Semi-Supervised Image Classification Course Project

Pseudo Learning Approach

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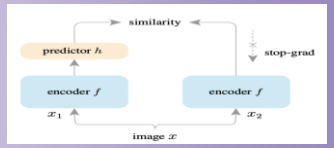
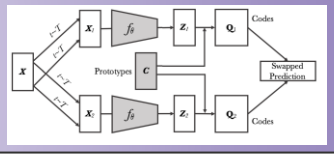
Methods Experimented

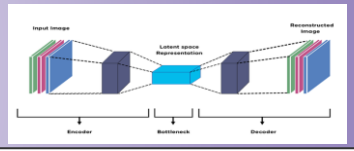
- Contrastive Learning
  - Performance largely depends on batch size
  - Benefits from long training trajectory



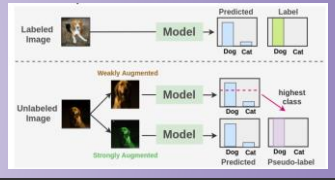
- Cluster Learning
  - Performance largely depends on memory



- AutoEncoder
  - Features learned do not perform well in classification



- Pseudo Labeling
  - Do not require too much computation capacity
  - Training time required is much less



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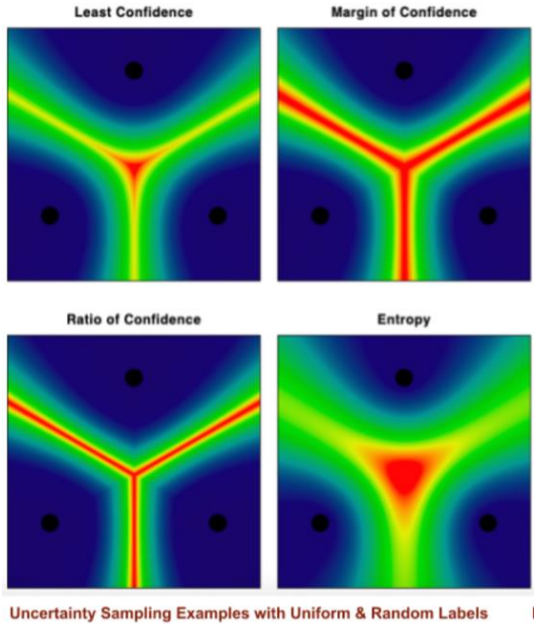
Extra Label Request

Step 1: Trained the original model
based unlabeling data and 5% labeled training data

Step 2: Select 2.5% Labeling Images
based on the **entropy** of the prediction of each unlabeled image

Step 3: Trained the model Extra
based unlabeling data and 7.5% labeled training data



Uncertainty Sampling Examples with Uniform & Random Labels

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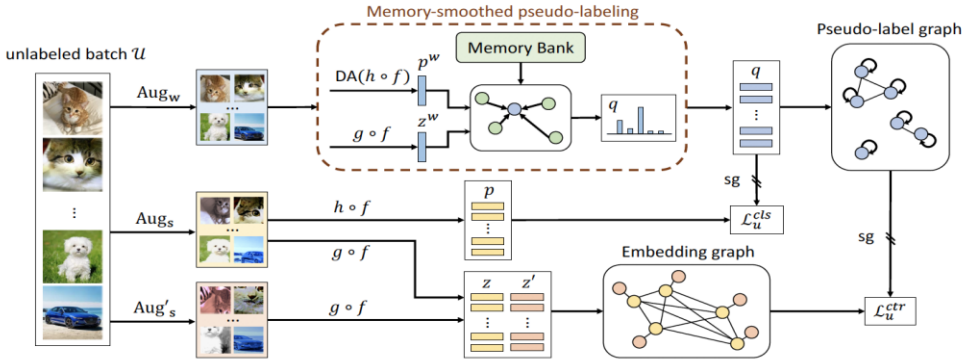
Framework of CoMatch



- $\boldsymbol{f}(\cdot)$: the encoder
- $\boldsymbol{h}(\cdot)$: the classification head
- $g(\cdot)$: the projection head

- Supervised classification loss on labeled data

$$\mathcal{L}_x = \frac{1}{B}\sum_{b=1}^{B} \mathrm{H}(y_b, p(y|\mathrm{Aug_w}(x_b)))$$

- Unsupervised classification loss on unlabeled data

$$\mathcal{L}_u^{cls} = \frac{1}{\mu B}\sum_{b=1}^{\mu B} \mathbb{1}(\max q_b \geq \tau)\mathrm{H}(q_b, p(y|\mathrm{Aug_s}(u_b)))$$

- The overall training objective

$$\mathcal{L} = \mathcal{L}_x + \lambda_{cls}\mathcal{L}_u^{cls} + \lambda_{ctr}\mathcal{L}_u^{ctr}$$

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Results

Self-supervised pre-training	Method	Epochs	Top-1 Accuracy 5% Label	Top-1 Accuracy 7.5% Label
None	FixMatch	300	29%	N/A
	CoMatch	400	50.8%	51%
AutoEncoder	AE	200	18%	N/A
Barlow Twins	Pretrain+ Fine-tune	100	24%	26%
SimCLR		300	21%	N/A

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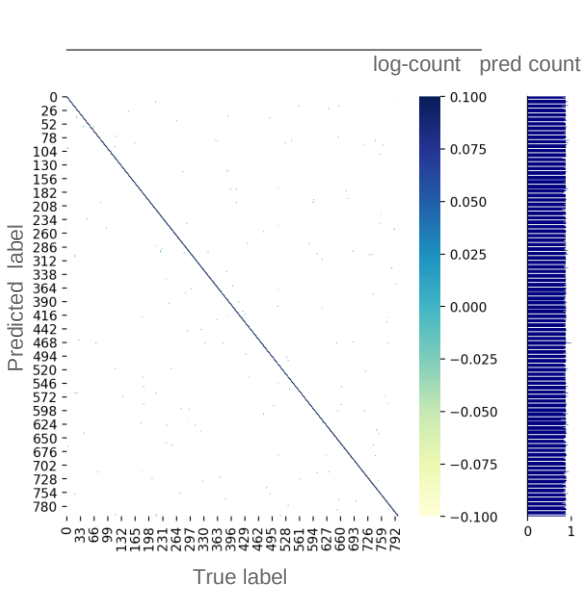
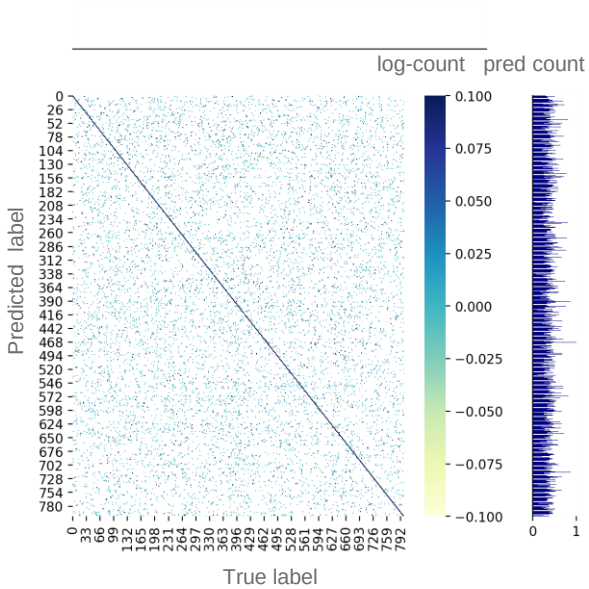
Predicted Labels Distribution

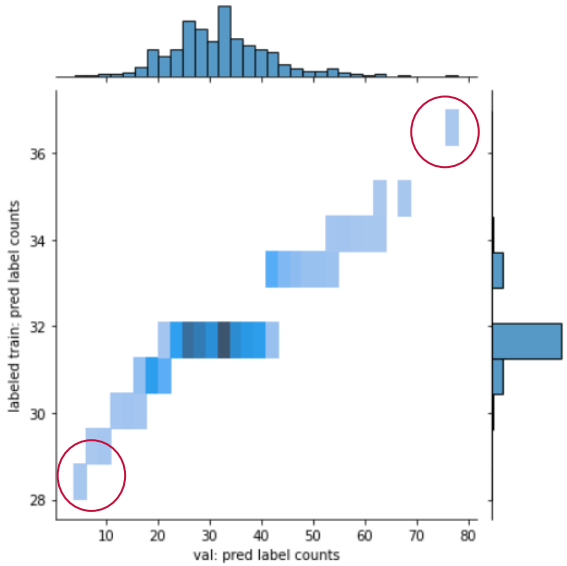
Plot 1.1 Confusion Matrix of Train



Plot 1.2 Confusion Matrix of Val



Plot 2: Train vs Val



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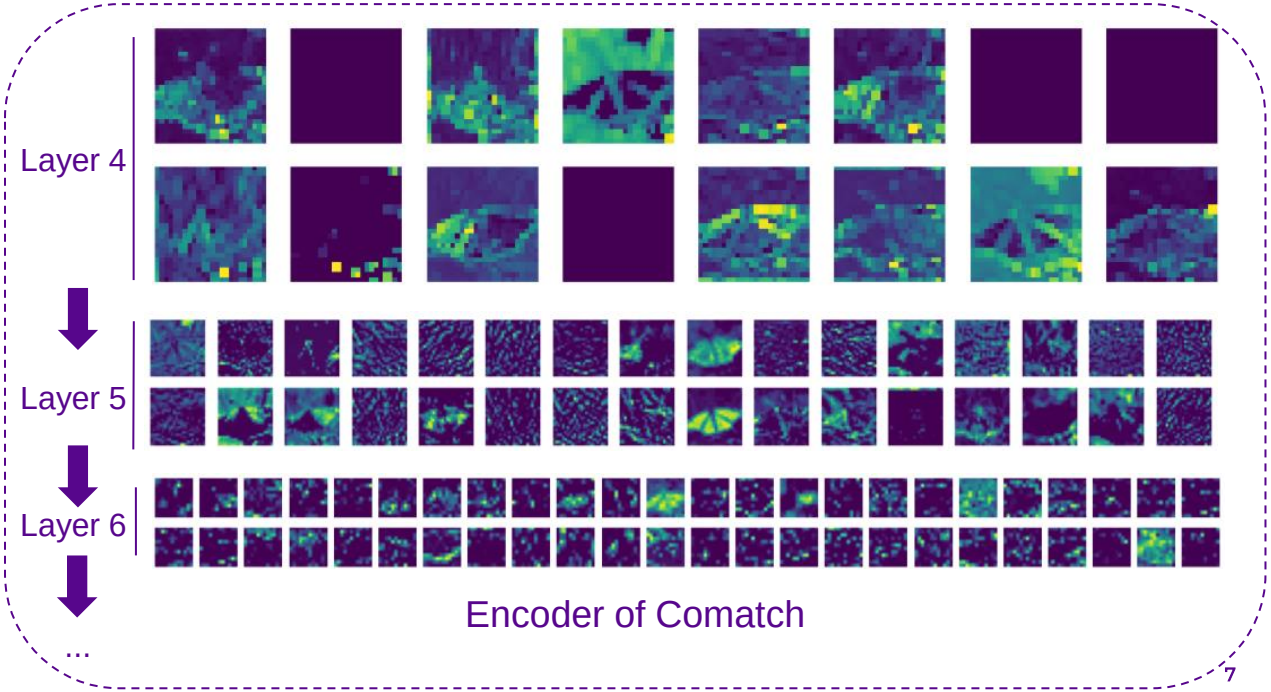
Visualization of Network

what did our model learn?

Features Learnt

- Shape of wings
- Texture of wings
- Background flowers
- ...



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Performance Analysis

what did our model not learn?

Shield

Hand Sanitizer

Type 1: Under-Classified

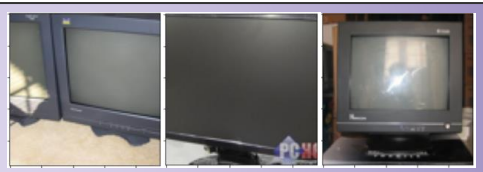
Challenging characters (too specific):

- Viewpoint variation
- Scale variation
- Intra-class variation

Type 2: Over-Classified

Characters (too general):

- Contain general features: rectangle
- Very flexible, could contain any object



Computer

Comic book cover

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