

# Introduction to Deep Learning with GPUs

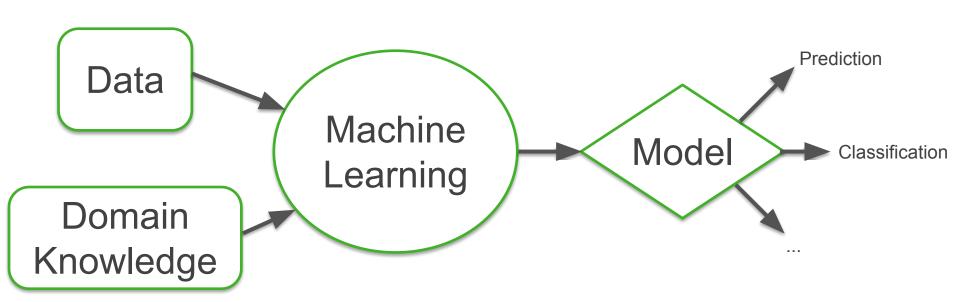
Jonathan Helmus, Anaconda Tom Augspurger, Anaconda

# Part 1: Machine Learning Basics in Anaconda





### What is Machine Learning?





### What can machine learning help us do?

#### Predict the future:

✓ "How much corn will I sell next month?"

#### Reveal hidden information:

✓ "How many truck tires likely fail to meet our durability specification based on the temperature data collected during their manufacture?"

### Identify structure in large data sets:

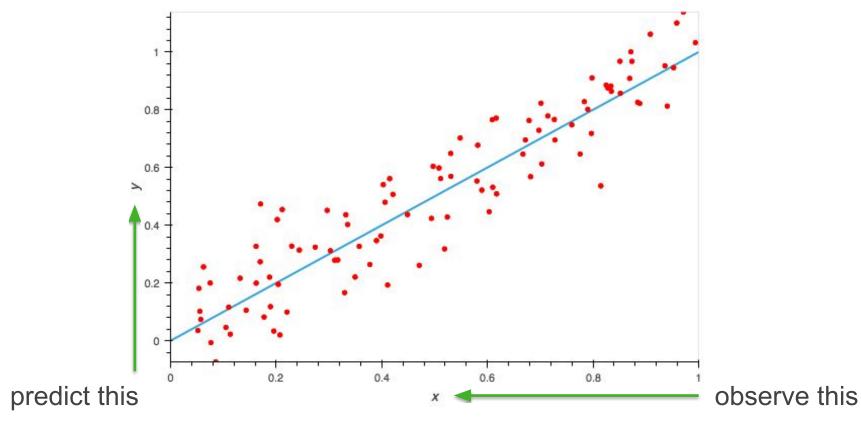
✓ "Can business loan applications be grouped by common attributes?"

### Find unusual trends:

✓ "Which items in my grocery store have seen an abnormal sales decrease outside of historical seasonal variation?"

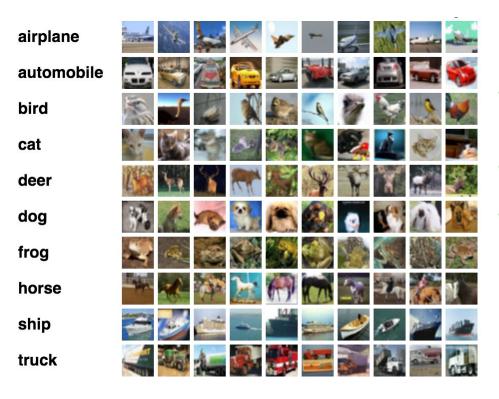


# **ML Categories: Regression**





### **ML Categories: Classification**

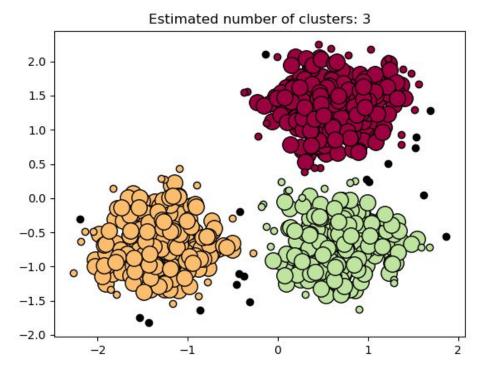


- Assign each sample to one or more categories.
- Categories known ahead of time
- Can be exclusive or inclusive



### **ML Categories: Clustering**

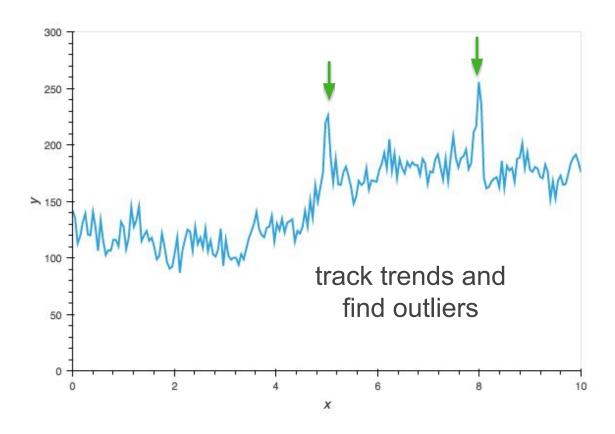
- Divide a set of items into groups
- Categories are not known ahead of time



http://scikit-learn.org/stable/auto\_examples/cluster/plot\_dbscan.html



## **ML Categories: Anomaly Detection**





# **ML** Categories: Generation



http://genekogan.com/works/style-transfer/

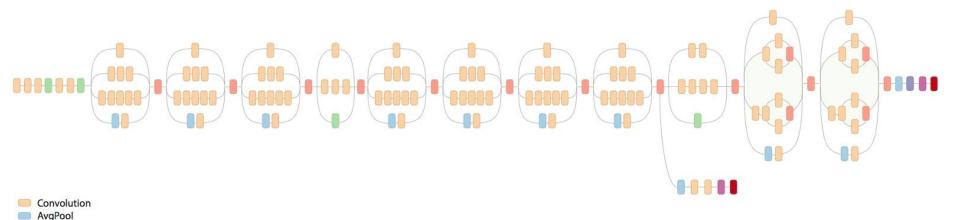


MaxPool Concat Dropout Fully connected

Softmax

### **Deep Learning**

### Inception v3 Network

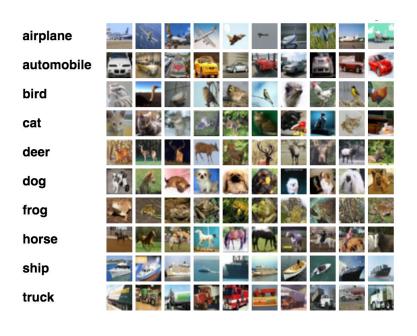


# of parameters: 23.8M

# of layers: ~140



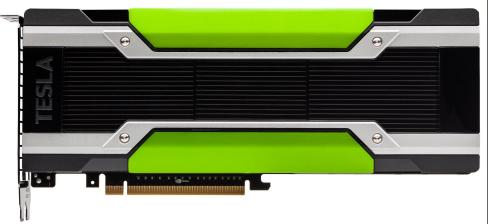
### Today's (Toy) Problem



- Can we classify small color images into one of 10 categories?
- Goal is better than 75% accuracy
- We will build a deep learning model and train it with GPUs.



### **Hardware: NVIDIA GPUs**



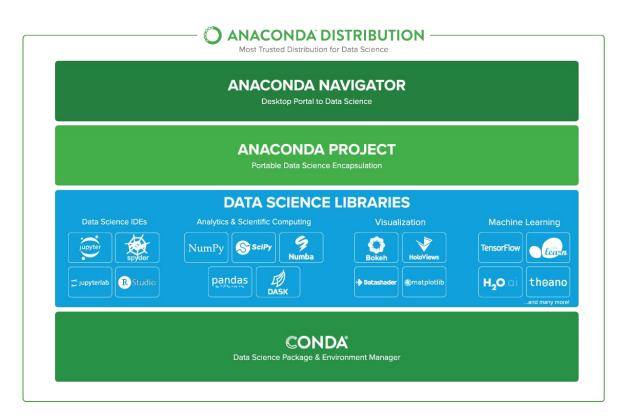
Tesla P100 3584 CUDA cores 9.3 TFLOPS (single precision) 16 GB Memory 732 GB/sec



× 56



### **Software: Anaconda Individual Edition**



Already installed in your tutorial environment



### **GPU-Accelerated Packages in Anaconda**













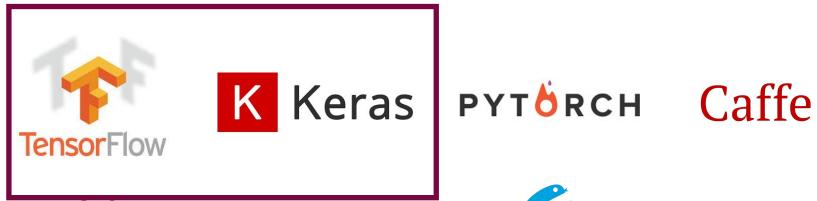








### **GPU-Accelerated Packages in Anaconda**











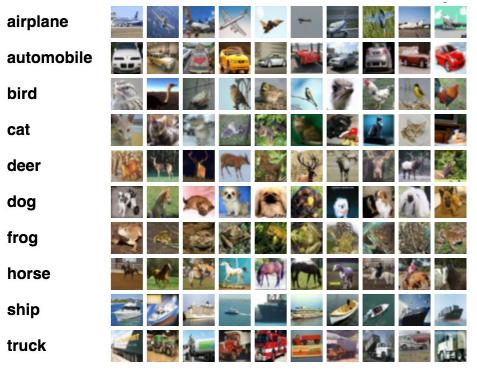








### **Data: CIFAR10 Image Set**



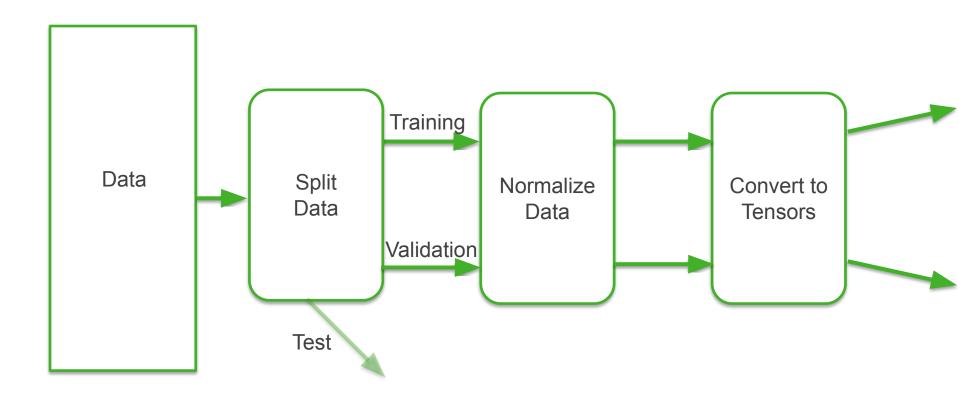
https://www.cs.toronto.edu/~kriz/cifar.html

Classic data set for benchmarking image classification

- 60,000 images
- 32x32 color pixels
- 10 classes
- 6000 images from each class
- Classes are mutually exclusive

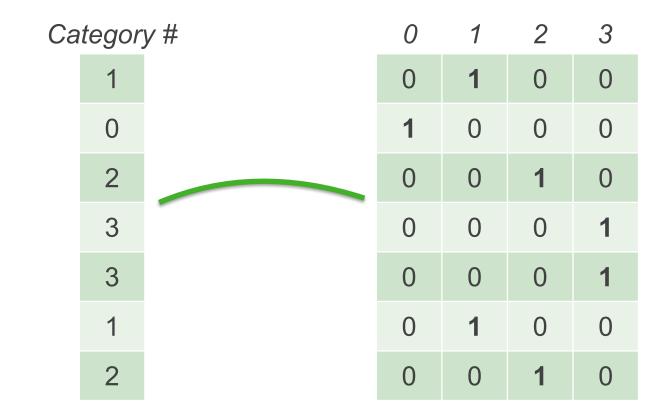


### **Data Preparation Process**





# **One-Hot Encoding of Category Variables**



# Exercise 1: Data Exploration and Prep



# Part 2: Introduction to Deep Learning with Keras





### What is a neural network?

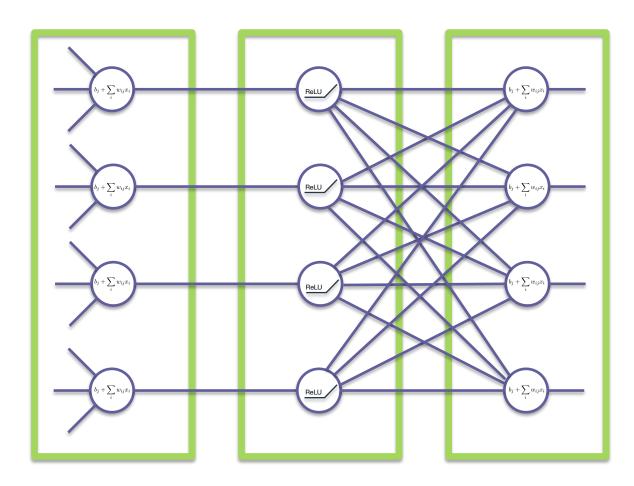
- A "biologically-inspired" method for making models out of simple computational units connected to form a large mesh
- Very flexible.
- Require a lot of data to train.
- Although described in physical terms (nodes, layers, etc), they are always implemented in software using array math.
- No relation to neuroscience, artificial general intelligence, or other sci-fi stuff.





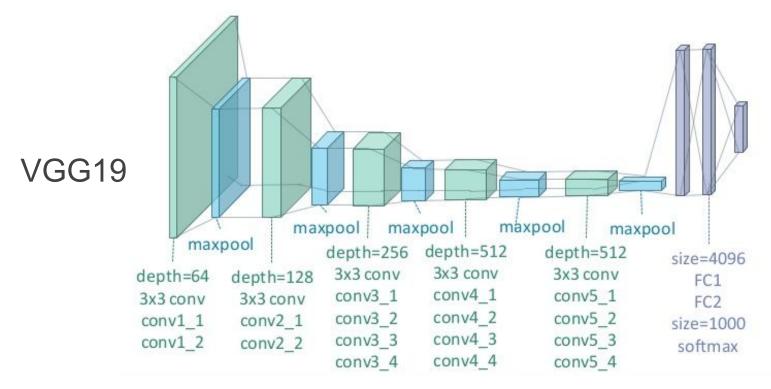


### **Network**





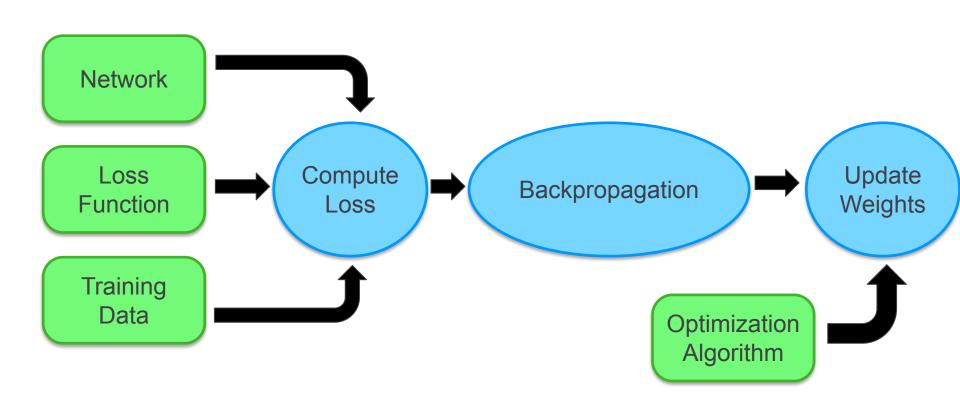
### **An Image Classification Network**



https://www.slideshare.net/ckmarkohchang/applied-deep-learning-1103-convolutional-neural-networks



### **Training a Network**



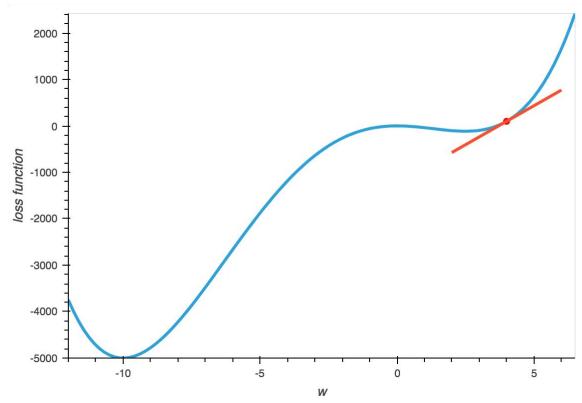


### **Loss Functions**

- The optimizer will try to minimize the loss function on the training data
- Picking a loss function depends on the kind of model you are building
- Some good default choices:
  - Regression: mean\_squared\_error
  - Binary classification: binary\_crossentropy
  - Multi-category classification: categorical\_crossentropy



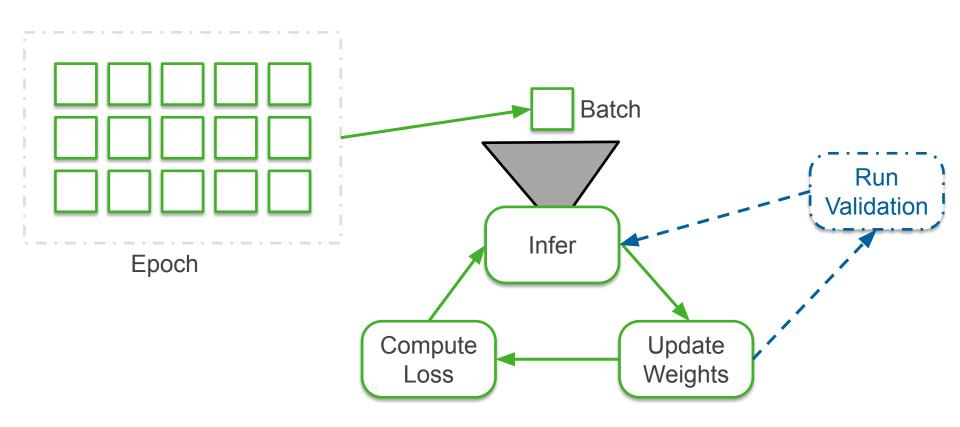
### **Backpropagation & Optimization**



- Work backwards through network to compute each weight affects loss function
- Optimization algorithm adjusts each weight according to some strategy.



### **Batches and Epochs**



# Exercise 2: Building and Training Models

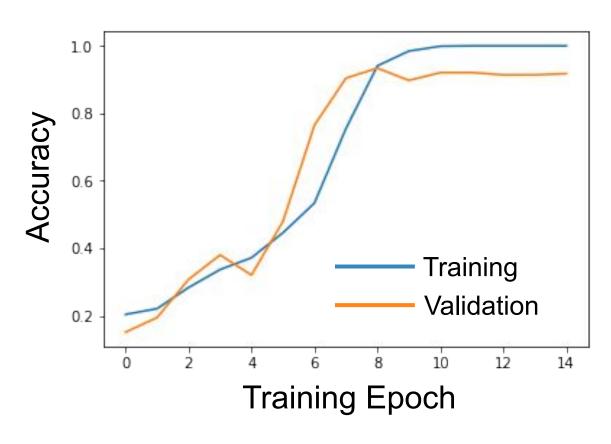


# Part 3: Evaluating Models





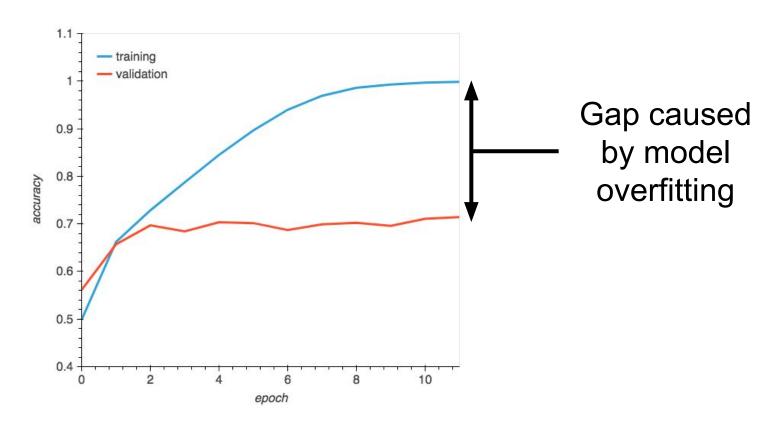
## Most important question in ML



How do I know when I am done?



## **Overfitting**



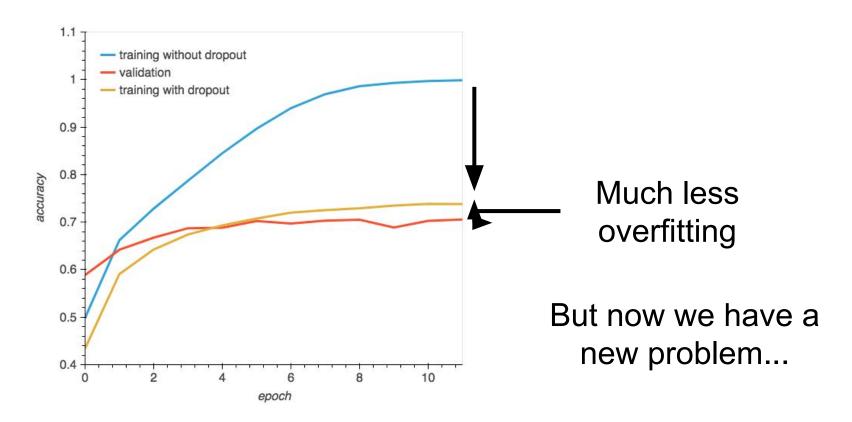


### What to do about overfitting?

- Overfitting does not mean your model is bad.
  - Most models will overfit after enough training epochs
  - The validation data accuracy is what you care about
- Techniques exist to control overfitting:
  - Regularization
  - Dropout layers
  - Reduce size of network
  - Get more data

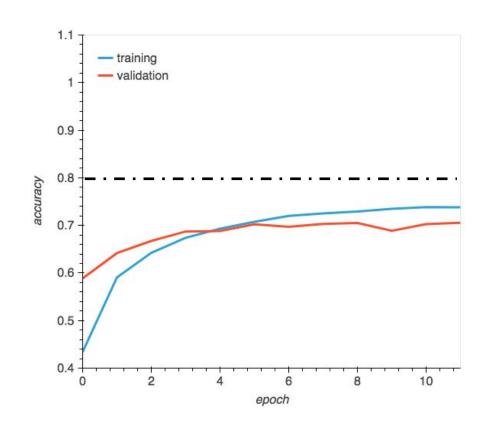


# **After Adding Dropout**





### **Underfitting**



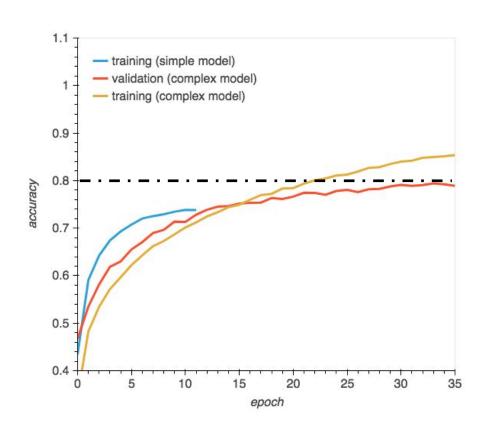
Model accuracy never reaches the goal.

### Possible causes:

- Model too simple?
- Not enough training data?
- Mislabeled data?
- Optimizer learning rate?
- ...



### **Fixing Underfitting**



### Changed 2 things

- Increased model complexity (added extra convolutional layers)
- Changed optimizer algorithm

Trial and error is still the norm...



### **Limitations of Accuracy**

- Accuracy is like the "check engine light"
- Can hide some problems
- Interpretation is hard if your training data is unbalanced
- Important to look at other measures:
  - False positive rate
  - False negative rates
  - Confusion matrix
  - Inspect fail cases!

# Part 4: Using Predefined Models and Deployment



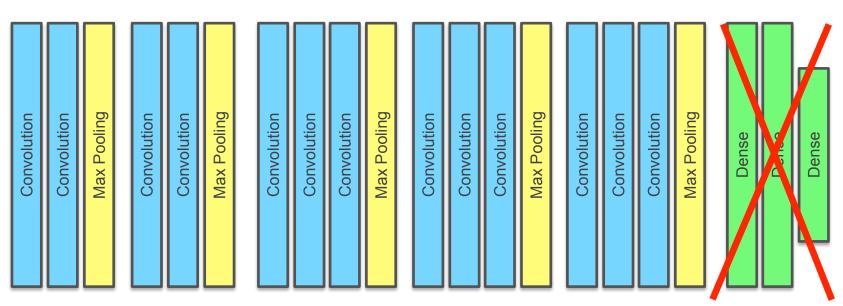


### **Building on Existing Models**

- In practice, you will generally use models defined by researchers, rather than construct new ones from scratch. Keras comes with quite a few:
  - VGG16
  - ResNet50
  - InceptionV3
  - MobileNet
  - NASNet
  - https://keras.io/applications/#documentation-for-individual-models
- Three approaches to retraining (slower to faster):
  - 1. Retrain existing architecture from scratch
  - 2. Retrain existing architecture starting from existing trained weights
  - 3. Retrain only the final dense layers



## **Transfer Learning**

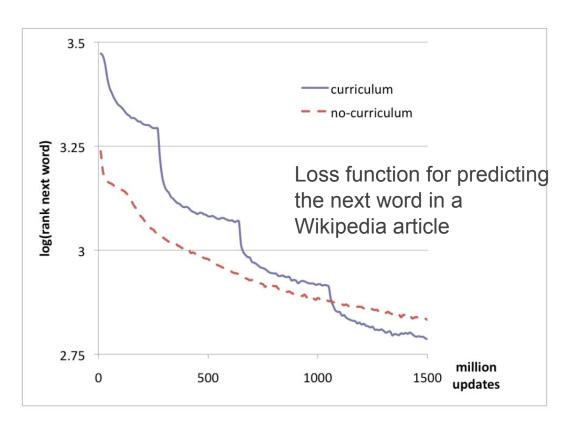


VGG16 Pretrained on ImageNet

Chop top layers off and retrain your own layers



## **Curriculum Learning**



- Train the model in multiple passes
- Use increasingly hard examples on each pass
- Easy if your data has a "difficulty" knob

Bengio, et al, ICML 2009



## **Using Multiple GPUs**

keras.utils.training\_utils.multi\_gpu\_model() Update Weights TITANV **Batch** 

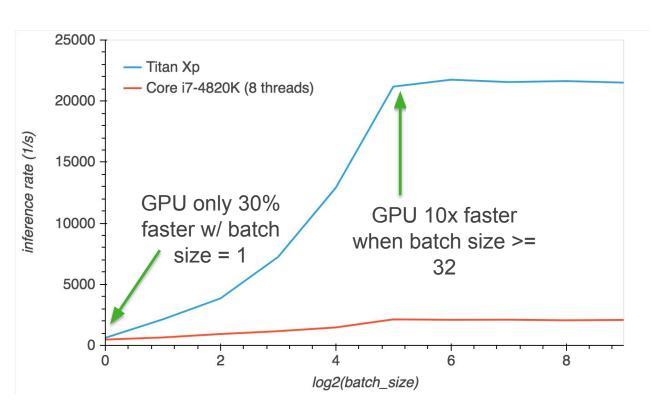


### **Getting to Deployment**

- This was the point of doing all this, right?
- Tools and best practices evolving rapidly
- Questions to consider:
  - What hardware is available in production?
  - Bulk processing or online processing? (or both?)
  - What is the performance requirement (throughput, latency)?
  - Does the model need optimization? (memory size or speed)
  - How should I package it, along with dependencies?



### **Determining Hardware Needs**



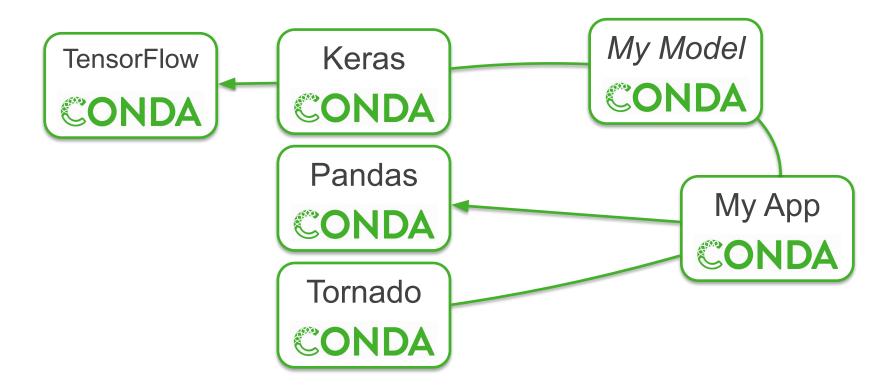
Inference in batches, or one at a time?

Do you need a GPU in production?

Smaller GPUs may also be be sufficient



### **Packing Models with Conda**





#### A Data Scientist's Job Is Never Done

- Important to monitor deployed models:
  - Does accuracy on new data match training/validation data?
  - Snapshot incorrect predictions for study
  - Keep expanding your training data
  - Make sure any data collection complies with your security and privacy policies
- Version your models, just like software!

# Exercise 3: Transfer Learning / Loading & Saving Models



## Conclusion





#### The Process

- 1. Define your problem
- 2. Identify your dataset
- 3. Design a network
- 4. Train the network
- 5. Check your work and iterate as needed
- 6. Package for production
- 7. Monitor deployed models for effectiveness



#### **GPU Requirements: Hardware & OS**

#### NVIDIA GPU

- Best results: Pascal, Volta, or Turing architectures, >4 GB of GPU memory
- Suggestions:
  - GeForce: GTX 1070, GTX 1080, RTX 2070, RTX 2080
  - Titan: Xp, V, RTX
  - Quadro: many models
  - Tesla: P100, V100
- You can use older GPUs to learn, but don't expect great performance.

#### CPU:

- Quad core
- 2x more CPU memory than your GPU

#### • OS:

- Linux 64-bit is preferrable
- Windows 64-bit also works
- macOS: no suitable NVIDIA GPUs in Macs made since 2014, external NVIDIA GPUs not officially supported, CUDA drivers incompatible with macOS 10.14
- Can also use cloud servers!



## **Cloud Availability**

#### Tesla K80

- Two GPUs on one card
- 2 x 2496 CUDA cores
  @ 0.56 GHz
- 2 x 12 GB memory
- Released: Nov 2014

#### Tesla P100

- 3584 CUDA cores@ 1.3 GHz
- 16 GB memory
- 732 GB/sec
- NVLink 1
- Released: April 2016

#### Tesla V100

- 5120 CUDA cores@ 1.3 GHz
- 16/32 GB memory
- 900 GB/sec
- NVLink 2
- Tensor Cores for DL
- Released: June 2017











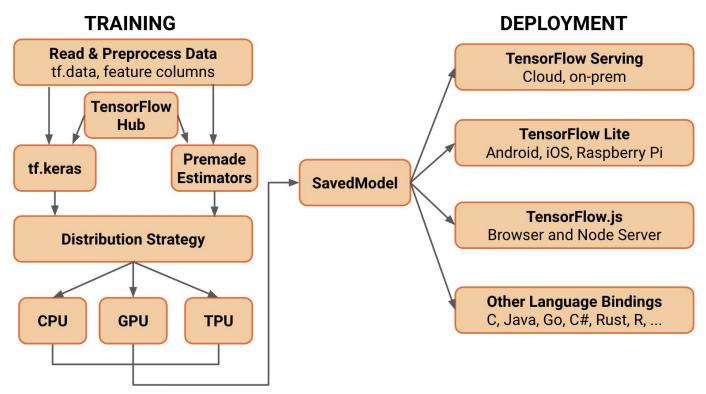








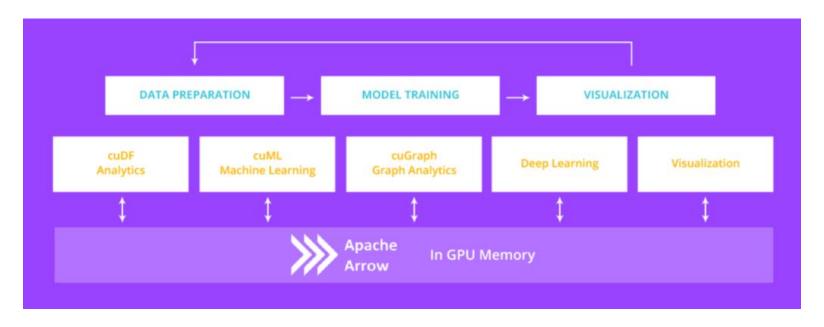
#### **Learn More: TensorFlow**



https://medium.com/tensorflow/whats-coming-in-tensorflow-2-0-d3663832e9b8



#### **Learn More: RAPIDS**



GPU-accelerated dataframes and traditional ML algorithms

https://medium.com/rapids-ai/the-road-to-1-0-building-for-the-long-haul-657ae1afdfd6



#### **Further Reading on Deep Learning**

• Tutorial Notebooks:

https://github.com/ContinuumIO/ac2020-dl-gpu

- Deep Learning with Python, by François Chollet <a href="https://www.manning.com/books/deep-learning-with-python">https://www.manning.com/books/deep-learning-with-python</a>
- Neural Network Playground (experiment in your browser!)
  <a href="http://playground.tensorflow.org/">http://playground.tensorflow.org/</a>
- Keras Documentation <a href="https://keras.io/">https://keras.io/</a>
- Want code examples? Google search for "Keras [use case]". Examples:

"keras image segmentation"

