max planck institut informatik
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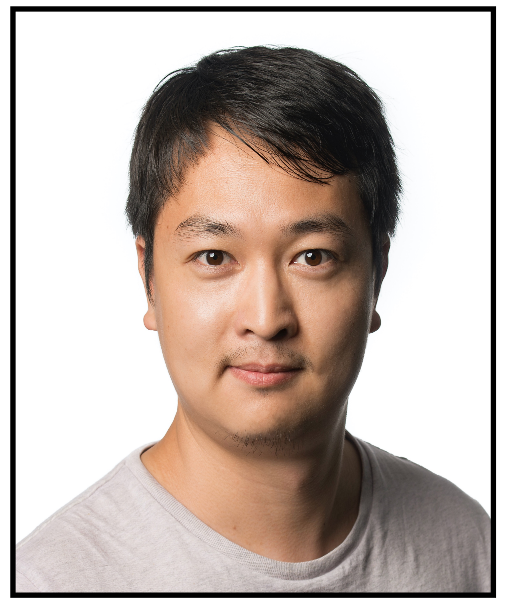
SIC Saarland Informatics Campus

Weakly-Supervised Domain Adaptive Semantic Segmentation with Prototypical Contrastive Learning


Anurag Das


Yongqin Xian*

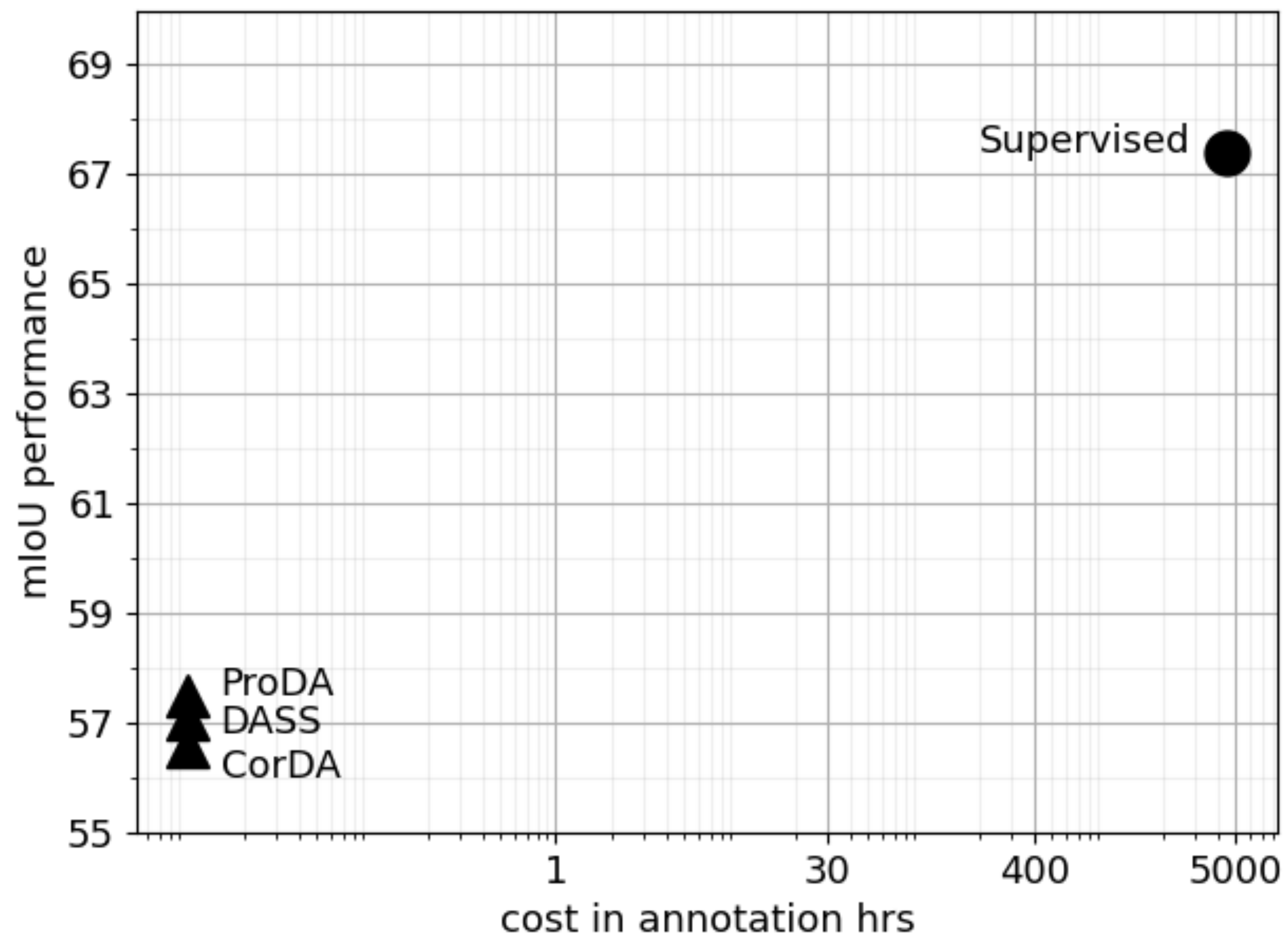

Dengxin Dai


Bernt Schiele

Max Planck Institute for Informatics, Saarland Informatics Campus
*ETH Zürich

Motivation

- **Huge performance gap** between Unsupervised Domain Adaptive Semantic Segmentation (UDASS) and Supervised Learning



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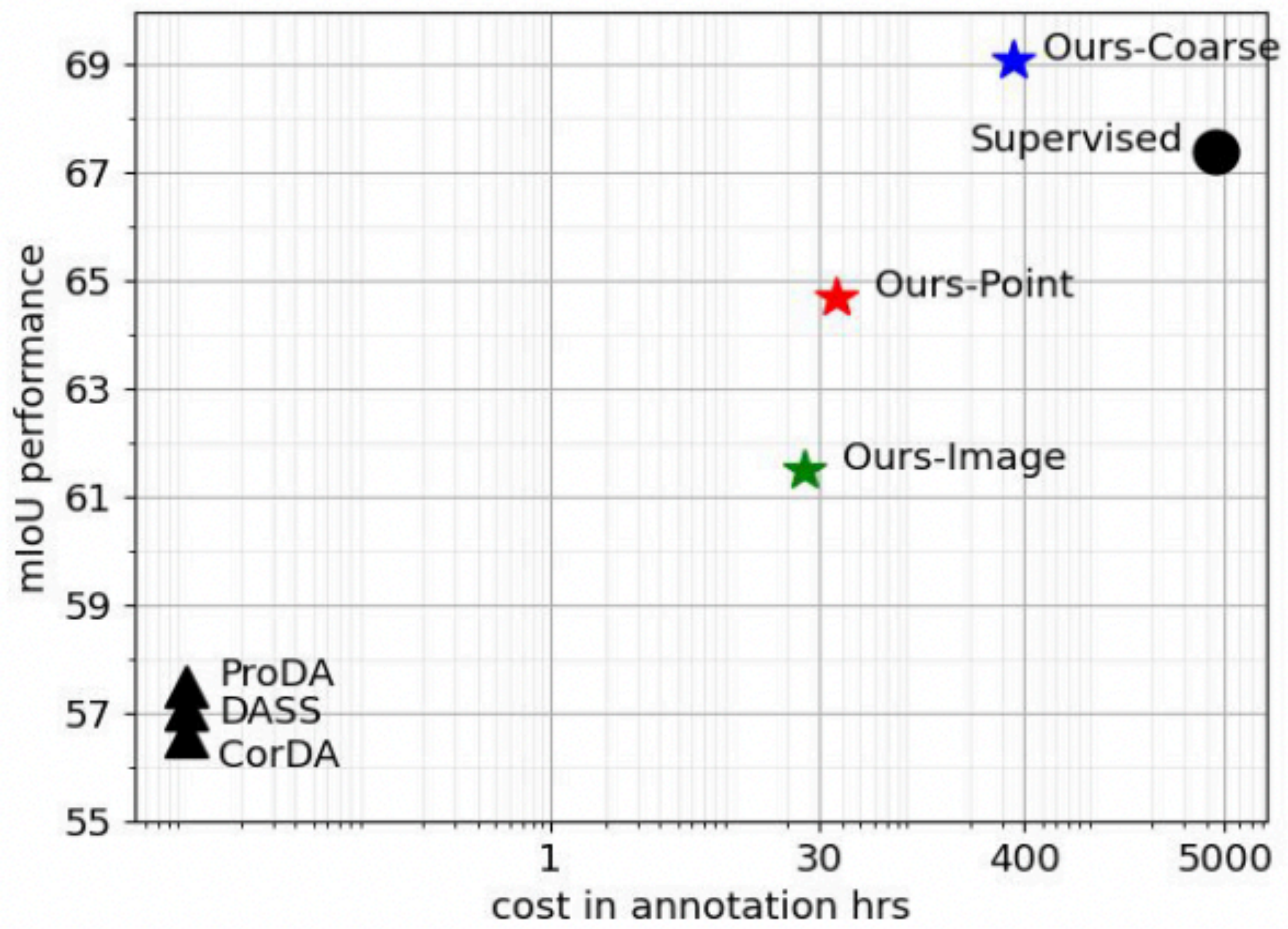
- **Huge performance gap** of Unsupervised Domain Adaptive Semantic Segmentation (UDASS) and Supervised Learning

- Idea : **Use additional cheap weak labels from real domain**

Road, Sidewalk, building, traffic sign, car, rider, sky, vegetation

Cost/image: 30 sec 45 sec 7 min 90 min



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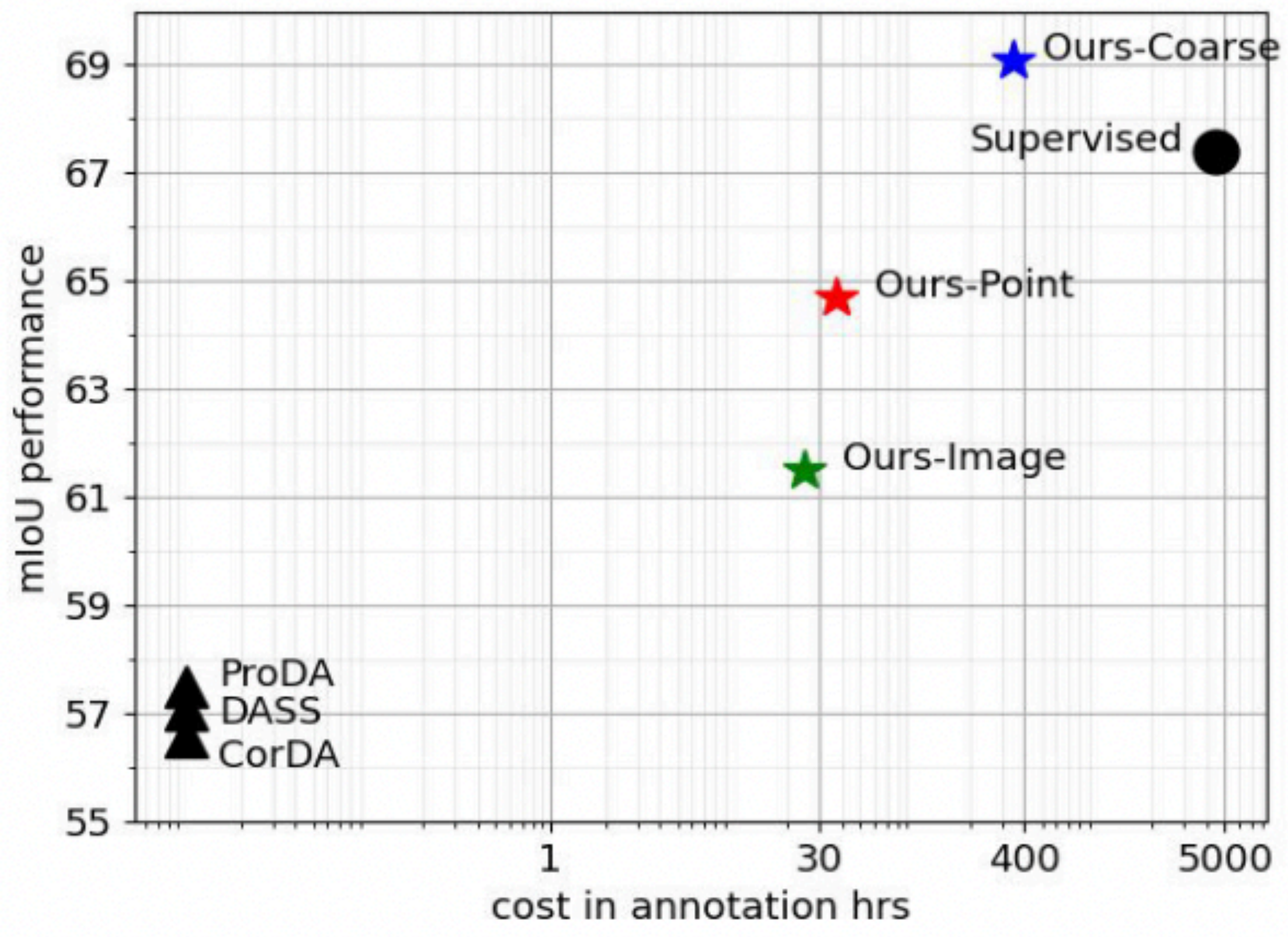

- Task : **Weakly Supervised Domain Adaptive Semantic Segmentation (WDASS)**

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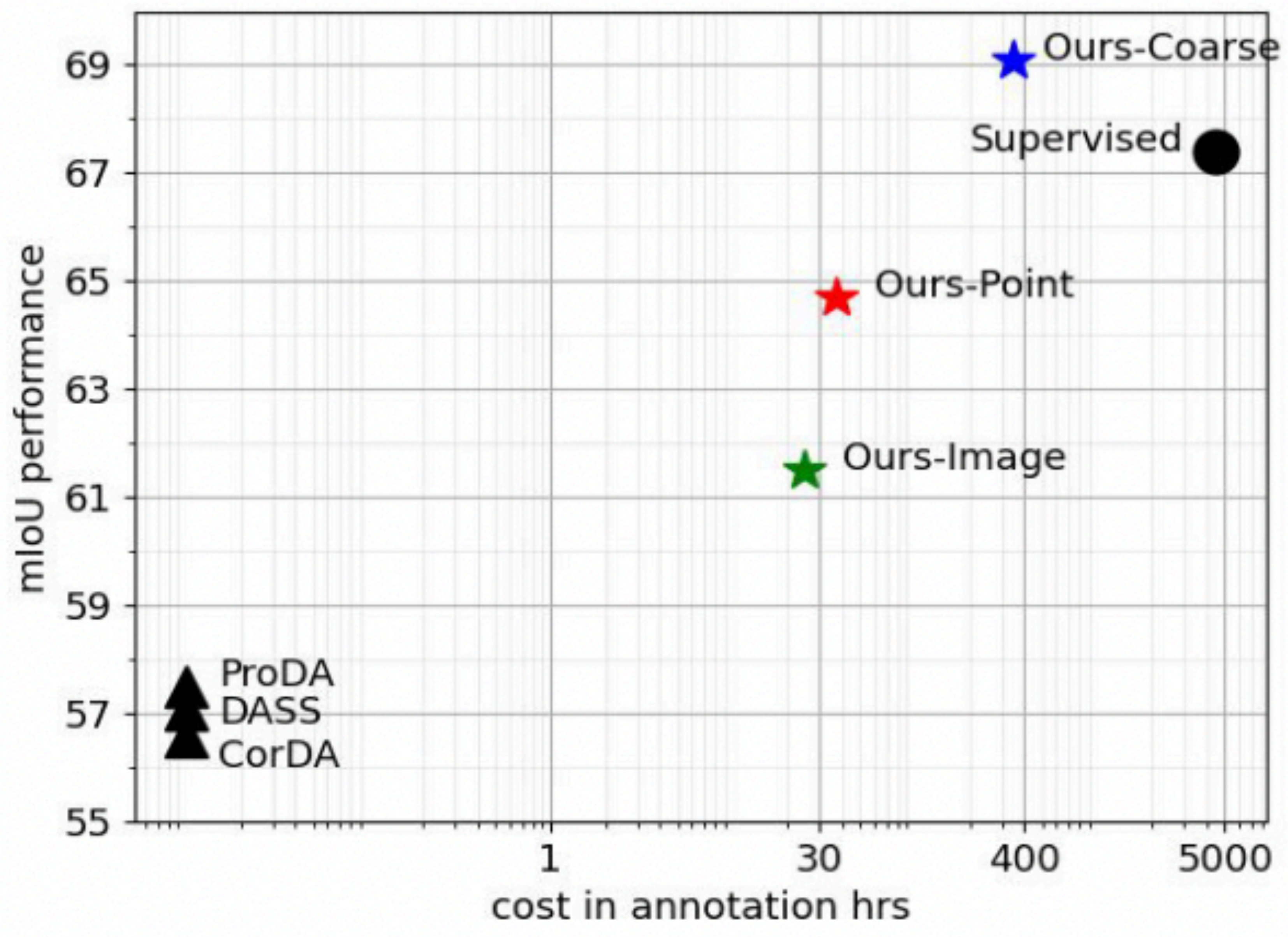

- Task : **Weakly Supervised Domain Adaptive Semantic Segmentation (WDASS)**

- Prior Works :
  - Ignore source-target feature alignment using weak labels
  - Lack of common framework for different weak labels

Contributions

- **Present common framework for WDASS task using image, point and coarse labels**
  - Two components :
    - Construct better prototypes using weak labels
    - Contrastive alignment of features using prototypes

- **Bridge the gap between UDASS and supervised learning**
  - Notably with coarse annotation our framework outperforms supervised learning

- **Show tradeoff between annotation cost vs performance for different weak labels**
  - Point label achieves better performance for low annotation budget

- **Achieves new state-of-the-art on WDASS for different weak labels**

Framework

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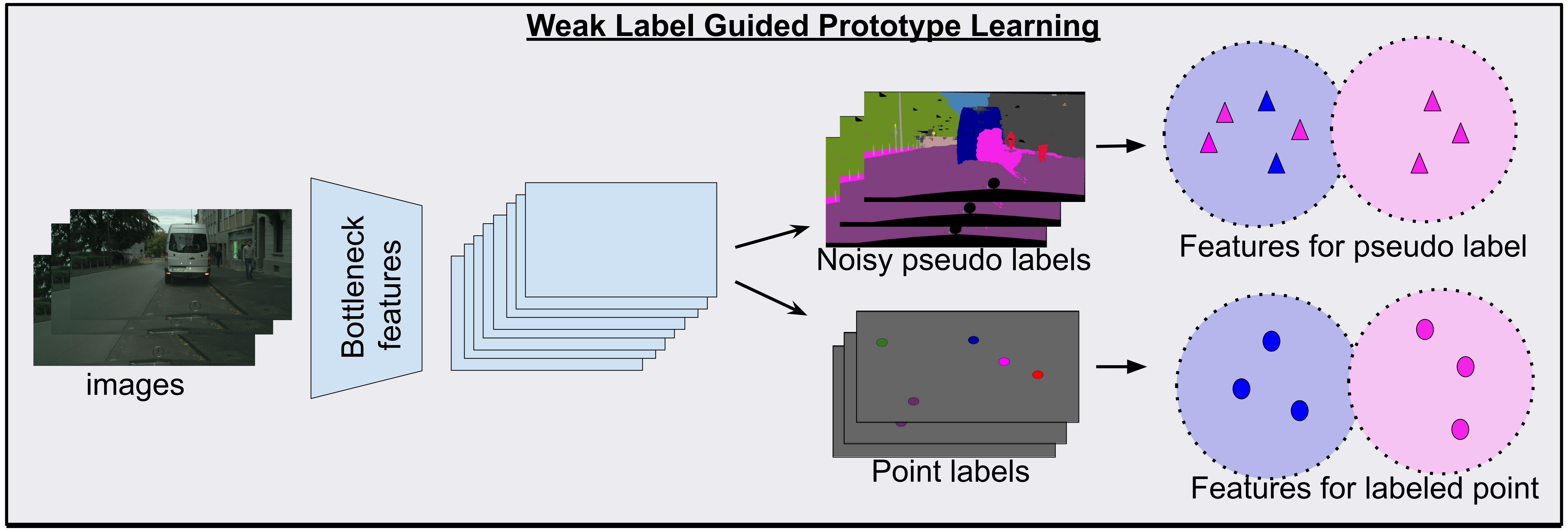
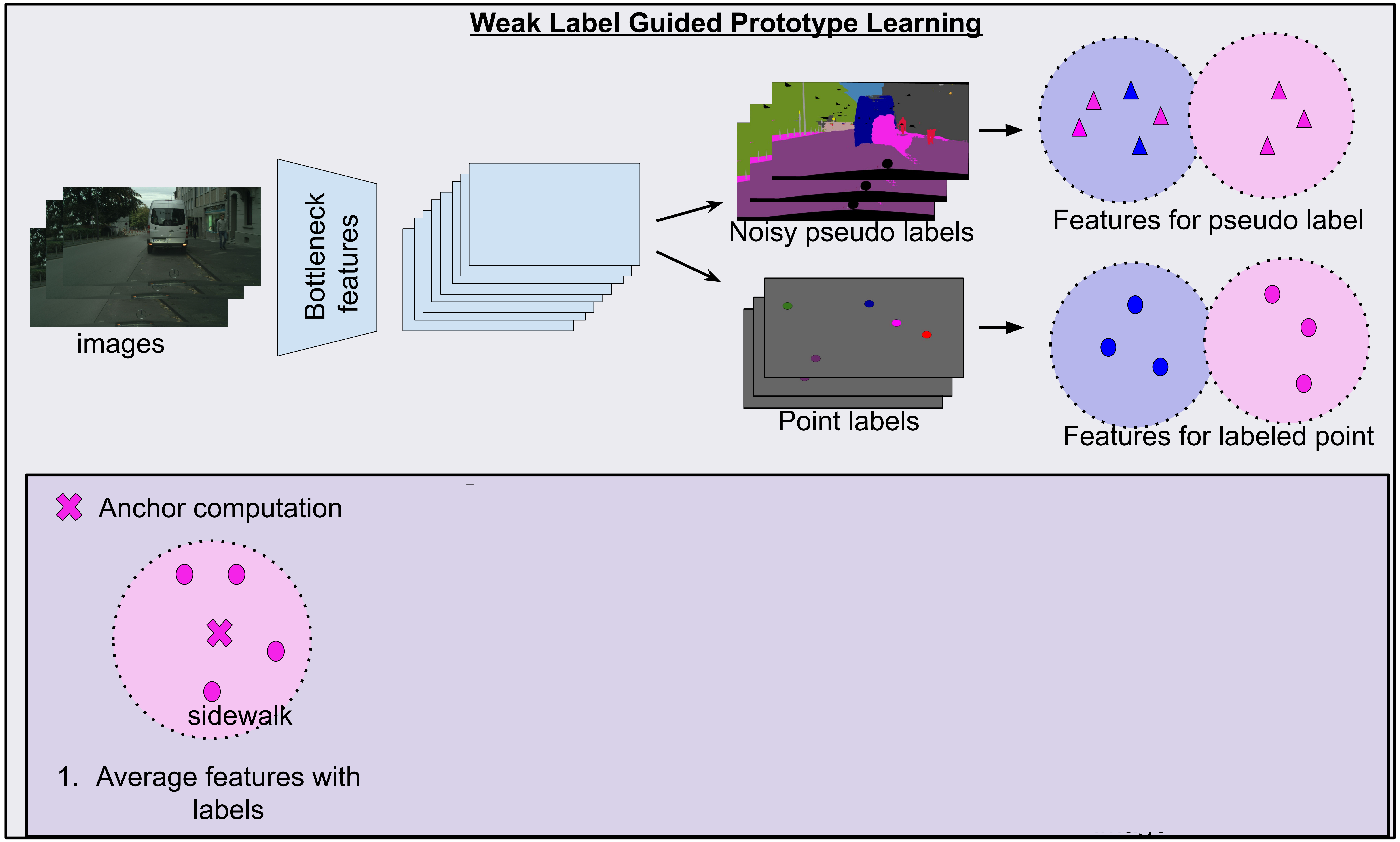


Weak Label Guided Prototype Learning
images
Bottleneck features
Noisy pseudo labels
Features for pseudo label
Point labels
Features for labeled point

Framework



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Anchor computation
sidewalk
1. Average features with labels

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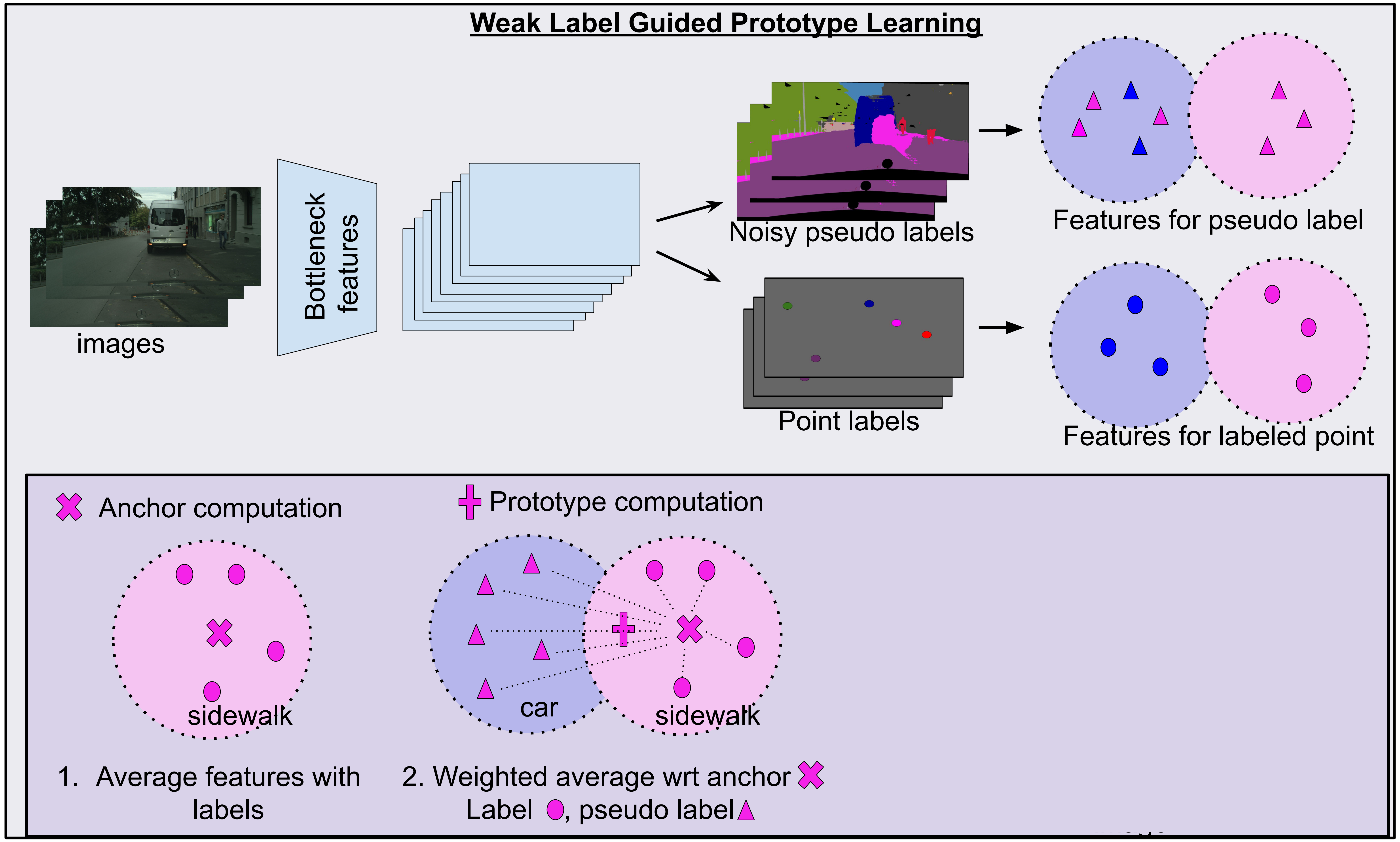

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Prototype computation
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car
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1. Average features with labels
2. Weighted average wrt anchor
Label , pseudo label

Framework

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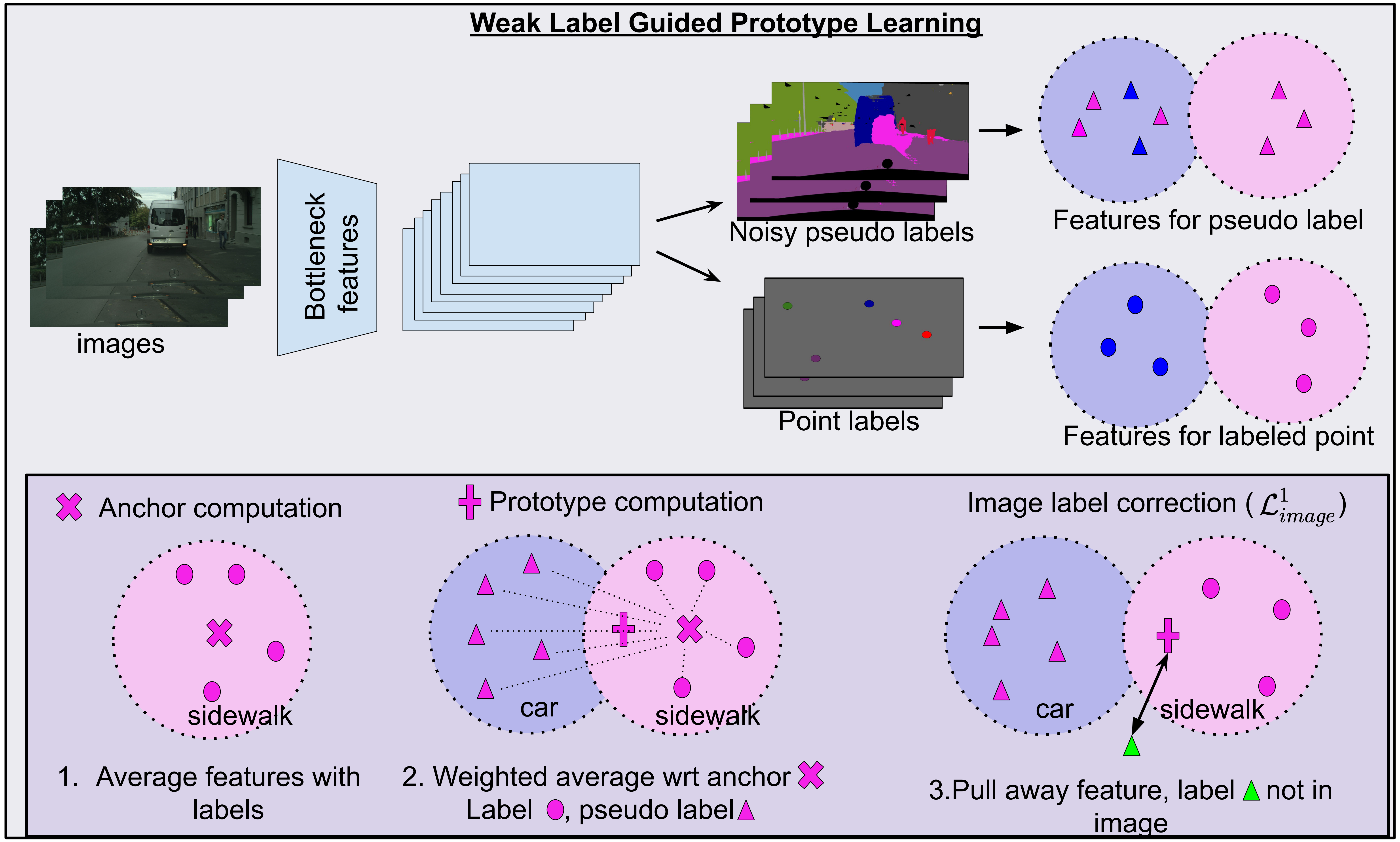
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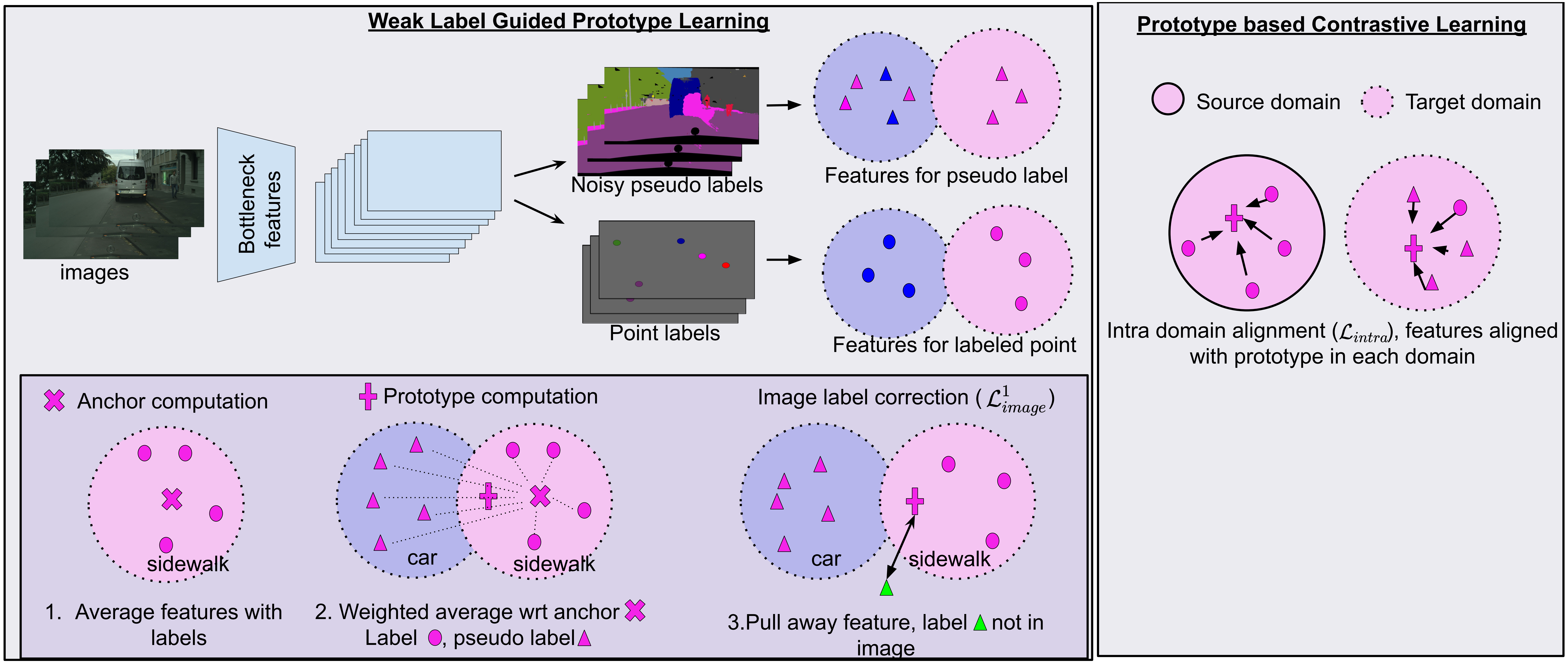
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Source domain
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Intra domain alignment ($\mathcal{L}_{intra}$), features aligned with prototype in each domain

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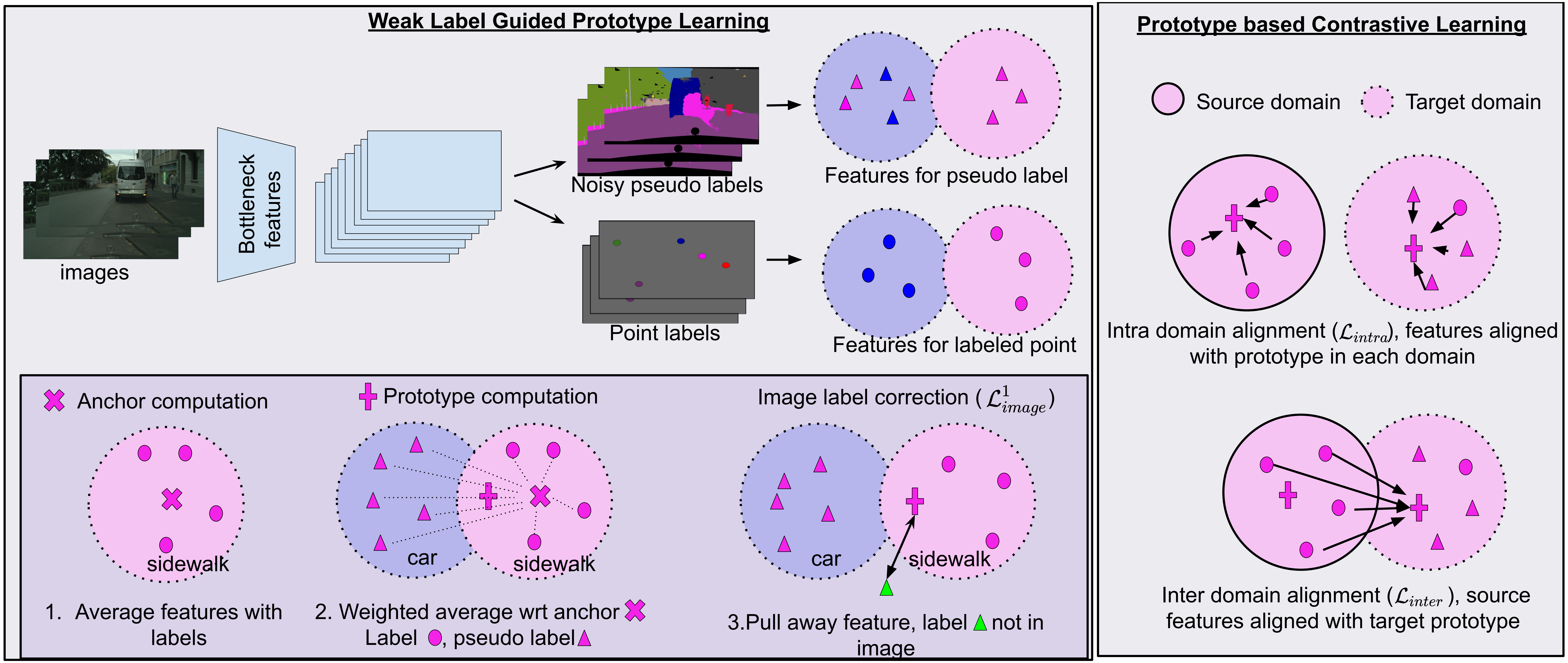

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Intra domain alignment ($\mathcal{L}_{intra}$), features aligned with prototype in each domain
Inter domain alignment ($\mathcal{L}_{inter}$), source features aligned with target prototype

Experimental setting

- **Standard UDASS setting**
  - GTA5 to Cityscapes
  - Synthia to Cityscapes
- **Additional weak labels from Cityscapes dataset**
  - image, point and coarse label
- **Metric for evaluation**
  - Mean Intersection of Union (mIoU) score
- **Segmentation network**
  - DeepLabv2 with ImageNet pre-training

Results (Comparison with SoTA)

	Method	GTA5 → Cityscapes mIoU	gap	Synthia → Cityscapes mIoU†	mIoU*	gap
	Source	36.6	+30.8	34.9	40.3	+33.6
UDA	CorDA[1]	56.6	+10.8	55.0	62.8	+11.1
	ProDA[2]	57.5	+9.9	55.5	62.0	+11.9
	DASS [3]	57.1	+10.3	55.6	62.9	+11.0
image	baseline	51.4	+16.0	36.1	39.1	+34.8
	WeakSegDA [4]	53.0	+14.4	50.6	58.5	+15.4
	Ours	**61.5**	**+5.9**	**61.3**	**63.9**	**+10.0**
point	baseline	54.9	+12.9	48.5	53.3	+20.6
	WeakSegDA [4]	56.4	+11.0	57.2	63.7	+10.2
	Ours	**64.7**	**+2.7**	**62.8**	**68.7**	**+5.2**
coarse	baseline	60.8	+6.6	54.6	59.1	+14.8
	Coarse-to-fine [5]	66.7	+0.7	61.6	67.2	+6.7
	Ours	**69.1**	**-1.7**	**66.0**	**71.0**	**+2.9**
	Supervised	67.4	0.0	68.8	73.9	0.0

- Our framework outperforms prior works and baseline by significant difference

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- Our framework outperforms prior works and baseline by significant difference
- Our framework bridges gap between UDA and supervised learning.
- For GTA5 to Cityscapes setting, coarse labels outperforms supervised learning.

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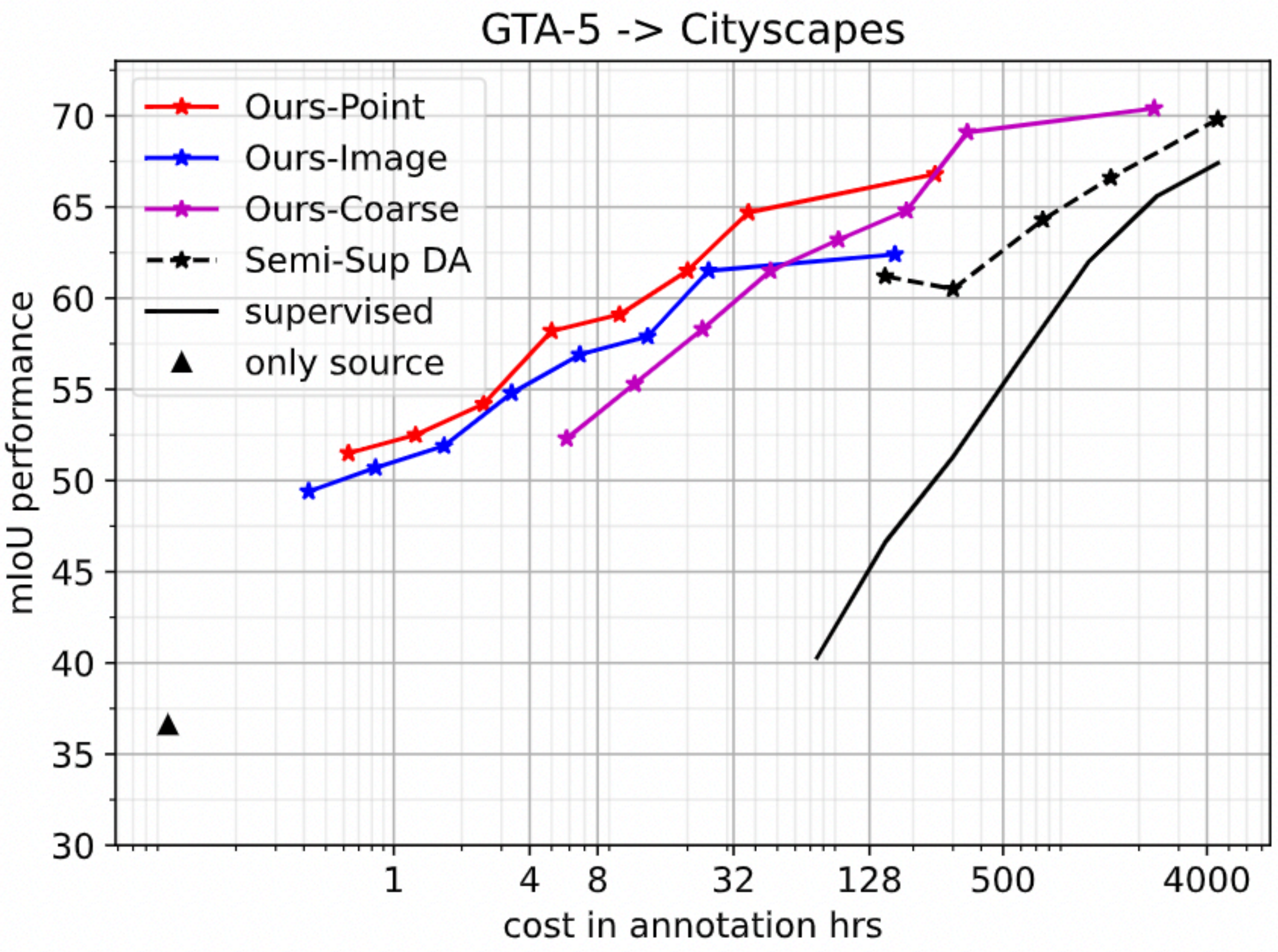
Results (Cost vs performance)



	Cost / image
Image label	30 sec
Point label	45 sec
Coarse label	7 min
Fine label	90 min

- Our framework using weak labels performs better than supervised learning and semi-supervised domain adaptation
- Within different weak labels, point labels gives best tradeoff for cost vs performance labels outperforms supervised learning.

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- **Poster Session:** WED-PM
- **Poster Id:** 293
- **Date and Time:** June 21, 4:30 pm - 6:00 pm