

Learning to See the Image

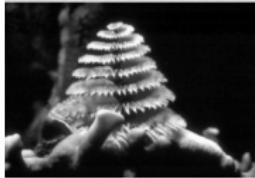
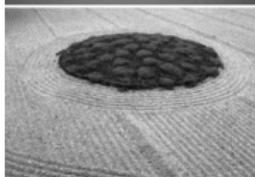
Stella Yu

Director, ICSI Vision Group
Senior Fellow, BIDS, UC Berkeley

ImageXD
30 March 2017



Seeing Pixel Groups Not Individual Pixels

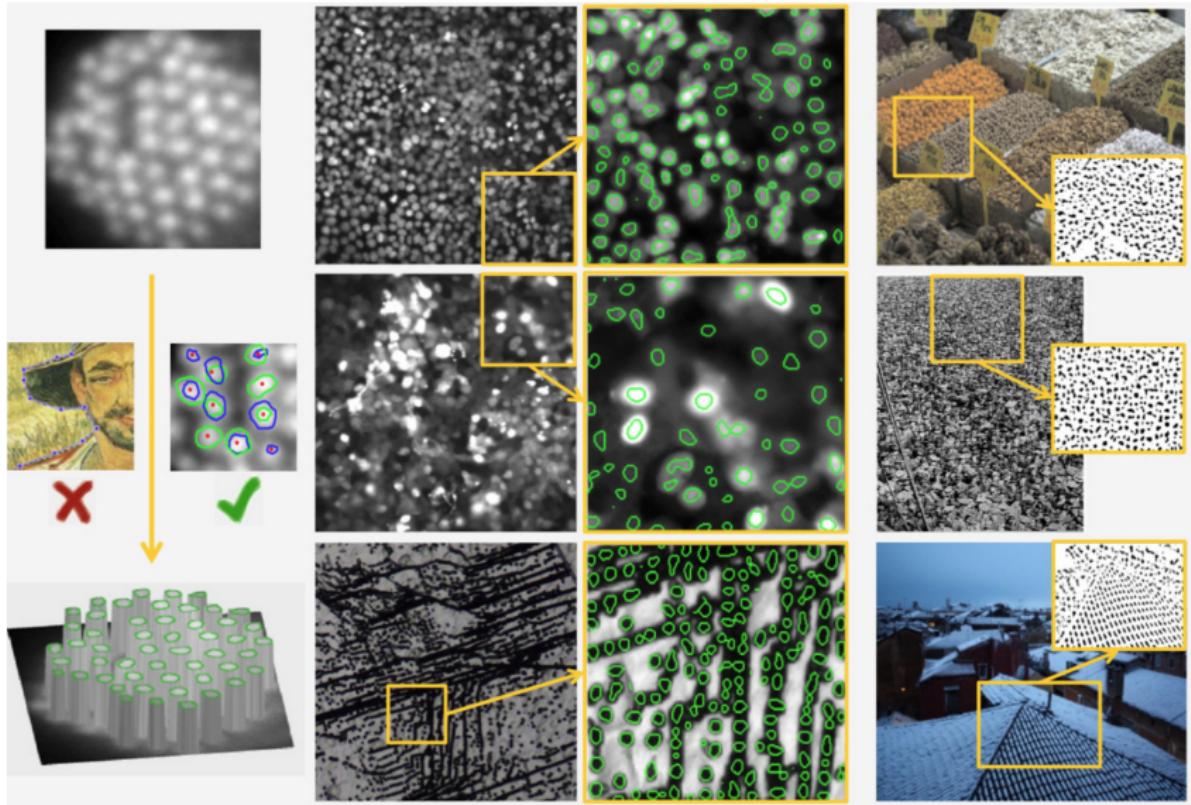


Challenge: Segmentation across Variety



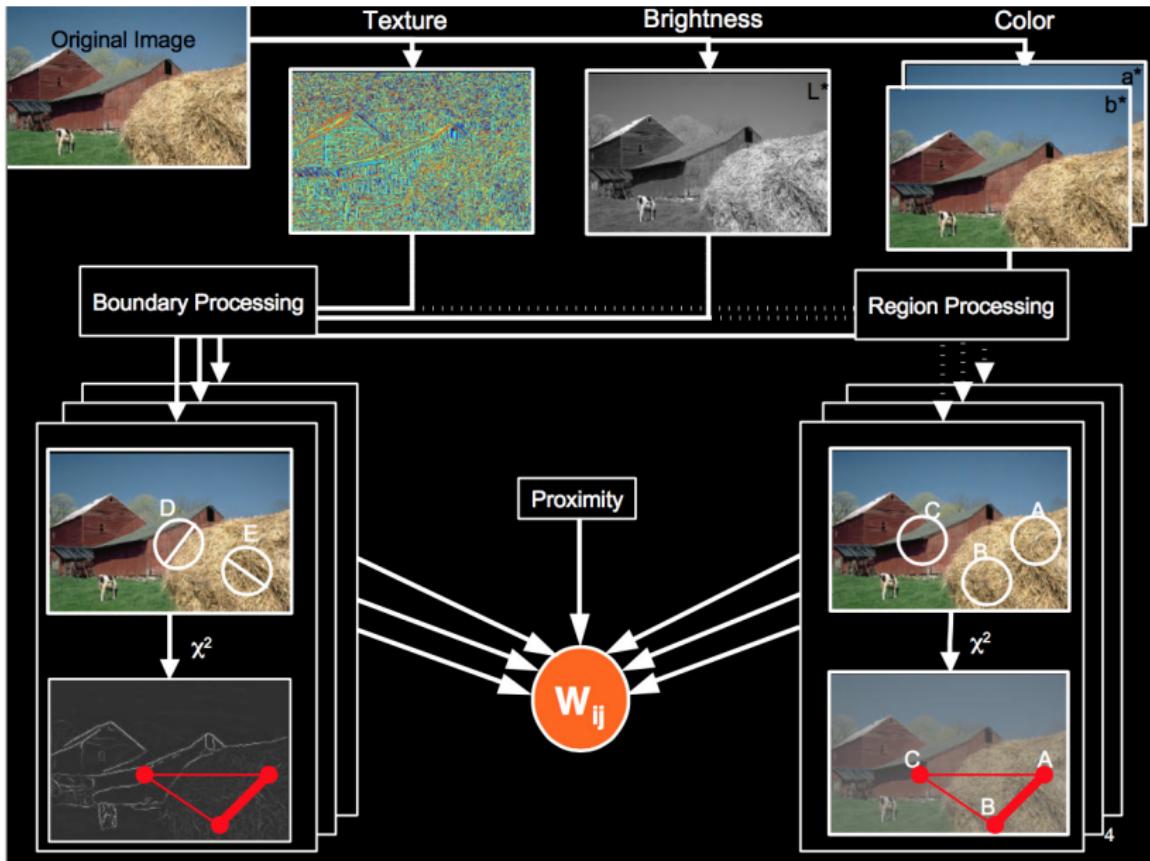
(Yu: CVPR 2004, CVPR 2005)

Finding Dots by Popping out Core Regions

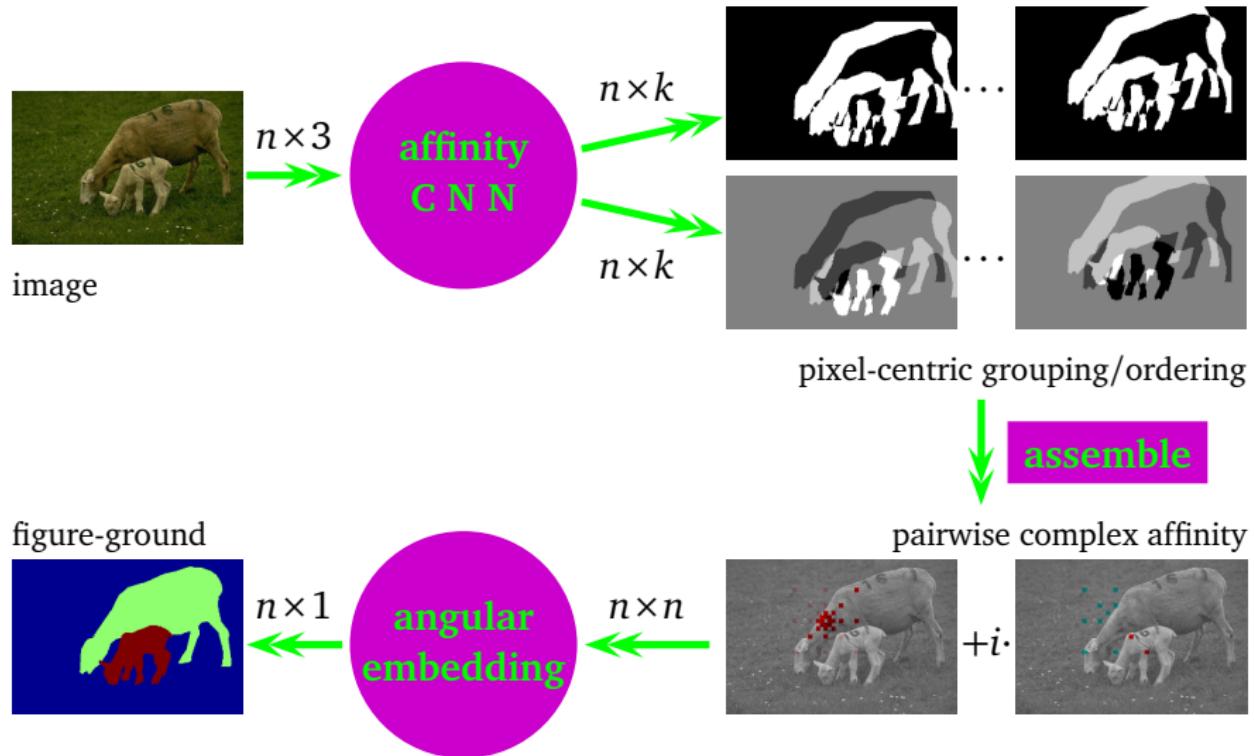


(Bernardis & Yu: CVPR 2010, MICCAI 2011, MedIA 2011)

Prior Art: From Features to Pairwise Pixel Affinity

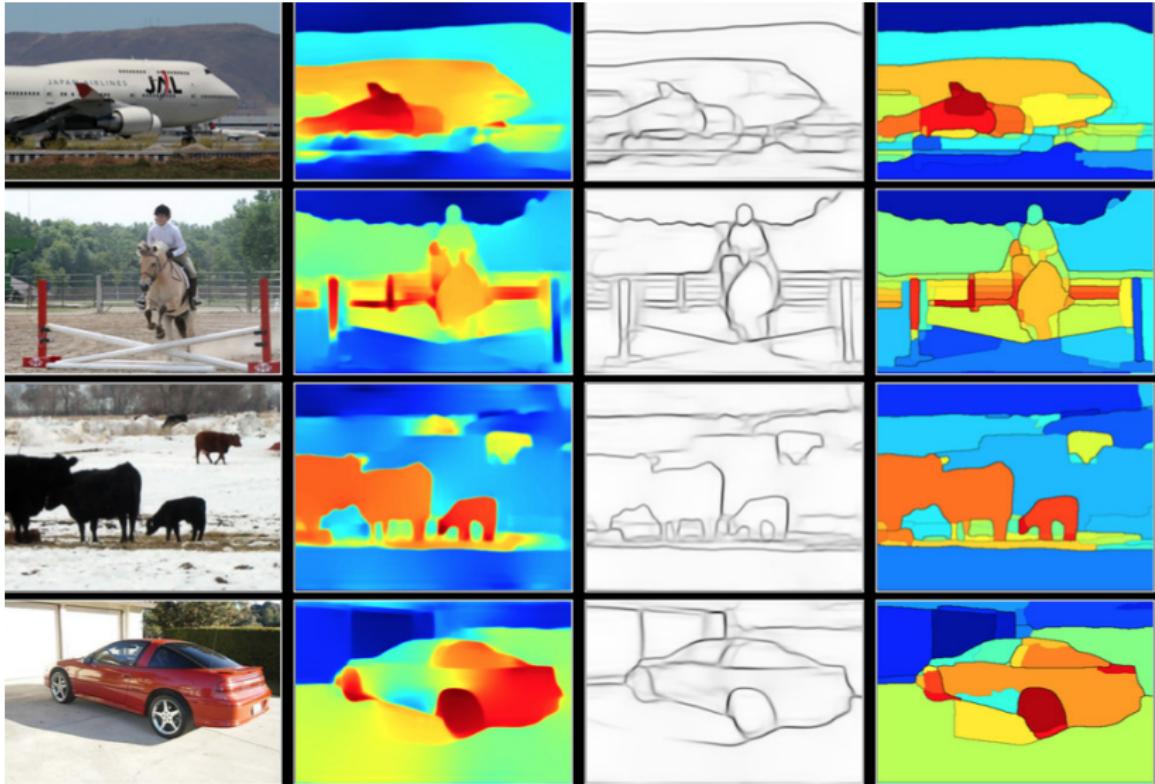


Affinity CNN: Learning Pixel-Centric Relations

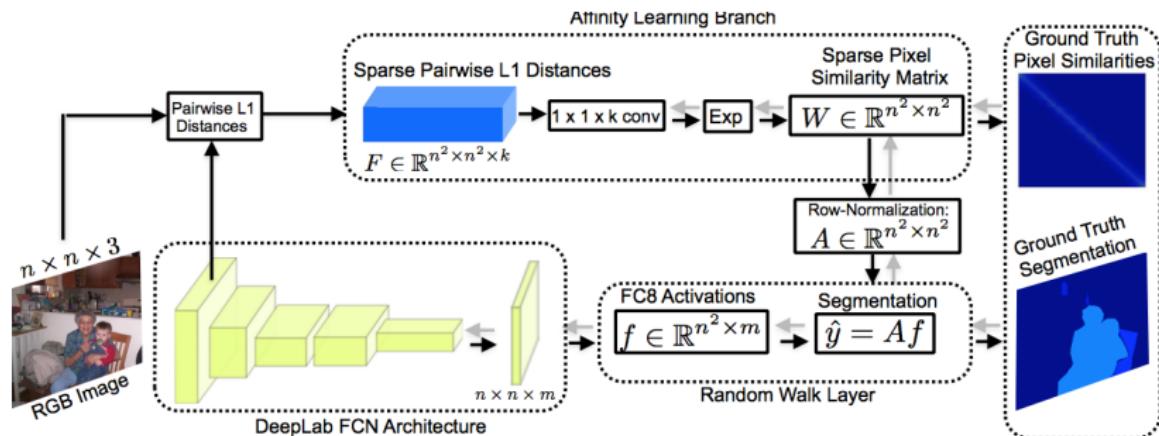


(Maire, Narihira, Yu: CVPR 2016)

Learning Pairwise Relations for Generalization

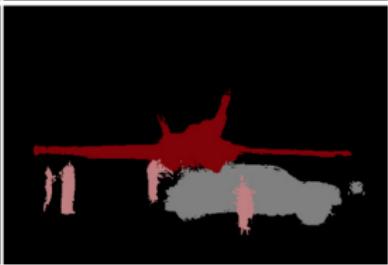
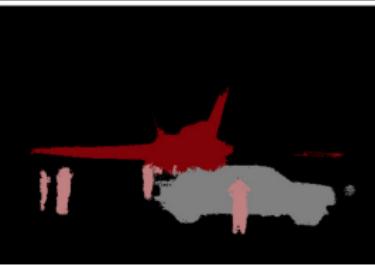
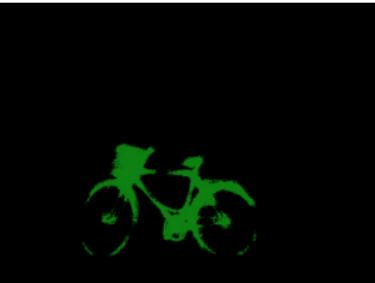


Learn Pairwise Relations and Semantic Labeling

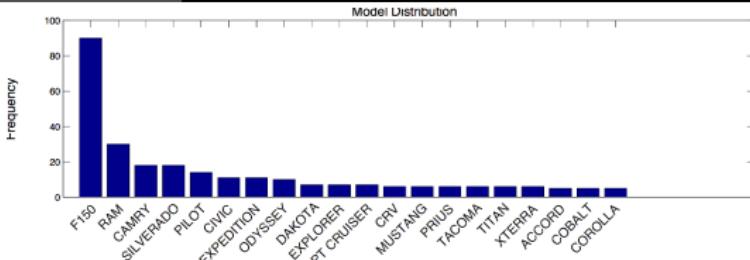
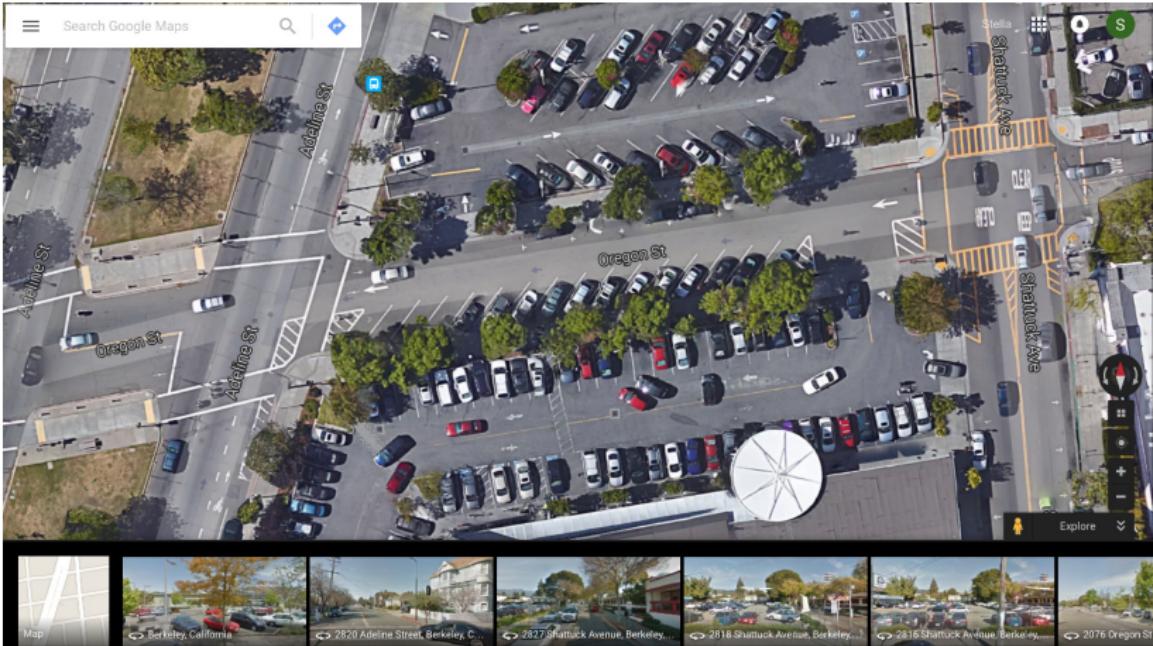


(Bertasius, Torresani, Yu, Shi: CVPR 2017)

Segmentation Challenge: Thin Structures



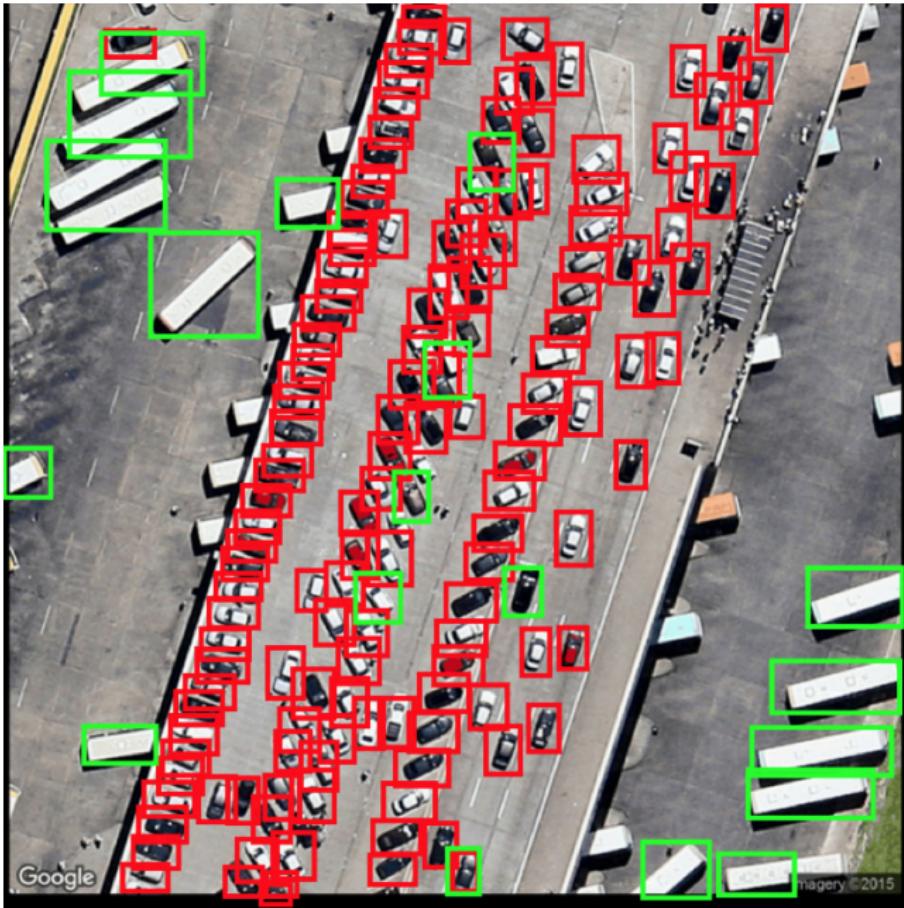
Summer Challenge: Fine-Grained Classification



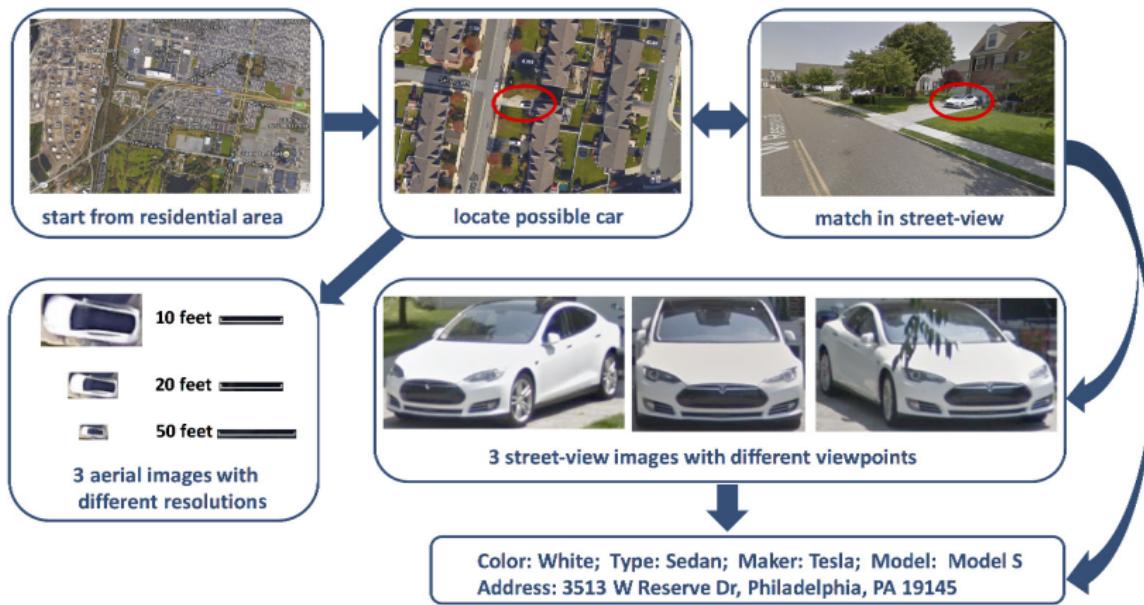
Car Detection and Classification In Aerial Images



Car Detection and Classification In Aerial Images



Cross-View Annotation: Fine-Grained Recognition



(Sun, Peng, Yu, Saenko: arXiv 2017)

1. First satellite-streetview fine-grained annotated car dataset.
2. CNN classifiers can learn from a few instances yet achieve significant better performance than human experts!

Cross-Resolution Integration: Knowledge Transfer

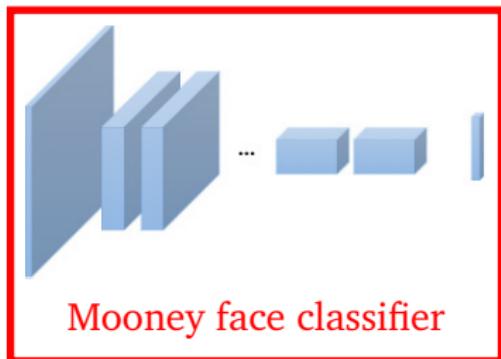
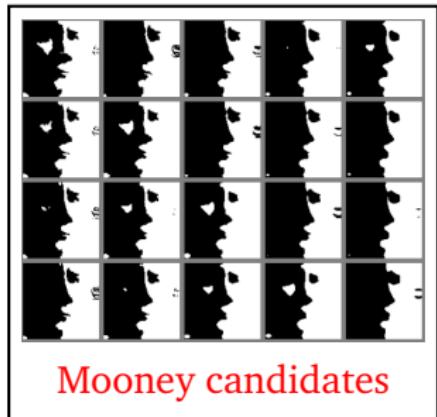
| | Train Data | Method | Test Data | Accuracy |
|----------------|---|------------|--|-------------------------|
| Stanford Cars |  | CNN |  | 80.3% oracle |
| |  | Our Method |  | 59.5% 50.4% baseline |
| UCSD Birds-200 |  | CNN |  | 67.7% oracle |
| |  | Our Method |  | 55.3% 51.3% baseline |

(Peng, Hoffman, Yu, Saenko: ICIP 2016)

Mooney Faces Handcrafted by Artists / Scientists



Deep Learning for Mooney Face Classification



(Ke, Yu, Whitney: VSS 2017)

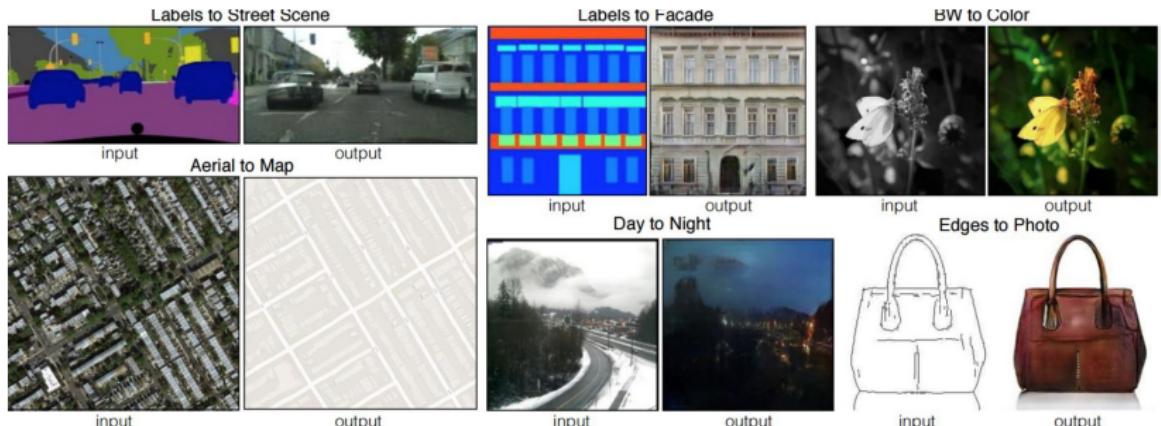
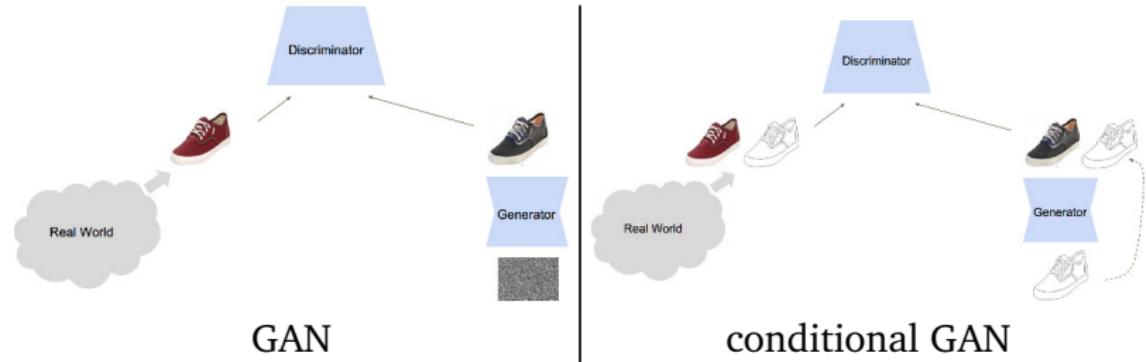
Learn A Mooney Face Classifier: Images



Learn A Mooney Face Classifier: Mooney



Cross-Modal Translation via Conditional GANs



(Isola, Zhu, Zhou, Efros: arXiv 2016)

Conditional GAN on Train: Mooney → Grayscale



Conditional GAN on Test: Mooney → Grayscale



Wildlife Ocular Survey from Low-flying Aircraft



WILDLIFE BIOLOGIST MORTALITY

1015

Job-related mortality of wildlife workers in the United States, 1937–2000

D. Blake Sasse

Abstract Wildlife biologists face a variety of job-related hazards that are unique to this profession, most of them involving the remote areas where work is performed and the unusual techniques used to study or manage wildlife. Information on biologists and others killed while conducting wildlife research or management was obtained from state and federal natural resources agencies, solicitations on wildlife-based internet discussion groups, and published obituaries. Ninety-one job-related deaths were documented from 1937 to 2000. Aviation accidents, drowning, car and truck accidents, and murder were the most common causes of death. Thirty-nine aviation accidents accounted for 66% of deaths, with aerodynamic stalls and power-line collisions being the most significant causes of accidents for which information was available. These safety threats should be taken into consideration during the design and planning of future research and management projects.

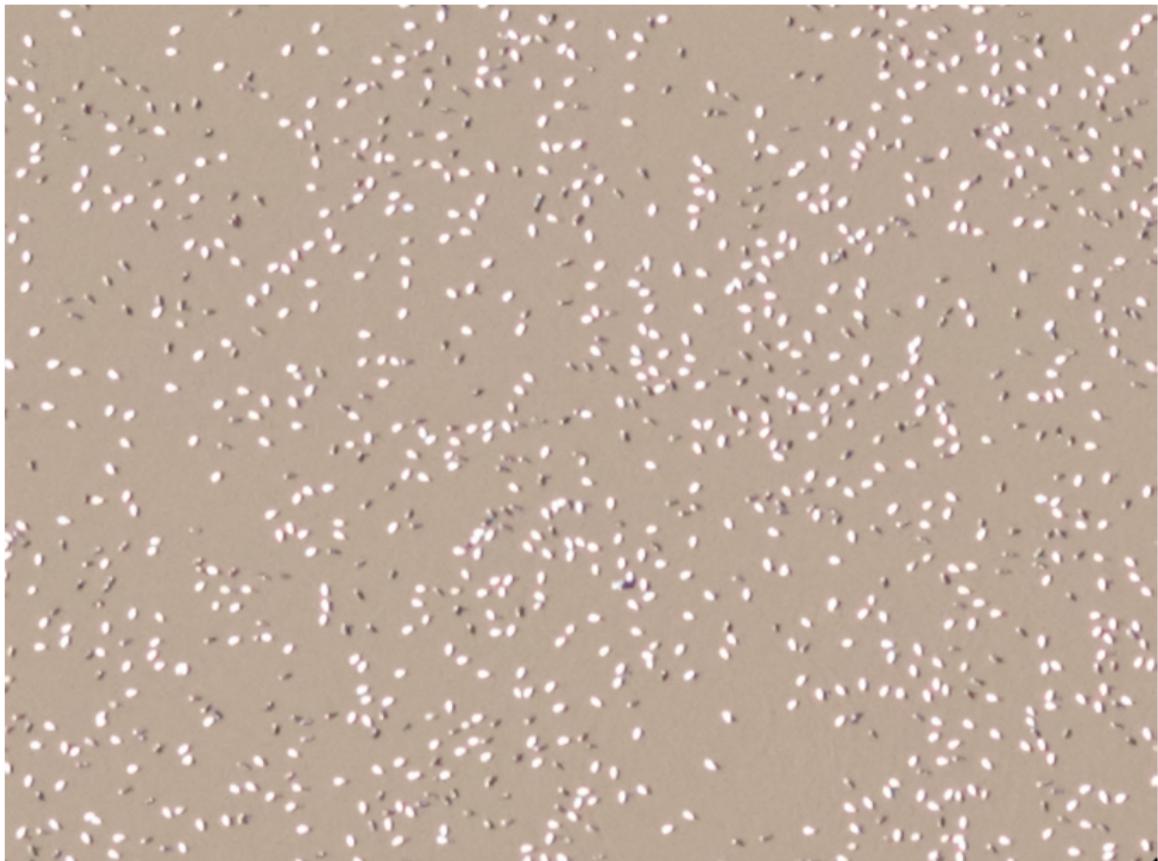
Key words aviation, history, mortality, safety, techniques



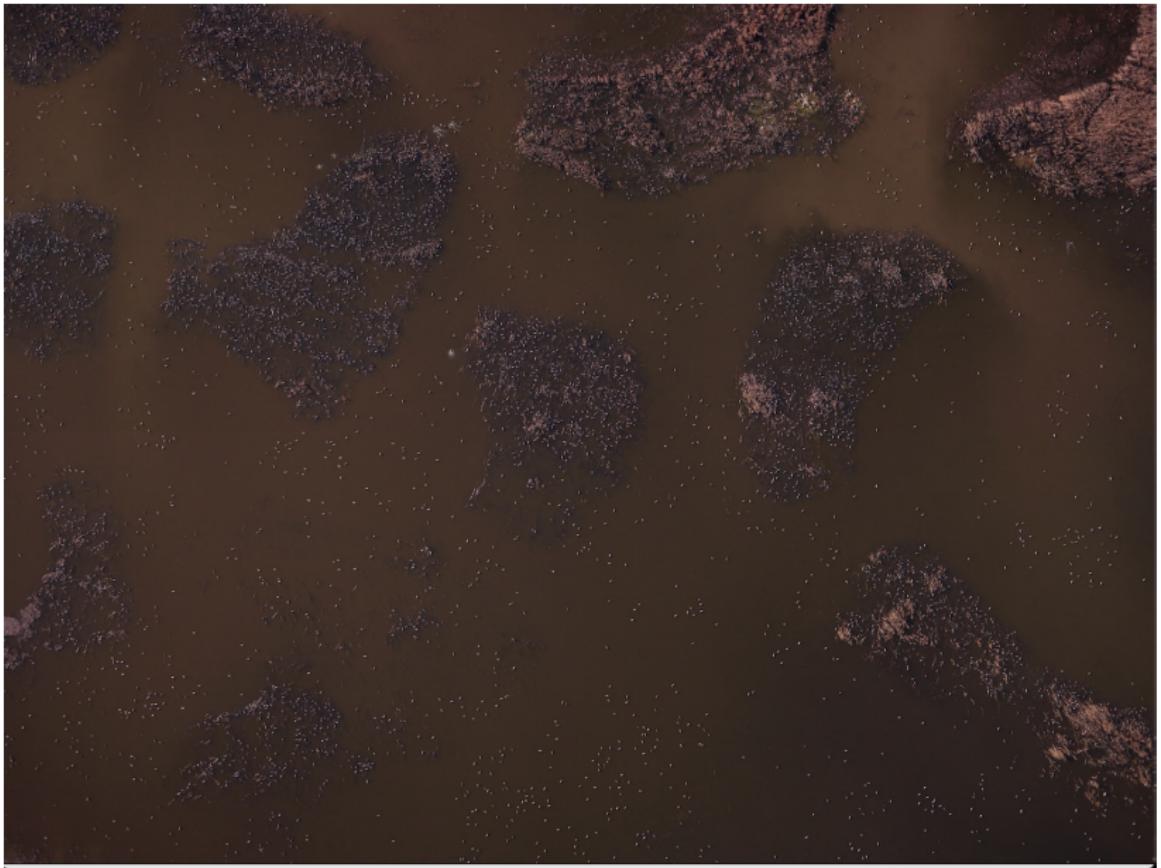
Detection, Classification, Counting of Wildlife



Detection, Classification, Counting of Wildlife



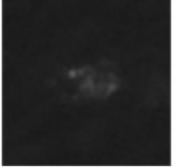
Detection, Classification, Counting of Wildlife



Detection, Classification, Counting of Wildlife

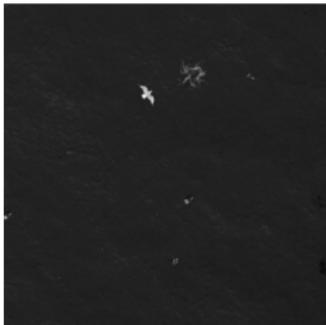


Fine-Grained Recognition: Bird, Sex, Activity, ...

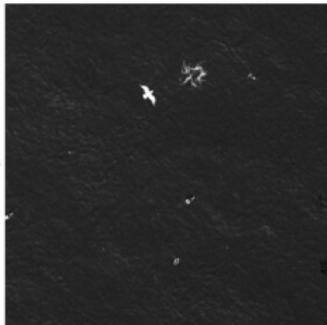
| Category | 400 AGL | 250 AGL |
|-----------------------|---|---|
| Male LTDU on water |  |  |
| Female LTDU on water |  |  |
| Unknown LTDU on water |  |  |
| LTDU diving |  |  |

Fine-Grained Recognition: Method in the Field

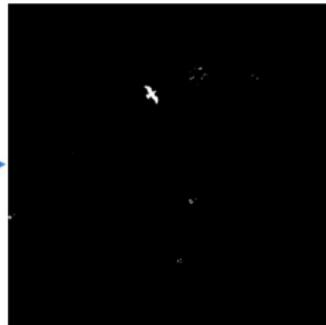
1. Input Image



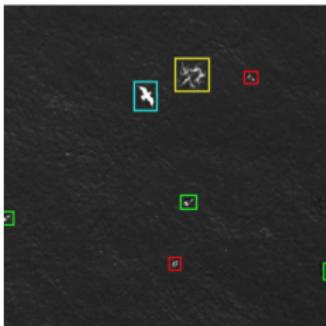
2. Contrast Enhancement



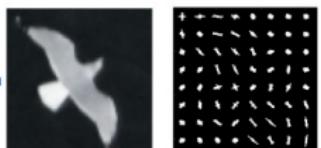
3. Binarization



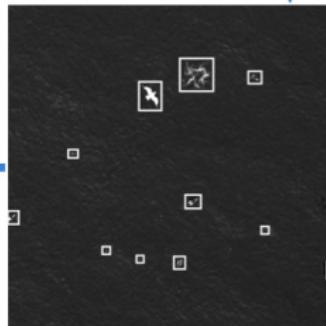
6. Classification



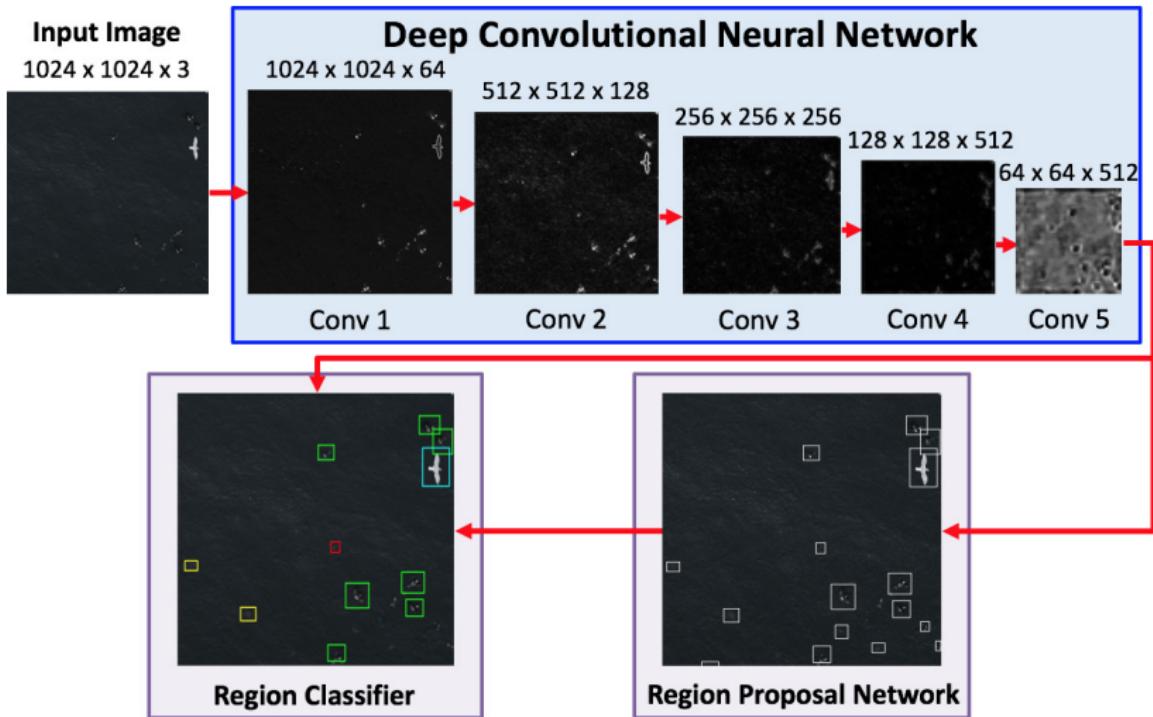
5. Crops & HOGs



4. Proposals

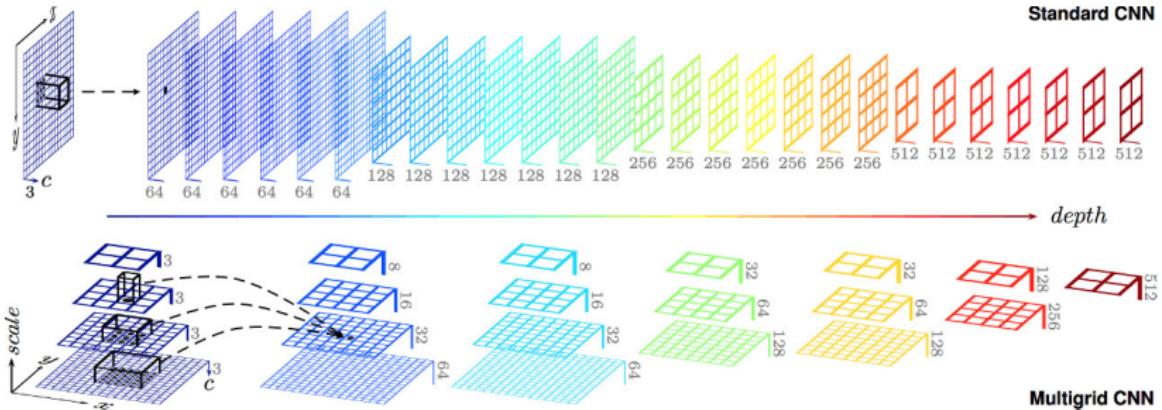


Fine-Grained Recognition: CNN 63% vs 40%



Migratory Bird Survey: Mark Koneff, Team @ USFWS, USGS etc

Neural Multigrid: A New CNN Meso-Architecture



- ▶ Old: As depth \uparrow , feature complexity \uparrow , spatial resolution \downarrow
- ▶ New: feature complexity and spatial resolution are decoupled
- ▶ More efficient communication within the network
- ▶ More effective classification, more refined segmentation

(Ke, Maire, Yu: CVPR 2017)

A Feedforward Neural Net for Spatial Transformer

| Input | True | U-NET | SG | H-SG | P-NMG | P-NMG |
|-------|------|-------|----|------|-------|-------|
| 2 | 7 | 7 | | | 9 | 7 |
| 1 | 0 | 0 | | | 0 | 0 |
| \ | 1 | 1 | | | 1 | 1 |
| 0 | 0 | 0 | | | 0 | 0 |
| ~ | 3 | 3 | | | 3 | 3 |
| * | 5 | 5 | | | 5 | 5 |
| * | 8 | 8 | | | 8 | 8 |

Scaling & Rotation & Affine & Translation

| Input | True | U-NET | Input | True | U-NET |
|------------------|------|-------|-------|------|-------|
| Rotation Only | | | | | |
| / | 1 | 1 | 4 | 4 | 4 |
| 0 | 0 | 0 | 7 | 7 | 7 |
| Affine Only | | | | | |
| 5 | 5 | 5 | 9 | 9 | 9 |
| 2 | 2 | 2 | ? | ? | ? |
| Translation Only | | | | | |

Stimulus-Dependent Receptive Field of Neurons

