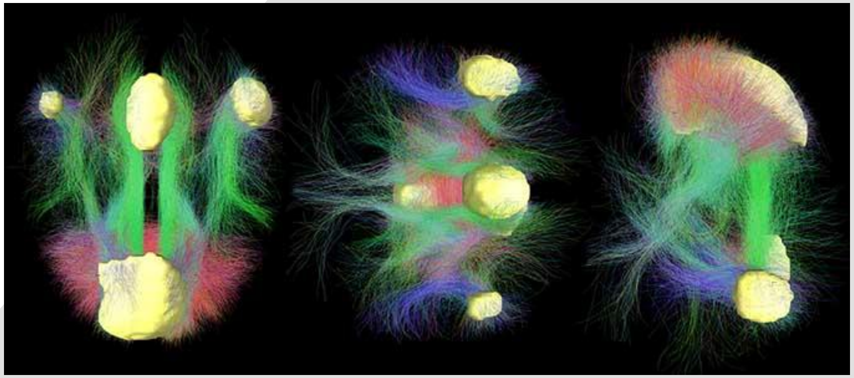
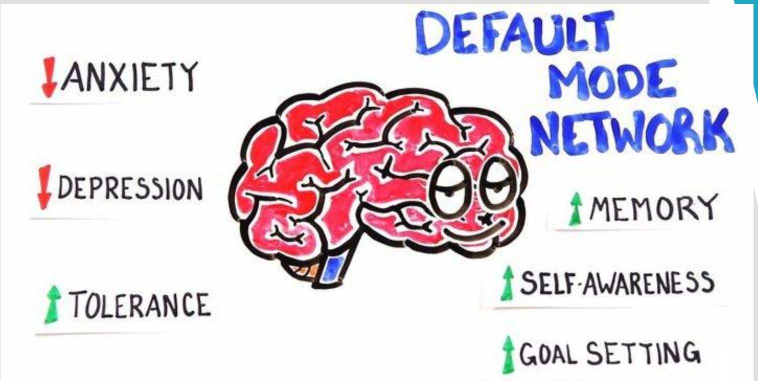
6장 *Deep learning for text and sequences*

“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.

6.1Working with text data

- 텍스트를 가지고 연구하는 분야
  natural-language understanding - document classification, 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
  새로 나오는 좋은 기술

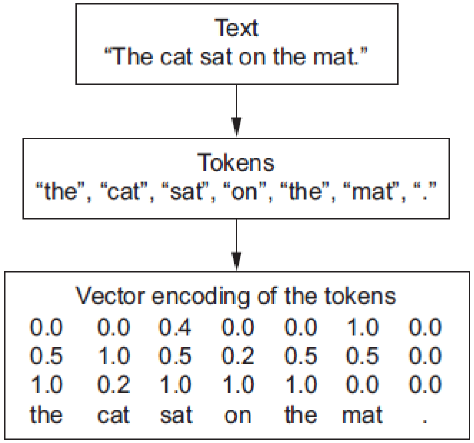


Figure 6.1 From text to tokens to vectors

6.1Working 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
for sample in samples:
    # split() 메서드를 사용해 샘플을 토큰으로 나눕니다.
    for word in sample.split():
        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))
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.]]]
```

6.1Working 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
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.
```

{'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. ... 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. ... 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.]]] '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 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.]]

# 계산된 단어 인덱스를 구합니다.
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

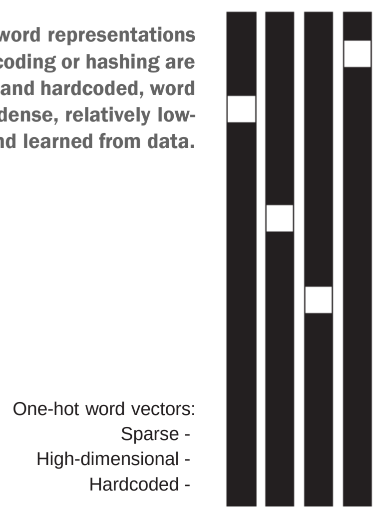
Listing 6.4 Using Keras for word-level one-hot encoding

```
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.]]
```

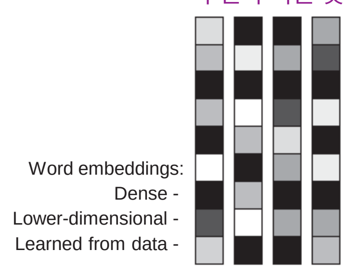
6.1.2 Using word embeddings

- 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.



원-핫 인코딩이 메모리 낭비가 너무 심해서
무언가 다른 뜻을 집어넣어 sparse->dense하게 만듬



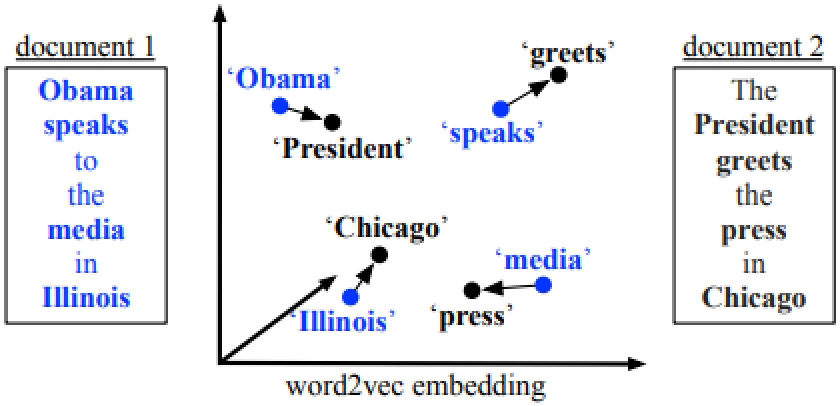
6.1Working with text data

- 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).
  - *pretrained word embeddings* - Load into your model word embeddings
- Let’s look at both.

6.1Working 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
- specific *directions* in the embedding space to be meaningful.



6.1Working with text data

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 typically feature thousands of such 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

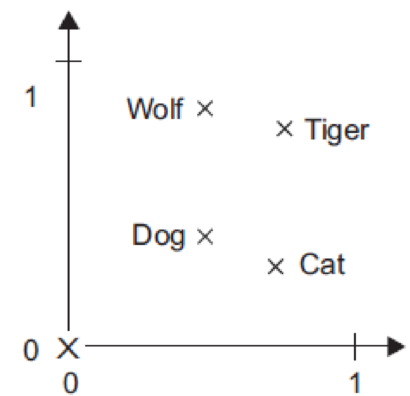


Figure 6.3 A toy example of a word-embedding space

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)
```

- the number of possible tokens (`1000`=1+maximum word index) and the sequence length (`64`).
- 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

6.1Working 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

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())
# 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)
```

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

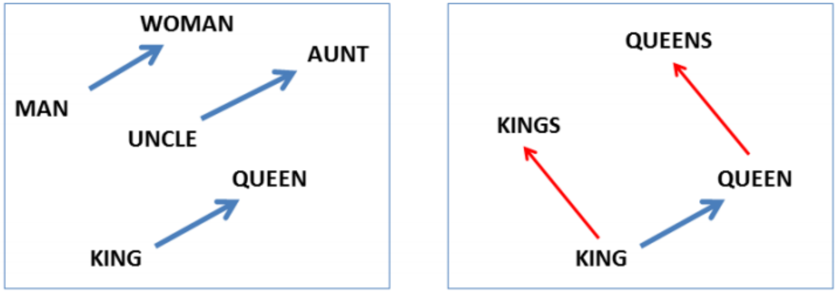
6.1Working with text data

- 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.
- each word in the input sequence separately, without considering 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" 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 that take into account each sequence as a whole.

6.1Working 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), developed by Tomas Mikolov at Google in 2013.
  - Word2vec dimensions capture specific semantic properties, such as genders
- 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.



(Mikolov et al., NAACL HLT, 2013)

	I	love	Programming	Math	tolerate	Biology	.
I	0	2	0	0	1	0	2
love	2	0	1	1	0	0	0
Programming	0	1	0	0	0	0	1
Math	0	1	0	0	0	0	1
tolerate	1	0	0	0	0	1	0
Biology	0	0	0	0	1	0	1
.	1	0	1	1	0	1	0

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

- embedding sentences in sequences of vectors, flattening them, and training a `Dense` layer on top.
- 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'
train_dir = os.path.join(imdb_dir, 'train')
labels = []
texts = []
for label_type in ['neg', 'pos']:
   dir_name = os.path.join(train_dir, label_type)
   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

- Let's vectorize the text and prepare a training and validation split.
- 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 word_index 생성
sequences = tokenizer.texts_to_sequences(texts)
word_index = tokenizer.word_index # {}
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
#first shuffles the data, because you're starting with data in which
samples are ordered (all negative first, then all positive)
np.random.shuffle(indices)
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)
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]