequential** data!

- NLP: NER, POS tagging, translation, sentiment analysis
- Numerical data: temperature, traffic, air quality...

INPUT	今	天	小	明	心	情	很	好
NER	X	X	PER	PER	X	X	X	X
POS	ND	ND	NB	NB	NA	NA	D	VH

RNN Architectures

Major types:

- Many-to-one: Sentiment analysis, topic classification...
- Many-to-many: NER, Translation...
- One-to-many: NER, Translation...
- One-to-one: *are you kidding?*

?? We will explain later!

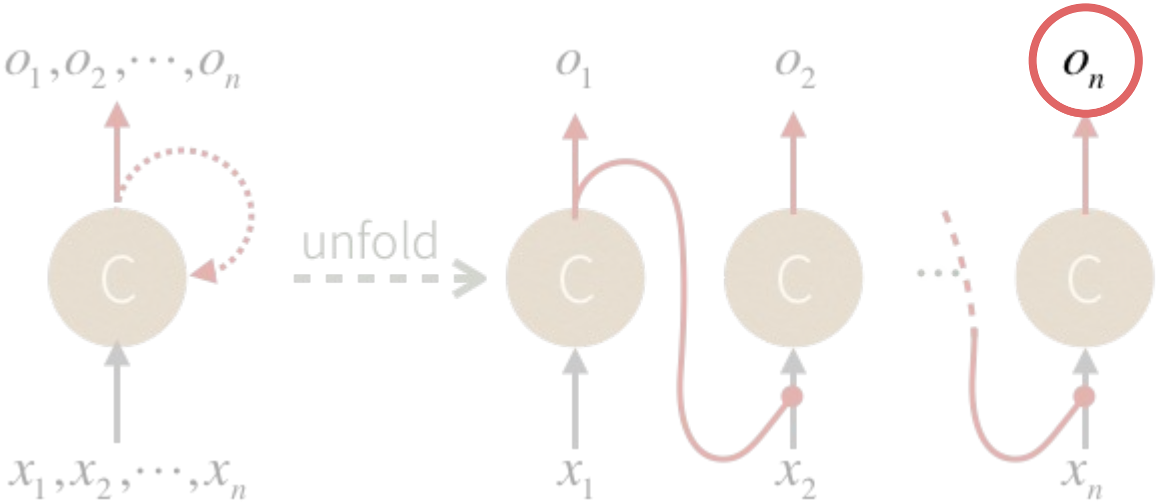
Many-to-one (I)

Major types:

- Many-to-one: Sentiment analysis

INPUT	今	天	小	明	心	情	很	好
OUTPUT								P

Many-to-one (II)



- Only calculate loss against **one** output

Many-to-many (I)

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Major types:

- Many-to-many: NER

INPUT	今	天	小	明	心	情	很	好
OUTPUT	X	X	PER	PER	X	X	X	X

Many-to-many (II)

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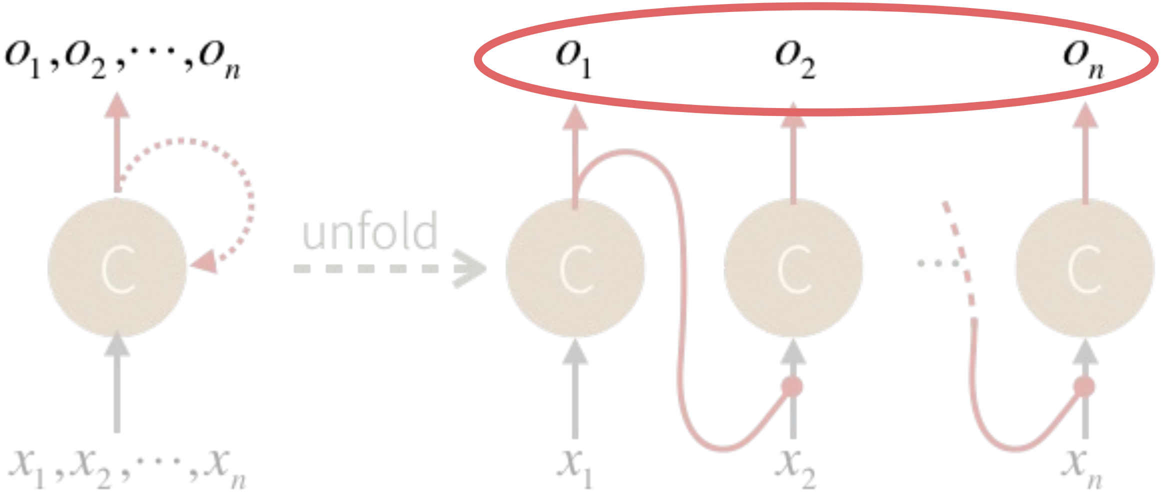

- Calculate loss against the **entire sequence**

One-to-Many (I)

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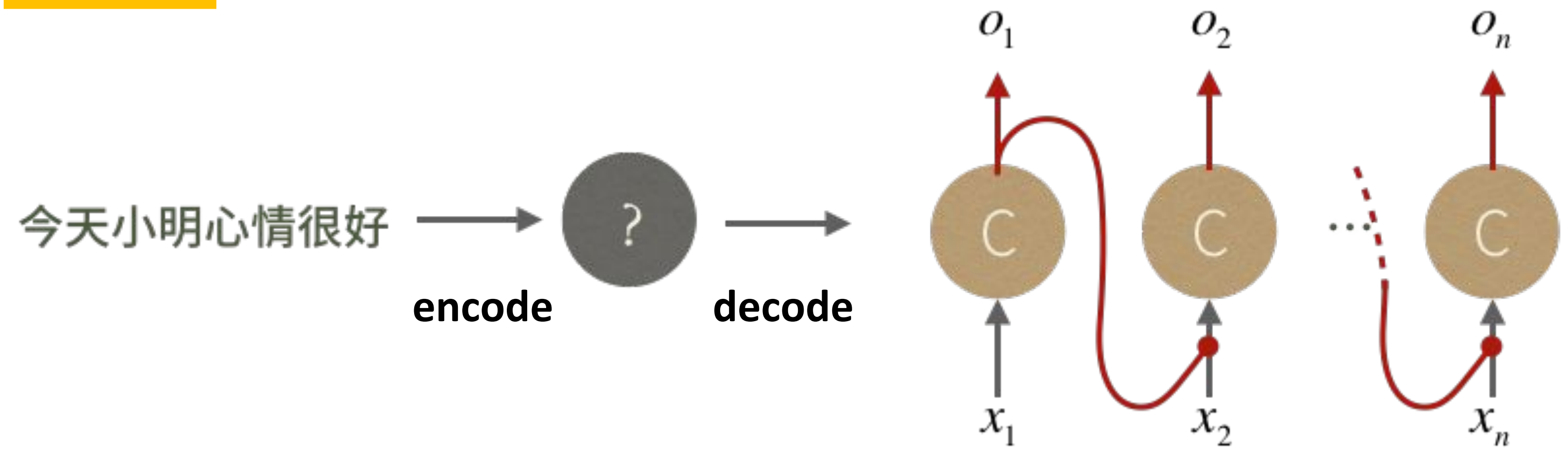
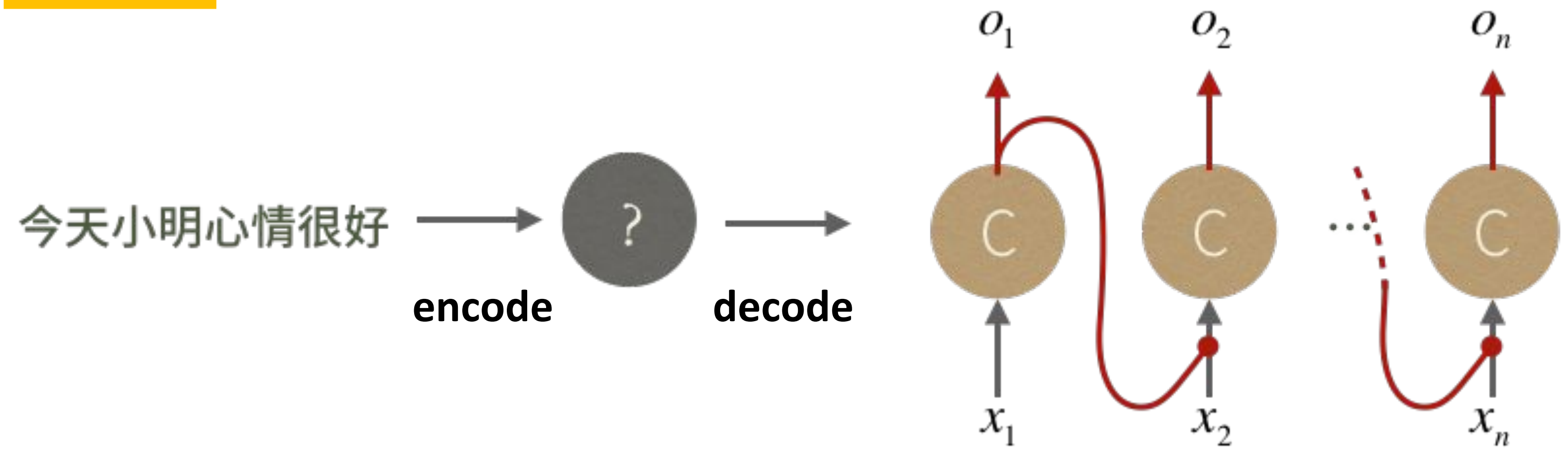


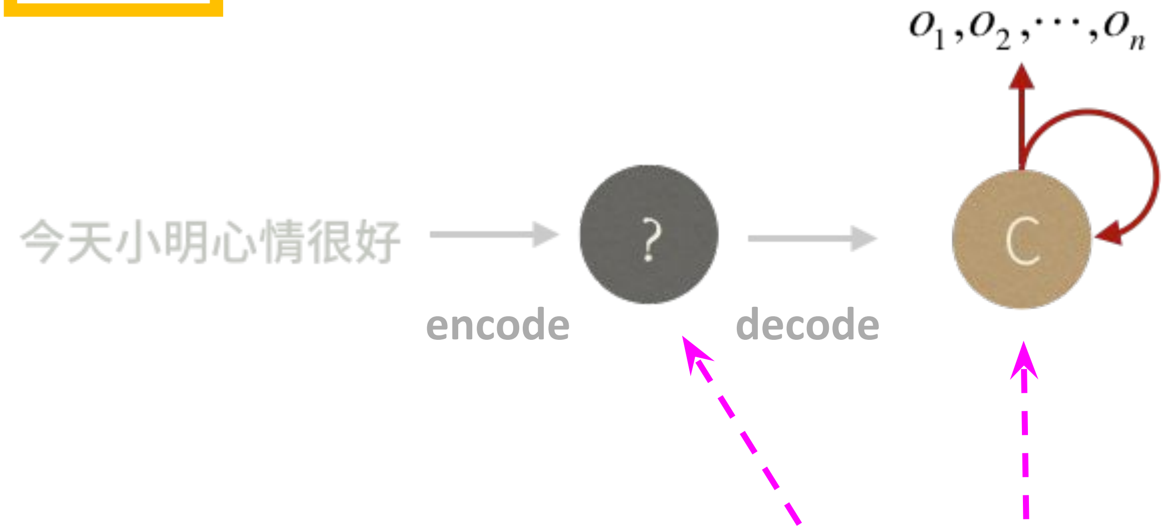
- First, **encode** the sequence into one vector
- Second, **decode** the vector into another sequence

One-to-Many (II)



- Calculate loss against the **entire sequence**
- Back-propagation will also train the encoder

One-to-Many (III)



- Two different networks here, **encoder** and **decoder**
- They can have different architectures! e.g., CNN + RNN

Sequence to sequence (seq2seq)

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- Both input and output are sequences
- Also called “encoder-decoder”
- Can be 1-to-m or m-to-m
- Can have different network architectures
- State-of-the-art in many NLP tasks
- We will talk more about them in Part II and III of this course

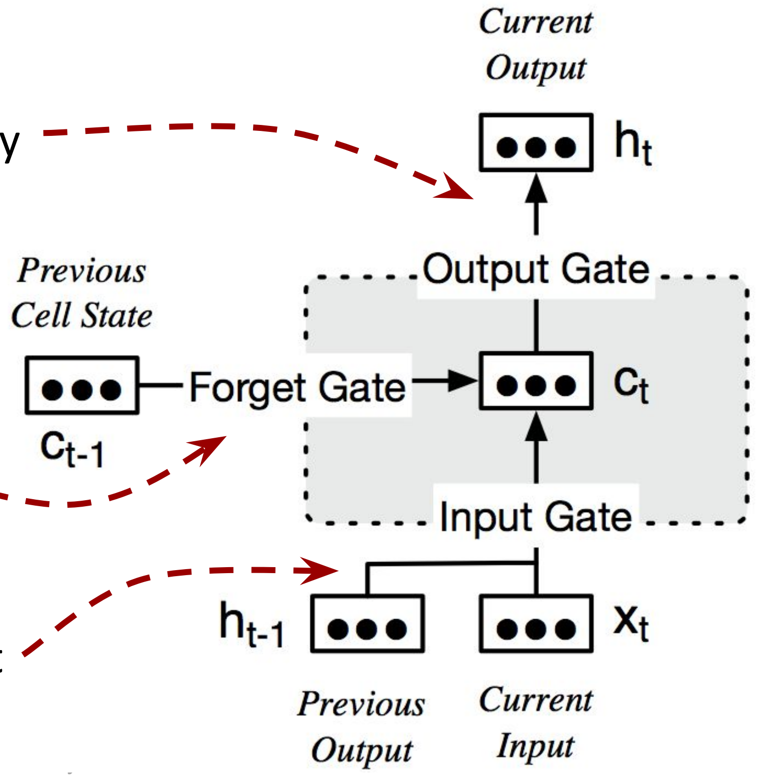
LSTM: concepts

Long Short-Term Memory

- Main concept: learning to forget
- Three **gates**: **input**, **output**, and **forget**
- Gates regulate the values of the input, output, and memory
- Value of the gates are learnable parameters of the model

An LSTM cell

- **Output**: regulate the output from memory
- **Forget**: regulate previous memory
- **Input**: regulate input and previous output



Learning to forget (and more)

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- ***W*** and ***U***: learned weights
- Gate values {0,1}, remember sigmoids?
- So, LSTM “learn” how to modulate gates from the value of input **x** and **h**
- New memory **c** = forget some old memory + input some new memory

$$\left\{\begin{aligned} \mathbf{i}_t &= \sigma(W_i\mathbf{x}_t + U_i\mathbf{h}_{t-1} + \mathbf{b}_i) \\ \mathbf{f}_t &= \sigma(W_f\mathbf{x}_t + U_f\mathbf{h}_{t-1} + \mathbf{b}_f) \\ \mathbf{o}_t &= \sigma(W_o\mathbf{x}_t + U_o\mathbf{h}_{t-1} + \mathbf{b}_o) \end{aligned}\right\}$$

$$\tilde{\mathbf{c}}_t = \tanh(W_c\mathbf{x}_t + U_c\mathbf{h}_{t-1} + \mathbf{b}_c)$$

$$\mathbf{c}_t = \mathbf{f}_t \circ \mathbf{c}_{t-1} + \mathbf{i}_t \circ \tilde{\mathbf{c}}_t$$

$$\mathbf{h}_t = \mathbf{o}_t \circ \tanh(\mathbf{c}_t)$$

Design Challenges: RNN

- Length!
  - Obviously, RNNs will not work for very long sequences
- Direction
  - Use **bidirectional** RNN to attempt to learn long sequences
- Depth
  - Can stack multiple RNNs
- Speed
  - Slow! Why?

Bidirectional RNN

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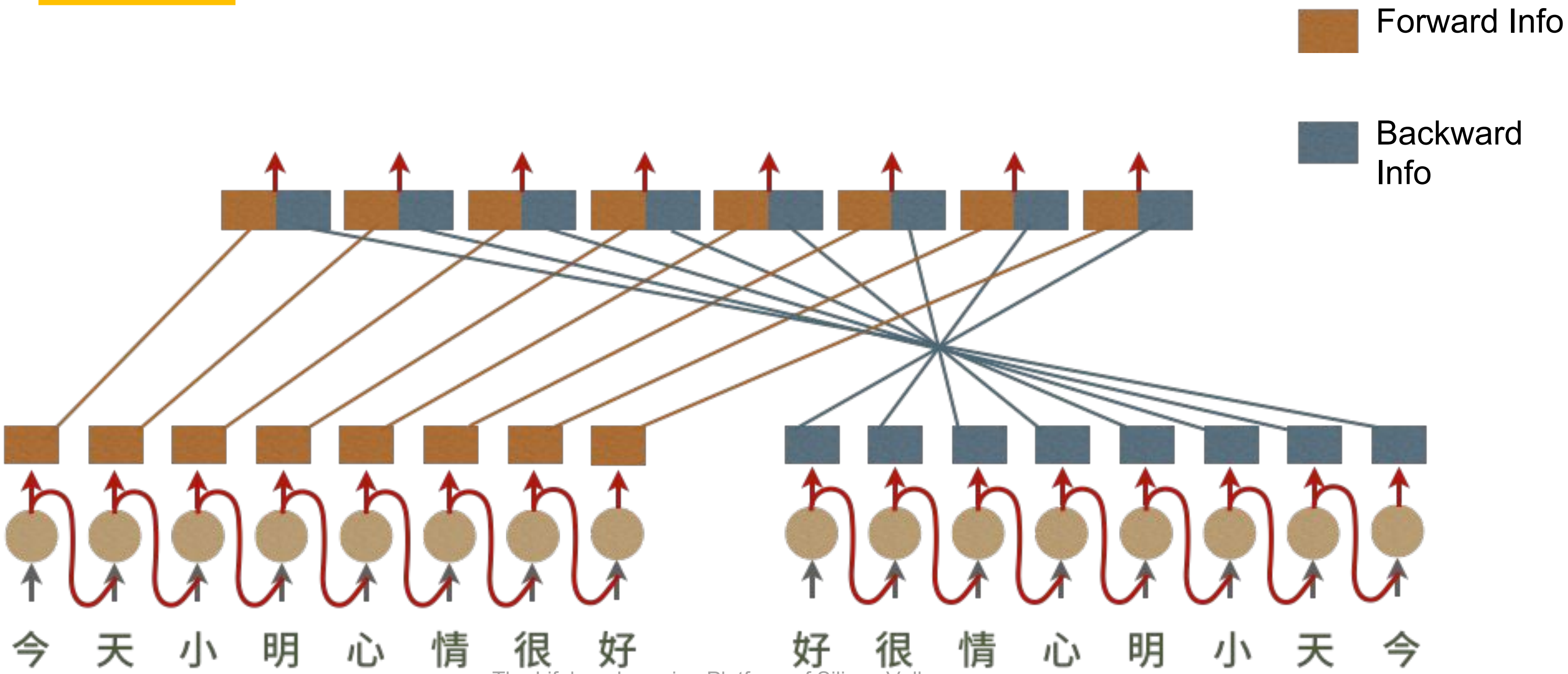

Deep RNN

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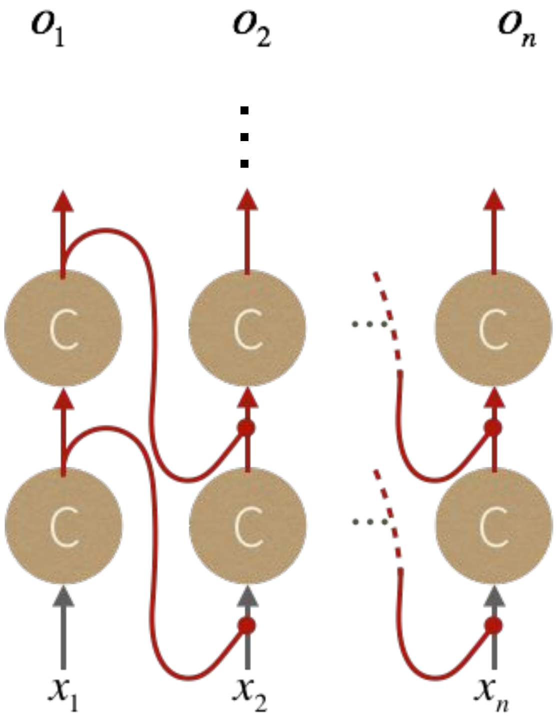

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Speed of RNN

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- Factors: sequence length and size of the RNN cell
    - The step ***t+1*** of the RNN cannot be computed until step ***t*** is completed
    - Size of RNN cell determines the number of parameters

Sentiment Analysis as Classification

Sequence Classification

- Many-to-one architecture
  - Input a sequence, obtain one class label
- In our sentiment analysis project: input a movie review, predict its sentiment as being “positive” or “negative”
- We will go to the code now

Code

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