Boosting Low-Data Instance Segmentation by Unsupervised Pretraining with Saliency Prompt

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Problem Definition and Contribution

Motivation

Query-based end-to-end instance segmentation (QEIS) methods would lose efficacy when only a small amount of training data is available since it's hard for the crucial queries/kernels to learn localization and shape priors.

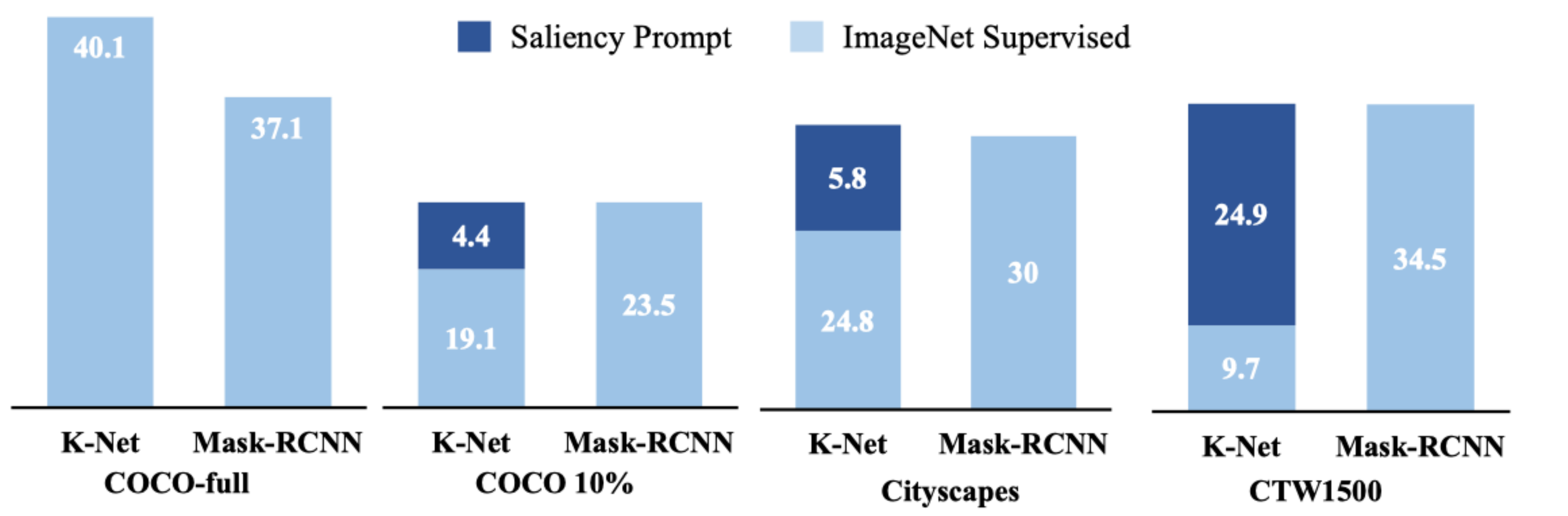


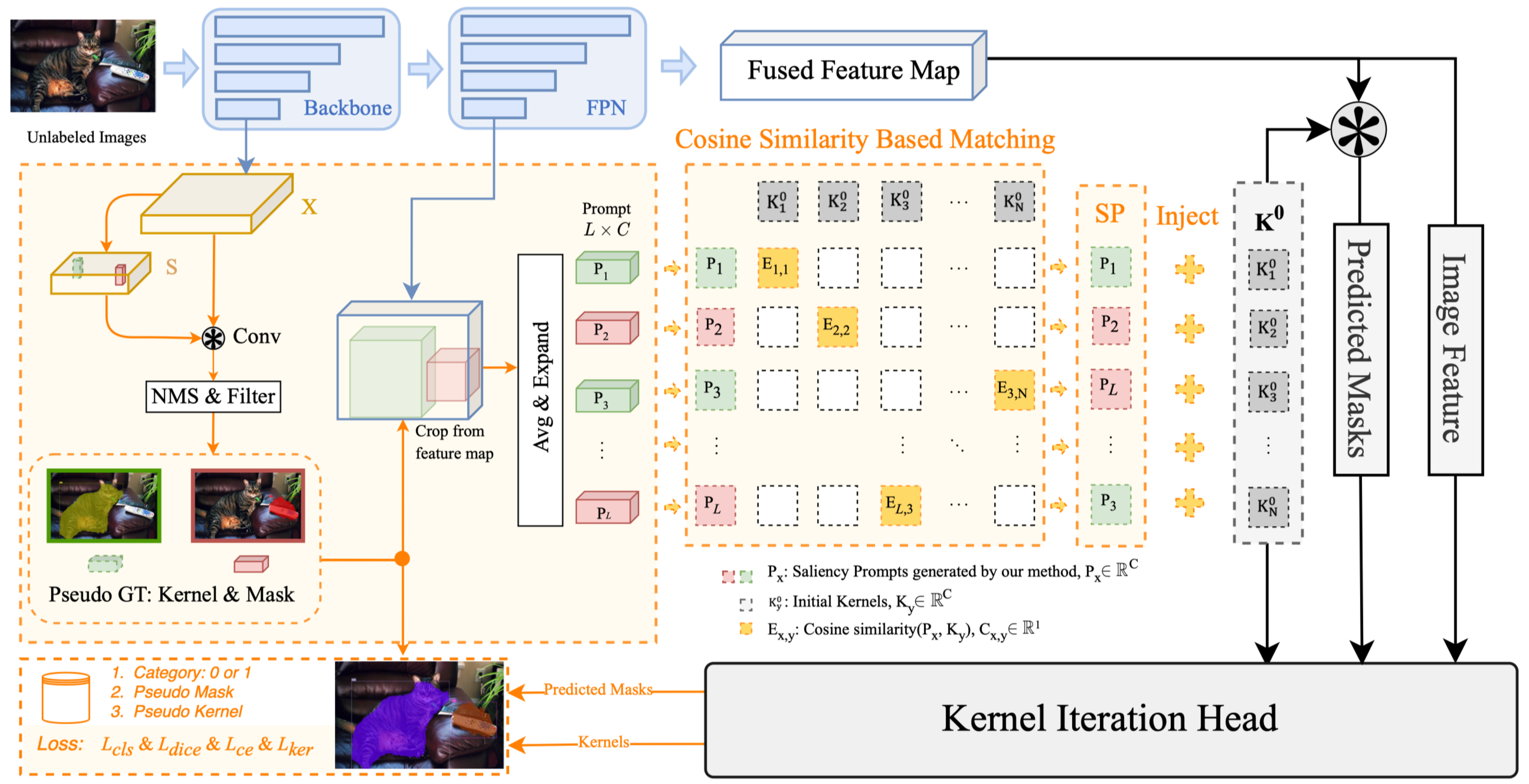
Figure 1: K-Net can outperform Mask-RCNN on large-scale datasets (COCO-full). However, on small datasets (the right three), it can not perform as well as Mask-RCNN since it's hard to learn localization and shape priors. Our proposed unsupervised pre-training method based on saliency prompt not only boosts the vanilla K-Net significantly, but also helps to achieve comparable performance compared with Mask-RCNN.

Key Contribution

1. This paper first points out that the QEIS models lack spatial distribution and shape awareness and perform poorly in low-data regimes.
2. Introduce a new pre-training method that boosts QEIS models by giving Saliency Prompt for queries/kernels.
3. From a practical perspective, our pre-training method helps QEIS models achieve a similar convergence speed and comparable performance with CNN-based models in low-data regimes.

Our Method

Overview.
Orange colors denotes our pre-training method with the corresponding supervision. Blue and gray modules denote a vanilla QEIS model, here we use K-Net for example.



- **Saliency Masks Proposal**

Responsible for generating pseudo masks from unlabeled images based on the saliency mechanism.

$$\mathbf{Y}_{i,j} = \mathrm{Conv}\left(\mathbf{S}_{i,j}, \mathbf{X}\right) \in \mathbb{R}^{H \times W}$$

- **Prompt-Kernel Matching**

Transfers pseudo masks into prompts and injects the corresponding localization and shape priors to the best-matched kernels.

$$\mathbf{E}_{n,l} = \frac{\mathbf{K}_n^0}{\|\mathbf{K}_n^0\|_2} \cdot \frac{\mathbf{P}_l}{\|\mathbf{P}_l\|_2}. \quad \delta(n) = \underset{l \in [1,\dots,L]}{\arg\max}\, \mathbf{E}_{n,l}.$$

- **Kernel Supervision**

Applied to supply supervision at the kernel level for robust learning.

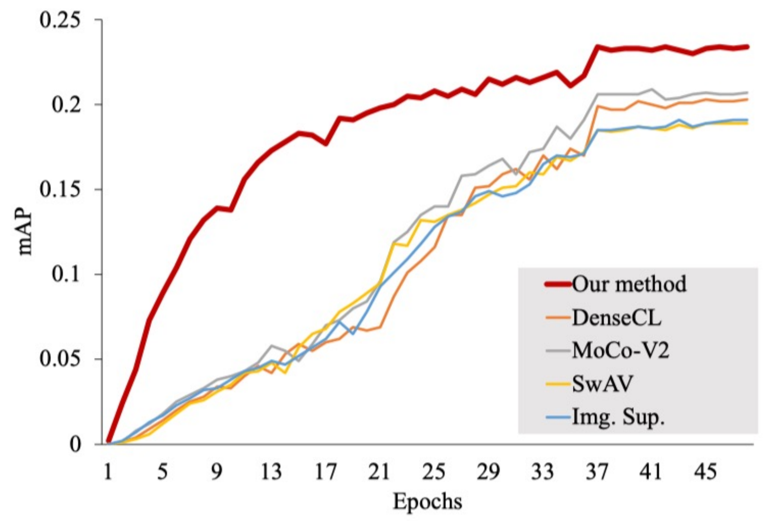
$$\mathcal{L}_{ker} = \sum_{l=0}^{L} \sum_{i} (1 - \mathrm{Cos}(\mathrm{Linear}(\mathbf{S}_l), \mathbf{K}_{n_l}^i)),$$

Experimental result

- **Compared with SOTA unsupervised methods**

Table 1. Instance segmentation fine-tune results on COCO with 5% and 10% annotated images based on K-Net.

	Pre-train	mAP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
5% images	Img. Sup.	14.8	29.1	13.7	4.3	15.5	24.4
	DenseCL	16.7	31.2	15.9	5.1	17.5	27.7
	SwAV	15.7	30.3	14.7	4.6	25.9	16.6
	MoCo-v2	17	32	16.2	5.3	18.3	27.1
	SP(ours)	**19.9**	**35.7**	**19.9**	**6.0**	**21.0**	**32.6**
10% images	Img. Sup.	19.1	35.7	18.2	6.7	20	31.6
	DenseCL	20.3	36.4	20.3	6.6	21.8	33.6
	SwAV	18.9	34.8	18.3	6.8	20.8	30.6
	MoCo-v2	20.7	37.7	20.4	6.4	22.1	34.2
	SP(ours)	**23.5**	**41.4**	**23.7**	**7.9**	**24.8**	**38.6**

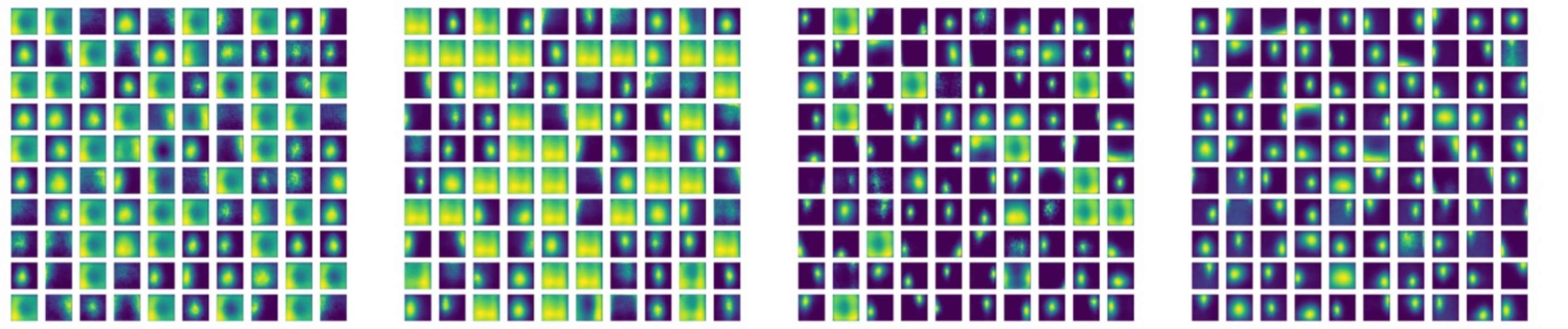


- **Deployed on QueryInst and Mask2Former**

Model	Pre-train	CTW1500 Epoch	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L	Cityscapes Epoch	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Mask2Former [7]	Img. Sup.	80	38.8	67.6	41.6	15.6	41.2	57.4	24	29.1	52.4	-	5.6	23.9	55
	DenseCL	80	43.2	71.6	48.5	18.4	47.6	59.9	24	27.5	48.9	-	5.2	23.8	53.7
	SwAV	80	41.2	69.1	46.1	17.6	45.2	58.1	24	30.3	53.3	-	5.4	23.3	59
	MoCo-v2	80	43.3	71.2	49.2	18.9	47.6	59.4	24	30.7	54.3	-	5.4	25.5	56.4
	SP(ours)	**20**	**52.9**	**83.4**	**62.1**	**29.4**	**56.4**	**67.6**	**24**	**31.8**	**55.8**	**-**	5.1	**26.5**	**59.0**
QueryInst [15]	Img. Sup.	80	28.3	53.7	28.6	9.8	29	41.8	24	29.1	53.2	-	6.7	27.4	50.7
	DenseCL	80	31.6	56.7	33.4	10.4	32.5	46.6	24	30.8	54.7	-	8.6	28.9	54.5
	SwAV	80	24.6	50	23.1	8.1	25	36.3	24	30.7	54.4	-	7.9	28.5	53.9
	MoCo-v2	80	31.6	56.8	32.8	12.6	32	45.8	24	31.4	54.4	-	8.1	28.4	56.1
	SP(ours)	**20**	**39.2**	**66.8**	**43.1**	**16.7**	**42.2**	**51.9**	**24**	**32.8**	**57.3**	**-**	**8.8**	**29.2**	**57.0**

These results indicate that our pretraining method can help the kernels/queries of QEIS models to learn localization and shape prior effectively and help gain competitive performance improvement.

- **Visual analysis for each query/kernel**



(a) Train from scratch. (b) Pre-trained by MoCo-v2. (c) Pre-trained by our method. (d) Trained on COCO train2017-full.

These results demonstrate that the kernels pre-trained with Saliency Prompt have learned effective spatial distribution and shape discrimination ability.

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