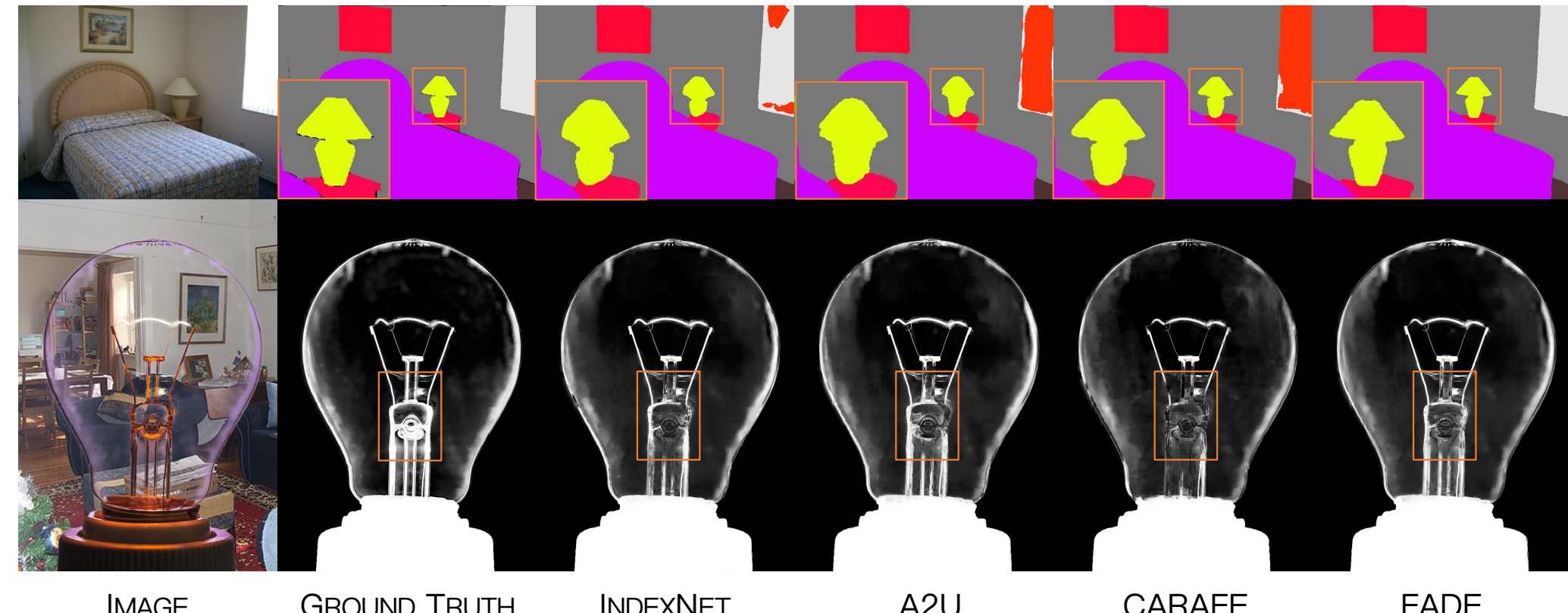


## Motivations & Contributions

**Observations:** Some tasks like semantic segmentation and instance segmentation are region-sensitive, while some tasks such as image super-resolution and image matting are detail-sensitive. It is difficult for the same upsampling operator to generate semantically consistent features and recover boundary details simultaneously.



### Motivations:

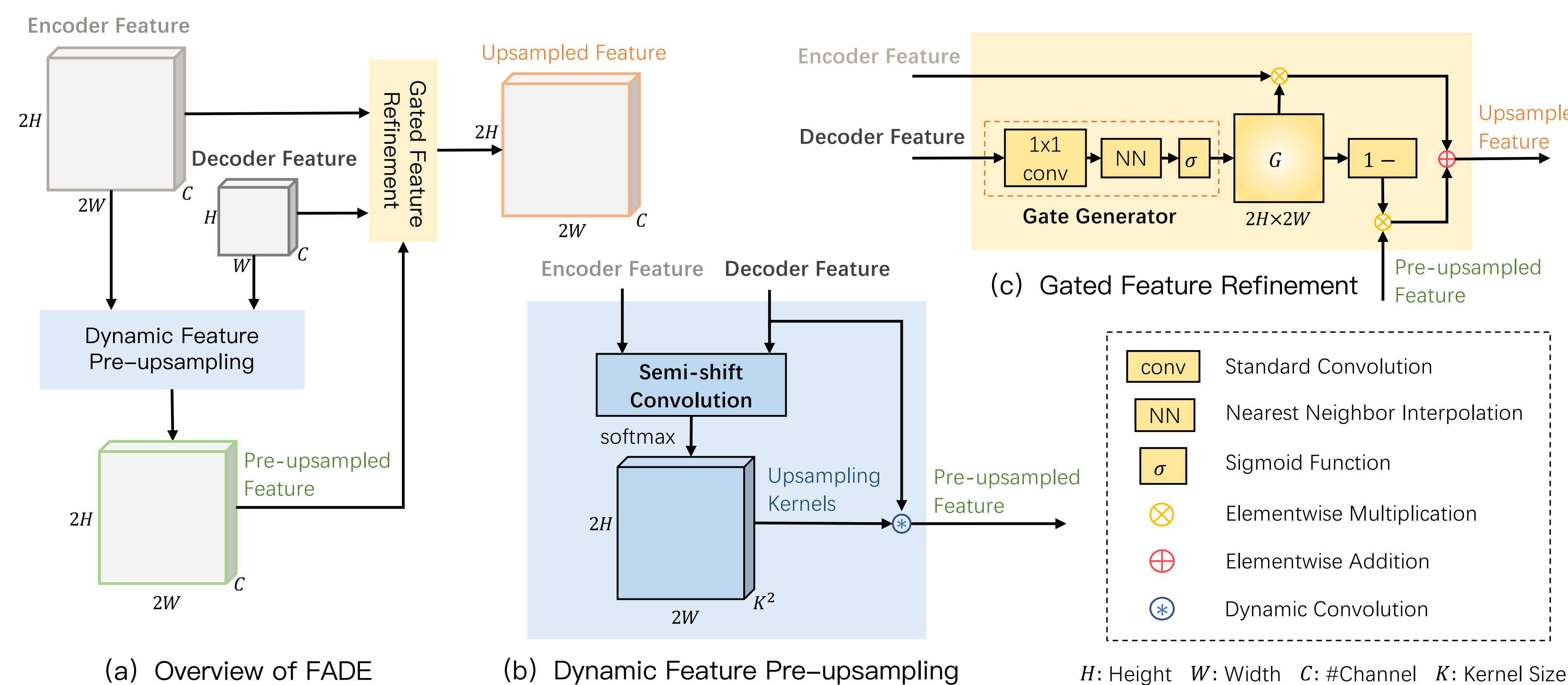
- Existing upsampling operators often can work well in either type of the tasks, but not both.
- There is not a task-agnostic feature upsampler in dense prediction.

### Contributions:

- We observe that what features (encoder or decoder) to use to generate the upsampling kernels matters. Using both can encourage task-agnostic upsampling.
- We present FADE, a novel, plug-and-play, and task-agnostic upsampling operator.

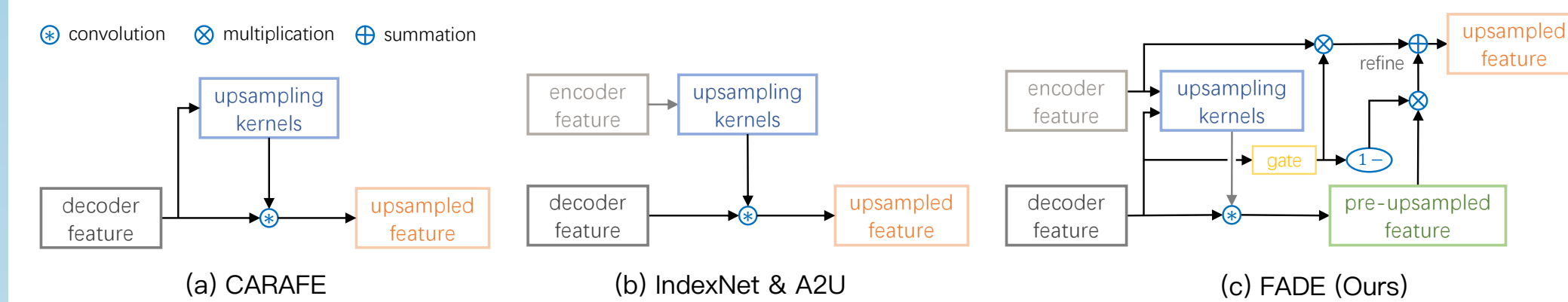
## Main Pipeline

From (a) the overview of FADE, feature up-sampling is executed by jointly exploiting the encoder and decoder feature with two key modules: a semi-shift convolutional operator in (b) and a decoder-dependent gating mechanism in (c).

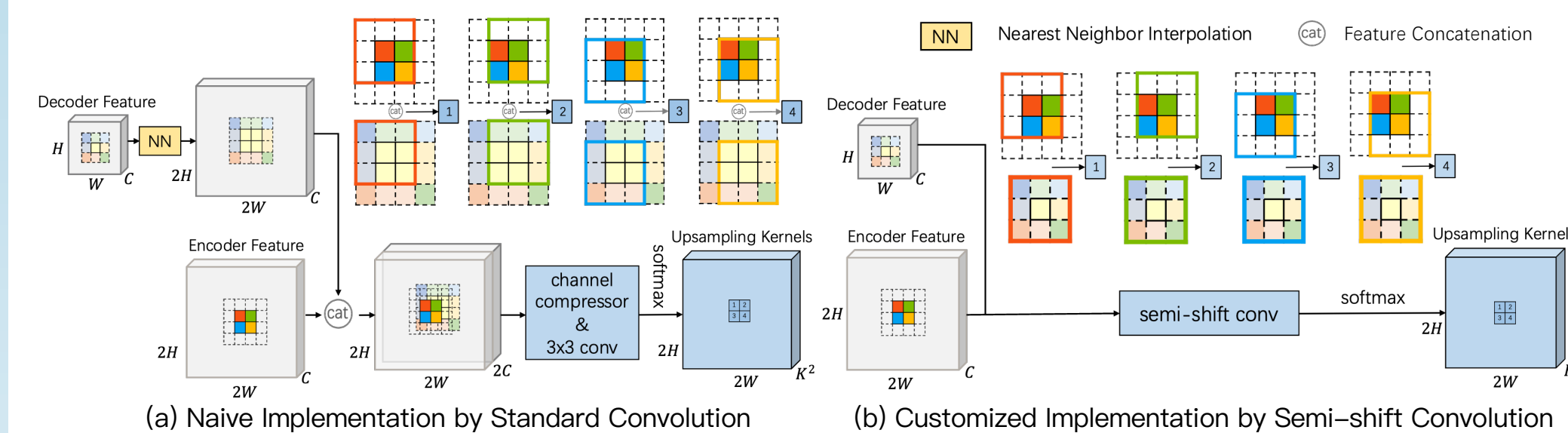


## Three Key Designs

### 1) Using both encoder and decoder features in generating upsampling kernels;



### 2) Semi-shift Convolution: Controlling per-point contribution in the upsampled feature;



The upsampling kernel weight takes the form:

$$w_m = \sum_{l=1}^d \sum_{i=1}^h \sum_{j=1}^h \beta_{ijlm} \sum_{k=1}^C \alpha_{kl}^{\text{en}} x_{ijk}^{\text{en}} + \quad (1)$$

$$\sum_{l=1}^d \sum_{i=1}^h \sum_{j=1}^h \beta_{ijlm} \left( \sum_{k=1}^C \alpha_{kl}^{\text{de}} x_{ijk}^{\text{de}} + a_l \right) + b_m \quad (2)$$

### 3) A Gating Mechanism: Per the pipeline (c),

$$\mathcal{F}_{\text{upsampled}} = \mathcal{F}_{\text{encoder}} \cdot \mathbf{G} + \mathcal{F}_{\text{pre-upsampled}} \cdot (1 - \mathbf{G}) \quad (3)$$

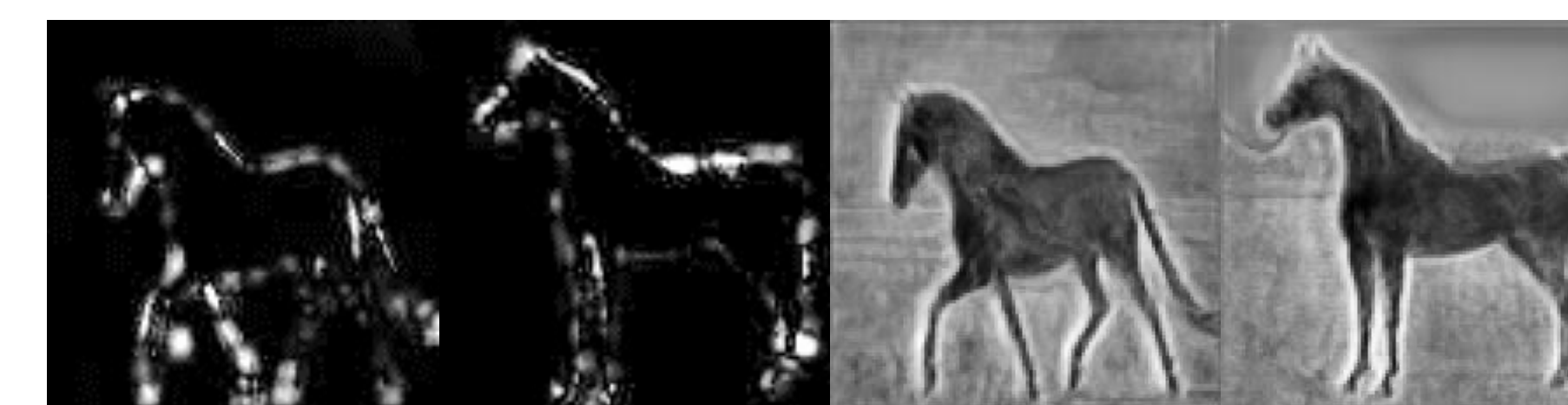
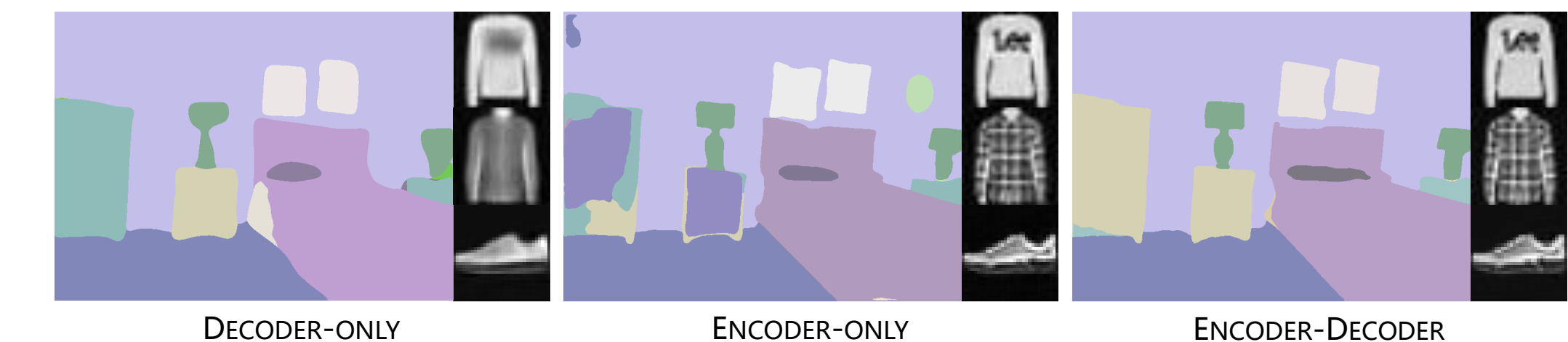
## Experimental Results

- We first use some experimental observations on toy datasets to showcase our motivation.
- We then validate FADE on large-scale dense prediction tasks, including image matting and semantic segmentation on the Adobe Composition-1k and ADE20K data sets, respectively.
- We further conduct ablation studies to justify each design choice of FADE.
- We also analyze computational complexity in terms of parameter counts and GFLOPs.

Results of semantic segmentation on SUN RGBD and image reconstruction on Fashion MNIST

	Segmentation accuracy metric $\uparrow$		Reconstruction accuracy metric $\uparrow$ error metric $\downarrow$			
	mIoU	bIoU	PSNR	SSIM	MAE	MSE
decoder-only	37.00	25.61	24.35	87.19	0.0357	0.0643
encoder-only	36.71	27.89	32.25	97.73	0.0157	0.0257
encoder-decoder	<b>37.59</b>	<b>28.80</b>	<b>33.83</b>	<b>98.47</b>	<b>0.0122</b>	<b>0.0218</b>

Visualizations of inferred mask and reconstructed results on SUN RGBD and Fashion-MNIST



GRADIENT MAP

GATE MAP

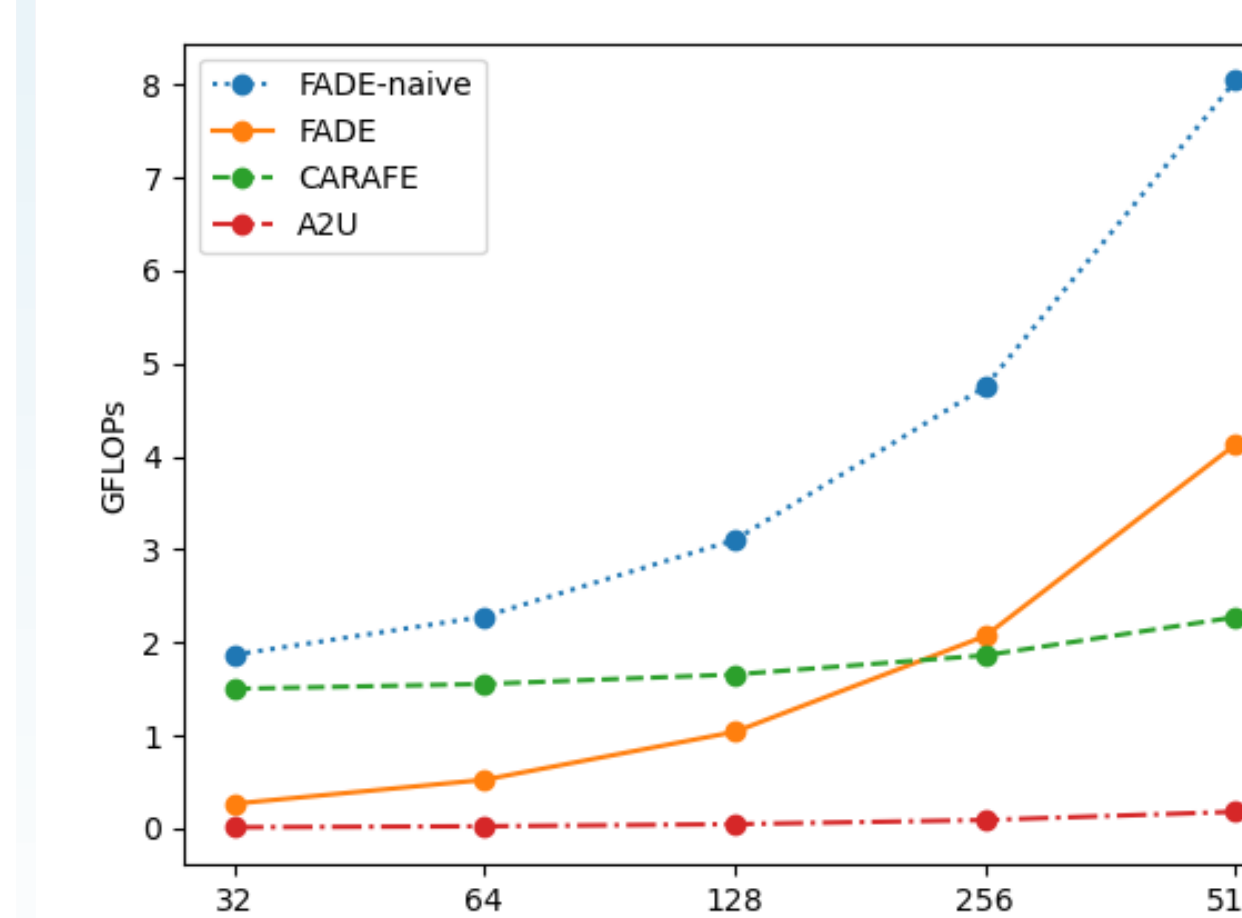
### Image Matting and Semantic Segmentation Results:

A2U Matting/ SegFormer	Matting - error $\downarrow$					Segm - accuracy $\uparrow$		
	SAD	MSE	Grad	Conn	$\Delta$ Param.	mIoU	bIoU	$\Delta$ Param.
Bilinear	37.31	0.0103	21.38	35.39	8.05M	41.68	27.80	13.7M
CARAFE	41.01	0.0118	21.39	39.01	+0.26M	42.82	29.84	+0.44M
IndexNet	34.28	0.0081	15.94	31.91	+12.26M	41.50	28.27	+12.60M
A2U	32.15	0.0082	16.39	29.25	+38K	41.45	27.31	+0.12M
FADE (Ours)	<b>31.10</b>	<b>0.0073</b>	<b>14.52</b>	<b>28.11</b>	+0.12M	<b>44.41</b>	<b>32.65</b>	+0.29M

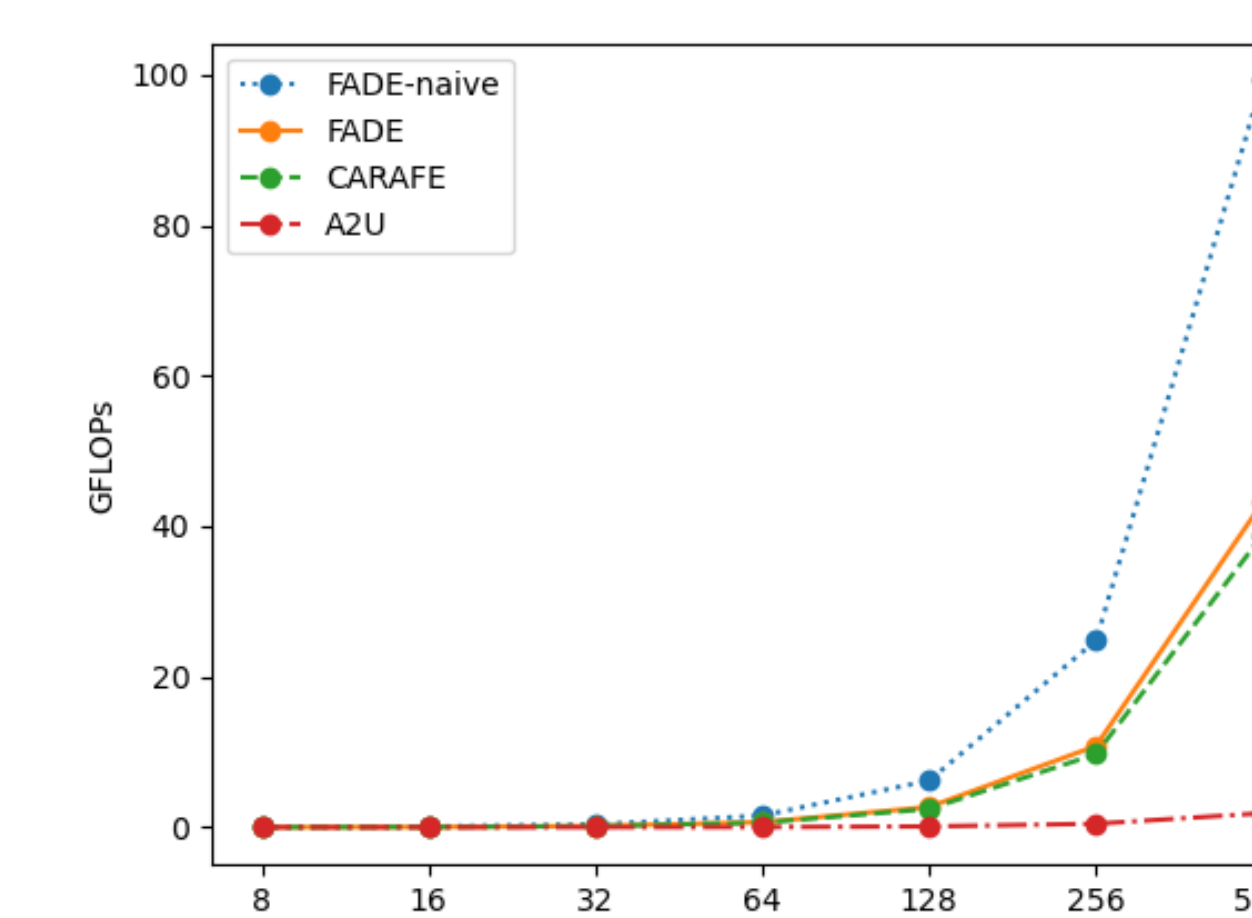
### Ablation Study:

No.	A2U Matting / SegFormer			Matting - error $\downarrow$				Segm - accuracy $\uparrow$	
	source of feat.	kernel gen.	fusion	SAD	MSE	Grad	Conn	mIoU	bIoU
B1	en			34.22	0.0087	15.90	32.03	42.75	31.00
B2	de			41.01	0.0118	21.39	39.01	42.82	29.84
B3	en & de	naive		32.41	0.0083	16.56	29.82	43.27	31.55
B4	en & de	semi-shift		31.78	0.0075	15.12	28.95	43.33	32.06
B5	en & de	semi-shift	skipping	32.64	0.0076	15.90	29.92	43.22	31.85
B6	en & de	semi-shift	gating	<b>31.10</b>	<b>0.0073</b>	<b>14.52</b>	<b>28.11</b>	<b>44.41</b>	<b>32.65</b>

### GFLOPs Comparison:

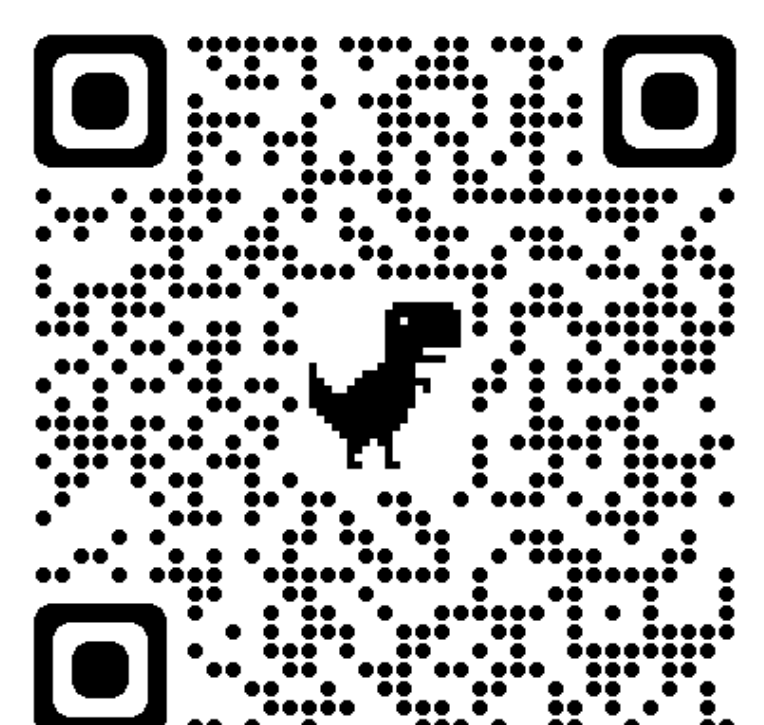


resolution=112



channels=256

### Code @ Github:



E-mail: hlu@hust.edu.cn (Hao Lu)