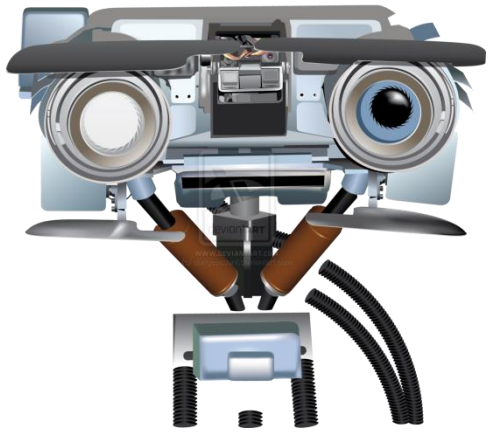
Announcements

Reminder: Class challenge out! Ends December 10th

- Lab this week: final review, class survey



On-device Machine Learning

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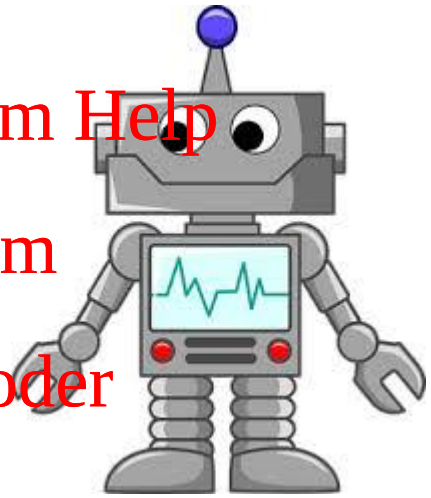
Creating an AI Model



model development

model deployment

What if the model you trained is too big/takes too long to run?

Reminder: memory representation

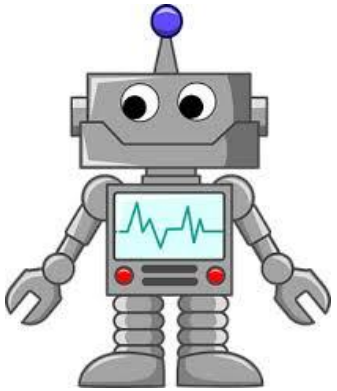
- Int – 4 bytes
- Float – 4 bytes
- Double – 8 bytes
- Binary variable – 1 byte

Aha! We can reduce memory by 1/4th if we can binarize the weights/features!

Binary features enable us to use hamming distance for fast similarity computation!

Why should I care?

resource scarce systems



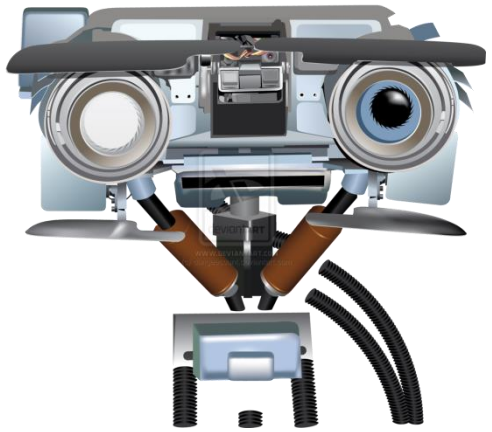
efficient features for search

Goals

- Efficiency
  - Inference speed
  - Memory reduction (either RAM or disk space)
- Limit Performance loss
- ~~Training time?~~

Today

- Network/Feature Quantization
- Parameter Pruning
- Knowledge Distillation



Feature Quantization

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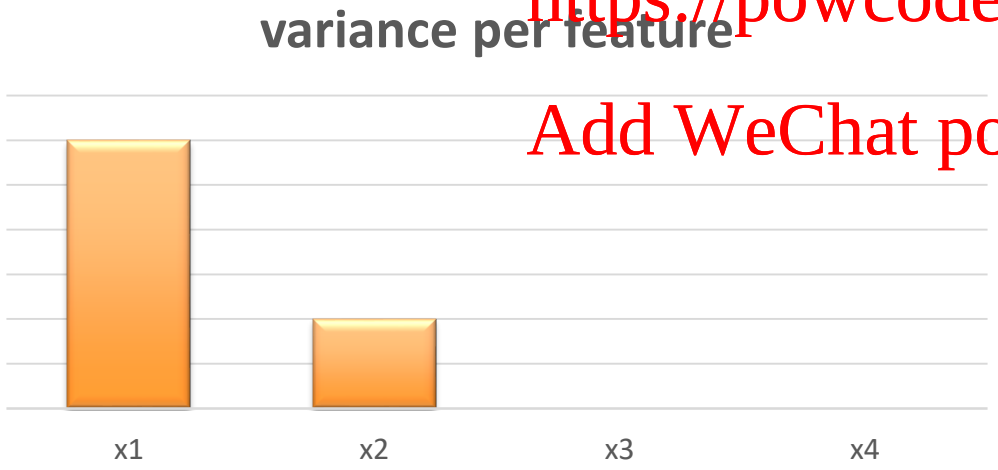
Simple feature quantization method - threshold

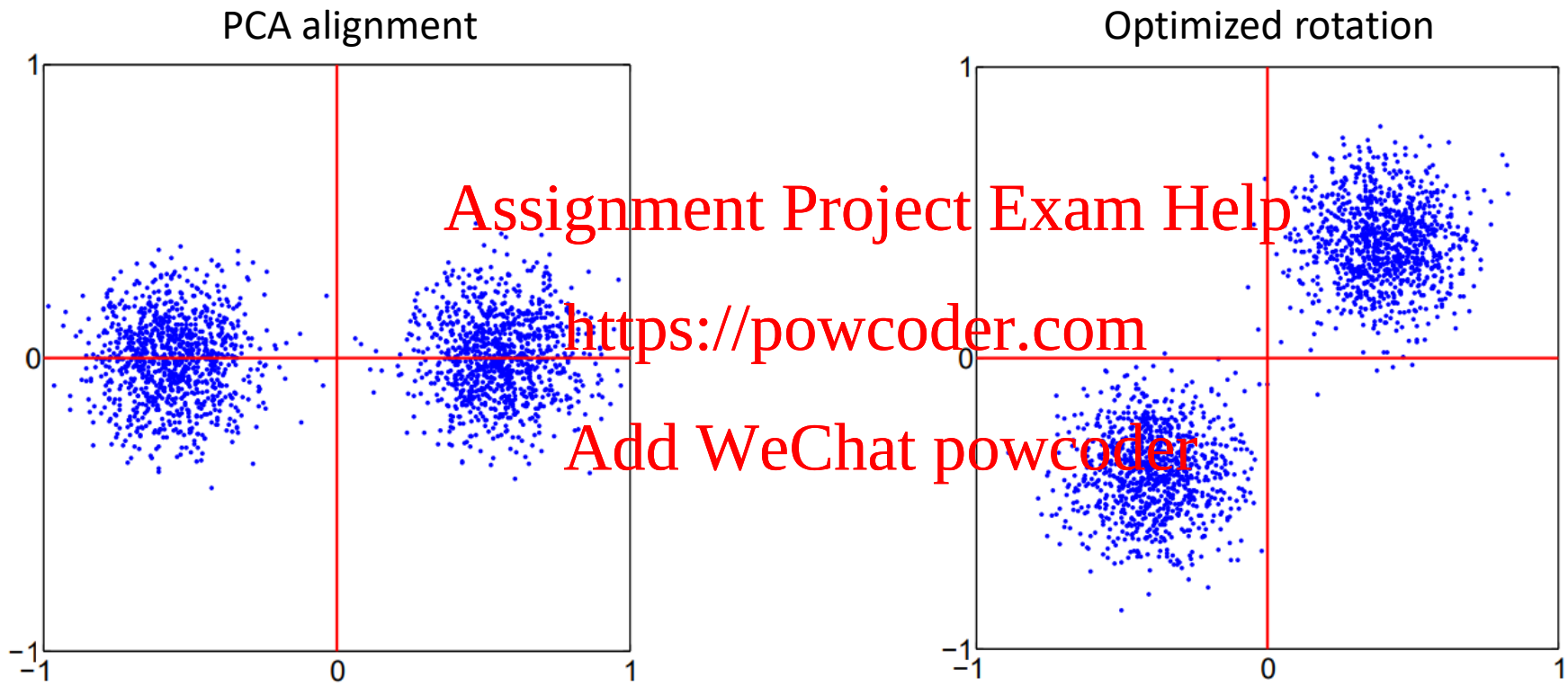
- Find the mean μ of each feature x_i in the training set, then binarize using $\mu > x_i$



Some features have more information than others

Also assumes the initial feature representation size is small enough

Iterative quantization



Paper reference: Iterative Quantization: A Procrustean Approach to Learning Binary Codes. Y. Gong and S. Lazebnik, CVPR 2011.

Quantization optimization

For orthogonal rotation matrix R and projected features V, minimize:

$$Q(B, R) = \|B - VR\|_F^2$$

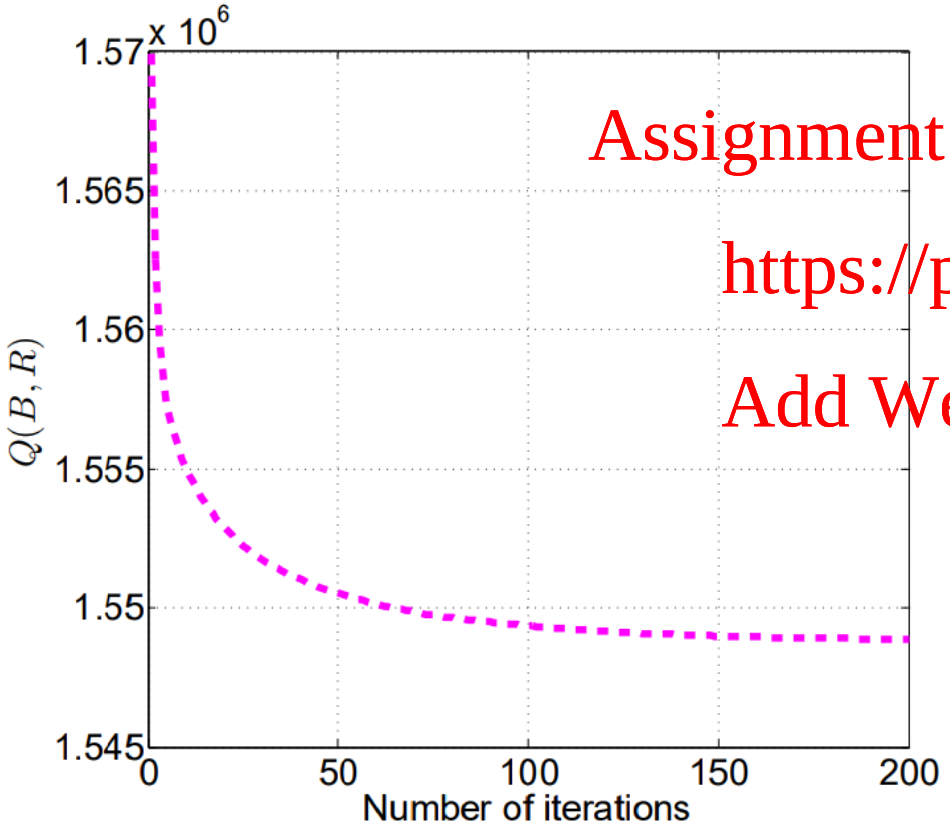
where B is a binary code matrix.

But it is dependent on two variables!

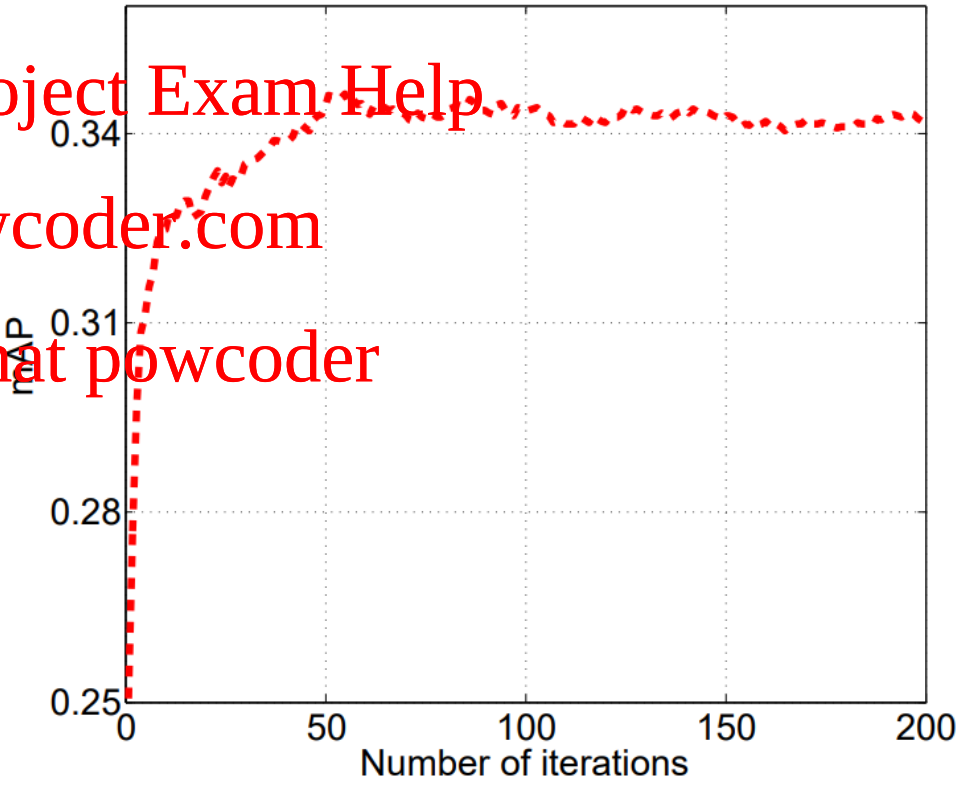
Fix one, update the other

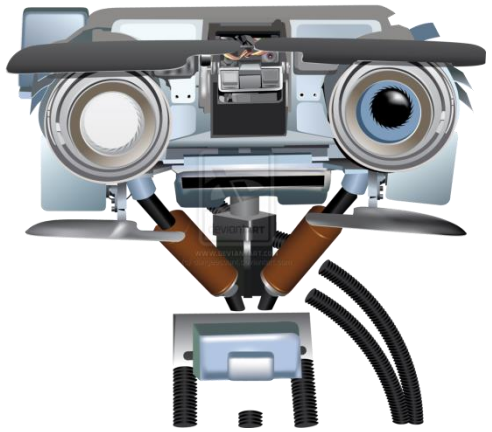
Performance over time

Cost function value



Euclidean neighbor precision





Network Quantization

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Convolutions in binary networks

figure credit: https://arxiv.org/pdf/2004.03333.pdf

Runtime comparison

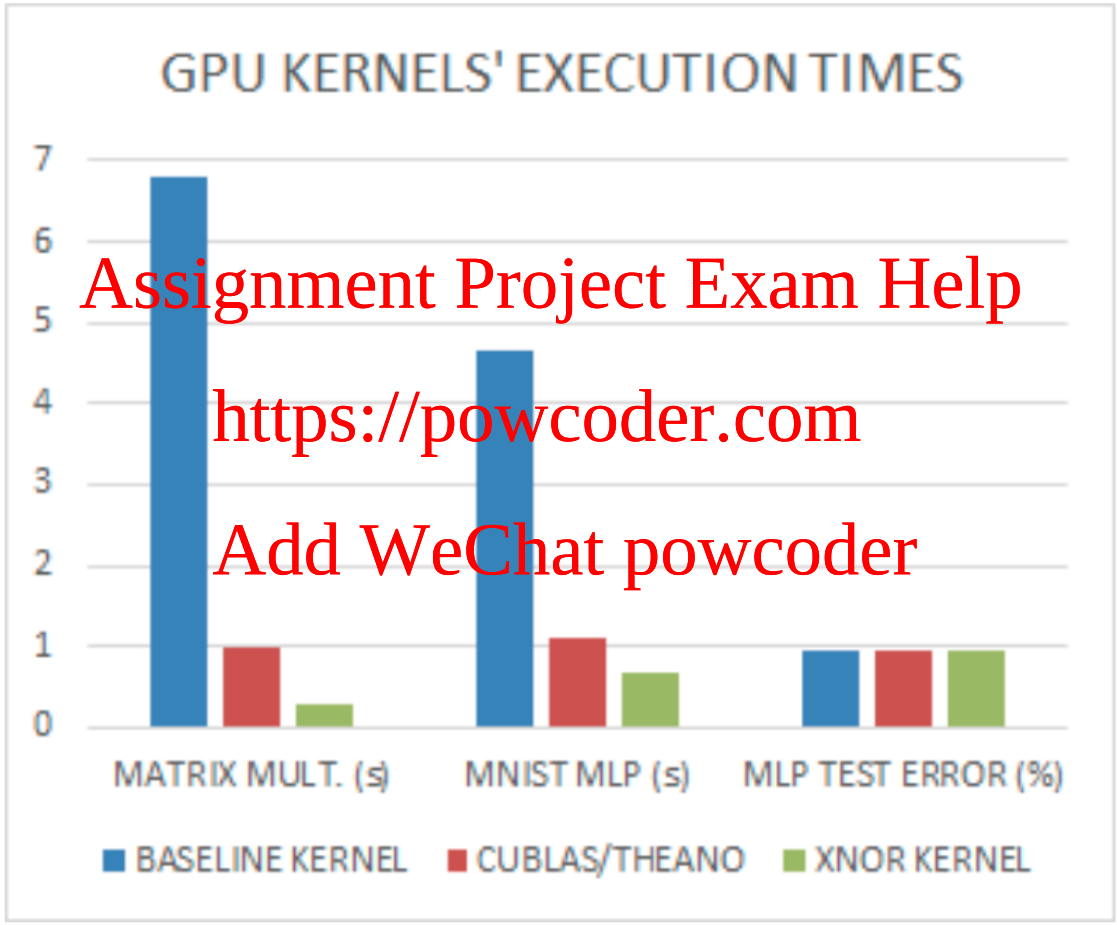
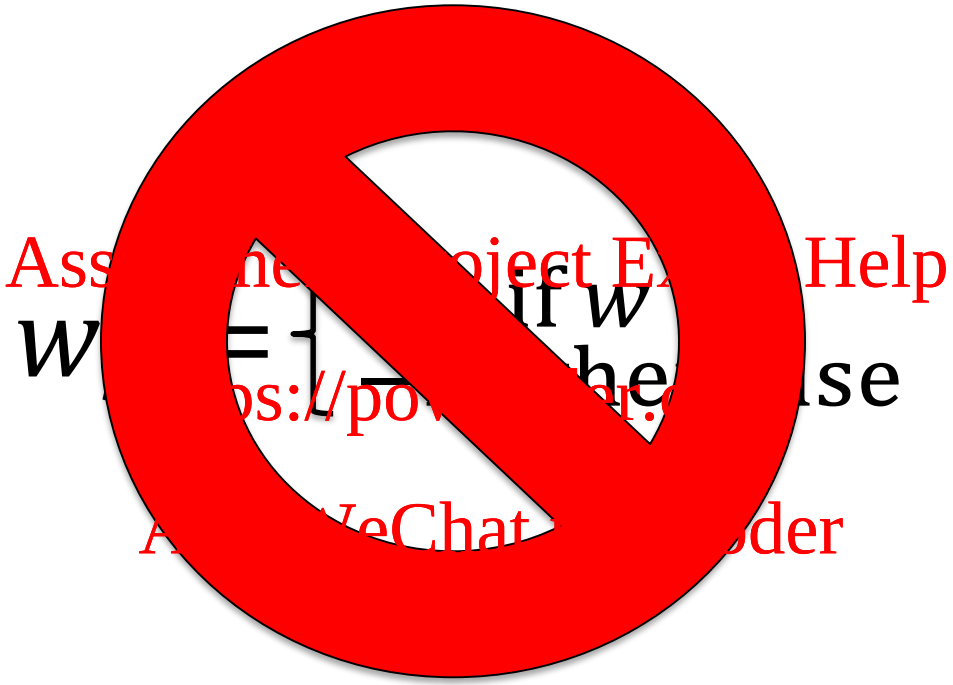


figure credit: Hubara et al., Binarized Neural Networks, NeurIPS, 2016

A simple approach



Results in significant loss of information!

Example of binarization

Simple method:

$$w = [0.1, 0.1, 0.1, 0.1]$$
$$= [1, 1, 1, 1]$$

A better approach

$$w_b = \begin{cases} +1 \text{ with probability } p = \sigma(w) \\ -1 \text{ with probability } 1 - p \end{cases}$$

$$\sigma(x) = \max\left(0, \min\left(1, \frac{x+1}{2}\right)\right)$$

Example of binarization

Reminder: $\sigma(x) = \max\left(0, \min\left(1, \frac{x+1}{2}\right)\right)$

Simple method:

$$w = [0.1, 0.1, 0.1, 0.1]$$

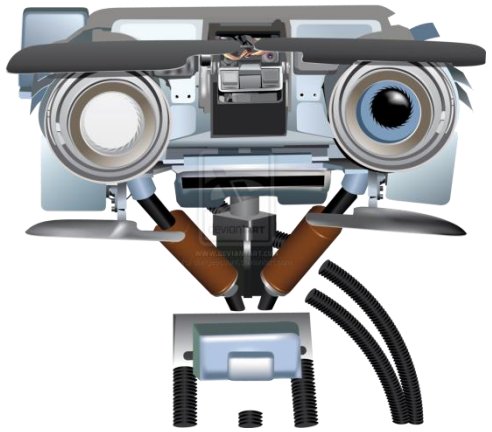
$$= [\ 1,\ \ 1,\ \ 1,\ \ 1]$$

Better approach:

$$w = [0.1, 0.1, 0.1, 0.1]$$

$$= [\ 1, -1, -1,\ \ 1]$$

Additional details: Courbariaux et al. BinaryConnect: Training Deep Neural Networks with binary weights during propagations. NeurIPS, 2015.



Parameter Pruning

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Remove unimportant weights

- Many weights may not affect performance much (if at all)
- Can save space and computation since you can skip operations*

Optimal Brain Damage (LeCun et al., NeurIPS, 1989)

- Find parameters that don't affect the training/validation error of the network.

1. Train your network
2. Compute the second-order derivatives h_{kk} for each parameter
3. Compute parameter saliencies $s_k = \frac{h_{kk}u_k}{2}$ ($u_k =$ next layer parameters)
4. Delete some low saliency parameters
5. Repeat

Does this really save space/time?

It depends….

1	1	0
0	1	0
1	1	1

For CNNs we can just prune entire filters instead!

Pruning entire filters in CNNs

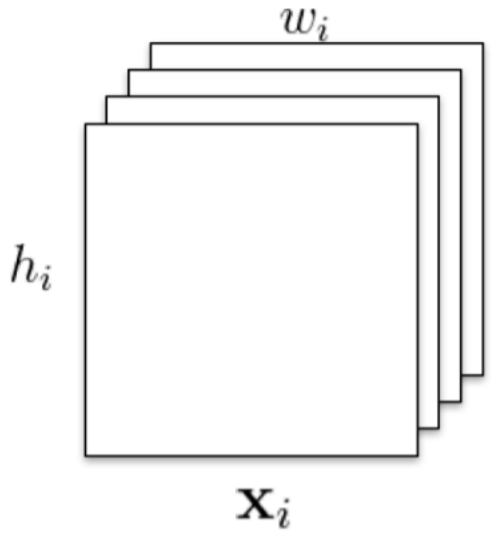


figure credit: Li et al., Pruning Filters for Efficient Convnets, ICLR, 2017

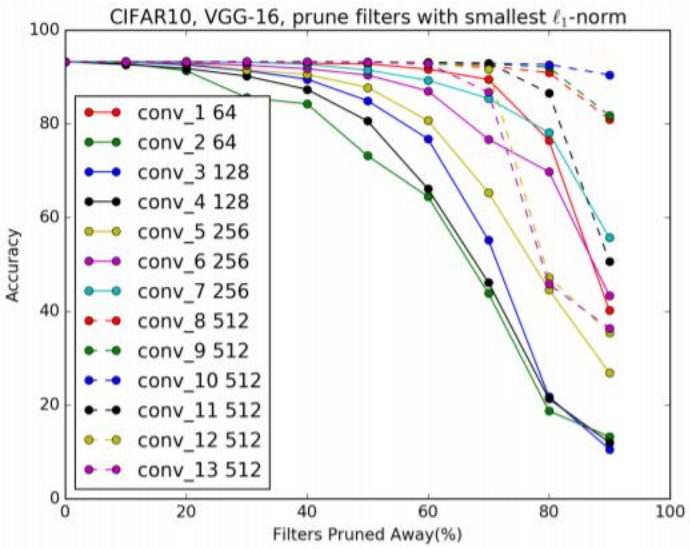
Pruning process

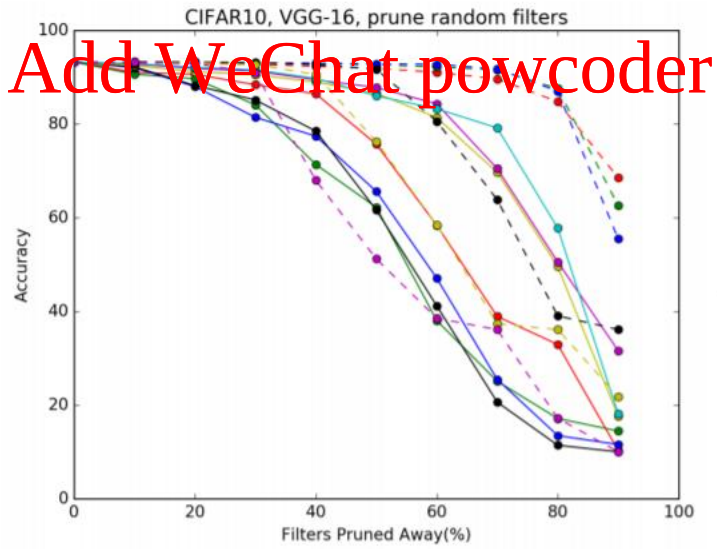
1. Train your neural network
2. Prune filters for layer l_k
3. Retrain your network
4. Repeat for layer l_{k+1}

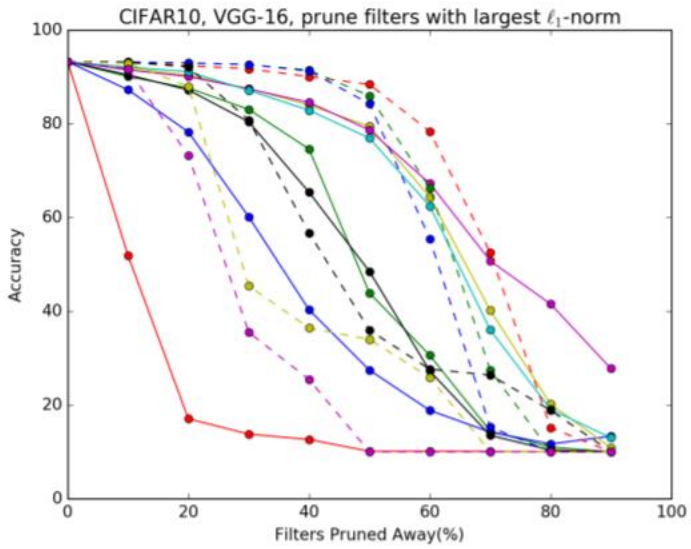
Why not all at once?

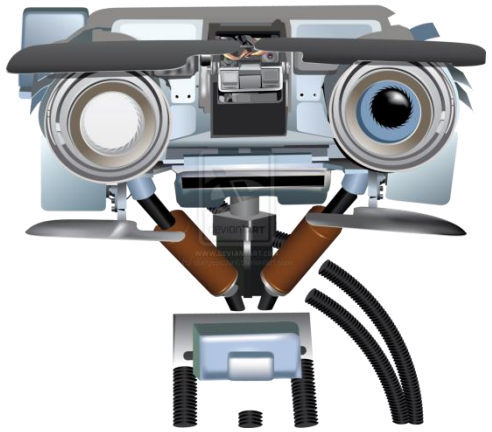
How to choose which filters to prune?

- Often the focus of many research papers.
- The approach of Li et al., Pruning Filters for Efficient Convnets, ICLR, 2017:
  - Rank filters $w_1, w_2, \ldots$ using $s_k = \|w_k\|_1$









Knowledge Distillation

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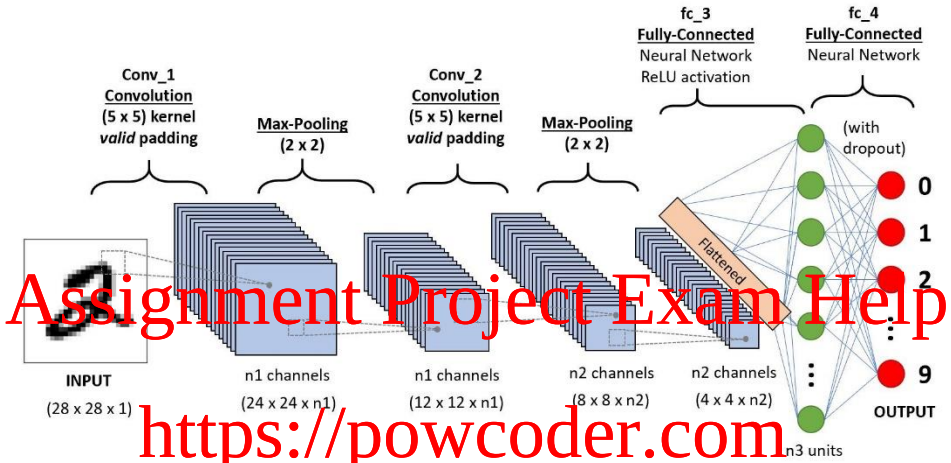
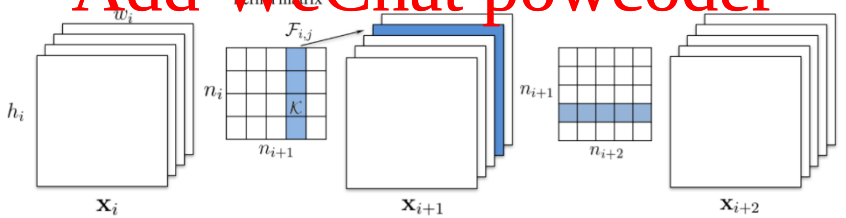
Creating an efficient network

Trained CNN



Why not train a more efficient network to begin with?

Pruning



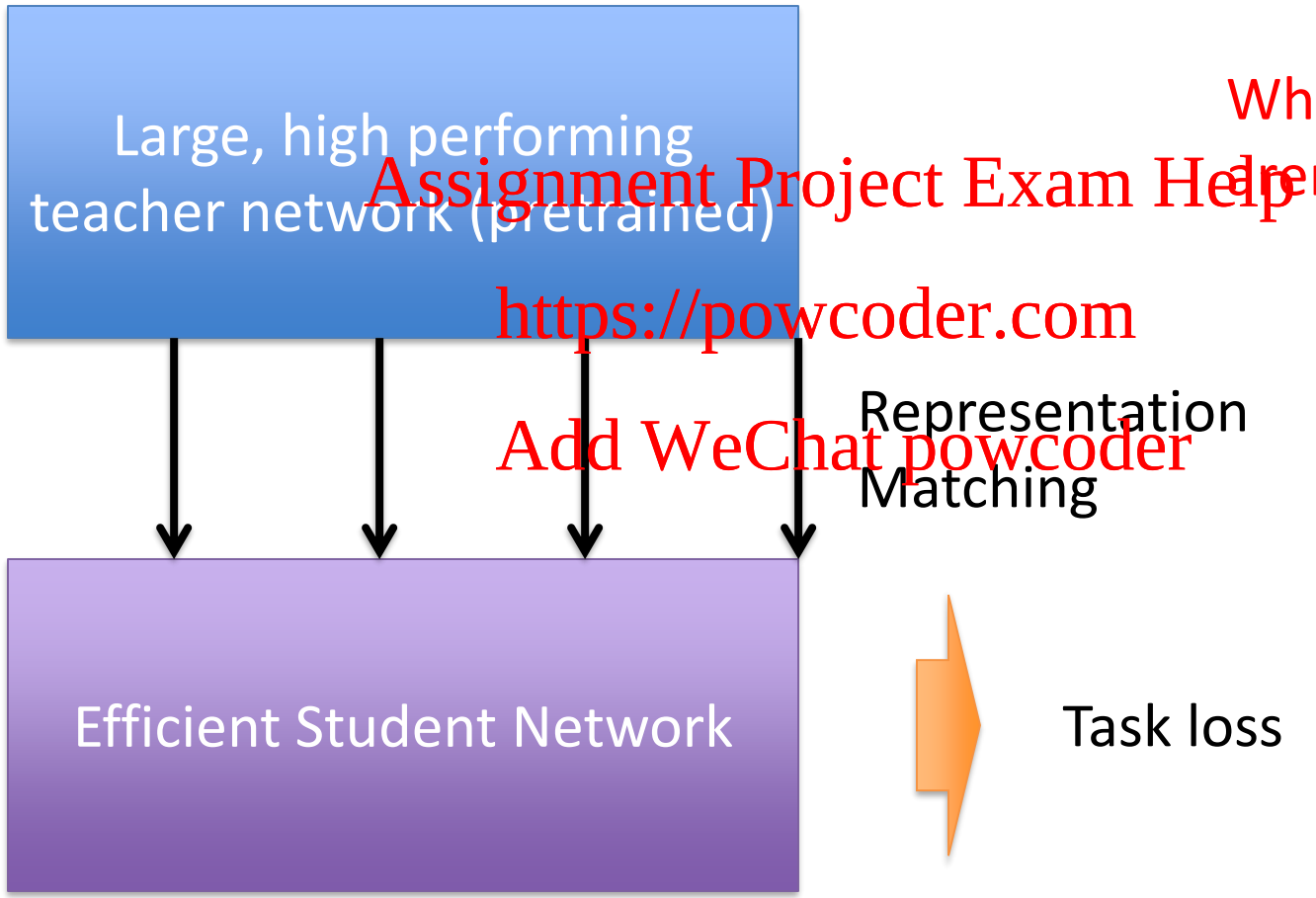
Efficient CNN!

CNN image credit: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Distillation idea

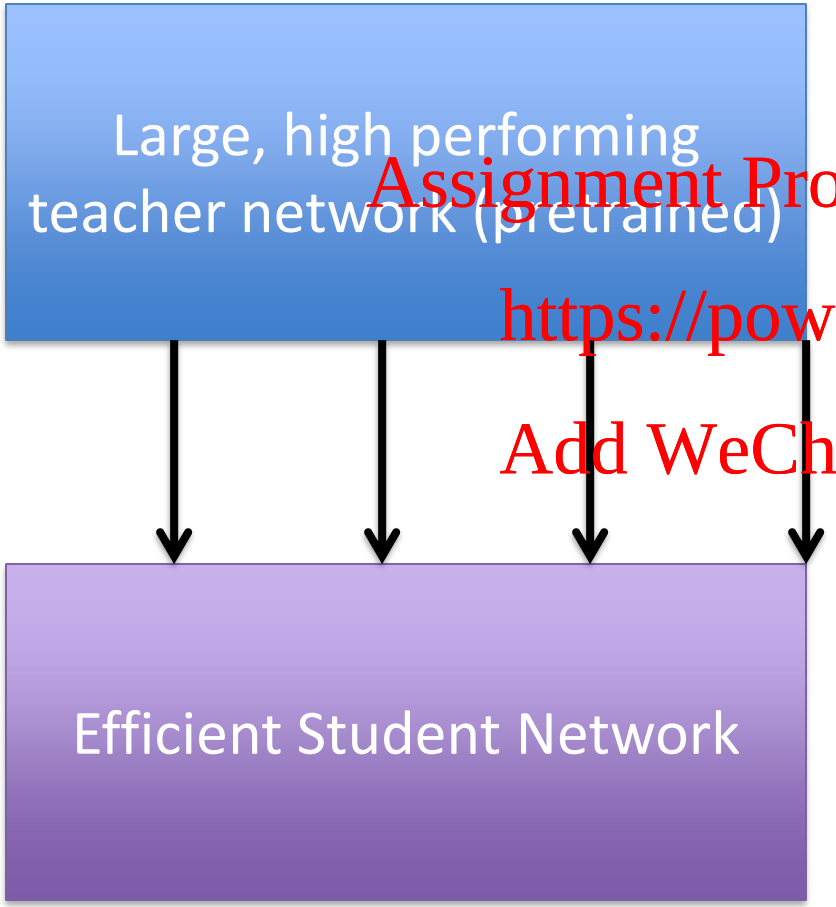
- Smaller, more efficient networks may not perform well
- We have an example of a network that achieves better performance
- Try to get the small network to mimic the large network

Learning with a student-teacher framework



What if the activations aren't the same size?

Learning with a student-teacher framework



What if the activations aren't the same size?

Representation Matching

Task loss + Representation Matching loss

Distillation loss (i.e. matching representations)

$$L_{distill}(a_t, a_s) = \|a_t - a_s\|_2^2$$

More generally considering a case where relevant information is extracted through some transformation function f, g for the teacher, student, respectively

$$L_{distill}(a_t, a_s) = \|f(a_t) - g(a_s)\|_2^2$$

Applications of distillation

- Creating an efficient student using a teacher network
- Can distill ensemble results into a single network

Method	Speech recognition accuracy
Baseline	58.9
Ensemble of 10 models	61.1
Distilled single model	60.8

reference: Hinton et al. Distilling the Knowledge in a Neural Network. NeurIPS 2014 Deep Learning Workshop
another useful paper: Heo et al. A Comprehensive Overhaul of Feature Distillation. ICCV, 2019.

Next Class

Final Review:

expect questions on material covered in the entire course in lectures, problem sets, LABs, and assigned reading

Course evaluations available (5-10 minutes to complete).
Please fill it out at: https://bu.campuslabs.com/courseeval