

# Respiratory Rate Determination by ECG Monitoring

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## 1 Introduction

### 1.1 Background

Pneumonia is the deadliest infectious disease to children under the age of 5, responsible for 740,180 deaths under 5 as of 2019 (World Health Organisation, 2022). The worsening symptoms of pneumonia can rapidly become life-threatening for young children if not treated on time. Nevertheless, the early stage of pneumonia with young children is often confused with other less serious respiratory disease with similar symptoms. On the other hand, a medical institution cannot provide comprehensive monitoring to all its patients for all potential symptoms of pneumonia due to limitation of resources. Thus it is of interest to develop light-weight, non-evasive methods for detecting the most common symptoms of pneumonia, as an early warning to serve as an indication of a need for further medical interventions.

In a research outlined in Shamo'on et al. (2004), tachypnoea (average respiratory rate  $> 50$  per minute) is one of the critical indicators of pneumonia in young children. However, the high volatility of breath rate in children poses a major challenge for manual counting that is both time-consuming and prone to error. In contrary, automated respiratory monitoring often involves machine-measurement of chest/abdomen movement or nasal airflow that are resource-costly and possibly invasive such that the discomfort from wearing the equipment might adversely affect its accuracy.

A potential solution to the problem above arises from the phenomenon of *respiratory sinus arrhythmia*, such that the instantaneous heart rates increase with inspiration and decrease during expiration (Larsen et al., 2010), by monitoring the periodicity of variation in the heart rate, it may be possible to determine one's respiratory rate with a simple, non-evasive method, such as by a pulse oximeter that is resource-friendly. As such, this project attempts to develop an efficient *predictive* algorithm to accurately and precisely determine respiratory rate from heart rate, as well as briefly discuss its limitations and direction for future works.

### 1.2 The data

The *apnea-ECG database* (Penzel et al., 2000) on *PhysioNet* (Goldberger et al., 2000) provides sufficiently large data sets of approximately eight hours long records of electrocardiogram and respiratory signals for eight subjects in a study for *sleep apnea*. The eight records consist of 100Hz signal from the electrocardiogram (ECG), respiratory effort from chest/abdomen movements, nasal airflow, and blood  $O_2$  saturation over time.

A major concern of using such data is the misalignment of objective for the researches. Study for apnea typically involves subjects with airway obstruction, a factor that must be considered for prior to building our model. Under the presumption that, subjects in our data might sometimes stop breathing, the response variable of interest should be robust from the presence of apnea. Therefore, the model will focus on exploring the algorithm for determining the respiratory rate from the ECG signal as a predictor for the respiratory rate implied by chest movements, assuming that for living humans, respiratory efforts are always present.

This study will divide records from the eight subjects into two sets:

- Subjects a01, a02, a03, a04 and b01 form the *training set*.
- Subjects c01, c02 and c03 form the *test set* for evaluation.

## 2 Methodologies and implementation

### 2.1 Data wrangling

#### 2.1.1 Processing ECG signals

The ECG signal does not provide the heart rate directly. Instead, it is a time series of varying electric potential that controls the rhythm of the contraction and relaxation of the heart muscle, with a magnitude of approximately 0.5mV in absolute value. Such a signal is often masked by unwanted noise, such as electric signals from pectoral muscle movement, creating a challenge in computing heart rate from the ECG signal.



Figure 1: Left: sudden spike in noise; right: frequency spectrum of the ECG signal

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#### Algorithm 1 5-20Hz band-pass filter with fast Fourier transform

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- 1: Take  $\mathbf{x} \in \mathbb{R}^n$  as the 100-Hz input
  - 2: Obtain  $\mathbf{y}$  by fast Fourier transform on  $\mathbf{x}$
  - 3: **for**  $t = 1, \dots, n$  **do**
  - 4:    $y_t \leftarrow \sum_{k=1}^n x_k \exp(-2\pi i(k-1)(t-1)/n)$
  - 5: **end for**
  - 6: Zero corresponding (Nyquist) frequency bins for 0-5, 20-50Hz
  - 7: **for**  $t = 1, \dots, n \wedge (t \in (0.2n, 0.8n) \vee t > 0.95n \vee t < 0.05n)$  **do**
  - 8:    $y_t \leftarrow 0 + 0i$
  - 9: **end for**
  - 10: Obtain  $\mathbf{z}$  by normalised inverse fast Fourier transform on  $\mathbf{y}$
  - 11: **for**  $t = 1, \dots, n$  **do**
  - 12:    $z_t \leftarrow \sum_{k=1}^n y_k \exp(2\pi i(k-1)(t-1)/n)/n$
  - 13: **end for**
  - 14: **return**  $\text{Re}(\mathbf{z}) \in \mathbb{R}^n$  as the 100-Hz output
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**Algorithm 2** R peak timestamping with phase correction

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```
1: Take the original  $\mathbf{x} \in \mathbb{R}^n$  and the filtered  $\mathbf{z} \in \mathbb{R}^n$  as the 100-Hz inputs
2: Set moving threshold  $\mathbf{b}$  as half of rolling maximum
3:  $(b_t | t = 1, \dots, 100) \leftarrow (+\infty)_{\times 100}$ 
4: for  $t = 101, \dots, n$  do
5:    $b_t \leftarrow \frac{1}{2} \max\{z_{t-100}, \dots, z_t\}$ 
6: end for
7: Create thresholding indicator  $\iota^{(1)}$ 
8: for  $t = 1, \dots, n$  do
9:    $\iota_t^{(1)} \leftarrow I(z_t > \max\{b_t, F_Z^{-1}(0.95)\})$ 
10: end for
11: Create concave-peak indicator  $\iota^{(2)}$ 
12: for  $t = 1, n$  do
13:    $\iota_t^{(2)} \leftarrow 0$ 
14: end for
15: for  $t = 2, \dots, n-1$  do
16:    $\iota_t^{(2)} \leftarrow I[z_{t+1} - z_t > 0] - I[z_t - z_{t-1} > 0] = -1$ 
17: end for
18: Preliminary timestamps for R peak  $\mathbf{p} \leftarrow (t = 1, \dots, n | \iota_t^{(1)} \wedge \iota_t^{(2)} \text{ is True})$ 
19: Remove abnormal timestamps in  $\mathbf{p}$  with R-R intervals of  $< 300\text{ms}$ 
20: Correct phase-shifts caused by fast Fourier transform
21: for  $t \in \{\mathbf{p}\}$  do
22:    $p|p = t \leftarrow \operatorname{argmax}_{i=t-4, \dots, t, \dots, t+4} x_i$ 
23: end for
24: return  $\mathbf{p}$  the timestamps of the R peak
```

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### 2.1.2 Heart rate derivation from ECG signals

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**Algorithm 3** Deriving instantaneous heart rates from R peak timestamps

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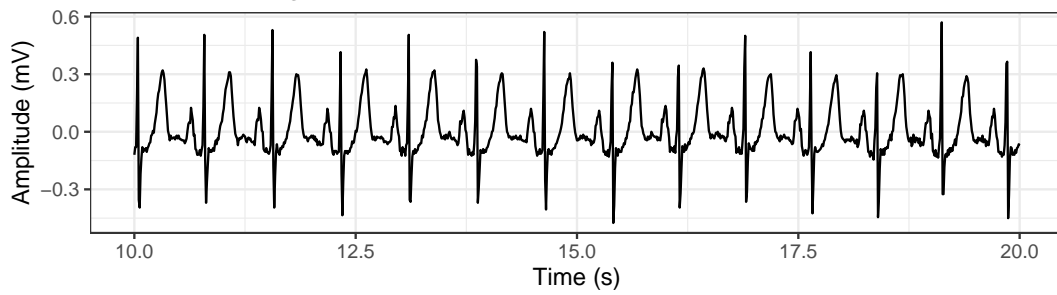
```
1: Take  $\mathbf{p}$  the timestamps of the R peak as the input, and  $\nu$  as an argument for the frequency unit of  $\mathbf{p}$ 
2:  $m \leftarrow \dim(\mathbf{p})$  dimension of  $\mathbf{p}$ 
3: Compute the R-R intervals  $\mathbf{d}$ 
4:  $(d_t | t = 1, \dots, p_1) \leftarrow (\text{NA})_{\times p_1}$ 
5:  $(d_t | t = p_1 + 1, \dots, p_m) \leftarrow ((p_2 - p_1)_{\times (p_2 - p_1)}, (p_3 - p_2)_{\times (p_3 - p_2)}, \dots, (p_m - p_{m-1})_{\times (p_m - p_{m-1})})^\top$ 
6: Convert R-R intervals into heart rates per minute  $\mathbf{h}$ 
7:  $\mathbf{h} \leftarrow 60 \cdot \nu / \mathbf{d}$ 
8: return  $\mathbf{h}$  the heart rates per minute at frequency  $\nu$ 
```

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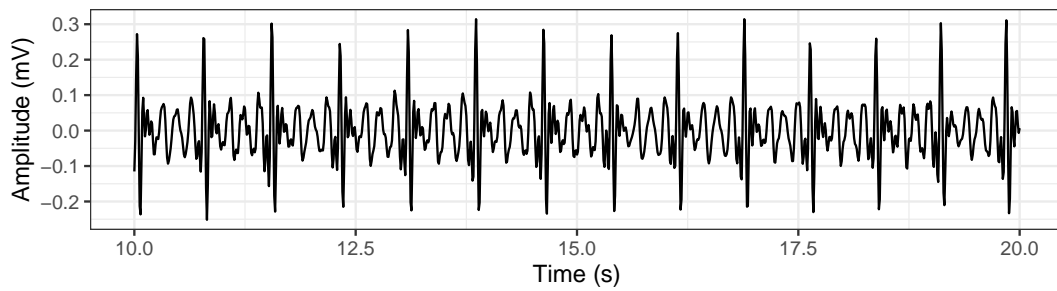


### 2.1.3 Visualising ECG signal processing

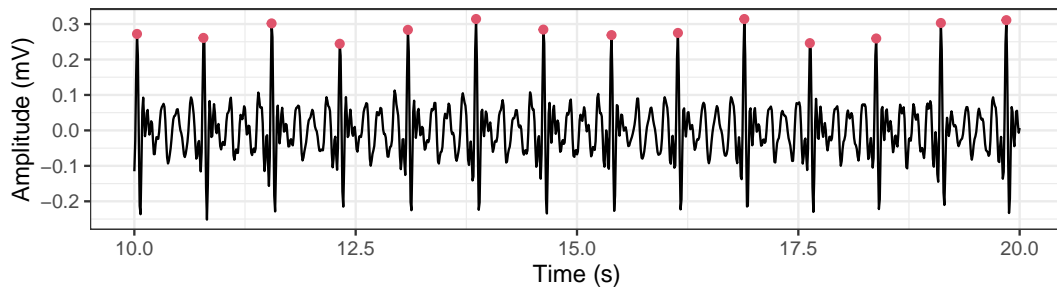
(1) Raw ECG signal



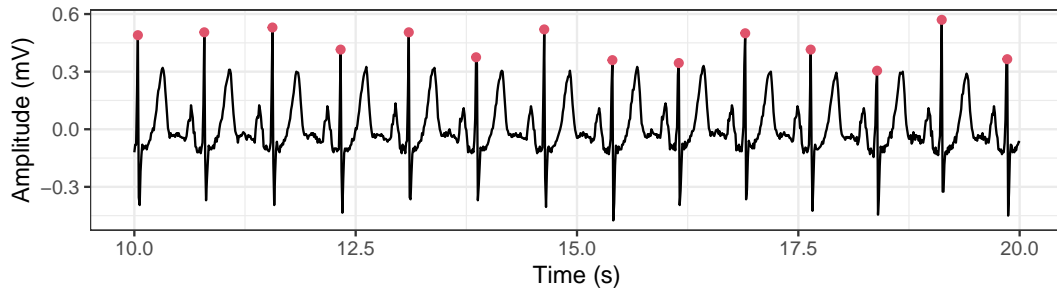
(2) FFT filter to suppress P and T waves



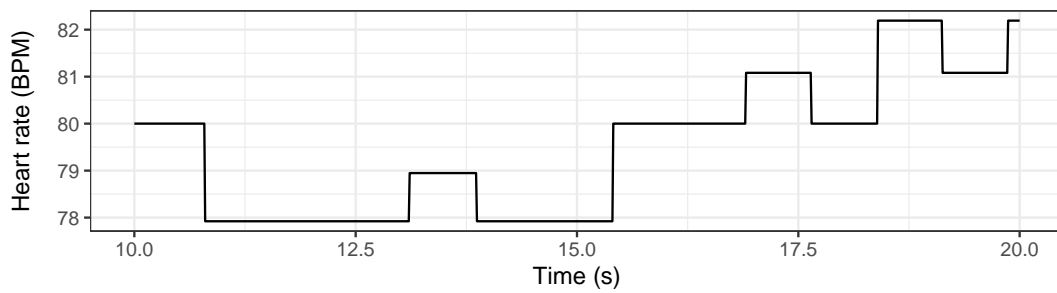
(3) Find R peak on filtered signal



(4) Map R peak to raw signal with phase correction



(5) Derive heart rate from R-R intervals



## 2.2 Modelling rate of breathing by heart rate

### 2.2.1 The smoothing spline crossing algorithm

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**Algorithm 4** Smoothing spline crossing for counting cycles of nonstationary pseudosinusoidal oscillations, for varying heart rates/chest movements

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- 1: Take a time series vector  $\mathbf{a}$  at any frequency, and the optional argument  $\lambda$  the regularisation parameter
  - 2:  $\mathbf{t} \leftarrow (1, \dots, \dim(\mathbf{a}))^\top$  as the indexing vector
  - 3: Construct B-spline bases  $\mathbf{B}$  derived from natural cubic spline bases about all possible knots of  $\mathbf{t}$
  - 4: Penalty matrix  $\mathbf{\Omega} \leftarrow \{\omega_{jk} = \int_T B_j''(s)B_k''(s)ds | B_j(t_i) = (\mathbf{B})_{ij}\}$
  - 5: **if** argument  $\lambda$  is missing **then**
  - 6:    $\lambda \leftarrow \operatorname{argmin}_{\lambda > 0} (1 - \operatorname{tr}(\mathbf{B}(\mathbf{B}^\top \mathbf{B} + \lambda \mathbf{\Omega})^{-1} \mathbf{B}^\top) / \dim(\mathbf{a}))^{-2} \|(\mathbf{I} - \mathbf{B}(\mathbf{B}^\top \mathbf{B} + \lambda \mathbf{\Omega})^{-1} \mathbf{B}^\top) \mathbf{a}\|^2$
  - 7: **end if**
  - 8:  $\hat{\mathbf{a}} \leftarrow \mathbf{B}(\mathbf{B}^\top \mathbf{B} + \lambda \mathbf{\Omega})^{-1} \mathbf{B}^\top \mathbf{a}$
  - 9: Count the number of times the curves  $(\mathbf{t}, \mathbf{a})$  and  $(\mathbf{t}, \hat{\mathbf{a}})$  cross (equivalent to zero-crossing for  $(\mathbf{t}, \mathbf{a} - \hat{\mathbf{a}})$ )
  - 10: **return** half of the count obtained above as the approximated cycles
- 

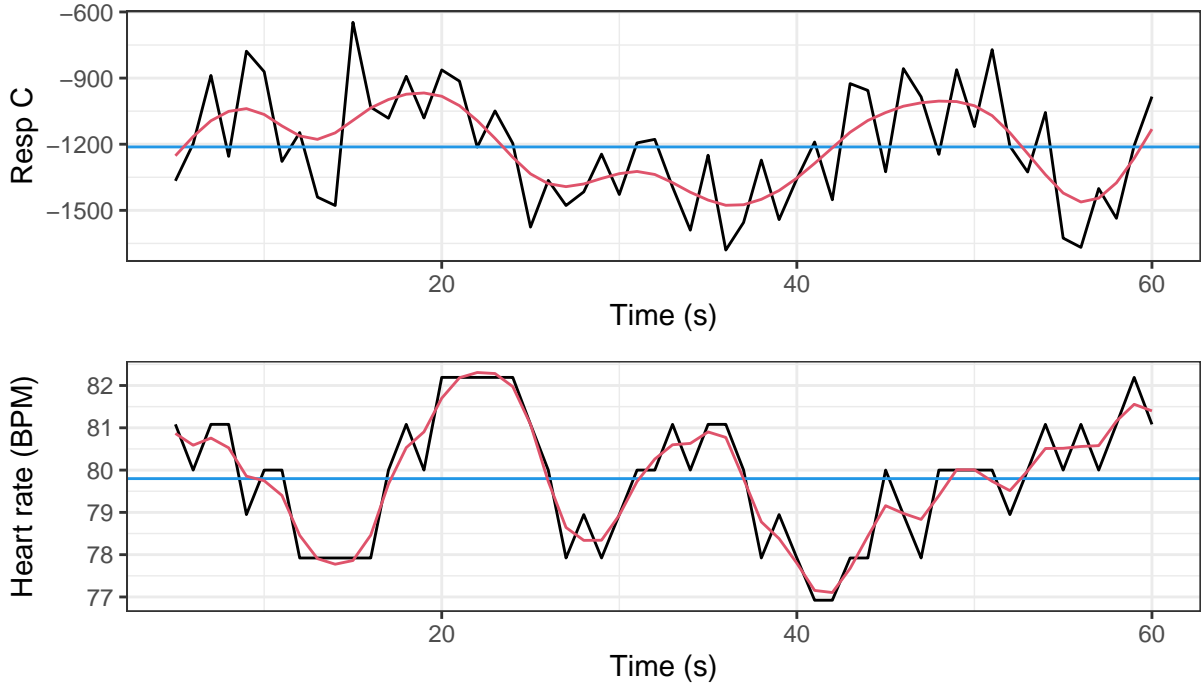


Figure 2: Time series of chest movement (top) and heart rates (bottom) at 1Hz for 1 minute. Blue: naive zero-crossing gives a count of 11.5 and 6 breaths; red: smoothing spline crossing gives a count of 19.5 and 16.5 breaths. We can clearly see that smoothing spline performs much better in counting breaths.

### 2.2.2 Model training

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**Algorithm 5** Deriving breath rate from heart rate based on chest movements

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- 1: Take  $\mathbf{h}$  the heart rates per minute and  $\mathbf{c}$  the chest movements signal (either at 100Hz or down-sampled) where both time series have aligned indices and identical frequency; and optional argument  $\lambda_{\text{opt}}$  (only in model evaluation with test data)
  - 2: For both  $\mathbf{h}$  and  $\mathbf{c}$ , remove elements of index where  $c_t = \text{NA}$
  - 3: **for** each record of all the subjects **do**
  - 4:   Partition each of  $\mathbf{h}$  and  $\mathbf{c}$  into segments of 60-second data
  - 5: **end for**
  - 6: Drop the remainder (last segment), which is less than 60 seconds
  - 7: **if**  $\mathbf{h}$  and  $\mathbf{c}$  for more than one subject is input **then**
  - 8:   Bind  $\mathbf{h}$  and  $\mathbf{c}$  of all subjects together
  - 9: **end if**
  - 10: **for** each 60-second segment of  $\mathbf{c}$  **do**
  - 11:   Pass each minute of  $\mathbf{c}$  into Algorithm 4 (the smoothing spline crossing, without specifying  $\lambda$ ) to compute the true rate of breath based on chest movements, and output  $\rightarrow \mathbf{r}$
  - 12: **end for**
  - 13: **if** argument  $\lambda_{\text{opt}}$  is missing **then**
  - 14:    $\lambda_{\text{opt}} \leftarrow \text{argmin}_{\lambda > 0} \|\mathbf{r} - \hat{\mathbf{f}}(\mathbf{h}; \lambda)\|^2$  where  $\hat{\mathbf{f}}$  is the Algorithm 4: applied on each minute of  $\mathbf{h}$  given  $\lambda$
  - 15: **end if**
  - 16:  $\hat{\lambda}_{\text{opt}} \leftarrow \lambda_{\text{opt}}$ : if its value is obtained by Step 14  $\hat{\lambda}_{\text{opt}}$  is the estimate of  $\lambda_{\text{opt}}$  derived from the training data; otherwise, if  $\lambda_{\text{opt}}$  is passed as an argument, then the purpose of this algorithm is model testing
  - 17: **for** each 60-second segment of  $\mathbf{h}$  **do**
  - 18:   Pass each minute of  $\mathbf{h}$  into Algorithm 4 (with argument of  $\lambda = \hat{\lambda}_{\text{opt}}$ ) to compute the derived rate of breath from heart rate, and output  $\rightarrow \hat{\mathbf{r}}$  which is the model's estimate of  $\mathbf{r}$ : the chest rate of breath
  - 19: **end for**
  - 20: **return** data matrix  $(\mathbf{r}, \hat{\mathbf{r}})$ , a bi-variate time series (minutely),  $\mathbf{r} :=$  "count of breaths by chest movements (observations)" and  $\hat{\mathbf{r}} :=$  "number of breaths derived by cardio-activities of that minute (fitted values)", and most importantly  $\hat{\lambda}_{\text{opt}}$  the trained parameter for our final model!
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## 2.3 Model diagnostics

The trained model implied that one's heart rate is useful for inferring the rate of breath, and the results are statistically significant based on the regularisation result. If there is null relationship between the heart rate and rate of breath, the trained model should have returned a *least-complex fit* such that  $L_2$  loss function (cross-validated MSE) is minimised at large  $\lambda$  and is monotonically decreasing. Hence, the obvious inverted bell curve exhibited by the regularised  $L_2$  loss with one minimum gives evidence against a *null-model fit*.

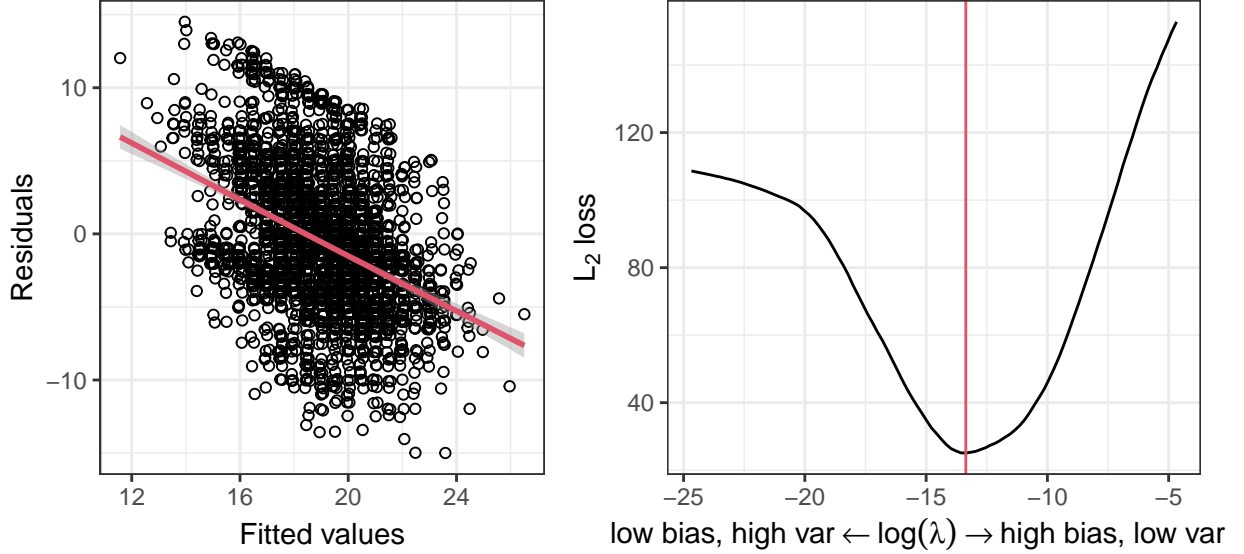


Figure 3: Left: the existence of residual trend, indicates a nonzero bias; right: visual representation of the bias-variance tradeoff via regularisation, the result indicates that the model is more useful than null model.

Notwithstanding the model being shown useful for predicting the rate of breath using the heart rate, it gives biased estimates for predictions. For all *best linear unbiased estimators* (BLUE), such as *least square estimators*, residuals:  $\mathbf{r} - \hat{\mathbf{f}}$ , are orthogonal (therefore, independent) to the fitted values:  $\hat{\mathbf{f}}$ . But, the final model gives  $\text{Corr}(\hat{\mathbf{f}}, \mathbf{r} - \hat{\mathbf{f}}) = -0.3976376$  implying  $\text{Bias}(\hat{\mathbf{f}}) = \mathbb{E}(\hat{\mathbf{f}}) - \mathbf{r} \neq \mathbf{0}$ . Such bias is introduced intentionally due to regularisation to reduce variance of the estimator  $\hat{\mathbf{f}}$ . More comparatively:

$$\begin{aligned} \text{BLUE minimises } \text{Var}(\hat{\mathbf{f}}) \text{ subject to } \text{Bias}(\hat{\mathbf{f}}) &= \mathbf{0} \\ \text{Regularised estimator minimises } \text{MSE}(\hat{\mathbf{f}}) &= \mathbb{E}((\mathbf{r} - \hat{\mathbf{f}})^2) = \text{Var}(\hat{\mathbf{f}}) + \text{Bias}(\hat{\mathbf{f}})^2 \end{aligned}$$

While BLUE has constraints  $\text{Bias}(\hat{\mathbf{f}}) = \mathbf{0}$  (always aims for maximising accuracy first), it unwantedly inflates the variance of the estimator. Whereas regularised estimator appeals to the *bias-variance tradeoff* seeks to directly minimise the cross-validated prediction error (as a function of  $L_2$  loss), that is decomposable to the sum of variance (imprecision) and bias-squared (inaccuracy) for any estimator (Hastie et al., 2009). It follows that, we relaxed the requirement of zero bias via introducing a small bias (sacrificed some accuracy) for a substantially larger drop in variance (massively improved precision) to achieve better predictive performance.

Despite prior anticipation of the bias being nonzero, it is of interest to test for its statistical and practical significance and see if it is acceptably low. For heart-rate-derived breath rate:  $\hat{\mathbf{f}}$ , as an estimator for breath rate based on chest movements:  $\mathbf{r}$ , we can draw a hypothesis test for  $\mathbf{r} = \beta\hat{\mathbf{f}}$ , and due to the linear nature in projecting the estimator (see Algorithm 4), we have the null and alternative hypotheses:



$$\begin{aligned}
H_0 : \text{The estimator } \hat{\mathbf{f}} \text{ is unbiased} &\iff \beta = 1 \\
H_1 : \text{The estimator } \hat{\mathbf{f}} \text{ is biased} &\iff \beta \neq 1
\end{aligned}$$

Therefore, under  $H_0$  :

$$\begin{aligned}
\frac{1}{\sigma^2} (1 - \hat{\beta})^\top \hat{\mathbf{f}}^\top \hat{\mathbf{f}} (1 - \hat{\beta}) &= \sigma^{-2} \hat{\mathbf{f}}^\top \hat{\mathbf{f}} (1 - \hat{\beta})^2 \\
&\sim \chi_1^2 \\
\text{where } \hat{\beta} &= (\hat{\mathbf{f}}^\top \hat{\mathbf{f}})^{-1} \hat{\mathbf{f}}^\top \mathbf{r}
\end{aligned}$$

Which gives the Wald's statistic (Wald, 1943):

$$\begin{aligned}
W &= \hat{\sigma}^{-2} \hat{\mathbf{f}}^\top \hat{\mathbf{f}} (1 - \hat{\beta})^2 \\
&= (\dim(\mathbf{r}) - 1) \|(\mathbf{1} - \hat{\mathbf{f}}(\hat{\mathbf{f}}^\top \hat{\mathbf{f}})^{-1} \hat{\mathbf{f}}^\top) \mathbf{r}\|^{-2} \hat{\mathbf{f}}^\top \hat{\mathbf{f}} (1 - (\hat{\mathbf{f}}^\top \hat{\mathbf{f}})^{-1} \hat{\mathbf{f}}^\top \mathbf{r})^2 \\
&= (\dim(\mathbf{r}) - 1) \|(\mathbf{1} - \hat{\mathbf{f}}(\hat{\mathbf{f}}^\top \hat{\mathbf{f}})^{-1} \hat{\mathbf{f}}^\top) \mathbf{r}\|^{-2} (\hat{\mathbf{f}}^\top \hat{\mathbf{f}} - \hat{\mathbf{f}}^\top \mathbf{r})^2
\end{aligned}$$

Applied to the results of our final model, we have the Wald's  $p$ -value  $\mathbb{P}(\chi_1^2 > W) = 2.983174 \times 10^{-13}$ , which provides a very strong evidence for the estimator  $\hat{\mathbf{f}}$  being biased. However, a further assessment on the 95% asymptotic confidence interval of  $\beta$ , (0.9521173, 0.9724053), indicates the bias is acceptable.

## 3 Conclusion and further research

### 3.1 Model evaluation

Despite we have justified the *goodness of fit* for the model, that the heart rate is useful for predicting respiratory rate, model diagnostics based on the training results might give an optimistic estimate for the prediction error. Hence, to neutrally assess the predictive performance of the model, its predictive power shall be tested in a separate *test* data set (c01-03), via *root mean squared error of prediction* (RMSEP).

When estimated optimal value of the regularisation parameter  $\lambda = 1.571851 \times 10^{-6}$  is used in the model and applied to the *test* data set, the RMSEP is approximately 5.49 breaths per minute (or 33.95% off the observed respiratory rate). Unfortunately but not surprisingly, it is difficult to, using cardio-activities alone, both *precisely* and *accurately* predict the respiratory rate using *classical* statistical methods. Nonetheless, the findings in this project delivered compelling evidence for the feasibility of respiratory rate prediction using heart rate as one of the predictors, and a direction for implementation.

A lack of information from the *training* data set is a major reason of the under-satisfactory predictive performance of the model. Despite the records are eight hours long at 100Hz each with approximately 3 million data points, the sufficiency in sample size is only useful for building a model robust to abnormal signal. However, merely five individuals are unlikely able to give an adequate generalisation for the population. As such, preferably, the model should be trained using random sample of at least hundreds (even thousands) of individuals, from target populations (children under 5), as a guidance for further researches in this topic.

### 3.2 Extending the model

Another major factor responsible for the low predictive power is due to the limitations of the *classical* statistical regime. In the following sections, two possible extensions to the model are briefly discussed.

#### 3.2.1 Bayesian approach and random effects models

The model outlined in this report naively assumed *fixed effects*, such that there exists a single true transformation to map the predictors to fitted values. Contextually, we were claiming that, the relationship of heart rate and respiratory rate is the same for all individuals, and it is unaffected by other factors.

A Bayesian extension to our model into a *random effects model* is able to free us from the assumption of *fixed effects*, which helps us model for additional physiological factors such as weight. It is worth noting that Bayesian statistical learning involves posterior computation, that often relies on stochastic simulation such as Markov chain Monte Carlo, which is much more time-consuming to train than the current model.

#### 3.2.2 Deep learning and double descent

Deep learning with *artificial neural networks* gives another direction for further researches. The advantage of deep learning over *classical* statistics is that it pushes the model beyond *bias-variance tradeoff*. While for *classical* methods the effective number of parameters cannot exceed the training sample size, the model complexity of neural network is not restricted by its training sample. Notwithstanding for both deep learning and *classical* methods, the predictive power suffers whenever the effective parameter size grows toward the training sample size, the over-parameterisation in neural networks allows for a second descent in the loss curve (also referred to as risk curve), in a phenomenon called the *double descent* (Belkin et al., 2019). Such effect of *double descent* has only recently been shown by research in *convolutional neural network*, *residual neural network* and *transformers* (Nakkiran et al., 2019).

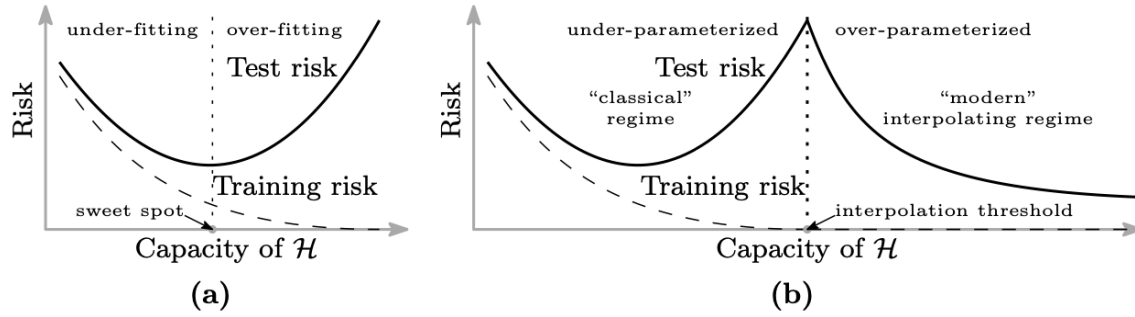


Figure 4: Visualisation in (Nakkiran et al., 2019): (a) Bias-variance tradeoff in classical methods. (b) Double descent loss curve from modern interpolating regime, potentially giving better predictions.

## 4 Appendix: model training workflow, code and output

### 4.1 Source code

The source codes for the functions used in the workflow are in the .R files at [/R](#).

### 4.2 Data wrangling and signal processing

```
training_set <- c("a01", "a02", "a03", "a04", "b01")
test_set <- c("c01", "c02", "c03")
hr <- fuse_data(map(
  sprintf("../data-bin/%s.dat", training_set),
  function(ecg_file) {
    ecg_file |>
      read_ecg() |>
      find_r_peaks() |>
      frequency() |>
      down_sample()
  }
))
resp <- fuse_data(map(
  sprintf("../data-bin/%sr.dat", training_set),
  function(resp_file) down_sample(read_resp(resp_file))
))
hr_test <- fuse_data(map(
  sprintf("../data-bin/%s.dat", test_set),
  function(ecg_file) {
    ecg_file |>
      read_ecg() |>
      find_r_peaks() |>
      frequency() |>
      down_sample()
  }
))
resp_test <- fuse_data(map(
  sprintf("../data-bin/%sr.dat", test_set),
  function(resp_file) down_sample(read_resp(resp_file))
))
write_rds(hr, "../R/hr.rds")
write_rds(resp, "../R/resp.rds")
write_rds(hr_test, "../R/hr-test.rds")
write_rds(resp_test, "../R/resp-test.rds")
```

### 4.3 Model training

```
hr <- read_rds("../R/hr.rds")
resp <- read_rds("../R/resp.rds")
resp_df <- resp_dataset(hr, resp)
```

```
attributes(resp_df)$opt_lambda
```

```
#>   opt_lambda  
#> 1.571851e-06
```

```
resp_df
```

```
#> # A tibble: 2,526 x 2  
#>   breath_chest breath_ecg  
#> *      <dbl>      <dbl>  
#> 1         19.5         15  
#> 2         22.5         16  
#> 3         23.5         17.5  
#> 4         20.5         18  
#> 5         20.5         18  
#> 6          23          15  
#> 7          16          18  
#> 8          20          21.5  
#> 9          20          17.5  
#> 10         18          16.5  
#> # i 2,516 more rows
```

```
summary(resp_df)
```

```
#>   breath_chest   breath_ecg  
#> Min.   : 5.50   Min.   :11.50  
#> 1st Qu.:15.00   1st Qu.:17.50  
#> Median :18.50   Median :19.00  
#> Mean   :18.46   Mean   :18.96  
#> 3rd Qu.:21.38   3rd Qu.:20.50  
#> Max.   :29.00   Max.   :26.50
```

## 4.4 Model diagnostics

```
c("R-F cor" = with(resp_df, cor(breath_chest - breath_ecg, breath_ecg)))
```

```
#>   R-F cor  
#> -0.3976376
```

```
test <- lm(breath_chest ~ 0 + breath_ecg, resp_df)  
c("p-value" = unname(pchisq(  
  sum(resp_df$breath_ecg^2) * (coef(test) - 1)^2 *  
    (nrow(resp_df) - 1) / sum(residuals(test)^2), 1,  
  lower.tail = FALSE  
)))
```

```
#>   p-value  
#> 2.983174e-13
```

```
confint(test)
```

```
#>                2.5 %    97.5 %  
#> breath_ecg 0.9521173 0.9724053
```

## 4.5 Model evaluation

```
hr_test <- read_rds("../R/hr-test.rds")  
resp_test <- read_rds("../R/resp-test.rds")  
resp_dt <- resp_dataset(hr_test, resp_test, 1.571851e-06)  
c(RMSEP = with(resp_dt, sqrt(mean((breath_chest - breath_ecg)^2))))
```

```
#>    RMSEP  
#> 5.489861
```

```
c("RMSEP percentage" = with(resp_dt, sqrt(mean((1 -  
  breath_ecg / breath_chest)^2))) * 100)
```

```
#> RMSEP percentage  
#>      33.94976
```

## References

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