



Deep Learning for Graphics

Supervised Applications

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Paul Guerrero

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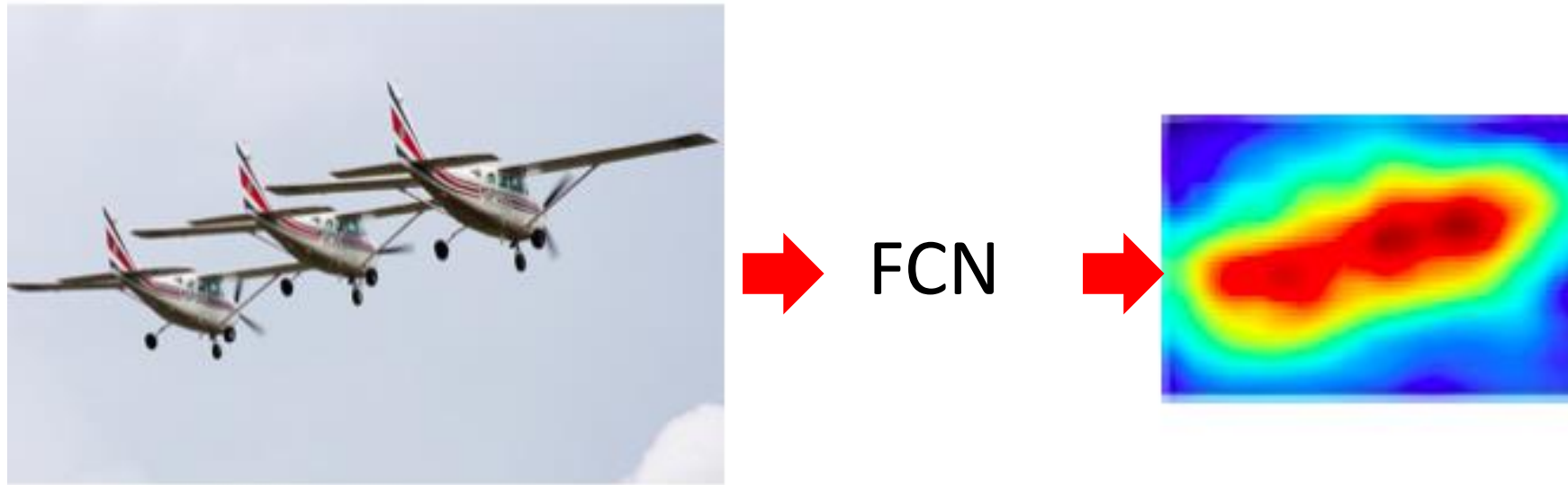
UCL



Timetable

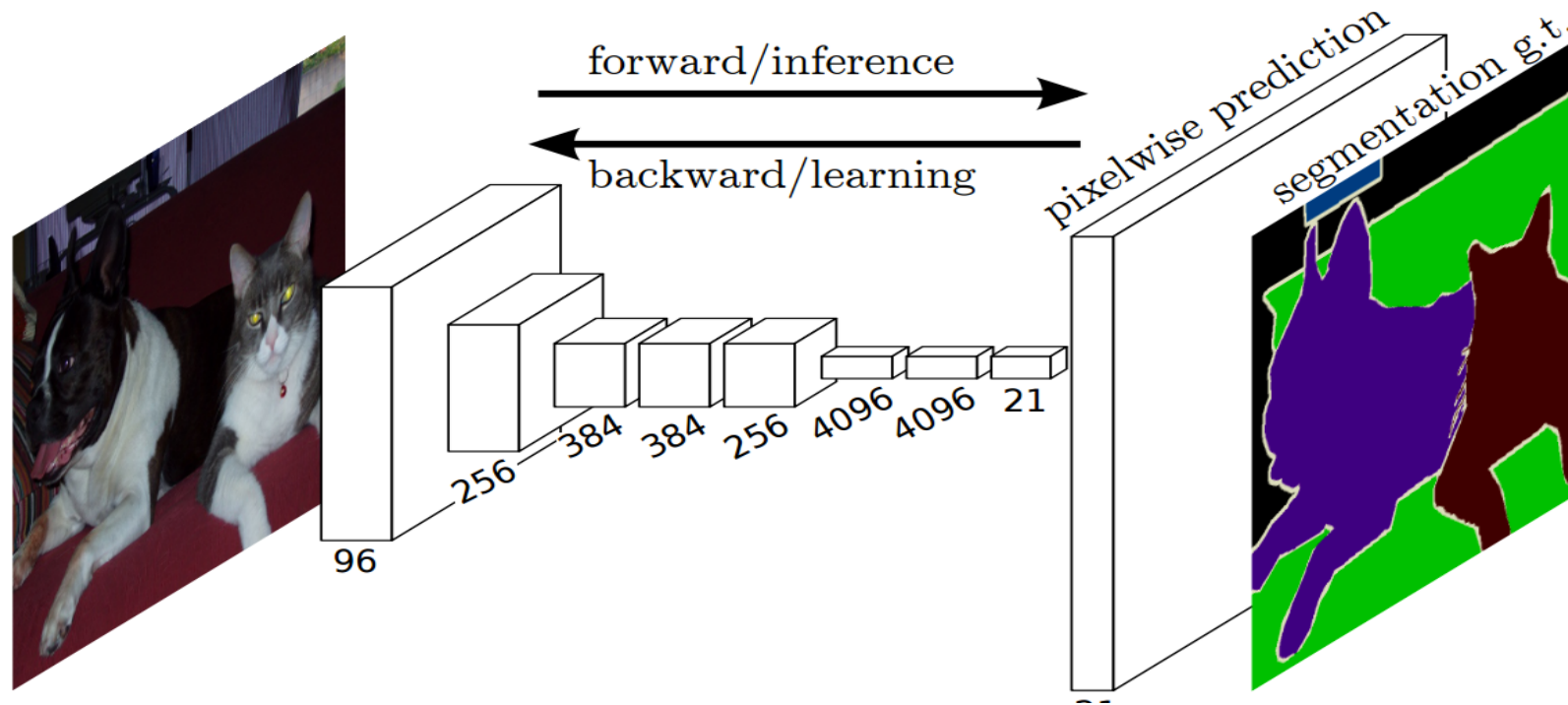
	Niloy	Iasonas	Paul	Vova	Kostas	Tobias
Introduction	X	X	X			X
Theory	X					
NN Basics		X				
Supervised Applications		X	X			X
Data						X
Unsupervised Applications			X			
Beyond 2D	X		X	X		
Outlook	X	X	X	X	X	X

Fully-Convolutional Network (FCN)



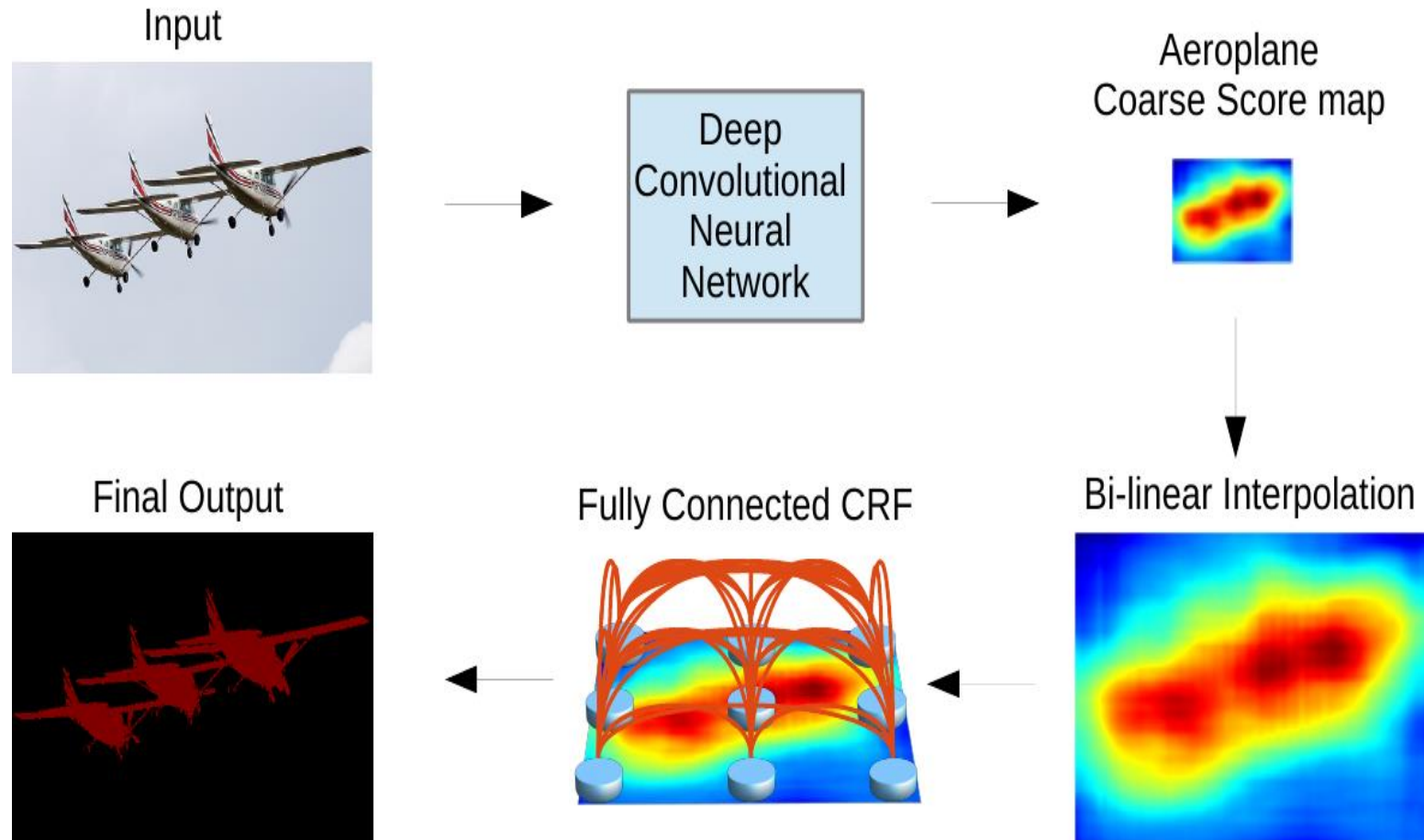
Fast (shared convolutions)
Simple (dense)

FCN-based semantic segmentation



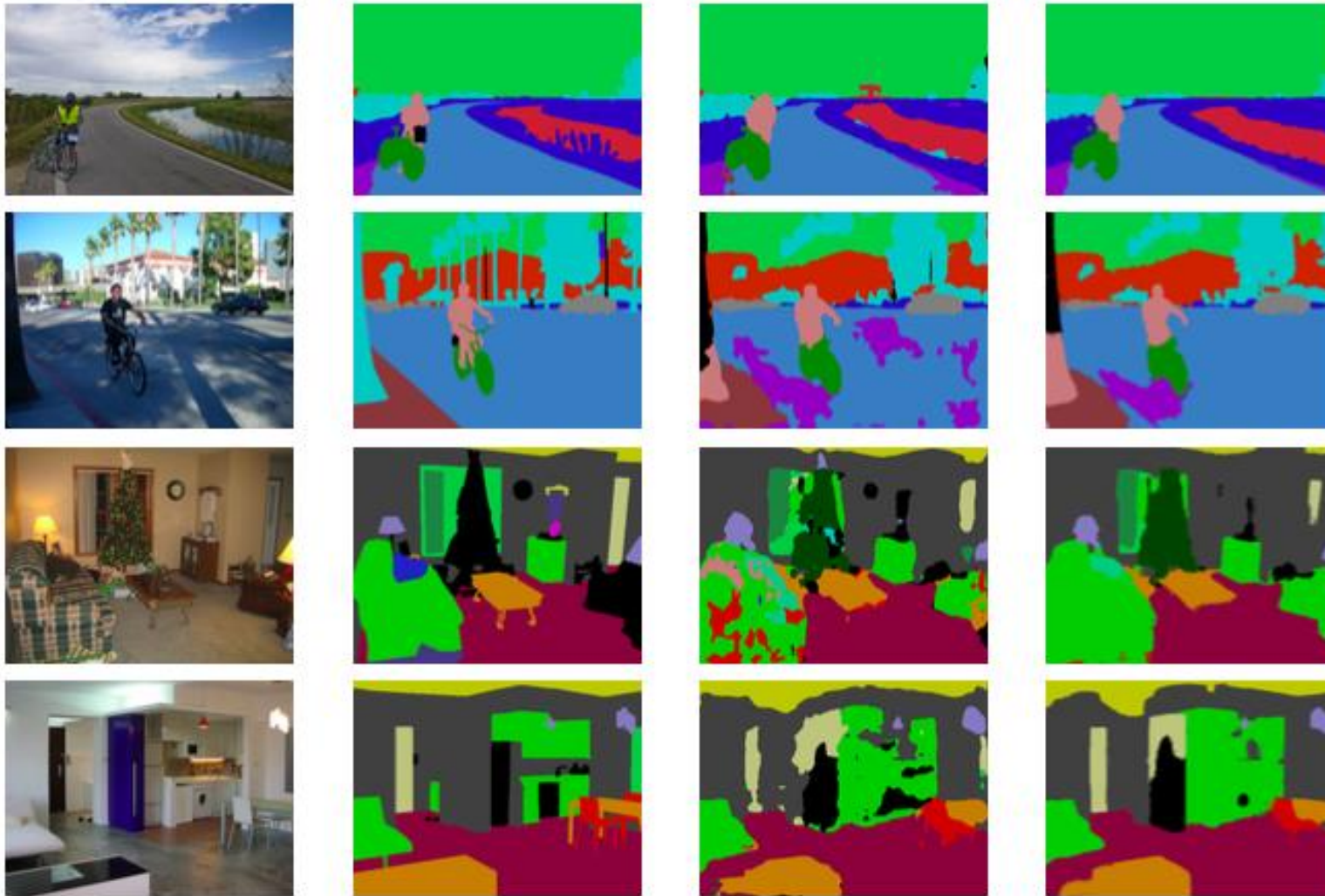
J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. *CVPR*, 2015

FCN-CRFs: Deeplab



L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy and A. Yuille,
Deeplab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs, PAMI 2016

DeepLab v2 results

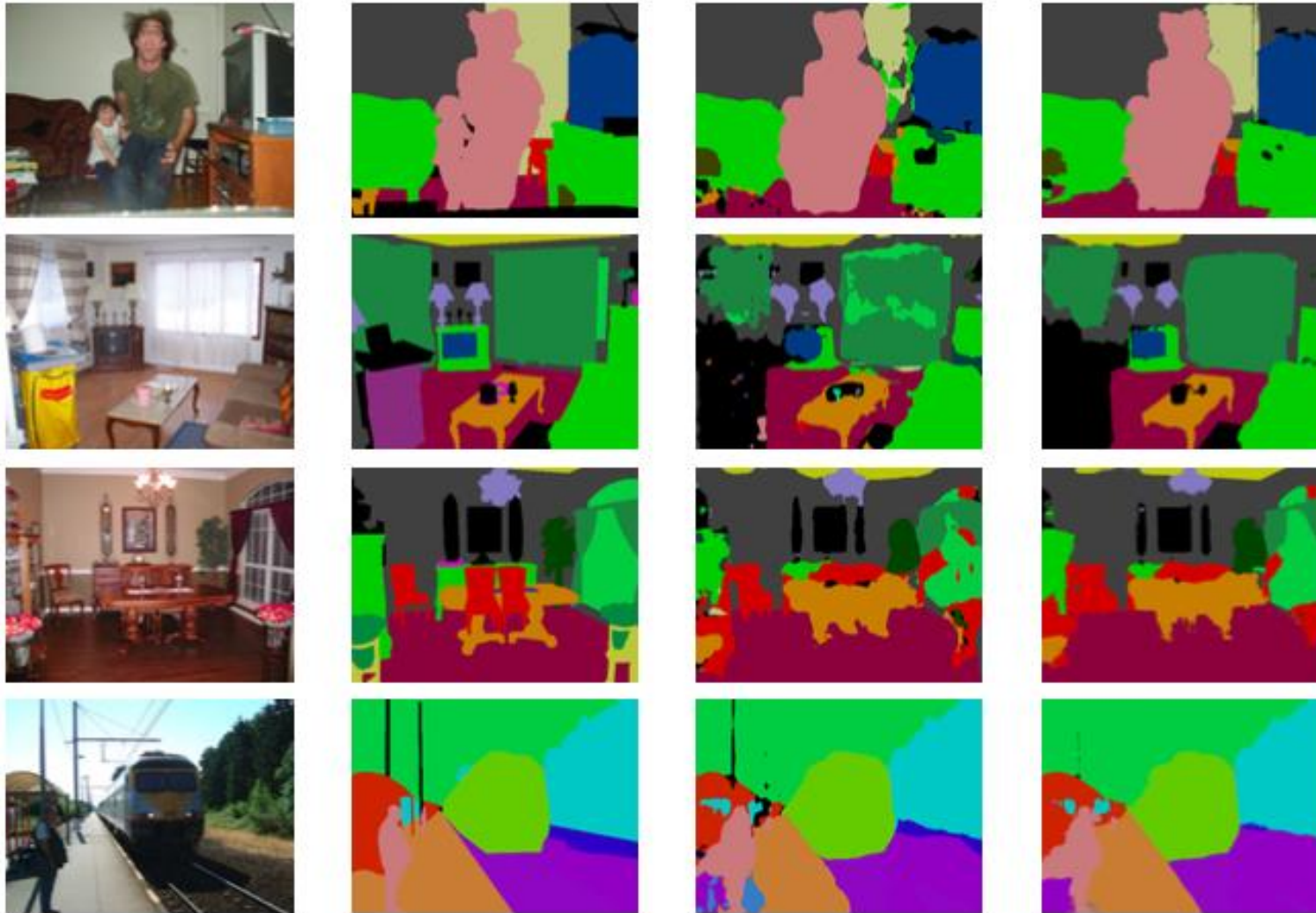


Ground truth

FCN

FCN-DCRF

Deeplab v2 results



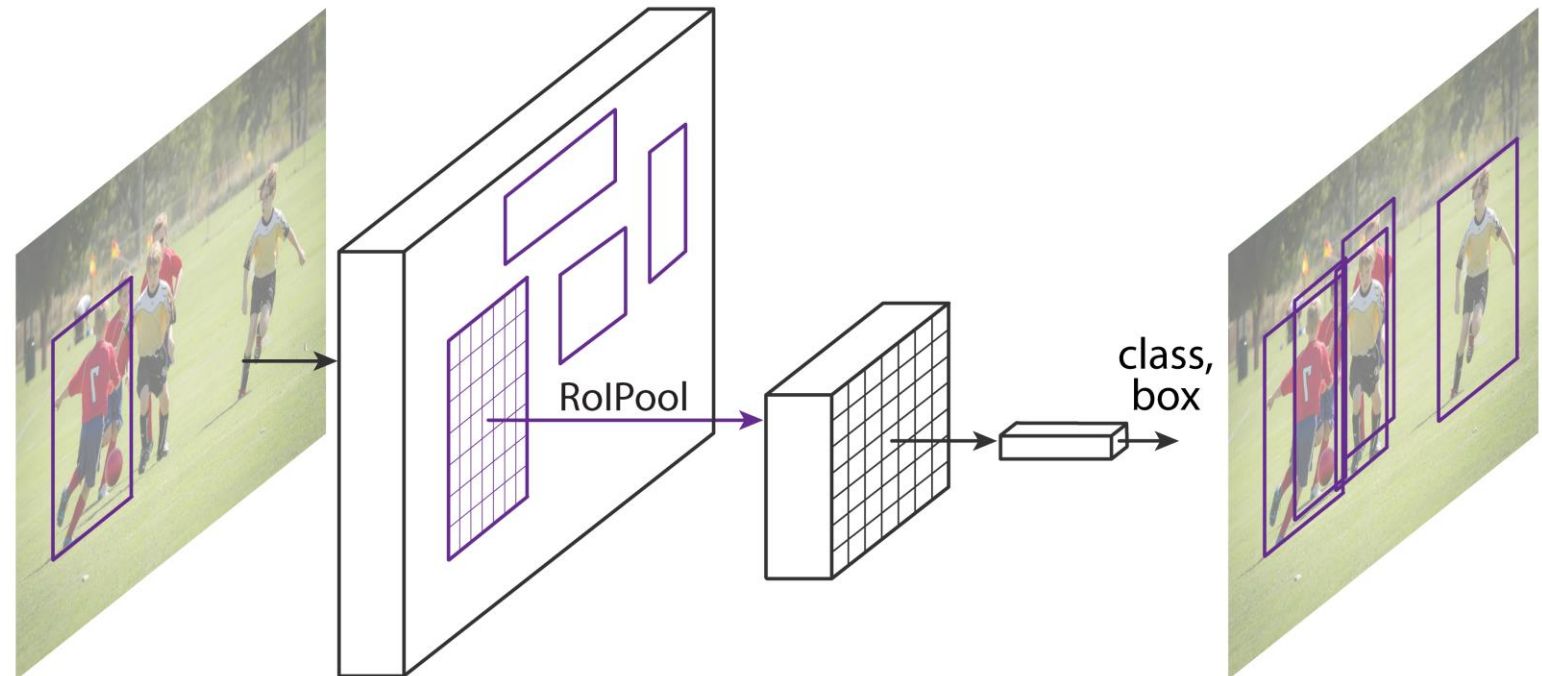
Ground truth

FCN

FCN-DCRF

Object Detection: Fast(er)-RCNN

- Fast/Faster R-CNN
 - ✓ Good speed
 - ✓ Good accuracy
 - ✓ Intuitive
 - ✓ Easy to use

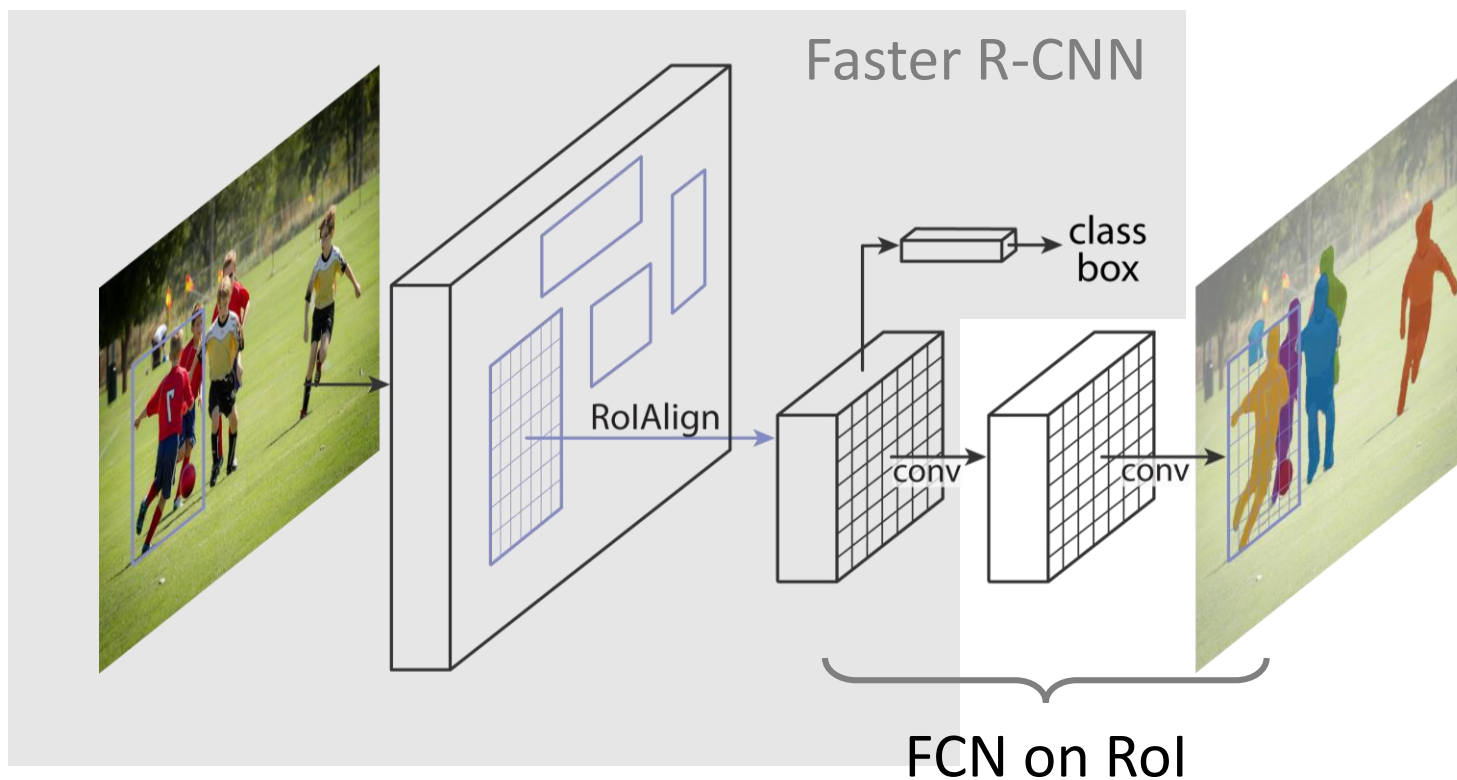


Ross Girshick. "Fast R-CNN". ICCV 2015.

Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

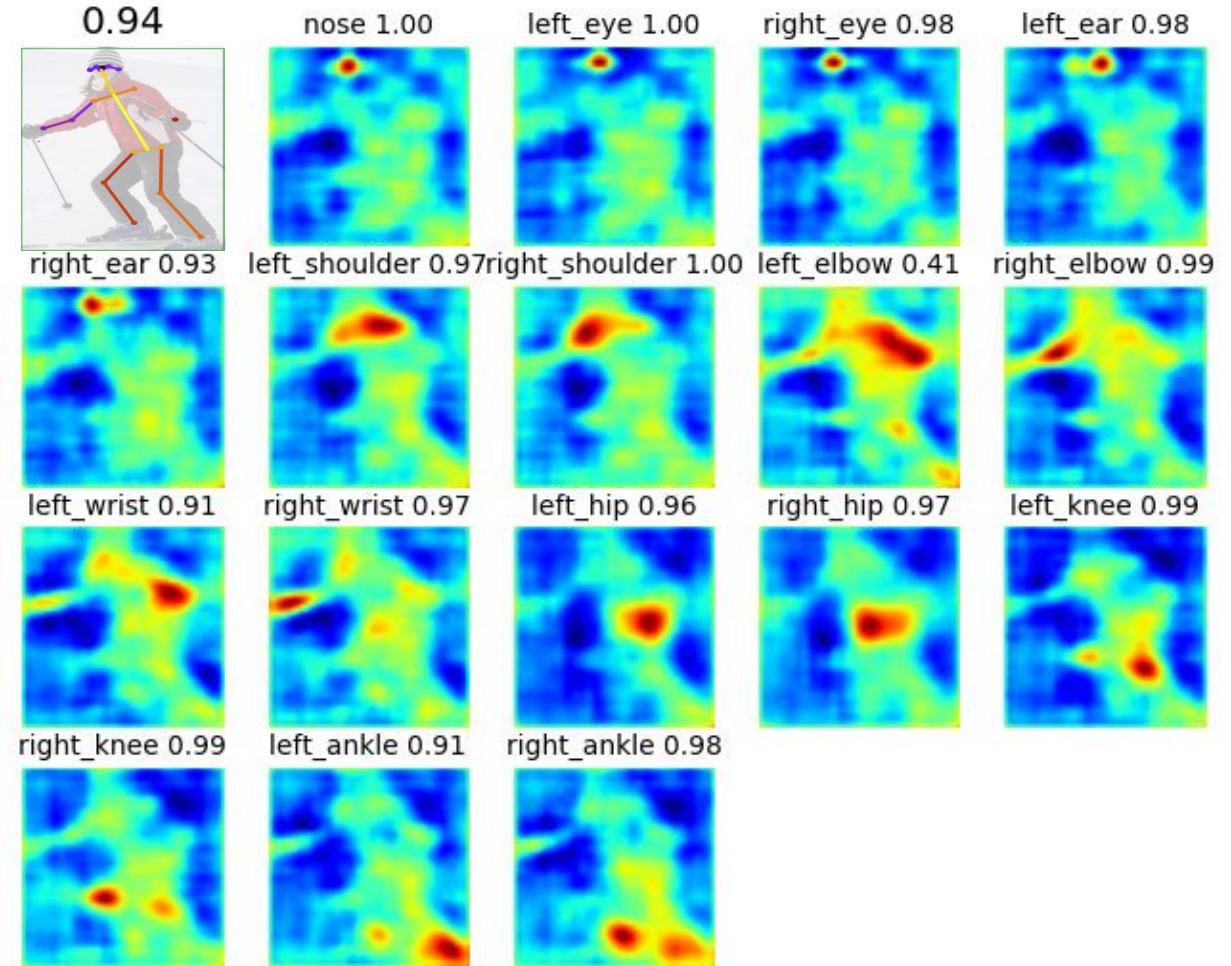
Mask R-CNN

- Mask R-CNN = **Faster R-CNN** with **FCN** on Rols



Mask R-CNN for Human Keypoint Detection

- 1 keypoint = 1-hot “mask”
- Human pose = 17 masks
- Softmax over **spatial locations**
 - e.g. 56^2 -way softmax on 56×56



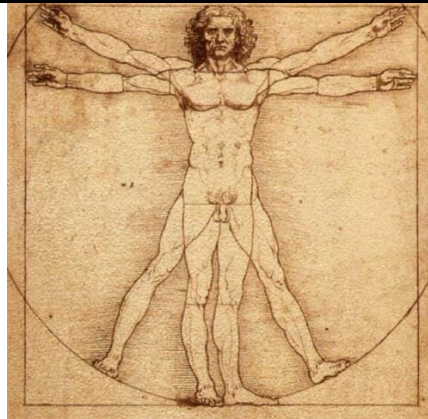
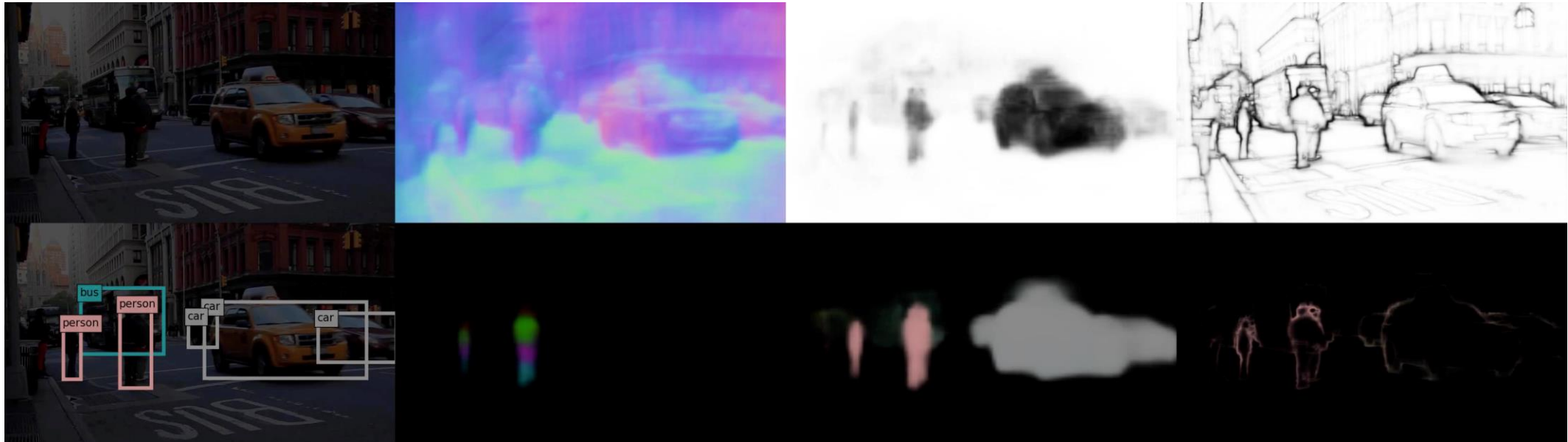
Mask R-CNN frame-by-frame



Mask R-CNN frame-by-frame



UberNet: a “universal” network for all tasks



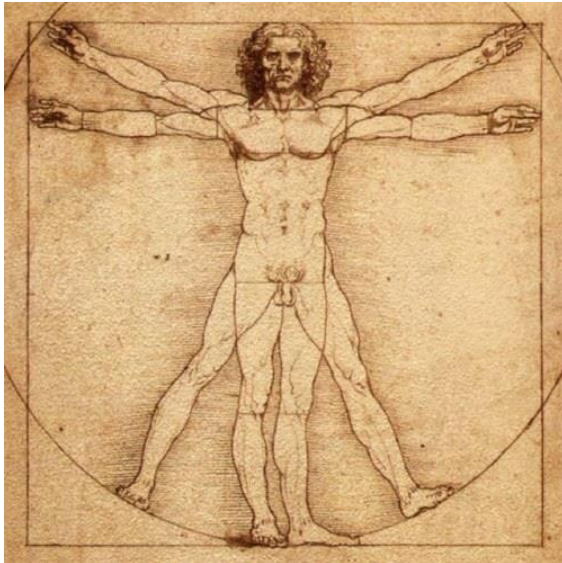
<https://github.com/jkokkin/UberNet>

I. Kokkinos, UberNet: Training a Universal CNN for *Low- Mid- and High-Level* Vision, CVPR 2017

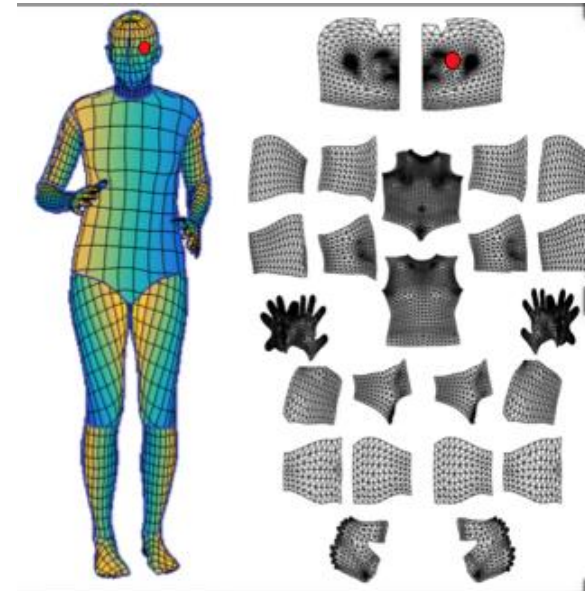
What is the ultimate vision task?

“Inverse graphics”: understand how an image was generated from a scene

If we focus on a single object category: surface-based models

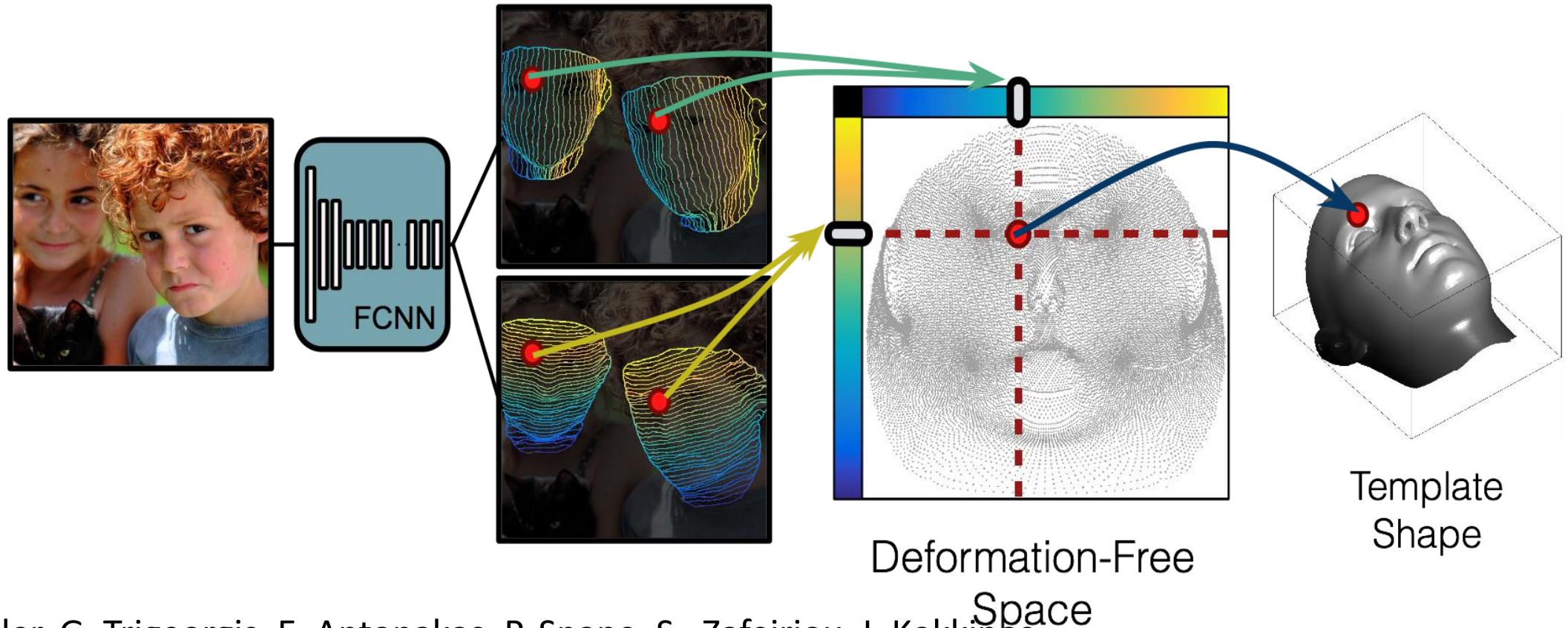


UberNet:
Universal Network



DensePose:
Unified model

DenseReg: dense image-to-face regression



R. A. Guler, G. Trigeorgis, E. Antonakos, P. Snape, S. Zafeiriou, I. Kokkinos,
DenseReg: Fully Convolutional Dense Shape Regression In-the-Wild, CVPR 2017

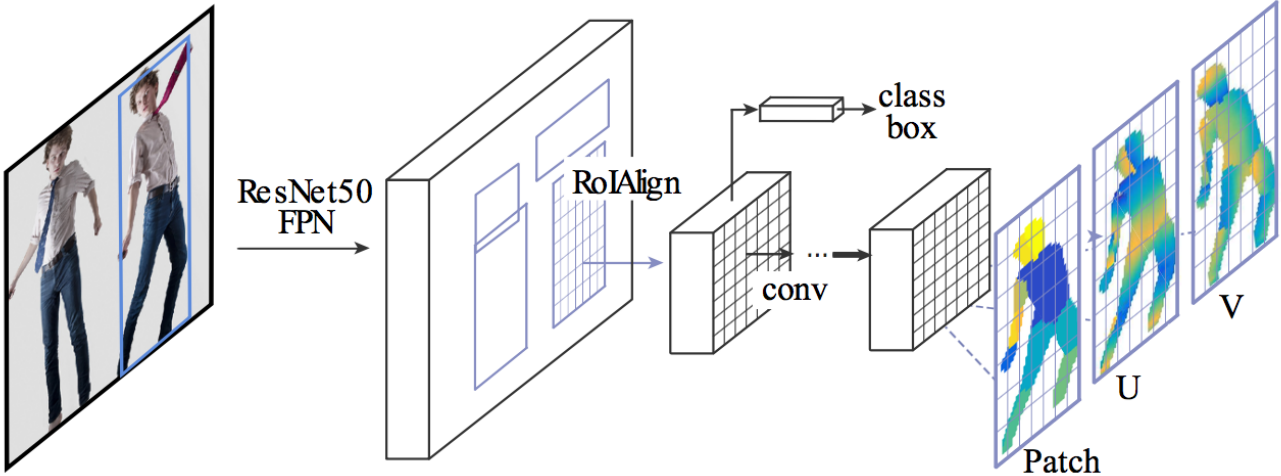
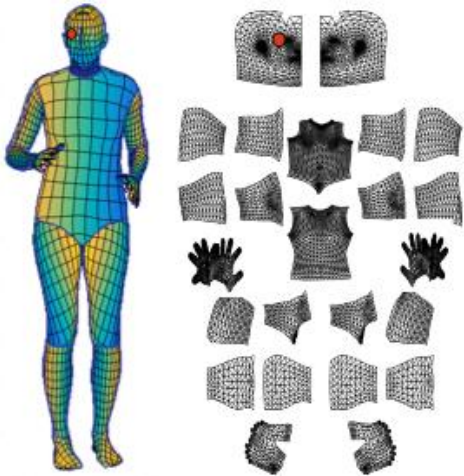
DensePose: dense image-to-body correspondence



DensePose-RCNN Results



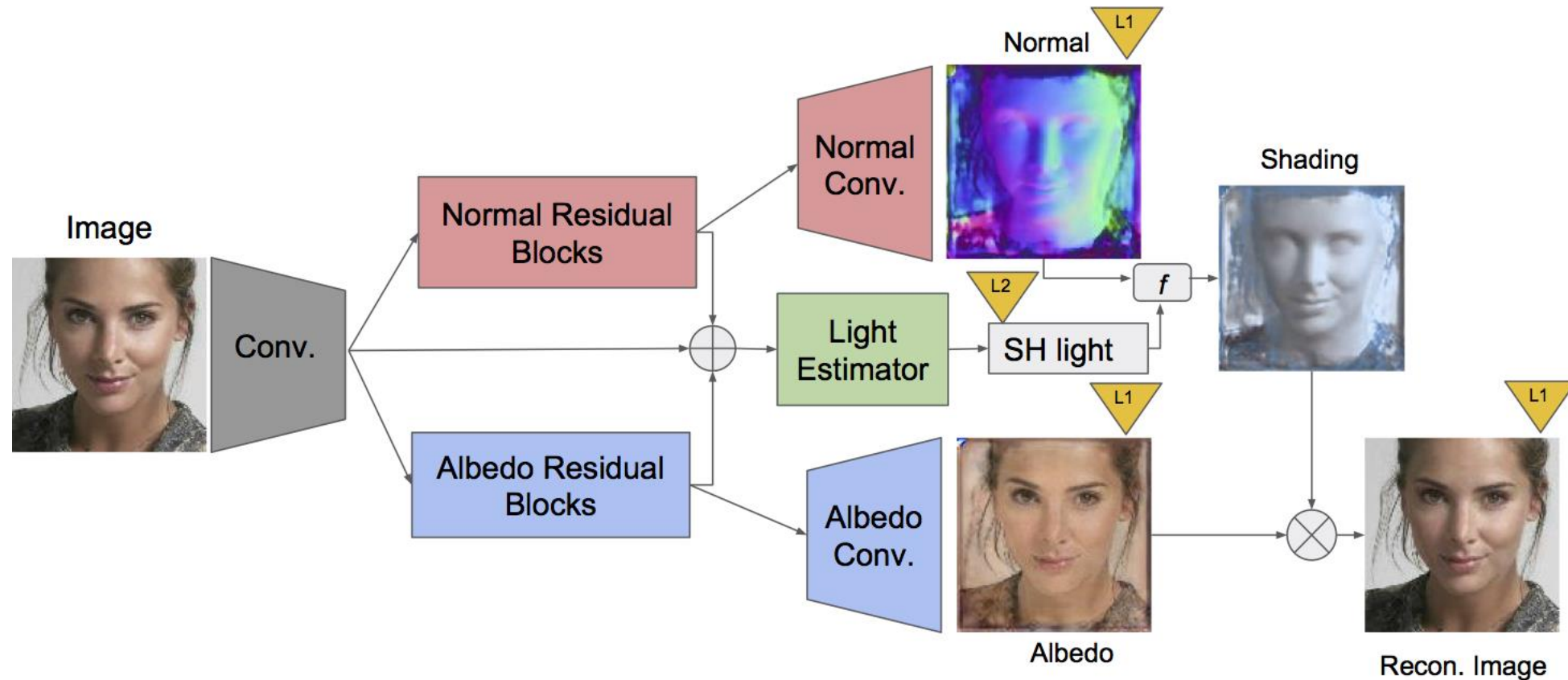
DensePose COCO Dataset



DensePose-RCNN: ~25 FPS



SFSNet: incorporating image formation in model



SfSNet: Learning Shape, Reflectance and Illuminance of Faces 'in the wild' Soumyadip Sengupta Angjoo Kanazawa Carlos D. Castillo David W. Jacobs, CVPR 2018

Beyond single frames: end-to-end optical flow

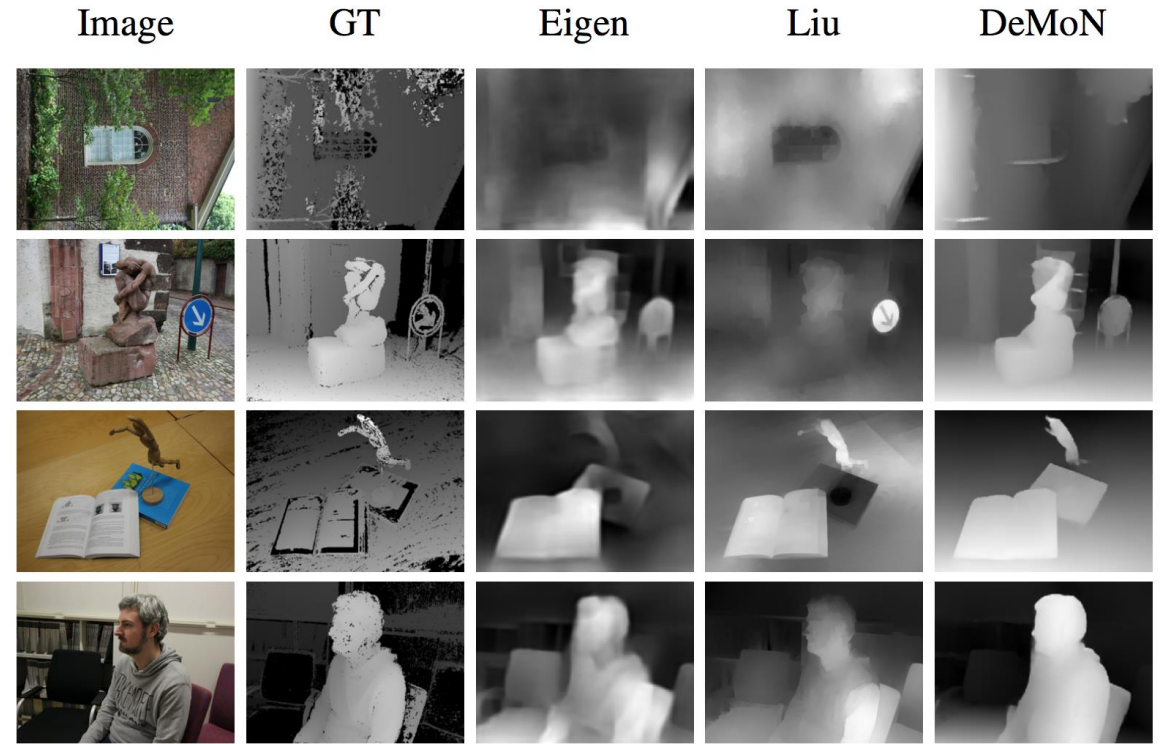
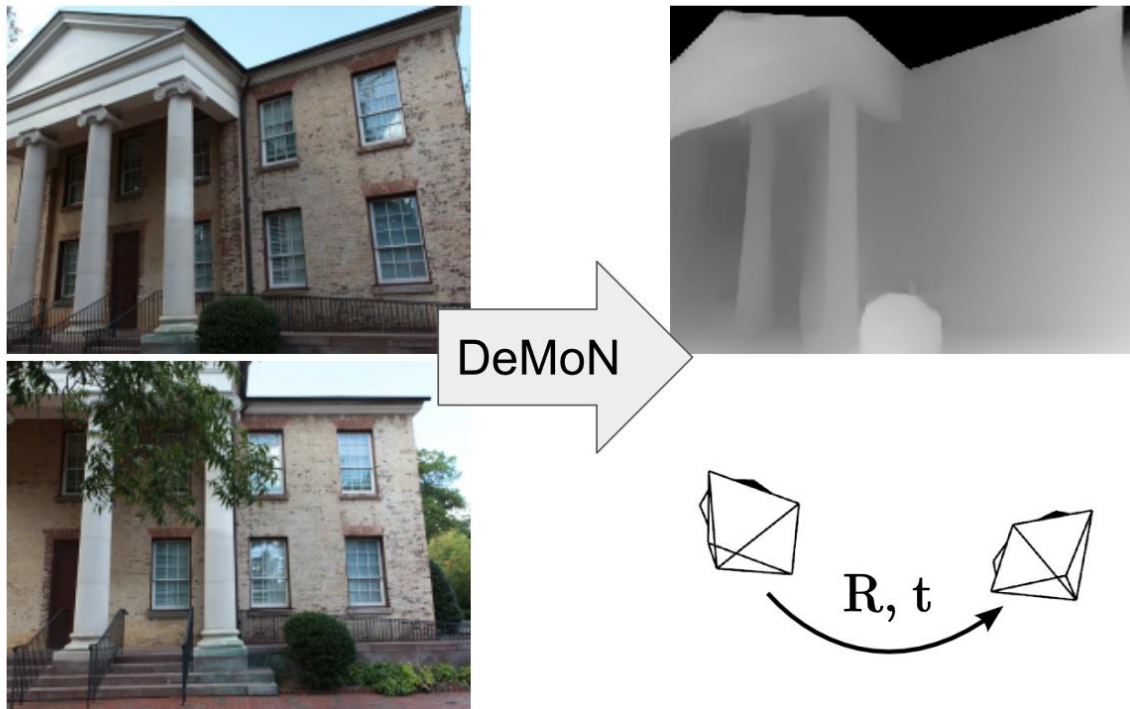
FlowNet 2.0: Evolution of Optical Flow Estimation with Deep Networks

Eddy Ilg, Nikolaus Mayer, Tonmoy Saikia, Margret Keuper, Alexey Dosovitskiy, Thomas Brox

University of Freiburg, Germany

—— Supplementary Material ——

End-to-end Structure From Motion

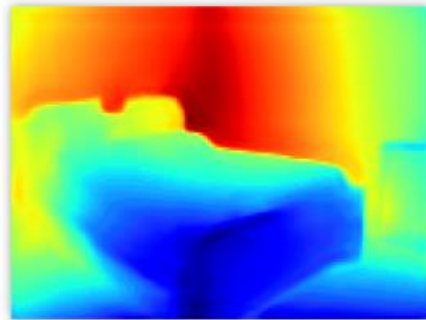


- DeMoN: Depth and Motion Network for Learning Monocular Stereo, B. Ummenhofer, et al, CVPR 2017
- Unsupervised learning of depth and ego-motion from video, T Zhou, M Brown, N Snavely, DG Lowe, CVPR 2017

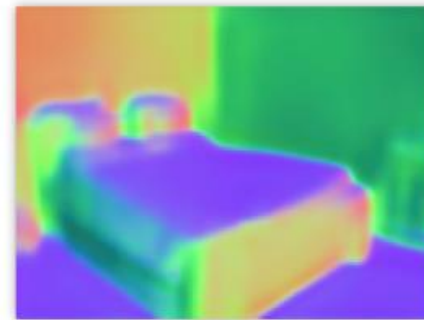
Monocular depth & normal estimation



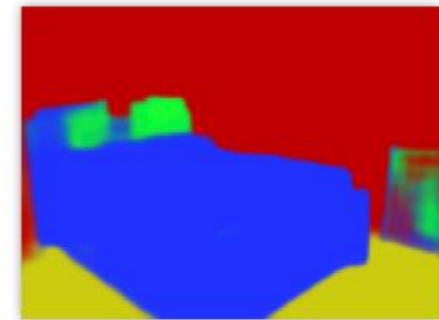
Input Image



Depth



Normals



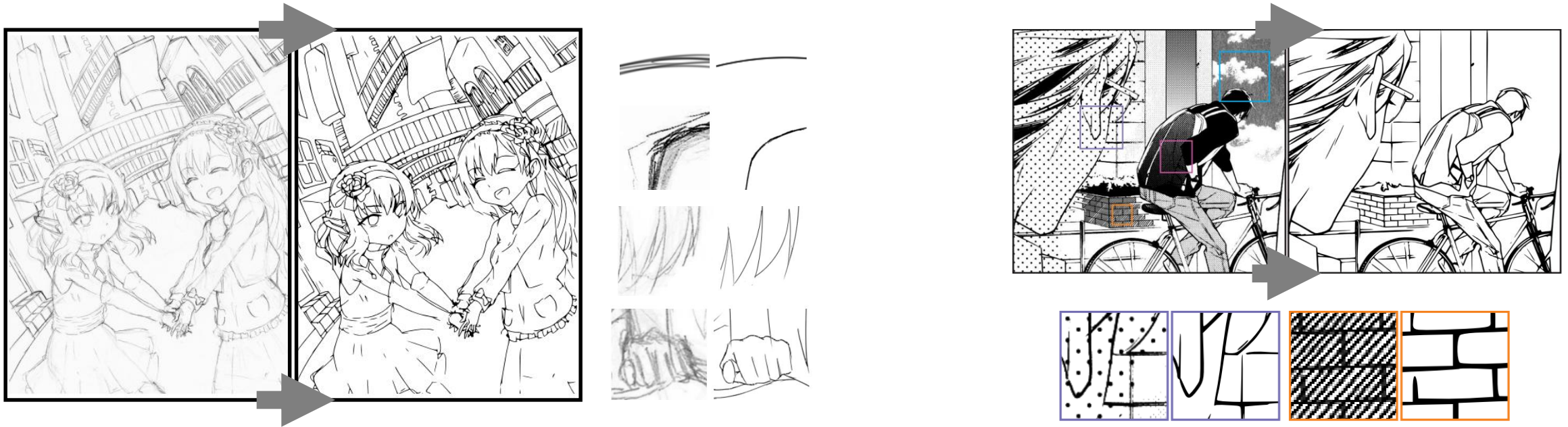
Labels

- D. Eigen and R. Fergus, Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture, ICCV 2015

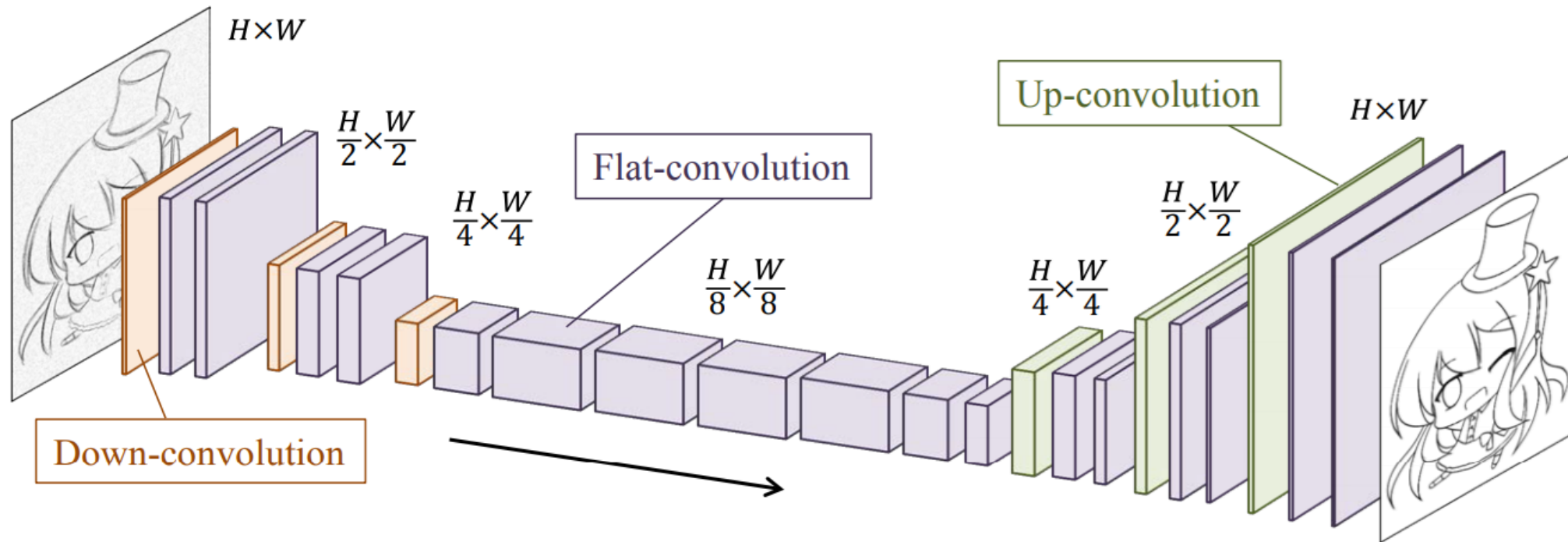
Graphics applications

Sketch Simplification

- *Learning to Simplify: Fully Convolutional Networks for Rough Sketch Cleanup*, Simon-Serra et al., 2016
- *Deep Extraction of Manga Structural Lines*, Li et al., 2017



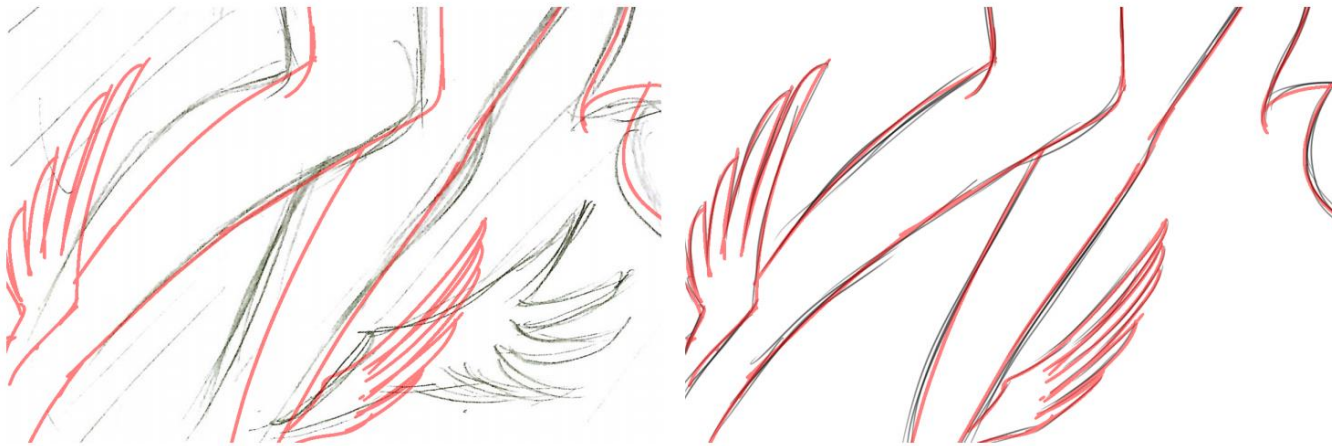
Sketch Simplification: *Learning to Simplify*



Learning to Simplify: Fully Convolutional Networks for Rough Sketch Cleanup, Simo-Serra et al.

Sketch Simplification: *Learning to Simplify*

- Loss for thin edges saturates easily
- Authors take extra steps to align input and ground truth edges



Pencil: input
Red: ground truth

Learning to Simplify: Fully Convolutional Networks for Rough Sketch Cleanup, Simo-Serra et al.

Image Decomposition

- A selection of methods:
- *Direct Intrinsic*, Narihira et al., 2015
- *Learning Data-driven Reflectance Priors for Intrinsic Image Decomposition*, Zhou et al., 2015
- *Decomposing Single Images for Layered Photo Retouching*, Innamorati et al. 2017

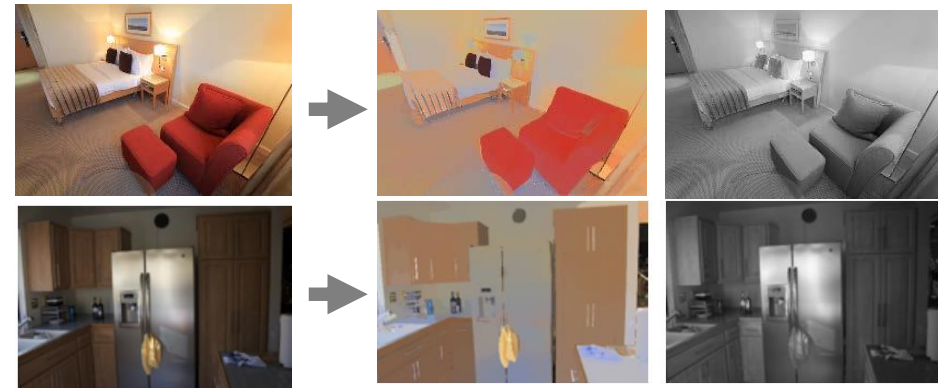
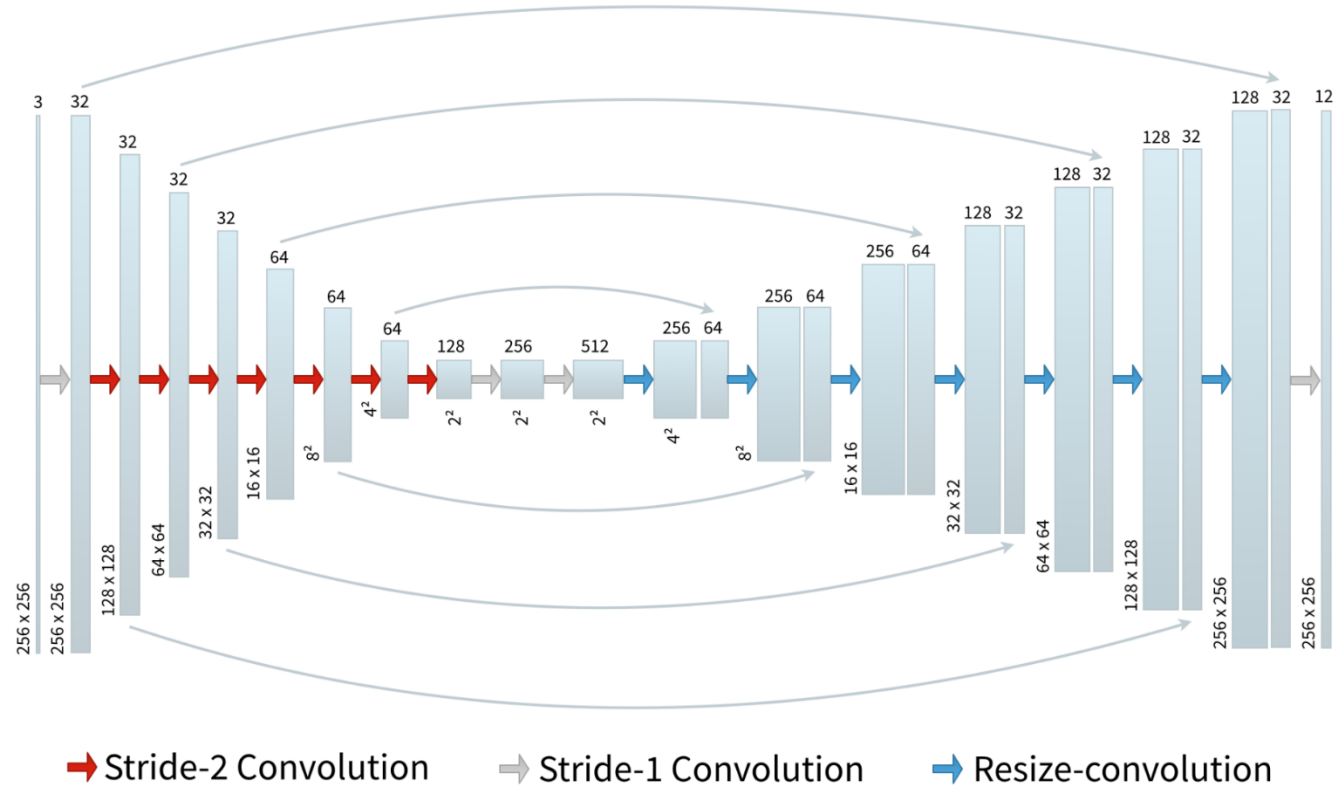
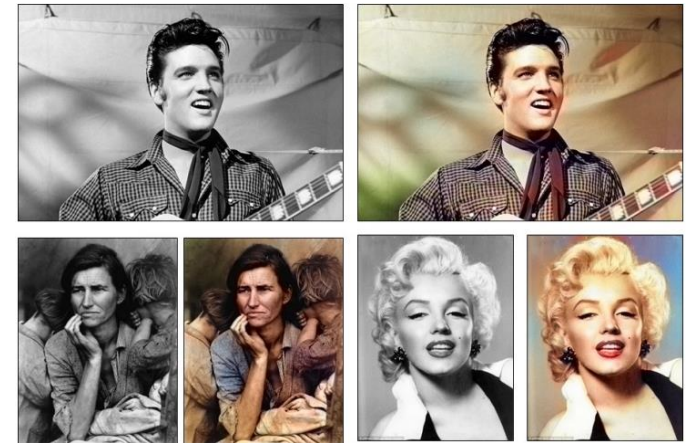


Image Decomposition: Decomposing *Single Images for Layered Photo Retouching*

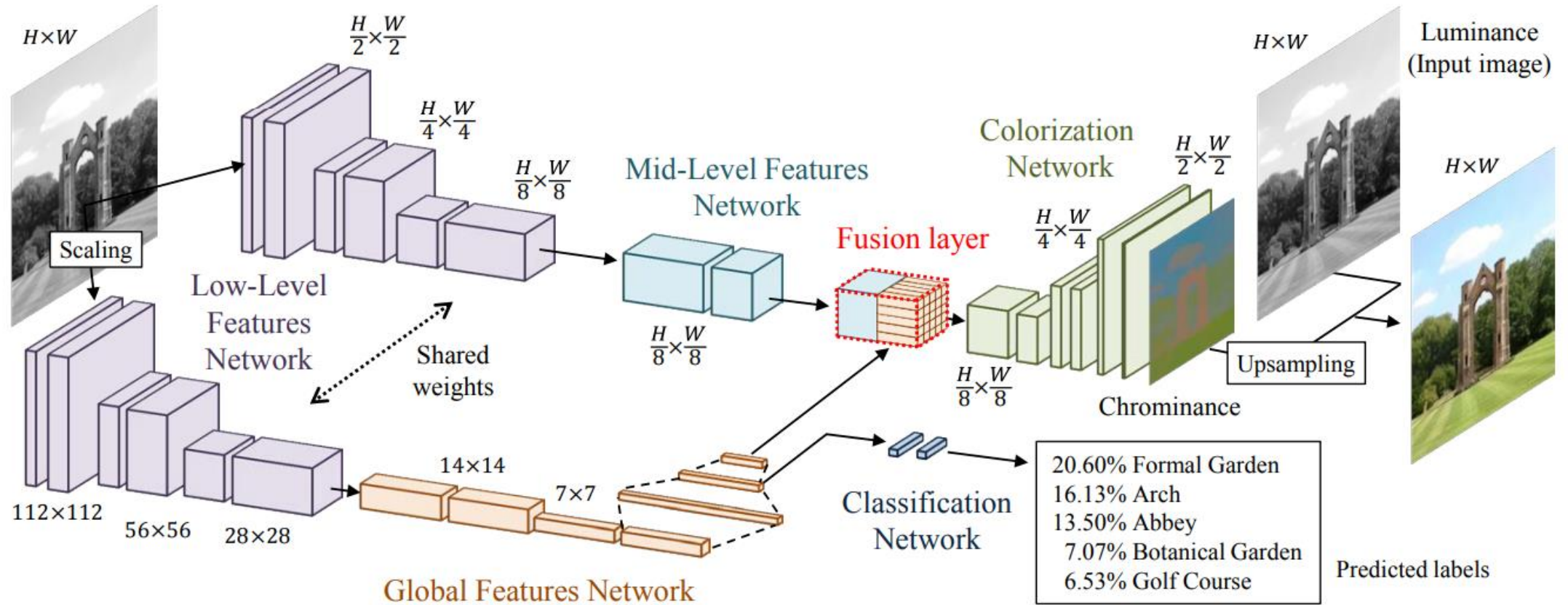


Colorization

- Concurrent methods:
 - *Let there be Color!*, lizuka et al., 2016
 - *Colorful Image Colorization*, Zhang et al. 2016
 - *Learning Representations for Automatic Colorization*, Larsson et al., 2016
 - *Real-Time User-Guided Image Colorization with Learned Deep Priors*, Zhang et al. 2017

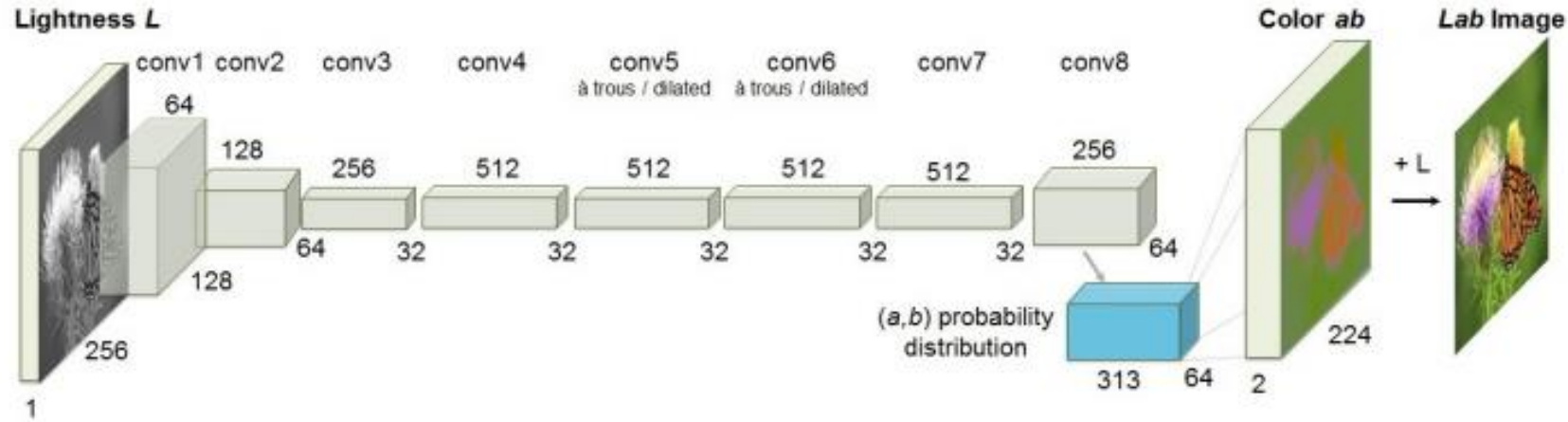


Colorization: *Let There Be Color!*



Let there be Color!: lizuka et al.

Colorization: *Colorful Image Colorization*



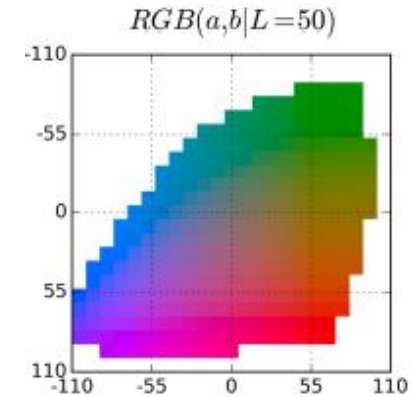
input

output

direct regression probability distr.

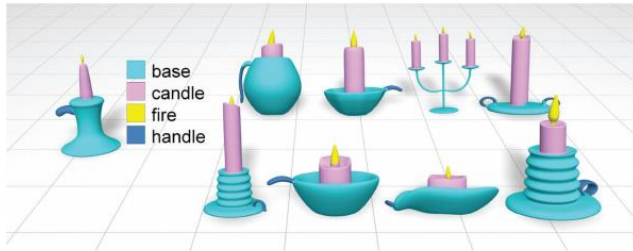


Image Credit: *Colorful Image Colorization*, Zhang et al.

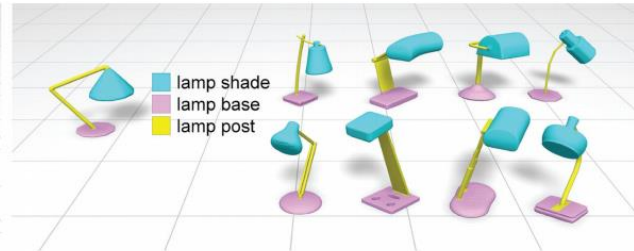


Mesh Labeling / Segmentation

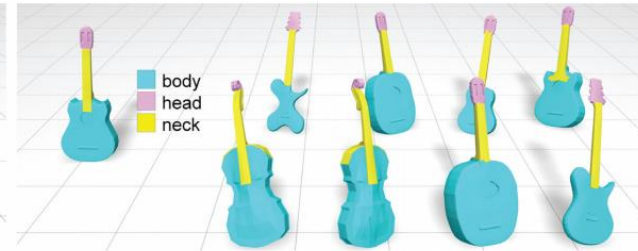
3D Mesh Labeling via Deep Convolutional Neural Networks, Guo et al. 2016



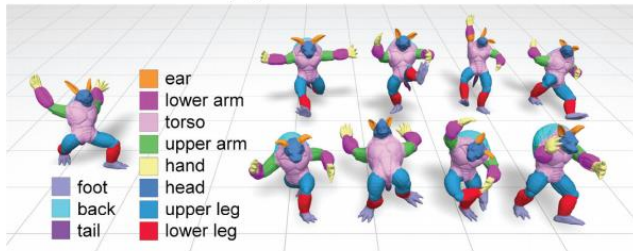
(a) candelabra



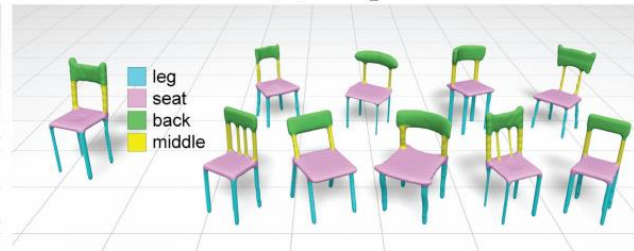
(b) lamp



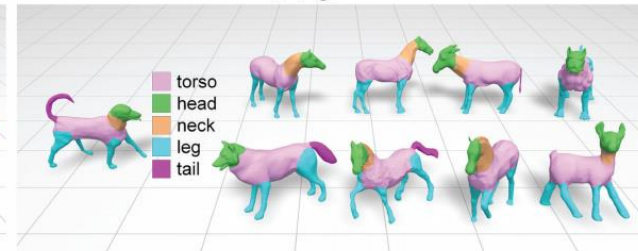
(c) guitar



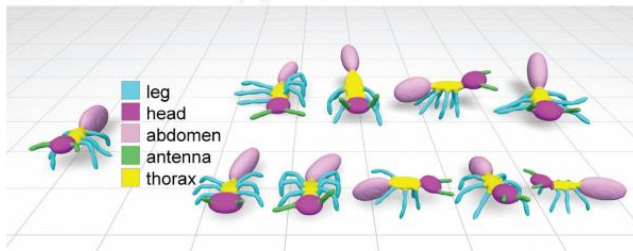
(d) armadillo



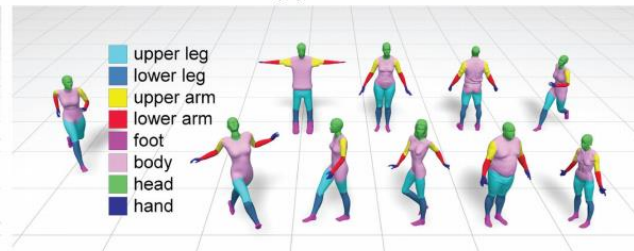
(e) chair



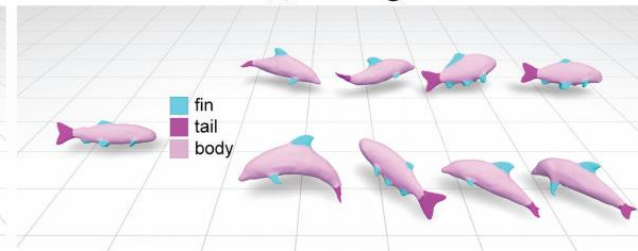
(f) fourleg



(g) ant

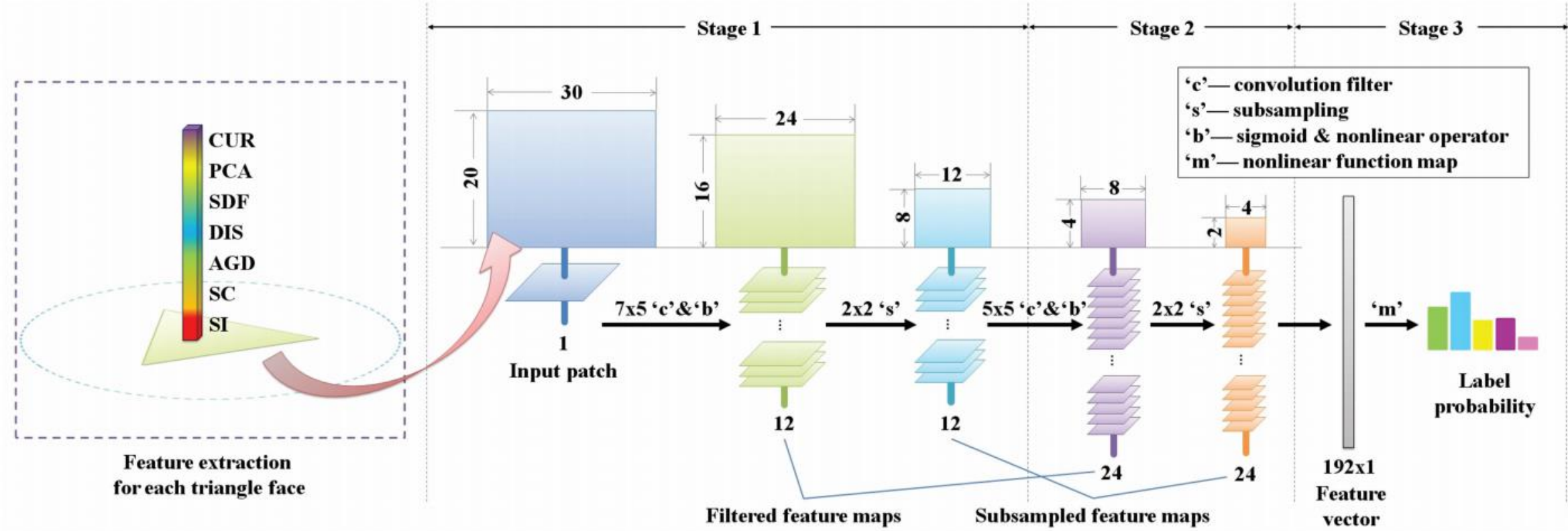


(h) human



(i) fish

Mesh Labeling / Segmentation



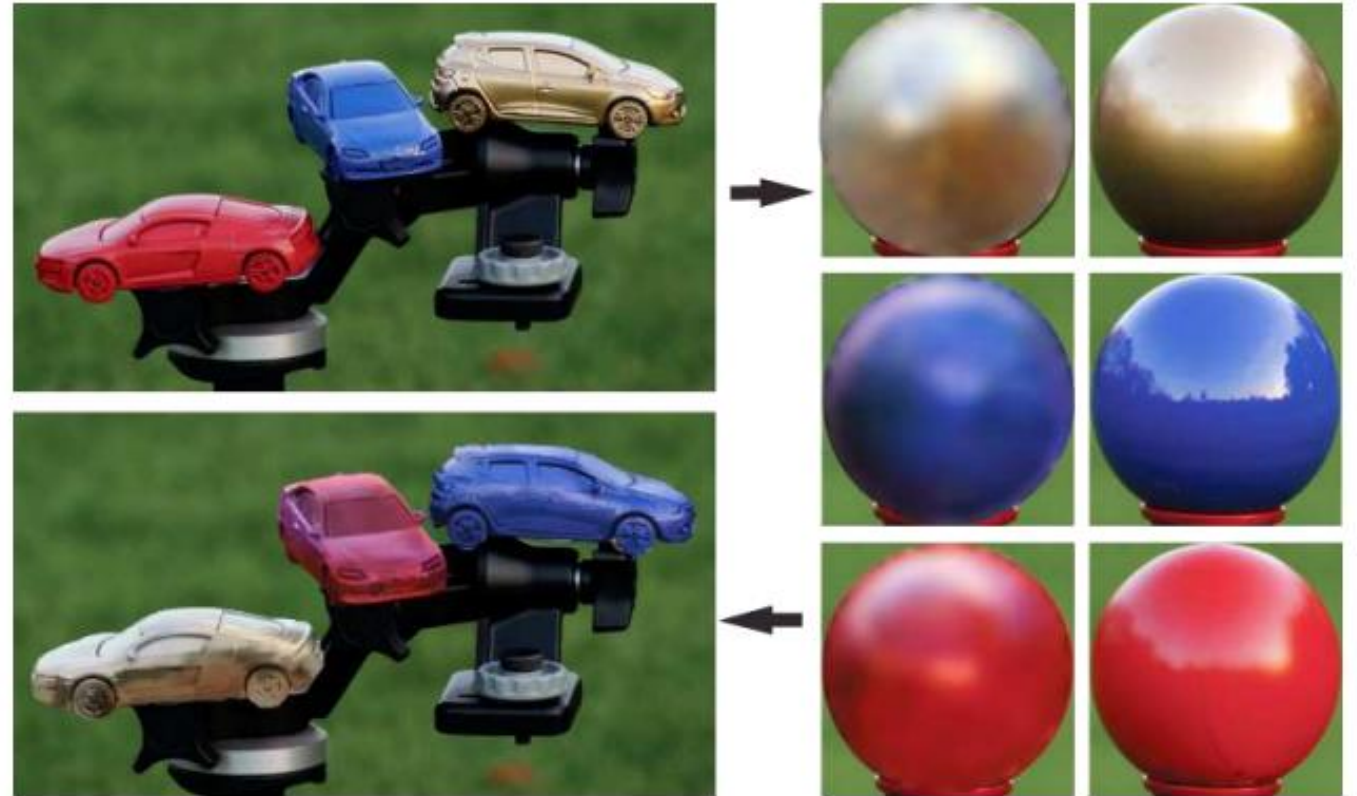
3D Mesh Labeling via Deep Convolutional Neural Networks, Guo et al.

LDR to HDR Image Reconstruction:

- Concurrently:
- *Deep Reverse Tone Mapping*, Endo et al. 2017
- *HDR image reconstruction from a single exposure using deep CNNs*, Eilertsen et al. 2017

Reflectance Maps

- Paint a sphere as if it is made of a material under a certain illumination of another object in a photo



Deep Reflectance Maps. Rematas et al. CVPR 2015

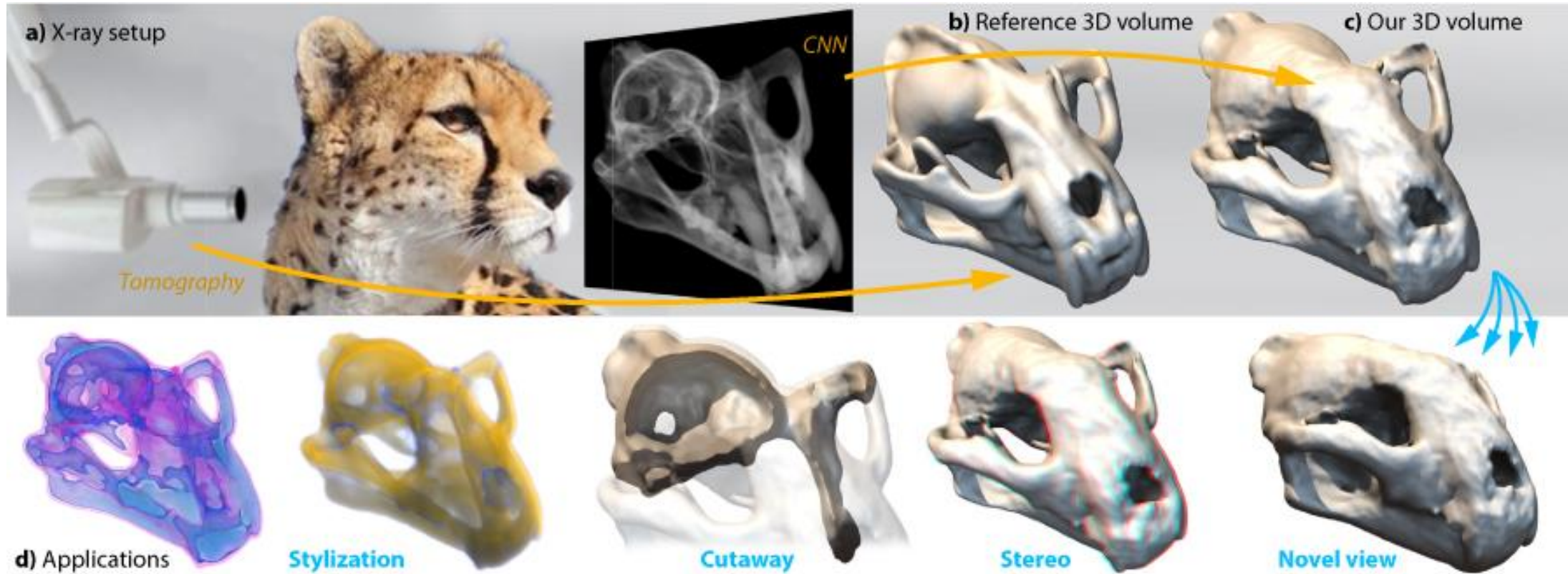
DeLight

- Factor BRDF and (HDR) Illumination



Reflectance and Natural Illumination from Single-Material Specular Objects Using Deep Learning. Georgoulis et al. **PAMI 2017**

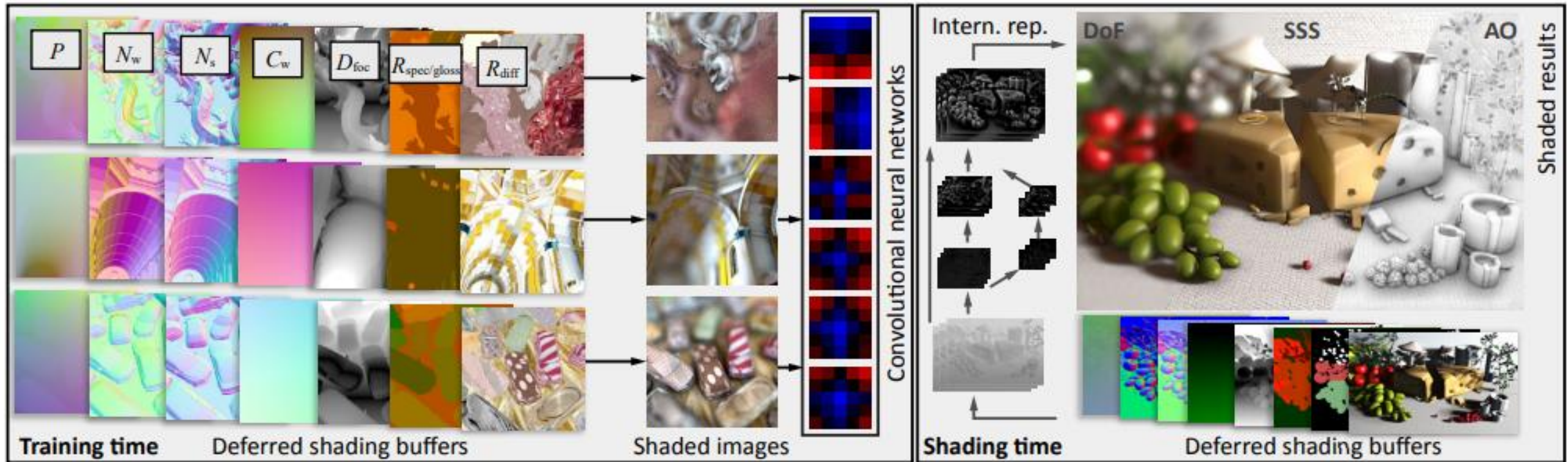
3D volumes from Xrays



Single-Image Tomography: 3D Volumes from 2D Cranial X-Rays. Henzler et al. EG 2018

Deep Shading

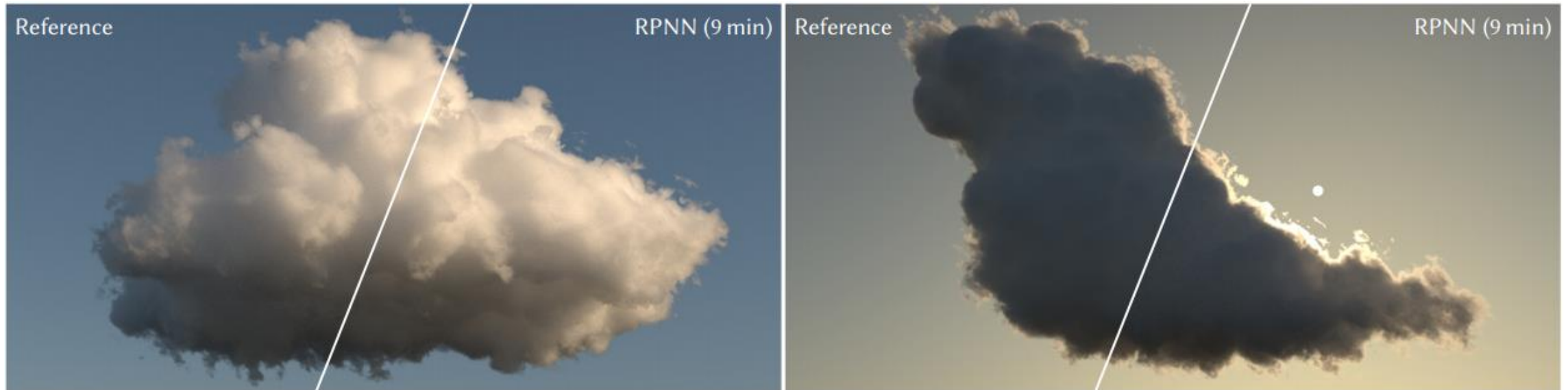
- Paint a z-buffer like a path tracer (AO, DOF, MB)



Deep Shading, Nalbach et al. EGSR 2017

Rendering Atmospherics

Deep Scattering: Rendering Atmospheric Clouds with Radiance-Predicting Neural Networks, Kallweit et al. SIGGRAPH Asia 2017

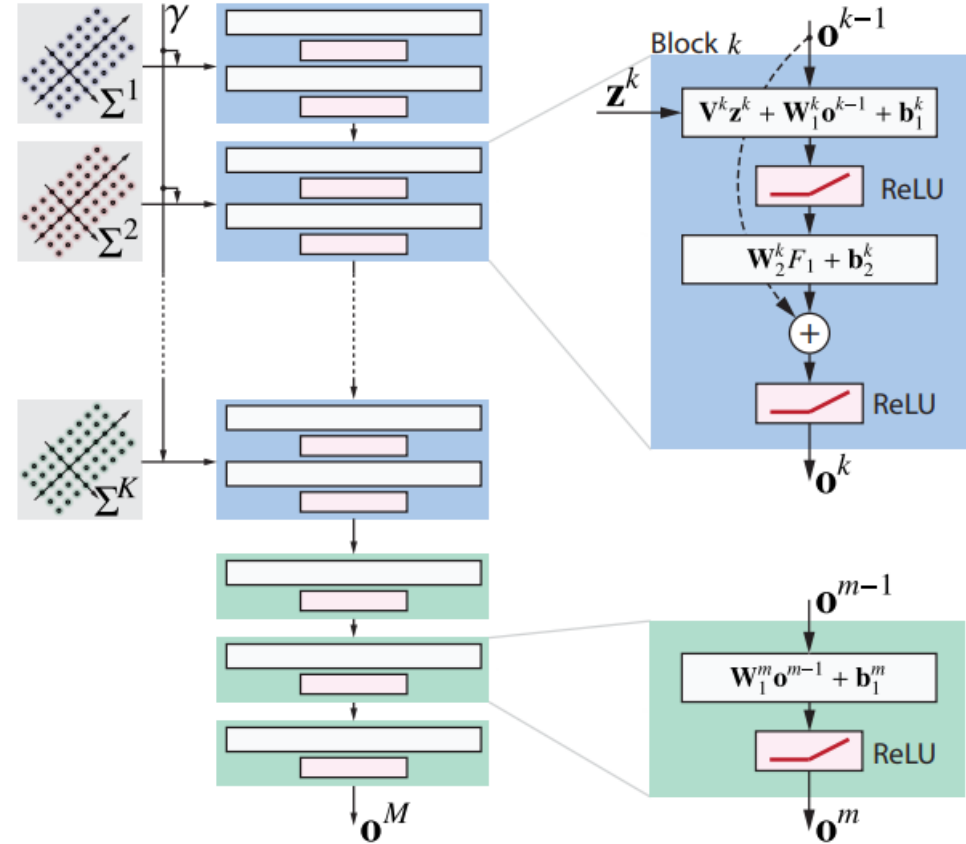
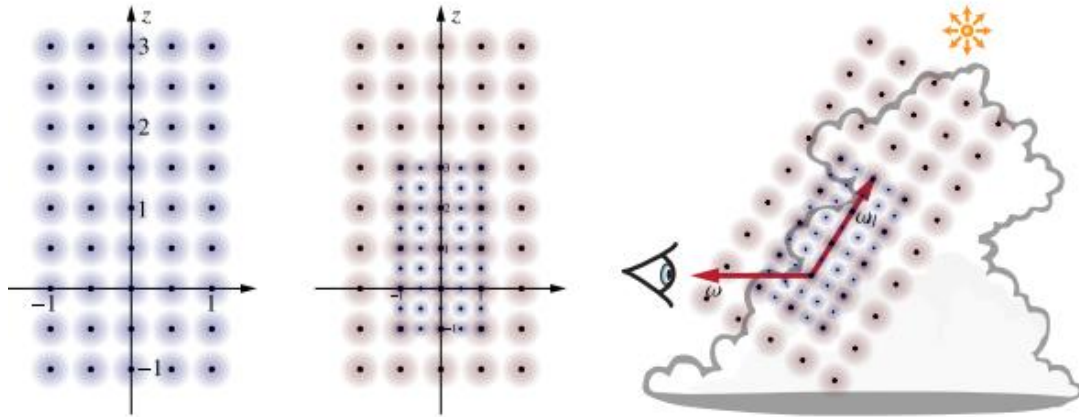


→
Speed up approx. 24 x

→
Speed up approx. 24 x

Rendering Atmospherics: *RPNN*

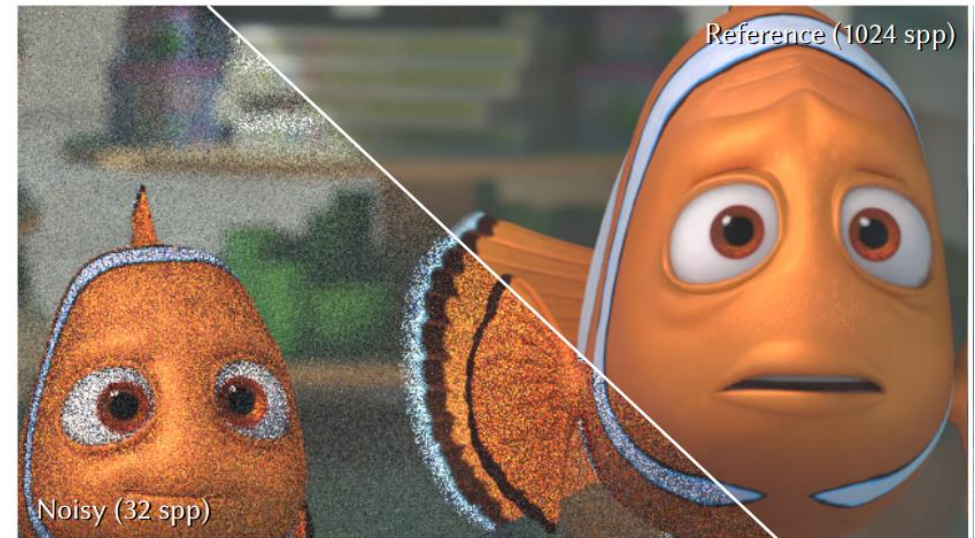
In: Hierarchical representation of a cloud patch
Out: incoming indirect radiance at patch center
 (incoming direct radiance is computed directly)



Deep Scattering: Rendering Atmospheric Clouds with Radiance-Predicting Neural Networks, Kallweit et al. **SIGGRAPH Asia 2017**

Denoising Renderings

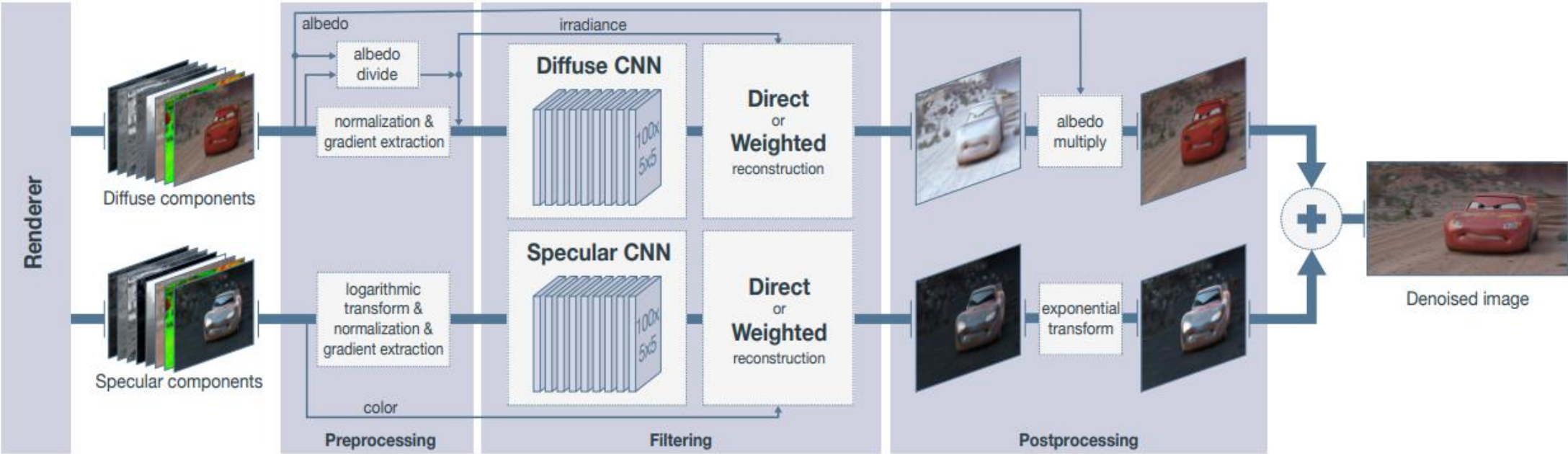
- Concurrent:
- *Kernel-Predicting Convolutional Networks for Denoising Monte Carlo Renderings*, Bako et al. 2017
- *Interactive Reconstruction of Monte Carlo Image Sequences using a Recurrent Denoising Autoencoder*, Chaitanya et al. 2017 (more on Autoencoders later)



TRAINING

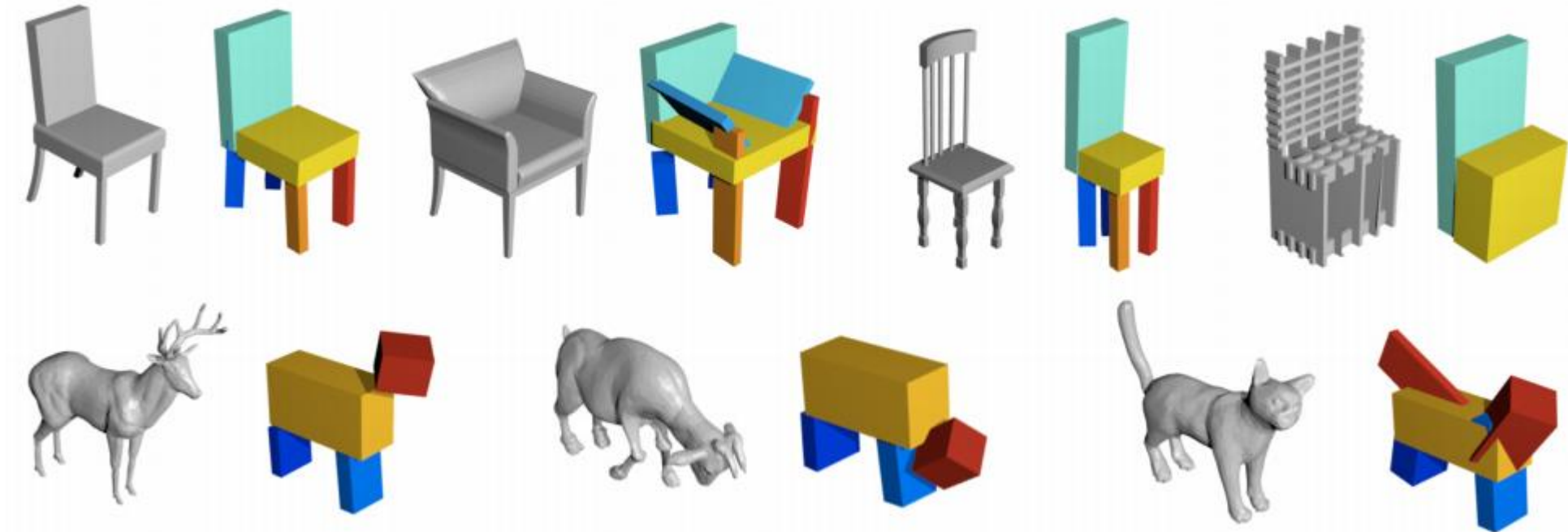
Kernel-Predicting Convolutional Networks for Denoising Monte Carlo Renderings, Bako et al.

Denoising Renderings:



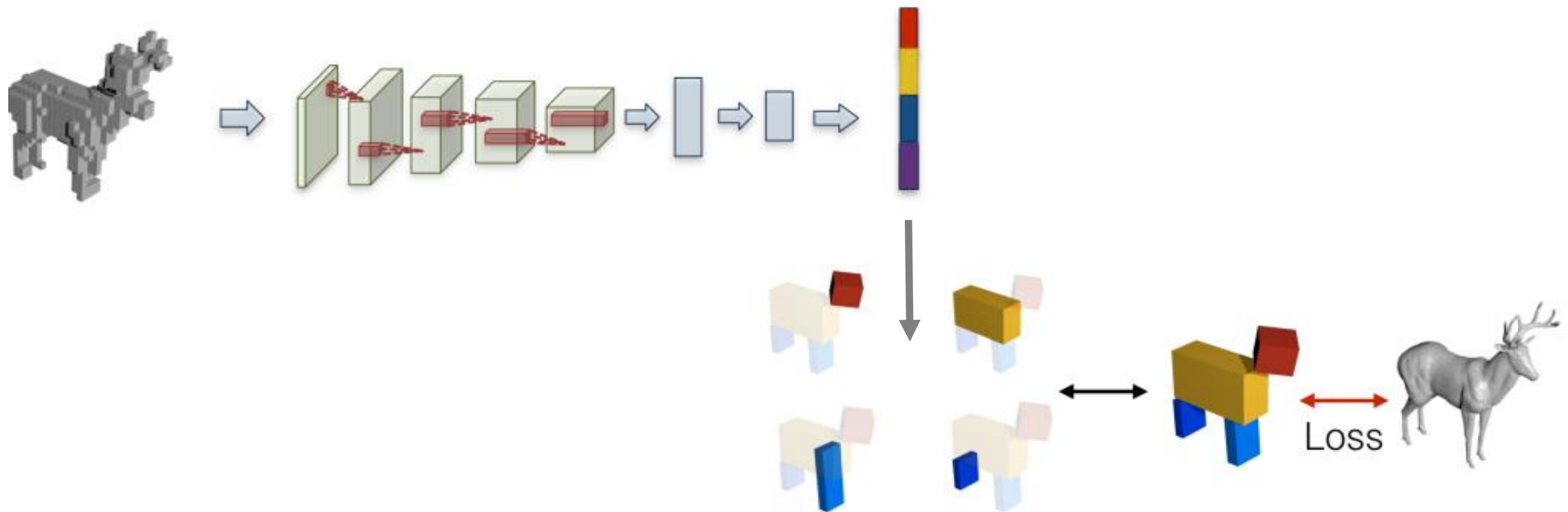
Kernel-Predicting Convolutional Networks for Denoising Monte Carlo Renderings, Bako et al. SIGGRAPH 2017

Geometry Abstraction / Simplification



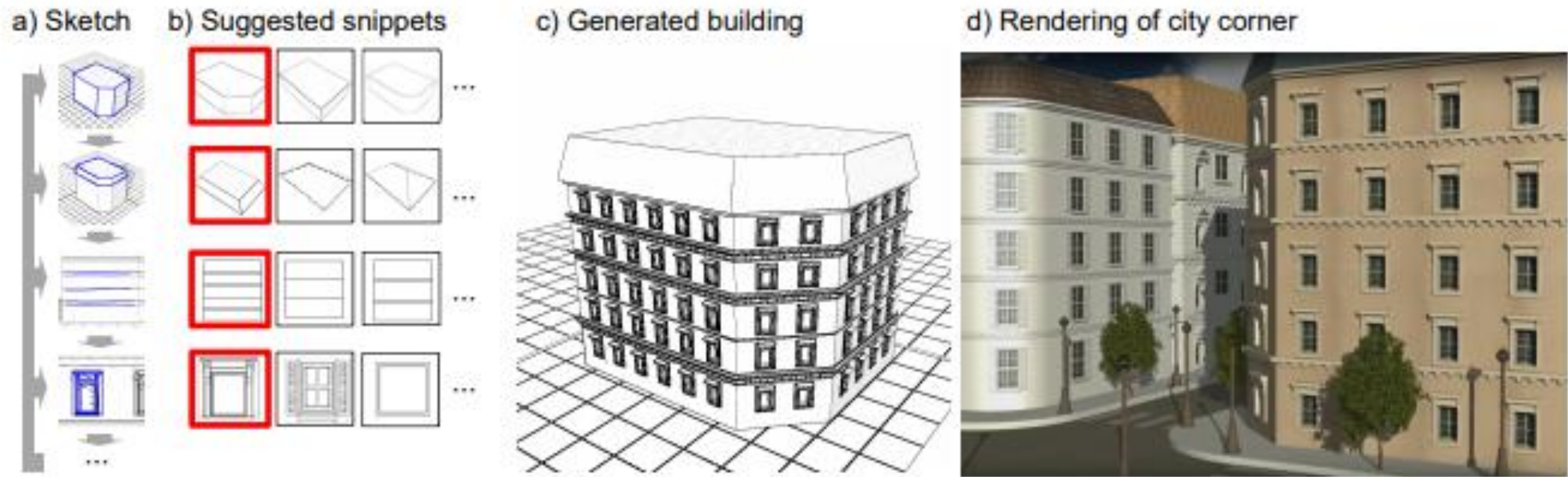
Learning Shape Abstractions by Assembling Volumetric Primitives, Tulsiani et al. 2016

Geometry Abstraction / Simplification:



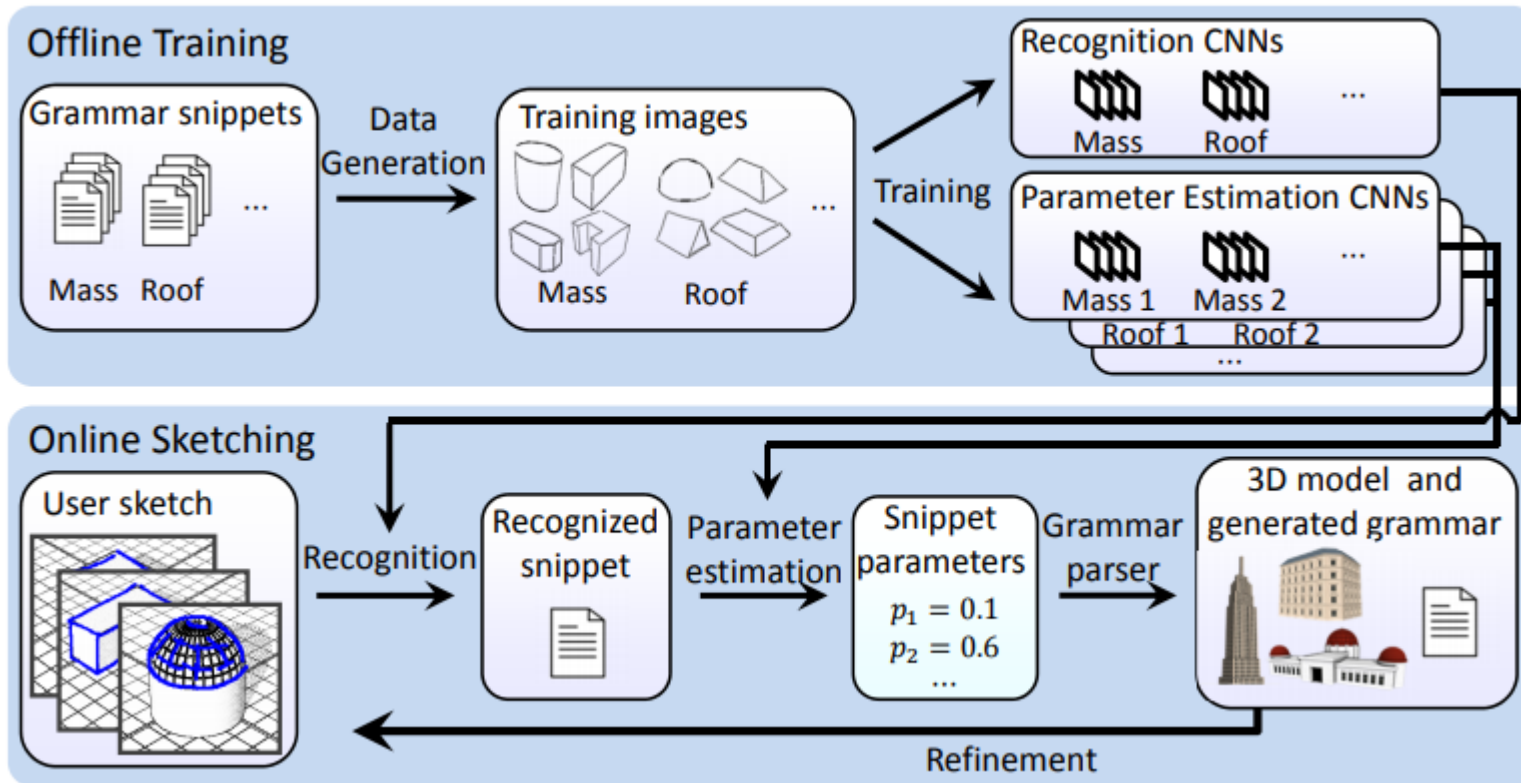
Learning Shape Abstractions by Assembling Volumetric Primitives, Tulsiani et al. 2016

Procedural Parameter Estimation



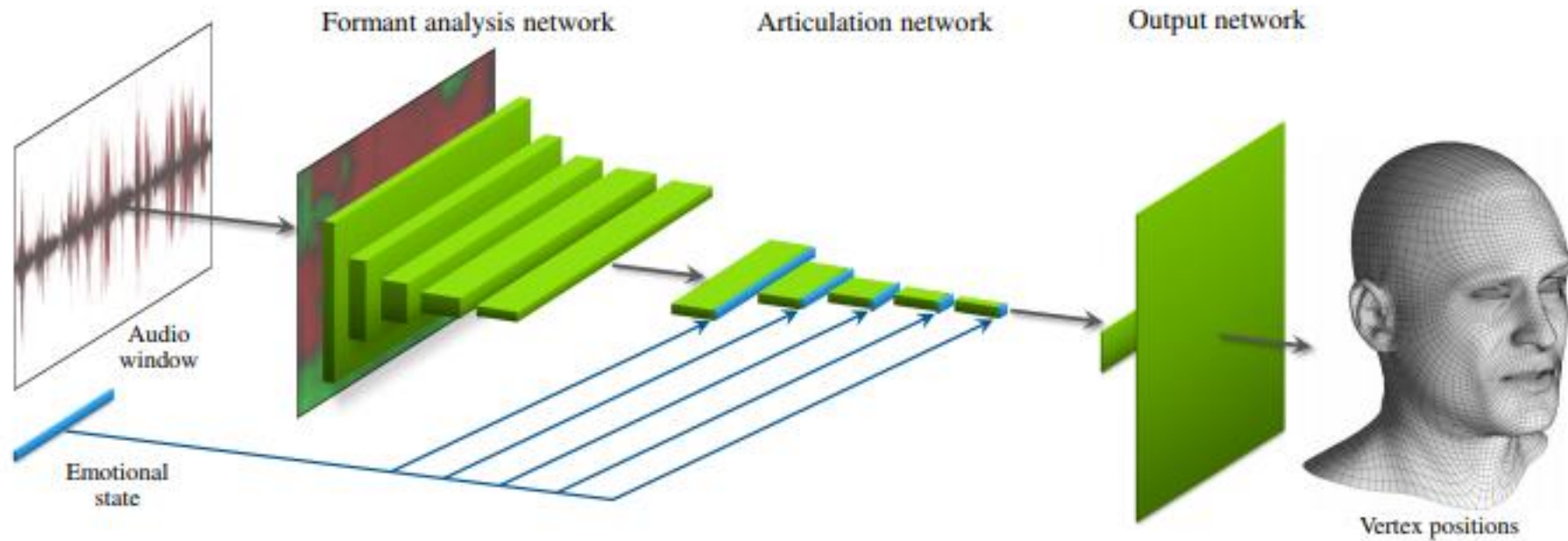
Interactive Sketching of Urban Procedural Models, Nishida et al. 2016

Procedural Parameter Estimation: *Interactive Sketching of Urban Procedural Models*



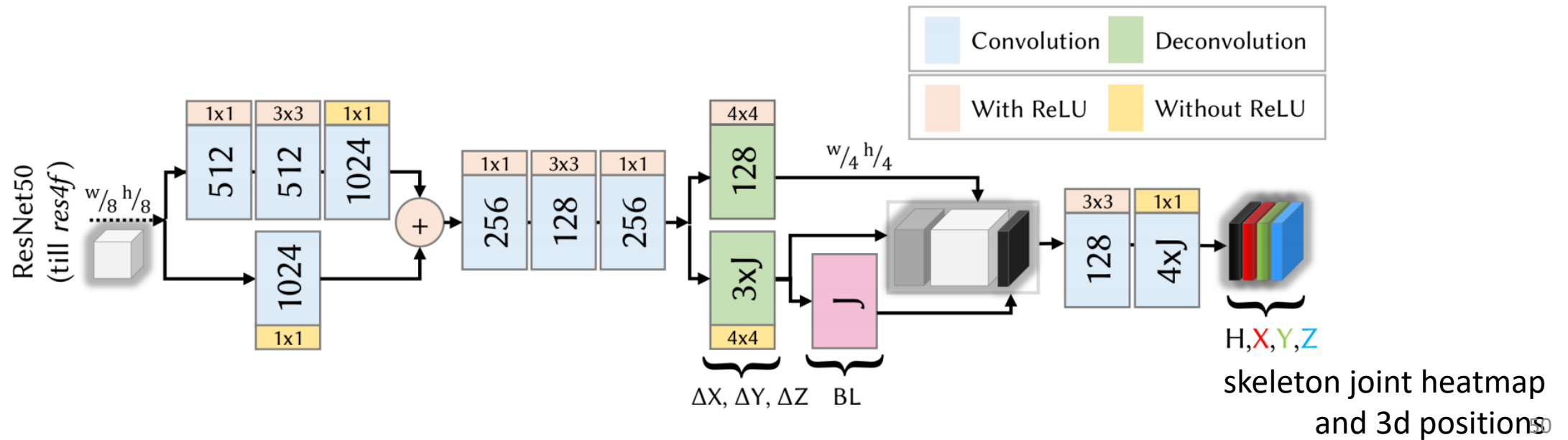
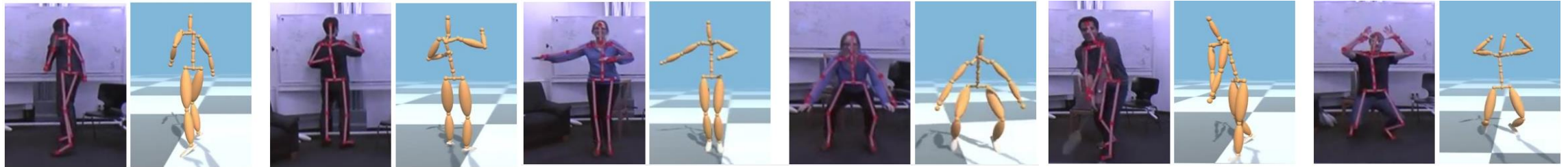
Interactive Sketching of Urban Procedural Models, Nishida et al.

Audio-driven facial animation



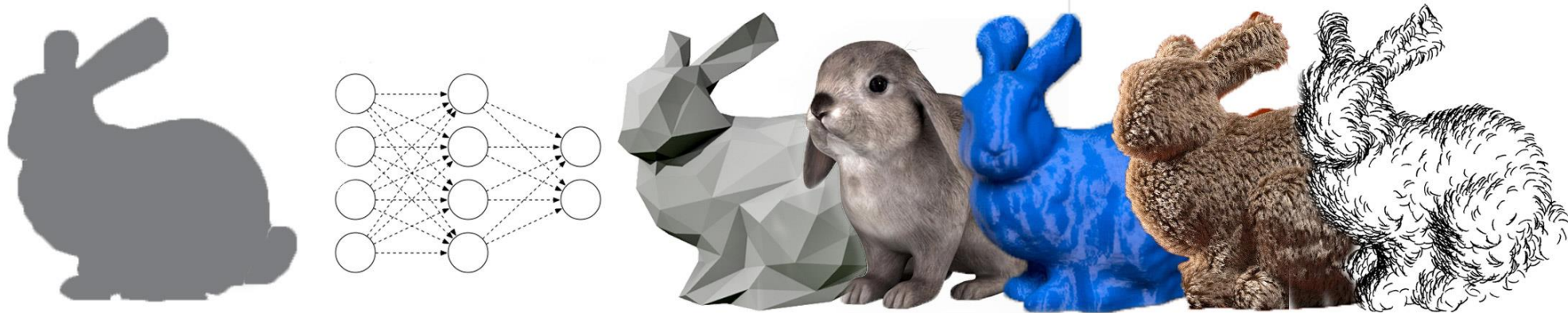
Audio-Driven Facial Animation by Joint End-to-End Learning of Pose and Emotion, Karras et al. 2017

3D Pose Estimation: *VNECT*



VNect: Real-time 3D Human Pose Estimation with a Single RGB Camera, Mehta et al., SIGGRAPH 2017

Thank you!



<http://geometry.cs.ucl.ac.uk/dl4g/>