Machine Learning (and Deep Learning) in just over 200 minutes with R

From basic linear models to neural networks

Presented at the 2021 SAGI Symposium via Zoom

Presented by Yoni Nazarathy

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R Material created by Ajay Hemanth

https://www.linkedin.com/in/ajayhemanth/

These slides are available at: https://yoninazarathy.com/TBD
R source code is available at: https://github.com/TBD

The University Of Queensland
AUSTRALIA

On the menu

1. The state of the art and the ML world
2. The ML workflow and common “practice” data sets
3. Some tools you know - used for ML
4. A walk in the random forest
5. Going deep

Who are you?
Biometricians, using R, using specialized software.
Strong understanding of statistics.

A: Linear Classifiers.
B: Google TensorFlow Ground
C: Dense Neural Nets (MLP)
D: Random Forests
E: Convolutional Neural Nets

About the speaker

https://yoninazarathy.com/

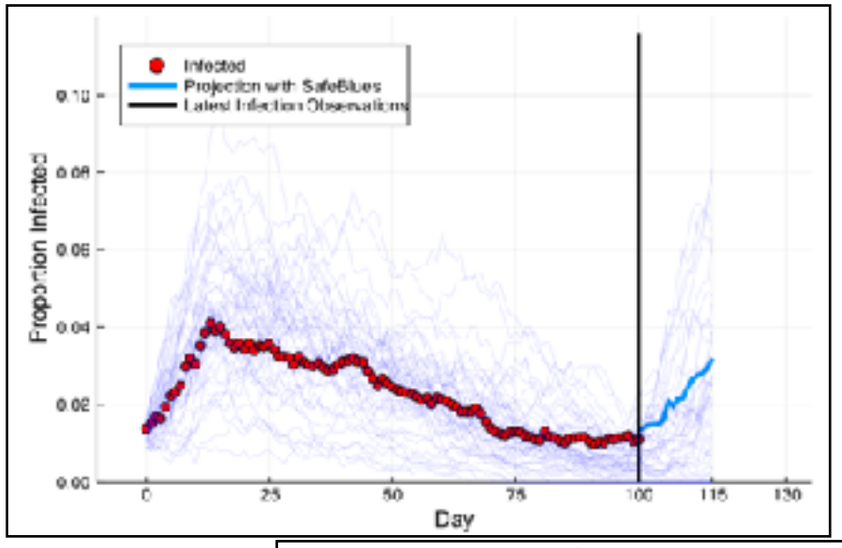
I am an Associate Professor at the School of Mathematics and Physics of The University of Queensland.

My expertise is in Machine Learning, Applied Probability, Statistics, Operations Research, Simulation, Scientific Computing, Control Theory, Queueing Theory, Scheduling, and Mathematical Education.

Application areas of my work include epidemics, wireless communication networks, bio-statistics, agriculture, power systems, software and hardware design, manufacturing logistics, healthcare logistics, and road traffic networks.

Current "Main" Project: Safe Blues

https://safeblues.org/



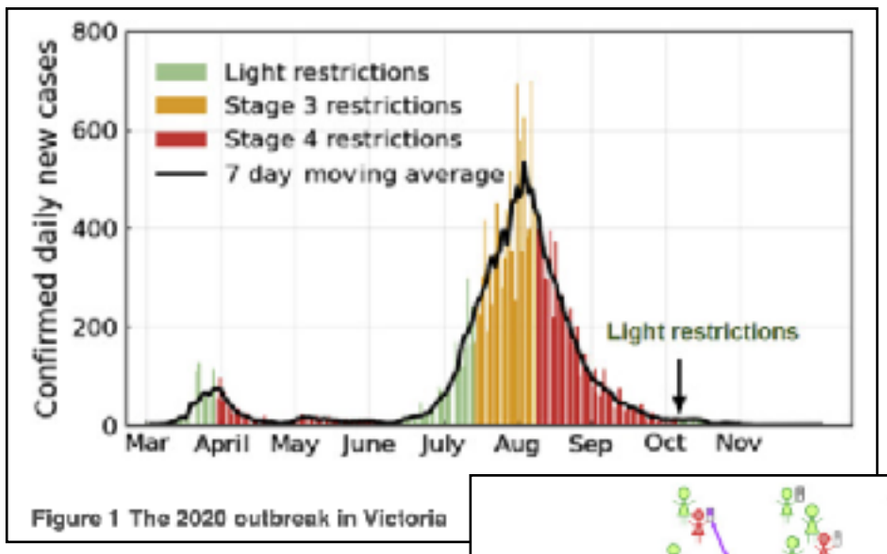
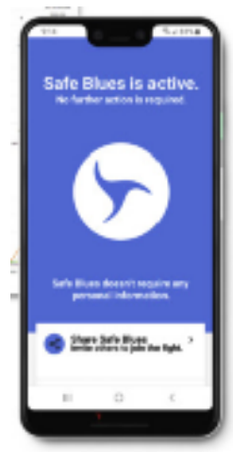
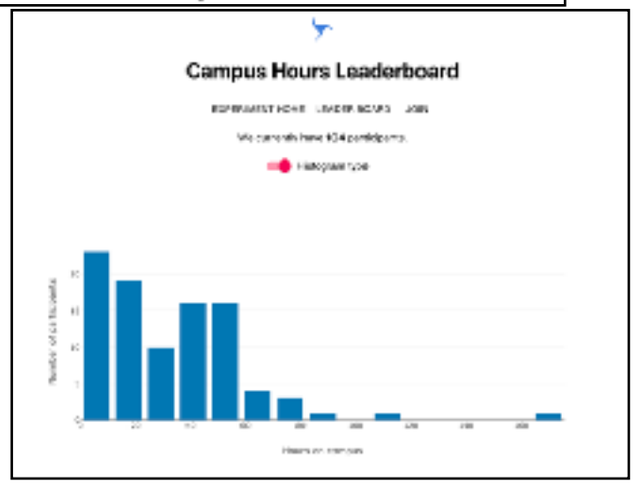
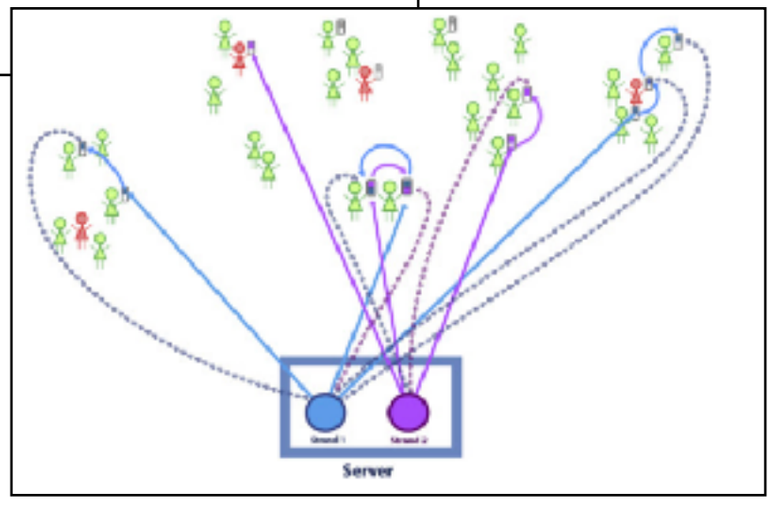


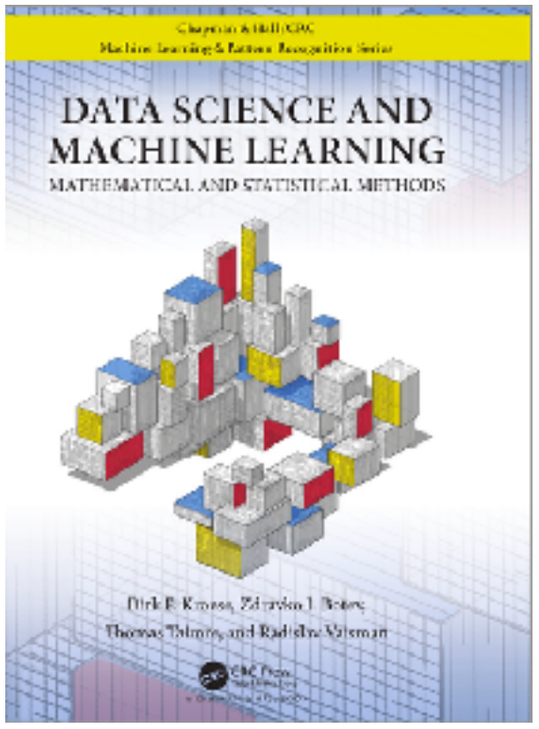
Figure 1 The 2020 outbreak in Victoria

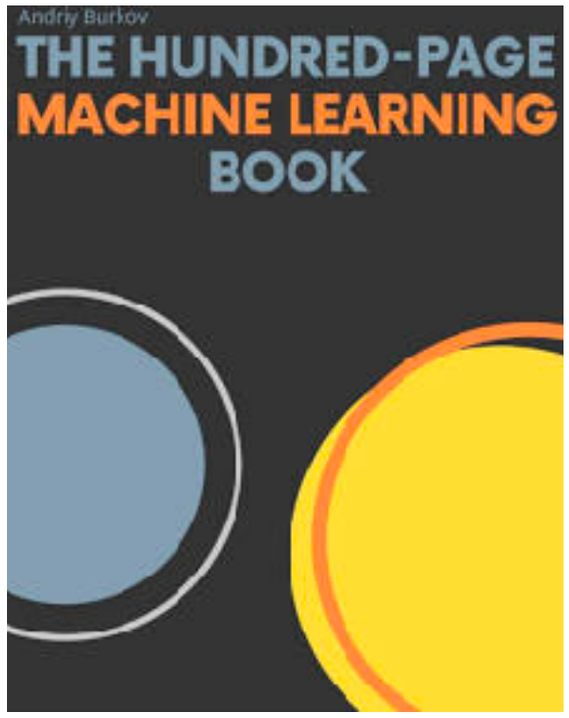


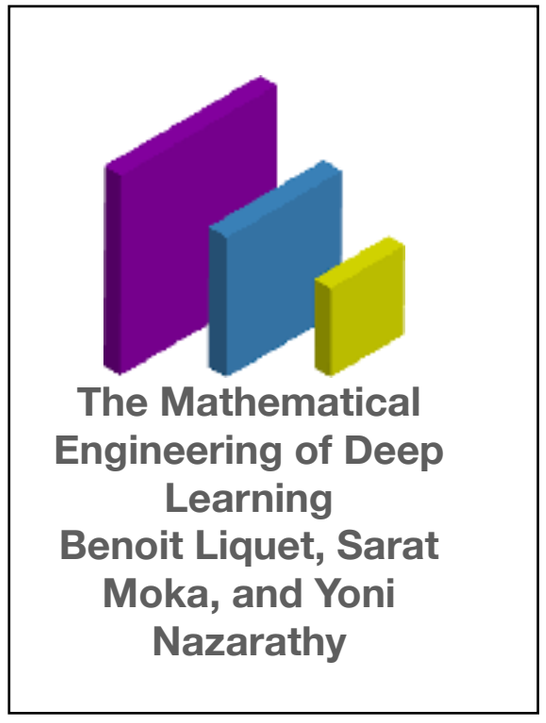


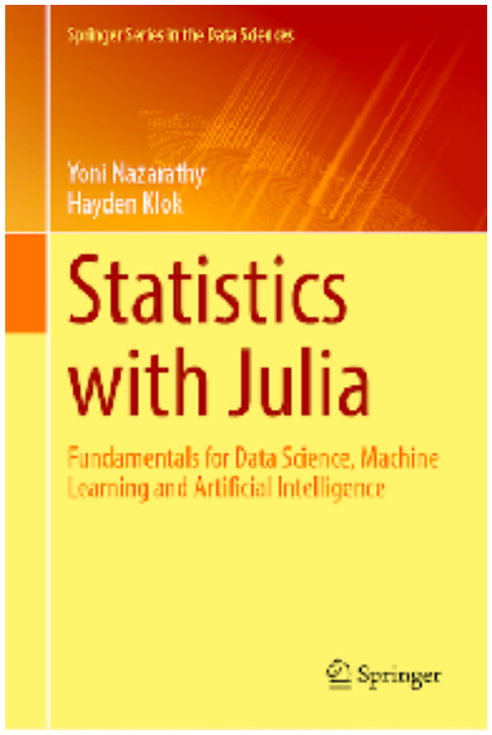


Some resources









https://people.smp.uq.edu.au/DirkKroese/DSML/

http://themlbook.com/

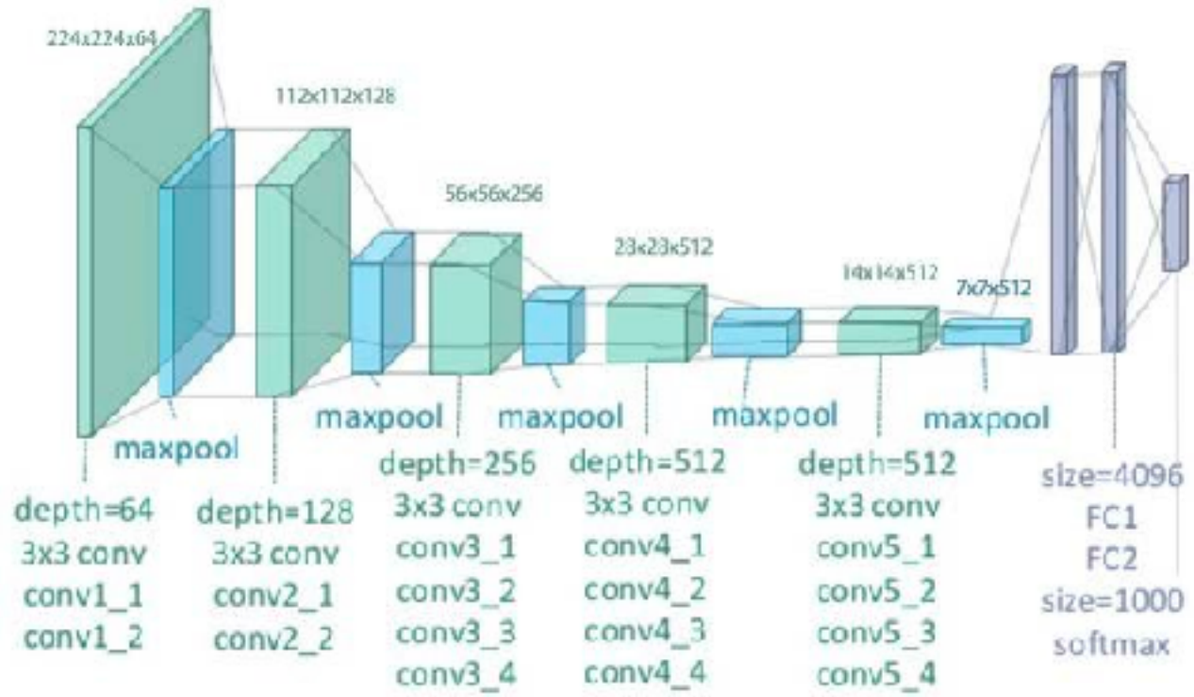
https://deeplearningmath.org/

https://statisticswithjulia.org/

Part 1: The state of the art and the ML world

```
using Metalhead
vgg = VGG19() #downloads about 0.5Gb of a pretrained neural network from the web
for (i,l) in enumerate(vgg.layers)
    println(i,": ", l)
end
```

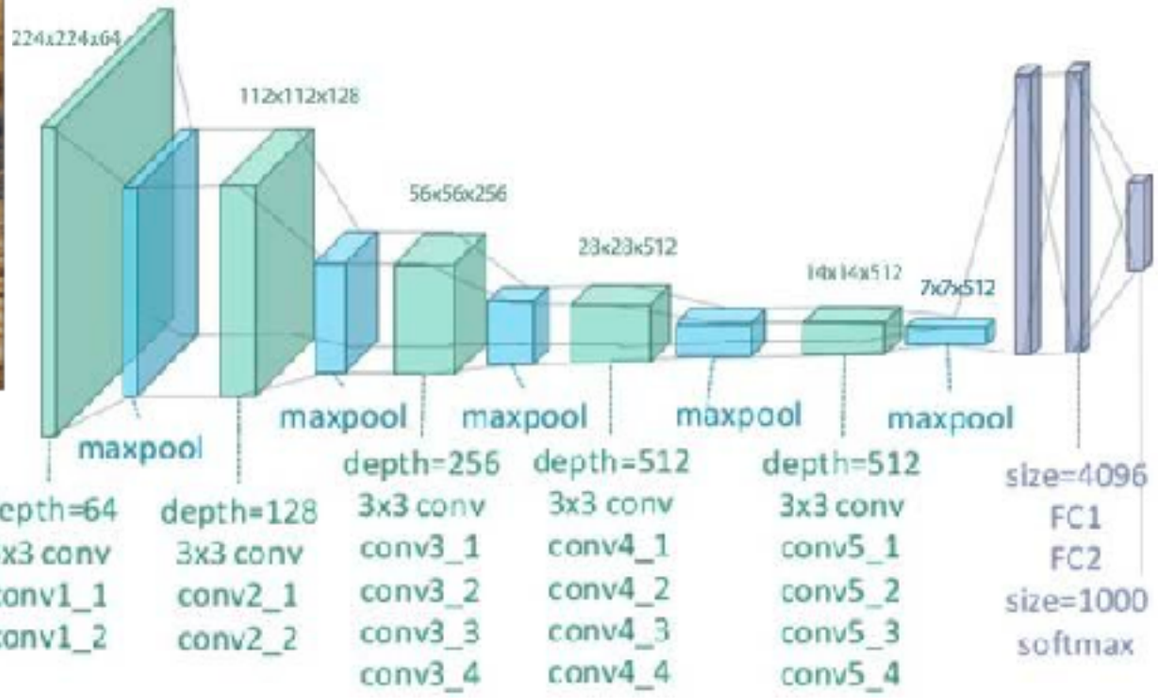
```
1: Conv((3, 3), 3=>64, relu)
2: Conv((3, 3), 64=>64, relu)
3: MaxPool((2, 2), pad = (0, 0, 0, 0), stride = (2, 2))
4: Conv((3, 3), 64=>128, relu)
5: Conv((3, 3), 128=>128, relu)
6: MaxPool((2, 2), pad = (0, 0, 0, 0), stride = (2, 2))
7: Conv((3, 3), 128=>256, relu)
8: Conv((3, 3), 256=>256, relu)
9: Conv((3, 3), 256=>256, relu)
10: Conv((3, 3), 256=>256, relu)
11: MaxPool((2, 2), pad = (0, 0, 0, 0), stride = (2, 2))
12: Conv((3, 3), 256=>512, relu)
13: Conv((3, 3), 512=>512, relu)
14: Conv((3, 3), 512=>512, relu)
15: Conv((3, 3), 512=>512, relu)
16: MaxPool((2, 2), pad = (0, 0, 0, 0), stride = (2, 2))
17: Conv((3, 3), 512=>512, relu)
18: Conv((3, 3), 512=>512, relu)
19: Conv((3, 3), 512=>512, relu)
20: Conv((3, 3), 512=>512, relu)
21: MaxPool((2, 2), pad = (0, 0, 0, 0), stride = (2, 2))
22: #44
23: Dense(25088, 4096, relu)
24: Dropout(0.5)
25: Dense(4096, 4096, relu)
26: Dropout(0.5)
27: Dense(4096, 1000)
28: softmax
```



The VGG19 Deep Neural network
(Image courtesy of Clifford K. Yang)

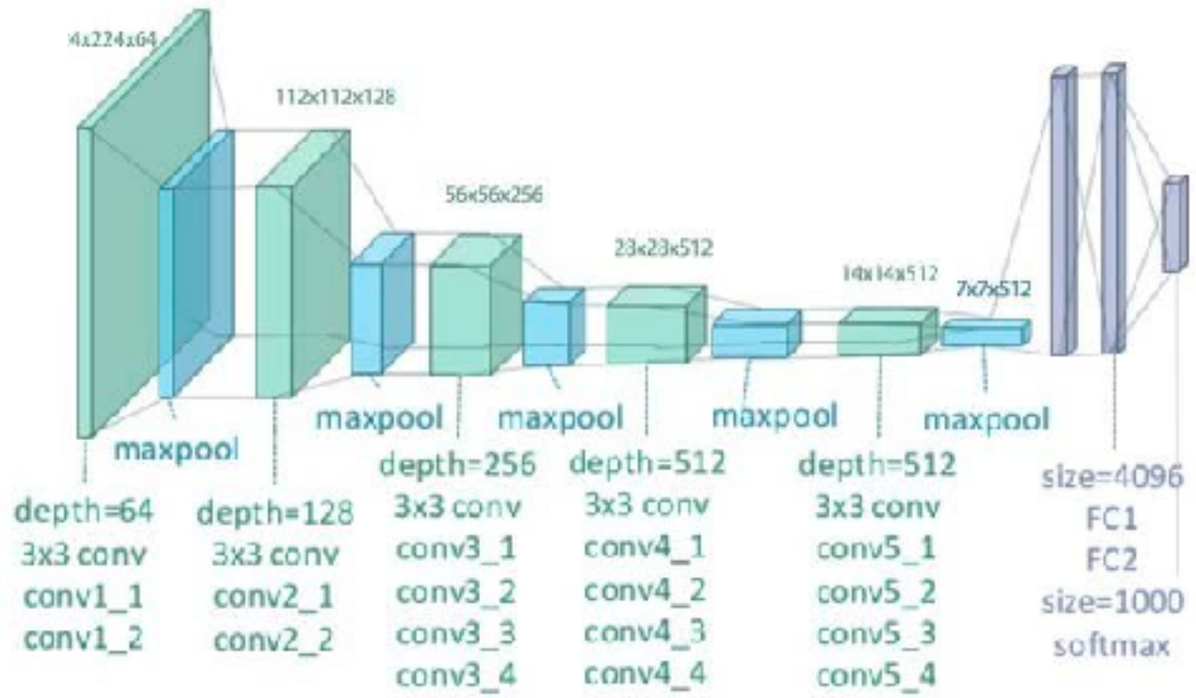
```
img = load("bicycle.jpg")
@show classify(vgg,img)
img
```

```
classify(vgg, img) = "mountain bike, all-terrain bike, off-roader"
```



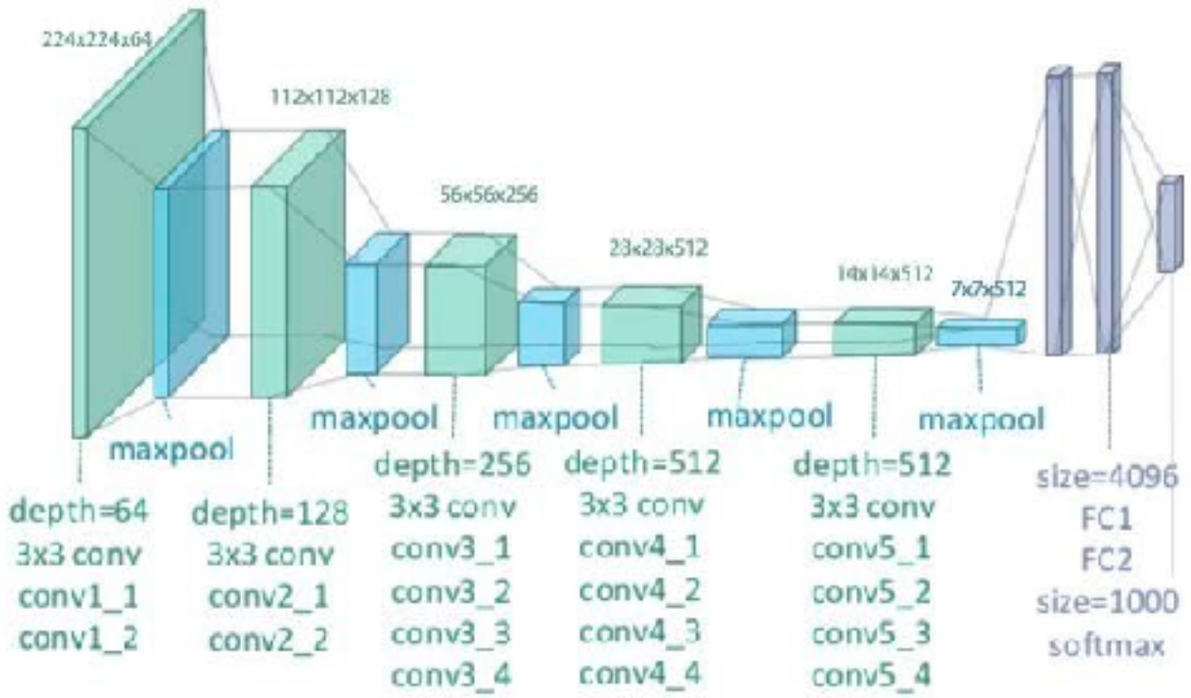
```
img = load("appleFruit.jpg")
@show classify(vgg,img)
img
```

```
classify(vgg, img) = "Granny Smith"
```



```
img = load("baby.jpg")
@show classify(vgg,img)
img
```

```
classify(vgg, img) = "diaper, nappy, napkin"
```



Data Science

Artificial Intelligence

Machine Learning

Deep Learning

Computer Science

Statistics

Statistical Learning

Neuroscience

Data Mining

Timeline of weak (narrow) AI

Weak AI
`Explosion' and Deep Learning

~2010 Machine Learning
Renaissance begins

~2000 Revival of machine learning

1980's Reinforcement Learning

1970 Reverse Mode Automatic Differentiation

1960's Neural Networks

1950 Turing Test Proposed

Timeline of strong AI (Artificial General Intelligence)

2010+ Weak AI Hype…

1970’s-80’s Expert Systems

1970's Thoughts and definitions about AGI

1950 Turing Test Proposed

Timeline of Deep Learning (prehistory)

"Deep Learning" is a thing!
Deep Learning = AI?

2012 (**AlexNet**): ImageNet Classification with Deep Convolutional Neural Networks, by Alex Krizhevsky, Ilya Sutskever and Geoffrey E. Hinton.

1998: (**Convolutional nets**): Gradient based learning applied to document recognition, by Yann Lecun, Leon Bottou, Yoshua Bengio and Patrick Haffne.

1982 (**Hopfield nets**): Neural networks and physical systems with emergent collective computational abilities, by John Hopfield.

1958 (**Perceptron**): The perceptron: a probabilistic model for information storage and organization in the brain, by Frank Rosenblatt.

Current Deep Learning

2017 (**Transformers**): Attention is all you need, by Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan Gomez, Lukasz Kaiser and Illia Polosukhin.

2016 (**Deep RL vs. Go**): Mastering the game of Go with deep neural networks and tree search, by David Silver, Aja Huang, Chris Maddison and others.

2015 (**ResNet**): Deep residual learning for image recognition, by Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun.

2015 (**Inception**): Going deeper with convolutions, by Christian Szegedy et. al.

2015 (**VGG**): Very deep convolutional networks for large-scale image recognition, by Karen Simonyan and Andrew Zisserman.

2014: (**GAN**): Generative adversarial nets, by Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville and Yoshua Bengio.

2014: (**ADAM**): Adam: A method for stochastic optimization, by Diederik Kingma and Jimmy Ba.

2013: (**Deep RL**): Playing Atari with Deep Reinforcement Learning by Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra and Martin Riedmiller.

2013: (**Inner layers**): Visualizing and Understanding Convolutional Networks, by Matthew Zeiler and Rob Fergus

2012 (**AlexNet**): ImageNet Classification with Deep Convolutional Neural Networks, by Alex Krizhevsky, Ilya Sutskever and Geoffrey E. Hinton.

The main activities of machine learning

- Supervised learning (Y = labels, X = features) → Regression / Classification
- Unsupervised learning (only X)
- Semi-supervised learning (hybrid)
- Reinforcement Learning (a time component)
- Generative modeling (generating new X's)

QQQQ: Note Yoni also on sequence data…

Part 2: The ML workflow and common “practice” data sets

The MNIST digits dataset

```
using Flux
imgs, labels = Flux.Data.MNIST.images(), Flux.Data.MNIST.labels();
@show length(imgs)
@show size(imgs[1])
@show labels[1:8]
imgs[1:8]
```

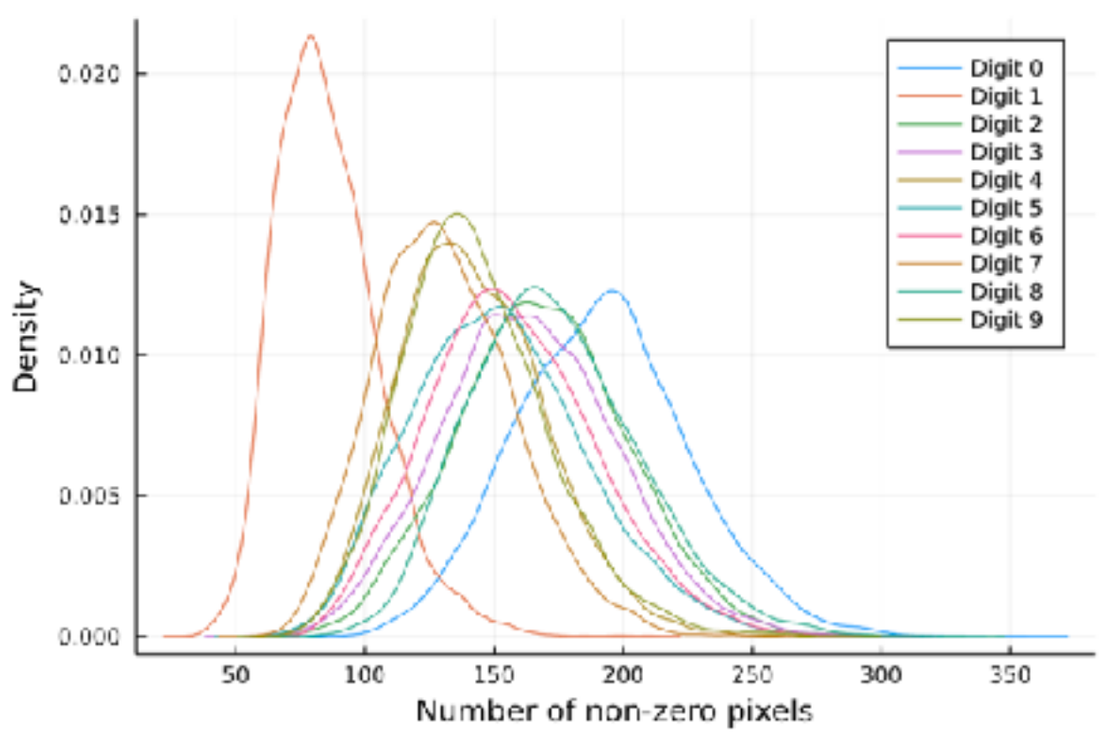
```
length(imgs) = 60000
size(imgs[1]) = (28, 28)
labels[1:8] = [5, 0, 4, 1, 9, 2, 1, 3]
```

Basic EDA for MNIST

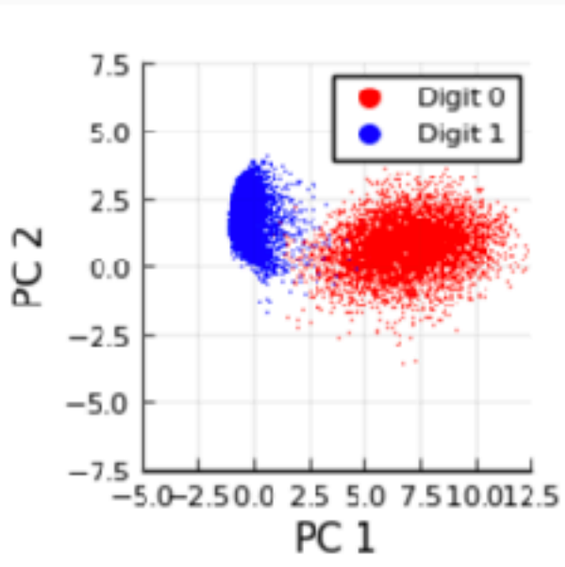
```
#Basic Exploratory Data Analysis (EDA) for MNIST
using Statistics, StatsPlots, Plots

x = hcat([vcat(float.(im)...) for im in imgs]...)

d, n = size(x)
@show (d,n)

onMeanIntensity = mean(filter((u)->u>0,x))
@show onMeanIntensity

prop0 = sum(x .== 0)/(d*n)
@show prop0

prop1 = sum(x .== 1)/(d*n)
@show prop1

print("Label counts: ", [sum(labels .== k) for k in 0:9])
```

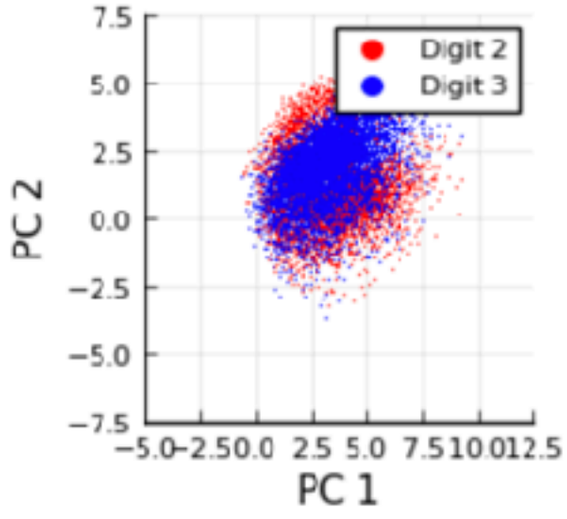
```
p = plot()
for k in 0:9
    onPixels = [ sum(x[:,i] .> 0) for i in (1:n)[labels .== k] ]
    p = density!(onPixels, label = "Digit $(k)")
end
plot(p,xlabel="Number of non-zero pixels", ylabel = "Density")
```

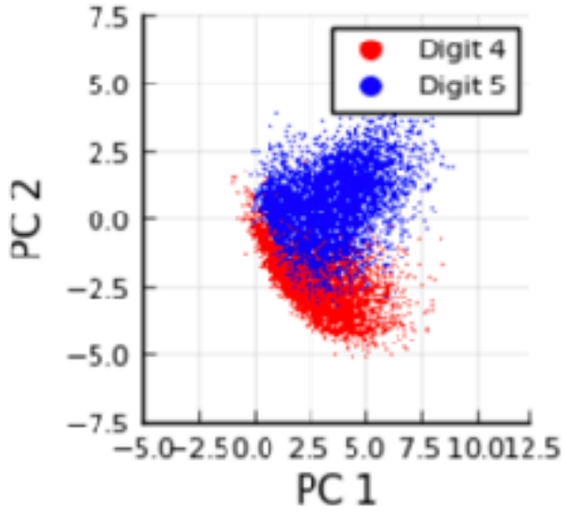
```
(d, n) = (784, 60000)
onMeanIntensity = Gray{Float32}(0.6833625f0)
prop0 = 0.8087977040816327
prop1 = 0.006681164965986395
Label counts: [5923, 6742, 5958, 6131, 5842, 5421, 5918, 6265, 5851, 5949]
```

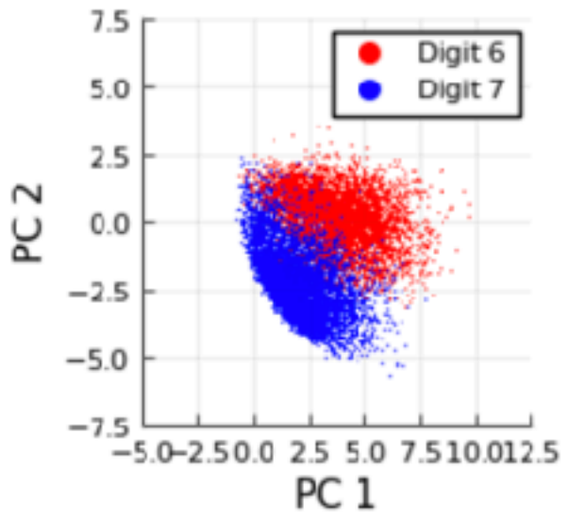


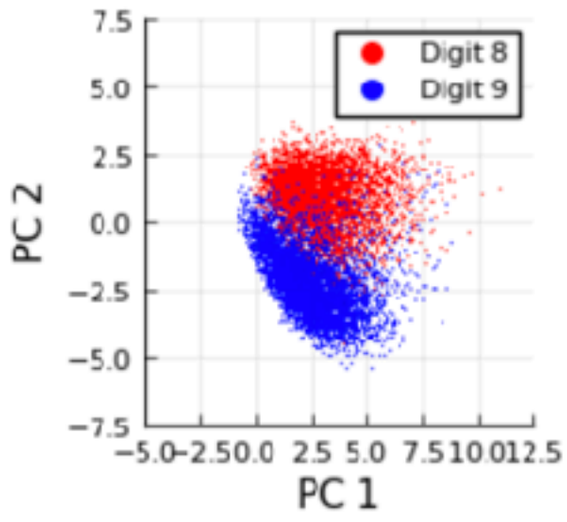
Breaking MNIST up via PCA (2 components)





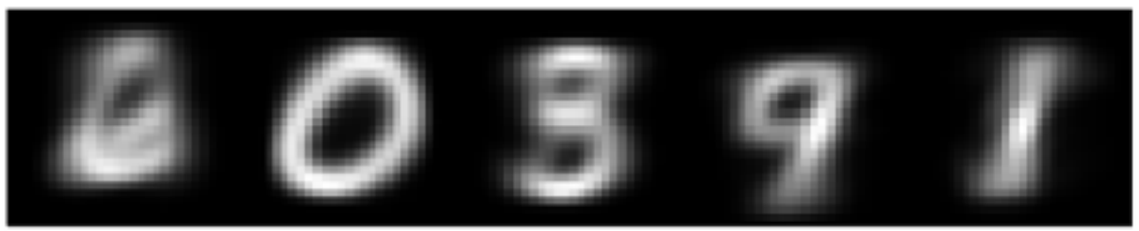






The centroids of k-means

k=3

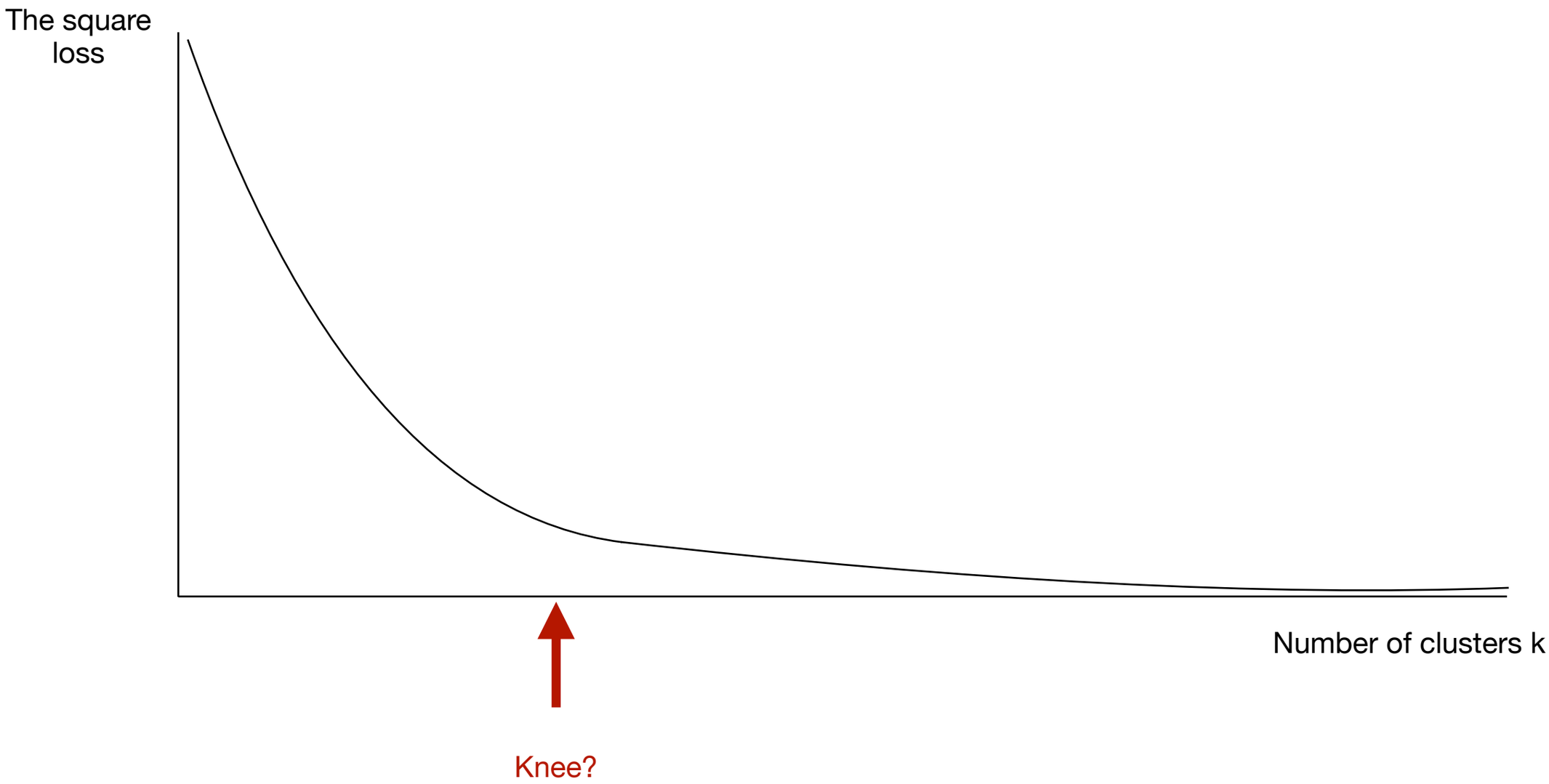


k=5

k=10

k=15

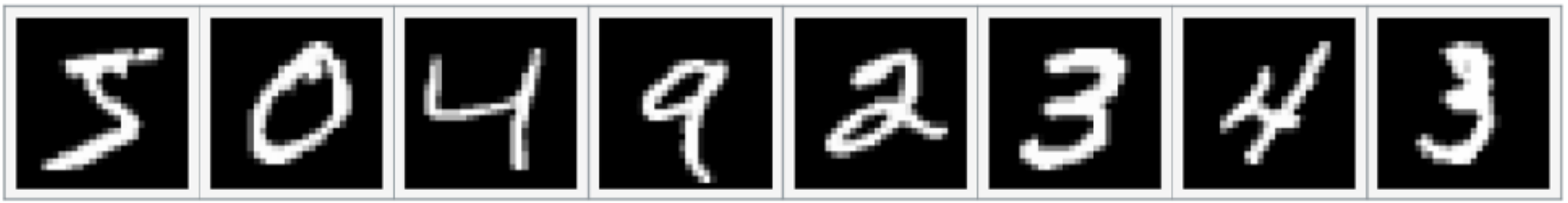
Finding the “knee”



A toy binary classifier digit 1, or not

```
imgs[labels .== 1][1:8]
```

```
imgs[labels .!= 1][1:8]
```



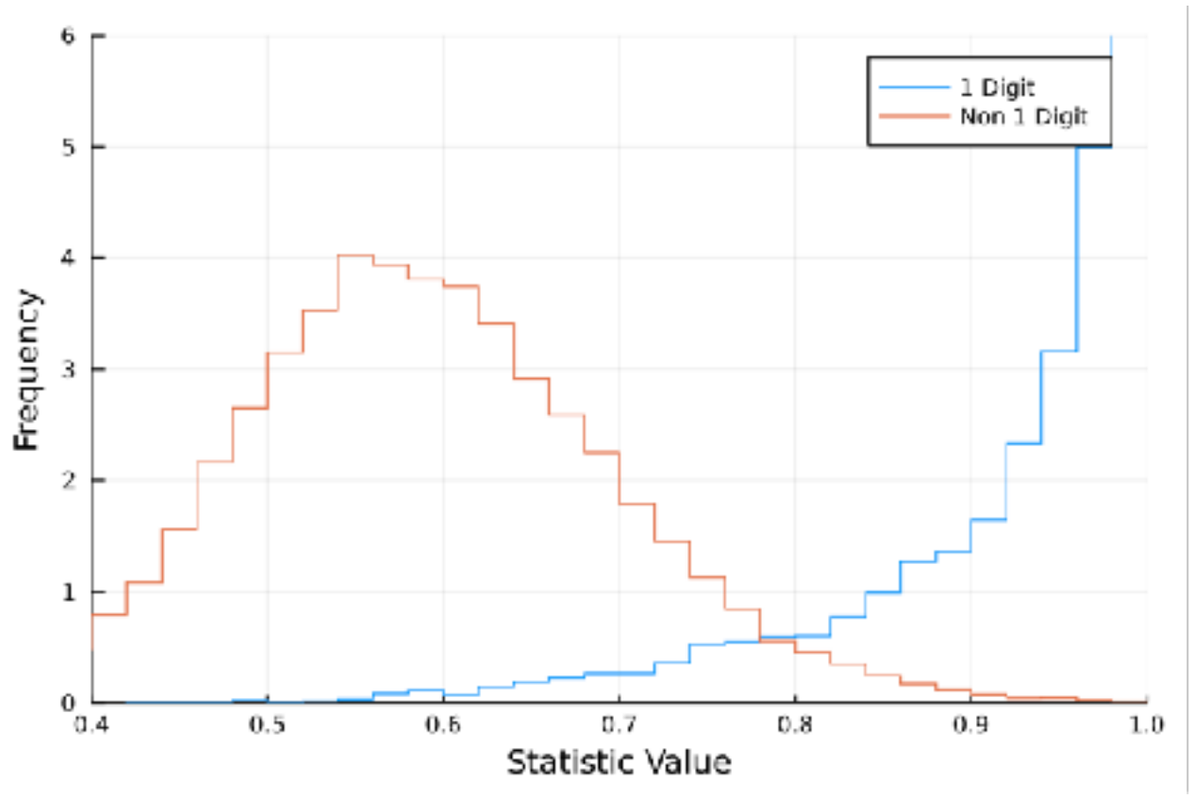
Define a statistic (specific to the digit 1) : Count the proportion of intensity around the peak per row:

$$\chi(x) = \frac{\sum_{i=1}^{28} \sum_{k=-2}^{2} x_{i,m(x,i)+k}}{\sum_{i=1}^{28} \sum_{j=1}^{28} x_{i,j}}, \quad \text{where} \quad m(x,i) = \text{argmax}_{j=1,\ldots,28}\, x_{i,j}$$

A classifier: $$\hat{f}_\theta(x) = \begin{cases} -1 & \chi(x) \le \theta, \\ +1 & \chi(x) > \theta\,. \end{cases}$$

A toy binary classifier digit 1, or not

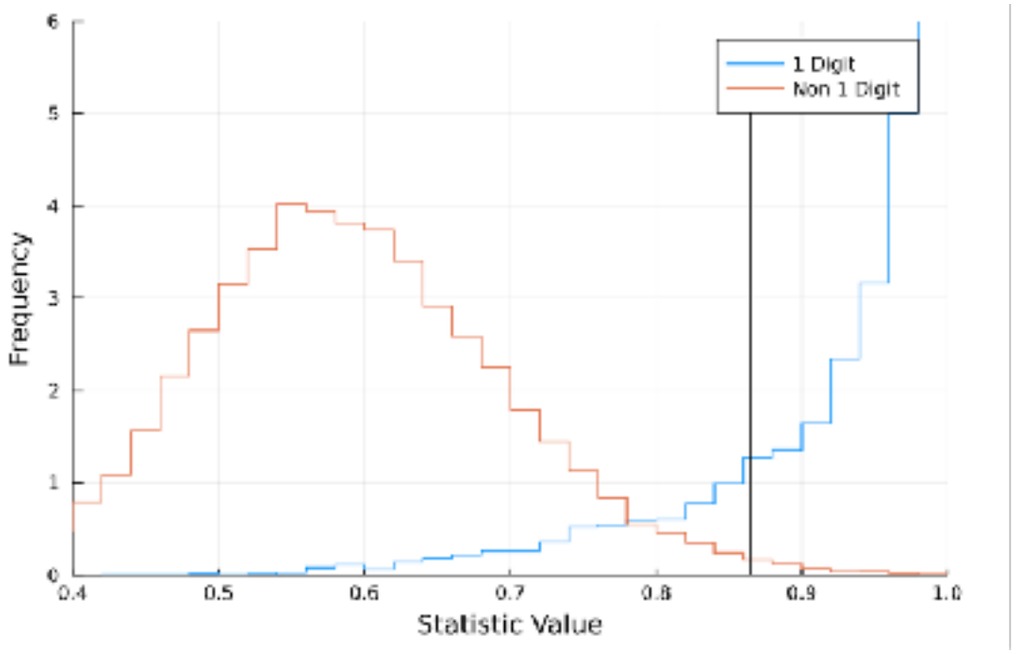
$$\chi(x) = \frac{\sum_{i=1}^{28} \sum_{k=-2}^{2} x_{i,m(x,i)+k}}{\sum_{i=1}^{28} \sum_{j=1}^{28} x_{i,j}}, \quad \text{where} \quad m(x,i) = \operatorname{argmax}_{j=1,\ldots,28} x_{i,j}$$



$$\hat{f}_\theta(x) = \begin{cases} -1 & \chi(x) \le \theta, \\ +1 & \chi(x) > \theta\,. \end{cases}$$

How to choose the threshold θ?

Say we chose it at $\theta = 0.865$



		Decision	
		Decide -1 (8,916)	Decide $+1$ (1,084)
Reality	Label is -1 (8,865)	True negative (8,781)	False positive (84)
	Label is $+1$ (1,035)	False negative (135)	True Positive (1000)

Say we chose it at $\theta = 0.865$

		Decision	
		Decide -1 (8,916)	Decide $+1$ (1,084)
Reality	Label is -1 (8,865)	True negative (8,781)	False positive (84)
	Label is $+1$ (1,035)	False negative (135)	True Positive (1000)

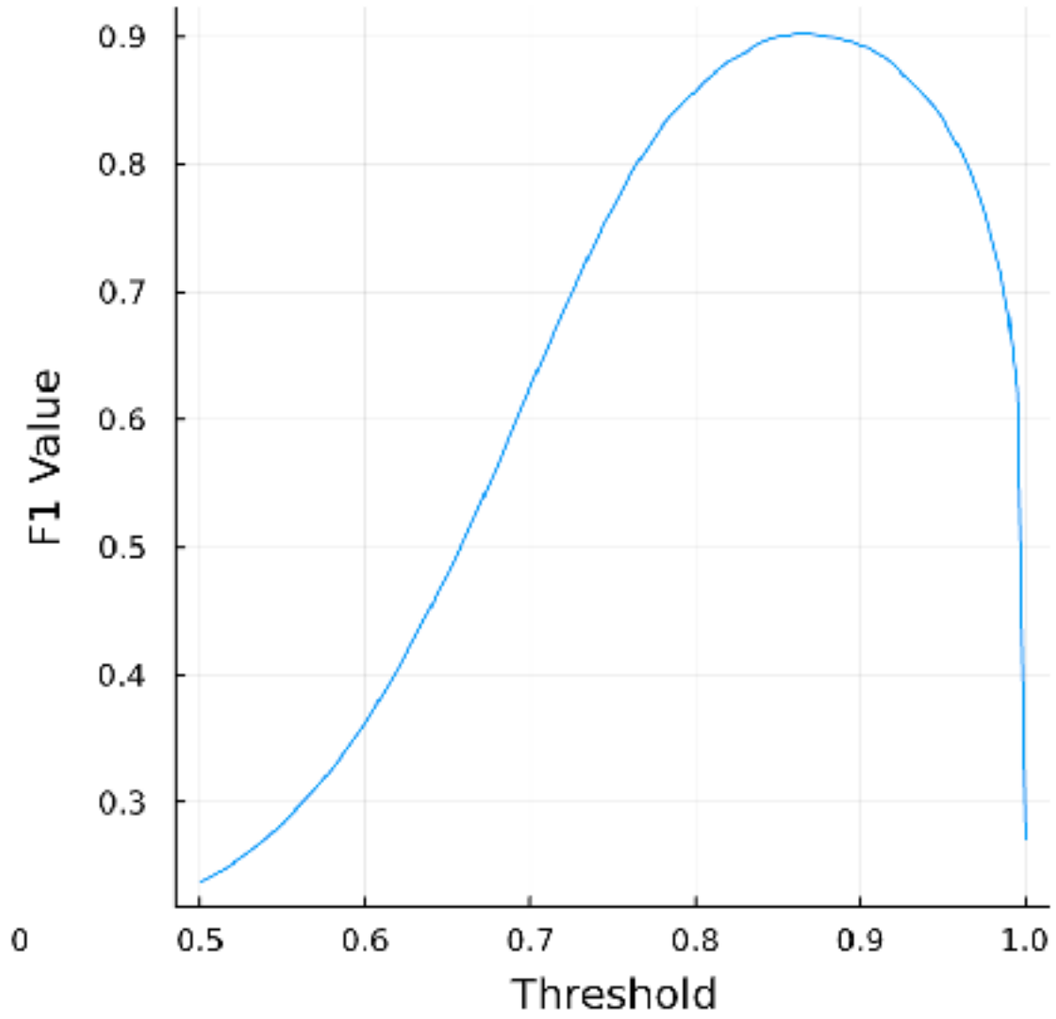
$$\text{Precision} = \frac{|\text{true positive}|}{|\text{true positive}| + |\text{false positive}|}, \qquad \text{Recall} = \frac{|\text{true positive}|}{|\text{true positive}| + |\text{false negative}|}.$$

$$\text{Precision} = \frac{1000}{1000 + 84} = 92.25\%, \qquad \text{Recall} = \frac{1000}{1000 + 135} = 88.11\%.$$

$$F_1 = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = 2\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 90.13\,\%$$

How we chose $\theta = 0.865$

$$F_1 = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = 2\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 90.13\,\%$$



Why not just accuracy?

$$\text{accuracy} = \frac{1}{m}\sum_{i=1}^{m} \mathbf{1}\left\{\hat{f}\left(x^{(i)}\right) = y_i\right\}$$

What can be a problem?

Recap:

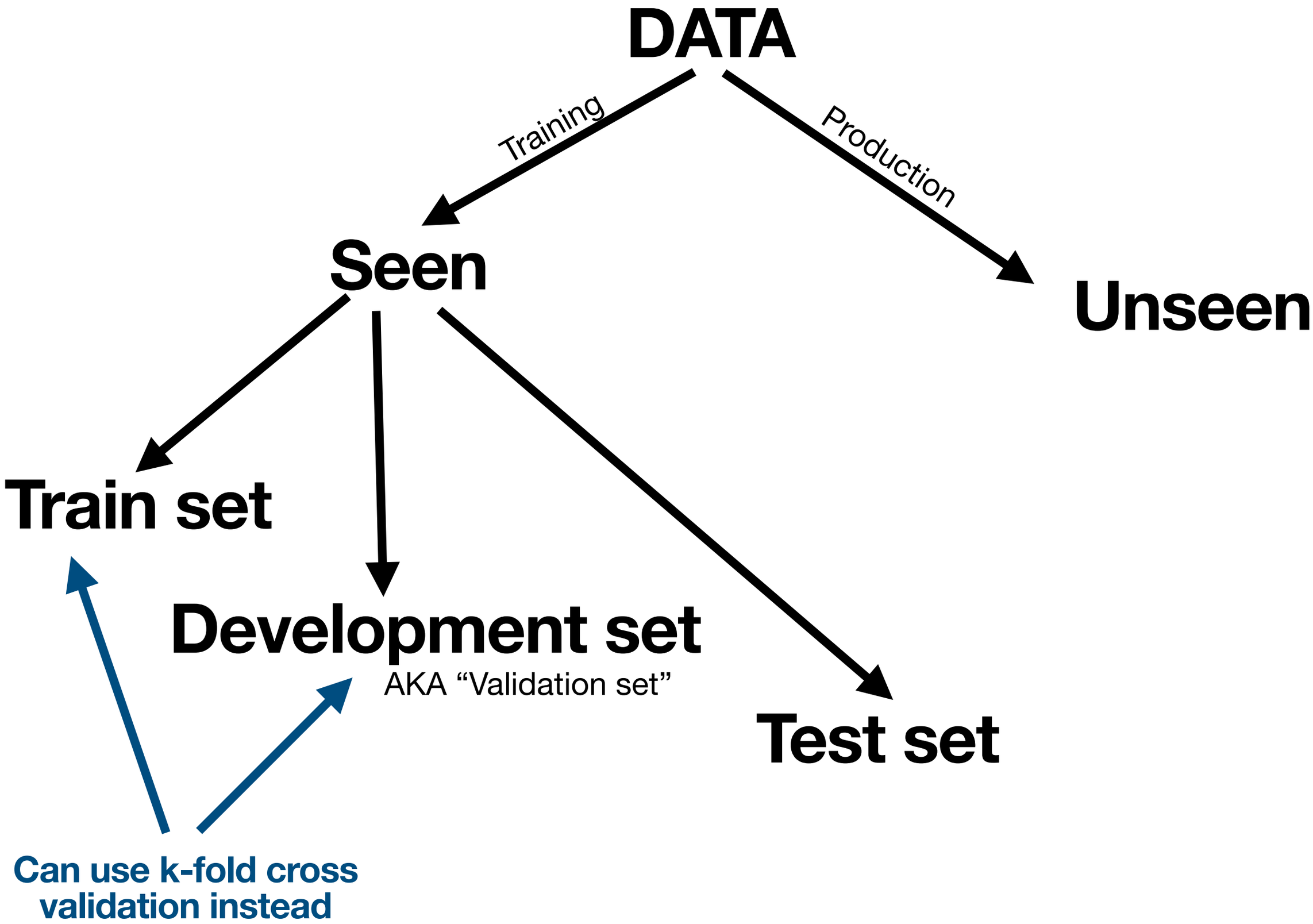
We “learned” the parameter θ

We had some hyper-parameters too:

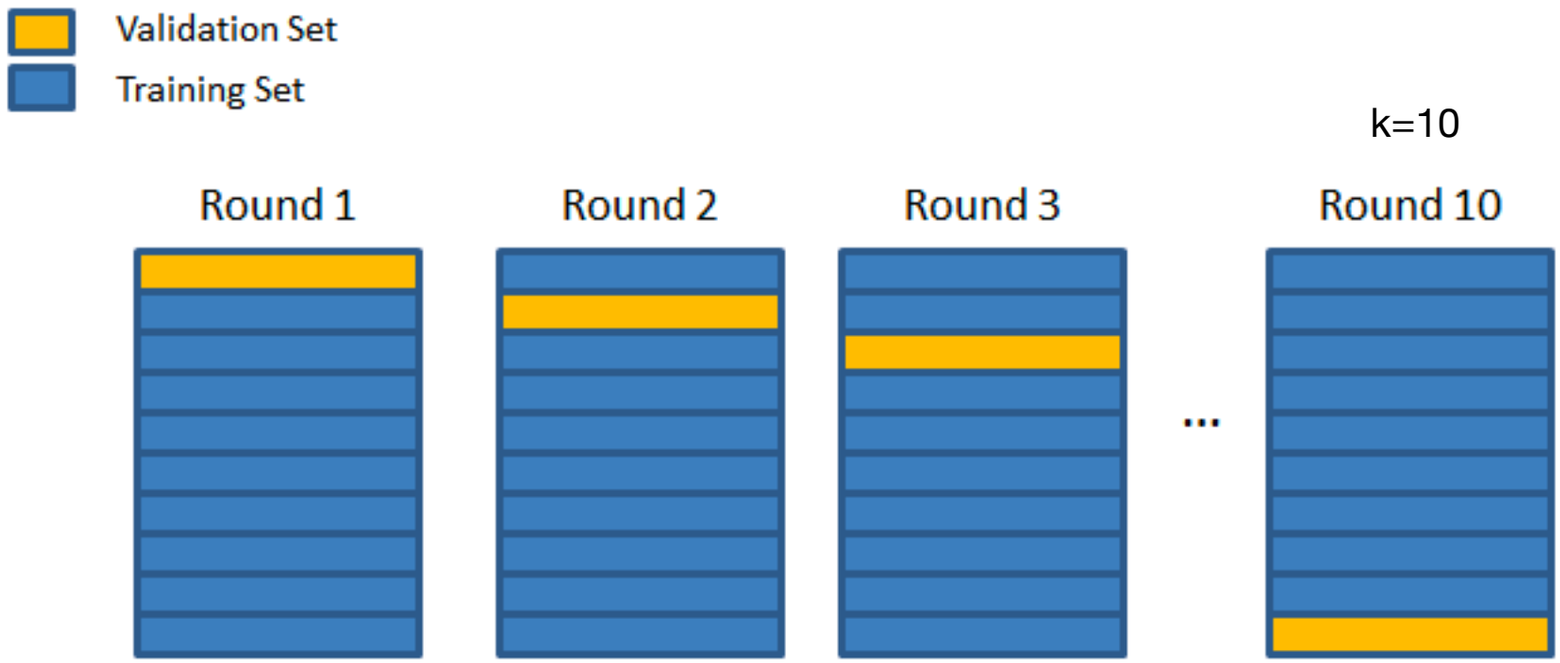
$$\chi(x) = \frac{\sum_{i=1}^{28} \sum_{k=-2}^{2} x_{i,m(x,i)+k}}{\sum_{i=1}^{28} \sum_{j=1}^{28} x_{i,j}}, \quad \text{where} \quad m(x,i) = \text{argmax}_{j=1,\ldots,28}\, x_{i,j}$$

How do we choose hyper-parameters?

How do we test our classifier?

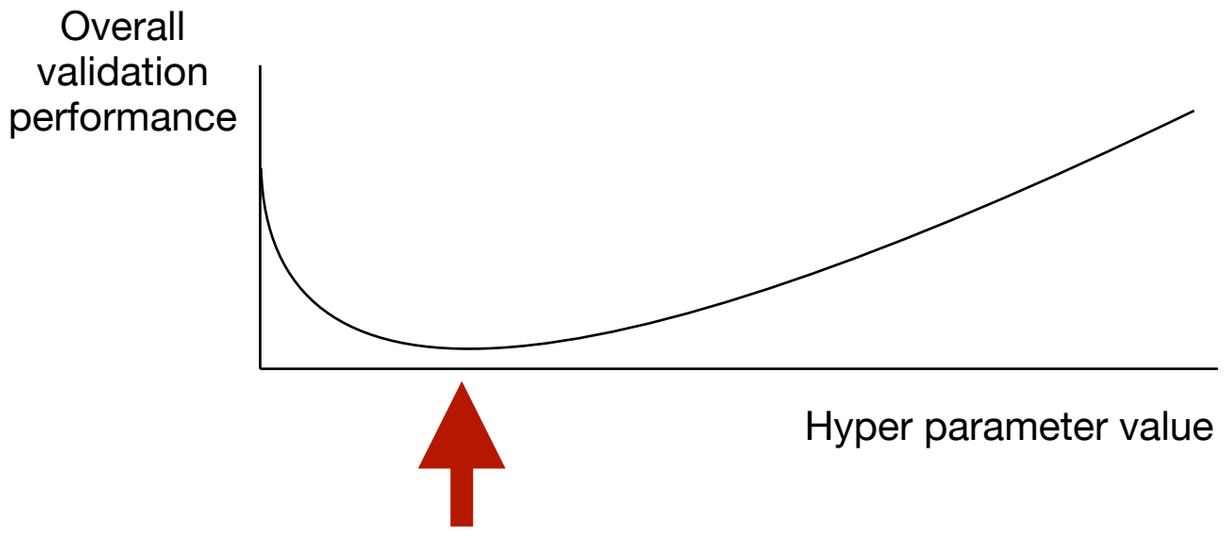

DATA
Training
Production
Seen
Unseen
Train set
Development set
AKA “Validation set”
Test set
Can use k-fold cross validation instead

K-fold cross validation



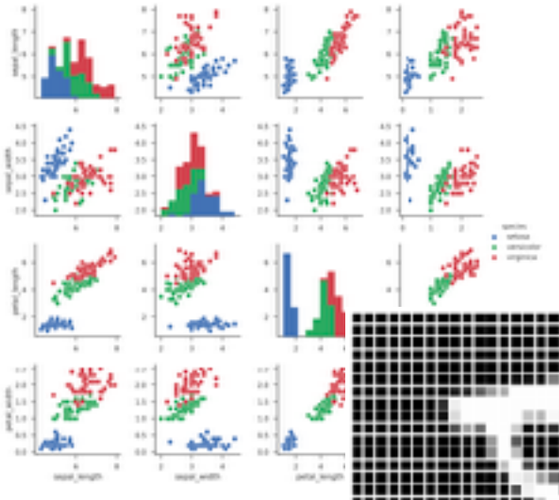
Validation performance:	87.3%	92.5%	91.2%	89.6%

Overall validation performance: mean(87.3, 92.5, 91.2, …. ,89.6)

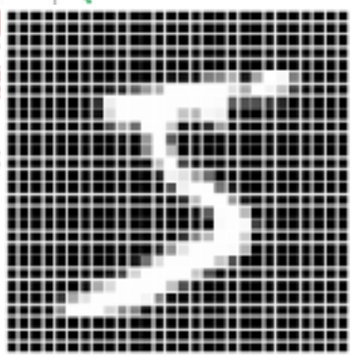


Some more popular “toy” datasets

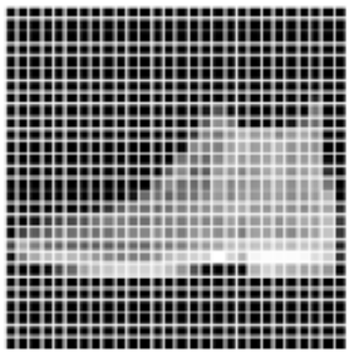
1. Iris Dataset



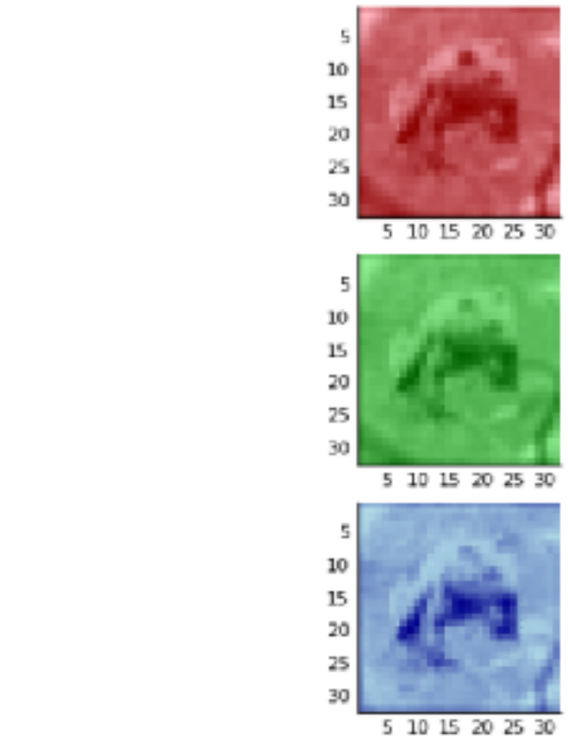
2. MNIST



3. Fashion MNIST



4. CIFAR-10



5. ImageNet

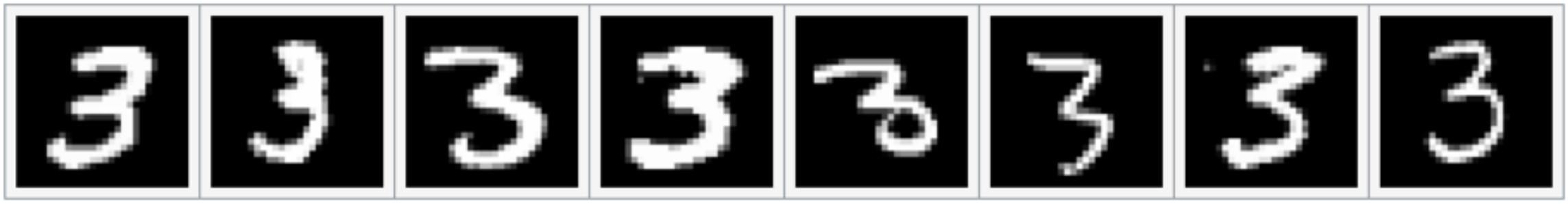
6. Twitter Sentiment Analysis

Part 3: Some tools you know - used for ML

A linear (binary) classifier

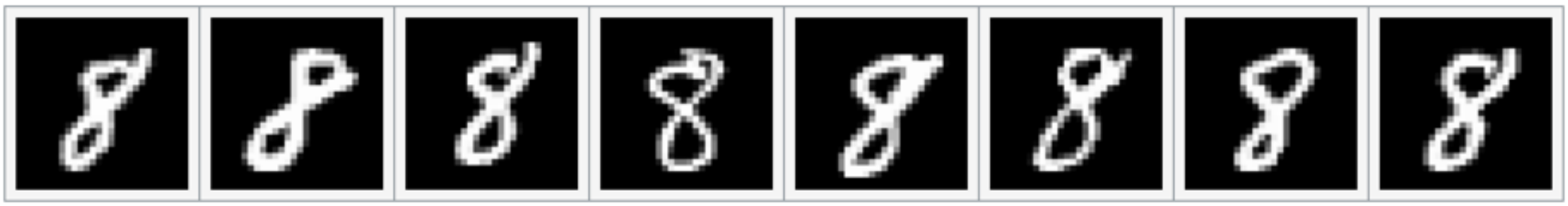
Positive (+1)

```
imgs[labels .== 3][1:8]
```

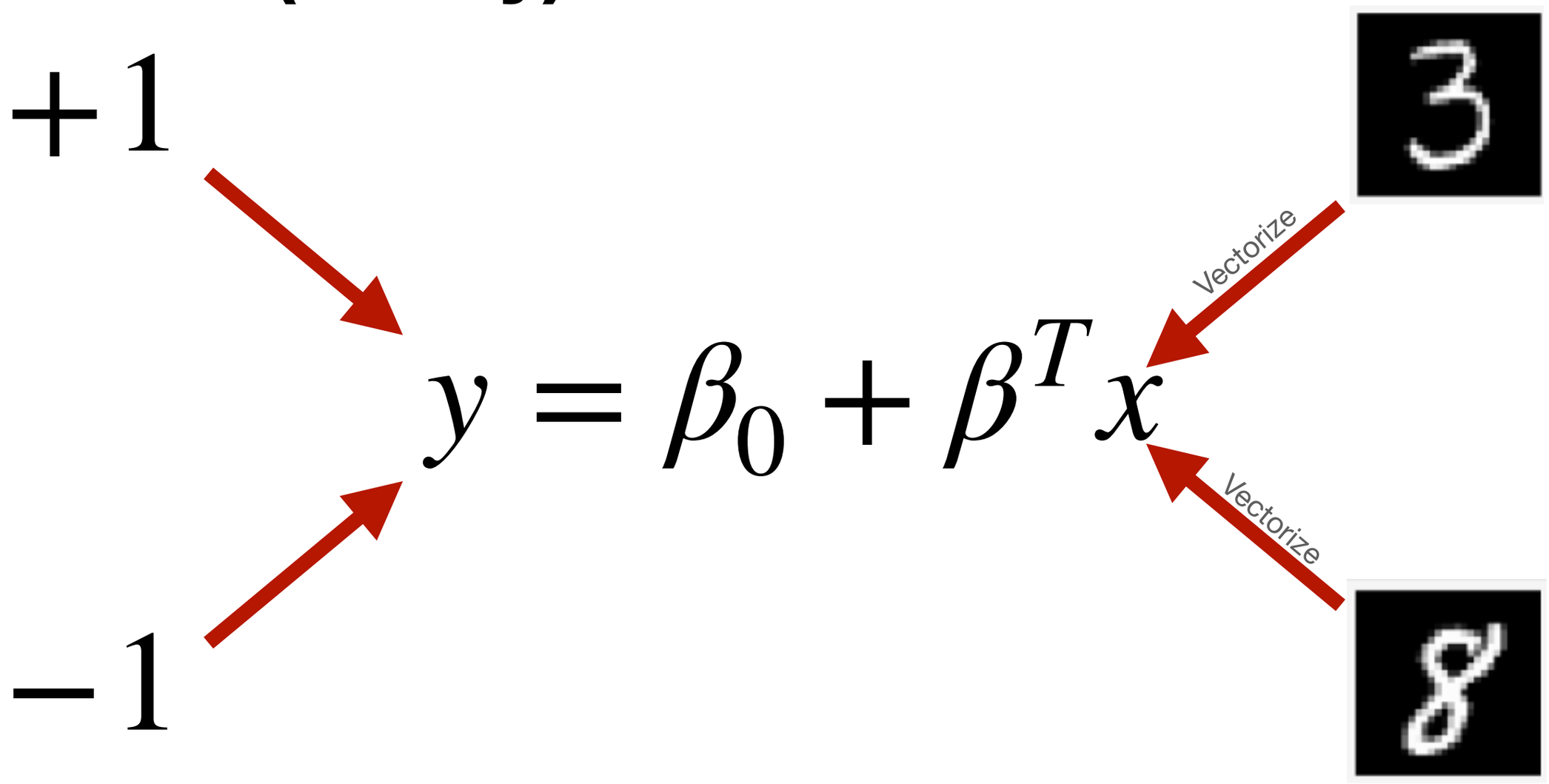


Negative (-1)

```
imgs[labels .== 8][1:8]
```



A linear (binary) classifier



Minimize: $\text{Loss}(x, y) = \sum_{i=1}^{m} (y_i - \beta_0 - \beta^T x_i)^2$

Classifier: $\hat{f}(x) = \text{sign}(\hat{\beta}_0 + \hat{\beta}^T x)$

A linear (binary) classifier

Minimize: $\text{Loss}(x, y) = \sum_{i=1}^{m} (y_i - \beta_0 - \beta^T x_i)^2 = ||y - A\beta||^2$

Sometimes

Option 1: $\hat{\beta} = A^{\dagger} y$ $\qquad A^{\dagger} = (A^T A)^{-1} A^T$

Option 2: $\hat{\beta}(0), \hat{\beta}(1), \hat{\beta}(2), \hat{\beta}(3), \ldots$ With (some form of) gradient descent

$$\hat{\beta}(t+1) = \hat{\beta}(t) - \eta \nabla L\left(\hat{\beta}(t)\right)$$

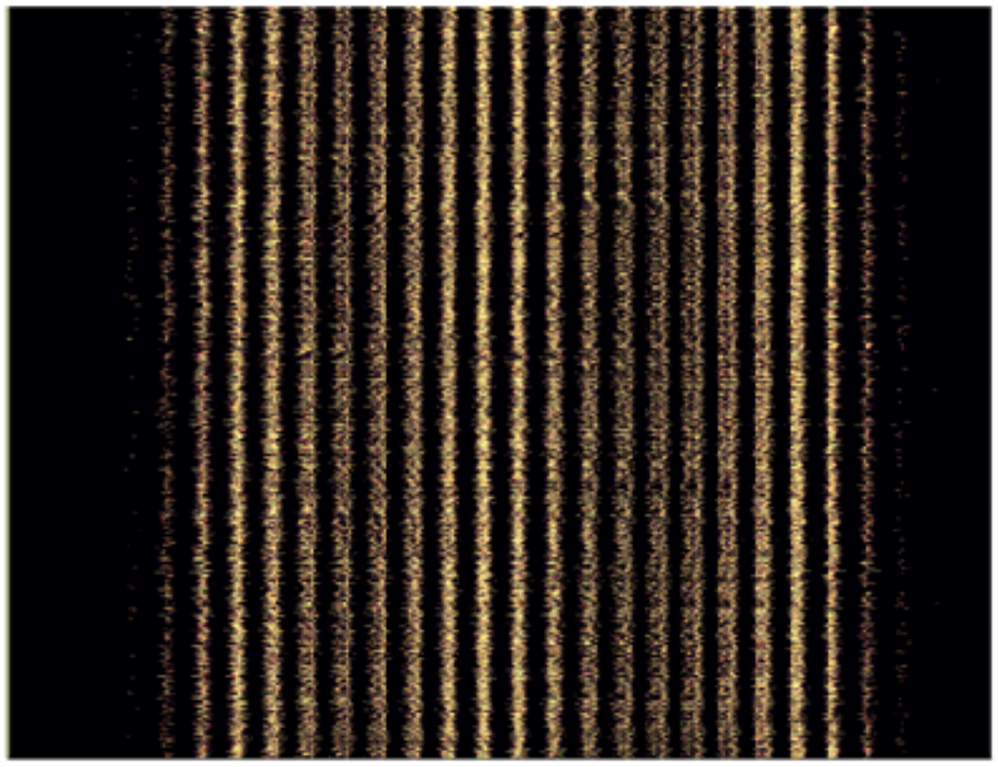
$$\nabla L\left(\beta\right) = 2A^T(A\beta - y)$$

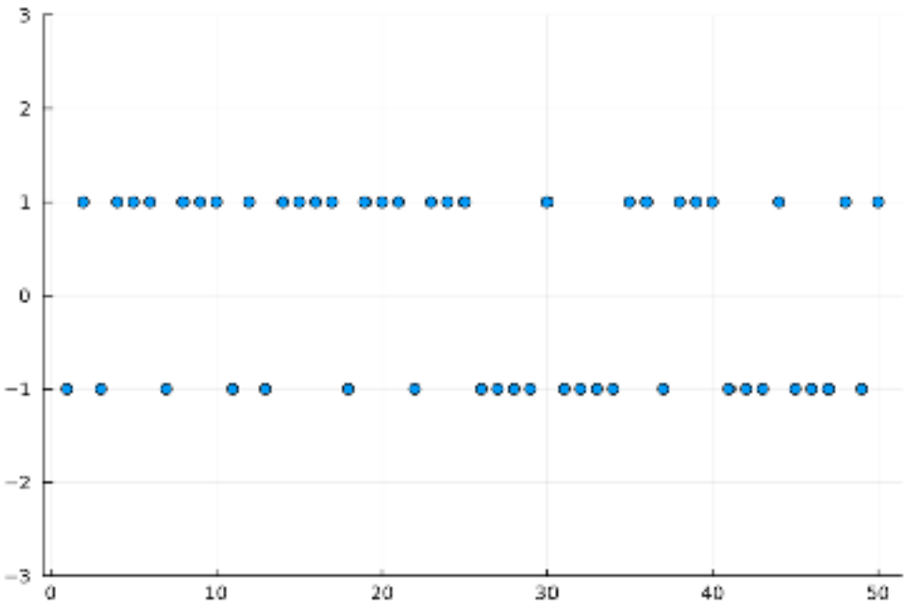
Let’s do it!

Sometimes

Option 1: $\hat{\beta} = A^{\dagger} y$ $\qquad A^{\dagger} = (A^T A)^{-1} A^T$

Option 2: $\hat{\beta}(t+1) = \hat{\beta}(t) - \eta 2 A^T (A\hat{\beta}(t) - y)$

$A =$ 

$y =$ 

$\ldots$

Activity A: MNIST digit classification with least squares

Exercise: Work on these datasets

Task 1a: $\hat{\beta} = A^{\dagger} y$

Task 1b: $\hat{\beta}(t+1) = \hat{\beta}(t) - \eta 2A^{T}(A\hat{\beta}(t) - y)$

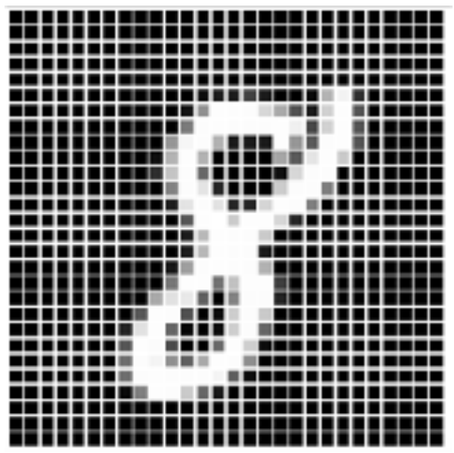
Task 2: Evaluate test accuracy

https://github.com/yoninazarathy/MathematicalEngineeringDeepLearning/blob/master/ML180Minutes/exercise.r

```r
#ML in 180 Minutes group/self exercise...

#Download training design matrix and labels
A <- read.csv(url("https://raw.githubusercontent.com/yoninazarathy/MathematicalEngineeringDeepLearning/master/ML180Minutes/A_3vs8_matrix_train.csv"))
y <- read.csv(url("https://raw.githubusercontent.com/yoninazarathy/MathematicalEngineeringDeepLearning/master/ML180Minutes/y_3vs8_vector_train.csv"))

#Download testing design matrix (each row is an image) for the digit "3" (positive)
A3test <- read.csv(url("https://raw.githubusercontent.com/yoninazarathy/MathematicalEngineeringDeepLearning/master/ML180Minutes/A_3_test.csv"))

#Download testing design matrix (each row is an image) for the digit "8" (negative)
A8test <- read.csv(url("https://raw.githubusercontent.com/yoninazarathy/MathematicalEngineeringDeepLearning/master/ML180Minutes/A_8_test.csv"))

#Task 1: Finding the least squares beta based on A and y.
  #Taks 1a: Do this via the pseudoinverse, or GLM, or similar.
  #Task 1b: Do this via an iterative gradient descent implementation
#Task 2: Evaluate the accuracy of the estimator(s) from task 1 on the accuracy
```

Multi-class: One vs. rest

```
using Flux.Data.MNIST, PyPlot, LinearAlgebra
using Flux: onehotbatch

imgs   = MNIST.images()
labels = MNIST.labels()
nTrain = length(imgs)

trainData = vcat([hcat(float.(imgs[i])...) for i in 1:nTrain]...);
trainLabels = labels[1:nTrain];

testImgs = MNIST.images(:test)
testLabels = MNIST.labels(:test)
nTest = length(testImgs)

testData = vcat([hcat(float.(testImgs[i])...) for i in 1:nTest]...);

A = [ones(nTrain) trainData];
Adag = pinv(A);
tfPM(x) = x ? +1 : -1
yDat(k) = tfPM.(onehotbatch(trainLabels,0:9)'[:,k+1])
bets = [Adag*yDat(k) for k in 0:9];

classify(input) = findmax([([1 ; input])'*bets[k] for k in 1:10])[2]-1

predictions = [classify(testData[k,:]) for k in 1:nTest]
confusionMatrix = [sum((predictions .== i) .& (testLabels .== j))
                   for i in 0:9, j in 0:9]
accuracy = 100*sum(diag(confusionMatrix))/nTest

println("Accuracy: ", accuracy,"%")
confusionMatrix
```



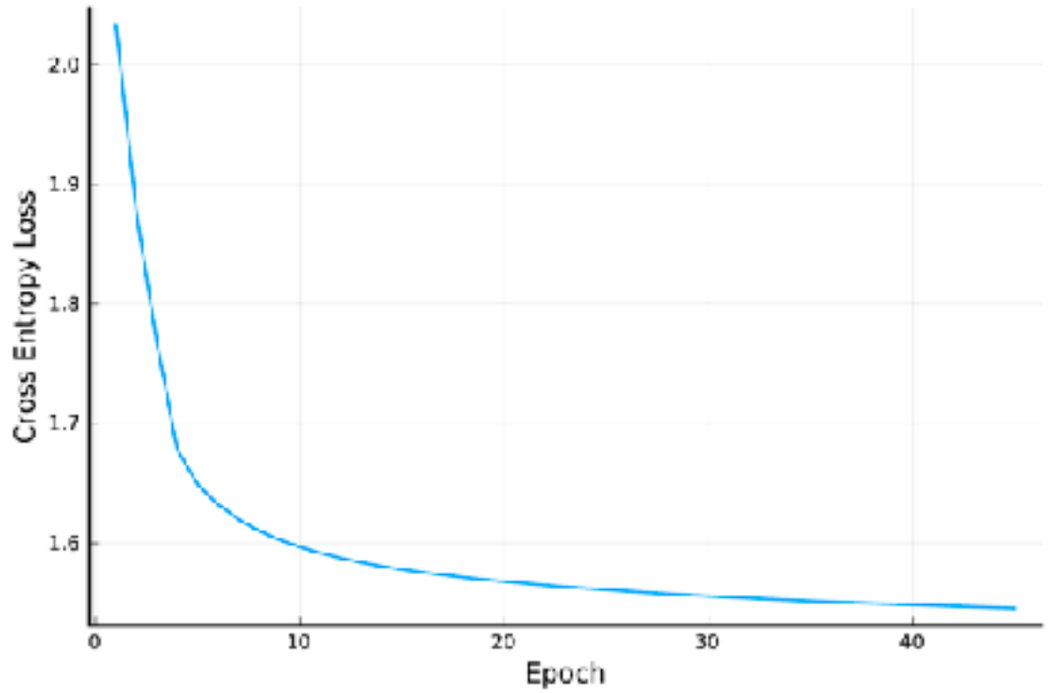
```
Accuracy: 86.03%

10×10 Array{Int64,2}:
 944     0    18     4     0    23    18     5    14    15
   0  1107    54    17    22    18    10    40    46    11
   1     2   813    23     6     3     9    16    11     2
   2     2    26   880     1    72     0     6    30    17
   2     3    15     5   881    24    22    26    27    80
   7     1     0    17     5   659    17     0    40     1
  14     5    42     9    10    23   875     1    15     1
   2     1    22    21     2    14     0   884    12    77
   7    14    37    22    11    39     7     0   759     4
   1     0     5    12    44    17     0    50    20   801
```

Basic statistics
(least squares/regression)

Logistic softmax regression

$$\sigma(u) = \frac{1}{1+e^{-u}} = \frac{e^u}{e^u+1}$$

$$\hat{y}(\tilde{x}) = \text{argmax}_{\ell=0,\ldots,9}\ \sigma(w^{(\ell)} \cdot \tilde{x} + b^{(\ell)}).$$



$$s(z) = \frac{1}{\sum_{j=1}^{K} e^{z_j}} \begin{bmatrix} e^{z_1} & e^{z_2} & \ldots & e^{z_K} \end{bmatrix}^T$$

$$\hat{y}(\tilde{x}) = \text{argmax}_{\ell=0,\ldots,9}\ s_\ell\left(W\tilde{x} + b\right)$$

Cross Entropy Loss: $-\sum_{i=1}^{n} \log(\hat{y}_{y_i+1})$

Part 4: A walk in the random forest

Random forest is a very “generic” algorithm

```
using Flux.Data.MNIST, DecisionTree, Random
Random.seed!(0)

trainImgs   = MNIST.images()
trainLabels = MNIST.labels()
nTrain = length(trainImgs)
trainData = vcat([hcat(float.(trainImgs[i])...) for i in 1:nTrain]...)

testImgs = MNIST.images(:test)
testLabels = MNIST.labels(:test)
nTest = length(testImgs)
testData = vcat([hcat(float.(testImgs[i])...) for i in 1:nTest]...)

numFeaturesPerTree = 10
numTrees = 40
portionSamplesPerTree = 0.7
maxTreeDepth = 10

model = build_forest(trainLabels, trainData,
                     numFeaturesPerTree, numTrees,
                     portionSamplesPerTree, maxTreeDepth)
println("Trained model:")
println(model)

predicted_labels = [apply_forest(model, testData[k,:]) for k in 1:nTest]
accuracy = sum(predicted_labels .== testLabels)/nTest
println("\nPrediction accuracy (measured on test set of size $nTest): ",accuracy)
```

```
Trained model:
Ensemble of Decision Trees
Trees:      40
Avg Leaves: 860.525
Avg Depth:  10.0

Prediction accuracy (measured on test set of size 10000): 0.9377
```

Activity B: MNIST digit classification with random forests

Part 5: Going Deep

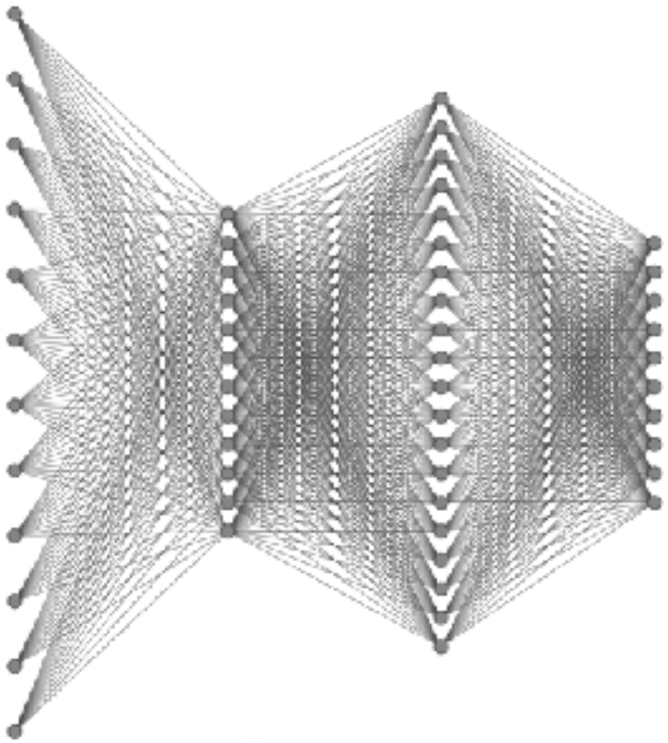
A Deep Neural Network is just a bit more than a linear model…

$\rho_i(\,\cdot\,) \equiv$ Activation function

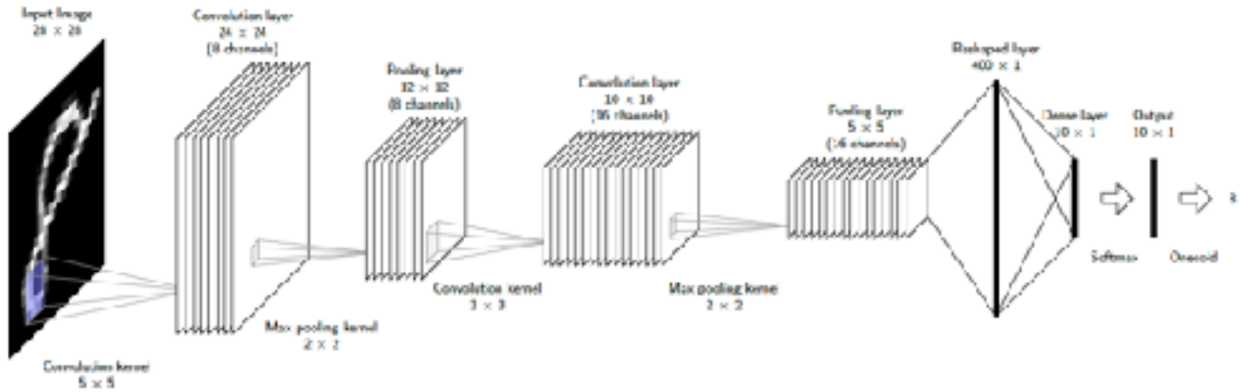
$$\tilde{f}(x) = s\Big(A_3\ \rho_2\big(A_2\ \underbrace{\rho_1\big(A_1\overbrace{x}^{\text{Input layer}} + b_1\big)}_{\text{First hidden layer}} + b_2\big) + b_3\Big)\,.$$

$$\underbrace{\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad}_{\text{Second hidden layer}}$$

$$\underbrace{\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad}_{\text{Output layer}}$$



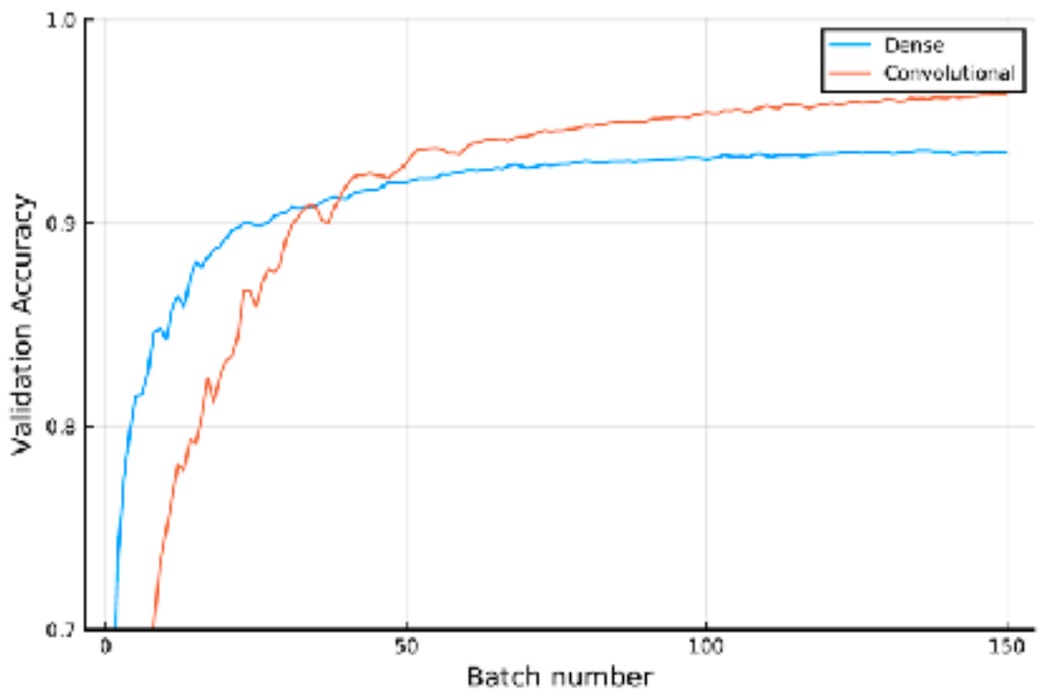
Dense



Convolutional

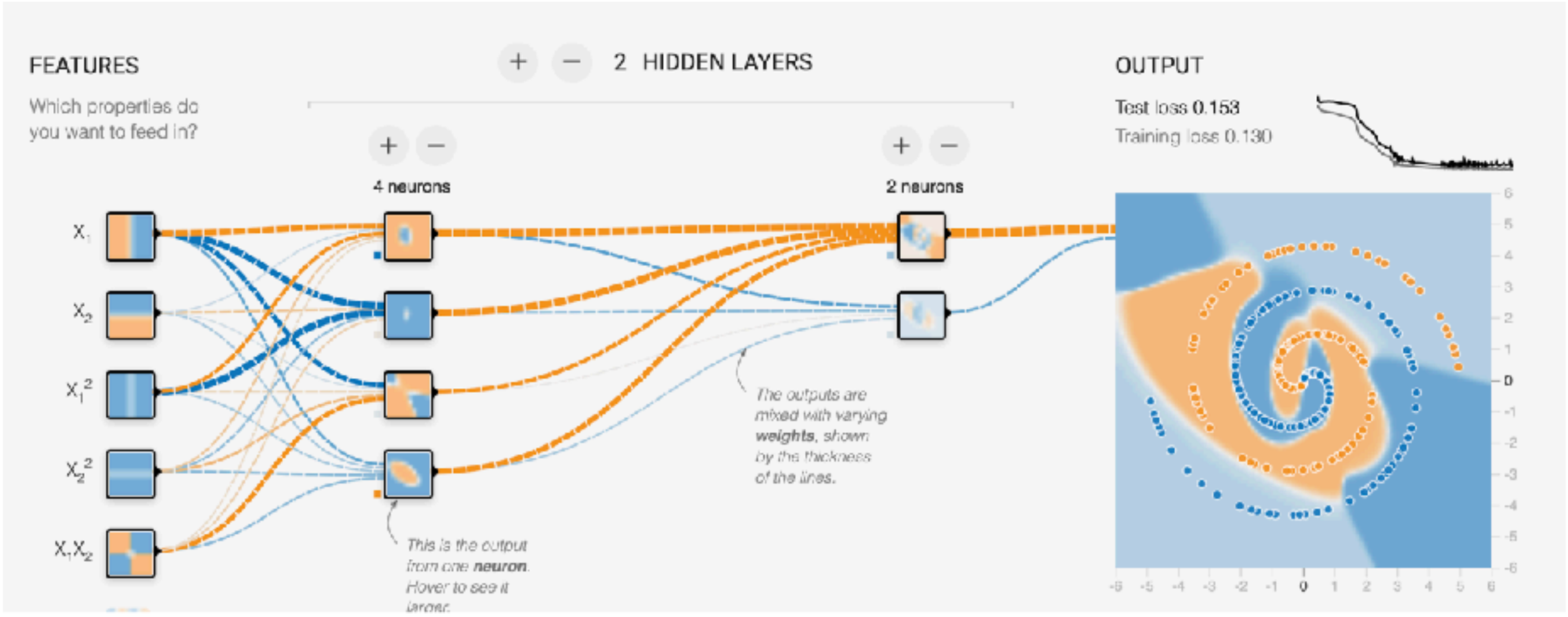
Training two neural network variants

```
using Flux, Flux.Data.MNIST, Statistics, Random, Plots
using Flux: onehotbatch, onecold, crossentropy, flatten
Random.seed!(0)

epochs = 30
eta = 5e-3
batchSize = 1000
trainRange, validateRange = 1:5000, 5001:10000

function minibatch(x, y, indexRange)
    xBatch = Array{Float32}(undef, size(x[1])..., 1, length(indexRange))
    for i in 1:length(indexRange)
        xBatch[:, :, :, i] = Float32.(x[indexRange[i]])
    end
    return (xBatch, onehotbatch(y[indexRange], 0:9))
end

trainLabels = MNIST.labels()[trainRange]
trainImgs = MNIST.images()[trainRange]
mbIdxs = Iterators.partition(1:length(trainImgs), batchSize)
trainSet = [minibatch(trainImgs, trainLabels, bi) for bi in mbIdxs]

validateLabels = MNIST.labels()[validateRange]
validateImgs = MNIST.images()[validateRange]
validateSet = minibatch(validateImgs, validateLabels, 1:length(validateImgs))

model1= Chain(flatten, Dense(784, 200,relu),Dense(200, 100,tanh),
              Dense(100, 10,sigmoid), softmax)

model2= Chain(Conv([5, 5], 1=>8, relu), MaxPool([2,2]),
              Conv([3, 3], 8=>16, relu), MaxPool((2,2)),
              flatten, Dense(400, 10), softmax)

opt1 = ADAM(eta); opt2 = ADAM(eta)
accuracyPaths = [[],[]]
accuracy(x, y, model) = mean(onecold(model(x)) .== onecold(y))
loss(x, y, model) = crossentropy(model(x), y)
cbF1() = push!(accuracyPaths[1],accuracy(validateSet..., model1))
cbF2() = push!(accuracyPaths[2],accuracy(validateSet..., model2))

model1(trainSet[1][1]); model2(trainSet[1][1])
for _ in 1:epochs
    Flux.train!((x,y)->loss(x,y,model1), params(model1), trainSet, opt1, cb=cbF1)
    Flux.train!((x,y)->loss(x,y,model2), params(model2), trainSet, opt2, cb=cbF2)
    print(".")
end

println("\nModel1 (Dense) accuracy = ", accuracy(validateSet..., model1))
println("Model2 (Convolutional) accuracy = ", accuracy(validateSet..., model2))
plot(accuracyPaths,label = ["Dense" "Convolutional"],
    ylim=(0.7,1.0), xlabel="Batch number", ylabel = "Validation Accuracy")
```



Activity C: Google Tensor flow Playground

https://playground.tensorflow.org/



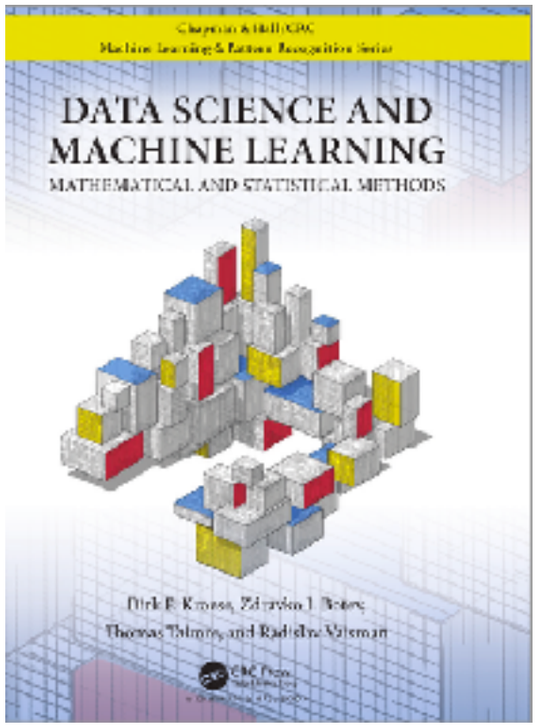
Activity D: MNIST Digit Classification with dense NN

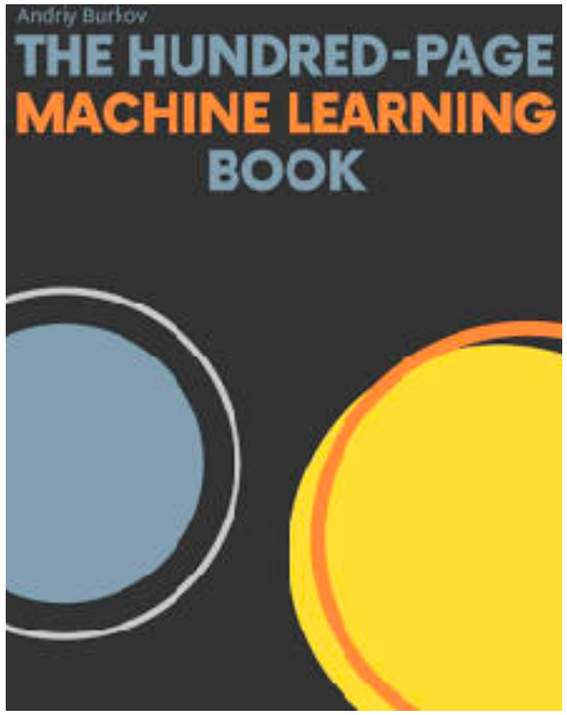
Activity E: MNIST Digit Classification with conv NN

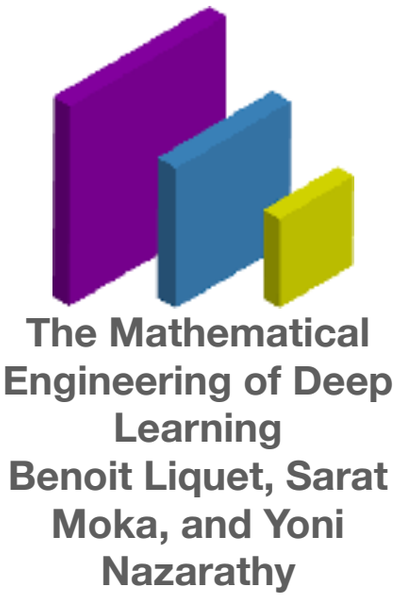
Activity F: CIFAR10 Digit Classification with conv NN

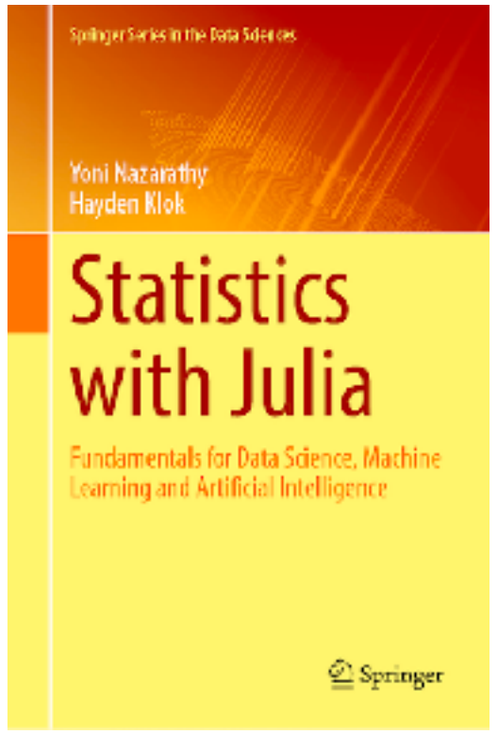
Closing

Some resources









https://people.smp.uq.edu.au/DirkKroese/DSML/

http://themlbook.com/

https://deeplearningmath.org/

https://statisticswithjulia.org/