# **Bounding Box Prediction**

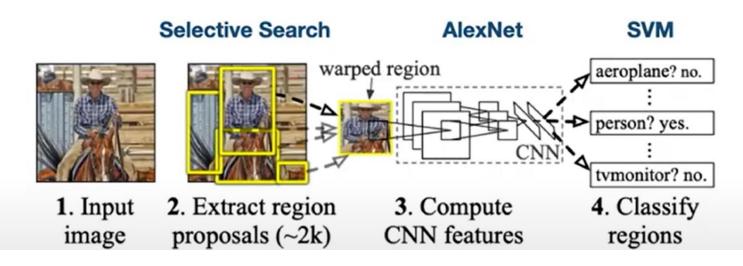
Transformers
Object Detection

#### How to sample boxes?

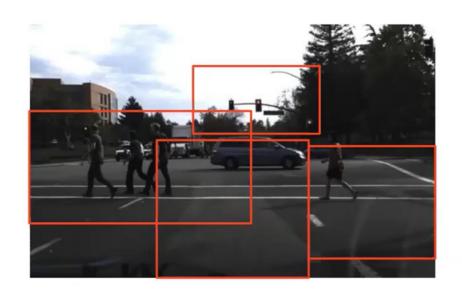
- sliding window expensive!
- region proposal

## Approach #1: R-CNN

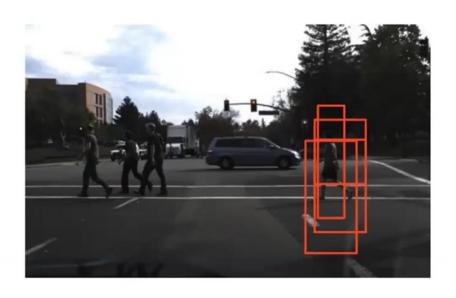
R-CNN (arXiv: 1311.2524)



# **Auxiliary Methods**



**Region Proposal** 



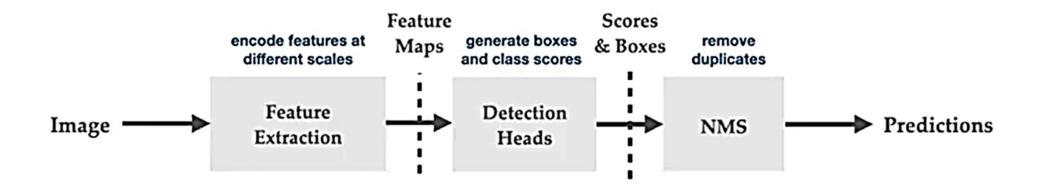
Non maximum suppression

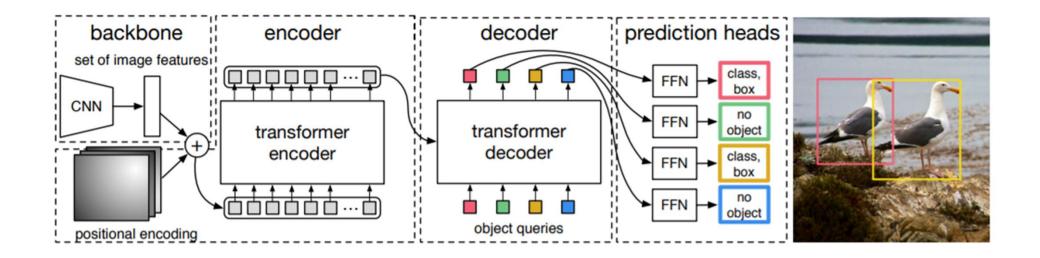
Transformers does not use these auxiliary methods for object detection like many other existing architectures.

They use Single Shot Detection (SSD) algorithm for bounding box predictions.

- · Some alternatives:
  - Fast(er) R-CNN end-to-end version of R-CNN
  - YOLO
  - Single Shot Multibox Detector

#### **SSD Algorithm**





## How to match?

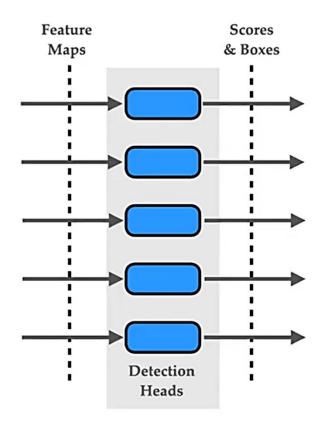


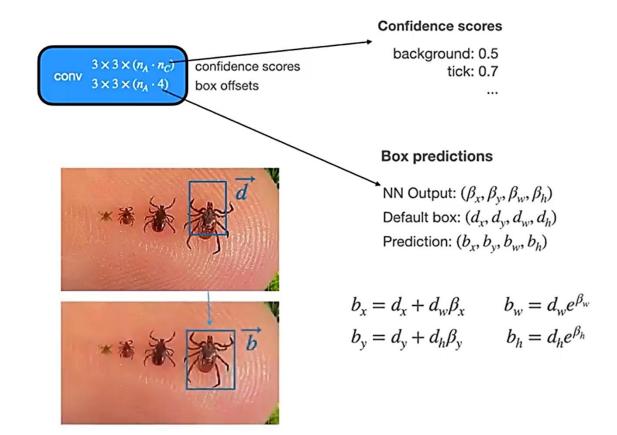
SSD matches a set of default bounding boxes. For an image size of 300x300, we have 8732 bounding boxes.

It uses IoU metric with a threshold (usually 50%) to find the accurate boxes. Out of 8732 bounding boxes, SSD selects top 200 boxes and perform non-maximal suppression to predict the final boxes.

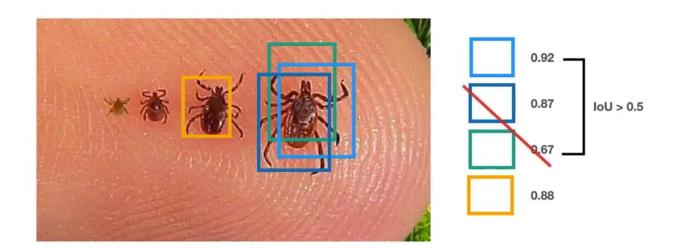
### **SSD Architecture**

#### **Multibox detector**

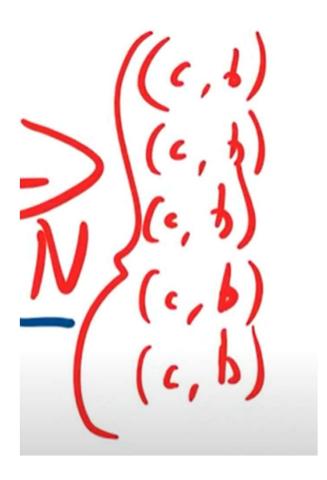


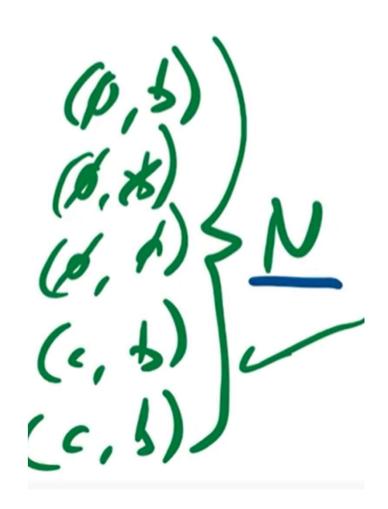


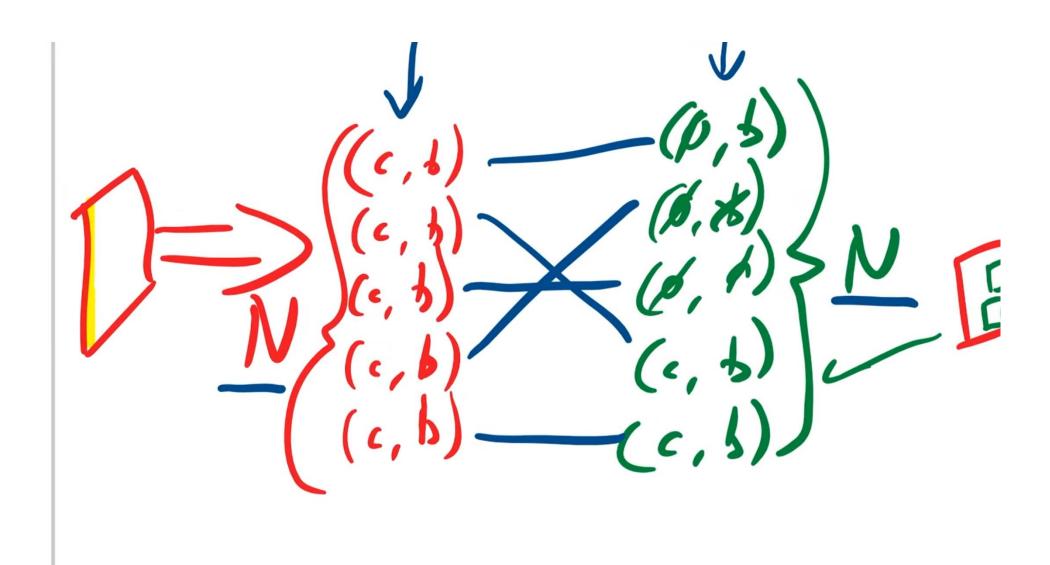
## **NMS**



# **Bipartite Matching Loss**







Hungarian Algorithm is responsible to get such matching.

#### Bipartite Loss:

$$\hat{\sigma} = \operatorname*{arg\,min}_{\sigma \in \mathfrak{S}_N} \sum_{i}^{N} \mathcal{L}_{\mathrm{match}}(y_i, \hat{y}_{\sigma(i)}),$$

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

#### **Bounding box Loss:**

 $\lambda_{\text{iou}} \mathcal{L}_{\text{iou}}(b_i, \hat{b}_{\sigma(i)}) + \lambda_{\text{L1}} ||b_i - \hat{b}_{\sigma(i)}||_1 \text{ where } \lambda_{\text{iou}}, \lambda_{\text{L1}} \in \mathbb{R} \text{ are hyperparameters.}$