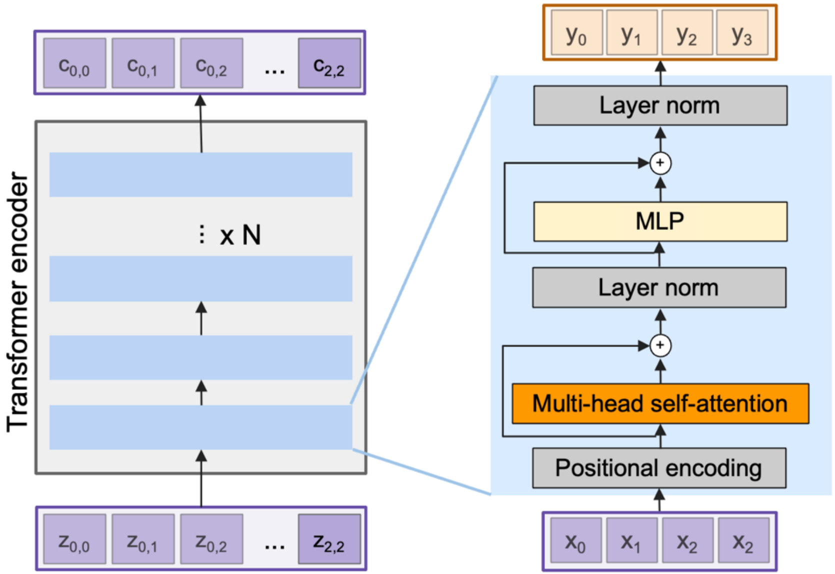
Lecture 9:
Detection, Segmentation, Visualization, and Understanding

Administrative Announcements

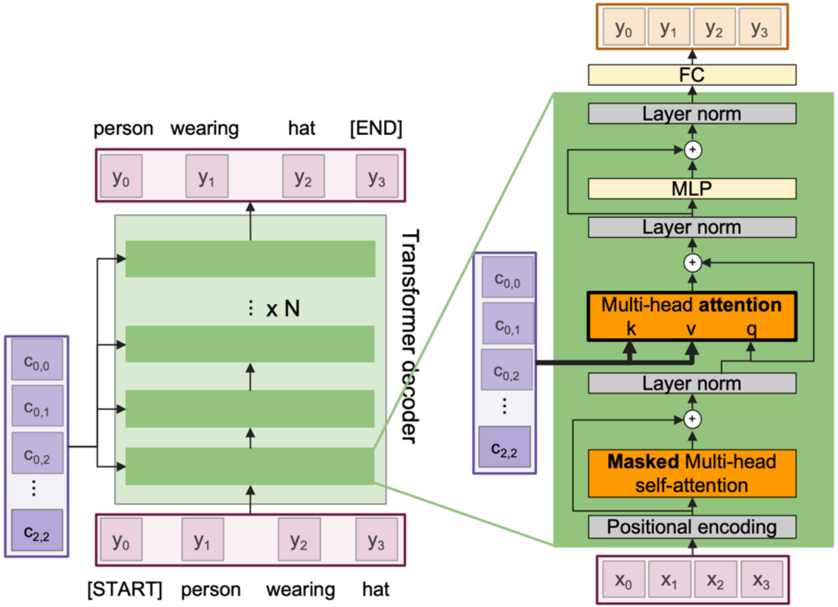
- Make sure to start Assignment 2 early. It is the longest of the three assignments, and the midterm and project milestone deadlines follow closely after the Assignment 2 deadline.

- Be sure to check out this Ed post for the best Colab practices to avoid unnecessary bugs and delays.

Last time: Transformer



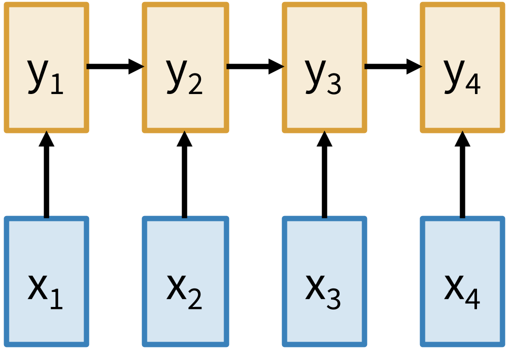
Encoder



Decoder

Three Ways of Processing Sequences

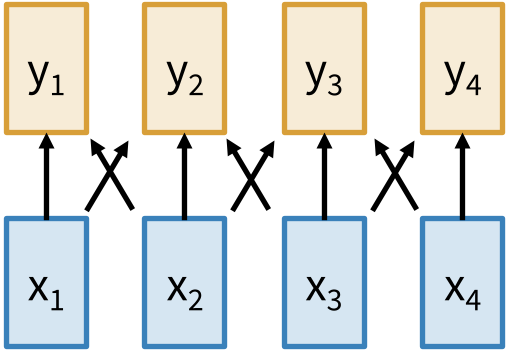
Recurrent Neural Network



Works on 1D ordered sequences

(+) Theoretically good at long sequences: O(N) compute and memory for a sequence of length N
(-) Not parallelizable. Need to compute hidden states sequentially

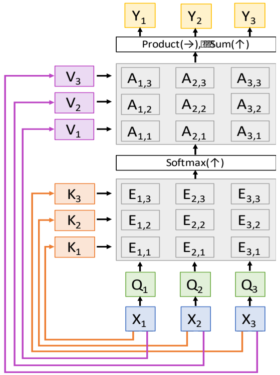
Convolution



Works on N-dimensional grids

(-) Bad for long sequences: need to stack many layers to build up large receptive fields
(+) Parallelizable, outputs can be computed in parallel

Self-Attention



Works on sets of vectors

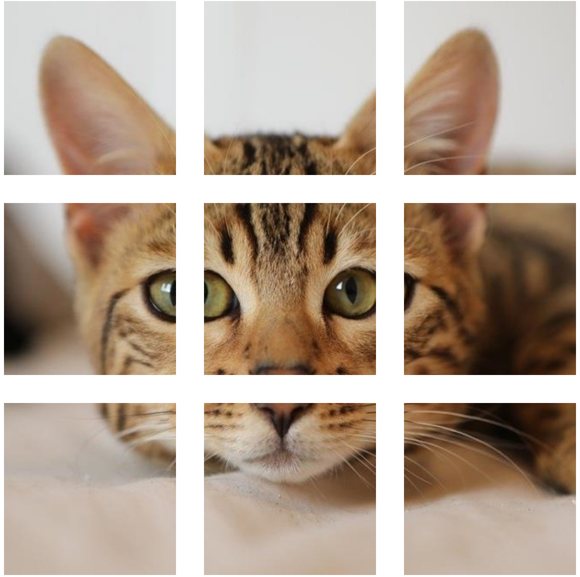
(+) Great for long sequences; each output depends directly on all inputs
(+) Highly parallel, it's just 4 matmuls
(-) Expensive: $O(N^2)$ compute, O(N) memory for sequence of length N

Vision Transformers (ViT)

Input image:
e.g. 224x224x3

Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

Vision Transformers (ViT)



Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

Vision Transformers (ViT)

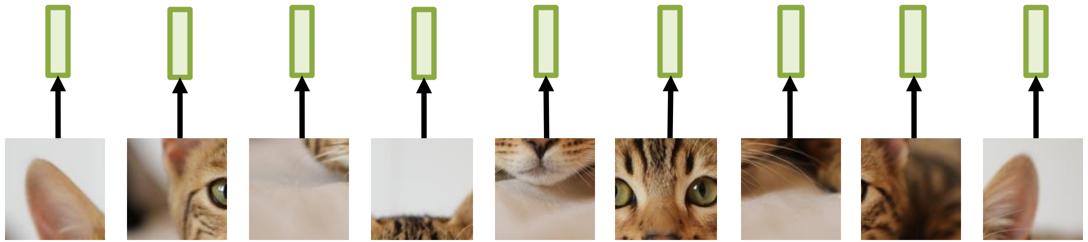
N input patches, each of shape 3x16x16

Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

Vision Transformers (ViT)

Linear projection to D-dimensional vector

N input patches, each of shape 3x16x16



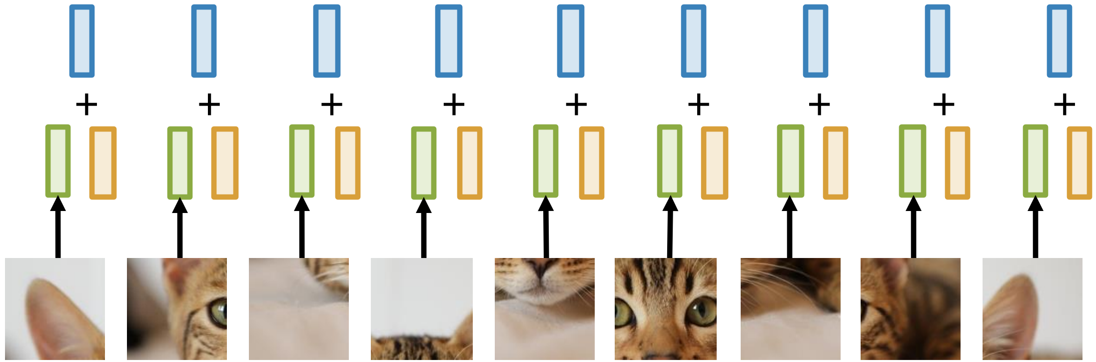
Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

Vision Transformers (ViT)

Add positional embedding: learned D-dim vector per position

Linear projection to D-dimensional vector

N input patches, each of shape 3x16x16



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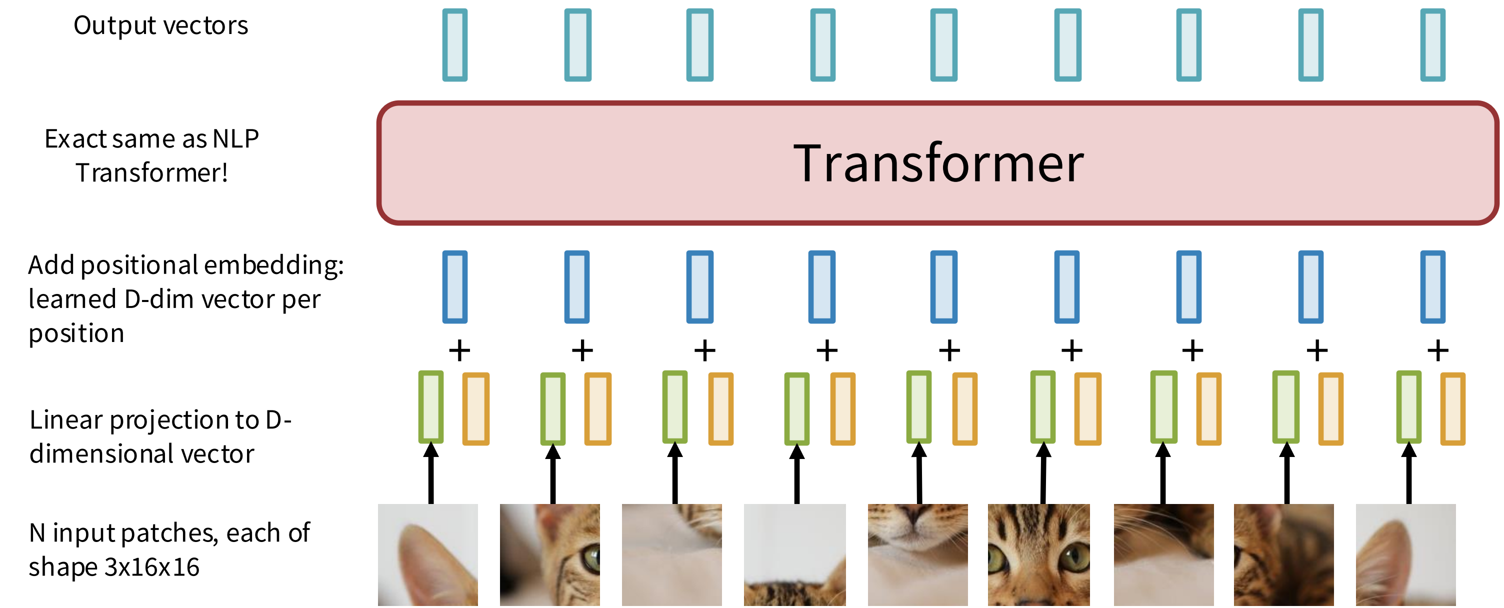

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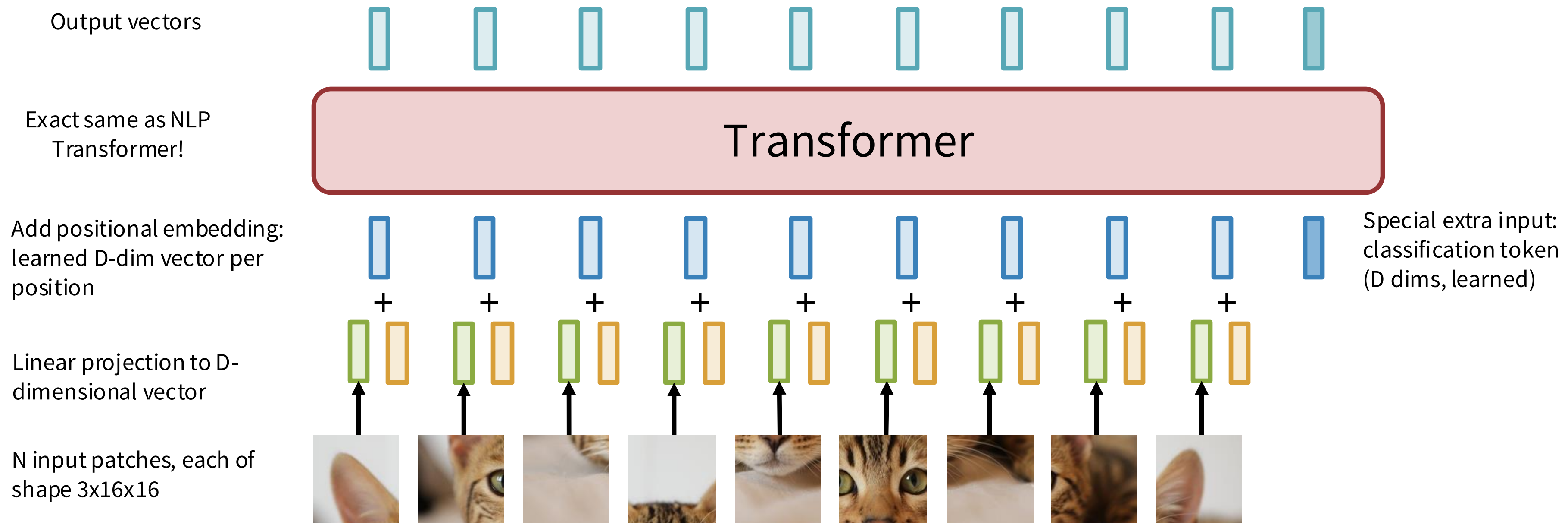


Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

Vision Transformers (ViT)

Linear projection to C-dim vector of predicted class scores

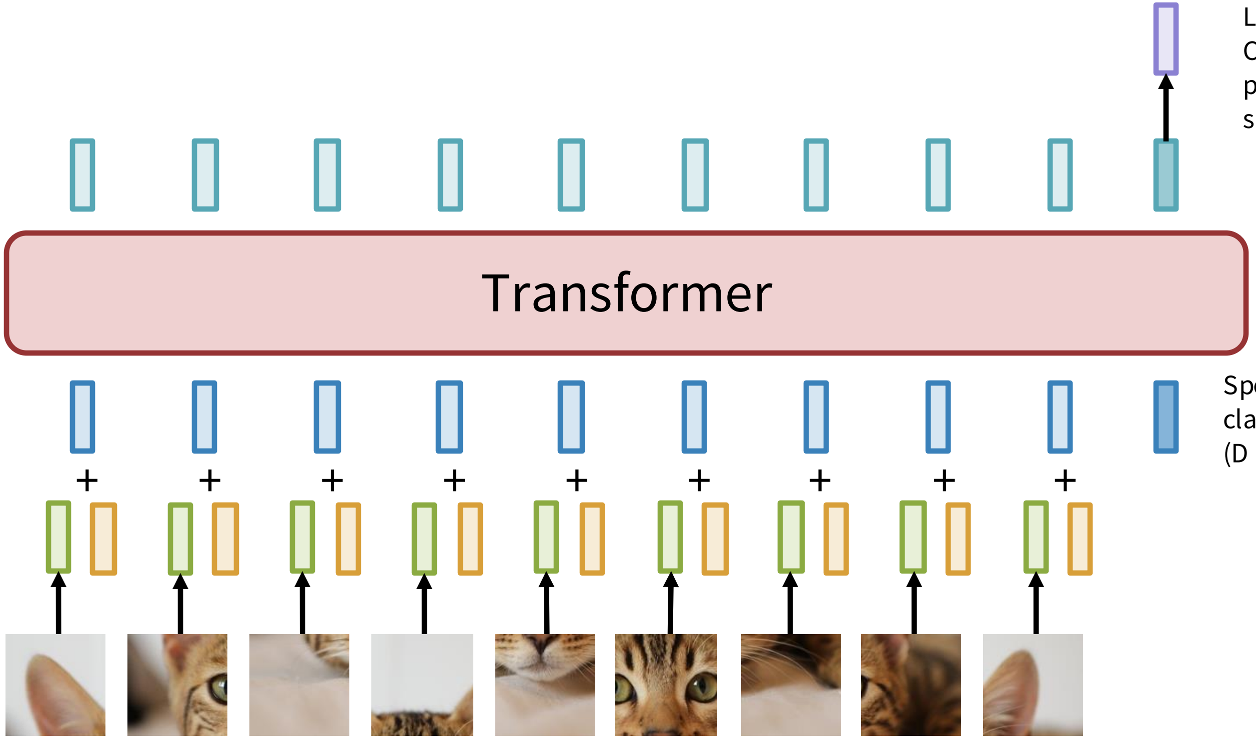
Output vectors

Exact same as NLP Transformer!

Add positional embedding: learned D-dim vector per position

Linear projection to D-dimensional vector

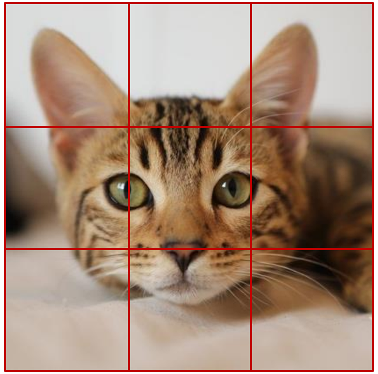
N input patches, each of shape 3x16x16



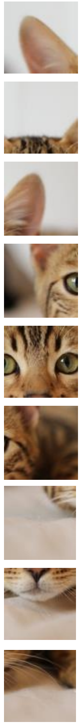
Special extra input: classification token (D dims, learned)

Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

Vision Transformers (ViT) – a similar approach (different classifier)



Input image:
e.g. 224x224x3

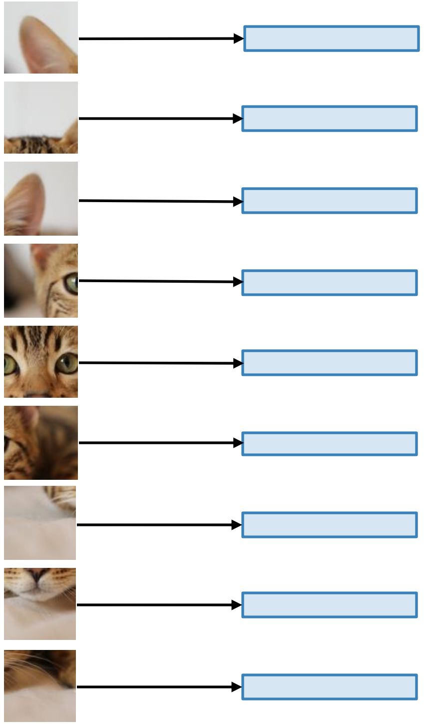


Break into patches
e.g. 16x16x3

Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

Vision Transformers (ViT)

Input image:
e.g. 224x224x3



Break into patches
e.g. 16x16x3

Flatten and apply a linear
transform 768 => D

Dosovitskiy et al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ICLR 2021

Vision Transformers (ViT)

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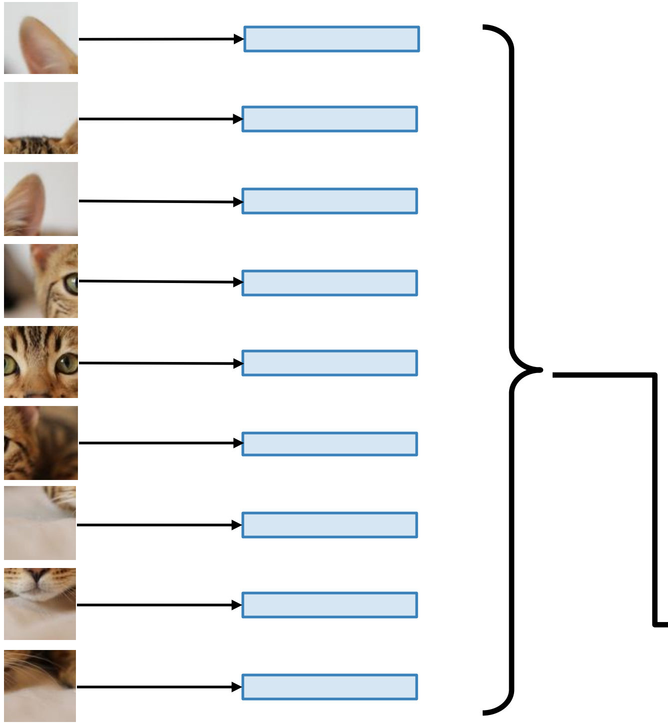
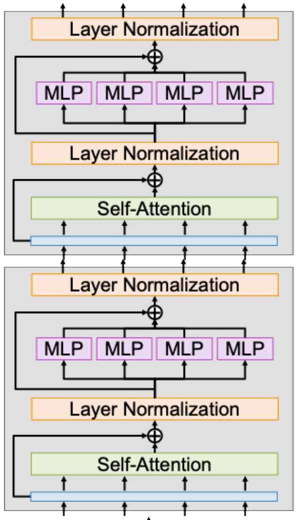




Break into patches
e.g. 16x16x3

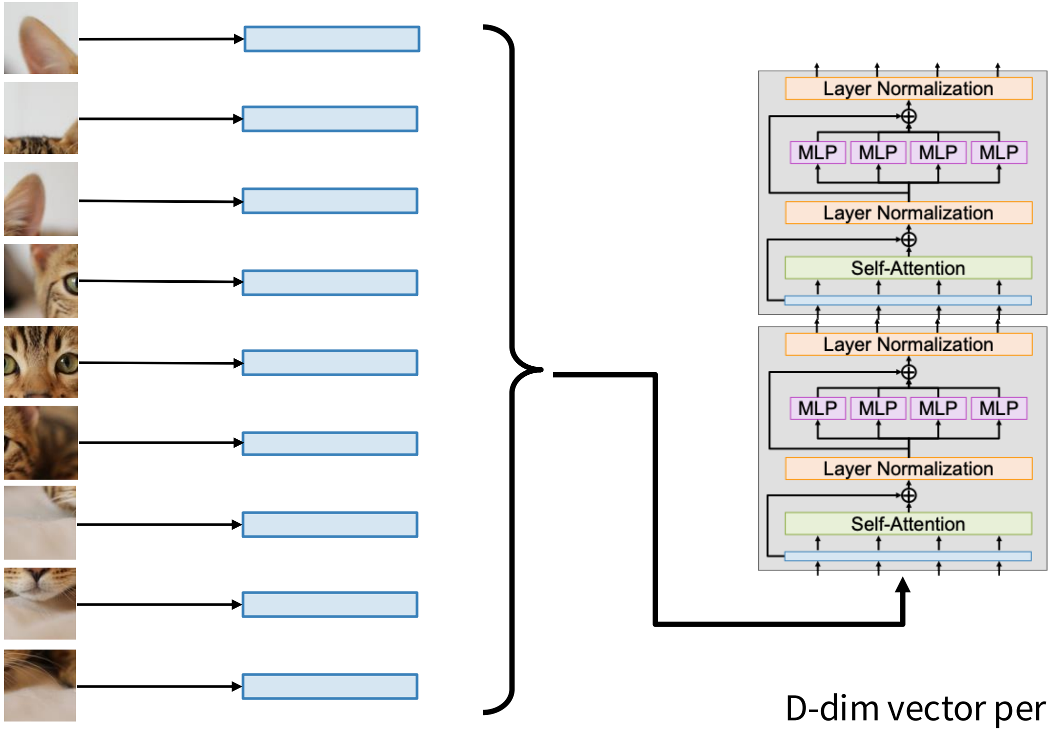
Flatten and apply a linear transform 768 => D

D-dim vector per patch are the input vectors to the Transformer

Dosovitskiy et al, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale", ICLR 2021

Vision Transformers (ViT)

Input image:
e.g. 224x224x3



Use positional encoding to tell the transformer the 2D position of each patch

Break into patches
e.g. 16x16x3

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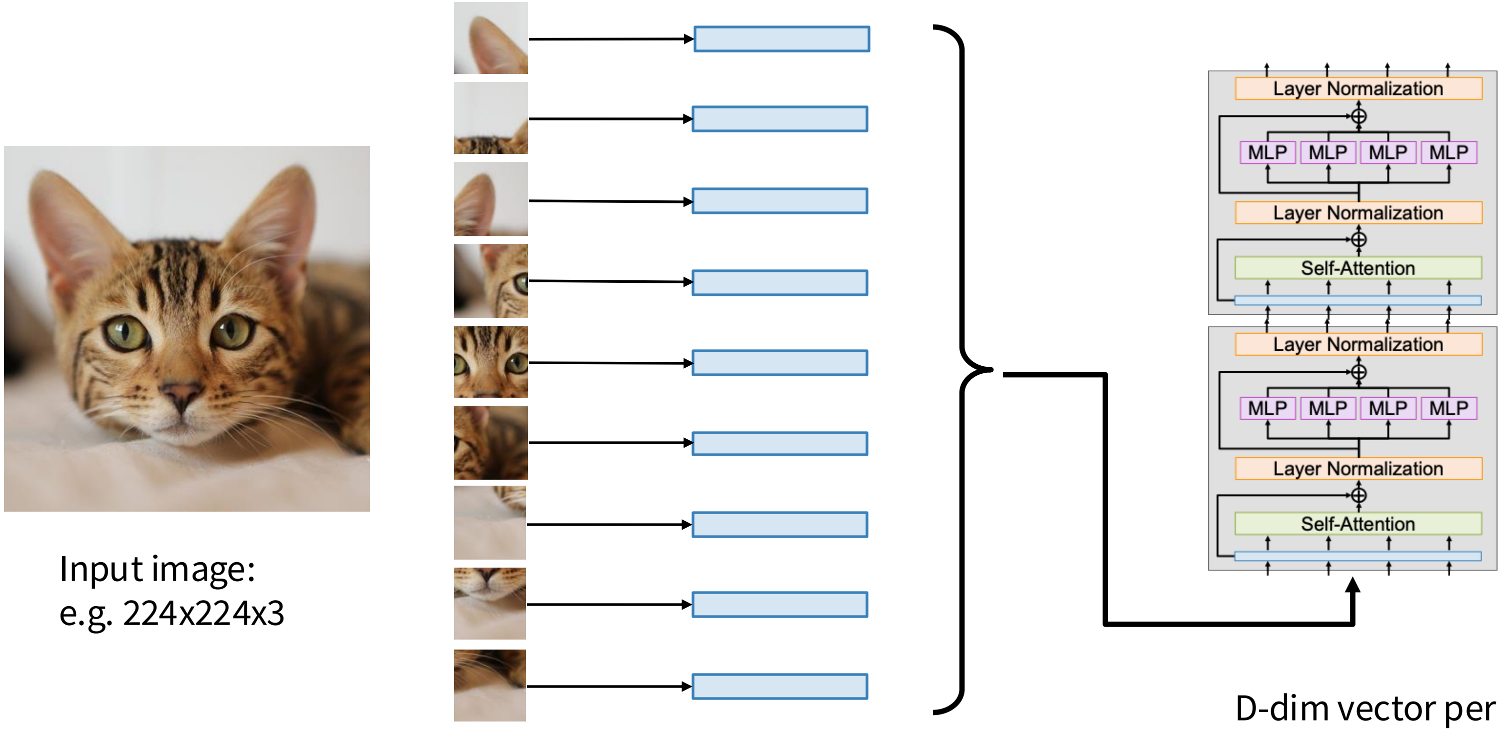

Don't use any masking; each image patch can look at all other image patches

Use positional encoding to tell the transformer the 2D position of each patch

Input image:
e.g. 224x224x3

Break into patches
e.g. 16x16x3

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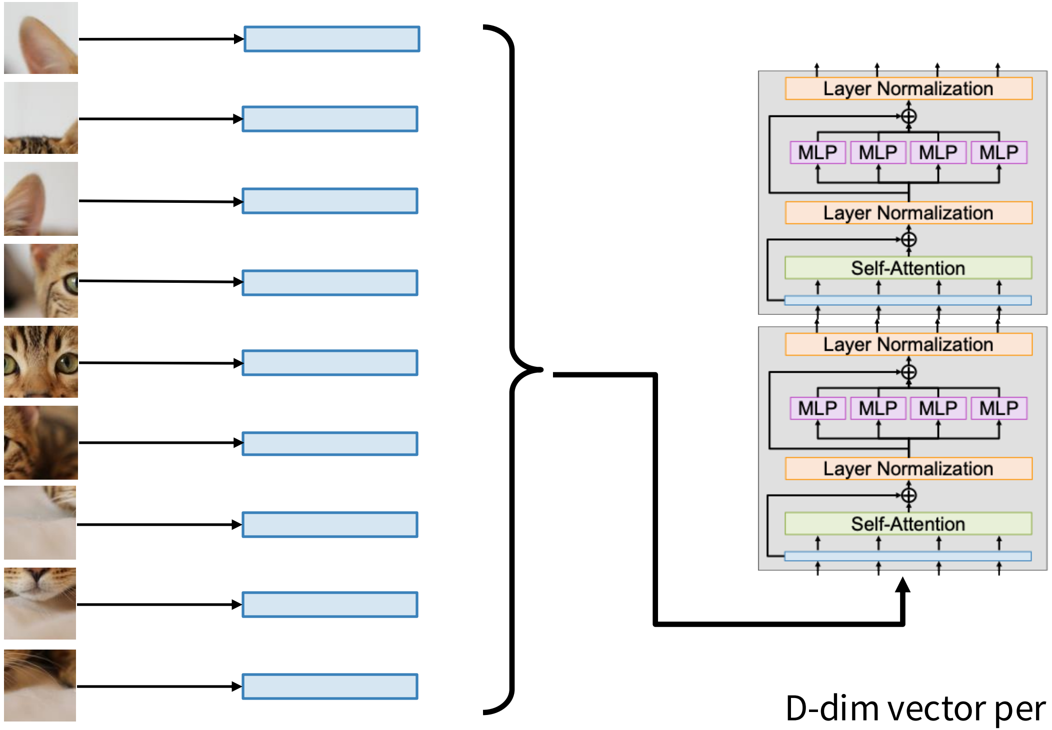

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Flatten and apply a linear transform 768 => D

D-dim vector per patch are the input vectors to the Transformer

Transformer gives an output vector per patch

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Use positional encoding to tell the transformer the 2D position of each patch

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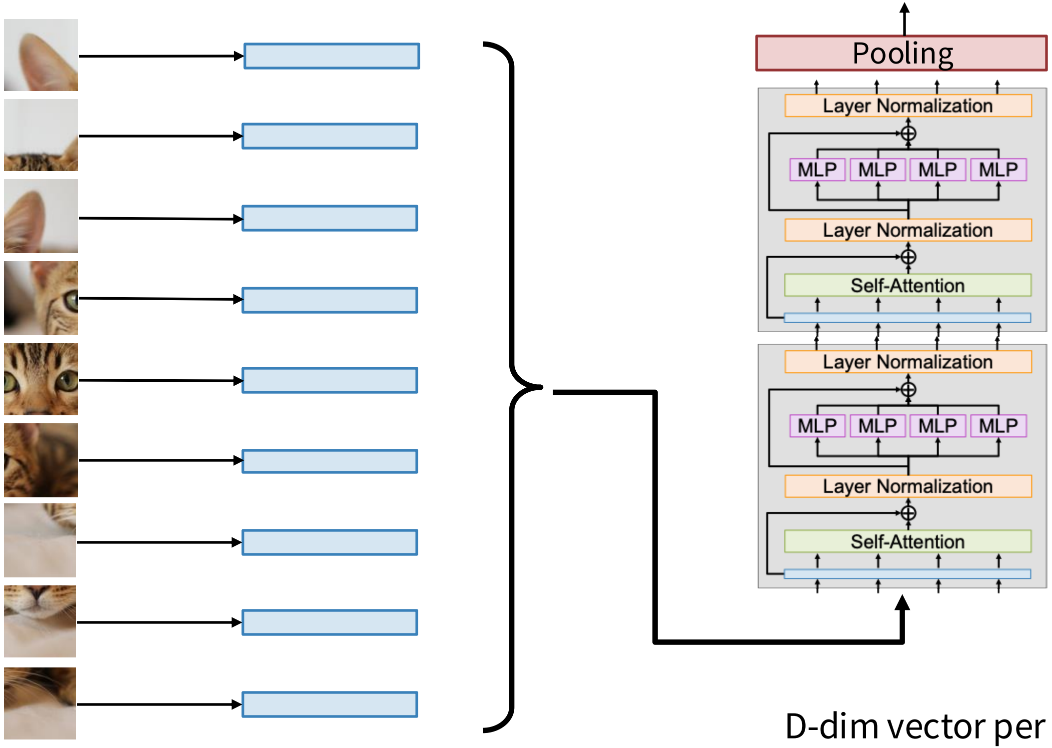
Input image:
e.g. 224x224x3



Average pool NxD vectors to 1xD, apply a linear layer D=>C to predict class scores

Transformer gives an output vector per patch

Don't use any masking; each image patch can look at all other image patches

Use positional encoding to tell the transformer the 2D position of each patch

Break into patches
e.g. 16x16x3

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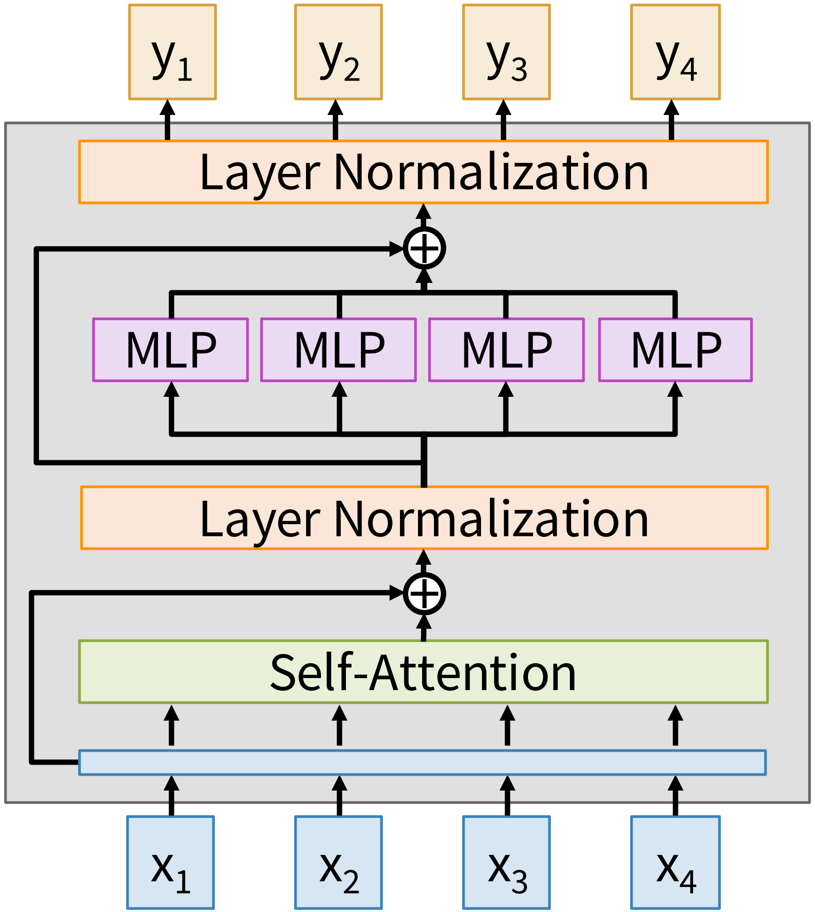
Tweaking Transformers

The Transformer architecture has not changed much since 2017.

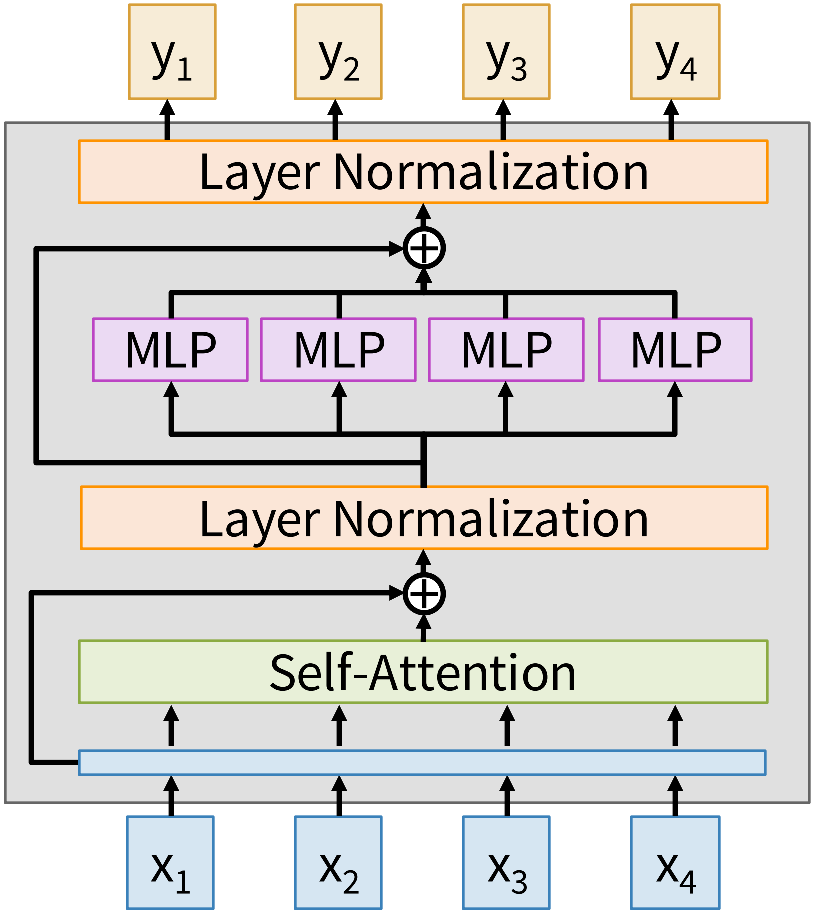
But a few changes have become common:



Pre-Norm Transformer

Layer normalization is outside the residual connections

Kind of weird, the model can't actually learn the identify function



Baevski & Auli, "Adaptive Input Representations for Neural Language Modeling", arXiv 2018

Pre-Norm Transformer

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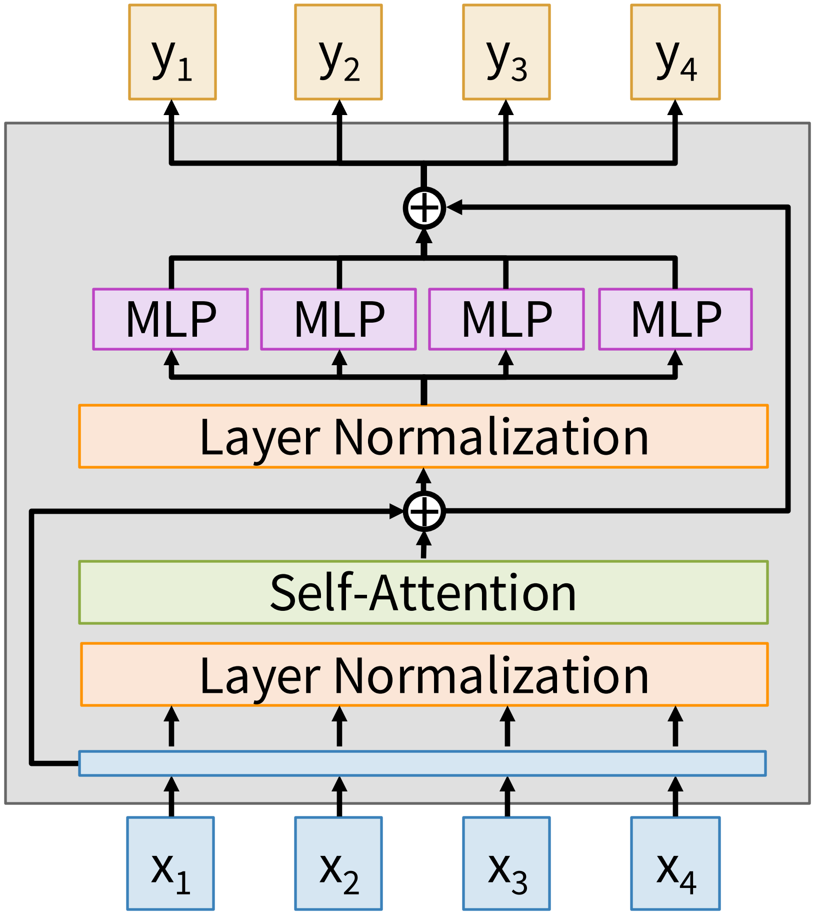
Kind of weird, the model can't actually learn the identify function

Solution: Move layer normalization before the Self-Attention and MLP, inside the residual connections. Training is more stable.



Baevski & Auli, "Adaptive Input Representations for Neural Language Modeling", arXiv 2018

RMSNorm

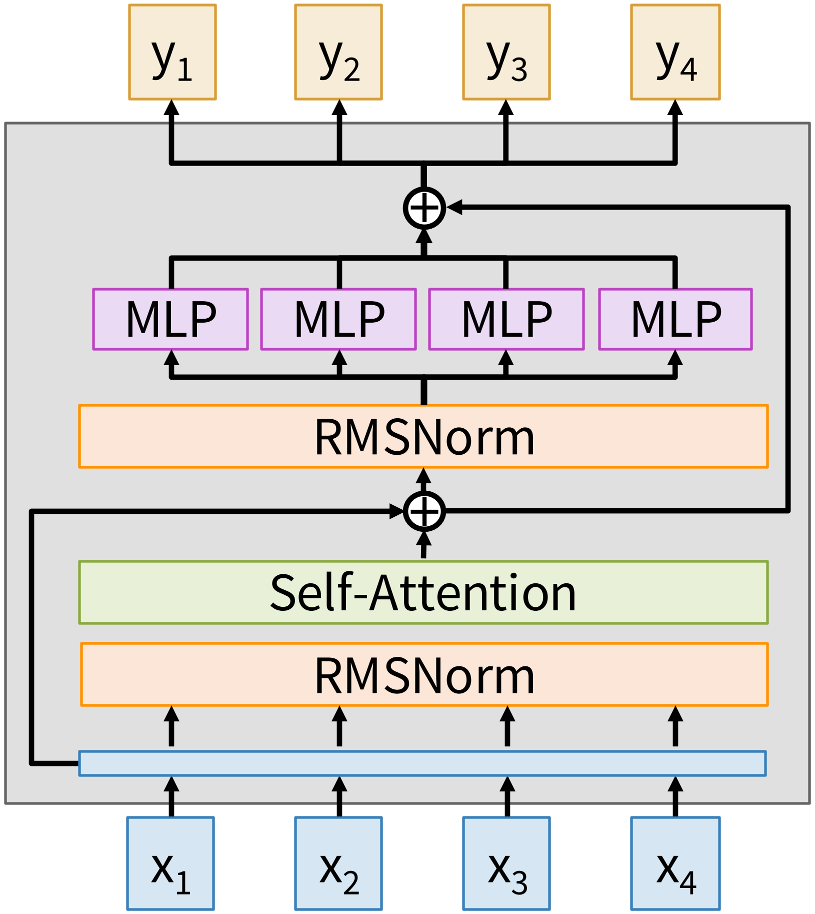
Replace Layer Normalization with Root-Mean-Square Normalization (RMSNorm)

Input: x [shape D]
Output: y [shape D]
Weight: γ [shape D]

$$y_i = \frac{x_i}{RMS(x)} * \gamma_i$$

$$RMS(x) = \sqrt{\varepsilon + \frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

Training is a bit more stable

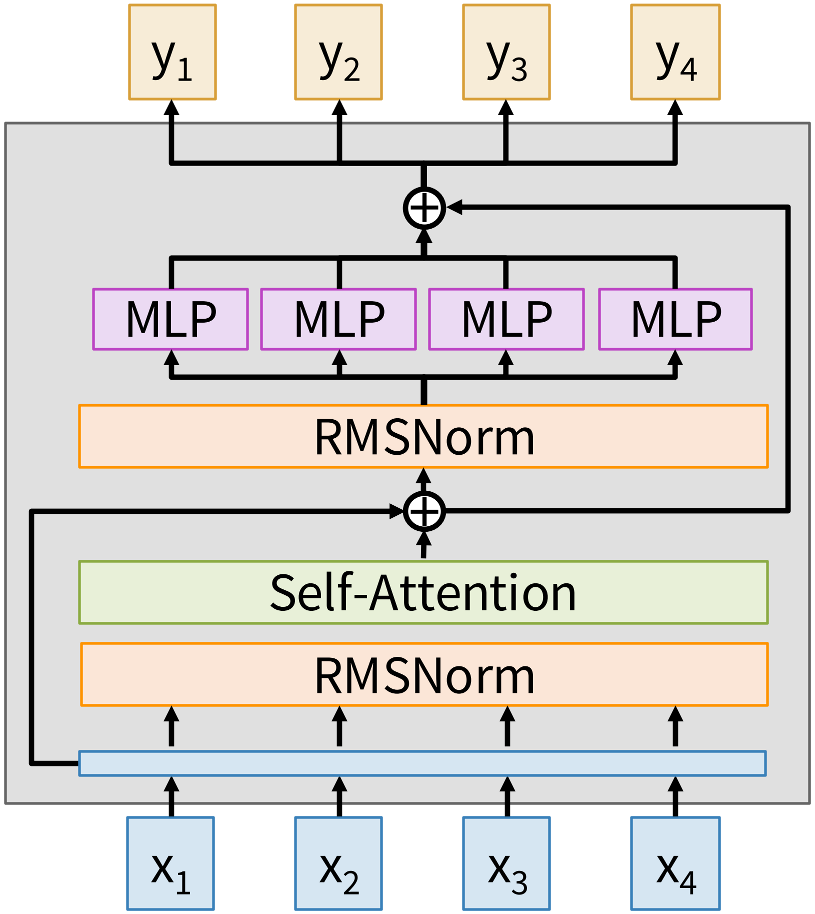


Zhang and Sennrich, “Root Mean Square Layer Normalization”, NeurIPS 2019

SwiGLU MLP

Classic MLP:

Input: X [N x D]
Weights: W_1 [D x 4D]
W_2 [4D x D]
Output: $Y = \sigma(XW_1)W_2$ [N x D]



Shazeer, "GLU Variants Improve Transformers", 2020

SwiGLU MLP

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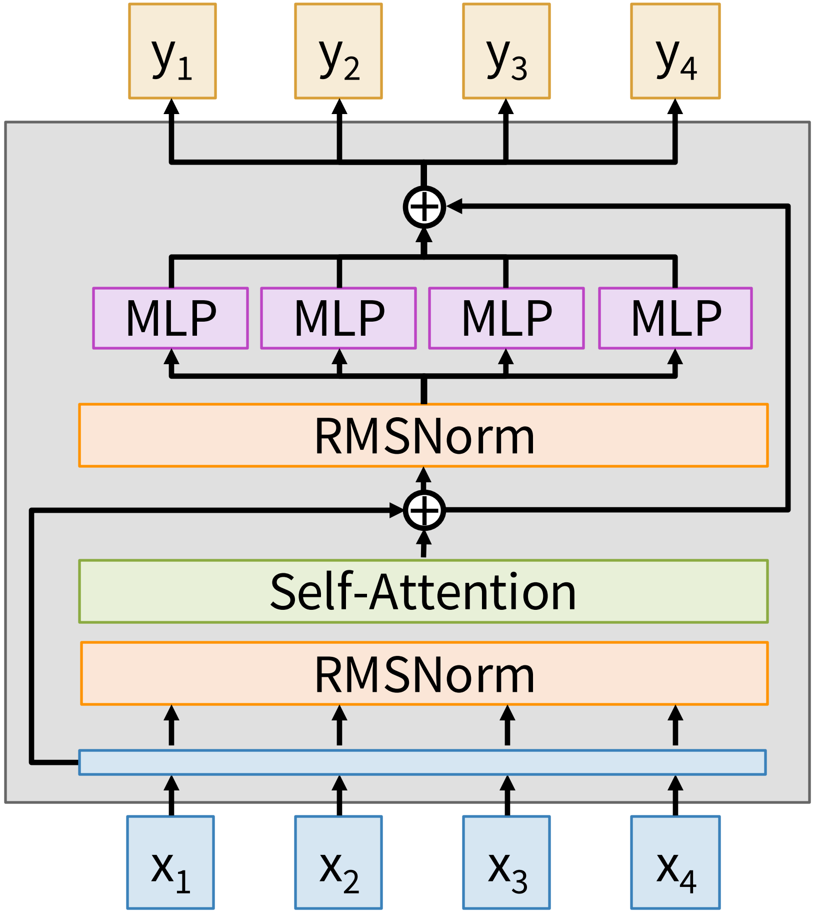
Output: $Y = \sigma(XW_1)W_2$ [N x D]

SwiGLU MLP:

Input: X [N x D]
Weights: W_1 , W_2 [D x H]
W_3 [H x D]
Output:

$$Y = (\sigma(XW_1) \odot XW_2)W_3$$

Setting H = 8D/3 keeps same total params

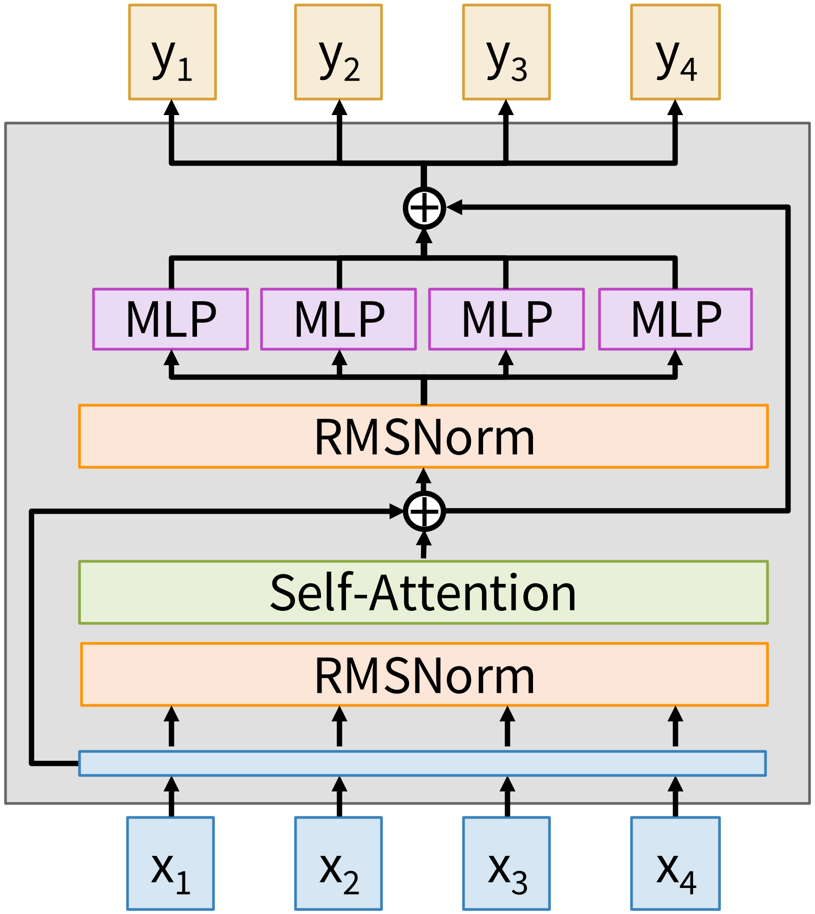


Shazeer, "GLU Variants Improve Transformers", 2020

Mixture of Experts (MoE)

Learn E separate sets of MLP weights in each block; each MLP is an expert

W_1: [D x 4D] => [E x D x 4D]
W_2: [4D x D] => [E x 4D x D]



Shazeer et al, "Outrageously Large Neural Networks: The Sparsely-Gated Mixture-of-Experts Layer", 2017

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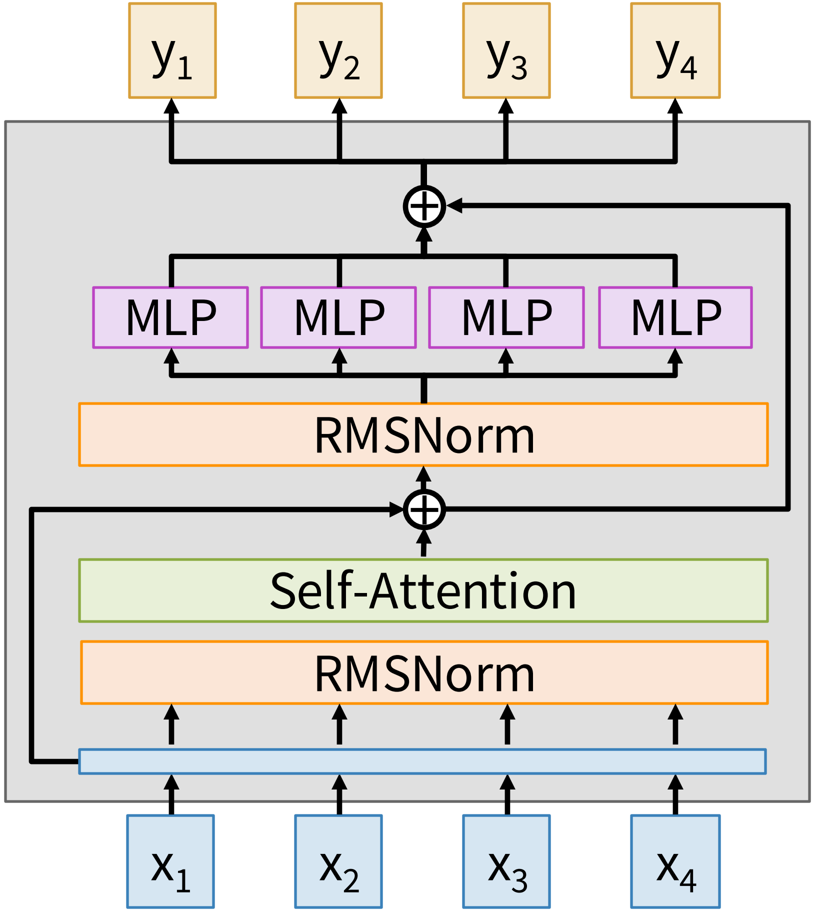
Each token gets routed to A < E of the experts. These are the active experts.

Increases params by E,
But only increases compute by A



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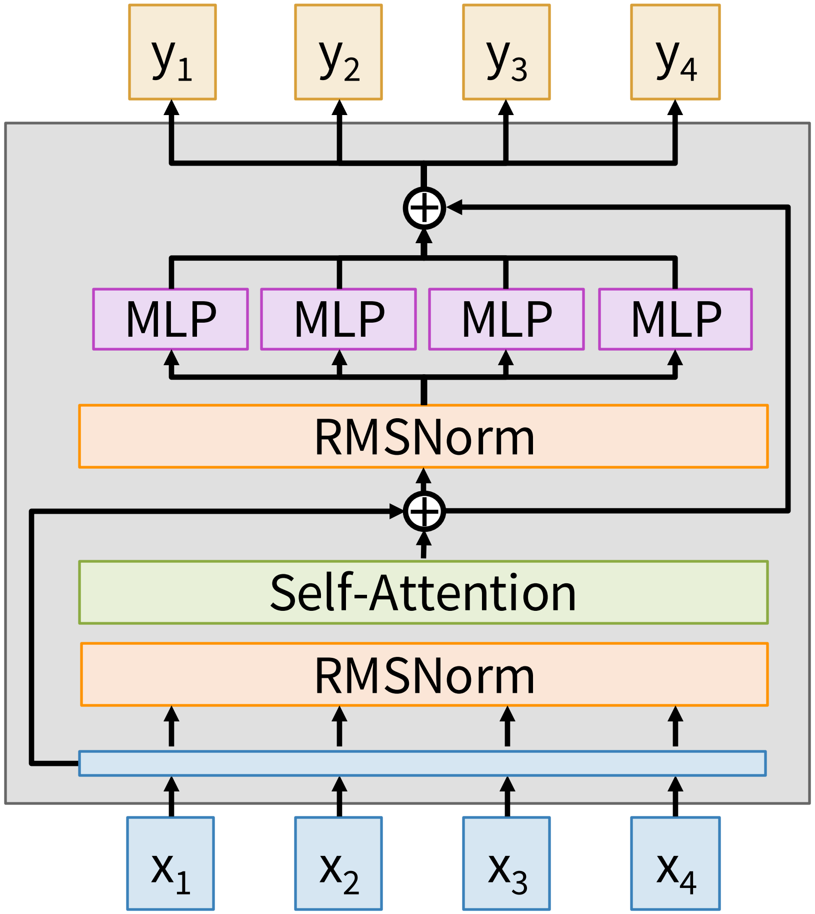
All of the biggest LLMs today (e.g. GPT4o, GPT4.5, Claude 3.7, Gemini 2.5 Pro, etc) almost certainly use MoE and have > 1T params; but they don't publish details anymore

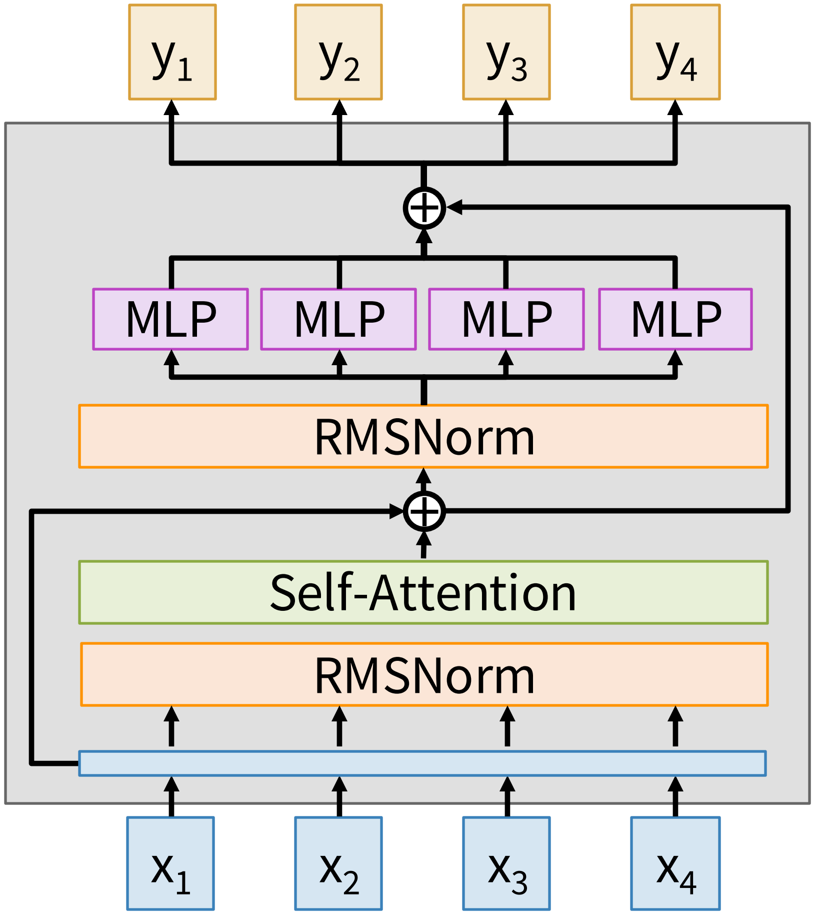


Tweaking Transformers

The Transformer architecture has not changed much since 2017.

But a few changes have become common:

- Pre-Norm: Move normalization inside residual
- RMSNorm: Different normalization layer
- SwiGLU: Different MLP architecture
- Mixture of Experts (MoE): Learn E different MLPs, use A < E of them per token. Massively increase params, modest increase to compute cost.



Today

- Transformers Recap
- **Computer Vision Tasks**
  - Semantic Segmentation
  - Object Detection
  - Instance Segmentation
- Visualization & Understanding
  - Model Layers Visualization
  - Saliency Maps
  - CAM & Grad-CAM

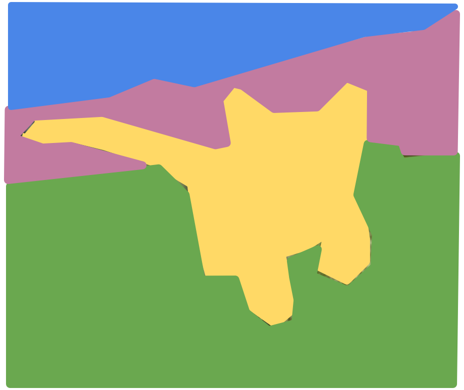
Computer Vision Tasks

Classification

CAT

No spatial extent

Semantic Segmentation



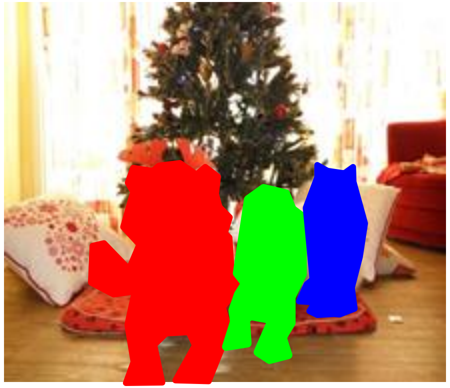
GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Multiple Object

Recall: Image Classification: A core task in Computer Vision

(assume given a set of possible labels)
{dog, cat, truck, plane, ...}

→ cat

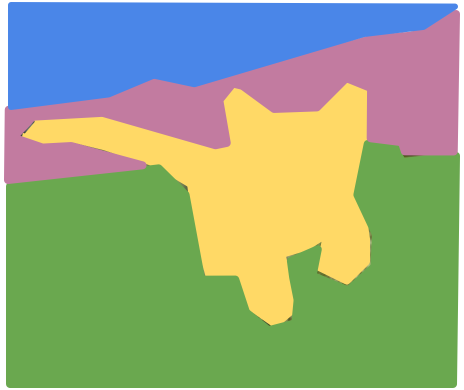
Semantic Segmentation

Classification

CAT

No spatial extent

Semantic Segmentation



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Object Detection

DOG, DOG, CAT

Instance Segmentation

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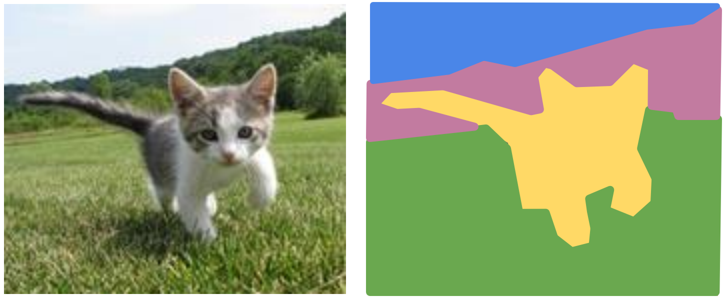
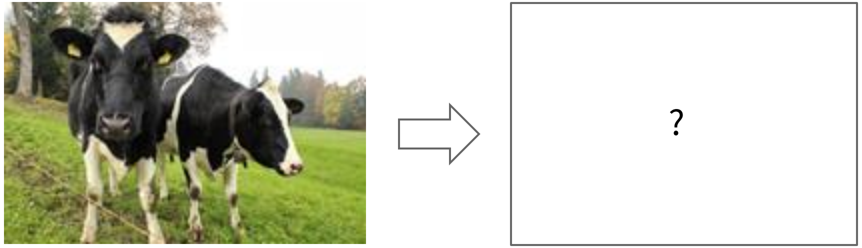
Multiple Object

Semantic Segmentation: The Problem



GRASS, CAT, TREE,
SKY, ...

Paired training data: for each training image, each pixel is labeled with a semantic category.



At test time, classify each pixel of a new image.

Semantic Segmentation Idea: Sliding Window

Full image

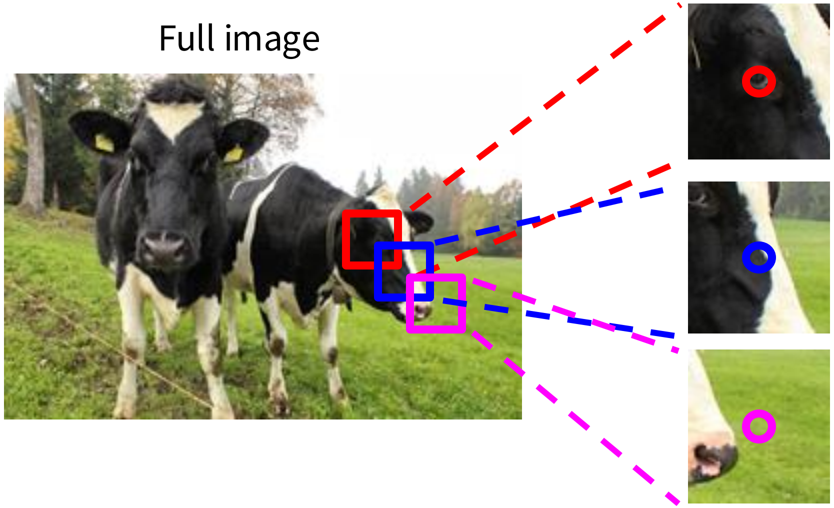
Semantic Segmentation Idea: Sliding Window

Full image

Impossible to classify without context

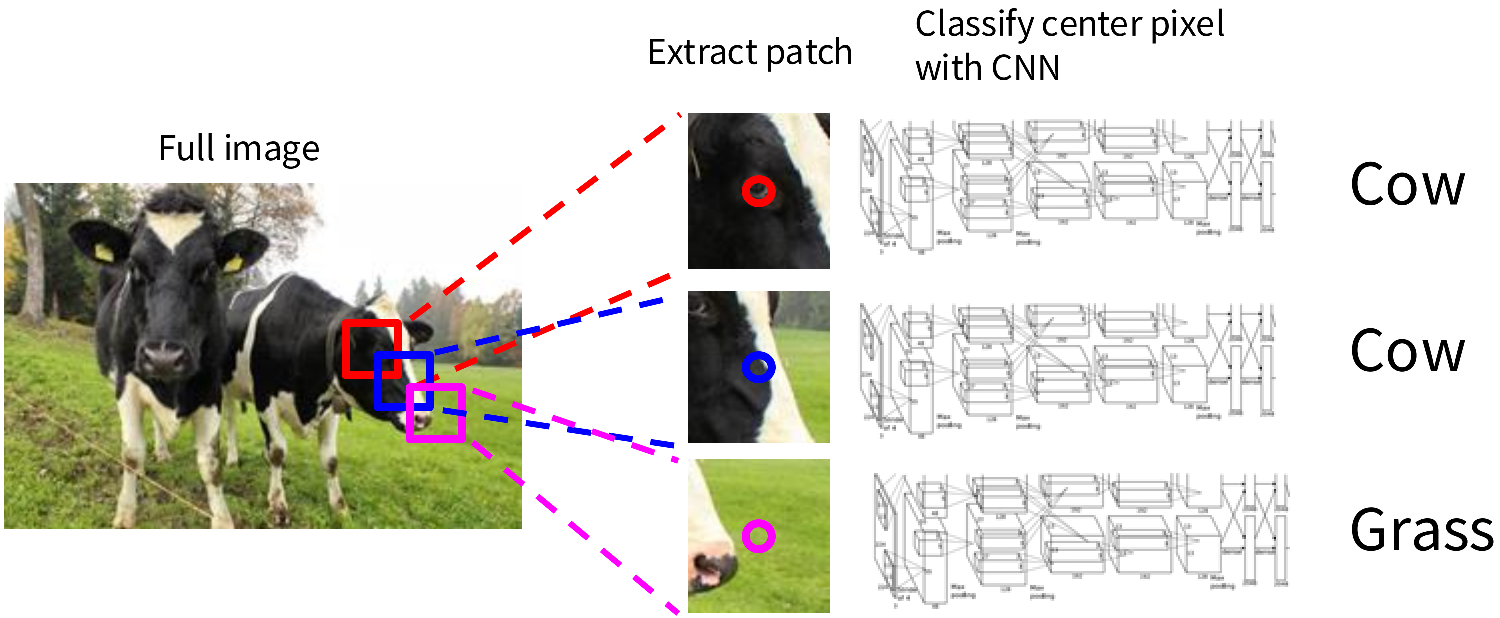
Q: how do we include context?

Semantic Segmentation Idea: Sliding Window



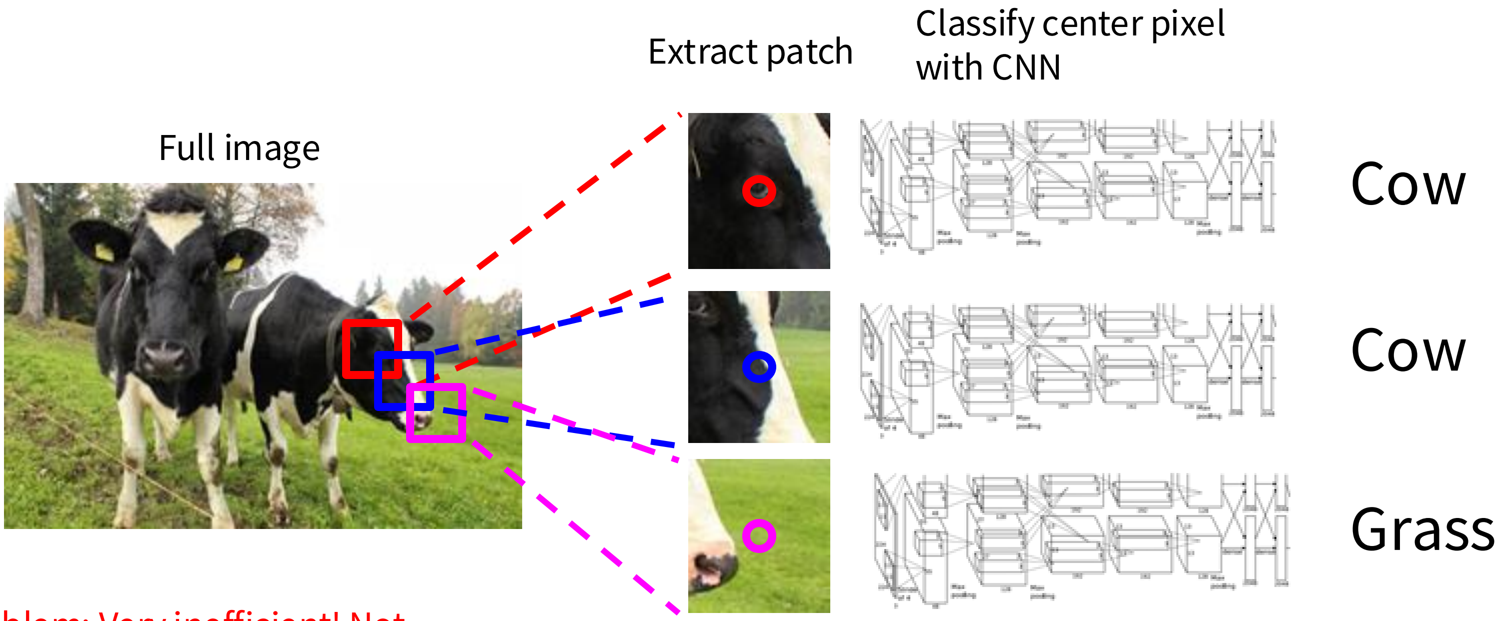
Q: how do we model this?

Semantic Segmentation Idea: Sliding Window



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 Idea: Sliding Window

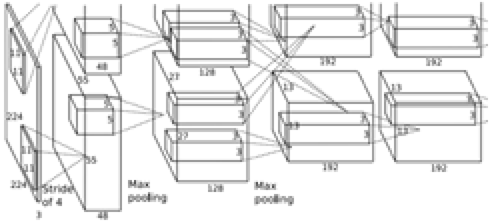


Problem: Very inefficient! Not reusing shared features between overlapping patches

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 Idea: Convolution

Full image

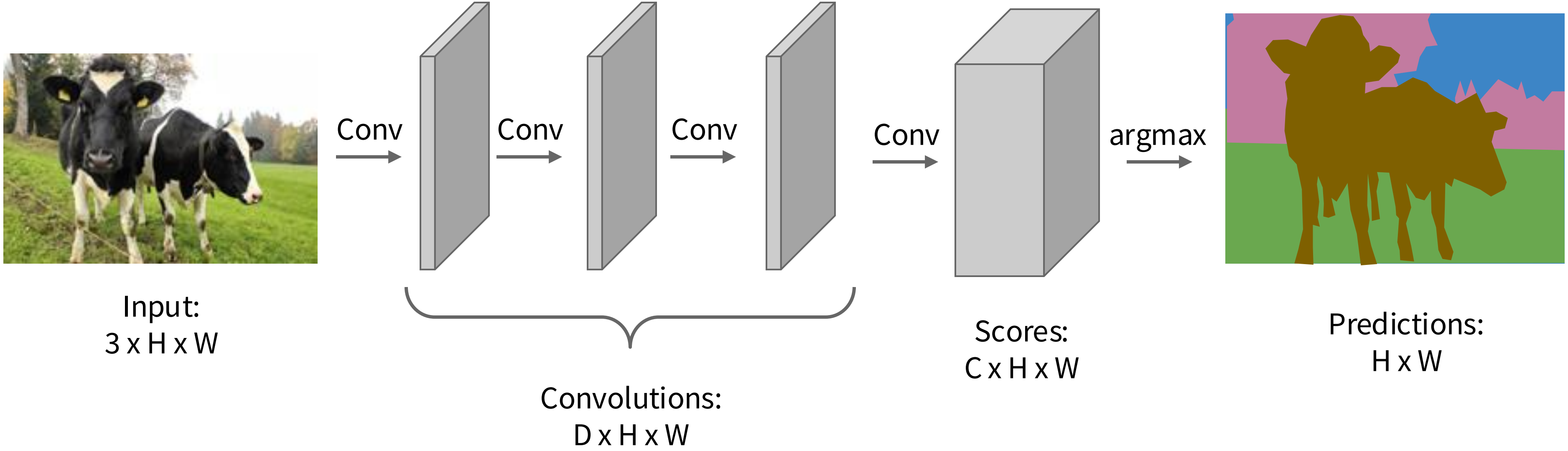


An intuitive idea: encode the entire image with conv net, and do semantic segmentation on top.

Problem: classification architectures often reduce feature spatial sizes to go deeper, but semantic segmentation requires the output size to be the same as input size.

Semantic Segmentation Idea: Fully Convolutional

Design a network with only convolutional layers without downsampling operators to make predictions for pixels all at once!



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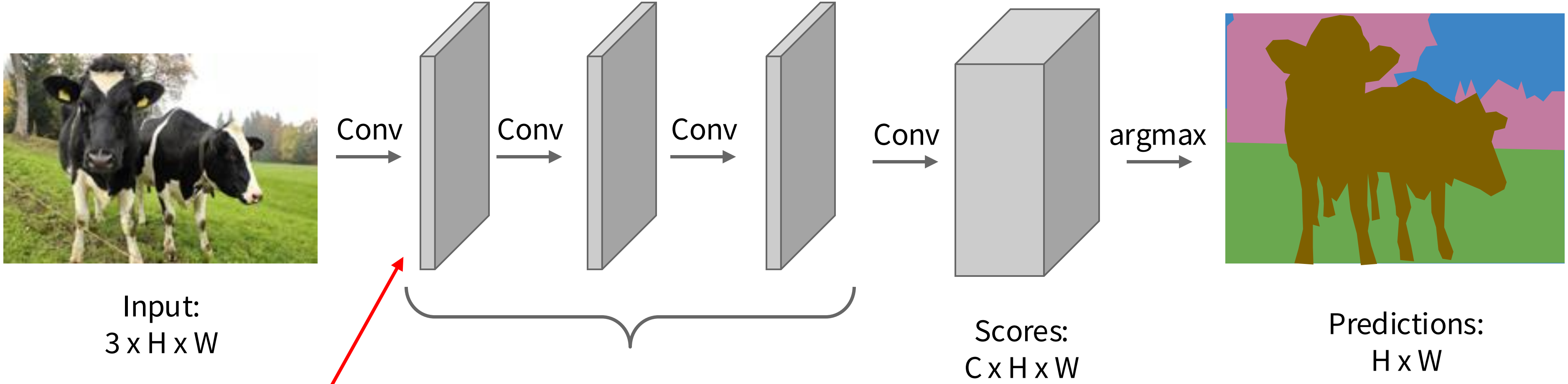
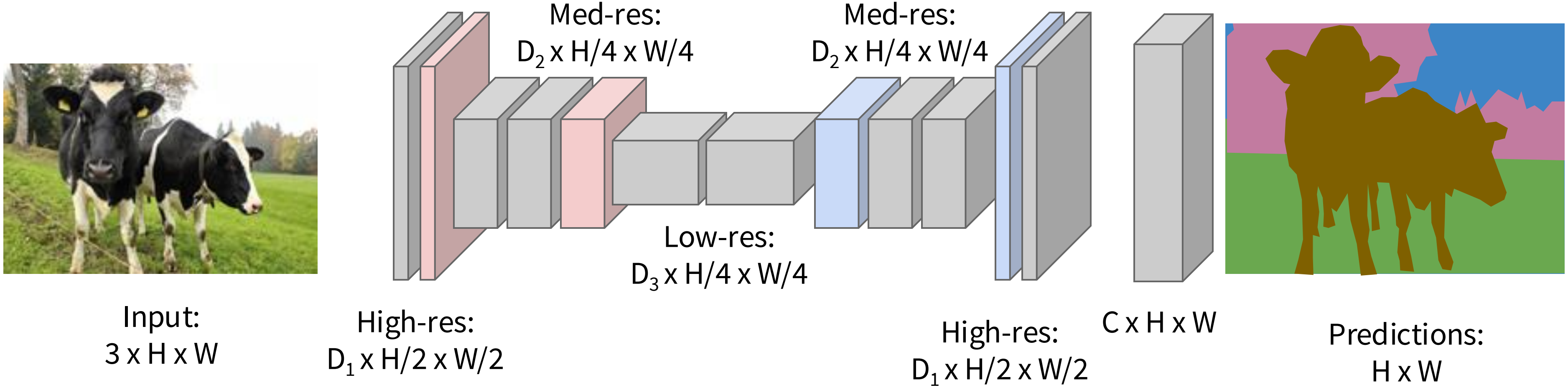


Convolutions:
D x H x W

Problem: convolutions at
original image resolution will be
very expensive ...

Semantic Segmentation Idea: Fully Convolutional

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



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

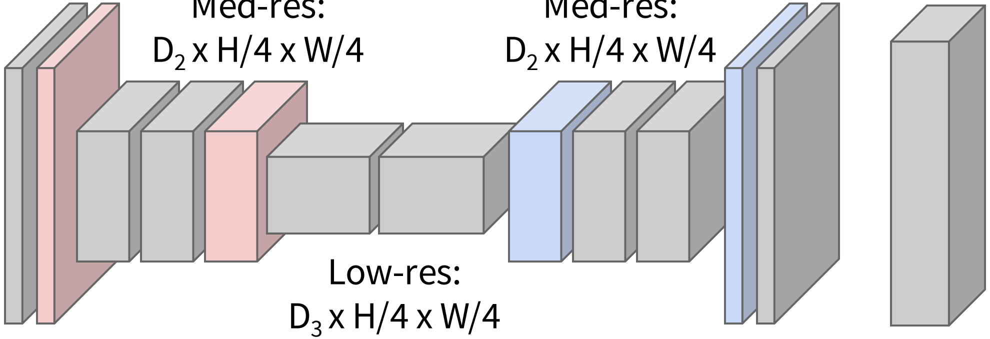
Semantic Segmentation Idea: Fully Convolutional

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

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

Low-res:
D_3 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

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

In-Network upsampling: “Unpooling”

Nearest Neighbor

1	2
3	4

Input: 2 x 2

→

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

Output: 4 x 4

“Bed of Nails”

1	2
3	4

Input: 2 x 2

→

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

Output: 4 x 4

In-Network upsampling: “Max Unpooling”

Max Pooling
Remember which element was max!

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

Input: 4 x 4

5	6
7	8

Output: 2 x 2

…

Rest of the network

Max Unpooling
Use positions from pooling layer

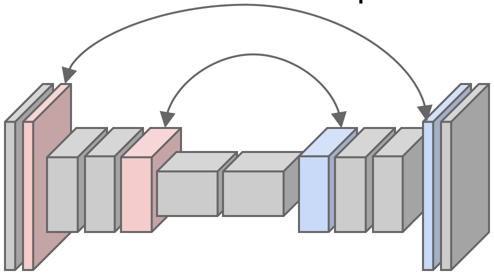
1	2
3	4

Input: 2 x 2

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

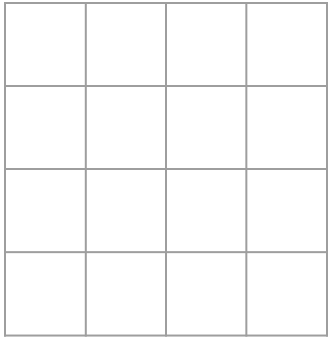
Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers

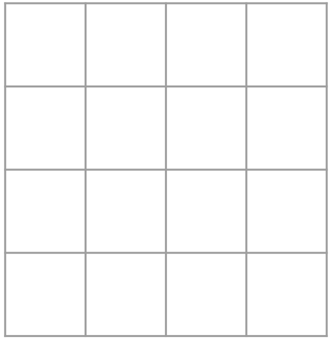


Learnable Upsampling

Recall: Normal 3 x 3 convolution, stride 1 pad 1



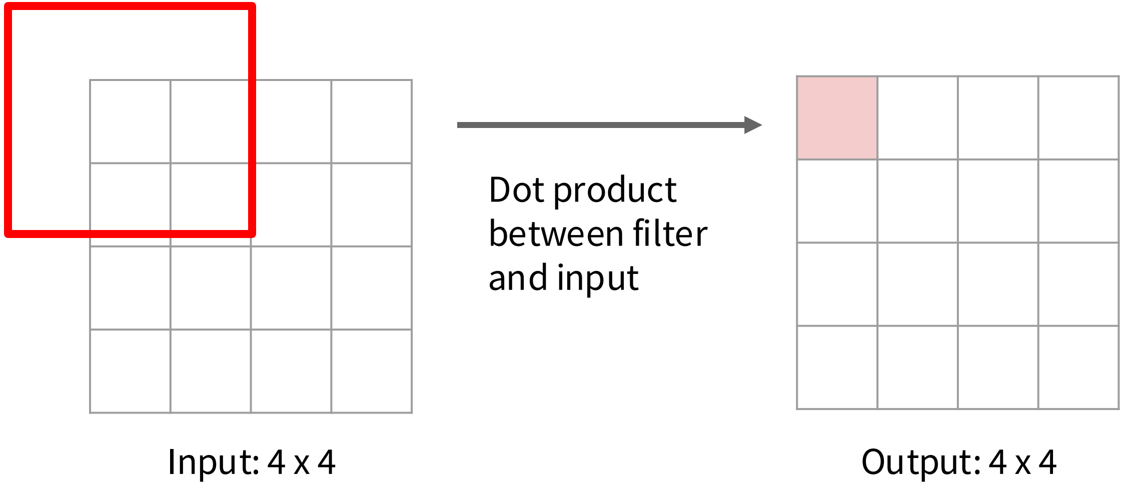
Input: 4 x 4



Output: 4 x 4

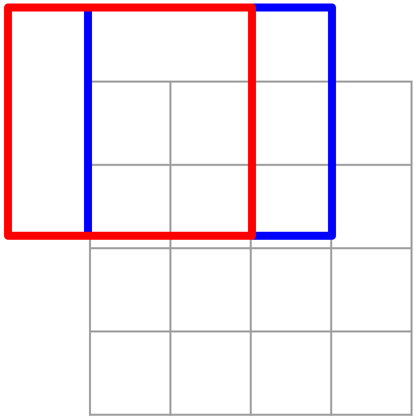
Learnable Upsampling

Recall: Normal 3 x 3 convolution, stride 1 pad 1

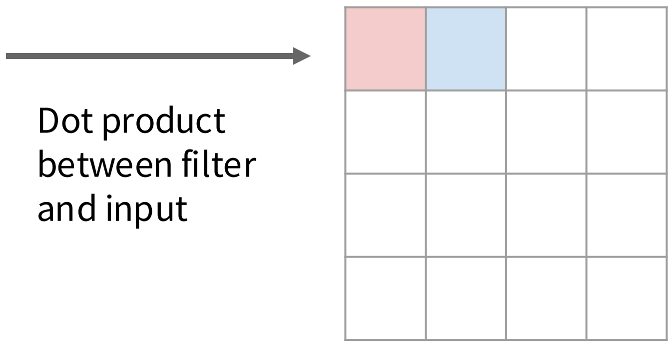


Learnable Upsampling

Recall: Normal 3 x 3 convolution, stride 1 pad 1

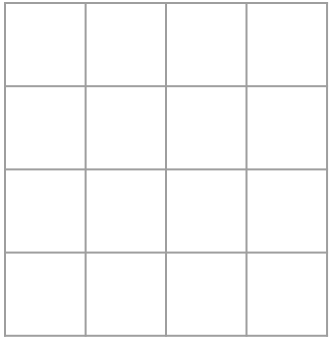


Dot product between filter and input

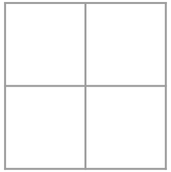


Learnable Upsampling

Recall: Normal 3 x 3 convolution, stride 2 pad 1



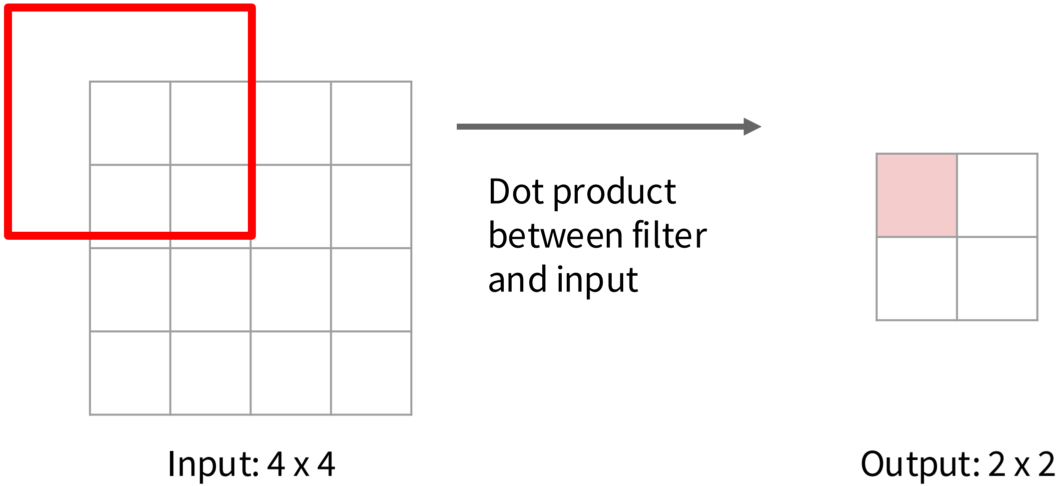
Input: 4 x 4



Output: 2 x 2

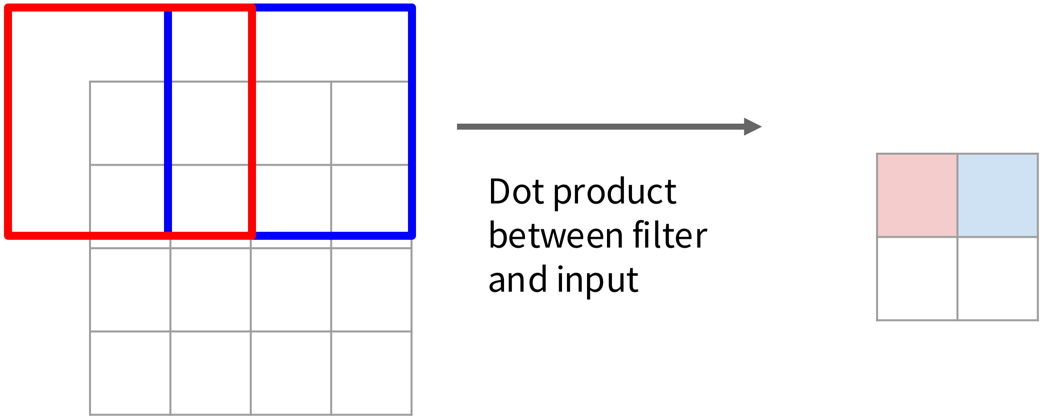
Learnable Upsampling

Recall: Normal 3 x 3 convolution, stride 2 pad 1



Learnable Upsampling

Recall: Normal 3 x 3 convolution, stride 2 pad 1



Input: 4 x 4

Dot product between filter and input

Output: 2 x 2

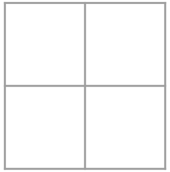
Filter moves 2 pixels in the input for every one pixel in the output

Stride gives ratio between movement in input and output

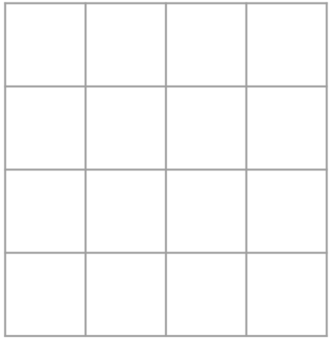
We can interpret strided convolution as “learnable downsampling”.

Learnable Upsampling: Transposed Convolution

3 x 3 transposed convolution, stride 2 pad 1



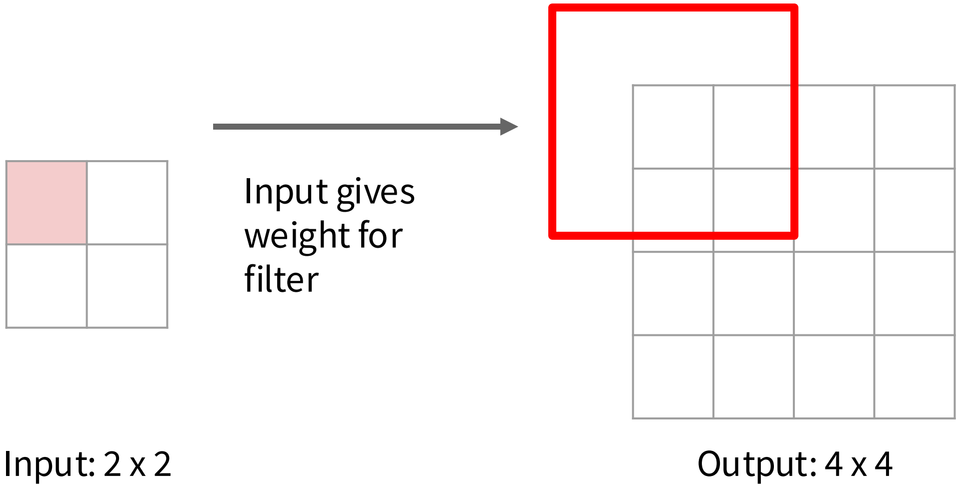
Input: 2 x 2



Output: 4 x 4

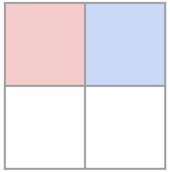
Learnable Upsampling: Transposed Convolution

3 x 3 transposed convolution, stride 2 pad 1



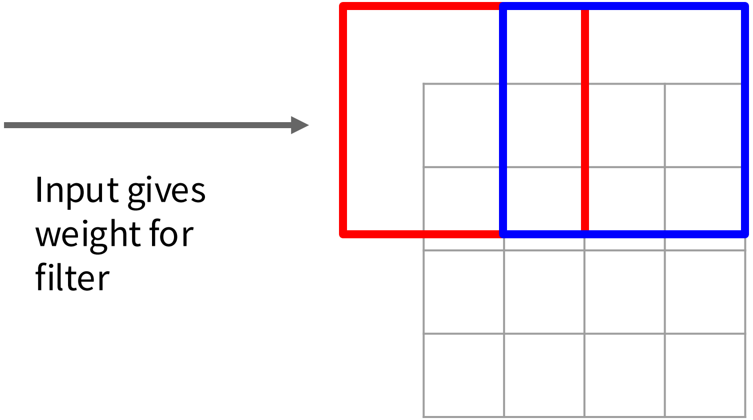
Learnable Upsampling: Transposed Convolution

3 x 3 transposed convolution, stride 2 pad 1



Input: 2 x 2

Input gives weight for filter



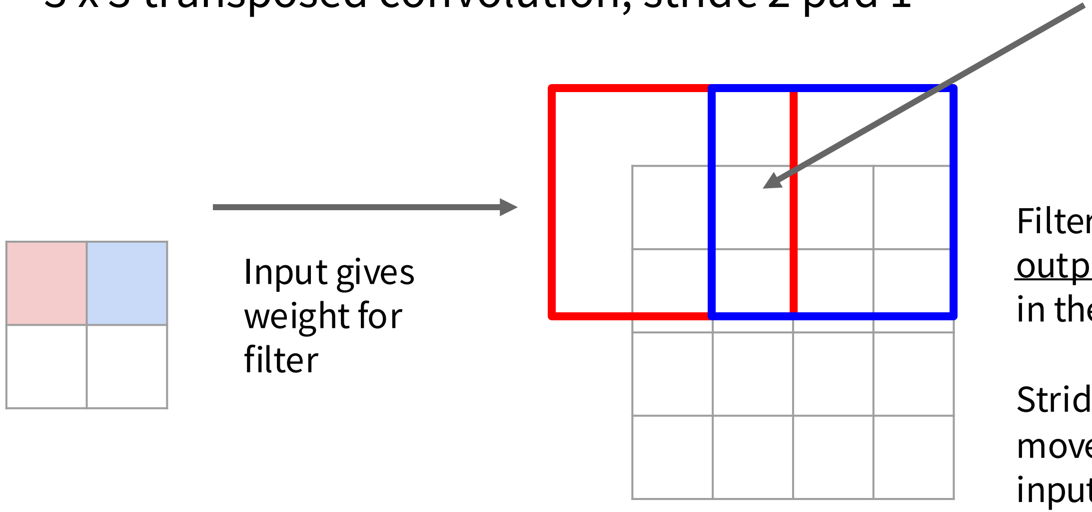
Output: 4 x 4

Filter moves 2 pixels in the <u>output</u> for every one pixel in the <u>input</u>

Stride gives ratio between movement in output and input

Learnable Upsampling: Transposed Convolution

3 x 3 transposed convolution, stride 2 pad 1



Input gives weight for filter

Sum where output overlaps

Input: 2 x 2

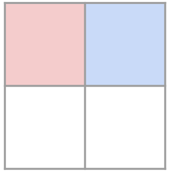
Output: 4 x 4

Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

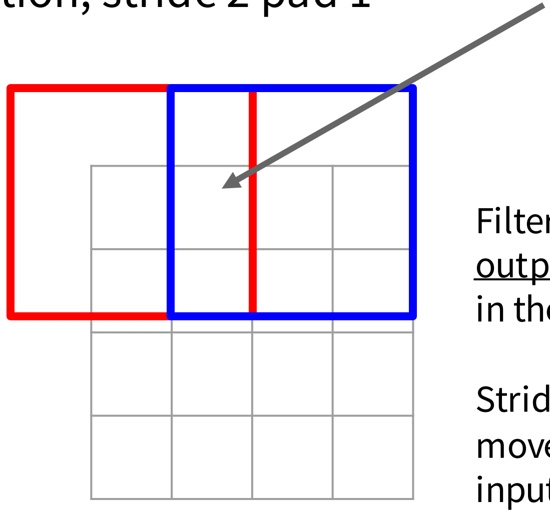
Learnable Upsampling: Transposed Convolution

3 x 3 transposed convolution, stride 2 pad 1



Input: 2 x 2

Input gives weight for filter



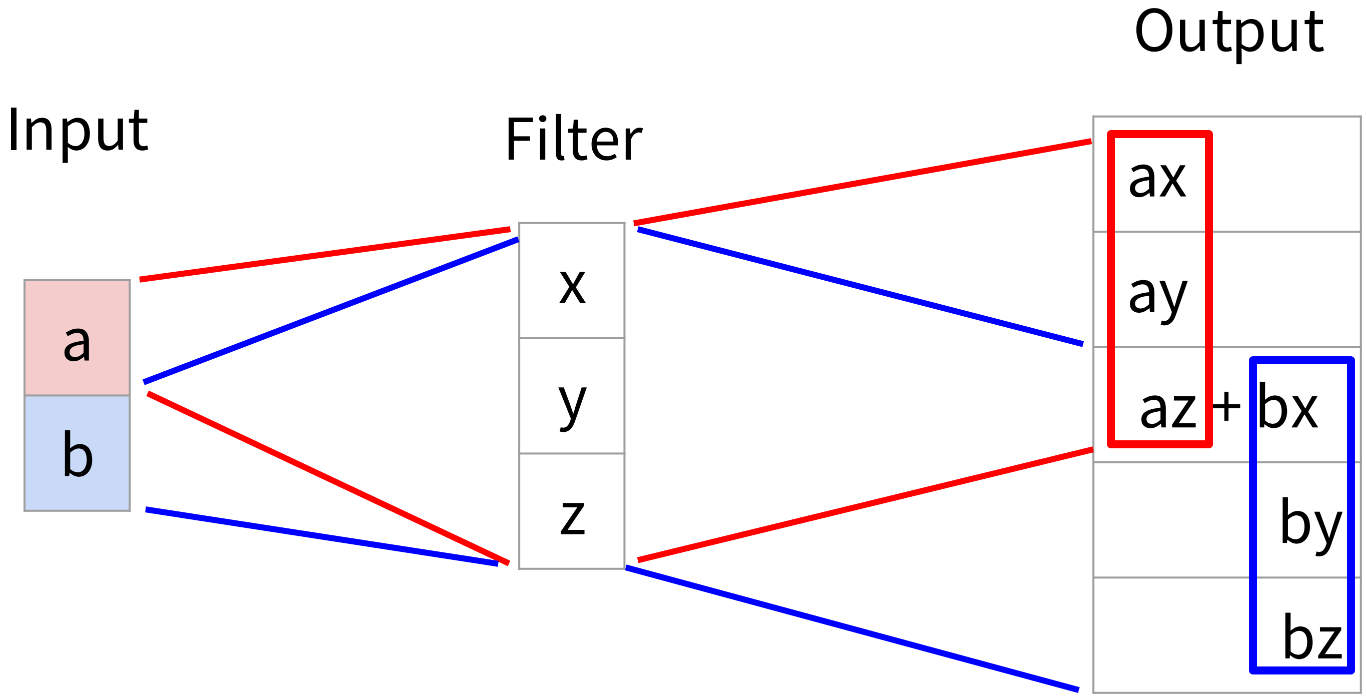
Output: 4 x 4

Sum where output overlaps

Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

Learnable Upsampling: 1D Example



Output contains copies of the filter weighted by the input, summing at where at overlaps in the output

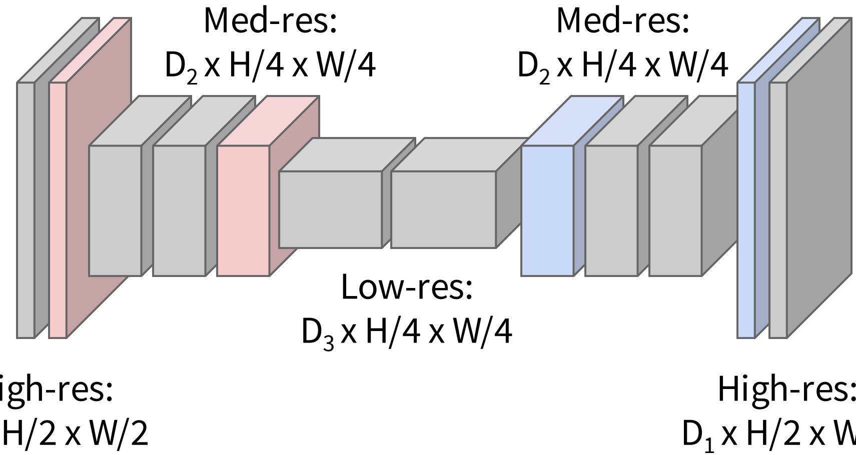
Semantic Segmentation Idea: Fully Convolutional

Downsampling: Pooling, strided convolution

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

Upsampling: Unpooling or strided transposed convolution

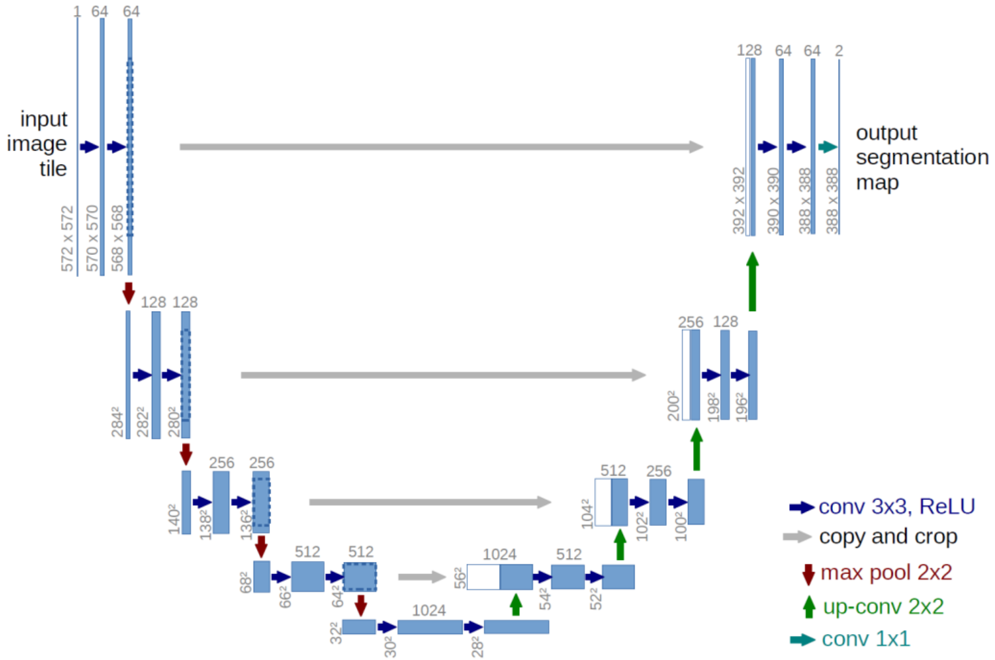
Input:
3 x H x W



Predictions:
H x W

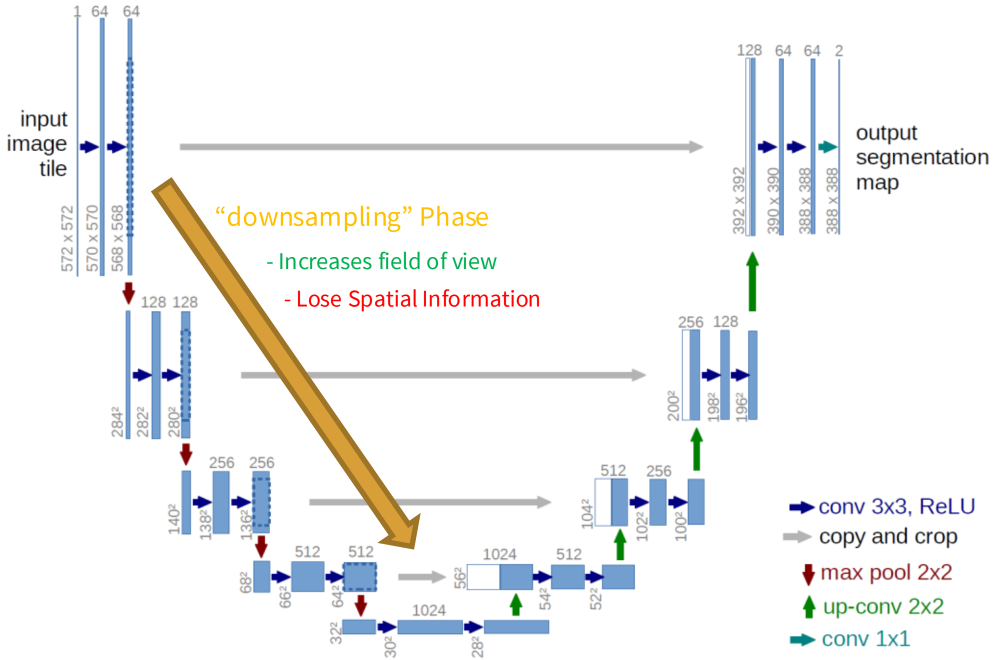
Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

U-Net



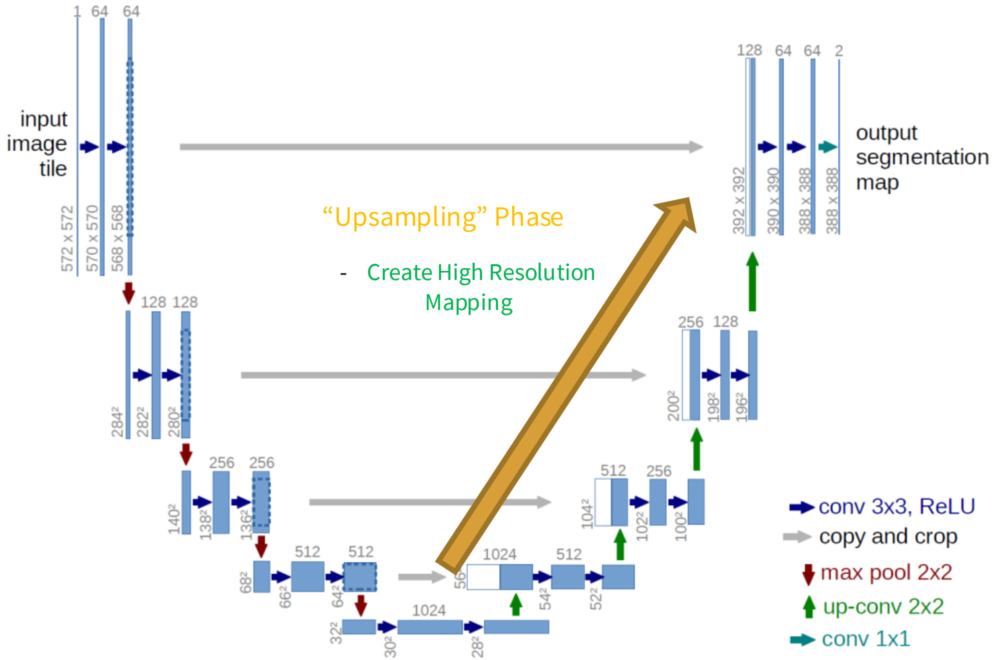
Ronneberger et al. (2015) U-net Architecture

U-Net



Ronneberger et al. (2015) U-net Architecture

U-Net

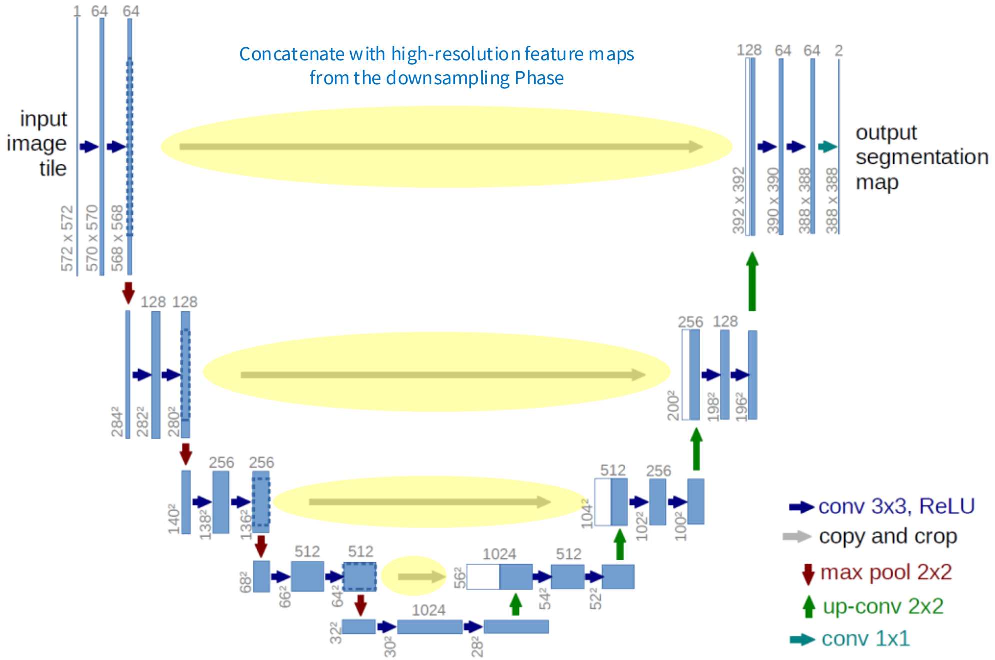


"Upsampling" Phase

- Create High Resolution Mapping

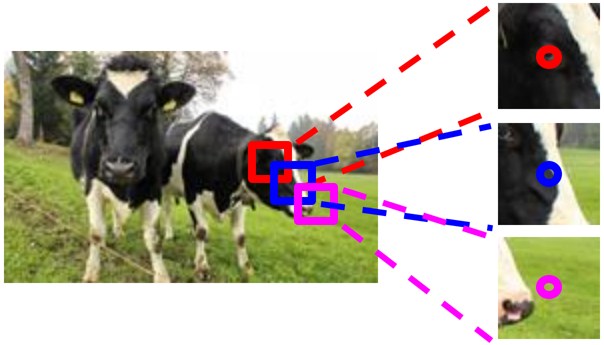
Ronneberger et al. (2015) U-net Architecture

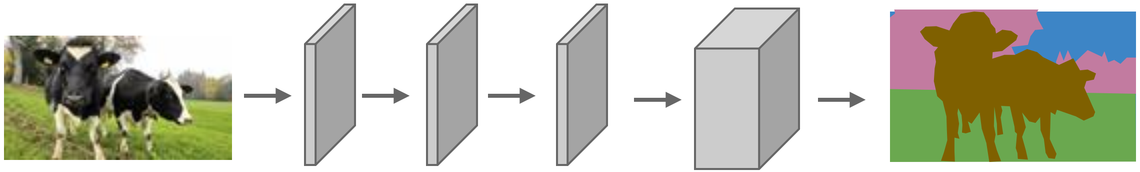
U-Net

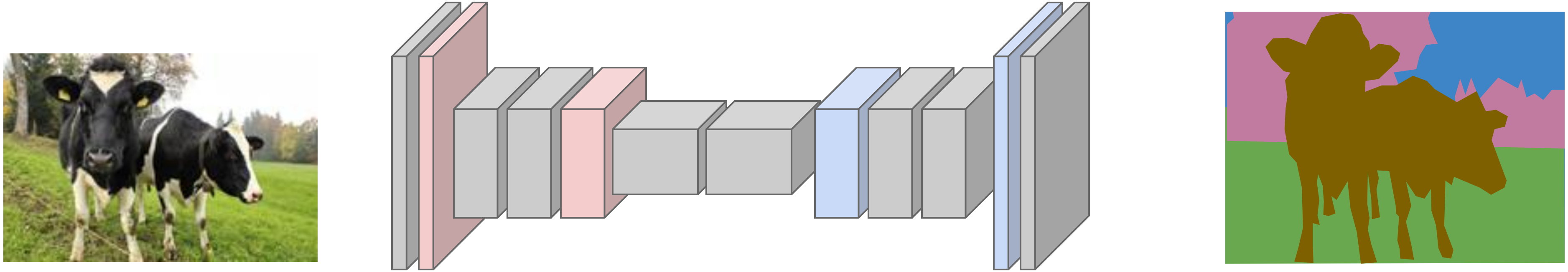


Ronneberger et al. (2015) U-net Architecture

Semantic Segmentation: Summary



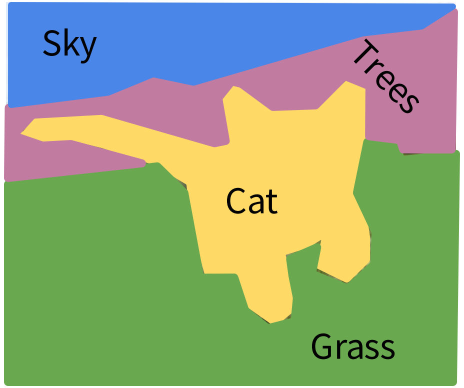


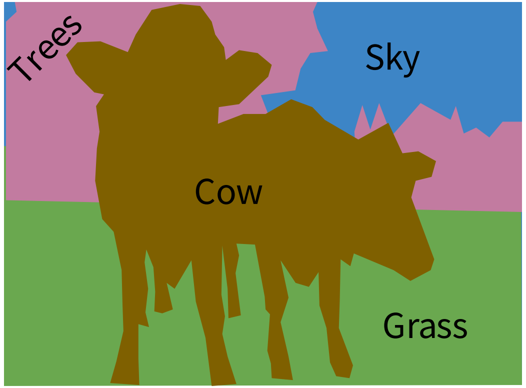


Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels





Object Detection

Classification

CAT

No spatial extent

Semantic Segmentation

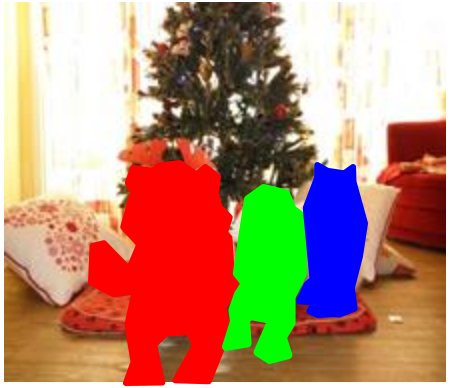
GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Multiple Object

Object Detection

Classification

CAT

No spatial extent

Semantic Segmentation

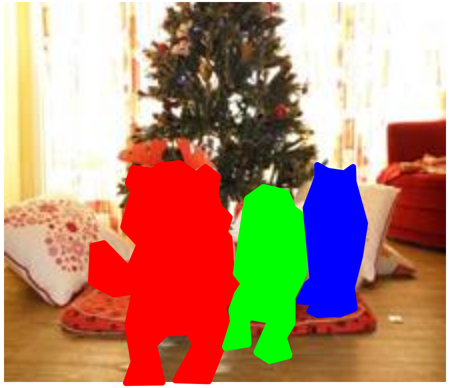
GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

Instance Segmentation

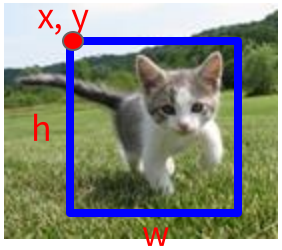


DOG, DOG, CAT

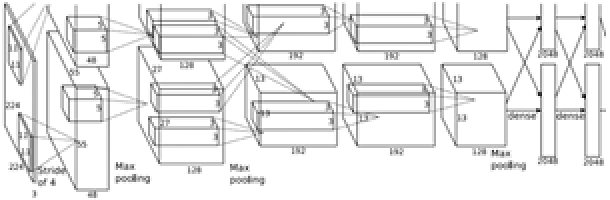
Multiple Object

Object Detection: Single Object

(Classification + Localization)



This image is CC0 public domain



Vector: 4096

Fully Connected: 4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Fully Connected: 4096 to 4

Box Coordinates
(x, y, w, h)

Object Detection: Single Object

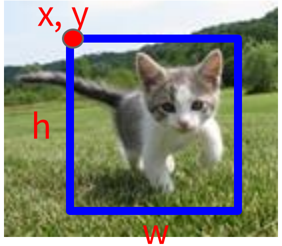
(Classification + Localization)

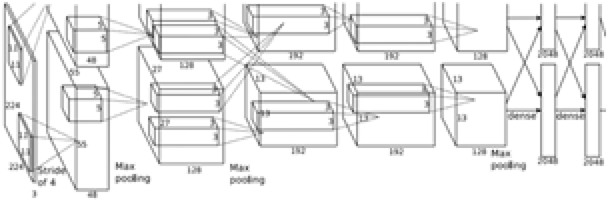
Correct label:
Cat

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Softmax
Loss

Fully
Connected:
4096 to 1000





Vector:
4096

Fully
Connected:
4096 to 4

Box
Coordinates
(x, y, w, h)

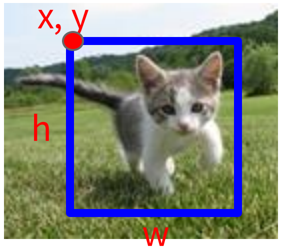
L2 Loss

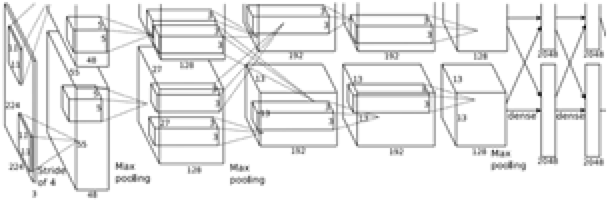
Correct box:
(x', y', w', h')

Treat localization as a regression problem!

Object Detection: Single Object

(Classification + Localization)





Vector: 4096

Fully Connected: 4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Correct label: Cat

Softmax Loss

Fully Connected: 4096 to 4

Box Coordinates (x, y, w, h)

Correct box: (x', y', w', h')

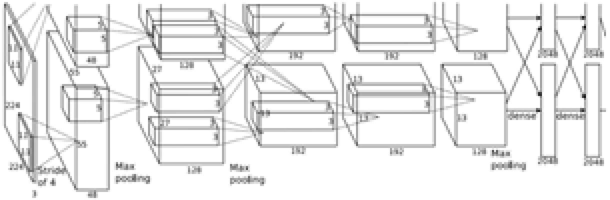
L2 Loss

Multitask Loss

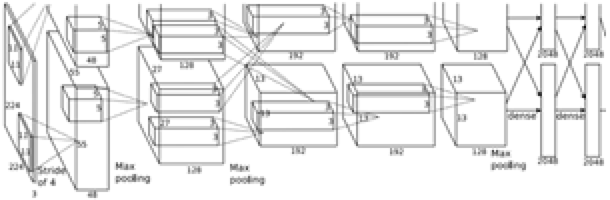
+ → Loss

Treat localization as a regression problem!

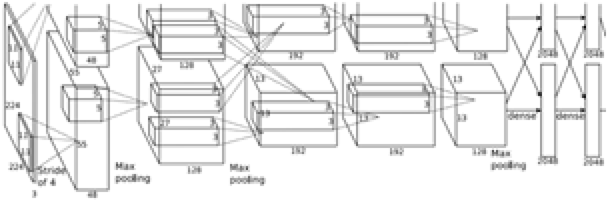
Object Detection: Multiple Objects

CAT: (x, y, w, h)

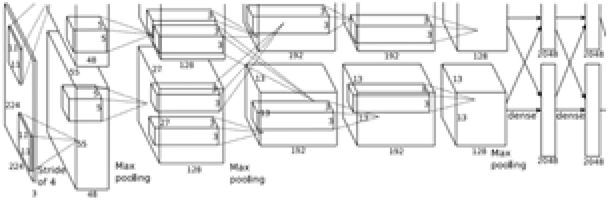
DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)

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

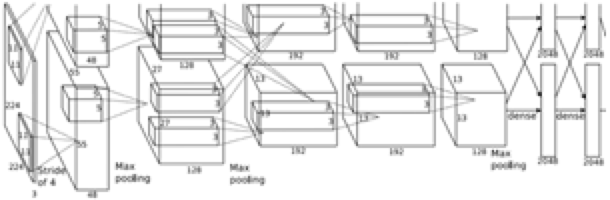
Object Detection: Multiple Objects

Each image needs a different number of outputs!



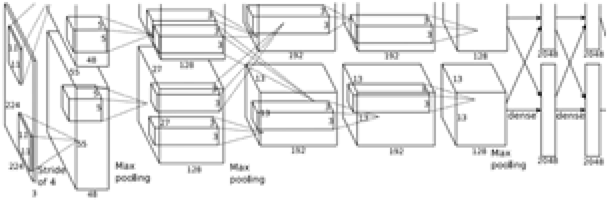
CAT: (x, y, w, h)

4 numbers



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

12 numbers

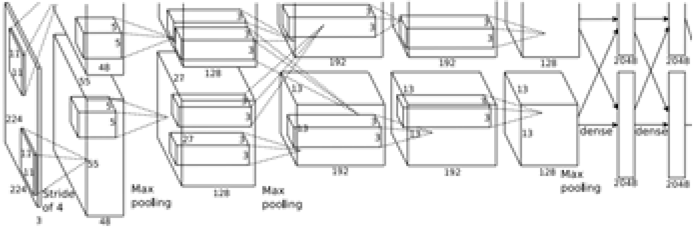


DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
….

Many numbers!

Object Detection: Multiple Objects

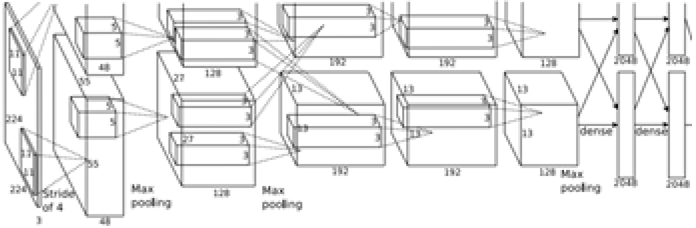
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection: Multiple Objects

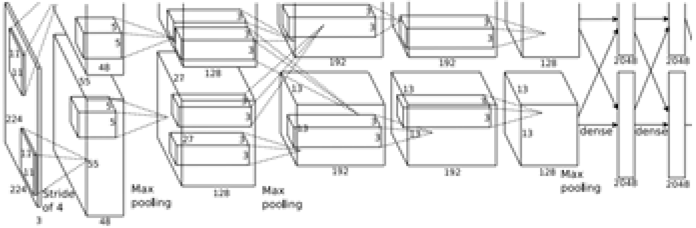
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

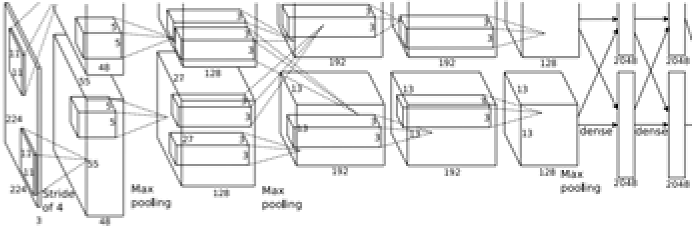
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

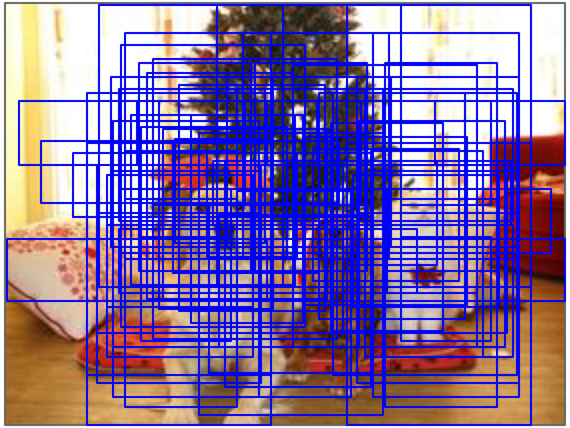
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



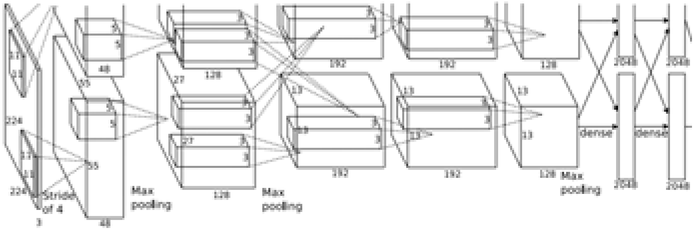
Dog? NO
Cat? YES
Background? NO

Q: What's the problem with this approach?

Object Detection: Multiple Objects



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

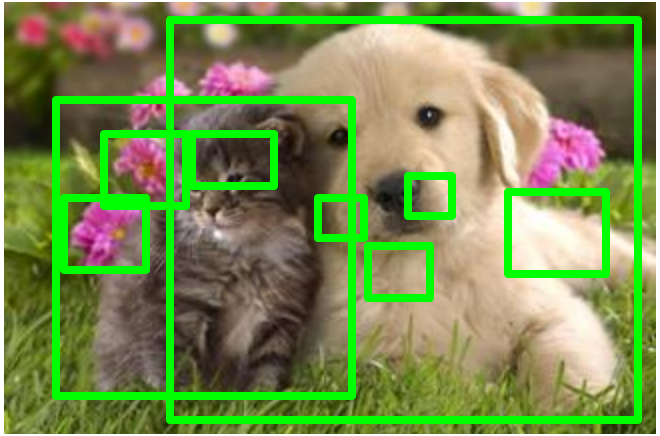


Dog? NO
Cat? YES
Background? NO

Problem: Need to apply CNN to huge number of locations, scales, and aspect ratios, very computationally expensive!

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

R-CNN

Input image

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

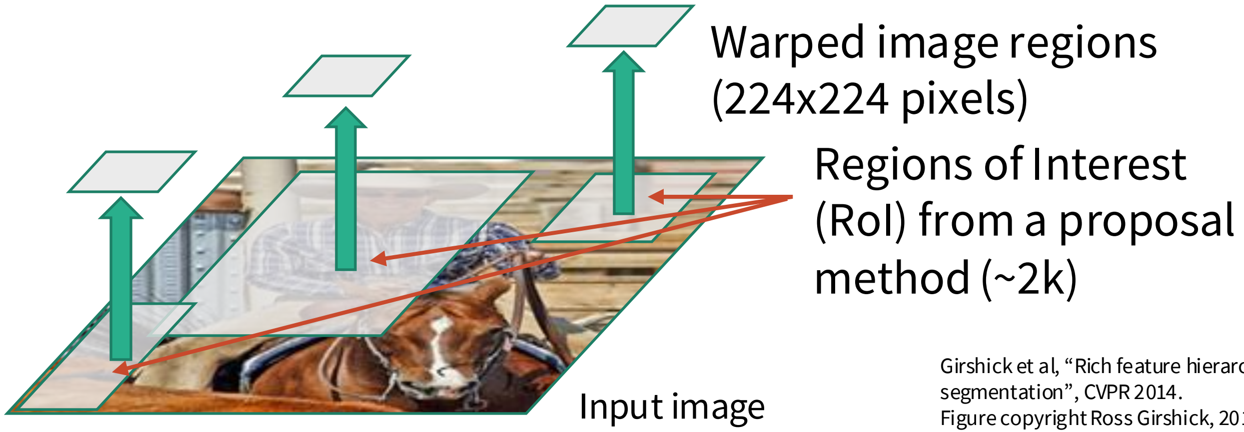
R-CNN

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

Input image

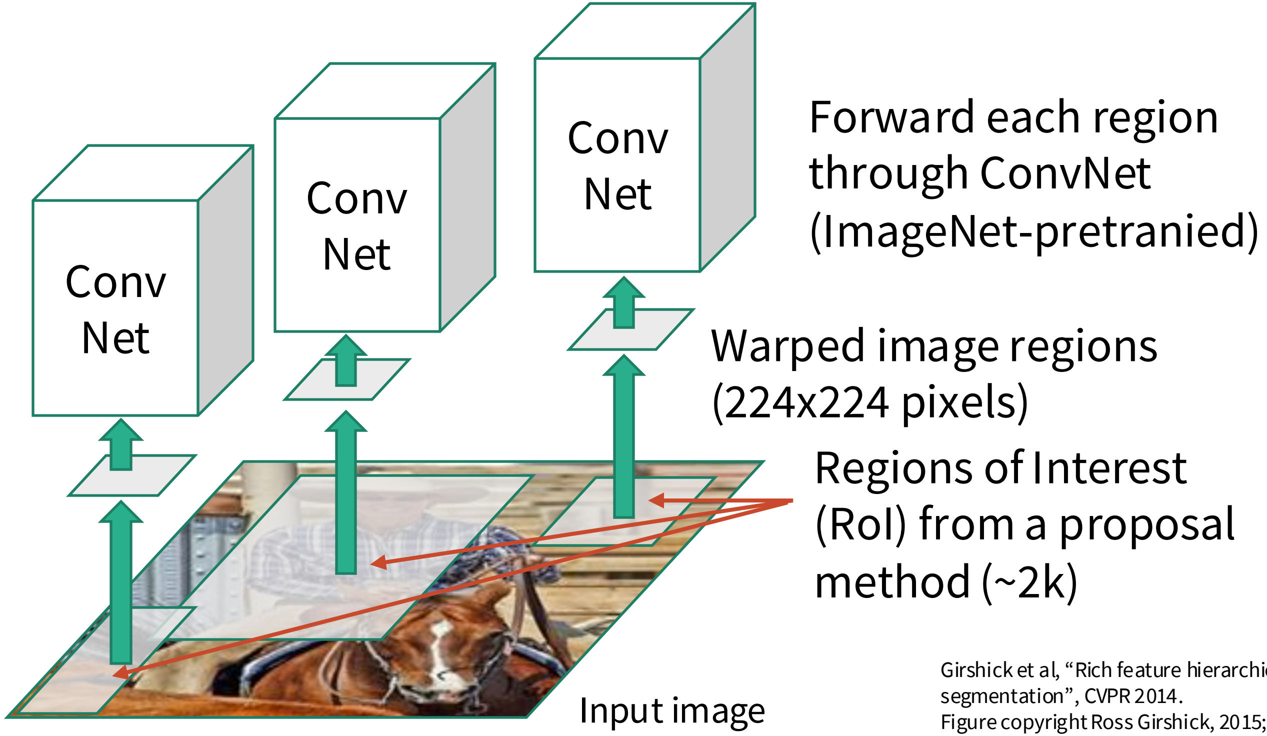
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

R-CNN



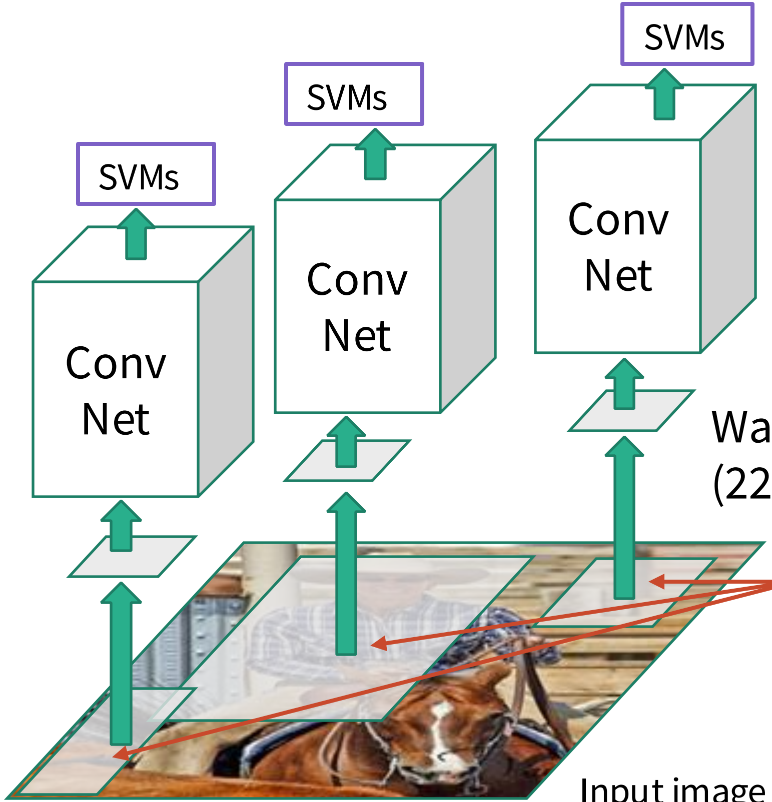
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

R-CNN



Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

R-CNN



Classify regions with SVMs

Forward each region through ConvNet (ImageNet-pretranied)

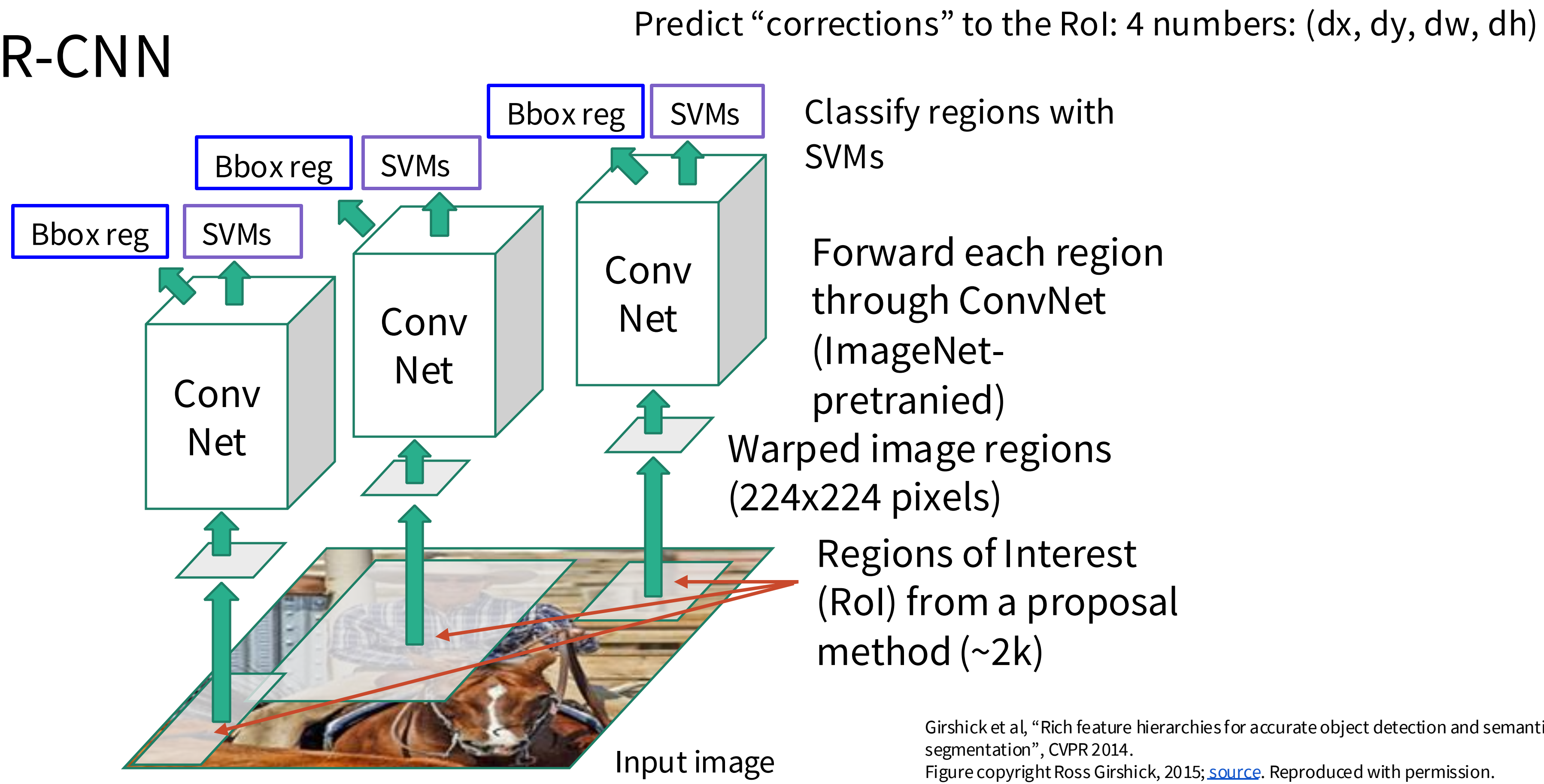
Warped image regions (224x224 pixels)

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

Input image

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

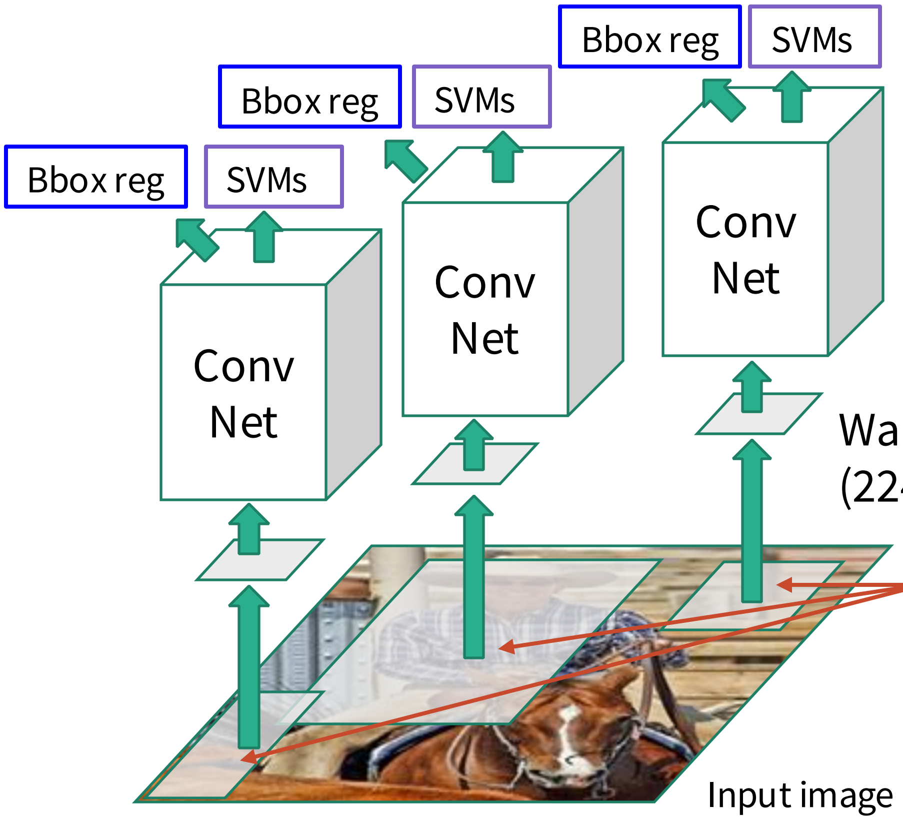
R-CNN



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

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)

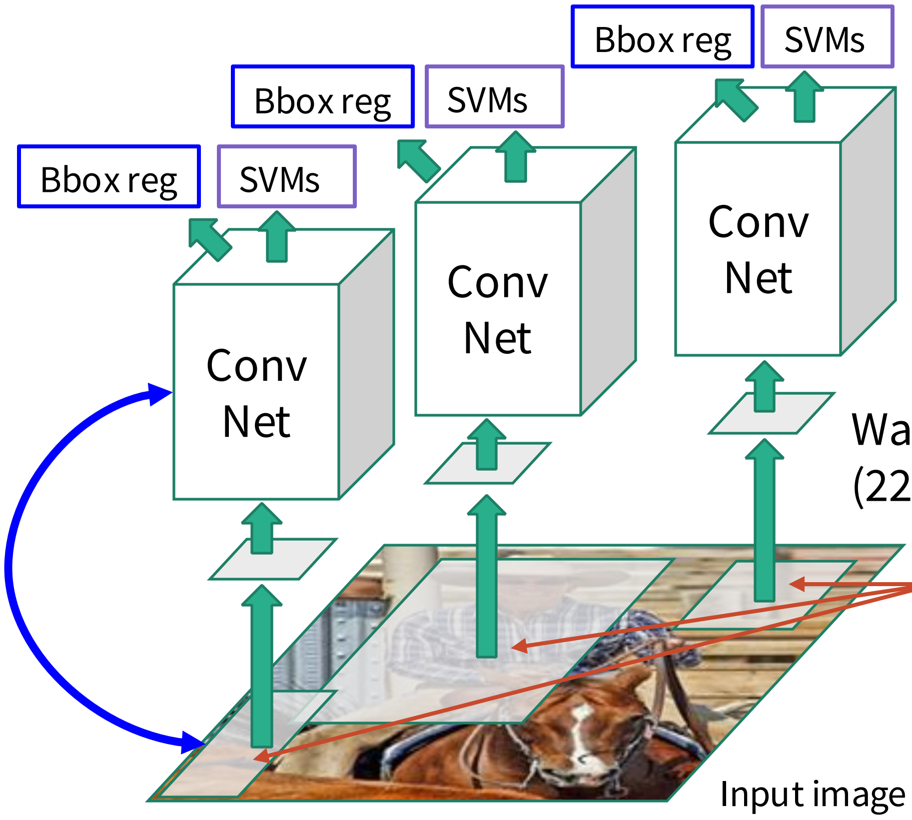
Regions of Interest (RoI) from a proposal method (~2k)

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

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

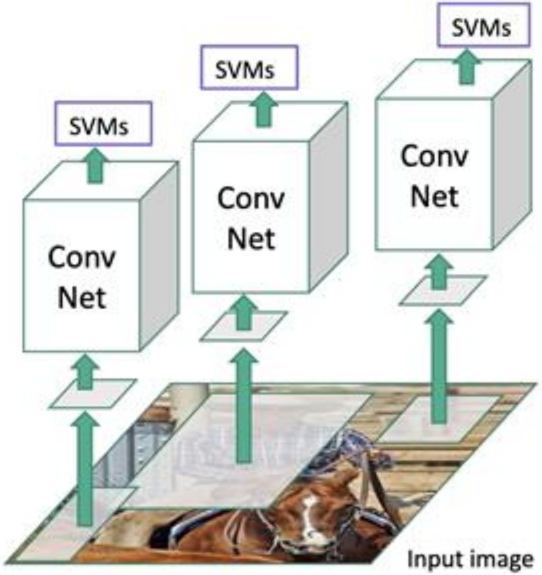
Idea: Pass the image through convnet before cropping! Crop the conv feature instead!

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

Fast R-CNN

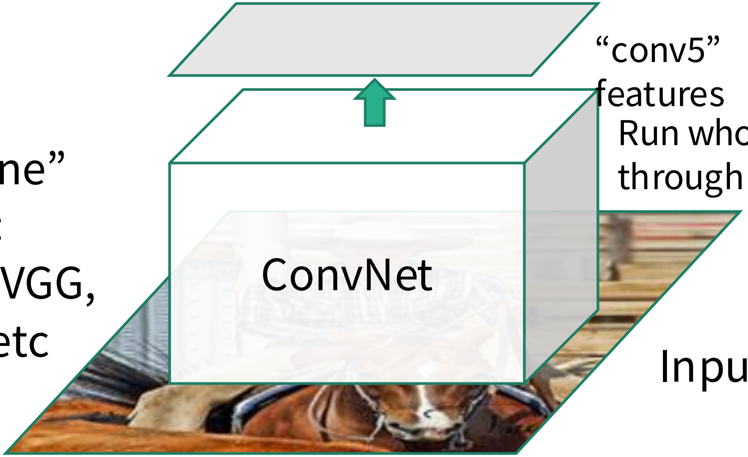
Input image

“Slow” R-CNN



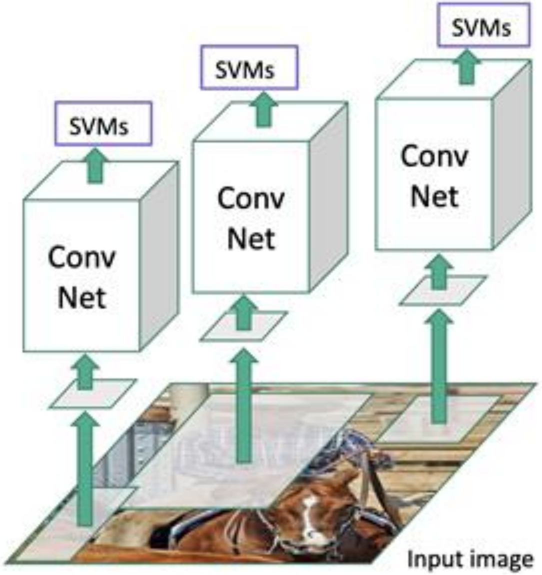
Girshick, “Fast R-CNN”, ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast R-CNN



"Backbone" network: AlexNet, VGG, ResNet, etc

"Slow" R-CNN

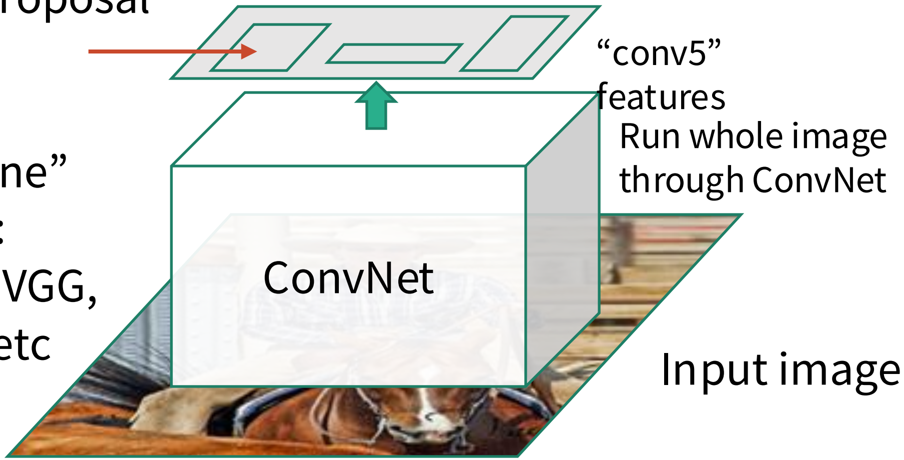


Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

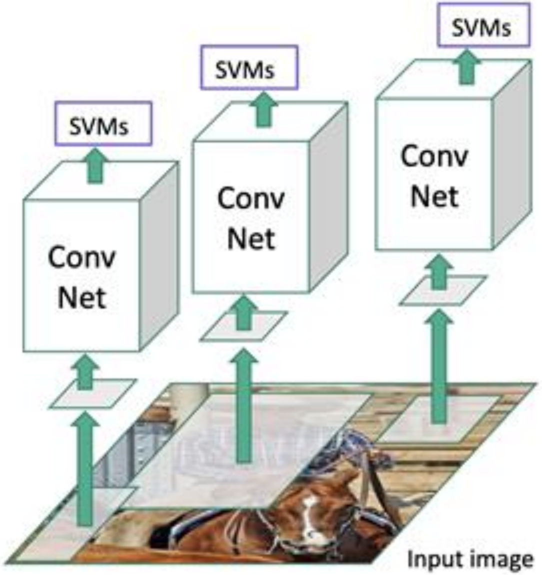
Fast R-CNN

Regions of Interest (RoIs) from a proposal method

"Backbone" network: AlexNet, VGG, ResNet, etc



"Slow" R-CNN



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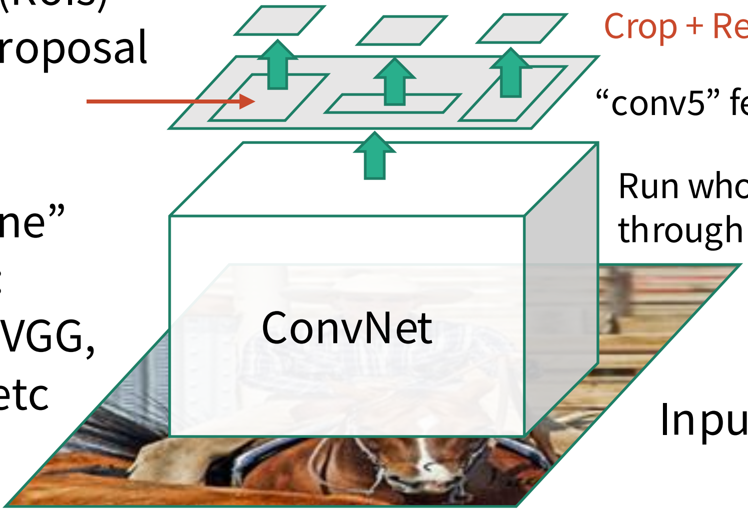
Fast R-CNN

Regions of Interest (RoIs) from a proposal method

"Backbone" network: AlexNet, VGG, ResNet, etc



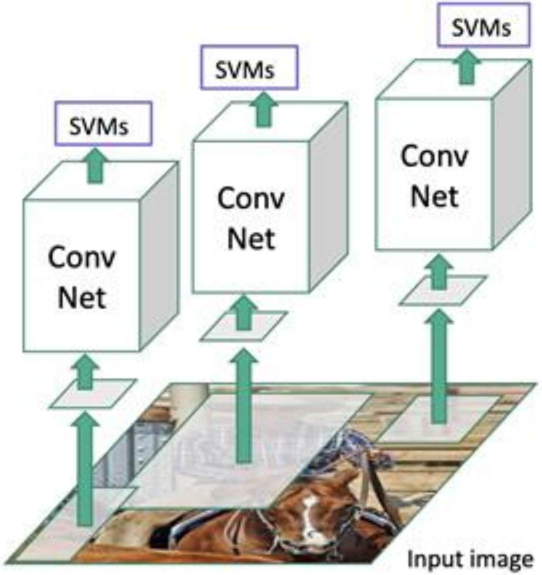
Crop + Resize features

"conv5" features

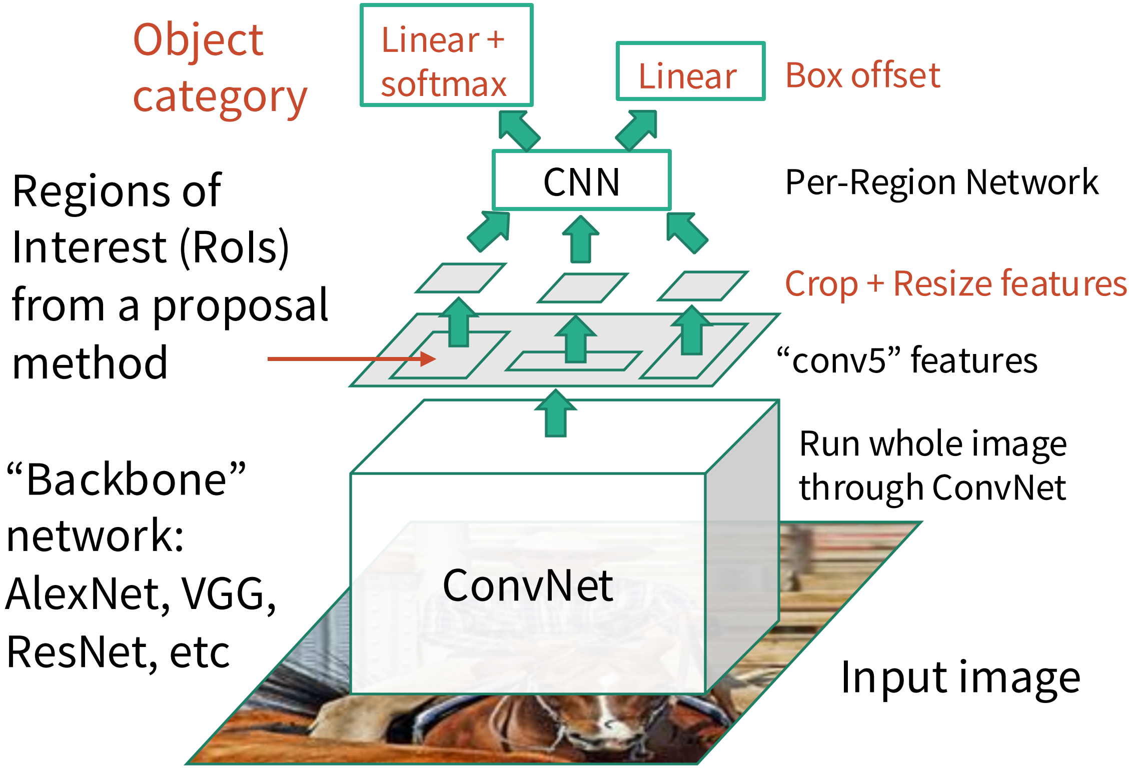
Run whole image through ConvNet

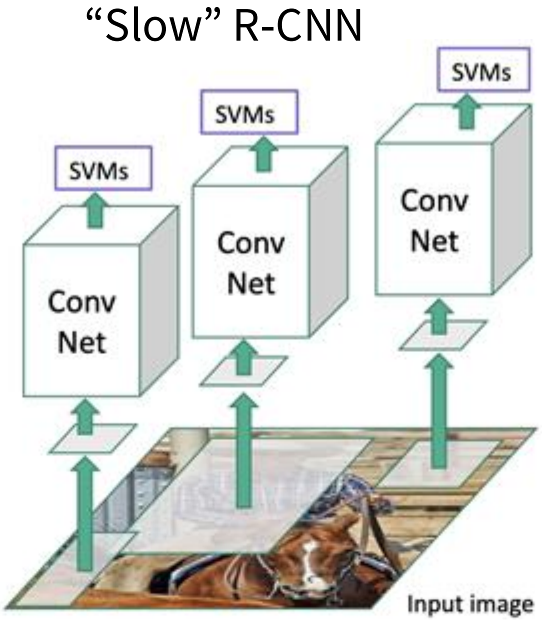
Input image

"Slow" R-CNN



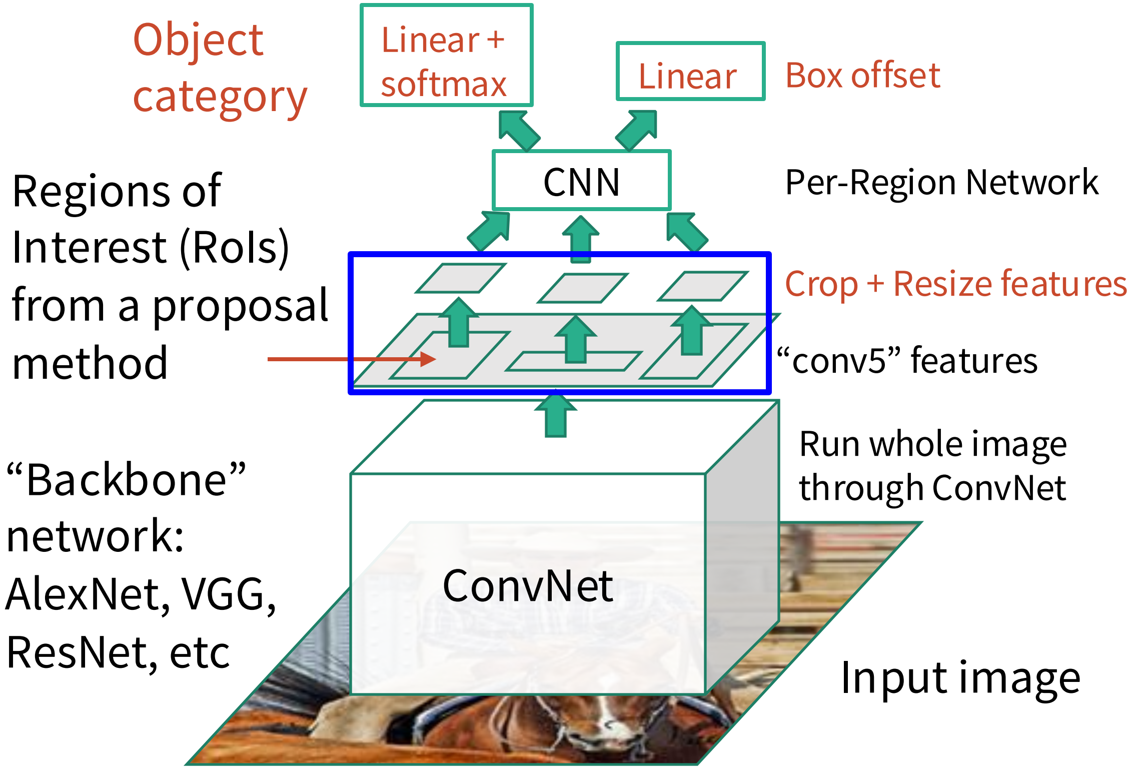
Fast R-CNN

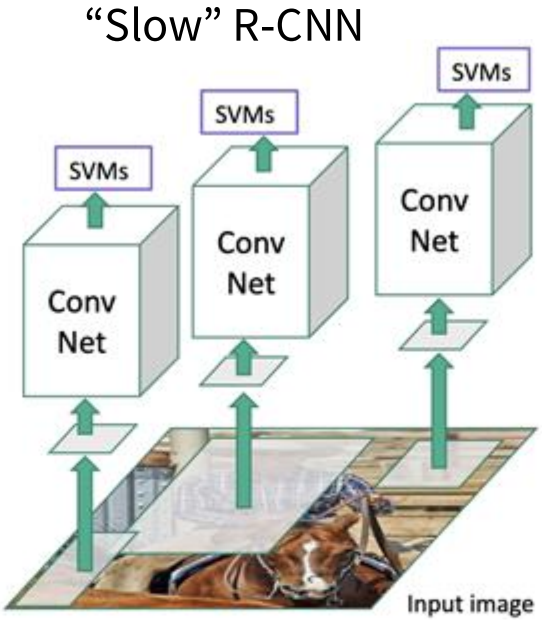




Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

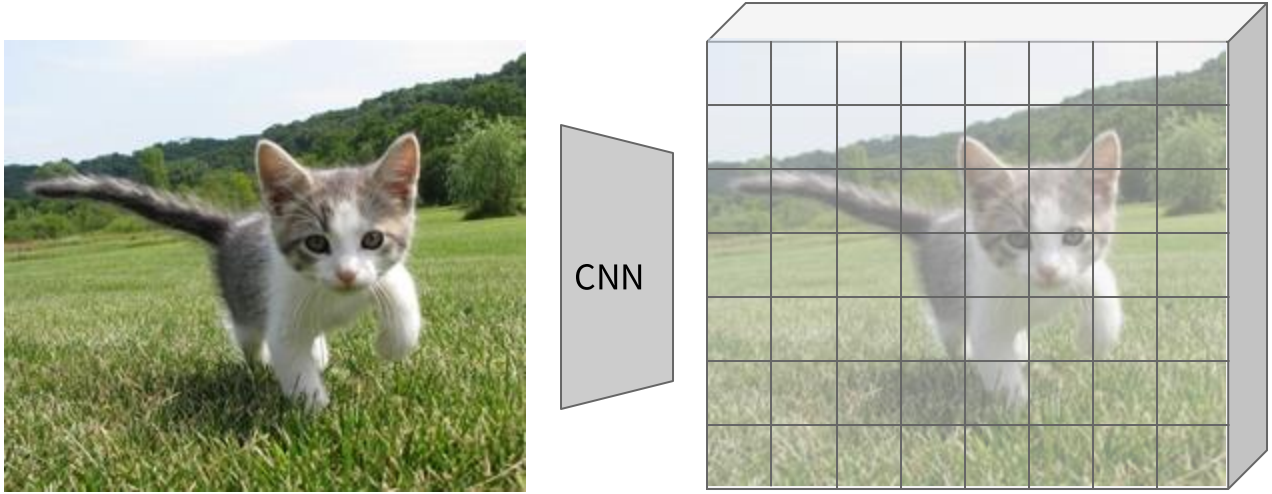
Fast R-CNN





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

Region Proposal Network



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

Image features
(e.g. 512 x 20 x 15)

Region Proposal Network

Imagine an anchor box of fixed size at each point in the feature map

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

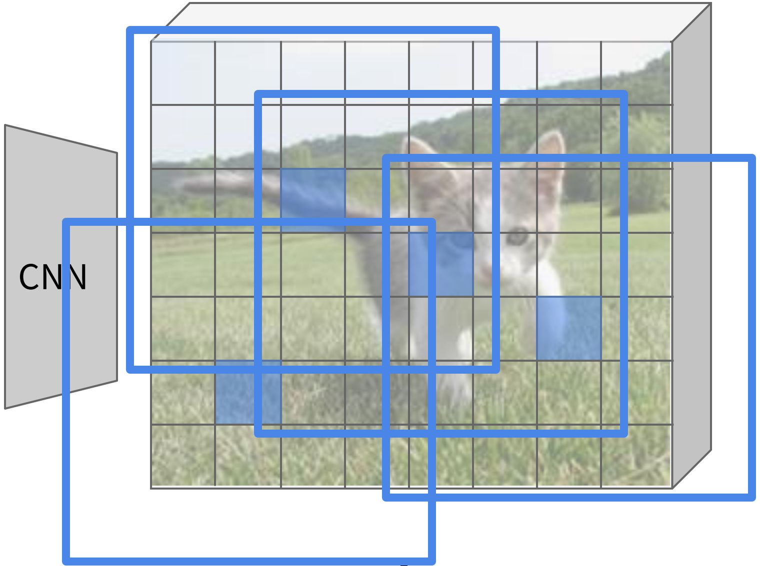
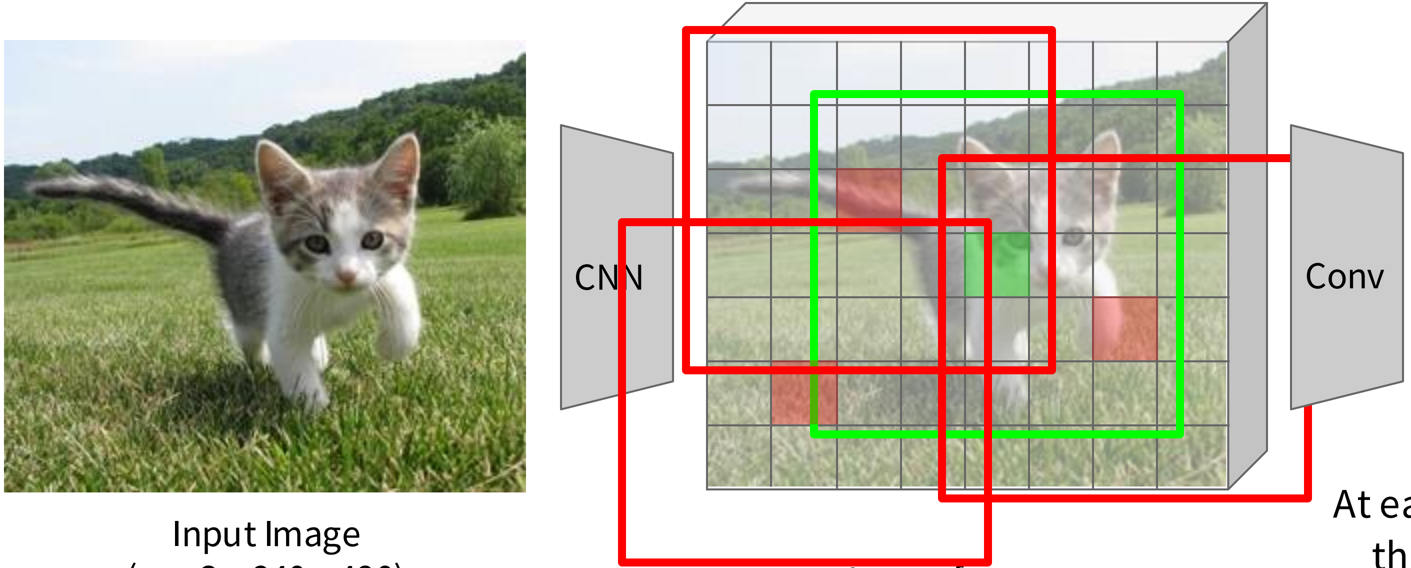


Image features
(e.g. 512 x 20 x 15)

Region Proposal Network

Imagine an anchor box of fixed size at each point in the feature map



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

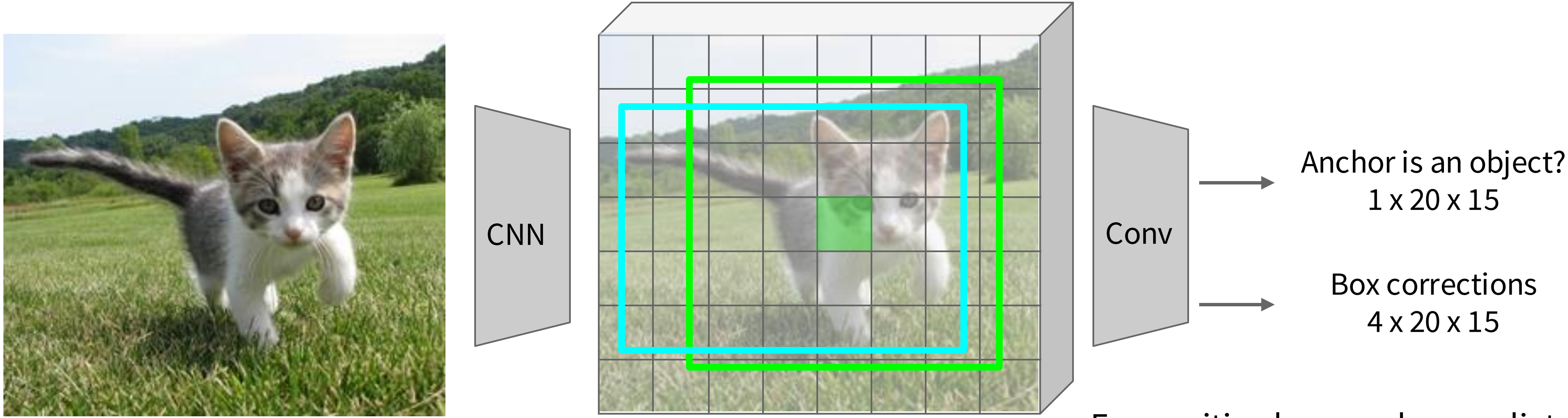
Image features
(e.g. 512 x 20 x 15)

Anchor is an object?
1 x 20 x 15

At each point, predict whether the corresponding anchor contains an object (binary classification)

Region Proposal Network

Imagine an anchor box of fixed size at each point in the feature map



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

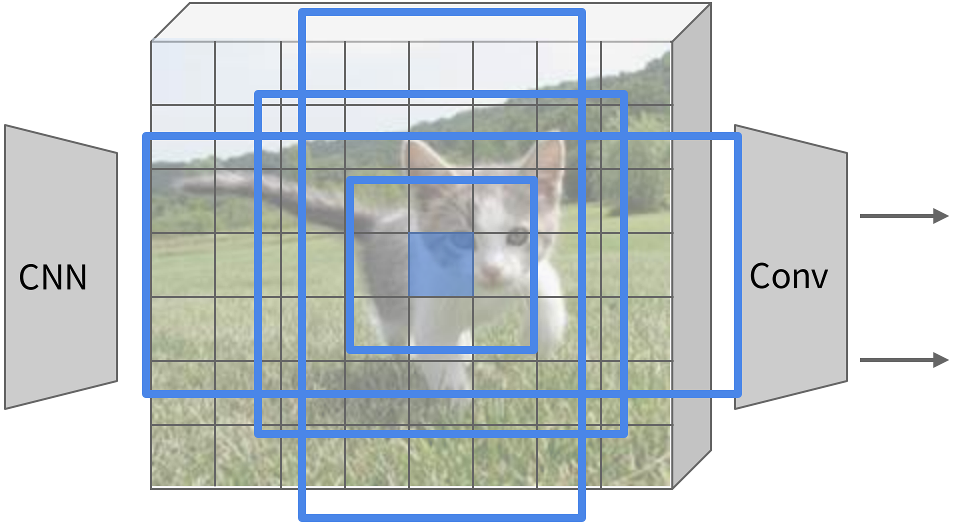
Image features
(e.g. 512 x 20 x 15)

For positive boxes, also predict a corrections from the anchor to the ground-truth box (regress 4 numbers per pixel)

Region Proposal Network

In practice use K different anchor boxes of different size / scale at each point

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



Anchor is an object?
K x 20 x 15

Box transforms
4K x 20 x 15

Image features
(e.g. 512 x 20 x 15)

Region Proposal Network

In practice use K different anchor boxes of different size / scale at each point

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

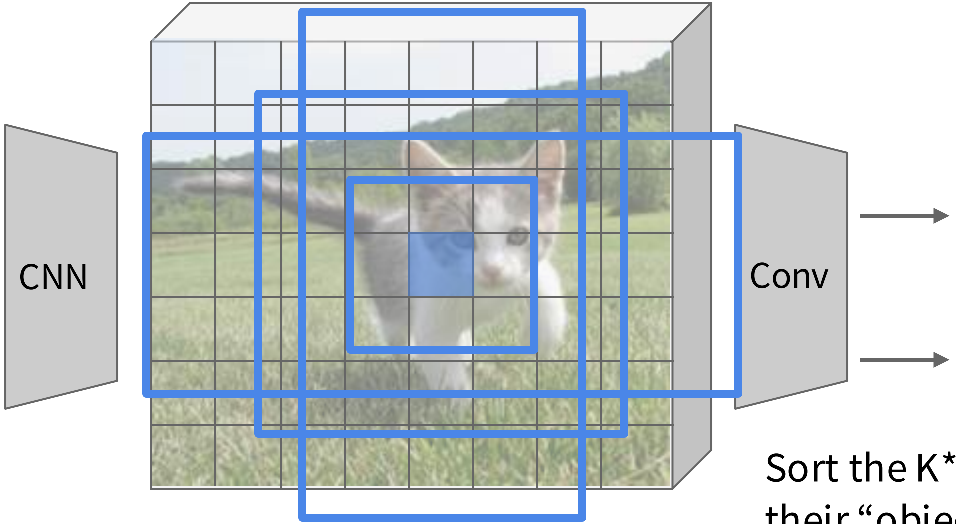


Image features
(e.g. 512 x 20 x 15)

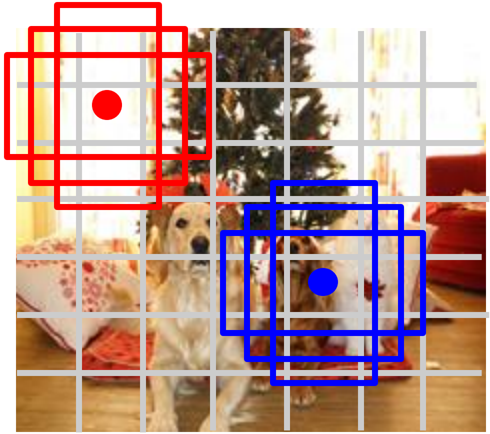
Anchor is an object?
K x 20 x 15

Box transforms
4K x 20 x 15

Sort the K*20*15 boxes by their "objectness" score, take top ~300 as our proposals

Single-Stage Object Detectors: YOLO / SSD / RetinaNet

Input image
3 x H x W



Divide image into grid
7 x 7

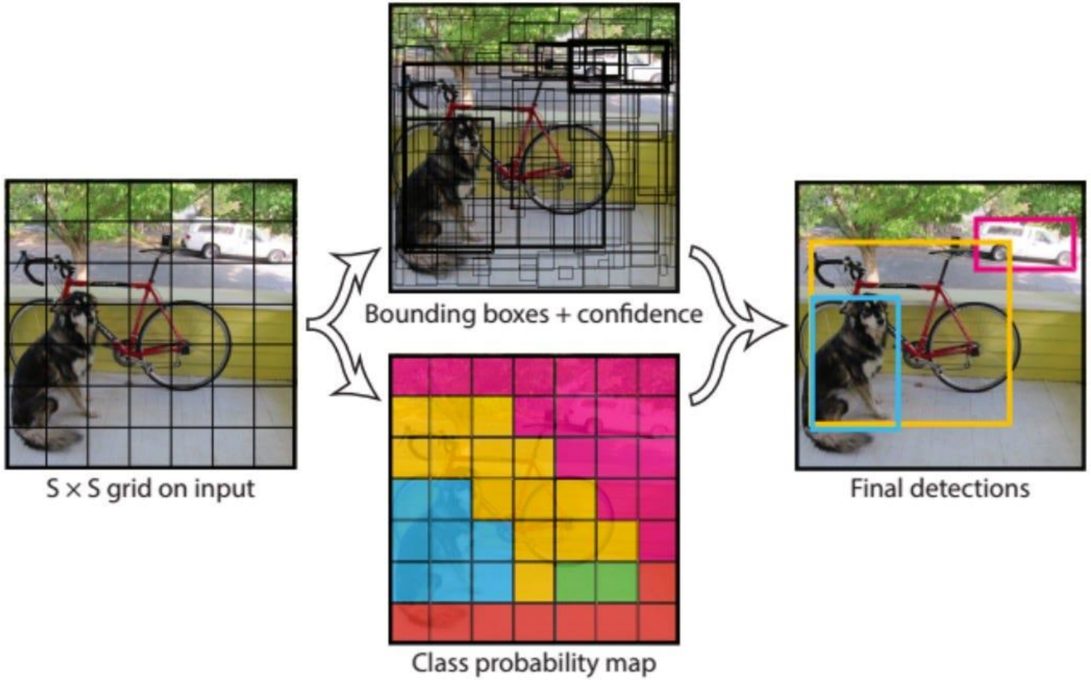
Image a set of base boxes
centered at each grid cell
Here B = 3

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)

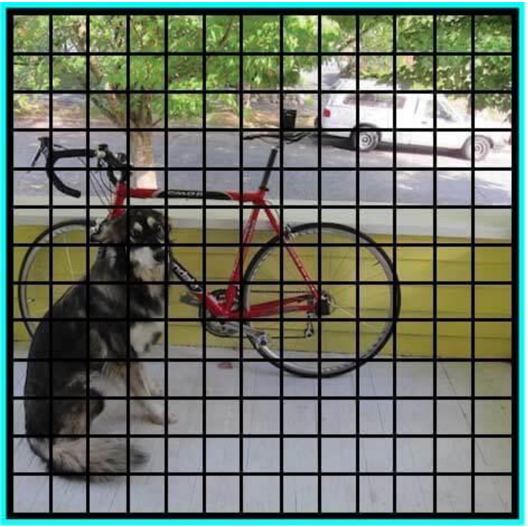
Redmon et al, "You Only Look Once: Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016
Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

YOLO (You Only Look Once) real-time object detection



Redmon et al. "You only look once: unified, real-time object detection (2015)."

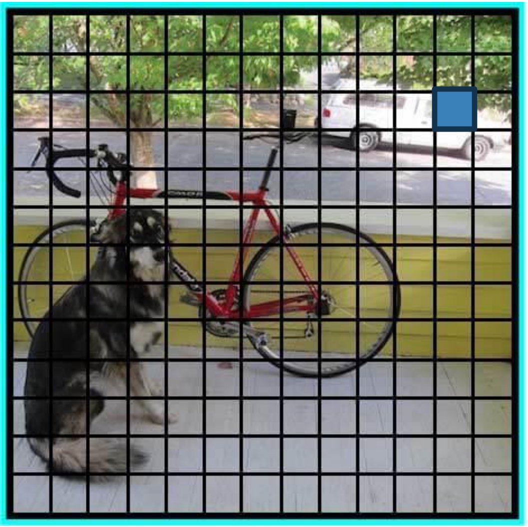
YOLO



SxS Grid

Redmon et al. "You only look once: unified, real-time object detection (2015)."

YOLO



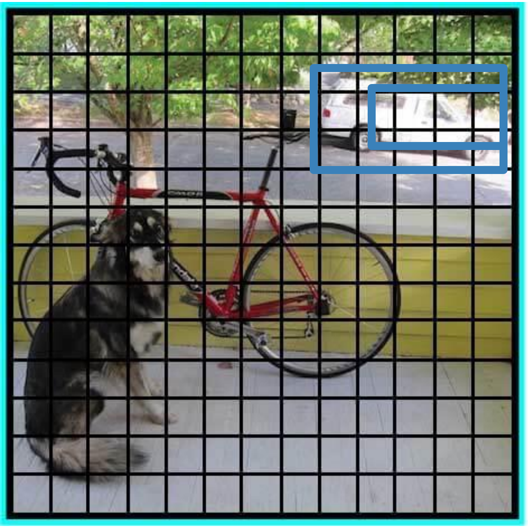
SxS Grid

For each box output:

- P(object): probability that the box contains an object
- B bounding boxes (x, y, h, w)
- P(class): probability of belonging to a class

Redmon et al. "You only look once: unified, real-time object detection (2015)."

YOLO



SxS Grid

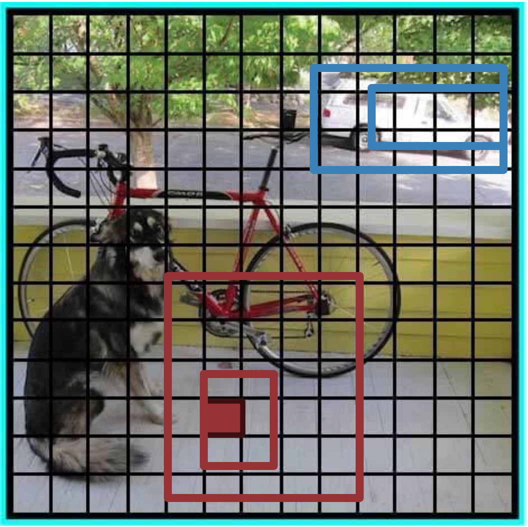
For each box output:

- P(object): probability that the box contains an object
- B bounding boxes (x, y, h, w)
- P(class): probability of belonging to a class

B=2

Redmon et al. "You only look once: unified, real-time object detection (2015)."

YOLO



SxS Grid

For each box output:

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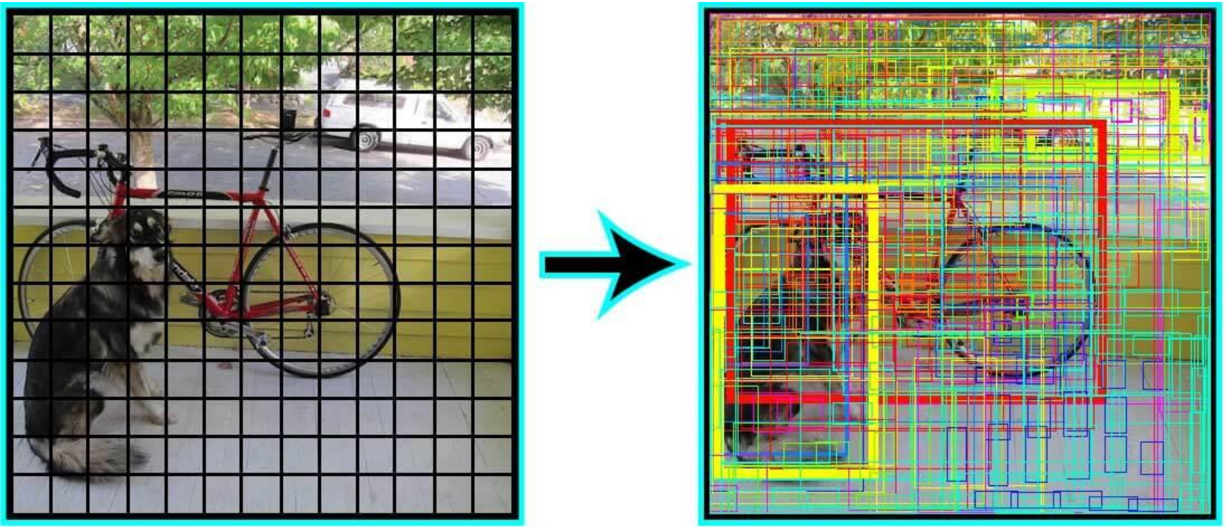
Redmon et al. "You only look once: unified, real-time object detection (2015)."

YOLO

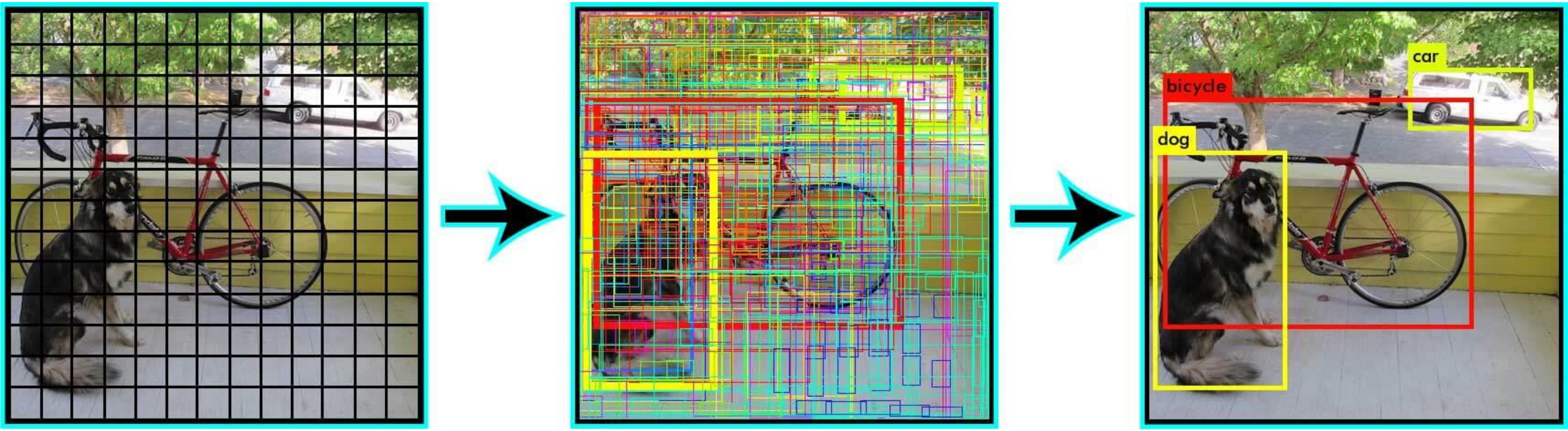


Many bounding boxes with different object probabilities

SxS Grid

Redmon et al. "You only look once: unified, real-time object detection (2015)."

YOLO



SxS Grid

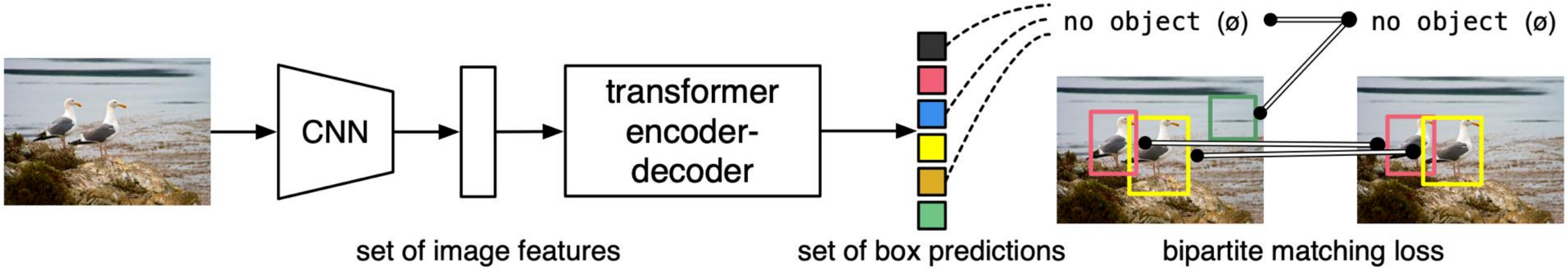
Redmon et al. "You only look once: unified, real-time object detection (2015)."

Object **De**tection with **Tr**ansformers: DETR

Simple object detection pipeline: directly output a set of boxes from a Transformer

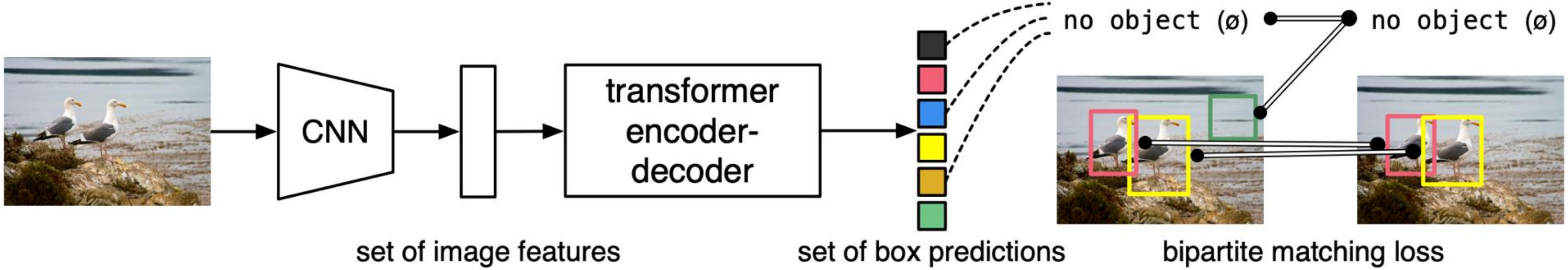
No anchors, no regression of box transforms

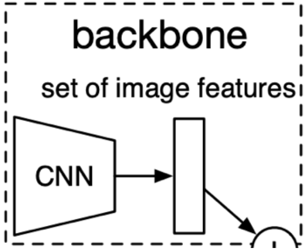
Match predicted boxes to GT boxes with bipartite matching; train to regress box coordinates



Carion et al, "End-to-End Object Detection with Transformers", ECCV 2020

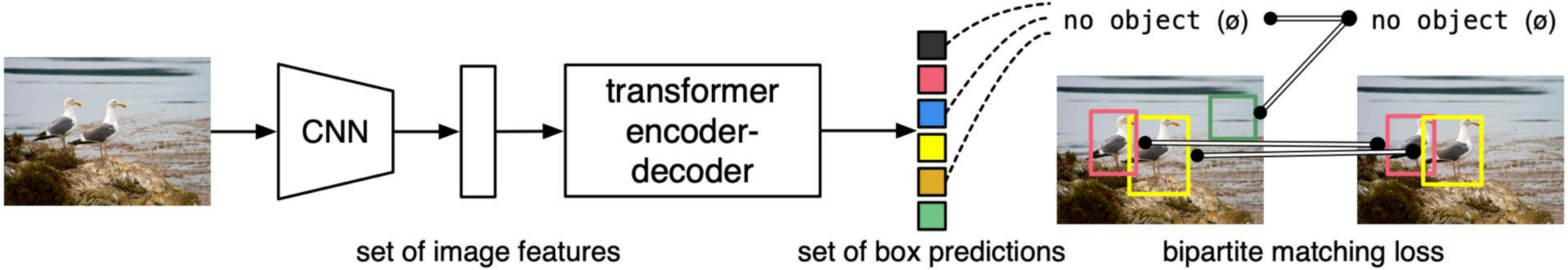
Object Detection with Transformers: DETR

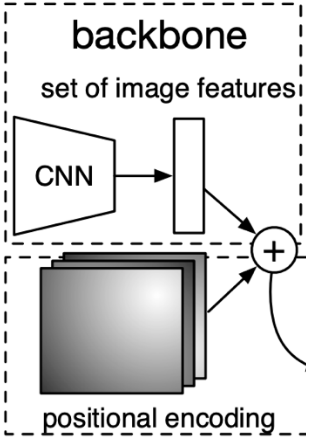




Carion et al, "End-to-End Object Detection with Transformers", ECCV 2020

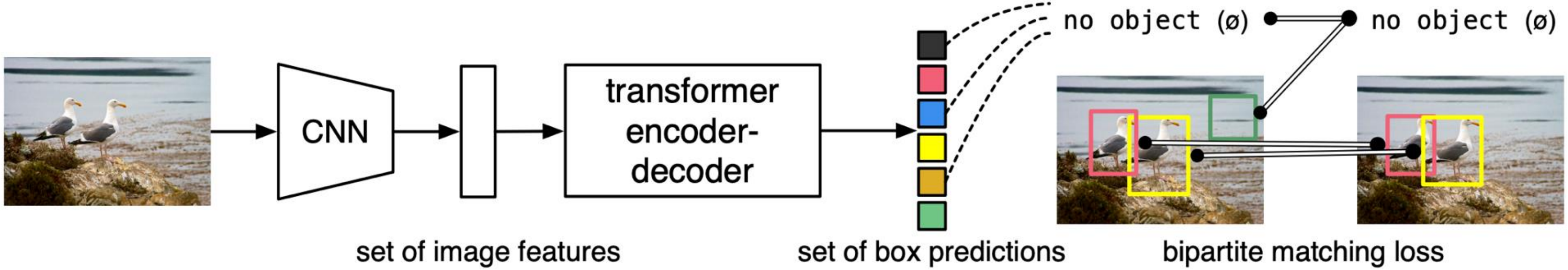
Object Detection with Transformers: DETR

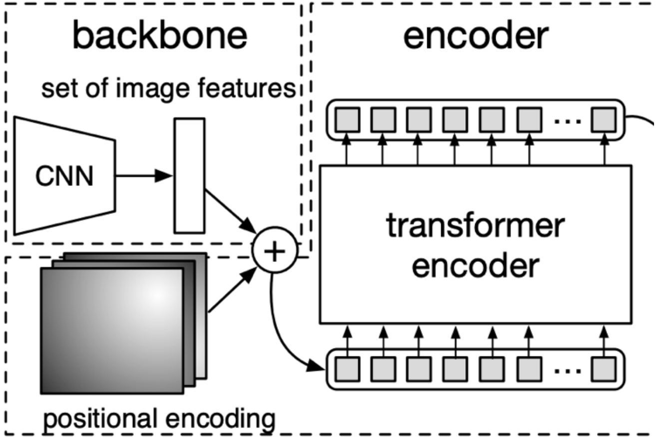




Carion et al, "End-to-End Object Detection with Transformers", ECCV 2020

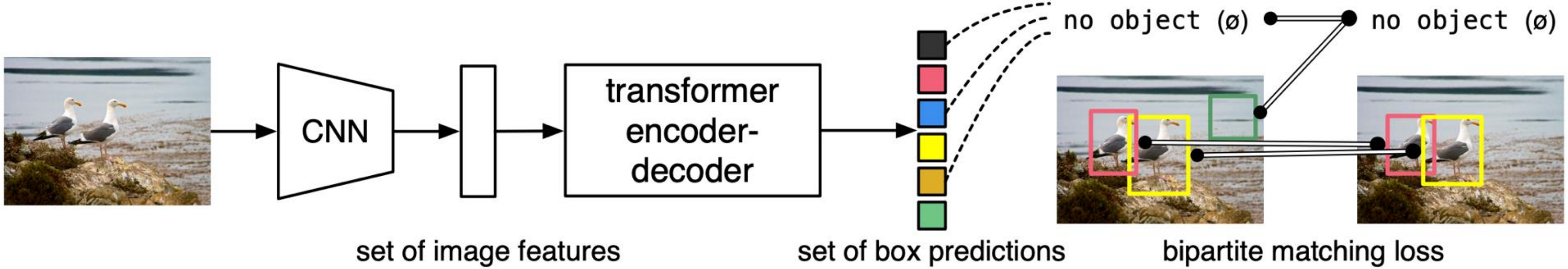
Object Detection with Transformers: DETR

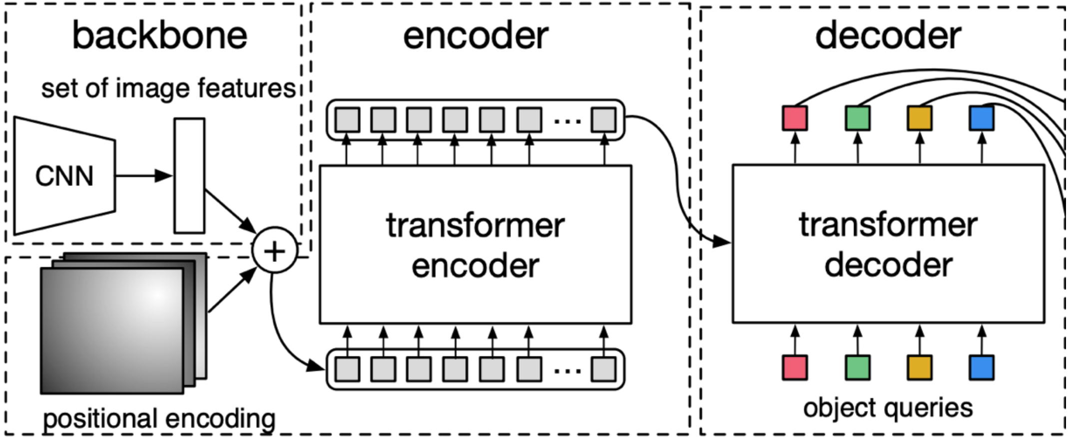




Carion et al, "End-to-End Object Detection with Transformers", ECCV 2020

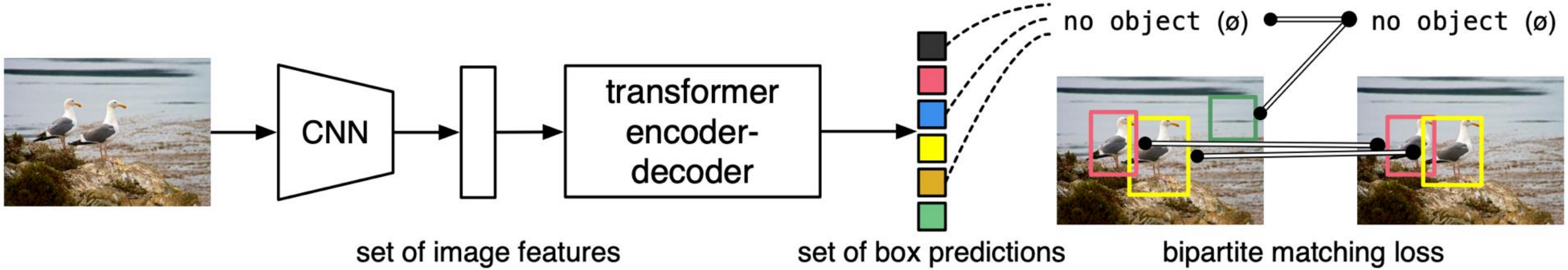
Object Detection with Transformers: DETR

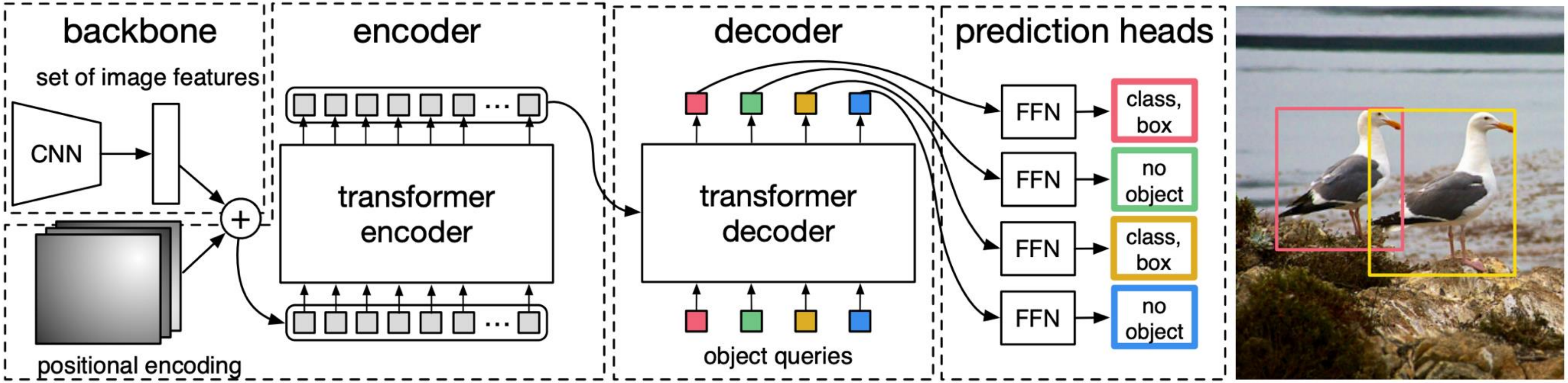




Carion et al, "End-to-End Object Detection with Transformers", ECCV 2020

Object Detection with Transformers: DETR





Carion et al, "End-to-End Object Detection with Transformers", ECCV 2020

Instance Segmentation

Classification

CAT

No spatial extent

Semantic Segmentation

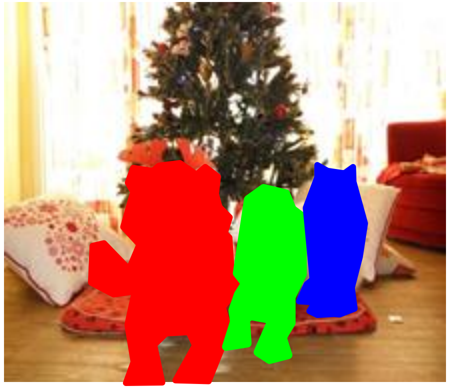
GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

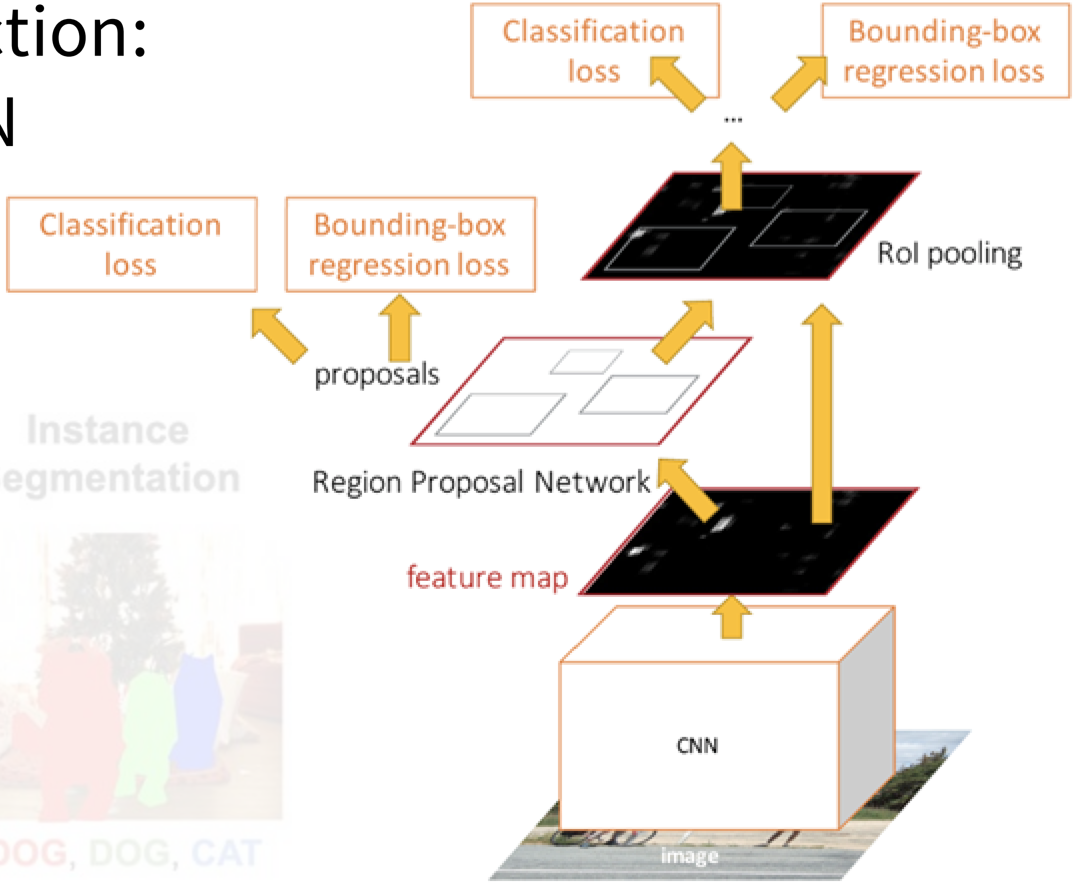
Instance Segmentation



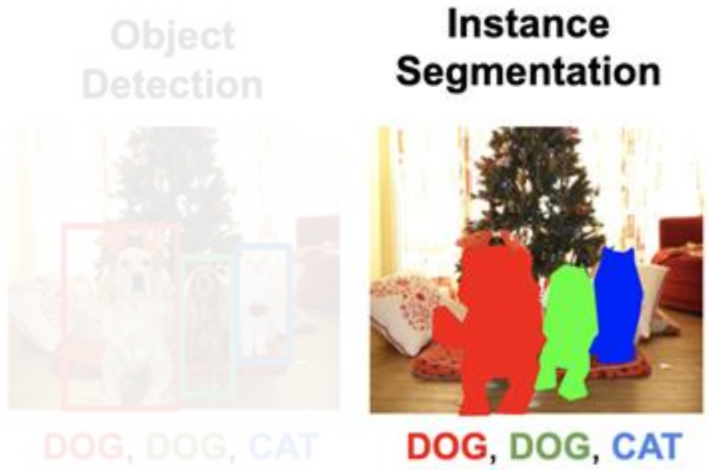
DOG, DOG, CAT

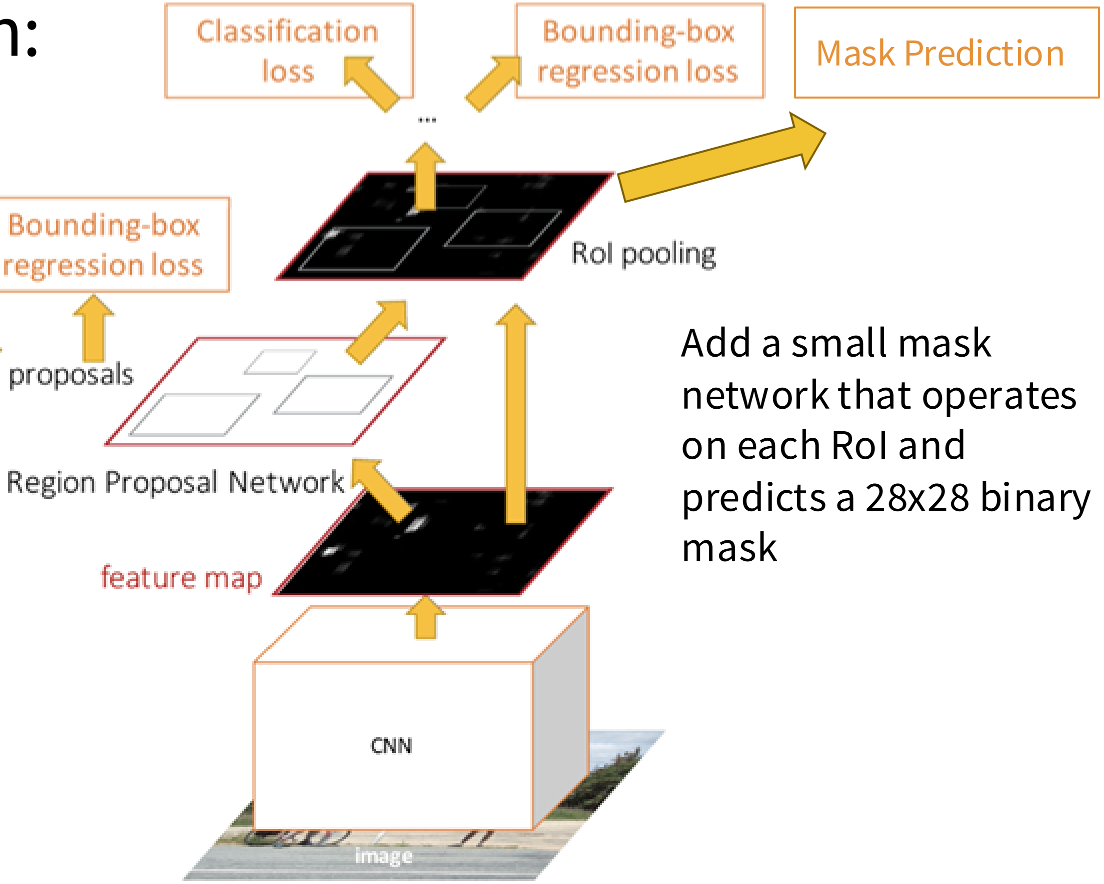
Multiple Object

Object Detection: Faster R-CNN



Instance Segmentation: Mask R-CNN

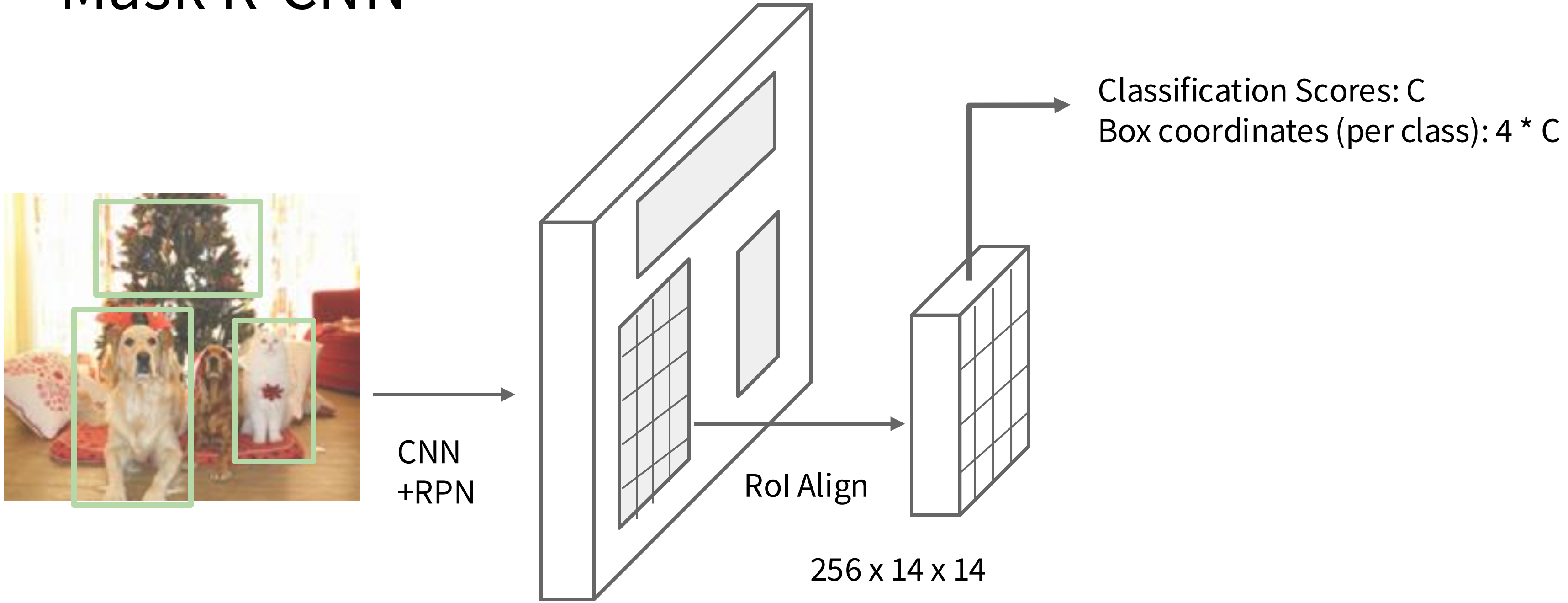




Add a small mask network that operates on each RoI and predicts a 28x28 binary mask

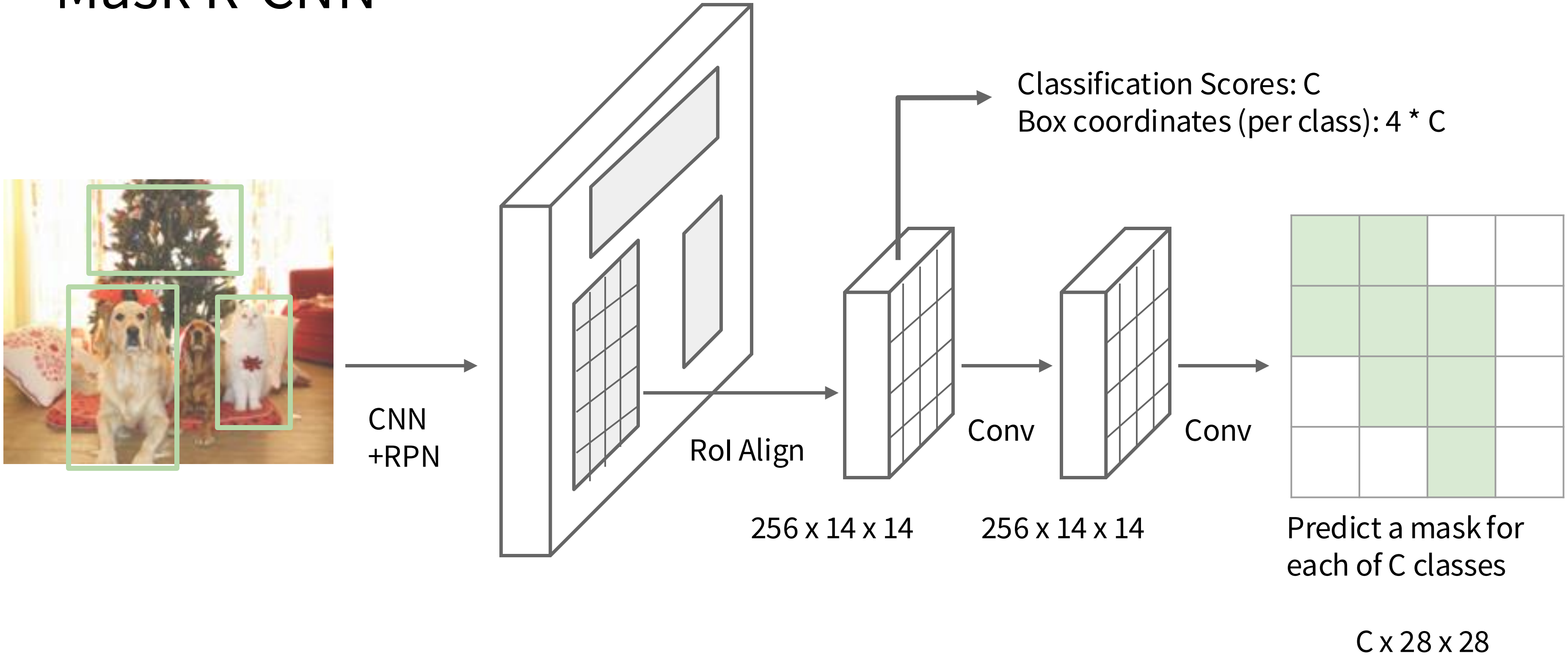
He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN



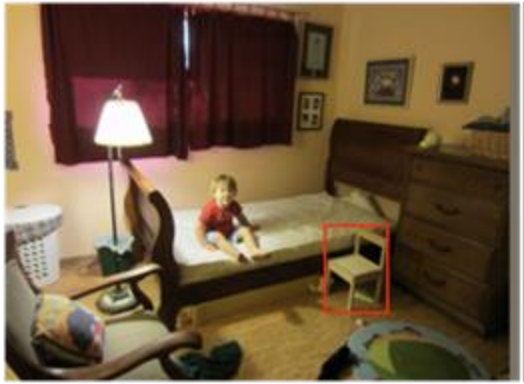
He et al, "Mask R-CNN", arXiv 2017

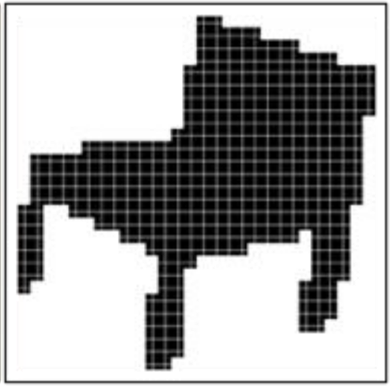
Mask R-CNN



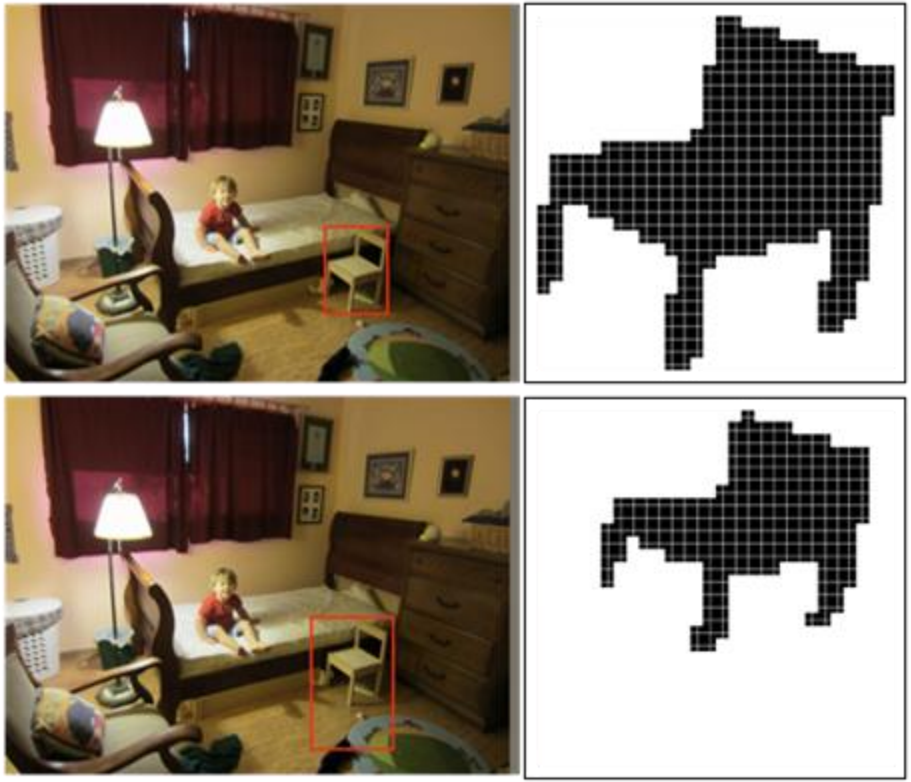
He et al, "Mask R-CNN", arXiv 2017

Mask R-CNN: Example Mask Training Targets

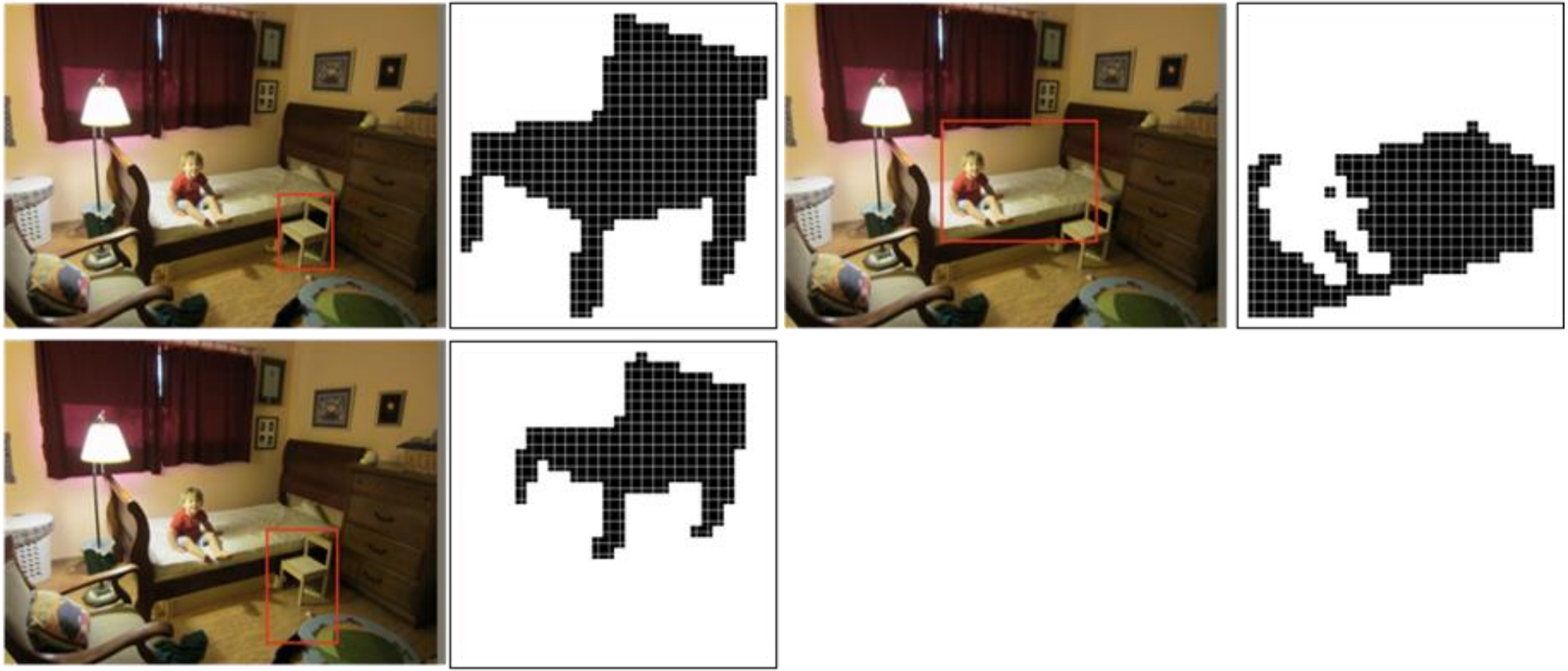




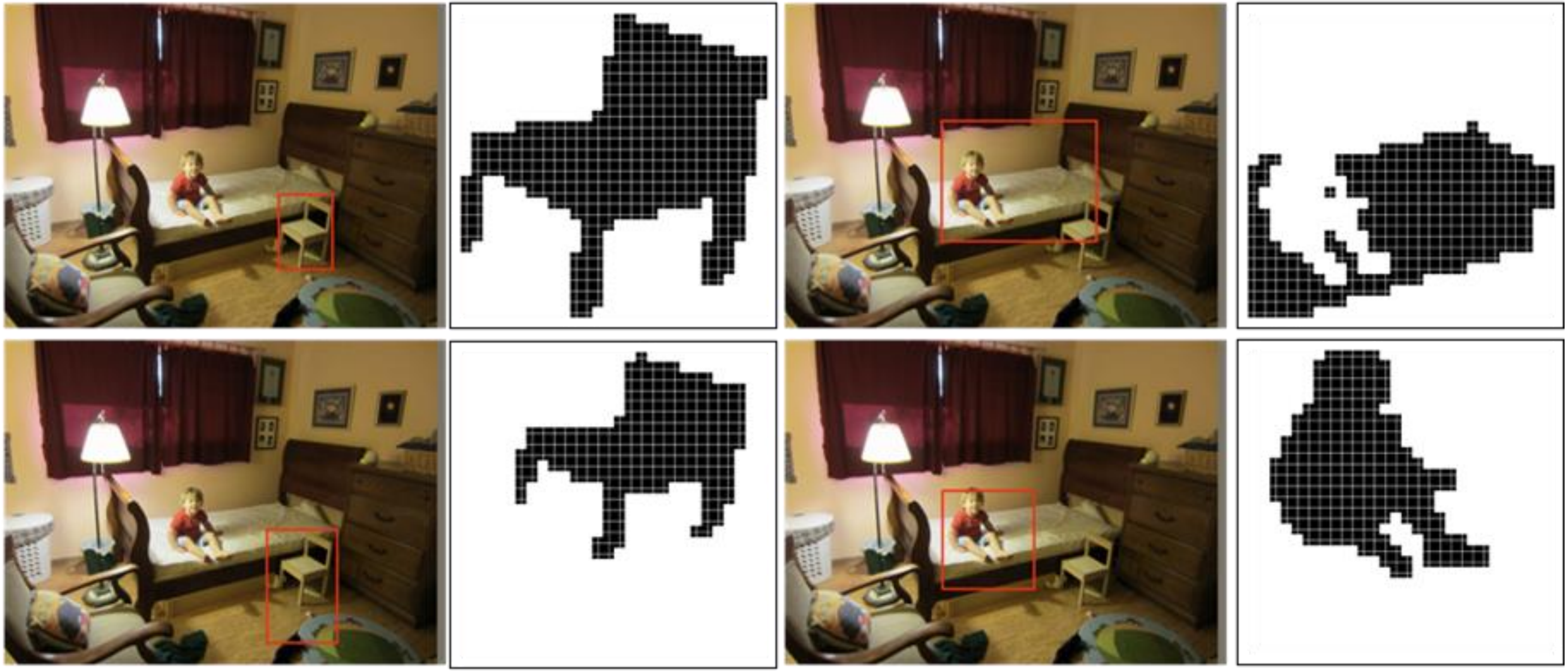
Mask R-CNN: Example Mask Training Targets



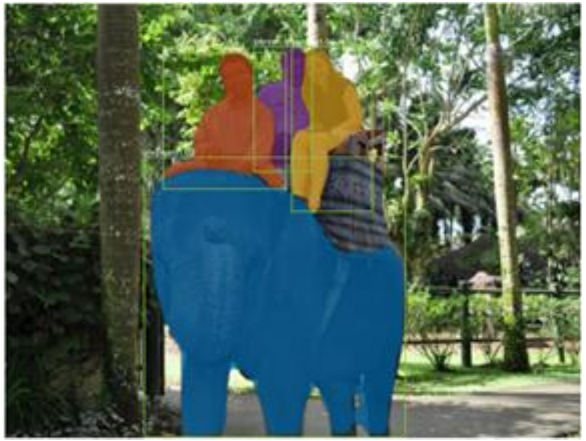
Mask R-CNN: Example Mask Training Targets



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

Open Source Frameworks

Lots of good implementations on GitHub!

TensorFlow Detection API:

https://github.com/tensorflow/models/tree/master/research/object_detection

Faster RCNN, SSD, RFCN, Mask R-CNN, ...

Detectron2 (PyTorch)

https://github.com/facebookresearch/detectron2

Mask R-CNN, RetinaNet, Faster R-CNN, RPN, Fast R-CNN, R-FCN, ...

Finetune on your own dataset with pre-trained models

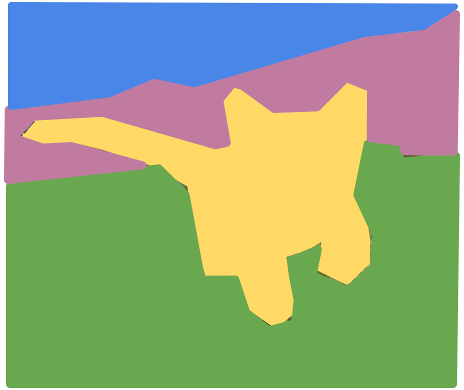
Recap: Lots of computer vision tasks!

Classification

CAT

No spatial extent

Semantic Segmentation



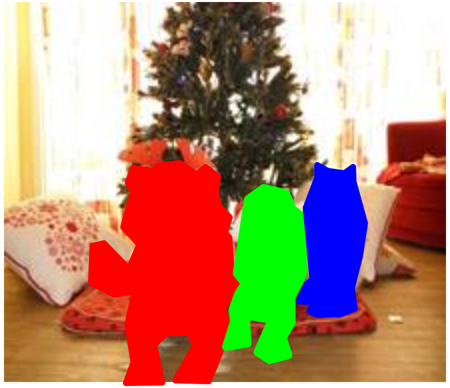
GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

Instance Segmentation



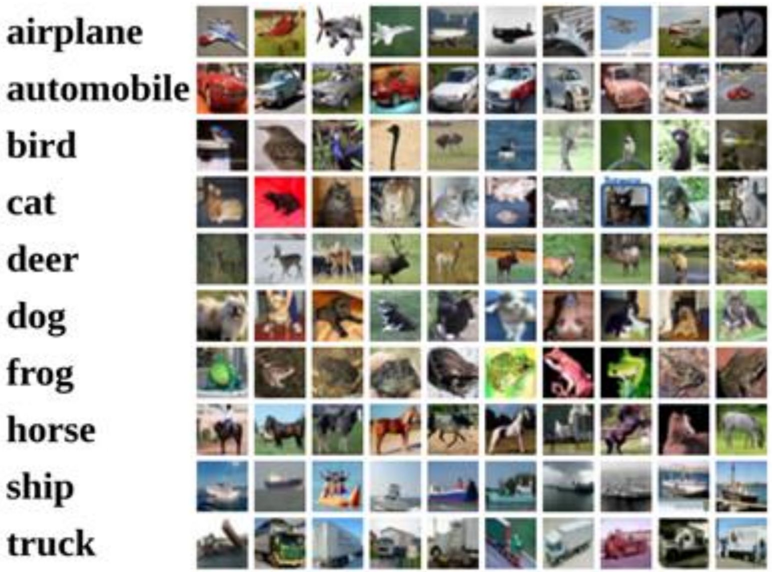
DOG, DOG, CAT

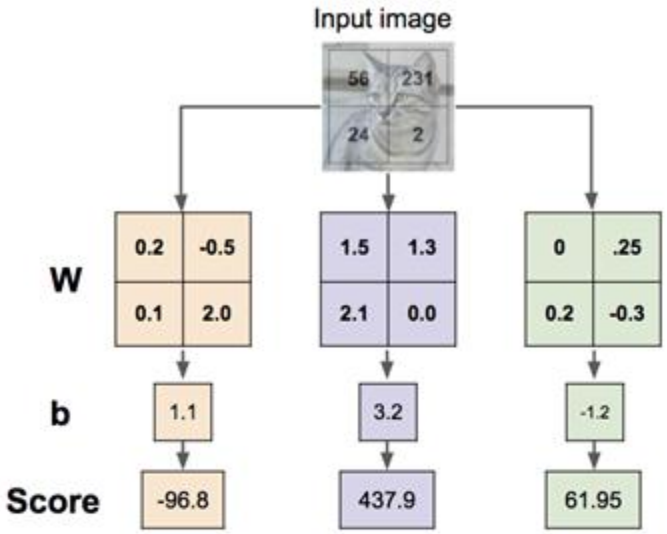
Multiple Object

Today

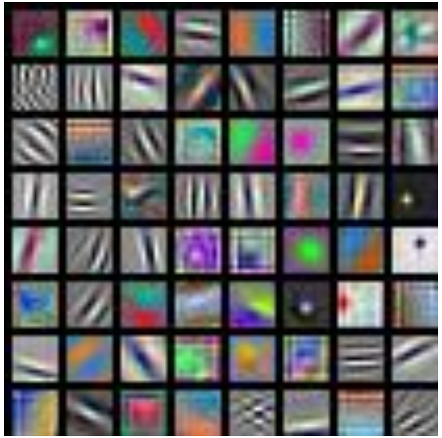
- Transformers Recap
- **Computer Vision Tasks**
  - Semantic Segmentation
  - Object Detection
  - Instance Segmentation
- Visualization & Understanding
  - Model Layers Visualization
  - Saliency Maps
  - CAM & Grad-CAM

Interpreting a Linear Classifier: Visual Viewpoint

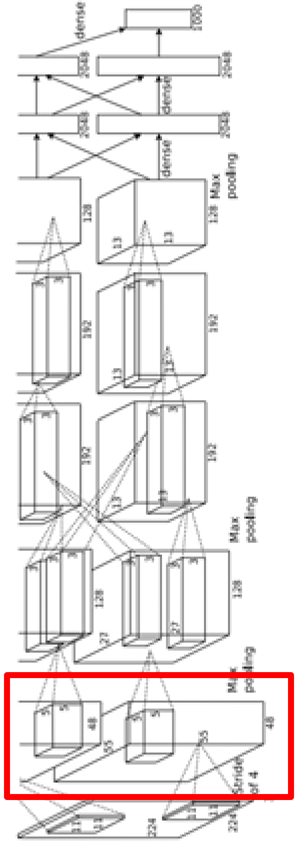




First Layer: Visualize Filters



AlexNet:
64 x 3 x 11 x 11



Krizhevsky, “One weird trick for parallelizing convolutional neural networks”, arXiv 2014
He et al, “Deep Residual Learning for Image Recognition”, CVPR 2016
Huang et al, “Densely Connected Convolutional Networks”, CVPR 2017

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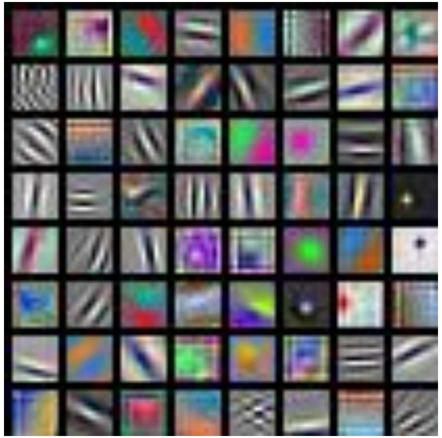
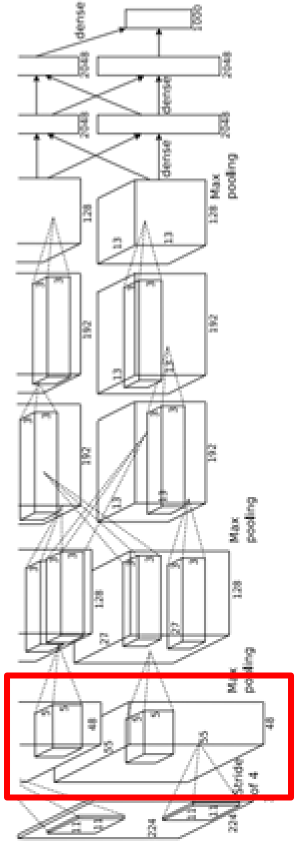


AlexNet:
64 x 3 x 11 x 11

ResNet-18:
64 x 3 x 7 x 7

ResNet-101:
64 x 3 x 7 x 7

DenseNet-121:
64 x 3 x 7 x 7



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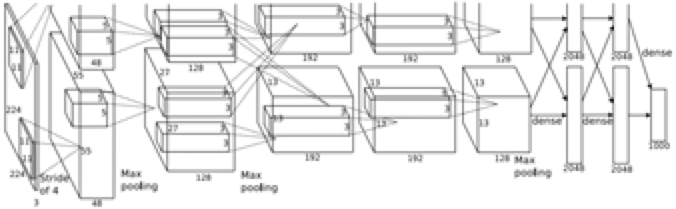
Which pixels matter: Saliency via Backprop

Forward pass: Compute probabilities



Dog

Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

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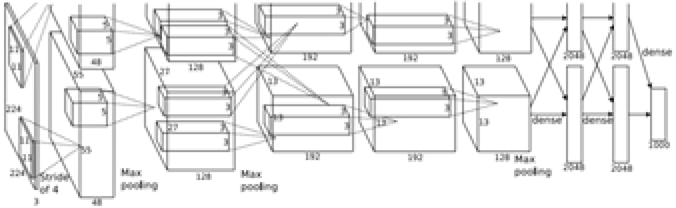

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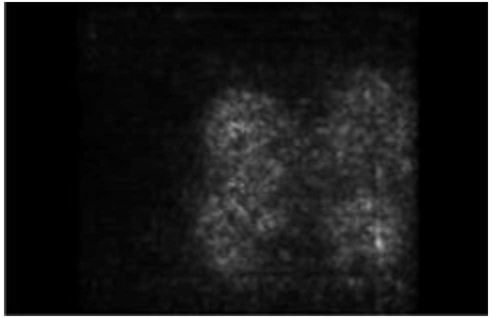
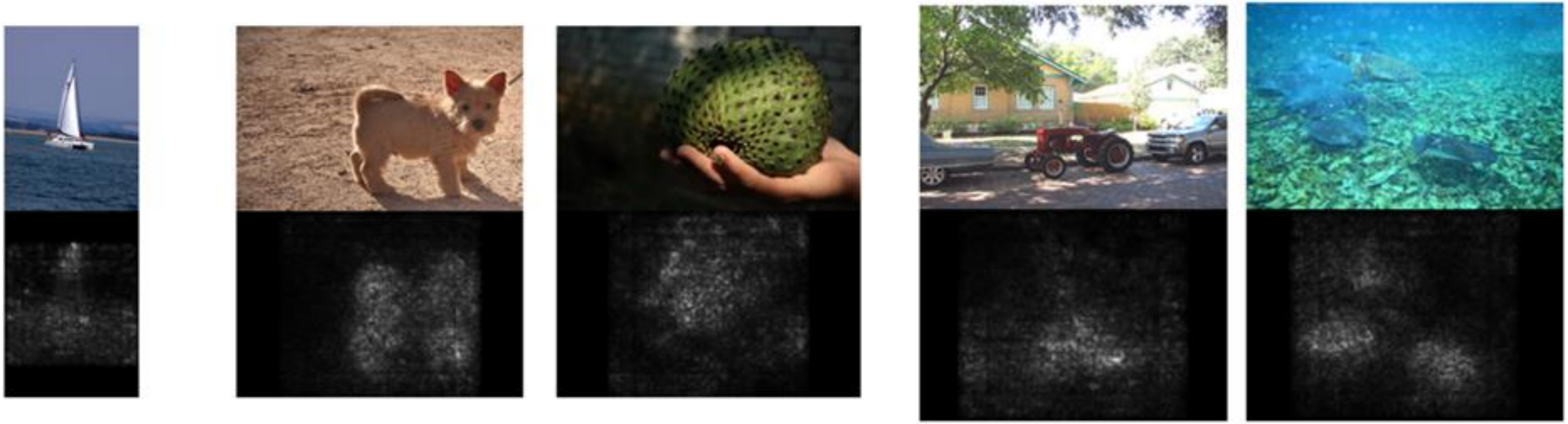


Compute gradient of (unnormalized) class score with respect to image pixels, take absolute value and max over RGB channels

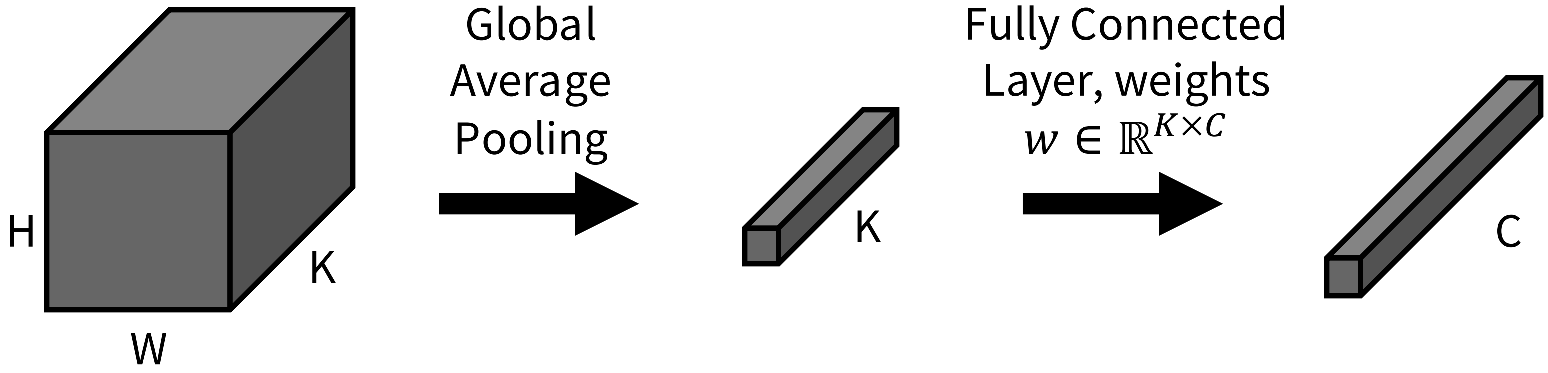
Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

Saliency Maps



Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

Class Activation Mapping (CAM)



Last layer CNN features:
$f \in \mathbb{R}^{H \times W \times K}$

Pooled features:
$F \in \mathbb{R}^{K}$

Class Scores:
$S \in \mathbb{R}^{C}$

Zhou et al, “Learning Deep Features for Discriminative Localization”, CVPR 2016

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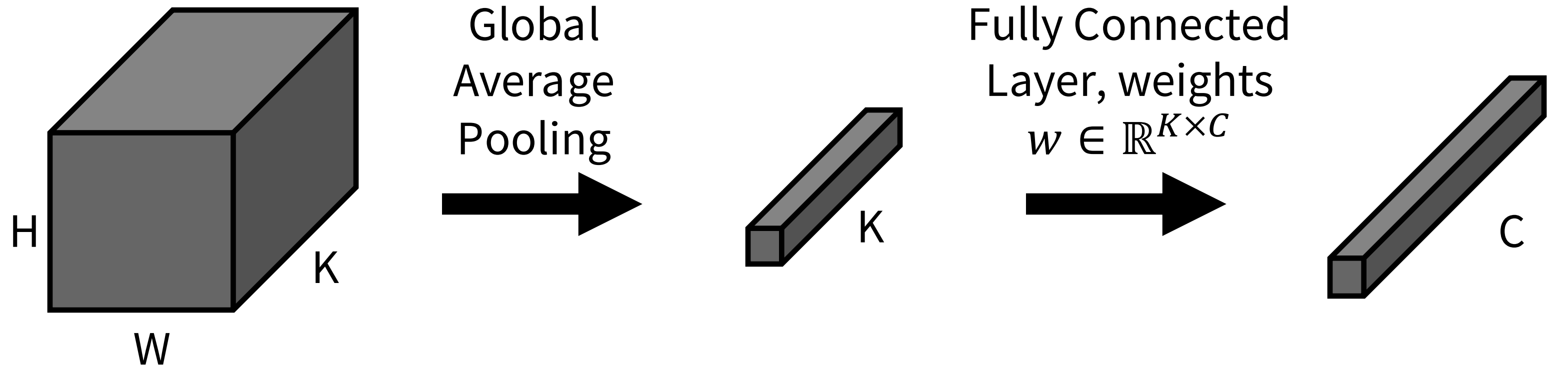

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$$F_k = \frac{1}{HW} \sum_{h,w} f_{h,w,k}$$

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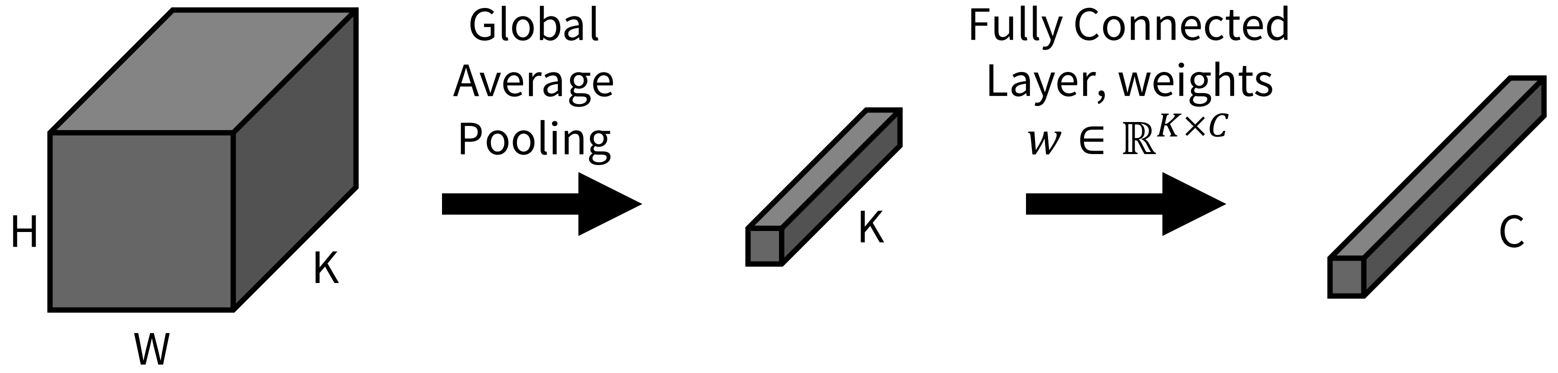

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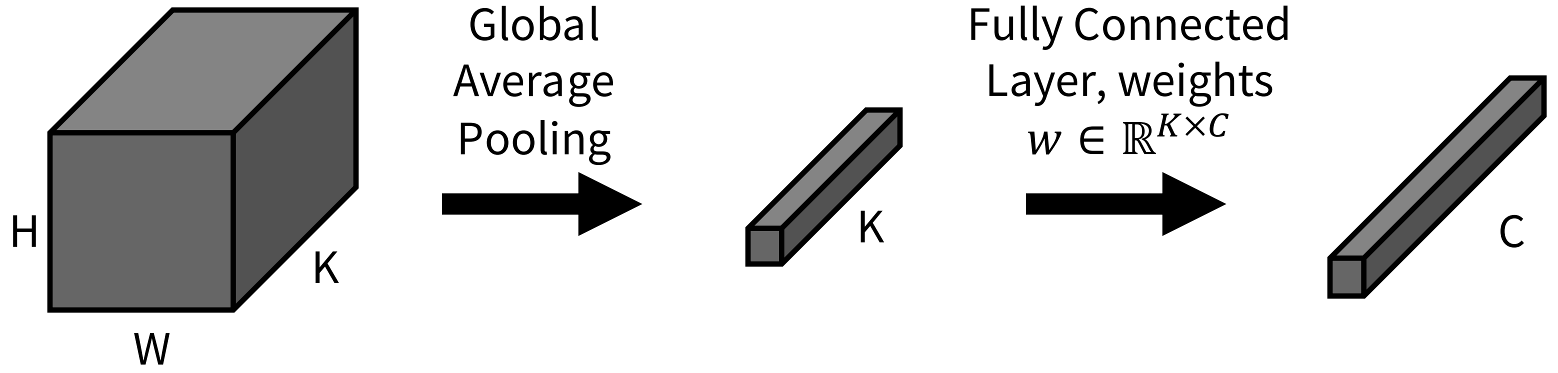

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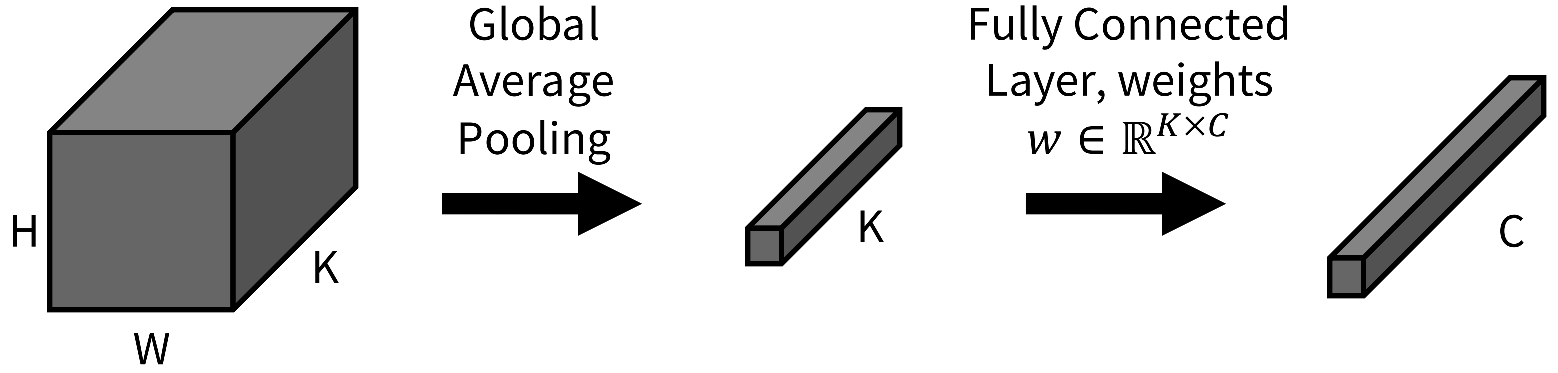

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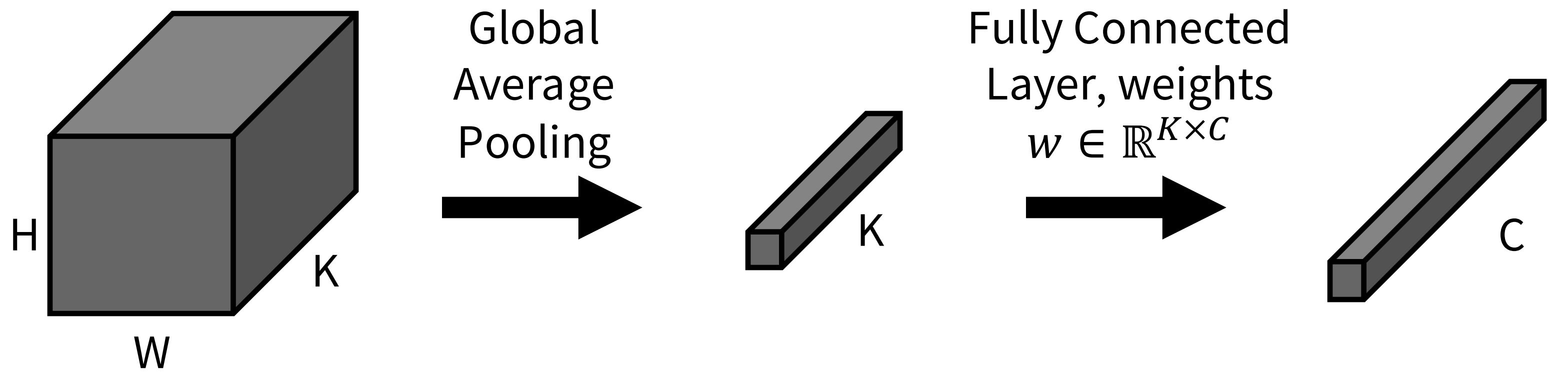

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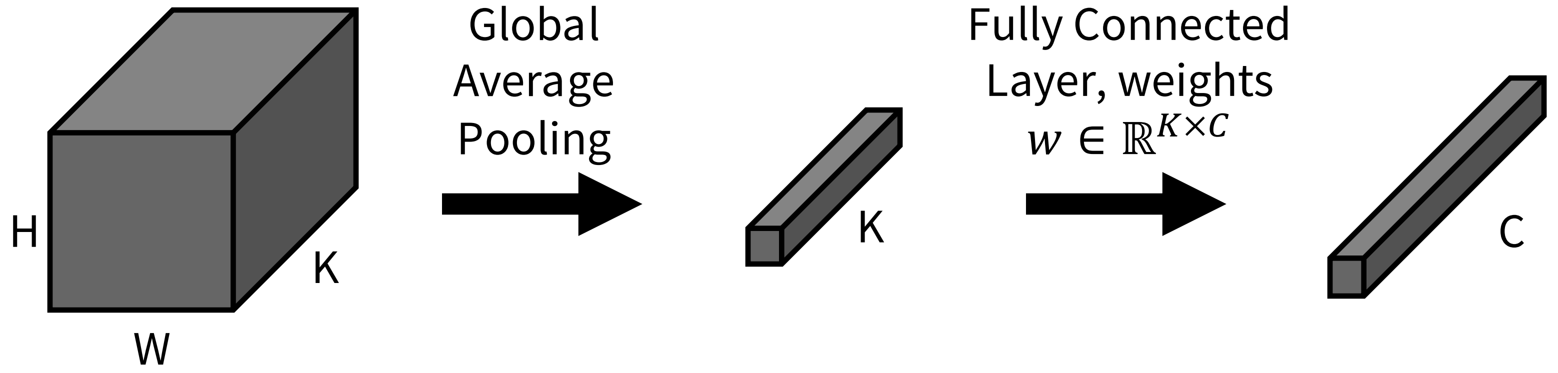

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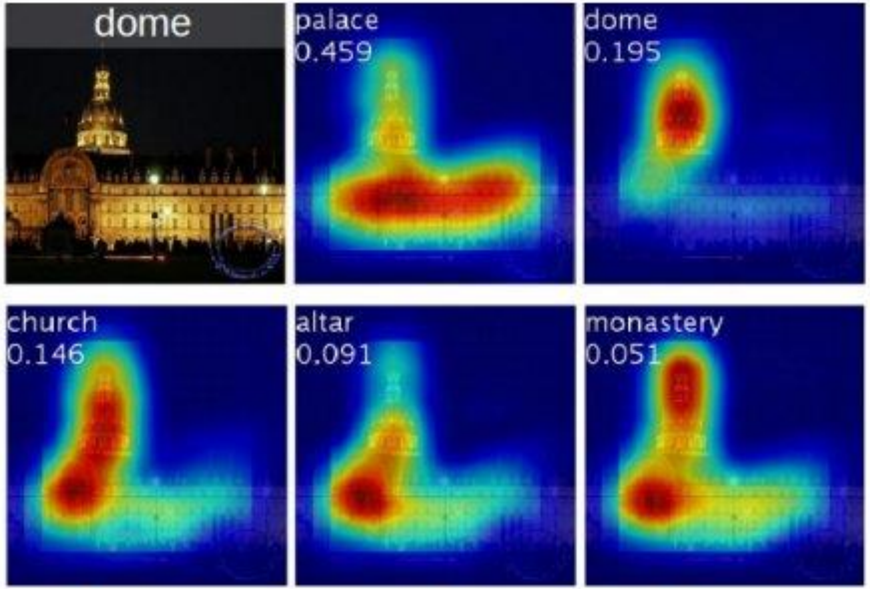
Class Activation Maps:
$\boldsymbol{M} \in \mathbb{R}^{\boldsymbol{C,H,W}}$

$$\boldsymbol{M_{c,h,w}} = \sum_k \boldsymbol{w_{k,c} f_{h,w,k}}$$

Zhou et al, "Learning Deep Features for Discriminative Localization", CVPR 2016

Class Activation Mapping (CAM)



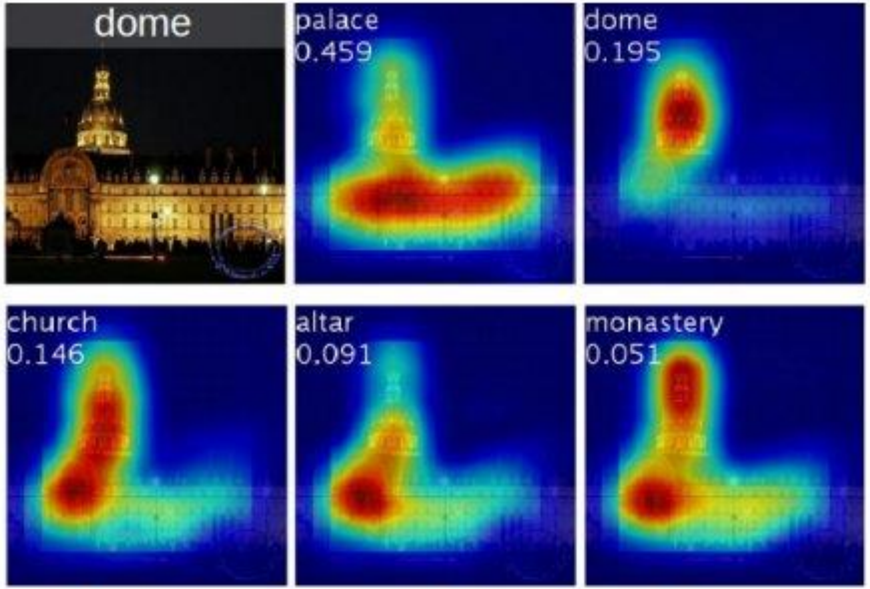
Class activation maps of top 5 predictions

Class activation maps for one object class

Zhou et al, "Learning Deep Features for Discriminative Localization", CVPR 2016

Class Activation Mapping (CAM)

Problem: Can only apply to last conv layer



Class activation maps of top 5 predictions

Class activation maps for one object class

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Gradient-Weighted Class Activation Mapping (Grad-CAM)

1. Pick any layer, with activations $A \in \mathbb{R}^{H \times W \times K}$

Selvaraju et al, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization", CVPR 2017

Gradient-Weighted Class Activation Mapping (Grad-CAM)

1. Pick any layer, with activations $A \in \mathbb{R}^{H \times W \times K}$
2. Compute gradient of class score S_c with respect to A:

$$\frac{\partial S_c}{\partial A} \in \mathbb{R}^{H \times W \times K}$$

Selvaraju et al, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization", CVPR 2017

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3. Global Average Pool the gradients to get weights $\alpha \in \mathbb{R}^K$:

$$\alpha_k = \frac{1}{HW} \sum_{h,w} \frac{\partial S_c}{\partial A_{h,w,k}}$$

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4. Compute activation map $M^c \in \mathbb{R}^{H,W}$:

$$M^c_{h,w} = ReLU\left(\sum_k \alpha_k A_{h,w,k}\right)$$

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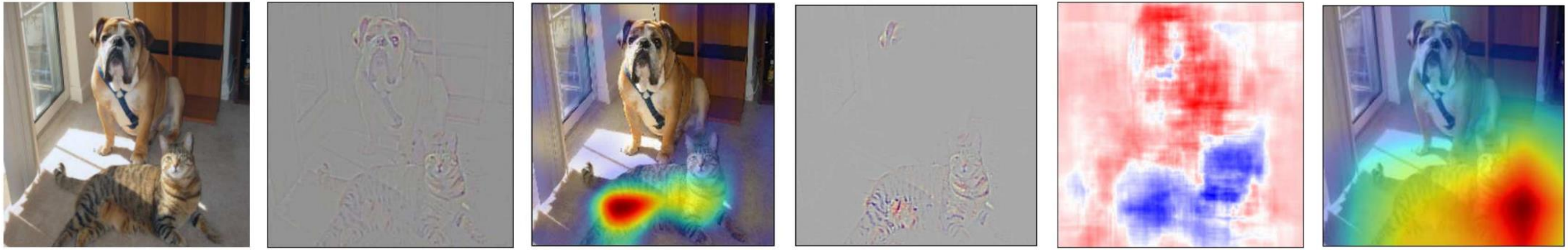
Gradient-Weighted Class Activation Mapping (Grad-CAM)

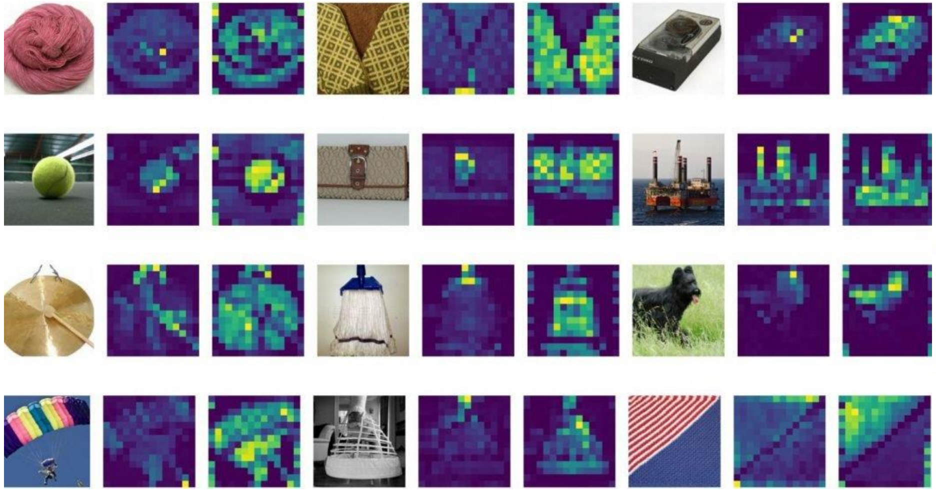


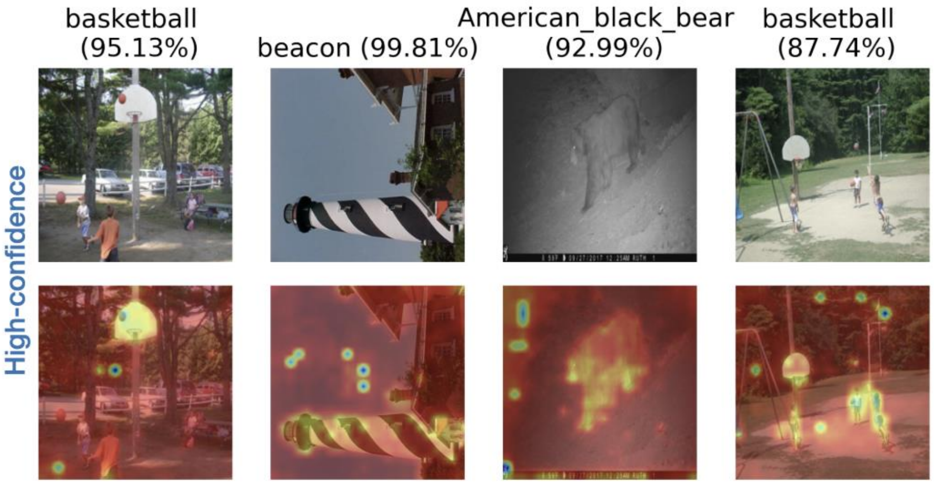
(a) Original Image (b) Guided Backprop 'Cat' (c) Grad-CAM 'Cat' (d) Guided Grad-CAM 'Cat' (e) Occlusion map for 'Cat' (f) ResNet Grad-CAM 'Cat'

(g) Original Image (h) Guided Backprop 'Dog' (i) Grad-CAM 'Dog' (j) Guided Grad-CAM 'Dog' (k) Occlusion map for 'Dog' (l) ResNet Grad-CAM 'Dog'

Selvaraju et al, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization", CVPR 2017

Visualizing ViT features





Chen et al., When Vision Transformers Outperform Resnets Without Pre-training Or Strong Data Augmentations, ICLR 2022; Paul and Chen, Vision Transformers are Robust Learners, AAAI 2022. Reproduced for educational purposes.

Today

- Transformers Recap

- **Computer Vision Tasks**
  - Semantic Segmentation
  - Object Detection
  - Instance Segmentation

- Visualization & Understanding
  - Model Layers Visualization
  - Saliency Maps
  - CAM & Grad-CAM

Next time: Video Understanding

Additional Reading Material

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & z & 0 & 0 & 0 \\ 0 & 0 & x & y & z & 0 \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ bx + cy + dz \end{bmatrix}$$

Example: 1D conv, kernel size=3, <u>stride=2</u>, padding=1

Convolution as Matrix Multiplication (1D Example)

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Example: 1D conv, kernel size=3, <u>stride=2</u>, padding=1

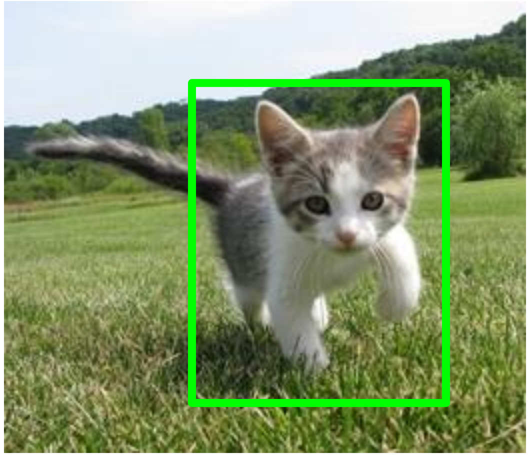
Transposed convolution multiplies by the transpose of the same matrix:

$$\vec{x} *^T \vec{a} = X^T\vec{a}$$

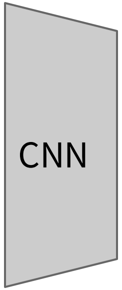
$$\begin{bmatrix} x & 0 \\ y & 0 \\ z & x \\ 0 & y \\ 0 & z \\ 0 & 0 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} ax \\ ay \\ az + bx \\ by \\ bz \\ 0 \end{bmatrix}$$

Example: 1D transposed conv, kernel size=3, <u>stride=2</u>, padding=0

Cropping Features: RoI Pool



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



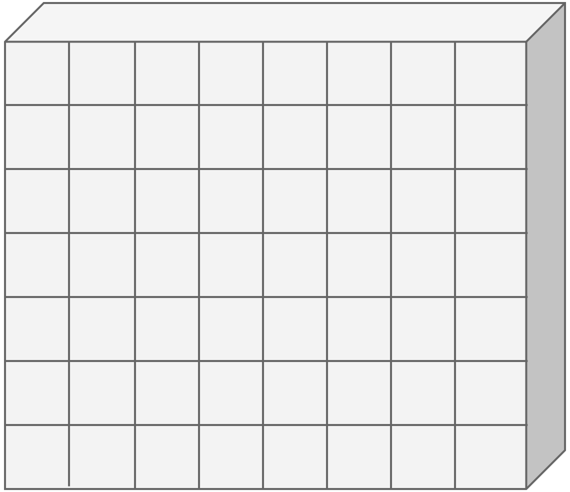


Image features: C x H x W
(e.g. 512 x 20 x 15)

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

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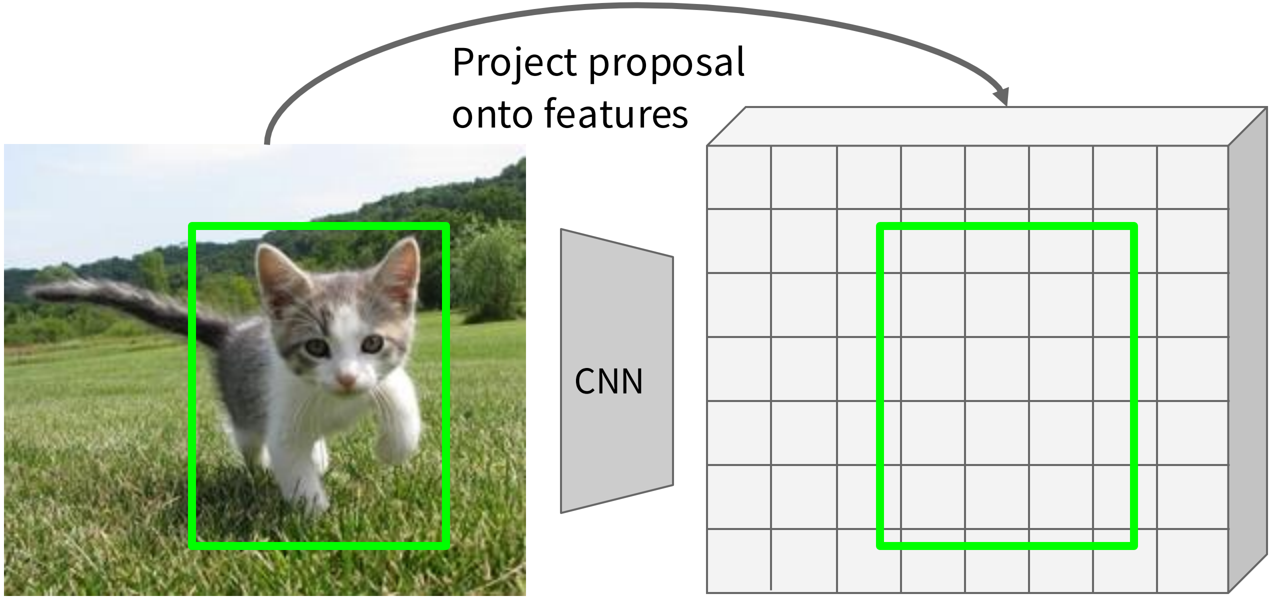

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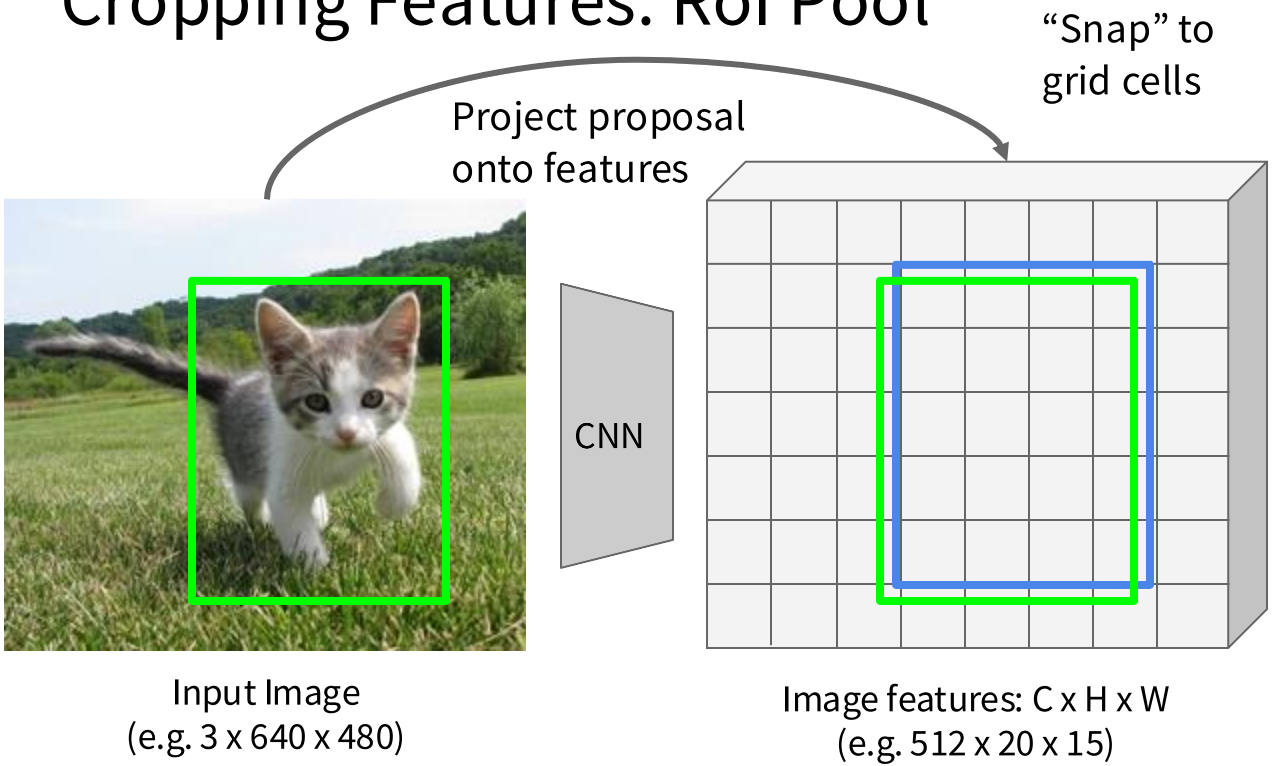

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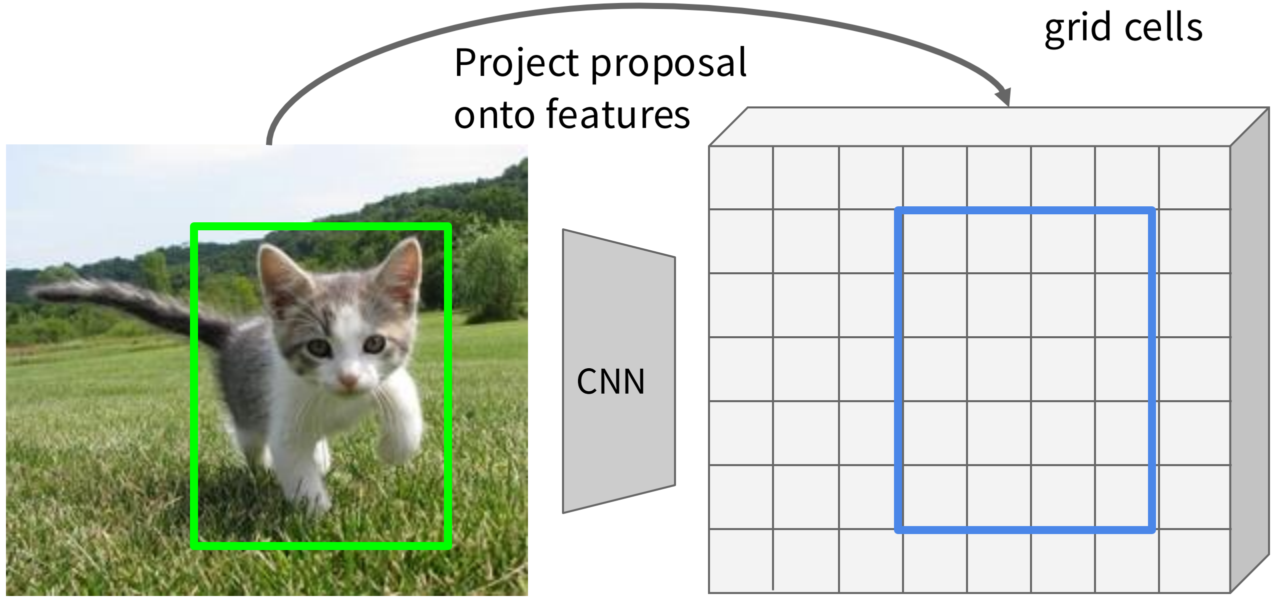

Input Image
(e.g. 3 x 640 x 480)

Image features: C x H x W
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Q: how do we resize the 512 x 5 x 4 region to, e.g., a 512 x 2 x 2 tensor?.

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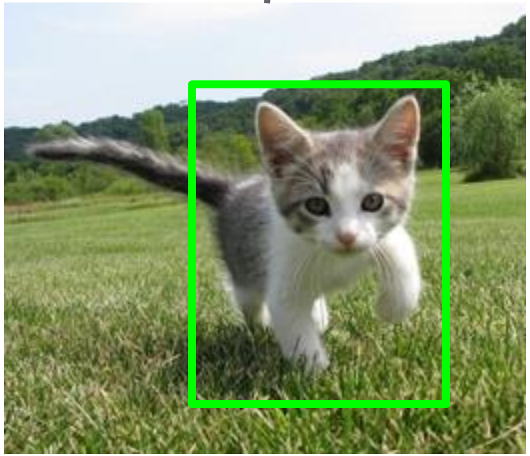
Cropping Features: RoI Pool

Project proposal
onto features

“Snap” to
grid cells

Divide into 2x2
grid of (roughly)
equal subregions



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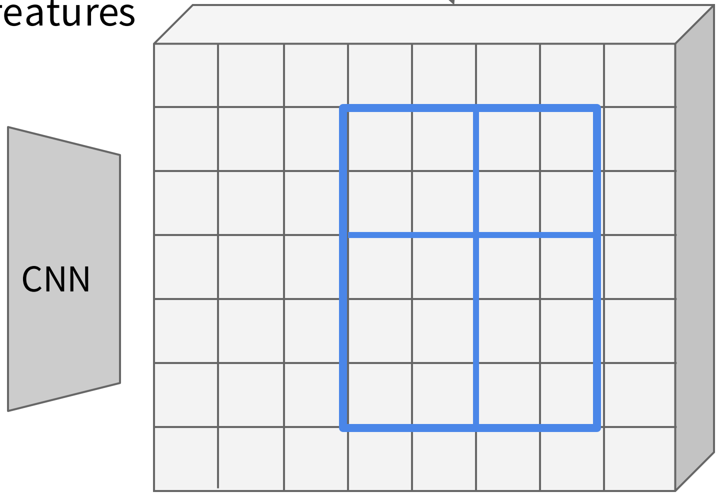

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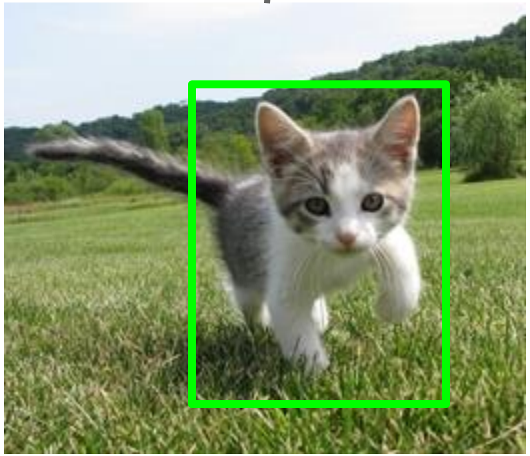
Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion



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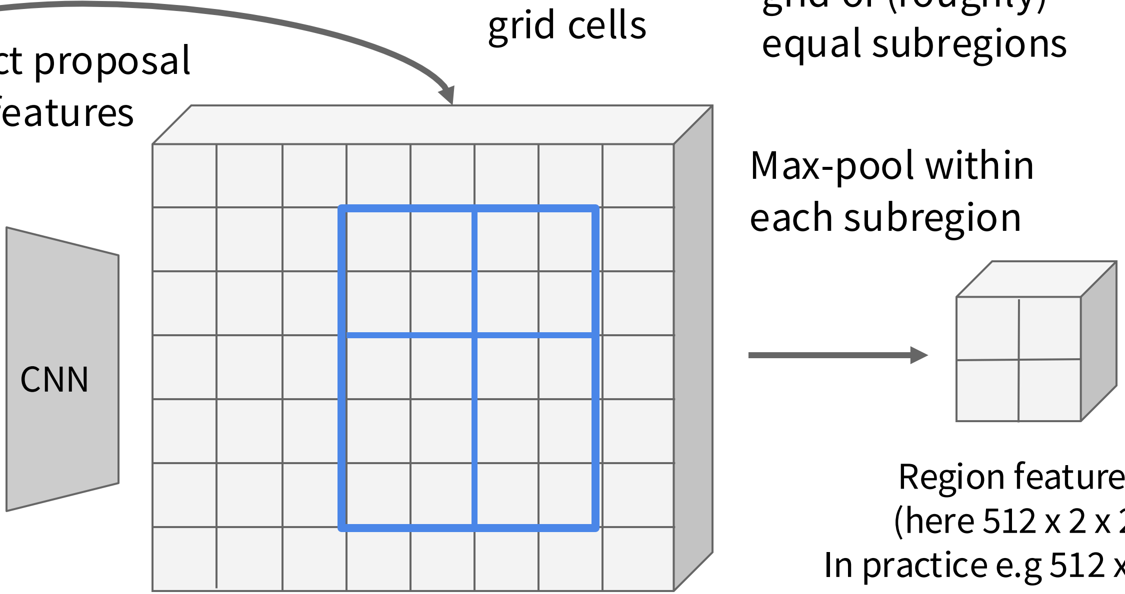

Image features: C x H x W
(e.g. 512 x 20 x 15)

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!

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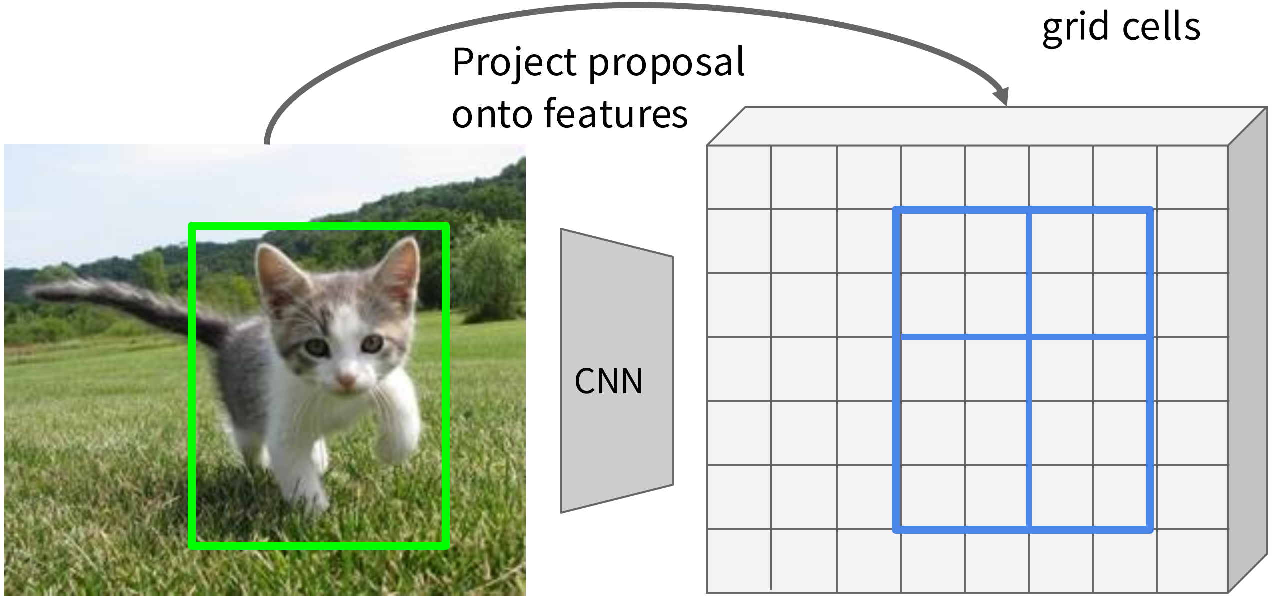
Cropping Features: RoI Pool



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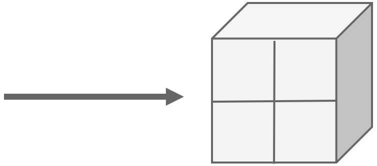


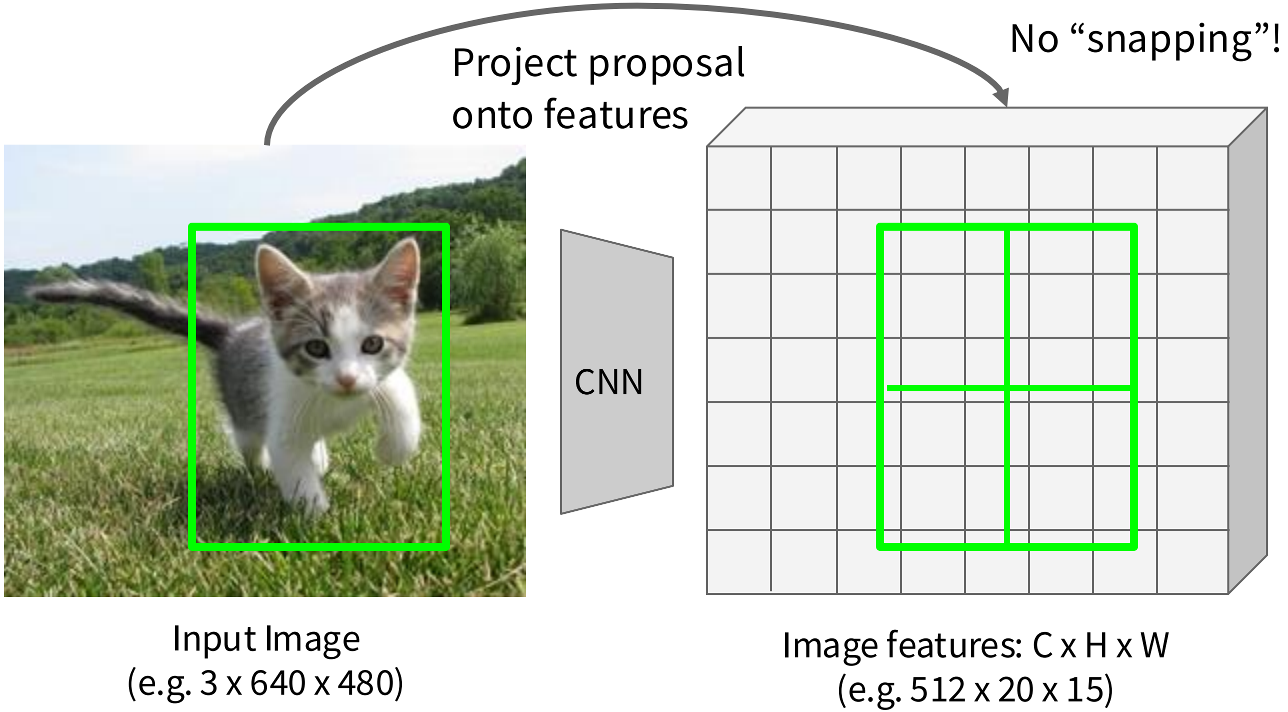
Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

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

Problem: Region features slightly misaligned

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

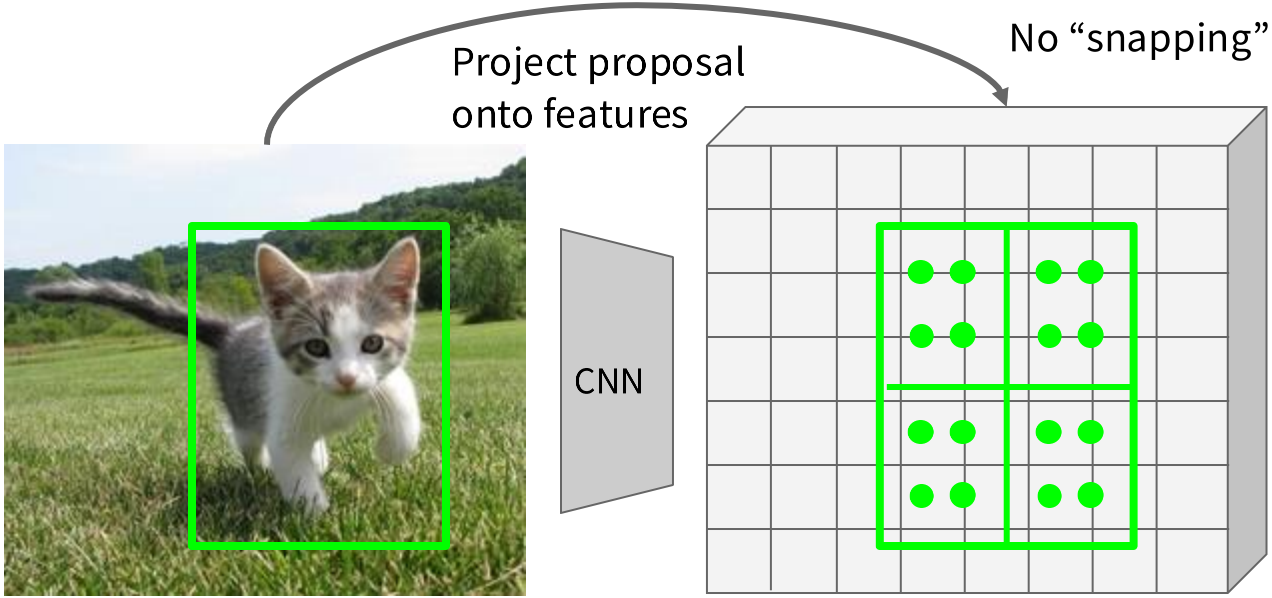
Cropping Features: RoI Align



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

Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation



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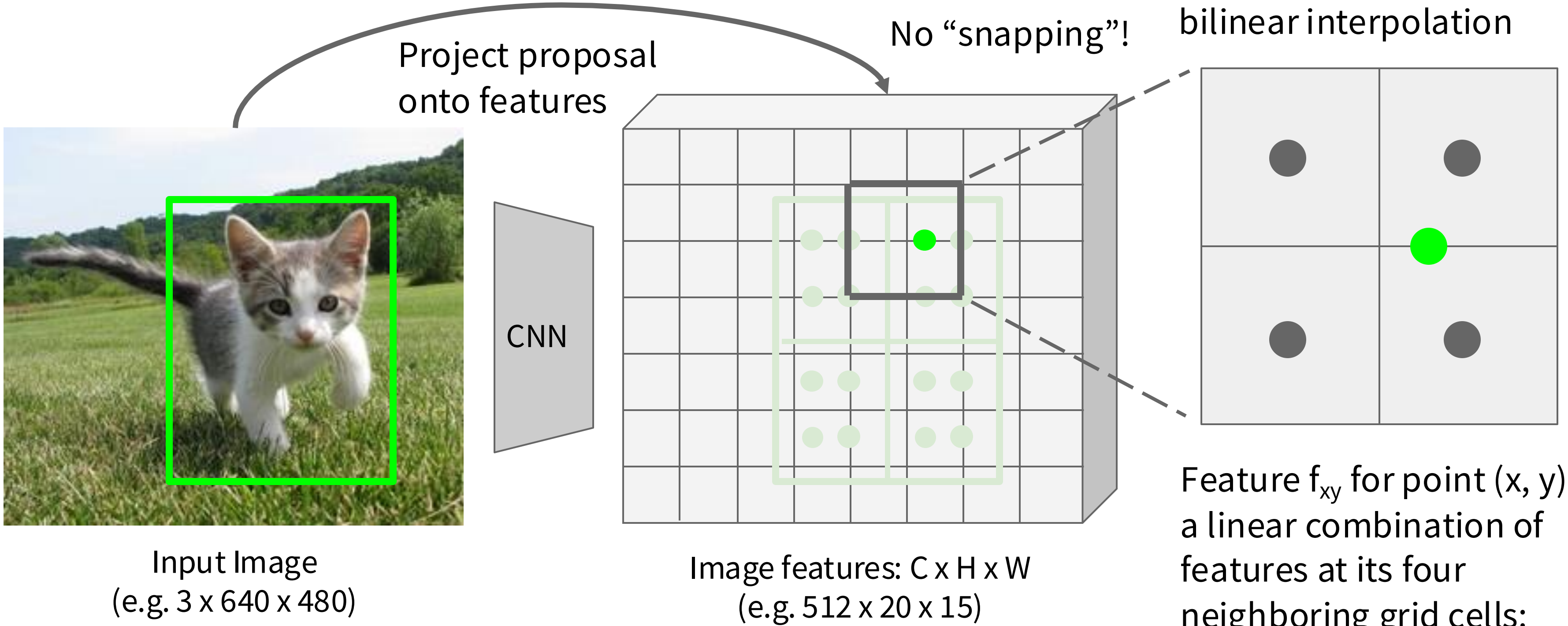
Cropping Features: RoI Align

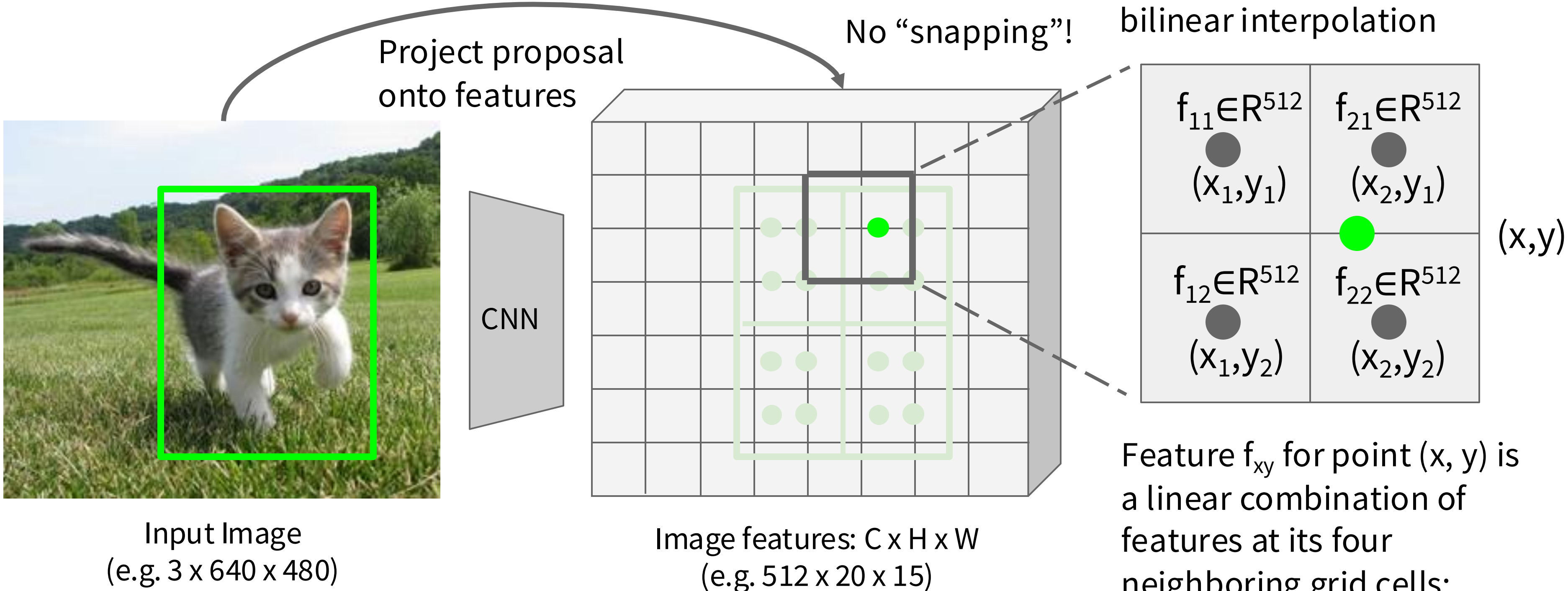


Sample at regular points in each subregion using bilinear interpolation

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

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

Cropping Features: RoI Align



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

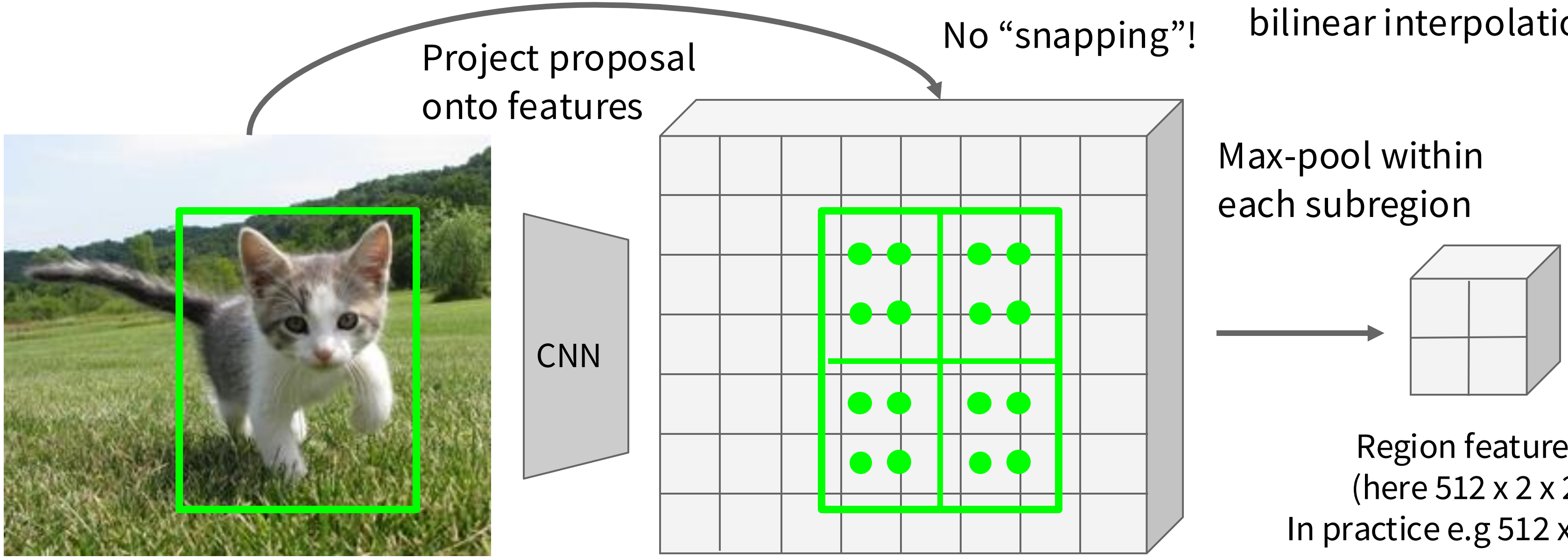
Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation

Project proposal onto features

No “snapping”!

Max-pool within each subregion



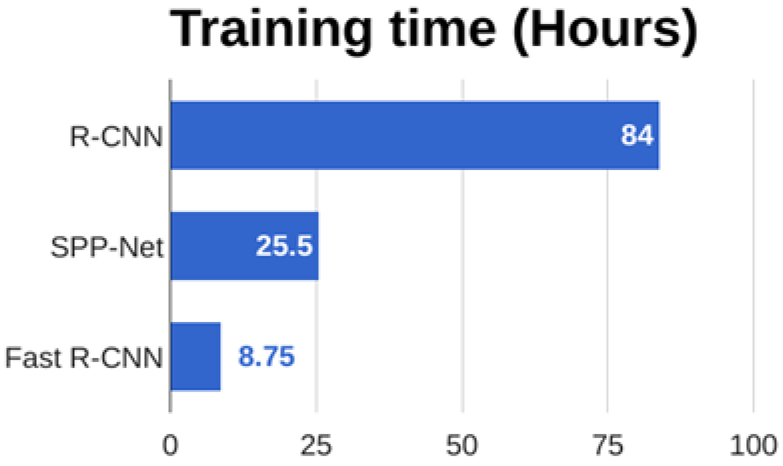
Input Image
(e.g. 3 x 640 x 480)

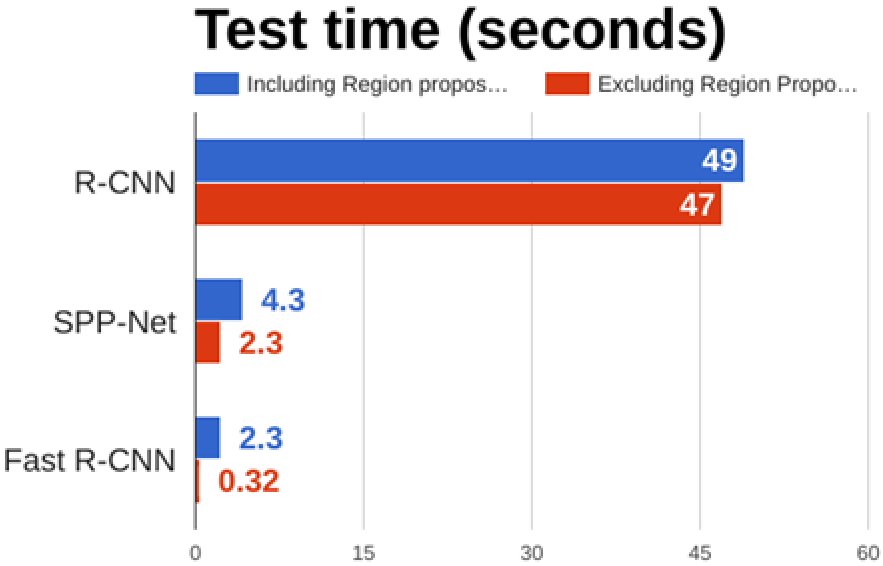
Image features: C x H x W
(e.g. 512 x 20 x 15)

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

He et al, “Mask R-CNN”, ICCV 2017

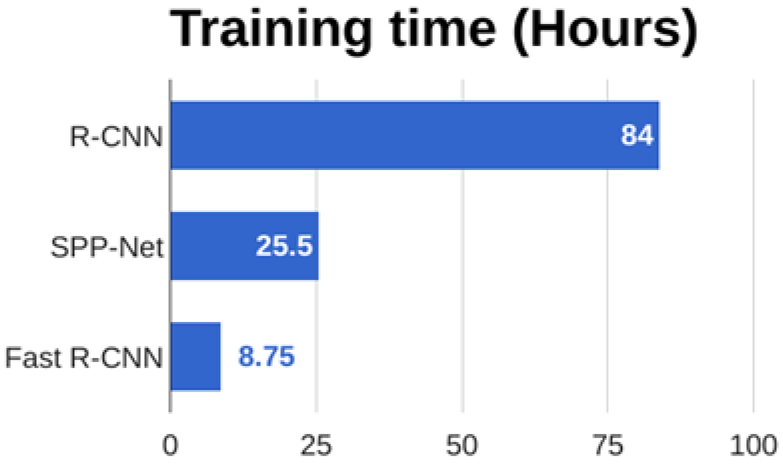
R-CNN vs Fast R-CNN

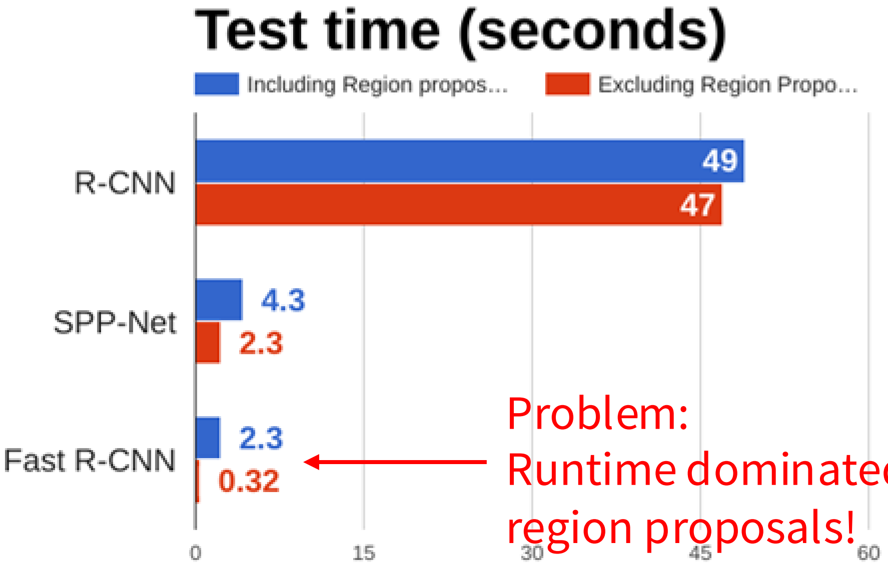




Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014
Girshick, "Fast R-CNN", ICCV 2015

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.
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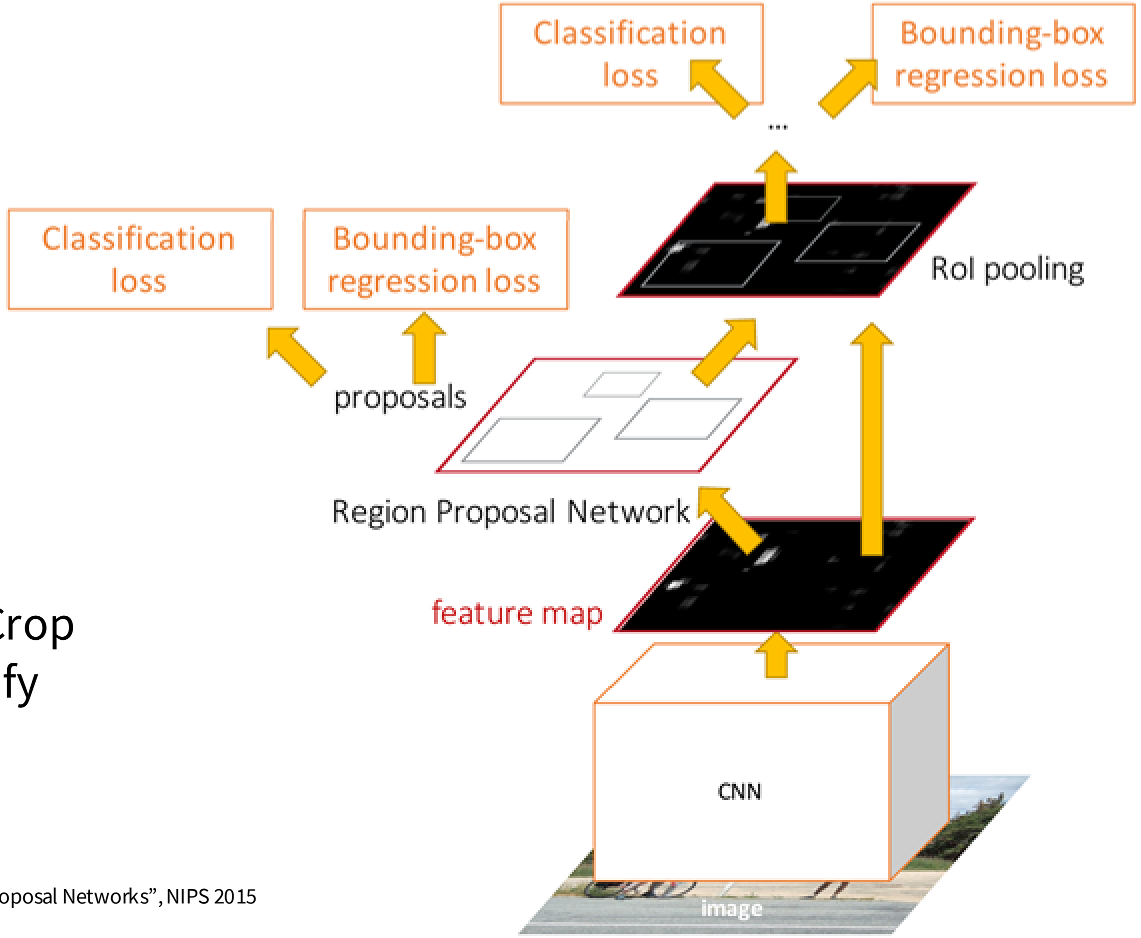
Faster R-CNN:

Make CNN do proposals!



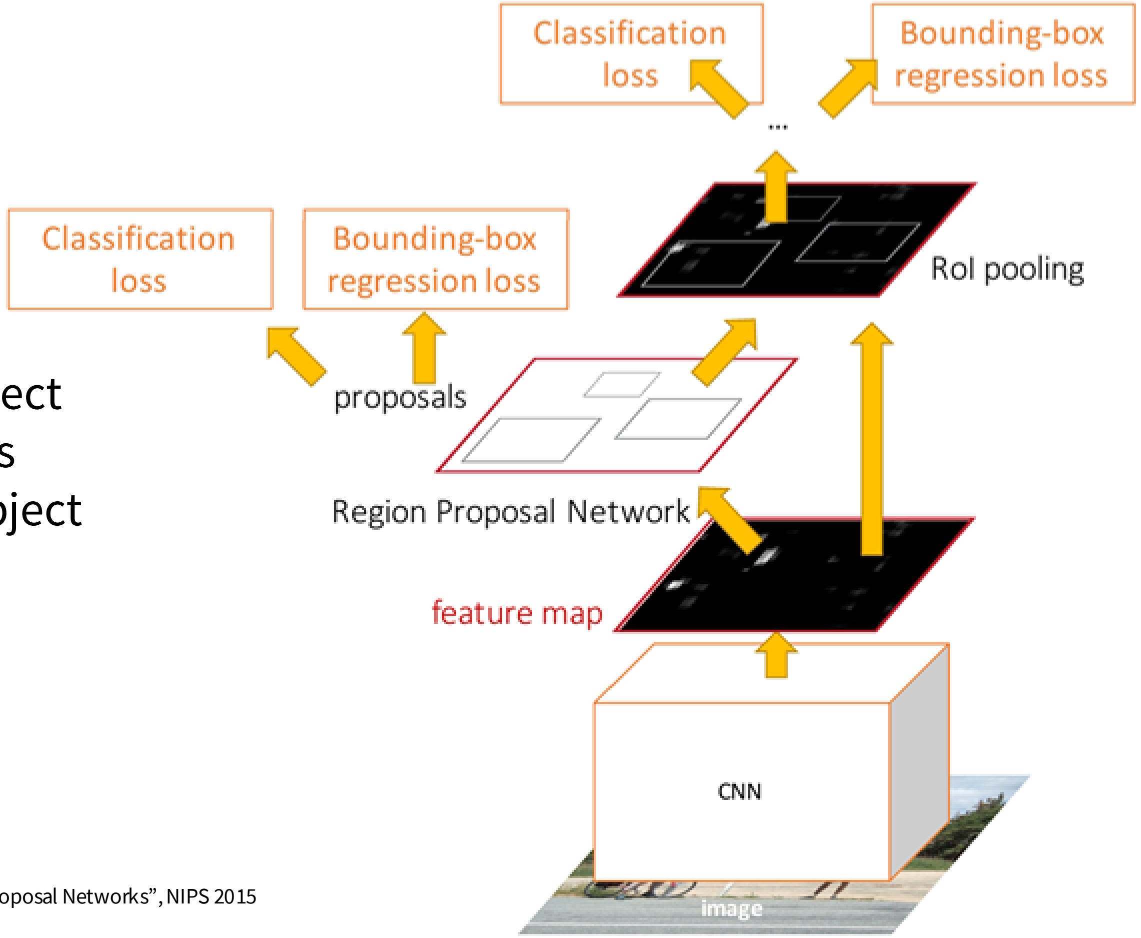
Insert Region Proposal Network (RPN) to predict proposals from features

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!



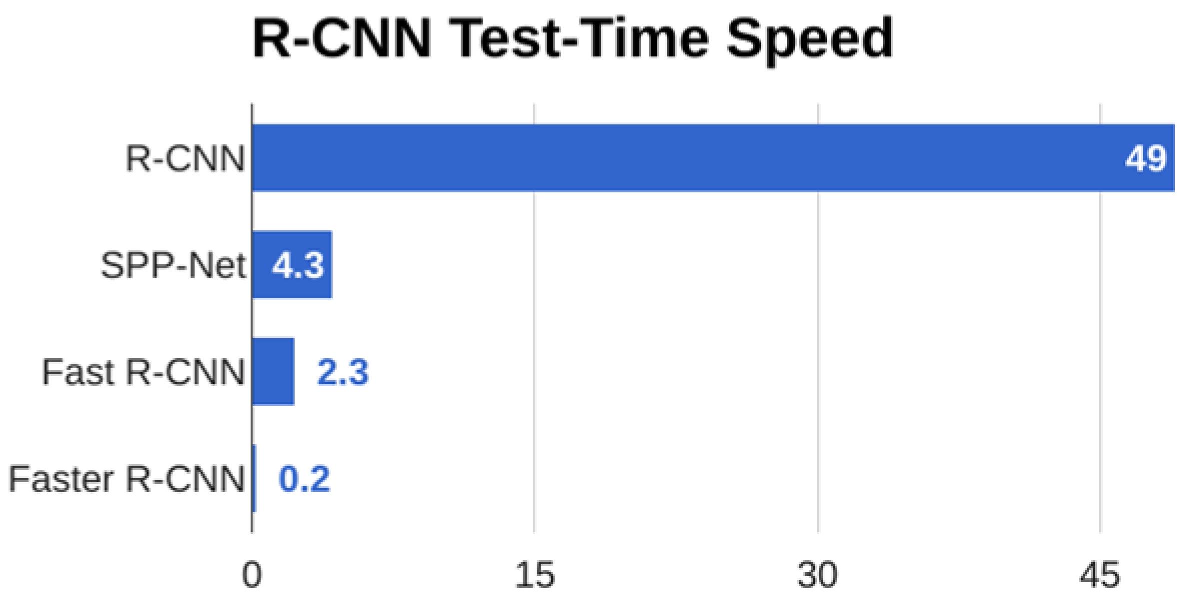
Jointly train with 4 losses:

1. RPN classify object / not object
2. RPN regress box coordinates
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

Faster R-CNN:

Make CNN do proposals!

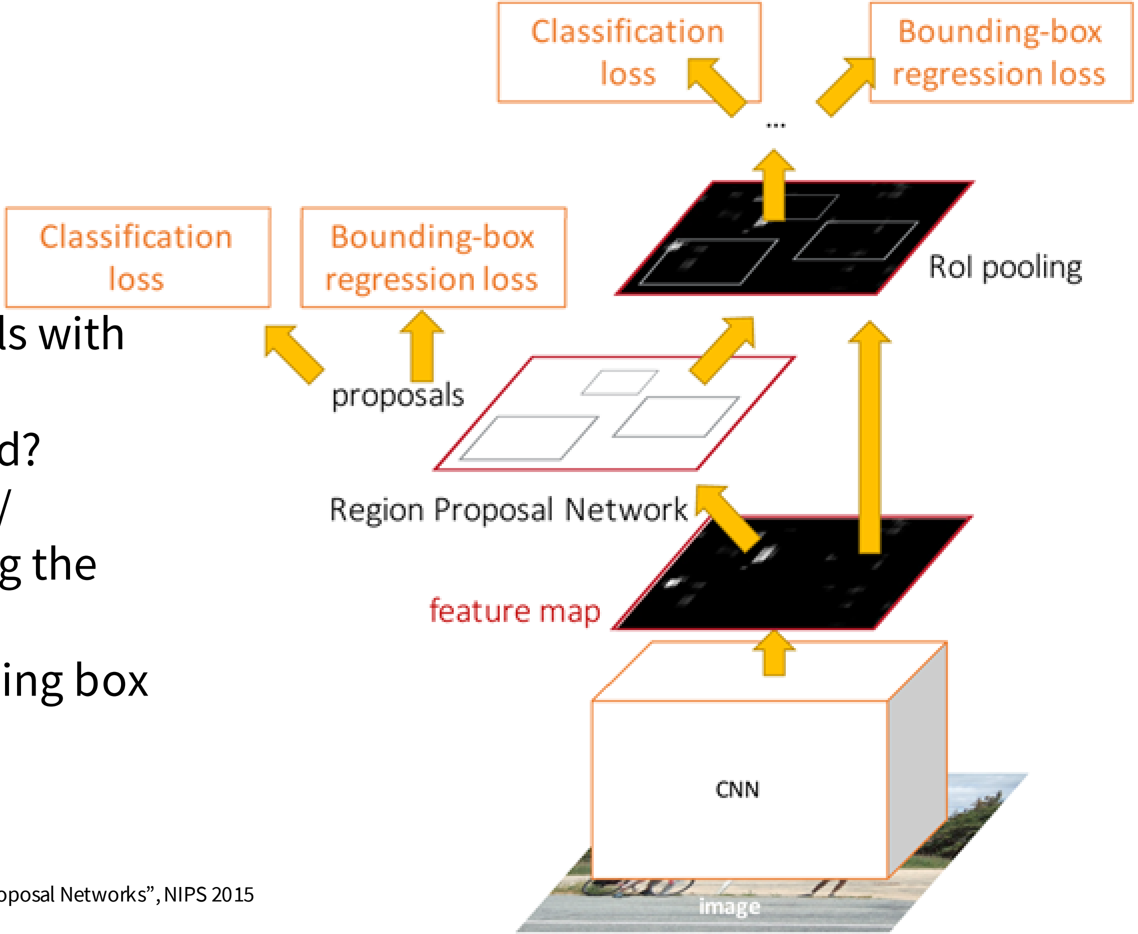


Faster R-CNN:

Make CNN do proposals!

Glossing over many details:

- Ignore overlapping proposals with non-max suppression
- How are anchors determined?
- How do we sample positive / negative samples for training the RPN?
- How to parameterize bounding box regression?



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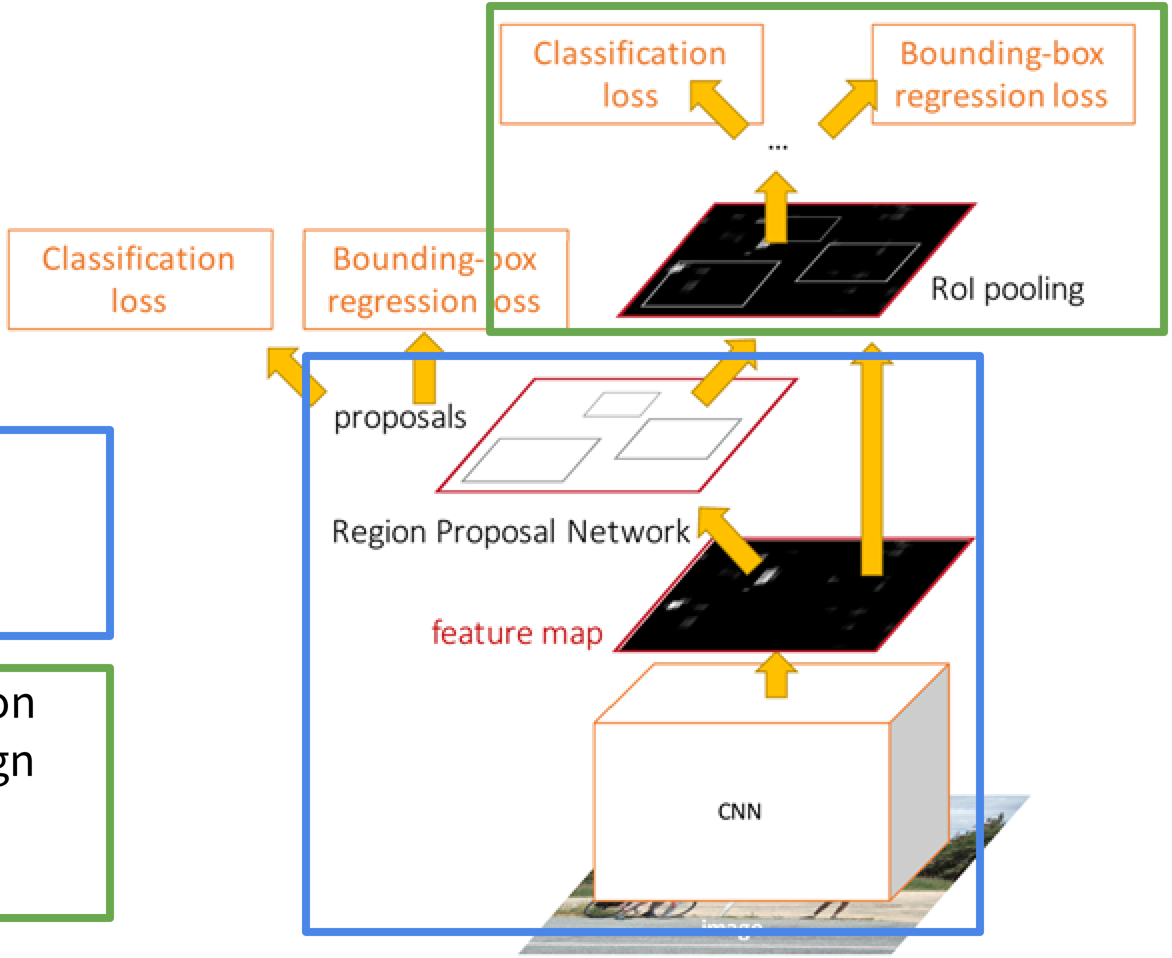
Faster R-CNN:

Make CNN do 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:

Make CNN do proposals!

Do we really need the second stage?

Faster R-CNN is a Two-stage object detector

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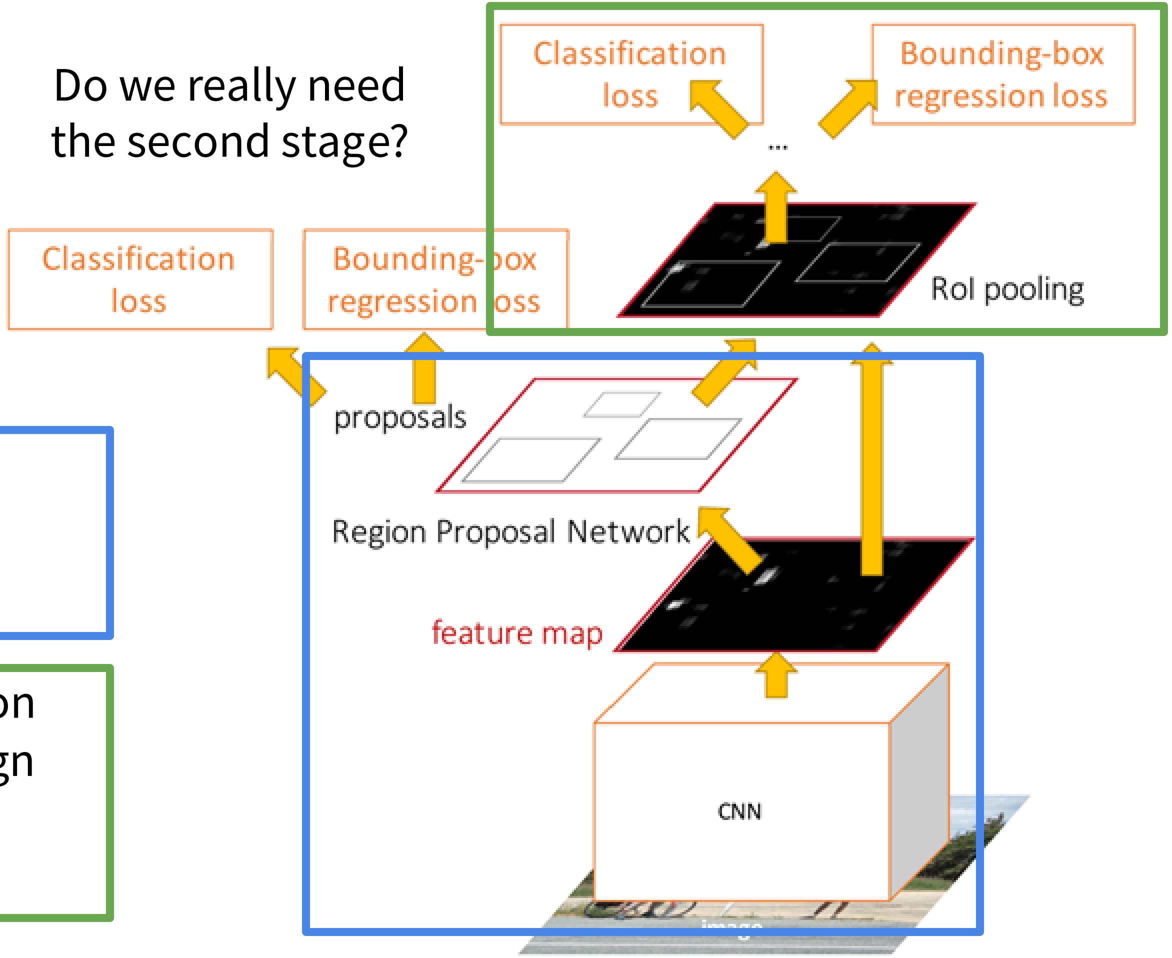

Object Detection: Lots of variables ...

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

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

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Zou et al, "Object Detection in 20 Years: A Survey", arXiv 2019

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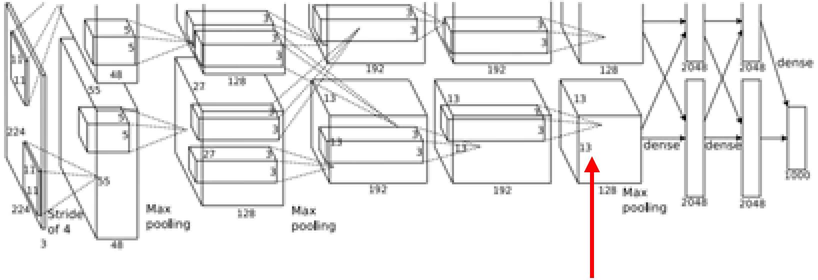
Intermediate Features via (guided) backprop

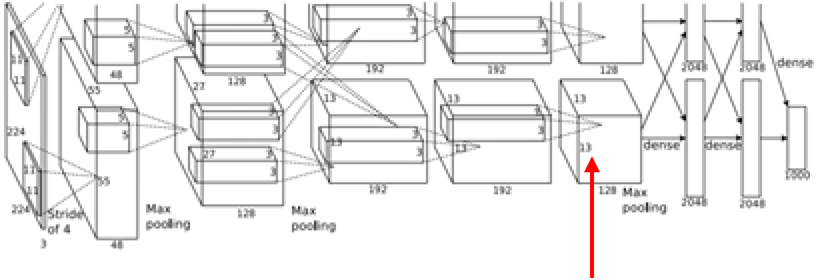


Pick a single intermediate channel, e.g. one value in 128 x 13 x 13 conv5 feature map

Compute gradient of activation value with respect to image pixels

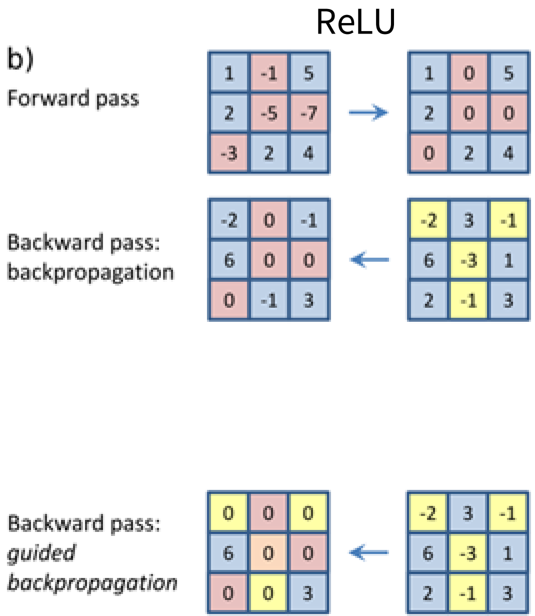
Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

Intermediate Features via (guided) backprop



Pick a single intermediate neuron, e.g. one value in 128 x 13 x 13 conv5 feature map

Compute gradient of neuron value with respect to image pixels

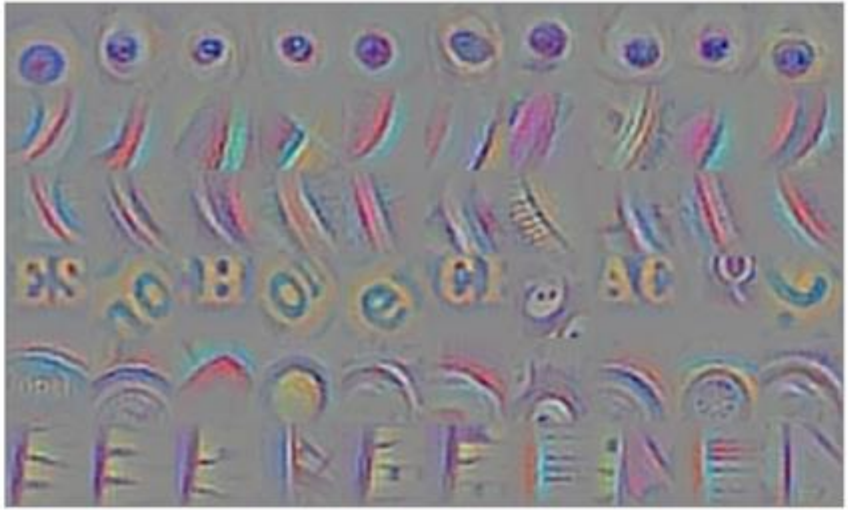


Images come out nicer if you only backprop positive gradients through each ReLU (guided backprop)

Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

Intermediate features via (guided) backprop

Maximally activating patches
(Each row is a different neuron)



Guided Backprop

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Intermediate features via (guided) backprop

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Guided Backprop

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