Mask RCNN, NIN

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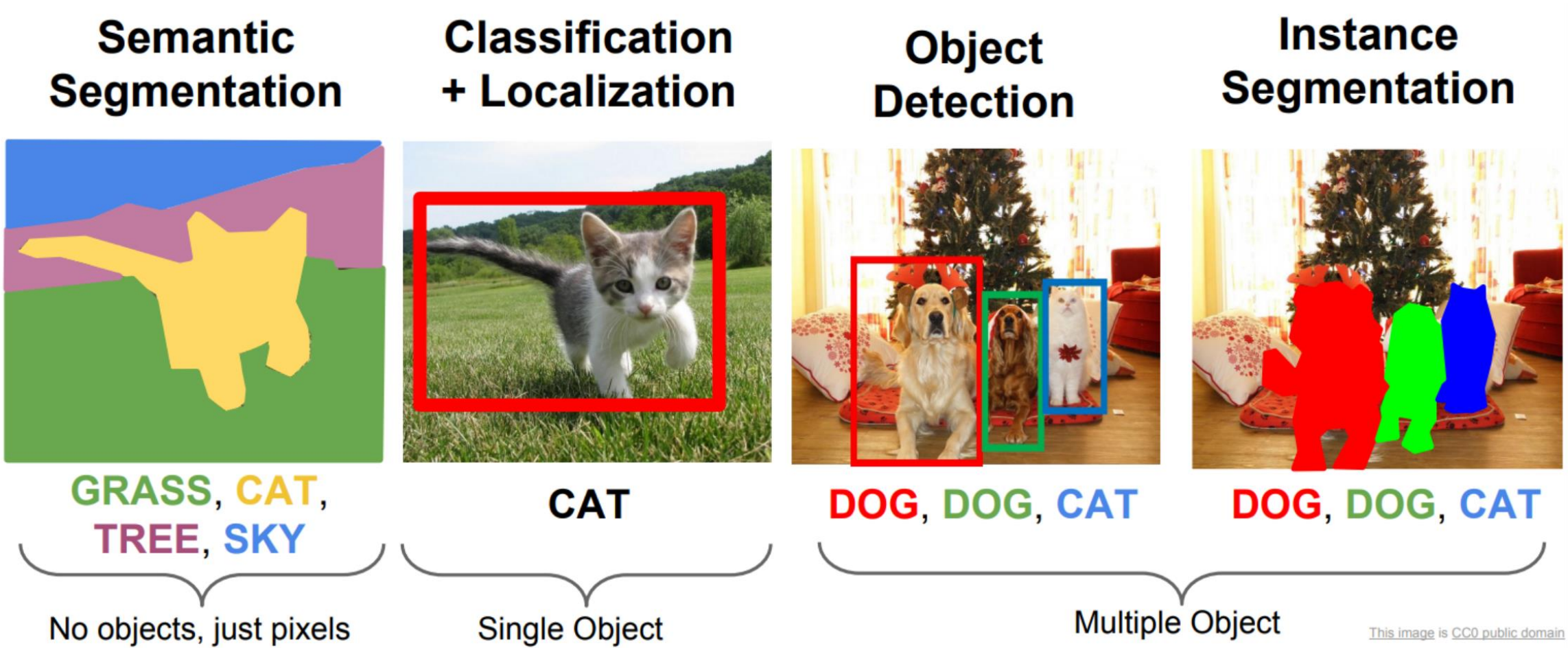
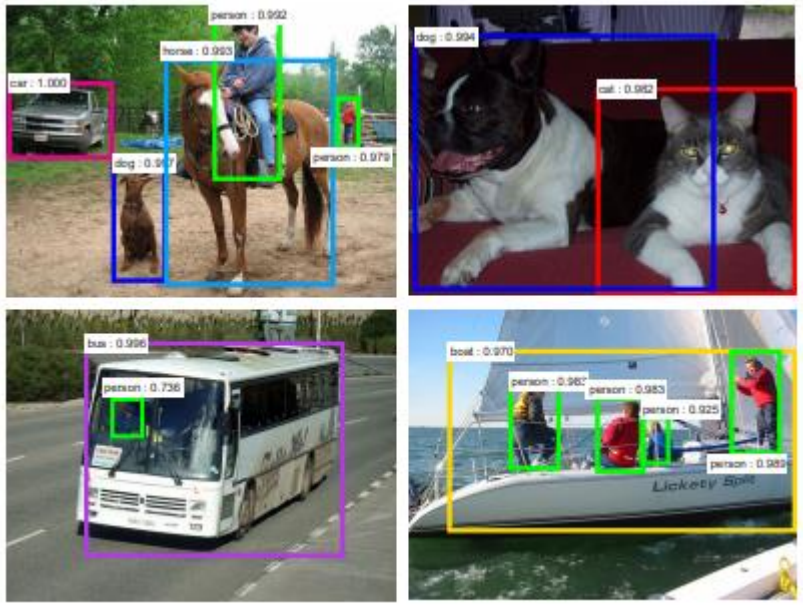
Object Detection



Introduction



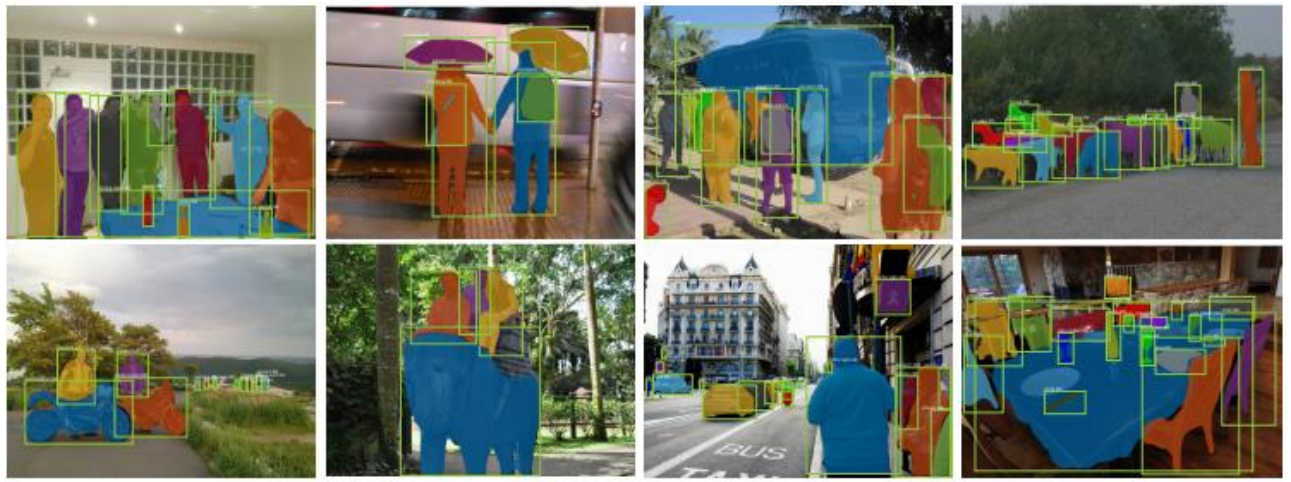
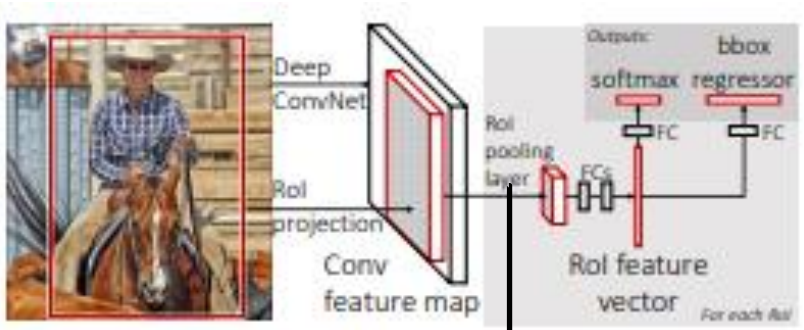


Figure 2. **Mask R-CNN** results on the COCO test set. These results are based on ResNet-101 [19], achieving a *mask* AP of 35.7 and running at 5 fps. Masks are shown in color, and bounding box, category, and confidences are also shown.

RoI Align



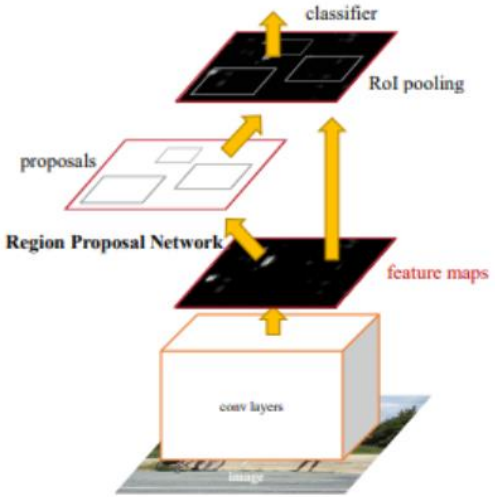


Figure 2: Faster R-CNN is a single, unified network for object detection. The RPN module serves as the 'attention' of this unified network.

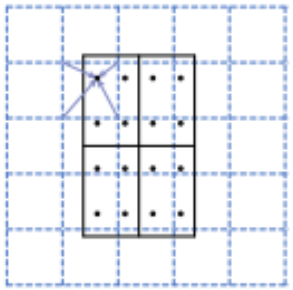
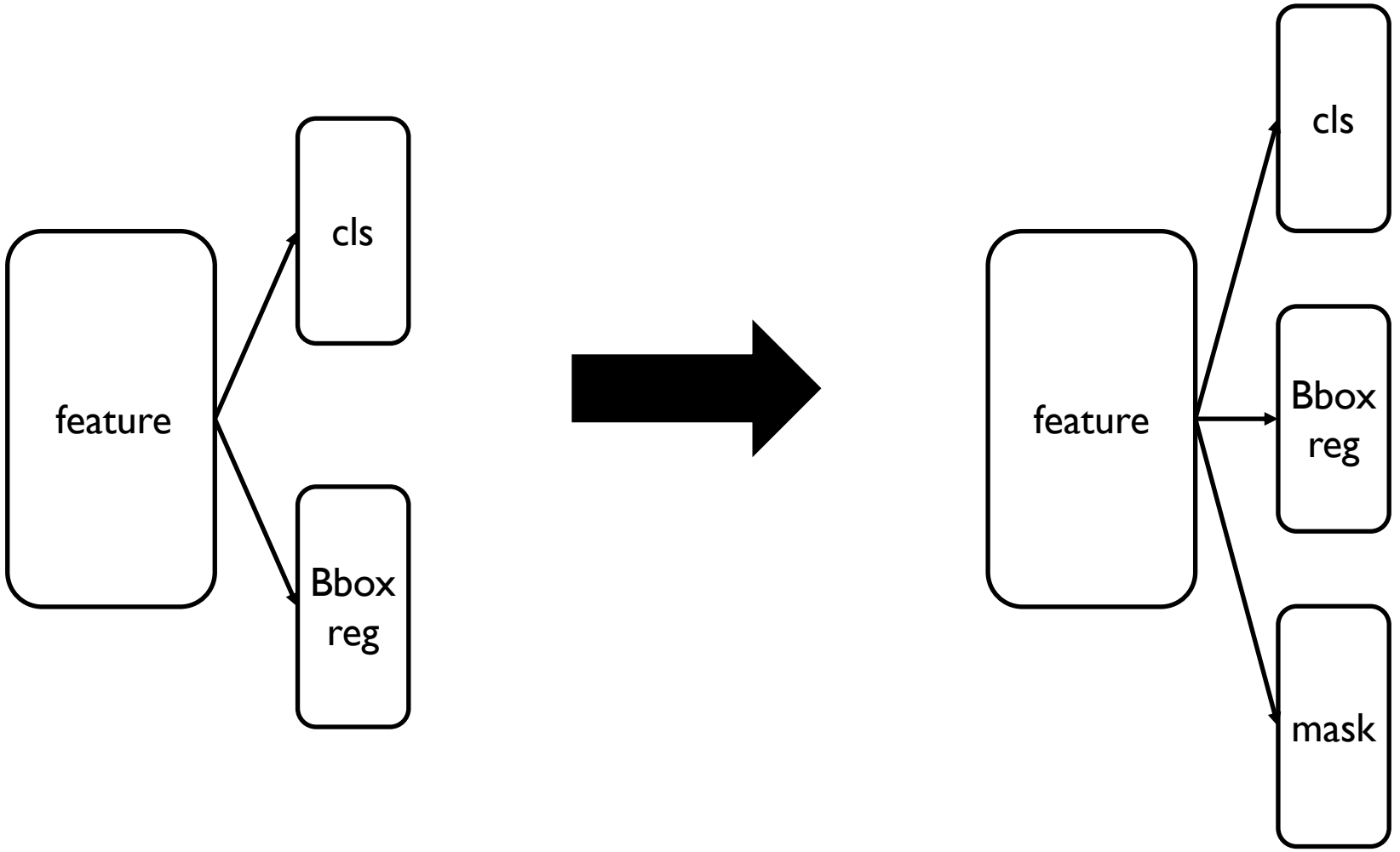


Figure 3. **RoIAlign:** The dashed grid represents a feature map, the solid lines an RoI (with 2×2 bins in this example), and the dots the 4 sampling points in each bin. RoIAlign computes the value of each sampling point by bilinear interpolation from the nearby grid points on the feature map. No quantization is performed on any coordinates involved in the RoI, its bins, or the sampling points.

Training Stage



Training Stage

- Loss Function

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i, p_i^*) + \lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i, t_i^*).$$

$$t_x = (x - x_a)/w_a, \quad t_y = (y - y_a)/h_a,$$
$$t_w = \log(w/w_a), \quad t_h = \log(h/h_a),$$
$$t_x^* = (x^* - x_a)/w_a, \quad t_y^* = (y^* - y_a)/h_a,$$
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$$+ L_{mask}$$

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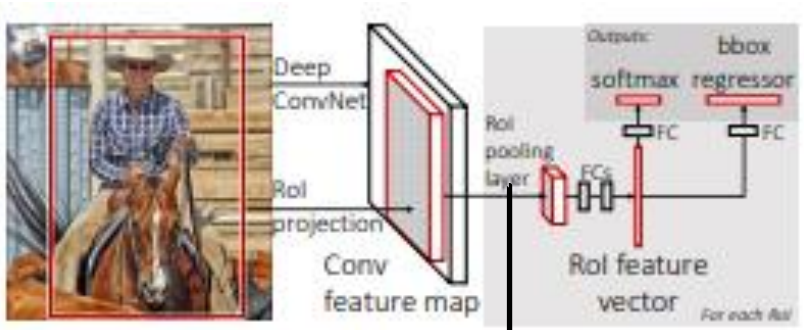
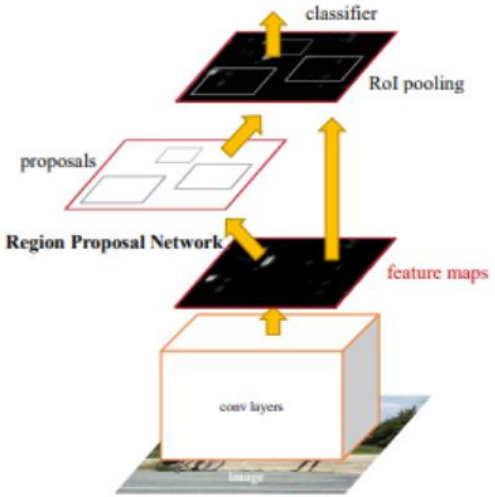
RoI Align





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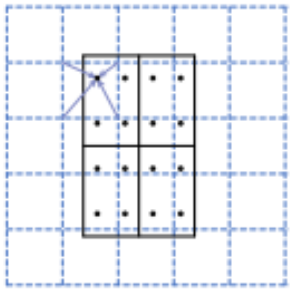

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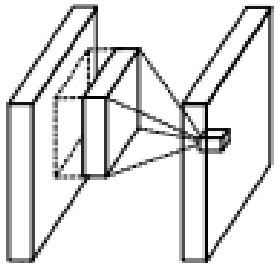
Experiments

Introduction

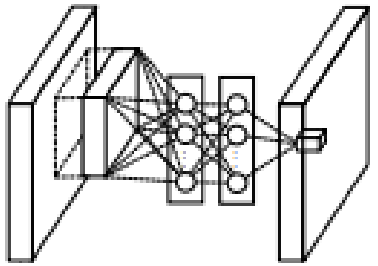
- CNN
  - Generalized Linear Model(GLM)
    - linear
  - FC layer
    - Prone to overfitting
    - Depend on dropout regularization
- NIN
  - Micro Network (MLP)
    - nonlinear
  - Global average pooling
    - Prevent overfitting
    - Itself a structural regularizer

MLP

- Multiplayer Perceptron



(a) Linear convolution layer



(b) Mlpconv layer

$$f_{i,j,k} = \max(w_k^T x_{i,j}, 0).$$

$$\begin{aligned} f^1_{i,j,k_1} &= \max({w^1_{k_1}}^T x_{i,j} + b_{k_1}, 0). \\ &\vdots \\ f^n_{i,j,k_n} &= \max({w^n_{k_n}}^T f^{n-1}_{i,j} + b_{k_n}, 0). \end{aligned}$$

MLP

- Multiplayer Perceptron

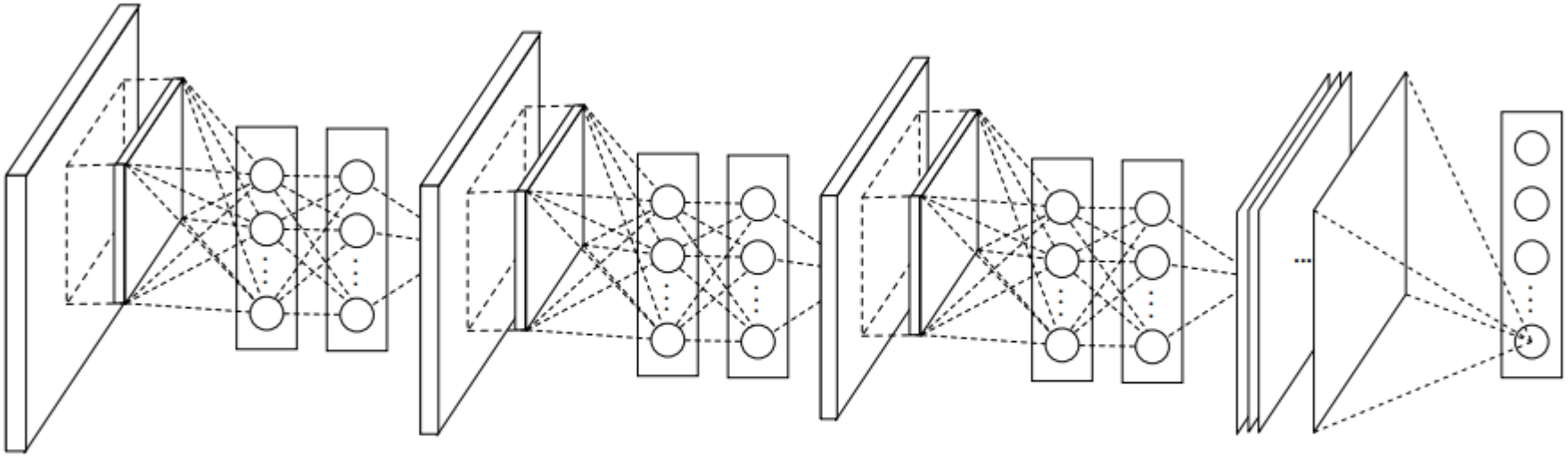


Figure 2: The overall structure of Network In Network. In this paper the NINs include the stacking of three mlpconv layers and one global average pooling layer.

Global Average Pooling

- Generate one feature map for each corresponding category of the classification task
- Instead of adding FC layers, take the average of each feature map
- Resulting vector is fed directly into the softmax layer
  - Enforcing correspondence between feature maps and categories
  - No parameter to optimize -> overfitting is avoided
  - Enforces feature maps to be confidence maps of concepts

Reference

Thank you