
A Brief Introduction of Berkeley Deep Drive (BDD)

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Deep Learning: A Buzzword

- **Alpha Go**
- **Already broadly adopted at many high-tech companies**
- **A flurry of investments**
- **A cluster of start-ups**

Deep Learning

- A Type of Machine Learning
- Machine Learning (Artificial Intelligence) systems acquire their knowledge, by **extracting patterns from raw data.**
- Data representation in deep learning
 - Mapping representation to output
 - Deep Learning introduces representation that are **expressed in other simpler representations** in multiple layers
 - Thus a Multi-Layer **Deep Structure.**

Illustration of a Deep Learning Model



Output:
object identity

3rd hidden layer:
object parts

2nd hidden layer:
corners and contours

1st hidden layer:
edges

Visible layer:
input pixels

Source:

- <http://www.deeplearningbook.org/contents/intro.html>

Deep Learning History

- Deep Learning dated back to 1940s, known as Cybernetics in 1940s-1960s
- Connectionism in 1980s-1990s
- Current resurgence started in 2006
- In recent years, Deep Learning has advanced significantly due to several contributing factors
 - Greater computing power (CPU, GPU, Network)
 - Higher availability and affordability of GPUs
 - Large collection of data samples available to train and test algorithms (such as ImageNet, with 14,197,122 images, 21841 synsets indexed)

End-to-End Learning for Vision, Text, Speech

What is Deep Learning?

Compositional Models

Learned End-to-End

Hierarchy of Representations

- vision: pixel, motif, part, object
- text: character, word, clause, sentence
- speech: audio, band, phone, word

concrete $\xrightarrow{\text{learning}}$ abstract

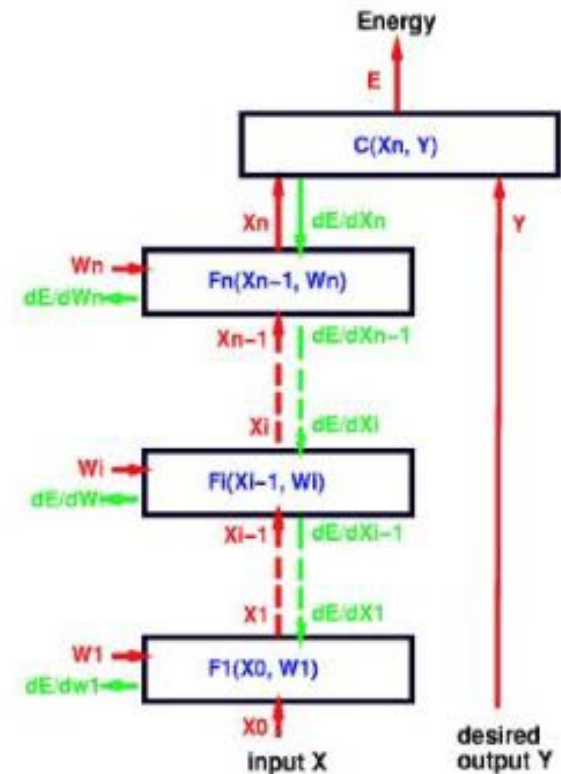


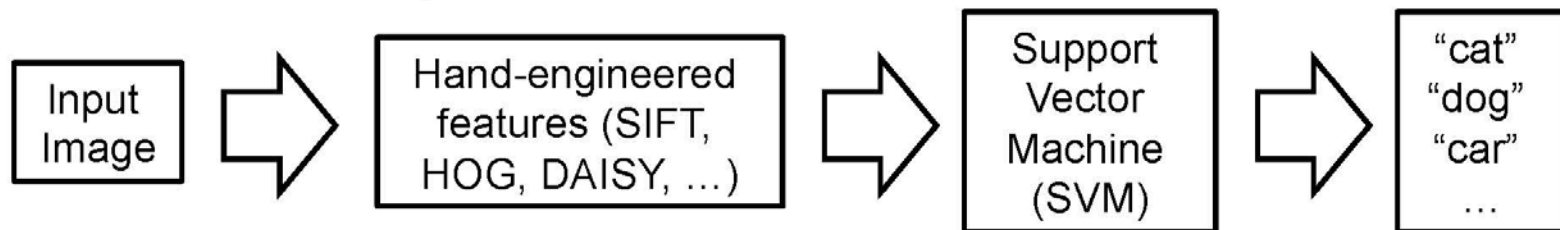
figure credit Yann LeCun, ICML '13 tutorial

Source: Berkeley Vision and Learning Center

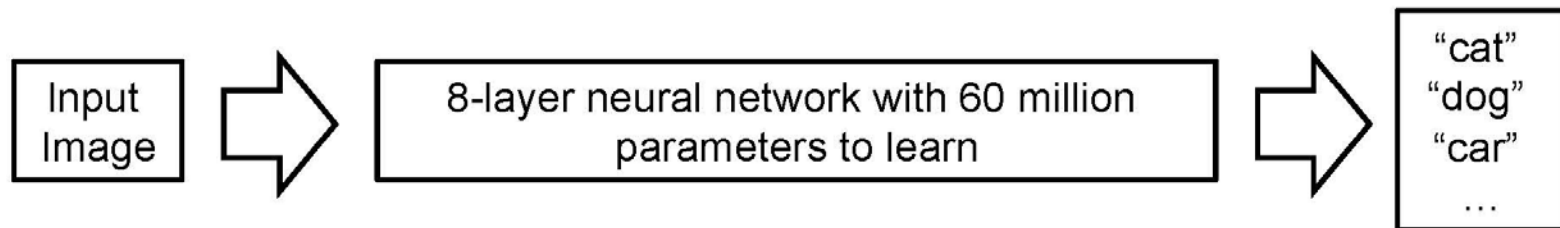
<http://caffe.berkeleyvision.org/>

Object Detection in Computer Vision

- State-of-the-art object detection until 2012:



- Deep Supervised Learning (Krizhevsky, Sutskever, Hinton 2012; also LeCun, Bengio, Ng, Darrell, ...):



- ~1.2 million training images from ImageNet [Deng, Dong, Socher, Li, Li, Fei-Fei, 2009]

Source: Pieter Abbeel presentation, 04/2016

Doing Better and Better

Performance

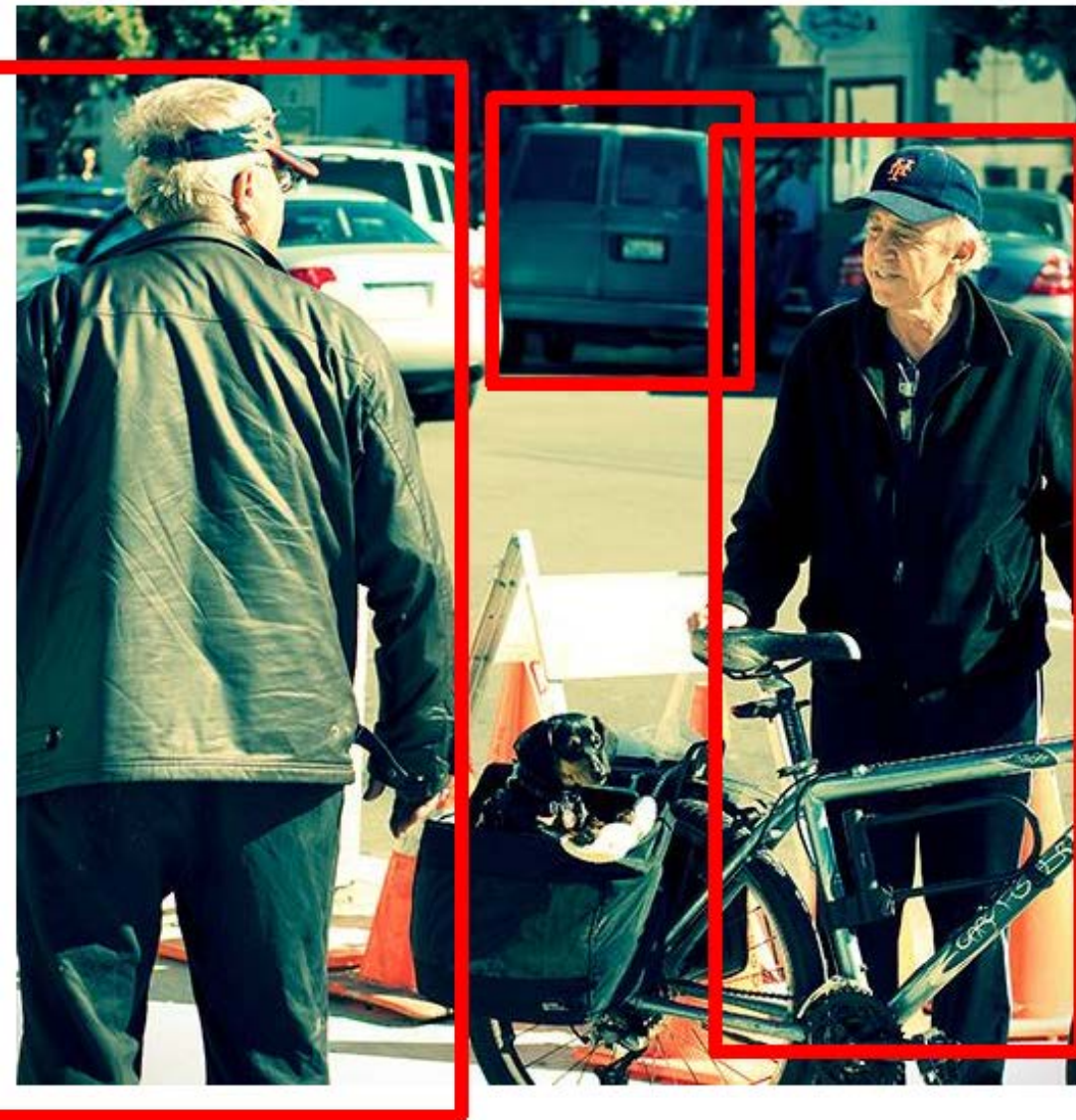
ImageNet Error Rate 2010-2014



graph credit Matt Zeiler, Clarifai

Source: Pieter Abbeel presentation, 04/2016

Large-scale Semantic Description



Object Detection

...

Source:
Trevor Darrell
presentation

Large-scale *Semantic Description*



Object Detection
Semantic Segmentation
Pose Estimation
Attribute Classification
Fine-Grained Recognition
Action Recognition

...



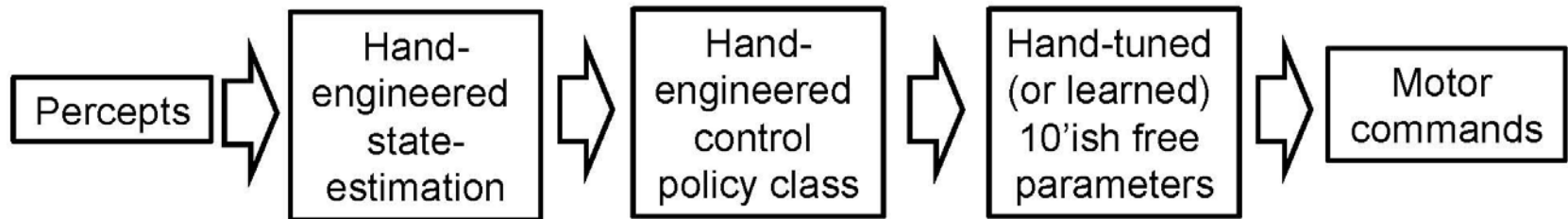
Hypothetically,

- **Recent Tesla Incident (May 2016, Florida)**
 - **Supposedly, the Tesla (camera + radar) sensor did not recognize the “side of truck” versus the background sky;**
- **Can a “deep learning” system recognize an object that is “not the same” as a typical target?**

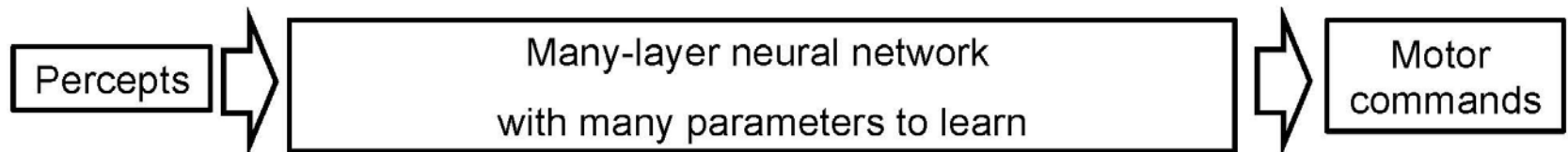
End-to-End Visuomotor

Robotics

- **Current state-of-the-art robotics**



- **Deep reinforcement learning**



Source: Pieter Abbeel presentation, 04/2016

State of the Art – Nvidia Example

Nvidia demo of Visuomotor Control (April 2016)

- End-to-End learning, implementation on Drive-PX2 platform
- trained a convolutional neural network (CNN) to map raw pixels from a single front-facing camera directly to steering commands
- With only human steering inputs as training signals; does not explicitly train the system to detect the outline of roads
- Avoided the needs to recognize human-designated features, such as lane markings, other cars, etc., nor did it include a number of “if-then” rules
- As of 03/2016, 72 hours of training data collected
- Use simulation to enhance training
- **98% of autonomy** (see Nvidia paper) in field testing

Criticism and Challenges

- **Formal and complete safety design verification**
 - Training data
 - Stability
 - Credit assignment
- **Compliance with functional safety (such as ISO-26262)**
 - safety assurance
- **Disruptive proposition of end-to-end solution**
 - Departure from conventional automotive model

Deep Learning at Berkeley

- **Berkeley Vision Learning Center**
 - A consortium that started in 2012
 - Tremendous advances in computer and deep learning.
 - **Open-source Caffe**, widely used globally
- **Berkeley Deep Drive (BDD) Center**
 - A consortium that started in Spring 2016
 - Seeking to merge deep learning with automotive perception and bring computer vision technology to the forefront.

Berkeley Deep Drive

A Research Alliance

to Investigate State-of-the-Art Technologies

in Computer Vision and Machine Learning

for Automotive Applications

Berkeley Deep Drive

- **Current members include:**
 - Audi/VW, Bosch, Ford, Honda, Hyundai, Nvidia, Panasonic, Qualcomm, Samsung, Toyota
 - GM, NXP, Sony recently joined
 - Nexar and Mapillary are contributing partners
 - Nexar provides 100,000 hours of driving videos yearly
 - Mapillary provides millions of images
- Several more are in agreement reviews

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- **Sponsors membership**
 - Access to faculty and students
 - Shared use of research outcome, codes and data, in repository
 - Commercial use of BDD software repository, without further licensing agreement with UC Berkeley
- **BDD project and scope of study**
 - Proposals submitted by campus PIs
 - Sponsors review and rate proposals
 - Panel consolidates and decides on final selection of projects to sponsors

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Categories of Exemplar Projects, 1 of 2

- **Deep Learning Methodologies**
 - Clockwork FCNs for Fast Video Processing
 - Cross-modal Transfer Learning
 - Deep Learning for Tracking
 - Fast Object Detection and Segmentation
 - Improving the Scaling of Deep Learning Networks by Characterizing and Exploiting Soft Convexity
 - Learning Deep Models Securely on Sensitive Imaging Data with Cryptographic Guarantees
 - Unsupervised Representation Learning for Autonomous Driving
- **Deep Learning Implementation**
 - Benchmarks and Leaderboard for Deep Reinforcement Learning
 - Design Space Exploration for Deep Neural Nets for Advanced Driver Assistance Systems
 - FPGA PRET Accelerators of Deep Learning Classifiers for Autonomous Vehicles
 - Learning to Drive Under Unstructured Conditions
 - Low Latency Deep Inference for Self-Driving Vehicles
 - Secure and Privacy-Preserving Deep Learning

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Categories of Exemplar Projects, 2 of 2

- **Detection and Perception**
 - Pedestrian Models in Urban Environment for Autonomous Driving and Database of Video Sequences for Model Training, Testing, and Implementation
 - Real-Time Perception/Prediction of Traffic Scene with Deep Learning for Autonomous Driving
 - Motion Prediction for Urban Autonomous Driving Based on Stochastic Policy Learned via Deep Neural Network
 - Inference of Drivers' Intent at Intersections
 - Outdoor Semantic Scene Segmentation via Multi-modal Sensor Fusion
 - **Driver-Vehicle Interaction**
 - Verifiable Control for (Semi)Autonomous Cars that Learn from Human (Re)Actions
 - Implicit Communication Through a Car's Motion
 - Understanding Driver Awareness for Smart Vehicles
 - Human-Machine Arbitration in Hybrid Driving Systems
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Future of AI / Deep Learning

- A progressive emergence
- A worldwide community
- Deep Learning for image and speech recognition widely deployed
 - Prospects for automated driving, medical imaging, robots, etc.
- Hardware for embedded applications needed
 - Nvidia, Qualcomm, etc.
- Probably a way to go for truly intelligent machine

Questions?

**Check out BDD website
bdd.Berkeley.edu**

Thank You!

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