CNN for object detection

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Agenda

1. What is object detection?
2. Traditional approach
3. R-CNN
4. Other methods
5. Transfer Learning
6. Experiments
7. Future plans

Object Detection – what is it

True Image

Semantic Segmentation

CAR, BACKGROUND

- No objects, just pixels

Object Detection – what is it

Classification + Localization

CAR

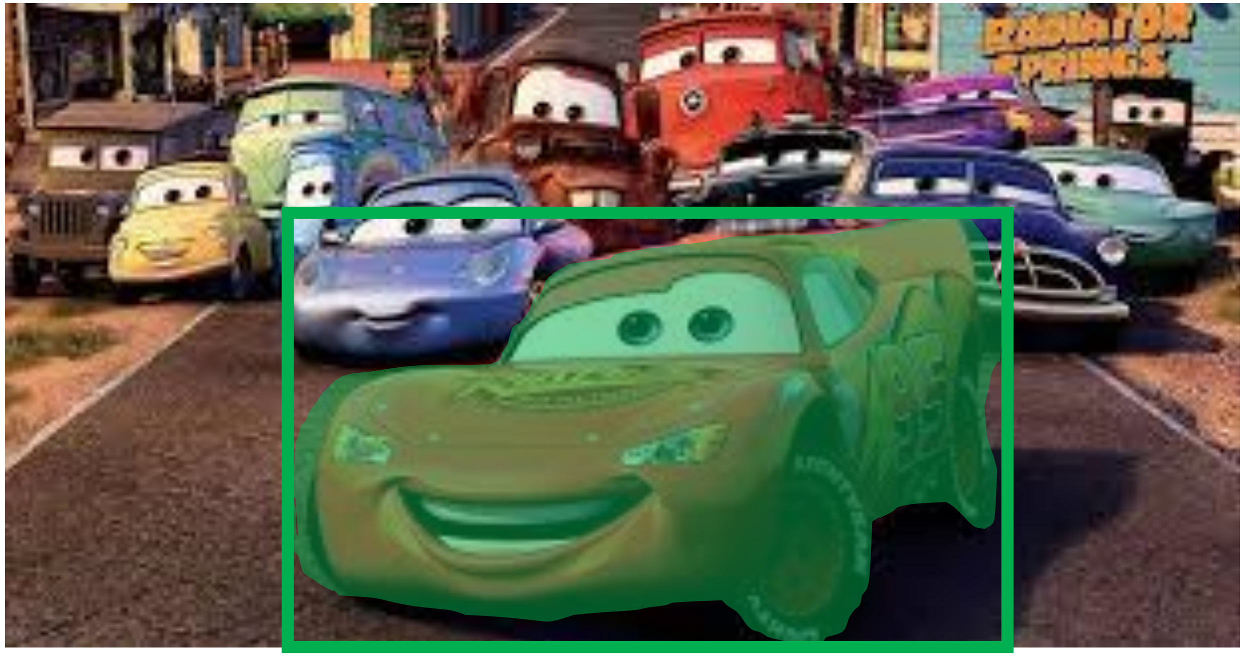
- Single object

Object Detection

- Multiple objects

Object Detection – what is it

Instance Segmentation



CAR

- Multiple objects

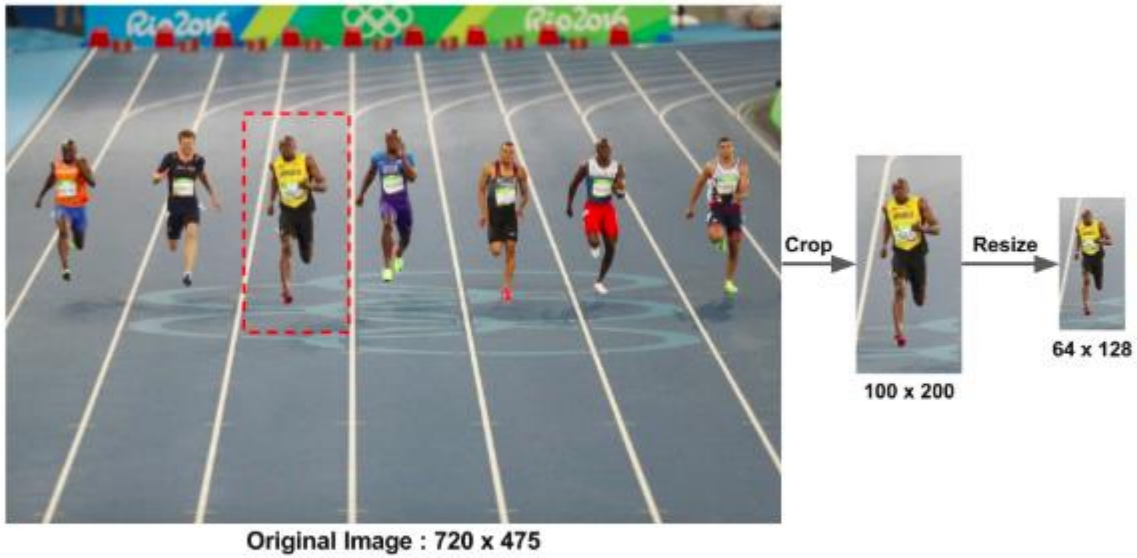
Object Detection – history – HOG

Histogram of Oriented Gradients

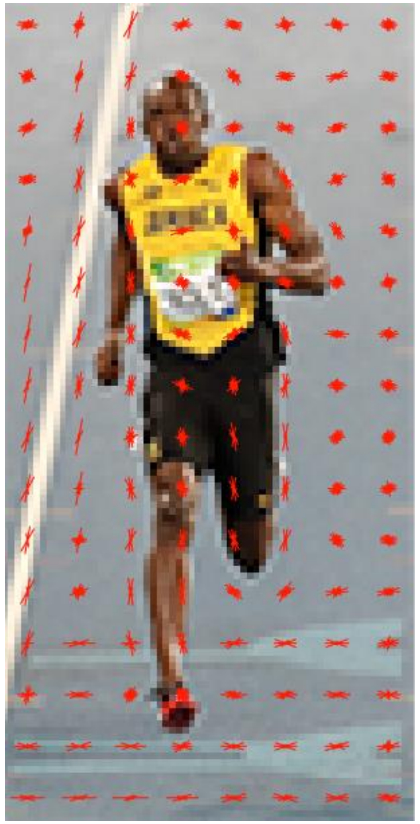
Method of feature selection consisting in the following steps:

1. Gradient calculation
2. Calculation of gradient magnitude and direction
3. Histogram creation
4. Block normalization

Input image



Histograms



https://www.learnopencv.com/histogram-of-oriented-gradients/

Object Detection – history – HOG

1. Gradient calculation

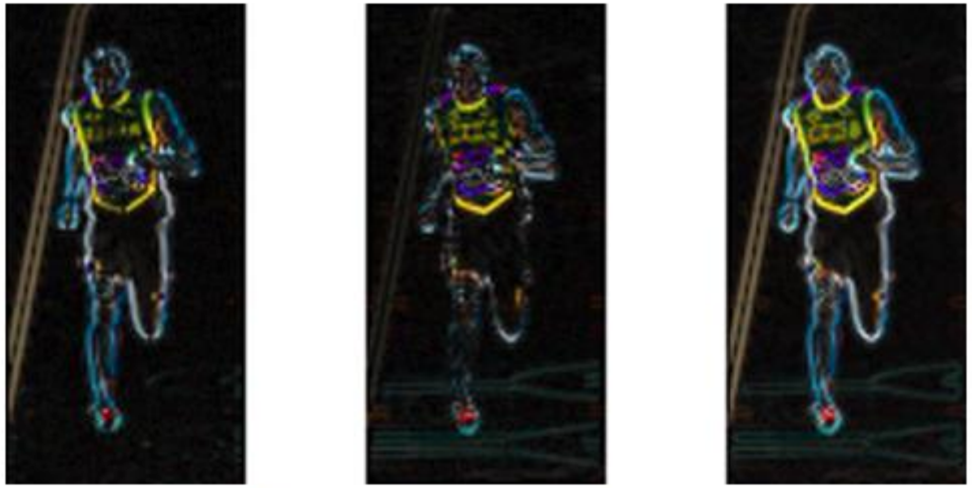
Gradient calculation in case of images is equivalent to filtering the image with the following filters, which are actually called Sobel filters.

Sobel filters

-1	**0**	**1**

-1
0
1

Gradients in x and y directions



Left : Absolute value of x-gradient. Center : Absolute value of y-gradient. Right : Magnitude of gradient.

https://www.learnopencv.com/histogram-of-oriented-gradients/

Object Detection – history – HOG

2. Calculation of gradient magnitude and direction

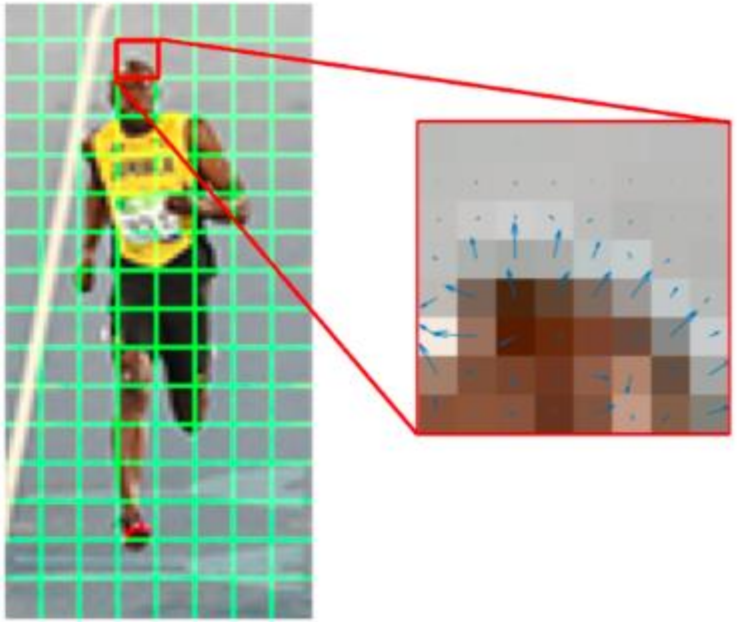
This step unifies the information coming from gradients in x and y directions providing the strength and the direction of the gradient.

Magnitude and direction equations

$$g = \sqrt{g_x^2 + g_y^2}$$

$$\theta = \arctan \frac{g_y}{g_x}$$

Gradients magnitude and direction



2	3	4	4	3	4	2	2
5	11	17	13	7	9	3	4
11	21	23	27	22	17	4	6
23	99	165	135	85	32	26	2
91	155	133	136	144	152	57	28
98	196	76	38	26	60	170	51
165	60	60	27	77	85	43	136
71	13	34	23	108	27	48	110

Gradient Magnitude

80	36	5	10	0	64	90	73
37	9	9	179	78	27	169	166
87	136	173	39	102	163	152	176
76	13	1	168	159	22	125	143
120	70	14	150	145	144	145	143
58	86	119	98	100	101	133	113
30	65	157	75	78	165	145	124
11	170	91	4	110	17	133	110

Gradient Direction

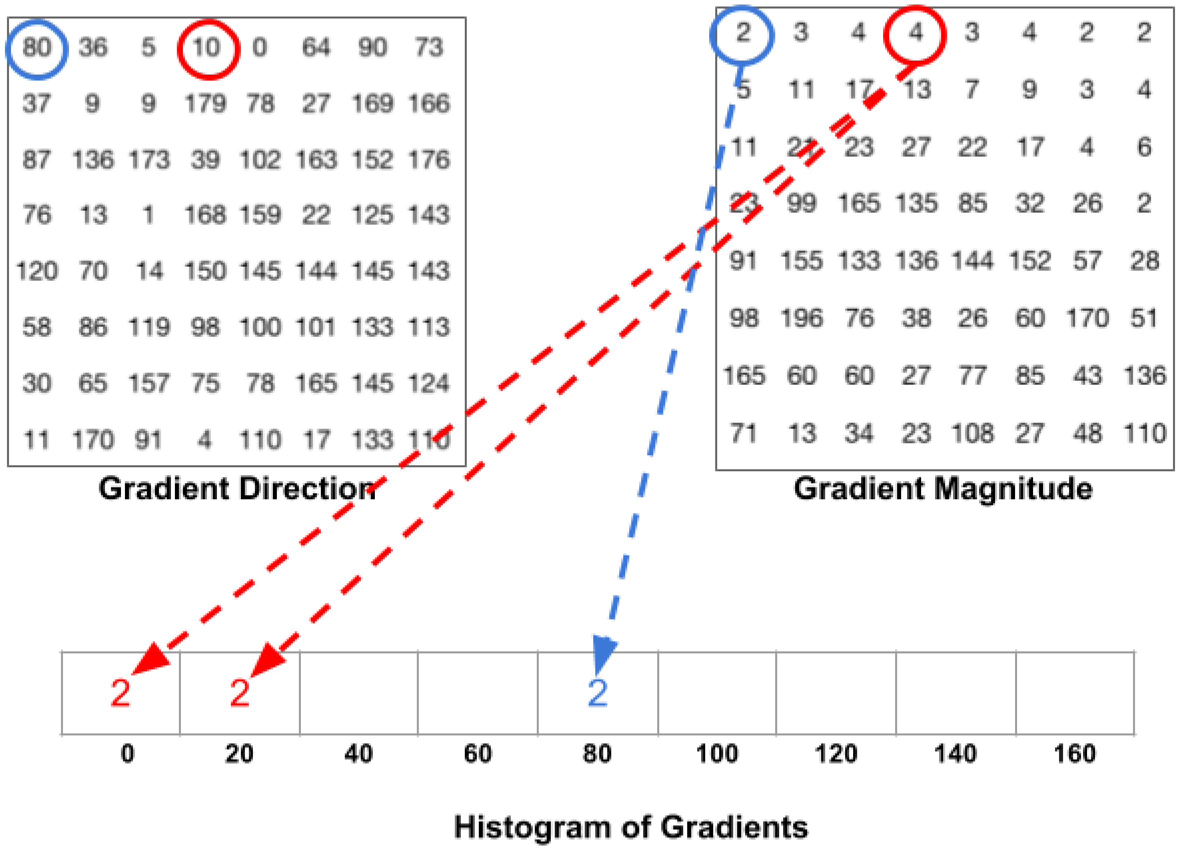
https://www.learnopencv.com/histogram-of-oriented-gradients/

Object Detection – history – HOG

3. Histogram creation

This step is the clue of the HOG method. Here the gradients of the image are transformed into a histogram. This step aims at:

- Making the representation more compact
- Denoising the representation

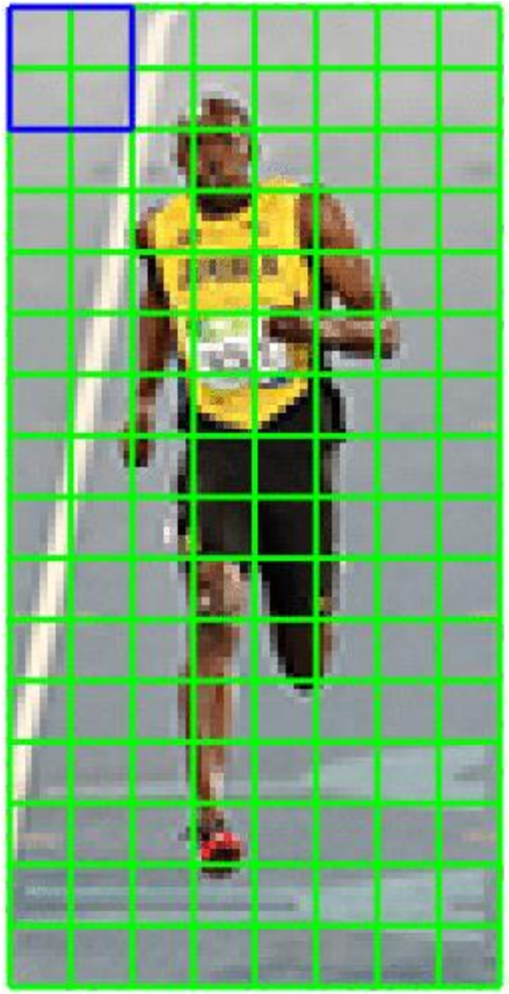


https://www.learnopencv.com/histogram-of-oriented-gradients/

Object Detection – history – HOG

4. Block normalization

Concatenating vectors for all of the histograms and normalizing them with the L2 norm (vector length).



Summary/key takeaways:

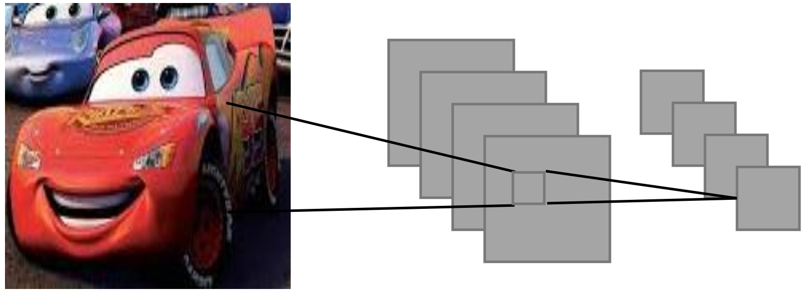
- Both the cell size and block size are hyperparameters that can be optimized

https://www.learnopencv.com/histogram-of-oriented-gradients/

Object Detection – regional convolutional neural networks

1. Input Image

3. CNN feature computation



2. Region of Interest proposal

4. Classification of regions

Airplane? No.

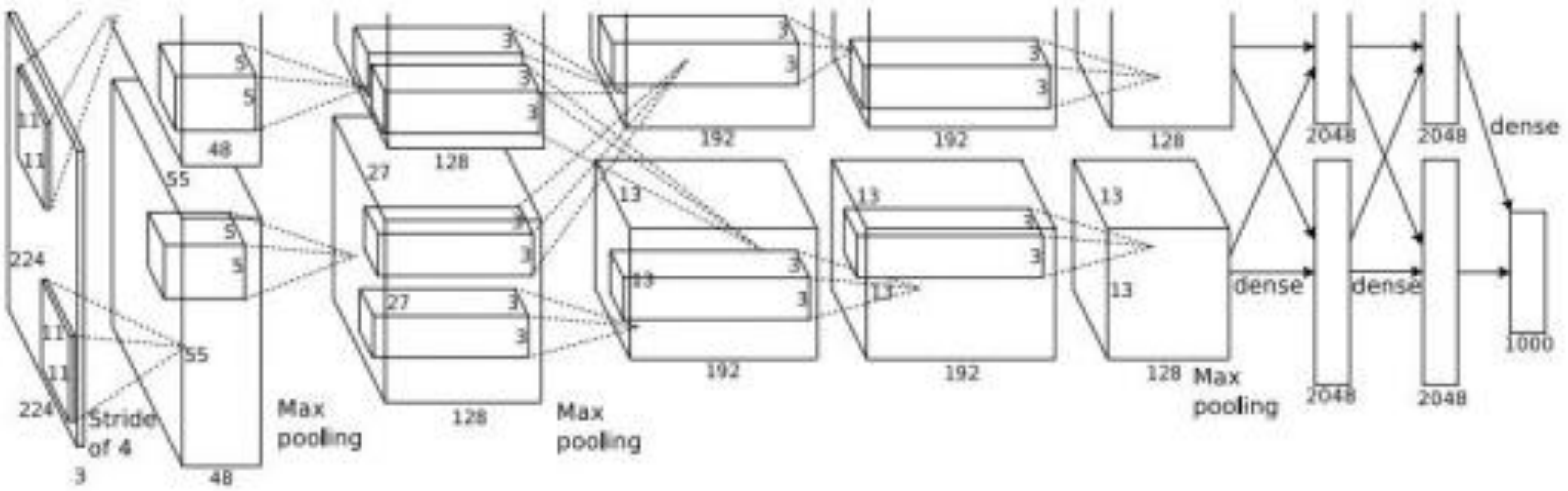
Car? Yes

Person? No

CNN architectures

History of CNN for classification - AlexNet

Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8



Interesting details:
- First use of ReLU
- Heavy data augmentation
- Dropout 0.5
- Batch size
- SGD Momentum
- Adaptive Learning rate
- L2 weight decay
- 7 Ensambles

http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf

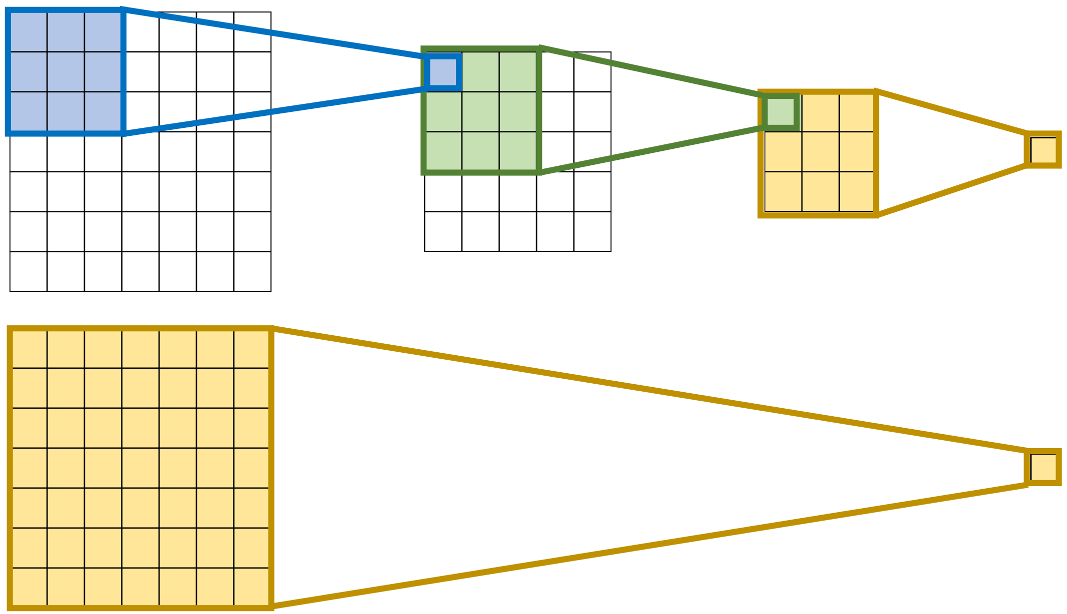
History of CNN for classification - VGG Net

Goal:
- Building deeper network with smaller filters

Motivation:
- Stacking multiple small filters can:
  - have the same effective receptive field as one bigger filter
  - have much less parameters
  - introduce more nonlinearities

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

History of CNN for classification - VGG Net



Parameter number:

3*(3x3) – 3*3^2 = 27

(7x7) – 7^2 = 49

This difference grows with the number of filters in each layer and the number of channels.

(Left) Own (Right) http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

History of CNN for classification - GoogleNet

Goal:

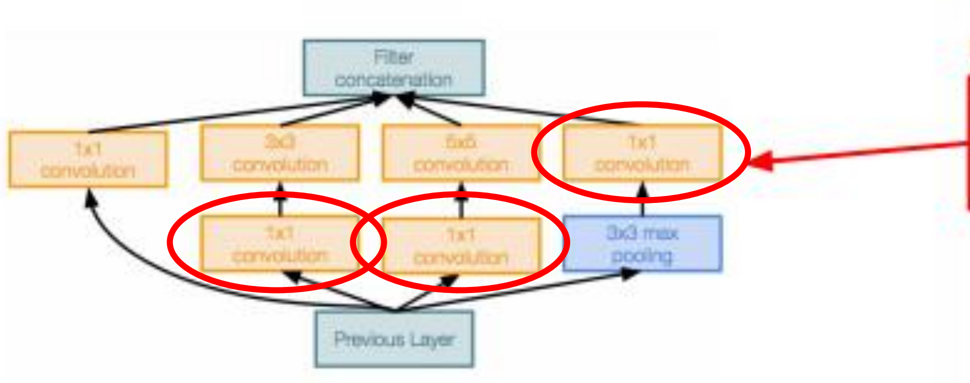
- Computational efficiency

How did they achieve it:

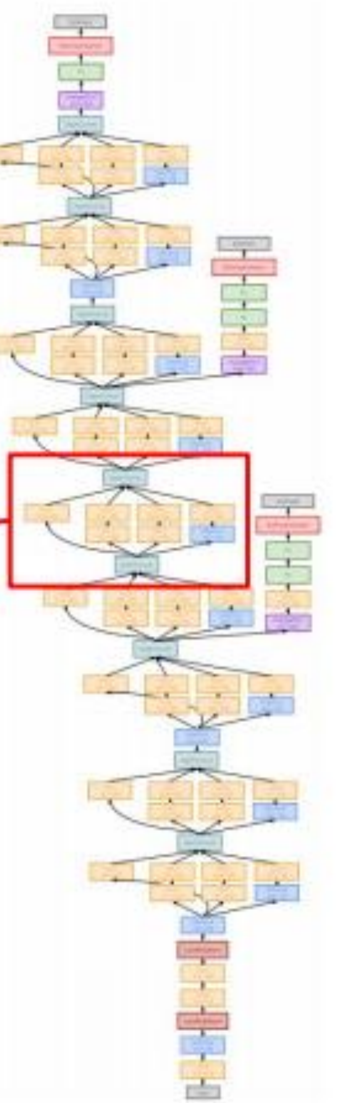
- Inception module
- No fully connected layers

Inception module:

- Various operations (convolutions and pooling) concatenated depth-wise (zero padding and stride adjusted to maintain spatial dimension)



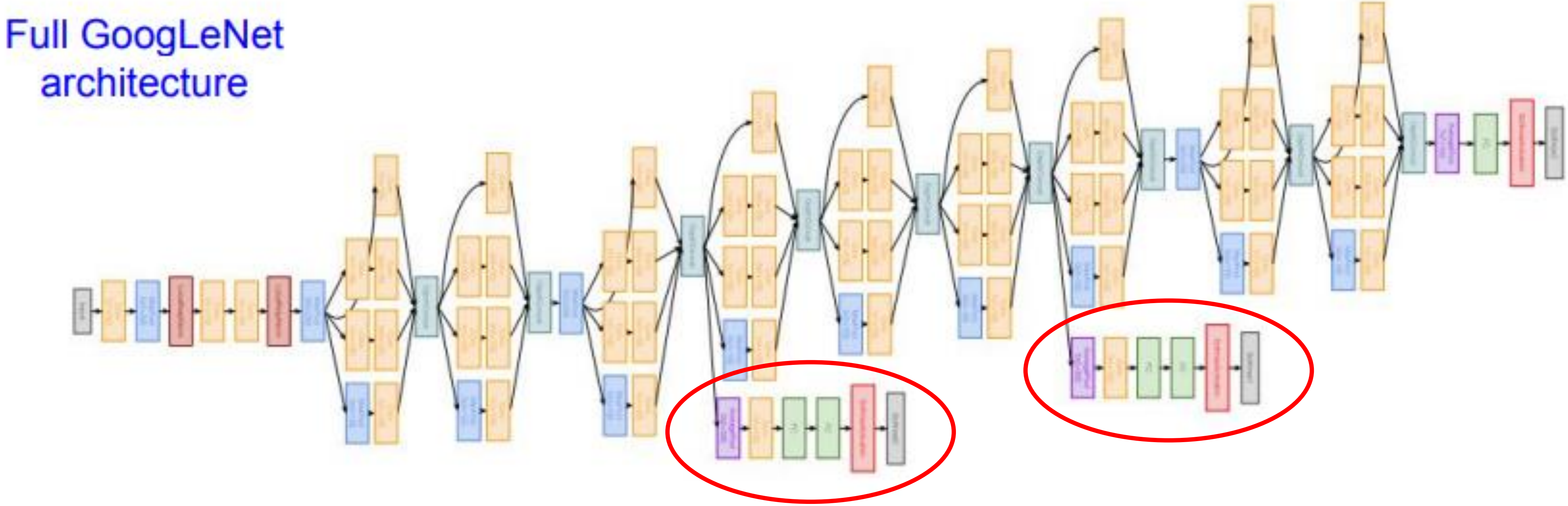
Inception module



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

History of CNN for classification - GoogleNet

Additional auxiliary classification outputs help backpropagation.



- 12x less parameters than AlexNet

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

History of CNN for classification - ResNet

Properties:

- Extremely deep (152 layer)

Motivation:

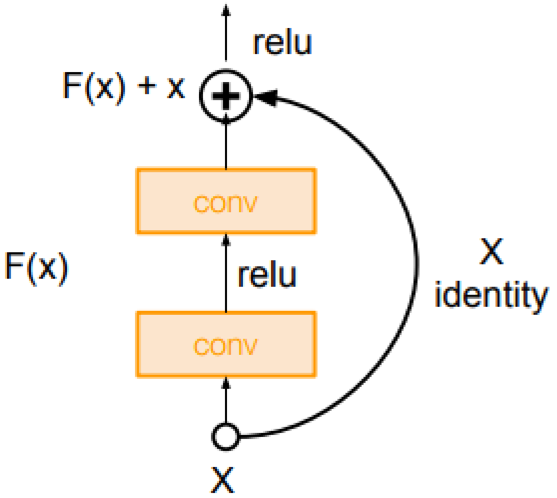
- Underlying assumption that deep model should perform at least as good as shallower models (or even better as by depth we increase model complexity and we expect at least training error to be lower)
- Experimentally it was not confirmed – probably an optimization problem

Solution:

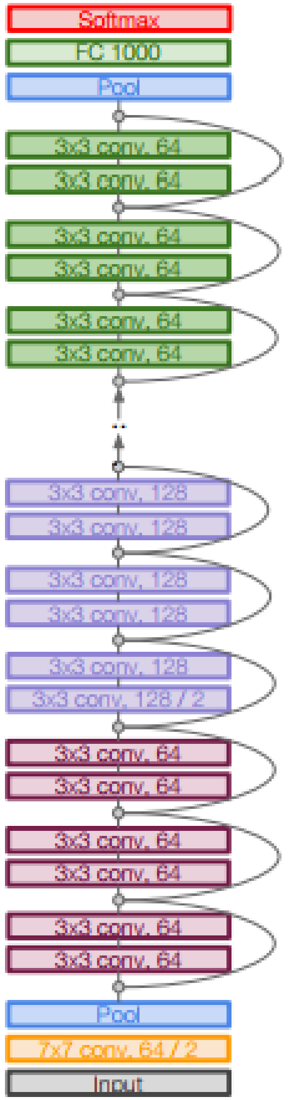
- Residual connection – instead of calculating the full activation map we only calculate the delta (residual)

$$H(x) = F(x) + x$$

- How do we need to modify the input to resolve our problem



Residual block



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

Region of Interest proposal methods

Object Detection – Region of Interest proposal

Sliding window

BACKGROUND

Object Detection – Region of Interest proposal

Sliding window

CAR

Main problems:

- The search space has to be reduced by using a regular grid, fixed scales, and fixed aspect ratios
- Most of the boxes selected this way do not contain any object

Object Detection – Region of Interest proposal

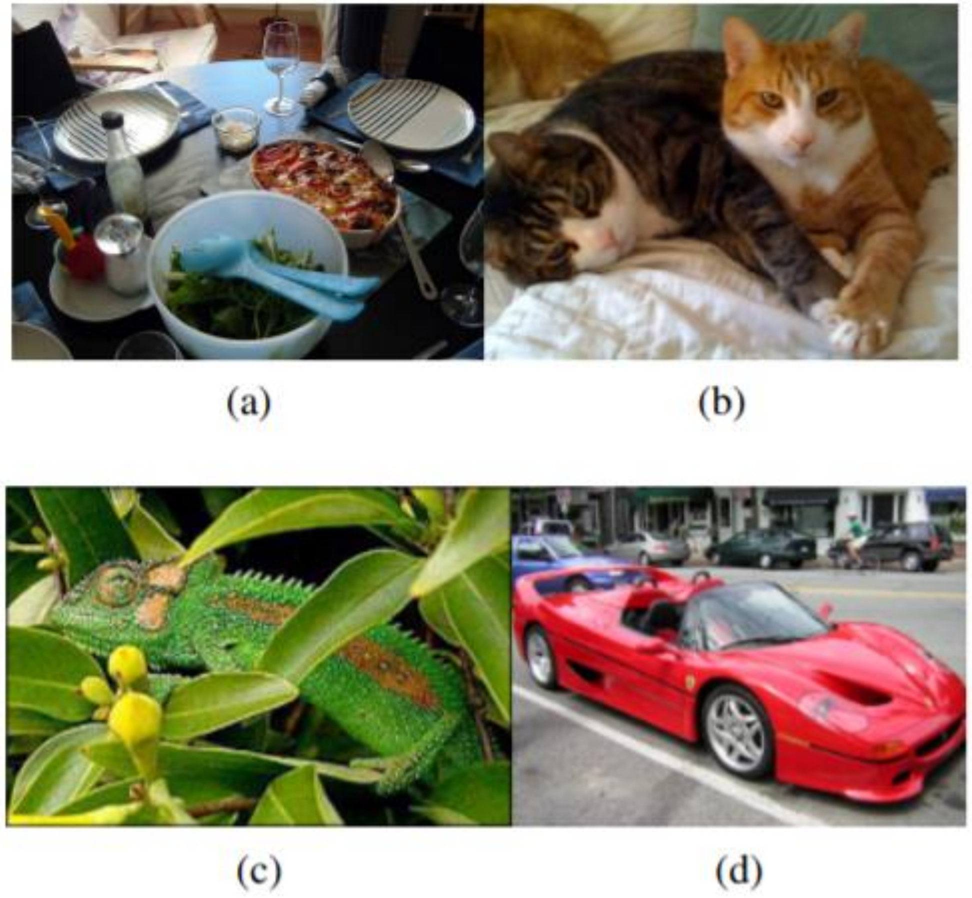
Selective Search

Motivation:

- Hierarchical relation of object in an image
- Differences in a single aspect of the image and similarity in others
  - Texture
  - Color
- Enclosing of some objects by other

Solution:

- Using a data-driven approach to steer the sampling

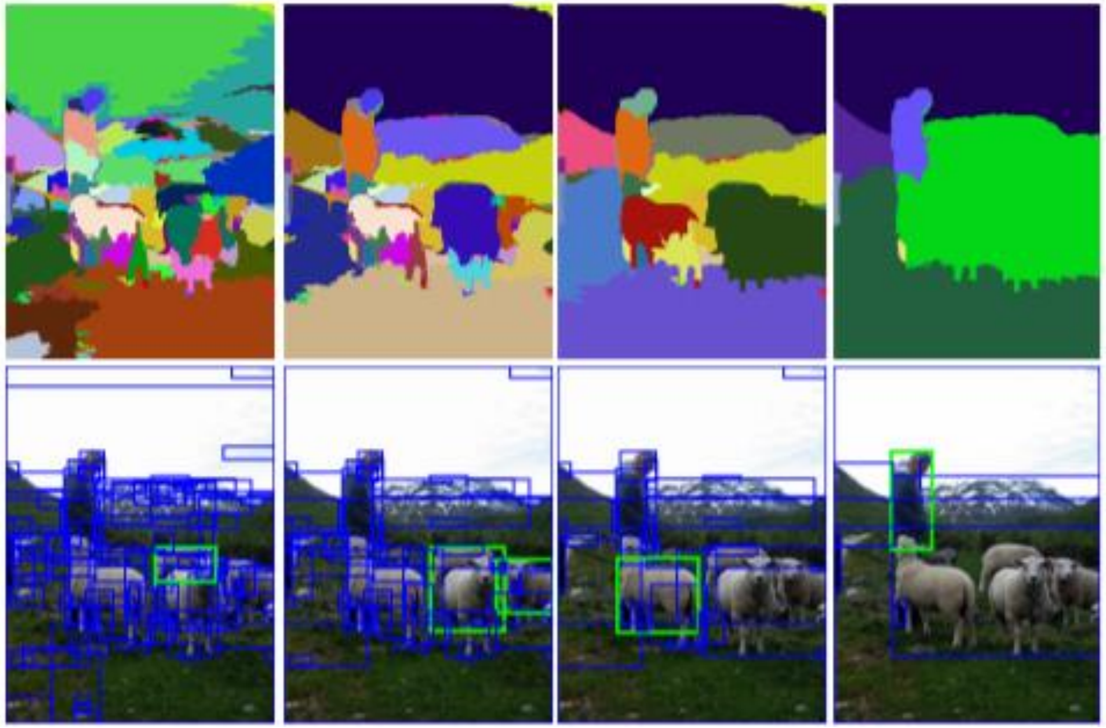


https://koen.me/research/pub/uijlings-ijcv2013-draft.pdf

Object Detection – Region of Interest proposal

Selective Search

Design consideration:
- Capture all scales
- Diversification
- Fast to compute



https://koen.me/research/pub/uijlings-ijcv2013-draft.pdf

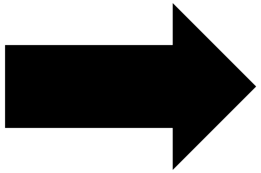
Object Detection – Region of Interest proposal

Selective Search

Complementary Similarity Measures

- Color
- Texture
- Size
- Fill

Full Score = C+T+S+F

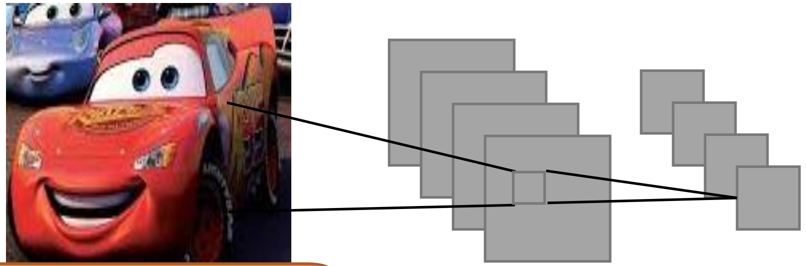


R-CNN architectures

Object Detection – overview – Regional CNN

1. Input Image

3. CNN feature computation



Alex Net

2. Region of Interest proposal

Selective Search

4. Classification of regions

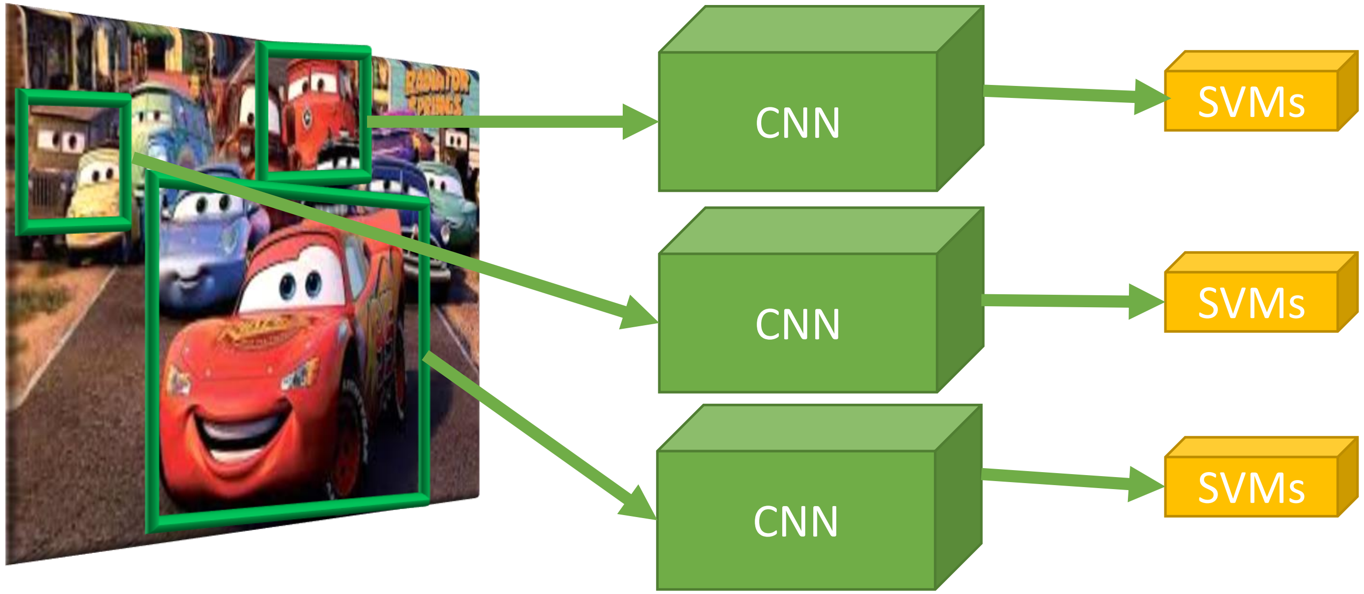
Airplane? No.

Car? Yes

Person? No

Class specific SVMs

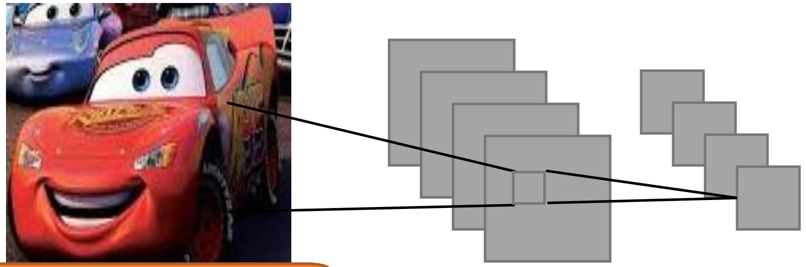
Object Detection – overview – Regional CNN



Object Detection – overview – Fast Regional CNN vol.2

1. Input Image

2&3. CNN feature computation



VGG16

2&3. Region of Interest proposal

Selective Search

4. Classification of regions

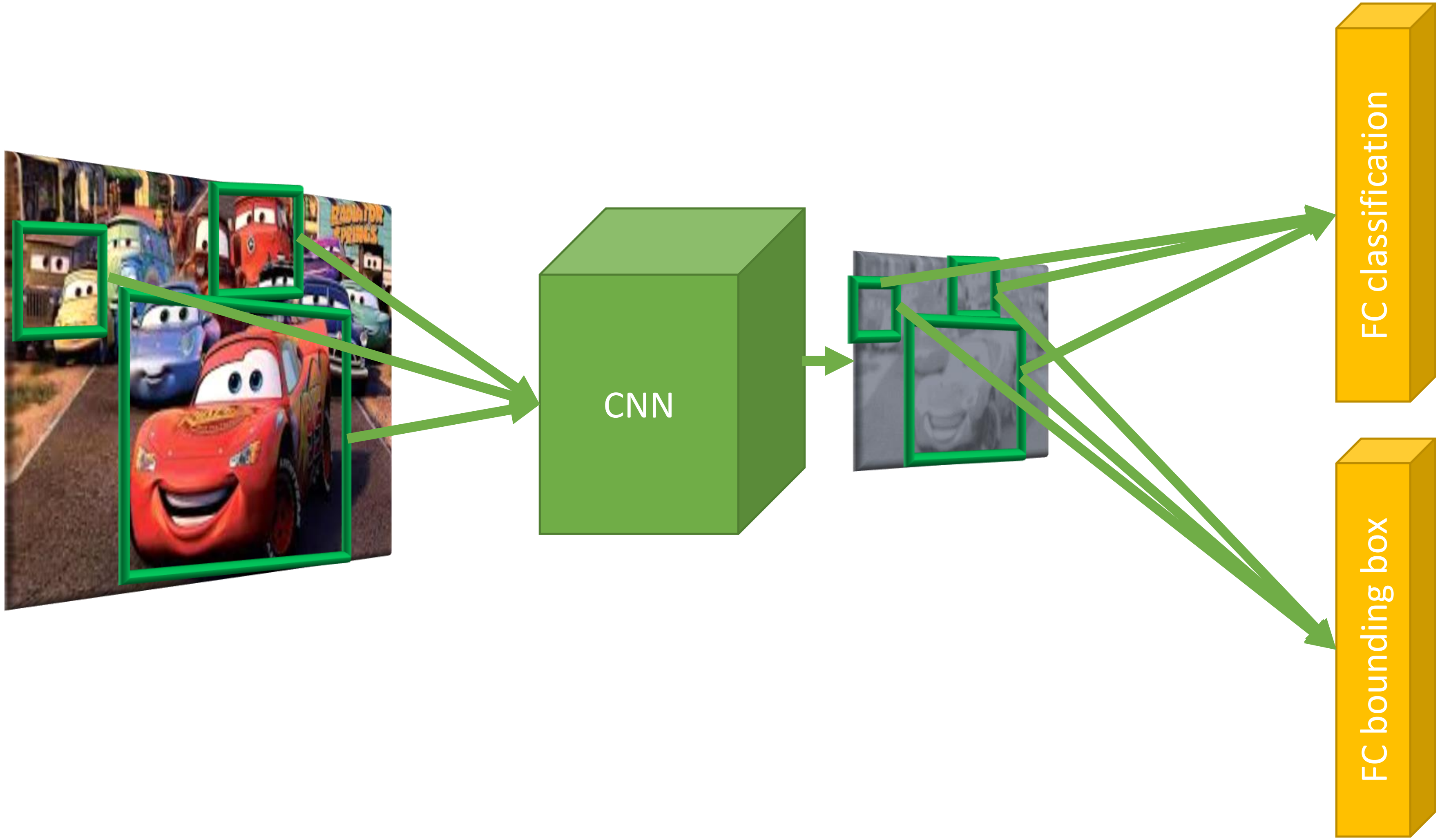
Airplane? No.

Car? Yes

Person? No

SoftMax

Object Detection – overview – Fast Regional CNN vol.2

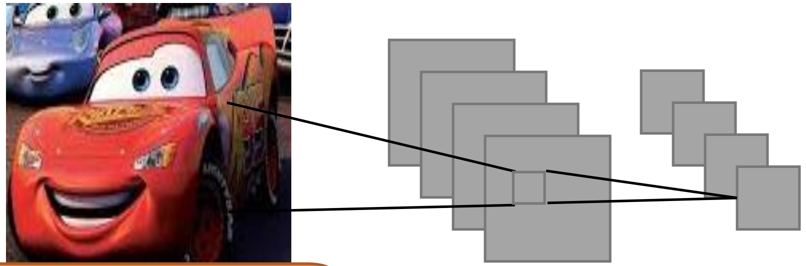


Own content

Object Detection – overview – Faster Regional CNN vol.3

1. Input Image

2. CNN feature computation



VGG16

3. Region of Interest proposal

Selective Search

4. Classification of regions

Airplane? No.

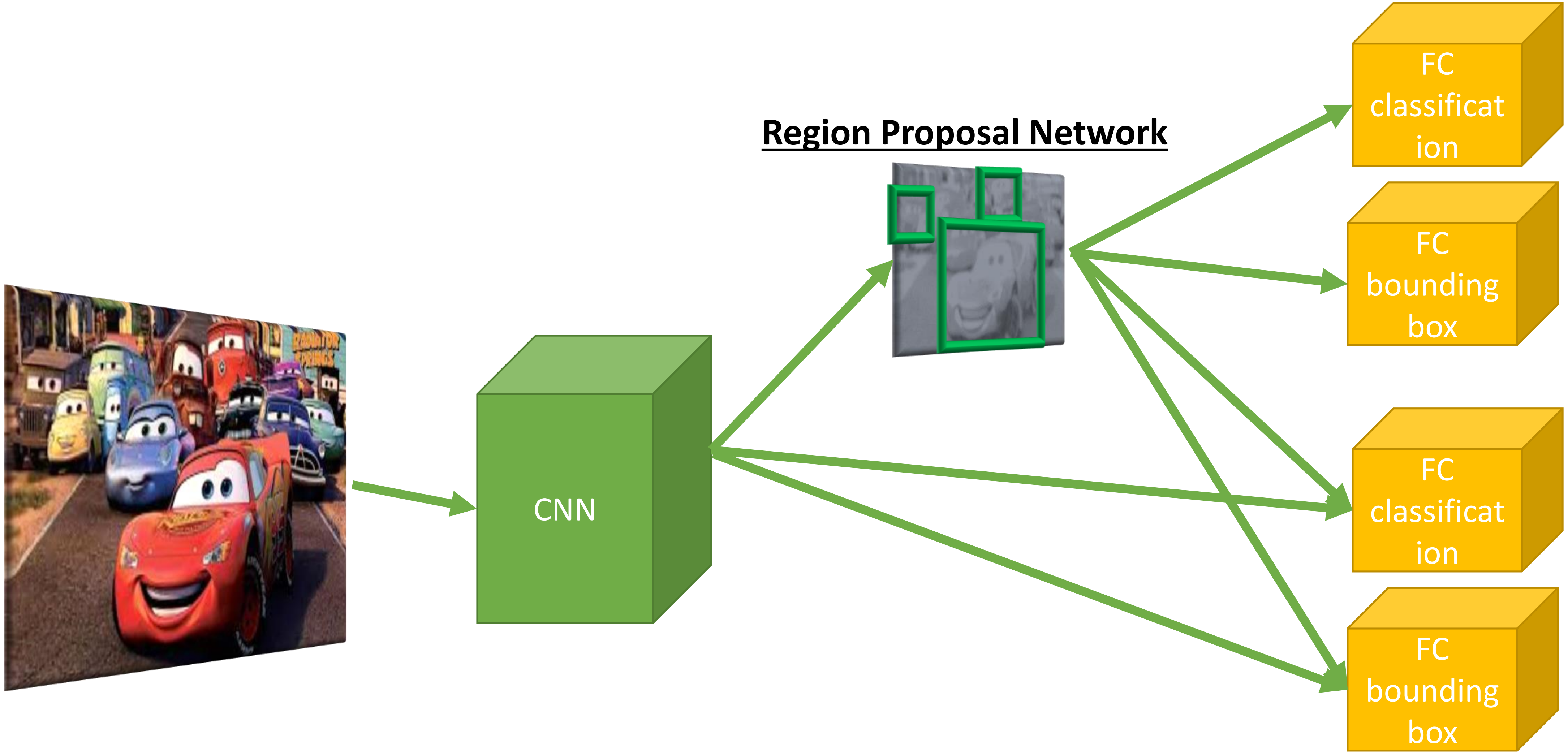
Car? Yes

Person? No

SoftMax

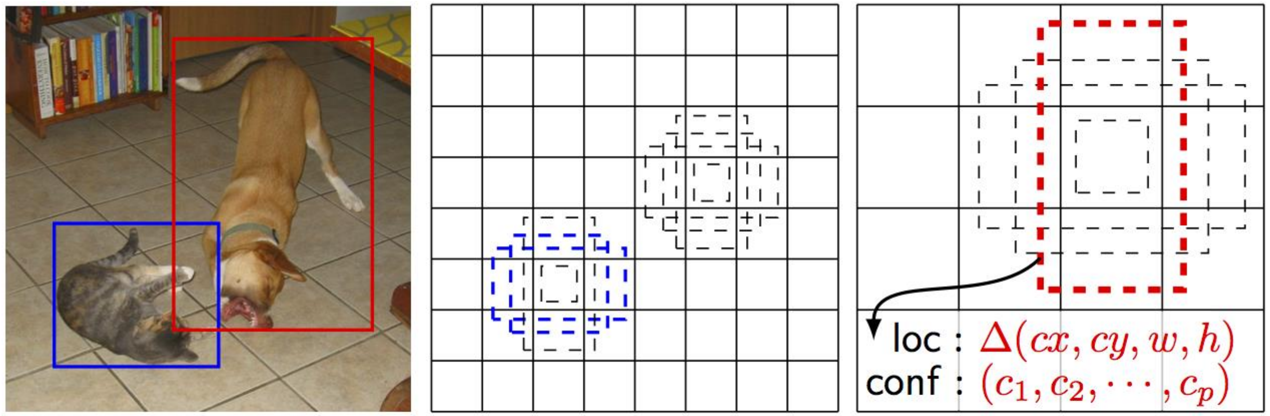
Own content

Object Detection – overview – Fast Regional CNN vol.2



Object Detection – overview – SSD

Single Shot MultiBox Detector



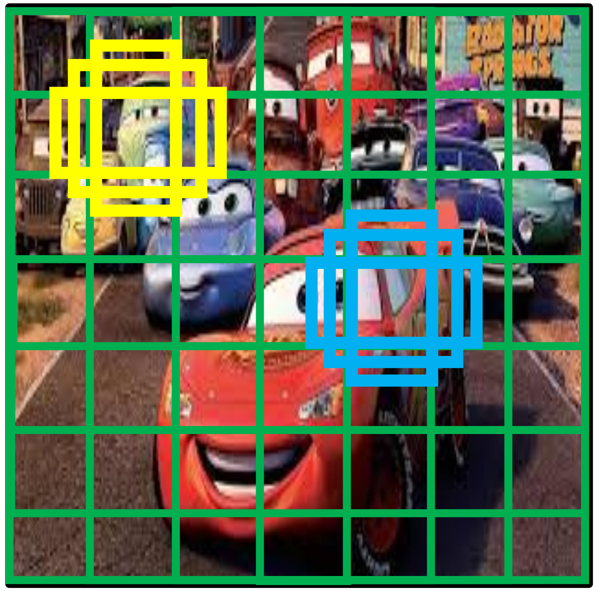
(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

Object Detection – overview – SSD

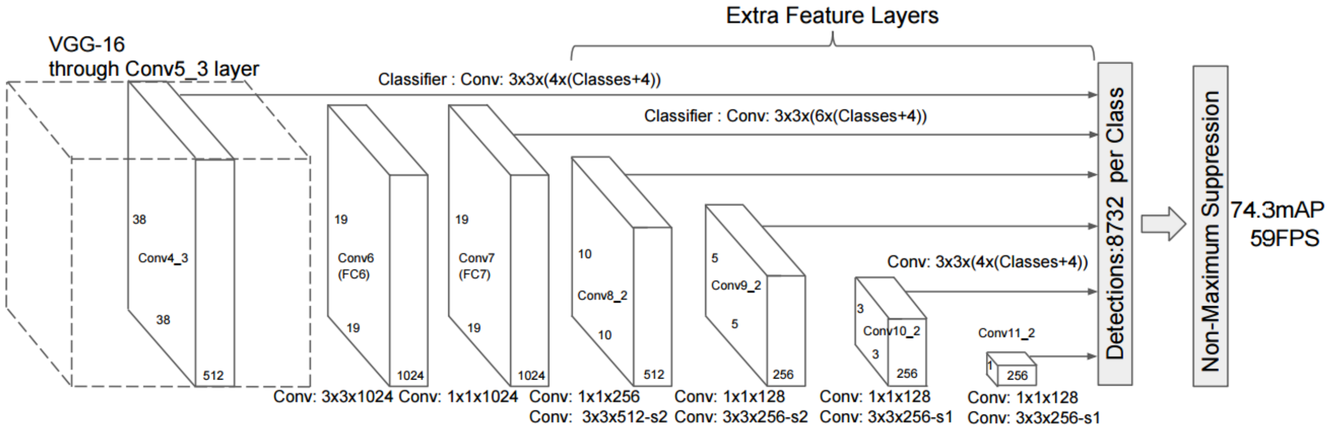
1. Input Image

2. CNN feature computation

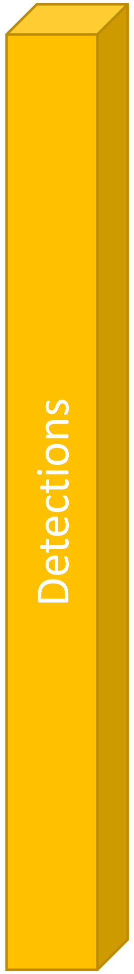
3. Classification of regions



Grid + anchor boxes



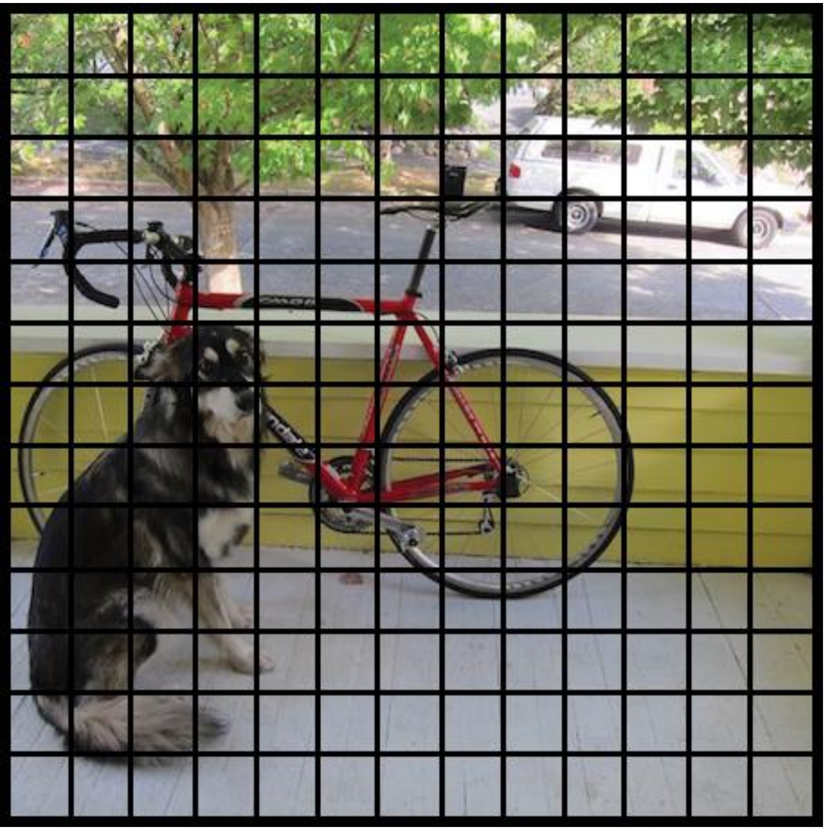
SSD

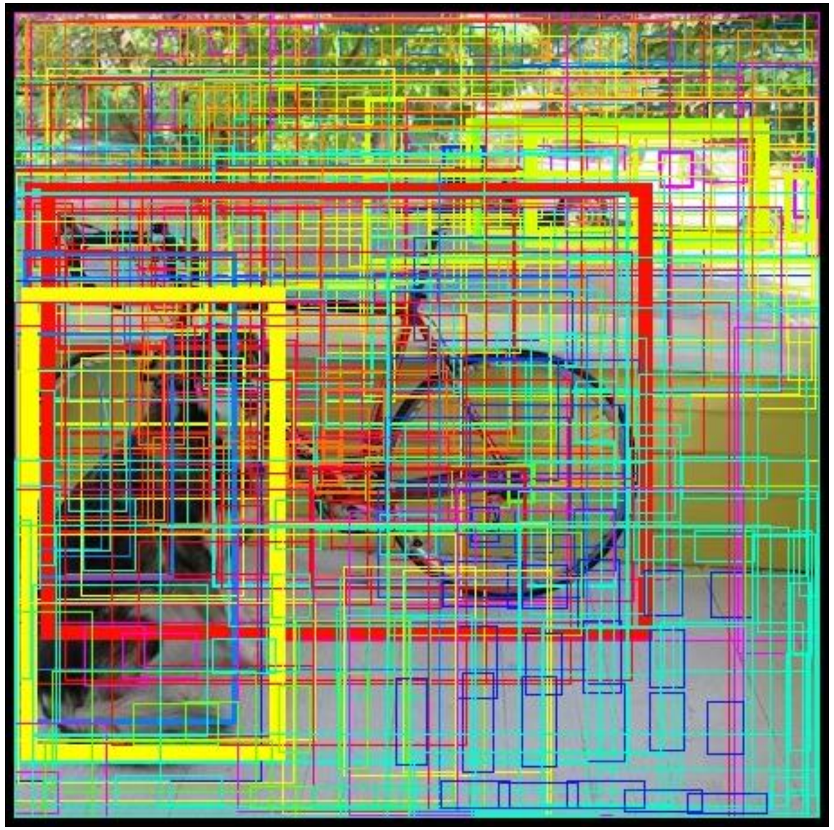


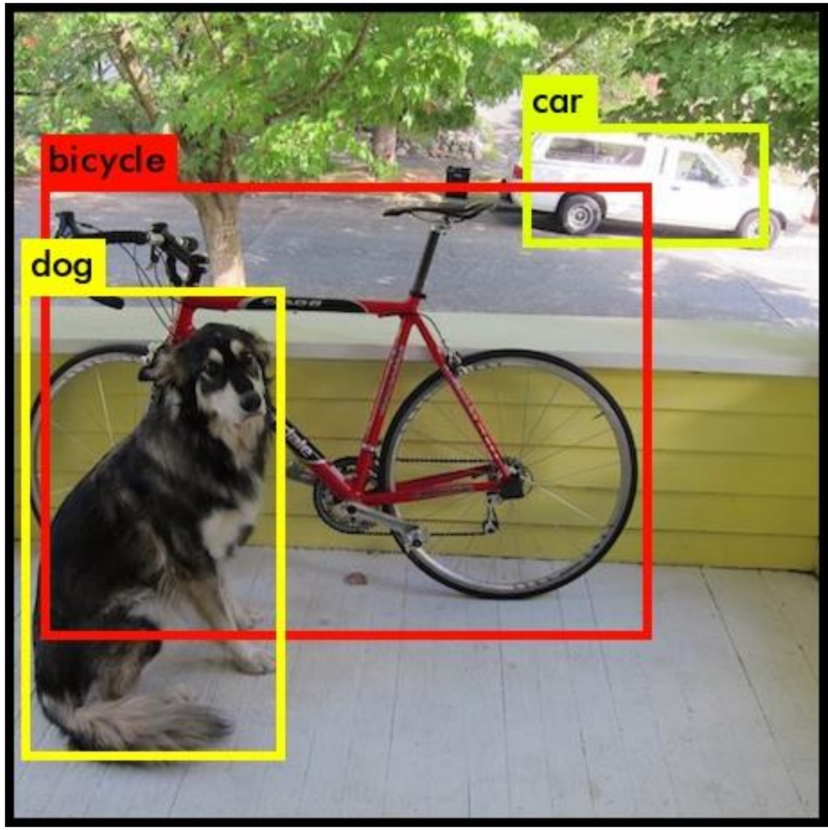
7x7x(5*B+C)

Own content

Object Detection – overview – YOLO







- **YOLO = You Only Look Once**

$S \times S \times (5 + C)$

x,y,w,h,conf

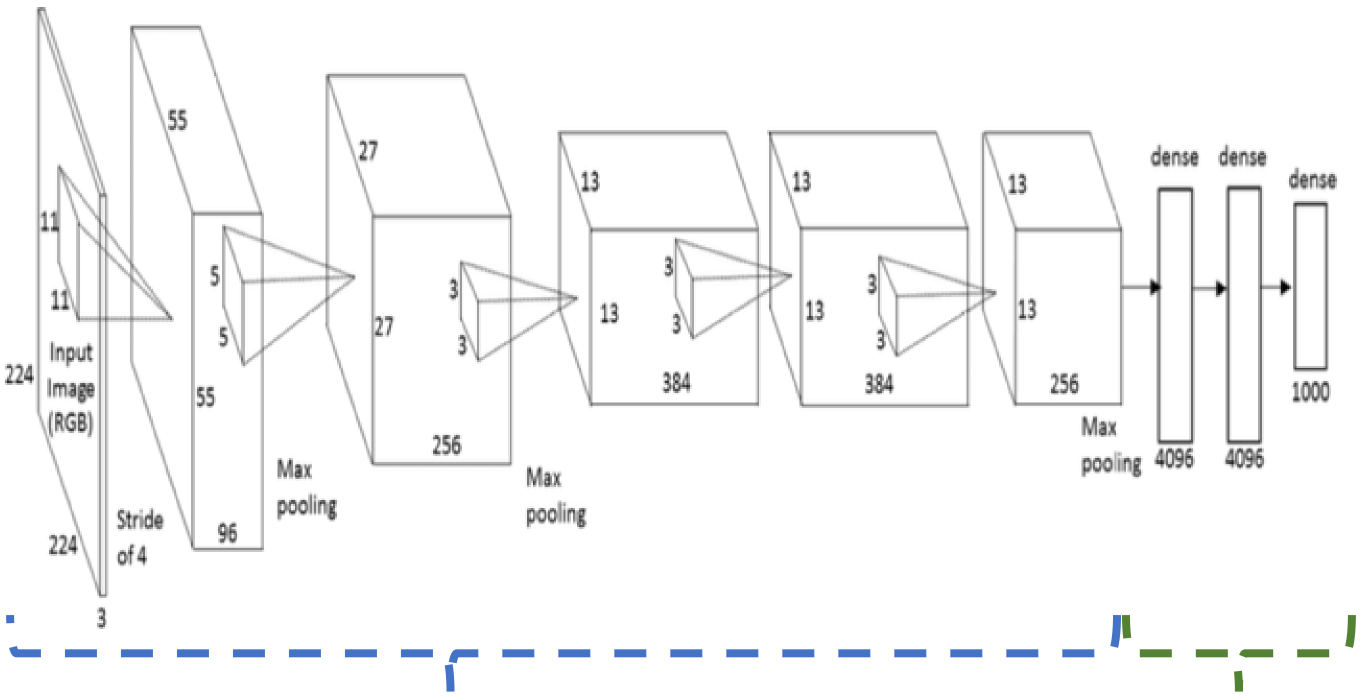
Transfer Learning

Object Detection – Transfer Learning

- **ConvNet as fixed feature extractor**. Take a ConvNet pretrained on ImageNet, remove the last fully-connected layer (this layer's outputs are the 1000 class scores for a different task like ImageNet), then treat the rest of the ConvNet as a fixed feature extractor for the new dataset. In an AlexNet, this would compute a 4096-D vector for every image that contains the activations of the hidden layer immediately before the classifier. We call these features **CNN codes**. It is important for performance that these codes are ReLUd (i.e. thresholded at zero) if they were also thresholded during the training of the ConvNet on ImageNet (as is usually the case). Once you extract the 4096-D codes for all images, train a linear classifier (e.g. Linear SVM or Softmax classifier) for the new dataset.
- **Fine-tuning the ConvNet**. The second strategy is to not only replace and retrain the classifier on top of the ConvNet on the new dataset, but to also fine-tune the weights of the pretrained network by continuing the backpropagation. It is possible to fine-tune all the layers of the ConvNet, or it's possible to keep some of the earlier layers fixed (due to overfitting concerns) and only fine-tune some higher-level portion of the network. This is motivated by the observation that the earlier features of a ConvNet contain more generic features (e.g. edge detectors or color blob detectors) that should be useful to many tasks, but later layers of the ConvNet becomes progressively more specific to the details of the classes contained in the original dataset. In case of ImageNet for example, which contains many dog breeds, a significant portion of the representational power of the ConvNet may be devoted to features that are specific to differentiating between dog breeds.
- **Black-box off the shelf model.** Using model that was already trained on a different data to resolve the same problem on the data at hand.

http://cs231n.github.io/transfer-learning/

Object Detection – Transfer Learning

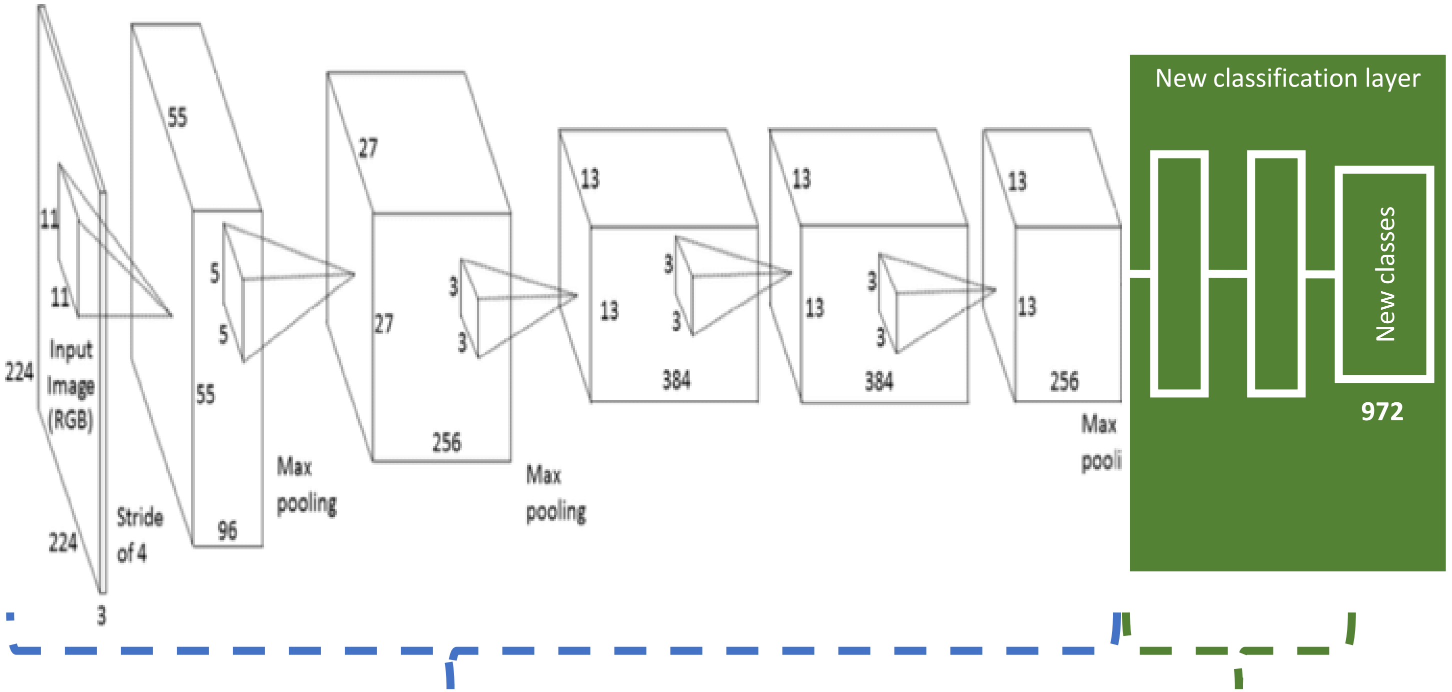


Part responsible for feature extraction
At initial layers the net extracts features like edges and colors. The deeper into the net we will go the more high level feature will be extracted. Examples of high level features: faces, wheels or text.

Categorization layer
This is a problem specific layer that uses the features extracted earlier to solve current problem.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. Imagenet classification with deep convolutional neural network. In Advances in Neural Information Processing Systems, 2012.

Object Detection – Transfer Learning



Part responsible for feature extraction

- Using information extracted from millions of images
- Possibility to fine-tune this part to extract specific features connected to problem at hand

Classification layer

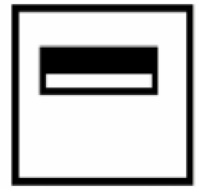
- Retrained for the problem at hand

Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. Imagenet classification with deep convolutional neural network. In Advances in Neural Information Processing Systems, 2012.

Experiment

Object Detection – Experiment Design

1. DATA PREPARATION



- **Haar cascade classifier**

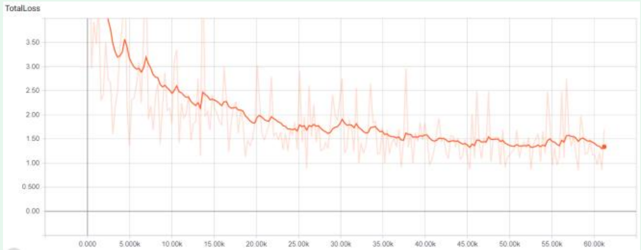
Generate TFRecord format

&

Create Label Map

2. CONFIGURATION & TRAINING

Pipeline configuration

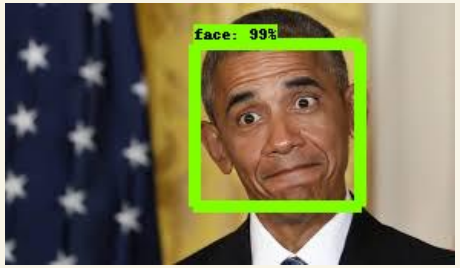


Training

3. VALIDATION

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

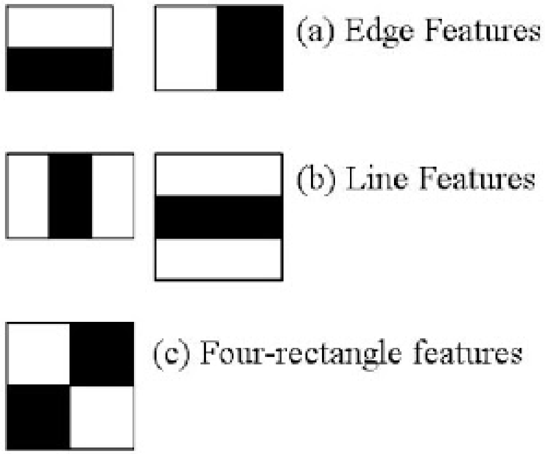
Graph export



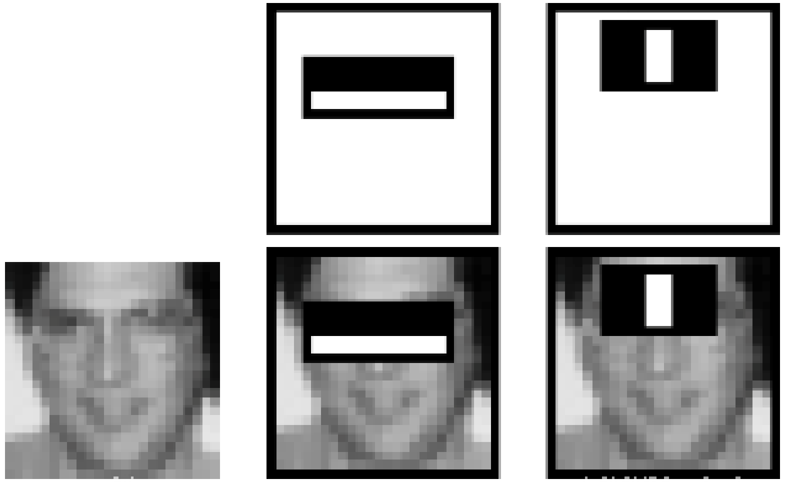
Results

Object Detection – Experiment Data preparation

- **HAAR FEATURES**



RELEVANT FEATURES

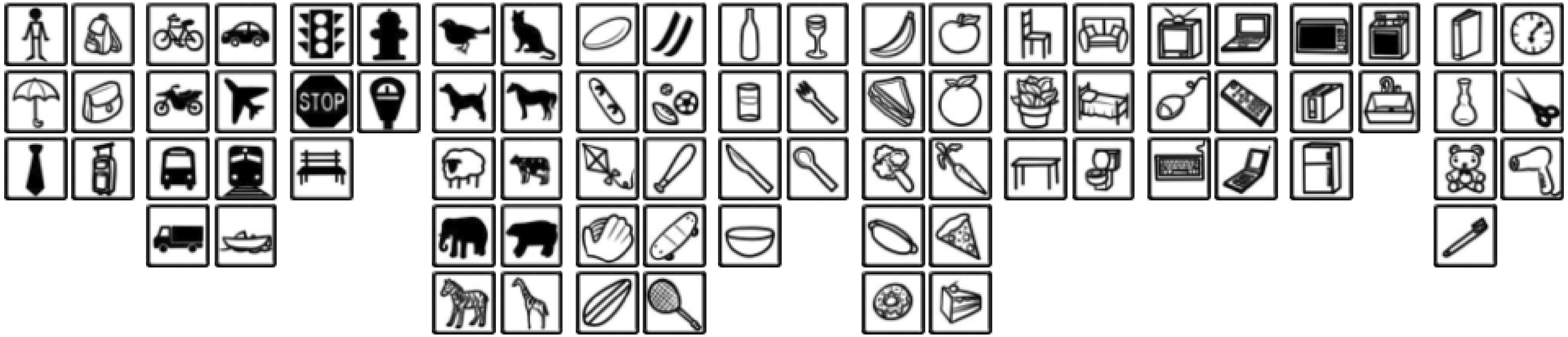


RAW DATA

LABELED DATA

Object Detection – Experiment Configuration & training

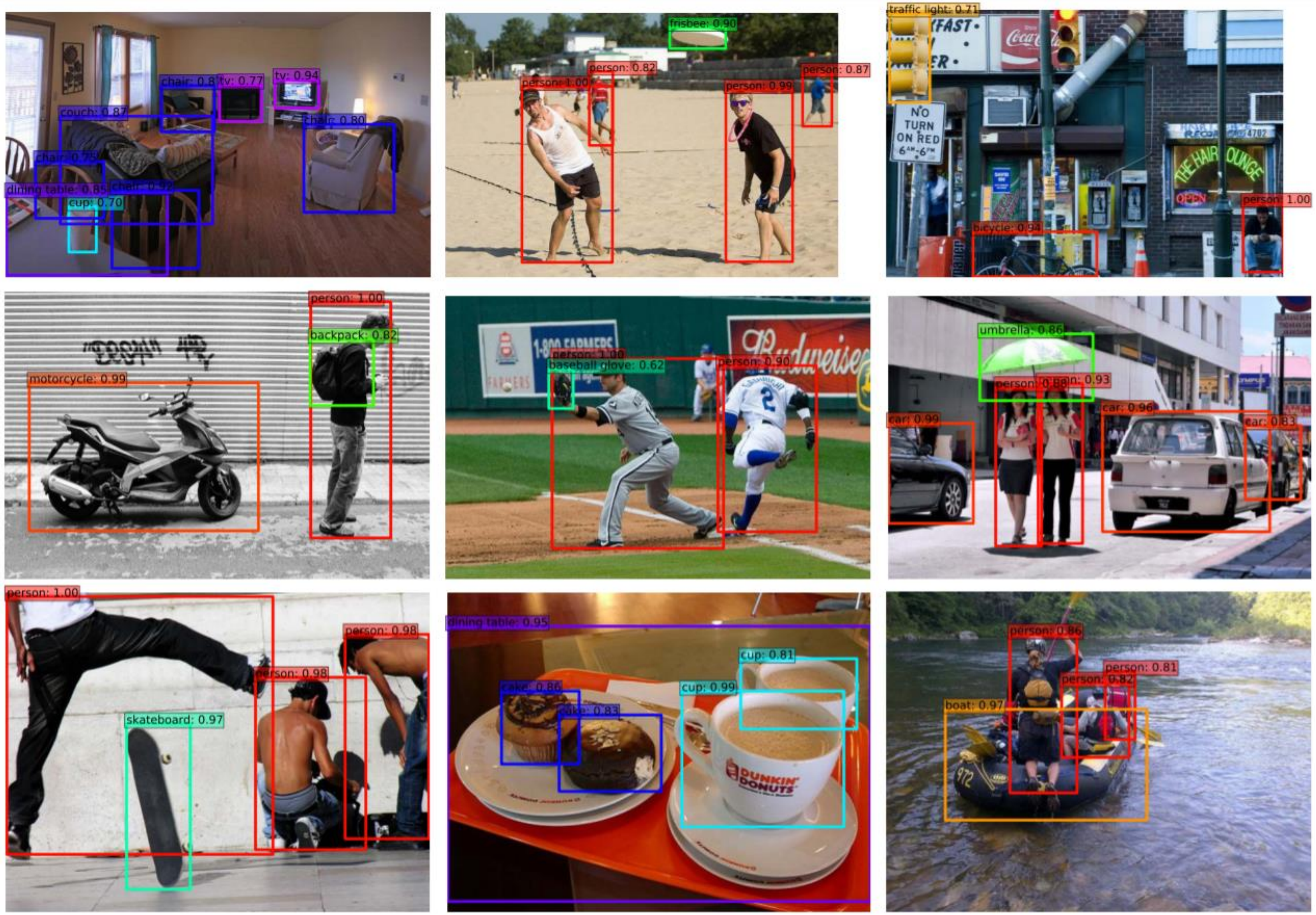
- **COCO dataset – Common Objects in Context**



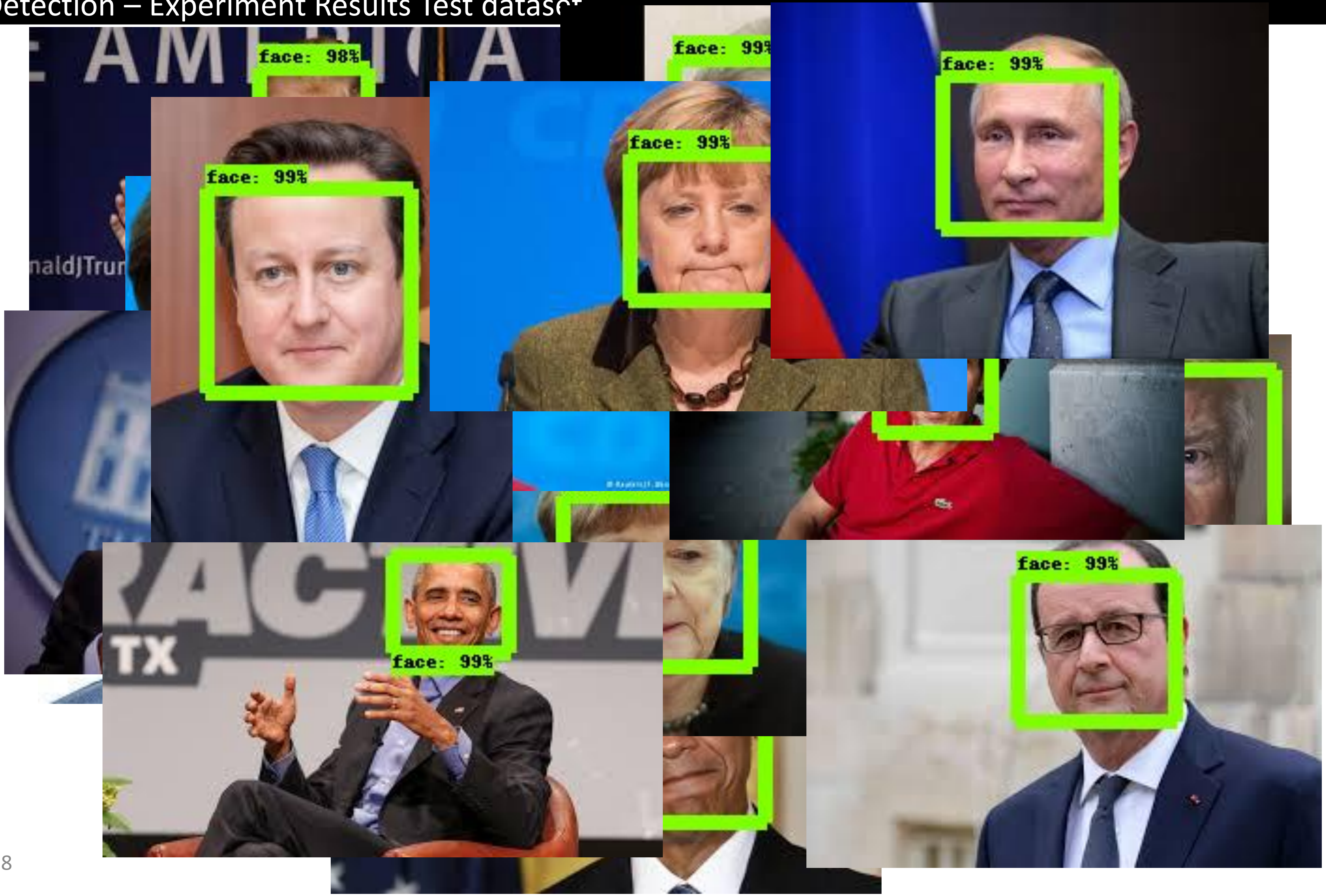
- 123,287 images
- 886,284 instances (labeled objects)

http://cocodataset.org/#explore

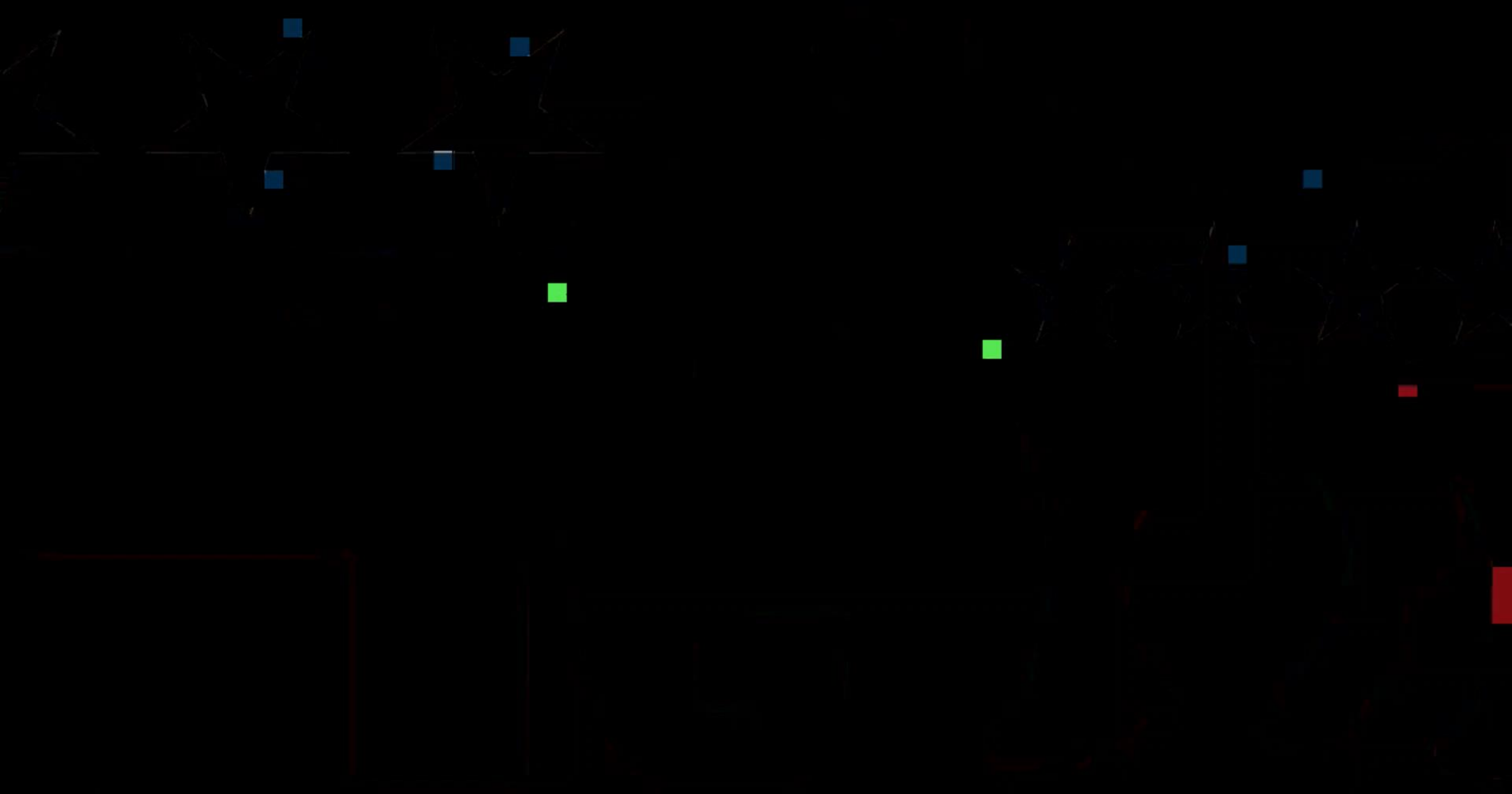
Object Detection – Experiment SSD results on COCO dataset



Object Detection – Experiment Results Test dataset



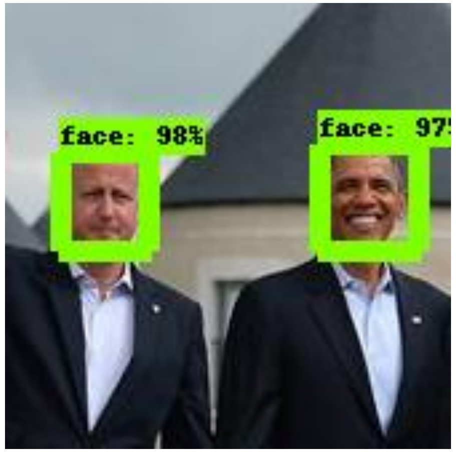
Own Content

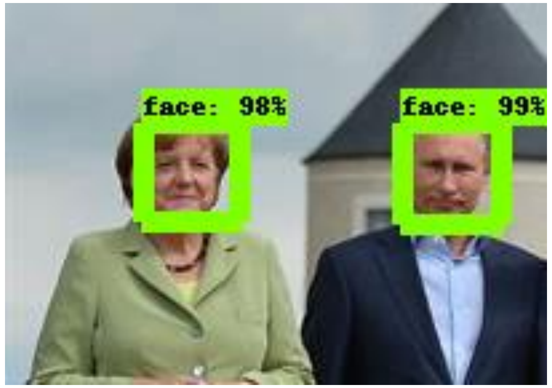


Object Detection – Experiment Learnings

Observations

- Scale of the class in the training images
- Different angels/views of the training class





Future plans

Object Detection – Transfer Learning

Adding new class to a previously trained object detection network.

Experiment design

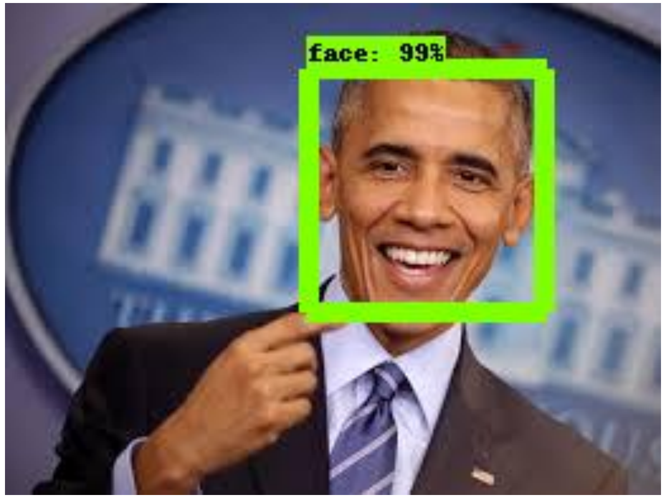
Comparison of 3 different object detection networks:

- Original SSD network trained on COCO dataset
- SSD network from point 1 retrained with images of faces and chairs
- SSD network from point 1 retrained with images of faces

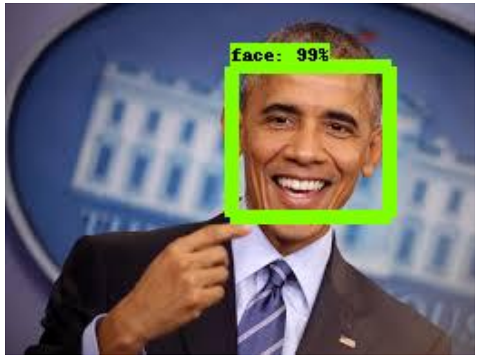
Detection comparison

Original SSD

Face+Chair retrained SSD

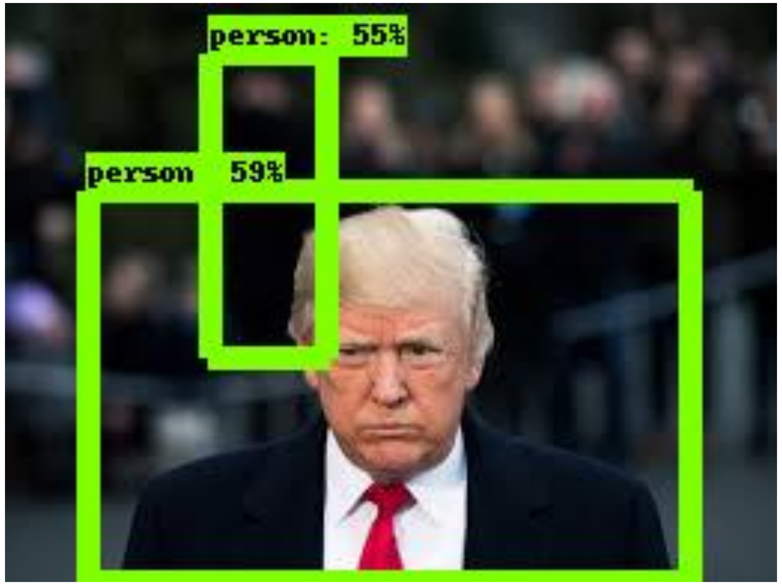


ONLY Face retrained SSD



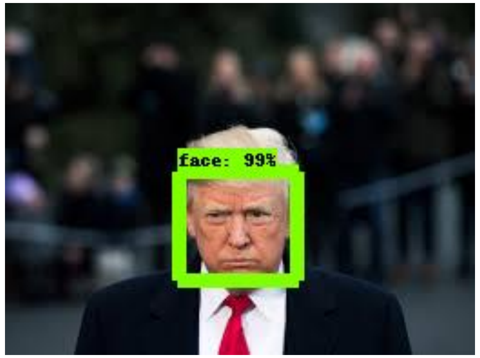
Detection comparison

Original SSD



Face+Chair retrained SSD

ONLY Face retrained SSD



Detection comparison

Original SSD

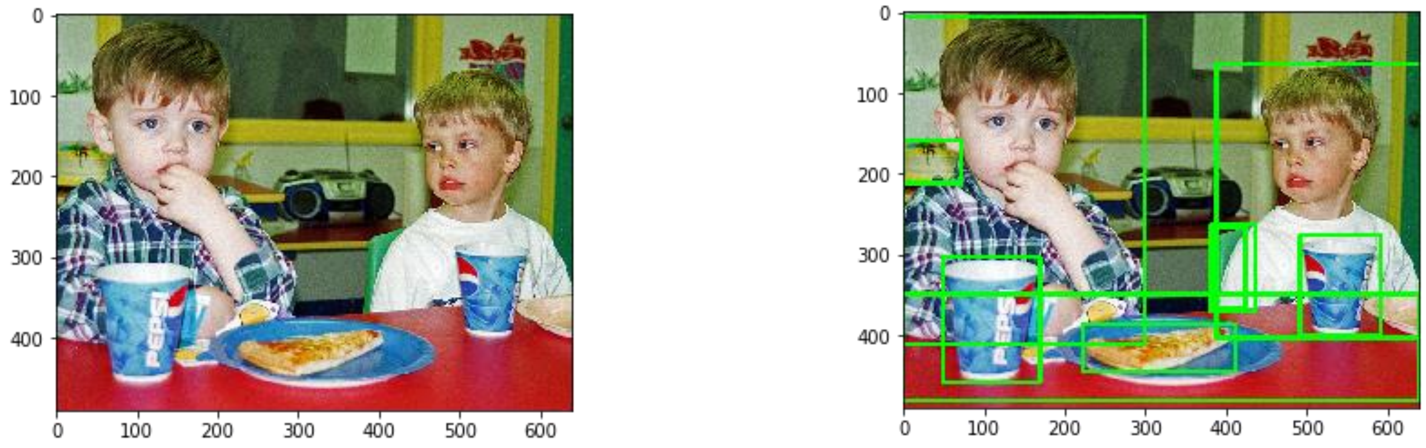
Face+Chair retrained SSD

Detection comparison - Summary

The object detection net trained on images of both faces and chairs:

- Performed worse as a face detector than the object detection net trained on images of faces alone
- Did not detect any of the chairs

Check for correct bbox position extraction



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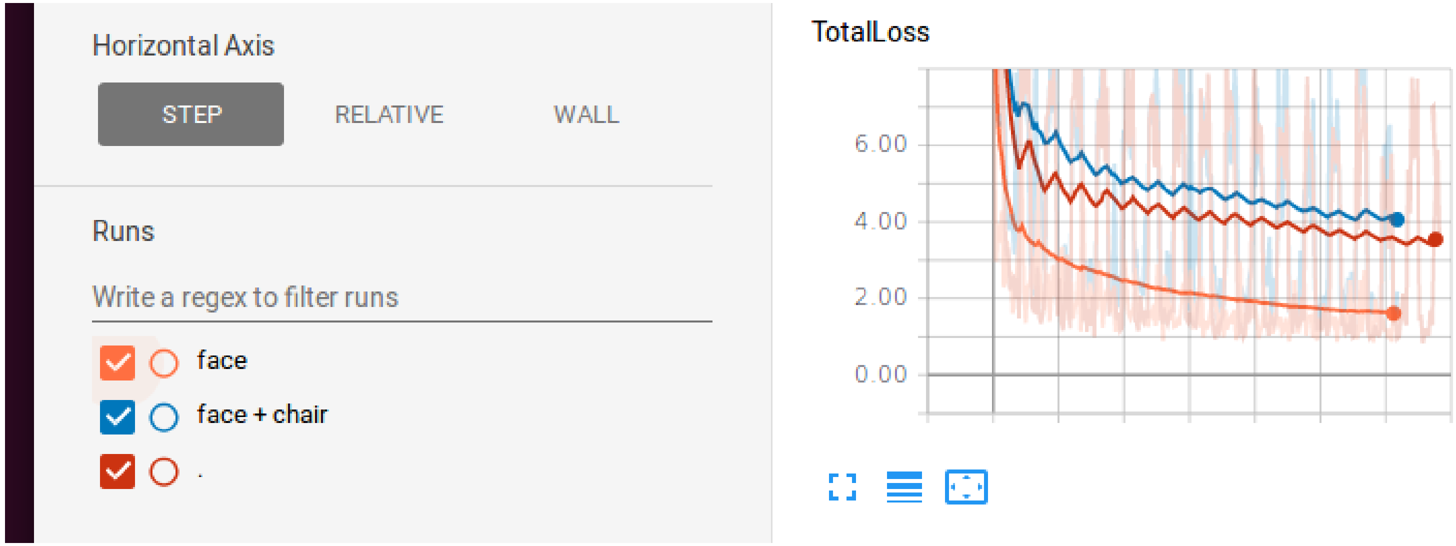
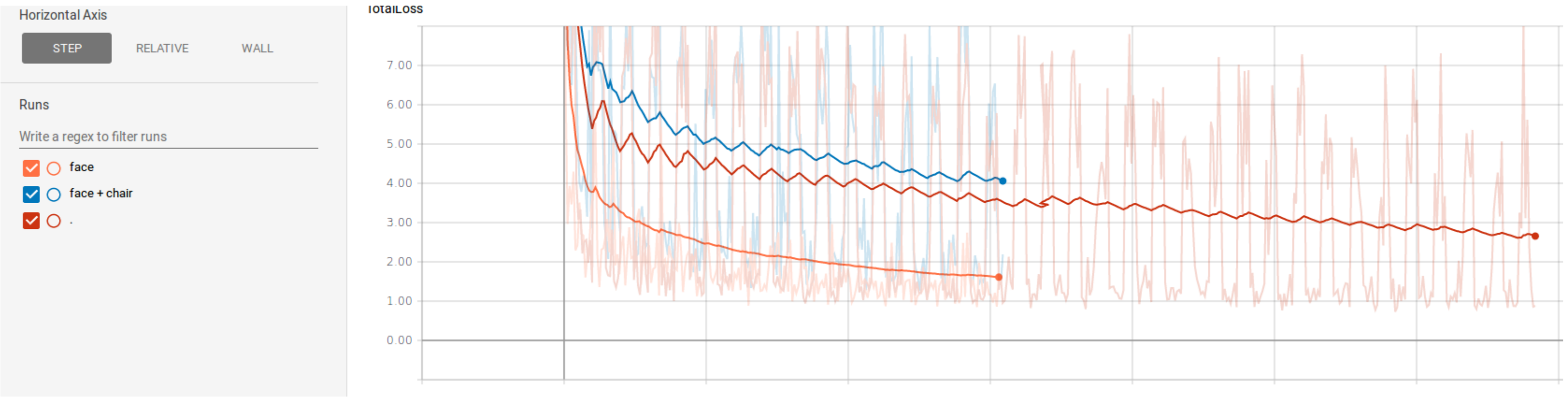
201426	67	000000201426.jpg	414419	201426	638.65	0.00	480.09	349.06
201426	1	000000201426.jpg	440231	201426	640.00	387.60	403.01	64.97
201426	47	000000201426.jpg	677913	201426	169.19	49.44	458.80	303.89
201426	47	000000201426.jpg	679377	201426	590.16	490.05	400.04	276.60
201426	59	000000201426.jpg	1075152	201426	410.72	221.33	445.96	386.49
201426	61	000000201426.jpg	1085132	201426	72.75	0.00	212.38	159.16
201426	1	000000201426.jpg	1213103	201426	298.40	0.00	410.72	6.61
201426	62	000000201426.jpg	1930281	201426	435.83	380.05	371.88	262.28

Check if any chairs are found if we only train for chair detection

Only one chair was found in test images.

Learning curves comparison





Detection comparison - Summary

The object detection net trained on images of both faces and chairs:

- Performed worse as a face detector than the object detection net trained on images of faces alone
- Did not detect any of the chairs

Conclusions & thoughts:

- Length of the learning process
- Incorrect input data – more suitable for localization & classification problem

Sources

- https://blog.athelas.com/a-brief-history-of-cnns-in-image-segmentation-from-r-cnn-to-mask-r-cnn-34ea83205de4
- Alexnet: https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks
- VGG: https://arxiv.org/pdf/1409.1556.pdf
- ResNet: https://arxiv.org/pdf/1512.03385.pdf
- R-CNN: https://arxiv.org/abs/1311.2524
- Fast R-CNN: https://arxiv.org/abs/1504.08083
- Faster R-CNN: https://arxiv.org/abs/1506.01497
- SDD: https://arxiv.org/pdf/1512.02325.pdf
- YOLO: https://pjreddie.com/media/files/papers/yolo.pdf