CLOCS: Contrastive Learning of Cardiac Signals

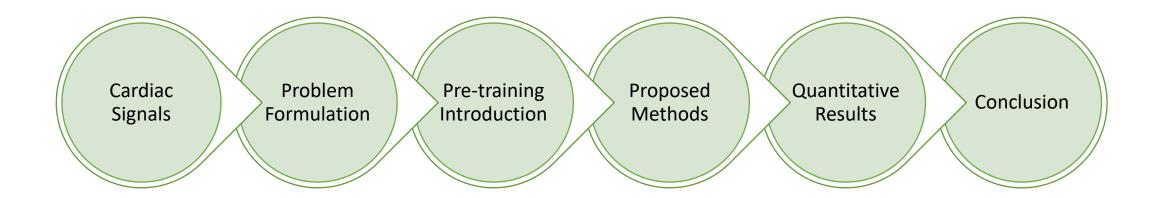
Invited Talk:
ML4CVD
Broad Institute

Dani Kiyasseh dani.kiyasseh@eng.ox.ac.uk August 25th, 2020





Roadmap







The Power of Cardiac Signals

Letter | Published: 07 January 2019

Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network

Awni Y. Hannun ⊡, Pranav Rajpurkar, Masoumeh Haghpanahi, Geoffrey H. Tison, Codie Bourn, Mintu P. Turakhia & Andrew Y. Ng

Letter | Published: 11 May 2020

Prediction of mortality from 12-lead electrocardiogram voltage data using a deep neural network

Sushravya Raghunath, Alvaro E. Ulloa Cerna, Linyuan Jing, David P. vanMaanen, Joshua Stough, Dustin N. Hartzel, Joseph B. Leader, H. Lester Kirchner, Martin C. Stumpe, Ashraf Hafez, Arun Nemani, Tanner Carbonati, Kipp W. Johnson, Katelyn Young, Christopher W. Good, John M. Pfeifer, Aalpen A. Patel, Brian P. Delisle, Amro Alsaid, Dominik Beer, Christopher M. Haggerty & Brandon K. Fornwalt

Letter | Published: 07 January 2019

Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram

Zachi I. Attia, Suraj Kapa, Francisco Lopez-Jimenez, Paul M. McKie, Dorothy J. Ladewig, Gaurav Satam, Patricia A. Pellikka, Maurice Enriquez-Sarano, Peter A. Noseworthy, Thomas M. Munger, Samuel J. Asirvatham, Christopher G. Scott, Rickey E. Carter & Paul A. Friedman

JAMA Cardiology | Original Investigation

Development and Validation of a Deep-Learning Model to Screen for Hyperkalemia From the Electrocardiogram

Conner D. Galloway, MSc; Alexander V. Valys, BS; Jacqueline B. Shreibati, MD; Daniel L. Treiman, BS; Frank L. Petterson, PhD; Vivek P. Gundotra; David E. Albert, MD; Zachi I. Attia, MSc; Rickey E. Carter, PhD; Samuel J. Asirvatham, MD; Michael J. Ackerman, MD, PhD; Peter A. Noseworthy, MD; John J. Dillon, MD; Paul A. Friedman, MD



Problem Formulation

Rate of data generation far exceeds that of labelling by expert annotators



Presence of small, labelled datasets

Presence of large, unlabelled datasets

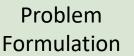


Research Question

How can we derive reliable clinical insights from small, labelled datasets while exploiting large, unlabelled datasets?







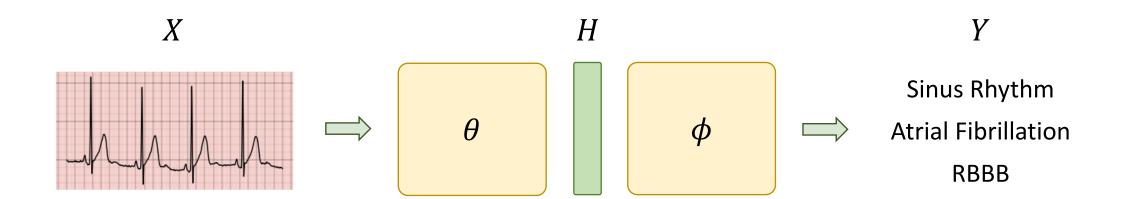
Proposed Methods



Cardiac Arrhythmia Classification

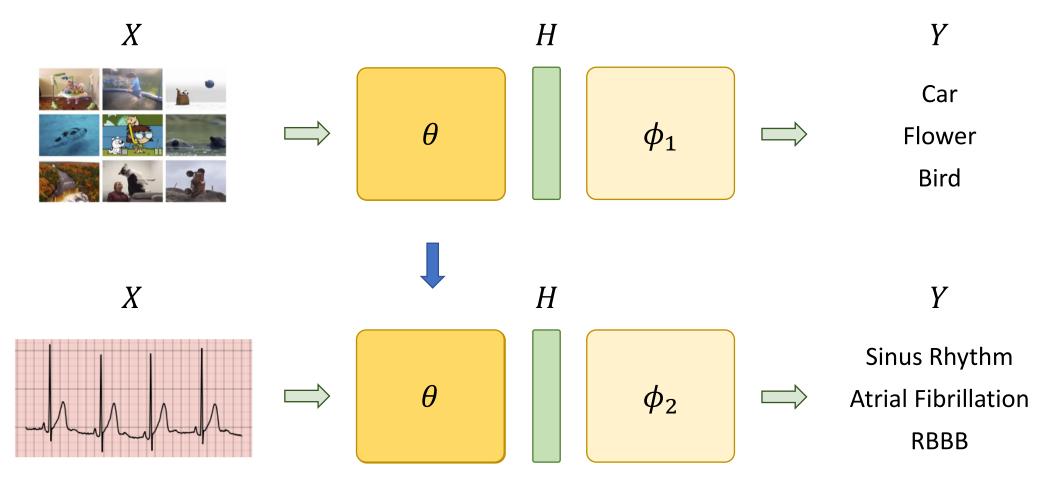
$$f_{\theta}: X \in \mathbb{R}^D \to H \in \mathbb{R}^E$$

$$g_{\phi}: H \in \mathbb{R}^E \to Y \in \mathbb{R}^C$$



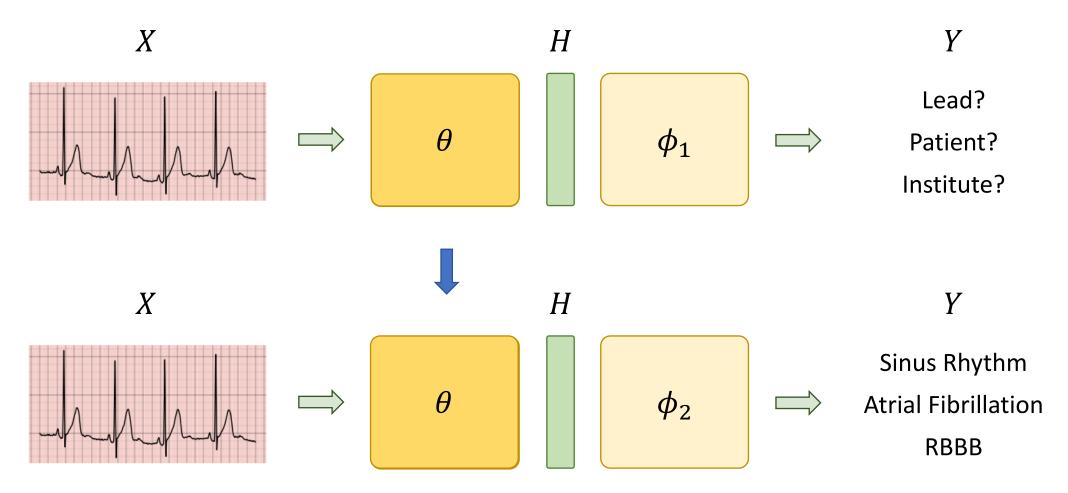


Supervised Pre-training



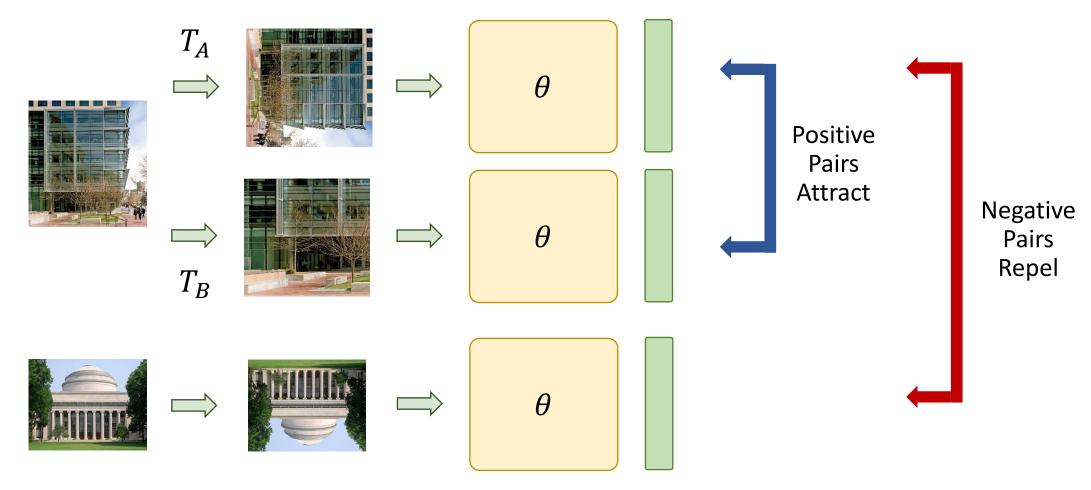


Self-supervised Pre-training





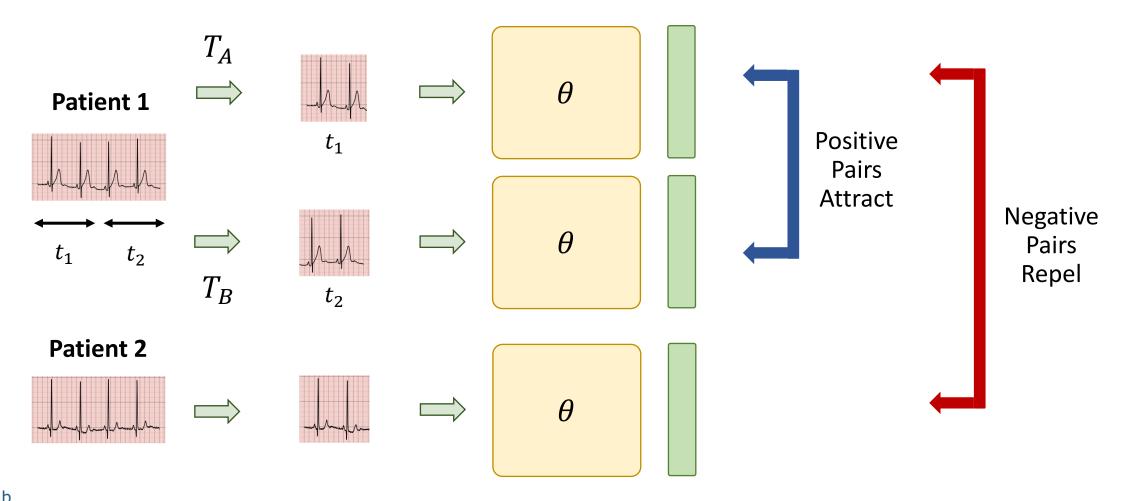
Contrastive Learning - SimCLR





Quantitative Results

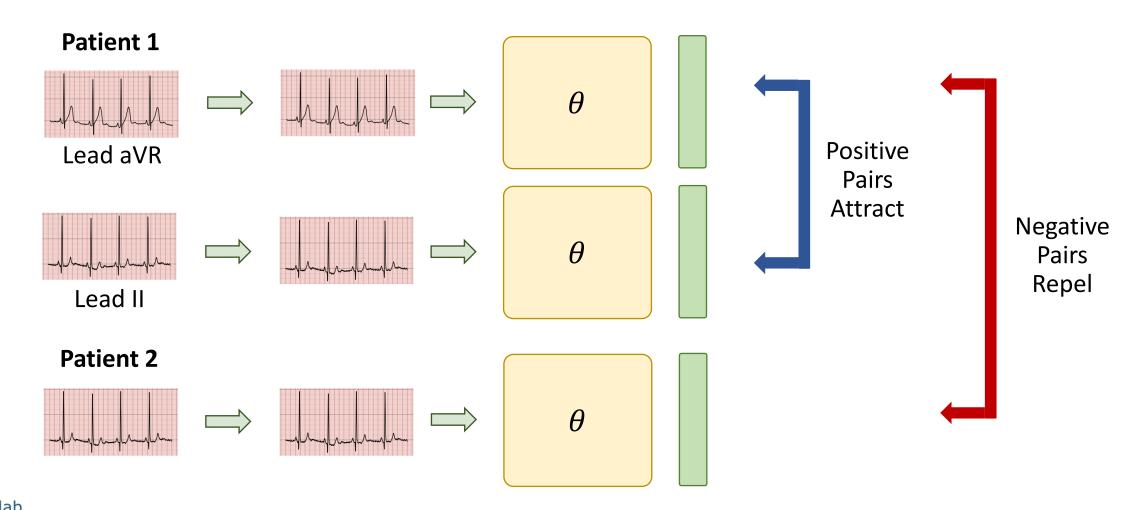
CMSC – Contrastive Multi-segment Coding





Cardiac	
Signals	

CMLC – Contrastive Multi-lead Coding





Cardiac			
Signals			

Quantitative Results

Noise Contrastive Estimation (NCE) Loss

For representations, h, and two transformations, A and B

$$\mathcal{L}_{NCE} = -E_{i \in P} \left[\log \left(\frac{e^{s(h_A^i, h_B^i)}}{\sum_j e^{s(h_A^i, h_B^j)}} \right) \right]$$

Cosine-similarity of two representations

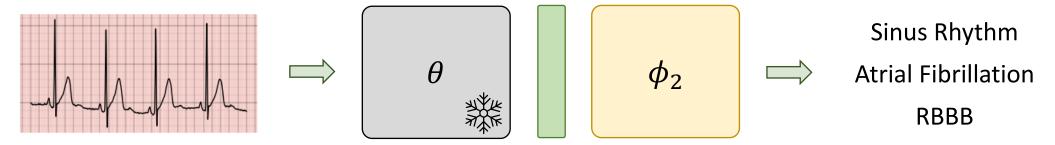
$$s(h_A^i, h_B^i) = \frac{h_A^i \cdot h_B^i}{\parallel h_A^i \parallel \parallel h_B^i \parallel} \cdot \frac{1}{\tau}$$



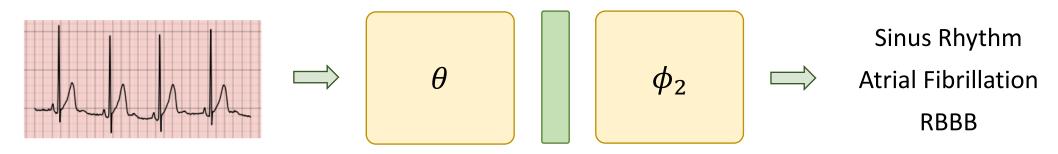


Evaluation Scenarios

Linear Evaluation (only update ϕ_2)



Transfer Capability of Representations (update both θ and ϕ_2)







Datasets

Dataset	# of Patients	# of Leads	# of Classes
PhysioNet 2020 ¹	6,877	12	9
Chapman ²	10,646	12	11
PhysioNet 2017 ³	8,528 (recordings)	1	4
Cardiology ⁴	328	1	12

Always used for self-supervised pre-training

Predominantly used for evaluation

⁴ Hannun, A. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nature Medicine, 25(1):65.





¹ Perez Alday, E. A., et al. (2020). Classification of 12-lead ECGs: the PhysioNet - Computing in Cardiology Challenge 2020 (version 1.0.0). *PhysioNet*.

² Zheng, J. et al. (2020). A 12-lead electrocardiogram database for arrhythmia research covering more than 10,000 patients. Scientific Data, 7(1):1–8.

³ Clifford, G. et al. (2017). Afib classification from a short single lead ECG recording: the physionet/computing in cardiology challenge 2017. In 2017 Computing in Cardiology, pages 1–4.

Linear Evaluation

- CMSC outperforms CMLC and CMSMLC
- CMSC outperforms state-of-the-art SimCLR by 15.8% on Chapman

Table 1: Test AUC of the linear evaluation of the representations at F=0.5, after having pre-trained on Chapman or PhysioNet 2020 with E=128. Pre-training and evaluating multi-lead datasets* using 4 leads (II, V2, aVL, aVR). Mean and standard deviation are shown across 5 seeds.

Dataset	Chapman*	PhysioNet 2020*		
SimCLR	0.738 ± 0.034	0.615 ± 0.014		
CMSC	0.896 ± 0.005	0.715 ± 0.033		
CMLC	0.870 ± 0.022	0.596 ± 0.008		
CMSMLC	0.847 ± 0.024	0.680 ± 0.008		



Transfer Capabilities of Representations

- CMSC outperforms state-of-the-art SimCLR in 5/6 of all experiments
- Greatest benefit observed for small datasets, e.g., Cardiology, PhysioNet 2017

Table 2: Test AUC in the fine-tuning scenario at F=0.5, after having pre-trained on Chapman or PhysioNet 2020 with E=128. Pre-training, fine-tuning, and evaluating multi-lead datasets* using 4 leads. Mean and standard deviation are shown across 5 seeds.

Pretraining Dataset		Chapman*	-		PhysioNet 2020*	
Downstream Dataset	Cardiology	PhysioNet 2017	PhysioNet 2020*	Cardiology	PhysioNet 2017	Chapman*
Random Init	0.678 ± 0.011	0.763 ± 0.005	0.803 ± 0.008	0.678 ± 0.011	0.763 ± 0.005	0.907 ± 0.006
SimCLR	0.676 ± 0.011	0.772 ± 0.010	0.823 ± 0.011	0.658 ± 0.027	0.762 ± 0.009	0.923 ± 0.010
CMSC	0.695 ± 0.024	0.773 ± 0.013	0.830 ± 0.002	$\textbf{0.714} \pm \textbf{0.014}$	0.7600 ± 0.013	$\textbf{0.932} \pm \textbf{0.008}$
CMLC	0.665 ± 0.016	0.767 ± 0.013	0.810 ± 0.011	0.675 ± 0.013	0.762 ± 0.007	0.910 ± 0.012
CMSMLC	$\textbf{0.717} \pm \textbf{0.006}$	$\textbf{0.774} \pm \textbf{0.004}$	0.814 ± 0.009	0.698 ± 0.011	$\textbf{0.774} \pm \textbf{0.012}$	0.930 ± 0.012



Doing More with Less

• CMSC outperforms a random initialization with 1/4th the number of labels

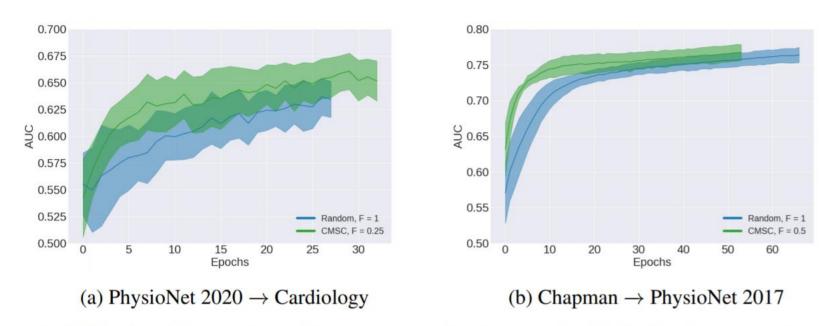


Figure 3: Validation AUC starting with a random and self-supervised initialization exposed to different amounts of labelled training data. Results are averaged across 5 seeds. Shaded area represents one standard deviation.





Patient-specific Representations

• CMSC learns representations that are unique to each patient

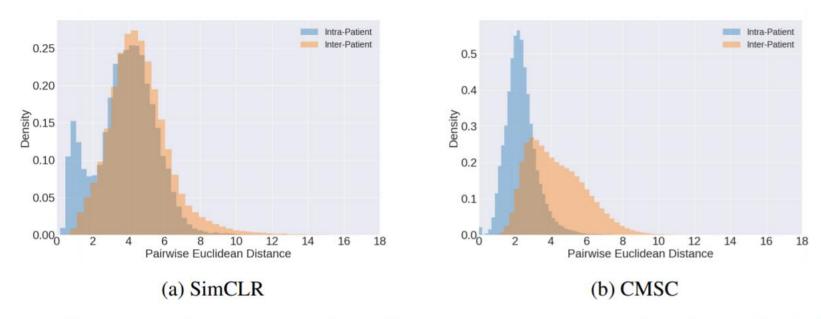


Figure 5: Distribution of pairwise Euclidean distance between representations (E=128) belonging to the same patient and those belonging to different patients. Self-supervision was performed on PhysioNet 2020. Notice the lower average intra-patient values and improved separability with CMSC.







Takeaways

 Self-supervised pre-training with CLOCS results in patient-specific representations

 CLOCS pre-training can improve the label-efficiency of learning on downstream medical tasks 4x

 CLOCS pre-training is most beneficial when downstream datasets are small and lack sufficient labels





Future Work

 Quantification of patient similarity for educational purposes and disease discovery

• Exploiting additional cardiac signals for self-supervised learning before transferring to ECG datasets







Glossary

