Chapter 10 – Introduction to Artificial Neural Networks with Keras

This notebook contains all the sample code and solutions to the exercises in chapter 10.

Run in Google Colab (https://colab.research.google.com/github/ageron/handson-ml2/blob/master/10_neural_nets_with_keras.ipynb)

Setup

First, let's import a few common modules, ensure MatplotLib plots figures inline and prepare a function to save the figures. We also check that Python 3.5 or later is installed (although Python 2.x may work, it is deprecated so we strongly recommend you use Python 3 instead), as well as Scikit-Learn ≥0.20 and TensorFlow ≥2.0.

In [1]:
```
# Python ≥3.5 is required
import sys
assert sys.version_info >= (3, 5)

# Scikit-Learn ≥0.20 is required
import sklearn
assert sklearn.__version__ >= "0.20"

try:
    # %tensorflow_version only exists in Colab.
    %tensorflow_version 2.x
except Exception:
    pass

# TensorFlow ≥2.0 is required
import tensorflow as tf
assert tf.__version__ >= "2.0"

# Common imports
import numpy as np
import os

# to make this notebook's output stable across runs
np.random.seed(42)

# To plot pretty figures
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)

# Where to save the figures
PROJECT_ROOT_DIR = "."
CHAPTER_ID = "ann"
IMAGES_PATH = os.path.join(PROJECT_ROOT_DIR, "images", CHAPTER_ID)
os.makedirs(IMAGES_PATH, exist_ok=True)

def save_fig(fig_id, tight_layout=True, fig_extension="png", resolution=30
0):
    path = os.path.join(IMAGES_PATH, fig_id + "." + fig_extension)
    print("Saving figure", fig_id)
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)

# Ignore useless warnings (see SciPy issue #5998)
import warnings
warnings.filterwarnings(action="ignore", message="^internal gelsd")
```

Perceptrons

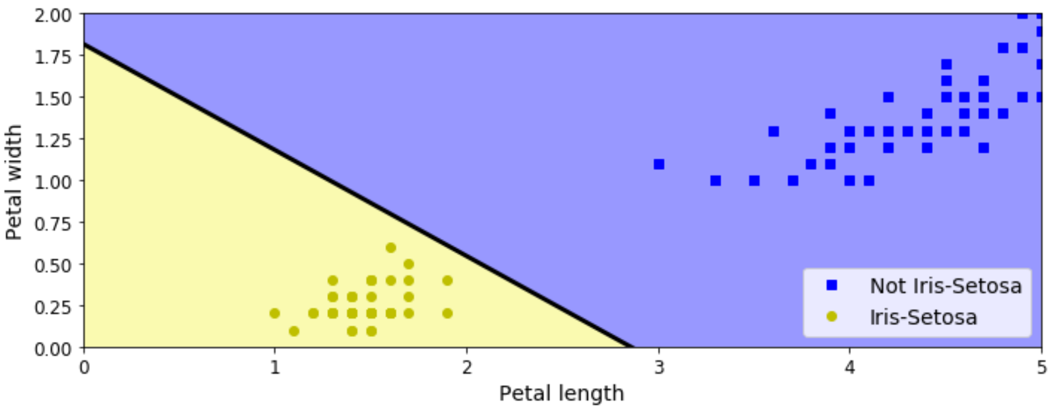
Note: we set `max_iter` and `tol` explicitly to avoid warnings about the fact that their default value will change in future versions of Scikit-Learn.

In [2]:
```python
import numpy as np
from sklearn.datasets import load_iris
from sklearn.linear_model import Perceptron

iris = load_iris()
X = iris.data[:, (2, 3)]  # petal length, petal width
y = (iris.target == 0).astype(np.int)

per_clf = Perceptron(max_iter=1000, tol=1e-3, random_state=42)
per_clf.fit(X, y)
```

Out[2]:
```
Perceptron(random_state=42)
```

In [3]:
```python
a = -per_clf.coef_[0][0] / per_clf.coef_[0][1]
b = -per_clf.intercept_ / per_clf.coef_[0][1]

axes = [0, 5, 0, 2]

x0, x1 = np.meshgrid(
        np.linspace(axes[0], axes[1], 500).reshape(-1, 1),
        np.linspace(axes[2], axes[3], 200).reshape(-1, 1),
    )
X_new = np.c_[x0.ravel(), x1.ravel()]
y_predict = per_clf.predict(X_new)
zz = y_predict.reshape(x0.shape)

plt.figure(figsize=(10, 4))
plt.plot(X[y==0, 0], X[y==0, 1], "bs", label="Not Iris-Setosa")
plt.plot(X[y==1, 0], X[y==1, 1], "yo", label="Iris-Setosa")

plt.plot([axes[0], axes[1]], [a * axes[0] + b, a * axes[1] + b], "k-", linew
idth=3)
from matplotlib.colors import ListedColormap
custom_cmap = ListedColormap(['#9898ff', '#fafab0'])

plt.contourf(x0, x1, zz, cmap=custom_cmap)
plt.xlabel("Petal length", fontsize=14)
plt.ylabel("Petal width", fontsize=14)
plt.legend(loc="lower right", fontsize=14)
plt.axis(axes)

save_fig("perceptron_iris_plot")
plt.show()
```

```
Saving figure perceptron_iris_plot
```

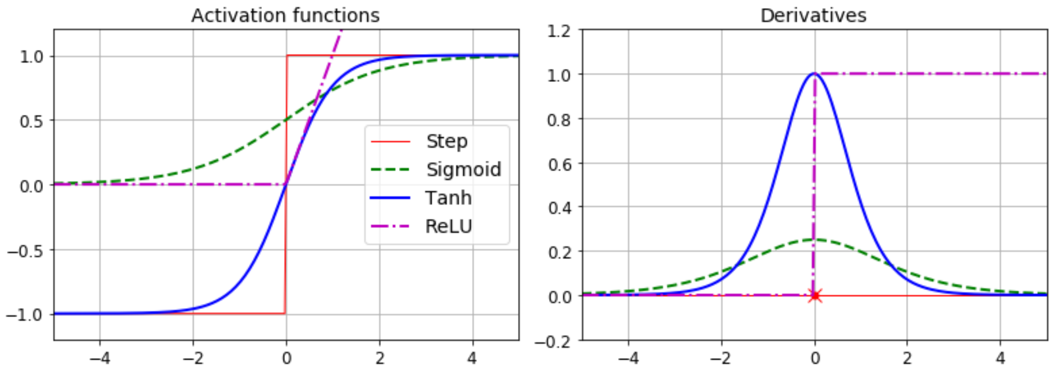


Activation functions

In [4]:
```
def sigmoid(z):
    return 1 / (1 + np.exp(-z))

def relu(z):
    return np.maximum(0, z)

def derivative(f, z, eps=0.000001):
    return (f(z + eps) - f(z - eps))/(2 * eps)
```

In [5]:
```
z = np.linspace(-5, 5, 200)

plt.figure(figsize=(11,4))

plt.subplot(121)
plt.plot(z, np.sign(z), "r-", linewidth=1, label="Step")
plt.plot(z, sigmoid(z), "g--", linewidth=2, label="Sigmoid")
plt.plot(z, np.tanh(z), "b-", linewidth=2, label="Tanh")
plt.plot(z, relu(z), "m-.", linewidth=2, label="ReLU")
plt.grid(True)
plt.legend(loc="center right", fontsize=14)
plt.title("Activation functions", fontsize=14)
plt.axis([-5, 5, -1.2, 1.2])

plt.subplot(122)
plt.plot(z, derivative(np.sign, z), "r-", linewidth=1, label="Step")
plt.plot(0, 0, "ro", markersize=5)
plt.plot(0, 0, "rx", markersize=10)
plt.plot(z, derivative(sigmoid, z), "g--", linewidth=2, label="Sigmoid")
plt.plot(z, derivative(np.tanh, z), "b-", linewidth=2, label="Tanh")
plt.plot(z, derivative(relu, z), "m-.", linewidth=2, label="ReLU")
plt.grid(True)
#plt.legend(loc="center right", fontsize=14)
plt.title("Derivatives", fontsize=14)
plt.axis([-5, 5, -0.2, 1.2])

save_fig("activation_functions_plot")
plt.show()
```

```
Saving figure activation_functions_plot
```



Building an Image Classifier

First let's import TensorFlow and Keras.

In [6]:
```
import tensorflow as tf
from tensorflow import keras
```

In [7]:
```
tf.__version__
```
Out[7]:
```
'2.1.0'
```

In [8]:
```
keras.__version__
```
Out[8]:
```
'2.2.4-tf'
```

Let's start by loading the fashion MNIST dataset. Keras has a number of functions to load popular datasets in `keras.datasets`. The dataset is already split for you between a training set and a test set, but it can be useful to split the training set further to have a validation set:

In [9]:
```
fashion_mnist = keras.datasets.fashion_mnist
(X_train_full, y_train_full), (X_test, y_test) = fashion_mnist.load_data()
```

The training set contains 60,000 grayscale images, each 28x28 pixels:

In [10]:
```
X_train_full.shape
```
Out[10]:
```
(60000, 28, 28)
```

Each pixel intensity is represented as a byte (0 to 255):

In [11]:
```
X_train_full.dtype
```
Out[11]:
```
dtype('uint8')
```

Let's split the full training set into a validation set and a (smaller) training set. We also scale the pixel intensities down to the 0-1 range and convert them to floats, by dividing by 255.

In [12]:
```
X_valid, X_train = X_train_full[:5000] / 255., X_train_full[5000:] / 255.
y_valid, y_train = y_train_full[:5000], y_train_full[5000:]
X_test = X_test / 255.
```

You can plot an image using Matplotlib's `imshow()` function, with a `'binary'` color map:

In [13]:
```
plt.imshow(X_train[0], cmap="binary")
plt.axis('off')
plt.show()
```

The labels are the class IDs (represented as uint8), from 0 to 9:

In [14]:
```
y_train
```

Out[14]:
```
array([4, 0, 7, ..., 3, 0, 5], dtype=uint8)
```

Here are the corresponding class names:

In [15]:
```
class_names = ["T-shirt/top", "Trouser", "Pullover", "Dress", "Coat",
               "Sandal", "Shirt", "Sneaker", "Bag", "Ankle boot"]
```

So the first image in the training set is a coat:

In [16]:
```
class_names[y_train[0]]
```

Out[16]:
```
'Coat'
```

The validation set contains 5,000 images, and the test set contains 10,000 images:

In [17]:
```
X_valid.shape
```

Out[17]:
```
(5000, 28, 28)
```

In [18]:
```
X_test.shape
```

Out[18]:
```
(10000, 28, 28)
```

Let's take a look at a sample of the images in the dataset:

In [19]:
```
n_rows = 4
n_cols = 10
plt.figure(figsize=(n_cols * 1.2, n_rows * 1.2))
for row in range(n_rows):
    for col in range(n_cols):
        index = n_cols * row + col
        plt.subplot(n_rows, n_cols, index + 1)
        plt.imshow(X_train[index], cmap="binary", interpolation="nearest")
        plt.axis('off')
        plt.title(class_names[y_train[index]], fontsize=12)
plt.subplots_adjust(wspace=0.2, hspace=0.5)
save_fig('fashion_mnist_plot', tight_layout=False)
plt.show()
```

```
Saving figure fashion_mnist_plot
```

In [20]:
```
keras.backend.clear_session()
np.random.seed(42)
tf.random.set_seed(42)
```

In [21]:
```
model = keras.models.Sequential([
    keras.layers.Flatten(input_shape=[28, 28]),
    keras.layers.Dense(300, activation="relu"),
    keras.layers.Dense(100, activation="relu"),
    keras.layers.Dense(10, activation="softmax")
])
```

In [22]:
```
model.layers
```

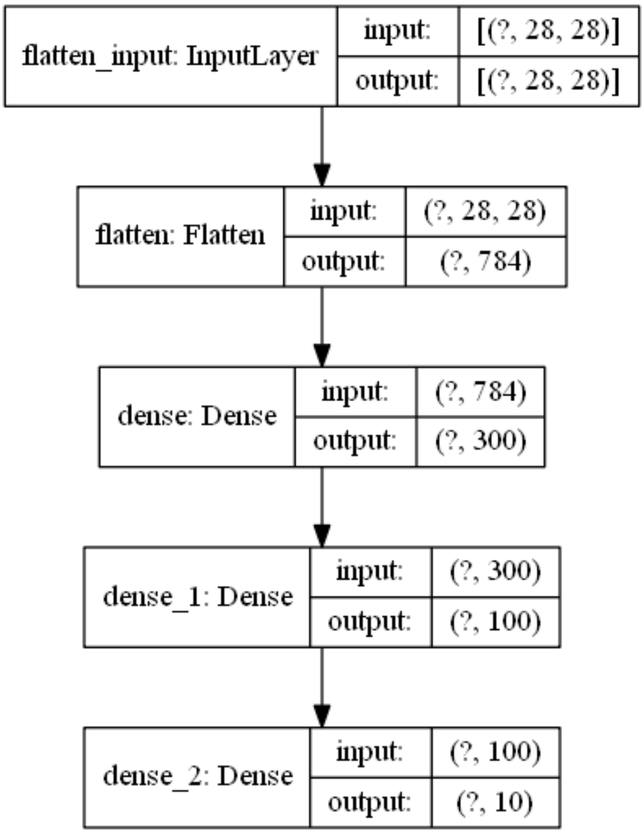
Out[22]:
```
[<tensorflow.python.keras.layers.core.Flatten at 0x22eb0840d48>,
 <tensorflow.python.keras.layers.core.Dense at 0x22eb084b748>,
 <tensorflow.python.keras.layers.core.Dense at 0x22eafe39808>,
 <tensorflow.python.keras.layers.core.Dense at 0x22eafe34148>]
```

In [23]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 784)               0
_________________________________________________________________
dense (Dense)                (None, 300)               235500
_________________________________________________________________
dense_1 (Dense)              (None, 100)               30100
_________________________________________________________________
dense_2 (Dense)              (None, 10)                1010
=================================================================
Total params: 266,610
Trainable params: 266,610
Non-trainable params: 0
_________________________________________________________________
```

In [24]:
```
keras.utils.plot_model(model, "my_fashion_mnist_model.png", show_shapes=True)
```

Out[24]:



In [25]:
```
hidden1 = model.layers[1]
hidden1.name
```

Out[25]: 'dense'

In [26]:
```
model.get_layer(hidden1.name) is hidden1
```

Out[26]: True

In [27]:
```
weights, biases = hidden1.get_weights()
```

In [28]:
```
weights
```

Out[28]:
```
array([[ 0.02448617, -0.00877795, -0.02189048, ..., -0.02766046,
         0.03859074, -0.06889391],
       [ 0.00476504, -0.03105379, -0.0586676 , ...,  0.00602964,
        -0.02763776, -0.04165364],
       [-0.06189284, -0.06901957,  0.07102345, ..., -0.04238207,
         0.07121518, -0.07331658],
       ...,
       [-0.03048757,  0.02155137, -0.05400612, ..., -0.00113463,
         0.00228987,  0.05581069],
       [ 0.07061854, -0.06960931,  0.07038955, ..., -0.00384101,
         0.00034875,  0.02878492],
       [-0.06022581,  0.01577859, -0.02585464, ..., -0.00527829,
         0.00272203, -0.06793761]], dtype=float32)
```

In [29]:
```
weights.shape
```

Out[29]:
```
(784, 300)
```

In [30]:
```
biases.shape
```

Out[30]:
```
(300,)
```

In [31]:
```
model.compile(loss="sparse_categorical_crossentropy",
              optimizer="sgd",
              metrics=["accuracy"])
```

This is equivalent to:

```
model.compile(loss=keras.losses.sparse_categorical_crossentropy,
              optimizer=keras.optimizers.SGD(),
              metrics=[keras.metrics.sparse_categorical_accuracy])
```

In [32]:
```
history = model.fit(X_train, y_train, epochs=30,
                    validation_data=(X_valid, y_valid))
```

```
Train on 55000 samples, validate on 5000 samples
Epoch 1/30
55000/55000 [==============================] - 4s 65us/sample - loss: 0.7226
- accuracy: 0.7642 - val_loss: 0.5075 - val_accuracy: 0.8314
Epoch 2/30
55000/55000 [==============================] - 3s 57us/sample - loss: 0.4843
- accuracy: 0.8321 - val_loss: 0.4538 - val_accuracy: 0.8486
Epoch 3/30
55000/55000 [==============================] - 3s 52us/sample - loss: 0.4413
- accuracy: 0.8465 - val_loss: 0.4385 - val_accuracy: 0.8490
Epoch 4/30
55000/55000 [==============================] - 3s 51us/sample - loss: 0.4128
- accuracy: 0.8549 - val_loss: 0.4163 - val_accuracy: 0.8562
Epoch 5/30
55000/55000 [==============================] - 3s 54us/sample - loss: 0.3926
- accuracy: 0.8617 - val_loss: 0.3817 - val_accuracy: 0.8636
Epoch 6/30
55000/55000 [==============================] - 3s 52us/sample - loss: 0.3770
- accuracy: 0.8667 - val_loss: 0.3729 - val_accuracy: 0.8680
Epoch 7/30
55000/55000 [==============================] - 3s 51us/sample - loss: 0.3626
- accuracy: 0.8733 - val_loss: 0.3699 - val_accuracy: 0.8710
Epoch 8/30
55000/55000 [==============================] - 3s 51us/sample - loss: 0.3517
- accuracy: 0.8749 - val_loss: 0.3666 - val_accuracy: 0.8696
Epoch 9/30
55000/55000 [==============================] - 3s 51us/sample - loss: 0.3420
- accuracy: 0.8772 - val_loss: 0.3438 - val_accuracy: 0.8786
Epoch 10/30
55000/55000 [==============================] - 3s 51us/sample - loss: 0.3326
- accuracy: 0.8814 - val_loss: 0.3511 - val_accuracy: 0.8794
Epoch 11/30
55000/55000 [==============================] - 3s 61us/sample - loss: 0.3241
- accuracy: 0.8835 - val_loss: 0.3357 - val_accuracy: 0.8816
Epoch 12/30
55000/55000 [==============================] - 3s 58us/sample - loss: 0.3159
- accuracy: 0.8871 - val_loss: 0.3310 - val_accuracy: 0.8846
Epoch 13/30
55000/55000 [==============================] - 3s 58us/sample - loss: 0.3073
- accuracy: 0.8903 - val_loss: 0.3325 - val_accuracy: 0.8826
Epoch 14/30
55000/55000 [==============================] - 3s 58us/sample - loss: 0.3017
- accuracy: 0.8920 - val_loss: 0.3243 - val_accuracy: 0.8880
Epoch 15/30
55000/55000 [==============================] - 3s 58us/sample - loss: 0.2953
- accuracy: 0.8937 - val_loss: 0.3173 - val_accuracy: 0.8892
Epoch 16/30
55000/55000 [==============================] - 3s 62us/sample - loss: 0.2898
- accuracy: 0.8966 - val_loss: 0.3251 - val_accuracy: 0.8888
Epoch 17/30
55000/55000 [==============================] - 3s 58us/sample - loss: 0.2833
- accuracy: 0.8987 - val_loss: 0.3178 - val_accuracy: 0.8920
Epoch 18/30
55000/55000 [==============================] - 3s 58us/sample - loss: 0.2781
- accuracy: 0.8999 - val_loss: 0.3102 - val_accuracy: 0.8908
Epoch 19/30
55000/55000 [==============================] - 3s 60us/sample - loss: 0.2729
- accuracy: 0.9021 - val_loss: 0.3205 - val_accuracy: 0.8836
Epoch 20/30
55000/55000 [==============================] - 3s 57us/sample - loss: 0.2680
- accuracy: 0.9044 - val_loss: 0.3219 - val_accuracy: 0.8852
Epoch 21/30
55000/55000 [==============================] - 3s 61us/sample - loss: 0.2635
- accuracy: 0.9041 - val_loss: 0.3007 - val_accuracy: 0.8944
Epoch 22/30
55000/55000 [==============================] - 3s 58us/sample - loss: 0.2575
- accuracy: 0.9076 - val_loss: 0.3103 - val_accuracy: 0.8878
Epoch 23/30
```

```
55000/55000 [==============================] - 3s 60us/sample - loss: 0.2538
- accuracy: 0.9084 - val_loss: 0.3001 - val_accuracy: 0.8910
Epoch 24/30
55000/55000 [==============================] - 3s 60us/sample - loss: 0.2492
- accuracy: 0.9103 - val_loss: 0.3096 - val_accuracy: 0.8870
Epoch 25/30
55000/55000 [==============================] - 3s 61us/sample - loss: 0.2452
- accuracy: 0.9121 - val_loss: 0.3114 - val_accuracy: 0.8892
Epoch 26/30
55000/55000 [==============================] - 4s 69us/sample - loss: 0.2408
- accuracy: 0.9145 - val_loss: 0.3263 - val_accuracy: 0.8850
Epoch 27/30
55000/55000 [==============================] - 3s 59us/sample - loss: 0.2367
- accuracy: 0.9151 - val_loss: 0.3117 - val_accuracy: 0.8852
Epoch 28/30
55000/55000 [==============================] - 4s 64us/sample - loss: 0.2323
- accuracy: 0.9177 - val_loss: 0.2921 - val_accuracy: 0.8950
Epoch 29/30
55000/55000 [==============================] - 4s 67us/sample - loss: 0.2288
- accuracy: 0.9190 - val_loss: 0.2970 - val_accuracy: 0.8920
Epoch 30/30
55000/55000 [==============================] - 4s 71us/sample - loss: 0.2256
- accuracy: 0.9192 - val_loss: 0.3016 - val_accuracy: 0.8902
```

In [33]:
```
history.params
```

Out[33]:
```
{'batch_size': 32,
 'epochs': 30,
 'steps': 1719,
 'samples': 55000,
 'verbose': 0,
 'do_validation': True,
 'metrics': ['loss', 'accuracy', 'val_loss', 'val_accuracy']}
```

In [34]:
```
print(history.epoch)
```

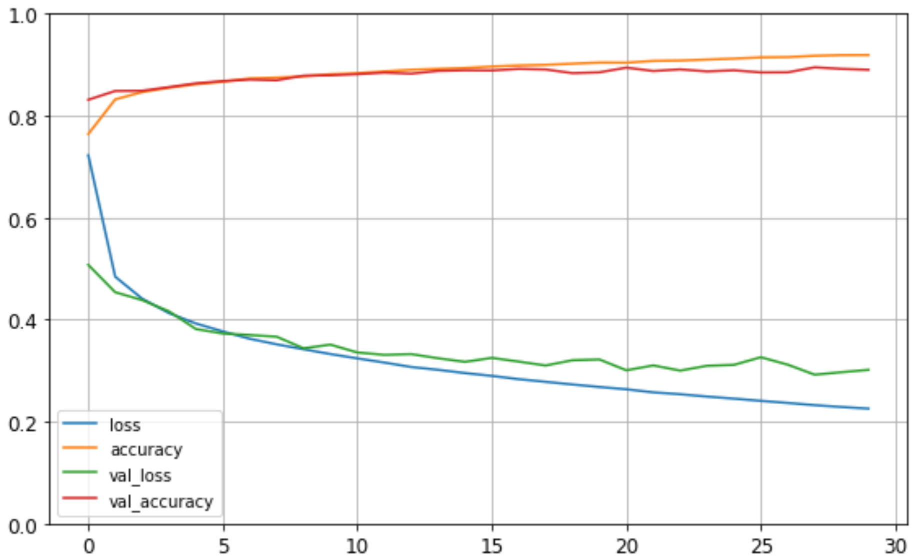
```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 2
1, 22, 23, 24, 25, 26, 27, 28, 29]
```

In [35]:
```
history.history.keys()
```

Out[35]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

In [36]:
```
import pandas as pd

pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1)
save_fig("keras_learning_curves_plot")
plt.show()
```

```
Saving figure keras_learning_curves_plot
```



In [37]:
```
model.evaluate(X_test, y_test)
```

```
10000/10000 [==============================] - 0s 34us/sample - loss: 0.3348
- accuracy: 0.8788
```

Out[37]:
```
[0.3347936288356781, 0.8788]
```

In [38]:
```
X_new = X_test[:3]
y_proba = model.predict(X_new)
y_proba.round(2)
```

Out[38]:
```
array([[0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.01, 0.  , 0.98],
       [0.  , 0.  , 0.99, 0.  , 0.01, 0.  , 0.  , 0.  , 0.  , 0.  ],
       [0.  , 1.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  ]],
      dtype=float32)
```

In [39]:
```
y_pred = model.predict_classes(X_new)
y_pred
```

Out[39]:
```
array([9, 2, 1], dtype=int64)
```

In [40]:
```
np.array(class_names)[y_pred]
```

Out[40]:
```
array(['Ankle boot', 'Pullover', 'Trouser'], dtype='<U11')
```

In [41]:
```
y_new = y_test[:3]
y_new
```

Out[41]:
```
array([9, 2, 1], dtype=uint8)
```

In [42]:
```
plt.figure(figsize=(7.2, 2.4))
for index, image in enumerate(X_new):
    plt.subplot(1, 3, index + 1)
    plt.imshow(image, cmap="binary", interpolation="nearest")
    plt.axis('off')
    plt.title(class_names[y_test[index]], fontsize=12)
plt.subplots_adjust(wspace=0.2, hspace=0.5)
save_fig('fashion_mnist_images_plot', tight_layout=False)
plt.show()
```

```
Saving figure fashion_mnist_images_plot
```

Regression MLP

Let's load, split and scale the California housing dataset (the original one, not the modified one as in chapter 2):

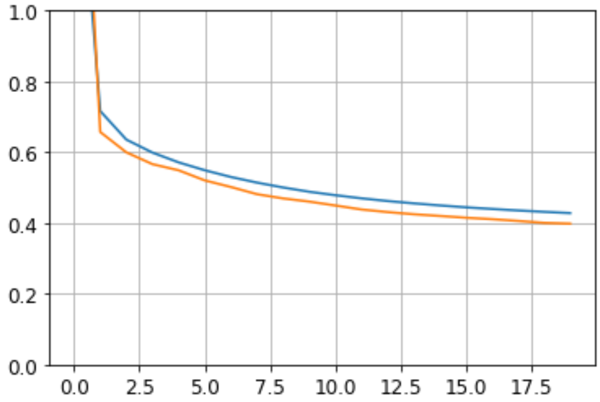
In [43]:
```
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

housing = fetch_california_housing()

X_train_full, X_test, y_train_full, y_test = train_test_split(housing.data,
housing.target, random_state=42)
X_train, X_valid, y_train, y_valid = train_test_split(X_train_full, y_train_
full, random_state=42)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_valid = scaler.transform(X_valid)
X_test = scaler.transform(X_test)
```

In [44]:
```
np.random.seed(42)
tf.random.set_seed(42)
```

In [45]:
```
model = keras.models.Sequential([
    keras.layers.Dense(30, activation="relu", input_shape=X_train.shape
[1:]),
    keras.layers.Dense(1)
])
model.compile(loss="mean_squared_error", optimizer=keras.optimizers.SGD(lr=1
e-3))
history = model.fit(X_train, y_train, epochs=20, validation_data=(X_valid, y
_valid))
mse_test = model.evaluate(X_test, y_test)
X_new = X_test[:3]
y_pred = model.predict(X_new)
```

```
Train on 11610 samples, validate on 3870 samples
Epoch 1/20
11610/11610 [==============================] - 1s 65us/sample - loss: 1.6205
- val_loss: 2.0374
Epoch 2/20
11610/11610 [==============================] - 0s 40us/sample - loss: 0.7162
- val_loss: 0.6571
Epoch 3/20
11610/11610 [==============================] - 0s 41us/sample - loss: 0.6356
- val_loss: 0.5996
Epoch 4/20
11610/11610 [==============================] - 0s 40us/sample - loss: 0.5989
- val_loss: 0.5662
Epoch 5/20
11610/11610 [==============================] - 0s 40us/sample - loss: 0.5713
- val_loss: 0.5489
Epoch 6/20
11610/11610 [==============================] - 0s 40us/sample - loss: 0.5491
- val_loss: 0.5204
Epoch 7/20
11610/11610 [==============================] - 0s 41us/sample - loss: 0.5301
- val_loss: 0.5018
Epoch 8/20
11610/11610 [==============================] - 0s 41us/sample - loss: 0.5142
- val_loss: 0.4815
Epoch 9/20
11610/11610 [==============================] - 0s 40us/sample - loss: 0.5004
- val_loss: 0.4695
Epoch 10/20
11610/11610 [==============================] - 0s 41us/sample - loss: 0.4883
- val_loss: 0.4605
Epoch 11/20
11610/11610 [==============================] - 0s 41us/sample - loss: 0.4786
- val_loss: 0.4495
Epoch 12/20
11610/11610 [==============================] - 0s 42us/sample - loss: 0.4697
- val_loss: 0.4382
Epoch 13/20
11610/11610 [==============================] - 0s 42us/sample - loss: 0.4621
- val_loss: 0.4309
Epoch 14/20
11610/11610 [==============================] - 0s 41us/sample - loss: 0.4556
- val_loss: 0.4247
Epoch 15/20
11610/11610 [==============================] - 0s 42us/sample - loss: 0.4497
- val_loss: 0.4200
Epoch 16/20
11610/11610 [==============================] - 1s 43us/sample - loss: 0.4443
- val_loss: 0.4149
Epoch 17/20
11610/11610 [==============================] - 0s 42us/sample - loss: 0.4397
- val_loss: 0.4108
Epoch 18/20
11610/11610 [==============================] - 0s 43us/sample - loss: 0.4354
- val_loss: 0.4059
Epoch 19/20
11610/11610 [==============================] - 0s 42us/sample - loss: 0.4315
- val_loss: 0.4003
Epoch 20/20
11610/11610 [==============================] - 0s 42us/sample - loss: 0.4281
- val_loss: 0.3981
5160/5160 [==============================] - 0s 22us/sample - loss: 0.4218
```

In [46]:
```
plt.plot(pd.DataFrame(history.history))
plt.grid(True)
plt.gca().set_ylim(0, 1)
plt.show()
```



In [47]:
```
y_pred
```

Out[47]:
```
array([[0.37310064],
       [1.6790789 ],
       [3.0817137 ]], dtype=float32)
```

Saving and Restoring

In [48]:
```
np.random.seed(42)
tf.random.set_seed(42)
```

In [49]:
```
model = keras.models.Sequential([
    keras.layers.Dense(30, activation="relu", input_shape=[8]),
    keras.layers.Dense(30, activation="relu"),
    keras.layers.Dense(1)
])
```

In [50]:
```
model.compile(loss="mse", optimizer=keras.optimizers.SGD(lr=1e-3))
history = model.fit(X_train, y_train, epochs=10, validation_data=(X_valid, y
_valid))
mse_test = model.evaluate(X_test, y_test)
```

```
Train on 11610 samples, validate on 3870 samples
Epoch 1/10
11610/11610 [==============================] - 1s 73us/sample - loss: 1.8423
- val_loss: 5.2165
Epoch 2/10
11610/11610 [==============================] - 1s 44us/sample - loss: 0.6876
- val_loss: 0.7732
Epoch 3/10
11610/11610 [==============================] - 1s 44us/sample - loss: 0.5954
- val_loss: 0.5446
Epoch 4/10
11610/11610 [==============================] - 1s 49us/sample - loss: 0.5553
- val_loss: 0.5425
Epoch 5/10
11610/11610 [==============================] - 1s 56us/sample - loss: 0.5268
- val_loss: 0.5539
Epoch 6/10
11610/11610 [==============================] - 1s 50us/sample - loss: 0.5049
- val_loss: 0.4701
Epoch 7/10
11610/11610 [==============================] - 1s 45us/sample - loss: 0.4852
- val_loss: 0.4562
Epoch 8/10
11610/11610 [==============================] - 1s 45us/sample - loss: 0.4706
- val_loss: 0.4452
Epoch 9/10
11610/11610 [==============================] - 1s 46us/sample - loss: 0.4576
- val_loss: 0.4406
Epoch 10/10
11610/11610 [==============================] - 1s 45us/sample - loss: 0.4476
- val_loss: 0.4185
5160/5160 [==============================] - 0s 24us/sample - loss: 0.4376
```

In [51]:
```
model.save("my_keras_model.h5")
```

In [52]:
```
model = keras.models.load_model("my_keras_model.h5")
```

In [53]:
```
model.predict(X_new)
```

Out[53]:
```
array([[0.551559 ],
       [1.6555369],
       [3.0014234]], dtype=float32)
```

In [54]:
```
model.save_weights("my_keras_weights.ckpt")
```

In [55]:
```
model.load_weights("my_keras_weights.ckpt")
```

Out[55]:
```
<tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x22eb3b551
08>
```