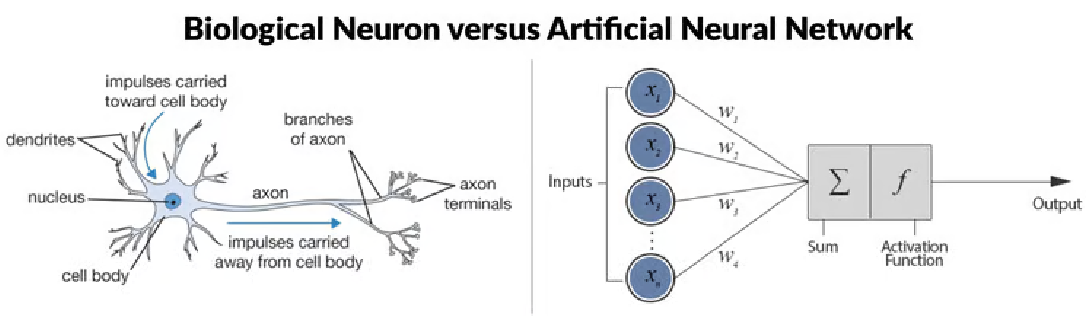
Keras

1. Introduction

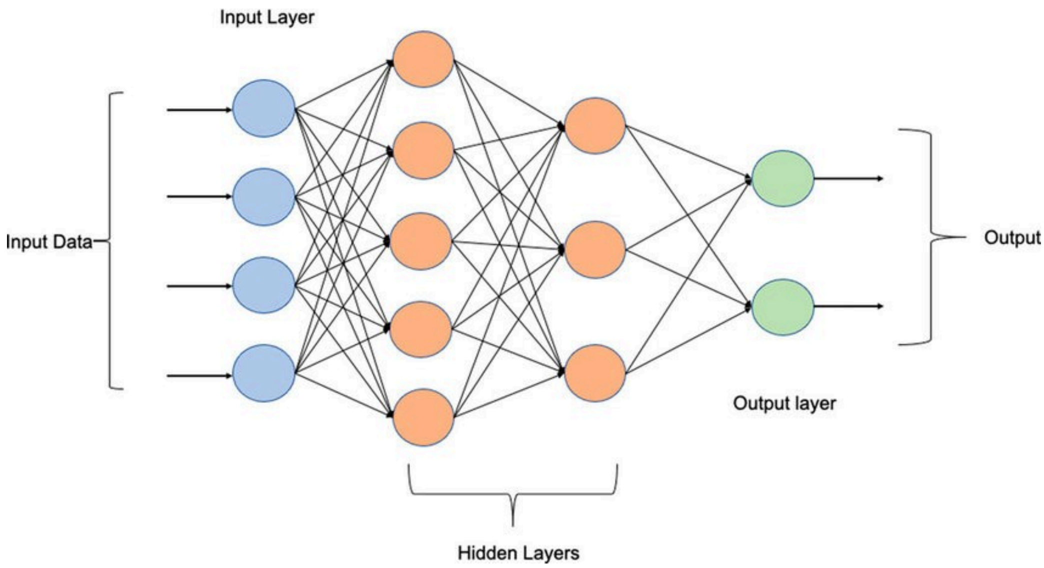
- High-Level library to build, train, and evaluate **Neural Networks** (**Deep Learning** models).
- Built-in data handling and preprocessing (i.e. image and text)
- Integration with different backends (**JAX**, **TensorFlow** or **PyTorch**).
- Various Neural Network architectures:
  - **Sequential Models**: Linear stacks of layers (most common for many standard deep learning tasks).
  - **Functional API**: More complex model (multi-input/multi-output, directed acyclic graphs DAGs or models with shared layers).
  - **Subclassing API**: Greater customization by implementing your own layers.
- Simple model interface:
  - `model = XXX()...` → `model.fit(X, y)` → `model.predict(X_new)` , `model.evaluate(X_new, y_new)`

Neural Networks (Artificial Neural Networks)

- Fundamental tools in Machine Learning
- Consists of interconnected nodes (neurons) organized into layers.
- Each neuron:
  1. Receives input signals
  2. Performs a computation on them (typically a sum)
  3. Applies an (non linear) activation function
  4. Produces an output signal that may be passed to other neurons



- **Input Layer**: Receives the raw input data. The number of neurons corresponds to the number of features in the data.
- **Hidden Layers**: One or more (*deep*) intermediate layers. They extract increasingly complex features.
- **Output Layer**: Produces the final prediction or classification. The number of neurons and the activation function in this layer depend on the task (1 for regression, N for classification)



In [1]:
```
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns

sns.set()
mpl.rcParams['figure.figsize'] = (5.33,4)
mpl.rcParams['axes.labelsize'] = 10  # Example: 14 points
mpl.rcParams['xtick.labelsize'] = 8  # Example: 12 points for x-axis ticks
mpl.rcParams['ytick.labelsize'] = 8  # Example: 12 points for y-axis ticks
```

Fashion MNIST

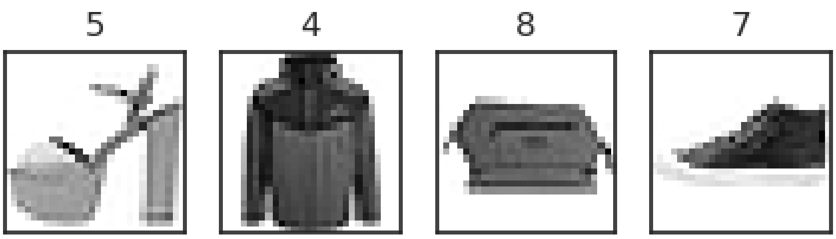
In [2]:
```
import kagglehub
path = kagglehub.dataset_download("zalando-research/fashionmnist")
train_df = pd.read_csv(path + '/fashion-mnist_train.csv')
test_df = pd.read_csv(path + '/fashion-mnist_test.csv')
```

```
Warning: Looks like you're using an outdated `kagglehub` version (installed: 0.3.10), please c
onsider upgrading to the latest version (0.3.12).
```

In [3]:
```
X_train = train_df.drop('label', axis=1).to_numpy()
y_train = train_df['label'].to_numpy()
X_test = test_df.drop('label', axis=1).to_numpy()
y_test = test_df['label'].to_numpy()
print(f'{X_train.shape=}\n{y_train.shape=}')
print(f'{X_train.shape=}\n{y_train.shape=}')
print(f'{X_test.shape=}\n{y_test.shape=}')
print(f'{X_train.max()=}\n{X_train.min()=}')
print(f'{X_test.max()=}\n{X_test.min()=}')
print(f'{np.unique(y_train)}')
```

```
X_train.shape=(60000, 784)
y_train.shape=(60000,)
X_train.shape=(60000, 784)
y_train.shape=(60000,)
X_test.shape=(10000, 784)
y_test.shape=(10000,)
X_train.max()=255
X_train.min()=0
X_test.max()=255
X_test.min()=0
[0 1 2 3 4 5 6 7 8 9]
```

In [4]:
```
with sns.axes_style('white'):
    for i,idx in enumerate(np.random.randint(0,X_train.shape[0],4)):
        plt.subplot(1, 4, i+1)
        plt.imshow(X_train[idx].reshape(28,28), cmap=plt.cm.gray_r)
        plt.title(f'{y_train[idx]}')
        plt.xticks([])
        plt.yticks([])
```



In [5]:
```
X_train = X_train / X_train.max()
X_test = X_test / X_test.max()
# shuffle training data...
rindex = np.arange(X_train.shape[0])
np.random.shuffle(rindex)
X_train = X_train[rindex].copy()
y_train = y_train[rindex].copy()
print(f'{X_train.shape=}\n{y_train.shape=}')
print(f'{X_test.shape=}\n{y_test.shape=}')
print(f'{X_train.max()=}\n{X_train.min()=}')
print(f'{X_test.max()=}\n{X_test.min()=}')
print(f'{np.unique(y_train)}')
```

```
X_train.shape=(60000, 784)
y_train.shape=(60000,)
X_test.shape=(10000, 784)
y_test.shape=(10000,)
X_train.max()=1.0
X_train.min()=0.0
X_test.max()=1.0
X_test.min()=0.0
[0 1 2 3 4 5 6 7 8 9]
```

2. `Sequential` model

- Linear Stack of Layers
- The output (tensor) of a layer is the input (tensor) of the next layer
- `model = Sequential([ A(), B(), C()... ])`
- Core Layers:

- `Input` . Often the first one, is a simple placeholder for the input tensor.
- `Dense` . Fully Connected Layer ($\mathbf{y} = \mathbf{W}\mathbf{x} + \mathbf{b}$). Every neuron in the layer receives input (a weighted sum + offset) from all the neurons in the preceding layer.
- `Activation` . Applies an activation function to the output of the preceding layer. Can often be specified directly within other layers
- `Flatten` . Converts a multi-dimensional input tensor into a one-dimensional tensor.

Activation Functions

- `sigmoid` . Outputs values between 0 and 1. Can suffer from vanishing gradients

$$f(x) = \frac{1}{1 + e^{-x}}$$

- `tanh` (Hyperbolic Tangent): Similar to sigmoid but centered around zero. Can also suffer from vanishing gradients

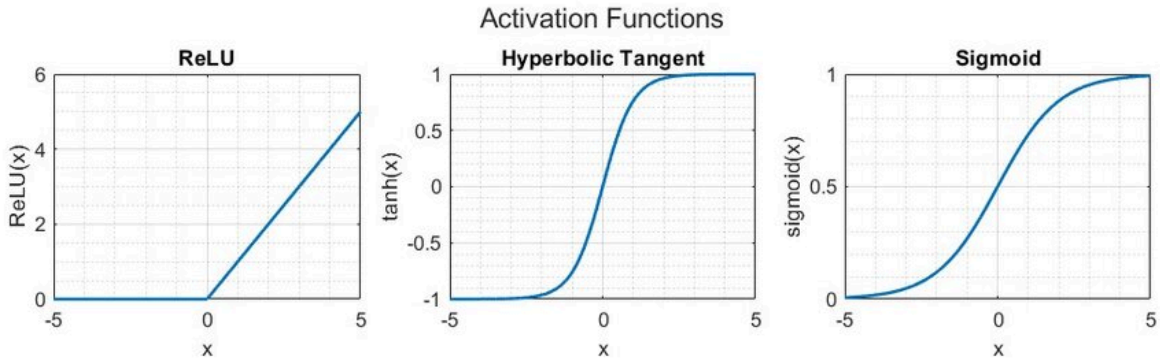
$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} = 2 \cdot sigmoid(2x) - 1$$

- `relu` (Rectified Linear Unit). Simple, efficient, and helps with the vanishing gradient problem. Can suffer from the "dying ReLU" problem (get stuck in the negative side).

$$f(x) = \max(0, x)$$

- `softmax` . Converts a vector of raw scores into a probability distribution over multiple classes.

$$f(x)_i = \frac{e^{x_i}}{\sum_j e^{-x_j}}$$



An example sequential model for fmnist data:

In [6]:
```
#Configuration of Keras backend (JAX) using only CPU
import os
os.environ["KERAS_BACKEND"] = "jax"
os.environ["JAX_PLATFORMS"] = "cpu"
```

In [7]:
```
from keras import Sequential
from keras.layers import Input, Dense, Activation

model = Sequential([
        Input(shape=(784,)),
```

```
        Dense(512),
        Activation('sigmoid'),
        Dense(128),
        Activation('tanh'),
        Dense(32),
        Activation('relu'),
        Dense(10),
        Activation('softmax')
])
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 512)	401,920
activation (Activation)	(None, 512)	0
dense_1 (Dense)	(None, 128)	65,664
activation_1 (Activation)	(None, 128)	0
dense_2 (Dense)	(None, 32)	4,128
activation_2 (Activation)	(None, 32)	0
dense_3 (Dense)	(None, 10)	330
activation_3 (Activation)	(None, 10)	0

Total params: 472,042 (1.80 MB)

Trainable params: 472,042 (1.80 MB)

Non-trainable params: 0 (0.00 B)

Activations can often be specified directly within other layers:

In [8]:
```
model = Sequential([
        Input(shape=(784,)),
        Dense(512, activation='sigmoid'),
        Dense(128, activation='tanh'),
        Dense(32, activation='relu'),
        Dense(10, activation='softmax'),
])
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 512)	401,920
dense_5 (Dense)	(None, 128)	65,664
dense_6 (Dense)	(None, 32)	4,128
dense_7 (Dense)	(None, 10)	330

Total params: 472,042 (1.80 MB)

Trainable params: 472,042 (1.80 MB)

Non-trainable params: 0 (0.00 B)

In [9]:
```
input_shape = X_train[0].shape
num_classes = np.unique(y_train).size
print(f'{input_shape =}\n{num_classes = }')

model = Sequential([
        Input(shape=input_shape),
        Dense(512, activation="relu"),
        Dense(128, activation="relu"),
        Dense(32, activation="relu"),
        Dense(num_classes, activation="softmax")
])
model.summary()
```

```
input_shape =(784,)
num_classes = 10
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
dense_8 (Dense)	(None, 512)	401,920
dense_9 (Dense)	(None, 128)	65,664
dense_10 (Dense)	(None, 32)	4,128
dense_11 (Dense)	(None, 10)	330

Total params: 472,042 (1.80 MB)

Trainable params: 472,042 (1.80 MB)

Non-trainable params: 0 (0.00 B)

Configure the learning process of the neural network before training it:

In [10]:
```
from keras.optimizers import Adam
from keras.losses import SparseCategoricalCrossentropy
from keras.metrics import Accuracy

model.compile(optimizer=Adam(),
              loss=SparseCategoricalCrossentropy(),
              metrics=['accuracy'])
```

If we are using the default arguments, many parameters can be set with their correspondent names:

In [11]:
```
print(f'{Adam().name = }')
print(f'{SparseCategoricalCrossentropy().name = }')
```

```
Adam().name = 'adam'
SparseCategoricalCrossentropy().name = 'sparse_categorical_crossentropy'
```

In [12]:
```
model.compile(optimizer="adam",
              loss="sparse_categorical_crossentropy",
              metrics=['accuracy'])
```

Fit the model and get a callback that records events that happen during the training process:

In [13]:
```
callback = model.fit(X_train, y_train, validation_split=0.2, epochs=10)
```

```
Epoch 1/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 6s 4ms/step - accuracy: 0.7730 - loss: 0.6492 - val_accuracy: 0.8405 - val_loss: 0.4306
Epoch 2/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - accuracy: 0.8587 - loss: 0.3845 - val_accuracy: 0.8696 - val_loss: 0.3578
Epoch 3/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 6s 4ms/step - accuracy: 0.8724 - loss: 0.3495 - val_accuracy: 0.8781 - val_loss: 0.3323
Epoch 4/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy: 0.8804 - loss: 0.3192 - val_accuracy: 0.8863 - val_loss: 0.3161
Epoch 5/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 7s 5ms/step - accuracy: 0.8903 - loss: 0.2988 - val_accuracy: 0.8842 - val_loss: 0.3237
Epoch 6/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy: 0.8955 - loss: 0.2841 - val_accuracy: 0.8913 - val_loss: 0.3062
Epoch 7/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 7s 4ms/step - accuracy: 0.8990 - loss: 0.2706 - val_accuracy: 0.8798 - val_loss: 0.3240
Epoch 8/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 6s 4ms/step - accuracy: 0.9033 - loss: 0.2578 - val_accuracy: 0.8878 - val_loss: 0.3121
Epoch 9/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 7s 5ms/step - accuracy: 0.9072 - loss: 0.2467 - val_accuracy: 0.8876 - val_loss: 0.3282
Epoch 10/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 6s 4ms/step - accuracy: 0.9110 - loss: 0.2356 - val_accuracy: 0.8962 - val_loss: 0.2985
```

`callback.history` contains a dictionary with the losses and metrics for each epoch:

In [14]:
```
callback.history
```

Out[14]:
```
{'accuracy': [0.8171666860580444,
  0.8606041669845581,
  0.8730624914169312,
  0.8818541765213013,
  0.8890833258628845,
  0.893708348274231,
  0.8989999890327454,
  0.9024375081062317,
  0.9065208435058594,
  0.9096458554267883],
 'loss': [0.5117257237434387,
  0.37997451424598694,
  0.34792351722717285,
  0.3206142485141754,
  0.30075812339782715,
  0.28705742955207825,
  0.2732927203178406,
  0.26102137565612793,
  0.24958518147468567,
  0.23922961950302124],
 'val_accuracy': [0.840499997138977,
  0.8695833086967468,
  0.878083348274231,
  0.8862500190734863,
  0.8842499852180481,
  0.8912500143051147,
  0.8797500133514404,
  0.8878333568572998,
  0.887583315372467,
  0.8961666822433472],
 'val_loss': [0.4305688142776489,
  0.3577728271484375,
  0.332341730594635,
  0.31607750058174133,
  0.3237145245075226,
  0.30622008442878723,
  0.3240238130092621,
  0.3120673894882202,
  0.32815074920654297,
  0.29852965474128723]}
```

In [15]:
```
hist = pd.DataFrame(callback.history)
hist.head()
```

Out[15]:

	accuracy	loss	val_accuracy	val_loss
0	0.817167	0.511726	0.840500	0.430569
1	0.860604	0.379975	0.869583	0.357773
2	0.873062	0.347924	0.878083	0.332342
3	0.881854	0.320614	0.886250	0.316078
4	0.889083	0.300758	0.884250	0.323715

In [16]:
```
hist = pd.DataFrame(callback.history)
hist.index += 1
```

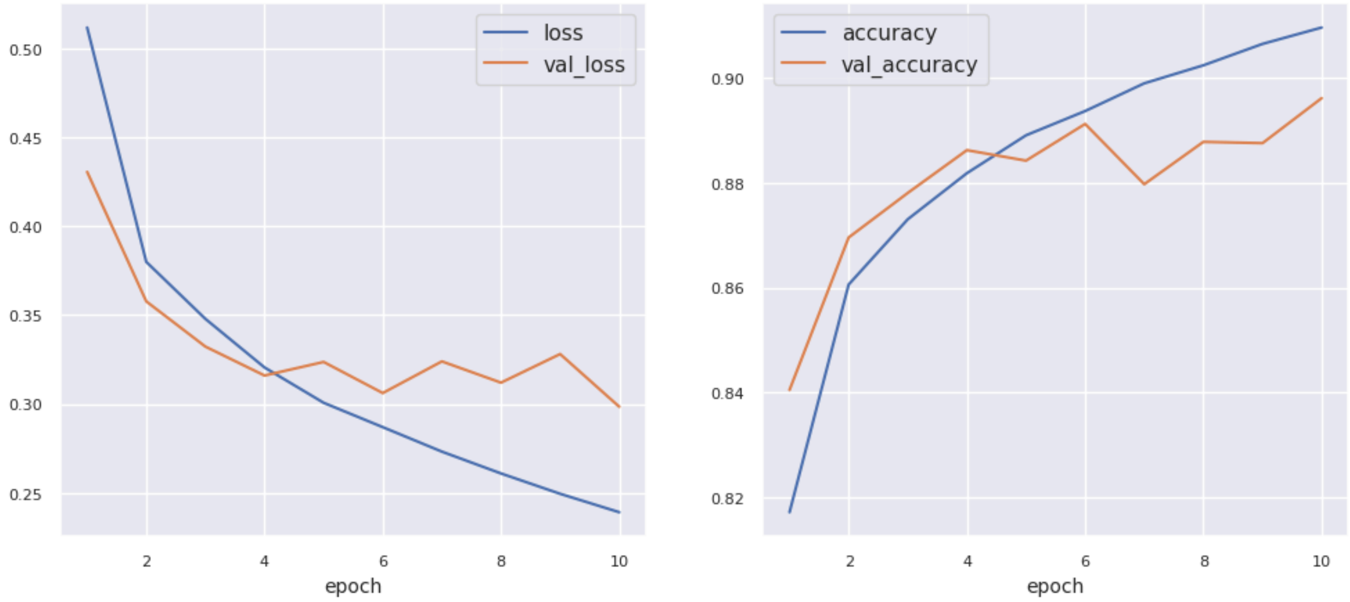
```
hist.index.name = 'epoch'
hist.head()
```

Out[16]:

epoch	accuracy	loss	val_accuracy	val_loss
1	0.817167	0.511726	0.840500	0.430569
2	0.860604	0.379975	0.869583	0.357773
3	0.873062	0.347924	0.878083	0.332342
4	0.881854	0.320614	0.886250	0.316078
5	0.889083	0.300758	0.884250	0.323715

In [17]:

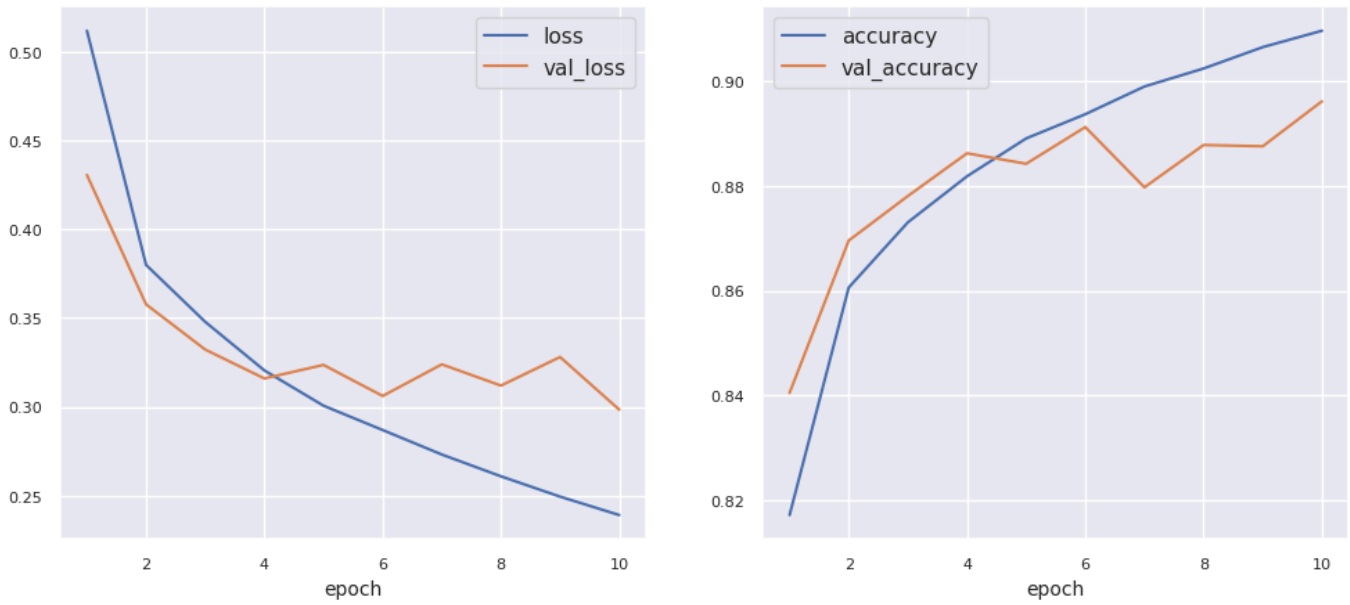
```
fig, (ax1,ax2) = plt.subplots(1, 2, figsize=(12, 5))
hist[['loss','val_loss']].plot(ax=ax1)
hist[['accuracy','val_accuracy']].plot(ax=ax2);
```



In [18]:

```
def plot_callback(callback):
    hist = pd.DataFrame(callback.history)
    hist.index += 1
    hist.index.name = 'epoch'
    hist.head()
    fig, (ax1,ax2) = plt.subplots(1, 2, figsize=(12, 5))
    hist[['loss','val_loss']].plot(ax=ax1)
    hist[['accuracy','val_accuracy']].plot(ax=ax2)

plot_callback(callback)
```



Increasing the complexity of the model (more neurons per layer and more layers) or training too much epoch could lead to overfitting. Running 80 epochs:

Regularizations

- **Weight Regularization**: Adds a penalty to the loss function based on the weights. Tends to sparsity in the weights.
  - L1 (Lasso), L2 (Ridge) or L1L2 (Elastic Net)
- **Activity Regularization**: Adds a penalty to the loss function based on the activations of a layer.
- **Dropout**: Randomly sets a fraction of the input units to 0 (during training). Encourages the network to learn more robust representations
- **Batch Normalization**: Normalizes the activations of a layer across the batch. Improves training stability and speed.
- **Early Stopping**: Stops the training process when the validation performance starts to degrade. Prevents overfitting

In [19]:

```
from keras.layers import Dropout

input_shape = X_train[0].shape
```

```python
num_classes = np.unique(y_train).size
print(f'{input_shape =}\n{num_classes = }')

model = Sequential([
        Input(shape=input_shape),
        Dense(512, activation="relu"),
        Dropout(0.4),
        Dense(128, activation="relu"),
        Dropout(0.4),
        Dense(32, activation="relu"),
        Dropout(0.4),
        Dense(num_classes, activation="softmax")
])
model.summary()
```

```
input_shape =(784,)
num_classes = 10
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
dense_12 (Dense)	(None, 512)	401,920
dropout (Dropout)	(None, 512)	0
dense_13 (Dense)	(None, 128)	65,664
dropout_1 (Dropout)	(None, 128)	0
dense_14 (Dense)	(None, 32)	4,128
dropout_2 (Dropout)	(None, 32)	0
dense_15 (Dense)	(None, 10)	330

Total params: 472,042 (1.80 MB)

Trainable params: 472,042 (1.80 MB)

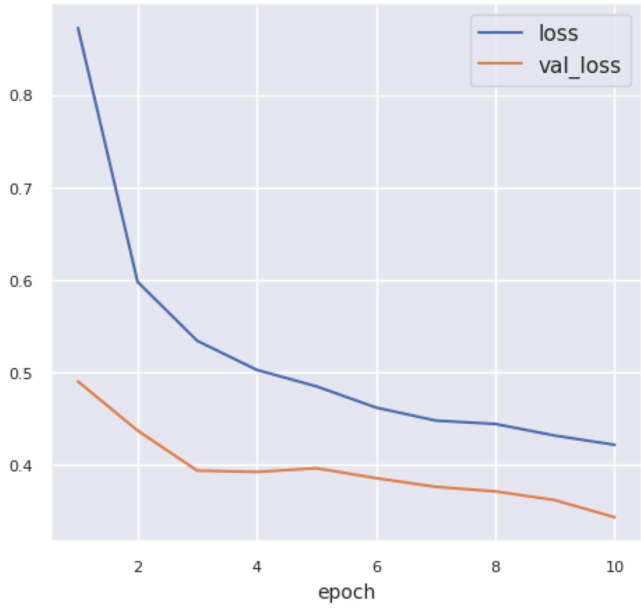
Non-trainable params: 0 (0.00 B)

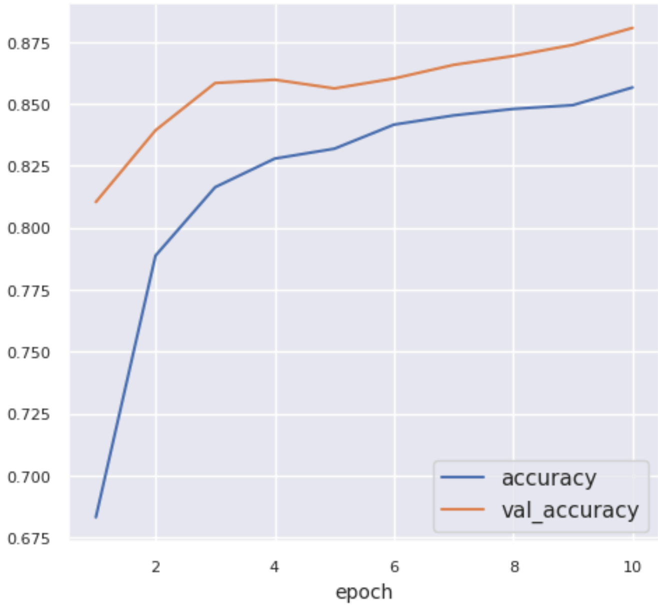
In [20]:
```python
model.compile(optimizer="adam",
              loss="sparse_categorical_crossentropy",
              metrics=['accuracy'])
callback = model.fit(X_train, y_train, validation_split=0.2, epochs=10)
```

```
Epoch 1/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 12s 7ms/step - accuracy: 0.5724 - loss: 1.1795 - val_accuracy: 0.8104 - val_loss: 0.4898
Epoch 2/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 12s 8ms/step - accuracy: 0.7786 - loss: 0.6186 - val_accuracy: 0.8393 - val_loss: 0.4366
Epoch 3/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy: 0.8150 - loss: 0.5419 - val_accuracy: 0.8584 - val_loss: 0.3933
Epoch 4/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy: 0.8254 - loss: 0.5055 - val_accuracy: 0.8597 - val_loss: 0.3918
Epoch 5/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy: 0.8331 - loss: 0.4790 - val_accuracy: 0.8562 - val_loss: 0.3959
Epoch 6/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy: 0.8396 - loss: 0.4612 - val_accuracy: 0.8602 - val_loss: 0.3851
Epoch 7/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy: 0.8416 - loss: 0.4564 - val_accuracy: 0.8658 - val_loss: 0.3757
Epoch 8/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - accuracy: 0.8472 - loss: 0.4476 - val_accuracy: 0.8693 - val_loss: 0.3708
Epoch 9/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - accuracy: 0.8502 - loss: 0.4371 - val_accuracy: 0.8738 - val_loss: 0.3613
Epoch 10/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 8s 6ms/step - accuracy: 0.8572 - loss: 0.4148 - val_accuracy: 0.8807 - val_loss: 0.3428
```

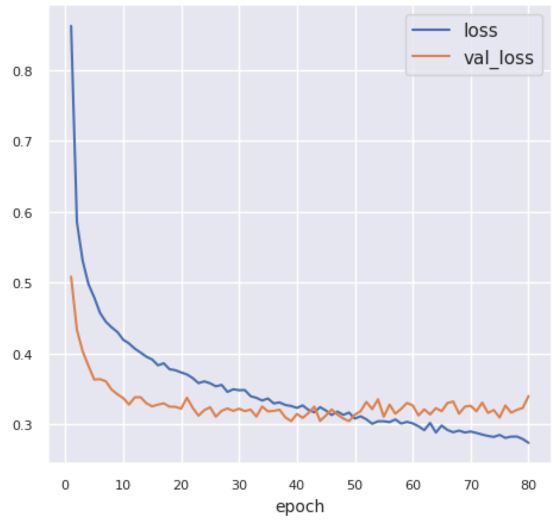
Fit the model and get a callback that records events that happen during the training process:

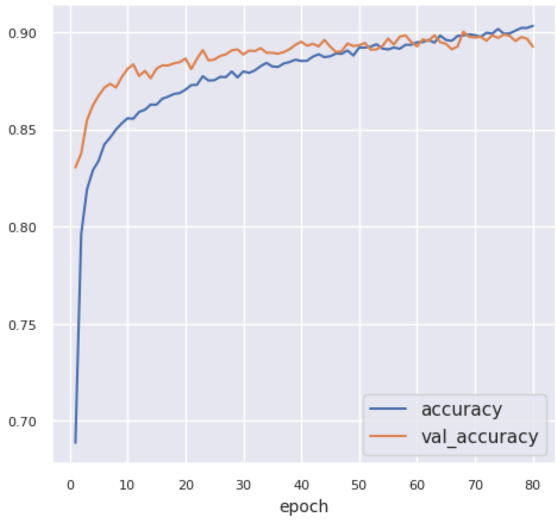
In [21]:
```
plot_callback(callback)
```





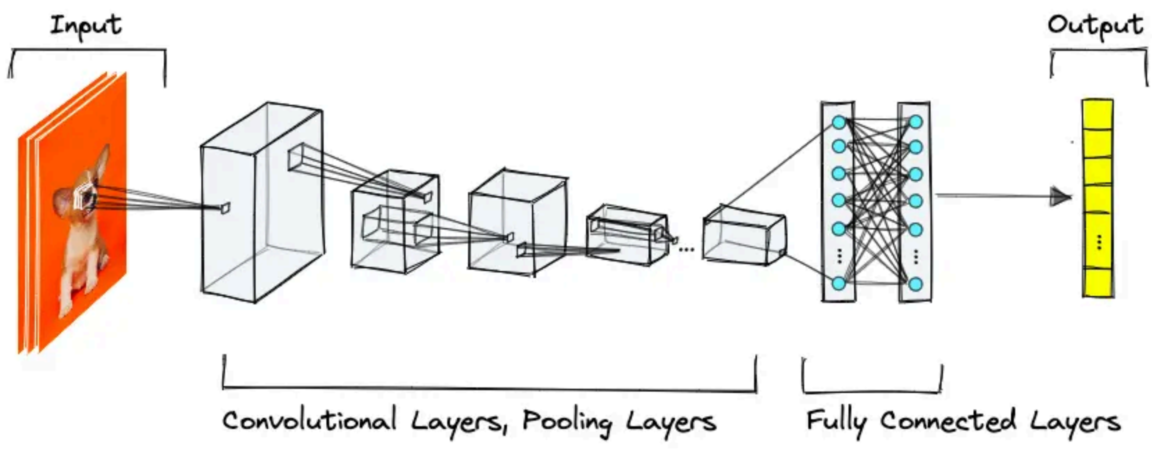
Running 80 epochs:





3. Convolutional Neural Network CNN

- Work on two (or more) dimensional data
- **Convolutional Layer**
    - Each neuron is connectet to a small, local region (neurons) of the previous layer through a **filter** (kernel).
    - Filters slide across the input data, performing element-wise multiplication and summing the results.
    - Each filter learns to identify a particular **pattern**
    - **Few parameters**: The same filter is used across the entire input map
- **Pooling Layer**
    - Reduces the size using aggregation functions (max, average...)



`Conv2D(filters, kernel_size, strides=(1, 1), padding='valid', data_format=None, dilation_rate=(1, 1), groups=1, activation=None, use_bias=True, kernel_initializer='glorot_uniform', bias_initializer='zeros', kernel_regularizer=None, bias_regularizer=None, activity_regularizer=None, kernel_constraint=None, bias_constraint=None, **kwargs`

- `filters: int` → number of filters
- `kernel_size: int or tuple/list of 2 integer` → size of the convolution window.

- `strides: int or tuple/list of 2 integer` → displacement (step size) of the kernel as it moves across the input.
- `padding: string, either "valid" or "same"` → controls how the input tensor is padded with zeros (`"valid"` means no padding). When `padding="same"` and `strides=1`, the output has the same size as the input.

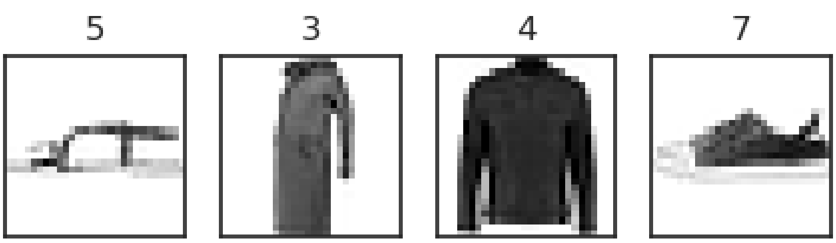
Pooling layers

- **Local Pooling**: uses a `pool_size` similar to Conv2D kernel_size.
  - Keeps the number of dimensions of the data
  - Purpose: downsampling, translation invariance
  - **MaxPooling2D**, **AveragePooling2D**
- **Local Pooling**: applied over the entire spatial dimension (width/height)
  - Reduces the number of dimensions of the data (width/height are collapsed)
  - Purpose: global feature aggregation, Convolutional to Dense layers adaptation
  - **GlobalMaxPooling2D**, **GlobalAveragePooling2D**

Data preparation

In [22]:
```
from math import isqrt
new_dim = isqrt(X_train.shape[1])
X_train = X_train.reshape((X_train.shape[0],new_dim,new_dim))
X_test = X_test.reshape((X_test.shape[0],new_dim,new_dim))
print(f'{X_train.shape=}\n{y_train.shape=}')
print(f'{X_test.shape=}\n{y_test.shape=}')
with sns.axes_style('white'):
    for i,idx in enumerate(np.random.randint(0,X_train.shape[0],4)):
        plt.subplot(1, 4, i+1)
        plt.imshow(X_train[idx], cmap=plt.cm.gray_r)
        plt.title(f'{y_train[idx]}')
        plt.xticks([])
        plt.yticks([])
```

```
X_train.shape=(60000, 28, 28)
y_train.shape=(60000,)
X_test.shape=(10000, 28, 28)
y_test.shape=(10000,)
```



Note: We could have imported the data directly from keras.datasets, with the correct shapes:

- `X_train.shape=(60000, 28, 28)`
- `X_test.shape=(10000, 28, 28)`

In [23]:
```
#from keras.datasets import fashion_mnist
#(X_train, y_train), (X_test, y_test) = fashion_mnist.load_data()
```

Defining the Model Architecture

We will use some default parameters:

- **Conv2D** → `strides=1` , padding='valid'
- **MaxPooling2D** → `strides=None` (equal to `pool_size`)

In [24]:
```
from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D, BatchNormalization

input_shape = *X_train[0].shape,1
num_classes = np.unique(y_train).size
print(f'{input_shape =}\n{num_classes = }')

model = Sequential([
        Input(shape=input_shape),

        Conv2D(32, kernel_size=(3, 3), activation='relu'),
        Conv2D(32, kernel_size=(3, 3), activation='relu'),
        MaxPooling2D(pool_size=(2, 2)),

        Conv2D(64, kernel_size=(3, 3), activation='relu'),
        Conv2D(64, kernel_size=(3, 3), activation='relu'),
        GlobalAveragePooling2D(),

        Dense(256, activation="relu"),
        Dense(num_classes, activation="softmax")
])
model.summary()
```

```
input_shape =(28, 28, 1)
num_classes = 10
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 32)	320
conv2d_1 (Conv2D)	(None, 24, 24, 32)	9,248
max_pooling2d (MaxPooling2D)	(None, 12, 12, 32)	0
conv2d_2 (Conv2D)	(None, 10, 10, 64)	18,496
conv2d_3 (Conv2D)	(None, 8, 8, 64)	36,928
global_average_pooling2d (GlobalAveragePooling2D)	(None, 64)	0
dense_16 (Dense)	(None, 256)	16,640
dense_17 (Dense)	(None, 10)	2,570

Total params: 84,202 (328.91 KB)

Trainable params: 84,202 (328.91 KB)

Non-trainable params: 0 (0.00 B)

This is going to be very slow on CPU, so just run 1 epoch...

In [25]:
```
model.compile(optimizer="adam",
              loss="sparse_categorical_crossentropy",
              metrics=['accuracy'])
callback = model.fit(X_train, y_train, validation_split=0.2, epochs=1)
```

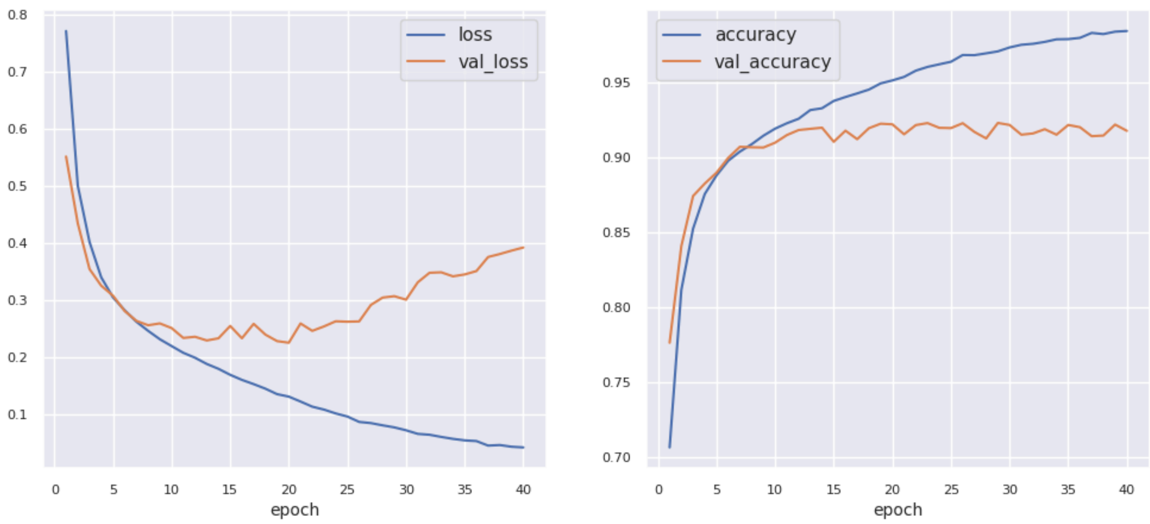
```
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 94s 62ms/step - accuracy: 0.6085 - loss: 1.0173 - val_accuracy:
0.7954 - val_loss: 0.5625
```

In [26]:
```
#plot_callback(callback)
```

How can we speed up execution:

1. Download the notebook & upload it to Google Colab
2. Change the line to `os.environ["JAX_PLATFORMS"] = ""`
3. Increase the number of epochs
4. Connect to a **GPU** instance
5. Run it!!!

Result for 40 epochs:



In [27]:
```
from keras import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, BatchNormalization

input_shape = *X_train[0].shape,1
num_classes = np.unique(y_train).size
print(f'{input_shape =}\n{num_classes = }')

conv2d_args = {'kernel_size':(3, 3), 'activation':'relu', 'strides':1, 'padding':'same'}
maxp2d_args = {'pool_size':(2, 2), 'padding':'valid', 'strides':2}
model = Sequential([
        Input(shape=input_shape),

        Conv2D(32, **conv2d_args),
        BatchNormalization(),
        Conv2D(32, **conv2d_args),
        BatchNormalization(),
        MaxPooling2D(**maxp2d_args),
        Dropout(0.25),

        Conv2D(64, **conv2d_args),
```

```
        BatchNormalization(),
        Conv2D(64, **conv2d_args),
        BatchNormalization(),
        MaxPooling2D(**maxp2d_args),
        Dropout(0.25),

        Conv2D(128, **conv2d_args),
        BatchNormalization(),
        Conv2D(128, **conv2d_args),
        BatchNormalization(),
        GlobalAveragePooling2D(),
        Dropout(0.25),

        Dense(256, activation='relu'),
        BatchNormalization(),
        Dropout(0.25),
        Dense(128, activation='relu'),
        BatchNormalization(),
        Dropout(0.25),
        Dense(64, activation='relu'),
        BatchNormalization(),
        Dropout(0.25),

        Dense(num_classes, activation='softmax'),
])

model.summary()
```

```
input_shape =(28, 28, 1)
num_classes = 10
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 28, 28, 32)	320
batch_normalization (BatchNormalization)	(None, 28, 28, 32)	128
conv2d_5 (Conv2D)	(None, 28, 28, 32)	9,248
batch_normalization_1 (BatchNormalization)	(None, 28, 28, 32)	128
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 32)	0
dropout_3 (Dropout)	(None, 14, 14, 32)	0
conv2d_6 (Conv2D)	(None, 14, 14, 64)	18,496
batch_normalization_2 (BatchNormalization)	(None, 14, 14, 64)	256
conv2d_7 (Conv2D)	(None, 14, 14, 64)	36,928
batch_normalization_3 (BatchNormalization)	(None, 14, 14, 64)	256
max_pooling2d_2 (MaxPooling2D)	(None, 7, 7, 64)	0
dropout_4 (Dropout)	(None, 7, 7, 64)	0
conv2d_8 (Conv2D)	(None, 7, 7, 128)	73,856
batch_normalization_4 (BatchNormalization)	(None, 7, 7, 128)	512
conv2d_9 (Conv2D)	(None, 7, 7, 128)	147,584
batch_normalization_5 (BatchNormalization)	(None, 7, 7, 128)	512
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 128)	0
dropout_5 (Dropout)	(None, 128)	0
dense_18 (Dense)	(None, 256)	33,024
batch_normalization_6 (BatchNormalization)	(None, 256)	1,024
dropout_6 (Dropout)	(None, 256)	0
dense_19 (Dense)	(None, 128)	32,896
batch_normalization_7 (BatchNormalization)	(None, 128)	512
dropout_7 (Dropout)	(None, 128)	0
dense_20 (Dense)	(None, 64)	8,256
batch_normalization_8 (BatchNormalization)	(None, 64)	256

dropout_8 (Dropout)	(None, 64)	0
dense_21 (Dense)	(None, 10)	650

Total params: 364,842 (1.39 MB)
Trainable params: 363,050 (1.38 MB)
Non-trainable params: 1,792 (7.00 KB)

In [28]:
```
model.compile(optimizer="adam",
              loss="sparse_categorical_crossentropy",
              metrics=['accuracy'])
callback = model.fit(X_train, y_train, validation_split=0.2, epochs=1)
```

```
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 252s 167ms/step - accuracy: 0.6474 - loss: 1.0300 - val_accurac
y: 0.8613 - val_loss: 0.3850
```

In [29]:
```
#plot_callback(callback)
```

Result for 40 epochs: