Safer End-to-End Autonomous Driving via Conditional Imitation Learning and Command Augmentation

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Abstract—Imitation learning is a promising approach to end-to-end training of autonomous vehicle controllers. Typically the driving process with such approaches is entirely automatic and black-box, although in practice it is desirable to control the vehicle through high-level commands, such as telling it which way to go at an intersection. In existing work this has been accomplished by the application of a branched neural architecture, since directly providing the command as an additional input to the controller often results in the command being ignored. In this work we overcome this limitation by learning a disentangled probabilistic latent variable model that generates the steering commands. We achieve faithful command-conditional generation without using a branched architecture and demonstrate improved stability of the controller, applying only a variational objective without any domain-specific adjustments. On top of that, we extend our model with an additional latent variable and augment the dataset to train a controller that is robust to unsafe commands, such as asking it to turn into a wall. The main contribution of this work is a recipe for building controllable imitation driving agents that improves upon multiple aspects of the current state of the art relating to robustness and interpretability.

I. INTRODUCTION

Traditionally, autonomous driving is done by a software pipeline consisting of perception, localization, planning, and control. However, in recent years an end-to-end approach, mapping perceptual inputs directly to steering actions, has gained popularity.

The dominant paradigm for end-to-end training of driving agents is imitation learning (IL) from human demonstration \cite{Alvinn,PilotNet,ReinforceIL,DeepRLControl,MixedIL,TemporalIL,DeepRLControl}. IL is a promising approach because humans are already good drivers and because making autonomous vehicles drive like humans makes them more predictable and therefore safer. It is very easy to obtain data for imitation learning, which can be done by recording trips of professional drivers in a dedicated fleet, but is also being done at massive scale in consumer vehicles by companies such as Tesla and Comma.ai.

The efforts in IL for autonomous driving were pioneered by Pomerleau \cite{Alvinn} in the Autonomous Land Vehicle in a Neural Network (ALVINN), which took as input an image from a front-facing camera and laser range measurements, and learned to output a set of quantized steering angles. More recently Bojarski et al. \cite{PilotNet} introduced PilotNet, a deep convolutional neural network that learns to issue steering commands for staying in lane based on video frames from a front-facing camera, trained by IL. A similar objective was also proposed by \cite{DeepRLControl} using reinforcement learning. However, neither of

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those models is able to navigate through intersections or accept commands of any kind. To remedy this problem, Codevilla et al. [1] performed end-to-end conditional imitation learning in a simulated environment to train a model capable of behaving as a "chauffeur" and manipulating vehicular dynamics such as steering angle and acceleration according to one of four high level commands, namely “stay in lane”, “turn right”, “turn left” or “go straight.” The first one is a default, while one of the latter three is issued when approaching an intersection.

In this paper we build on the aforementioned work of Codevilla et al., who developed an architecture that takes as input a camera image and measured vehicle speed, and outputs the action to perform, consisting of the steering angle and the amounts of acceleration and braking applied. An important problem identified in that work is that concatenating the command with the perceptual input and feeding them both into a neural network trained to imitate human behavior often leads to the network ignoring the command at test time. We refer to this non-branched model as DNN. Due to this problem, they employ a branched architecture, effectively training a separate network for each command where the perceptual input is processed by several shared layers before being passed to command-specific layers that output the steering action. We refer to this model as Branched-DNN. While this approach works in a simple setting where only four commands are used, it does not scale to higher numbers of commands. Inspecting the code provided by Codevilla et al. [1] we found that they use additional hand-coded heuristics to ameliorate this problem. We refer to their model including the aforementioned heuristics as Branched-Heuristics.

We overcome this limitation by replacing the neural network used with a disentangled latent variable model [8], with an interpretable variable corresponding to the command being executed. We learn conditional distributions in this model by optimizing neural networks mapping between different variables jointly with inference networks approximating the posterior distribution over the latents, depicted in figure 2. We optimize the standard variational objective called the evidence lower bound (ELBO) for training and find that the learned representation is sufficiently disentangled to reliably perform conditional generation by setting the com-

1https://github.com/carla-simulator/imitation-learning
mand latent variable to the desired value. With this simple setup we obtain a controller significantly more stable and natural-looking than the branched model of Codevilla et al., without employing any additional runtime code to promote smoother turning or prevent the vehicle from stopping, which were needed to make the branched model work in practice. We refer to our model as the Neural Directable Imitation Driver (NDID).

While executing a turn on command is a desirable property of autonomous vehicles, in a practical application we would also expect the system to be robust to unsafe commands. This is because both human pilots and automatic navigation systems sometimes issue such unsafe commands, which the human drivers know not to execute. The particular unsafe commands we are concerned with in this paper, which result in all the aforementioned models steering the vehicle off road and crashing, are asking the vehicle to turn when there is no road to turn into and conversely not telling it to turn at a T-shaped intersection. See Figure 1 for illustration.

In order to obtain such behavior we further extend our probabilistic model with separate latent variables corresponding to the command being issued and to the command being executed. We train this model on the originally collected dataset, performing automatic data augmentation depicted in Table II and described in Section III. This results in a model robust to bad commands, which cause the other models we test to drive off the road. We call this model the Command Augmented Neural Directable Imitation Driver (CANDID).

The main contributions of this paper are:

- a deep probabilistic model for imitation learning that allows command conditional generation without utilizing a branching architecture,
- improved performance achieved on the benchmark introduced by Codevilla et al., [1] without the need for hand-coded heuristics employed in the original model
- a model and dataset augmentation scheme that allows the controller to learn to reject unsafe commands.

The first two are described in Section II while the third one is described in Section III.

II. LATENT VARIABLE MODEL FOR COMMAND CONDITIONAL DRIVING

Our first contribution is a probabilistic latent variable model for generating steering actions based on perceptual inputs and directional commands. We work in the setting introduced by Codevilla et al. [1], using the dataset and baseline provided by the authors of that paper. Specifically, we used a dataset of trips completed by a human driver using CARLA [2], which is an open source driving simulator developed using Unreal Engine 4. It features two distinct towns with complete urban environments, although like [1] we only use a single driving agent in a static environment and no traffic signals.

All training data is extracted from trips within the first town and models are subsequently evaluated on navigational tasks in both towns that were unseen during training. Drivers are instructed to keep the car below 60 km/h and within lanes, obeying command signals according to routing instructions provided to them, but ignoring traffic signals. A total of four commands are possible: stay in lane, proceed straight at an intersection, turn right, and turn left, corresponding to the integers between 0 and 3. A centered camera image at 600 × 800 resolution, acceleration, steer angle, and speed are provided as perceptual inputs to the autonomous driving agent.

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Our approach is to replace the branched neural network generating actions with a probabilistic latent variable model, depicted in Figure 2a. The latent variable is z, which is continuous and represents the uninterpretable "mental state" of the driving agent. The model also includes observable variables c, which is a discrete command, a, which is the action consisting of a steering angle and the amount of force applied to the braking and acceleration pedals, and x, which is the perceptual input consisting of a frame captured by the camera and the vehicle velocity. Note that the distributions of all other variables are conditional on x but we do not model the distribution p(x), treating x as given. All the conditional distributions are parameterized by neural networks, the weights of which are optimized to match the data collected from human demonstration.

More specifically, our model takes a 512-dimensional input feature vector x, created from
the concatenation of a convolutional image module and fully-connected speed module as described in [1]. We use a 64-dimensional Gaussian conditional prior \( p(z \mid x) \), whose mean and variance are parameterized by a two layer neural network (256 and 64 hidden units). We also use a categorical prior over four discrete commands, which is again parameterized by a two layer neural network (256 and 4 hidden units). Finally, we sample the appropriate command through the generative distribution \( p(c \mid z, x) \), and the appropriate action through the distribution \( p(a \mid c, z, x) \), each of which is parameterized by a two-layer neural network (256 and 4, and 256 and 3 hidden units, respectively).

Our goal is to learn the conditional distributions in this model by maximizing the marginal likelihood of the collected data \( p(a, c \mid x) \), but computing it directly is not tractable in this model due to required integration over \( z \). To overcome this difficulty we jointly learn the model and an inference network \( q(z \mid a, c, x) \) which aims to approximate the posterior distribution \( p(z \mid a, c, x) \) by minimizing the Kullback-Leibler divergence \( KL(q||p) \), which is known as amortized inference [9]. The weights of networks in the model and the weights of inference networks are updated jointly through stochastic gradient descent to optimize the standard variational objective called the evidence lower bound (ELBO), defined as

\[
\mathbb{E}_{q_{\phi}(z|x,a,c)} \left[ \log \frac{p_{\theta}(z,a,c \mid x)}{q_{\phi}(z \mid x,a,c)} \right] \leq \log p_{\theta}(a,c \mid x)
\]

where \( \phi \) and \( \theta \) parameterize the inference and generative networks, respectively. We choose \( q(z \mid a, c, x) \) to be a Gaussian parameterized by the mean and log variance inferred from a two-layer encoder neural network (256 and 64 hidden units).

This approach to model learning was introduced by Kingma and Welling [10] as a variational autoencoder (VAE). Although mathematically our model is very similar, we emphasize that NDID is not a VAE in the usual sense, since we do not attempt to reconstruct the scene from the latent variables. It could be regarded as a conditional VAE [11] of the action given perceptual inputs, but such an interpretation is misleading since the dimension of \( z \) is larger than the dimension of \( a \). Additionally, after the model is trained we are never interested in the posterior over \( z \) and the inference network is not used at all at test time. It is merely an aid for efficient model learning.

We seek to learn a disentangled latent representation, where the information about the direction being taken is encoded only in \( c \) and not in \( z \), which can generally be difficult to achieve [8], [12], [13]. However, we have found that in our case training with the standard ELBO disentangles the representation enough to reliably perform conditional generation so we have not taken any additional steps to ensure disentanglement. Conditional generation here means setting \( c \) to the desired value, then sampling \( z \sim p(z \mid x) \) and \( a \sim p(a \mid c,z,x) \).

Qualitatively we find that our model NDID not only obeys the commands issued but also executes turns more smoothly and at more human-like speeds than Branched-Heuristics, as illustrated by the video accompanying this paper, despite NDID not using any hand-crafted adjustments to generated actions. Quantitatively, we evaluate our model on the benchmark used by Codevilla et al. [1], which consists of a series of driving tasks. Each task is comprised of an initial location where the agent is initialized, and a final destination that the agent must navigate to using high level commands provided by

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**TABLE I:** Performance of our model NDID compared against existing models on the navigational benchmark used by Codevilla et al. [1]. All training data was recorded in Town 1. Branched-Heuristics is the full model used by Codevilla et al., Branched-DNN is the same model without the hand-crafted adjustments to generated actions, and DNN is a non-branching neural controller that received the command as input.

| Model           | Success Rate | Km Between Infraction |
|-----------------|--------------|-----------------------|
|                 | Town 1       | Town 2                | Town 1       | Town 2    |
| DNN             | 56%          | 32%                   | 0.76         | 0.14      |
| Branched-DNN    | 73%          | 54%                   | 1.45         | 0.90      |
| Branched-Heuristics | 84%        | 61%                   | 2.12         | 1.08      |
| NDID            | 88%          | 71%                   | 6.80         | 4.53      |
TABLE II: Illustration of our data augmentation scheme facilitating robustness to badly issued commands. 

\((x, a)\) and \((x', a')\) are arbitrary pairs of sensory inputs and vehicle actions present in the non-augmented dataset. In the non-augmented dataset the “stay in lane” command is only issued outside of intersections where turn commands should be ignored, so in those situations the controller should always execute “stay in lane”. Turn commands indicate a presence of an intersection, where “stay in lane” corresponds to a missing command, in which case the controller should take an action known to be safe. The augmentation we use in that case is to change the issued command to “stay in lane” but keep the executed command the same. We apply these augmentations throughout the dataset, apart from that we leave all the examples in the dataset unchanged.

| Image | Speed | Command     | Command Issued   | Command Executed |
|-------|-------|-------------|------------------|------------------|
| x     | a     | stay in lane| stay in lane     | stay in lane     |
| ·     | ·     | ·           | ·                | ·                |
| ·     | ·     | ·           | ·                | ·                |
| x'    | a'    | left turn   | left turn        | left turn        |
| ·     | ·     | ·           | ·                | ·                |

an A* topological planner. We measure both the fraction of these trips where the vehicle is able to reach the destination, as well as the error-free travel distance as driving infractions occur, such as leaving the lane or colliding with fixed obstacles. The results are presented in Table I and show our model outperforming the existing approaches.

III. COMMAND AUGMENTATION FOR INCREASED SAFETY

A common underlying assumption for all the models presented in the previous section is that the commands are always issued correctly and correspond to actions that make sense. However, in practice no navigation system, including a human giving directions, is going to be perfect and the controller should be able to recognize when it is not possible to execute a given command and choose a safe action instead.

Recall that the command represents instructions from a human or a higher level map-based controller. However, such a controller may erroneously issue the incorrect command (for example, commanding a left turn where none is possible on a straight stretch of road) or fail to issue a command at all (for example, failing to issue left or right turn commands at a T-intersection). In such scenarios all the models presented in the previous section would drive off the road and crash, which is not acceptable for a realistic controller.

To remedy this, we extend our probabilistic model to demarcate from the command issued, \(c_{\text{iss}}\), and the command that the vehicle executes, \(c_{\text{exe}}\). The corresponding graphical model is presented in Figure 2. We train the model to recognize whether the command issued is safe to execute, and if not to choose a safe one. We achieve this by augmenting the original dataset without modifying the training procedure. We call the resulting model CANDID.

The importance of data augmentation in generalization of autonomous driving agents is well documented [5], [2], [14], [15], [16]. In particular, Codevilla et al. [1] report the importance of noise injection on input scenes during training to improve driving stability during evaluation in simulation. Here we additionally introduce our own augmentation, affecting only \(c_{\text{iss}}\) and \(c_{\text{exe}}\), not the images.

Concretely, we augment the dataset in two ways to achieve i) robustness against unsafe commands and ii) sensible default driving when no commands are provided, respectively. Our data augmentation scheme is presented in Table II. We chose to use only those augmentations since they are easy to perform automatically, but in a production system it may be worth the effort to perform more extensive augmentations manually.
TABLE III: Performance of our model CANDID on a benchmark that includes badly issued commands. All the other models presented in this table reliably fail when given a bad command, their success rate being non-zero only due to presence of very short driving tasks.

| Model         | Success Rate | Km Per Infraction |
|---------------|--------------|-------------------|
|               | Town 1 | Town 2 | Town 1 | Town 2 |
| DNN           | 13%    | 7%    | 0.46   | 0.12   |
| Branched-DNN  | 16%    | 11%   | 0.57   | 0.23   |
| Branched-Heuristics | 19%    | 10%   | 0.53   | 0.21   |
| NDID          | 18%    | 11%   | 0.62   | 0.25   |
| CANDID        | 83%    | 65%   | 5.93   | 3.13   |

To train this model we again maximize the ELBO, now conditioning on both sensory input $x$ as well as the issued command $c_{iss}$.

$$E_{q_\phi(z|x,a,c_{exe})} \left[ \log \frac{p_\theta(z, a, c_{exe} | x, c_{iss})}{q_\phi(z | x, a, c_{exe})} \right] \leq \log p_\theta(a, c_{exe} | x, c_{iss})$$

where once again $\phi$ and $\theta$ parameterize the inference and generative networks, respectively. Note that CANDID uses the multinomial prior described in Section II for $c_{iss}$. A three-layer neural network (128, 64 and 4 hidden units) parameterizes the generative distribution $p(c_{exe} | c_{iss}, z, x)$. Otherwise CANDID uses the same architectures as NDID.

To evaluate how our model reacts to unsafe commands, we introduce turn commands when the vehicle is proceeding along straight stretches of road where no turns are possible. All the models presented in Section II veer off the road, whereas CANDID ignores the unsafe command and proceeds straight ahead, as illustrated in the accompanying video. Note that if desired we can still force the vehicle to make a turn into the sidewalk by setting the value of $c_{exe}$ rather than $c_{iss}$.

Secondly, we provide the vehicle only with the "stay in lane" command and observe how it behaves at a T-intersection. All the models from Section II obey the command and proceed directly into the barrier at the end of the intersection. Our CANDID model trained on the augmented dataset is able to turn right smoothly and avoid the crash, as illustrated in the accompanying video.

For quantitative evaluation we use the same set of driving tasks we used in Section II but randomly change 10% of all commands issued by the simulator to an alternative command (e.g. the vehicle may be told to turn left instead of right at a particular intersection, or to turn when proceeding along a straight stretch of road). The results are presented in Table III and show that performance severely degrades for all models except CANDID. Longer navigational episodes reliably fail for the first four methods, but their performances are buttressed by shorter drives present in the evaluation suite. This is evidenced by the extremely low number of kilometers traversed per infraction.

IV. CONCLUSION

In this paper we have presented a technique for building robust autonomous vehicle controllers that can be directed by navigational commands without trusting them blindly. We accomplished this by applying probabilistic latent variable models trained using a variational approximation to maximum marginal likelihood (ELBO). We have demonstrated that our model handles the issued commands as desired, obeying the safe commands and disregarding the unsafe ones, in a simple simulated environment.

We envision multiple immediate extensions to this work. For example, we would like to try our model with other types of commands, such as telling the vehicle to start and stop, overtake, or yield. Our method should be applicable in this scenarios without modification, but they would require collecting additional annotated data. Another interesting direction is training our model in a semi-supervised fashion where the command is only available for a small subset of data. The structure of our model makes it easy to incorporate semi-supervised methods from the variational autoencoder literature, such as [17].

Finally, we are looking forward to applying our method to the task of driving in the real world.
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