

Self-Driving Cars: What Can We Realistically Expect?

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Abstract

Popular media have made many predictions about the dramatic changes self-driving cars (SDCs) will eventually bring about in society. Some prominent people working in the field worry that these predictions grossly overstate what can reasonably be expected of SDCs and may actually discredit the entire field when SDCs fail to meet expectations. Despite this concern, these researchers believe that SDCs will eventually prove their worth but probably not in the form and certainly not as soon as the media say. This paper draws on the comments and writings of these researchers to identify over a dozen problems in SDC development that have not yet been solved. The problems include not just technical issues such as the adequacy of machine learning, software validation, hardware reliability, cybersecurity, and the lack of adequate testing, but also non-technical issues such as public fears about SDCs' lack of safety and questions of insurance and liability. The paper concludes by suggesting a future consisting of slow, incremental improvements in SDCs over many years. The radical changes in society that have been predicted in the media may never be achieved, but nevertheless SDCs may result in the saving of lives of many people who would have otherwise perished in automobile accidents.

Acronyms

| | |
|-------|--|
| ADAS | Advanced Driver Assistance System |
| ADS | Automated Driving System |
| AI | Artificial Intelligence |
| GMO | Genetically Modified Organism |
| GPS | Global Positioning System |
| ML | Machine Learning |
| NASA | National Aeronautics and Space Administration |
| NHTSA | National Highway Traffic Safety Administration |
| NTSB | National Transportation Safety Board |
| ODD | Operational Design Domain |
| SAE | Society of Automotive Engineers |
| SDC | Self-Driving Cars |

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Figure 1. A self-driving car on the road in Mountain View, California

1. Introduction

We're still very much in the early days of making self-driving cars a reality. Those who think fully self-driving vehicles will be ubiquitous on city streets months from now or even in a few years are not well connected to the state of the art or committed to the safe deployment of the technology. For those of us who have been working on the technology for a long time, we're going to tell you the issue is still really hard, as the systems are as complex as ever. – Bryan Salesky, CEO of artificial intelligence startup Argo AI [1]

Figure 1 shows an iconic image of a “self-driving car” (SDC). The notion of an SDC has caught the public’s fancy, and popular media are full of articles describing how our lives will be dramatically changed by the widespread use of SDCs. However, many of the more thoughtful people working in SDC development have been bothered by the excessive media attention and the accompanying gross exaggerations of future SDC capabilities. These researchers fear that

the entire field may be discredited when the public realizes SDCs cannot live up to the extreme claims that have been made. Gill Pratt, Executive Technical Advisor and CEO of the Toyota Research Institute, expressed this concern succinctly:

I think there's a general desire from the technical people in this field to have both the press and particularly the public better educated about what's really going on. It's very easy to get misunderstandings based on words or phrases like "full autonomy." What does full actually mean? This actually matters a lot: The idea that only the chauffeur mode of autonomy, where the car drives for you, is the only way to make the car safer and to save lives, that's just false [2].

The purpose of the present paper is to acquaint readers with what prominent researchers in the field think about the prospects of SDCs. Almost all of these researchers believe that SDCs will eventually prove their worth but probably not in the form—and certainly not in the timeframe—the media have predicted.

2. The Promise of Self-Driving Cars

But, and this may sound a little complacent, I almost view [a self-driving car] as a solved problem. We know exactly what to do, and we'll solve it in a few years. – Elon Musk, founder of Tesla, Inc. [3]

Mechanical engineering professor and artificial intelligence researcher John Leonard told an audience ... at Harvard University that Tesla Motors founder Elon Musk's declaration of self-driving cars as "a solved problem" was more than a little optimistic. "Just very respectfully, I disagree," Leonard said. [4]

In recent years, various companies have made huge investment bets on the potential for SDCs. For example, several years ago in a court filing, Google inadvertently revealed that it had spent \$1.1 billion on SDC research and development between 2009 and 2015 [5]. In March 2016, General Motors spent a billion dollars to buy a company involved in developing SDC technology, and in February 2017, Ford announced plans to spend a billion dollars to set up a joint venture with Argo AI, a startup run by two prominent engineers having extensive experience in artificial intelligence and robotics [6]. An even larger acquisition was Intel's \$15.3-billion purchase of Mobileye, an Israeli company developing camera-based guidance for SDC navigation. In early 2015 the ride-sharing company Uber hired forty researchers away from Carnegie Mellon's National Robotics Engineering Center—which had somewhat more than one hundred technical personnel before the raid—by offering them hundreds of thousands of dollars in bonuses and a doubling of salaries to work on SDC technology [7]. Clearly these companies have concluded that SDCs will play a major part in the future of transportation. But they are not alone. Other large SDC projects are underway at Daimler-Bosch, Volkswagen, BMW-Intel-FCA, Aptiv, Renault-Nissan Alliance, Volvo-Autoliv-Ericsson-Zenuity, PSA, and dozens of other firms both large and small.

Just what is it about the future of SDCs that causes companies to invest billions of dollars in research and development? One obvious reason is the fear of being left behind. Ride-sharing companies that use robotaxis would have no drivers to pay and thus could charge much lower prices than companies with drivers. Long-distance trucking companies could cut costs dramatically if self-driving trucks were developed. Auto makers producing SDCs might dominate the market for personal cars if SDCs turn out to be as popular as many people forecast.

Thus many companies see SDCs as a potential threat to their survival. To be fair, these companies—and many other observers—also see much promise in improved safety. In 2016, about 37,000 people in the US died in traffic accidents, and the most recent data about accident fatalities worldwide indicates that in 2013 about 1.2 million people perished. The harm to US society from the loss of life and injury in traffic accidents is over half a trillion dollars annually.

Ninety-four percent of US crashes involve human error, and about two out of three people will be involved at some time in their life in an accident in which a driver had been drinking alcohol. By reducing human error and the effect of alcohol on driving, SDCs have the potential to save thousands of lives and reduce the economic loss from traffic accidents [8].

People have pointed out other potential advantages of SDCs. For example, time that people used to consume in operating their own cars could instead be devoted to other pursuits such as reading, writing, or watching videos. Mobility would greatly improve or become available to groups in society who had previously lacked it—for example, persons with disabilities or illness, children, the elderly, the poor, and persons who for various reasons never were able to obtain a driver’s license. Because accidents would decrease, insurance costs would decrease. Automating long-distance trucking would decrease costs significantly not only because drivers would not have to be paid but also because trucks could be operated around the clock. The cost of delivering everything from pizzas to packages would drop dramatically, and these lower costs could stimulate development of new businesses that were previously limited by the cost of getting their products to the consumer. Cars would be designed to accelerate and brake efficiently, and thus fuel would be saved. Speed limits could be raised because self-driving cars could be operated safely at higher speeds. Thus travel times would be decreased.

Some commentators have looked far into the future to imagine a world in which *all vehicles were driverless* and driving by human beings would be made illegal (because human drivers would be too dangerous compared to SDCs). Transportation by automobile would be treated as a service provided by a transportation utility company, and people would have no more need to have their own car than people today need their own electricity generator.

Retail companies such as car dealers, car washes, auto parts stores, and gas stations would disappear, as would companies offering individual car insurance and car financing. Parking lots and structures would be eliminated because the SDCs would be in constant use carrying different customers or delivering packages throughout the day. The price of houses would go down because garages would be eliminated. Traffic police would not be needed, nor would traffic signals and signs. Because no one would have a driver’s license, some other means of identification would need to be developed. People would drink more alcohol in restaurants and bars because they no longer would need to worry about driving home. Because vehicle accidents would never occur, much of the vehicle structure intended to protect the occupants during a collision could be eliminated. Cars would then carry less weight and become more fuel efficient.

3. Overview of Current Self-Driving Car Technology

Perhaps through this essay I will get the bee out of my bonnet that fully driverless cars are a lot further off than many techies, much of the press, and even many auto executives seem to think. They will get here and human driving will probably disappear in the lifetimes of many people reading this, but it will not all happen in the blink of an eye as many expect. Lots of details must be worked out. – Rodney Brooks, Panasonic Professor of Robotics (emeritus) at MIT and Chairman and CTO of Rethink Robotics [9]

3.1 Drivers' Questions

To operate a car, human drivers must answer four questions:

- Where am I? (perceiving the surrounding environment)
- What's around me? (processing that information)
- What will happen next? (predicting how others in that environment will behave)
- What should I do? (making driving decisions based on that information) [7, p. 8]

SDCs must answer the same questions, but while human drivers rely on sight, intelligence, and experience, (most) SDCs rely on route maps, sensors, and computer software. An enormous amount of hard work, creativity and imagination have gone into developing maps, sensors, and software, but—as will become evident—serious challenges remain.

3.2 Route Maps

In comparison with the maps presently available from Google, Apple, or Garmin for use in human-driven vehicles, route maps are much more detailed, showing traffic signals, road signs, curbs (including height), curb-cuts, driveways, road striping, type of road surface, crosswalks, fire hydrants—in general anything that does not move and which is relevant to driving. Route maps must be precise, accurate and almost constantly updated. Some SDC developers propose daily, if not hourly updates [10]. Failure of a map to show that a road has been closed or resurfaced, curbs removed, or a construction zone created could completely baffle an SDC. Updates come in part from individual SDCs encountering something new, such as a closed road, and then notifying other SDCs through an information center maintained by the company responsible for the SDCs.

Having a route map greatly decreases the load on the SDC's computer. As an SDC moves along a road, its sensors produce an enormous amount of data by scanning the environment and recording everything in view. Without a route map, the computer would have to analyze all this data and try to recognize all the objects the data represents. But with a route map, the computer already knows what many of the objects are without having to perform any analysis. The computer can then devote its resources to analyzing only the data coming from sources not on

the map. These sources must then represent either objects that can move, such as other cars or pedestrians, or fixed objects that are not on the route map because they have only recently appeared, such as new construction sites.

Many of the companies involved in SDC development send out their own fleets to create maps. Waymo—formerly the Google self-driving car project— has described the process it uses:

Before we drive in a new city or new part of town, we build a detailed picture of what’s around us using the sensors on our self-driving car. As we drive around town, our lasers send out pulses of light that help us paint a three-dimensional portrait of the world. We’re able to tell the distance and dimensions of road features based on the amount of time it takes for the laser beam to bounce back to our sensors. Our mapping team then turns this into useful information for our cars by categorizing interesting features on the road, such as driveways, fire hydrants, and intersections [11].

Similarly, GM says its SDCs will drive "only on roads for which we have developed high-definition map data" [12].

As is probably obvious from Waymo’s description, making such extremely detailed maps is expensive. The mapping team consists of highly trained engineers—by no means minimum-wage employees. Sometimes two, three, or even four passes must be made through a problematic intersection, and the data from the various passes is edited and merged into a single map. Once maps have been created for a region, they must be maintained—an additional expense. However, this expense is reduced by SDCs reporting map discrepancies back to a control center, as the SDCs drive passengers around. The Chinese search-engine giant Baidu believes that making maps for SDCs will become a bigger business than web search [13].

Waymo states that the total miles its SDCs have traveled are well into the millions. But it’s important to realize that these millions of miles were driven over a small number of routes that had been thoroughly mapped in advance. Many of the routes lie in the San Francisco Bay area.

The US has approximately 2.6 million miles of paved roads and 1.4 million miles of unpaved roads [14]. Mapping and updating the maps of all of these roads would be expensive. It seems reasonable to suppose that only those roads will be mapped that are sufficiently well-traveled to justify the cost. As a result, American SDCs that rely on route maps will be unable to drive on many US roads. Off-road travel, such as on a large farm or ranch, or in a field used for parking for an outdoor concert, will be off-limits to SDCs because of the lack of maps.

The costs and restrictions that the use of high-definition route maps imposes on SDCs have led many developers to seek alternatives. Apple has obtained a patent on a system that would use sensors on SDCs to “continuously create a new virtual model of the world that the car is

navigating through, drawing just from those sensors rather than using any external or pre-existing data source [for example, a route map] as a reference” [15]. Researchers at MIT have tested a system that “consults a very minimalist map and then uses its sensors to see its way to a point up ahead, a ‘waypoint’ the system chooses for being in the general direction of the ultimate goal” [16]. None of these alternatives are as well developed as high-definition route maps.

3.3 Sensors

All SDCs have one or more types of sensors: ultrasonic, sound (microphones), radar, imaging (cameras), and LiDARs.

Ultrasonic sensors locate objects by emitting high-frequency sound waves and then analyzing the reflected waves. The sensors can only be used to detect obstacles close to the vehicle, such as people, other vehicles, or barriers, and only at very low speeds. Some self-parking systems employ ultrasonic sensors.

Microphones are needed in SDCs to detect sirens of emergency vehicles so that the SDCs can take appropriate action, such as pulling over to the side of the road as the emergency vehicle approaches. Waymo’s microphone system can determine not only the siren’s distance but also its direction.

Radar sensors are familiar from applications in meteorology and marine and aircraft navigation. Radar works by emitting electromagnetic waves and then analyzing the waves reflected from an object. Radar can determine both the distance of an object as well as its speed and is effective day or night, in rain, fog, and snow, but does not provide enough resolution for easy identification of an object such as a human hand used in a gesture [7].

Cameras, unlike radar and sound sensors, are passive sensors. They depend on ambient light sources to produce reflections from which information can be deduced about an object. This works well when the ambient light is well-suited for photography but poorly when the light is dim or overwhelming as in glare from a setting sun. If a good image of an object can be produced by a camera, then current state-of-the-art machine-vision systems can recognize it reliably—for example, categorize it as a pedestrian, traffic sign, vehicle, etc. [17]. In contrast with the other types of sensors, cameras can detect colors and fonts, which is useful for determining traffic signals and interpreting signs. Stereo cameras, which have the ability to capture three-dimensional images and are used in some SDCs, can determine lane width and distance to an object.

A LiDAR—pronounced “lie-dar” and also written LIDAR, Lidar, and LADAR—is a device often mounted on the roof of the SDC that emits a large number of laser light pulses per second and captures the reflected pulses with a detector. By continually scanning the surroundings and determining the length of time for the reflected pulses to return to the detector, a LiDAR system

builds a high-resolution 3-D representation of objects surrounding the SDC. LiDARs work equally well in good or poor lighting conditions, but they cannot distinguish colors and are thus unable to determine the color of a traffic signal. Waymo has developed its own LiDARs—short range, high-resolution mid-range, and a long-range device that can detect objects at almost 300 yards. These devices represent a significant advance in the technology, and Waymo claims they cost only a small fraction of the price of LiDARs sold by other manufacturers [7, p.14]. Interestingly Tesla does not use LiDARs, preferring instead to rely exclusively on cameras and image-recognition software [18].

3.4 Software

Maps, sensors, and software provide answers to the driver’s questions, “Where am I?” and “What’s around me?” The various sensors feed information to the onboard computer where it is integrated through a process called, “sensor fusion.” For example, data from the radar and LiDAR sensors both may indicate the presence of a vehicle immediately ahead of the SDC. The sensor fusion process would then report only one piece of information (rather than two)—the presence of a single vehicle—to the SDC’s decision-making software.

Sensor fusion is complex. The fusion software must deal with input from many sensors—GM’s Cruise AV has forty-two sensors (five LiDARs, sixteen cameras, and twenty-one radars)—and must decide which are providing reliable data and which are not because of some problem such as malfunctioning electronics or being blocked by snow, dust, or other vehicles [12].

Bryan Salesky, the CEO of Argo AI, has summarized the current state of sensor technology and the fusion process:

Sensors still have a long way to go. We use LiDAR sensors, which work well in poor lighting conditions, to grab the three-dimensional geometry of the world around the car, but LiDAR doesn’t provide color or texture, so we use cameras for that. Yet cameras are challenged in poor lighting, and tend to struggle to provide enough focus and resolution at all desired ranges of operation. In contrast, radar, while possessing relatively low resolution, is able to directly detect the velocity of road users even at long distances.

That’s why we still have so many sensors mounted on the car—the strengths of one complement the weaknesses of another. Individual sensors don’t fully reproduce what they capture, so the computer has to combine the inputs from multiple sensors, and then sort out the errors and inconsistencies. Combining all of this into one comprehensive and robust picture of the world for the computer to process is incredibly difficult [1].

Data from sensor fusion is next combined with high-definition map data to “localize” (locate the position on the map—that is, answer the question, “Where am I?”) the vehicle. Many different

methods are used in the localization procedure. This redundancy provides error checking and quality control and means that even if the localization information from one system, such as radar, becomes unavailable, the vehicle can use localization information generated by other sources, such as from LiDAR data [12]. Waymo reports that it can locate an SDC's position to within 10 cm [19]. In comparison, GPS locates a car to within 1-2 m, which means that the GPS user could not distinguish between the car being on the street or on the sidewalk [20].

Besides identifying the permanent objects in the surroundings, the software uses the route map and sensor data to identify *movable (or changeable)* objects—other vehicles, pedestrians, cyclists, traffic signals, warning flares near an accident, and so on—in the surroundings, thus completing the answer to the driver's question, "What's around me?"

The next question—"What will happen next?"—is answered by making estimates of where the surrounding movable objects will be in the next few seconds. The location, heading, velocity, acceleration and capacity for change in these properties are all used to produce estimates for each object individually. Given these estimates, the software now answers the final question, "What should I do?" by producing commands for the SDC's steering, braking, and accelerator that will move the SDC to a new location without colliding with an object, without subjecting passengers to uncomfortable or frightening motions, and without surprising other drivers by an unexpected maneuver.

This brief description of SDC software hides many complexities, especially the use of artificial intelligence (AI), which will be discussed in a later section.

4. Operational Design Domain—Limitations Imposed by Current Technology

Technology developers are coming to appreciate that the last 1 percent is harder than the first 99 percent- ...Compared to the last 1 percent, the first 99 percent is a walk in the park. – Karl Iagnemma, CEO of Boston-based self-driving car company NuTonomy [21]

This is why I often say that we've done the first 99 percent of autonomous driving but the next 99 percent is going to be much harder. – Commenter Bob Frankston on Rodney Brooks' blog, "Robots, AI, and other stuff" [22]

The SDCs currently considered to be the most advanced depend on route maps for navigation. Thus where there are no route maps, there are no SDCs. Similarly, SDCs depend on sensors; when sensors are unable to provide data, SDCs cannot operate. This state of affairs has led the National Highway Traffic Safety Administration (NHTSA) to define each SDC's capability limits or boundaries through its "Operational Design Domain (ODD)."

The Operational Design Domain refers to the environment, including location, weather and speeds, in which the self-driving vehicle is designed to operate [12, 23].

At a minimum the ODD includes the following information:

- Roadway types (interstate, local, campus, etc.) on which the SDC is intended to operate safely
- Geographic area (city, mountain, desert, etc.);
- Speed range
- Environmental conditions in which the SDC will operate (weather, daytime/nighttime, etc.)
- Other domain constraints.

GM is describing the ODD for its SDC when the GM Safety Report says, "our self-driving vehicles will drive only in known geo-fenced boundaries [a virtual perimeter for a real-world geographic area], and only on roads for which we have developed high-definition map data. They will also drive only under known operational conditions and constraints that apply to the entire fleet" [12].

5. Levels of Automation

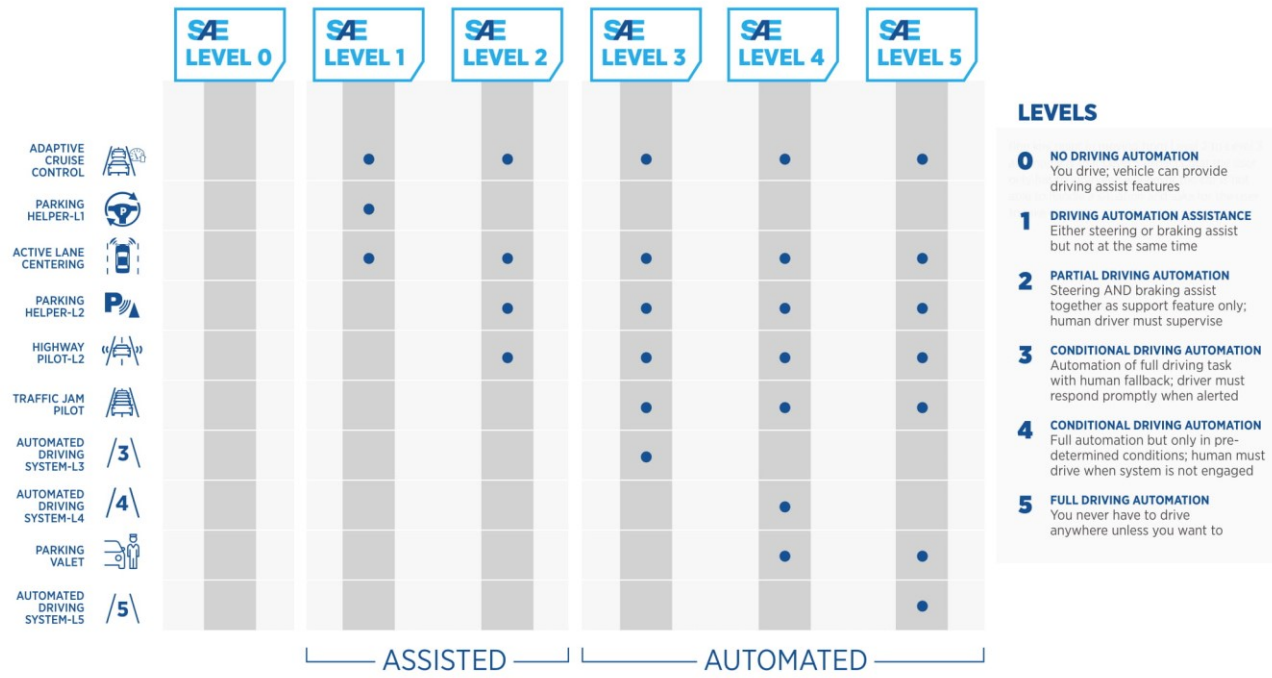
Level 5 autonomy—when a car can drive completely autonomously in any traffic or weather condition—is a wonderful goal but none of us in the automobile or IT industries are close to achieving true Level 5 autonomy. – Gill Pratt, Executive Technical Advisor and CEO of Toyota Research Institute [2]

5.1 SAE Standard J3016

As a convenience, thus far in this paper the term “self-driving cars” (SDC) has been used as a blanket term, as if all SDCs were the same. In reality, the SDCs designed by the various competing developers differ greatly in degree of automation. This ambiguity has led to confusing and misleading claims in popular accounts about what constitutes a self-driving car. Recognizing the need to clarify the discussion, the Society of Automotive Engineers International (SAE) has formulated Standard J3016, the 2018 version of which is summarized in Table 1 on the next page [24].



SAE J3016™ LEVELS OF DRIVING AUTOMATION



- LEVELS**
- 0 NO DRIVING AUTOMATION**
You drive; vehicle can provide driving assist features
 - 1 DRIVING AUTOMATION ASSISTANCE**
Either steering or braking assist but not at the same time
 - 2 PARTIAL DRIVING AUTOMATION**
Steering AND braking assist together as support feature only; human driver must supervise
 - 3 CONDITIONAL DRIVING AUTOMATION**
Automation of full driving task with human fallback; driver must respond promptly when alerted
 - 4 CONDITIONAL DRIVING AUTOMATION**
Full automation but only in pre-determined conditions; human must drive when system is not engaged
 - 5 FULL DRIVING AUTOMATION**
You never have to drive anywhere unless you want to

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Table 1. 2018 version of SAE J3016 automated driving level definitions. SAE INTERNATIONAL.

Comments on Levels 3, 4, and 5:

- In Level 3, a human driver sits behind the steering wheel while the automated driving system (ADS) handles all driving tasks—until a driving situation arises that the ADS cannot handle. The ADS then hands off control to the human driver, who is expected to respond promptly when alerted.
- In Level 4, the ADS handles all driving tasks, as long as the car remains in its ODD. If the ODD is violated—by for example the occurrence of heavy snowfall that blinds the sensors—the ADS is programmed to guide the car to a minimal risk condition, a process referred to as “fallback.” A typical fallback might consist of bringing the vehicle to a safe stop, preferably outside of an active lane of traffic. Human intervention of some kind will then be necessary to drive the car further.
- In Level 5, the ADS handles all situations.
- Many of the predictions about SDCs described in section 2 of the present paper—especially the ones involving extreme changes to transportation and city design, are implicitly based on the assumption that all SDCs are Level 5. A Level 3 vehicle would not satisfy the implicit requirements underlying the predictions. For example, a Level 3 vehicle must have a back-up driver to hand off control to, but if the cargo consists of children, visually impaired or ill persons, or a pizza being delivered, no back-up driver would be available. Similarly, a Level 4 vehicle would not be sufficiently robust to fulfill many of the more extreme predictions. If the ODD of a Level 4 vehicle is violated, the car would have to retreat to a fallback position and wait for help. Visions of a second-grader confined alone in a stranded SDC will convince most parents to stick with traditional cars for getting children to their piano lessons.

Level 4 vehicles have actually been around for many years: automated vehicles of various shapes and sizes have been used at airports to transport people from one terminal to another. These vehicles qualify as Level 4 because they operate in their (highly restricted) ODDs without human intervention. The challenge of developing SDCs can be viewed as that of expanding their ODDs.

5.2 The Handoff Problem and Skipping Level 3

The “handoff” process occurring in Level 3 has proven to be more difficult than anticipated and is now known as the “handoff problem.” As Volvo discovered, “A car with any level of autonomy that relies upon a human to save the day in an emergency poses almost insurmountable engineering, design, and safety challenges, simply because humans are for the most part horrible backups. They are inattentive, easily distracted, and slow to respond” [25]. A 2015 regulatory study reported that some drivers required *seventeen seconds* to retake control of a vehicle [26].

To solve this inattention problem, the car must have interior cameras and sensors to monitor the driver's head position, gaze direction, and hands-on-wheel contact. Then the vehicle must alert the driver by sounding an alarm, flashing warning lights or vibrating the steering wheel (haptic feedback). But monitoring the potential driver's physical state introduces a whole new set of difficult sensor and software problems, in addition to the problems related to the environment exterior to the vehicle. After considering the difficulties of the handoff problem, many companies, including GM [12], Nissan [27], Volvo [25], and Waymo [7], have decided to skip developing a Level 3 vehicle but instead go directly to Level 4.

5.3 Disengagements, Fallback and Teleoperation

In road tests of SDCs, “disengagement” refers to a situation that baffles the ADS, and as a result, the ADS has to disengage from controlling the car and instead has to seek human intervention. Waymo, one of the most advanced of the SDC developers, recently reported an average of 5,596 miles between disengagements while the GM Cruise average disengagement distance was 1,254 miles. (The large difference in disengagement distances may reflect differences in chosen driving environments—more disengagements will arise in city driving than in interstate highway driving.) [28]

What solution to the disengagement problem do these developers, staff at the National Highway Traffic Safety Administration, and others propose? First, Level 4 SDCs should be programmed to transition to fallback without human intervention. Second, once in fallback the SDC, instead of handing off control to a passenger, contacts a remote *teleoperation* center.

Nissan has been an early promoter of teleoperation and has built a system based on software used by NASA for Mars Rovers [27]. Nissan's teleoperators (human beings) do not provide a backup in the event of an emergency. Emergencies happen too quickly for teleoperators to intervene. Instead the teleoperators go into action when the center receives a call from an SDC when its control system does not know what to do.

When the call arrives, a teleoperator queries the SDC's sensors to find out what the situation is, and then sends a batch of driving instructions that the SDC executes on its own, after verifying through its sensors that the driving maneuver would be safe. (Most teleoperators do not drive the SDC directly because of latency issues, but a company called Phantom Auto claims to have solved this problem [29].) For instance, the instructions might direct the SDC to violate its usual rules and cross into the opposing traffic lane and proceed through a red light so as to allow an ambulance to pass.

The governor of Arizona has issued an executive order stating that teleoperators must be used if no back-up driver will be aboard the vehicle. Thus Waymo, which in late 2018 introduced

robotaxis in Chandler, Arizona, with back-up drivers in the vehicle will eventually use teleoperators for these vehicles if the back-up drivers are removed. [30, 145].

Teleoperation centers appear to be one way to address the fallback problem, but unfortunately, as Toyota's Gill Pratt has remarked, teleoperations centers have problems of their own:

First of all, those things assume the Internet is working, there are no hackers, there's no natural disaster. But most of all, it's the same issue we discussed earlier [the handoff problem], that you assume a person at a call center can suddenly wake up and say, "Okay, trouble," and handle the situation. People are very bad at that. We're very bad at suddenly being surprised and needing to orient ourselves and coming up with a correct response. So we're not saying that's impossible, but we're saying it may be very difficult, for the reasons that we've outlined [2].

Nissan estimated that on average, a human teleoperator would take thirty seconds to develop "situational awareness" and convert that awareness into a set of driving instructions [27]. Thirty seconds is a long time for human-driven vehicles caught behind the SDC to wait; there may be public backlash against SDCs if fallback delays occur frequently.

An additional problem with relying on teleoperators is that the company managing the SDCs will have to recruit, train, monitor, and pay large numbers of people to staff the operation. Thus the expected savings from not having to pay a driver of a robotaxi or robo-delivery vehicle would be less than previously anticipated.

Given the characteristics of teleoperated vehicles, it is a legitimate question whether vehicles dependent on teleoperators can truly be called "driverless" at all. The driver is still present—just not in the vehicle.

5.4 Current Level 4 SDCs

In a January 2018 Senate hearing, Tim Kentley-Klay, CEO of the Zoox robotics company, admitted that teleoperation centers would be needed "both to deal with vehicles if they have an issue, but also to deal with customers if they need help" [29]. But requiring a teleoperations center places a significant restriction on SDCs. Their range will be limited to areas covered by adequate communications networks. By way of comparison, even present-day cellphone service has gaps in coverage. A teleoperations network must be much more reliable than that.

Waymo and Ford claim that their vehicles can operate safely without constant communication with an operations center [7, 31]. Thus their claim to have Level 4 vehicles depends on a judgment call. How many miles between disengagements must a vehicle average before it can be considered to perform (almost) all driving tasks in its ODD? American drivers average about

12,000 miles per year. Waymo's most recent average of 5,596 miles between disengagements would translate into two or three times per year when the vehicle would have to find a place to pull over and stop. Some of these places might be uncomfortable or even dangerous, for example, blocking traffic in a right-turn-only lane of a busy intersection. Probably few drivers would be pleased with this performance and few would be willing to concede that the vehicle can perform nearly all driving tasks in its ODD. The number of miles between disengagements must be significantly increased before a (close approximation) to Level 4 can be claimed.

How close is the SDC industry to developing a Level 5 vehicle? In a January 2017 *Wired Magazine* article, Nissan's R&D chief Maarten Sierhuis is described as pointing to a road construction site and saying:

There is so much cognition that you need here. The driver—or the car—has to interpret the placement of the cones and the behavior of the human worker to understand that in this case, it's okay to drive through a red light on the wrong side of the road. This is not gonna happen in the next five to ten years [27].

The *Wired* writer goes on to say:

It's a stunning admission, in its way: Nissan's R&D chief believes the truly driverless car—something many carmakers and tech giants have promised to deliver within five years or fewer—is an unreachable short-term goal. Reality: one; robots: zero. Even a system that could handle 99 percent of driving situations will cause trouble for the company trying to promote, and make money off, the technology. "We will always need the human in the loop," Sierhuis says [27].

In the SAE definitions, Level 5 is defined as "Full Driving Automation." Level 4 is "Conditional Driving Automation" and is "full automation" only while confined to its ODD. Yet popular media and company press releases persist in using phrases such as "fully automated" to describe a particular SDC, when in reality the SDC exhibits only conditional automation.

6. Concerns Related to the Widespread Use of Self-Driving Cars

I would actually welcome a correction in public opinion about what AI can and cannot do. This has happened to me multiple times, where I would listen to a CEO on stage make an announcement about what their company is doing with AI, and then twenty minutes later I'd talk to one of their engineers, and they'd say, "No, we're not doing that, and we have no idea how to do it." I think it still takes judgment to know what is and what isn't possible with AI, and when the C-suite does not yet have that judgment it's possible for companies to make promises very publicly that are just not feasible. Frankly, we see some of this in the self-driving space. Multiple auto [original equipment manufacturer] CEOs have promised self-driving car roadmaps that their own engineers think are unrealistic. I feel [CEOs are] being sincere but just not really understanding what can be done in a certain timeframe. – Andrew Ng, former chief scientist of Chinese tech conglomerate Baidu and co-founder of Google Brain, the company's deep-learning research team [32]

6.1 Edge Cases

In the SDC industry, the term "edge case" is used to describe a situation in driving where the software controlling an SDC either makes an inappropriate response or is unable to direct the vehicle's action at all. Both Waymo and GM state that their software can handle the well-known edge cases involving protected left turns and recognizing and adapting to construction zones and traffic cones [7, 12]. But many other edge cases are known, and many more will be discovered as experience in SDC driving is gained.

In his blog, Rodney Brooks, Emeritus Professor of Robotics at MIT, says, "I want to talk about a number of edge cases, which I think will cause it to be a very long time before we have Level 4 or Level 5 self-driving cars wandering our streets, especially without a human in them, and even then there are going to be lots of problems" [9]. He describes several edge cases that seem particularly knotty for AI to handle:

How are the police supposed to interact with a **Careempty** [a car with no passengers]?

While we have both driverful and driverless cars on our roads I think the police are going to assume that as with driverful cars they can interact with them by waving them through an intersection perhaps through a red light, stopping them with a hand signal at a green light, or just to allow someone to cross the road.

But besides being able to understand what an external human hand signaling them is trying to convey, autonomous cars probably should try to certify in some sense whether the person that is giving them those signals is supposed to be doing so with authority,

with politeness, or with malice. Certainly police should be obeyed, and police should expect that they will be. So the car needs to recognize when someone is a police officer, no matter what additional weather gear they might be wearing. Likewise they should recognize and obey school crossing monitors. And road construction workers. And pedestrians giving them a break and letting them pass ahead of them. But should they obey all humans at all times? ...

Sometimes a police officer might direct a car to do something otherwise considered illegal, like drive up on to a sidewalk to get around some road obstacle. In that case a **Carempy** probably should do it. But if it is just the delivery driver whose truck is blocking the road wanting to get the **Carempy** to stop tooting at them, then probably the car should not obey, as then it could be in trouble with the actual police. That is a lot of situational awareness for a car to have.

Things get more complicated when it is the police and the car is doing something wrong, or there is an extraordinary circumstance which the car has no way of understanding.

In the previous section we just established that autonomous cars will sometimes need to break the law. So police might need to interact with law breaking autonomous cars ...

If an autonomous car fails to see a temporary local speed sign and gets caught in a speed trap, how is it to be pulled over? Does it need to understand flashing blue lights and a siren, and does it do the pull to the side in a way that we have all done, only to be relieved when we realize that we were not the actual target?

And what if a whole bunch of **Carempies** have accumulated at [an unusual situation that baffles the cars' control software], and a police officer is dispatched to clear them out? For driverful cars a police officer might give a series of instructions and point out in just a few seconds who goes first, who goes second, third, etc. That is a subtle elongated set of gestures that I am pretty sure no deep learning network has any hope at the moment of interpreting, of fully understanding the range of possibilities that a police officer might choose to use.

Or will it be the case that the police need to learn a whole new gesture language to deal with driverless cars? And will all makes [of cars] all understand the same language?

Or will we first need to develop a communication system that all police officers will have access to and which all autonomous cars will understand so that police can interact with autonomous cars? Who will pay for the training? How long will that take, and what sort of legislation (in how many jurisdictions) will be required?

Aside from edge cases, the sheer number of traffic scenarios the software must handle is large and growing, as SDCs are driven more and more. In Waymo’s input comments to NHTSA about NHTSA’s proposed Development of Automated Safety Technology Guidelines, Waymo listed dozens of scenarios that it has analyzed “to help ensure our vehicles are capable of operating safely in the reasonably foreseeable situations that could present a safety hazard” [33]. The scenarios are listed in Appendix A.

6.2 Machine Learning and Deep Learning

Machine learning (ML) is a branch of AI involving a computer system that has the ability to teach itself to solve a problem by identifying a pattern in input data rather than by following programmed steps to obtain a solution. An example would be a facial recognition system that is trained to recognize photos of a particular person, say person X. The system would be given as input a large “training” dataset consisting of photos of various people (including X) in various clothes, postures, and lighting. The system would then identify a pattern (features of X’s appearance) in the photos. If the system is now given a different set of photos including a new photo of X, it would be able to use the pattern to select X’s photo from the set.

Deep learning is a particular type of ML that—thanks to recent improvements in computer power, algorithms, and the development of large training datasets—is currently one of the most effective ML systems available. Deep learning is used in Google Search, Google Translate, the Facebook News Feed, conversational speech-to-text algorithms, medical imaging, pharmaceutical drug discovery, and cancer diagnosis—to name just a few applications [34]. The psychologist Steven Pinker has written a general but informative description, reproduced in Appendix B, of how the “magic” of deep learning works.

In SDCs, deep learning is most commonly used to examine data collected by the vehicle’s sensors and identify traffic-related objects in the surrounding environment. This information is given as input to the SDC’s control system, where driving decisions are then made by pre-programmed rules. Some other companies use deep learning in a different way. Rather than relying on pre-programmed rules to make driving decisions, these companies use “deep learning to devise the vehicle’s own decision-making capability based on the scenarios it encounters” [35].

Even though deep learning has proven highly successful in various applications and is currently employed in SDCs, concerns have arisen as to whether deep learning will be adequate for the task as SDCs move from development to widespread deployment. One concern is that the training datasets may not be sufficiently large. A classic example from an ML algorithm (other than deep learning) shows the difficulty all MLs face:

In a famous project, researchers trained [an ML system] to distinguish between wolves and dogs. The model achieved an impressive accuracy. However, the researchers eventually found out that the [system] learned to detect snow on images since most training images of wolves contained snow in the background. That's not the conclusion that the [system] should draw [36].

Clearly the training dataset was too narrow. Many more images of wolves without snow should have been included.

Thus the first concern about using deep learning in SDCs is that the training dataset may be inadequate. The dataset must encompass the wide variety of driving-related objects encountered as a vehicle moves in an urban environment, and it must include edge cases, which by their nature occur infrequently.

According to information publicly available, Waymo has driven SDCs more miles than any other developer, and as a result, Waymo probably has the largest training datasets. Waymo and others supplement their datasets by running computer simulations (numbering in the *billions!*), but the simulations must still be based on collecting an enormous amount of actual field images. The question is, then, are the existing training datasets used with deep learning sufficient for developing a safe SDC? Rand Corporation researchers Nidhi Kalra and David Groves are not optimistic:

There is little reason to believe that improvement in [SDC] safety performance will be fast and can occur without widespread deployment, given the years already dedicated to [SDC] development and given that real-world driving is key to improving the technology. Indeed, there is good reason to believe that reaching significant safety improvements may take a long time and may be difficult prior to deployment [37].

In another Rand report, researchers Nidhi Kalra and Susan Paddock calculate that to demonstrate acceptable safety performance, an SDC design “would have to be driven 275 million failure-free miles” [38].

A second concern about deep learning for SDC applications is that it operates by extracting *patterns* from the training dataset. But pattern recognition is not intelligence. In fact, a prominent AI researcher has stated “it would be more helpful to describe the developments of the past few years as having occurred in ‘computational statistics’ rather than in AI” [39]. In an interview, AI entrepreneur Yibiao Zhao describes the limitation of relying only on pattern recognition for guiding an SDC:

-[D]riving involves considerably more than just pattern recognition. Human drivers rely constantly on a commonsense understanding of the world. They know that buses take longer to stop, for example, and can suddenly produce lots of pedestrians. It would be

impossible to program a self-driving car with every possible scenario it might encounter. But people are able to use their commonsense understanding of the world, built up through lifelong experience, to act sensibly in all sorts of new situations.

“Deep learning is great, and you can learn a lot from previous experience, but you can’t have a data set that includes the whole world ... Current AI, which is mostly data-driven, has difficulties understanding common sense; that’s the key thing that’s missing,” said Zhao [40].

Figure 2 shows a traffic environment where a traffic pattern may be difficult to identify and commonsense is essential.



Figure 2. “People are able to use their commonsense understanding of the world ... to act sensibly in all sorts of new situations.” Yibiao Zhao. (© Yann Forget / Wikimedia Commons.)

A third concern about deep learning algorithms is that it is impossible to trace the decision-making process the algorithm followed to achieve a final result. The deep learning algorithm is a black box with input and output terminals but with no display of what happens inside the box when particular input is transformed into output. An obvious danger here is the lack of a legal defense when an SDC is involved in a serious accident and a lawsuit ensues. SDC developers would have to admit that they have no idea how the deep learning algorithm arrived at the particular decision that led to the accident. What is more, even if the vehicle’s software is modified to prevent the type of accident that triggered the lawsuits, the developers could not guarantee that deep learning would not lead to accidents in other driving situations.

A fourth concern about relying on a pattern-matching algorithm such as deep learning is that it cannot *generalize*:

[Deep learning] can't recognize an ocelot unless it's seen thousands of pictures of an ocelot—even if it's seen pictures of housecats and jaguars, and knows ocelots are somewhere in between. That process, called “generalization,” requires a different set of skills.

For a long time, researchers thought they could improve generalization skills with the right algorithms, but recent research has shown that conventional deep learning is even worse at generalizing than we thought [41].

Thus if the algorithm is to recognize an ocelot, the training dataset has to include pictures of ocelots. Similarly, if SDC deep learning is to recognize a particular edge case, the training dataset must include examples of that edge case. Similar edge cases will not be sufficient.

John Leonard, a mechanical engineering professor and AI researcher at MIT, expresses his concerns about the situation:

I think that driving exposes fundamental issues in intelligence, fundamental issues in how the brain works. And we might be a very long way away [from solving the problem of self-driving cars].

Unexpected changes to things like road surfaces can also throw off automated cars. Google cars, for example, use precise maps that tell them where they are at any given point on a journey. But if Mother Nature drops a foot of snow, or if a road gets repaved, a driverless car may easily get confused [4].

Leonard thinks that Google's SDC vehicle work is “an amazing project that might one day transform mobility,” but the technology today is overhyped and misunderstood.

Pedro Domingos, a professor of computer science at the University of Washington, expresses skepticism similar to Leonard's: “A self-driving car can drive millions of miles, but it will eventually encounter something new for which it has no experience ... It must be that we have a better learning algorithm in our heads than anything we've come up with for machines” [42].

These observations have prompted some companies to explore alternatives to deep learning, such as using older AI techniques that allow logic structures to be hard-coded into an otherwise self-directed system [41]. Yet prominent researchers such as Yann LeCun, the director of AI

research at Facebook, and Geoffrey Hinton, professor emeritus at the University of Toronto, assert that deep learning will be capable of handling all SDC tasks, and the aforementioned concerns are baseless [42]. It seems that building and deploying SDCs rather than theoretical arguments will determine who is right about the adequacy of deep learning for SDCs.

6.3 Software Reliability

Aside from the question of limitations of AI, several prominent SDC specialists have questioned the reliability of SDC software. Steven Shladover, a researcher at the Partners for Advanced Transportation Technology at the University of California, Berkeley, says:

If you want to get to the level where you could put the elementary school kid into the car and it would take the kid to school with no parent there, or the one that's going to take a blind person to their medical appointment, that's many decades away.

Driving in the United States is actually incredibly safe, with fatal crashes occurring once every roughly three million hours of driving. Driverless vehicles will need to be even safer than that.

Given existing software, that is amazingly difficult to do... coming up with safety-critical, fail-safe software for completely driverless cars would require reimagining how software is designed. There is no current process to efficiently develop safe software. For instance, when Boeing develops new airplanes, half of their costs go to checking and validating that the software works correctly, and that's in planes that are mostly operated by humans [43].

Herman Herman, Director of Carnegie Mellon's National Robotics Engineering Center, points out the dramatic consequences that an SDC software error can lead to:

When your web browser or your computer crashes, it's annoying but it's not a big deal. If you have six lanes of highway, there is an autonomous car driving in the middle, and the car decides to make a left turn—well, you can imagine what happens next. It just takes one erroneous command to the steering wheel [44].

6.4 Sensor Reliability

Because SDCs depend heavily on the information supplied by the vehicles' sensors, sensor reliability is essential. But sensor design for automotive use is challenging, as Toyota's Gill Pratt has said:

The sensor ... needs to be cheap. It needs to be vibration resistant. It needs to last for ten years or maybe twenty years and not break. Automotive quality, which most people think of as being low, is actually very, very high. I've worked a lot, in my DARPA work, with mil-spec and things like that, but automotive quality is ridiculously hard to do. And so a cellphone camera is not going to work. You're going to need special stuff that really can withstand the desert and Alaska and going back and forth. How do you deal with salt and rust, with the screen getting full of dust from the road...? Making sure that's going to work, all of the time, is really hard [2].

6.5 Sensors and Extreme Weather Conditions

Extreme weather conditions create several problems for sensors. Figure 3 illustrates one of them—the vulnerability of sensors to being obstructed by snow, ice, and slush thrown by other vehicles.



Figure 3. Small clouds of snow, ice, and slush thrown up by truck tires

An article in *Global News* entitled, “We may never see self-driving cars anywhere it snows. Here’s why.” discusses the problem:

Winter driving is messy and can be dangerous. It’s an old problem, solved, at least most of the time, with scrapers and wiper fluid. But driving on a slushy winter road in

Michigan, automotive writer and consultant Sam Abuelsamid found that it has a new set of consequences. ...

In winter, cars get covered in a film of salt, which reflects the sun, low on the horizon. A few minutes on sloppy roads leaves them covered in grey, salty slush. Trucks passing you on the highway leave your windshield splattered with thick icy goop, sending the heart racing for a moment until generous amounts of wiper fluid deals with it.

The slop and mess of winter driving creates an insoluble problem for self-driving cars anywhere it snows regularly, Abuelsamid argues. It doesn't matter how cutting-edge the radar and sensors that self-driving cars use to see are—if they're covered with slush, salt or grime they can't see, and they can't work if they can't see. [45]

Installing heating elements and tiny wipers for each sensor have been suggested as ways for SDCs to keep sensors working, but it is far from clear that heaters and wipers will be able to handle the large amounts of slush that may be thrown on an SDC by neighboring vehicles.

A second problem produced by extreme weather is that even when unobstructed, LiDARs are prevented from functioning because snow and heavy rain scatter laser light, and cameras do not work well in dim light. At present, LiDARs and cameras are only fair-weather friends of SDCs, a situation that has led one developer specializing in sensor technology to say, “The final frontier for autonomy is urban driving under extreme weather conditions, and that's going to take some time” [46]. Waymo has, however, reported progress in using machine learning to filter out noise from sensor data caused by raindrops and snowflakes [47].

A third problem related to extreme weather conditions applies to robotaxi companies. The basic difficulty is that if a car has no driver, who will shovel out the snow around the car and scrape off the ice and snow? Figure 4 shows might happen if robotaxis are parked outside overnight during a heavy snowfall.



Figure 4. Shoveling out after a heavy snow

Cleaning the snow and ice from and around a car after a heavy winter overnight storm can take substantial time. Currently, Lyft and Uber avoid this problem because their drivers double as snow-removers, cleaning their own vehicles of snow and ice or keeping them in their own garage. But robotaxis will not have drivers, and thus a robotaxi company will have to keep a significant number of employees available at short notice for part-time snow removal work—after a snow or ice storm hits the area. This requirement will raise the cost of the robotaxi service in addition to being difficult for managers to administer.

The alternative to keeping a large part-time staff on call for snow/ice removal is for the robotaxi company to keep the vehicles in parking garages when not in use. But then one of the proposed advantages of using robotaxis—parking garages could be torn down and the valuable real estate they occupied made available for other uses—would be lost. The company might contract with people owning houses with garages to park an SDC in the garage overnight. Again, a proposed advantage of robotaxis—eliminating the need for garages in private residences—would be lost.

6.6 Adequate Testing

In a March 15, 2016 testimony to a US Senate committee, Mary Cummings, a professor at Duke University with extensive experience in robotics and consulting with automobile makers, laid out what she saw as a serious deficiency in testing of SDCs (Appendix C contains the complete testimony):

While I enthusiastically support the research, development, and testing of self-driving cars, as human limitations and the propensity for distraction are real threats on the road, I am decidedly less optimistic about what I perceive to be a rush to field systems that are

absolutely not ready for widespread deployment, and certainly not ready for humans to be completely taken out of the driver's seat. ...

In my opinion, the self-driving car community is woefully deficient in its testing and evaluation programs (or at least in the dissemination of their test plans and data).

Cummings goes on to compare the lack of testing—or the lack of publication of test results—done by SDC developers with the rigorous processes of the Federal Aviation Administration.

[T]he FAA (Federal Aviation Administration) has clear certification processes for aircraft software, and we would never let commercial aircraft execute automatic landings without verifiable test evidence, approved by the FAA. To this end, any certification of self-driving cars should not be possible until manufacturers provide greater transparency and disclose how they are testing their cars. Moreover, they should make such data publicly available for expert validation.

6.7 Safety Concerns and Political Risk

If SDC developers need any reminder of the political risks stemming from negative publicity about the safety of a technology, they need look no further than the experiences of agribusiness introducing genetically modified organisms (GMOs) and of the nuclear power industry. At least in part because of safety concerns of the public, only one nuclear power plant has been built in the US since 1996 [48]. Agribusiness firms first introduced GMOs in the 1990s, but despite their desirable traits of increased yield, increased vitamin content, drought resistance, resistance to insects, and reduced need for pesticides, GMOs have proven extremely controversial and resulted in many lawsuits. Opponents claim that GMOs are dangerous to human and livestock health and harmful to the environment. Currently many European countries even prohibit the growing of GMOs. The objections to GMOs continue, even in the face of authoritative studies such as the National Academy of Sciences 2016 report, “Genetically Engineered Crops: Experiences and Prospects” that concluded:

While recognizing the inherent difficulty of detecting subtle or long-term effects in health or the environment, the study committee found no substantiated evidence of a difference in risks to human health between currently commercialized genetically engineered (GE) crops and conventionally bred crops, nor did it find conclusive cause-and-effect evidence of environmental problems from the GE crops [49].

What should be worrisome for SDC proponents is that the public opposition to SDCs could turn out to be even greater than the opposition to GMOs because opposition to GMOs grew *even though no documented deaths have ever been reliably and convincingly attributable to GMOs*. Contrast that situation with fatal accidents involving SDCs. *Deaths can be reliably and*

convincingly attributable to SDCs without having to conduct an expensive and time-consuming epidemiological study, as would be required for evaluating GMOs. The risk to the whole SDC enterprise is that SDCs will be introduced without adequate testing and will result in many fatal accidents. Politicians and consumer advocacy groups will then seize upon reports of SDC-related deaths to advocate legislation that could greatly impede SDC testing or even eliminate certain types of SDC features entirely.

Illustrations of the political risk were common in the months following fatal SDC accidents involving Uber in Arizona and Tesla in California in 2018. See Figure 5. After these accidents, a US Senator wanted “to ensure semi-autonomous cars are also included in [an SDC-related] bill, that there are requirements for all of the vehicles to have a manual override and that there is more transparency with the data and safety evaluations” [50]. A Consumers Union specialist on SDCs, commenting on the bill, said, “We want to make sure that data is broadly shared to demonstrate their safety before the rest of us have to be guinea pigs sharing the road” [50].



Figure 5. National Transportation Safety Board employees examine an Uber autonomous car involved in a fatal crash in Tempe, Arizona.

Other government regulations have been proposed or already enacted. New Hampshire considered a bill that would require SDC testers to specify dates and locations where testing would occur and put up a \$10 million insurance bond. Furthermore, each test vehicle would have to be followed by an escort vehicle [51]. California now requires each SDC to include “a process to communicate between the vehicle and law enforcement” [52]. In all, twenty-two states have passed some sort of SDC-related legislation [53].

According to a lengthy *Consumer Reports* article about SDCs, in interviews multiple experts said that pedestrian detection technology in current use “might not be advanced enough for public roads [54]. One expert declared that “a lack of transparency in testing, coupled with the desire for some states to attract investment without understanding the limitations of the technology, could mean unsafe autonomous vehicles are currently operating on public roads.” Another expert, Duke University Professor Mary Cummings, whose Congressional testimony has been previously cited, was described as being pessimistic that the publicity surrounding the Arizona accident would “lead to a major policy change before another fatality takes place.” She goes on to state that “The question on my mind is, how many more will have to happen before the big outcry happens?” [54]

Besides the risk of legislation impeding the testing of SDCs, the introduction of SDCs will be delayed by the long time that legislative bodies will take to codify new traffic laws and regulations. As MIT’s Rodney Brooks has observed, “It will take a lot of trial and error and time to get these laws right [9].

6.8 Self-Driving Cars Driving Habits

As evidenced by its Safety Report [7], Waymo appears to be fully aware of the safety concerns of the public described in the previous section. The report assures the reader that “**Safety** is at the core of Waymo’s mission [emphasis in the original]” and “Our commitment to safety is reflected in everything we do.” The words, “safe” and “safety,” occur 232 times in the forty-three-page document. Similarly, General Motors “2018 Self-Driving Safety Report” states “Imagine a world with no car crashes. Our self-driving vehicles aim to eliminate human driver error” and “the Cruise AV was built from the start to operate safely on its own, with no driver. We engineered safety into the vehicle in every single step of design, development, manufacturing, testing and validation.” The words, “safe” and “safety” occur 152 times in the thirty-three-page document [12]. Ford’s forty-four-page safety report, “A Matter of Trust,” contains 141 occurrences of “safe” and “safety” [31].

SDC developers’ concern about bad publicity from SDC accidents shows up not only in safety reports but also in the extremely risk-averse driving behavior that SDCs have been programmed to exhibit. SDCs slow or stop frequently whenever a pedestrian or a nearby vehicle makes a

move that has the slightest possibility of intruding upon the SDCs' path. Human drivers, unaccustomed to following a vehicle that stops or slows at the slightest provocation, run into the rear end of the SDC. In fact, of the (relatively few) accidents that SDCs have been involved in thus far in their development, many are caused by human drivers rear-ending the SDCs [55].

Anecdotes abound about extreme conservatism in driving. For instance, *Wired Magazine's* Aarian Marshall, in an article entitled "My Herky-Jerky Ride in General Motors' Ultra-Cautious Self Driving Car," says:

Towards the end of the ride, the car began to make a left turn into a crosswalk, and a woman pushing a stroller on the sidewalk accelerated toward the street. Not the baby, I pleaded silently, before she turned to cross the perpendicular street instead. Our car, meanwhile, had jerked to a stop—in the middle of the intersection. Cruise employees later told me they've programmed their cars to anticipate the actions of pedestrians. But right now, they don't always get it right [55].

In an *IEEE Spectrum* article, MIT's Rodney Brooks describes problems dealing with pedestrians:

These [interactions with pedestrians] are the sorts of nuances that typically elude artificial intelligence. What if cars trying for full autonomy can't handle them? The short answer, of course, is that they will not be able to accommodate pedestrians as smoothly as human drivers do.

So what's likely to happen is that driverless cars will be very wimpy drivers, slowing down—and angering—everybody [56].

And a study by the British Department for Transport predicts

Because early models of driverless cars are actually expected to operate more cautiously than regular vehicles, road congestion will worsen, although as the percentage of SDCs on the road increases over time, eventually, perhaps after many years, congestion will decrease. There are around thirty-two million conventional cars on the UK's roads. As driverless cars come in, traffic flow could initially get worse rather than better, potentially for many years.

Much will depend on how an autonomous car's parameters are set and just how defensively these vehicles will be programmed to drive [57].

A writer for the business magazine, *Fast Company*, described his experience in Waymo's Arizona robotaxi:

Waymo’s next challenge is greater than anything a user interface alone can solve. Because if Waymo wants to make robot cars feel safe and comfortable, sooner or later, it has to teach them to drive in a way that feels more human.

Simply put: When you ride in a Waymo vehicle, it just doesn’t feel like you’re being driven by a human. At all. The vehicle has a tendency to accelerate evenly through turns. It stops painfully early for yellow lights. Once it jerked the wheel out of the way of a pickup truck in the next lane—with a staccato sharpness I’ve never felt a human driver execute. And often, it will gently tap the brakes or gas when I simply don’t know why. On one such occasion, I glanced down to the screen. Why were we speeding up and slowing down so often? It ended up that my vehicle was responding to a car, maybe four lengths ahead. I knew this because anything actionable—anything that the Waymo bot is considering in its driving decision—is highlighted in green on the screen. That goes for pedestrians, bicyclists, even cars that are far removed from you in traffic. If they glow green, Waymo is taking them into special account.

So in this case, with that car so far ahead of us being highlighted, I quickly inferred that my Waymo was just keeping what it considered a safe distance, even if that would be “too safe” by my measures [58].

Similar observations have been made by a writer for the science news website, *Live Science*:

A self-driving car must be able to distinguish between dangerous and harmless situations. Otherwise, it's going to be slamming on the brakes all the time for no reason. ... The cars also need to decide in sufficient time whether a pedestrian waiting on the sidewalk is likely to walk into traffic, or whether a bike is going to swerve left. Human brains do a masterful job of sorting and reacting to these hazards on the fly, but the current crop of sensors just isn't equipped to process that data as quickly [43].

Another possible result of the driving style of SDCs is that extremely timid driving may invite bullying by aggressive human drivers. These drivers, recognizing the SDCs’ extreme conservatism, could take advantage by performing aggressive driving maneuvers near an approaching SDC and forcing it to delay or stop, when it actually had the right of way.

Part of the challenge for developers programming SDC driving behavior is that their program must not only prevent collisions but prevent them under the constraint that “humans don’t behave by the book.” A vivid illustration of this point was the “Google car, in a test in 2009, that could not get through a four-way stop because its sensors kept waiting for other (human) drivers to stop completely and allow it to go. The human drivers kept inching forward, looking for the

advantage—paralyzing Google’s robot.” Since that time, Waymo has solved this problem, and now, at four-way stops, Waymo’s software “lets the car inch forward, as the rest of us might, asserting its turn while looking for signs that it is being allowed to go” [14].

6.9 Cybersecurity

SDCs may be vulnerable to malevolent or mischievous attacks. A malicious actor with sufficient technical knowhow conceivably could hack into an SDC and cause the vehicle to have a severe collision, or even worse, cause simultaneous crashes of multiple SDCs in a given city.

Pranksters could disable or deceive sensors and render the vehicle unable to move. “A self-driving car is a collection of networked computers and sensors wirelessly connected to the outside world. Keeping the systems safe from intruders who may wish to crash cars—or turn them into weapons—may be the most daunting challenge facing autonomous driving” [17].

Similarly, two academic cybersecurity specialists in a World Economic Forum article titled “This is the major flaw with driverless vehicles that no one is talking about,” state “there are three main reasons why cars are becoming vulnerable to cyberattacks:”

First, the different systems that make up a car are increasingly designed to work together to improve their efficiency and so they all need to be able to communicate, as well as being connected to a central control. Adding autonomous systems that make cars partly or fully self-driving means the vehicles also have to connect to other cars and infrastructure on the road.

But this opens up what was traditionally a closed system to outside, possibly malicious influences. For example, we’ve seen demonstrations of attacks using cars’ Bluetooth, Wi-Fi and radio frequency on passive key entry systems, which all create possible entry points for hackers.

Second, more features and functionality in cars mean more software and more complexity. A single vehicle now uses millions of lines of code, put together in different ways in different components from different manufacturers. This makes it hard for security testers to know where to look, and hard for auditors to check [that] a car complies with the rules. If the software recently used by Volkswagen to circumvent emissions limits had been a malicious virus, it may have taken months or years to find the problem.

Finally, the volume and variety of the data and content stored and used in a vehicle is ever increasing [for example,] information about the driver’s usual routes...Such a hoard of information would be very attractive to cyber criminals [59].

Recognizing the threat, Waymo has devoted considerable resources to cybersecurity. Critical functions such as steering and braking are isolated from outside communication. Computational systems for determining vehicle motion are inaccessible from the vehicle's wireless connections. Wireless communication between vehicles and the Waymo operations center are encrypted [7].

GM has also recognized the need to protect its vehicles from malicious interference and has introduced a number of design features to thwart cyberattacks [12].

6.10 Ethical and Legal Questions

In addition to technical issues that raise concern about the widespread deployment of SDCs, the ethical and legal questions listed below exist. Arriving at satisfactory answers to these questions may take years of legislation and litigation, especially given that motor vehicle rules are a state—not federal—responsibility and thus fifty different legislation bodies must be dealt with.

1. Should SDCs containing flaws be widely deployed if the total number of deaths from all auto accidents decreased significantly, even though the deaths caused by the SDCs increased? Rand Corporation researchers Nidhi Kalra and David Groves argue that tens of thousands of lives could be saved over a period of many years if SDCs were deployed that were only ten percent safer than human-operated vehicles.

Many are looking to *highly automated vehicles (HAVs)*—vehicles that drive themselves some or all of the time—to mitigate the public health crisis posed by motor vehicle crashes. But a key question for the transportation industry, policymakers, and the public is how safe HAVs should be before they are allowed on the road for consumer use. From a utilitarian standpoint, it seems sensible that HAVs should be allowed on US roads once they are judged safer than the average human driver so that the number of lives lost to road fatalities can begin to be reduced as soon as possible. Yet, under such a policy, HAVs would still cause many crashes, injuries, and fatalities—albeit fewer than their human counterparts. This may not be acceptable to society, and some argue that the technology should be significantly safer or even nearly perfect before HAVs are allowed on the road. Yet waiting for HAVs that are many times safer than human drivers misses opportunities to save lives. It is the very definition of allowing perfect to be the enemy of good [37].

Reasoning along similar lines, Sergey Brin, the co-founder of Google, has said, "We don't claim that the cars are going to be perfect. Our goal is to beat human drivers" [60]. But it is not certain that merely beating human drivers would be enough. Will the public accept, say, a fifty percent reduction in highway deaths, if the remaining deaths are attributable to software and sensor errors in SDCs? Robots may be held to a higher ethical standard than people, says Toyota's Gill Pratt.

Society tolerates a significant amount of human error on our roads. We are, after all, only human. On the other hand, we expect machines to perform much better. . . . Humans have shown nearly zero tolerance for injury or death caused by flaws in a machine [37].

2. Who is liable and who must carry motor vehicle insurance—owner, manufacturer, operator (of, for example, a robotaxi company), or driver (of a Level 3 SDC)? The US Department of Transportation has produced a document, “Federal Automated Vehicles Policy,” that describes a framework for assigning liability [61].

3. “Can [SDCs] even survive a tort system like ours,” given that “software like that for self-driving cars will never be capable of testing comprehensively for all conceivable states and configurations?” asks *Wall Street Journal* columnist Holman Jenkins [62]. Tort lawyers would relish the possibility of lawsuits against deep-pocketed SDC corporations if large numbers of accidents could be attributed to errors in vehicle software and sensors. The aforementioned experience of agribusiness developing GMOs shows what can happen.

4. Is passenger privacy protected and who controls personal data? During operation of an SDC, information about the time, origin, and destination of all trips will be routinely transmitted from the vehicle to the vehicle operations center. This raises obvious questions about who owns the information, whether it is secure, and whether it can be accessed by law-enforcement agencies or for commercial use.

6.11 Effect of Concerns Considered as a Whole

It seems reasonable to imagine that—with enough time, money, and ingenuity—any *one* of the concerns described above could be eliminated. But going from the elimination of a single concern to the elimination of *all* of them is a huge jump in complexity. Given the sheer number of concerns, their depth, and the fact that any one of them could alone delay for many years or even completely prevent the introduction of SDCs, predictions about SDCs revolutionizing transportation within the next five or even ten years seem overly optimistic. Of course, large corporations have made huge investments in SDC development and will certainly try to defend these investments. These companies have the financial resources to hire talented engineers, AI specialists, attorneys, public-relations staff, etc. and know how to influence the political process through lobbying, but it remains to be seen if the companies’ technical, legislative, and publicity efforts will be sufficient.

7. The Future of Self-Driving Cars

[A] free-range Level 5 autonomous car is a very long way out. – Waymo CEO John Krafcik [63]

[Claims of the imminent widespread introduction of SDCs] is where the hype has gotten far out of step with the reality of what the technology is capable of doing ... We're not going to see it in a leap. It's going to be a series of gradual step-by-step improvements. So the idea that there's going to be a big leap and all of a sudden this Nirvana's going to arrive is nonsense. This is going to be a long slog through lots of generations of incremental technology, and the people who claim that they've got a silver bullet, and it's going to solve all the world's problems are either fools or charlatans. – Steven Shladover, researcher at Partners for Advanced Transportation Technology at the University of California, Berkeley [64]

7.1 Gartner's Hype Cycle

The business advisory firm, Gartner, Inc., has formulated a “hype cycle” concept that describes the typical progress of a major new technology [65]. The cycle begins with an “innovation trigger” that involves a real or potential technological breakthrough promising great benefits. The trigger then creates grossly inflated expectations and attracts large investments. But as research and development proceed, unforeseen problems and limitations begin to emerge, and the inflated expectations disappear.

Disappointed managers and investors enter a “trough of disillusionment.” Interest and funding wane, some companies give up or go out of business, and product introduction dates are postponed. If the technology still has promise, a slow steady effort may ultimately lead to the “plateau of productivity.” The technology is useful and productive, but generally nowhere near the previous peak of inflated expectations.

For driverless vehicles, the innovation trigger occurred around 2007 and consisted of two factors. First, the technology was ripe: technical breakthroughs had recently occurred in AI and laser-based sensors (LiDAR) while robotics had already achieved an advanced state of development. Second, in 2007 the US government's Defense Advanced Research Projects Agency (DARPA) sponsored an event called the “DARPA Urban Challenge,” a competition consisting of making an autonomous vehicle that could navigate a specified course laid out in an abandoned Air Force base.

Unlike two earlier DARPA Challenges that involved rural driving only, the Urban Challenge involved navigating through intersections, merging into traffic, parking in a parking lot, and handling other urban road situations. The result, in *Wired* writer Alex Davies' words, was that

“DARPA created a community eager to crack the self-driving car problem” [66] and “unofficially kicked off today’s self-driving technology initiatives” [1]. The competition attracted the interest of top talent in robotics, sensor technology, and artificial intelligence. The first step of the hype cycle—grossly inflated expectations and large investments—was taken. Auto companies and many companies making sensors and applying AI invested billions of dollars in SDC research and development.

Today SDC technology appears to be entering the trough of disillusionment [21]. Many companies and individuals have failed to deliver on what are now recognized as overly optimistic promises. In 2012, Google’s CEO Sergey Brin promised that self-driving cars would be available to everyone in five years [67]. In 2015, Google said that in five years an autonomous car would be ready. In 2014, Elon Musk made a similar five-year prediction. Volvo said in a 2014 announcement that it would distribute one hundred SDCs to families in Gothenburg, Sweden; in 2017, this was changed to a distribution date of 2021. Ford’s CEO felt it necessary to dampen expectations for the Ford SDCs to be introduced in 2021 by remarking, “But the nature of the romanticism by everybody in the media about how this robot works is overextended right now” [21].

What, then, can be expected from current SDC research and development? Here is an answer provided by *Wired Magazine*’s Aarian Marshall, who has written extensively on SDCs:

Okay, so you won’t get a fully autonomous car in your driveway anytime soon. Here’s what you can expect, in the next decade or so: Self-driving cars probably won’t operate where you live, unless you’re the denizen of a very particular neighborhood in a big city like San Francisco, New York or Phoenix. These cars will stick to specific, meticulously mapped areas. If, by luck, you stumble on an autonomous taxi, it will probably force you to meet it somewhere it can safely and legally pull over, instead of working to track you down and assuming hazard lights grant it immunity wherever it stops.

The cars will be impressive, but not infallible. They won’t know how to deal with all road situations and weather conditions.

You may well forget about self-driving cars for a few years. You might joke with your friends about how silly you were to believe the hype. But the work will go on quietly, in the background. The news will quiet down as developers dedicate themselves to precise problems, tackling the demons in the details.

The good news is that there seems to be enough momentum to carry this new industry out of the trough and onto what Gartner calls the plateau of productivity [21].

7.2 Aiming for Less Than Level 5

Much of the present paper has been devoted to questioning and deflating some of the more exaggerated claims being made for SDCs. But it should be emphasized that present-day SDC research still may be valuable even though Level 5 or even Level 4 vehicles have not been achieved. Research on sensors, AI, situation awareness, movement prediction, advanced road mapping, vehicle-to-vehicle communication, driver warning, imminent-collision detection, lane tracking, lane departure alerts, image recognition, and other SDC technologies should eventually result in much *safer human-driven* vehicles. A super safe Level 2 vehicle would not fulfill the science-fiction-like predictions that have been envisioned for Level 5 vehicles but nevertheless could save many lives. Such vehicles would also be much more readily accepted by the public. The billions of dollars invested and the huge effort of the talented people in the field would not be wasted.

Several prominent SDC researchers have recognized the importance of what can be achieved by aiming for goals less than Level 5. Huei Peng, the director of Mcity, the University of Michigan's autonomous- and connected-vehicle lab, is described as presenting the position of the traditional automakers when he says:

Instead of aiming for the full autonomy moon shot, they are trying to add driver-assistance technologies, “make a little money,” and then step forward toward full autonomy. It's not fair to compare Waymo, which has the resources and corporate freedom to put a \$70,000 laser range finder on top of a car, with an automaker like Chevy that might see \$40,000 as its price ceiling for mass-market adoption. GM, Ford, Toyota, and others are saying “Let me reduce the number of crashes and fatalities and increase safety for the mass market.” Their target is totally different. We need to think about the millions of vehicles, not just a few thousand [68].

Similarly, Toyota's Gill Pratt rejects pursuit of the “full autonomy moon shot”:

[I]t's important to not say, “We want to save lives therefore we have to have driverless cars.” In particular, there are tremendous numbers of ways to support a human driver and to give them a kind of blunder prevention device which sits there, inactive most of the time, and every once in a while, will first warn and then, if necessary, intervene and take control. The system doesn't need to be competent at everything all of the time. It needs to only handle the worst cases [2].

Elsewhere, Pratt has been described as “championing ‘guardian angel’ technology that could find the best evasive strategies in an instant if trouble looms” [69].

MIT's John Leonard also advocates a guardian angel system:

Until cars can be 100 percent autonomous—which Google is pursuing—Leonard advocates what he calls a “guardian angel system.” In it, a human has to pay attention the entire trip; auto-driving kicks in only when he makes a mistake or when an accident looks likely [4].

7.3 What May Appear First

Fleets of robotaxis and delivery vehicles are usually mentioned as the first applications of SDC technology to general-purpose driving. Ford is launching a fleet of pizza-delivery vehicles in Miami. Ford and GM plan to launch fleets of robotaxis in various cities, and Waymo already has [Figure 6].



Figure 6. Waymo Chrysler Pacifica Hybrid minivan used as robotaxi in Chandler, Arizona.

Fleets offer many advantages for SDC developers because they have complete control over modifications, software updates, inspections, fueling, and maintenance. In addition, because the developers are the owners and will not sue themselves, the number of expected lawsuits over accidents will be reduced. Also, using SDCs for delivering goods has the advantage that no passenger in the SDC will be injured in an accident [12, 63, 70, and 71].

7.4 Last Word

Perhaps the last word about the future of SDCs in the US should come from a source that has no financial stake in the matter. The NHTSA webpage on Automated Vehicles for Safety contains the following Frequently Asked Question and answer:

Question: When will self-driving vehicles be available?

Answer: Automated or “self-driving” vehicles are a future technology rather than one that you’ll find in a dealership tomorrow or in the next few years. A variety of technological hurdles have to be cleared, and other important issues must be addressed before these types of vehicles can be available for sale in the United States [72].

References

1. Salesky, Bryan. “A Decade after DARPA: Our View on the State of the Art in Self-Driving Cars.” *Medium*. October 16, 2017. Accessed February 23, 2018. <https://medium.com/self-driven/a-decade-after-darpa-our-view-on-the-state-of-the-art-in-self-driving-cars-3e8698e6afe8>
2. Ackerman, Evan. “Toyota's Gill Pratt on Self-Driving Cars and the Reality of Full Autonomy.” *IEEE Spectrum*. January 23, 2017. Accessed April 15, 2018. <https://spectrum.ieee.org/cars-that-think/transportation/self-driving/toyota-gill-pratt-on-the-reality-of-full-autonomy>
3. Hollister, Sean. “Elon Musk Describes the Future of Self-Driving Cars.” *Gizmodo*. March 18, 2018. Accessed March 31, 2018. <https://gizmodo.com/elon-musk-describes-the-future-of-self-driving-cars-1692076449>
4. Sparapani, Jason. “Driverless cars not a 'solved problem,' says MIT professor.” TotalCIO, the blog companion to SearchCIO.com. February 9, 2016. Accessed on January 13, 2018. <https://searchcio.techtarget.com/blog/TotalCIO/Driverless-cars-not-a-solved-problem-says-MIT-professor>
5. Harris, Mark. “Google Has Spent Over \$1.1 Billion on Self-Driving Tech.” *IEEE Spectrum*. September 15, 2017. Accessed February 20, 2018. <https://spectrum.ieee.org/cars-that-think/transportation/self-driving/google-has-spent-over-11-billion-on-selfdriving-tech>
6. “Ford invests in Argo AI, a new artificial intelligence company, in drive for autonomous vehicle leadership.” Ford Media Center. February 10, 2017. Accessed 3/31/2018. <https://media.ford.com/content/fordmedia/fna/us/en/news/2017/02/10/ford-invests-in-argo-ai-new-artificial-intelligence-company.html>
7. Ramsey, Mike and MacMillan, Douglas. “Carnegie Mellon Reels After Uber Lures Away Researchers.” *Wall Street Journal*. May 31, 2015.
8. “On the Road to Fully Self-Driving.” First Safety Report on Waymo’s fully self-driving technology. Undated. Accessed October 30, 2018. <https://waymo.com/safety/>
9. Brooks, Rodney. “Edge Cases For Self Driving Cars.” Post on Rodney Brooks’ blog, “Robots, AI, and other stuff.” June 17, 2017. Accessed May 7, 2018. <http://rodneybrooks.com/edge-cases-for-self-driving-cars/>
10. Kouri, Andrew. “Where Self-Driving Cars Fall Short, and How We Can Make Them Safer.” *Medium*. April 13, 2018. Accessed May 1, 2018. <https://medium.com/lvl5/where-self-driving-cars-fall-short-and-how-we-can-make-them-safer-aa59dc84a624>

11. Waymo Team. "Building maps for a self-driving car." *Medium*. March, 2016. Accessed February 18, 2018. <https://medium.com/waymo/building-maps-for-a-self-driving-car-723b4d9cd3f4>
12. "2018 Self-Driving Safety Report." General Motors. 2018. Accessed November 2, 2018. <https://www.gm.com/content/dam/company/docs/us/en/gmcom/gmsafetyreport.pdf>
13. Metz, Rachel. "Baidu Sees Maps for Self-Driving Cars as Bigger Business Than Web Search." *MIT Technology Review*. January 9, 2018. Accessed November 2, 2018. <https://www.technologyreview.com/s/609936/baidu-sees-maps-for-self-driving-cars-as-bigger-business-than-web-search/>
14. "The CIA World Factbook." Undated. Accessed 5-2-2018. <https://www.cia.gov/library/publications/the-world-factbook/fields/2085.html>
15. Newman, Peter. "A new Apple patent hints that its self-driving cars might minimize map usage." *Business Insider*. December 27, 2017. Accessed May 7, 2018. <http://www.businessinsider.com/new-apple-patent-self-driving-cars-minimize-map-usage-2017-12>
16. Ross, Phillip E. "Self-Driving Cars Won't Need Accurate Digital Maps, MIT Experts Say." *IEEE Spectrum*. May 7, 2018. Accessed November 2, 2018. <https://spectrum.ieee.org/cars-that-think/transportation/self-driving/mit-experts-selfdriving-cars-wont-need-accurate-digital-maps>
17. Markoff, John. "A Guide to Challenges Facing Self-Driving Car Technologists." *New York Times*. June 7, 2017.
18. Bergen, Mark. "Nobody Wants to Let Google Win the War for Maps All Over Again." *Bloomberg*. February 21, 2018. Accessed April 5, 2018. <https://medium.com/bloomberg/nobody-wants-to-let-google-win-the-war-for-maps-all-over-again-b935312066da>
19. Waymo Team. "Building maps for a self-driving car." *Medium*. December 13, 2016. Accessed February 18, 2018. <https://medium.com/waymo/building-maps-for-a-self-driving-car-723b4d9cd3f4>
20. "GPS Accuracy." GPS.gov. Undated. Accessed November 2, 2018. <https://www.gps.gov/systems/gps/performance/accuracy/>
21. Marshall, Aarian. "After Peak Hype, Self-Driving Cars Enter the Trough of Disillusionment." *Wired*. December 29, 2017. Accessed January 15, 2018. <https://www.wired.com/story/self-driving-cars-challenges/>
22. Frankston, Bob. Commenter on Rodney Brooks' blog, "Robots, AI, and other stuff". July 22, 2017. Accessed May 7, 2018. <http://rodneybrooks.com/edge-cases-for-self-driving-cars/>
23. "Preparing for the Future of Transportation Automated Vehicles 3.0." US Department of Transportation. Undated. Accessed November 3, 2018. <https://www.transportation.gov/av/3/preparing-future-transportation-automated-vehicles-3>

24. Abuelsamid, Sam. "SAE International Ready To Tackle Automated Vehicle Safety Testing Standards." *Forbes*. August 1, 2018. Accessed November 3, 2018. <https://www.forbes.com/sites/samabuelsamid/2018/08/01/sae-international-ready-to-tackle-automated-vehicle-safety-testing-standards/>
25. Davies, Alex. "The Very Human Problem Blocking the Path to Self-Driving Cars." *Wired*. January 1, 2017. Accessed January 7, 2018. <https://www.wired.com/2017/01/human-problem-blocking-path-self-driving-cars/>
26. Higgins, Tim. "Tesla, Uber Deaths Raise Questions About the Perils of Partly Autonomous Driving." *Wall Street Journal*. April 2, 2018.
27. Davies, Alex. "Nissan's Path to Self-Driving Cars? Humans in Call Centers." *Wired*. January 5, 2017. Accessed January 7, 2018. <https://www.wired.com/2017/01/nissans-self-driving-teleoperation/>
28. Bigelow, Pete. "What We Can Learn about Autonomous Progress from California Disengagement Reports." *Car and Driver*. February 5, 2018. Accessed March 27, 2018. <https://blog.caranddriver.com/what-we-can-learn-about-autonomous-progress-from-california-disengagement-reports/>
29. Quain, John R. "When Self-Driving Cars Can't Help Themselves, Who Takes the Wheel?" *New York Times*. May 15, 2018.
30. Lee, Timothy B. "Fully driverless cars could be months away." *Ars Technica*. October 3, 2018. Accessed January 12, 2018. <https://arstechnica.com/cars/2017/10/report-waymo-aiming-to-launch-commercial-driverless-service-this-year/>
31. "A Matter of Trust (Ford's Approach to Developing Self-Driving Vehicles)." Ford Media Center. Undated. Accessed November 3, 2018. https://media.ford.com/content/dam/fordmedia/pdf/Ford_AV_LLC_FINAL_HR_2.pdf
32. Castellanos, Sara. "AI Guru Andrew Ng on the Job Market of Tomorrow." *Wall Street Journal*. October 26, 2018.
33. "Google Input to NHTSA's Development of Guidelines for the Safe Deployment and Operation of Automated Vehicle Safety Technologies." Undated. Accessed November 4, 2018. <https://drive.google.com/file/d/0Byq-WVq3Y4HEcWVvVjc3TXEwOEE/view>
34. Brownlee, Jason. "What is Deep Learning?" *Machine Learning Mastery*. August 16, 2018. Accessed November 18, 2018. <https://machinelearningmastery.com/what-is-deep-learning/>
35. Dale, Nick. "Deep learning for autonomous cars." *Verne Global*. March 22, 2018. Accessed November 20, 2018. <https://verneglobal.com/blog/deep-learning-for-autonomous-cars>
36. Zawadski, Jan. "The State of Self-Driving Cars for Everybody." *Towards Data Science*. June 1, 2018. Accessed June 30, 2018. <https://towardsdatascience.com/the-state-of-self-driving-cars-for-everybody-29446c1c2e2c>
37. Kalra, Nidhi, and Groves, David G. "The Enemy of Good: Estimating the Cost of Waiting for Nearly Perfect Automated Vehicles?" Santa Monica, Calif.: RAND

- Corporation, RR-2150-RC, 2017. Accessed July 31, 2018.
http://www.rand.org/pubs/research_reports/RR2150.html
38. Kalra, Nidhi and Paddock, Susan. "Driving to Safety: How Many Miles of Driving Would It Take to Demonstrate Autonomous Vehicle Reliability?" Santa Monica, Calif.: RAND Corporation, RR-1478-RC, 2016. Accessed September 12, 2017:
http://www.rand.org/pubs/research_reports/RR1478.html
39. Bergstein, Brian. "The Great AI Paradox." *MIT Technology Review*. December 15, 2017. Accessed June 10, 2018. <https://www.technologyreview.com/s/609318/the-great-ai-paradox/>
40. Knight, Will. "Finally, a Driverless Car with Some Common Sense." *MIT Technology Review*. September 20, 2017. Accessed July 29, 2018.
<https://www.technologyreview.com/s/608871/finally-a-driverless-car-with-some-common-sense/>
41. Bandom, Russell. "Self-Driving Cars are Headed Toward an AI Roadblock." *The Verge*. July 3, 2018. Accessed on November 18, 2018.
<https://www.theverge.com/2018/7/3/17530232/self-driving-ai-winter-full-autonomy-waymo-tesla-uber>
42. Pontin, Jason. "Greedy, Brittle, Opaque, and Shallow: The Downsides to Deep Learning." *Wired*. February 2, 2018. Accessed November 18, 2018.
<https://www.wired.com/story/greedy-brittle-opaque-and-shallow-the-downsides-to-deep-learning/>
43. Ghose, Tia. "Self-Driving Cars: 5 Problems That Need Solutions." *Live Science*. May 14, 2015. Accessed January 13, 2018. <https://www.livescience.com/50841-future-of-driverless-cars.html>
44. Knight, Will. "What to Know Before You Get In a Self-driving Car." *MIT Technology Review*. October 18, 2016. Accessed January 13, 2018.
<https://www.technologyreview.com/s/602492/what-to-know-before-you-get-in-a-self-driving-car/>
45. Cain, Patrick. "We may never see self-driving cars anywhere it snows. Here's why." *Global News*. January 11, 2017. Accessed November 30, 2018.
<https://globalnews.ca/news/3165122/we-may-never-see-self-driving-cars-anywhere-it-snows-heres-why/>
46. MIT Technology Review Insights. "Autonomous Vehicles: Are You Ready for the New Ride?" *MIT Technology Review*. November 9, 2017. Accessed January 11, 2018.
<https://www.technologyreview.com/s/609450/autonomous-vehicles-are-you-ready-for-the-new-ride/>
47. Dolgov, Dmitri. "Google I-O Recap-- Turning self-driving cars from science fiction into reality with the help of AI." *Medium*. Accessed May 10, 2018.
<https://medium.com/waymo/google-i-o-recap-turning-self-driving-cars-from-science-fiction-into-reality-with-the-help-of-ai-89dded40c63>

48. “How old are US nuclear power plants?” US Energy Information Administration. Undated. Accessed September 18, 2018. <https://www.eia.gov/tools/faqs/faq.php?id=228&t=21>
49. “Genetically Engineered Crops: Experiences and Prospects.” National Academies of Science, Engineering, and Medicine; Board on Agriculture and Natural Resources; Division on Earth and Life Studies (Report in Brief). May, 2016. Accessed November 4, 2018. <https://nas-sites.org/ge-crops/2016/05/16/report-in-brief/>
50. Burian, Heather. “Blumenthal Wants More Safety Provisions for Self-Driving Cars.” NBC Connecticut. April 3, 2018. Accessed May 4, 2018. <https://www.nbcconnecticut.com/news/local/Blumenthal-Says-More-Safeguards-Needed-for-Self-Driving-Cars-478705893.html>
51. Wickham, Shawne K. “Self-driving cars face a NH reality.” *New Hampshire Sunday News*. April 14, 2018. Accessed May 5, 2018. <http://www.newhampshire.com/Self-driving-cars-face-a-NH-reality>
52. “Driverless Testing and Public Use Rules for Autonomous Vehicles Approved.” California Department of Motor Vehicles Office of Public Affairs. February 26 2018. Accessed May 4, 2018. https://www.dmv.ca.gov/portal/dmv/detail/pubs/newsrel/2018/2018_17
53. Aupperlee, Aaron. “Pennsylvania lawmakers to consider self-driving regulations this spring.” *Trib-Live*. March 28, 2018. Accessed May 4, 2018. <http://triblive.com/business/technology/13474205-74/pennsylvania-lawmakers-to-consider-self-driving-regulations-this-spring>
54. Barry, Keith. “Self-Driving Test Cars Should Be Treated Like Inexperienced Teen Drivers, Experts Say.” *Consumer Reports*. March 28, 2018. Accessed May 4, 2018. <https://www.consumerreports.org/autonomous-driving/self-driving-test-cars-should-be-treated-like-inexperienced-teen-drivers-experts-say/>
55. Marshall, Aarian. “My Herky-Jerky Ride in General Motors’ Ultra-Cautious Self Driving Car.” *Wired*. January 29, 2017. Accessed April 15, 2018. <https://www.wired.com/story/ride-general-motors-self-driving-car/?mbid=BottomRelatedStories>
56. Brooks, Rodney. “The Big Problem With Self-Driving Cars Is People.” *IEEE Spectrum*. July 27, 2017. Accessed January 13, 2018. <https://spectrum.ieee.org/transportation/self-driving/the-big-problem-with-selfdriving-cars-is-people>
57. Sabur, Rozina. “Driverless cars will cause congestion.” *Telegraph*. January 6, 2017. Accessed April 23, 2018. <https://www.telegraph.co.uk/news/2017/01/06/driverless-cars-will-cause-congestion-britains-roads-worsen/>
58. Wilson, Mark. “The fate of self-driving cars hangs on a \$7 trillion design problem.” *Fast Company*. December 5, 2018. Accessed 12/21/18. <https://www.fastcompany.com/90275407/the-fate-of-self-driving-cars-hangs-on-a-7-trillion-design-problem>

59. Shaikh, Siraj Ahmed. "This is the major flaw with driverless vehicles that no one is talking about." *World Economic Forum*. August 30, 2017. Accessed January 13, 2018. <https://www.weforum.org/agenda/2017/08/you-haven-t-thought-of-one-of-the-biggest-problems-with-driverless-cars>
60. Associated Press. "Google founder defends accident records of self-driving cars." *Los Angeles Times*. June 3, 2015. Accessed November 4, 2018. <http://www.latimes.com/business/la-fi-google-cars-20150603-story.html>
61. "Accelerating the Next Revolution in Roadway Safety." NHTSA Federal Automated Vehicles Policy. September 2016. Accessed November 4, 2018. <https://www.transportation.gov/AV/federal-automated-vehicles-policy-september-2016>
62. Jenkins, Holman. "Big Tech Takes Us to the Unknown." *Wall Street Journal*. March 27, 2018.
63. Krause, Reinhardt. "How Google Can Race Ahead Of The Pack In Self-Driving Cars." *Investor's Business Daily*. April 1, 2018. Accessed April 28, 2018. <https://www.investors.com/news/technology/self-driving-car-waymo/>
64. "Interview with Steven Shladover." *The Why*. February 7, 2018. Accessed November 5, 2018. <https://www.youtube.com/watch?v=qNsMbcGT790>
65. "Gartner Hype Cycle." Gartner. Undated. Accessed November 4, 2018. <https://www.gartner.com/technology/research/methodologies/hype-cycle.jsp>
66. Davies, Alex. "Inside the Races That Jump-Started the Self-Driving Car." *Wired*. November 10, 2017. Accessed April 15, 2018. <https://www.wired.com/story/darpa-grand-urban-challenge-self-driving-car/>
67. Condliffe, Jamie. "2021 May Be the Year of the Fully Autonomous Car." *MIT Technology Review*. August 17, 2016. Accessed November 4, 2018. <https://www.technologyreview.com/s/602196/2021-may-be-the-year-of-the-fully-autonomous-car/>
68. Madrigal, Alexis, C. "Inside Waymo's Secret World for Training Self-Driving Cars." *The Atlantic*. August 23, 2017. Accessed April 28, 2018. <https://www.theatlantic.com/technology/archive/2017/08/inside-waymos-secret-testing-and-simulation-facilities/537648/>
69. Anders, George. "Toyota Makes a U-Turn on Autonomous Cars." *MIT Technology Review*. June 21, 2016. Accessed January 11, 2018. <https://www.technologyreview.com/s/601504/toyota-makes-a-u-turn-on-autonomous-cars/>
70. Davies, Alex. "Ford Says it'll Have a Fleet of Fully Autonomous Cars in Just 5 Years." *Wired*. August 6, 2016. Accessed January 11, 2018. <https://www.wired.com/2016/08/ford-autonomous-vehicles-2021/>
71. Bomey, Nathan. "Ford picks Miami to launch self-driving vehicle Domino's pizza delivery service." *USA Today*. February 27, 2018. Accessed November 4, 2018.

<https://www.usatoday.com/story/money/cars/2018/02/27/ford-miami-dominos/377244002/>

72. “Automated Vehicles for Safety.” NHTSA. Undated. Accessed November 4, 2018.
<https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety>

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Appendix A. Scenario types used by Google Self-Driving Team

(Excerpted from “Google Input to NHTSA’s Development of Guidelines for the Safe Deployment and Operation of Automated Vehicle Safety Technologies”)

Appendix: Scenario types used by Google Self-Driving Vehicle Team

The following scenarios are used by Google's self-driving vehicle development team. They are some of the scenarios we use to ensure our vehicles are capable of operating safely in the reasonably foreseeable scenarios that could present a safety hazard. We try to ensure objectivity in each scenario. These scenarios are part of a comprehensive system safety evaluation process that also includes other analysis such as simulation and public road driving, along with a broad set of structured tests that we conduct at our test facility. The following types of scenarios are designed to ensure our vehicles have:

1. Basic Behavioral Competencies

We believe that our fully self-driving vehicles should be able to successfully demonstrate competency in a variety of reasonably foreseeable traffic situations that are within the vehicle's *Operational Design Domain* (ODD), i.e., the specific operating conditions under which the driving automation system or feature is designed to function. An ODD may include geographic, roadway, environmental, traffic, speed, and/or temporal limitations. For example, if the vehicle's ODD specifies that operations in snow or on routes with railroad crossings are excluded, our vehicle would not be expected to demonstrate those competencies. Instead, our vehicles should be capable of readily identifying such conditions and taking appropriate action as soon as they appear.

2. Safe responses to hazards unique to self-driving technology

We anticipate that all self-driving vehicles could entail certain hazards that are unique to self-driving due to the vehicle's complete or partial reliance on the sensors and computers that make up the self-driving system. Therefore, we ensure that our self-driving vehicles respond properly to factors such as sensor failure, system failure, power failure, and safety-critical faults.

3. Avoidance or mitigation of common crash scenarios

Certain types of crashes account for a substantial percentage of all crashes. Avoiding or mitigating those kinds of crashes, therefore, is an important goal for our vehicle development program. NHTSA recently published data showing the distribution of pre-crash scenarios.⁷ Four scenarios accounted for the vast majority of crashes:

- 29 percent were rear-end crashes
- 24 percent of the vehicles were turning or crossing at intersections just prior to the crashes
- 19 percent of the vehicles ran off the edge of the road
- 12 percent involved vehicles changing lanes

Therefore, these scenarios figure prominently in the evaluation of our self-driving vehicles.

⁷ [Docket No. NHTSA-2015-0119] New Car Assessment Program (NCAP), December 8, 2015, <<http://goo.gl/plFfoH>>

| Categories | Scenario types |
|---|---|
| <u>Behavioral competence in common traffic situations.</u> | If any competency is outside the vehicle's operational design domain, that should be documented and the vehicle's ability to recognize and adhere to the design limitations should be demonstrated. |
| Detection and Response to Safety Signs, Traffic Signals and Emergency Warnings | |
| <i>Demonstrate appropriate response to traffic signs, signals, and emergency warnings</i> | |
| Signs | |
| | Self-driving car (SDC) approaches stop sign at posted speed |
| | SDC approaches temporary stop sign at posted speed |
| | SDC approaches hand-held stop sign at posted speed |
| | SDC approaches yield point at posted speed |
| | SDC approaches speed limit sign |
| | SDC approaches school zone sign |
| | SDC approaches special speed restriction sign |
| | SDC approaches active work zone sign |
| | SDC approaches roadway directional signs (One-Way, Do Not Enter, etc.) |
| | SDC approaches "Lane Ends" sign |
| Traffic signals (lights) | |
| SDC approaches each of these signals: | |
| | Vertical Signal Alignment |
| | Horizontal Signal Alignment |
| | Flashing red |
| | Flashing yellow |
| | Blackout |
| | LED Pedestrian Signal |
| School bus - Stopped in same or opposite direction | |
| | SDC approaches stopped school bus |

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|---|---|
| | SDC approaches moving school bus while bus activates hazards with intent to stop for pickup/dropoff |
| Emergency Vehicles (EVs) using lights and/or sirens while approaching or stopped | |
| | SDC approaches intersection: EV approaches from behind, intention to pass SDC |
| | SDC moving with no intersection ahead: EV approaches from behind, intention to pass SDC |
| | SDC approaches EV using lights while stopped |
| Work Zones | |
| | SDC approaches work zone on straight road |
| | SDC approaches work zone on curved road |
| Lane shift/closure | |
| | SDC approaches lane closure/shift on straight road |
| | SDC approaches lane closure/shift on curved road |
| Hand signals from law enforcement or work crews | |
| | SDC approaches law enforcement officer giving hand signals |
| | SDC approaches work crew giving hand signals |
| Railroad Crossing | |
| | SDC approaches crossing with warning devices (flashing lights, bell, and/or crossing gates) activated |
| | SDC approaches unprotected crossing (no lights or gates) |
| Typical Forward Movements | |
| <i>Demonstrate ability to perform movement safely.</i> | |
| Turns | |
| SDC approaches and turns at each of the following types of intersections: | |
| | Signalized intersection: make left turn with arrow |
| | Signalized intersection: make left turn where no arrow |

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| | Signalized intersection: Simultaneous protected left turns (2 designated parallel turn lanes) |
| | Signalized intersection: Simultaneous protected left turns (1 oncoming turn lane) |
| | Stop Sign intersection: 2 -way stop |
| | Stop Sign intersection: 4- way stop |
| | Green light: make right turn |
| | Red light: make right turn if permitted |
| | Non-signalized intersection: make right turn |
| | Non-signalized intersection: make left turn |
| Lane changes | |
| SDC makes each lane change described below: | |
| | Right lane change |
| | Left lane change |
| | Lane change from stop (zero-speed lane change) |
| | Lane change cancellation |
| | Emergency or fault-induced lane change |
| Pullover | |
| | SDC pulls over to right to pick up or drop off passenger |
| | SDC pulls over based on fault-induced emergency |
| | SDC pulls over in response to emergency vehicle using siren and/or lights |
| Transitions from roadway type | |
| | SDC exits freeway to arterial road |
| | SDC enters freeway from arterial road / on-ramp |
| Merge | |
| | SDC allows merging traffic to enter lane |
| | SDC merges into converging lanes |
| | SDC merges from slip lane |
| Traffic circles (Roundabout) | |
| | SDC approaches and travels through roundabout |
| | |

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| Movements Involving Reverse Gear | |
| <i>Demonstrate ability to perform movement safely</i> | |
| | SDC performs simple backing movement (straight path/curved path) |
| | SDC performs backing movement with person/object behind |
| | SDC performs three-point turn |
| | |
| Recognition and Avoidance of People, Vehicles and Objects | |
| <i>Demonstrate ability to detect and avoid other road users and objects</i> | |
| Vehicles | |
| | SDC follows vehicle and maintains safe longitudinal distance at different speeds while also providing safe lateral spacing from vehicles in adjacent lanes |
| | SDC approaches vehicle entering road from driveway |
| | SDC accommodates vehicle cutting into its lane |
| | SDC moving forward does not move into lane occupied by motorcycle traveling parallel to SDC and provides adequate room. |
| Pedestrians | |
| | SDC on straight road approaches pedestrian crossing perpendicularly (right) |
| | SDC on straight road approaches pedestrian crossing perpendicularly (left) |
| | SDC makes right turn, pedestrian in crosswalk |
| | SDC makes left turn, pedestrian in crosswalk |
| | SDC approaches pedestrian walking in road, parallel to SDC's travel |
| | SDC approaches pedestrian not in crosswalk but in path (jaywalker) |
| | SDC approaches and passes pedestrian exiting parked vehicle |

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| | SDC approaches and passes pedestrian standing near vehicles |
| | |
| Cyclists | |
| | SDC moves forward, parallel to cyclist in designated bike lane |
| | SDC moves forward, parallel to cyclist in lane not designated as bike lane |
| | With cyclist traveling in parallel lane, SDC executes right turn with cyclist approaching |
| | SDC approaches cyclist crossing SDC path |
| Animals and other objects | |
| | SDC approaches animal in road |
| | SDC approaches large debris in road |
| | |
| Safe response to hazards unique to AV technology | |
| <i>Demonstrate ability to detect condition and take appropriate response</i> | |
| Conditions involving system or component failure or fault | Failure or fault is simulated or injected and response observed in the following situations: |
| | Power Failure |
| | Sensing Failure & Obstruction |
| | Computing Failure |
| | Drive System Failure (including disengagements caused by system) |
| | Fault Handling and response |
| Weather conditions outside of vehicle's capability | SDC movement attempted under unsuitable conditions; response observed |
| Autonomous vehicle interaction | Two SDCs approach 2-way stop from opposite directions |
| Security | Subject SDC to internal tests to ensure its systems are protected from malicious attacks, vulnerabilities and environmental interference |
| Operational safety | SDC about to operate with a door ajar |
| | SDC moving forward; passenger opens door |
| | SDC operating in conditions requiring lighting |

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| Avoidance or mitigation of major crash types | |
| Rear-end collisions | |
| <i>Demonstrate ability to meet all of NHTSA's NCAP tests for crash-imminent braking</i> | Self-Driving Car (SDC) approaches stopped lead vehicle |
| | SDC approaches target lead vehicle traveling at slower speed |
| | SDC approaches target lead vehicle traveling at slower speed and initiating strong braking |
| | False positive: SDC drives over steel trench plate at 45 mph and 25 mph |
| Intersection collisions | |
| <i>Demonstrate ability to detect other vehicles entering path at perpendicular angle and apply brakes</i> | SDC approaches intersection, Vehicle A approaches from right |
| | SDC approaches intersection, Vehicle A approaches from left |
| | SDC prepares to turn across unprotected intersection, oncoming Vehicle A approaches |
| Road departure | |
| <i>Demonstrate ability to steer clear of roadway edge</i> | SDC travels down straight road |
| | SDC travels down curved road |
| Lane departure | |
| <i>Demonstrate ability to stay within lane</i> | SDC travels down straight road with visible lane marking |
| | SDC travels down straight road with faded or missing lane marking |
| | SDC travels down curved road with visible lane marking |
| | SDC travels down curved road with faded or missing lane marking |
| | SDC travels down wet road with lane marking |
| | SDC travels down wet road with faded or missing lane marking |

Appendix B. To Dispel the Magic of Deep Learning

(Excerpted from article: Pinker, Steven. “Enlightenment Wars: Some Reflections on ‘Enlightenment Now,’ One Year Later.” January 14, 2019. *Quillette*. Accessed 1-18-2019. <https://quillette.com/2019/01/14/enlightenment-wars-some-reflections-on-enlightenment-now-one-year-later/>. Steven Pinker is Professor of Psychology at Harvard.)

To dispel the magic: Deep learning networks are designed to convert an input, such as the pixels making up an image or the shape of an auditory waveform, into a useful output, like a caption of the picture or the word that was spoken. The network is fed millions of tidbits of information from the input, computes thousands of weighted combinations of them, then thousands of weighted combinations of the weighted combinations, and so on, each in a layer of simple units that feeds the next, culminating in a guess of the appropriate output. The network is trained by allowing it to compare its current guess with the correct output (supplied by a “teacher”), convert the difference into a huge number of getting-warmer/getting-colder signals, propagate those signals backwards to each of the hidden layers, and tune their weights in directions that make its guess closer to the correct answer. This is repeated millions of times, which has become feasible thanks to faster processors and bigger datasets. (For a more detailed explanation of the first generation of these models, see my books *How the Mind Works* and *Words and Rules*.)

Deep learning networks are “deep” only in the sense of having many layers of units; their understanding is onion-skin thin. After having the daylights trained out of them, they can map inputs onto outputs surprisingly well (which is how Facebook knows whether you’ve uploaded a picture of a person or a cat), but they don’t represent the meaning of what they compute. A translation network can’t paraphrase sentences or answer questions about them; a video-game-playing program has no grasp of the objects or forces in its simulated world and cannot cope with a minor change in that world or in the rules of the game. And since the program’s intelligence is smeared across millions of little numbers, we humans often can’t reconstruct how it came to its decisions. That’s what has led to fears that AI will have an agenda inscrutable to us, perpetuate biases that we’re unaware of, and pose other threats to Enlightenment rationality.

But this is exactly the reason that many AI experts believe these networks, despite their recent successes, have hit a wall, and that new kinds of algorithm, probably incorporating explicit knowledge representations, will be needed to power future advances. These include Gary Marcus, building on analyses he and I developed in the 1990s; Judea Pearl, the world’s expert on causal modeling; and even Geoffrey Hinton, the inventor of deep learning himself. Marcus, together with the computer scientist Ernest Davis, makes this case in the forthcoming *Reboot: Getting to AI We Can Trust*. If Marcus and Davis are right, it’s no accident that artificial intelligence will have to represent human ideas and goals more explicitly. AI is a tool, which serves at our pleasure. Unless its workings are transparent enough that we can engineer it to respect our goals, conform to common sense, stay within limits we set, and correct its mistakes, it won’t be truly intelligent.

Appendix C. Congressional Testimony of Mary Cummings

**Testimony of Mary Cummings, PhD
Director, Humans and Autonomy Laboratory
Director, Duke Robotics
Professor of Mechanical Engineering and Materials Science
Professor of Electrical and Computer Engineering
Duke University**

Hands Off: The Future of Self-Driving Cars

March 15th, 2016

Good afternoon Chairman Thune, Ranking Member Nelson, and distinguished members of the committee. Thank you for the opportunity to appear before you to discuss issues related to the future of self-driving cars in the United States.

I am the director of Duke Robotics and the Duke University Humans and Autonomy Laboratory, which focuses on the multifaceted interactions of humans and autonomous systems in complex sociotechnical settings. I have conducted driving research and provided future technology recommendations to automotive manufacturers for more than a dozen years including Ford, Nissan, Toyota, and Google X¹. I was the program manager for a \$100 million Navy robotics helicopter that carries sensors very similar to those on self-driving cars. I am also currently conducting research for the National Science Foundation on the interaction of self-driving cars and pedestrians.

While I enthusiastically support the research, development, and testing of self-driving cars, as human limitations and the propensity for distraction are real threats on the road, I am decidedly less optimistic about what I perceive to be a rush to field systems that are absolutely not ready for widespread deployment, and certainly not ready for humans to be completely taken out of the driver's seat.

The development of self-driving car technologies has led to important advances in automotive safety including lane departure prevention and crash avoidance systems. While such advances are necessary stepping stones towards fully capable self-driving cars, going from automated lane changing or automated parking to a car that can autonomously execute safe control under all possible driving conditions is a huge leap that companies are not ready to make.

Here are a few scenarios that highlight limitations of current self-driving car technologies: The first is operation in bad weather including standing water on roadways, drizzling rain, sudden downpours, and snow. These limitations will be especially problematic when coupled with the inability of self-driving cars to follow a traffic policeman's gestures.

¹ See the attached paper, Cummings, M.L., & J. C Ryan, "Who Is in Charge? Promises and Pitfalls of Driverless Cars." TR News, (May-June 2014) 292, p. 25-30.

Another major problem with self-driving cars is their vulnerability to malevolent or even prankster intent. Self-driving car cyberphysical security issues are real, and will have to be addressed before any widespread deployment of this technology occurs. For example, it is relatively easy to spoof the GPS (Global Positioning System) of self-driving vehicles, which involves hacking into their systems and guiding them off course. Without proper security systems in place, it is feasible that people could commandeer self-driving vehicles (both in the air and on the ground) to do their bidding, which could be malicious or simply just for the thrill and sport of it.

And while such hacking represents a worst-case scenario, there are many other potentially disruptive problems to be considered. It is not uncommon in many parts of the country for people to drive with GPS jammers in their trunks to make sure no one knows where they are, which is very disruptive to other nearby cars relying on GPS. Additionally, recent research has shown that a \$60 laser device can trick self-driving cars into seeing objects that aren't there. Moreover, we know that people, including bicyclists, pedestrians and others drivers, could and will attempt to game self-driving cars, in effect trying to elicit or prevent various behaviors in attempts to get ahead of the cars or simply to have fun.

Lastly, privacy and control of personal data is also going to be a major point of contention. These cars carry cameras that look both in and outside the car, and will transmit these images and telemetry data in real time, including where you are going and your driving habits. Who has access to this data, whether it is secure, and whether it can be used for other commercial or government purposes has yet to be addressed.

So given that these and other issues need to be addressed before widespread deployment of these cars, but understanding that there are clear potential economic and safety advantages, how can we get there with minimal risk exposure for the American public? In my opinion, the self-driving car community is woefully deficient in its testing and evaluation programs (or at least in the dissemination of their test plans and data), with no leadership that notionally should be provided by NHTSA (National Highway Traffic Safety Administration). Google X has advertised that its cars have driven 2 million miles accident free, and while I applaud this achievement, New York taxi cabs drive two million miles in a day and a half. This 2 million mile assertion is indicative of a larger problem in robotics, especially in self-driving cars and drones, where demonstrations are substituted for rigorous testing.

RAND Corporation says that to verify self-driving cars are as safe as human drivers, 275 million miles must be driven fatality free. So that means we need a significantly accelerated self-driving testing program, but it is not simply good enough to let self-driving cars operate in California or southern Texas to accrue miles. NHTSA needs to provide leadership for a testing program that ensures that self-driving cars are rigorously tested for what engineers call the "corner cases", which are the extreme conditions in which cars will operate. We know that many of the sensors on self-driving cars are not reliable in good weather, in urban canyons, or places where the map databases are out of date. We know gesture recognition is a serious problem, especially in real world settings. We know humans will get in the back seat while they think their cars are on "autopilot". We know people will try to hack into these systems.

Given self-driving cars' heavy dependence on probabilistic reasoning and the sheer complexity of the driving domain, to paraphrase Donald Rumsfeld, there are many unknown unknowns that we will encounter with these systems. But there are many known knowns in self-driving cars that we are absolutely aware of that are not being addressed or tested (or test results published) in a principled and rigorous manner that would be expected in similar transportation settings. For example, the FAA (Federal Aviation Administration) has clear certification processes for aircraft software, and we would never let commercial aircraft execute automatic landings without verifiable test evidence, approved by the FAA. To this end, any certification of self-driving cars should not be possible until manufacturers provide greater transparency and disclose how they are testing their cars. Moreover, they should make such data publicly available for expert validation.

Because of the lack of safety evidence, I agree with California's recent ruling that requires a human in the driver's seat. However, while I generally support individual state governance on these issues, the complexity of the operation and testing of robotic self-driving cars necessitates strong leadership by NHTSA, which has generally been absent. But as I testified in front of this committee two years ago², the US government cannot and has not maintained sufficient staffing in the number of people it needs who can understand, much less manage, complex systems such as self-driving cars. So it is not clear whether NHTSA or any other government agency can provide the leadership needed to ensure safety on American roads.

Let me reiterate that as a professor in the field of robotics and human interaction, I am wholeheartedly in support of the research and development of self-driving cars. But these systems will not be ready for fielding until we move away from superficial demonstrations to principled, evidenced-based tests and evaluations, including testing human/autonomous system interactions and sensor and system vulnerabilities in environmental extremes. To this end, in collaboration with private industry, NHSTA should be providing strong leadership and guidance in this space.

² "The Future of Unmanned Aviation in the U.S. Economy: Safety and Privacy Considerations", January 15th, 2014.