Towards Domain-Agnostic Contrastive Learning

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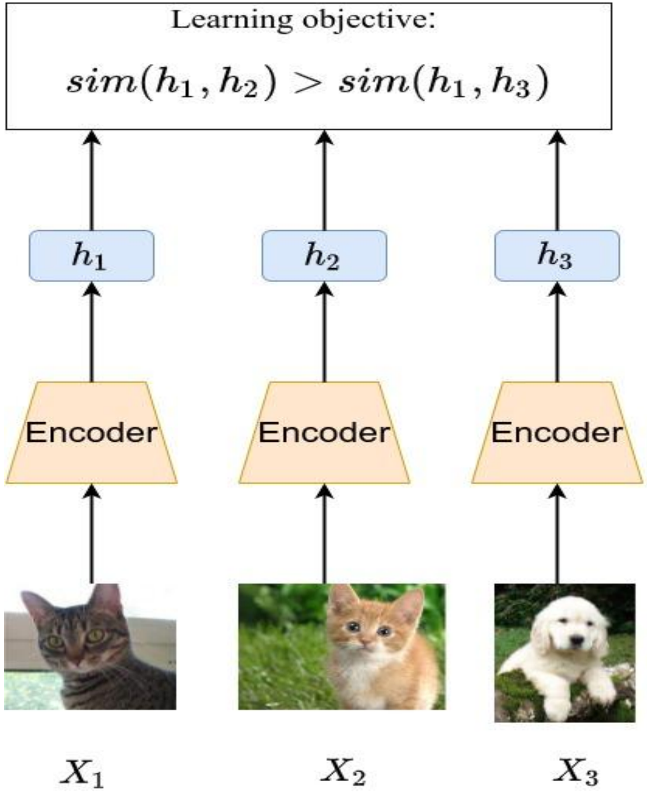
Contrastive Learning



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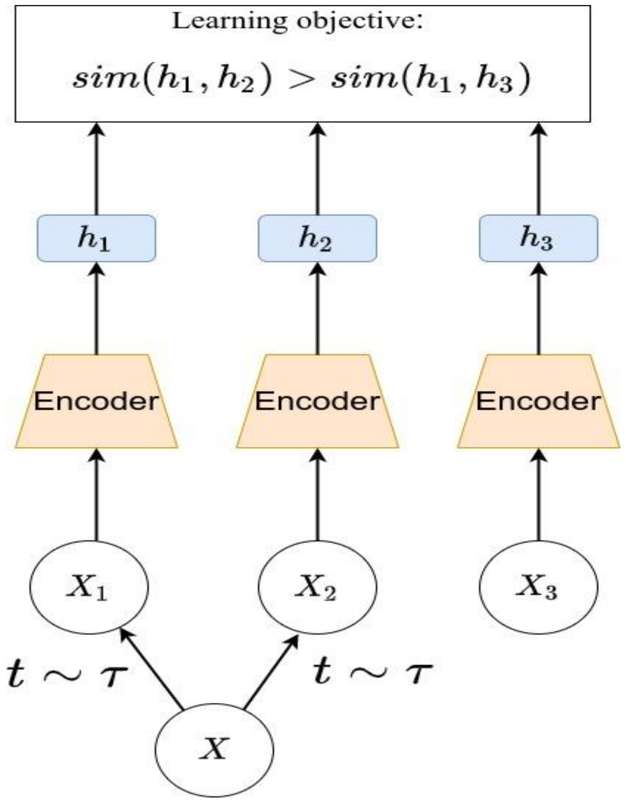

Limitations

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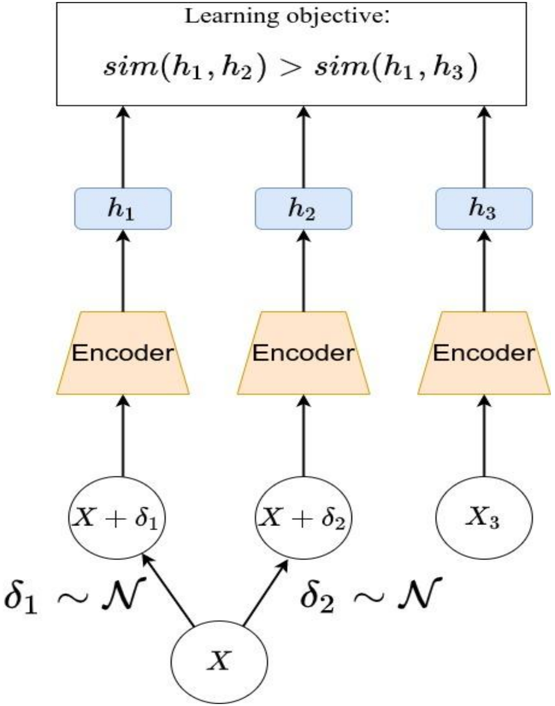
Might not be available for some application domains such as tabular data, graph-structured data.

Gaussian Noise



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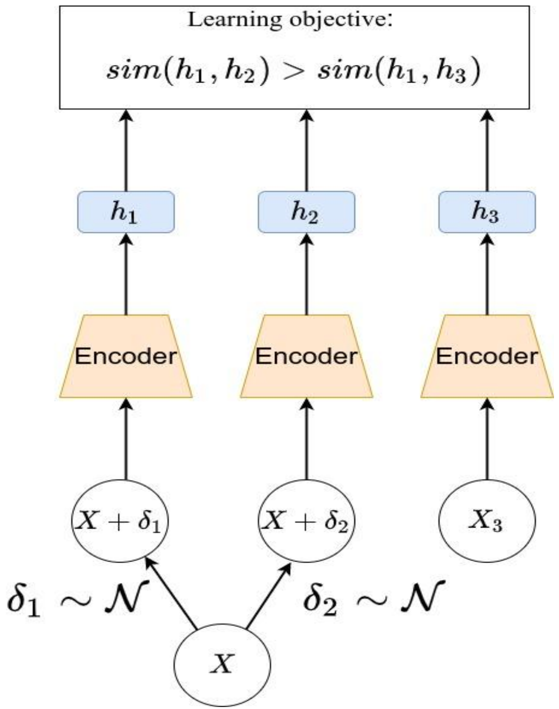

Let us consider X to be an 2D image.

In this case, to maximize the similarity between positive pair, the network can learn just to take an average over the neighboring pixels to remove the noise.

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Domain-Agnostic Contrastive Learning (DACL)

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Binary-Mixup : $X^+ = X \odot M + \tilde{X} \odot (1 - M)$

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- For images DACL falls short off the sota methods such as SimCLR, however SimCLR+DACL can improve the performance of SimCLR alone.

Theoretical Analysis

Properties of **Gaussian-Noise** and **Mixup-Noise** based Contrastive Learning in a **binary classification task**.

Contrastive loss $\approx$ Modified classification loss+ error term

We then prove that Mixup-Noise induces a better regularization effect when compared to Gaussian Noise

Thank You for your attention!