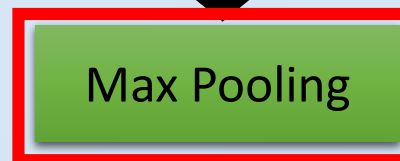
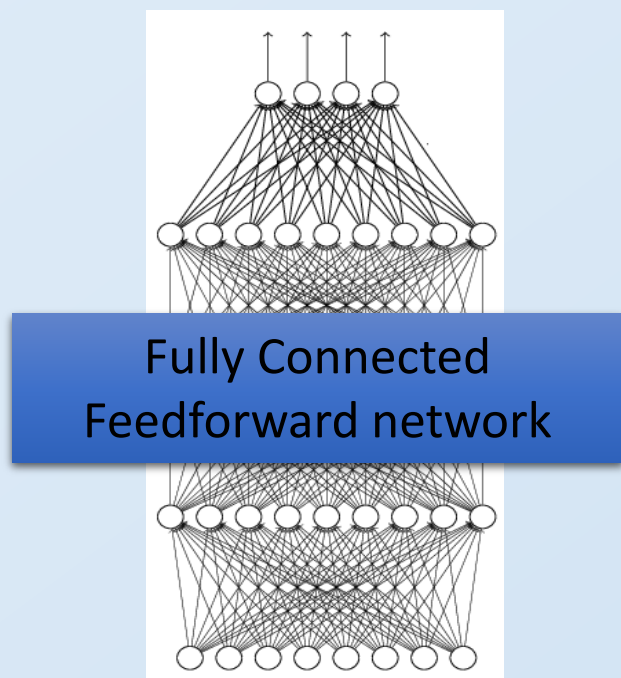


# Convolutional Neural Networks

# The whole CNN

cat dog .....

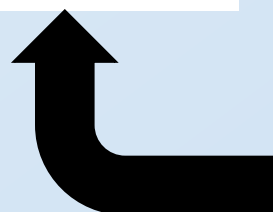


Can repeat many times

A red curly bracket on the right side of the diagram groups the "Max Pooling" boxes and the "Convolution + RELU" boxes between them, indicating that these steps can be repeated multiple times.

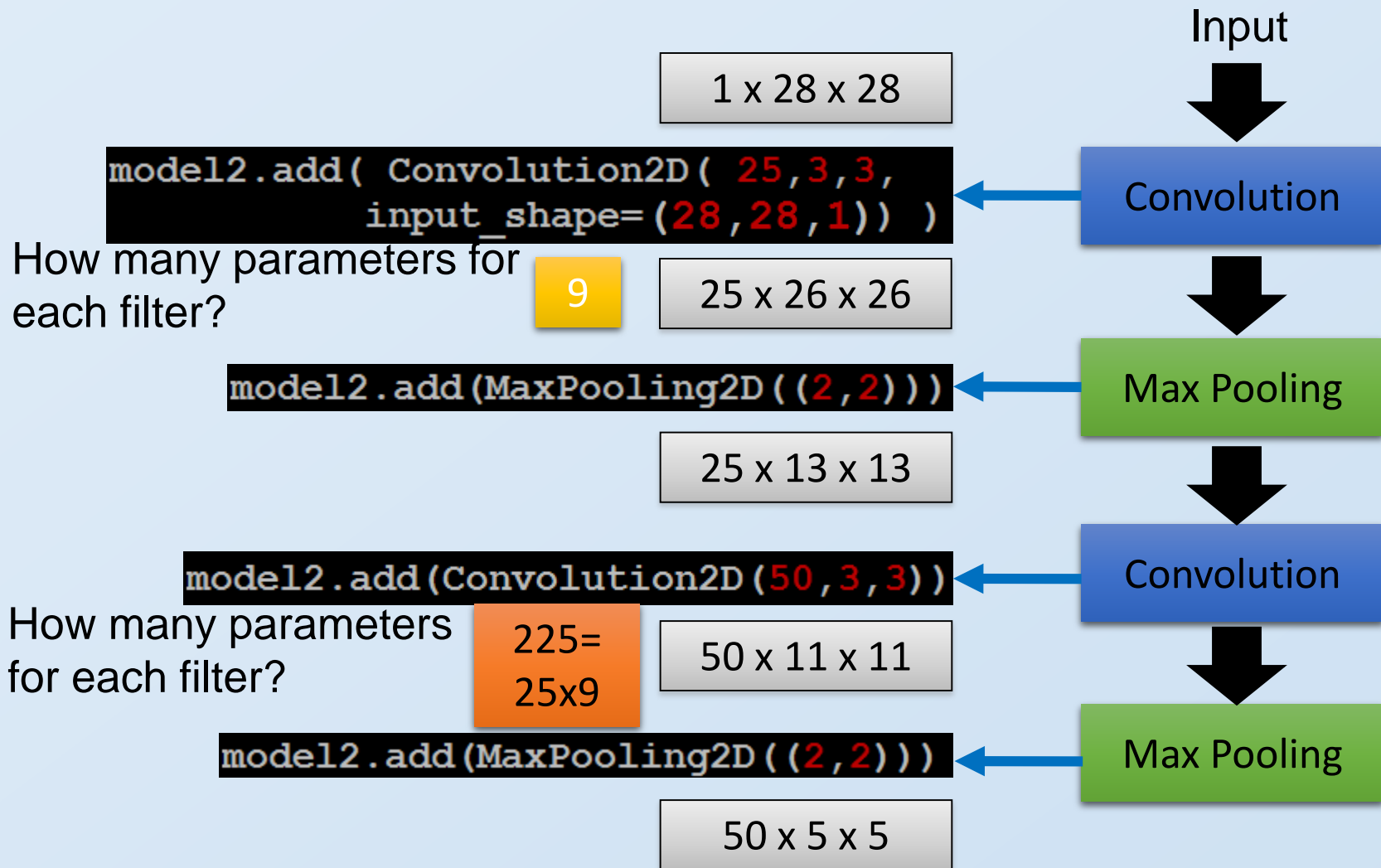
Flattened

An orange rectangular box containing the text "Flattened". A thick black arrow points from the bottom of the second "Max Pooling" box to this box.



# CNN in Keras

Only modified the *network structure* and *input format* (vector -> 3-D array)



# Convolutional Neural Networks using keras and tensorflow

```
import tensorflow as tf
from tensorflow.keras.layers import *
from keras.models import Model
from keras.optimizers import Adam, SGD

# Define CNN model
def create_model():
    model = tf.keras.models.Sequential()
    model.add(tf.keras.layers.Conv2D(32, (3, 3),
        input_shape=(28,28,1), activation='relu'))
    model.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
    model.add(tf.keras.layers.Conv2D(64, (3, 3), activation='relu'))
    model.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2),
        padding='same'))
    model.add(tf.keras.layers.Flatten())
    model.add(tf.keras.layers.Dense(64,activation = 'relu'))
    model.add(tf.keras.layers.Dense(10,activation = 'softmax'))
    return model
```

# Convolutional Neural Networks using keras and tensorflow

```
# Read Data
(x_train, y_train), (x_test, y_test) =
    tf.keras.datasets.mnist.load_data()
x_train = np.expand_dims(x_train, -1)/255
x_test = np.expand_dims(x_test, -1)/255

# Convert y to one-hot
y_train = tf.keras.utils.to_categorical(y_train, 10)
y_test = tf.keras.utils.to_categorical(y_test, 10)

model = create_model()
model.summary() # Prints model structure
```

# Convolutional Neural Networks using keras and tensorflow

```
model.summary() # Prints model structure
```

```
Model: "sequential_2"
```

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_4 (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_5 (Conv2D)	(None, 11, 11, 64)	18496
max_pooling2d_5 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten_2 (Flatten)	(None, 2304)	0
dense_4 (Dense)	(None, 64)	147520
dense_5 (Dense)	(None, 10)	650

```
Total params: 166,986
```

```
Trainable params: 166,986
```

```
Non-trainable params: 0
```

# Convolutional Neural Networks using keras and tensorflow

```
model = create_model()
model.summary() # Prints model structure

# Compile model - Build computation graph
model.compile(loss="categorical_crossentropy",
              optimizer="adam", metrics=["accuracy"])

# Fit model and store results in history object
history = model.fit(x_train, y_train, batch_size=128, epochs=20,
                  validation_data=(x_test, y_test))
```

# Convolutional Neural Networks using keras and tensorflow

```
# Read Data
(x_train, y_train), (x_test, y_test) =
    tf.keras.datasets.mnist.load_data()
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```



# Convolutional Neural Networks using keras and tensorflow

```
# Fit model and store results in history object
history = model.fit(x_train, y_train, batch_size=128, epochs=10,
                    validation_data=(x_test, y_test))
```

```
Epoch 1/10 469/469 [=====] - 43s 93ms/step - loss: 0.2240 - accuracy: 0.9348 -
val_loss: 0.0599 - val_accuracy: 0.9820
```

```
Epoch 2/10 469/469 [=====] - 43s 92ms/step - loss: 0.0591 - accuracy: 0.9821 -
val_loss: 0.0449 - val_accuracy: 0.9860
```

```
Epoch 3/10 469/469 [=====] - 43s 92ms/step - loss: 0.0430 - accuracy: 0.9868 -
val_loss: 0.0379 - val_accuracy: 0.9868
```

```
Epoch 4/10 469/469 [=====] - 43s 92ms/step - loss: 0.0331 - accuracy: 0.9898 -
val_loss: 0.0374 - val_accuracy: 0.9881
```

```
Epoch 5/10 469/469 [=====] - 43s 92ms/step - loss: 0.0260 - accuracy: 0.9919 -
val_loss: 0.0346 - val_accuracy: 0.9889
```

```
Epoch 6/10 469/469 [=====] - 43s 92ms/step - loss: 0.0210 - accuracy: 0.9935 -
val_loss: 0.0333 - val_accuracy: 0.9887
```

```
Epoch 7/10 469/469 [=====] - 43s 92ms/step - loss: 0.0176 - accuracy: 0.9947 -
val_loss: 0.0318 - val_accuracy: 0.9897
```

```
Epoch 8/10 469/469 [=====] - 43s 92ms/step - loss: 0.0138 - accuracy: 0.9956 -
val_loss: 0.0308 - val_accuracy: 0.9905
```

```
Epoch 9/10 469/469 [=====] - 43s 92ms/step - loss: 0.0101 - accuracy: 0.9968 -
val_loss: 0.0321 - val_accuracy: 0.9910
```

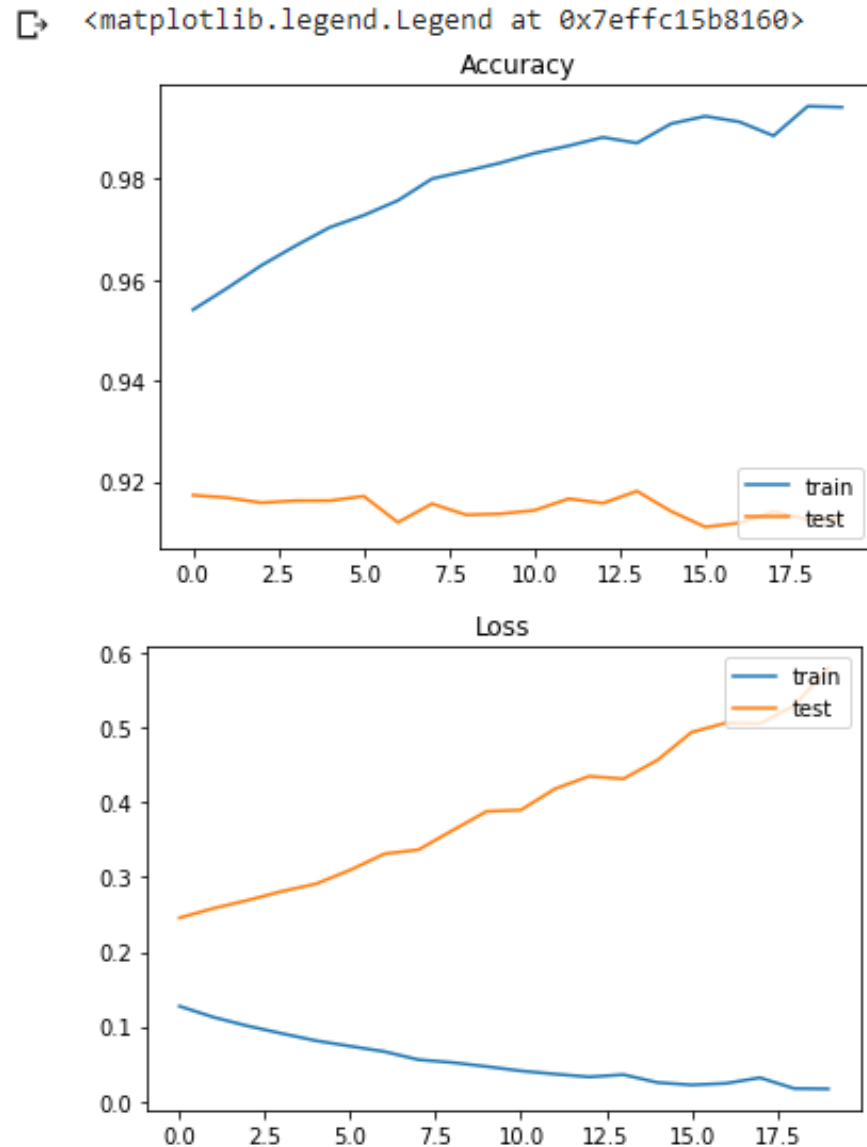
```
Epoch 10/10 469/469 [=====] - 43s 92ms/step - loss: 0.0104 - accuracy: 0.9967 -
val_loss: 0.0318 - val_accuracy: 0.9901
```

# Convolutional Neural Networks using keras and tensorflow

```
# Plot loss and accuracy during training
fig, ax = plt.subplots()
ax.plot(history.history['accuracy'],label = 'train')
ax.plot(history.history['val_accuracy'],label = 'test')
ax.set_title('Accuracy')
ax.legend(loc='lower right')

fig, ax = plt.subplots()
ax.plot(history.history['loss'],label = 'train')
ax.plot(history.history['val_loss'],label = 'test')
ax.set_title('Loss')
ax.legend(loc='upper right')
```

# Convolutional Neural Networks using keras and tensorflow



# Improving your model

## Changes in the architecture

- Add layers
- Add units in layers already present
- Modify strides – make sure you don't waste computation by discarding information
- Problem – larger networks are prone to overfitting
- Convolution layers with non-unit stride as replacement for maxpooling

## Activation functions

- Softmax usually works best for classification
- Relu, elu and Selu units work well for hidden layers

# Improving your model

## Regularization

- L1, L2 regularization – penalties for weight magnitudes; smaller weights are less likely to overfit
- Dropout – ignore some randomly-chosen units in every batch; make units learn independent features

## Optimizer

- Adam tends to work best
- All optimizers are sensitive to initial learning rate

## Batch size

- Smaller batches create more weight updates, but make training slower

## Batch normalization

- Normalizes layer activations for every batch – tends to keep gradients in same value range during training