Self-Driving Cars

Lecture 2 – Imitation Learning

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Agenda

2.1 Approaches to Self-Driving

2.2 Deep Learning Recap

2.3 Imitation Learning

2.4 Conditional Imitation Learning

2.1
Approaches to Self-Driving

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Autonomous Driving

Dominating Paradigms:

- Modular Pipelines
- End-to-End Learning (Imitation Learning, Reinforcement Learning)
- Direct Perception

Autonomous Driving: Modular Pipeline

Examples:

- [Montemerlo et al., JFR 2008]
- [Urmson et al., JFR 2008]
- Waymo, Uber, Tesla, Zoox, . . .

Autonomous Driving: Modular Pipeline

Autonomous Driving: Modular Pipeline

Autonomous Driving: Modular Pipeline

Autonomous Driving: Modular Pipeline

Sensory Input

Modular Pipeline

Low-level Perception → Scene Parsing → Path Planning → Vehicle Control

Steer

Gas

Brake

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Autonomous Driving: Modular Pipeline

Autonomous Driving: Modular Pipeline

Pros:

- Small components, easy to develop in parallel
- Interpretability

Cons:

- Piece-wise training (not jointly)
- Localization and planning heavily relies on HD maps

HD maps: Centimeter precision lanes, markings, traffic lights/signs, human annotated

Autonomous Driving: Modular Pipeline

- Piece-wise training difficult: not all objects are equally important!

Ohn-Bar and Trivedi: Are All Objects Equal? Deep Spatio-Temporal Importance Prediction in Driving Videos. PR, 2017.

Autonomous Driving: Modular Pipeline

- HD Maps are expensive to create (data collection & annotation effort)

https://www.geospatialworld.net/article/hd-maps-autonomous-vehicles/

Autonomous Driving: End-to-End Learning

Examples:

- [Pomerleau, NIPS 1989]
- [Bojarski, Arxiv 2016]
- [Codevilla et al., ICRA 2018]

Autonomous Driving: End-to-End Learning

Pros:

- End-to-end training
- Cheap annotations

Cons:

- Training / Generalization
- Interpretability

Autonomous Driving: Direct Perception

Examples:

- [Chen et al., ICCV 2015]
- [Sauer et al., CoRL 2018]
- [Behl et al., IROS 2020]

Autonomous Driving: Direct Perception

Pros:

- Compact Representation
- Interpretability

Cons:

- Control typically not learned jointly
- How to choose representations?

2.2
Deep Learning Recap

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Supervised Learning

- **Learning:** Estimate parameters $\mathbf{w}$ from training data $\{(x_i, y_i)\}_{i=1}^{N}$
- **Inference:** Make novel predictions: $y = f_{\mathbf{w}}(x)$

Linear Classification

Logistic Regression

$$\hat{y} = \sigma(\mathbf{w}^\top \mathbf{x} + w_0) \quad \sigma(x) = \frac{1}{1 + e^{-x}}$$

- Let $\mathbf{x} \in \mathbb{R}^2$
- Decision boundary: $\mathbf{w}^\top \mathbf{x} + w_0 = 0$
- Decide for class $1 \Leftrightarrow \mathbf{w}^\top \mathbf{x} > -w_0$
- Decide for class $0 \Leftrightarrow \mathbf{w}^\top \mathbf{x} < -w_0$
- Which problems can we solve?

Linear Classification

Linear Classifier:

Class 1 $\Leftrightarrow \mathbf{w}^\top \mathbf{x} > -w_0$

$$\underbrace{\begin{pmatrix} 1 & 1 \end{pmatrix}}_{\mathbf{w}^\top} \underbrace{\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}}_{\mathbf{x}} > \underbrace{0.5}_{-w_0}$$

x_1	x_2	OR(x_1,x_2)
0	0	0
0	1	1
1	0	1
1	1	1

Linear Classification

Linear Classifier:

Class 1 $\Leftrightarrow \mathbf{w}^\top \mathbf{x} > -w_0$

$$\underbrace{\begin{pmatrix} 1 & 1 \end{pmatrix}}_{\mathbf{w}^\top} \underbrace{\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}}_{\mathbf{x}} > \underbrace{1.5}_{-w_0}$$

x_1	x_2	AND(x_1,x_2)
0	0	0
0	1	0
1	0	0
1	1	1

Linear Classification

Linear Classifier:

Class 1 $\Leftrightarrow \mathbf{w}^\top \mathbf{x} > -w_0$

$$\underbrace{\begin{pmatrix} -1 & -1 \end{pmatrix}}_{\mathbf{w}^\top} \underbrace{\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}}_{\mathbf{x}} > \underbrace{-1.5}_{-w_0}$$

x_1	x_2	NAND(x_1,x_2)
0	0	1
0	1	1
1	0	1
1	1	0

Linear Classification

Linear Classifier:

Class 1 $\Leftrightarrow \mathbf{w}^\top \mathbf{x} > -w_0$

$$\underbrace{\begin{pmatrix} ? & ? \end{pmatrix}}_{\mathbf{w}^\top} \underbrace{\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}}_{\mathbf{x}} > \underbrace{?}_{-w_0}$$

x_1	x_2	XOR(x_1,x_2)
0	0	0
0	1	1
1	0	1
1	1	0

Linear Classification

Linear classifier with non-linear features $\boldsymbol{\psi}$:

$$\mathbf{w}^\top \underbrace{\begin{pmatrix} x_1 \\ x_2 \\ x_1 x_2 \end{pmatrix}}_{\boldsymbol{\psi}(\mathbf{x})} > -w_0$$

x_1	x_2	$\psi_1(\mathbf{x})$	$\psi_2(\mathbf{x})$	$\psi_3(\mathbf{x})$	XOR
0	0	0	0	0	0
0	1	0	1	0	1
1	0	1	0	0	1
1	1	1	1	1	0

- Non-linear features allow linear classifier to solve non-linear classification problems!

Representation Matters

- But how to choose the transformation? Can be very hard in practice.
- Yet, this was the dominant approach until the 2000s (vision, speech, ..)
- In deep/representation learning we want to learn these transformations

Non-Linear Classification

Linear Classifier:

Class 1 $\Leftrightarrow \mathbf{w}^\top \mathbf{x} > -w_0$

XOR(x_1, x_2) =
AND(OR(x_1, x_2),NAND(x_1, x_2))

x_1	x_2	XOR(x_1,x_2)
0	0	0
0	1	1
1	0	1
1	1	0

Non-Linear Classification

$$\text{XOR}(x_1, x_2) = \text{AND}(\text{OR}(x_1, x_2), \text{NAND}(x_1, x_2))$$

The above expression can be rewritten as a **program of logistic regressors:**

$$h_1 = \sigma(\mathbf{w}_{OR}^\top \mathbf{x} + w_{OR})$$
$$h_2 = \sigma(\mathbf{w}_{NAND}^\top \mathbf{x} + w_{NAND})$$
$$\hat{y} = \sigma(\mathbf{w}_{AND}^\top \mathbf{h} + w_{AND})$$

Note that $\mathbf{h}(\mathbf{x})$ is a non-linear feature of $\mathbf{x}$.
We call $\mathbf{h}(\mathbf{x})$ a **hidden** layer.

Multi-Layer Perceptrons

- MLPs are **feedforward** neural networks (no feedback connections)
- They **compose** several non-linear functions $\mathbf{f}(\mathbf{x}) = \hat{\mathbf{y}}(\mathbf{h}_3(\mathbf{h}_2(\mathbf{h}_1(\mathbf{x}))))$ where $\mathbf{h}_i(\cdot)$ are called **hidden layers** and $\hat{\mathbf{y}}(\cdot)$ is the **output layer**
- The data specifies only the behavior of the output layer (thus the name "hidden")
- Each layer i comprises multiple **neurons** j which are implemented as **affine transformations** $(\mathbf{a}^\top \mathbf{x} + \mathbf{b})$ followed by non-linear **activation functions** (g):

$$h_{ij} = g(\mathbf{a}_{ij}^\top \mathbf{h}_{i-1} + \mathbf{b}_{ij})$$

- Each neuron in each layer is **fully connected** to all neurons of the previous layer
- The overall length of the chain is the **depth** of the model $\Rightarrow$ "Deep Learning"

MLP Network Architecture

- Neurons are grouped into layers, each neuron **fully connected** to all prev. ones
- **Hidden layer** $\mathbf{h}_i = g(\mathbf{A}_i\mathbf{h}_{i-1} + \mathbf{b}_i)$ with **activation function** $g(\cdot)$ and weights $\mathbf{A}_i, \mathbf{b}_i$

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Deeper Models allow for more Complex Decisions

2 Hidden Neurons

5 Hidden Neurons

15 Hidden Neurons

https://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html

Output and Loss Functions

- The **output layer** is the last layer in a neural network which computes the output
- The **loss function** compares the result of the output layer to the target value(s)
- Choice of output layer and loss function depends on task (discrete, continuous, ..)

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Output Layer

- For classification problems, we use a sigmoid or softmax non-linearity
- For regression problems, we can directly return the value after the last layer

Loss Function

- For classification problems, we use the (binary) cross-entropy loss
- For regression problems, we can use the ℓ_1 or ℓ_2 loss

Activation Functions

- Hidden layer $\mathbf{h}_i = g(\mathbf{A}_i \mathbf{h}_{i-1} + \mathbf{b}_i)$ with **activation function** $g(\cdot)$ and weights $\mathbf{A}_i, \mathbf{b}_i$
- The activation function is frequently applied **element-wise** to its input
- Activation functions must be **non-linear** to learn non-linear mappings

Activation Functions

Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

tanh

$$\tanh(x)$$

ReLU

$$\max(0, x)$$

Leaky ReLU

$$\max(0.1x, x)$$

Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

Convolutional Neural Networks

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Convolutional Neural Networks

- Multi-layer perceptrons don't scale to high-dimensional inputs
- ConvNets represent data in 3 dimensions: width, height, depth (= feature maps)
- ConvNets interleave discrete convolutions, non-linearities and pooling
- Key ideas: sparse interactions, parameter sharing, equivariant representation

Fully Connected vs. Convolutional Layers

- **Fully connected layer:** #Weights $= W \times H \times C_{out} \times (W \times H \times C_{in} + 1)$
- **Convolutional layer:** #Weights $= C_{out} \times (K \times K \times C_{in} + 1)$ ("weight sharing")
- With C_{in} input and C_{out} output channels, layer size $W \times H$ and kernel size $K \times K$
- Convolutions are followed by non-lineary activation functions (e.g., ReLU)

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Padding

Idea of Padding:

- Add boundary of appropriate size with zeros (blue) around input tensor

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Downsampling

- Downsampling **reduces the spatial resolution** (e.g., for image level predictions)
- Downsampling **increases the receptive field** (which pixels influence a neuron)

Pooling

- Typically, stride $s = 2$ and kernel size $2 \times 2 \Rightarrow$ **reduces spatial dimensions** by 2
- Pooling has **no parameters** (typical pooling operations: max, min, mean)

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- Pooling has **no parameters** (typical pooling operations: max, min, mean)

Fully Connected Layers

- Often, convolutional networks comprise fully connected layers at the end

Optimization

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Optimization

Optimization Problem: (dataset $\mathcal{X}$)

$$\mathbf{w}^* = \underset{\mathbf{w}}{\operatorname{argmin}} \; \mathcal{L}(\mathcal{X}, \mathbf{w})$$

Gradient Descent:

$$\mathbf{w}^0 = \mathbf{w}^{\text{init}}$$

$$\mathbf{w}^{t+1} = \mathbf{w}^t - \eta \, \nabla_{\mathbf{w}} \mathcal{L}(\mathcal{X}, \mathbf{w}^t)$$

- Neural network loss $\mathcal{L}(\mathcal{X}, \mathbf{w})$ is **not convex**, we have to use gradient descent
- There exist **multiple local minima**, but we will find only one through optimization
- Good news: it is known that **many local minima** in deep networks **are good ones**

Backpropagation

- Values are efficiently computed forward, gradients backward
- Modularity: Each node must only "know" how to compute gradients wrt. its own arguments
- One fw/bw pass per data point:

$$\nabla_{\mathbf{w}} \mathcal{L}(\mathcal{X}, \mathbf{w}) = \sum_{i=1}^{N} \underbrace{\nabla_{\mathbf{w}} \mathcal{L}(\mathbf{y}_i, \mathbf{x}_i, \mathbf{w})}_{\text{Backpropagation}}$$

Gradient Descent

Algorithm:

1. Initialize weights $\mathbf{w}^0$ and pick learning rate η
2. For all data points $i \in \{1, \ldots, N\}$ do:
   2.1 Forward propagate $\mathbf{x}_i$ through network to calculate prediction $\hat{\mathbf{y}}_i$
   2.2 Backpropagate to obtain gradient $\nabla_{\mathbf{w}} \mathcal{L}_i(\mathbf{w}^t) \equiv \nabla_{\mathbf{w}} \mathcal{L}(\hat{\mathbf{y}}_i, \mathbf{y}_i, \mathbf{w}^t)$
3. Update gradients: $\mathbf{w}^{t+1} = \mathbf{w}^t - \eta \frac{1}{N} \sum_i \nabla_{\mathbf{w}} \mathcal{L}_i(\mathbf{w}^t)$
4. If validation error decreases, go to step 2, otherwise stop

Challenges:

- Typically, millions of parameters $\Rightarrow \dim(\mathbf{w}) =$ 1 million or more
- Typically, millions of training points $\Rightarrow N =$ 1 million or more
- Becomes extremely expensive to compute and does not fit into memory

Stochastic Gradient Descent

Solution:

- The total loss over the entire training set can be expressed as the expectation:

$$\frac{1}{N}\sum_i \mathcal{L}_i(\mathbf{w}^t) = \mathbb{E}_{i\sim\mathcal{U}\{1,N\}}\left[\mathcal{L}_i(\mathbf{w}^t)\right]$$

- This expectation can be approximated by a smaller subset $B \ll N$ of the data:

$$\mathbb{E}_{i\sim\mathcal{U}\{1,N\}}\left[\mathcal{L}_i(\mathbf{w}^t)\right] \approx \frac{1}{B}\sum_b \mathcal{L}_b(\mathbf{w}^t)$$

- Thus, the gradient can also be approximated by this subset (=minibatch):

$$\frac{1}{N}\sum_i \nabla_{\mathbf{w}}\mathcal{L}_i(\mathbf{w}^t) \approx \frac{1}{B}\sum_b \nabla_{\mathbf{w}}\mathcal{L}_b(\mathbf{w}^t)$$

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Stochastic Gradient Descent

Algorithm:

1. Initialize weights $\mathbf{w}^0$, pick learning rate η and minibatch size $|\mathcal{X}_{\text{batch}}|$
2. Draw random minibatch $\{(\mathbf{x}_1, \mathbf{y}_1), \ldots, (\mathbf{x}_B, \mathbf{y}_B)\} \subseteq \mathcal{X}$ (with $B \ll N$)
3. For all minibatch elements $b \in \{1, \ldots, B\}$ do:
   3.1 Forward propagate $\mathbf{x}_b$ through network to calculate prediction $\hat{\mathbf{y}}_b$
   3.2 Backpropagate to obtain batch element gradient $\nabla_{\mathbf{w}} \mathcal{L}_b(\mathbf{w}^t) \equiv \nabla_{\mathbf{w}} \mathcal{L}(\hat{\mathbf{y}}_b, \mathbf{y}_b, \mathbf{w}^t)$
4. Update gradients: $\mathbf{w}^{t+1} = \mathbf{w}^t - \eta \frac{1}{B} \sum_b \nabla_{\mathbf{w}} \mathcal{L}_b(\mathbf{w}^t)$
5. If validation error decreases, go to step 2, otherwise stop

First-order Methods

There exist many variants:

- SGD
- SGD with Momentum
- SGD with Nesterov Momentum
- RMSprop
- Adagrad
- Adadelta
- Adam
- AdaMax
- NAdam
- AMSGrad

Adam is often the method of choice due to its robustness.

Learning Rate Schedules

- A fixed learning rate is too slow in the beginning and too fast in the end
- Exponential decay: $\eta_t = \eta\alpha^t$
- Step decay: $\eta \leftarrow 0.5\eta$ (every K iterations)

He, Zhang, Ren andSun: Deep Residual Learning for Image Recognition. CVPR, 2016.

Regularization

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Capacity, Overfitting and Underfitting

Capacity too low

Capacity about right

Capacity too high

- **Underfitting:** Model too simple, does not achieve low error on training set
- **Overfitting:** Training error small, but test error (= generalization error) large
- **Regularization:** Take model from third regime (right) to second regime (middle)

Early Stopping and Parameter Penalties

Early stopping:

- Dashed: Trajectory taken by SGD
- Trajectory stops at $\tilde{\mathbf{w}}$ before reaching minimum training error $\mathbf{w}^*$

L2 Regularization:

- Regularize objective with L_2 penalty
- Penalty forces minimum of regularized loss $\tilde{\mathbf{w}}$ closer to origin

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Dropout

Idea:

- During training, **set neurons to zero** with probability μ (typically $\mu = 0.5$)
- Each binary mask is one model, changes randomly with every training iteration
- Creates **ensemble "on the fly"** from a single network with shared parameters

Srivastava, Hinton, Krizhevsky, Sutskever and Salakhutdinov: Dropout: a simple way to prevent neural networks from overfitting. JMLR, 2014.

Data Augmentation

- Best way towards better generalization is to **train on more data**
- However, data in practice often limited
- Goal of data augmentation: create **“fake” data** from the existing data (on the fly) and add it to the training set
- New data must **preserve semantics**
- Even **simple operations** like translation or adding per-pixel noise often already greatly improve generalization
- `https://github.com/aleju/imgaug`

2.3
Imitation Learning

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Imitation Learning: Manipulation

Imitation Learning: Car Racing

Trainer
(Human Driver)

Trainee
(Neural Network)

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Imitation Learning in a Nutshell

Hard coding policies is often difficult ⇒ Rather use a data-driven approach!

- **Given:** demonstrations or demonstrator
- **Goal:** train a policy to mimic decision
- **Variants:** behavior cloning (this lecture), inverse optimal control, . . .

Formal Definition of Imitation Learning

- State: $s \in \mathcal{S}$ — may be partially observed (e.g., game screen)
- Action: $a \in \mathcal{A}$ — may be discrete or continuous (e.g., turn angle, speed)
- Policy: $\pi_\theta : \mathcal{S} \to \mathcal{A}$ — we want to learn the policy parameters θ
- Optimal action: $a^* \in \mathcal{A}$ — provided by expert demonstrator
- Optimal policy: $\pi^* : \mathcal{S} \to \mathcal{A}$ — provided by expert demonstrator
- State dynamics: $P(s_{i+1}|s_i, a_i)$ — simulator, typically not known to policy
  Often deterministic: $s_{i+1} = T(s_i, a_i)$ — deterministic mapping
- Rollout: Given s_0, sequentially execute $a_i = \pi_\theta(s_i)$ & sample $s_{i+1} \sim P(s_{i+1}|s_i, a_i)$ yields trajectory $\tau = (s_0, a_0, s_1, a_1, \dots)$
- Loss function: $\mathcal{L}(a^*, a)$ — loss of action a given optimal action a^*

Formal Definition of Imitation Learning

General Imitation Learning:

$$\underset{\theta}{\operatorname{argmin}}\ \mathbb{E}_{s\sim P(s|\pi_\theta)}\left[\mathcal{L}\left(\pi^*(s), \pi_\theta(s)\right)\right]$$

- State distribution $P(s|\pi_\theta)$ depends on rollout determined by current policy π_θ

Behavior Cloning:

$$\underset{\theta}{\operatorname{argmin}}\ \underbrace{\mathbb{E}_{(s^*,a^*)\sim P^*}\left[\mathcal{L}\left(a^*, \pi_\theta(s^*)\right)\right]}_{=\sum_{i=1}^{N}\mathcal{L}\left(a_i^*,\pi_\theta(s_i^*)\right)}$$

- State distribution P^* provided by expert
- Reduces to supervised learning problem

Challenges of Behavior Cloning

- Behavior cloning makes IID assumption
  - Next state is sampled from states observed during expert demonstration
  - Thus, next state is sampled independently from action predicted by current policy
- What if π_θ makes a mistake?
  - Enters new states that haven't been observed before
  - New states not sampled from same (expert) distribution anymore
  - Cannot recover, catastrophic failure in the worst case
- What can we do to overcome this train/test distribution mismatch?

DAgger

Data Aggregation (DAgger):

- Iteratively build a set of inputs that the final policy is likely to encounter based on previous experience. Query expert for aggregate dataset
- But can easily overfit to main mode of demonstrations
- High training variance (random initialization, order of data)

Ross, Gordon and Bagnell: A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning. AISTATS, 2011.

DAgger with Critical States and Replay Buffer

Key Ideas:

1. Sample **critical states** from the collected on-policy data based on the utility they provide to the learned policy in terms of driving behavior
2. Incorporate a **replay buffer** which progressively focuses on the high uncertainty regions of the policy's state distribution

Prakash, Behl, Ohn-bar, Chitta and Geiger: Exploring Data Aggregation in Policy Learning for Vision-based Urban Autonomous Driving. CVPR, 2020.

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ALVINN: An Autonomous Land Vehicle in a Neural Network

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ALVINN: An Autonomous Land Vehicle in a Neural Network

- Fully connected 3 layer neural net
- 36k parameters
- Maps road images to turn radius
- Directions discretized (45 bins)
- Trained on simulated road images!
- Tested on unlined paths, lined city streets and interstate highways
- 90 consecutive miles at up to 70 mph

Pomerleau: ALVINN: An Autonomous Land Vehicle in a Neural Network. NIPS, 1988.

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PilotNet: End-to-End Learning for Self-Driving Cars

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PilotNet: System Overview

- Data augmentation by 3 cameras and virtually shifted / rotated images assuming the world is flat (homography), adjusting the steering angle appropriately

Bojarski et al.: End-to-End Learning for Self-Driving Cars. Arxiv, 2016.

PilotNet: Architecture

- Convolutional network (250k param)
- Input: YUV image representation
- 1 Normalization layer
  - Not learned
- 5 Convolutional Layers
  - 3 strided 5x5
  - 2 non-strided 3x3
- 3 Fully connected Layers
- Output: turning radius
- Trained on 72h of driving

Bojarski et al.: End-to-End Learning for Self-Driving Cars. Arxiv, 2016.

PilotNet: Video

Bojarski et al.: End-to-End Learning for Self-Driving Cars. Arxiv, 2016.

VisualBackProp

- Central idea: find **salient image regions** that lead to high activations
- Forward pass, then iteratively scale-up activations

Bojarski et al.: VisualBackProp: Efficient Visualization of CNNs for Autonomous Driving. ICRA, 2018.

VisualBackProp

Bojarski et al.: VisualBackProp: Efficient Visualization of CNNs for Autonomous Driving. ICRA, 2018.

VisualBackProp

Figure 7: Images used in experiments to show the effect of image-shifts on steer angle.

- Test if shift in salient objects affects predicted turn radius more strongly

Bojarski et al.: VisualBackProp: Efficient Visualization of CNNs for Autonomous Driving. ICRA, 2018.

2.4
Conditional Imitation Learning

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Conditional Imitation Learning

(a) Aerial view of test environment (b) Vision-based driving, view from onboard camera (c) Side view of vehicle

Codevilla, Müller, López, Koltun and Dosovitskiy: End-to-End Driving Via Conditional Imitation Learning. ICRA, 2018.

Conditional Imitation Learning

Idea:

- Condition controller on **navigation command** $\mathbf{c} \in$ {left,right,straight}
- High-level navigation command can be provided by consumer GPS, i.e., telling the vehicle to **turn left/right** or go **straight** at the next intersection
- This removes the task ambiguity induced by the environment
- State $\mathbf{s}_t$: current image Action $\mathbf{a}_t$: steering angle & acceleration

Codevilla, Müller, López, Koltun and Dosovitskiy: End-to-End Driving Via Conditional Imitation Learning. ICRA, 2018.

Comparison to Behavior Cloning

Behavior Cloning:

- Training Set:

$$\mathcal{D} = \{(a_i^*, s_i^*)_{i=1}^N\}$$

- Objective:

$$\underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{N} \mathcal{L}\left(a_i^*, \pi_\theta(s_i^*)\right)$$

- Assumption:

$$\exists f(\cdot) : a_i = f(s_i)$$

Often violated in practice!

Conditional Imitation Learning:

- Training Set:

$$\mathcal{D} = \{(a_i^*, s_i^*, c_i^*)_{i=1}^N\}$$

- Objective:

$$\underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{N} \mathcal{L}\left(a_i^*, \pi_\theta(s_i^*, c_i^*)\right)$$

- Assumption:

$$\exists f(\cdot, \cdot) : a_i = f(s_i, c_i)$$

Better assumption!

Codevilla, Müller, López, Koltun and Dosovitskiy: End-to-End Driving Via Conditional Imitation Learning. ICRA, 2018.

Conditional Imitation Learning: Network Architecture

(a)

(b)

- This paper proposes two network architectures:
  - (a) Extract features $C(\mathbf{c})$ and concatenate with image features $I(\mathbf{i})$
  - (b) Command $\mathbf{c}$ acts as switch between specialized submodules
- Measurements $\mathbf{m}$ capture additional information (here: speed of vehicle)

Codevilla, Müller, López, Koltun and Dosovitskiy: End-to-End Driving Via Conditional Imitation Learning. ICRA, 2018.

Conditional Imitation Learning: Noise Injection

- Temporally correlated noise injected into trajectories ⇒ drift (only 12 minutes)
- Record driver's (=expert's) corrective response ⇒ recover from drift

Codevilla, Müller, López, Koltun and Dosovitskiy: End-to-End Driving Via Conditional Imitation Learning. ICRA, 2018.

CARLA Simulator

Town 1 (training) Town 2 (testing)

`http://www.carla.org`

Codevilla, Müller, López, Koltun and Dosovitskiy: End-to-End Driving Via Conditional Imitation Learning. ICRA, 2018.

Conditional Imitation Learning

Codevilla, Santana, Lopez and Gaidon: Exploring the Limitations of Behavior Cloning for Autonomous Driving. ICCV, 2019.

Neural Attention Fields

- An MLP iteratively **compresses** the high-dimensional input into a compact representation $\mathbf{c}_i$ ($\mathbf{c} \neq$ nav. command) based on a **BEV query location** as input
- The model predicts **waypoints** and auxiliary **semantics** which aids learning

Chitta, Prakash and Geiger: Neural Attention Fields for End-to-End Autonomous Driving. ICCV, 2021.

Summary

Advantages of Imitation Learning:

- Easy to implement
- Cheap annotations (just driving while recording images and actions)
- Entire model trained end-to-end
- Conditioning removes ambiguity at intersections

Challenges for Imitation Learning?

- Behavior cloning uses IID assumption which is violated in practice
- Direct mapping from images to control $\Rightarrow$ No long term planning
- No memory (can't remember speed signs, etc.)
- Mapping is difficult to interpret ("black box"), despite visualization techniques