

iDisc: Internal Discretization for Monocular Depth Estimation

Luigi Piccinelli, Christos Sakaridis, Fisher Yu

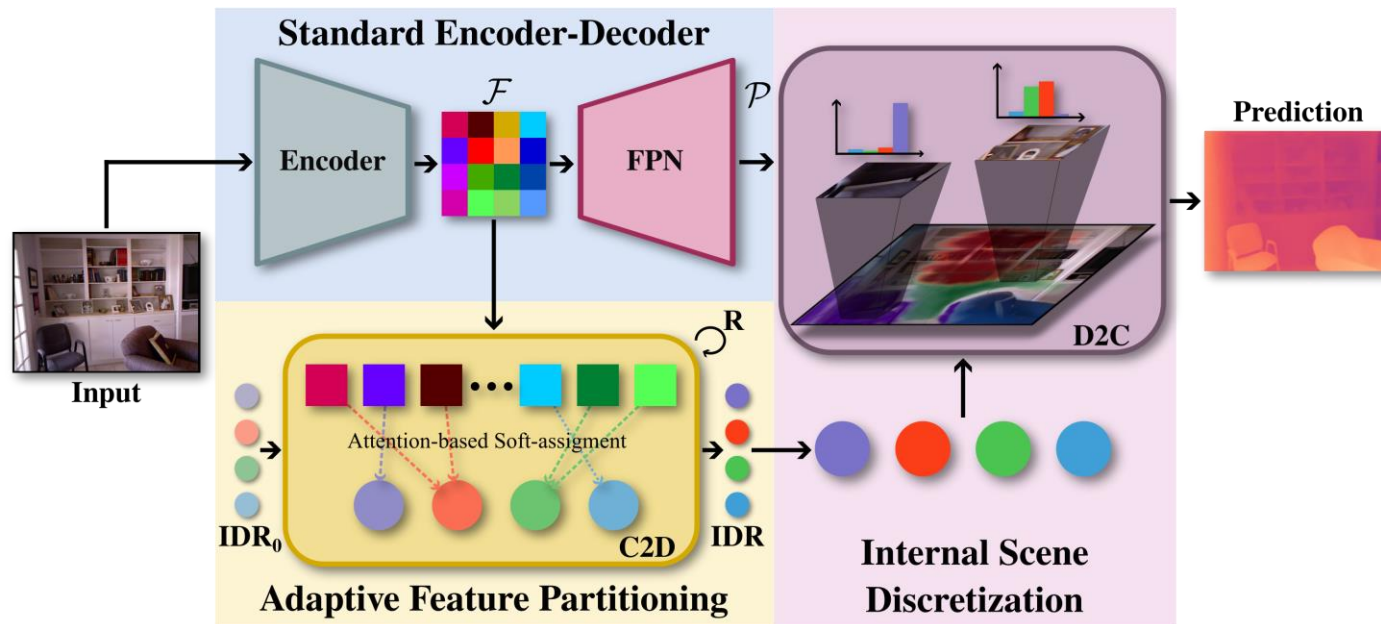
Poster THU-PM-083

Project page: `vis.xyz/pub/idisc`

Code and models: `github.com/SysCV/idisc`

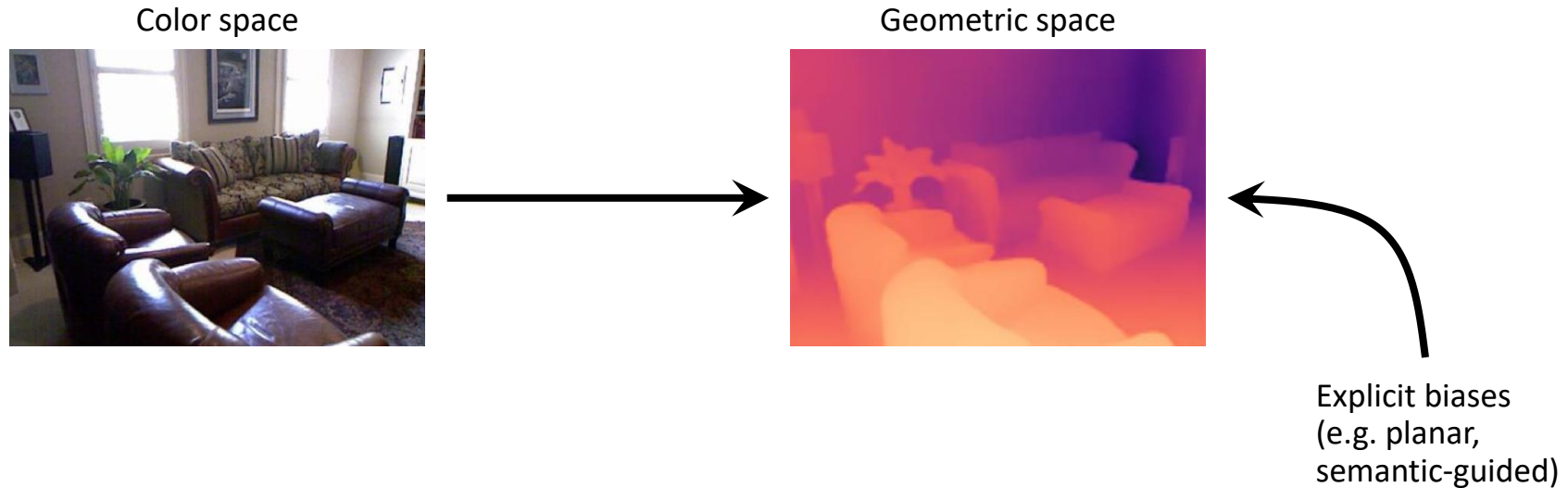
Overview iDisc

- Lift any handcrafted bias imposed on the scene representation.
- One assumption only: scene is a discrete set of high-level concepts.
- iDisc meta-learns the best internal representations.



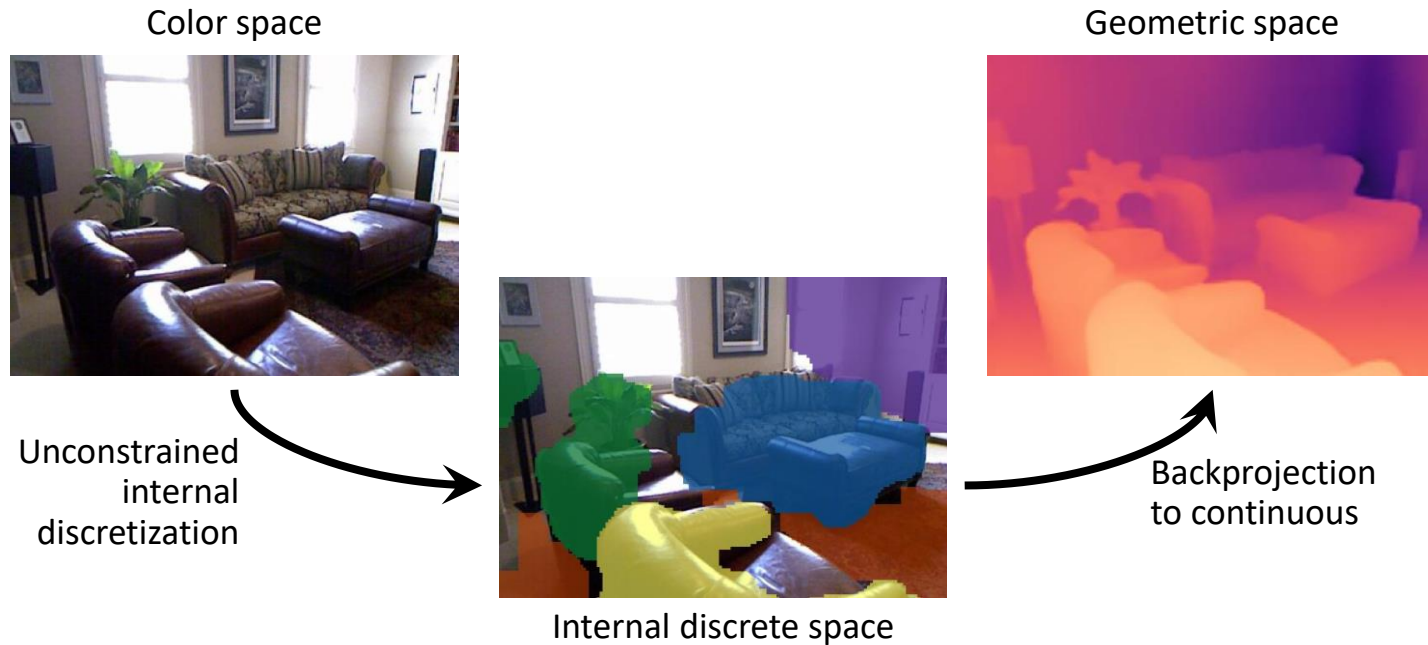
Monocular and biases

- Ill-posed problem, priors are needed.
- Typically, the scene representation is handcraftedly biased.
- Can it learn how to generate appropriate “priors” for the given input?



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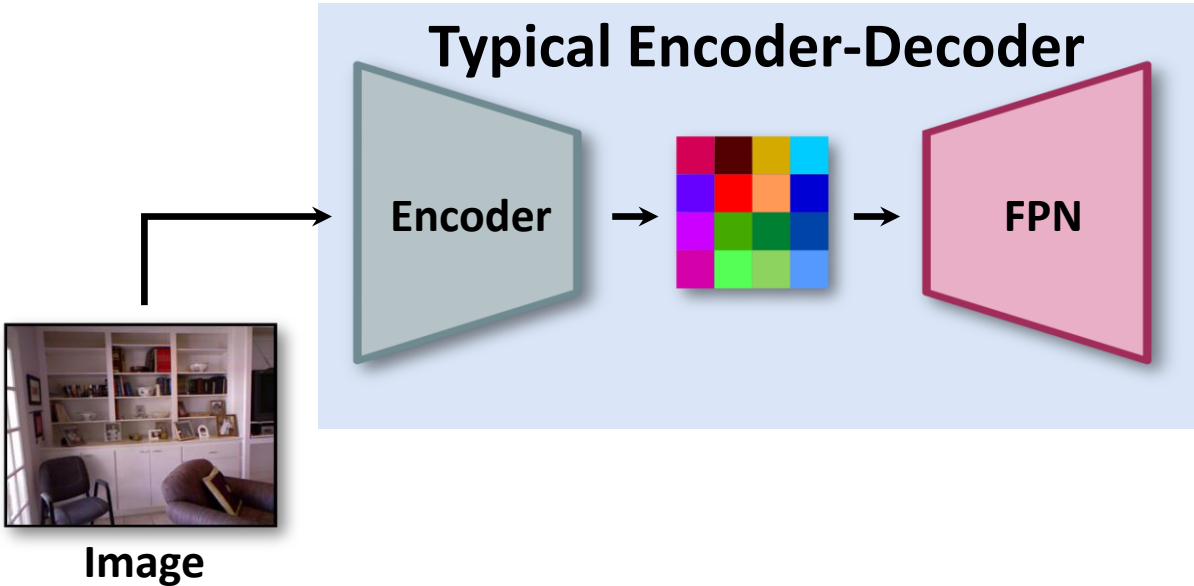


What is a concept?

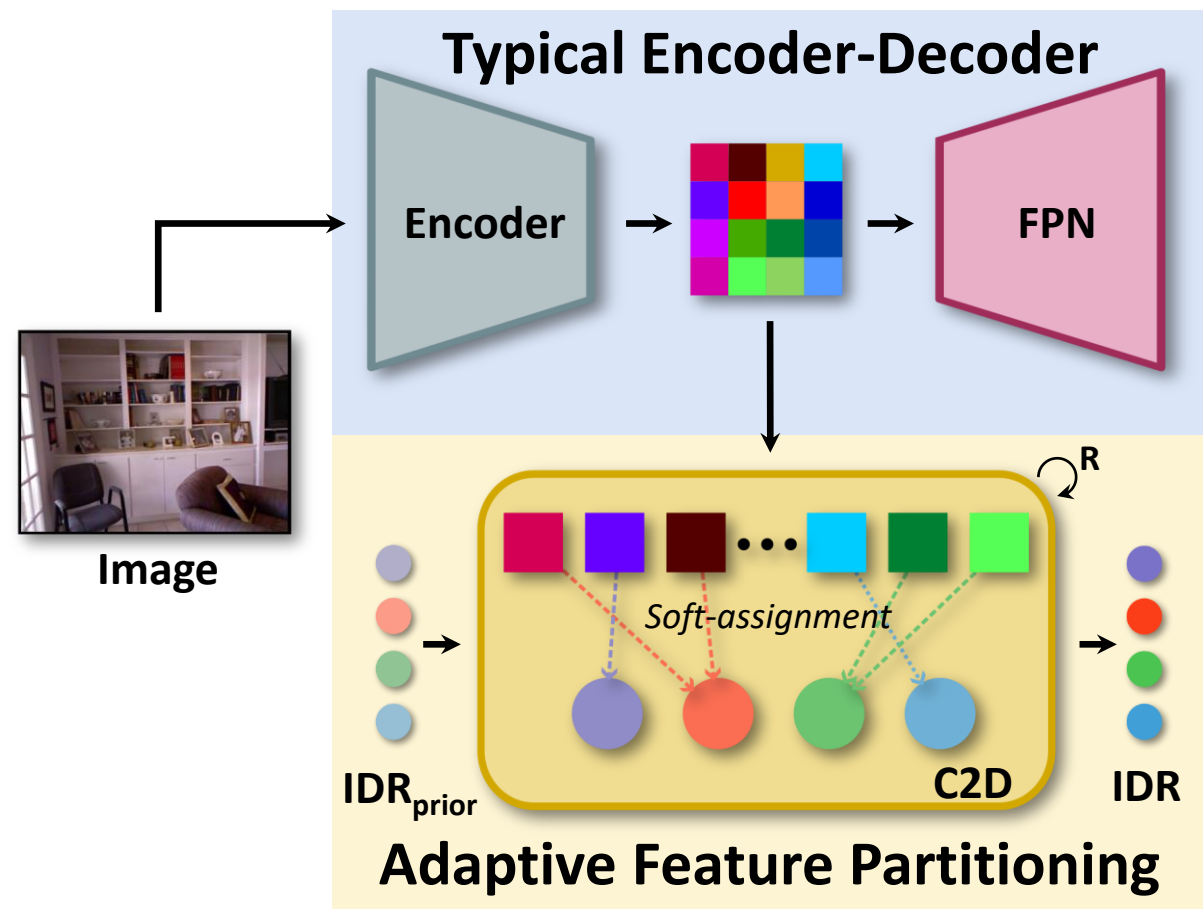
- Set of high-level structures deemed appropriate to describe the scene.
- Internal discrete representations learned without any supervision.



Architecture



Architecture



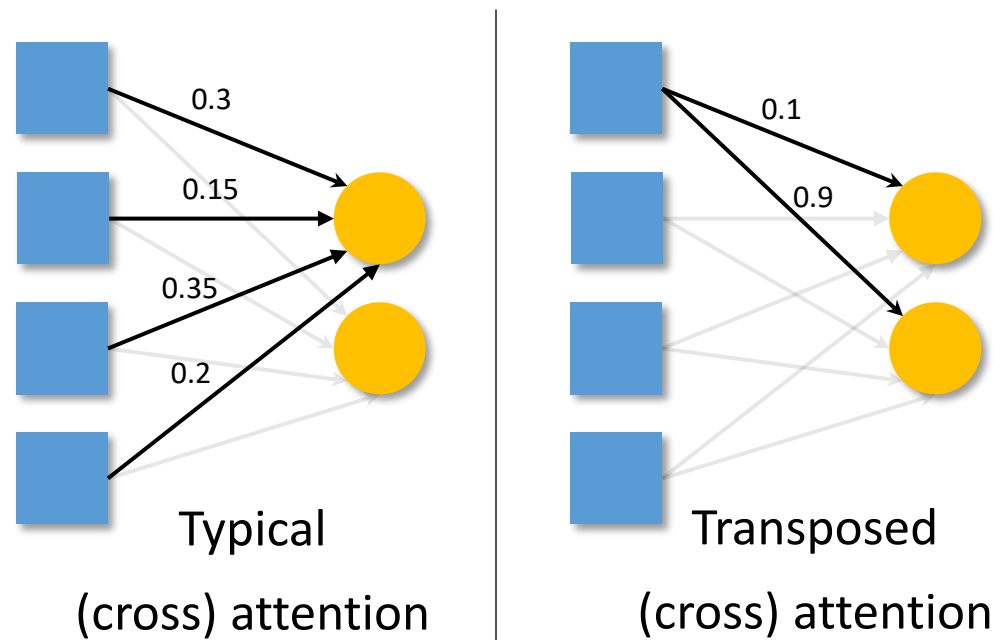
$$Q_{i+1} = [\text{softmax}(\mathbf{K}Q_i^{[T]})]^{[T]} \mathbf{V}$$

Partitioning

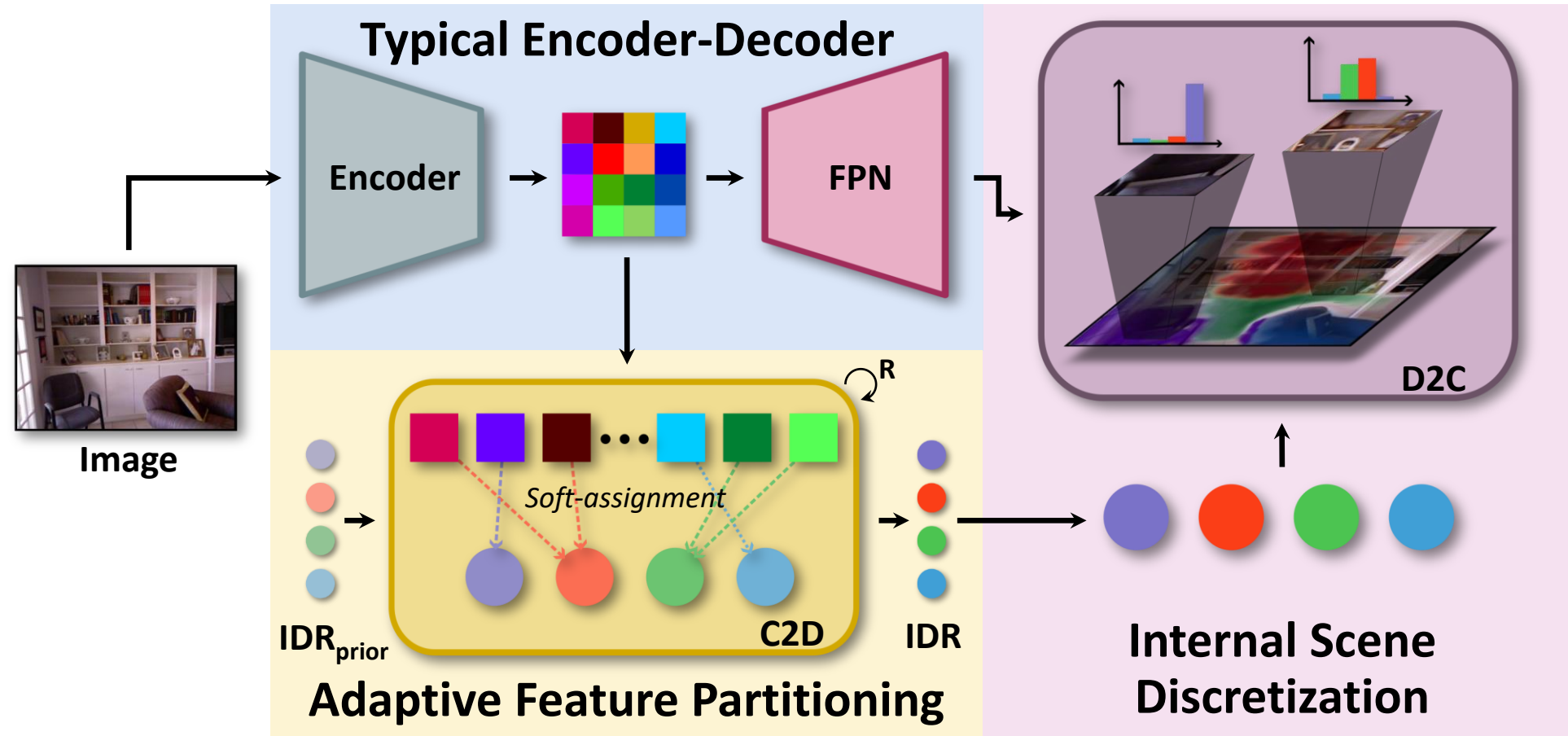
$$Q_0 = \mathbf{IDR}_{\text{prior}}$$

$$\mathbf{IDR} = Q_R$$

Adaptive



Architecture



$$D_{i+1} = \text{softmax}(\mathbf{Q}_i \mathbf{K}_i^T) \mathbf{V}_i + D_i, \quad i \in 0..N$$

$$\mathbf{Q}_i = f_{Q_i}(\mathbf{P})$$

$$\mathbf{K}_i = f_{K_i}(\text{IDR})$$

$$\mathbf{V}_i = f_{V_i}(\text{IDR})$$

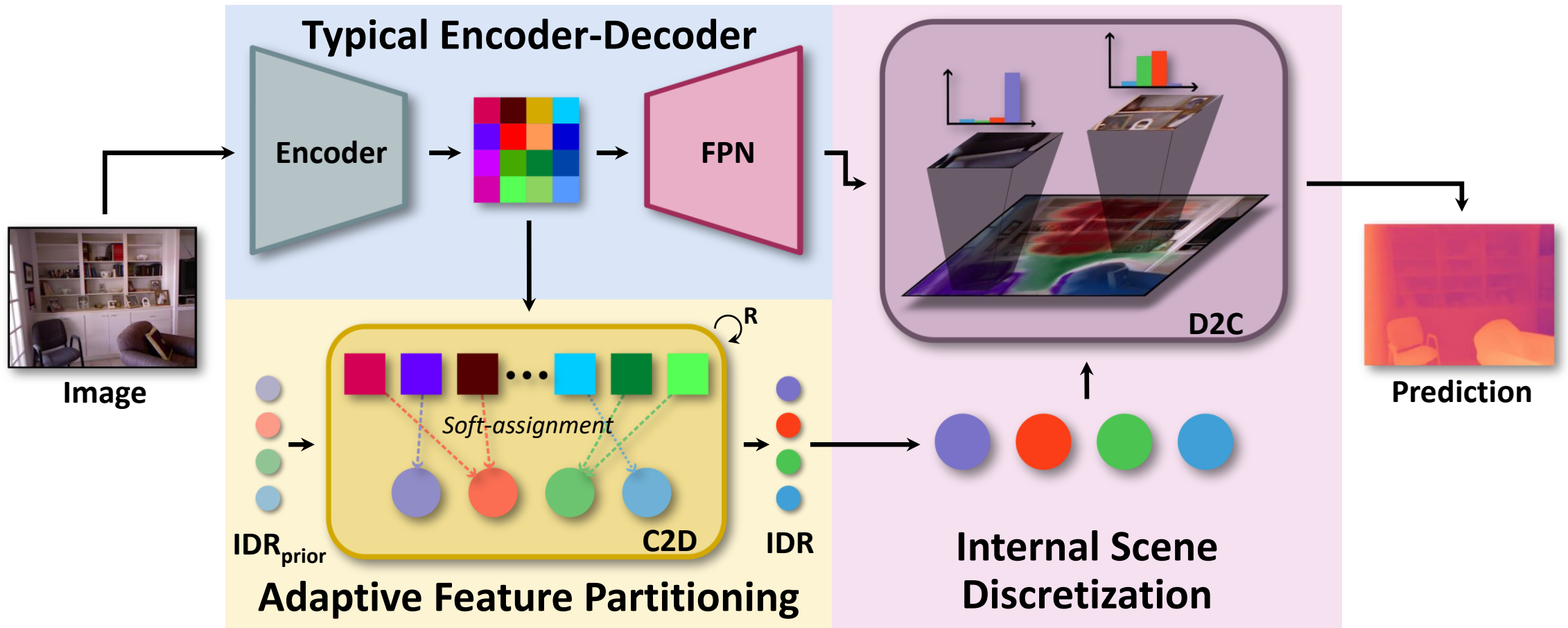
Degenerates to standard depth discretization if:

$$\mathbf{Q} = f_Q(\mathbf{P}), \quad \mathbf{F} = \mathbf{K} \|\mathbf{v}$$

$$D_0 = \emptyset, \quad N = 0, \quad R = 0$$

$$\Rightarrow \mathbf{D} = \text{softmax}(\mathbf{Q} \mathbf{K}^T) \mathbf{v}$$

Architecture



Quantitative results (common benchmarks)

Table 1. NYU-Depth v2 official test set results.

Method	$\delta_1 \uparrow$	RMS \downarrow	A.Rel \downarrow
BTS	0.964	2.459	0.057
AdaBins	0.964	2.360	0.058
DPT	0.965	2.315	0.059
NeWCRF	0.974	2.129	0.052
iDisc	0.977	2.067	0.050

Quantitative results (common benchmarks)

Table 2. KITTI-Eigen split validation set results.

Method	$\delta_1 \uparrow$	RMS \downarrow	A.Rel \downarrow
BTS	0.885	0.392	0.110
AdaBins	0.903	0.364	0.103
DPT	0.904	0.357	0.110
NeWCRF	0.922	0.334	0.095
iDisc	0.940	0.313	0.086

Table 3. KITTI official online benchmark results.

Method	$SI_{\log} \downarrow$	iRMS \downarrow	A.Rel \downarrow
ViP-DeepLab	10.80	11.77	0.089
NeWCRF	10.39	11.03	0.084
PixelFormer	10.29	10.84	0.082
iDisc	9.89	10.73	0.081

Quantitative results (proposed benchmarks)

Table 4. Results on Argoverse1.1 proposed split.

Method	$\delta_1 \uparrow$	RMS \downarrow	A.Rel \downarrow
BTS	0.780	8.319	0.267
AdaBins	0.750	8.686	0.195
NeWCRF	0.707	9.437	0.232
iDisc	0.821	7.567	0.163

Table 5. Results on DDAD proposed split.

Method	$\delta_1 \uparrow$	RMS \downarrow	A.Rel \downarrow
BTS	0.757	10.11	0.186
AdaBins	0.748	10.24	0.201
NeWCRF	0.702	10.98	0.219
iDisc	0.809	8.898	0.163

Quantitative results (generalization)

Table 6. Zero-shot testing SI_{\log} results.

Method	SUN	Diode	Argoverse	DDAD
BTS	14.25	23.78	51.80	40.51
AdaBins	13.20	22.54	52.33	50.71
NeWCRF	11.27	18.69	46.77	44.24
iDisc	10.91	18.11	33.35	29.37

Table 7. NYU-Surface v2 official test set results.

Method	$11.5^\circ \uparrow$	RMS \downarrow	Median \downarrow
GeoNet	0.484	26.9	11.8
GeoNet++	0.502	26.7	11.2
Bae et al.	0.622	23.5	7.5
iDisc	0.638	22.8	7.3



Ground Truth



AdaBins



NeWCRF



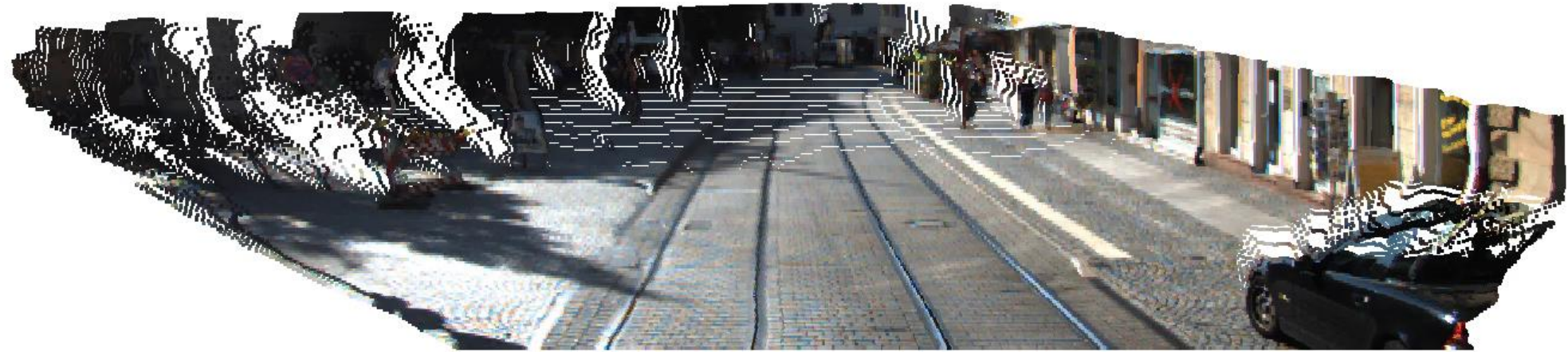
Ours



Ground Truth



Ours





Input image



4 IDR attentions



Depth output



Normals output

Conclusion

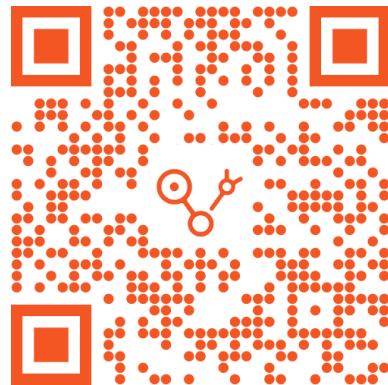
- Despite the ill-posed problem, handcrafted biases are limiting.
- Input-dependent representations allow better generalization.
- General architecture for any dense real-valued tasks.



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