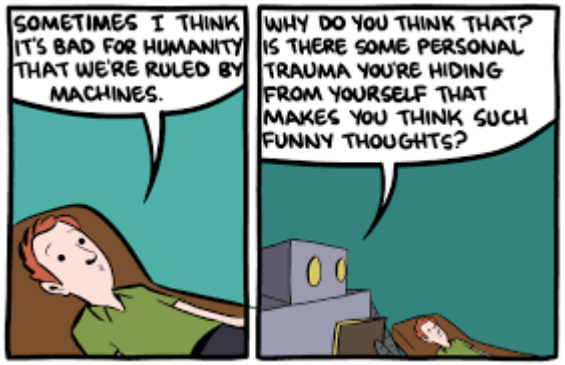
Artificial Intelligence:

welcoming our new robot overlords

Thomas Britton

Sept 2019



Driven by Laziness

Artificial Intelligence

"This work is really tedious, yet requires a lot of troubleshooting and problem solving. Maybe I can get a machine to do it for me."

Machine Learning

"It's really difficult to program this computer to understand what I need it to do. Maybe it can teach itself how to do it, if I can help it along by distilling the data into the meaningful examples and exposing enough of these examples to the computer.

Deep Learning

"I don't know the best way to distill the data into meaningful examples. Maybe if I can give it TONS of data, it can figure out what's important from the data without my help.

Adopted from: https://medium.com/eliza-effect/ai-ml-and-deep-learning-whats-the-difference-ba6bb2223589

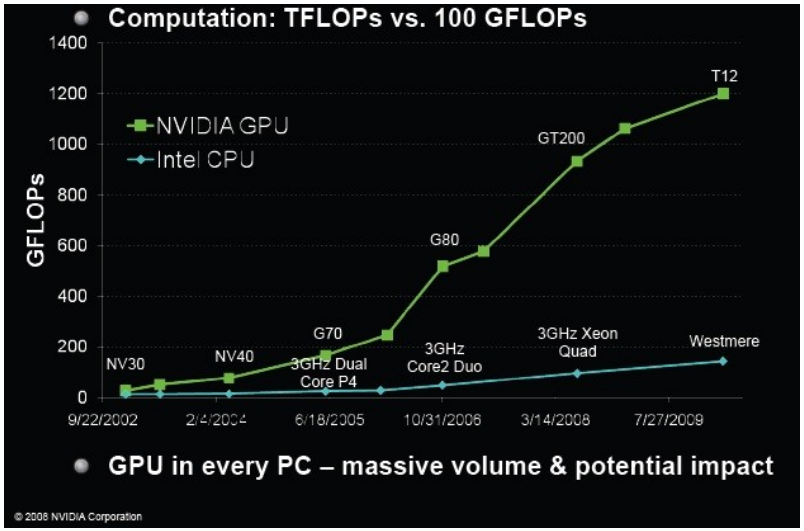
Brenda Ng

Brief History

- 1956
  - “Artificial Intelligence” coined at a conference
  - One attendee: "Within a generation [...] the problem of creating 'artificial intelligence' will substantially be solved," Minsky
  - The first “A.I. Winter” 1974-1980 after interest declines due in part to a lack of progress
- 1980s
  - Resurgence in interest
  - Second A.I. Winter 1987-1993, thanks in part to market collapse of general purpose computers

Brief History (cont.)

- In the late 90s there were notable achievements in A.I. (e.g. Deep Blue)
  - Then the dotcom bubble popped…
    - AI continued on thanks in part to rapid developments in hardware
- Late 2000s and beyond
  - Rapid power increase
  - Watson (Jeopardy! 2011)
  - AlphaGo (Go 2015)
  - DeepMind (Starcraft 2019)



Why Now?

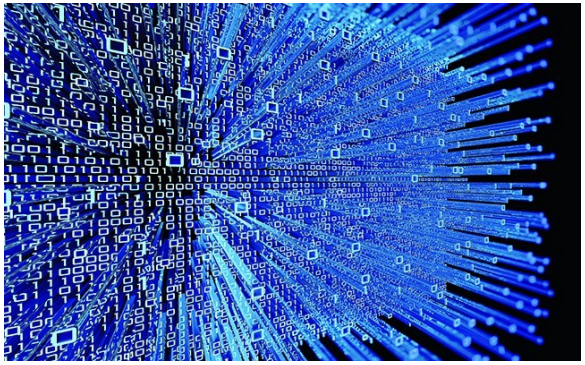
- We have the hardware
  - Even consumer grade components have the power

- We have the software
  - High level APIs are enabling even hobbyists to play with A.I.

PYTORCH

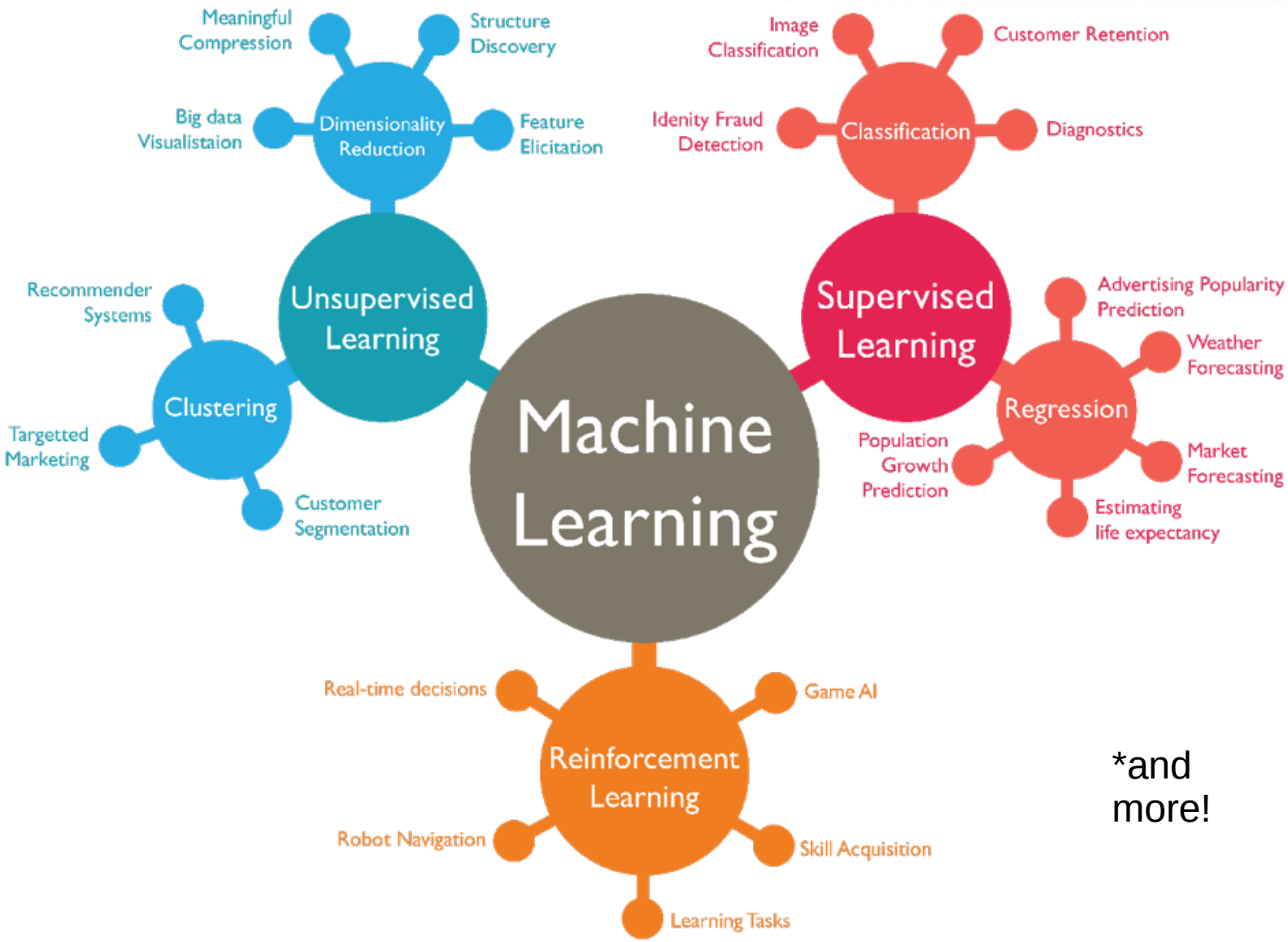
TensorFlow

Keras



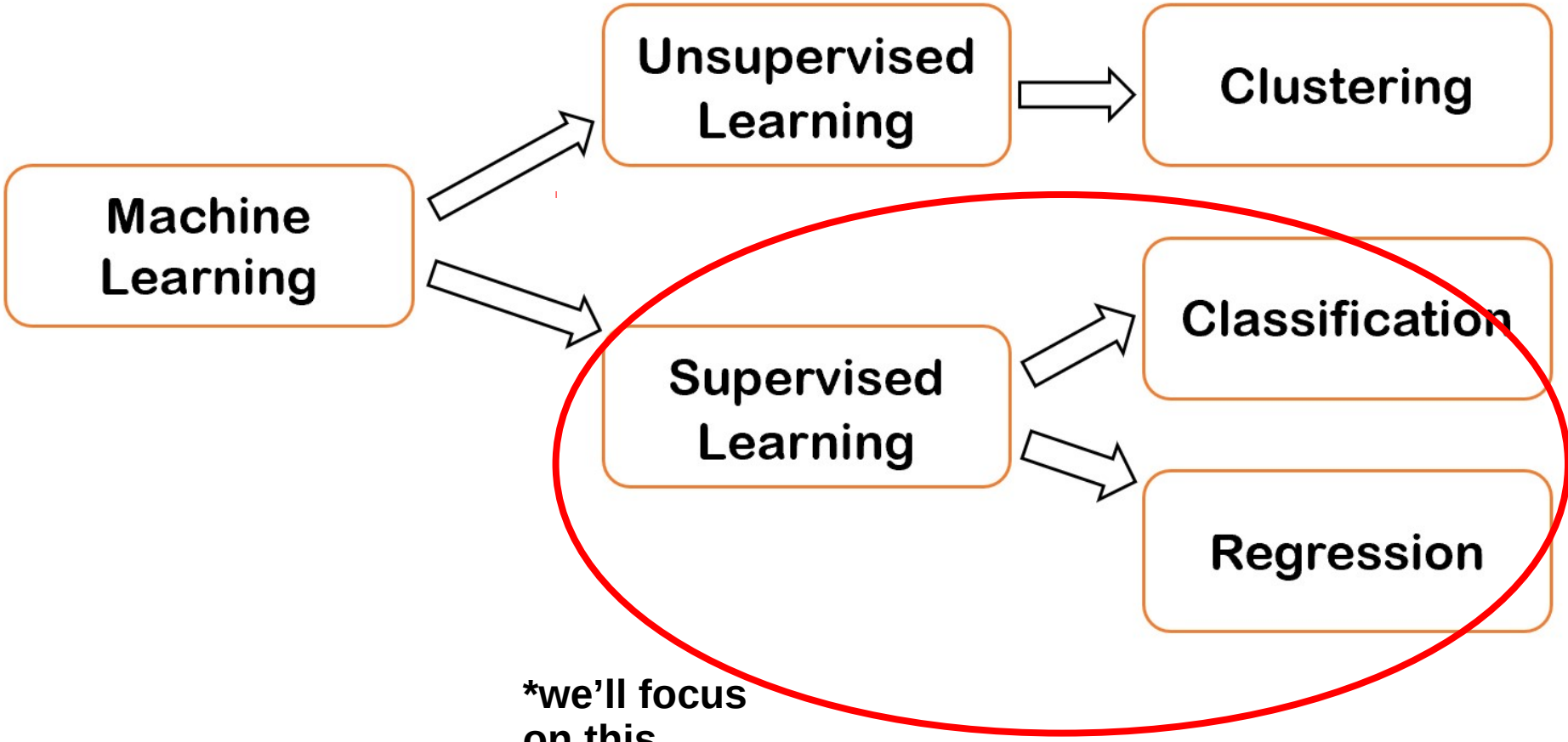
- We have the data!

Machine Learning Flavors



*and more!

Learning Types



***we'll focus on this branch**

Learning Types

Machine Learning

Clustering

Classification

Regression

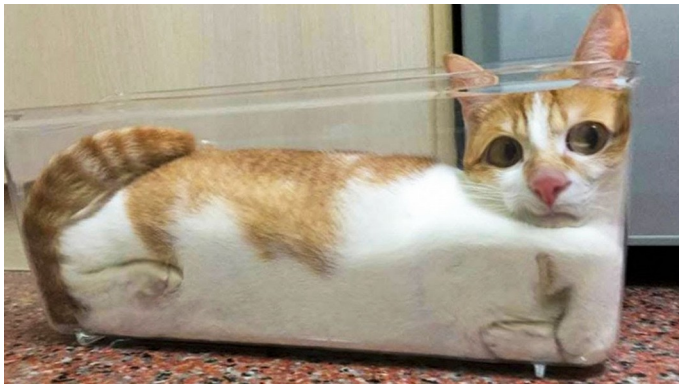
Supervised Learning

- You need a set of labeled data
  - The more examples the better

- Show the child an example from the set and tell it the label. Hopefully, in time, it begins to learn the relationship between input and output.
  - Each pass through these sets is an **epoch**

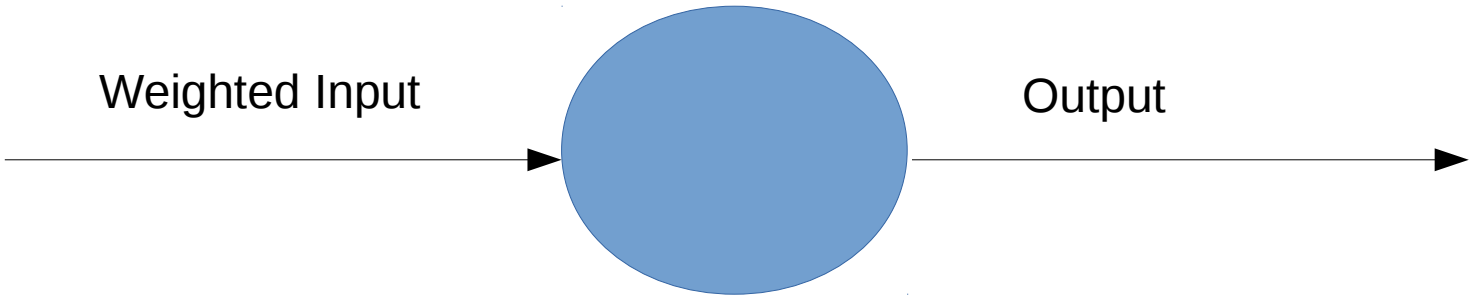
Supervised Learning

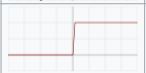
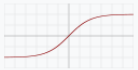
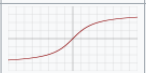
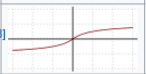
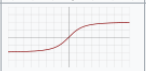
- Me: “What animal is this?”
- Declan: “Cat”
- Me: “Yeah! That’s right!”
- Me: “What’s this one?”
- Declan: “ummmm…Dog!”
- Me: “Noooooo….that’s a cat!”



Thanks to r/aww for the labeled data set

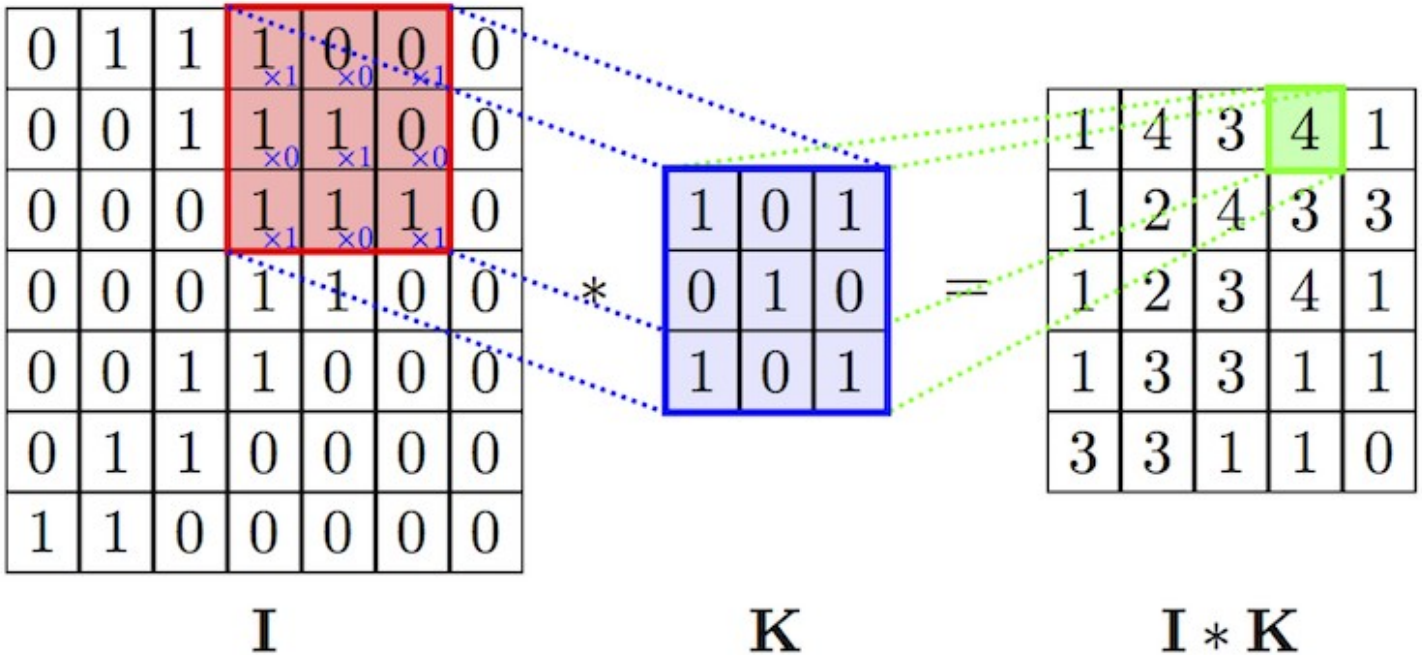
Anatomy of a Neuron



		Activation function			
Identity					
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$	$\{0, 1\}$	C^{-1}
Logistic (a.k.a. Sigmoid or Soft step)		$f(x) = \sigma(x) = \frac{1}{1+e^{-x}}$ [1]	$f'(x) = f(x)(1 - f(x))$	$(0, 1)$	C^{∞}
TanH		$f(x) = \tanh(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})}$	$f'(x) = 1 - f(x)^2$	$(-1, 1)$	C^{∞}
SQNL[9]		$f(x) = \begin{cases} 1 & : x > 2.0 \\ x - \frac{x^2}{4} & : 0 \leq x \leq 2.0 \\ x + \frac{x^2}{4} & : -2.0 \leq x < 0 \\ -1 & : x < -2.0 \end{cases}$	$f'(x) = 1 \mp \frac{x}{2}$	$(-1, 1)$	C^2
ArcTan		$f(x) = \tan^{-1}(x)$	$f'(x) = \frac{1}{x^2+1}$	$\left(-\frac{\pi}{2}, \frac{\pi}{2}\right)$	C^{∞}
ArSinH		$f(x) = \sinh^{-1}(x) = \ln\left(x + \sqrt{x^2+1}\right)$	$f'(x) = \frac{1}{\sqrt{x^2+1}}$	$(-\infty, \infty)$	C^{∞}
ElliotSig[10][11][9] Softsign[12][13]		$f(x) = \frac{x}{1+\lvert x\rvert}$	$f'(x) = \frac{1}{(1+\lvert x\rvert)^2}$	$(-1, 1)$	C^1
Inverse square root unit (ISRU)[14]		$f(x) = \frac{x}{\sqrt{1+\alpha x^2}}$	$f'(x) = \left(\frac{1}{\sqrt{1+\alpha x^2}}\right)^3$	$\left(-\frac{1}{\sqrt{\alpha}}, \frac{1}{\sqrt{\alpha}}\right)$	C^{∞}
Inverse square root linear unit (ISRLU)[14]		$f(x) = \begin{cases} \frac{x}{\sqrt{1+\alpha x^2}} & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} \left(\frac{1}{\sqrt{1+\alpha x^2}}\right)^3 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$\left(-\frac{1}{\sqrt{\alpha}}, \infty\right)$	C^2
Rectified linear unit (ReLU)[15]		$f(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ x & \text{for } x > 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ 1 & \text{for } x > 0 \end{cases}$	$[0, \infty)$	C^0

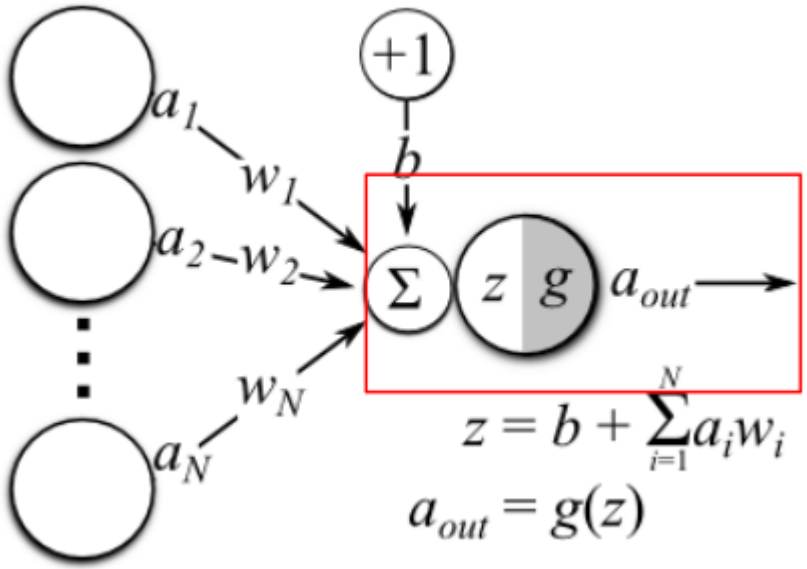
Convolutions (an aside)

- "Kernels" scan over a matrix (images usually)
  - Each kernel runs over the whole image. Computation scales with "image" size, number of parameters does not change.



Multi Layer Perceptron Example

One neuron



1) sum inputs*weights

2)add bias

3)push through non-linearity

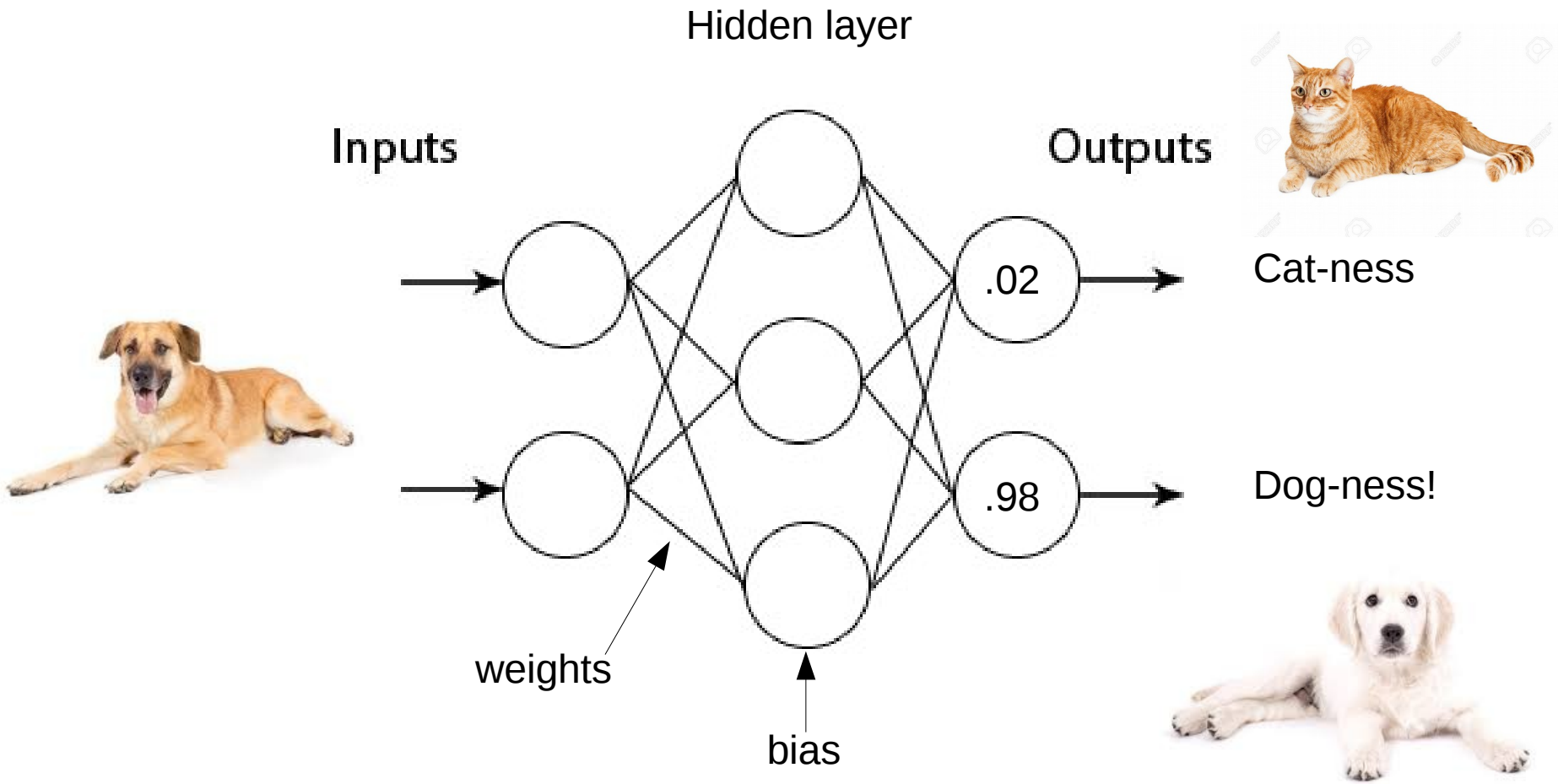
$$\hat{y} = a_{out} = sigmoid(z)$$

$$sigmoid(z) = \frac{1}{1 + e^{-z}}$$

hackernoon

Anatomy of a Model

- A simple model for classification:



Back Propagation

- A “loss” (cost) function is used to compare the model’s output and the target output (label)
  - We try to minimize the loss (or “cost”)
- The gradient of the loss function with respect to any given weight or bias is used to alter the weights and biases.

$$W_{k+1} \leftarrow W_k - \alpha \nabla L(W_k)$$

weight

Loss function

The Long and Short of it

- You are trying to approximate a function
  - The approximate function you learn is built on a series of simpler function

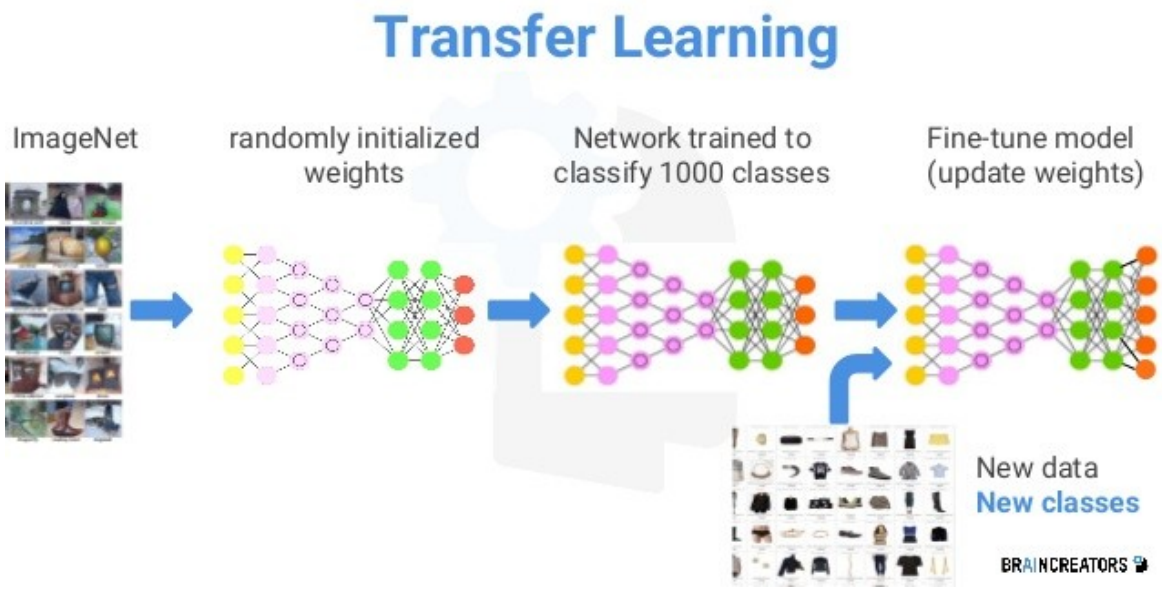
The Universal Approximation Theorem

"a single hidden layer neural network with a linear output unit can approximate any continuous function arbitrarily well, given enough hidden units" -- Hornik, 1991, http://zmjones.com/static/statistical-learning/hornik-nn-1991.pdf

- To "train" a machine you need to update the weights and biases to minimize the difference between the machine's output and the desired output

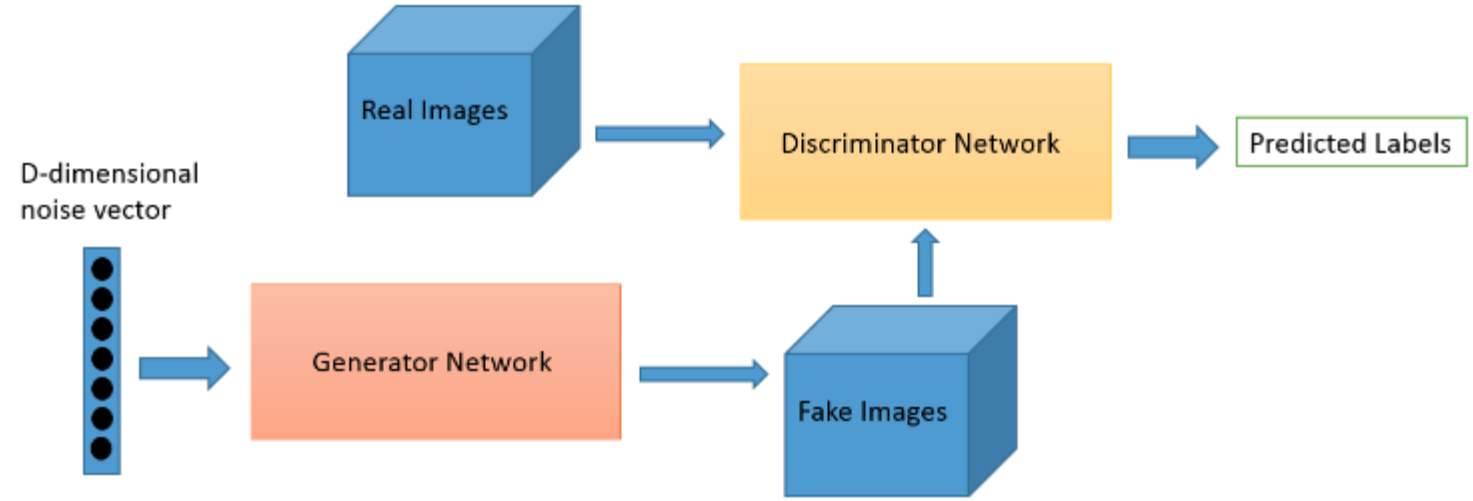
Transfer Learning

- Avoid the long arduous process of performing the training (and all the pitfalls) with TRANSFER LEARNING!



GANs

- Generative Adversarial Networks
  - Forger vs detective
- Difficult to train
  - Mode collapse, discriminator too good/bad….



Credit: O'Reilly

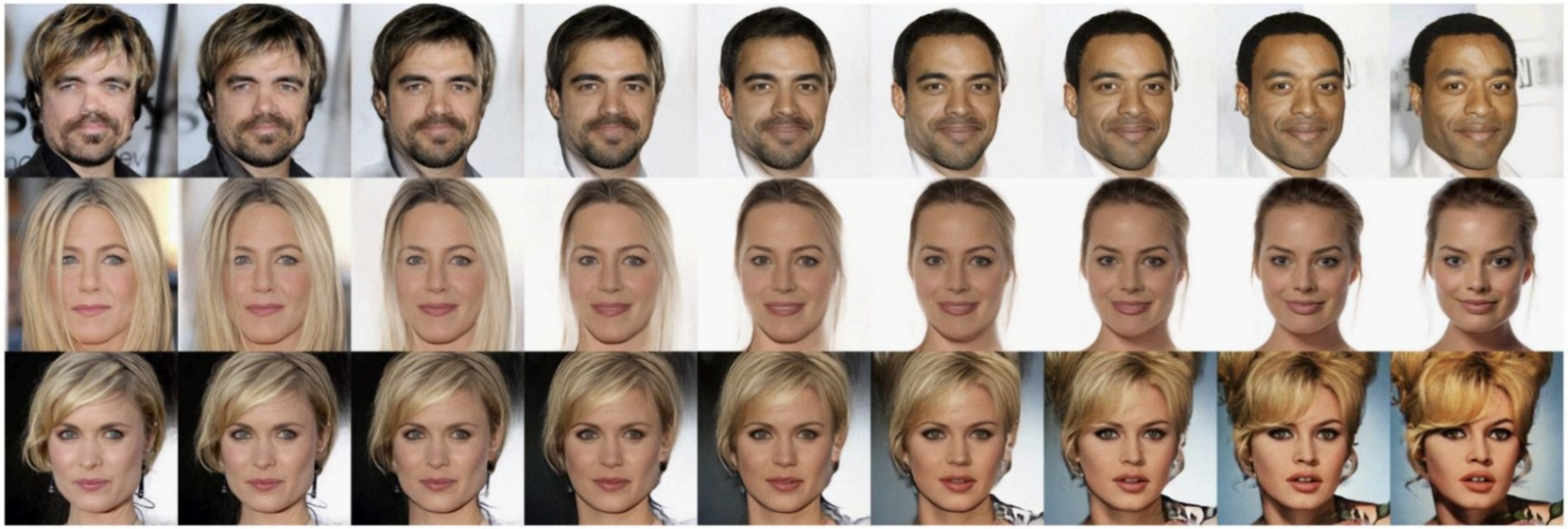
GANs

- Rapid evolution.
  - None of these people are real

[Image credit: Ian Goodfellow tweet “4.5 years of GAN progress on face generation”]

GANs

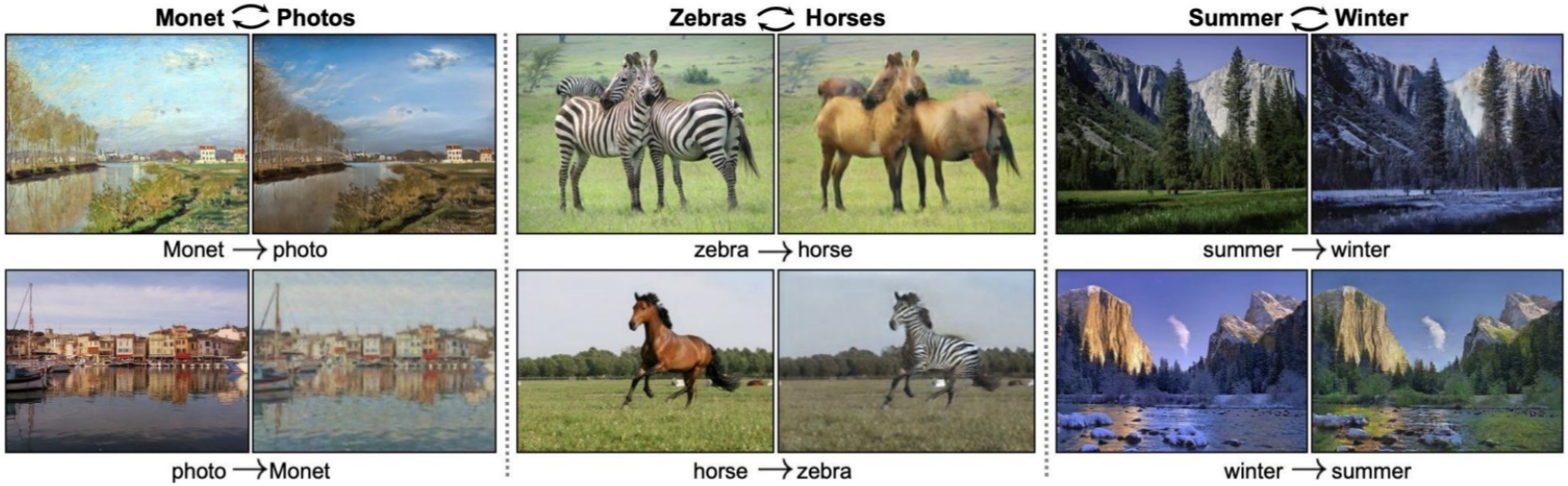
- Interpolation



[Kingma and Dhariwal, 2018]

GANs

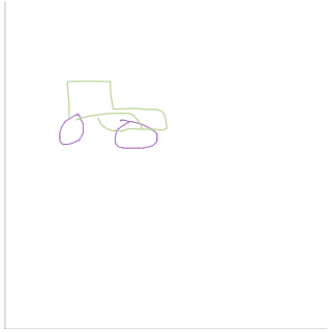
- Style transfer
  - Cyclic GANs



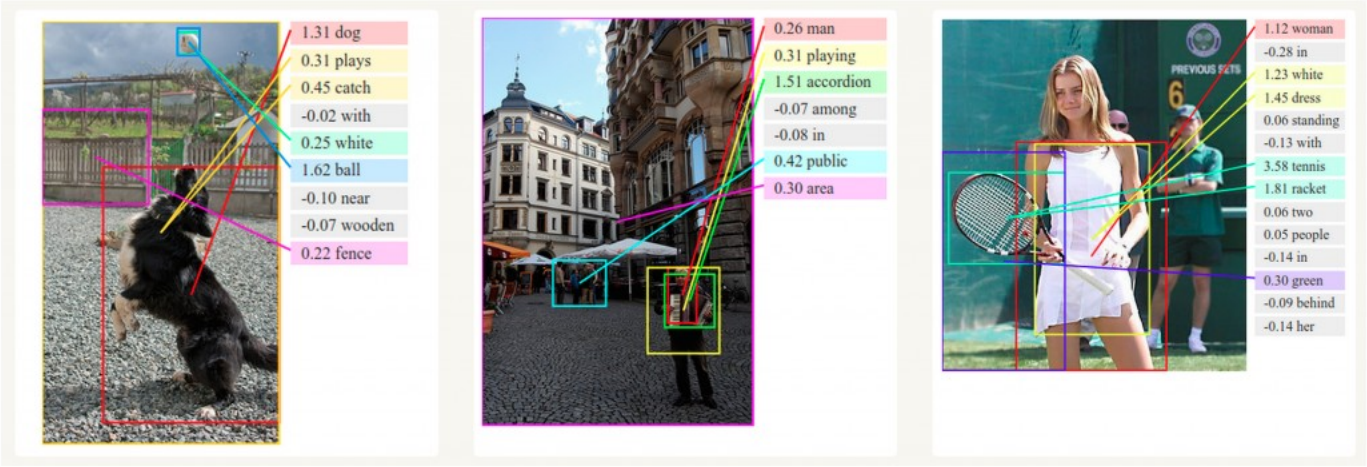
[Zhu et al., 2017]

RNNs

- Recurrent Neural Nets
  - Knows something about prior state(s)
- Useful for predictive problems
- Natural Language
  - Context is often key
- Novel labeling



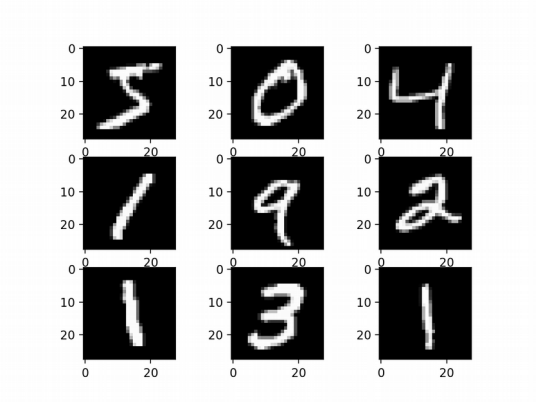
sketch RNN



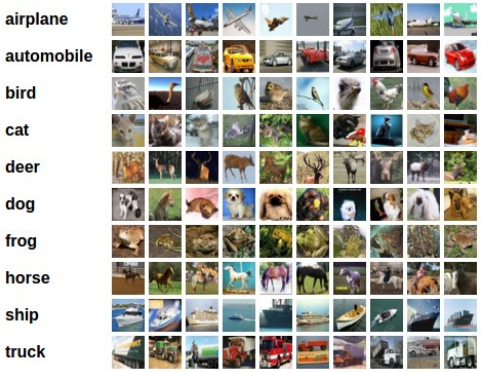
Deep Visual-Semantic Alignments for Generating Image Descriptions. Source: http://cs.stanford.edu/people/karpathy/deepimagesent/

So We Have a Model…

- Now it needs data
  - The more the better
- Curated sets
  - MNIST
    - 28x28x1 Hand written digits (0→9)
      - This is a lie….each “image” is a 1x784 vector….

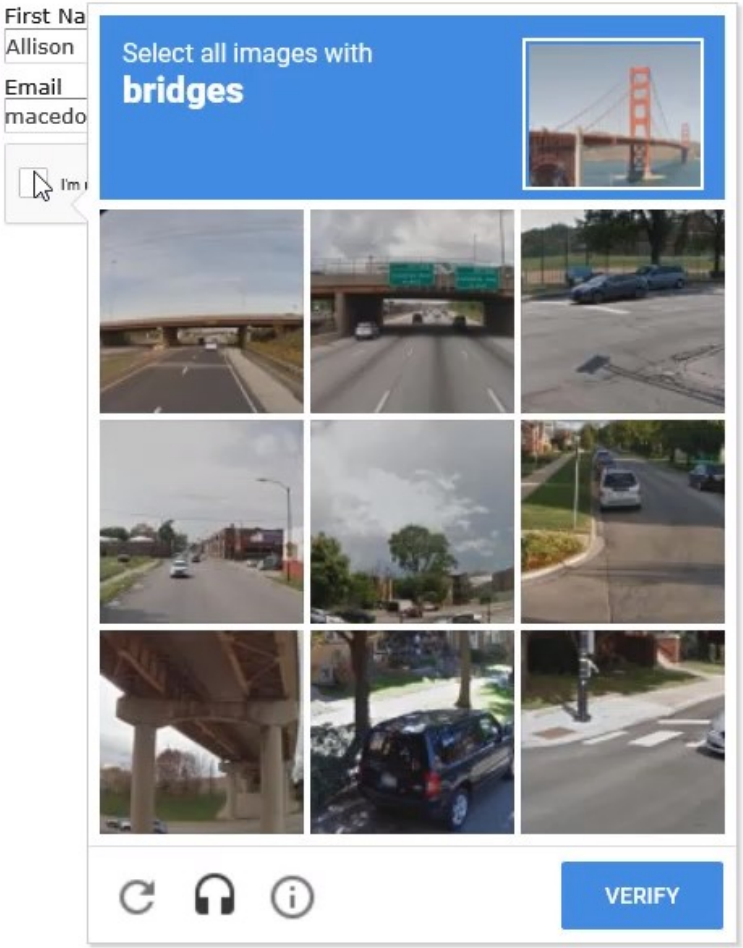


  - Imagenet
    - Based on wordNet (more than 100,000 “synsets”)
      - Aim to provide 1000 avg images per synset (word/noun)
      - 256x256x3 pixel images
      - 14.2M images (and labels) and growing



Captcha Connection

- So where do we get all the data we need?
- Turns out you have been training A.I. this whole time!
  - Ironic if you ask me



Gathering Data

- In fact, getting the labeled data is of such importance that Google is in the game

Cloud AutoML Vision

Human labeling

SEND FEEDBACK

Contents

Google's human labeling service

Beta

This product is in a pre-release state and might change or have limited support. For more information, see the product launch stages.

Human labeling enables you to label images in your training dataset at scale. Well-labeled content results in better training data, which results in more accurate predictions from your model.

- Use Google's integrated human labeling service
- Use a labeling partner

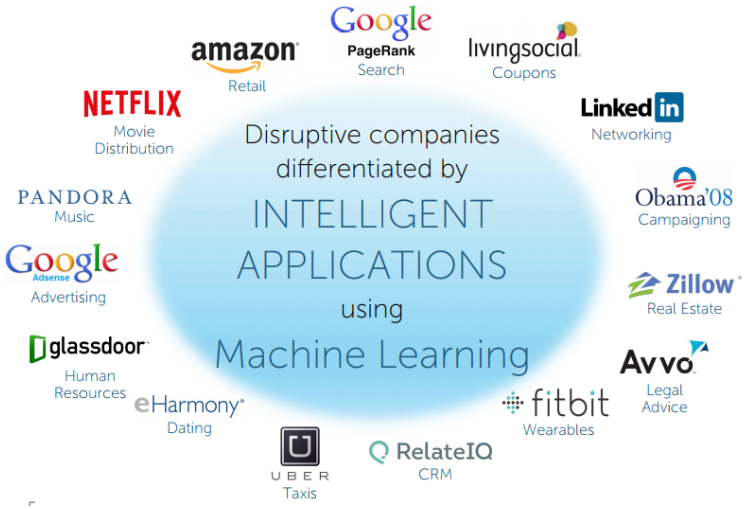
Google's human labeling service

Gathering Data (cont.)

- Tesla put hooks in their workflow to make it possible to gather examples similar to a target.

Industry Uses

- Beyond the promise of self-driving vehicles A.I. has found its way into almost every aspect of modern life
  - Every time you see “you might like…”
  - Every time you text
  - Digital assistants
  - Weather predictions
  - Customer service
  - Increasingly in medicine

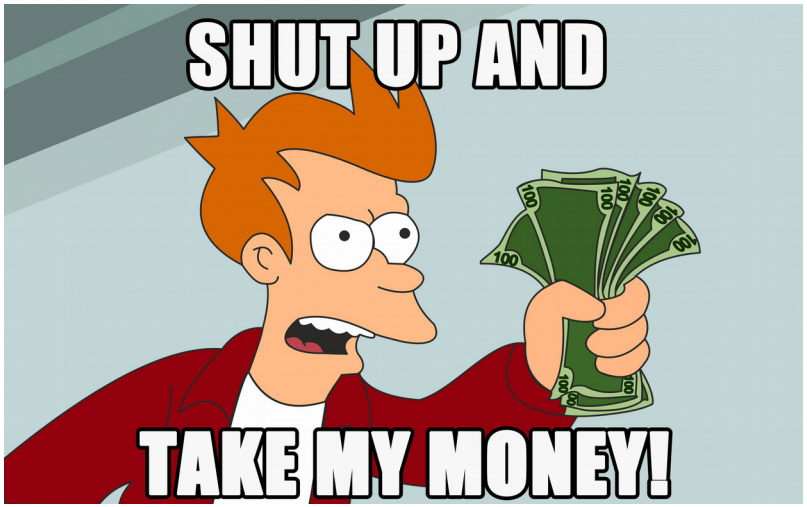


Now We are Ready

- So you are ready to start a disruptive A.I. company that promotes business synergy by customizing user experience via a blockchain to ensure trust and security….now that you mention it….

Introducing JCoin

The currency of science



Bias

- Like anything technological
  - Garbage in garbage out!

Personality from images? (please think again)

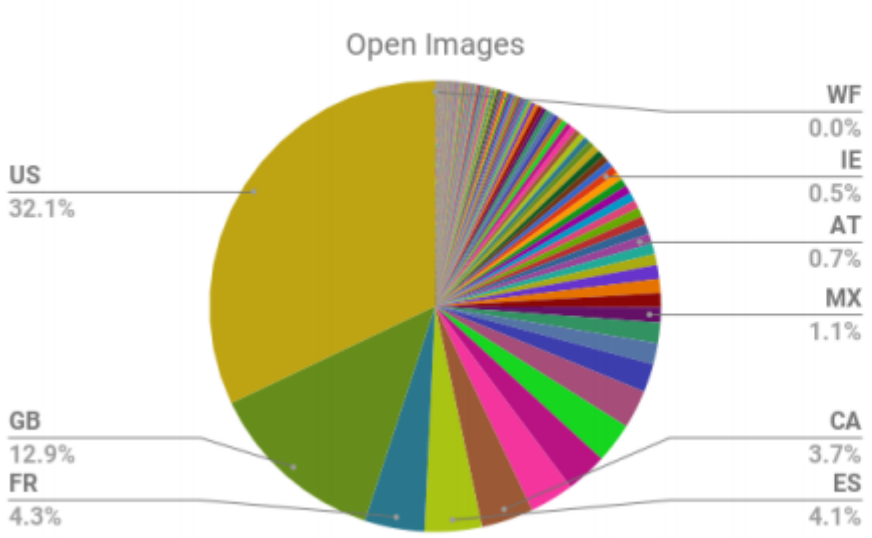
"Faception is first-to-technology and first-to-market with proprietary computer vision and machine learning technology for **profiling people** and revealing their personality **based only on their facial image.**"

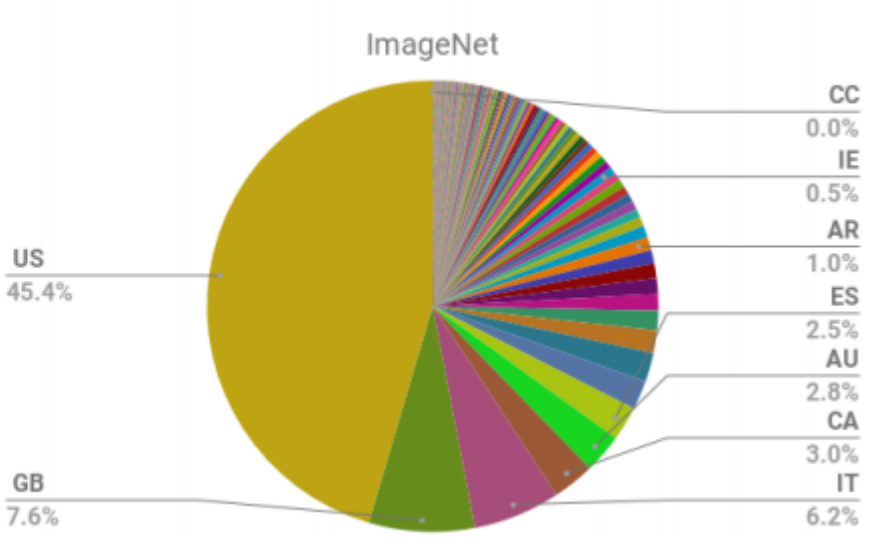
- Faception startup

Emily Denton
Research Scientist, Google Brain

Bias Example

- ImageNet biased to the US
  - What if the car learns it needs to see headlights on the left of the image?





No Classification without Representation: Assessing Geodiversity Issues in Open Data Sets for the Developing World
Shankar et al

Bias

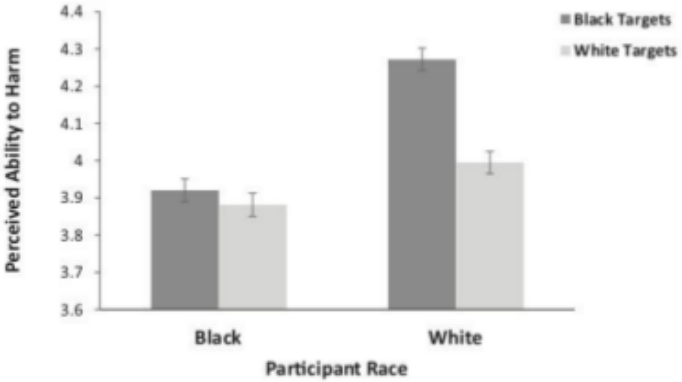
- It may come from the people doing the labels

Implicit racial stereotypes

Higher implicit prejudice was associated with a greater readiness to perceive anger in Black faces
[Kurt and Bodenhausen. Facing prejudice: implicit prejudice and the perception of facial threat]

Biased perception of young Black men as more threatening than white counterparts
[Wilson et al. Racial Bias in Judgments of Physical Size and Formidability: From Size to Threat]

Emily Denton
Research Scientist, Google Brain



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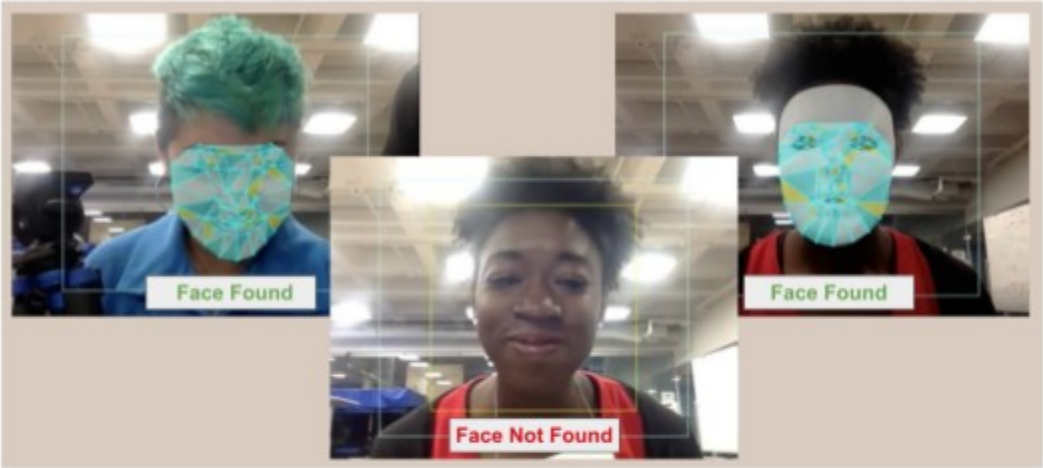
Actual Impacts

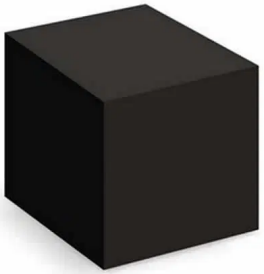


The Coded Gaze: Unmasking Algorithmic Bias
Joy Buolamwini

Emily Denton
Research Scientist, Google Brain

Careful

- It is very important to mitigate bias by ensuring that your A.I. is learning what you want it to
  - Application dependent
    - A.I. only learns from the training set



- Physics has the benefit of simulation and tighter parameter space
  - All of human experience vs all of a kinematic region

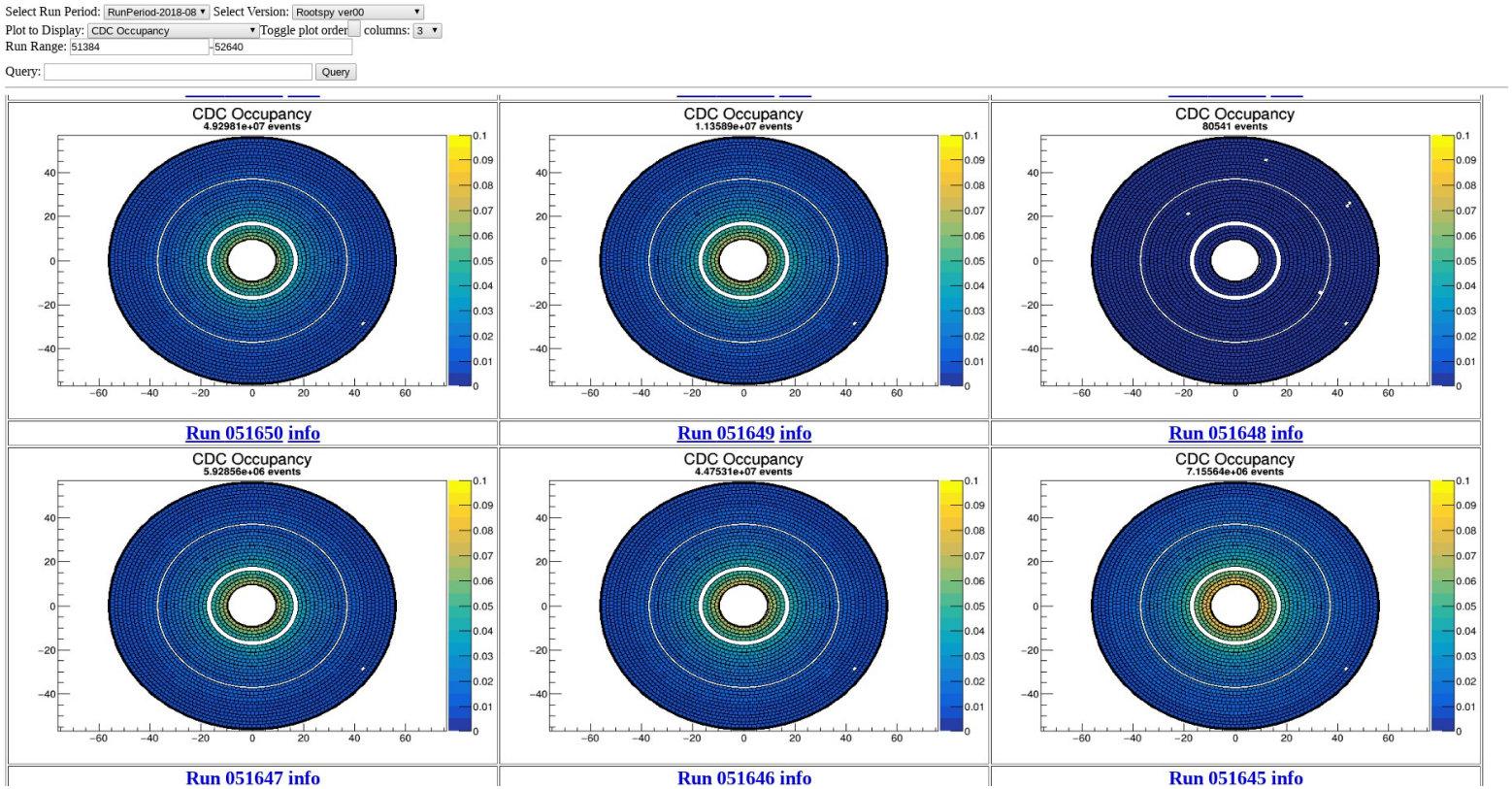
Following in Industry's Footsteps

- Can we apply A.I. to a problem at the lab?
  - My project checklist:
    - Is it image based?
      - Utilize all the machine vision work
    - Do I already have a large data sample?
      - Have arguably the hardest part done
    - How lazy am I?
      - Very...

DATA QUALITY MONITORING!

Data Quality Monitoring

The Data is Already There!

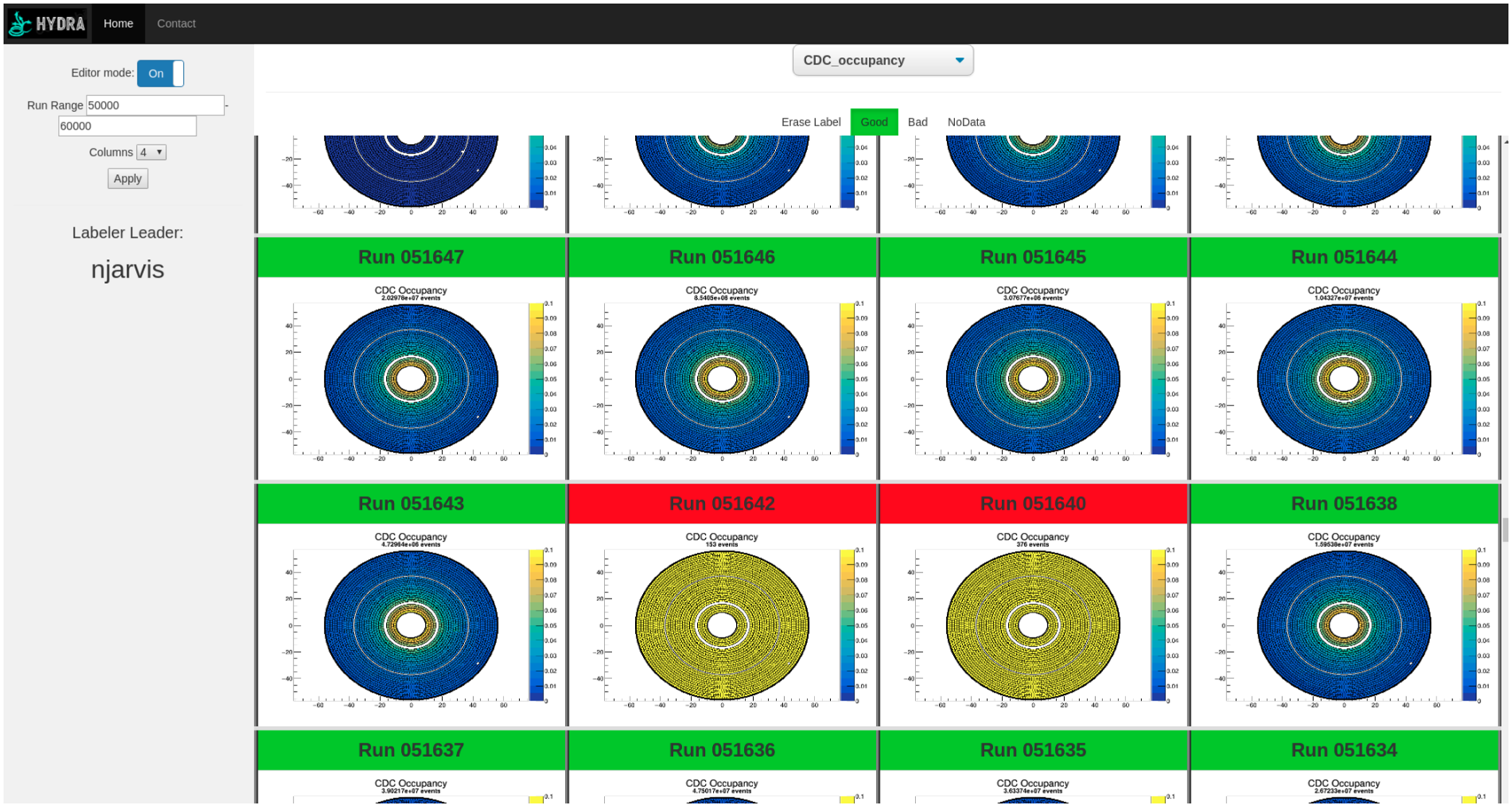


The Challenge

- **Every run** produces an initial 22 plots. More thorough monitoring is performed offline and produces 109 plots. With a run lasting ~3 hours every day there are between ~175 and 875 plots to look at.
  - To preserve sanity I look at closer to 175 plots, but there is no reason a machine couldn't aid in looking at all of them...
- Often times a single plot being "off" is not an indication of problems. Need to look at all the plots to determine cause and severity
  - Trigger studies: Often look like big problems but are not. Can be hard to catch when shift logs have scant details

Labeling That Data

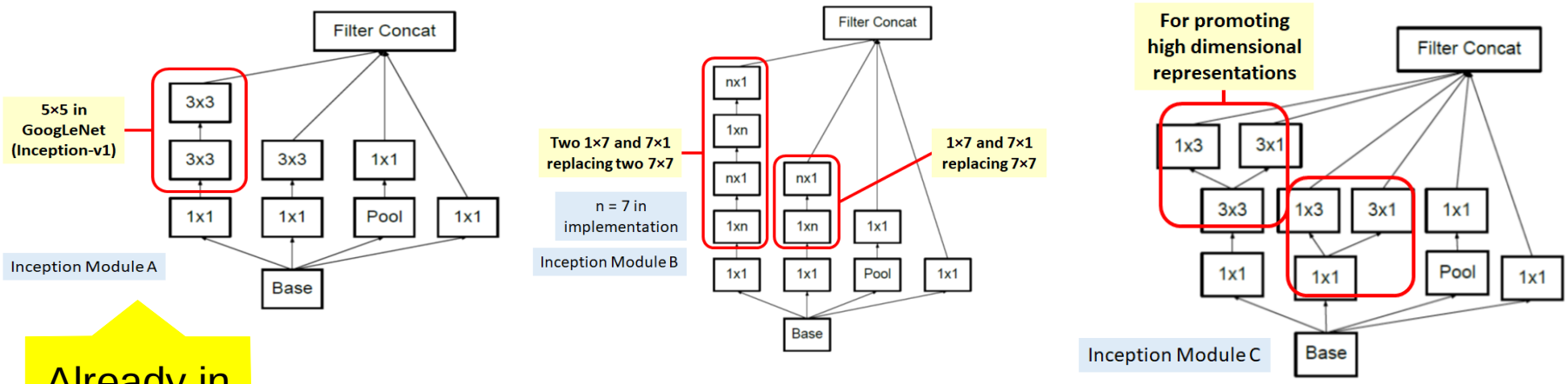
- Webpage:



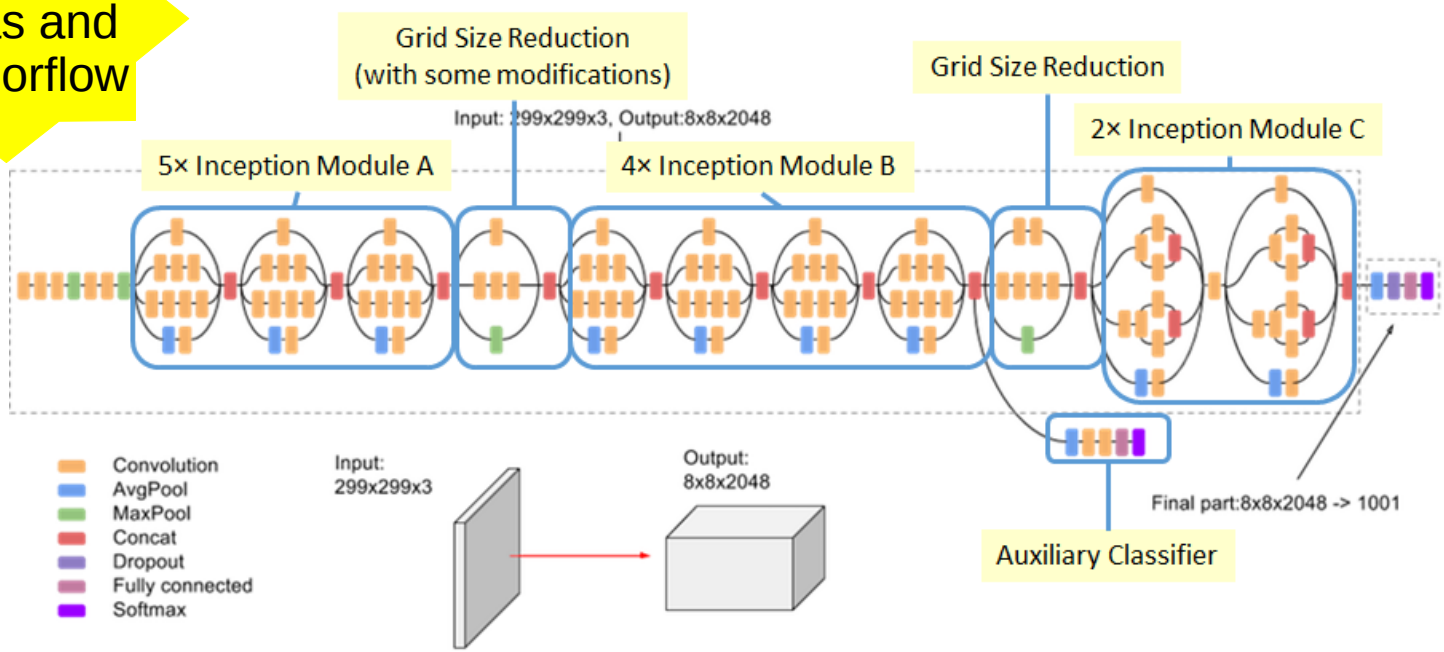
Software

- Chose Keras/Tensorflow as it seemed to be the most widely used
  - Lots of tutorials, examples and references

The Inception v3 Network



Already in Keras and Tensorflow



Introducing Hydra

- Hydra aims to be an extensible framework for training and managing A.I. for near real time monitoring
  - In the future the system can:
    - Diagnose potential issues
    - Provide real time calibrations
    - Auto-documentation
- Most importantly, allow me to embrace my inner sloth:

Koboldpress.com

Early Results

- Trained models are ~99.5% accurate when compared to experts
  - Worst false positive is when the machine says everything is fine….but it isn't

Early Results

- Confusion Matrix

Tolerance Cuts

- Applying a confidence cut of <93% reduces this false positive mode from 11 cases out of 6662 (0.17%) to 2 out of 6662 (0.03%)
  - Remediation: retrain with more data matching these examples
- Not only does the system not get tired it doesn't need to be fed (except by data)
  - Should reduce the number of plots that need looking at by upwards of 95%
  - Allow shift takers and experts to focus on bigger better things

Other Projects Around the Lab

- Charged Particle Tracking
- Particle Identification
- A.I. Environmental Background Radiation Characterization
- Hadron-Photon Separation in Calorimetry
- SRF Fault Classification
- A.I.-driven detector design

Conclusion

- What you buy, what you see, what you hear, and what you do; it's all influenced by A.I.
- It is coming to JLab and promises to change a lot

AI is disruptive.

It won't replace the scientist, but scientists who use AI will replace those who don't.*

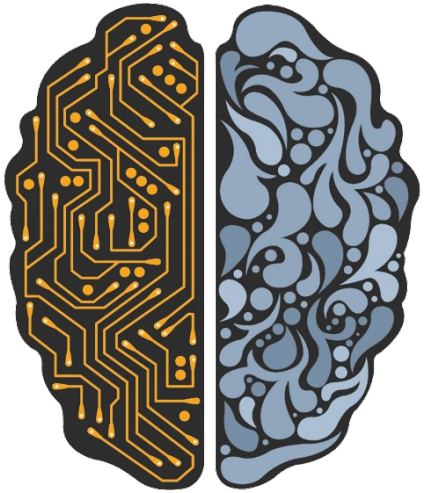
*Adapted from a Microsoft report, "The Future Computed"

Interested in Learning More?

Come to the A.I. Lunch Series

Wednesdays 12pm-1pm

CC F324-25



join #ml channel on slack!

https://jlab12gev.slack.com/messages/CFTBERJGK

Questions?