Contrastive Learning of Electrocardiogram signals for the inference of cardiac pressure

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Abstract

Abnormal cardiac signals in an electrocardiogram (ECG) are used to screen the heart condition. Physicians oftentimes order diagnostic tests which include invasive procedures. For instance, the function of the left heart can be precisely measured by the pulmonary capillary wedge pressure (PCWP) which is invaisve. To reduce the risk of such invasive procedures, we can build a model to infer PCWP using non-invasive ECG screening. Moreover, we can leverage the vast amount of unlabeled ECG dataset to learn a useful representation. Yet, an important question remains; what are the good views (Tian et al. (2020)) of ECGs for contrastive learning? Previous works have tried to include ECGs from the same patients (Diamant et al. (2021)), different augmentations from the same ECG (Gopal et al. (2021)), and different projections of the same ECG (Kiyasseh et al. (2021)) to define proper 'views' for contrastive learning. However, none of them has tried to explore the various views from different ECGs and compare those. In this project, we define different views according to *age, sex, racial groups* with and without augmentation (scaling, adding Gaussian noise, shifting, augmentation on spectrogram domain (Park et al. (2019)). Then compare the learned representation over the downstream task - classification and regression of PCWP.

References

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Appendix A.

Some more details about those methods, so we can actually reproduce them. After the blind review period, you could link to a repository for the code also. *MLHC values both rigorous evaluation as well as reproduciblity.*