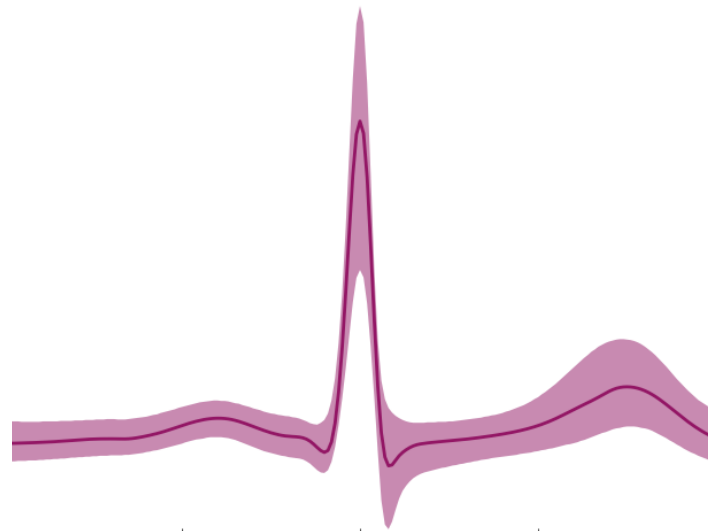
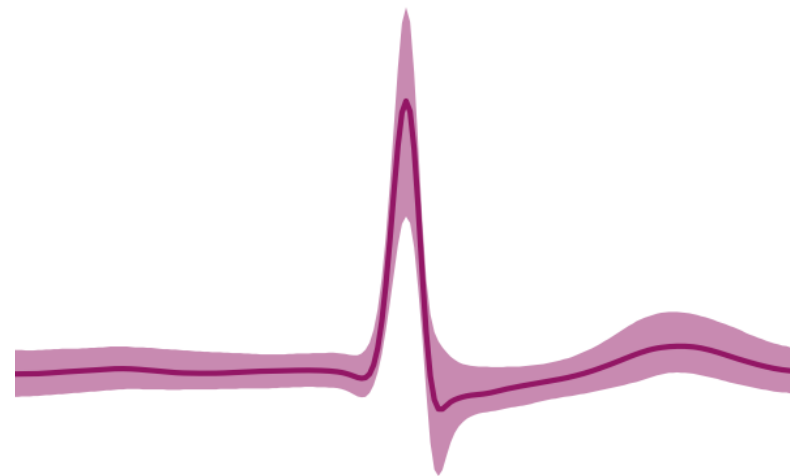
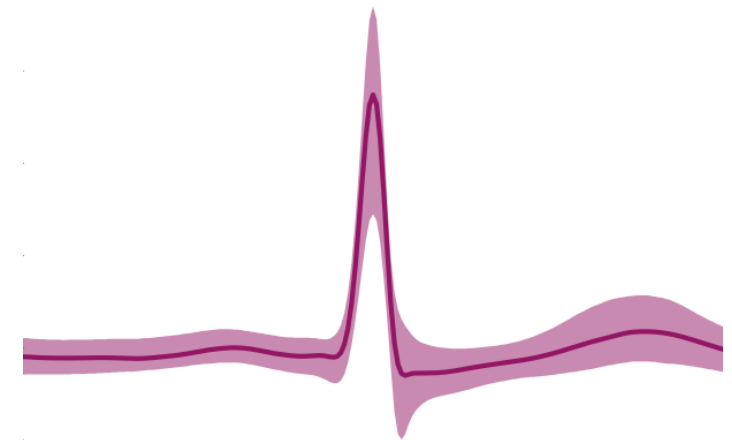


Normal Beat**Atrial Fibrillation****Other Arrhythmia**

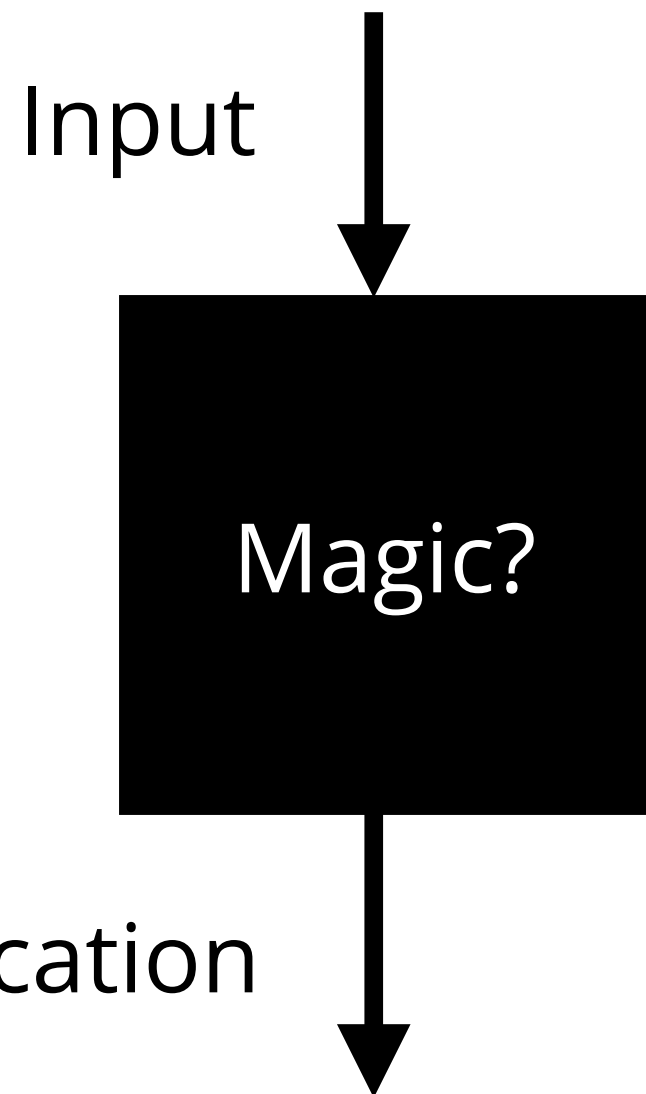
Beat by Beat:

Classifying Cardiac Arrhythmias with Recurrent Neural Networks

Patrick Schwab, Gaetano C. Scebba, Jia Zhang, Marco Delai and Walter Karlen

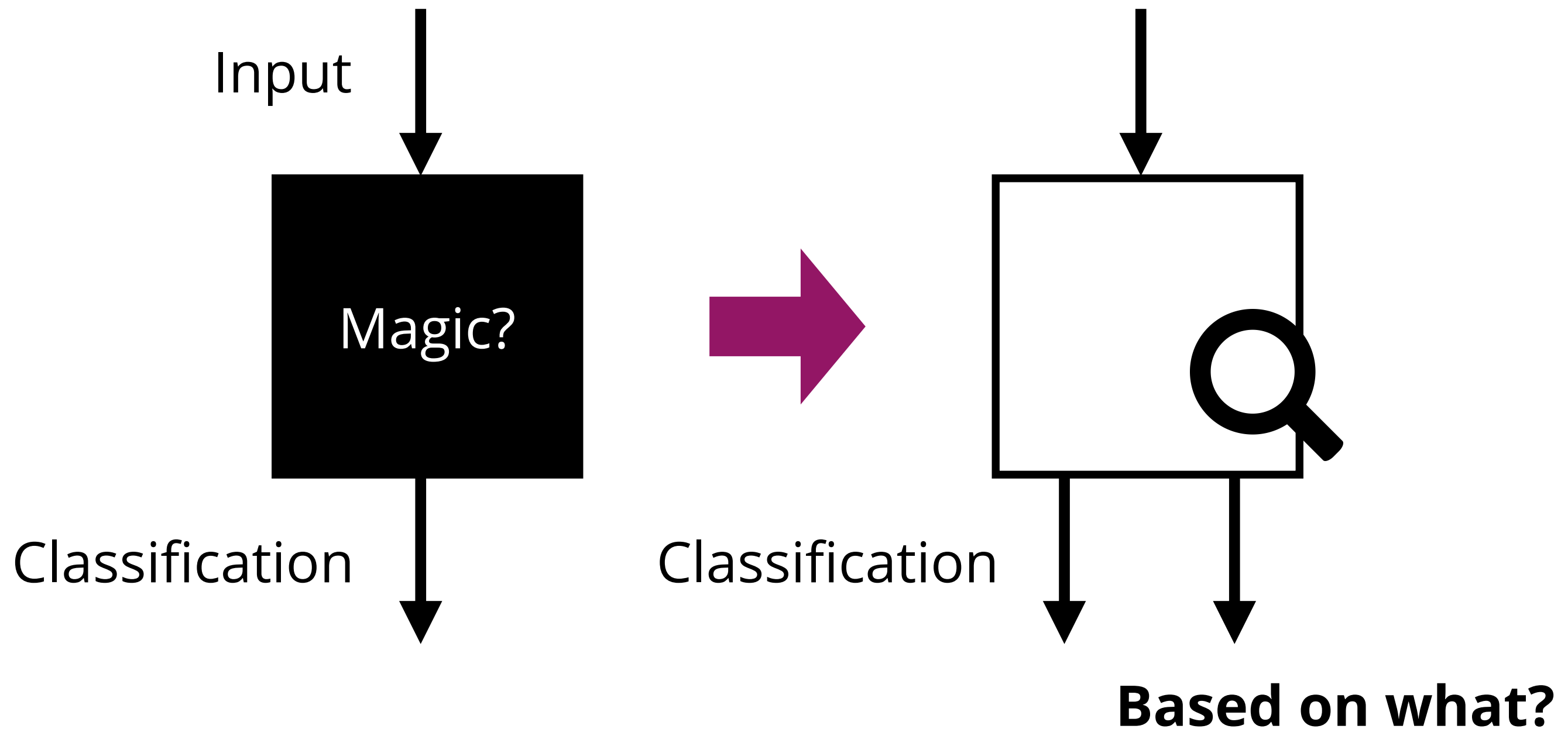
Bonus Challenge

Black Box Models

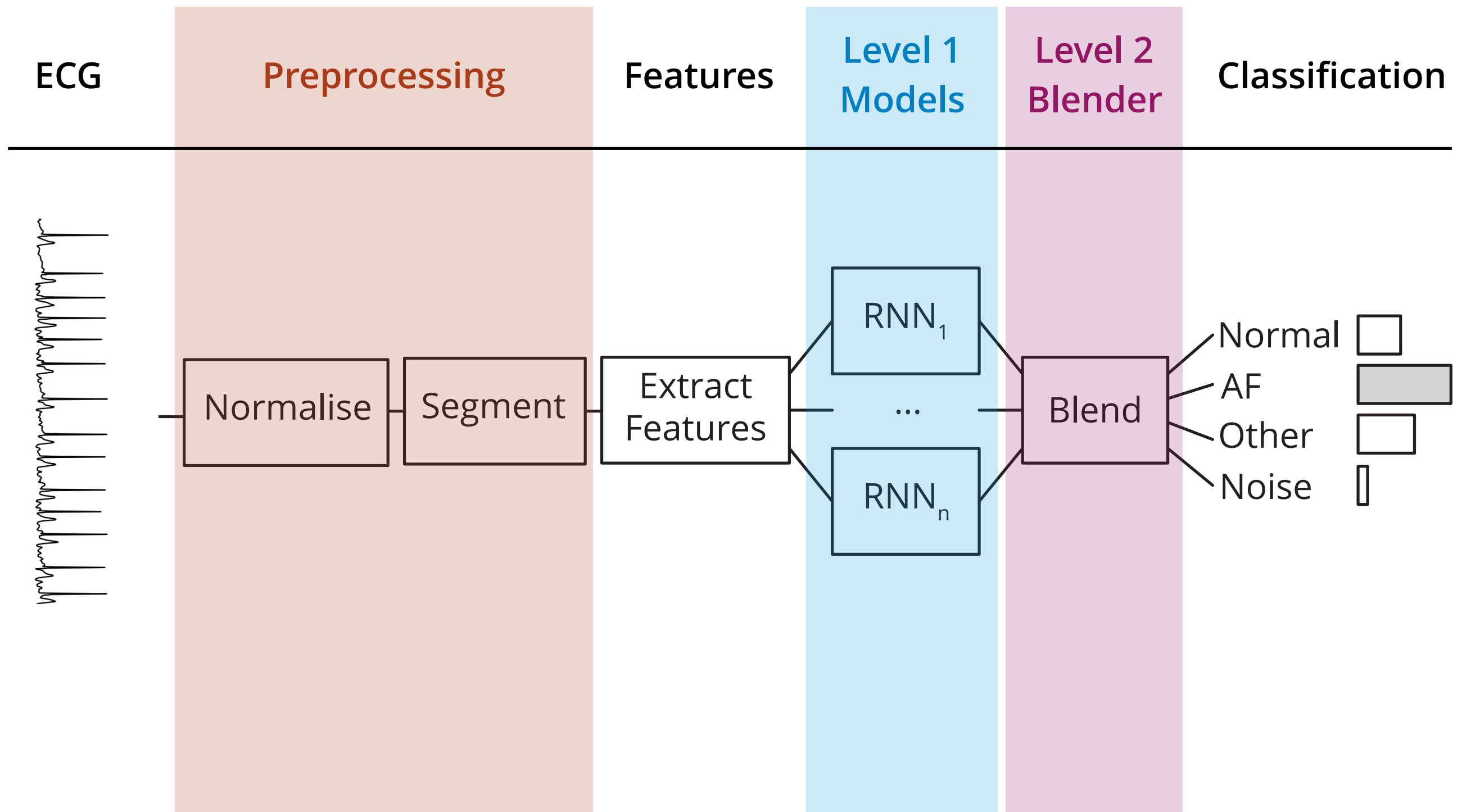


Bonus Challenge

Black Box Models

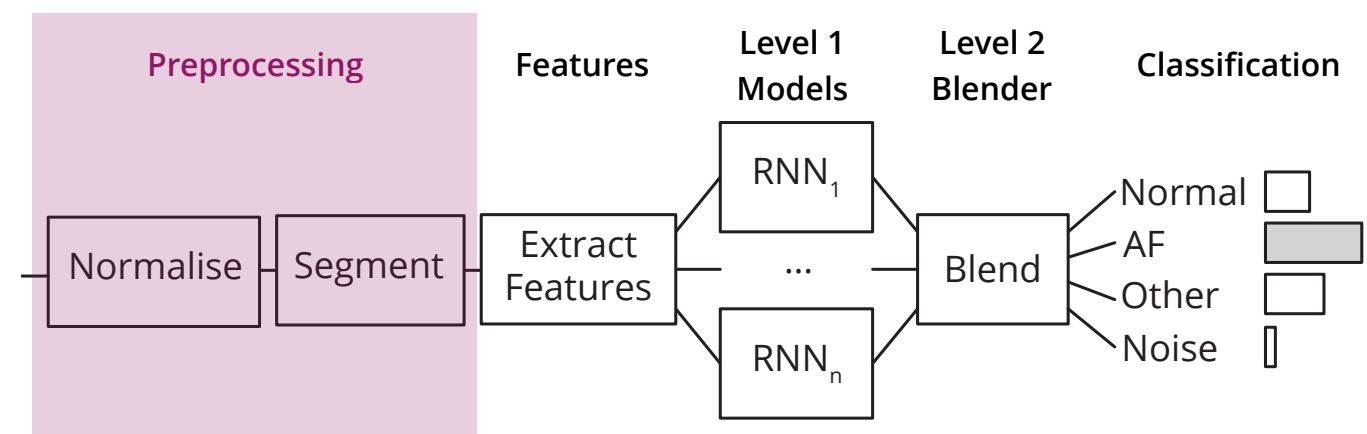


Pipeline



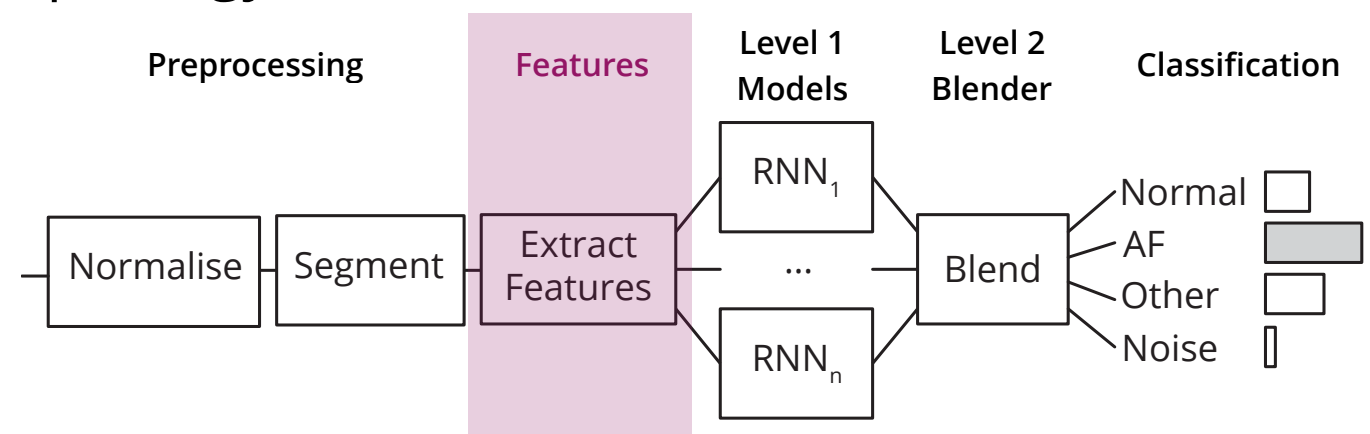
Capturing the Temporal Dimension

- *Idea:* Sequence learning over Heartbeats
- Utilise natural heartbeat segmentation
 - From ~9000 time steps to just ~45 time steps for each record.
- Allows us to relate decisions to individual heartbeats.



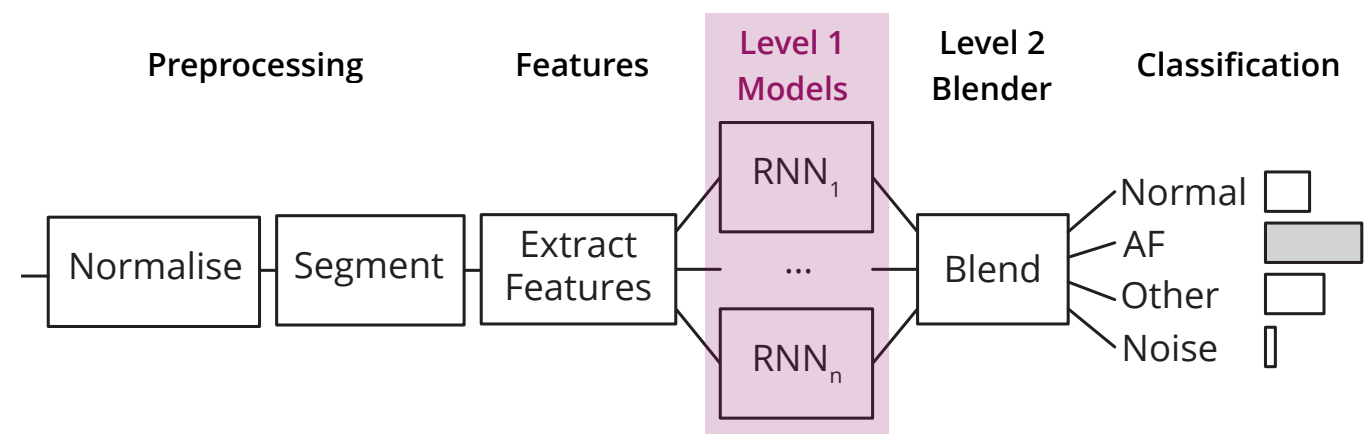
Features

- For *each heartbeat*, we extract:
 - δRR with $(n-1)^{\text{st}}$ heart beat
 - Relative Wavelet Energy (RWE) on 5 frequency bands
 - Total Wavelet Energy
 - R Amplitude
 - Q Amplitude (relative to R)
 - QRS-Duration
 - Wavelet entropy (WE)
 - Low-dimensional embedding of morphology



Level 1 Models

- We train several base models in varying configurations:
 - 1-vs-k and 1-vs-1 binary classification
 - Subsets of features
 - Different hyperparameters and model architectures
- In order to learn a *diverse* set of base models that *complement* each other



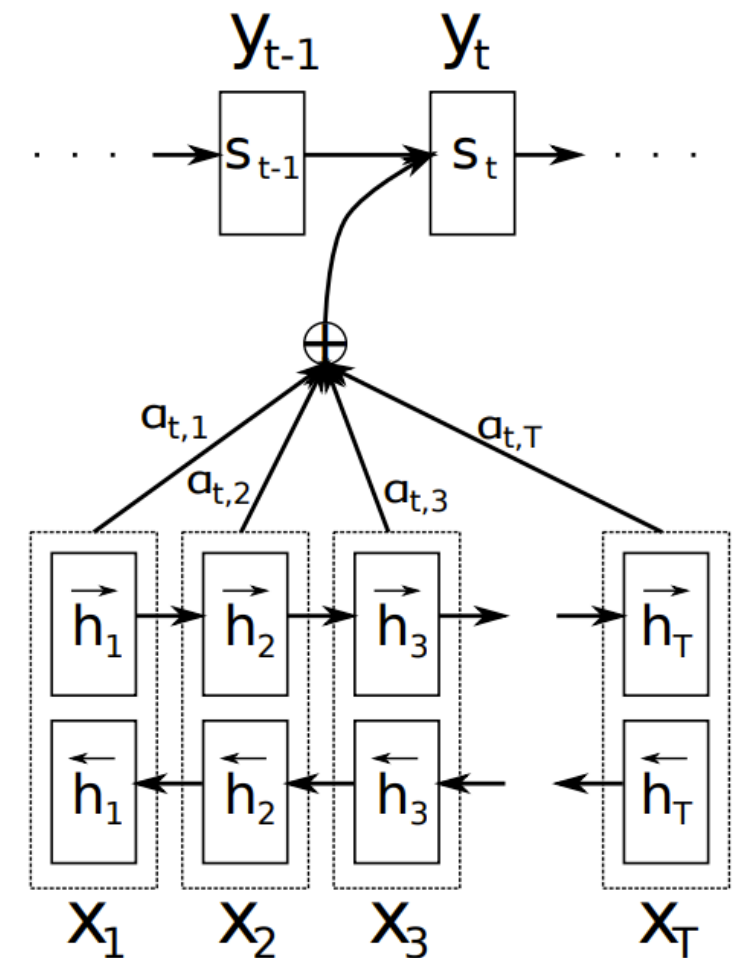
Attention over Heartbeats

$$u_t = \tanh(W_{beat}h_t + b_{beat}) \quad (1)$$

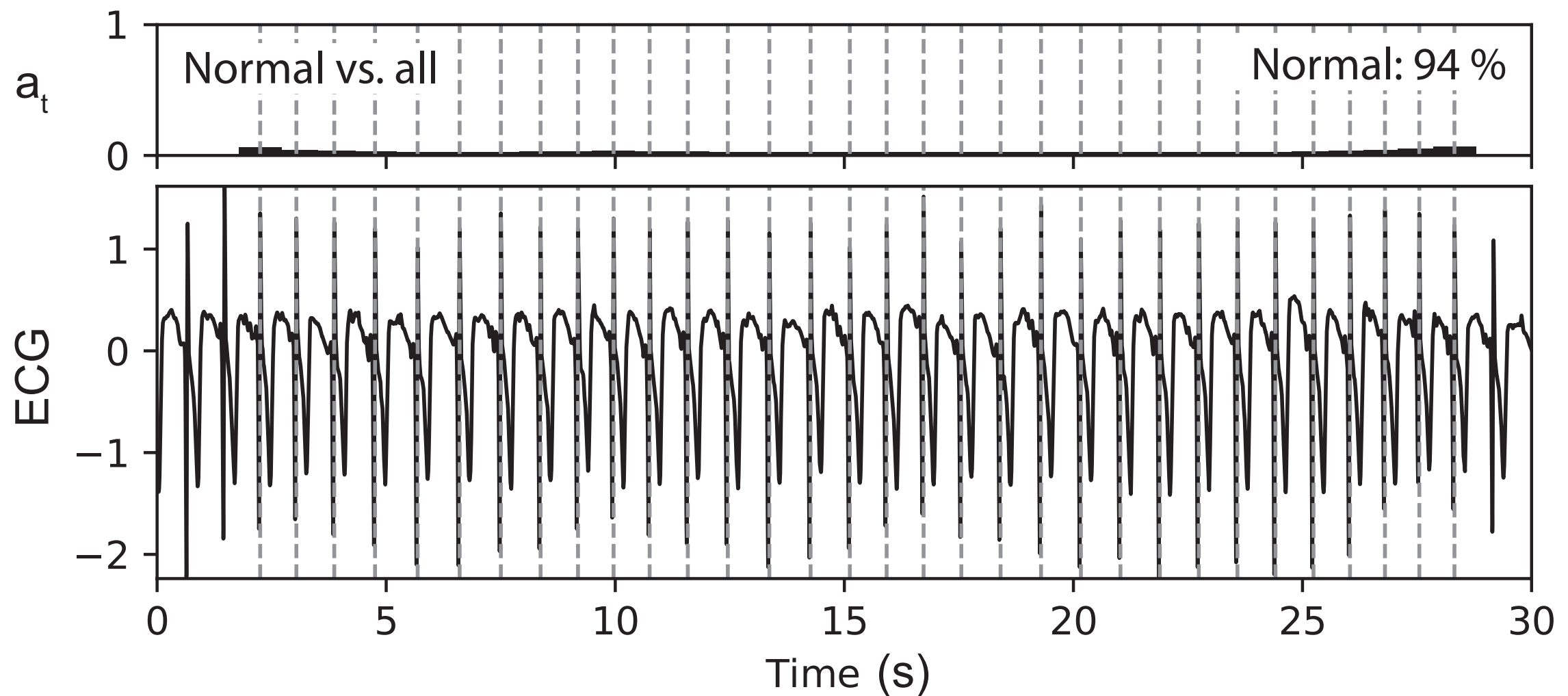
$$a_t = \text{softmax}(u_t^T u_{beat}) \quad (2)$$

$$c = \sum_t a_t h_t \quad (3)$$

u_t ... hidden representation of h_t
 W_{beat}, b_{beat} ... single-hidden-layer multi-layer perceptron (MLP)
 u_{beat} ... hidden representation of most informative beat
 a_t ... attention factors
 c ... context vector



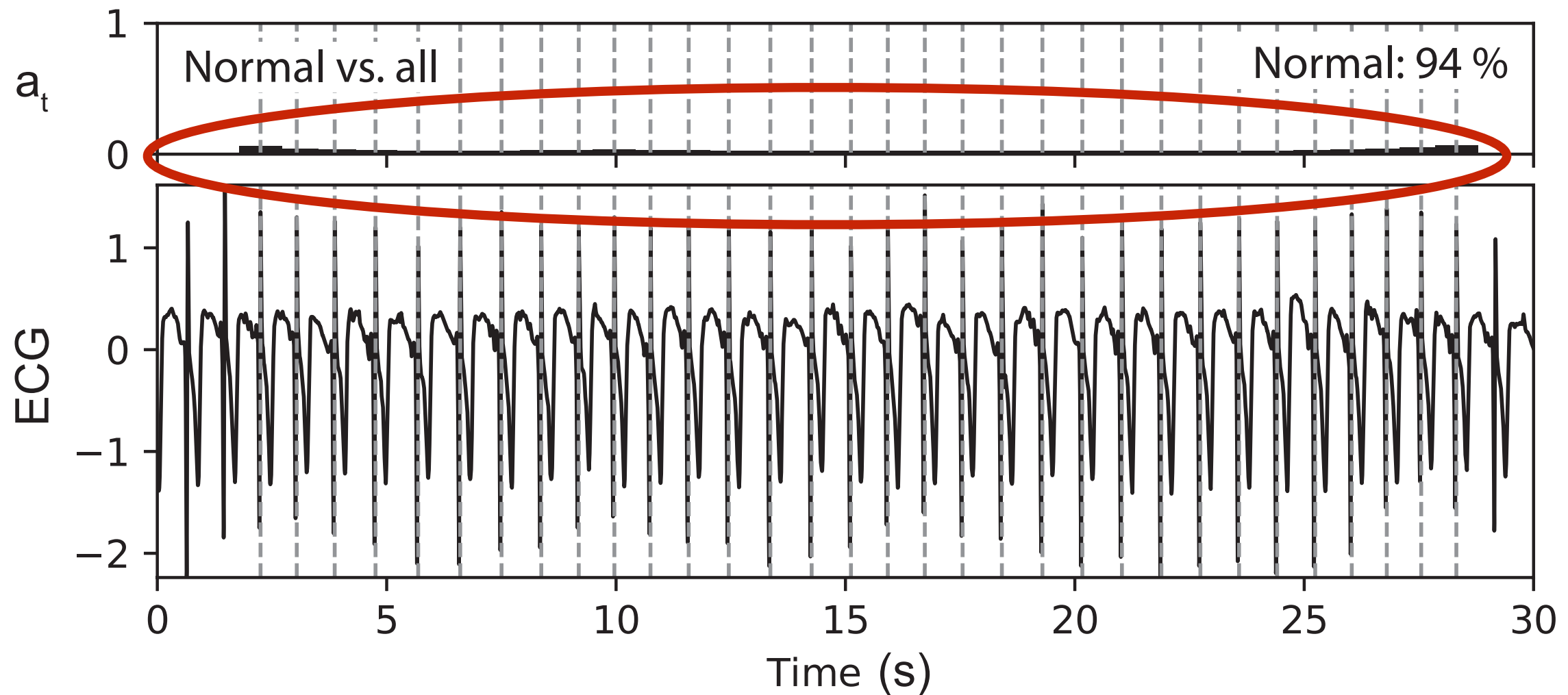
Attention (Sinus Rhythm)



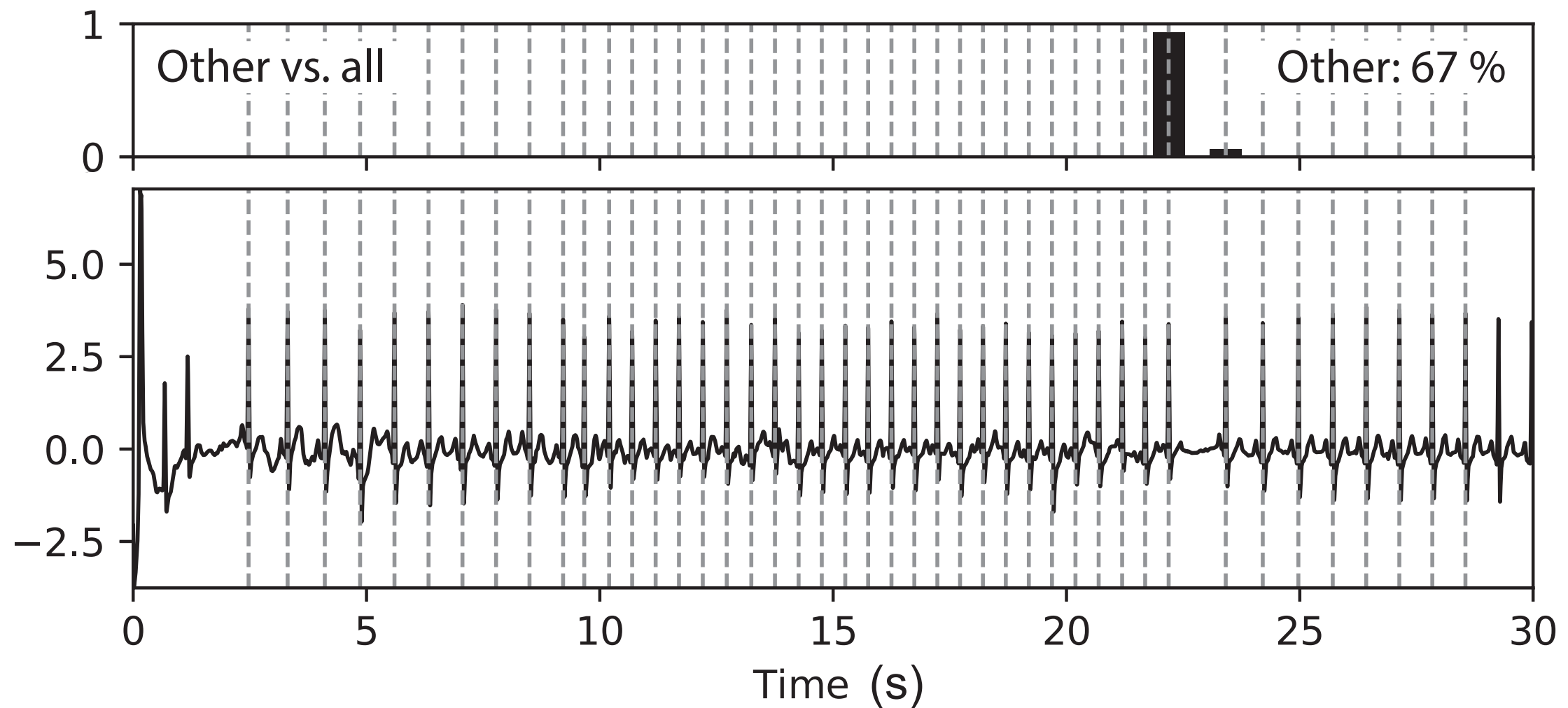
Attention (Sinus Rhythm)

Typical pattern:

Roughly equally weighted - all beats equally informative.

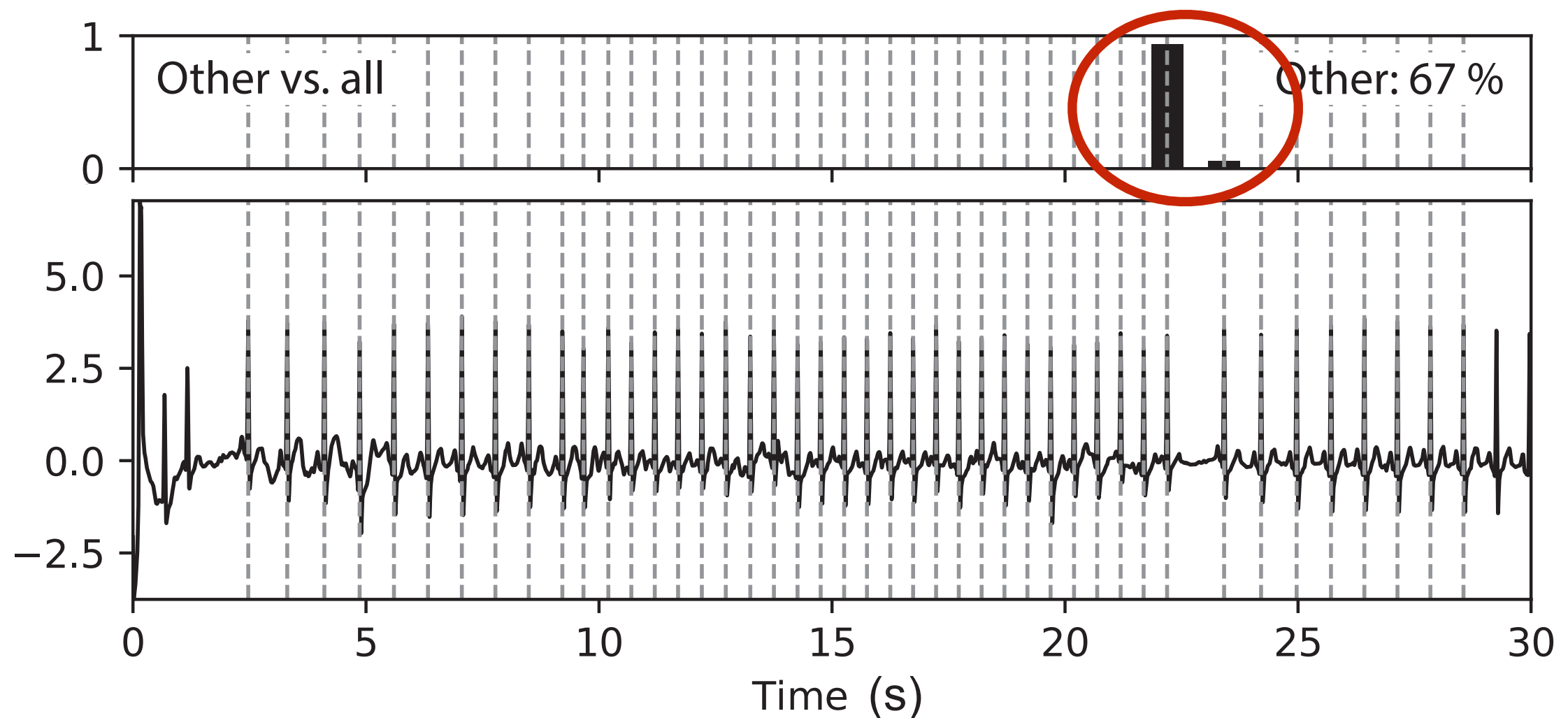


Attention (Other Arrhythmia)



Attention (Other Arrhythmia)

Almost exclusive focus on irregular heartbeat.



Results

Confusion Matrix (Validation Set)

		Predicted Class			
		Normal	AF	Other	Noisy
Actual Class	Normal	86,53 %	0,96 %	11,53 %	0,96 %
	AF	6,89 %	79,31 %	13,79 %	0,00 %
	Other	18,08 %	7,44 %	73,40 %	1,00 %
	Noisy	0,00 %	0,00 %	18,18 %	81,81 %

Confusion Matrix (Validation Set)

Room for improvement!

Predicted Class

Actual Class	Predicted Class			
	Normal	AF	Other	Noisy
Normal	86,53 %	0,96 %	11,53 %	0,96 %
AF	6,89 %	79,31 %	13,79 %	0,00 %
Other	18,08 %	7,44 %	73,40 %	1,00 %
Noisy	0,00 %	0,00 %	18,18 %	81,81 %

F1-Scores

Validation Set (20%)

$$F_{1,Normal} = 0.88$$

$$F_{1,AF} = 0.75$$

$$F_{1,Other} = 0.72$$

$$F_{1,Noisy} = 0.78$$

$$F_{1,Total} = 0.78$$

Private Test Set P2 (PhysioNet 2017)

$$F_{1,Normal} = 0.90$$

$$F_{1,AF} = 0.78$$

$$F_{1,Other} = 0.68$$

—

$$F_{1,Total} = 0.79$$

Conclusion

- Decisions that are communicable increase *trust* in automated systems.
- In order to create novel insights from large datasets, we need to understand *what* our models learn.
- **We can and should have it all: The classification performance of a deep-learning model *and* comprehensible decisions.**

Questions?

Schwab et al. (2017). *Beat by Beat: Classifying Cardiac Arrhythmias with Recurrent Neural Networks*.
Computing in Cardiology Conference (CinC 2017), Rennes, France, September 24-27, 2017

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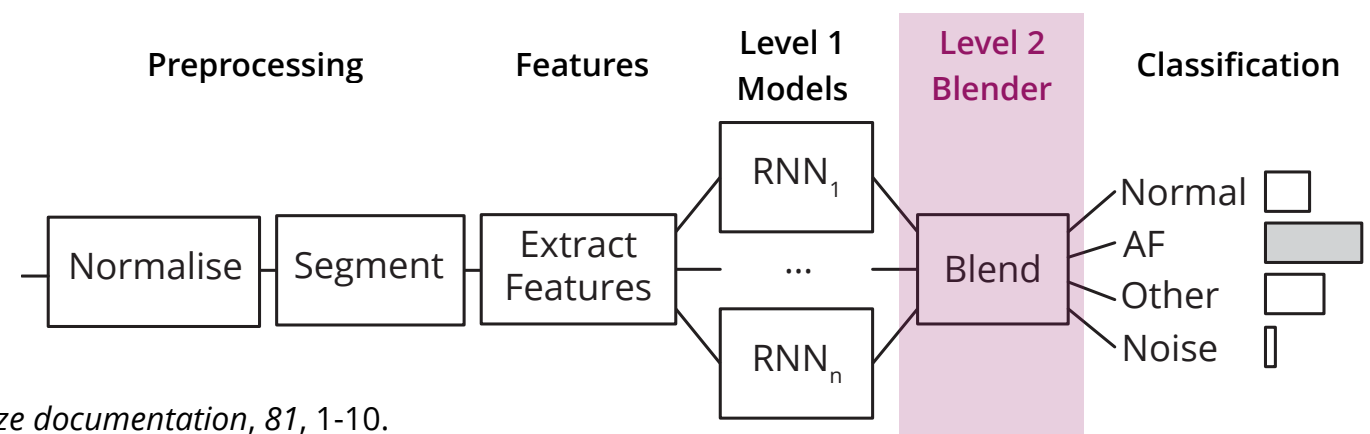
patrick.schwab@hest.ethz.ch

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Appendix

Level 2 Blender

- Combine predictions from base models into final classification score
- Increasing overall accuracy by combining multiple models' outputs
- Using a multi-layer perceptron (MLP)



Koren, Y. (2009). The BellKor Solution to the Netflix Grand Prize. *Netflix prize documentation*, 81, 1-10.