

INDS 4997 / Capstone in Data Science

Instructor: Mehdi Maadooliat

DEEP LEARNING IN R

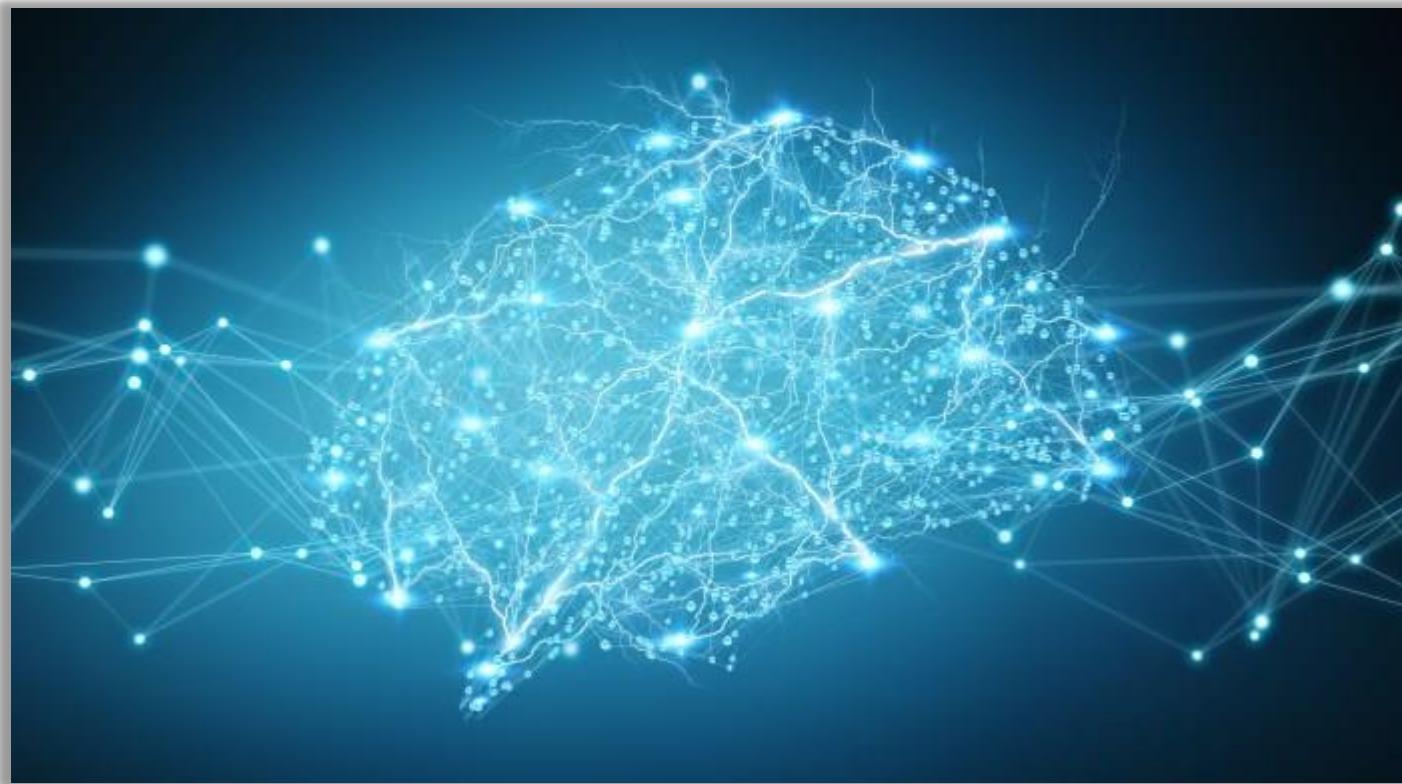
**FULLY CONNECTED
NEURAL NETWORK**

**CONVOLUTIONAL
NEURAL NETWORK TUTORIAL**



Department of Mathematical and Statistical Sciences

DEEP LEARNING: MYTHS AND TRUTHS

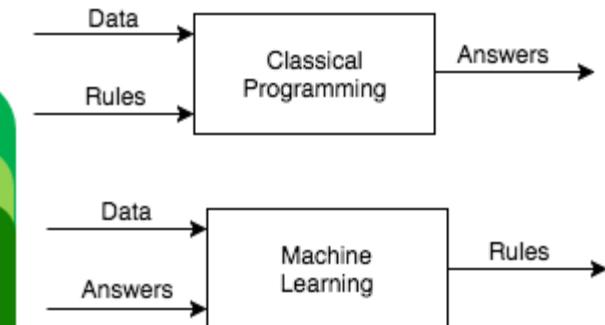
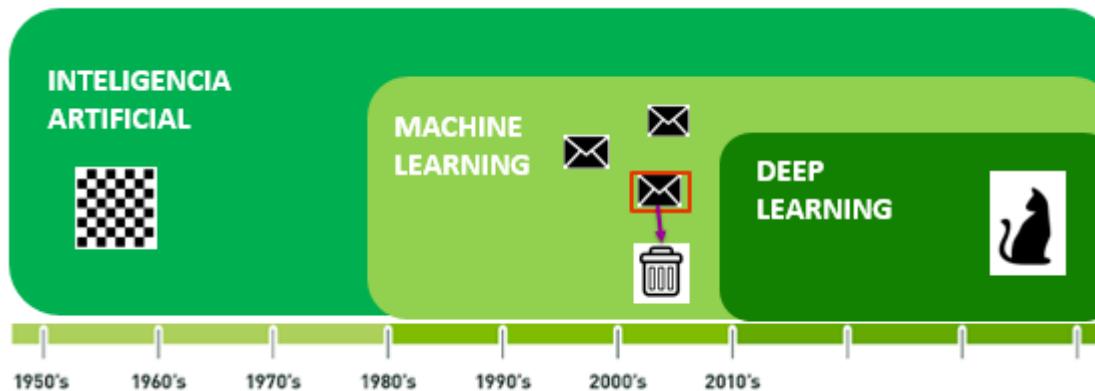


CLASSICAL PROGRAMMING VS MACHINE LEARNING

- Deep learning is often presented as algorithms that “work like the brain”, that “think” or “understand”.

Reality is however quite far from this dream

- AI: *the effort to automate intellectual tasks normally performed by humans.*



- ML: Could a computer surprise us? Rather than programmers crafting data-processing rules by hand, could a computer automatically learn these rules by looking at data?

RECIPES OF A MACHINE LEARNING ALGORITHM

■ *Input data points, e.g.*

- if the task is speech recognition, these data points could be sound files of people speaking
- If the task is image tagging, they could be picture files

■ *Examples of the expected output*

- In a speech-recognition task, these could be human-generated transcripts of sound files
- In an image task, expected outputs could tags such as "dog", "cat", and so on

■ *A way to measure whether the algorithm is doing a good job*

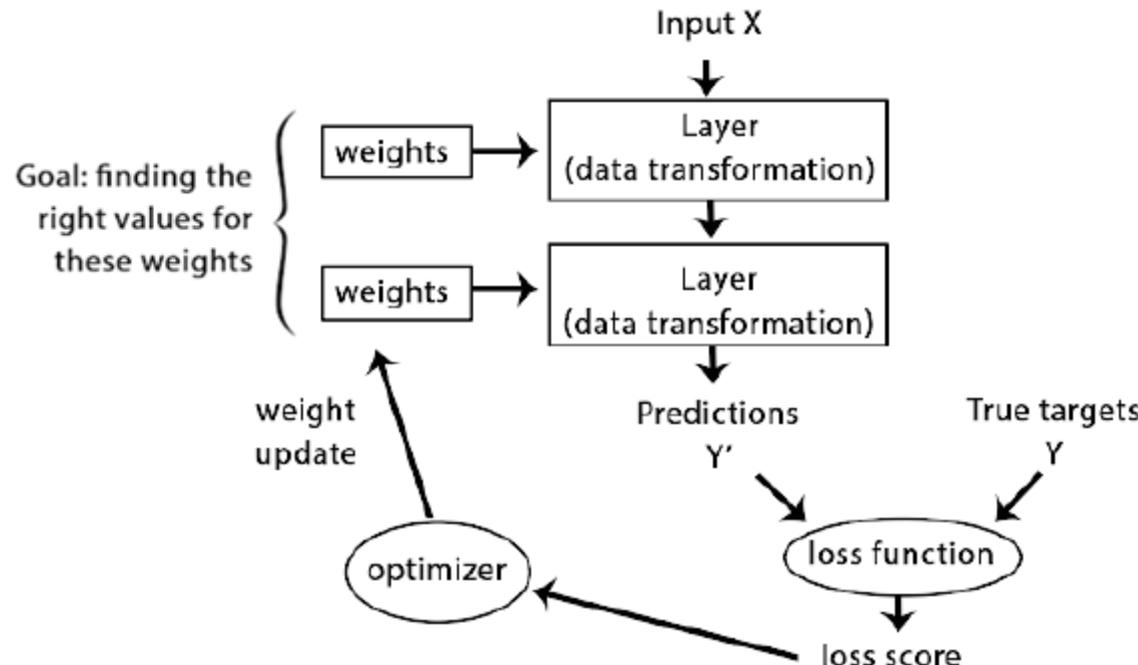
- This is necessary in order to determine the distance between the algorithm's current output and its expected output.
- The measurement is used as a feedback signal to adjust the way the algorithm works. This adjustment step is what we call *learning*.

$$MSE = \frac{1}{n} \sum_{\text{number of observations}} \left(y_i - \hat{f}(x_i) \right)^2$$

Also called " \hat{y}_i ".

ANATOMY OF A NEURAL NETWORK

- The *input data* and corresponding *targets*
- *Layers*, which are combined into a *network (or model)*
- The *loss function*, which defines the feedback signal used for learning
- The *optimizer*, which determines how learning proceeds



LENET-5: A PIONEERING 7-LEVEL CNN

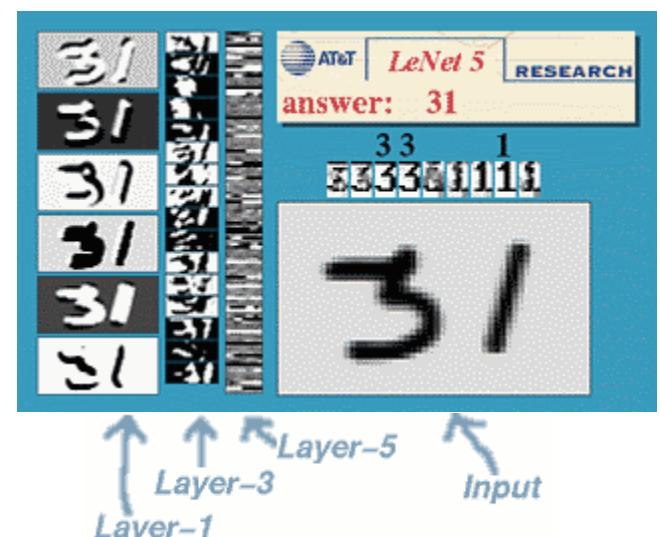


Yann LeCun > Turing Award

Turing Award
2019

Winner

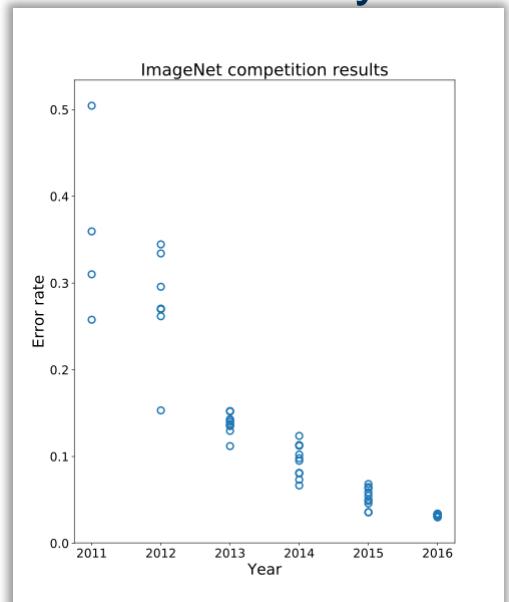
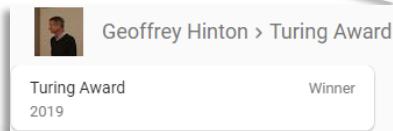
- The first successful practical application of neural nets came in 1989 from Bell Labs, when Yann LeCun combined the earlier ideas of convolutional neural networks and backpropagation, and applied them to the problem of classifying handwritten digits.
- The resulting network, dubbed *LeNet*, was used by the USPS in the 1990s to automate the reading of ZIP codes on mail envelopes.
- LeNet-5 was applied by several banks to recognize hand-written numbers on checks digitized in 32x32 pixel images.



WHY 30+ YEARS GAP?

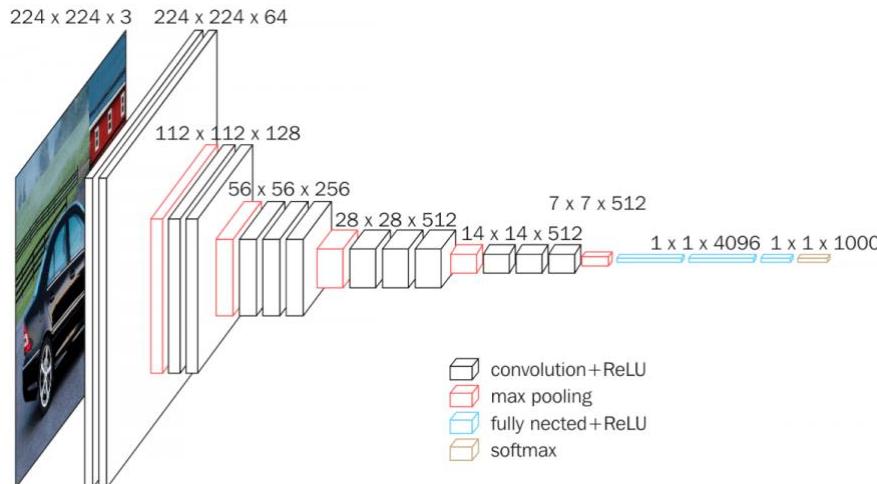


- In 2011, Dan Ciresan from IDSIA (Switzerland) began to win academic image-classification competitions with GPU-trained deep neural networks
- in 2012, a team led by Alex Krizhevsky and advised by Geoffrey Hinton was able to achieve a top-five accuracy of 83.6%--a significant breakthrough (in 2011 it was only 74.3%).
- Three forces are driving advances in ML:
 - Hardware
 - Datasets and benchmarks
 - Algorithmic advances



VGG16 – CNN FOR CLASSIFICATION AND DETECTION

- VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford
- The model achieves 92.7% top-5 test accuracy in ImageNet. It was one of the famous model submitted to ILSVRC-2014.
- It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another.
- VGG16 was trained for weeks using NVIDIA Titan Black GPU's.



```
summary(vgg16_imagenet_model)
```

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
... (entire model not shown) ...		
fc2 (Dense)	(None, 4096)	16781312
predictions (Dense)	(None, 1000)	4097000
Total params:	138,357,544	
Trainable params:	138,357,544	
Non-trainable params:	0	

Is DEEP LEARNING REALLY A BLACK Box?

■ Deep Learning Image Classification with Keras

- [Shiny Demo](#)

Deep Learning Image Classification with Keras By Jasmine Dumas Model Resources

Keras is a user-friendly neural networks API. This application uses the [ResNet50 model](#), with weights pre-trained on [ImageNet](#) to enable fast experimentation for prediction of images classes including:

- Animals 🐾
- Plants 🌱
- Activities ⛹
- Food 🍔

Select an image from your local machine:

Browse... Cudahy Hall (image) Upload complete

Image Preview



François Chollet @fchollet Follow

"Neural networks" are a sad misnomer. They're neither neural nor even networks. They're chains of differentiable, parameterized geometric functions, trained with gradient descent (with gradients obtained via the chain rule). A small set of highschool-level ideas put together

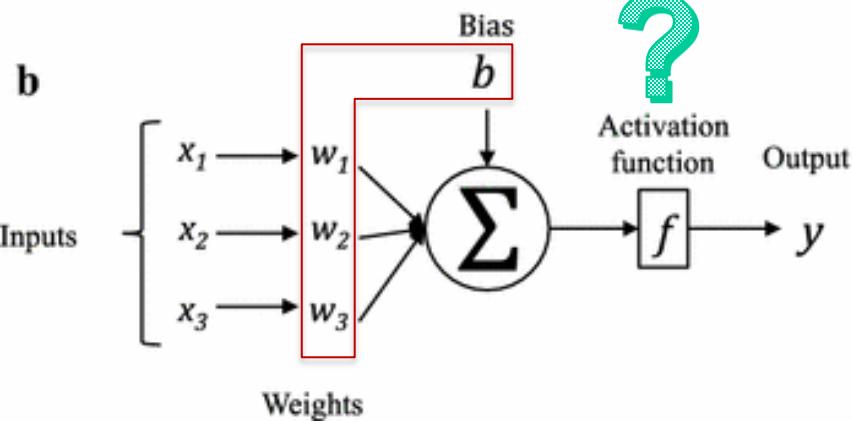
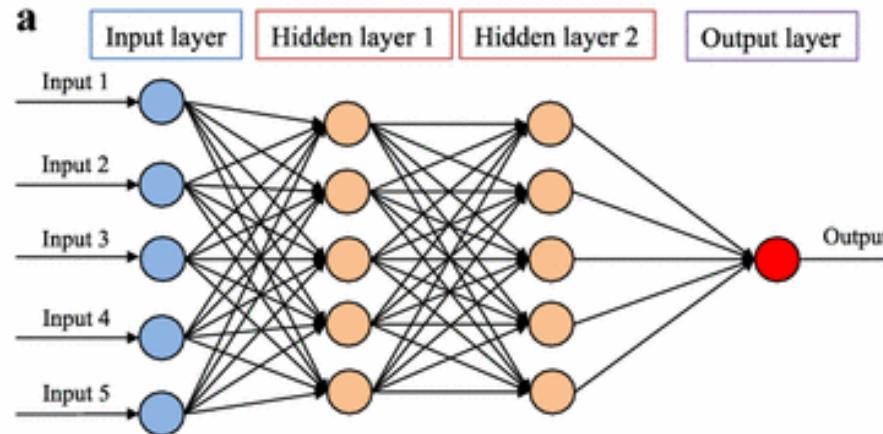
11:58 AM - 12 Jan 2018

1,319 Retweets 3,423 Likes

Results

	class_name	class_description	score	explore_class_on_imagenet
1	n03028079	church	0.10751248896122	Explore church on ImageNet
2	n04252225	snowplow	0.0888242274522781	Explore snowplow on ImageNet
3	n03388043	fountain	0.0620528757572174	Explore fountain on ImageNet

A NEURAL NETWORK – PARAMETERS- ACTIVATION FUNCTION



Activation functions

Name	Plot	Equation	Derivative
Identity		$f(x) = x$	$f'(x) = 1$
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$
Logistic (a.k.a Soft step)		$f(x) = \frac{1}{1 + e^{-x}}$	$f'(x) = f(x)(1 - f(x))$
TanH		$f(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
ArcTan		$f(x) = \tan^{-1}(x)$	$f'(x) = \frac{1}{x^2 + 1}$
Rectified Linear Unit (ReLU)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Parameteric Rectified Linear Unit (PReLU) [2]		$f(x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Exponential Linear Unit (ELU) [3]		$f(x) = \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} f(x) + \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
SoftPlus		$f(x) = \log_e(1 + e^x)$	$f'(x) = \frac{1}{1 + e^{-x}}$

LINEAR MODEL – BEST LINEAR UNBIASED EST.

Consider the model

$$Y = X\beta + \epsilon$$

where $Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix}$ $X = \begin{pmatrix} 1 & X_{11} & X_{12} & \dots & X_{1p} \\ 1 & X_{21} & X_{22} & \dots & X_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{n1} & X_{n2} & \dots & X_{np} \end{pmatrix}$ $\beta = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}$ $\epsilon = \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{pmatrix}$

Based on this model we get the following expansion for the first subject:

$$Y_1 = \beta_0 + \beta_1 X_{11} + \beta_2 X_{12} + \dots + \beta_p X_{1p} + \epsilon_1$$

Then using matrix calculus we find that the least squares estimate for β is given by

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

Hence, the least squares regression line is $\hat{Y} = X\hat{\beta}$.

$$\hat{e} = \begin{pmatrix} \hat{e}_1 \\ \hat{e}_2 \\ \vdots \\ \hat{e}_n \end{pmatrix} := Y - \hat{Y}$$

In R:

- `lm.fit <- lm(Y~X)`
- `Y.hat <- lm.fit$fitted`
- `e.hat <- lm.fit$resid`

REDIDUAL (SUR)REALISM – REVERSE INVERSE PROBLEM

- The end user provides $\hat{e} = \begin{pmatrix} \hat{e}_1 \\ \hat{e}_2 \\ \vdots \\ \hat{e}_n \end{pmatrix}$ and $\hat{Y} = \begin{pmatrix} \hat{Y}_1 \\ \hat{Y}_2 \\ \vdots \\ \hat{Y}_n \end{pmatrix}$
- Redidual (Sur)Realism provides (generates)

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix}$$

and

$$X = \begin{pmatrix} 1 & X_{11} & X_{12} & \dots & X_{1p} \\ 1 & X_{21} & X_{22} & \dots & X_{2p} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & X_{n1} & X_{n2} & \dots & X_{np} \end{pmatrix}$$

Statistical Computing and Graphics

Residual (Sur)Realism

Leonard A. STEFANSKI

WE SHOW HOW TO CONSTRUCT MULTIPLE LINEAR REGRESSION DATA SETS WITH THE PROPERTY THAT THE PLOT OF RESIDUALS VERSUS PREDICTED VALUES FROM THE LEAST SQUARES FIT OF THE CORRECT MODEL REVEALS A HIDDEN IMAGE OR MESSAGE. YOU ARE READING ONE SUCH RESIDUAL PLOT.

Residual
Predicted

1. INTRODUCTION

For example, imagine the reaction of a student who, upon completing an assignment of fitting a given multiple linear regression model and examining residual plots, is confronted with the residual plot in Figure 1(a), which contradicts G.E.P. Box's famous quotation about all models being wrong in the same way that Professor Jones's discovery under the Roman numeral ten contradicted his assertion that X never marks the spot (a residual plot version of which appears in Figure 1(b)). Of course, if the regression assignment is due just prior to a "big game," then the student might be more intrigued by residual plots of the sort in Figures 1(c) and (d). Figure 1(e) depicts Homer Simpson explaining how to embed images in regression residual plots. And if the residual plots in (a)–(e) are not attention-getting enough, the student who is unexpectedly confronted with the residual plot in Figure 1(f) is certainly going to be buffaloed (perhaps "bisoned" is taxonomically more correct but not grammatically).

REDIDUAL (SUR)REALISM – SIMULATION

- Here \hat{e} and \hat{Y} are vectors of length 10118
- Using “Redidual (Sur)Realism” we generate
- $X = [X_1 \ X_2 \ \dots \ X_5]$ and Y , where X_j ’s and Y are vectors of length 10118

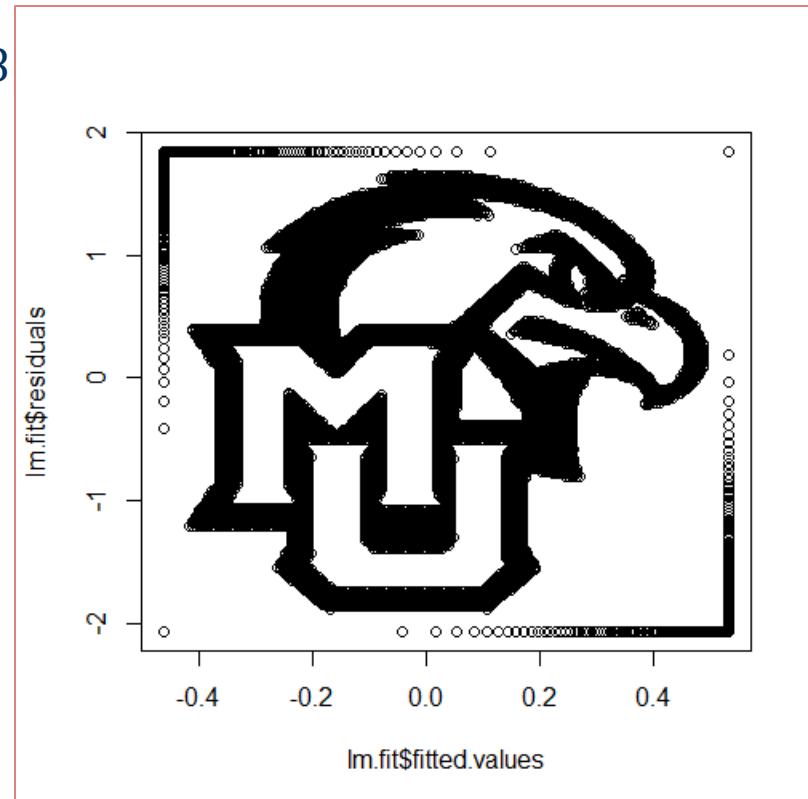
```
> library(dplyr)
> as.tbl(mu.logo)
# A tibble: 10,118 x 6
      Y     X1     X2     X3     X4     X5
  <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
1 1.65 -23.3 -0.487  1.97 -0.198  1.65
2 1.58  6.51 -0.370 -1.54  0.793 -0.803
3 1.59  4.68  0.294 -2.08 -0.0318 0.0216
4 1.59  8.22 -0.435 -2.31  0.470 -0.350
5 1.60 -8.80  1.08  1.73 -1.31  -1.16
6 1.60 -7.05 -1.26  0.912  0.0508 -0.417
7 1.61 -1.06  1.34 -1.16  1.78  0.108
8 1.61  3.98 -0.993 -1.26  1.32  -0.481
9 1.62  0.585  0.0143 -0.446  0.939 -0.730
10 1.62 -10.9   0.182  0.330  2.26  0.709
# ... with 10,108 more rows
```

```
> mu.logo <- data.frame(read.csv("mu-logo.csv"))
> lm.fit <- lm(Y~X1+X2+X3+X4+X5, data=mu.logo)
> plot(lm.fit$fitted.values, lm.fit$residuals)
```

For interested readers:
Regression Shiny App

Code to generate similar data
“mu-logo.csv”

Residual plot



\hat{Y}

SOME DEEP LEARNING PACKAGES IN R

R Package	Description
nnet	Software for feed-forward neural networks with a single hidden layer, and for multinomial log-linear models.
neuralnet	Training of neural networks using backpropagation
h2o	R scripting functionality for H2O
RSNNS	Interface to the Stuttgart Neural Network Simulator (SNNS)
tensorflow	Interface to TensorFlow
deepnet	Deep learning toolkit in R
darch	Package for Deep Architectures and Restricted Boltzmann Machines
rnn	Package to implement Recurrent Neural Networks (RNNs)
FCNN4R	Interface to the FCNN library that allows user-extensible ANNs
rcppDL	Implementation of basic machine learning methods with many layers (deep learning), including dA (Denoising Autoencoder), SdA (Stacked Denoising Autoencoder), RBM (Restricted Boltzmann machine) and DBN (Deep Belief Nets)
deepr	Package to streamline the training, fine-tuning and predicting processes for deep learning based on darch and deepnet
MXNetR	Package that brings flexible and efficient GPU computing and state-of-art deep learning to R

REGRESSION USING NEURAL NETWORK

```
> library("neuralnet");
> net1 <- neuralnet(Y~X1+X2+X3+X4+X5, data=mu.logo, hidden=0, act.fct=function(x) {x})
> plot(net1)

> lm.fit
call:
lm(formula = Y ~ X1 + X2 + X3 + X4 + X5, data = mu.logo)

Coefficients:
(Intercept)          X1           X2           X3           X4           X5
  0.9761206   0.1886051   0.1203780   0.9476638   0.0123327   0.9670491

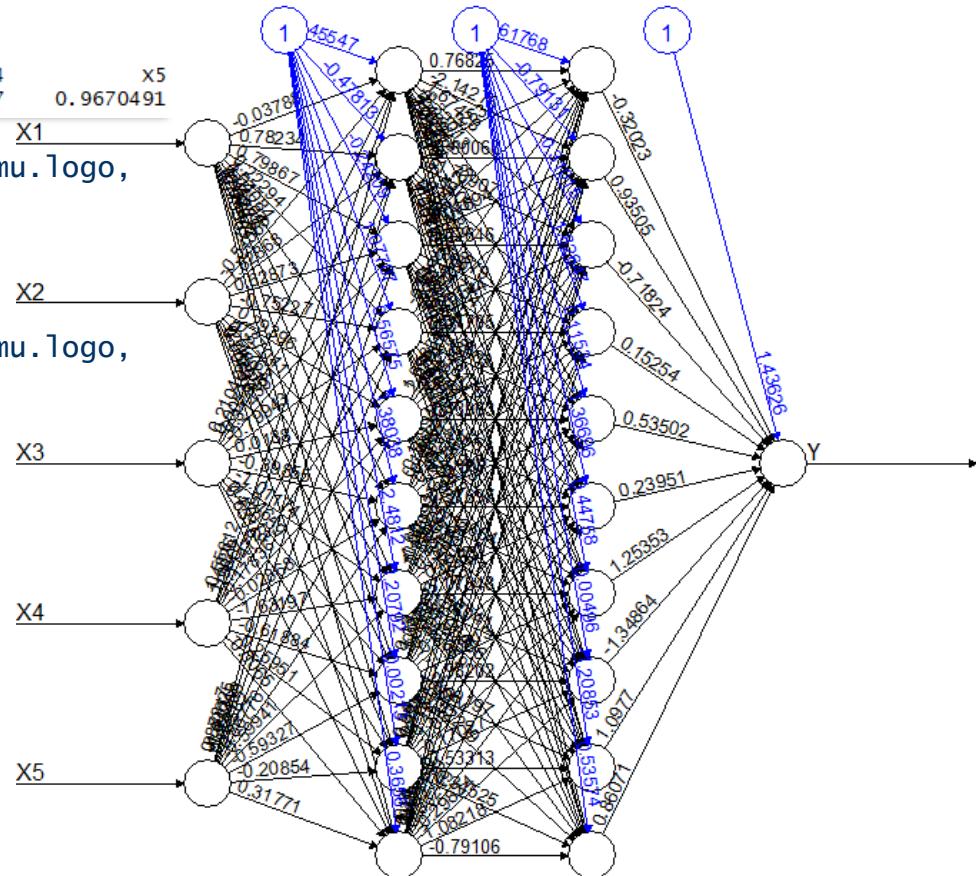
> net2 <- neuralnet(Y~X1+X2+X3+X4+X5, data=mu.logo,
  hidden=10, act.fct=function(x) {x})
> plot(net2)

> net3 <- neuralnet(Y~X1+X2+X3+X4+X5, data=mu.logo,
  hidden=c(10,10),
  act.fct=function(x) {x})
> plot(net3)

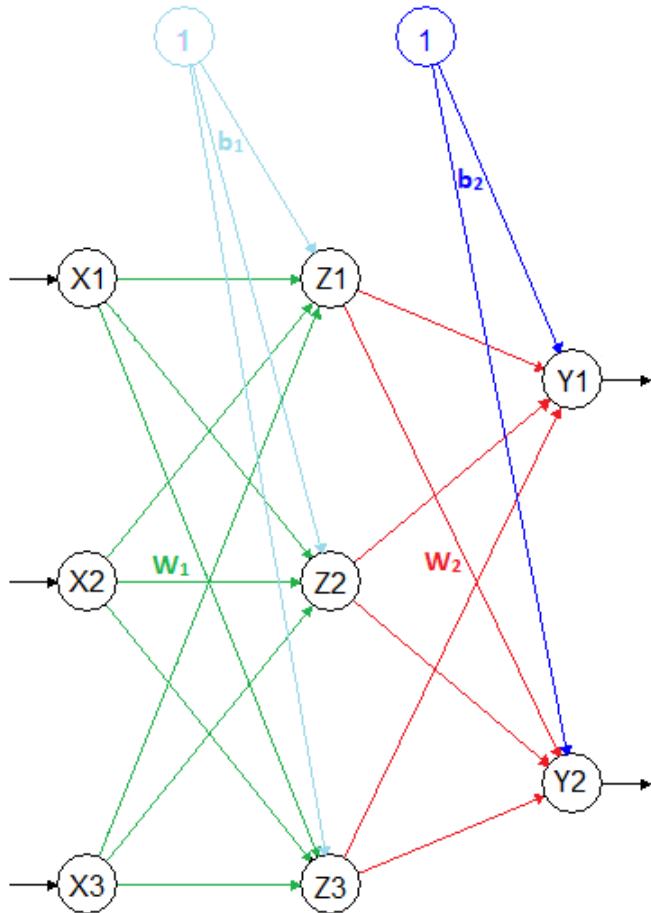
> errors <- c(net1$result.matrix[1],
  net2$result.matrix[1],
  net3$result.matrix[1])

> errors
[1] 5058.5 5058.5 5058.5
> net1$err.fct
function (x, y)
{
  1/2 * (y - x)^2
}

> sum(lm.fit$residuals^2)/2
[1] 5058.5
```

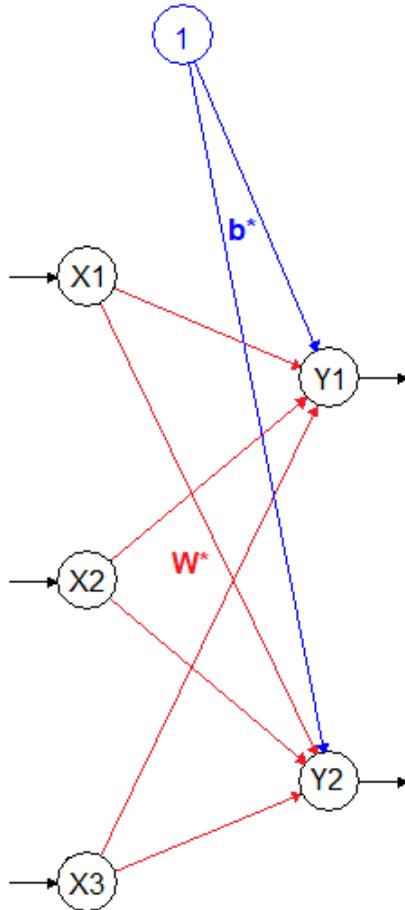


LINEAR ACTIVATION FUNCTION – HIDDEN LAYERS DISAPPEARS



- $Z = W_1 X + b_1$
- $Y = W_2 Z + b_2$
- $$Y = W_2 \{W_1 X + b_1\} + b_2 \\ = \{W_2 W_1\} X + W_2 b_1 + b_2$$

LINEAR ACTIVATION FUNCTION – HIDDEN LAYERS DISAPPEARS



- $Z = W_1 X + b_1$
- $Y = W_2 Z + b_2$

- $$Y = W_2 \{W_1 X + b_1\} + b_2$$
$$= \{W_2 W_1\} X + W_2 b_1 + b_2$$

- $Y = W^* X + b^*$

LINEAR REGRESSION USING NEURAL NETWORK

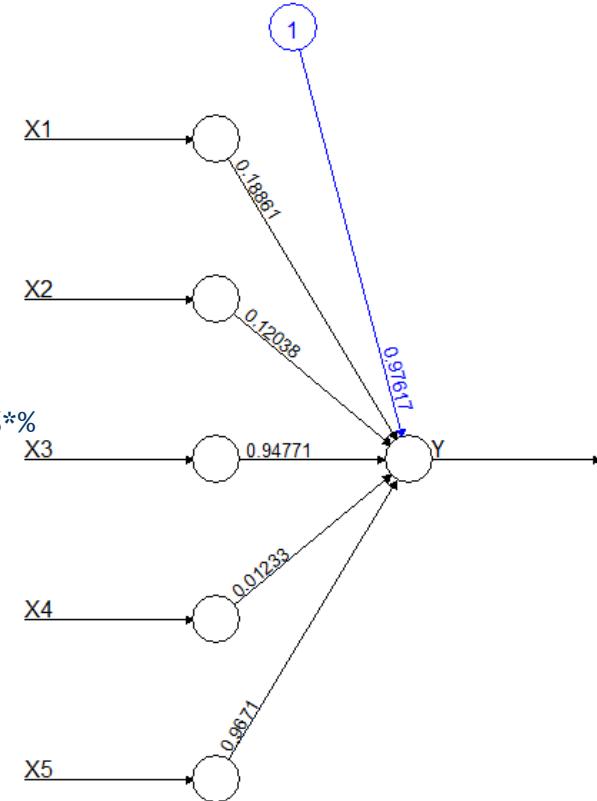
```
> par(mfrow=c(2,2))
> plot(lm.fit$fitted.values, lm.fit$residuals)
> plot(net1$net.result[[1]], net1$data$Y - net1$net.result[[1]])
> plot(net2$net.result[[1]], net1$data$Y - net2$net.result[[1]])
> plot(net3$net.result[[1]], net1$data$Y - net3$net.result[[1]])
```

Track the estimated weights (last slide):

```
> lm.fit$coefficients
(Intercept)      x1       x2       x3       x4       x5
  0.9761   0.1886   0.1204   0.947   0.0123   0.9670

> net1$weights[[1]][[1]]
> net2$weights[[1]][[1]] %*% net2$weights[[1]][[2]][-1,] +
  c(net2$weights[[1]][[2]][1,], rep(0,5))
> net3$weights[[1]][[1]] %*% net3$weights[[1]][[2]][-1,] %*%
  net3$weights[[1]][[3]][-1,] +
  c(net3$weights[[1]][[2]][1,] %*%
  net3$weights[[1]][[3]][-1,] +
  net3$weights[[1]][[3]][1,], rep(0,5))

 [,1]
[1,] 0.97610998898
[2,] 0.18860998898
[3,] 0.12038804889
[4,] 0.94766800091
[5,] 0.01233289489
[6,] 0.96709804209
```



NEURAL NETWORK

- `mulogo <- data.frame(cbind(mu.logo, matrix(rnorm(prod(dim(net1$covariate))),nc=5)))`
- `net4 <- neuralnet(Y~x1+x2+x3+x4+x5+X1.1+X2.1+X3.1+X4.1+X5.1, data=mulogo, hidden=0, linear.output=TRUE, act.fct=function(x) {x})`
- `plot(lm.fit$fitted.values, lm.fit$residuals)`
- `plot(net4$net.result[[1]], net4$data$Y-net4$net.result[[1]])`
- `plot(net4)`

Function “neuralnet” Arguments:

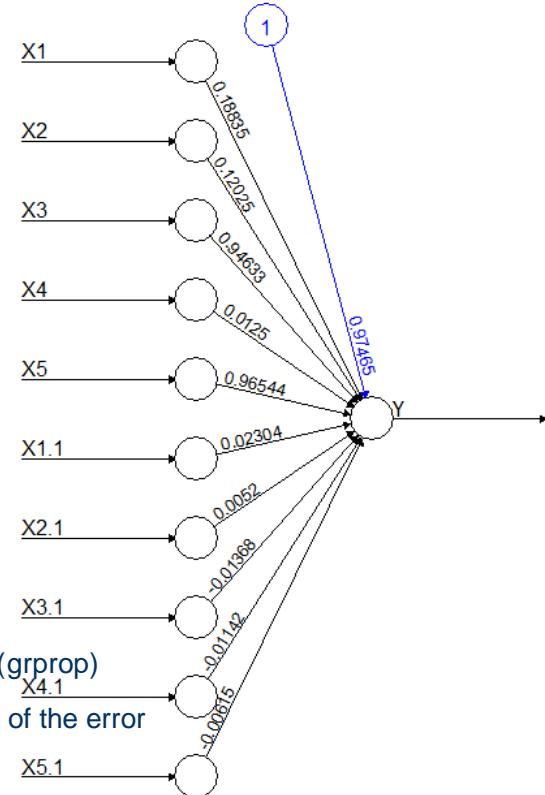
- `neuralnet(formula, data, hidden = 1, threshold = 0.01, stepmax = 1e+05, rep = 1, startweights = NULL, learningrate = NULL, learningrate.limit = NULL, algorithm = "rprop+", err.fct = "sse", act.fct = "logistic", exclude = NULL, constant.weights = NULL)`

algorithm : The following algorithms are possible:

- 'backprop' : backpropagation
- 'rprop+' : the resilient backpropagation with weight backtracking
- 'rprop-' : the resilient backpropagation without weight backtracking
- 'sag' and 'slr' : induce the usage of the modified globally convergent algorithm (grprop)

err.fct : 'sse' and 'ce' or a differentiable function that is used for the calculation of the error

act.fct : 'logistic' and 'tanh' or a user defined differentiable activation function

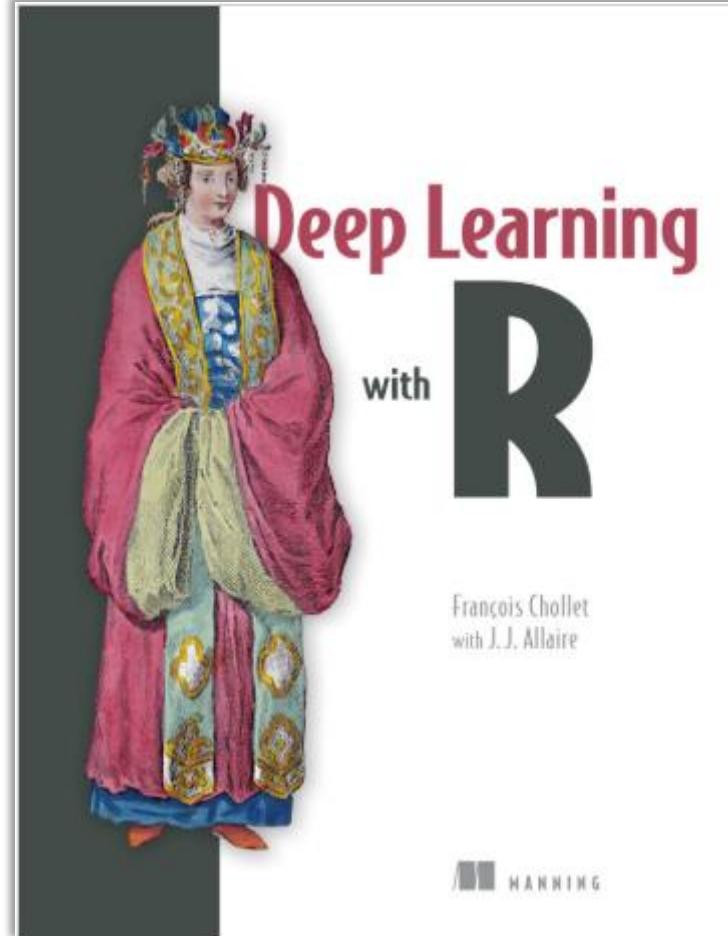


DEEP LEARNING WITH R TENSORFLOW – KERAS



Machine Learning with TensorFlow and R

J.J. Allaire — CEO, RStudio



COMPARISON OF DEEP LEARNING SOFTWARE

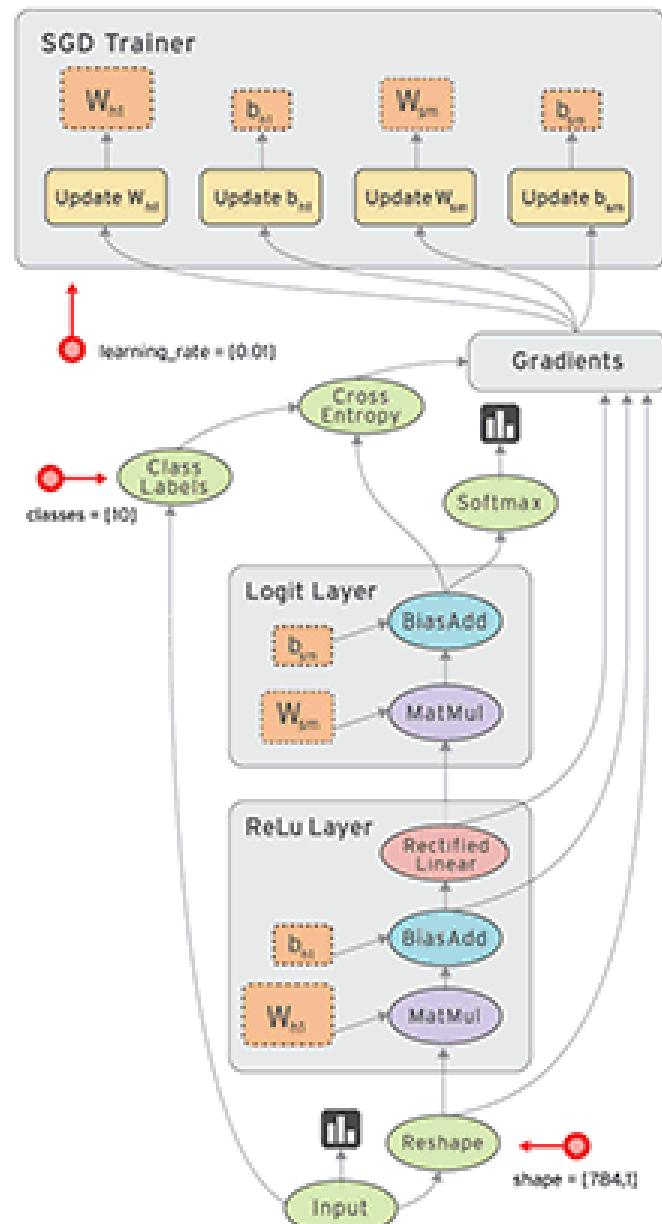
Software	Initial Release	Software license ^[a]	Open source	Written in	OpenMP support	CUDA support	Automatic differentiation ^[1]	Has pretrained models	Recurrent nets	Convolutional nets	RBM/DBNs	Parallel execution (multi node)	Actively Developed
Wolfram Mathematica	1988	Proprietary	No	C++, Wolfram Language, CUDA	Yes	Yes	Yes	Yes[64]	Yes	Yes	Yes	Under Development	Yes
MATLAB + Neural Network Toolbox		Proprietary	No	C, C++, Java, MATLAB	No	Yes	No	Yes ^{[18][19]}	Yes[18]	Yes[18]	No	With Parallel Computing Toolbox[20]	Yes
Microsoft Cognitive Toolkit(CNTK)	2016	MIT license ^[21]	Yes	C++	Yes[26]	Yes	Yes	Yes[27]	Yes[28]	Yes[28]	No[29]	Yes[30]	Yes
PyTorch	2016	BSD	Yes	Python, C, CUDA	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes
Apache MXNet	2015	Apache 2.0	Yes	Small C+core library	Yes	Yes	Yes[36]	Yes[37]	Yes	Yes	Yes	Yes[38]	Yes
Keras	2015	MIT license	Yes	Python	Only if using Theano as backend	Yes	Yes	Yes[15]	Yes	Yes	Yes	Yes[16]	Yes
TensorFlow	2015	Apache 2.0	Yes	C++, Python, CUDA	No	Yes	Yes[46]	Yes[47]	Yes	Yes	Yes	Yes	Yes
Chainer	2015	BSD	Yes	Python	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Theano	2007	BSD	Yes	Python	Yes	Yes	Yes ^{[49][50]}	Through Lasagne's model zoo[51]	Yes	Yes	Yes	Yes[52]	No
Torch	2002	BSD	Yes	C, Lua	Yes	Yes ^{[59][60]}	Through Twitter's Autograd ^[61]	Yes[62]	Yes	Yes	Yes	Yes[63]	No
BigDL	2016	Apache 2.0	Yes	Scala		No		Yes	Yes	Yes			
Caffe	2013	BSD	Yes	C++	Yes	Yes	Yes	Yes[4]	Yes	Yes	No	?	
Neural Designer		Proprietary	No	C++	Yes	No	?	?	No	No	No	?	
OpenNN	2003	GNU LGPL	Yes	C++	Yes	Yes	?	?	No	No	No	?	
Intel Math Kernel Library		Proprietary	No		Yes[13]	No	Yes	No	Yes[14]	Yes[14]			No
Deeplearning4j	2014	Apache 2.0	Yes	C++, Java	Yes	Yes ^{[6][7]}	Computational Graph	Yes[8]	Yes	Yes	Yes	Yes[9]	
Intel Data Analytics Acceleration Library	2015	Apache License 2.0	Yes	C++, Python, Java	Yes	No	Yes	No		Yes		Yes	
Dlib	2002	Boost Software License	Yes	C++	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Apache SINGA	2015	Apache 2.0	Yes	C++	No	Yes	?	Yes	Yes	Yes	Yes	Yes	Yes

WHY TENSORFLOW IN R?

- Hardware independent
 - CPU (via Eigen and BLAS)
 - GPU (via CUDA and cuDNN)
 - TPU (Tensor Processing Unit)
- Supports automatic differentiation
- Distributed execution and large datasets
- Very general built-in optimization algorithms (SGD, Adam) that don't require that all data is in RAM
- TensorFlow models can be deployed with a low-latency C++ runtime
- R has a lot to offer as an interface language for TensorFlow

WHAT IS TENSOR "FLOW"?

- You define the graph in R
- Graph is compiled and optimized
- Graph is executed on devices
- Nodes represent computations
- Data (tensors) flows between them



REAL-WORLD EXAMPLES OF DATA TENSORS

■ 2D tensors

- Vector data—^{2-d tensor}(samples, features)

Samples	Age	ZIP code
1	12	123-524
2	36	234-567
3	12	349-874
...		
9,999	45	874-988
10,000	56	888-234
...		



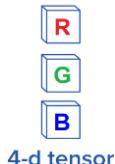
■ 3D tensors

- Grayscale Images—(samples, height, width)
- Time-series data or sequence data—(samples, timesteps, features)

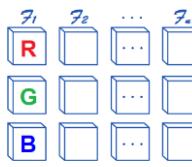
```
head(data.matrix(iris), n = 10)
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
[1,]	5.1	3.5	1.4	0.2	1
[2,]	4.9	3.0	1.4	0.2	1
[3,]	4.7	3.2	1.3	0.2	1
[4,]	4.6	3.1	1.5	0.2	1
[5,]	5.0	3.6	1.4	0.2	1
[6,]	5.4	3.9	1.7	0.4	1
[7,]	4.6	3.4	1.4	0.3	1
[8,]	5.0	3.4	1.5	0.2	1
[9,]	4.4	2.9	1.4	0.2	1
[10,]	4.9	3.1	1.5	0.1	1

■ 4D tensors

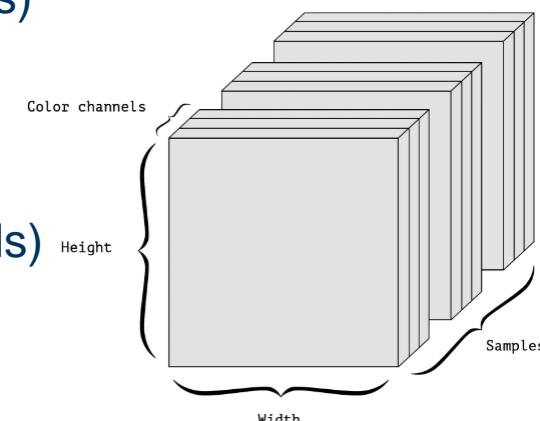
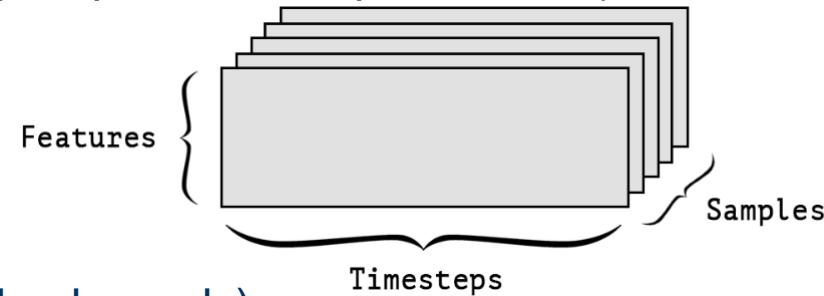


- Color Images—(samples, height, width, channels)



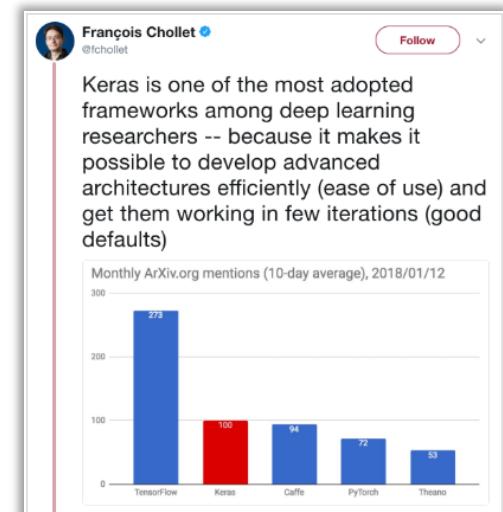
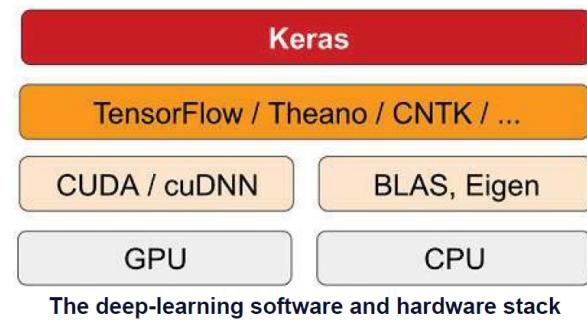
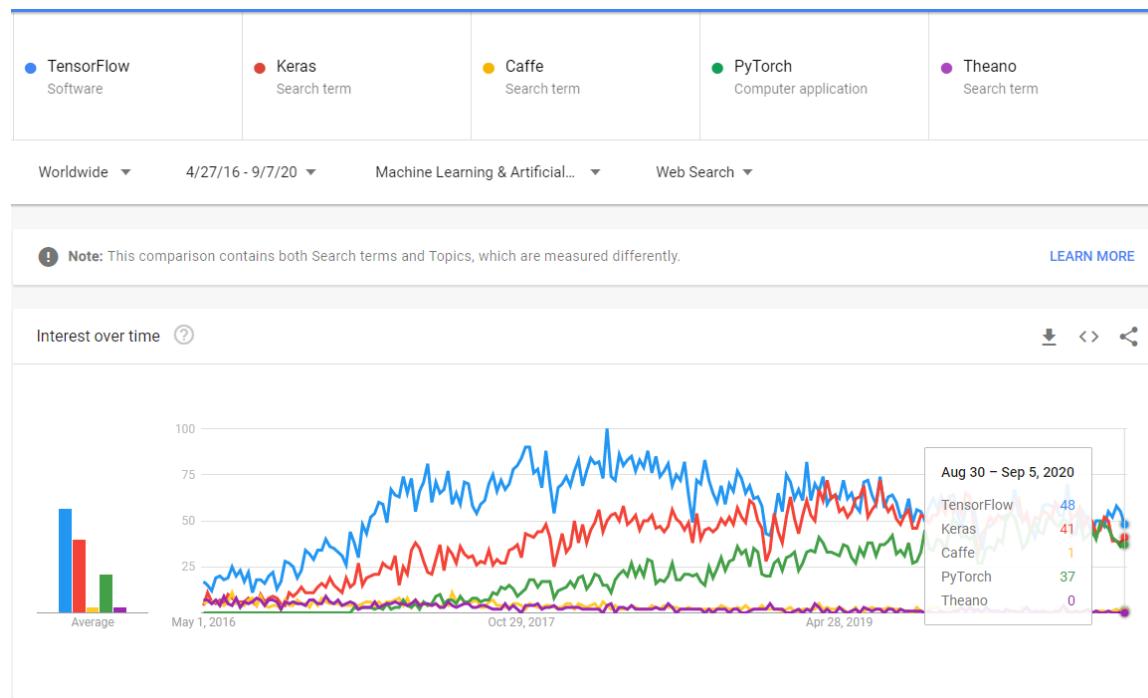
■ 5D tensors

- Video—(samples, frames, height, width, channels)



WHY KERAS?

- It allows the same code to run seamlessly on CPU or GPU.
- It has a user-friendly API that makes it easy to quickly prototype deep-learning models.



INSTALLING KERAS

- First, install the keras R package:
 - `devtools::install_github("rstudio/keras")` OR
 - `Install.packages("keras")`
- To install both the core Keras library as well as the TensorFlow backend
 - `library(keras)`
 - `install_keras()`
- You need Python installed before installing TensorFlow
 - Anaconda (Python distribution), a free and open-source software
- You can install TensorFlow with GPU support
 - required NVIDIA® drivers,
 - CUDA Toolkit v9.0, and
 - cuDNN v7.0

are needed: https://tensorflow.rstudio.com/tools/local_gpu.html

INSTALLING KERAS (MAC AND LINUX) CONT...

The screenshot shows the RStudio interface with the following components:

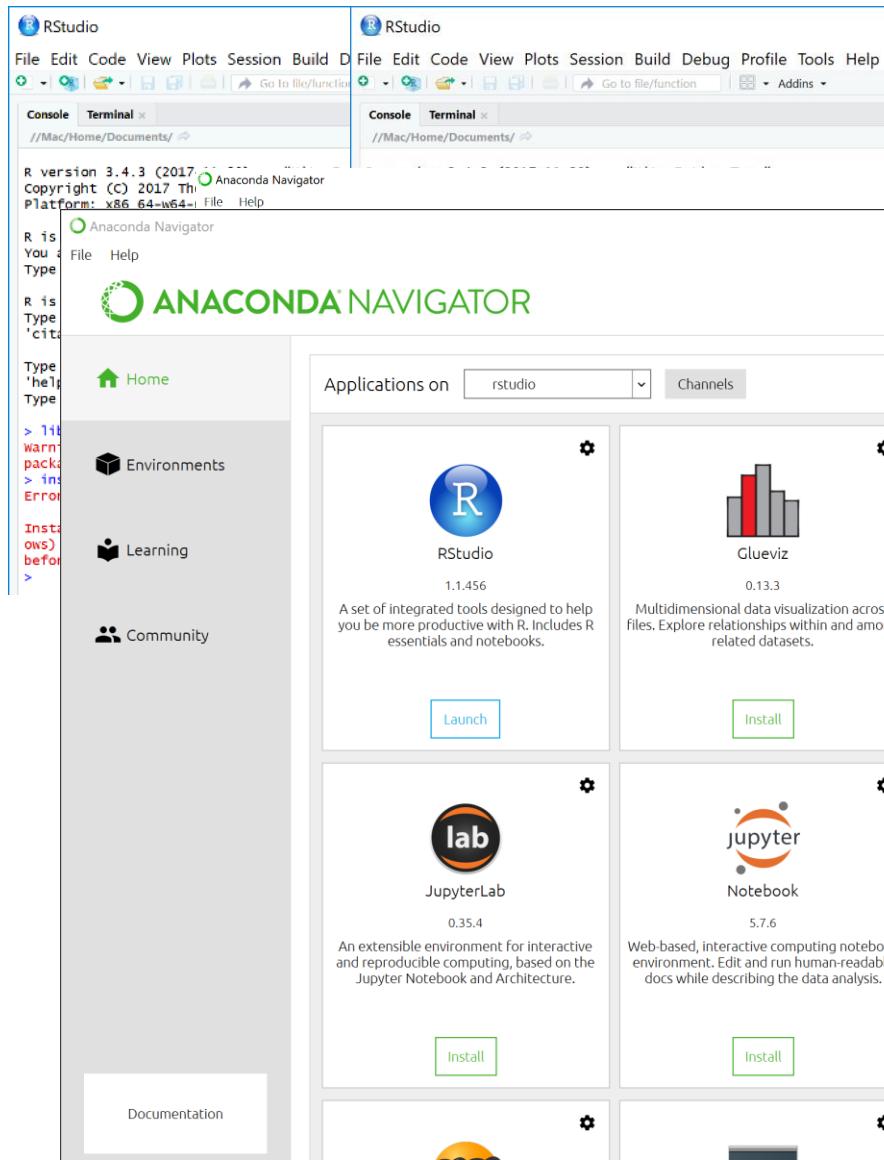
- Top Bar:** Shows the title "RStudio" and a browser tab "Not secure | sctc.mscs.mu.edu:8787".
- Toolbar:** Includes icons for various applications like Headlines, Money, Google Sheets, and YouTube.
- Menu Bar:** Contains File, Edit, Code, View, Plots, Session, Build, Debug, Profile, Tools, Help, and Addins.
- Environment Tab:** Displays the message "Environment is empty".
- Files Tab:** Shows a file tree under "Home" with items like .history, Desktop, Documents, Downloads, Music, Pictures, Public, R, Templates, and Videos.
- Console Tab:** Displays the R command history and output:

```
1:1 (Top Level) <--> R Script
Console Terminal x
~/
** .
** preparing package for lazy loading
** help
*** installing help indices
** building package indices
** installing vignettes
** testing if installed package can be loaded
* DONE (keras)

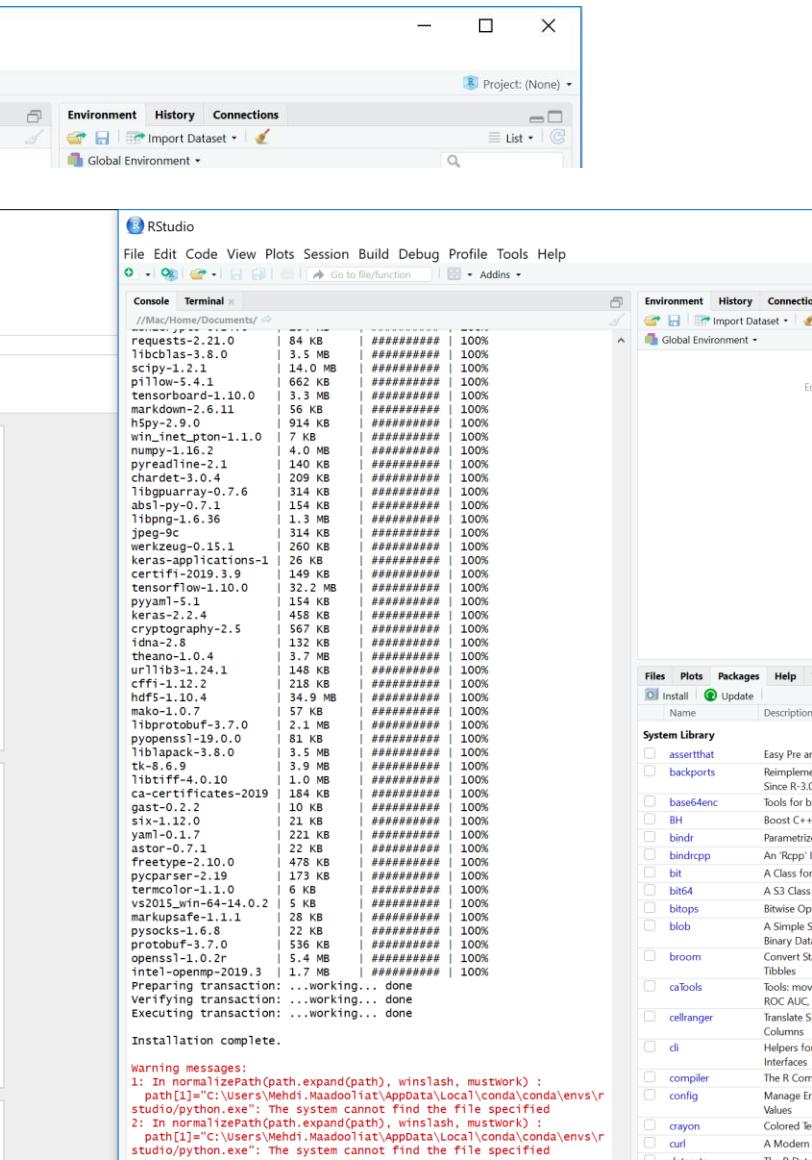
The downloaded source packages are in
  '/tmp/Rtmp86xPn0/downloaded_packages'
> library("keras")
> install_keras()
Error: Prerequisites for installing TensorFlow not available.

Execute the following at a terminal to install the prerequisites:
$ sudo apt-get install python-pip
$ sudo apt-get install python-virtualenv
> |
```

INSTALLING KERAS (WINDOWS) CONT...



The screenshot shows the Anaconda Navigator interface. On the left sidebar, there are links for Home, Environments, Learning, and Community. The main area displays two applications: RStudio (version 1.1.456) and Glueviz (version 0.13.3). Both have 'Launch' and 'Install' buttons. Below them are JupyterLab (version 0.35.4) and Jupyter Notebook (version 5.7.6), also with 'Install' buttons. A 'Documentation' link is at the bottom.



The screenshot shows the RStudio environment. The top menu bar includes File, Edit, Code, View, Plots, Session, Build, Debug, Profile, Tools, and Help. The top right shows 'Project: (None)'. The main area has tabs for Console and Terminal, both showing the path //Mac/Home/Documents/. The Environment tab is active, showing the Global Environment. The bottom right shows a file browser with sections for Files, Plots, Packages, and Help. A terminal window on the right shows the command 'install.packages("keras")' being run, with output indicating the download and installation of various packages like requests, tensorflow, keras, etc., with progress bars.

DEVELOPING A DEEP NN WITH KERAS

- Step 1 - Define your training data:
 - input tensors and target tensors.
- Step 2 - Define a network of layers (or *model*)
 - that maps your inputs to your targets.
- Step 3 - Configure the learning process by choosing
 - a loss function,
 - an optimizer,
 - and some metrics to monitor.
- Step 4 - Iterate on your training data by calling the
 - **fit()** method of your model.

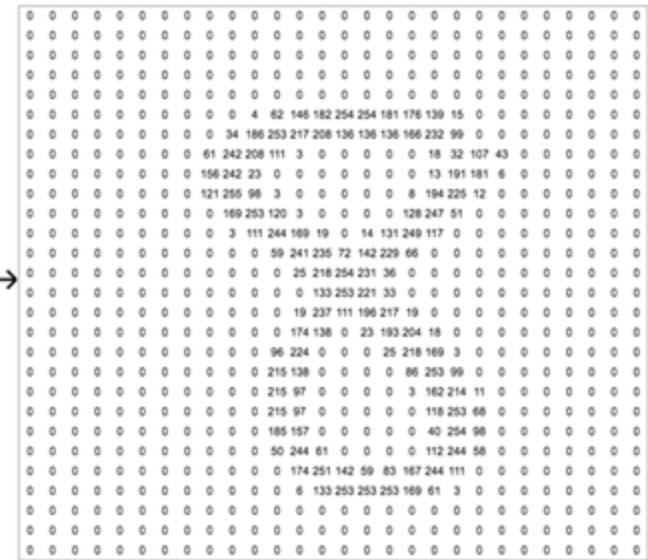
KERAS: STEP 1 – DATA PREPROCESSING

- `library(keras)`
- `# Load MNIST (Modified National Institute of Standards and Technology) images datasets
c(c(x_train, y_train), c(x_test, y_test)) %<-% dataset_mnist()`
- `# Flatten images and transform RGB values into [0,1] range`
- `x_train <- array_reshape(x_train, c(nrow(x_train), 784))`
- `x_test <- array_reshape(x_test, c(nrow(x_test), 784))`
- `x_train <- x_train / 255`
- `x_test <- x_test / 255`
- `# Convert class vectors to binary class matrices`
- `y_train <- to_categorical(y_train, 10)`
- `y_test <- to_categorical(y_test, 10)`

```
> dim(x_train)  
[1] 60000 28 28  
> dim(x_test)  
[1] 10000 28 28
```

```
> dim(y_train)  
[1] 60000  
> dim(y_test)  
[1] 10000  
> head(y_train)  
[1] 5 0 4 1 9 2
```

```
> to_categorical(c(5,0,4,1,9,2),10)  
[,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]  
[1,] 0 0 0 0 0 1 0 0 0 0  
[2,] 1 0 0 0 0 0 0 0 0 0  
[3,] 0 0 0 0 1 0 0 0 0 0  
[4,] 0 1 0 0 0 0 0 0 0 0  
[5,] 0 0 0 0 0 0 0 0 0 1  
[6,] 0 0 1 0 0 0 0 0 0 0
```



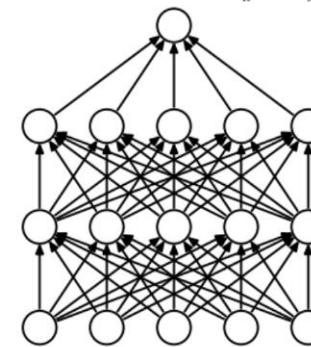
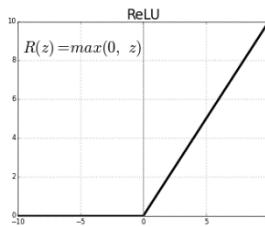
KERAS: STEP 2 – MODEL DEFINITION

```
➤ model <- keras_model_sequential()  
➤ model %>%  
  layer_dense(units = 256, activation = 'relu', input_shape = c(784)) %>%  
  layer_dropout(rate = 0.4) %>%  
  layer_dense(units = 128, activation = 'relu') %>%  
  layer_dropout(rate = 0.3) %>%  
  layer_dense(units = 10, activation = 'softmax')
```

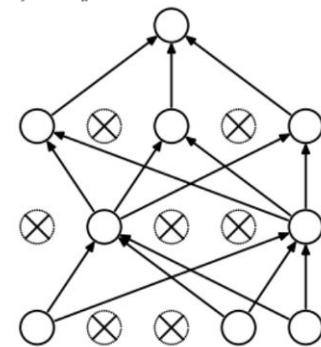
```
> summary(model)
```

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 256)	200960
dropout_3 (Dropout)	(None, 256)	0
dense_5 (Dense)	(None, 128)	32896
dropout_4 (Dropout)	(None, 128)	0
dense_6 (Dense)	(None, 10)	1290

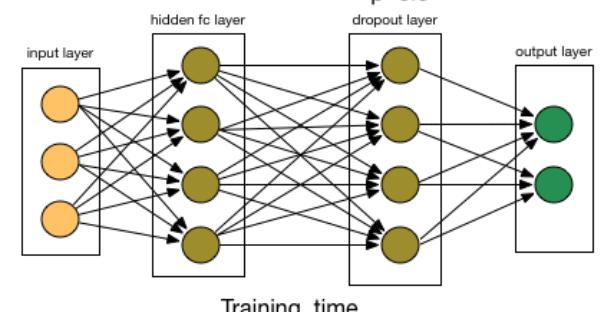
Total params: 235,146
Trainable params: 235,146
Non-trainable params: 0



(a) Standard Neural Net

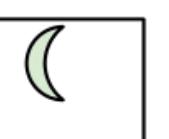
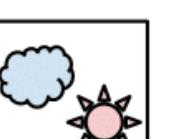


(b) After applying dropout.



- Number of parameters in the model:
 - $(784+1)*256 + (256+1)*128 + (128+1)*10 =$
 - $200,960 + 32,896 + 1,290 = 235,146$

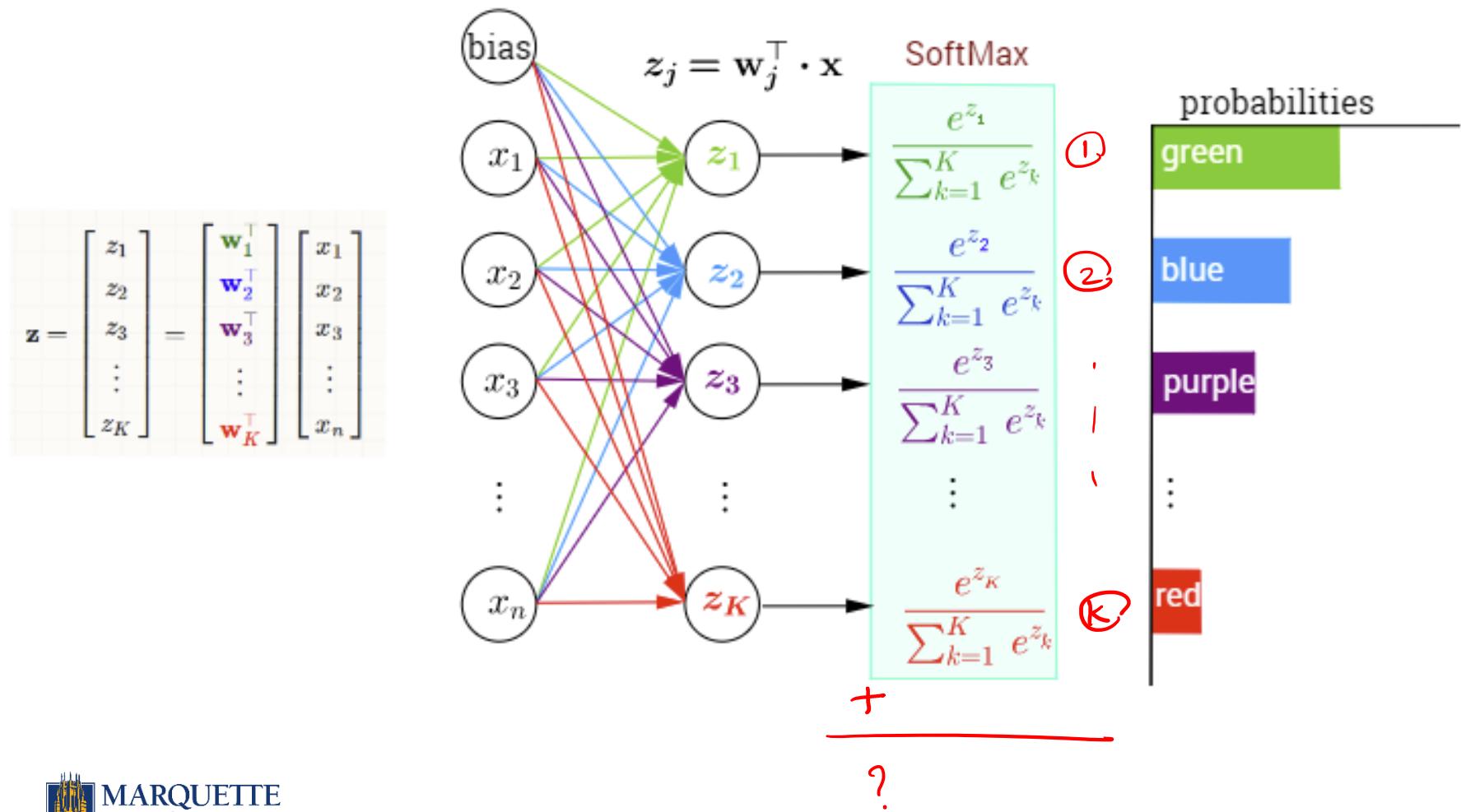
MULTI-CLASS VS MULTI-LABEL CLASSIFICATION

$C = 3$	Samples	Samples
  	  	  
	Labels (t)	Labels (t)
	[0 0 1] [1 0 0] [0 1 0]	[1 0 1] [0 1 0] [1 1 1]

MULTI-CLASS VS MULTI-LABEL CLASSIFICATION

CONT...

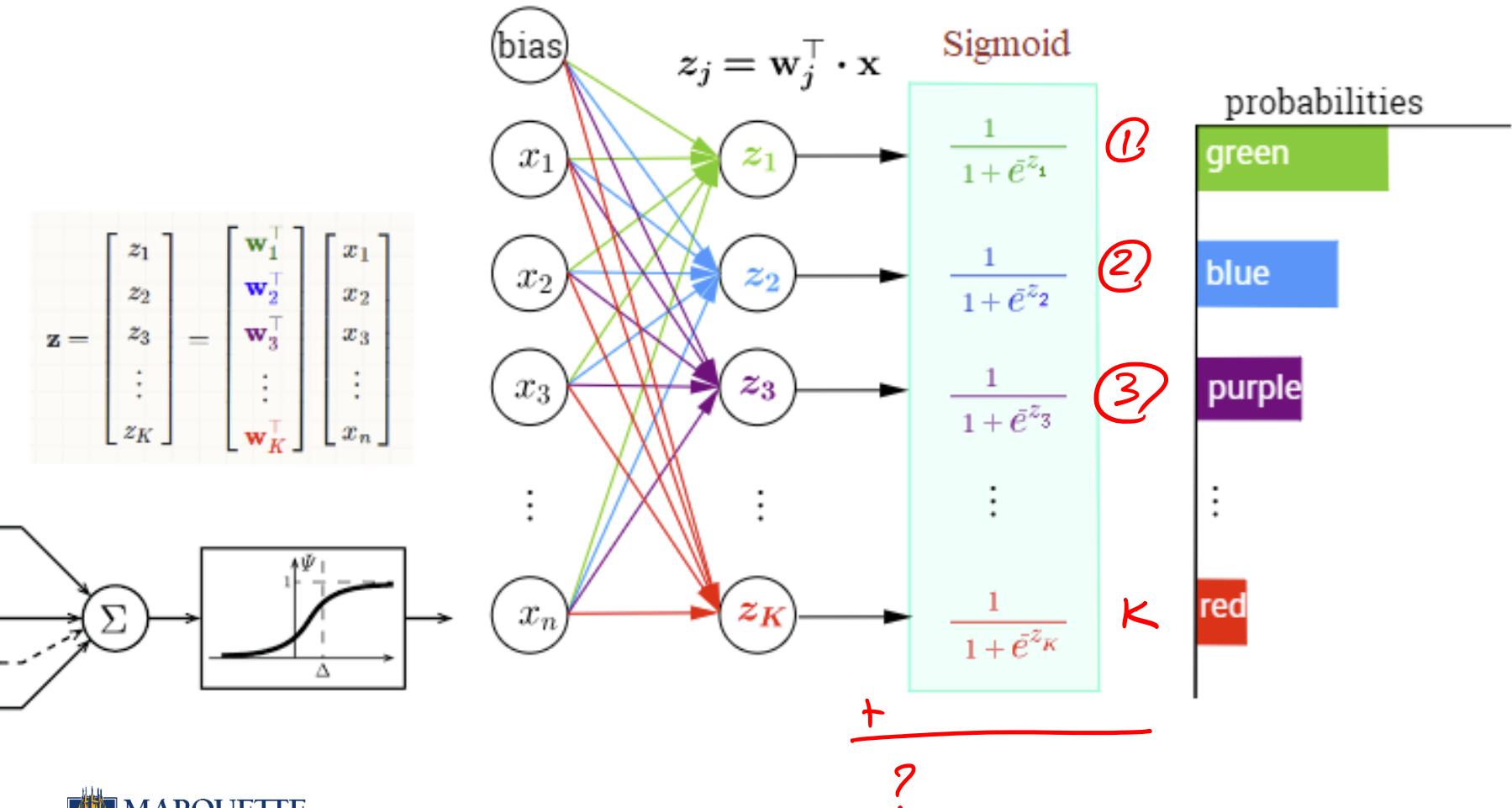
Multi-Class Classification with NN and SoftMax Function



MULTI-CLASS vs MULTI-LABEL CLASSIFICATION

CONT...

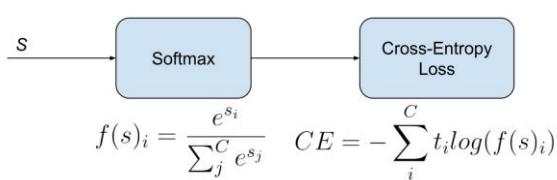
Multi-Label Classification with NN and Sigmoid Function



KERAS: STEP 3 – COMPILE MODEL

- Model compilation prepares the model for training by:
 1. Converting the layers into a TensorFlow graph
 2. Applying the specified loss function and optimizer
 3. Arranging for the collection of metrics during training

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



$$\hat{\mathbf{y}} = \begin{bmatrix} 0.1 \\ 0.5 \\ 0.4 \end{bmatrix}$$
$$\mathbf{y} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$
$$D(\hat{\mathbf{y}}, \mathbf{y}) = - \sum_j y_j \ln \hat{y}_j$$

Choosing the right last-layer activation and loss function for your model

Problem type	Last-layer activation	Loss function
Binary classification	sigmoid	binary_crossentropy
Multiclass, single-label classification	softmax	categorical_crossentropy
Multiclass, multilabel classification	sigmoid	binary_crossentropy
Regression to arbitrary values	None	mse
Regression to values between 0 and 1	sigmoid	mse OR binary_crossentropy

Keras API: Losses

<https://tensorflow.rstudio.com/keras/reference/#section-losses>

```
loss_binary_crossentropy()  
loss_categorical_crossentropy()  
loss_categorical_hinge()  
loss_cosine_proximity()  
loss_hinge()  
loss_kullback_leibler_divergence()  
loss_logcosh()  
loss_mean_absolute_error()  
loss_mean_absolute_percentage_error()  
loss_mean_squared_error()  
loss_mean_squared_logarithmic_error()  
loss_poisson()  
loss_sparse_categorical_crossentropy()  
loss_squared_hinge()
```

Keras API: Optimizers

<https://tensorflow.rstudio.com/keras/reference/#section-optimizers>

```
optimizer_adadelta()  
optimizer_adagrad()  
optimizer_adam()  
optimizer_adamax()  
optimizer_nadam()  
optimizer_rmsprop()  
optimizer_sgd()
```

Keras API: Metrics

<https://tensorflow.rstudio.com/keras/reference/#section-metrics>

```
metric_binary_accuracy()  
metric_binary_crossentropy()  
metric_categorical_accuracy()  
metric_categorical_crossentropy()  
metric_cosine_proximity()  
metric_hinge()  
metric_kullback_leibler_divergence()  
metric_mean_absolute_error()  
metric_mean_absolute_percentage_error()  
metric_mean_squared_error()  
metric_mean_squared_logarithmic_error()  
metric_poisson()  
metric_sparse_categorical_crossentropy()  
metric_sparse_top_k_categorical_accuracy()  
metric_squared_hinge()  
metric_top_k_categorical_accuracy()
```

KERAS: STEP 4 – MODEL TRAINING

- Use the **fit()** function to train the model for 10 epochs using batches of 128 images:

```
➤ history <- model %>% fit(  
➤   x_train, y_train,  
➤   batch_size = 128,  
➤   epoch = 10,  
➤   validation_split = 0.2  
➤ )
```

- Feed 128 samples at a time to the model (batch_size = 128)
- Traverse the input dataset 10 times (epochs = 10)
- Hold out 20% of the data for validation (validation_split = 0.2)

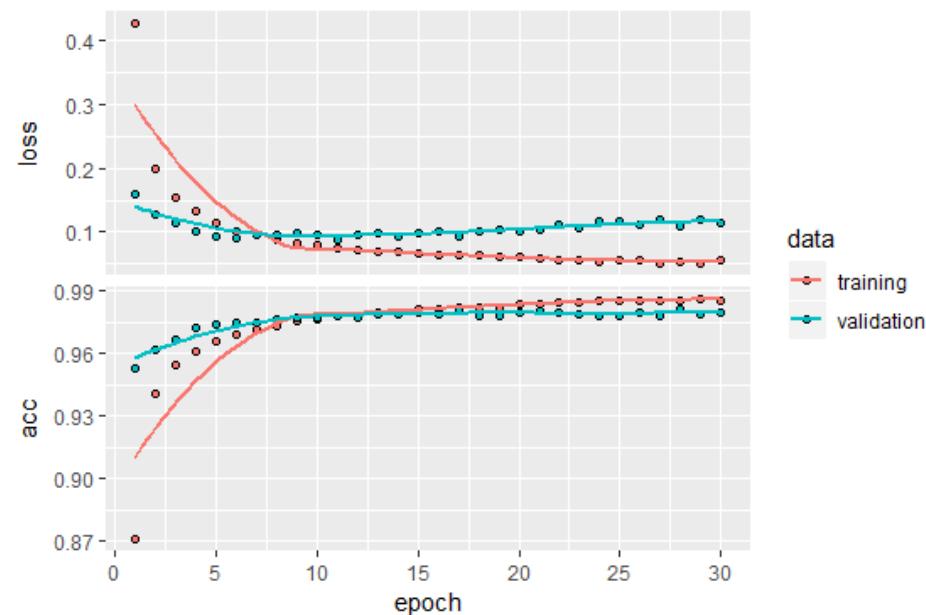
```
> model %>% evaluate(x_test, y_test)  
10000/10000 [=====] - 0s 29us/step  
$`loss`  
[1] 0.1085284375  
  
$acc  
[1] 0.9816
```

KERAS: EVALUATION AND PREDICTION

➤ `plot(history)`

➤ `model %>% predict_classes(x_test[1:100,])`

```
[1] 7 2 1 0 4 1 4 9 6 9 0 6 9 0 1 5 9 7  
[19] 3 4 9 6 6 5 4 0 7 4 0 1 3 1 3 4 7 2  
[37] 7 1 2 1 1 7 4 2 3 5 1 2 4 4 6 3 5 5  
[55] 6 0 4 1 9 5 7 8 9 3 7 4 6 4 3 0 7 0  
[73] 2 9 1 7 3 2 9 7 7 6 2 7 8 4 7 3 6 1  
[91] 3 6 9 3 1 4 1 7 6 9
```



➤ `round(model %>% predict(x_test[1:9,]),5)`

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]	[,10]
[1,]	0	0	0	0.00000	0	0.00000	0.00000	1	0	0.00000
[2,]	0	0	1	0.00000	0	0.00000	0.00000	0	0	0.00000
[3,]	0	1	0	0.00000	0	0.00000	0.00000	0	0	0.00000
[4,]	1	0	0	0.00000	0	0.00000	0.00000	0	0	0.00000
[5,]	0	0	0	0.00000	1	0.00000	0.00000	0	0	0.00000
[6,]	0	1	0	0.00000	0	0.00000	0.00000	0	0	0.00000
[7,]	0	0	0	0.00000	1	0.00000	0.00000	0	0	0.00000
[8,]	0	0	0	0.00002	0	0.00000	0.00000	0	0	0.99998
[9,]	0	0	0	0.00000	0	0.01416	0.98584	0	0	0.00000

KERAS DEMO

The screenshot shows an RStudio interface with the following components:

- Code Editor:** Displays the `MNIST.R` script. The code performs the following steps:
 - Step 1: Loads MNIST datasets and flattens them.
 - Step 2: Creates a sequential model with three hidden layers (256, 128, 10 units) and a final sigmoid layer for binary class matrices.
 - Step 3: Compiles the model with categorical crossentropy loss, RMSprop optimizer, and accuracy metric.
 - Step 4: Fits the model to the training data with a batch size of 128.
- Console:** Shows the R command history corresponding to the code in the editor.
- Environment:** Shows variables in the global environment: `history`, `x_test`, `x_train`, `y_test`, `y_train`, and `model`.
- Plots:** Displays two line plots. The top plot shows `loss` and `val_loss` over 10 epochs, with `loss` decreasing from ~0.55 to ~0.08 and `val_loss` decreasing from ~0.20 to ~0.08. The bottom plot shows `acc` and `val_acc` over 10 epochs, with both increasing from ~0.84 to ~0.97.

■ https://keras.rstudio.com/articles/tutorial_basic_classification.html

KERAS API: LAYERS

- 65 layers available (you can also create your own)

`layer_dense()`

Add a densely-connected NN layer to an output.

`layer_dropout()`

Applies Dropout to the input.

`layer_batch_normalization()`

Batch normalization layer (Ioffe and Szegedy, 2014).

`layer_conv_2d()`

2D convolution layer (e.g. spatial convolution over images).

`layer_max_pooling_2d()`

Max pooling operation for spatial data.

`layer_gru()`

Gated Recurrent Unit - Cho et al.

`layer_lstm()`

Long-Short Term Memory unit.

`layer_embedding()`

Turns positive integers (indexes) into dense vectors of fixed size.

`layer_reshape()`

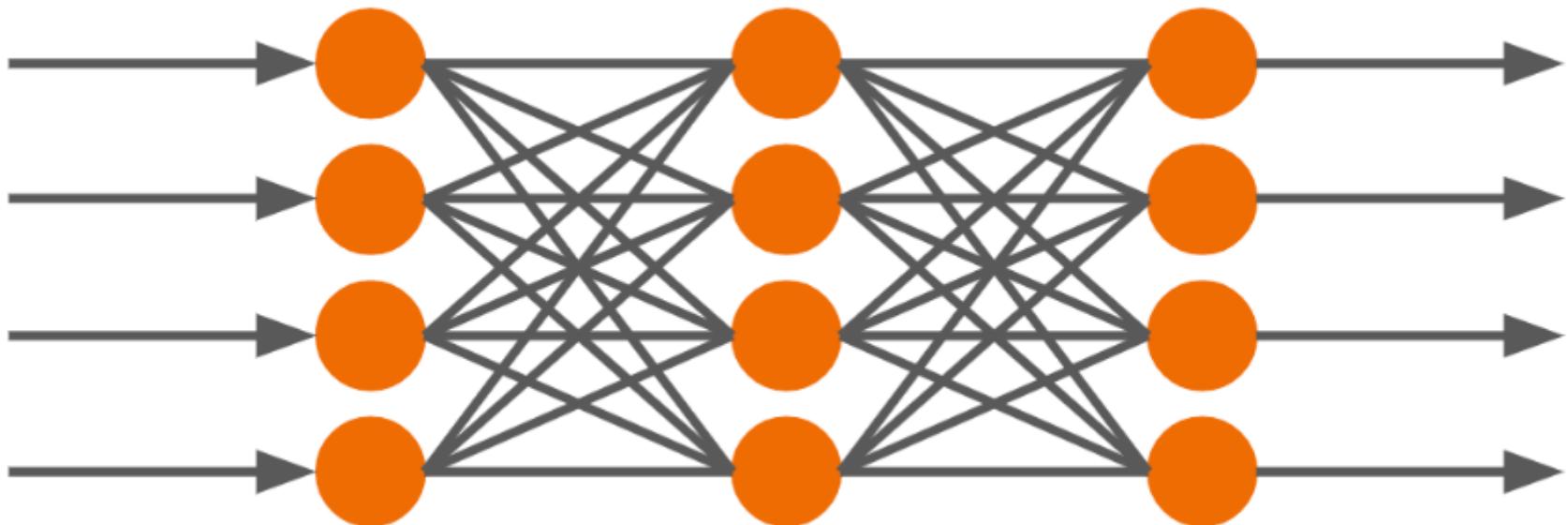
Reshapes an output to a certain shape.

`layer_flatten()`

Flattens an input.

KERAS API: DENSE LAYERS

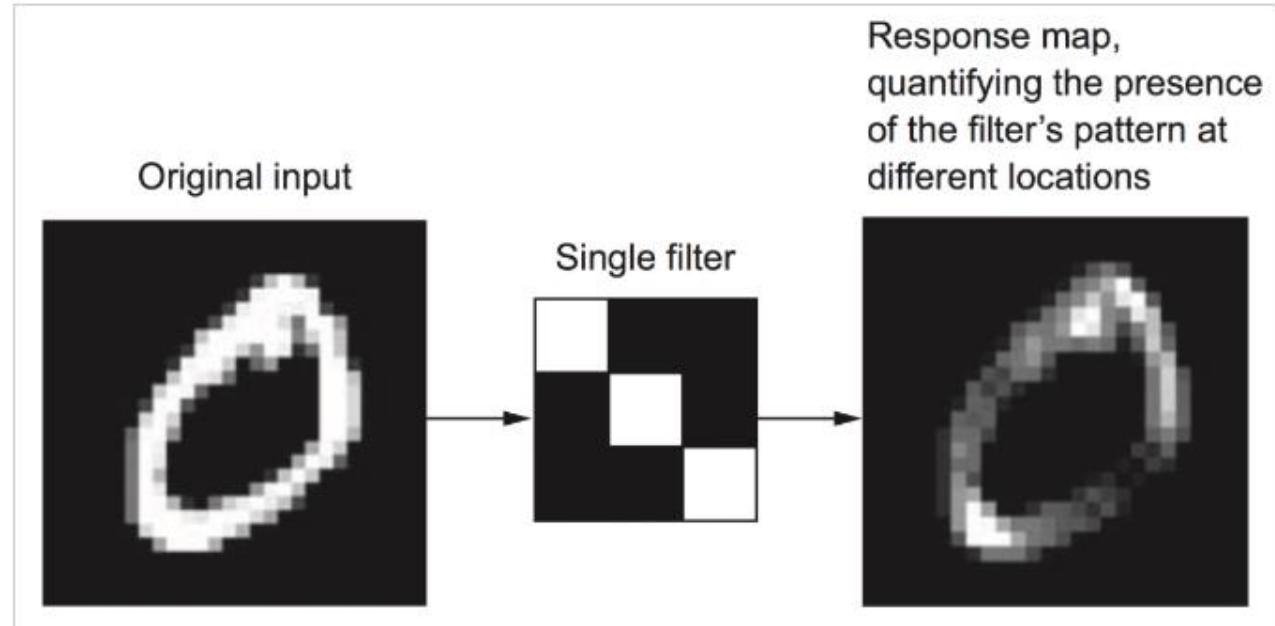
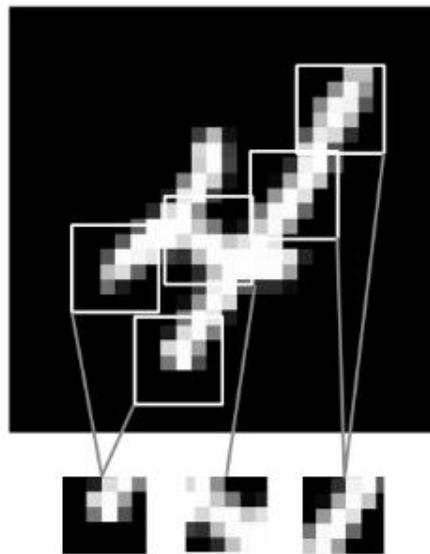
- Classic "fully connected" neural network layers
 - `layer_dense()`



- `layer_dense(units = 64, kernel_regularizer = regularizer_l1(0.01))`
- `layer_dense(units = 64, bias_regularizer = regularizer_l2(0.01))`

KERAS API: CONVOLUTIONAL LAYERS

- Filters for learning local (translation invariant) patterns in data
 - `layer_conv_2d()`



Response map,
quantifying the presence
of the filter's pattern at
different locations

CONVOLUTION (MATHEMATICAL DEFINITION)

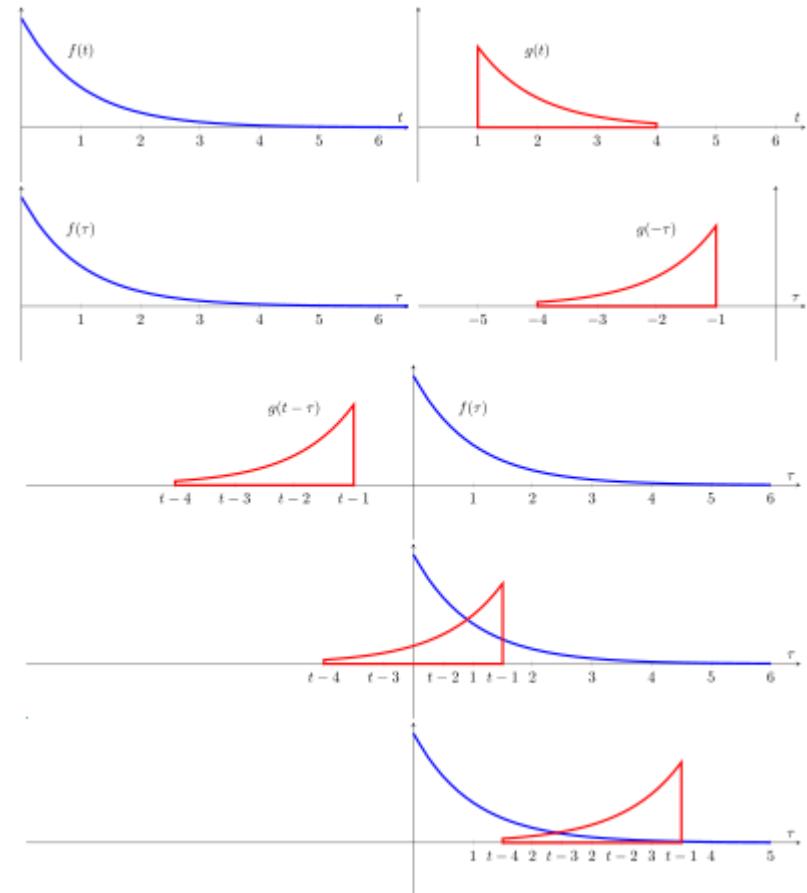
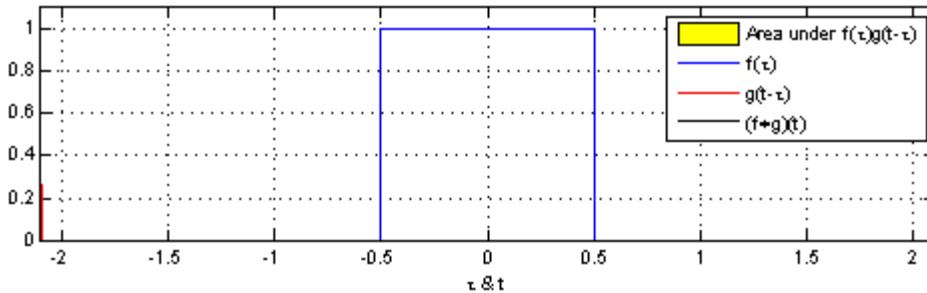
Definition [edit]

The convolution of f and g is written $f*g$, denoting the operator with the symbol $*$.^[B] It is defined as the integral of the product of the two functions after one is reversed and shifted. As such, it is a particular kind of integral transform:

$$(f * g)(t) \triangleq \int_{-\infty}^{\infty} f(\tau)g(t - \tau) d\tau.$$

An equivalent definition is (see [commutativity](#)):

$$(f * g)(t) \triangleq \int_{-\infty}^{\infty} f(t - \tau)g(\tau) d\tau.$$



CONVOLUTION IN ENGINEERING WORLD

- In mathematics, Convolution is an operation which does the integral of the product of 2 functions (e.g., 2 signals), with one of the signals flipped.

$$X \quad \begin{array}{|c|c|c|c|c|} \hline 0 & 1 & 2 & 3 & 3 \\ \hline \end{array}$$

$$W \quad \begin{array}{|c|c|c|} \hline 1 & -1 & 2 \\ \hline \end{array} \quad \begin{array}{|c|c|c|} \hline 2 & -1 & 1 \\ \hline \end{array}$$

$$\begin{array}{|c|c|c|c|c|} \hline 0 & 1 & 2 & 3 & 3 \\ \hline \end{array} \quad 1 * 0 = 0$$

$$\begin{array}{|c|c|c|c|c|} \hline 0 & 1 & 2 & 3 & 3 \\ \hline \end{array} \quad 3$$

$$\begin{array}{|c|c|c|} \hline 2 & -1 & 1 \\ \hline \end{array}$$

$$\begin{array}{|c|c|c|} \hline 2 & -1 & 1 \\ \hline \end{array}$$

$$\begin{array}{|c|c|c|c|c|} \hline 0 & 1 & 2 & 3 & 3 \\ \hline \end{array} \quad (-1 * 0) + (1 * 1) = 1$$

$$\begin{array}{|c|c|c|c|c|} \hline 0 & 1 & 2 & 3 & 3 \\ \hline \end{array} \quad 4$$

$$\begin{array}{|c|c|c|} \hline 2 & -1 & 1 \\ \hline \end{array}$$

$$\begin{array}{|c|c|c|} \hline 2 & -1 & 1 \\ \hline \end{array}$$

$$\begin{array}{|c|c|c|c|c|} \hline 0 & 1 & 2 & 3 & 3 \\ \hline \end{array} \quad (0 * 2) + (-1 * 1) + (2 * 1) = 1$$

$$\begin{array}{|c|c|c|c|c|} \hline 0 & 1 & 2 & 3 & 3 \\ \hline \end{array} \quad 3$$

$$\begin{array}{|c|c|c|} \hline 2 & -1 & 1 \\ \hline \end{array}$$

$$\begin{array}{|c|c|c|} \hline 2 & -1 & 1 \\ \hline \end{array}$$

CONVOLUTION

0	1	2	3	3	6
---	---	---	---	---	---

2	-1	1
---	----	---

Output: X

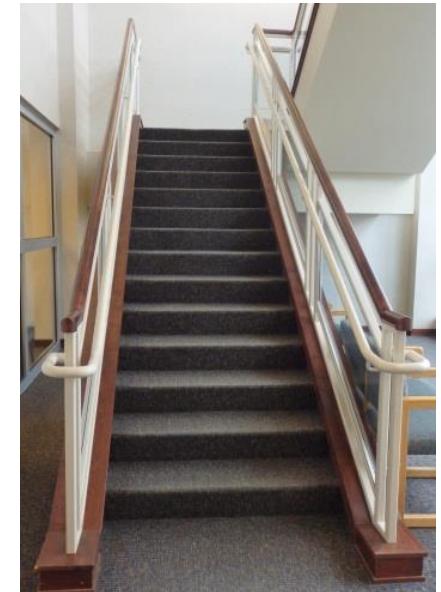
0	1	1	3	4	3	6
---	---	---	---	---	---	---

CONVOLUTIONAL NEURAL NETWORKS: WHY?

- Why do shallow fully connected neural networks not work when the input is an image?
- There are two main reasons:

(1) The input consists of 42,000 numbers, therefore many weights are needed for each node in the hidden Layer. Saying 100 nodes in the first layer, this corresponds to 4,200,000 weight parameters required to define only this layer. More **parameters** mean that **more training data** is needed to prevent **overfitting**. This leads to more time required to train the model.

(2) Processing by Fully Connected Deep Feed Forward Networks requires that the image data be transformed into a linear 1-D vector. This results in a **loss of structural information**, including correlation between pixel values in 2-D.



$$[100 * 140 * 3] = 42,000$$

CONVOLUTIONAL NEURAL NETWORKS: THE LAYERS

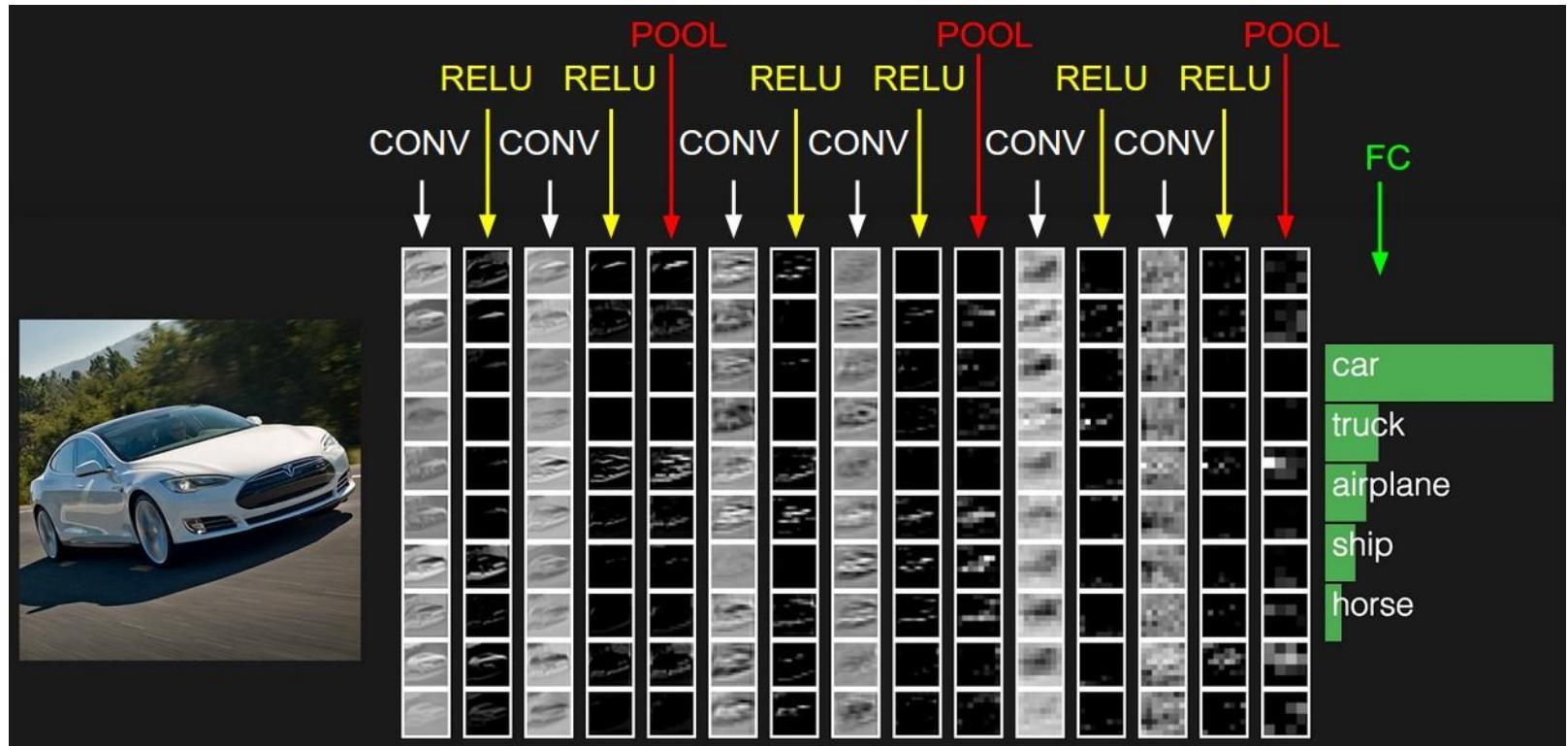
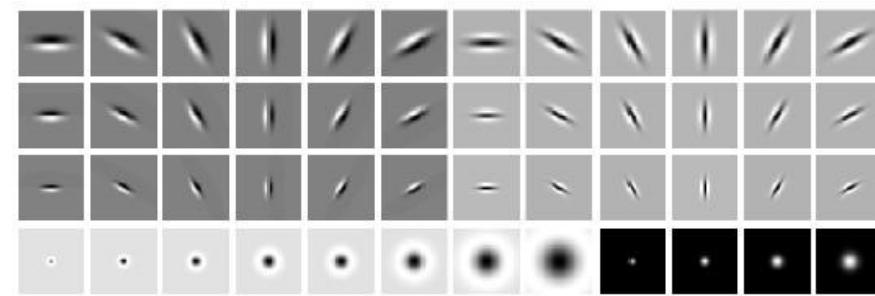


Image from: <http://cs231n.github.io/convolutional-networks/>

CONVOLUTION AS FEATURE EXTRACTION

bank of K filters



K feature maps

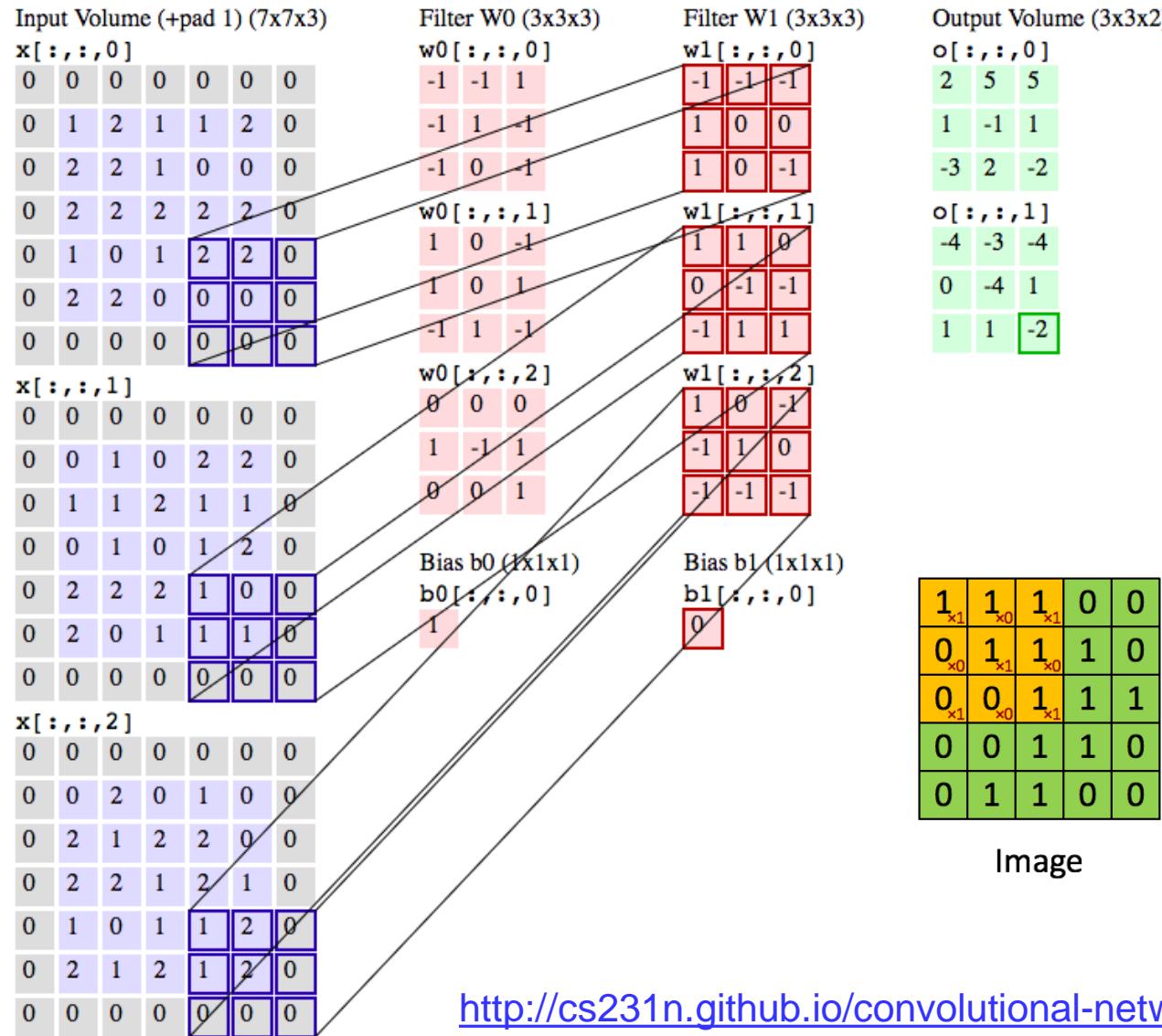


image



feature map

CONVOLUTIONAL LAYER DEMO



1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

4		

Image

Convolved Feature

<http://cs231n.github.io/convolutional-networks/#conv>

CONVOLUTIONAL LAYER

- In CNN, we are working with **multiple filters**. Each filter looks for a specific kind of **feature/pattern/concept** in the input image. For example, we want our convolution layer to look for 6 different patterns. So, our convolution layer will have 6 number of $5 \times 5 \times 3$ filters, each one looks for a specific pattern on the image.

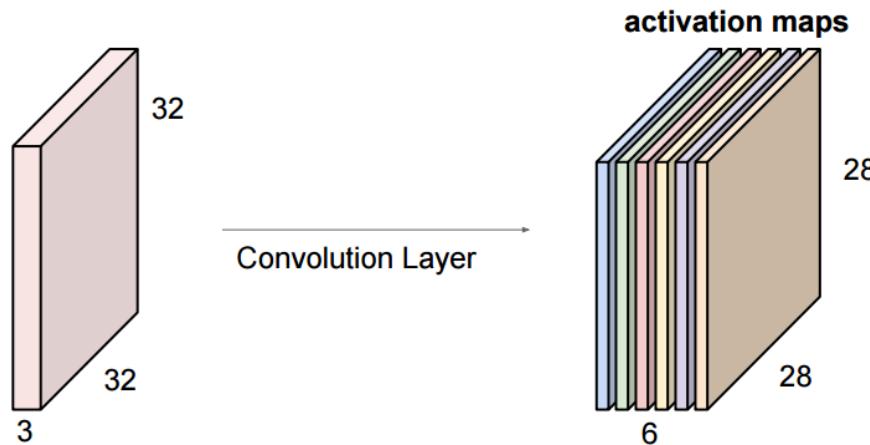
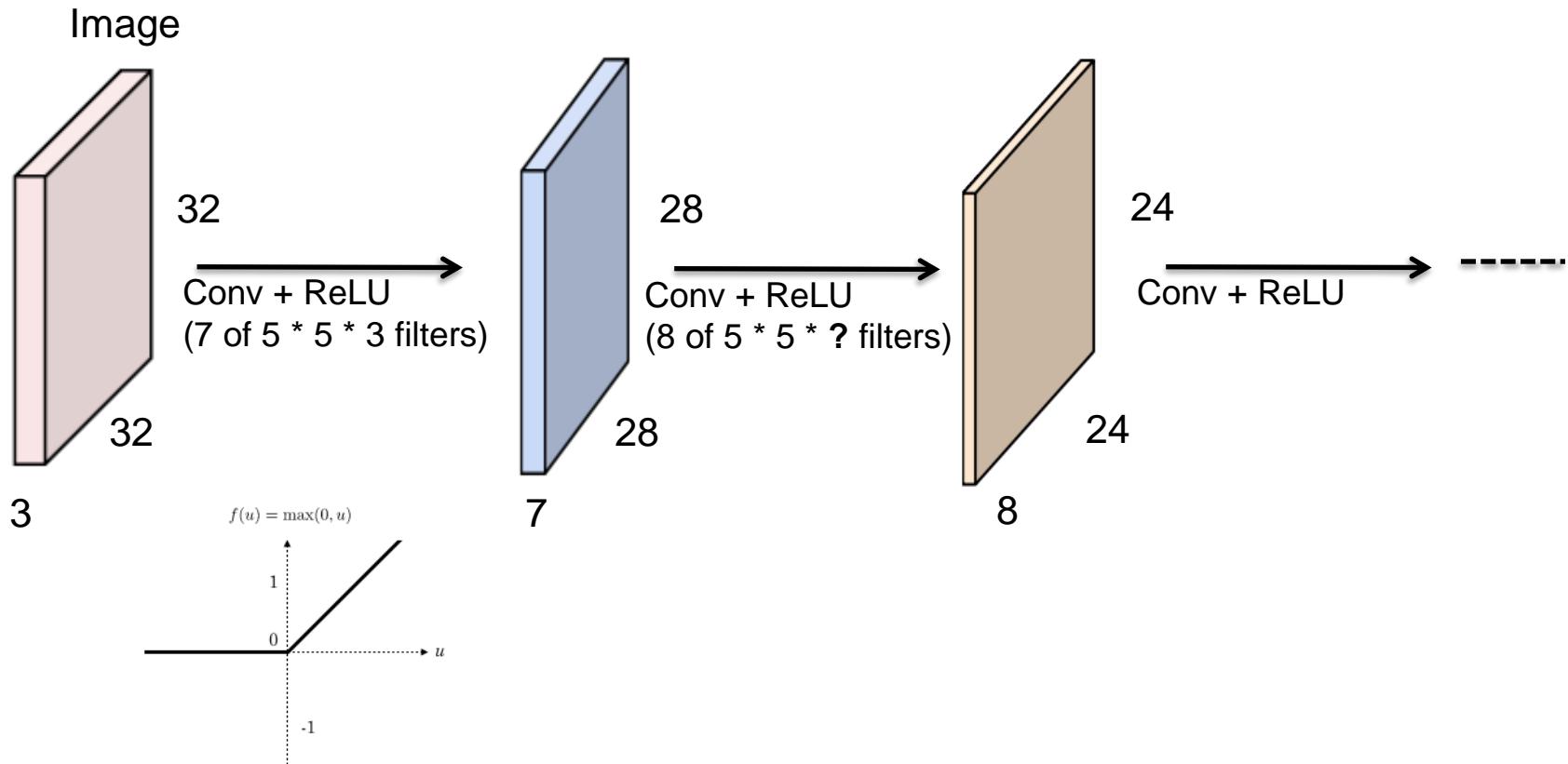


Image from: <https://legacy.gitbook.com/book/leonardoaraujosantos/artificial-intelligence>

- Stacking these up to make a new image of size $28 * 28 * 6$

CONVOLUTIONAL LAYER

- Convolution itself is a linear kind of operation. There is a need to add at the end of the convolution layer a non-linear layer, called ReLU activation. ReLU is the max function($x, 0$) with input x matrix from a convolved image. ReLU then sets all negative values in the matrix x to zero and all other values are kept constant.



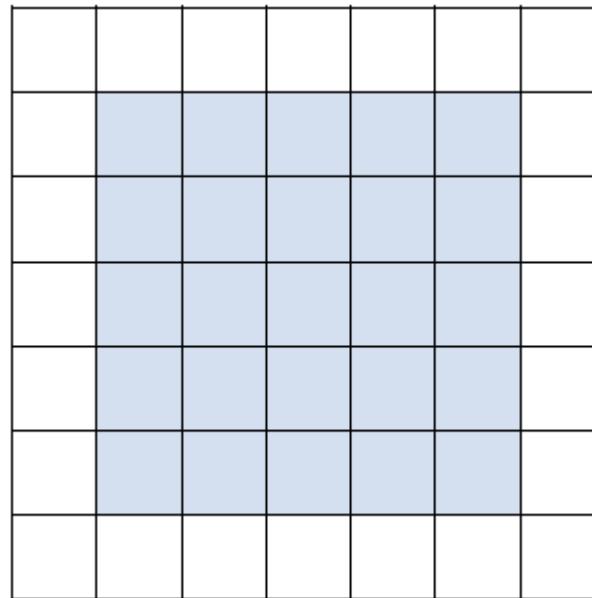
CONVOLUTIONAL NEURAL NETWORKS: A CLOSER LOOK

Input image: $7 * 7$

Filter size: $3 * 3$

Stride: 1

Output: $5 * 5$



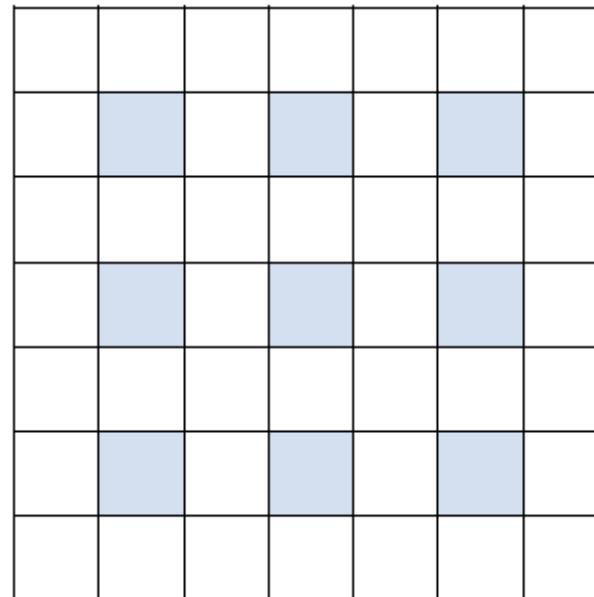
CONVOLUTIONAL NEURAL NETWORKS: A CLOSER LOOK

Input image: $7 * 7$

Filter size: $3 * 3$

Stride: 2

Output: $3 * 3$

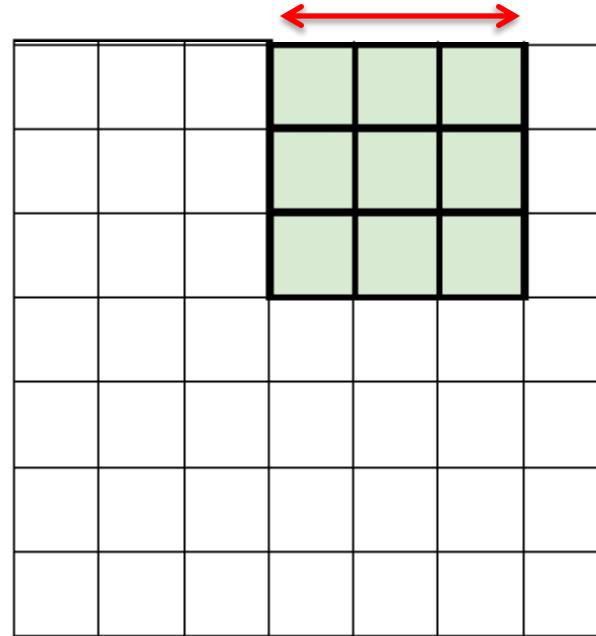


CONVOLUTIONAL NEURAL NETWORKS: A CLOSER LOOK

Input image: $7 * 7$

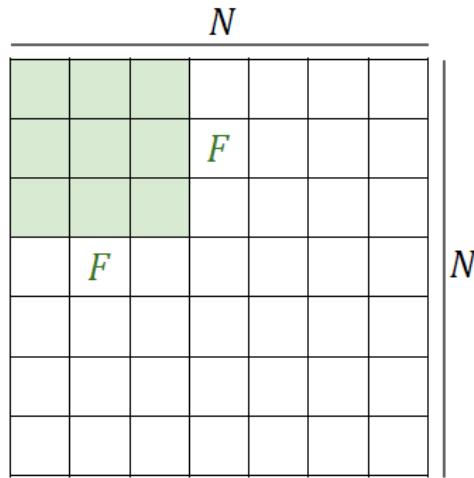
Filter size: $3 * 3$

Stride: 3



CONVOLUTIONAL NEURAL NETWORKS: A CLOSER LOOK

Output Size = $(N - F) / \text{Stride} + 1$



$$N = 7 \quad F = 3$$

$$\text{Stride} = 1 \quad \text{Output Size} = (7 - 3) / 1 + 1 = 5$$

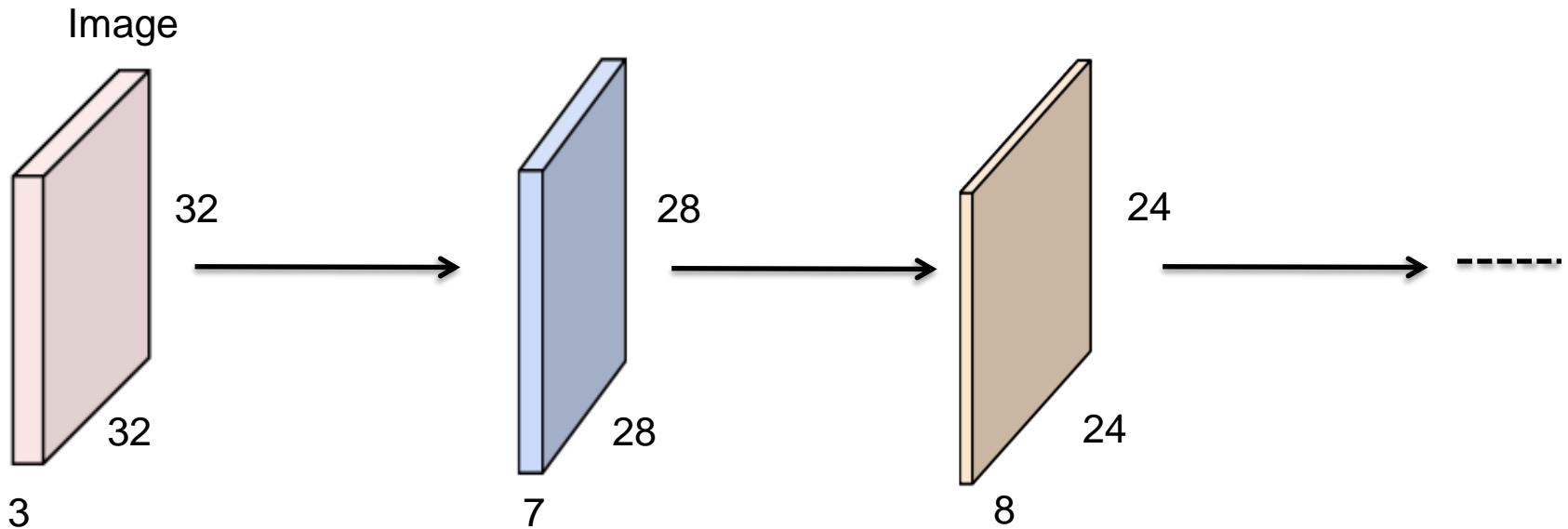
$$\text{Stride} = 2 \quad \text{Output Size} = (7 - 3) / 2 + 1 = 3$$

$$\text{Stride} = 3 \quad \text{Output Size} = (7 - 3) / 3 + 1 = 2.33 \quad \text{X}$$

Image from: <http://cs231n.github.io/convolutional-networks/>

CONVOLUTIONAL NEURAL NETWORKS

- We are condensing the data spatially! Too fast! What does that mean?



- Solution?

Zero Padding (pad): Add zeros on the image border to let the convolution output size be the same as the input image size.

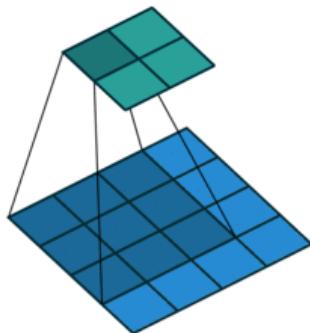
CONVOLUTIONAL NEURAL NETWORKS

Input Size: 4 * 4

Filter Size: 3 * 3

Stride: 1

Padding: 0 (No Padding)



Input Size: 5 * 5

Filter Size: 3 * 3

Stride: 1

Padding: 1

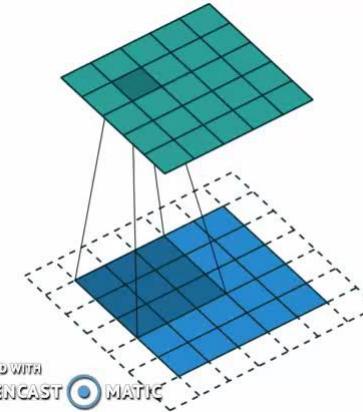


Image from: https://leonardoaraujosantos.gitbooks.io/artificial-intelligence/content/convolutional_neural_networks.html

CONVOLUTIONAL NEURAL NETWORKS

Convolutional Layer:

It takes a data volume of size $W_1 * H_1 * D_1$

Hyper Parameters:

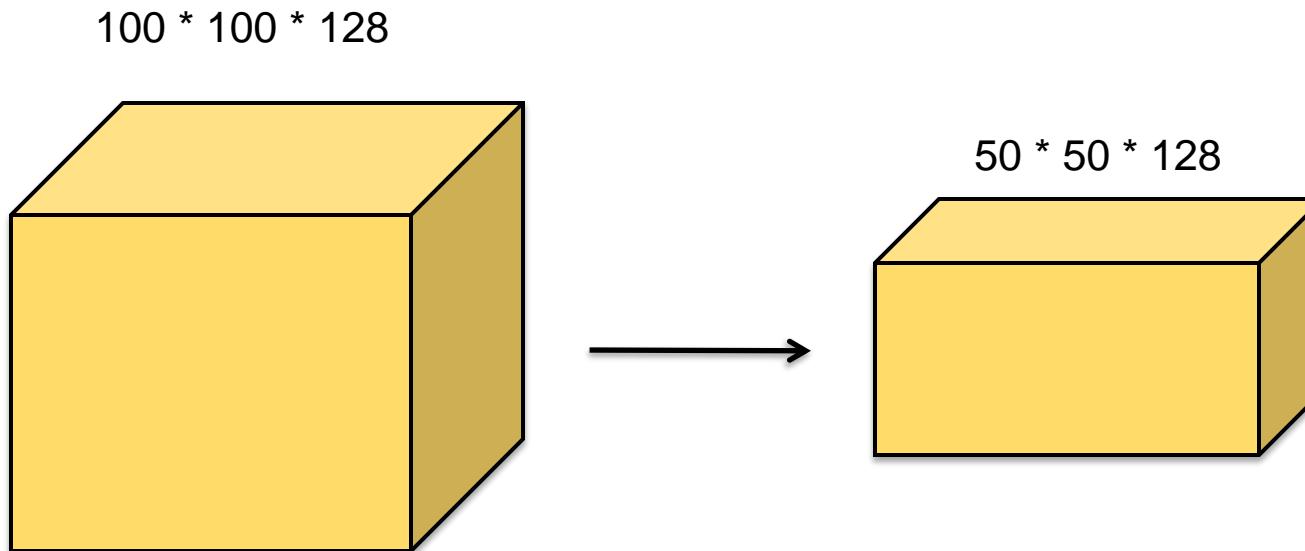
- Number of Filters (K)
- Filter Size (F)
- Stride (S)
- Zero Padding (P)

Common Configurations:

- $K = 32, 64, 128, \dots$
- $F = 3, S = 1, P = 1$
- $F = 5, S = 1, P = 2$
- $F = 5, S = 2, P = 2$

MAX POOL (POOLING)

It performs downsampling across the spatial dimensions (width, height). The representation would be smaller and more manageable.



MAX POOL (POOLING): HOW IT WORKS?

Filter Size: $2 * 2$

Stride: 2

5	6	7	8
2	10	4	11
7	9	3	5
8	6	7	1

5	6	7	8
2	10	4	11
7	9	3	5
8	6	7	1



10	11
9	7

CONVOLUTIONAL NEURAL NETWORKS

Max Pool Layer:

It takes a data volume of size $W_1 * H_1 * D_1$

Hyper Parameters:

- Filter Size (F)
- Stride (S)

Common Configurations:

- $F = 2, S = 2$
- $F = 3, S = 2$

FULLY CONNECTED LAYER

- It computes the class scores.
- This layer takes an input volume (the output of the Conv + ReLU + Pooling layer preceding it) and outputs an **N** dimensional vector, where **N** is the number of classes that we want to choose. For example, if we want to develop an object detection for Doors, Stairs, and Signs, then **N** would be 3.
- Each number in this **N** dimensional vector shows the probability of a class. For example, if the resulting vector for is [.1 .1 .80] for [Doors, Stair, Sign], then this represents a 10% probability that the image is a door, 10% probability that the image is a stair, and 80% probability that the image is sign.

CNN ARCHITECTURE: REVIEW

- **Input:** In our scenario, it holds the raw pixel values of an image (e.g., an image of width 32, height 32, and with three color channels R,G,B).
- **Convolutional Layer:** This layer filters (convolve) the inputs to provide very useful information appropriate for object modeling. These convolutional layers help to automatically extract the most valuable information for the task at hand without human designed feature selection. This layer will result in data volume such as [32 * 32 * 16] if we used for example 16 filters.
- **ReLU Layer:** will apply a pixelwise activation function, such as the $\max(0,x)$ thresholding at zero. This layer keeps the size of the data volume unchanged (e.g., [32 * 32 * 16]).
- **Pooling Layer:** It does a downsampling operation across the spatial dimensions (width, height), and will result in data volume such as [16 * 16 * 16].
- **Fully Connected Layer:** This layer computes the class scores, and it will result in volume of size [1 * 1 * 3], where each of those 3 numbers correspond to a class score, such as among the 3 categories (doors, stairs, signs).

KERAS DEMO (MNIST CNN)

The screenshot shows the RStudio interface with several files open in the left pane: MNIST.R, keras-Regression.R, residplots.r, Untitled1*, Untitled1*, and code.R*. The main pane displays R code for loading the MNIST dataset and defining a model. The right pane shows the Global Environment, listing variables like history, x_test, and x_train. A plot in the bottom right corner shows accuracy (blue line) and validation accuracy (green line) over 10 epochs, both starting at approximately 0.84 and rising to about 0.90.

```
> ###### STEP 1 #####
> library(keras)
> # Load MNIST images datasets (built in to keras)
> c(x_train, y_train), c(x_test, y_test)) %<-% dataset_mnist()
>
> ###### STEP 4 #####
> history <- model %>% fit(
+   x_train, y_train,
```

CONV layer: Number of Parameters

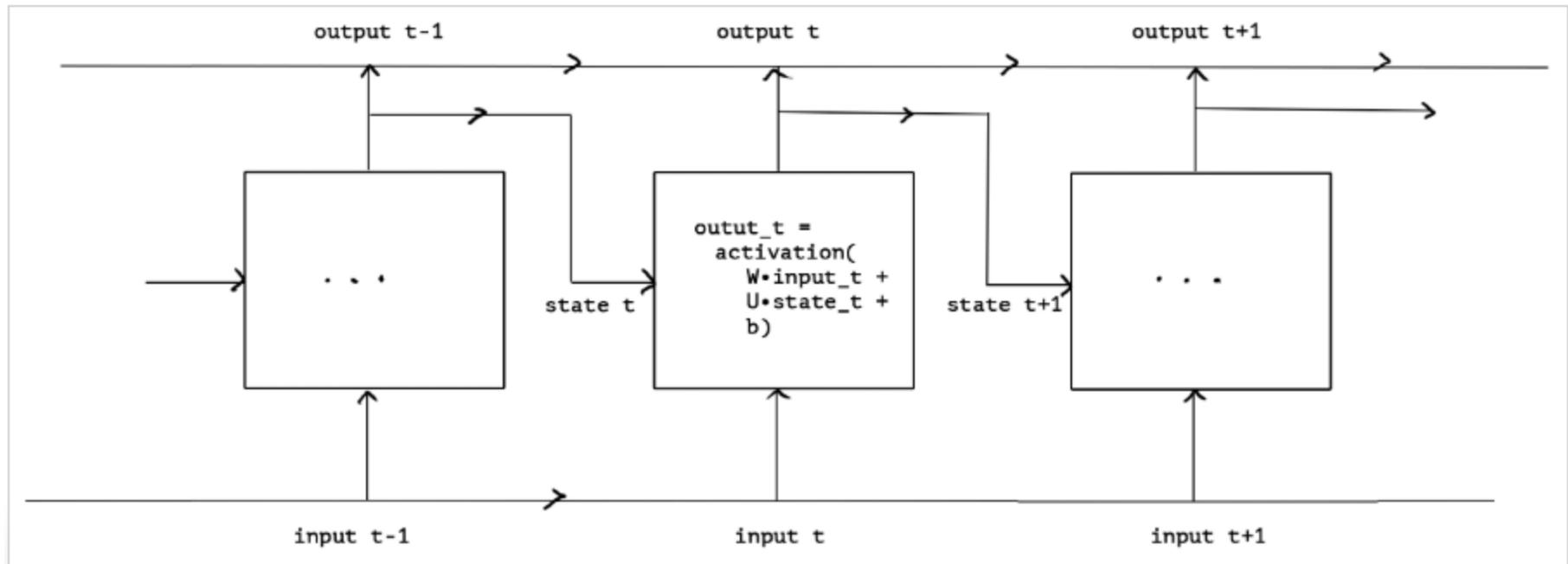
To calculate the learnable parameters here, all we have to do is just multiply the by the shape of **width m**, **height n**, **previous layer's filters d** and account for all such filters **k** in the **current layer**. Don't forget the bias term for each of the filter. Number of parameters in a CONV layer would be : $((m * n * d) + 1) * k$, added 1 because of the bias term for each filter. The same expression can be written as follows:
((shape of width of the filter * shape of height of the filter * number of filters in the previous layer + 1) * number of filters). Where the term "filter" refer to the number of filters in the current layer.

- https://tensorflow.rstudio.com/guide/keras/examples/mnist_cnn/

KERAS API: RECURRENT LAYERS

- Layers that maintain state based on previously seen data

- `layer_simple_rnn()`
- `layer_gru()`
- `layer_lstm()`



KERAS API: EMBEDDING LAYERS

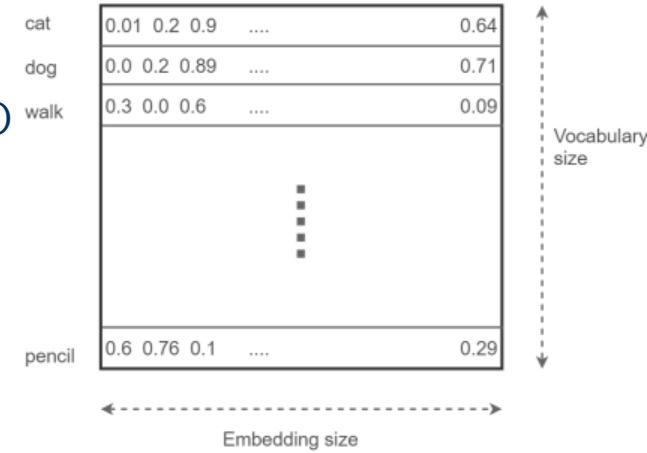
- Vectorization of text that reflects semantic relationships between words

```
> model <- keras_model_sequential() %>%
>   layer_embedding(input_dim = 10000, output_dim = 8,
>                     input_length = 20) %>%
>   layer_flatten() %>%
>   layer_dense(units = 1, activation = "sigmoid")
```

How to represent a word?

Problem: distance between words using one-hot encodings always the same

dog	[1 0 0 0 0 0 0 0 0]
cat	[0 1 0 0 0 0 0 0 0]
walk	[0 0 1 0 0 0 0 0 0]



- Learn the embeddings jointly with the main task you care about (e.g. classification); or
- Load pre-trained word embeddings (e.g. Word2vec, GloVe)

KERAS DEMO (TEXT CLASSIFICATION)

The screenshot shows the RStudio interface with the following components:

- Code Editor:** Displays the `MNIST.R` script containing Keras code for text classification. The code includes data loading, flattening, and reshaping of images, one-hot encoding of labels, and the definition of a sequential model with three hidden layers (256, 128, 10 units) and a final sigmoid layer for binary classification.
- Environment View:** Shows the global environment with variables: `history`, `x_test`, `x_train`, `y_test`, `y_train`, and `model`.
- Plots:** Two line plots showing training and validation metrics over 10 epochs. The top plot shows loss (blue line with circles) decreasing from ~0.55 to ~0.08, and validation loss (green line with squares) decreasing from ~0.20 to ~0.08. The bottom plot shows accuracy (blue line with circles) increasing from ~0.84 to ~0.97, and validation accuracy (green line with squares) increasing from ~0.94 to ~0.97.
- Console:** Displays the R session history, showing the execution of the script and the resulting model definition.

- https://keras.rstudio.com/articles/tutorial_basic_text_classification.html

RECOMMENDED READINGS

■ Datacamp Tutorials:

- Keras: Deep Learning in R
 - <https://www.datacamp.com/community/tutorials/keras-r-deep-learning>
- Keras Tutorial: Deep Learning in Python
 - <https://www.datacamp.com/community/tutorials/deep-learning-python>
- TensorFlow Tutorial For Beginners
 - <https://www.datacamp.com/community/tutorials/tensorflow-tutorial>

■ Deep Learning Specializations in Coursera

■ Keras in R

- <https://keras.rstudio.com/>
- <https://tensorflow.rstudio.com/keras/articles/examples/>

■ Tensorflow in R

- <https://tensorflow.rstudio.com/>
- <https://tensorflow.rstudio.com/tutorials/>

SOME R EXAMPLES

- <https://keras.rstudio.com/index.html#tutorials>
 - [Basic Classification](#) — classify images of clothing.
 - [Text Classification](#) — classifies movie reviews as positive or negative.
 - [Basic Regression](#) — predict the price of homes in a Boston suburb.
 - [Overfitting and Underfitting](#) — two common regularization techniques
 - [Save and Restore Models](#) — save and share models.
- <https://keras.rstudio.com/articles/examples/> (36 examples)
- <https://tensorflow.rstudio.com/gallery/> (18 examples)
 - [Image classification on small datasets](#)
 - [Time series forecasting with recurrent networks](#)
 - [Deep learning for cancer immunotherapy](#)
 - [Credit card fraud detection using an autoencoder](#)
 - [Classifying duplicate questions from Quora](#)
 - [Deep learning to predict customer churn](#)
 - [Learning word embeddings for Amazon reviews](#)
 - Work on explainability of predictions
 - [Visualizing activations](#)
 - [LIME: Local Interpretable Model-Agnostic Explanations](#)

KERAS FOR R CHEATSHEET

■ <https://github.com/rstudio/cheatsheets/raw/master/keras.pdf>

More layers

CONVOLUTIONAL LAYERS

- `layer_conv_1d()` 1D, e.g. temporal convolution
- `layer_conv_2d_transpose()` Transposed 2D (deconvolution)
- `layer_conv_2d()` 2D, e.g. spatial convolution over Images
- `layer_conv_3d_transpose()` Transposed 3D (deconvolution)
- `layer_conv_3d()` 3D, e.g. spatial convolution over volumes
- `layer_conv_lstm_2d()` Convolutional LSTM
- `layer_separable_conv_2d()` Depthwise separable 2D
- `layer_upsampling_1d()`
- `layer_upsampling_2d()`
- `layer_upsampling_3d()` Upsampling layer
- `layer_zero_padding_1d()`
- `layer_zero_padding_2d()`
- `layer_zero_padding_3d()` Zero-padding layer
- `layer_cropping_1d()`
- `layer_cropping_2d()`
- `layer_cropping_3d()` Cropping layer

POOLING LAYERS

- `layer_max_pooling_1d()`
- `layer_max_pooling_2d()`
- `layer_max_pooling_3d()` Maximum pooling for 1D to 3D
- `layer_average_pooling_1d()`
- `layer_average_pooling_2d()`
- `layer_average_pooling_3d()` Average pooling for 1D to 3D
- `layer_global_max_pooling_1d()`
- `layer_global_max_pooling_2d()`
- `layer_global_max_pooling_3d()` Global maximum pooling
- `layer_global_average_pooling_1d()`
- `layer_global_average_pooling_2d()`
- `layer_global_average_pooling_3d()` Global average pooling

ACTIVATION LAYERS

- `layer_activation(object, activation)` Apply an activation function to an output
- `layer_activation_leaky_relu()` Leaky version of a rectified linear unit
- `layer_activation_parametric_relu()` Parametric rectified linear unit
- `layer_activation_thresholded_relu()` Thresholded rectified linear unit
- `layer_activation_elu()` Exponential linear unit

DROPOUT LAYERS

- `layer_dropout()` Applies dropout to the input
- `layer_spatial_dropout_1d()`
- `layer_spatial_dropout_2d()`
- `layer_spatial_dropout_3d()` Spatial 1D to 3D version of dropout

RECURRENT LAYERS

- `layer_simple_rnn()` Fully-connected RNN where the output is to be fed back to input
- `layer_gru()` Gated recurrent unit - Cho et al
- `layer_cudnn_gru()` Fast GRU implementation backed by CuDNN
- `layer_lstm()` Long-Short Term Memory unit - Hochreiter 1997
- `layer_cudnn_lstm()` Fast LSTM implementation backed by CuDNN

LOCALLY CONNECTED LAYERS

- `layer_locally_connected_1d()`
- `layer_locally_connected_2d()` Similar to convolution, but weights are not shared, i.e. different filters for each patch

Preprocessing

SEQUENCE PREPROCESSING

- `pad_sequences()` Pads each sequence to the same length (length of the longest sequence)
- `skipgrams()` Generates skipgram word pairs
- `make_sampling_table()` Generates word rank-based probabilistic sampling table

TEXT PREPROCESSING

- `text_tokenizer()` Text tokenization utility
- `fit_text_tokenizer()` Update tokenizer internal vocabulary
- `save_text_tokenizer(); load_text_tokenizer()` Save a text tokenizer to an external file
- `texts_to_sequences(); texts_to_sequences_generator()` Transforms each text in texts to sequence of integers
- `texts_to_matrix(); sequences_to_matrix()` Convert a list of sequences into a matrix
- `text_one_hot()` One-hot encode text to word indices
- `text_hashing_trick()` Converts a text to a sequence of indexes in a fixed-size hashing space
- `text_to_word_sequence()` Convert text to a sequence of words (or tokens)

IMAGE PREPROCESSING

- `image_load()` Loads an image into PIL format.
- `flow_images_from_data()`
- `flow_images_from_directory()` Generates batches of augmented/normalized data from images and labels, or a directory
- `image_data_generator()` Generate minibatches of image data with real-time data augmentation.
- `fit_image_data_generator()` Fit image data generator internal statistics to some sample data
- `generator_next()` Retrieve the next item
- `image_to_array(); image_array_resize()`
- `image_array_save()` 3D array representation



Pre-trained models

Keras applications are deep learning models that are made available alongside pre-trained weights. These models can be used for prediction, feature extraction, and fine-tuning.

- `application_xception()`
- `xception_preprocess_input()`
- Xception v1 model
- `application_inception_v3()`
- `inception_v3_preprocess_input()`
- Inception v3 model, with weights pre-trained on ImageNet
- `application_inception_resnet_v2()`
- `inception_resnet_v2_preprocess_input()`
- Inception-ResNet v2 model, with weights trained on ImageNet
- `application_vgg16(); application_vgg19()`
- VGG16 and VGG19 models
- `application_resnet50()` ResNet50 model
- `application_mobilenet()`
- `mobilenet_preprocess_input()`
- `mobilenet_decode_predictions()`
- `mobilenet_load_model_hdf5()`
- MobileNet model architecture

IMAGENET

ImageNet is a large database of images with labels, extensively used for deep learning

- `imagenet_preprocess_input()`
- `imagenet_decode_predictions()`
- Preprocesses a tensor encoding a batch of images for ImageNet, and decodes predictions

Callbacks

A callback is a set of functions to be applied at given stages of the training procedure. You can use callbacks to get a view on internal states and statistics of the model during training.

- `callback_early_stopping()` Stop training when a monitored quantity has stopped improving
- `callback_learning_rate_scheduler()` Learning rate scheduler
- `callback_tensorboard()` TensorBoard basic visualizations

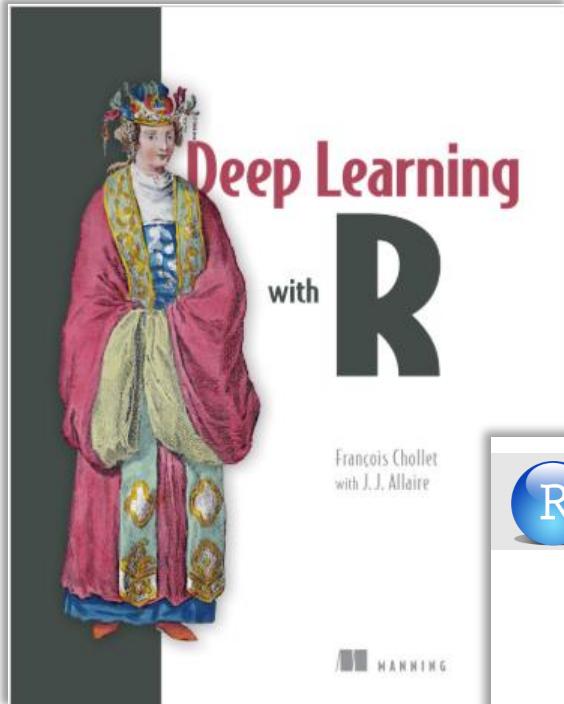
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REFERENCES



Machine Learning with
TensorFlow and R

J.J. Allaire — CEO, RStudio

QUESTIONS?
THANK YOU!



Yoshua Bengio > Turing Award

Turing Award
2019

Winner

