Surrogate Loss Learning for DTW

Abstract

In Time Series analysis Dynamic Time Warping (DTW) is a technique used to quantify similarity between two time sequences which might be varying in length and speed. Research has manifested that DTW, which is a metric can also be used as a loss function for training deep learning networks. The basic implementation of DTW makes use of 'min' operation which is non-differentiable. In order to use DTW as loss function, authors proposed soft-DTW which is differentiable as it makes use of soft-min instead of min operation. The pitfall of this approach is that its closely dependent on hyper-parameter γ and focuses only on shape error between two sequences. As an extension to this, Shape and Time **Distortion Loss** (DILATE) was proposed which along with shape error considers time delay as well. Quadratic complexity and efficiency depending on parameter γ are a stumbling block to these functions.

Considering these factors, surrogate loss functions turns out to be best alternative for non-differential or computationally complex loss functions. As suggested by the authors in Learning Surrogate Losses, we would try to develop a surrogate loss function for Shape and Time Distortion Loss (DILATE) as meta-level neural network that will approximate the desired loss. This network will be trained initially with train data-set such that Shape and Time Distortion Loss (DILATE) is differentiable during training and then the training of prediction model will be carried out. In perspective of DTW we'd like to make use of attention networks for surrogate loss training.

References

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