Object Detection & RNNs

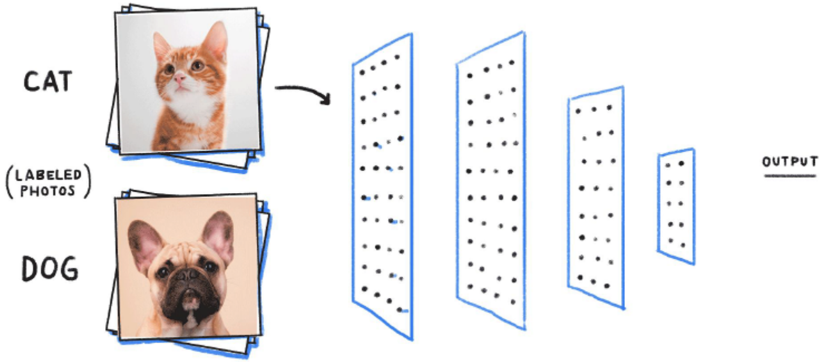
Zhuoyi Huang

Partial slides credit to JunYoung Gwak

1. Object Detection

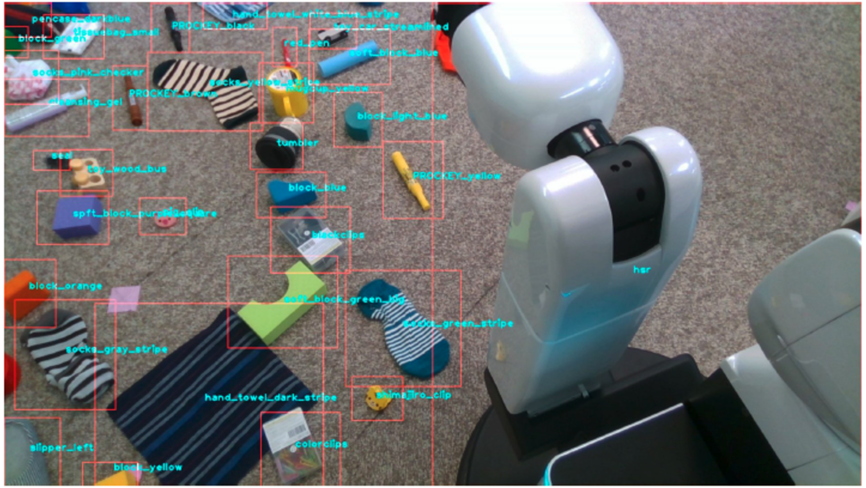
Motivation

- **Image classification**: often assume there is a single object in the image



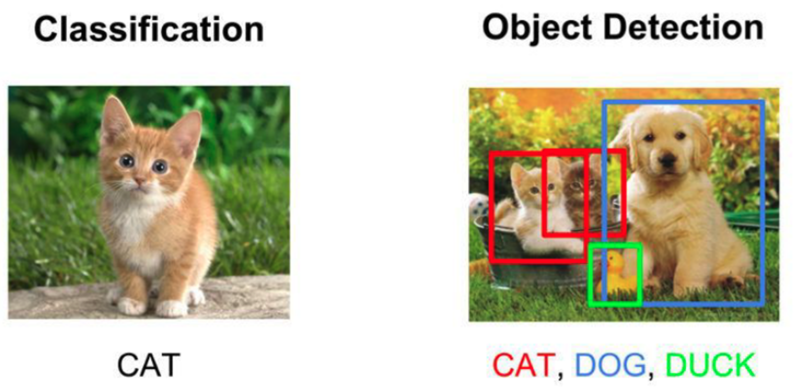
Motivation

- **Image classification**: often assume there is a single object in the image
- Real-world images can include multiple instances of objects with the same/different classes



Motivation

- **Image classification**: often assume there is a single object in the image
- Real-world images can include multiple instances of objects with the same/different classes
- **Object Detection**: produce bounding boxes that surround each instance



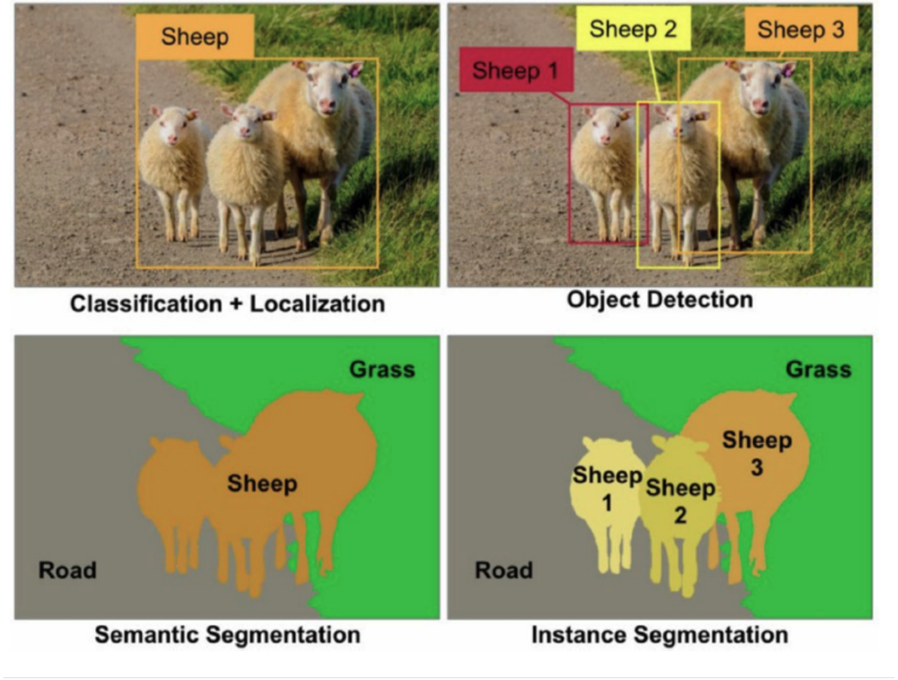
Problem Definition: Object Detection

Object Detection

- Input: Image
- Output: multiple **instances** of
  - object location (bounding box)
  - object class

Instance

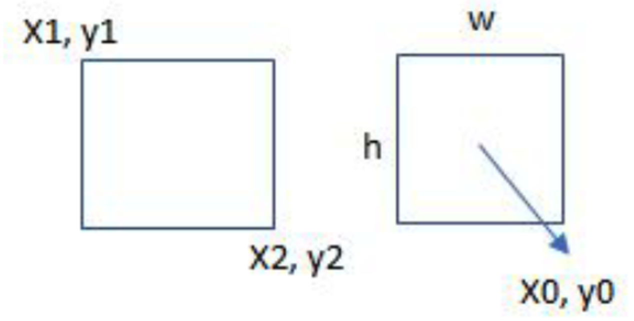
- Distinguishes individual objects, in contrast to considering them as a single semantic class



Problem Definition: Object Detection

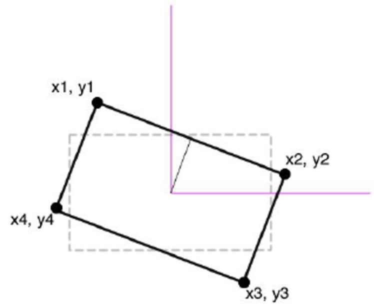
Object Detection

- Input: Image
- Output: multiple instances of
    - **object location (bounding box)**
    - object class



Bounding box

- Rigid box that confines the instance
- Multiple possible parametrizations
    - (width, height, center x, center y)
    - (x1, y1, x2, y2)
    - (x1, y1, x2, y2, rotation)



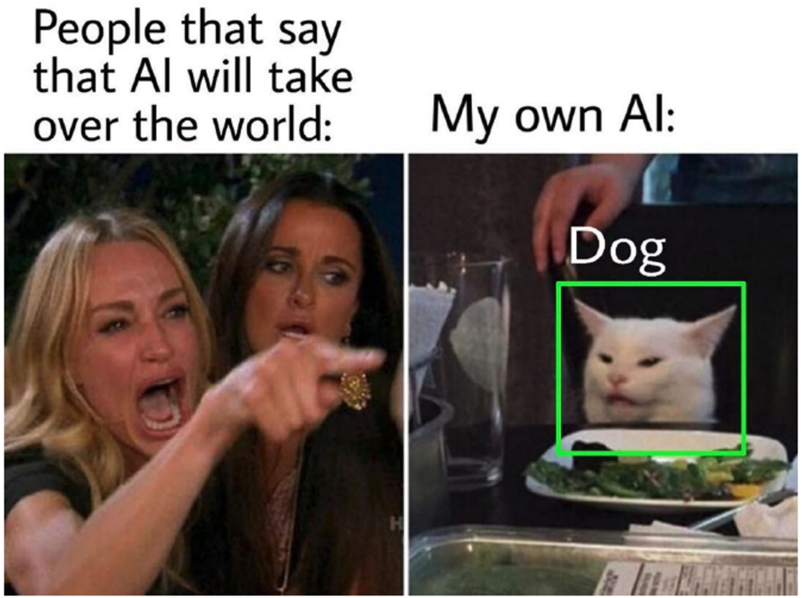
Problem Definition: Object Detection

Object Detection

- Input: Image
- Output: multiple instances of
    - object location (bounding box)
    - **object class**

Object class

- Semantic class of the instance
    - Similar to image classification
    - Predict a vector of scores

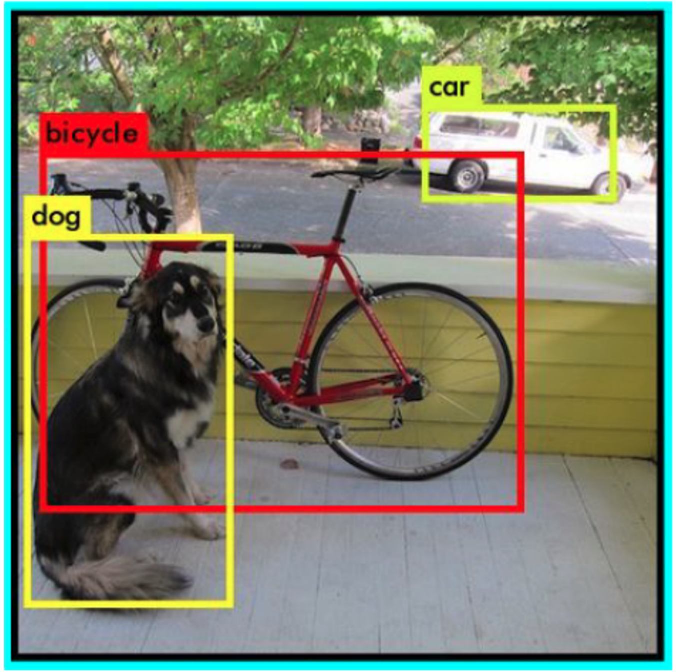


Modern Object Detection Architecture

- R-CNN
- Fast R-CNN
- Faster R-CNN
- Mask R-CNN
- SSD
- YOLO (v1, v2, v3, v4)
- FPN
- DETR

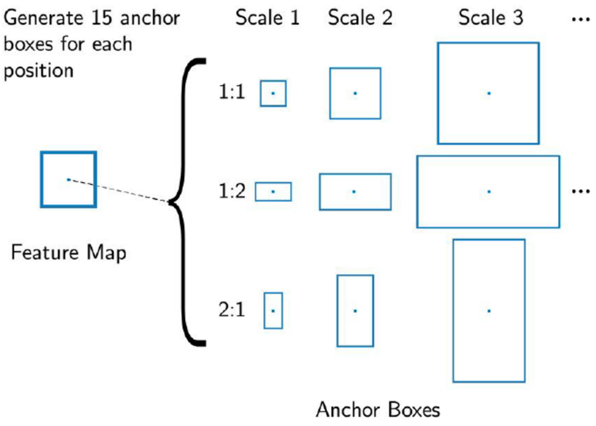
Object Detection: how can we detect multiple instances?

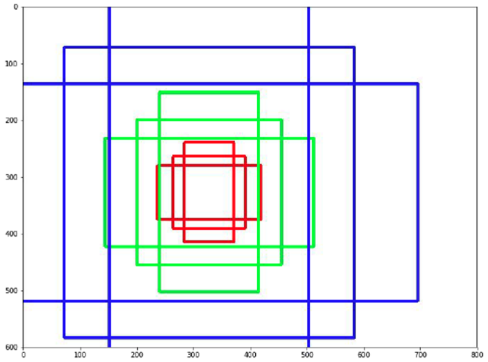
- Boxes can be centered at any location in the image
- Varying width/height
- Sliding window: infeasible



Object Detection: Anchor Boxes!

- Neural network prefers discrete prediction over continuous regression
- Preselect templates of bounding boxes to alleviate the regression problem
- For each anchor box, NN decides
  - Does it contain an object? (objectness classification)
  - Small refinement to the box (object localization)

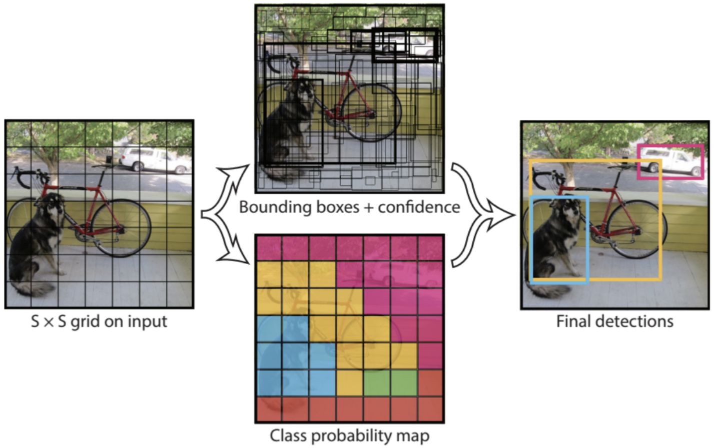




Object Detection: Single-Stage and Two-Stage Architectures

Stage 1

- For every output pixels
  - For every anchor boxes
    - Predict bounding box offsets
    - Predict anchor confidence (objectness/class)
- Output
  - Bounding boxes if single-stage
  - Region proposals (region-of-interest, RoI) if two-stage



Stage 2

- For RoI
  - Perform pooling using the RoI (RoI pooling)
  - Predict bounding box offsets
  - Predict object class

Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

Object Detection: Single-Stage and Two-Stage Architectures

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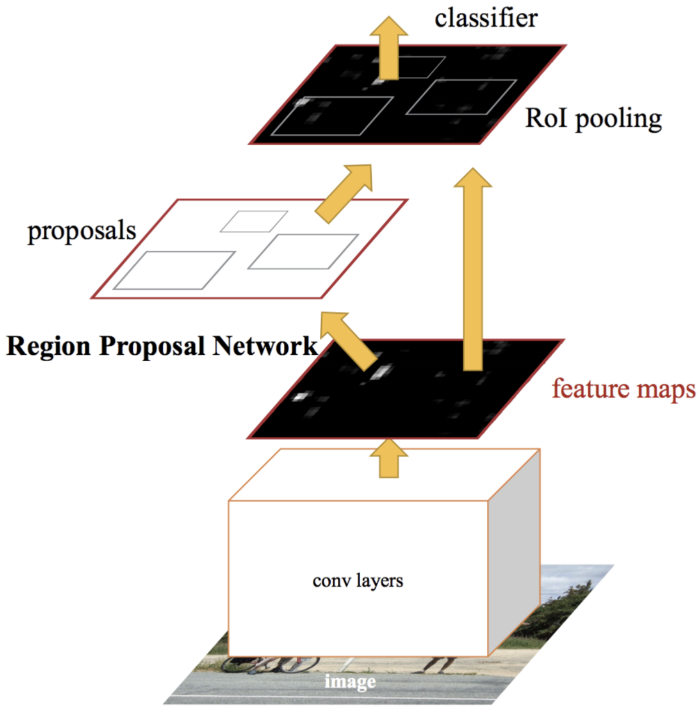

Ren, Shaoqing, et al. "Faster r-cnn: Towards real-time object detection with region proposal networks." *arXiv preprint arXiv:1506.01497* (2015).

Object Detection: Single-Stage vs Two-Stage Architectures

- Single-Stage
  - + Faster
  - - Can perform worse on small objects due to the low resolution of feature maps

- Two-Stage
  - + Performance is often higher
  - + Easily extendable to various instance-based tasks
  - - Slow

Details for Two-Stage Object Detectors

Stage 1

- **For every output pixels**
  - For every anchor boxes
    - Predict bounding box offsets
    - Predict anchor confidence (objectness/class)
- Output
  - Region proposals (region-of-interest, RoI)

Stage 2

- For RoI
  - Perform pooling using the RoI (RoI pooling)
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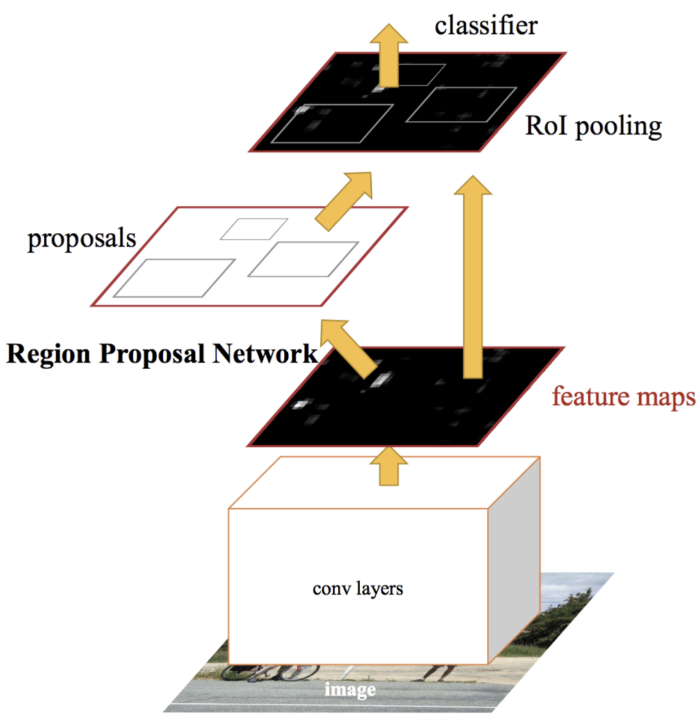

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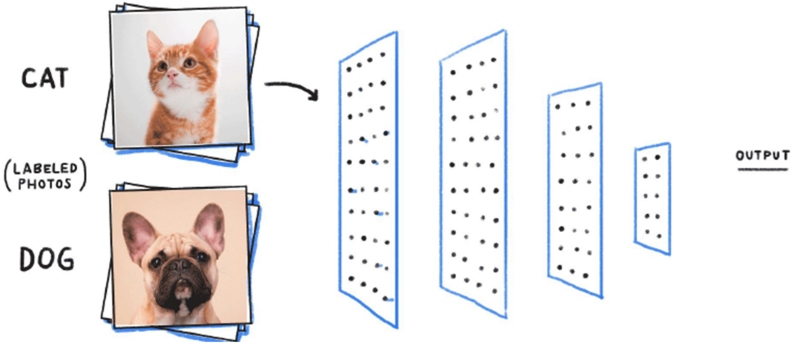
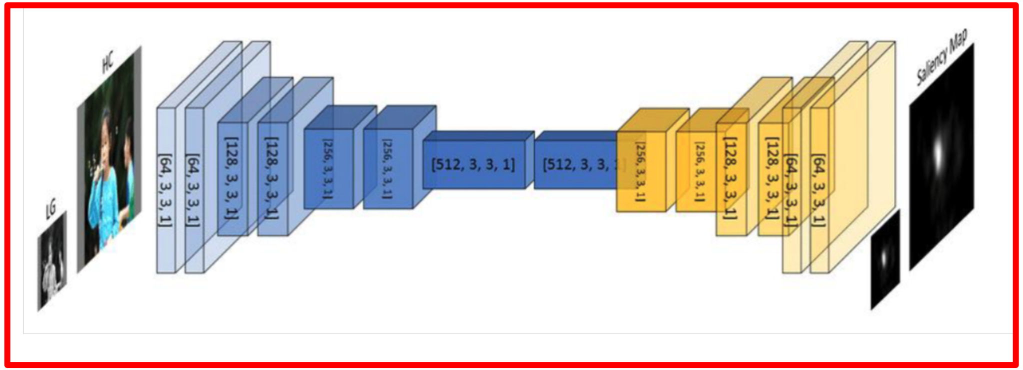
Feature extractor

- Every pixel makes prediction
- Image classification: single output





Details for Two-Stage Object Detectors

Stage 1

- For every output pixels
  - **For every anchor boxes**
    - Predict bounding box offsets
    - Predict anchor confidence (objectness/class)
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  - Perform pooling using the RoI (RoI pooling)
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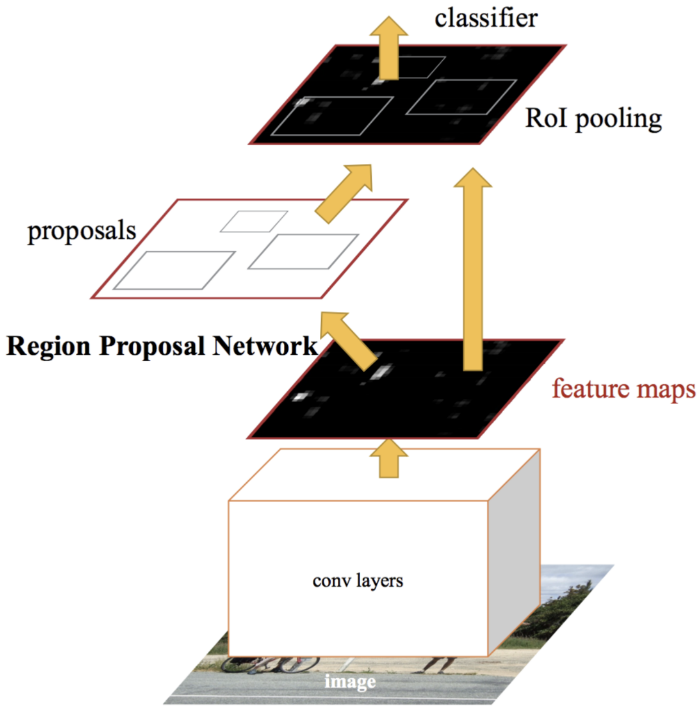

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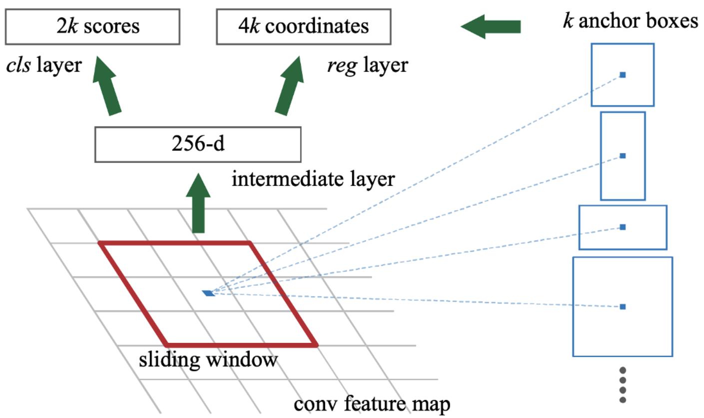
Extract Anchor Boxes

- For each output pixel
    - "Objectness" classification
    - Regression
- Often thousands of anchors for an image
- Pass anchors that correspond to ground-truth locations to the next stage, plus negative anchors



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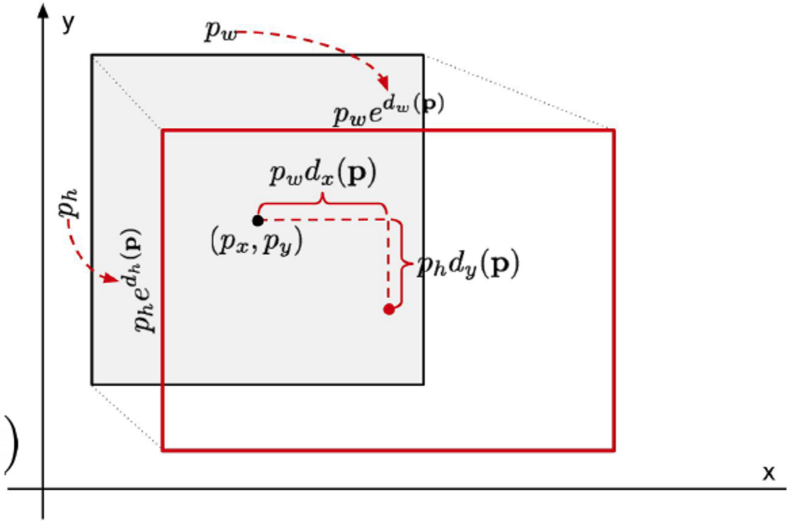
Bounding Box Regression

Given

- Anchor box size (p_w, p_h)
- Output pixel center location (p_x, p_y)

Predict bounding box refinement toward b

- Log-scaled scale relative ratio
  $d_w = \log(b_w / p_w), d_h = \log(b_h / p_h)$
- Relative center offset
  $d_x = (b_x - p_x)/p_w, d_y = (b_y - p_y)/p_h$



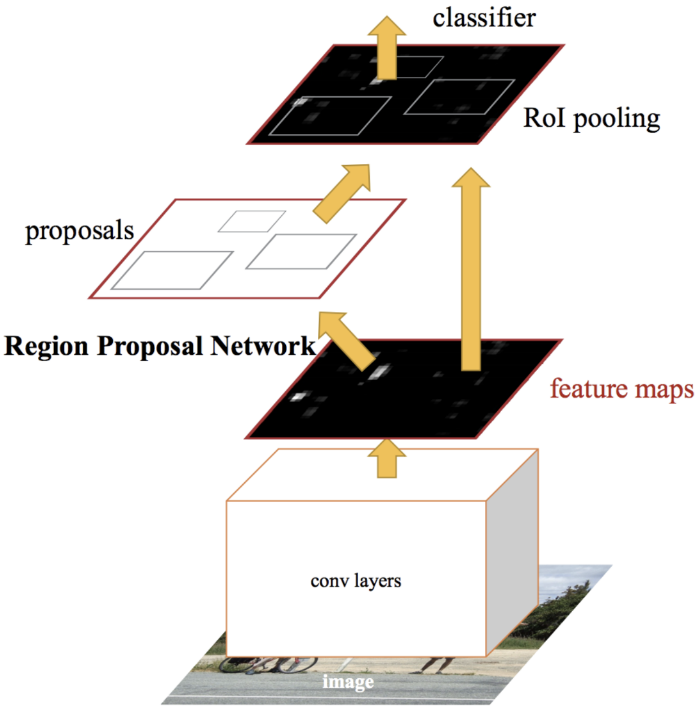
Details for Two-Stage Object Detectors

Stage 1

- For every output pixels
  - For every anchor boxes
    - Predict bounding box offsets
    - Predict anchor confidence (objectness/class)
- Output
  - Region proposals (region-of-interest, RoI)

Stage 2

- For each RoI
  - **Perform pooling using the RoI (RoI pooling)**
  - Predict bounding box offsets
  - Predict object class



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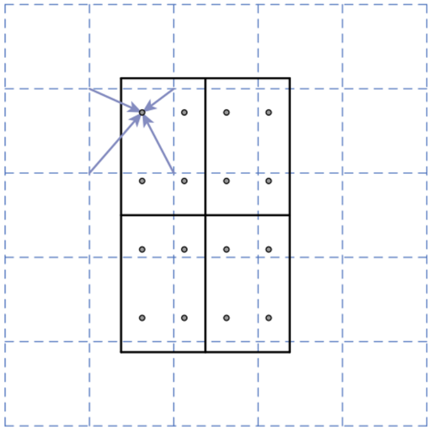
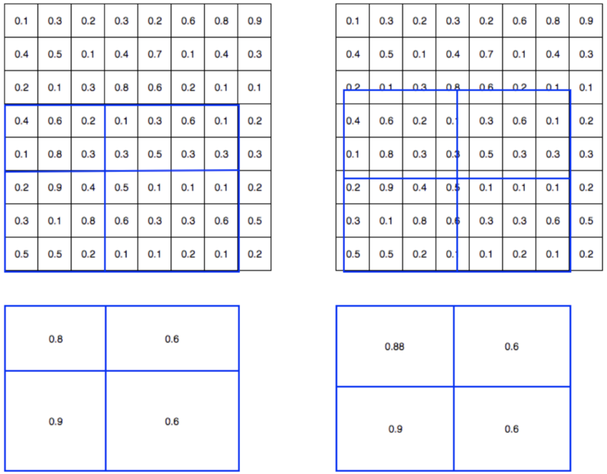
RoI Pooling

- Given region-of-interests (RoIs), we want to pool from the backbone features





He, Kaiming, et al. "Mask r-cnn." *Proceedings of the IEEE international conference on computer vision*. 2017.

https://jonathan-hui.medium.com/image-segmentation-with-mask-r-cnn-ebe6d793272

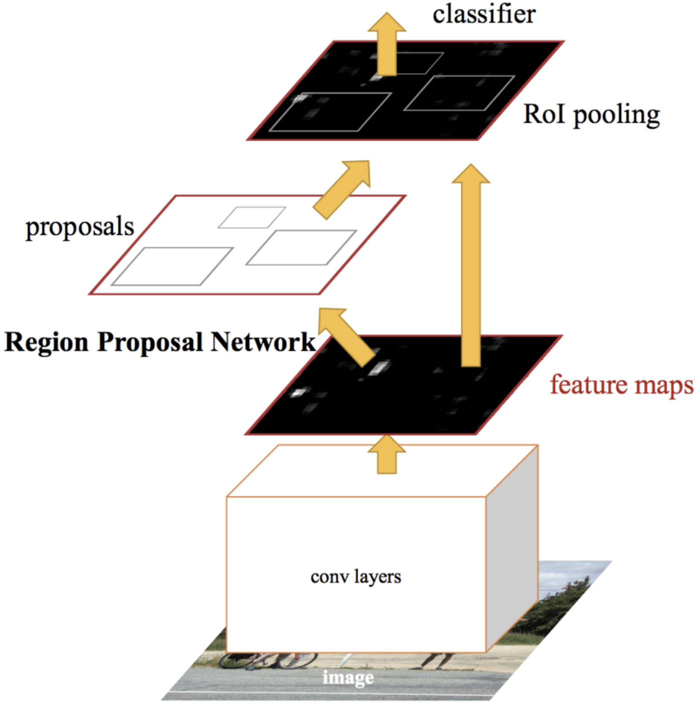
Details for Two-Stage Object Detectors

Stage 1

- For every output pixels
  - For every anchor boxes
    - Predict bounding box offsets
    - Predict anchor confidence (objectness/class)
- Output
  - Region proposals (region-of-interest, RoI)

Stage 2

- For each RoI
  - Perform pooling using the RoI (RoI pooling)
  - **Predict bounding box offsets**
  - **Predict object class (semantic class / background)**



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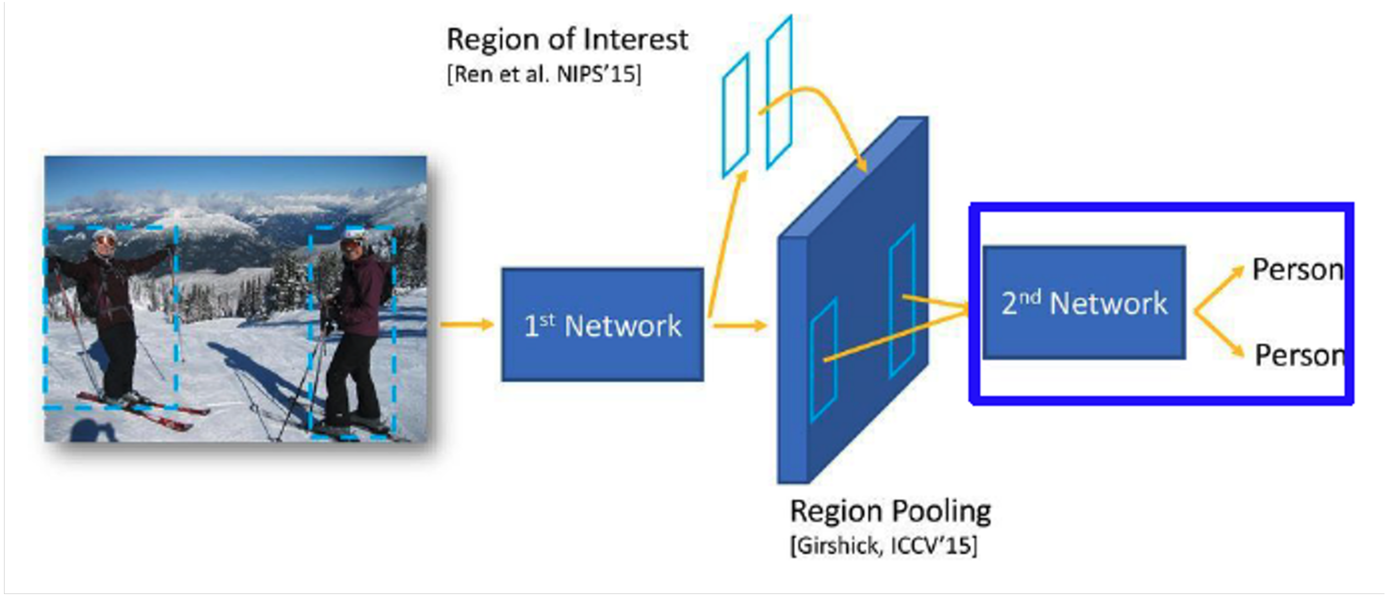
Details for Two-Stage Object Detectors



Are We Done?

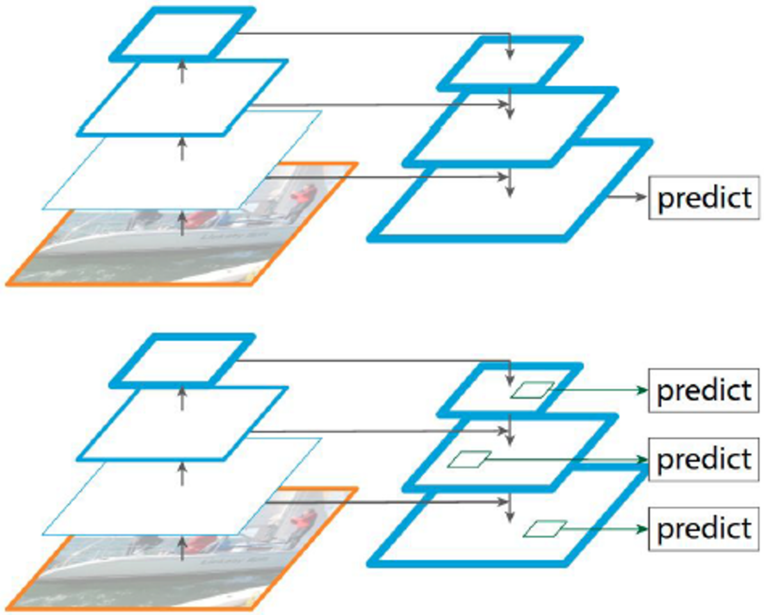
- Prediction might contain multiple boxes of the same instance

Post-Processing: Non-Maximum Suppression

- For boxes overlapping with each other above a threshold: keep the one with the maximum confidence score
- Implementation
    - Sort by confidence
    - For each box (conf high to low)
        - If overlaps with confirmed predictions above a threshold
            - Discard
        - Else
            - Add to predictions

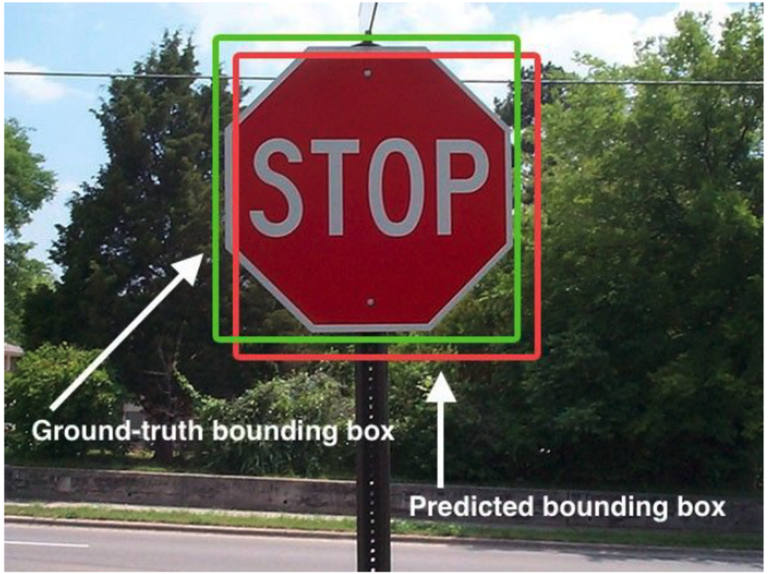
Feature Pyramid Network as the feature extractor

- Traditional backbone
  - Small feature maps have larger receptive field and contain better-extracted overall semantic information
  - Want this semantic information in larger feature maps for prediction
- Feature Pyramid Network
  - Richer representation
  - Enables multi-scale predictions



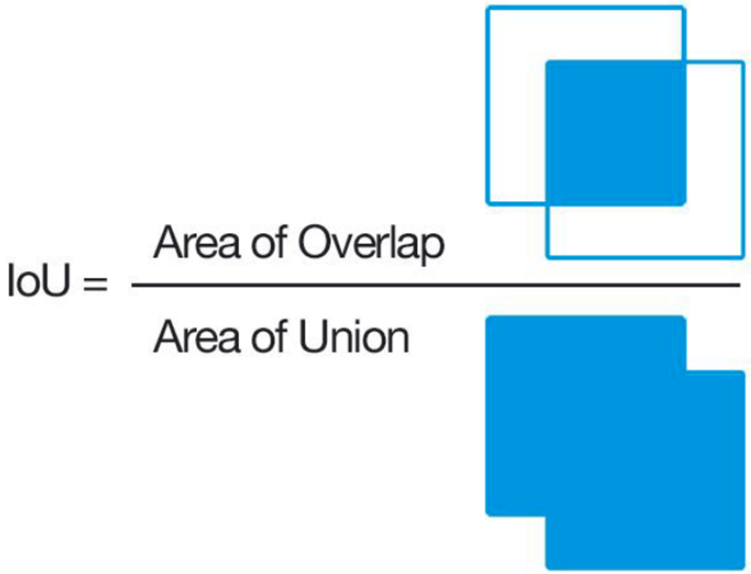
How should we evaluate our results?

- Start with the most simple case
- Given
  - a single ground-truth box
  - a single predicted box



How should we evaluate our results?

- Start with the most simple case
- Given
  - a single ground-truth box
  - a single predicted box
- Use Intersection-over-Union (IoU)

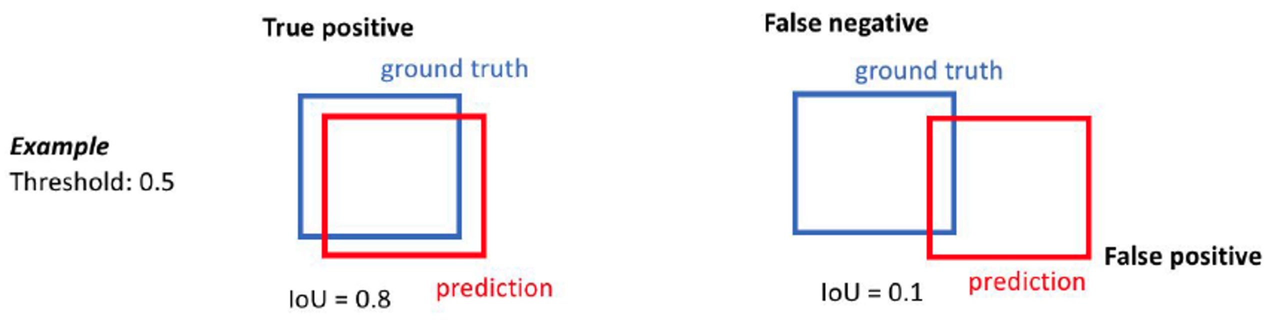


What if there are multiple boxes?

- Multiple ground-truth boxes
- Multiple predictions
- Might include
  - True positive (prediction matched with GT)
  - False positive (prediction not matched with any GT)
  - False negative (GT not matched with any prediction

Bounding Box Matching

- Use IoU threshold
- Matched if
  - IoU above certain threshold
  - Class prediction is correct
  - GT not matched with other boxes (1-to-1)

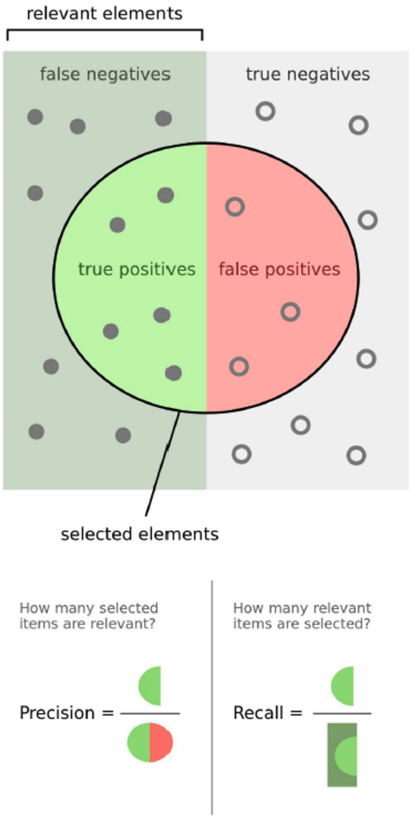


Evaluation Metrics: Precision and Recall

- **True Positive (TP)**
- **False Negative (FN)**
- **False Positive (FP)**

Precision = TP / (TP + FP)

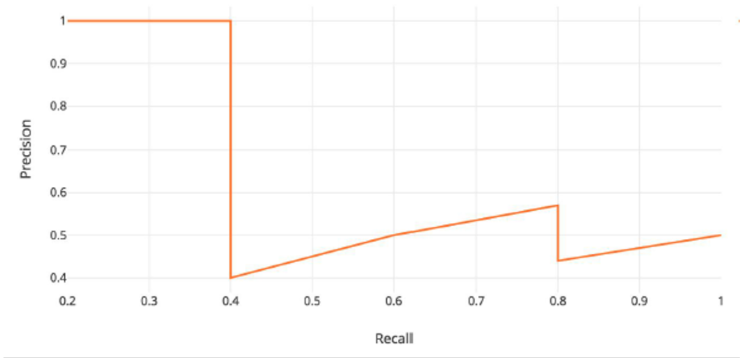
Recall = TP / (TP + FN)



Evaluation Metrics: Average Precision

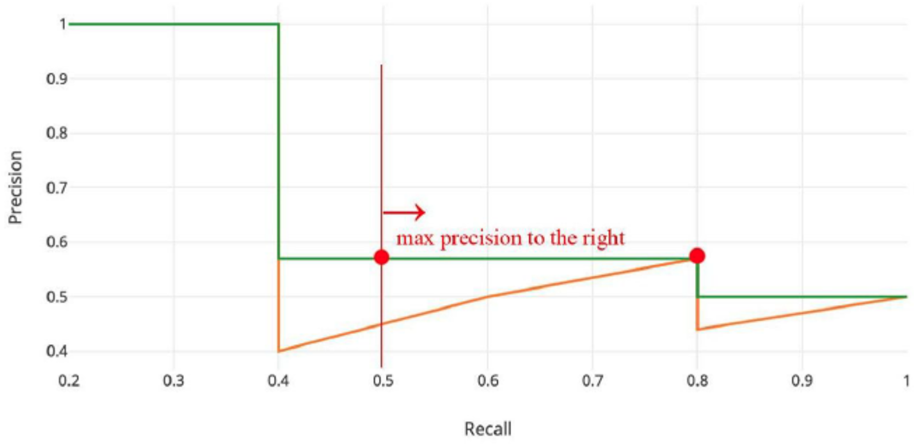
- Go through every prediction in descending order of the prediction confidence
- Plot Precision-Recall Curve
- Area below the curve is **Average Precision (AP)**

Rank	Correct?	Precision	Recall
1	True	1.0	0.2
2	True	1.0	0.4
3	False	0.67	0.4
4	False	0.5	0.4
5	False	0.4	0.4
6	True	0.5	0.6
7	True	0.57	0.8
8	False	0.5	0.8
9	False	0.44	0.8
10	True	0.5	1.0



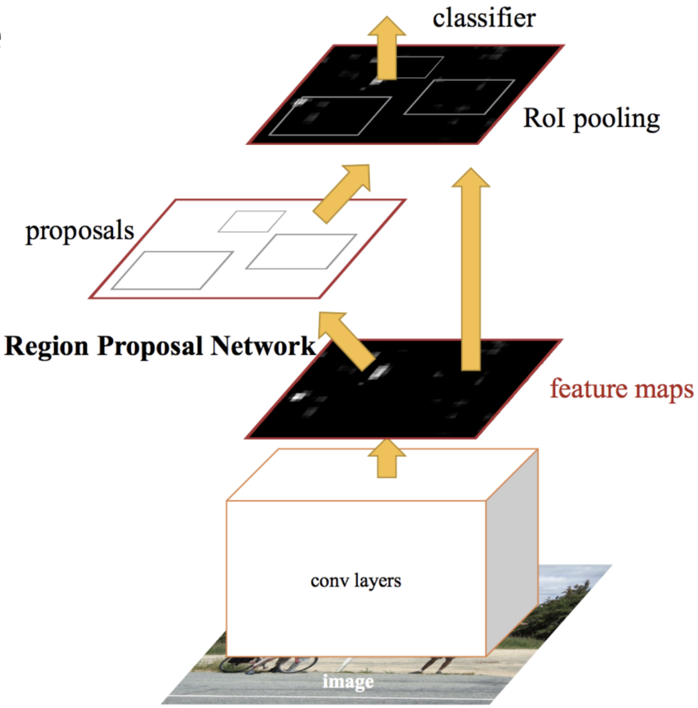
Evaluation Metrics: Average Precision

- To make AP more stable to score ordering, we sometimes take max precision to the right of the PR curve
- Use different IoU threshold for matching
  - AP50, AP75, AP95: match IoU threshold of 0.5, 0.75, 0.95
  - AP: average of AP with match IoU threshold of [0.5, 0.55, 0.6, ..., 0.95]



Two-Stage Detectors can do more!

- In addition to detecting boxes, at the final stage using RoI features, we can predict
  - 3D bounding boxes
  - Instance segmentation
  - Keypoints (human pose)
  - Meshes
  - Scene graphs
  - ...
- A family of R-CNNs!



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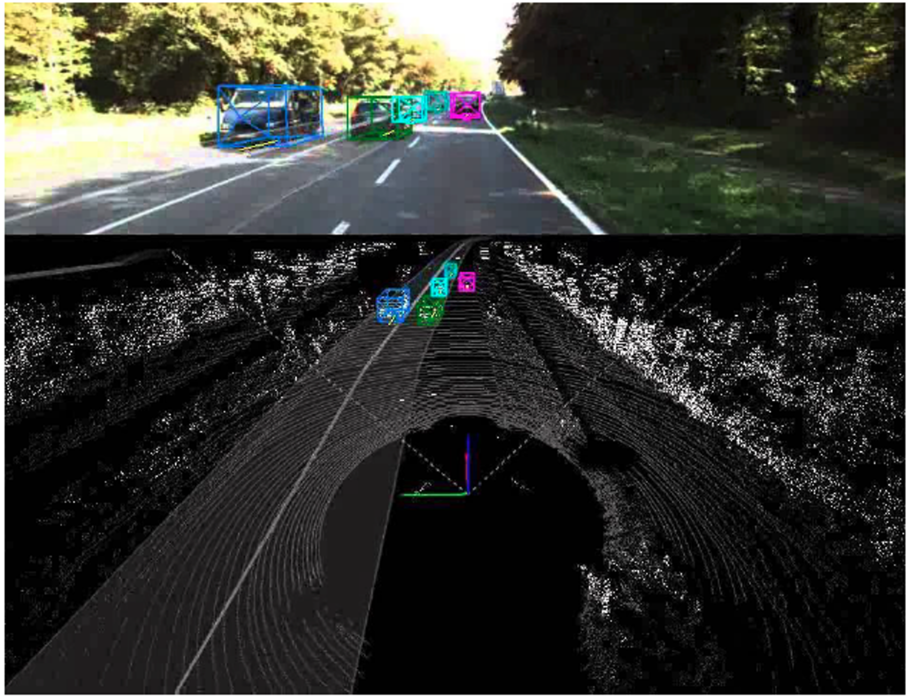
3D Object Detection

- Input
  - 2D image and/or 3D point cloud
- Output
  - 3D bounding box
    - Center location: x, y, z
    - Bounding box size: w, h, l
    - Rotation



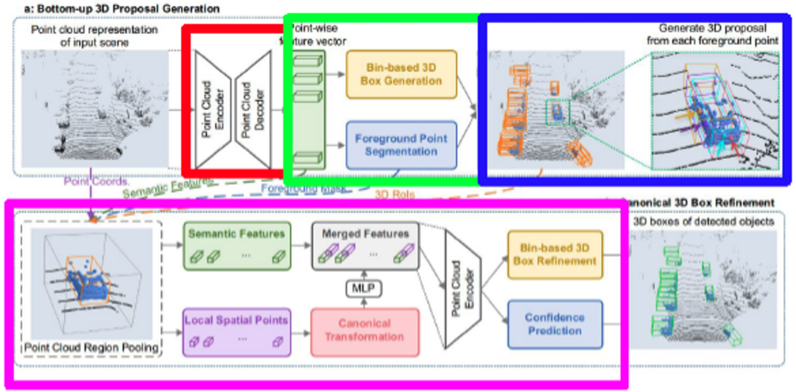
3D Object Detection

Stage 1

- For every output pixel (from backbone)
  - For every anchor boxes
    - Predict bounding box offsets
    - Predict anchor confidence

(Optional, if two-stage networks) Stage 2

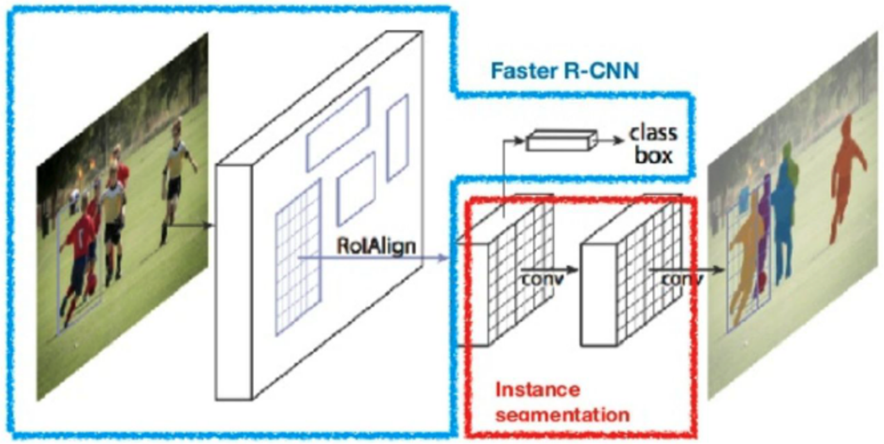
- For every region proposals
  - Predict bounding box offsets
  - Predict its semantic class



For example, Point R-CNN

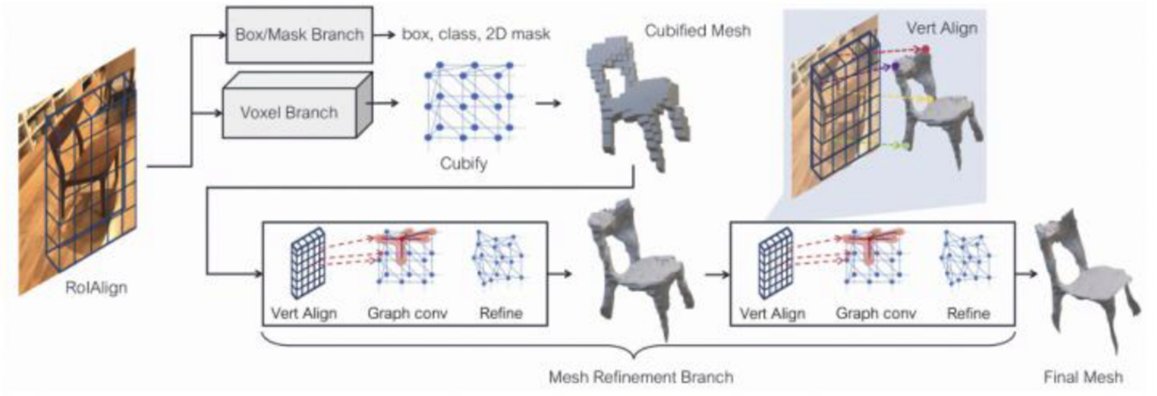
Mask R-CNN

- Final stage parallel to box prediction
  - Predict instance mask using a convolution head
- RoI Align especially helpful for segmentation by aggregating fine-grained features



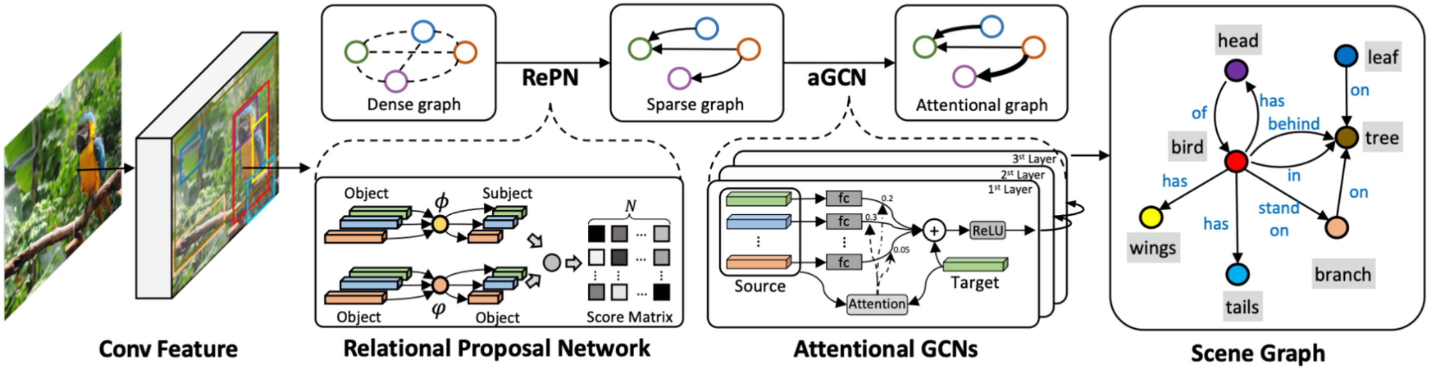
Mesh R-CNN

- Final stage parallel to box prediction
  - Predict voxels
  - Align and refine meshes with graph convolution



Graph R-CNN

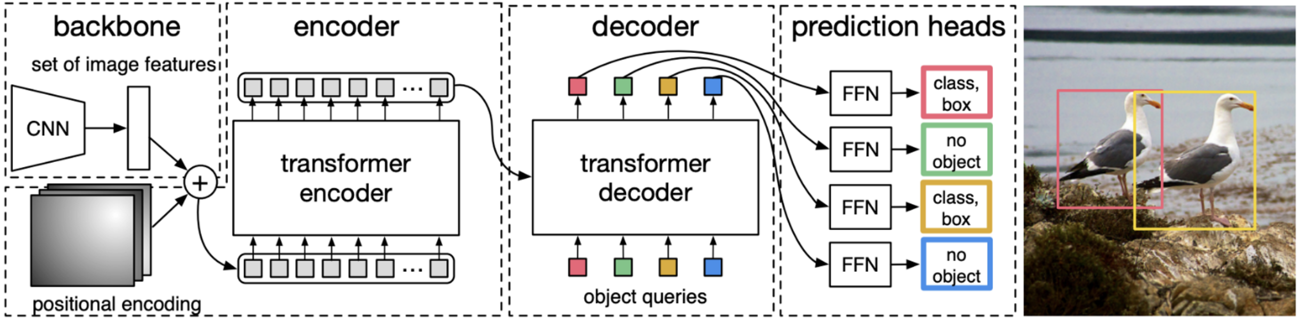
- Object detection + relationship detection
- Additional Relation Proposal Network
- Use Graph Convolution Network (GCN) for scene graph refinement



Yang, Jianwei, et al. "Graph r-cnn for scene graph generation." *Proceedings of the European conference on computer vision (ECCV)*. 2018.

DETR: End-to-End Object Detection with Transformers

- Using Transformer to directly produce boxes
- Predict objects (much larger than number of boxes) using learned fixed number of object queries



Carion, Nicolas, et al. "End-to-end object detection with transformers." *European Conference on Computer Vision*. Springer, Cham, 2020.

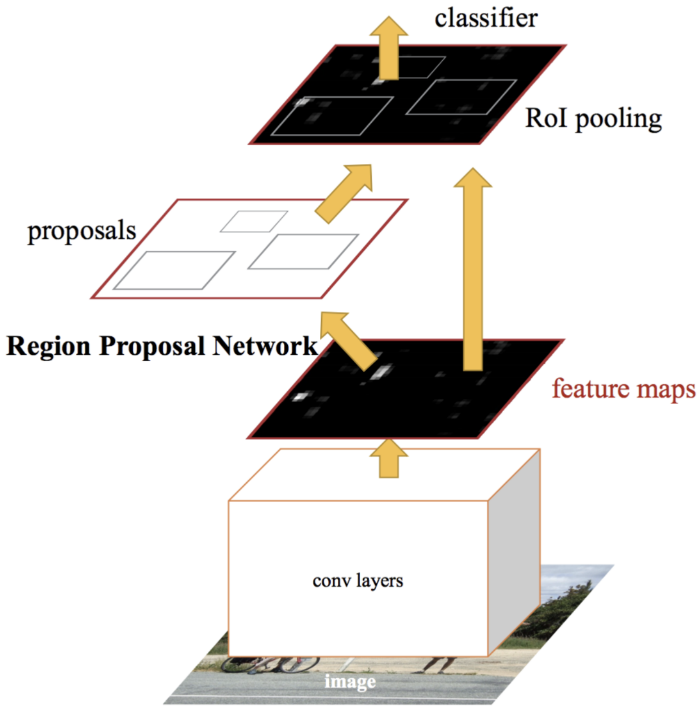
Conclusion

Stage 1

- For every output pixels
  - For every anchor boxes
    - Predict bounding box offsets
    - Predict anchor confidence (objectness/class)
- Output
  - Region proposals (region-of-interest, RoI)

Stage 2

- For each RoI
  - Perform pooling using the RoI (RoI pooling)
  - Predict bounding box offsets
  - Predict object class (semantic class / background)
  - Predict other stuff! (segmentation, pose, mesh, etc.)
- Non-maximum Suppression



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Implementing a Detector: Detectron2

- Open-source software for object detection and more
- Developed by Facebook with PyTorch
- Easily extendable with extensive documentations

2. RNNs

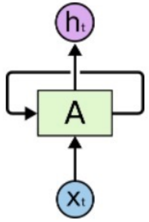
Recurrent Neural Networks

Traditional Neural Networks

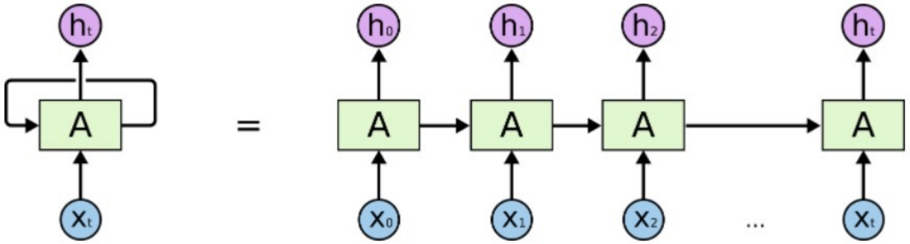
- Can’t use its reasoning about previous events to inform later ones.

Recurrent Neural Networks

- Networks with loops allow information to persist.
- Chain-like, multiple copies of the same network



Recurrent Neural Networks have loops.



An unrolled recurrent neural network.

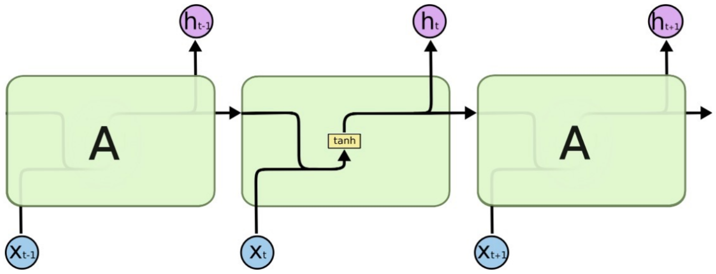
LSTM Networks

Recurrent Neural Networks

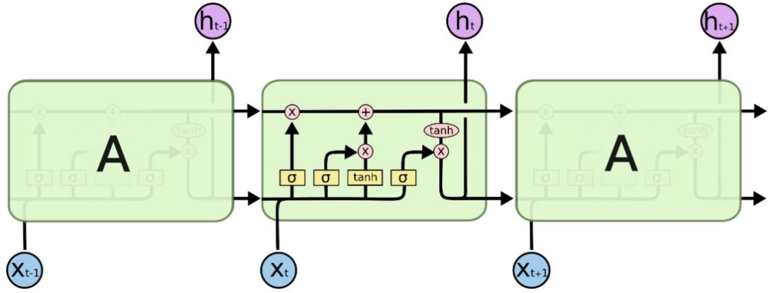
- Difficult to handle long-term dependencies.
- Explained in [Hochreiter (1991) [German]] and [Bengio, et al. (1994)]

Long Short Term Memory Networks (LSTMs)

- A special kind of RNN.
- The repeating module has a different structure.

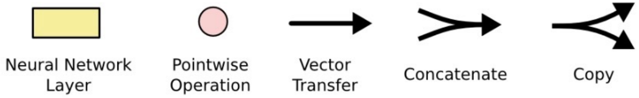


The repeating module in a standard RNN contains a single layer.



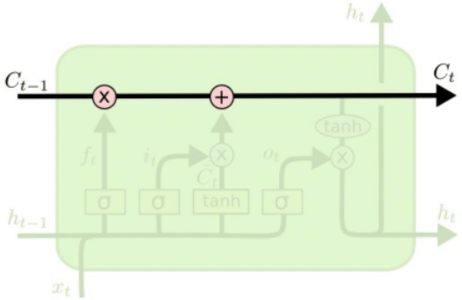
The repeating module in an LSTM contains four interacting layers.

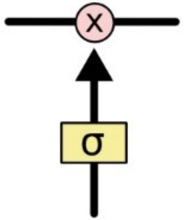
Core Idea Behind LSTM Networks



Key to LSTMs

- Cell state:
    - Only some minor linear interactions, information flow unchanged.
- “Gates”
    - Remove or add information to the cell state:
    - Composed of:
        - Sigmoid neural net layer: output 0 - 1
        - Pointwise multiplication operation





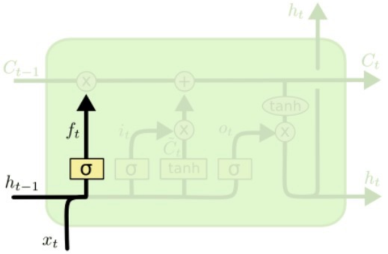
Step-by-Step LSTM walk through

1. Throw away information from the cell state

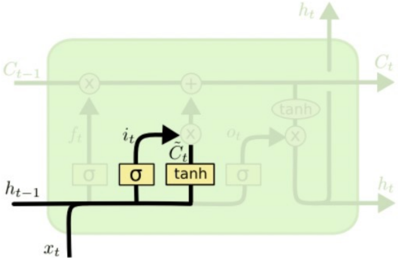
- Forget gate layer
  - For each number in the Cell State C_{t-1}: Input h_{t-1}, x_t, output a number between 0 and 1.

2. Store new information in the cell state

- Input gate layer
  - Sigmoid layer, output between 0 and 1, decides which values we'll update.
- A tanh layer
  - Creates a vector of new candidate values $\tilde{C}_t$

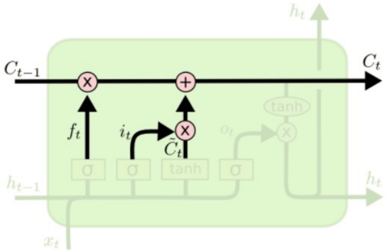


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

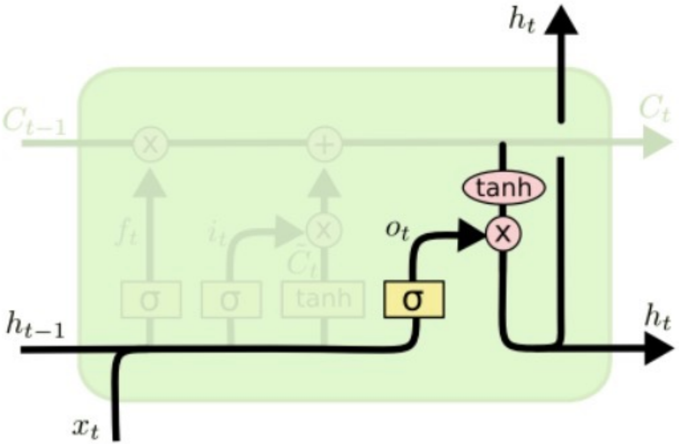


$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Step-by-Step LSTM walk through

3. Output – A filtered cell state version

- Sigmoid gate layer
  - Decides what parts of the cell state we're going to output.
- Cell State tanh layer
  - Input : Cell state
  - Output: Push the values to be between −1 and 1
- Multiply the above two, and get the final output h_t.



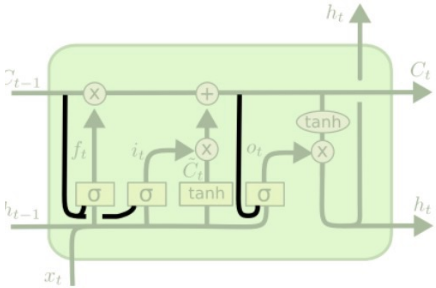
$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Variants on LSTM

1. Adding “peephole connections”

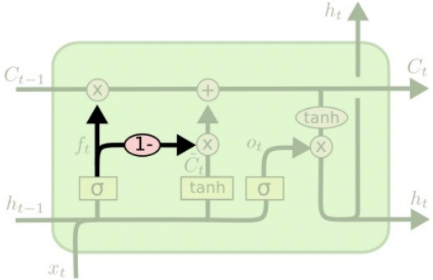
- Let the gate layers look at the cell state



$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \ + \ b_o\right)$$

2. Use coupled forget and input gates

- Instead of separately deciding what to forget and what we should add new information to, we make those decisions together.

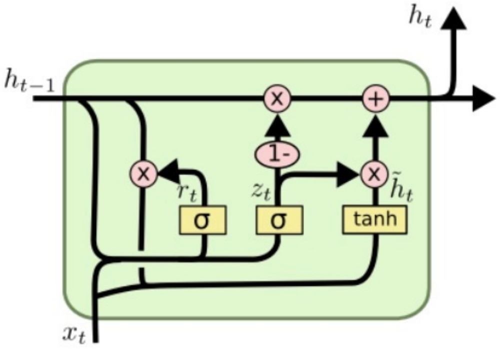


$$C_t = f_t * C_{t-1} + \boldsymbol{(1 - f_t)} * \tilde{C}_t$$

Variants on LSTM

1. Gated Recurrent Unit (GRU)

- Combines the forget and input gates into a single “update gate”.
- Merges the cell state and hidden state.
- Simpler than standard LSTM models, growing increasingly popular.



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

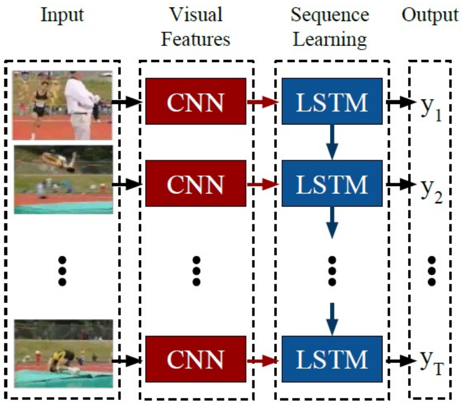
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

RNNs take advantage of sequences

- Sequences are not only text or music, they can also be videos (sets of images).
- E.g. Understand actions in videos: Using RNNs to focus on tracking the convolutional features.
- Using RNNs and CNNs together is possible, and in fact, it could be the most advanced use of Computer Vision we have.
- Action classification, movie generation …



Suggested Readings

- Rich feature hierarchies for accurate object detection and semantic segmentation
- Fast R-CNN
- Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks
- Mask R-CNN
- Fast Point R-CNN
- Mesh R-CNN
- Graph R-CNN for Scene Graph Generation
- You Only Look Once: Unified, Real-Time Object Detection
- SSD: Single Shot MultiBox Detector
- End-to-End Object Detection with Transformers
- Detectron2
- Recurrent Models of Visual Attention