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Learning Affinity with Hyperbolic Representation for Spatial Propagation

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ICML 2023

Affinity & Spatial Propagation

What is Affinity?

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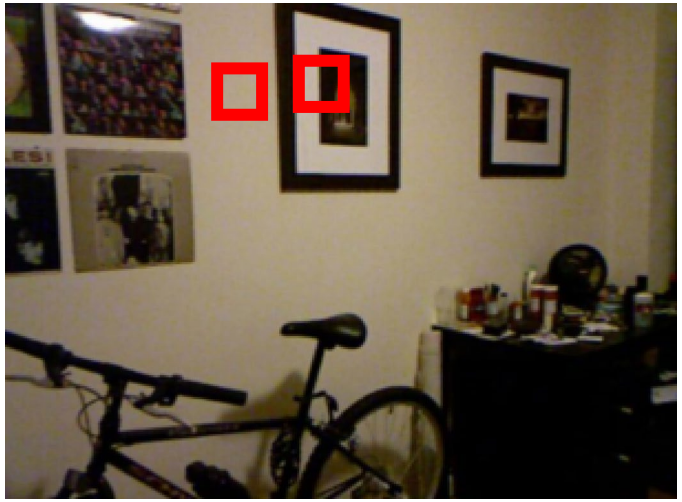
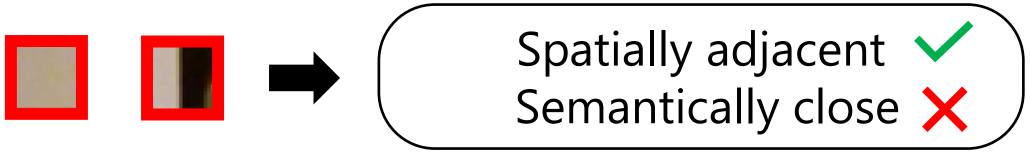
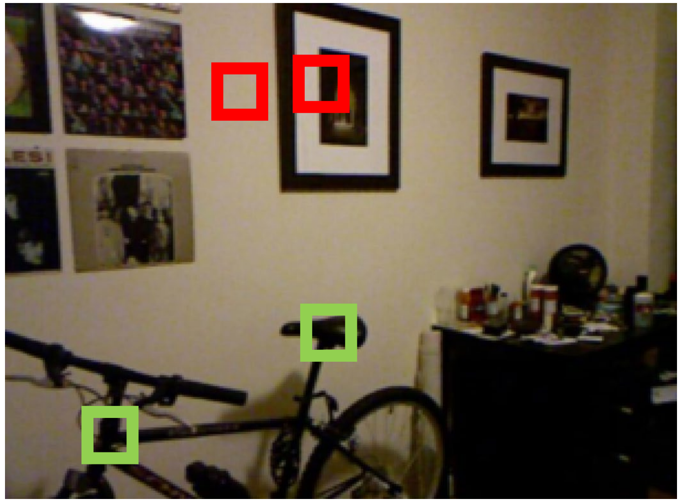


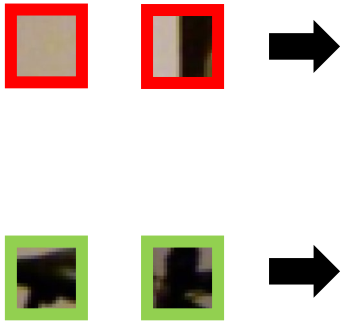


Affinity & Spatial Propagation

What is Affinity?

- ➢ Affinity describes *relationships* between pair of pixels or regions.





Spatially adjacent ✓
Semantically close ✗

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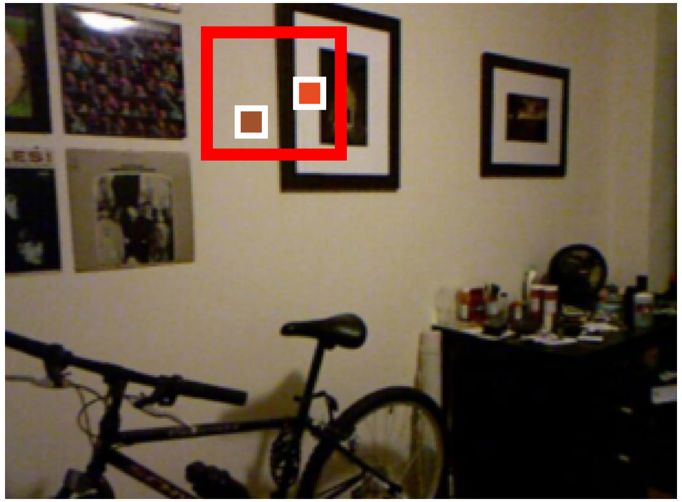
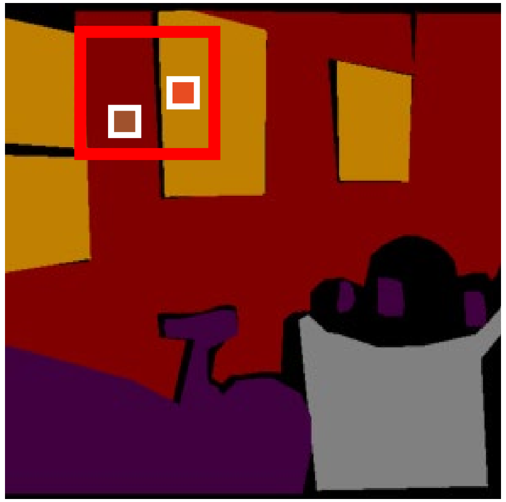




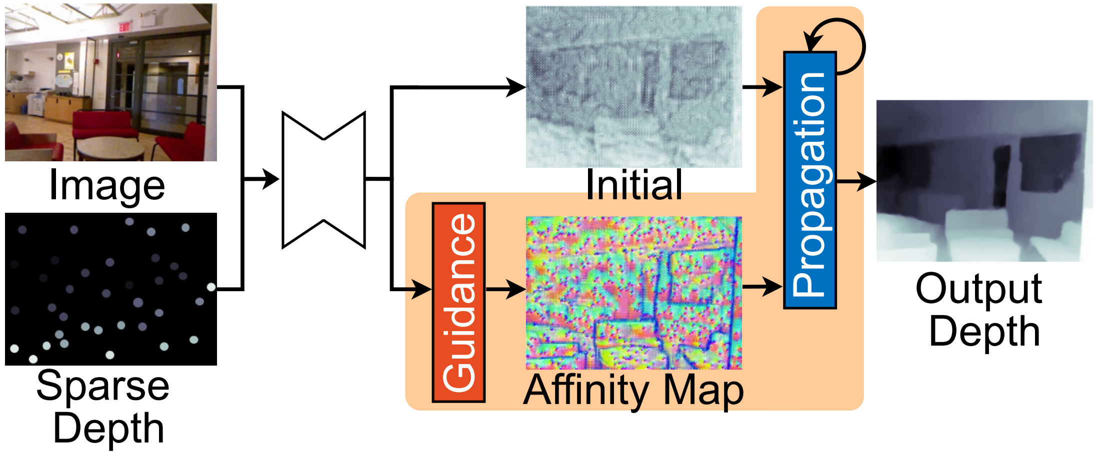
Semantic Label

Depth Label

Affinity & Spatial Propagation

Spatial Propagation Network (SPN)

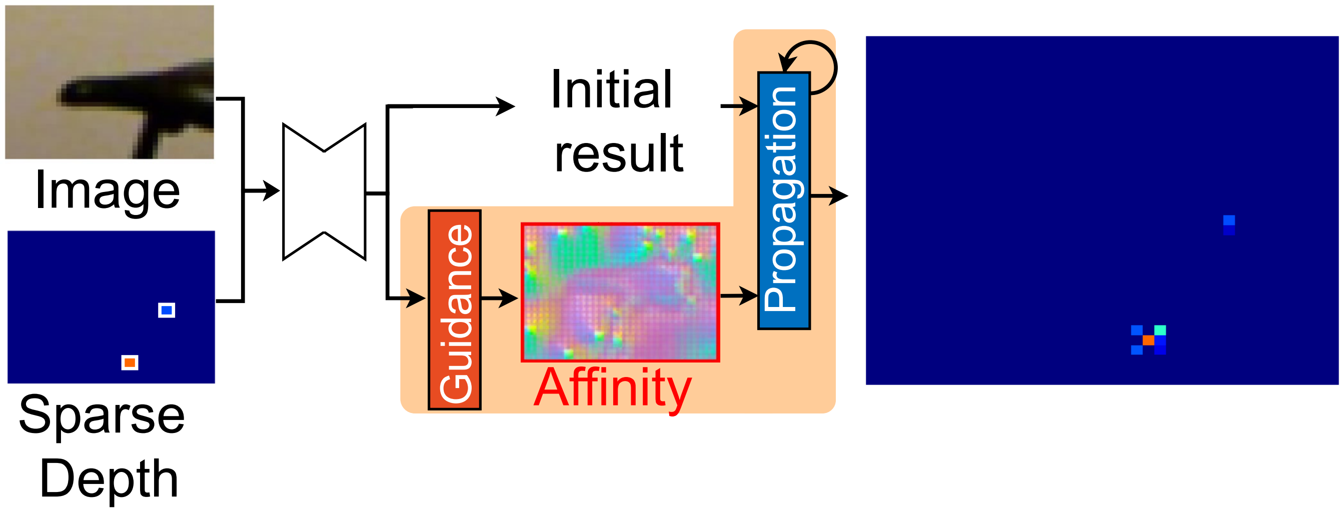
- It contains a *guidance network* and *a propagation module*.
- The *guidance network* learns pixel-wise relationships, *affinity*.
- Using the learned *affinity*, the *propagation module* can improve the details by incorporating contextual information.



[CSPN] Xinjing et al. Depth estimation via affinity learned with convolutional spatial propagation network. In ECCV, 2018

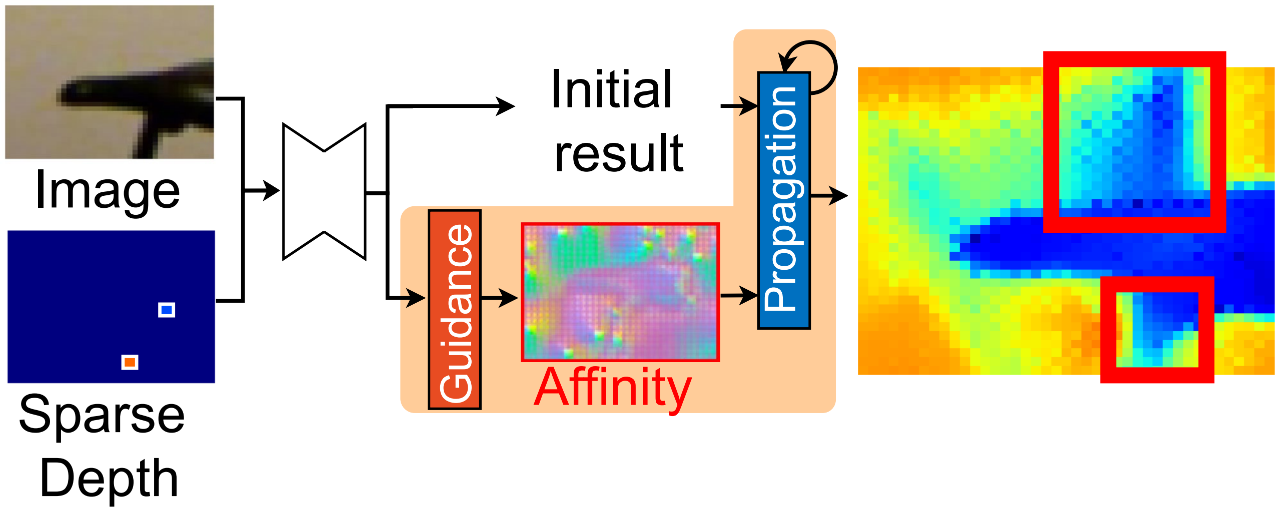
Problem Definition

Occurrence of bleeding error



Problem Definition

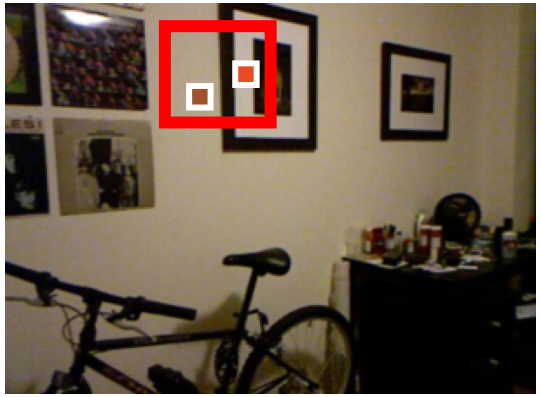
Occurrence of bleeding error



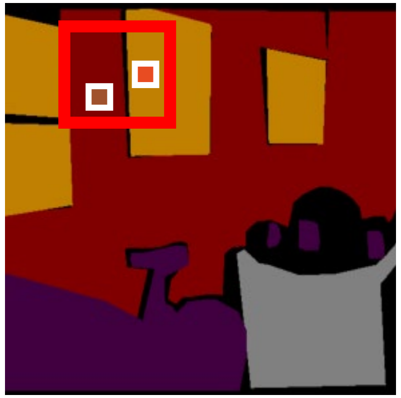
➢ To alleviate the vagueness of measuring pixel affinity, a **hierarchical structure** was proposed as a solution in several pioneer studies.
- Edge-preserving filter (Bao et al., 2013; Dai et al., 2015)
- Non-local cost aggregation (Yang, 2012; 2014)
- Measure the image boundary connectivity (Tu et al., 2016)

Hierarchical Structures in Affinity Learning

Pixel hierarchy in spatial propagation task

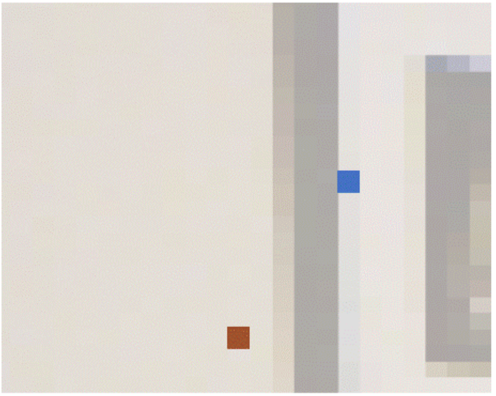


Image

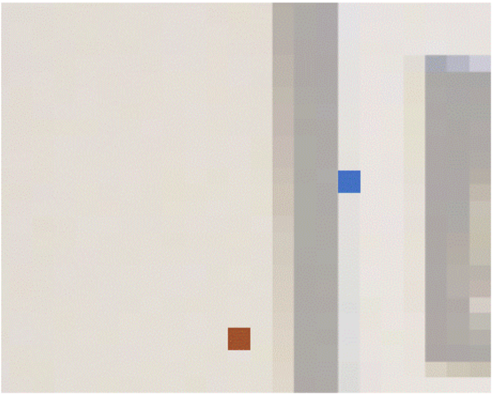


Semantic Label

Depth Label



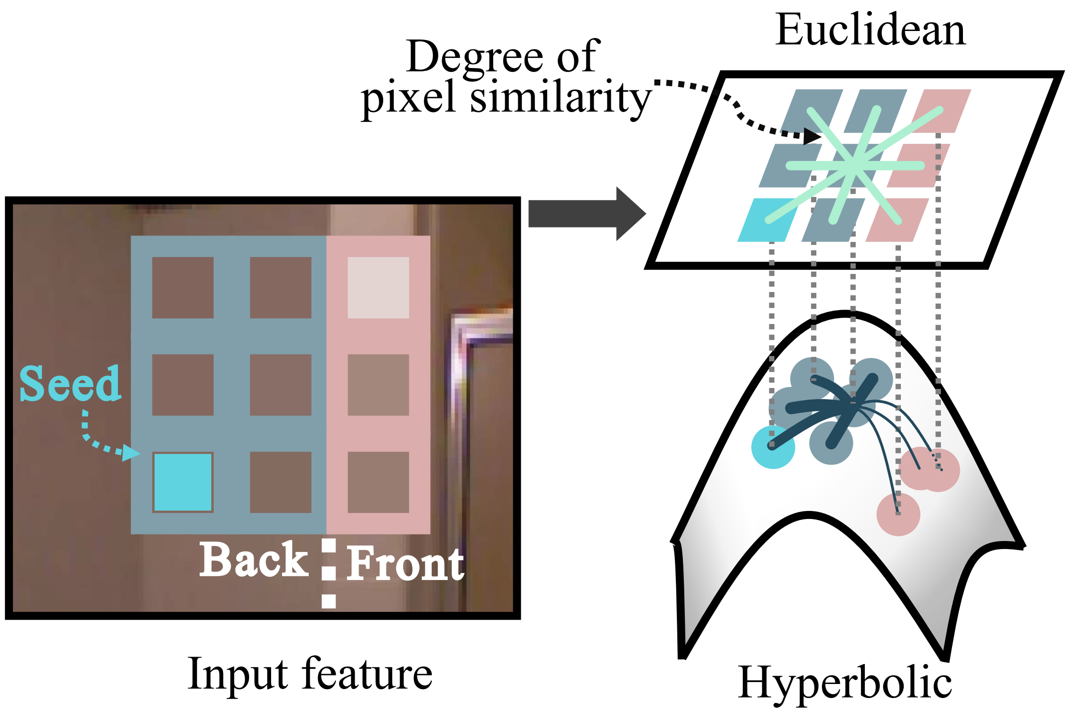
Iteration 0

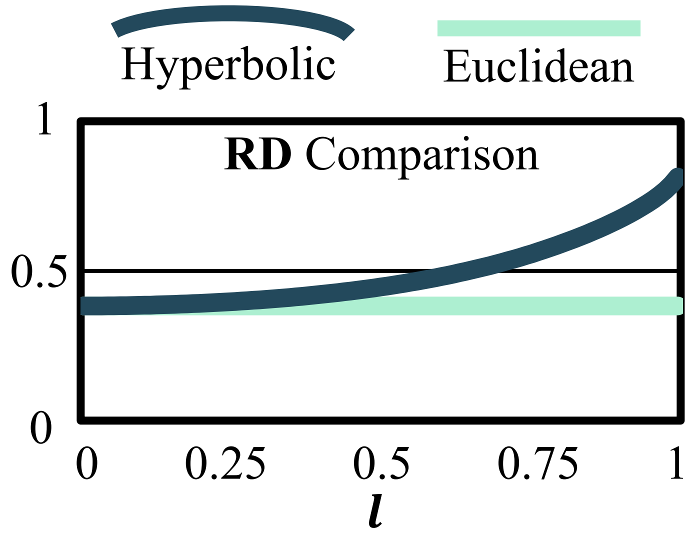


Semantic Segmentation

Depth Completion

Hyperbolic Embedding for Hierarchical Structure

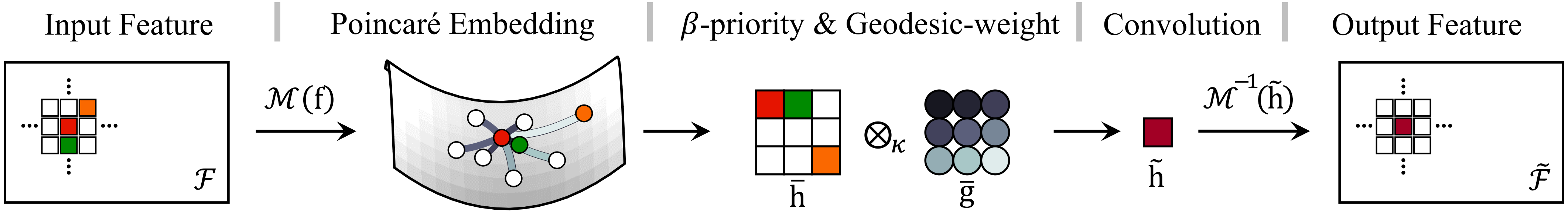




- **[Exponential growth property]** Compared to Euclidean space, the volume of hyperbolic space grows exponentially with the radius, allowing exponentially growing hierarchies and tree-like structures.
- **[Distinction Property]** By embedding pixel features into hyperbolic space, it alleviates the bleeding problem by enhancing the "Distinction" between unrelated pixel features.

Working of HAM

Hyperbolic Affinity learning Module (HAM)



Working of HAM

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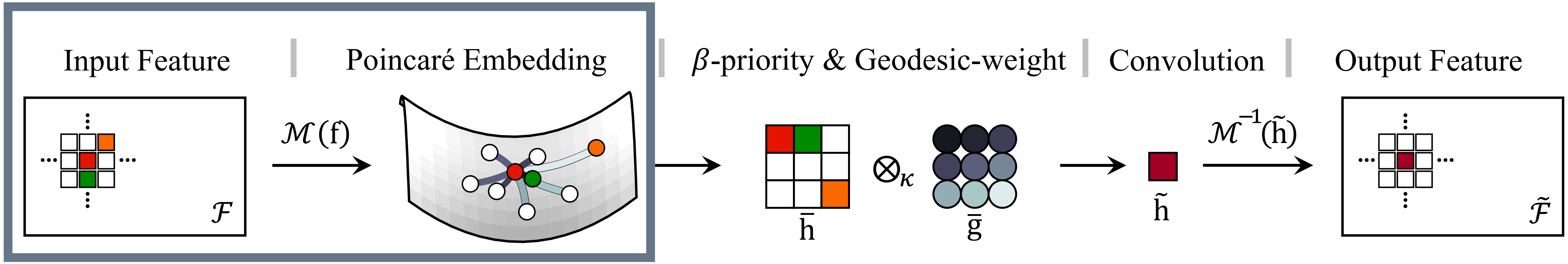

Working of HAM

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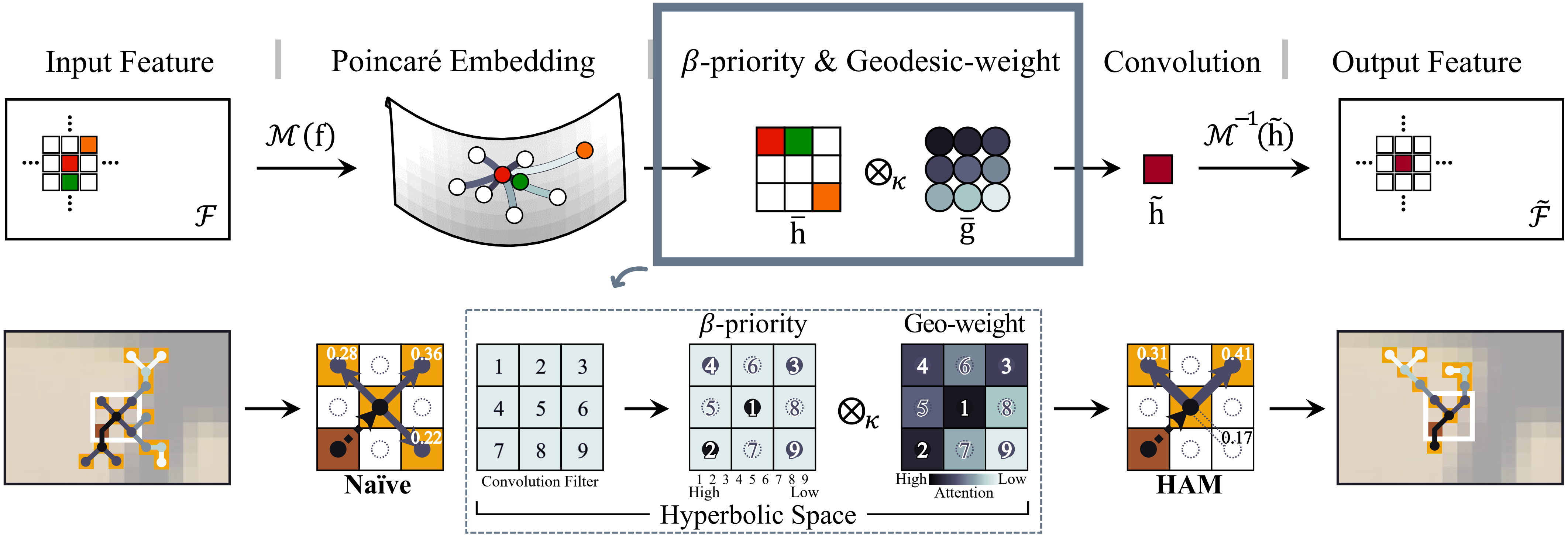

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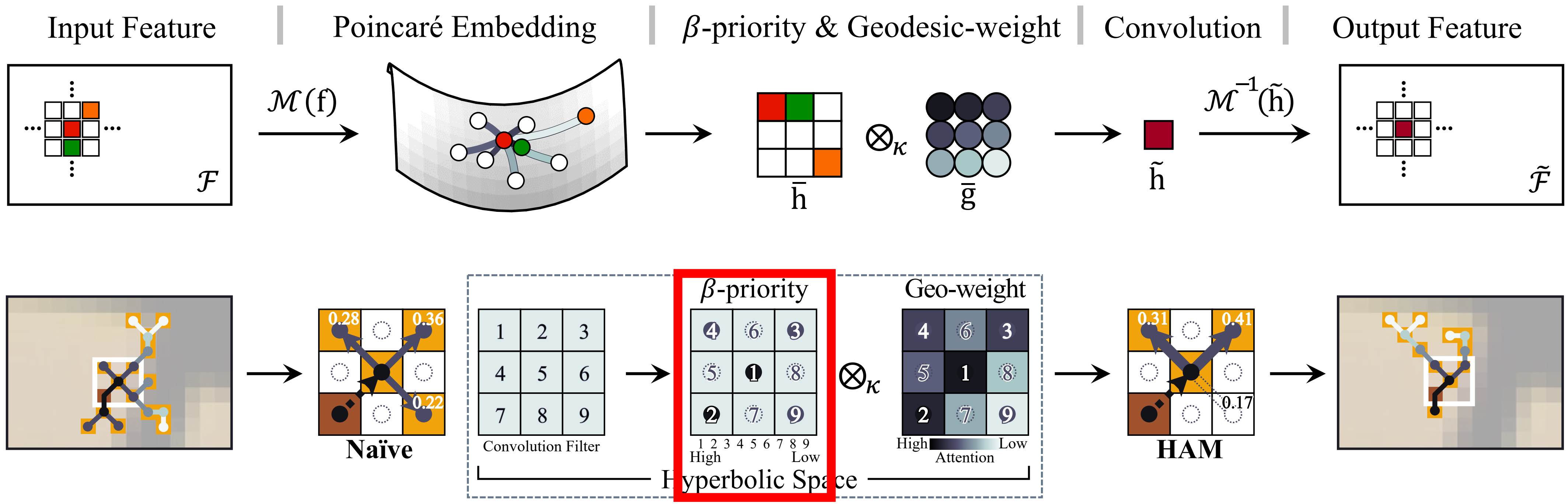
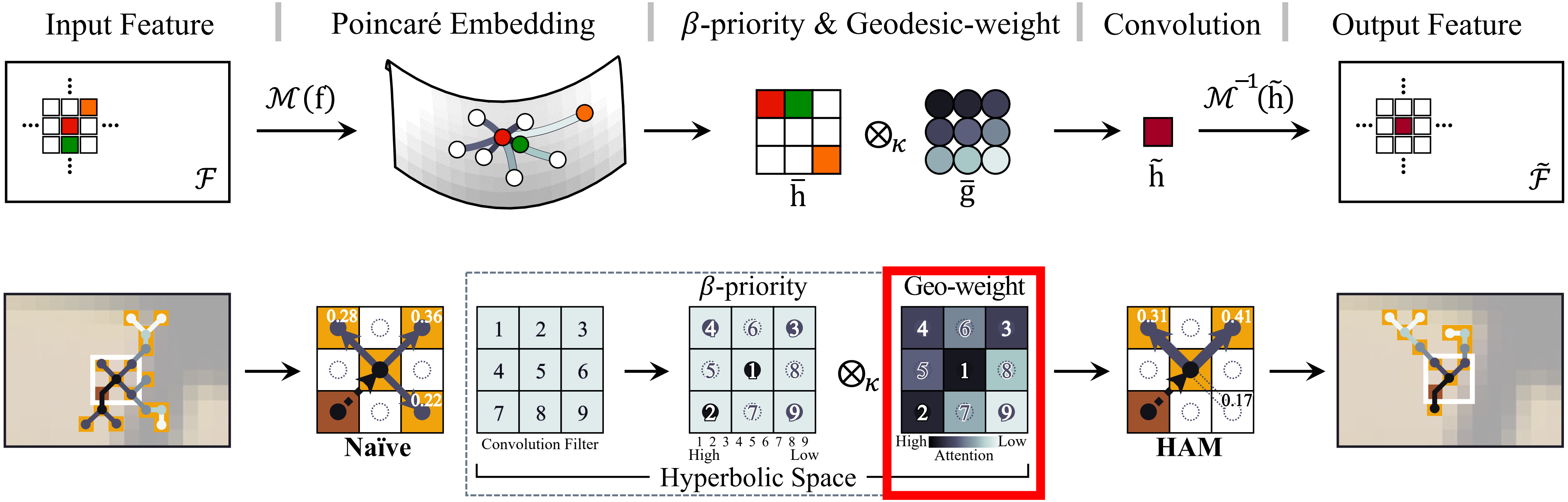


Beta-priority

- Assign a priority for the closer hyperbolic feature vectors.
- Rearranges features in the order of the distance between a reference pixel and its neighbors.

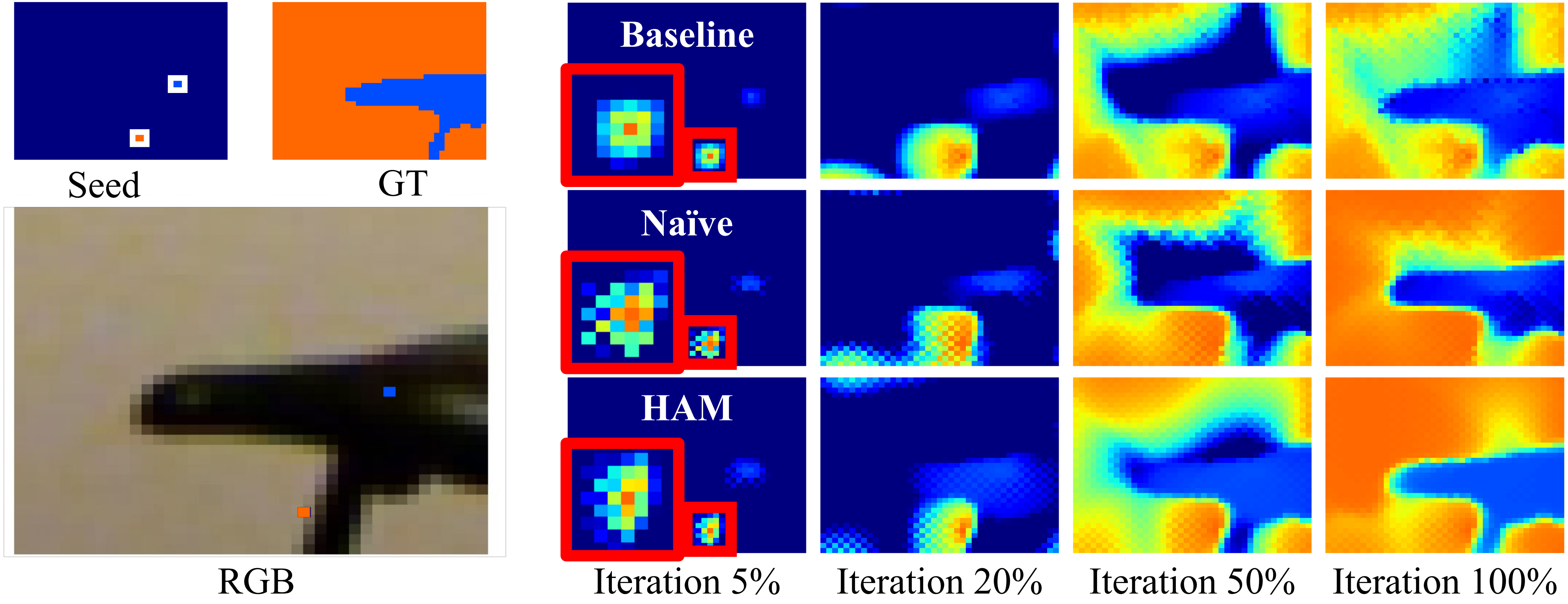
Working of HAM



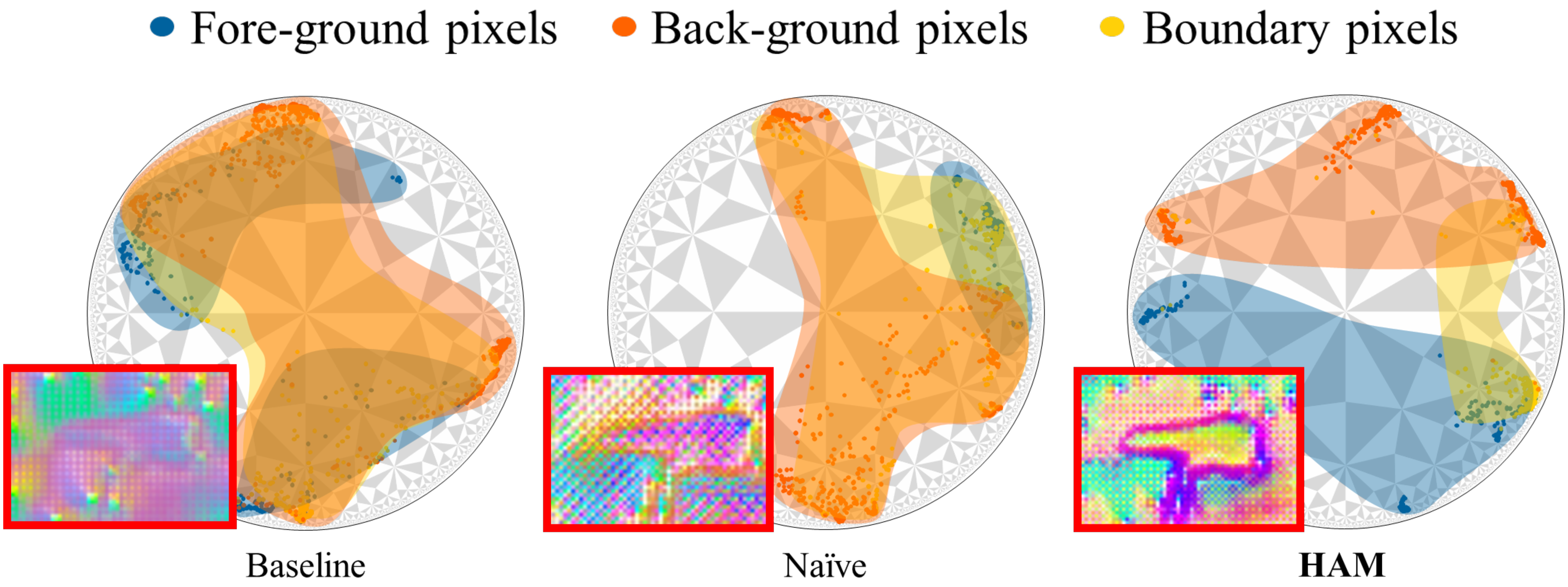
Geodesic weight

- Selectively aggregate pixel information with high affinity values.
- Normalize the geodesic distances among pixels and conduct weighted aggregation.

Experiments & Results



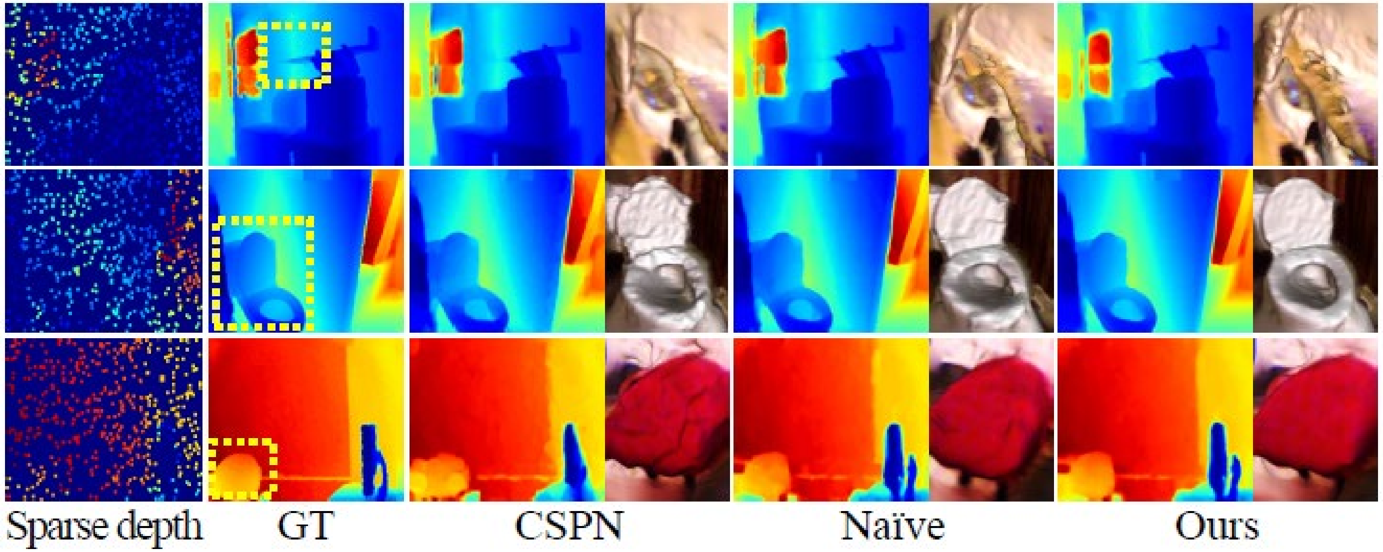
Experiments & Results



Experiments & Results

Depth Completion

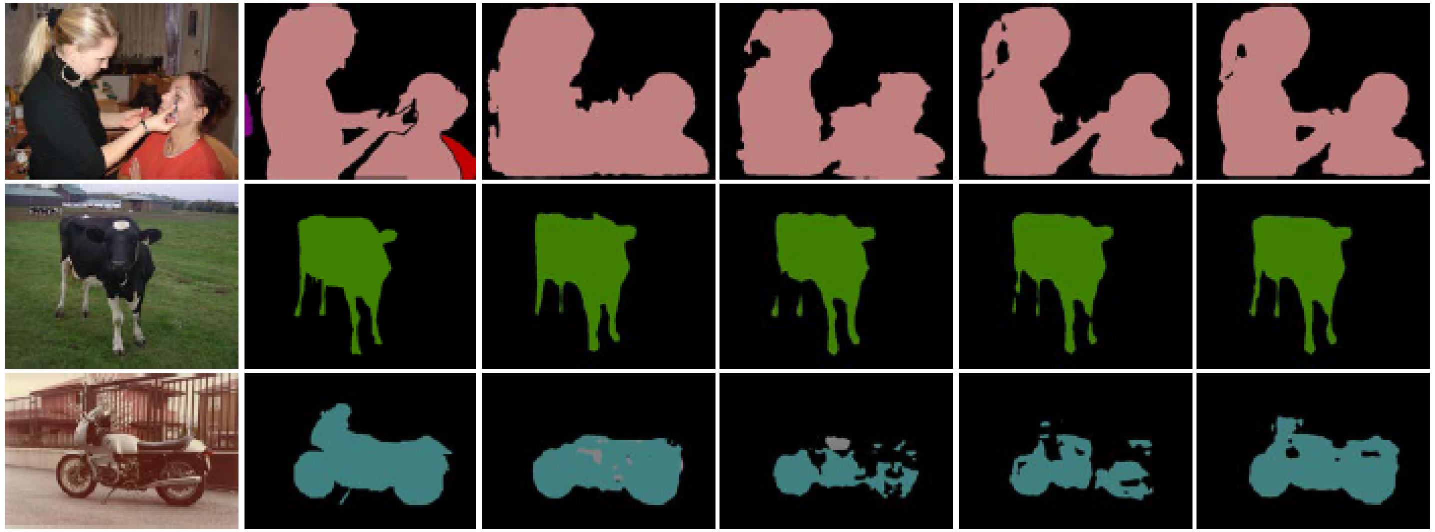
	NYUv2						ScanNet						Virtual-KITTIv2					
	RMSE	MAE	iRMSE	iMAE	REL	$\delta^1_{1.25}$	RMSE	MAE	iRMSE	iMAE	REL	$\delta^1_{1.25}$	RMSE	MAE	iRMSE	iMAE	REL	$\delta^1_{1.25}$
CSPN	0.116	0.048	0.018	0.007	0.017	0.993	0.080	0.027	0.027	**0.009**	0.014	**0.993**	12.233	8.261	0.035	0.023	0.606	0.529
Naïve	0.108	0.043	0.017	**0.006**	0.015	**0.994**	0.078	0.027	**0.026**	**0.009**	0.014	**0.993**	10.946	7.266	0.034	0.022	0.539	0.542
Ours	**0.102**	**0.036**	**0.016**	**0.006**	**0.014**	**0.994**	**0.073**	**0.024**	0.027	**0.009**	**0.013**	**0.993**	**9.612**	**6.661**	**0.030**	**0.021**	**0.489**	**0.561**



Experiments & Results

Semantic Segmentation

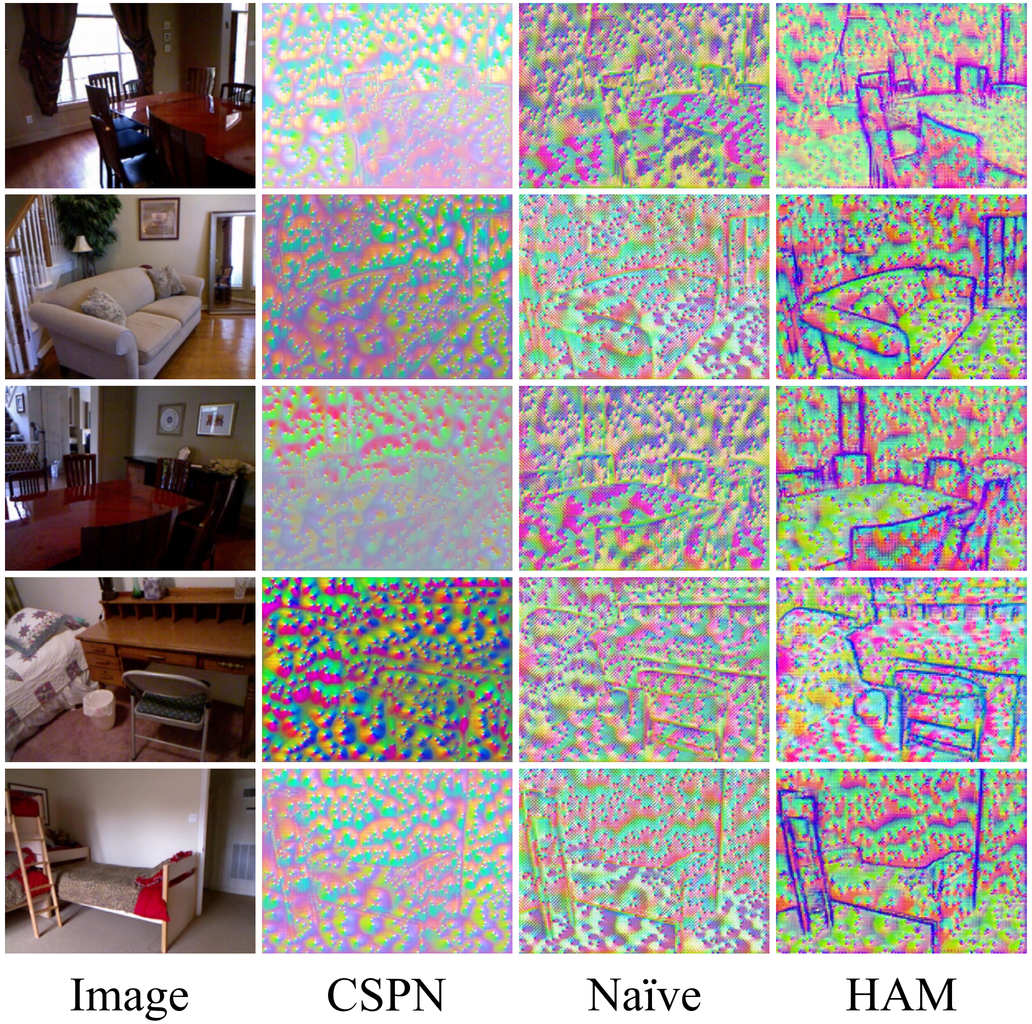
	Pascal Context		NYUv2		ADE20K	
	mIoU	Pix-Acc	mIoU	Pix-Acc	mIoU	Pix-Acc
Sim-Deeplab	57.12	72.69	28.42	57.09	21.69	60.09
DifNet	59.77	74.19	28.91	57.48	23.30	63.21
Naïve	60.18	74.51	28.19	56.78	23.44	63.92
Ours	**60.30**	**74.81**	**30.45**	**58.97**	**25.28**	**63.94**



Input image GT Sim-Deeplab DifNet Naïve Ours

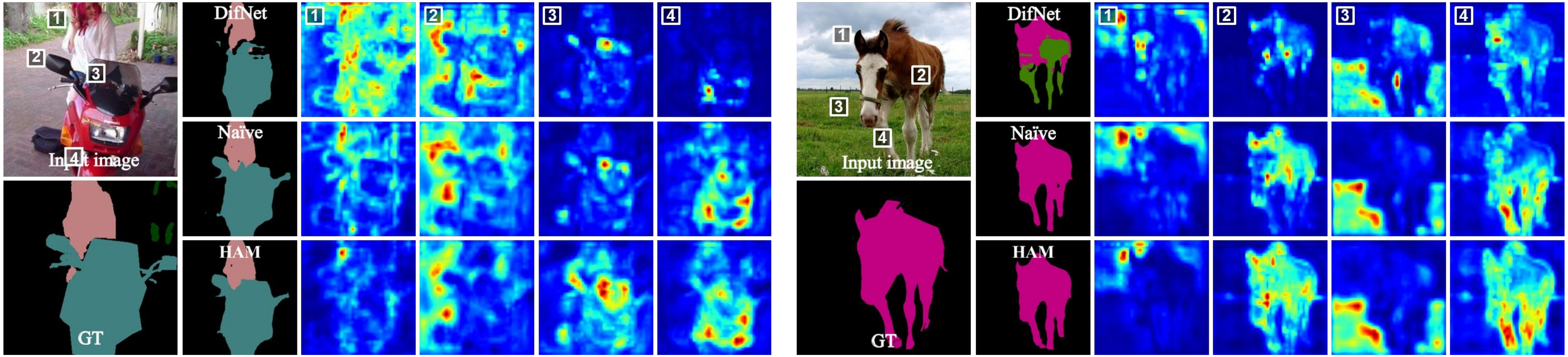
Experiments & Results

Qualitative comparison of affinity maps



Experiments & Results

Illustrations of similarity maps



Thanks for your attention!

Learning Affinity with Hyperbolic Representation for Spatial Propagation

[Github]

https://github.com/JinhwiPark/HyperbolicSpatialPropagation