Dive into Deep Learning in 1 Day

1 Basics · 2 Convnets · 3 Computation · **4 Sequences**

ODSC 2019

Alex Smola
http://courses.d2l.ai/odsc2019/

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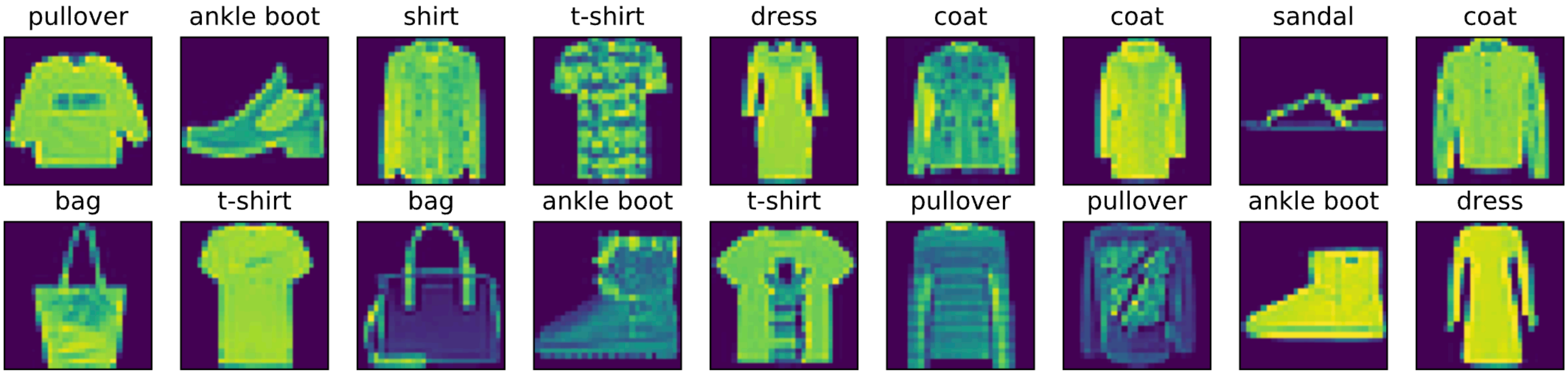
Outline

- Sequence models and language models
- Recurrent neural networks (RNN)
- GRU and LSTM
- Deep RNNs, Bi-RNNs

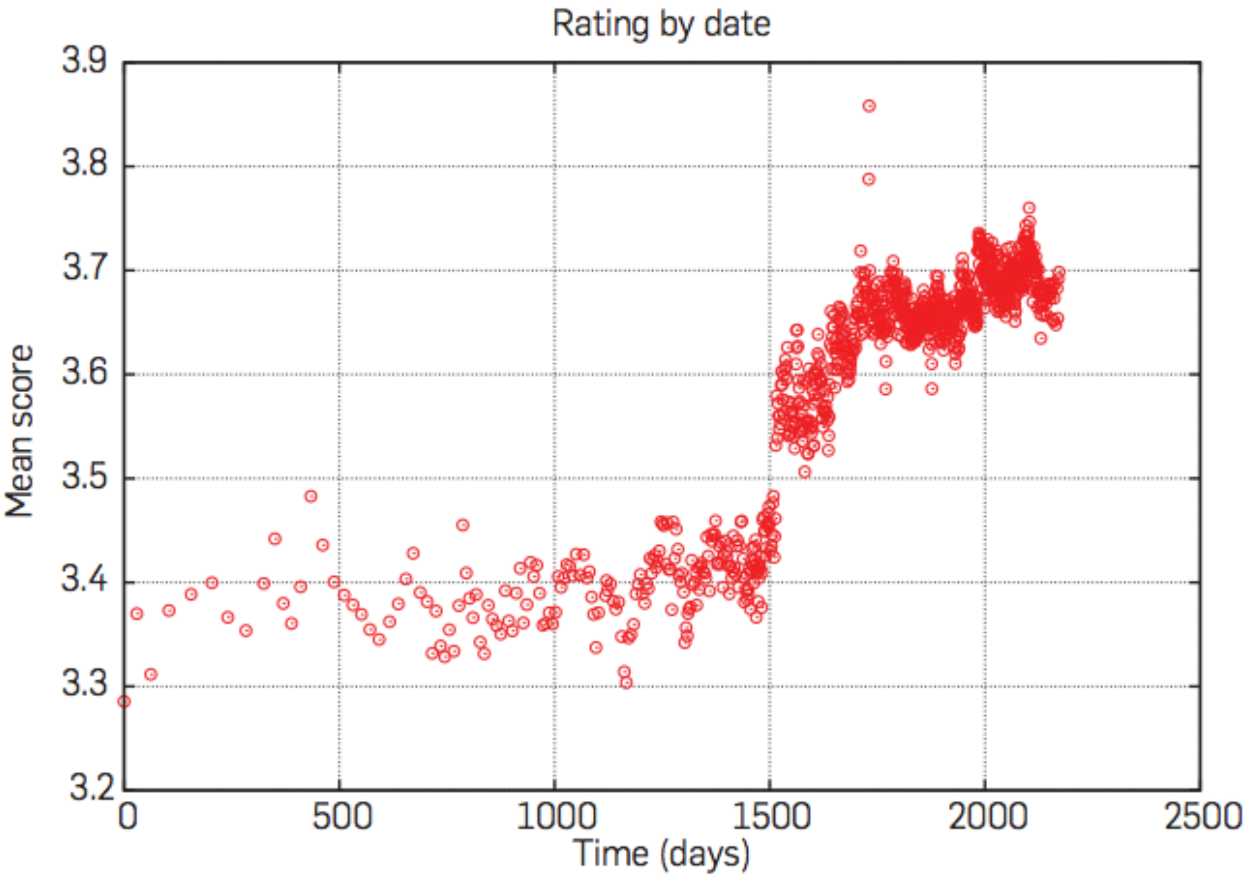
Dependent Random Variables

Data

- So far, collect observation pairs (x_i, y_i) for training
- Assume examples are independent and identically distributed (IID)
  The order of the data does not matter



Time matters (Koren, 2009)



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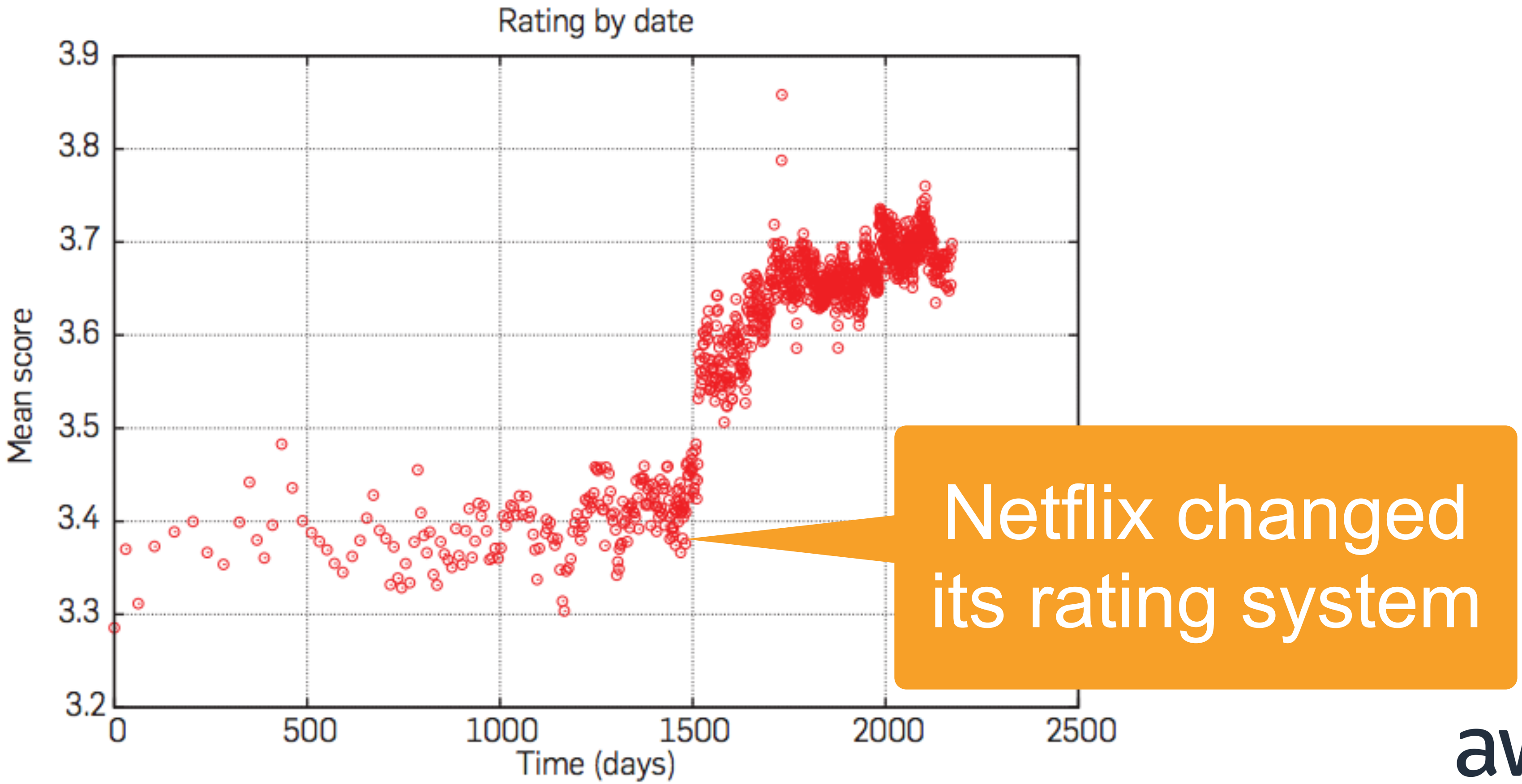

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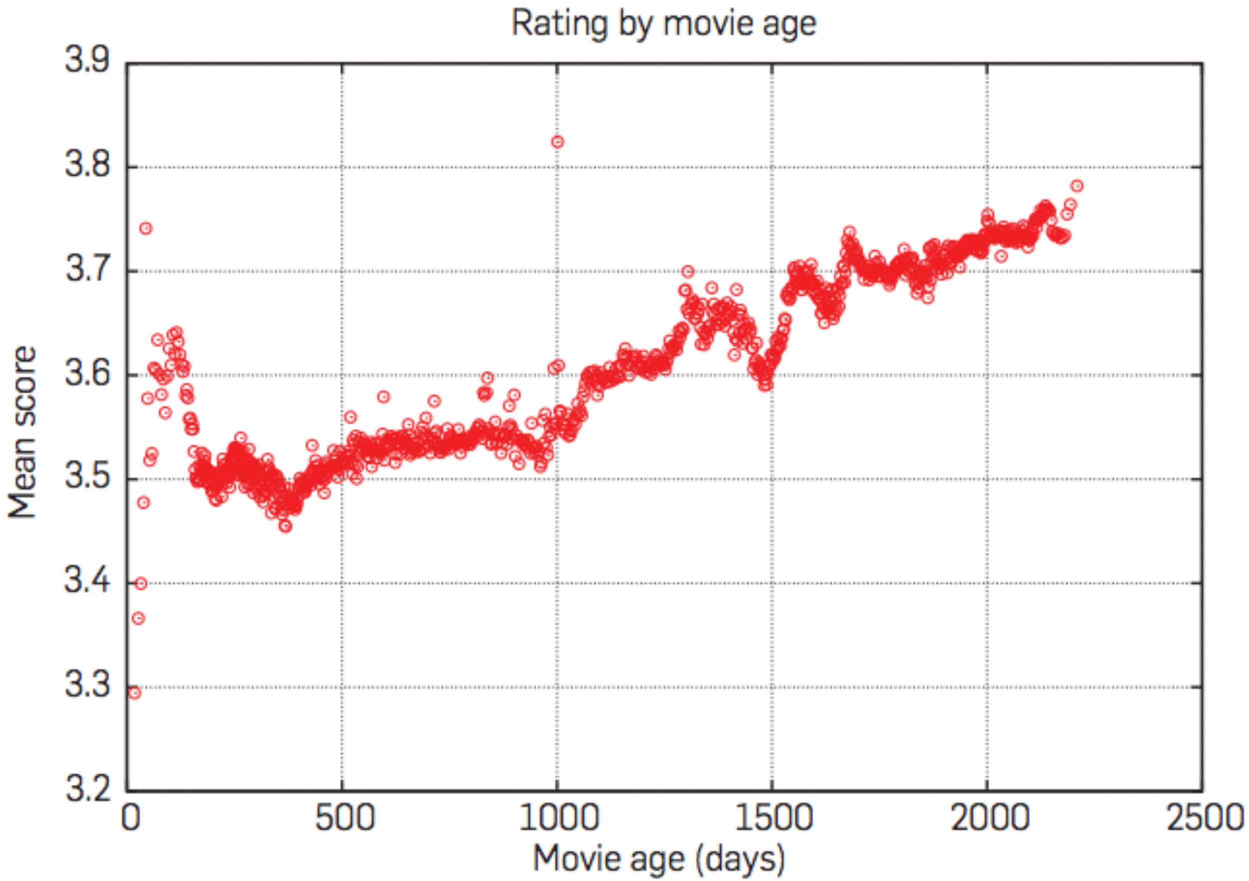

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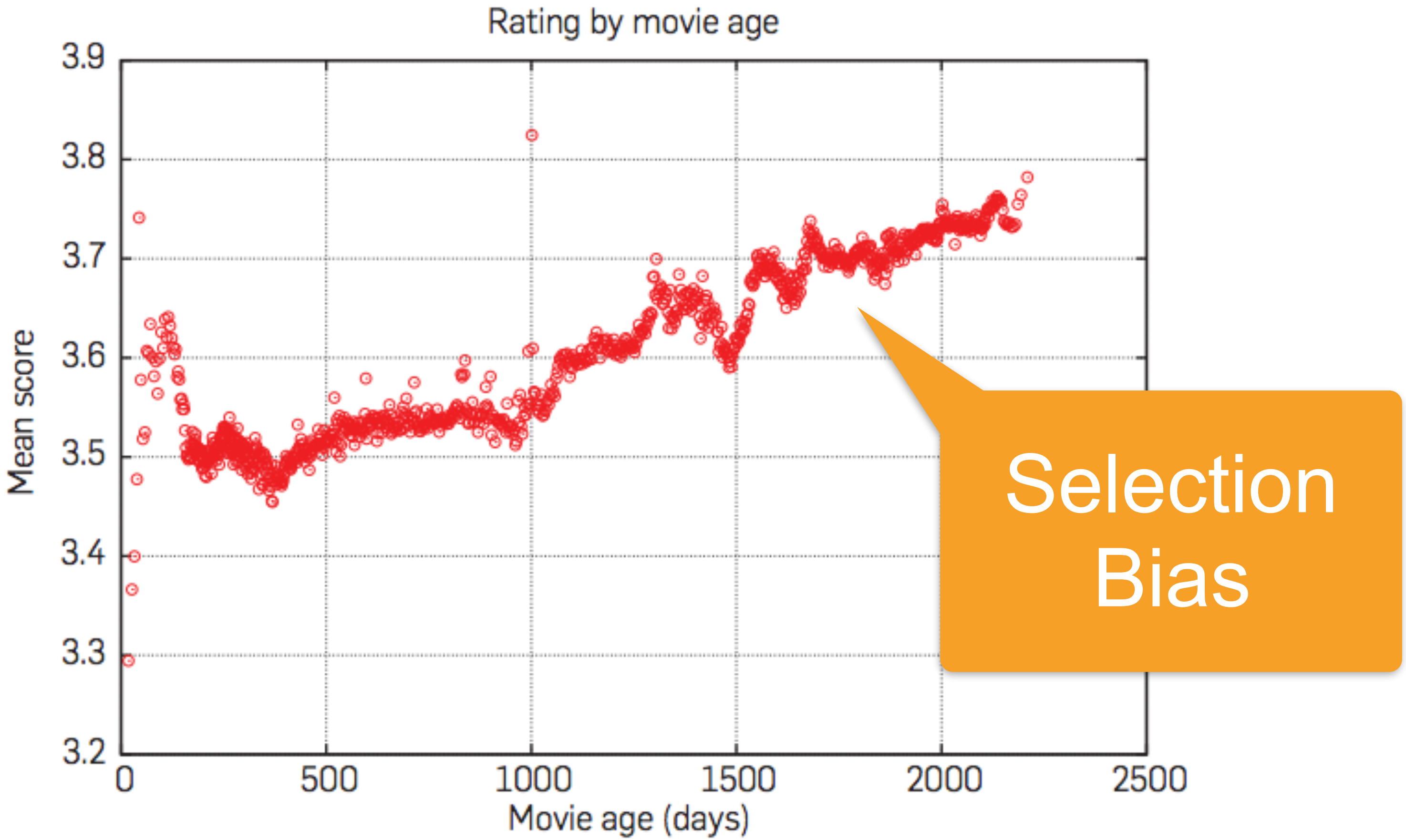

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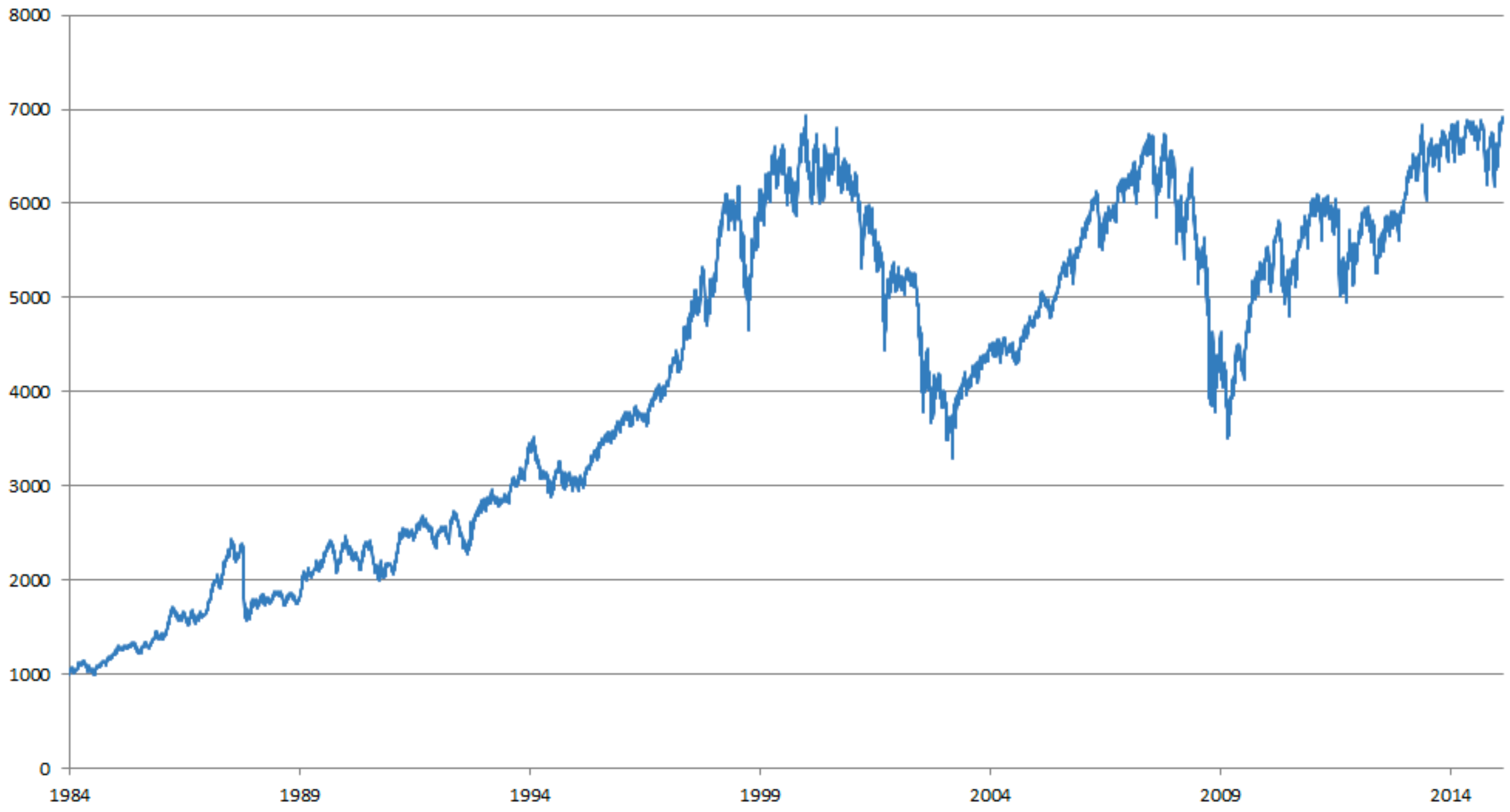
FTSE 100



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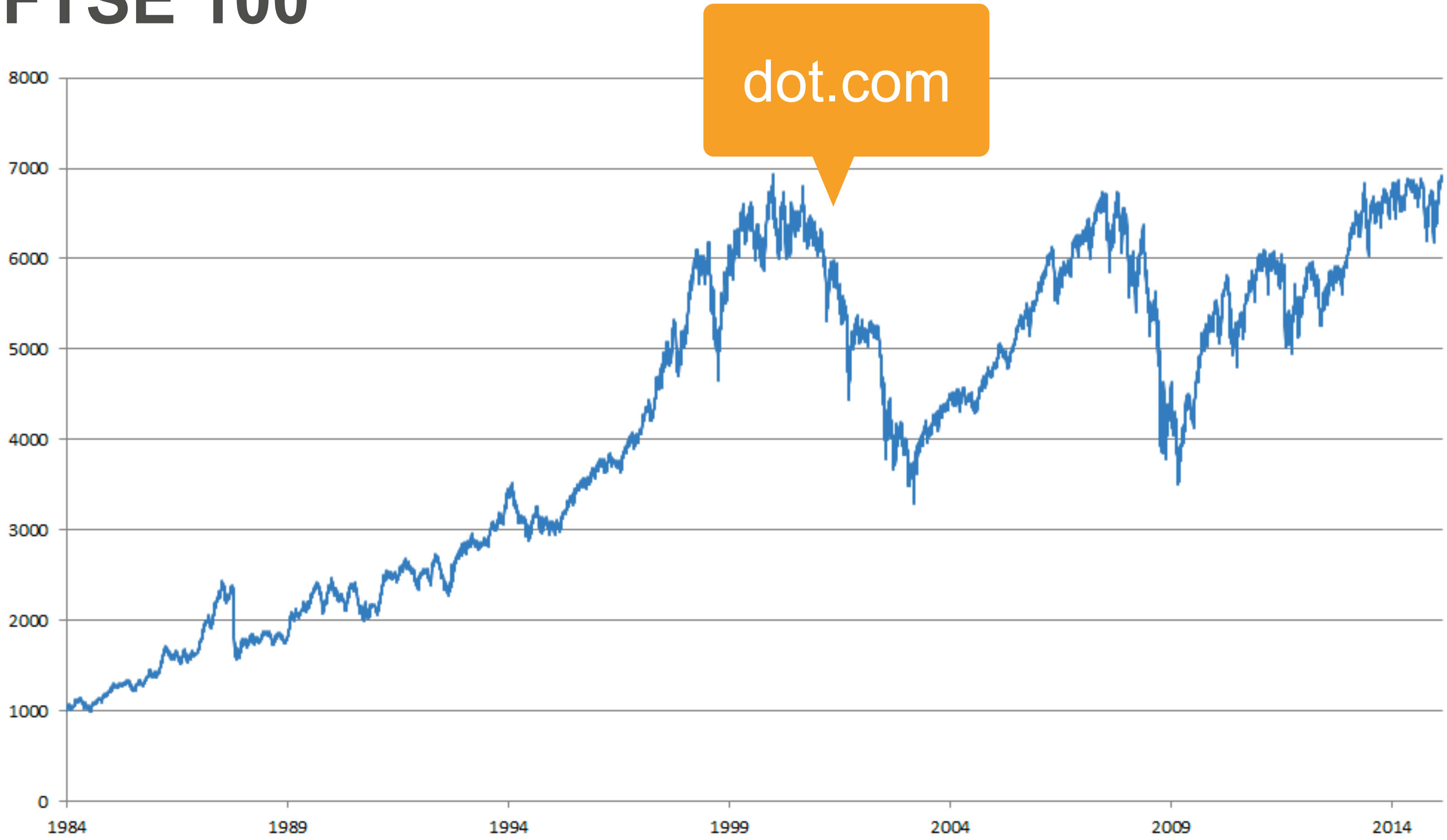
FTSE 100



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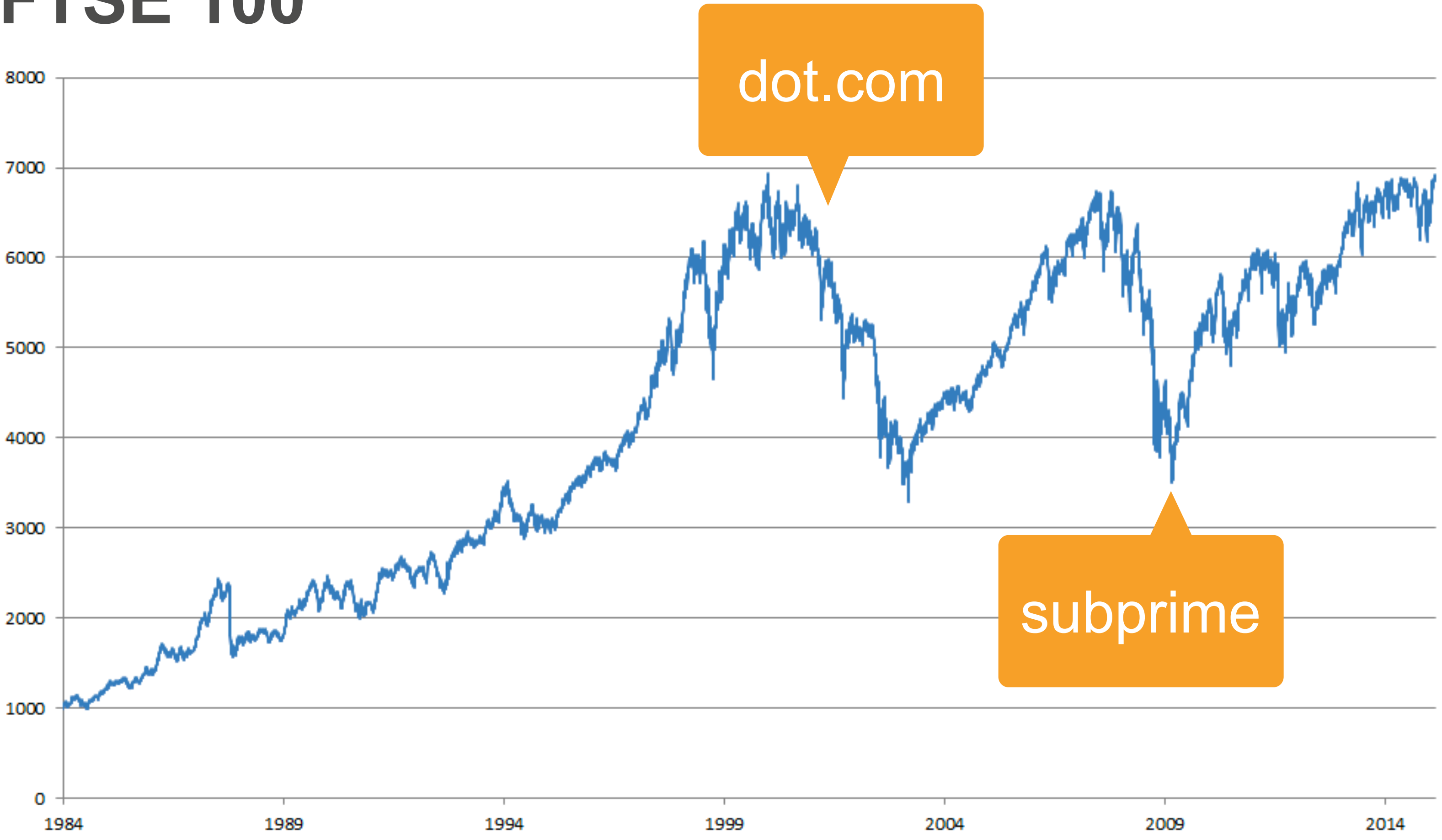
FTSE 100



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rate cuts

rating agencies

Q2 earnings

orange hair tweets

TL;DR - Data usually isn't IID

inventory

Christmas

Black Friday

prime day

back to school

Language Models

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Language Modeling

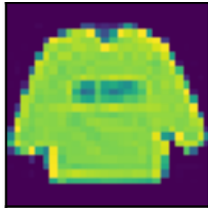
- Goal: predict the probability of a sentence, e.g.

$$p(\text{Deep}, \text{learning}, \text{is}, \text{fun}, .\ )$$

- A fundamental task in Natural Language Processing
  - Typing - predict the next word
  - Machine translation - `dog bites man` vs `man bites dog`
  - Speech recognition
    `to recognize speech` vs `to wreck a nice beach`

Text Preprocessing

- Sequence data has long dependency (very costly)
- Truncate into shorter fragments
- Transform examples into mini-batches with ndarrays



(batch size, width, height, channel)

```
The Time Traveller (for so it will be
was expounding a recondite matter to u
twinkled, and his usually pale face wa
fire burned brightly, and the soft rad
lights in the lilies of silver caught
passed in our glasses. Our chairs, bei
caressed us rather than submitted to b
luxurious after-dinner atmosphere when
free of the trammels of precision. And
```

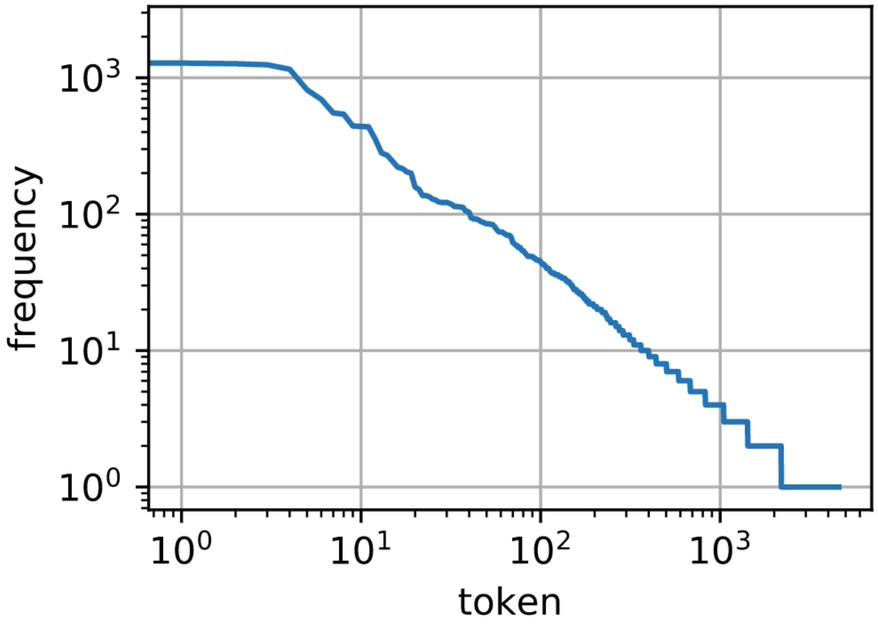
(batch size, sentence length)

Tokenization

- Basic Idea - map text into sequence of tokens
  - “Deep learning is fun” -> [“Deep”, “learning”, “is”, “fun”, “.”]
- **Character Encoding** (each character as a token)
  - Small vocabulary
  - Doesn’t work so well (needs to learn spelling)
- **Word Encoding** (each word as a token)
  - Accurate spelling
  - Doesn’t work so well (huge vocabulary = costly multinomial)
- **Byte Pair Encoding** (Goldilocks zone)
  - Frequent subsequences (like syllables)

Vocabulary

- Find unique tokens, map each one into a numerical index
  - “Deep” : 1, “learning” : 2, “is” : 3, “fun” : 4, “.” : 5
- The frequency of words often obeys a power law distribution
  - Map the tailing tokens, e.g. appears < 5 times, into a special “unknown” token



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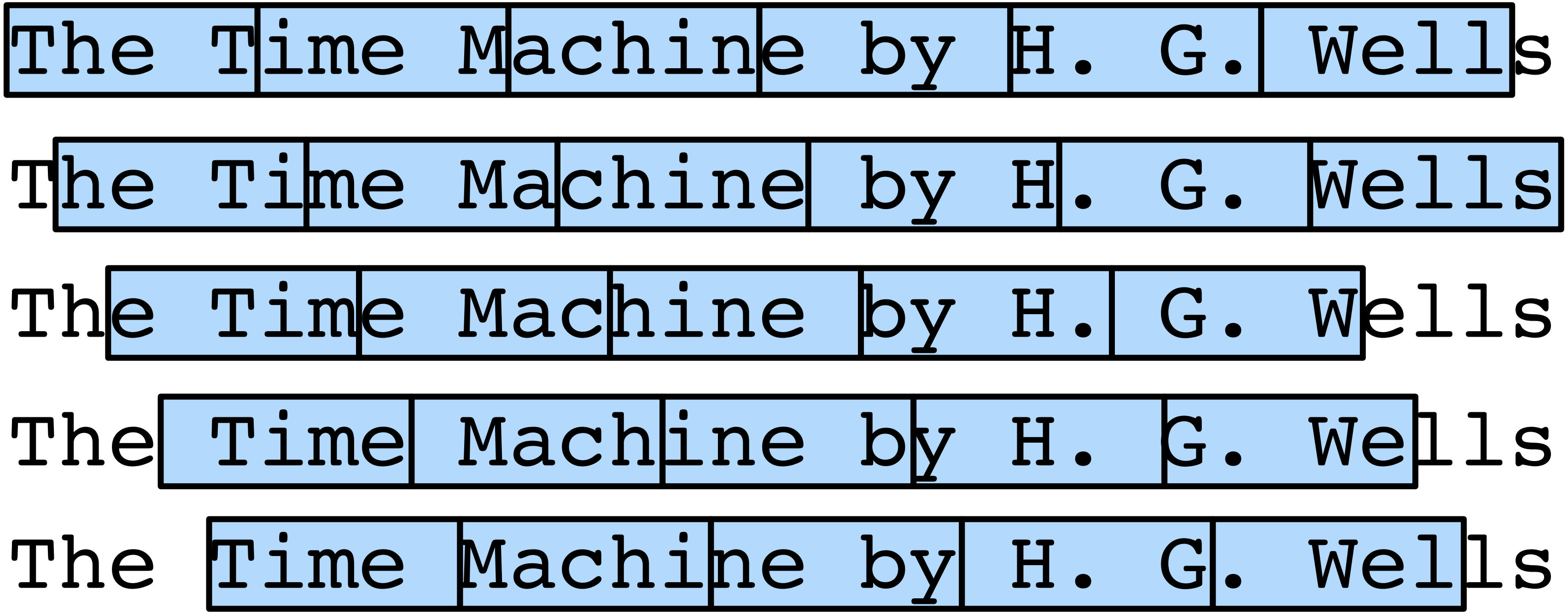
Minibatch Generation

The Time Machine by H. G. Wells



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Text Preprocessing Notebook

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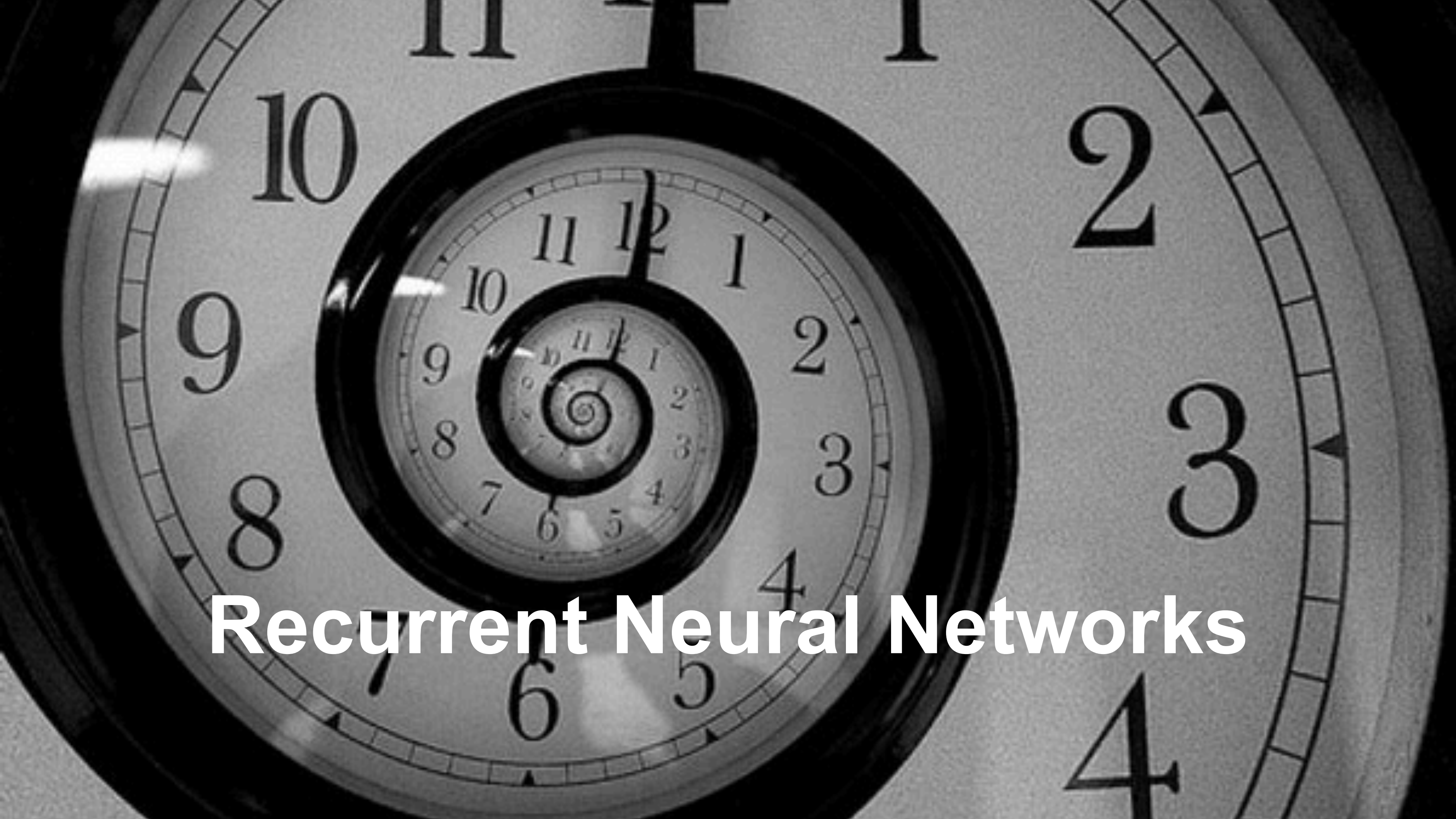
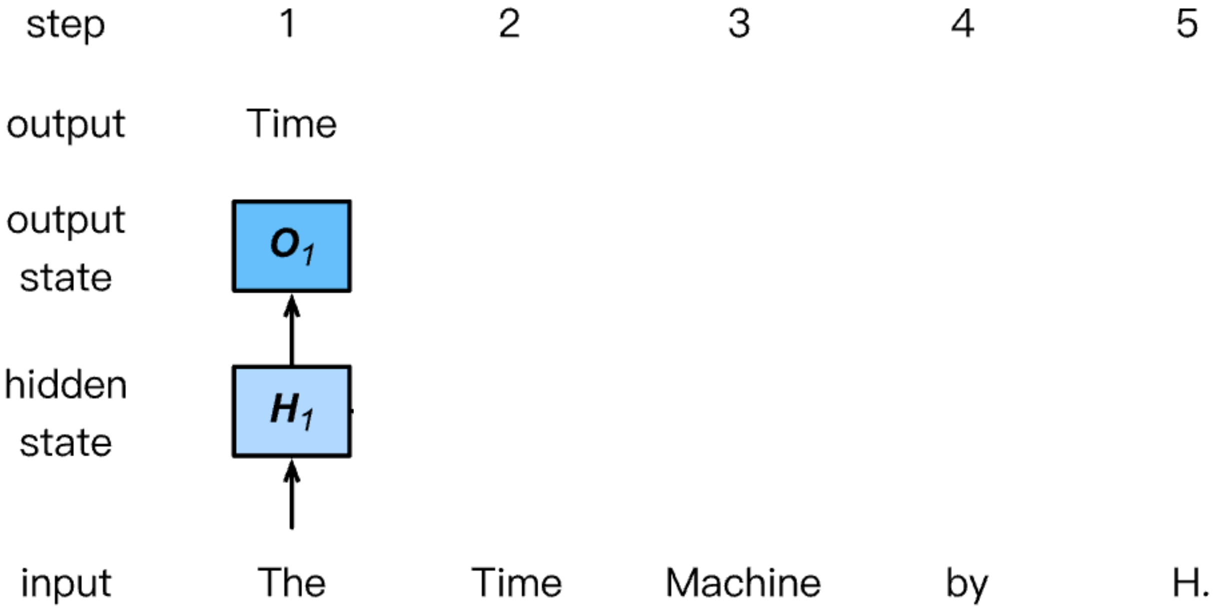
Recurrent Neural Networks



Steps in a Language Model

step	1	2	3	4	5
output					
output state					
hidden state					
input	The	Time	Machine	by	H.

Steps in a Language Model



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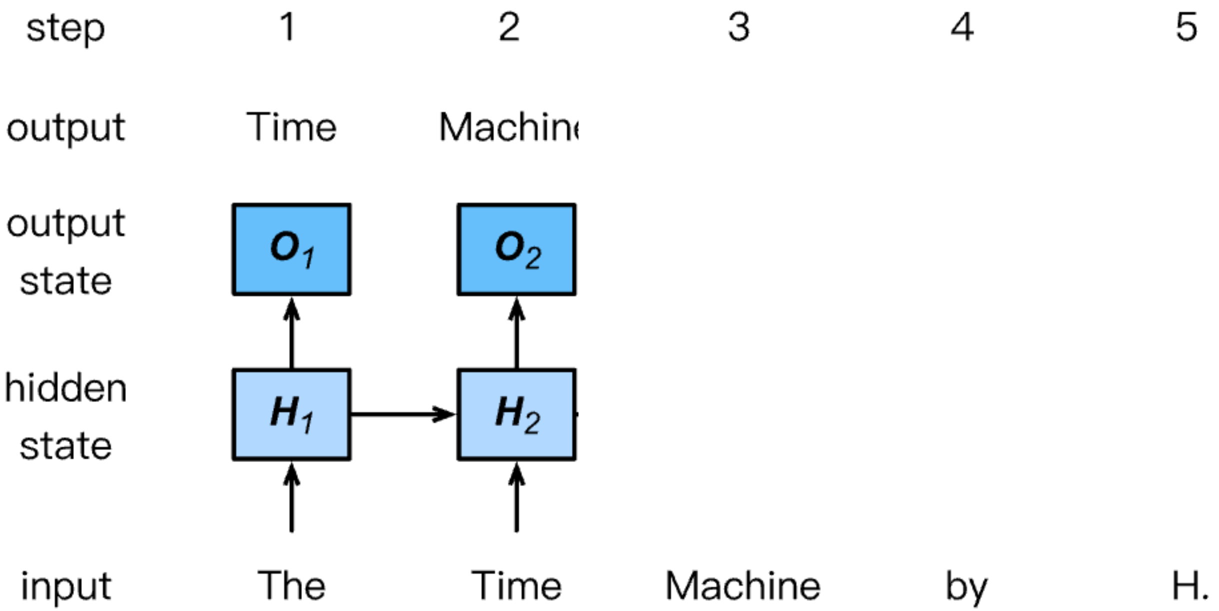
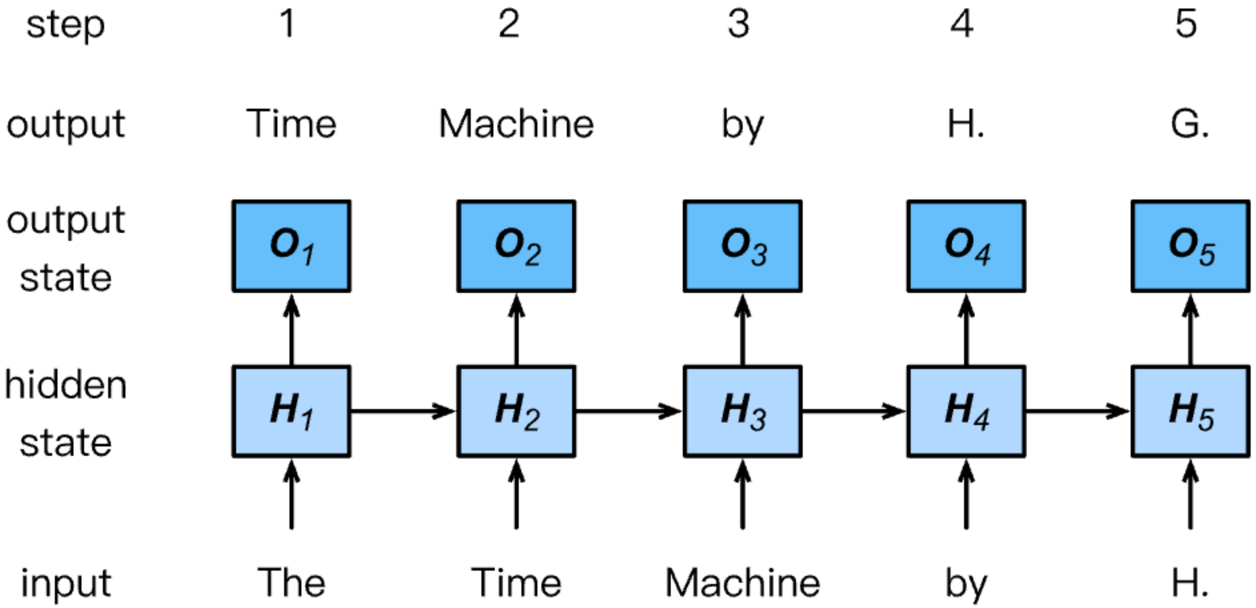
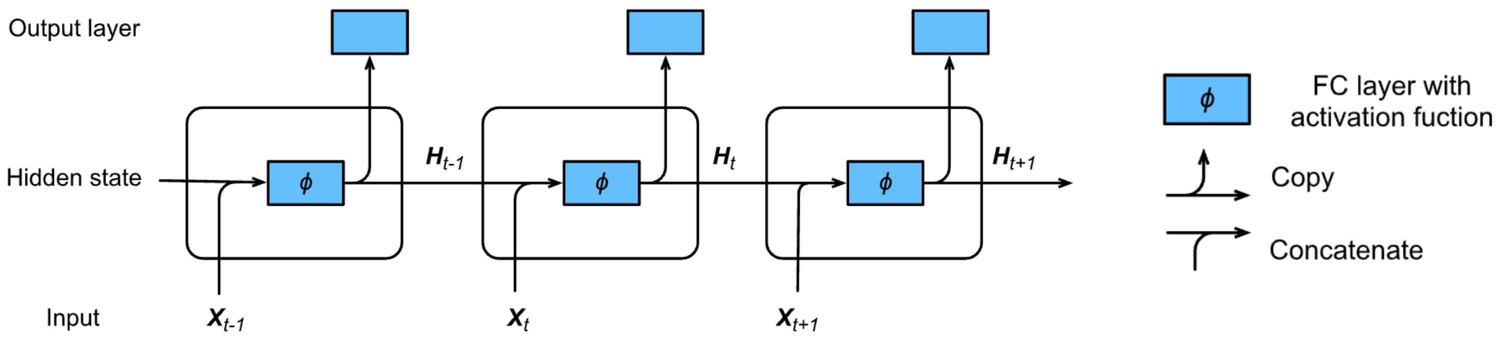
Steps in a Language Model



Steps in a Language Model



Recurrent Networks with Hidden States



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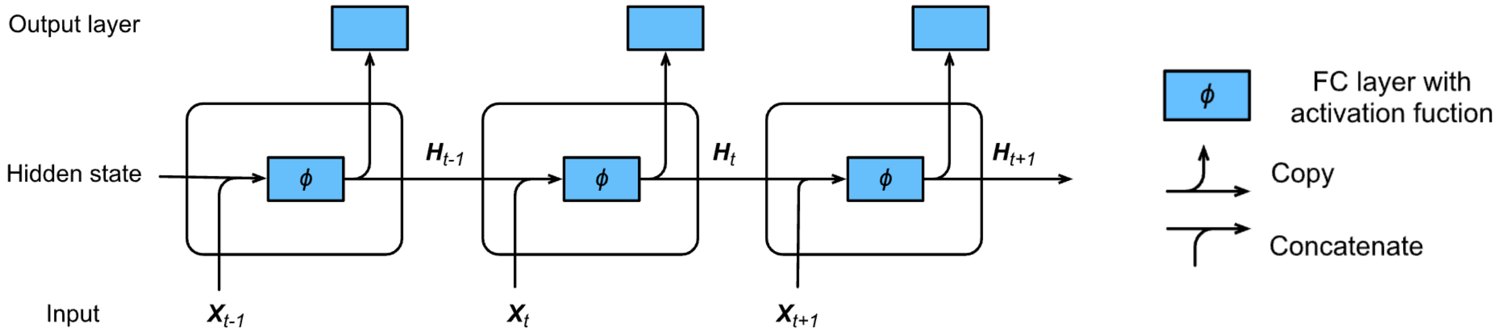

- Hidden State update

$$\mathbf{H}_t = \phi(\mathbf{W}_{hh}\mathbf{H}_{t-1} + \mathbf{W}_{hx}\mathbf{X}_{t-1} + \mathbf{b}_h)$$

- Observation update

$$\mathbf{o}_t = \mathbf{W}_{ho}\mathbf{H}_t + \mathbf{b}_o$$

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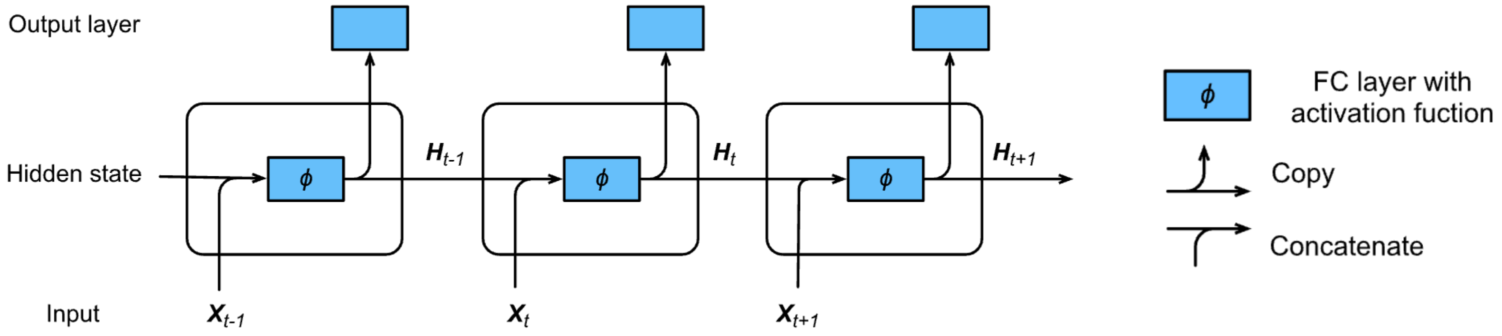
Recurrent Networks with Hidden States



- Hidden State update

$$\mathbf{H}_t = \phi(\boxed{\mathbf{W}_{hh}\mathbf{H}_{t-1}} + \mathbf{W}_{hx}\mathbf{X}_{t-1} + \mathbf{b}_h)$$

- Observation update

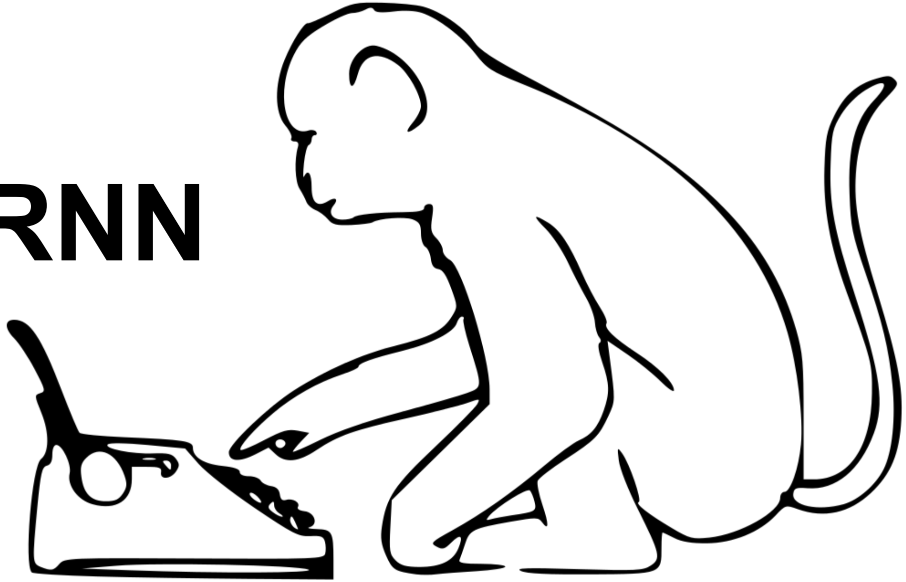
$$\mathbf{o}_t = \mathbf{W}_{ho}\mathbf{H}_t + \mathbf{b}_o$$

- Compare to MLP

$$\mathbf{H}_t = \phi(\mathbf{W}_{hx}\mathbf{X}_{t-1} + \mathbf{b}_h)$$

$$\mathbf{o}_t = \mathbf{W}_{ho}\mathbf{H}_t + \mathbf{b}_o$$

Implementing an RNN Language Model



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Input Encoding

- Need to map input numerical indices to vectors
  - Pick granularity (words, characters, subwords)
  - Map to indicator vectors

```
npx.one_hot(np.array([0, 2]), len(vocab))
```

```
array([[1., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       [0., 0., 1., 0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
```

RNN with hidden state mechanics

- Input: vector sequence $\mathbf{x}_1, \ldots, \mathbf{x}_T \in \mathbb{R}^d$
- Hidden states: $\mathbf{h}_1, \ldots, \mathbf{h}_T \in \mathbb{R}^h$ where $\mathbf{h}_t = f(\mathbf{h}_{t-1}, \mathbf{x}_t)$
- Output: vector sequence $\mathbf{o}_1, \ldots, \mathbf{o}_T \in \mathbb{R}^p$ where $\mathbf{o}_t = g(\mathbf{h}_t)$
  - *p* is the vocabulary size
  - $\mathbf{o}_{t,j}$ is confident score that the *t*-th token in the sequence equals to *j*-th token in the vocabulary
- Loss: measure the classification error on *T* tokens

Perplexity

- Typically measure accuracy with log-likelihood
  - This makes outputs of different length incomparable (e.g. bad model on short output has higher likelihood than excellent model on very long output)
  - Normalize log-likelihood to sequence length

$$-\sum_{t=1}^{T} \log p(y_t \mid \text{model}) \text{ vs. } \pi := -\frac{1}{T} \sum_{t=1}^{T} \log p(y_t \mid \text{model})$$

- Perplexity is exponentiated version $\exp(\pi)$
  (effectively number of possible choices on average)

Gradients

- Long chain of dependencies for backprop
  - Need to keep a lot of intermediate values in memory
  - Butterfly effect style dependencies
  - Gradients can vanish or diverge
- Clipping to prevent divergence

$$\mathbf{g} \leftarrow \min\left(1, \frac{\theta}{\|\mathbf{g}\|}\right)\mathbf{g}$$

rescales to gradient of size at most θ

RNN Notebook

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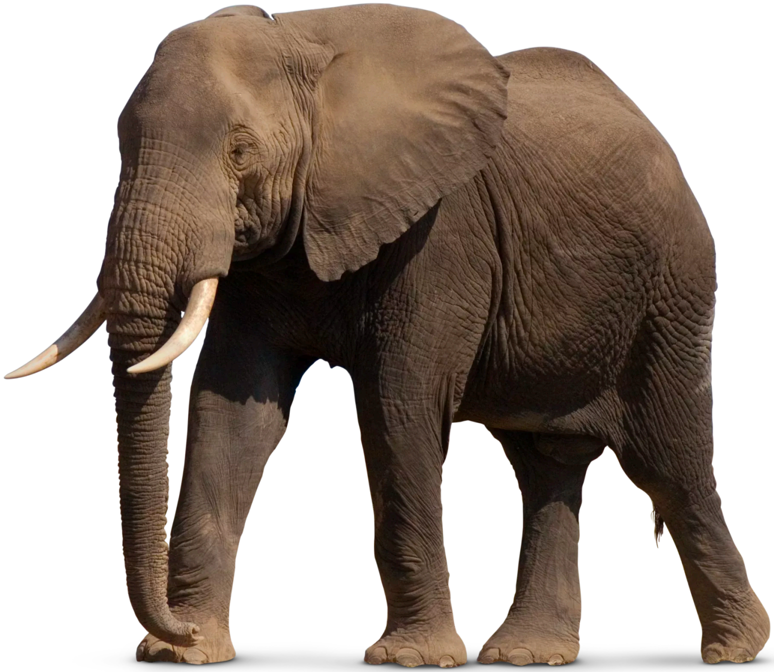
Long Short Term Memory



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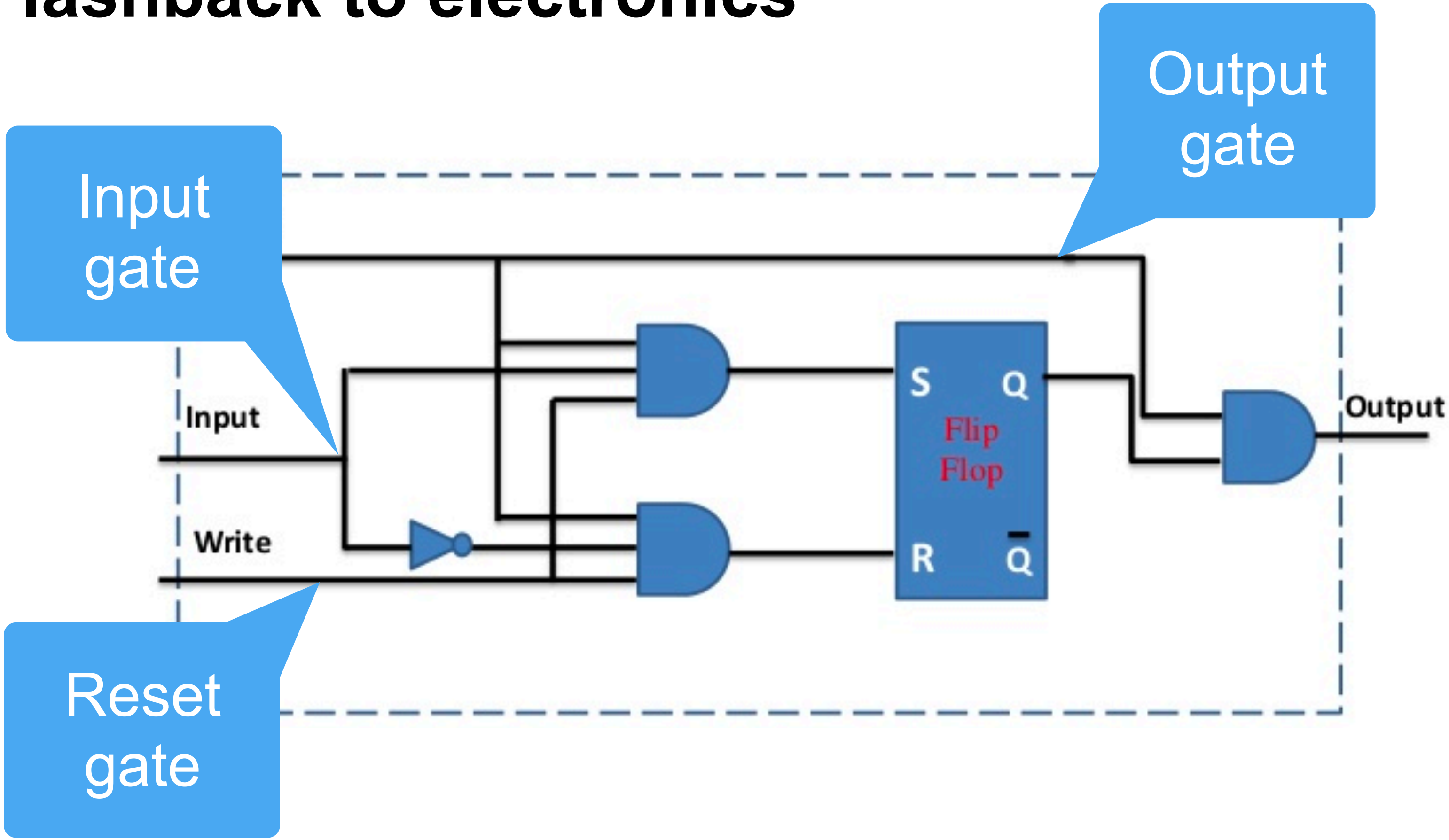
Flashback to electronics



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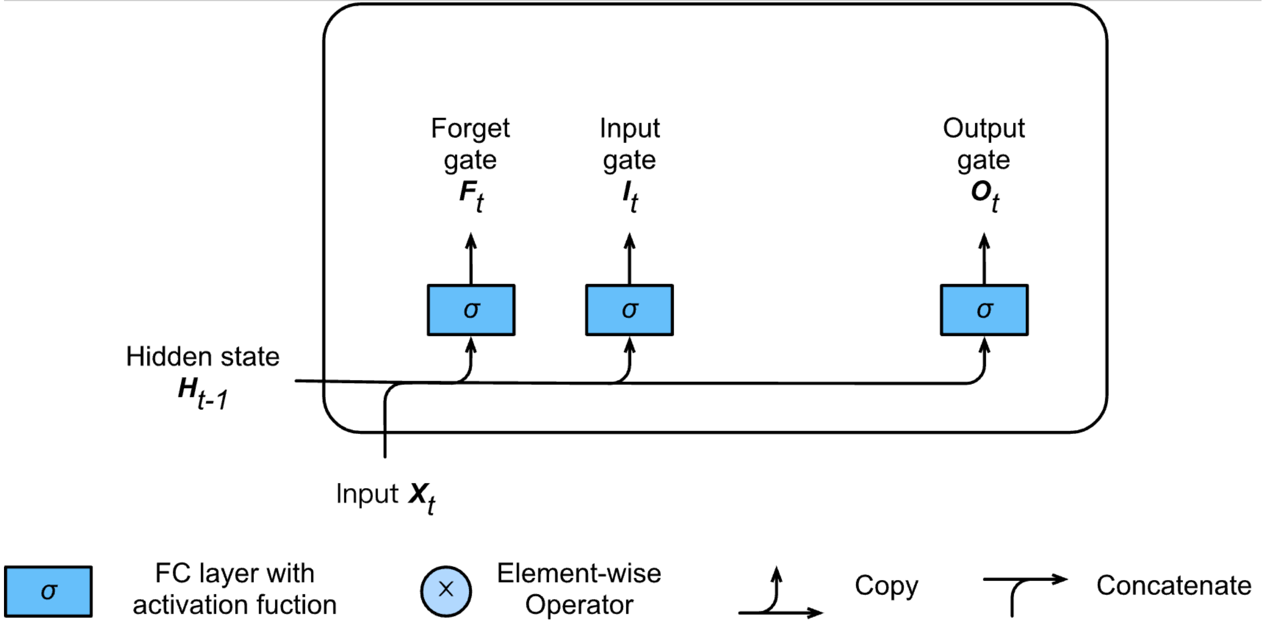
Long Short Term Memory

- **Forget gate**
  Shrink values towards zero
- **Input gate**
  Decide whether we should ignore the input data
- **Output gate**
  Decide whether the hidden state is used for the output generated by the LSTM

- **Hidden state** and **Memory cell**

Gates

$$I_t = \sigma(X_t W_{xi} + H_{t-1} W_{hi} + b_i)$$
$$F_t = \sigma(X_t W_{xf} + H_{t-1} W_{hf} + b_f)$$
$$O_t = \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o)$$



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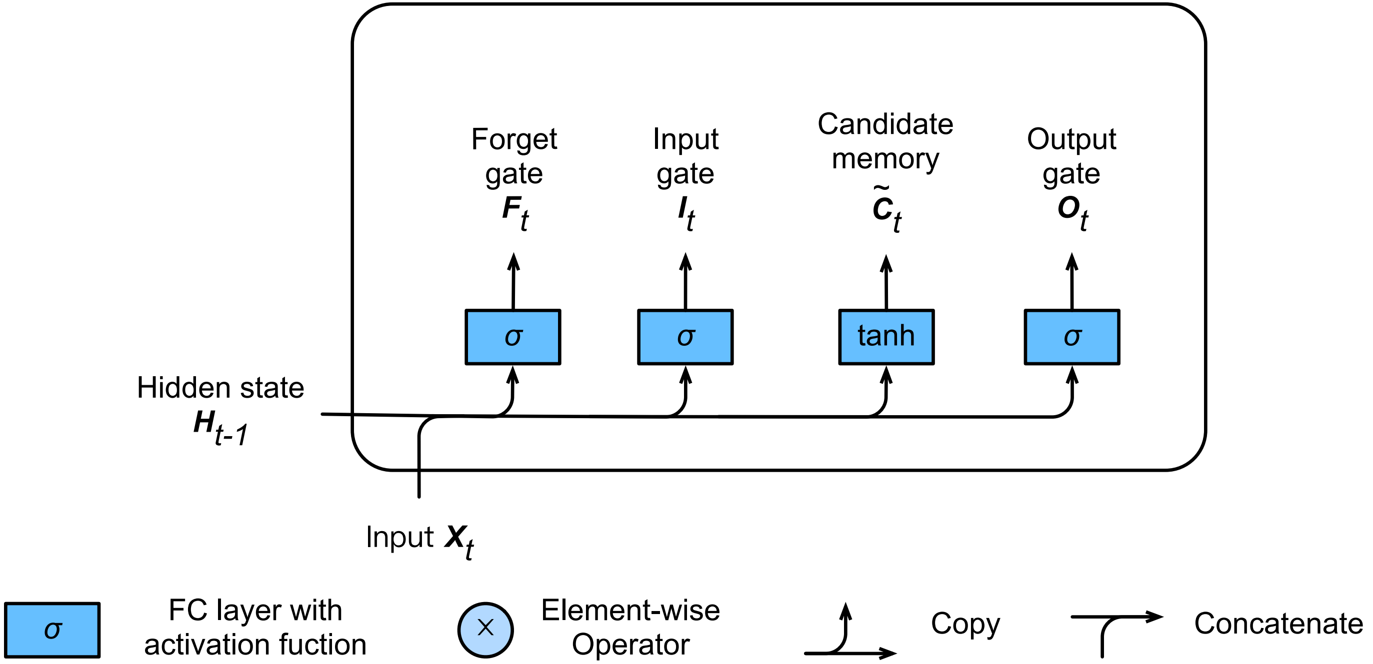
Candidate Memory Cell

$$\tilde{C}_t = \tanh(X_t W_{xc} + H_{t-1} W_{hc} + b_c)$$



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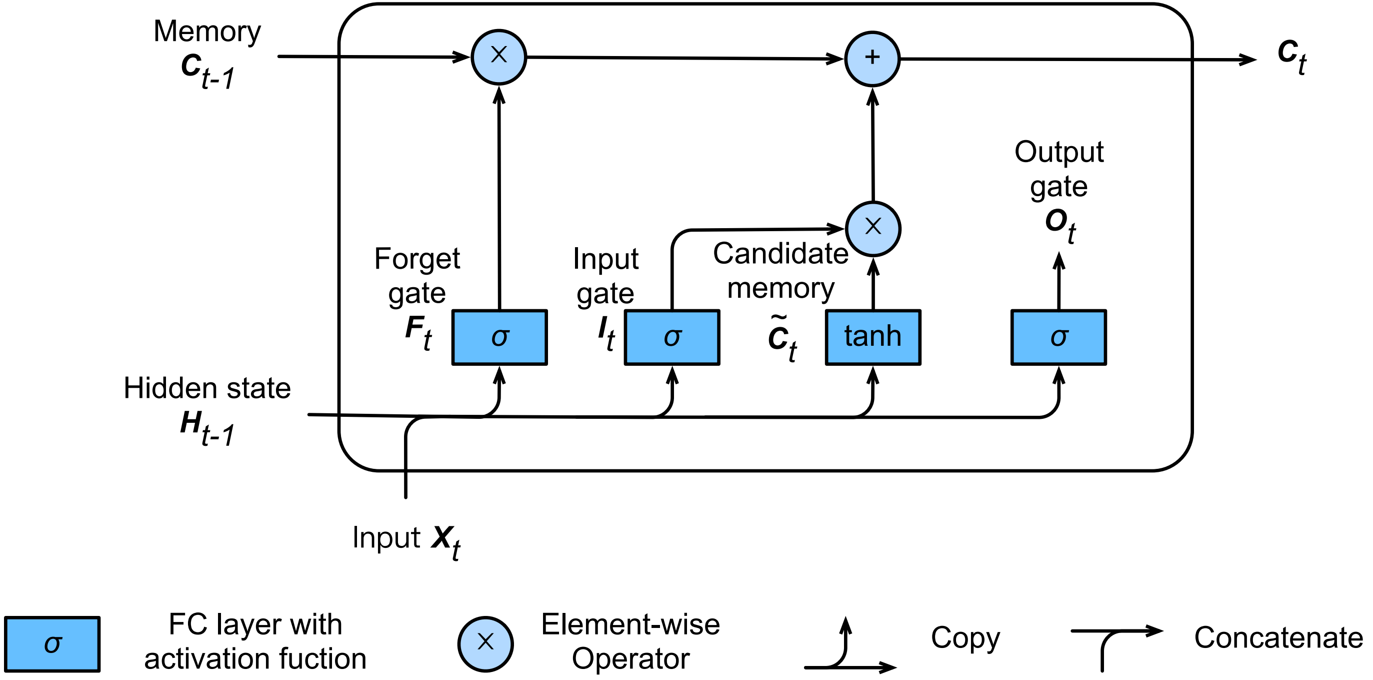
Memory Cell

$$C_t = F_t \odot C_{t-1} + I_t \odot \tilde{C}_t$$



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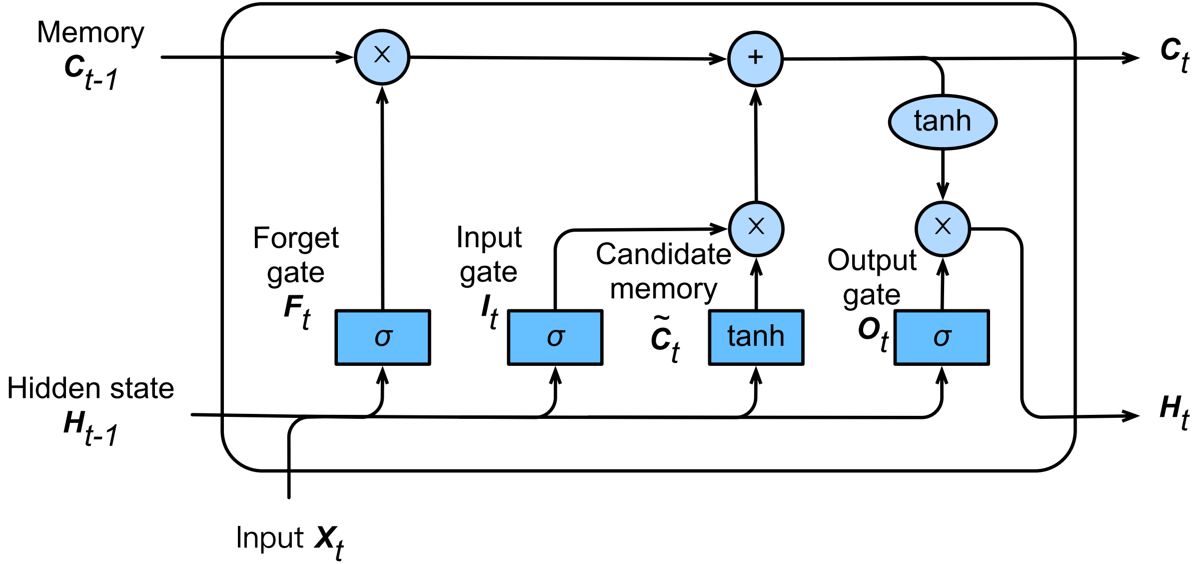
Hidden State / Output

$$H_t = O_t \odot \tanh(C_t)$$



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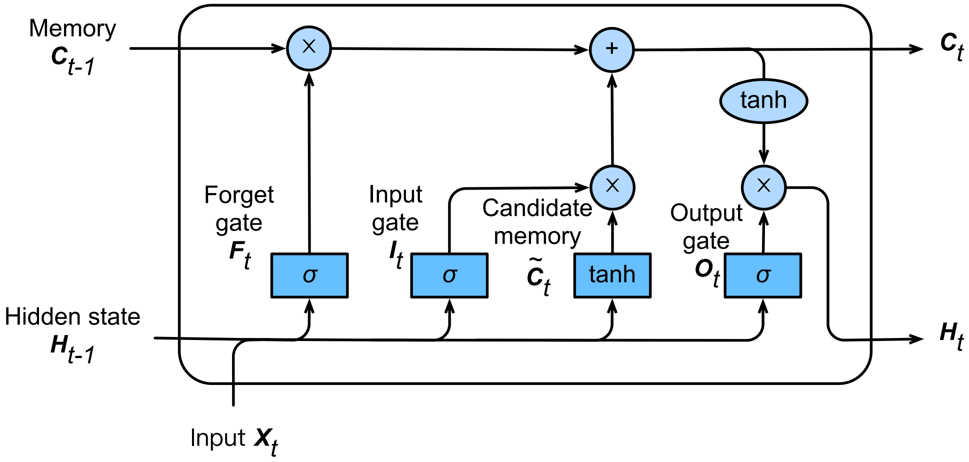
Hidden State / Output



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$$F_t = \sigma(X_t W_{xf} + H_{t-1} W_{hf} + b_f)$$

$$O_t = \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o)$$

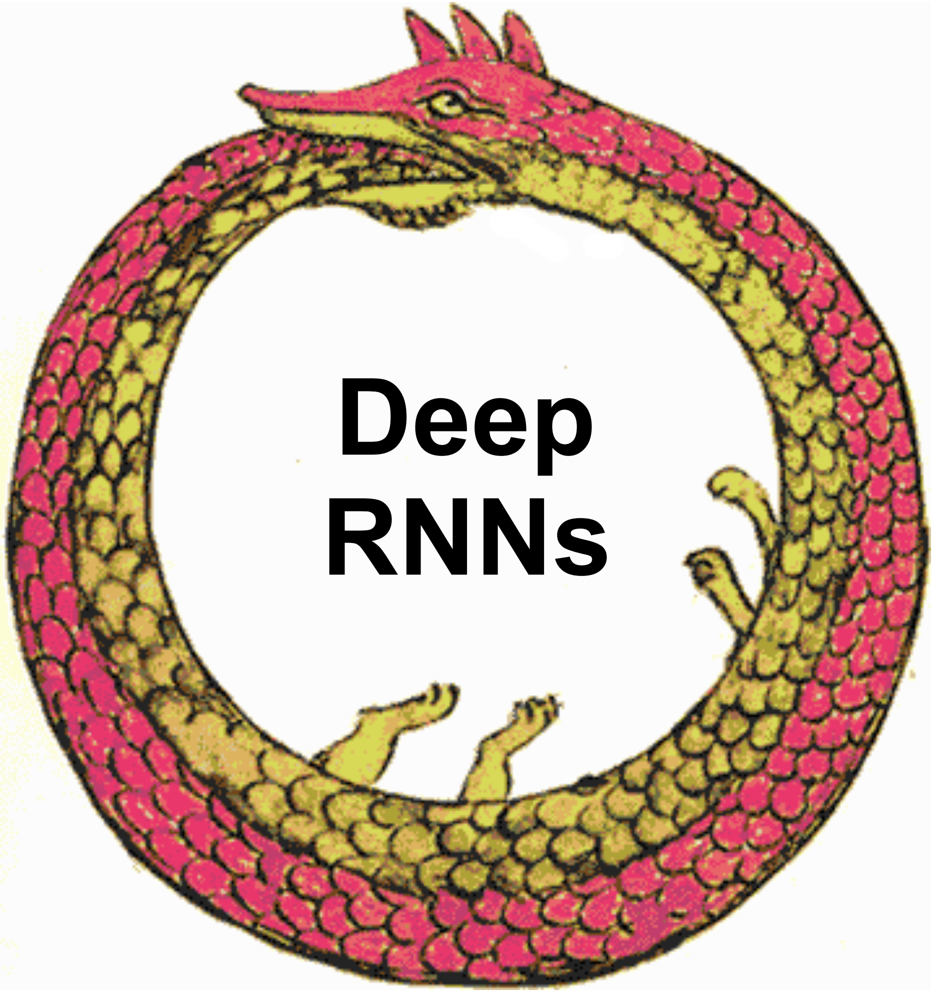
$$\tilde{C}_t = \tanh(X_t W_{xc} + H_{t-1} W_{hc} + b_c)$$

$$C_t = F_t \odot C_{t-1} + I_t \odot \tilde{C}_t$$

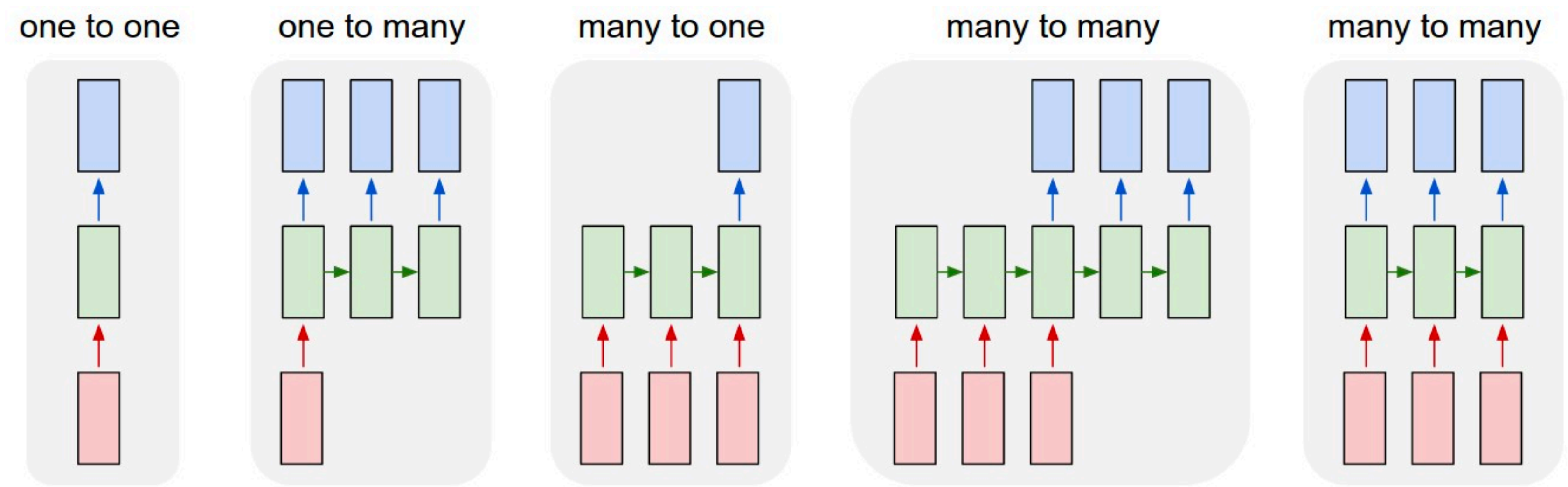
$$H_t = O_t \odot \tanh(C_t)$$

LSTM Notebook

Deep RNNs



Using RNNs

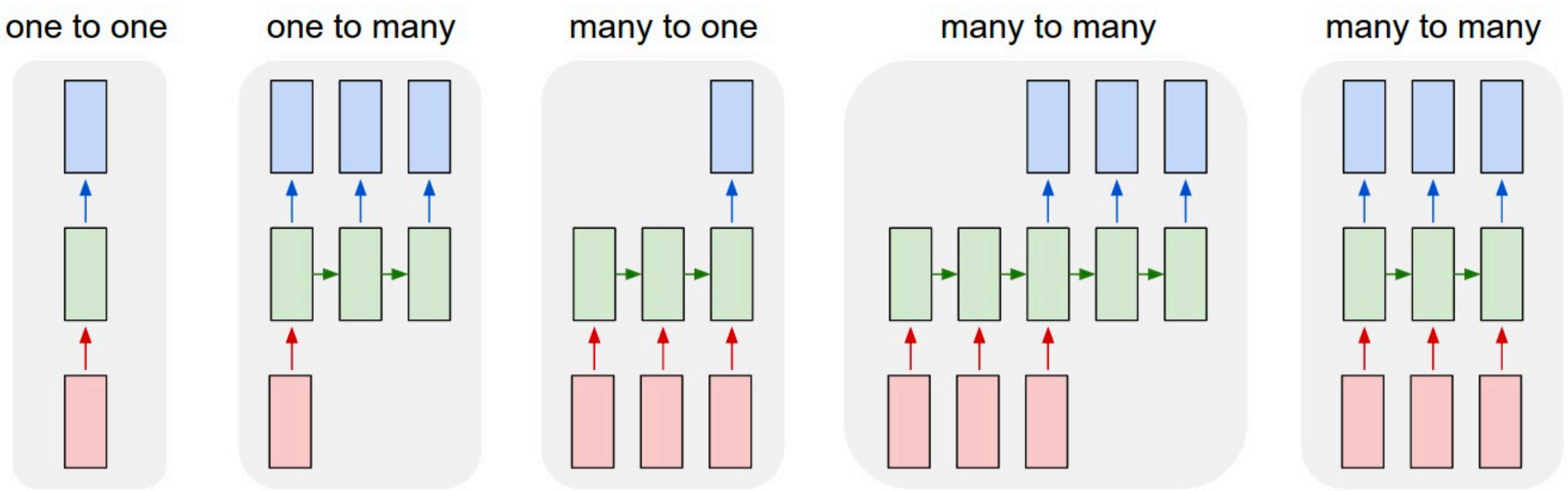


- Encode sequence
- Decode sequence
- Do both

(image courtesy of karpathy.github.io)

aws

Using RNNs



Poetry Generation

Sentiment Analysis

Document Classification

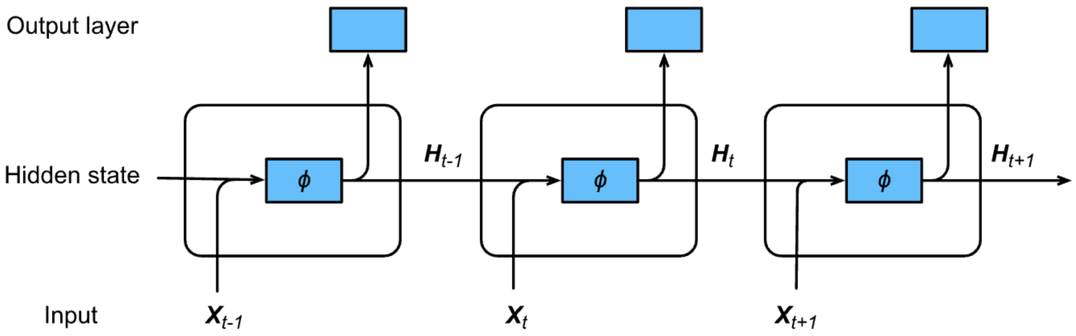
Question Answering

Machine Translation

Named Entity Tagging

(image courtesy of karpathy.github.io)

Recall - Recurrent Neural Networks



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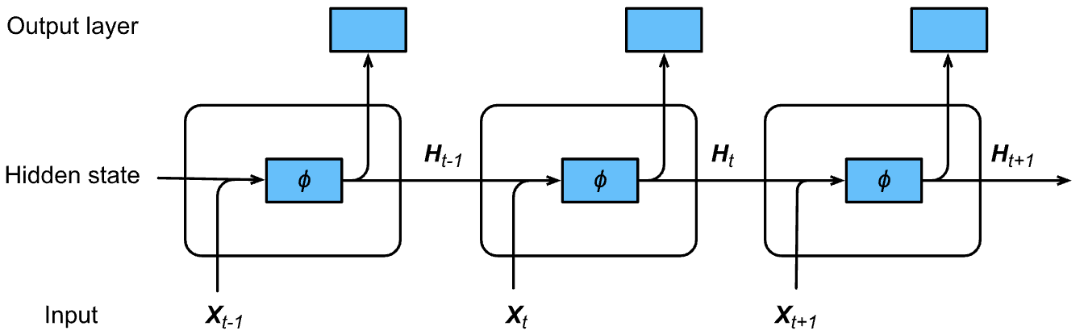

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How to make more nonlinear?

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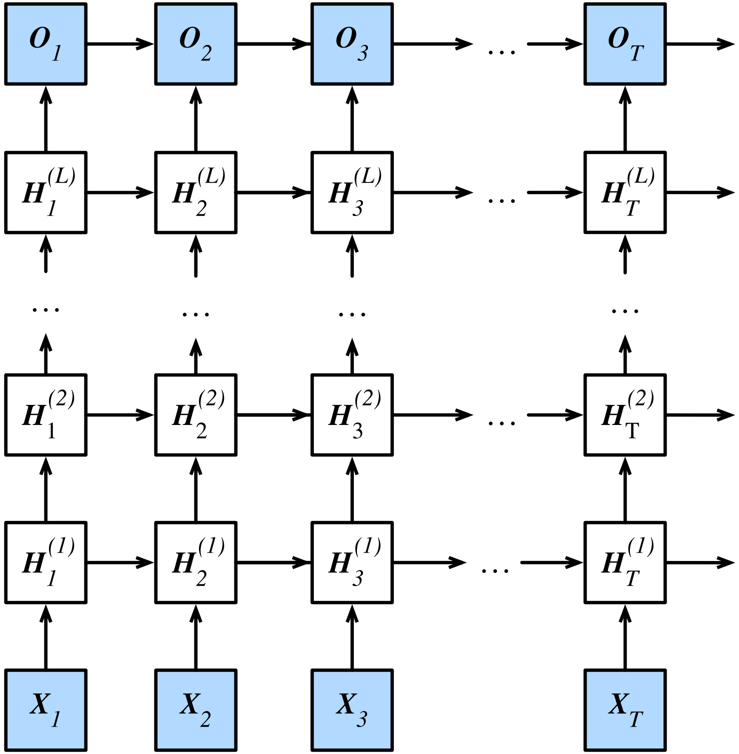
We go deeper per layer



- Shallow RNN
  - Input
  - Hidden layer
  - Output
- Deep RNN
  - Input
  - **Hidden layer**
  - **Hidden layer**

    ...
  - Output

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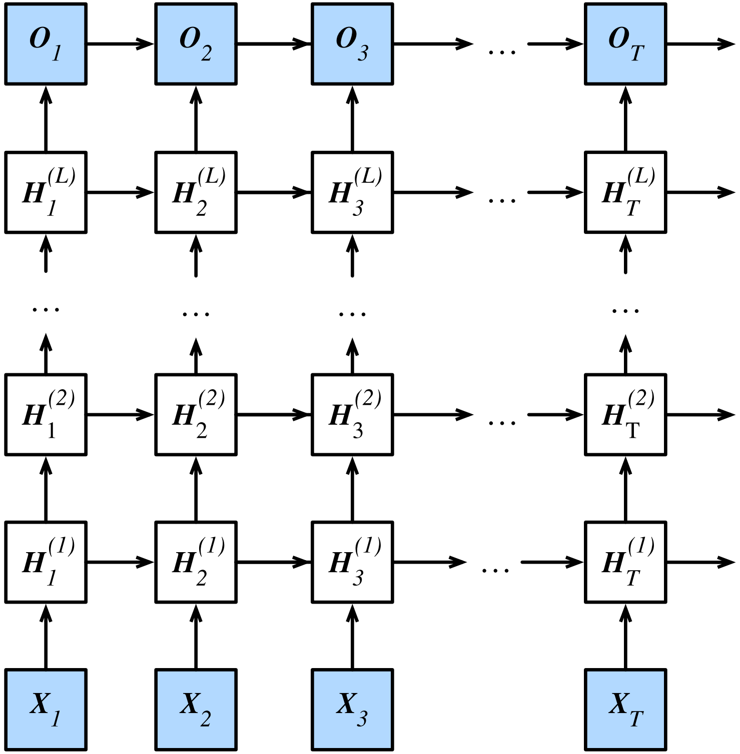
Plan B - We go deeper (multiple layers)



$$\mathbf{H}_t = f(\mathbf{H}_{t-1}, \mathbf{X}_t)$$
$$\mathbf{O}_t = g(\mathbf{H}_t)$$

$$\mathbf{H}_t^1 = f_1(\mathbf{H}_{t-1}^1, \mathbf{X}_t)$$
$$\mathbf{H}_t^j = f_j(\mathbf{H}_{t-1}^j, \mathbf{H}_t^{j-1})$$
$$\mathbf{O}_t = g(\mathbf{H}_t^L)$$

Bidirectional RNNs

The Future Matters

```
I am _____
I am _____ very hungry,
I am _____ very hungry, I could eat half a pig.
```

The Future Matters

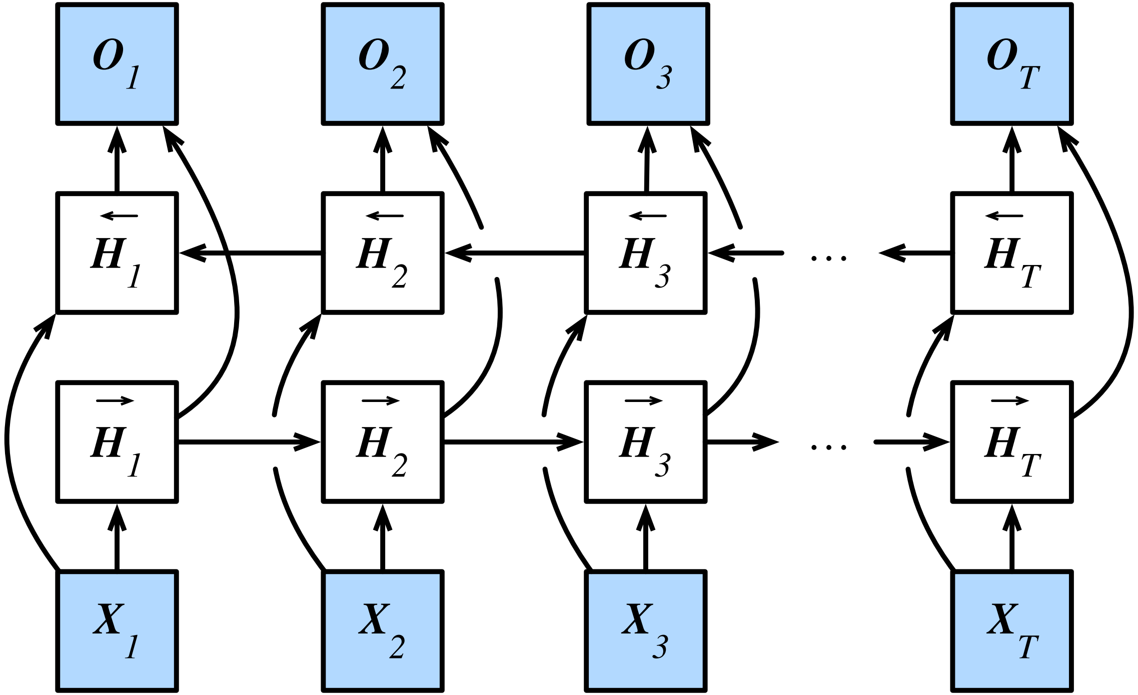
```
I am happy.
I am not    very hungry,
I am very   very hungry, I could eat half a pig.
```

The Future Matters

```
I am happy.
I am not    very hungry,
I am very   very hungry, I could eat half a pig.
```

- Very different words to fill in, depending on past and **future** context of a word.
- RNNs so far only look at the past
- In interpolation (fill in) we can use the future, too.

Bidirectional RNN



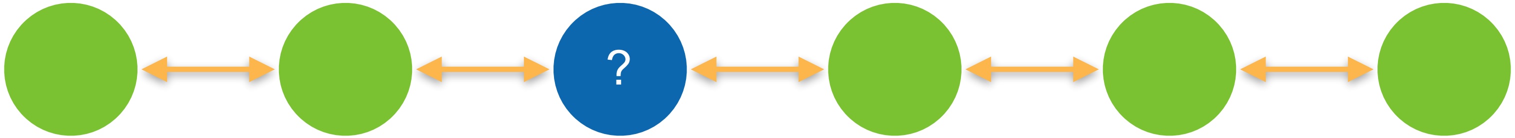
- One RNN forward
- Another one backward
- Combine both hidden states for output generation

```
Perplexity 1.2, 86219 tokens/sec on gpu(0)
time travellererererererererererererererererererererererererer
travellererererererererererererererererererererererererer
```

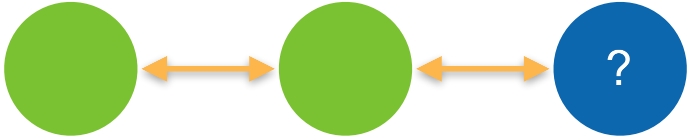
This does not work for sequence generation

Reasons

- Training time



- Test time



Can still use it to **encode** the sequence

Summary

- RNN stores sequence information in hidden state
- GRU and LSTM use more sophisticated gates to handle long sequence information
- RNNs can go deeper and bi-directional

Contents in D2L.ai

- Covered today
- Partial covered today
- Not covered

Math

- Linear algebra
- Prob & statistics
- Gradient

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- Image classification
- Softmax regression
- Multilayer perceptron

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- Loss function
- Regularization
- Model selection
- Environment

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- Convolution, LeNet
- Alex, VGG, Inception, ResNet

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Performance

- Numerical stability
- multi-GPU Training

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Machine learning

- Loss function
- Regularization
- Model selection
- Environment

Basic programming

- NDarray
- Autograd
- Gluon

Basic models

- Linear regression
- Image classification
- Softmax regression
- Multilayer perceptron

Performance

- Numerical stability
- multi-GPU Training

CNNs

- Convolution, LeNet
- Alex, VGG, Inception, ResNet

CV

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- Seq2seq w/ attention
- Transformer
- BERT

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Optimization

- Convex Optimization
- Momentum, RMSProp, Adam

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Next steps

- Textbook: numpy.d2l.ai
- Toolkit for computer vision: gluon-cv.mxnet.io
- Toolkit for natural language processing: gluon-nlp.mxnet.io
- Toolkit for time series: gluon-ts.mxnet.io
- Toolkit for graph neural networks: dgl.ai
- Deep learning compiler: tvm.ai