



MANGO  
SOLUTIONS

# Deep Learning in R with Keras

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# Agenda

- Introduction to Deep Learning
- First neural network with Keras
- Networks for Spatial Data (CNN)
- What next?



# About Me

- Me:



Principal Data Scientist @ Mango



@dougashton

- Mango



@mangothecat



mangothecat



training@mango-solutions.com



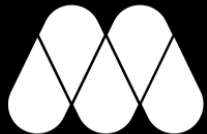
# About Them

Big thank you to co-writers

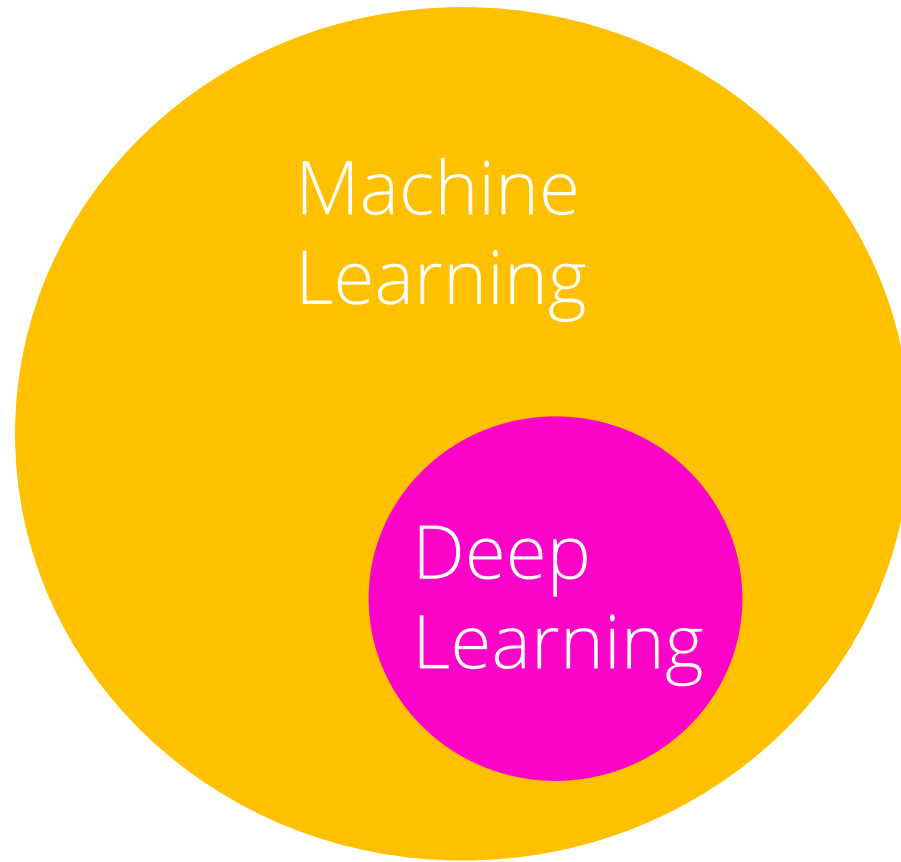
- Aimée Gott
- Owen Jones
- Alex Pavlides
- Mark Sellors\*



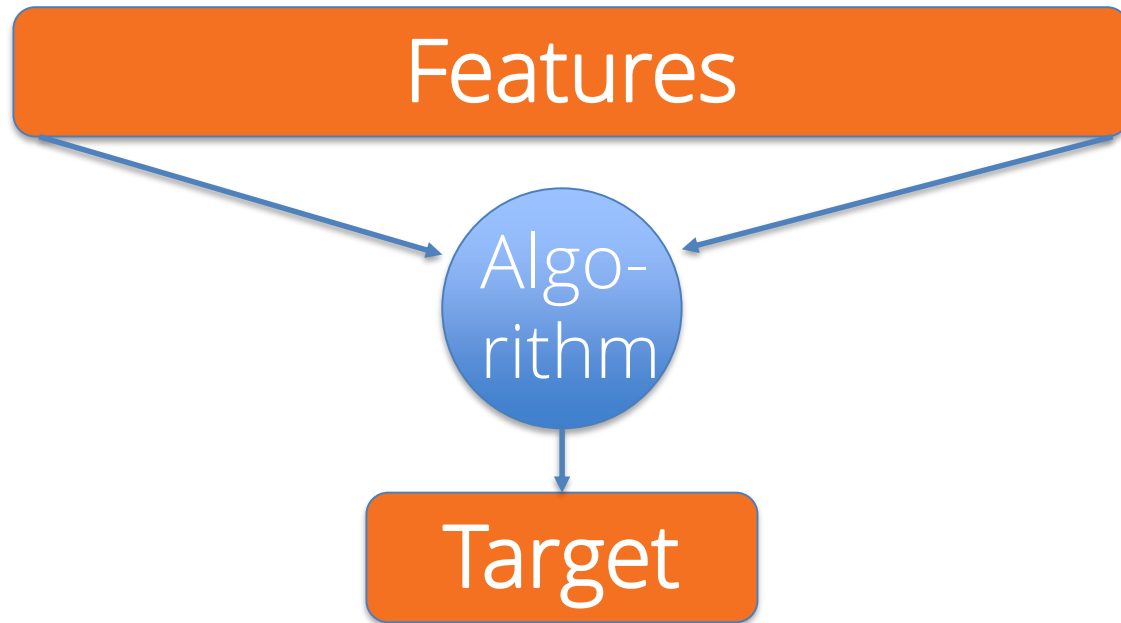
# Introduction to Deep Learning



# What is Deep Learning?



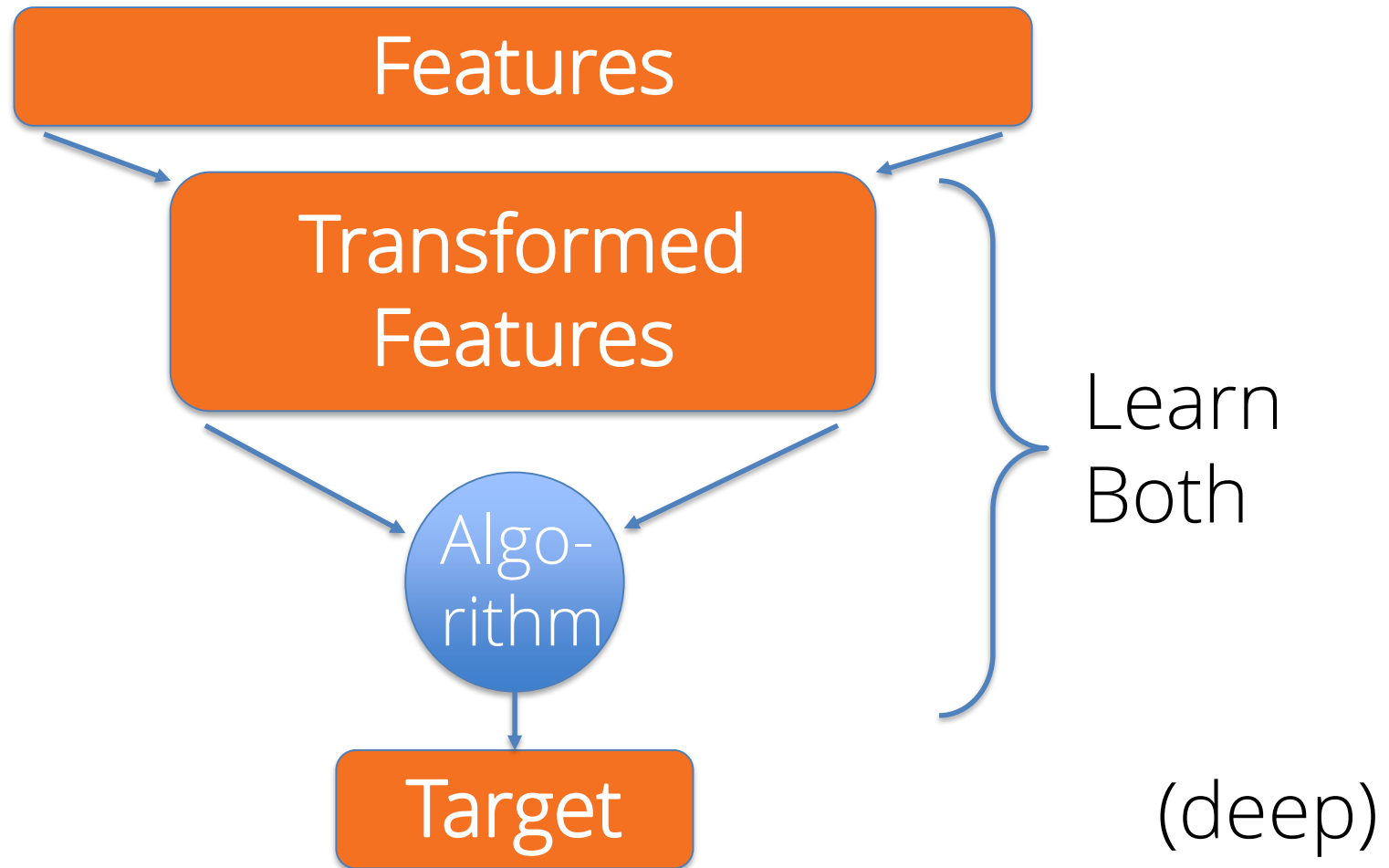
# What is Deep Learning?



(shallow)



# What is Deep Learning?





# What Does it Solve?

- Unstructured
  - Features are learned rather than designed
- Big
  - Generally need lots of data
- Familiar
  - Can reuse models on new problems



# Why Now?

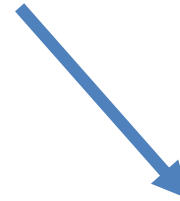
- Breakthrough in underlying algorithm
  - Back Propagation
- Massive increase in computer power
  - GPU / TPU
- Much larger datasets available
- Keras...



# Neural Networks



nodes



edges

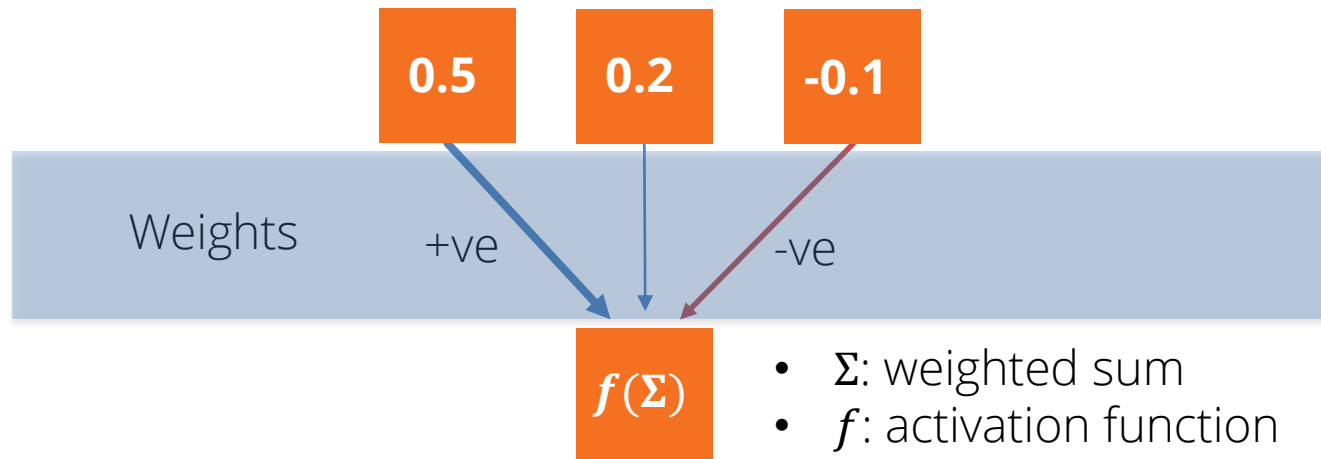


# A Neuron

0.2



# Neurons

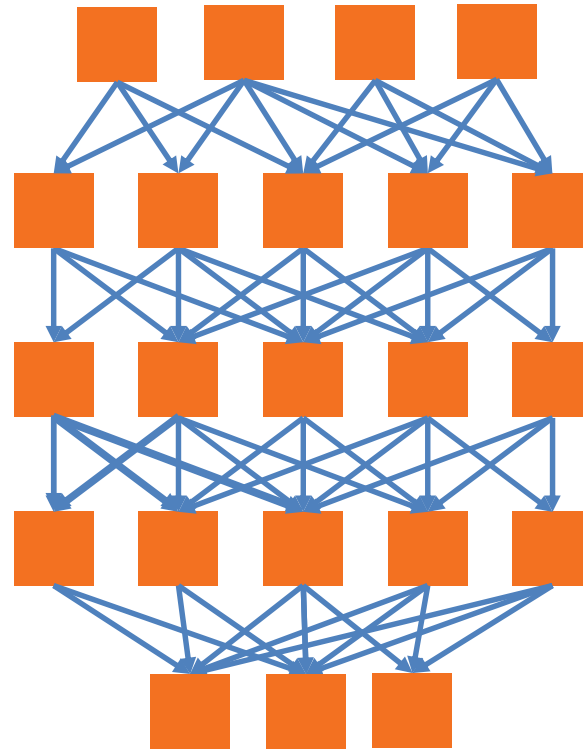


# Neural Network

Input layer

Hidden layers

Output layer



More  
abstract



# Iris Neural Network

`iris[1,1:4]`

Sepal.Length	Sepal.Width	Petal.Width	Petal.Length
5.1	3.5	1.4	0.2

Features  $x$

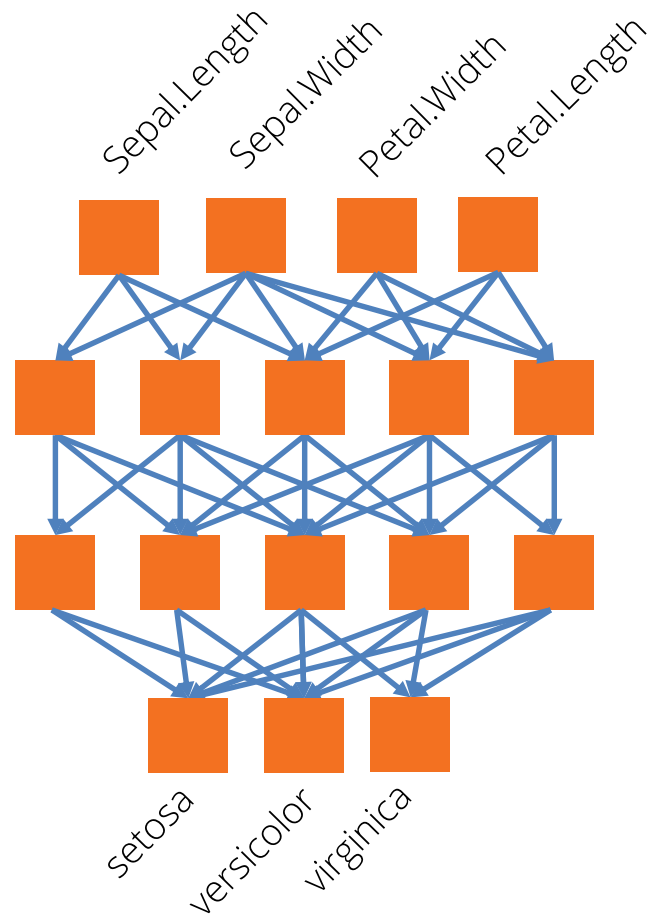
`iris[1,5]`

1	0	0
setosa	versicolor	virginica

Target  $y$



# Iris Neural Network





# TensorFlow

- Turns equations into dataflow graphs
  - <https://www.tensorflow.org>
- Efficient numerical solver
- Built for CPU, GPU, and TPU
- Not only for neural networks

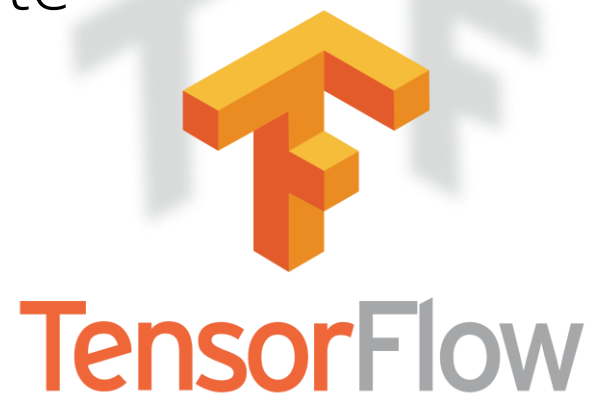


TensorFlow



# TensorFlow and R

- RStudio built an R interface
  - <https://tensorflow.rstudio.com>
- Python <-> R handled by reticulate
  - <https://rstudio.github.io/reticulate>



# Keras

- High level interface specifically for neural networks
  - <https://keras.io>
  - François Chollet
- Works with multiple backends
  - TensorFlow, CNTK, Theano



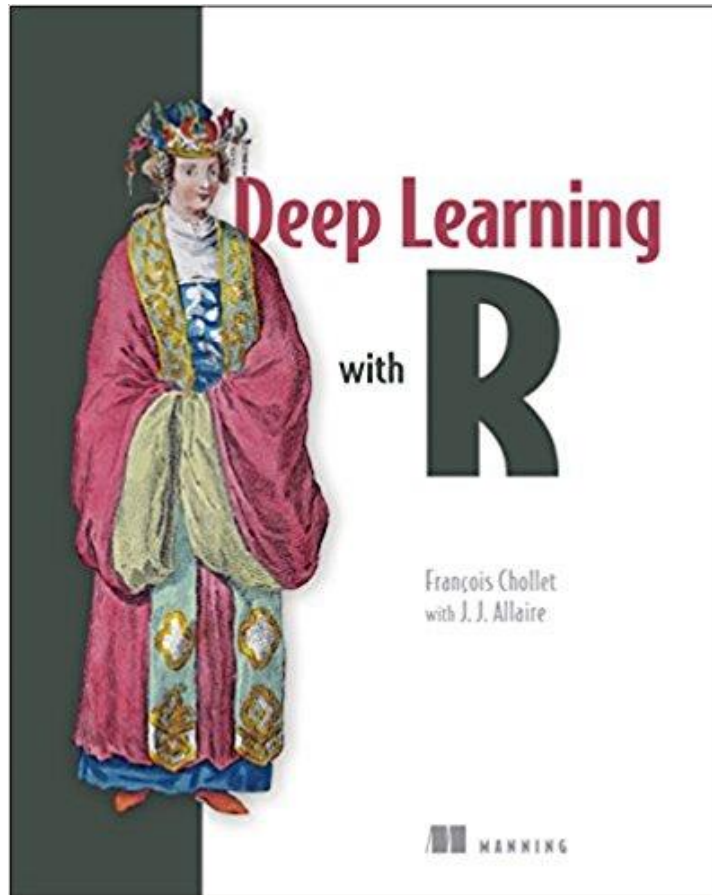
Keras

# Keras and R

- Rstudio built an interface to Keras
  - <https://keras.rstudio.com>
- Works with multiple backends
  - TensorFlow, CNTK, Theano



# Keras and R Book

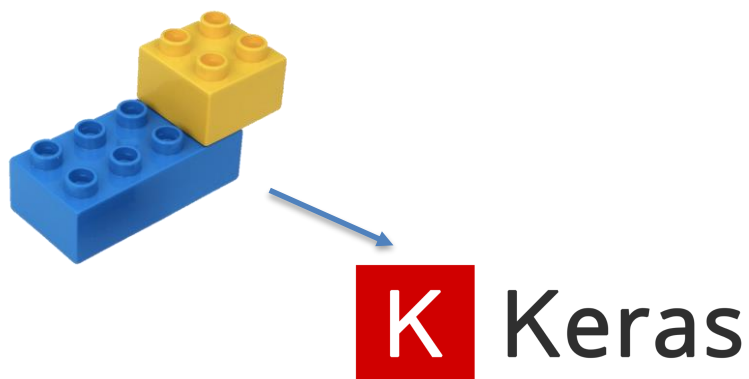


Deep Learning with R  
- François Chollet  
- J. J. Allaire

Manning



# How it fits together



$$\sigma = \sum_i z_i$$
$$p_j = \frac{e^{x^T w_j}}{\sum_k e^{x^T w_k}}$$



TensorFlow

00100110



# Alternatives for R Users

- MXNet
  - <https://mxnet.incubator.apache.org/api/r/>
- H2O Deep Water
  - <https://www.h2o.ai/deep-water/>



# RStudio Server

<http://odsc.mangodatalabs.com>

- Username/Password from card
- All libraries pre-installed
- Copy code out at the end
  - Server won't be checkpointed

[github.com/mangothecat/keras-workshop](https://github.com/mangothecat/keras-workshop)





# On your own machine

```
install.packages(c("tidyverse",  
                  "caret",  
                  "keras"))
```

```
library(keras)  
install_keras() # can take a while
```



# Limit CPU Use

```
library(keras)  
# Use this to limit cpu  
use_session_with_seed(1234)
```

Because otherwise tensorflow might take all the cores





# First Keras Model





# First Keras Model

- Prepare Data
- Model
- Evaluate



# Prepare Data



# Prepare Data

- Split train and test
- Numeric Matrices/Arrays
  - Factors
  - Scaling
  - Missing values



# Prepare - Split Data

```
library(caret)
library(tidyverse)

## Sample IDs for training set
trainID <- createDataPartition(iris$Species, p = 0.8)

trainingData <- iris %>%
  slice(trainID$Resample1)

testData <- iris %>%
  slice(-trainID$Resample1)

fullData <- list(train = trainingData,
                 test = testData)
```



# Prepare - One Hot Encode

```
dummy <- dummyVars(~ Species,  
                    data = iris)
```

```
irisDummy <- map(fullData, predict,  
                  object = dummy)
```

```
head(irisDummy$train)
```





# Prepare - Centre Scaling

```
numericIris <- map(fullData,  
                    select_if,  
                    is.numeric)
```

```
scaledIris <- map(numericIris,  
                  scale)
```



# Prepare - NAs

- Can't have NAs
- Impute 0 (mean)
  - `map(scaledIris, replace_na, replace = 0)`
- Or look at caret preprocessors
- No NAs in `iris`



# Prepare - Matrices

```
## Create x and y matrix
```

```
xIris <- map(scaledIris, as.matrix)
```

```
yIris <- map(irisDummy, as.matrix)
```



# Model



# Model

- Networks can have complex shapes
- Sequential models are linear stack

```
model <- keras_model_sequential()
```
- Model objects *change in place*



# Model - Layers

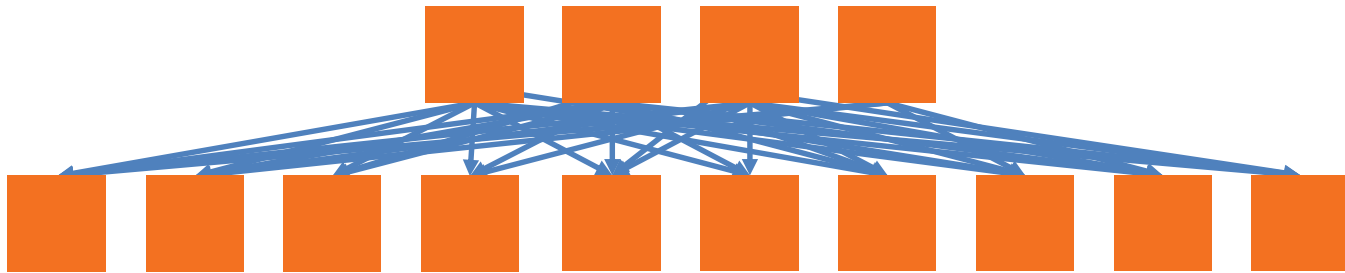
```
model %>%
```

```
  layer_dense(units = 10,  
              input_shape = 4)
```

- Only need `input_shape` **once**
- Shape doesn't include observations



# Model - Dense Layers



```
model %>%
```

```
  layer_dense(units = 10,  
              input_shape = 4)
```



# Model - Softmax Layer

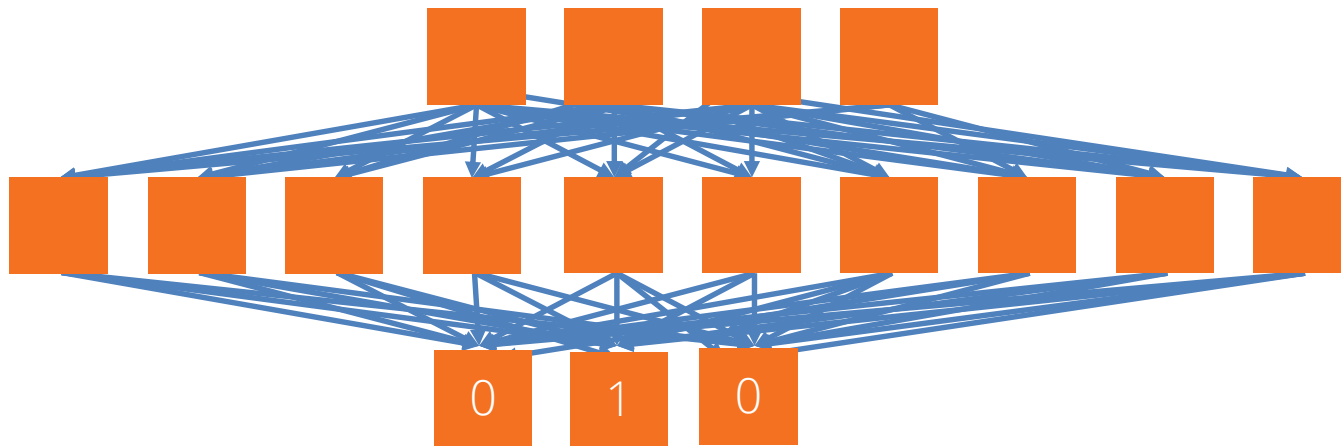
```
model %>%  
  layer_dense(units = 3,  
              activation = 'softmax')
```

- Usually on the output
- Use for categorical output





# Model - Softmax Layer



# Model - Summary

```
> model
```

```
Model
```

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 10)	50
dense_2 (Dense)	(None, 3)	33
Total params: 83		
Trainable params: 83		
Non-trainable params: 0		



# Compile

```
model %>% compile(  
  optimizer = 'rmsprop',  
  loss = 'categorical_crossentropy',  
  metrics = 'accuracy'  
)
```

- Optimizer: Mostly rmsprop
- Metrics: Mostly accuracy
- Loss: 3 main choices



# Compile - Loss

Output	Loss Function
Binary Classification	binary_crossentropy
Multi-class Classification (single label)	categorical_crossentropy
Multi-class Classification (multiple labels)	binary_crossentropy
Regression	mse



# Fit

```
history <-  
  model %>%  
    fit(xIris$train,  
        yIris$train,  
        epochs = 100,  
        validation_data =  
          list(xIris$test,  
              yIris$test))
```



# Exercise

- Get the iris model working
- Try adding a layer



# Evaluate



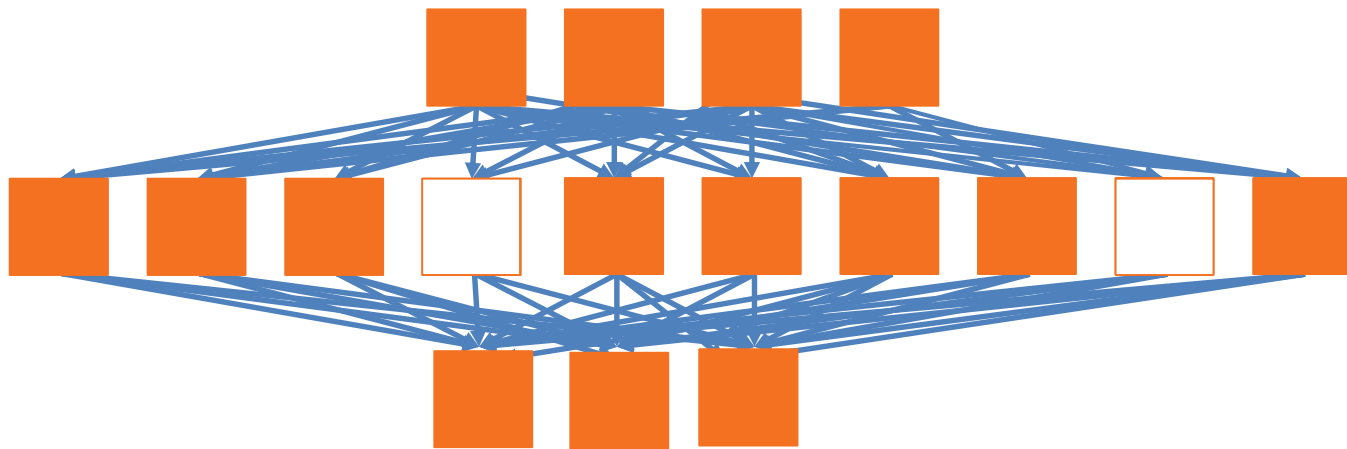
# Improving the Model

- Change number of hidden units
- Add more layers
- Add dropout
  - Helps prevent overfitting
- Mostly trial and error

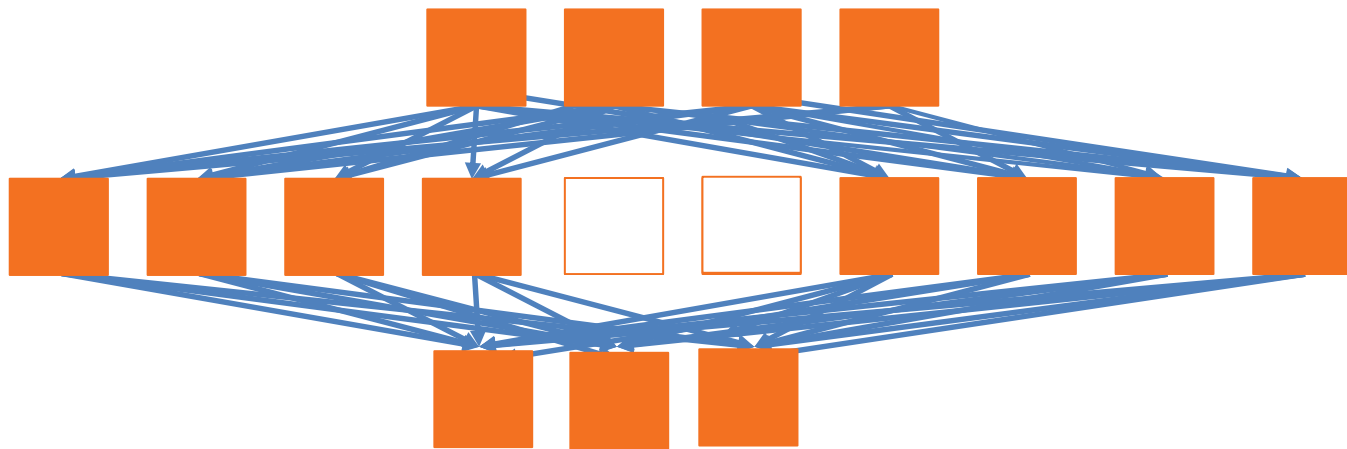




# Dropout



# Dropout



# Exercise

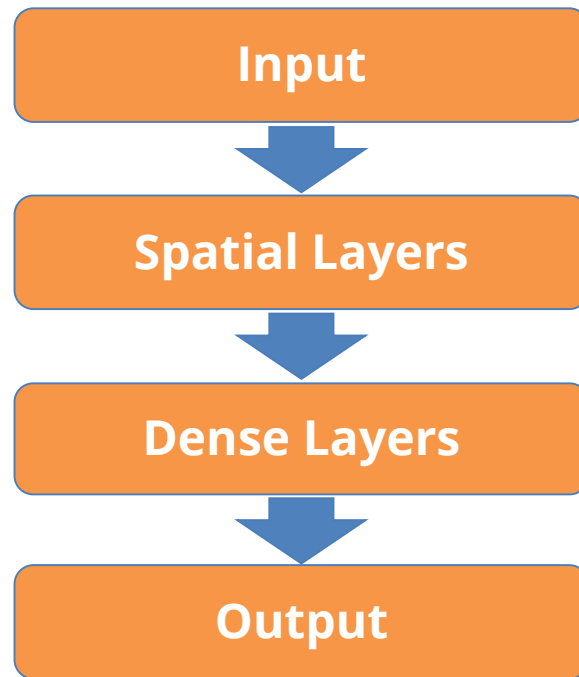
- Build a simple model for mtcars to predict mpg
  - Scale, one-hot-encode
  - Single output unit with linear activation
- How does it do against 1m?



# Networks for Spatial Data



# Convolutional Neural Networks



# Walking Data

```
walking <- readRDS("/data/walking.rds")
```

```
xWalk <- readRDS("/data/xWalk.rds")
```

```
yWalk <- readRDS("/data/yWalk.rds")
```



# Walking Data

- Accelerometer data from the UCI
- Filtered to walking activity
- Can we recognise someone by their gait?
- Chopped into 5 second chunks

```
> dim(walking$x)
```

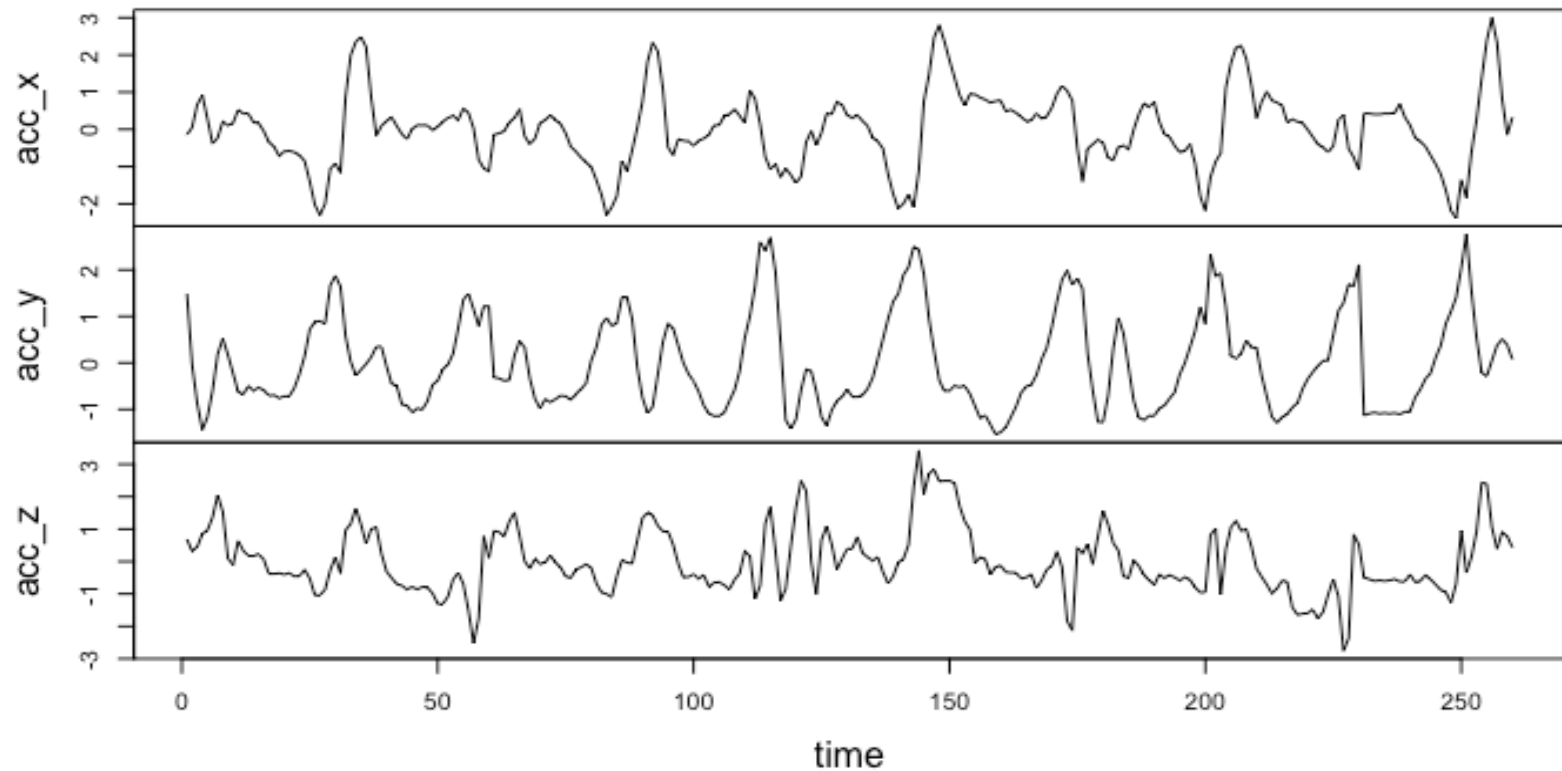
```
[1] 6792 260 3
```





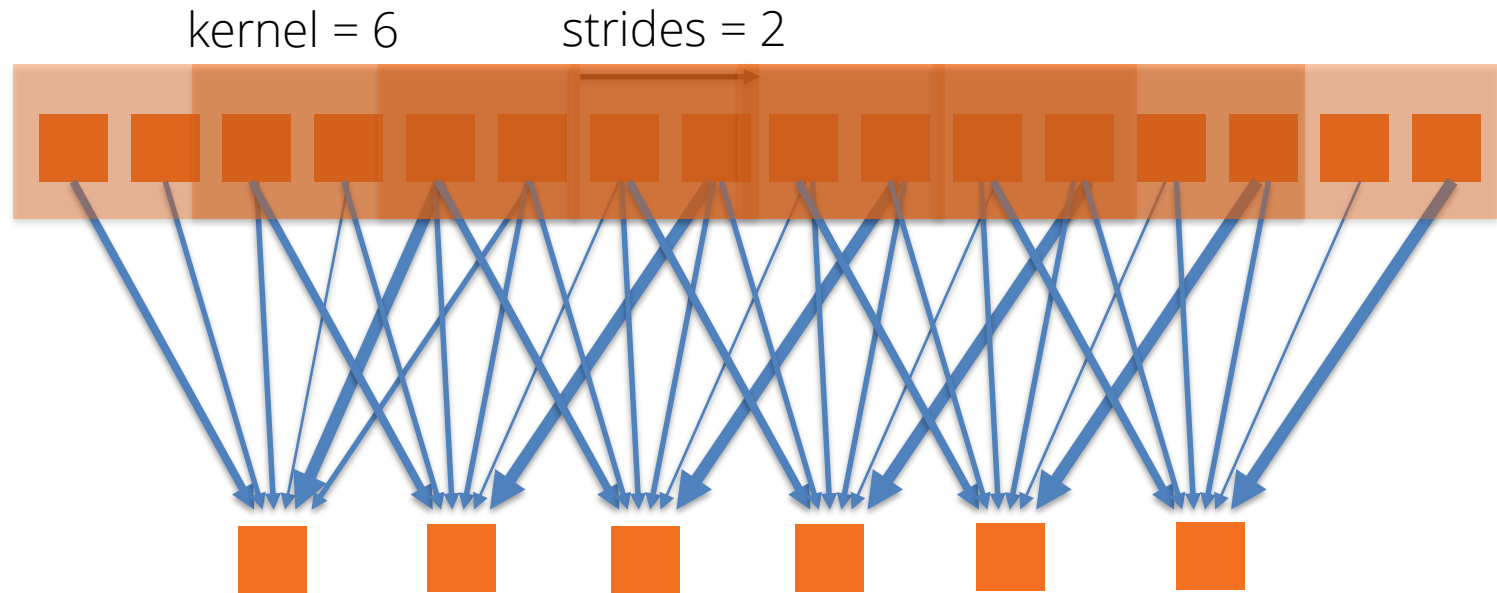
# Walking Data

**Single Time Series**

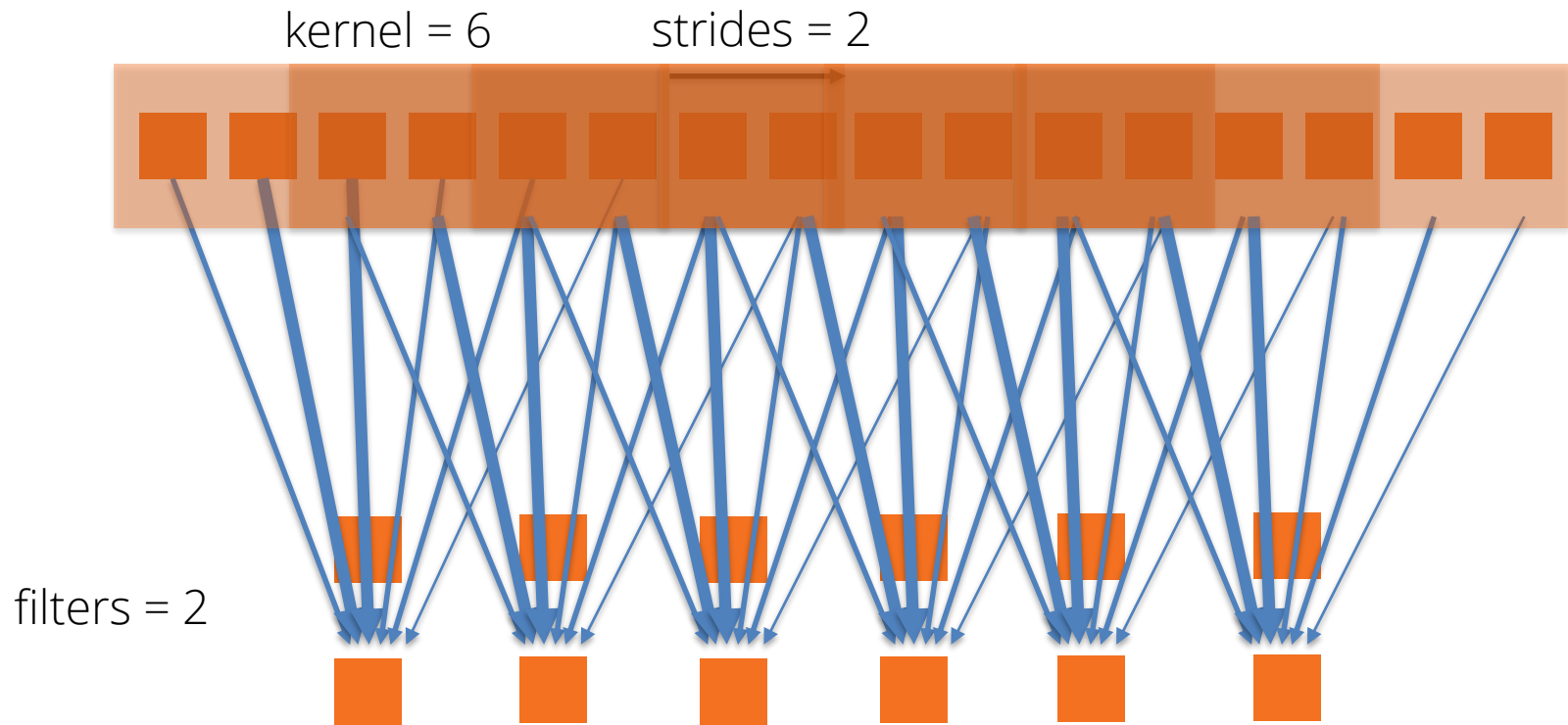




# Convolution Layer

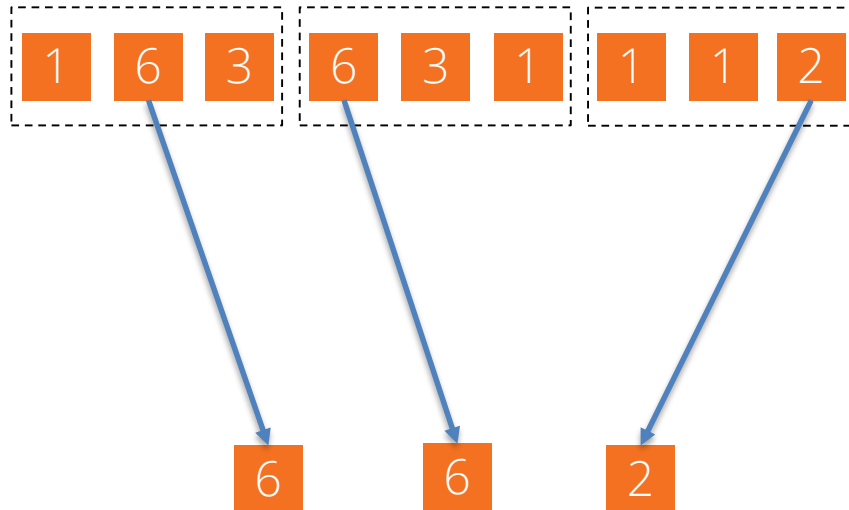


# Convolution Layer - Filters

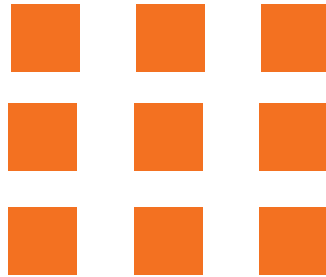


# Max Pooling

pool\_size = 3



# Flattening

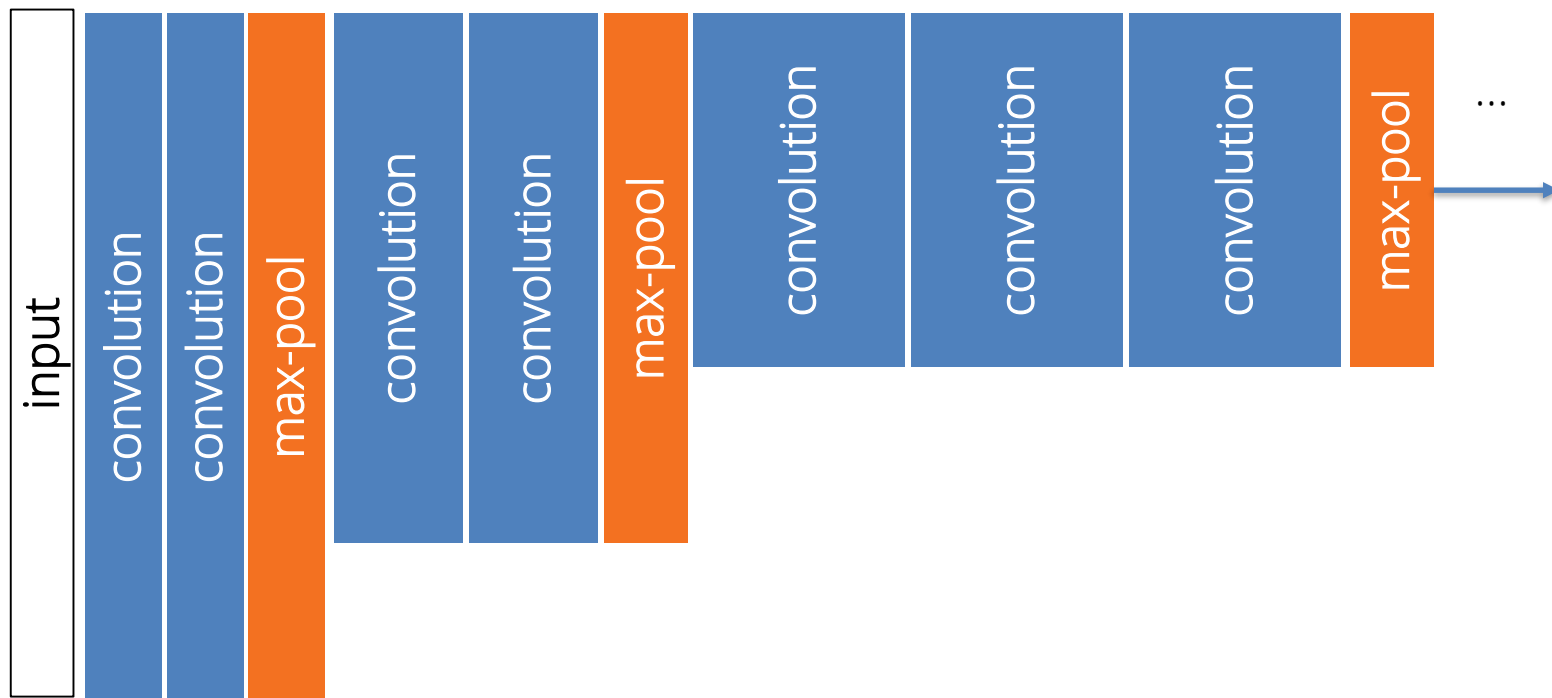


# Exercise

- Try adding more conv layers to your model
- Does dropout improve overfitting?



# CNN Architectures - VGG



# What Next?

- Pre-trained Networks
- CloudML

Reusable →

