Week 5: Smart cars

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# Smart Cars

The most powerful artificial intelligence applications use machines to enhance human capabilities rather than replace them (Heer, 2019; Boire, 2017). For instance, a person can write a more profound business case than a machine; however, the same machine will have fewer misspellings and grammatical errors. This dichotomy exists because humans specialize in contextualizing thought versus automation use patterns to make predictions (Schleer et al. 2019). Smart vehicles are an area of research that seeks to fuse this symbiotic relationship. As this partnership flourishing, it will continue creating advancements across safety, convenience resource optimization, and smart city integrations.

# Practical Applications of Intelligence

Machine learning can enhance every aspect of the drive, from extending the physical parts’ lifespan to increasing the driver’s overall satisfaction. Figure 1 contains a non-exhaustive taxonomy subset of these situations, such as reducing wear and tear and object detection. While building the taxonomy, the critical placement consideration was focusing on that aspect’s core use cases. Many items, such as Voice Assistance (VA), could arguably live under the Safety pillar. However, safety systems could exist in the same capacity even though more traditional input interfaces.

Figure 1: Taxonomy of Use-Cases

## Safety Control Systems

Annually, 32,000 Americans die from automotive accidents, and another 2 million are injured (CDC, 2016). These statistics are unacceptably high and require innovations that increase all participants’ safety on the road (see Figure 2). Artificial intelligence can assist these scenarios by collecting sensor data and then predicting risks and opportunities. However, numerous open problems exist across the safety domain. These challenges should not discourage investments in these areas as they are essential to address.

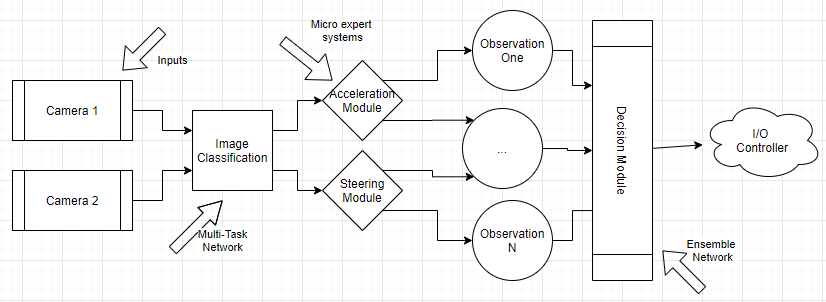
Figure 2: Taxonomy of Participants and Example Challenges

For example, several manufacturers, like Suburu and Lexus, include audible collision alerts during lane changes or reversing. While these capabilities exist today, they are often incomplete models due to the high volume of edge cases, such as children fetching a ball from the street. Even after detecting the example child, several open problems span ethical and philosophical debate. Lex (2017) asks *if avoiding the pedestrian requires killing the driver— what calculus dictates that autonomous decision*? These situations might play-out in fractions of a second, limiting the value of human intuition. Since concrete answers do not exist, machines must resort to static guardrails (e.g., slamming on the breaks or swerving) that can risk a multi-vehicle accident.

## Convenience Systems

During a road trip, there are often long monotonous segments necessary to arrive at the destination. This requirement forces the driver to expel significant amounts of concentration relative to the mundane task. Instead, auto-pilot systems can take the wheel and allow the motorist to relax and participate in leisure activities (e.g., conversing with passengers). Some manufactures tackle these needs with adaptive cruise control technologies. This approach is useful in static environments (e.g., open highways) but encounters limitations in more dynamic environments (e.g., urban cities). Researchers are closing this gap by including more sensors feeding into sophisticated reinforcement learning algorithms, but continuing to scale these monolithic expert systems is challenging (Fridman, 2020).

Figure 3: Example Microservice Architecture



V-TORCS (Virtual The Open Racing Car Simulation) and other modern architectures address these issues using combinations of ensemble and multi-task learning methods (Li et al. 2019). Consider a decision process that feeds camera frames into an image classification Convolutional Neural Network (CNN) to extract objects and contextualize the environment (see Figure 3). CNN algorithms mimic an eye’s biological structures by normalizing neighboring pixels blocks together to derive structure (Keller et al. 2016). These results continue into various expert subsystems that control the car, such as turning the wheel or accelerating. Subsystems output observations ensemble into a decision model that directs the I/O controller. Like other microsystem architectures, each subsystem’s implementation can evolve independently of peer components—enabling greater agility and innovation.

## Optimization Systems

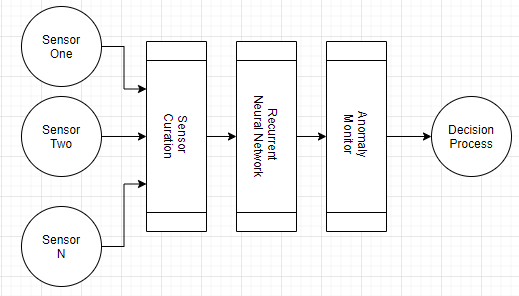
Modern personal vehicles have a lifespan of over 200,000 miles and often travel 24,000 miles per year (Ford, 2012). Assuming a driver purchases a $25,000 car and keeps it that entire usable period, they will likely spend at least that much on fuel and repairs (see Table 1).

Table 1: Ongoing Fees

|  |  |
| --- | --- |
| Line Item | Total |
| 200,000 miles @ 30 miles/gallon | 6,667 gallons |
| x $2.50/gallon | $16,700 |
| + Typical Repairs | $10,000 |
|  |  |
| Total Costs | $26,700 |

Data scientists can improve this situation by introducing micro-optimization systems across the auto-mobile. For instance, traditional cruise control maintains a specific speed (e.g., 70mph) without considering any environmental context. Meanwhile, a smarter system can factor in the road’s incline, the driver’s profile, and metrics about the trip to meet a dynamic profile ranging from, e.g., 65-70mph. As this idea expands outward, it results in collections of micro-optimizers that monitor all aspects of the driving experience, potentially saving hundreds of dollars in fuel.

Figure 4: Preventative Maintenance System



When the driver has advance notice that a component is likely to fail, they can schedule the maintenance and minimize costs. Preventative Maintenance Systems (PMS) provides this capability by first collecting component-level telemetry and looking for anomalous metrics (see Figure 4). For instance, an engine monitoring solution might observe the RPMs (Revolutions per Minute) and electrical output. Sensor time series data tends to noisy and requires a curation process (e.g., Kalman filter) to remove noise and derive a stable signal (Jackson & Rege, 2019). Next, the stable signal flows into a Recurrent Neural Network (RNN), which uses sequences of previous tokens to predict future values (Keller et al. 2016). When the observations deviate outside of these predictions, an anomaly exists and needs surfacing to a decision control process.

## Smart City Integration

The future evolution of city planning makes urban areas highly connected with fast wireless networking and intelligent machines emitting enormous telemetry data volumes (Balduccini et al. 2018). A central participant in this ecosystem is the autonomous vehicle, as it transmits metrics to infrastructure (V2I) and other drivers (V2V). These metadata fields will enable more efficient traffic shaping, alertness to potential risks, and more insights into driver patterns (Tong et al. 2019). For instance, today, each driver inputs their GPS destination and follows the route in an isolated silo. Tomorrow, aspects of those routing decisions can become centralized, resulting in less route congestion. While ideas of this ideal state are already coming to life in areas like Seattle, Boston, and New York; the large scale implementation is still aways out (Cohen, 2013). Completely modernizing these areas will require significant infrastructure investments, consensus on V2X communication protocols, and machines that implement those standards. Until then, machine learning technologies will need to synthesis those capabilities by making predictions by pairing vehicle-local sensors with remote web services.

# Conclusion

Artificial intelligent systems are superior to humans at identifying patterns in data, then predicting the best next action. However, their skills at understanding and rationalizing about more profound contexts is still an open problem. When systems use artificial intelligence to augment human decision processes, it results in a powerful partnership.

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