Guided Research Project: A comprehensive study of MixUp Operations in SSL settings with Medical Imaging.

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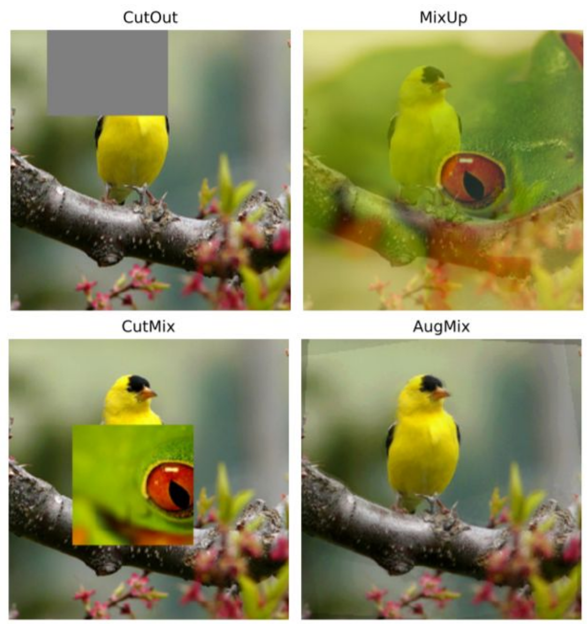

Fig1. Different Regularization Methods, Adopted from [11].

Abstract. In the last few years, deep neural networks (DNNs) have shown impressive success in different real-life problems such as computer version, speech recognition, and medical imaging. DNNs demand a huge amount of high quality labeled data, which is very expensive and difficult to find. To overcome the above limitations, the semi-supervised learning (SSL) paradigm has been widely used in the literature [1]. SSL methods utilize few labeled data in a combination with a large amount of the unlabeled data in the training process. SSL methods can be divided into different categories, however, the current state-of-art (SOTA) methods [2-4] are considered as holistic approaches that combine consistency regularization [5], pseudo labeling [6], and data augmentation and regularization methods [7]. The goal of regularization methods [7-13] is to prevent the network from memorizing the training data and to enhance the robustness by augmenting the model with new virtual examples. The new data is generated through a linear or convex operation between two original data points from the training dataset such that the new examples are close to the original data but still useful to the network, Fig.1. Although this simple operation is useful and shows superior performance, yet studying the mixed data and how close they are to the original data and how their representations are close to the representations of original data needs further investigation. On the other hand, all of the aforementioned regularization methods were applied in computer vision tasks, yet, few of them were applied to the medical data in fully-supervised [14-17] or in semi-supervised [18] settings . Thus, understanding these methods is of high importance when it comes to the medical applications. To realize this, we will split the project into two phases: Phase I: Investigate both Input Mixup and Manifold Mixup on

toy examples to study the influence of (i) Different data complexity (linearly separable gaussian, swiss roll, half moons, etc.), (ii) Activation functions (tanh, relu, lrelu, siren [19]), (iii) Normalization methods (Batch, Instance, Group,...etc.), and (iv) Data Shift (Covariate Shift, Biased). Phase II: Investigate other Mixup Operations on Medical Data with unified architecture [18].

Roadmap:

- Familiarize yourself with the current literature on semi-supervised learning paradigme [1, 5-6], modern regularization methods [7-13], and current SOTA SSL methods (4 weeks)

Phase I:

- Implement different regularization methods on toy examples. (2 weeks)
- Implement and analyse regularization methods using different data complexity. (2 weeks)
- Implement and analyse regularization methods using different activation functions. (2 weeks)
- Implement and analyse regularization methods using different normalization methods. (2 weeks)
- Implement and analyse regularization methods under data shift. (2 weeks)

Phase II:

- Implement a few more regularization methods and rerun the previous experiments on medical data (4 weeks)
- Writing and summarizing the findings in the project report. (4 weeks)
- Final Presentation (2 weeks)

Research Questions:

Q1) How diverse is the generated (mixed) data to the original data given the data complexity, hyper-parameters (activation, and normalization), and data shit?

Q2) Are the generated (mixed) data useful for SSL training?

Q3) Which one of the previous methods work best for medical data?

Requirements:

- Solid background in Machine/Deep Learning
- Familiar with Unet, ResNet, CNN, ...etc.
- Sufficient knowledge of Python programming language and libraries (Scikit-learn, NumPy, Tensorboard, tSNE...)
- Experience with a mainstream deep learning framework such as PyTorch or Tensorflow.
- Machine/Deep learning hands-on experience

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