UNIT III: Neural Networks: Anatomy of Neural Network, Introduction to Keras: Keras, TensorFlow, Theano and CNTK, Setting up Deep Learning Workstation, Classifying Movie Reviews: Binary Classification, Classifying newswires: Multiclass Classification.

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3.1. Anatomy of a neural network

Training a neural network revolves around the following objects:

- *Layers*, which are combined into a *network* (or *model*)
- The *input data* and corresponding *targets*
- The *loss function*, which defines the feedback signal used for learning
- The *optimizer*, which determines how learning proceeds

You can visualize their interaction as illustrated in figure 3.1: the network, composed of layers that are chained together, maps the input data to predictions.

The loss function then compares these predictions to the targets, producing a loss value: a measure of how well the network's predictions match what was expected.

The optimizer uses this loss value to update the network's weights.

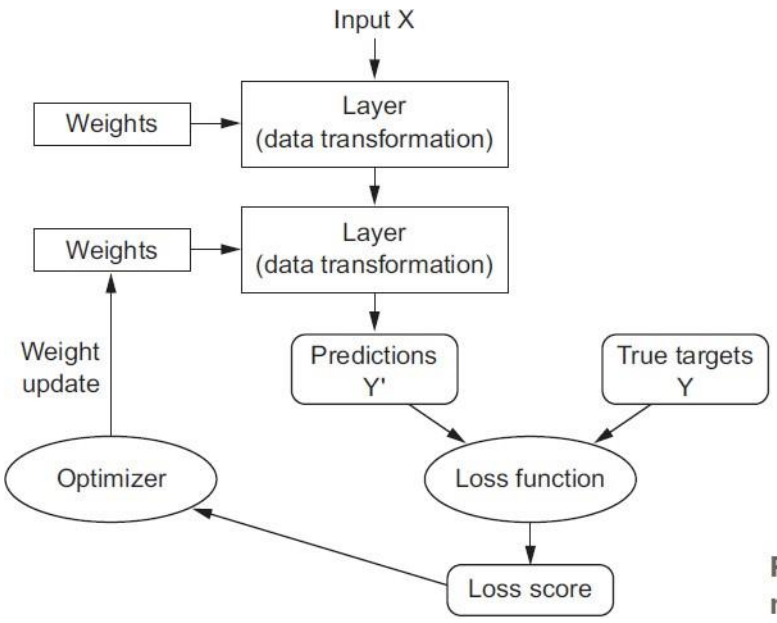


Figure 3.1 Relationship between the network, layers, loss function, and optimizer

3.1.1 Layers: the building blocks of deep learning

The fundamental data structure in neural networks is the *layer*.

A layer is a data-processing module that takes as input one or more tensors and that outputs one or more tensors. Some layers are stateless, but more frequently layers have a state.

Different layers are appropriate for different tensor formats and different types of data processing.

For instance, simple vector data, stored in 2D tensors of shape (samples, features), is often processed by *densely connected* layers, also called *fully connected* or *dense* layers (the Dense class in Keras). Sequence data, stored in 3D tensors of shape (samples, timesteps, features), is typically processed by *recurrent* layers such as an LSTM layer. Image data, stored in 4D tensors, is usually processed by 2D convolution layers (Conv2D).

Building deep-learning models in Keras is done by clipping together compatible layers to form useful data-transformation pipelines.

Consider the following example

```
from keras import layers

layer = layers.Dense(32, input_shape=(784,))
```

A dense layer with 32 output units

We're creating a layer that will only accept as input 2D tensors where the first dimension is 784 (axis 0, the batch dimension, is unspecified, and thus any value would be accepted). This layer will return a tensor where the first dimension has been transformed to be 32.

When using Keras, you don't have to worry about compatibility, because the layers you add to your models are dynamically built to match the shape of the incoming layer. For instance, suppose you write the following

```
from keras import models
from keras import layers

model = models.Sequential()
model.add(layers.Dense(32, input_shape=(784,)))
model.add(layers.Dense(32))
```

The second layer didn't receive an input shape argument—instead, it automatically inferred its input shape as being the output shape of the layer that came before.

3.1.2 Models: networks of layers

A deep-learning model is a directed, acyclic graph of layers. The most common instance is a linear stack of layers, mapping a single input to a single output.

But as you move forward, you'll be exposed to a much broader variety of network topologies. Some common ones include the following:

- Two-branch networks
- Multihead networks
- Inception blocks

Picking the right network architecture is more an art than a science; and although there are some best practices and principles you can rely on, only practice can help you become a proper neural-network architect.

3.1.3 Loss functions and optimizers: keys to configuring the learning process

Once the network architecture is defined, you still have to choose two more things:

a) *Loss function (objective function)*—The quantity that will be minimized during training. It represents a measure of success for the task at hand.

b) *Optimizer*—Determines how the network will be updated based on the loss function.

3.2 Introduction to Keras

Keras is a deep-learning framework for Python that provides a convenient way to define and train almost any kind of deep-learning model. Keras was initially developed for researchers, with the aim of enabling fast experimentation.

Keras has the following key features:

- ❖ It allows the same code to run seamlessly on CPU or GPU.
- ❖ It has a user-friendly API that makes it easy to quickly prototype deep-learning models.

- ❖ It has built-in support for convolutional networks (for computer vision), recurrent networks (for sequence processing), and any combination of both.
- ❖ It supports arbitrary network architectures: multi-input or multi-output models, layer sharing, model sharing, and so on. This means Keras is appropriate for building essentially any deep-learning model, from a generative adversarial network to a neural Turing machine.

Keras is distributed under the permissive MIT license, which means it can be freely used in commercial projects. It's compatible with any version of Python from 2.7 to 3.6 (as of mid-2017).

Keras has well over 200,000 users, ranging from academic researchers and engineers at both startups and large companies to graduate students and hobbyists.

Keras is used at Google, Netflix, Uber, CERN, Yelp, Square, and hundreds of startups working on a wide range of problems. Keras is also a popular framework on Kaggle, the machine-learning competition website, where almost every recent deep-learning competition has been won using Keras models.

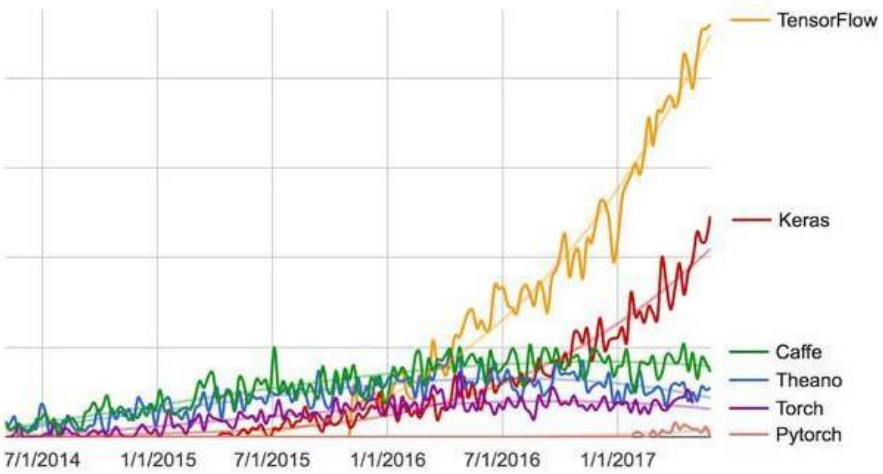


Figure: Google web search interest for different deep-learning frameworks over time

3.2.1 Keras, TensorFlow, Theano, and CNTK

Keras is a model-level library, providing high-level building blocks for developing deep-learning models.

It doesn't handle low-level operations such as tensor manipulation and differentiation. Instead, it relies on a specialized, well-optimized tensor library to do so, serving as the *backend engine* of Keras. Rather than choosing a single tensor library and tying the implementation of Keras to that library, Keras handles the problem in a modular way (see figure 3.3); thus several different backend engines can be plugged seamlessly into Keras.

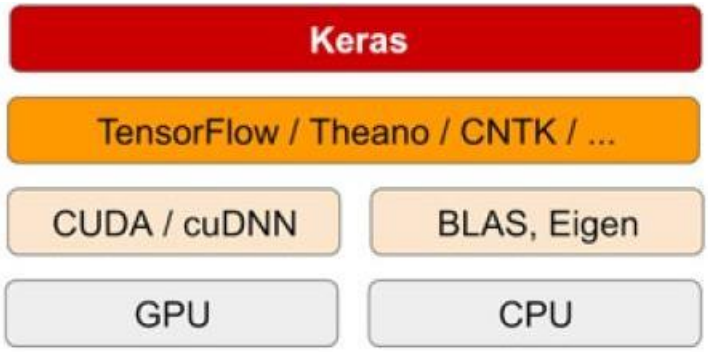


Figure 3.3 The deep-learning software and hardware stack

Currently, the three existing backend implementations are the TensorFlow backend, the Theano backend, and the Microsoft Cognitive Toolkit (CNTK) backend. In the future, it's likely that Keras will be extended to work with even more deep-learning execution engines.

- TensorFlow, CNTK, and Theano are some of the primary platforms for deep learning today.
- Theano (http://deeplearning.net/software/theano) is developed by the MILA lab at *Université de Montréal*, TensorFlow (www.tensorflow.org) is developed by Google, and
- CNTK (https://github.com/Microsoft/CNTK) is developed by Microsoft

Any piece of code that you write with Keras can be run with any of these backends without having to change anything in the code.

3.2.2 Developing with Keras: a quick overview

You've already seen one example of a Keras model: the MNIST example. The typical Keras workflow looks just like that example:

1. Define your training data: input tensors and target tensors.
2. Define a network of layers (or *model*) that maps your inputs to your targets.
3. Configure the learning process by choosing a loss function, an optimizer, and some metrics to monitor.
4. Iterate on your training data by calling the fit() method of your model.

There are two ways to define a model: using the Sequential class (only for linear stacks of layers, which is the most common network architecture by far) or the *functional API* (for directed acyclic graphs of layers, which lets you build completely arbitrary architectures).

3.3. Setting up Deep Learning Workstation

Before you can get started developing deep-learning applications, you need to set up your workstation. It's highly recommended, although not strictly necessary, that you run deep-learning code on a modern NVIDIA GPU

If you don't want to install a GPU on your machine, you can alternatively consider running your experiments on an AWS EC2 GPU instance or on Google Cloud Platform. But note that cloud GPU instances can become expensive over time.

3.3.1 Jupyter notebooks: the preferred way to run deep-learning experiments

- Jupyter notebooks are a great way to run deep-learning experiments.
- They're widely used in the data-science and machine-learning communities.
- A *notebook* is a file generated by the Jupyter Notebook app (https://jupyter.org), which you can edit in your browser.
- It mixes the ability to execute Python code with rich text-editing capabilities for annotating what you're doing.
- A notebook also allows you to break up long experiments into smaller pieces that can be executed independently, which makes development interactive and means you don't have to rerun all of your previous code if something goes wrong late in an experiment

3.3.2 Getting Keras running: two options

To get started in practice, we recommend one of the following two options:

1. Use the official EC2 Deep Learning AMI (https://aws.amazon.com/amazonai/amis), and run Keras experiments as Jupyter notebooks on EC2. Do this if you don't already have a GPU on your local machine.

2. Install everything from scratch on a local Unix workstation. You can then run either local Jupyter notebooks or a regular Python codebase. Do this if you already have a high-end NVIDIA GPU.

3.3.3 Running deep-learning jobs in the cloud: pros and cons

There are many pros and cons to running deep-learning jobs in the cloud. Here are some of the most important ones:

Pros:

- Scalability: Cloud computing provides virtually unlimited scalability, so you can easily add or remove resources as needed. This is essential for deep learning, as training models can be very demanding on resources.
- Cost-effectiveness: Cloud computing can be very cost-effective for deep learning, especially if you only need to use the resources for a short period of time. You can also pay for the resources you use, so you're not wasting money on unused capacity.
- Ease of use: Cloud computing platforms make it easy to set up and run deep-learning jobs. Many platforms provide pre-configured machine learning environments, so you don't have to worry about setting up the infrastructure yourself.
- Collaboration: Cloud computing makes it easy to collaborate on deep learning projects. You can share data and models with other team members, and you can also run jobs on multiple machines in parallel.
- Security: Cloud computing providers offer a high level of security for your data. Your data is encrypted in transit and at rest, and you can control who has access to it.

Cons:

- Latency: There can be some latency when running deep-learning jobs in the cloud, as the data has to travel to and from the cloud servers. This can be a problem for real-time applications.
- Vendor lock-in: If you choose to use a particular cloud provider, you may become locked in to their platform. This can make it difficult to switch providers if you're not happy with their services.
- Complexity: Cloud computing can be complex, especially if you're not familiar with it. There are a lot of different services and features to choose from, and it can be difficult to know which ones are right for you.

3.3.4 What is the best GPU for deep learning?

If you’re going to buy a GPU, which one should you choose? The first thing to note is that it must be an NVIDIA GPU. NVIDIA is the only graphics computing company that has invested heavily in deep learning so far, and modern deep-learning frameworks can only run on NVIDIA cards

3.4. Classifying Movie Reviews: Binary Classification

Two-class classification, or binary classification, may be the most widely applied kind of machine-learning problem. In this example, you'll learn to classify movie reviews as positive or negative, based on the text content of the reviews.

3.4.1 The IMDB dataset

You'll work with the IMDB dataset: a set of 50,000 highly polarized reviews from the Internet Movie Database. They're split into 25,000 reviews for training and 25,000 reviews for testing, each set consisting of 50% negative and 50% positive reviews.

Listing 3.1 Loading the IMDB dataset

```
from keras.datasets import imdb

(train_data, train_labels), (test_data, test_labels) = imdb.load_data(
    num_words=10000)
```

The argument num_words=10000 means you'll only keep the top 10,000 most frequently occurring words in the training data. Rare words will be discarded. This allows you to work with vector data of manageable size

The variables train_data and test_data are lists of reviews; each review is a list of word indices (encoding a sequence of words). train_labels and test_labels are lists of 0s and 1s, where 0 stands for *negative* and 1 stands for *positive*:

```
>>> train_data[0]
[1, 14, 22, 16, ... 178, 32]

>>> train_labels[0]
1
```

Because you're restricting yourself to the top 10,000 most frequent words, no word index will exceed 10,000:

>>> max([max(sequence) for sequence in train_data])

output: 9999

For kicks, here's how you can quickly decode one of these reviews back to English words:

```
word_index = imdb.get_word_index()
reverse_word_index = dict(
    [(value, key) for (key, value) in word_index.items()])
decoded_review = ' '.join(
    [reverse_word_index.get(i - 3, '?') for i in train_data[0]])
```

word_index is a dictionary mapping words to an integer index.

Reverses it, mapping integer indices to words

Decodes the review. Note that the indices are offset by 3 because 0, 1, and 2 are reserved indices for "padding," "start of sequence," and "unknown."

3.4.2 Preparing the data

You can't feed lists of integers into a neural network. You have to turn your lists into tensors. There are two ways to do that:

1. Pad your lists so that they all have the same length, turn them into an integer tensor of shape (samples, word_indices), and then use as the first layer in your network a layer capable of handling such integer tensors (the Embedding layer, which we'll cover in detail later in the book).

2. One-hot encode your lists to turn them into vectors of 0s and 1s. This would mean, for instance, turning the sequence [3, 5] into a 10,000-dimensional vector that would be all 0s except for indices 3 and 5, which would be 1s. Then you could use as the first layer in your network a Dense layer, capable of handling floating-point vector data.

Let's go with the latter solution to vectorize the data, which you'll do manually for maximum clarity

Listing 3.2 Encoding the integer sequences into a binary matrix

```
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)
```

Creates an all-zero matrix of shape (len(sequences), dimension)

Sets specific indices of results[i] to 1s

Vectorized training data

Vectorized test data

Here's what the samples look like now:

```
>>> x_train[0]
```

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

You should also vectorize your labels, which is straightforward:

```
y_train = np.asarray(train_labels).astype('float32')
```

```
y_test = np.asarray(test_labels).astype('float32')
```

3.4.3 Building your network

The input data is vectors, and the labels are scalars (1s and 0s): this is the easiest setup you'll ever encounter. A type of network that performs well on such a problem is a simple stack of fully connected (Dense) layers with relu activations: Dense(16, activation='relu').

Listing 3.3 The model definition

```
from keras import models
from keras import layers

model = models.Sequential()
model.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

What are activation functions, and why are they necessary?

Without an activation function like `relu` (also called a *non-linearity*), the `Dense` layer would consist of two linear operations—a dot product and an addition:

```
output = dot(W, input) + b
```

So the layer could only learn *linear transformations* (affine transformations) of the input data: the *hypothesis space* of the layer would be the set of all possible linear transformations of the input data into a 16-dimensional space. Such a hypothesis space is too restricted and wouldn't benefit from multiple layers of representations, because a deep stack of linear layers would still implement a linear operation: adding more layers wouldn't extend the hypothesis space.

In order to get access to a much richer hypothesis space that would benefit from deep representations, you need a non-linearity, or activation function. `relu` is the most popular activation function in deep learning, but there are many other candidates, which all come with similarly strange names: `prelu`, `elu`, and so on.

Finally, you need to choose a loss function and an optimizer. Because you're facing a binary classification problem and the output of your network is a probability (you end your network with a single-unit layer with a sigmoid activation), it's best to use the binary_crossentropy loss. It isn't the only viable choice: you could use, for instance, mean_squared_error. But crossentropy is usually the best choice when you're dealing with models that output probabilities.

Listing 3.4 Compiling the model

```
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

3.4.4 Validating your approach

In order to monitor during training the accuracy of the model on data it has never seen before, you'll create a validation set by setting apart 10,000 samples from the original training data

```
In [14]: # Input for Validation
         X_val = X_train[:10000]
         partial_X_train = X_train[10000:]

         # Labels for validation
         y_val = y_train[:10000]
         partial_y_train = y_train[10000:]
```

You'll now train the model for 20 epochs (20 iterations over all samples in the x_train and y_train tensors), in mini-batches of 512 samples. At the same time, you'll monitor loss and accuracy on the 10,000 samples that you set apart. You do so by passing the validation data as the validation_data argument.

```
In [15]: history = model.fit(partial_X_train,
                             partial_y_train,
                             epochs=20,
                             batch_size=512,
                             validation_data=(X_val, y_val))
```

let's use Matplotlib to plot the training and validation loss side by side (see figure 3.7), as well as the training and validation accuracy (see figure 3.8).

Listing 3.9 Plotting the training and validation loss

```
import matplotlib.pyplot as plt

history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs = range(1, len(acc) + 1)

plt.plot(epochs, loss_values, 'bo', label='Training loss')
plt.plot(epochs, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```

"bo" is for "blue dot."

"b" is for "solid blue line."

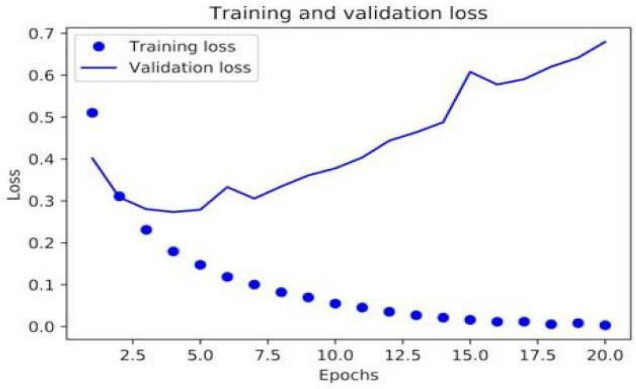


Figure 3.7 Training and validation loss

As you can see, the training loss decreases with every epoch, and the training accuracy increases with every epoch. That's what you would expect when running gradientdescent optimization—the quantity you're trying to minimize should be less with every iteration.

3.5. Classifying newswires: Multiclass Classification

In this example, we will build a model to classify Reuters newswires into 46 mutually exclusive topics. Because we have many classes, this problem is an instance of multiclass classification; and because each data point should be classified into only one category, the problem is more specifically an instance of single-label, multiclass classification. If each data point could belong to multiple categories (in this case, topics), you'd be facing a multilabel, multiclass classification problem.

Reuters dataset

We will work with the Reuters dataset, a set of short newswires and their topics, published by Reuters in 1986. It's a simple, widely used toy dataset for text classification. There are 46 different topics; some topics are more represented than others, but each topic has at least 10 examples in the training set. Like IMDB and MNIST, the Reuters dataset comes packaged as part of Keras.

In [1]:
```
import numpy as np
import pandas as pd
import warnings
import tensorflow as tf # import tensor flow
import numpy as np
import keras
from tensorflow.keras import layers
import matplotlib.pyplot as plt
```

2.

Load Dataset

In [2]:
```
from tensorflow.keras.datasets import reuters
(train_data, train_labels), (test_data, test_labels) = reuters.load_data(num_words=10000)
```

3.

In [3]:
```
len(train_data),len(test_data)
```

Out[3]:
```
(8982, 2246)
```

The argument num_words=10000 restricts the data to the 10,000 most frequently occurring words found in the data. You have 8,982 training examples and 2,246 test examples:

In [4]:
```
print(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, 4
51, 4329, 17, 12]
```

4. Data Prep

vectorize the input data

```
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)#1
x_test = vectorize_sequences(test_data)#2
```

1. Verctorize training data
2. Vencotrize testing data

vectorize the label with the exact same code as in the previous 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)#1
one_hot_test_labels = to_one_hot(test_labels)#2
```

1. Verctorize training labels
2. Vencotrize testing labels

Note that there is a built-in way to do this in Keras:

```
from tensorflow.keras.utils import to_categorical
one_hot_train_labels = to_categorical(train_labels)
one_hot_test_labels = to_categorical(test_labels)
```

5. Building the model

This topic-classification problem looks similar to the previous movie-review classificationq: in both cases, we are trying to classify short snippets of text. But there is a new constraint here: the number of output classes has gone from 2 to 46. The dimensionality of the output space is much larger.

In a stack of Dense layers like that we have been using, each layer can only access information present in the output of the previous layer. If one layer drops some information relevant to the classification problem, this information can never be recovered by later layers: each layer can potentially become an information bottleneck. In the previous example, we used 16-dimensional intermediate layers, but a 16-dimensional space may be too limited to learn to separate 46 different classes: such small layers may act as information bottlenecks, permanently dropping relevant information. For this reason we will use larger layers. Let's go with 64 units.

Model Defination

```
model = keras.Sequential([
  layers.Dense(64, activation='relu'),
  layers.Dense(64, activation='relu'),
  layers.Dense(46, activation='softmax')
])
```

Note about this architecture:

1. We end the model with a Dense layer of size 46. This means for each input sample, the network will output a 46-dimensional vector. Each entry in this vector (each dimension) will encode a different output class.
2. The last layer uses a softmax activation. You saw this pattern in the MNIST example. It means the model will output a probability distribution over the 46 different output classes — for every input sample, the model will produce a 46-dimensional output vector, where output[i] is the probability that the sample belongs to class i. The 46 scores will sum to 1.
3. The best loss function to use in this case is categorical_crossentropy. It measures the distance between two probability distributions: here, between the probability distribution output by the model and the true distribution of the labels. By minimizing the distance between these two distributions, you train the model to output something as close as possible to the true labels.

6. Compile the model

```
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Validation of the approach

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

```
x_val = x_train[:1000]
partial_x_train = x_train[1000:]
y_val = one_hot_train_labels[:1000]
partial_y_train = one_hot_train_labels[1000:]
```

let's train the model for 20 epochs.

Training the model

```
history = model.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

Epoch 1/20

16/16 [==============================] - 2s 81ms/step - loss: 3.1029 - accuracy: 0.4079 - val_loss: 1.7132 - val_accuracy: 0.6440

Epoch 2/20

16/16 [==============================] - 1s 38ms/step - loss: 1.4807 - accuracy: 0.6992 - val_loss: 1.2964 - val_accuracy: 0.7230

Epoch 3/20

16/16 [==============================] - 1s 36ms/step - loss: 1.0763 - accuracy: 0.7762 - val_loss: 1.1460 - val_accuracy: 0.7380

Epoch 4/20

16/16 [==============================] - 1s 36ms/step - loss: 0.8441 - accuracy: 0.8245 - val_loss: 1.0389 - val_accuracy: 0.7810

Epoch 5/20

16/16 [==============================] - 1s 37ms/step - loss: 0.6595 - accuracy: 0.8658 - val_loss: 0.9456 - val_accuracy: 0.8050

Epoch 6/20

16/16 [==============================] - 1s 37ms/step - loss: 0.5237 - accuracy: 0.8945 - val_loss: 0.9203 - val_accuracy: 0.8040

Epoch 7/20

16/16 [==============================] - 1s 36ms/step - loss: 0.4181 - accuracy: 0.9160 - val_loss: 0.8765 - val_accuracy: 0.8140

Epoch 8/20

16/16 [==============================] - 1s 35ms/step - loss: 0.3485 - accuracy: 0.9316 - val_loss: 0.8895 - val_accuracy: 0.8060

Epoch 9/20

16/16 [==============================] - 1s 36ms/step - loss: 0.2829 - accuracy: 0.9390 - val_loss: 0.8829 - val_accuracy: 0.8110

Epoch 10/20

16/16 [==============================] - 1s 36ms/step - loss: 0.2246 - accuracy: 0.9479 - val_loss: 0.9112 - val_accuracy: 0.8140

Epoch 11/20

16/16 [==============================] - 1s 36ms/step - loss: 0.1894 - accuracy: 0.9532 - val_loss: 0.9060 - val_accuracy: 0.8120

Epoch 12/20

16/16 [==============================] - 1s 37ms/step - loss: 0.1765 - accuracy: 0.9538 - val_loss: 0.9068 - val_accuracy: 0.8160

Epoch 13/20

16/16 [==============================] - 1s 37ms/step - loss: 0.1610 - accuracy: 0.9529 - val_loss: 0.9394 - val_accuracy: 0.8100

Epoch 14/20

16/16 [==============================] - 1s 37ms/step - loss: 0.1438 - accuracy: 0.9574 - val_loss: 0.9254 - val_accuracy: 0.8190

Epoch 15/20

16/16 [==============================] - 1s 35ms/step - loss: 0.1305 - accuracy: 0.9584 - val_loss: 0.9666 - val_accuracy: 0.8060

Epoch 16/20

16/16 [==============================] - 1s 37ms/step - loss: 0.1291 - accuracy: 0.9562 - val_loss: 0.9537 - val_accuracy: 0.8120

Epoch 17/20

16/16 [==============================] - 1s 36ms/step - loss: 0.1140 - accuracy: 0.9593 - val_loss: 1.0202 - val_accuracy: 0.8020

Epoch 18/20

16/16 [==============================] - 1s 38ms/step - loss: 0.1167 - accuracy: 0.9567 - val_loss: 0.9942 - val_accuracy: 0.8070

Epoch 19/20

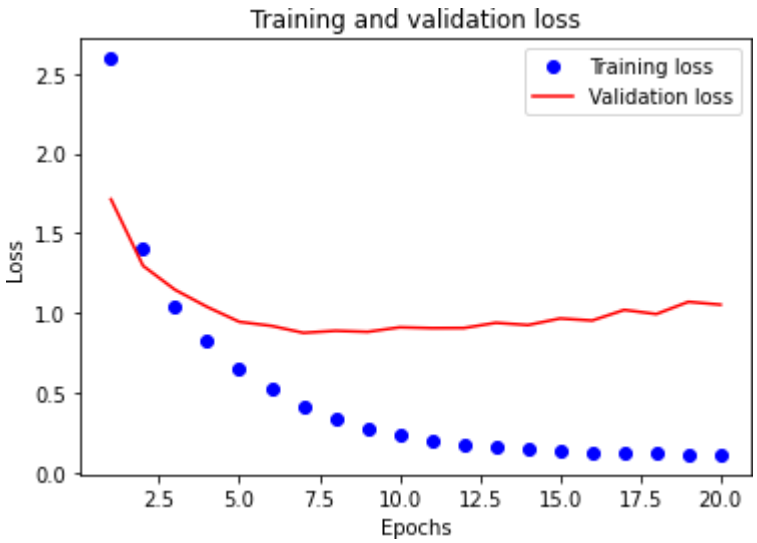
16/16 [==============================] - 1s 38ms/step - loss: 0.0972 - accuracy: 0.9669 - val_loss: 1.0709 - val_accuracy: 0.7960

Epoch 20/20

16/16 [==============================] - 1s 34ms/step - loss: 0.1035 - accuracy: 0.9607 - val_loss: 1.0530 - val_accuracy: 0.8020

7. Plotting the training and validation loss

```
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, 'r', label='Validation loss')

plt.title('Training and validation loss')

plt.xlabel('Epochs')

plt.ylabel('Loss')

plt.legend()

plt.show()
```


Training and validation loss
Training loss
Validation loss
Loss
Epochs
0.0
0.5
1.0
1.5
2.0
2.5
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0