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PhD. Program in Electronics: Advanced Electronic
Systems. Intelligent Systems

**Predictive Techniques for Scene
Understanding by using Deep
Learning in Autonomous Driving
applications**

PhD. Thesis Presented by
Carlos Gómez Huélamo

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A mi Madre, allá donde esté

*“En este vasto mundo
navegáis en pos de un sueño,
surcando el ancho mar
que se extiende frente a vosotros.
El puerto de destino es el mañana
cada día más incierto.
Encontrad el camino,
cumplid vuestros sueños,
estáis todos en el mismo barco
y vuestra bandera es la libertad”*

Opening 3 de One Piece

Autor: The Babystars

Acknowledgements

Esta Tesis Doctoral supone el culmen a cuatro años (Abril 2019 - Abril 2023) realmente duros, cargado de emociones, triunfos, pandemias, estafas y tropiezos, todo a partes iguales. Este es probablemente (aunque como diría Sean Connery interpretando a James Bond en 1983, *Never Say Never Again*) mi último gran documento individual, académicamente hablando.

Durante mi etapa universitaria (2013 hasta el momento, 2023) he tenido ciertos momentos puntuales en los que he sentido un salto cualitativo como profesional: El primero fue en el segundo cuatrimestre de segundo de carrera, cuando las cosas se pusieron tensas con Control II e Informática Industrial. Vaya sudores. El segundo probablemente fue con el fallecimiento de mi madre durante mi ERASMUS+ en Irlanda. Duros y oscuros momentos, alejado de mis seres queridos. El tercer momento llega en segundo de máster, durante mi querido ERASMUS+ en Finlandia, donde compagino una estancia preciosa en Tampere con el máster y un pre-inicio de doctorado. Me equivoqué al empezar tan pronto con la beca, "queriendo cobrar" cuanto antes, en vez de terminar tranquilamente el TFM y plantear la tesis, pero eso no lo sabría hasta tiempo después. Pero no es hasta la tesis donde empezaron los quebraderos de cabeza reales. Continuamente altibajos, mala planificación por mi parte, momentos puntuales donde me equivoqué rotundamente al empeñarme en soldar una estructura compleja para nuestro vehículo sin ayuda, no estudiar PyTorch tras el congreso WAF 2018 tras la sugerencia de mi tutor, no enfocarme en técnica individual hasta bien entrado el doctorado, no querer hacer nada hasta que no tuviese la teoría perfectamente asimilada, tener demasiado respeto a la Inteligencia Artificial y escurrir el bulto de mi tesis en un compañero mientras yo me dedicaba a integrar y corregir los bugs del grupo que para mí *era lo fácil*. Mal. Todo mal. Pero todo cambió tras mi segunda estancia, en Estados Unidos, cuando tras llorar por no entender el camino a seguir, nadie que me ayudara, decidí crear mi propio camino, con paciencia y fé, práctica y error compaginado con lectura de artículos, para mejorar mi confianza y autoestima, y finalmente logré empezar a entender lo que era el Deep Learning. Gracias a todos mis errores, desventuras y discusiones, a día de hoy, excepto momentos inevitables, me encuentro con muchísima capacidad para atacar y gestionar prácticamente cualquier problema, consultar documentación y organizarme, aunque esta sigue siendo mi tarea

pendiente.

Cada año, desde hace ya varios, mi primera publicación en Instagram viene seguida de la frase "Trabaja duro en silencio y deja que tu éxito haga todo el ruido". Filosofía Kaizen, de mejora y aprendizaje continuo, para así cada día entender el mundo un poquito mejor. Si toda la dedicación y estudio que he depositado en este trabajo sirven para algo en mi futuro, sé que todo el esfuerzo habrá merecido la pena.

Después de este particular monólogo, a lo cual soy muy propenso y de lo cual mis amigos y compañeros no cesan en su empeño de recordádmelo, debo, como no puede ser de otra manera, dar paso a los agradecimientos.

En primer lugar, me gustaría agradecer a mis profesores del grupo RobeSafe, especialmente a mis tutores Luis Miguel Bergasa Pascual y Rafael Barea Navarro, por ofrecerme estar en el grupo (así como aguantarme) durante todos estos años e intentar que tuviésemos el mejor *experimental setup* y *roadmap* en el laboratorio, aunque no fuese siempre sencillo. Sin dudas considero realmente interesante la temática propuesta en esta tesis doctoral, predicción de agentes en el contexto de vehículo inteligente, ya que entra en el plano filosófico sobre cómo razonar el futuro de los objetos y cómo podría afectar a la capacidad ejecutiva del agente que deba tomar una decisión. Mi mente hace tiempo que cambió y me fijo siempre que conduzco de todo lo que intento reproducir con mis estudios. Habrá que seguir esta tendencia muy de cerca en los próximos años, porque personalmente considero que sus aplicaciones son fantásticas.

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"Te quiero más que ayer, pero menos que mañana. Hoy, y siempre"

Mi querido lector, disculpa mi monólogo de agradecimientos, es mi forma de ser y la cual tengo por bandera, aunque creo que ha quedado bonito. Podría decir mil anécdotas más de mi doctorado, pero como diría Aragorn, legítimo Rey de Gondor, enfrente de la

mismísima Puerta Negra: *Hoy no es ese día.*

Vamos a la lectura importante, que empiece el *Rock and Roll* !!

Resumen

TBD

Palabras clave: Autonomous Driving, Deep Learning, Motion Prediction, Scene Understanding.

Abstract

TBD

Keywords: Autonomous Driving, Deep Learning, Motion Prediction, Scene Understanding.

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Chapter 1

Introduction

*Aaay, el oro, la fama, el poder.
Todo lo tuvo el hombre que en su día se autoproclamó
el rey de los piratas, ¡GOLD ROGER!
Mas sus últimas palabras no fueron muy afortunadas:
"¿¡MI TESORO!? Lo dejé todo allí, buscadlo si queréis,
ojalá se le atragante al rufián que lo encuentre.*

Opening 1 de One Piece: "We are"

Autor original: Hiroshi Kitadani

1.1. Motivation

Autonomous Driving (AD) have held the attention of technology enthusiasts and futurists for some time as evidenced by the continuous research and development in Intelligent Transportation Systems (ITS) over the past decades, being one of the emerging technologies of the *Fourth Industrial Revolution*, and particularly of the Industry 4.0.

The concept *Fourth Industrial Revolution* or Industry 4.0 was first introduced by Klaus Schwab , CEO (Chief Executive Officer) of the World Economic Forum, in a 2015 article in Foreign Affairs (American magazine of international relations and United States foreign policy). A technological revolution can be defined as a period in which one or more technologies are replaced by other kinds of technologies in a short amount of time. Hence, it is an era of accelerated technological progress featured by Researching, Development and Innovation whose rapid application and diffusion cause an abrupt change in society. In particular, the *Fourth Industrial Revolution* conceptualizes rapid change to industries, technology, processes and societal patterns in the 21st century due to increasing inter-connectivity and smart automation. This industrial revolution focuses on operational efficiency, being the following four themes which summarize it:

- Decentralized decisions: Ability of cyber physical systems to make decisions on their own and to perform their tasks as autonomously as possible.
- Information transparency: Provide operators with comprehensive information to make decisions. Inter-connectivity allows operators to gather large amounts of information and data from all points in the manufacturing process in order to identify key areas or aspects that can benefit from improvement to enhance functionality.
- Technical assistance: Ability to assist humans with unsafe or difficult tasks and technological facility of systems to help humans in problem-solving and decision-making.
- Interconnection: Ability of machines, sensors, devices and people to communicate and connect with each other via the Internet of Things (IoT) or the Internet of People (IoP).

Based on the aforementioned principles, this revolution is expected to be marked by breakthroughs in emerging technologies in fields such as nanotechnology, quantum computing, 3D printing, Internet of Things (IoT), fifth-generation wireless technologies (5G), Robotics, Computer Vision (CV), Artificial Intelligence (AI) or the scope of this PhD thesis, Autonomous Driving Stacks (ADSs). The sum of all these advances are resulting in machines that can potentially see, hear and what is more important, think, moving more deftly than humans.

An [ADS](#), also referred in the literature as Intelligent Vehicle (IV), driverless car or autonomous car, is a vehicle that can sense its surrounding and moving safely with little or even no human input. These [ADSs](#) must combine a variety of sensors to understand the traffic scenario, like RADAR (RAdio Detection A Ranging), LiDAR (Light Detection and Ranging), cameras, Inertial Measurement Unit (IMU), wheel odometry, GNSS (Global Navigation Satellite System) or ultrasonic sensors, and detect, track and predict (which is the main purpose of this thesis) the most relevant obstacles around the ego-vehicle. Then, advanced control and planning systems process this sensory information in combination with a predefined global route to calculate the corresponding control commands to drive throughout the environment, ensuring a safe driving.

The dream of seeing fleets of [ADSs](#) efficiently delivering goods and people to their destination has fueled billions of dollars and captured consumer's imaginations in investment in recent years. Nevertheless, according to the "Autonomous driving's future: Convenient and connected" report, published by the global management consulting firm McKinsey & Company in January 2023, even after some setbacks have pushed out timelines for [AD](#) launches and delayed customer adoption, the transportation community still broadly agrees that [AD](#) has the potential to transform consumer behaviour, transportation and

society at large. AD is considered as one of the solutions to the before mentioned problems and one of the greatest challenges of the automotive industry today.

Statistics show that 69 % of the population in the European Union (EU), including associated states, lives in urban areas. According to the World Health Organization, nearly one third of the world population will live in cities by 2030, leading to an overpopulation in most of them. Aware of this problem, the Transport White Paper published by the European Commission in 2011 indicated that new forms of mobility ought to be proposed so as to provide sustainable solutions for people and goods safely. For example, regarding safety, it sets the ambitious goal of halving the overall number of road deaths in the EU between 2010 and 2020. Nevertheless, this goal does not seem to be easy since only in 2014 more than 25,700 people died on the roads in the EU, many of them caused by an improper behaviour of the driver on the road. A similar study made by the National Highway Traffic Safety Administration (NHTSA, transportation organization of the United States) reported in 2015 that around 94 % of traffic accidents happen because of human error. In that sense, the existence of reliable and economically affordable ADSs are expected to create a huge impact on society affecting social, demographic, environmental and economic aspects. It can produce substantial value for the auto industry, drivers and society, making driving safer, more convenient and more enjoyable. While the human driver or not could select whether to drive, in autonomous mode hours on the road previously spent driving could be used to work, watch a funny movie or even to video call a friend. For employees with long commutes, AD might shorten the workday, increasing worker productivity. Since workers, specially those related to digital jobs or related fields, may perform their jobs from an ADS, they could more easily move further away from the office, which, in turn, could attract more people to suburbs and rural areas. Besides this, it is estimated to cause a reduction in road deaths, reduce fuel consumption and harmful emission associated and improve traffic flow, as well as an improvement in the overall driver comfort and mobility in groups with impaired faculties, such as disable or elderly people, providing them with mobility options that go beyond car-sharing services or public transportation. Other industrial applications of autonomous vehicles are agriculture, retail, manufacturing, commercial and freight transport or mining.

1.2. Historical Context

ADSs have become a challenge for auto competitions and technology companies, which has derived in an intense competition. Though today companies such as Mercedes, Ford or Tesla are racing to build ADSs for a radically changing consumer world, the research

and development of autonomous robots is not new.

In 1500, centuries before the invention of the automobile, Leonardo da Vinci designed a cart that could move without being pulled or pushed. In 1868, Robert Whitehead invented a torpedo that could propel itself underwater in order to be a game-changer for naval fleets all over the world. In terms of robotic solutions for intelligent mobility, the study was started in the 1920s, being the concept of Autonomous Car defined in Futurama, an exhibit at the 1939 New York World's Fair. General Motors created the exhibit to display its vision of what the world would look like in 20 years, including an automated highway system that would guide ADS. By 1958, General Motors made this concept a reality (at least as a proof of concept) being the car's front end embedded with sensors to detect the current flowing through a wire embedded in the road. The first semi-automated car was developed in 1977 by Japan's Tsukuba Mechanical Engineering Laboratory. The vehicle reached speeds up to 30 km/h with the support of an elevated rail.



Figure 1.1: Stanley, 2005 DARPA Grand Challenge winner
Source: *Stanford university*

Nevertheless, the first truly autonomous cars appeared in the 1980s with Carnegie Mellon University's Navlab and ALV projects funded by the USA company DARPA (Defense Advanced Research Projects Agency) in 1984 and EUREKA Prometheus project (1987) developed by Mercedes-Benz and Bundeswehr University Munich's. By 1985, the ALV project had shown self-driving speeds on two-lane roads of 31 km/h with obstacle avoidance added in 1986 and off-road driving in day and night conditions by 1987. Furthermore, from the 1960s through the second DARPA Grand Challenge in 2005 (212 km off-road course near the California-Nevada state line, surpassed by all but one of the 23 finalists), automated vehicle research in the United States was primarily funded by DARPA, the US Army and US Navy, yielding rapid advances

in terms of speed, car control, sensor systems and driving competence in more complex conditions. This caused a boost in the development of autonomous prototypes by companies and research organizations, most of them from the United States. Figure 1.1 shows Stanley, the 2005 DARPA Gran Challenge winner, from Stanford university.

Even though self-driving cars have not yet displaced conventional cars, there can be found several examples of how it has become a hot topic for powerful companies such as Delphi Automotive Systems, Audi, BMW, Tesla, Mercedes-Benz or Waymo.

In 2005 Delphi broke the Navlab's record achievement (driving 4,584 km while remaining 98 % of the time autonomously) by piloting an Audi, improved with Delphi technology, over 5,472 km through 15 states while remaining in self-driving mode 99 % of the time. Moreover, in 2005 the USA states of Michigan, Virginia, California, Florida, Nevada and the capital, Washington D.C., allowed the testing of automated cars on public roads.

In 2017, Audi stated that its A8 car prototype would be automated at speeds up to 60 km/h by using its perception system named "Audi AI". Also, in 2017 Waymo (self-driving technology development company subsidiary of Alphabet Inc) started a limited trial of a self-driving taxi service in Phoenix, Arizona.

Figure 1.2 shows the total number of autonomous test miles and miles per disengagement in California (Dec 2019 - Nov 2020) by some of the most important AD technology development companies around the world. The concept disengagement is quite useful to assess the quality of an ADS, defined as the deactivation of the autonomous mode when a failure of the autonomous technology is detected or when a safe operation requires that the autonomous vehicle test driver disengages the autonomous mode, resulting in control being seized by the human driver.

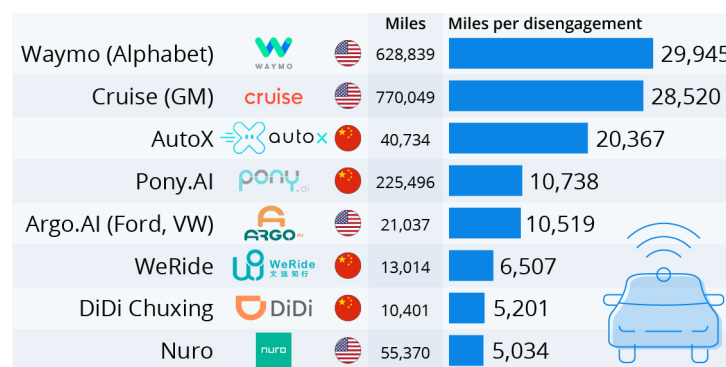


Figure 1.2: Number of autonomous test miles and miles per disengagement (Dec 2019 - Nov 2020)

Source: *DMV California, via The Last Driver License Holder*

At the moment of writing this thesis (2023), many vehicles on the road are considered to be semi-autonomous due to safety features like braking systems, assisted parking, lane boundaries detection or predict the long-term behaviour of the users around the vehicle to execute the most optimal action in a safely way. Regarding this, the Society of Automotive Engineers (SAE) published the concept of autonomy levels in 2014, as part of its "Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems" report. Figure 1.3 illustrates the six levels of autonomy (the higher the level, the more autonomous the car is), where it can be appreciated that Level Zero means "No Automation", being the acceleration, braking and steering controlled by a human driver at all times, and Level Five represents Full Automation, where there is a full-time automation of all driving tasks on any road, under any conditions, whether there is a human on board or not.

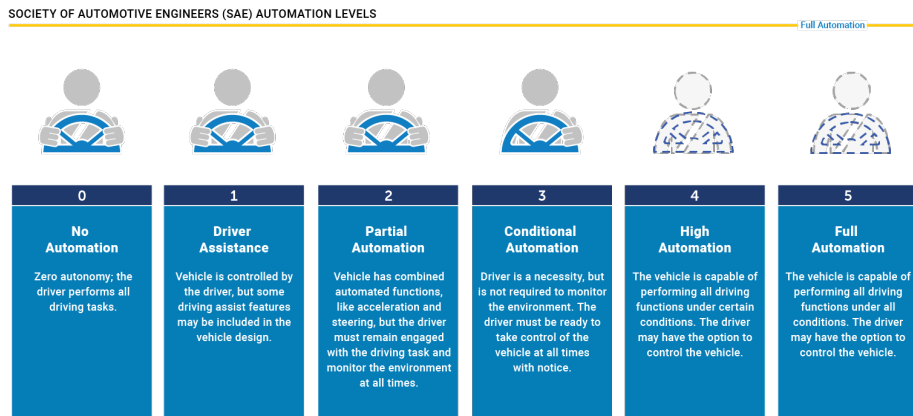


Figure 1.3: Society of Automotive Engineers (SAE) automation levels
Source: *NHTSA (National Highway Traffic Safety Administration)*

In that sense, today most vehicles only included basic Advanced Driver Assistance Systems (ADAS), but major advancements in AD capabilities are on the horizon. According to a 2021 McKinsey consumer survey, growing demand for AD systems could create billions of dollars in revenue. Based on a consumer interest in AD features and commercial solutions available on the market today, ADAS and AD could generate between \$300 and \$400 billions in the passenger car market by 2035. Figure 1.4 illustrates an interesting study reporting the revenues of ADAS and AD from Level 1 (Driver Assistance) to Level 4 (High Automation). As expected, Level 5 is excluded from this study due to the huge difficulties the automotive companies would have to face to adapt their systems under totally different environmental conditions.

1.3. Autonomous Driving architecture

To sum up what commented above, increasing the level of autonomous navigation in mobile robots (from agriculture to public and private transport) are expected to create

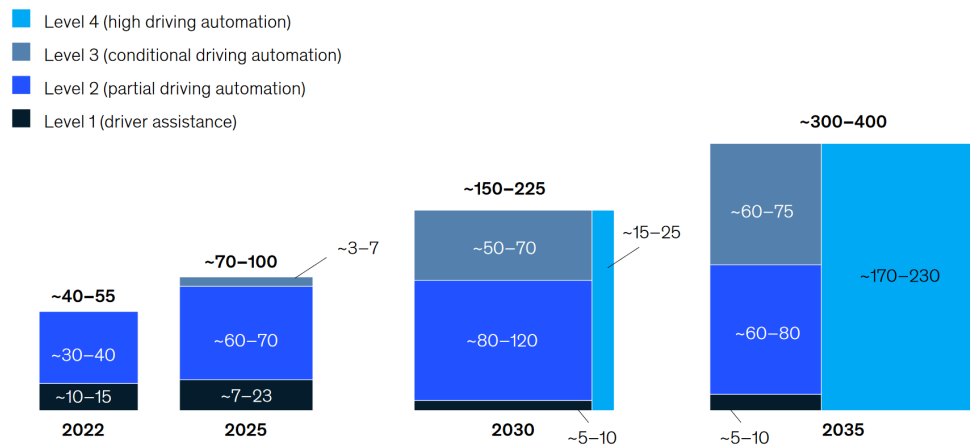


Figure 1.4: Advanced Driver Assistance systems (ADAS) and Autonomous Driving (AD) revenues in \$ billion
Source: *McKinsey Center for Future Mobility*

tangible business benefits to those users and companies employing them. However, designing an autonomous navigation system does not seem to be an easy task. In the State-of-the-Art (SOTA) we can distinguish two main kind of software architectures: End-to-End and modular. Figure 1.5 illustrates the entire AD architecture starting from sensing, all the way to longitudinal (throttle/brake) and lateral (steering angle) control of the vehicle, which are the commanded signals that feed the low-level electronic system that moves the vehicle, like a drive-by-wire system [1]. End-to-End are considered black-box models, where a single neural network performs the driving task (throttle/steering/brake) from raw sensor data, in such a way the error be may vanished since intermediate representations are jointly optimized, but these are not very interpretable. On the other hand, modular architectures (considered as glass models as counterpart to End-to-End approaches) separate the driving task into individually programmed or trained modules. This solution is more interpretable, since the know-how of a research group or company is easily transferred, they allow parallel development, being the standard solution in industrial research, but the error is propagated, where intermediate representations can led to suboptimal performance. For example, incorrect object detection can lead to low-quality tracking and motion prediction.

Considering the features of the research group and main projects (Techs4AgeCar, AI-VATAR) where this thesis has been developed, we integrate our algorithms in a software modular approach. An example of modular An example of modular approach is shown in Figure 1.6. Despite the fact in the literature some authors include certain modules in different layers, specially motion prediction algorithms, which are usually classified as a perception algorithm, but sometimes is included as part of the planning or decision-making layers, we can hierarchically break down (from raw data to the driving task) a standard AD architecture into the following software layers:

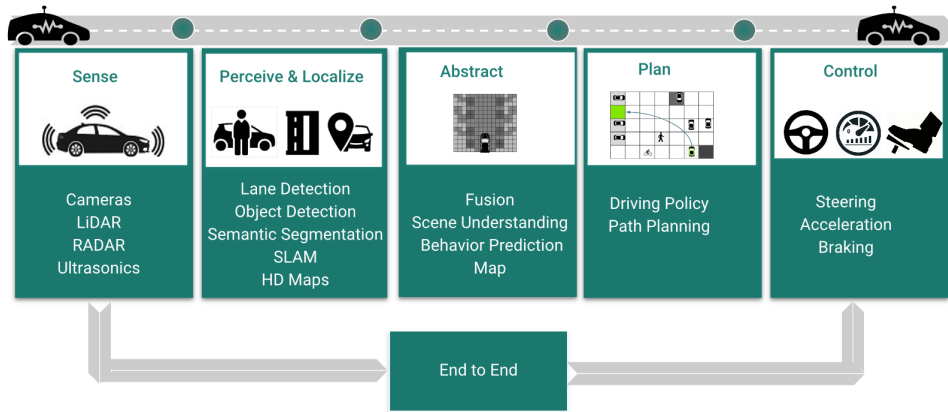


Figure 1.5: Autonomous Driving Stack (ADS) modular vs end-to-end pipeline

Source: *Vrunet: Multi-task learning model for intent prediction of vulnerable road users* [2]

- **Localization layer:** Positions and locates the vehicle on a map with real-time and centimetric accuracy approach. The main source of information is a robust differential-GNSS, though IMUs, wheel odometry and even cameras are commonly employed.
- **Perception layer:** Understand the environment around the ego-vehicle thanks to the information collected by the sensors. If defined as multi-stage, the perception layer first detects the most relevant obstacles, then track them over time to finalize long-term predict with plausible predictions. In order to perform object detection, LiDAR, camera and RADAR are the main sensors that provide the corresponding raw data. Additionally, HD map information is frequently used in the motion prediction tasks by most [SOTA](#) algorithms.
- **Mapping layer:** Responsible for creating a topologic, semantic and geographical modeling of the environment through which the vehicle drives, being the HD Map graph the most common source of information.
- **Planning layer:** This layer is comprised of three components: route, behavioural and trajectory planner. The route planner computes the most optimal (in terms of distance, time and so forth and so on) global route from some predefined start and goal. It uses the localization and mapping output. On the other hand, the behaviour planner, also referred as decision-making layer by some authors, it performs high-level decision-making of driving behaviours such as lane changes or progress through intersections, mostly focused on the previously computed global route and current localization. It can be seen as an atomization of the global route in different behaviors to reach the goal. Finally, the trajectory planner, also known as local planner, generates a time schedule for how to follow a path given constraints such as position, velocity and acceleration in order to meet the previously decided behaviour and taking into account the prediction from the perception layer, avoiding obstacles in optimal direction and speed conditions.

- Control layer: Once the local plan is calculated, the control layer is responsible for generating the commands that are sent to the actuators. It receives as input some waypoints from the calculations made in the trajectory planner. Once these waypoints are received, most authors perform spline interpolations and a velocity profile that ensures a smooth and continuous trajectory.

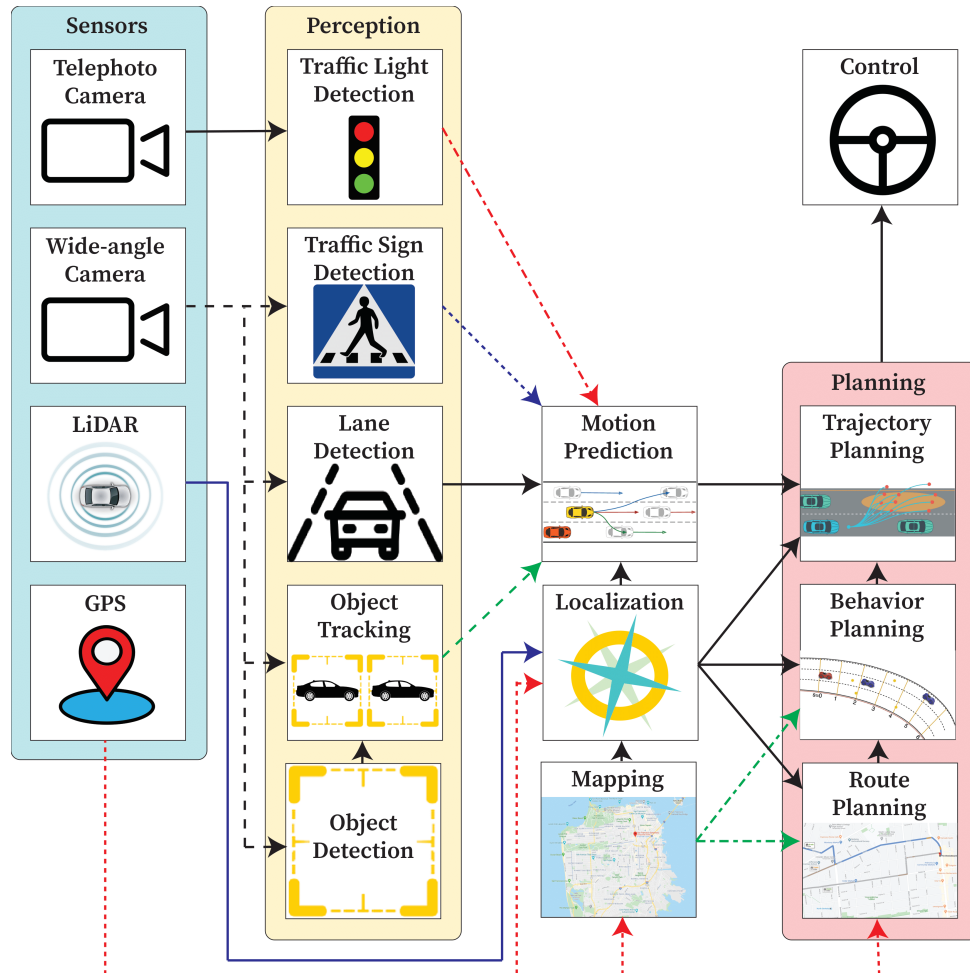


Figure 1.6: Autonomous Driving Stack (ADS) modular pipeline

Source: *Pylot: A modular platform for exploring latency-accuracy tradeoffs in autonomous vehicles* [3]

1.4. Problem statement

As commented in previous sections, in order to operate efficiently and safely in highly dynamic, complex and interactive driving scenarios, [ADS](#) need to smartly reason like human beings via predicting future motions of surrounding traffic participants during navigation. Nevertheless, achieving accurate and robust Motion Prediction (MP) in one of the most difficult and interesting challenges to achieve full-autonomy, since it is equivalent to a bridge between the former stages of the perception layer, where the scene is understood detecting and tracking static and dynamic objects of the environment, and

the planning a control layer, where the driving commands are sent to the vehicle. Here are some of the most important challenges:

1. Heterogeneity of traffic participants. Traffic participants (specially those which are dynamic) can be roughly classified as cyclists, pedestrians or other vehicles. The prediction model should be capable of differentiating the motion patterns of heterogeneous traffic participants, in such a way fine-grained classification (detection module) is quite beneficial to include additional metadata along with the past observations.
2. Complexity of road structure. Road structures are highly diverse and complex, specially in highways and urban areas, which noticeably affect the motion behaviours of traffic participants.
3. Variable number of interactive agents. The prediction model must deal with a number of associated traffic participants within a certain area that can vary from time to time, such as intersections or roundabouts. Then, while driving, a comprehensive representation of the scene must be able to accommodate an arbitrary number of involved traffic participants.
4. Multimodality of driving behaviours. In real-world, despite we know the behaviour our vehicle will carry out, the motion patterns of other traffic participants can be considered inherently multimodal since there is usually more than one reasonable option for a driver to choose, specially in intersections, when the number of lanes increases or even in the same lane with different velocity profiles (constant velocity, sudden break, sudden acceleration). In that sense, a robust and reliable **MP** model is expected to be human-like and capture different plausible motion modalities where an agent can travel in the prediction horizon.
5. Complex interdependencies among traffic participants and road infrastructure. Agent-Agent, Agent-Road and Road-Road interdependencies are of great importance for **MP** and interaction modeling, even more taking into account the complexity of road structures and heterogeneity of traffic participants aforementioned. As expected, an agent future trajectory will be affected not only by its own past trajectory and driving objectives (given by the behaviour planner) but also by other surrounding agents past trajectories, traffic rules and physical constraints.

1.5. Objectives and Structure of this work

The main scope of this thesis is to study the **SOTA** and development of novel and efficient interaction-aware Deep Learning based **MP** models, focusing on long-term (from 3 to 6 s) prediction horizon and **AD**, where traffic participants can range from trucks

to pedestrians, instead of models focused on pedestrian trajectory prediction. The main inputs that will be used throughout this work are the physical (map) information and historical states (that may include agent position, velocity, orientation, object type and category) of traffic participants in Bird's Eye View (BEV), assuming these objects have been previously tracked by our ego-vehicle (also referred as the autonomous car). Though the evaluation of these methods will be done using a single target agent, as proposed by some of the most important prediction datasets, like Argoverse 1 [4] and Argoverse 2 [5], some of the proposed methods will be trained considering multi-agent. In this thesis, the solutions to the aforementioned challenges will be discussed and investigated progressively. In order to achieve the main scope, the following objectives will be met:

1. Research of [SOTA MP](#), focused on Deep Learning (DL) and the [AD](#) paradigm.
2. Propose of several [MP](#) architectures, studying the progressive incorporation of [DL](#) mechanisms and different sources of information and metadata, achieving [SOTA](#) accuracy while reducing in millions of parameters previous models as well as inference time.
3. Validate the proposed models in downstream applications, such as decision-making or behavioural planning, taking into account former stages of the perception layer (detection and tracking) instead of static files (benchmarks) in hyper-realistic simulation, as a preliminary stage before implementing it in a real-world vehicle.

The organization of this document has been done as follows:

- Chapter 2 reviews the most important features and methods of physics-based and learning-based [MP](#) methods. The physics-based methods are reviewed according to a taxonomy similar to existing reviews. The learning-based methods are reviewed based on two classification criteria: scene representation and trajectory decoding.
- Chapter 3 presents a technical background, mostly focused on [DL](#) mechanisms to deal with temporal sequences and interactions, to deeply understand the proposed methods.
- Chapter 4 illustrates the different prediction models developed in the thesis using different validation environments, from unimodal physic-based prediction to the final model of the thesis which takes into account agents interactions, map information and past observations using a novel scene representation with heuristic proposals, graph-based encoding, [DL](#)-based goal proposals and motion refinement.
- Chapter 5 addresses the integration of the final model of the thesis with upstream and downstream modules to contribute the entire pipeline and closed-loop for [AD](#).
- Chapter 6 summarizes the thesis and provides some promising directions for future work in the areas of [MP](#) and validation.

Chapter 2

Related Works

*Llegaré a ser el mejor, El mejor que habrá jamás
Mi causa es ser su entrenador, Tras poderlos capturar.
Viajaré a cualquier lugar, Llegaré a cualquier rincón
Y al fin podré desentrañar, El poder de su interior.
¡Pokémon! Hazte con todos (solos tú y yo),
Es mi destino, mi misión
¡Pokémon! Tú eres mi amigo fiel,
Nos debemos defender.*

Opening 1 de Pokémon: "Gotta catch 'em all!"

Autor original: Jason Paige

2.1. Introduction

<https://www2.eecs.berkeley.edu/Pubs/TechRpts/2020/EECS-2020-111.pdf>

[6]

2.2. Physic-based Motion Prediction

Physics-based trajectory prediction (PTP) methods represent the motion of vehicles with dynamic or kinematic motion models compliant with the laws of physics. A future trajectory is predicted via state evolution based on these models. Linear models (constant velocity (CV) and constant acceleration (CA) models), which assume straight motion, are the simplest models. The straight motion assumption of CV and CA oversimplifies vehicular motion because of rotation ignorance. Curvilinear models take into consideration the turn rate (TR) of the vehicle. Similar to linear models, curvilinear models contain two types, namely Constant Turn Rate and Velocity (CTRV) and Constant Turn Rate and Acceleration (CTRA) models. Coupling steering angle and velocity leads to Constant Steering Angle and Velocity (CSAV) and Constant t Steering Angle and Acceleration (CSAA) models. Authors of [25] compare and evaluate these models. More details of

these models can be found in their work. These models can be used for physics-based trajectory prediction in many ways. Inspired by the taxonomies provided in [23, 24], we subdivide physics-based methods into state retention-based methods, reachable set-based methods, Monte Carlo simulation-based methods, and state estimation-based methods. State retention methods produce a single trajectory according to the target vehicle’s current states, while reachable set-based methods produce a union of all reachable states. Monte Carlo simulation-based methods try to approximate the distribution of the target vehicle’s future motion, and state estimation-based methods introduce uncertainty estimation into physics-based methods

2.3. Deep Learning based Motion Prediction

2.4. Vehicle Motion Prediction

Chapter 3

Theoretical Background

*Desde que el mundo cambió, estamos mucho más unidos
con los Digimon, luchamos juntos contra el mal.*

*Algo extraño pasaba, Digievolucionaban,
en tamaño y color, ellos son los Digimon.*

Opening 1 de Digimon: "Butterfly"

Autor original: Kōji Wada

3.1. Kalman Filtering

3.2. Convolutional Neural Networks

3.3. Recurrent Neural Networks

3.4. Generative Adversarial Networks

3.5. Attention Mechanisms

3.6. Graph Neural Networks

3.7. Training losses

Chapter 4

Predictive Techniques for Scene Understanding

Avanzad, sin temor a la oscuridad.

Luchad jinetes de Theoden.

Caerán las lanzas, se quebrarán los escudos.

Aún restará la espada.

Rojos será el día, hasta el nacer del sol.

*Cabalgad, cabalgad, cabalgad hacia la desolación
y el fin del mundo. Muerte, muerte, muerte.*

Discurso de Theoden, Rey de Rohan

El Señor de los Anillos: El Retorno del Rey

4.1. SmartMOT

4.2. GAN based Vehicle Motion Prediction

4.3. Exploring Map Features

4.4. Leveraging traffic context via GNN

4.5. Improving efficiency of Vehicle Motion Prediction

Chapter 5

Applications in Autonomous Driving

*La fuerza de tus convicciones determina tu éxito,
no el número de tus seguidores.*

Reamus Lupin

Harry Potter y Las Reliquias de la Muerte, Parte 2

5.1. Motion Prediction Datasets

5.2. Multi-Object Tracking

5.3. Decision-Making

5.4. Holistic Simulation

Chapter 6

Conclusions and Future Works

*El mundo no es todo alegría y color, es un lugar terrible
y por muy duro que seas es capaz de arrodillarte a
golpes y tenerte sometido a golpes permanente si no se
lo impides; Ni tú ni yo ni nadie golpea mas fuerte que la
vida. Pero no importa lo fuerte que golpeas, sino lo
fuerte que pueden golpearte y los aguantas mientras
avanzas, hay que soportar sin dejar de avanzar.*

¡Así es como se gana!

*Si tú sabes lo que vales, vé y consigue lo que mereces
pero tendrás que soportar los golpes y no puedes estar
diciendo que no estás donde querías llegar por culpa de
él o de ella, eso lo hacen los cobardes y tú no lo eres.*

TÚ ERES CAPAZ DE TODO.

Discurso de Rocky a su hijo

Rocky Balboa

6.1. Conclusions

6.2. Future Works

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