JUNE 18-22, 2023
CVPR
VANCOUVER, CANADA

Poster:
TUE-AM-314

Orthogonal Annotation Benefits Barely-supervised Medical Image Segmentation

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Github: https://github.com/HengCaiNJU/DeSCO.

Overview

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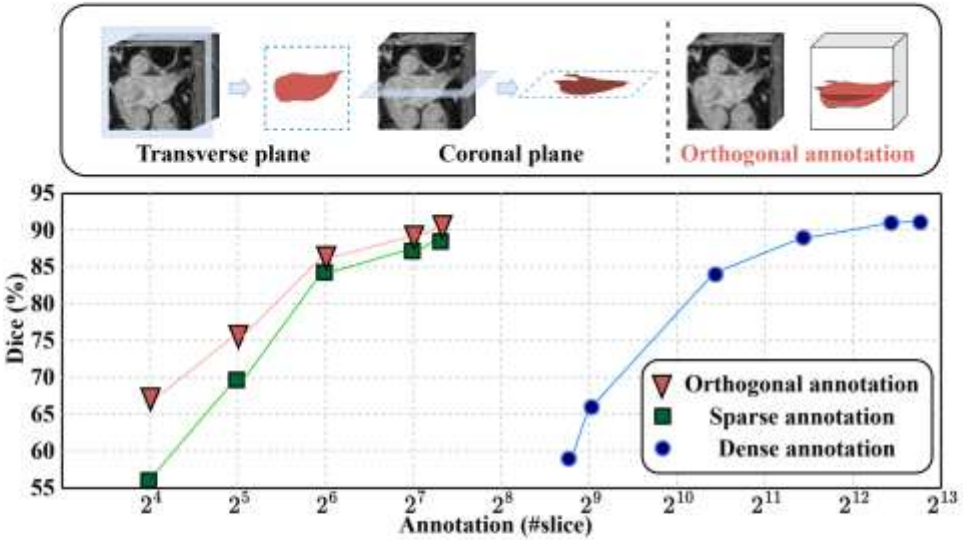
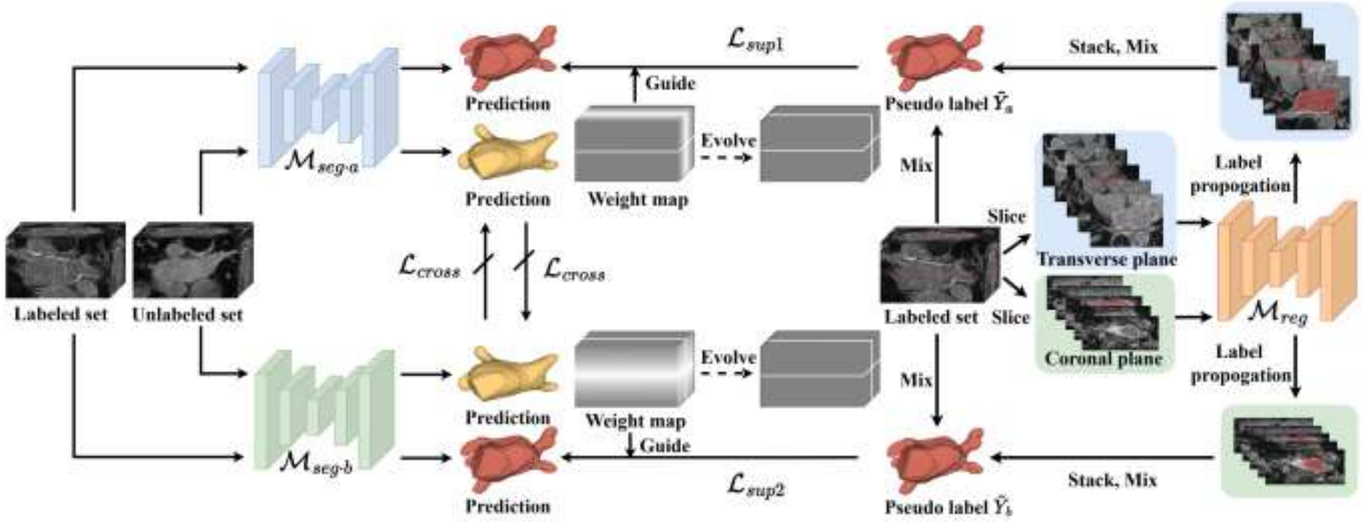




Our orthogonal annotation

which only labels two slices in two orthogonal directions

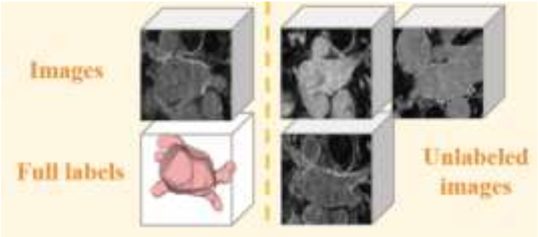
Our DeSCO paradigm

which learns from dense pseudo label and sparse annotation

Motivation

Less

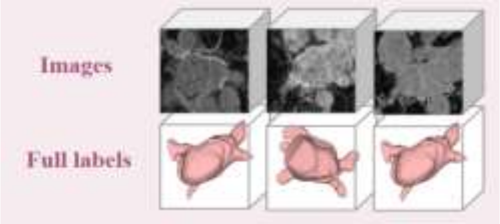
Semi-supervised segmentation



Still time-consuming

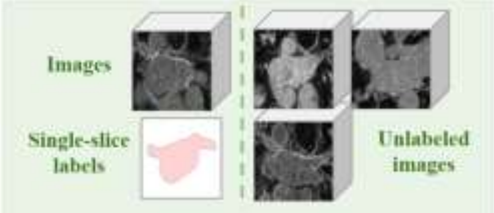
Even less

Supervised segmentation

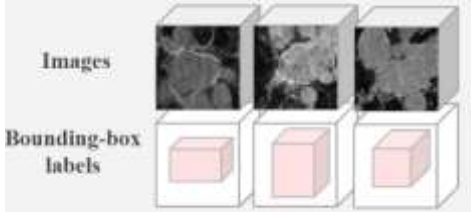


e.g., 1000 hours for KiTS19

Barely-supervised segmentation



Weakly supervised segmentation



Suboptimal performance

Coarse

Precise

Orthogonal annotation

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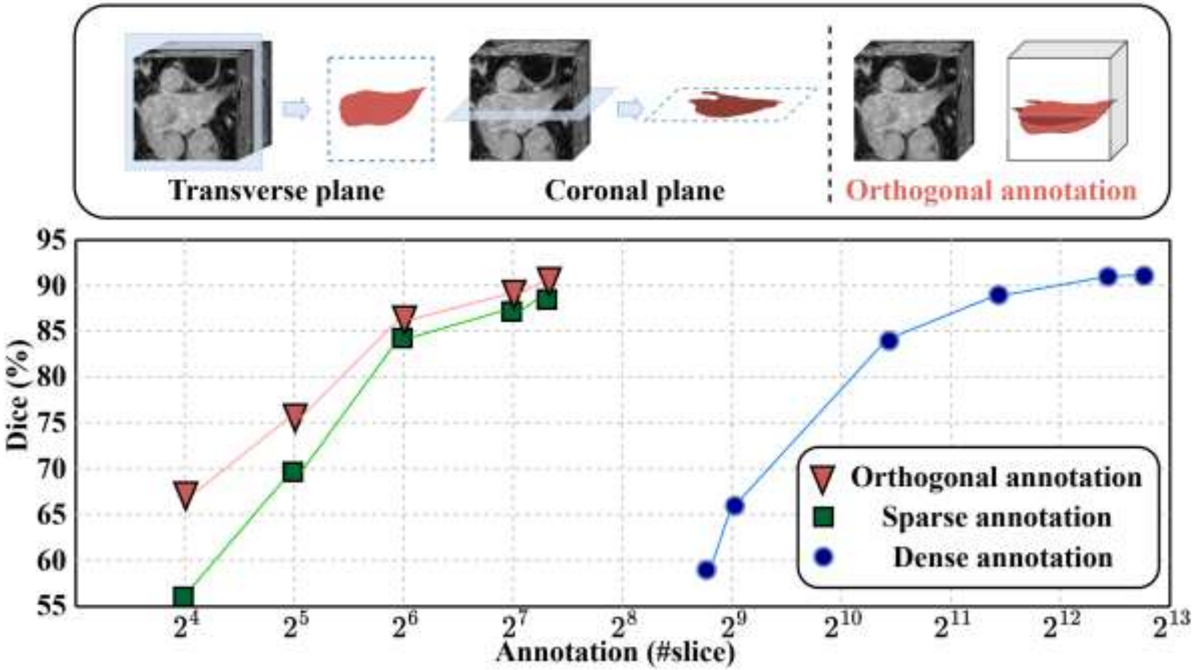
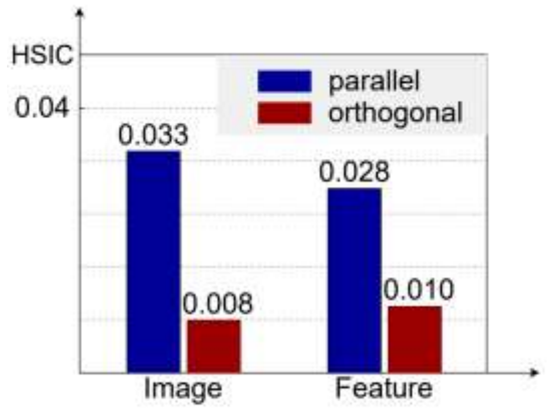
Why orthogonal?

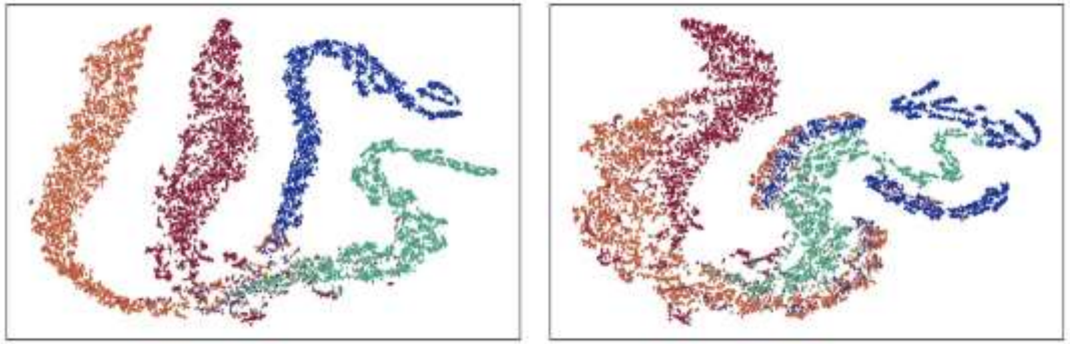


- Less redundant annotation
- Complementary information in 3D volumes

Orthogonal annotation

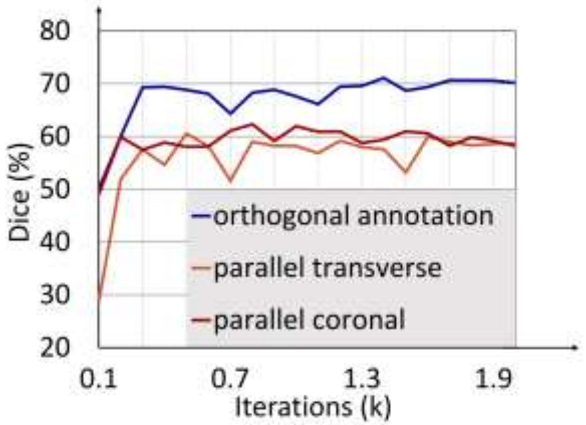


(1)



(a) model t_1 and t_2 (b) model t_1 and c

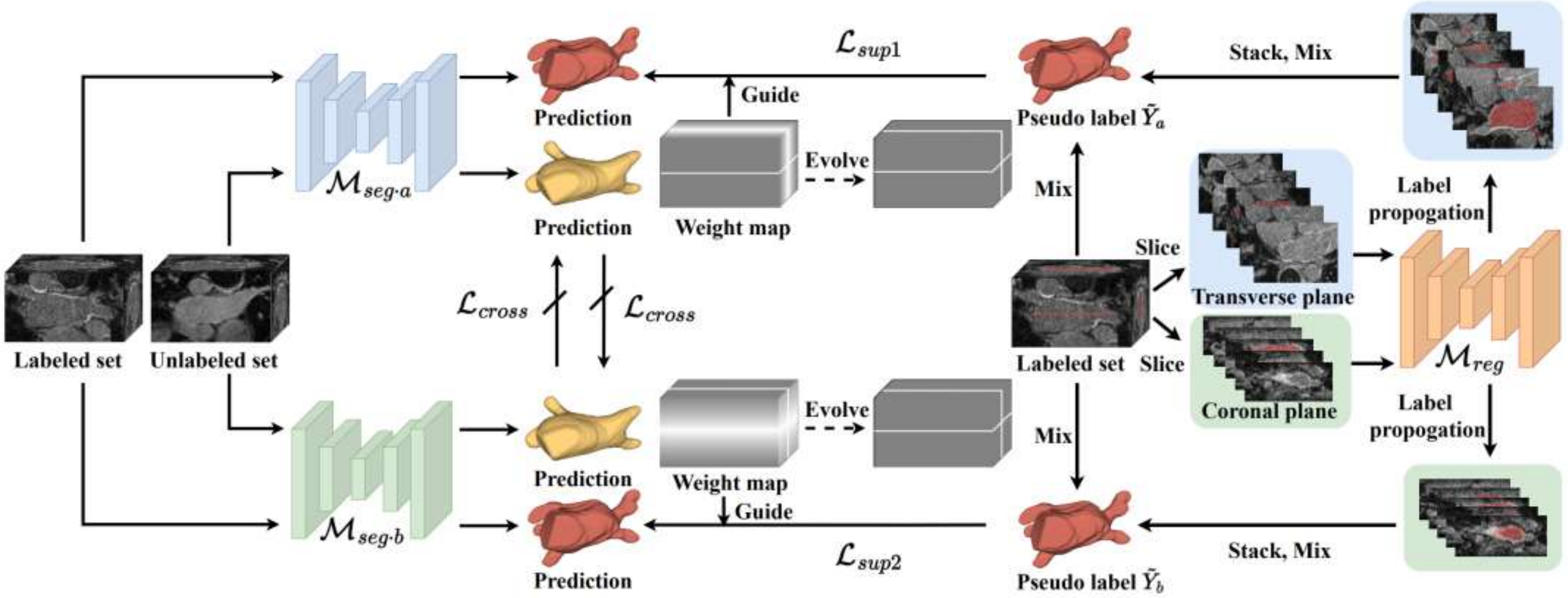
(2)



(3)

1. OA preserves the disparity.
2. OA enhances consistency from different directions.
3. OA provides a promising initialization.

Dense-Sparse Co-Training



- In early stage, the models learn from dense registration pseudo label, improving performance quickly and steadily.
- In later stage, while receiving constraits from sparse ground truth annotation, the models revise the mistake introduced by inaccurate pseudo label through cross supervision.

Experiments

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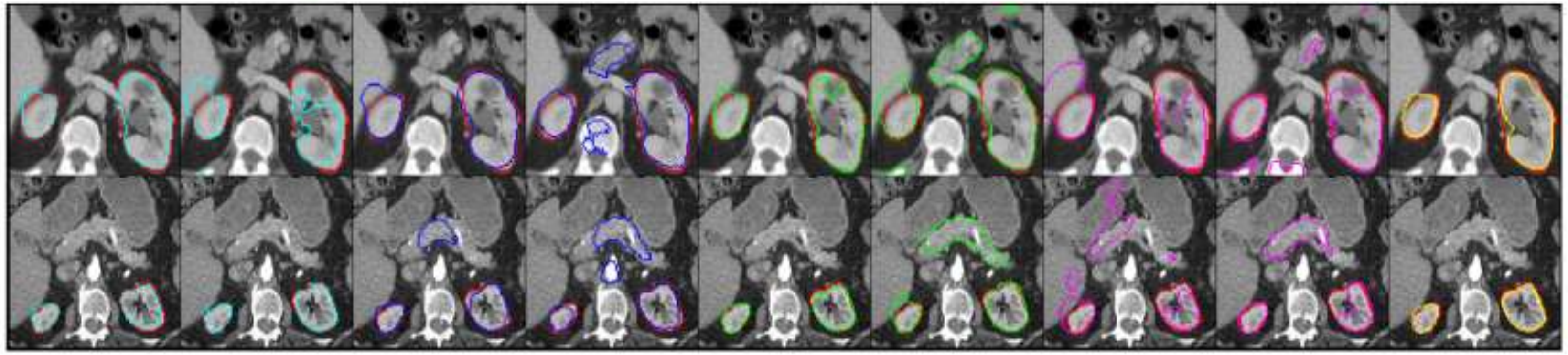
Dense: dense registration pseudo label
Sparse: Sparse orthogonal annotation

Method		Venue	Setting	Scans Used		Metrics			
				L / U Volumes	Labeled Slices	Dice (%)	Jaccard (%)	HD (voxel)	ASD (voxel)
Barely-supervised	MT [36]	NIPS'17	Dense	5 / 185	10	78.16±1.99	66.96±1.41	17.15±5.93	5.40±2.25
			Sparse	5 / 185	10	32.16±13.78	20.41±11.04	67.42±12.73	32.35±9.83
	CPS [10]	CVPR'21	Dense	5 / 185	10	76.51±5.81	64.67±6.69	17.71±8.67	5.74±3.50
			Sparse	5 / 185	10	8.87±2.87	4.68±1.58	81.60±10.15	41.21±5.38
	CTBCT [25]	MIDL'22	Dense	5 / 185	10	80.65±0.83	69.99±2.27	14.88±6.07	4.28±1.88
			Sparse	5 / 185	10	17.87±0.87	9.88±0.55	76.06±8.57	37.83±5.17
	CoraNet [34]	TMI'22	Dense	5 / 185	10	43.08±28.61	33.27±23.87	24.17±3.88	8.61±2.11
			Sparse	5 / 185	10	28.64±25.05	18.90±19.44	72.62±22.57	35.22±13.43
	Ours	**this paper**	-	5 / 185	10	**86.93±2.78**	**78.33±3.21**	**11.61±2.15**	**3.28±0.51**
Semi-supervised	MT [36]	NIPS'17	-	5 / 185	320	84.98±4.68	76.51±5.63	16.51±0.18	4.61±0.83



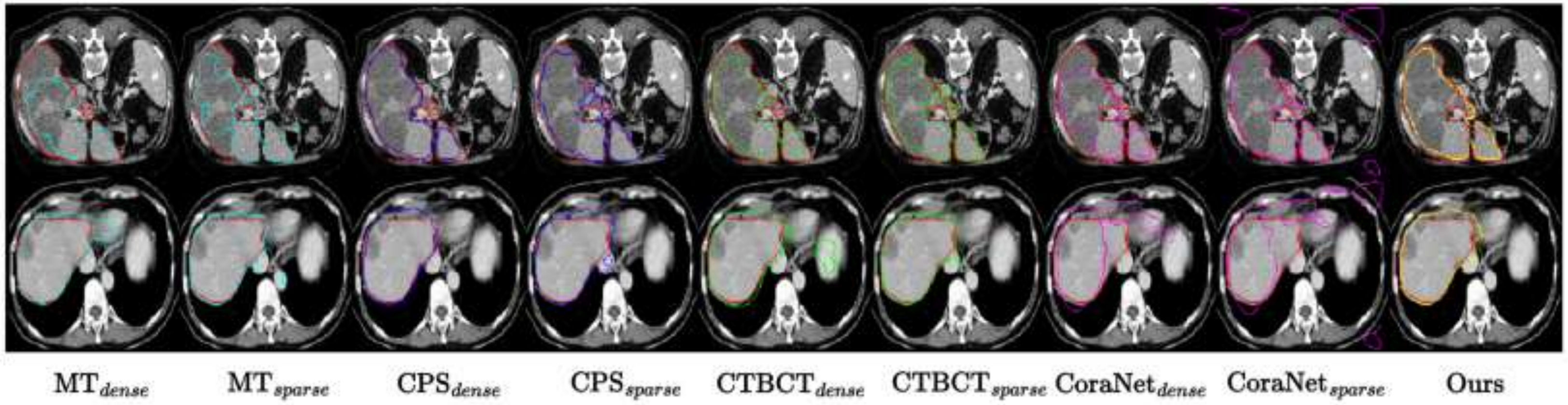
MT_{dense} MT_{sparse} CPS_{dense} CPS_{sparse} $CTBCT_{dense}$ $CTBCT_{sparse}$ $CoraNet_{dense}$ $CoraNet_{sparse}$ Ours

KiTS 19 dataset

Experiments

Dense: dense registration pseudo label
Sparse: Sparse orthogonal annotation

Method		Venue	Setting	Scans Used		Metrics			
				L / U Volumes	Labeled Slices	Dice (%)	Jaccard (%)	HD (voxel)	ASD (voxel)
Barely-supervised	MT [36]	NIPS'17	Dense	5 / 95	10	81.76±4.82	69.73±7.01	28.87±13.85	8.57±4.03
			Sparse	5 / 95	10	56.82±25.76	43.83±28.78	74.03±34.02	31.41±17.58
	CPS [10]	CVPR'21	Dense	5 / 95	10	73.86±10.13	59.73±13.16	32.78±14.68	10.73±5.20
			Sparse	5 / 95	10	20.46±2.15	11.48±1.35	92.27±3.03	41.34±2.09
	CTBCT [25]	MIDL'22	Dense	5 / 95	10	79.68±5.45	66.95±7.41	30.46±13.36	9.18±4.12
			Sparse	5 / 95	10	40.07±7.95	25.52±6.24	71.83±11.41	29.49±5.44
	CoraNet [34]	TMI'22	Dense	5 / 95	10	80.17±1.77	68.97±3.16	19.42±7.47	4.34±0.50
			Sparse	5 / 95	10	36.84±8.20	23.13±6.03	95.89±1.94	43.25±2.03
	Ours	**this paper**	-	5 / 95	10	**89.24±1.37**	**81.10±2.28**	**10.05±2.42**	**2.27±0.45**
Semi-supervised	MT [36]	NIPS'17	-	5 / 95	320	90.77±1.91	83.62±3.11	18.32±7.17	4.95±1.81



LiTS dataset

10 slices

3% annotation

close performance

Thanks!