Carnegie Mellon University

18-649 Guest Lecture: Machine Learning

Tianshu Huang

- (1) When should I use ML / DL?
- (2) How do I develop and deploy ML to the edge?

This lecture brought to you by: **RadarML**

Interested in machine learning research and working with **real systems**, not just canned datasets?

Embedded HW/SW development for learning-enabled radar applications **Machine learning** for radar and radar+X fusion

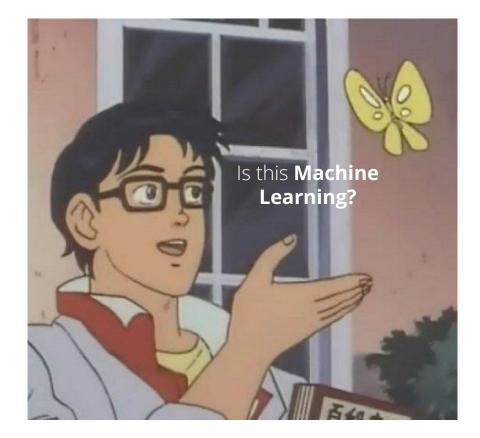
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"AI"

We don't serve their kind here auickmeme

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- m. Lu filing



Empirical risk minimization:

- 1. Data
- 2. Risk function (e.g. accuracy, loss)
- 3. What model minimizes the risk function on the data?

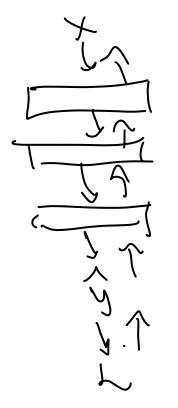


Example: digit classification

A lot of date -> deep learning

THIS IS YOUR MACHINE LEARNING SYSTEM? YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE. WHAT IF THE ANSWERS ARE WRONG? JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT. DATA https://xkcd.com/1838/

Deep Learning



STOP DOING DEEP LEARNING

- PERCEPTRONS WERE ONLY EVER MEANT TO BE FULLY CONNECTED
- THOUSANDS OF PAPERS yet NO REAL-WORLD USE FOUND for going deeper than ONE LAYER
- Wanted to add more nonlinearity anyway for a laugh? We had a tool for that: It was called "KERNEL METHODS"
- "Yes please give me a network that can PAY ATTENTION TO ITSELF. Please give me PRETRAINED WEIGHTS for my YOLO-9000" - Statements dreamed up by the utterly Deranged

LOOK at what "Research Scientists" have been demanding your Respect for all this time, with the statistical methods & optimization algorithms we built for them

(This is REAL "Deep Learning", done by REAL "ML Engineers"):



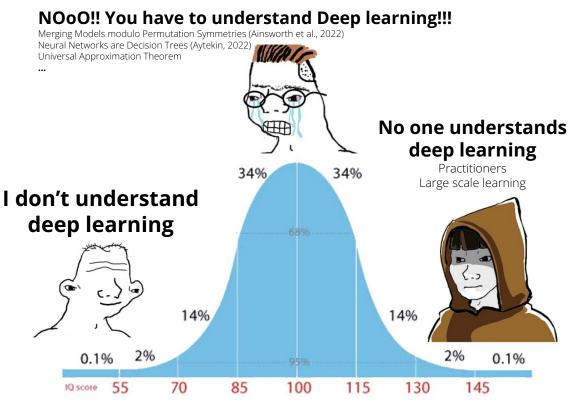
"Hello I would like to learn 1.6 TRILLION parameters please"

They have played us for absolute fools

https://www.reddit.com/r/okbuddyphd/comments/n2m6vz/stop_doing_deep_learning/

Deep Learning

The Higher Mysteries



The Natural Image Manifold

The **natural image manifold** is a surface embedded in a **high dimensional space** that is:

- (1) low-dimensional,
- (2) highly nonlinear, and
- (3) locally smooth.

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-imager, video text - andip - health data " (except continues - fer sensors, fer observations)

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Practical Deep Learning





See Adversarial Robustness.

Image from "Robust Physical-World Attacks on Deep Learning Models," Eykholt et al, 2018.

Pre-Trained Models & Transfer Learning



15

Practical Deep Learning

- Train from scratch?
- Transfer learn?
- Fully pre-trained model?





Deep Learning on the Edge



Please inspect your power cables if you own a RTX 4090, even if you don't use it for deep learning.

Deep Learning on the Edge

- Trained a neural network with a given architecture
- Weights are 32-bit float
- Fixed power budget

Simplest is Best

- Cloud offloading
- Reduce input resolution
- Don't use deep learning

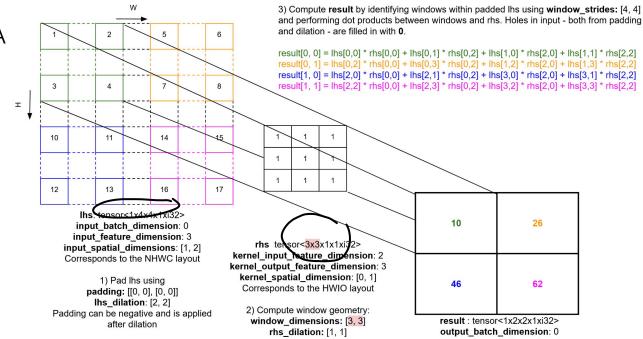


Use better software

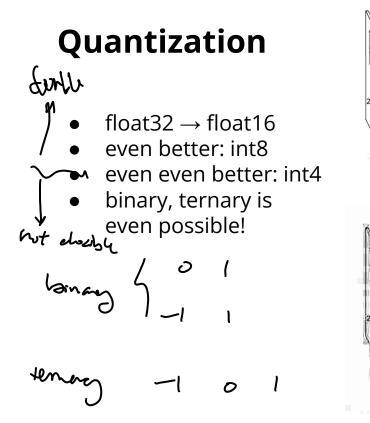
- Compilers, e.g. XLA
- Custom CUDA / accelerator code

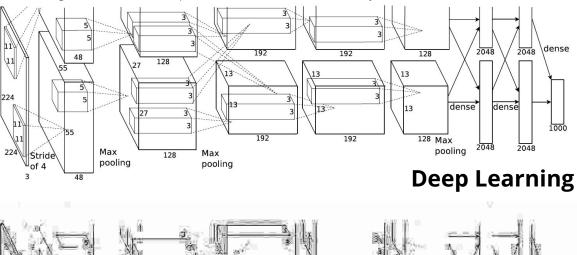
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output_feature_dimension: 3 output_spatial_dimensions: [1, 2] "ImageNet Classification with Deep Convolutional Neural Networks," Krizhenvsky et al., 2012 (AlexNet - First "true" ConvNet)





132

1925

197

192

Max peoling

1.78

Max

pooling

21

dense

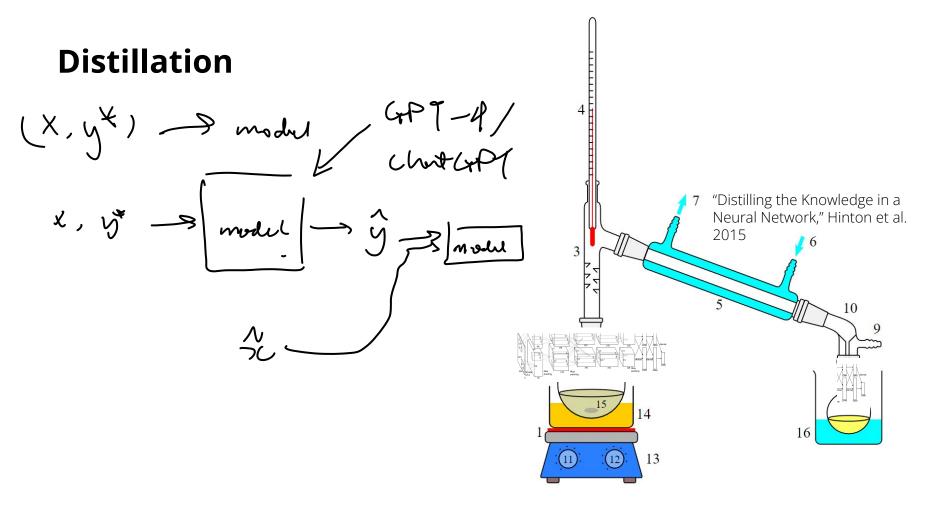
dense

booling

128 MB

Quantized Deep Learning

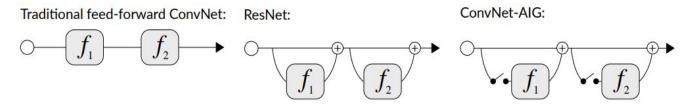
dense



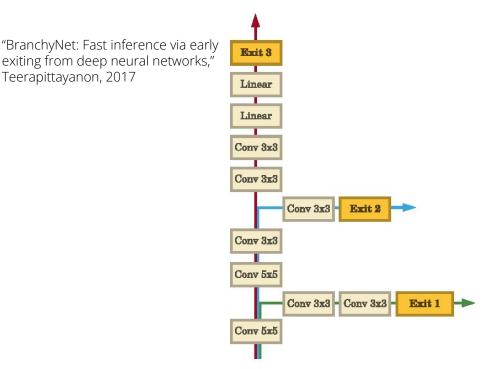
Adaptive Inference

- Different numbers of layers
- Different input resolution
- ...

"Convolutional Networks with Adaptive Inference Graphs," Veit & Belongie, 2018



Teerapittayanon, 2017



TL;DR

- 1. Don't use machine learning
- 2. Don't use deep learning
- 3. Don't use deep learning on the edge (do it in the cloud)
- 4. Don't train deep learning models (use a pre-trained model optimized for edge deployment)
- 5. Don't train deep learning from scratch (use transfer learning)
- 6. Give up (or take a machine learning class)

Q&A

- Distributed/federated training
- Edge training
- GPU vs CPU vs TPU
- Deep learning frameworks
- ML accelerators
- ML Compilers
- Efficient Architectures
- Anything ML related

