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PROTOCON: Pseudo-label Refinement via Online Clustering and Prototypical Consistency for Efficient Semi-supervised Learning

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What is PROTOCON?

PROTOCON is a memory-efficient semi-supervised image classification method. It introduces a label refinement strategy to mitigate confirmation bias in label-scarce regime to better leverage unlabeled data.

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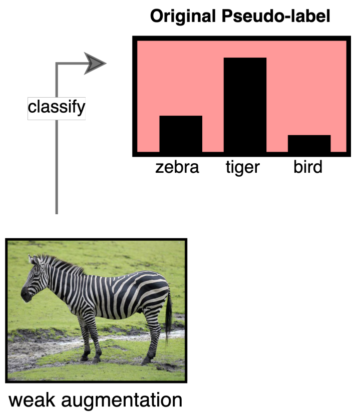

unlabeled image

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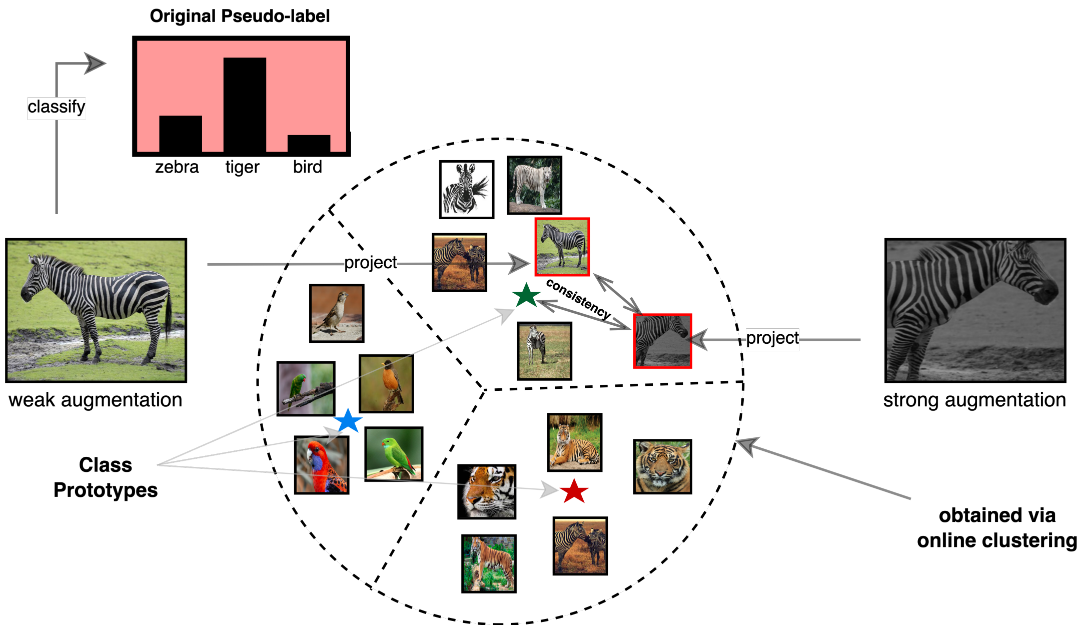

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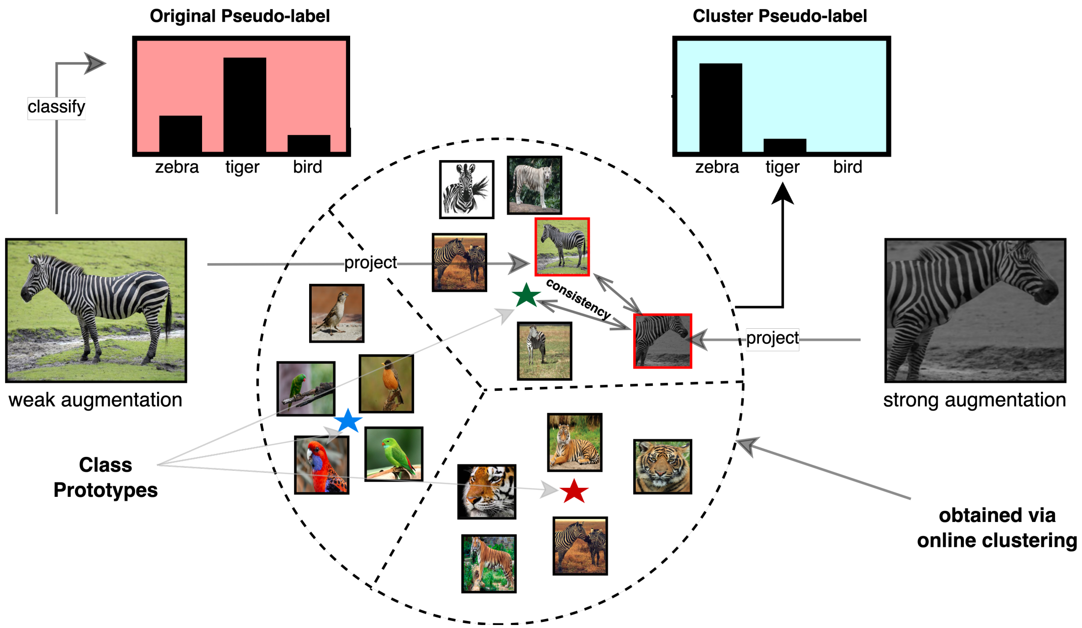

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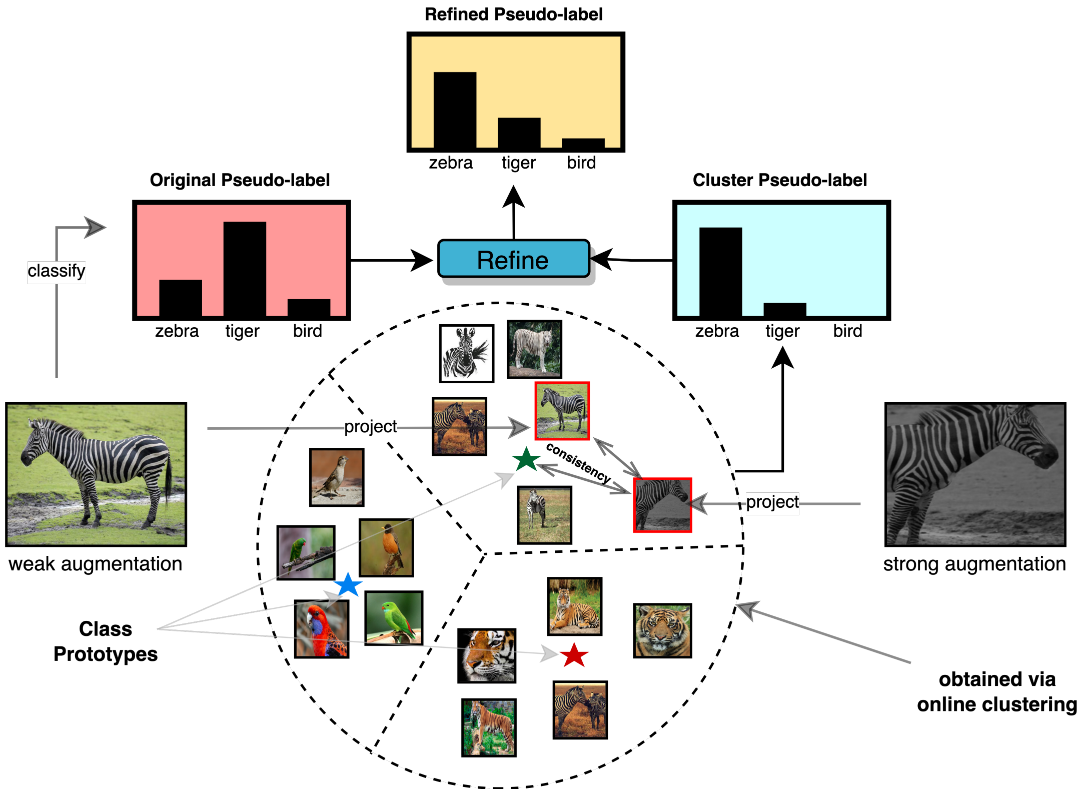

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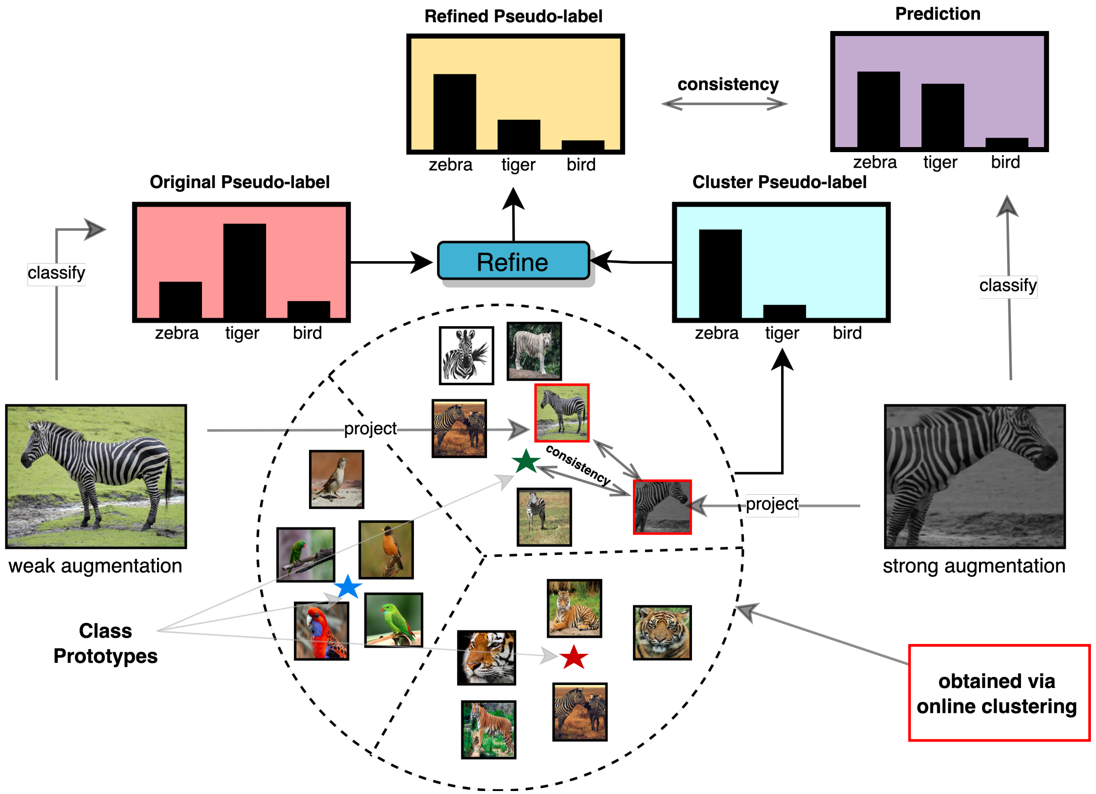


16x reduction in memory requirements

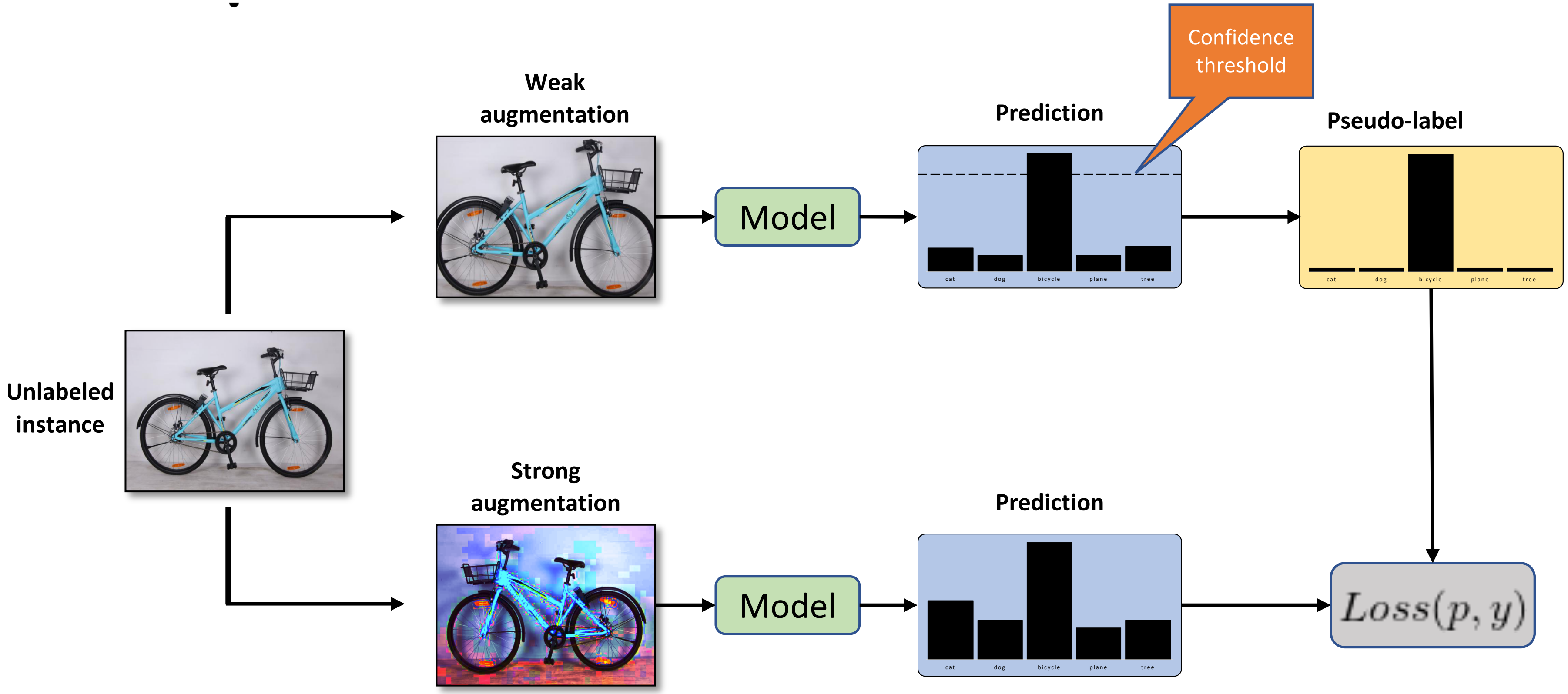
SoTA performance on SSL benchmarks

Now in More Details

Background : Confidence-based Pseudo-labeling with consistency regularization

- FixMatch for semi-supervised learning [1]

1) Obtain pseudo-labels based on weak augmentation



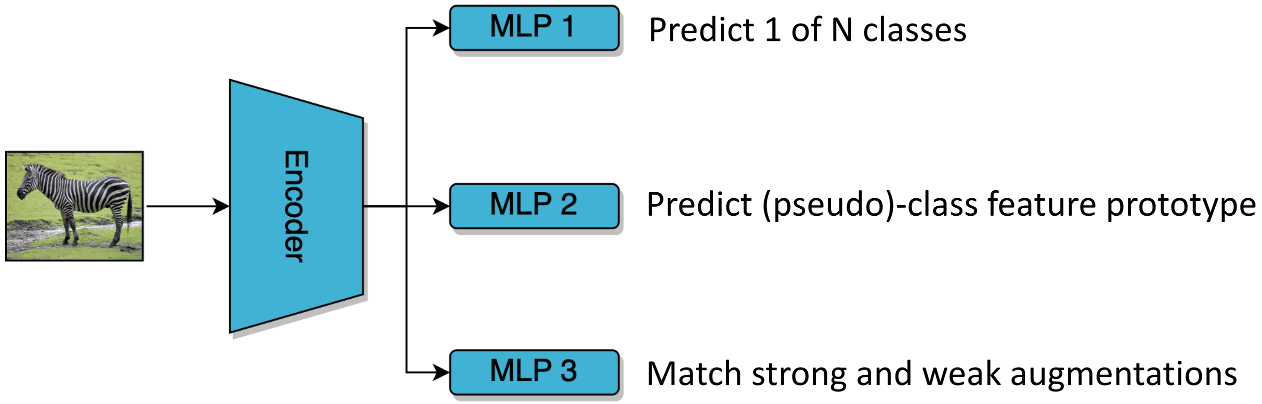
2) Enforce pseudo-label consistency for strong augmentation.

[1] Sohn, Kihyuk, et al. "FixMatch: Simplifying Semi-Supervised Learning with Consistency and Confidence." *Advances in Neural Information Processing Systems* 33 (2020).

PROTOCON: Refining pseudo-labels via multiple learning tasks

How to effectively combine different learning objectives (tasks) to improve pseudo-label quality

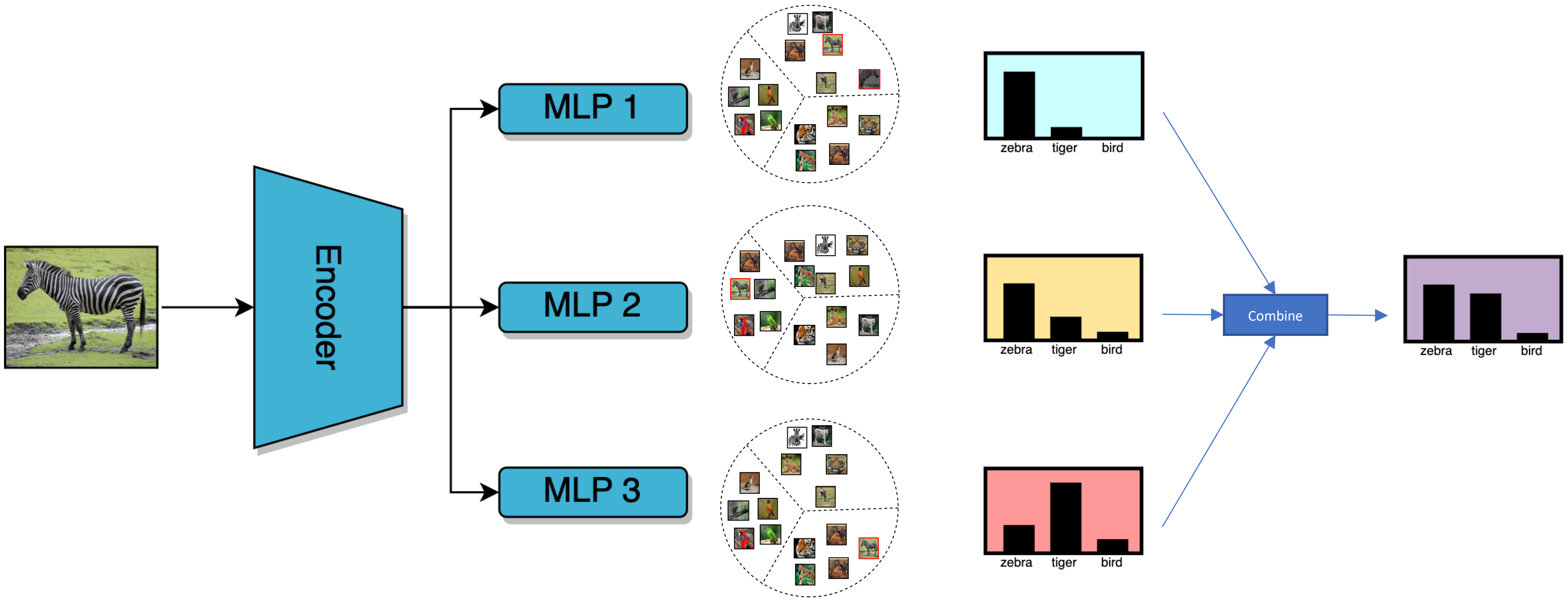
Multiple projector networks with a shared backbone where each network implements a specific learning objective



Each representation space learns a different, yet relevant, mapping/view of the data

Refining pseudo-labels via multiple learning tasks

A sample's neighbourhood differs from one representation space to another

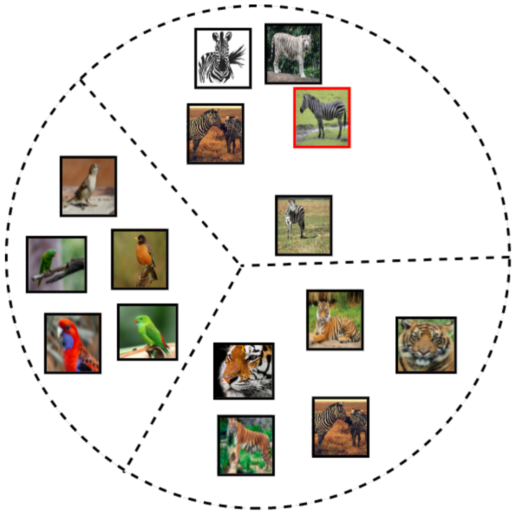


We can obtain a pseudo-label for each image in each space as a weighted average of its N-nearest neighbours'

Then our final pseudo-label (used to train the network) is a combination of all the different pseudo-labels

Identifying N-nearest Neighbours

How to identify the N-nearest neighbours in a scalable memory-efficient manner as we train



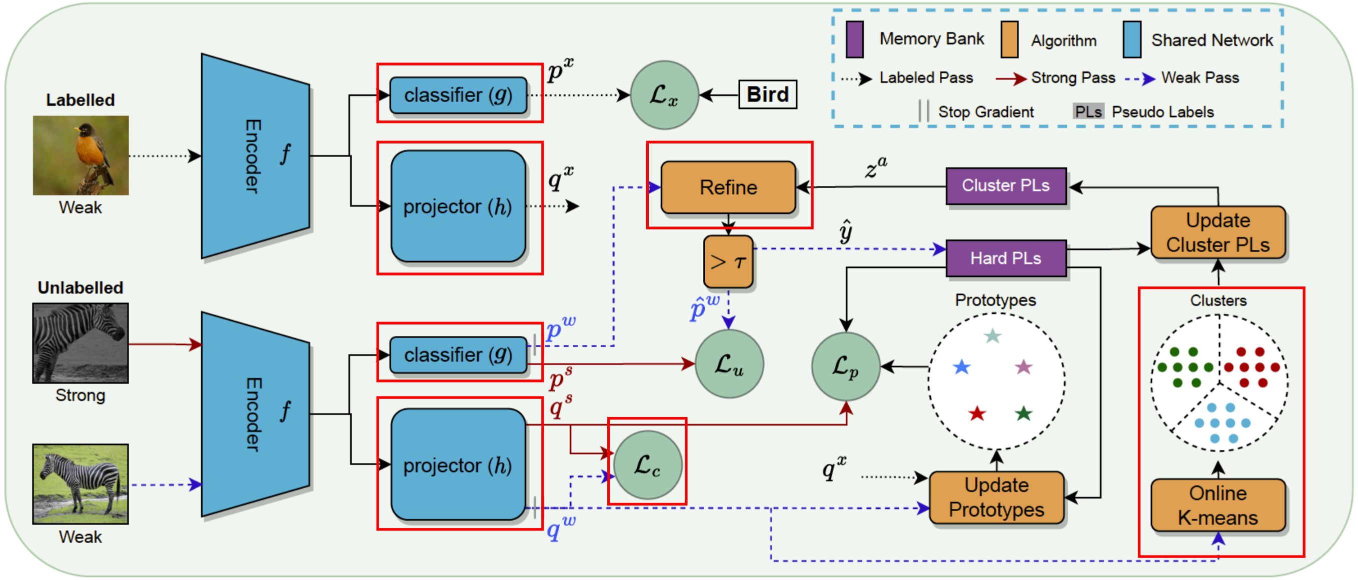
Offline clustering is slow and memory intensive

<u>Online</u> <u>constrained</u> K-means clustering

Online: K-means centroids are updated each mini-batch as training proceeds

Constrained: To ensure each sample has N samples in its cluster

Putting it all together



Achieves **<u>16x</u>** reduction in memory requirements compared to offline methods

State-of-the-art on SSL benchmarks for Image classification in label-scarce regime (2-10 images/class)

Experimental Results

- SoTA performance on SSL image classification benchmarks

Total labeled samples	CIFAR-10 20	CIFAR-10 40	CIFAR-10 80	CIFAR-100 200	CIFAR-100 400	CIFAR-100 800	Mini-ImageNet 400	Mini-ImageNet 1000
FixMatch [38]	82.32±9.77	86.29±4.50	92.06±0.88	35.37±5.68	51.15±1.75	61.32±0.92	17.18±6.22	39.03±3.99
FixMatch + DA [3, 38]	83.84±8.35	86.98±3.40	92.29±0.86	41.28±6.03	52.65±2.32	62.12±0.79	19.40±5.87	40.92±4.71
CoMatch [22]	87.37±8.47	93.09±1.39	93.97±0.62	47.92±4.83	58.17±3.52	**66.15±0.71**	21.29±6.19	40.98±3.52
SimMatch [48]	89.31±7.73	94.51±2.56	94.89±1.32	46.01±6.12	57.95±2.37	65.50±0.93	25.75±5.90	39.76±3.77
FixMatch + DB [42]	89.02±6.37	94.60 ±1.31	95.60 ±0.12	46.36±5.05	57.88±3.34	64.84±0.85	27.37±7.01	41.05±3.34
ProtoCon	**90.51±4.02**	**95.20±1.8**	**96.11±0.20**	**48.25±4.87**	**59.53±2.94**	65.91±0.57	**29.15±6.98**	**45.83±4.15**
delta against best baseline	+1.20	+0.60	+0.51	+0.33	+1.36	-0.24	+1.78	+4.78

- Strong performance on ImageNet

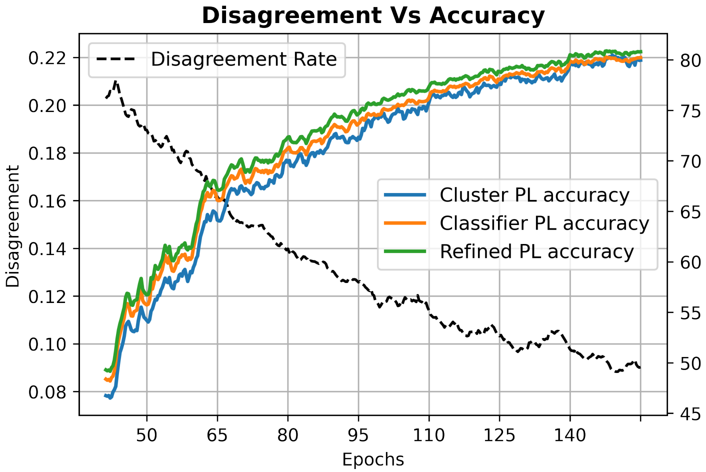
Method	Pre.	Epochs	0.2%	1%	10%
Supervised	✗	300	–	25.4	56.4
Representation learning methods:					
SwAV [8]	✓	800	–	53.9	70.2
SimCLRv2++ [12]	✓	1200	–	60.0	70.5
DINO [9]	✓	300	–	55.1	67.8
PAWS++ [2]	✓	300	–	66.5	**75.5**
PL & consistency methods:					
MPL [31]	✗	800	–	65.3†	73.9
CoMatch [22]	✗	400	44.3†	66.0	73.6
FixMatch [38]	✗	300	–	51.2	71.5
FMatch + DA [3, 38]	✗	300	41.1†	53.4	71.5†
FMatch + EMAN [7]	✓	850	43.6	60.9	72.6
FMatch + DB [42]	✗	300	45.8†	63.0†	71.7†
FMatch + DB + EMAN [42]	✓	850	47.9	63.1	72.8†
ProtoCon	✗	300	47.8	65.6	73.1
ProtoCon + EMAN [7]	✓	850	**50.1**	**67.2**	73.5
delta against best baseline			+2.2	+0.7	-2.0

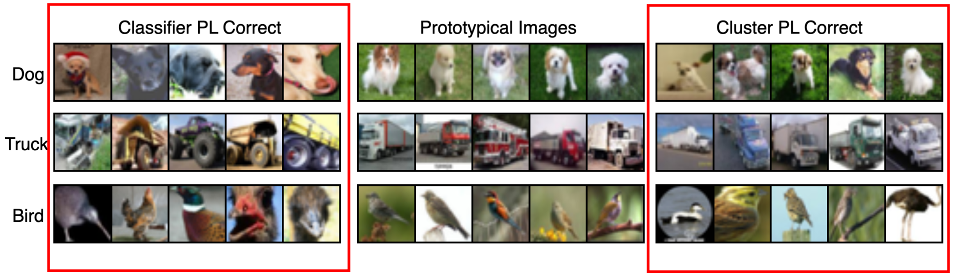
- Cross-domain superiority

Total labeled samples	Clipart 690	Clipart 1380	Clipart 2760	Sketch 690	Sketch 1380	Sketch 2760
FixMatch [38]	30.21	41.21	51.29	12.73	21.65	33.07
CoMatch [22]	35.49	48.62	54.98	24.30	33.71	41.02
FixMatch + DB [42]	38.97	51.44	58.31	25.34	35.58	43.98
ProtoCon	**43.72**	**55.66**	**61.32**	**33.94**	**43.51**	**50.88**
delta	+4.75	+4.22	+3.01	+8.60	+7.93	+6.90

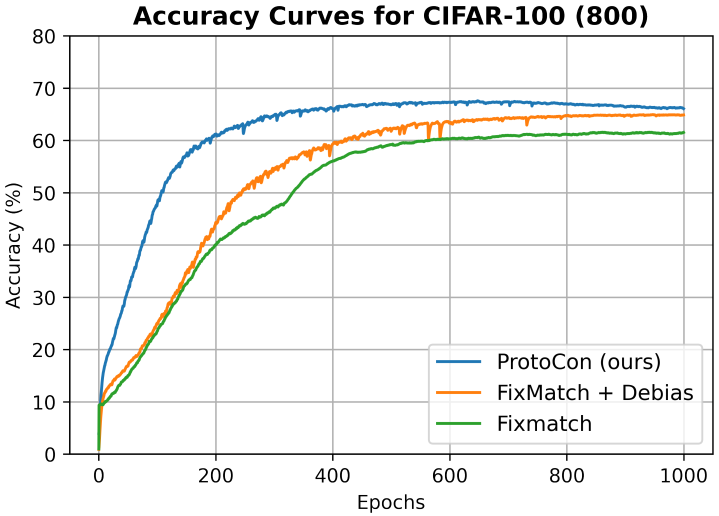
Experimental Results

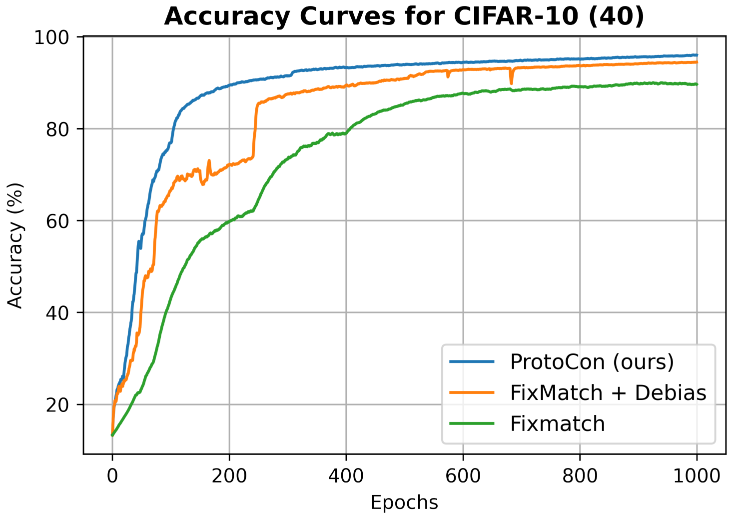
- Diversity helps





- Improved convergence





Thank you for listening

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Paper

Code