Deep Learning for Autonomous Driving

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Mobileye

IM**VC** dimension,
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Autonomous Driving

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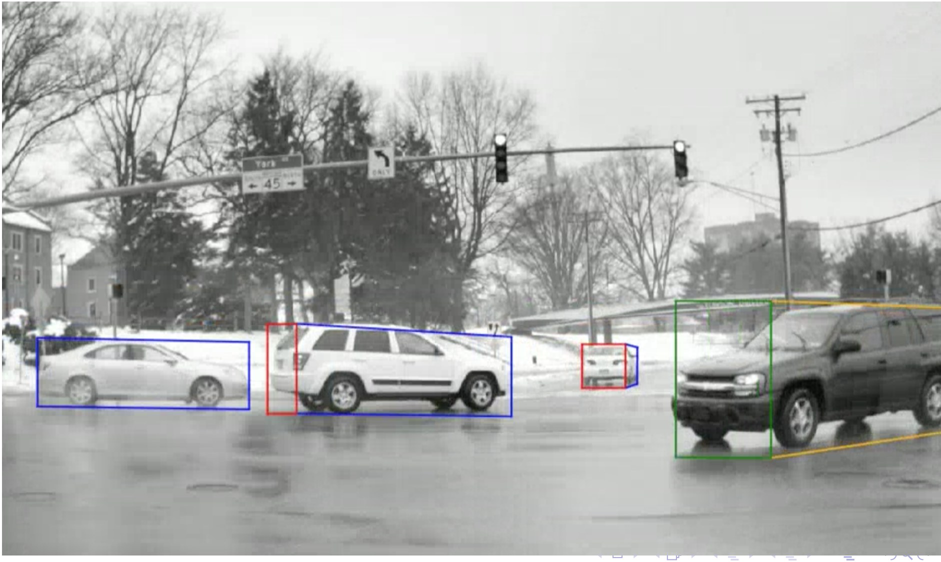

Major Sub-Problems

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- Static objects: Road edge, curbs, guard rails, ...
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Driving Policy:

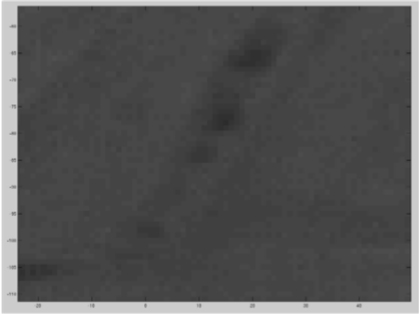
- Planning: e.g.
  - Change lane now because you need to take a highway exit soon
  - Slow down because someone is likely to cut into your lane
- Negotiation: e.g.
  - Merge into traffic
  - Roundabouts, 4-way stops

Challenges

- Everything should run in real time
- Difficult driving conditions
- Robustness: No margin for severe errors
- Unpredictable behavior of other drivers/pedestrians
- Beyond "bounding box": need to understand the entire image and must utilize contextual information

Example: Free Space

Where can I drive ?



Example: Free Space

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Need context !

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- Why Are Deep Networks Powerful?
  - **Theorem:**
    Any function that can be implemented by a Turing machine in T steps can also be expressed by a T-depth network
  - **Generalization:**
    Deep networks are both expressive and generalizing (meaning that the learned model works well on **unseen examples**)

Additional Benefits of Deep Learning

- Hierarchical representations for every pixel ("pooling")
- Spatial sharing of computation ("convolutions")
- Accelerate computation by dedicated hardware ("lego")
- "Development language": by designing architectures and loss functions
- Modeling of complex spatial-temporal structures (using RNNs)

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- Current algorithms fail for some trivial problems
  - Parity of more than 30 bits
  - Multiplication of large numbers
  - Modeling of piece-wise curves
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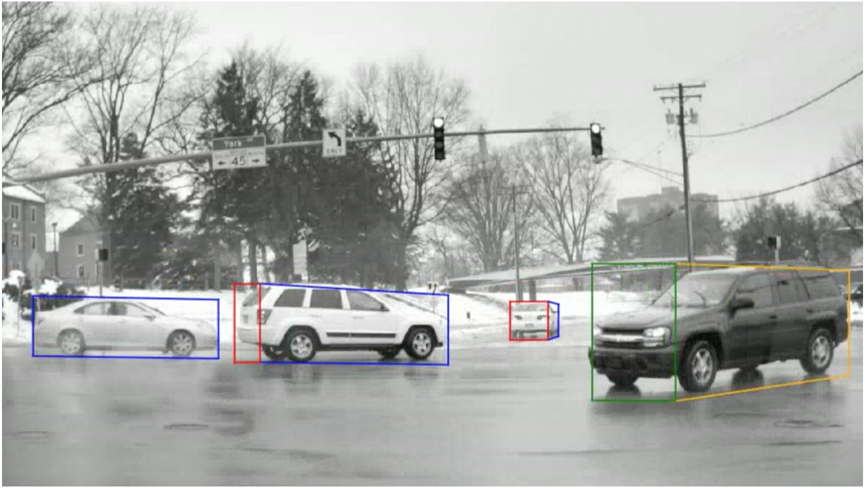
- In practice: Deep learning is useful only when it is combined with smart modeling/engineering
- In practice: Domain knowledge is very helpful
- In practice: Architectural transfer only works for similar problems
- In practice: Standard training algorithms are not always satisfactory for automotive applications

Example: Typical vs. Rare Cases



Typical vs. Rare Cases

Failures of Existing Methods for Rare Cases

- State-of-the-art training methods are variants of Stochastic Gradient Descent (SGD)
- SGD is an iterative procedure
- At each iteration, a random training example is picked
- The random sample is used to estimate an update direction
- The weights of the network are updated based on this direction

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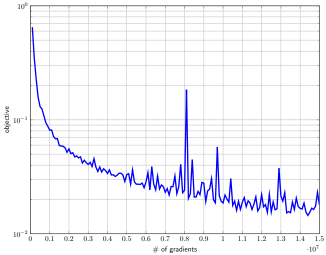
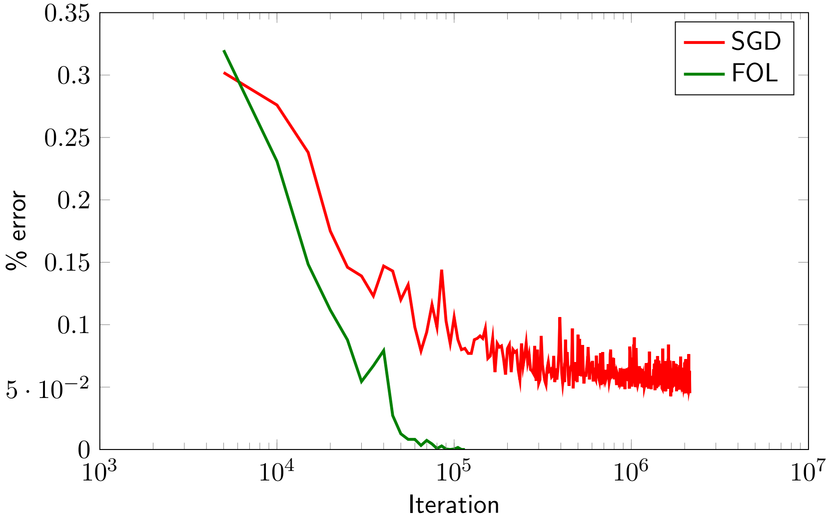


SGD finds an o.k. solution very fast, but significantly slows down at the end. Why?

- Rare mistakes: Suppose all but 1% of the examples are correctly classified. SGD will now waste 99% of its time on examples that are already correct by the model
- High variance, even close to the optimum

Requires Novel Algorithms



Deep Learning for Driving Policy

- Input: Detailed semantic environmental modeling
- Output: Where to drive and an what speed

Reinforcement Learning

Goal: Learn a policy, mapping from states to actions

Learning Process:

For $t = 1, 2, \ldots$

- Agent observes state s_t
- Agent decides on action a_t based on the current policy
- Environment provides reward r_t
- Environment moves the agent to next state s_{t+1}

Reinforcement Learning vs. Supervised Learning

- In SL, actions do not effect the environment, therefore we can collect training examples in advance, and only then search for a policy
- In SL, the effect of actions is local, while in RL, actions have long-term effect
- In SL we are given the correct answer, while in RL we only observe a reward

Reinforcement Learning: Existing Approaches

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- Yields a Markov Decision Process (MDP) — Can couple all the future into the so-called Q function

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- Yields a Markov Decision Process (MDP) — Can couple all the future into the so-called Q function
- Inadequate for driving policy — Next state depends on other drivers

A Decomposable Approach for Reinforcement Learning

Decompose the problem into

1. Supervised Learning problems
   - Predict the near future
   - Predict the intermediate reward
2. and then explicitly optimize over the policy using Recurrent Neural Network

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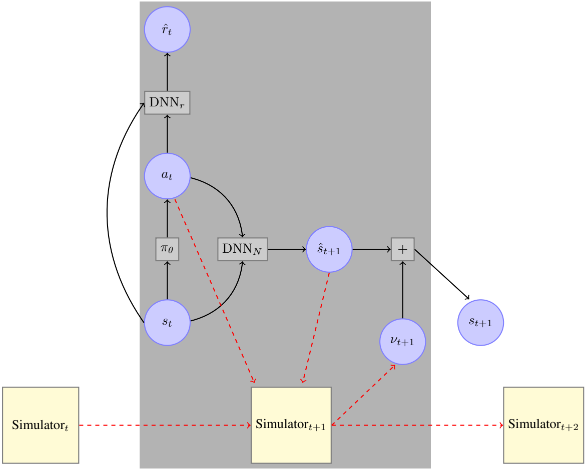
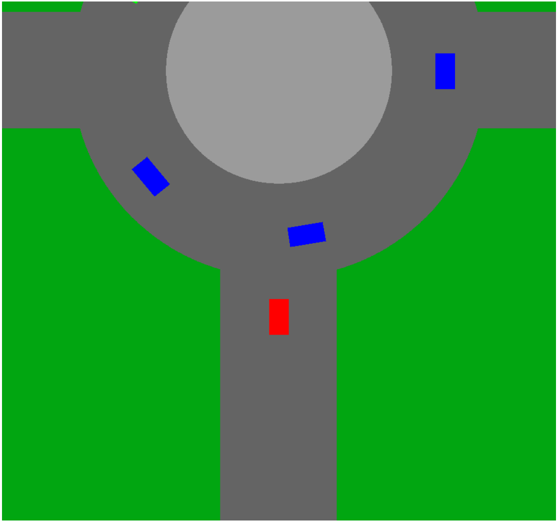


Illustration



Summary

- The Deep Learning Revolution: Stunning empirical success in hard AI tasks
- Existing deep Learning algorithms fail for some trivial problems
- Prior knowledge is still here, it just shifted its shape
- A deeper theoretical understanding of deep learning is the most important open problem in machine learning ...