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Pseudo-label Guided Contrastive Learning for Semi-supervised Medical Image Segmentation

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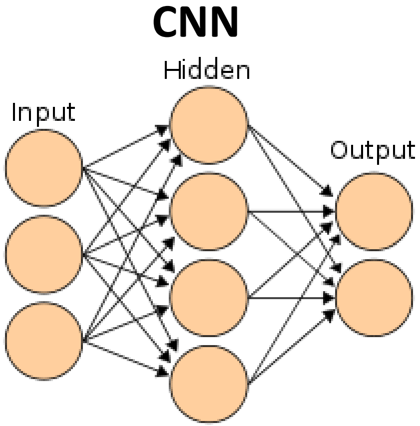
Overview

- We propose a pseudo-label guided contrastive learning (PLGCL) framework
- Pseudo-labels generated from SemiSL aids CL by providing additional guidance
- Class-discriminative feature learning in CL aids multi-class segmentation in SemiSL
- Introduce a novel contrastive loss term on top of InfoNCE loss [Oord *et al.*]
- Alleviates the requirement of pretext training
- Outperforms SoTA in medical image segmentation tasks from three different modalities (CT, MRI, Histopathology)

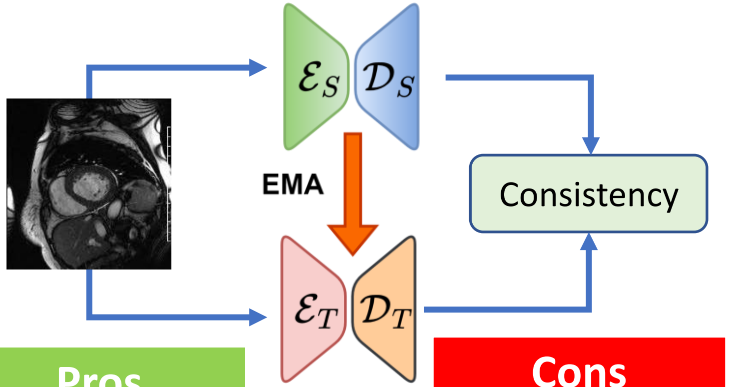
[Oord *et al.*, 2018]: Representation learning with contrastive predictive coding

SemiSL and SSL in Medical Image Segmentation

Lots of annotations

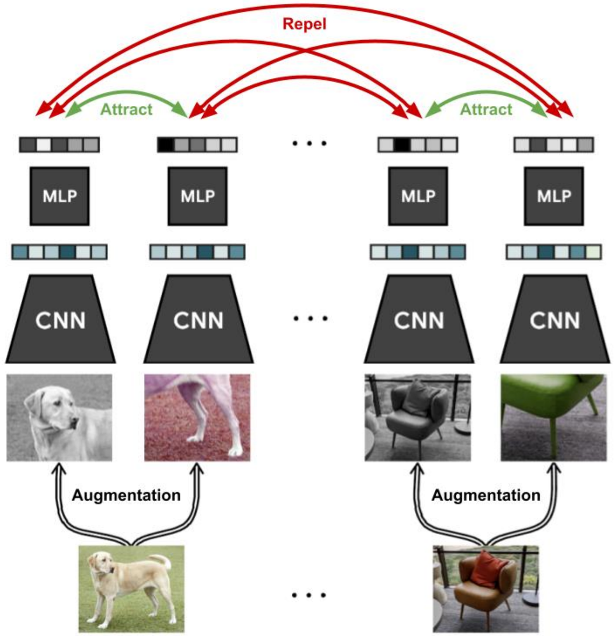


Limited annotations



Pros
Consistent Predictions
Supervision on unlabeled data

Cons
Reduced model diversity
Limited performance
Biased pseudo-label



SimCLR (Chen *et al.*, 2020)

Pros
No labels required
Global representation learning

Cons
Class collision
Specific pre-text task
Unsusceptible to domain shifts

Our Solution: Combining SemiSL in CL

Problem 1: Class collision – semantically similar objects forcefully contrasted in CL

Solution: We propose average patch-entropy based patch sampling for guided sampling of *pos.* and *neg.*

$$Ent_{i,j}^{k} = \frac{\sum_{m \in P_{i,j}^{k}} \mathcal{F}(I_i'^{k}(m))}{|P_{i,j}^{k}|}, \text{ where}$$

$$\mathcal{F}(x) = -x\log(x) - (1-x)\log(1-x)$$

Problem 2: Defining pretext task difficult, insusceptibility to multiple domains for CL

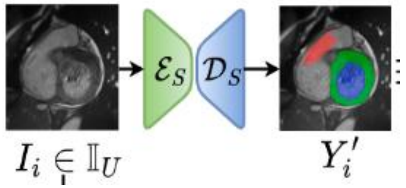
Solution: Alleviate pretext training, instead use single training stage. Produces SoTA performance on multiple modalities (CT, MRI, Histopathology)

Problem 3: Biased pseudo-labels, limited segmentation performance in SemiSL

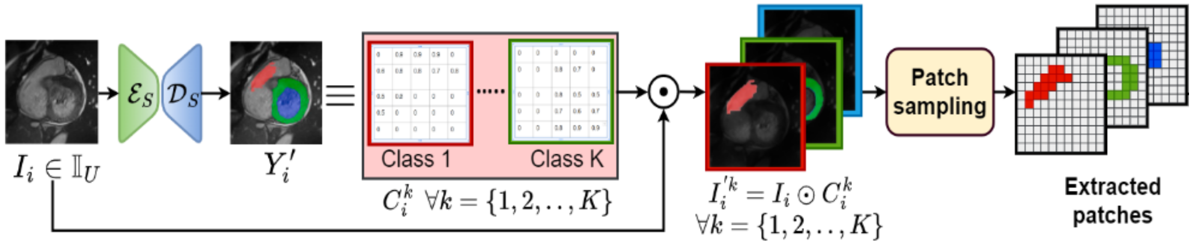
Solution: Class-specific information learnt in CL aids multiclass segmentation performance. Pseudo-labels generated in SemiSL provides additional guidance to unsupervised metric learning, i.e. CL

Proposed Method

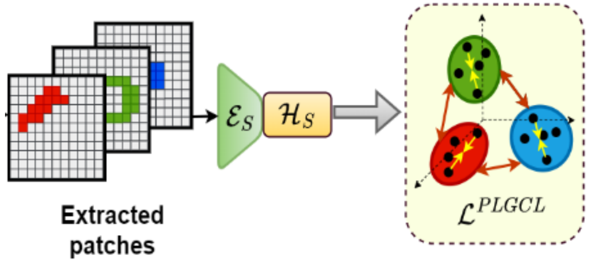
Step 1: Generate pseudo-label Y_i' from input image I_i



Step 2: Generate class-wise patches from Y_i'

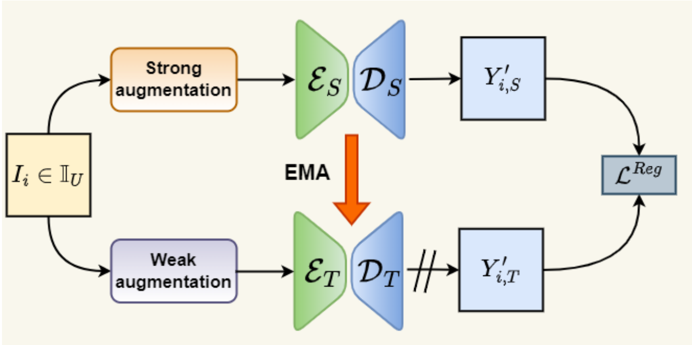


Step 3: Extract feature embeddings, define *pos.* and *neg.* for CL and compute contrastive loss



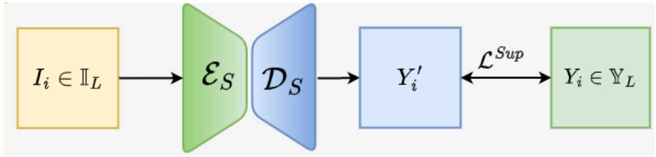
$$\mathcal{L}_u^{PLGCL} = -\mathbf{E}_{\mathcal{J}} \log \frac{\exp(f_u^T \cdot f_v^{k+}/\tau)}{\exp(f_u^T \cdot f_v^{k+}/\tau) + \sum_{k_-} \sum_{v} \exp(f_u^T \cdot f_v^{k-}/\tau)}$$

Step 4: Refine pseudo-labels using mean-teacher network



$$\mathcal{L}_i^{Reg} = CE\Big[\mathcal{D}_S\Big(\mathcal{E}_S(I_i^s)\Big), \mathcal{D}_T\Big(\mathcal{E}_T(I_i^w)\Big)\Big]$$

Step 5: Utilize labelled data in supervised training



$$\mathcal{L}_i^{Sup} = CE\Big[\mathcal{D}_S\Big(\mathcal{E}_S(I_i)\Big), Y_i\Big]$$

Step 6: Compute total loss, model trained iteratively

$$\mathcal{L}_i^{total} = \frac{1}{|\mathcal{B}_L|} \sum_{I_i \in \mathcal{B}_L} \mathcal{L}_i^{Sup} + \beta \frac{1}{|\mathcal{B}_U|} \sum_{I_i \in \mathcal{B}_U} \mathcal{L}_i^{Reg} + \gamma \frac{1}{|\mathcal{B}|} \sum_{I_i \in \mathcal{B}} \mathcal{L}_i^{PLGCL}$$

Results

Method	labeled data (%)	Evaluation Metrics		
		DSC ↑	HD95 ↓	ASD ↓
UA-MT [65]	10%	0.816	12.35	3.62
Double-UA [56]		0.833	5.31	1.92
MC-Net [59]		0.863	7.08	2.08
MC-Net+ [58]		0.871	6.68	2.00
SASSNet [29]		0.841	5.03	1.40
DTC [32]		0.827	10.81	2.99
LCLPL [10]		0.881	5.11	1.81
Ours		0.891	4.98	1.80
UA-MT [65]	20%	0.857	4.06	1.54
URPC [34]		0.851	4.26	1.77
MC-Net [59]		0.878	3.91	1.52
MC-Net+ [58]		0.885	4.35	1.54
SASSNet [29]		0.871	5.84	2.15
DTC [32]		0.863	6.14	2.11
LCLPL [10]		0.905	3.91	1.51
Ours		0.912	3.82	1.49
Supervised	100%	0.923	3.66	1.41

(a) ACDC

Method	labeled data (%)	Evaluation Metrics		
		DSC ↑	HD95 ↓	ASD ↓
UA-MT [65]	2.50%	0.871	11.74	3.56
SASSNet [29]		0.888	8.32	2.34
CoraNet [45]		0.882	8.21	2.44
DTC [32]		0.885	7.99	2.40
GBDL [51]		0.898	6.85	1.78
Triple-UA [52]		0.878	7.94	2.42
Double-UA [56]		0.887	8.04	2.34
Ours		0.905	6.75	1.75
UA-MT [65]	10%	0.883	9.46	2.89
SASSNet [29]		0.891	7.54	2.51
CoraNet [45]		0.898	7.23	1.81
DTC [32]		0.894	7.31	1.91
GBDL [51]		0.911	6.38	1.51
Triple-UA [52]		0.887	7.55	2.12
Double-UA [56]		0.895	7.42	2.16
Ours		0.919	6.32	1.51
Supervised	100%	0.934	6.10	1.44

(b) KiTS19

Method	labeled data (%)	Evaluation Metrics		
		DSC↑	HD95↓	ASD↓
ICT [48]	10%	0.862	1.52	2.39
Double-UA [56]		0.877	1.45	2.56
HCE [26]		0.874	1.31	2.44
DTC [32]		0.841	1.81	2.61
TCSM [30]		0.853	1.52	2.46
UA-MT [65]		0.816	1.89	2.58
Ours		0.882	1.50	2.42
ICT [48]	20%	0.866	1.46	2.22
Double-UA [56]		0.883	1.28	2.06
HCE [26]		0.885	1.23	2.11
DTC [32]		0.859	1.70	2.24
TCSM [30]		0.877	1.41	2.36
UA-MT [65]		0.856	1.69	2.13
Ours		0.891	1.24	2.01
Supervised	100%	0.911	1.19	1.88

(c) CRAG

Table: Quantitative comparison with SoTA

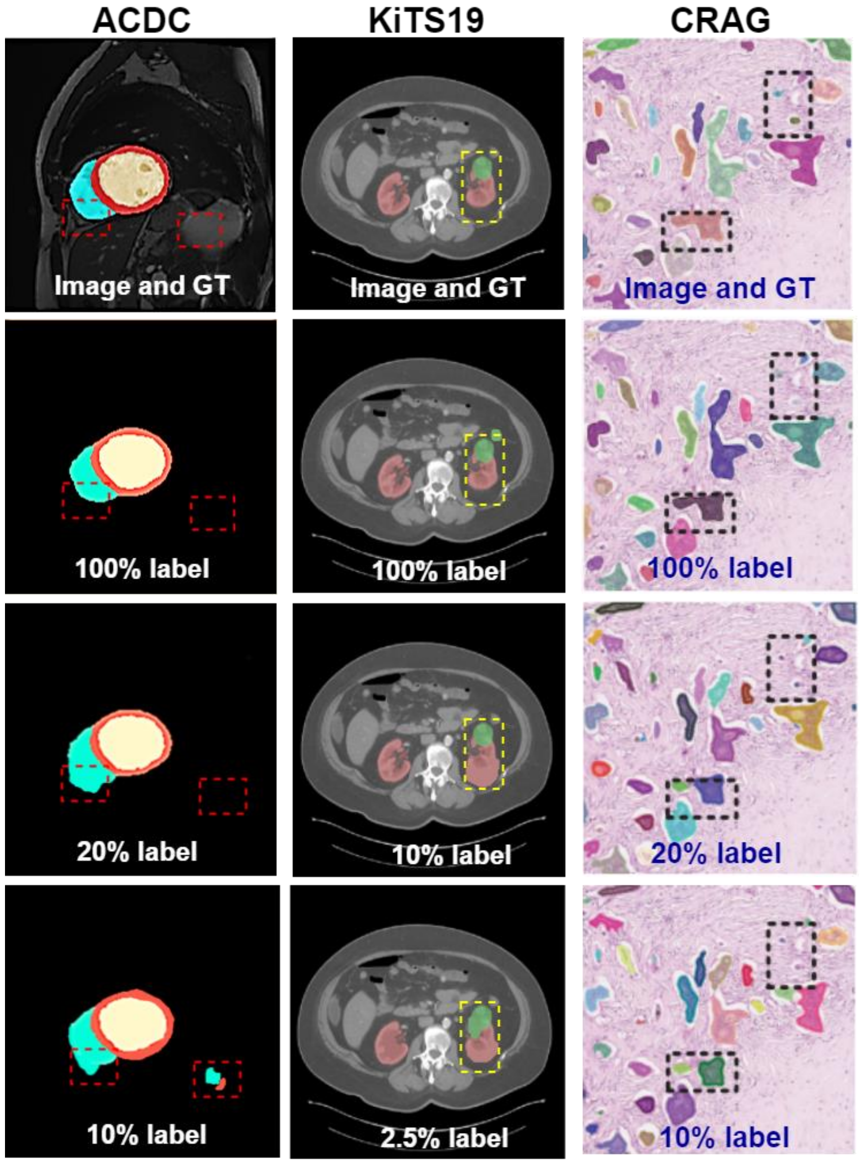


Figure: Qualitative visualization

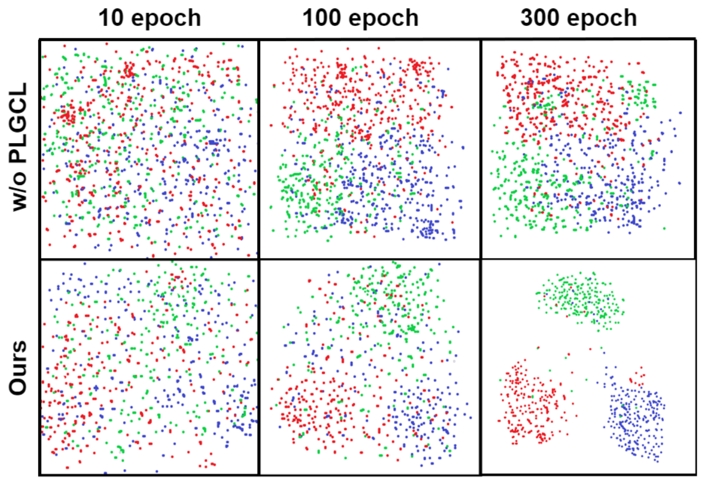
Ablation Experiments

Table: Quantitative analysis for contribution of individual components

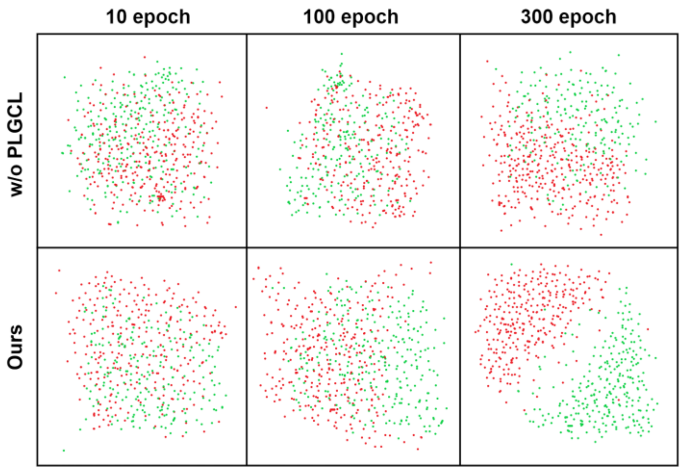
Method		ACDC			KiTS19			CRAG		
Warm-up	PLGCL	DSC↑	HD95↓	ASD↓	DSC↑	HD95↓	ASD↓	DSC↑	HD95↓	ASD↓
×	×	0.799	8.77	4.44	0.831	8.04	3.11	0.813	2.36	3.44
✓	×	0.822	7.54	3.61	0.855	7.72	2.62	0.819	2.04	3.52
×	✓	0.885	5.21	2.04	0.901	6.41	1.81	0.873	1.64	2.53
✓	✓	0.891	4.98	1.80	0.919	6.32	1.51	0.882	1.50	2.42

Table: Comparison of different metrics for patch sampling on the ACDC dataset.

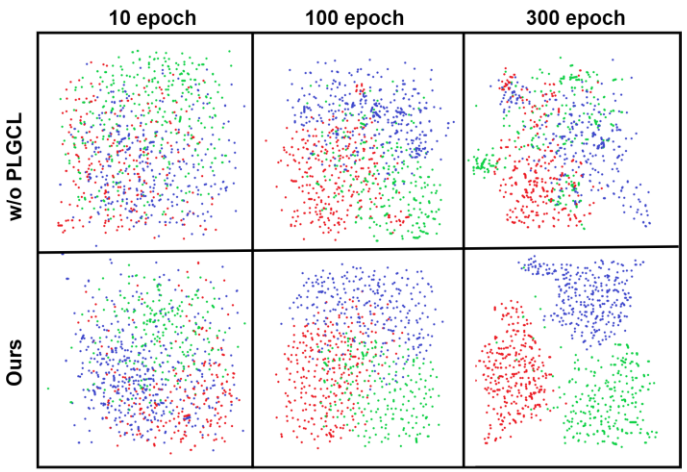
Similarity metric	Label = 10%			Label = 20%		
	DSC↑	HD95↓	ASD↓	DSC↑	HD95↓	ASD↓
Cosine similarity	0.820	9.118	6.016	0.832	7.611	4.445
Class Confidence	0.873	5.091	2.878	0.877	4.497	2.014
Entropy (**ours**)	0.891	4.980	1.802	0.912	3.823	1.491



(A) ACDC



(B) CRAG



(A) KiTS19

Figure: Clustering performance with and without PLGCL

Conclusion

- We propose a novel pseudo-label guided patch-based contrastive learning approach for medical image segmentation
- Pseudo-label from semi-supervised learning improves contrastive learning and vice versa
- We also introduce a new contrastive loss named PLGCL which is defined as the expectation of InfoNCE loss over the joint distribution of positives and negatives
- We also introduce a guided positive and negative sampling strategy for CL using average patch entropy.
- Achieves SoTA performance for multiclass medical image segmentation on three datasets from multiple modalities (CT, MRI, Histopathology)

Thank You

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