Self-Driving Cars

Lecture 3 – Direct Perception

Kumar Bipin

Robotics, Computer Vision, System Software

BE, MS, PhD (MMMTU, IISc, IIIT-Hyderabad)

Agenda

3.1 Direct Perception

3.2 Conditional Affordance Learning

3.3 Visual Abstractions

3.4 Driving Policy Transfer

3.5 Online vs. Offline Evaluation

3.1
Direct Perception

Kumar Bipin

Approaches to Self-Driving

+ Modular + Interpretable - Expert decisions - Piece-wise training

+ End-to-end + Simple - Generalization - Interpretable - Data

Kumar Bipin

Direct Perception

Idea of Direct Perception:

- **Hybrid model** between imitation learning and modular pipelines
- Learn to predict interpretable **low-dimensional intermediate representation**
- **Decouple** perception from planning and control
- Allows to exploit **classical controllers** or **learned controllers** (or hybrids)

Direct Perception for Autonomous Driving

(a) angle (b) in lane: toMarking (c) in lane: dist (d) on mark.: toMarking (e) on marking: dist (f) overlapping area

Affordances:

- **Attributes** of the environment which **limit space of actions** [Gibson, 1966]
- In this case: 13 affordances

Chen, Seff, Kornhauser and Xiao: Learning Affordance for Direct Perception in Autonomous Driving. ICCV, 2015.

Overview

- **TORCS Simulator:** Open source car racing game simulator
- Network: **AlexNet** (5 conv layers, 4 fully conn. layers), 13 output neurons
- Training: Affordance indicators trained with ℓ_2 loss

Chen, Seff, Kornhauser and Xiao: Learning Affordance for Direct Perception in Autonomous Driving. ICCV, 2015.

Affordance Indicators and State Machine

always:
1) angle: angle between the car's heading and the tangent of the road

"in lane system", when driving in the lane:
2) toMarking_LL: distance to the left lane marking of the left lane
3) toMarking_ML: distance to the left lane marking of the current lane
4) toMarking_MR: distance to the right lane marking of the current lane
5) toMarking_RR: distance to the right lane marking of the right lane
6) dist_LL: distance to the preceding car in the left lane
7) dist_MM: distance to the preceding car in the current lane
8) dist_RR: distance to the preceding car in the right lane

"on marking system", when driving on the lane marking:
9) toMarking_L: distance to the left lane marking
10) toMarking_M: distance to the central lane marking
11) toMarking_R: distance to the right lane marking
12) dist_L: distance to the preceding car in the left lane
13) dist_R: distance to the preceding car in the right lane

Figure 4: **Complete list of affordance indicators in our direct perception representation.**

```
while (in autonomous driving mode)
  ConvNet outputs affordance indicators
  check availability of both the left and right lanes
  if (approaching the preceding car in the same lane)
    if (left lane exists and available and lane changing allowable)
      left lane changing decision made
    else if (right lane exists and available and lane changing allowable)
      right lane changing decision made
    else
      slow down decision made
  if (normal driving)
    center_line= center line of current lane
  else if (left/right lane changing)
    center_line= center line of objective lane
  compute steering command
  compute desired_speed
  compute acceleration/brake command based on desired_speed
```

Figure 5: **Controller logic.**

Chen, Seff, Kornhauser and Xiao: Learning Affordance for Direct Perception in Autonomous Driving. ICCV, 2015.

Controller

Steering controller:

$$s = \theta_1(\alpha - d_c/w)$$

- s: steering command θ_1: parameter
- α: relative orientation d_c: distance to centerline w: road width

Speed controller: ("optimal velocity car following model")

$$v = v_{max}\left(1 - \exp\left(-\theta_2\, d_p - \theta_3\right)\right)$$

- v: target velocity v_{max} maximal velocity
- d_p: distance to preceding car $\theta_{2,3}$: parameters

Chen, Seff, Kornhauser and Xiao: Learning Affordance for Direct Perception in Autonomous Driving. ICCV, 2015.

TORCS Simulator

- TORCS: Open source car racing game `http://torcs.sourceforge.net/`

Chen, Seff, Kornhauser and Xiao: Learning Affordance for Direct Perception in Autonomous Driving. ICCV, 2015.

Results

Chen, Seff, Kornhauser and Xiao: Learning Affordance for Direct Perception in Autonomous Driving. ICCV, 2015.

Network Visualization

- Left: Averaged top 100 images activating a neuron in first fully connected layer
- Right: Maximal response of 4th conv. layer (note: focus on cars and markings)

Chen, Seff, Kornhauser and Xiao: Learning Affordance for Direct Perception in Autonomous Driving. ICCV, 2015.

3.2
Conditional Affordance Learning

Kumar Bipin

How can we transfer this idea to cities?

Kumar Bipin

Conditional Affordance Learning

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

CARLA Simulator

- Goal: drive from A to B as fast, safely and comfortably as possible
- Infractions:
  - Driving on wrong lane
  - Driving on sidewalk
  - Running a red light
  - Violating speed limit
  - Colliding with vehicles
  - Hitting other objects

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Affordances

Affordances:

- Distance to centerline
- Relative angle to road
- Distance to lead vehicle
- Speed signs
- Traffic lights
- Hazard stop

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Affordances

Affordances:

- Distance to centerline
- Relative angle to road
- Distance to lead vehicle
- Speed signs
- Traffic lights
- Hazard stop

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Overview

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Controller

Longitudinal Control

- Finite-state machine
- PID controller for cruising
- Car following model

Lateral Control

- Stanley controller
- $\delta(t) = \psi(t) + \arctan\left(\frac{kx(t)}{u(t)}\right)$
- Damping term

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Parameter Learning

Perception Stack:

- Multi-task learning: single forward pass $\Rightarrow$ fast learning and inference
- Dataset: random driving using controller operating on GT affordances $\Rightarrow$ 240k images with GT affordances
- Loss functions:
  - Discrete affordances: Class-weighted cross-entropy (CWCE)
  - Continuous affordances: Mean average error (MAE)
- Optimized with ADAM (batch size 32)

Controller:

- Ziegler-Nichols

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Data Collection

Data Collection:

- Navigation based on true affordances & random inputs

Data Augmentation:

- No image flipping
- Color, contrast, brightness
- Gaussian blur & noise
- Provoke rear-end collisions
- Camera pose randomization

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Results

	Training conditions				New weather				New town				New town and new weather			
Task	MP	CIL	RL	CAL	MP	CIL	RL	CAL	MP	CIL	RL	CAL	MP	CIL	RL	CAL
Straight	98	95	89	**100**	**100**	98	86	**100**	92	**97**	74	93	50	80	68	**94**
One turn	82	89	34	**97**	95	90	16	**96**	61	59	12	**82**	50	48	20	**72**
Navigation	80	86	14	**92**	**94**	84	2	90	24	40	3	**70**	47	44	6	**68**
Nav. dynamic	77	**83**	7	**83**	**89**	82	2	82	24	38	2	**64**	44	42	4	**64**

Baselines:

- MP = Modular Pipeline [Dosovitskiy et al., CoRL 2017]
- CIL = Conditional Imitation Learning [Codevilla et al., ICRA 2018]
- RL = Reinforcement Learning A3C [Mnih et al., ICML 2016]

Results

Conditional Navigation

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Results

Speed Signs

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Results

Car Following

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Results

Hazard Stop

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Attention

Attention to Hazard Stop

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Attention

Attention to Red Light

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Path Planning

Optimal Path (green) vs. Traveled Path (red)

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Failure Cases

Hazard Stop: False Positive

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Failure Cases

Hazard Stop: False Negative

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

Failure Cases

Red Light: False Positive

Sauer, Savinov and Geiger: Conditional Affordance Learning for Driving in Urban Environments. CoRL, 2018.

3.3
Visual Abstractions

Kumar Bipin

Does Computer Vision Matter for Action?

Does Computer Vision Matter for Action?

- Analyze various intermediate representations: segmentation, depth, normals, flow, albedo
- Intermediate representations improve results
- Consistent gains across simulations / tasks
- Depth and semantic provide largest gains
- Better generalization performance

Zhou, Krähenbühl and Koltun: Does computer vision matter for action? Science Robotics, 2019.

Visual Abstractions

What is a good visual abstraction?

- Invariant (hide irrelevant variations from policy)
- Universal (applicable to wide range of scenarios)
- Data efficient (in terms of memory/computation)
- Label efficient (require little manual effort)

Figure Credit: Alexander Sax

Semantic segmentation:

- Encodes task-relevant knowledge (e.g. road is drivable) and priors (e.g., grouping)
- Can be processed with standard 2D convolutional policy networks

Disadvantage:

- Labelling time: ~90 min for 1 Cityscapes image

Zhou, Krähenbühl and Koltun: Does computer vision matter for action? Science Robotics, 2019.

Label Efficient Visual Abstractions

Questions:

- What is the trade-off between annotation time and driving performance?
- Can selecting specific semantic classes ease policy learning?
- Are visual abstractions trained with few images competitive?
- Is fine-grained annotation important?
- Are visual abstractions able to reduce training variance?

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Label Efficient Visual Abstractions

Model:

- Visual abstraction network $a_\psi : \mathbf{s} \mapsto \mathbf{r}$ (state $\mapsto$ abstraction)
- Control policy $\pi_\theta : \mathbf{r}, \mathbf{c}, v \mapsto \mathbf{a}$ (abstraction, command, velocity $\mapsto$ action)
- Composing both yields $\mathbf{a} = \pi_\theta(a_\psi(\mathbf{s}))$ (state $\mapsto$ action)

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Label Efficient Visual Abstractions

Datasets:

- n_r images annotated with semantic labels $\mathcal{R} = \{\mathbf{s}^i, \mathbf{r}^i\}_{i=1}^{n_s}$
- n_a images annotated with expert actions $\mathcal{A} = \{\mathbf{s}^i, \mathbf{a}^i\}_{i=1}^{n_a}$
- We assume $n_r \ll n_a$

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Label Efficient Visual Abstractions

Training:

- Train visual abstraction network $a_\phi(\cdot)$ using semantic dataset $\mathcal{R}$
- Apply this network to obtain control dataset $\mathcal{C}_\phi = \{a_\psi(\mathbf{s}^i), \mathbf{a}^i\}_{i=1}^{n_a}$
- Train control policy $\pi_\theta(\cdot)$ using control dataset $\mathcal{C}_\phi$

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Control Policy

Model:

- CILRS [Codevilla et al., ICCV 2019]

Input:

- Visual abstraction $\mathbf{r}$
- Navigational command $\mathbf{c}$
- Vehicle velocity v

Output:

- Action/control $\hat{\mathbf{a}}$ and velocity $\hat{v}$

Loss:

- $\mathcal{L} = ||\mathbf{a} - \hat{\mathbf{a}}||_1 + \lambda \, ||v - \hat{v}||_1$

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Visual Abstractions

Privileged Segmentation (14 classes):

- Ground-truth semantic labels for 14 classes
- Upper bound for analysis

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Visual Abstractions

Privileged Segmentation (6 classes):

- Ground-truth semantic labels for 2 stuff and 4 object classes
- Upper bound for analysis

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Visual Abstractions

Inferred Segmentation (14 classes):

- Segmentation model trained on 14 classes
- ResNet and Feature Pyramid Network (FPN) with segmentation head

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Visual Abstractions

Inferred Segmentation (6 classes):

- Segmentation model trained on 2 stuff and 4 object classes
- ResNet and Feature Pyramid Network (FPN) with segmentation head

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Visual Abstractions

Hybrid Detection and Segmentation (6 classes):

- Segmentation model trained on 2 stuff classes: road, lane marking
- Object detection trained on 4 object classes: vehicle, pedestrian, traffic light (r/g)

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Evaluation

Training Town

Test Town

- CARLA 0.8.4 NoCrash benchmark
- Random start and end location
- Metric: Percentage of successfully completed episodes (success rate)

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Traffic Density

Empty Regular Dense

- Difficulty varies with number of dynamic agents in the scene
- Empty: 0 Agents Regular: 65 Agents Dense: 220 Agents

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Identifying Most Relevant Classes (Privileged)

- 14 classes: road, lane marking, vehicle, pedestrian, green light, red light, sidewalk, building, fence, pole, vegetation, wall, traffic sign, other
- 7 classes: road, lane marking, vehicle, pedestrian, green light, red light, sidewalk, ~~building, fence, pole, vegetation, wall, traffic sign, other~~
- 6 classes: road, lane marking, vehicle, pedestrian, green light , red light, ~~sidewalk~~
- 5 classes: road, ~~lane marking~~, vehicle, pedestrian, green light, red light

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Identifying Most Relevant Classes (Privileged)

- Moving from 14 to 6 classes does not hurt driving performance (on contrary)
- Drastic performance drop when lane markings are removed

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Identifying Most Relevant Classes (Privileged)

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Identifying Most Relevant Classes (Inferred)

- Small performance drop when using inferred segmentations
- 6-class representation consistently improves upon 14-class representation
- We use the 6-class representation for all following experiments

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Hybrid Representation

- Performance of hybrid representation matches standard segmentation
- Annotation time (segmentation): $\sim$ 300 seconds per image and per class
- Annotation time (hybrid): $\sim$ 20 seconds per image and per class

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

Summary

Trained with 6400 finely annotated images and 14 classes
Annotation time $\approx$ 7500 hours, policy success rate = 50%

Trained with 1600 coarsely annotated images and 6 classes
Annotation time $\approx$ 50 hours, policy success rate = 58%

Behl, Chitta, Prakash, Ohn-Bar and Geiger: Label Efficient Visual Abstractions for Autonomous Driving. IROS, 2020.

3.4
Driving Policy Transfer

Kumar Bipin

Driving Policy Transfer

Problem:

- Driving policies learned in simulation often do not transfer well to the real world

Idea:

- Encapsulate driving policy such that it is not directly exposed to raw perceptual input or low-level control (input: semantic segmentation, output: waypoints)
- Allows for transferring driving policy without retraining or finetuning

Müller, Dosovitskiy, Ghanem and Koltun: Driving Policy Transfer via Modularity and Abstraction. CoRL, 2018.

Waypoint Representation

Representation:

- Input: Semantic segmentation (per pixel “road” vs. “non-road”)
- Output: 2 waypoints (distance to vehicle, relative angle wrt. vehicle heading)
  - One sufficient for steering, second one for braking before turns

Müller, Dosovitskiy, Ghanem and Koltun: Driving Policy Transfer via Modularity and Abstraction. CoRL, 2018.

Results

Success Rate over 25 Navigation Trials

- Driving Policy: Conditional Imitation Learning (branched)
- Control: PID controller for lateral and longitudinal control
- Results: Full method generalizes best ("+" = with data augmentation)

Müller, Dosovitskiy, Ghanem and Koltun: Driving Policy Transfer via Modularity and Abstraction. CoRL, 2018.

Results

Müller, Dosovitskiy, Ghanem and Koltun: Driving Policy Transfer via Modularity and Abstraction. CoRL, 2018.

3.5
Online vs. Offline Evaluation

Kumar Bipin

Online vs. Offline Evaluation

- Online evaluation (i.e., using a real vehicle) is expensive and can be dangerous
- Offline evaluation on a pre-recorded validation dataset is cheap and easy
- Question: How predictive is offline evaluation (a) for the online task (b)?
- Empirical study using CIL on CARLA trained with MSE loss on steering angle

Codevilla, Lopez, Koltun and Dosovitskiy: On Offline Evaluation of Vision-based Driving Models. ECCV, 2018.

Online Metrics

- Success Rate: Percentage of routes successfully completed
- Average Completion: Average fraction of distance to goal covered
- Km per Infraction: Average driven distance between 2 infractions

Remark: The current CARLA metrics Infraction Score and Driving Score are not considered in this work from 2018, but would likely lead to similar conclusions.

Codevilla, Lopez, Koltun and Dosovitskiy: On Offline Evaluation of Vision-based Driving Models. ECCV, 2018.

Offline Metrics

Metric name	Parameters	Metric definition
Squared error	–	$\frac{1}{\lvert V\rvert}\sum_{i\in V}\lVert\mathbf{a}_i-\widehat{\mathbf{a}}_i\rVert^2$
Absolute error	–	$\frac{1}{\lvert V\rvert}\sum_{i\in V}\lVert\mathbf{a}_i-\widehat{\mathbf{a}}_i\rVert_1$
Speed-weighted absolute error	–	$\frac{1}{\lvert V\rvert}\sum_{i\in V}\lVert\mathbf{a}_i-\widehat{\mathbf{a}}_i\rVert_1\, v_i$
Cumulative speed-weighted absolute error	T	$\frac{1}{\lvert V\rvert}\sum_{i\in V}\left\lVert\sum_{t=0}^{T}(\mathbf{a}_{i+t}-\widehat{\mathbf{a}}_{i+t})v_{i+t}\right\rVert_1$
Quantized classification error	σ	$\frac{1}{\lvert V\rvert}\sum_{i\in V}\left(1-\delta\left(Q(\mathbf{a}_i,\sigma),Q(\widehat{\mathbf{a}}_i,\sigma)\right)\right)$
Thresholded relative error	α	$\frac{1}{\lvert V\rvert}\sum_{i\in V}\theta\left(\lVert\widehat{\mathbf{a}}_i-\mathbf{a}_i\rVert-\alpha\lVert\mathbf{a}_i\rVert\right)$

- $\mathbf{a}/\hat{\mathbf{a}}$: true/predicted steering angle $|V|$: #samples in validation set
- v : speed $\delta(\cdot)$: Kronecker delta function θ: Heaviside step function
- $Q \in \{-1, 0, 1\}$: Quantization $x < -\sigma$ $-\sigma \leq x < \sigma$ $x \geq \sigma$

Codevilla, Lopez, Koltun and Dosovitskiy: On Offline Evaluation of Vision-based Driving Models. ECCV, 2018.

Results: Online vs. Online

- Generalization performance (town 2, new weather), radius = training iteration
- 45 different models varying dataset size, augmentation, architecture, etc.
- Success rate correlates well with average completion and km per infraction

Codevilla, Lopez, Koltun and Dosovitskiy: On Offline Evaluation of Vision-based Driving Models. ECCV, 2018.

Results: Online vs. Offline

- All metrics not well correlated, Mean Square Error (MSE) performs worst
- Absolute steering error improves, speed weighting is not important

Codevilla, Lopez, Koltun and Dosovitskiy: On Offline Evaluation of Vision-based Driving Models. ECCV, 2018.

Results: Online vs. Offline

- Cumulating the error over time does not improve the correlation
- Quantized classification and thresholded relative error perform best

Codevilla, Lopez, Koltun and Dosovitskiy: On Offline Evaluation of Vision-based Driving Models. ECCV, 2018.

Case Study

- Model 1: Trained with single camera & ℓ_2 loss (=bad model)
- Model 2: Trained with three cameras & ℓ_1 loss (=good model)
- Predictions of both models noisy, but Model 1 predicts occasionally very large errors leading to crashes, however the average prediction error is similar

Codevilla, Lopez, Koltun and Dosovitskiy: On Offline Evaluation of Vision-based Driving Models. ECCV, 2018.

Case Study

- Model 1 crashes in every trial but model 2 can drive successfully
- Illustrates the difficulty of using offline metrics for predicting online behavior

Codevilla, Lopez, Koltun and Dosovitskiy: On Offline Evaluation of Vision-based Driving Models. ECCV, 2018.

Summary

- Direct perception predicts intermediate representations
- Low-dimensional affordances or classic computer vision representations (e.g., semantic segmentation, depth) can be used as intermediate representations
- Decouples perception from planning and control
- Hybrid model between imitation learning and modular pipelines
- Direct methods are more interpretable as the representation can be inspected
- Effective visual abstractions can be learned using limited supervision
- Planning can also be decoupled from control for better transfer
- Offline metrics are not necessarily indicative of online driving performance