Lecture 13: Segmentation

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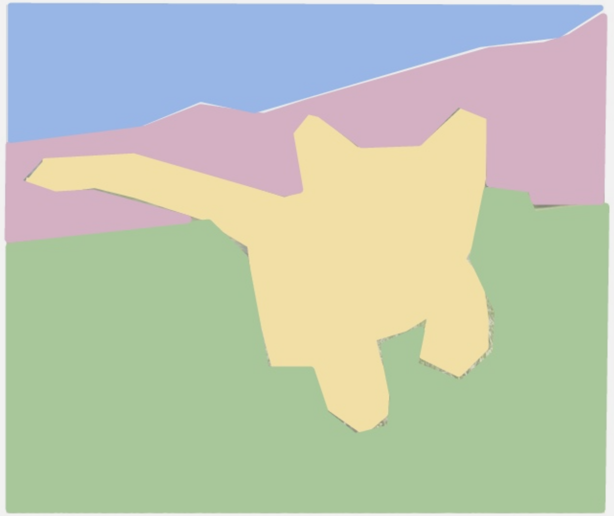
Course Website:
Scan Me!

Classification

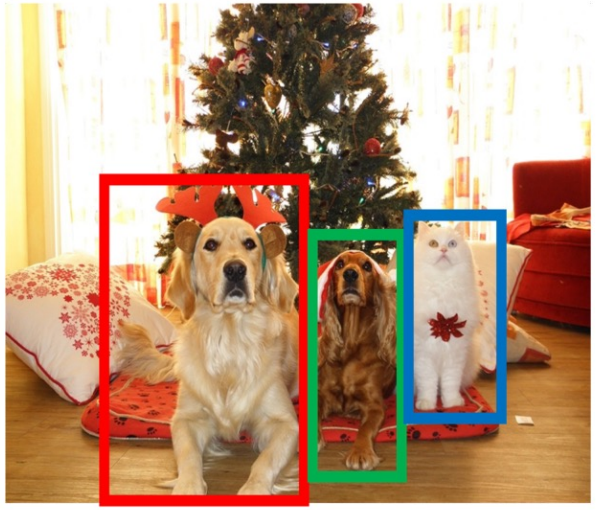
CAT

Semantic Segmentation



GRASS, CAT, TREE, SKY

Object Detection



DOG, DOG, CAT

Instance Segmentation

DOG, DOG, CAT

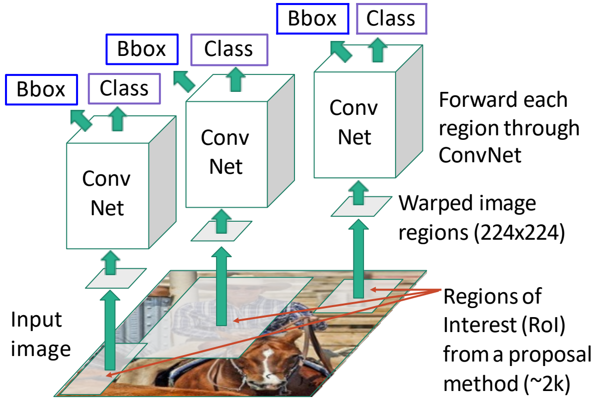
No spatial extent

No objects, just pixels

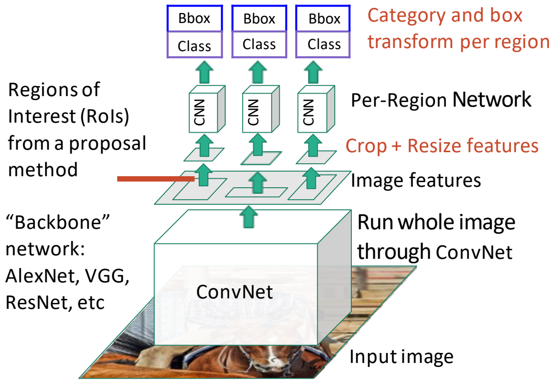
Multiple Objects

Recap

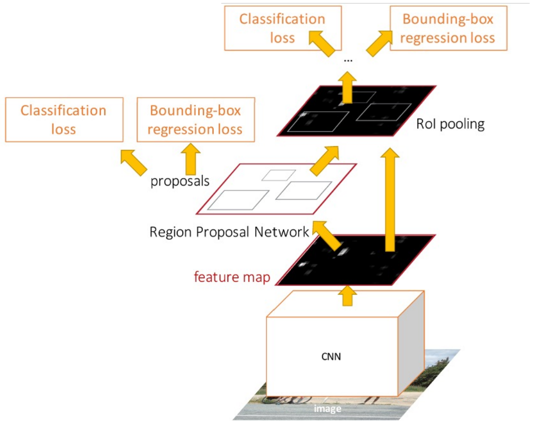
"Slow" R-CNN: Run CNN independently for each region



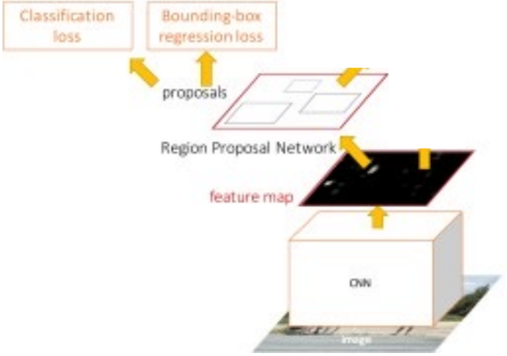
Fast R-CNN: Apply differentiable cropping to shared image features



Faster R-CNN: Compute proposals with CNN

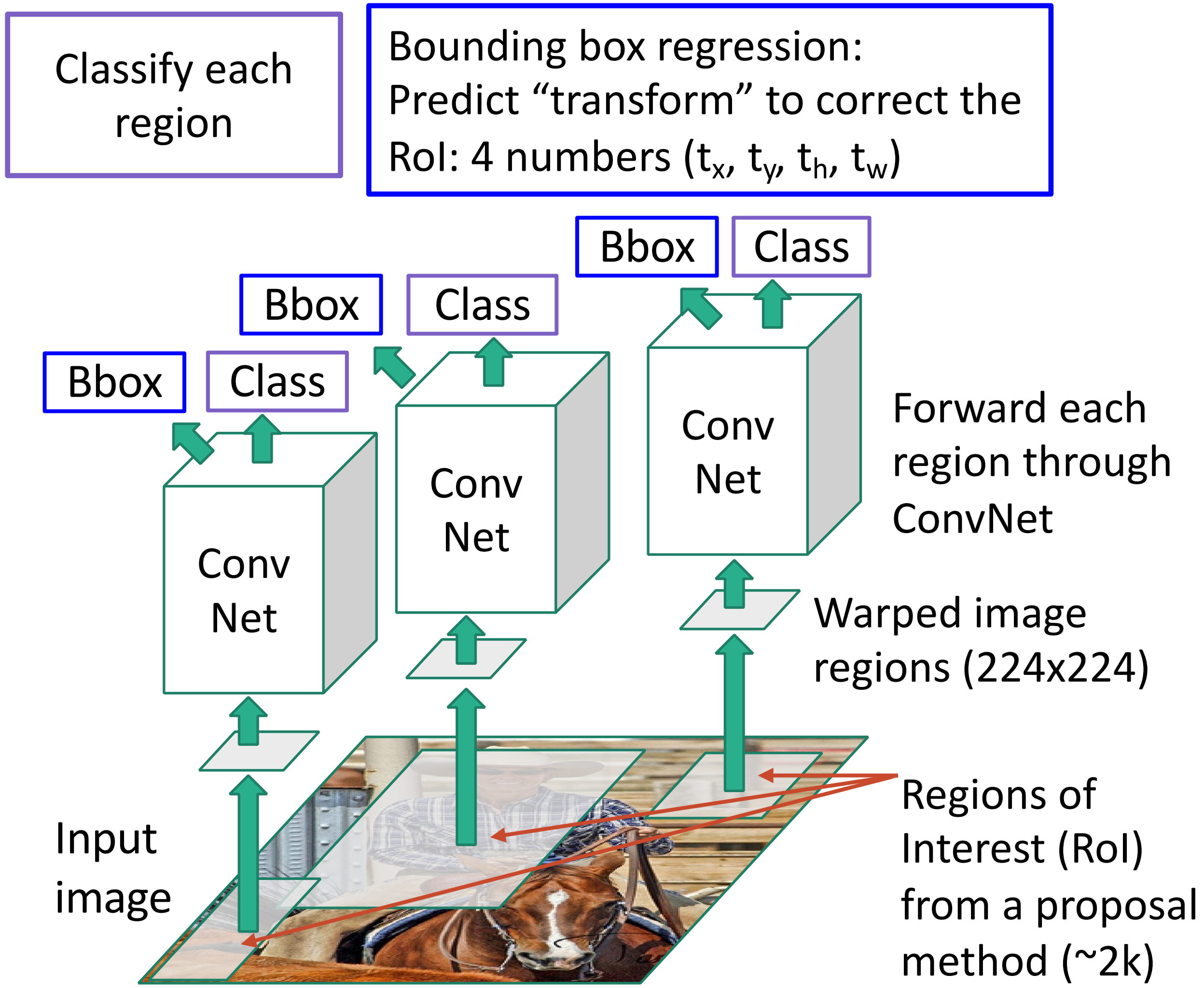


Single-Stage: Fully convolutional detector

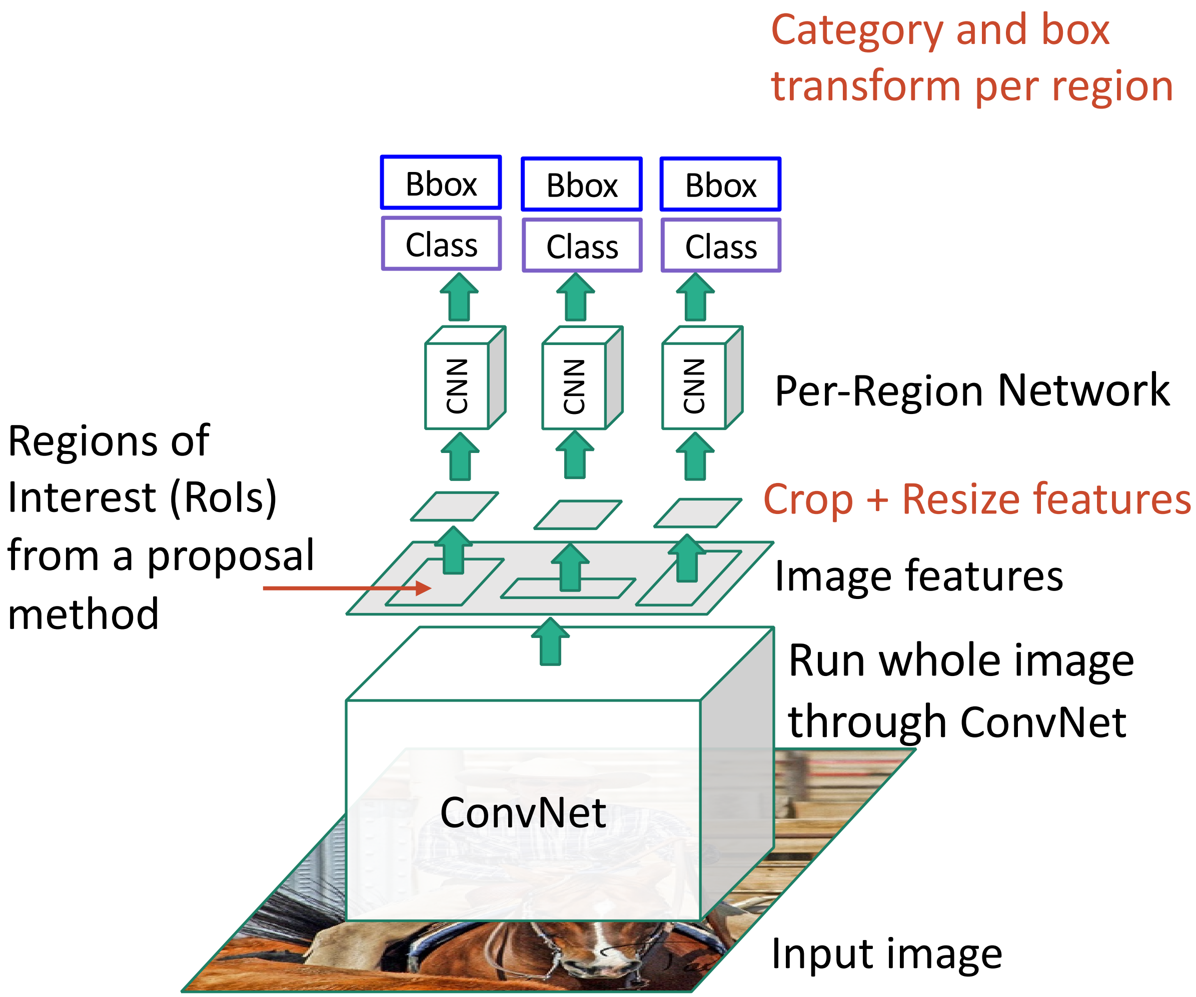


With anchors: RetinaNet
Anchor-Free: FCOS

R-CNN: Region-Based CNN



Fast R-CNN

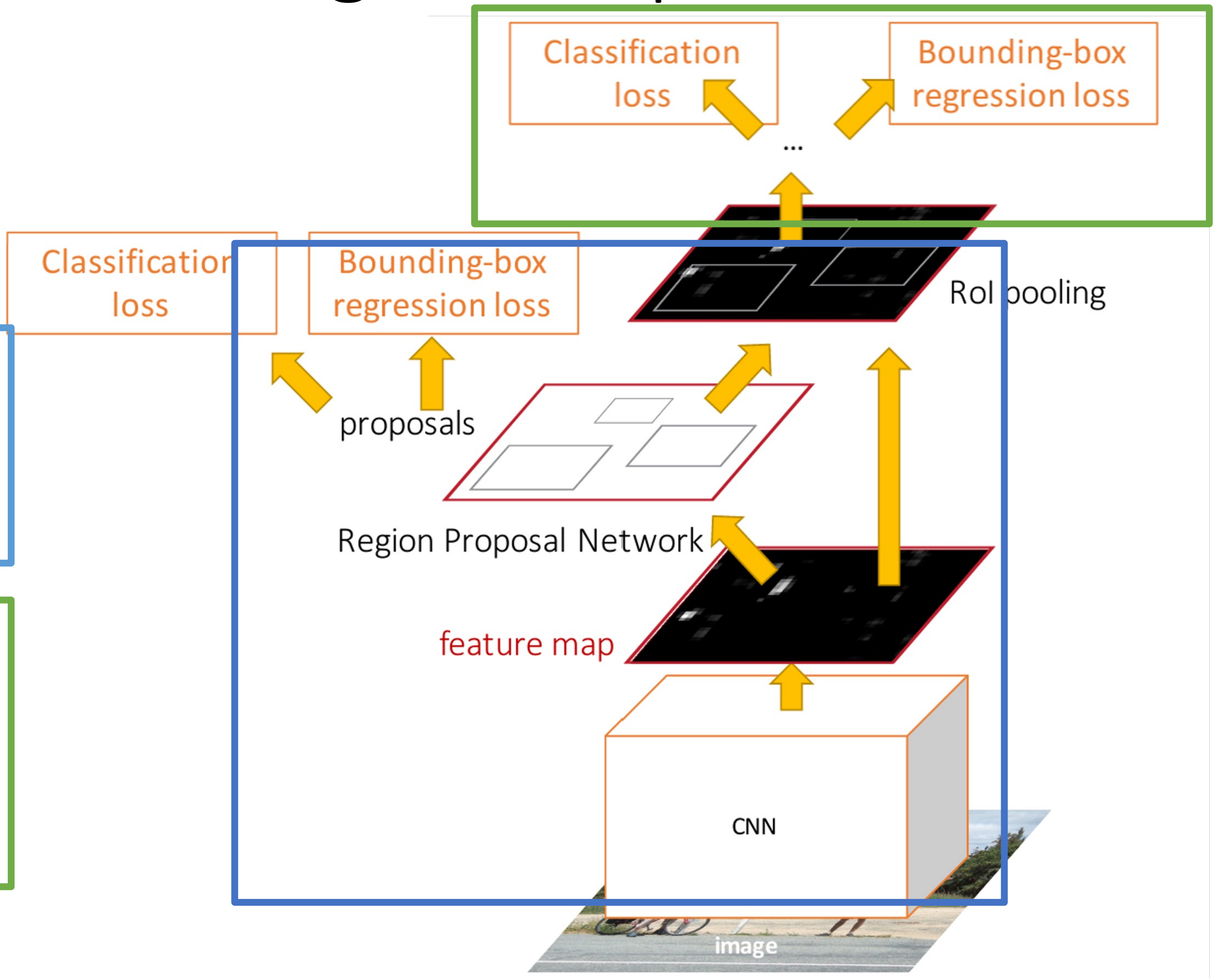


Faster R-CNN: Learnable Region Proposals

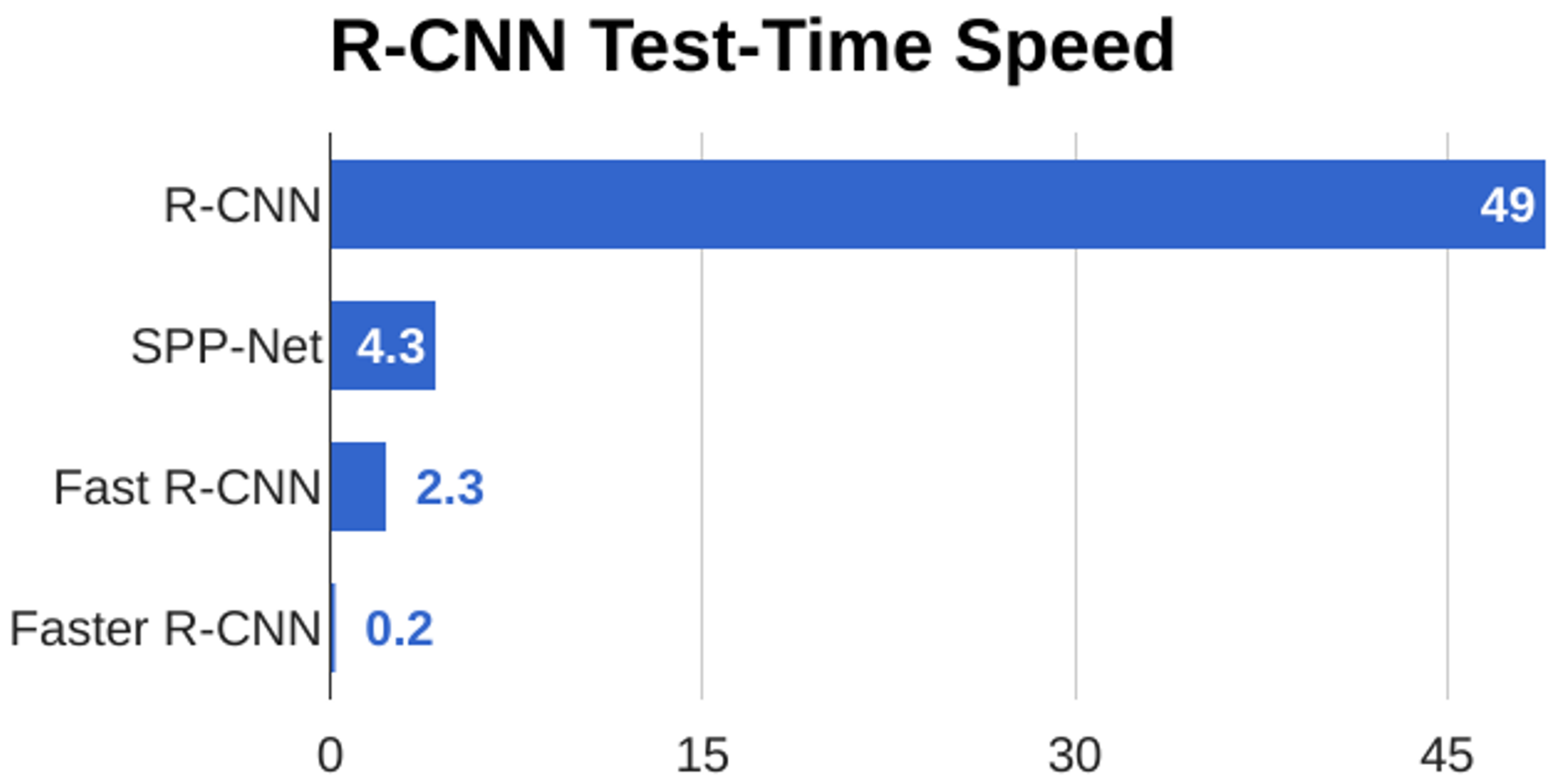
Faster R-CNN is a
Two-stage object detector

First stage: Run once per image
- Backbone network
- Region proposal network

Second stage: Run once per region
- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



Faster R-CNN: Learnable Region Proposals

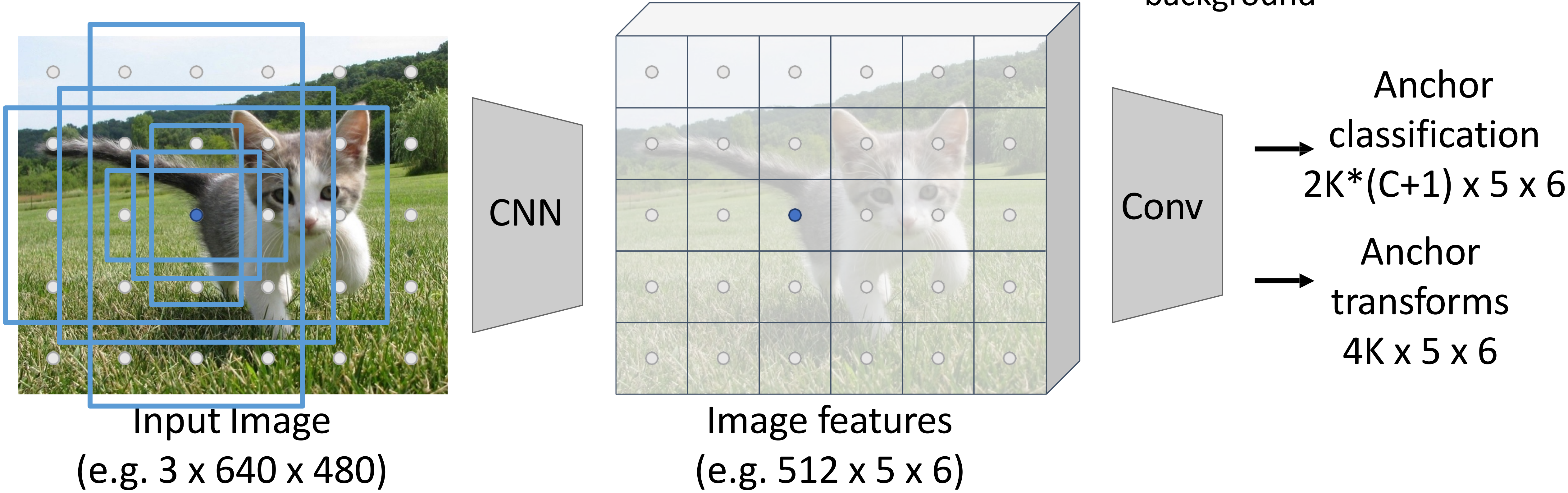


Single-Stage Detectors: RetinaNet

Similar to RPN – but rather than classify anchors as object/no object, directly predict object category (among C categories) or background

Run backbone CNN to get features aligned to input image

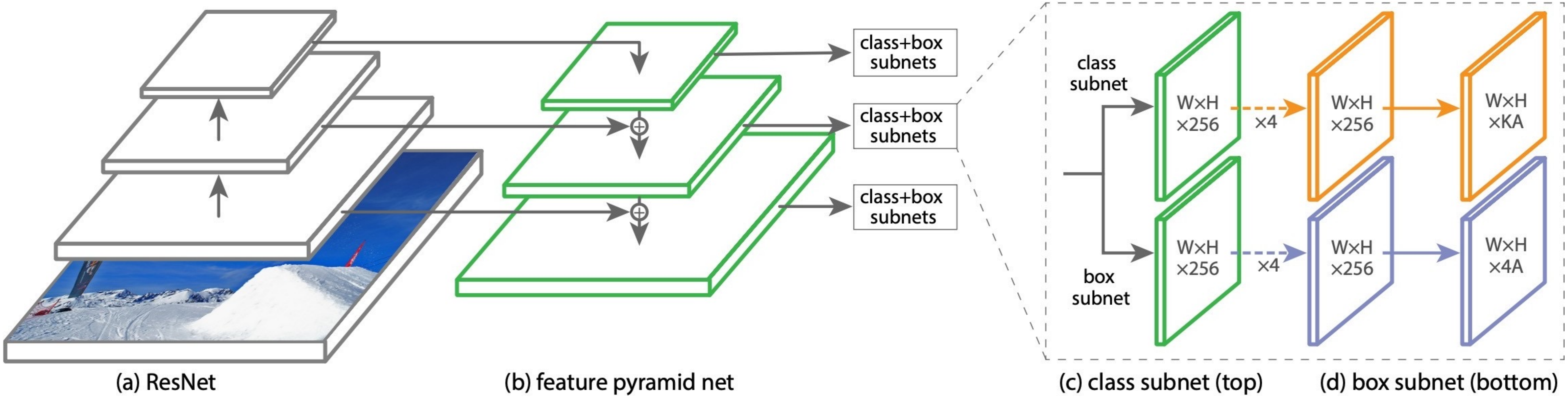
Each feature corresponds to a point in the input



Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

Single-Stage Detectors: RetinaNet

In practice, RetinaNet also uses Feature Pyramid Network to handle multiscale



Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

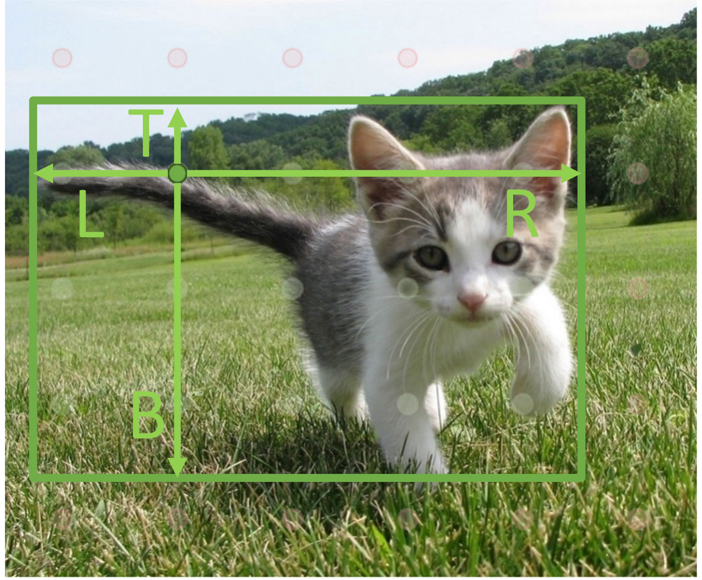
Figure credit: Lin et al, ICCV 2017

Single-Stage Detectors: FCOS ("Anchor-free" detector)

Run backbone CNN to get features aligned to input image

Each feature corresponds to a point in the input

Finally, predict "centerness" for all positive points (using logistic regression loss)



Input Image
(e.g. 3 x 640 x 480)

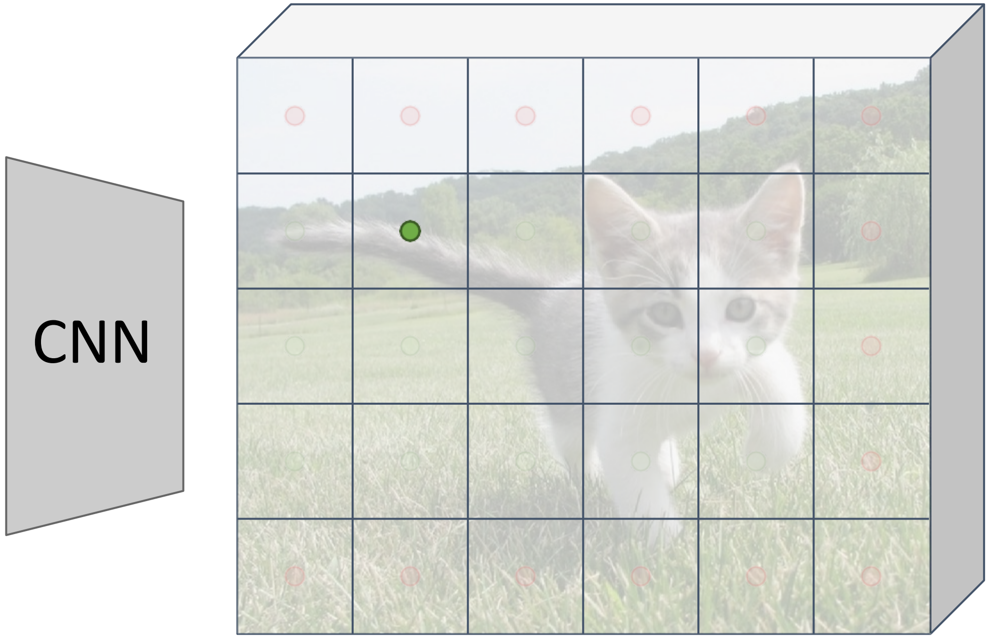
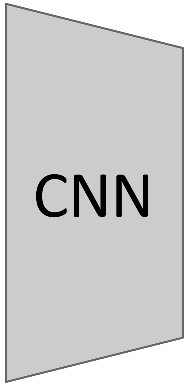


Image features
(e.g. 512 x 5 x 6)



→ Class scores
C x 5 x 6

→ Box edges
4 x 5 x 6

→ Centerness
1 x 5 x 6

$$centerness = \sqrt{\frac{\min(L,R)}{\max(L,R)} \cdot \frac{\min(T,B)}{\max(T,B)}}$$

Ranges from 1 at box center to 0 at box edge

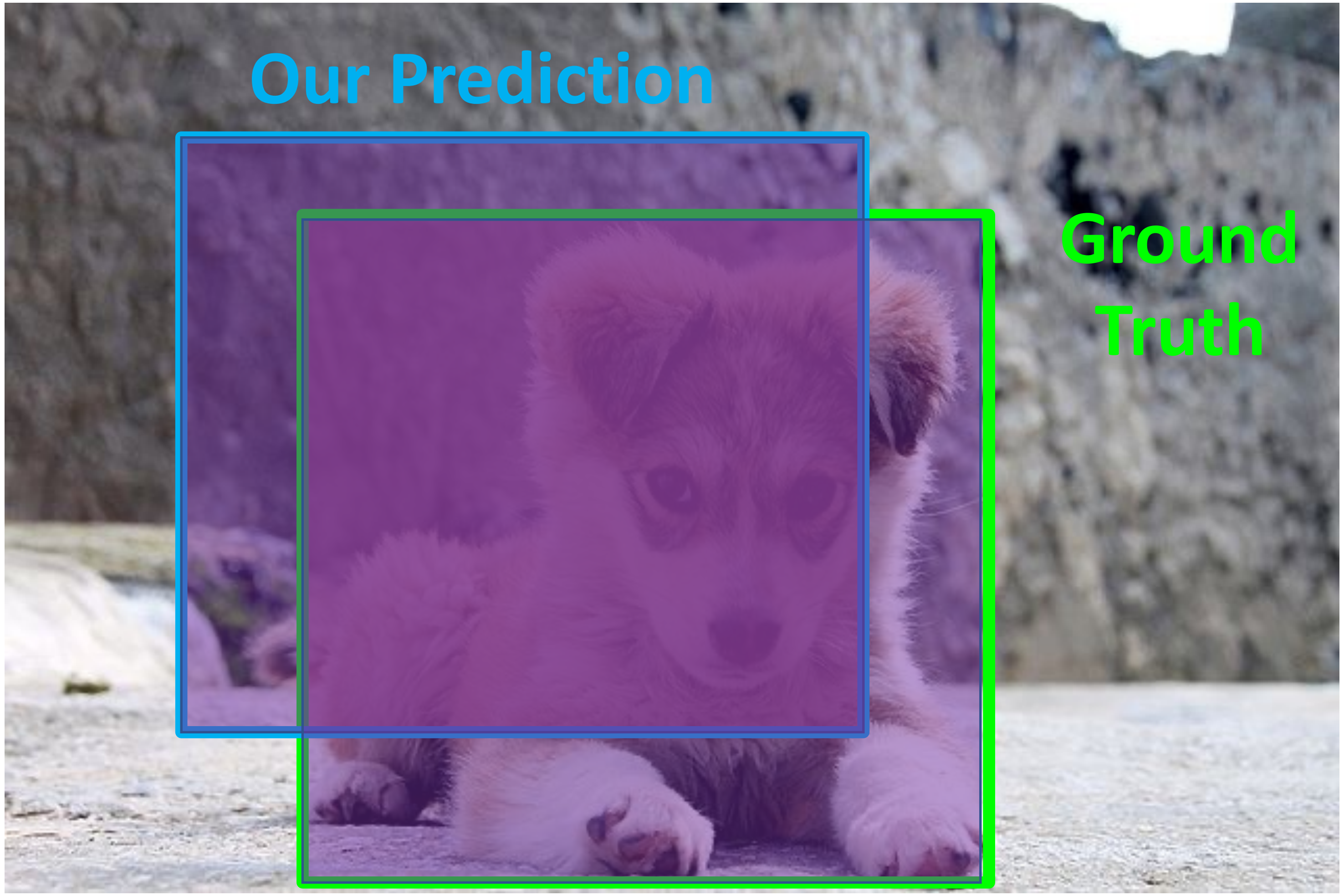
Test-time: predicted "confidence" for the box from each point is product of its class score and centerness.

Comparing Boxes: Intersection over Union (IoU)

How can we compare our prediction to the ground-truth box?

Intersection over Union (IoU)
(Also called "Jaccard similarity" or "Jaccard index"):

$$\frac{\textit{Area of Intersection}}{\textit{Area of Union}}$$

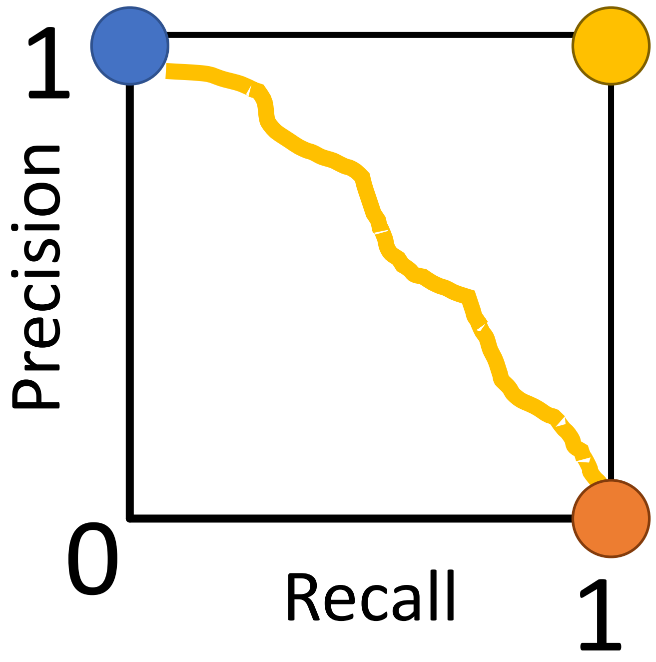


Precision & Recall

- True detection: high intersection over union
  - Choose IoU threshold
- Precision: #true detections / #detections
- Recall: #true detections / #true positives

Car AP = 0.65
Cat AP = 0.80
Dog AP = 0.86
mAP@0.5 = 0.77

Reject everything: no mistakes



Ideal!

Summarize by area under curve (avg. precision)

Accept everything: Miss nothing

mAP@0.5 = 0.77
mAP@0.55 = 0.71
mAP@0.60 = 0.65
...
mAP@0.95 = 0.2

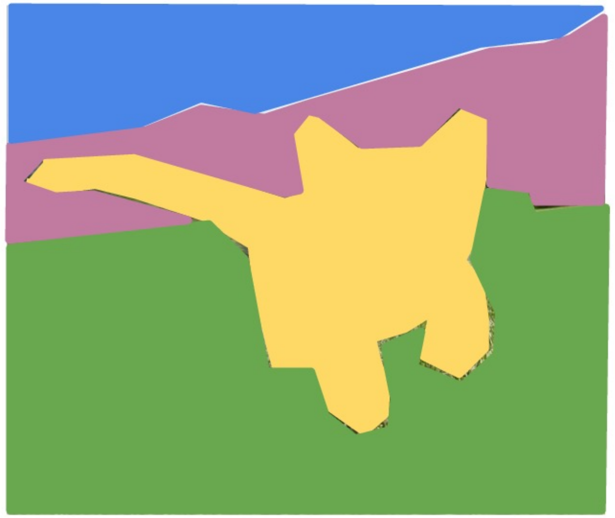
COCO mAP = 0.4

Today's class

Classification

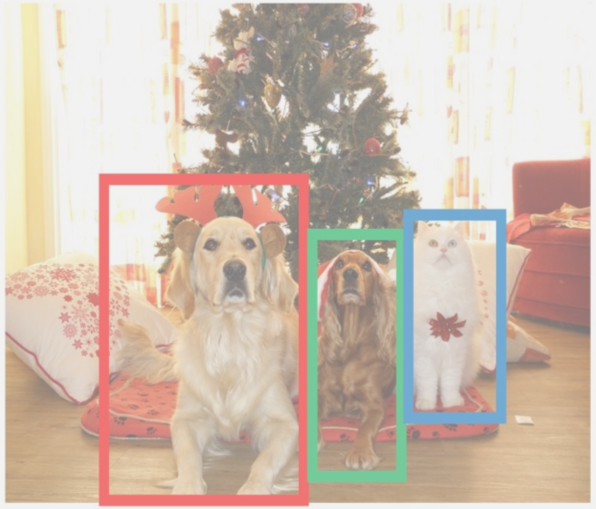
CAT

Semantic Segmentation



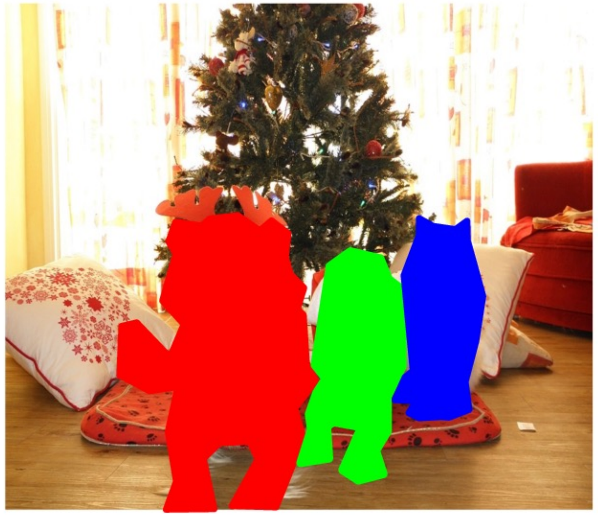
GRASS, CAT, TREE, SKY

Object Detection



DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

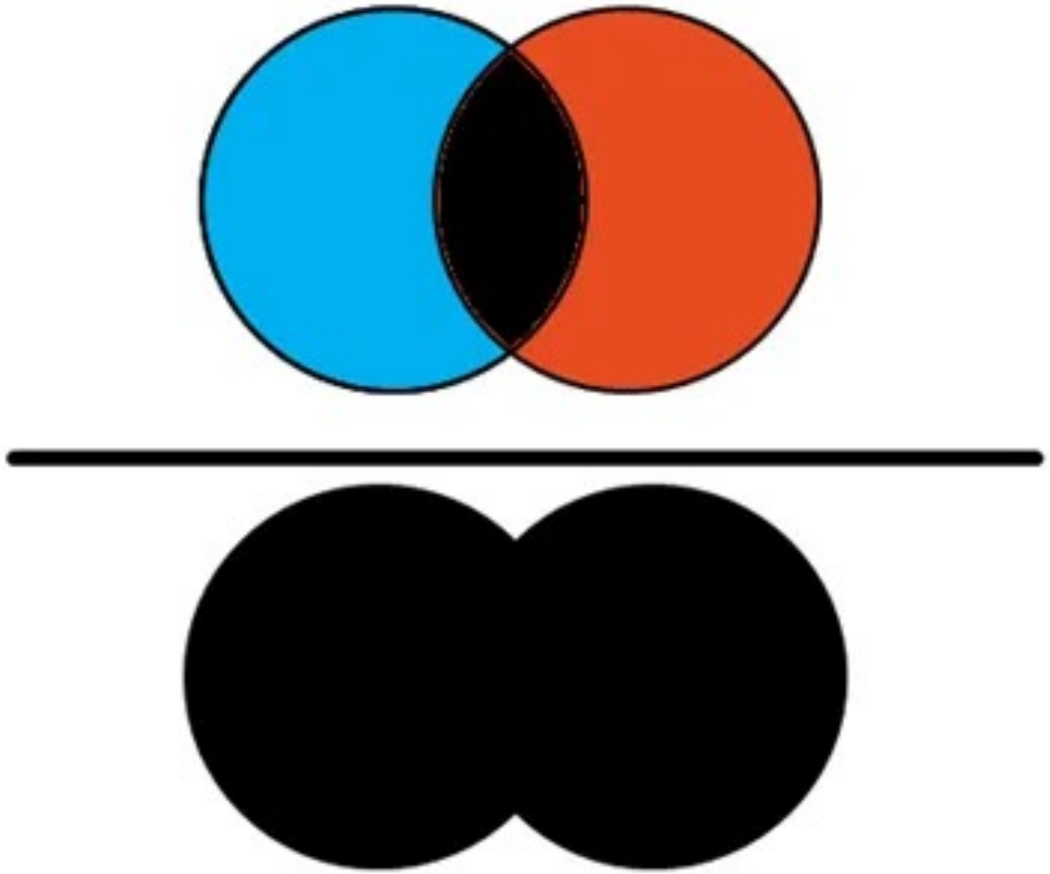
No spatial extent

No objects, just pixels

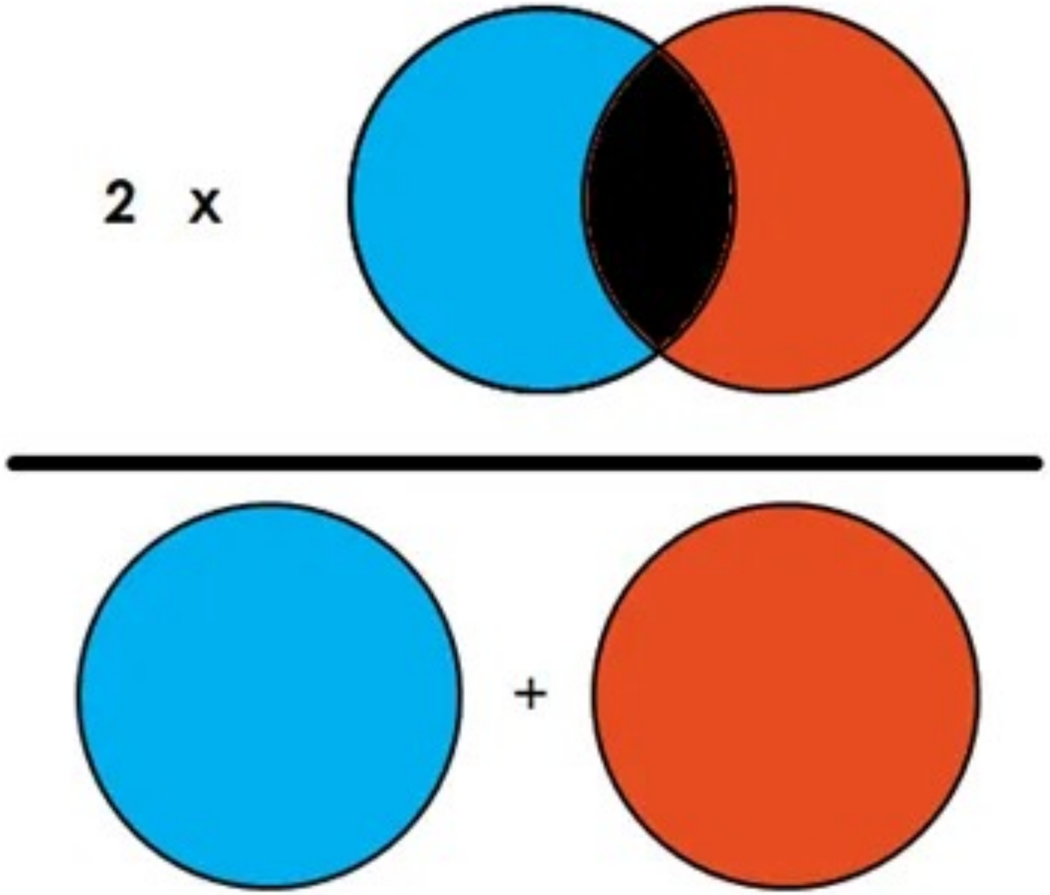
Multiple Objects

How to measure segmentation accuracy?

IoU (Intersection over Union)



DICE Score (F score)



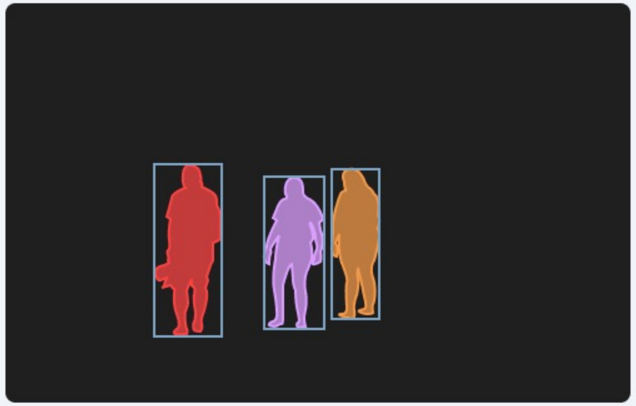
Report mean IoU or DICE score over the test dataset

https://towardsdatascience.com/metrics-to-evaluate-your-semantic-segmentation-model-6bcb99639aa2

Semantic Segmentation vs. Instance Segmentation vs. Panoptic Segmentation

(a) Image

(b) Semantic Segmentation



(c) Instance Segmentation

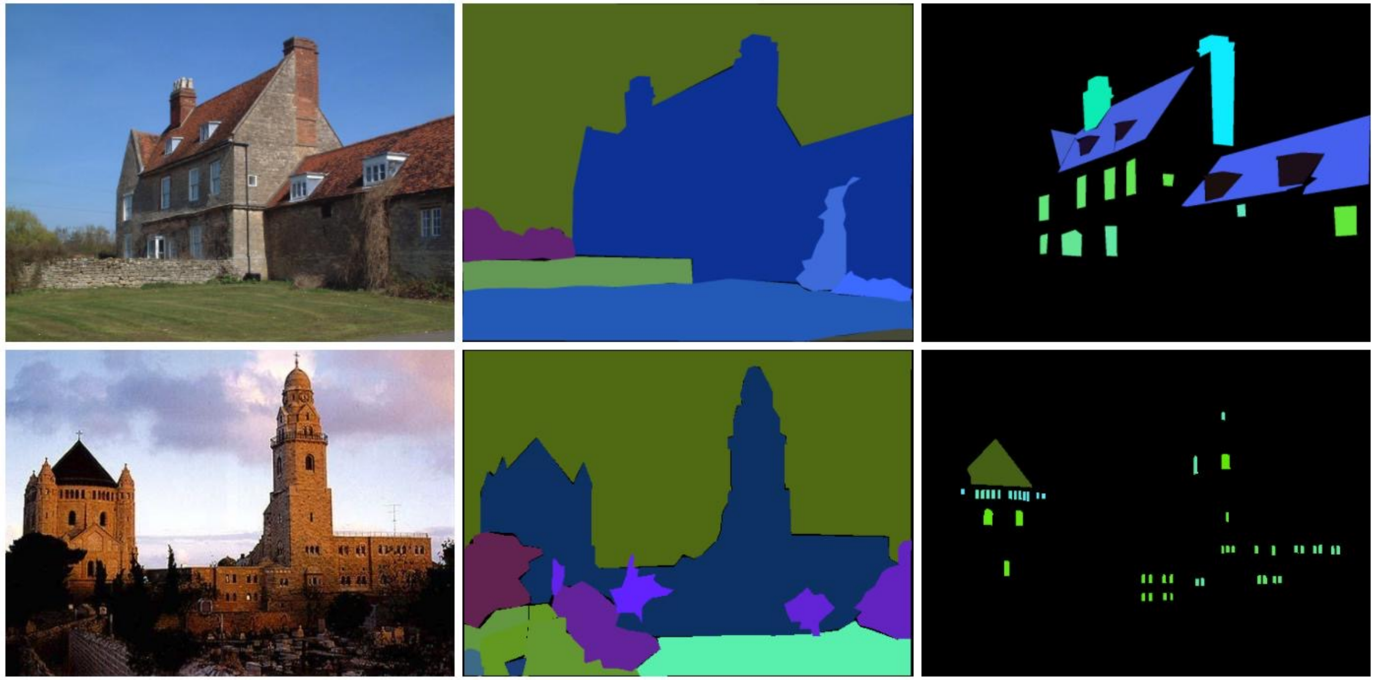
(d) Panoptic Segmentation

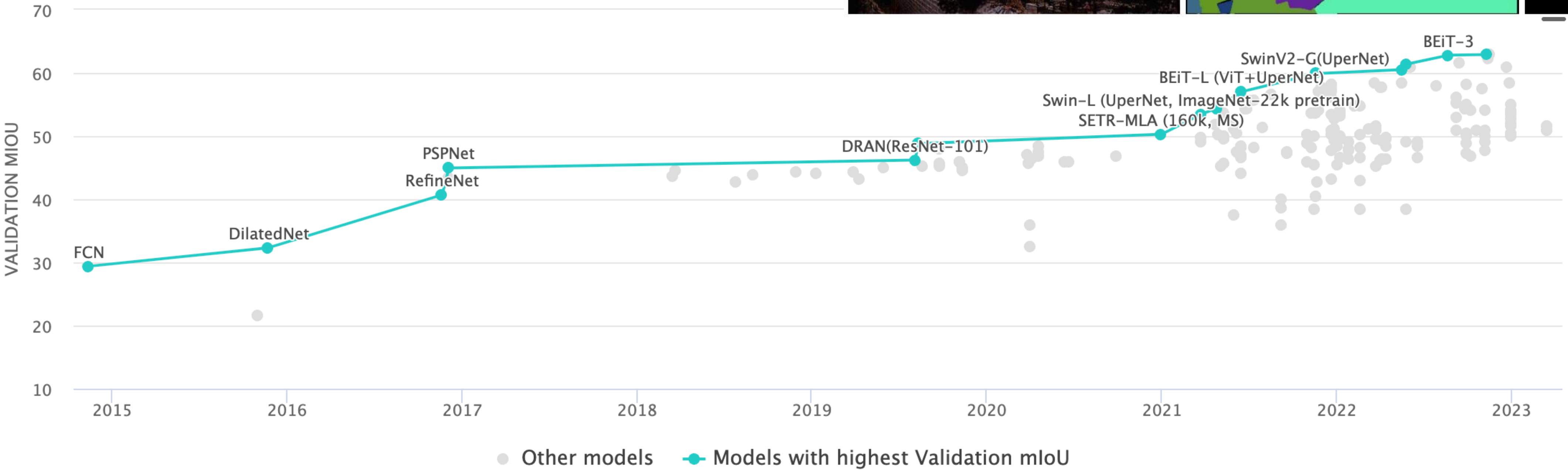
V7 Labs

Most popular Semantic Segmentation dataset: ADE20k

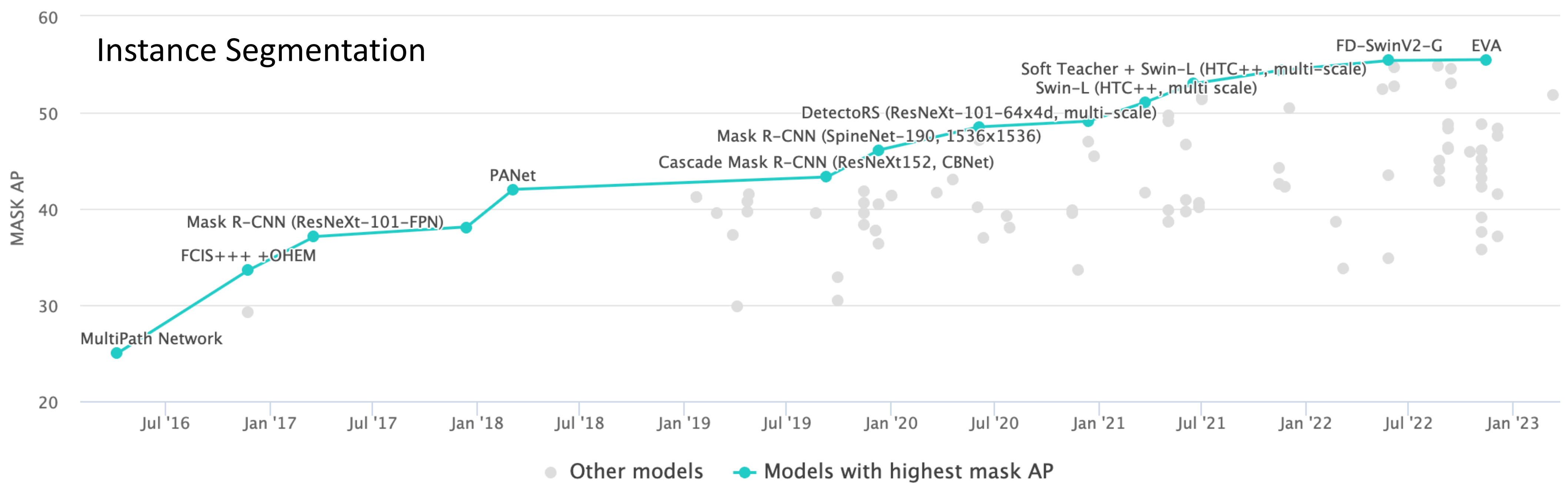
- 20K scene-centric images exhaustively annotated with pixel-level objects and object parts labels.

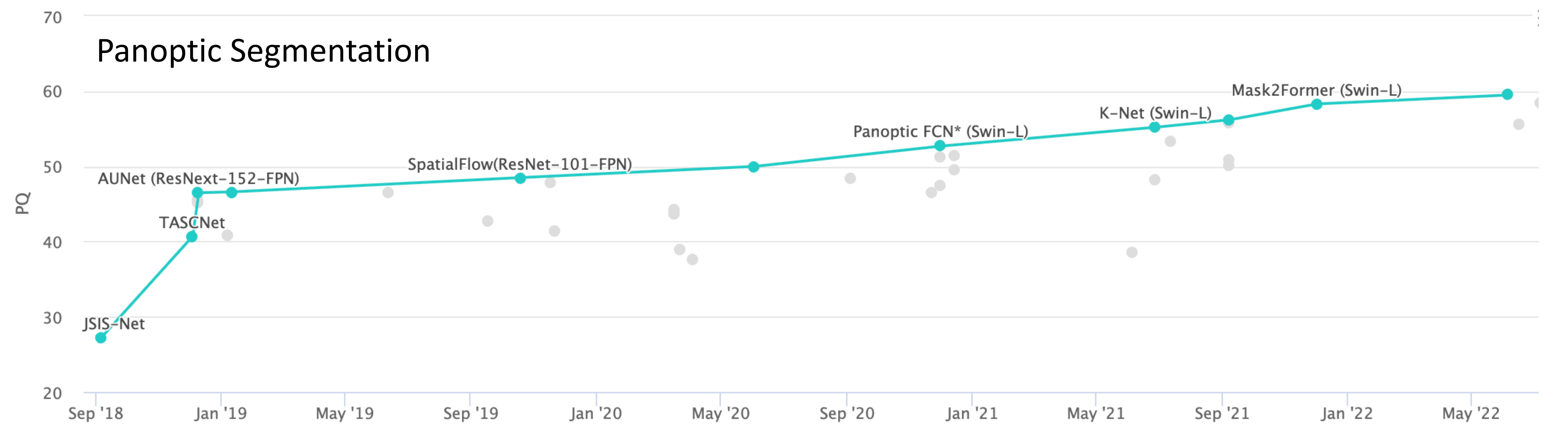
- 150 semantic categories, which include stuffs like sky, road, grass, and discrete objects like person, car, bed.





Most popular Instance & Panoptic Segmentation dataset: MS COCO

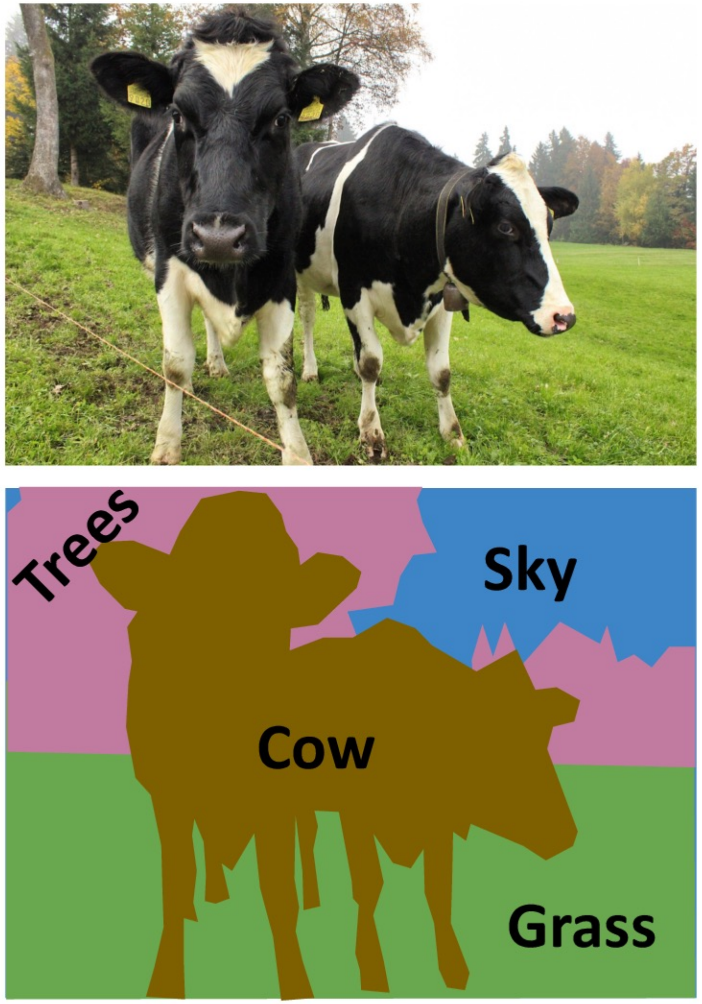




Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels

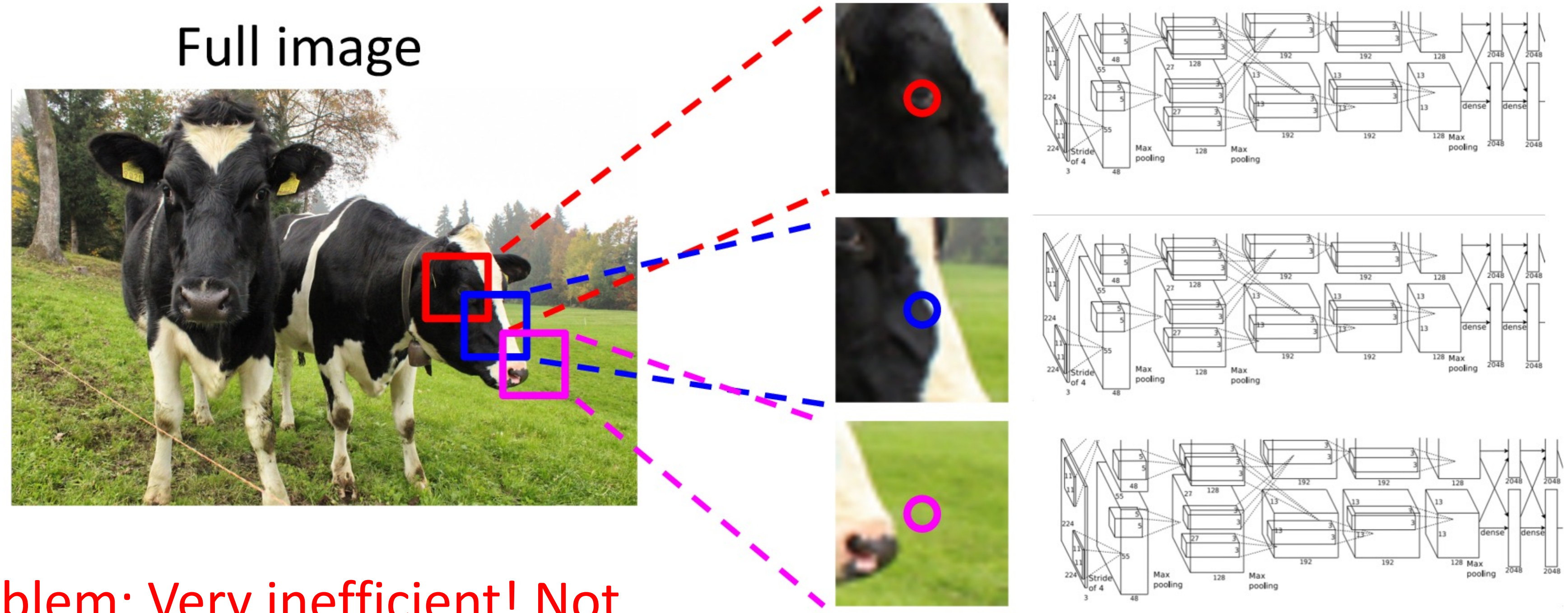


Semantic Segmentation Idea: Sliding Window

Full image

Extract patch

Classify center pixel with CNN



Cow

Cow

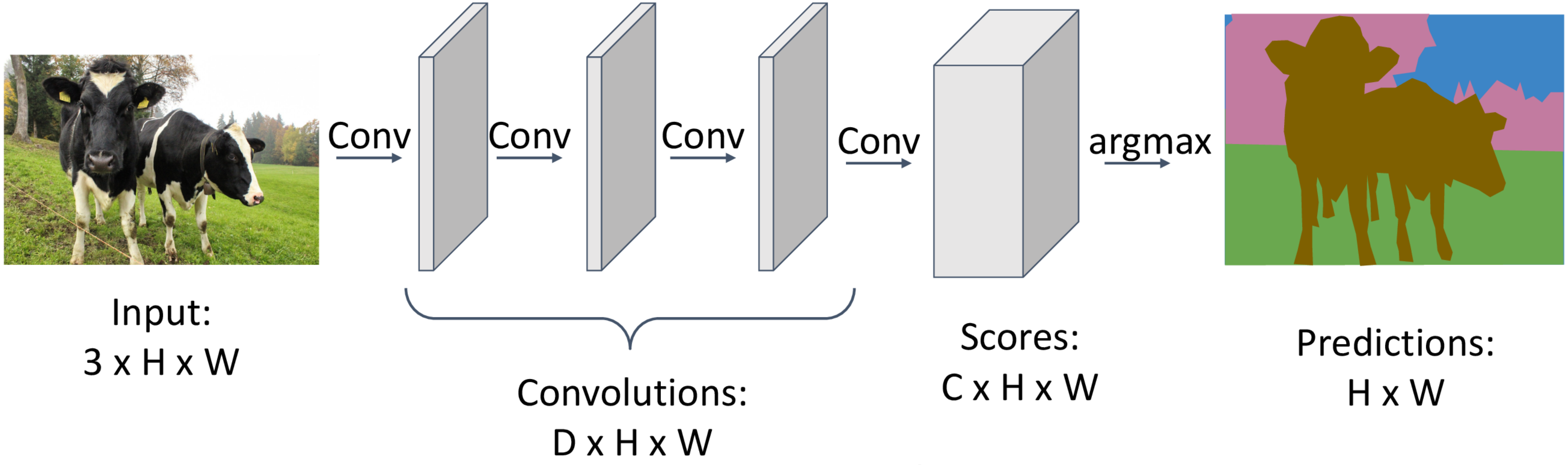
Grass

Problem: Very inefficient! Not reusing shared features between overlapping patches

Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013
Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

Semantic Segmentation: Fully Convolutional Network

Design a network as a bunch of convolutional layers to make predictions for pixels all at once!



Loss function: Per-Pixel cross-entropy

Long et al, "Fully convolutional networks for semantic segmentation", CVPR 2015

Problem #1: Effective receptive field size is linear in number of conv layers: With L 3x3 conv layers, receptive field is 1+2L

Problem #2: Convolution on high res images is expensive! Recall ResNet stem aggressively downsamples

Semantic Segmentation: Fully Convolutional Network

Downsampling: Pooling, strided convolution

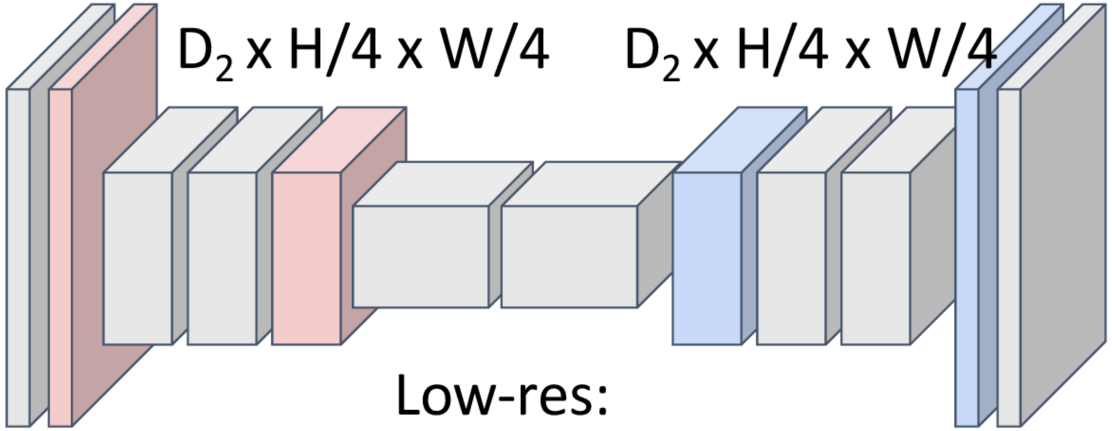
Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling: ???

Input:
3 x H x W

Med-res:
D_2 x H/4 x W/4

Med-res:
D_2 x H/4 x W/4



High-res:
D_1 x H/2 x W/2

Low-res:
D_3 x H/4 x W/4

High-res:
D_1 x H/2 x W/2

Predictions:
H x W

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

In-Network Upsampling: “Unpooling”

Bed of Nails

1	2
3	4

Input
C x 2 x 2

1	0	2	0
0	0	0	0
3	0	4	0
0	0	0	0

Output
C x 4 x 4

Nearest Neighbor

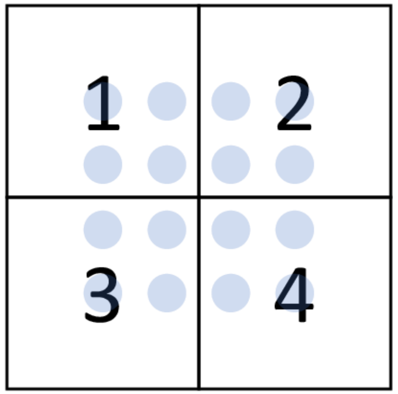
1	2
3	4

Input
C x 2 x 2

1	1	2	2
1	1	2	2
3	3	4	4
3	3	4	4

Output
C x 4 x 4

In-Network Upsampling: Bilinear Interpolation



1.00	1.25	1.75	2.00
1.50	1.75	2.25	2.50
2.50	2.75	3.25	3.50
3.00	3.25	3.75	4.00

Input: C x 2 x 2

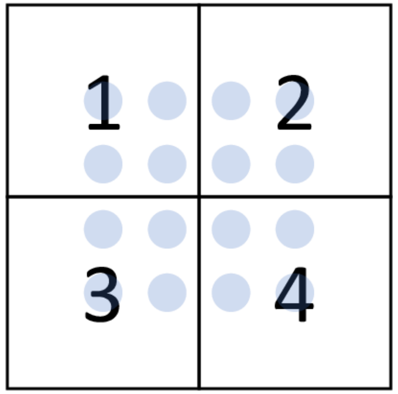
Output: C x 4 x 4

$$f_{x,y} = \sum_{i,j} f_{i,j} \max(0, 1 - |x - i|) \max(0, 1 - |y - j|) \quad i \in \{\lfloor x \rfloor - 1, \dots, \lceil x \rceil + 1\}$$

$$j \in \{\lfloor y \rfloor - 1, \dots, \lceil y \rceil + 1\}$$

Use two closest neighbors in x and y
to construct linear approximations

In-Network Upsampling: Bicubic Interpolation



0.68	1.02	1.56	1.89
1.35	1.68	2.23	2.56
2.44	2.77	3.32	3.65
3.11	3.44	3.98	4.32

Input: C x 2 x 2

Output: C x 4 x 4

Use **three** closest neighbors in x and y to construct **cubic** approximations
(This is how we normally resize images!)

In-Network Upsampling: “Max Unpooling”

Max Pooling: Remember which position had the max

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

→

5	6
7	8

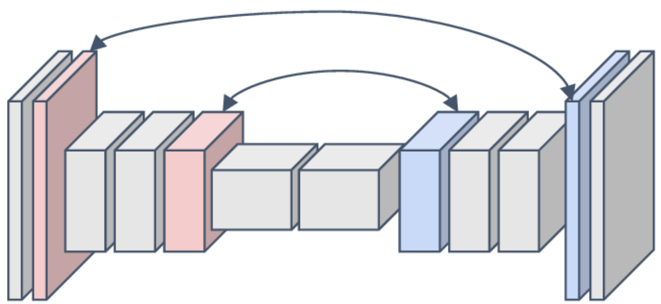
→ Rest of net →

1	2
3	4

→

Max Unpooling: Place into remembered positions

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

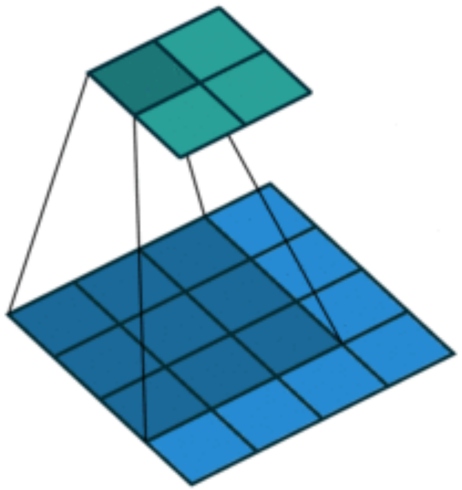


Pair each downsampling layer with an upsampling layer

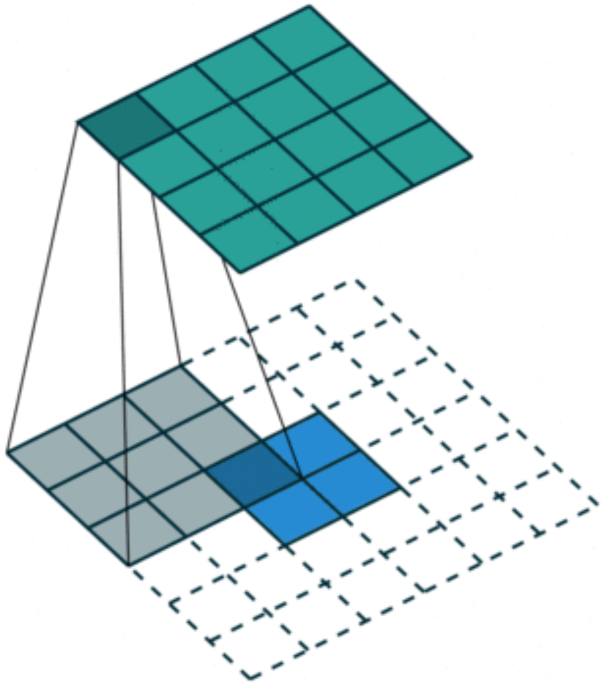
Noh et al, “Learning Deconvolution Network for Semantic Segmentation”, ICCV 2015

Regular vs Transposed Convolution

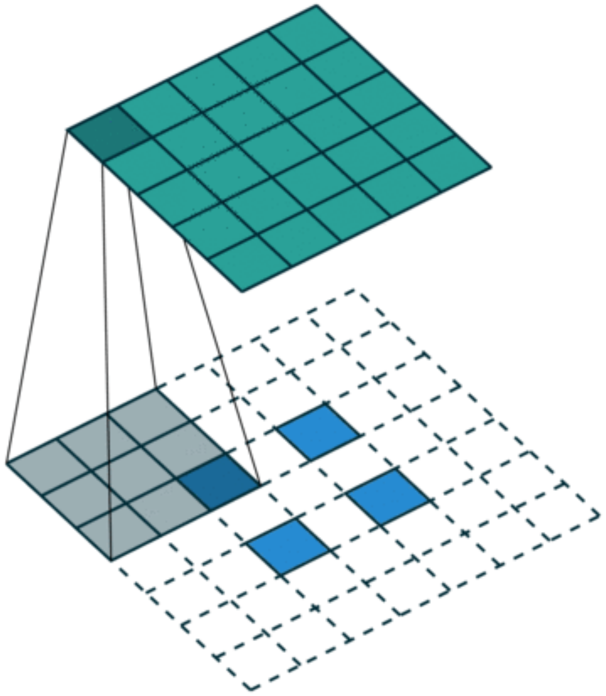
Filter size is 3x3



Regular Convolution
reduces feature size



Transposed convolution increases feature size



Strided transpose convolution

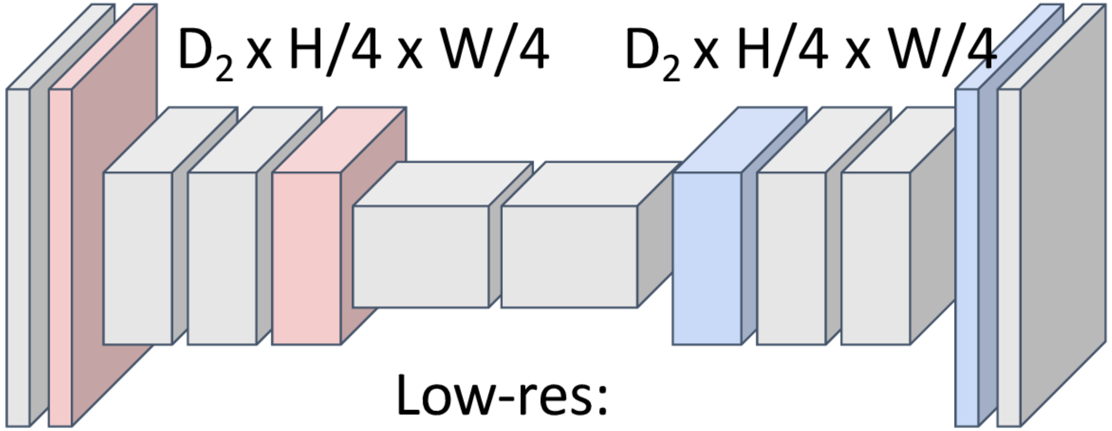
Semantic Segmentation: Fully Convolutional Network

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Downsampling: Pooling, strided convolution

Upsampling: ???

Input: $3 \times H \times W$



Med-res: $D_2 \times H/4 \times W/4$

Med-res: $D_2 \times H/4 \times W/4$

High-res: $D_1 \times H/2 \times W/2$

Low-res: $D_3 \times H/4 \times W/4$

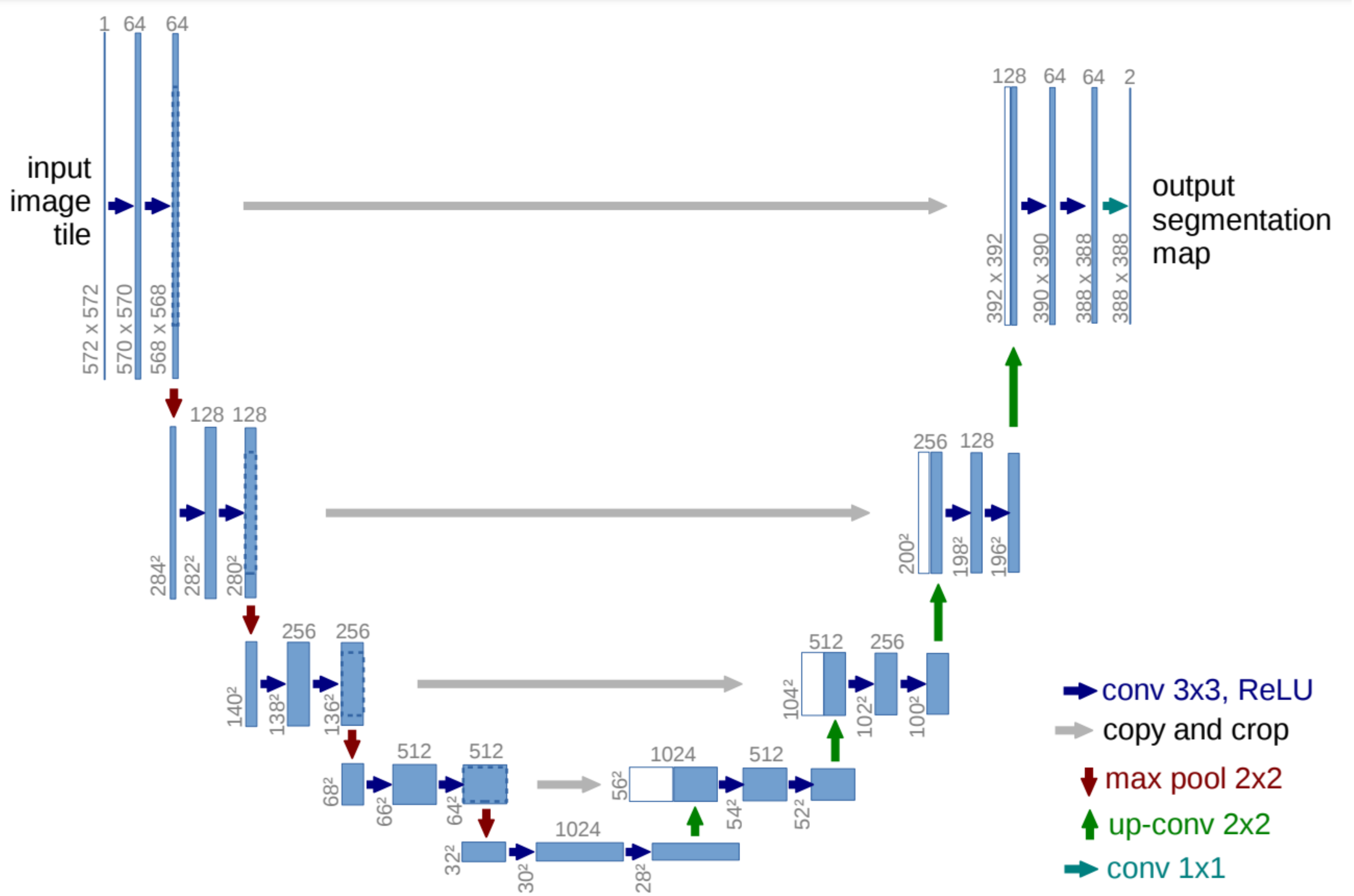
High-res: $D_1 \times H/2 \times W/2$

Predictions: $H \times W$

Upsampling:
Bilinear Upsampling (non learnable)
Strided Transpose Convolution (learnable)

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

U-Net for segmentation



SOTA Detection + Segmentation

Swin Transformer

Ranked #13 Object Detection on COCO test-dev | Ranked #6 Instance Segmentation on COCO test-dev (using additional training data)

Ranked #10 Semantic Segmentation on ADE20K (using additional training data)

Ranked #24 Action Classification on Kinetics-400 (using additional training data)

This repo is the official implementation of "Swin Transformer: Hierarchical Vision Transformer using Shifted Windows" as well as the follow-ups. It currently includes code and models for the following tasks:

> **Image Classification**: Included in this repo. See get_started.md for a quick start.

> **Object Detection and Instance Segmentation**: See Swin Transformer for Object Detection.

> **Semantic Segmentation**: See Swin Transformer for Semantic Segmentation.

> **Video Action Recognition**: See Video Swin Transformer.

> **Semi-Supervised Object Detection**: See Soft Teacher.

> **SSL: Contrasitive Learning**: See Transformer-SSL.

> **SSL: Masked Image Modeling**: See get_started.md#simmim-support.

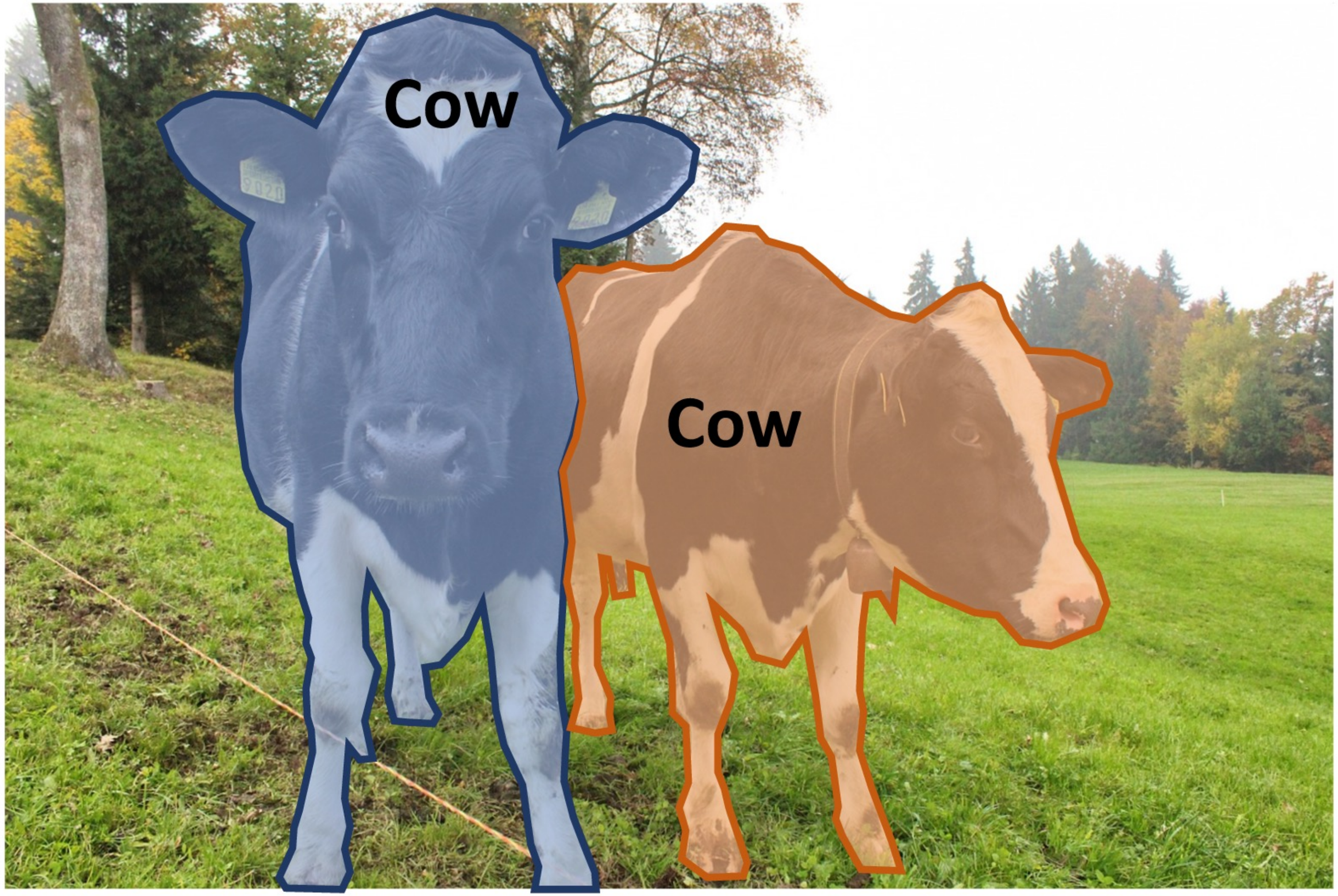
> **Mixture-of-Experts**: See get_started for more instructions.

> **Feature-Distillation**: See Feature-Distillation.

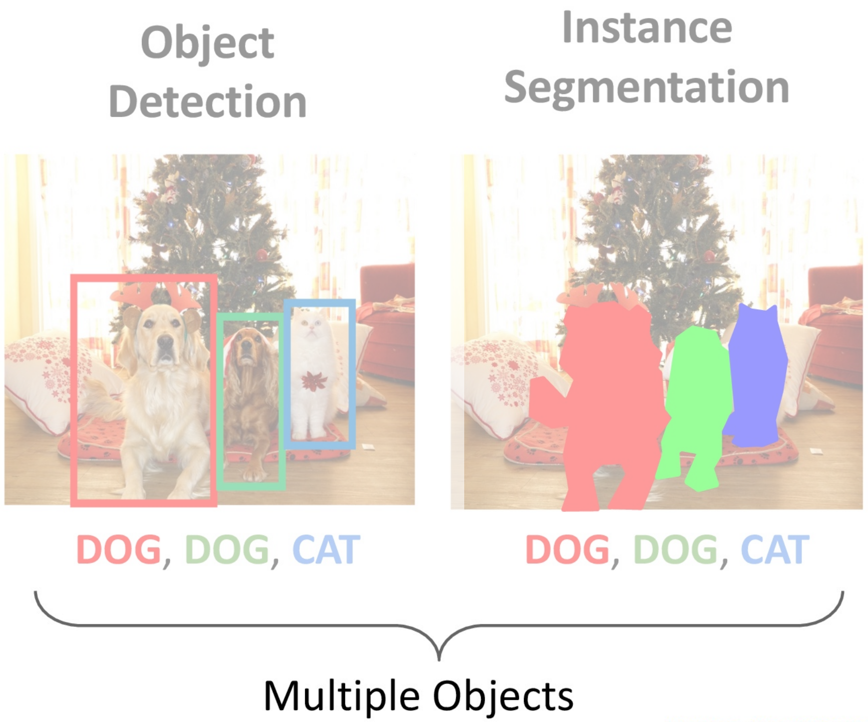
Computer Vision Tasks: Instance Segmentation

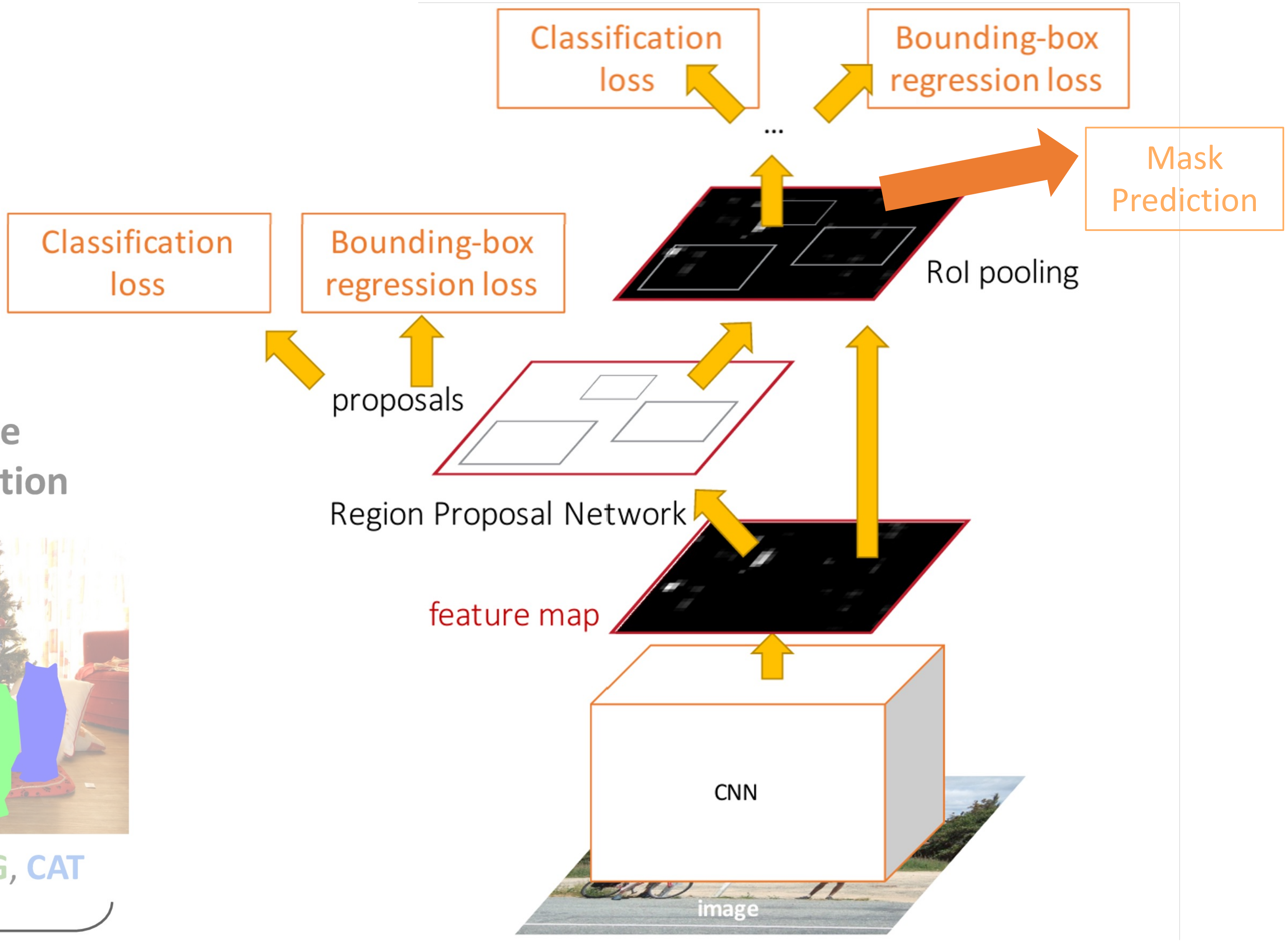
Instance Segmentation: Detect all objects in the image, and identify the pixels that belong to each object (Only things!)

Approach: Perform object detection, then predict a segmentation mask for each object!

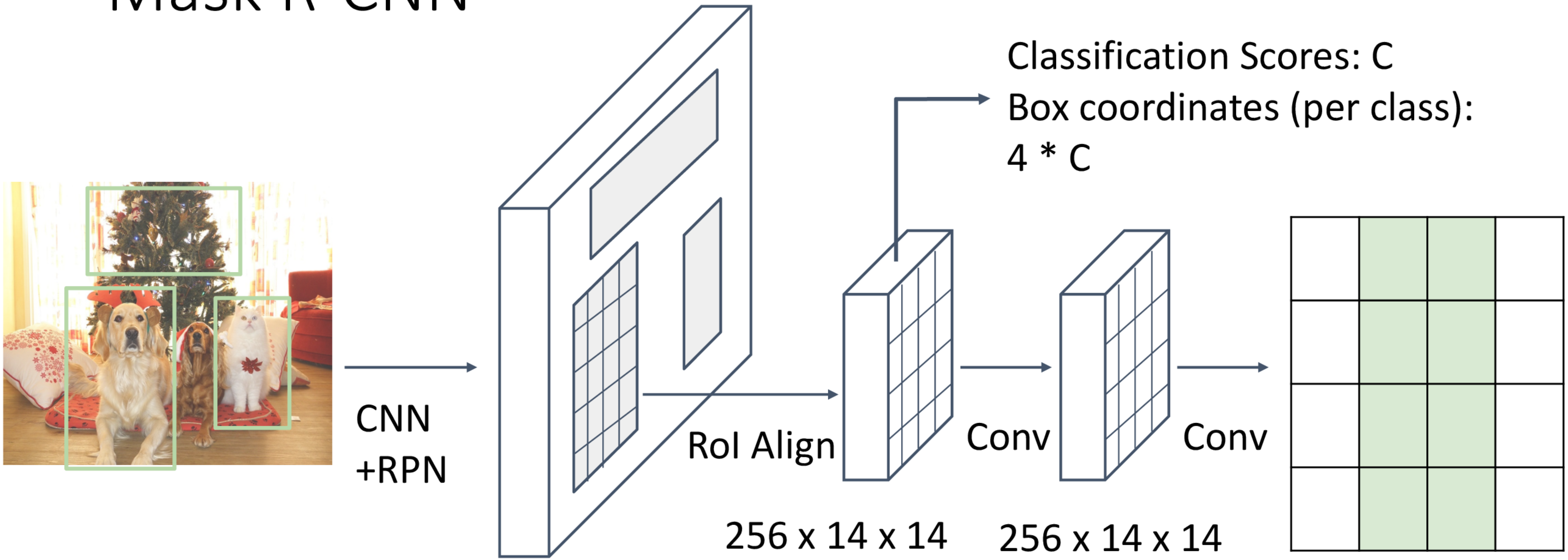


Instance segmentation with Mask R-CNN





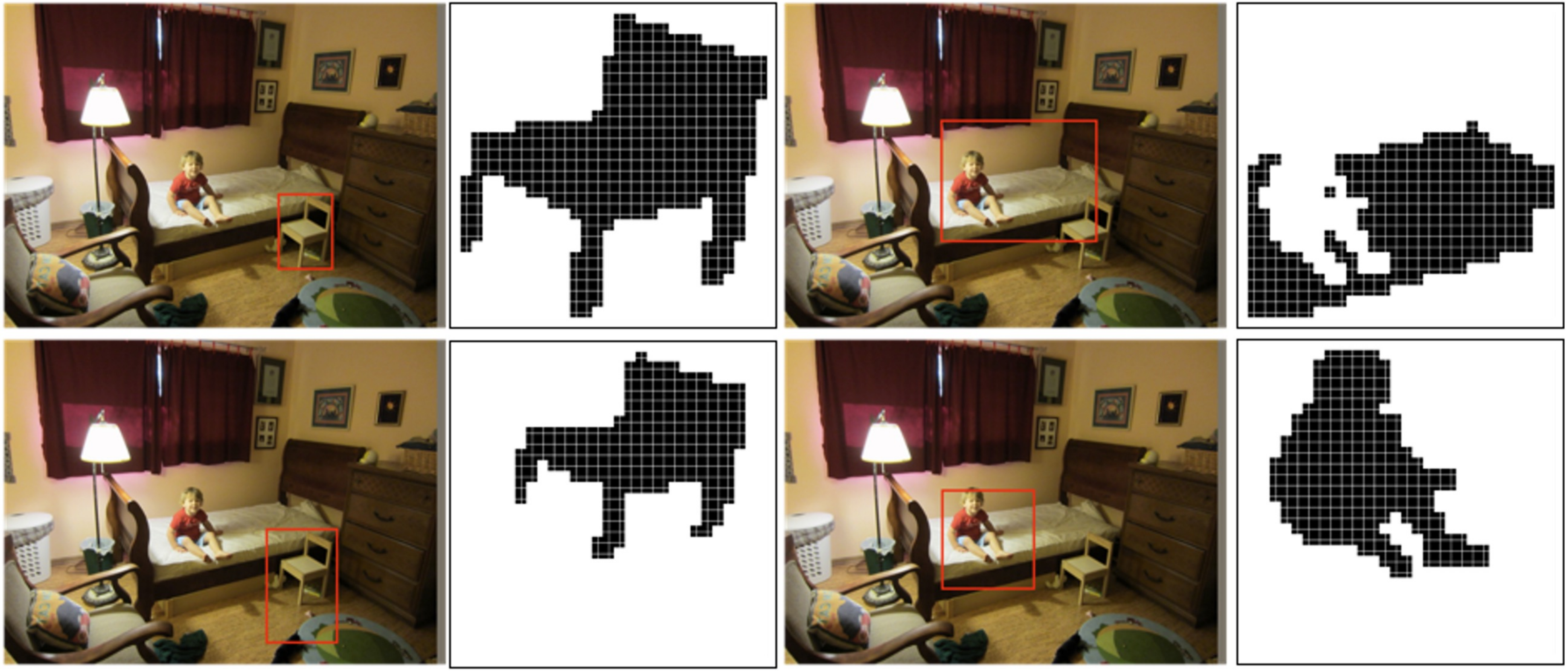
Mask R-CNN



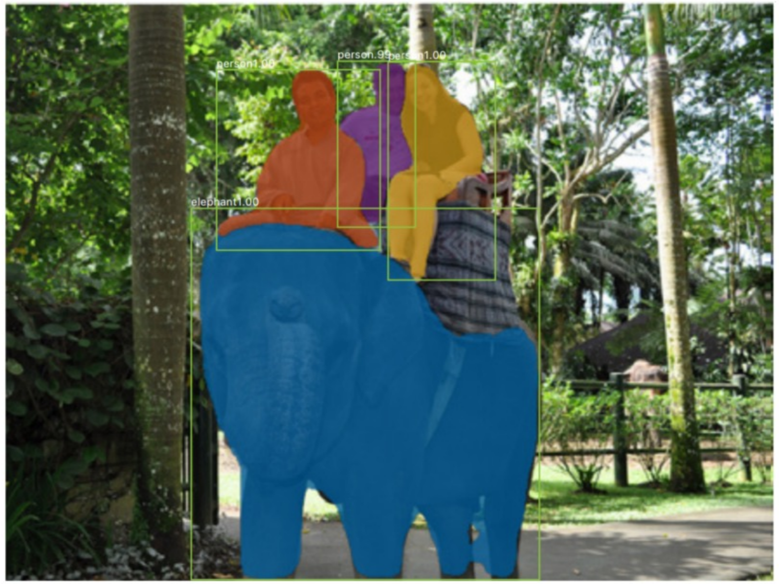
Predict a mask for each of C classes:
C x 28 x 28

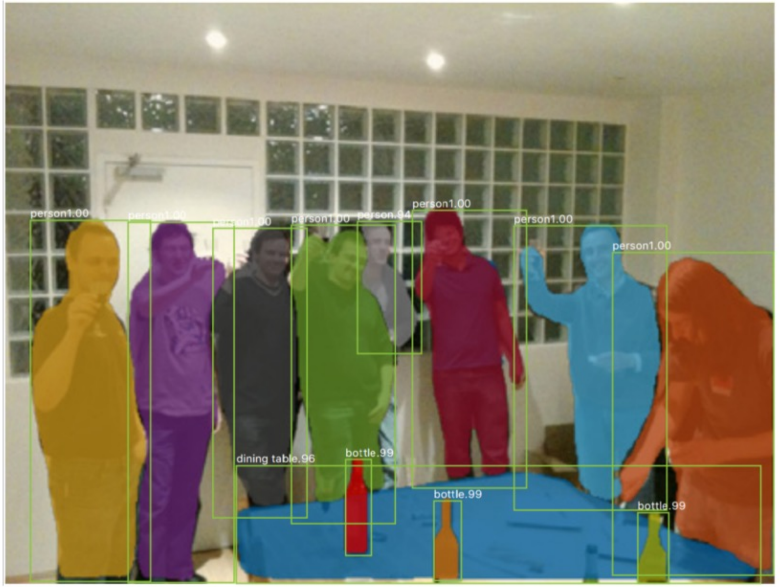
He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN: Example Training Targets



Mask R-CNN: Very Good Results!





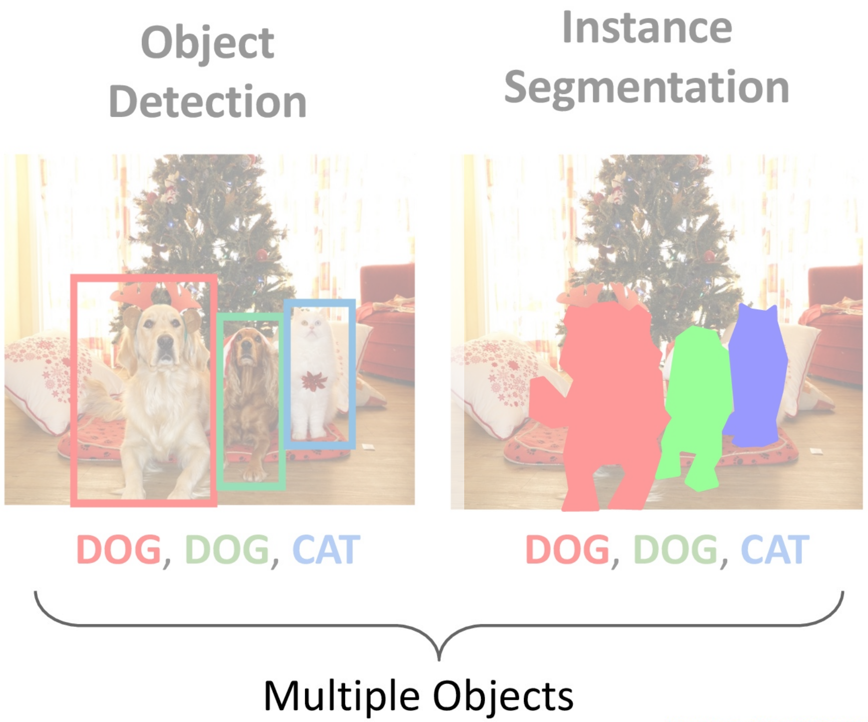
Can we generalize Faster R-CNN architecture to other Vision tasks?

Beyond Instance Segmentation: Human Keypoints

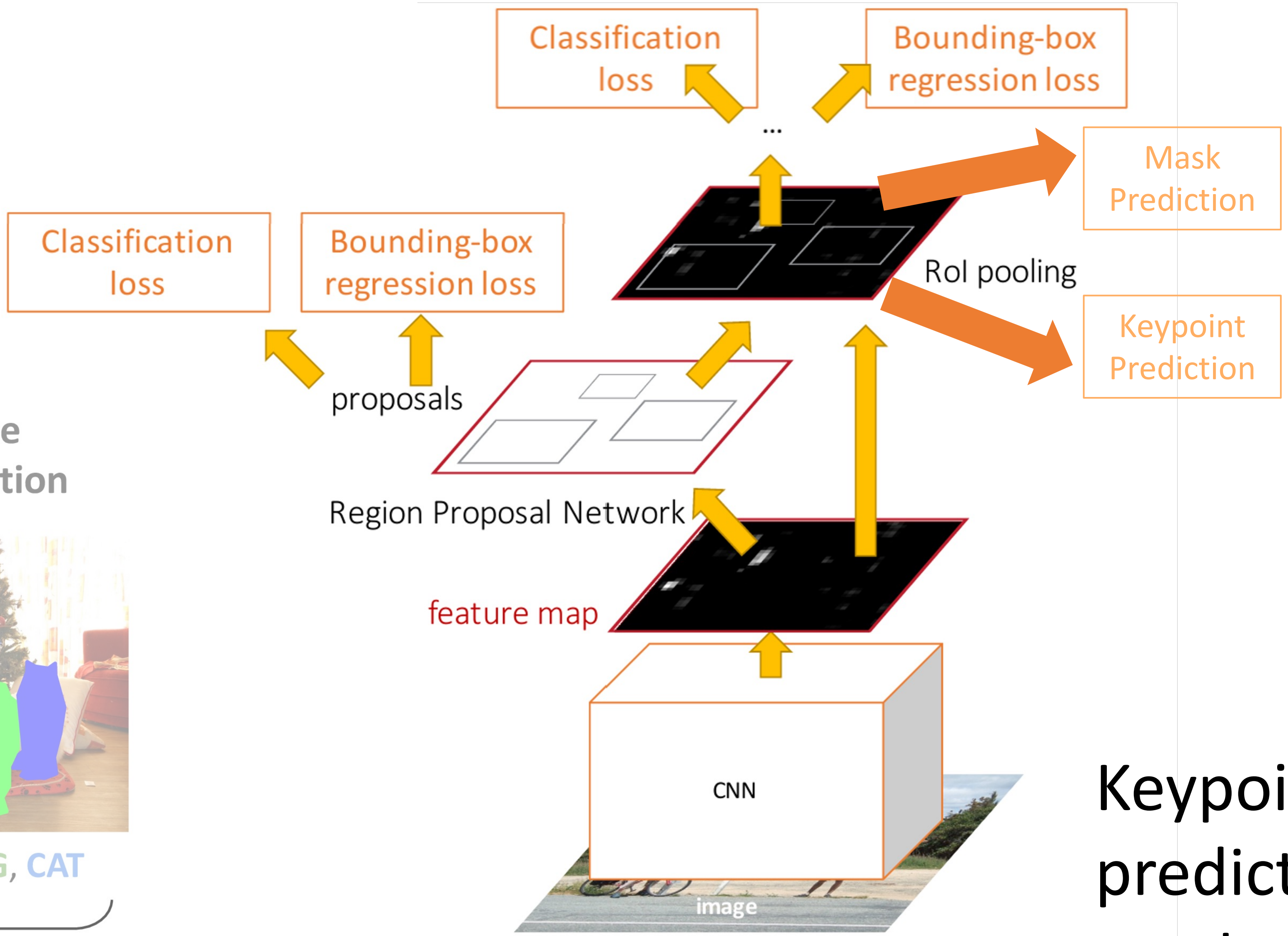
Represent the pose of a human by locating a set of **keypoints**

e.g. 17 keypoints:
- Nose
- Left / Right eye
- Left / Right ear
- Left / Right shoulder
- Left / Right elbow
- Left / Right wrist
- Left / Right hip
- Left / Right knee
- Left / Right ankle

Instance segmentation with Mask R-CNN

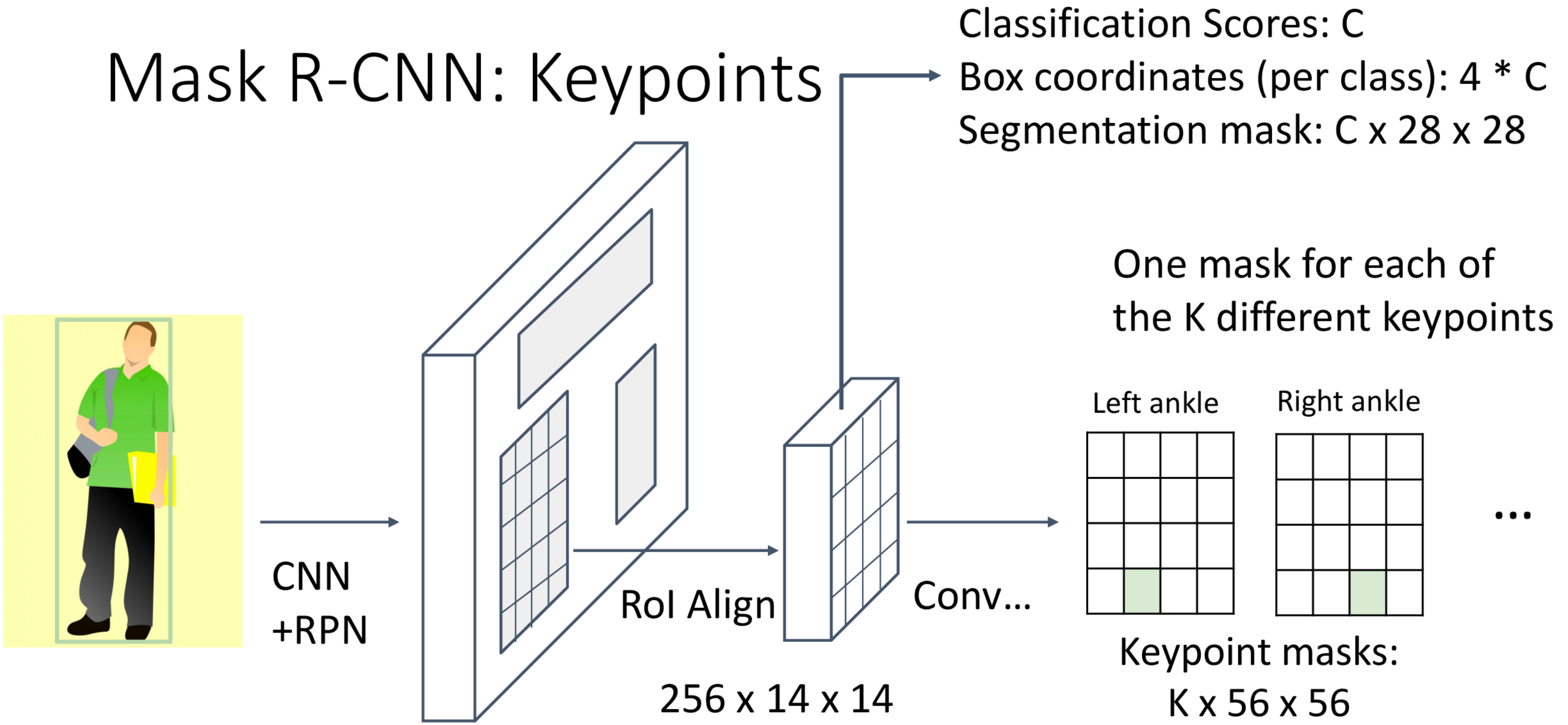


This image is CC0 public domain



Keypoint prediction with Mask R-CNN

Mask R-CNN: Keypoints

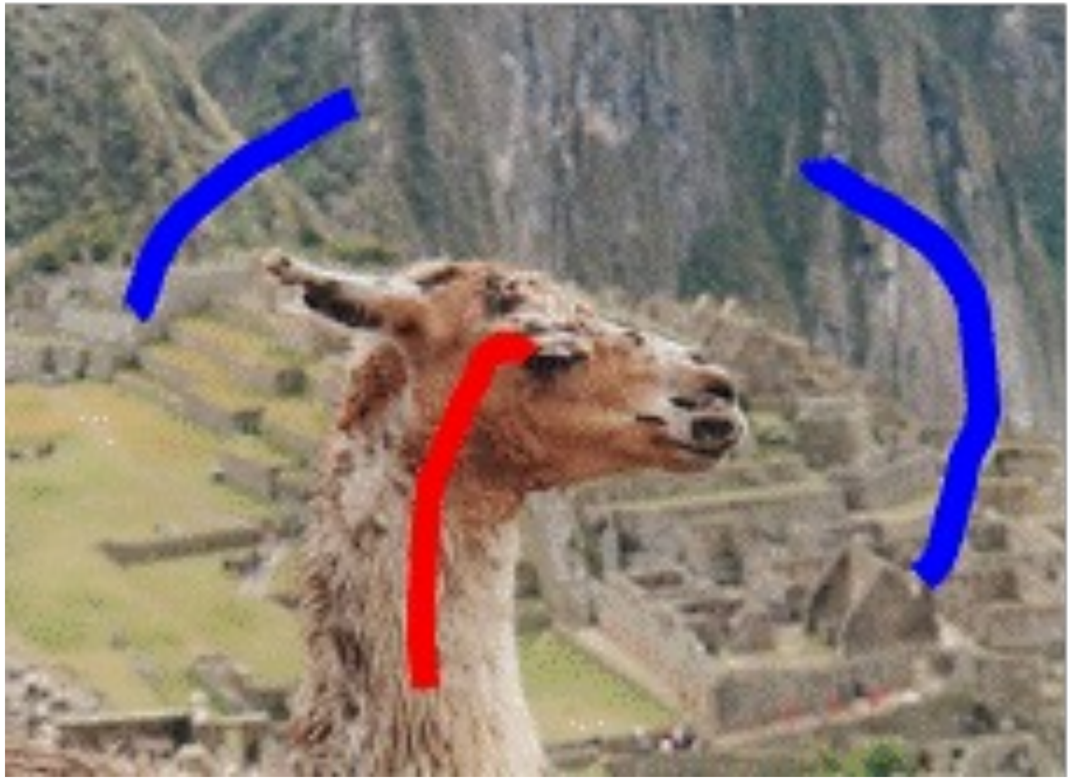


Ground-truth has one “pixel” turned on per keypoint. Train with softmax loss

He et al, “Mask R-CNN”, ICCV 2017

Interactive Segmentation with Scribbles

(Red = foreground, blue= background)



Earlier works of segmentation used Graph Cut techniques to solve this problem.

Normalized cuts and image segmentation

J Shi, J Malik - IEEE Transactions on pattern analysis and …, 2000 - ieeexplore.ieee.org

… have smaller **cut** value than the **cut** that partitions … **cut** cost as a fraction of the total edge connections to all the nodes in the graph. We call this disassociation measure the **normalized cut** (…

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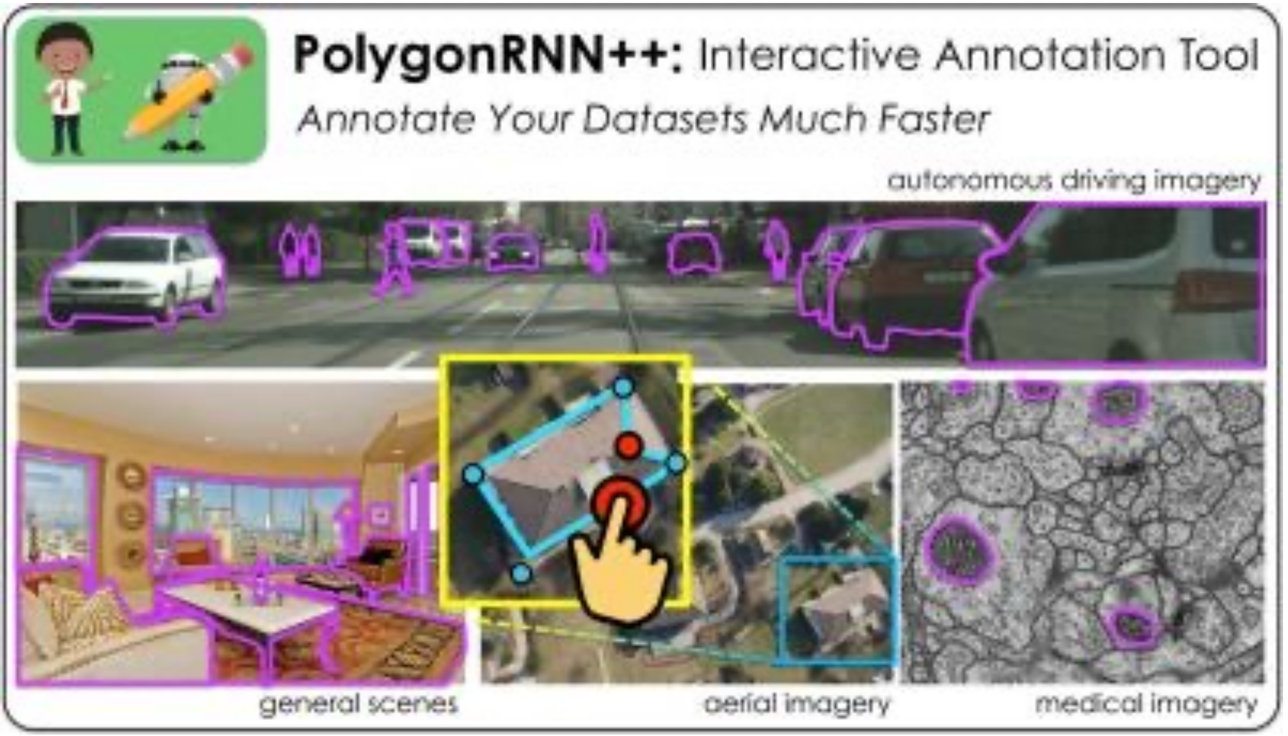
Deep Extreme Cut (DEXTR): From Extreme Points to Object Segmentation, CVPR 2018

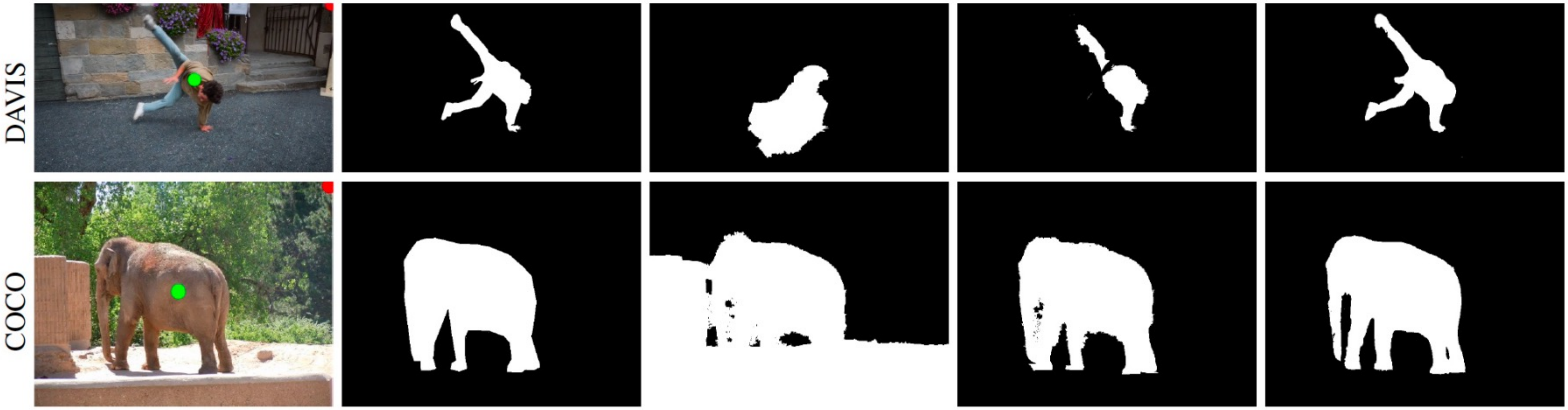
Interactive Segmentation with few points



Efficient Annotation of Segmentation Datasets
with Polygon-RNN++, CVPR 2018

Interactive Segmentation with 2 points

(Green = foreground, red= background)



(a) Input (b) Ground truth (c) Graph cuts (d) DOS (e) Our approach

Interactive Image Segmentation with Latent Diversity, CVPR 2018

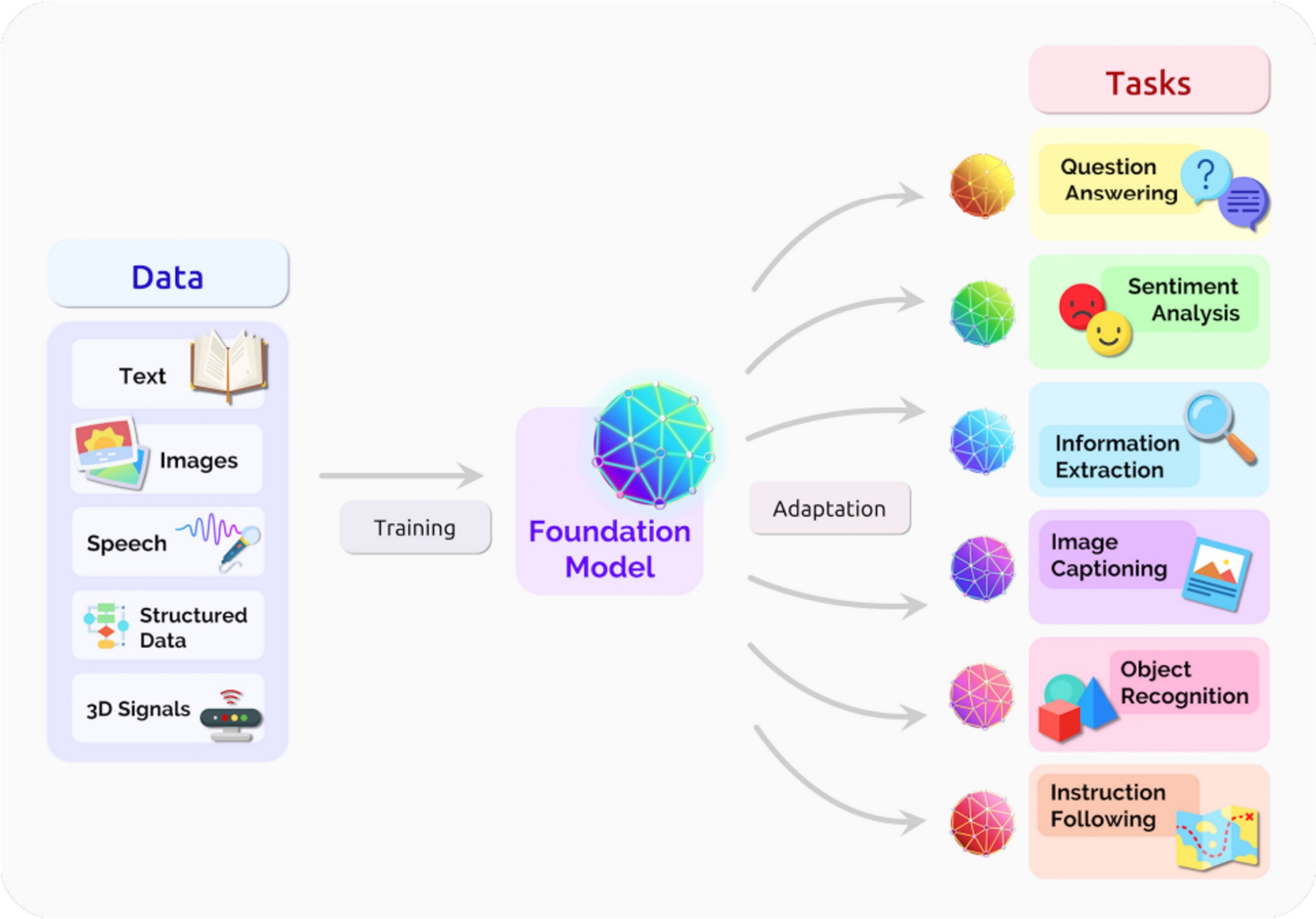
Interactive Segmentation with points

SimpleClick: Interactive Image Segmentation with Simple Vision Transformers, Liu et al. 2022.

Foundation Models and Promptable Segmentation

Slide credits: Qin Liu

A foundation model can centralize the information from various modalities.



Slide Credits: Qin Liu

Segment Anything Model (SAM): the first foundation model for promptable segmentation.

Prompt it with interactive points and boxes

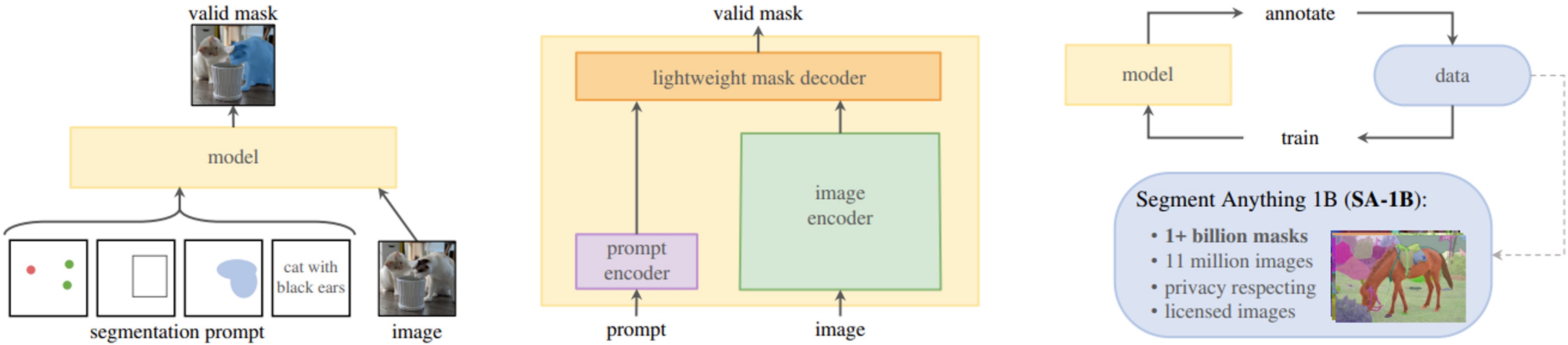
Automatically segment everything in an image

Generate multiple valid masks for ambiguous prompts

Try the demo: https://segment-anything.com/demo

Slide Credits: Qin Liu

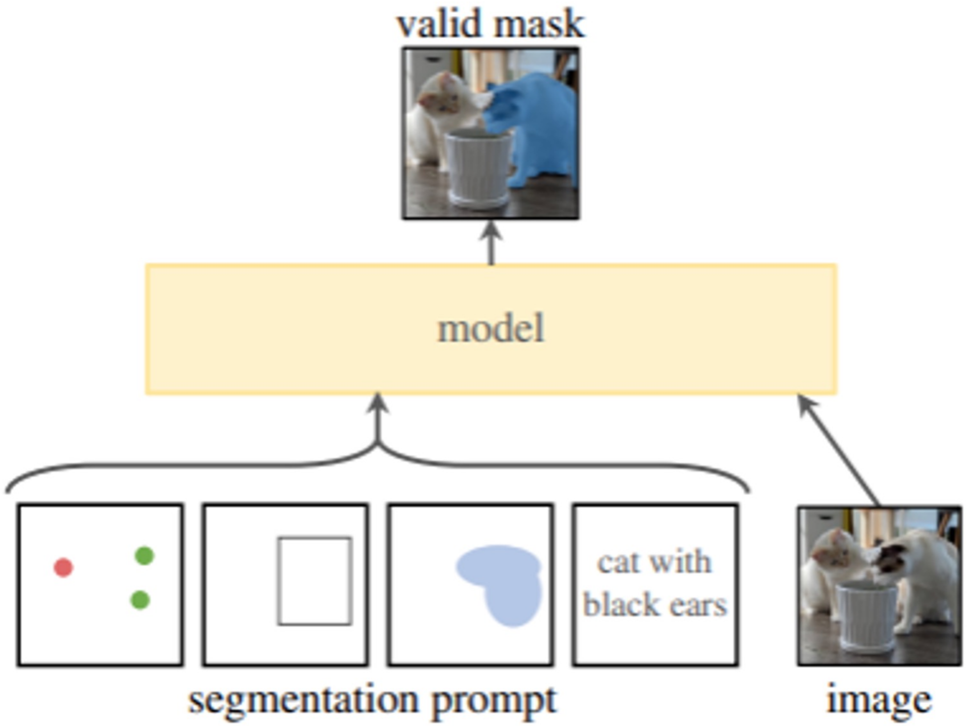
SAM is built with three interconnected components: A task, an model, and a data engine.



(a) **Task**: promptable segmentation (b) **Model**: Segment Anything Model (**SAM**) (c) **Data**: data engine (top) & dataset (bottom)

Slide Credits: Qin Liu

Task: Promptable Segmentation



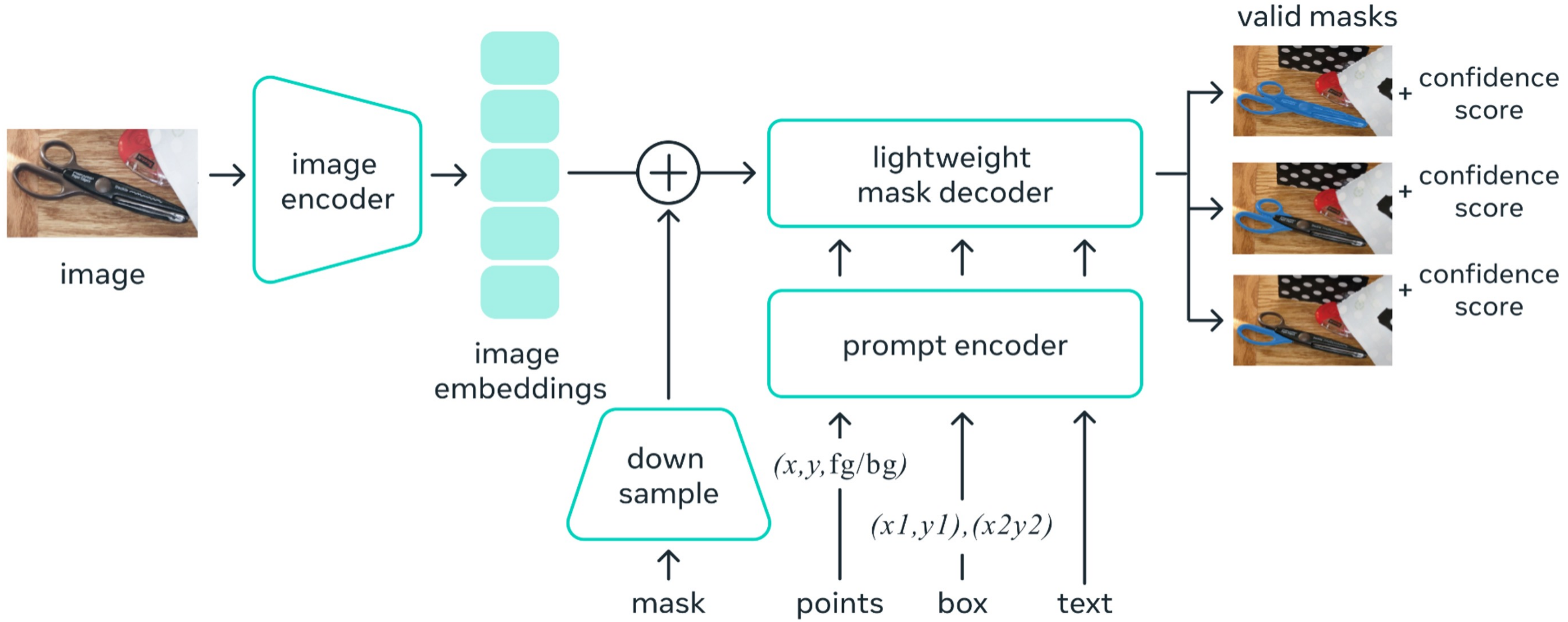
(a) **Task**: promptable segmentation

- SAM considers two sets of prompts: ***sparse*** (clicks, boxes, text) and ***dense*** (masks).
- SAM's promptable design enables flexible integration with other systems (i.e., used as ***component*** in larger systems).

Slide Credits: Qin Liu

Model: Segment Anything Model (SAM)

- A heavyweight ***image encoder*** outputs an image embedding.
- A lightweight ***prompt encoder*** efficiently queries the image embedding.
- A lightweight ***mask decoder*** produces object masks and confidence scores.



Slide Credits: Qin Liu

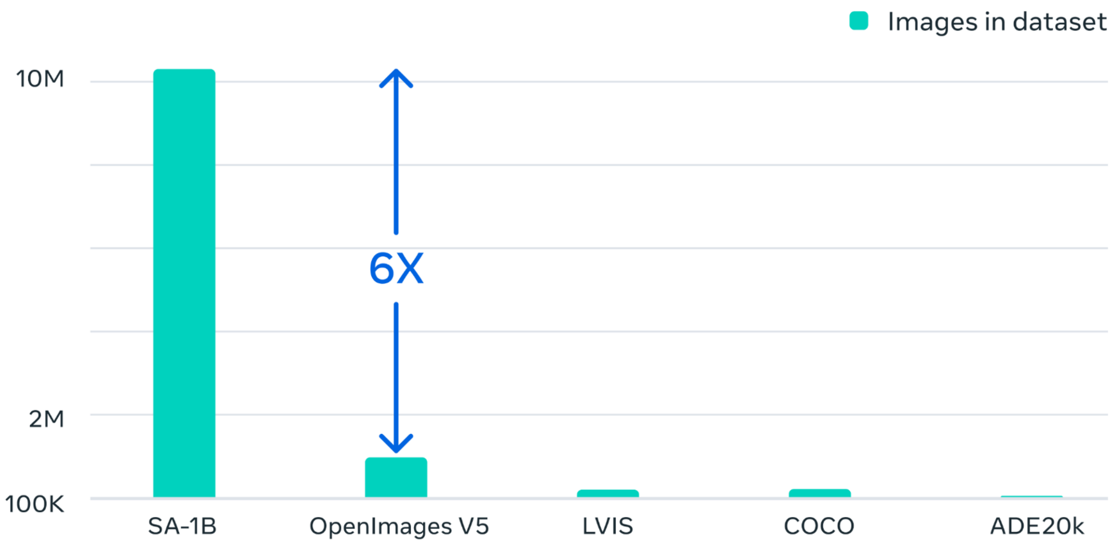
Ambiguity-Aware Segmentation

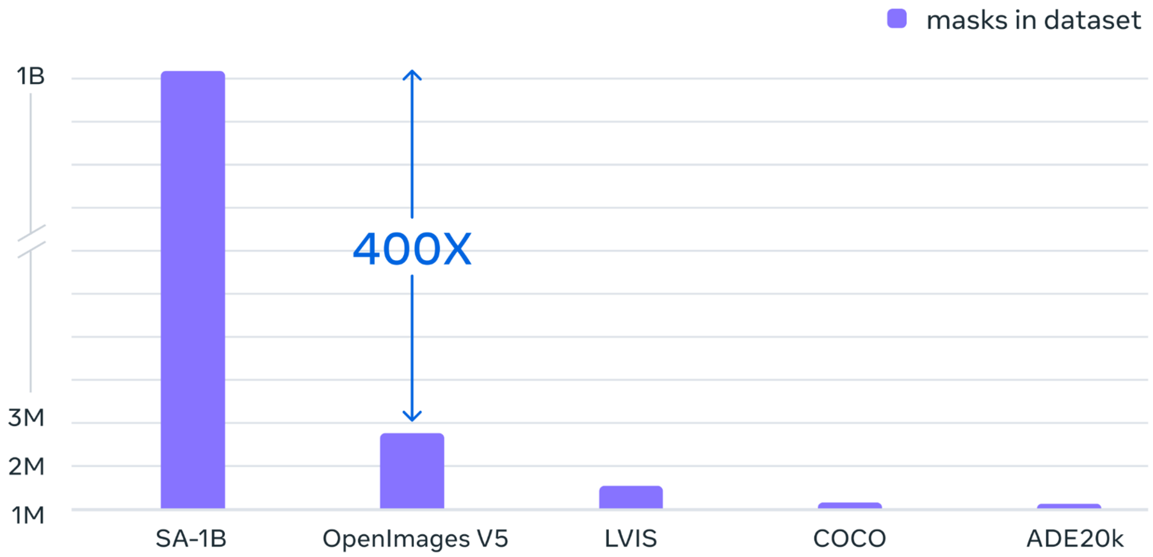
- SAM is designed to predict multiple masks (i.e., 3 masks: whole, part, subpart) for a single prompt.
- During training, the model only backprops the minimum loss over masks.
- To rank masks, the model predicts a confidence score (i.e., estimated IoU) for each mask.

Slide Credits: Qin Liu

Dataset: SA-1B

- Built with a SAM model in the loop
- 11M images with 1.1B segmentation masks
- 400x more masks than any prior segmentation dataset

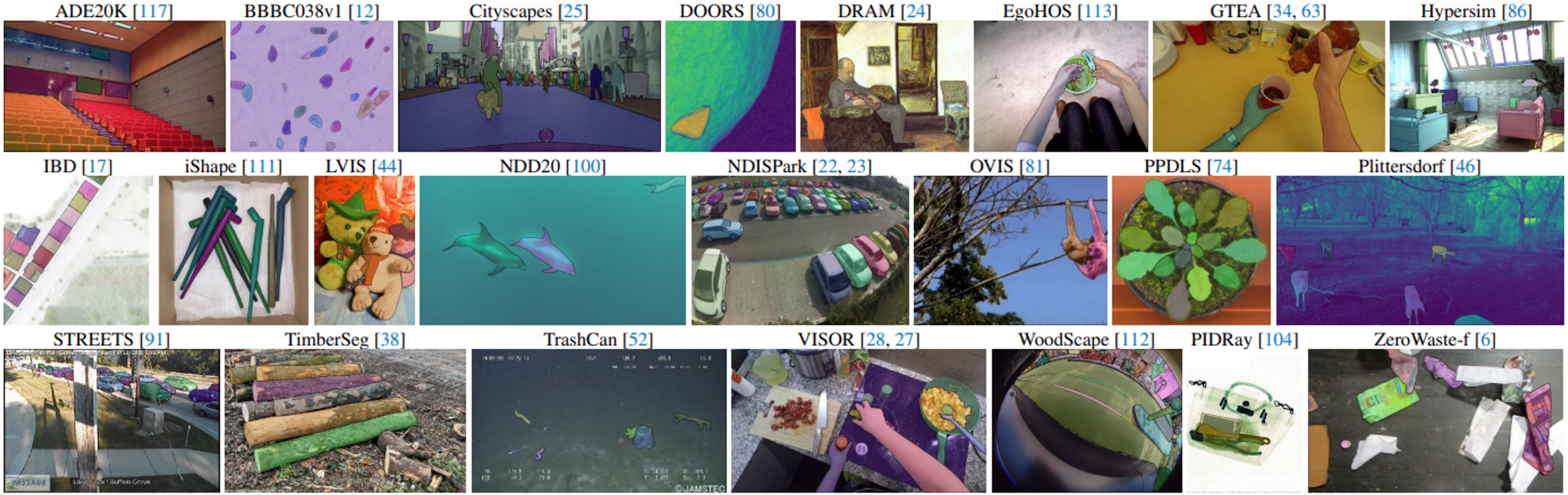




Slide Credits: Qin Liu

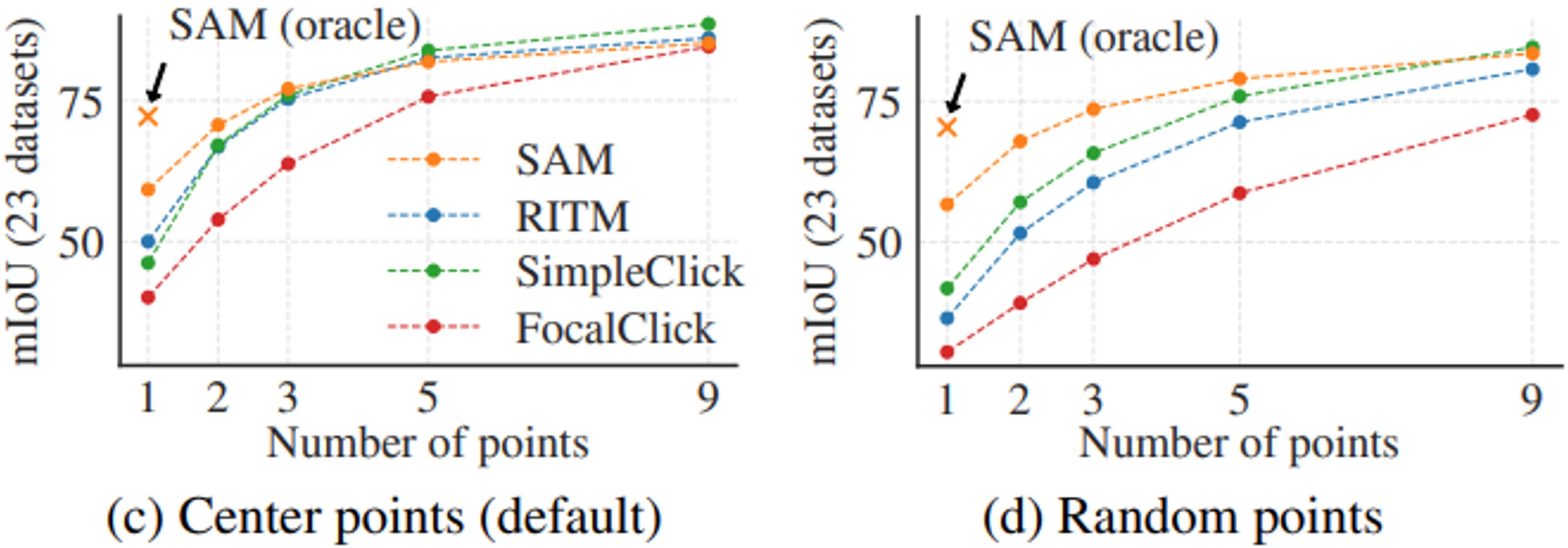
Task 1: Zero-Shot Single Point Valid Mask Evaluation

- Training dataset: the whole SA-1B dataset
- Test datasets: 23 diverse segmentation datasets (only validation/test sets??)



Slide Credits: Qin Liu

Task 1: Zero-Shot Single Point Valid Mask Evaluation



SAM significantly outperforms baselines with 1 point and is on par with more points.

Slide Credits: Qin Liu

Limitations

- SAM may miss fine structures, hallucinate small disconnected components at times, and produce wrong boundaries.
- SAM is expected to be outperformed by dedicated interactive segmentation methods (e.g., SimpleClick) when many points are provided.
- SAM is expected to be outperformed by domain-specific tools (e.g., ilastik).
- SAM's performance on the text-to-mask task is not entirely robust.
- While SAM is initialized with a self-supervised technique (i.e., MAE), the vast majority of its capabilities come from large-scale ***supervised*** training.

Slide Credits: Qin Liu

Grounded-Segment-Anything

Text Prompt: Bench

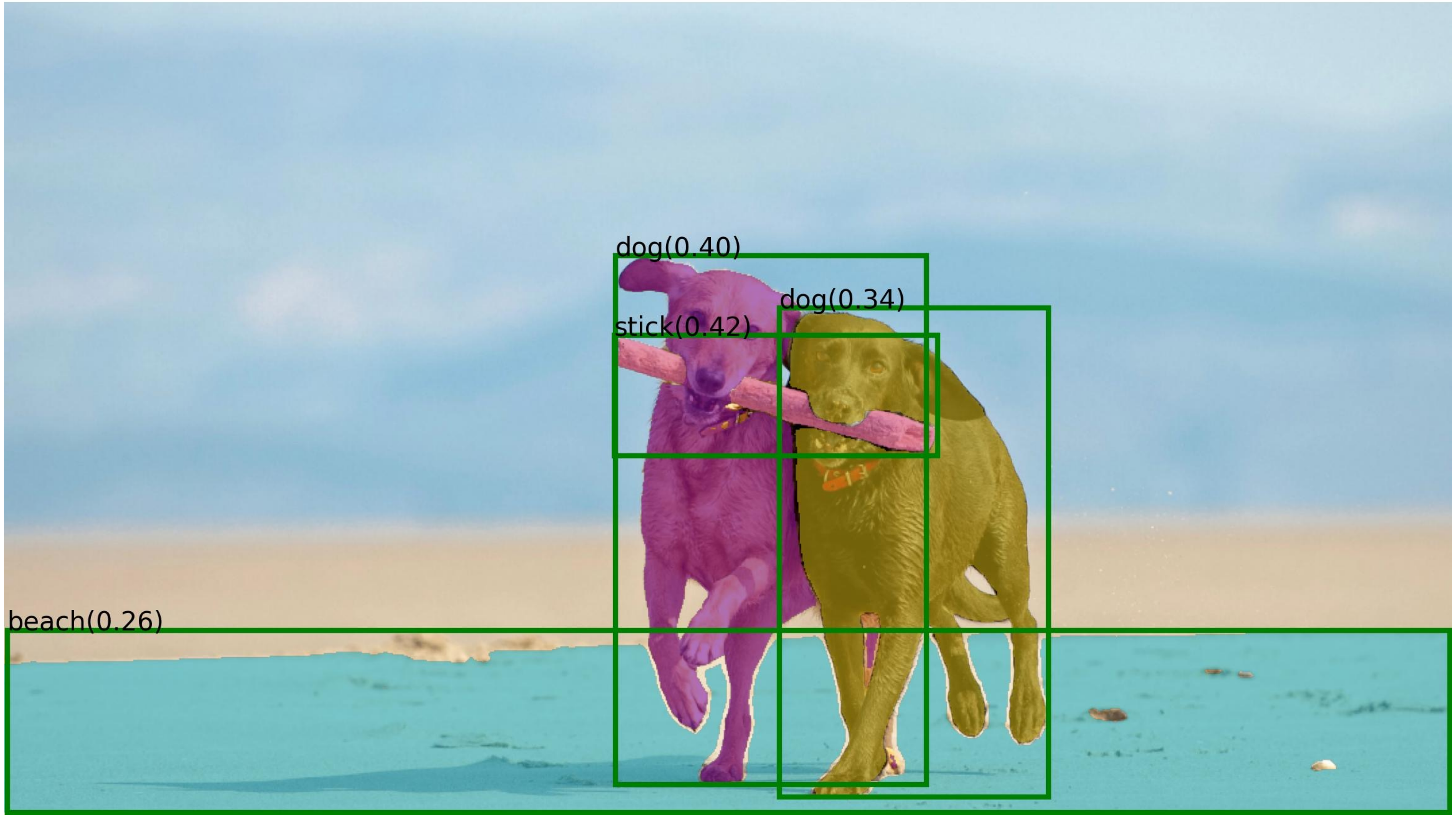
Grounded-SAM Output

Stable-Diffusion Inpainting
A Sofa, high quality, detailed

BLIP + Grounded-SAM: Automatic Label System!

Using BLIP to generate caption, extract tags and using Grounded-SAM for box and mask generating. Here's the demo output:

there are two dogs playing with a stick on the beach



Video Object Segmentation

DAVIS: Densely Annotated VIdeo Segmentation

Unsupervised: the user does not interact with the algorithm to obtain the segmentation masks. Methods should provide a set of object candidates.

Semi-supervised: user inputs full mask of the object of interest in the first frame only.

Interactive: user gives iterative refinement inputs to the algorithm, in the form of a scribble, to segment the objects of interest.

Beyond Segmentation: Alpha Matting

Image

Alpha matte

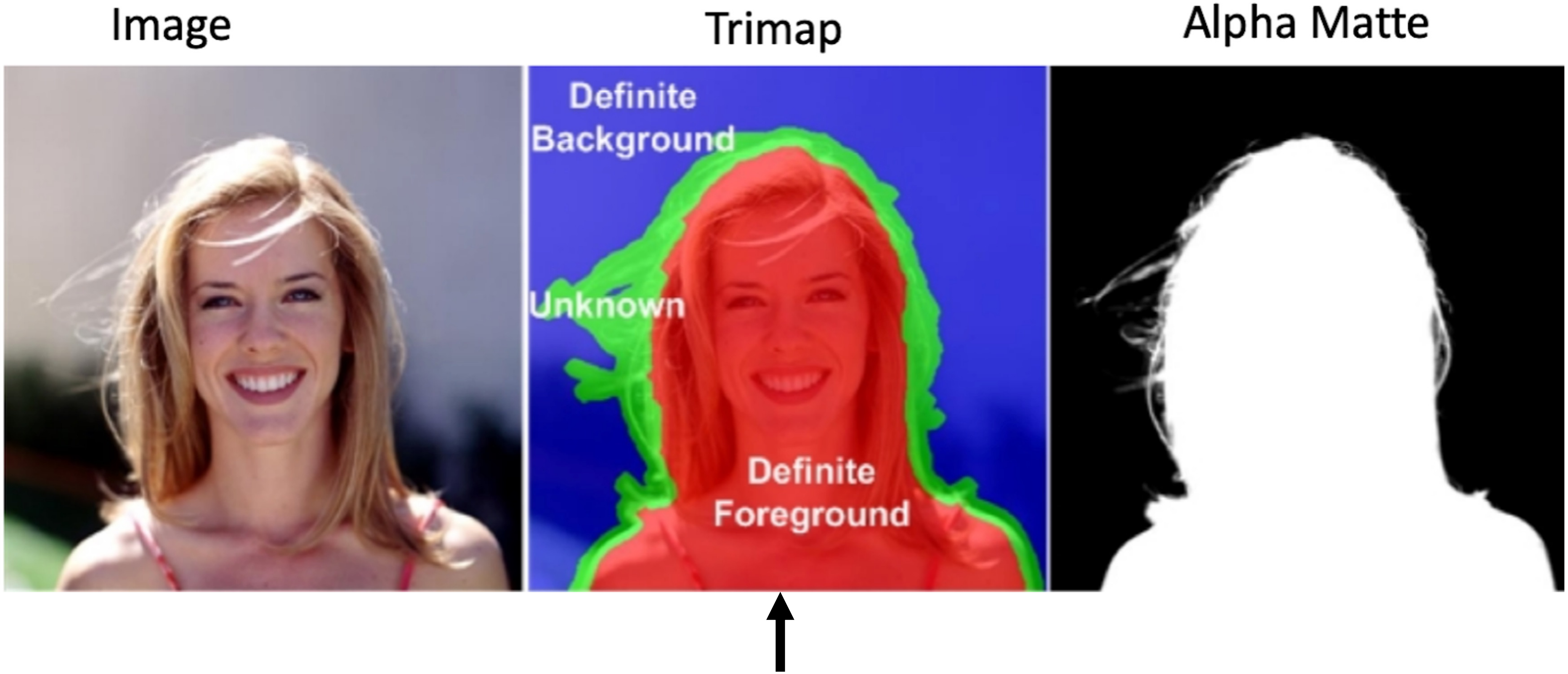
Composed Image

Foreground layer

$$I = \alpha * F + (1 - \alpha) * B$$

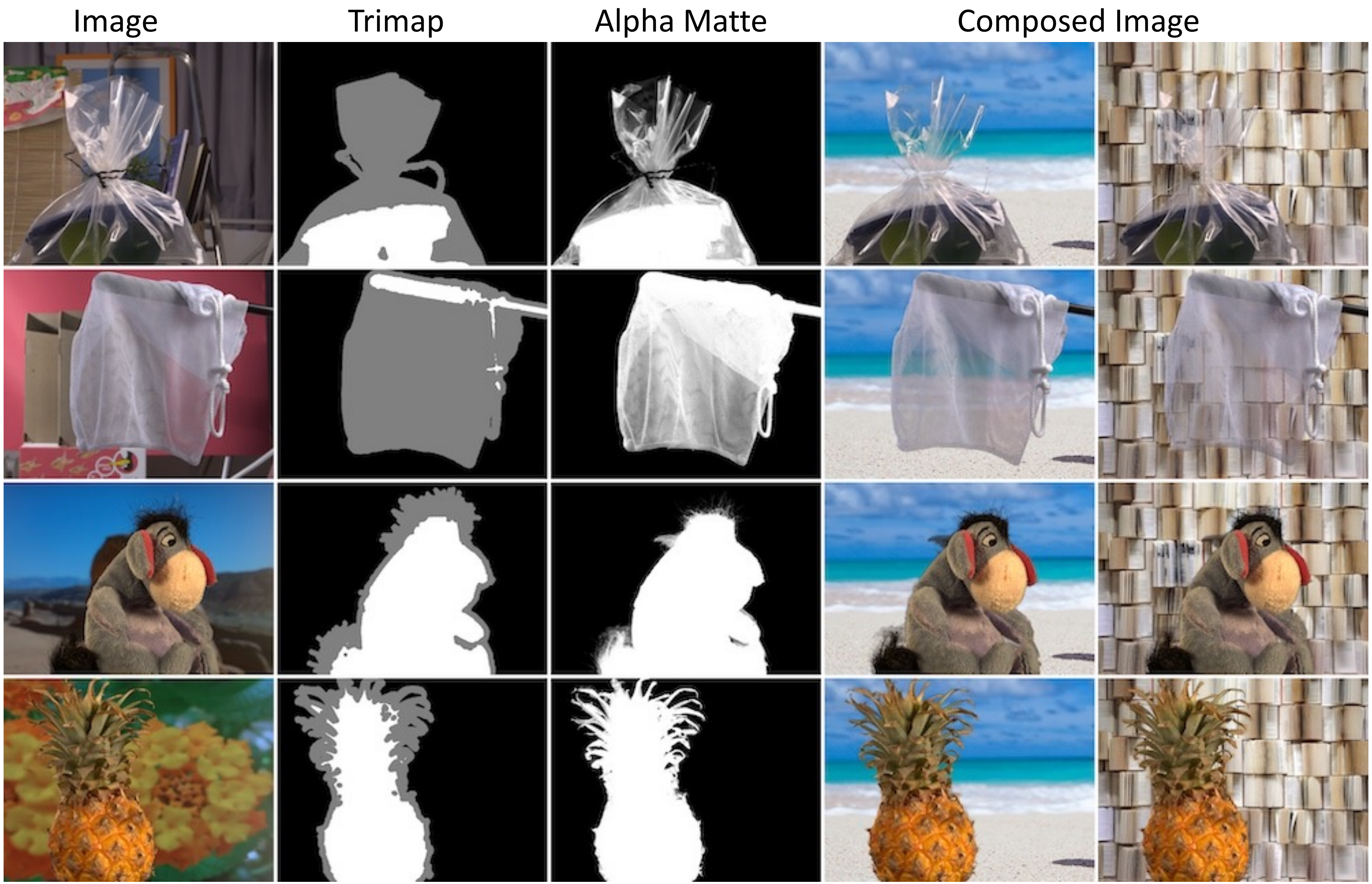
Under-constrained!

Solving Matting with user annotation!



User Annotation during inference

Image Matting with Trimap

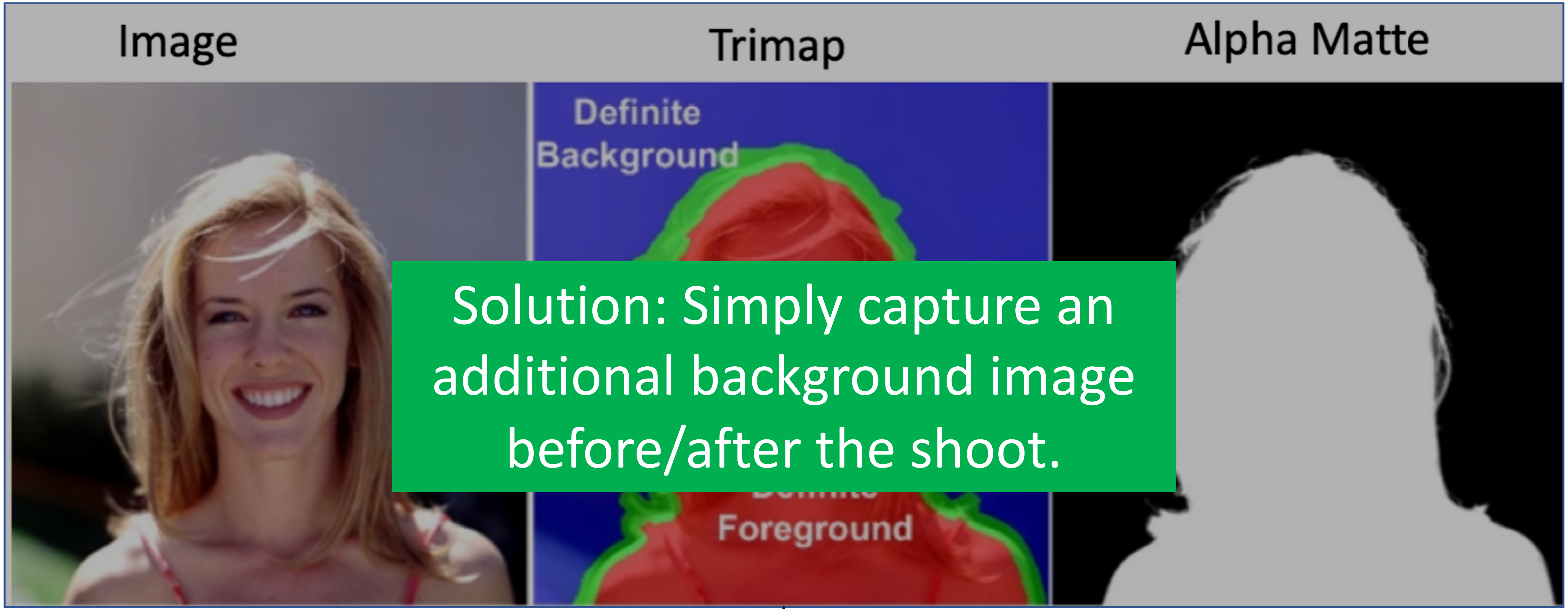


Information Flow Matting

Background Subtraction Segmentation Vs Matting

- Binary Mask
- No color separation

Solving Matting with user annotation!



Solution: Simply capture an additional background image before/after the shoot.

User Annotation during inference

Expensive – especially for a video

Background Matting: The World is Your Green Screen

Soumyadip Sengupta
Vivek Jayaram
Brian Curless
Steve Seitz
Ira Kemelmacher-Shlizerman

University of Washington

Original Video

Replaced Background

Challenges: Lack of High-Quality Training Data

Instances from Adobe Matting Dataset (Ground Truth)

Alpha

Foreground

✓ **Very High Quality**

Manually extracted alpha and foreground

✗ **Very Few Training Samples**

Only 500+ samples in total

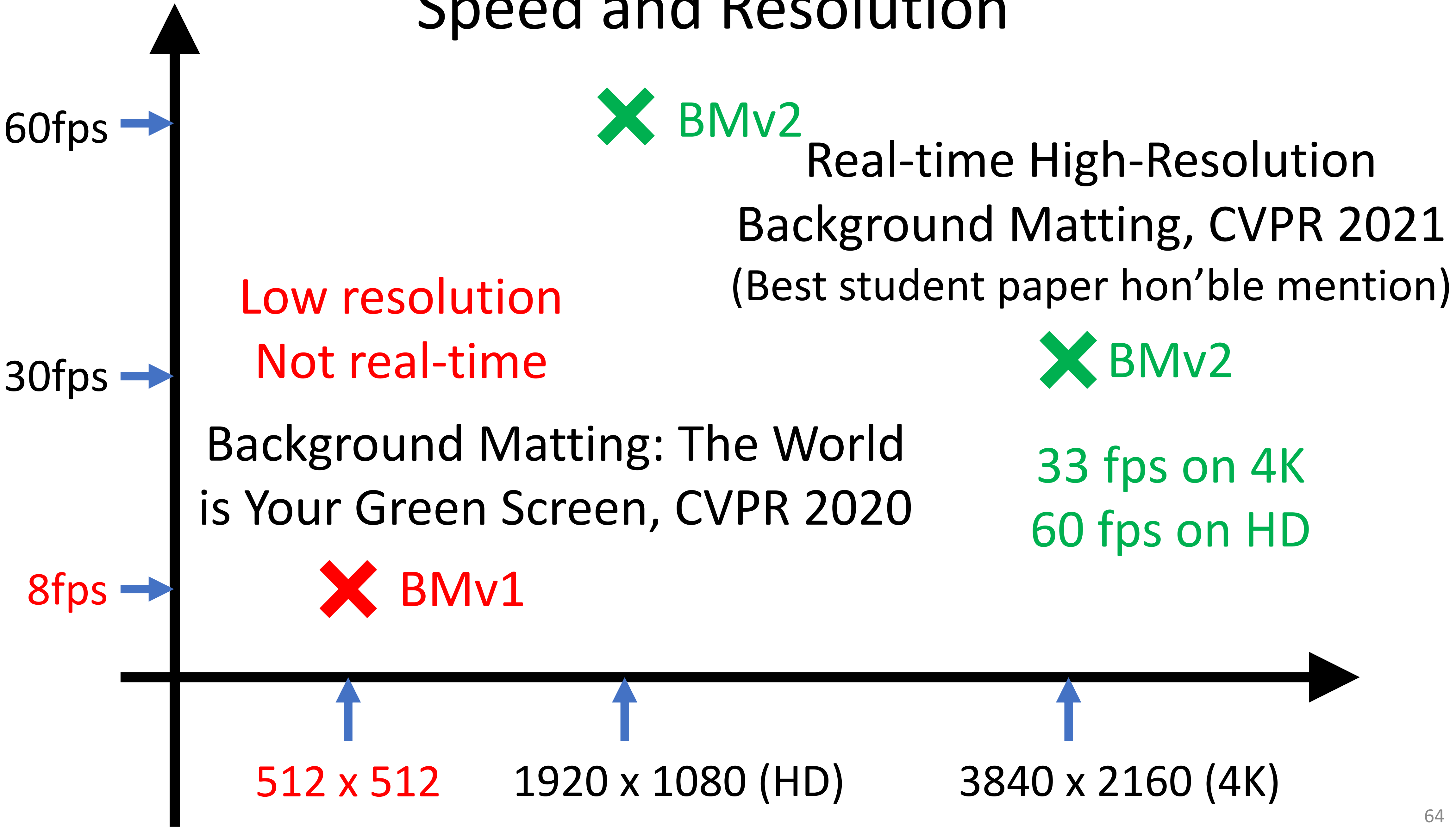
Technical solutions:

- Make the problem easy with user interaction
- Create realistic synthetic data
- Unsupervised Finetuning on real data.

Adobe Matting Dataset
+
Distinctions-646 Dataset

ML models trained on this data alone, fails to generalize.

Speed and Resolution



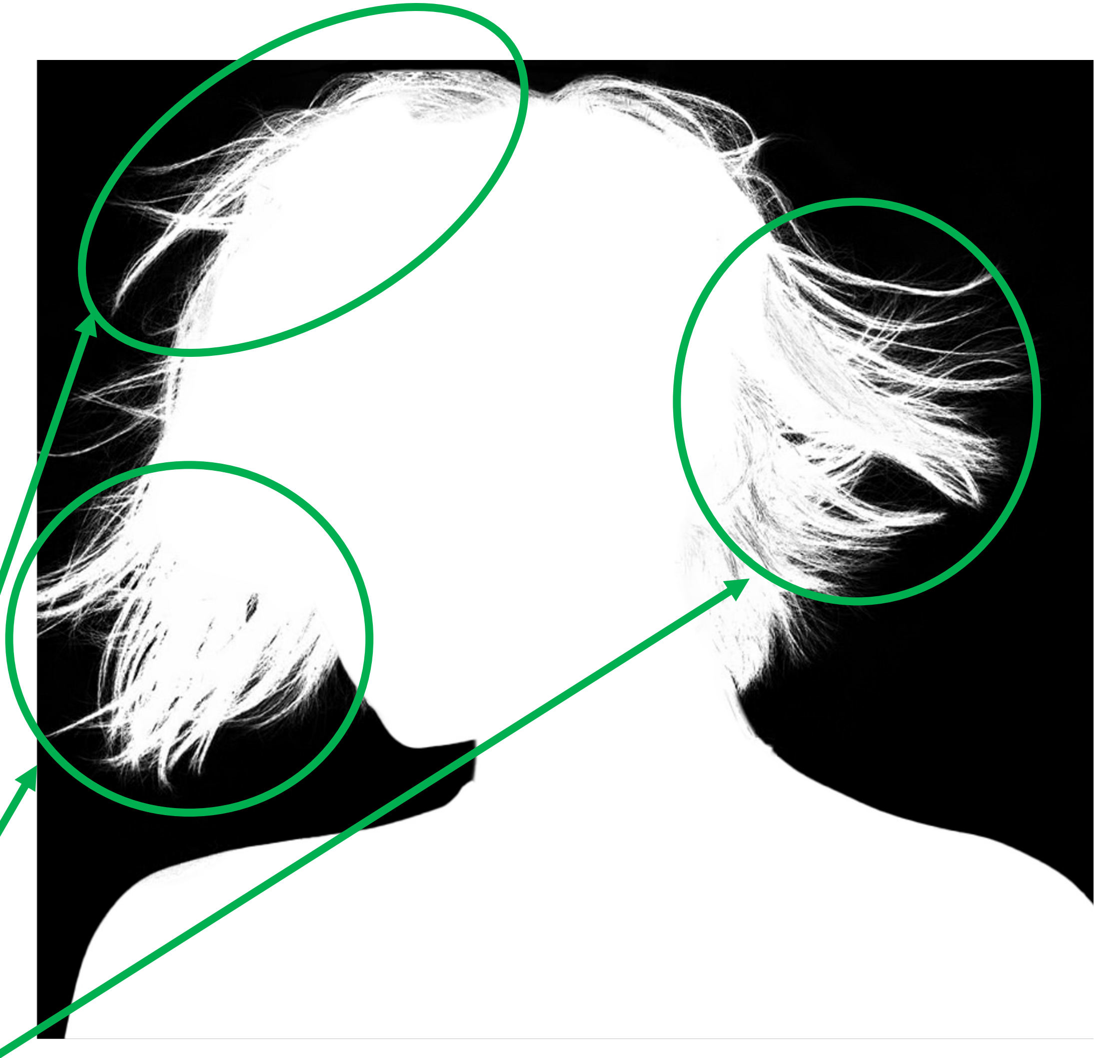
Measured on Nvidia RTX 2080 Ti with batch size 1


Mute
Start Video
Security
Participants
1
Share Screen
Record
Breakout Rooms
End

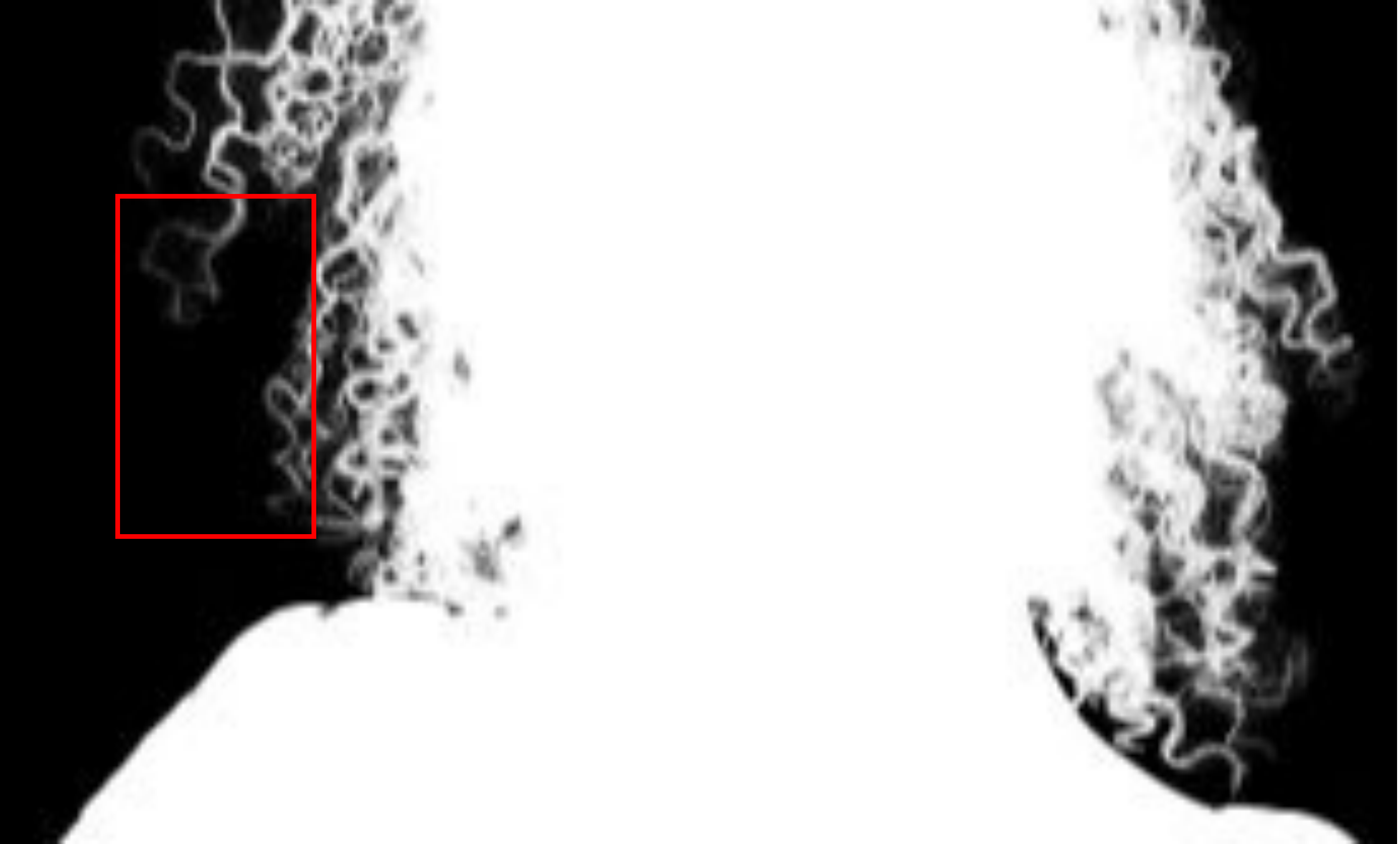
Observation: Only few regions are transparent.

Solution:

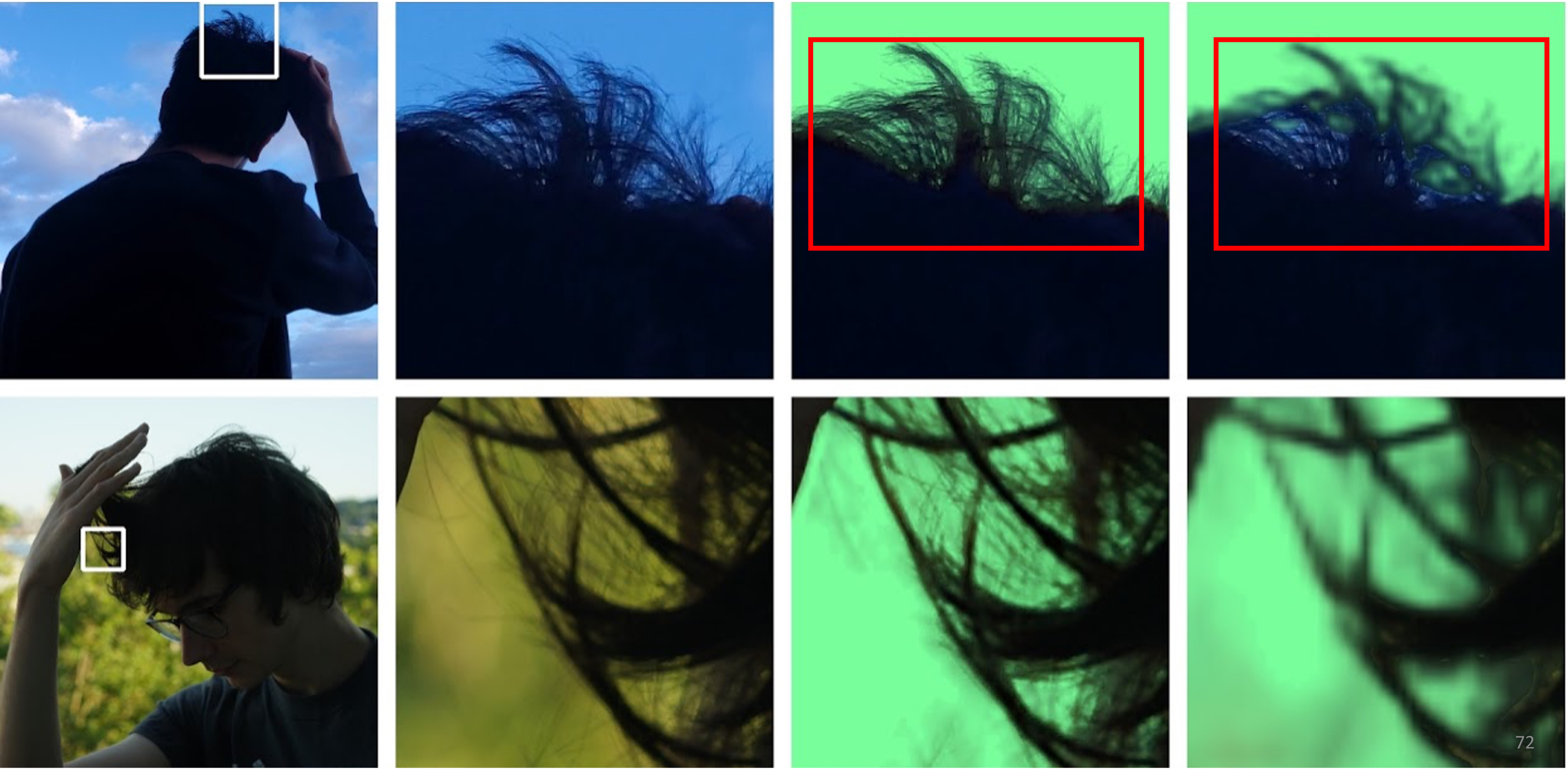
- Predict alpha matte at low resolution
- Only refine transparent regions at high-res.



How do we find transparent regions to refine at high-res?



Input | Input (zoomed) | BMv2 [CVPR 2021] | BMv1 [CVPR 2020]



Drawbacks of Background Matting:

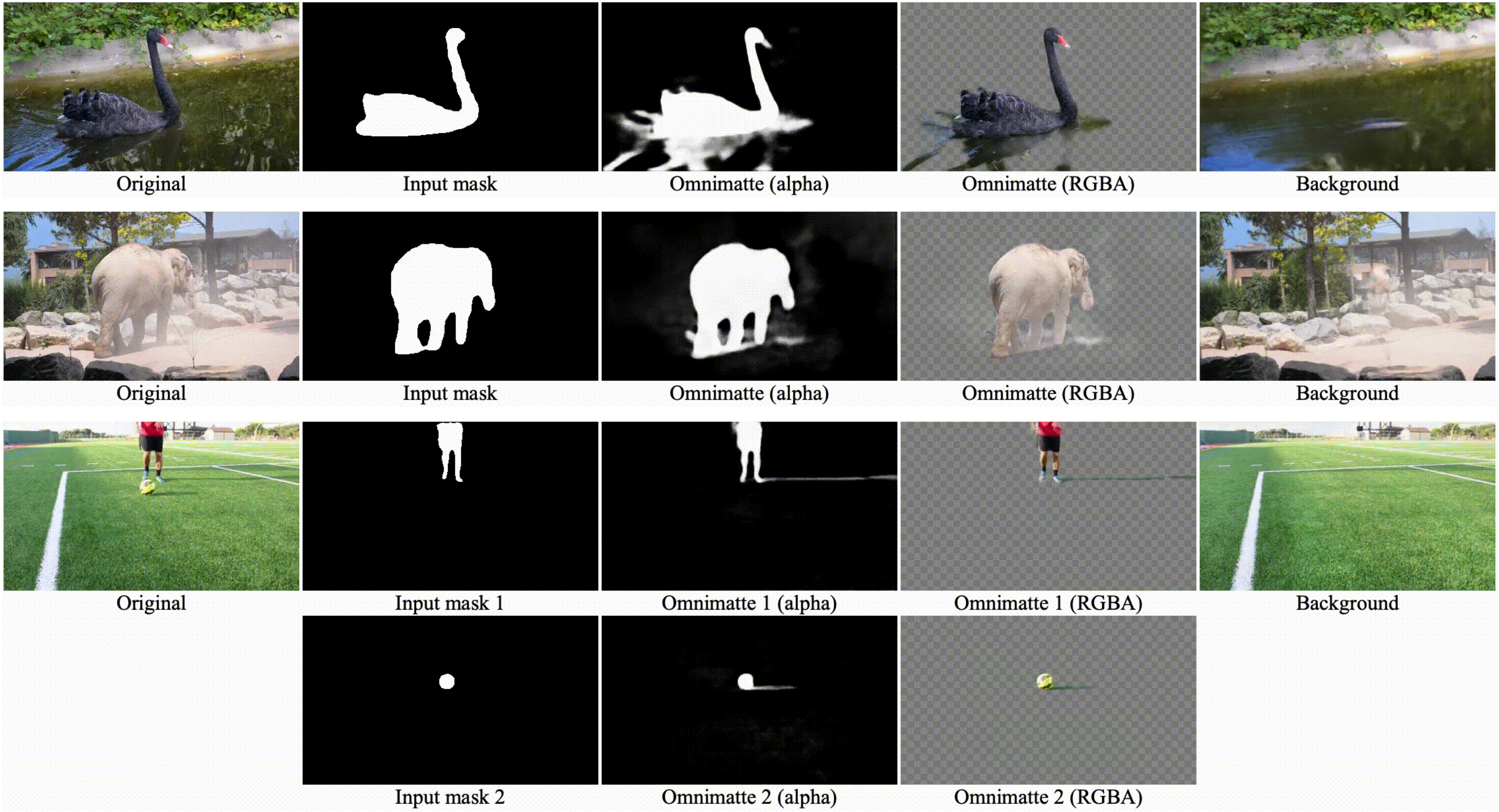
✗ requires explicit background capture.

✗ can't handle large camera motion.

Idea: Use RNN to aggregate temporal motion information to separate foreground and background

Robust Video Matting, WACV 2022.

Alpha Matting in presence of foreground-background interaction



Omnimatte: Associating Objects and Their Effects in Video, Siggraph 2020


Input

OmnimatteRF: Robust Omnimatte with 3D Background Modeling

Recap

- Semantic segmentation: detect masks of specific object classes
- Instance segmentation: detect masks of each instances of specific object class
- Panoptic segmentation: Semantic + Instance combined.

Evolution of Neural network architectures to solve segmentation:

- Fully convolutional networks (VGGlike)
- Mask R-CNN (instance segmentation)
- U-Net
- Transformer based architecture (Swin V2)

Interactive Segmentation (scribbles, points, text prompts etc):

- Segment Anything (SAM)
- Way more robust than semantic/instance segmentation

Beyond Image segmentation:

- Video object segmentation (unsupervised, weak-supervised, interactive)
- Alpha Matting

Slide Credits

- **EECS 442/498 [Computer Vision], by Justin Johnson & David Fouhey, U Michigan.**