



DEEP LEARNING IN COMPUTER VISION

Slim FRIKHA

Lead Computer Vision AI Researcher - RIMINDER

DEEP LEARNING PRACTICAL COURSE
ECOLE POLYTECHNIQUE, 12/04/2018

Program & Course Logistics

- **Course 1 :** (05-04-18)
 - Introduction to Deep Learning - Mouhidine SEIV (Riminder)
- **Course 2 :** (12-04-18)
 - **Deep Learning in Computer Vision** - Slim FRIKHA (Riminder)
- **Course 3 :** (19-04-18)
 - Deep Learning in NLP - Paul COURSAUX (Riminder)
- **Course 4 :** (26-04-18)
 - Efficient Methods and Compression for Deep Learning - INVITED GUEST
- **Course 5:** (03-05-18)
 - Introduction to Deep Learning Frameworks - INVITED GUEST
- **Course 6:** (10-05-18)
 - Deployment in Production and Parallel Computing - INVITED GUEST

Location: Ecole Polytechnique from 6:30 pm to 7:30pm



<https://github.com/riminder>

Talk outline

- I. Computer vision overview*
- II. Deep learning for image classification*
- III. Deep learning for object detection and semantic segmentation*
- IV. Human versus Machine*

Why computer vision is important

Google images search

Microsoft Kinect

Google Street View

Credit Card scanner

Self-driving cars

OCR in ATM check deposits

Smartphone face unlock

Number plate recognition

Vision Biometrics

3-D Printing



Tasks overview

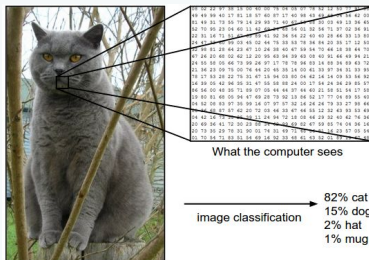
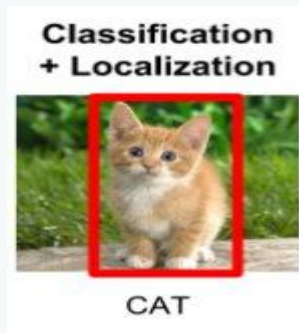
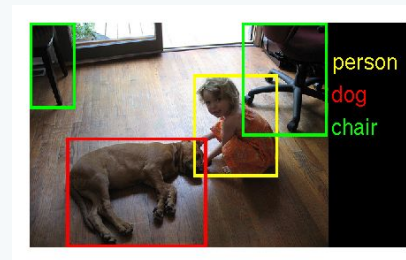


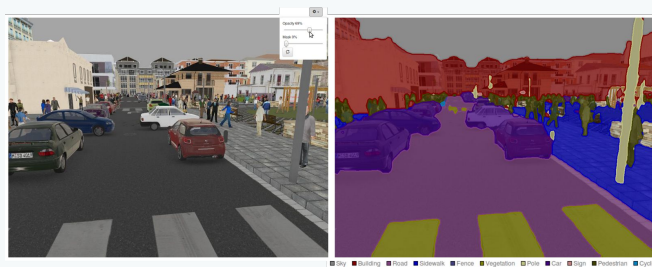
Image classification



Object localization



Object detection



Semantic segmentation

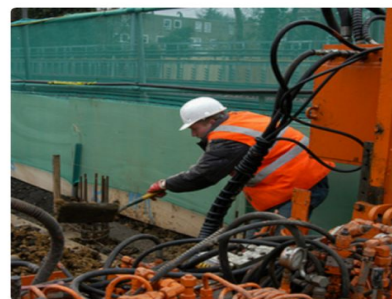
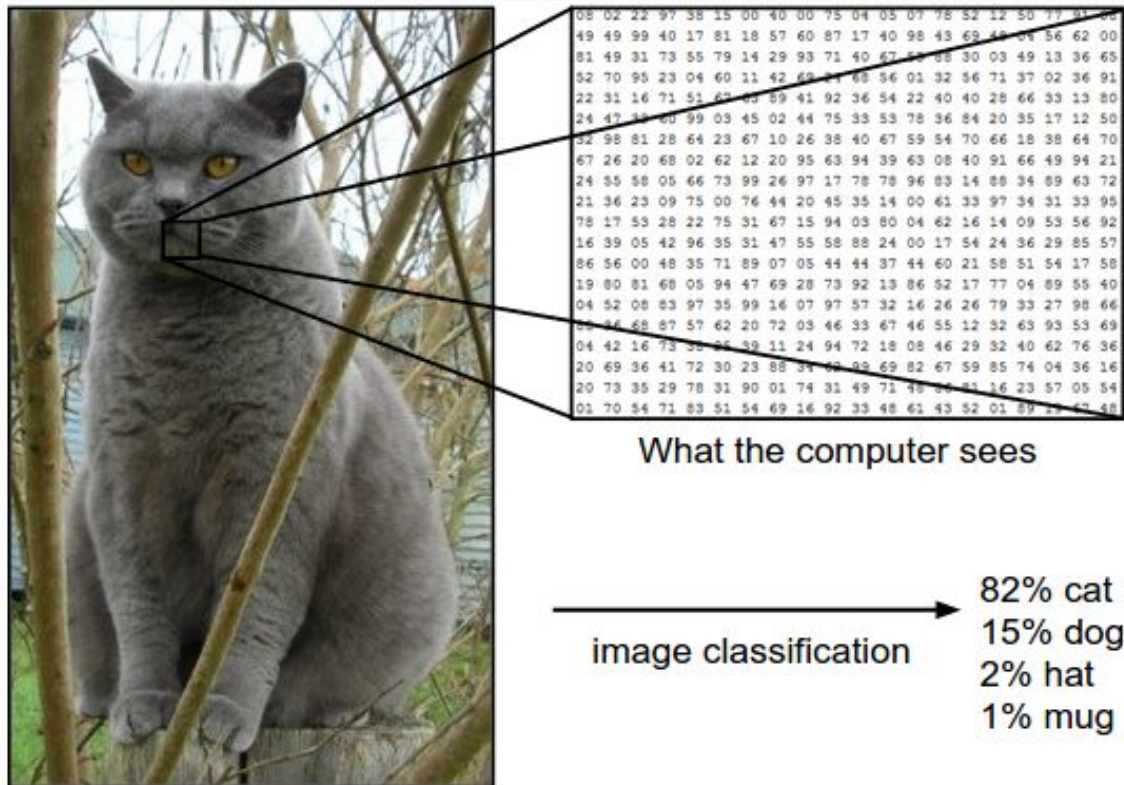


Image captioning

Image classification problem



Why convolutions?

Classical machine learning: input format, features engineering

Dense layers: too many parameters

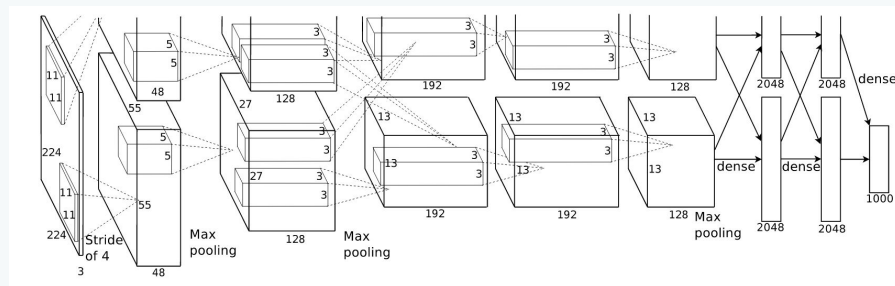
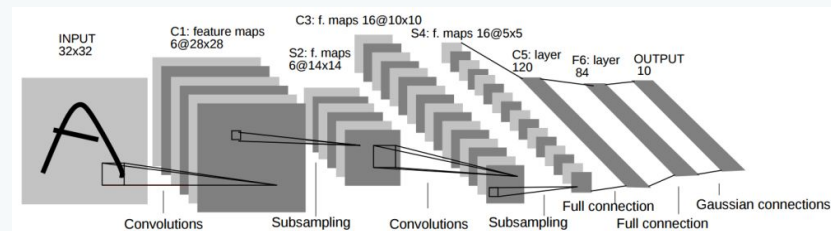
Recurrent neural networks: 1D sequences, loss of spatial information

Convolutional Neural Networks

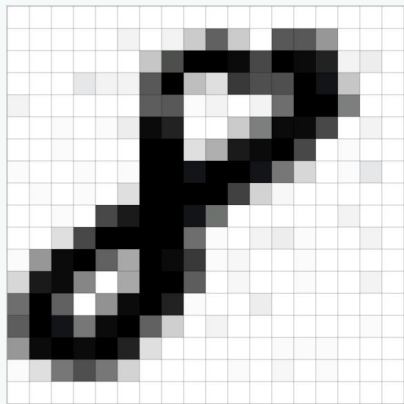
Neurocognitron [Fukushima 1980]

LeNet-5 [Lecun 1998]

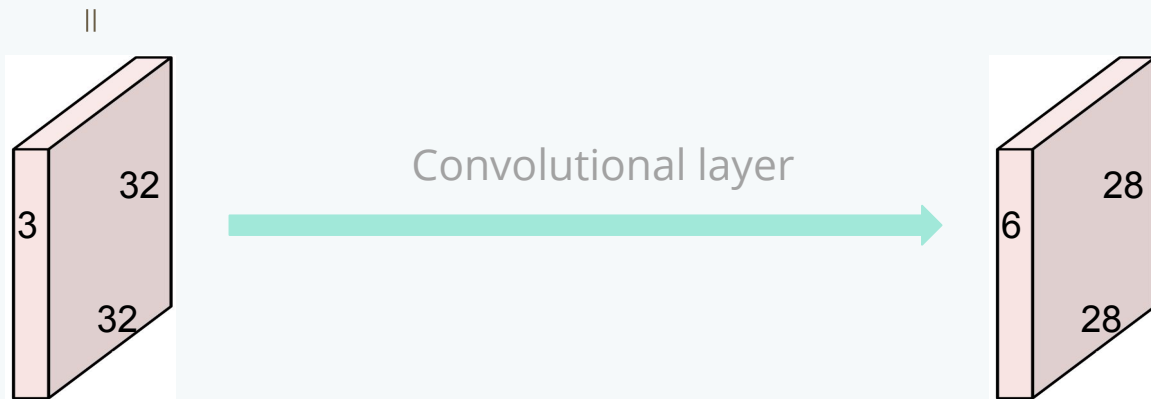
Alexnet [Krizhevsky, Sutskever, Hinton 2012]



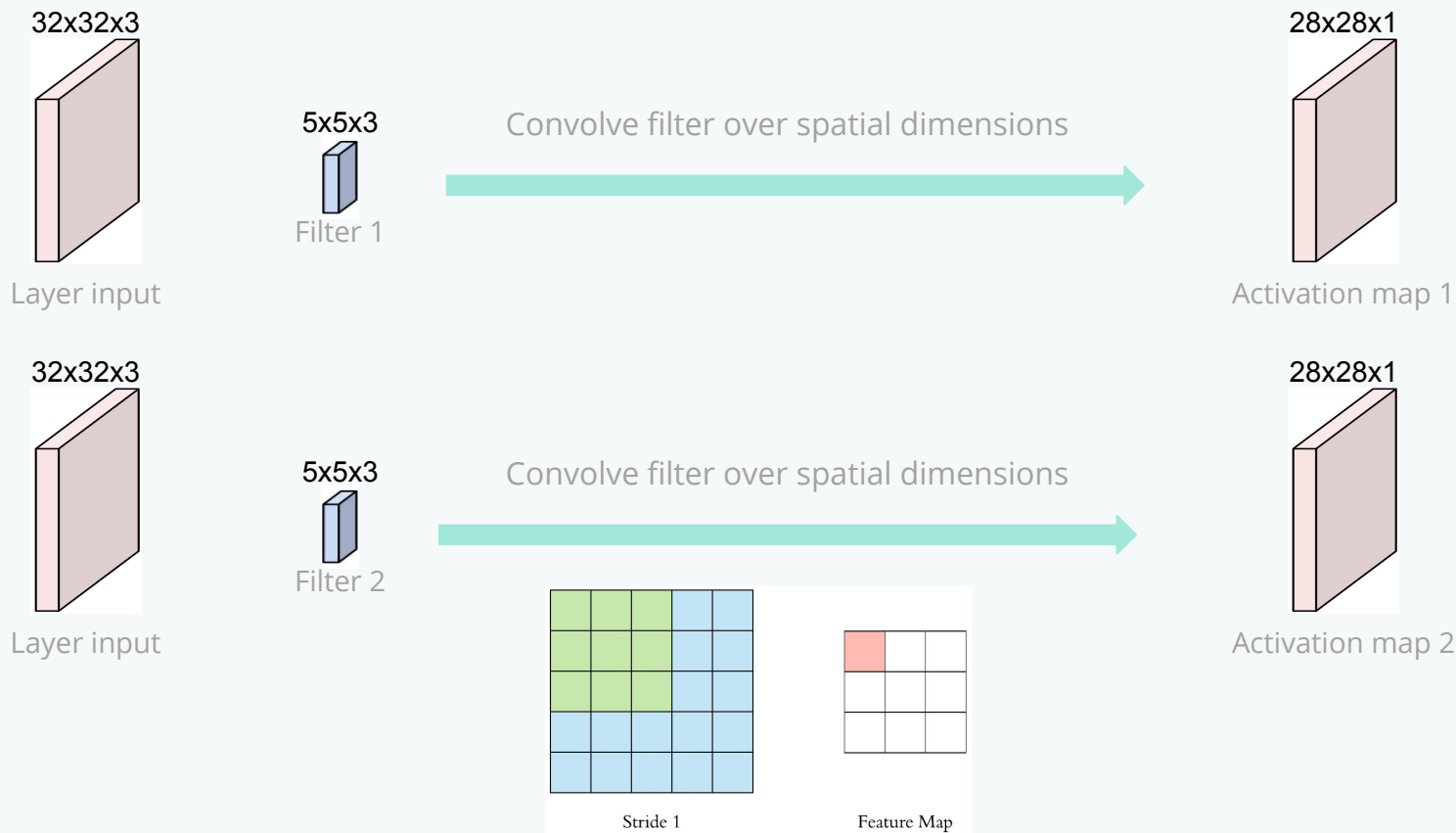
What is a convolution layer?



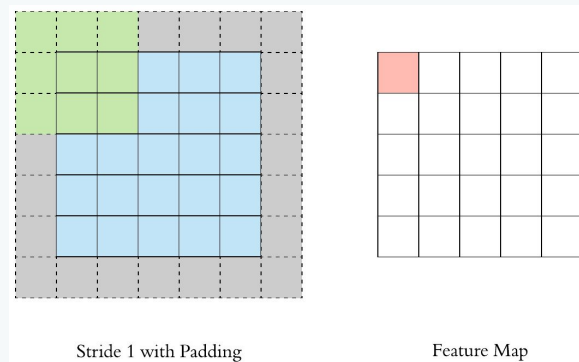
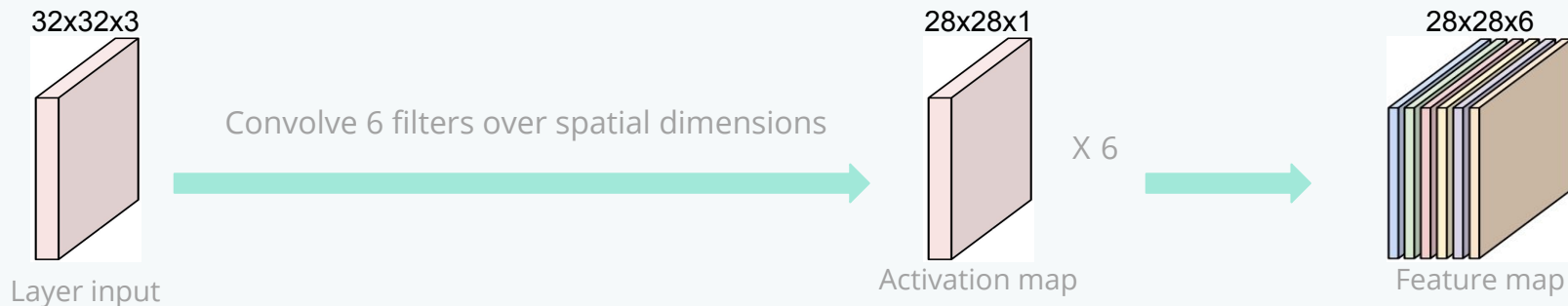
An image is just a 3D array of numbers



Convolution operation



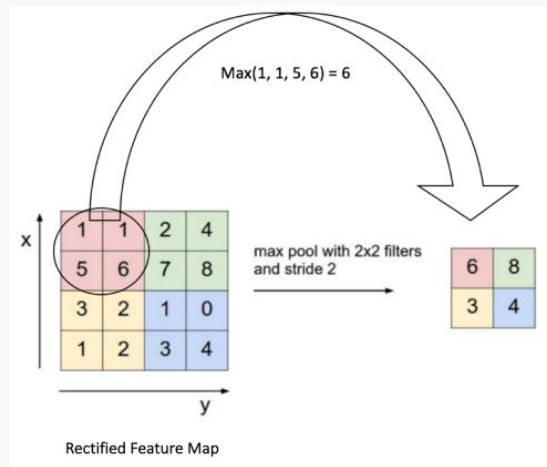
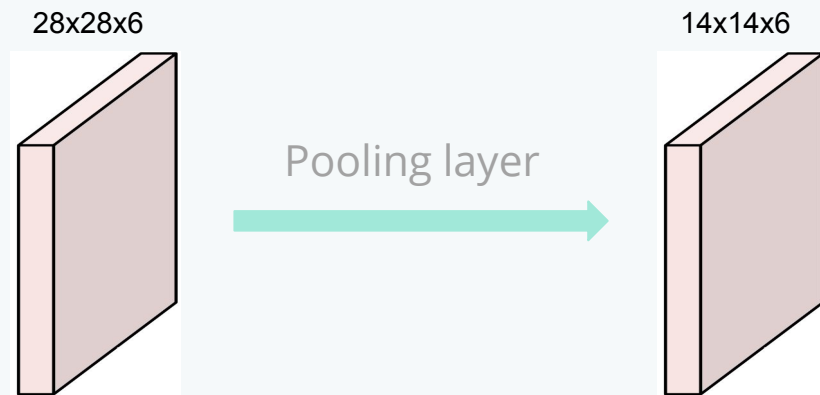
Convolution operation



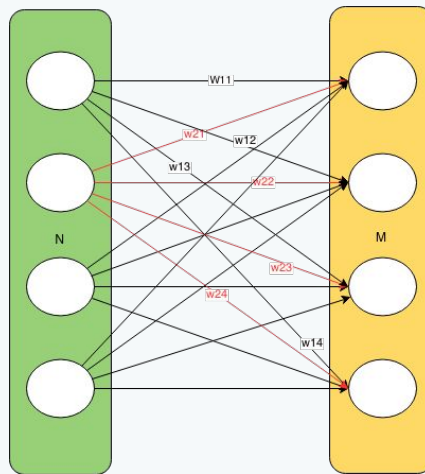
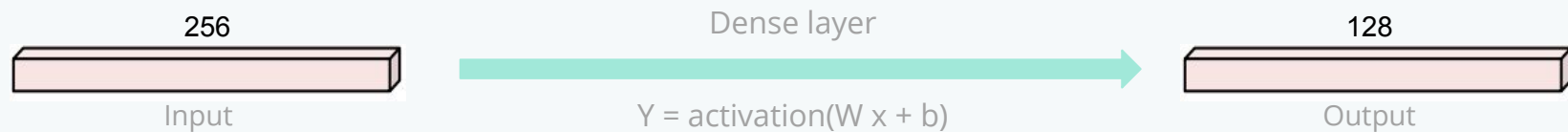
Pooling operation

Pooling = downscaling spatial dimension

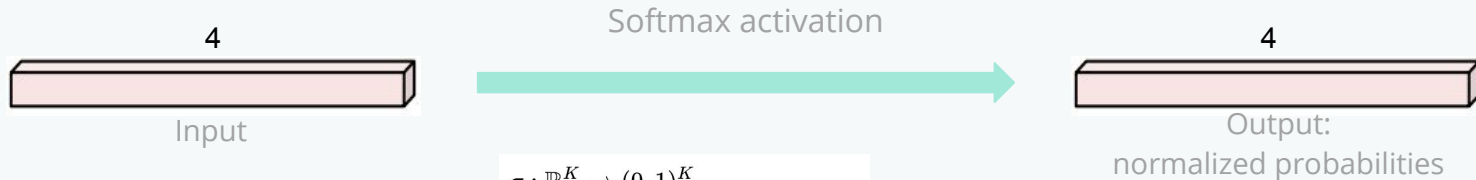
Different types: Max, Average, Sum etc.



Fully connected layer



Softmax activation

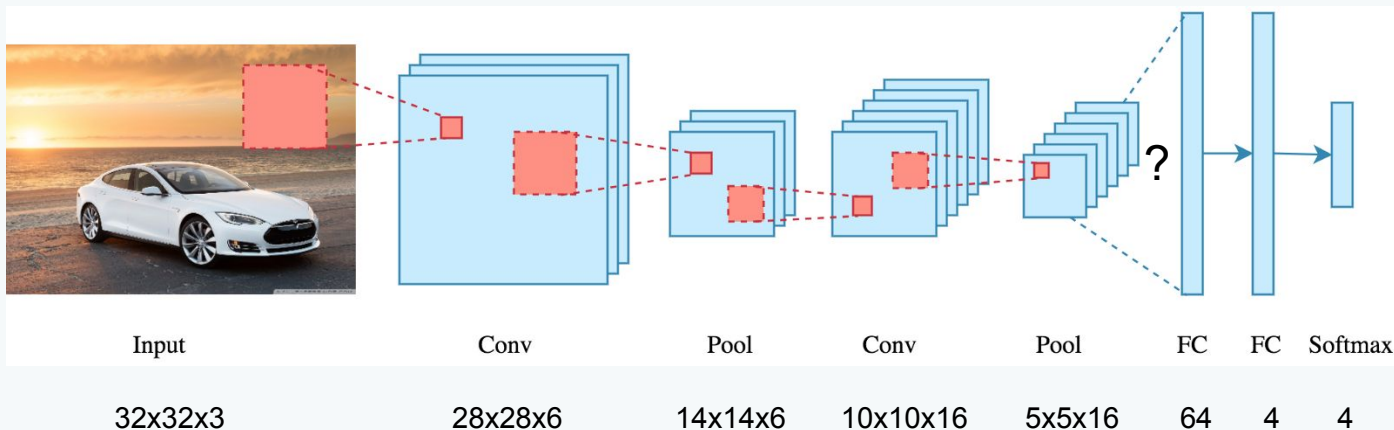
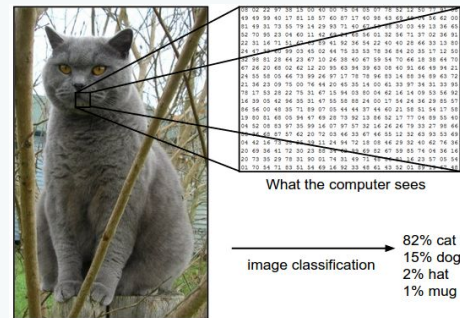


$$\sigma : \mathbb{R}^K \rightarrow (0, 1)^K$$
$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}} \quad \text{for } j = 1, \dots, K.$$

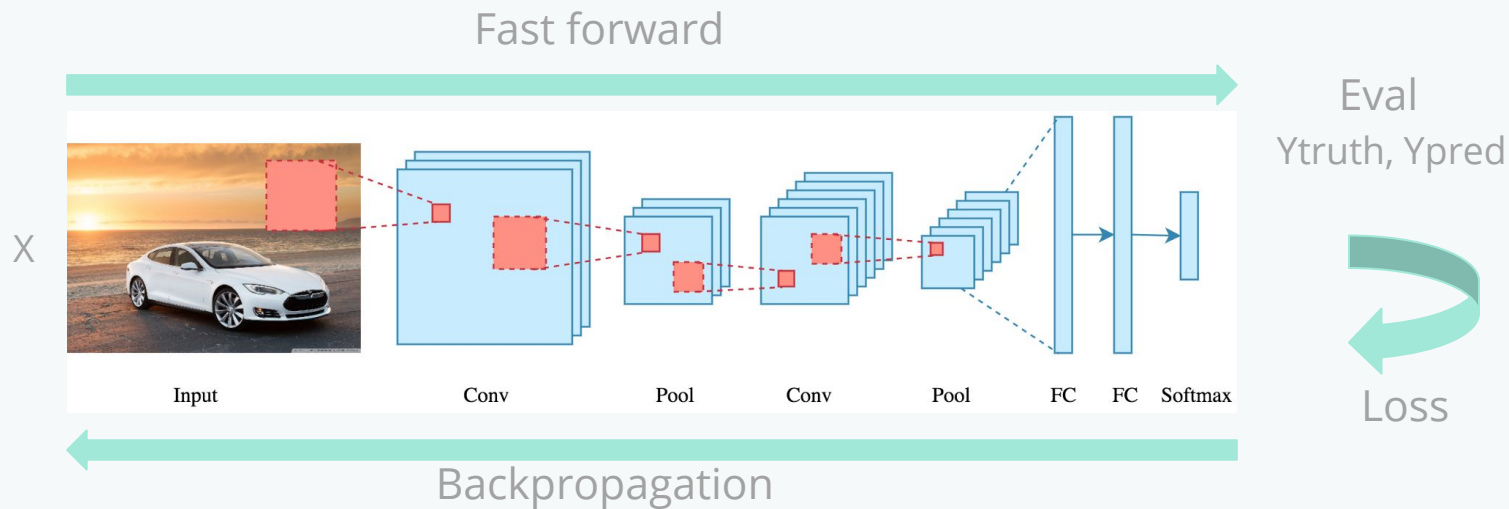
	Scoring Function	Unnormalized Probabilities	Normalized Probabilities
Dog	-3.44	0.0321	0.0006
Cat	1.16	3.1899	0.0596
Boat	-0.81	0.4449	0.0083
Airplane	3.91	49.8990	0.9315

CNN architecture

CNN
=
Convolutions + pooling + fully connected



Training CNNs



Regularization: data augmentation

Horizontal / vertical flip

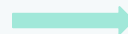
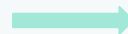
Color jitter

Random crops and scales

Translation

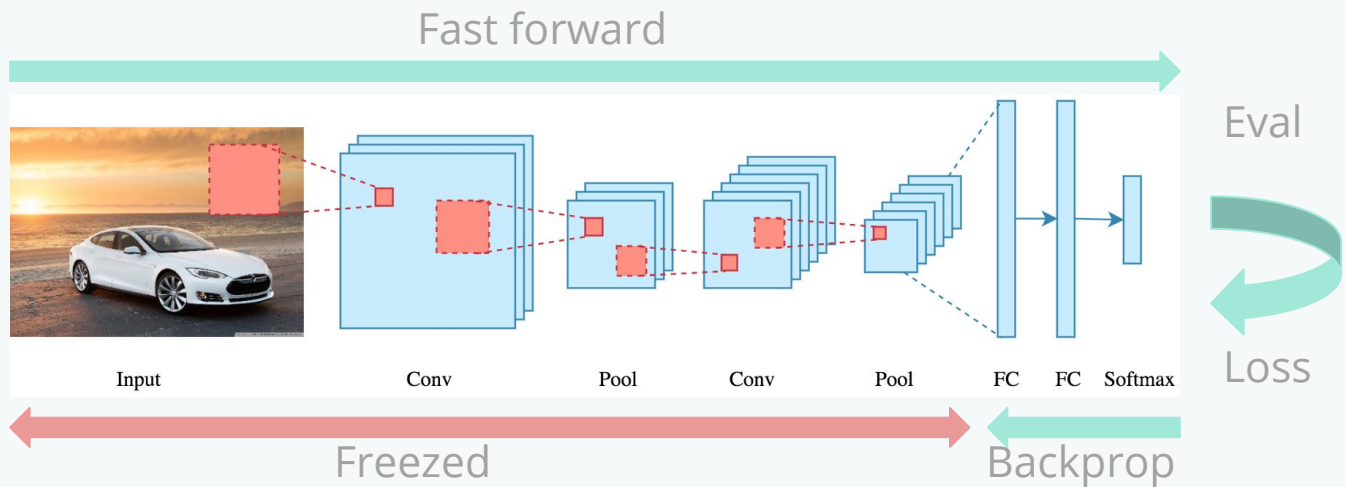
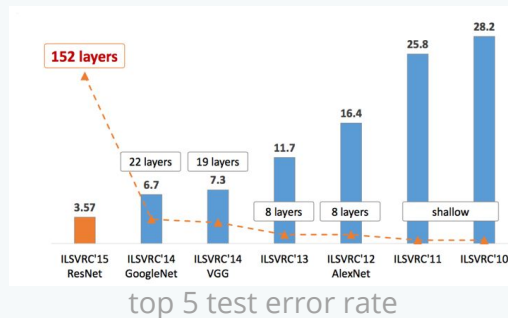
Rotation

Stretching ...

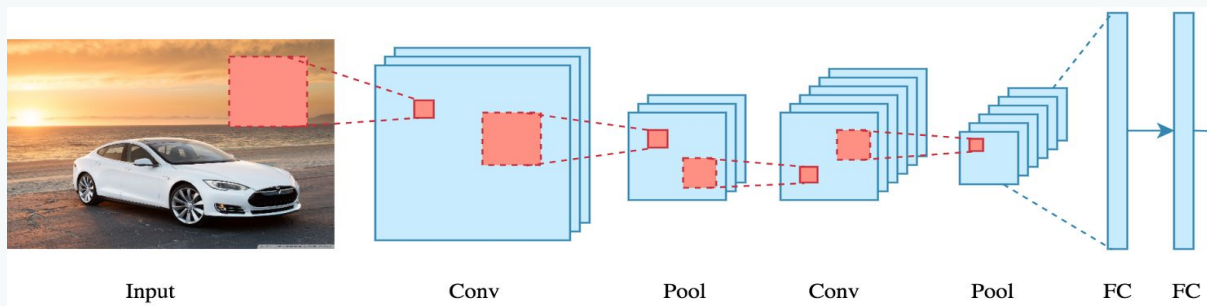


Generalization: transfer learning

AlexNet (2012)
ZF Net (2013)
VGG Net (2014)
GoogLeNet (2015)
Microsoft ResNet (2015)...



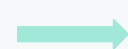
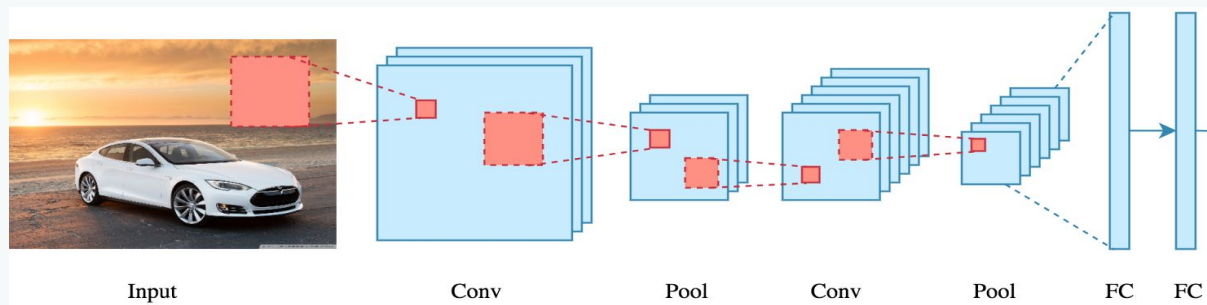
Object localization



→ Class

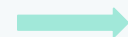
→ Bounding box

Objects detection

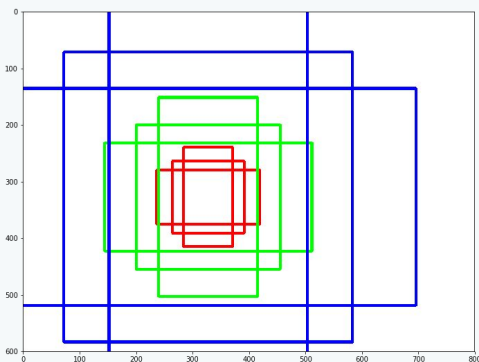


Class

$\times N$



Bounding box

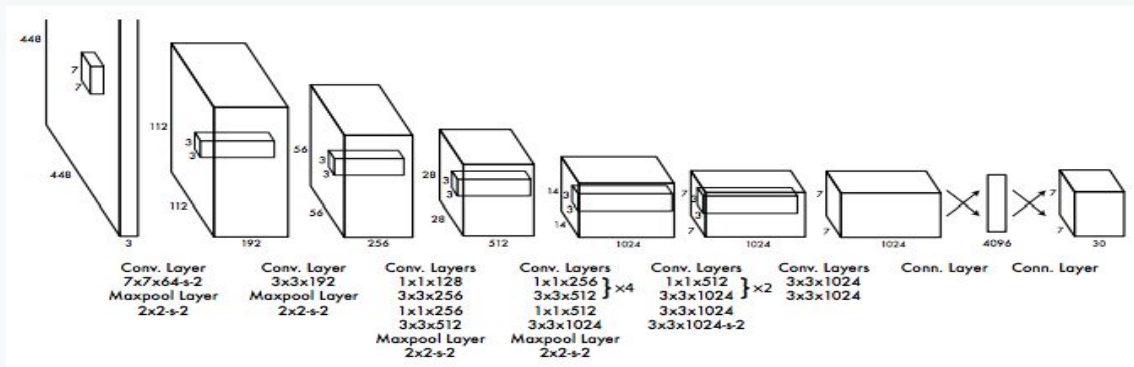


The diagram illustrates the Region Proposal Network (RPN) architecture. It starts with an input image of a dog. This image is processed by a CNN, which outputs feature maps. Simultaneously, a set of anchors/boxes is generated, each with an associated size. These anchors/boxes are fed into a Region Proposal Layer (RPL). The RPL also receives input from the CNN's feature maps. The RPL outputs a set of regions. These regions are then processed by a filter (Keep Top Anchors, Non-maximum Suppression). The filtered regions are then processed by ROI Pooling. The ROI Pooling output is then fed into a Classifier and a Regressor. The Classifier outputs the final classification (Object or Background?), and the Regressor outputs the refined bounding box.

```
graph TD; Input[Input Image] --> CNN; Input --> Anchors[Anchors/Boxes]; Anchors -- Size --> RPL[Region Proposal Layer]; RPL --> Regions[Regions]; Regions --> Filter[Filters Keep Top Anchors, Non-maximum Suppression]; Filter --> ROI[ROI Pooling]; CNN --> ROI; ROI --> Classifier; ROI --> Regressor; Classifier --> Output[Object or Background?]; Regressor --> Output[Refined Bounding Box];
```

Objects detection: YOLO

Input
 $448 \times 448 \times 3$



Output
 $S \times S \times (B * 5 + C)$

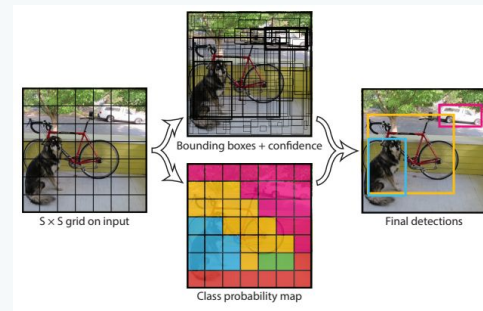
YOLO architecture example: $S=7$, $B=2$, $C=30$

$S \times S$ grid

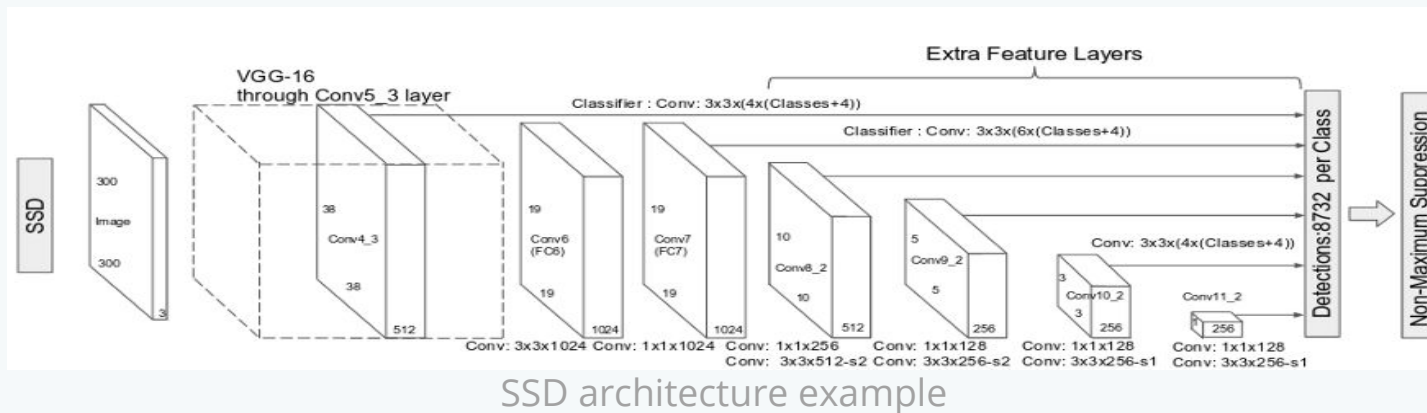
Each grid cell predicts B bounding boxes and confidence scores for those boxes

Each grid cell predicts **one** set C conditional class probabilities

Faster than Faster R-CNN but not as accurate as



Objects detection: SSD

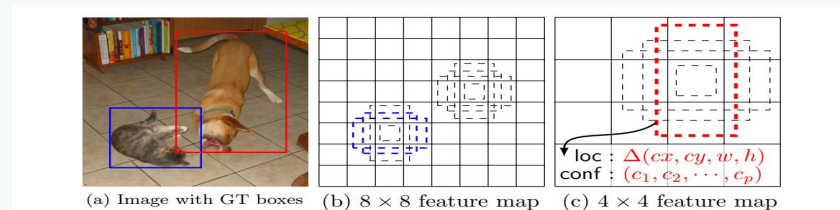


Combination of multiple ideas:

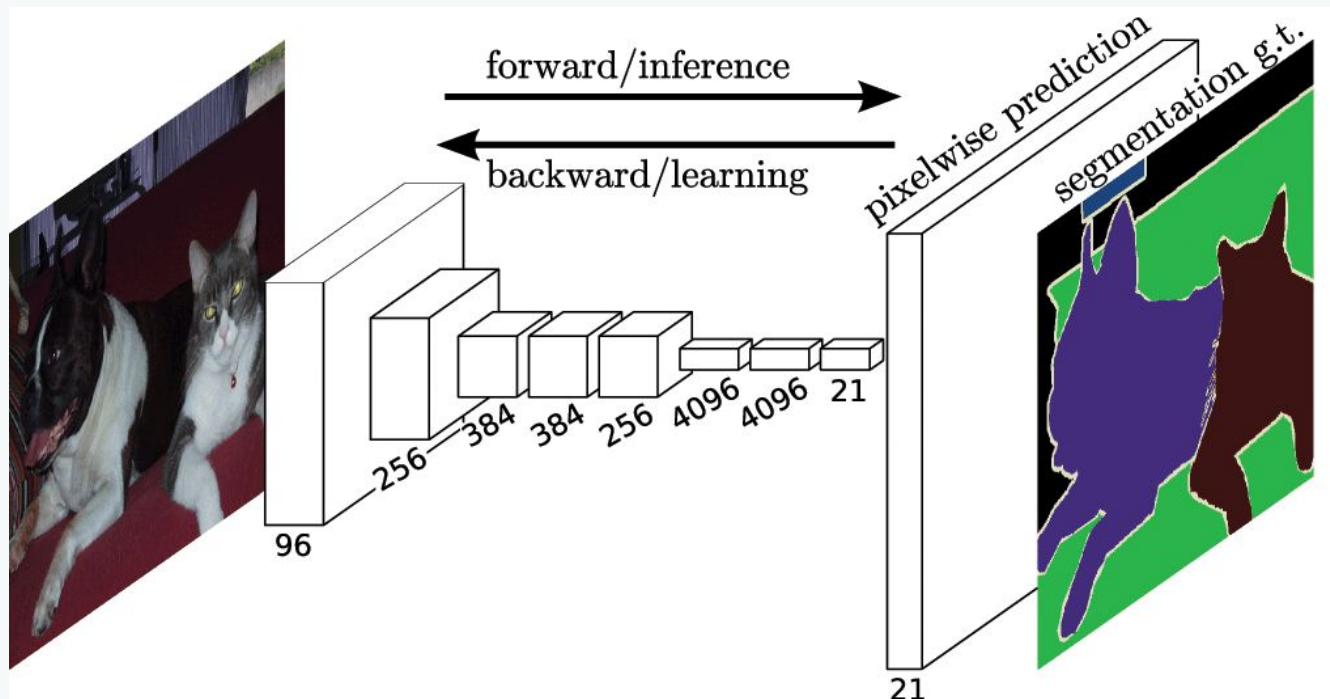
- anchor boxes
- single NN like YOLO
- multi scale support

Faster than Faster R-CNN but not as accurate

Slower than YOLO but more accurate



Semantic segmentation

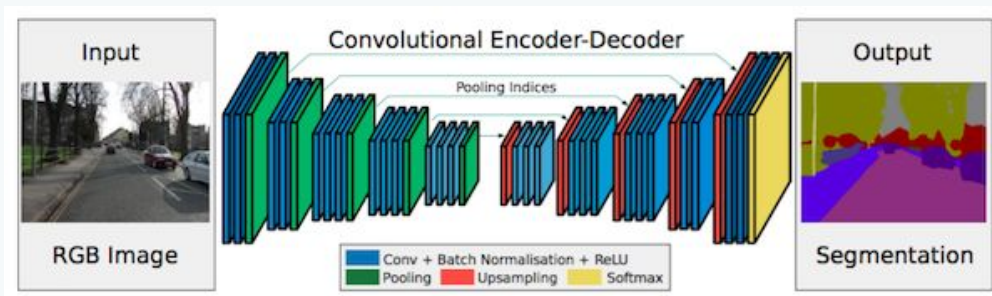


Semantic segmentation

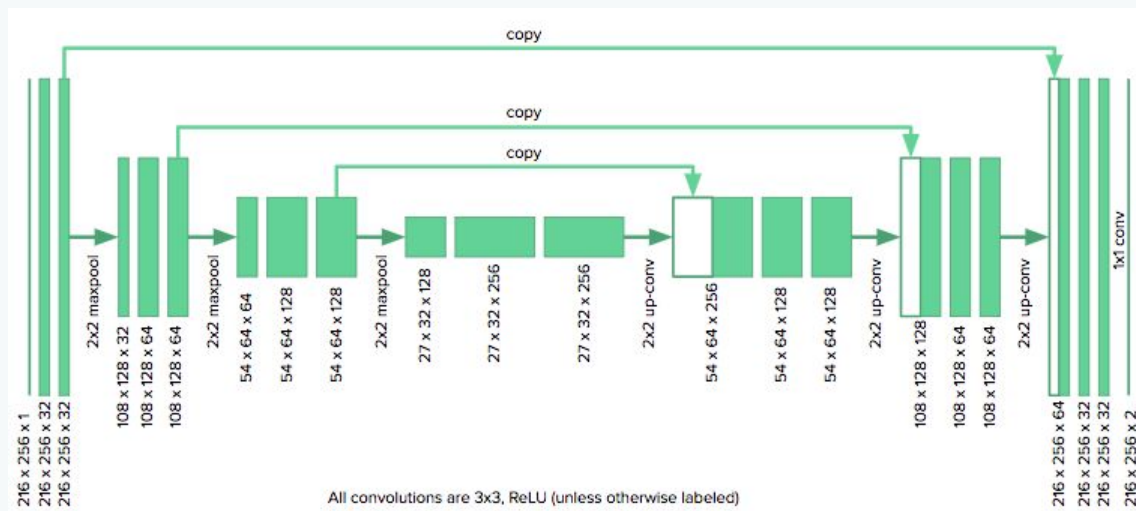
Multiple architecture and ideas too:

- FCN
- SegNet
- U-Net
- Dilated Convolutions
- DeepLab (v1 & v2)
- PSPNet
- DeepLab v3...

Semantic segmentation: encoder decoder

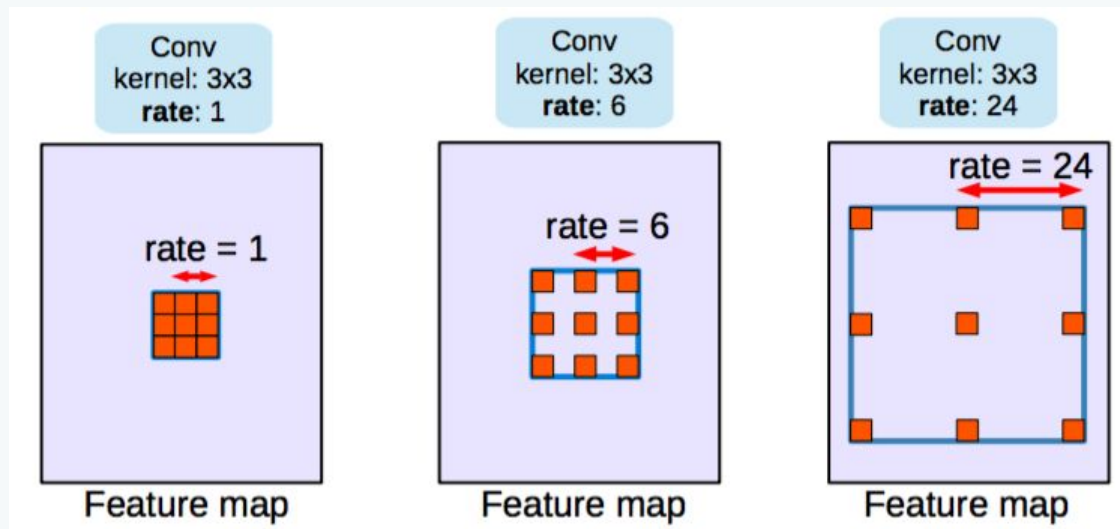


SegNet
architecture

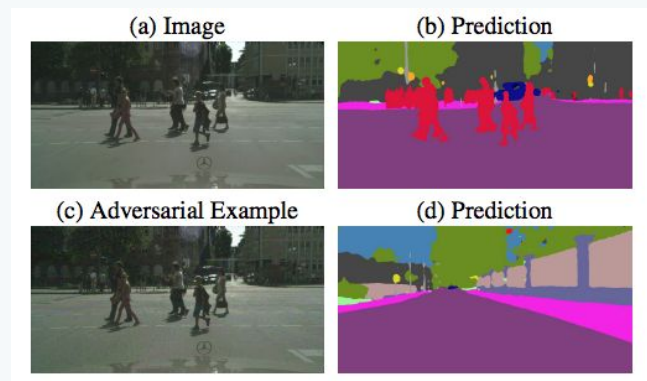
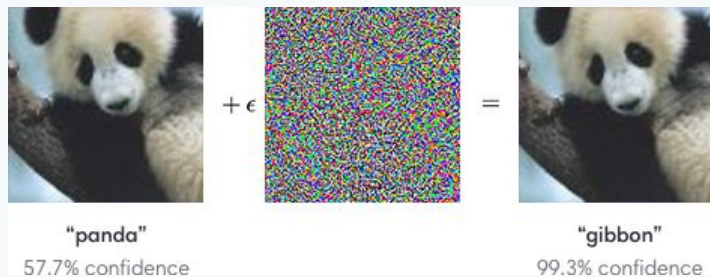


U-Net
architecture

Semantic segmentation: atrous convolutions



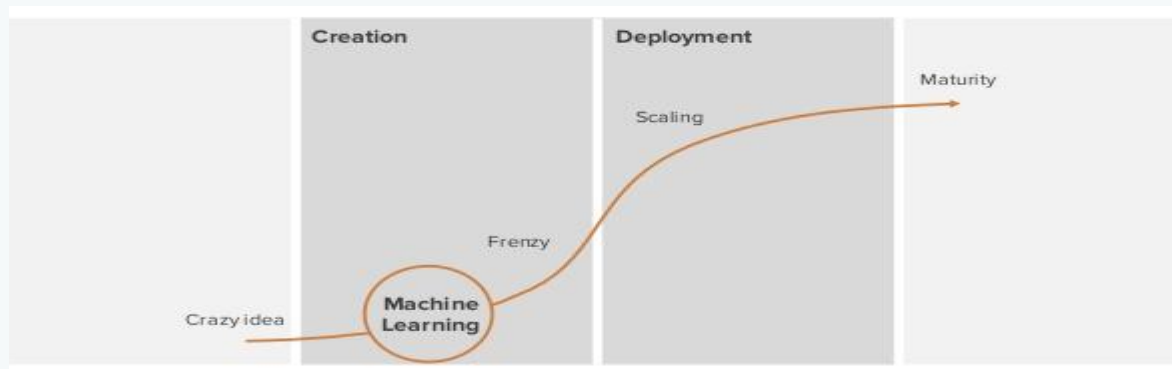
Adversarial Attacks



Conclusion

NNs can be better than human for specific simple tasks (classification)

Machine learning is only “at the beginning of the S-Curve”



Machine learning S-Curve

One cool thing



Semantic segmentation to improve
FIFA 18 graphics



POINT OF CONTACT



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Sources

- ✍ <https://medium.com/@alonbonder/ces-2018-computer-vision-takes-center-stage-9abca8a2546d>
- ✍ <http://cs231n.github.io/classification/>
- ✍ <http://cv-tricks.com/object-detection/faster-r-cnn-yolo-ssd/>
- ✍ <https://blog.goodaudience.com/using-convolutional-neural-networks-for-image-segmentation-a-quick-intro-75bd68779225>
- ✍ <https://towardsdatascience.com/image-captioning-in-deep-learning-9cd23fb4d8d2>
- ✍ <http://cs231n.stanford.edu/syllabus.html>
- ✍ <https://medium.com/@ageitgey/machine-learning-is-fun-part-3-deep-learning-and-convolutional-neural-networks-f40359318721>
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- ✍ <https://medium.com/diaryofawannapreneur/yolo-you-only-look-once-for-object-detection-explained-6f80ea7aaa1e>
- ✍ <https://medium.com/@ManishChablani/ssd-single-shot-multibox-detector-explained-38533c27f75f>
- ✍ <https://towardsdatascience.com/understanding-ssd-multibox-real-time-object-detection-in-deep-learning-495ef744fab>
- ✍ <https://blog.openai.com/adversarial-example-research/>
- ✍ <https://www.semanticscholar.org/paper/Adversarial-Examples-that-Fool-Detectors-Lu-Sibai/dfa14959ae31c6c95ae508dd847dc7d67f04fad9>
- ✍ <https://futureoflife.org/2017/05/01/machine-learning-security-iclr-2017/>
- ✍ <http://blog.enabled.com.au/artificial-general-intelligence/>
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