

```
In [1]: import keras
        from keras.models import Sequential
        from keras.layers import Dense, Activation, Flatten
        from keras.layers import Dropout, Conv2D, MaxPooling2D, BatchNormalization
        from keras.optimizers import Adam, SGD, RMSprop

        import numpy as np
        import tensorflow as tf

        tf.get_logger().setLevel('ERROR')
```

Using TensorFlow backend.

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.

We recommend you [upgrade \(https://www.tensorflow.org/guide/migrate\)](https://www.tensorflow.org/guide/migrate) now or ensure your notebook will continue to use TensorFlow 1.x via the `%tensorflow_version 1.x` magic: [more info \(https://colab.research.google.com/notebooks/tensorflow_version.ipynb\)](https://colab.research.google.com/notebooks/tensorflow_version.ipynb).

```
In [0]: num_classes = 10
```

```
In [3]: from keras.datasets import mnist
        (x_train, y_train), (x_test, y_test) = mnist.load_data()
        x_train = x_train.astype(np.float32) / 255
        x_test = x_test.astype(np.float32) / 255

        x_train = np.expand_dims(x_train, -1)
        x_test = np.expand_dims(x_test, -1)

        y_train = keras.utils.to_categorical(y_train, 10)
        y_test = keras.utils.to_categorical(y_test, 10)

        print('x_train shape:', x_train.shape)
        print(x_train.shape[0], 'train samples')
        print(x_test.shape[0], 'test samples')
```

```
x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
```

Exercise 2

```
In [0]: model = Sequential()
        model.add(Flatten(input_shape=(28,28,1)))
        model.add(Dense(512))
        model.add(Activation('relu'))
        model.add(Dropout(0.2))

        model.add(Dense(512))
        model.add(Activation('relu'))
        model.add(Dropout(0.2))

        model.add(Dense(10))
        model.add(Activation('softmax'))

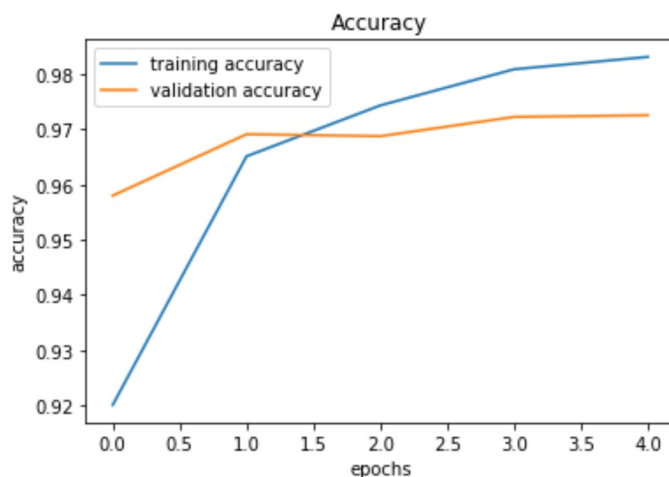
        model.compile(Adam(lr=0.001), loss=keras.losses.categorical_crossentropy, metrics=
        ['accuracy'])
```

```
In [5]: history = model.fit(x_train, y_train,
                             batch_size=64,
                             epochs=5,
                             verbose=1,
                             validation_split=0.33)
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

Train on 40199 samples, validate on 19801 samples
Epoch 1/5
40199/40199 [=====] - 4s 105us/step - loss: 0.2615 - acc: 0.9201 - val_loss: 0.1388 - val_acc: 0.9580
Epoch 2/5
40199/40199 [=====] - 3s 71us/step - loss: 0.1133 - acc: 0.9651 - val_loss: 0.1050 - val_acc: 0.9691
Epoch 3/5
40199/40199 [=====] - 3s 70us/step - loss: 0.0798 - acc: 0.9743 - val_loss: 0.1008 - val_acc: 0.9687
Epoch 4/5
40199/40199 [=====] - 3s 72us/step - loss: 0.0607 - acc: 0.9808 - val_loss: 0.1013 - val_acc: 0.9722
Epoch 5/5
40199/40199 [=====] - 3s 70us/step - loss: 0.0532 - acc: 0.9831 - val_loss: 0.0963 - val_acc: 0.9725
Test loss: 0.08604762646773888
Test accuracy: 0.9732

```
In [6]: import matplotlib.pyplot as plt

plt.plot(history.history['acc'], label='training accuracy')
plt.plot(history.history['val_acc'], label='validation accuracy')
plt.title('Accuracy')
plt.xlabel('epochs')
plt.ylabel('accuracy')
plt.legend()
plt.show()
```



Exercise 3

```
In [0]: model2 = Sequential()
model2.add(Conv2D(32, (3, 3), padding='same',
                  input_shape=x_train.shape[1:]))
model2.add(Activation('relu'))
model2.add(Dropout(0.2))
model2.add(Conv2D(64, (3, 3)))
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size=(2, 2)))

model2.add(Conv2D(128, (3, 3), padding='same'))
model2.add(Activation('relu'))
model2.add(Dropout(0.2))
model2.add(Conv2D(128, (3, 3)))
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size=(2, 2)))

model2.add(Flatten())
model2.add(Dense(10))
model2.add(Activation('softmax'))

model2.compile(loss=keras.losses.categorical_crossentropy,
               optimizer=keras.optimizers.Adam(),
               metrics=['accuracy'])
```

```
In [8]: model.summary()  
        model2.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
flatten_1 (Flatten)	(None, 784)	0
dense_1 (Dense)	(None, 512)	401920
activation_1 (Activation)	(None, 512)	0
dropout_1 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 512)	262656
activation_2 (Activation)	(None, 512)	0
dropout_2 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 10)	5130
activation_3 (Activation)	(None, 10)	0
Total params: 669,706		
Trainable params: 669,706		
Non-trainable params: 0		

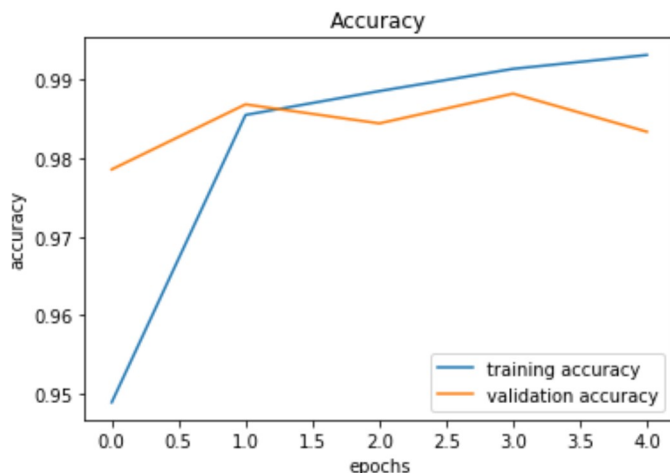
Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 28, 28, 32)	320
activation_4 (Activation)	(None, 28, 28, 32)	0
dropout_3 (Dropout)	(None, 28, 28, 32)	0
conv2d_2 (Conv2D)	(None, 26, 26, 64)	18496
activation_5 (Activation)	(None, 26, 26, 64)	0
max_pooling2d_1 (MaxPooling2D)	(None, 13, 13, 64)	0
conv2d_3 (Conv2D)	(None, 13, 13, 128)	73856
activation_6 (Activation)	(None, 13, 13, 128)	0
dropout_4 (Dropout)	(None, 13, 13, 128)	0
conv2d_4 (Conv2D)	(None, 11, 11, 128)	147584
activation_7 (Activation)	(None, 11, 11, 128)	0
max_pooling2d_2 (MaxPooling2D)	(None, 5, 5, 128)	0
flatten_2 (Flatten)	(None, 3200)	0
dense_4 (Dense)	(None, 10)	32010
activation_8 (Activation)	(None, 10)	0
Total params: 272,266		
Trainable params: 272,266		
Non-trainable params: 0		

```
In [9]: history = model2.fit(x_train, y_train,
                             batch_size=64,
                             epochs=5,
                             verbose=1,
                             validation_split=0.33)
score = model2.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Train on 40199 samples, validate on 19801 samples
Epoch 1/5
40199/40199 [=====] - 8s 187us/step - loss: 0.1674 - ac
c: 0.9489 - val_loss: 0.0710 - val_acc: 0.9786
Epoch 2/5
40199/40199 [=====] - 6s 142us/step - loss: 0.0489 - ac
c: 0.9855 - val_loss: 0.0448 - val_acc: 0.9869
Epoch 3/5
40199/40199 [=====] - 6s 142us/step - loss: 0.0357 - ac
c: 0.9886 - val_loss: 0.0492 - val_acc: 0.9844
Epoch 4/5
40199/40199 [=====] - 6s 142us/step - loss: 0.0261 - ac
c: 0.9914 - val_loss: 0.0394 - val_acc: 0.9882
Epoch 5/5
40199/40199 [=====] - 6s 143us/step - loss: 0.0204 - ac
c: 0.9932 - val_loss: 0.0600 - val_acc: 0.9834
Test loss: 0.04129169438488316
Test accuracy: 0.9856
```

```
In [10]: plt.plot(history.history['acc'], label='training accuracy')
plt.plot(history.history['val_acc'], label='validation accuracy')
plt.title('Accuracy')
plt.xlabel('epochs')
plt.ylabel('accuracy')
plt.legend()
plt.show()
```



Exercise 4

Calculation for Conv Layers: $(\text{Kernel_Width} \times \text{Kernel_Height} \times \text{Input_Channels} + 1) \times \text{Number_Filters} \setminus // + 1$ is for biases

Calculation for Dense Layers: $\text{Input_Dim} \times \text{Output_Dim}$

Exercise 5

CNNs are better suited for large image data as the amount of parameters of conv layers does not depend on the spatial input dimensions (in contrast to dense layers)

Exercise 6

Strided Convolutions: Stride defines the spatial step-size of the kernel of a convolutional layer. For a stride $n > 1$ (1 would be the default convolution) the kernel is only evaluated in every n th position thus resulting in a smaller spatial output dimension.

Max Pooling: Returns the single largest value within its receptive field. For non- or not fully overlapping receptive fields (e.g. use of stride) and a pool size $> 1 \times 1$ the output will be smaller than its input.

CIFAR10

```
In [11]: from keras.datasets import cifar10
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
x_train = x_train.astype(np.float32) / 255
x_test = x_test.astype(np.float32) / 255

y_train = keras.utils.to_categorical(y_train, 10)
y_test = keras.utils.to_categorical(y_test, 10)

print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')

x_train shape: (50000, 32, 32, 3)
50000 train samples
10000 test samples
```

```
In [0]: model3 = Sequential()
model3.add(Conv2D(input_shape=x_train[0,:,:,:].shape, filters=32, kernel_size=(3,
3), padding="same"))
model3.add(BatchNormalization())
model3.add(Activation('relu'))
model3.add(Conv2D(filters=64, kernel_size=(3,3), padding="same"))
model3.add(BatchNormalization())
model3.add(Activation('relu'))
model3.add(MaxPooling2D(pool_size=(2, 2)))
model3.add(Conv2D(filters=64, kernel_size=(3,3), padding="same"))
model3.add(BatchNormalization())
model3.add(Activation('relu'))
model3.add(Conv2D(filters=64, kernel_size=(3,3), padding="same"))
model3.add(BatchNormalization())
model3.add(Activation('relu'))
model3.add(Flatten())
model3.add(Dropout(0.5))
model3.add(Dense(128))
model3.add(Activation('relu'))
model3.add(Dense(num_classes, activation="softmax"))
model3.compile(loss='categorical_crossentropy', optimizer=Adam(lr=0.001), metrics=
['accuracy'])
```

```
In [14]: model3.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
=====		
conv2d_5 (Conv2D)	(None, 32, 32, 32)	896
batch_normalization_1 (Batch Normalization)	(None, 32, 32, 32)	128
activation_9 (Activation)	(None, 32, 32, 32)	0
conv2d_6 (Conv2D)	(None, 32, 32, 64)	18496
batch_normalization_2 (Batch Normalization)	(None, 32, 32, 64)	256
activation_10 (Activation)	(None, 32, 32, 64)	0
max_pooling2d_3 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_7 (Conv2D)	(None, 16, 16, 64)	36928
batch_normalization_3 (Batch Normalization)	(None, 16, 16, 64)	256
activation_11 (Activation)	(None, 16, 16, 64)	0
conv2d_8 (Conv2D)	(None, 16, 16, 64)	36928
batch_normalization_4 (Batch Normalization)	(None, 16, 16, 64)	256
activation_12 (Activation)	(None, 16, 16, 64)	0
flatten_3 (Flatten)	(None, 16384)	0
dropout_5 (Dropout)	(None, 16384)	0
dense_5 (Dense)	(None, 128)	2097280
activation_13 (Activation)	(None, 128)	0
dense_6 (Dense)	(None, 10)	1290
=====		
Total params: 2,192,714		
Trainable params: 2,192,266		
Non-trainable params: 448		


```
In [15]: history = model3.fit(x_train, y_train,
                             batch_size=128,
                             epochs=20,
                             verbose=1,
                             validation_split=0.16)
score = model3.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

Train on 42000 samples, validate on 8000 samples

Epoch 1/20

42000/42000 [=====] - 7s 164us/step - loss: 1.6904 - acc: 0.4372 - val_loss: 1.3672 - val_acc: 0.4974

Epoch 2/20

42000/42000 [=====] - 6s 134us/step - loss: 1.0367 - acc: 0.6316 - val_loss: 1.3962 - val_acc: 0.5676

Epoch 3/20

42000/42000 [=====] - 6s 136us/step - loss: 0.8372 - acc: 0.7052 - val_loss: 0.9667 - val_acc: 0.6627

Epoch 4/20

42000/42000 [=====] - 6s 138us/step - loss: 0.7372 - acc: 0.7373 - val_loss: 1.0293 - val_acc: 0.6579

Epoch 5/20

42000/42000 [=====] - 6s 135us/step - loss: 0.6639 - acc: 0.7630 - val_loss: 0.8704 - val_acc: 0.7021

Epoch 6/20

42000/42000 [=====] - 6s 137us/step - loss: 0.6017 - acc: 0.7861 - val_loss: 0.9566 - val_acc: 0.6883

Epoch 7/20

42000/42000 [=====] - 6s 138us/step - loss: 0.5589 - acc: 0.8024 - val_loss: 0.8497 - val_acc: 0.7114

Epoch 8/20

42000/42000 [=====] - 6s 136us/step - loss: 0.5155 - acc: 0.8197 - val_loss: 1.0059 - val_acc: 0.6886

Epoch 9/20

42000/42000 [=====] - 6s 136us/step - loss: 0.4755 - acc: 0.8307 - val_loss: 0.7957 - val_acc: 0.7309

Epoch 10/20

42000/42000 [=====] - 6s 137us/step - loss: 0.4447 - acc: 0.8418 - val_loss: 0.7924 - val_acc: 0.7369

Epoch 11/20

42000/42000 [=====] - 6s 137us/step - loss: 0.4089 - acc: 0.8557 - val_loss: 0.9105 - val_acc: 0.7285

Epoch 12/20

42000/42000 [=====] - 6s 136us/step - loss: 0.3834 - acc: 0.8646 - val_loss: 0.6806 - val_acc: 0.7749

Epoch 13/20

42000/42000 [=====] - 6s 136us/step - loss: 0.3604 - acc: 0.8711 - val_loss: 0.9370 - val_acc: 0.7300

Epoch 14/20

42000/42000 [=====] - 6s 136us/step - loss: 0.3393 - acc: 0.8792 - val_loss: 0.7943 - val_acc: 0.7552

Epoch 15/20

42000/42000 [=====] - 6s 136us/step - loss: 0.3182 - acc: 0.8860 - val_loss: 0.7162 - val_acc: 0.7735

Epoch 16/20

42000/42000 [=====] - 6s 137us/step - loss: 0.2977 - acc: 0.8921 - val_loss: 0.8306 - val_acc: 0.7590

Epoch 17/20

42000/42000 [=====] - 6s 136us/step - loss: 0.2753 - acc: 0.9008 - val_loss: 0.7934 - val_acc: 0.7566

Epoch 18/20

42000/42000 [=====] - 6s 137us/step - loss: 0.2644 - acc: 0.9059 - val_loss: 0.8136 - val_acc: 0.7636

Epoch 19/20

42000/42000 [=====] - 6s 135us/step - loss: 0.2505 - acc: 0.9102 - val_loss: 0.8338 - val_acc: 0.7640

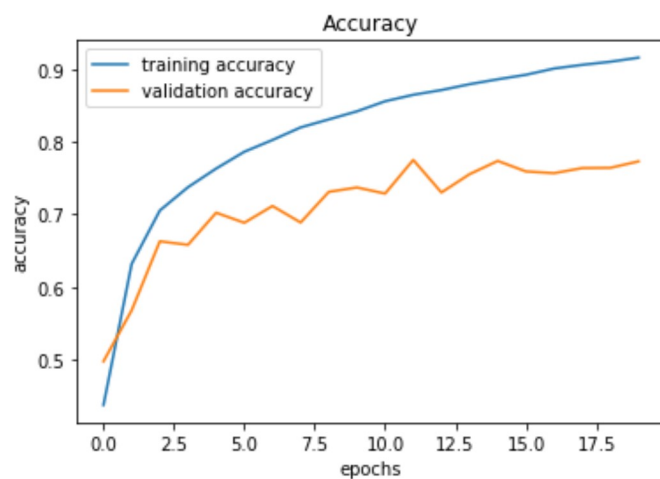
Epoch 20/20

42000/42000 [=====] - 6s 136us/step - loss: 0.2338 - acc: 0.9158 - val_loss: 0.7986 - val_acc: 0.7729

Test loss: 0.8293685411453247

Test accuracy: 0.7715

```
In [16]: plt.plot(history.history['acc'], label='training accuracy')
plt.plot(history.history['val_acc'], label='validation accuracy')
plt.title('Accuracy')
plt.xlabel('epochs')
plt.ylabel('accuracy')
plt.legend()
plt.show()
```



In [0]: