SAMPLE INVARIANT SELF-SUPERVISED PRE-TASK FOR ECG SIGNAL PROCESSING

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Autoencoders are widely used as a Self-Supervised learning pre-task method in different fields of applications. Electrocardiography (ECG) signals can be treated as infinite quasi-periodic and should be sampled to be processed via machine learning methods, while two samples taken from the same signal at minimal time difference will be different. It means that sampling information is required to reconstruct the signal sample and will be preserved in the autoencoder latent space embedding. However, this information is redundant for most real-world tasks, such as signal classification. This study explores a sample invariant autoencoder training method for the electrocardiography (ECG) signals.

The main idea is to split latent space signal representation into two parts, where the first part is used for signal features, while the second one contains sampling information. A basic autoencoder model training problem can be denoted as:

$$||X^T - F(W_1, G(W_2, X))|| > \min$$

where W_1 , W_2 – encoder and decoder weights; F, G – functions that model decoder and encoder correspondingly; X^T – a signal sample of a size T. The encoder's output is $Z^N = G(W_2, X)$. In the proposed method the encoder model also learns to predict offset value d from some canonical sample form. An offset value is then passed to the decoder part alongside Z^N . Training is performed with triplets of samples where the first two samples are taken from the same signal and the third from different. To force the model to remove sampling information from embedding Z^N the reconstruction loss used in the autoencoder is combined with triplet loss to minimize the difference between intra- and inter-sample distances.

$$L = \sum_{i-1,3} ||X^{T_i} - X^{T_i}|| + a * \max(||Z^{N_1} - Z^{N_2}|| - ||Z^{N_1} - Z^{N_3}|| + m, 0),$$

where X^{T}_{i} , X^{T}_{i} – original and reconstructed samples; Z^{N}_{1} , Z^{N}_{2} , Z^{N}_{3} – samples' latent space embeddings; a, m – model hyperparameters.

Intra-sample and inter-sample standard deviation were calculated for both the traditional autoencoder and the proposed model. 50 samples were randomly selected from 50 different signals. Then samples were converted to latent space embeddings using the encoder part of the model. The intra-signal standard deviation (STD) was calculated as the mean STD for clusters of samples for every signal. Then the Intersignal STD was calculated as the mean STD among clusters of samples, where each cluster contains a single sample from every signal presented in the test dataset. Finally, intra-sample embedding density was calculated as a relation of intra- and inter-sample mean STDs. The proposed method demonstrates higher intra-sample embedding density related to the traditional autoencoder without valuable loss in reconstruction precision. Future work plans to analyze the performance of this method on various target tasks and refine the neural network architecture to suit the task of sample offset extraction better.