Advanced Section #3: CNNs and Object Detection

AC 209B: Data Science

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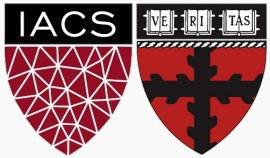


Lecture Outline

Convnets review

Classic Networks

Residual networks

Other combination blocks

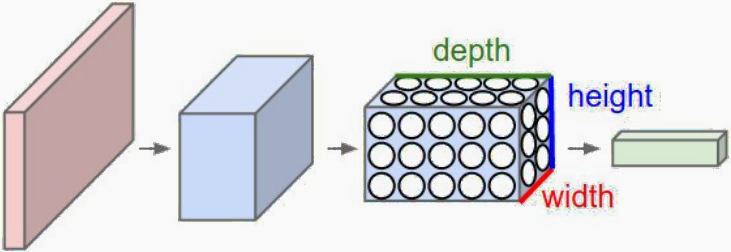
Object recognition systems

Face recognition systems

Convnets review

Motivation for convnets

- Less parameters (weights) than a FC network.
- Invariant to object translation.
- Can tolerate some distortion in the images.
- Capable of generalizing and learning features.
- Require grid input.



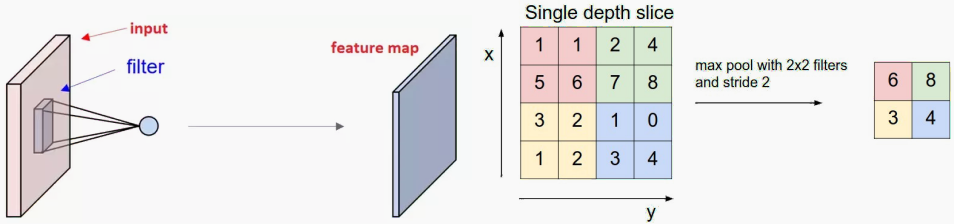
Source: http://cs231n.github.io/

CNN layers

- Convolutional layer: formed by **filters**, **feature maps**, and **activation functions**.
  - Convolution can be ***full***, ***same*** or ***valid***.

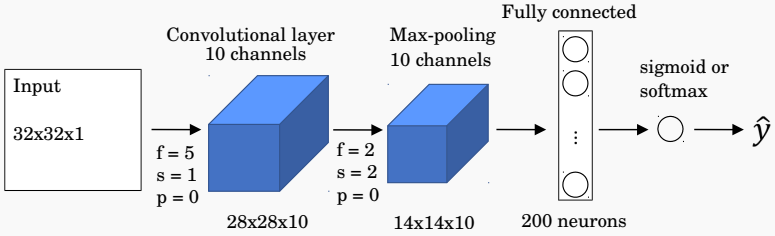
$$n_{\text{output}} = \left\lfloor \frac{n_{\text{input}} - f + 2p}{s} + 1 \right\rfloor.$$

- Pooling layers: reduces overfitting.
- Fully connected layers: mix spacial and channel features together.



Source: http://cs231n.github.io/

Introductory convolutional network example

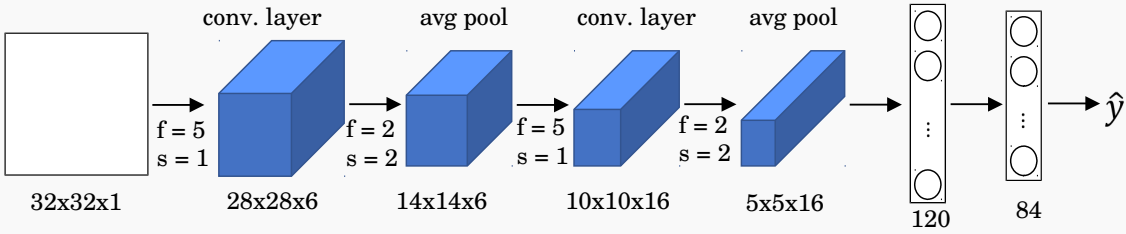


- Training parameters:
  - 250 weights on the conv. filter + 10 bias terms.
  - 0 weights on the max-pool.
  - $13 \times 13 \times 10 = 1,690$ output elements after max-pool.
  - $1,690 \times 200 = 338,000$ weights + 200 bias in the FC layer.
  - Total: 338,460 parameters to be trained.

Classic Networks

LeNet-5

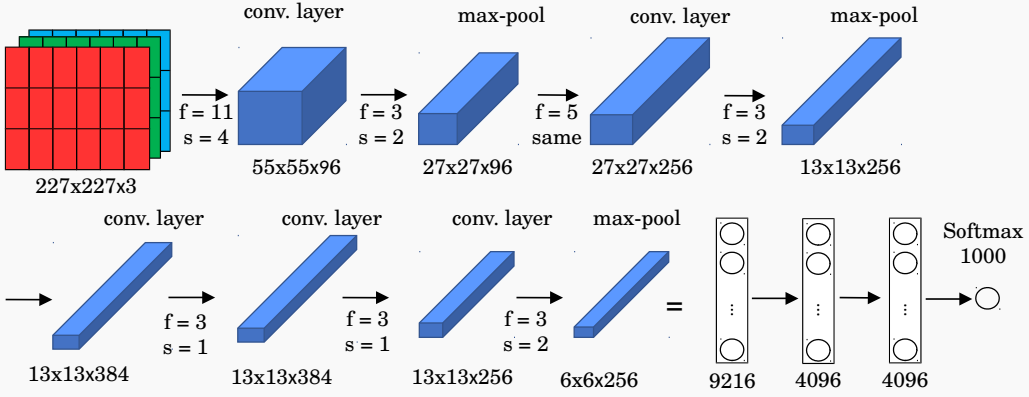
- Formulation is a bit outdated considering current practices.
- Uses convolutional networks followed by pooling layers and finishes with fully connected layers.
- Starts with high dimensional features and reduces their size while increasing the number of channels.
- Around 60k parameters.



Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.

AlexNet

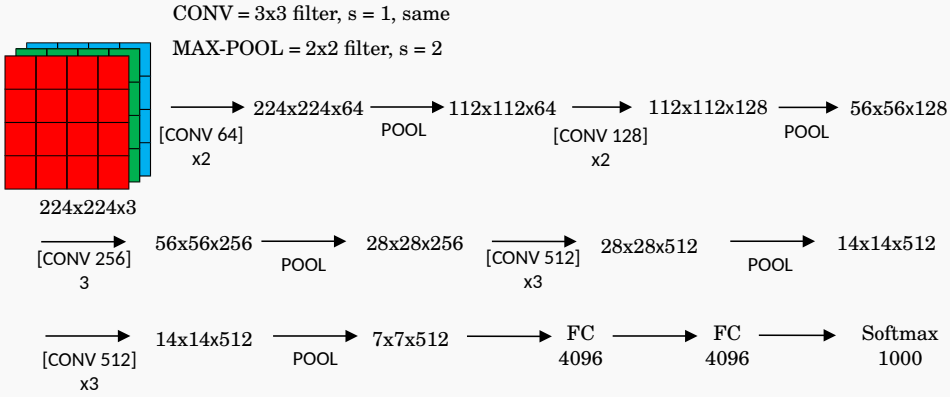
- 1.2 million high-resolution (227x227x3) images in the ImageNet 2010 contest;
- 1000 different classes; NN with 60 million parameters to optimize ($\sim$ 255 MB);
- Uses ReLu activation functions;. GPUs for training; 12 layers.



Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, pp. 1097–1105, 2012

VGG-16 and VGG-19

- ImageNet Challenge 2014; 16 or 19 layers; 138 million parameters (522 MB).
- Convolutional layers use 'same' padding and stride $s = 1$.
- Max-pooling layers use a filter size $f = 2$ and stride $s = 2$.

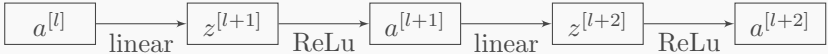


Karen Simonyan and Andrew Zisserman, "Very deep convolutional networks for large-scale image recognition," 2014.

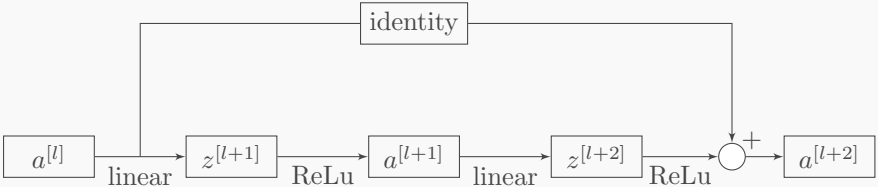
Residual networks

Residual block

- Residual nets appeared in 2016 to train very deep NN (100 or more layers).
- Their architecture uses 'residual blocks'.
- Plain network structure:



- **Residual network block**:



Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, "Deep residual learning for image recognition," in *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016.

Equations of the residual block

- Plain network:

$$
\begin{aligned}
a^{[l]} &= g(z^{[l]}) \\
z^{[l+1]} &= W^{[l+1]}a^{[l]} + b^{[l+1]} \\
a^{[l+1]} &= g(z^{[l+1]}) \\
z^{[l+2]} &= W^{[l+2]}a^{[l+1]} + b^{[l+2]} \\
a^{[l+2]} &= g(z^{[l+2]})
\end{aligned}
$$

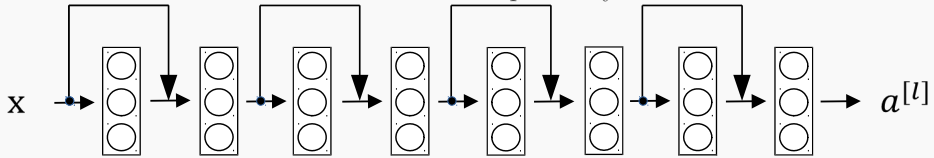
- Residual block:

$$
\begin{aligned}
a^{[l]} &= g(z^{[l]}) \\
z^{[l+1]} &= W^{[l+1]}a^{[l]} + b^{[l+1]} \\
a^{[l+1]} &= g(z^{[l+1]}) \\
z^{[l+2]} &= W^{[l+2]}a^{[l+1]} + b^{[l+2]} \\
a^{[l+2]} &= g(z^{[l+2]} + a^{[l]})
\end{aligned}
$$

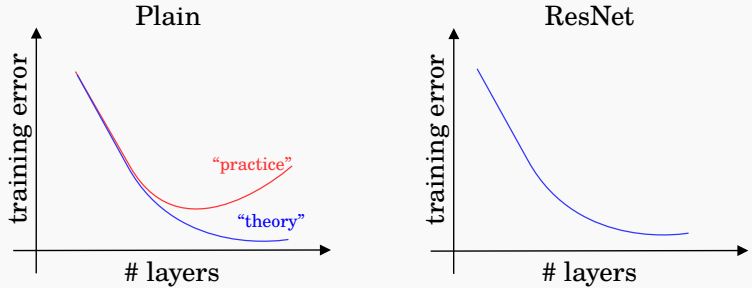
- With this extra connection gradients can travel backwards more easily.
- The residual block can very easily learn the identity function by setting $W^{[l+2]} = 0$ and $b^{[l+2]} = 0$.
- In such case, $a^{[l+2]} = g(a^{[l]}) = a^{[l]}$ for ReLu units.
  - It becomes a flexible block that can expand the capacity of the network, or simply transform into a identity function that would not affect training.

Residual network

- A residual network stacks residual blocks sequentially.



- The idea is to allow the network to become deeper without increasing the training complexity.

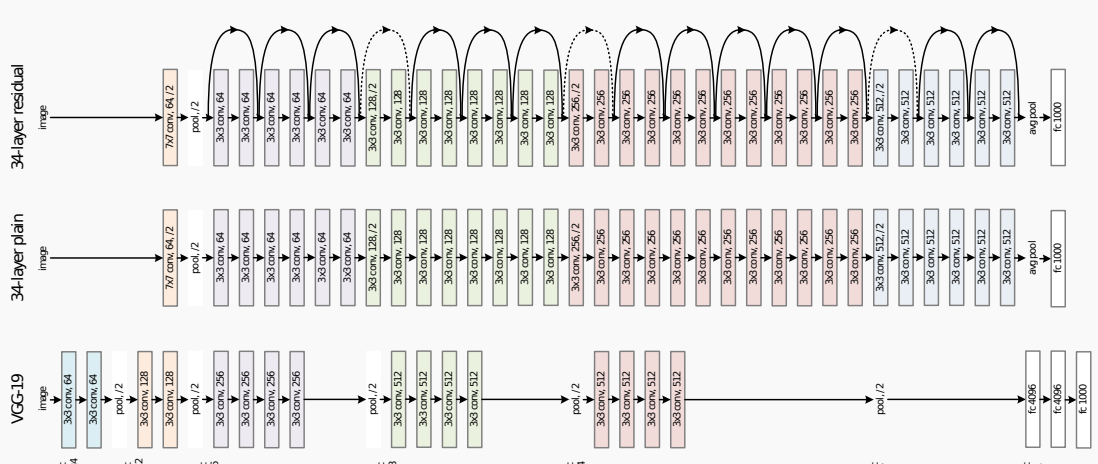


Residual network

- Residual networks implement blocks with convolutional layers that use ‘same’ padding option (even when max-pooling).
  - This allows the block to learn the identity function.
- The designer may want to reduce the size of features and use ‘valid’ padding.
  - In such case, the shortcut path can implement a new set of convolutional layers that reduces the size appropriately.

Number of Layers	Number of Parameters
ResNet 18	11.174M
ResNet 34	21.282M
ResNet 50	23.521M
ResNet 101	42.513M
ResNet 152	58.157M

Residual network 34 layer example



Source: He2016

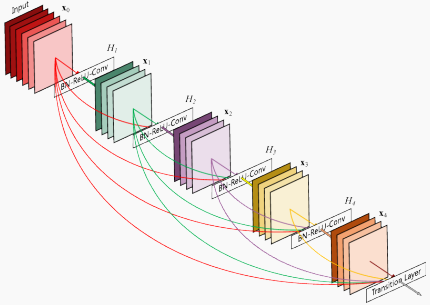
Classification error values on Imagenet

- Alexnet (2012) achieved a top-5 error of 15.3% (second place was 26.2%).
- ZFNet (2013) achieved a top-5 error of 14.8% (visualization of features).

method	top-1 err.	top-5 err.
VGG [40] (ILSVRC'14)	-	8.43†
GoogLeNet [43] (ILSVRC'14)	-	7.89
VGG [40] (v5)	24.4	7.1
PReLU-net [12]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	19.38	4.49

Dense Networks

- **Goal:** allow maximum information (and gradient) flow $\longrightarrow$ connect every layer directly with each other.
- DenseNets exploit the potential of the network through feature reuse $\longrightarrow$ no need to learn redundant feature maps.
- DenseNets layers are very narrow (e.g. 12 filters), and they just add a small set of new feature-maps.



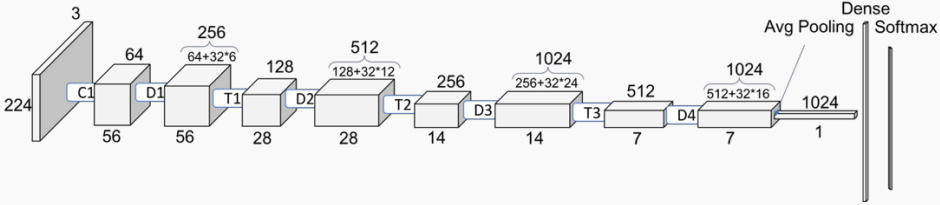
Dense Networks II

- DenseNets do not sum the output feature maps of the layer with the incoming feature maps but concatenate them:

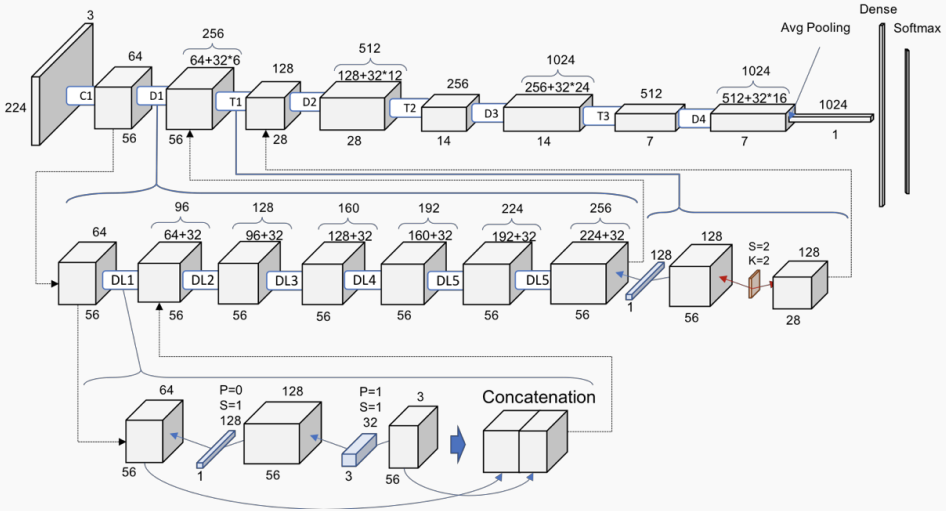
$$a^{[l]} = g([a^{[0]}, a^{[1]}, \ldots, a^{[l-1]}])$$

- D imensions of the feature maps remains constant within a block, but the number of filters changes between them $\longrightarrow$ **growth rate**:

$$k^{[l]} = k^{[0]} + k \cdot (l-1)$$



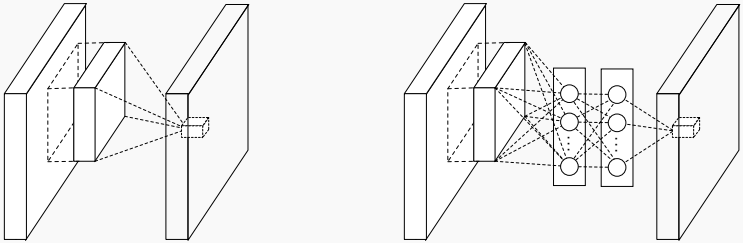
Dense Networks III: Full architecture



Other combination blocks

Network in network

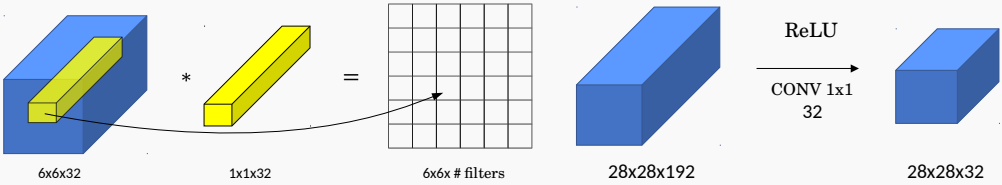
- Influential concept in the deep learning literature [Lin2013].
- Authors goal was to generate a deeper network without simply stacking more layers.
- They replace few filters with a smaller perceptron layers:
  - It is compatible with the backpropagation logic of neural nets.
  - It can itself be a deep model leading to rich separation between latent features.
- There is a ReLu operation after every neuron:
  - A richer nonlinear function approximator can serve as a better feature extractor.



Min Lin, Qiang Chen, and Shuicheng Yan, "Network in network," 2013.

1x1 Convolution

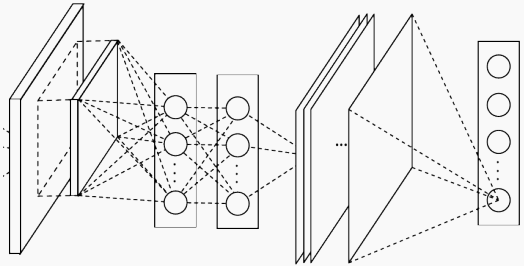
- A particular case from the previous concept are 1x1 convolutions.



- If the input had two dimensions, the 1×1 convolution would correspond to a scalar multiplication.
- With a greater number of channels (say, 32), the convolutional filter will have $1 \times 1 \times 32$ elements (more than a simple scaling) + **non-linear activation**.
- 1x1 convolution leads to dimension reductionality $\rightarrow$ ***feature pooling*** technique.
  - Reduces the overfitting capacity of the network.
- FC layers can be regarded as 1x1 convolutions if they go after a FC layer.

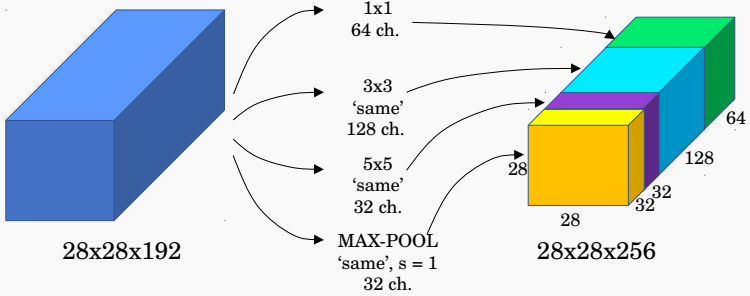
Global Average Pooling

- Another idea from [Lin2013] is a technique to simplify the last layers of CNNs.
- In traditional CNNs, feature maps of the last convolution layer are flattened and passed on to one or more fully FC, which are then passed on to softmax.
  - An estimate says that the last FC layers contain 90% of parameters of the NN.
- Global Average Pooling uses a FC layer with as many outputs as the number of classes being predicted.
- Then, each map is averaged given rise to the raw scores of the classes and fed to softmax.
  - No new parameters to train (unlike the FC layers), leading to less overfitting.
  - Robust to spatial translations of the input.



Inception module

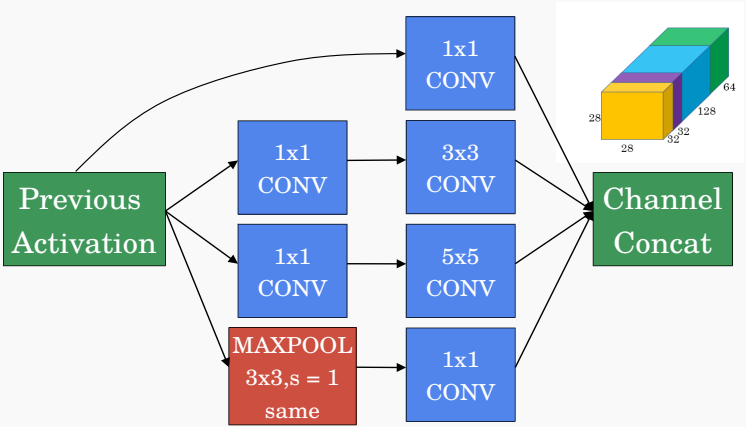
- The motivation behind inception networks is to use more than a single type of convolutional layer at each layer.
- Use 1×1, 3×3, 5×5 convolutional layers, and max-pooling layers in parallel.
- All modules use ***same*** convolution.
- Naïve implementation:



Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich, "Going deeper with convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 1–9.

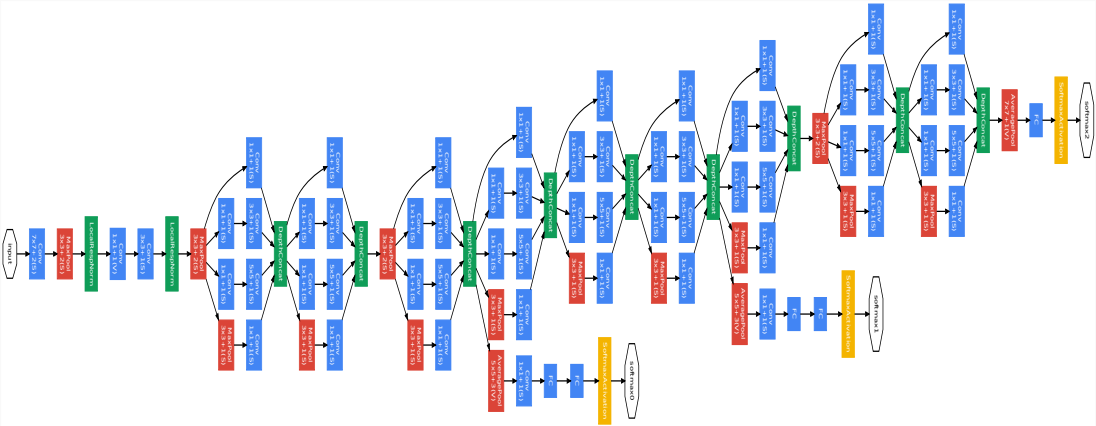
Inception module with dimension reductions

- Use 1×1 convolutions that reduce the size of the channel dimension.
  - The number of channels can vary from the input to the output.



GoogLeNet network

- The inception network is formed by concatenating other inception modules.
- It includes several softmax output units to enforce regularization.



Summary of networks

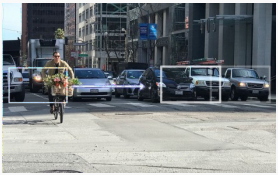
- We are now reaching top-5 error rates lower than human manual classification.

Year	CNN	Developed by	Place	Top-5 error rate	No. of parameters
1998	LeNet(8)	Yann LeCun et al			60 thousand
2012	AlexNet(7)	Alex Krizhevsky, Geoffrey Hinton, Ilya Sutskever	1st	15.3%	60 million
2013	ZFNet()	Matthew Zeiler and Rob Fergus	1st	14.8%	
2014	GoogLeNet(19)	Google	1st	6.67%	4 million
2014	VGG Net(16)	Simonyan, Zisserman	2nd	7.3%	138 million
2015	ResNet(152)	Kaiming He	1st	3.6%	

Object recognition systems

Sliding-window detectors

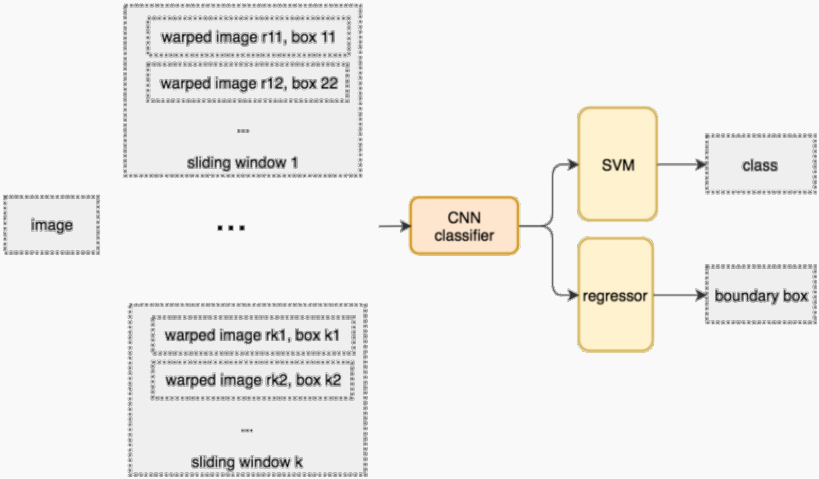
- Brute force approach $\longrightarrow$ several window sizes moved throughout the image.
- Patches are cut and warped $\longrightarrow$ passed through a classification CNN.

- Pseudo-code:

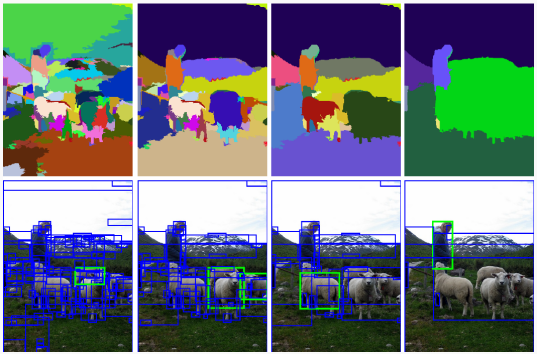
```
for window in windows
        patch = get_patch(image, window)
        results = detector(patch)
```

Sliding window architecture



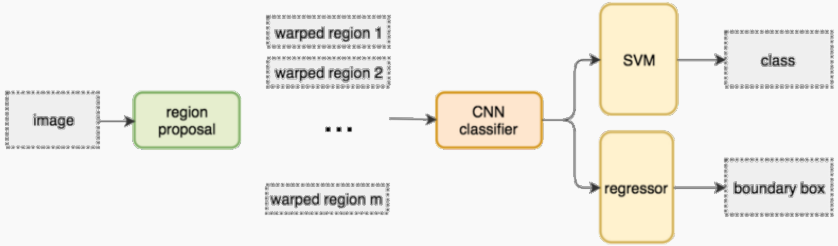
Selective Search

- **Goal:** Reduce number of proposed windows $\longrightarrow$ Regions of interest (ROI).
- Start with single pixel as individual groups $\longrightarrow$ pair groups w/ **similarity**.
  - Capture all scales: use hierarchical algorithm.
  - Diversification: multiple strategies that consider all use cases.
  - Fast to Compute: should not become a bottleneck?



R-CNN

- Use ROI proposal and feed a CNN.

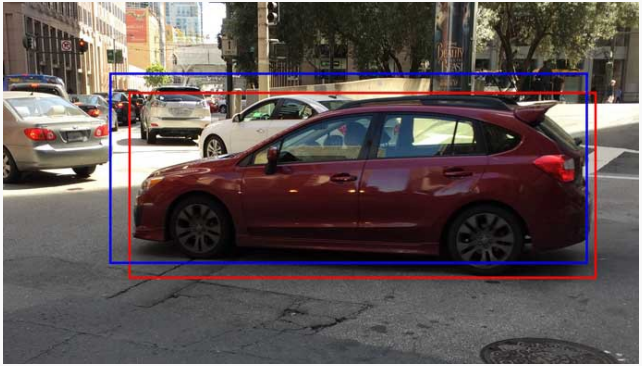


- Pseudo-code:

```
ROIs = region_proposal(image)
for ROI in ROIs
        patch = get_patch(image, ROI)
        results = detector(patch)
```

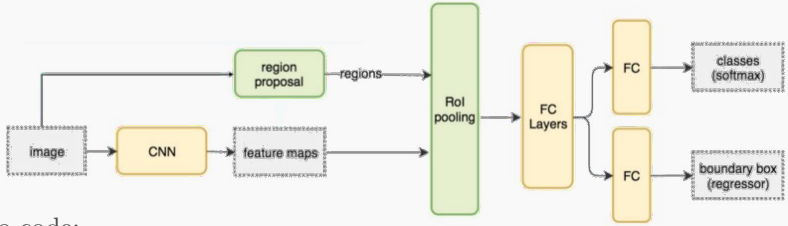
Boundary box regressor

- ROI computation is expenseive.
- In order to reduce computation $\longrightarrow$ simplify the ROI proposal.
- Refine the anchors $\longrightarrow$ FC layer and regression loss.



Fast R-CNN

- R-CNN is slow in training & inference $\longrightarrow$ repeat feature extractions 2,000 times.
- Use a feature extractor (a CNN) to extract features for the whole image first.
- Warp the patches to a fixed size using ROI pooling and feed them to FC layers.

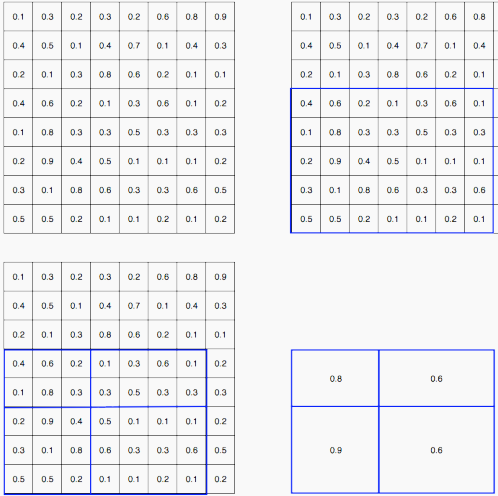


- Pseudo-code:

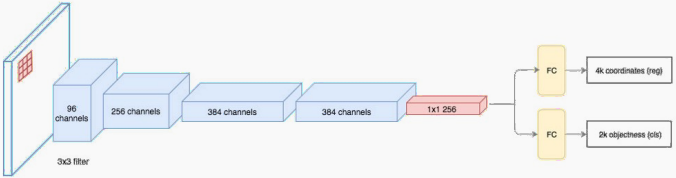
```
feature_maps = process(image)
ROIs = region_proposal(image)
for ROI in ROIs
        patch = roi_pooling(feature_maps, ROI)
        results = detector2(patch)
```

ROI Pooling

- Perform max-pooling operations on feature maps for regions of different sizes.

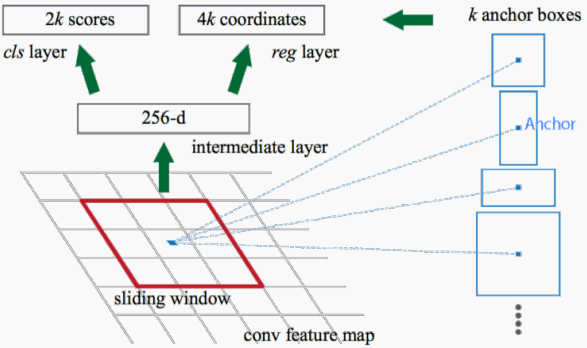


- Substitute the **region proposal** with a **Region proposal network** (RPN).
- For each location in the feature maps, RPN makes k guesses.



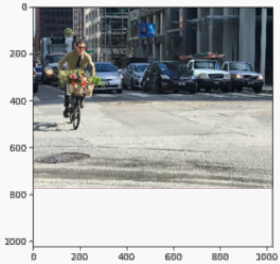
RPN (Region Proposal Network)

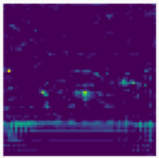
- Faster R-CNN uses far more anchors. It deploys 9 anchor boxes: 3 different scales at 3 different aspect ratio. Using 9 anchors per location, it generates 2 9 objectness scores and 4 9 coordinates per location.

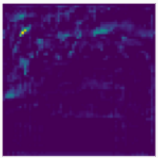


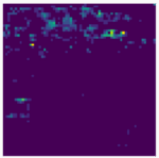
Visualizing ROI proposals

1. Perform ROI proposals (RPN or distance algorithm) $\longrightarrow$ feed to CNN.
2. Output boundary box (refinements) and objectiveness score.
3. **Perform per class non-maximum suppression** $\longrightarrow$ removes duplicate objects.



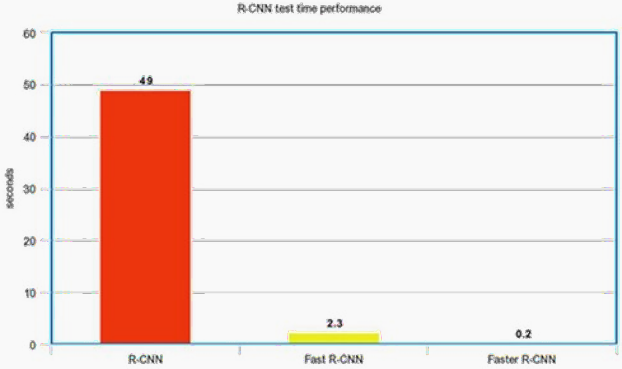






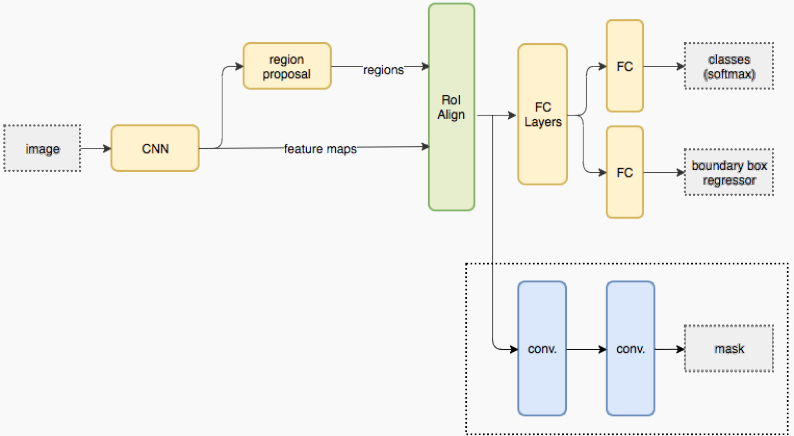
Performance for R-CNN methods

- Faster R-CNN is even much faster.



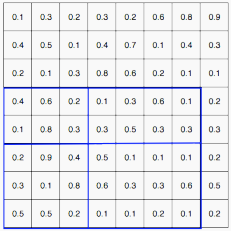
Mask R-CNN

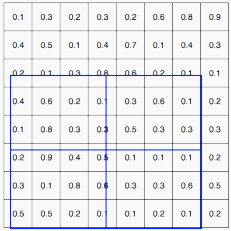
- From Faster R-CNN we add another CNN to mask regions.
- The additional CNN mask is only for coloring.

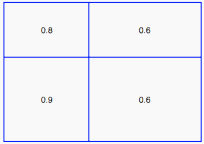


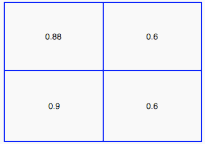
ROI Align

- Refinement of the ROI pooling.
- Makes every target cell to have the same size.
- It also applies interpolation.









	AP	AP_{50}	AP_{75}	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}
RoIPool	23.6	46.5	21.6	28.2	52.7	26.9
RoIAlign	**30.9**	**51.8**	**32.1**	**34.0**	**55.3**	**36.4**
	+7.3	*+ 5.3*	*+10.5*	*+5.8*	*+2.6*	*+9.5*

Single Shot Detectors

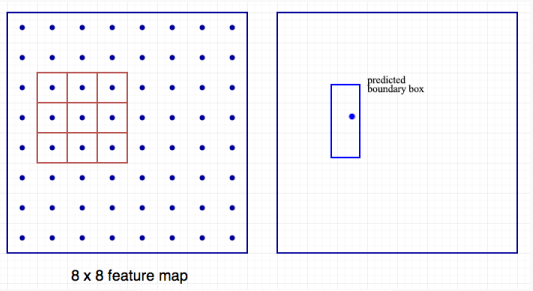
- **Goal:** Do not generate ROI proposals.

```
feature_maps = process(image)
results = detector(feature_maps)          # No more separate step for ROIs.
```

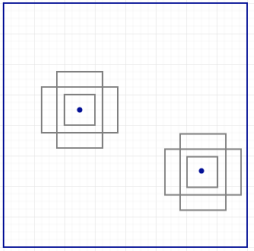
- Sliding windows/ROIs requires too many shapes to cover most objects.
- Then use detectors to predict class and boundary box $\longrightarrow$ this is expensive.
- Single shot detectors predict both boundary box and class at the same time.
- These networks are trained end to end $\longrightarrow$ they are very fast, and increases accuracy w.r.t. to purpose oriented subnetworks.
- Single shot detector often trades accuracy with real-time processing speed.

Single Shot Detectors II

- **ROI based:**



- **Single Shot:**

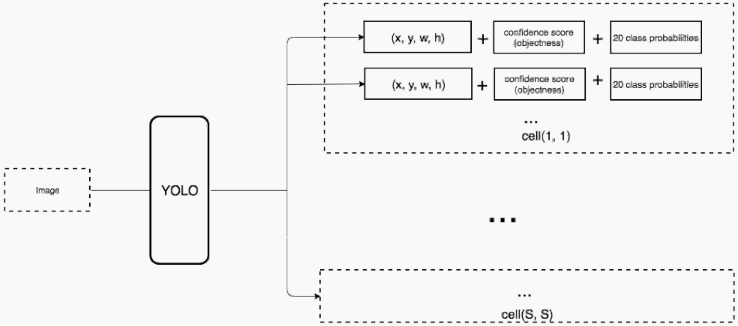


YOLO Architecture

- Number of predicted parameters on output feature maps 8×8:

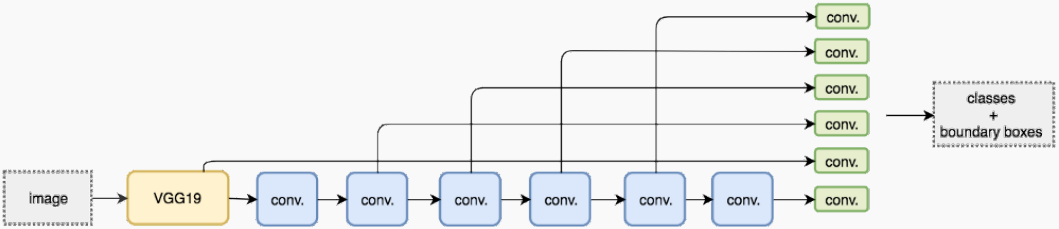
$$8 \times 8 \times D \longrightarrow (S, S, B \cdot 5 + C) = 8 \times 8 \times B \times 5 + 20 \text{ for C=20.}$$

- YOLO has evolved to YOLOv2, YOLO9000 and YOLOv3, with iprovements (such as multiscale, multiple box predictions, location box, word tree search, FPN, etc.).



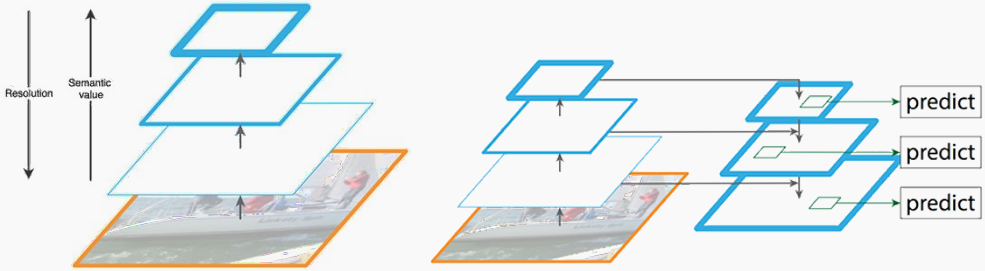
SSD Architecture

- Uses a CNN as a feature extractor $\longrightarrow$ same as Faster R-CNN.
- Then add custom convolution layers to make predictions.
- Previous model can detect large objects only $\longrightarrow$ make independent object detections from multiple feature maps.



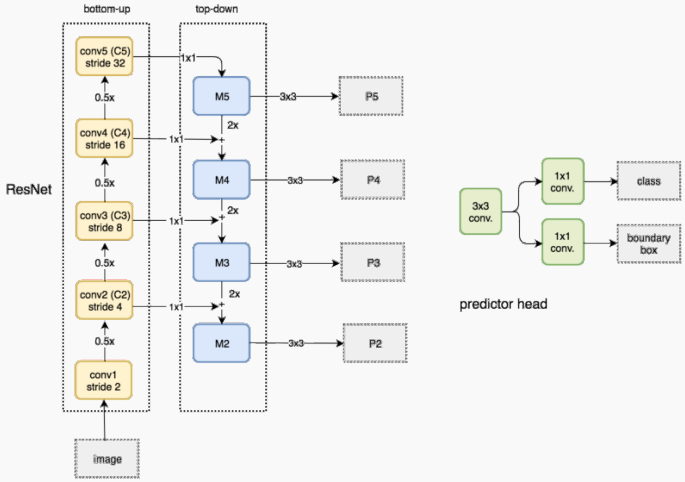
Feature Pyramid Networks (FPN)

- Feature extractor to improve accuracy and speed.
- It helps to generate higher quality features.
- On higher layers the semantic value increases; vs. spatial resolution.
- We can mix the information flow.



Feature Pyramid Networks (FPN) II

- FPNs can work with object detectors $\longrightarrow$ RPNs and clasifiers:



Face recognition systems

Face recognition systems

- Verification
  - **Input:** Image from a person to identify and a ID.
  - **Objective:** decide whether the input image corresponds to the ID.
- Recognition
  - **Database** of K people.
  - **Input:** Image from a person to identify.
  - **Objective:** Identify the person in the database or reject recognition.
- Recognition is a much harder problem than verification for a specified performance.

One-shot learning

Verification:

- We only have a single photo to learn the characteristics of a given person.
- Then, given a new photo, output if they correspond to the same person.
- We can construct a similarity function or distance between images:

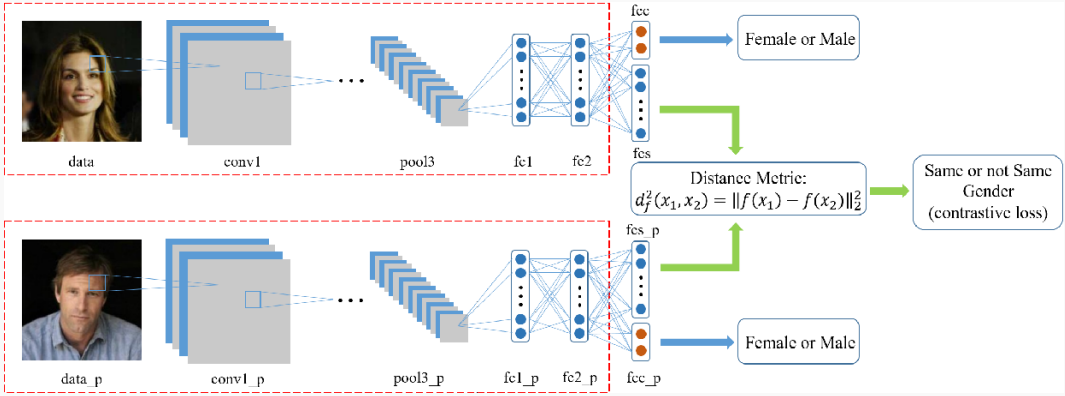
$$d(\text{img1}, \text{img2})$$

  - Then, set a threshold to balance accuracy and precision.

Siamese network

- Build a NN to generate a latent representation of an image.
- Perform two independent calculations on the input.
- Construct a loss function to determine distance between latent features:

$$f(x, y) = \|f(x) - f(y)\|^2 = \|a_x^{[L]} - a_y^{[L]}\|^2$$



Loss functions

- Loss should be small for the same person and far apart for different people.
- Use cross-entropy and define:

$$f(x, y) = \sum_i w_i |a_i^{[L](x)} - a_i^{[L](y)}| + b_i$$

- χ^2 loss:

$$f(x, y) = \sum_i w_i \frac{(a_i^{[L](x)} - a_i^{[L](y)})^2}{(a_i^{[L](x)} + a^{[L](y)})}$$

  - The representations in DeepFace are normalized between 0 and 1 to reduce the sensitivity to illumination changes.

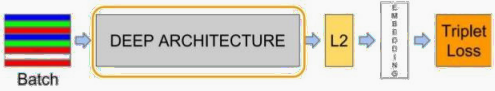
Triplet loss

- Given three images A, P, N:

$$\|f(A) - f(P)\|^2 + \alpha < \|f(A) - f(N)\|^2$$

$$\mathcal{L}(A, P, N) = \min\left(\|f(A) - f(P)\|^2 - \|f(A) - f(N)\|^2 + \alpha, 0\right)$$

- Training:



- Evaluation:

$$f(x, y) = \|a_x^{[L]} - a_y^{[L]}\|^2 \lesseqgtr \tau$$

- Train on 10k pictures of 1k persons.
- Need to choose triplets that are "hard to train on.

Schroff, Florian, Dmitry Kalenichenko, and James Philbin. "Facenet: A unified embedding for face recognition and clustering." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 815-823. 2015.

Questions?