## Affinity CNN:

# Learning Pixel-Centric Pairwise Relations for Figure/Ground Embedding

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## Segmentation and Figure/Ground Results



Ground



Image

#### Ground-truth

## Segmentation and Figure/Ground Results



Image



#### Image



#### Image





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#### Image





うてん 叫 ふせきょうせき (日)

#### Image





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#### Image





Image





もって 叫 しゃうきゃ ふゆき ふりゃ

Image











•  $\Theta(\cdot, \cdot)$  stores pairwise relationships





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   > Embedding procedure:
  - ▶ Input:  $\{\Theta(p,q), \Theta(p,r), \ldots\}$
  - Output:  $\{\theta(p), \theta(q), \theta(r), \ldots\}$

such that  $\Theta(p,q) \approx F(\theta(p),\theta(r))$ 





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- $F(\cdot, \cdot)$  is a simple decoding function
- Embedding θ(·) is a globally consistent representation of the pairwise local relationships Θ(·, ·)



Segmentation + Figure/Ground

Image







Figure

Ground



Segmentation+Figure/Ground

- $\Theta(p,q)$  is an offset
  - Is p in the same region as q?
  - Is p in front of/behind q?
- C(p,q): confidence on  $\Theta(p,q)$





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Implementation

• CNN estimates  $\Theta(p,q)$ , C(p,q)



Image

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Implementation

- CNN estimates  $\Theta(p,q)$ , C(p,q)
- Sparse multiscale connectivity: each p connects to k neighbors





#### pixel-centric grouping/ordering







[Yu, PAMI 2012]



[Yu, PAMI 2012]



minimize:  $\varepsilon = \sum_{p} \frac{\sum_{q} \hat{C}(p,q)}{\sum_{p,q} C(p,q)} \cdot |z(p) - \tilde{z}(p)|^2$ 

[Yu, PAMI 2012]



Relax to generalized eigenproblem  $Wz = \lambda Dz$  where:

$$D = \text{Diag}(C1_n)$$
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Normalized Cuts is the special case:  $\Theta = 0$ 

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#### Eigenvectors



Z<sub>0</sub>  $z_1$ 





Squishing trick: rescale  $\Theta$  by

$$\frac{\pi}{2}(1_n^T|\Theta|1_n)^{-1}$$

prior to embedding

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## **Complex-Valued Affinities**



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Probability estimates:

e(p) = Pr(p lies on a boundary)  $b(p,q) = Pr(\operatorname{seg}(p) \neq \operatorname{seg}(q))$   $f(p,q) = Pr(\operatorname{figural}(p,q) | \operatorname{seg}(p) \neq \operatorname{seg}(q)))$  $g(p,q) = Pr(\operatorname{figural}(q,p) | \operatorname{seg}(p) \neq \operatorname{seg}(q)))$ 

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Transition error probabilities:

$$egin{aligned} & E_B(p,q) = b(p,q) \ & E_F(p,q) = 1 - (1-e(p))b(p,q)(1-e(q))f(p,q) \ & E_G(p,q) = 1 - (1-e(p))b(p,q)(1-e(q))g(p,q) \end{aligned}$$

 $B: \ binding \quad F: \ ground \rightarrow figure \quad G: \ figure \rightarrow ground$ 

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**B**: binding **F**: ground  $\rightarrow$  figure **G**: figure  $\rightarrow$  ground

Convert error probabilities to confidence :

$$C_B(p,q) = \exp(-E_B(p,q)/\sigma_b)$$
  
 $C_F(p,q) = \exp(-E_F(p,q)/\sigma_f)$   
 $C_G(p,q) = \exp(-E_G(p,q)/\sigma_g)$ 

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► Apply rotational action of figure/ground transitions:

$$egin{aligned} W_B(p,q) &= C_B(p,q) \ W_F(p,q) &= C_F(p,q) \exp(i\phi) \ W_G(p,q) &= C_G(p,q) \exp(-i\phi) \end{aligned}$$

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Sum transition forces and symmetrize:

$$egin{aligned} & W(p,q) = W_{B}(p,q) + W_{F}(p,q) + W_{G}(p,q) \ & W \leftarrow (W+W^{*})/2 \end{aligned}$$

## Generalized Affinity



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#### Affinity Learning

#### Ground-truth: Berkeley Segmentation Dataset



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## Affinity Learning

# Target $(\tilde{b}, \tilde{f})$ and learned (b, f) signals



#### Affinity Learning - CNN Architecture



Trained using log loss between target and prediction
 Left/right mirroring of examples

# **Results Comparison**



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## **Results Comparison**



#### Benchmark: Project onto Ground-truth Regions



#### Benchmark: Boundary Ownership Correctness



#### Benchmark: Project onto Our Regions



Sac

## Benchmark: Boundary Ownership Correctness



Sac

#### Benchmarks: Quantitative Performance

Segmentation:	Figure/Ground Prediction Accuracy				
Ground-truth	R-ACC	B-ACC	B-ACC-50	B-ACC-25	
F/G: Ours	0.62	0.69	0.72	0.73	
F/G: [Maire, ECCV 2010]	0.56	0.58	0.56	0.56	

Segmentation:	Figure/Ground Prediction Accuracy					
Ours	R-ACC	B-ACC	B-ACC-50	B-ACC-25		
F/G: Ours	0.66	0.70	0.69	0.67		
F/G: [Maire, ECCV 2010]	0.59	0.62	0.61	0.58		

R-ACC: Pairwise region accuracy

B-ACC: Boundary ownership accuracy

B-ACC-25: B-ACC on 25% most foreground regions in each image B-ACC-50: B-ACC on 50% most foreground regions in each image

#### Cross-Domain Generalization: Horses



Image

F/G

Boundaries

Seg + F/G

#### Cross-Domain Generalization: PASCAL





pixel-centric grouping/ordering



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# Thank You!