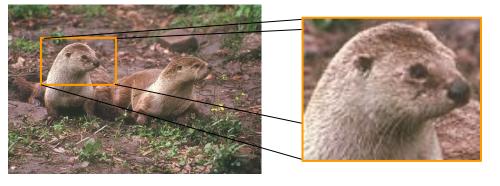
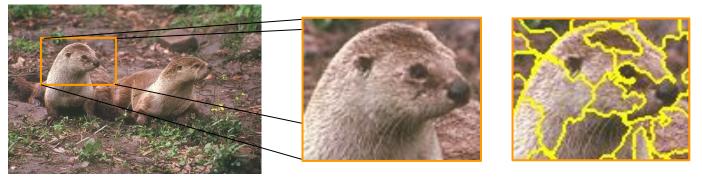
## Soft Superpixel Neighborhood Attention



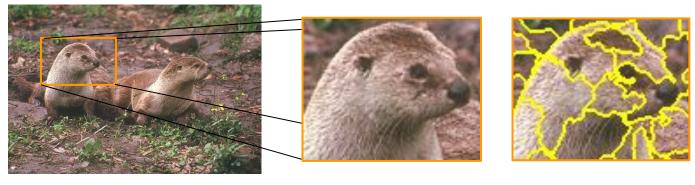
Images contain deformable boundaries



Images contain deformable boundaries

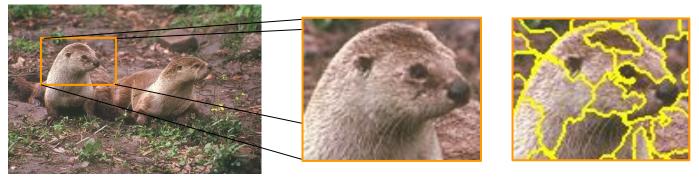


Images contain deformable boundaries

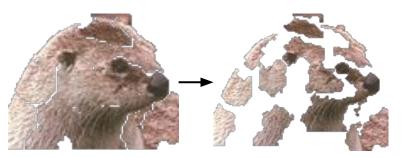


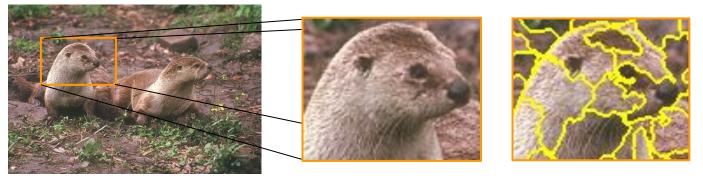
Images contain deformable boundaries



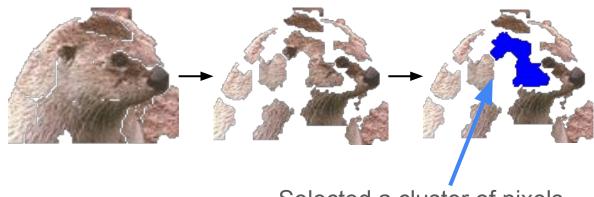


Images contain deformable boundaries

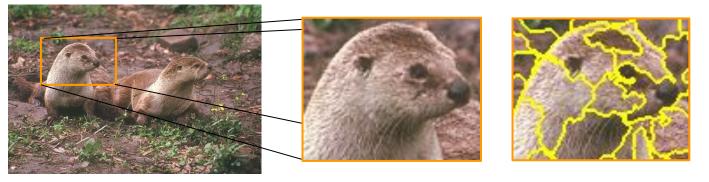




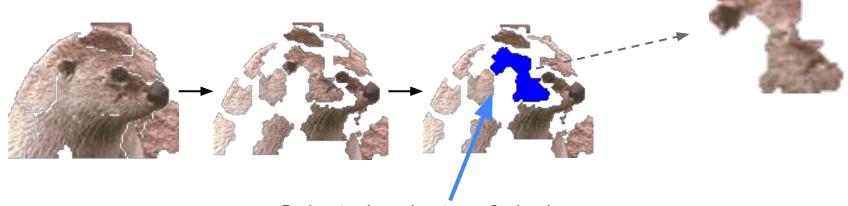
Images contain deformable boundaries



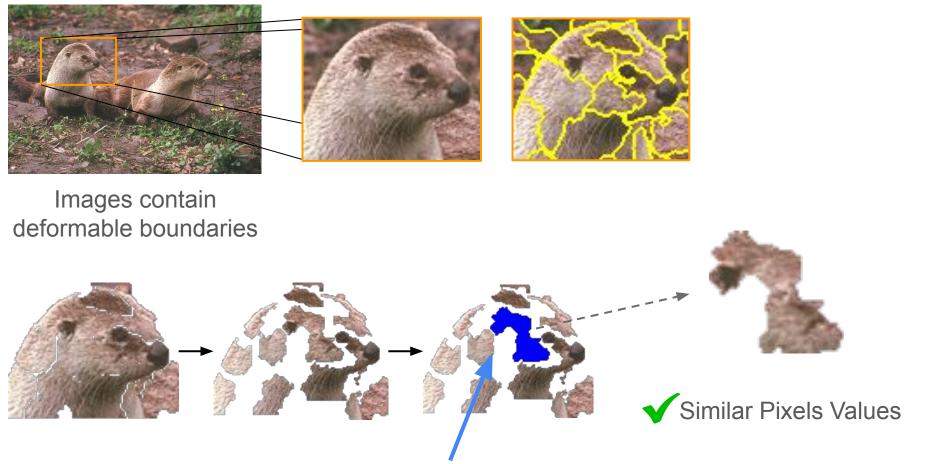
Selected a cluster of pixels



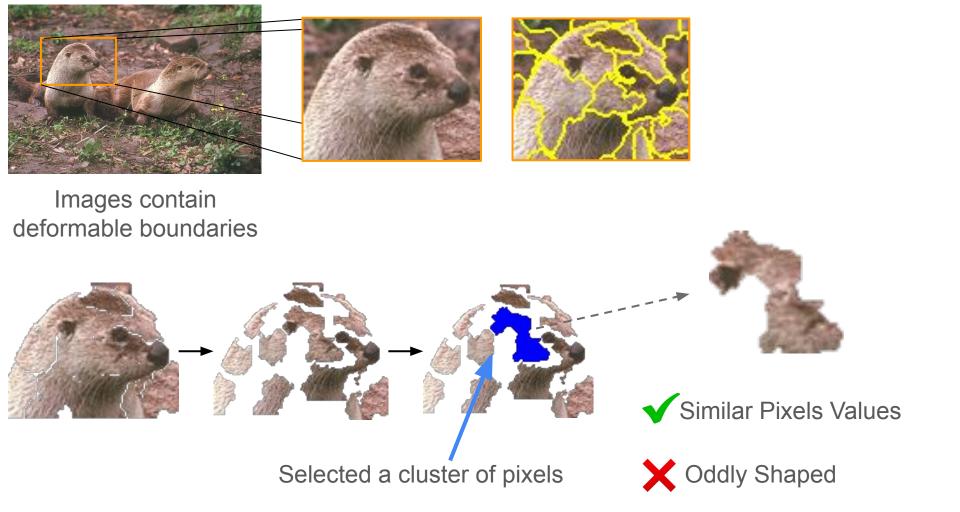
Images contain deformable boundaries



Selected a cluster of pixels



Selected a cluster of pixels

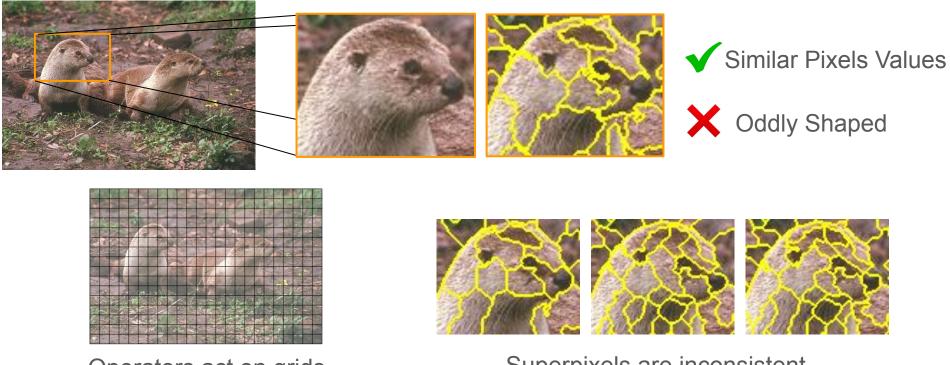






Operators act on grids

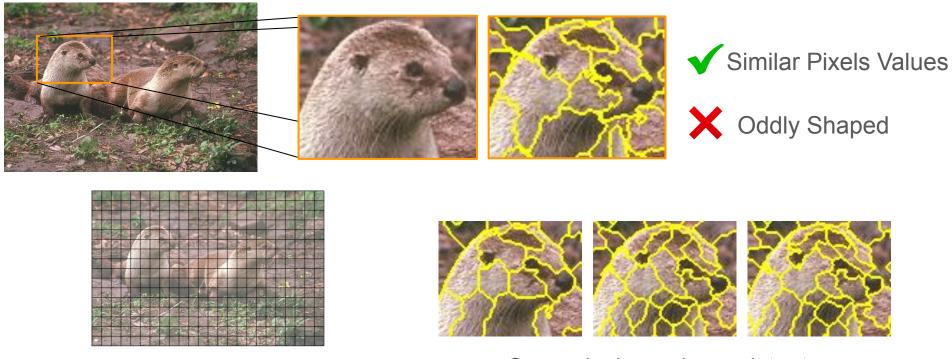
## Q1. How do we principally incorporate superpixels into DNN modules?



Operators act on grids Superpixels are inconsistent

Q1. How do we principally incorporate superpixels into DNN modules?

Q2. How do we address the inconsistency among superpixel assignments?

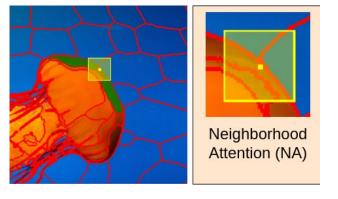


Operators act on grids Superpixels are inconsistent

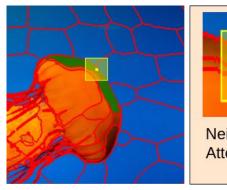
Q1. How do we principally incorporate superpixels into DNN modules?

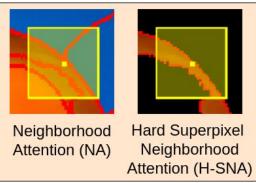
Neighborhood Attention

Q2. How do we address the inconsistency among superpixel assignments?



$$f_{\text{NA}}^{(i)}(\boldsymbol{x}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} \boldsymbol{v}_j, \qquad w_{i,j} = \frac{\exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_j)\right)}{\sum_{j' \in \mathcal{N}(i)} \exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_{j'})\right)}$$



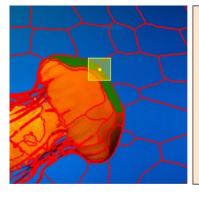


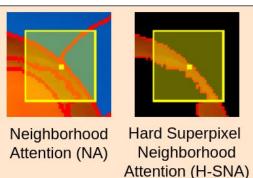
$$\hat{m{S}}$$
 Superpixel Assignment

$$f_{\text{NA}}^{(i)}(\boldsymbol{x}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} \boldsymbol{v}_j, \qquad w_{i,j} = \frac{\exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_j)\right)}{\sum_{j' \in \mathcal{N}(i)} \exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_{j'})\right)}$$

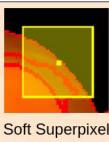
$$\mathbb{1}[\hat{s}_i = \hat{s}_j] \cdot \exp\left(\lambda_{\mathsf{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_j)\right)$$

$$f_{\text{H-SNA}}^{(i)}(\boldsymbol{x}; \hat{\boldsymbol{s}}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} \boldsymbol{v}_j, \qquad w_{i,j} = \frac{\mathbb{1}[\hat{s}_i = \hat{s}_j] \cdot \exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_j)\right)}{\sum_{j' \in \mathcal{N}(i)} \mathbb{1}[\hat{s}_i = \hat{s}_{j'}] \cdot \exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_{j'})\right)}$$









Soft Superpixel Neighborhood Attention (SNA)

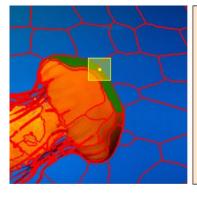
Superpixel **Assignment** 

$$f_{\mathrm{NA}}^{(i)}(\boldsymbol{x}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} \boldsymbol{v}_j,$$

$$f_{\text{NA}}^{(i)}(\boldsymbol{x}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} \boldsymbol{v}_j, \qquad w_{i,j} = \frac{\exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_j)\right)}{\sum_{j' \in \mathcal{N}(i)} \exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_{j'})\right)}$$

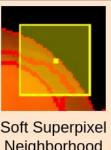
$$f_{\text{H-SNA}}^{(i)}(\boldsymbol{x}; \hat{\boldsymbol{s}}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} \boldsymbol{v}_j, \qquad w_{i,j} = \frac{\mathbb{1}[\hat{s}_i = \hat{s}_j] \cdot \exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_j)\right)}{\sum_{j' \in \mathcal{N}(i)} \mathbb{1}[\hat{s}_i = \hat{s}_{j'}] \cdot \exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_{j'})\right)}$$

$$f_{\text{SNA}}^{(i)}(\boldsymbol{x}; \hat{\boldsymbol{\pi}}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} \boldsymbol{v}_j, \qquad w_{i,j} = \frac{\exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_j)\right) \sum_{s=1}^{N_{\text{sp}}} \hat{\boldsymbol{\pi}}^{(i,s)} \hat{\boldsymbol{\pi}}^{(j,s)}}{\sum_{j' \in \mathcal{N}(i)} \exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_{j'})\right) \sum_{s=1}^{N_{\text{sp}}} \hat{\boldsymbol{\pi}}^{(i,s)} \hat{\boldsymbol{\pi}}^{(j',s)}}$$









Soft Superpixel Neighborhood Attention (SNA)

Superpixel **Assignment** 

$$f_{\mathrm{NA}}^{(i)}(\boldsymbol{x}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} \boldsymbol{v}_j,$$

$$f_{\text{NA}}^{(i)}(\boldsymbol{x}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} \boldsymbol{v}_j, \qquad w_{i,j} = \frac{\exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_j)\right)}{\sum_{j' \in \mathcal{N}(i)} \exp\left(\lambda_{\text{at}} d(\boldsymbol{q}_i, \boldsymbol{k}_{j'})\right)}$$

$$f_{ ext{H-SNA}}^{(i)}(oldsymbol{x}; \hat{oldsymbol{s}}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} oldsymbol{v}_j,$$

$$w_{i,j} = \frac{\mathbb{1}[\hat{s}_i = \hat{s}_j] \cdot \exp(\lambda_{at} d)}{\sum_{j' \in \mathcal{N}(i)} \mathbb{1}[\hat{s}_i = \hat{s}_{j'}] \cdot \exp}$$
 How did we get this?

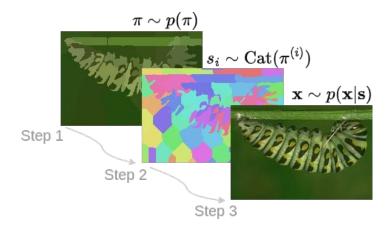
$$f_{ ext{SNA}}^{(i)}(oldsymbol{x};\hat{oldsymbol{\pi}}) = \sum_{j \in \mathcal{N}(i)} w_{i,j} oldsymbol{v}_j,$$

$$w_{i,j} = \frac{\exp\left(\lambda_{\text{at}}d(\boldsymbol{q}_i, \boldsymbol{k}_j)\right) \sum_{s=1}^{N_{\text{sp}}} \hat{\boldsymbol{\pi}}^{(i,s)} \hat{\boldsymbol{\pi}}^{(j,s)}}{\sum_{j' \in \mathcal{N}(i)} \exp\left(\lambda_{\text{at}}d(\boldsymbol{q}_i, \boldsymbol{k}_{j'})\right) \sum_{s=1}^{N_{\text{sp}}} \hat{\boldsymbol{\pi}}^{(i,s)} \hat{\boldsymbol{\pi}}^{(j',s)}}$$

Sample superpixel probabilities  $\pi \sim p(\pi)$ Sample the superpixel assignment given the probabilities  $s_i | \pi^{(i)} \sim p(s_i | \pi^{(i)})$ Sample the image pixel given the superpixel assignment  $x | s \sim p(x | s)$  Sample superpixel probabilities

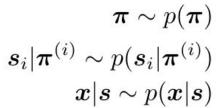
Sample the superpixel assignment given the probabilities Sample the image pixel given the superpixel assignment

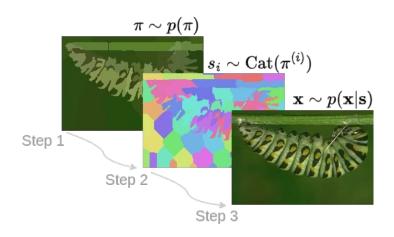
$$egin{aligned} oldsymbol{\pi} & \sim p(oldsymbol{\pi}) \ oldsymbol{s}_i | oldsymbol{\pi}^{(i)} & \sim p(oldsymbol{s}_i | oldsymbol{\pi}^{(i)}) \ oldsymbol{x} | oldsymbol{s} & \sim p(oldsymbol{x} | oldsymbol{s}) \end{aligned}$$



Sample superpixel probabilities

Sample the superpixel assignment given the probabilities Sample the image pixel given the superpixel assignment





$$f_{\text{SNA}}^{(i)}(\tilde{\boldsymbol{x}}; \boldsymbol{\pi}) = D^*(\tilde{\boldsymbol{x}}_i; \sigma, \boldsymbol{\pi}) = \operatorname{arg\,min}_D \left[ \|D(\tilde{\boldsymbol{x}}_i; \boldsymbol{\pi}, \sigma) - \boldsymbol{x}_i\|^2 \right]$$

## Gaussian Denoising

Attn.	SNA			H-SNA	NA [2]		
Learn $\lambda_{at}$	<b>~</b>	<b>✓</b>				<b>~</b>	
Sp. Model	$g_{\phi, \mathrm{Deep}}$	$g_{\phi, \mathrm{SLIC}}$	$g_{\phi, \mathrm{Deep}}$	$g_{\phi, \mathrm{SLIC}}$	$g_{\phi, \mathrm{SLIC}}$		
$\sigma$	31.96	32.08	32.07	32.19	30.88	30.87	31.10
10	0.869	0.871	0.865	0.871	0.810	0.850	0.850
20	29.01	28.72	28.77	29.08	25.56	27.12	26.96
	0.838	0.815	0.819	0.804	0.630	0.774	0.743
30	27.70	26.94	27.25	27.51	22.37	25.69	24.91
	0.805	0.777	0.764	0.763	0.512	0.743	0.687
Deno Params $(\theta)$	195	195	195	195	195	195	195
Aux Params $(\phi)$	8.8k	8.8k	4.4k	4.4k	0	4.4k	0
Fwd Time (ms)	30.20	45.05	27.06	40.58	28.86	4.64	2.08
Bwd Time (ms)	38.72	80.93	40.00	51.35	32.54	6.06	4.67
Fwd Mem (GB)	1.90	2.30	1.87	2.28	1.96	0.23	0.21
Bwd Mem (GB)	3.27	3.68	3.25	3.66	3.13	0.27	0.25

$$\hat{\boldsymbol{y}}_{\text{Deno}} = \text{Simple Network}_{\theta,\phi}(\boldsymbol{x}) = f_{\text{Attn}}\left(\boldsymbol{x}\boldsymbol{W}_0, g_{\phi}(\boldsymbol{x}\boldsymbol{W}_0)\right)\boldsymbol{W}_1 + \boldsymbol{x}\boldsymbol{W}_0\boldsymbol{W}_1$$

## Gaussian Denoising

Attn.	SNA			H-SNA	NA [2]		
Learn $\lambda_{\rm at}$	<b>~</b>	<b>✓</b>				~	
Sp. Model	$g_{\phi, \mathrm{Deep}}$	$g_{\phi,  ext{SLIC}}$	$g_{\phi, \mathrm{Deep}}$	$g_{\phi, \mathrm{SLIC}}$	$g_{\phi, \mathrm{SLIC}}$		
$\sigma$	31.96	32.08	32.07	32.19	30.88	30.87	31.10
10	0.869	0.871	0.865	0.871	0.810	0.850	0.850
20	29.01	28.72	28.77	29.08	25.56	27.12	26.96
	0.838	0.815	0.819	0.804	0.630	0.774	0.743
30	27.70	26.94	27.25	27.51	22.37	25.69	24.91
	0.805	0.777	0.764	0.763	0.512	0.743	0.687
Deno Params $(\theta)$	195	195	195	195	195	195	195
Aux Params $(\phi)$	8.8k	8.8k	4.4k	4.4k	0	4.4k	0
Fwd Time (ms)	30.20	45.05	27.06	40.58	28.86	4.64	2.08
Bwd Time (ms)	38.72	80.93	40.00	51.35	32.54	6.06	4.67
Fwd Mem (GB)	1.90	2.30	1.87	2.28	1.96	0.23	0.21
Bwd Mem (GB)	3.27	3.68	3.25	3.66	3.13	0.27	0.25

$$\hat{\boldsymbol{y}}_{\text{Deno}} = \text{Simple Network}_{\theta,\phi}(\boldsymbol{x}) = f_{\text{Attn}}\left(\boldsymbol{x}\boldsymbol{W}_0, g_{\phi}(\boldsymbol{x}\boldsymbol{W}_0)\right)\boldsymbol{W}_1 + \boldsymbol{x}\boldsymbol{W}_0\boldsymbol{W}_1$$

