Deep Learning for Computer Vision

113-1/Fall 2024

https://cool.ntu.edu.tw/courses/41702 (NTU COOL)

http://vllab.ee.ntu.edu.tw/dlcv.html (Public website)

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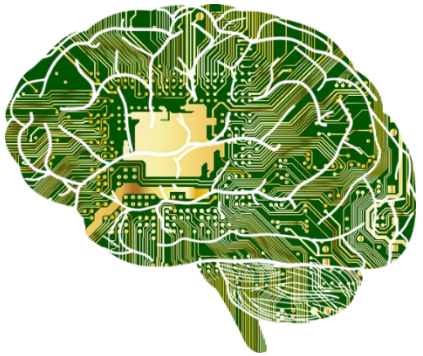
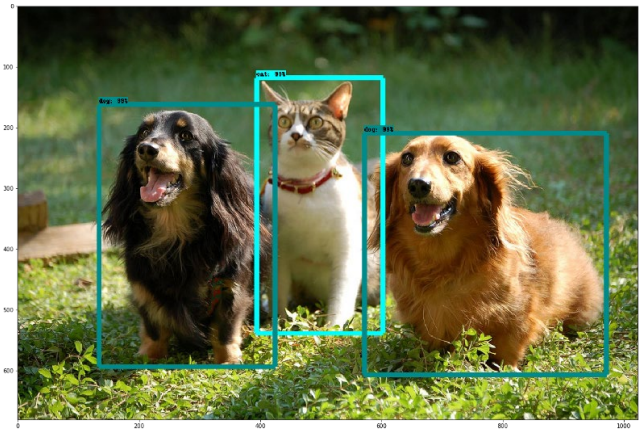
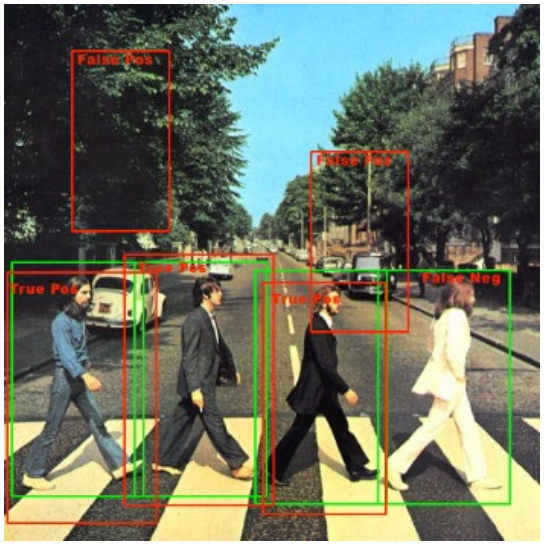
What to Covered Today…

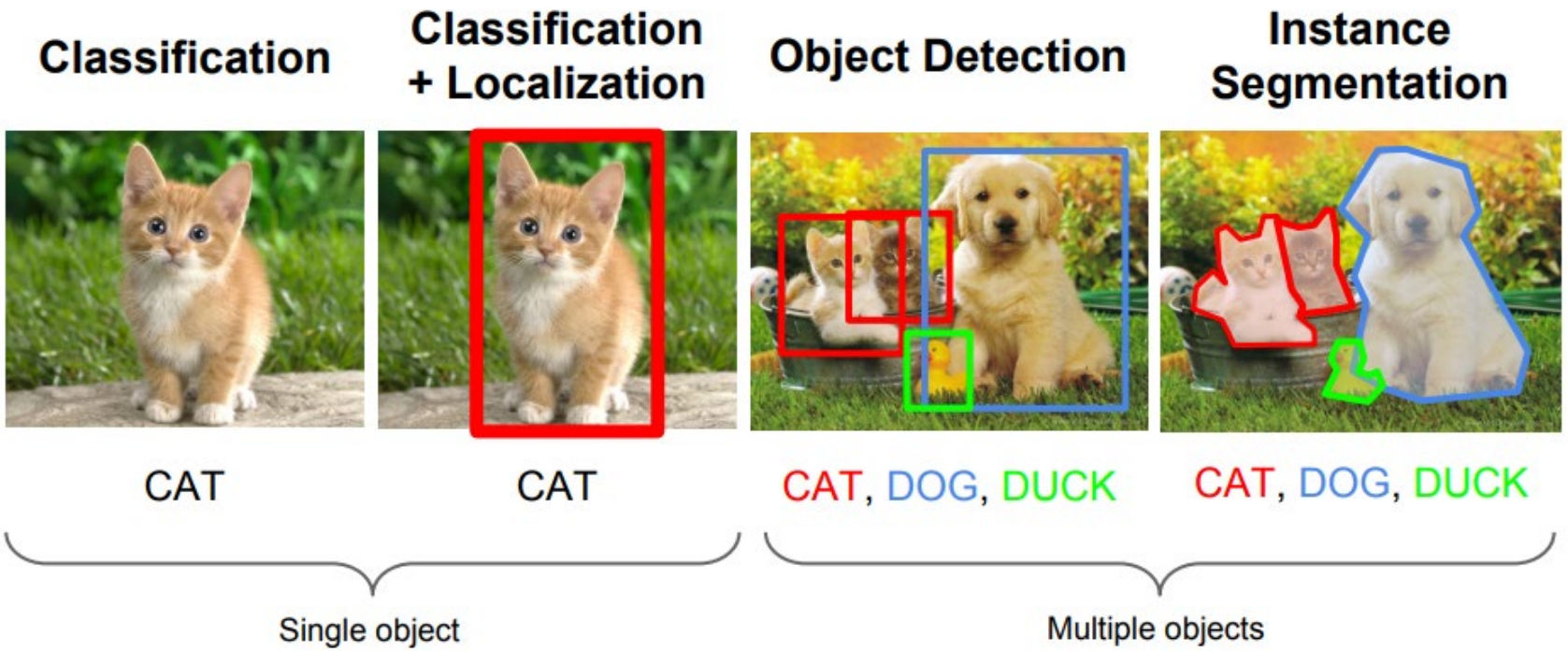
- **Object Detection**
  - Detection via Sliding Windows
  - Two-Stage vs. Single-Stage Detectors
  - Transformer-based Detectors
  - 3D Detection & Grounding







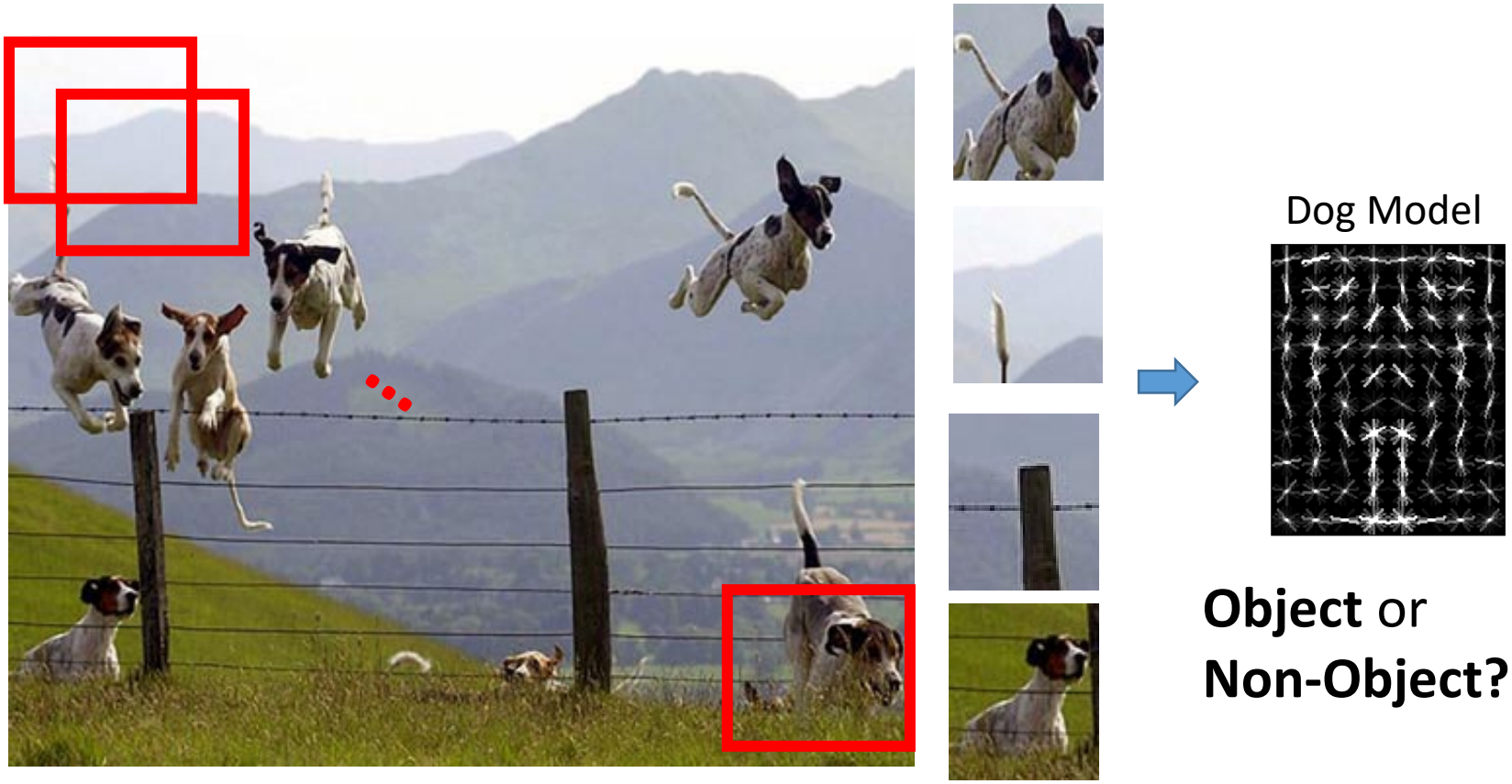
Roadmap



Slide from A. Karpathy

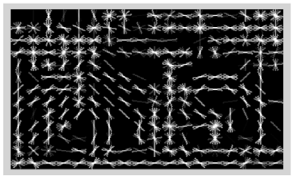
Object Detection

- Focus on object search: “Where is it?”
- Build templates that quickly differentiate object patch from background patch

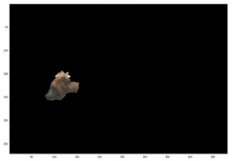


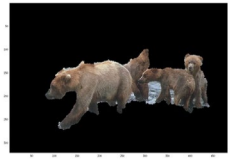
General Process of Object Recognition

Specify Object Model



Generate Hypotheses





Score Hypotheses

Gradient/region based or CNN features, usually based on summary representation with classification/voting results

Resolve Detection

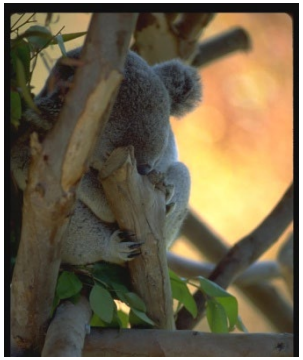
Rescore each proposed object based on the entire candidate set

Challenges in Modeling the Object Classes

Illumination

Object pose

Clutter



Occlusion

Intra-class appearance

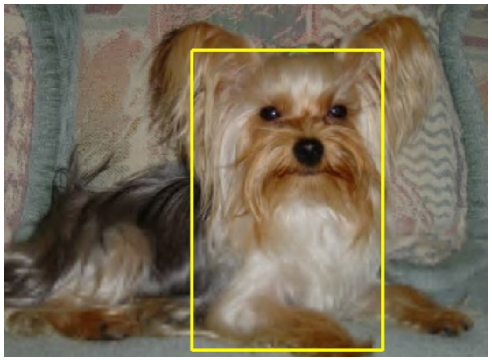
Viewpoint

Slide from K. Grauman, B. Leibe

Challenges in Modeling the Non-object Classes

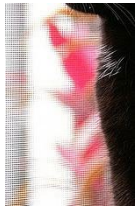
True Detection

Bad Localization

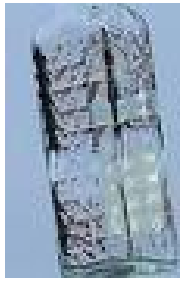


Confused with Similar Object

Misc. Background



Confused with Dissimilar Objects



Detection by Classification

- CNN-based Methods

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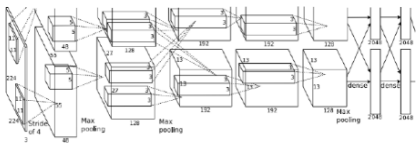


Treat localization as a regression problem!

Vector: 4096

Fully Connected: 4096 to 1000

Fully Connected: 4096 to 4

"What"

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

Correct label: Cat

Softmax Loss

Weighted Sum

Loss

Box Coordinates (x, y, w, h)

L2 Loss

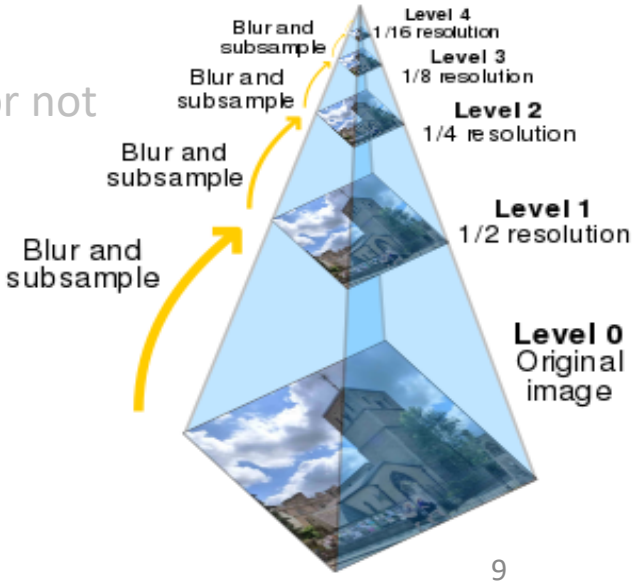
"Where"

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

Slide credit: UMich EECS 498-007

Detection by Classification (cont'd)

- Sliding Windows
  - "Slide" a box within the input image, or even across image scales (see below)
  - Classify each cropped image region inside the box and determine if it's an object of interest or not
  - E.g., HOG (person) detector by Dalal and Triggs (2005)
    Deformable part-based model by Felzenswalb et al. (2010)
    Real-time (face) detector by Viola and Jones (2001)
- Region (Object) Proposals
  - Generate region (object) proposals
  - Classify each proposal and determine it's an object or not



Detection by Classification (cont'd)

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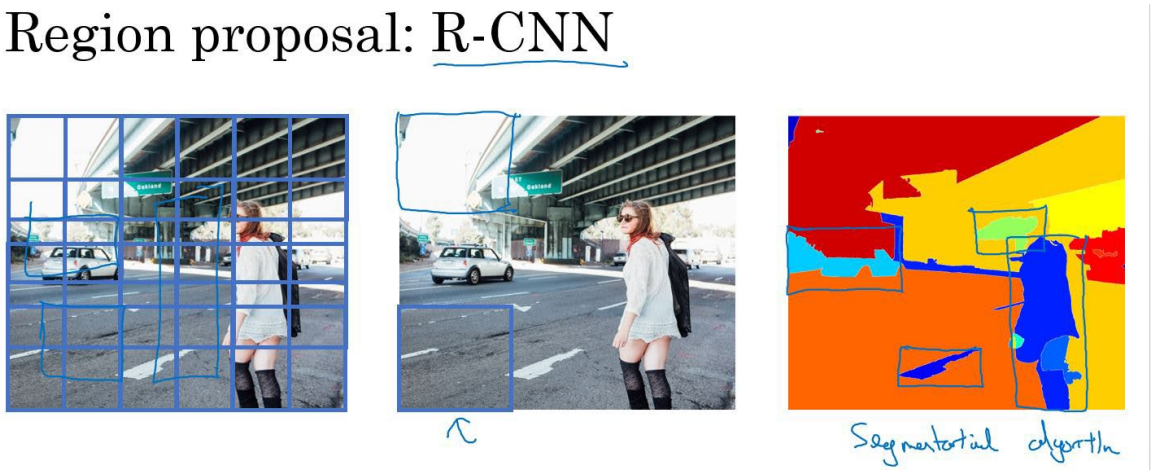
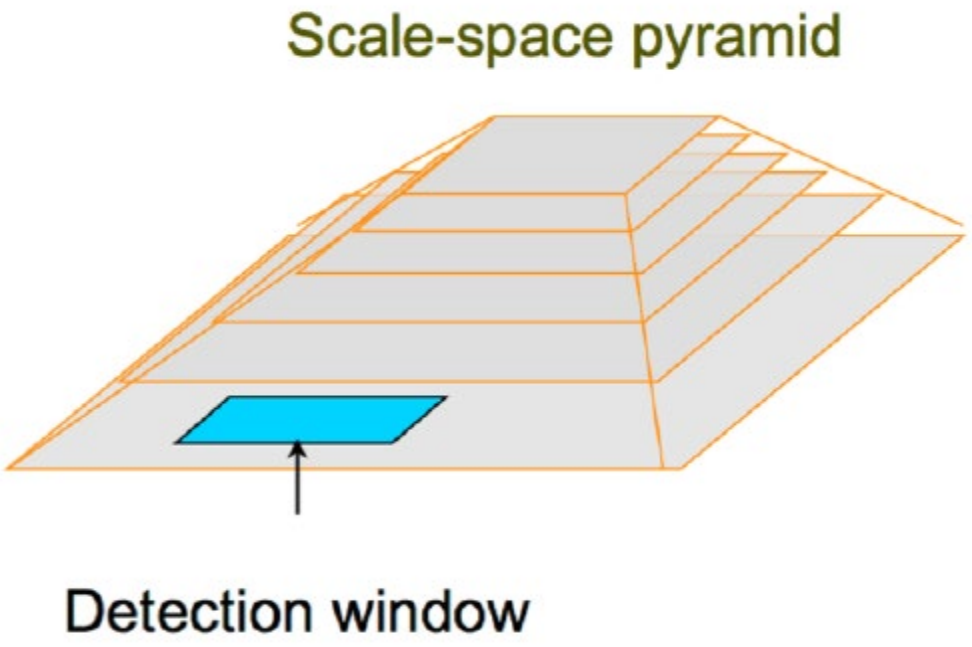
  - Generate region (object) proposals -> how?
  - Classify each proposal and determine it's an object or not



Before the Resurgence of CNN: The HOG Detector

- Histogram of Oriented Gradients (HOG)
- Sliding window detectors finds the objects in 4 steps:
  - Inspect every window
  - Extract features in window
  - Classify & accept window if score > threshold
  - Clean-up (post-processing) stage

- Step 1: Inspect every window
  - Objects can vary in sizes, what to do?
  - Sliding window + image pyramid!



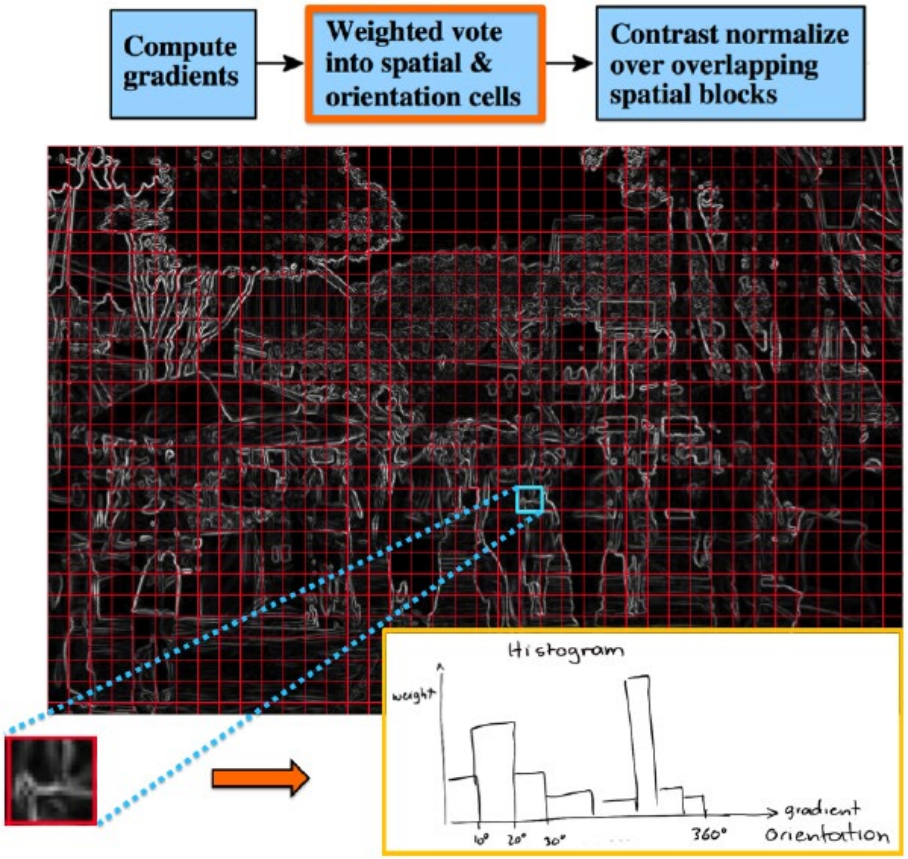
- Step 2: Extract Features in Window
  - Histogram of Gradients (HOG) features
  - Ways to compute image gradients…

Mask Type	1D centered	1D uncentered	1D cubic-corrected	2x2 diagonal	3x3 Sobel
Operator	[-1, 0, 1]	[-1, 1]	[1, -8, 0, 8, -1]	$\begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$ $\begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}$	$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$ $\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$
Miss rate at 10^{-4} FPPW	11%	12.5%	12%	12.5%	14%

(Miss rate: smaller is better)

This gradient filter gives the best performance

- Step 2: Extract Features in Window
  - Histogram of Gradients (HOG) features
  - Divide the image into non-overlapping cells (grids) of 8 x 8 pixels
  - Compute a histogram of orientations in each cell, resulting in a 9-dimensional feature vector.



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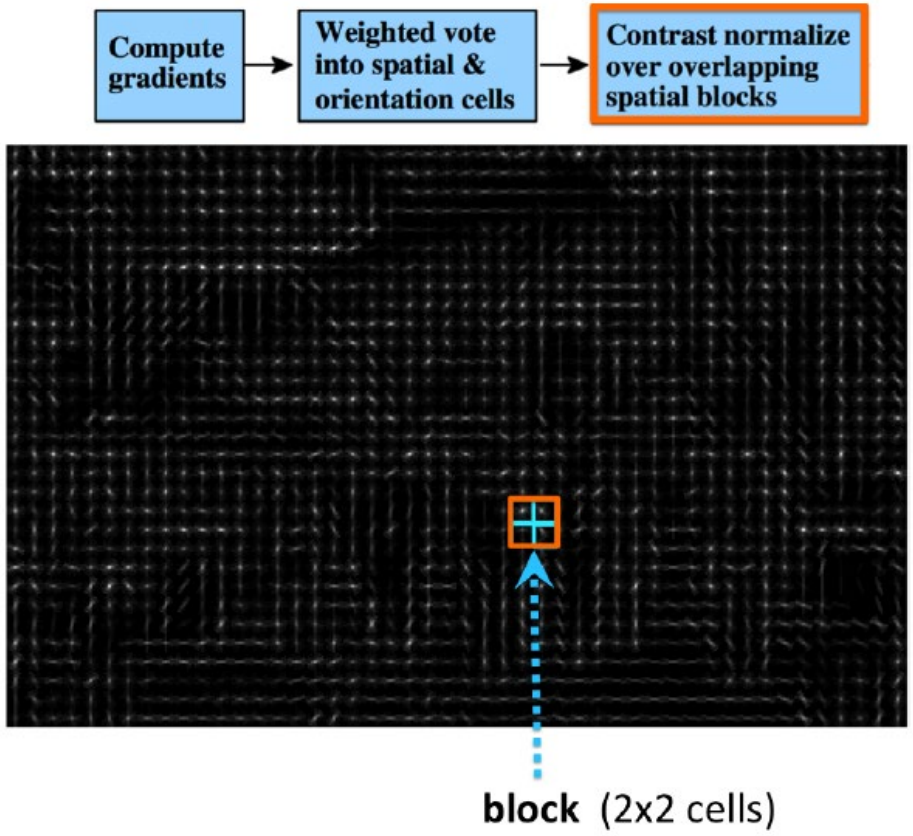
  - We now take blocks, where each has 2 x 2 cells, for HOG normalization.



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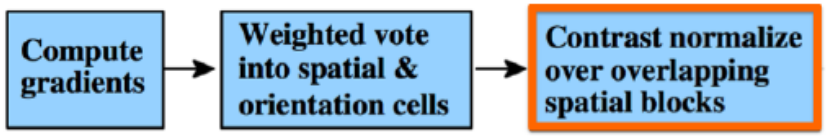
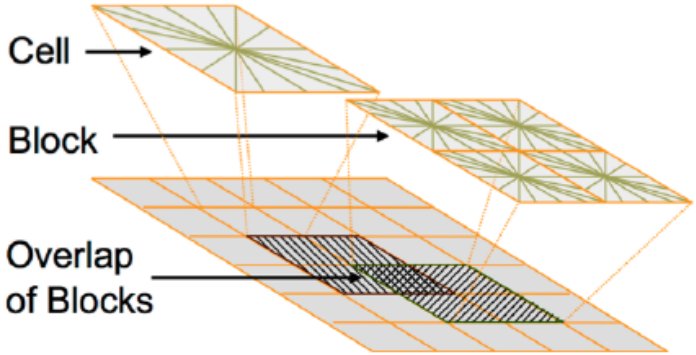
  - Normalize each feature vector, such that each block has unit norm. This does not change the dim of the feature, just the magnitude.

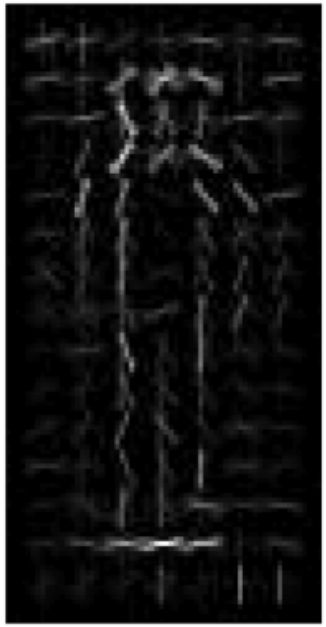




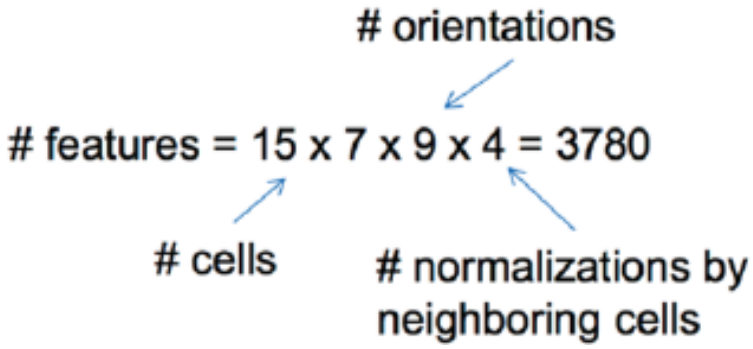
Feature vector *f* = [..., ..., ...]

L2 normalization in each block: $\mathbf{f} = \frac{\mathbf{f}}{\sqrt{||\mathbf{f}||_2^2 + \epsilon^2}}$

- Step 2: Extract Features in Window
  - Normalize each feature vector, such that each block has unit norm. This does not change the dim of the feature, just the magnitude.
  - For each class of *person*, window is 15 x 7 HOG cells.
  - Each cell is in 4 blocks thus has 4 different normalizations; we make each as a feature representation (in 3780 dimensions).
  - We vectorize each feature matrix in each window.



Final descriptor for window
(**person class in this case**)

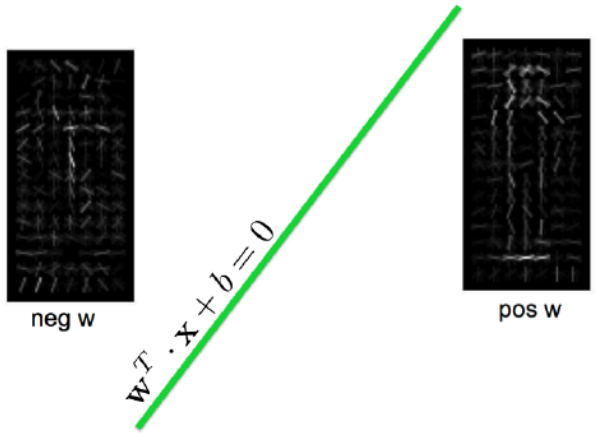


- Step 3: Detection (classify & accept window if score > threshold)
  - Training:

    learn a linear/nonlinear classifier to predict
    the presence of object class in each window

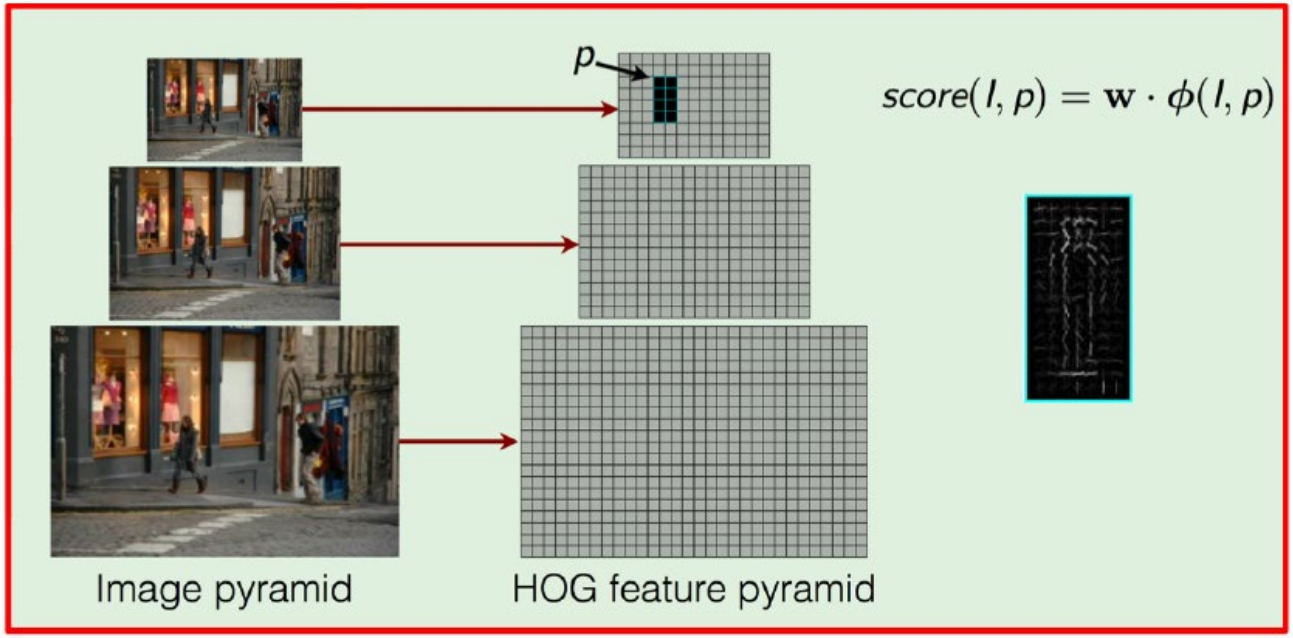
positive training examples

negative training examples

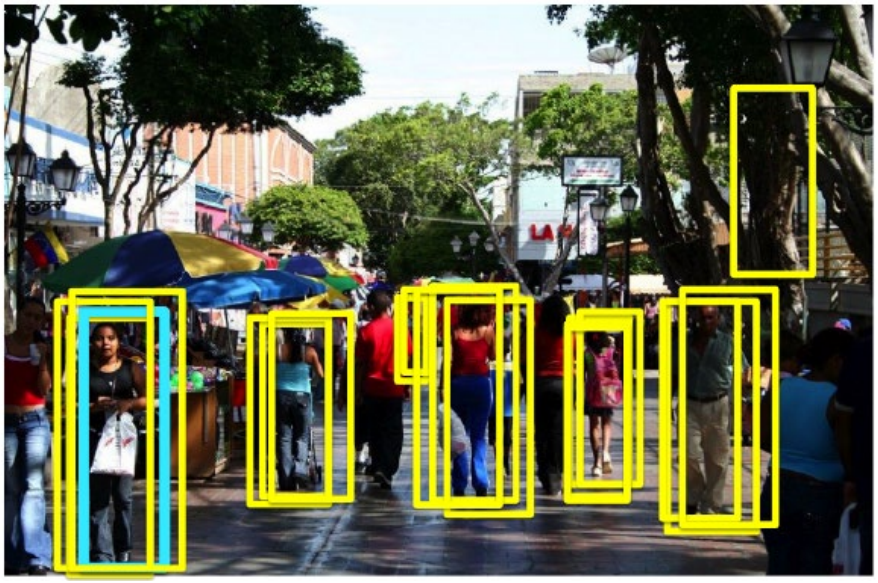


Train classifier. SVM (Support Vector Machines) is typically used.

- Step 3: Detection (Classify & accept window if score > threshold)
  - Training
  - Testing:
    Compute the score $\mathbf{w}^T\mathbf{x}+\mathbf{b}$ in each location, which can be viewed as performing cross-correlation (or convolution) with template **w** (and add bias **b**).



- Step 4: **Cleaning-Up**
  - Perform a greedy algorithm of **non-maxima suppression (NMS)** to pick the bounding box with highest score



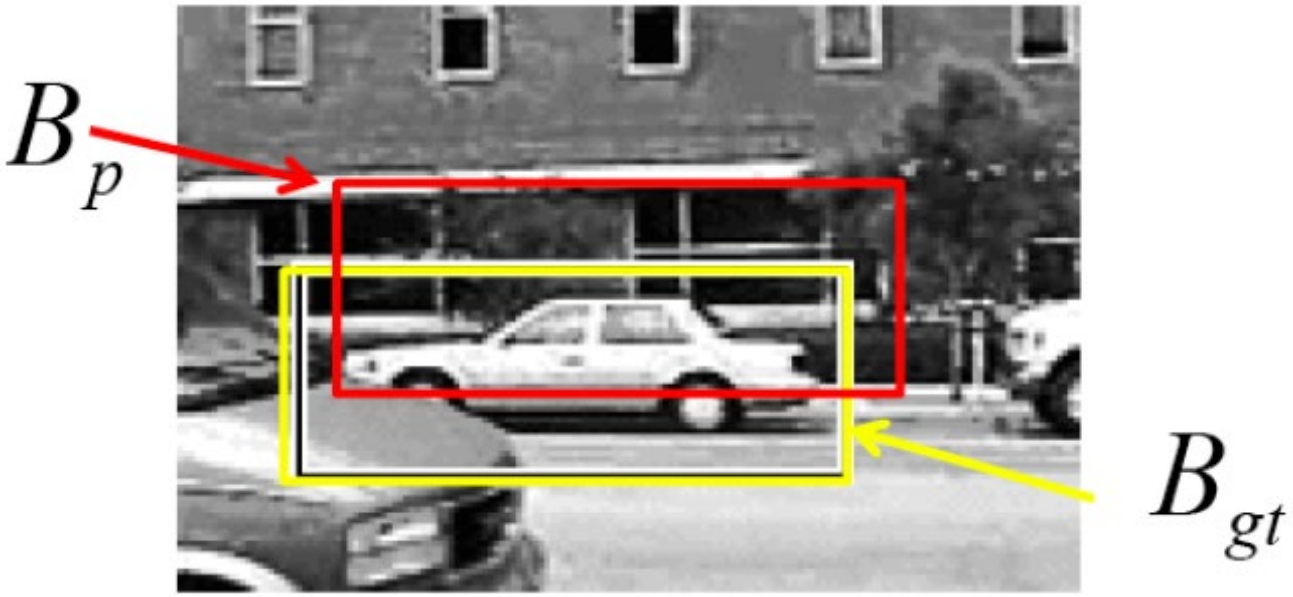
Non-maxima suppression (NMS)

$$\text{overlap} = \frac{\text{area}(box_1 \cap box_2)}{\text{area}(box_1 \cup box_2)} > 0.5$$

- Remove all boxes that overlap more than XX (typically 50%) with the chosen box

- **Evaluation**
  - IoU (intersection over union)
    - E.g, detection is correct if IoU between bounding box and ground truth > 50%

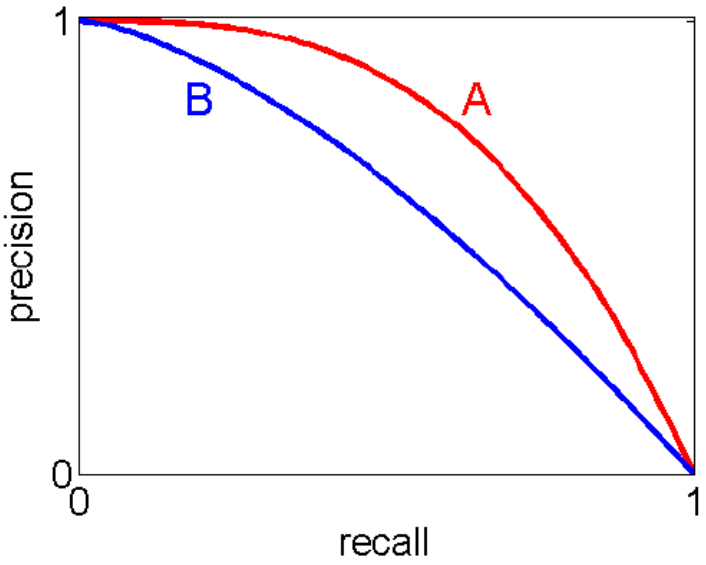
$$a_0 = \frac{\text{area}(B_p \cap B_{gt})}{\text{area}(B_p \cup B_{gt})}$$



- **Evaluation**
  - IOU (intersection over union)
    - Mean IOU (mIOU): average IOU across classes
  - Precision & Recall
    - Sort all the predicted boxes according to scores, in a descending order
    - For each location in the sorted list,
      we compute precision and recall obtained when using top k boxes in the list.

$$\text{recall} = \frac{\#\text{correct boxes}}{\#\text{ground-truth boxes}}$$

$$\text{precision} = \frac{\#\text{correct boxes}}{\#\text{all predicted boxes}}$$

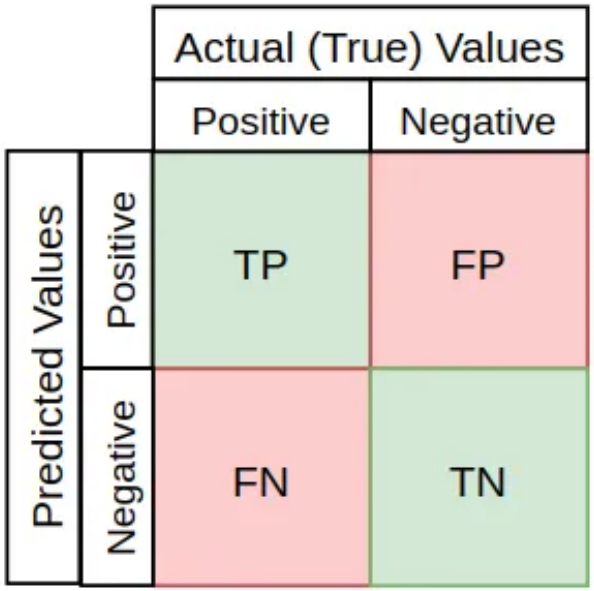


- Evaluation
  - IOU (intersection over union)
  - Precision and Recall

$$\textbf{Precision} = \frac{\text{True Positive}}{\text{Predicted Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

$$\textbf{Recall} = \frac{\text{True Positive}}{\text{Actual Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

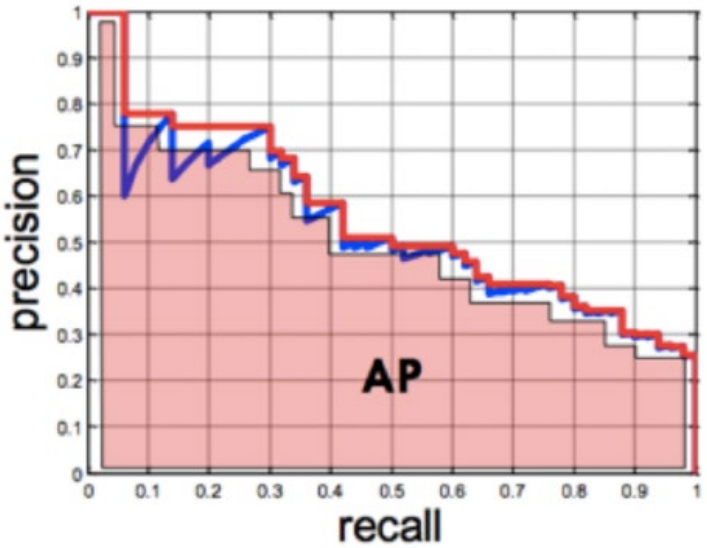
$$\textbf{Accuracy} = \frac{\text{True Positive + True Negative}}{\text{Total}}$$



  - F1-score: harmonic mean of P & R, i.e.,

$$2 * \frac{\text{Precision * Recall}}{\text{Precision + Recall}}$$

- Evaluation (cont'd)
  - IoU (intersection over union)
  - Precision, Recall, F1-score
  - Average Precision (AP):
    - Compute the area under P-R curve
    - mean Average Precision (mAP): average of AP across classes



Something to Think About…

- Sliding window detectors work
  - *very well* for faces
  - *fairly well* for cars and pedestrians
  - *badly* for cats and dogs

- Why are some classes easier than others?

What to Covered Today…

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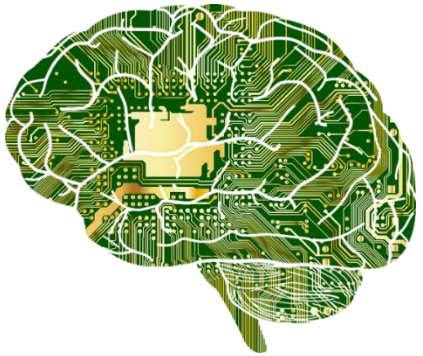
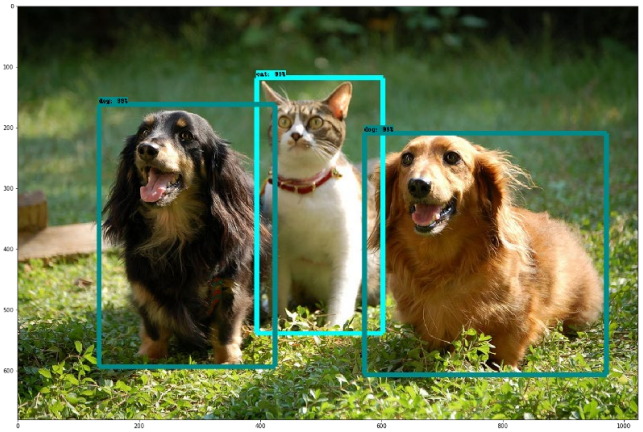
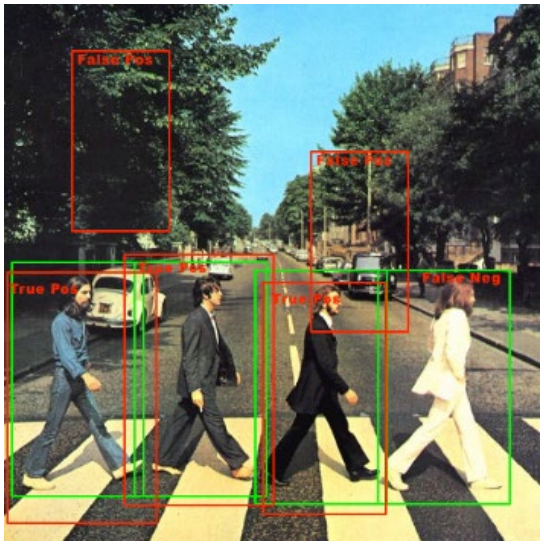
  - Detection via Sliding Windows
  - Two-Stage vs. Single-Stage Detectors
  - Transformer-based Detectors
  - 3D Detection

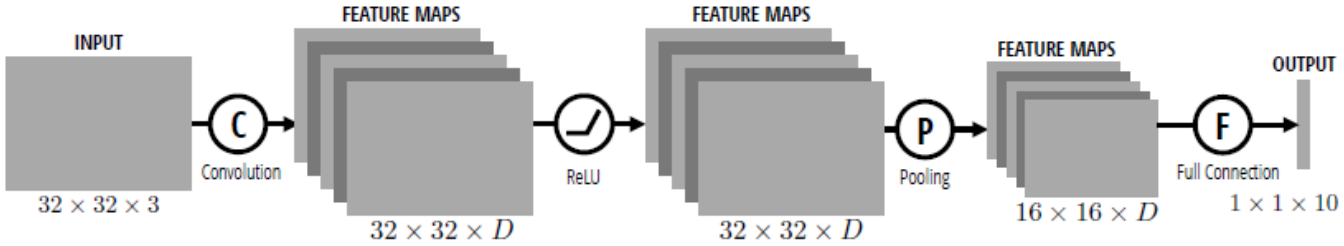


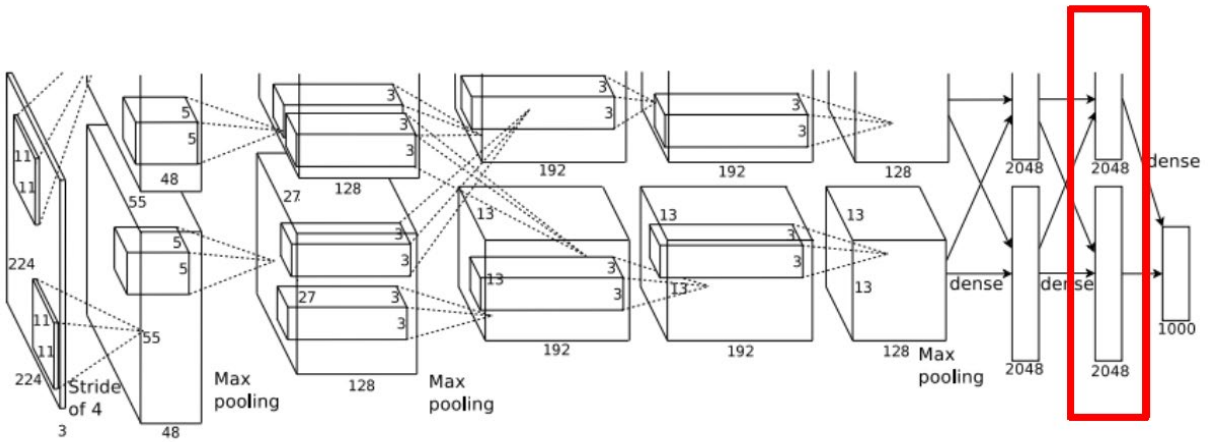




Recall that

- Visual Features derived by Convolutional Neural Networks



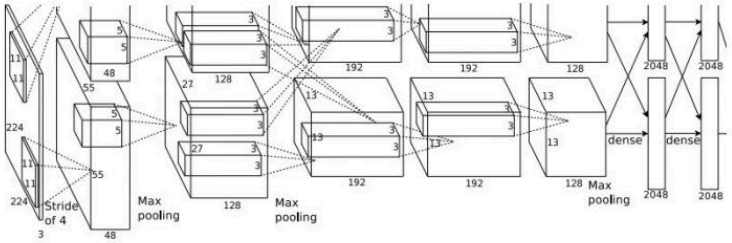


CNN as Feature Extractor

Image credit: Justin Johnson

CNN as Feature Extractor

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



Dog? YES
Cat? NO
Background? NO

Slides by Justin Johnson

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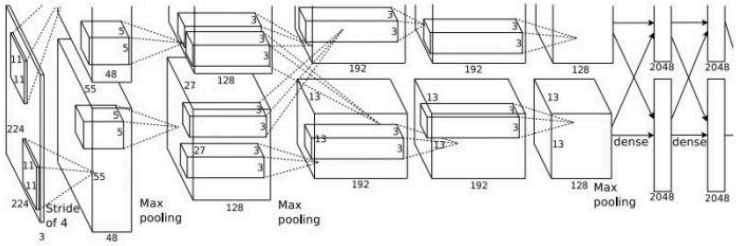

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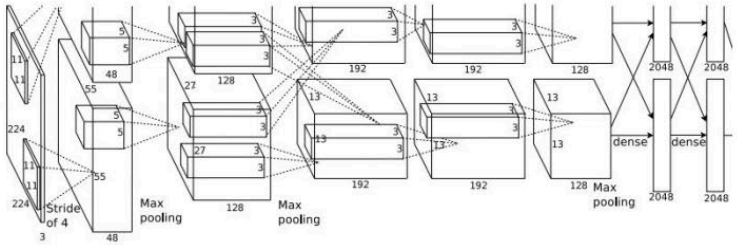

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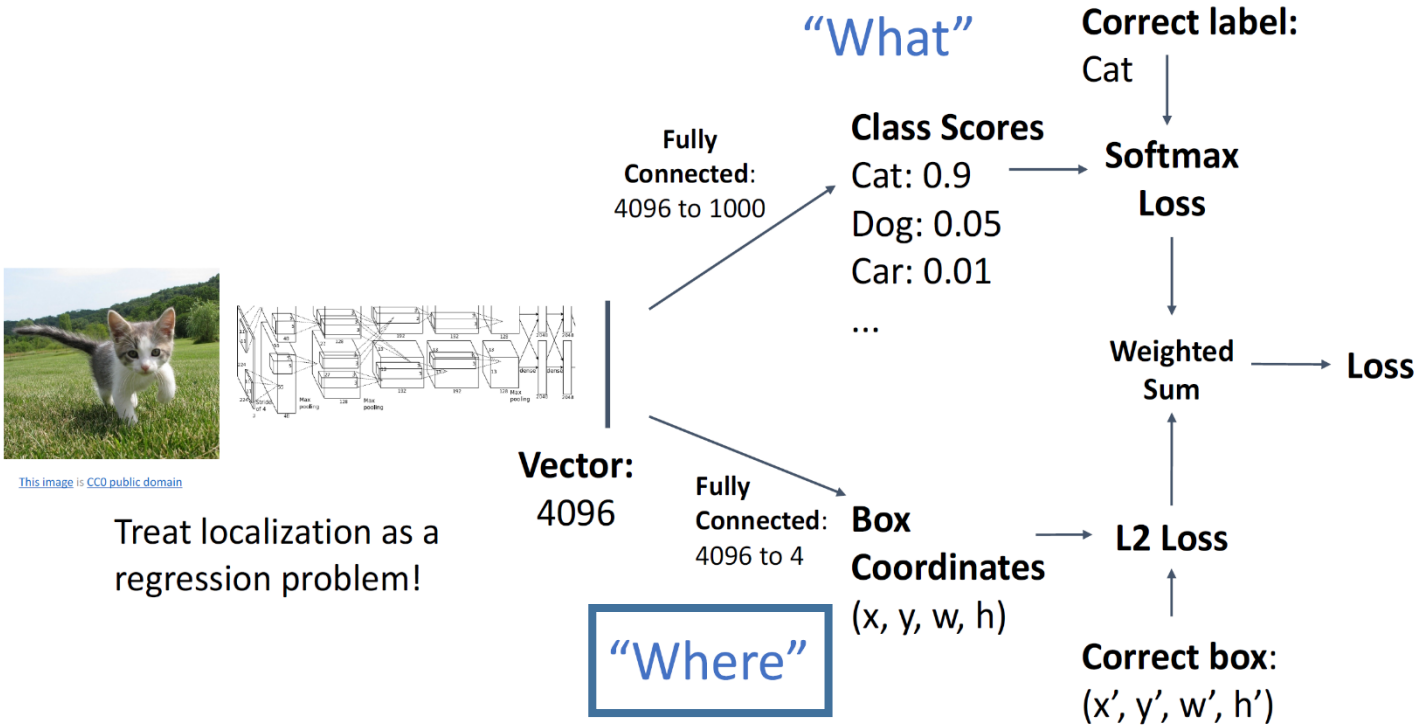
Slides by Justin Johnson

CNN as Feature Extractor

- What could be the problems?
  - Suppose we have an image of 600 x 600 pixels.
    If sliding window size is 20 x 20,
    then have (600-20+1) x (600-20+1) = ~330,000 windows to compute.
  - What if more accurate results are needed,
    need to perform multi-scale detection by
    - Resize image
    - Multi-scale/shape sliding windows
  - For each image, we need to forward pass image regions through CNN for at least ~330,000 times. -> **Slow!!!**

Recap: CNN for Object Detection

- Need to deal with more than one object
  - How?



Slide credit: UMich EECS 498-007

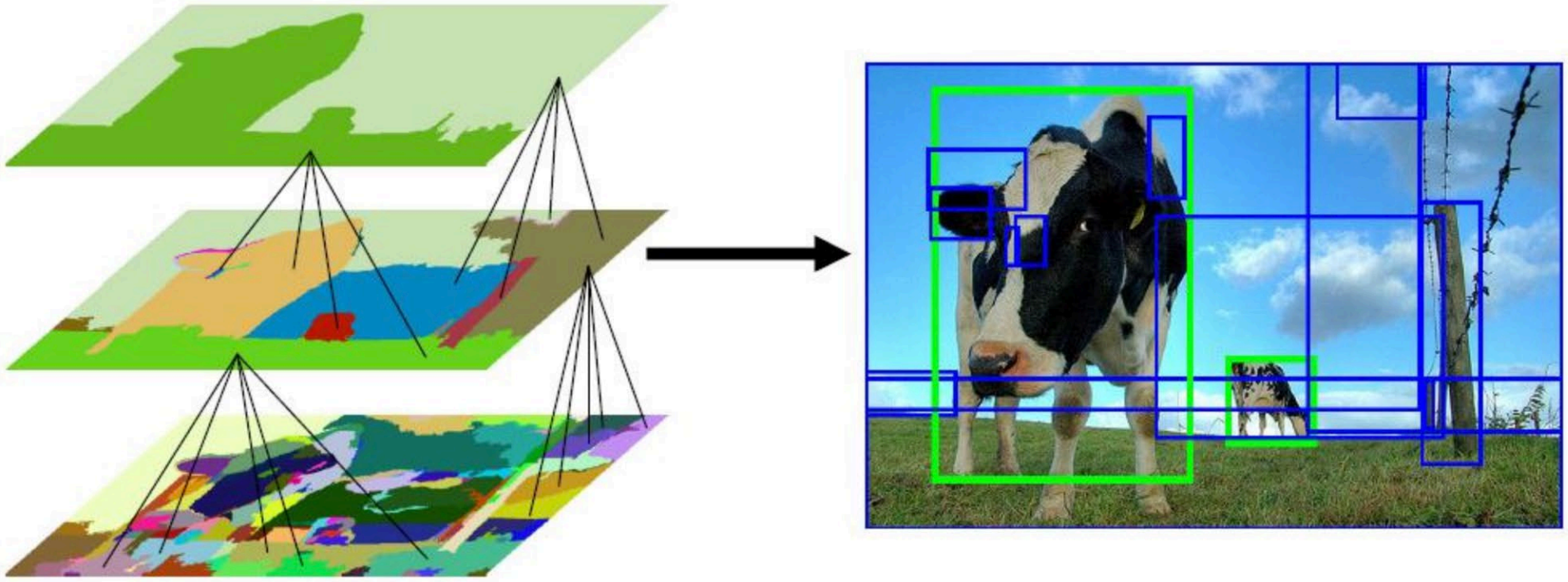
Two-Stage vs. One-Stage Object Detection

Methods

- Sliding Windows
- **Two−stage Frameworks**
  - R−CNN
  - Fast R−CNN
  - Mask R−CNN
  - ⋮
- **One−stage Frameworks**
  - YOLO
  - YOLOv2
  - YOLOv3
  - ⋮

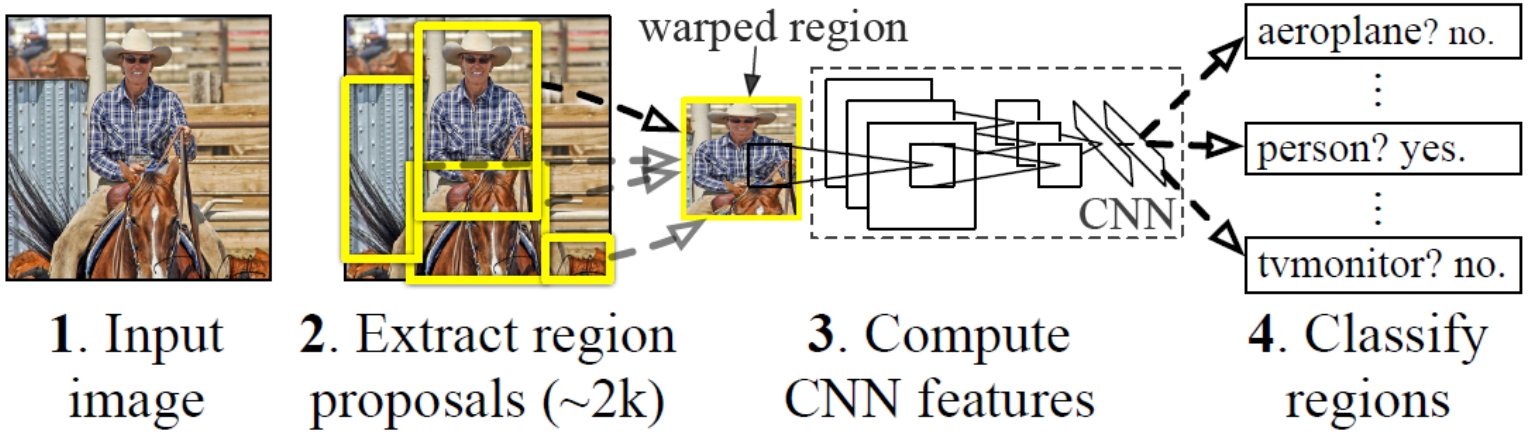
Region Proposal

- Solution
  - Use pre-processing algorithms to filter out some regions first, and feed the regions of interest (i.e., region proposals) into CNN
  - E.g., selective search



Uijilings et al. IJCV 2013

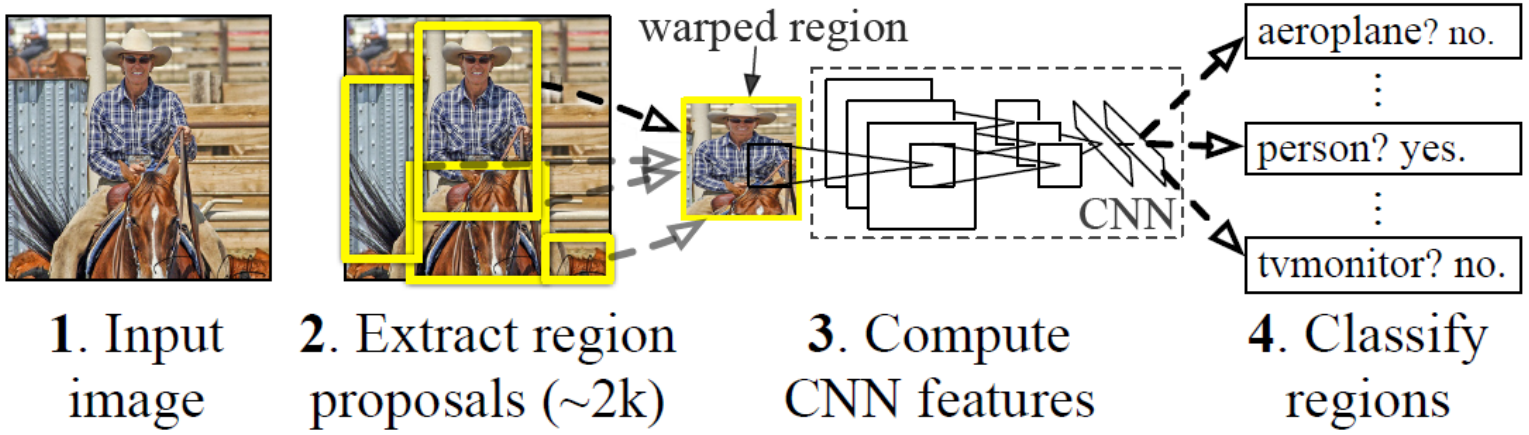
R-CNN (Girshick et al. CVPR 2014)



- Replace sliding windows with "selective search" region proposals (Uijilings et al. IJCV 2013)
- Extract rectangles around regions and resize to 227x227 pixels
- Extract features with fine-tuned CNN (e.g., initialized with network pre-trained on ImageNet)
- Classify last layer of network features with linear classifiers (e.g., SVM/MLP), and refine bounding box localization (bbox regression) simultaneously

http://arxiv.org/pdf/1311.2524.pdf

R-CNN (Girshick et al. CVPR 2014)

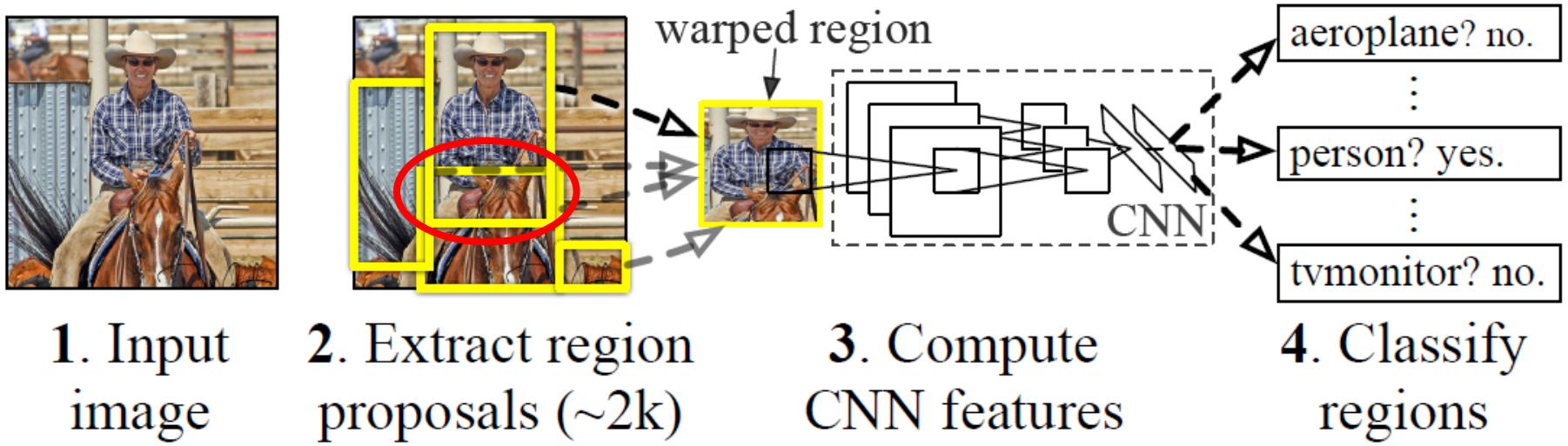


- Ad hoc training objectives:
  - Object class: Fine-tune network with softmax classifier (log loss)
  - Object class: Train post-hoc linear SVMs for each class (hinge loss)
  - Bbox location: Train post-hoc bounding-box regressors (least squares loss)
- Training is extremely slow with lots of disk space.
- Implementation/testing cannot be done in real time.

http://arxiv.org/pdf/1311.2524.pdf

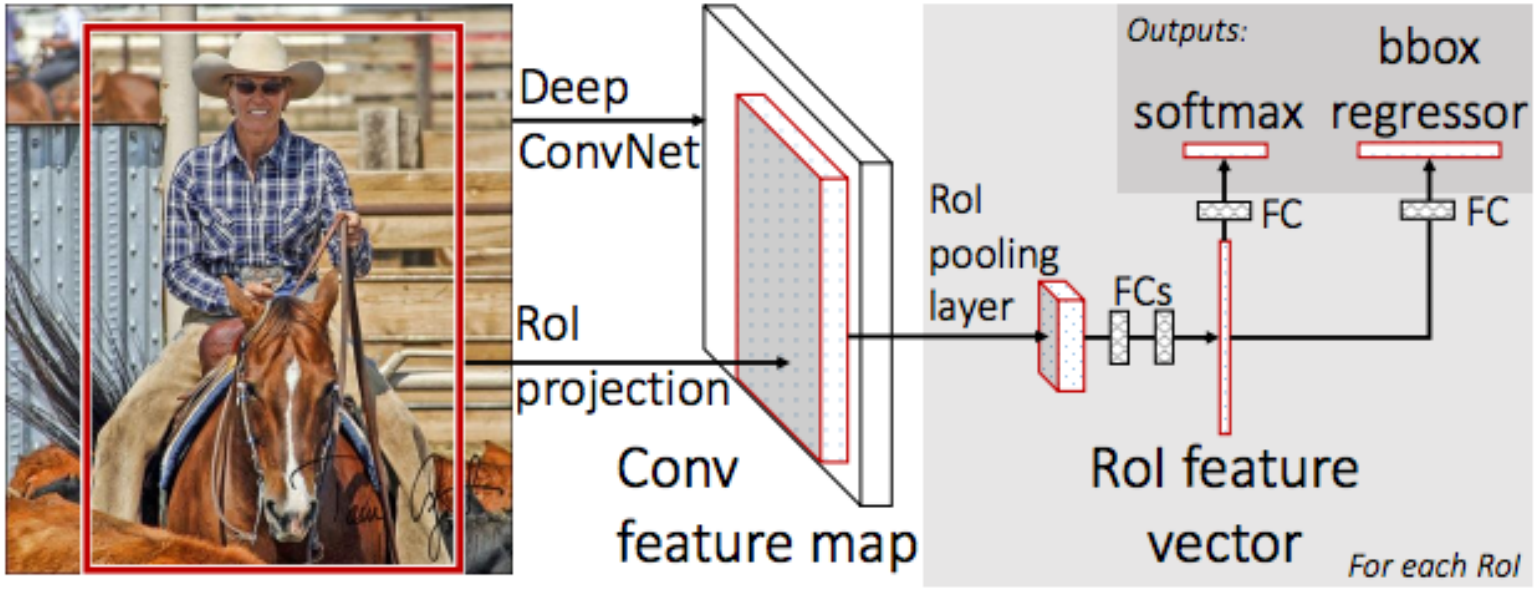
R-CNN (Girshick et al. CVPR 2014)

- What could be the problems?
  - Repetitive computation!
    For overlapping regions, we feed it multiple times into CNN



Fast R-CNN (Girshick ICCV 2015)

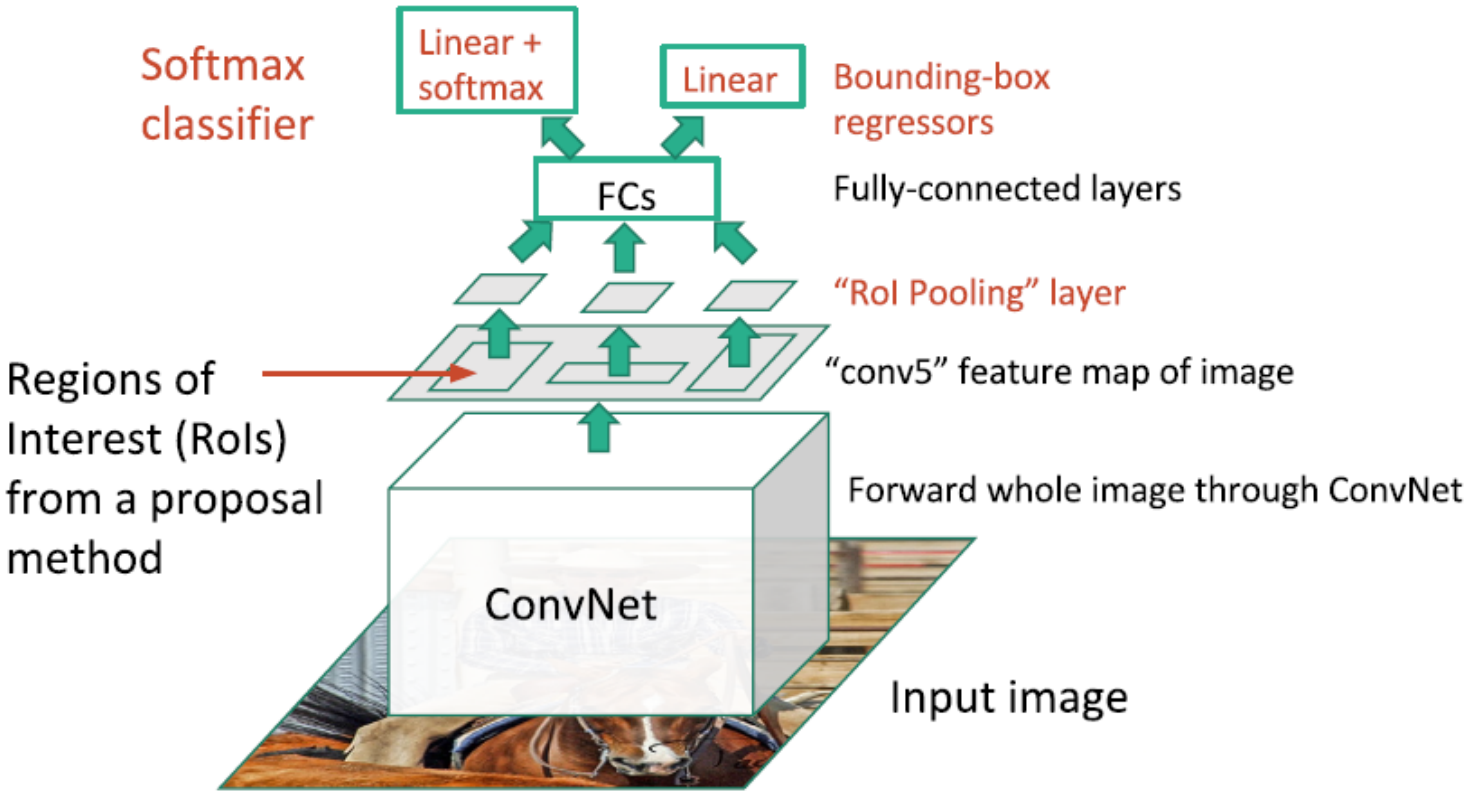
- Solution
  - Why not feed the whole image into CNN only once?
  - Then, crop the feature map instead of the image itself



https://arxiv.org/pdf/1504.08083.pdf

Fast R-CNN (Girshick ICCV 2015)

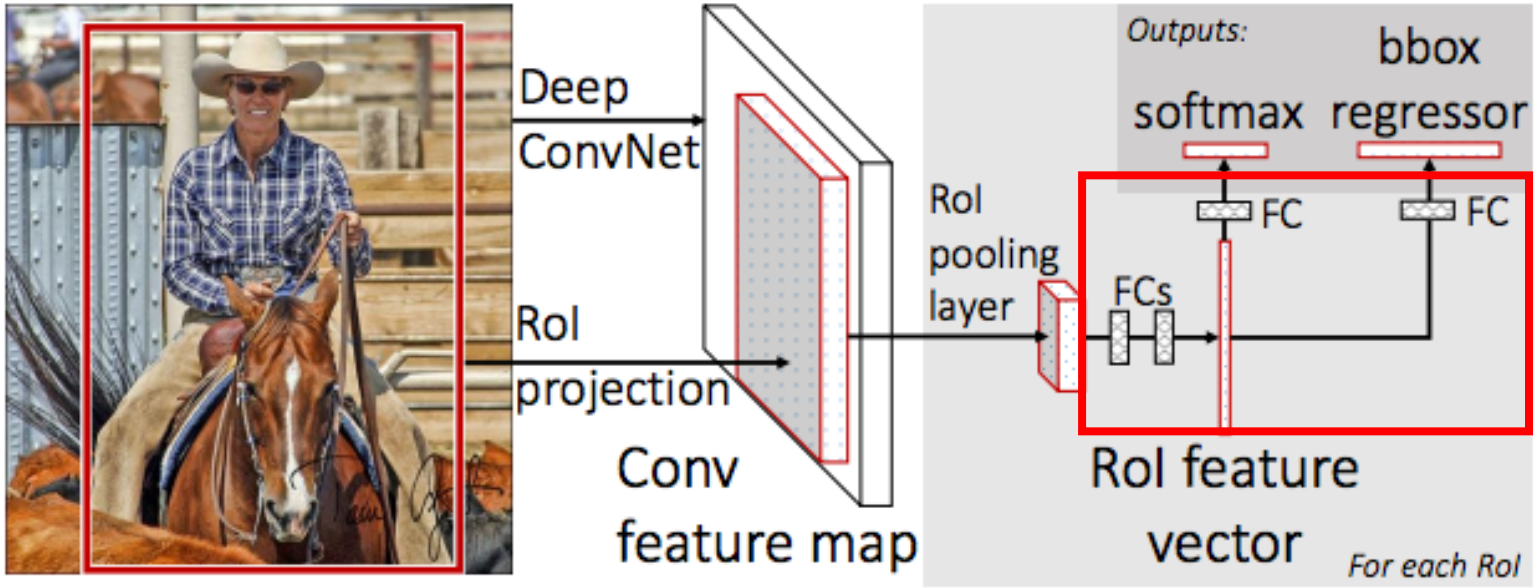
- Solution



https://arxiv.org/pdf/1504.08083.pdf

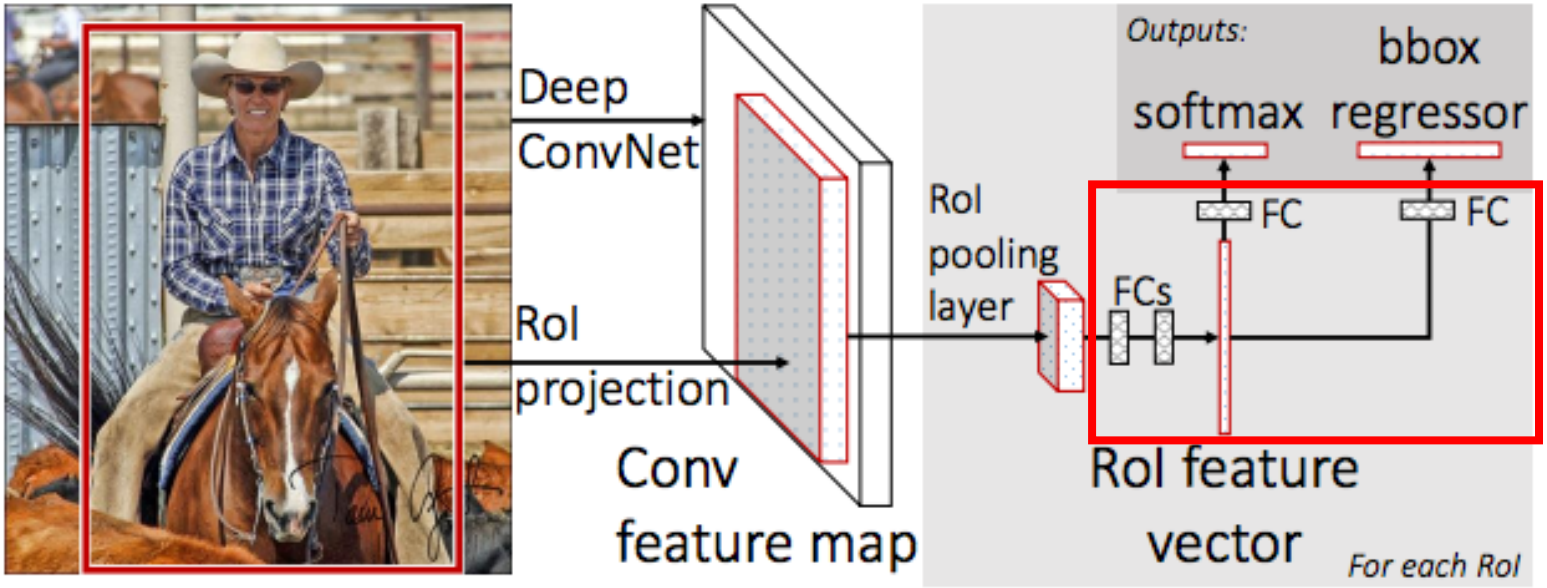
Fast R-CNN (Girshick ICCV 2015)

- Wait…what about the image feature to be processed?
  - Any potential problem?



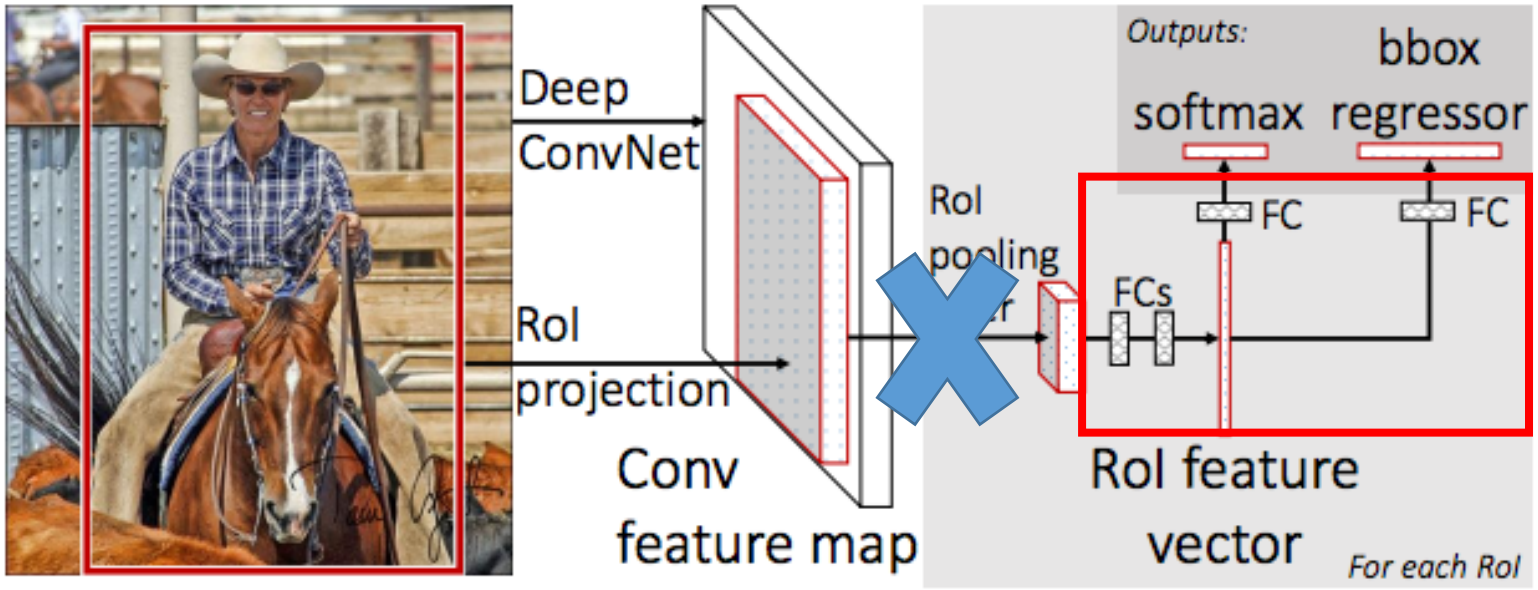
Fast R-CNN (Girshick ICCV 2015)

- Features need to be of the same size.
- How to crop features?
  - Since we have fully-connected layers, the size of feature map for each bounding box should be a fixed number



Fast R-CNN (Girshick ICCV 2015)

- How to crop features?
  - Since we have fully-connected layers, the size of feature map for each bounding box should be a fixed number
  - Resize/Interpolate the feature map as fixed size?
    - Not optimal. This operation is hard to backprop.
      -> we cannot train the conv layers in CNNs…

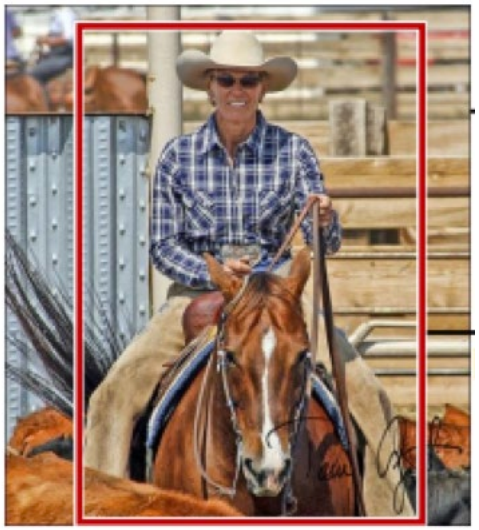


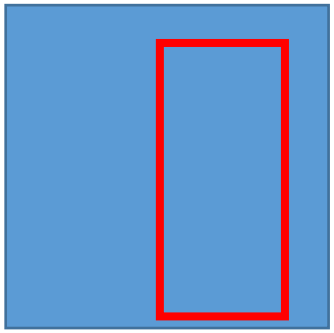
Fast R-CNN (Girshick ICCV 2015)

- How to crop features?
  - Since we have fully-connected layers, the size of feature map for each bounding box should be a fixed number
  - Resize/Interpolate the feature map as fixed size?
    - Not optimal. This operation is hard to backprop.
      -> we cannot train the conv layers for this problem…
- RoI Pooling
  - How to crop regions of various sizes but resulting in the same size?

RoI Pooling

- Step 1:
  Get bounding box for feature map from bounding box for image
  - Due to the (down)convolution/pooling operations,
    feature map would have a smaller size than the original image.





Feature map

RoI Pooling

- Step 2:
  Divide cropped feature map into fixed number of sub-regions
  - The last column and last row might be smaller

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15

Feature map
4 x 4 x 1

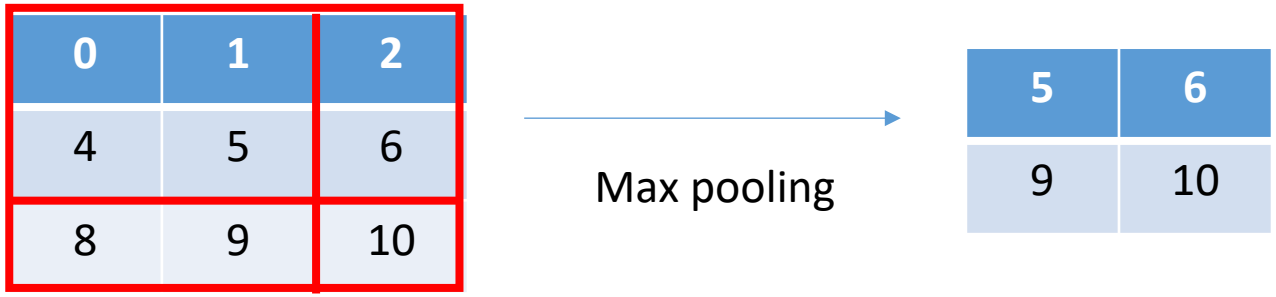
Make it as
2x2 grids

0	1	2
4	5	6
8	9	10

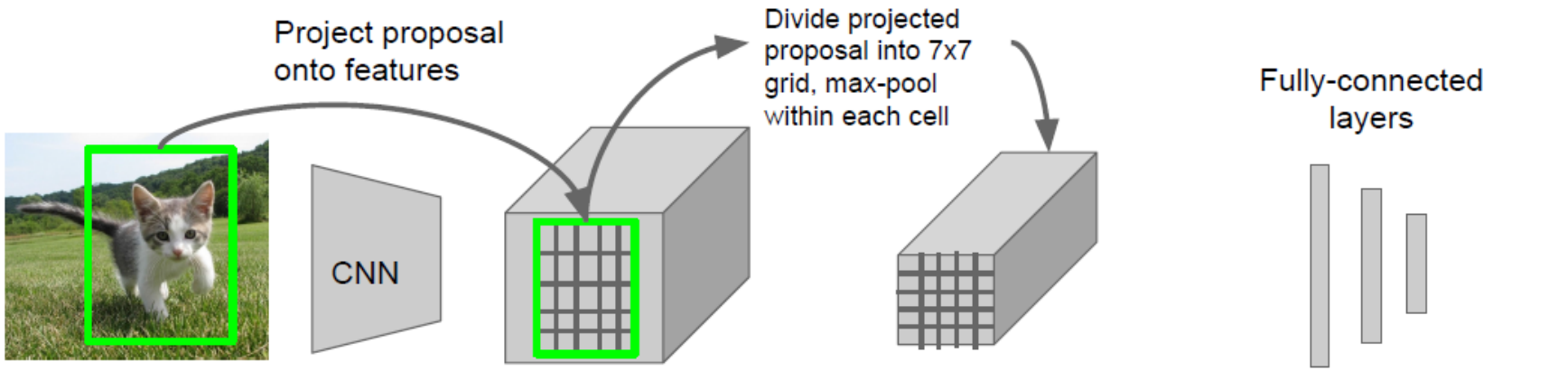
1	2	3
5	6	7
9	10	11
13	14	15

RoI Pooling

- Step 3:
  For each sub-region, perform max pooling (pick the max one)



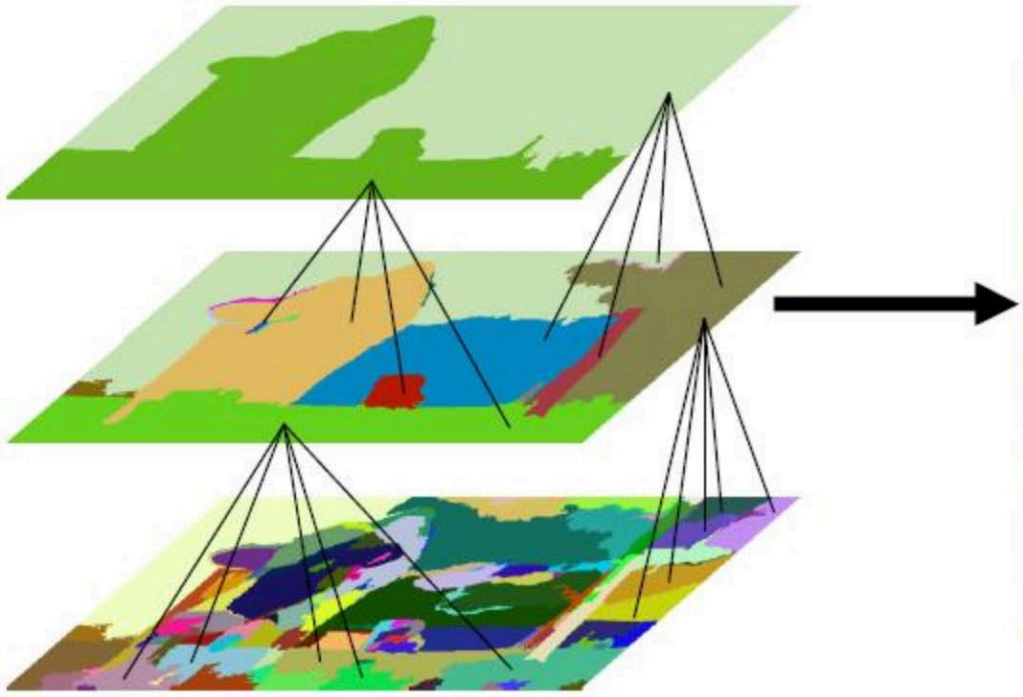
RoI Pooling

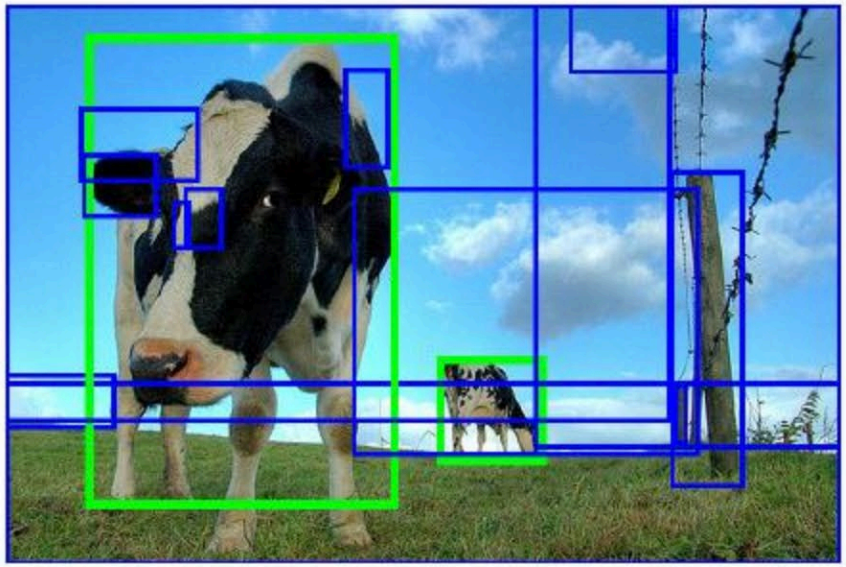


Girshick, "Fast R-CNN", ICCV 2015.

Fast R-CNN (Girshick ICCV 2015)

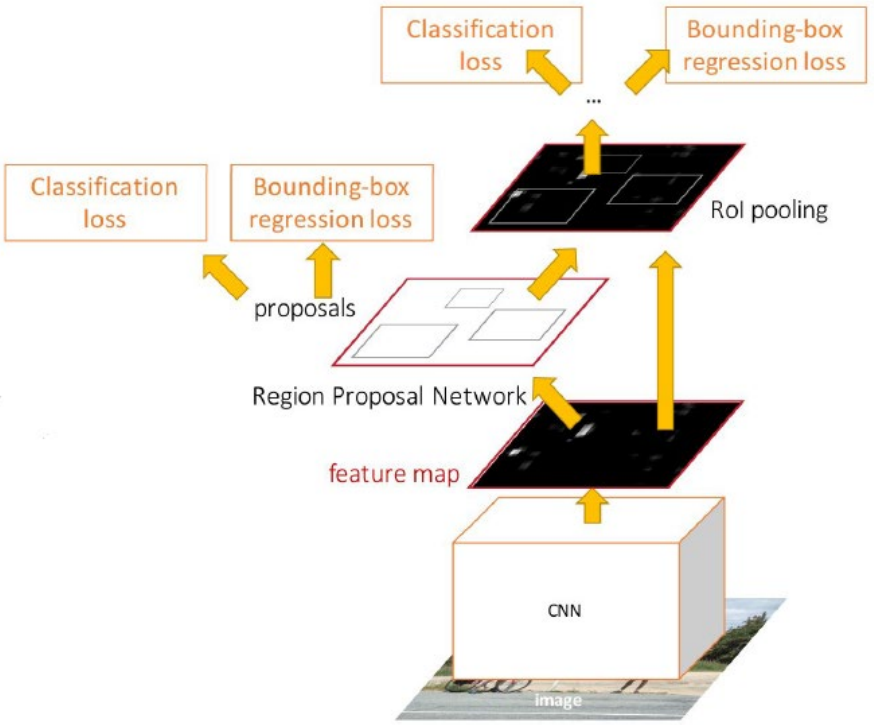
- What could be the problems?
  - We still need to collect the region proposals from a pre-processing step, which does not allow end-to-end learning.





Faster R-CNN (Ren et al. NIPS/NeurIPS 2015)

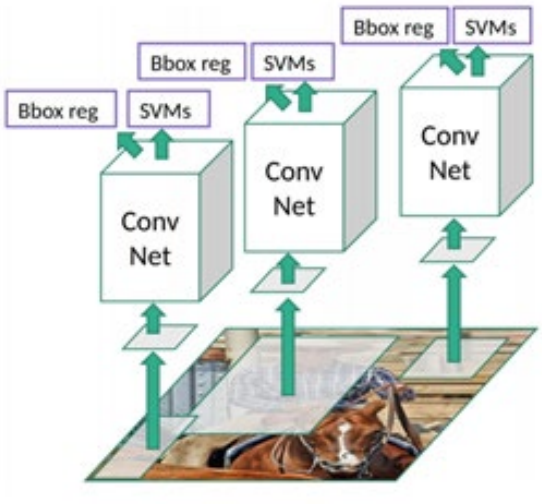
- Solution
  - Why not generate region proposals using CNN?
    -> Insert Region Proposal Network (RPN) to predict proposals from features
  - Jointly train with 4 losses:
    - RPN classification loss
    - RPN regress box coordinates
    - Final classification loss
    - Final box coordinates

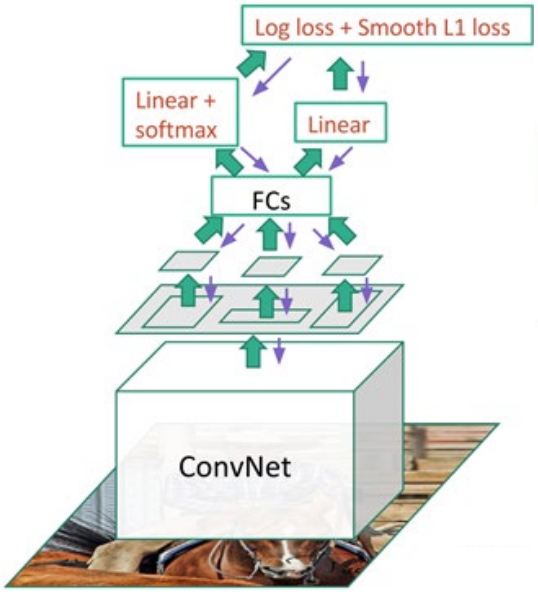


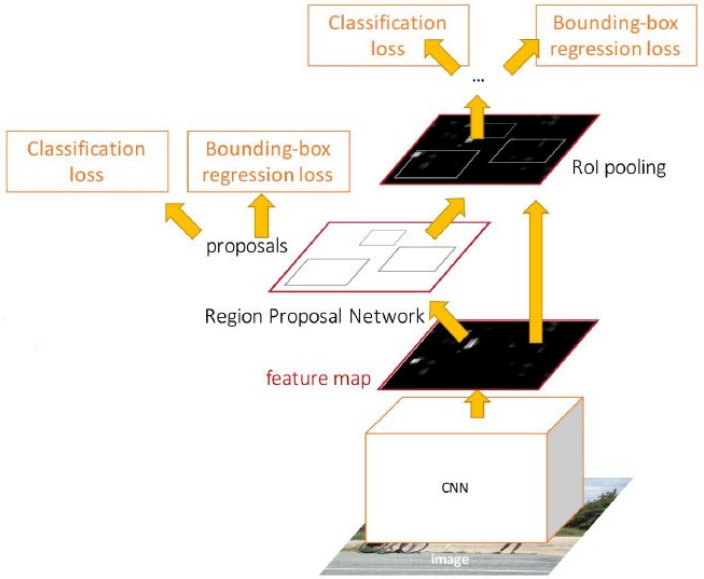
https://arxiv.org/pdf/1506.01497.pdf

Image credit: http://zh.gluon.ai/chapter_computer-vision/object-detection.html

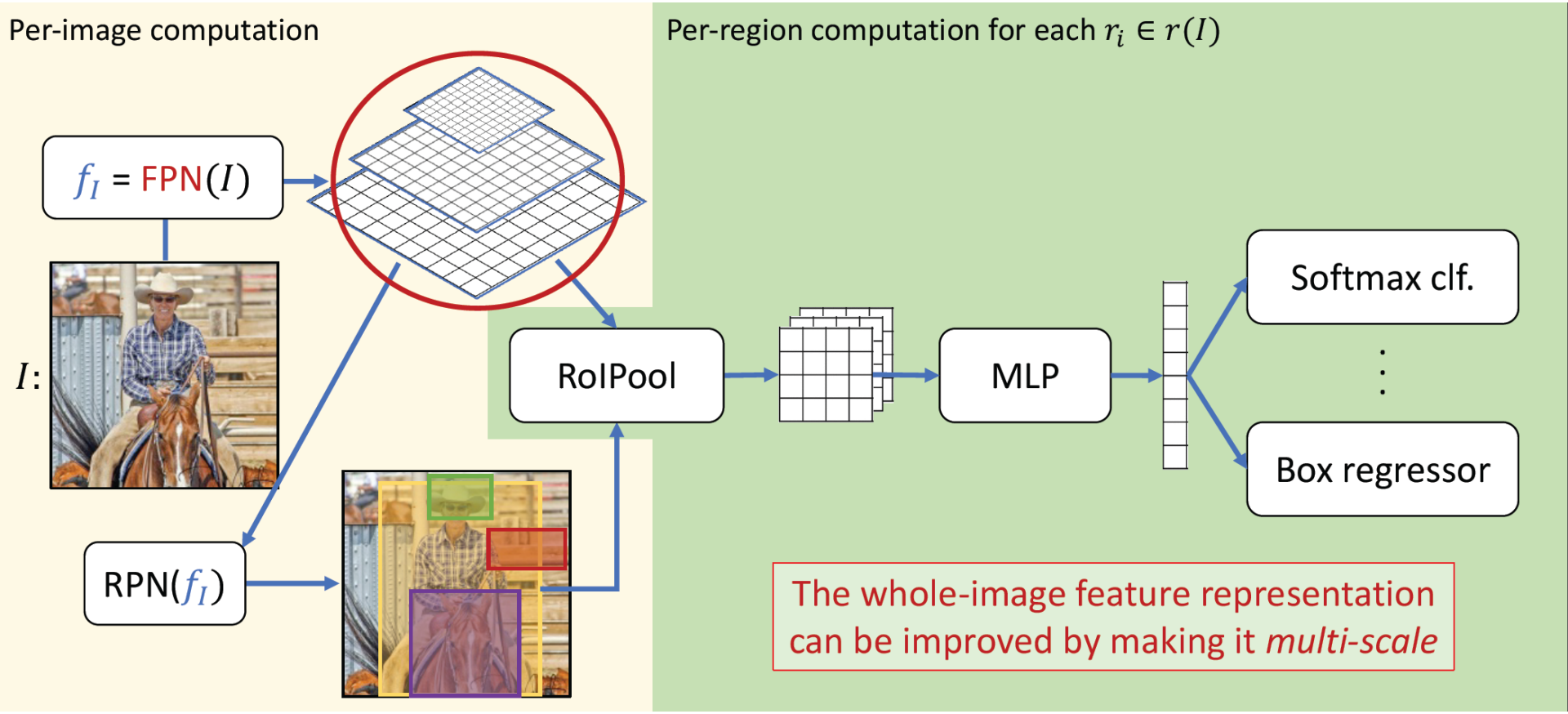
R-CNN, Fast R-CNN, & Faster R-CNN







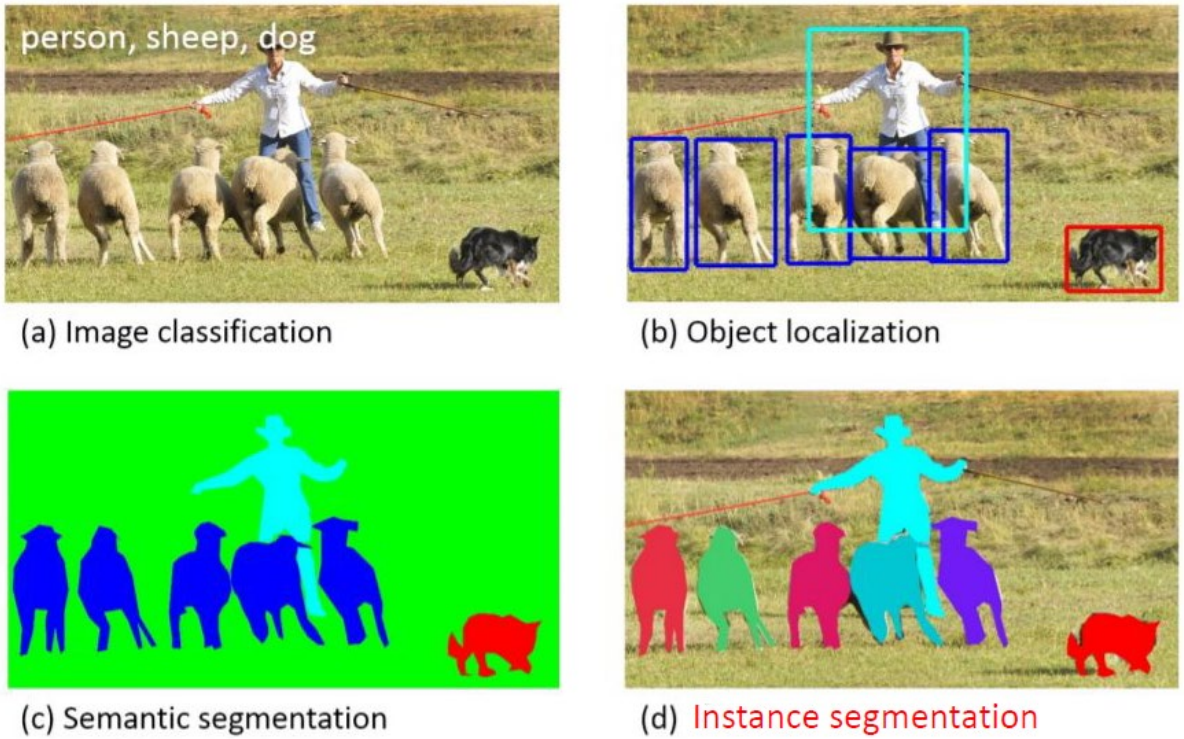
Faster R-CNN with Feature Pyramid Network



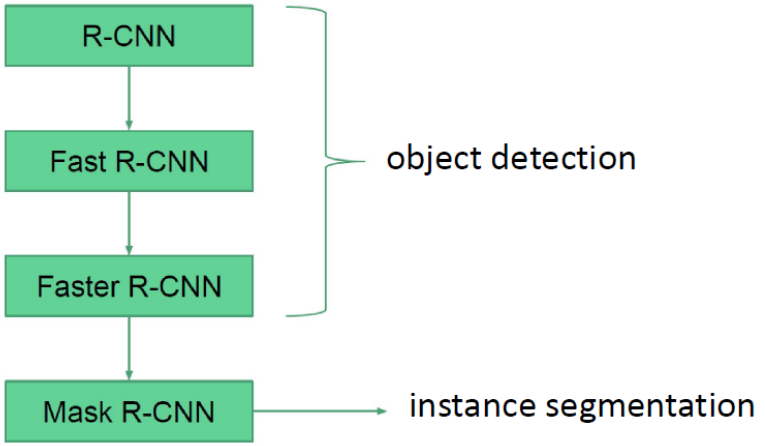
Slide credit: Ross Girshick

Faster R-CNN (Ren et al. NIPS 2015)

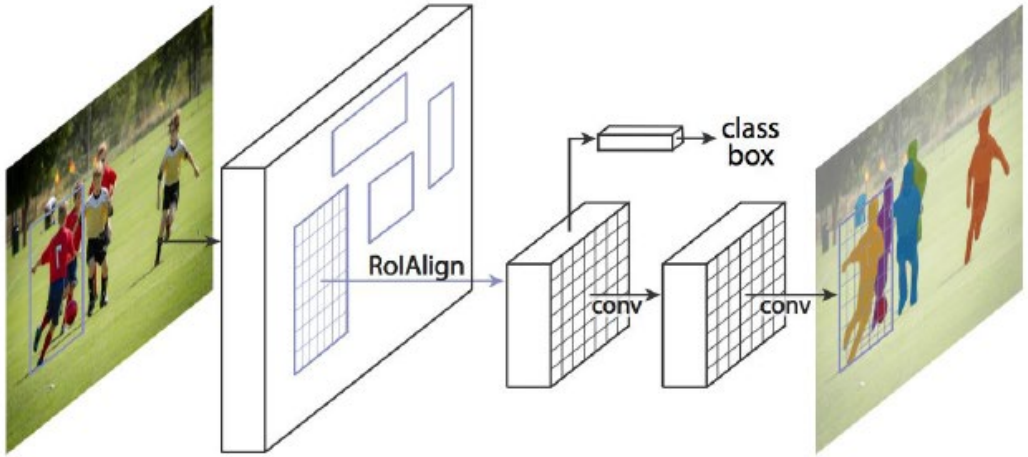
- What could be the problems
  - Two-stage detection pipeline is still too slow for real-time detection in videos…
  - What about instance-wise information?



Mask R-CNN (ICCV2017)

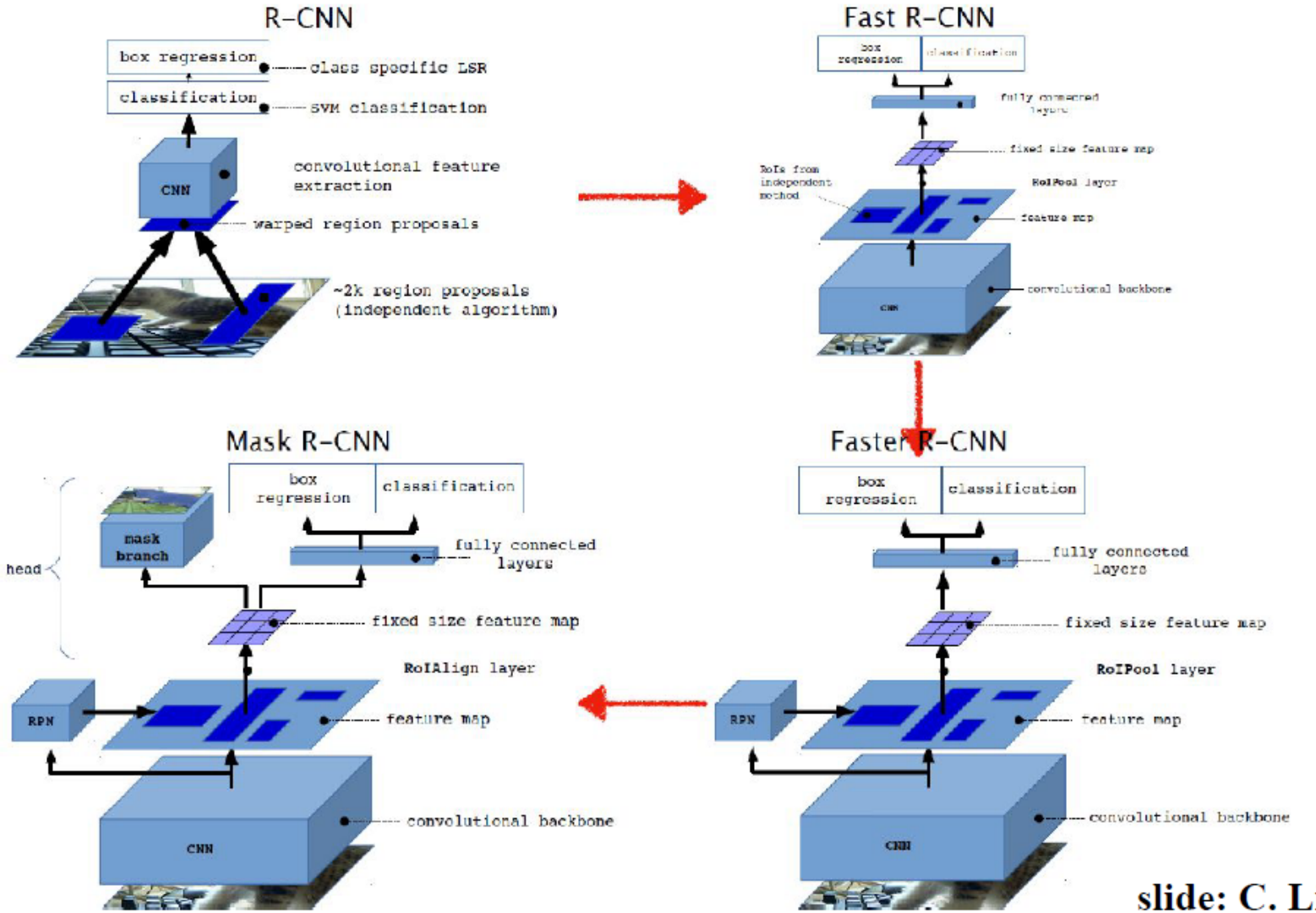


- Still a 2-stage detector
- Goals:
  - Refined detection + precise segmentation
  - Faster R-CNN + FCN
- Overall design:
  - Use of ResNet or feature pyramid net for feature extraction
  - Use RPN to produce proposals (w/ ROI align)
  - Use one detection branch for box classification + regression
  - Use one



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

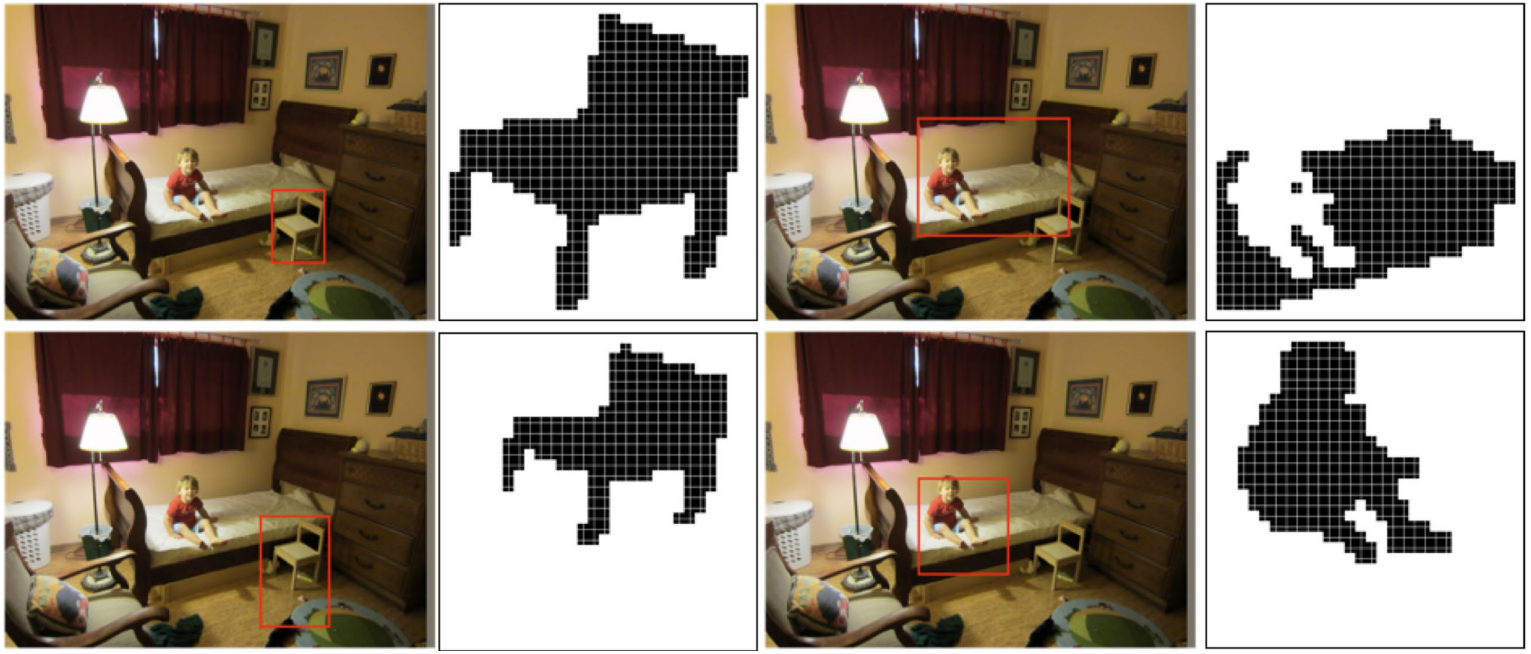
R-CNN Family



slide: C. Lim

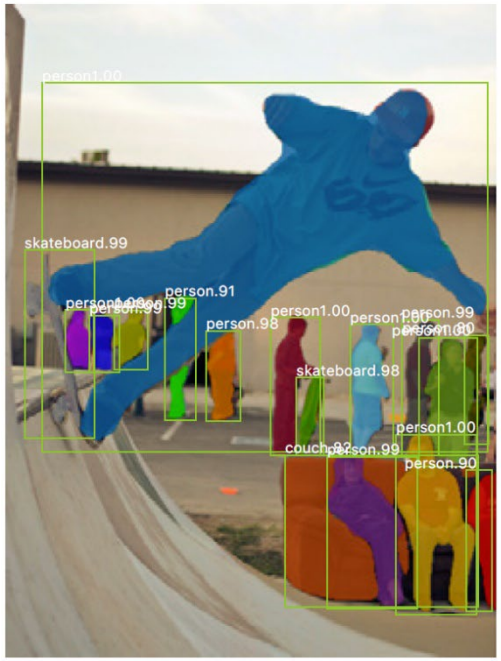
Mask R-CNN (cont'd)

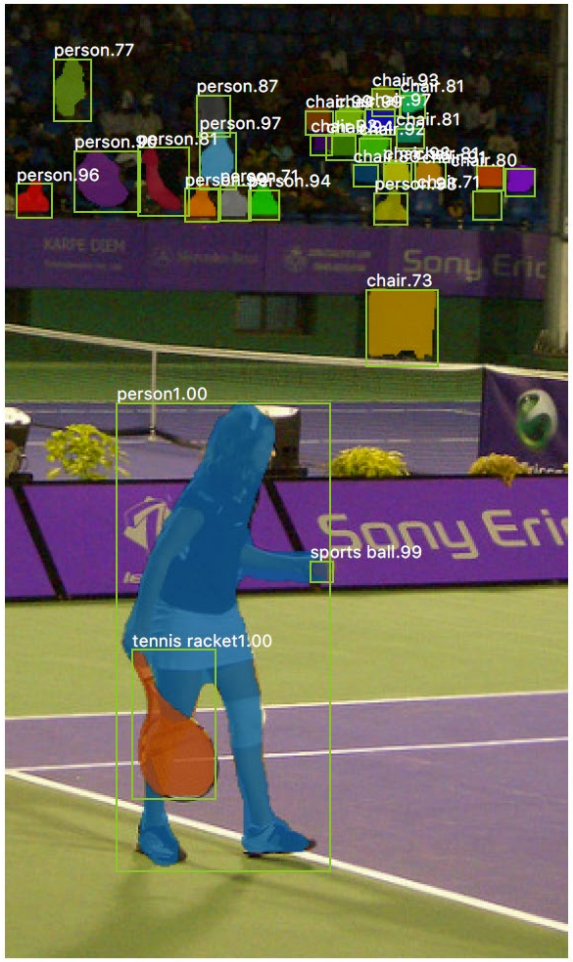
- Example Training Data (requires pixel-level labels)



Mask R-CNN

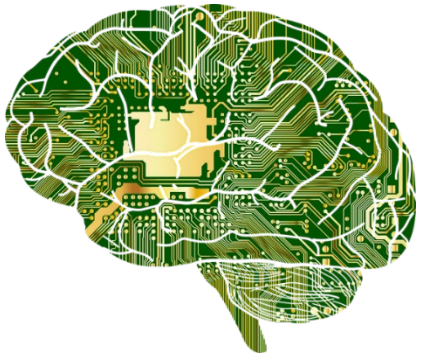
- Very good results!
  - running at 5fps though

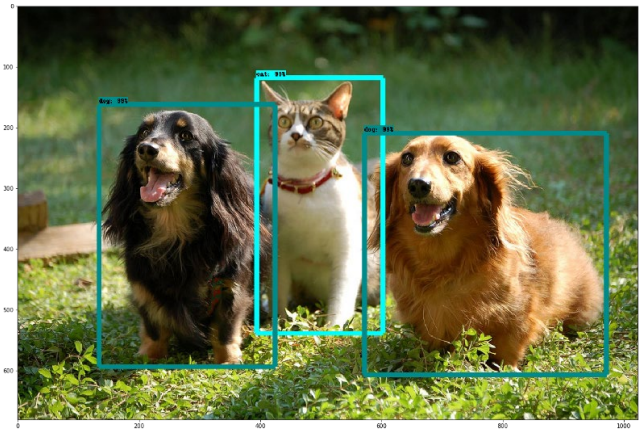


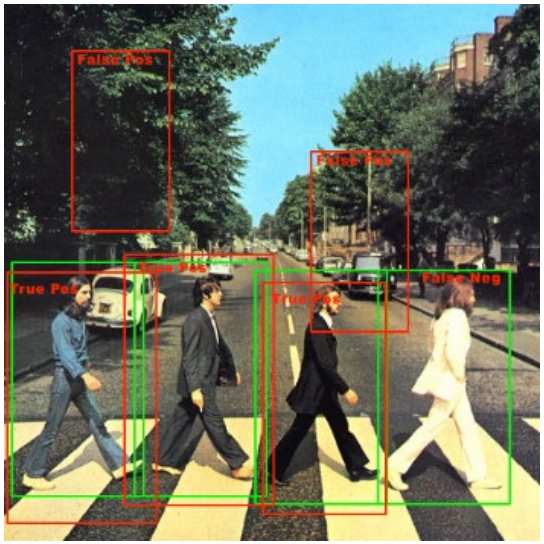


What to Covered Today…

- **Object Detection**
  - Detection via Sliding Windows
  - Two-Stage vs. Single-Stage Detectors
  - Transformer-based Detectors
  - 3D Detection

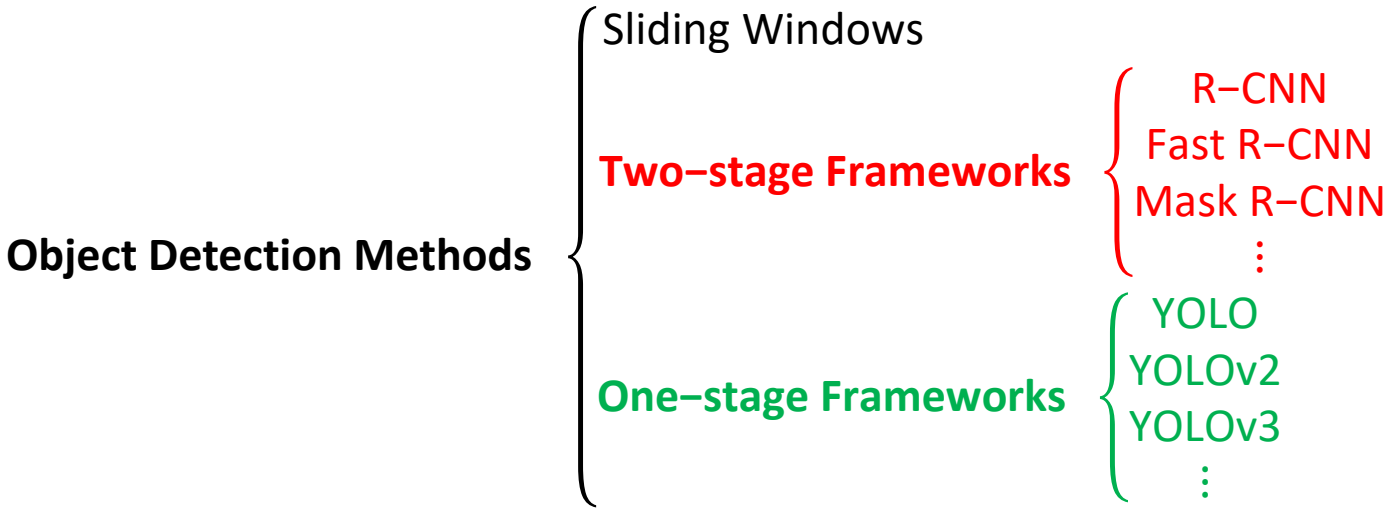






Recap

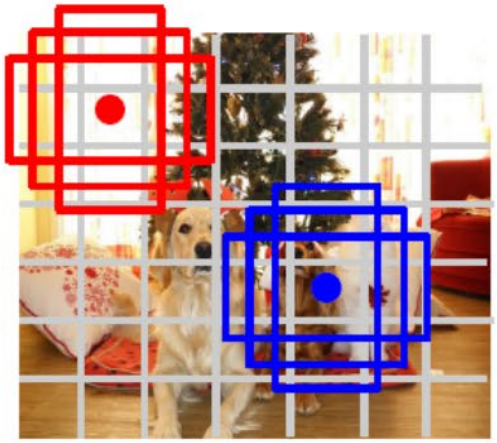
- So far, the introduced methods follow a **two-stage** framework.
  1. Region Proposal
  2. Per-Region Classification/Regression
- Can we make it faster by integrating the above two steps into one single network?



One-Stage Object Detection: Detection without Proposals

Go from input image to tensor of scores with one big convolutional network!

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)

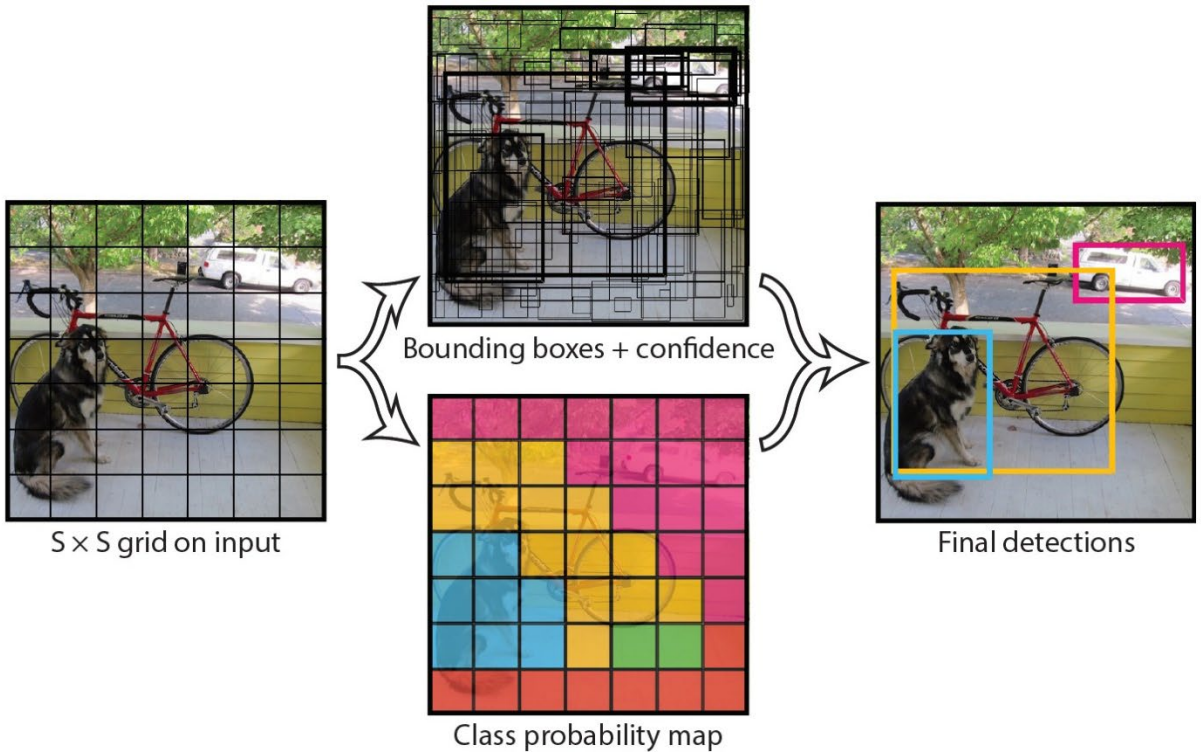
Output:
7 x 7 x (5 * B + C)

Redmon et al, "You Only Look Once: Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016

You Only Look Once (YOLO)

Divide the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities.

These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.



You Only Look Once (YOLO)

class confidence score = box confidence score × conditional class probability

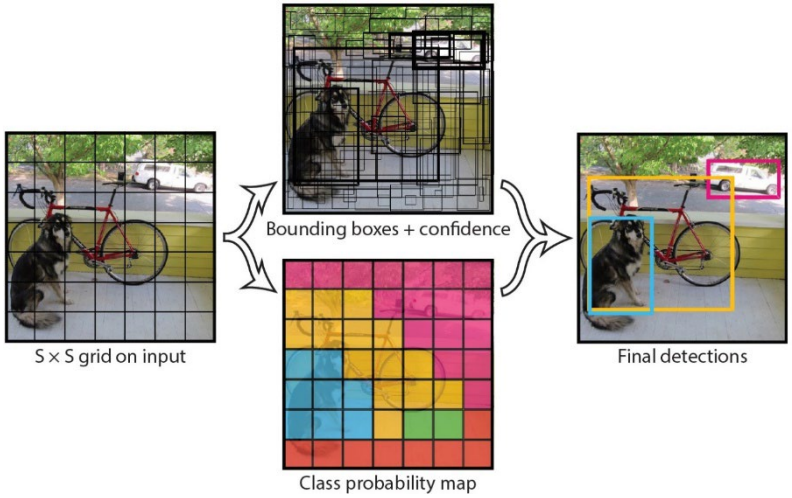
$$\begin{aligned}
\text{box confidence score} &\equiv P_r(object) \cdot IoU \\
\text{conditional class probability} &\equiv P_r(class_i|object) \\
\text{class confidence score} &\equiv P_r(class_i) \cdot IoU \\
&= \text{box confidence score} \times \text{conditional class probability}
\end{aligned}$$

where

$P_r(object)$ is the probability the box contains an object.
IoU is the IoU (intersection over union) between the predicted box and the ground truth.
$P_r(class_i|object)$ is the probability the object belongs to $class_i$ given an object is presence.
$P_r(class_i)$ is the probability the object belongs to $class_i$

You Only Look Once (YOLO)

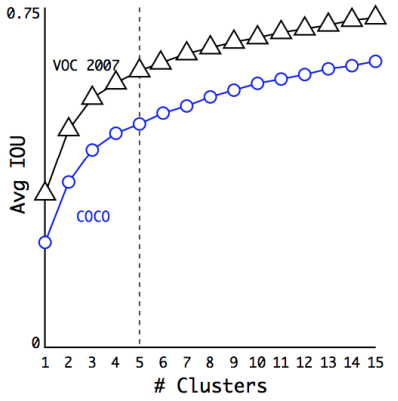
- **Fast**.
  Good for real-time processing.
- **End-to-end learnable**.
  Predictions (object locations and classes) are made from one **single network**.
- **Access to the entire image**.
  Region proposal methods limit the classifier to the specific region.
  YOLO **accesses to the whole image** in predicting boundaries.
  With additional context, result in fewer false positives in background areas.
- **Spatial diversity**.
  Detect one object per grid cell. It enforces spatial diversity in making predictions.

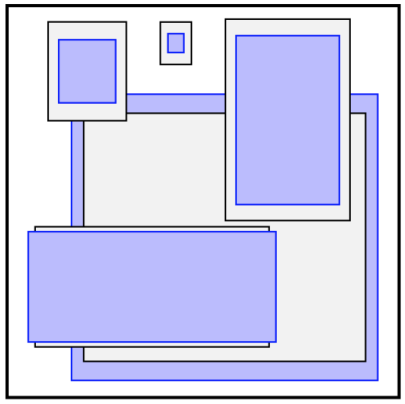


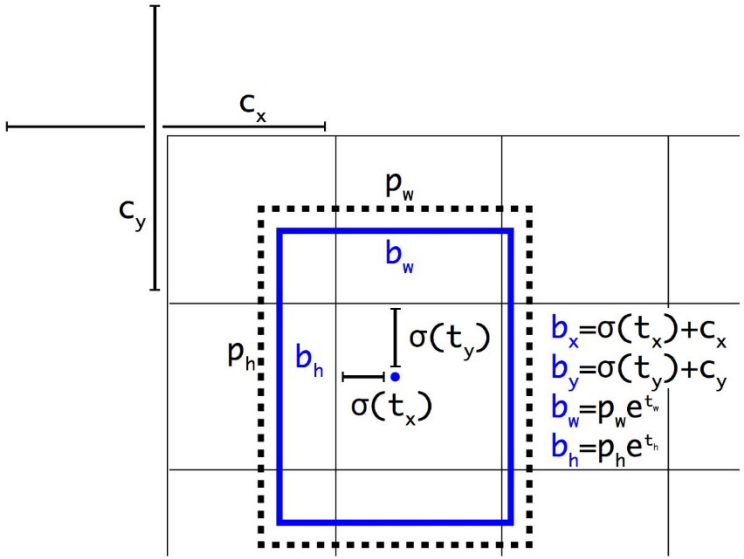
YOLOv2

- **Predetermined bounding box shape** (*anchor boxes*)
  Guesses that are common for real-life objects using *k*-means clustering
  $\Longrightarrow$ Predicts **offsets** rather than bounding boxes themselves
- **Move the class prediction from the cell level to the boundary box level**
  Each *bounding box* (instead of each *cell*) produces a class prediction

$$S \times S \times (B * 5 + C) \Longrightarrow S \times S \times (B * (5 + C))$$



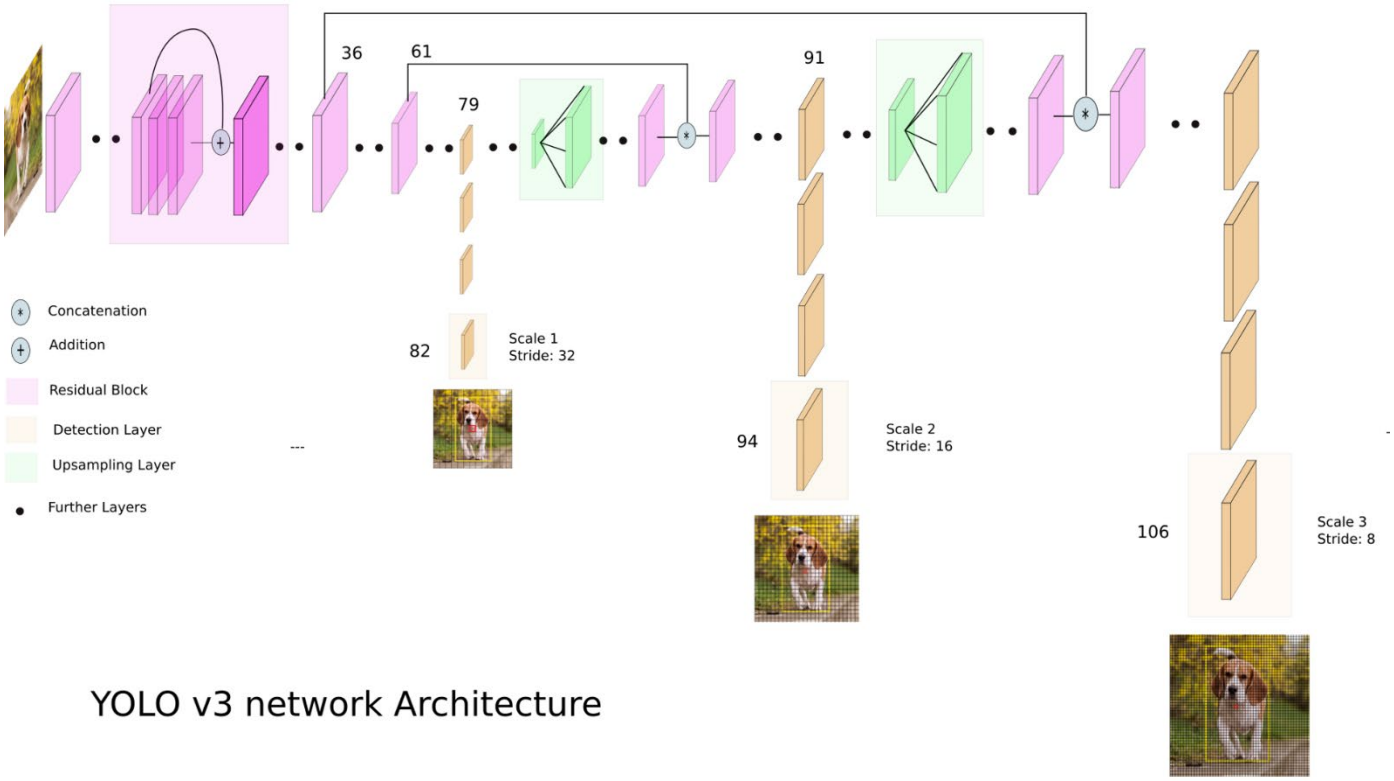




YOLOv3

- **Feature Pyramid Networks** (FPN) **like Feature Pyramid**
  YOLOv3 makes predictions at 3 different scales (similar to the FPN).

$$S \times S \times (3 * (5 + C))$$



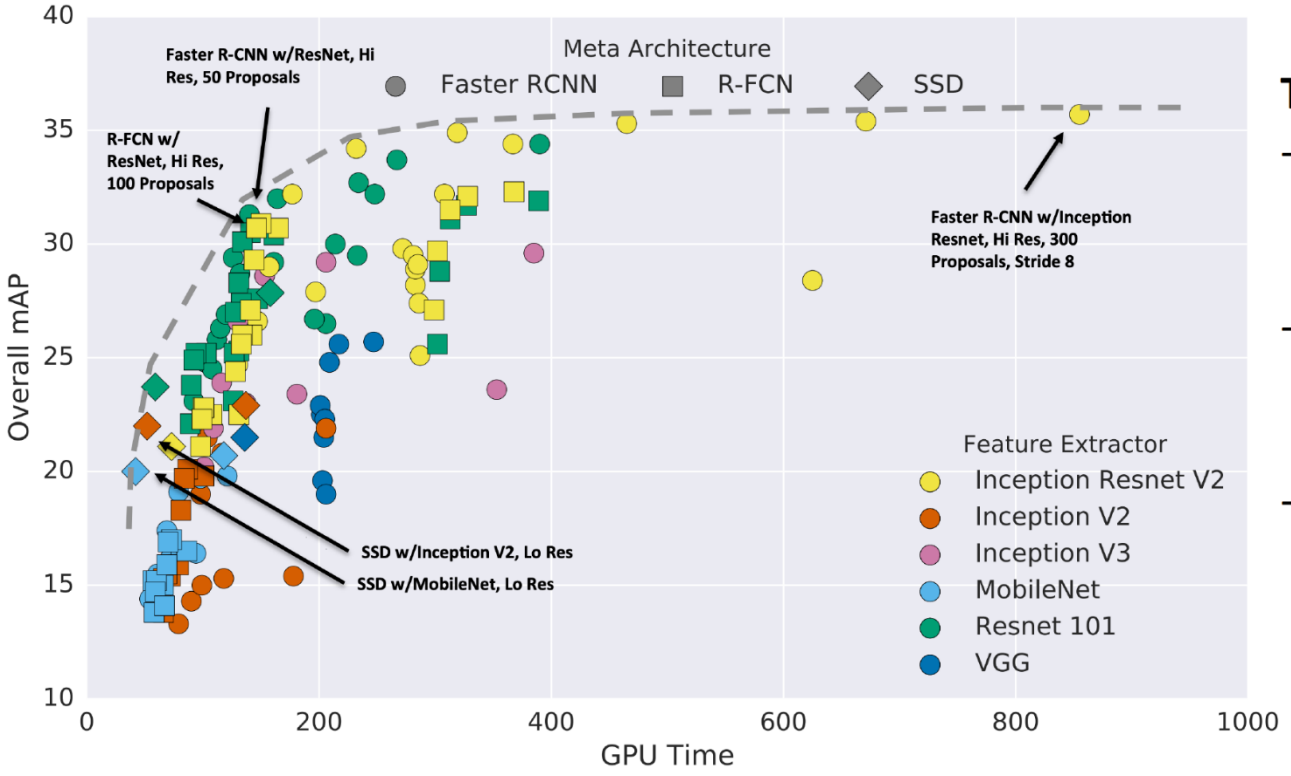
YOLO v3 network Architecture

Recap

Object Detection Methods

- Sliding Windows
- **Two−stage Frameworks** (High Accuracy, Slow)
  - R−CNN
  - Fast R−CNN
  - Mask R−CNN
  - ⋮
- **One−stage Frameworks** (Good Accuracy, Very Fast)
  - YOLO
  - YOLOv2
  - YOLOv3
  - ⋮

Remarks

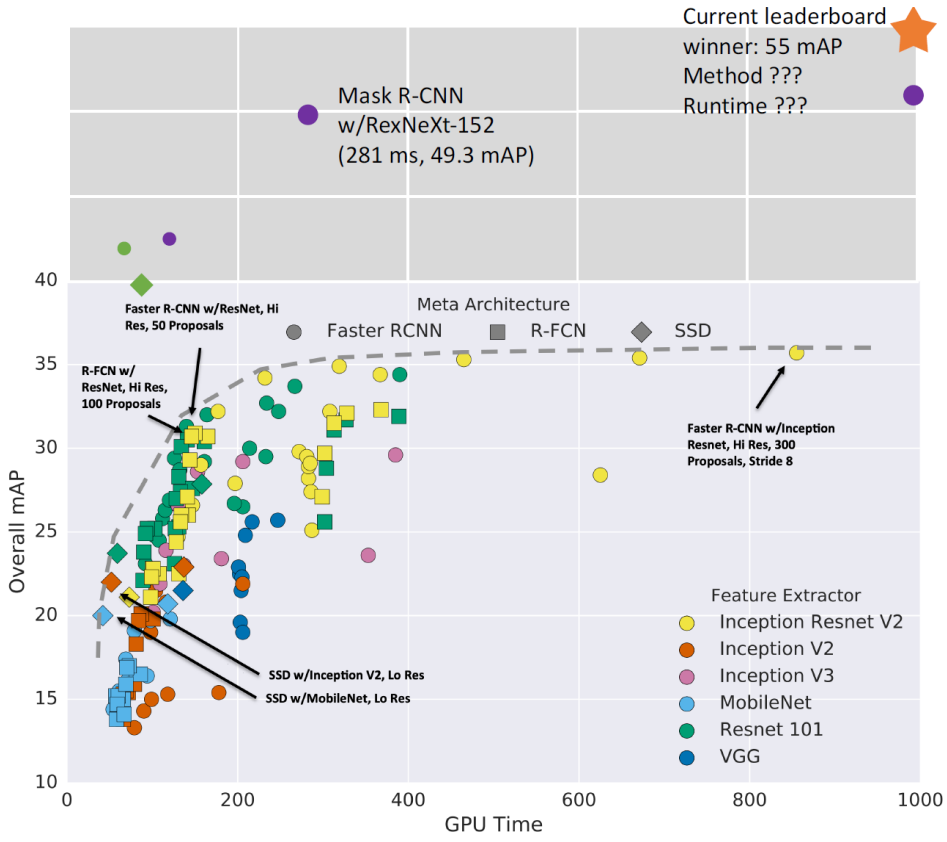


Takeaways:

- Two stage method (Faster R-CNN) get the best accuracy, but are slower
- Single-stage methods (SSD) are much faster, but don't perform as well
- Bigger backbones improve performance, but are slower

Slide credit: UMich EECS 498-007

Remarks (cont'd)



These results are a few years old … since then GPUs have gotten faster, and we've improved performance with many tricks:

- Train longer!
- Multiscale backbone: Feature Pyramid Networks
- Better backbone: ResNeXt
- Single-Stage methods have improved
- Very big models work better
- Test-time augmentation pushes numbers up
- Big ensembles, more data, etc

Slide credit: UMich EECS 498-007

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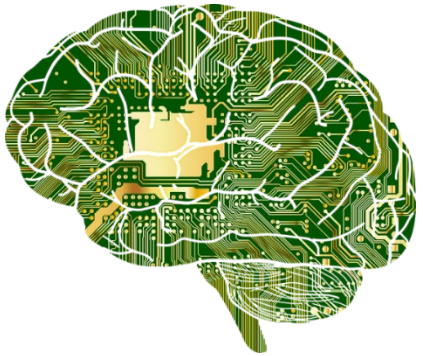
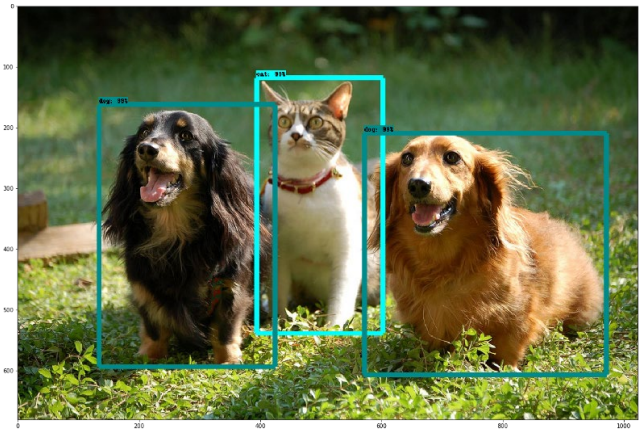
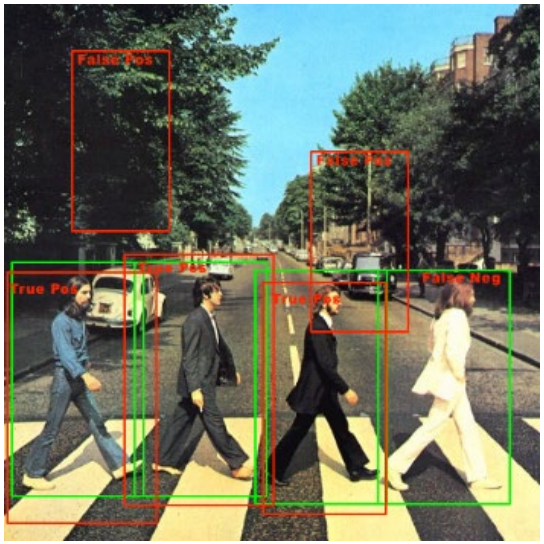
  - 3D Detection

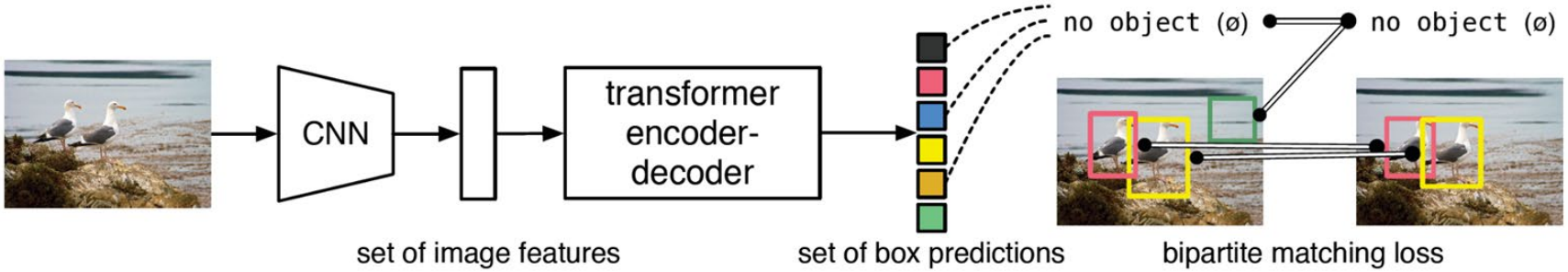






DEtection TRansformer (DETR) (ECCV'20)

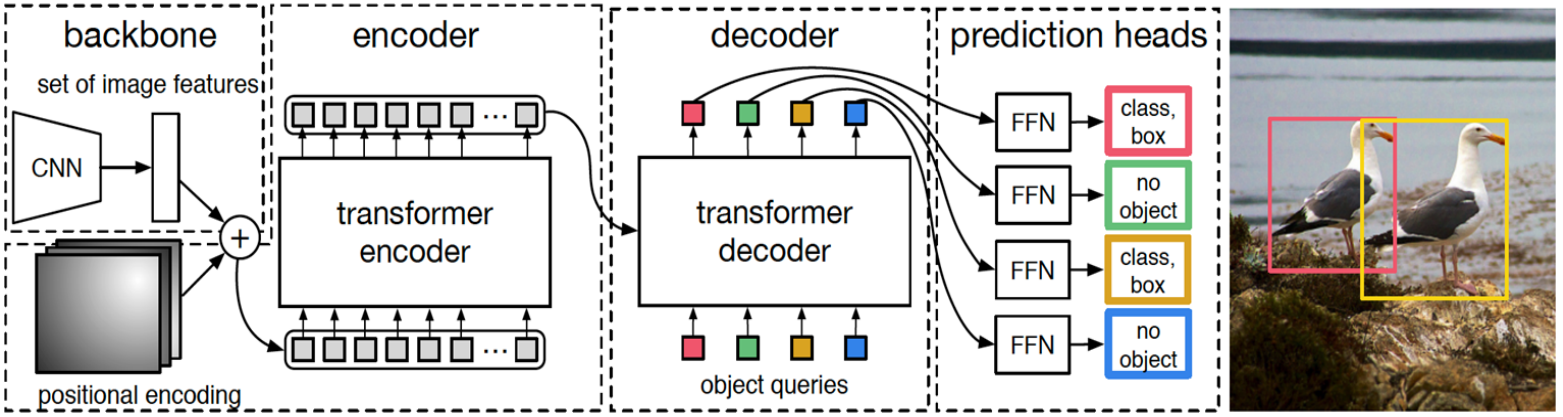
- Proposed by Facebook AI
- Previous methods rely on NMS to matching predictions to ground truth bboxes
  - Designing NMS involves lots of manual tuning
  - NMS can sometimes incorrectly suppress true positive detections
- DETR views object detection as direct set prediction problem => no more NMS



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

Framework of DETR

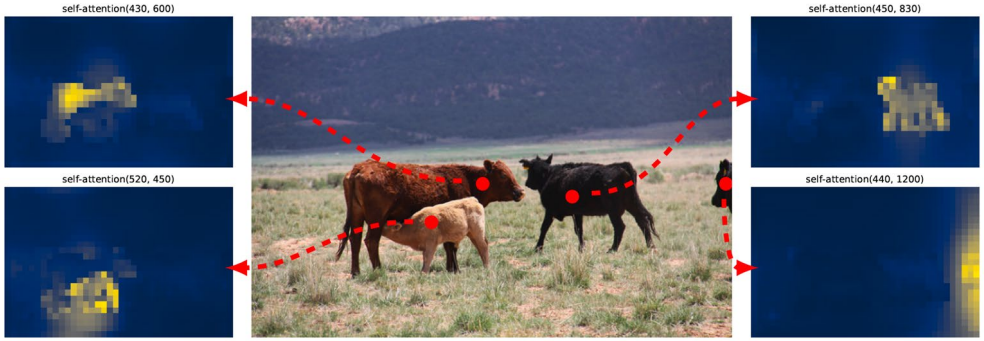
- CNN
  - Feature extraction with CNN
- Transformer
  - Generate N guesses
  - N is set to a relatively high number (~100)
- FFN
  - Predict class logits and bounding box



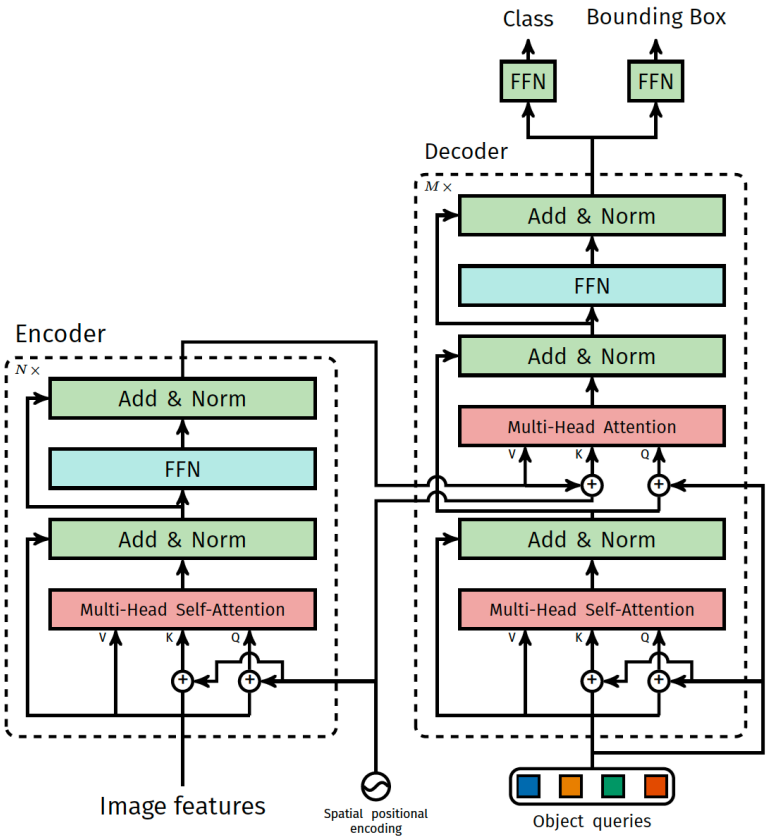
Carion et al., "End-to-End Object Detection with Transformers", ECCV 2020

Framework of DETR (cont'd)

- Transformer captures global semantics and disentangles objects simultaneously
- Decoder inputs: N learnable queries



Attention maps of self-attention layers in encoder



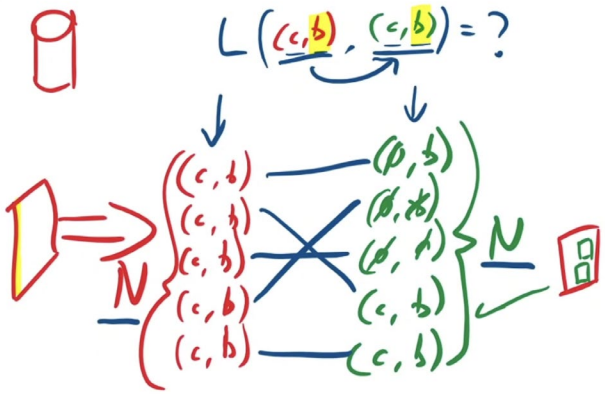
Carion et al., "End-to-End Object Detection with Transformers", ECCV 2020

Bipartite Matching Loss in DETR

- **Goal:**
  Assign each prediction to a ground truth object (or "no object" ∅)
  - Solve bipartite matching with **Hungarian algorithm**
- **Loss**
  Cross entropy loss + bounding box loss

$$\mathcal{L}_{\text{Hungarian}}(y, \hat{y}) = \sum_{i=1}^{N} \left[-\log \hat{p}_{\hat{\sigma}(i)}(c_i) + \mathbb{1}_{\{c_i \neq \varnothing\}} \mathcal{L}_{\text{box}}(b_i, \hat{b}_{\hat{\sigma}}(i)) \right]$$

$$\mathcal{L}_{\text{box}}(b_{\sigma(i)}, \hat{b}_i) = \lambda_{\text{iou}} \mathcal{L}_{\text{iou}}(b_{\sigma(i)}, \hat{b}_i) + \lambda_{\text{L1}} ||b_{\sigma(i)} - \hat{b}_i||_1$$



- Plays the same role as NMS
  - Force unique matching between prediction & GT; permutation invariant

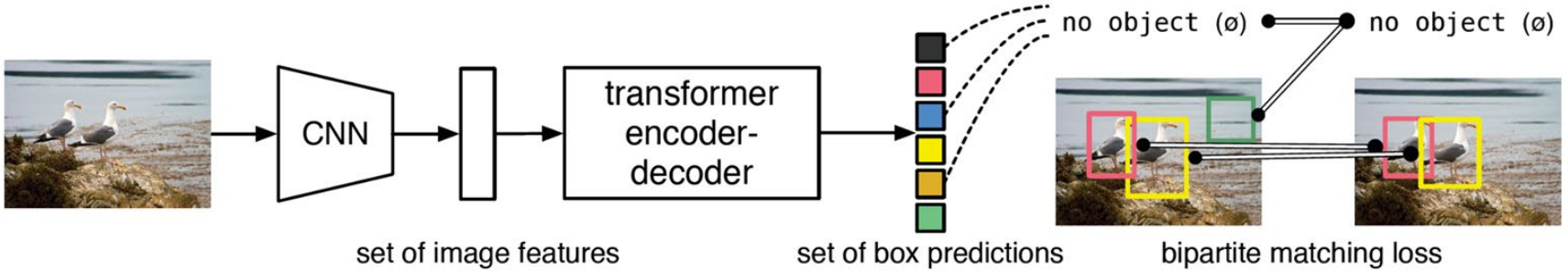
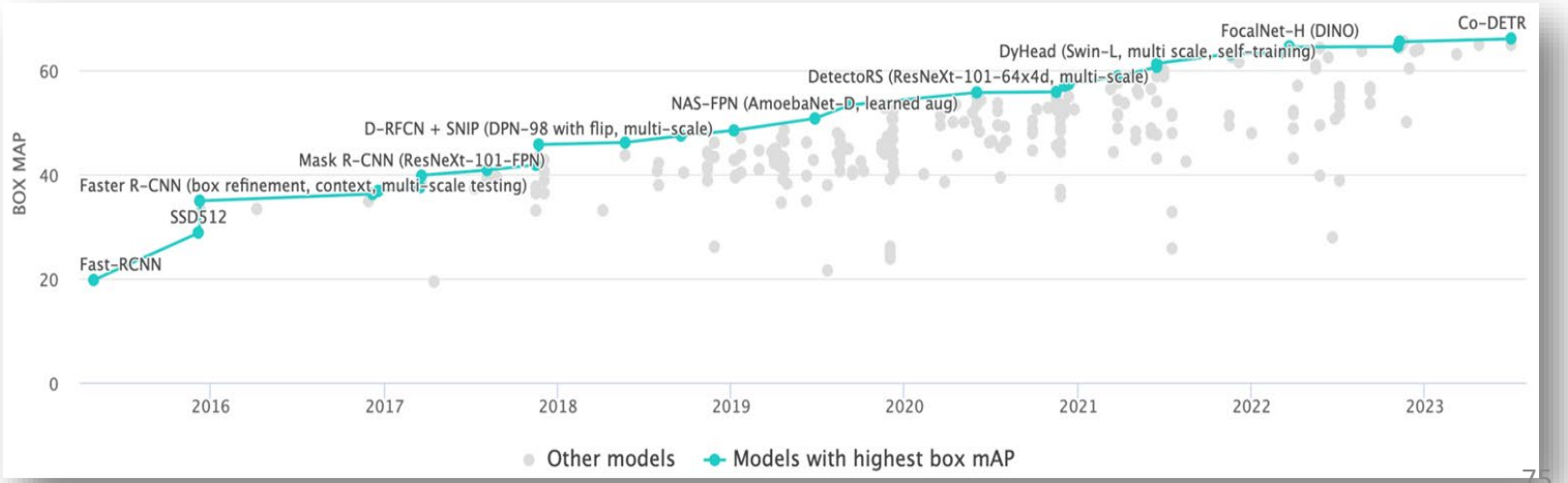


Image credit: "DETR: End-to-End Object Detection with Transformers (Paper Explained)"
https://youtu.be/T35ba_VXkMY?si=3om17kAQzN2q9R_M&t=701

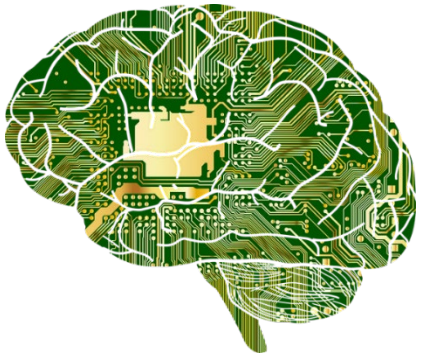
Final Remarks for DETR

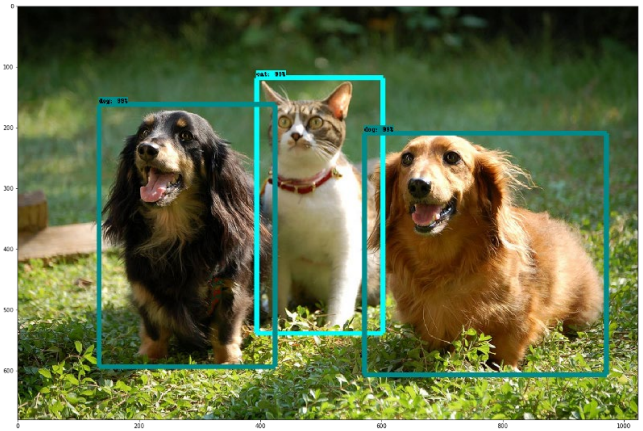
- **Simplicity**
  Simple to implement; less hand-designed components.
- **End-to-End learnable**
  No region proposal; no NMS for post-processing
- **Attends to the entire image**
  Transformer allows the model to capture global context of the image.
- **Current State-of-the-Art**
  Variants of DETR score very well on well-known datasets like MSCOCO

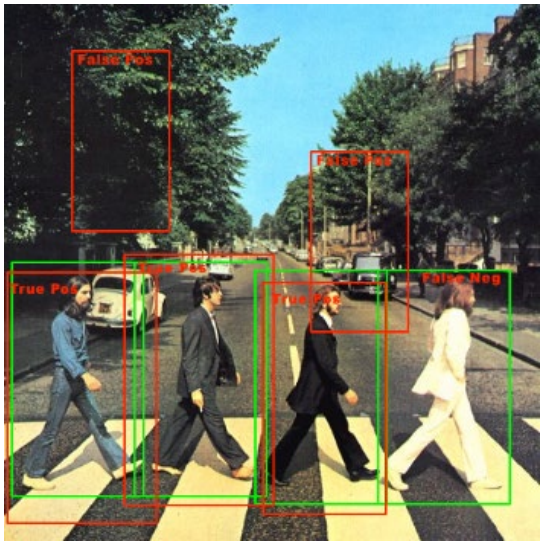


What to Covered Today…

- **Object Detection**
  - Detection via Sliding Windows
  - Two-Stage vs. Single-Stage Detectors
  - Transformer-based Detectors
  - 3D Detection & Grounding

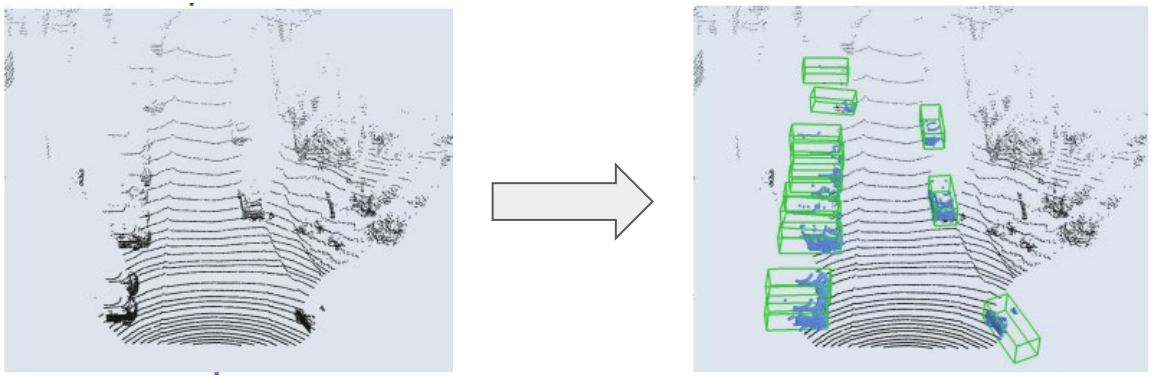






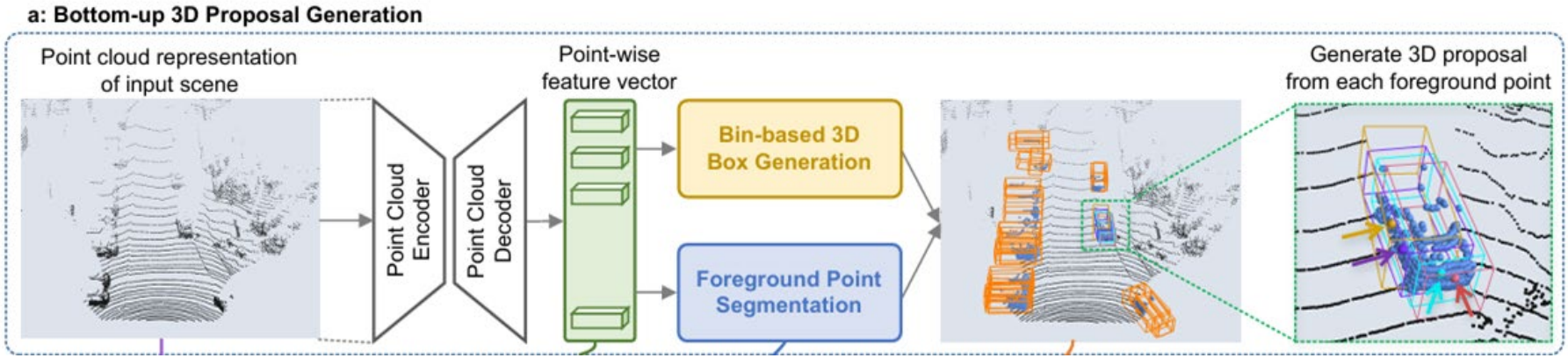
Intro of 3D Detection

- Produce 3D bounding boxes with the following inputs:
  - 3D point clouds
  - 2D images



Supervised 3D Detection

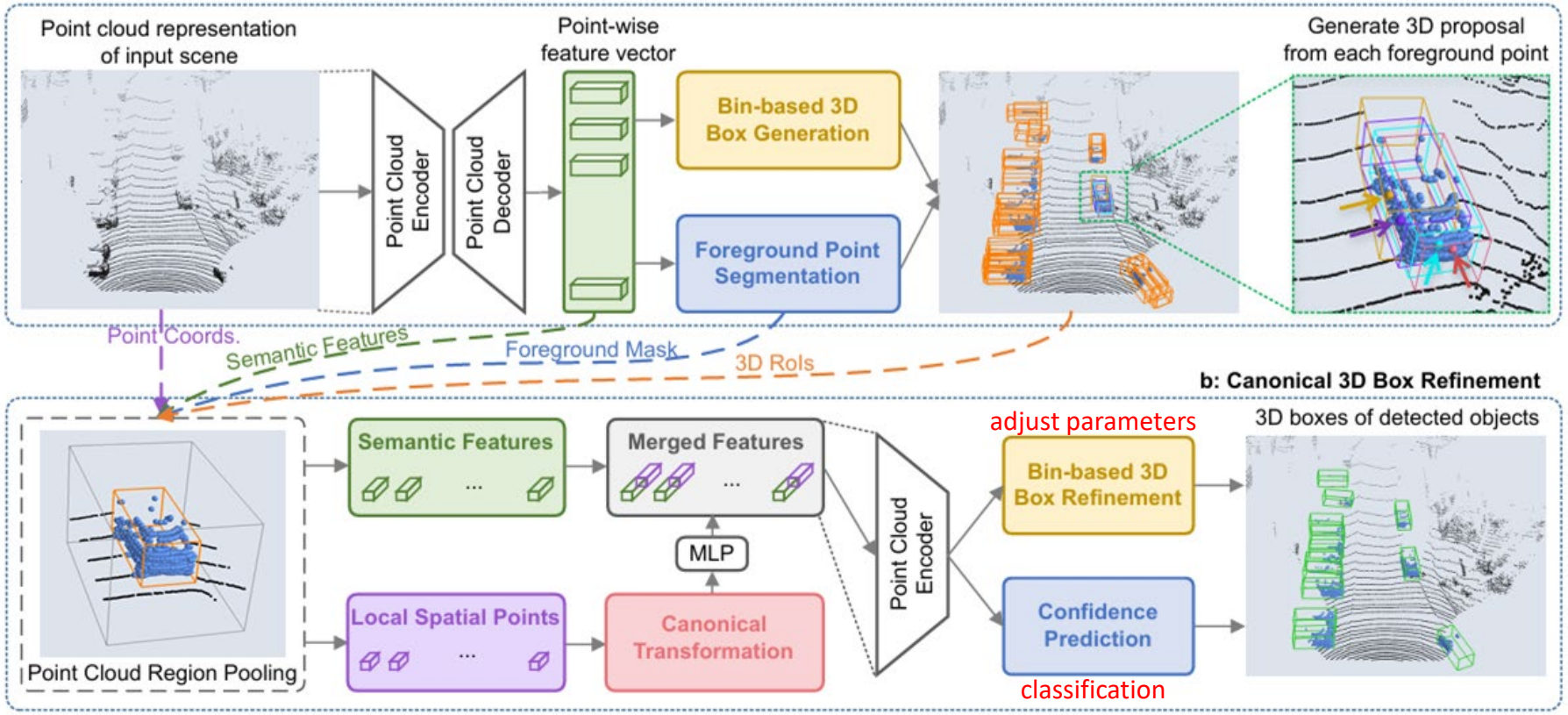
- PointRCNN (CVPR 2019)
  - segment foreground points
  - generate 3D bounding box proposals for each foreground point (i.e., center, box size, & orientation)



PointRCNN: 3D Object Proposal Generation and Detection from Point Cloud

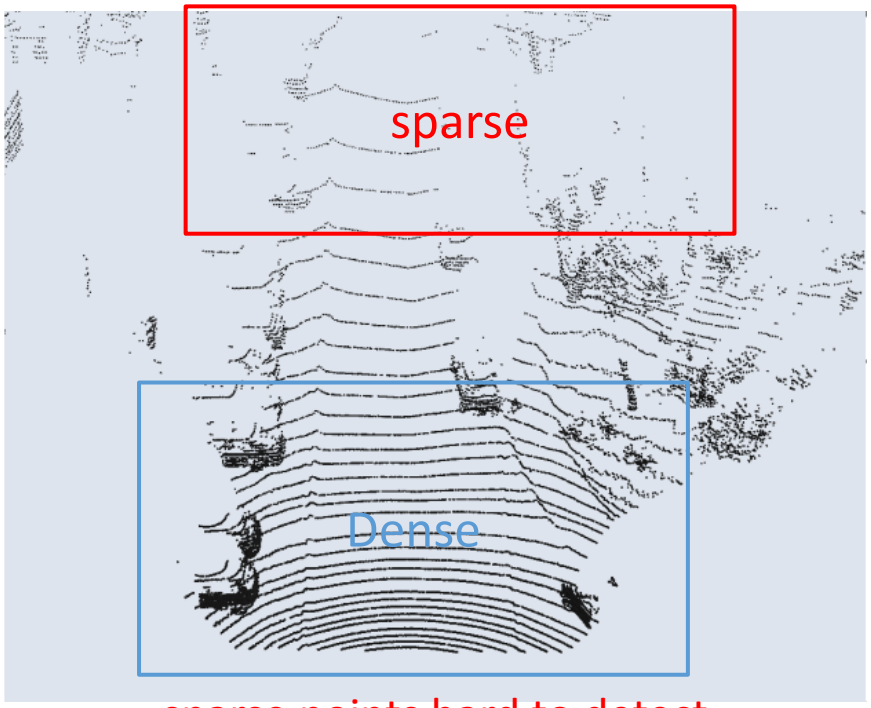
Supervised 3D Detection (cont'd)

- For each bounding box and points inside
  - transform point coordinate by treating *bounding box center* as origin
  - concate point **coordinate** (low-level) and **feature** (high-level) for all points and encode a global feature for each box
  - output classification score (confidence) for each box & preserve high-score box as final prediction

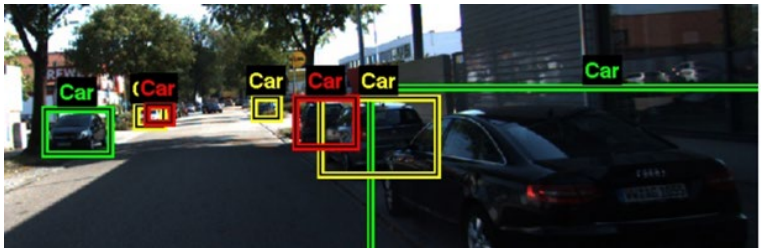


PointRCNN: 3D Object Proposal Generation and Detection from Point Cloud

- Problem of PointRCNN:
  - Data collection -> need to reduce the need of labeled 3D bounding box
  - Points far from camera are too sparse -> need other information to help



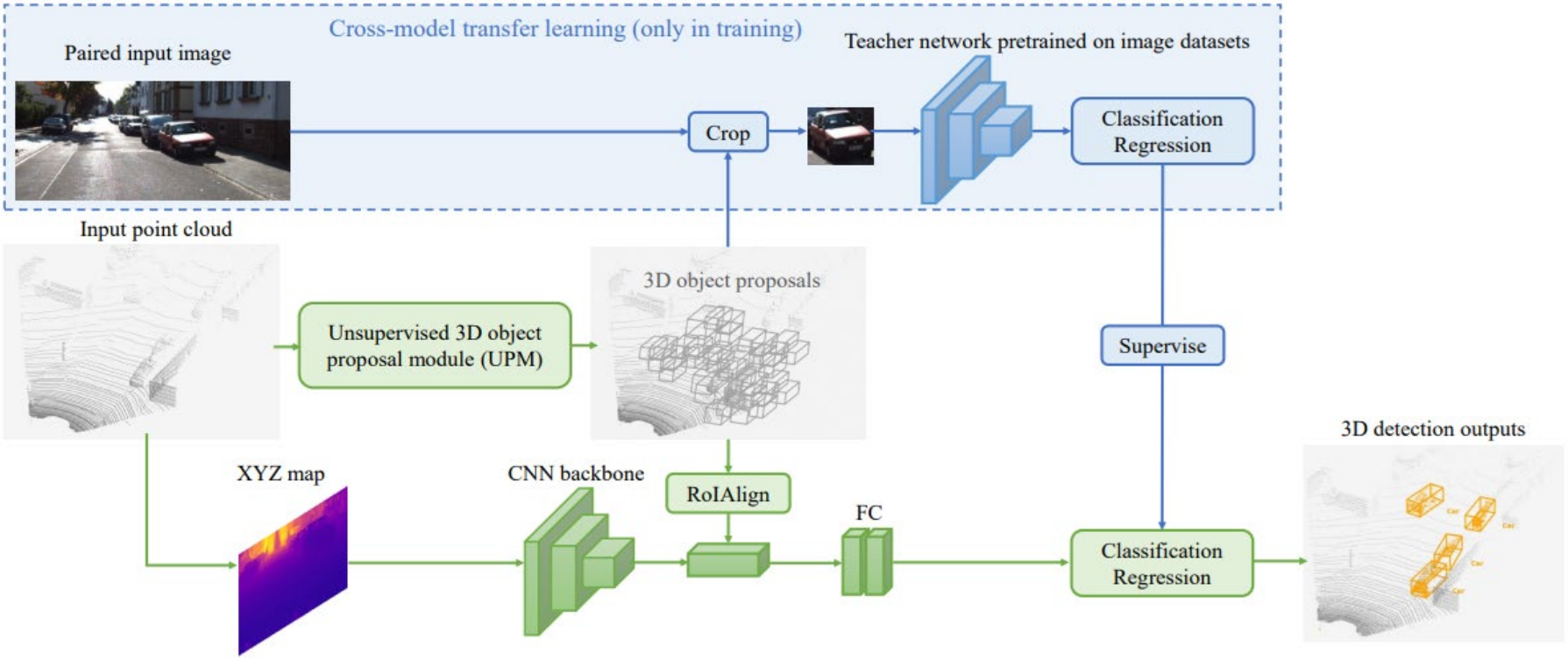
sparse points hard to detect



Can we leverage 2D boxes?

Weakly-Supervised 3D Detection

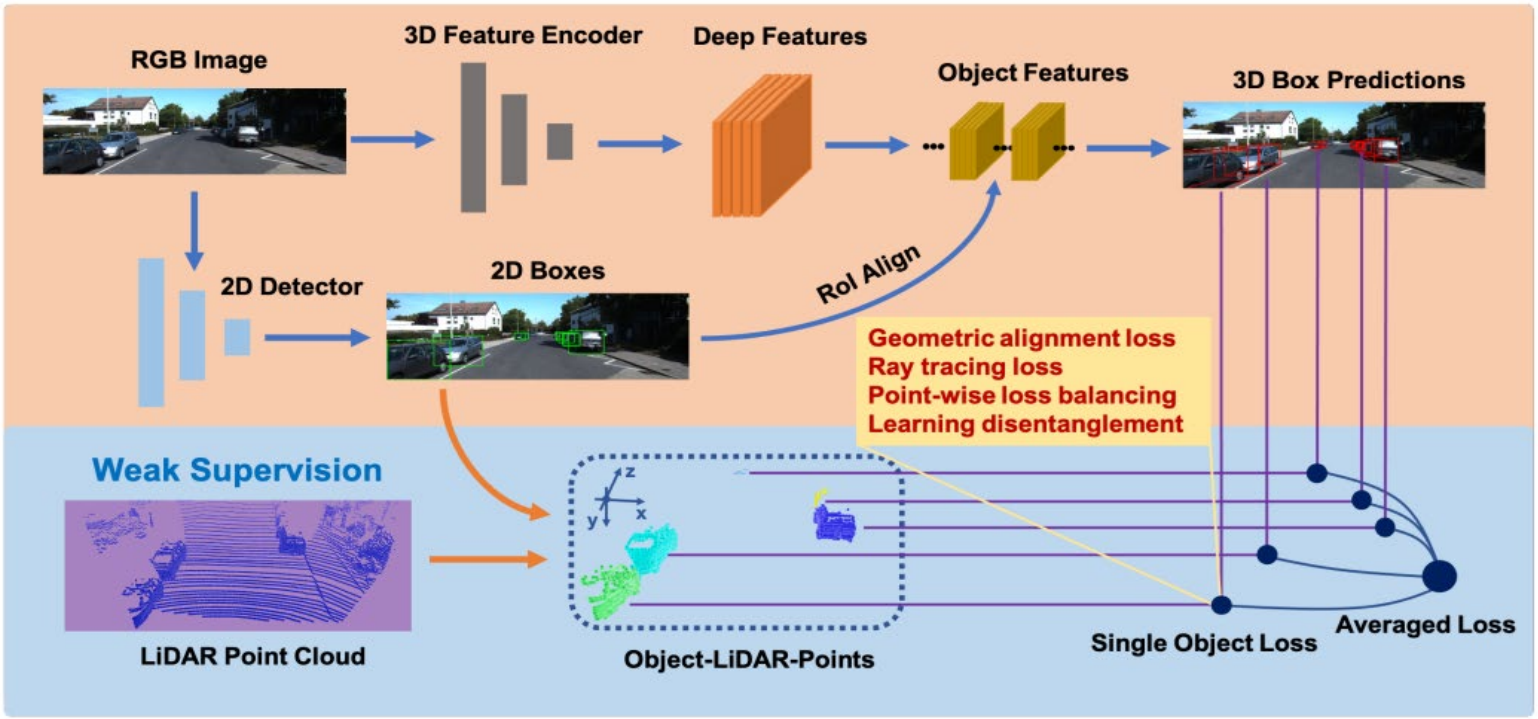
- VS3D (ACM MM 2021):
  - Use pre-trained 2D classifier and detector to guide 3D prediction
  - 2D projection of 3D bounding box should perfectly match a 2D bounding box



Weakly Supervised 3D Object Detection from Point Clouds

Weakly-Supervised 3D Detection

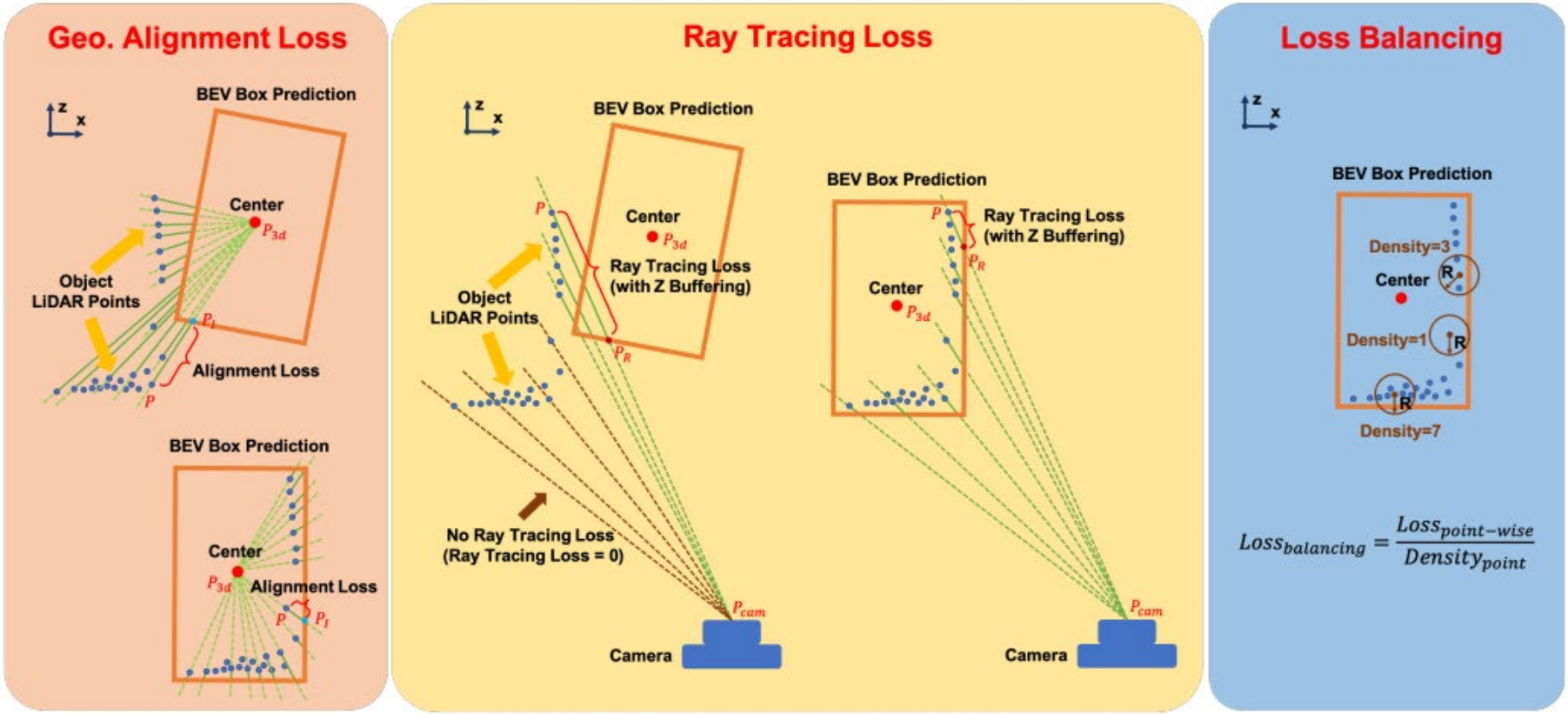
- WeakM3D (ICLR 2022):
  - 2D image + 3D point cloud as inputs
  - Also use 2D detector as strong prior
  - Introduce many loss for regularization



WeakM3D: Towards Weakly Supervised Monocular 3D Object Detection

Weakly-Supervised 3D Detection (cont'd)

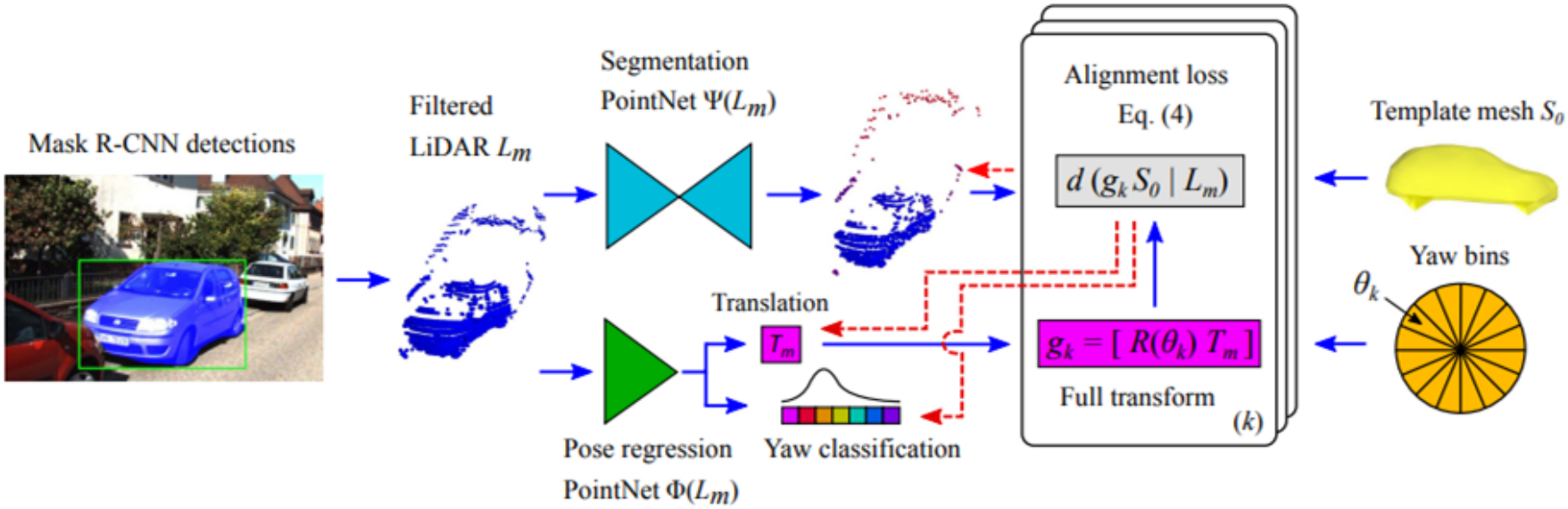
- WeakM3D (ICLR 2022) (cont'd):
  - Alignment loss ensure most points align to ***at most 2 sides*** of predicted bbox
  - Ray tracing loss ensure point-camera ray panetrates through bbox ***without*** touching any others
  - Loss balancing ensure that the sparse regions not neglected



WeakM3D: Towards Weakly Supervised Monocular 3D Object Detection

Weakly-Supervised 3D Detection (cont'd)

- McCraith et.al (ICRA 2022):
  - Use a human-designed mesh of car to find matching points in 3D space
  - Treat the bounding box of the aligned mesh as final predcition



More references for 3D detection

- Supervised
  - PatchNet: A Simple Face Anti-Spoofing Framework via Fine-Grained Patch Recognition (CVPR 2022)
  - PointPillars: Fast Encoders for Object Detection from Point Clouds (CVPR 2019)
  - Deep Hough Voting for 3D Object Detection in Point Clouds (ICCV 2019)
- Weakly-supervised
  - FGR: Frustum-Aware Geometric Reasoning for Weakly Supervised 3D Vehicle Detection (ICRA 2021)
  - Weakly Supervised 3D Object Detection from Lidar Point Cloud (ECCV 2020)
  - Weakly Supervised Monocular 3D Object Detection Using Multi-View Projection and Direction Consistency (CVPR 2023)
  - Weakly Supervised Monocular 3D Detection with a Single-View Image (CVPR 2024)

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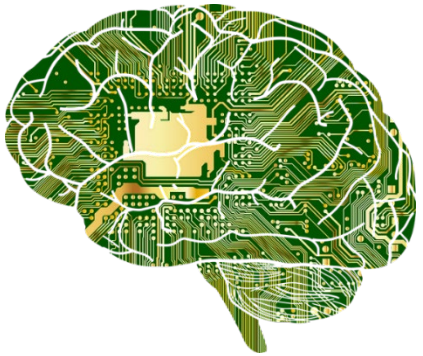
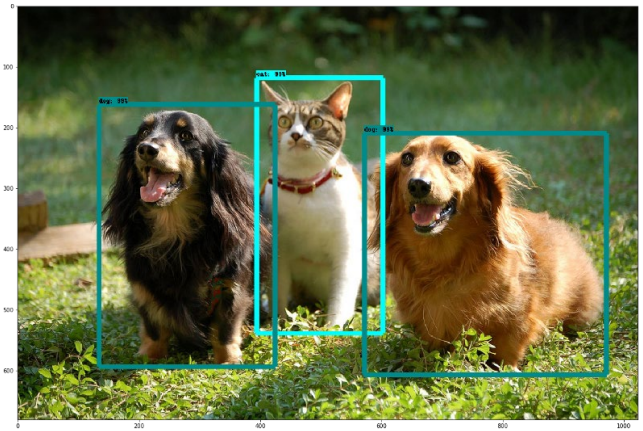
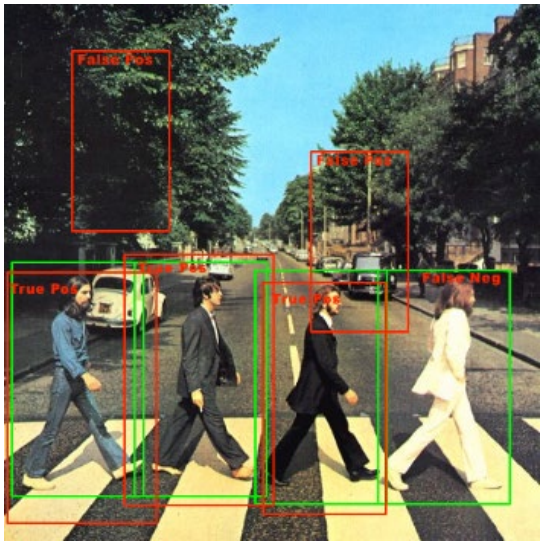
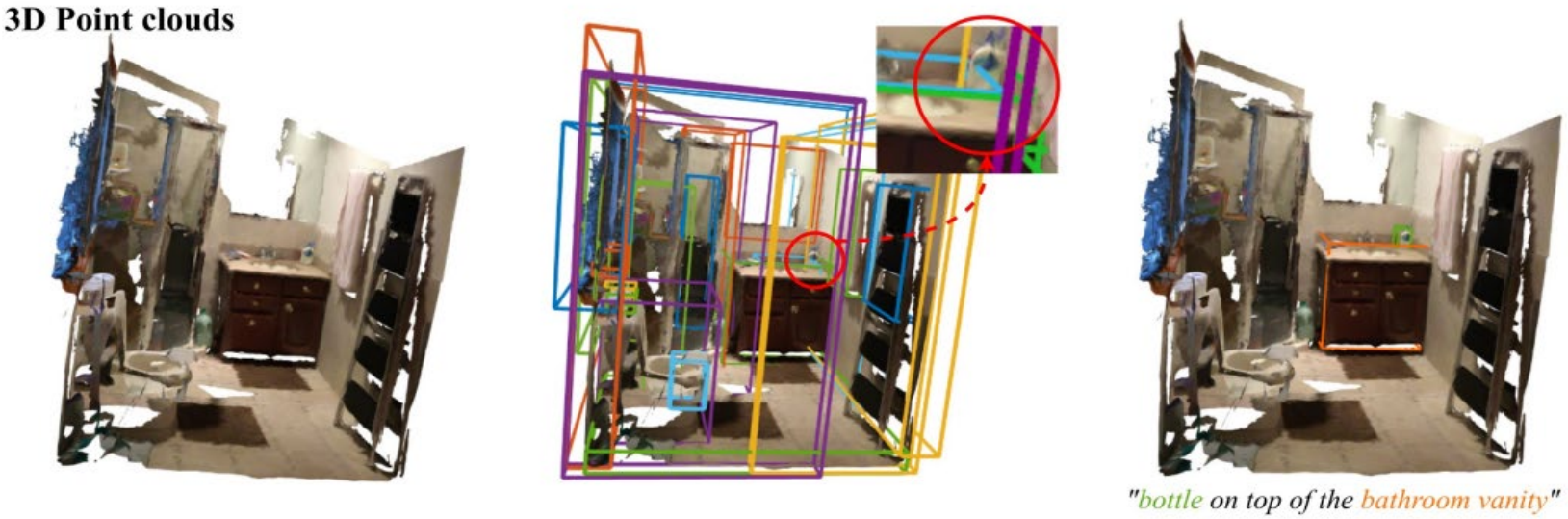






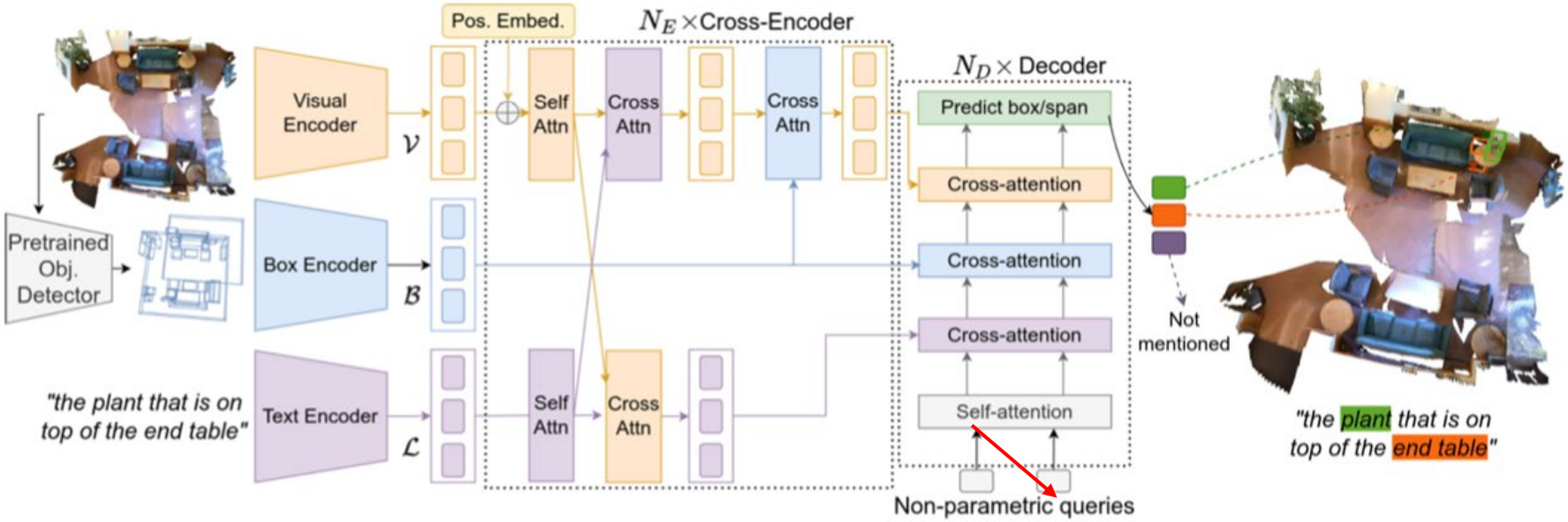
Intro of 3D Visual Grounding (3DVG)

- Find target object with text prompt as query
- Input prompt contains a target object and anchor objects
  - Target: Object that the query text want to find (only one)
  - Anchor: Objects that are mentioned in the text whichhave spatial relation with the target (can have many of them)
- In general 3VG setting:
  - 3D bbox proposal are given (directly provided by the dataset)
  - Only target object has ground-truth label (even for FS settings)



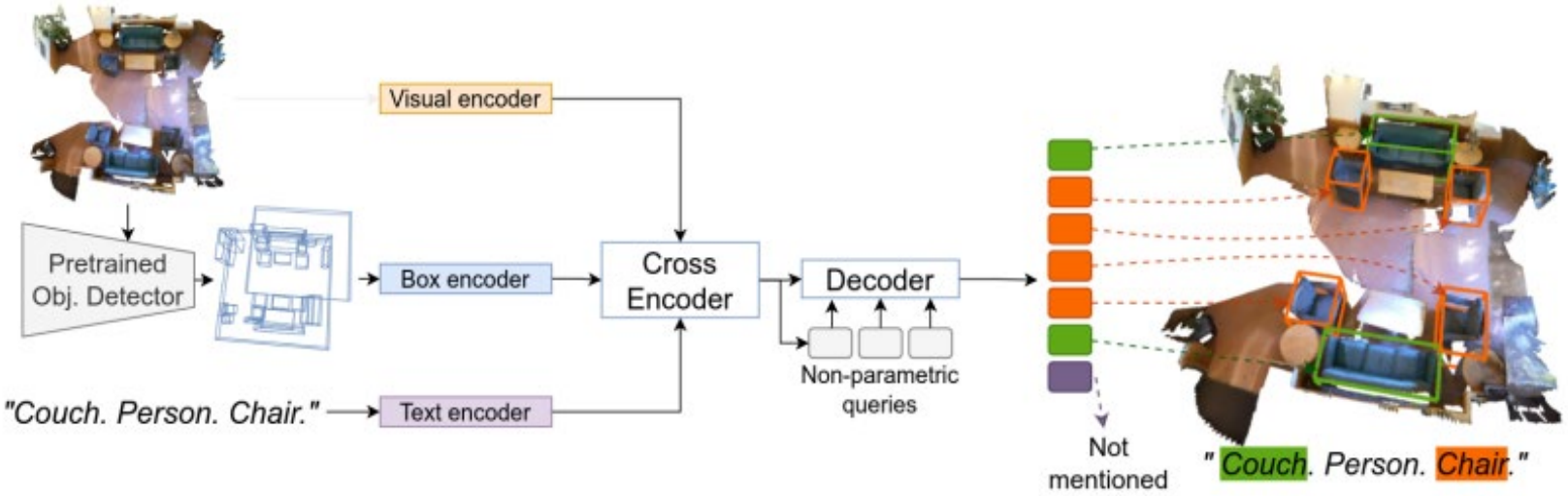
Fully-supervised 3DVG

- **BUTD-DETR (ECCV 2022)**
  - Use colored point cloud as input
  - obtain object proposal (and class pred.) from pre-trained 3D detector
  - Transfomer-based decoder to cross-attend visual-textual features
    - Non-parametric queries: treat each proposal as a token (global feature of each proposal as input)



encode points inside each proposal as input token feature

- BUTD-DETR (ECCV 2022) (cont'd)
  - Synthesize query texts for pre-training
    - direct combine random object classes
    - treat the last mentioned object as target, others as anchors

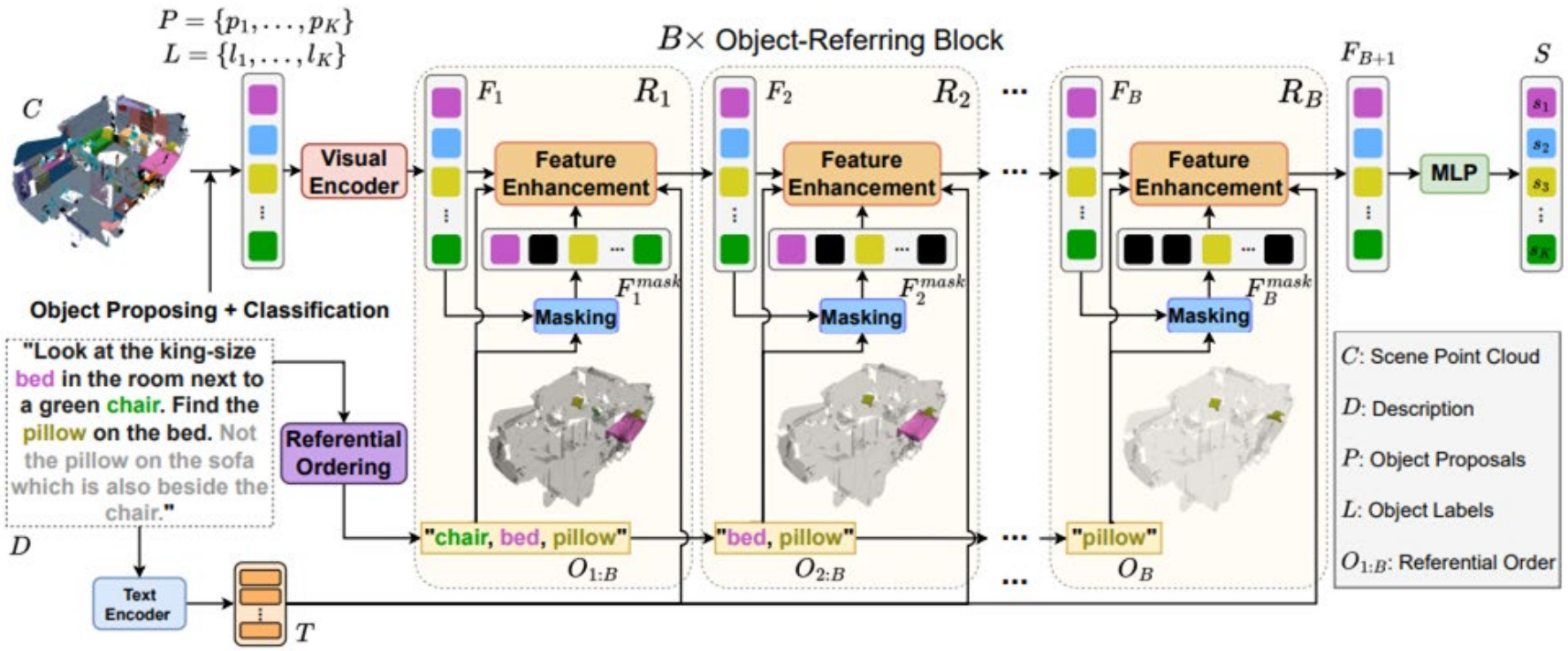


Data-Efficient 3DVG

- Data-Efficient 3D **Vi**sual **G**rounding via **O**rder-Aware **R**eferring (ViGOR), WACV 2025, VLL@NTU

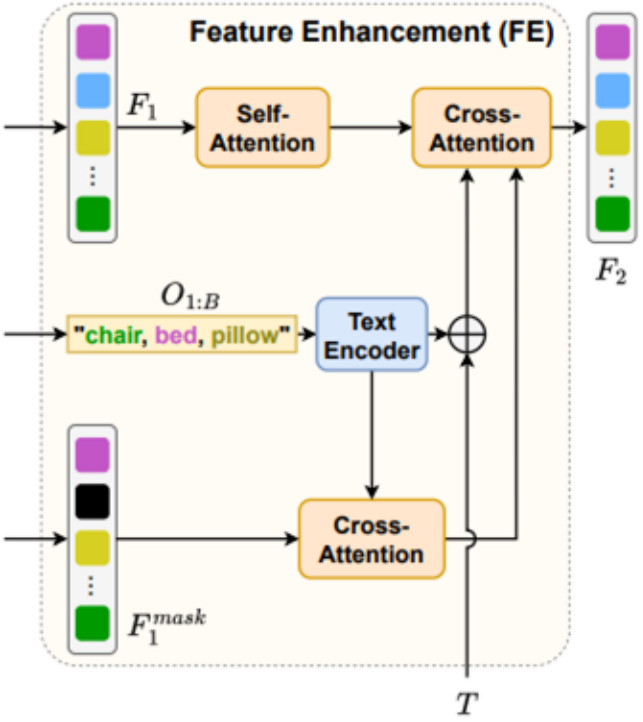
Data-Efficient 3DVG (cont'd)

- ViGOR, WACV 2025
  - Leverage LLM to produce the referring order for 3DVG (anchor -> target)
  - Apply several referring blocks to progressively find the target object
    - Each block contains feature enhancement to focus on anchor/target objects



Data-Efficient 3DVG (cont'd)

- Feature enhancement in each block
  - Upper branch: pass ***all*** proposal features
  - Middle branch: encode texts of the ***anchor/target objects*** from the referential order
  - Lower branch: mask features of other classes (not belong to anchor or target) and enhance anchor/target feature



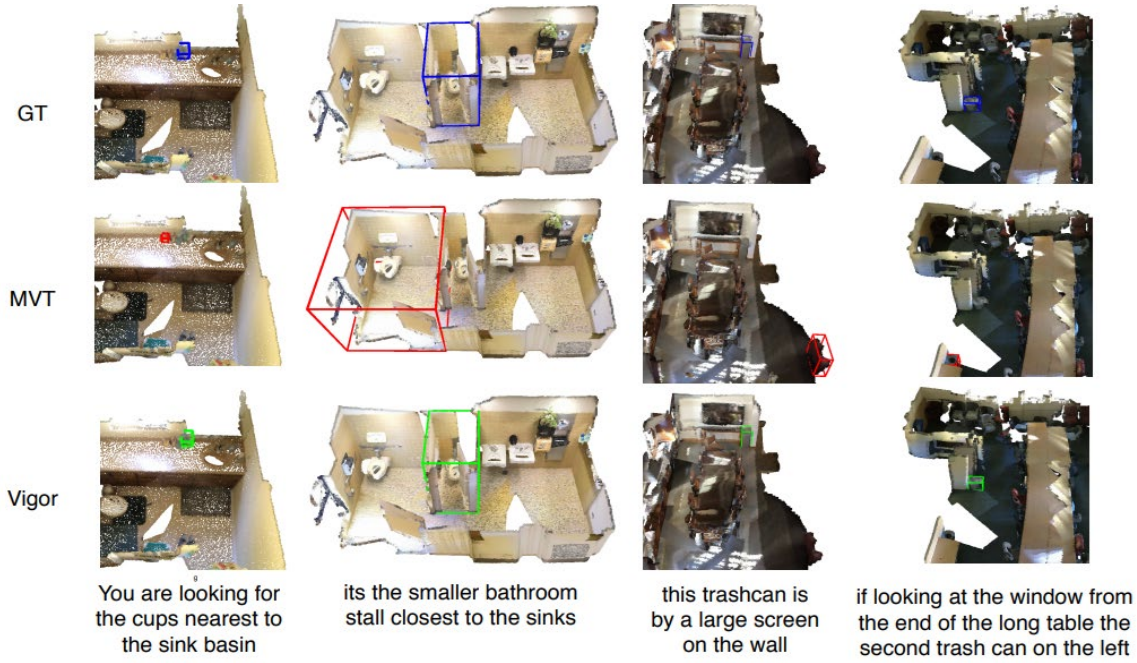
Results

- NR3D dataset
  - contains 707 indoor point cloud scenes from ScanNet
  - 28715/7485 descriptions in the training/testing set, each has a target object label
- Quantitative evaluation
  - Only train for 1~10 % of **description-target training pairs**
    - Unlabeled descriptions (and their corresponded scenes) in training set are ***not*** used
  - Our 1% better than many methods with 10% data

Method	Labeled Training Data			
	1%	2.5%	5%	10%
Referit3D [2]	4.4	13.6	20.3	23.3
TransRefer3D [17]	11.0	16.1	21.9	25.7
SAT [46]	11.6	16.0	21.4	25.0
BUTD-DETR [21]	24.2	28.6	31.2	33.3
MVT [20]	9.9	16.1	21.6	26.5
MVT + CoT3DRef [5]	9.4	17.3	26.5	38.2
ViL3DRel + CoT3DRef [5]	22.38	27.25	33.77	38.4
Vigor (Ours)	**33.5**	**36.1**	**41.5**	**46.0**

More references of 3DVG

- Traditional
  - Multi-View Transformer for 3D Visual Grounding (CVPR 2022)
  - Language Conditioned Spatial Relation Reasoning for 3D Object Grounding (NeurIPS 2022)
- Data-efficient
  - NS3D: Neuro-Symbolic Grounding of 3D Objects and Relations (CVPR)
  - CoT3DRef: Chain-of-Thoughts Data-Efficient 3D Visual Grounding (ICLR 2024)



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