A Note on Latency Variability of Deep Neural Networks for Mobile Inference

Luting Yang  
UC Riverside  

Bingqian Lu  
UC Riverside  

Shaolei Ren  
UC Riverside

Abstract
Running deep neural network (DNN) inference on mobile devices, i.e., mobile inference, has become a growing trend, making inference less dependent on network connections and keeping private data locally. The prior studies on optimizing DNNs for mobile inference typically focus on the metric of average inference latency, thus implicitly assuming that mobile inference exhibits little latency variability. In this note, we conduct a preliminary measurement study on the latency variability of DNNs for mobile inference. We show that the inference latency variability can become quite significant in the presence of CPU resource contention. More interestingly, unlike the common belief that the relative performance superiority of DNNs on one device can carry over to another device and/or another level of resource contention, we highlight that a DNN model with a better latency performance than another model can become outperformed by the other model when resource contention be more severe or running on another device. Thus, when optimizing DNN models for mobile inference, only measuring the average latency may not be adequate; instead, latency variability under various conditions should be accounted for, including but not limited to different devices and different levels of CPU resource contention considered in this note.

1 INTRODUCTION
The unmatched predictive power of deep neural networks (DNNs) has been successfully attested by numerous applications, including speech/image recognition, malware detection, health care, among others [1]. Traditionally, due to the prohibitively large DNN model size and computational requirement, the inference tasks of DNNs for resource-constrained mobile devices are usually offloaded to data centers or distributed high-performance servers. For example, a mobile device that needs to perform inference (e.g., image style transfer) can send its request to a remote cloud where pre-trained DNNs are hosted, and then subsequently receives the inference result via communication networks. While data centers still remain the mainstream platform for DNN training, executing DNN inference entirely and directly on mobile devices (a.k.a., mobile inference or on-device inference) has been quickly trending, as evidenced by the Facebook app that integrates built-in DNNs (e.g., for real-time image style transfer) and supports mobile inference for billions of active users [2]. Compared to offloading-based inference, the key advantages of mobile inference include being less reliant on network connection and also, more importantly, better protecting privacy by keeping user’s (possibly sensitive) data locally without transferring it to a remote cloud or platform.

The emergence of DNN-powered mobile inference is made possible by the increasingly more powerful computing capabilities of mobile systems as well as recent progress in DNN model compression [3–6]. Concretely, state-of-the-art DNN neural architecture search and model compression techniques, such as weight pruning/quantization in either structure or non-structured manners [5, 7–11], can remarkably reduce the DNN size and cut the average inference latency to the order of tens/hundreds of milliseconds or even less, yet without significantly compromising the inference accuracy. To improve performance, an additional term accounting for the latency is often factored into the loss function or constraints during DNN training/compression [8, 12].

While the average latency of DNN inference is an important performance metric, latency variability is also equally, if not more, crucial for users’ quality of experience. Consider a simple scenario where a mobile user live streams its activities with DNN-based style transfer in real time. Clearly, a low average latency but a high variability in DNN inference can easily make the user feel frustrated with the app.

In practice, it is rare to have a real mobile app, except for toy projects, which does nothing but only DNN inference (e.g., pure image classification without other functionalities). Instead, DNN inference is typically combined with other tasks: DNN-based vision and tracking are only part of mobile augment reality applications [13], whereas DNN-based style transfer is running concurrently with communications activities for live streaming applications. More generally, DNN inference on mobile devices can be executed under an extremely diverse set of runtime conditions, such as time-varying resource contention caused by concurrent threads, different numbers of background services, dynamic system settings (e.g., CPU speed and battery status) and even ambient temperature, which are all potentially interfering factors for DNN inference and can contribute to the inference latency variability.

Nonetheless, the existing studies on DNN model compression and neural architecture search for mobile inference [5, 7–11] typically focus on and measure the average inference latency in a static (and often idealized) environment where the DNN model is running with little interference from the aforementioned factors. For example, the reported inference latency of mobile DNN models hosted on TensorFlow [14] only mentions a single performance value “measured on Pixel 3 on Android 10” without further details regarding the actual runtime condition. Thus, the average inference latency measured in an idealized setting can only represent the best-case performance, and fails to capture the actual latency in a practical environment with significant variabilities.

In this note, we conduct a preliminary measurement study on the latency variability of DNNs for mobile inference. In particular, we consider eight popular DNNs and run them on two mobile devices (listed in Tables 2 and 1) under a diverse set of runtime conditions. We explicitly focus on how the background apps and
CPU resource contention (created by concurrent threads within the same app as DNN inference) affect the inference latency of DNN-based image classification on mobile devices. We find that the number of background apps has little impact on the inference latency, and the inference latency variability is reasonably small in a static environment with little CPU resource contention for most DNN models under our investigation. Nonetheless, our measurement results also highlight that when the number of concurrent threads varies and creates different levels of CPU resource contention, both the average latency and latency variability can vary significantly. Interestingly and also counter-intuitively, one DNN model with a lower average latency and/or latency variability than another model can become outperformed by the other model when running on another device and/or CPU contention becomes more severe.

Our study implies that only measuring the average latency of a DNN model in a static and contention-free environment is inadequate to fully quantify the actual performance for mobile inference: the relatively better latency performance of a DNN model than that of another model under one condition does not necessarily carry over to another device and/or another level of CPU resource contention. This warrants more investigation into the urgent issue of latency variability that is crucial for user experience. Thus, we take the liberty that, in addition to the already-considered metrics such as inference accuracy and average latency, the latency variability under a diverse set of conditions with time-varying resource contention levels should also be measured and compared when optimizing DNNs for mobile inference.

2 METHODOLOGY

In general, the inference latency is jointly affected by the DNN model, mobile device the DNN is running on, as well as the device’s runtime condition and resource management policies. For example, mobile devices have very diverse configurations and thus exhibit different inference latencies even for the same DNN model: high-end devices can have powerful CPUs/GPUs along with purpose-built accelerators to speed up inference, whereas nearly 75% of Facebook’s mobile users are powered by CPUs of at least seven years old [2]. Moreover, the inference latency can also be subject to runtime system condition (e.g., number of concurrent threads) and resource management policies.

Given a DNN model running on a mobile device, we focus on the impact of two runtime factors — the number of background apps and the level of CPU contention — on the inference latency. Our experiment setup is described as follows.

**Overview.** We build an image classification app hosted on Tensorflow Lite for Android [14], which continuously takes input images and provides real-time classification results. The app is installed on two mobile devices, whose details are listed in Table 1.

In line with the official source code, the inference latency is calculated as the sum of time to load the input image and the time to run model inference. For a model on a device, it takes a small (roughly constant) time to load each image regardless of experiment conditions we have tested. For example, on Samsung S5e, the per-image loading times for MobileNet V2Q and Inception V4Q are only about 5ms and 15ms, respectively. For each DNN model under each condition, we run more than 1,000 inference tasks. We log the inference latency for each image and save it for offline analysis.

At the core of the app is a pre-trained DNN model. In this note, we choose eight official models from TensorFlow Lite in two categories: MobileNet models which are lightweight and specifically tailored to resource-constrained mobile devices at the expense of inference accuracy, and Inception models which reduce the computational cost while maintaining a good accuracy performance [14]. The details of the DNN models are listed in Table 2. Although we can choose any other DNN models including more advanced ones for measurement, we focus on these eight official models because they are popularly used as benchmarks.

Unless otherwise stated, all our latency measurement results will be shown in error bars, indicating the 5th, 25th, 75th, and 95th percentile as well as average latencies.

**Background apps.** To investigate the impact of background apps on inference latency, before running our image classification app in the foreground mode, we open and then turn into the background mode the following apps in order: Facebook, Youtube, Messenger, Google Search, Google Maps, Instagram, Snapchat, Google Play, Gmail, Pandora Radio, which are top 10 most used apps in the U.S. If we consider $n$ background apps, we will put the top $n$ apps into the background.

### Table 1: Device Configuration

| Device Name | CPU (GHz) | Cores | RAM (GB) | RAM Freq. (MHz) | OS | Display | Battery (mAh) |
|------------|----------|------|---------|----------------|----|---------|---------------|
| Samsung Tab A | 2        | 4    | 2       | 933            | 9.0| 1280 x 800 | 5100          |
| Samsung Tab S5e | 2     | 8    | 4       | 1866           | 9.0| 2560 x 1600 | 7040          |

### Table 2: DNN Model Configuration with Estimated Parameters

| Model Name | Million MACs | Million Param. | Size (Mb) | Accuracy | Nodes | Layers |
|------------|--------------|----------------|----------|----------|-------|--------|
| MobileNet_V1_0.75_192_Quant (V1Q) | 233 | 2.59 | 2.6 | 66.1% | 5984 | 30 |
| MobileNet_V2_1.0_224_Quant (V2Q) | 300 | 3.42 | 3.4 | 78.8% | 2810 | 25 |
| MobileNet_V1_0.75_192 (V1F) | 233 | 2.59 | 10.3 | 67.1% | 5984 | 30 |
| MobileNet_V2_1.0_224 (V2F) | 300 | 3.47 | 14 | 90.6% | 2810 | 25 |
| Inception_V3_Quant (V3Q) | 5900 | 23.9 | 23 | 77.5% | 18400 | 159 |
| Inception_V4_Quant (V4Q) | 16800 | 55.8 | 41 | 79.5% | 32480 | 160 |
| Inception_V3 (V3F) | 5900 | 23.9 | 93.3 | 77.9% | 18400 | 159 |
| Inception_V4 (V4F) | 16800 | 55.8 | 170.7 | 80.1% | 32480 | 160 |
3 MEASUREMENT RESULTS

This section presents our measurement results. The key findings are: (1) background apps have little impact on the inference latency; and (2) CPU contention results in a huge inference latency variability. Interestingly, not all DNN models are equally robust against CPU contention than others: a model that has a similar latency performance with another model given mild CPU contention can become much worse than the other model when the CPU contention becomes more severe. Moreover, two models exhibiting similar latencies on one device can behave very differently on another device.

3.1 Impact of Background Apps

We first show in Fig. 1 the latencies of two different DNN models on the two mobile devices, under different numbers of background apps. It can be seen that while latency variability inevitably exists, it is rather minimum. For example, Inception V3F exhibits a < 5% variability on the two mobile devices. Although MobileNet V2Q has a relatively larger variability in percentage, its absolute variability is still small. The results for the other DNN models on these devices are similar and hence omitted for brevity. The little inference latency variability with respect to the number of background apps is partly attributed to the Android’s resource management, which separates background apps and foreground apps. Moreover, when put into the background mode, the apps only keep minimum ongoing activities and hence result in little resource contention.

3.2 Impact of CPU Contention

While background apps do not create aggressive CPU contention, we now turn to the impact CPU contention on latency variability created by concurrent threads within the same foreground app.

We first show in Fig. 2 a snapshot of CPU/memory usage and latencies of MobileNet V2Q on Samsung Tab S5e by gradually increasing the number of concurrent threads (roughly every 2 minutes). We also show the moving average latency over the most recent 20 seconds. Since our launched concurrent threads are all computing-intensive, the memory usage does not noticeably vary when we increase the number of concurrent threads. As expected, with more concurrent threads, the CPU usage increases and so does the inference latency. Moreover, the latency variability is also significant, differing from the case in which we only increase the number of background apps that do not utilize CPU resources.

Next, from Fig. 3 to Fig. 6, we show the latency measurement results for eight DNN models on two mobile devices, under different numbers of concurrent threads. Note that as in other error-bar plots, we show the 5th, 25th, 75th and 95th percentile and average latencies, excluding top and bottom 5% latencies. The “x% active” in the figure captions indicates each thread has a probability of x% to perform computation for each time slot of 5ms. We can observe the following:

- First, for any given DNN model running on a device, the average latency increases with more CPU contention created by more
concurrent threads. Nonetheless, not all DNN models have the same amount of latency variability increase. For example, the latency of MobileNet V1Q increases but still exhibits a fairly small variability on both devices. On the other hand, the latency variability of MobileNet V1F becomes significantly larger with more CPU contention. This shows that given the same device, different DNN models have different robustness in terms of latency variability.

Second, given the same device, one DNN model that has a similar latency performance with another model in the event of low CPU contention can become much worse than the other model when the CPU contention becomes higher. For example, when running on Samsung Tab A, MobileNet V1F has a similar or better latency performance compared to V2Q when the number of concurrent threads is less than 4, but the latency performance of V1F becomes significantly worse than V2Q when more concurrent threads are launched. We focus on the comparison between V1F and V2Q, because they have similar inference accuracies shown in Table 2. While MobileNet V1Q and V2F have significantly different latency performances whose relative superiority remains unchanged under different conditions, these two models have very different accuracies. Thus, using V1Q vs. V2F depends on how one weighs the inference accuracy and latency. The same observation can also be made for Inception V3F and V4Q on Samsung Tab S5E. This implies that an improved performance of average latency and latency variability under one condition does not mean the model will always have better performance under another condition. Thus, our results highlight the need of considering different runtime conditions when optimizing DNN models for mobile inference.

Last but not least, two models exhibiting similar latencies on one device can behave very differently on another device. The existing research on DNN model optimization for mobile inference typically considers a small number of or only one mobile device and reports the average latency, implicitly assuming that the better latency performance of DNN model on one device will translate
into a better performance on another device (although the absolute latency will vary depending on the actual device). Nonetheless, our measurement results invalidate this assumption. For example, when running on Samsung Tab S5e with two concurrent threads, MobileNet V1F is comparable to or better than V2Q in terms of latency, but V2Q becomes better than V1F in terms of latency and variability when running on Samsung Tab A. The same observation can be made for Inception V3F and V4Q when running on Samsung Tab S5e and Tab A, respectively, under six or eight concurrent threads. Our results highlight that the relative superiority of latency performance of DNN models depends on the mobile device that runs the model (due to operating system, hardware configuration, etc.). Thus, when optimizing DNN models for mobile inference, one should cover as many mobile devices as possible.

4 RELATED WORK

To enable DNN deployment on resource-constraint mobile devices, various model compression methods have been proposed, including network and weight pruning [15, 16, 18–19], weight quantization [20, 21], low-rank matrix approximation [22, 21], knowledge distillation [23], and/or a combination of basic compression techniques [24–26]. These studies focus on optimizing and measuring the average inference latency in an static (and often idealized) environment with little resource contention.

Another recent study [3] considers dynamically deciding between on-device mobile inference and offloading-based inference for DNNs. While it confirms that there exists some latency variability for mobile inference, it does not investigate the impact of runtime condition (e.g., the number of concurrent CPU-intensive threads) on inference latency. Our study explicitly focuses on the latency variability of DNNs under different CPU contentions, which are common in practice [2].

5 CONCLUSION

In this note, we present a preliminary study on the latency variability of DNNs for mobile inference. While the number of background apps has marginal impact, the inference latency can dramatically increase with a significant variability given more CPU contention. More interestingly, one DNN model with a better latency performance than another model can be outperformed by the other model when running on another device and/or CPU contention becomes more severe.

Our measurement study also opens up an interesting set of questions. Why are some DNN models more robust against resource contention than others? Why do the relative performance of DNN models change under different levels of CPU contention and/or on different devices? How to mitigate inference latency variability of DNN models for mobile inference?

REFERENCES

[1] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. MIT Press, 2016. http://www.deeplearningbook.org.
[2] C.-J. Wu, D. Brooks, K. Chen, D. Chen, S. Choudhury, M. Dukhan, K. Hazelwood, E. Isaac, Y. Jia, B. Jia, T. Leyvand, H. Lu, Y. Lu, L. Qiao, B. Reagan, J. Spisak, F. Sun, A. Tulloch, P. Vajda, X. Wang, Y. Wang, B. Wasti, Y. Wu, R. Xian, S. Yoo, and P. Zhang. “Machine learning at Facebook: Understanding inference at the edge,” in HPCA, 2019.
[3] S. S. Ogden and T. Guo. “Characterizing the deep neural networks inference performance of mobile applications,” in arXiv, 2019, https://arxiv.org/abs/1909.04783.
[4] W. Liu, X. Ma, S. Lin, S. Wang, X. Qian, X. Lin, Y. Wang, and B. Ren. “Patdnn: Achieving real-time DNN execution on mobile devices with pattern-based weight pruning,” in ASPLOS, 2020.
[5] S. Han, H. Mao, and W. J. Dally. “Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding,” in ICLR, 2016.
[6] G. Gobieski, B. Lucia, and N. Beckmann. “Intelligence beyond the edge: Inference on intermittent embedded systems,” in ASPLOS, 2019.
[7] W. Wen, C. Wu, Y. Wang, Y. Chen, and H. Li. “Learning structured sparsity in deep neural networks,” in NIPS, 2016.
[8] B. Wu, X. Dai, P. Zhang, Y. Wang, F. Sun, Y. Wu, Y. Tian, P. Vajda, Y. Jia, and K. Keutzer. “FBNet: Hardware-aware efficient ConvNet design via differentiable neural architecture search,” in CVPR, pp. 10726–10734, 2019.
[9] N. Liu, X. Ma, Z. Xu, Y. Wang, J. Tang, and J. Ye. “AutoCompress: An automatic dnn structured pruning framework for ultra-high compression rates,” in AAAI, 2020.
[10] S. Han, F.-M. Guo, W. Niu, X. Lin, J. Tang, R. Ku, B. Ren, and Y. Wang. “Ponny: The missing but desirable sparsity in DNN weight pruning for real-time execution on mobile device,” in AAAI, 2020.
[11] X. Xu, Y. Ding, S. X. Hu, M. Niemier, J. Cong, Y. Hu, and Y. Shi. “Scaling for edge inference of deep neural networks,” Nature Electronics, vol. 1, no. 4, p. 216, 2018.
[12] Y. Cheng, D. Wang, P. Zhou, and T. Zhang. “Model compression and acceleration for deep neural networks: The principles, progress, and challenges,” IEEE Signal Processing Magazine, vol. 35, pp. 126–136, Jan 2018.
[13] K. Asif, M. Chen, and X. Chen. “A novel approach for reducing the inference time of deep neural networks on mobile devices,” in ICML, 2018.
[14] S. Srinivas and R. V. Babu. “Data-free parameter pruning for deep neural networks,” in arXiv preprint arXiv:1810.03466, 2018.
[15] F. A. S. and D. W. J. Dally. “Learning both weights and connections for efficient neural networks,” in Advances in neural information processing systems, pp. 1135–1143, 2015.
[16] L. LeCun, J. S. Denker, and S. A. Solla. “Optimal brain damage,” in Advances in neural information processing systems, pp. 998–665, 1990.
[17] H. Li, A. Kadav, I. Durdanovic, H. Samet, and H. P. Graf. “Pruning filters for efficient convnets,” in arXiv preprint arXiv:1608.08710, 2016.
[18] M. Courbariaux, I. Hubara, D. Soudry, R. El-Yaniv, and Y. Bengio. “Binarized neural networks: Training deep neural networks with weights and activations constrained to+ 1 or−1,” in arXiv preprint arXiv:1602.02830, 2016.
[19] M. Rastegari, V. Ordonez, J. Redmon, and A. Farhadi, “Xnor-net: Imagenet classification using binary convolutional neural networks,” in European Conference on Computer Vision, pp. 525–542, Springer, 2016.
[20] E. L. Denton, W. Zaremba, J. Bruna, Y. LeCun, and R. Fergus. “Exploiting linear structure within convolutional networks for efficient evaluation,” in Advances in neural information processing systems, pp. 1269–1277, 2014.
[21] V. Lebedev, Y. Ganin, M. Rakhuba, I. Oseledets, and V. Lempitsky. “Speeding up convolutional neural networks using fine-tuned cp-decomposition,” in arXiv preprint arXiv:1412.6553, 2014.
[22] G. Hinton, O. Vinyals, and J. Dean. “Distilling the knowledge in a neural network,” in arXiv preprint arXiv:1503.02531, 2015.
[23] J. S. Ogden and T. Guo. “Characterizing the deep neural networks inference performance of mobile applications,” in arXiv, 2019, https://arxiv.org/abs/1909.04783.
[24] S. Tan, K. K. W. Ng, S. T. T. C. Yau, B. S. Y. K. Law, and R. T. R. C. Yuen. “A note on latency variability of deep neural networks for mobile inference,” in Conference XXX, 2020, USA.