Team G-RMI: Google Research & Machine Intelligence

Alireza Fathi (alirezafathi@google.com)

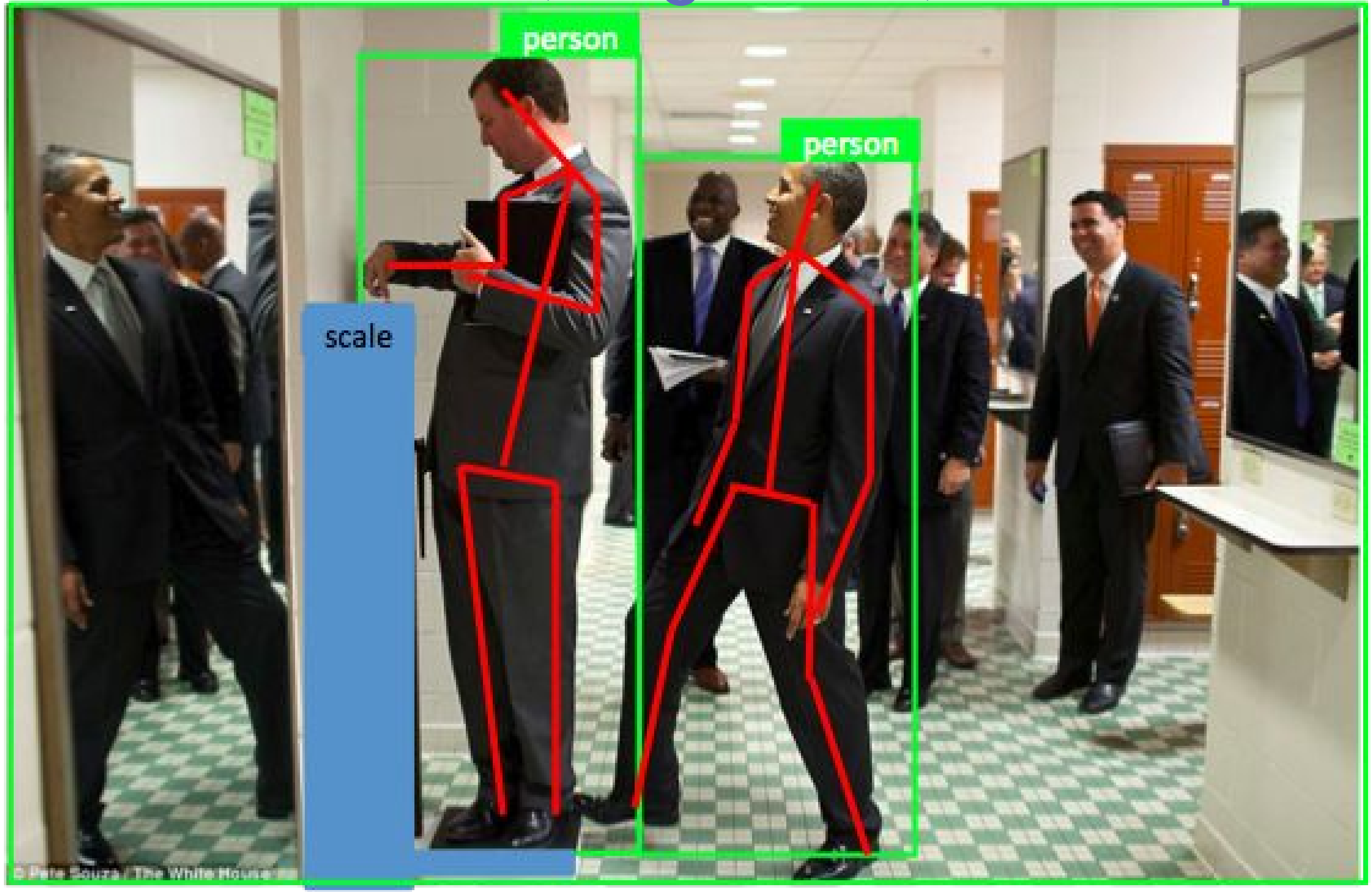
Nori Kanazawa, Kai Yang, George Papandreou, Tyler Zhu, Jonathan Huang, Vivek Rathod, Chen Sun, Kevin Murphy, et al.

Google: Mobile First to AI First

Beyond image classification...

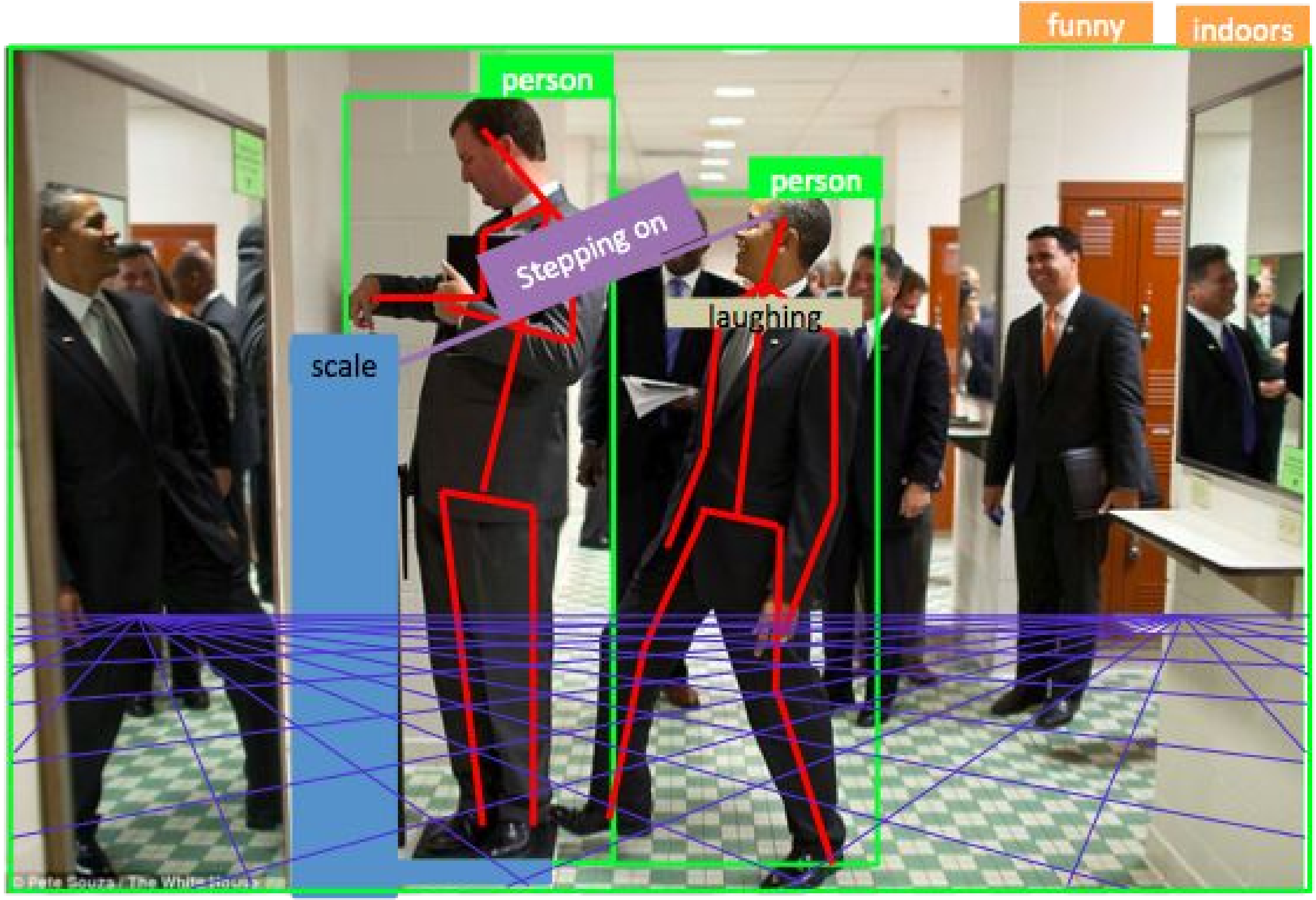
Source: http://karpathy.github.io/2012/10/22/state-of-computer-vision/

What we need: boxes, segments, human pose



Based on a figure from Jia Deng

And also: attributes, relations, 3-d, ...

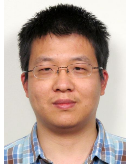


This Talk

- **Semantic Stuff Segmentation**
- Object Instance Segmentation
- Human Pose Estimation

Team Members

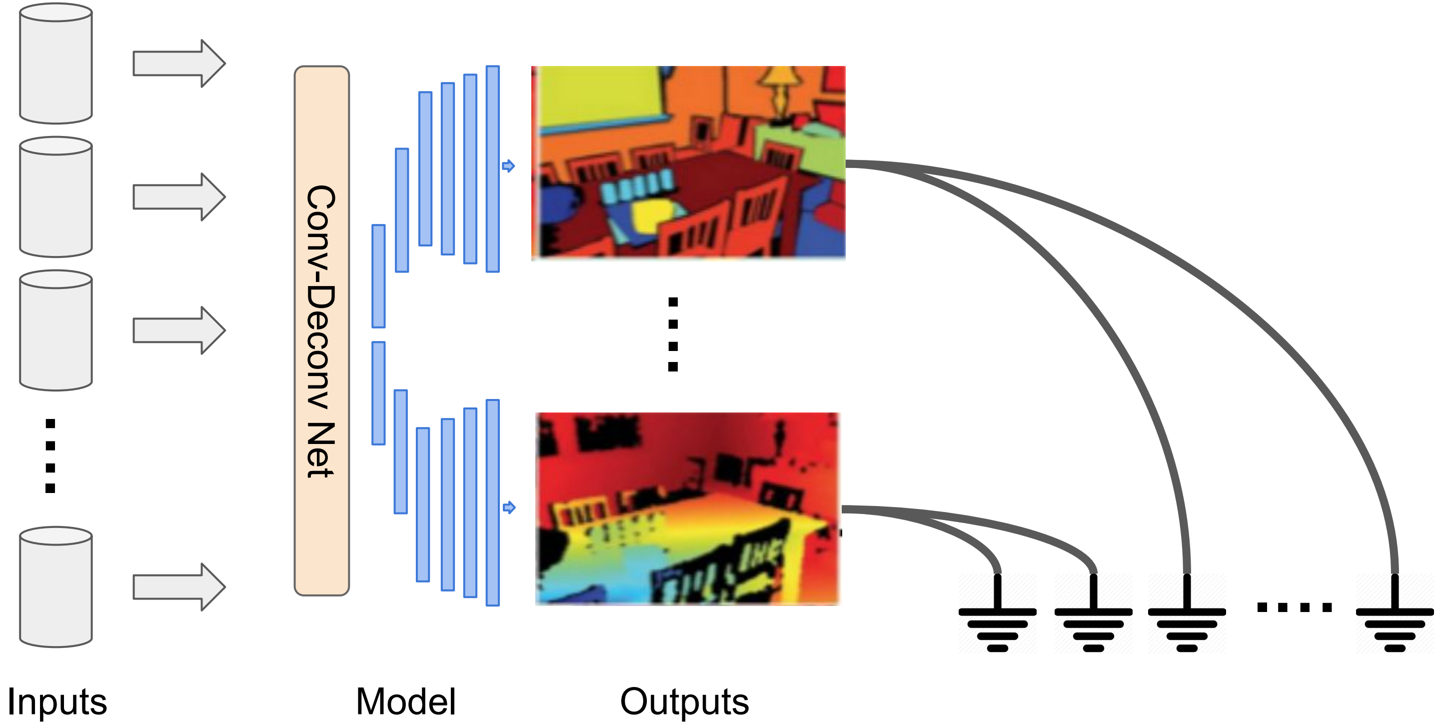
Alireza Fathi



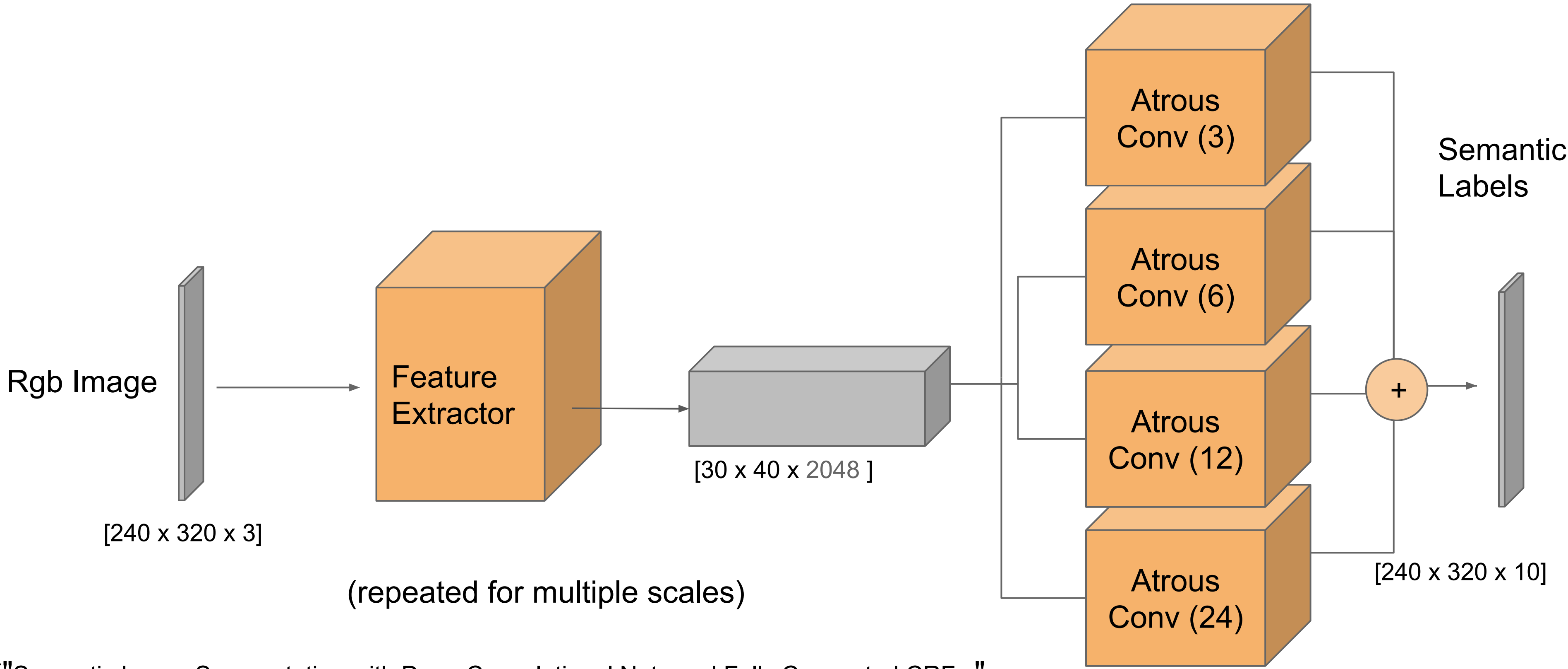
Kai Yang

Kevin Murphy

Masternet (DenseLab)



A Model based on DeepLab for Semantic Segmentation



*"Semantic Image Segmentation with Deep Convolutional Nets and Fully Connected CRFs ", **Liang-Chieh Chen, George Papandreou**, Iasonas Kokkinos, Kevin Murphy, Alan L. Yuille. ICLR'15, CVPR'16, PAMI'17.

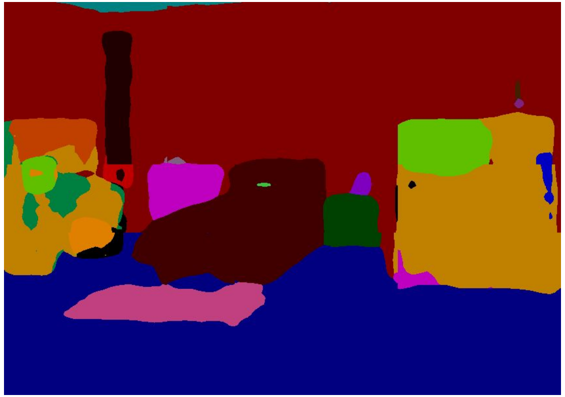
Tricks for improving results

- Feature extractor
  - Inception resnet gives around 3% improvement in comparison to Resnet101.
- Initial checkpoint (Not used for the competition)
  - Starting from a COCO semantic segmentation checkpoint gives a 2-3% boost in comparison to starting from an ImageNet classification checkpoint.
- Ensembling
  - We get around 3-4% improvement in performance by ensembling 5 models.
- Batch size
  - Larger batch size and smaller crop size seems to be better than smaller batch size but larger crop size. We use a batch size of 72.
- Balancing classes
  - We get around 1% improvement by balancing the loss among different classes.
- Moving average? Focal loss? New network architectures?

Example results on ADE20K

Image

Groundtruth

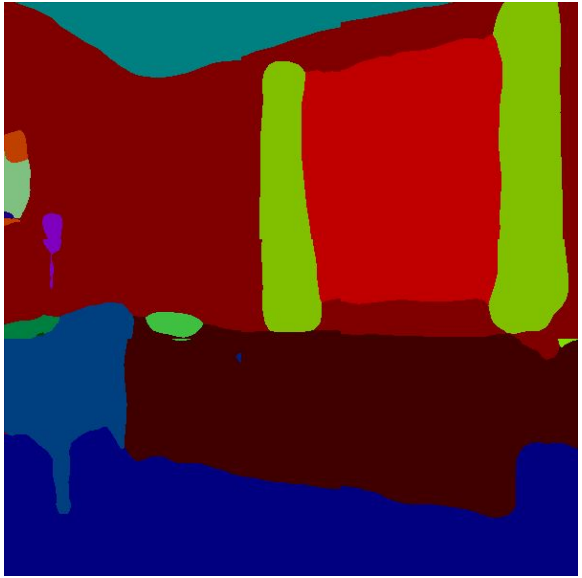


Prediction

Example results on ADE20K

Image

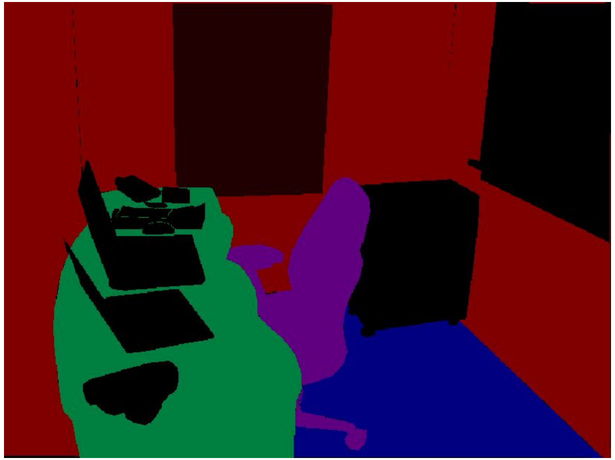
Groundtruth



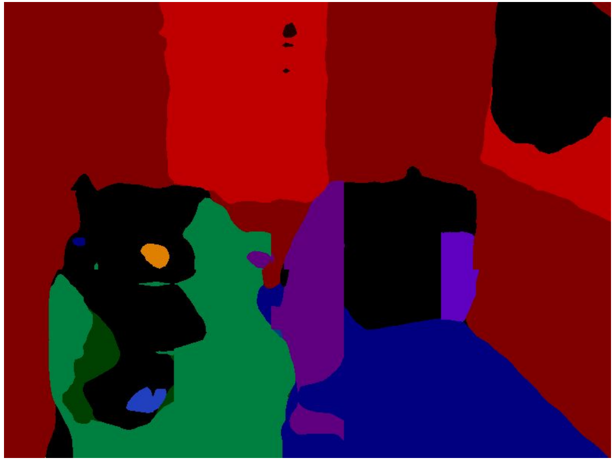
Prediction

Example results on ADE20K

Image



Groundtruth



Prediction

Example results on Coco Stuff

Image

Groundtruth

Prediction

Example results on Coco Stuff

Image

Groundtruth

Prediction

Example results on Coco Stuff

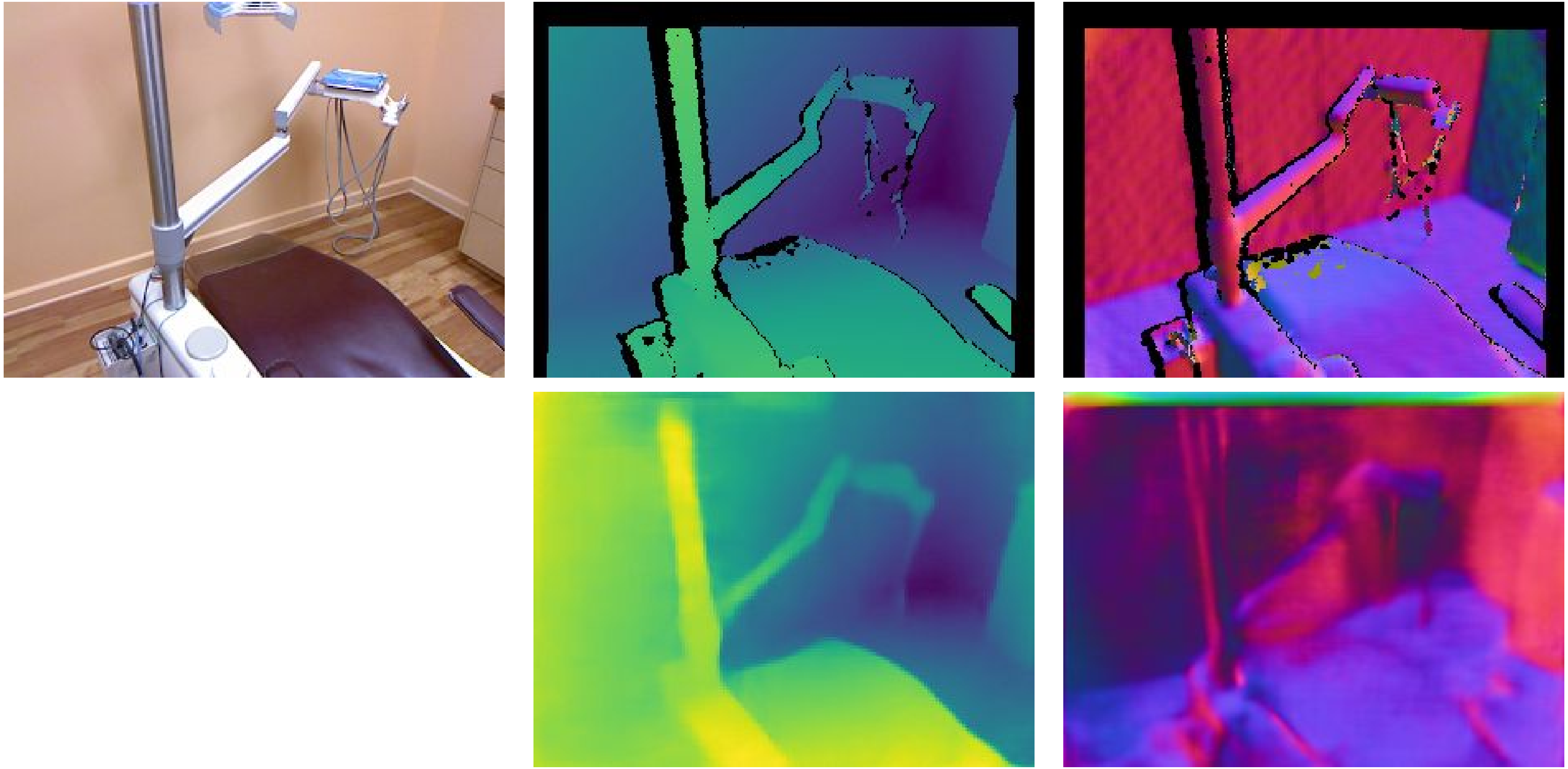
Image

Groundtruth

Prediction

Boundary Detection

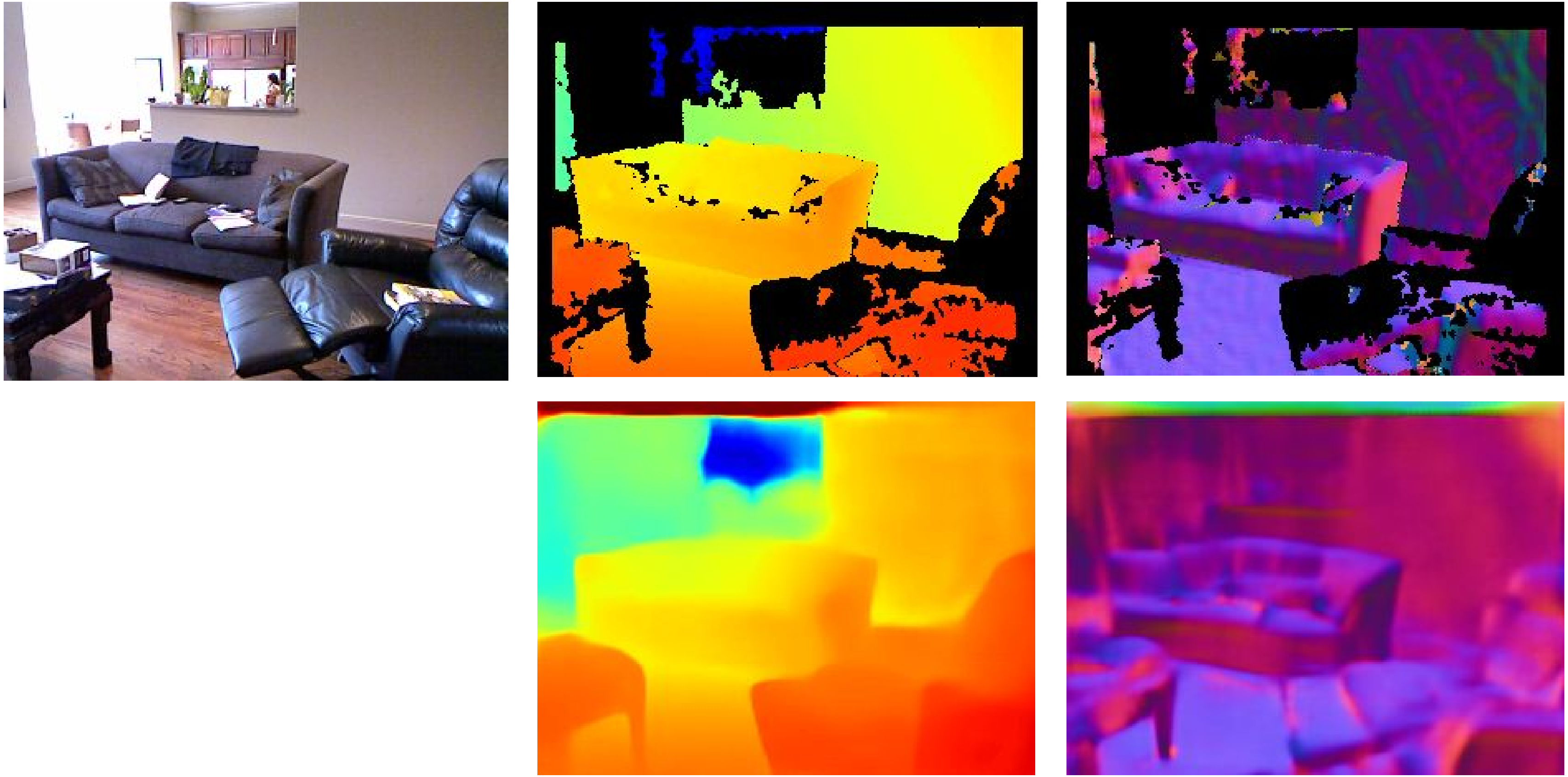
Depth/Surface Normal Prediction



Groundtruth

Prediction

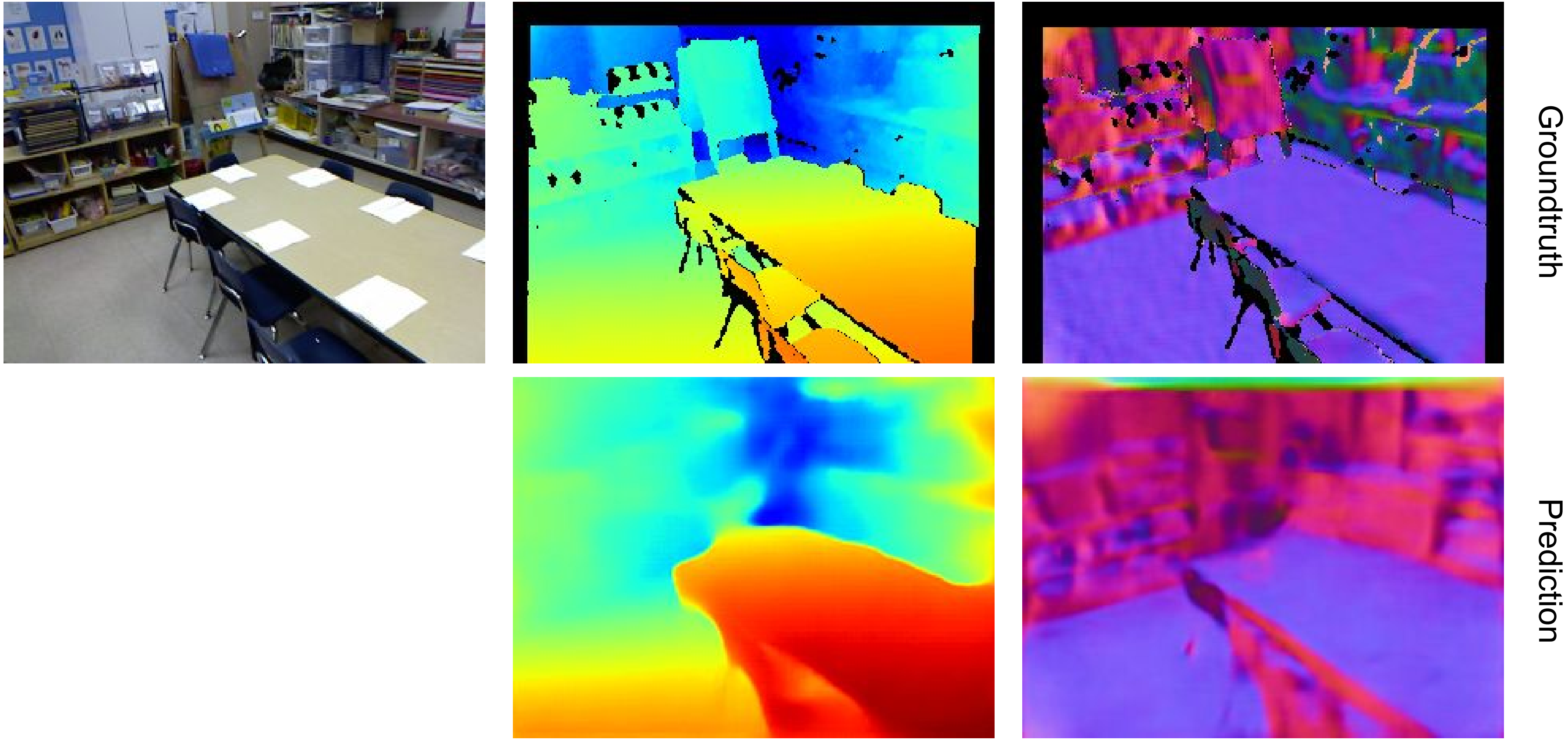
Depth/Surface Normal Prediction



Groundtruth

Prediction

Depth/Surface Normal Prediction



This Talk

- Semantic Stuff Segmentation
- **Object Instance Segmentation**
- Human Pose Estimation

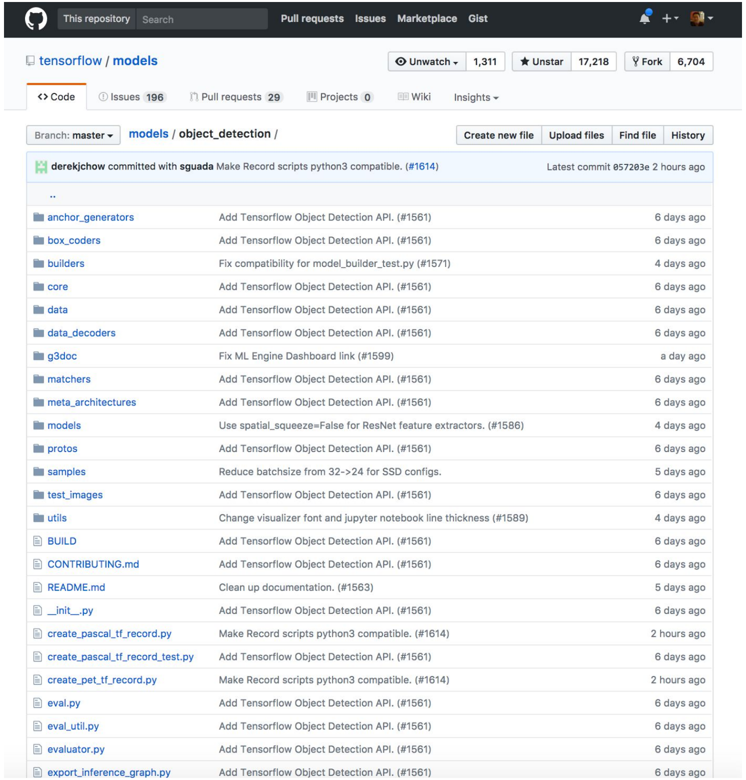
Team Members

Alireza
Fathi

Nori
Kanazawa

Kevin
Murphy

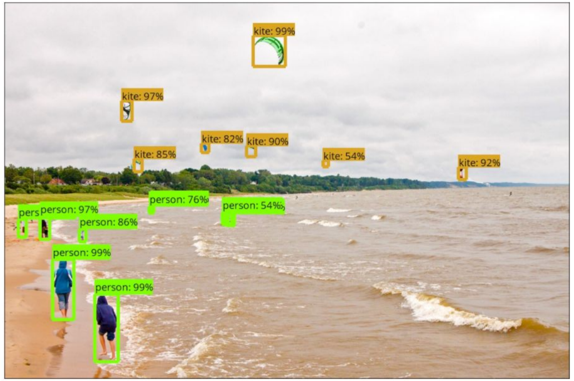
Available open source: pre-trained models or train your own on GCloud



README.md

Tensorflow Object Detection API

Creating accurate machine learning models capable of localizing and identifying multiple objects in a single image remains a core challenge in computer vision. The TensorFlow Object Detection API is an open source framework built on top of TensorFlow that makes it easy to construct, train and deploy object detection models. At Google we've certainly found this codebase to be useful for our computer vision needs, and we hope that you will as well.



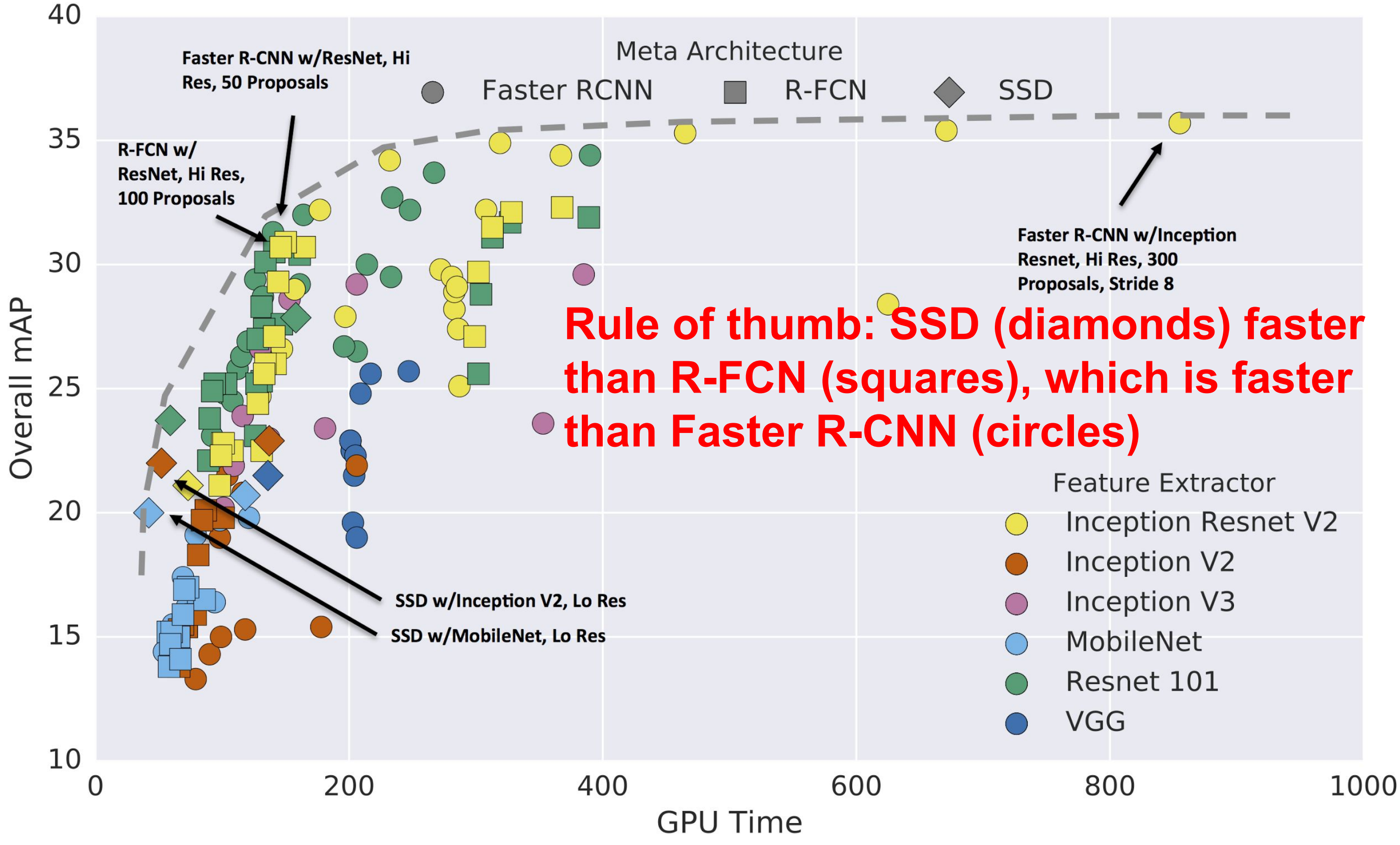
Contributions to the codebase are welcome and we would love to hear back from you if you find this API useful. Finally if you use the Tensorflow Object Detection API for a research publication, please consider citing:

```
"Speed/accuracy trade-offs for modern convolutional object detectors."
Huang J, Rathod V, Sun C, Zhu M, Korattikara A, Fathi A, Fischer I, Wojna Z,
Song Y, Guadarrama S, Murphy K, CVPR 2017
```

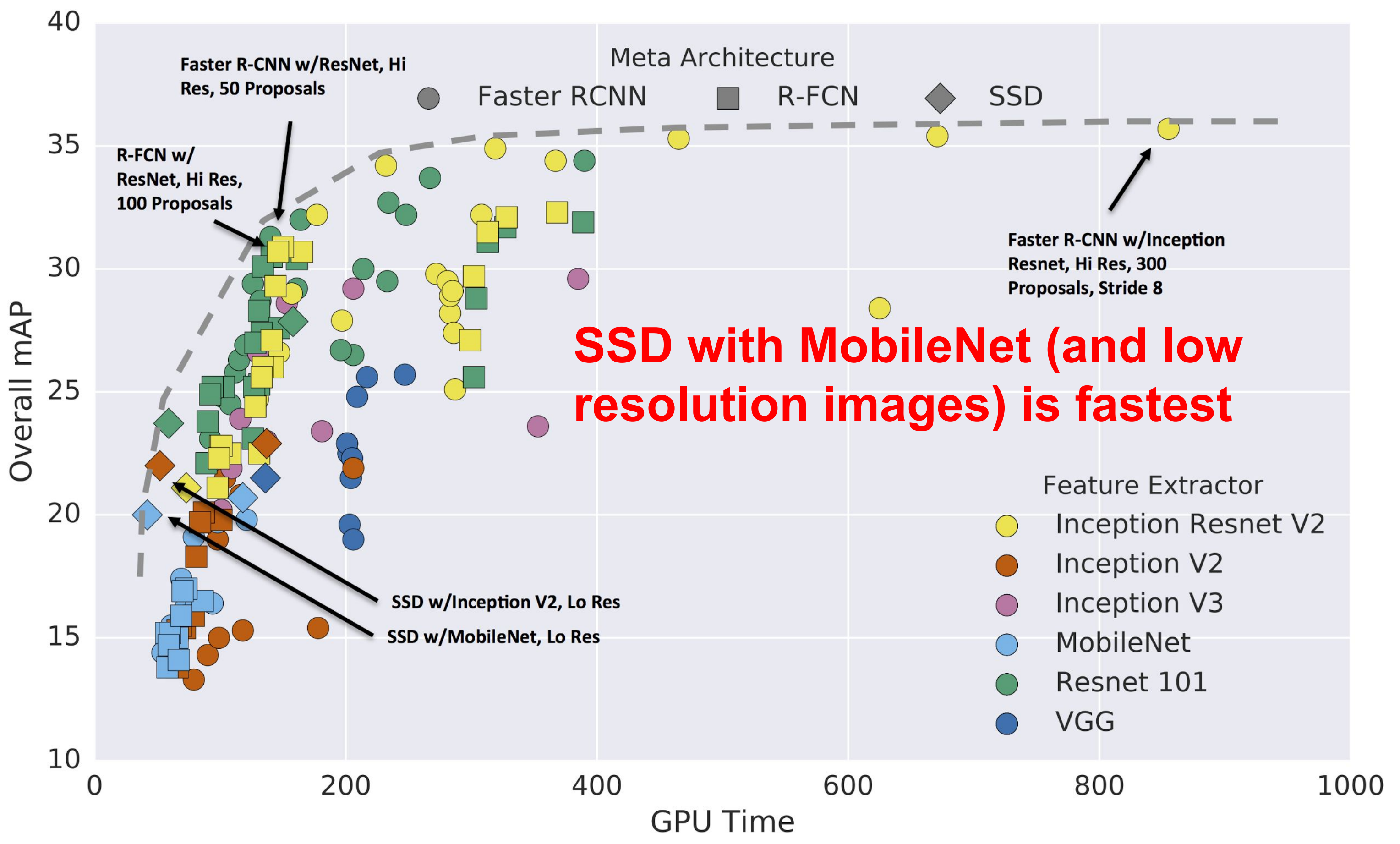
[link][bibtex]

TensorFlow Object Detection API

Meta-architecture	SSD, Faster R-CNN, R-FCN
Feature Extractor	Mobilenet, VGG, Inception V2, Inception V3, Resnet-50, Resnet-101, Resnet-152, Inception Resnet v2
Learning schedule	Manually Stepped, Exponential Decay, etc
Location Loss function	L2, L1, Huber, IOU
Classification Loss function	SigmoidCrossEntropy, SoftmaxCrossEntropy



Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., ... & Murphy, K. Speed/accuracy trade-offs for modern convolutional object detectors. CVPR 2017



Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., ... & Murphy, K. Speed/accuracy trade-offs for modern convolutional object detectors. CVPR 2017

Mask R-CNN

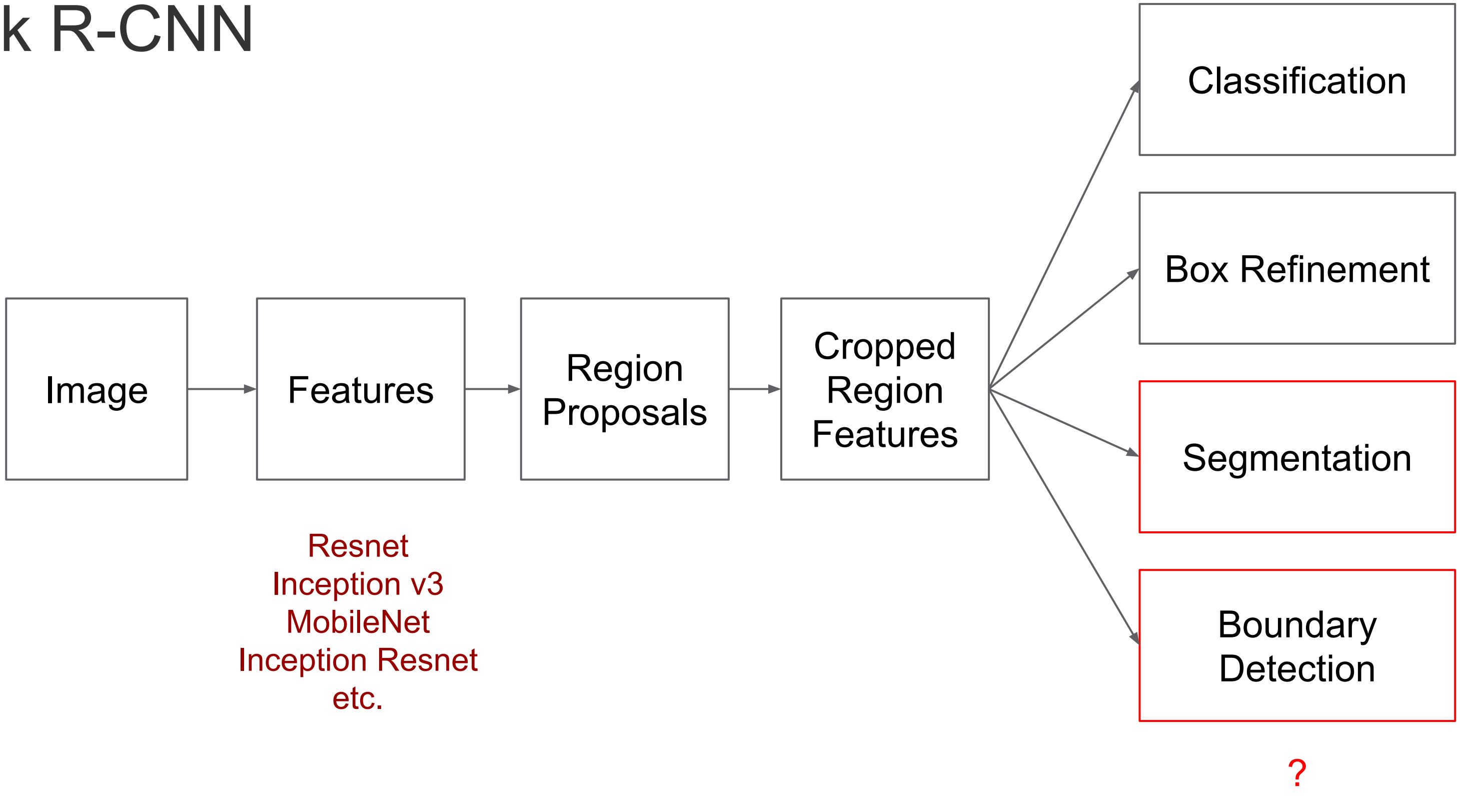
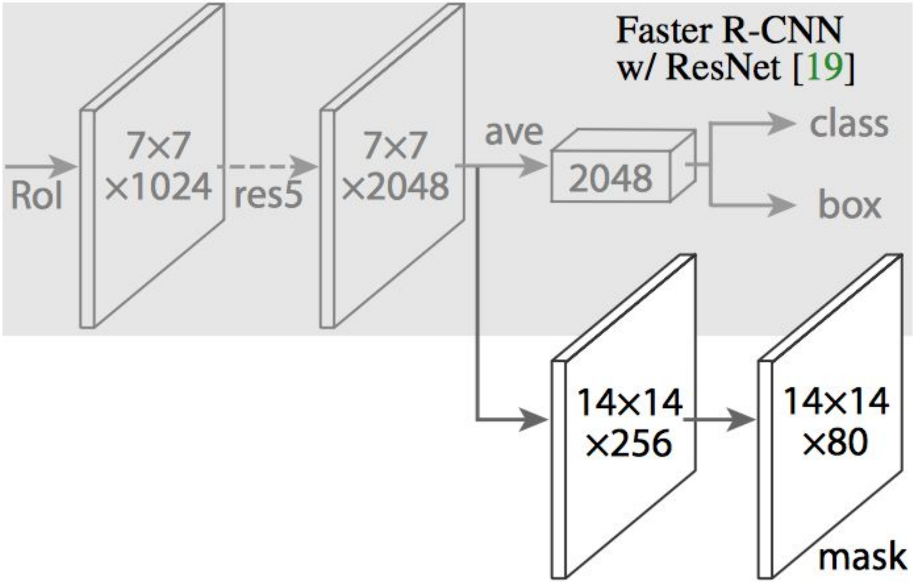
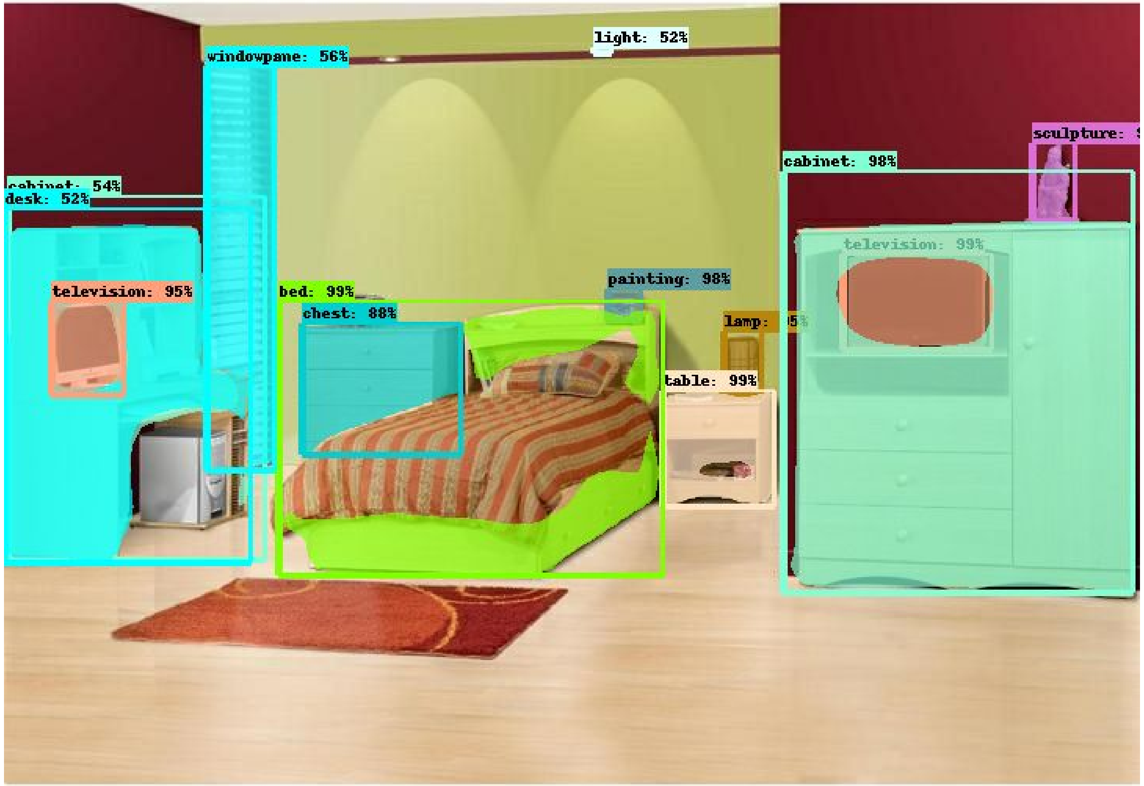


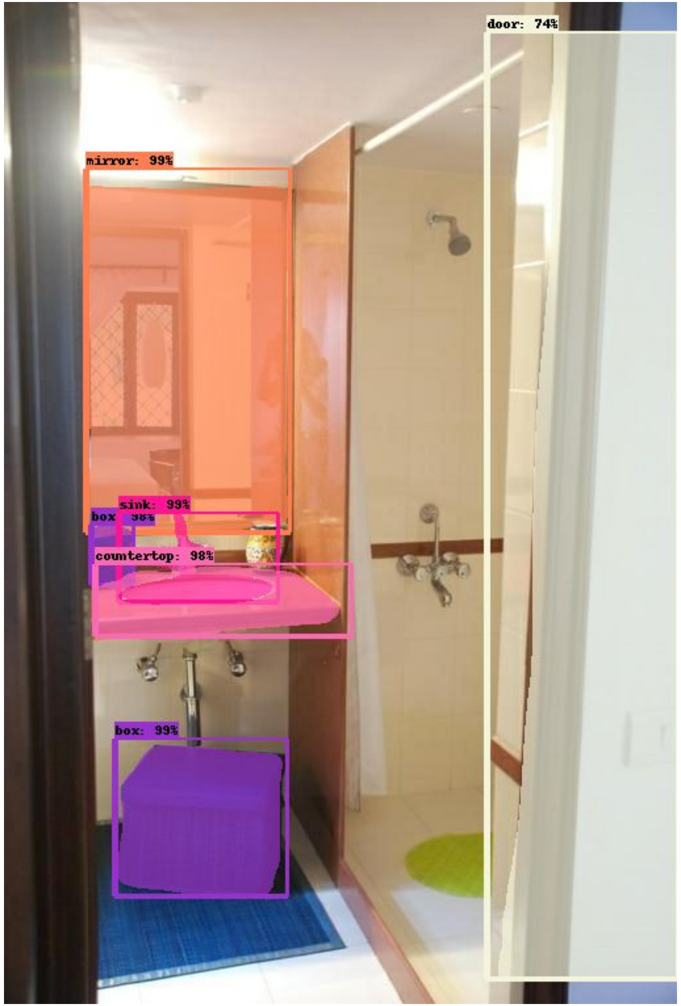
Image
Features
Region Proposals
Cropped Region Features
Classification
Box Refinement
Segmentation
Boundary Detection
Resnet
Inception v3
MobileNet
Inception Resnet
etc.
?

Mask R-CNN: Segmentation Head

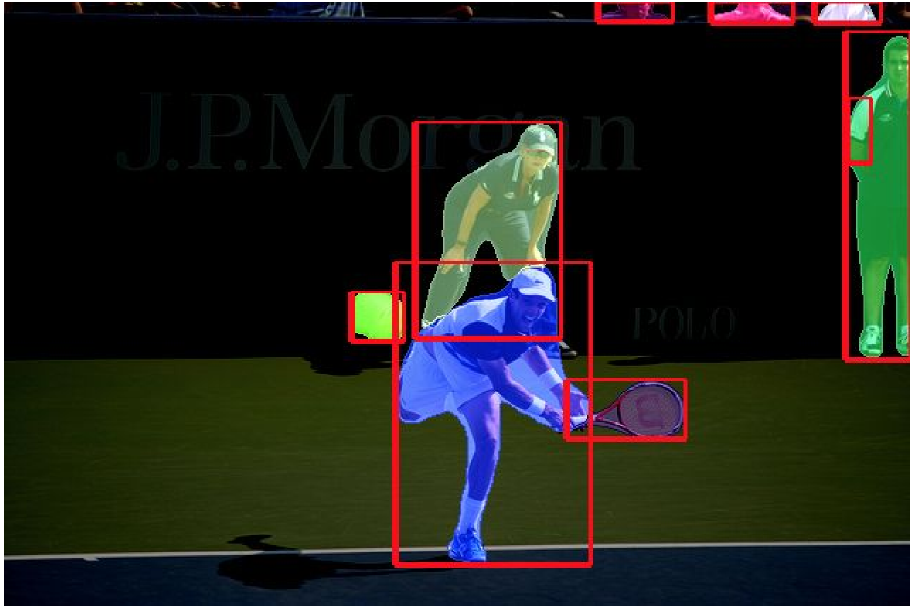


Example results from ADE20K

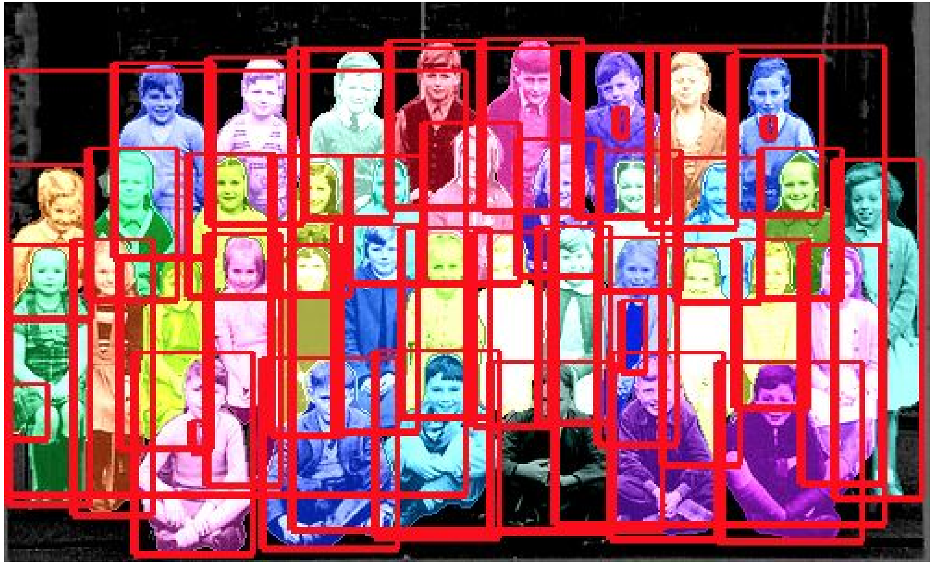




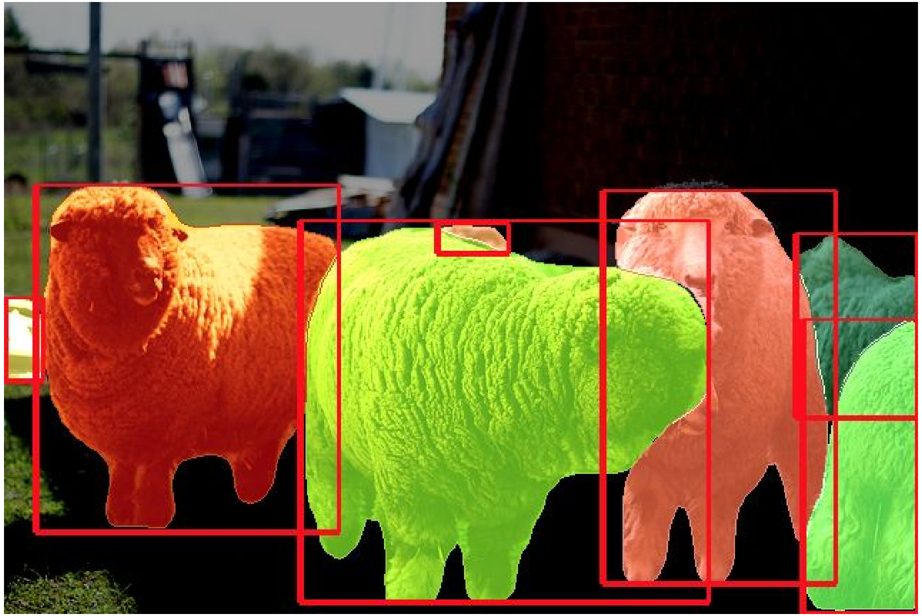
Example results from MS COCO



Example results from MS COCO



Example results from MS COCO



Object Instance Segmentation

Coming soon on GitHub under tensorflow/models

Instance Segmentation API

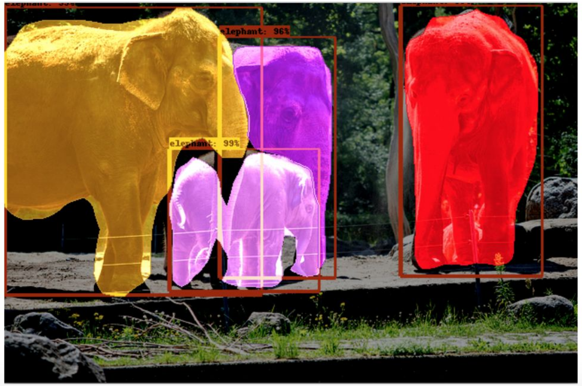
Search this site | Search

Home | In Depth Overview | Contributors | References | FAQ

What is Instance Segmentation?

Updated 2017-08-14

Instance segmentation is the problem of identifying individual instances of objects and their categories (such as person and car) in an image. It differs from object detection in that the output is a mask representing the shape of each object, rather than just a bounding box. It differs from semantic segmentation in that our goal is not just to classify each pixel with a label (or as background), but also to distinguish individual instances of the same class.



Page Info

- View source
- Edit this page
- File a bug

Tricks for improving results

- Input image size
  - 600 to 800 gives around 1.5-2% improvement on MSCOCO
- Network stride
  - Changing inception resnet from stride 16 to stride 8 gives around 1% improvement
- Using intermediate layers
  - Intermediate layers for mask prediction part of the network gives around 0.8% improvement
- Weight of the mask prediction loss
  - I found the best balance given the current architecture is to give weight 4.0 to mask loss
- Mask size
  - Changing mask prediction size from 16 to 32 gives around 0.15% improvement
- Number of convolutions in mask prediction head
  - Increasing number of conv2d layers from 1 to 3 improves performance by 0.3%

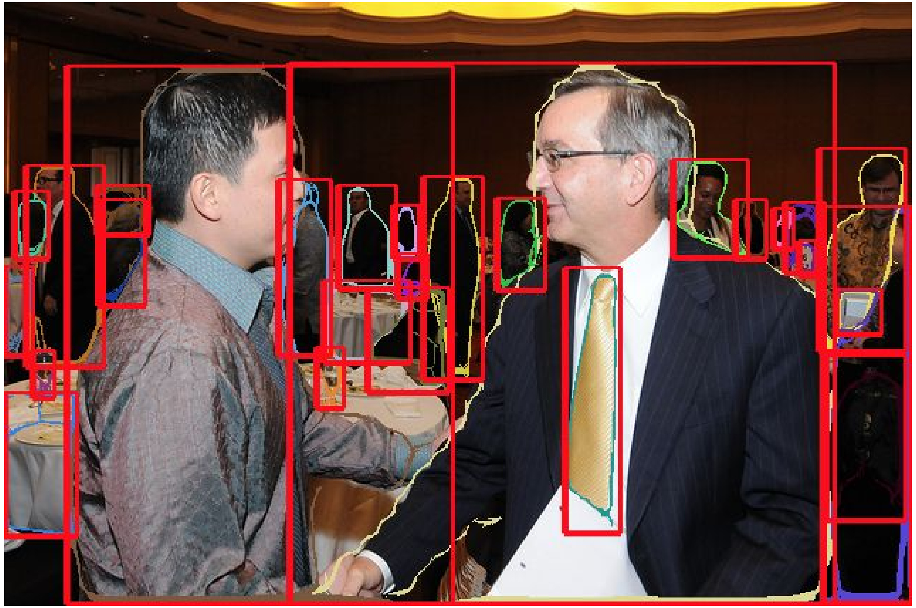
Boundary and mask prediction

- Gives around 0.5% improvement

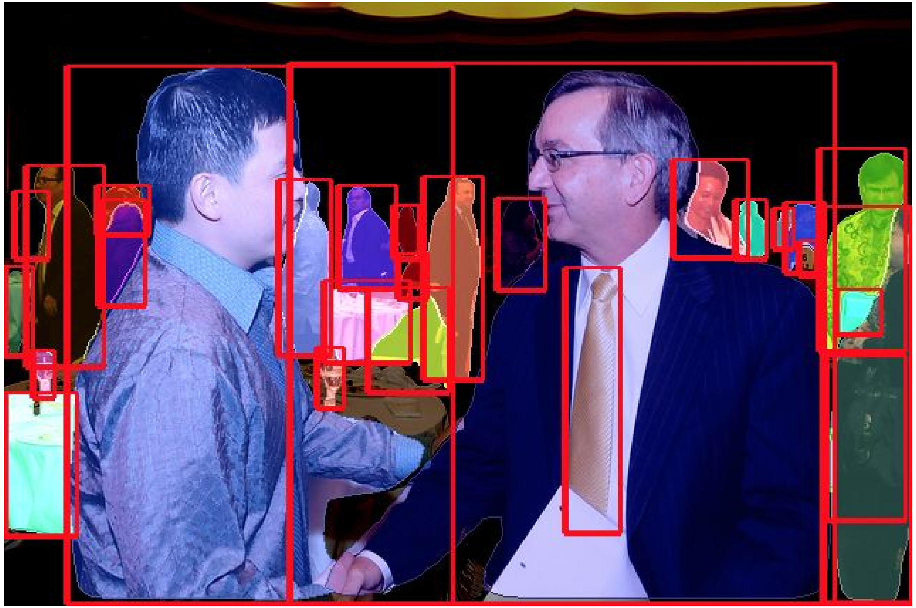
Boundary Prediction

Mask Prediction

Boundary and mask prediction

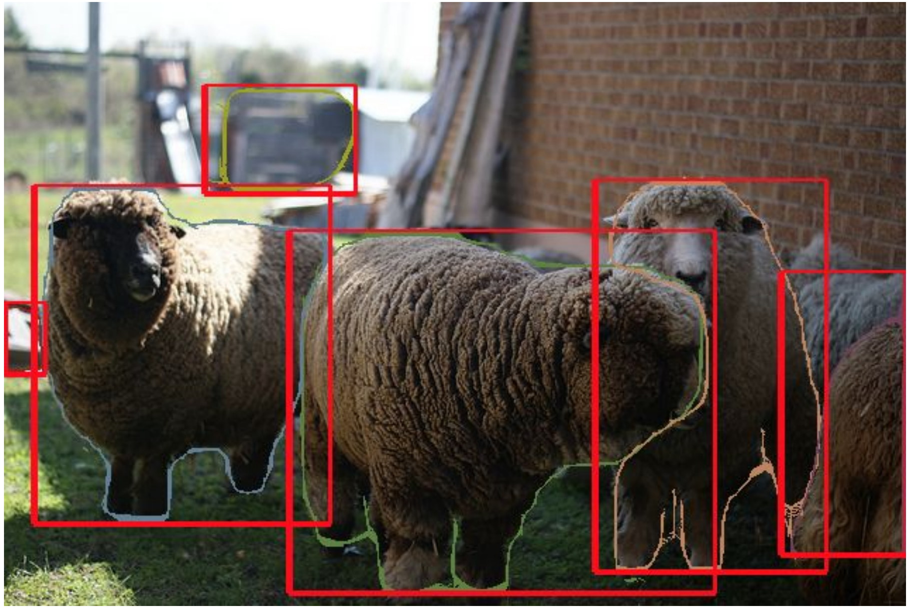


Boundary Prediction

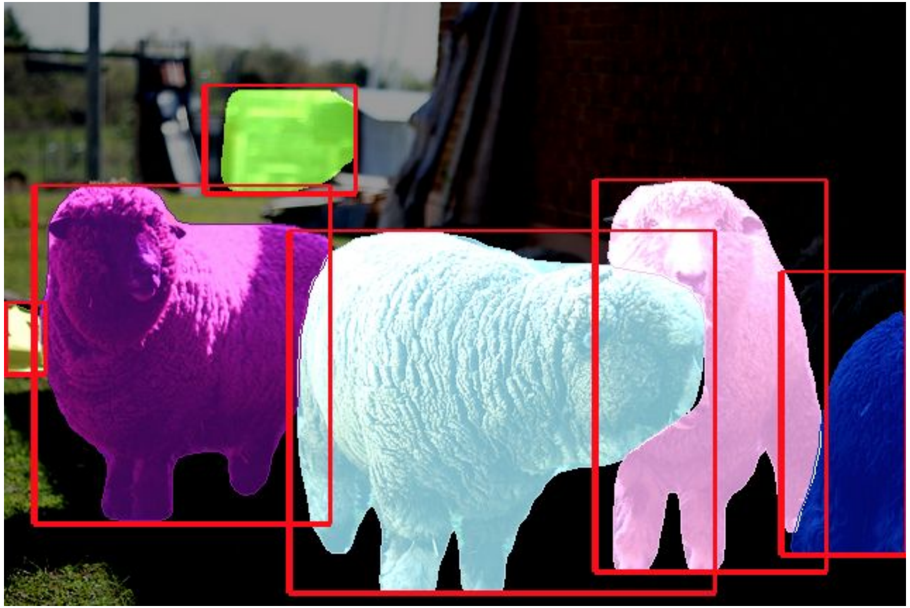


Mask Prediction

Boundary and mask prediction



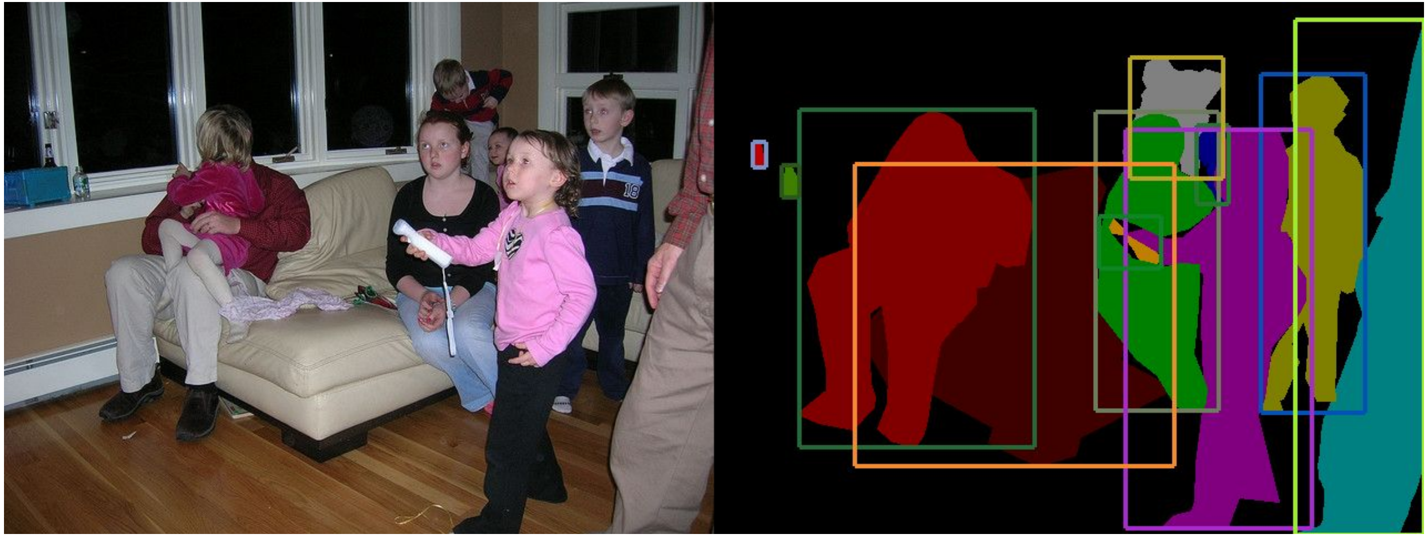
Boundary Prediction



Mask Prediction

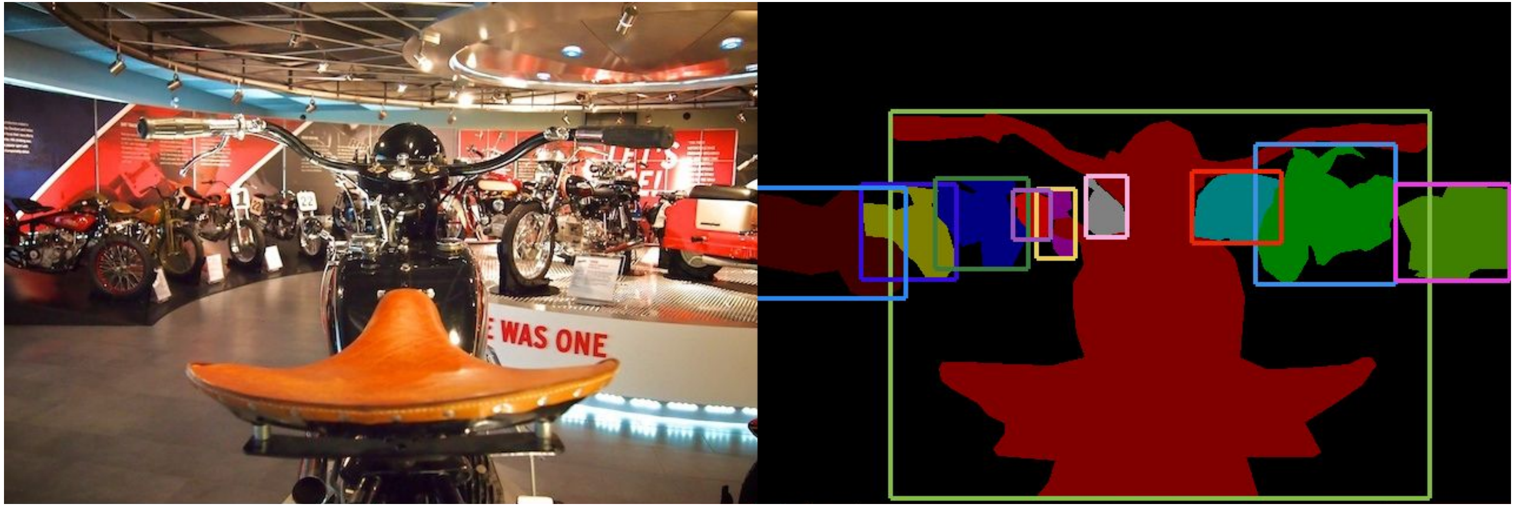
Issues in Box-based Mask Prediction 1/3

- Sometimes there are multiple instances of the same object in a box.



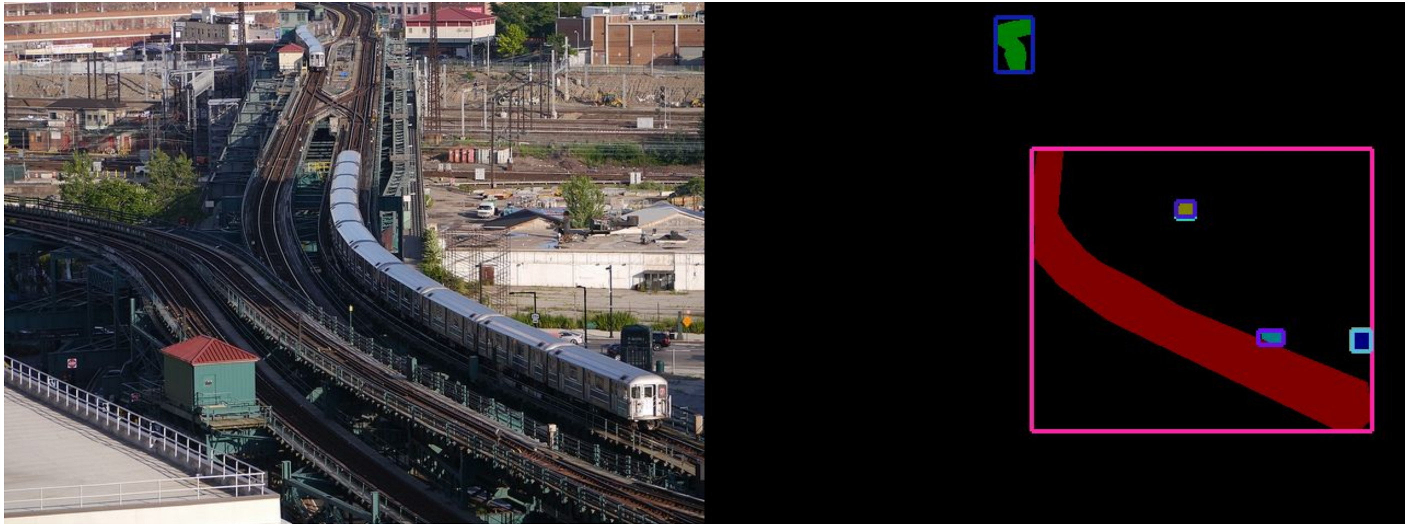
Issues in Box-based Mask Prediction 1/3

- Sometimes there are multiple instances of the same object in a box.



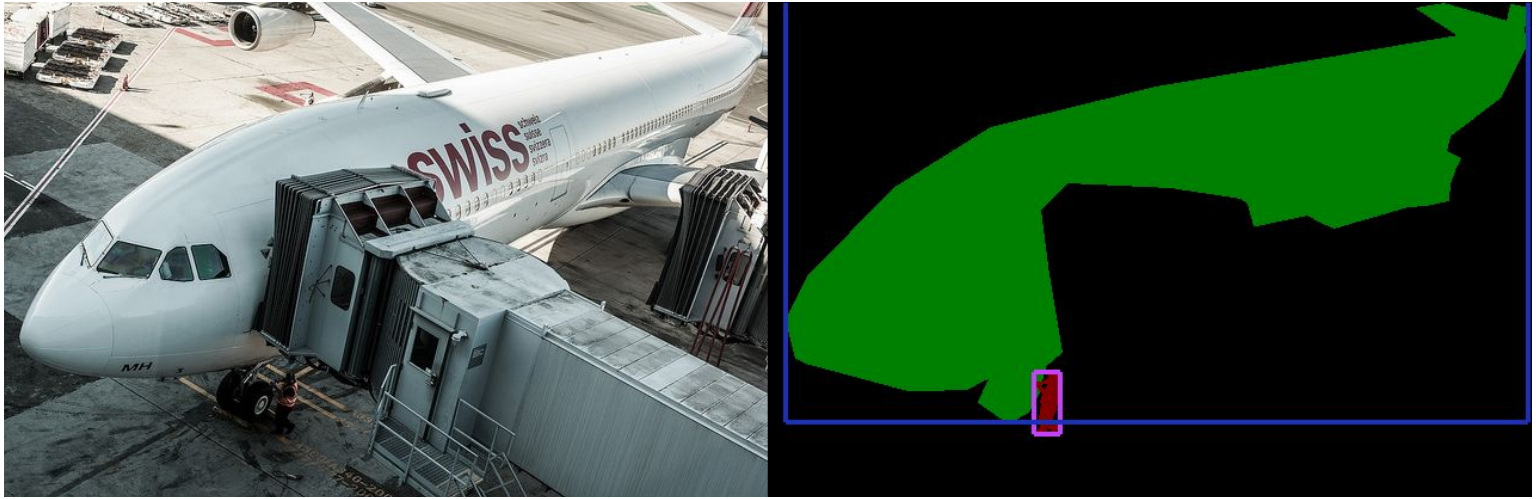
Issues in Box-based Mask Prediction 2/3

- Some objects are thin and appear diagonal in image. Barely occupy 10% of the given box!



Issues in Box-based Mask Prediction 2/3

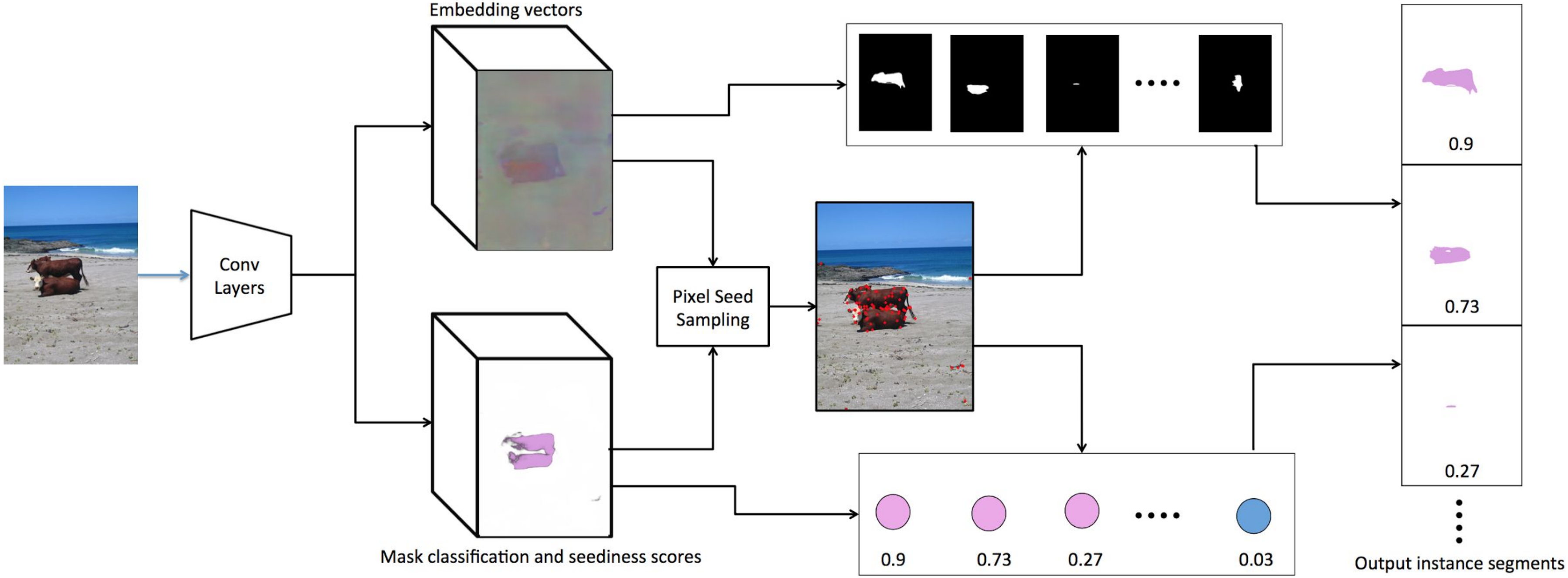
- Some objects are thin and appear diagonal in image. Barely occupy 10% of the given box!



Issues in Box-based Mask Prediction 3/3

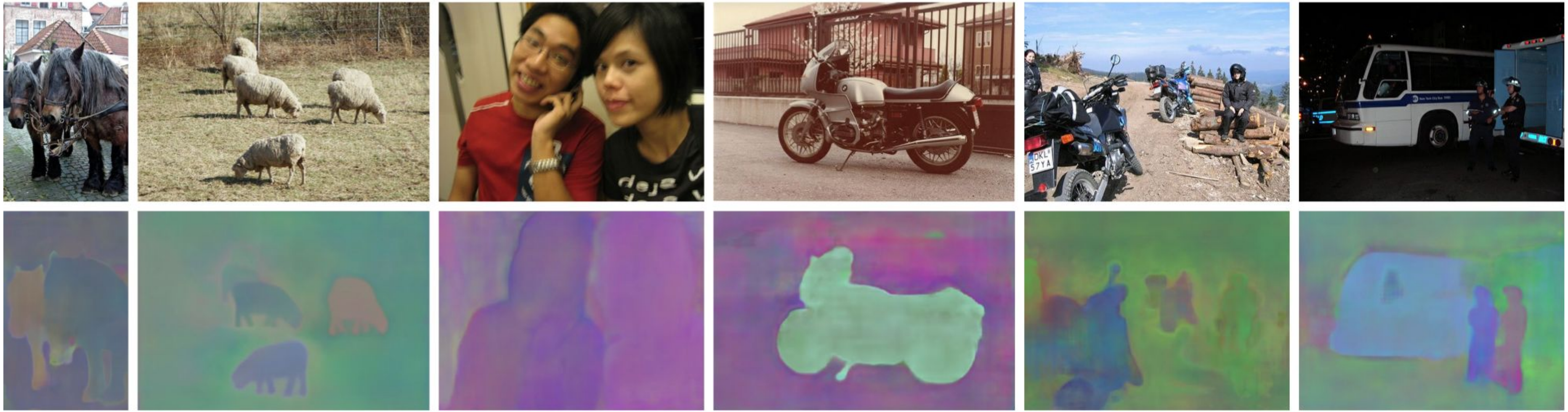
- Some things are objects, and some are stuff such as grass, sky, etc. Not meaningful to put a box around stuff.
- Sometimes objects are occluded.

WIP: Bottom-up (Box-Free) Instance Segmentation

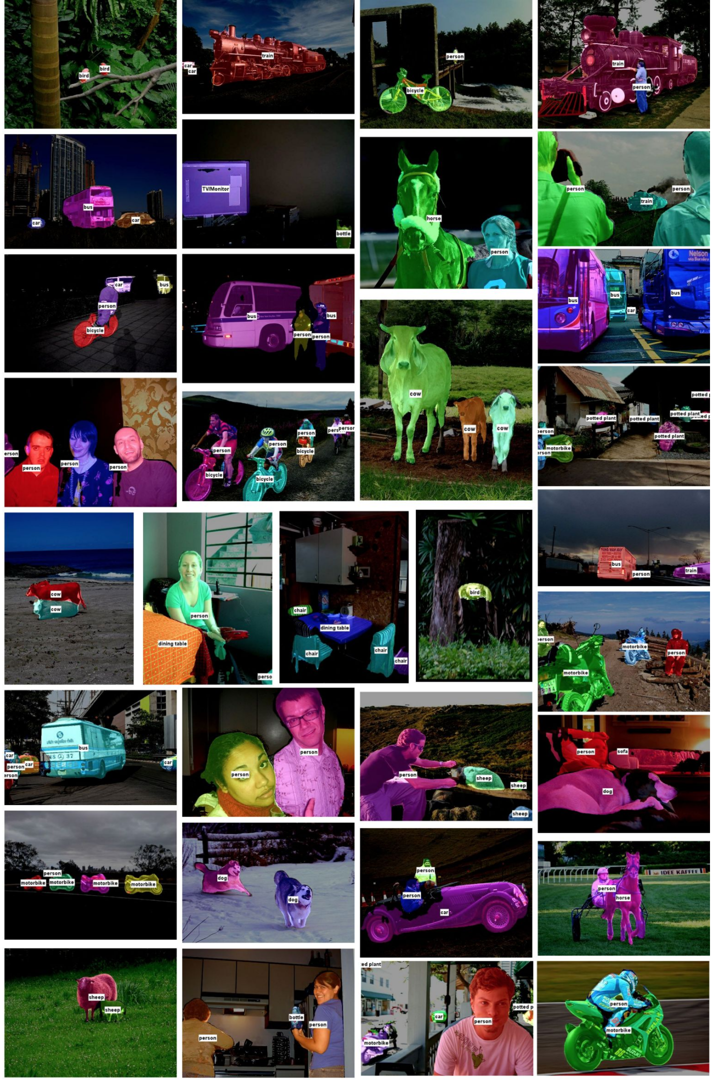


Fathi, Wojna, Rathod, Wang, Song, Guadarrama, Murphy, Semantic Instance Segmentation via Deep Metric Learning, arXiv 1703.10277

Projection of Embedding Vectors to RGB Space



Qualitative Results



This Talk

- Semantic Stuff Segmentation
- Object Instance Segmentation
- **Human Pose Estimation**

Team Members

George Papandreou

Tyler Zhu

Nori Kanazawa

Alex Toshev

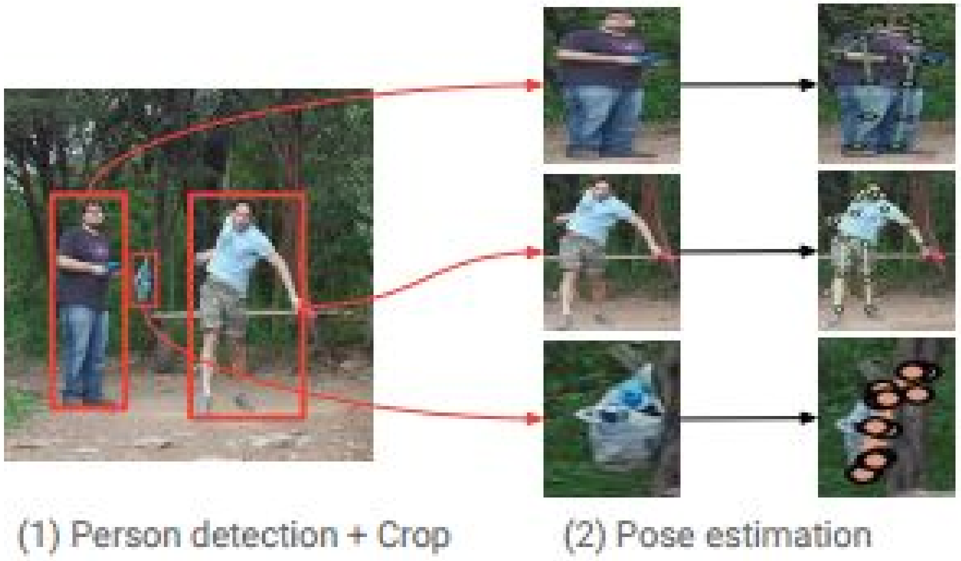
Jonathan Tompson

Chris Bregler

Hartwig Adam

Kevin Murphy

Top-down (2-stage) pipeline



"[Towards Accurate Multi-person Pose Estimation in the Wild]",
George Papandreou, Tyler Zhu, Nori Kanazawa, Alexander Toshev,
Jonathan Tompson, Chris Bregler, Kevin Murphy. CVPR'17.

Person Detection

1. Uses our open source object detection system*, which won COCO-Det 2016.
2. Faster-RCNN, with ResNet-101 feature extractor, trained on person vs non-person (COCO data).
3. Single model (no ensemble), single-crop eval.
4. Output stride=8 via atrous convolution.
5. Image resized to 800 min side or 1200 max side.

Box AP for person (testdev): 0.487

**Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., ... & Murphy, K. Speed/accuracy trade-offs for modern convolutional object detectors. CVPR 2017*

Heatmap Output

- Heatmap field for each keypoint
  - 17 channels (1 within a disk around each keypoint, 0 outside)
  - Sigmoid cross entropy loss
- Intermediate and final CNN layers

Crop | Target | Net-Layer52 | Net-Layer101

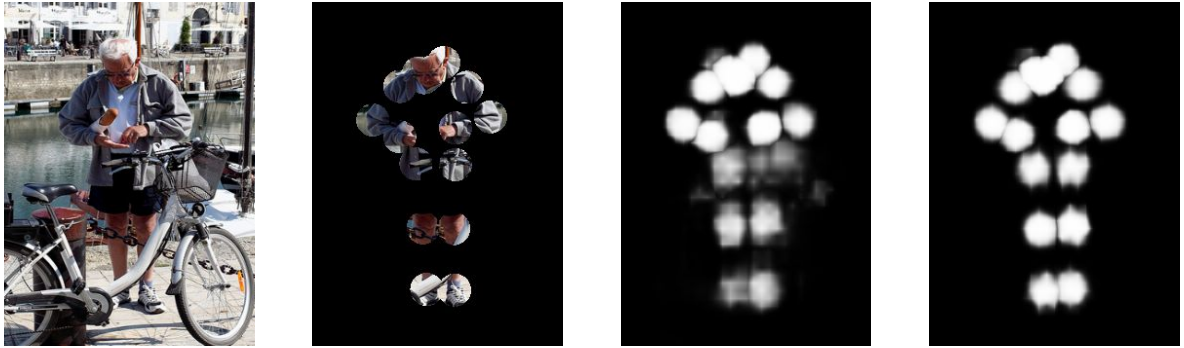
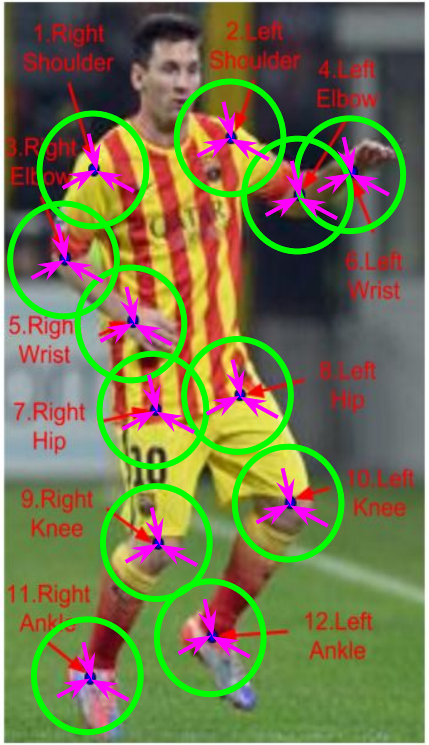
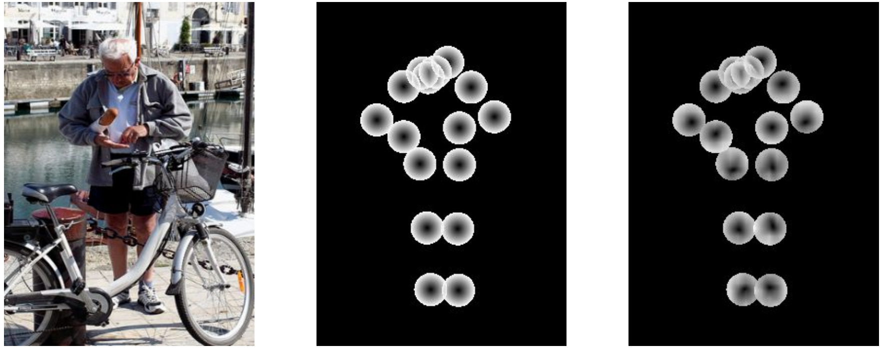


photo credit: Andrew Taylor

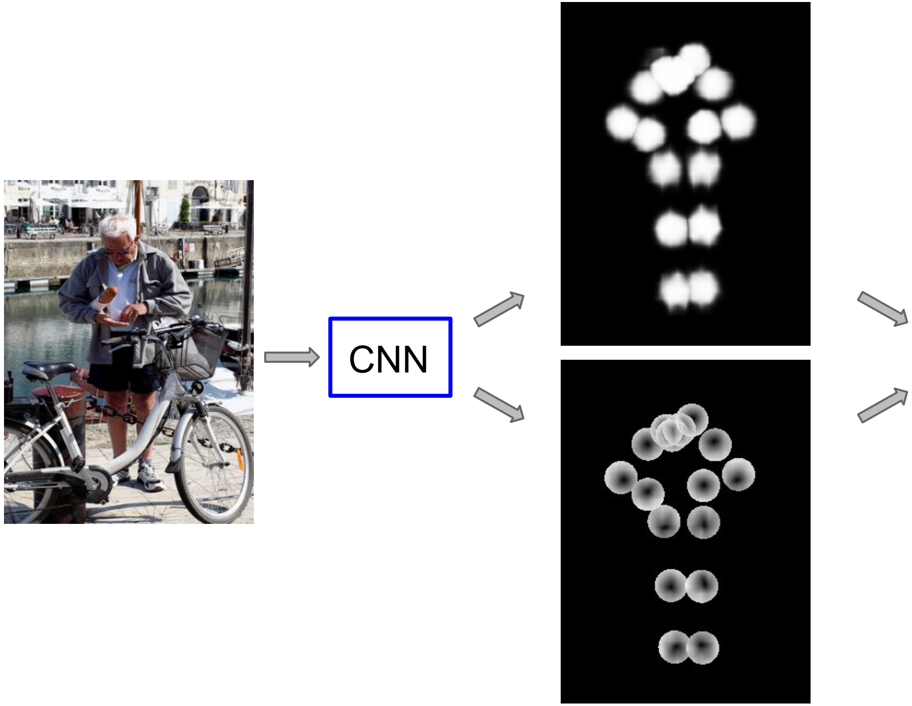
Offset Output



- Offset field towards the center of the disk
  - 34 channels for x- and y- offsets
  - Huber loss, only active within disks
- Intermediate and final CNN layers



Fusing Heatmaps and Offsets via Hough Voting

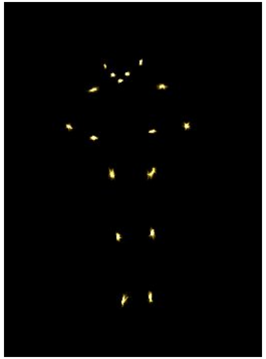


Heatmaps G_i

Offsets F_i

Heatmap Bilinear kernel Offset

$$P_i(x_i) = \sum_x G_i(x) \cdot K(x_i - x - F_i(x))$$



Hough arrays P_i

<u>Algo</u>: *Offset-guided Hough voting*

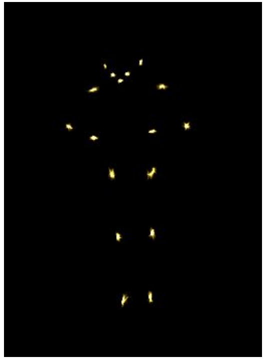
For each point in the heatmap:

(1) Transfer its mass by the corresponding offset.

(2) Accumulate into one 2-D Hough array per part.

Final Pose Prediction: Keypoint Position and Score

CNN +
Hough Voting



Fused activation maps

argmax

Keypoint Position (x_i, y_i)

max

Keypoint score s_i

Mean

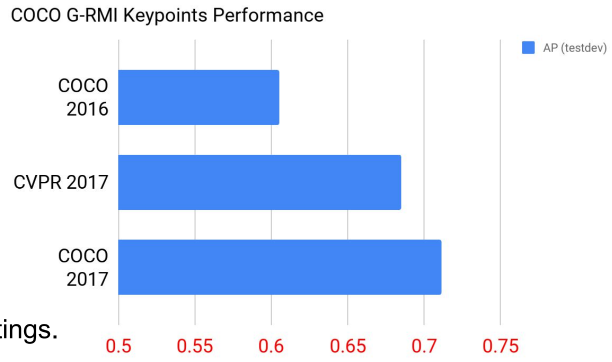
Instance score s

Google

Our Progress on COCO-Keypoints Benchmark

- Submission to COCO-2016 keypoints
  - AP: 0.605 (COCO+internal*, ranked #2)
- Improvements[1] for CVPR 2017 paper
  - AP: 0.649 (COCO)
  - AP: 0.685 (COCO+internal)
- Improvements[2] for COCO-2017 competition:
  - AP: 0.669 (COCO)
  - AP: 0.710 (COCO+internal, ranked #4)

All AP numbers use testdev



*Internal dataset (400k people, 130k images).

[1]Exponential moving average of parameters, better model and system tuning and hyperparameter settings.

[2]Intermediate supervision for all heatmap+offsets+displacements, resnet-152, better feature alignment, longer training without decreasing learning rate.

COCO Keypoints Results (testdev)

	AP	AP@.5	AP@.75	AP (M)	AP (L)	AR	AR@.5	AR@.75	AR (M)	AR (L)
Ours COCO-2016 #2 (COCO+internal)	0.605	0.822	0.662	0.576	0.666	0.662	0.866	0.714	0.619	0.722
CMU-Pose COCO-2016 #1 paper	0.618	0.849	0.675	0.571	0.682	0.665	0.872	0.718	0.606	0.746
Mask-RCNN paper	0.631	0.873	0.687	0.578	0.714	0.697	0.916	0.749	0.637	0.778
Associative Embedding paper	0.655	0.868	0.723	0.606	0.726	0.702	0.895	0.760	0.646	0.781
Ours (COCO-only)	0.669	0.864	0.736	0.640	0.720	0.716	0.892	0.776	0.661	0.791
Ours (COCO+internal)	0.696	0.872	0.766	0.670	0.742	0.742	0.903	0.804	0.692	0.811
Ours (COCO+internal) ResNet-152	0.710	0.879	0.777	0.690	0.752	0.758	0.912	0.819	0.714	0.820

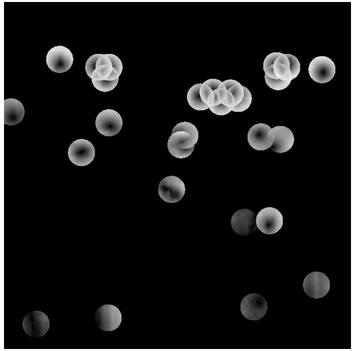
WIP*: Bottom-up part detection + grouping

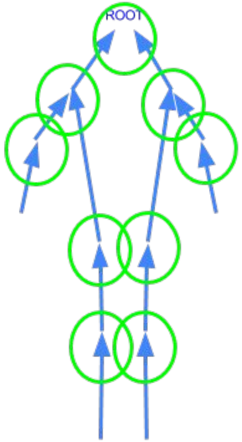
3 fully convolutional outputs

K binary heatmaps

K 2d offsets

K^2 pairwise offsets





*G. Papandreou et al, CVPR'18

Each part predicts offset to other parts. Greedy decoding.

Top-down vs bottom-up

Feature	**Top-Down (box based)**	**Bottom-Up (grouping based)**
Speed	Slower (time $\propto$ #people)	Faster (time independent of #people)
Accuracy	Higher (zoom in on image)	Lower on small instances
Flexibility/ modularity	Higher (cf MaskRCNN)	Lower
Model size/ complexity	Larger (more code, params)	Smaller

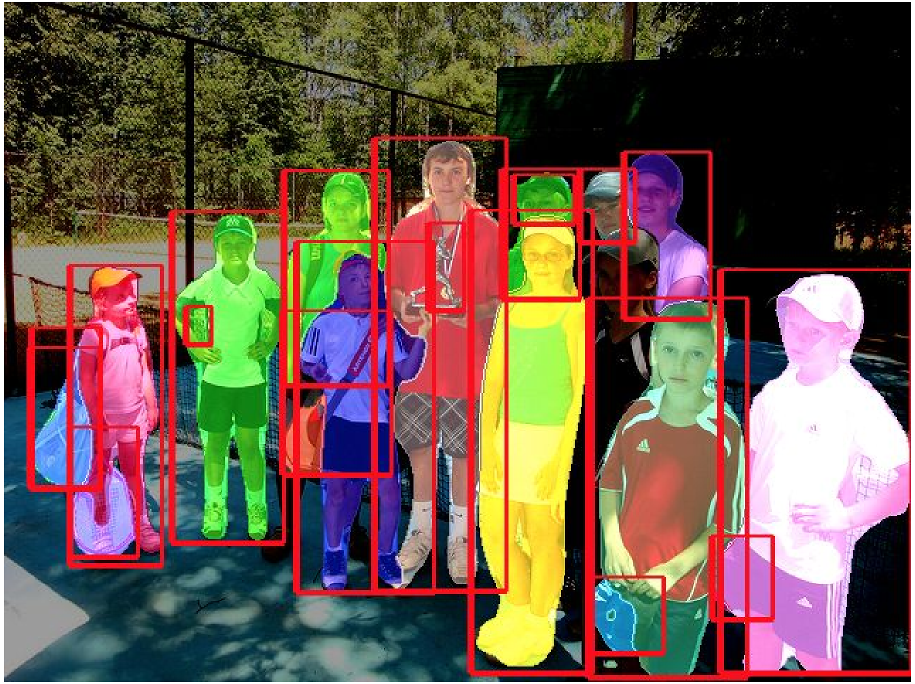
Multi-Person Pose Estimation Demo

Thanks!

SPEAKER
Alireza Fathi

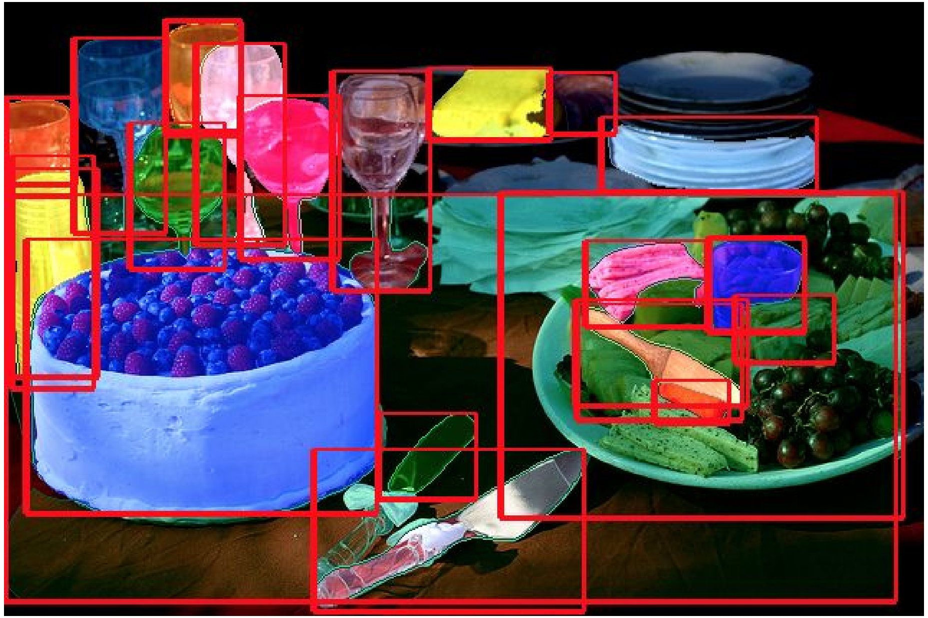
Special thanks to
Nori Kanazawa, Kai Yang, Kevin Murphy, Derek Chow, Ian Fischer, Sergio Guadarrama, Jonathan Huang, Anoop Korattikara, Kevin Murphy, Vivek Rathod, Yang Song, Chen Sun, Matt Tang, Zbigniew Wojna, Menglong Zhu, George Papandreou, Rahul Sukthankar.

Example results from MS COCO

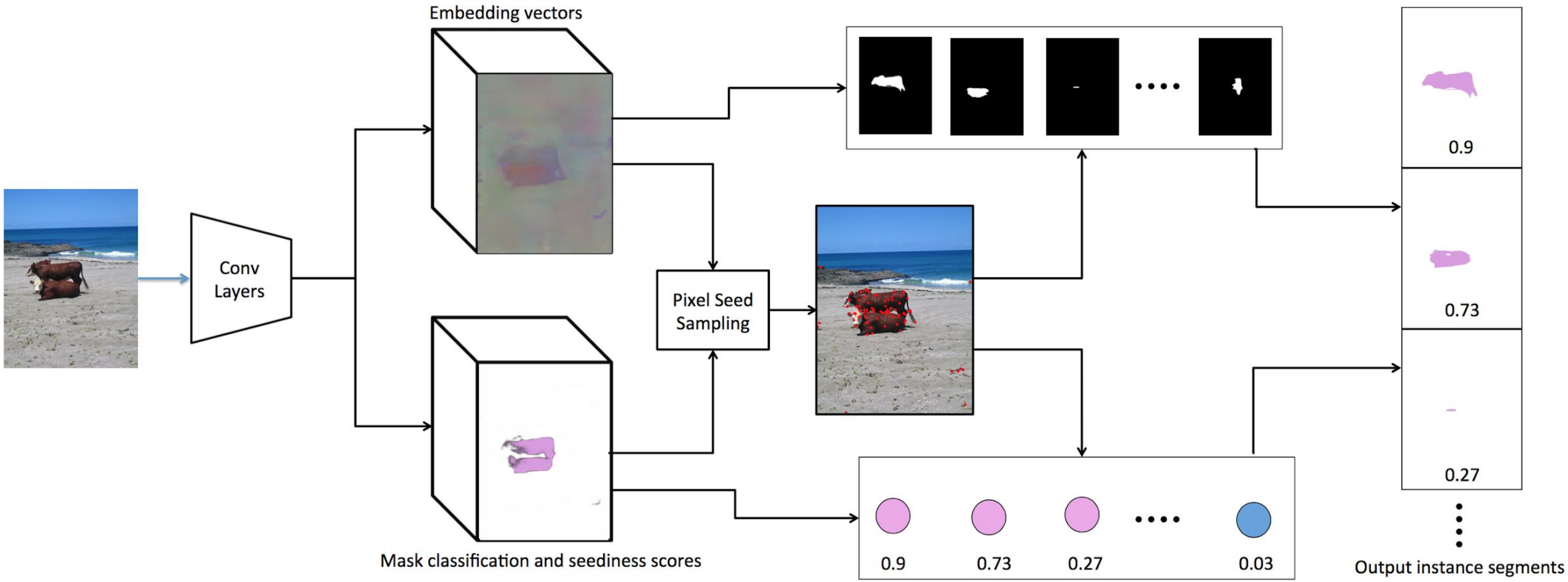


Example results from MS COCO

Example results from MS COCO



Towards Box-Free (Bottom-up) Instance Segmentation



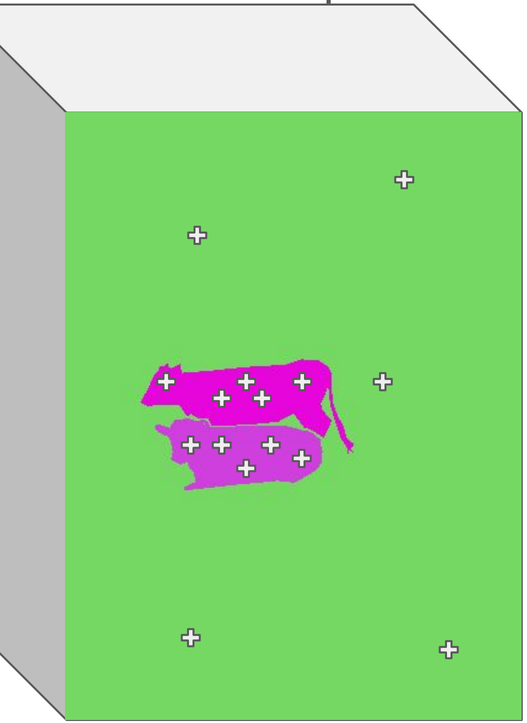
Fathi, Wojna, Rathod, Wang, Song, Guadarrama, Murphy, Semantic Instance Segmentation via Deep Metric Learning, arXiv 1703.10277

Embedding Loss

- K Samples of N-pair loss.

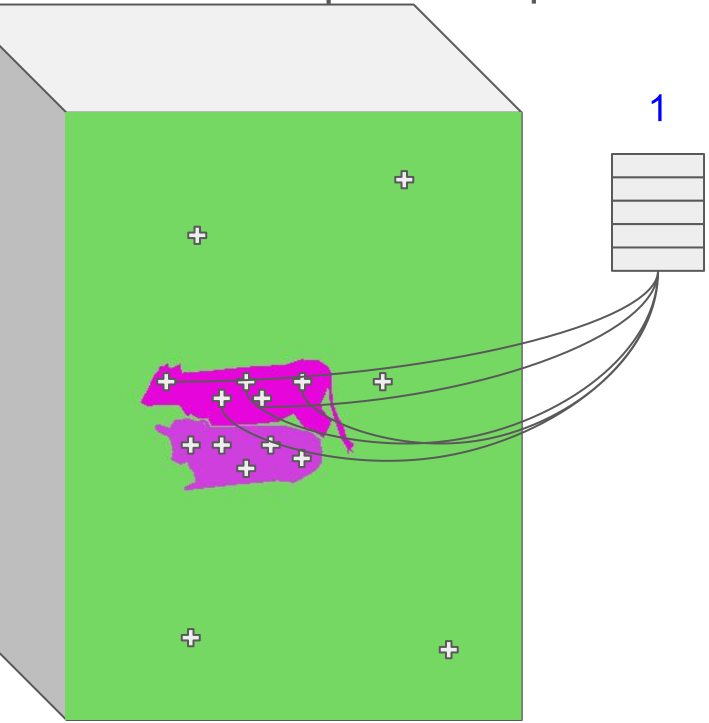
Embedding Loss

- K Samples of N-pair loss.



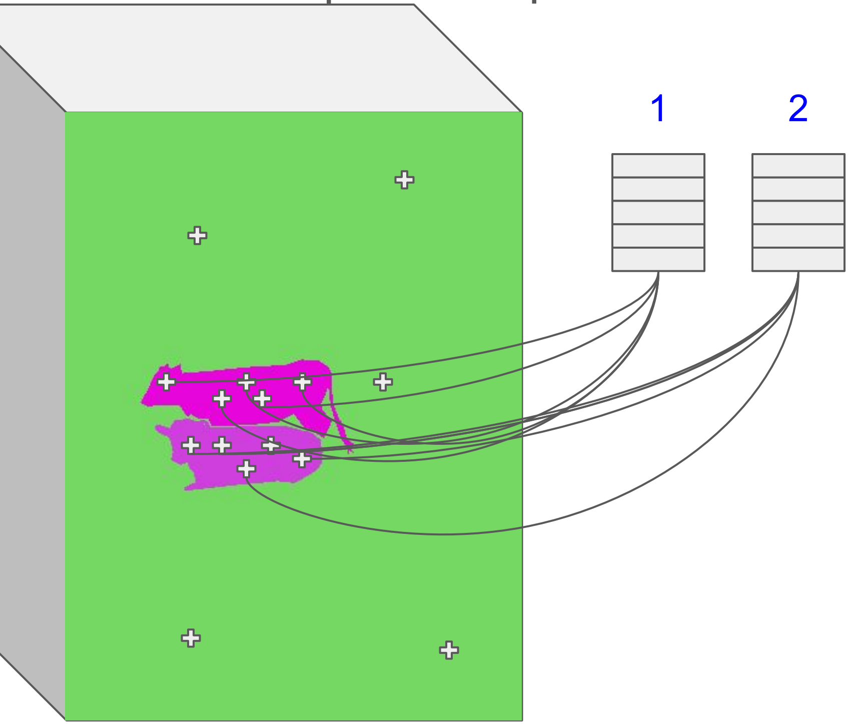
Embedding Loss

- K Samples of N-pair loss.



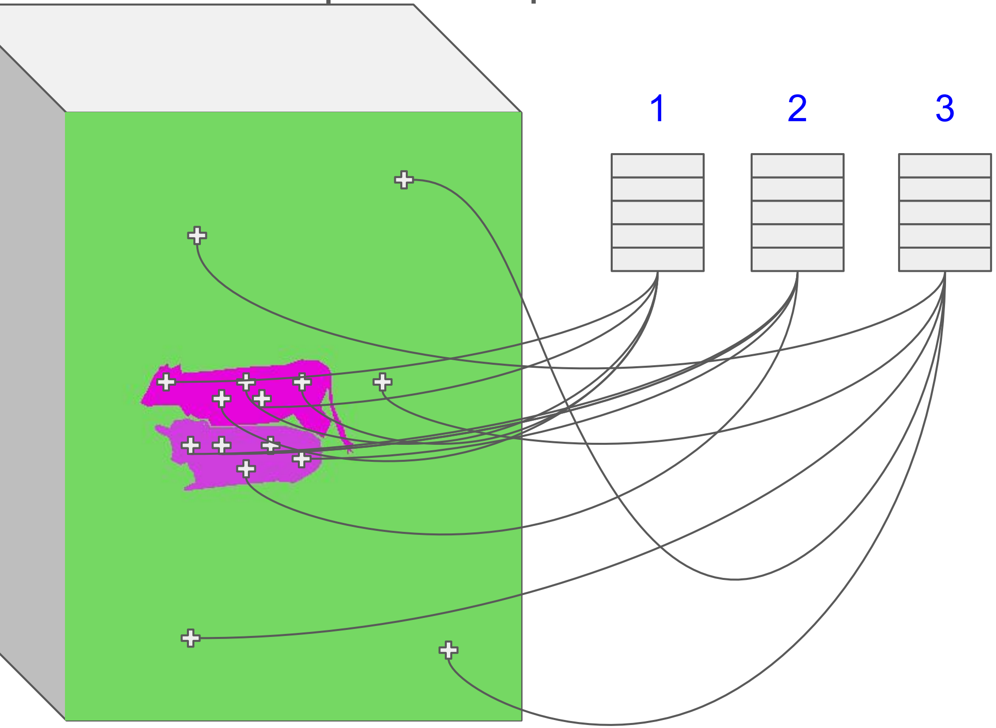
Embedding Loss

- K Samples of N-pair loss.



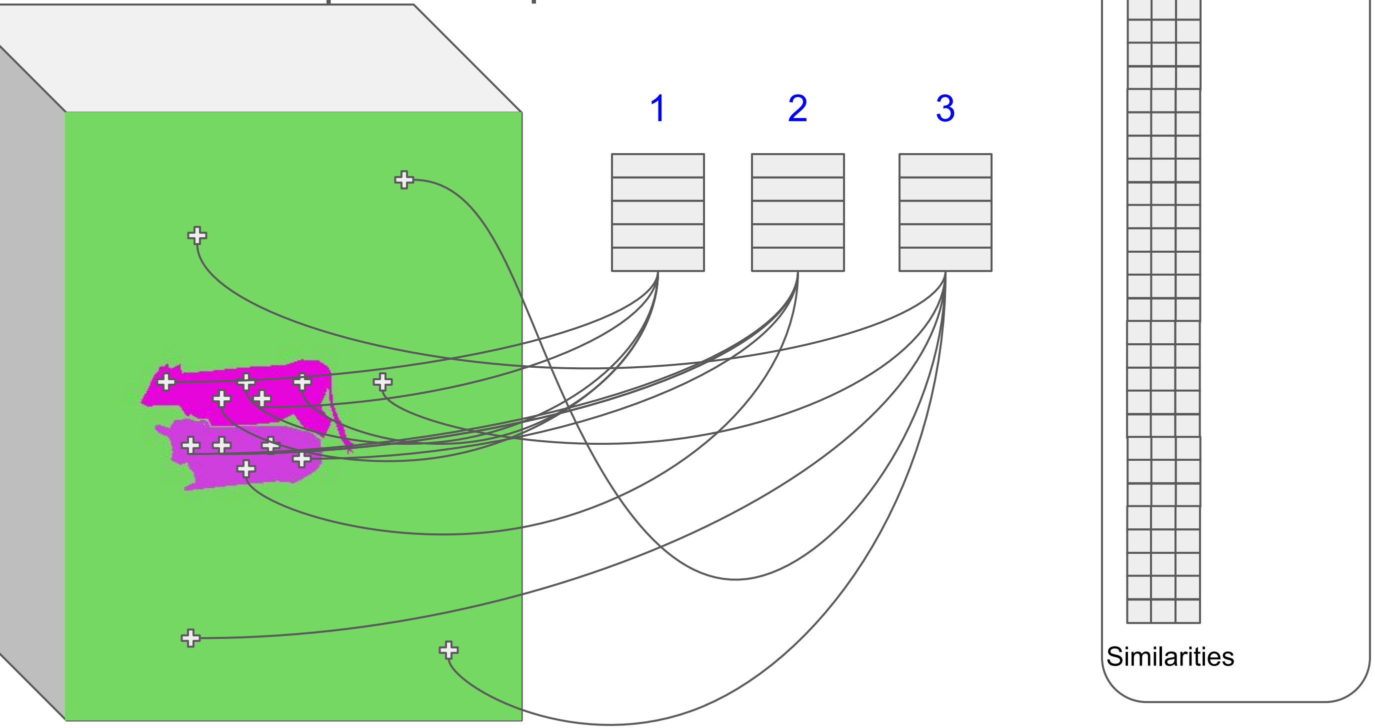
Embedding Loss

- K Samples of N-pair loss.



Embedding Loss

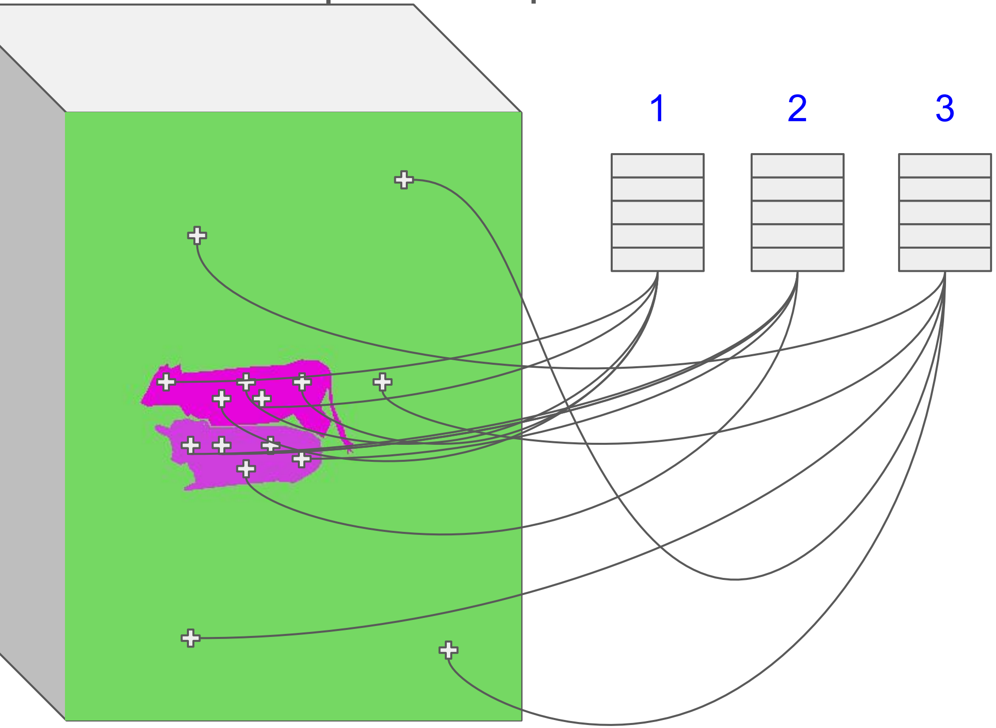
- K Samples of N-pair loss.

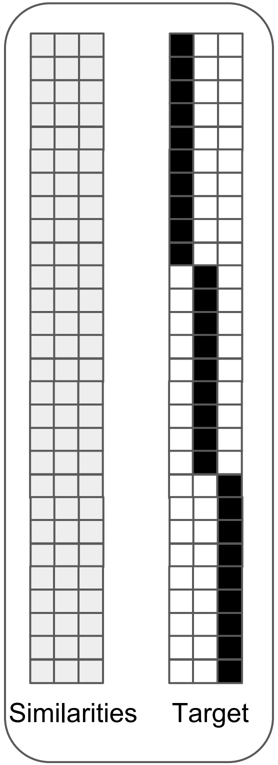


- Randomly Pick an embedding vector from class c_i. Lets call it e_1.
- Randomly pick one embedding vector from each class c_i, c_j, ….
- Compute the similarity between e_1 and the other n embedding vectors.
- We like the similarity between e_1 and the vector belonging to class c_i be high, and the similarity with embedding vectors belonging to other classes be low.

Embedding Loss

- K Samples of N-pair loss.

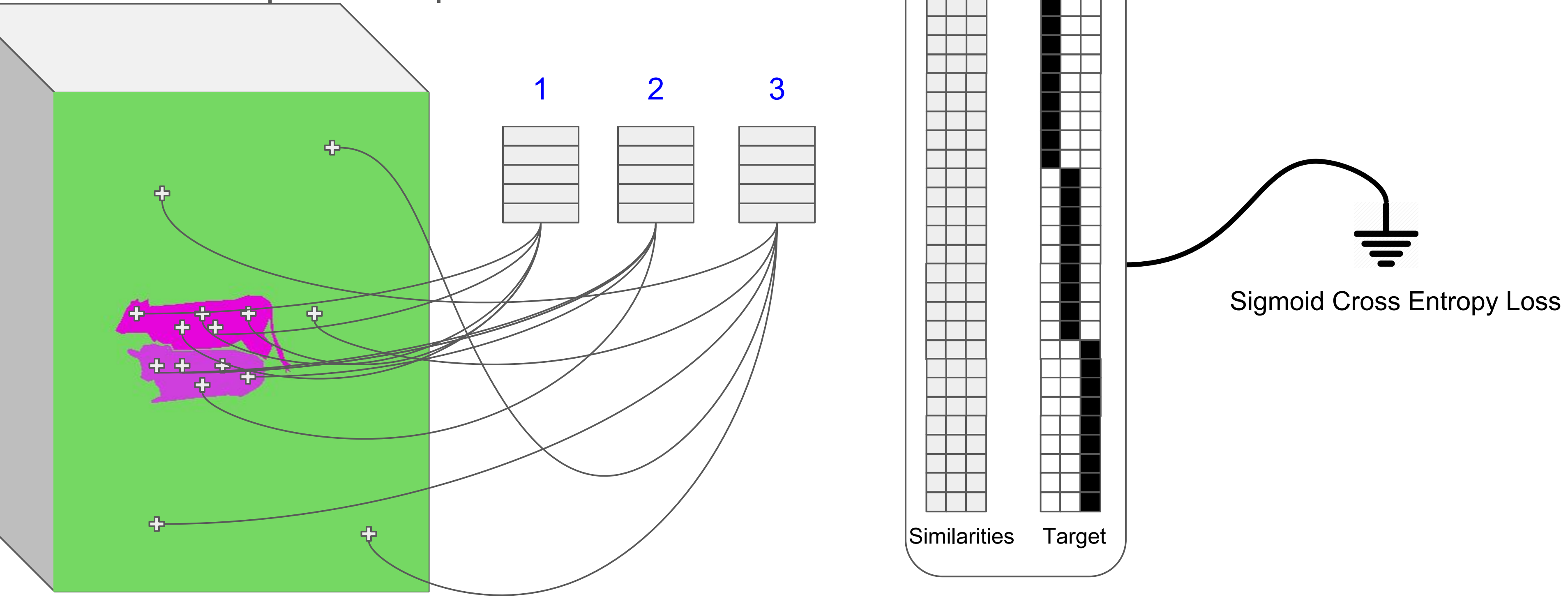




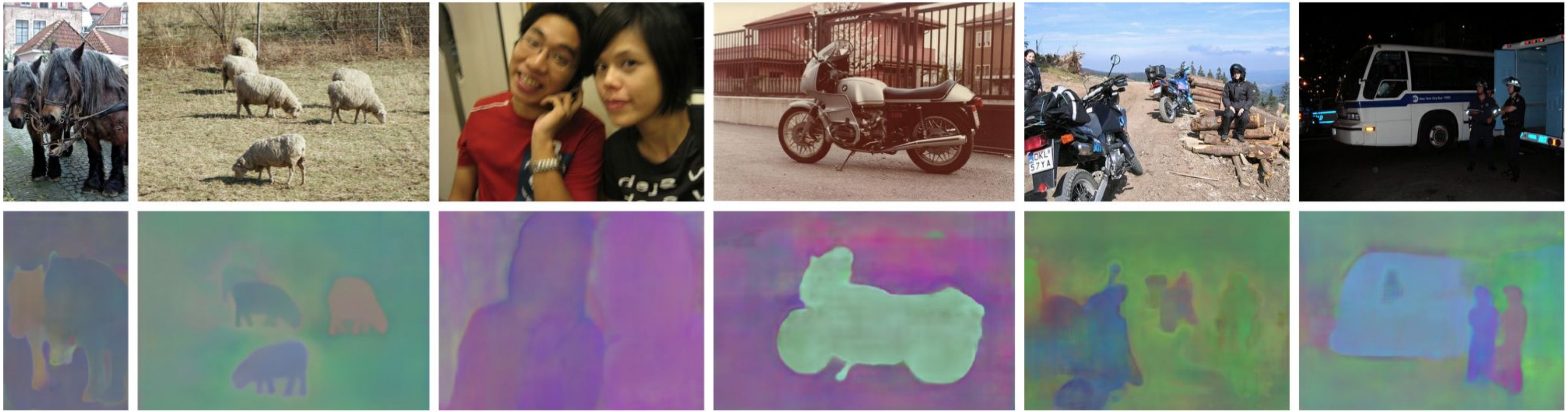
- Randomly Pick an embedding vector from class c_i. Lets call it e_1.
- Randomly pick one embedding vector from each class c_i, c_j, ….
- Compute the similarity between e_1 and the other n embedding vectors.
- We like the similarity between e_1 and the vector belonging to class c_i be high, and the similarity with embedding vectors belonging to other classes be low.

Embedding Loss

- K Samples of N-pair loss.



Projection of Embedding Vectors to RGB Space



Qualitative Results