In the past year we have made major progress with our self-driving model car project. We have developed a robust design with embedded GPUs, put a fleet of these model cars in the field, collected 72+ hours of driving data, trained a small but powerful network to control the cars, and obtained access to an area with varied with terrain for our continuing driving research. Our goals for the coming year are 1) to collect 1000 hours of data with our expanding car fleet driving and interacting in our flexible research ‘arena’, 2) with this data and the neural networks trained with it, qualitatively advance our understanding of autonomous driving, and 3) transfer this learning to the full-sized drive-by-wire vehicles to be acquired by BDD in early 2017.

Key to autonomy is the ability to understand the environment. For most animals, visual perception\textsuperscript{1,2,3} is a critical modality for doing this. Another challenge in understanding the environment, whatever the modality used, is to have some comprehension of the other autonomous beings in it and what their goals and motivations are. In cognitive science this is referred to as theory of mind\textsuperscript{4,5}. Both of these unsolved scientific problems are critical to safe driving, as drivers often signal their intentions and psychological stance using subtle car maneuvers or bodily gestures. We regard autonomous driving, not as an engineering problem, but as a major scientific challenge on several fronts. Critical to scientific research is development of a model system which contains the problems under study, but as few other complexities as possible. In our first year of BDD research, we have developed such a system.

The first task once we received BDD funding was to construct a robust model car system with an embedded device\textsuperscript{6} for computation. In the process of developing this research platform, it was our good fortune to collaborate with Gregory Kahn of Pieter Abbeel’s lab. With a robust car, the next steps were obvious: to build a lot of cars (Fig. 1), and to collect a lot of data (Fig. 2).
We sought not merely to teach the cars to drive in one type of situation, but to learn general principles of ground navigation. We therefore began collecting data in diverse environments, some of which are shown in Fig. 2. Bright sunlight, evening, and night (during which the car drives with attached lights) obviously present very different image statistics. Rain and muddy areas lend different characteristics to daylight scenes. Variation in car speed was also included. Interior and racetrack stand out as completely different from the rest. Given such diverse data, surpassing in complexity previous supervised learning datasets, we hypothesized that the simple deep neural network guiding the car would have to generalize basic properties of these environments in order to drive in them.

After backpropagation training of a simple deep neural network on these data, we found that the cars could drive remarkably well both on suburban sidewalks (video) and forest paths (video). In an effort to understand how the network accomplishes this, we studied individual network nodes to see how training shaped them. (For network details, see our October report). In Fig. 3 we show examples of the receptive field characteristics of nodes that receive input directly from the stereo video. Since the input has both temporal and stereo components, each node's receptive field has a selectivity pattern in each of four patches corresponding to left and right stereo camera at time $t_{-1}$ (i.e., 33 ms in the past) and time $t_0$ (i.e., current time). We observed four basic classes of nodes, corresponding to orientation detectors, motion detectors, depth detectors, and chromatic detectors with elements of the other detectors combined, with interesting implications for neuroscience research. Together these remarkably well-formed first layer receptive fields erase any doubt that sufficient data for network training can be obtained with model cars. Study of higher level nodes, which combine these filters in complex combinations, is now underway.

From the beginning of our project, the goal was to have the many cars operating within an ‘arena’ which would constitute our model system. Cars are constrained to the arena by miniature traffic cones, which they are trained to avoid, as well as GPS coordinates as a failsafe — a flexible system that allows for easy alteration in arena terrain from session to session within the research area (Fig. 5). The key concept is that the behavior of the cars adds to the richness of the environment. We have now begun to experiment with this, as shown in Fig.4, top image. Here, four model cars were set on collision courses and then turned over to self-driving mode. The model guiding each car was not trained to contend with this type of situation. Nonetheless, as the cars drew closer, each car began to veer away to avoid collision, as indicated by the black trajectory curves (video). The lower part of Fig. 4 shows the cars as the turning is underway. Aside from turning, the cars could vary speed or even stop to avoid collisions, an emergent property not intentionally trained into the network (video). This demonstrates that even before entering the arena, the trained model brings some general driving knowledge which is valuable in multi-car situations. As we accumulate hundreds of hours of data with the cars driving together, we expect much more complex patterns of behavior to emerge from our models. Adapting models to full size cars will pose new challenges. Thus, this process will begin as soon as the cars arrive. We are excited about 2017!

Collision avoidance

Figure 3. Receptive fields of convolutional nodes

Figure 4. Emergent driving behavior

Figure 5. Multi-terrain area for model car research
References


6) NVIDIA's Jetson TX1 with 256 CUDA cores


