

CVPR
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Focus on Background: Exploring SAM's Potential in Few-shot Medical Image Segmentation with Background-centric Prompting

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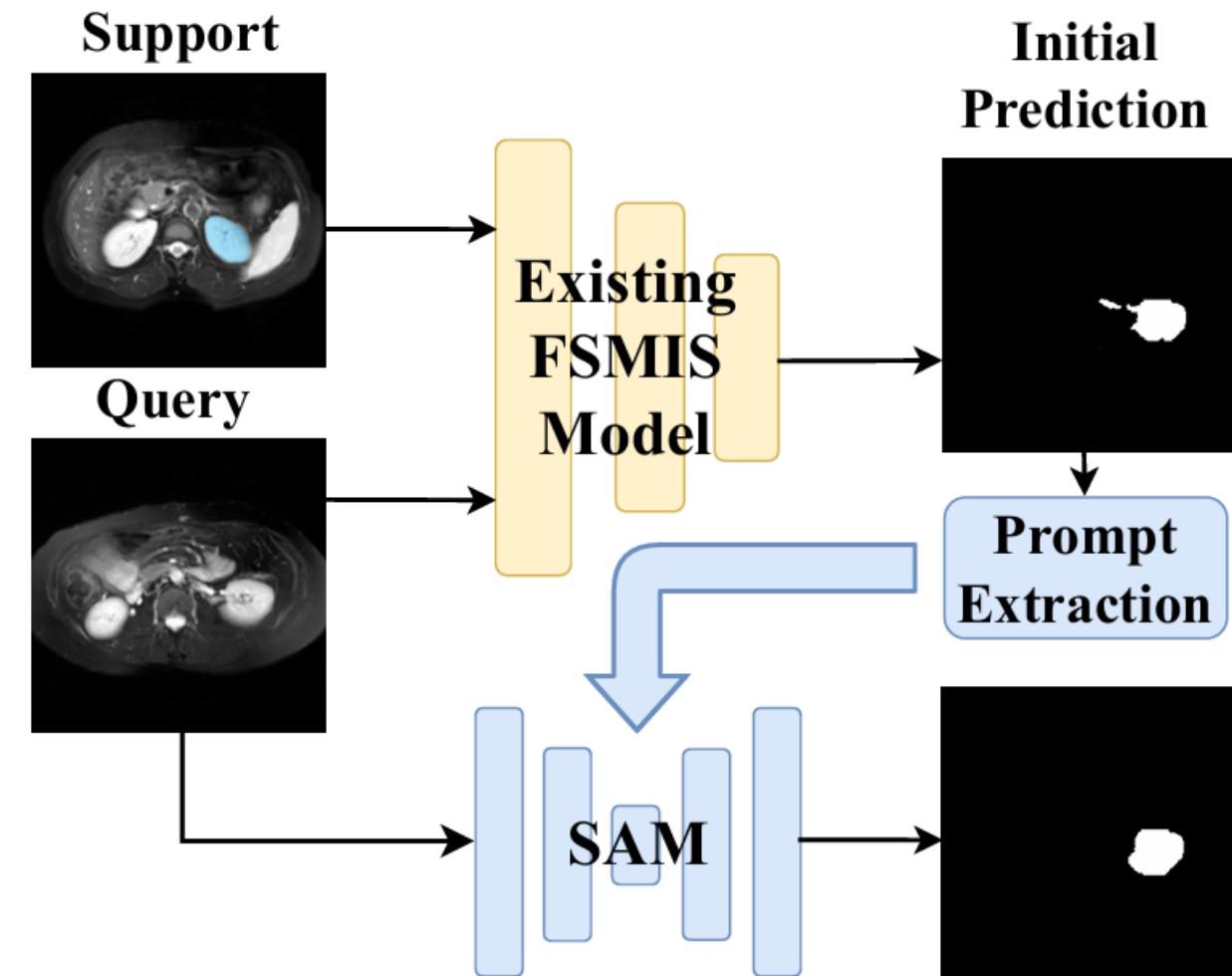
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Data61 ❤️ CRISO

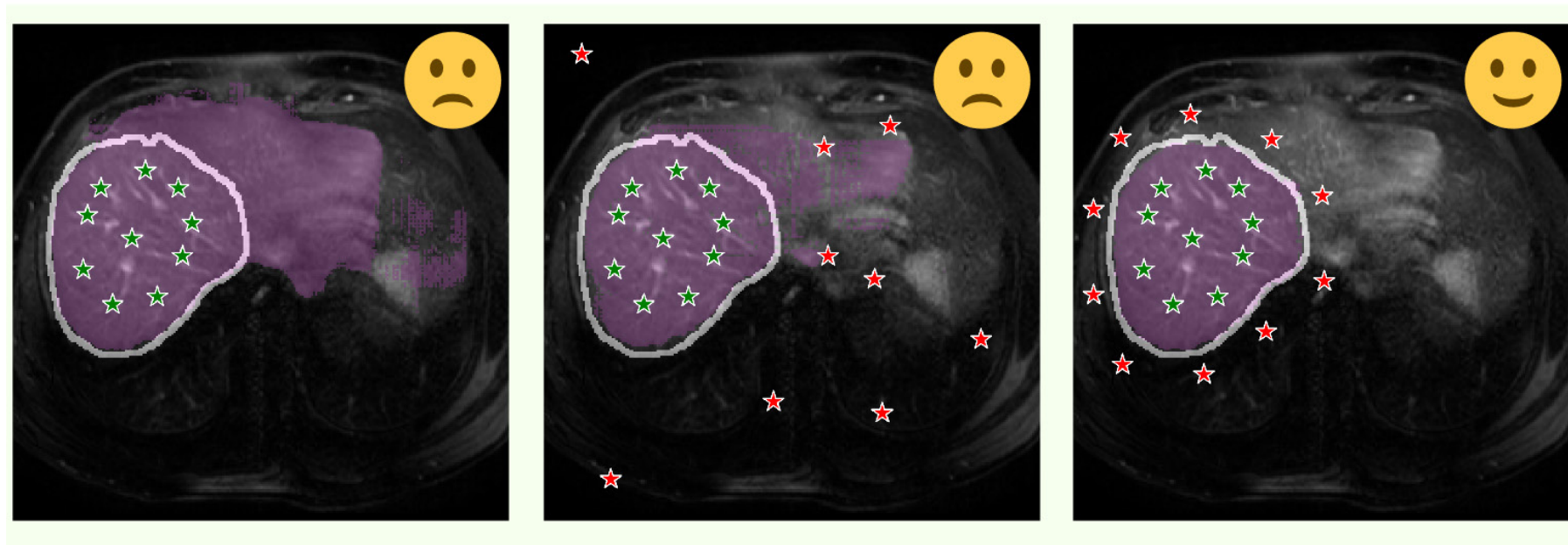
Background

SAM's **promptable and category-agnostic** segmentation capabilities naturally align with the goals of FSMIS.



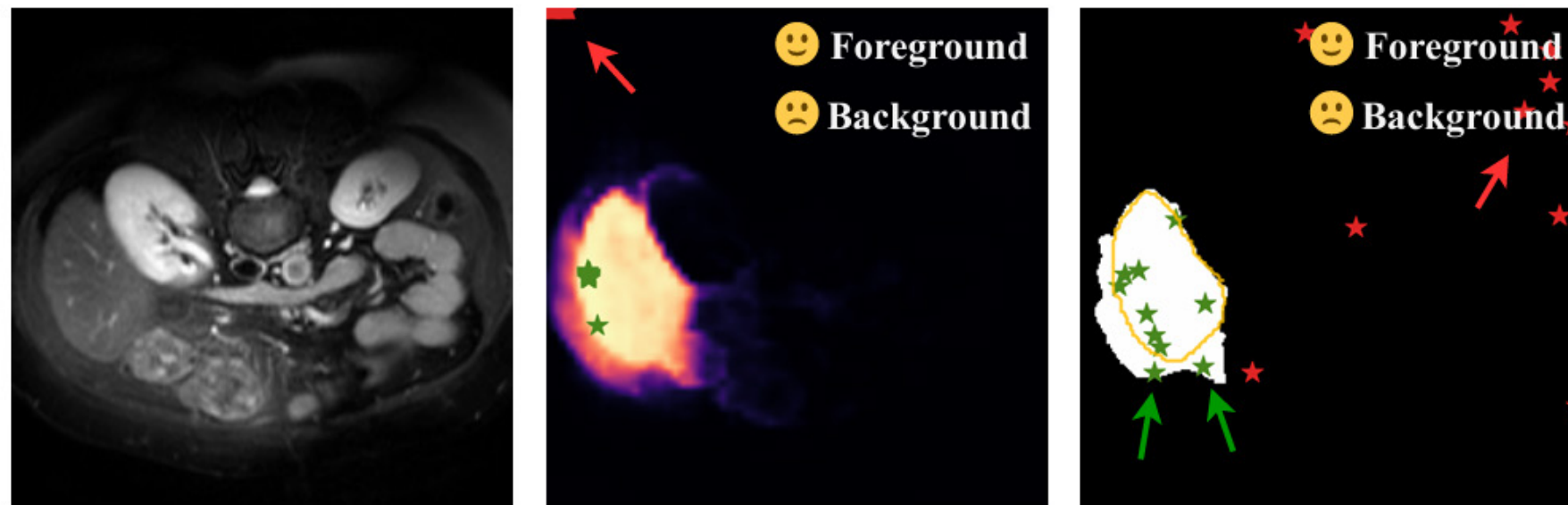
Ayzenberg, Lev, Raja Giryes, and Hayit Greenspan. "Protosam: One-shot medical image segmentation with foundational models." *arXiv preprint arXiv:2407.07042* (2024).

Motivation

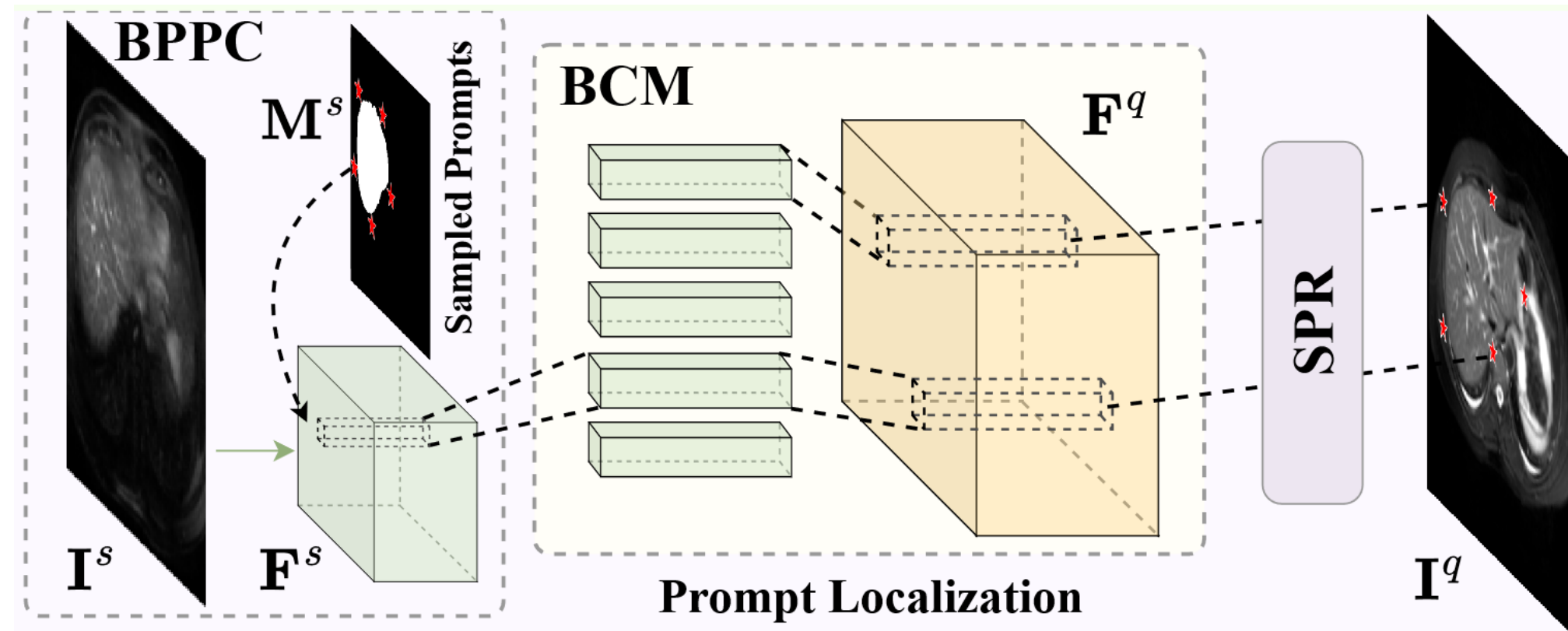


SAM frequently **over-segments** medical images. Precise **background** prompts can effectively constrain this.

Segmentation (confidence)-based methods **fail to** obtain precise background prompts!



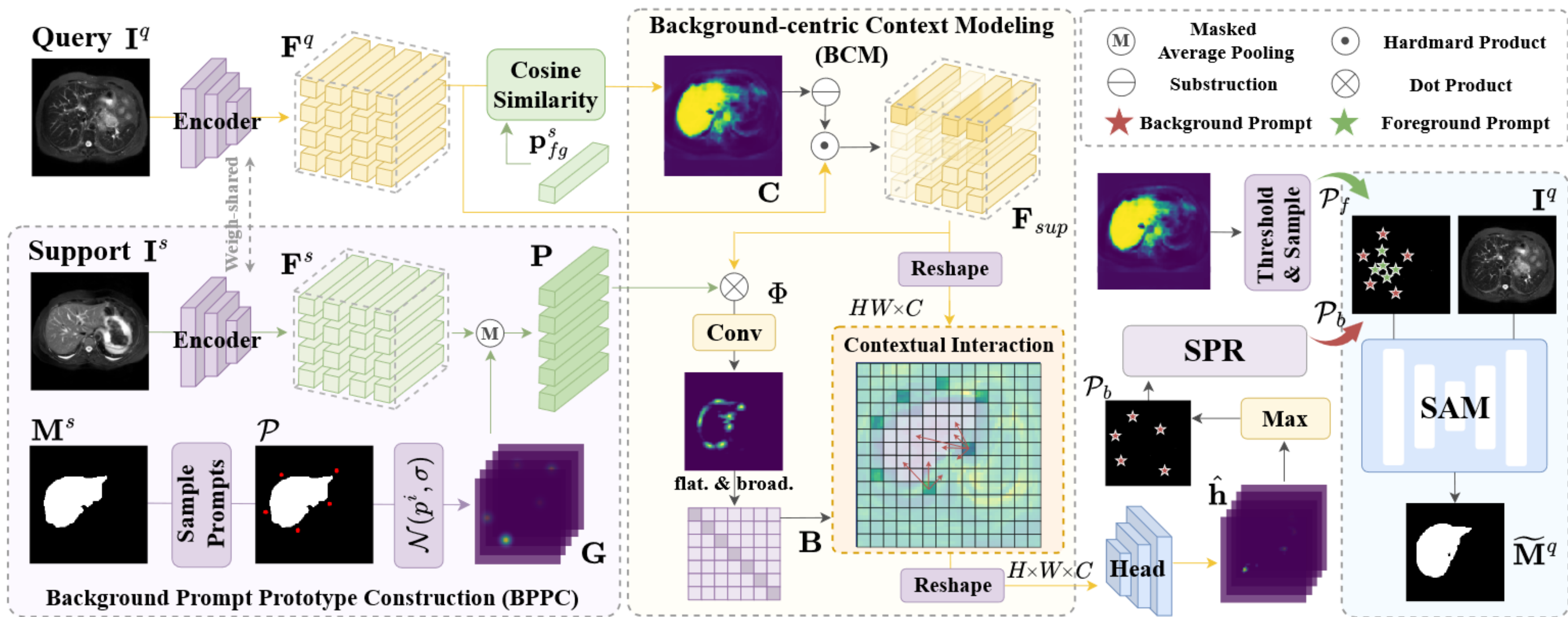
Motivation



Segmentation \rightarrow Prompt Localization + SAM

Directly Localize Background Prompts!

Method: FoB Prompt Generator



- Background-centric. Category-agnostic.
- Trained Independently of SAM to Learn Prompting.

Results

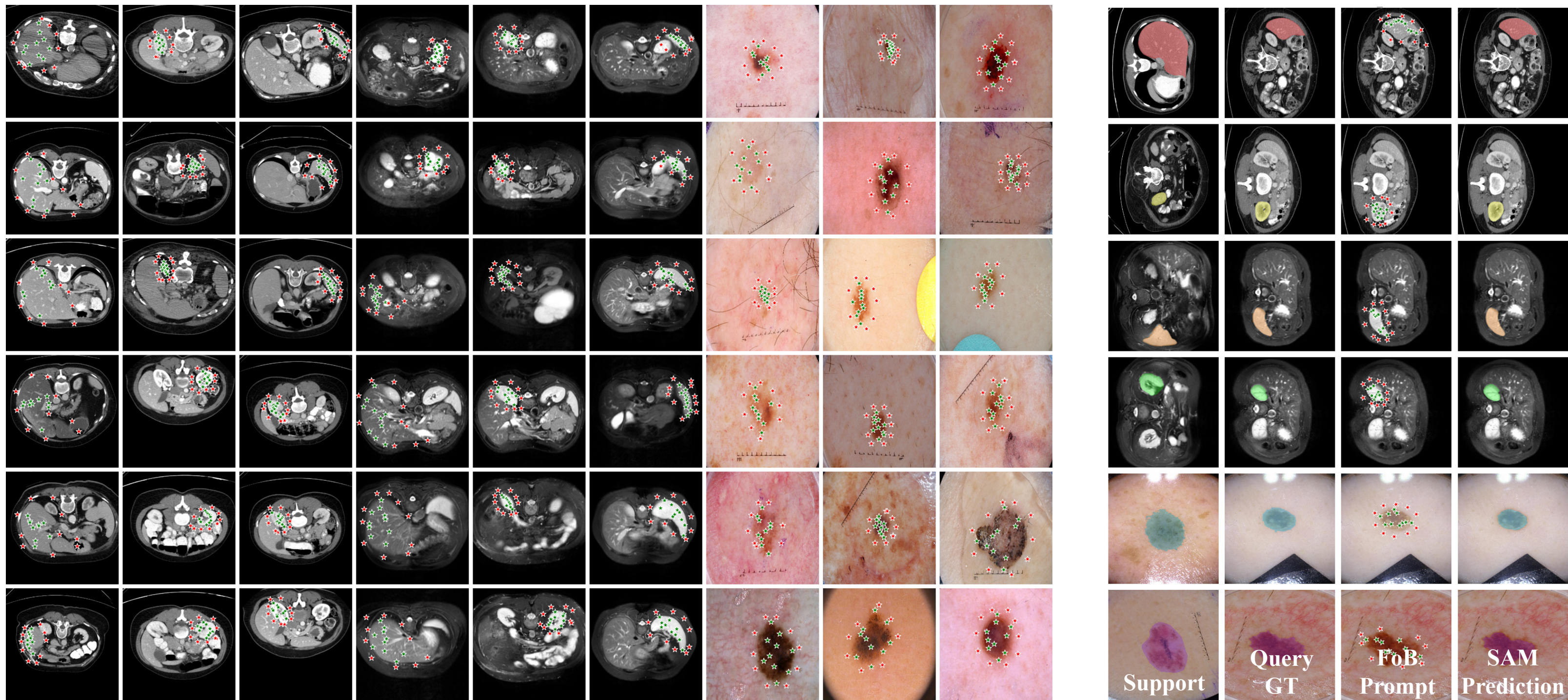
In-domain Evaluation

	Methods	Abd-MRI					Abd-CT					Skin-DS			
		Liv	RK	LK	Spl	Avg.	Liv	RK	LK	Spl	Avg.	Mel	Nev	SK	Avg.
Setting I	ALPNet [31]	76.1	85.18	81.92	72.18	78.84	78.29	71.81	72.36	70.96	73.35	66.32	61.65	59.57	62.51
	RPT [50]	82.86	89.82	80.72	76.37	82.44	82.57	72.58	77.05	79.13	77.83	77.81	75.42	70.28	74.50
	GMRD [5]	81.42	90.12	83.96	76.09	82.90	79.6	74.46	81.7	78.31	78.52	79.23	72.78	71.32	74.44
	PGRNet [12]	83.27	87.44	81.44	81.72	83.47	82.48	79.88	74.23	72.09	77.17	71.39	70.21	65.87	69.16
	ProtoSAM [2]	83.14	82.36	82.75	77.98	81.56	84.79	75.67	71.31	70.24	75.50	73.61	76.26	68.37	72.75
	AM-SAM [33]	76.12	84.95	84.17	80.36	81.40	87.28	86.01	84.37	87.11	86.19	–	–	–	–
	FoB + S-2D	77.09	89.45	83.58	79.82	82.49	85.54	80.02	79.18	78.06	80.70	85.87	88.51	80.02	84.80
	FoB + SAM	85.61	88.18	84.76	79.31	84.46	86.51	86.51	87.29	84.54	86.21	78.93	77.12	73.81	76.62
Setting II	ALPNet [31]	73.05	78.39	73.63	67.02	73.02	73.67	54.82	63.34	60.25	63.02	56.17	50.67	49.18	52.01
	RPT [50]	76.37	86.01	78.33	75.46	79.04	75.24	67.73	72.99	70.8	71.69	76.07	76.97	69.86	74.30
	GMRD [5]	80.25	86.66	78.65	73.25	79.70	80.39	76.17	77.4	75.3	77.32	77.21	74.12	70.97	74.10
	ProtoSAM [2]	81.94	81.43	71.46	76.51	77.83	87.84	71.04	69.44	65.5	73.45	75.33	72.01	68.74	72.03
	AM-SAM [33]	79.70	81.46	70.28	70.80	75.56	85.40	84.02	82.78	83.97	84.04	–	–	–	–
	FoB + S-2D	75.32	87.07	75.46	75.32	78.29	75.25	78.97	79.89	75.82	77.48	85.53	87.02	78.86	83.80
	FoB + SAM	82.43	87.91	78.21	73.30	80.46	82.29	85.91	88.55	82.43	84.80	76.68	77.77	72.22	75.56

Cross-domain Evaluation

	Methods	Liv	RK	LK	Spl	Avg.
CT → MRI	RobustEMD [51]	60.16	70.26	66.34	53.71	62.61
	FAMNet [3]	73.01	74.68	57.28	58.21	65.79
	FoB + SAM	75.05	79.57	70.38	68.21	73.30
MRI → CT	RobustEMD [51]	69.82	50.34	63.79	59.88	60.95
	FAMNet [3]	73.57	61.89	57.79	65.78	64.75
	FoB + SAM	81.36	58.81	57.18	70.71	67.02

Results



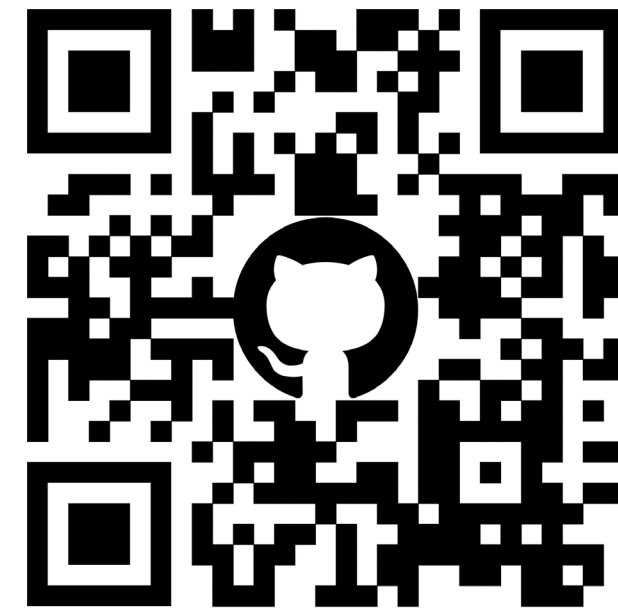
Conclusion

- We **reformulate** SAM-based FSMIS as a prompt localization problem and design a dedicated prompt generator FoB, which focuses on **background prompts**.
- Our method effectively exploits the support segmentation information and leverages the contextual dependencies of medical image features to enable precise background prompt localization through matching.
- Our method achieves **state-of-the-art performance** on three medical image datasets, and exhibiting strong cross-domain generalization.

Resources



Paper



Code



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