Using Machine Learning to Predict Extubation Readiness in Extreme Preterm Infants

Pascale Gourdeau

Supervisor: Pr Doina Precup

Problem and Motivation

- Nearly all extreme preterm infants need to undergo endotracheal intubation and mechanical ventilation (ETT-MV) in order to survive.
- **ETT-MV complications** ➔ pneumonia, air leaks, airway trauma, bronchopulmonary dysplasia (BPD)
- 1 week ETT-MV ➔ 2.7 fold increase of developing BPD
- Extubate **as early as possible** but possibility of **extubation failure** (needing reintubation)
- **Reintubation risks** ➔ tube blockage, traumatic injuries, lung or airway collapse, infections, severe bradycardia
- Cardiorespiratory and neurological injuries ➔ long-term disabilities

- **Extubation failure rates** ➔ 25-35%
- Determining extubation readiness: **imprecise scientific foundation**
- **Goal**: develop a tool to predict extubation readiness using cardiorespiratory and clinical data
- **Challenge**: exploit structure of time series used for prediction

Background and Related Work

- **Previous study** on extubation readiness done on 56 babies[4]
- **Features:** derived from various cardiorespiratory signals using AUREA[5], a system characterizing respiratory activity
- **Classifiers**: Support Vector Machines (SVM) (best) and Logistic Regression (LR)
- **Results:**
  - ➔ Specificity: 83%
  - ➔ Sensitivity: 74%
- **Drawbacks:**
  - ➔ High number of false positives
  - ➔ Feature extraction did not leverage structure of time series

---

- **SVM** ➔ powerful classification algorithm
- Map $x \rightarrow \phi(x)$ to higher dimensional space ➔ features linearly separable
- Uses **kernels**
- Non-linear separation
- 1 baby = 3,000 instances (1 minute at 50 Hz)

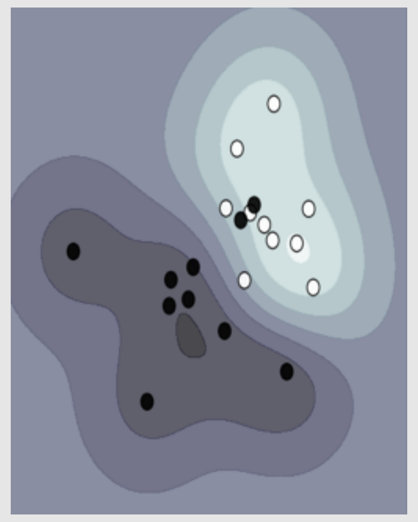


Fig. 1: A visualization of SVM

- Dynamic Time Warping (DTW) ➔ measures difference between two time series

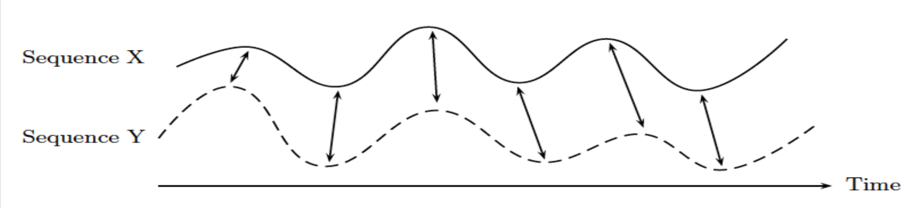
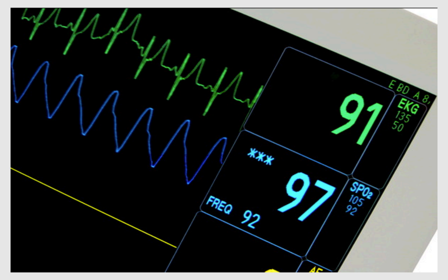


Fig. 2: A visualization of DTW

Approach and Uniqueness

- Previous study: hardcoded scripts or code not recorded ➔ need for highly flexible pipeline
- Pipeline:

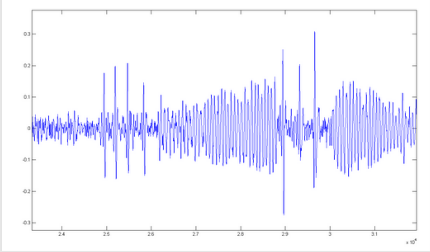
Raw Signals



- ECG, PPG
- O2 saturation
- Respiratory movement (ABD, RCG)

↓

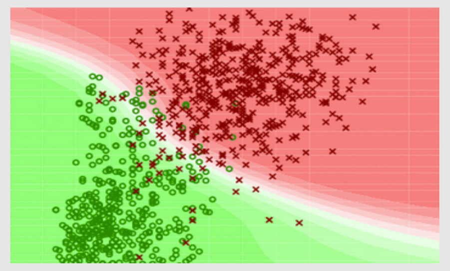
Feature Extraction



- Signal processing and analysis (AUREA)
- Dynamic Time Warping

↓

Classification

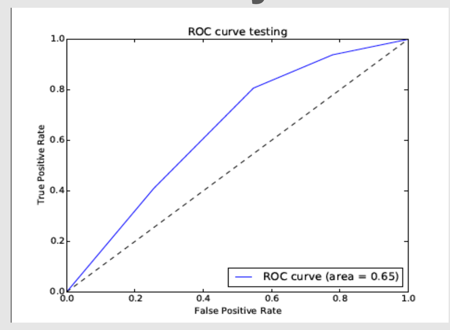


- Support Vector Machines
- Logistic Regression
- Cross-validation opts

(scikit-learn python package)

↓

Analysis



- ROC Curves
- Heatmaps
- Predictions over time

- **DTW implementation** in MATLAB to exploit structure of the time series
- **Spontaneous Breathing Trial** (SBT):
  45 minutes after ETT-MV, patients are put on continuous positive airway pressure ventilation (CPAP), a lower ventilation setting, for 5 minutes
- **Compare** ETT-MV and ETT-CPAP metrics and signals using a sliding window ➔ new time series
- New dataset: only **30 babies**

Results and Contribution

- Pipeline thoroughly documented, available on bitbucket for other team members

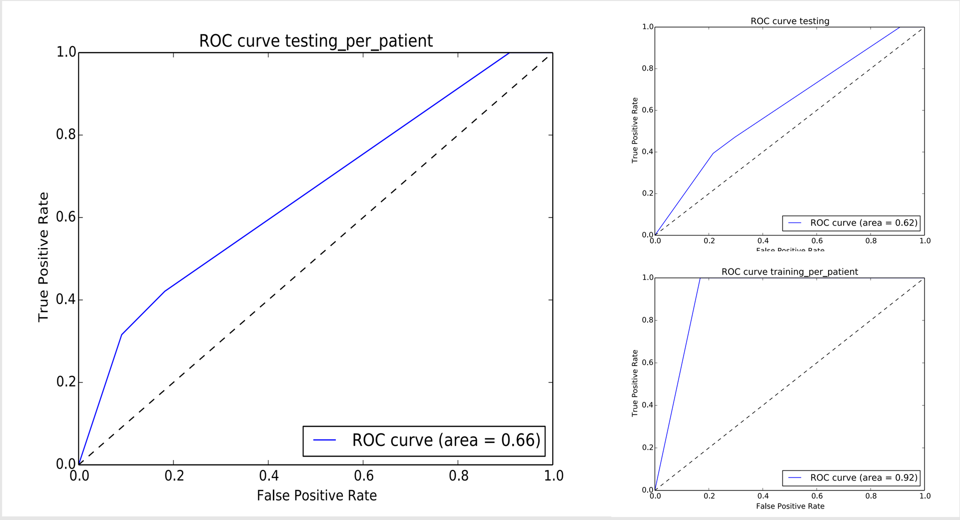


Fig. 3: SVM with respiratory metrics only

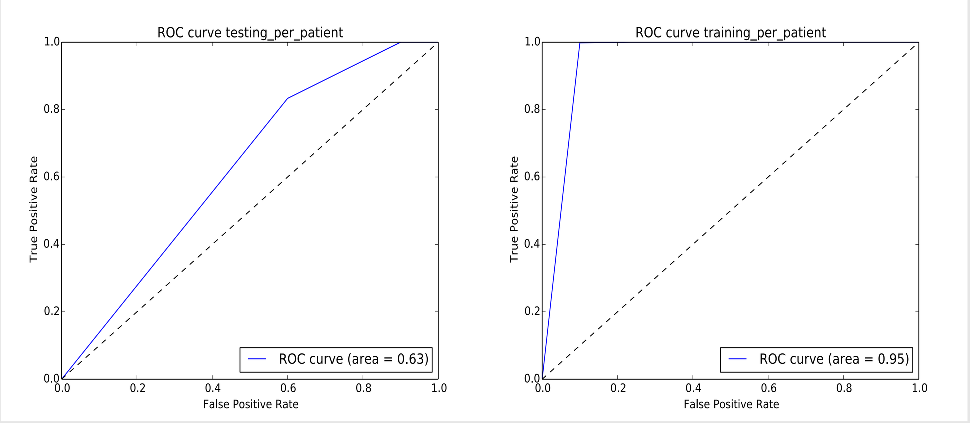


Fig. 4: SVM with DTW features only (5 s. sequence)

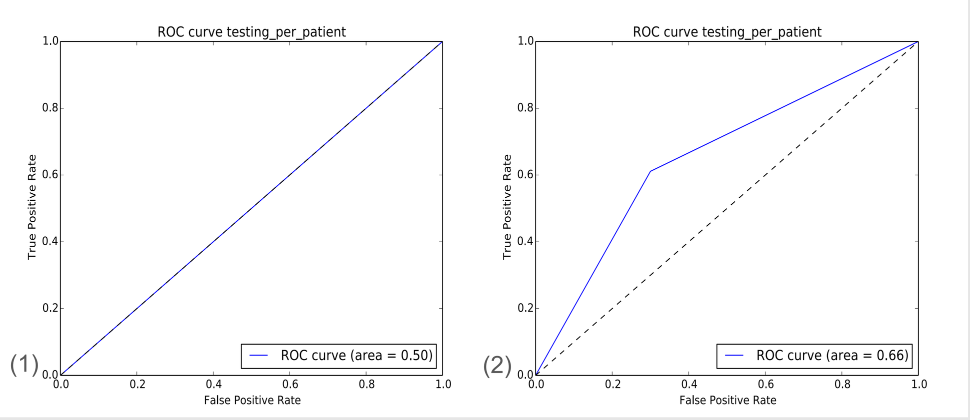


Fig. 5: LR with SVM without (1) and with (2) DTW

- TPR and FPR generated by varying *C* and γ
- SVM classification with cardiorespiratory metrics performed relatively well
- DTW as new feature improves LR and gives us the best classifier ➔ worth investigating further

Future Work

- Growing dataset (ongoing collection)
- Investigation of feature selection techniques
- Adding clinical features to classification
- Exploring new classifiers such as random forests
- Performing classifier ➔ develop a confidence measure to give a probabilistic prediction of extubation readiness in lieu of a binary prediction outcome
- More regularization measures to reduce overfitting

Acknowledgements

- Pr Doina Precup for providing me with great guidance and wisdom throughout the summer
- Pierre-Luc Bacon for letting me use some of his code as backbone for my work
- Lara Kanbar and Carlos Robles-Rubio for their precisous help with the AUREA system
- Everyone on the project, especially Wissam Shalish for letting me attend an extubation

Contact Information

Email: pascale.gourdeau@mail.mcgill.ca

RL Lab: www.rl.cs.mcgill.ca

References

[1] P .G. Davis, D.J. Henderson-*Smart "Nasal continuous positive airways pressure immediately after extubation for preventing morbidity in preterm infants."* Cochrane Database Syst Rev pp. CD000143, 2003.

[2] F. Hermeto, M. N. Bottino, K. Vaillancourt, and G. M. Sant'Anna, *"Implementation of a respiratory therapist-driven protocol for neonatal ventilation: impact on the premature population"*, Pediatrics, vol.123, pp. e907-16, May 200

[3] C.E. Shangle, R.H. Haas, F. Vaida, W.D. Rich, N.N. Finer, *"Effects of endotracheal intubation and surfactant on a 3-channel neonatal electroencephalogram."*, Pediatrics vol. 161, pp. 252- 257, 2012.

[4] Precup, D., C. A. Robles-Rubio, K. A. Brown, L. Kanbar, J. Kaczmarek, S. Chawla, G. M. Sant'Anna, and R. E. Kearney. *"Prediction of Extubation Readiness in Extreme Preterm Infants Based on Measures of Cardiorespiratory Variability."* in Eng. in Med. and Biol. Soc., 2012 Ann. Int. Conf. of the IEEE, San Diego, USA, 2012, pp.5630-633.

[5] C. A. Robles-Rubio, K. A. Brown and R. E. Kearney, *"Automated Unsupervised Respiratory Event Analysis"*, in Proc. 33rd IEEE Ann. Int. Conf. Eng. Med. Biol. Soc., Boston, USA, 2011, pp.3201-3204.

[6] M. Muller, Information Retrieval for Music and Motion, Ch. 4, Springer, 2007, ISBN 978-3-540-74047-6, p.70.

The scikit-learn (python) and DTW (MATLAB) packages were used.