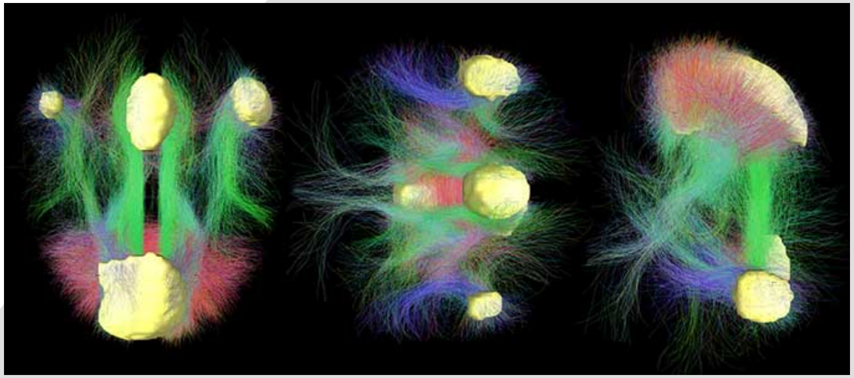
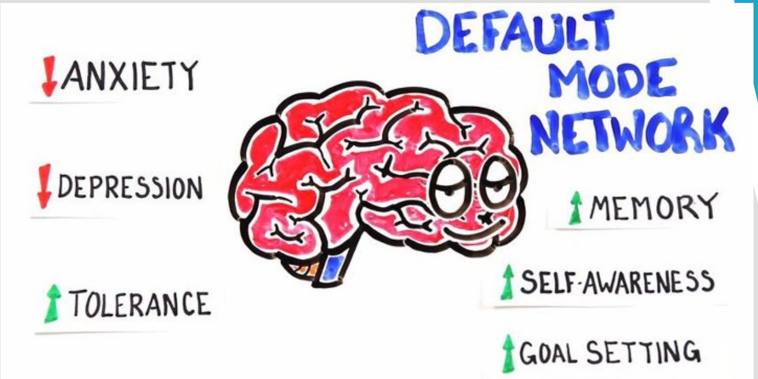
6장 *Deep learning for text and sequences*

"default mode network"





This chapter covers

- Preprocessing text data into useful representations – tokens to vectors
- Working with recurrent neural networks
- Using 1D convnets for sequence processing

This chapter covers

- sequences of word, timeseries, and sequence data in general
- *recurrent neural networks* and *1D convnets*
- Applications of these algorithms include the following:
  - Document classification - identifying the topic of an article or the author of a book
  - Sequence-to-sequence learning - English sentence into French
  - Sentiment analysis - classifying the sentiment of tweets or movie reviews as positive or negative
  - Timeseries forecasting - predicting the future weather given recent weather data

1. sentiment analysis on the IMDB dataset
2. temperature forecasting.

6.1 Working with text data

- natural-language understanding - document classification(topic), sentiment analysis, author identification, and even question-answering (QA)
- Deep learning for natural-language processing is pattern recognition applied to words, sentences, and paragraphs
- Vectorizing text is the process of transforming text into numeric tensors.
  - Segment text into words, and transform each word into a vector.
  - Segment text into characters, and transform each character into a vector.
  - Extract n-grams of words or characters, and transform each n-gram into a vector.
- N-grams are overlapping groups of multiple consecutive words or characters.
- tokens - break down text (words, characters, or n-grams)
- tokenization - breaking text into such tokens
- two major ones: one-hot encoding of tokens, and token embedding

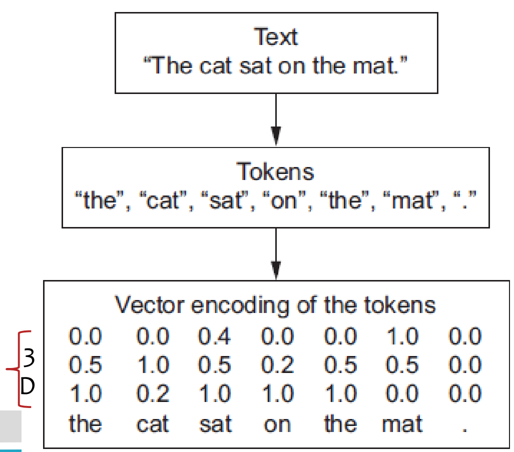


Figure 6.1 From text to tokens to vectors

6.1 Working with text data

Understanding n-grams and bag-of-words (BoW)

- Word n-grams are groups of *N* (or fewer) consecutive words that you can extract from a sentence.
- "The cat sat on the mat." – set of 2-grams:

{"The", "The cat", "cat", "cat sat", "sat", "sat on", "on", "on the", "the", "the mat", "mat"} *bag-of-2-grams*

- It may also be decomposed into the following set of 3-grams:

{"The", "The cat", "cat", "cat sat", "The cat sat", "sat", "sat on", "on", "cat sat on", "on the", "the", "sat on the", "the mat", "mat", "on the mat"} *bag-of-3-grams*

- Because bag-of-words isn't an order-preserving tokenization method (the tokens generated are understood as a set, not a sequence, and the general structure of the sentences is lost)
- unavoidable feature-engineering tool when using lightweight, shallow text-processing models such as logistic regression and random forests.

6.1.1 One-hot encoding of words and characters

- One-hot encoding - turn a token into a vector
- IMDB and Reuters examples - done with words
- a unique integer index with every word - binary vector of size N (the size of the vocabulary)
- one-hot encoding can be done at the character level

6.1 Working with text data

Listing 6.1 Word-level one-hot encoding (toy example)

```
import numpy as np
samples = ['The cat sat on the mat.', 'The dog ate my homework.']
# 데이터에 있는 모든 토큰의 인덱스를 구축합니다
token_index = {} # dictionary - {key:value}; {'The': 1 }
for sample in samples:
    # split() 메서드를 사용해 샘플을 토큰으로 나눕니다.
    for word in sample.split(): # key - word
        if word not in token_index :
            token_index[word] = len(token_index) + 1
            # 인덱스 0은 사용하지 않습니다.
# {'The': 1, 'cat': 2, 'sat': 3, 'on': 4, 'the': 5, 'mat.': 6, 'dog': 7, 'ate': 8, 'my': 9, 'homework.': 10}
# 샘플을 벡터로 변환
max_length = 10
results = np.zeros((len(samples), max_length, max(token_index.values())+1))#(2,10,11)
for i, sample in enumerate(samples):
    for j, word in list(enumerate(sample.split()))[:max_length]:
        index = token_index.get(word)
        results[i, j, index] = 1.
```

```
[[[0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0.] The
  [0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0.] cat
  [0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0.] sat
  [0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0.] on
  [0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0.] the
  [0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0.] mat.
  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
  [0. 0. 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.] The
  [0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0.] dog
  [0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0.] ate
  [0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0.] my
  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1.] homework.
  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
  [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]]
```

6.1 Working with text data

Listing 6.2 Character-level one-hot encoding (toy example)

```
import string
samples = ['The cat sat on the mat.', 'The dog ate my homework.']
characters = string.printable  # 출력 가능한 모든 ASCII 문자, 100개
token_index = dict(zip(characters,  range(1, len(characters) + 1)))
max_length = 50

results = np.zeros((len(samples), max_length,
    max(token_index.values())+1))
for i, sample in enumerate(samples):
    for j, character in enumerate(sample[:max_length]):
        index = token_index.get(character)
        results[i, j, index] = 1.
```

token_index = {'0': 1, '1': 2, '2': 3, '3': 4, '4': 5, '5': 6, '6': 7, '7': 8, '8': 9, '9': 10, 'a': 11, 'b': 12, 'c': 13, 'd': 14, 'e': 15, 'f': 16, 'g': 17, 'h': 18, 'i': 19, 'j': 20, 'k': 21, … ,'A': 37, 'B': 38, … , '\x0c': 100}

[[[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. 0. … 0. 0. 0.]] 'The cat sat on the mat.'

[[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. … 0. 0. 0.] [0. 0. 0. … 0. 0. 0.]]] 'The dog ate my homework.'

6.1 Working with text data

Listing 6.3 Using Keras for word-level one-hot encoding

```
from keras.preprocessing.text import Tokenizer
samples = ['The cat sat on the mat.', 'The dog ate my homework.']
# 가장 빈도가 높은 1,000개의 단어만 선택하도록 Tokenizer 객체를 만듭니다.
tokenizer = Tokenizer(num_words=1000)
# Turns strings into lists of integer indices by word_index
tokenizer.fit_on_texts(samples) # 입력에 맞게 내부의 word_index를 중복 없이 만드는 함수
# tokenizer.word_index = {'the': 1, 'cat': 2, 'sat': 3, 'on': 4, 'mat': 5, 'dog': 6, 'ate': 7, 'my': 8, 'homework': 9}

# Turns strings into lists of integer indices
sequences = tokenizer.texts_to_sequences(samples)
# Sequences = [[1, 2, 3, 4, 1, 5], [1, 6, 7, 8, 9]]

# directly get the one-hot binary representations.
# Vectorization modes other than one-hot encoding are supported by this tokenizer!
one_hot_results = tokenizer.texts_to_matrix(samples, mode='binary')
# one_hot_results = [[0. 1. 1. 1. 1. 1. 0. 0. 0. 0. 0. ... 0. 0. 0.]
#                    [0. 1. 0. 0. 0. 0. 1. 1. 1. 1. 0. ... 0. 0. 0.]]

word_index = tokenizer.word_index
print('Found %s unique tokens.' % len(word_index))
# Found 9 unique tokens.
```

6.1 Working with text data

- *one-hot hashing* - vocabulary is too large to handle explicitly
- hash words into vectors of fixed size with a very lightweight hashing function
- saves memory and allows online encoding of the data
- *hash collisions*: two different words may end up with the same hash

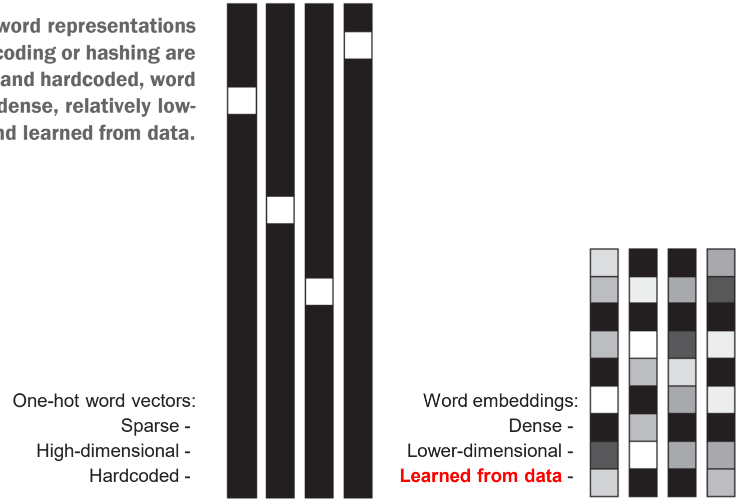
Listing 6.4 Using Keras for word-level one-hot encoding

```
samples = ['The cat sat on the mat.', 'The dog ate my homework.']
# 1,000개 이상의 단어가 있다면 hash collisions
dimensionality = 1000
max_length = 10
results = np.zeros((len(samples), max_length, dimensionality))
for i, sample in enumerate(samples):
    for j, word in list(enumerate(sample.split()))[:max_length]:
      # Hashes the word into a random integer index between 0 and 1,000
        index = abs(hash(word)) % dimensionality
        results[i, j, index] = 1.
# in case of dimensionality = 20 →
results[0] =
[[0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.] The
 [0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.] cat
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0.] sat
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0.] on
 [0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.] the
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0.] mat
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]
```

6.1.2 Using word embeddings

- one-hot encoding are binary, sparse, very high-dimensional (20,000-dimensional or greater)
- dense *word vectors* also called *word embeddings* - low-dimensional floating-point vectors in 256-, 512-, or 1,024-dimensional when dealing with very large vocabularies
- pack more information into far fewer dimensions

Figure 6.2 Whereas word representations obtained from one-hot encoding or hashing are sparse, high-dimensional, and hardcoded, word embeddings are dense, relatively low-dimensional, and learned from data.



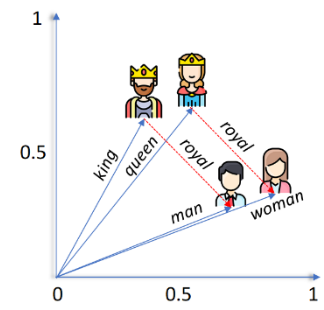
6.1Working with text data

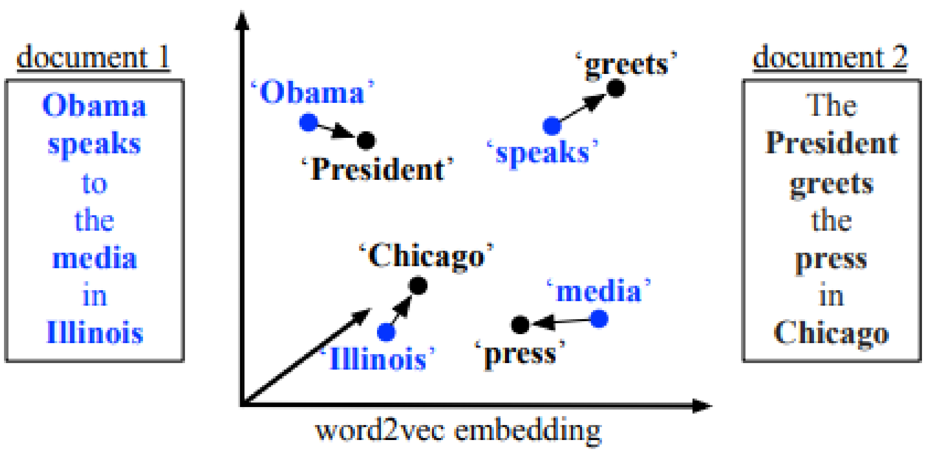
- There are two ways to obtain word embeddings:
  - Learn word embeddings jointly with the main task you care about (such as document classification or sentiment prediction → **weights** in a neural network).
  - *pretrained word embeddings* - Load into your model word embeddings
- Let’s look at both.

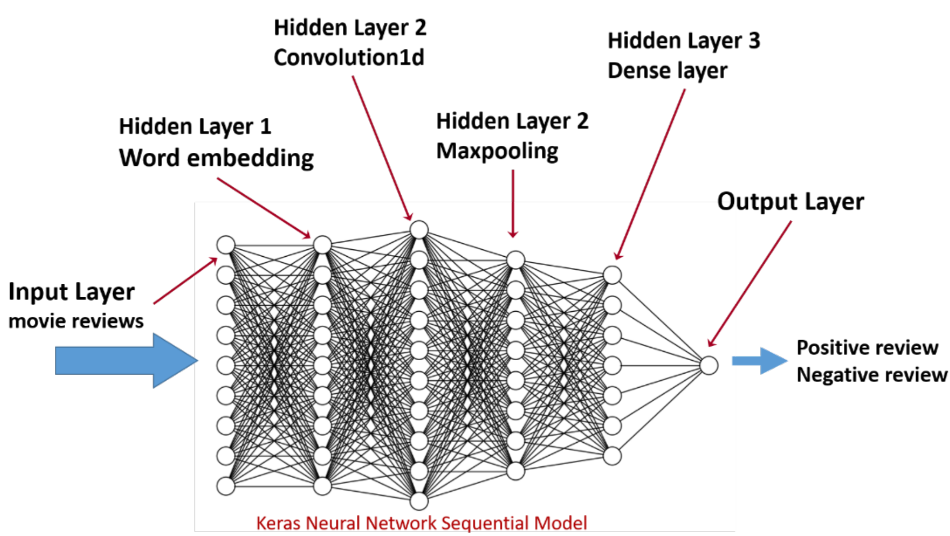
6.1 Working with text data

LEARNING WORD EMBEDDINGS WITH THE EMBEDDING LAYER

- choose the vector at random - embedding space has no structure: the interchangeable words *accurate* and *exact* end up with completely different embeddings
- synonyms to be embedded into similar word vectors
- geometric distance (such as L2 distance) between any two word vectors to relate to the semantic distance between the associated words







LEARNING WORD EMBEDDINGS WITH THE EMBEDDING LAYER

- *cat*, *dog*, *wolf*, and *tiger* - semantic relationships between these words can be encoded as geometric transformations.
- "from pet to wild animal" - from *cat* to *tiger* and from *dog* to *wolf*
- "from canine to feline" vector from *dog* to *cat* and from *wolf* to *tiger*
- "gender" and "plural" vectors - "female" vector + vector "king" → vector "queen," "plural" vector + vector "king" → "kings."
- Word-embedding spaces - interpretable and potentially useful vectors.

Dimensions

Word vectors				
dog	-0.4	0.37	0.02	-0.34
cat	-0.15	-0.02	-0.23	-0.23
lion	0.19	-0.4	0.35	-0.48
tiger	-0.08	0.31	0.56	0.07
elephant	-0.04	-0.09	0.11	-0.06
cheetah	0.27	-0.28	-0.2	-0.43
monkey	-0.02	-0.67	-0.21	-0.48
rabbit	-0.04	-0.3	-0.18	-0.47
mouse	0.09	-0.46	-0.35	-0.24
rat	0.21	-0.48	-0.56	-0.37

animal
domesticated
pet
fluffy

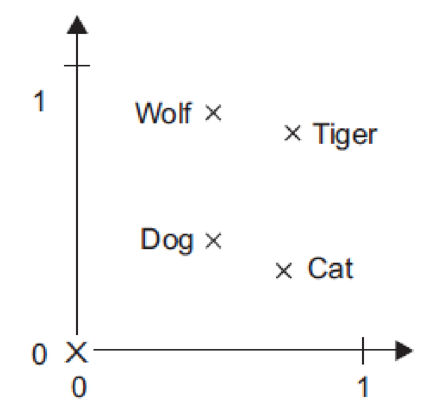


Figure 6.3 A toy example of a word-embedding space

6.1 Working with text data

- learning the weights of a layer: the `Embedding` layer

Listing 6.5 Instantiating an `Embedding layer`

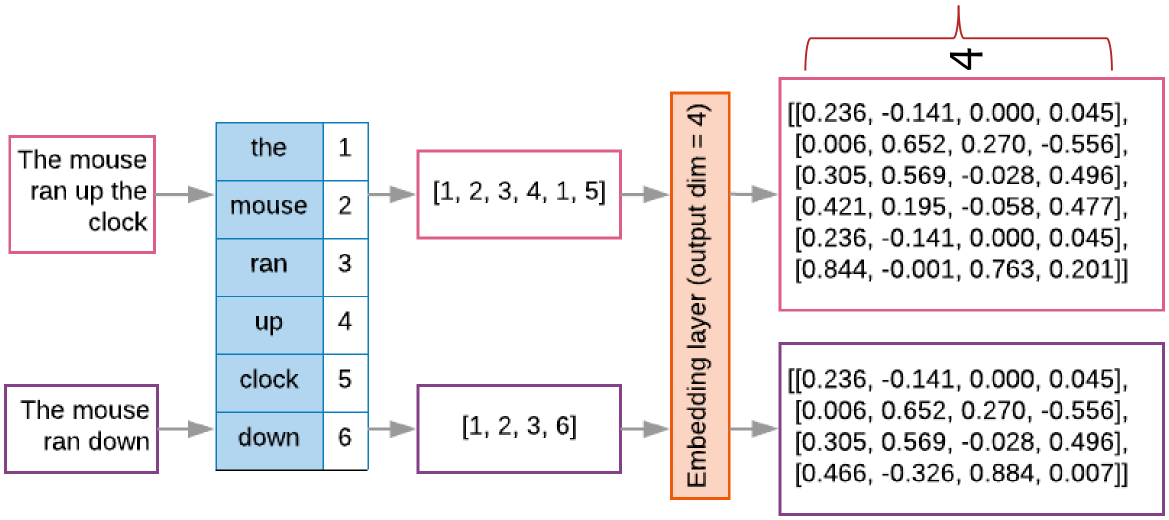
```
from keras.layers import Embedding
embedding_layer = Embedding(1000, 64)
#(batch, input_length)
```

- The `Embedding` layer is best understood as a dictionary that maps integer indices (which stand for specific words) to dense vectors.
- It takes integers as input, it looks up these integers in an internal dictionary, and it returns the associated vectors. It's effectively a dictionary lookup.

Word index → Embedding layer → Corresponding word vector

6.1 Working with text data

- The `Embedding` layer takes as input a 2D tensor of integers, of shape `(samples, sequence_length)`, where each entry is a sequence of integers.
- It can embed sequences of variable lengths: `(32, 10)` (batch of 32 sequences of length 10) or `(64, 15)` (batch of 64 sequences of length 15).
- All sequences in a batch must have the same length, though (because you need to pack them into a single tensor), so sequences that are shorter than others should be padded with 0s, and sequences that are longer should be truncated.



6.1 Working with text data

- This layer returns a 3D floating-point tensor of shape `(samples, sequence_ length, embedding_dimensionality)`.

- Such a 3D tensor can then be processed by an RNN layer or a 1D convolution layer (both will be introduced in the following sections).

- `Embedding` layer - its weights (its internal dictionary of token vectors) are initially random → gradually adjusted via backpropagation → embedding space (specialized for the specific problem)

- IMDB movie-review sentiment-prediction - the top 10,000 most common words and cut off the reviews after only 20 words.

- input integer sequences (2D integer tensor) → embedded sequences (3D float tensor) → flatten the tensor to 2D → train a single `Dense` layer on top for classification → 8-dimensional embeddings for each of the 10,000 words

6.1 Working with text data

Listing 6.6 Loading the IMDB data for use with an `Embedding` layer

```
from keras.datasets import imdb
from keras import preprocessing

max_features = 10000 # Number of words to consider as features
maxlen = 20 # Cuts off the text after this number of words
            #(among the max_features most common words)

(x_train, y_train), (x_test, y_test) = imdb.load_data(
        num_words=max_features) # Loads the data as lists of integers

x_train = preprocessing.sequence.pad_sequences(x_train, maxlen=maxlen)
# lists of integers → a 2D integer tensor of shape (samples, maxlen)
x_test = preprocessing.sequence.pad_sequences(x_test, maxlen=maxlen)
# padded with 0s for shorter sequences or truncated for longer sequences
```

6.1 Working with text data

Listing 6.7 Using an Embedding layer and classifier on the IMDB data

```
from keras.models import Sequential
from keras.layers import Flatten, Dense

model = Sequential()

model.add(Embedding(10000, 8, input_length=maxlen))
# Specifies the maximum input length to the Embedding layer
# so you can later flatten the embedded inputs.
# Output of the activations have shape (samples, maxlen, 8) of 3D with 8 Output.

model.add(Flatten()) # 160
# Flattens the 3D tensor of embeddings into a 2D tensor of shape (samples, maxlen * 8)
model.add(Dense(1, activation='sigmoid')) # Adds the classifier on top
model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
model.summary()

history = model.fit(x_train, y_train,
          epochs=10, batch_size=32, validation_split=0.2)
          # training dataset-8000개, test dataset-2000개
```

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, 20, **8**)	80000
flatten_1 (Flatten)	(None, 160)	0
dense_1 (Dense)	(None, 1)	161

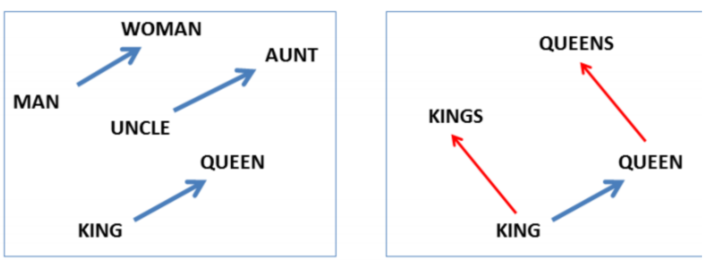
6.1Working with text data

- You get to a validation accuracy of ~76%, which is pretty good considering that you're only looking at the first 20 words in every review.
- no inter-word relationships and sentence structure (for example, this model would likely treat both "this movie is a bomb" and "this movie is the bomb-짱" as being negative reviews).
- It's much better to add recurrent layers or 1D convolutional layers on top of the embedded sequences to learn features.

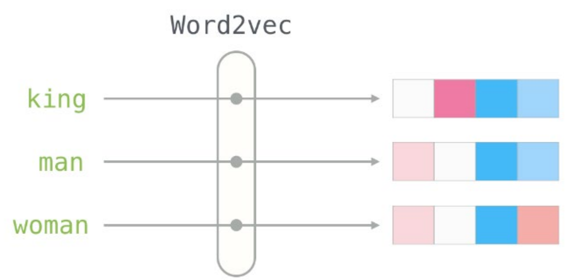
6.1 Working with text data

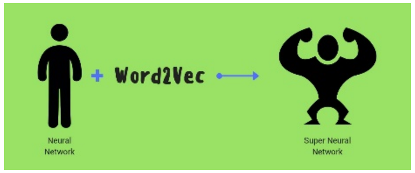
USING PRETRAINED WORD EMBEDDINGS

- little training data?
- precomputed embedding space - highly structured and exhibits useful properties by using word-occurrence statistics, using a variety of techniques, some involving neural networks.
- Word2vec algorithm ([https:// code.google.com/archive/p/word2vec](https://code.google.com/archive/p/word2vec)), developed by Tomas Mikolov at Google in 2013.
  - Word2vec dimensions capture specific semantic properties, such as genders



(Mikolov et al., NAACL HLT, 2013)





USING PRETRAINED WORD EMBEDDINGS

- GloVe, https://nlp.stanford.edu/projects/glove, by Stanford researchers in 2014.
  - factorizing a matrix of word co-occurrence statistics obtained from millions of English tokens, Wikipedia data and Common Crawl data.

Window based co-occurrence matrix

- Example corpus:
  - I like deep learning.
  - I like NLP.
  - I enjoy flying.

counts	I	like	enjoy	deep	learning	NLP	flying	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

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6.1.3 Putting it all together: from raw text to word embeddings

- pretrained word embeddings
- the original text data instead of using the pretokenized IMDB data packaged in Keras

DOWNLOADING THE IMDB DATA AS RAW TEXT

- download the raw IMDB dataset from http://mng.bz/0tIo.
- Uncompress it.
- collect the individual training reviews into a list of strings, one string per review.
- collect the review labels (positive/negative) into a `labels` list.

6.1 Working with text data

Listing 6.8 Processing the labels of the raw IMDB data

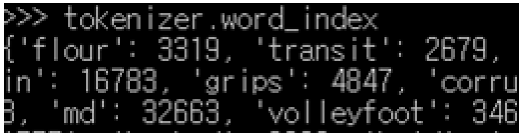
```
import os
imdb_dir = '/Users/fchollet/Downloads/aclImdb'
          # deep-learning-with-python-notebooks-master
train_dir = os.path.join(imdb_dir, 'train')
labels = []
texts = []
for label_type in ['neg', 'pos']: # read data from train_dir: /pos 12,500, /neg 12,500
   dir_name = os.path.join(train_dir, label_type) # …/neg or …/pos
   for fname in os.listdir(dir_name):
      if fname[-4:] == '.txt':
       f = open(os.path.join(dir_name, fname))
       texts.append(f.read())
       f.close()
       if label_type == 'neg':
         labels.append(0)
       else:
         labels.append(1)
```

6.1 Working with text data

TOKENIZING THE DATA

- pretrained word embeddings - restricting the training data to the first 200 samples (otherwise, task-specific embeddings are likely to outperform)

Listing 6.9 Tokenizing the text of the raw IMDB data




```
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
import numpy as np
maxlen = 100  # Cuts off reviews after 100 words
training_samples = 200 # Trains on 200 samples
validation_samples = 10000 # Validates on 10,000 samples
max_words = 10000 # Considers only the top 10,000 words in the dataset
tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(texts) # 입력에 맞게 내부 list 생성
sequences = tokenizer.texts_to_sequences(texts) #단어 인덱스만 가져옴
word_index = tokenizer.word_index # 88,582 unique words, 모든 단어 포함
print('Found %s unique tokens.' % len(word_index))
data = pad_sequences(sequences, maxlen=maxlen)
labels = np.asarray(labels)
print('Shape of data tensor:', data.shape)
print('Shape of label tensor:', labels.shape)
```

```
Found 88582 unique tokens
Shape of data tensor:(25000, 100)
Shape of label tensor :(25000,)
```

6.1 Working with text data

```
indices = np.arange(data.shape[0]) # 25,000 - [0 1 2 ... 24997 24998 24999]
# first shuffles the data, all negative first, then all positive
np.random.shuffle(indices) # [23739  2813   974 ...   167 23722 19124]
data = data[indices]
labels = labels[indices]
x_train = data[:training_samples] # 200
y_train = labels[:training_samples] # 200
x_val = data[training_samples:
         training_samples + validation_samples] # 10,000
y_val = labels[training_samples:
         training_samples + validation_samples] # 10,000
```

x_val: (10000, 100) # `maxlen = 100`

x_val: [[128 1480 413 ... 188 335 543] [7 11 6 ... 52 867 97] [23 1487 14 ... 2 65 2776]
... [0 0 0 ... 42 35 615] [480 2 327 ... 39 568 3920] [9141 59 1463 ... 128 232 4572]]

y_val: (10000,)

y_val: [0 1 1 ... 1 0 1]

DOWNLOADING THE GLOVE WORD EMBEDDINGS

- Go to https:// nlp.stanford.edu/p rojects/glove, and download the precomputed embeddings from 2014 English Wikipedia. It's an 822 MB zip file called glove.6B.zip, containing 100-dimensional embedding vectors for 400,000 words (or nonword tokens). Unzip it.
- Let's parse the unzipped file (a .txt file) to build an index that maps words (as strings) to their vector representation (as number vectors).

Listing 6.10 Parsing the GloVe word-embeddings file

```
glove_dir='/Users/fchollet/Downloads/glove.6B' #word+100 dim vector
embeddings_index = {}  # 400,000 words
f = open(os.path.join(glove_dir, 'glove.6B.100d.txt'))
for line in f:
   values = line.split()
   word = values[0]
   coefs = np.asarray(values[1:], dtype='float32')
   embeddings_index[word] = coefs
f.close()
print('Found %s word vectors.' % len(embeddings_index))
# Found 400000 word vectors
print(len(embeddings_index.get('cat')))#100-dimensional embedding vectors
# 100
#[ 0.23088  0.28283 ...  -0.71493 ]
# Word = sandberger
# Coefs = [0.28365 -0.6263,,, -0.15701]
```

6.1 Working with text data

- Next, you'll build an embedding matrix that you can load into an `Embedding` layer. It must be a matrix of shape `(max_words, embedding_dim)` - `(10000, 100)`

- Note that index 0 isn't supposed to stand for any word or token—it's a placeholder.

```
# embeddings_index = {}   # 400,000 words
```

Listing 6.11 Preparing the GloVe word-embeddings matrix

```
embedding_dim = 100 # len(embeddings_index.get('cat'))
embedding_matrix = np.zeros((max_words, embedding_dim)) # max_words=10000
for word, i in word_index.items(): # [('the', 1), ('and', 2), ... ,('hued', 88582)])
    if i < max_words: # max_words=10000
        embedding_vector = embeddings_index.get(word) #
        if  embedding_vector is not None: # exist in embeddings_index
            embedding_matrix[i] = embedding_vector
#else-Words not found in the embedding index will be all zeros.
# ... [0. 0. 0. ... 0. 0.][-0.038194 -0.24487001 ... 0.27061999]  -  (10000, 100)
```

6.1 Working with text data

DEFINING A MODEL

- Let's parse the unzipped file (a .txt file) to build an index that maps words (as strings) to their vector representation (as number vectors).

Listing 6.12 Model definition

```
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model = Sequential()
model.add(Embedding(max_words, embedding_dim,#max_words=10000,embedding_dim=100
                    input_length=maxlen))   # maxlen = 100, p.25: pad_sequences
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 100, 100)          1000000
_________________________________________________________________
flatten_1 (Flatten)          (None, 10000)             0
_________________________________________________________________
dense_1 (Dense)              (None, 32)                320032
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 33
=================================================================
```

LOADING THE GLOVE EMBEDDINGS IN THE MODEL

- The `Embedding` layer has a single weight matrix: a 2D float matrix where each entry *i* is the word vector meant to be associated with index *i*.
- Load the GloVe matrix you prepared into the `Embedding` layer, the first layer in the model
- freeze the Embedding layer (set its trainable attribute to **False**)

***

Listing 6.13 Loading pretrained word embeddings

```
model.layers[0].set_weights([embedding_matrix])
#                                            (10000, 100)
model.layers[0].trainable = False
```

TRAINING AND EVALUATING THE MODEL

- Compile and train the model.

Listing 6.14 Training and evaluation into the Embedding

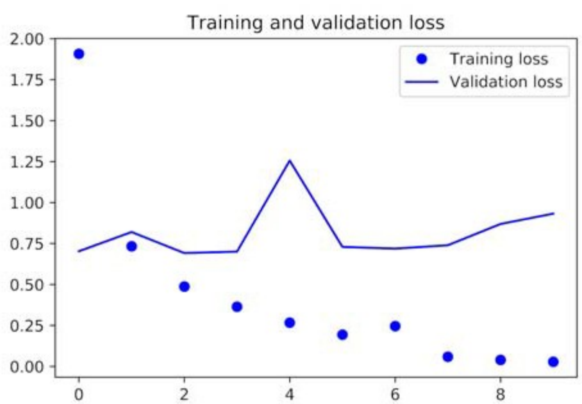
```
model.compile(optimizer='rmsprop',
      loss='binary_crossentropy', metrics=['acc'])
history = model.fit(x_train, y_train,
      epochs=10, batch_size=32,
validation_data=(x_val, y_val))
model.save_weights('pre_trained_glove_model.h5')
```

- Now, plot the model's performance over time (see figures 6.5 and 6.6)

Listing 6.15 Plotting the results layer

```
import matplotlib.pyplot as plt
acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(acc) + 1)
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy') plt.legend()
plt.figure()
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```

Figure 6.5 Training and validation loss when using pretrained word embeddings



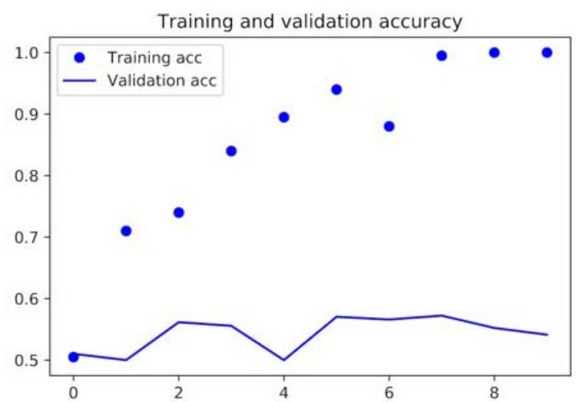


Figure 6.6 Training and validation accuracy when using pretrained word embeddings

6.1Working with text data

- The model quickly starts overfitting, which is unsurprising given the small number of training samples. Validation accuracy has high variance for the same reason, but it seems to reach the high 50s.
- so few training samples - performance is heavily dependent on exactly which 200 samples you choose randomly.

- without loading the pretrained word embeddings and without freezing the embedding layer. In that case, you'll learn a task-specific embedding of the input tokens, which is generally more powerful than pretrained word embeddings when lots of data is available.
- But in this case, you have only 200 training samples. Let's try it (see figures 6.7 and 6.8).

6.1 Working with text data

Listing 6.16 Training the same model *without pretrained* word embeddings

```
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model = Sequential()
model.add(Embedding(max_words, embedding_dim, input_length=maxlen))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.summary()

model.compile(optimizer='rmsprop',
     loss='binary_crossentropy', metrics=['acc'])
history = model.fit(x_train, y_train,
        epochs=10, batch_size=32,
        validation_data=(x_val, y_val))
```

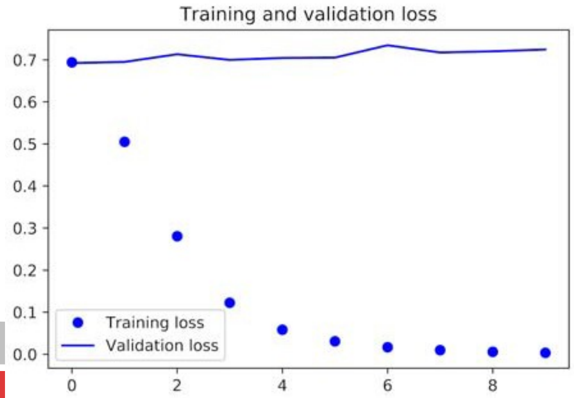


Figure 6.7 Training and validation loss without using pretrained word embeddings

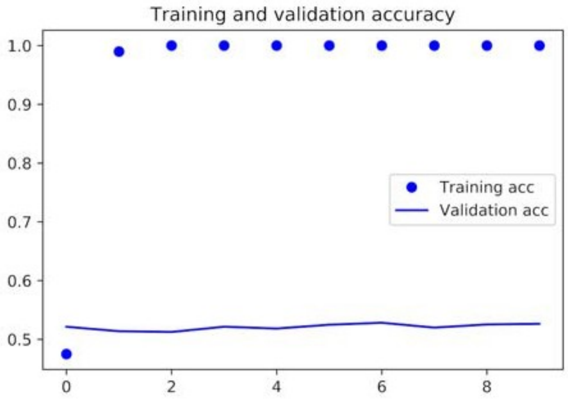


Figure 6.8 Training and validation accuracy without using pretrained word embeddings

6.1 Working with text data

- Validation accuracy stalls in the low 50s. So in this case, pretrained word embeddings outperform jointly learned embeddings. If you increase the number of training samples, this will quickly stop being the case—try it as an exercise.
- Finally, let's evaluate the model on the test data. First, you need to tokenize the test data.

Listing 6.17 Tokenizing the data of the test set

```
test_dir = os.path.join(imdb_dir, 'test')
labels = []
texts = []

for label_type in ['neg', 'pos']:
    dir_name = os.path.join(test_dir, label_type)
    for fname in sorted(os.listdir(dir_name)):
        if fname[-4:] == '.txt':
            f = open(os.path.join(dir_name, fname))
            texts.append(f.read())
            f.close()
            if label_type == 'neg':
                labels.append(0)
            else:
                labels.append(1)

sequences = tokenizer.texts_to_sequences(texts)
x_test = pad_sequences(sequences, maxlen=maxlen)
y_test = np.asarray(labels)
```

- Next, load and evaluate the first model

Listing 6.18 Evaluating the model on the test set

```
model.load_weights('pre_trained_glove_model.h5')
model.evaluate(x_test, y_test)
```

- You get an appalling test accuracy of 56%. Working with just a handful of training samples is difficult!

  - Turn raw text into something a neural network can process
  - Use the **Embedding** layer in a Keras model to learn task-specific token embeddings
  - Use pretrained word embeddings to get an extra boost on small natural-language-processing problems

- 실습 - raw IMDB data를 GloVe word-embeddings file을 이용하여 다음과 같이 변경하여 분류하세요
  - 변경 가능한 변수 조정
  - Train data 조정
  - 모델 수정
  - 결과 - 분류율과 분석 결과

6.2Understanding recurrent neural networks

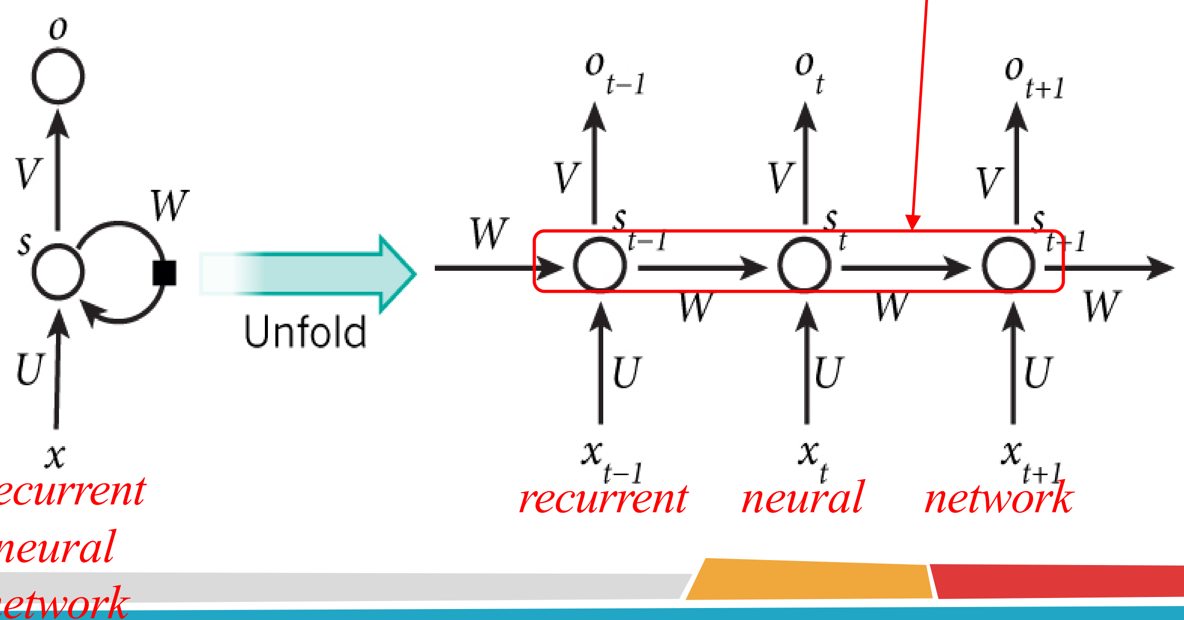
- A major characteristic of all neural networks is that they have no memory - *no state kept in between inputs*

- feedforward networks - IMDB example: an entire movie review was transformed into a single large vector and processed in one go.

- word by word (eye saccade by eye saccade) - from past information → constantly updated as new information

6.2Understanding recurrent neural networks

- A *recurrent neural network* (RNN) - it processes sequences by iterating through the sequence elements and maintaining a *state* containing information relative to what it has seen so far.

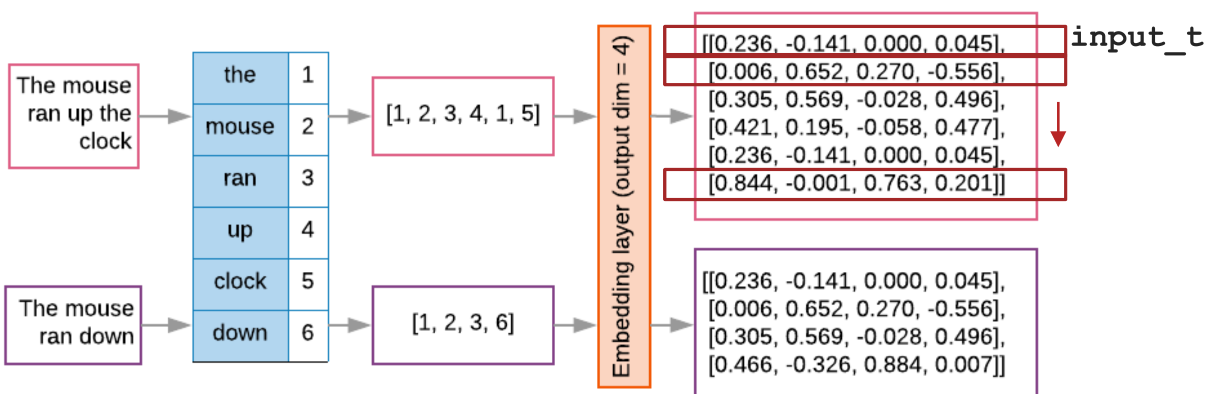


6.2Understanding recurrent neural networks

- RNN takes as input a sequence of vectors - 2D tensor of size (timesteps, input_features)
- set the state for the next step to be this previous output.
- *initial state* - all-zero vector

Listing 6.19 Pseudocode RNN

```
state_t = 0 # The state at t
for input_t in input_sequence:
# Iterates over sequence elements
   output_t = f(input_t, state_t)
   state_t = output_t
   # The previous output becomes
   # the state for the next iteration.
```

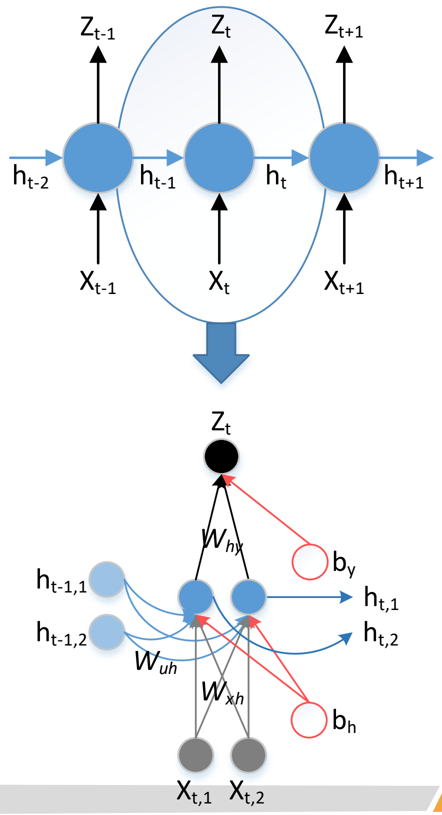


6.2 Understanding recurrent neural networks

- `f`: input and state → `W` and `U`, and a bias vector

Listing 6.20 More detailed pseudocode for the RNN

```
state_t = 0 # h
for input_t in input_sequence:
    output_t=activation(dot(W,input_t) + dot(U,state_t)+b)
    state_t = output_t
```

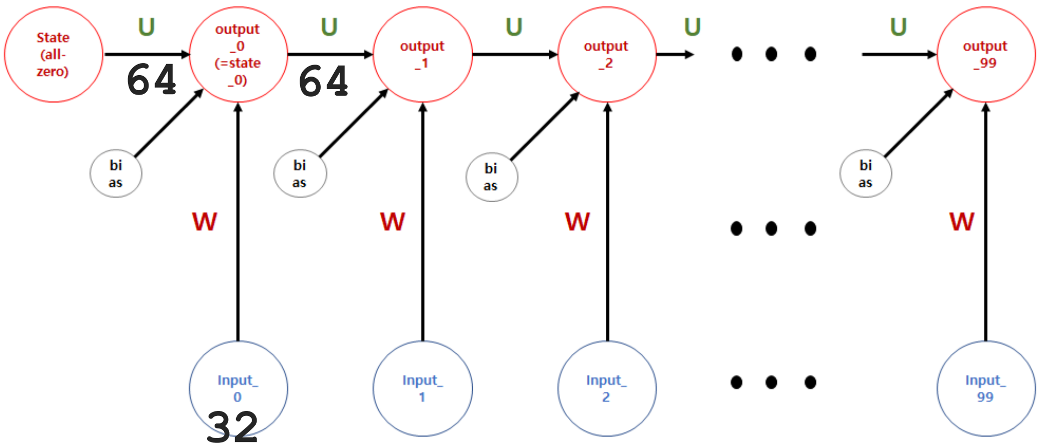


6.2Understanding recurrent neural networks

- naive Numpy implementation of the forward pass of the simple RNN.

Listing 6.21 Numpy implementation of a simple RNN

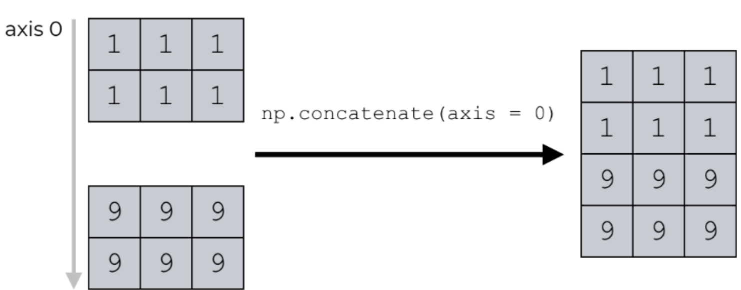
```
import numpy as np
timesteps = 100 # Number of timesteps in the input sequence
input_features = 32 # Dimensionality of the input feature space
output_features = 64 # Dimensionality of the output feature space
inputs = np.random.random((timesteps, input_features))
# Input data: random noise for the sake of the example
state_t = np.zeros((output_features,))
# Initial state: all-0 vector
W = np.random.random((output_features, input_features)) # (64,32)
U = np.random.random((output_features, output_features)) # (64,64)
b = np.random.random((output_features,)) # (64,)
# 1 random weight matrices
```

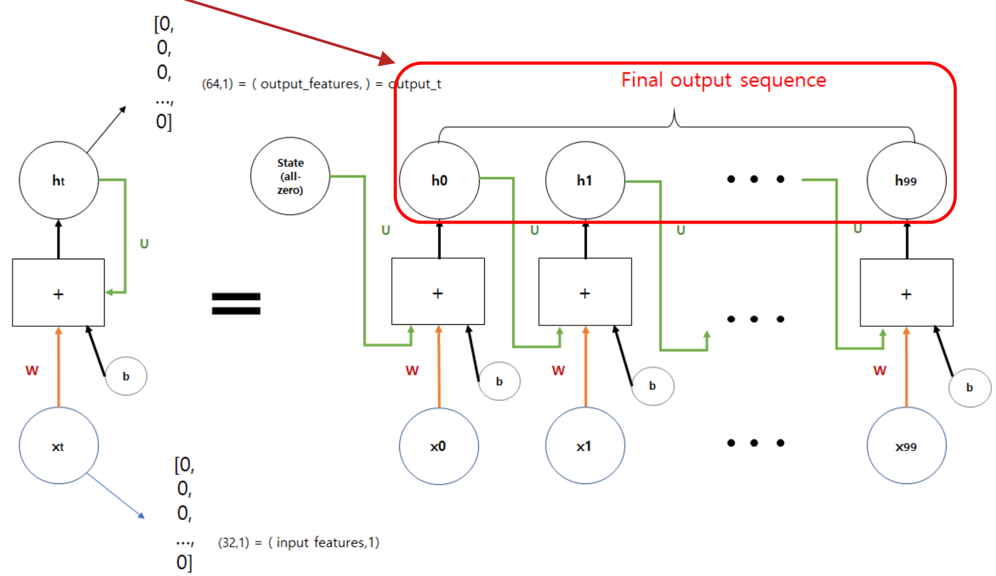


6.2 Understanding recurrent neural networks

```
successive_outputs = []
for input_t in inputs: # a vector of shape (input_features,)
    output_t = np.tanh(np.dot(W, input_t) + np.dot(U, state_t) + b)
    # Combines the input with the current state (the previous output)
    successive_outputs.append(output_t) #Stores this output in a list
    state_t = output_t
    # Updates the state of the network for the next timestep
final_output_sequence = np.concatenate(successive_outputs, axis=0)
# The final output is a 2D tensor of
# shape (timesteps, output_features), shape = (100, 64)
```

Setting axis=0 concatenates along the row axis

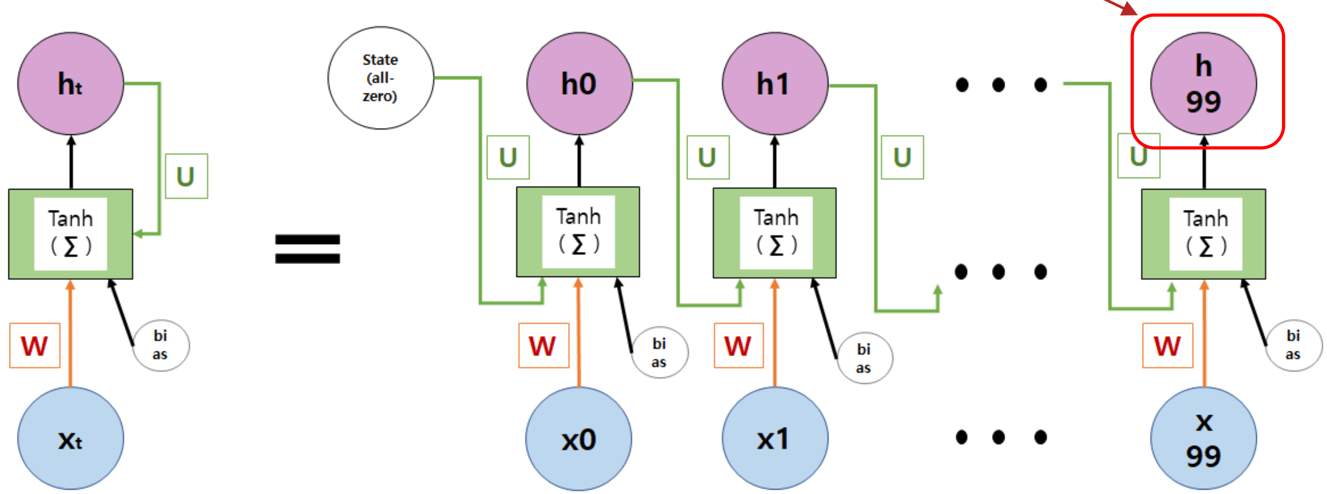




6.2 Understanding recurrent neural networks

```
output_t = np.tanh(np.dot(W, input_t) + np.dot(U, state_t) + b)
```

NOTE The final output is a 2D tensor of shape `(timesteps, output_features)` at time `t`. Only the last output (`output_t`) at the end of the loop is needed, because it already contains information about the entire sequence.



6.2 Understanding recurrent neural networks

6.2.1 A recurrent layer in Keras

- `SimpleRNN` layer:

```
from keras.layers import SimpleRNN
```

- There is one minor difference: `SimpleRNN` processes batches of sequences, like all other Keras layers

`(timesteps, input_features)`→
`(batch_size, timesteps, input_features)`

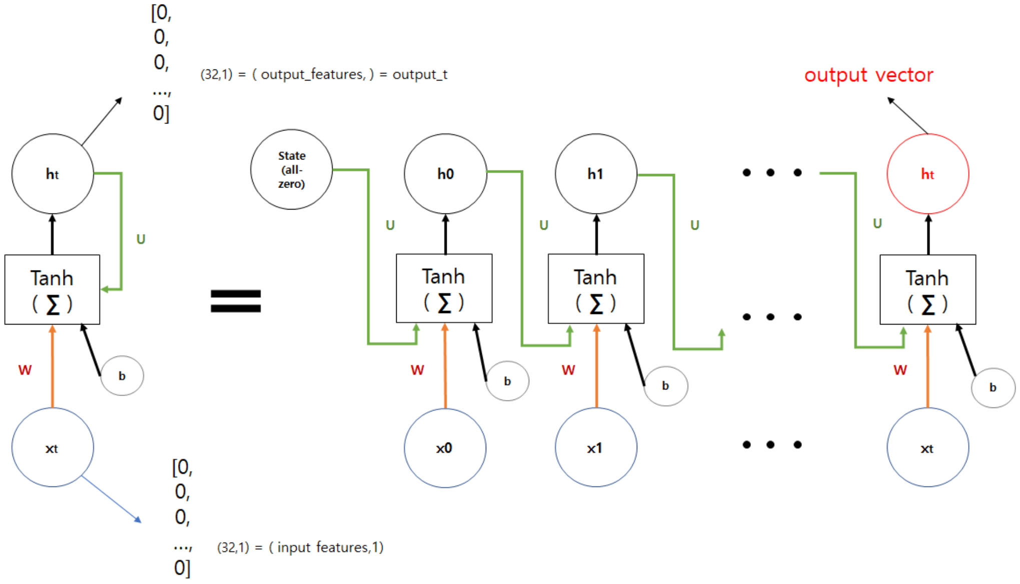
- two different modes of return
  - (batch_size, timesteps, output_features) - the full sequences of successive outputs
  - (batch_size, output_features) - only the last output for each input sequence
- These two modes are controlled by the return_sequences constructor argument.

6.2 Understanding recurrent neural networks

- SimpleRNN and returns only the output at the last timestep:

```
>>> from keras.models import Sequential
>>> from keras.layers import Embedding, SimpleRNN
>>> model = Sequential()
>>> model.add(Embedding(10000,32)) # (max_features, output dim)
>>> model.add(SimpleRNN(32))
>>> model.summary()
```

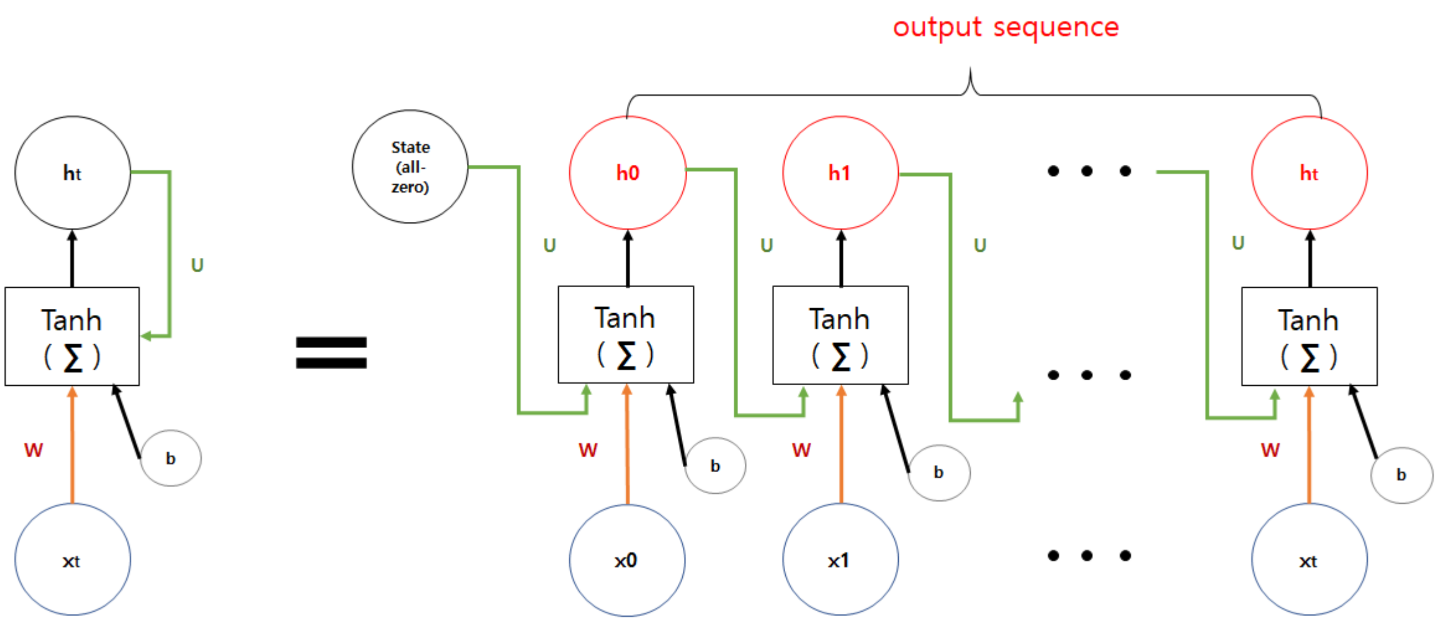
```
Layer (type)                Output Shape          Param #
==================================================
embedding_22(Embedding)  (None,None,32)   320000
simplernn_10(SimpleRNN)  (None,32)        2080 = (32*32*2+32)
```



- The following example returns the full state sequence:

```
>>> model = Sequential()
>>> model.add(Embedding(10000, 32))
>>> model.add(SimpleRNN(32, return_sequences=True))
>>> model.summary()
```

Layer (type)	Output Shape	Param #
embedding_23(Embedding)	(None,None,32)	320000
simplernn_11(SimpleRNN)	(None,**None**,32)	2080



6.2 Understanding recurrent neural networks

- stack several recurrent layers:

```
>>> model = Sequential()
>>> model.add(Embedding(10000, 32))
>>> model.add(SimpleRNN(32, return_sequences=True))
>>> model.add(SimpleRNN(32, return_sequences=True))
>>> model.add(SimpleRNN(32, return_sequences=True))
>>> model.add(SimpleRNN(32)) # Last layer only returns the last output
>>> model.summary()
Layer (type)                  Output Shape             Param #
================================================================
embedding_3(Embedding)       (None, None, 32)         320000
simple_rnn_3(SimpleRNN)      (None, None, 32)
simple_rnn_4(SimpleRNN)      (None, None, 32)         2080
simple_rnn_5(SimpleRNN)      (None, None, 32)         2080
simple_rnn_6(SimpleRNN)      (None, 32)               2080
```

6.2 Understanding recurrent neural networks

- IMDB movie-review-classification problem - First, preprocess the data.

Listing 6.22 Preparing the IMDB data

```
from keras.datasets import imdb
from keras.preprocessing import sequence
max_features = 10000  # Number of words to consider as features
maxlen = 500  # Cuts off texts after this many words
batch_size = 32
(input_train, y_train), (input_test, y_test) =
            imdb.load_data(num_words=max_features)
print(len(input_train), 'train sequences') # 25000
print(len(input_test), 'test sequences') # 25000
input_train = sequence.pad_sequences(input_train, maxlen=maxlen)
input_test = sequence.pad_sequences(input_test, maxlen=maxlen)
print('input_train shape:', input_train.shape) # (25000, 500)
print('input_test shape:', input_test.shape) # (25000, 500)
```

6.2 Understanding recurrent neural networks

- Train an Embedding layer and a SimpleRNN layer.

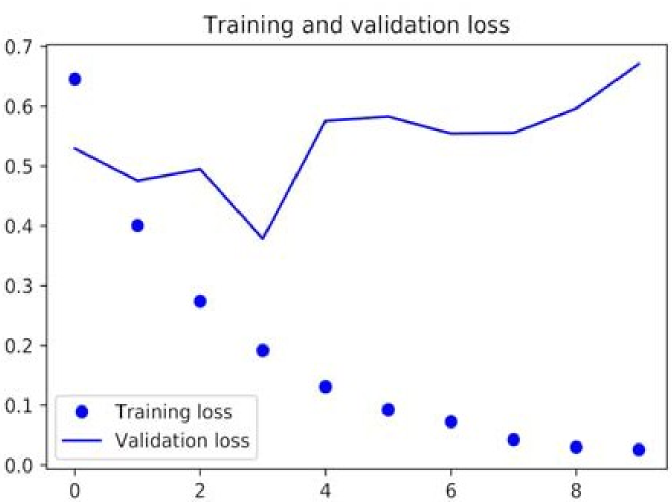
Listing 6.23 Training the model with `Embedding` and `SimpleRNN` layers

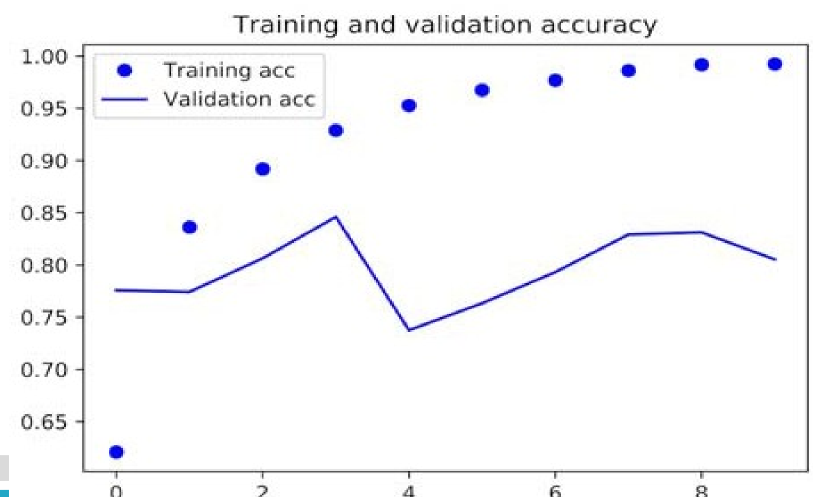
```
from keras.layers import Dense
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(SimpleRNN(32))
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop', loss='binary_crossentropy',
        metrics=['acc'])
history = model.fit(input_train, y_train,
       epochs=10, batch_size=128, validation_split=0.2) #20%
```

6.2 Understanding recurrent neural networks

Listing 6.24 Plotting results

```
import matplotlib.pyplot as pltacc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(acc) + 1)
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```





6.2Understanding recurrent neural networks

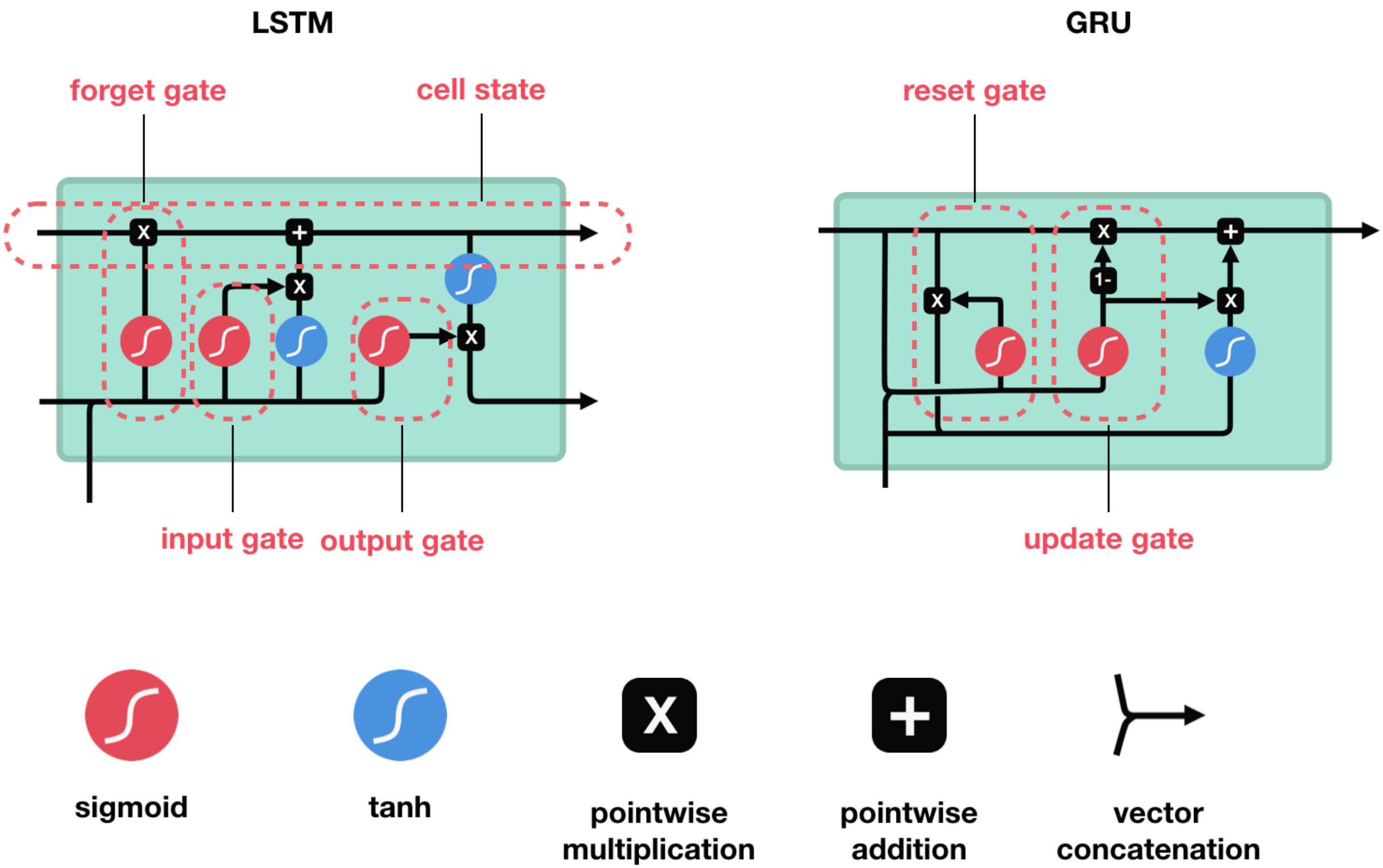
- In chapter 3, test accuracy - 88%
- recurrent network - 85% validation accuracy
- Inputs only the first 500 words - less information than the earlier baseline model.
- `SimpleRNN` - No good at processing long sequences, such as text (vanishing information).
- Other types of recurrent layers perform much better.

6.2.2 A Understanding the LSTM and GRU layers

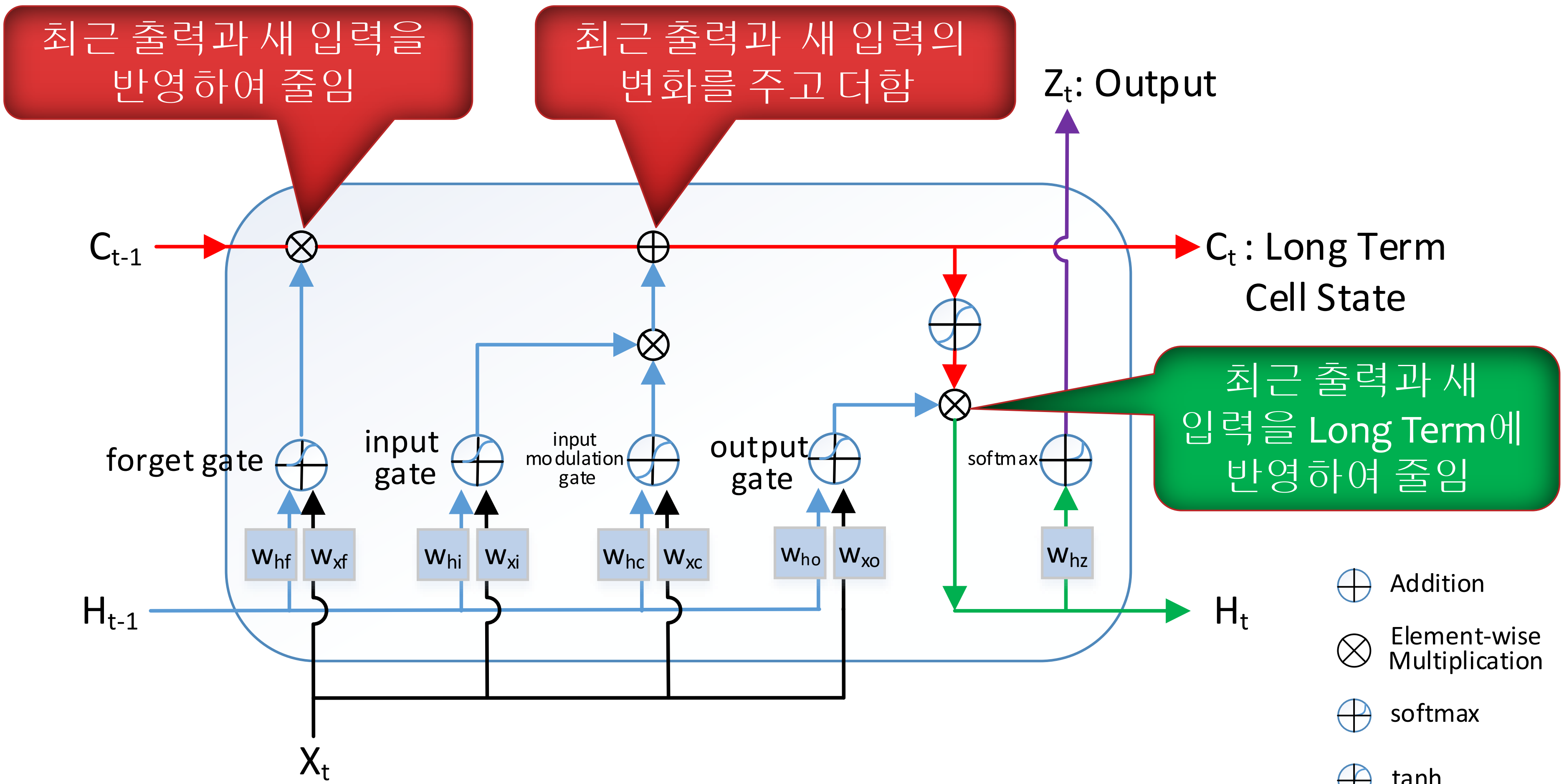
- `LSTM` and `GRU` - `SimpleRNN` has a major issue: long-term dependencies are impossible to learn.
- This is due to the *vanishing gradient problem*, an effect that is similar to what is observed with non-recurrent networks (feedforward networks) studied by Hochreiter, Schmidhuber, and Bengio in the early 1990s.
- Long Short-Term Memory (LSTM) algorithm was developed by Hochreiter and Schmidhuber in 1997.
- Carry Track (C) information across many timesteps to save information for later, thus preventing older signals from gradually vanishing during processing.

LSTM-GRU Architecture - overview

https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21

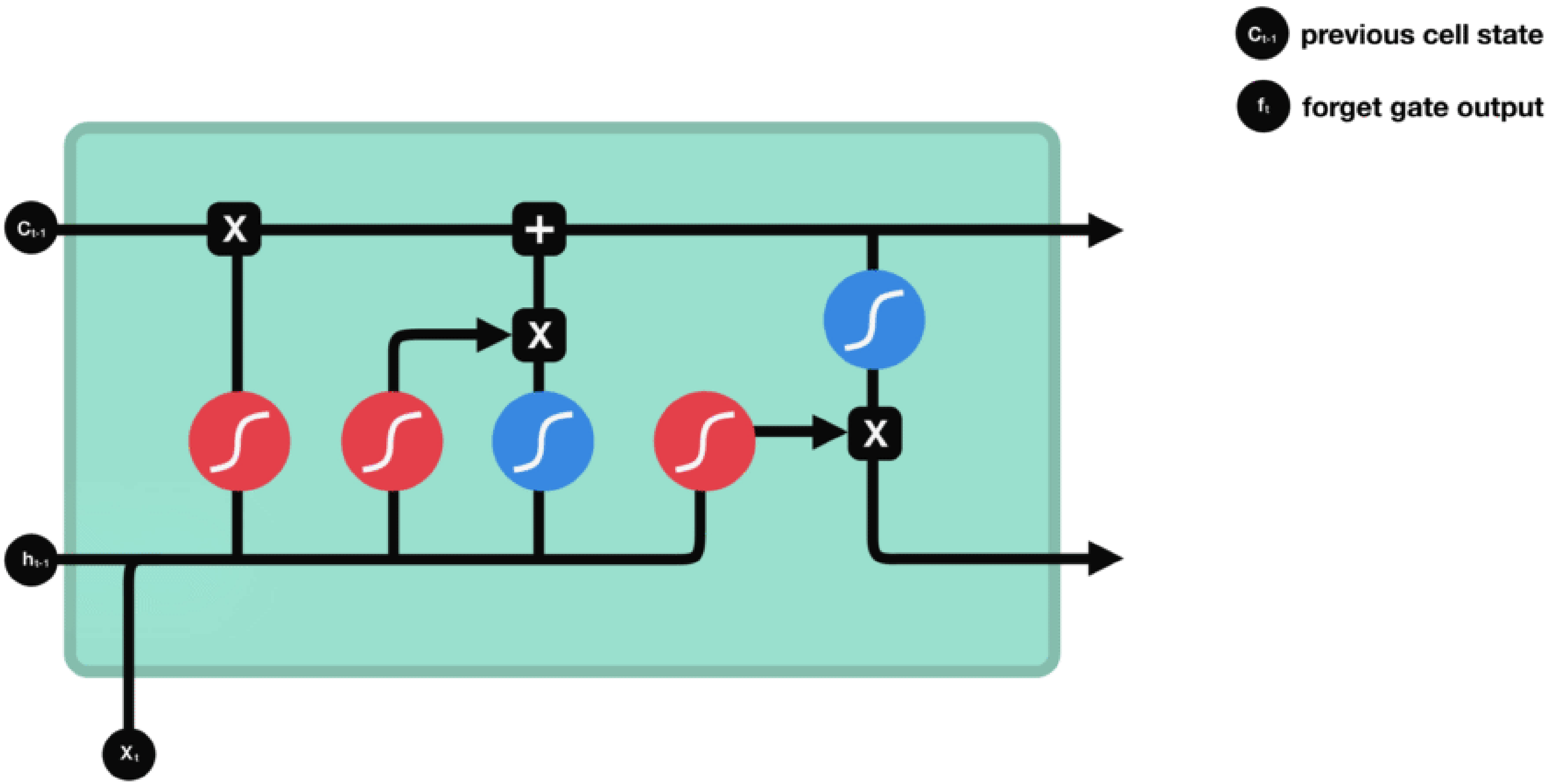


LSTM Architecture - overview



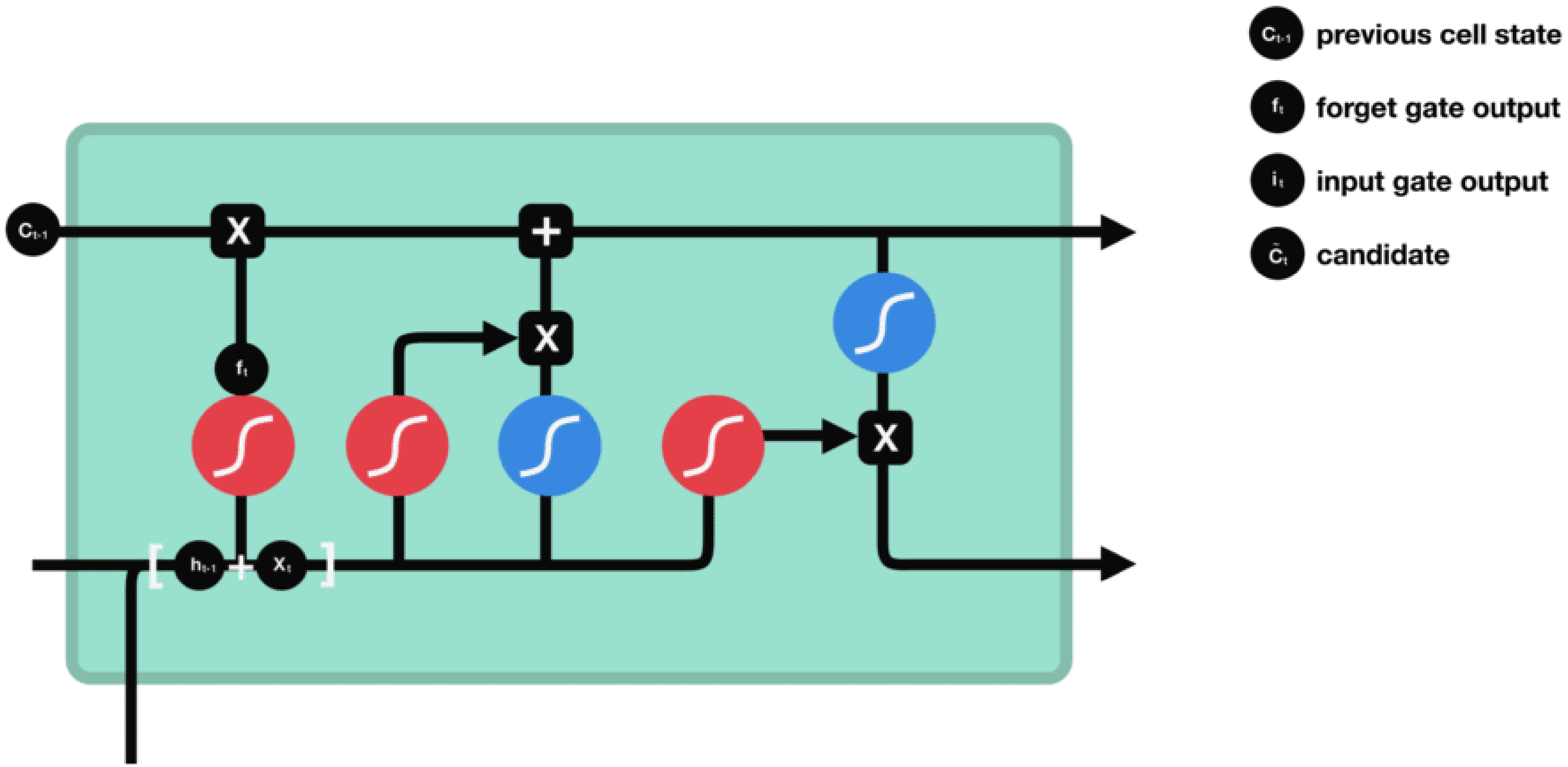
LSTM Cell

LSTM Architecture - overview



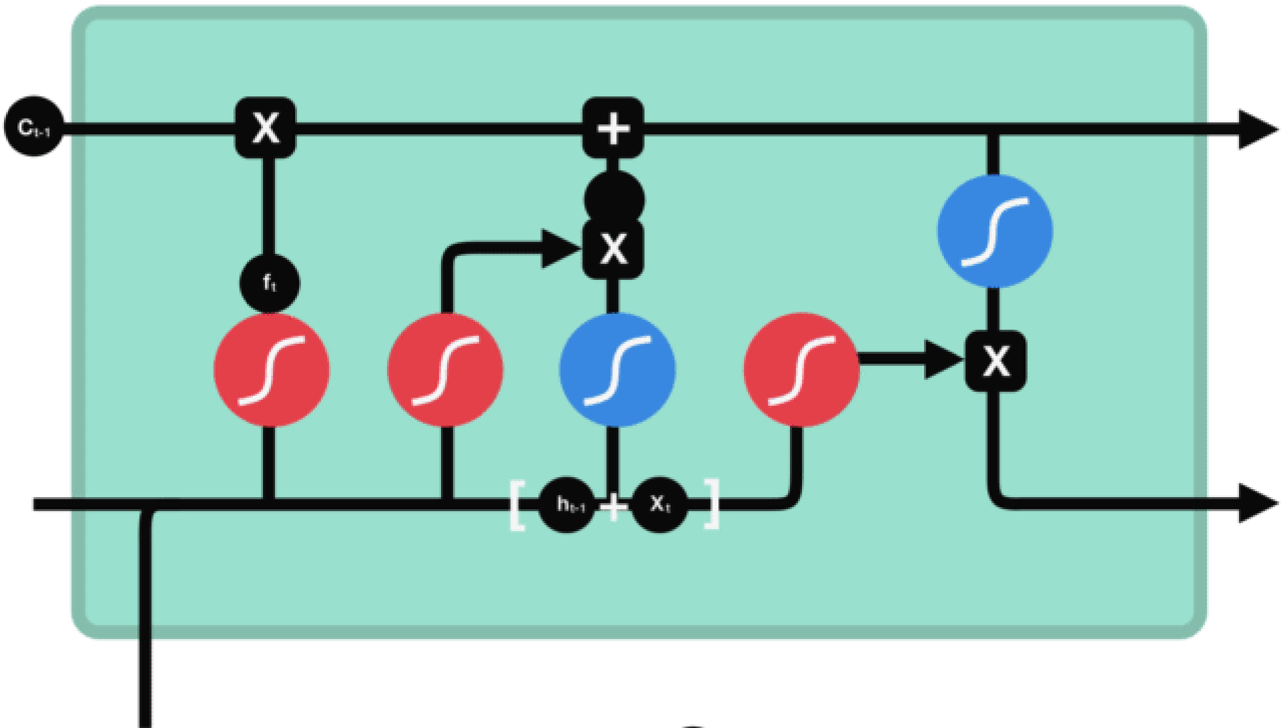
Forget gate operations

LSTM Architecture - overview



Input gate operations

LSTM Architecture - overview

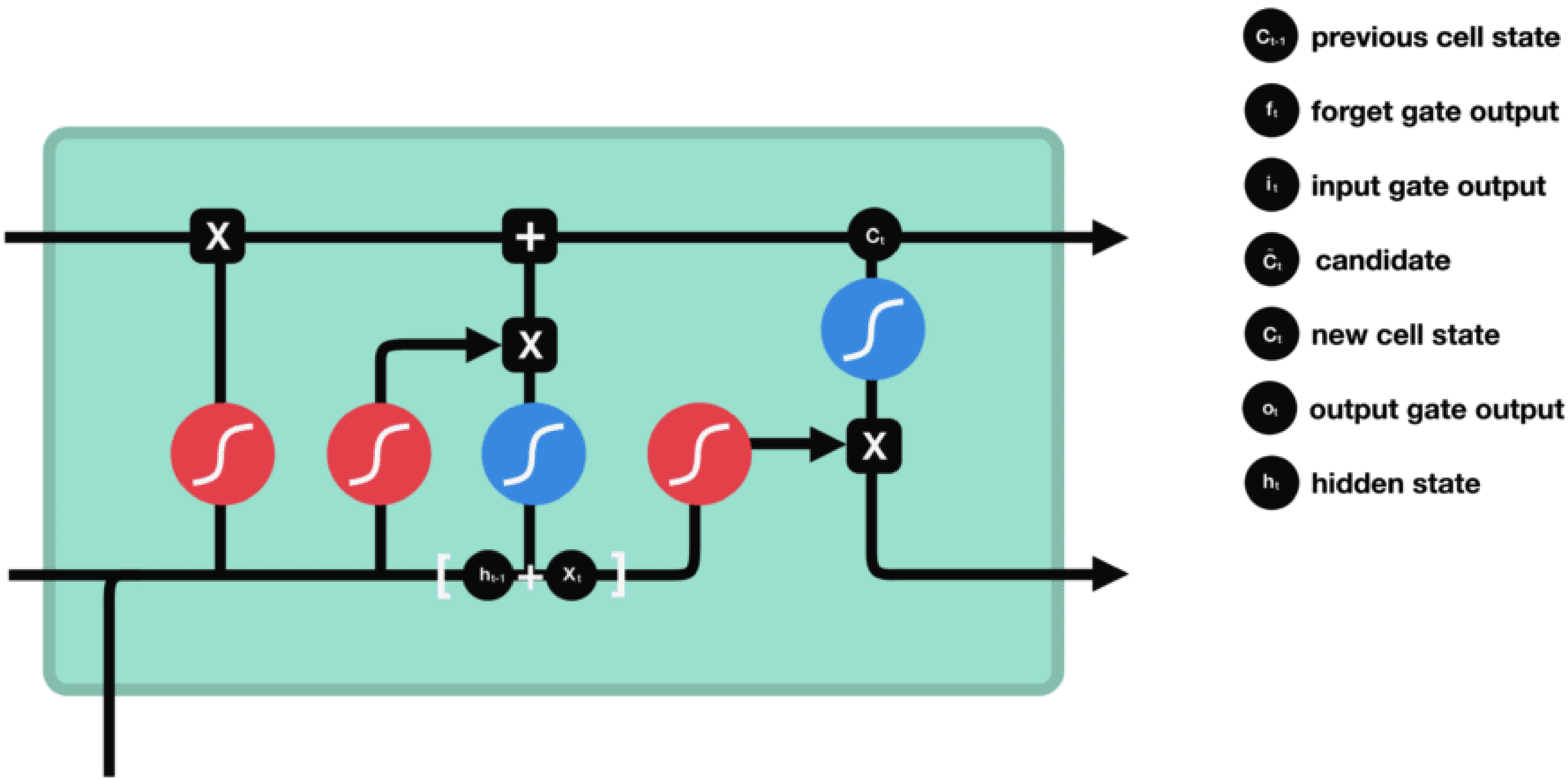


- C_{t-1} previous cell state
- f_t forget gate output
- i_t input gate output
- $\tilde{C}_t$ candidate
- C_t new cell state

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

Calculating cell state

LSTM Architecture - overview



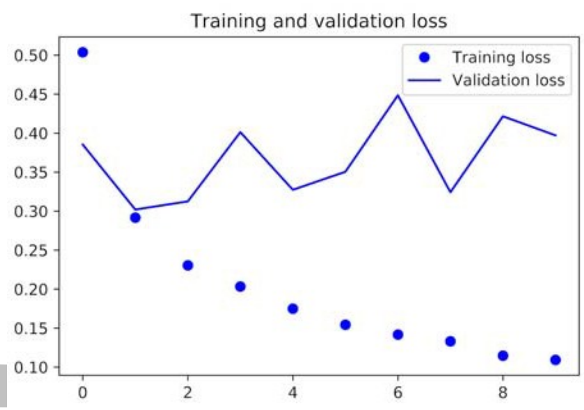
output gate operations

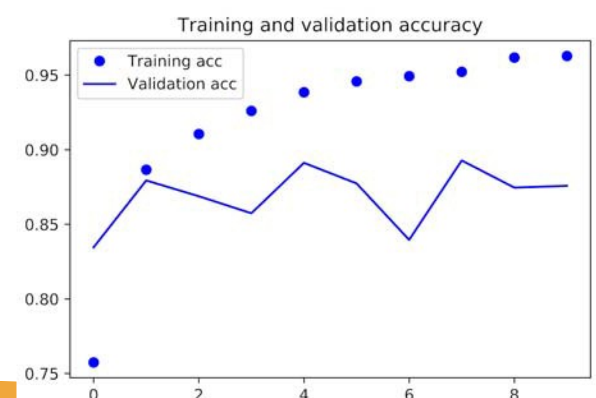
6.2.3A concrete LSTM example in Keras

- set up a model using an LSTM layer and train it on the IMDB data (see figures 6.16 and 6.17).
- similar to the one with SimpleRNN - specify the output dimensionality of the LSTM layer; leave every other argument (there are many) at the Keras defaults.

Listing 6.27 Using the LSTM layer in Keras

```
from keras.layers import LSTM
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop',
     loss='binary_crossentropy', metrics=['acc'])
history = model.fit(input_train, y_train,
          epochs=10, batch_size=128, validation_split=0.2)
```





6.2 Understanding recurrent neural networks

6.2.3 A concrete LSTM example in Keras

- achieve up to 89% validation accuracy with less vanishing-gradient problem—and slightly better than the fully connected approach from chapter 3
- less data than you were in chapter 3 by truncating sequences after 500 timesteps, whereas in chapter 3 (10,000), you were considering full sequences.
- Why isn't LSTM performing better?
  - no effort to tune hyperparameters such as the embeddings dimensionality or the LSTM output dimensionality.
  - lack of regularization
  - analyzing the global, long-term structure of the reviews (what LSTM is good at) isn't helpful for a sentiment-analysis problem.
  - well solved by looking at what words occur in each review, and at what frequency in FCN
  - the strength of LSTM will become apparent: in particular, question-answering and machine translation

6.2.4 Wrapping up

- Now you understand the following:
  - What RNNs are and how they work
  - What LSTM is, and why it works better on long sequences than a naive RNN
  - How to use Keras RNN layers to process sequence data
- Next, advanced features of RNNs