Detection of electronic components for mobile applications

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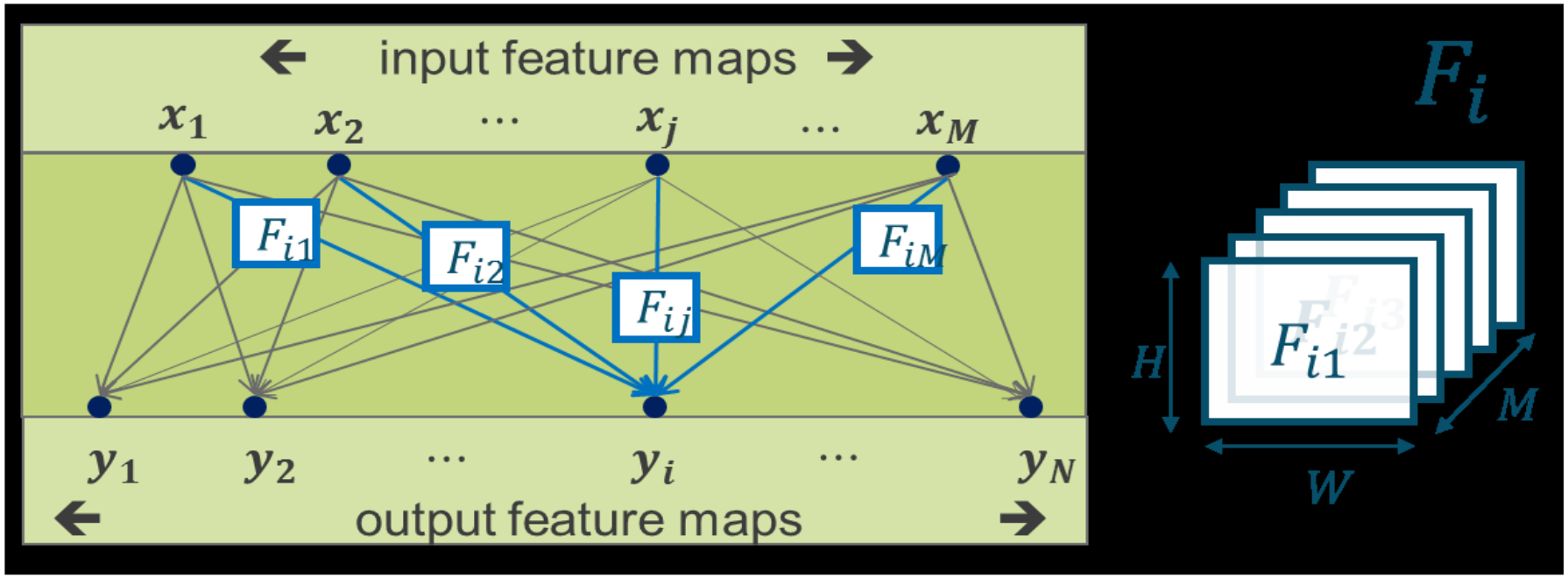
Agenda

1. CNN architecture
2. Object detection networks
3. Experiments on resistors detection
4. Compression of detection networks

Object detection

- Production lines in factories
- Self driving car
- Drones
- Humanoid robots
- etc.

CNN architectures



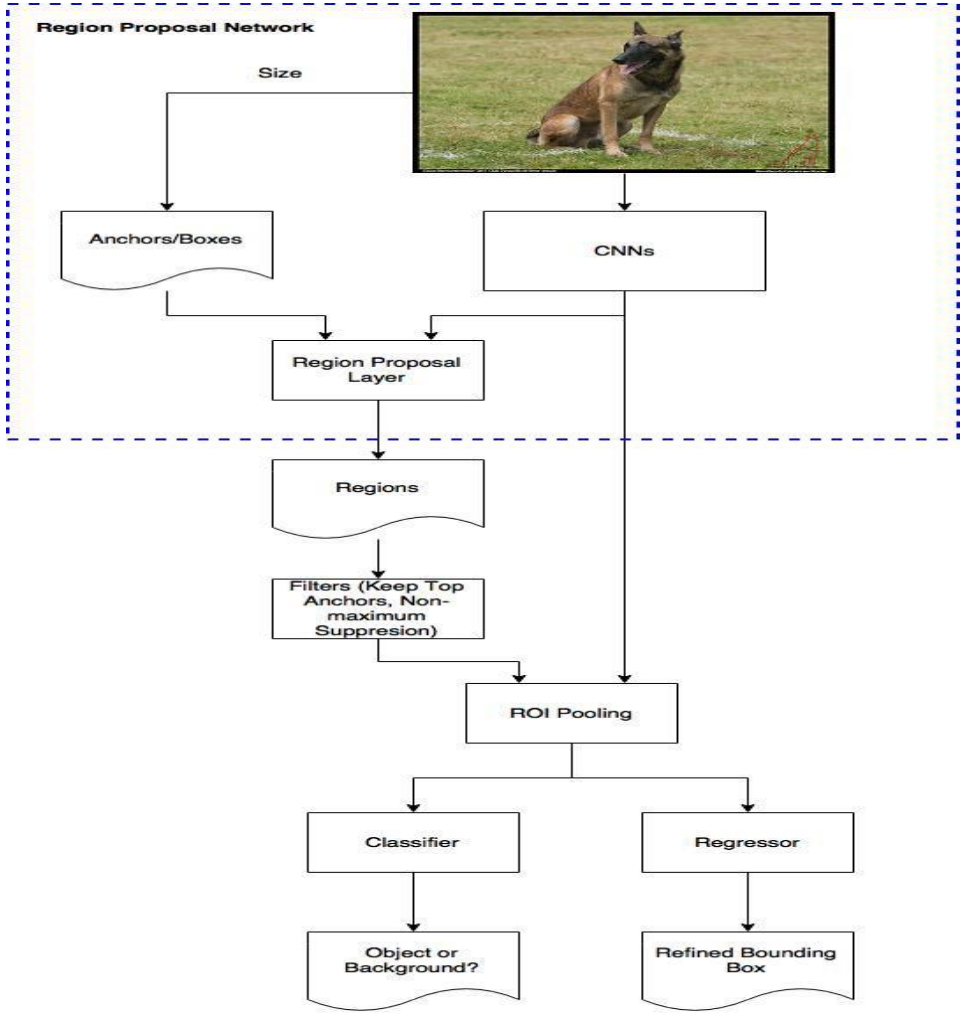
CNN architectures

- Alexnet, Zfnet
- VGG-16, VGG-19
- Resnet
- Inception
- Inception resnet
- Nasnet

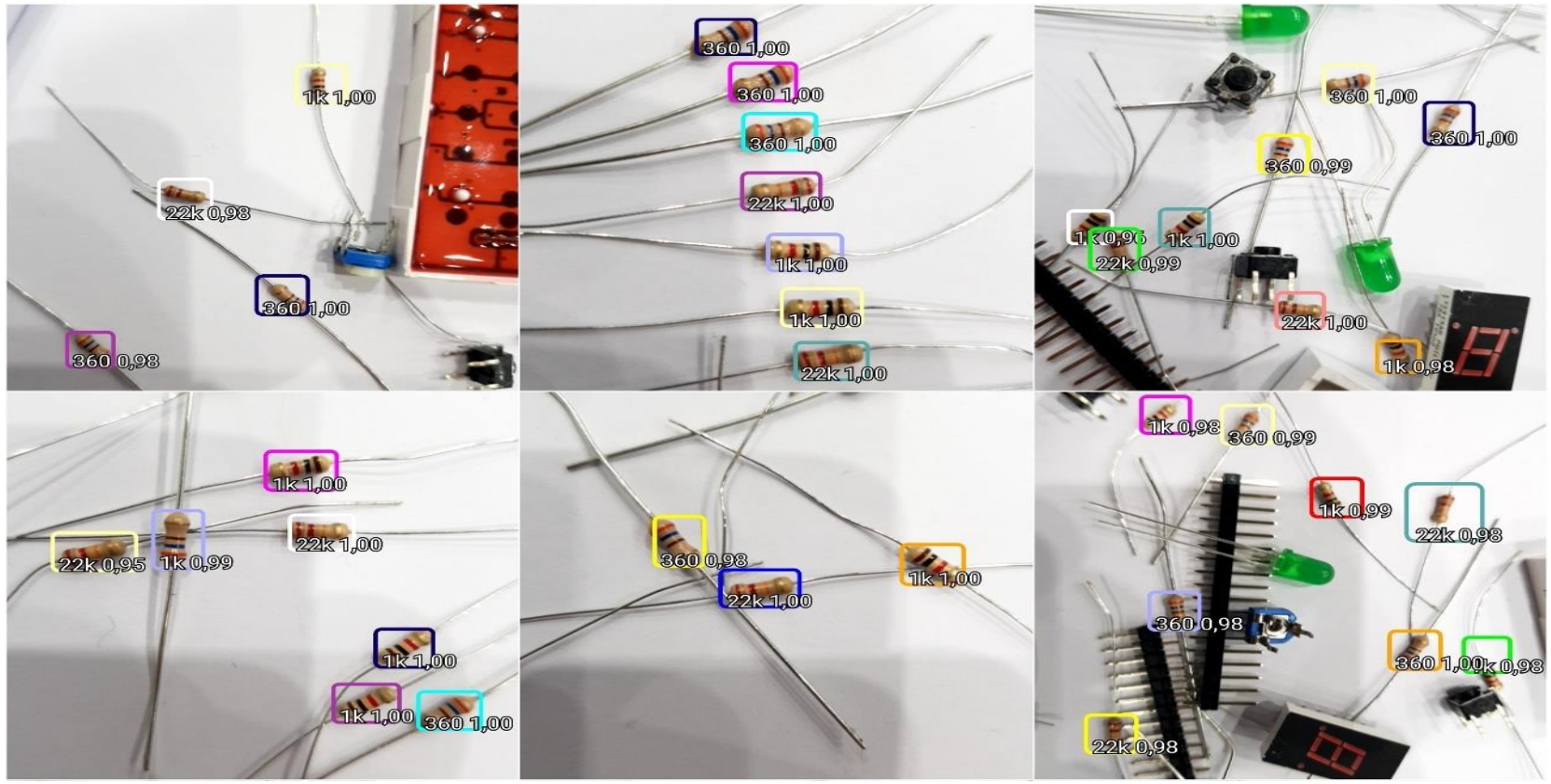
Object detection networks

- r-cnn
- fast and faster r-cnn
- yolo
- ssd
- mask r-cnn

Object detection architectures



Experiments



Experiments

network model	N classes	N training steps	N epochs	mAP	mAP@ .50IoU	total loss	avg. inference time pre-quantization	avg. inference time post-quantization	porteable to Android
faster_rcnn_inception_v2	1	3000	48	**0.554**	**0.972**	**0.200**	-	-	no
ssd_mobilenet_v1_coco	1	3000	48	0.243	0.687	4.749	175ms	130ms	yes
ssd_mobilenet_v1_coco	3	3000	110	0.048	0.226	9.704	-	121ms	yes
ssd_mobilenet_v1_coco	3	12000	440	0.507	0.970	3.143	-	**120ms**	yes

Compression of object detection networks

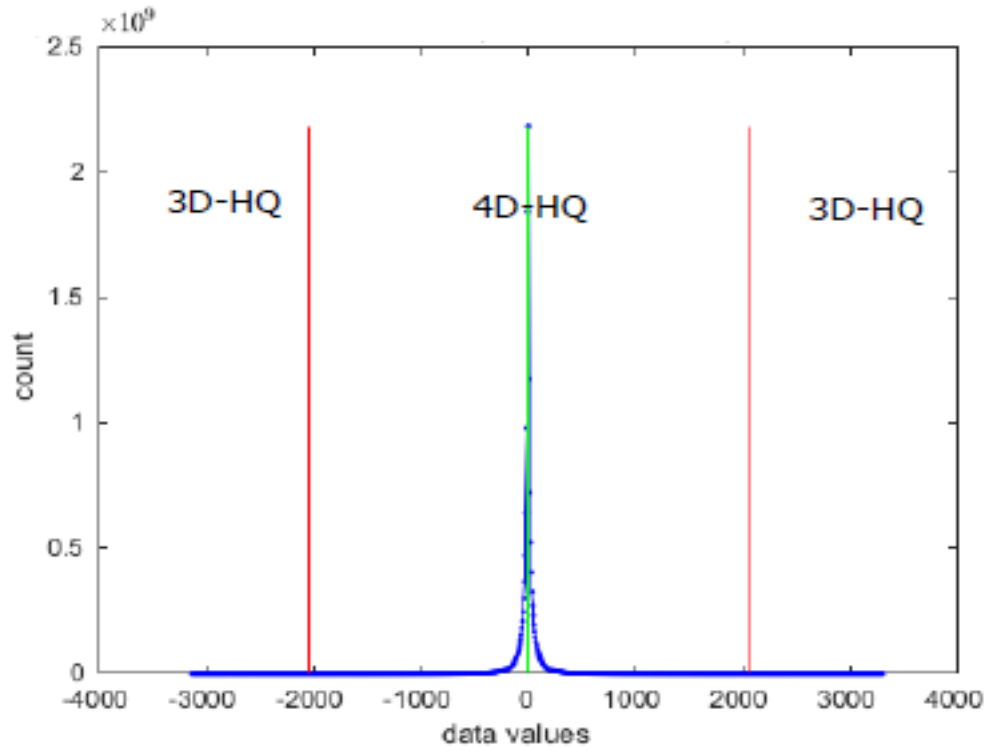
Format $< \text{coeff}, \text{data} >$	Relative Complexity [M MACs]
$< 8b, 8b >$	$224 = HPWMN$
$< 4b, 8b >$	$112 = \frac{1}{2} < 8b, 8b >$
$< 4b, 4b >$	$56 = \frac{1}{4} < 8b, 8b >$
$< \text{flp}, \text{flp} >$	$\geq 2016 = 9 < 8b, 8b >$
$N = 256, P = 27^2, M = 48, H = W = 5$	

Compression of object detection networks

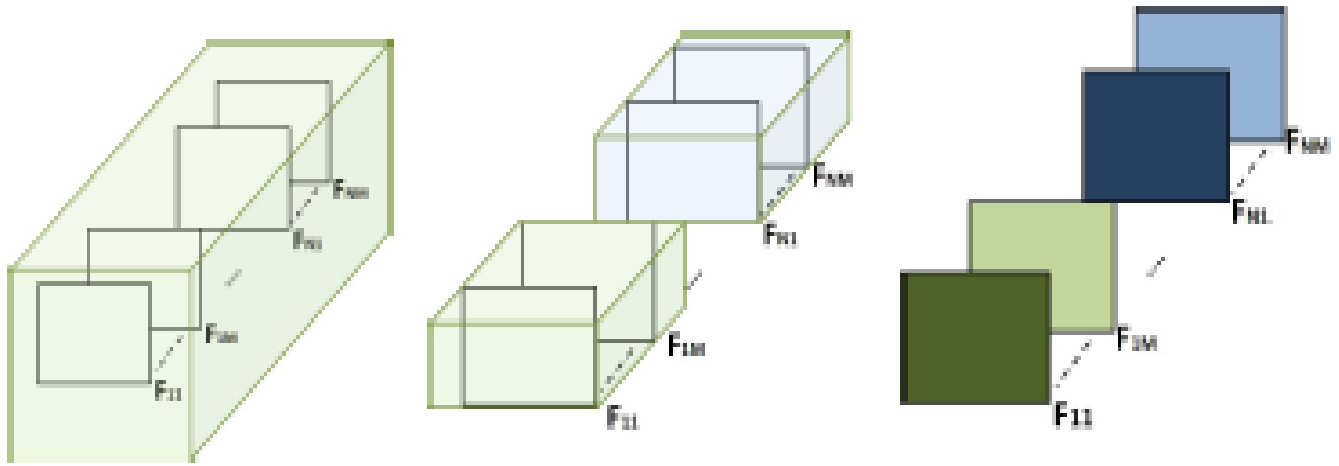
- Quantization
- Pruning
- K-means clustering
- Dimensionality reduction of filters
- All of these methods with and without retraining

Quantization - activations sparsity

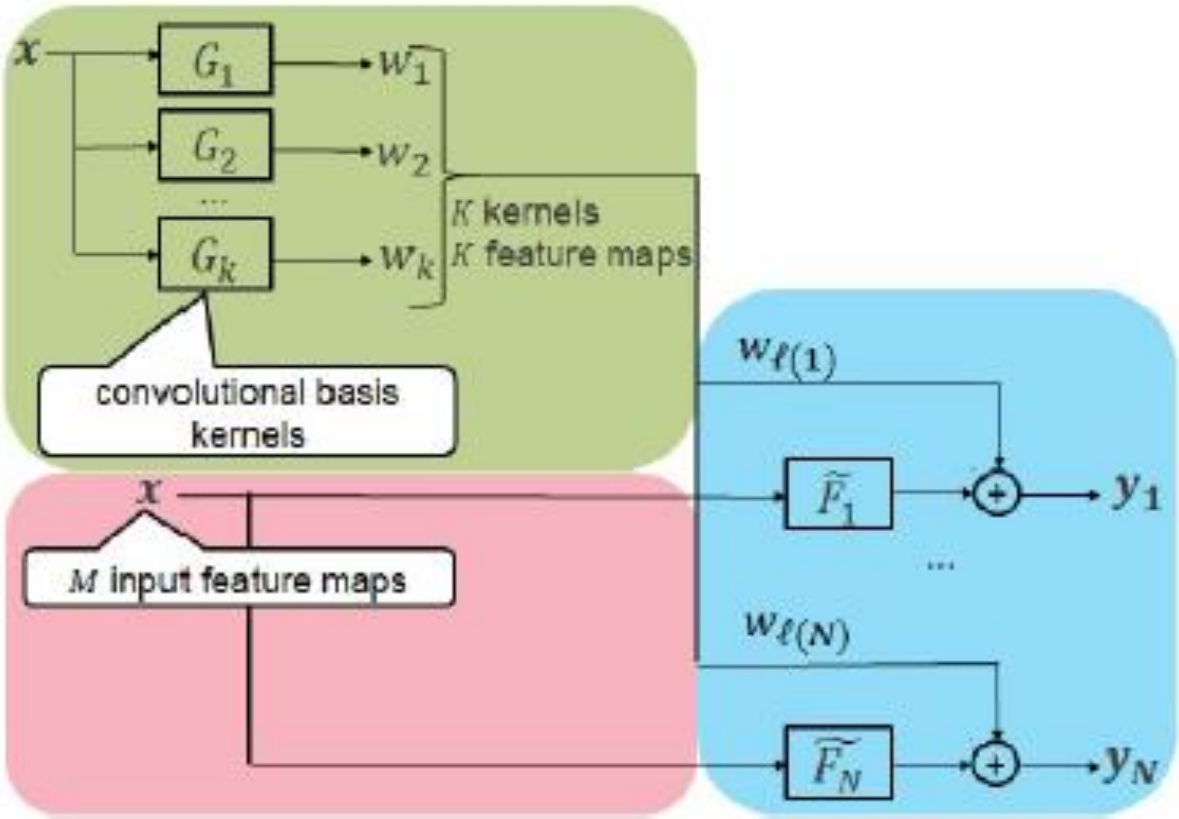
- histogram analysis



Quantization - 3D, 4D



Quantization - K-means clustering



Pruning

Algorithm 1 Pruning algorithm based on random hill climbing

```
1: Input: number_of_buckets_to_which_hist_is_divided
2: Input: drop_in_accuracy_threshold
3: compute_hist_coeff_of_all_layers
4: layer = random_or_prioritized_choose_layer_for_pruning()
5: for number_of_iterations do
6:     if (top_1-baseline) < drop_in_accuracy_thresh then
7:         prune_next_bucket_from_hist()
8:     else
9:         reverse_pruning_bucket_from_hist()
10:    end if
11:    fitness = compute_new_fitness()
12:    top1 = compute_accuracy()
13:    if fitness < best_fitness then
14:        next_solution = current_solution
15:    else
16:        next_solution = best_solution
17:    end if
18:    layer_sensitivity_update
19: end for
```

Pruning

- high sparsity – sparse matrix cudnn operations with conv layers
- in case of fully connected sparse matrix multiplication
- fully connected up to 80-90% sparsity
- Yolo_v2 - set of constant bounding boxes (**y**ou **o**nly **l**ook **o**nce)
- Less the 1% in mAP on COCO and VOC Pascal with 8 bit precision
- about 25-30% of average sparsity, weighted close to 50%

Reinforcement learning for compression

- Q - learning
- Actor critic (policy gradient with Q learning)
- use for choosing layers for pruning, steps and other parameters
- choosing layers for compression
- combination - compression, pruning, quantization

GAN (Adversarial networks) for small object detection