Week 5: Smart cars

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TIM-8150: Artificial Intelligence

November 1, 2020

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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 device will have fewer misspellings and grammatical errors. This dichotomy exists because humans specialize in contextualizing thought versus using patterns to make predictions (Schleer et al., 2019). Intelligent vehicles are an area of research that seeks to fuse this symbiotic relationship. This partnership will continue creating advancements in safety, convenience, resource utilization, and autonomous 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 of uses-cases for artificial intelligence in motor vehicles, such as reducing wear and tear and object detection. The central application topic is the primary deciding factor for item assignment within the tree. Many items, such as Voice Assistance (VA), could arguably live under a different pillar, safety. However, safety systems could exist in the same capacity using more traditional input interfaces, making this example fall under convenience.

Figure 1: Taxonomy of Example 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 in these scenarios by collecting sensor data and predicting risks and opportunities. However, numerous open problems exist throughout the safety domain. These challenges should not discourage investments in these areas as they are essential to public safety.

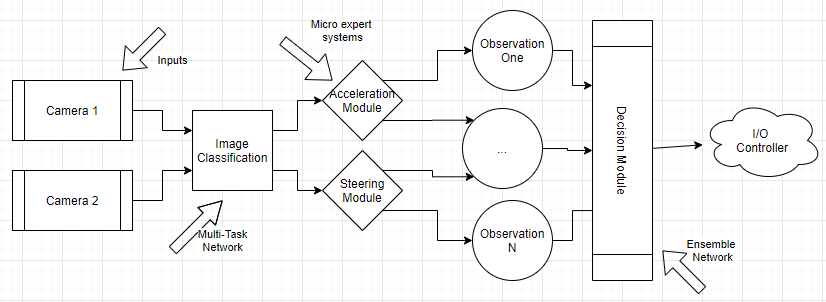
Figure 2: Taxonomy of Participants and Example Challenges

For example, several manufacturers, like Subaru 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. Several open problems span ethical and philosophical debate even after detecting the example child. Lex (2017) asksif 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 could risk a multi-vehicle accident.

## Convenience Systems

There are often long monotonous segments necessary to arrive at the destination during a road trip. 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 manufacturers tackle these needs with adaptive cruise control technologies. This approach is helpful 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 that feed into sophisticated reinforcement learning algorithms (Fridman, 2020). However, continuing to scale these monolithic expert systems is challenging.

Figure 3: Example Microservice Architecture



V-TORCS (Virtual The Open Racing Car Simulation) and other modern architectures address these issues using 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 pixel blocks to derive structure (Keller et al., 2016). These results flow into various expert subsystems that control the car, such as turning the wheel or accelerating. An ensemble of subsystem observations merges into a broader system-wide decision model that contains one or more I/O (Input/Output) controllers. Like other microsystem architectures, each subsystem’s implementation can evolve independently of peer components—enabling greater agility and innovation.

## Optimization Systems

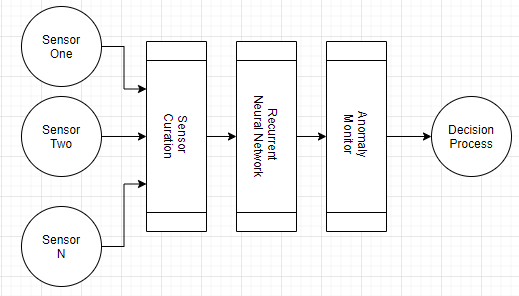
Modern personal vehicles have a lifespan of over 200,000 miles and often travel 24,000 miles per year (Ford, 2012). Assuming a driver purchases a $25,000 car and keeps it that entire usable period, they will likely spend at least that much on fuel and repairs (see Table 1). Data scientists can improve this situation by introducing micro-optimization systems across the automobile. For instance, traditional cruise control maintains a specific speed (e.g., 70mph) without considering any environmental context. Meanwhile, a more intelligent system can factor in the road’s incline, the driver’s profile, and metrics about the trip to create a dynamic profile ranging from, e.g., 65-70mph. As this idea expands outward, it collects micro-optimizers that monitor all aspects of the driving experience, potentially saving hundreds of dollars in costs.

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 |

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 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 the electrical output. Sensor time series data are noisy and require a curation process (e.g., Kalman filter) to derive a stable moving average signal (Jackson & Rege, 2019). Next, the curated signal flows into a Recurrent Neural Network (RNN), which uses sequences of previous tokens to predict future values (Keller et al., 2016). An anomaly exists when new observations deviate from these predictions and needs to surface in a decision control process.

Figure 4: Preventative Maintenance System



## 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). The autonomous vehicle is a central participant in this ecosystem, as it transmits metrics to infrastructure (V2I) and other vehicles (V2V). These metadata feeds will enable more efficient traffic shaping, alertness to potential risks, and more insights into driver patterns (Tong et al., 2019). For instance, 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 major cities like Seattle, Boston, and New York, the large-scale implementation is still years out (Cohen, 2013). Completely modernizing these areas will require significant infrastructure investments, consensus on V2X communication protocols, and machines that implement those standards. Machine learning technologies will need to synthesize those capabilities by making predictions by pairing vehicle-local sensors with ubiquitous cloud services.

# Conclusions

Three takeaways of this paper are (1) that artificial systems need to augment human processes; (2) a suitable starting place is safety and cost optimization; and (3) intelligent cities are several years away, requiring cloud services to fill that void.

The most powerful artificial intelligence applications use machines to enhance human capabilities rather than replace them. Motor vehicles contain many integration points. Machine learning can handle tedious aspects of the journey with greater precision and accuracy than humans. After freeing the driver from the burden of mundane work, she can focus on value-differentiating traveling qualities, such as talking with passengers and thinking about the day ahead. Meanwhile, intelligent systems remain vigilant in the background looking for risks like a child running into the road. Another collection of machine learning tasks revolves around cruise control capabilities. These systems keep us out of harm’s way and reduce wear-and-tear on internal parts. Looking further into the future, the integration of intelligent vehicles within smart cities promises more efficient traffic shaping and risk awareness. However, the necessary infrastructure investments are unlikely to arise in the next decade. Instead, machine learning will pair vehicular telemetry into ubiquitous cloud computing to provide a similar experience.

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