CS 4644-DL / 7643-A: LECTURE 21
DANFEI XU

- 2D Computer Vision (Continued)
- 3D Vision: Representations and Neural Rendering

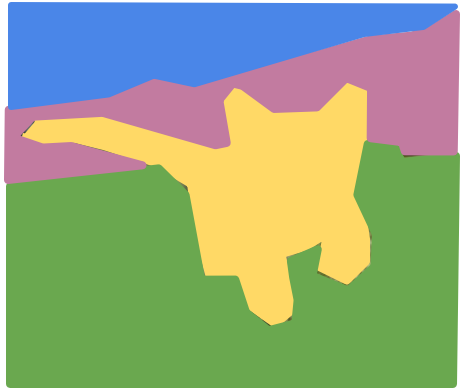
Computer Vision Tasks

Classification

CAT

No spatial extent

Semantic Segmentation



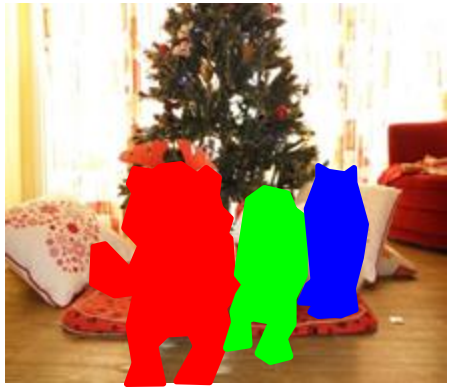
GRASS, **CAT**, **TREE**, **SKY**

No objects, just pixels

Object Detection

DOG, **DOG**, **CAT**

Instance Segmentation



DOG, **DOG**, **CAT**

Multiple Object

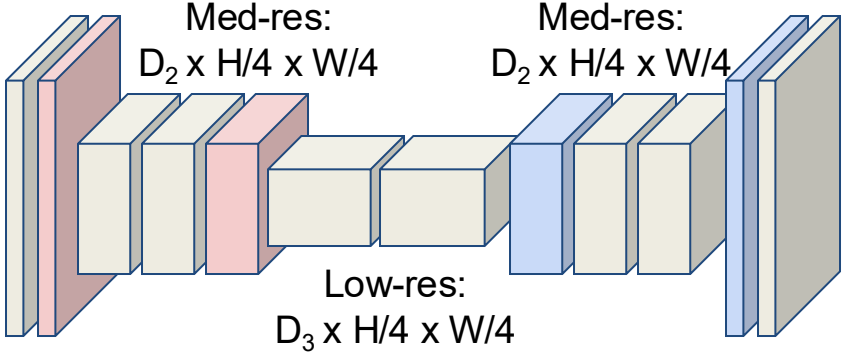
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided convolution

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

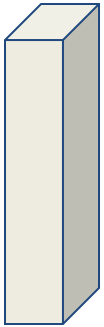
Upsampling:
???

Input:
3 x H x W



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

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

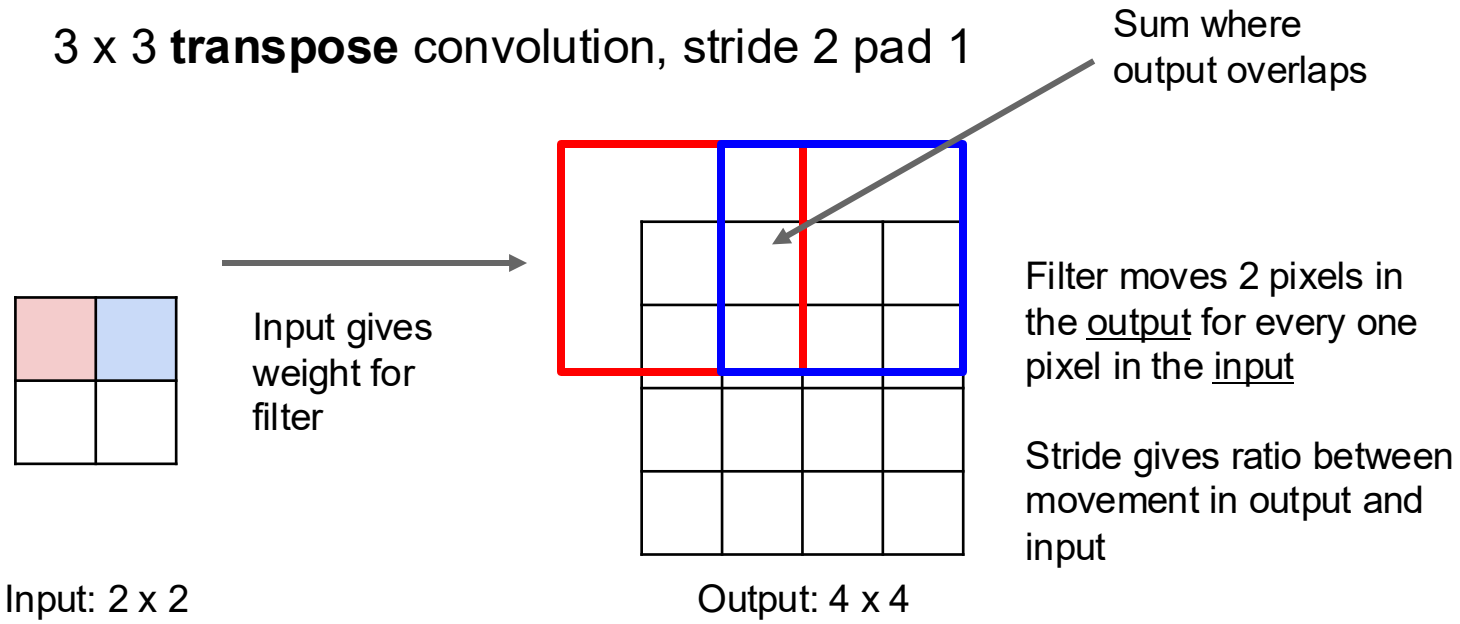


C x H x W

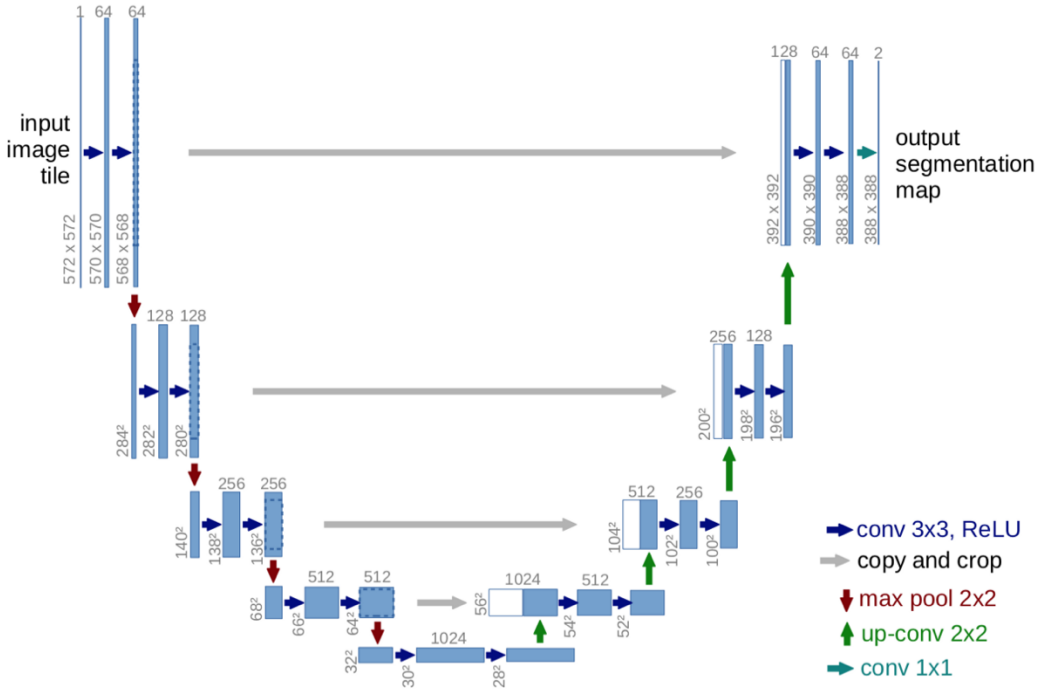
Predictions:
H x W

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

Learnable Upsampling: Transposed Convolution



Semantic Segmentation: U-Net



Idea: Concatenate feature maps from the downsampling stage with the features in the upsampling stage.

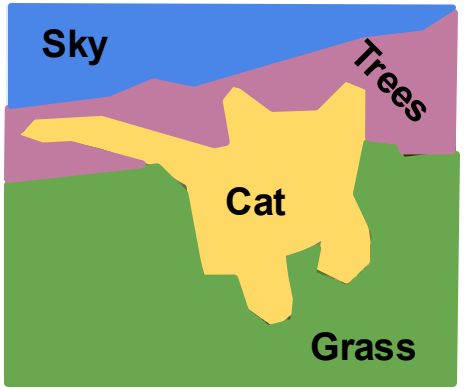
Very commonly used today!

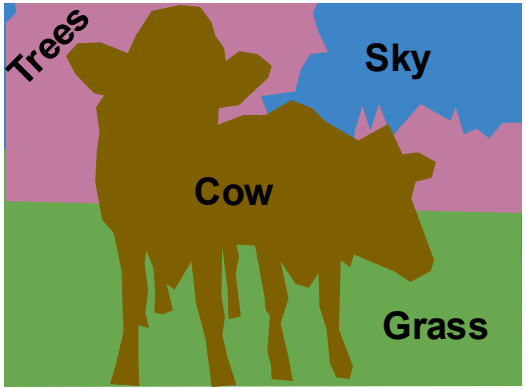
Ronneberger O, Fischer P, Brox T, 2015

Semantic Segmentation

Label each pixel in the image with a category label

Don’t differentiate instances, only care about pixels





Object Detection

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CAT

No spatial extent

Semantic Segmentation

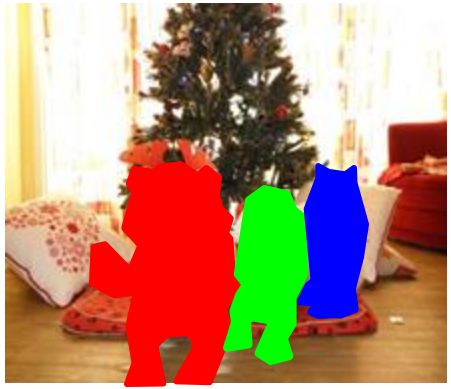
GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

Instance Segmentation

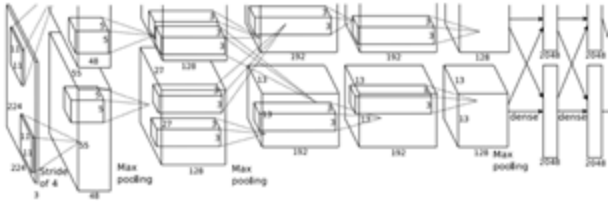


DOG, DOG, CAT

Multiple Object

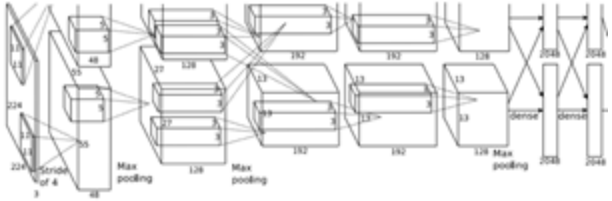
Object Detection: Multiple Objects

Each image needs a different number of outputs!



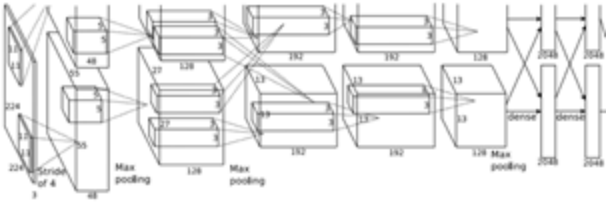
CAT: (x, y, w, h)

4 numbers



DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)

12 numbers

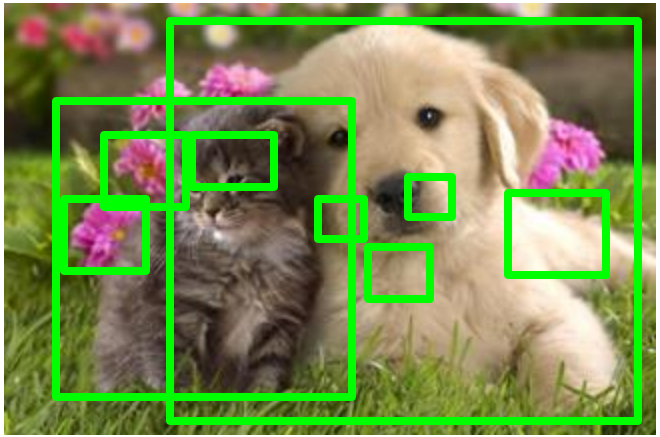


DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
….

Many numbers!

Region Proposals: Selective Search

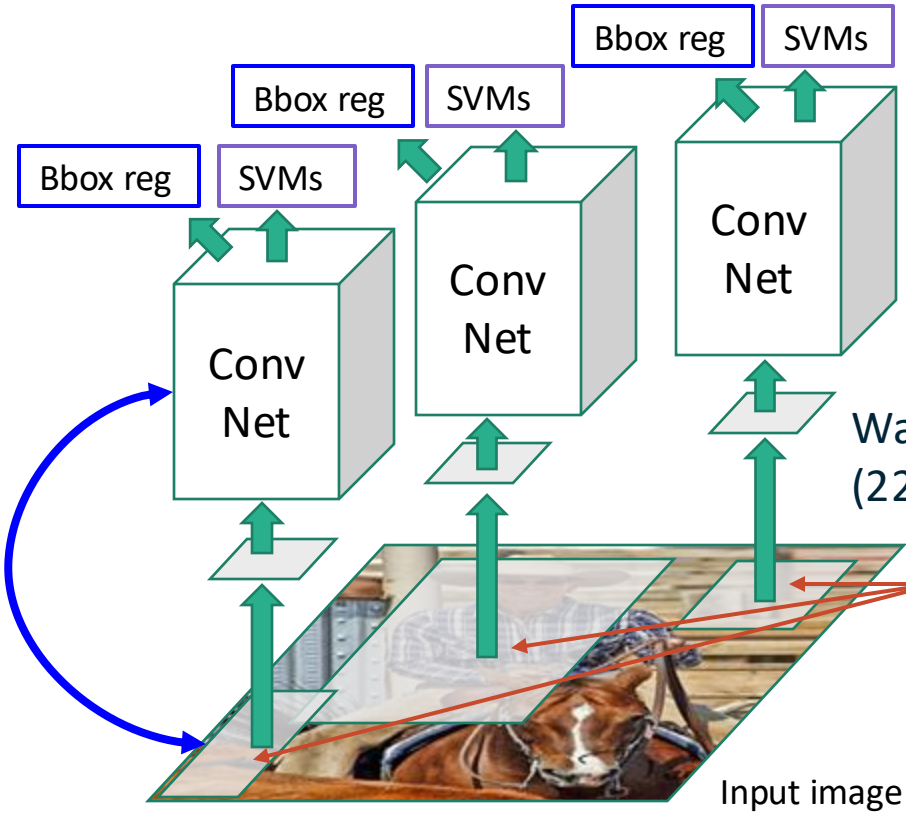
- Find “blobby” image regions that are likely to contain objects
- Relatively fast to run; e.g. Selective Search gives 2000 region proposals in a few seconds on CPU



Alexe et al, “Measuring the objectness of image windows”, TPAMI 2012
Uijlings et al, “Selective Search for Object Recognition”, IJCV 2013
Cheng et al, “BING: Binarized normed gradients for objectness estimation at 300fps”, CVPR 2014
Zitnick and Dollar, “Edge boxes: Locating object proposals from edges”, ECCV 2014

"Slow" R-CNN

Predict "corrections" to the RoI: 4 numbers: (dx, dy, dw, dh)



Classify regions with SVMs

Forward each region through ConvNet

Warped image regions (224x224 pixels)

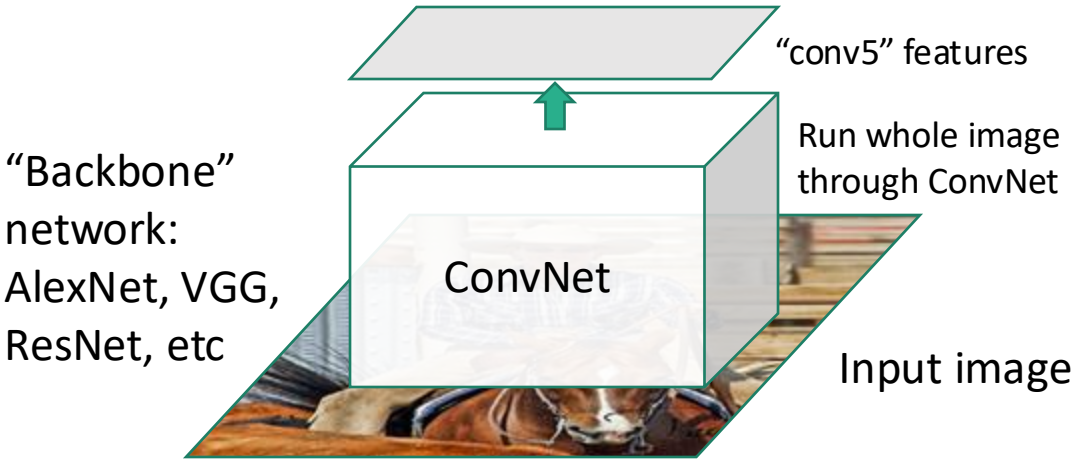
Regions of Interest (RoI) from a proposal method (~2k)

Problem: Very slow! Need to do ~2k independent forward passes for each image!

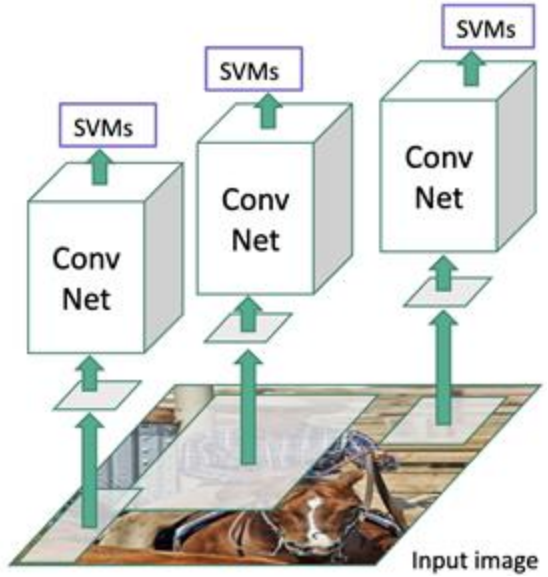
Idea: Pass the image through convnet before cropping! Crop the conv feature instead!

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

Fast R-CNN

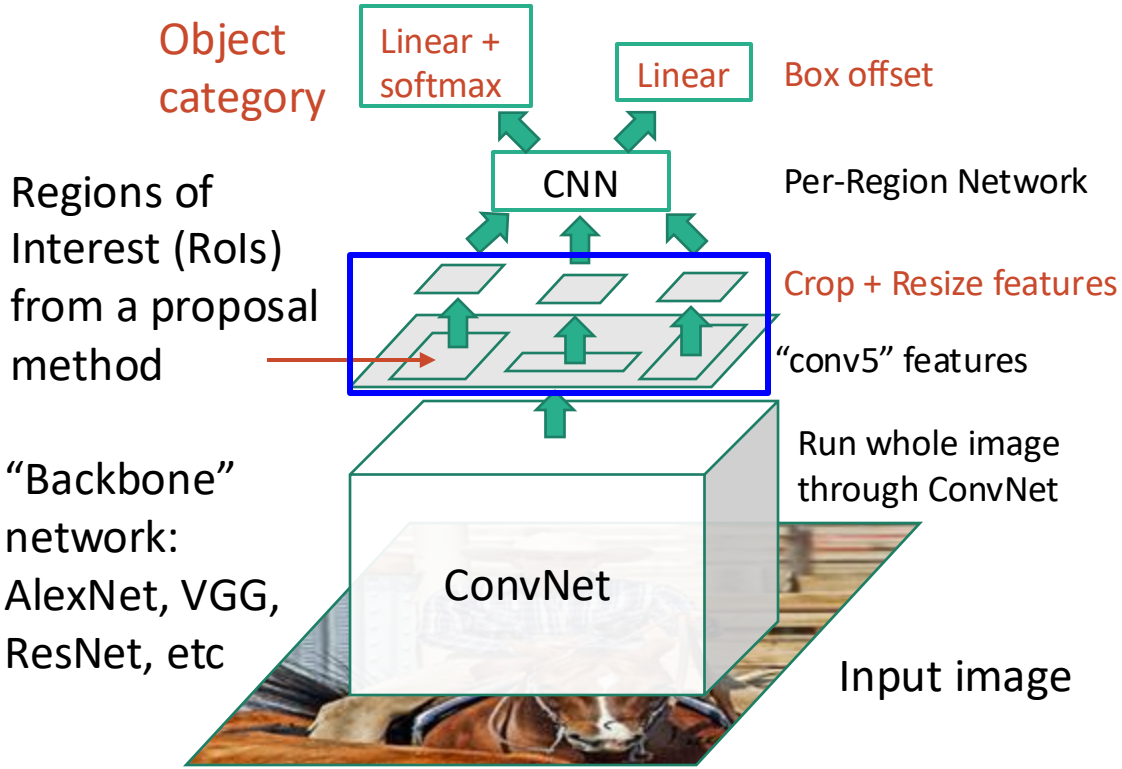


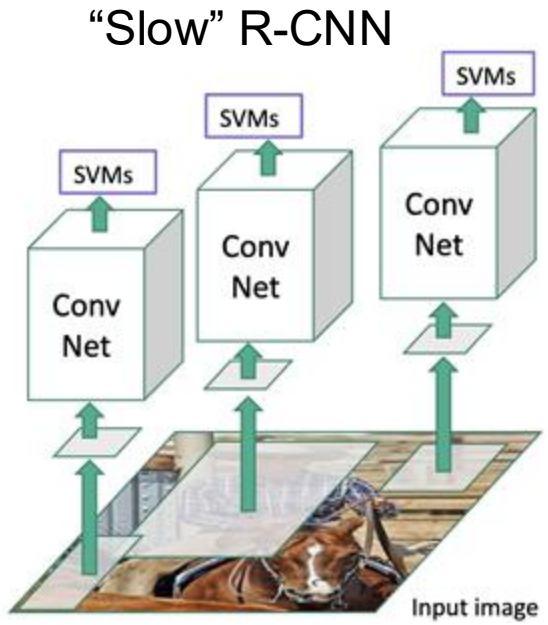
“Slow” R-CNN



Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

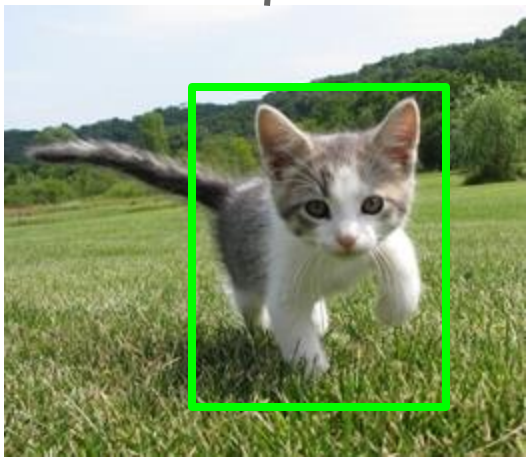
Fast R-CNN





Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Cropping Features: RoI Pool



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

CNN

Project proposal onto features

"Snap" to grid cells

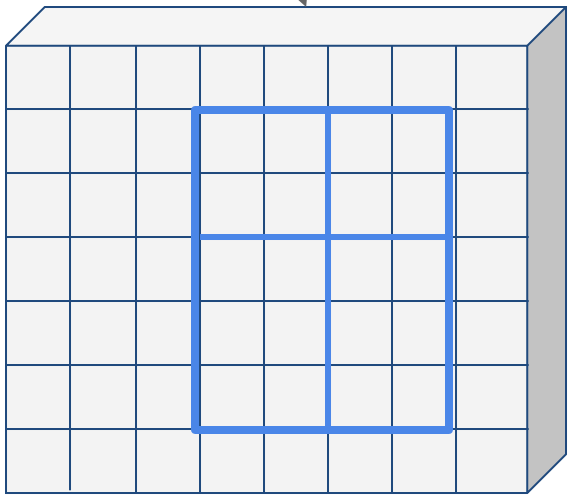
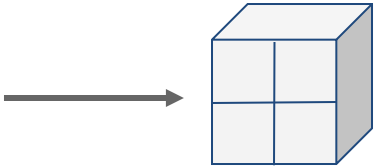


Image features: C x H x W
(e.g. 512 x 20 x 15)

Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion



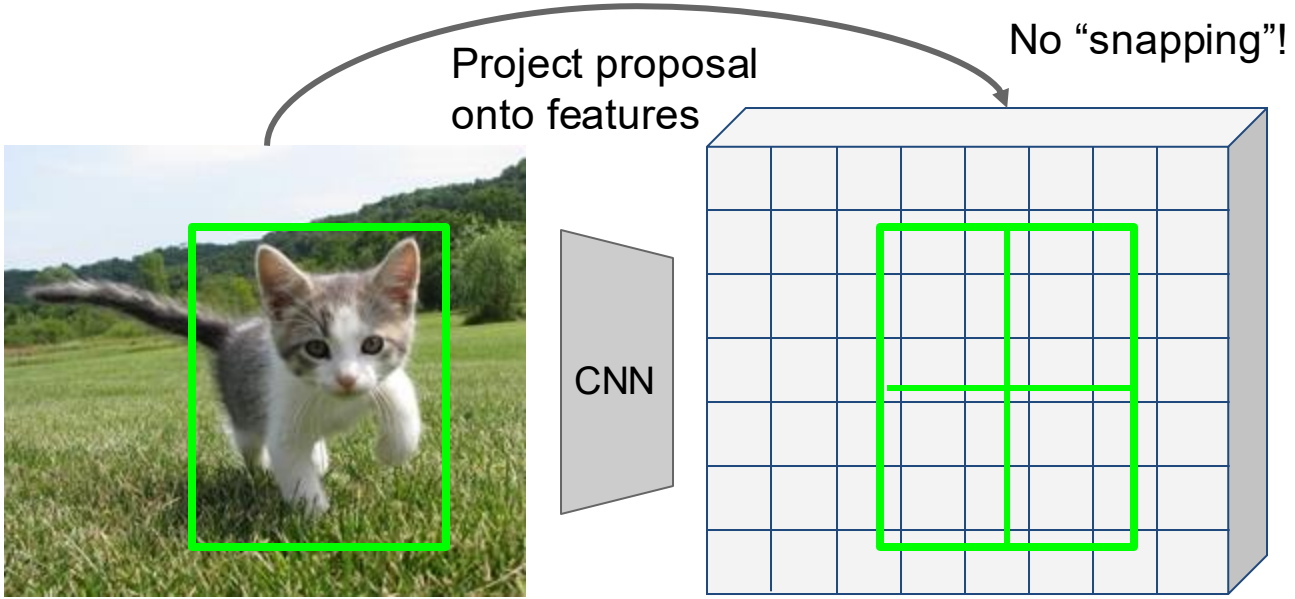
Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

Region features always the same size even if input regions have different sizes!

Problem: Region features slightly misaligned

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

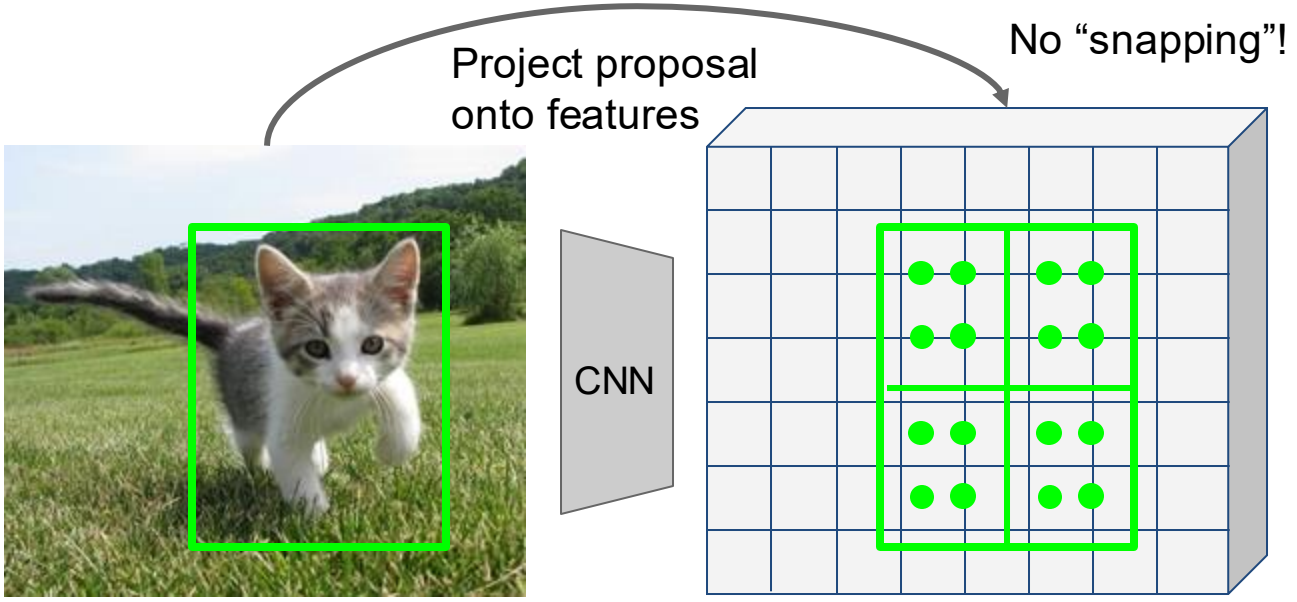
Cropping Features: RoI Align



He et al, “Mask R-CNN”, ICCV 2017

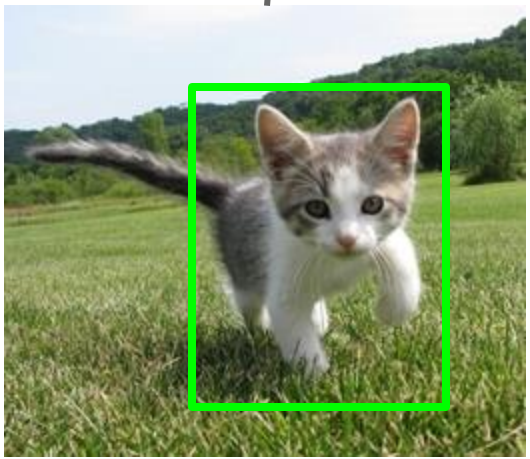
Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation



He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align

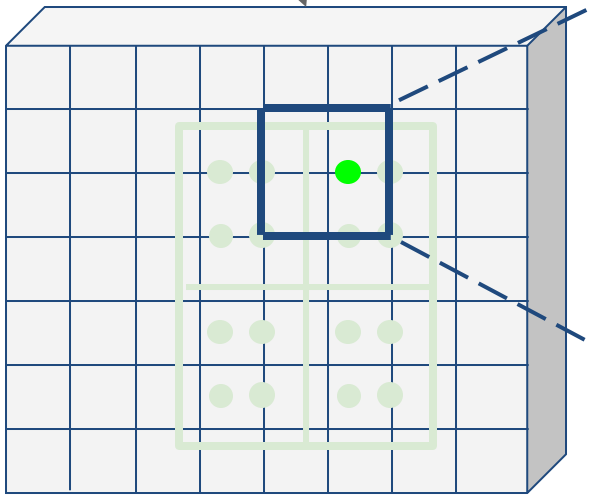


Input Image
(e.g. 3 x 640 x 480)

Project proposal onto features

No “snapping”!

CNN



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(e.g. 512 x 20 x 15)

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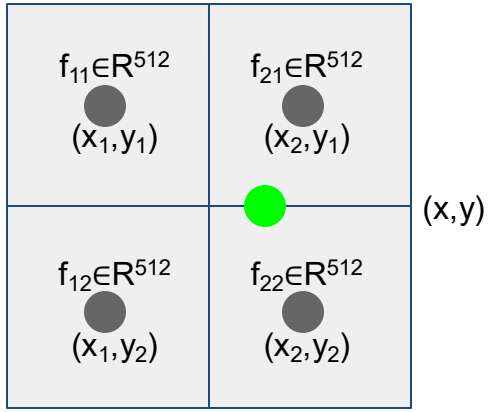


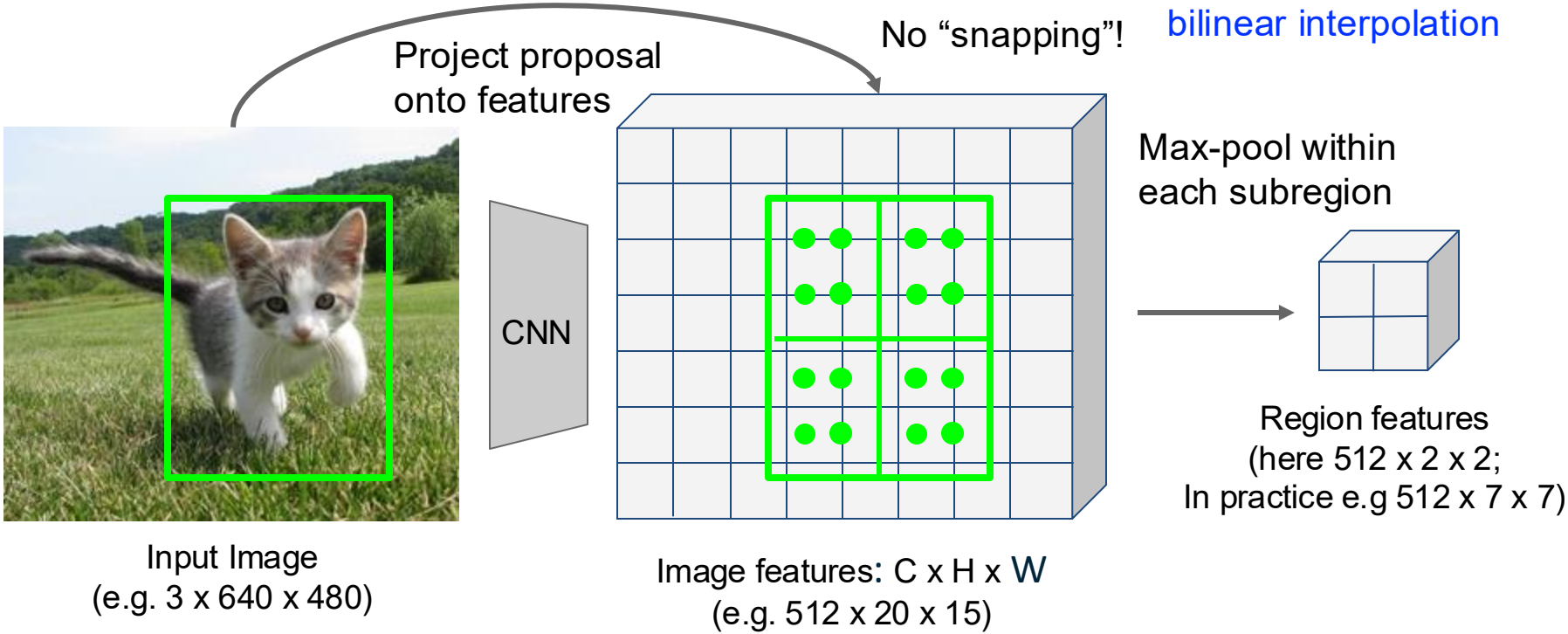
Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

$$f_{xy} = \sum_{i,j=1}^{2} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_j|)$$

He et al, “Mask R-CNN”, ICCV 2017

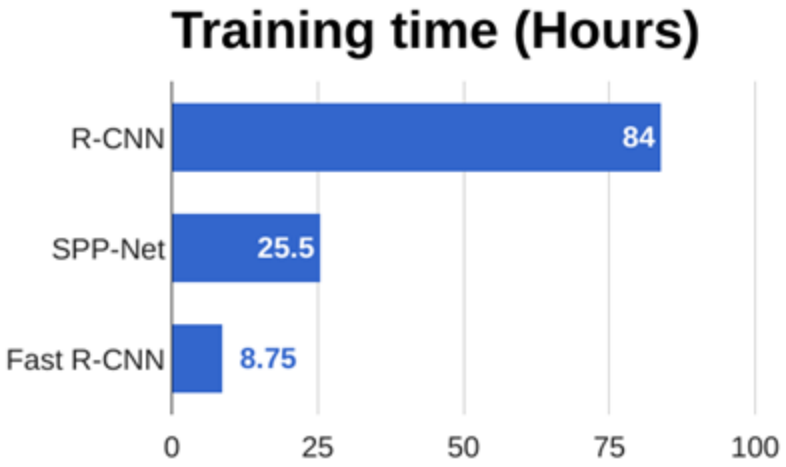
Cropping Features: RoI Align

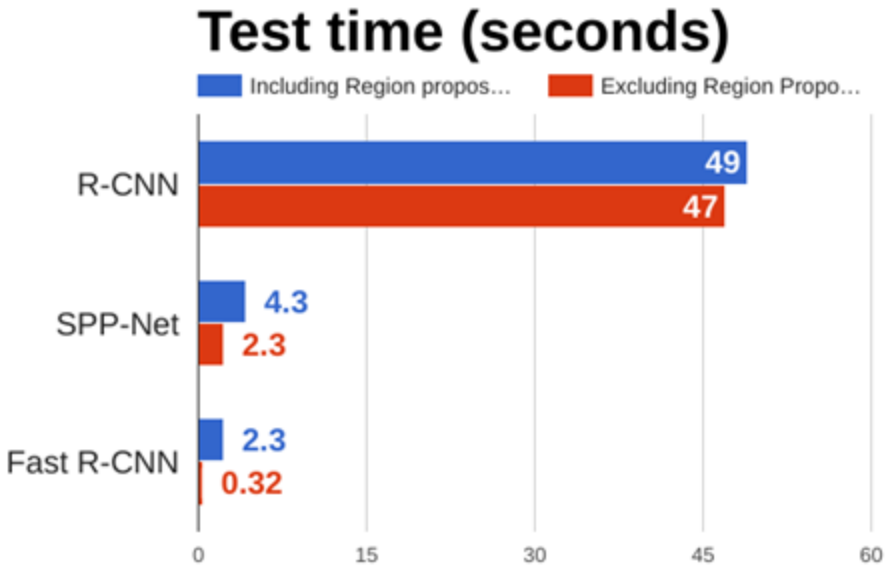
Sample at regular points in each subregion using bilinear interpolation



He et al, “Mask R-CNN”, ICCV 2017

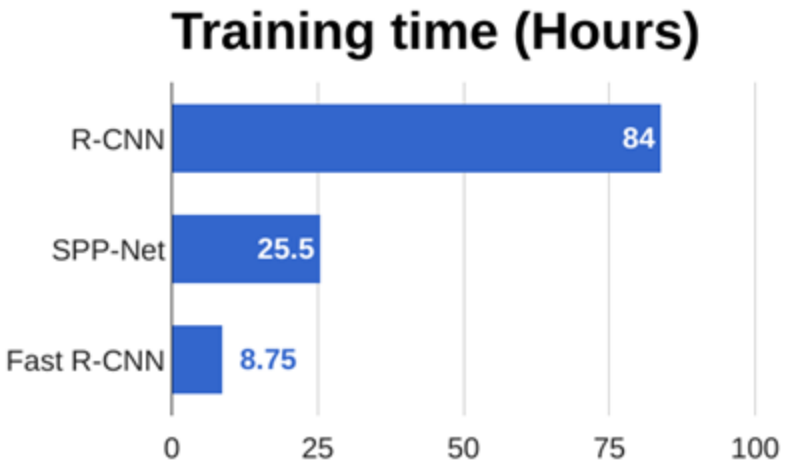
R-CNN vs Fast R-CNN

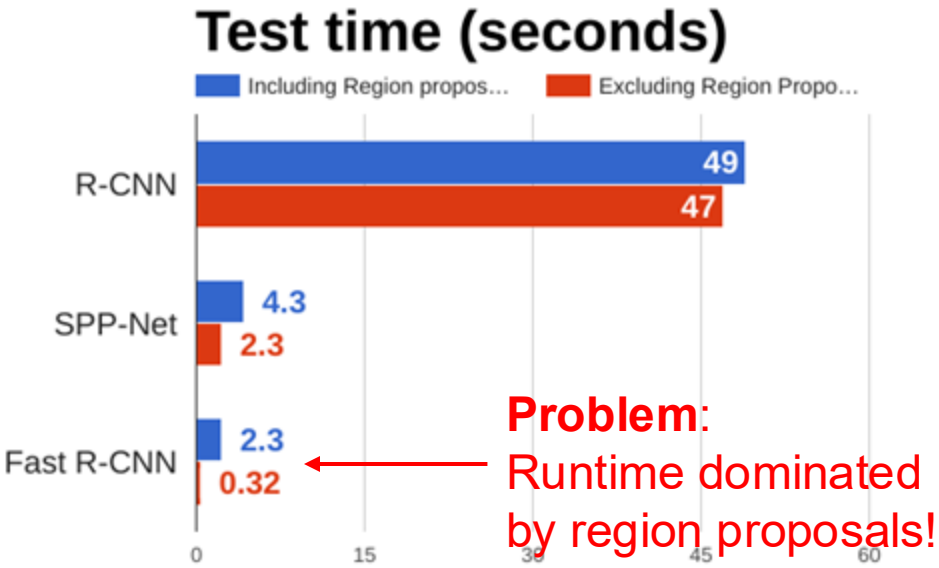




Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
He et al, “Spatial pyramid pooling in deep convolutional networks for visual recognition”, ECCV 2014
Girshick, “Fast R-CNN”, ICCV 2015

R-CNN vs Fast R-CNN





Problem:
Runtime dominated by region proposals!

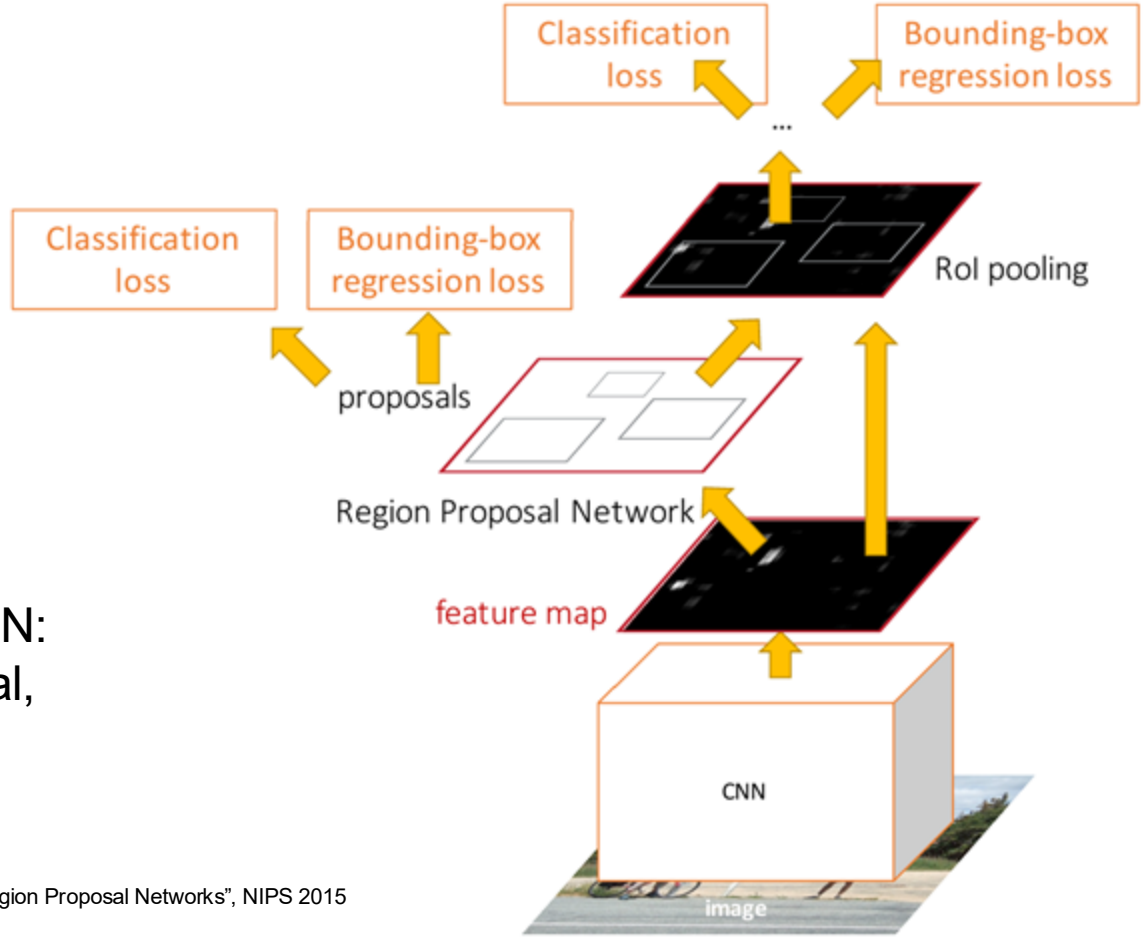
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
He et al, “Spatial pyramid pooling in deep convolutional networks for visual recognition”, ECCV 2014
Girshick, “Fast R-CNN”, ICCV 2015

Faster R-CNN:

Make CNN do proposals!

Insert **Region Proposal Network (RPN)** to predict proposals from features

Otherwise same as Fast R-CNN: Crop features for each proposal, classify each one



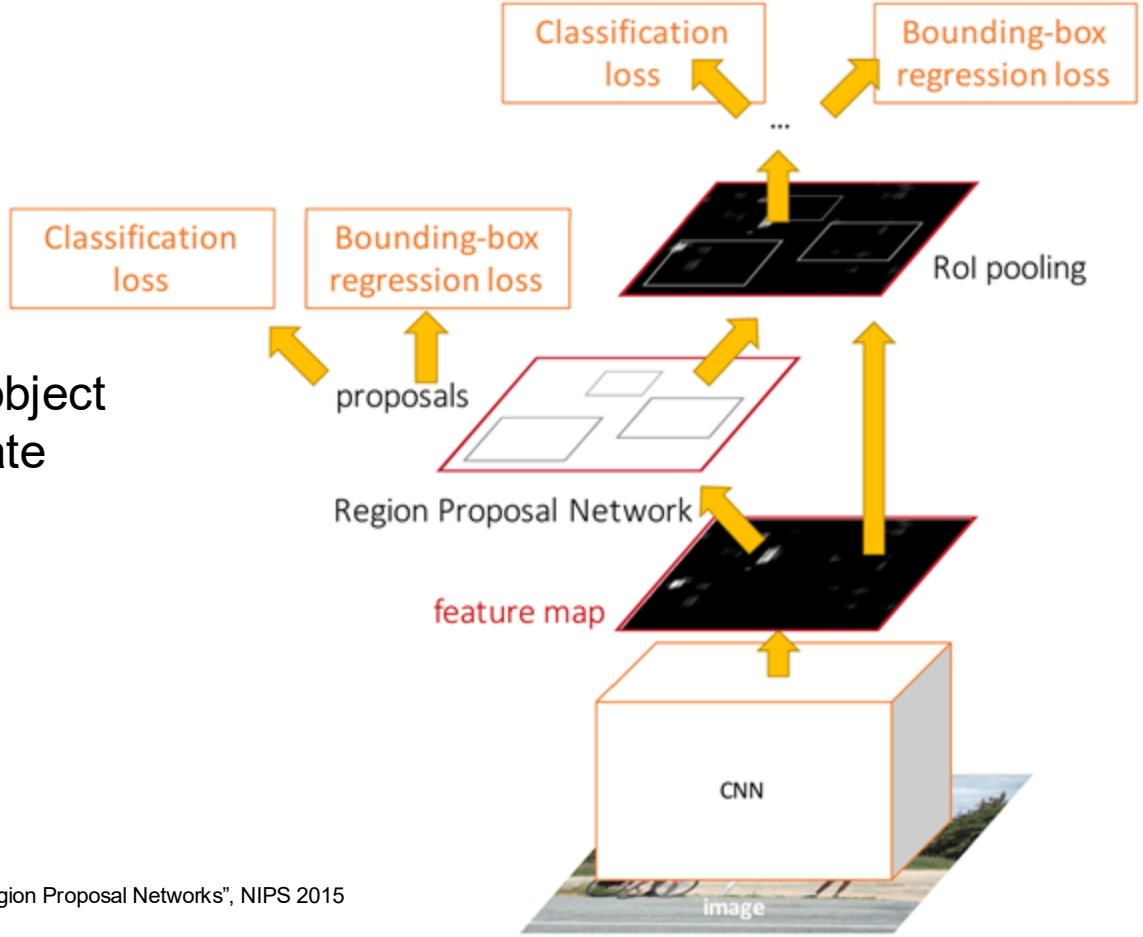
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Faster R-CNN:

Make CNN do proposals!

Jointly train with 4 losses:

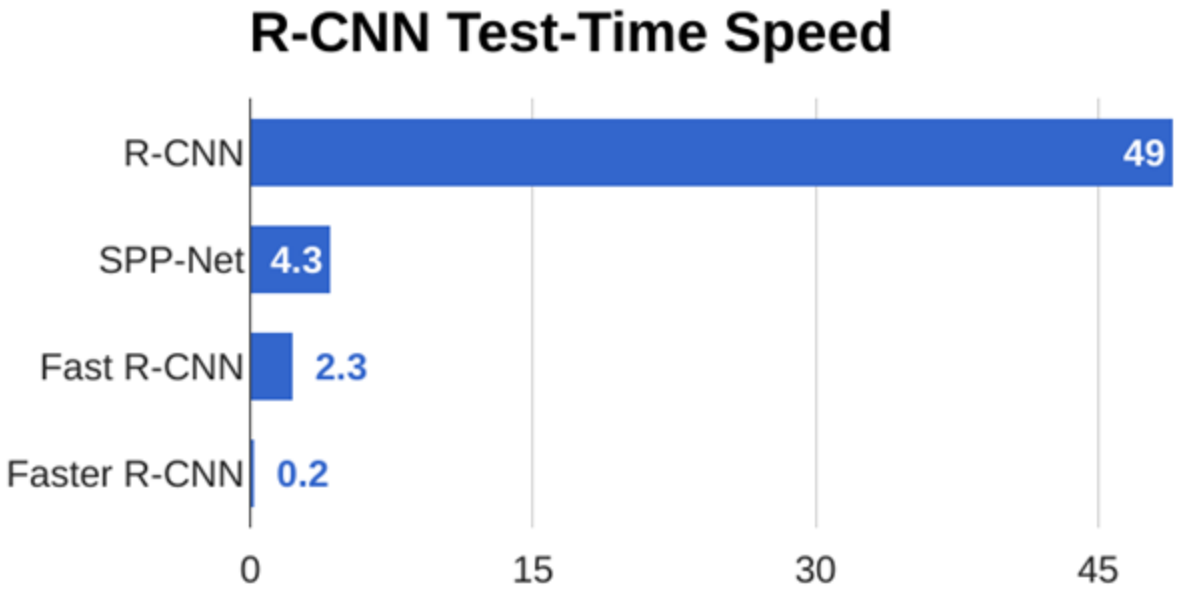
1. RPN classify object / not object
2. RPN regress box coordinate residuals
3. Final classification score (object classes)
4. Final box coordinates



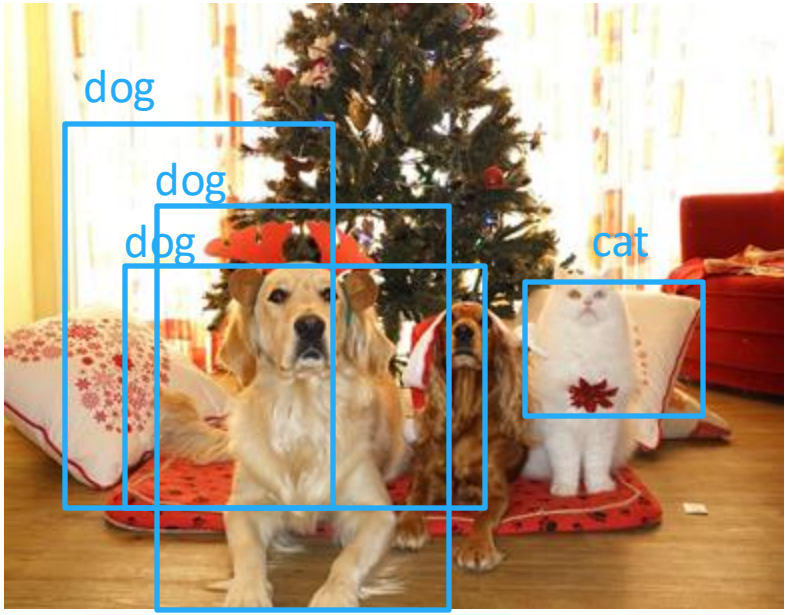
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015
Figure copyright 2015, Ross Girshick; reproduced with permission

Faster R-CNN:

Make CNN do proposals!



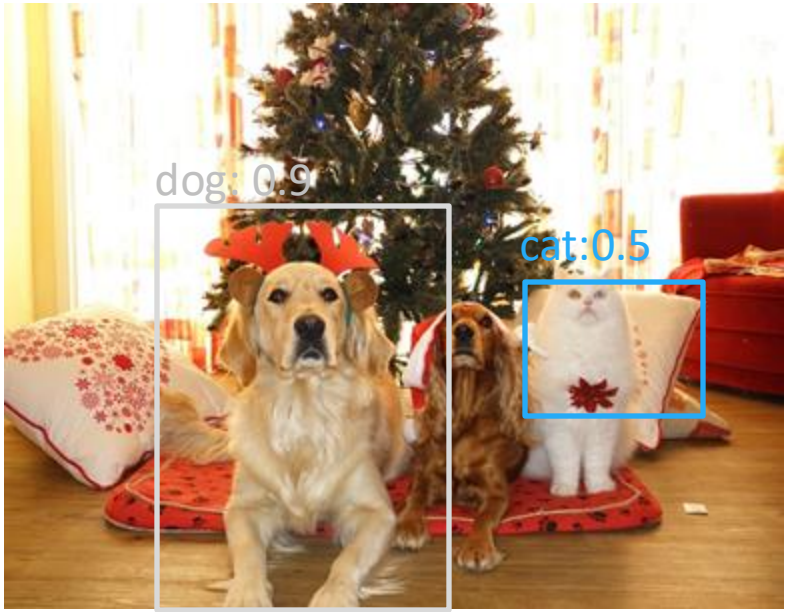
Which prediction to pick?



Problem: Detectors almost always generate more box predictions than the number of objects in the image!
E.g., 300 is an upper bound how many objects we wish to detect.

We need to remove the **redundant predictions!**

Non-Max Suppression (NMS)



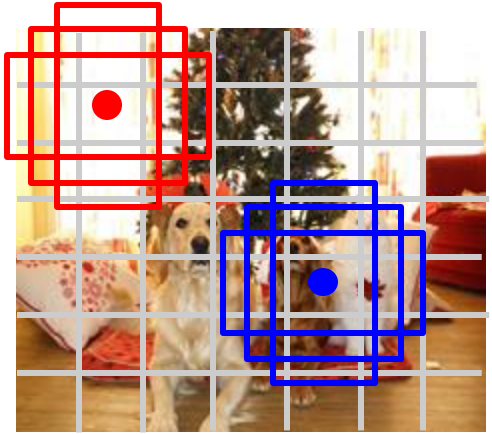
Intuitively: locally pick the box that has the highest “objectless” or class score and suppress other boxes that have significant overlap with the chosen box

Step 1: Pick highest-score prediction box
Step 2: Remove bounding boxes with **Intersection over Union (IoU) scores** higher than certain threshold (e.g., 0.5)

Go back to step 1

Single-Stage Object Detectors: YOLO / SSD / RetinaNet

Input image
3 x H x W



Divide image into grid
7 x 7

Image a set of **base boxes** centered at each grid cell
Here B = 3

Within each grid cell:

- Regress from each of the B base boxes to a final box with 5 numbers: (dx, dy, dh, dw, confidence)
- Predict scores for each of C classes (including background as a class)
- Looks a lot like RPN, but category-specific!

Output:
7 x 7 x (5 * B + C)

Redmon et al, "You Only Look Once: Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016
Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

Object Detection: Lots of variables ...

Backbone Network
VGG16
ResNet-101
Inception V2
Inception V3
Inception ResNet
MobileNet

"Meta-Architecture"
Two-stage: Faster R-CNN
Single-stage: YOLO / SSD
Hybrid: R-FCN

Image Size
 # Region Proposals
…

Takeaways
Faster R-CNN is slower but more accurate

SSD is much faster but not as accurate

Bigger / Deeper backbones work better

Huang et al, "Speed/accuracy trade-offs for modern convolutional object detectors", CVPR 2017
Zou et al, "Object Detection in 20 Years: A Survey", arXiv 2019

R-FCN: Dai et al, "R-FCN: Object Detection via Region-based Fully Convolutional Networks", NIPS 2016
Inception-V2: Ioffe and Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015
Inception V3: Szegedy et al, "Rethinking the Inception Architecture for Computer Vision", arXiv 2016
Inception ResNet: Szegedy et al, "Inception-V4, Inception-ResNet and the Impact of Residual Connections on Learning", arXiv 2016
MobileNet: Howard et al, "Efficient Convolutional Neural Networks for Mobile Vision Applications", arXiv 2017

Instance Segmentation

Classification

CAT

No spatial extent

Semantic Segmentation

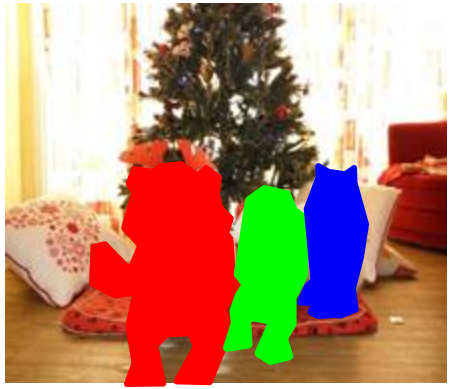
GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

Instance Segmentation

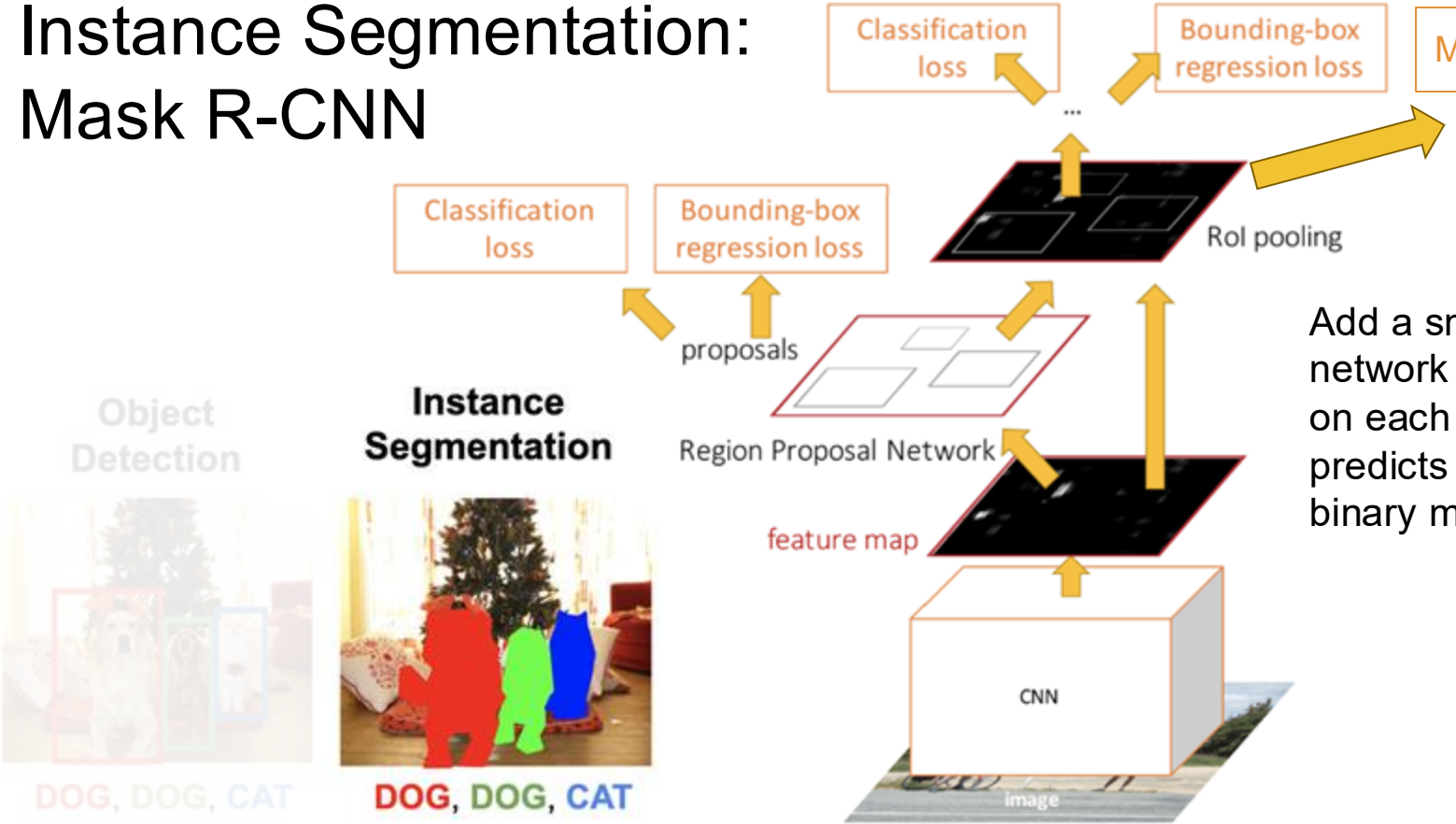


DOG, DOG, CAT

Multiple Object

Object Detection: Faster R-CNN

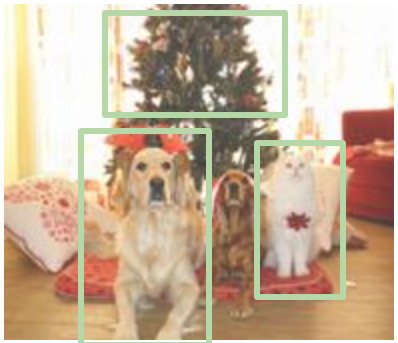
Instance Segmentation: Mask R-CNN



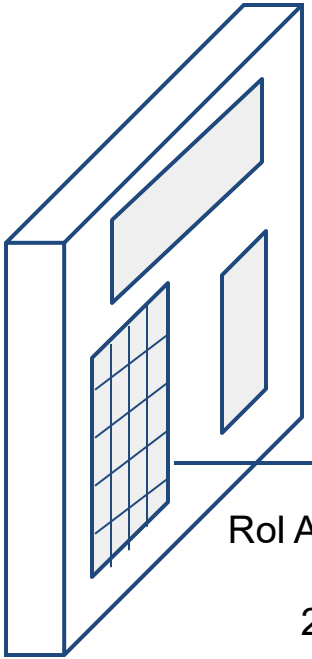
Add a small mask network that operates on each RoI and predicts a 28x28 binary mask

He et al, “Mask R-CNN”, ICCV 2017

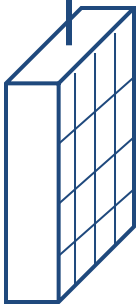
Mask R-CNN



CNN
+RPN

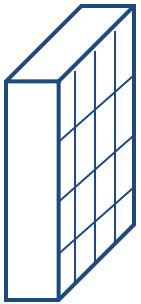


RoI Align



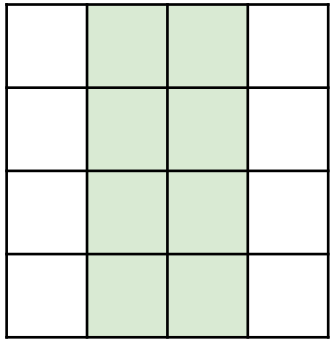
256 x 14 x 14

Conv



256 x 14 x 14

Conv



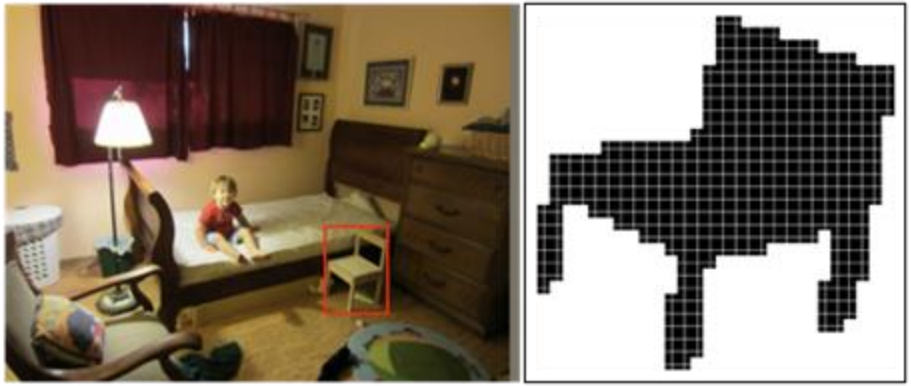
Predict a mask for
each of C classes

C x 28 x 28

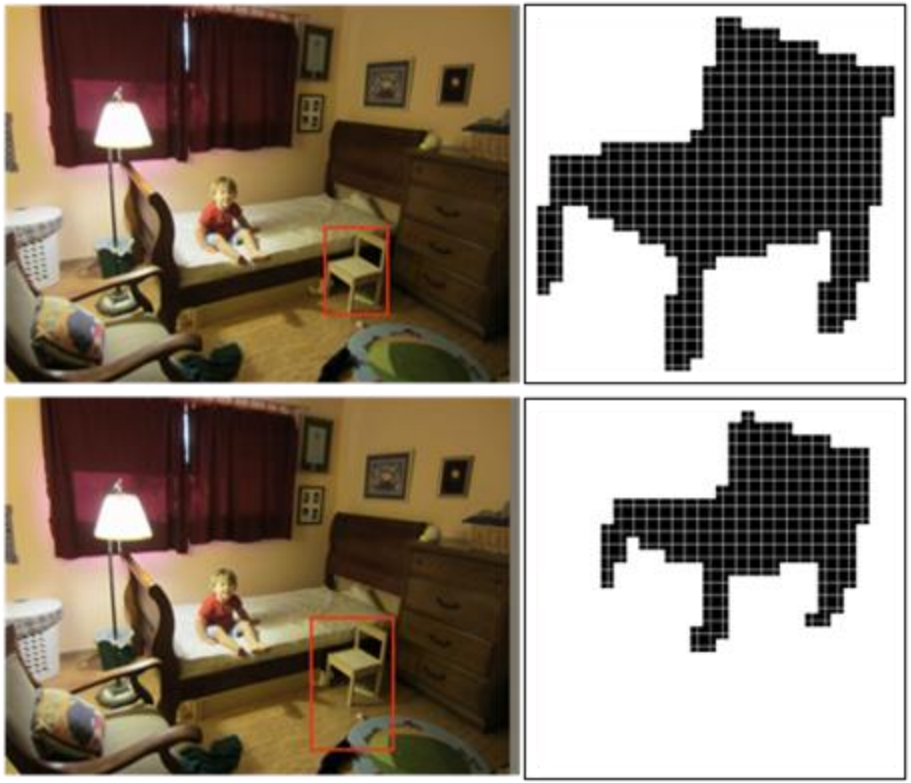
Classification Scores: C
Box coordinates (per class): 4 * C

He et al, “Mask R-CNN”, arXiv 2017

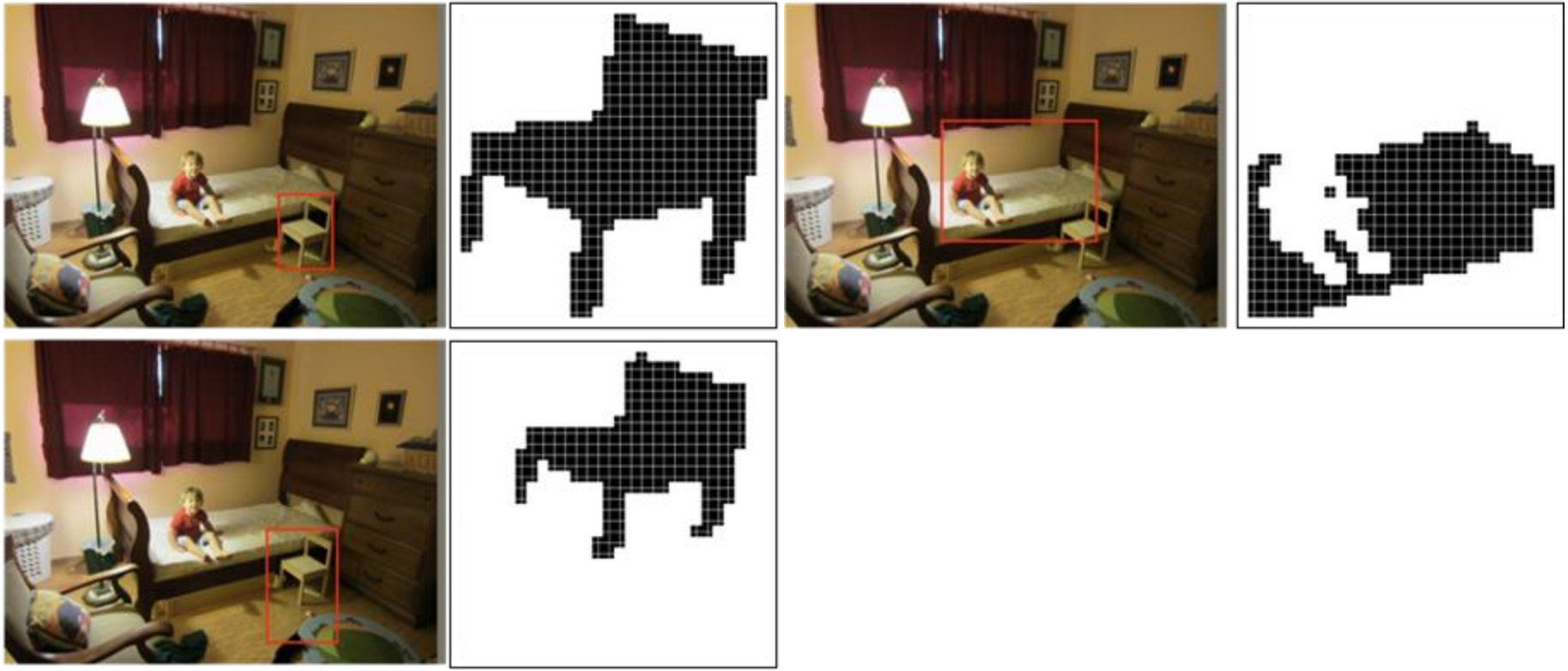
Mask R-CNN: Example Mask Training Targets



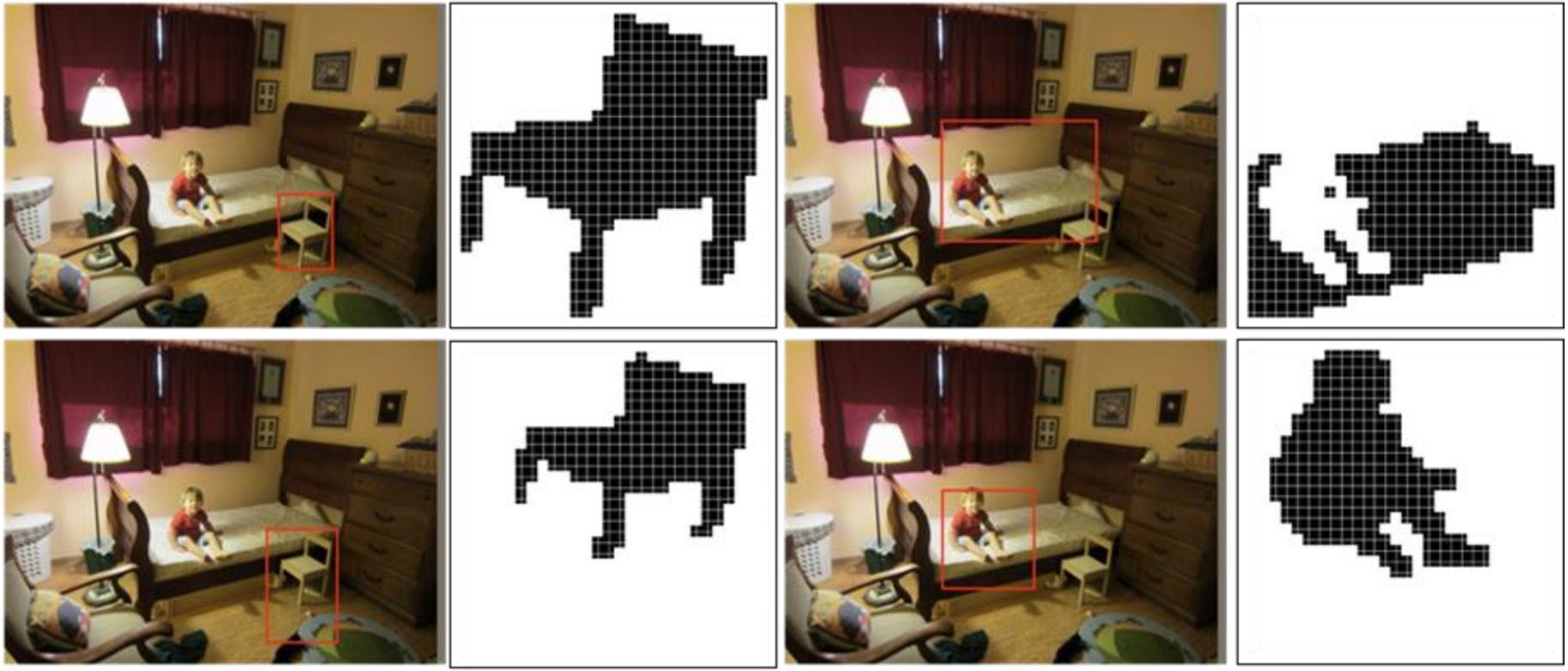
Mask R-CNN: Example Mask Training Targets



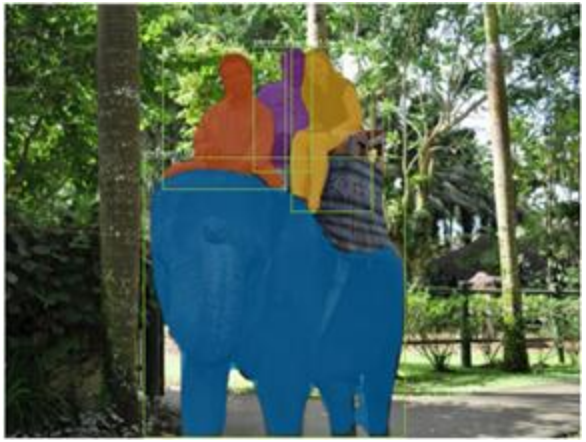
Mask R-CNN: Example Mask Training Targets



Mask R-CNN: Example Mask Training Targets

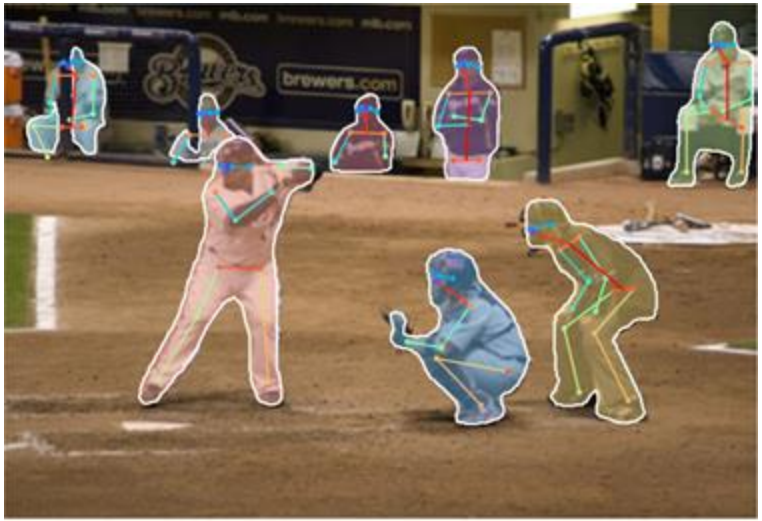


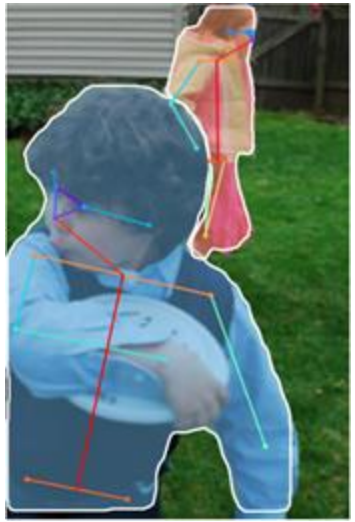
Mask R-CNN: Very Good Results!



He et al, “Mask R-CNN”, ICCV 2017

Mask R-CNN
Also does pose

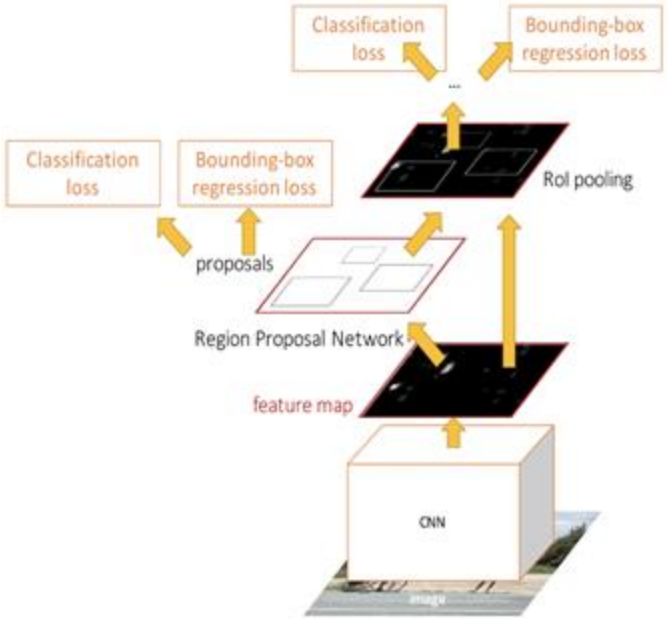




He et al, “Mask R-CNN”, ICCV 2017

RCNN Series

- **R-CNN**: Per-region detection, hand-crafted region proposal
- **Fast R-CNN**: Shared feature extraction, RoI Pooling, Anchors
- **Faster R-CNN**: Region Proposal Networks, RoI Align
- **Mask R-CNN**: Instance Segmentation



Detectors are becoming more complex!
Many hyperparameters to tune for each components …
Can we simplify it?

End-to-End Object Detection with Transformers

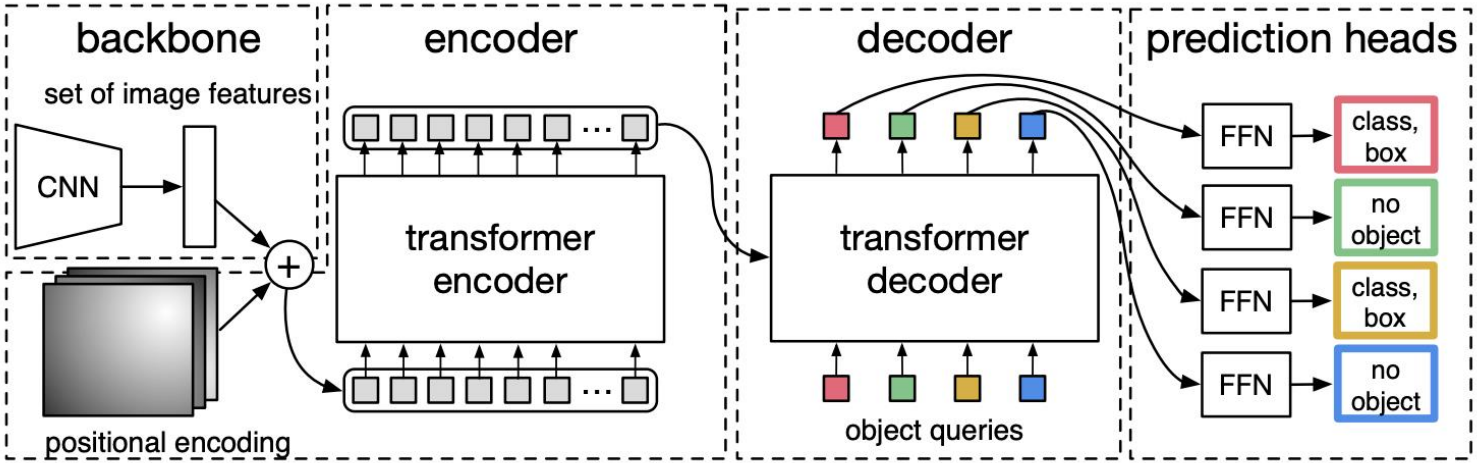
Nicolas Carion*, Francisco Massa*, Gabriel Synnaeve, Nicolas Usunier,
Alexander Kirillov, and Sergey Zagoruyko

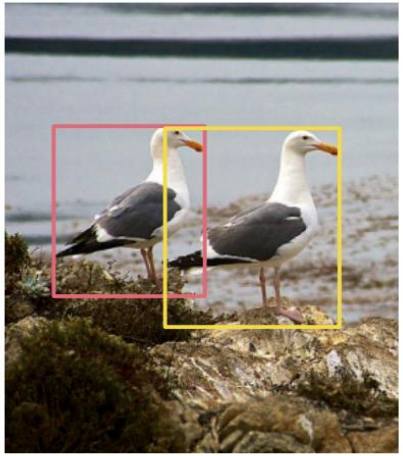
Facebook AI

Key ideas:

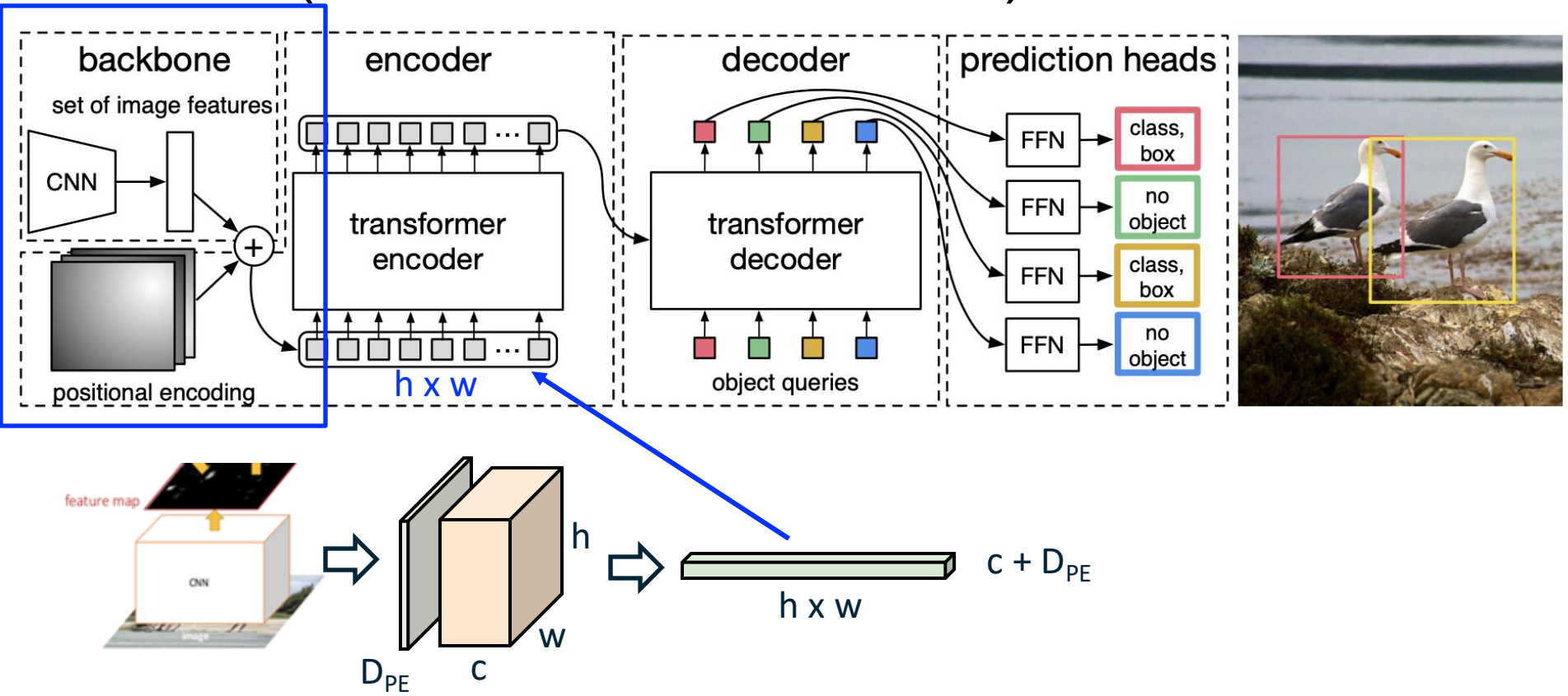
- Detection as a **set-to-set prediction** problem
- Use Transformer to model the detection problem

DETR (DEtection TRansformer)

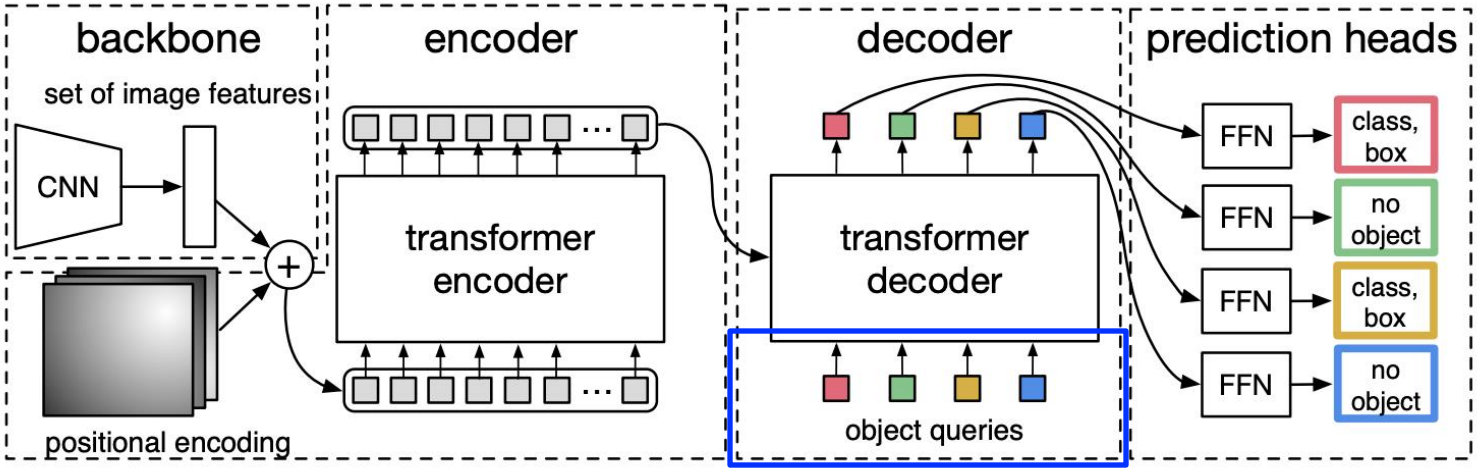


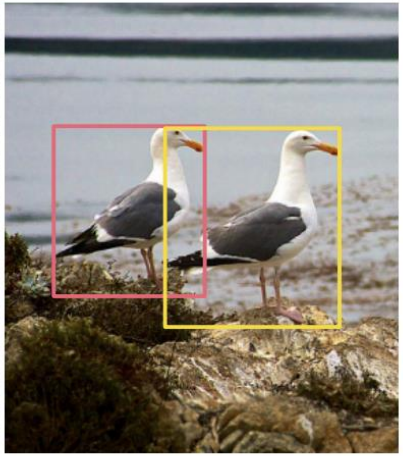


DETR (DEtection TRansformer)



DETR (DEtection TRansformer)

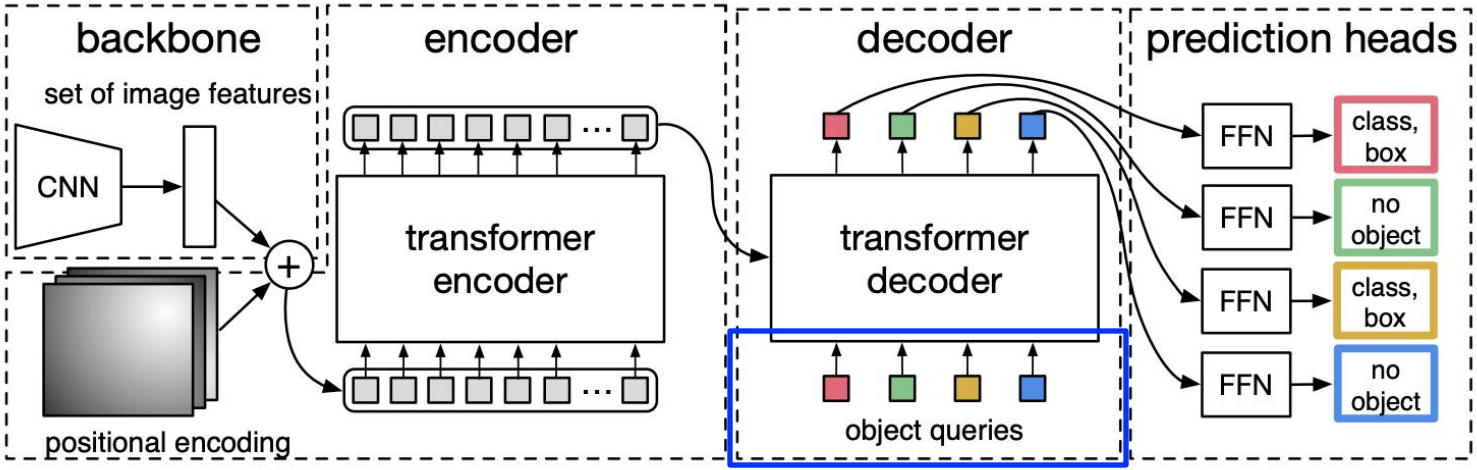


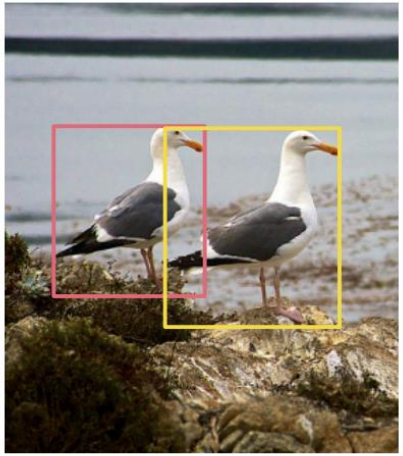


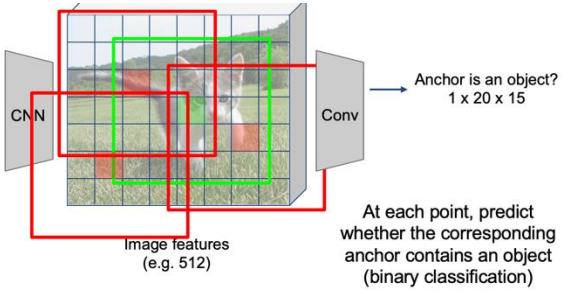
A fixed set of *learnable embeddings*,
e.g., 300 size-N vectors

Q: Why?

DETR (DEtection TRansformer)







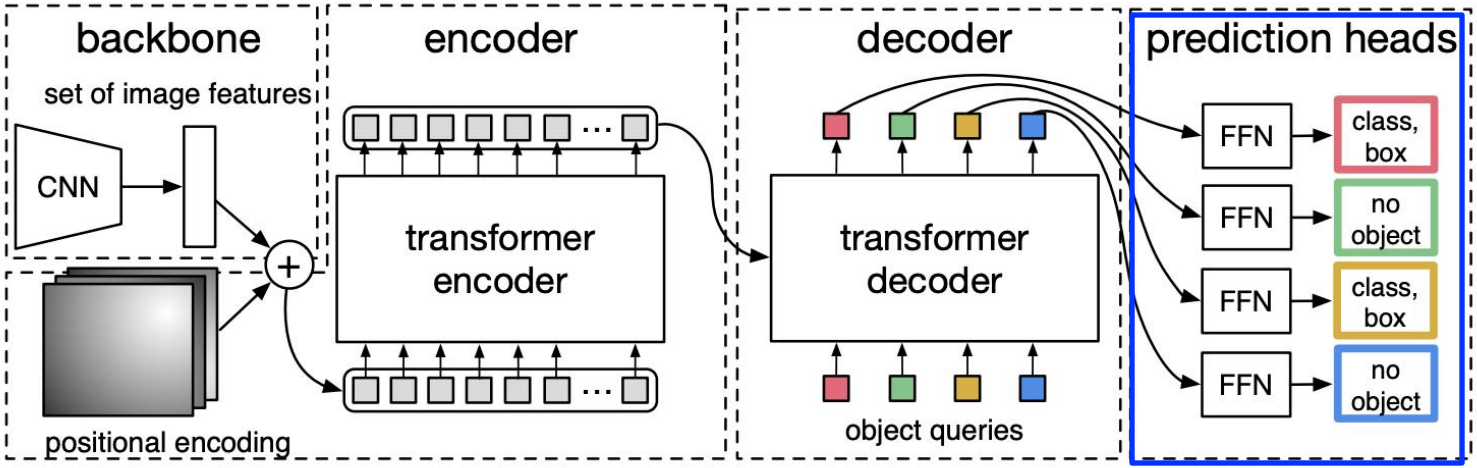
A fixed set of learnable embeddings, e.g., 300 size-N vectors

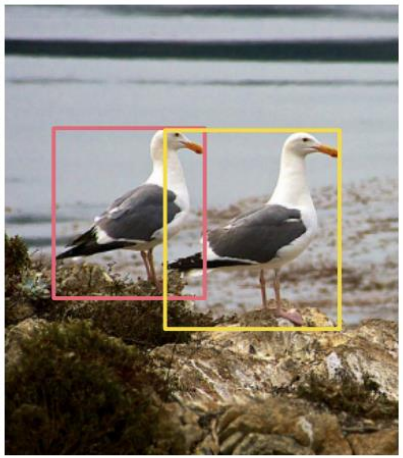
Q: Why?

A: Break the symmetry of predictions, so that each prediction is different.

Analogous to anchors in *R-CNN, but **no spatial location**

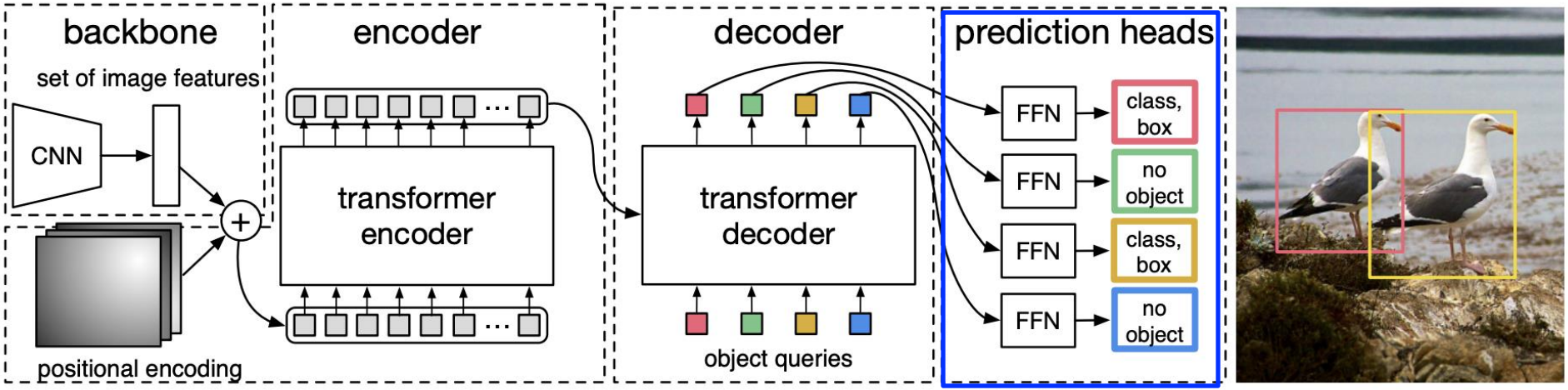
DETR (DEtection TRansformer)





Problem: We don't know which query corresponds to which ground truth during training! We can't predetermine a fixed order like in sequence decoding.

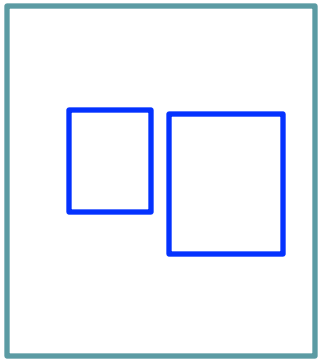
DETR (DEtection TRansformer)



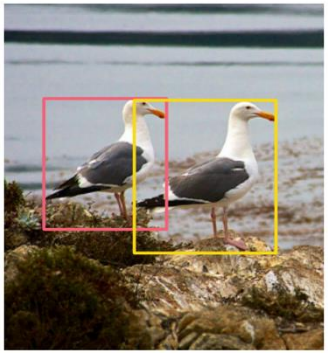
Problem: We don't know which query corresponds to which ground truth during training! We can't predetermine a fixed order like in sequence decoding.

Solution: Set matching loss --- train your model to generate a set of predictions that matches ground truth regardless of its order.

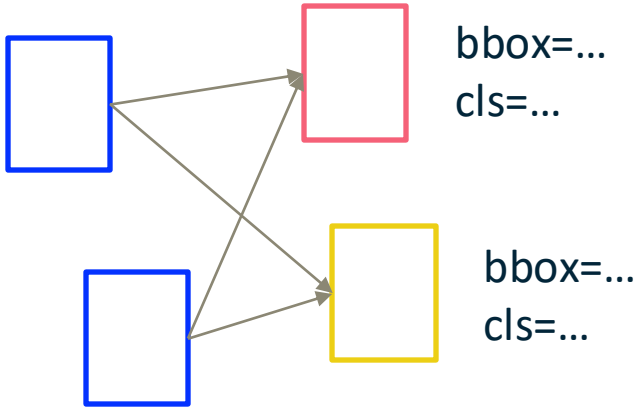
Hangarian Loss (Set Matching Loss)



Prediction



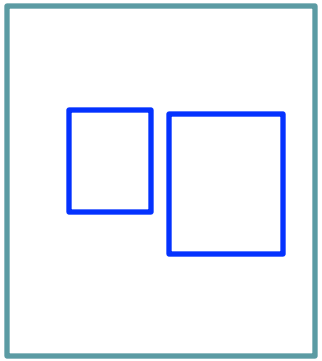
Ground Truth



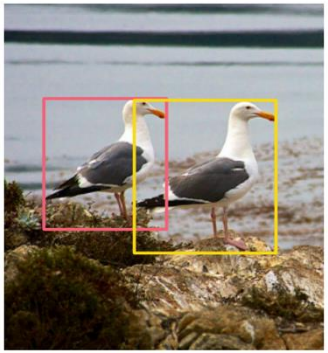
Goal: minimize bipartite distance

Problem: each query should be trained to match one ground truth. We don’t know the matching!

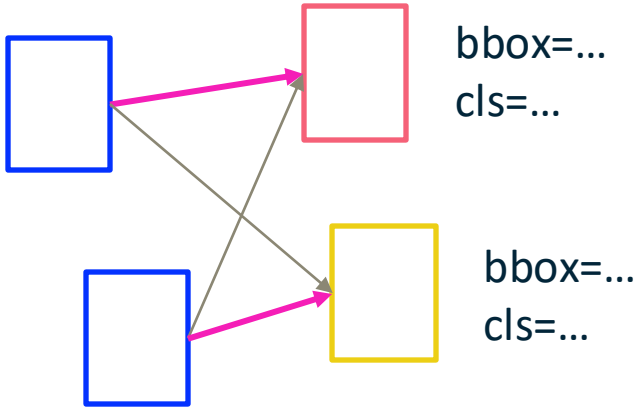
Hangarian Loss (Set Matching Loss)



Prediction



Ground Truth



Goal: minimize bipartite distance

1. **Hungarian matching:** find the minimum-loss bipartite matching between prediction and ground truth given the current prediction.
2. **Minimize matched loss:** Given the matched prediction and ground truth, minimize the detection loss (bounding box distance and classification CE loss)

DETR vs. FasterRCNN

Model	GFLOPS/FPS	#params	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Faster RCNN-DC5	320/16	166M	39.0	60.5	42.3	21.4	43.5	52.5
Faster RCNN-FPN	180/26	42M	40.2	61.0	43.8	24.2	43.5	52.0
Faster RCNN-R101-FPN	246/20	60M	42.0	62.5	45.9	25.2	45.6	54.6
Faster RCNN-DC5+	320/16	166M	41.1	61.4	44.3	22.9	45.9	55.0
Faster RCNN-FPN+	180/26	42M	42.0	62.1	45.5	26.6	45.4	53.4
Faster RCNN-R101-FPN+	246/20	60M	44.0	63.9	**47.8**	**27.2**	48.1	56.0
DETR	86/28	41M	42.0	62.4	44.2	20.5	45.8	61.1
DETR-DC5	187/12	41M	43.3	63.1	45.9	22.5	47.3	61.1
DETR-R101	152/20	60M	43.5	63.8	46.4	21.9	48.0	61.8
DETR-DC5-R101	253/10	60M	**44.9**	**64.7**	47.7	23.7	**49.5**	**62.3**

Similar size, simpler, and (mostly) better!

We are still detecting a fixed number of object with finite vocabulary …

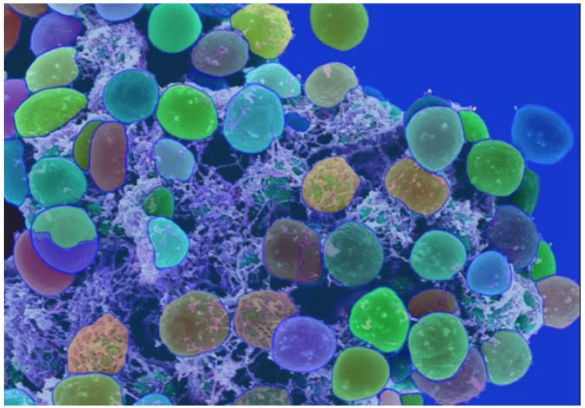
Segment Anything

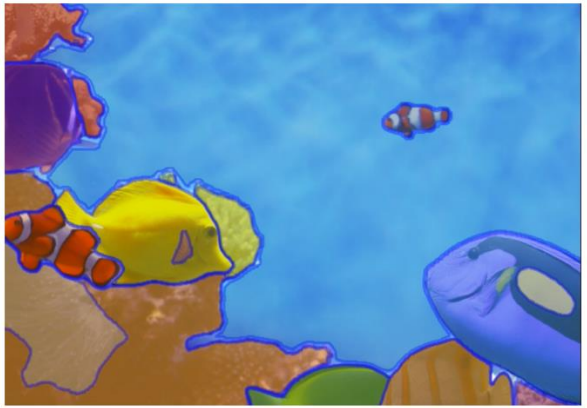
Alexander Kirillov[1,2,4] Eric Mintun[2] Nikhila Ravi[1,2] Hanzi Mao[2] Chloe Rolland[3] Laura Gustafson[3]
Tete Xiao[3] Spencer Whitehead Alexander C. Berg Wan-Yen Lo Piotr Dollár[4] Ross Girshick[4]
[1]project lead [2]joint first author [3]equal contribution [4]directional lead
Meta AI Research, FAIR

Key ideas:

- Query-based prediction instead of fixed set-to-set prediction
- Large-scale training data with auto-labeling

Foundation Image Segmentation Models





SegmentAnything (Meta AI, 2023)

Try it yourself! https://segment-anything.com/demo#

Foundation Image Segmentation Models

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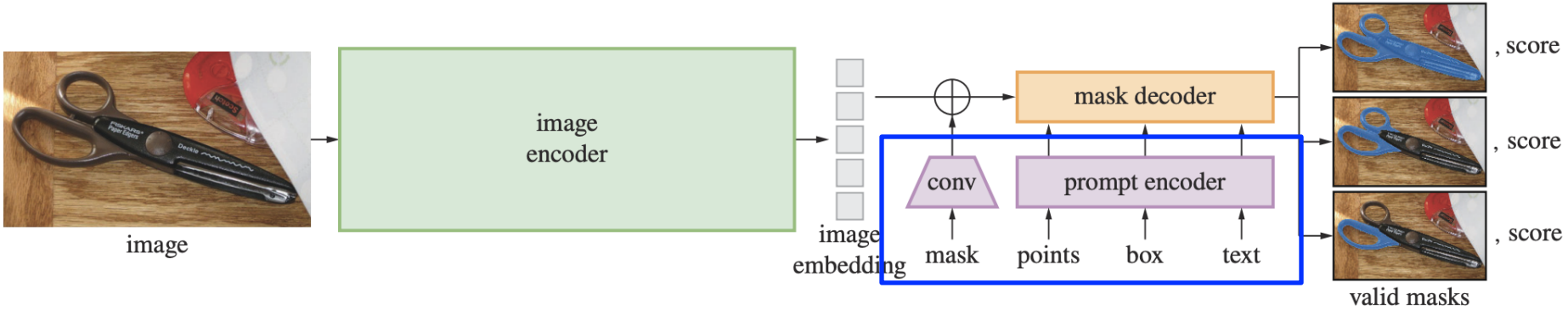
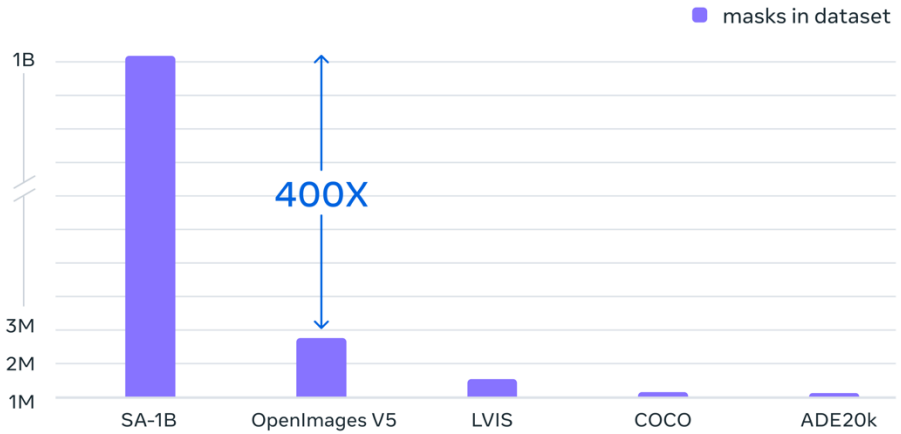
Foundation Image Segmentation Models

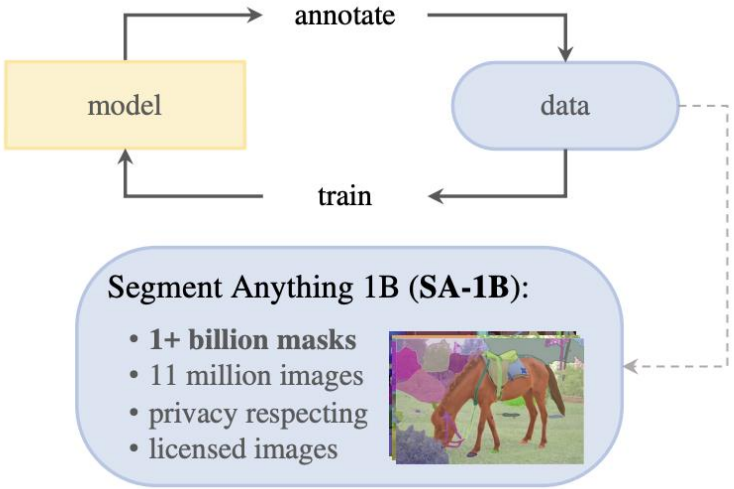


No more learned embeddings. Query anything you want!

SegmentAnything (Meta AI, 2023)

Foundation Image Segmentation Models





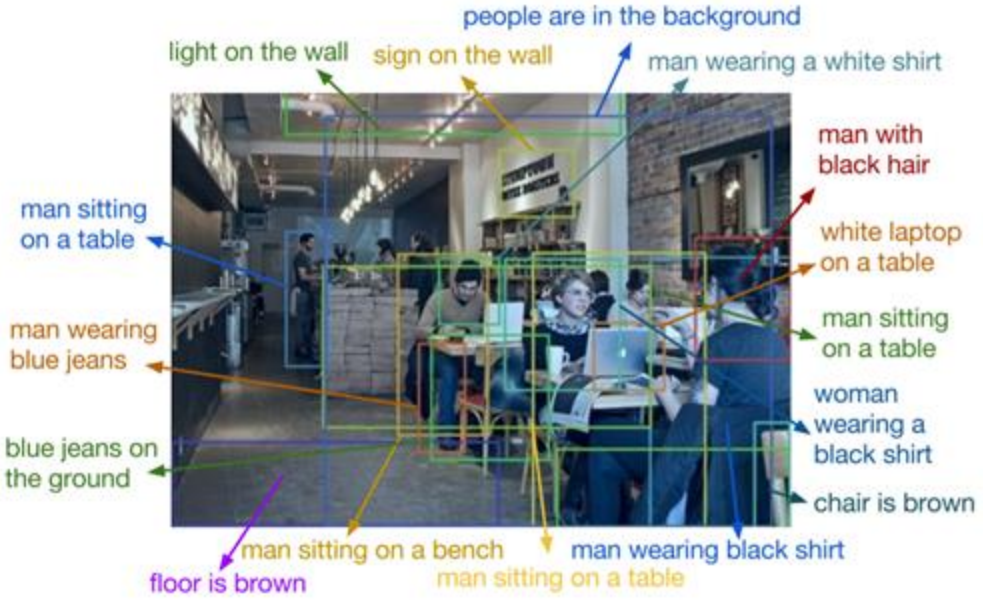
SegmentAnything (Meta AI, 2023)

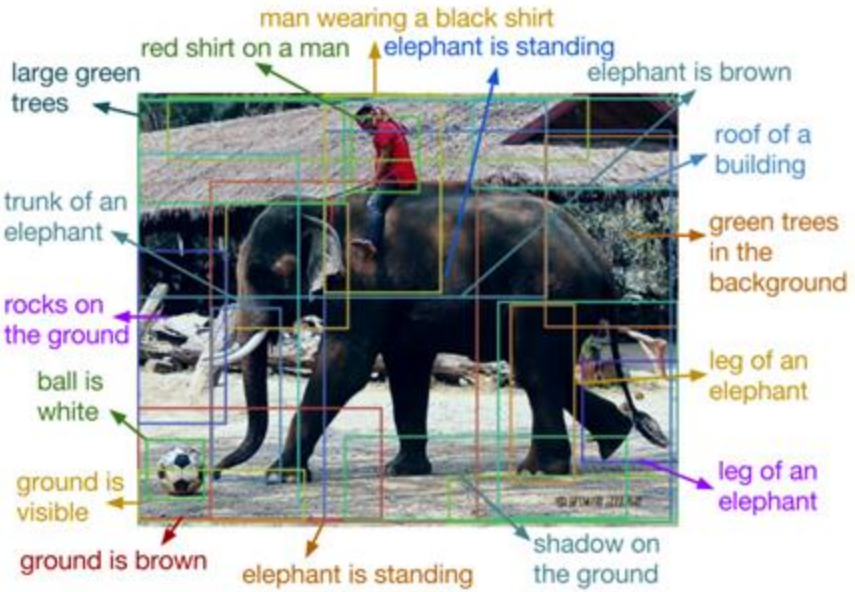
Summary: Segmentation and Detection

- Object segmentation and detection are most common application of computer vision research.
- They have driven decades of advancement in Autonomous Vehicles, Robotics, traffic analytics, and basically any devices that have camera and adequate computing power (e.g., Smart Phone)
- Segmentation and Detection with DNNs evolved through similar paths (sliding window, feature sharing, input-output, alignment etc.)
- We have a new wave of foundation detection and segmentation models driven by Transformer + ConvNet + large dataset

Beyond 2D Object Detection...

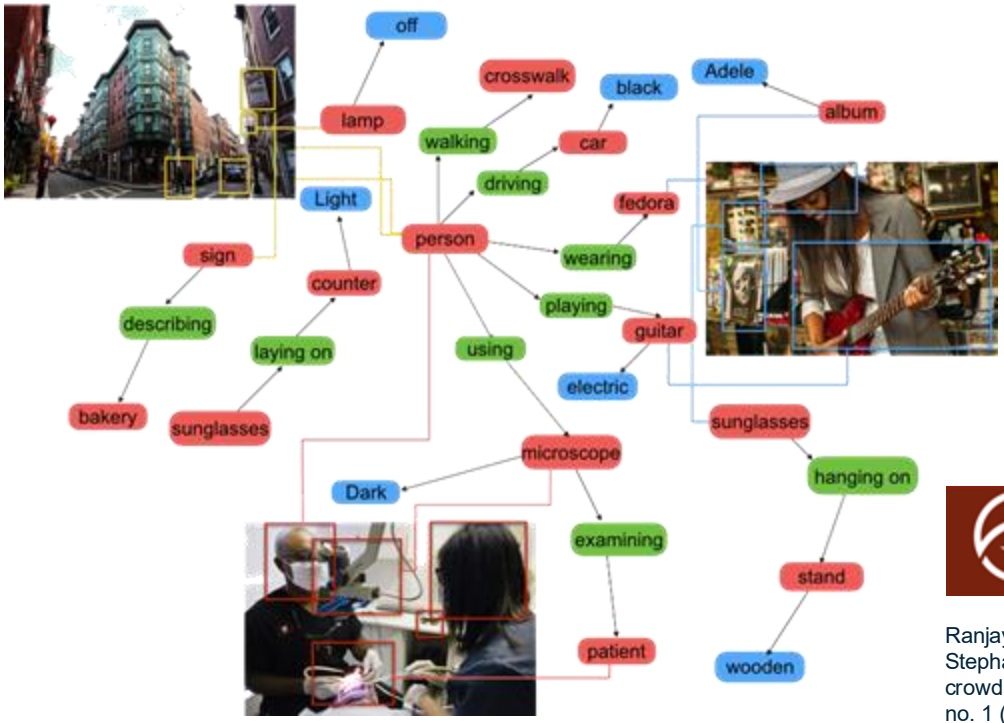
Object Detection + Captioning = Dense Captioning





Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016

Objects + Relationships = Scene Graphs

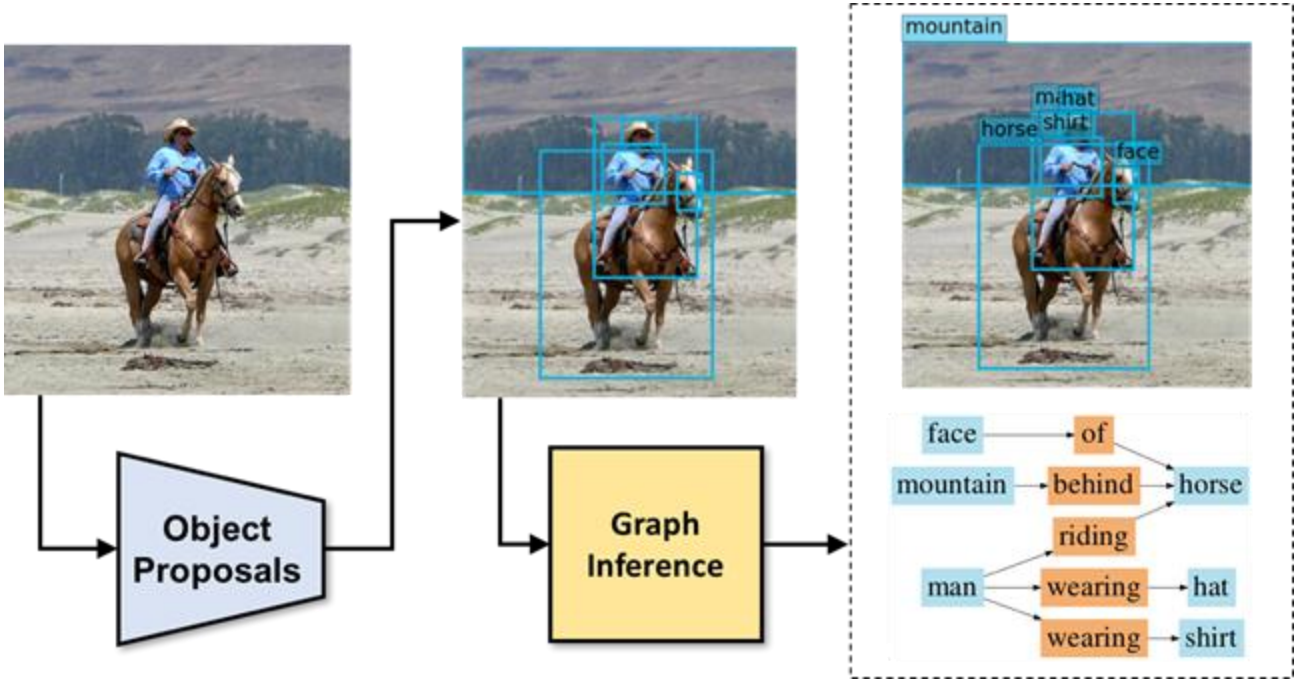


108,077 Images
5.4 Million Region Descriptions
1.7 Million Visual Question Answers
3.8 Million Object Instances
2.8 Million Attributes
2.3 Million Relationships
Everything Mapped to Wordnet Synsets

VISUALGENOME

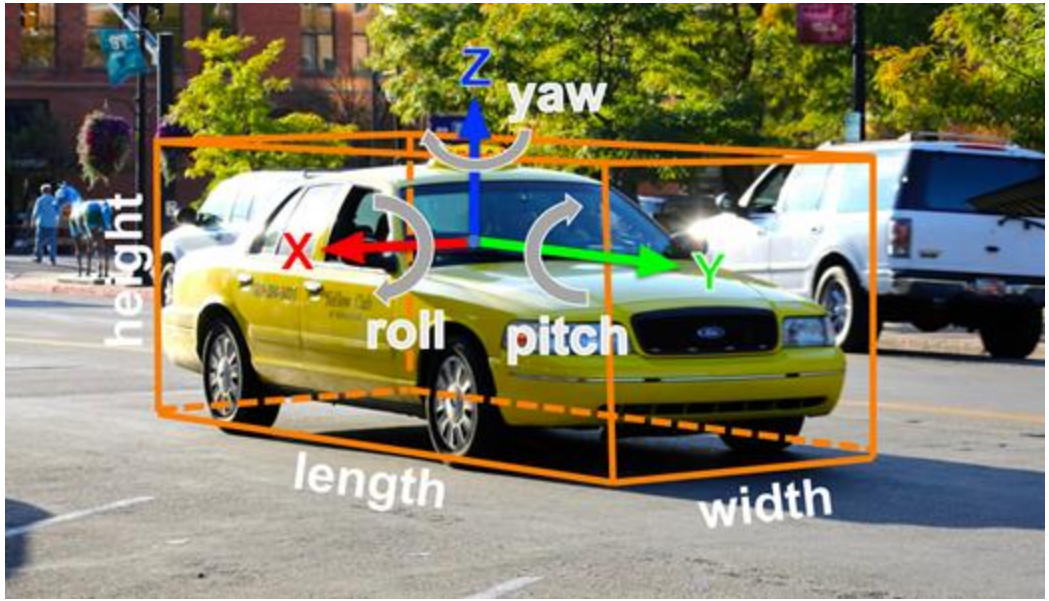
Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen et al. "Visual genome: Connecting language and vision using crowdsourced dense image annotations." International Journal of Computer Vision 123, no. 1 (2017): 32-73.

Scene Graph Prediction



Xu, Zhu, Choy, and Fei-Fei, “Scene Graph Generation by Iterative Message Passing”, CVPR 2017

3D Object Detection



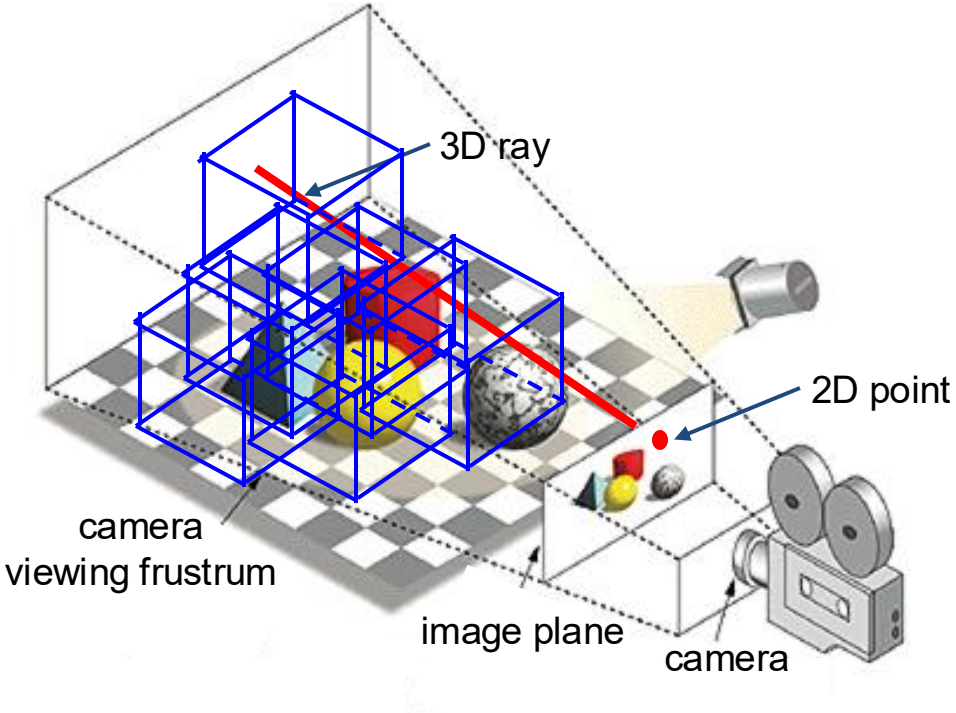
2D Object Detection:
2D bounding box
(x, y, w, h)

3D Object Detection:
3D oriented bounding box
(x, y, z, w, h, l, r, p, y)

Simplified bbox: no roll & pitch

Much harder problem than 2D object detection!

3D Object Detection: Simple Camera Model



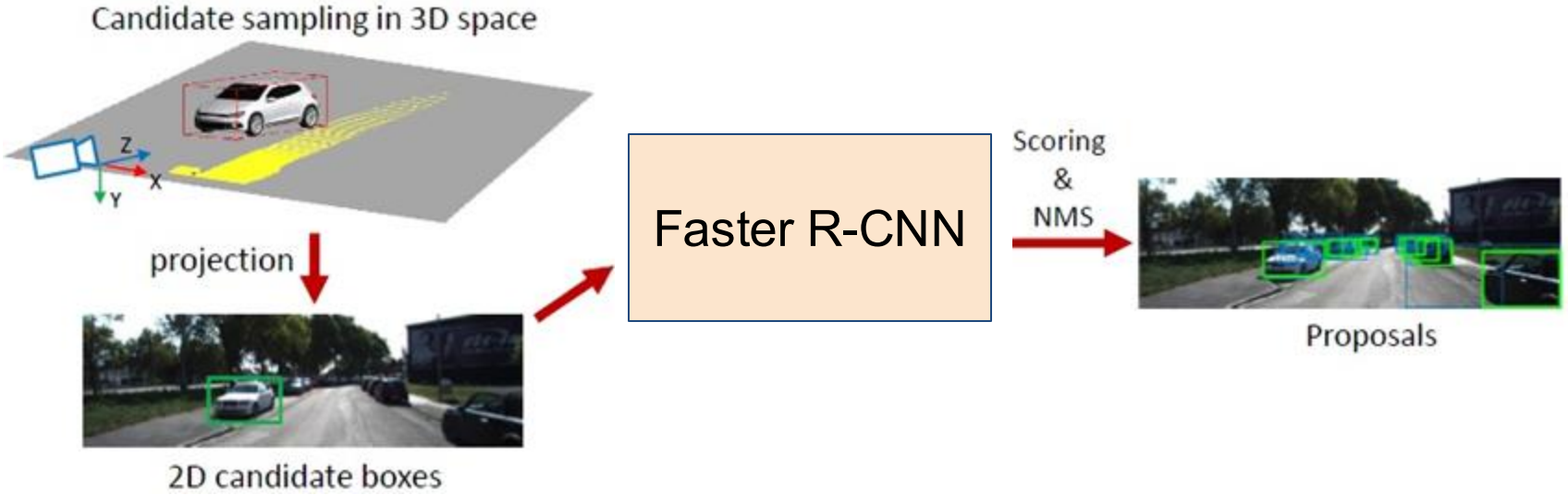
A point on the image plane corresponds to a **ray** in the 3D space

A 2D bounding box on an image is a **frustrum** in the 3D space

Localize an object in 3D:
The object can be anywhere in the **camera viewing frustrum**!

Image source: https://www.pcmag.com/encyclopedia_images/_FRUSTUM.GIF

3D Object Detection: Monocular Camera



- Same idea as Faster RCNN, but proposals are in 3D
- 3D bounding box proposal, regress 3D box parameters + class score

Chen, Xiaozhi, Kaustav Kundu, Ziyu Zhang, Huimin Ma, Sanja Fidler, and Raquel Urtasun. "Monocular 3d object detection for autonomous driving." CVPR 2016.

How to Represent 3D Data?

```
[[105 112 108 111 104  99 106  99  96 103 112 119 104  97  93  87]
 [ 91  98 102 106 104  79  98 103  99 105 123 136 110 105  94  85]
 [ 76  85  90 105 120 105  87  96  95  99 115 112 106 103  99  85]
 [ 99  81  81  93 120 131 127 100  95  98 102  99  96  93 101  94]
 [106  91  61  64  69  91  88  85 101 107 109  98  75  84  96  95]
 [114 108  85  55  55  69  64  54  64  87 113 129  98  74  84  91]
 [133 137 147 103  65  81  80  65  52  54  74  84 102  93  85  82]
 [120 137 144 140 109  95  86  70  62  65  63  63  60  73  86 101]
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 [127 125 131 147 133 127 126 131 111  96  89  75  61  64  72  84]
 [115 114 109 123 150 148 131 118 113 109 100  92  74  65  72  78]
 [ 89  93  90  97 108 147 131 118 113 114 113 109 106  95  77  80]
 [ 63  77  86  81  77  79 102 123 117 115 117 125 125 130 115  87]
 [ 62  65  82  89  78  71  80 101 124 126 119 101 107 114 131 119]
 [ 63  65  75  88  89  71  62  81 120 138 135 105  81  98 110 118]
 [ 87  65  71  87 106  95  69  45  76 130 126 107  92  94 105 112]
 [118  97  82  86 117 123 116  66  41  51  95  93  89  95 102 107]
 [164 146 112  80  82 120 124 104  76  48  45  66  88 101 102 109]
 [157 170 157 120  93  86 114 132 112  97  69  55  70  82  99  94]
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 [123 107  96  86  83 112 153 149 122 109 104  75  80 107 112  99]
 [122 121 102  80  82  86  94 117 145 148 153 102  58  78  92 107]
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```
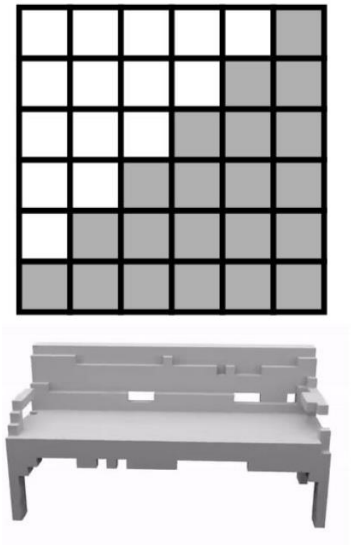
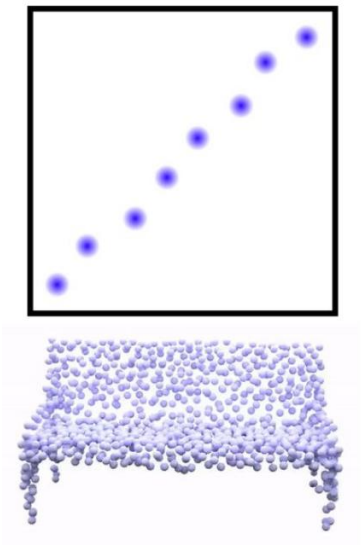

?

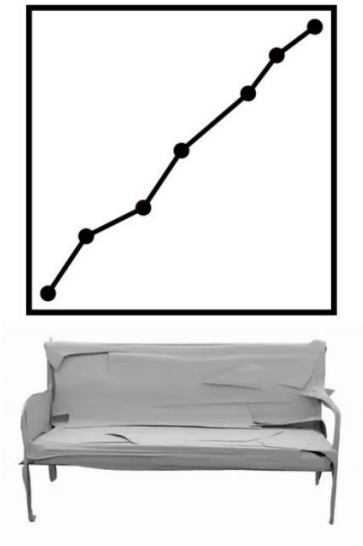
3D Representations



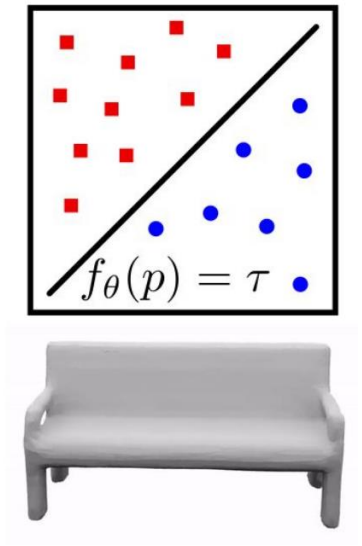
Occupancy Grid
[h, w, l]



Point Cloud
[num_pts, 3]



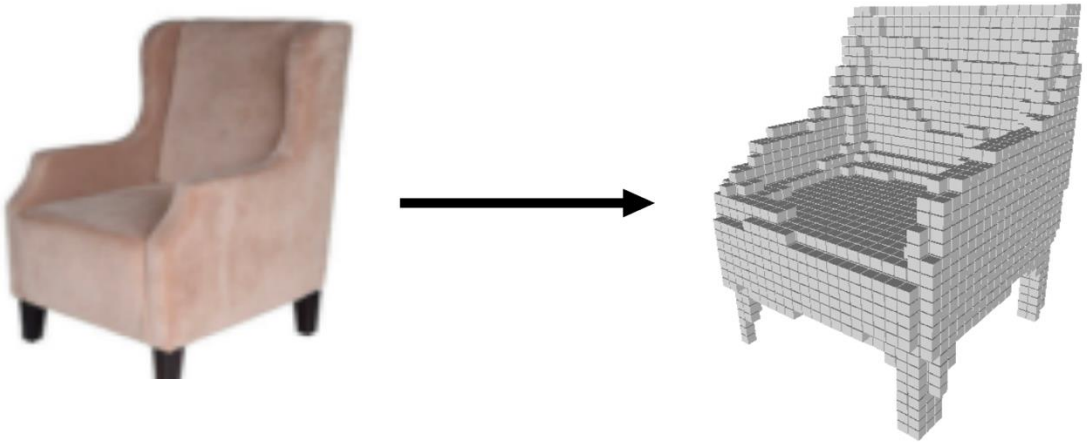
Surface Mesh
(edge list, face list, vertex list)



Implicit Functions
(x, y, z -> d)

Figure credit: Autonomous Vision Group

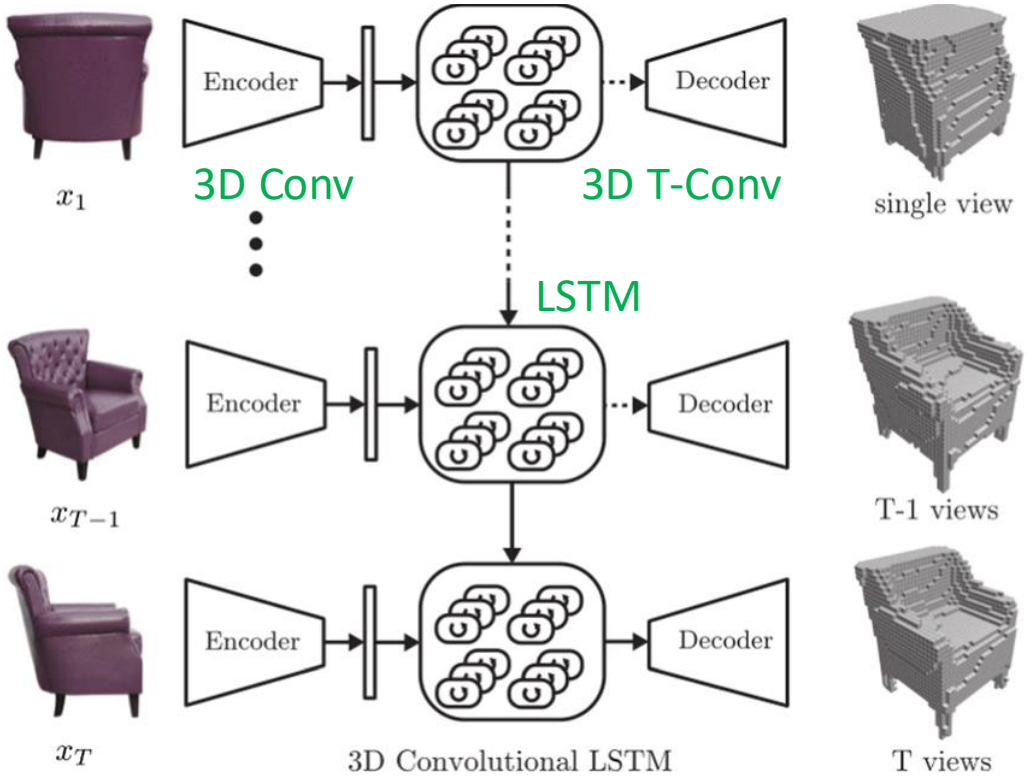
3D Occupancy Grid



Represent the “occupancy” of objects in 3D space with a 3D voxel grid

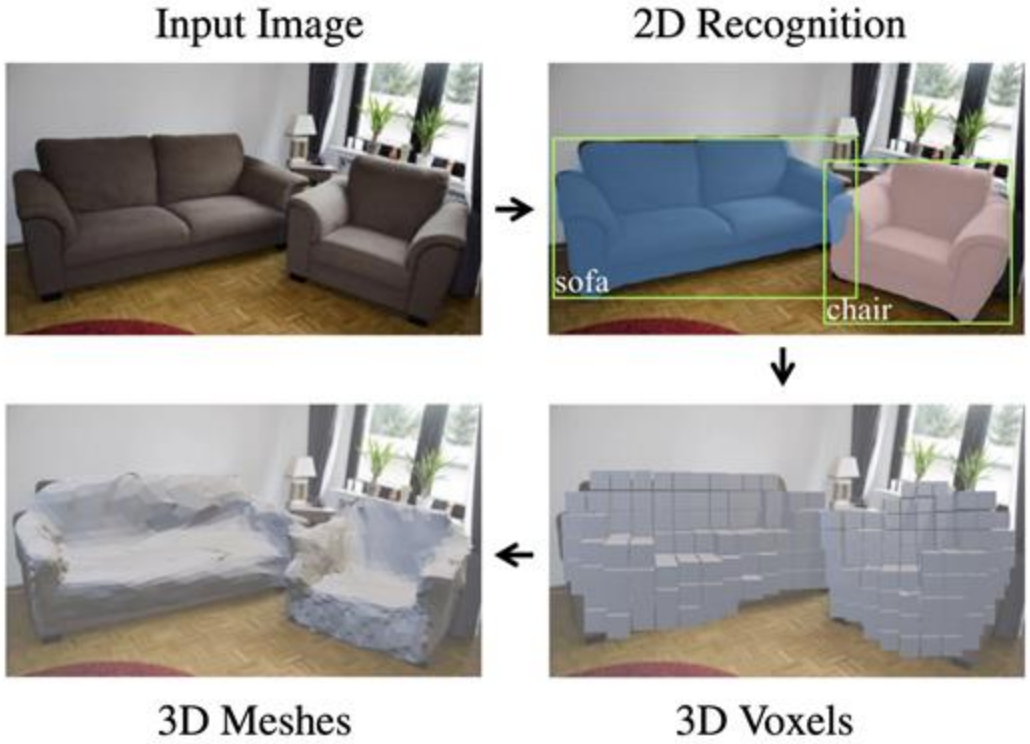
- $V \in \{0,1\}^{[H,W,L]}$
- Just like segmentation in Masked-RCNN, but in 3D!
- Conceptually simple
- Not trivial to scale to high-resolution shapes

Predicting 3D Voxel Grid with 3D ConvNet



Cho et al. 2016, 3D-R2N2: A Unified Approach for Single and Multi-view 3D Object Reconstruction

Detection + Reconstruction: Mesh R-CNN



Gkioxari et al., Mesh RCNN, ICCV 2019

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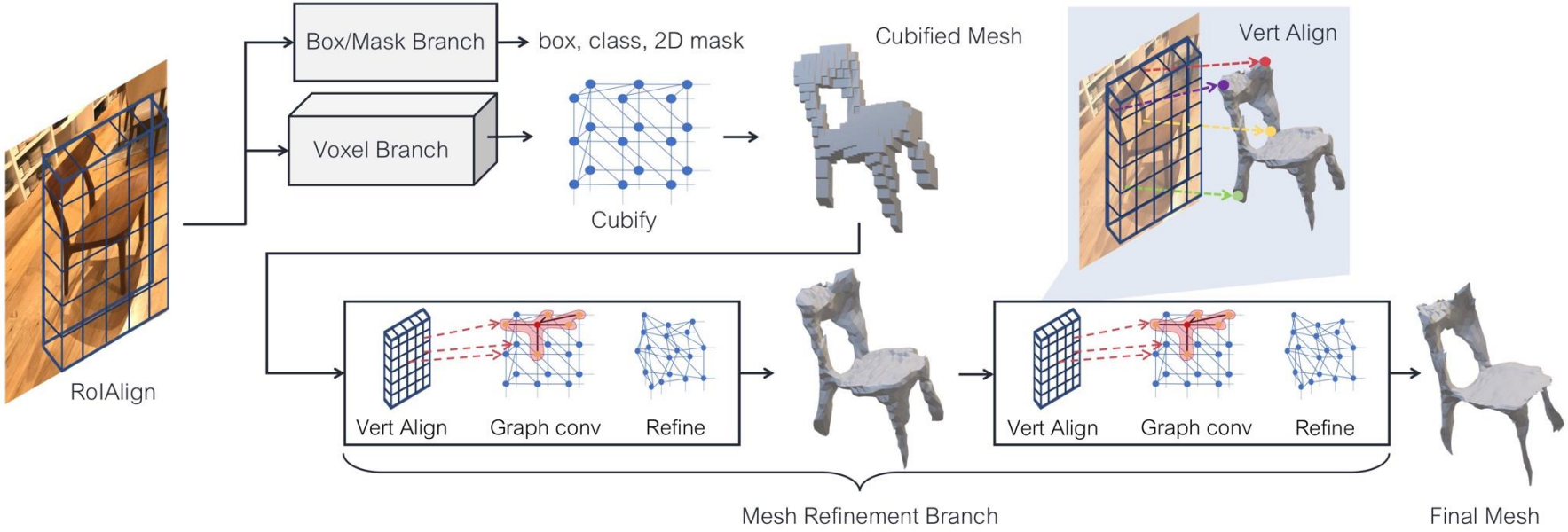
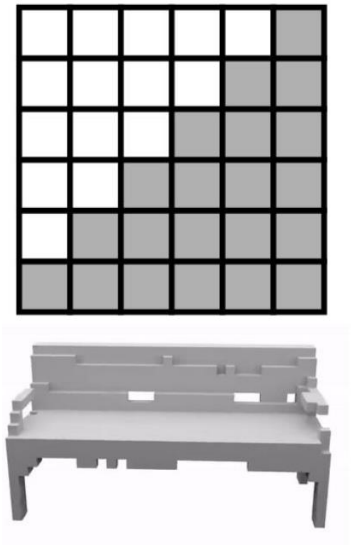
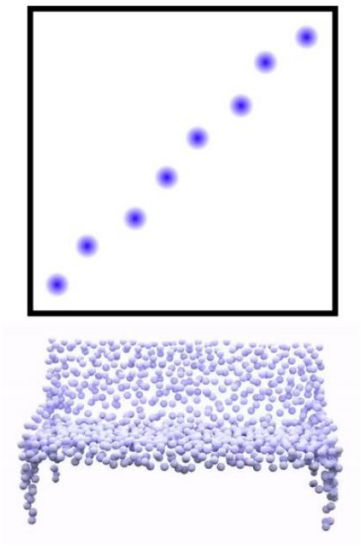


Gkioxari et al., Mesh RCNN, ICCV 2019

3D Representations



Occupancy Grid
[h, w, l]



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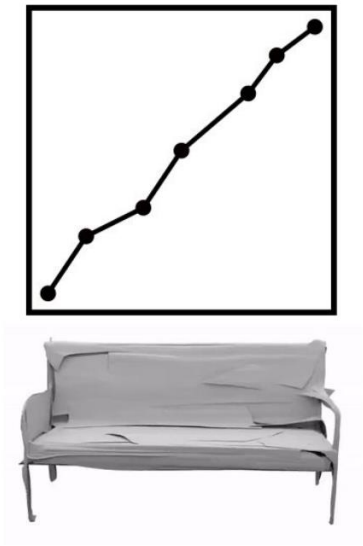

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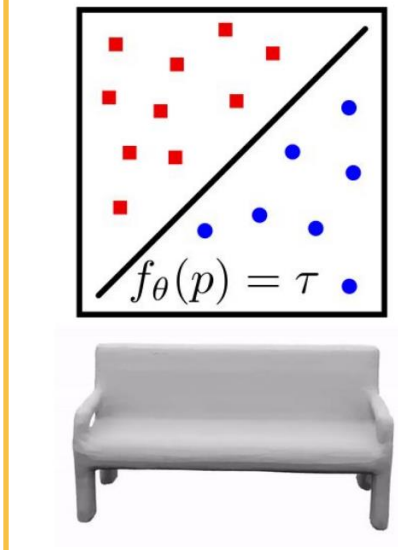
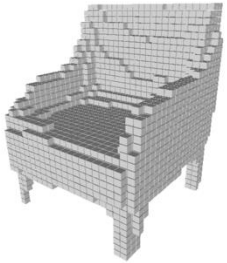


Implicit Functions
(x, y, z -> d)

Figure credit: Justin Johnson

What is an implicit representation for 3D data?

Example: representing a 3D occupancy grid



Explicit: A tensor of **3D voxel grid** $V \in \{0,1\}^{[H,W,L]}$

Implicit: A **function** that maps locations to occupancies

$$F_\theta : x, y, z \rightarrow \{0,1\}$$

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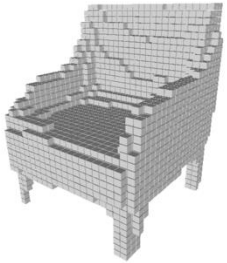

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Implicit representation describes 3D shapes using **mathematical functions** rather than explicit voxels, points, or mesh.

Example: Signed Distance Function

$$F_\theta : \mathbb{R}^3 \rightarrow \mathbb{R}$$

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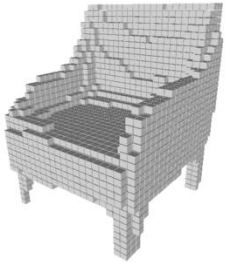

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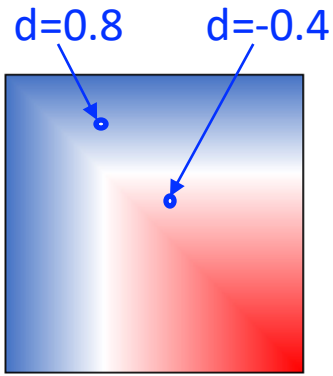
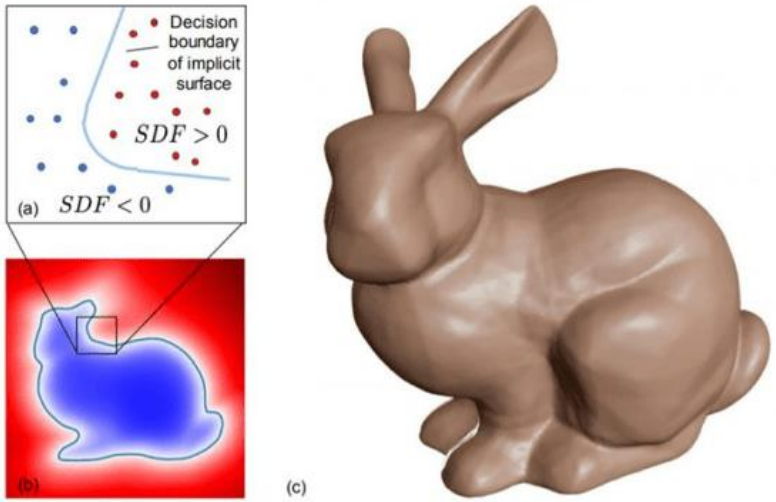


SDF distance map

How far is a point from the nearest surface, and is the point *inside or outside* of the shape?

What is an implicit representation for 3D data?



DeepSDF representation applied to the Stanford Bunny: (a) depiction of the underlying implicit surface SDF = 0 trained on sampled points inside SDF < 0 and outside SDF > 0 the surface, (b) 2D cross-section of the signed distance field, (c) rendered 3D surface recovered from SDF = 0.

Can we train NNs to represent more than just geometry of a 3D shape?

Park et al., DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation

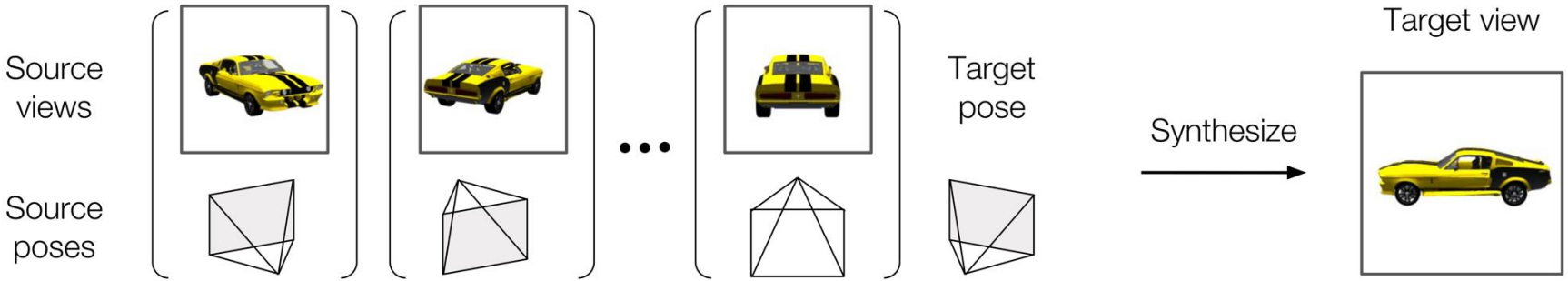
Implicit 3D Representation: Beyond Geometry

$$f_\theta(viewpoint) = Image$$

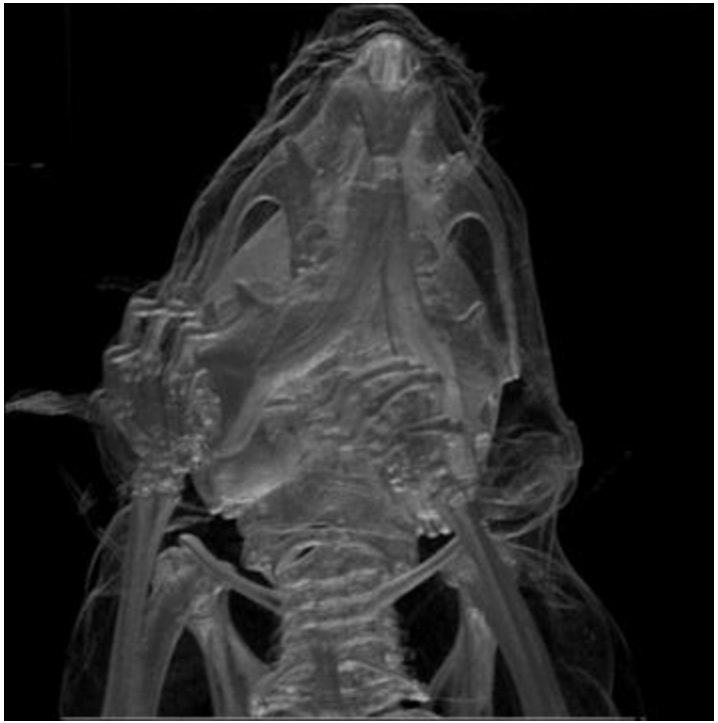
Goal: Learn an implicit 3D representation function that maps any camera viewpoint to full RGB images

Can we implicitly represent a full 3D scene, including its fine-grained geometry (e.g., surface occupancy) and appearance?

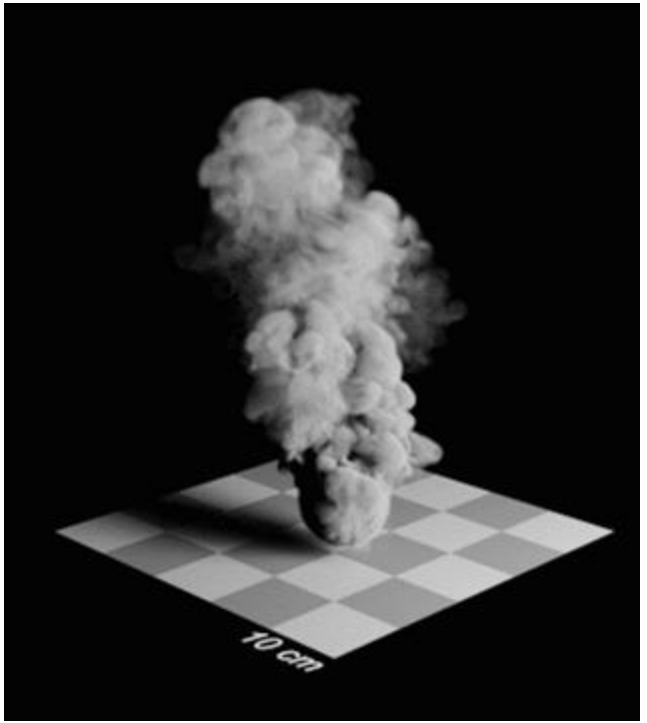
Problem: Novel View Synthesis



Basics: Volume Rendering

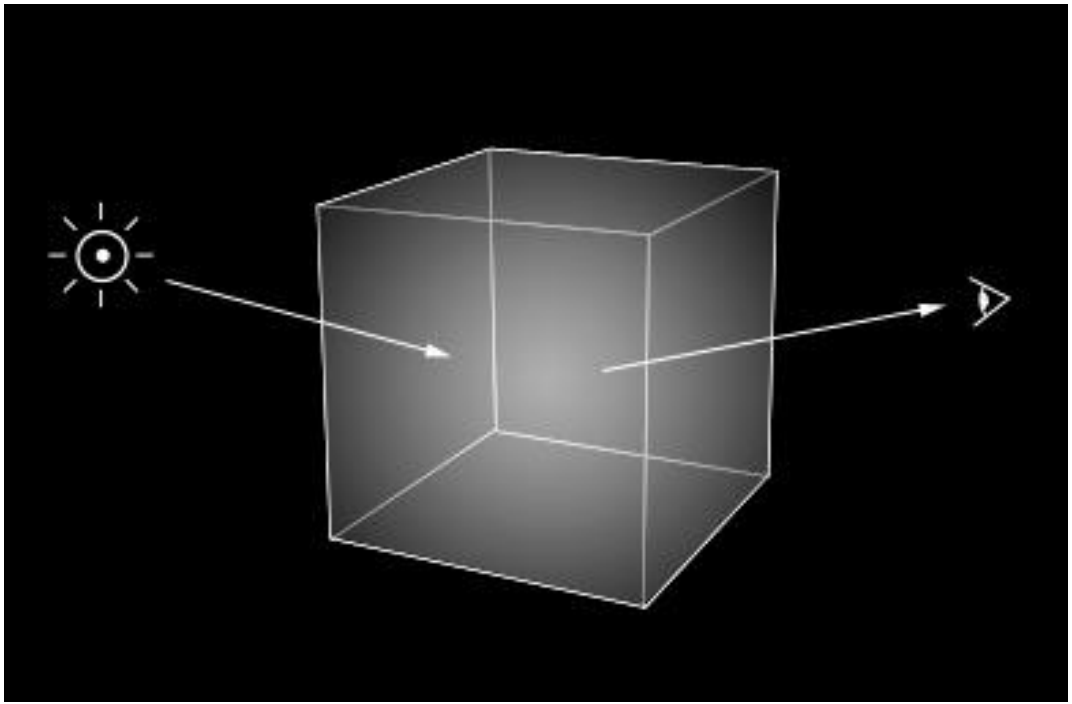


https://en.wikipedia.org/wiki/Volume_rendering



https://coronarenderer.freshdesk.com/support/solutions/articles/12000045276-how-to-use-the-corona-volume-grid-

Volume Rendering: Scene Representation



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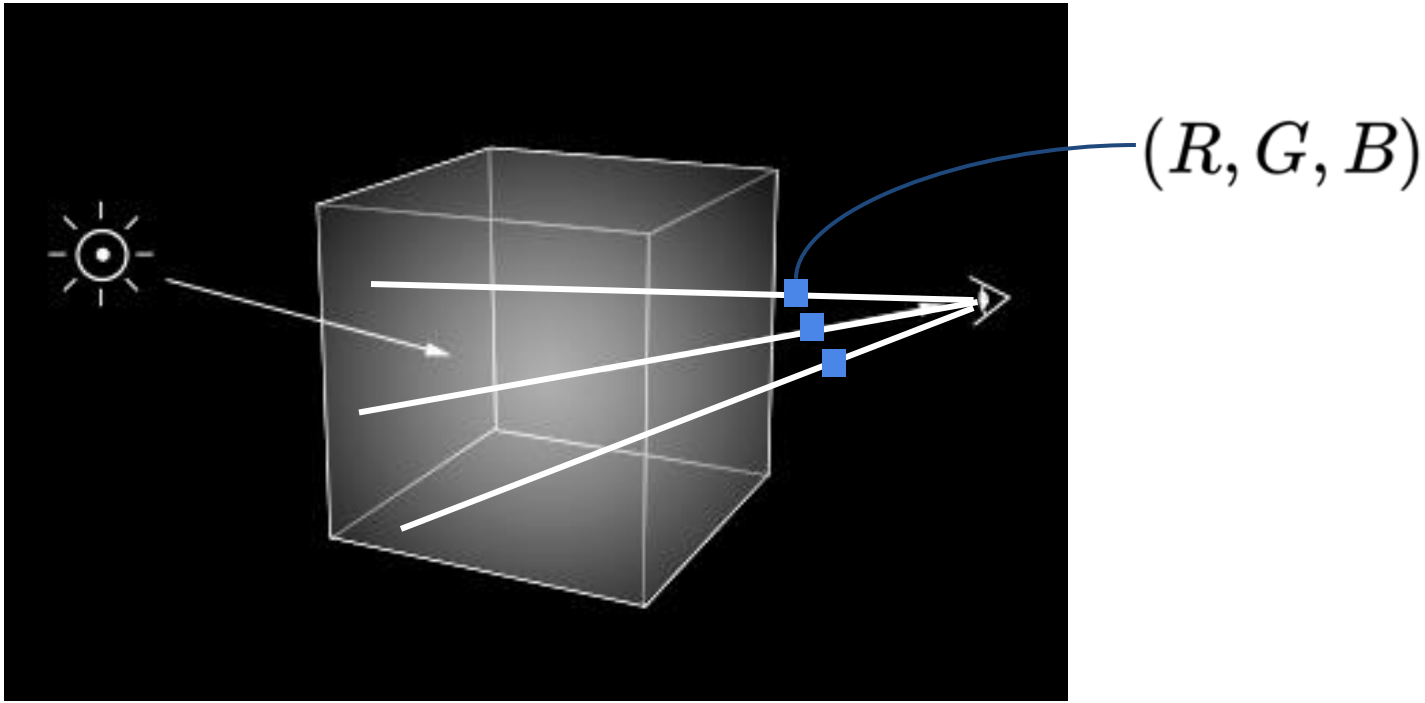
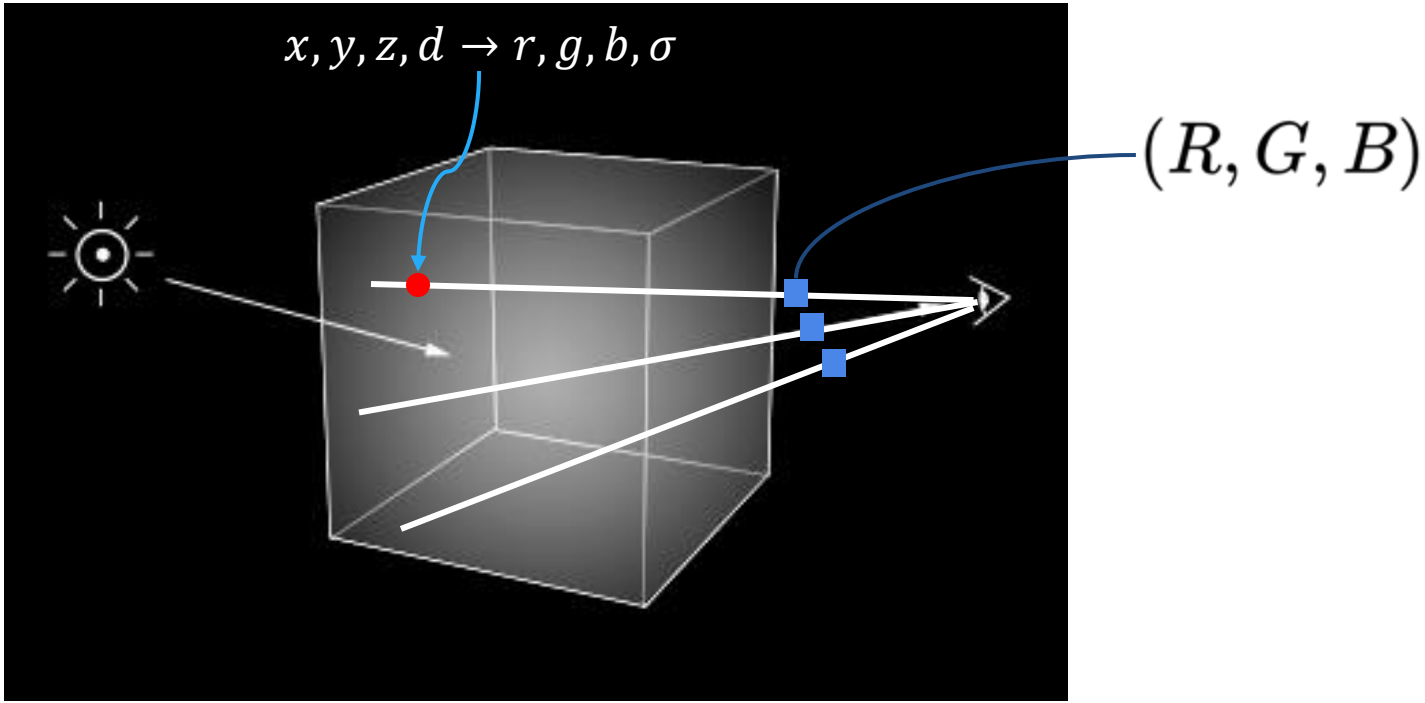


Volume Rendering: Scene Representation

Each location (x, y, z) emits certain color r, g, b when viewed with direction d.
We represent point occupancy continuously as density d.



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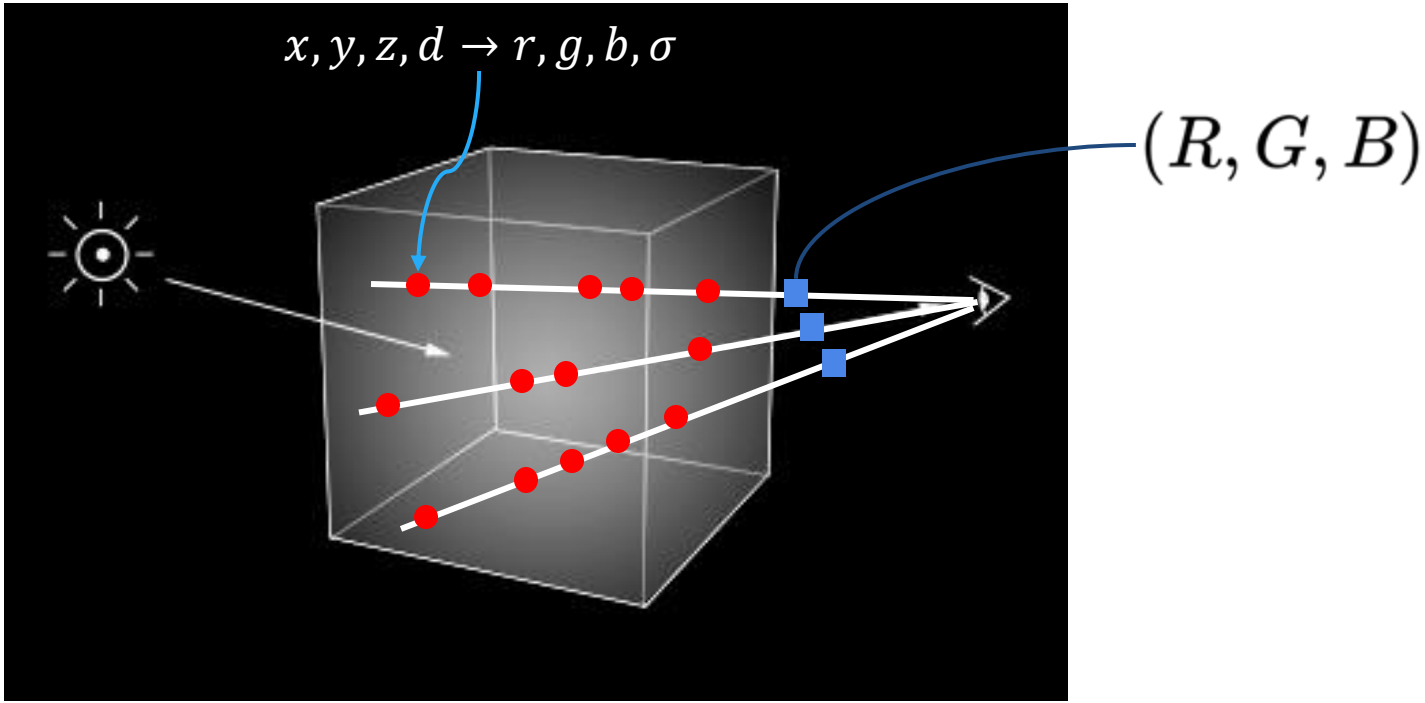
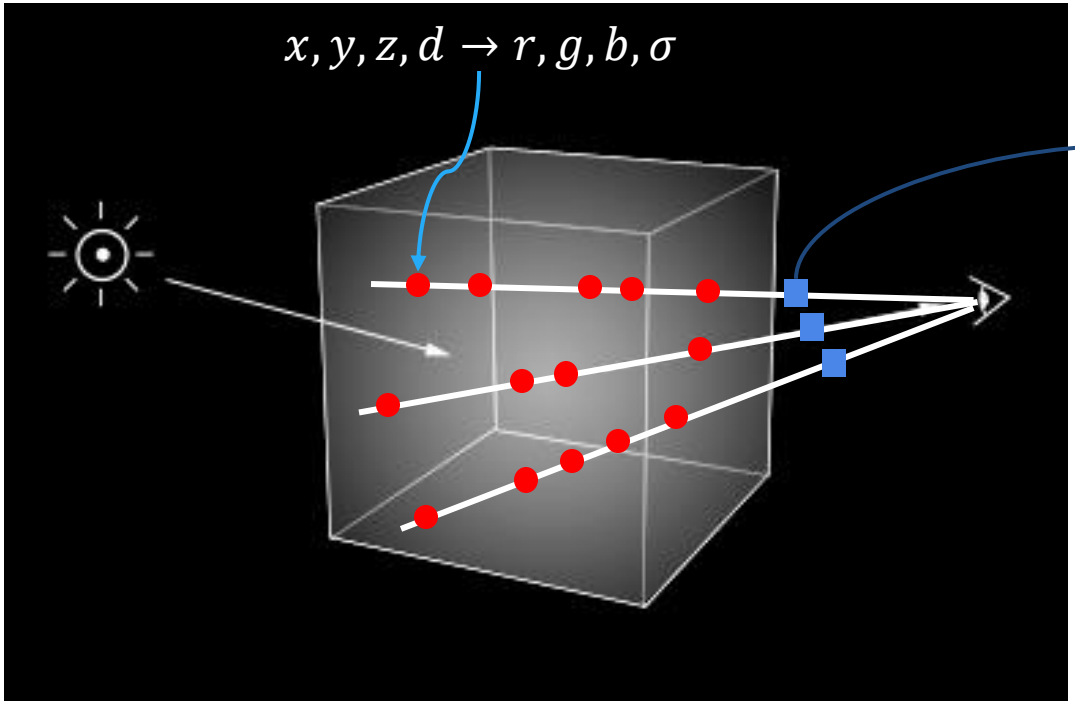
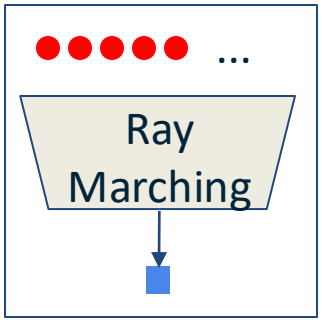


Volume Rendering: Ray Marching

Ray Marching: Integrate color and density of points along a ray (via discretization) to render an RGB value. Render many points -> An image!

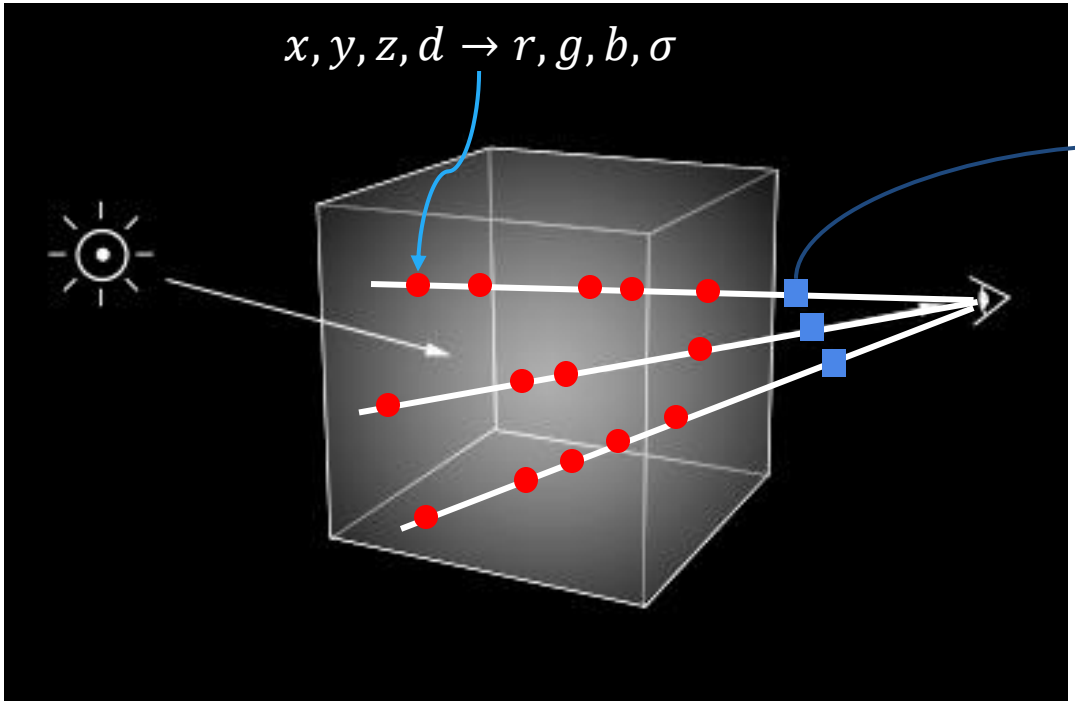


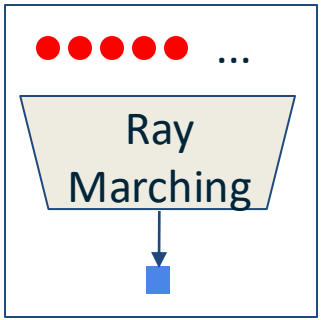


This is Differentiable!

Volume Rendering: Ray Marching

Idea: Train a neural network to represent the ray marching volume rendering function: $F_\theta(x, y, z, d) \rightarrow (r, g, b, \sigma)$. **Each NN encodes a 3D scene.**





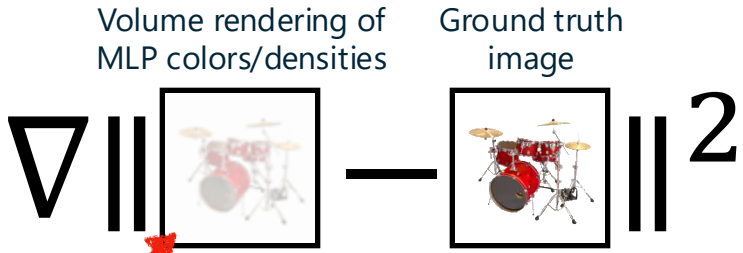
This is Differentiable!

NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis

Ben Mildenhall[1⋆] Pratul P. Srinivasan[1⋆] Matthew Tancik[1⋆]
Jonathan T. Barron[2] Ravi Ramamoorthi[3] Ren Ng[1]

[1]UC Berkeley [2]Google Research [3]UC San Diego

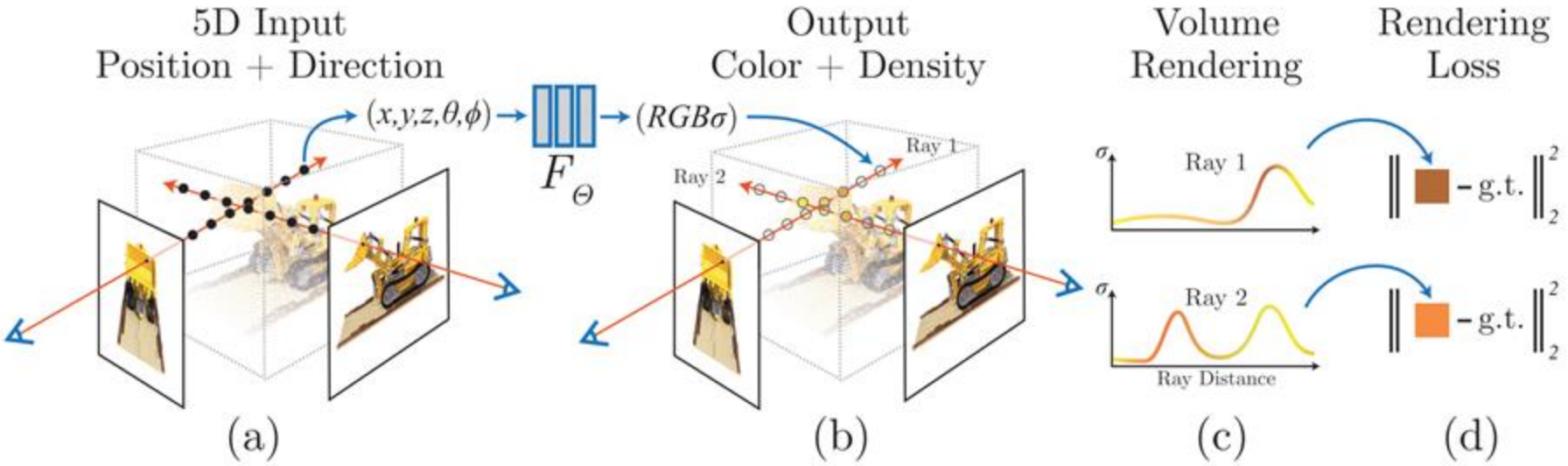
Train a Single Neural Network to Reproduce the Ground Truth Images of a Scene



$$F_\theta(x, y, z, d) = (r, g, b, \sigma)$$

Adapted from material from Pratul Srinivasan

NeRF Overview



NeRF: Optimization

The volume density $\sigma(\mathbf{x})$ can be interpreted as the differential probability of a ray terminating at an infinitesimal particle at location $\mathbf{x}$. The expected color $C(\mathbf{r})$ of camera ray $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$ with near and far bounds t_n and t_f is:

$$C(\mathbf{r}) = \int_{t_n}^{t_f} T(t)\sigma(\mathbf{r}(t))\mathbf{c}(\mathbf{r}(t), \mathbf{d})dt\,, \text{ where } T(t) = \exp\left(-\int_{t_n}^{t} \sigma(\mathbf{r}(s))ds\right). \quad (1)$$

Solution: Numerically estimate the integral (quadrature).

1. Discretize the ray into bins.
2. Sample point in each bin.
3. Compute numerical integration.

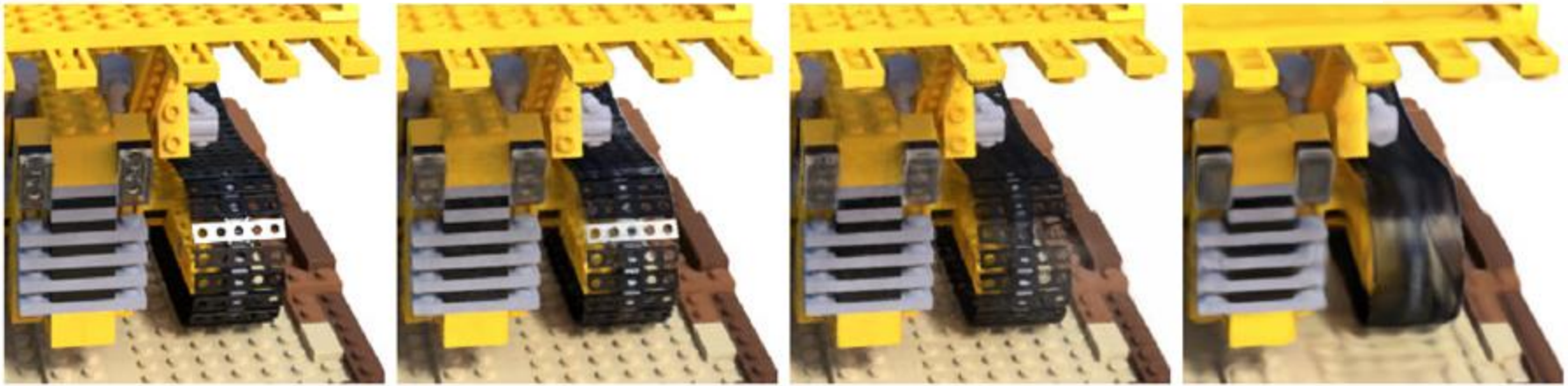
$$\hat{C}(\mathbf{r}) = \sum_{i=1}^{N} T_i(1 - \exp(-\sigma_i\delta_i))c_i\,, \text{ where } T_i = \exp\left(-\sum_{j=1}^{i-1} \sigma_j\delta_j\right)$$

Key Insight 1: Positional Encoding

Challenge: Having F_θ operate directly on (x, y, z, d) performs poorly.

Solution: Positional encoding

$$\gamma(p) = \left(\sin\left(2^0\pi p\right), \cos\left(2^0\pi p\right), \cdots, \sin\left(2^{L-1}\pi p\right), \cos\left(2^{L-1}\pi p\right)\right)$$



Ground Truth | Complete Model | No View Dependence | No Positional Encoding

Key Insight 2: Hierarchical Volume Rendering

Challenge: Waste of compute on empty space.

Solution: coarse-to-fine prediction.

$$\hat{C}_c(\mathbf{r}) = \sum_{i=1}^{N_c} w_i c_i \,, \qquad w_i = T_i(1 - \exp(-\sigma_i \delta_i)) \,. \tag{5}$$

Normalizing these weights as $\hat{w}_i = w_i / \sum_{j=1}^{N_c} w_j$ produces a piecewise-constant PDF along the ray. We sample a second set of N_f locations from this distribution using inverse transform sampling, evaluate our "fine" network at the union of the first and second set of samples, and compute the final rendered color of the ray $\hat{C}_f(\mathbf{r})$ using Eqn. 3 but using all $N_c + N_f$ samples. This procedure allocates more

NeRF encodes convincing view-dependent effects using directional dependence

Slide credit: Noah Snavely

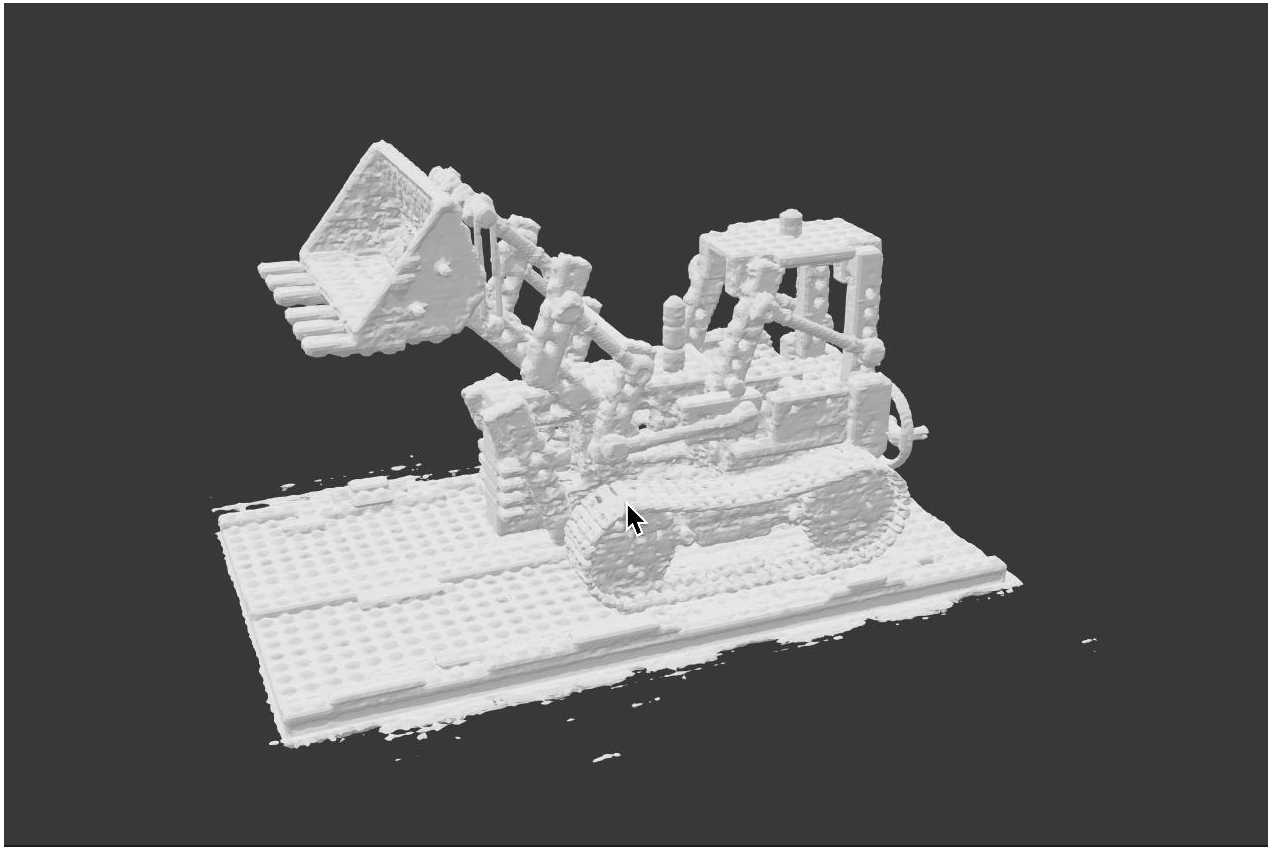
NeRF encodes convincing view-dependent effects using directional dependence

Slide credit: Noah Snavely

NeRF encodes detailed scene geometry with occlusion effects

Slide credit: Noah Snavely

NeRF encodes detailed scene geometry

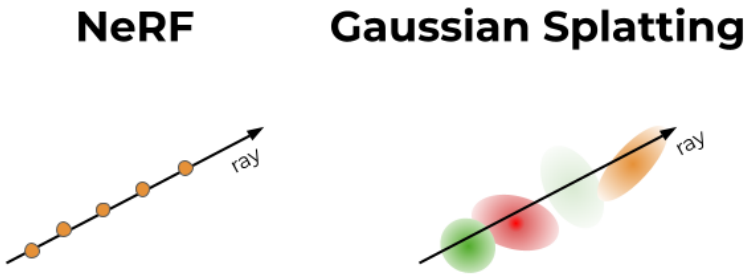


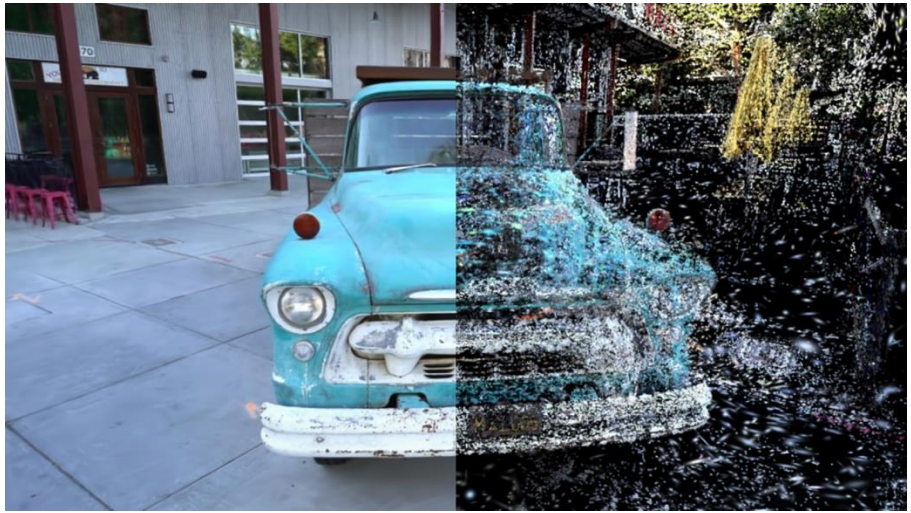
Slide credit: Noah Snavely

3D Gaussian Splatting (Kerbl and Kopanas et al., 2023)

Key idea: 3D Gaussians as an **explicit representation** of a scene

- Train Gaussian blobs via inverse rendering (similar to NeRF)
- Store scene as Gaussian blobs instead of neural network weights (NeRF)
- Much faster during inference, but takes a lot of space to store





Summary: 3D Representation and Neural Rendering

- Representation matters a lot for 3D computer vision tasks (detection, reconstruction, etc.)
- 3D Voxels are intuitive representation of space but struggles with high-resolution shape and large scenes
- Implicit function emerge as a new paradigm in representing scenes with Neural Networks
- Neural volume rendering: represent scenes implicit as point-direction to color-density neural networks. Photorealistic rendering, slow to train and evaluate
- More recent works on trading off space and time

Next Time: Vision Language Models