3장 Getting started with neural networks

"기회와 준비가 만났을 때 ... "





- more than two classes?
- classify Reuters newswires into 46 mutually exclusive topics *multi-class* classification

3.5.1 The Reuters dataset

- ▶ a set of short newswires and their topics, published by **Reuters** in 1986 for text classification
- ▶ 46 different topics; each topic has at least 10 examples in the training set
- Like IMDB and MNIST, the **Reuters** dataset comes packaged as part of Keras.

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5. Classifying newswires: a multiclass classification example



Listing 3.12 Loading the Reuters

```
from keras.datasets import reuters
(train_data, train_labels), (test_data, test_labels) =
    reuters.load_data(num_words=10000)
```

- num_words=10000 restricts the data to the 10,000 most frequently occurring words found in the data
- ▶ 8,982 training examples and 2,246 test examples:

```
>>> len(train_data) 8982  
>>> len(test data) 2246
```

• each example is a list of integers (word indices):

```
>>> train_data[10]
[1, 245, 273, 207, 156, 53, 74, 160, 26, 14, 46, 296, 26, 39, 74, 2979,3554, 14, 46, 4689, 4329, 86, 61, 3499, 4795, 14, 61, 451, 4329, 17, 12]
```

label: 0 and 45, a topic index

```
>>> train_labels[10]
2
```



3.5.2 Preparing the data

• vectorize the data - 46 different topics; each topic has at least 10 examples in the training set

Listing 3.14 Encoding the data

```
import numpy as np

def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1.
    return results

x_train = vectorize_sequences(train_data)

x_test = vectorize_sequences(test_data)
```



3.5.2 Preparing the data

▶ One-hot encoding (*categorical encoding*) - an all-zero vector with a 1 in the place of the label index. Here's an example:

```
def to_one_hot(labels, dimension=46):
    results = np.zeros((len(labels), dimension))
    for i, label in enumerate(labels):
        results[i, label] = 1.
    return results

one_hot_train_labels = to_one_hot(train_labels)

one_hot_test_labels = to_one_hot(test_labels)

built-in way to do this in Keras, in the MNIST example:

from keras.utils.np_utils import to_categorical

one_hot_train_labels = to_categorical(train_labels)
one_hot_test_labels = to_categorical(test_labels)
```



3.5.3 Building your network

- the number of output classes 46
- use larger layers with 64 units

Listing 3.15 Model definition

```
from keras import models
from keras import layers
model = models.Sequential()
```

```
Meet Softmax \sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}} for j=1,...,K.

Z

Linear Softmax \sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}} for j=1,...,K.

Softmax \sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}} for j=1,...,K.
```

```
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(46, activation='softmax'))
```

- There are two other things you should note about this architecture:
 - the network will output a 46-dimensional vector
 - The last layer uses a softmax activation a *probability distribution* over the 46 different output classes output[i] is the probability that the sample belongs to class i. The 46 scores will sum to 1.

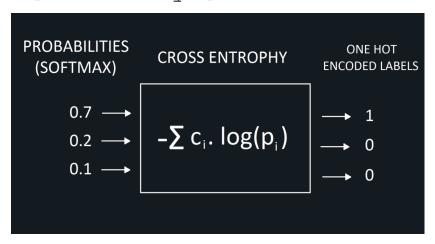


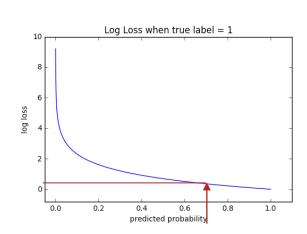


3.5.3 Building your network

loss function - categorical_crossentropy, distance between the probability distribution output by the network and the true distribution of the labels, minimizing the distance

Listing 3.16 Compiling the model







3.5.4 Validating your approach

Let's set apart 1,000 samples in the training data to use as a validation set.

Listing 3.17 Setting aside a validation set

```
x_val = x_train[:1000]
partial_x_train = x_train[1000:] #7982

y_val = one_hot_train_labels[:1000]
partial_y_train = one_hot_train_labels[1000:]
```

Now, let's train the network for 20 epochs.

Listing 3.18 Training the model



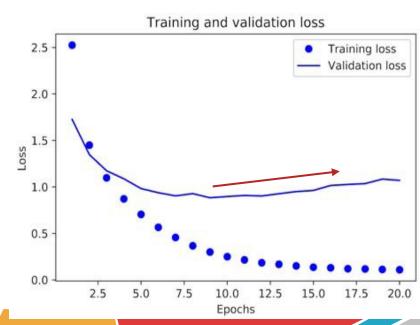
3.5.4 Validating your approach

let's display its loss and accuracy curves (see figures 3.9 and 3.10)

Listing 3.19 Plotting the training and validation loss

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

Figure 3.9 Training and validation loss





3.5.4 Validating your approach

let's display its loss and accuracy curves (see figures 3.9 and 3.10)

Listing 3.20 Plotting the training and validation accuracy

```
plt.clf()
acc = history.history['acc']
val_acc = history.history['val_acc']
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

Output

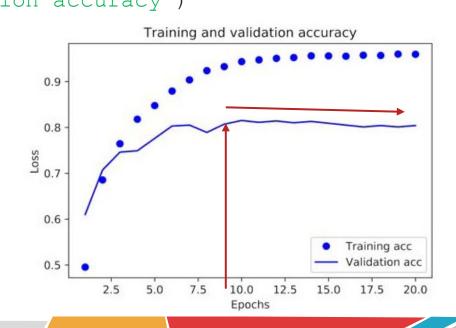
Training and validation accuracy

Output

Description:

Output
```

Figure 3.10 Training and validation accuracy





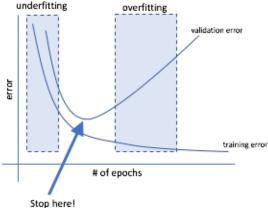
3.5.4 Validating your approach

The network begins to overfit after **nine** epochs. Let's train a new network from scratch for nine epochs and then evaluate it on the test set.

Listing 3.21 Retraining a model from scratch

• Here are the final results:

```
>>> results [0.9565213431445807, 0.79697239536954589]
```





3.5.5 Generating predictions on new data

You can verify that the predict method of the model instance returns a probability distribution over all 46 topics. Let's generate topic predictions for all of the test data.

Listing 3.22 Generating predictions for new data

```
predictions = model.predict(x_test)
```

Each entry in predictions is a vector of length 46:

```
>>> predictions[0].shape
(46,)
```

The coefficients in this vector sum to 1:

```
>>> np.sum(predictions[0])
1.0
```

The largest entry is the predicted class:

```
>>> np.argmax(predictions[0]) # 1.0이 있는 위치의 index 값 4
[0., 0., 0., 0., 1., 0., ... , 0.]
```



3.5.6 A different way to handle the labels and the loss

We mentioned earlier that another way to encode the labels would be to cast them as an integer tensor, like this:

```
y_train = np.array(train_labels) #
y_test = np.array(test_labels) #
```

▶ loss function –

```
categorical_crossentropy → sparse_categorical_crossentropy:
```

```
model.compile(optimizer='rmsprop',
```

If your targets are one-hot encoded, use

But if your targets are integers, use

categorical_crossentropy

index	normal	neptune	smurf	
0	1	0	0	
1	0	1	0	
2	0	0	1	
3	1	0	0	
4	1	0	0	
5	1	0	0	

sparse_categorical_crossentropy

normal = 1	index	у
neptune= 2	0	1
smurf= 3	1	2
	2	3
	3	1
	4	1
	5	1





- 3.5.7 The importance of having sufficiently large intermediate layers
- final outputs are 46-dimensional, intermediate layers << 46-dimensional: for example, 4-dimensional.

Listing 3.23 A model with an information bottleneck

The network now peaks at \sim 71% validation accuracy, an 8% absolute drop.



3.5.8 Further experiments

- Try using larger or smaller layers: 32 units, 128 units, and so on.
- You used two hidden layers. Now try using a single hidden layer, or three hidden layers.

3.5.9 Wrapping up

- Here's what you should take away from this example:
- classify N classes, Dense output layer of size N.
- multiclass classification problem softmax activation to output a probability distribution over the *N* output classes.
- categorical crossentropy minimizes the distance between the probability distributions output
- There are two ways to handle labels in multiclass classification:
 - one-hot encoding using categorical_crossentropy as a loss function
 - the labels as integers using the sparse categorical crossentropy loss function
- multiclass classification problem avoid creating information bottlenecks