Towards Characterizing Knowledge Distillation of PPG Heart Rate Estimation Models

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Abstract

Heart rate estimation from photoplethysmography (PPG) signals generated by wearable devices such as smartwatches and fitness trackers has significant implications for the health and well-being of individuals. Neural models designed to estimate heart rate are largely deployed on wearable devices and thus must adhere to strict memory and latency constraints. In this workshop submission, we explore and characterize how large pre-trained PPG models may be distilled to smaller models appropriate for real-time inference on the edge. We evaluate four distillation strategies: *hard distillation*, *soft distillation*, *decoupled knowledge distillation (DKD)*, and *feature distillation* through comprehensive sweeps of teacher and student model capacities. We present a characterization of the resulting scaling laws describing the relationship between model size and performance. This early investigation lays the groundwork for practical and predictable methods for building edge-deployable models for physiological sensing.

1 Introduction

Wearable devices such as smartwatches and fitness trackers have enabled the collection of in-situ datasets of sensor signals with the potential to support individuals in tracking and monitoring their health and well-being. Amongst other signals, photoplethysmography (PPG), a method for optical estimation of blood volume pulse (BVP), has shown utility in allowing individuals to gauge their cardiovascular health [14, 9, 6]. The growing ubiquity of wearable devices has led to the accumulation of large PPG datasets [5, 10, 7] and the subsequent training of large neural models useful in estimating cardiac function (e.g., heart rate and heart rate variability among other cardiovascular conditions) [6, 16, 17, 12, 9]. These developments represent significant progress towards end-user applications, such as providing real-time feedback in exercise contexts (e.g., heart rate response to exercise intensity) as well as passive screening of diseases (e.g., hypertension).

Despite the success of these large models across a variety of sensor data tasks, their significant computational requirements pose a barrier to adoption and limit their utility. While edge models (e.g., those running on wearables) better preserve privacy and better support real-time feedback, large sensor models may struggle to realize these gains. More work is thus needed to develop and characterize methods for enabling large physiological sensing models to effectively scale to the edge.

Prior work has established the utility of knowledge distillation [4, 2], where efficient student models learn from larger, high capacity, pretrained teacher models. For example, DistilBERT [13] found success in optimizing language models for edge deployments while retaining performance. More similar to wearable physiological sensing, prior work has found success in distilling audio [8] and accelerometer models [15] useful for human activity recognition. However, while knowledge distillation has been established as a powerful tool in developing compute-efficient models, there has been little exploration into the characterization of these methods, making it difficult to predict

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the performance of a distilled model. Only recently have scaling laws that govern the distillation of language models been established to predictably compute distilled language model performance [1].

Building off these ideas, this workshop submission takes a first step towards establishing predictable distillation performance in the domain of physiological sensing. Specifically, for the task of PPG heart rate estimation, we evaluate four distillation strategies across different student and teacher model capacities and characterize the effect of these variables on distilled model size. We further compare the interplay between model computational requirements (i.e., memory consumption and inference time) and distilled performance. We find that distilled models improve upon models trained from scratch, that the decoupled knowledge distillation strategy outperforms other evaluated strategies, and the performance of distilled models follow a characterizable exponential scaling curve.

2 Methods

Distillation Experiment Setup. We characterize the distillation scaling behavior of physiological sensing models across a number of teacher and student model sizes. Specifically, we employ the variant of a 1D-ResNet backbone [3] used by [5] to classify the instantaneous heart rate given a PPG signal window. To vary model capacity, we sweep across the number of residual blocks (i.e., resulting in an approximately exponential sweep of model parameters) for student and teacher models, as illustrated in Table 1. We further explore the following four distillation strategies:

- *Hard Distillation:* The teacher model's predictions (i.e., the final $argmax$ output) are used as labels for training the student model, helping it mimic the discrete decision boundaries of the teacher.
- *Soft Distillation:* The student model is trained on the output probability distributions of the teacher model, encoding richer information about inter-class relationships and uncertainty [4].
- *Decoupled Knowledge Distillation (DKD):* The teacher model's outputs are separated into target class and non-target class distillation components in the student model's loss to introduce flexibility in weighting the significance of true label and incorrect label probabilities [18].
- *Feature Distillation:* Moving beyond operating on model outputs, in *feature distillation*, the student model is trained to match the learned feature maps of the teacher model, aligning its intermediate representation space [11].

Heart rate detection performance is evaluated via Mean Absolute Error (MAE) in beats per minute (BPM). The performance of all distilled student models are evaluated against a corresponding model of the same size trained from scratch rather than distilled from a teacher model.

Table 1: Experimental variables for characterizing the process of distilling PPG models.

Name	**Description**	**Values**
Strategy	Procedure for distillation	Hard Distillation, Soft Distillation, Decoupled Knowledge Distillation, Feature Distillation
Teacher size	# of residual blocks (# of parameters) in teacher model	2 (33,724), 3 (44,156), 4 (54,588), 5 (97,852), 6 (139,196), 8 (221,884), 10 (534,460), 12 (863,676)
Student size	# of residual blocks (# of parameters) in student model	1 (23,292), 2 (33,724), 3 (44,156), 4 (54,588), 5 (97,852), 6 (139,196), 8 (221,884), 10 (534,460)

Datasets. For all experiments, we leverage 3 free-living PPG datasets containing a total of 107 hours of PPG sensor signals: WildPPG [5], PPG-DaLiA [10], GalaxyPPG [7]. Following prior work, we use only the green channel of the PPG sensor, resampled to 25 Hz and segmented into 8-second windows with 2-second strides [5, 10]. Each dataset includes heart rate ground truth (in beats per minute) derived via an electrocardiogram (ECG) signal. We generate subject-independent train-test splits by taking data from 80% of the subjects for training, and data from 20% of the subjects for evaluation. We conduct 2-fold cross validation across all experiments.

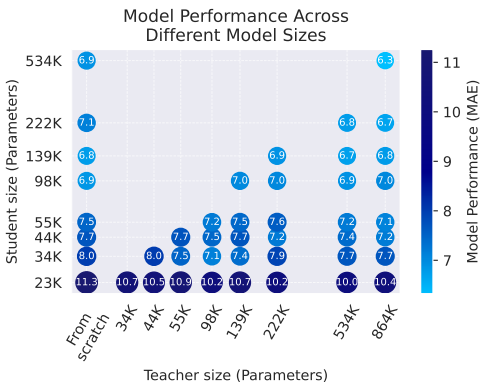

Figure 1: Model performance across different teacher and student model sizes. Color and size both encode the same MAE metric. The "From scratch" column denotes baseline models trained from scratch rather than with distillation.

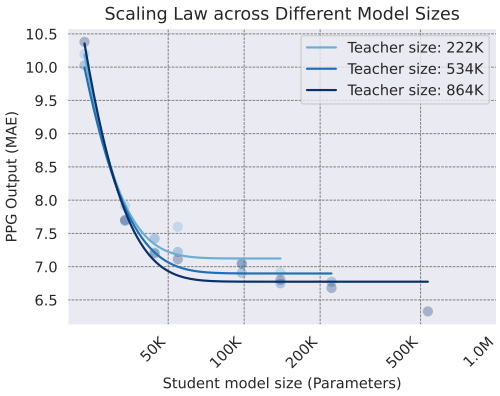

Figure 2: Scaling law for modeling distilled model performance across different teacher and student sizes. Note that experimental conditions with smaller teacher sizes yielded too few data points to effectively fit a curve to.

3 Results

Distilled models outperform those trained from scratch. In Figure 1, we show the results of our distillation experiment using the *soft distillation* strategy. The left-most column, "From scratch", denotes baseline models of a given size trained from scratch rather than distillation. We find that this baseline is consistent with prior work (e.g., the target model size with 8-blocks yields a similar MAE to the result using the same model reported in [5]). In general, we observe that smaller models exhibit worse MAE performance, and that distillation always improves performance over training from scratch. We note that larger teacher models generally exhibit improved performance, and hypothesize that too-large models may overfit easily, resulting in degradation. These results support that significant gains can be obtained in terms of performance from model distillation.

Table 2: Model performance (MAE) across different distillation strategies and student model sizes. Teacher model size is fixed at 12 blocks.

Distillation	**Student Model Size (Blocks)**							
Strategy	**1**	**2**	**3**	**4**	**5**	**6**	**8**	**10**
Hard	11.734	10.418	9.256	7.478	7.208	6.983	6.830	6.493
Soft	10.380	7.703	7.200	7.111	7.042	6.801	6.679	6.327
DKD	**8.899**	**6.772**	**6.689**	**6.849**	**6.522**	**6.291**	**5.959**	**5.759**
Feature	9.397	7.200	6.952	6.914	6.872	6.800	6.659	6.409

***DKD* outperforms other strategies.** As shown in Table 2, we find that *DKD* performs the best of the four strategies evaluated across all model size configurations, including across different teacher sizes not shown in the table. *DKD* is followed in performance by *feature distillation*, then *soft distillation*, and finally *hard distillation*. Out of the logit-based strategies, *hard distillation* performed the worst due to the lack of information encoded in its discrete labels, and *soft distillation* performed marginally better. *DKD*, on the other hand, poses the clearest advantage in being able to flexibly weigh true label and incorrect label probabilities, particularly in our task framing where the classification bins are semantically ordinal. Our experiments used $\alpha = 1$ and $\beta = 8$ such that that non-target class distillation (NCKD) probabilities are weighed 8 times more than target class distillation (TCKD) probabilities. Our results indicate that while our small models may not have the capacity to learn a rich representation when trained from scratch, regressing to richer labels (via distillation), than the original BPM ground truths, allows the student models to successfully learn the internal representation of the larger teacher models, leading to improved performance.

We thus show that our student models are small enough to learn a strong internal representation independently given a rich enough label.

Varying model size exhibits predictable scaling. In Figure 2, we show a preliminary experiment regarding characterizing distillation in the physiological sensing domain. Specifically, following prior work on the scaling laws for language model distillation [1], we derive scaling curves that map the size of student models to their distilled performance. For varying teacher sizes, we find the following scaling law equations:

- Teacher size = 8 blocks (221k params): $y = 11.704 * e^{-1.338x} + 7.121$
- Teacher size = 10 blocks (534k params): $y = 9.690 * e^{-1.378x} + 6.888$
- Teacher size = 12 blocks (863k params): $y = 11.607 * e^{-1.172x} + 6.755$

We observe that performance seemingly begins to saturate at student models of size 6 residual blocks (139k params). We also note that although this figure shows fit curves for results obtained using the *soft distillation* strategy, the *DKD* and *feature distillation* strategies also adhered to these curves while the *hard distillation* strategy produced a much sharper saturation at an earlier point (i.e., at a smaller model size).

Table 3: System compute benchmarking for distilled model inference. Inference time is reported in seconds (mean $\pm$ standard deviation) and peak GPU memory is reported in megabytes.

Time & Memory	**Model Size (Blocks)**								
Metrics	1	2	3	4	5	6	8	10	12
Inference Time (s)	0.512±0.025	0.938±0.028	1.340±0.0316	1.787±0.144	2.177±0.192	2.622±0.167	3.357±0.147	4.419±0.115	4.758±0.130
Memory Usage (MB)	9.468	9.646	9.824	10.002	10.623	11.275	12.568	18.440	23.483

Distillation can lead to large gains in memory consumption and inference time. Table 3 shows system benchmarking of these models on an Nvidia RTX 2080-Ti GPU. Although this is not representative of our final application scenario (e.g., microprocessors in wearable devices), we include these results to show the relative improvement made possible by distillation. For example, distilling a 12-block model (i.e., the largest model we considered) to a 1-block model results in a nearly 90% decrease in inference time and 60% decrease in memory usage with only a 30% reduction in MAE performance.

4 Discussion and Conclusion

Dataset generalization. In this workshop submission, we presented an initial investigation into the distillation of heart rate estimation models. Our evaluation used a naive cross-validation scheme with shuffling samples from three datasets. We are interested in further studying the generalizability of these distilled models across datasets (i.e., by training on one dataset and testing on another).

Model architecture. Our preliminary investigation utilized a straightforward ResNet backbone model trained with supervision as the teacher model. We are interested in continuing our experiments using larger models trained with more recent contrastive approaches (e.g., we note that the model in [12] will be open source soon) to investigate how the potentially richer features learned in a self-supervised fashion might be distilled into smaller models.

Novel distillation strategies. We leveraged three approaches to distillation already documented in the literature to provide baseline characterizations of these heart rate estimation models. Leveraging insights from these experiments, and through participation and discussion in the NeurIPS TS4H workshop, we are excited to develop new methods of distillation that are particularly well-suited for this class of tasks.

This paper provides an initial demonstration of how knowledge distillation can be used to adapt large heart rate estimation models for resource-constrained wearable devices. Our preliminary evaluation shows that distilled models consistently outperform those trained from scratch, with *DKD* outperforming all other evaluated strategies. We also characterized a scaling law that confirms distillation enables substantial reductions in memory usage and inference time for a modest trade-off in performance. These findings provide an encouraging path forward for deploying powerful, real-time health monitoring models on the edge.

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