

Machine Learning

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- Building machines that learn from examples rather than explicit programming a specific task
- Solve problems that have been difficult to solve otherwise (object recognition, text translation, speech recognition, ...)
- How to build adaptive systems
- How do brains work (real intelligence)

Google

amazon

facebook



DeepMind



Microsoft

THE BIG BANG IN DEEP LEARNING



DNN



BIG DATA



GPU

“The GPU is the workhorse of modern A.I.”

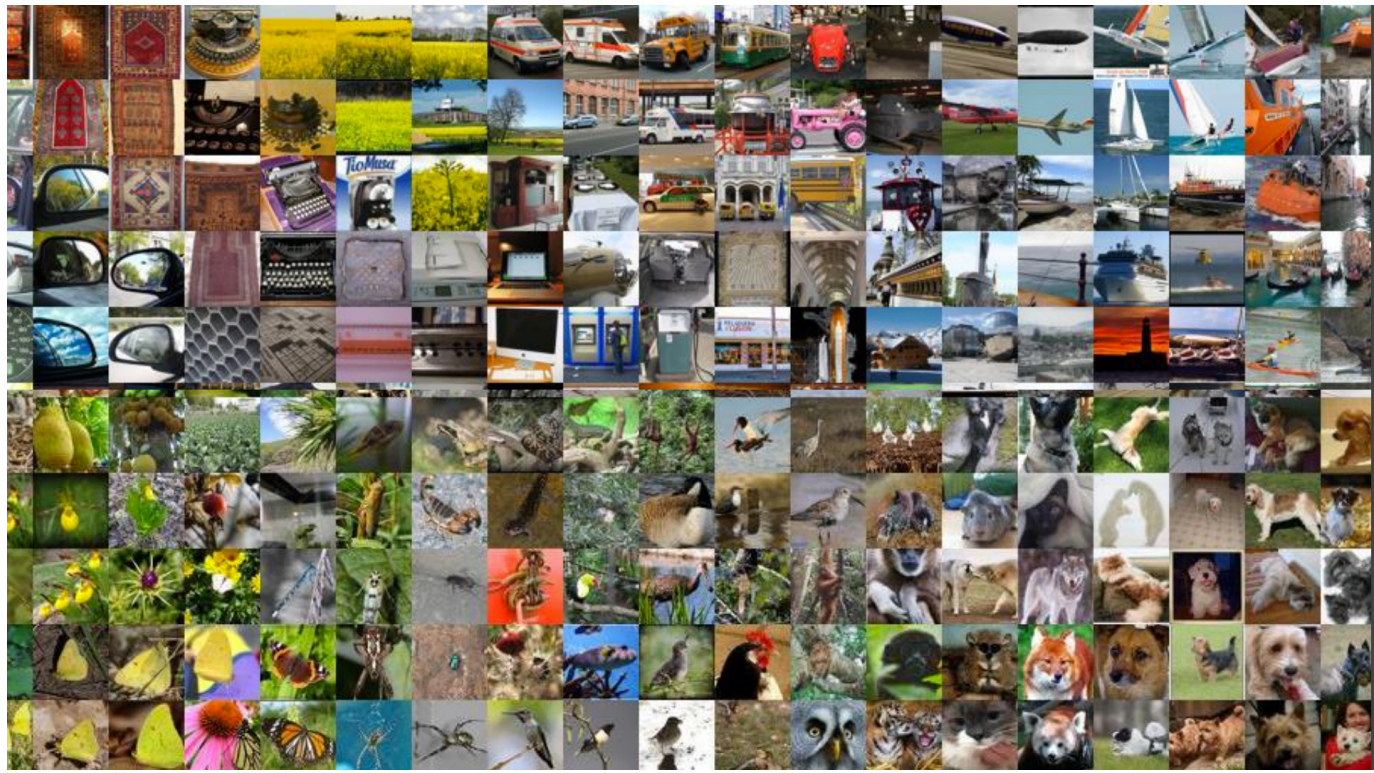
POPULAR
SCIENCE

ImageNet

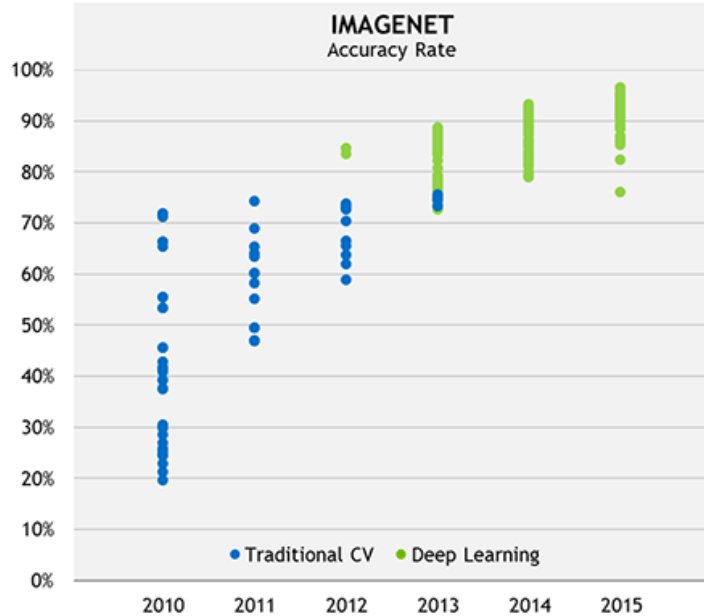
Released in 2009

1.2 Million Images

More than 1000 classes

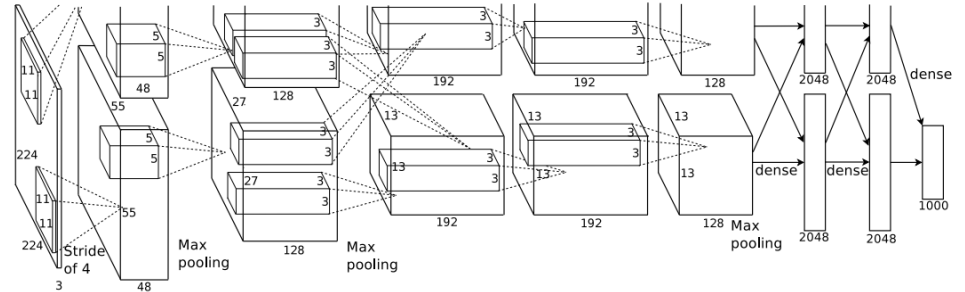


2015: A MILESTONE YEAR IN COMPUTER SCIENCE

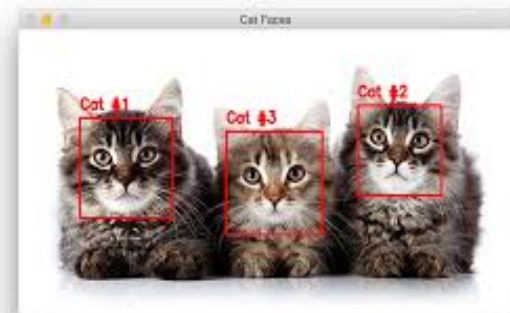
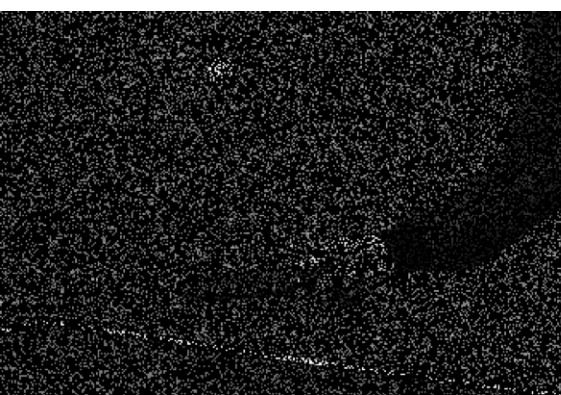


Alex Net

Alex Krizhevsky, Ilya Sutskever,
and Geoffrey Hinton 2012



LeCun: “Facebook uses networks
with 50-100 layers”



First Name

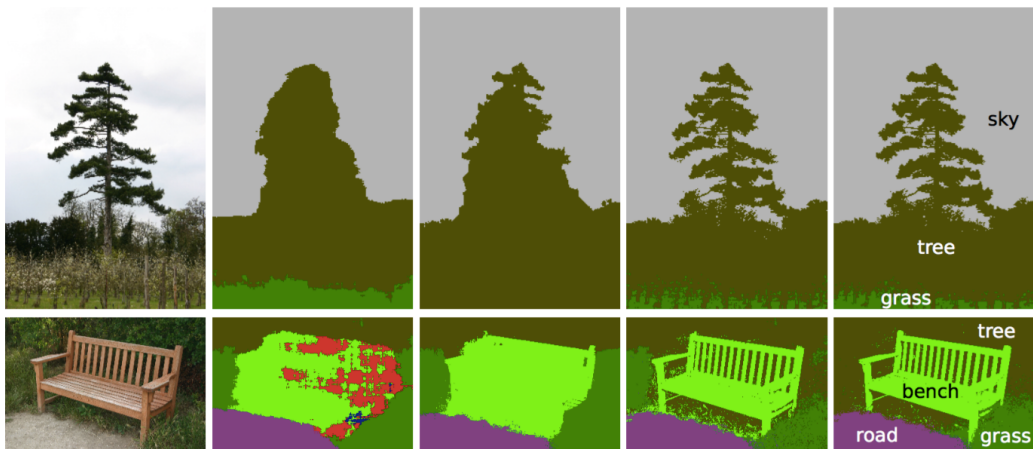
L O R I

Last Name

W A L T E R S



Semantic Segmentation



(a) Image

(b) Unary classifiers

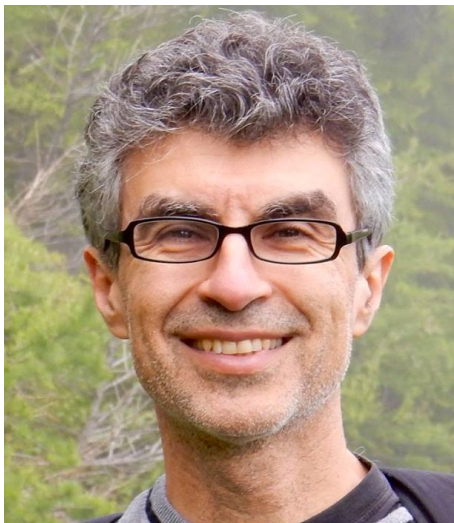
(c) Robust P^n CRF

(d) Fully connected CRF, MCMC inference, 36 hrs

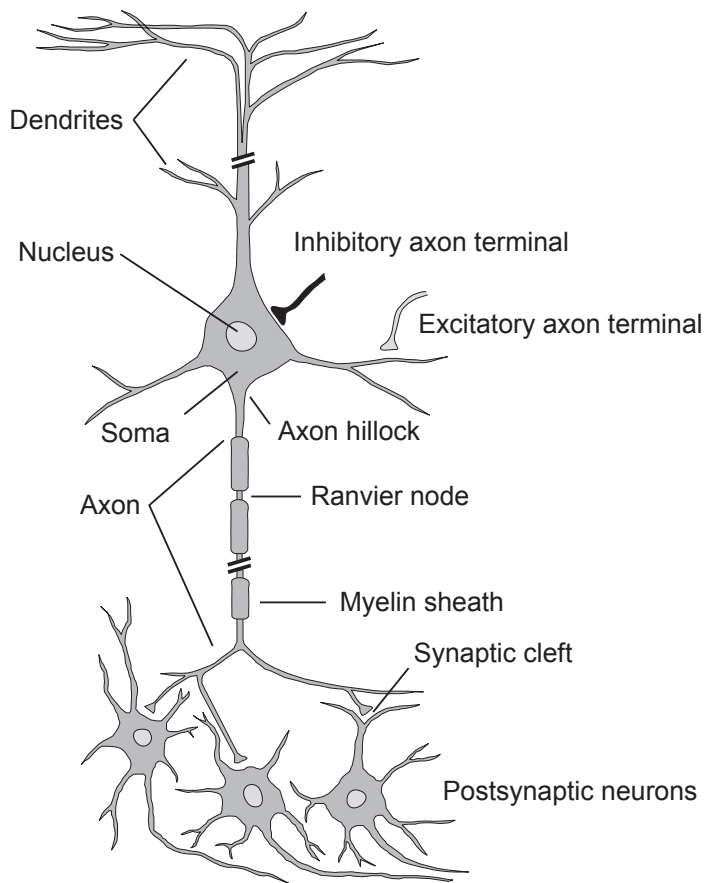
(e) Fully connected CRF, our approach, 0.2 seconds

A little History

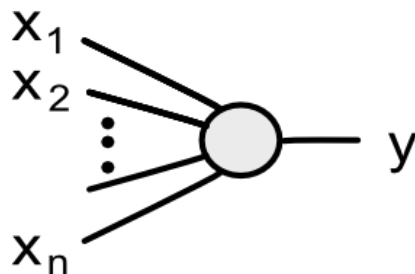




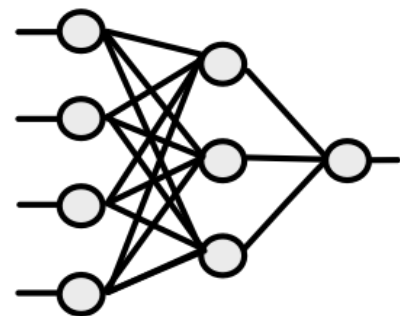
Schematic neuron

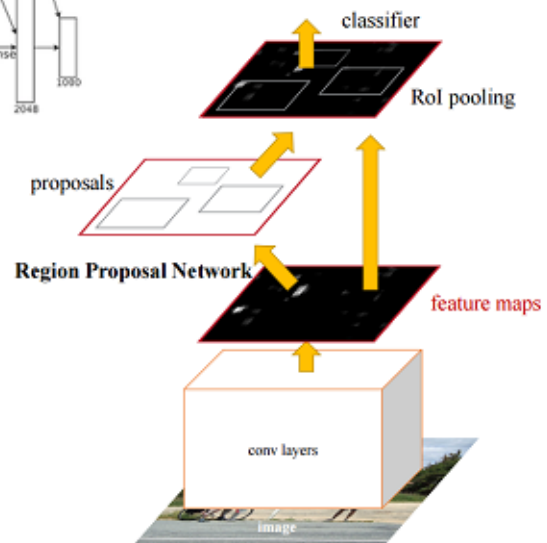
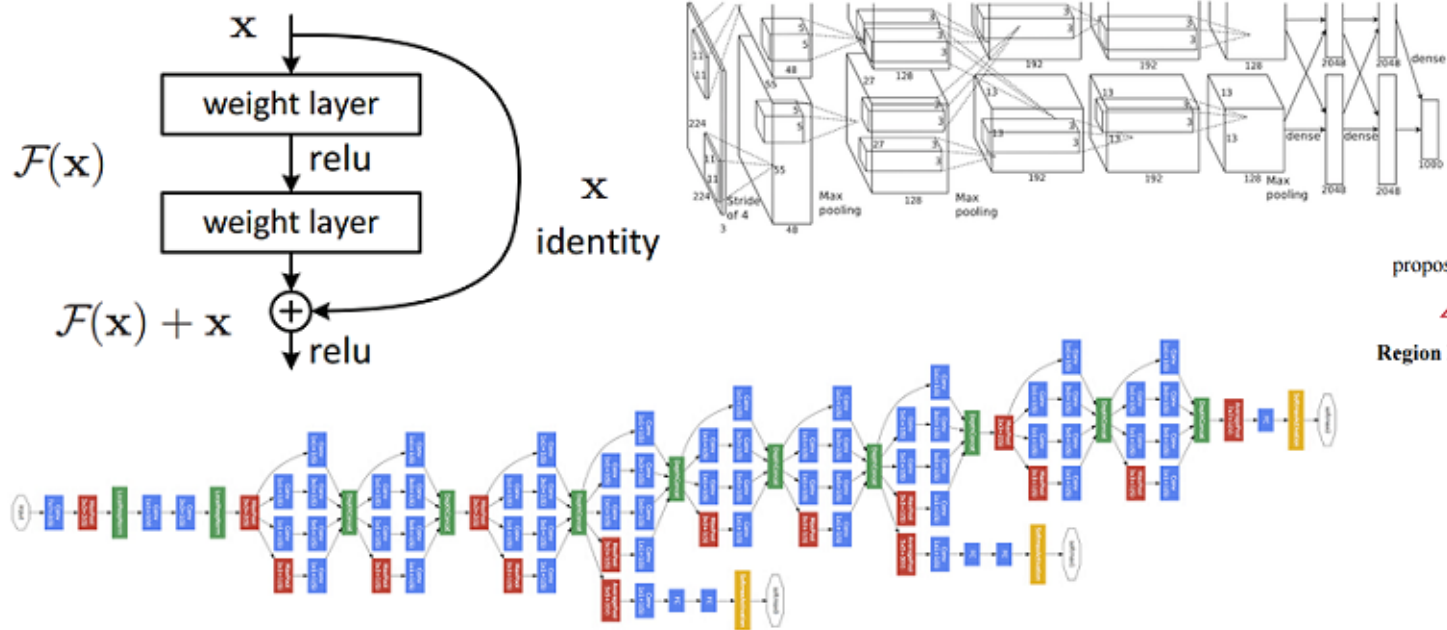


A: Node (neuron)

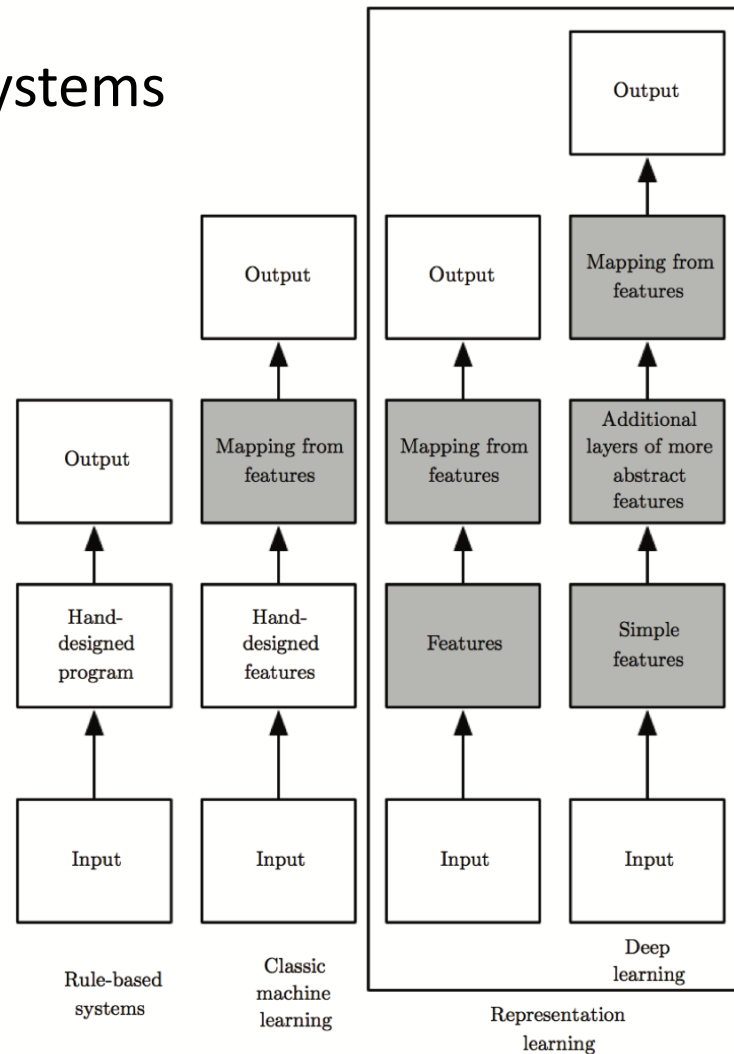


B: Network



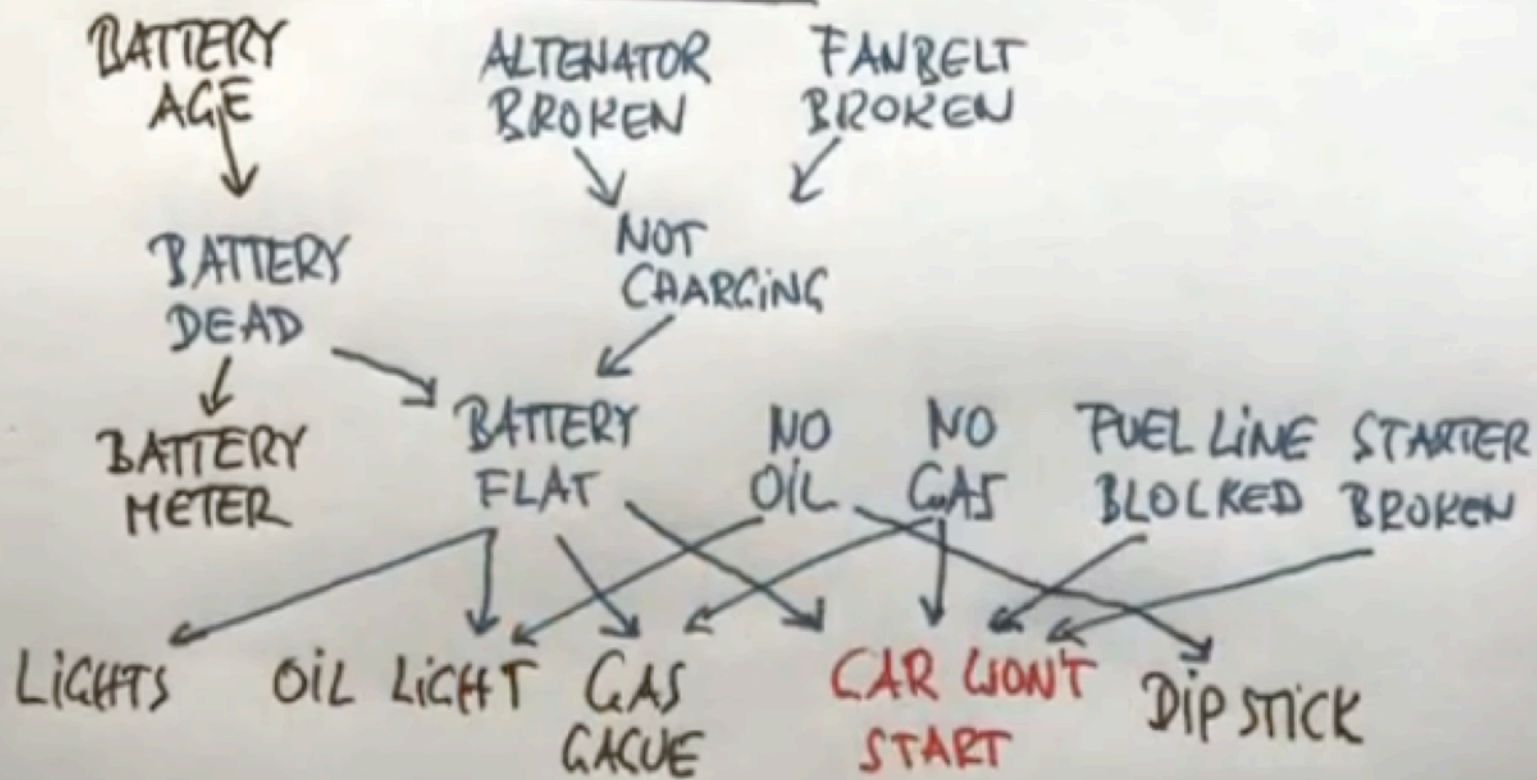


Evolution of machine learning systems



from Goodfellow, Bengio, Courville 2015

BAYES NETWORK



Symbolic vs subsymbolic AI

Symbolic programming
Explicit Rules
Ontologies

Neural Networks
Deep Learning
SVM, Decision Trees, LDA, ...

Bayes

Supervised Learning

Unsupervised Learning

Reinforcement Learning

Tool	Uses	Language
Scikit-Learn	Classification, Regression, Clustering	Python
Spark MLlib	Classification, Regression, Clustering	Scala, R, Java
Weka	Classification, Regression, Clustering	Java
Caffe	Neural Networks	C++, Python
TensorFlow	Neural Networks	Python

Mathematical representation

Functional form

Probabilistic form

True underlying world:

$$y = f(\mathbf{x})$$

$$p(Y = y|\mathbf{x})$$

Model:

$$\hat{y} = \hat{f}(\mathbf{x}; \mathbf{w})$$

$$p(\hat{Y} = \hat{y}|\mathbf{x}; \theta)$$

Learning:

$$w_i \leftarrow w_i - \alpha \nabla \mathcal{L}$$

$$\mathbf{w}^* = \operatorname{argmax}_{\mathbf{w}} p(\mathbf{w}|y, \mathbf{x})$$