LEARNING BLOOD OXYGEN FROM RESPIRATION SIGNALS

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ABSTRACT

Monitoring blood oxygen is critical in a variety of medical conditions including COVID-19. For almost a century, pulse oximetry has been the only noninvasive method for measuring blood oxygen. While highly useful, pulse oximetry has important limitations. It requires wearable sensors, which can be cumbersome for older patients. It is also known to be biased when used for dark-skinned subjects. In this paper, we demonstrate, for the first time, the feasibility of predicting oxygen saturation from breathing. By eliminating dependency on oximetry, we eliminate bias against skin color. Further, since breathing can be monitored without body contact by analyzing the radio signal in the environment, we show that oxygen too can be monitored without any wearable devices. We introduce a new approach for leveraging auxiliary variables and tasks via a multi-headed neural network model. Empirical results show that our model achieves good accuracy on existing medical datasets and can potentially be used to monitor the recovery of COVID-19 patients.

1 INTRODUCTION

Oxygen saturation refers to the amount of oxygen in the blood – that is the fraction of oxygen-saturated hemoglobin relative to the total blood hemoglobin. Normal oxygen levels range from 94% to 100%. Lower oxygen can be dangerous, and if severe, leads to brain and lung failure (Taylor et al., 1951; Díaz-Regañón et al., 2002; Lapinsky et al., 1999). COVID-19 patients are particularly susceptible to reduced blood oxygen. The National Institutes of Health (NIH) recommends monitoring blood oxygen in COVID-19 patients and aiming to keep their oxygen about 92–96% (NIH). Oxygen monitoring is particular important for older COVID-19 patients, who tend to arrive in the hospital with alarmingly low oxygen saturation, reducing their chances of survival (Levitan).

Today, the only noninvasive approach for measuring oxygen saturation (SpO2) is pulse oximetry. It works by shining light on one's figure (or other body parts). Since oxygen-saturated hemoglobin has a bright red color, oxygen saturation can be measured by estimating the absorbance of the red-colored waves relative to other colors. While pulse oximetry is a very useful technology, it can be unsuitable for some of the most vulnerable COVID patients. Oximetry requires the patient to wear a finger clip or other sensors, which can be cumbersome and hard to remember for older patients with dementia or cognition problems. Further, since it relies on measuring light absorbance, it is affected by skin color and tend to overestimate blood oxygen in dark-skinned subjects (Feiner et al., 2007).

In this paper, we introduce a new approach for monitoring blood oxygen that could be more appropriate for older patients or those with dark skin color. We propose to learn oxygen saturation from respiration signals. Recent advances in wireless sensing have demonstrated the feasibility of obtaining accurate measurements of the respiration signal from analyzing the radio waves that bounce off people's bodies, without any physical contact (Adib et al., 2015; Yue et al., 2018). Hence, if oxygen saturation is predictable from breathing, we can sense one's oxygen in a contactless way without any wearable sensors. Further, unlike pulse oximetry, such oxygen sensing method would be oblivious to skin color.

We model the problem as a sequence-to-sequence learning and introduce a neural network that maps respiration signals to the corresponding oxygen saturation. A key innovation in our model is a new design for leveraging auxiliary variables. The standard approach in the literature for leveraging auxiliary variables would either provide those variables to the model as inputs or try to predict them as auxiliary tasks. We demonstrate empirically that for our problem neither of these approaches is beneficial. We show that in some cases, the gradient of the model can take vastly different and

even divergent values given the auxiliary variable. In such a scenario, it is better to learn different models for different values of the variable. This motivates us to propose an alternative design for incorporating auxiliary information. We introduce a multi-headed model where the value of the auxiliary variable is used to gate the learning through the appropriate head.

We evaluate our model on multiple medical datasets, and compare it with various baselines. Our empirical results show that the average absolute error in predicting oxygen saturation on the tested medical data is 1.6%, which is comparable to the accuracy of consumer pulse oximeters (whose average error ranges from 0.4% to 3.5% (Lipnick et al., 2016)). Further, by testing the model on data that include the RF modality, we show that the model generalizes to breathing signals extracted from radio waves, opening the door for continuous contactless monitoring of blood oxygen. Finally, using longitudinal data from one COVID-19 patient, we validate that the predicted oxygen values are consistent with the patient's recovery process.

In summary, this paper makes the following contributions:

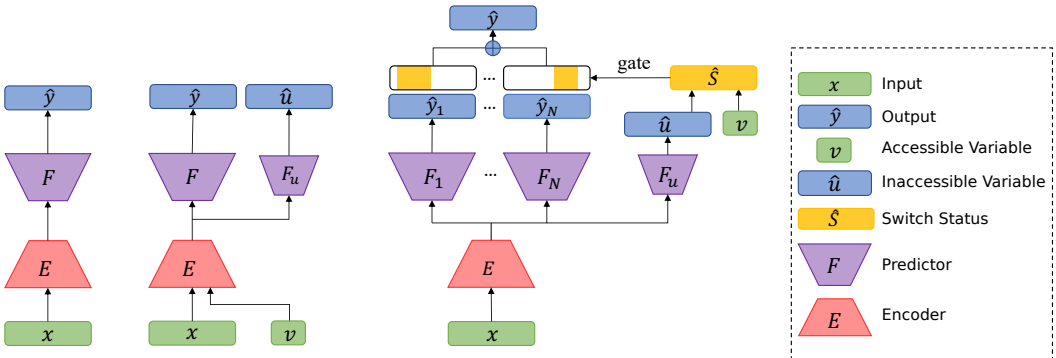
- The paper is the first to predict blood oxygen from respiration signals. This provides a novel noninvasive way for monitoring oxygen saturation, and improves our understanding of the relationship between these two physiological signals.
- The paper introduces a new approach for leveraging auxiliary variables. We analyze the gradient of a vanilla model with respect to the variable; if the gradient is divergent or vastly different for different values of the variable, we use a multi-headed neural network gated by the variable.
- The paper is the first to demonstrate the feasibility of contactless oxygen prediction from radio signals. Such a design can facilitate in-home monitoring of COVID-19 patients, particularly older patients who may have problems remembering to wear and charge oxygen sensors. This is validated by predicting oxygen saturation from RF-based breathing signals, and providing a case study of a COVID-19 patient as he transitions from being COVID-19 positive to negative.

2 Related Work

Predicting Oxygen Saturation. Past work on oxygen prediction focuses on inferring future oxygen values from recent measurements. Several papers use auto-regressive models that take past SpO2 readings and predict the SpO2 in the near future (ElMoaqet et al., 2013; 2014; 2016). Others use an auto-regressive model to model the photoplethysmogram (PPG) signal, which is the raw data obtained from a pulse oximeter (Lee et al., 2011). Some past work predicts changes in SpO2 in the five minutes after adjusting ventilator setting (Ghazal et al., 2019). Our work differs from these methods in that it predicts oxygen saturation from breathing, a completely different physiological signal. Further, we show the feasibility of oxygen prediction without body contact by inferring oxygen from radio-based breathing estimates.

Contactless Sensing with Radio Frequency Signals. The past decade has seen a rapid growth in research on passive sensing using radio frequency (RF) signals. Early work has demonstrated the possibility of sensing one's respiration and heart rate using radio signals (Adib et al., 2015). Building on this work, researchers have found that by carefully analyzing the RF signals that bounce off the human body, they can monitor a variety of health metrics including sleep, respiration, heart-rate, gait, falls, and even human emotions (Nguyen et al., 2016; Wang et al., 2017; Yue et al., 2018; Hsu et al., 2017; Wang et al., 2016; Tian et al., 2018; Zhao et al., 2016; Jiang et al., 2018). Our work adds a new piece to the global picture of predicting vital signals from radio waves.

Learning with Auxiliary Variables. Improving machine learning model by leveraging auxiliary variables is a well-known idea. Treating auxiliary variables as extra input features is a simple but effective method, and has been shown useful in computer vision (Forsyth & Ponce, 2002), health profiling (Wang et al., 2019), and traffic prediction (Liao et al., 2018). Auxiliary learning (Liu et al., 2019) provides an alternative approach for leveraging auxiliary variables by taking them as secondary supervisors. It has been shown beneficial in multiple domains including object detection (Mordan et al., 2018), sequence modelling (Collobert & Weston, 2008; Dong et al., 2015), reinforcement learning (Wilson et al., 2007), and visual odometry (Valada et al., 2018). Our work explores a third way of using auxiliary variables. We focus on partitioning the data space by those auxiliary variables based on analyzing how they affect the gradient of the primary task. We show that a wise partition facilitates model learning and leads to better results.



(a) Backbone (b) Multi-Task (c) Multi-Headed

Figure 1: Illustrations of different models. (a) is the vanilla backbone model, which takes a sequence of breathing signal as input, and predicts the corresponding sequence of oxygen saturation. (b) is the multi-task model that has extra input v, and predicts extra output $\hat{u}$. (c) is the multi-headed model that generates multiple predictions under different status, and the final output is obtained by combining these predictions with the estimated status.

3 METHOD

3.1 PROBLEM FORMULATION

Our task is to predict oxygen saturation based on respiration signals. Let the breathing signal be $x \in \mathbb{R}^{1\times f_b T}$ and the corresponding oxygen saturation be $y \in \mathbb{R}^{1\times f_o T}$, we aim at learning a sequence-to-sequence model that maps x to y. Here, T denotes the length of the segments (in seconds), f_b and f_o are the sampling frequencies of the breathing and oxygen data. In practice, we have high sampling rates for both respiration and oxygen saturation, i.e., $f_b = 10Hz$ and $f_o = 1Hz$. This allows us to capture instantaneous changes in these signals.

Moreover, we are particularly interested in monitoring oxygen saturation during sleep time. This is because blood oxygen typically drops during sleep, and supplemental oxygen is medically necessary if oxygen level drops to 88% or lower for 5 consecutive minutes during sleep (Becattini et al., 2018).

3.2 BACKBONE MODEL

As the relation between respiration x and oxygen y could be highly complicated, we use a deep neural network to map x to y. We start with the backbone model shown in Figure 1(a), which consists of an encoder $E(\cdot;\theta_e)$ and a predictor $F(\cdot;\theta_f)$. The encoder is composed of a fully convolution network (FCN) followed by a bidirectional transformers (BERT) module (Devlin et al., 2018). The FCN extracts local features from the raw respiration signal, then the BERT module captures long-term dependencies based on those features. This design has two benefits. First, it can extract both local and global information from the respiration signal. Second, it works for variable length respiration signals. The predictor F is composed of several De-convolution layers, which up-samples the extracted features to the same time resolution of oxygen saturation. Formally, we have $E : \mathbb{R}^{1\times f_b T} \to \mathbb{R}^{n\times \alpha f_b T}$ and $F : \mathbb{R}^{n\times \alpha f_b T} \to \mathbb{R}^{1\times f_o T}$ where n is the size of the breathing feature and α is the down-sampling factor ($1/240$ in our model). The model is trained with a L_1 loss, i.e., $\mathcal{L}_o(F, E) = \frac{1}{T}\|\hat{y} - y\|_1$, where $\hat{y} = F(E(x))$ is the model prediction. Thanks to the elaborately designed model architecture, even with a simple L_1 loss, this model has achieved 1.66% error (see Table. 1), which is a reasonably good result. More details on this model are available in appendix A.

3.3 LEVERAGING AUXILIARY VARIABLES & THE MULTI-HEADED MODEL

In the medical domain, typically, there exist many physiological indices that could potentially help improve the model. From the viewpoint of machine learning, physiological indices can be viewed as auxiliary variables that could be beneficial to train the model. During testing, auxiliary variables can be categorized into two types: accessible and inaccessible. We denote accessible variables as v and inaccessible variables as u. In the learning procedure, a common practice is to use accessible

variable as extra inputs and use inaccessible variables for auxiliary tasks. Figure 1(b) illustrates such framework where F_u denotes a predictor of the auxiliary task u. We call the design in Figure 1(b) the *Multi-Task* model. Despite its intuitive appeal, in practice, this model may not always lead to improvements. As shown in Table 1, the Multi-Task model even causes a performance drop on the SHHS dataset[1].

In our work, we investigate an alternative approach that uses auxiliary variables as switches. The idea is based on the hypothesis that some variable h affects the targeted input-output relationship in a very non-smooth way. For example, assuming h is a binary variable. The mapping from input x to output y conditioned on variable h equal to 0 is significantly different from the mapping when the variable v is 1, i.e., $y(x|h = 0)$ and $y(x|h = 1)$ are two distinct functions. In this case, instead of learning function $y(x, h)$, we propose to use variable h as a switch to partition the data space and learn the functions $y(x|h = 0)$ and $y(x|h = 1)$ separately. We realize this idea in our *Multi-Headed* model illustrated in Figure 1(c). We first define a switch function $S(v, u) : \mathcal{V} \times \mathcal{U} \to [N]$ where $v \in \mathcal{V}$ and $u \in \mathcal{U}$ are accessible/inaccessible variables and N is the number of switch status. The model has N heads $\{F_i\}_{i=1}^N$ to make the prediction $\hat{y}_i = F_i(E(x))$ for every switch status separately. It also has a predictor F_u to infer u. During testing time, based on the accessible auxiliaries v and estimated inaccessible auxiliaries $\hat{u}$, we get the estimated switch status $\hat{S} = S(v, \hat{u})$. Then we output the final prediction $\hat{y} = \hat{y}_{\hat{S}}$. In the case of oxygen prediction, $\hat{y}_i$ and the switch $\hat{S}$ are time series, we use $\hat{y}_i^t$ and $\hat{S}^t$ to denote their value at time step t. As shown in Figure 1(c), the final prediction is the gated combination of every head's output, $\hat{y}^t = \hat{y}^t_{\hat{S}^t}$. One might argue that the Multi-Task model can also learn such a compositional function via first learning the function in different cases separately, then learning to throw the data to the right function based on the auxiliary variables. However, in practice, such incorrect model inductive bias introduces unnecessary difficulty in the learning procedure and typically leads to bad performance. In our experiments, we show, with a more preferable inductive bias, the Multi-Headed model outperforms the Multi-Task model with a clear gap.

In the above description, we assume a good switch function exists. In this paragraph, we answer the critical question: which auxiliary variables should be used as switches? We introduce, gradient diagnosis, a simple but effective way to test the influence of variable v on the task of learning function $y(x)$. We first train a vanilla model with no auxiliary variables, e.g., our backbone model. We then use the validation set to check the predictor $F(\cdot; \theta_f)$'s loss gradient $\nabla_{\theta_f}\mathcal{L}$. For each possible value $a \in \mathcal{V}$ of variable v, we compute the gradients averaged on data samples when v equals a, i.e., $\nabla_{\theta_f}\mathcal{L}|_{v=a} = \mathbb{E}_{(x,y)\sim p(x,y|v=a)}\nabla_{\theta_f}\mathcal{L}(F(E(x)), y)$. Such gradient indicates the direction to improve the model when $v = a$. Intuitively, if gradients $\nabla_{\theta_f}\mathcal{L}|_{v=a}$ are similar for all values a, it means variable v does not change the loss function drastically. So it is considerable to use one model to handle all values of v. However, if those gradients are vastly different from each other, forcing one model to work for all values of v may cause the learning to fail.

Taking our oxygen prediction as an example, we conduct such gradient diagnosis on multiple variables including (a) Sleep stages: awake, light sleep (N1,N2), deep sleep (N3), rapid eye movement (REM); (b) Gender: male vs. female; (c) Asthma: having asthma or not; (d): Smoking: non-smoker, current smoker, former smoker; (e) Education: less than 15 years vs. greater than 15 years; (f): Height: lower than 160cm or higher than 160cm; (g) Aspirin: taking aspirin or not. Figure 2 visualizes the cosine similarity of the gradients computed on the medical dataset SHHS. We clearly see that the gradient directions are altered by the sleep stage, gender, asthma and smoking while less affected by the height, aspirin and education level. These result is quite interesting. For example, although it is hard to see why gender affects the oxygen-breathing function from the first glance, there are medical evidence that show gender matters. Due to differences between women's and men's respiratory system, women consume more oxygen when breathing compared to men (Ramonatxo, 2003), especially during exercise (Reybrouck & Fagard, 1999), and men's oxygen saturation is naturally higher than women (Ricart et al., 2008). As for sleep stages, it is a known fact that it influences the oxygen saturation. For example, pointed out by Choi et al. (2016), that oxygen saturation differs significantly during REM and Non-REM sleep. It is also understandable that asthma affects oxygenation since asthma causes difficulty in breathing. It is also supported by medical findings that smoking reduces oxygen saturation (Özdal et al., 2017). Since it is a long-term effect, no matter if a

[1]More dataset details are provided in Section 4.1

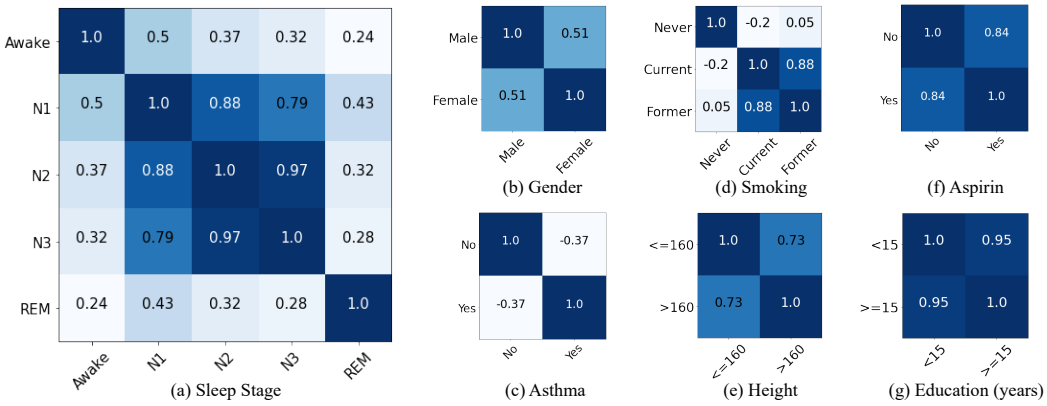


Figure 2: Gradient cosine similarities of different variables.

smoker quits or not, his/her oxygen pattern is already altered. This may explains why the gradient similarity is high between current smoker and former smoker.

Based on our gradient diagnosis, we pick sleep stage and gender as auxiliary variables for our task. Other variables are possible. However, we pick these two variables because gender is almost always accessible during testing; and while sleep stages are usually not available during testing, luckily past work shows that sleep stages can be inferred from respiration signals (Zhao et al., 2017). Hence, our model can estimate the sleep stages and use the estimates to do the switching. Further, from Figure 2(a), we can see the gradients for awake, REM and sleeping (N1,N2,N3) are very dissimilar from each other while the gradients are much more similar within the group of N1,N2,N3. So we design the switch function to consider N1,N2,N3 as one sleep stage. In total, we have six switch status due to the combinations of gender and sleep stages. Our model has six heads for each switch status.

4 Experiments

We present the results of empirical evaluation on medical datasets and RF data. We evaluate the models using the average absolute error between the predicted oxygen saturation $\hat{y}$ and the ground-truth y. The error is first averaged for every night for each subject, i.e., $\frac{1}{T}\sum_{t=1}^{T}\|y^t - \hat{y}^t\|$. We then report the mean and standard deviation of per-night averaged errors of the dataset.

4.1 Datasets

Medical Datasets. We leverage three publicly-available medical datasets: Sleep Heart Health Study (*SHHS*) (Zhang et al.), Multi-Ethnic Study of Atherosclerosis (*MESA*) (Chen et al., 2015), and Osteoporotic Fractures in Men Study (*MrOS*) (Blackwell et al., 2011). Each dataset contains the polysomnography (PSG) signals of subjects. The first two datasets have males and females, whereas the last one has male subjects. The PSG data includes full-night respiration signals and the corresponding oxygen saturation (SpO2) and sleep stage labels. The data has three types of respiration channel measured with: a nasal probe, a breathing belt on the chest, and a breathing belt on the abdomen. We denote it as *BB-respiration signals*. The datasets also contain subjects' bio-information such as gender, age, etc. SHHS, MESA, and MrOS contains 2651, 2056, and 1026 subjects, respectively. We randomly split the training and testing sets for SHHS, MESA, and MrOS as 1855/796, 1439/617, and 718/308, and keep the same splits in all experiments. We note that the subjects in these studies have an age range between 40 and 95, and suffer from a variety of diseases as indicated by the studies names. This allows for a wider range of oxygen variability beyond the typical range of healthy individuals.

RF Dataset. We collect a small PSG dataset that contains the standard PSG channels mentioned above as well as an RF-based inference of the respiration signal, i.e., *RF-respiration signals*. The dataset is collected in the sleep lab in the university and contains 31 nights of data from 14 individuals. All subjects in this study are healthy. Each subject is monitored using the standard PSG

Table 1: Prediction error (mean $\pm$ std) of different models for three medical datasets.

Model	SHHS	MESA	MrOS	Overall
Single-Headed	1.68 ± 1.56	1.59 ± 1.58	1.76 ± 1.56	1.66 ± 1.53
Multi-Task	1.69 ± 1.57	1.51 ± 1.56	1.71 ± 1.57	1.62 ± 1.53
PCGrad-Adapted	1.74 ± 1.58	1.62 ± 1.57	1.74 ± 1.53	1.71 ± 1.54
Multi-Headed	$\mathbf{1.62 \pm 1.54}$	$\mathbf{1.48 \pm 1.51}$	$\mathbf{1.66 \pm 1.51}$	$\mathbf{1.58 \pm 1.49}$

channels as in the medical datasets above (SpO2, respiration belts, sleep stages, etc.). Additionally, a radio device is installed in the room to collect RF signals, which are then processed to extract the subject's respiration in accordance with Adib et al. (2015). Therefore, in this dataset, each subject has both the BB-respiration signals and the RF-respiration signals.

4.2 Models

As we describe in Section 3, our models focus on predicting oxygen from breathing while leveraging auxiliary gender and sleep stage information. We evaluate the following models: (a) *Single-Headed*: the vanilla backbone model. (b) *Multi-Task*: the model that takes gender as an extra input and is trained with sleep stages as an auxiliary task. (c) *Multi-Headed*: the model that uses multiple heads to predict oxygen level for different switch status. (d) We also compare with an adaptation of the Projecting Conflicting Gradient *PCGrad-Adapted*. The original PCGrad was proposed for improved multi-task learning to deal with scenarios where the various tasks have divergent gradients (Yu et al., 2020). In that case, PCGrad projects the divergent gradients along consistent directions. In our context, the gradients of the tasks themselves – i.e., oxygen prediction and sleep stage prediction – do not diverge. Hence, simply applying PCGrad to our problem should be no different from the Multi-Task model. However, we can adapt PCGrad to be more suitable for our problem. In our case, the gradients of subgroups (i.e., subjects with different status) in the input data with respect to the main task can be divergent or significantly different. We can think of learning a mapping from breathing to oxygen for different subject status as different sub-tasks. Then, we can augment our backbone model with PCGrad applied to these sub-tasks. Specifically, to train the single predictor F, We compute 6 different losses based on the six subject status corresponding to our 6-headed model. For each subject status i, we have an oxygen prediction loss $\mathcal{L}_o^i$ for that status. Mathematically, $\mathcal{L}_o^i(F, E) = (\sum_{t:S^t=i} 1)^{-1} \sum_{t:S^t=i} |F(E(x_b))^t - y^t|$. We compute the predictor's gradients $\nabla_{\theta_f} \mathcal{L}_o^i$ for each loss and update the predictor by the gradient calibrated by PCGrad.

4.3 Evaluation on Medical Datasets

Quantitative Results. Table 1 reports the absolute error of all models for the three medical datasets. The table reveals two main results. First, all baselines perform reasonably well and have average prediction errors between 1.58% and 1.7%. These errors are relatively low and comparable to the errors of consumer pulse oximeters whose average error is in the range 0.4-3.5% (Lipnick et al., 2016). It is important to keep in mind that all baselines are based on our backbone model, which already embodies our design for learning this new task. Thus, these results show for the first time that respiration signals have a predictive power for learning oxygen saturation.

Second, Table 1 also shows that the Multi-Headed model outperforms the other baselines on all datasets. This demonstrates that the Multi-Headed design is more effective at leveraging relevant auxiliary variables than the other methods.

Qualitative Results. Figure 3 visualizes the predicted oxygen saturation of the Multi-Headed model and the Multi-Task model on a male subject in the SHHS dataset. As the ground-truth oxygen saturation are integers, we rounded the predicted oxygen saturation into integers. The background color indicates different sleep stages. The 'light grey' and 'white' corresponds to 'REM' and 'Awake', respectively. For clarity, we use one color 'dark grey' for all three non-REM 'Sleep' stages, N1, N2, and N3. We observe that the Multi-Headed model consistently performs better than the Multi-Task model over the whole night. In non-REM 'Sleep', the ground-truth oxygen saturation is more stable. The Multi-Headed model predicts more accurate oxygen than the Multi-Task model. In the 'REM' stage, people usually have lower oxygen saturation with larger variance. The Multi-Headed model

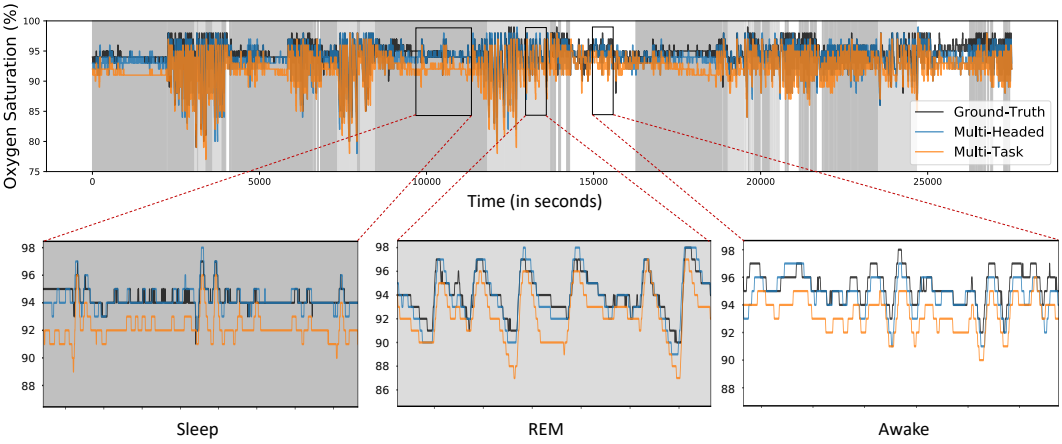
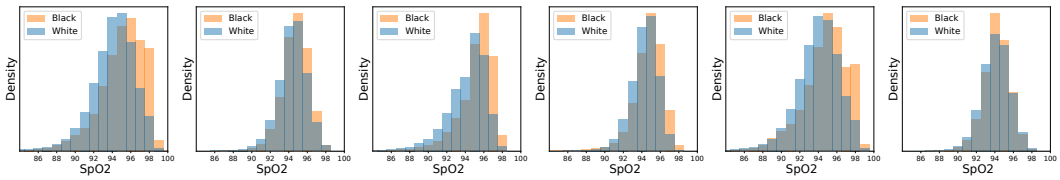


Figure 3: Visualization of the oxygen saturation predicted by the Multi-Task model and the Multi-Headed model on a male subject in SHHS dataset. The background color indicates sleep stages. The 'dark grey', 'light grey' and 'white' corresponds to 'Sleep' (N1, N2, N3), 'REM' and 'Awake'.



(a) SHHS GT (b) SHHS Pred (c) MESA GT (d) MESA Pred (e) MrOS GT (f) MrOS Pred

Figure 4: Distributions of the ground-truth SpO2 readings ((a), (c), (e)), and the predicted SpO2 ((b), (d), (f)) by Multi-Headed model for the two races.

predicts the ups and downs and captures the changes in blood oxygen. In the 'Awake' stage, the Multi-Headed model predicts the more dramatic changes, while the Multi-Task model has a larger bias. This experiment demonstrates that the way we incorporate the sleep stages into the model improves the performance across different sleep stages.

Error Analysis and Relation to Skin Color. One important issue to keep in mind is that our model learns from ground-truth data measured using pulse oximeters (today oximetry is the only way for continuous noninvasive monitoring of blood oxygen). Hence, to understand the prediction errors and their potential causes, we plot in Figure 4 the distributions of the ground-truth SpO2 and the predicted SpO2 by the Multi-Headed model for different races, for all datasets. Interestingly, the ground-truth SpO2 from oximetry shows a clear discrepancy between black and white subjects. In particular, the ground-truth oxygen distributions show that black subjects have higher blood oxygen. This is compatible with past findings that pulse oximeter overestimates blood oxygen in dark-skinned subjects (Feiner et al., 2007). In contrast, the model prediction shows much more similar oxygen distributions for the two races. It is interesting that while the model learned from what seems to be biased ground-truth, the results show that the model was able to correct, to some extent, for this bias. Admittedly, these observations are inductive since there is no way to measure the exact errors in the ground-truth labels.

The distributions in Figure 4 also show that the model tends to miss the very high and very low oxygen values. This is expected given that only a very small percentage of the ground-truth data falls in the tails. One would expect that the performance on very high and very low oxygen values would improve if there is sufficient training data in those ranges.

4.4 Evaluation on RF Dataset

In this section, we evaluate whether our model, which is trained on respiration measured using a breathing belt, can generalize to predicting oxygen from respiration signals measured via radio waves. We directly apply a Multi-Headed model trained on the BB-respiration signals in medical

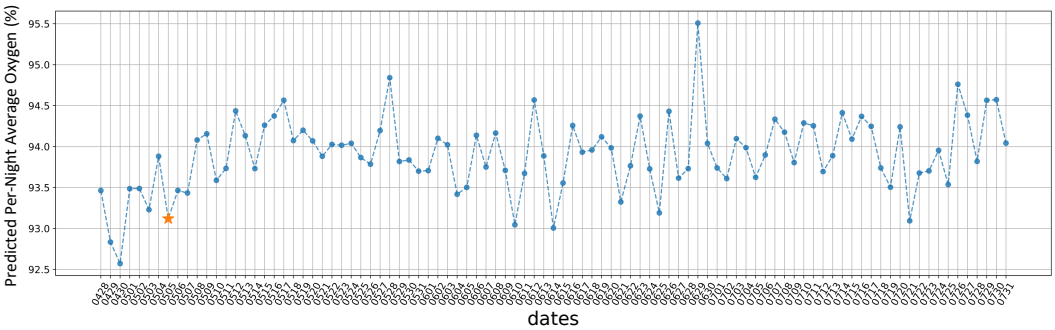


Figure 5: The predicted per-night averaged oxygen saturation for a COVID-19 patient from Apr 28 to July 31, 2020. The patient turned negative for COVID-19 on May 5, 2020 (marked by the star).

Table 2: Prediction error for the RF dataset using BB-respiration signals or RF-respiration signals.

BB-respiration signals				RF-respiration signals			
Awake	Sleep	REM	All	Awake	Sleep	REM	All
1.37	1.30	1.27	1.30	1.65	1.24	1.35	1.28

datasets, to the RF dataset. For comparison, we test the model on both RF-respiration signals and BB-respiration signals from the RF dataset. The results are shown in Table 2. We observe that the model works well on RF dataset with a small prediction error, no matter which breathing signal is used. The prediction error of using the RF-respiration signals (1.28%) is even slightly lower than using the BB-respiration signals (1.30%). This is because the noise in the respiration measured using RF signal is different from the noise in the breathing belt measurements. The noise in the RF-based measurements tend to increase with motion and hence we see that the model prediction error is higher for the aware stage. In contrast, the error in the breathing belt depends on the sleep posture and the positioning of the belt on the body. Also, comparing with the error from previous section, we find the model is performing better on the RF dataset than on the medical datasets, i.e., 1.30% vs. 1.62%. We believe the reason is that the RF dataset is collected with healthy individuals and hence has less complexity and is easier to predict. These results show the first demonstration of predicting oxygen saturation from radio signals without any body contact.

4.5 Application to Monitoring COVID-19 Patients

Finally, we show a case study of a COVID-19 patient. An 88-year old male was monitored from April 28 till July 31, with a contactless radio device. The subject tested COVID-19 positive prior to the monitoring, and was declared COVID-19 negative on May 5. The objective of the case study is to compare the results of a completely passive contactless monitoring approach to information collected from the medical doctor and the professional caregiver attending to the subject.

Figure 5 shows the average oxygen saturation predicted by the Multi-Headed model for each of the monitored nights. May 5 is highlighted with a star as the day on which the patient was declared COVID-19 negative. The results in the figure show a clear trend of increased oxygen level as the patient transitioned to becoming COVID-19 negative. They also show that improvement in blood oxygen did not stop on the day the patient became COVID-free; it rather continued to ramp up for almost two weeks after that date, and eventually reached a steady level. While there is no ground-truth measurements of the oxygen for this completely passive case study, the results are consistent with the doctor notes about patient recovery and general expectations for a symptomatic COVID-19 patient who recovered without escalation of his COVID-19 symptoms.

5 Conclusion

We demonstrate the feasibility of predicting blood oxygen saturation from respiration signals. We start by proposing a vanilla model, and then explore the oxygen-related physiological variables and propose a better preformed multi-headed model which effectively incorporate these variables. Our model is directly applicable to respiration measured by wireless signals for contactless oxygen prediction. We also show a potential use case of monitoring the recovery of COVID-19 patients.

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A Model Architecture and Implementation Details

As we described in section 3, our vanilla model mainly consists of an encoder and a predictor. The encoder has 9 layers of 1-D convolutional layers (Conv-Norm-RReLU) and shrink the temporal dimension of the features by 240 times, and then followed by several bi-directional multi-head self-attention layers (Devlin et al., 2018) to aggregate the temporal information at the bottleneck. Specifically, we use 8 layers, 8 heads with hidden-size 256, intermediate-size 512 of self-attention and the max position embeddings is 2400. The decoder contains 7 layers of 1-D de-convolutional layers (DeConv-Norm-RReLU). We also use a skip connection (Ronneberger et al., 2015) by concatenating the convolutional layers in the encoder to the de-convolutional layers in the predictor. Figure 6 illustrate the overall network architecture. We keep encoder and predictor architectures be the same for all models. All models are implemented using PyTorch.

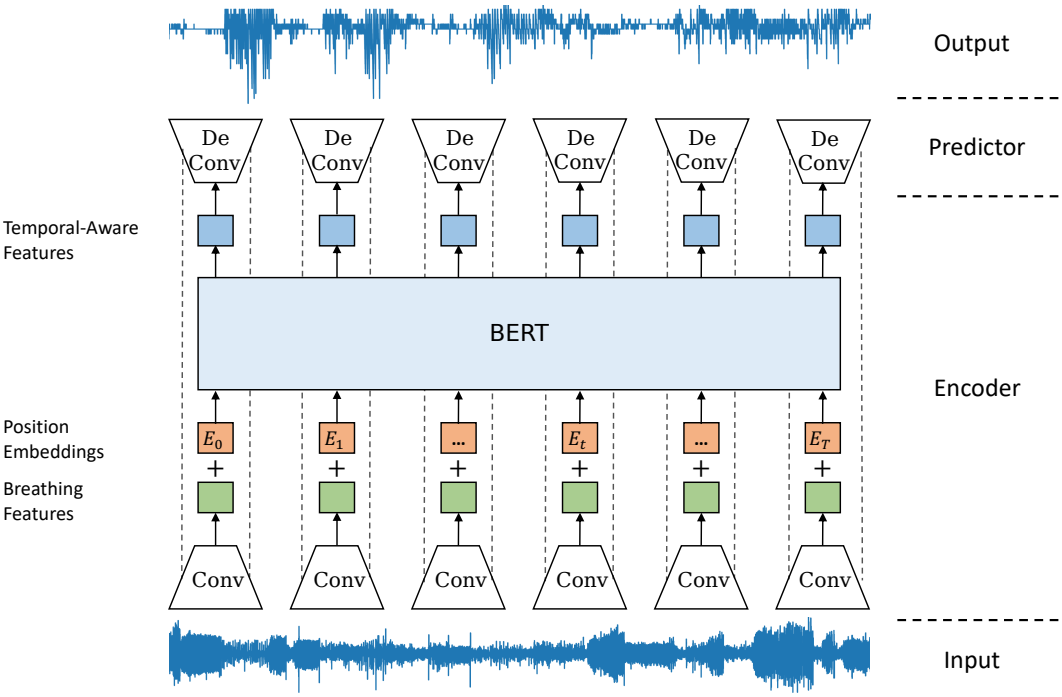

Figure 6: Network architecture for the vanilla model.

Because the blood oxygen saturation is related to the sleep stage and sleep cycle, which indicates the non-local dependencies. Instead to segment the breathing signal into short-clips, the breathing signals we used in all the experiments lasts several hours per night. Typically, as the bottleneck shrinks 240 times and has a max position embedding 2400, we can process as long as $240 * 2400/3600 \approx 16$ hours breathing data.

B More visualizations on medical datasets

We include more visualizations of the oxygen saturation predicted by the *Multi-Headed* model for the medical datasets: MESA (Figure 7 and Figure 8), MrOS (Figure 9 and Figure 10). In the plots, The background color indicates different sleep stages. The 'dark grey', 'light grey' and 'white' corresponds to 'Sleep' (N1, N2, N3), 'REM' and 'Awake', respectively.

B.1 MESA

The examples in Figure 7 show our model's ability to capture the regular fluctuations of the oxygen saturation dynamics. While the examples in Figure 8 show our model accurately detecting the region of the low oxygen saturation which highlights its usefulness of monitoring patients.

B.2 MROS

Looking at the zoomed in range (a) and (b) from Figure 9, we find the model exhibits larger error when the ground truth SpO2 reading goes lower. It is mainly caused by the imbalanced label from the training set, since subjects usually experience much less time of having low oxygen level (like below 90%) then having a normal oxygen level between 94% to 100%.

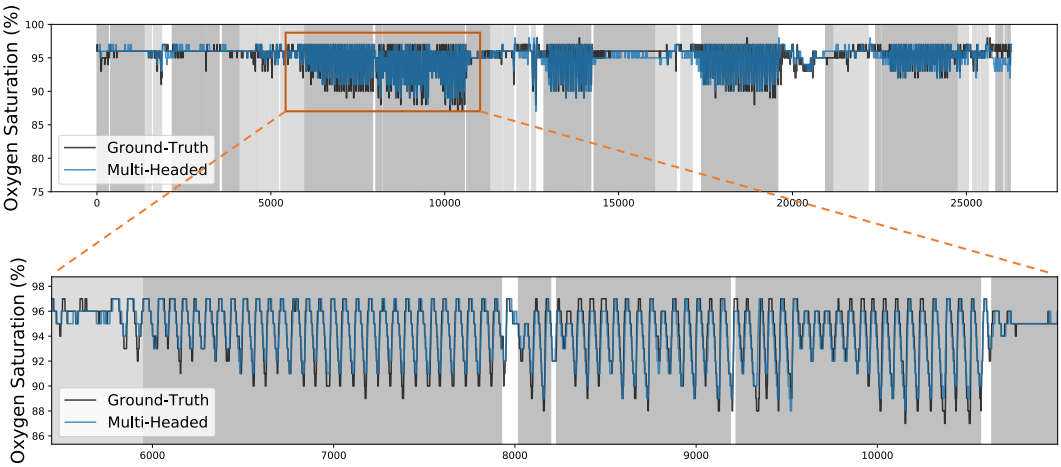

Figure 7: *MESA* Example 1.

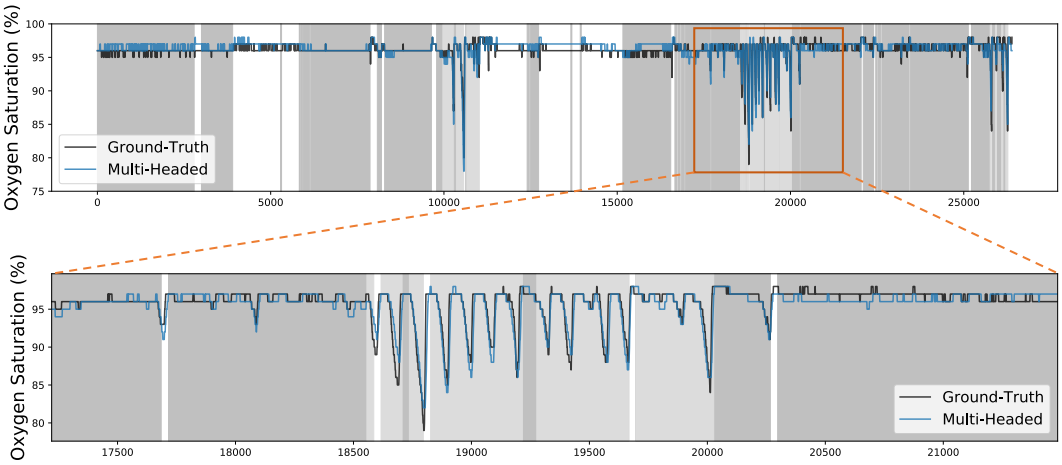

Figure 8: *MESA* Example 2.

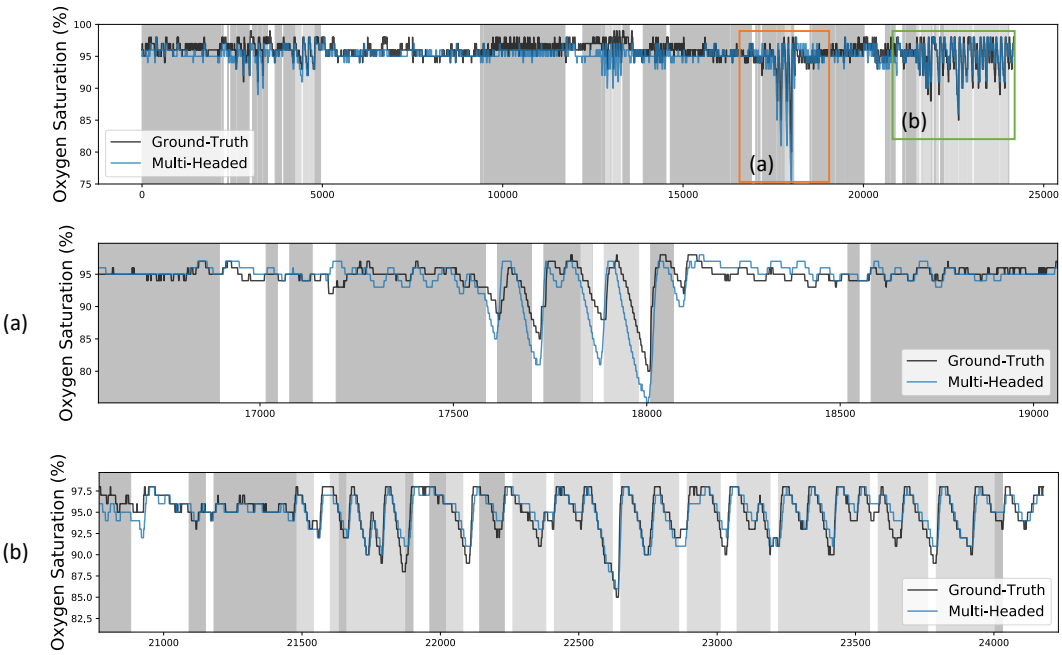

Figure 9: *MrOS* Example 1.

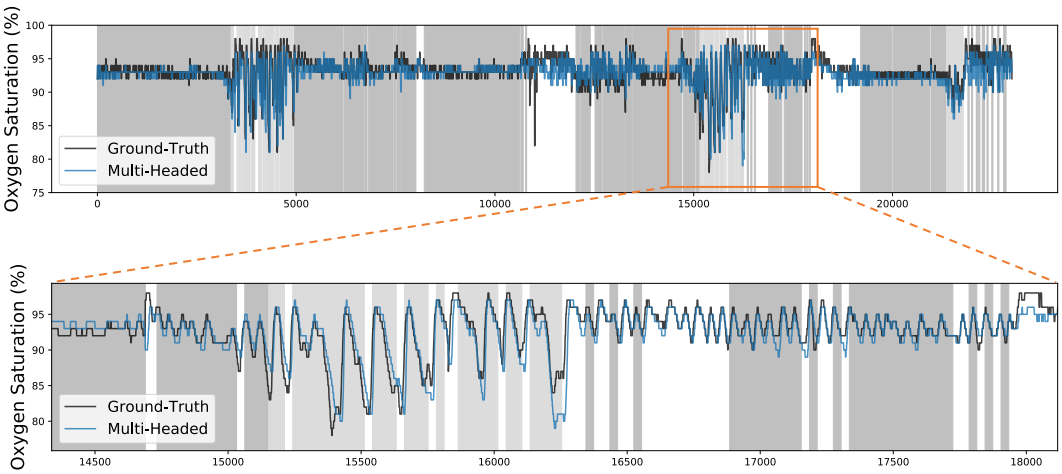

Figure 10: *MrOS* Example 2.