Shared Mobile-Cloud Inference for Collaborative Intelligence

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Abstract

As AI applications for mobile devices become more prevalent, there is an increasing need for faster execution and lower energy consumption for neural model inference. Historically, the models run on mobile devices have been smaller and simpler in comparison to large state-of-the-art research models, which can only run on the cloud. However, cloud-only inference has drawbacks such as increased network bandwidth consumption and higher latency. In addition, cloud-only inference requires the input data (images, audio) to be fully transferred to the cloud, creating concerns about potential privacy breaches. We demonstrate an alternative approach: shared mobile-cloud inference. Partial inference is performed on the mobile in order to reduce the dimensionality of the input data and arrive at a compact feature tensor, which is a latent space representation of the input signal. The feature tensor is then transmitted to the server for further inference. This strategy can improve inference latency, energy consumption, and network bandwidth usage, as well as provide privacy protection, because the original signal never leaves the mobile. Further performance gain can be achieved by compressing the feature tensor before its transmission.
1 Introduction

Collaborative intelligence is an AI model deployment strategy that allows shared inference between the cloud and the edge device. It has been shown to provide benefits in terms of energy usage and inference latency in certain scenarios [1]. Typically, an AI model, such as a deep neural network, is split into an edge sub-model and a cloud sub-model. Feature tensors computed by the edge sub-model are transmitted to the cloud for the remainder of the inference process.

At NeurIPS 2019, we held a live demo to showcase an Android app demonstrating shared inference strategies and comparing them against cloud-only and mobile-only inference. ResNet [2] and VGG [3] models were preloaded onto the Android device and were run using the TensorFlow Lite interpreter. We also had two servers emulating the cloud, each with a GeForce GTX TITAN X GPU. One server was placed on our demo site’s LAN and the other was remote (located in a nearby city). Using the local server for inference worked well for all configurations, but using the remote server for inference only performed well for configurations that minimized the usage of network bandwidth (e.g. shared inference strategies).

Inference on mobile GPUs tends to run slower than inference on server GPUs. With our equipment, a single ResNet-34 inference took 160 ms on the mobile and 20 ms on the server. However, a server-only inference process is constrained by the available bandwidth: low upload speeds can dramatically influence the total end-to-end inference times. Furthermore, consumers also are wary of the financial costs that come from mobile data usage. Shared inference strategies attempt to lessen the negatives of server-only inference by transmitting less data over the network, while still deferring heavier computations to the server.

To demonstrate how shared inference may result in better overall inference times, consider the plot in Figure 2. For ResNet-34, shared inference using 8-bit quantized tensors is faster than mobile client-only inference for upload bit rates larger than 450 KB/s, and both are faster than cloud-only inference over the range of bit rates tested. For this experiment, no further compression of tensors was applied, apart from 8-bit quantization.

These experiments were conducted on a Samsung Galaxy S10 phone running Qualcomm Snapdragon 845 SoC, with maximum available upload bit rate of 3 MB/s; and a remote server located within 5 km and average ping time of 5 ms. The inference process for a new input image begins as soon as
Figure 2: A plot demonstrating how total inference time varies depending on available upload bit rate. Model under test: ResNet-34. Mobile client: Samsung Galaxy S10 phone (Qualcomm Snapdragon 845) on WiFi network with maximum available upload bit rate of 3 MB/s. Server: within 5 km and with average ping time of 5 ms.

the previous image is completely inferred. It is interesting to note that when using shared inference strategies, it is possible to obtain higher throughputs by performing mobile client-side inference on the next input image while waiting for the server to respond.

A repository containing a demo Android app and Python library utilities to assist in splitting models and conducting further analysis is made publicly available[1]

2 Methodology

In order to deploy a deep neural network in a collaborative intelligence setting, one needs to decide at which layer to split the model into the edge sub-model and the cloud sub-model[1]. Desirable split layer properties include:

- Minimal aggregate computation from preceding layers
- Small output tensor size
- Compressibility of output tensor data
- Stability of tensor output values w.r.t. minor changes in input frames

Because the ResNet models contain BatchNorm[4] layers, the output neuron values of BatchNorm layers can be treated as a normally distributed random variable, \( y_{ijk} \sim N(\mu = 0, \sigma^2 = 1) \). Furthermore, the distribution of neuron values for the following layers may also sometimes approximate a normal distribution. This is visualized in Figure 3. For a normal random variable, over 99% of values lie within 3 standard deviations from the mean, so the tensor can be quantized over the interval \([\mu - 3\sigma, \mu + 3\sigma]\). For the demo app, we opted for 8-bit uniform quantization, though research shows[5] that even fewer bits can be used without a significant drop in accuracy. Converting from 32-bit floating point values to 8-bit integers results in an immediate 4x reduction in the size of the tensor data. However, feature tensors may be further compressed using standard codecs such as JPEG

[1] https://github.com/YodaEmbedding/collaborative-intelligence
Figure 3: Histogram of output neuron values from 8th add layer of ResNet-34. The neuron values resemble a normal distribution, and so nearly all neuron values are contained within the interval $[-2, 2]$. This is largely due to the BatchNorm layer preceding the skip connection as well as the BatchNorm layer within the non-identity skip branch. These BatchNorm layers help ensure the output activations resemble a normal random variable.

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3 Conclusion

Using shared inference techniques, an edge device is able to perform computationally expensive inferences under a larger variety of network conditions than server-only inference is capable of, owing to the reduced bandwidth usage. Moreover, the resulting inference times can be lower than edge-only or cloud-only inference. Though we have only investigated shared inference strategies with preexisting models such as ResNet, VGG, and YOLO [8], it is likely that models well-suited towards shared inference strategies could be designed, containing layers that exhibit the useful properties described in Section 2.

References

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