EE 628
Deep Learning
Fall 2019

Lecture 12

11/14/2019

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Department of Electrical and Computer Engineering

Overview

- Last lecture we covered
  - Finish implementing RNN
  - GRUs and LSTMs
  - Attention Mechanism

- Today, we will cover
  - Advanced topics in Computer Vision

Computer vision

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- Then, we will explore various methods of object detection.
- After that, we will learn how to use fully convolutional networks to perform semantic segmentation on images.
- Then, we explain how to use style transfer technology

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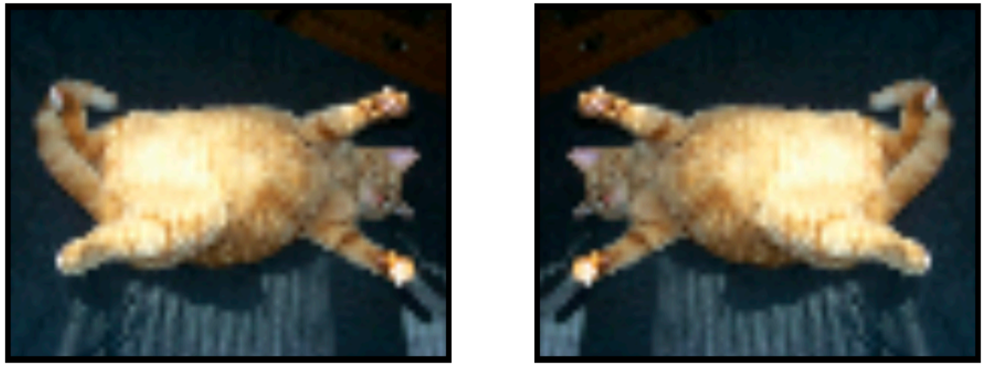
- Another way to explain image augmentation is that randomly changing training examples can reduce a model’s dependence on certain properties, thereby improving its capability for generalization.
- It can be said that image augmentation technology contributed greatly to the success of AlexNet.

Common Image Augmentation Methods

Flip



Crop

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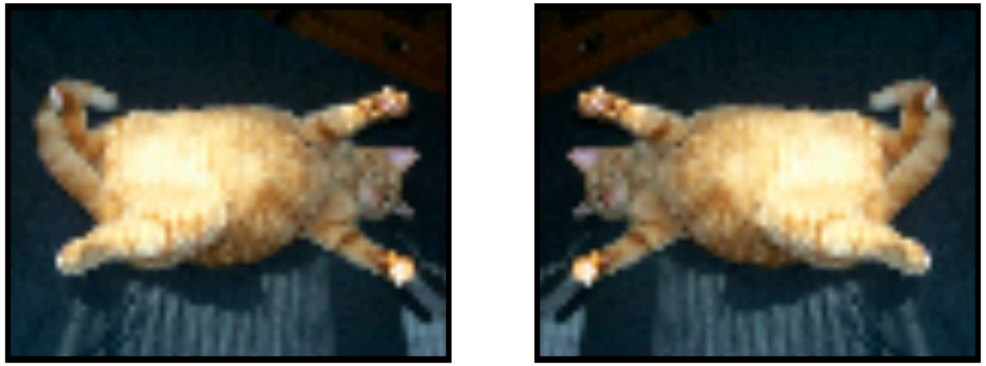

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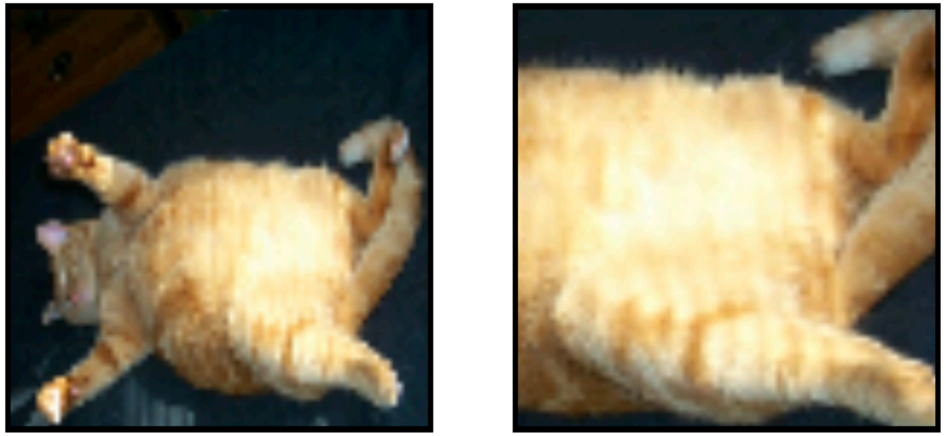

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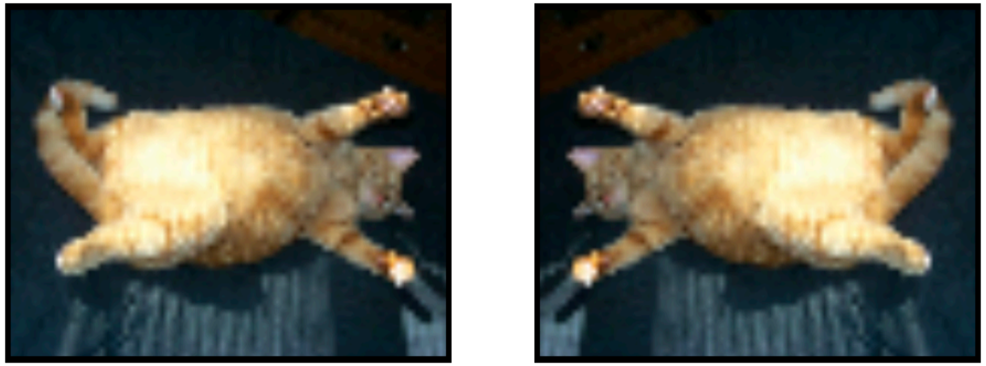
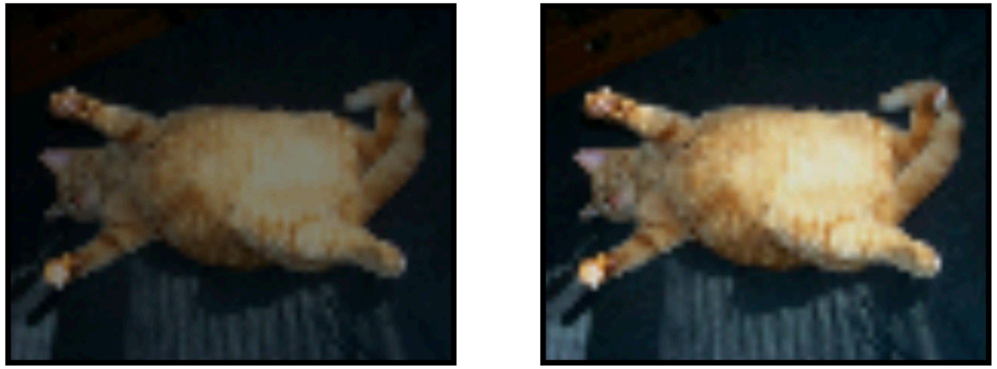


Change Color



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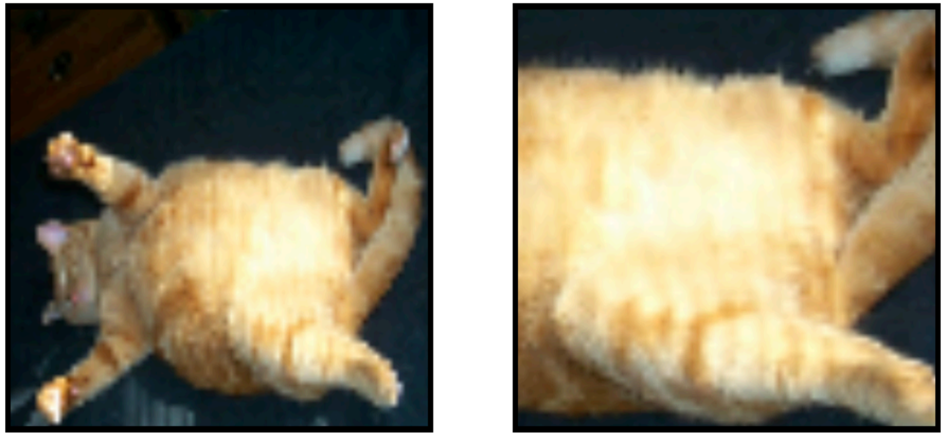

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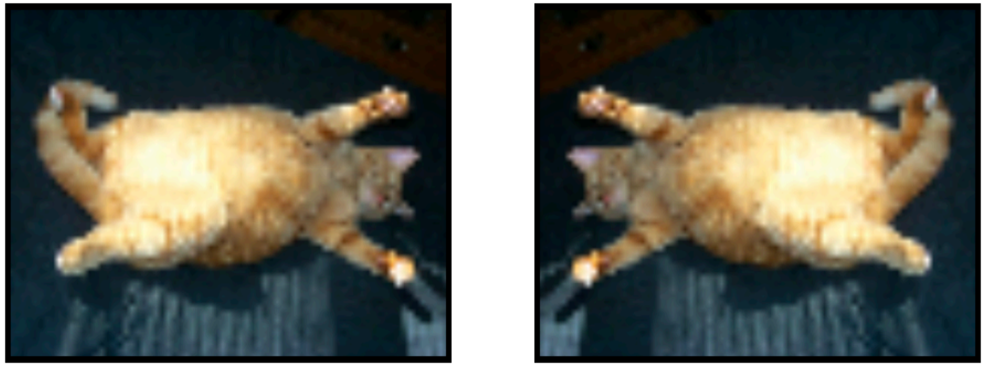

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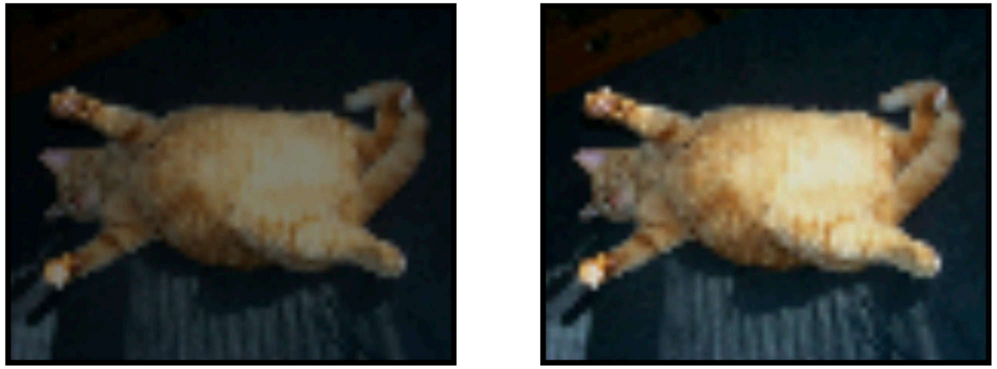

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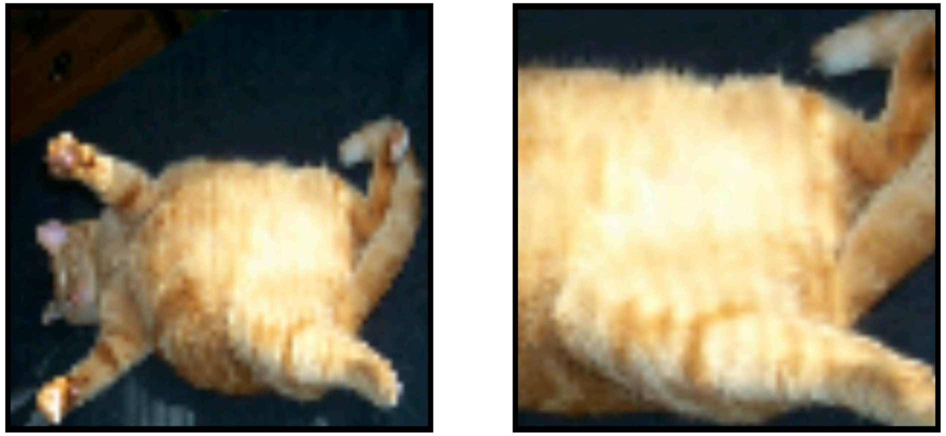
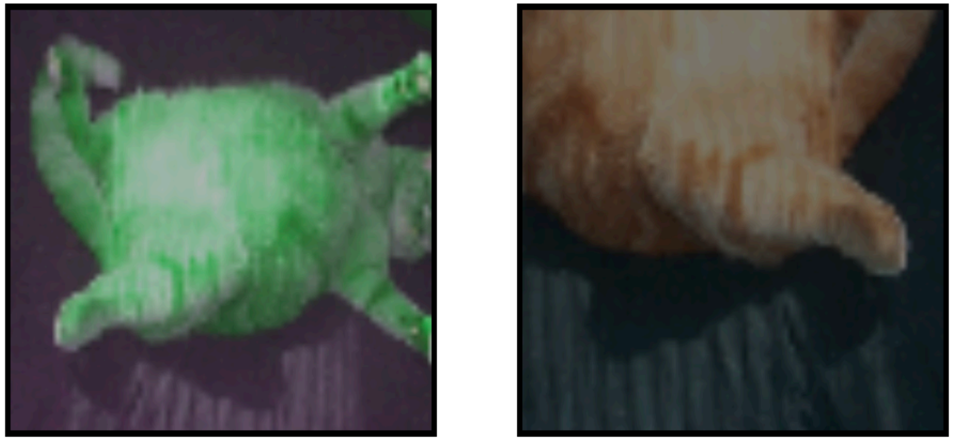


Overlaying multiple methods



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- In order to deal with the above problems, an obvious solution is to collect more data.
- However, collecting and labeling data can consume a lot of time and money.

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- For example, although the images in ImageNet are mostly unrelated to chairs, models trained on this data set can extract more general image features that can help identify edges, textures, shapes, and object composition.
- These similar features may be equally effective for recognizing a chair.
- Now, we introduce a common technique in **transfer learning:** **fine tuning**.

Fine Tuning

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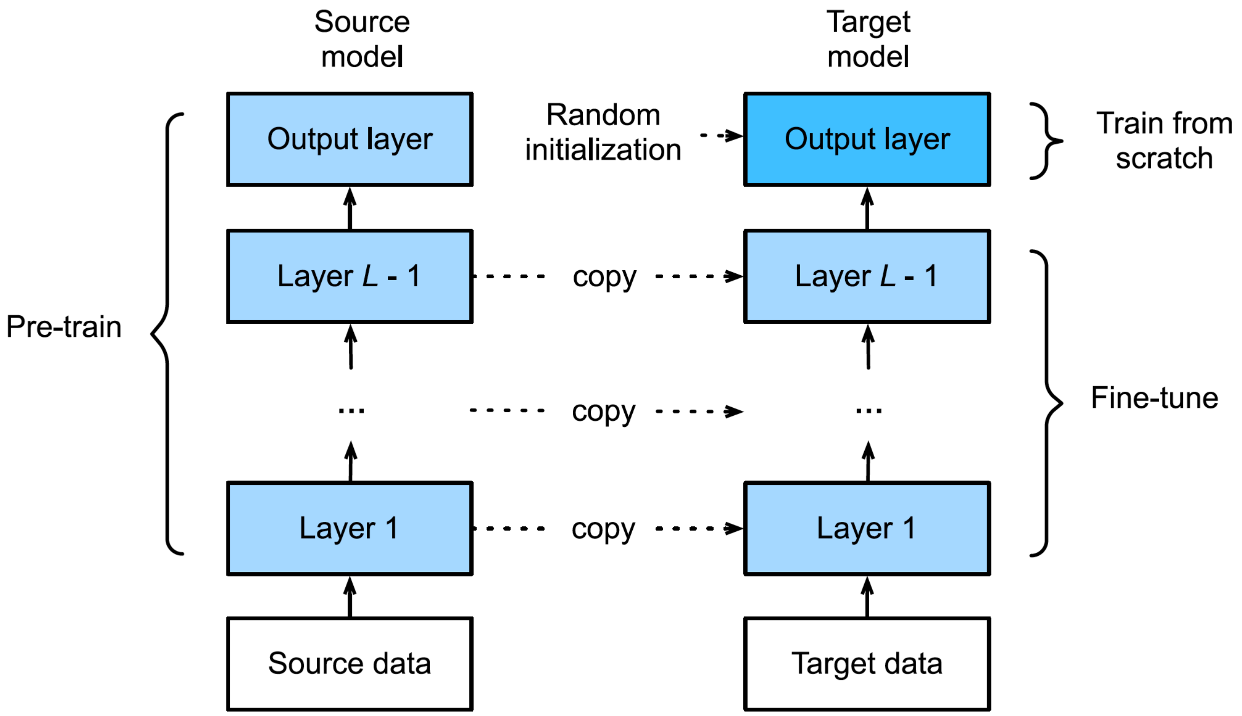

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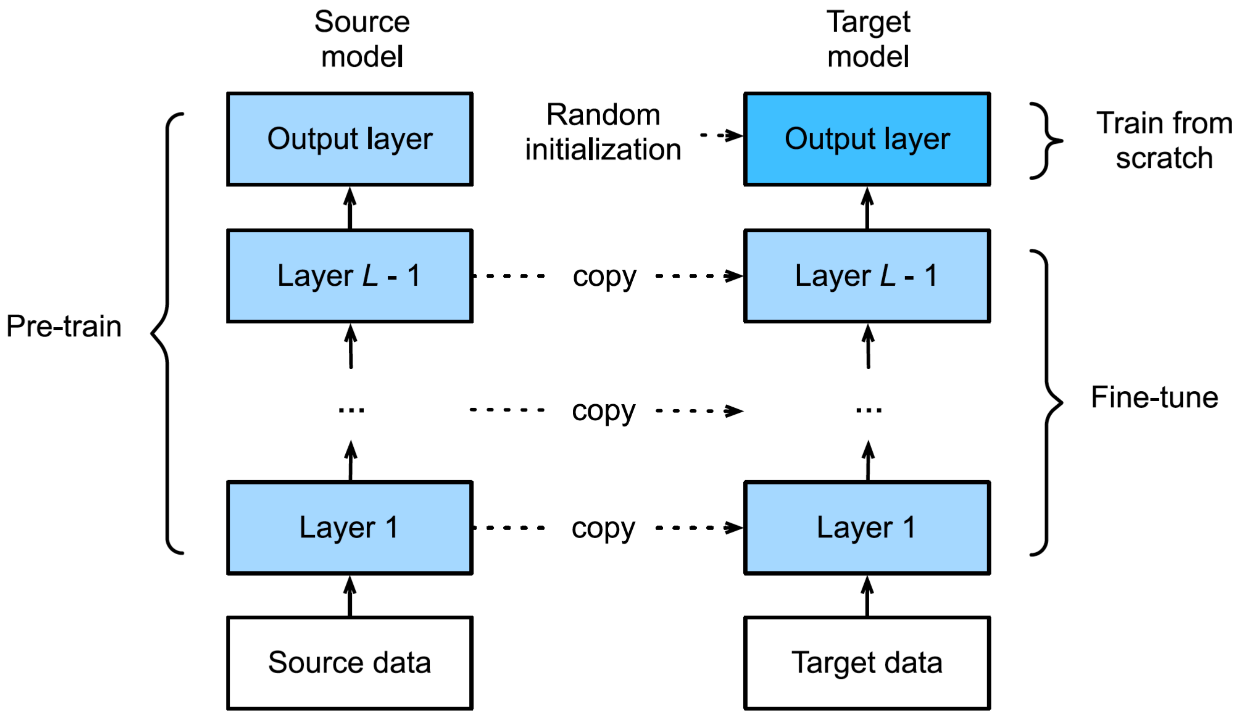

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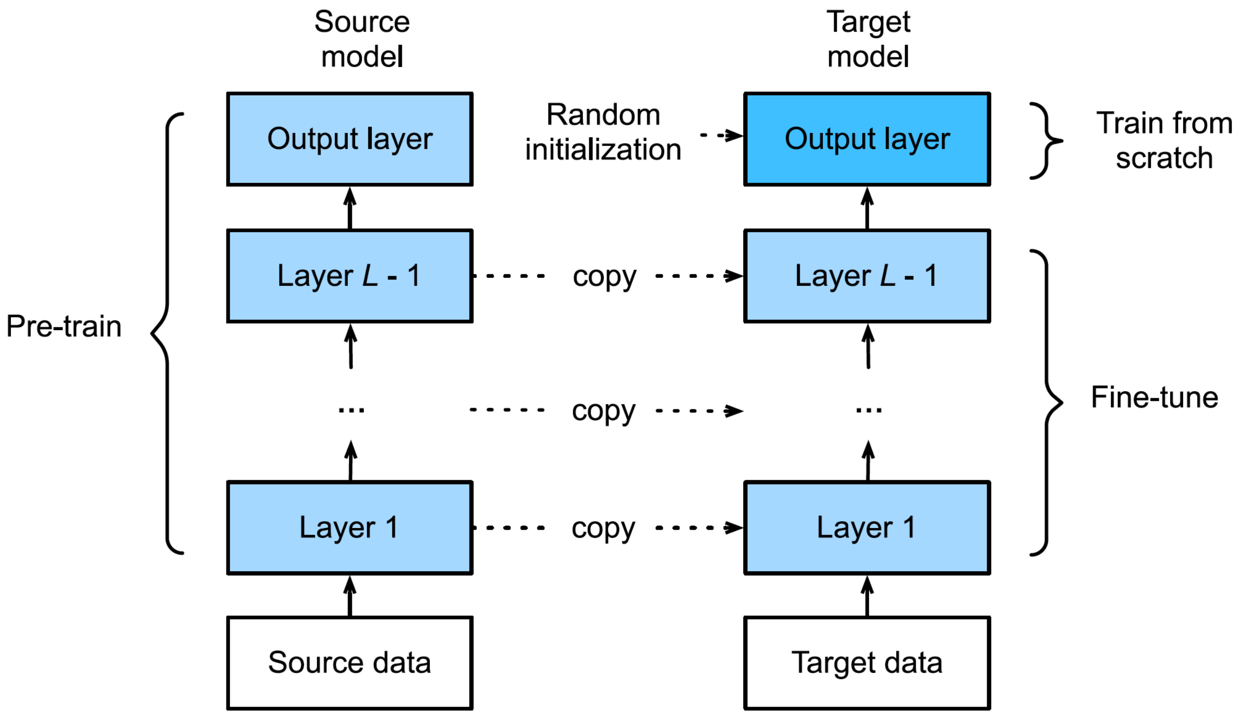

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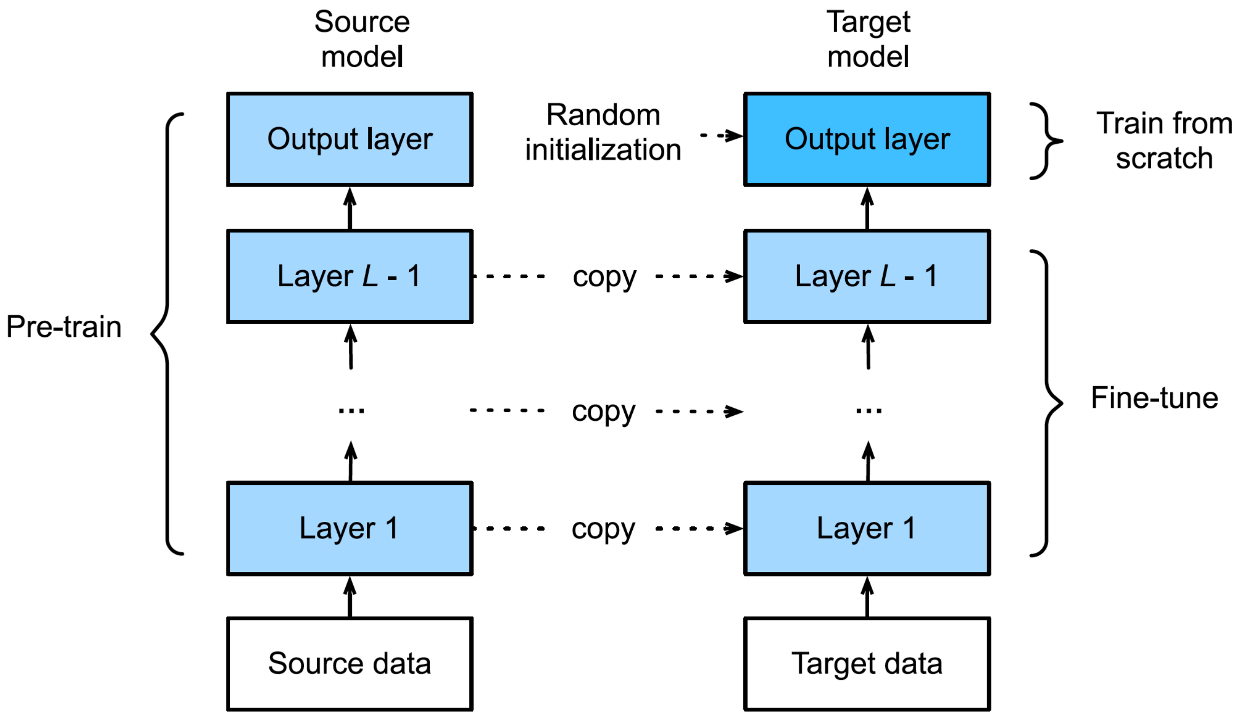

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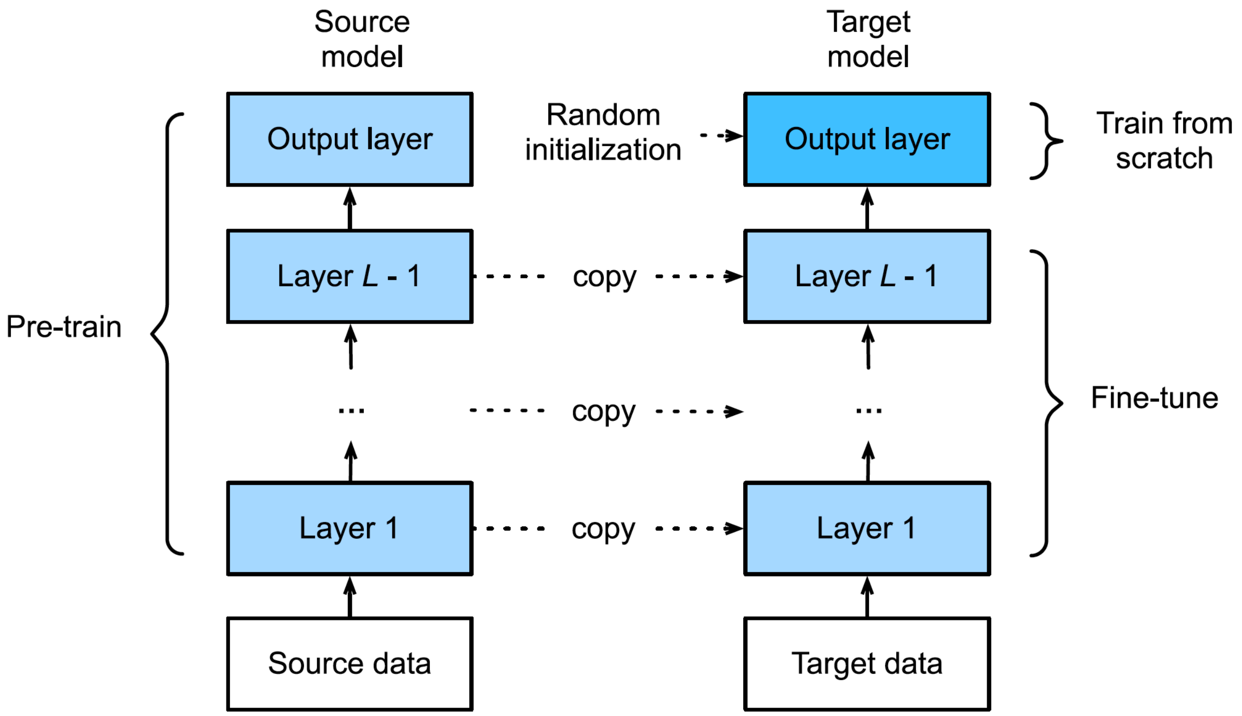
4. Train the target model on a target data set, such as a chair data set.



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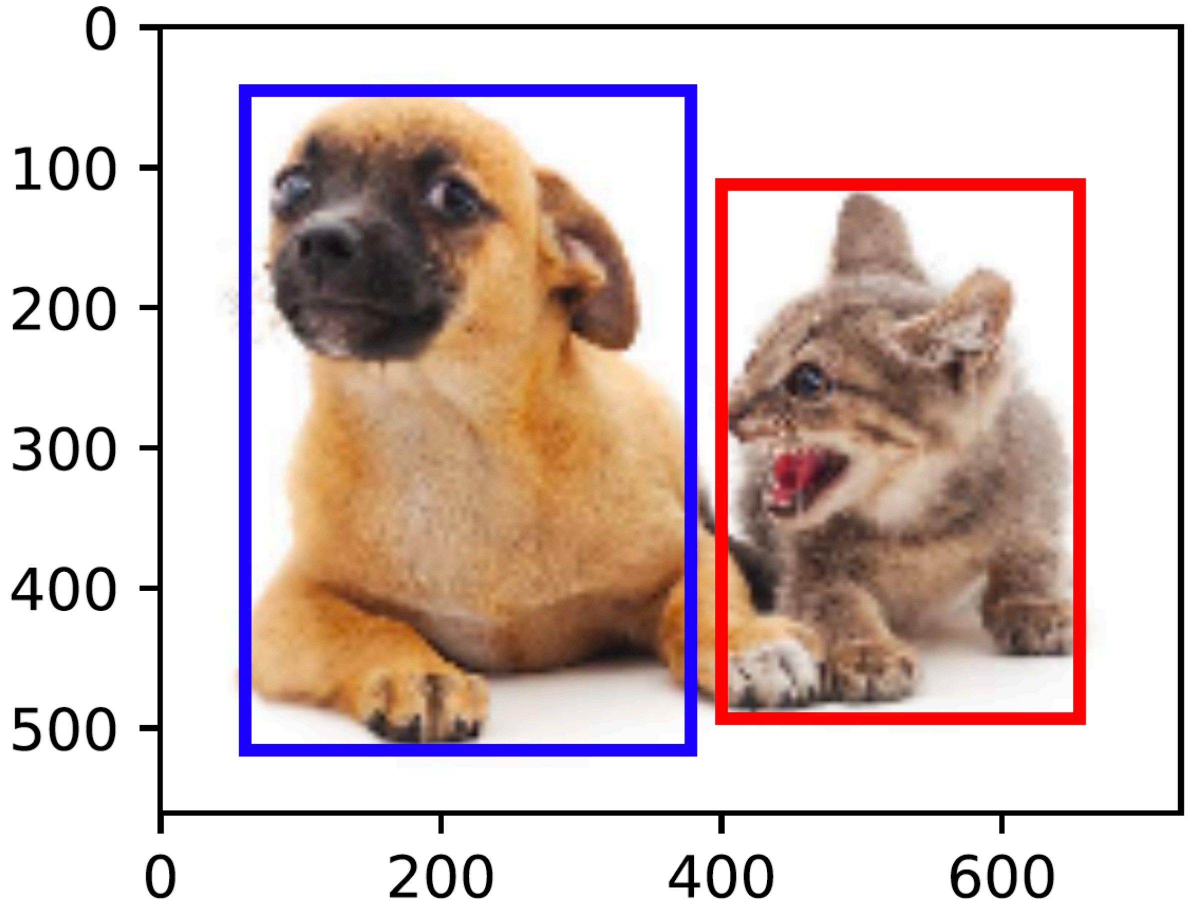
    - Systems in the security field need to detect abnormal targets, such as intruders or bombs.

Bounding Boxes

- In object detection, we usually use a bounding box to describe the target location.



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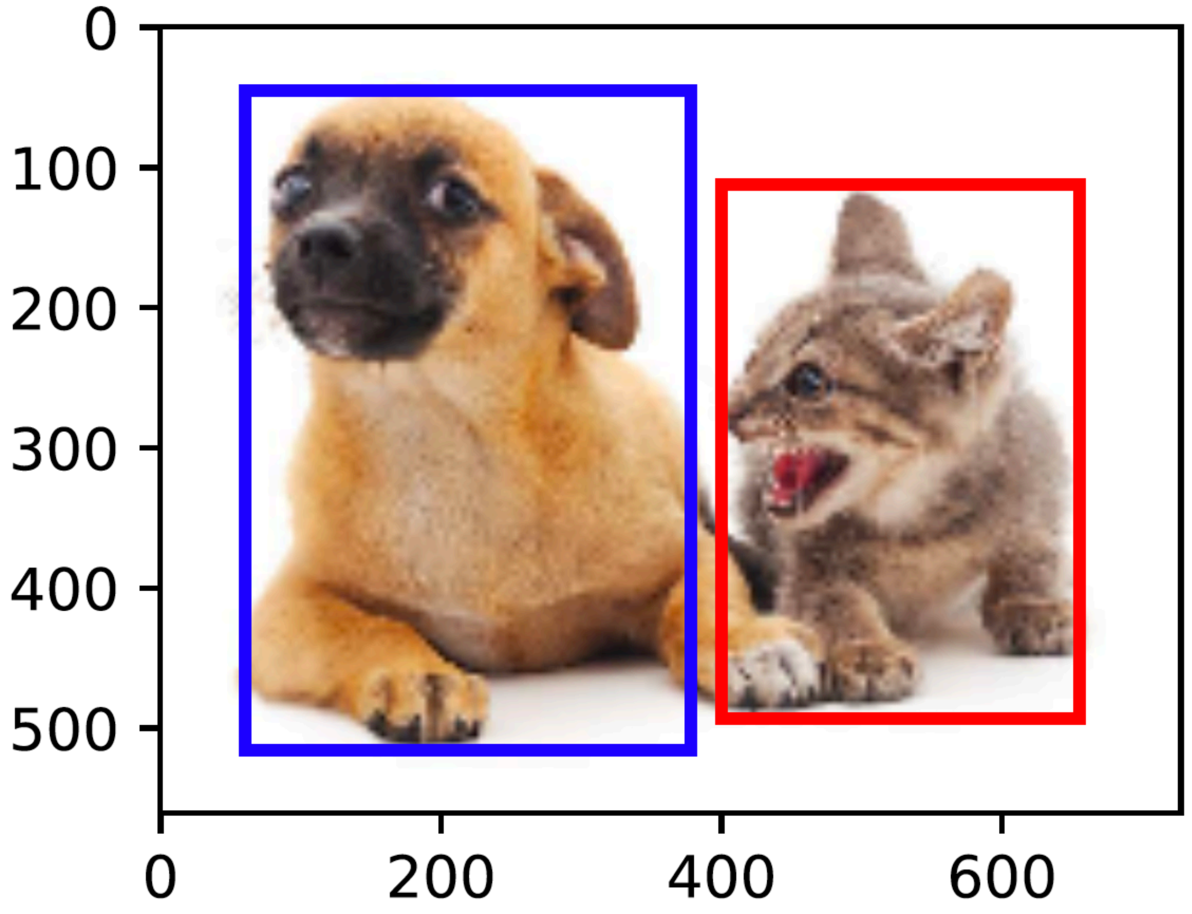

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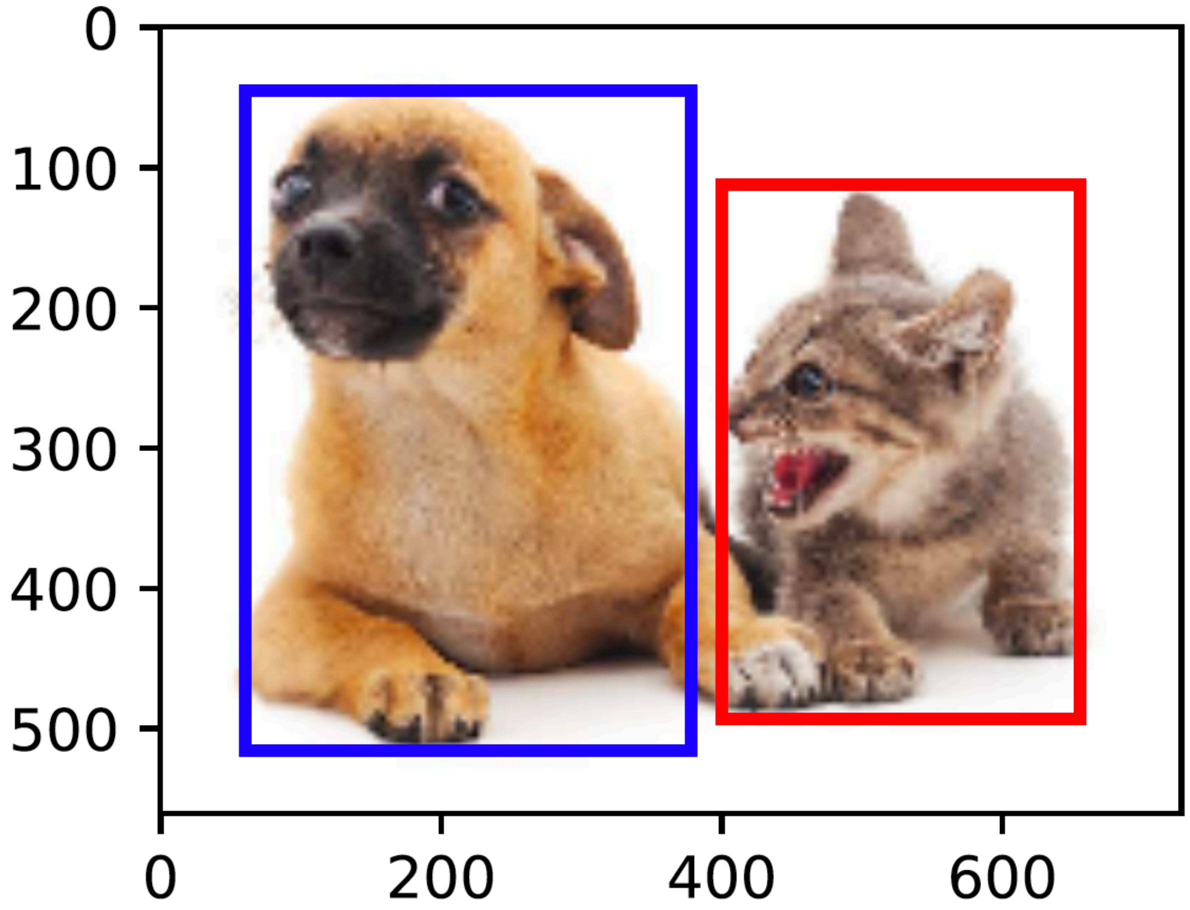

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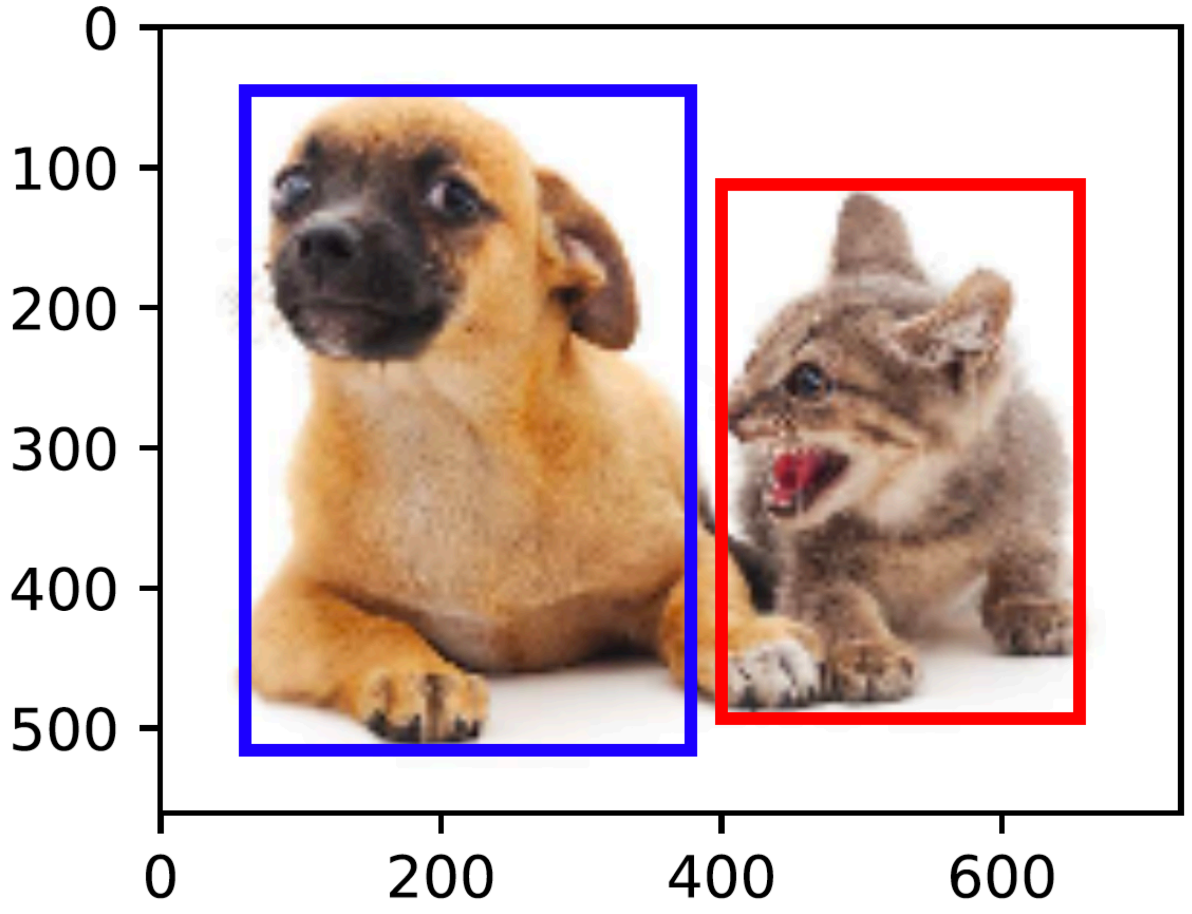


```python
# bbox is the abbreviation for bounding box
dog_bbox, cat_bbox = [60, 45, 378, 516], [400, 112, 655, 493]
```

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- These bounding boxes are called **anchor boxes**.

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- Let's set a set of sizes $s_1, \ldots, s_n$ and a set of aspect ratios $r_1, \ldots, r_m$. If we use a combination of all sizes and aspect ratios with each pixel as the center, the input image will have a total of $whmn$ anchor boxes.

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- Although these anchor boxes may cover all ground-truth bounding boxes, the computational complexity is often excessive.

Generate Multiple Anchor Boxes

- Therefore, we are usually only interested in a combination containing s_1 or r_1 sizes and aspect ratios, that is:

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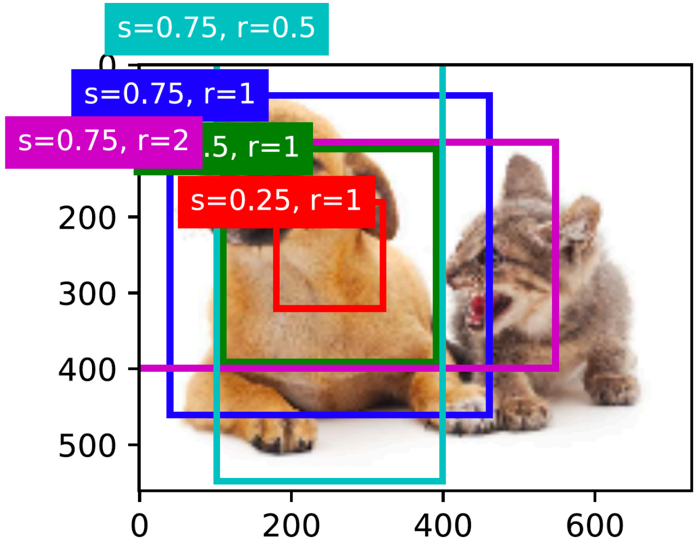
```
Y = contrib.nd.MultiBoxPrior(X, sizes=[0.75, 0.5, 0.25], ratios=[1, 2, 0.5])
```



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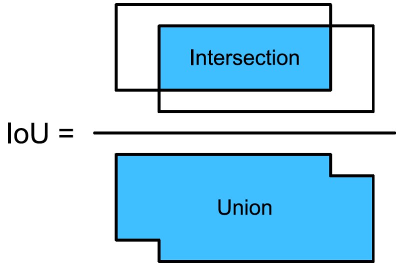

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- So how do we assign ground-truth bounding boxes to anchor boxes similar to them?

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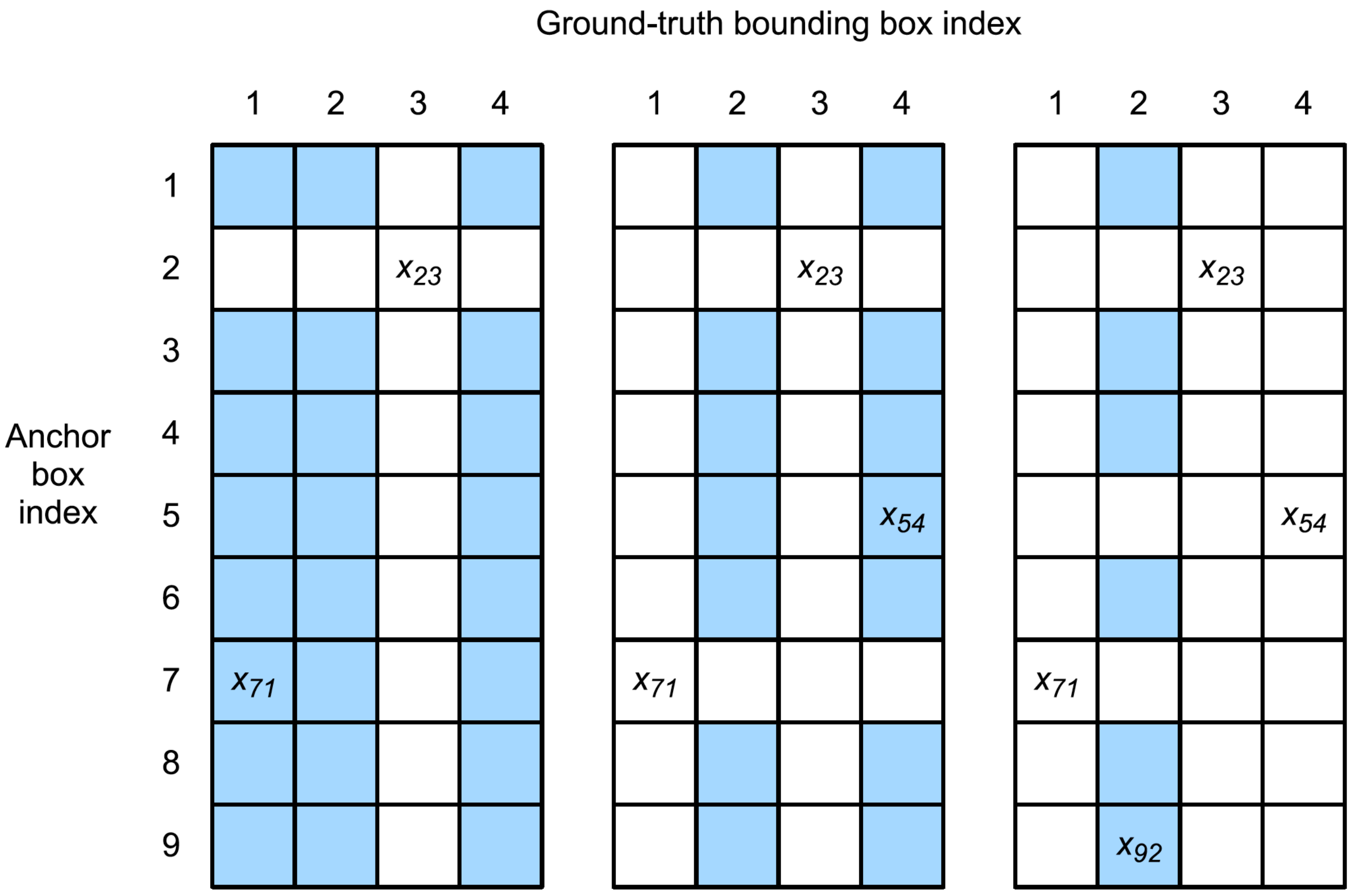

Fig. 14.4.2: Assign ground-truth bounding boxes to anchor boxes.

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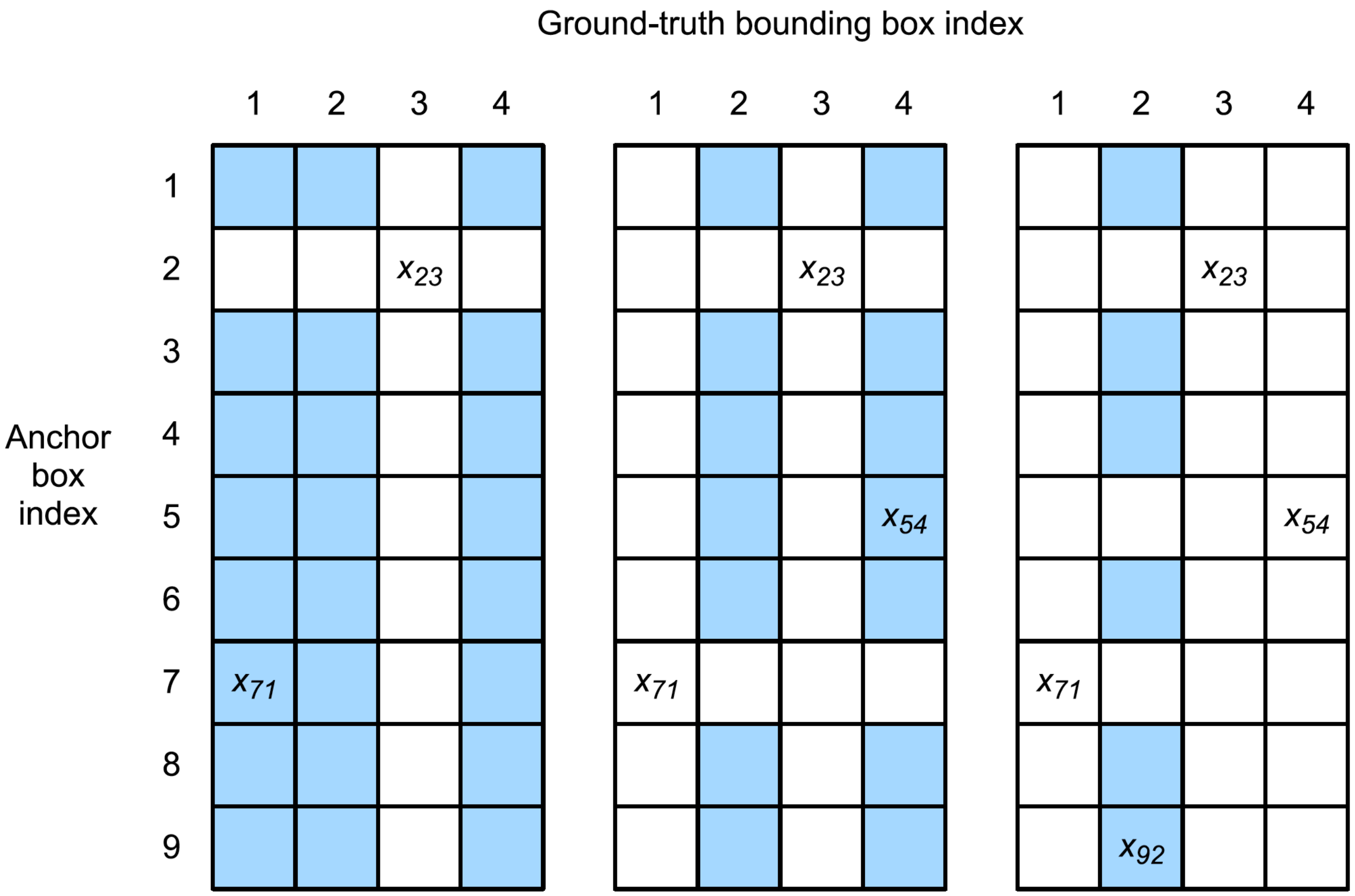
- Assume the anchor boxes in the image are $A_1, \ldots, A_{n_a}$
- And the ground truth bounding boxes are $B_1, \ldots, B_{n_b}$



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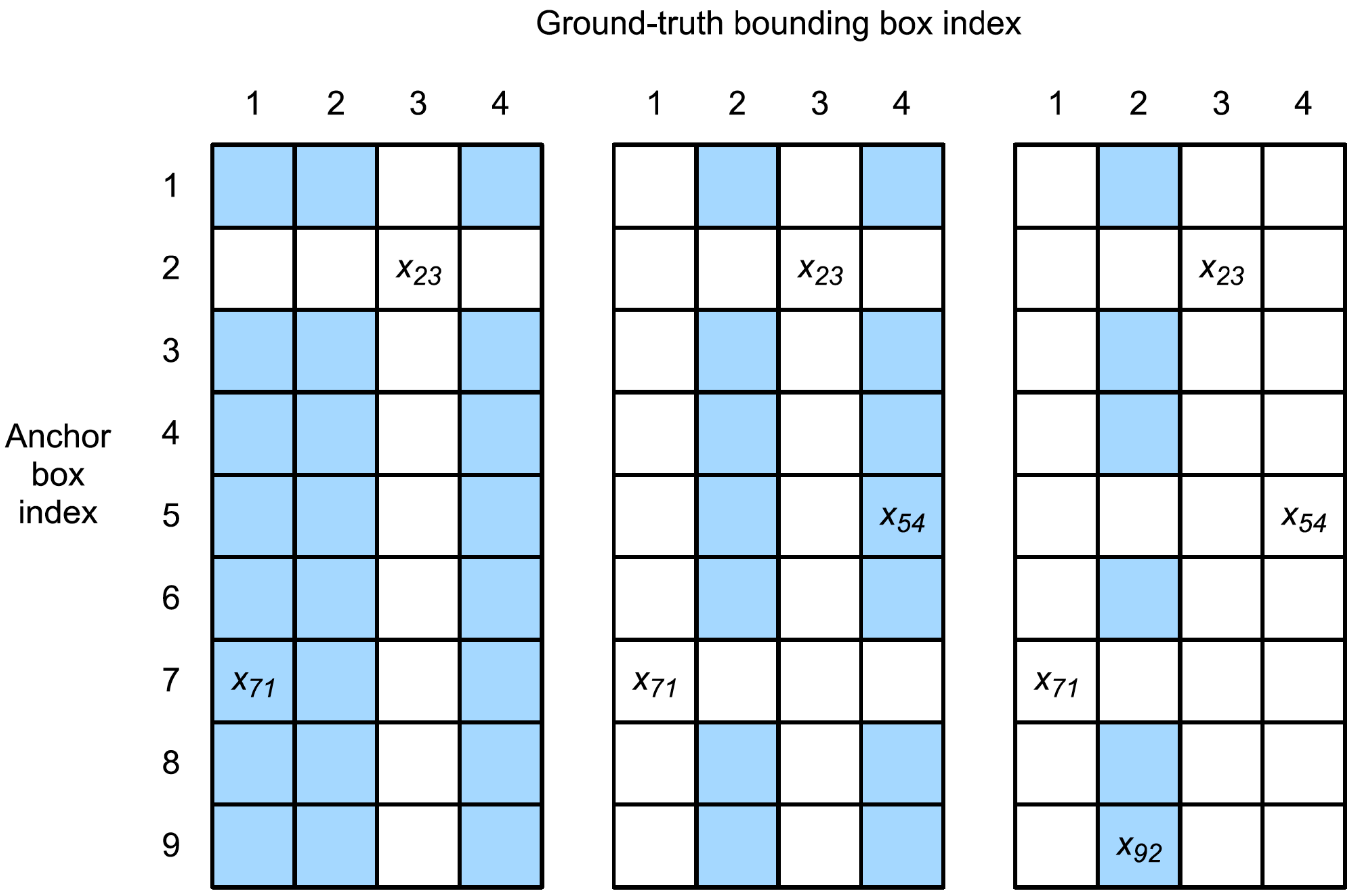

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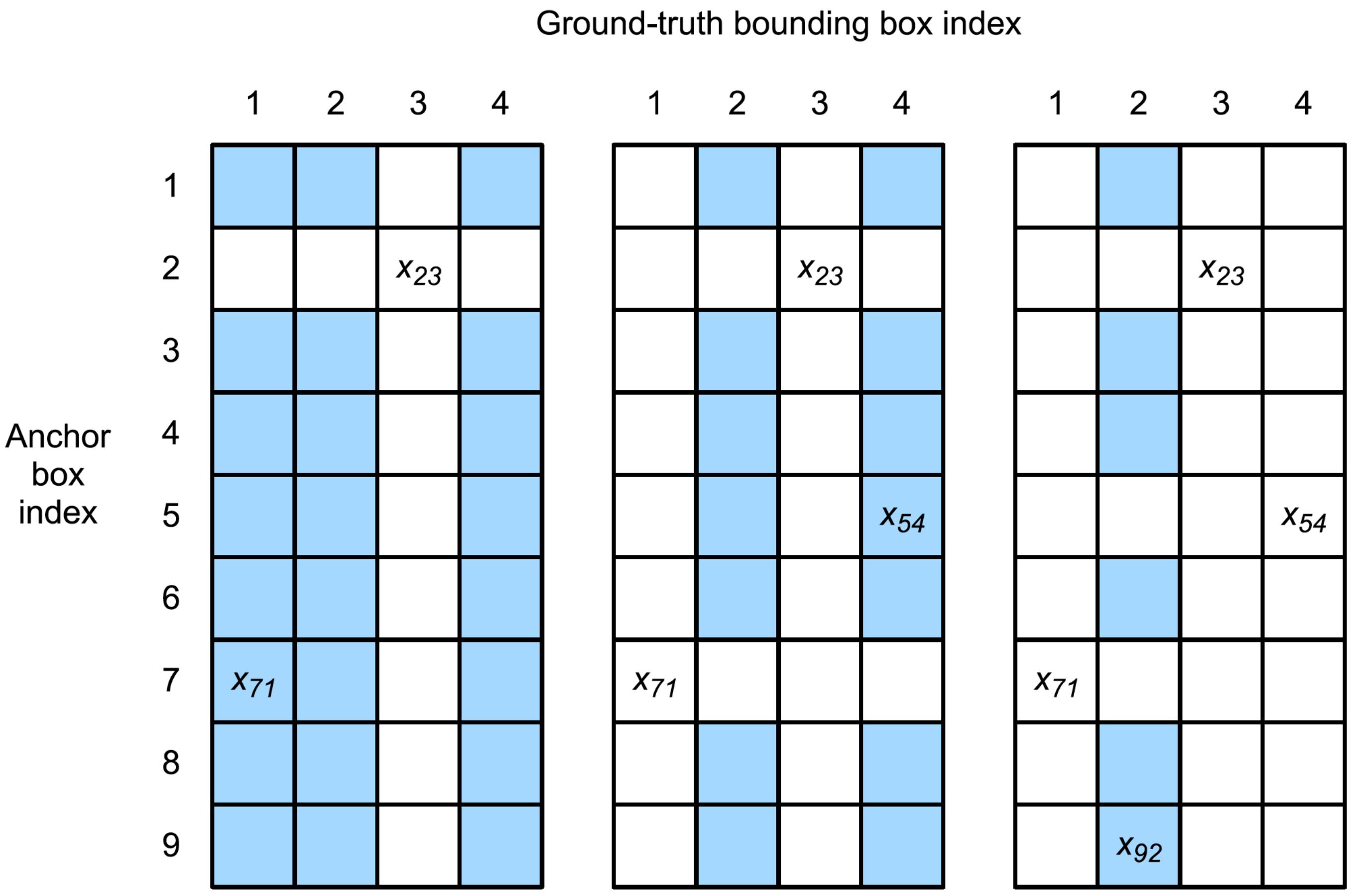

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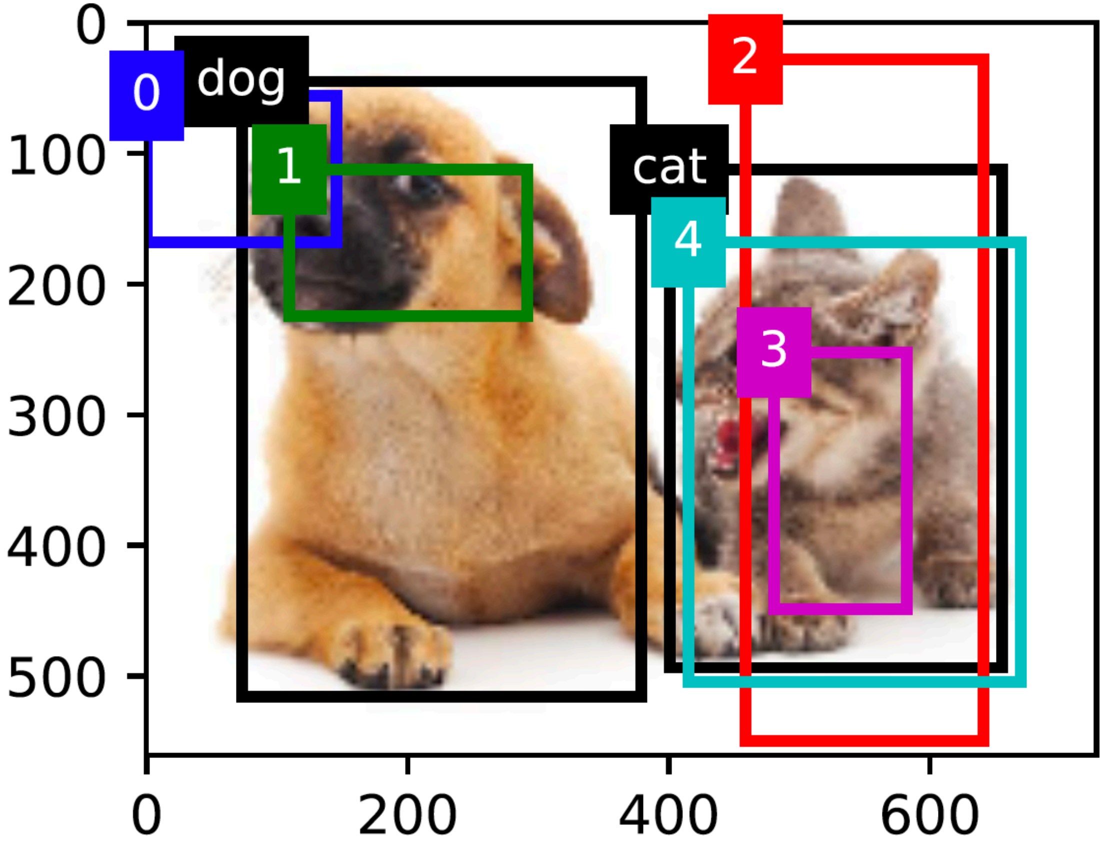
Labeling Training Set Anchor Boxes

1: dog
2: cat



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- A common technique is to label the offset of A as

$$\left(\frac{\frac{x_b - x_a}{w_a} - \mu_x}{\sigma_x}, \frac{\frac{y_b - y_a}{h_a} - \mu_y}{\sigma_y}, \frac{\log \frac{w_b}{w_a} - \mu_w}{\sigma_w}, \frac{\log \frac{h_b}{h_a} - \mu_h}{\sigma_h} \right)$$

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- A commonly used method is called non-maximum suppression (NMS).

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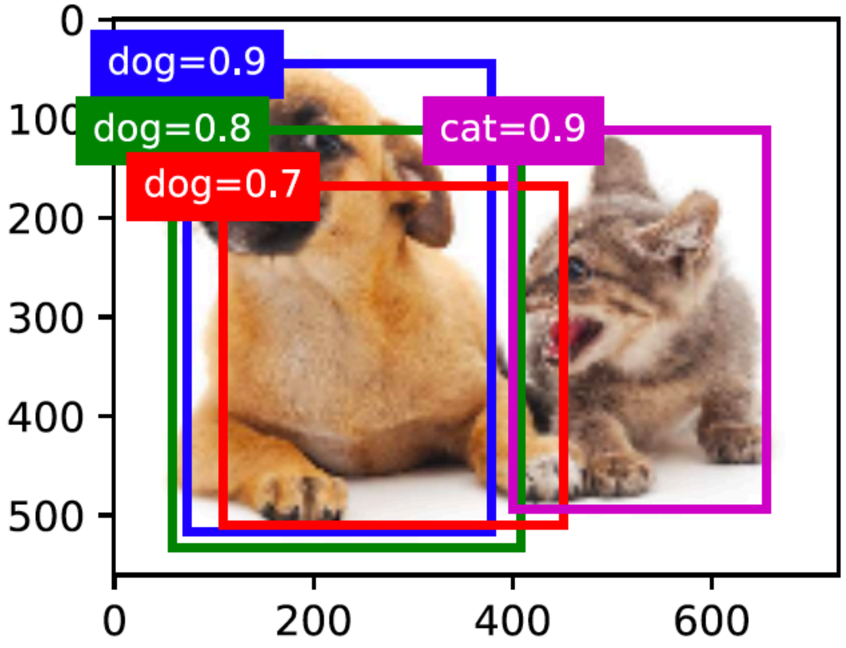
- Finally, output all prediction bounding boxes in the list L

Output Bounding Boxes for Prediction



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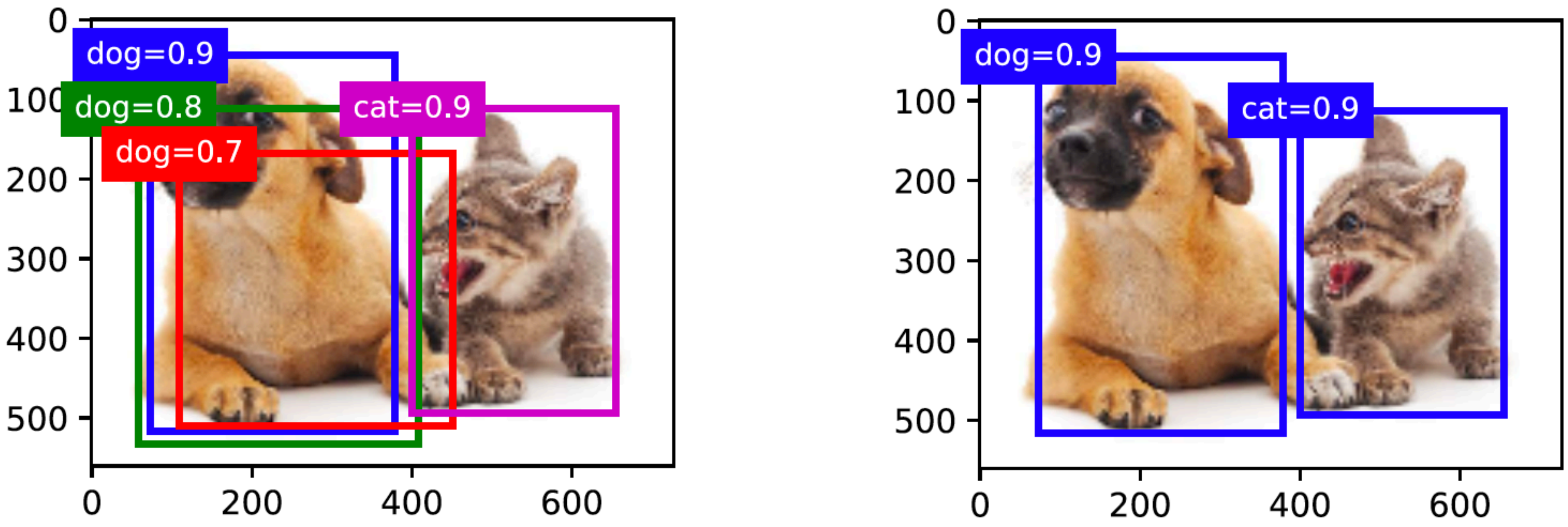

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- It is not difficult to reduce the number of anchor boxes.
- We can apply uniform sampling on a small portion of pixels from the input image and generate anchor boxes centered on the samples pixels.

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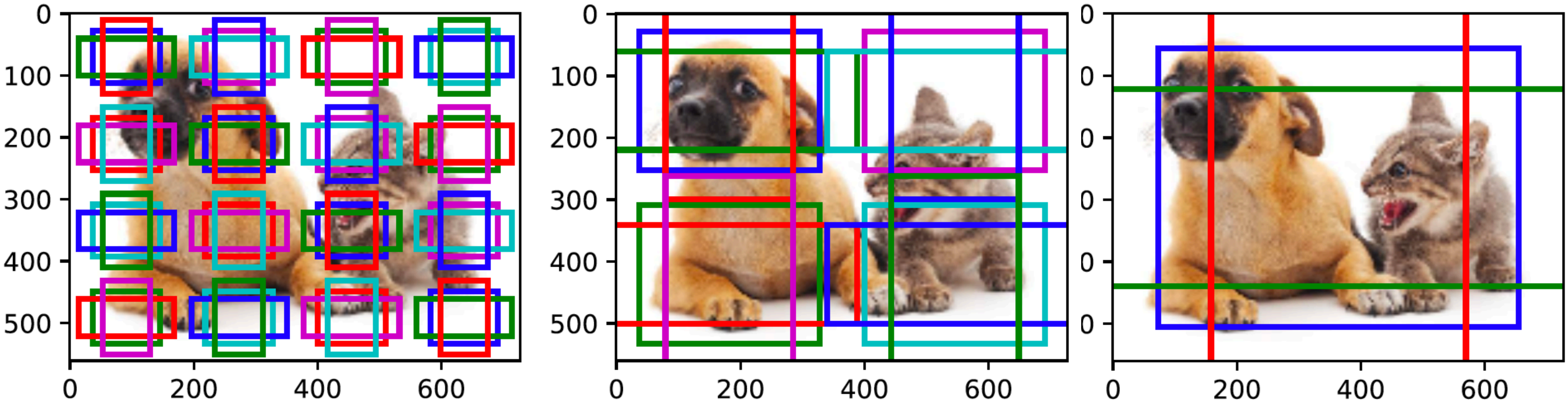
  - Each of these objects 4, 2, and 1 possible positions on an image
- Therefore, when using smaller anchor boxes to detect smaller objects, we can sample more regions; when using larger anchor boxes to detect larger objects, we cam sample fewer regions.

Multiscale object detection



Object Detection Data Set (Pikachu)

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- This quick and easy model is already widely used.
- Some of the design concepts and implementation details of this model are also applicable to other object detection models.

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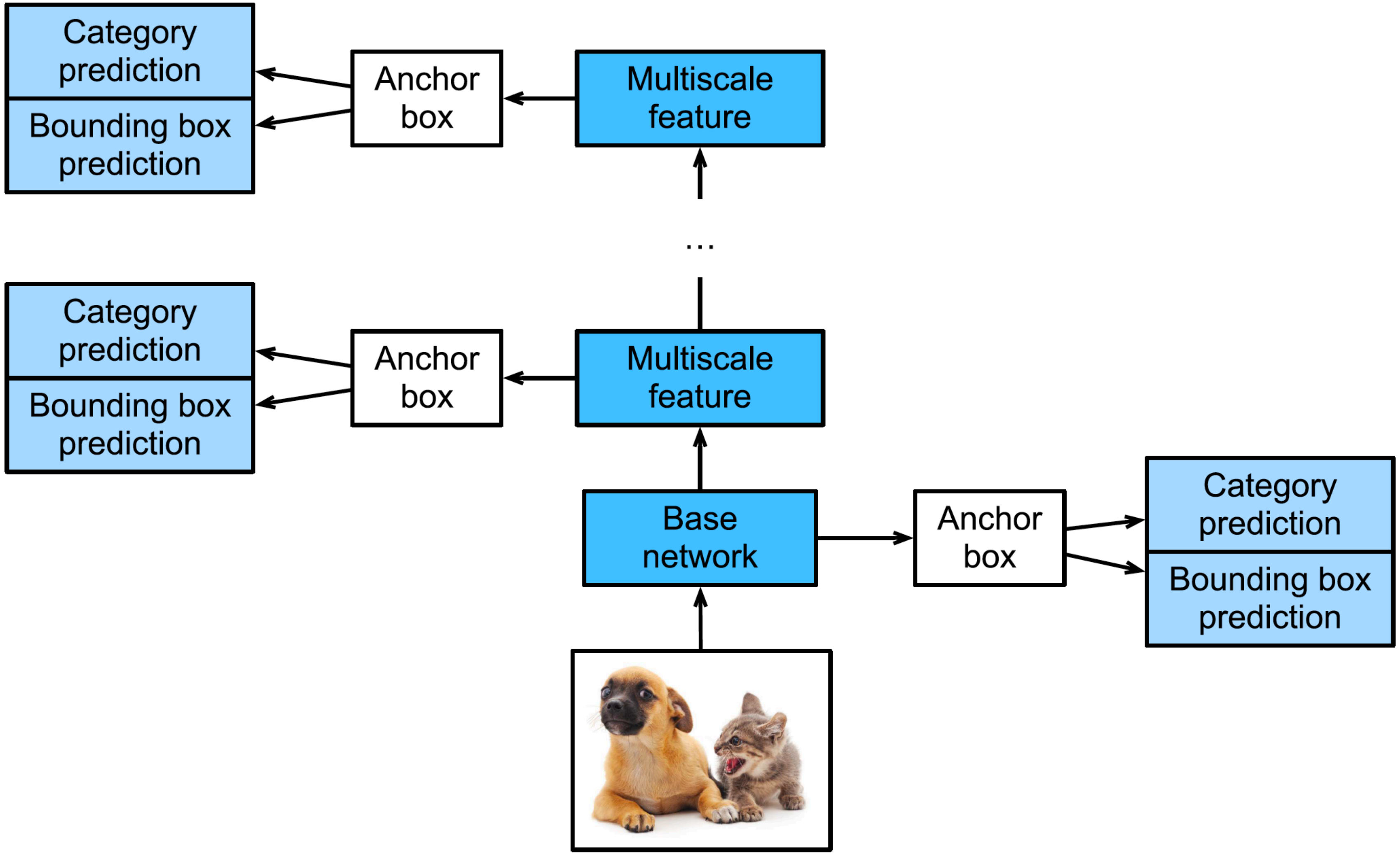

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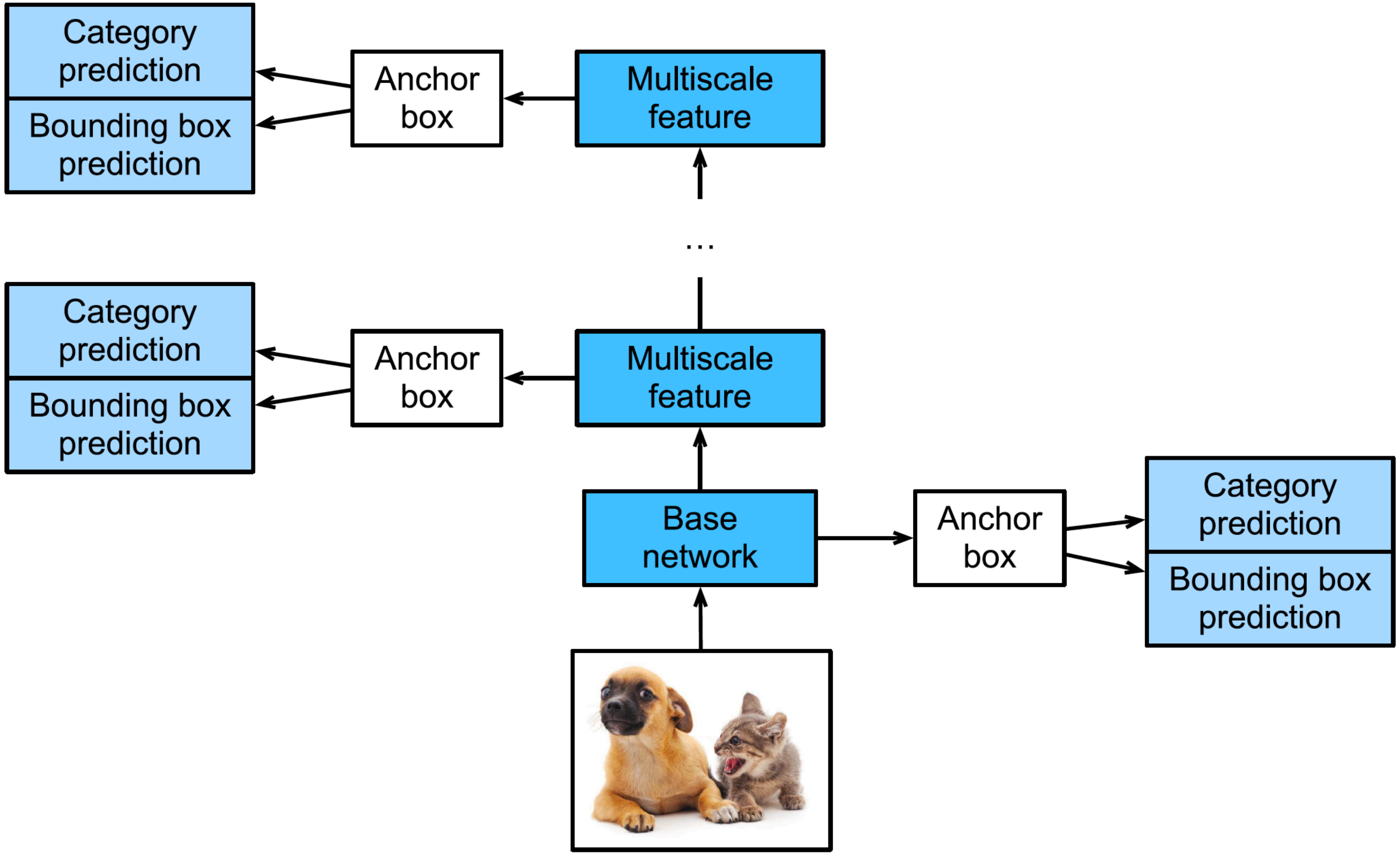

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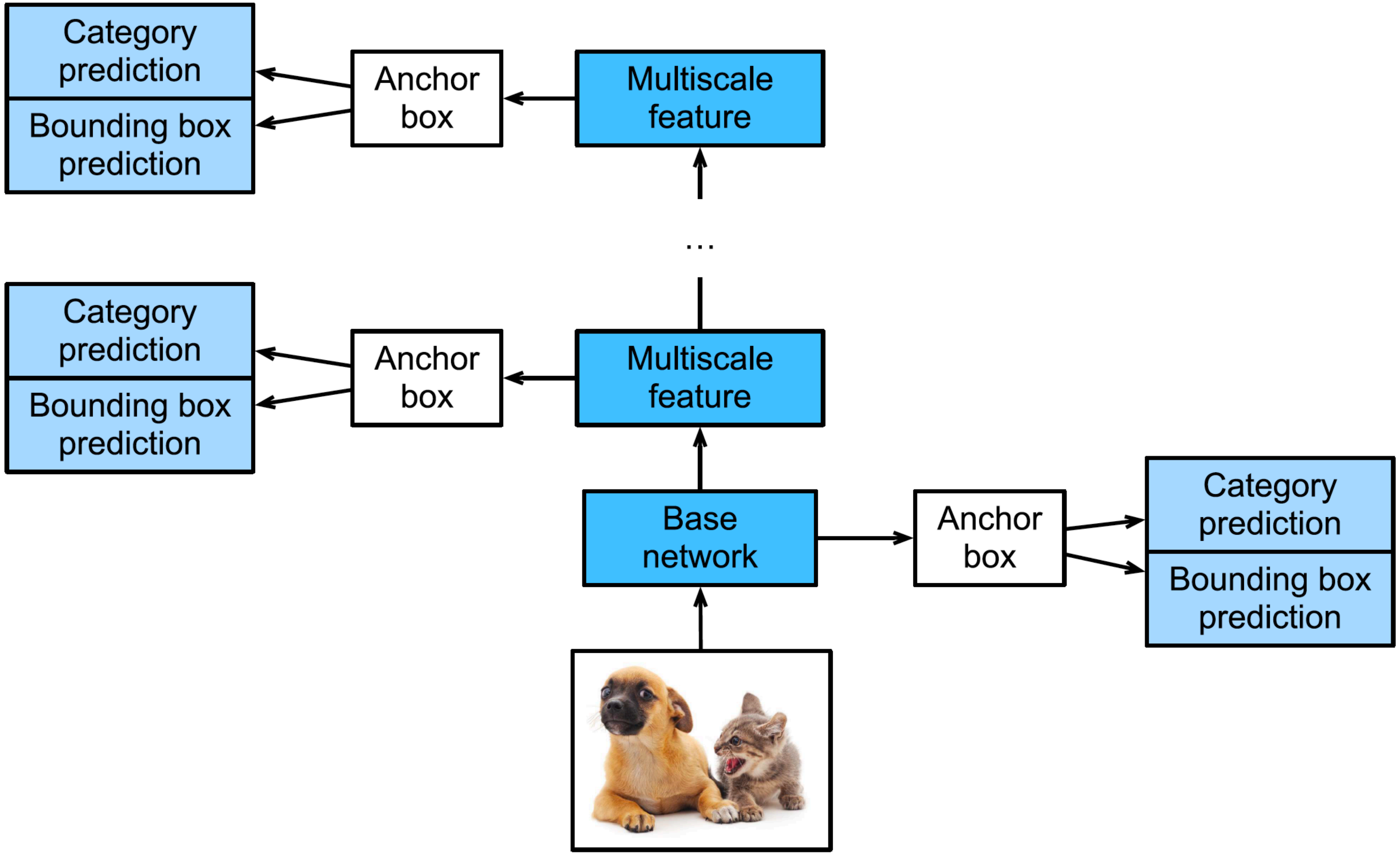

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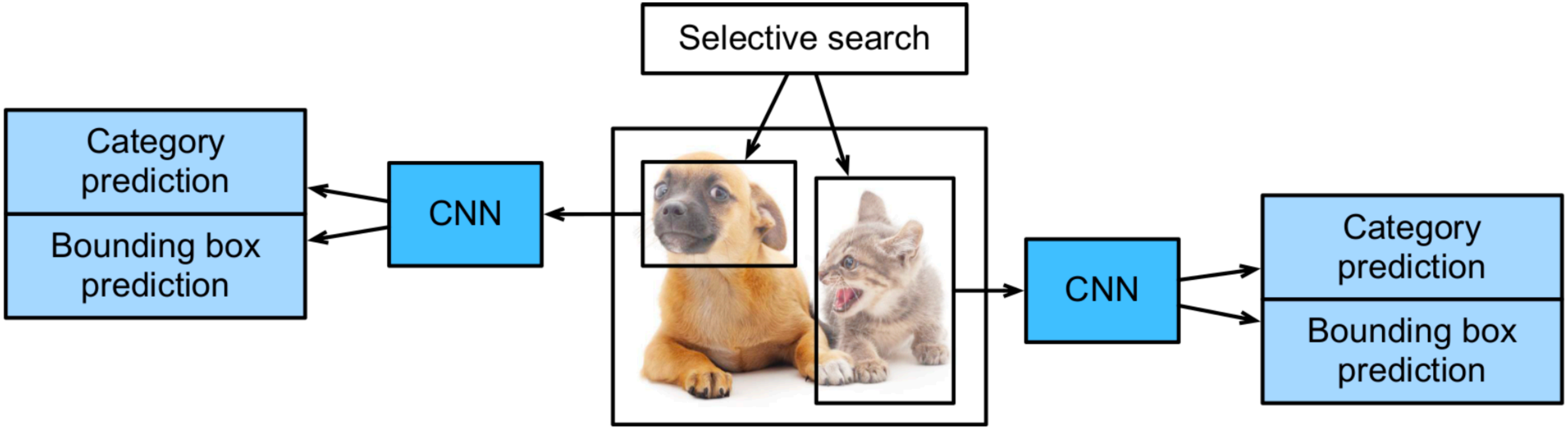
- As the SSD generates different numbers of anchor boxes of different sizes based on the base network block and each multiscale feature block and then predicts the categories and offsets (i.e., predicted bounding boxes) of the anchor boxes in order to detect objects of different sizes, SSD is a multiscale object detection model.

Region-based CNNs (R-CNNs)

- R-CNN models first select several proposed regions from an image (for example, anchor boxes are one type of selection method) and then label their categories and bounding boxes (e.g., offsets).



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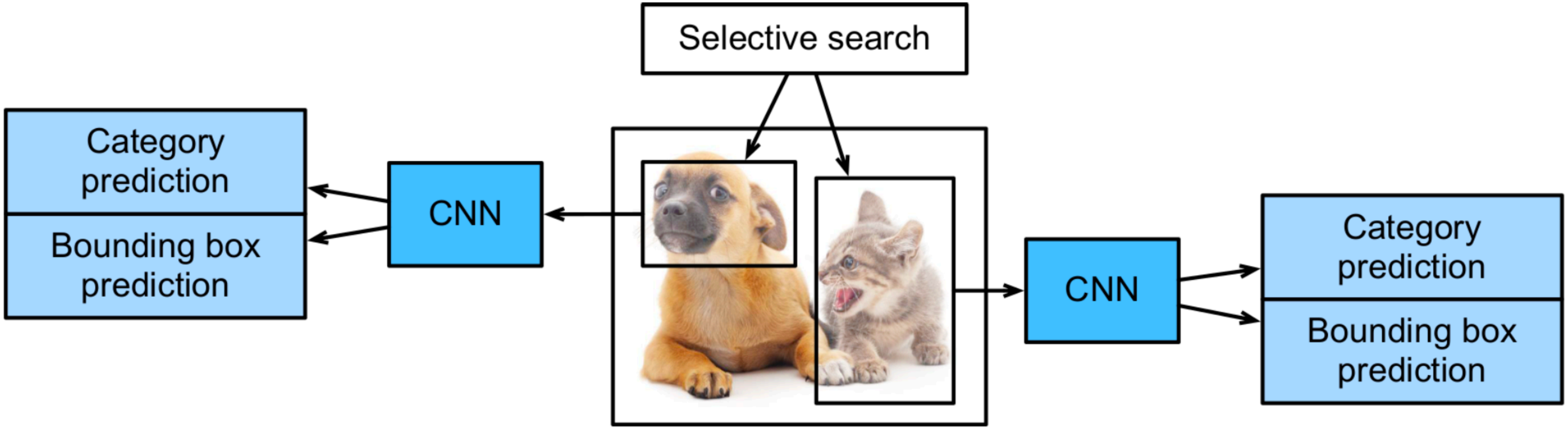

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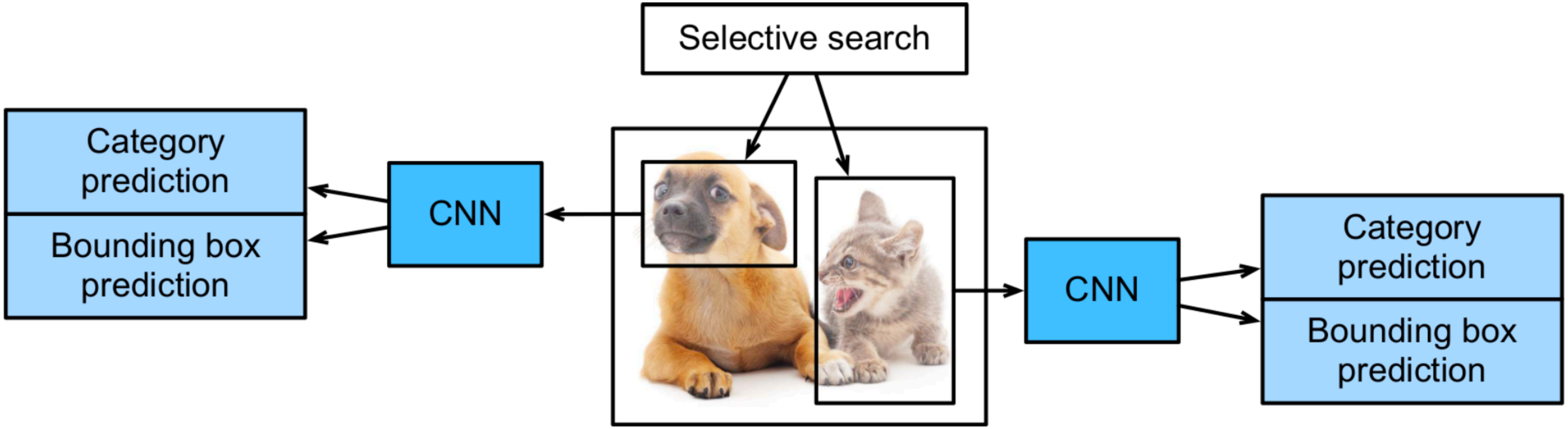
- Afterwards, we use the features of each proposed region to predict their categories and bounding boxes.



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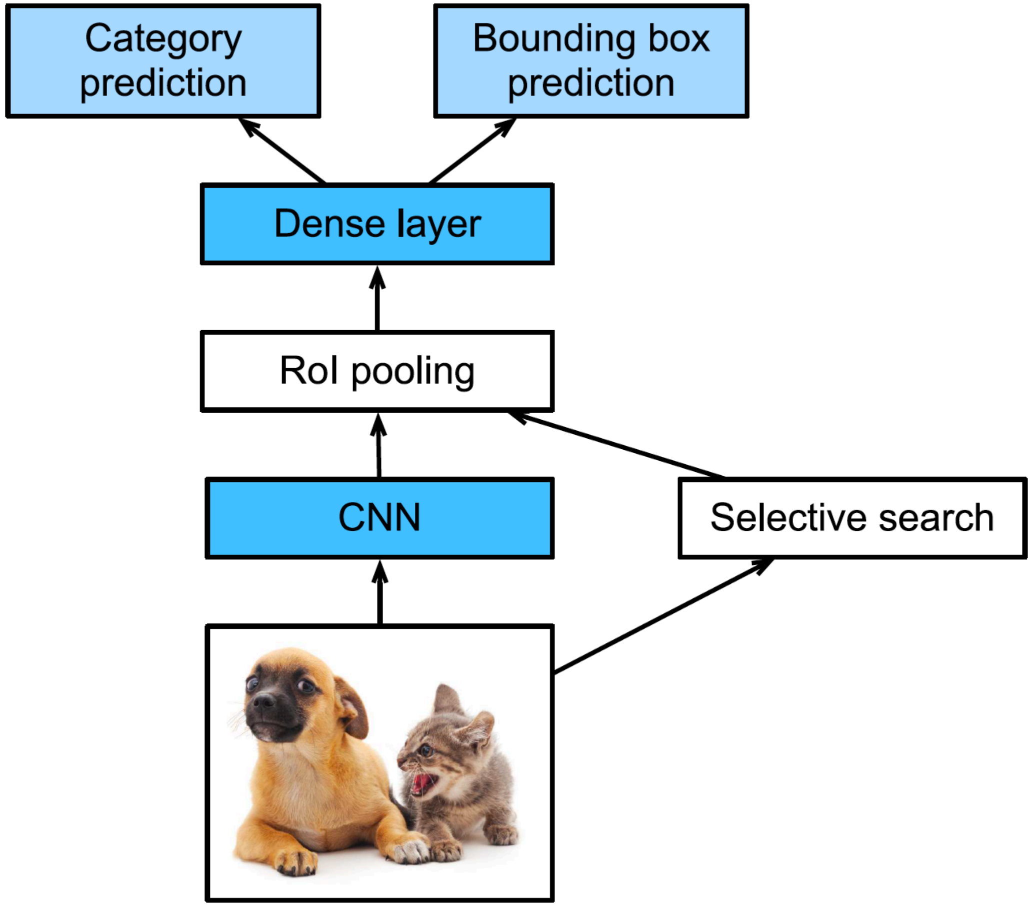
    3. The features and labeled category of each proposed region are combined as an example to train multiple support vector machines for object classification. Here, each support vector machine is used to determine whether an example belongs to a certain category.

Fast R-CNN

- The main downside of R-CNN is the slow speed.



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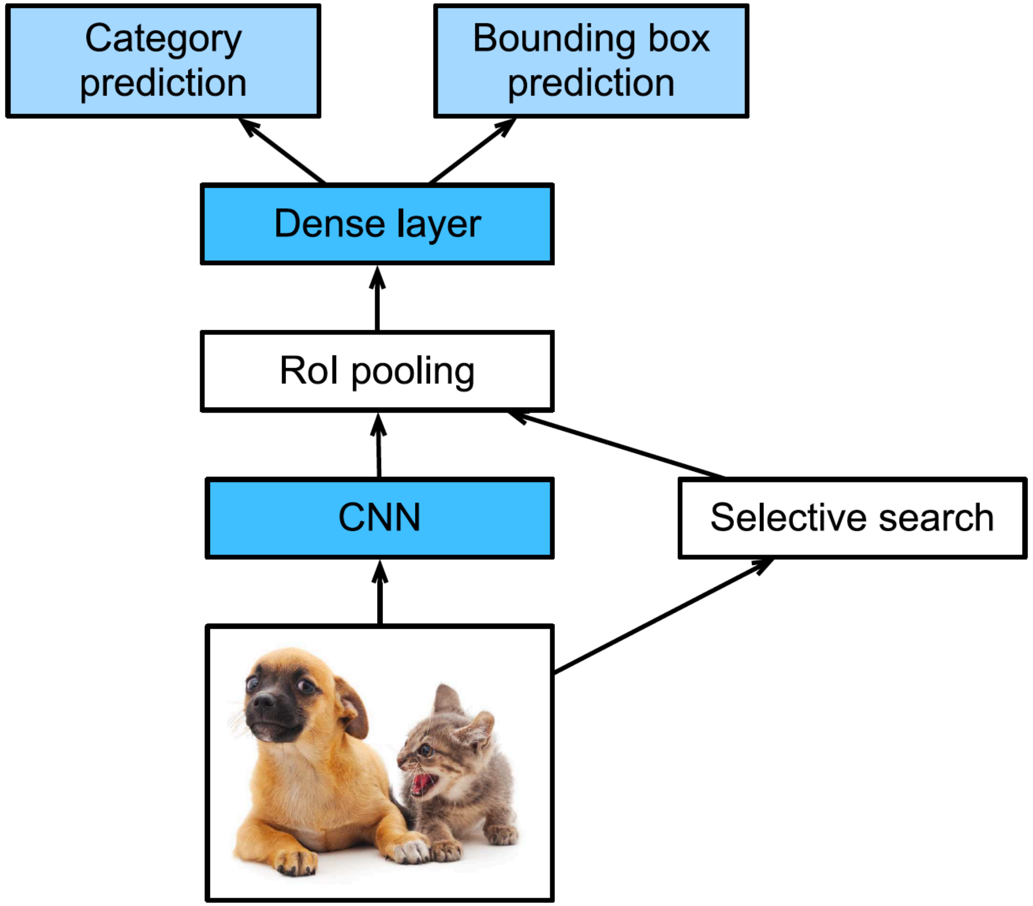

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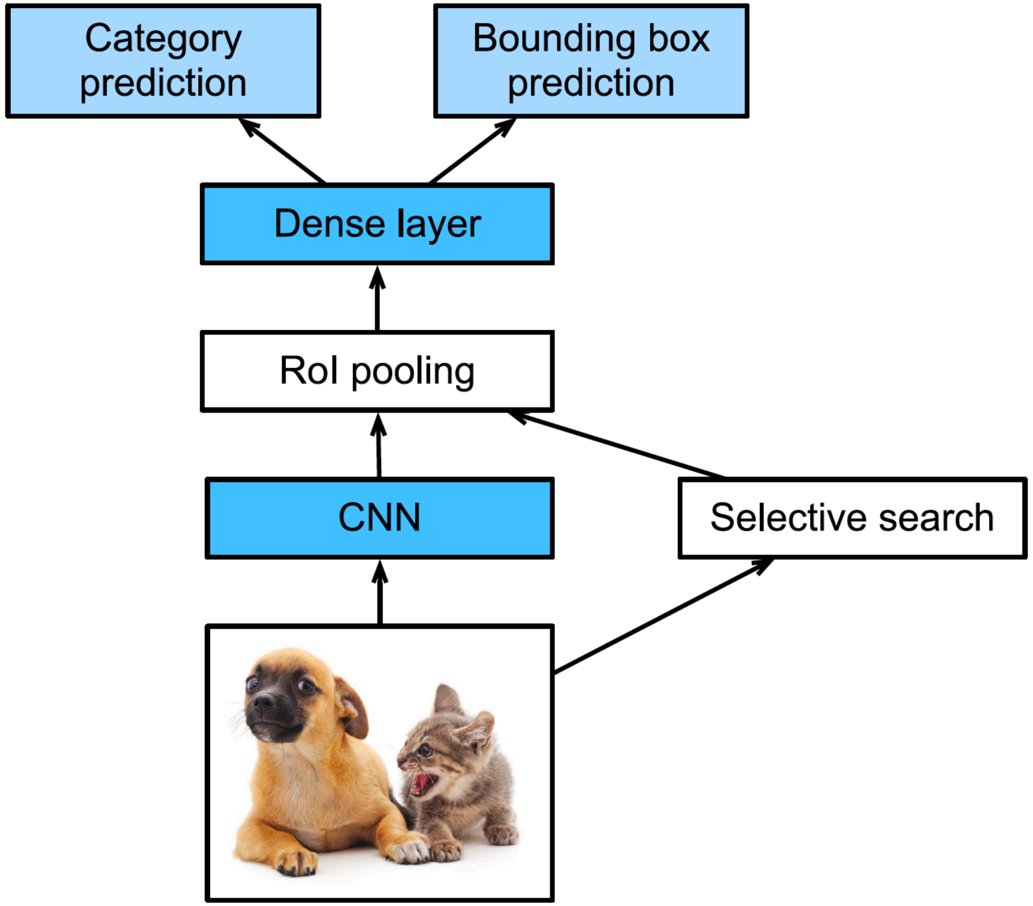

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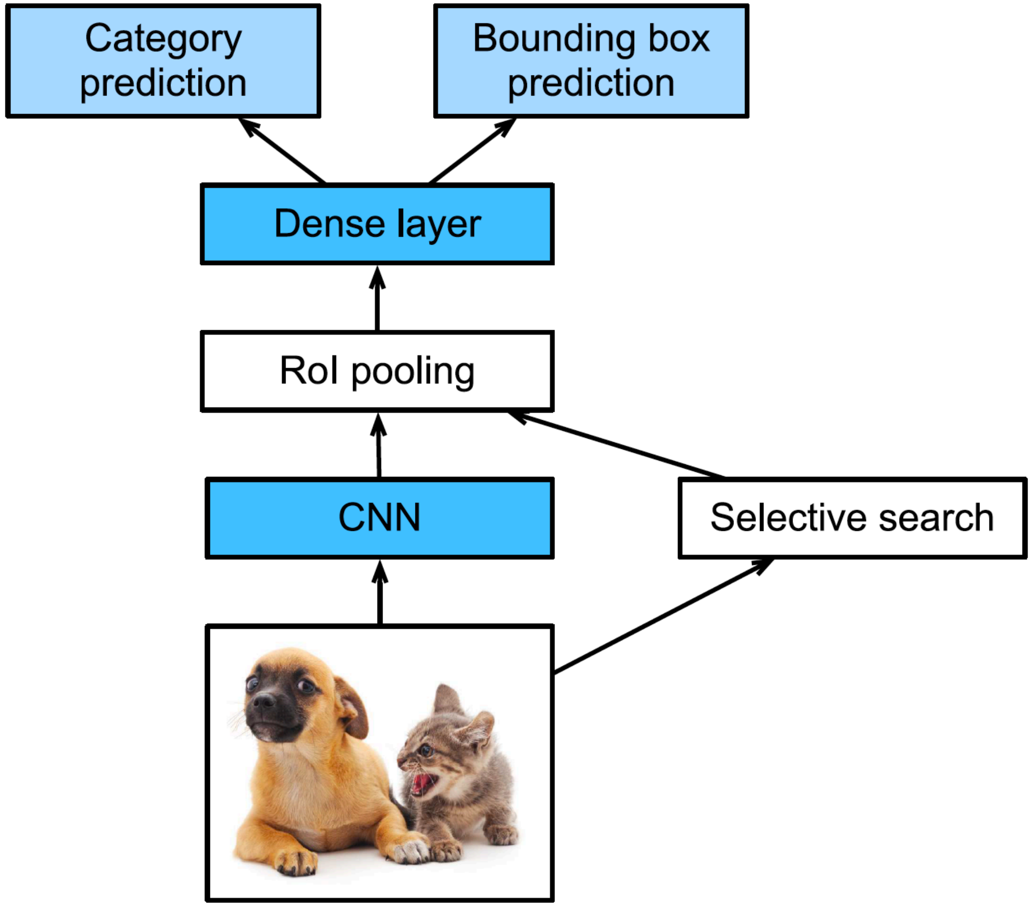
- Fast R-CNN improves on the R-CNN by only performing CNN forward computation on the image as a whole.



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  4. A fully connected layer is used to transform the output shape to n x d, where d is determined by the model design.
  5. During category prediction, the shape of the fully connected layer output is again transformed to n x q and we use softmax regression (q is the number of categories). During bounding box prediction, the shape of the fully connected layer output is again transformed to n x 4.

Faster R-CNN

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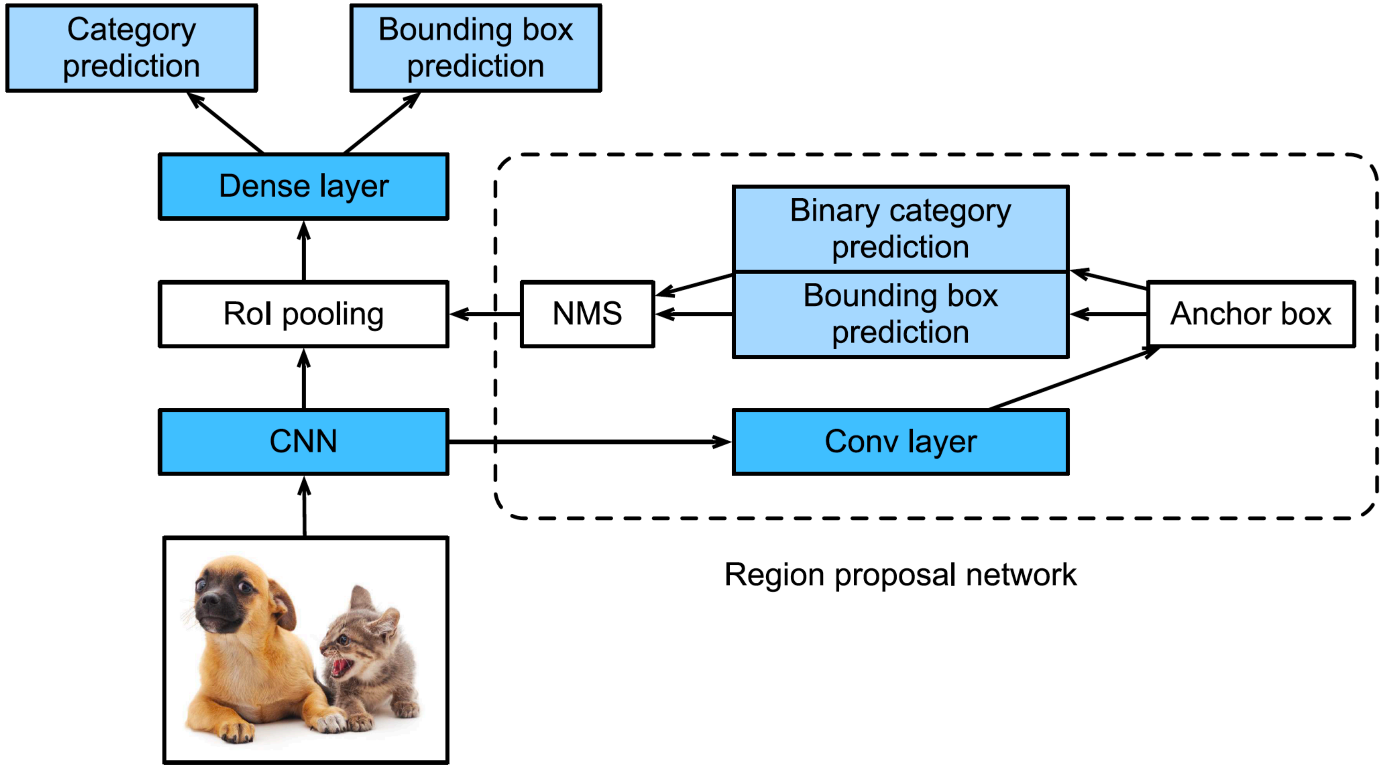

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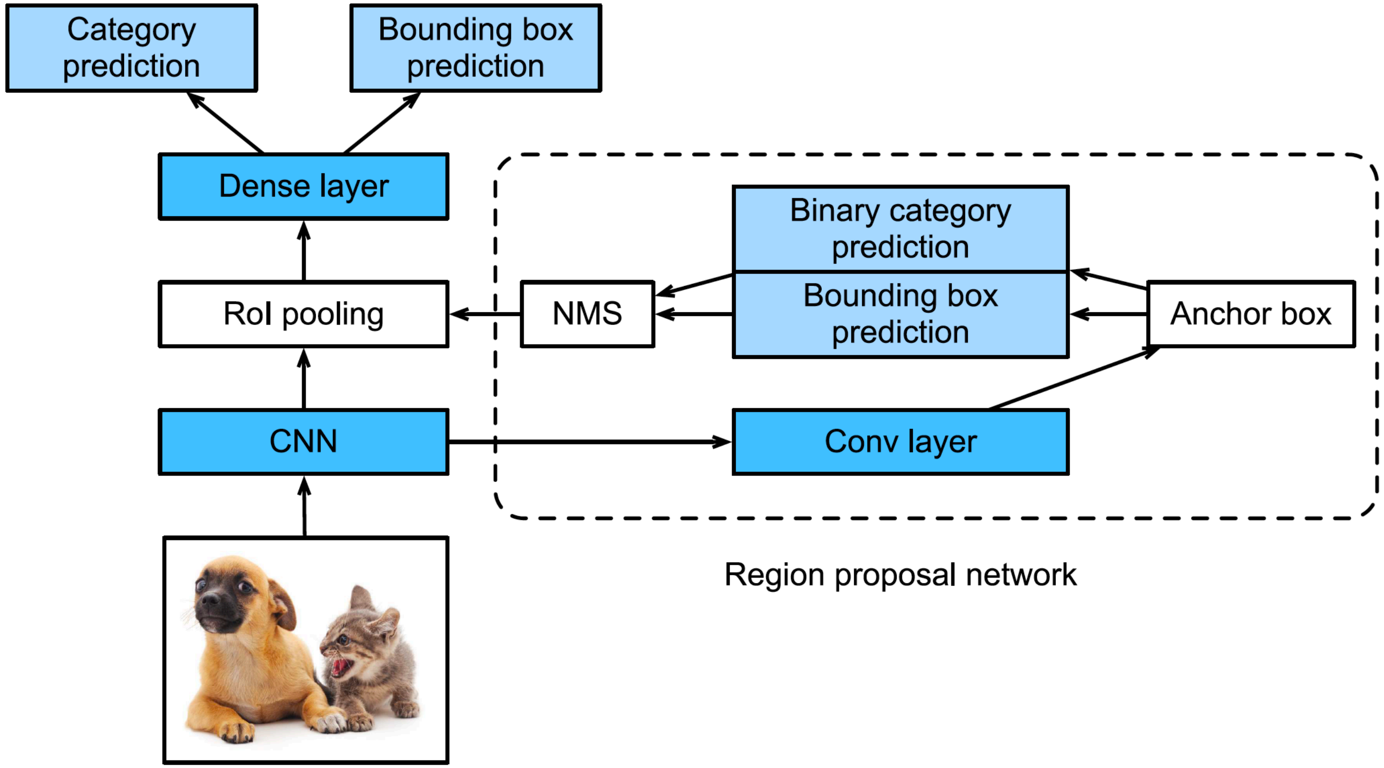

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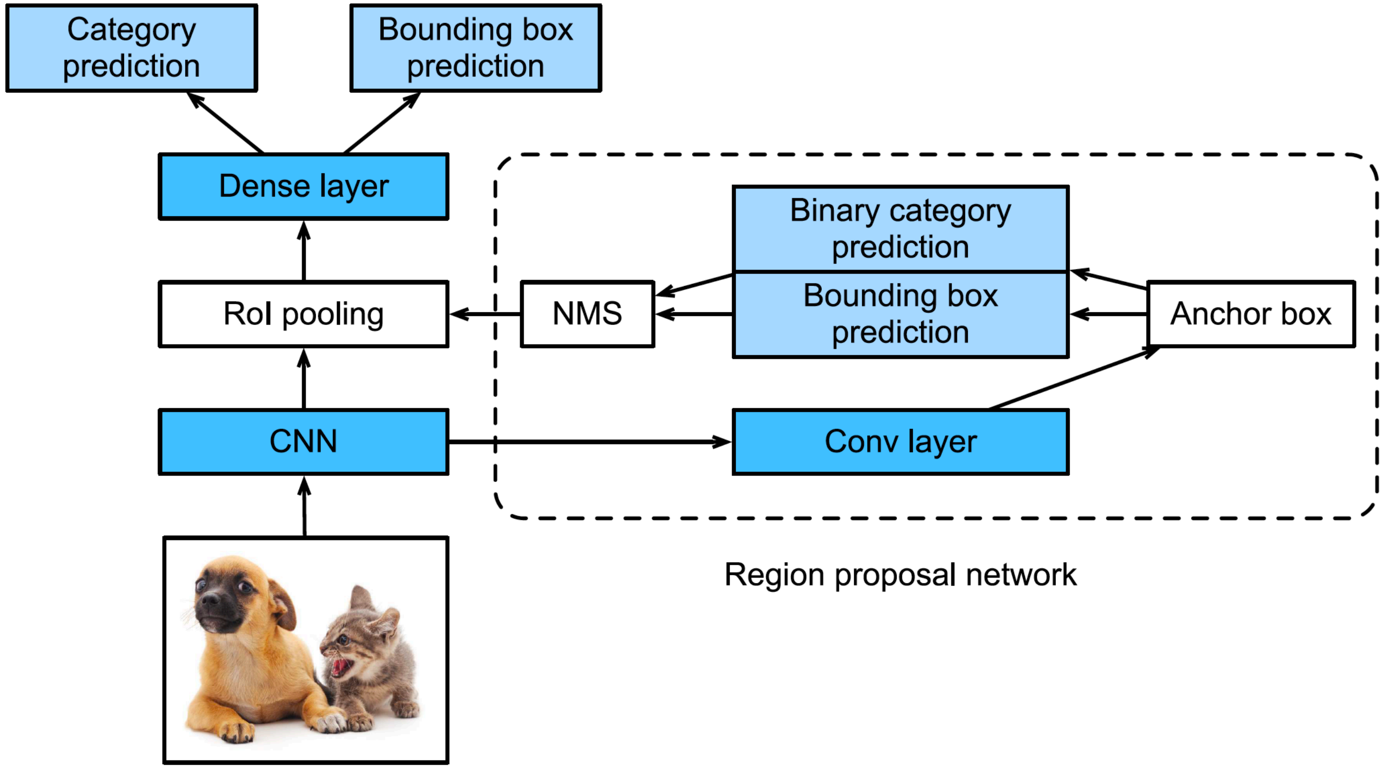
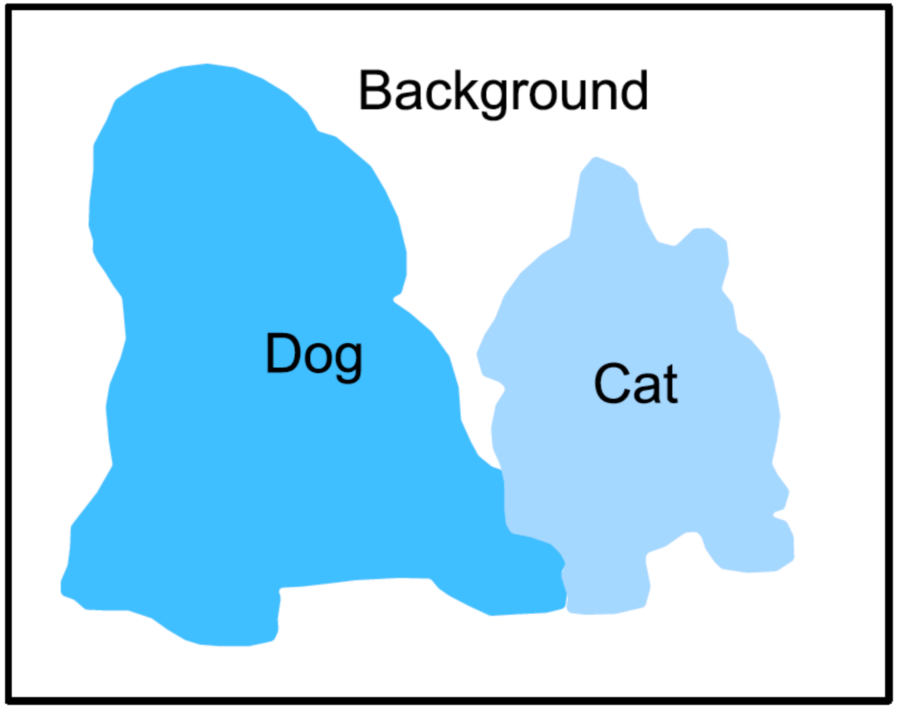
- Faster R-CNN replaces selective search with a region proposal network.
- This reduces the number of proposed regions generated, while ensuring precise object detection.



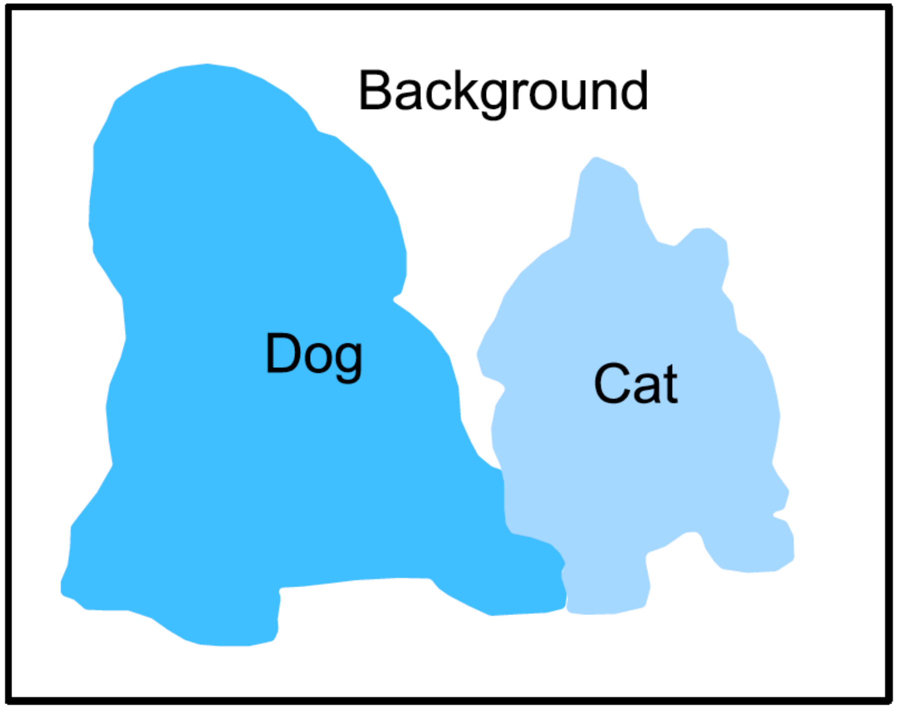
Semantic Segmentation

- So far, we only used rectangular bounding boxes to label and predict objects in images.



Semantic Segmentation and Data Sets

- So far, we only used rectangular bounding boxes to label and predict objects in images.
- Now, we will look at semantic segmentation, which attempts to segment images into regions with different semantic categories.



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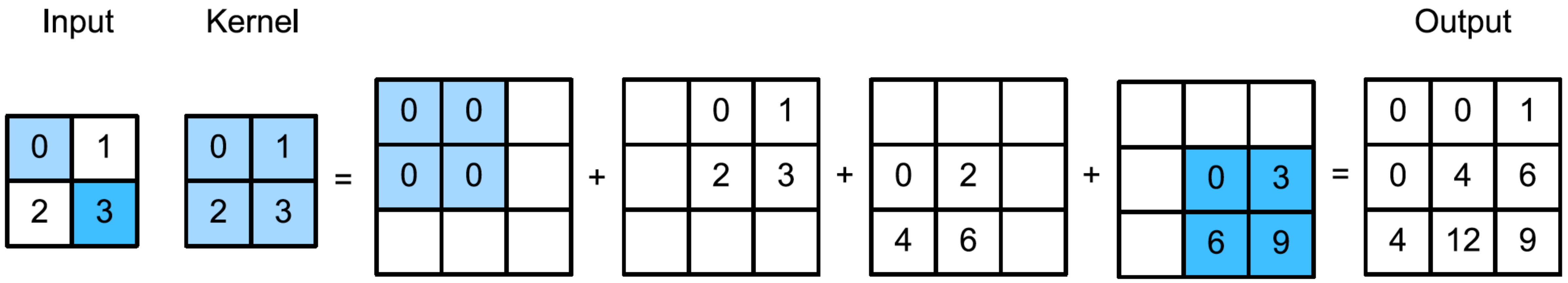
- Applications such as semantic segmentation and generative adversarial networks however, require to predict values for each pixel and therefore needs to increase input width and height.
- Transposed convolution, also named fractionally-strided convolution or deconvolution, serves this purpose.

Basic 2D Transposed Convolution

- Let’s consider a basic case that both input and output channels are 1, with 0 padding and 1 stride.
- Below figure illustrates how transposed convolution with a 2 x 2 kernel is computed on the 2 x 2 input matrix.



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- This way the predictions have a one-to-one correspondence with input image in spatial dimension (height and width).
- Given a position on the spatial dimension, the output of the channel dimension will be a category prediction of the pixel corresponding to the location.

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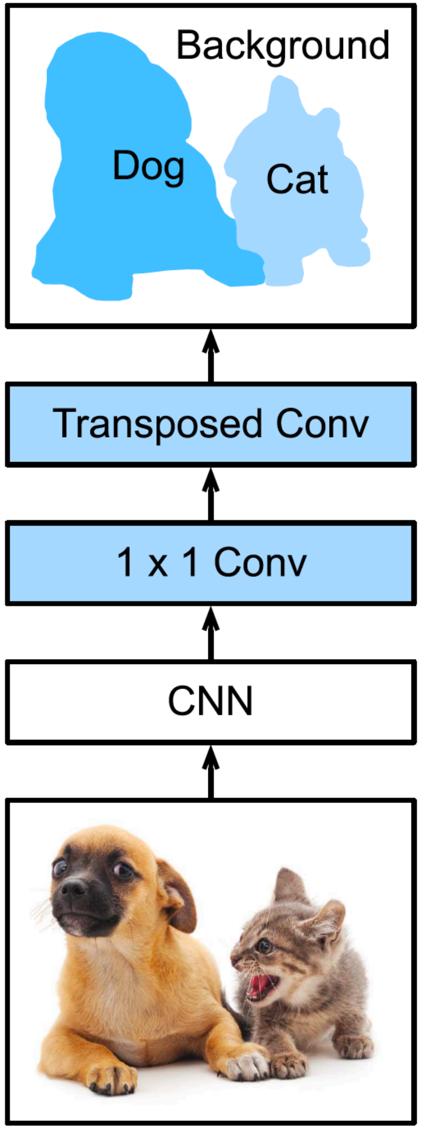

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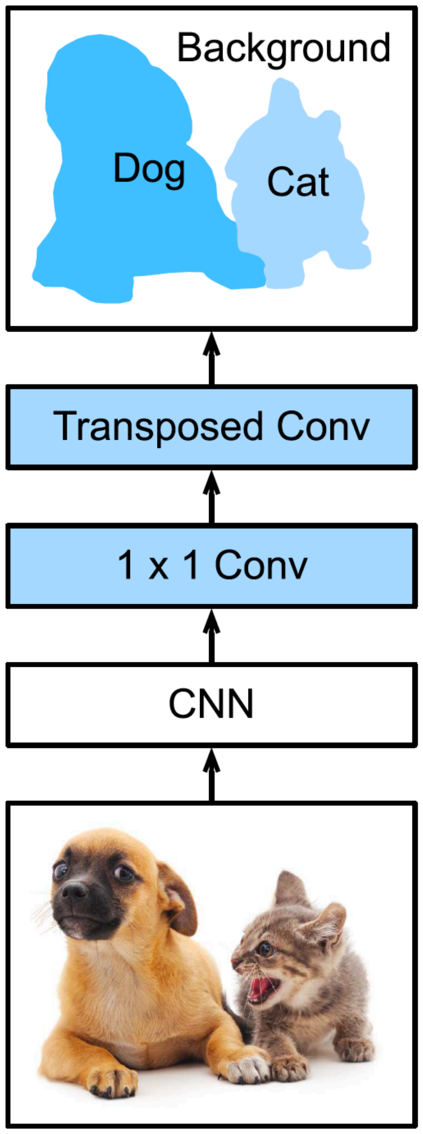
- Then transforms the number of channels into the number of categories through the 1 x 1 convolution layer.



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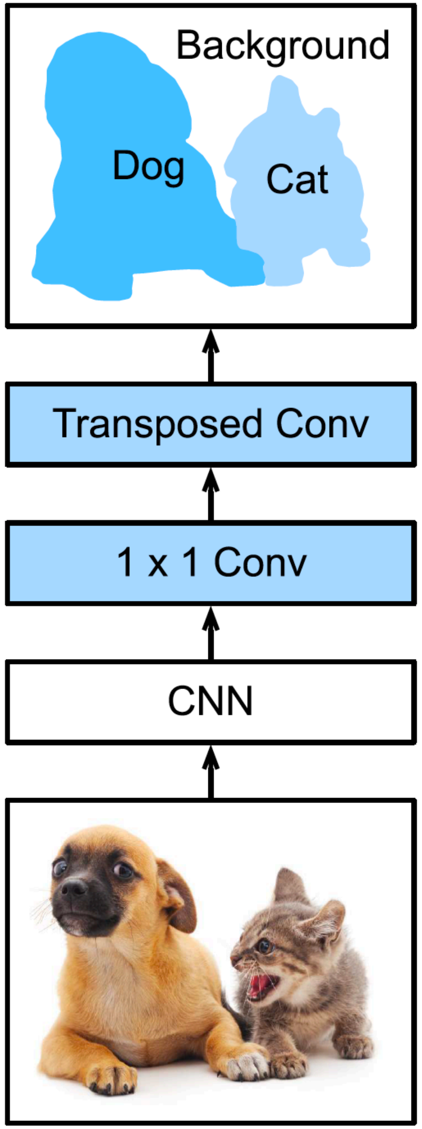

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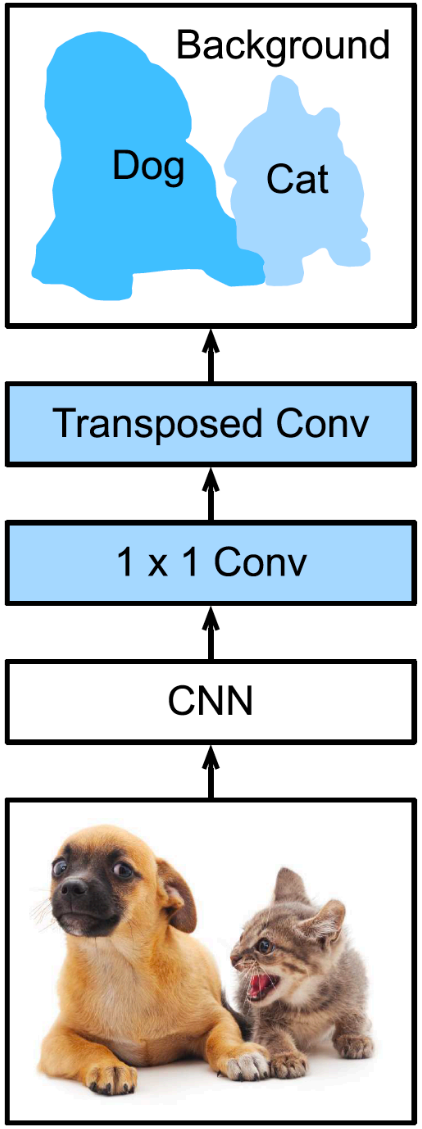
- The model output has the same height and width as the input image and has a one-to-one correspondence in spatial positions.



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- And finally transforms the height and width of the feature map to the size of the input image by using the transposed convolution layer.
- The model output has the same height and width as the input image and has a one-to-one correspondence in spatial positions.
- The final output channel contains the category prediction of the pixel of the corresponding spatial position.