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ACTIVEMATCH: END-TO-END SEMI-SUPERVISED ACTIVE REPRESENTATION LEARNING

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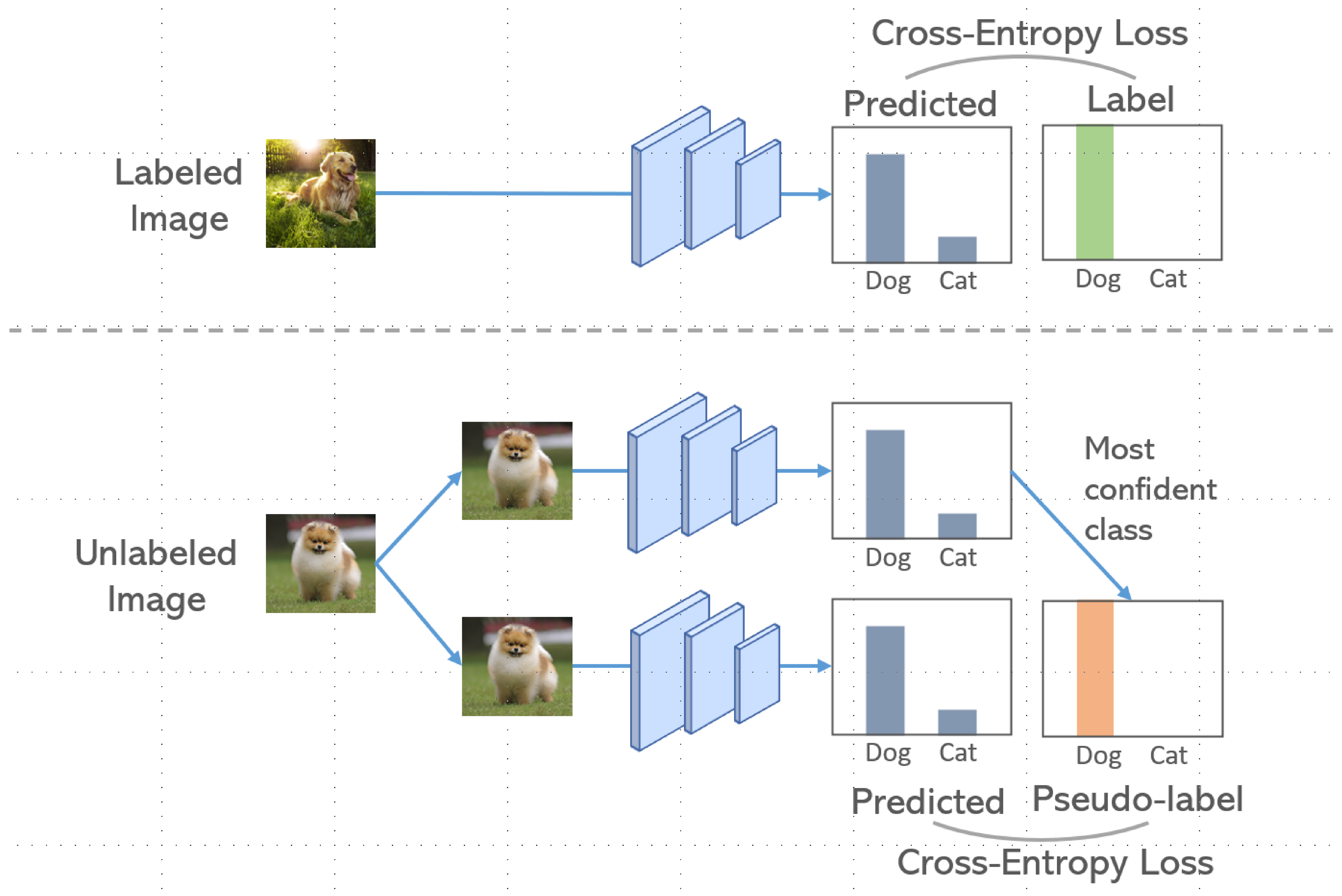
Introduction

Semi-supervised learning (SSL) is an efficient framework that can train models with both labeled and unlabeled data, but may generate ambiguous and non-distinguishable representations when lacking adequate labeled samples.



In this paper, following the SSL setting, we propose a novel representation learning method, namely ActiveMatch, which combines contrastive learning and active learning into an end-to-end learning framework.

The contributions of our paper are summarized as follows:

- Proposed ActiveMatch is a novel representation learning approach that combines SSL, contrastive learning, and active learning to address the issue of training with a small amount of labeled data.
- Unlike several other methods which use contrastive learning as pre-training and then fine-tune the network based on SSL, ActiveMatch uses an end-to-end training scheme, which simplifies the training process and helps to improve the accuracy.
- ActiveMatch outperforms previous SSL methods on standard benchmarks such as CIFAR-10, CIFAR-100, and SVHN with only a few labeled samples.

* These two authors have equal contributions to this work.
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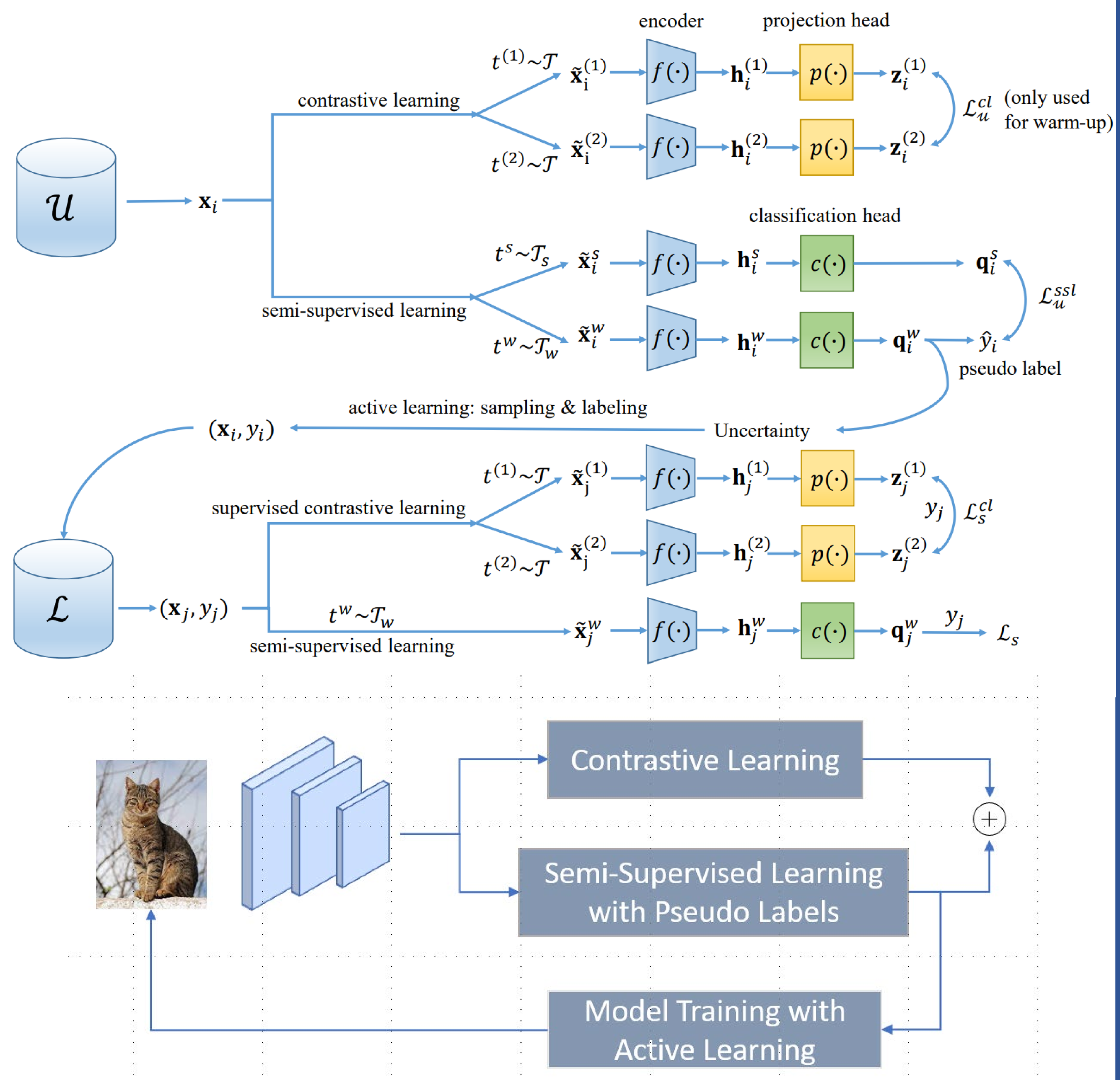
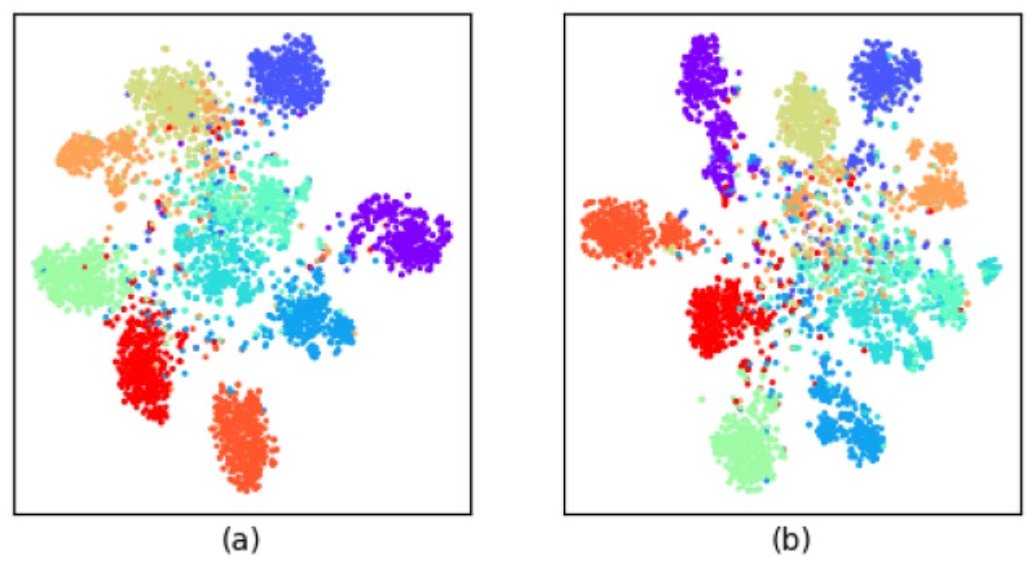
Methods



Results



t-SNE plots of representations learned by two SSL methods on the first 10 classes of CIFAR-100.
a) ActiveMatch trained with 2000 labels.
b) FixMatch trained with 2000 labels.

Results

CIFAR-10

Method	50 labels	100 labels	200 labels
Fully Supervised [1]	**96.23**	**96.23**	**96.23**
MixMatch [2]	57.36	71.82	86.76
FixMatch [3]	75.16	88.99	91.39
ActiveMatch (ours)	**78.25**	**89.24**	**92.20**

CIFAR-100

Method	500 labels	1000 labels	2000 labels
Fully Supervised	**80.27**	**80.27**	**80.27**
MixMatch	18.67	32.64	48.08
FixMatch	36.62	47.64	56.12
ActiveMatch (ours)	**40.26**	**52.20**	**60.33**

State-of-the-art performance

SVHN

Method	100 labels	200 labels
Fully Supervised	**98.41**	**98.41**
MixMatch	80.33	95.62
FixMatch	**97.00**	**97.55**
ActiveMatch (ours)	96.97	97.47

Ablation Study

Method	100 labels	200 labels
ActiveMatch	**89.24**	**92.20**
ActiveMatch (without AL)	87.76	89.91
ActiveMatch (without $\mathcal{L}_S^{cl}$)	87.34	88.89

[1] K. Zhang, et al, Residual networks, IEEE TCSVT, 2018.
[2] D. Berthelot, et al, Mixmatch, NeurIPS, 2019.
[3] K. Sohn, et al, Fixmatch, NeurIPS, 2020.

Conclusion

- ActiveMatch leverages a relatively small labeled dataset and a large unlabeled dataset to achieve state-of-the-art performance on the image classification task.
- ActiveMatch shows how active learning can help to improve the performance of SSL.
- We believe that it is worth further investigations on how advanced active learning algorithms can provide more benefits to semi-supervised learning.