Inference, Deployment, and Compression

CS4787/5777 Lecture 27 — Fall 2022

Review: Inference

- Suppose that our training loss function looks like

$$f(w) = \frac{1}{n} \sum_{i=1}^{n} \ell(h_w(x_i); y_i)$$

- Inference is the problem of computing the prediction

$$h_w(x_i)$$

Why should we care about inference?

- **Train once, infer many times**
  - Many production machine learning systems just do inference

- Often want to run inference on **low-power edge devices**
  - Such as cell phones, security cameras
  - **Limited memory** on these devices to store models

- Need to get **responses to users quickly**
  - On the web, users won't wait more than a second

Metrics for Inference

- Important metric: **accuracy**
  - Inference accuracy can be **close to test accuracy** — if data from same distribution
- Important metric: **throughput**
  - **How many examples** can we classify in some amount of time
- Important metric: **latency**
  - **How long** does it take to get a prediction for a single example
- Important metric: **model size**
  - **How much memory** do we need to store/transmit the model for prediction
- Important metric: **energy use**
  - **How much energy** do we use to produce each prediction
- Important metric: **cost**
  - How much money will all this cost us

Tradeoffs

- When designing an ML system for inference, there are **trade-offs** among all these metrics!
  - Most "techniques" do not give free improvements, but have some trade-off where some metrics get better and others get worst

- There is **no one-size-fits-all "best" way to do ML inference**.

- We need to decide **which metric we value the most**
  - Then keep that in mind as we design the system

Improving the performance of inference

What tools do we have in our toolbox?

Choosing our hardware: CPU vs GPU

- For training, people generally use GPUs for their high **throughput**
- But for inference, the right choice is less clear
- For small networks, CPUs can have the edge on **latency**
  - And CPUs are generally cheaper…lower **cost**
- CPU-like architectures are often a good choice for low-power systems, since it's easier to put a low-power CPU on a mobile device
  - Many mobile chips are now CPU/GPU hybrids, so line is blurred here

Altering the batch size

- Just like with learning, we can **make predictions in batches**

- Increasing the batch size helps **improve parallelism**
  - Provides more work to parallelize and an additional dimension for parallelization
  - This improves **throughput**

- But increasing the batch size can make us do more work before we can return an answer for any individual example
  - Can **negatively affect latency**

Demo

Latency vs Throughput

Inference on neural networks

- Just need to **run the forward pass of the network**.
  - A bunch of matrix multiplies and non-linear units.

- Unlike backpropagation for learning, here we do not need to keep the activations around for later processing.

- This makes inference a much simpler task than learning.
  - Although it can still be costly — it's a lot of linear algebra to do.

Neural Network Compression

- Find an **easier-to-compute network** with similar accuracy
  - Or find a network with **smaller model size**, depending on the goal

- Most compression methods are **lossy**, meaning that the compressed network may sometimes predict differently

- **Many techniques** for doing this
  - We'll see some in the following slides

Simple Technique: "Old-School" Compression

- Just apply a standard lossless compression technique to the weights of your neural network.
  - **Huffman coding** works here, for example.
  - Even something very general like **gzip** can be beneficial.

- This **lowers the stored model size without affecting accuracy**

- But this does mean we **need to decompress eventually**, so it comes at the cost of some compute & can affect start-up latency.

Low-precision arithmetic for inference

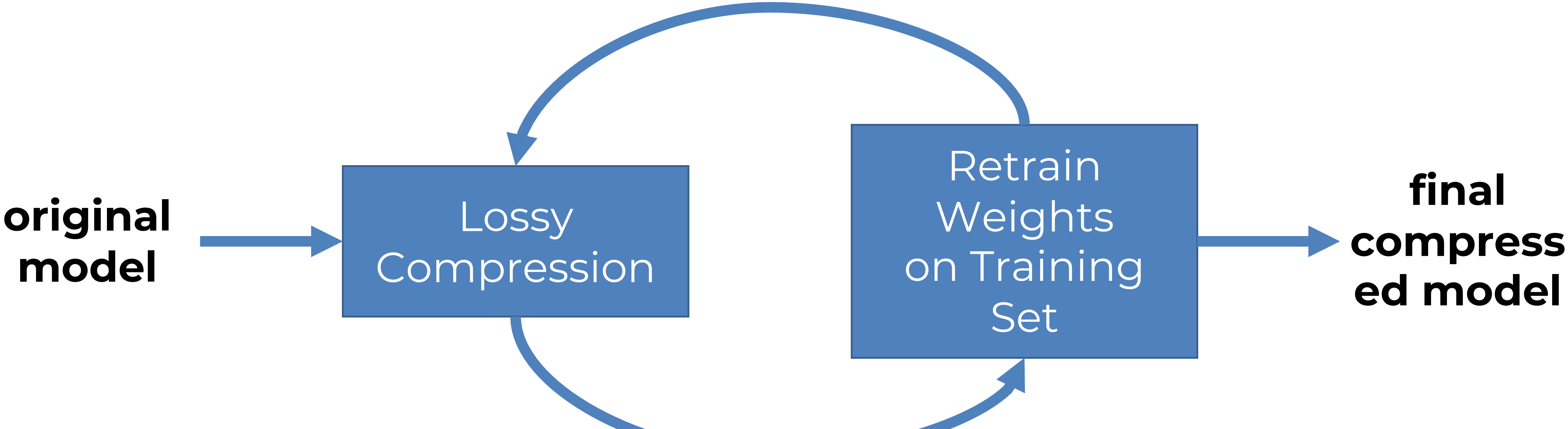
- Very simple technique: just use low-precision arithmetic in inference
- Can make any signals in the model low-precision
- Simple **heuristic for compression**: keep lowering the precision of signals until the accuracy decreases
  - Can often get down below 16 bit numbers with this method alone
- **Binarization/ternarization** is low-precision arithmetic in the extreme

Pruning

- **Remove activations** that are usually zero
  - Or that don't seem to be contributing much to the model
  - Good heuristic: remove the smallest X% of weights
- Effectively creates **a smaller model**
  - This makes it easy to retrain, since we're just training a smaller network
- There's always the question of whether training a smaller model in the first place would have been as good or better.
  - But usually pruning is observed to produce benefits.

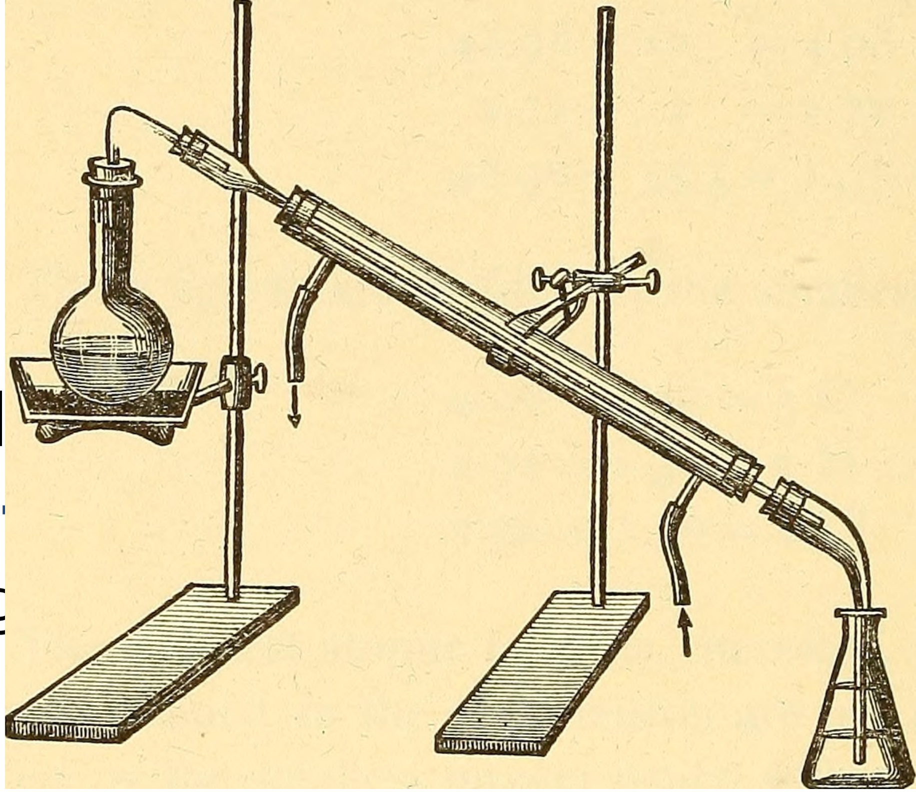
Fine-Tuning

- Powerful idea: apply a lossy compression operation, then **retrain the model** to improve accuracy



- A general way of "getting back" accuracy lost due to lossy compression.

Knowledge distillation



- Idea: take a large/complex model and
  smaller network to match its outpu
  - E.g. Hinton et. al. "Distilling the Knowledg
    Neural Network."
- Often used for distilling **ensemble models** into a single network
  - Ensemble models average predictions from multiple independently-trained models into a single better prediction
  - Ensembles often **win Kaggle competitions**
- Can also **improve the accuracy** in some cases.

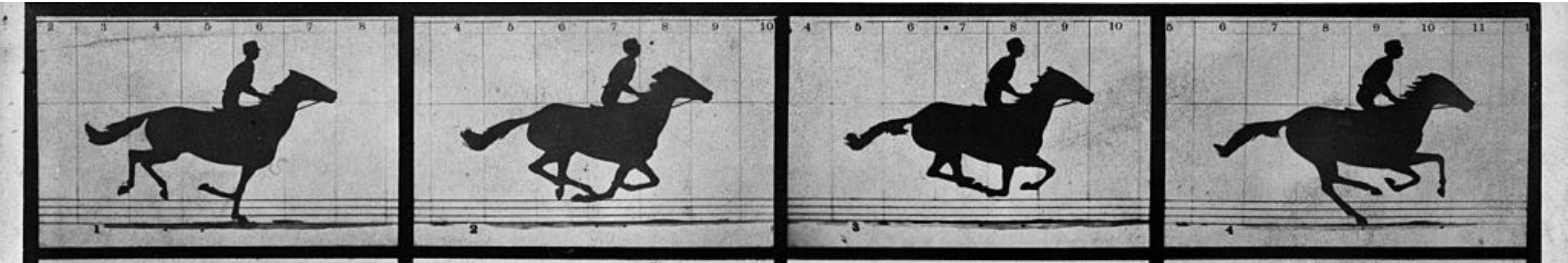
Efficient architectures

- Some neural network architectures are **designed to be efficient at inference time**
  - Examples: MobileNet, ShuffleNet, SqueezeNet
- These networks are often based on sparsely connected neurons
  - This limits the number of weights which makes models smaller and easier to run inference on
- To be efficient, we can just **train one of these networks in the first place** for our application.

Re-use of computation

- For video and time-series data, there is a lot of **redundant information** from one frame to the next.

- We can try to **re-use some of the computation** from previous frames.
  - This is less popular than some of the other approaches here, because it is not really general.



The last resort for speeding up DNN inference

- **Train another, faster type of model** that is not a deep neural network
  - For some real-time applications, you can't always use a DNN
- If you can get away with **a linear model**, it's almost always much faster.
- Also, **decision trees** tend to be quite fast for inference.
- …but with how technology is developing, we're **seeing more and more support for fast DNN inference**, so this will become less necessary.

Where do we run inference?

Inference in the cloud

- Most inference today is run on **cloud platforms**
- The cloud supports **large amounts of compute**
  - And makes it easy to access it and make it reliable
- This is a good place to put AI that needs to think about data
- For interactive models, **latency** is critical

Inference on edge devices

- Inference can run on your **laptop or smartphone**
  - Here, the size of the model becomes more of an issue
  - Limited smartphone memory
- This is good for **user privacy and security**
  - But not as good for companies that want to keep their models private
- Also can be used to deploy **personalized models**

Inference on sensors

- Sometimes we want **inference right at the source**
  - On the sensor where data is collected

- Example: a surveillance camera taking video
  - Don’t want to stream the video to the cloud, especially if most of it is not interesting.

- **Energy use** is very important here.