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Semi-Supervised Image Classification

Trend and Applications of Computer Vision

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Initial Source

A Survey on Deep Semi-supervised Learning

Xiangli Yang, Zixing Song, Irwin King, *Fellow, IEEE,* Zenglin Xu, *Senior Member, IEEE*

Abstract—Deep semi-supervised learning is a fast-growing field with a range of practical applications. This paper provides a comprehensive survey on both fundamentals and recent advances in deep semi-supervised learning methods from perspectives of model design and unsupervised loss functions. We first present a taxonomy for deep semi-supervised learning that categorizes existing methods, including deep generative methods, consistency regularization methods, graph-based methods, pseudo-labeling methods, and hybrid methods. Then we provide a comprehensive review of 52 representative methods and offer a detailed comparison of these methods in terms of the type of losses, contributions, and architecture differences. In addition to the progress in the past few years, we further discuss some shortcomings of existing methods and provide some tentative heuristic solutions for solving these open problems.

Background

- Dataset can be divided into 2 subset:
  - Labeled;
  - Unlabeled;
- **Objective**: Learning with small set of unlabeled examples:
  - L << U.

$$\min_{\theta} \underbrace{\sum_{x \in X_L, y \in Y_L} \mathcal{L}_s(x, y, \theta)}_{\text{supervised loss}} + \alpha \underbrace{\sum_{x \in X_U} \mathcal{L}_u(x, \theta)}_{\text{unsupervised loss}} + \beta \underbrace{\sum_{x \in X} \mathcal{R}(x, \theta)}_{\text{regularization}}$$

Pseudo-labeling

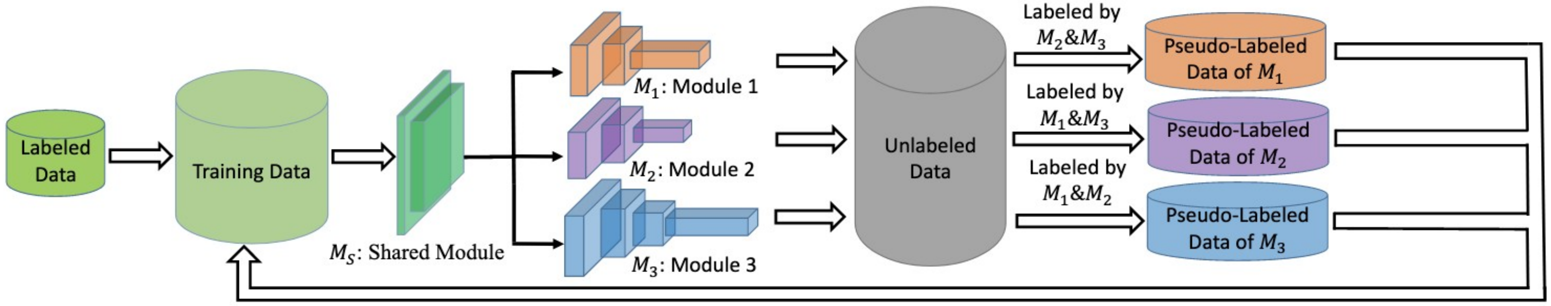
- PL methods use confident predictions to drive the search:
  - Network jointly trained with labeled and unlabeled data;
  - High confidence predictions on unlabeled data used as pseudo-labe

Prediction $\quad\quad\quad\quad\quad\quad\quad\quad$ Pseudo-label

$$[0.2, 0.1, 0.7, 0.0] \longrightarrow [0, 0, 1, 0]$$

  - The corresponding samples are added to the labeled set and used for supervised training;
  - Unlabeled data can also be used for regularization;
- Methods:
  - Entropy Minimization;
  - Tri-Net.

Tri-net



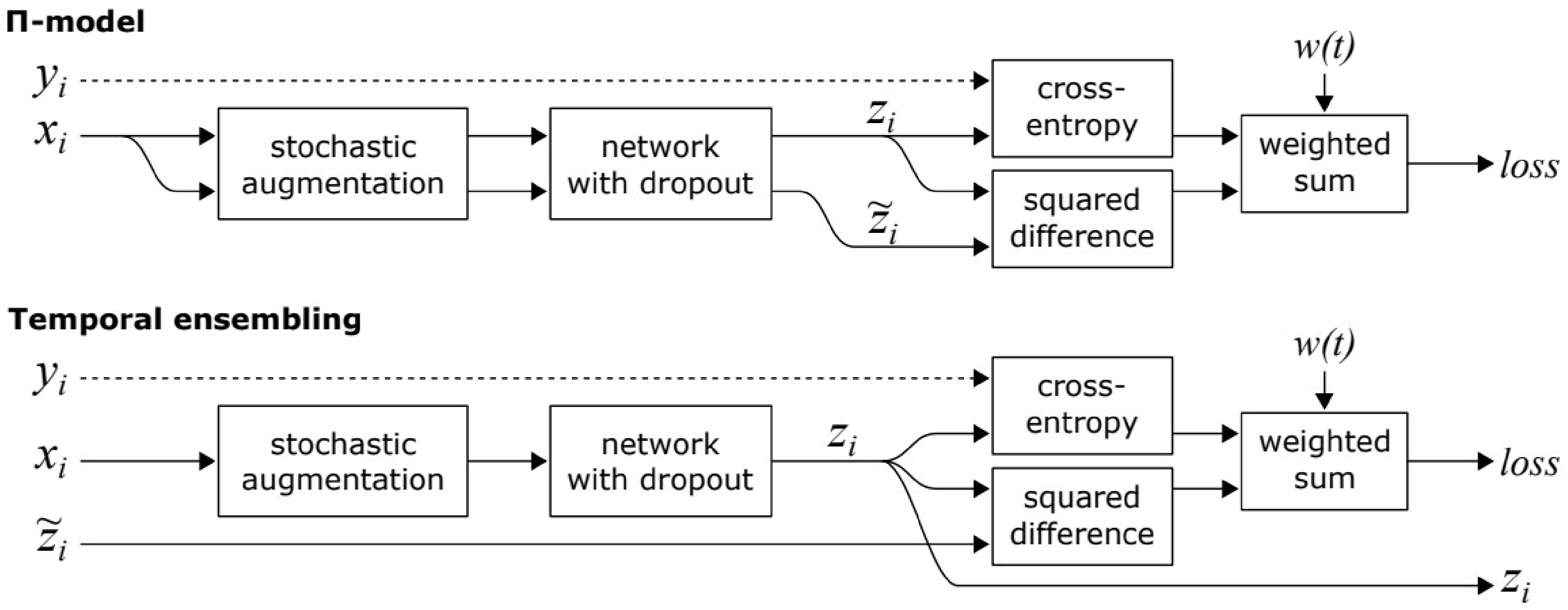
- Three classifiers and separated labeled datasets;
- Each dataset augmented with pseudo-labeled samples;
- Pseudo-Labels computation is based on agreement.

Chen et al., Tri-net for Semi-Supervised Deep Learning, 2018

Consistency Regularization

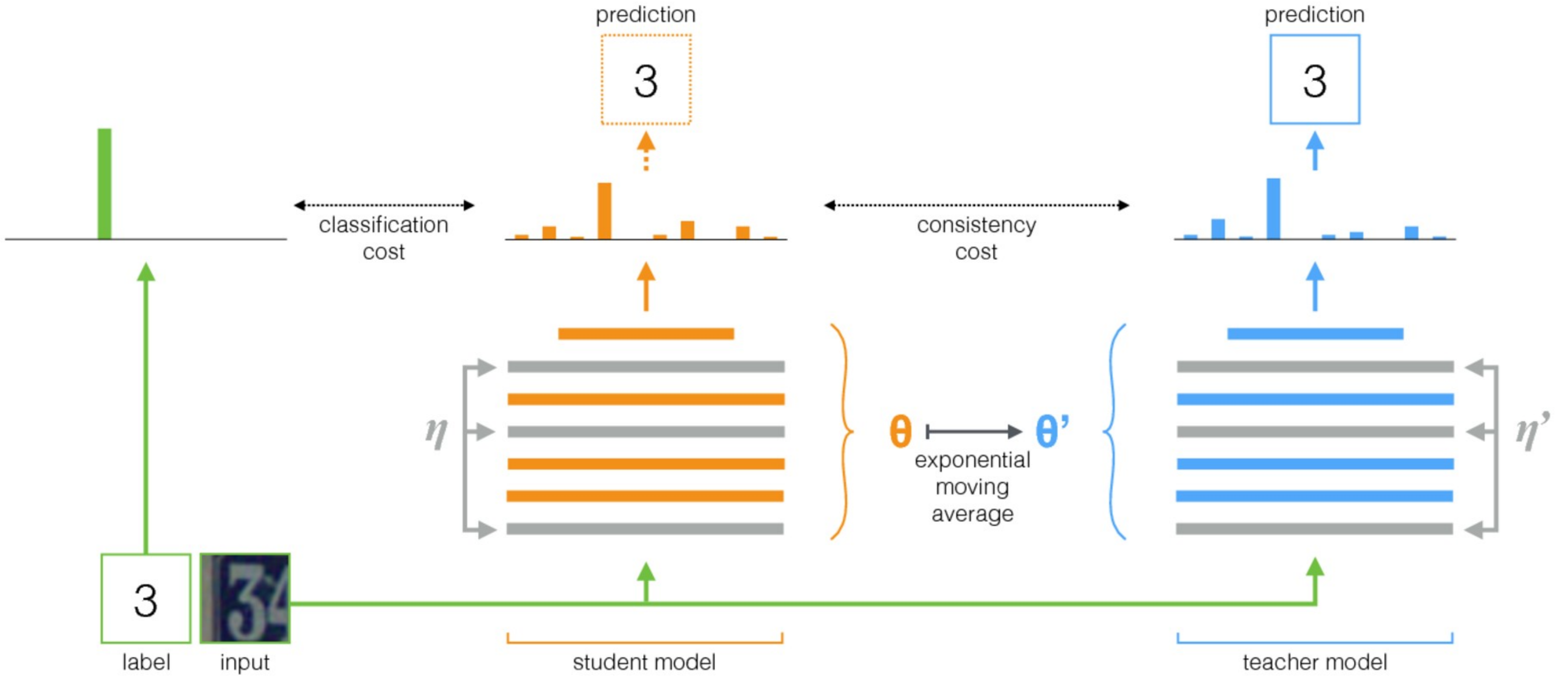
- Consistency regularization term applied to the final loss;
- Force similar outputs to different perturbations of the same sample;
- *Methods*:
  - Π-Model;
  - Temporal Ensembling;
  - Mean Teacher;
  - Virtual Adversarial Training.

Π-Model & Temporal Ensembling



Laine and Alia, Temporal Ensembling for Semi-Supervised Learning, 2016

Mean Teacher



Tarvainen and Valpola, Mean teachers are better role models, 2017

Virtual Adversarial Training

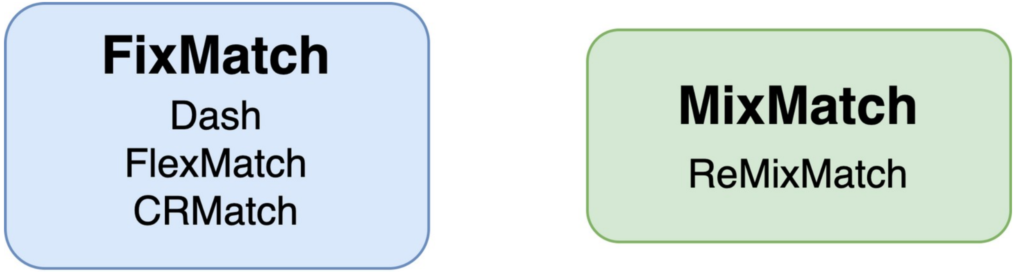
$$LDS(x) = D\left[h_{\hat{\theta},\hat{\phi}}(x), h_{\theta,\phi}(x + r_{\text{vadv}})\right]$$

$$r_{\text{vadv}} = \underset{r;\|r\|_2 \leq \epsilon}{\operatorname{argmax}} D\left[h_{\hat{\theta},\hat{\phi}}(x), h_{\theta,\phi}(x + r)\right]$$

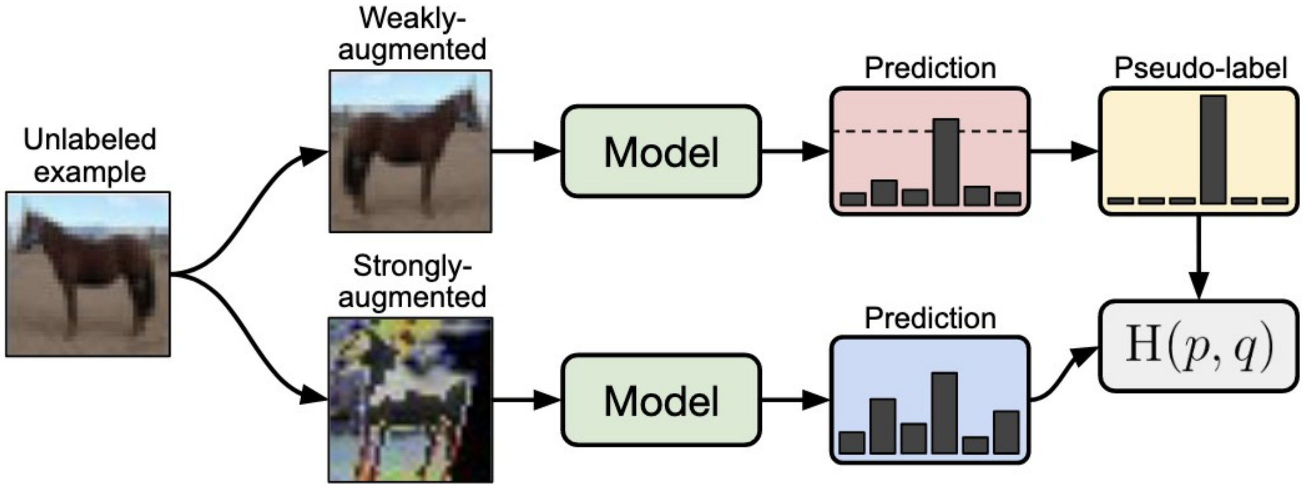
Miyato et al., Virtual Adversarial Training, 2017

Hybrid methods

- Methods that combine Pseudo Labeling and Consistency Regularization;
- Two families:



FixMatch

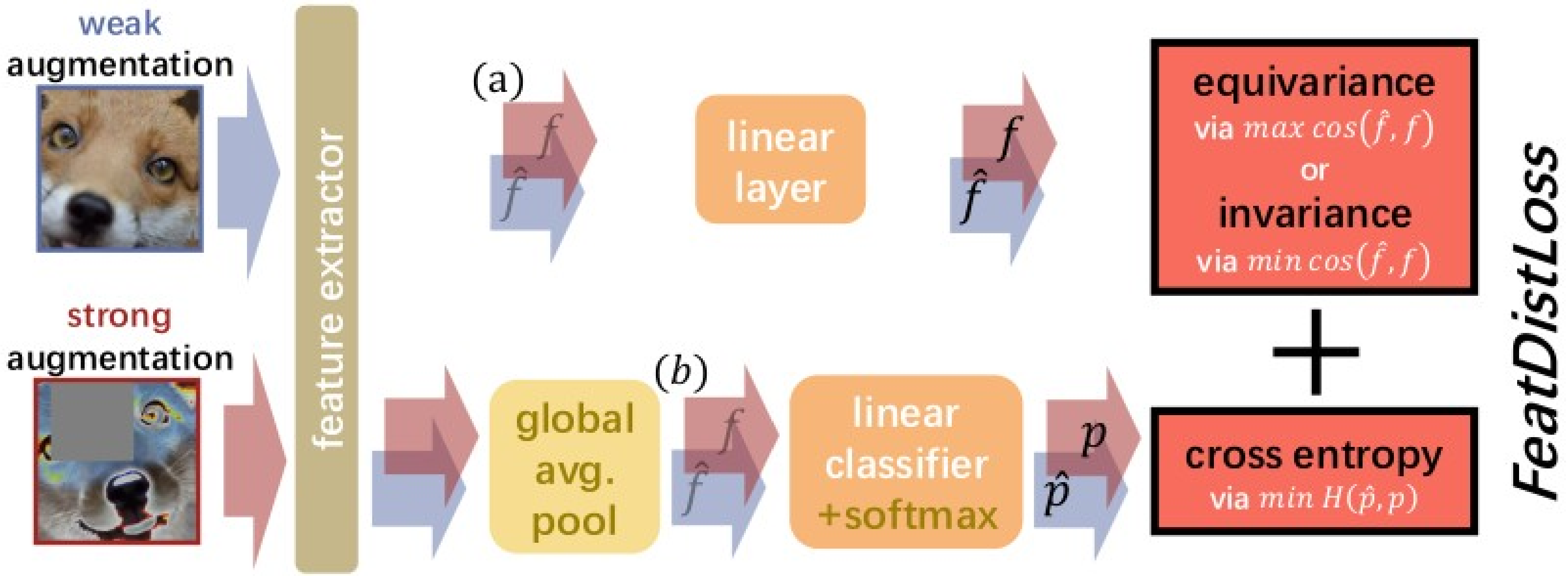


Follow-up:

- Dash
- FlexMatch

Sohn et al., FixMatch: Simplifying Semi-Supervised Learning with Consistency and Confidence, 2020

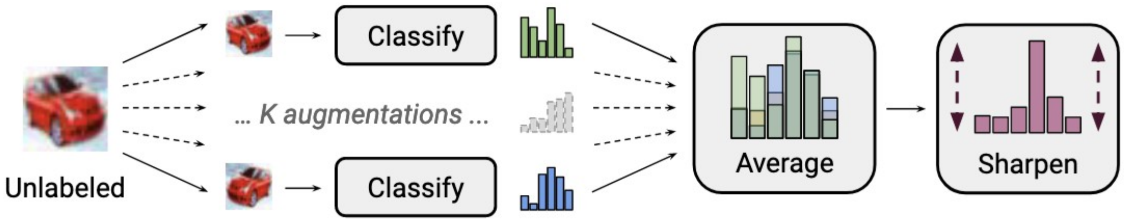
CRMatch



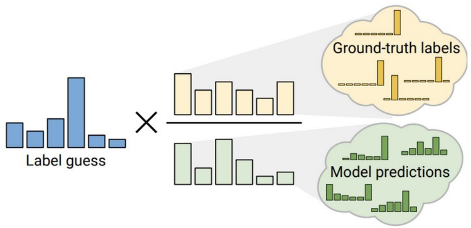
Fan et al., Revisiting Consistency Regularization for Semi-supervised Learning, 2021

MixMatch & ReMixMatch

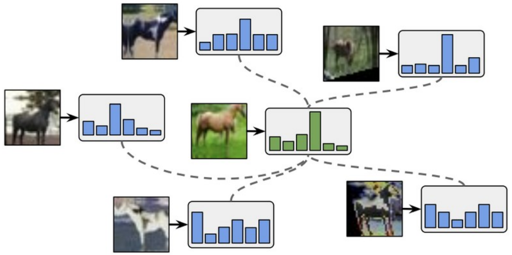
MixMatch



ReMixMatch



Distribution alignment



Augmentation Anchoring

Berthelot et al., MixMatch and ReMixMatch, both 2019

USB

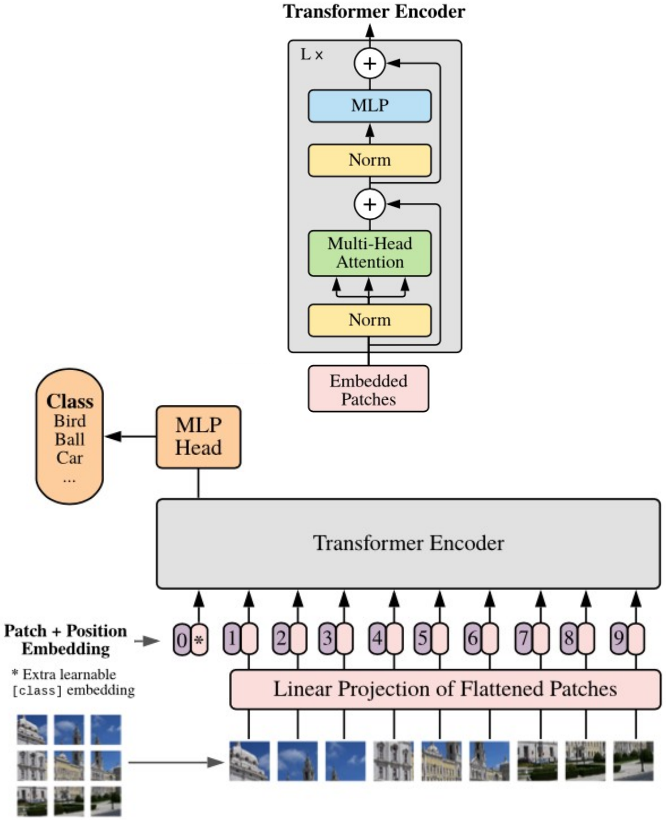
USB: A Unified Semi-supervised Learning Benchmark for Classification

Yidong Wang[1,2,3*], Hao Chen[4*], Yue Fan[5*], Wang Sun[6], Ran Tao[4], Wenxin Hou[7], Renjie Wang[8], Linyi Yang[2], Zhi Zhou[8], Lan-Zhe Guo[8], Heli Qi[9], Zhen Wu[8], Yu-Feng Li[8], Satoshi Nakamura[9], Wei Ye[10], Marios Savvides[4], Bhiksha Raj[4], Takahiro Shinozaki[3], Bernt Schiele[5], Jindong Wang[1†], Xing Xie[1], Yue Zhang[2†]

[1]Microsoft Research Asia, [2]Westlake University, [3]Tokyo Institute of Technology, [4]Carnegie Mellon University, [5]Max-Planck-Institut für Informatik, [6]Tsinghua University, [7]Microsoft STCA, [8]Nanjing University, [9]Nara Institute of Science and Technology, [10]Peking University

USB

- PyTorch benchmark for Semi-supervised classification;
- Audio, Text, and Vision domains;
- Most of the presented methods are implemented;
- Each approach trains a ViT-Small.



Wang et al., USB: A Unified Semi-supervised Learning Benchmark for Classification, 2022

Experiments

- We conducted experiments on 6 different approaches;
- When choosing them we tried to include:
  - Basic methods;
  - Popular methods;
  - State of the Art methods;
- Dataset used: CIFAR-100 due to restricted computational resources;
- Hardware: a single NVIDIA Tesla K80 GPU.

Experiments

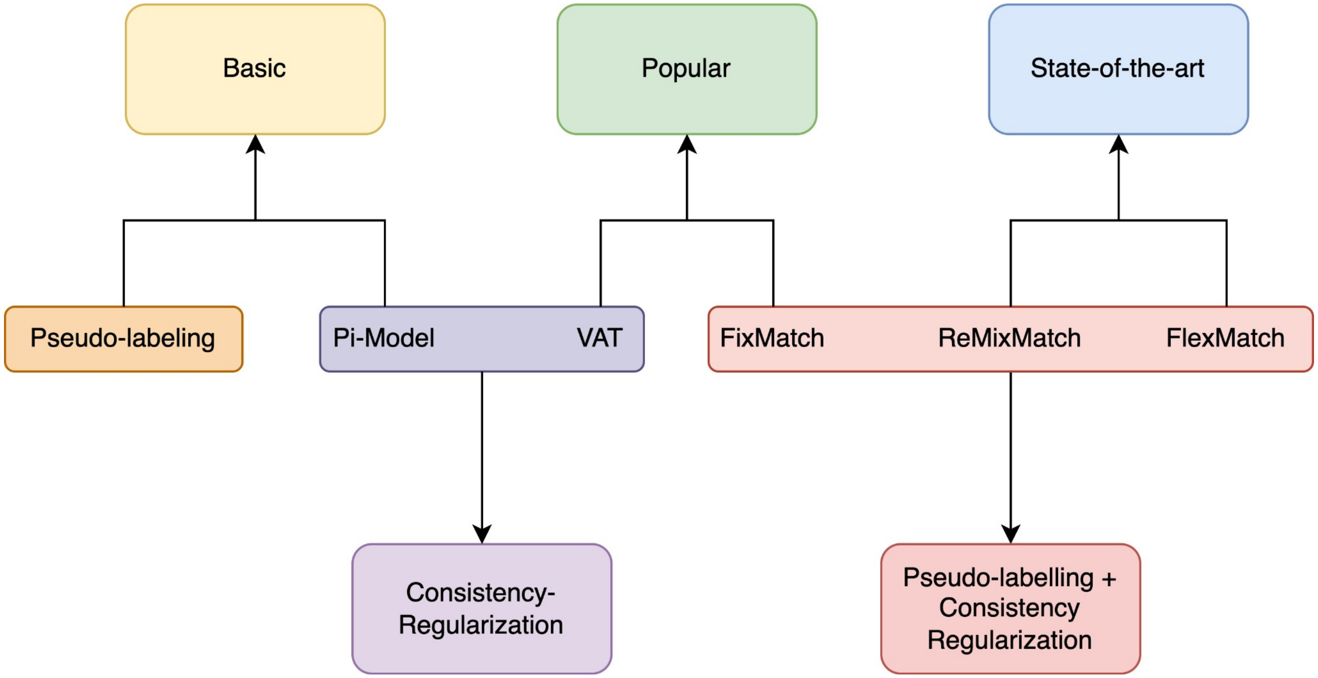


TABLE I
ACCURACIES ON CIFAR-100 WITH 200 AND 400 LABELS.

	Method	200 labels	400 labels
USB	Pseudo-Labeling	$66.84_{\pm 1.20}$	$74.71_{\pm 0.67}$
	Π-model	$63.76_{\pm 0.27}$	$73.51_{\pm 0.64}$
	Mean Teacher	$64.39_{\pm 0.38}$	$74.03_{\pm 0.37}$
	VAT	$68.39_{\pm 1.37}$	$78.71_{\pm 0.32}$
	MixMatch	$62.57_{\pm 0.58}$	$73.83_{\pm 0.24}$
	ReMixMatch	$\mathbf{79.15}_{\pm 1.42}$	$\mathbf{83.20}_{\pm 0.59}$
	FixMatch	$69.55_{\pm 0.65}$	$80.52_{\pm 0.93}$
	Dash	$69.81_{\pm 1.34}$	$81.10_{\pm 0.42}$
	CRMatch	$70.57_{\pm 1.11}$	$81.50_{\pm 0.26}$
	FlexMatch	$72.92_{\pm 0.90}$	$82.33_{\pm 0.66}$
Ours	Pseudo-Labeling	66.84	74.05
	Π-Model	64.06	74.33
	VAT	67.95	77.80
	ReMixMatch	72.83	**80.76**
	FixMatch	69.30	77.17
	FlexMatch	**73.32**	76.03
Lower Bound	*Supervised*	$64.37_{\pm 0.07}$	$73.92_{\pm 0.50}$
Upper Bound	*Fully Supervised*	$91.56_{\pm 0.07}$	

Results

- Comparison between USB results and ours;
- Some methods are worse due to insufficient computational power.

Next milestone

- Implementation of a method and support for TinyImagenet dataset not present in USB;
- Evaluation of SSL in the case of cross-domain training on Adaptiope.

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Thanks for your attention