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How machine learning drive the development of autonomous cars

A study of emerging technologies and the evolving value chain

Master's Thesis in the Master's Programme
Quality and Operation Management & Management and Economics of Innovation

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Abstract

Autonomous cars have gained much attention in the past few years. Partially automated features are sold to consumers, and advance autonomous test vehicles are driving on public roads. These features and vehicles have caused a debate about their safety as they have been involved in a couple of fatal crashes in recent years. To simultaneously develop autonomous cars and features without compromising safety is a big challenge for the automotive industry, which is investing heavily in technology.

This thesis aims to describe constraints in advanced driver-assistance systems (ADAS) and autonomous driving (AD) developed with machine learning techniques, how companies are adapting to this new technology demand, and current development paths towards autonomous cars. A model of the development of ADAS/AD was created by interviewing industry experts and a literature review. Companies efforts in the area were identified by searching databases and reading news articles and press releases.

Data is a valuable asset but requires extensive work to be useful when developing ADAS/AD. Collecting data per se is not considered as a challenging task. Instead, the difficulty is to collect data about edge-cases, that is, rare situations occurring maybe once in a human lifetime of driving. Another key takeaway is the inherent difficulty of creating consistent datasets to train neural networks with, as it requires humans to interpret subjective situations the same way.

Incumbent firms in the automotive industry are accompanied by startups and established technology companies from outside the industry in trying to develop and capture value from ADAS/AD. Collaborations and acquisitions are prominent ways to get desired know-how and secure supply of critical components. A schematic overview of the relationships in the industry is mapped to give the reader an idea of the sophisticated ecosystem companies are part of through investments, acquisitions, spin-offs and collaborations.

Efforts to capture value from ADAS/AD can be divided into two branches. One being OEMs developing and offering ADAS in consumer products aiming to develop autonomous driving gradually. The second is characterized by companies targeting autonomous robo-taxi solutions in geo-fenced areas. Although both approaches are facing many similar challenges, they also differ in specific areas such as operational design domain.

Keywords: Machine Learning, Computer Vision, Autonomous cars, Value chain, Business ecosystem.

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Filip Lundqvist & Robin de Richelieu, Gothenburg, June 2019

Nomenclature

Advanced driver assistance system (ADAS) *- driver support features requiring constant human supervision. ADASs can handle human tasks such as steering, braking, or accelerating as a way to make the driving more comfortable and safe.*

Annotated, Labeled, or Training Data *- refers to data that have been classified through an annotation process and is ready to be used for training a neural network.*

Artificial Intelligence (AI) *- an intelligent agent mimicking of the human brain's ability to obtain information, see relationships, draw conclusions, solve problem, plan, and learn from experience.*

Autonomous car *- also known as self-driving car, and driverless car refers to a car which can handle some of, or all, the human tasks of driving a car.*

Autonomous Driving (AD) *- fully automated driving features with level 4-5 in autonomous scale that can drive a vehicle under limited to all conditions.*

Deep learning *- is a machine learning techniques using neural networks with many hidden layers for tasks such as speech recognition, language understanding, and image classification.*

Deep neural network *- is an artificial neural network containing many hidden layers.*

Machine learning *- is a subcategory of artificial intelligence and is based on the idea of computers generating models and rules from data instead of being explicitly programed.*

Operational design domain *- refers to the operating conditions where an autonomous car or feature are designed to function.*

Robo-taxi *- is an autonomous car serving customers as a taxi.*

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Introduction

This chapter gives the reader a brief background to why autonomous features and cars are relevant and the context of the thesis. Additionally, purpose, research questions, and delimitations are defined to establish the scope of the thesis.

1.1 Background

According to the U.S. National Highway Traffic Safety Administration (NHTSA), 94% of severe crashes in 2016 were caused by humans (NHTSA, 2019). In the U.S alone, 37,000 fatalities were caused by motor vehicles crashes (NHTSA, 2019). In 2016, the number of deaths in road traffic accidents worldwide was 1.35 million and the leading cause of death for children and young adults aged 5-29 (WHO, 2018). The rate of road traffic deaths varies significantly among regions. Africa and South-East Asia have the highest rates with 26.6 and 20.7 deaths per 100,000 population respectively. In the other end of the continuum are countries in the Americas and Europe with 15.6 and 9.3 deaths per 100,000 population respectively (WHO, 2018).

Thus, increasing road safety is a matter concerning many actors in a society, not least the automotive industry. NHTSA describes five eras of road safety starting with passive safety features such as seat belts and anti-locking brakes (NHTSA, 2019). Gradually safety features have become more advanced, proactive, and automated. NHTSA name the current era of safety as partially automated with features such as adaptive cruise control and lane keeping assist. The next era is called fully automated which is indicated to arrive year 2025+ (NHTSA, 2019).

In a perfect world, all road crashes caused by human errors could be eliminated by autonomous cars. Autonomous cars have been predicted to save billions worth of dollars as a result of a reduced number of crashes, increased productivity, and other benefits such as reduced fuel consumption and reduced congestion (Römer, Gaenzle, & Weiss, 2016).

Today software accounts for around 10% of the vehicle content of a large car (Burkacky, et al., 2018). This segment is approximated to grow by 11% per year until it hits 30% in 2030 (Burkacky, et al., 2018). An increasing share of software solutions is impacting the value chain and the automotive industry's demand for new technology end expertise (Burkacky et al., 2018).

1.2 Research Problem

One challenge with autonomous cars is to make them able to perceive their surroundings. Humans are capable of distinguishing the differences between pedestrians, bicyclist, other vehicles, and animals and can read subtle clues to what these objects will do next (Abuelsamid & Gartner, 2018). Computer vision is an interdisciplinary field covering a host of techniques to acquire, process, analyze, and understand complex input data aiming to replace the human vision system (Huang, 1996; Jähne and Haussecker, 2000).

Machine learning, a subcategory of artificial intelligence, is being addressed as an increasingly important piece to solving the autonomous car puzzle (Huval et al., 2015). Abuelsamid and Gartner (2018, p.3) endorse this and argues that machine learning based on deep neural networks is "[...]widely considered to be the key to the successful development of highly automated vehicles.". Luckow et al. (2016) also emphasize how machine learning and deep neural networks have improved computer vision dramatically. Improvements in storage capacity and compute capabilities are two enabling factors making computation heavy deep neural networks more successful and an increasingly researched area (Huval et al., 2015).

As opposed to a human, a deep neural network requires a huge amount of training data or examples of objects to distinguish them from each other (Abuelsamid & Gartner, 2018). These examples need to be labelled to make sense for a neural network. Labelling, or annotating, is simply to add an explanatory label to something and could be a bounding box around a car with a virtual label saying "car". Creating large-scale annotated datasets is labour intensive and costly (Janai et al., 2017). Thus, data in general, and training data in particular, is a desirable asset.

Advancements in machine learning are driving the development of advanced driver-assistance systems (ADAS) and autonomous driving (AD) technology. Incumbent OEMs (original equipment manufacturers), established technology companies, and startups are all trying to position themselves in order to capitalize on the new market demands (Burkacky et al., 2018). Recent investments and acquisitions in the industry as indicators of this. Intel acquired Mobileye, an Israeli ADAS/AD company, for $15.3 billion in 2017 (Cohen, et al., 2017). Google acquired DeepMind, an artificial intelligence company, in 2014 for about $400 million (Reuters, 2014). General Motors acquired an AD startup called Cruise Automation in 2016 for $581 million, in which both Honda and SoftBank invested $2.75 billion and $2.2 billion respectively in 2018 (Hawkins, 2018). An extensive list could be made of investments, partnerships, and acquisitions made in ADAS/AD and the technology revolving it.

These efforts witness about an industry in change. The traditional tier positions start to fade where tier 2 and tier 3 suppliers try to reposition themselves within the value chain (Burkacky, et al., 2018). The repositioning is done by upgrading their current technology stack and move from applications and features towards operating systems (Burkacky, et al., 2018).

The tier 1 suppliers of electronic systems try to move in the direction towards technology giants and OEMs tries to moves further up the value chain to be able to protect the essence of their technical differentiation and distinction (Burkacky, et al., 2018).

However, Ritter and Gemünden (2003) point out that, in the network economy, a firm's competitiveness does not only depend on its internal competence but also on its ability to interact with its environment. Iansiti and Levien (2004) also emphasizes the importance of the external ecosystem and argues that traditional models of strategy neglect this and the role of co-creation of value.

1.3 Purpose and Research Questions

The purpose of this thesis is to provide a deeper understanding of how the development of machine learning in computer vision solutions for advanced driver-assistance system and autonomous driving affects companies positions in the automotive value chain and how they aim to capture value. The purpose is considered as fulfilled by answering the following research questions:

- How is advanced driver-assistance system and autonomous driving developed by using machine learning techniques in computer vision and which are the current constraints?
- How is the development of advanced driver-assistance system and autonomous driving affecting the competitive landscape?
- Which are currently the most prominent way to capture value from advanced driver-assistance systems and autonomous driving?

1.4 Delimitation

Although this thesis is deeply rooted in technology, the reader should not expect to get a detailed insight into how machine learning or different technologies work. Instead, the scope of this study is limited to give the reader an overview of the main components and technologies of ADAS/AD. Autonomous car technology spans over many technological areas whereas this thesis will only study computer vision techniques using deep neural networks and the revolving business ecosystem. The technology overview will serve as a support to understand the positions of companies within the business ecosystem. The area of application is limited to autonomous cars although the technology might be similar in other application areas. Due to that only non-confidential data has been gathered, the result should not be seen as an absolute truth but rather as a compass.

2

Theoretical Framework

This chapter provides the reader with a framework of theories and models that this thesis builds upon. Value chain, value network, and business ecosystem are central theories complemented with vertical and horizontal integration.

2.1 Value chain

The value chain concept is circled with some terminological confusion and overlap depending on in which context it is being used (Kaplinsky and Morris, 2000). The value chain was introduced by Porter in 1985 to explain how activities within a firm contribute to creating competitive advantage (Porter, 1985). Porter (1985) divide the value chain into primary and supporting activities within a firm. The value chain is in its' turn embedded in an extended value system which is a larger stream of activities including other firms as well (Porter, 1985). Kaplinsky and Morris (2000) argue that the notion of the value chain is more commonly referring to the linkages between firms rather than within them as Porter defined it. They argue that the value chain is a concept that describes the full range of activities of bringing a product or service from concept to final delivery to a customer, including disposal after use (Kaplinsky and Morris, 2000). Peppard and Rylander (2006) are also using the value chain concept with the logic that each company holds a position in the chain providing the next link with inputs. This thesis will adopt the definition where the value chain is regarded as linkages between companies.

Disregarding terminological ambiguities, understanding both internal and external linkages and value creation is essential when determining the vertical scope of a firm and what makes it competitive (Porter, 1985; Kaplinsky & Morris, 2000). Identifying core competencies help a firm determine which activities to outsource and which to pursue. Mapping the flow of goods and services help a firm in identifying other essential companies within the value chain. However, Peppard and Rylander (2006) argue that this mainly holds in traditional manufacturing industries. Furthermore, they argue that as products and services become dematerialised, the value chain concept becomes inappropriate to uncover sources of value in many industries. This linear model does not account for alliances, competitors and other members in business networks (Peppard & Rylander, 2006). Verna (2000) support this and also argues that the traditional value chain originates from the industrial age and is an old and linear way of describing how value is created.

2.2 Network and Ecosystem Approaches

The value chain approach mainly emphasizes the internal linkages within firms and a sequential flow while a network implies multidimensional linkages (Turati & Ruta, 2002). Alternative approaches, such as networks (Powell, 1990), value networks (Verna, 2000), and business ecosystems (Moore, 1996; Iansiti & Levien, 2004; Anggraeni et al., 2007; Basole et al., 2015) include actors outside the value chain in a higher degree.

2.2.1 Value Network

Porter's original value chain has since it was introduced been adapted and expanded to fit the dynamic modern economy better and consider value creation beyond a single firm. Verna (2000) refers to this broader view as a value network (Verna, 2000). The value network is a system with dynamic exchanges between strategic partners, suppliers, customers, and other actors that create economic value. In addition to services and goods, the value network includes knowledge transfer and intangible benefits as value generation between firms (Verna, 2000). Knowledge transfer is exchanges of strategic information, planning knowledge, process knowledge, technical know-how, collaborative design, policy development which all are connected to the core product or service value chain. Intangible benefits are exchanges that stretch beyond the actual service or product and can be customer loyalty, sense of community, co-branding opportunities, or image enhancement (Verna, 2000).

Verna (2000) deems that knowledge transfer and intangible benefits become increasingly important components when services and products get more complicated. Hence, including knowledge and intangible factors refines the analysis of value creation. The value network can be mapped out as a type of flow chart with each node representing a firm or group of people. Arrows that connects the nodes represent one of the three value generating categories which are; products or services; knowledge; and intangible benefits. This perspective helps to analyze the value creation from many different perspectives such as goals, time, costs, value added, result, and resources (Verna, 2000).

Powell (1990) is, in essence, also describing network forms of organizations as a way to generate value. Network forms of organizations are filling the gap in the traditional view of market-hierarchy as a continuum (Powell, 1990). He identifies know-how, demand for speed, and trust as three critical components of networks. Know-how is often related to intangible and tacit knowledge that is hard to transfer or codify and is typically highly mobile knowledge as it exists in the minds of talented people. Powell (1990) argues that networks emphasize lateral communication and mutual obligation which is well-suited in an environment with a skilled workforce and where know-how is applicable in different fields of activities. In this context, the demand for speed address the situation where an incumbent firm is faced with intense technology competition and need to reposition themselves.

Competition makes firms join forces with other companies, suppliers, and researchers to reduce risk and share expenses of development efforts (Powell, 1990). Porter and Fuller (1986) argue that partnerships and coalitions are faster means of getting desired know-how instead of developing it internally and less costly and less irreversible than a merger.

2.2.2 Business Ecosystems

Similar to the value network concept, business ecosystems rely on interconnected firms in complex systems of relationships (Basole et al., 2015). Moore (1996, p.26) defined business ecosystems as "An economic community supported by a foundation of interacting organizations and individuals - the organisms of the business world[...]". He argues that an ecosystem includes customers, suppliers, lead producers, competitors, and other stakeholders. The members of a business ecosystem are coevolving over time, shaping their capabilities and roles and usually align themselves with the direction set by central firms in the ecosystem (Moore, 1996).

Iansiti and Levien (2004) also allege that traditional models of strategy emphasize capabilities within firms and business models neglecting the importance of the external relationships of firms. By adopting a business ecosystem approach, value is regarded as being co-produced by different economic actors, such as suppliers, partners, allies, and customers (Iansiti & Levien, 2004). Previously, individual firms have been thought to battle other individual firms. Iansiti and Levien (2004) argue that this is no longer the case, and instead ecosystems of interconnected organizations are competing against each other where leaders must view individual companies within their ecosystem as equally important as their own to succeed.

Iansiti and Levien (2004) argue that the ecosystem of the automotive industry historically has held strong and conservative bonds with its supplier, which has prevented new niches from emerging. Connections with other companies with a similar view of what the future will look like are essential to managing the unknown future were technological changes affect how the ecosystem is organized. The ecosystem must be able to manage disruptions and sudden technological change in order to survive. Companies that are well integrated with each other can easier predict which changes that will come and mitigate the effects of external shocks (Iansiti & Levien, 2004).

Dominant players in an ecosystem tend to absorb the value created by other companies (Iansiti & Levien, 2004). An ecosystem must share the value between its participants. The common theme for business that has become extraordinary successful is the investment to build tight connections and strong relationships with other business to shape the ecosystem. Otherwise, it becomes vulnerable and often leads to its collapse, where the dominant player often is the long term loser (Iansiti & Levien, 2004).

2.3 Automotive Value Chain

Heneric et al. (2005) and Lind et al. (2012) both provide examples of how the automotive value chain can be structured. Heneric et al. (2005) divide the automotive value chain into five steps including Tier 3-, Tier 2-, Tier 1 suppliers, OEM, and Retail. Lind et al. (2012) refine this model by dividing the value chain into six steps including, Raw material suppliers, Refined raw material suppliers, Components suppliers, System suppliers, Car manufacturers, Car dealers. Each step has their internal value chain and therefore is these models not meant to show all parts included in a car and Lind et al. (2012) mention that for instance software is missing.

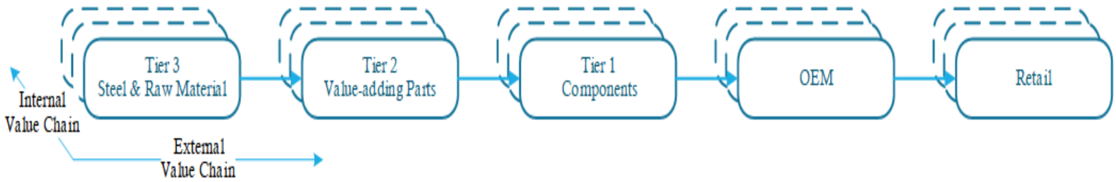

Figure 2.1: The value chain described by Heneric et al. (2005).

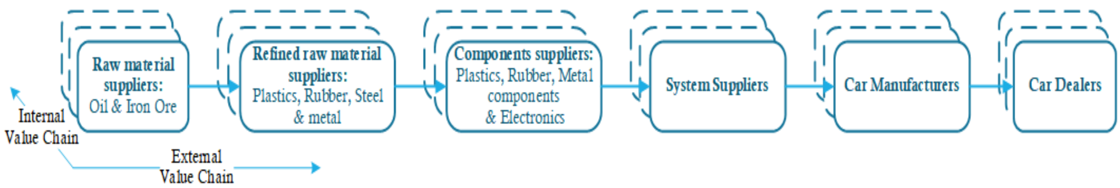

Figure 2.2: *The value chain described by Lind et al. (2012).*

2.4 Vertical Integration

Kenton (2018) view vertical integration as when a company takes control over several production or distribution steps in its value chain. This type of strategy is often connected with cost reduction and efficiency improvement. Either by acquiring an existing business or internal expansion into other steps of the value chain. When a business is active in other verticals, this means that the business also creates value by producing other types of product or service in comparison to its original core competence. When a company controls several parts in the supply chain cost reduction and efficiency improvement among other advantages can be achieved by example reducing turnaround times and transportation expenses (Kenton, 2018).

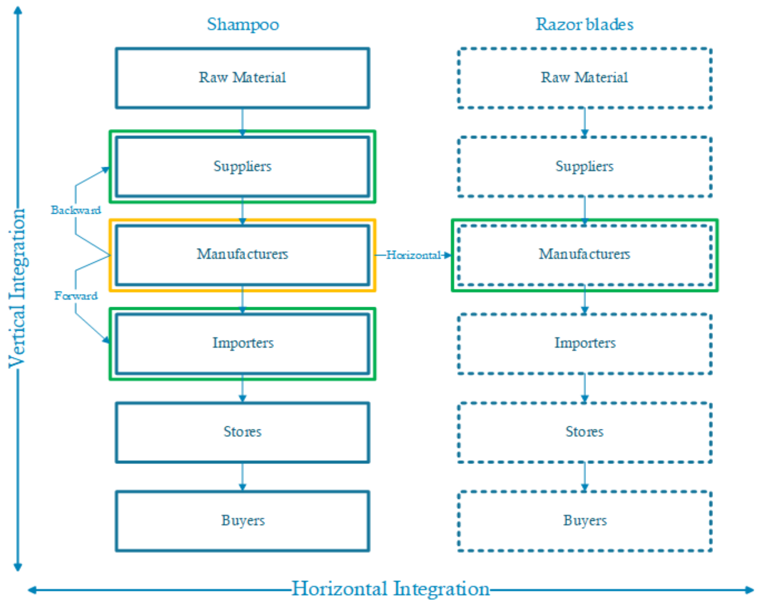

Figure 2.3: Illustration of the different strategies of expanding a business.

Kenton (2018) describes two types of vertical integration. Forward integration (downstream), and backward integration (upstream). A firm is integrating forward when taking control over downstream activities, towards end customers, following the output of the original business. An example could be a forest company acquiring a sawmill. Backward integration would be a sawmill company getting their own forest and thus control upstream activities in the value chain (Kenton, 2018).

2.4.1 Advantages of Vertical Integration

How the steps of vertical integration look like differs between industries. However, Zhang (2013) argues that cost reduction is the main reason for vertical integration and is independent of the industry. This approach does not suit all types of companies, it depends on what the business strategy objectives are. Companies that gain their competitive advantage from being cost leaders will be more beneficial of vertical integration (Zhang, 2013).

2.4.2 Disadvantages of Vertical Integration

Zhang (2013) means that vertical integration also has its complications, especially on an operating performance level. By shifting focus from the core competence toward a cost reduction approach will affect the company's performance from example, a quality perspective, due to the trade offs decisions that have been made.

2.5 Horizontal Integration

Kenton (2018) view that horizontal integration as when a company expand its business into new or similar industries as to where they are currently positioned. Horizontal integration is a strategy that aims to strengthen the competitiveness by increased market power in the value chain, differentiated product offering, economies of scale, or expand to new markets. A retailer selling clothes can integrate horizontally by adding accessories to the product offering. By adding accessories, the retailer will be able to increase revenues in a way that would not have been possible by only selling clothes (Kenton, 2019).

2.5.1 Advantages of Horizontal Integration

The idea behind horizontal integration is to create synergy effects (Kenton, 2019). Cost synergies can involve reduced purchasing cost of raw material due to higher order volumes, sharing production or distribution facilities, and take advantage of shared R&D expenditures. Synergies can also be created by combining markets or products. An example from 2005 is when Procter & Gamble acquired, Gillette. Both companies were active at the same level in the value chain of hygiene-related products. With the merge, Procter & Gamble were able to create synergies to lower product development and marketing cost per product. The acquisition also allowed Procter & Gamble to increase the growth of each business' market with cross-selling opportunities from a broader range of product offerings (Kenton, 2019).

2.5.2 Disadvantages of Horizontal Integration

Horizontal integration could still have complications. One case is when expected synergies do not materialize, or even worse, giving negative synergies that reduce the value of the business. Example of negative synergies can be increased overhead costs as larger firms can become more complex to manage and become inflexible and unwieldy. Merges can cause differences in company culture or leadership styles to clash resulting in reduced efficiency (Kenton, 2019).

3

Methods

This chapter provides the reader with information about how this master's thesis was conducted. According to Edmondson and McManus (2007), it is essential to create a method that is suitable for the study. They suggest a funnel model with an iterative process with feedback and modifications at the different steps in the study process which have been used as a foundation of this thesis (Edmondson & Mcmanus, 2007).

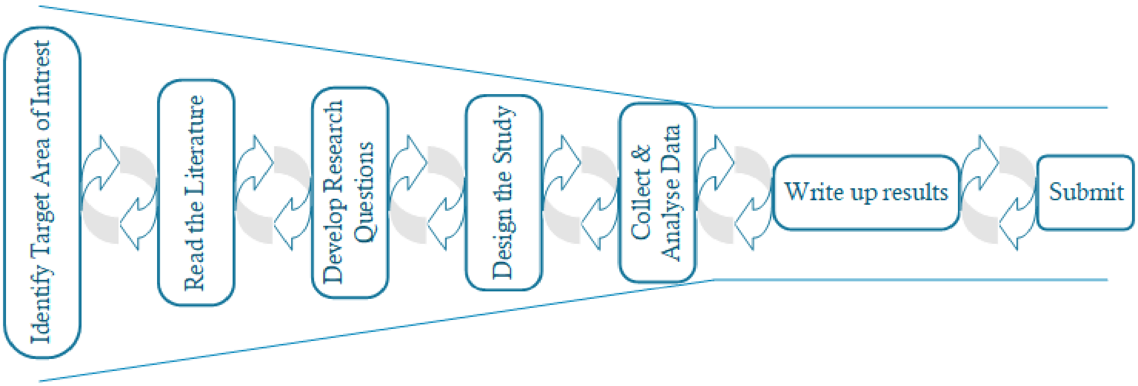

Figure 3.1: Funnel model. Source: Edmondson and McManus (2007)

3.1 Research Strategy

The thesis aims to map and highlight the position of companies within the value chain and its ecosystem for the development of ADAS/AD from a computer vision viewpoint. A base model for the ADAS/AD value chain has been developed by combining various articles and literature about big data and computer vision. The base value chain has then been quality checked and further developed by interviewing experts in order to become an accurate representation of the real value chain. The selection of experts was based on well-recognised names with useful insight into the industry, and each expert serves as a representative for a specific step in the base value chain. The selection of experts has been based on a T-structure approach (CHAIR, 2019), which means that there has been a mix between experts with specific knowledge in one vertical step in the value chain and experts with a broader perspective over the whole value chain.

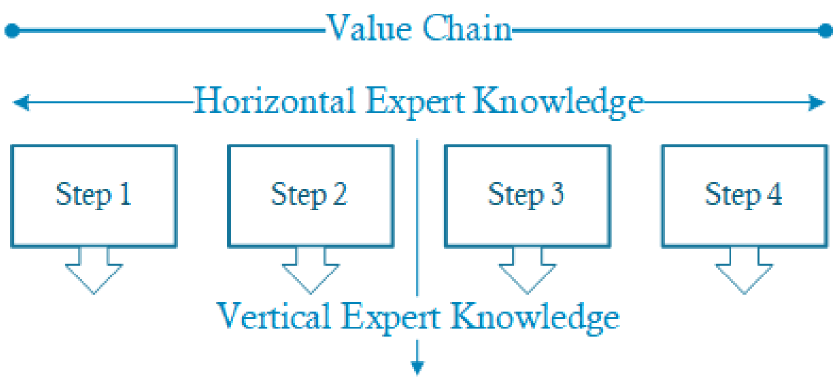

Figure 3.2: Strategy for interview for developing the value chain.

Edmondson and McManus (2007) state that even if there is no best way of crafting a research design, it is more likely that qualitative research strategies will be more successful in topics with limited knowledge. This is usually done in an inductive approach. The complexity of finding a relevant theory for this research in an immature industry has led to the conclusion that the study needs to take an abductive approach. Dudovskiy (2015) describes that an abductive approach works its way from incomplete observation and from that make the best possible explanation for the research question. An abductive approach is suitable when a research field lack theory to explain observations or phenomena (Dudovskiy, 2015).

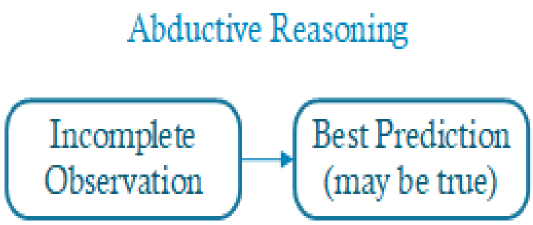

Figure 3.3: How abductive reasoning works Dudovskiy (2015).

3.1.1 Qualitative and Quantitative Research Considerations

Porter (2008) suggest that when analysing an ecosystem there should not be to much focus on qualitative data to increase validity. Instead of a mix, where qualitative data is backed up with quantitative data, should be used. Since the research questions focus on understanding an immature industry were data, in general, is hard to acquire and many players are startups or private companies which do not have any obligation to make numbers official, this study will only be able to take a qualitative approach.

3.2 Research Design

For the theory to be valid, it is crucial that the thesis is related to reality in an empirical way (Glaser & Strauss, 1967). This connection is especially important when analysing an ecosystem where the focus is on understanding the social aspects that define the environment. By choosing to conduct the study as a case study, there will be a substantial advantage in empirical validity (Eisenhardt, 1989). Even if case studies are particularly suitable for developing new theory (Voss, Tsikriktsis, & Frohlich, 2002) focus of the research is not to do that. Instead, the abductive approach will be used to collect empirical data to identify patterns and trends of how the ecosystem functions today from both technical and economic aspects which then is analysed with existing theories.

3.3 Research Methods

The research method describes the different types of data and collection techniques used in the thesis (Bryman & Bell, 2011). Bryman (2012) mentions that the research strategy, -design and -techniques have different limitations and sets the standard for what is a possible and reasonable conclusion by answering the research questions.

The development and research around machine learning and ADAS/AD have rapidly expanded in recent years (Huval et al., 2015). The industry is in a fluid state due to the early phase where products are in an R&D stage and knowledge in the topic develops quickly. Due to this rapid change, there is very little research on this topic, especially on the business side. In the technical domain, there is some research. Due to the rapid change in technology, research quickly becomes obsolete. Hence, data from updated sources is essential in this thesis.

3.3.1 Research Process

The research follows the suggested steps from figure 4 and consist of three major phases; Define; Case study; and Conclusions. These phases overlap each other to some extent as a consequence of the iterative approach that ensures the gathered information aligns with the research questions.

In the first phase, Define, the focus is to gain insight on the development of autonomous cars, both from a technical and a business perspective, to understand how the research questions should be formulated. The abductive approach set the standard for what type of information could be gathered. An essential part of the Define-phase is to understand what topics are relevant and discussed within the industry today. Insights of relevant topics were collected by attending the kick-off conference of Chalmers AI Research Centre (CHAIR) and a seminar about machine learning at Knitech. The CHAIR conference was also used as a strategy to identify experts for the interviewers in the Case study-phase.

In Case study-phase, insight from the Define-phase was used as the foundation for creating the empirical results. In the Case study-phase focus was to gather, transform, and analyse data. Between the Define-phase and Case study-phase, there was an iterative process to refine and ensure the relevance of the research questions. Insight from the Define phase was used as the baseline for developing the prototype of the value chain. The baseline value chain was then set in an iterative improvement step to improve the model with the help of the expert interview. Interviews were held with experts within different areas of the value chain. In total, seven experts were interviewed, each session was based on open questions around the model and from their area of expertise. The model was improved after each session with the insight gained from the interviews. Interview questions were sent out in advance and in addition to those, complementary questions were asked during the interview. The interviews were given the option to be anonymous and read the report before publishing. The most important findings from the interview regarding the value chain and the technology were summarised in the empirical results.

The last step of the Case study-phase was to start mapping companies within the value chain. Information about companies was retrieved from CrunchBase, a database which gathers in-depth company information such as investments, acquisitions, and funding rounds. Additionally, companies homepages and news articles were used to track down companies and their collaborations. Which information to collect about the companies was inspired by the value network model by Verna (2000).

The results from the Case study-phase was analysed with the theory explained in chapter 2, followed by final conclusions and elaboration on further research. It is essential to understand that because of the research abductive nature the answers will only be able to reflect the best-known truth of today. How the value chain appears to be at the current state should not be interpreted as the absolute truth. Thus, it is important to understand that the results can change and be interpreted in other ways depending on technical development and factors of the ecosystem.

3.3.2 Data Gathering Methods

Most of the theory in this thesis have been obtained by searching keywords connected to the research questions. The search was done via Chalmers library database, Google Scholar, and Google Search. Furthermore, the theory has been collected from references found in other master thesis and other articles that are relevant to the topic. However, the market of computer vision solutions based on deep neural networks is still immature and many of the companies that are relevant for this research are in an early stage and is considered as startups. Hence, public information is limited and was mainly gathered from news articles, home pages, and interviews rather than annual reports.

Below is the different type of sources of knowledge that was used in the study.

- **Databases:** CrunchBase, where information about investors and owners can be found, has been used to gather quantitative and qualitative data to map company's value creation connections in the business ecosystem.
- **News articles, research articles, and consultancy reports:** was the primary data source about technology, companies, and market trends.
- **Web pages and topic forums:** were used to better understand the technology side, development progress and business models of different OEMs.
- **Expert interviews:** were used to gather info about trends in the market and get a better understanding about the value chain. Each interview was recorded with permission from the interviewee and varied in length from 30-60 minutes. The interviewees are:

Interviews

Alexey Voronov	Senior Researcher	RISE	3-05-2019
Andreas Geiger	Professor of computer science	Autonomous Vision Group	8-04-2019
Daniel Langkilde	CTO	Annotell	29-03-2019
Erik Rosén	Technical Expert Deep Learning	Zenuity	11-04-2019
Marcus Hedberg	CPM	Aptiv	23-04-2019
Nasim Farahini	CTO	Camqom	11-04-2019
Per Lundberg	Machine Learning specialist	CEVT	13-04-2019

- **Conference:** gave a broad understanding of which knowledge that is important and found attractive candidates to interview.

3.4 Quality of Research

Bryman (2012) argues that to ensure an appropriate quality the aspects of reliability, validity, and transferability need to be taken into account. Triangulation is used to ensure the validity of the data gathered (Bryman, 2012). Case studies as a research method have some drawbacks that are important to understand when evaluating the results. One of the significant risks of conducting a case study is that theory easily tends to be complicated, making it applicable in only a few situations (Eisenhardt, 1989).

Bryman (2012) explains that the nature of qualitative studies results in that much data is collected and processed. Replications are therefore hard to perform. However, a clear description of the method facilitates replications (Bryman, 2012). The general approach this thesis has makes it transferable to use in other business cases where the value chain and the business ecosystem can be used as analysing tools.

3.5 Ethical Consideration

Easterby-Smith et al. (2015) describe the following ethical principles as essential to being covered in a study:

Ensure with the companies that it is acceptable to perform the research.
This only apply to the expert interviews. Public information is not accounted for in this principle.

Give continuous transparency information about how the research is being performed and what the aim of the study is.
Companies and interviewees were informed about the purpose of the research before the information was gathered. The method have been explicit of how each step have been performed and how the information have come to use.

If there are any confidential data in the research make sure that those included in the study have the option to be anonymous and that the data is being protected.
Before each interview, interviewees were given the opportunity to be anonymous. Each interviewee were also able to approve citings before publishing.

Avoid drawing to generalising conclusions since this can lead to misconducting research.
To avoid generalising have the report been transparent in its method and its limitations of what type of conclusions that are possible to make.

4

Technology Overview

In this chapter, the aim is to give the reader an overview of the technology that constitutes an autonomous car. First, the concept of an autonomous car and ADAS/AD is explained in a broader sense with the help of the different levels of automation. Second, the main tasks of an autonomous car are explained. Last, computer vision, as a critical area in an autonomous car, is divided into software and hardware used in the development today.

4.1 Levels of Automation

When describing autonomous cars, it is necessary to classify levels of automation as many features in a car makes driving more or less automated. Society of Automotive Engineers (SAE) International provide a classification system ranging from no automation at level 0 to full automation at level 5 (SAE, 2018). According to this classification system, level 0-2 is regarded as "driver support features" while level 3-5 is considered "automated driving features".

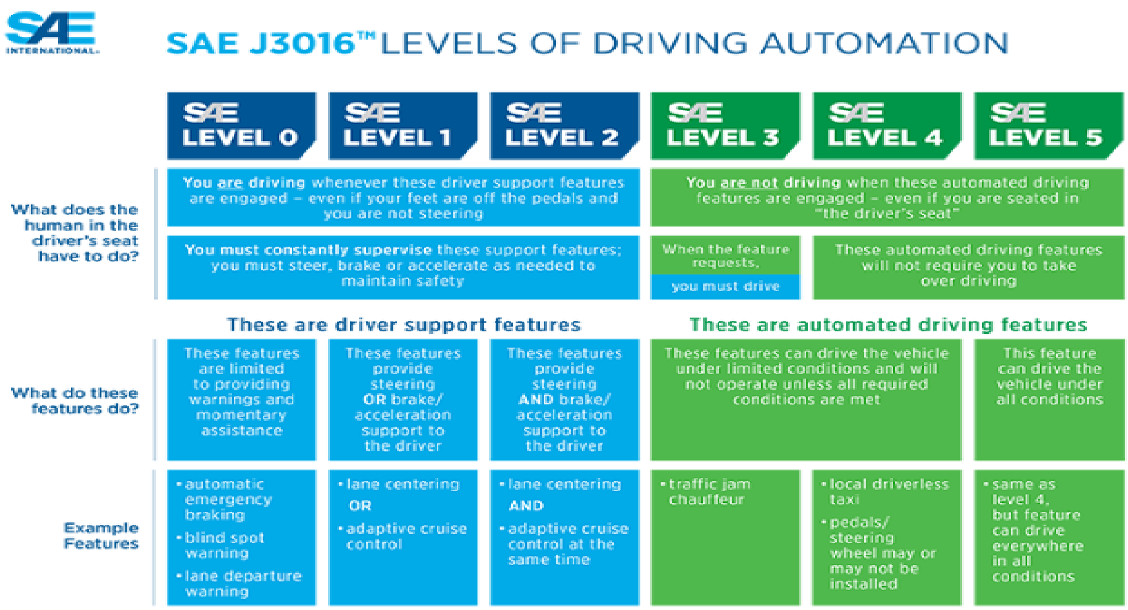

Figure 4.1: SAE International's levels of driving automation, SAE International (2018).

Takács, Rudas, Bösl, and Haidegger (2018) refers to the SAE classifications system and describes level 0-2 as the commonly referred advanced driver-assistance systems (ADAS). These features are just supporting the driver and require constant human supervision. Level 3-5 ranges from partially to fully automated driving features. Takács et al. (2018) also point out that it is hard to define strict boundaries from a technical point of view. Furthermore, they suggest a rule of thumb stating that level 0-2 can be solved with traditional sensor-processing algorithms and currently available hardware while level 3-5 depends on advanced machine learning and deep learning techniques.

4.2 Key Technologies of an Autonomous Car

An autonomous cars main characteristic is to transport humans or objects to predetermined targets without humans performing the driving (Zhao, Liang, and Chen, 2017). Such a car requires many technologies performing multiple tasks that need to be coordinated in a high-level sense-plan-control chain (Takács et al., 2018). Zhao et al. (2017) are in essence describing the same chain as Tackács et al. (2018) but frames it as environment perception, a car navigation system, and car control. Zhao et al. (2017) also add path planning which can be included in the car navigation system.

4.2.1 Environment Perception

If a car should be able to make its own decisions it needs to understand its environment by collecting and interpreting data. All the data gathering is managed by perception sensors, such as cameras, LiDARs (light detection and ranging), and radars (Choi, 2016). The data collected is helping the car detect vehicles, traffic lights, pedestrians, and other objects of interest. Data from multiple sensors are fused to give the control unit in the car one comprehensive picture of the surroundings to base decision on (Zhao, et al., 2017). In chapter 4.4.1 more about the features of the different sensor is found. The focus of this thesis will be on the environmental perception technology of an autonomous car.

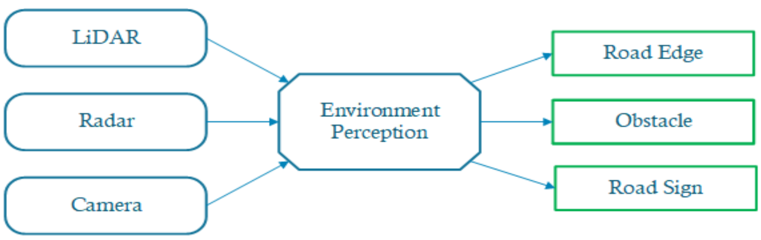

Figure 4.2: Description of environment perceptions ecosystem, Zhao, et al., (2017)

4.2.2 Car Navigation System and Path Planning

Zhao et al. (2017) explain two issues in particular that need to be solved when it comes to navigating an autonomous car. The first one is to determine the current location of the vehicle, and the second one is which path the car should take to reach its final destination. For a human, this is a relatively easy task, but for a machine to be able to replace this task, things become much more complicated. Therefore, an autonomous car needs a system for navigation (see figure 4.3). Geographic information and global positioning (GPS) is required to determine the latitude and longitudinal position accurately. Other sources of data input are digital HD maps which are used for the path planning calculations. The path planning model calculates a driving route by determining its position through GPS and combining it with HD maps. In comparison to many other types of technologies, path planning is instead a well-developed technology and commercially available (Zhao, et al., 2017), e.g. Google Maps.

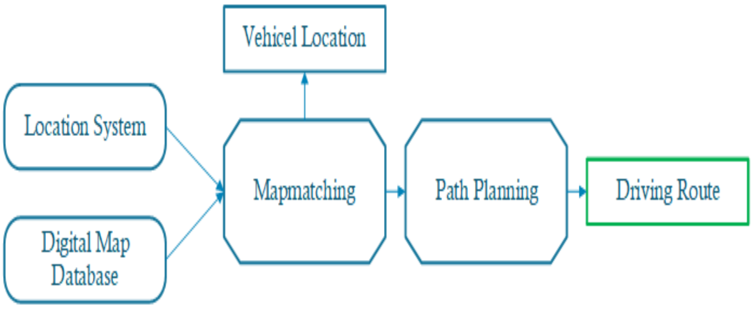

Figure 4.3: Description of the car navigation system, Zhao, et al., (2017)

4.2.3 Vehicle Control

Managing speed and direction with the help from the cars status perception and the development of the vehicle's control method is the task of vehicle controls explains Zhao, et al., (2017). In figure 4.4 a better understanding of how vehicle control fit in the self-driving framework. The input data is used to calculate the direction and speed of the vehicle environment perception, vehicle status, driving target, traffic regulations and driving knowledge. This information feds into the perception module also called TPU where the vehicle control algorithm processes the input data. After the algorithm has processed the data it passes forward to the vehicle control system where the execution of those actions the vehicle is about to take happens. The control platform which decides what type of action to take is seen as the core of the self-driving vehicle. Some example of functionalities that the vehicle control system handle is car anti-lock braking system, auxiliary brake system, car radar anti-collision system and cruise control system (Zhao, et al., 2017).

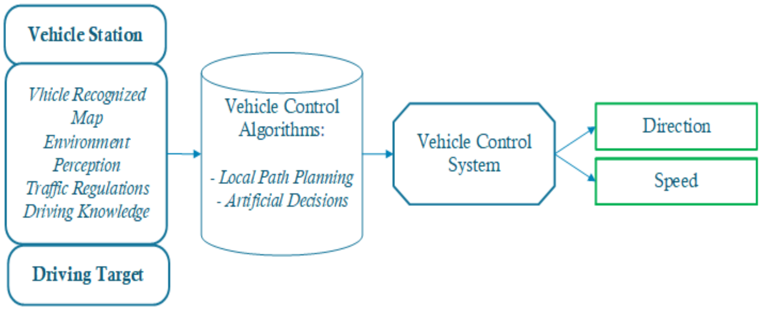

Figure 4.4: Parts included in the vehicle control system, Zhao, et al., (2017)

4.3 Computer Vision

Computer vision is an interdisciplinary field covering a host of techniques to acquire, process, analyze, and understand complex input data aiming to replace the human vision system (Huang, 1996; Jähne and Haussecker, 2000). Klette (2014) view computer vision as the area of making computers interpret the world with the help of sensors such as cameras, radars, and LiDARS. Computer vision can be used to estimate the distance between an object and the sensor, estimate the number of people in an area, and object recognition among other things. The field of computer vision is not new. However, it is not until recent years, when processing power and sensors have become more advanced, the application areas have grown. Advancements in this domain have made computer vision a critical technology for the development of autonomous car technology (Klette, 2014).

Davies (2018) illustrate how computer vision functions in a simple way in figure 4.5 where a set of labelled data of 25 bit (5x5) is used. Data in the upper part of the figure is the "training data that has been used to train the computer to recognise, for instance, how the letter D should look like in 25 bit. To see if the computer identify the letters test data is used for validation. The computer compares the test data with what it has been learned and assign it with a percentage degree to which label it most likely belongs to. One method to determine if there is a match between the training set and the test pattern is by measuring the Hamming distance. This method measures the differences in length of the comparing image in order, to sum up, how similar they are. There are other methods for analysing an image and depending on the choice of the method there will be a trade-off when it comes to the results of accuracy, robustness, cost or other variables (Davies, 2018).

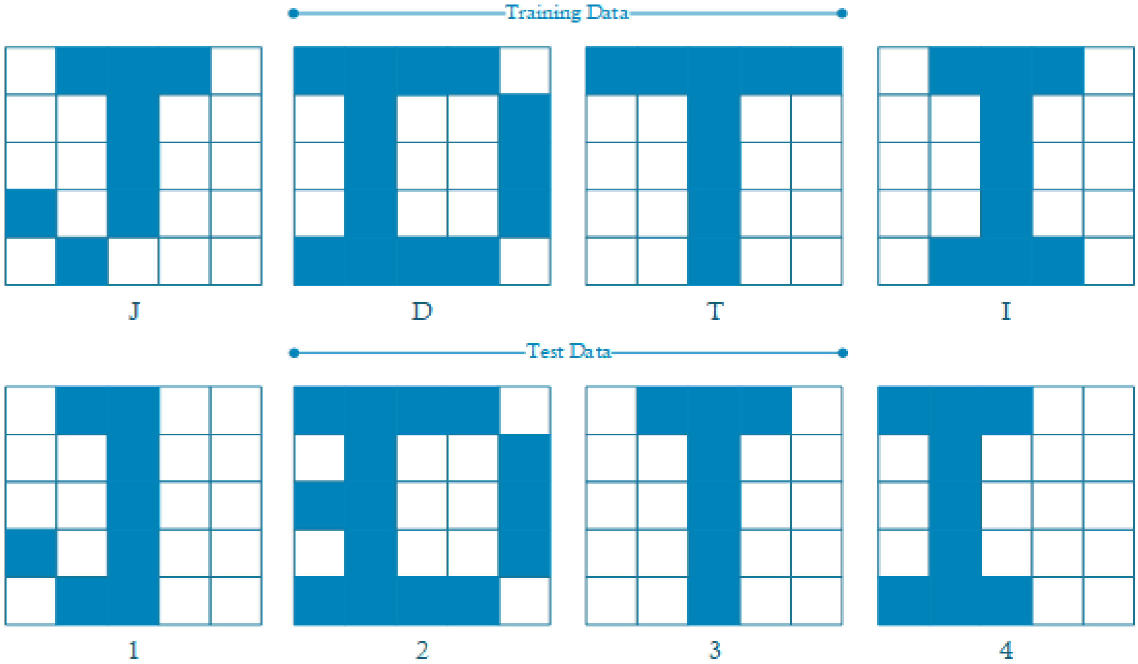

Figure 4.5: Illustration of how image recognition works, Davies (2018)

What is essential to understand is that computers are not intelligent. Computers will only do what it has been taught to do (Davies, 2018). The computer would struggle if the test data were in another resolution or in lowercase letters. Thus, the computer needs to be trained with examples of other resolution and lowercase letters to successfully recognize the letters. This is one of the reasons why computer vision becomes a complex task when there is a lot of unique scenarios to take into account (Davies, 2018). Applying this logic to autonomous cars materializes a major challenge as the number of unique scenarios an autonomous car might face is virtually infinite. Training data is therefore crucial for supervised machine learning systems. Other complications that could affect the complexity are shifting light, other models of sensors, noise levels, processing power, amount of data, and consensus over standardisation (Davies, 2018).

4.4 Hardware

This section includes a description of the most relevant type of hardware used in the development of ADAS/AD. It is only the hardware that connects to computer vision that will be taken into account.

4.4.1 Sensors

There is no consensus in the industry on which combination of sensors to use for autonomous cars. Some players argue that vision and radar system is enough when others claim that LiDAR sensors also need to be included to create a redundant system (Burkacky et al., 2018). Following is a description of the most common type of sensors used.

4.4.1.1 LiDAR (Laser) System

Waymo (2018) describes Light Detection and Ranging (LiDAR) as a type of sensor that uses laser beams that shoots out in a 360-degree perspective. When the beam hit an objective the sensor measure the time it takes until the beam gets back to the sensor. When the LiDAR sensor has enough measurement points it creates a 3D point cloud of the surrounding. The LiDAR sensor comes in various types depending on the distance they are supposed to be used for. The sensor functions both day and night but can struggle in heavy rain or snowfall. The different types of LiDAR that are used by Waymo is:

- **Short-range LiDAR:** Creates an uninterrupted view around the vehicle.
- **Mid-range LiDAR:** A for high-resolution 3D point cloud.
- **Long-range LiDAR:** A powerful new generation that's detects objects far away (Waymo, 2018).

4.4.1.2 Vision (Camera) System

Waymo (2018) use cameras in order to view the world as a human would, cameras are used as sensors for the vision system. These cameras are positioned to give a 360-degree field of view around the vehicle. The vision system with its high resolutions can detect colours which are suitable for tasks such as spot traffic lights, detecting school buses, emergency vehicles, and construction zones. The cameras are optimized to work together for longe range in both daylight and low light scenarios (Waymo, 2018).

4.4.1.3 Radar System

Waymo (2018) describes how a radar sensor is used to perceive objects and their movements. This is measured by wavelengths that the radar is sending out. This technique is suitable for rainy, fogy or snow conditions day and night. Just like the other sensor, the radar sensors are also placed to obtain a 360-degree field of view (Waymo, 2018).

4.4.1.4 Supplemental Sensors

Supplemental sensors can vary between different companies. Waymos cars use additional sensors such as audio detection system for detecting emergency vehicle and GPS to have an accurate perception of the vehicle localisation (Waymo, 2018). Other automakers include ultrasonic sensors to detect objects close to the vehicle.

4.4.2 Computing

ADAS/AD requires a high amount of computing power both for training the neural network and when processing live input data when driving. Training a deep neural network can be a complex and time-consuming task. Nasim Farahini explains that the training requires a significant amount of processor power, and this needs to be performed on specialised computers with built-in AI accelerator, which is a type of microprocessor. However, companies do not necessarily want to own and maintain their own computers for training these algorithms. Cloud computing is a possible solution in which computations can be performed via external parties, e.g. Google cloud. All input data gathered from sensors need to be processed in a central computer in the car. Computing all the data is challenging. A potential solution is to use cloud computing via the 5g bandwidth to minimise the required computing power of the car. However, this is not a sufficient technology yet as it implies high latency which becomes a problem when the computing needs to be performed in real time [1].

4.5 Software

In this chapter the reader will find a description of the essential type of techniques and tools that are used today for building computer vision software for the autonomous car.

4.5.1 Artificial Intelligence

Artificial Intelligence refers to an intelligent agent who is a system that acts intelligently to reach a goal. The system can learn from experience, adapt to changing environments and changing goals with limited perceptual abilities and with a finite number of computations (Poole, Mackworth & Goebel, 1998).
Maini (2017) argues that the rapid increase of computer processing and data storage have changed the field of what is possible to accomplish with AI. The technology is based on a wide range of concepts like probability, logic, mathematics, linguistics, philosophy, neuroscience, and decision theory. The term artificial intelligence is comprehensive and is an umbrella name for technologies such as robotics, computer vision, natural language processing and machine learning (Maini, 2017).

[1] Nasim Farahini, CTO at Camqom, 11-04-2019.

4.5.2 Machine Learning

Machine learning is a subcategory of artificial intelligence according to Maini (2017), further he explains that it is the scientific study of algorithms and statistical models that computer systems rely on instead of being explicitly programmed to solve each task. Machine learning is often referred to as the core subcategory of artificial intelligence. Machine learning algorithms can identify observed data patterns by training the algorithm to recognise and interpret input (e.g. images, video, text). The algorithm's goal is to respond appropriately to reach a predefined objective. Machine learning eliminates the usage of explicit pre-programmed rules and models. Eliminating explicit programming can be a beneficial approach in applications areas where it is hard to define the rules (Maini, 2017).

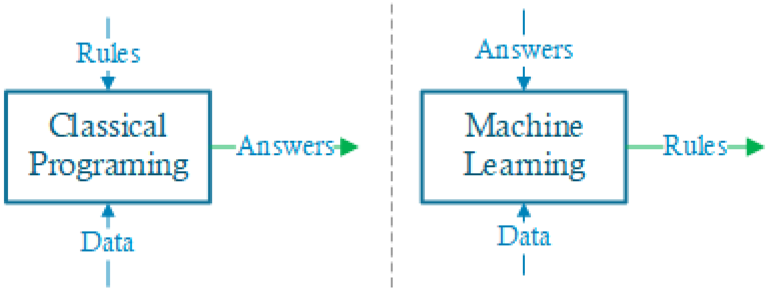

Figure 4.6: Differences between traditional programming and machine learning, Grossetti (2018)

According to Dwivedi (2018), the amount of data in the world is growing by each day, and over 80% of the data classifies as unstructured audios, videos, photos, documents, and graphs. To interpret all this data and finding patterns within reasonable time and accuracy is nearly impossible for humans. Machine learning solves this problem to some extent and is divided into three subcategories of supervised learning, unsupervised learning, and reinforced learning (Dwivedi, 2018).

Features and labels are the base for the input data in the machine learning algorithm (Camacho et al., 2018). Labels are the output of the model and are what the machine learning algorithm aims to predict. In the learning process, the machine learning algorithm is trained with input data which accurately predicts the output labels. The training process is done by identifying the optimal set of model parameter and convert it into the input data (Camacho, et al., 2018).

The process of finding these parameters is called training, and is an iterative process. The training is repeated in the following order (Camacho, et al., 2018).

1. Parameters are estimated
2. Model performance is evaluated
3. Errors identified and corrected
4. The process repeats until the performance (reduction of errors) of the model cannot be improved more.

Camacho et al. (2018) point out that the goal of the training process is to make the machine learning algorithm reliable in predicting new input data. Models are considered as properly trained when both the training and validation data sets are accepted. A machine learning algorithm can be accurate in its predictions for the training data while still having low precision on the validation data (Camacho, et al., 2018).

4.5.2.1 Supervised Machine Learning

Supervised machine learning includes labelled data also called annotated data (Dwivedi, 2018). Labelled data is data with an explanatory label attached to features, such as a car, and is used when training an algorithm. Both the input- and output data is known in supervised learning, and the way the algorithm is learning is by comparing the inputs with the outputs to see how much the model deviates (Dwivedi, 2018).

Janai, Güney, Behl, & Geiger (2017) explains that supervised machine learning is being used to develop object recognition capabilities for autonomous cars, giving a car the ability to identify objects such as pedestrians, bicycles, and cars. The algorithms are improved by feeding training data to make the car correctly identify objects when driving.

4.5.2.2 Unsupervised Machine Learning

In comparison to supervised learning, the training of unsupervised learning is based on unlabeled data (Dwivedi, 2018). Unlabeled refers to data there is no previous knowledge about, making it impossible to categorize by labelling it (Grossetti, 2018). Dwivedi (2018) explains that the goal with an unsupervised approach is to identify patterns and structure in the input data which is raw and not pre-processed. The output is unknown, so the result is much harder to quality check. That is why training data and test data cannot be distinguished (Dwivedi, 2018). Since the data cannot be classified, another method called clustering is used to separate the data into different groups (Grossetti, 2018). Input data get labelled when it has been assigned to a cluster (Dwivedi, 2018). There is no clear way of deciding the number of clusters or the method of calculating the cluster (Grossetti, 2018). Instead, it is gut feeling and trial and error that decide approach. There are many different types of clustering methods, and most of them are geometry based on their way of working. Some of the methods used for clustering is the following categories (Grossetti, 2018):

Hard Clustering:
- Hierarchical methods (agglomerative and divisive)

Soft Clustering
- Fuzzy methods: gives confusion matrices.

More complex methods
- Density-based methods

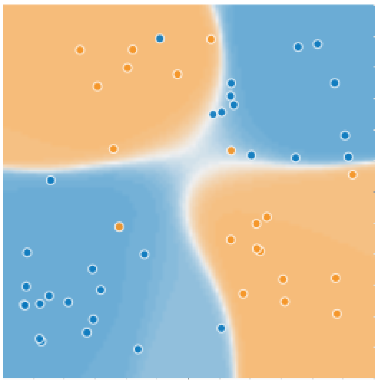

Figure 4.7: Cluster segmentation used in Unsupervised learning.

4.5.2.3 Reinforced Machine Learning

Marr (2018) alleges that reinforced learning differs a lot from the two previous methods of how to develop a machine learning algorithm. Instead of teaching the machine learning algorithm with the help of trained data, the reinforced learning method has a trial and error approach. In this way of learning, the machine learning algorithm does not have any previous knowledge of how to interpret its tasks. To handle this task are performed with a focus on maximising a reward function which is pre-programmed to steer the learning process. By focusing on maximising reward, will the algorithm learn what is the best approach to achieve the desired outcome (Marr, 2018).

Marr (2018) compares reinforced learning to how it works to learn to ride a bicycle. When making the wrong moves on the bicycle you will fall and hurt yourself, and this feedback is taken into account to improve. The same thing is done by the computer when using reinforced learning, however with a high amount of iterations that tune the algorithm (Marr, 2018).

4.5.3 Neural Networks

Camacho et al. (2018) argue that deep learning has become one of the most popular subcategories within machine learning. Deep learning relies on a neural network as its architecture which is very good to compute high volume data with high complexity in comparison to traditional machine learning. A neural network is based on the idea of how neurons from the human brain functions and are replicated in an artificial structure. The network builds up from individual neurons that are stacked together in layers. The neurons in the layer are then interconnected to the neurons in the next layer and so on were all connections together creates the network (see figure 4.9). Each neuron and layer in the network has its function and information is transmitted through the network in order to make predictions (Camacho et al., 2018).

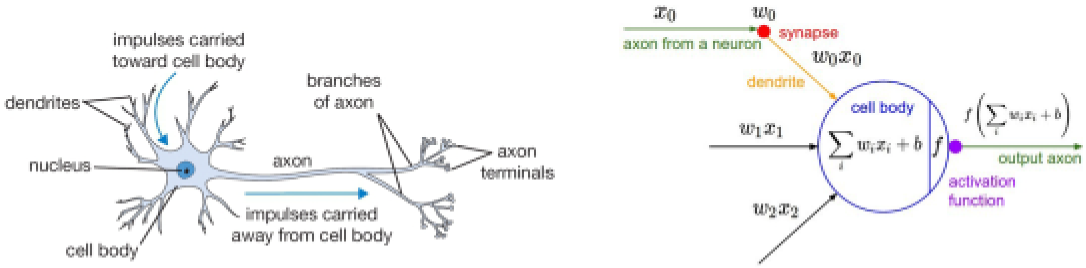

Figure 4.8: Comparison between a real neuron and a artificial neuron, Grossetti (2018).

Layers are divided into three categories; input layer, hidden layer, and output layer (Camacho et al., 2018). All neural networks consist of one input layer and one output layer while the number of hidden layers varies and distinguish deep learning from other machine learning techniques using a neural network. “Deep” implies multiple hidden layers. Figure 4.9 illustrated how the neural network function. It receives raw data to the input layer. The raw data is then distributed out to neurons in the first hidden layer. The data goes through all the hidden layers which transform the raw data by mathematical functions to representations that help the machine to identify its patterns. When the data reaches the output layer, it refers back to the problem in hand and gives it a classification. As the report focuses on supervised learning, the neural network needs to be trained with labelled data to make accurate predictions of the output data (Camacho, et al., 2018).

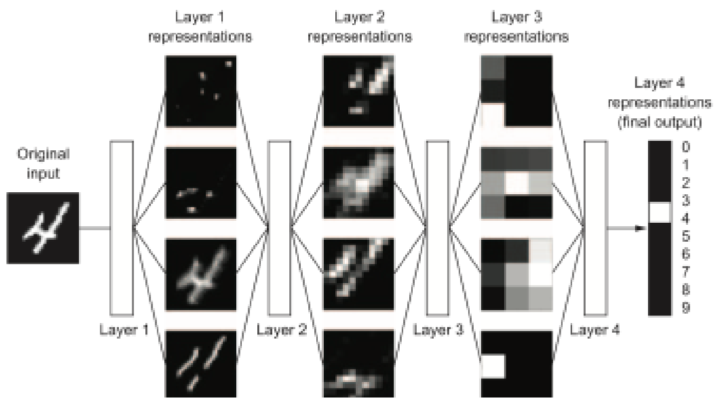

Figure 4.9: Illustration of how a neural network functions, Grossetti (2018)

Camacho et al. (2018) point out that the number of hidden layers and how they function is a problem with deep learning. It is nearly impossible for a human, who can only control the input data, to understand how the neural network makes its decisions due to its enormous complexity. Luckily this gap can be reduced by letting the machine understand these layers by continuously toning parameters to reduce the prediction error, which is called the backpropagation. Another significant drawback is that the network requires a considerable amount of data when being trained. The reason for this is because there usually is a massive amount of hidden layers that need training (Camacho, et al., 2018).

Sellam et al. (2018) argue that, although neural networks are showing impressive results in a wide range of areas, it is still unclear what high-level logic they follow and how and why neural networks are so effective. Understanding how trained neural networks works will improve experimentation and development of models, help to identify biases in current models, and explain predictions (Sellam et al., 2018). A broader verification and inspection framework for neural networks would further support the understanding and development of models (Sellam et al., 2018).

4.5.3.1 Training Data

Abuelsamid and Gartner (2018) argue that using data follows the logic of "garbage in, garbage out". Training data, which is annotated (also known as labelled) data, is a vital part of supervised machine learning as it determines the consistency and accuracy of the algorithm. Before any data can be used to train a neural network it must first be understood, curated, and annotated (Abuelsamid and Gartner, 2018).

Dingli (2011) explains that the meaning of annotations comes from labels and annotating is the action of adding notes or labels to define or explain something. The purpose of annotating is not to change the object but instead adding value in the form of defining the objects by labelling them into categories (Dingli, 2011). The usage of different media formats has broadened the meaning of annotations. Dingli (2011, p.3) define annotations as " [...] comments, notes, explanations, or other types of external remarks that can be attached to any Web document or a selected part of the document without actually needing to touch the document.".

Gili-Jiménez et al. (2016) point out that the demand for annotated data has increased by large quantities due to the growing demand for video and image processing. Concerning images, annotating is about labelling objects that appear in the image. From a technical point of view, this means that every pixel that is inside this annotated area have the same label. In reality, the annotation process is done by marking the object by writing a polygon or a simple shape often a rectangle around the object in an annotation software program. The cost and time it takes to annotate a picture depending on its complexity, e.g. depending on the accuracy, the annotations need to have (Gil-Jiménez et al., 2016). Janai et al. (2017) also argue that creating large-scale training data is labour intensive and costly.

According to Gil-Jiménez et al. (2016), videos and images that shall be annotated, or have been, can come from different sources. One source can be public image databases such as ImageNet (ImageNet, 2016). However, public databases tend to be too generic and limited in scope to build software for autonomous cars (Abuelsamid & Gartner 2018). Annotating a video can be a hideous task as it essentially consists of a lot of images. Annotating every frame in a video will quickly become a time-consuming effort. This problem can partially be solved by skipping a few frames and predict movements of objects between annotated frames. (Gil-Jiménez, et al., 2016).

5 Findings

In this chapter, the aim is to give the reader insight into the gathered empirical data. The findings are divided into two parts. The first part is about data gathered from interviews regarding the value chain. In the second part, data from CrunchBase and companies webpages are used to describe the characteristics of companies within the business ecosystem.

5.1 Computer Vision Value Chain

The value chain describes the different steps in enabling ADAS/AD solutions based on deep learning technologies is very generic says Andreas Geiger. Even if the hardware is excluded to giving the value chain a better overview, it is essential to not forget that both hardware and software need to work together to match the functionality and generate data. An example of this is when the amount of data increases it also create implications on power consumption, processing power and transfer speed which is essential for computer vision solutions to make fast decisions[2].

Erik Rosén argues that deep learning has disrupted the computer vision industry, affecting both the software and hardware side. Working with the software is more flexible because of adaptability. When choosing a hardware supplier, the choose need to be based on how software technology will develop in the future. Nvidia has its very general GPUs, which is not a cost-effective way but flexible if there is significant progress in the research world. Many in the industry use development platforms and tools from Nvidia[3].

It is essential to understand the differences between ADAS and AD, in the past, people have believed that it would be a steady way were combining ADAS functions builds up to the fully autonomous driving. However, it is not that many people that believe that any more[2]. Erik Rosén explains that in the industry, some actors advocate that level 1-2 is called ADAS while level 4-5 is called AD, and that it is unclear what level 3 is. AD requires a lot more validation data, stricter, and different requirements in comparison to ADAS. Thus, the development of AD is more expensive and slower[3]. Current vision-based systems are not on a sufficient level to reach human capacity (level 4-5) for many tasks were 99.99999% accuracy is needed[2].

[2]Andreas Geiger, Professor of computer science, 8-04-2019.
[3]Erik Rosén: Technical Expert - Deep Learning at Zenuity, 11-04-2019.

The software must be able to handle everything that can happen says Erik Rosén.For ADAS, the focus is on building the function and comfort as well as possible for the driver. For some companies, this may not be the case because they want the driver to be attentive and therefore add features that make it less comfortable. For AD, the focus is mainly on safety and comfort comes in second hand[3].

5.1.1 Model Deployment (Start)

In developing computer vision functions Erik Rosén explains that everything starts with an understanding of what problem you want to solve, "a user case". When the problem is identified it evolves to the idea of what the network should do and the development of a neural network is initiated. The network sets the standard for how the other steps in the value chain should be carried out, e.g. guides which data that needs to be collected and annotated[3].

Marcus Hedberg says that the demand for what functionality that should be included in an autonomous car that derives from OEMs and industry visionaries[4]. Further down in the value chain, there is less overview of what the requirements are and where they come from[5]. Even if there is an understanding of the functionality of the demanded features, much of the discussion is about how to ensure that the software can be delivered[4].

5.1.2 Data Acquiring

Daniel Langkilde explains that, with a developed idea of what problem that should be solved and how the neural network will be developed sets the standard for what data the algorithm needs. The data consist of information on what the sensors say about the world at a specific time. Different combination of sensors is used depending on the requirements. The most common sensor types are LiDAR, camera, and radar. It is essential that this data is collected in different ways to cover special situations to achieve high reliability. When using a combination of sensors, they need to be time synchronized. An example is when using LiDAR and cameras, the 3D point clouds from the LiDAR must be synchronized with the pictures from the camera, to accurately determine objects positions in relation to the car[5].

5.1.3 Curation

Gathered raw data needs to be managed in a curation step to fit machine learning applications better (AltexSoft, 2018). In this phase, the focus is mainly on formatting, cleansing, and sampling. Anonymisation is relevant in those cases were a picture from the public environment is used that involves people and licence plates as examples. Formatting data is the task of making sure that the data has the right format.

[3]Erik Rosén: Technical Expert - Deep Learning at Zenuity, 11-04-2019.
[4]Marcus Hedberg: CPM at Aptiv, 23-04-2019.
[5]Daniel Langkilde, CTO at Annotell, 29-03-2019.

When the data is gathered from several different inputs formatting becomes increasingly important. In the data collecting process, data can contain imperfections. Some images may become blurry or have other defects that make them useless. Hence, data cleansing aims to remove inconsistency in the data. Data cleansing can also include adding missing data to the original raw data. Managing big data sets is time-consuming and can be computation heavy. Therefore, data sampling is used as a method to lower the complexity of training and do it faster by dividing the data into smaller portions (AltexSoft, 2018).

5.1.4 Annotations

Annotation is one of the most critical parts of the value chain[3]. The most significant cost generation comes from training data and not from programmers or purchasing GPUs[5]. One reason for this is that much data is required to train these high capacity models because it includes many parameters[2]. Even if data takes up more of business costs than it has done in the past, it is possible to find savings elsewhere[3]. Because of the time consuming and costly efforts behind annotations, it has become a prominent hotspot for startups to entry[3].

Daniel Langkilde points out that the customer wants to use as little training data as possible, and it should be done as fast as possible without compromising with quality. So fully charged efficiency is starting by annotating the right thing. One problem here is that the customer must have good insight into what high-quality training data is. If the customer does not know what high-quality training data is, then it is hard to guarantee the performance. Training data and validating data are the two types of data that is produced at the annotating phase. The training data, which is used to train the neural network with, requires high quality. Validation data which, is used to evaluate the performance of the neural networks, require a greater amount of data although not as high quality[5].

5.1.5 Data Processing

When the neural network is developed and the training data set is complete it is time to move to the data processing phase says Erik Rosén. The first step in this phase is to train the neural network with the training data. When the network has reached a sufficient level for its parameters, it needs to be validated. Validating is when the algorithm is checked with the validation data that it does what it is supposed to do. It is difficult to argue that the algorithm does the right things when it is not tested for all the data points. The problem with neural networks is that no one knows exactly how they work[3]. There are methods to visualise neural networks because there need to be something to confirm why it is going wrong, but with deep learning, it is in large extent a black box[2].

[3]Erik Rosén: Technical Expert - Deep Learning at Zenuity, 11-04-2019.
[5]Daniel Langkilde, CTO at Annotell, 29-03-2019.
[2]Andreas Geiger, Professor of computer science, 8-04-2019.

Andreas Geiger says that simulations in a virtual environment can be used when testing the algorithm. The virtual environment is not yet on the level of fidelity that is required to do a seamless transition over to how it would work in reality. Therefore, it is not sufficient to train an algorithm on simulations[2].

5.1.6 Model Deployment (Finish)

If the algorithm does not perform as expected, each step of development has a feedback loop to improve something from a previous step says Erik Rosén. It may be a problem, requiring the algorithm to be retrained. Maybe the data needs to be annotated in another way, selection of new data, change the input data. These iterations can take place between all steps.When the algorithm has reached a sufficient level that is expected from the customer ends the development process, and the algorithm fulfils a use case[3].

5.1.7 Complications

Erik Rosén explains a few special occasions that can change the rules of the value chain to some extent. The first one it the usage of sensor type. Neural networks are susceptible to different sensor models. So if an algorithm has been trained with data from one camera sensor and when its finish is implemented in a car with another camera model is there a high risk that the algorithm starts to behave weirdly[3]. The technique is not on the production level yet for making this transfer between sensors seems smooth and being easy without fully reannotate everything[2].

The other one is if any changes are made to the driving algorithm, the one that controls the car, which means that old data for validation becomes obsolete to use on the model and therefore need to start working on new raw data[3].

[2] Andreas Geiger, Professor of computer science, 8-04-2019.
[3] Erik Rosén: Technical Expert - Deep Learning at Zenuity, 11-04-2019.

5.2 Companies in the Value Chain

This section describes a selection of companies in the value chain of ADAS/AD solutions. The companies have been categorised with inspiration from Jay (2018) to make it easier to understand where they fit in the value chain. Those empirical findings which are considered to be most significant from each category will be summarised and described below. The gathered information about companies consists of localisation, description of the business model, what technology they are working on from computer vision, investment information, and relations between organisations. All the individual information about the companies can be found in Appendix 1.

5.2.1 Ecosystem

What type of expertise that is needed in the future ecosystem is unclear. Andreas Geiger explains that some car companies have the engineering skills of building a car but lack the software skills, and some companies have the engineering skills of developing software but not cars[2]. Erik Rosén says that there are still many unanswered questions even for ADAS solutions so there is no consensus in which solution will be the winning in the industry. Thus, winners in the short-term might turn out to be long-term losers and vice versa[3].

Andreas Geiger implies that it is much harder to hire outstanding technology people for car companies compared to big technology companies. Big technology companies hire top candidates, which usually finds an offer from Google more attractive were they publish excellent research. Car manufacturers ramp up from zero, they have their electrical and mechanical engineers, but these are not AI people. So what can be seen now in the industry is that companies fight to acquire this type of competencies[2].

Marcus Hedberg explains that it is essential to find other participants in the ecosystem to collaborate with in order to speed up the development. Because of the uncertainty, this leads to trying out different types of collaborations. One thing is for sure, and that is hardware will be a smaller part of the total value. Today best practices start to come from, e.g. Google and Apple instead of the more traditional automotive companies[4].

[2]Andreas Geiger, Professor of computer science, 8-04-2019.
[3]Erik Rosén: Technical Expert - Deep Learning at Zenuity, 11-04-2019.
[4]Marcus Hedberg: CPM at Aptiv, 23-04-2019.

5.2.2 Annotation Platform

Annotations are seen as one of the most significant bottlenecks in the value chain because of its cost and time intensiveness when developing neural networks[5].Many developers of computer vision solution have decided that it is better to outsource annotations to companies whos not having their core competence in that domain[3]. This shift has led to steady growth for annotation companies were many are in a startup stage and trying to differentiate themselves with different approaches to solve the customer's problem[3]. Even if there are a large variety of annotation companies all of them should not be seen as competitors. Annotations are of different severity and therefore have different quality constraints[6]. Therefore, annotation companies can be divided into two essential groups. The first type with those who work on application towards industries with high-quality requirement (e.g. automotive, radiology). The second one who is working towards industries with lower quality requirement (e.g. surveillance systems). The annotation companies in this study have a connection to the automotive industry and therefore are considered to have customers with high demands on quality. Daniel Langkilde says high quality is described as the accuracy and precision needed both for the annotated object and between annotators, it can be that objects should be annotated with a 2-pixels accuracy, but the annotations need to have excellent precision between them of were 2-pixel accuracy is. The problems lie in who can guarantee high quality when the customer does not know how good the training data needs to be[5].

It is clear that all annotation companies provide an annotation platform. However, the approach between companies differs after that. A few companies provide the platform and let the customer handle the annotation themselves. The most common approach is more of a complete solution were that the annotation company also helps with the annotation of both training- and validation data. The annotation process differs between companies the most common one for high-quality annotations is that the company has its team of annotators. Crowdsourcing is another approach which is used but not that common for high quality annotation companies due to the lack of knowledge of the competence of the annotator. A third approach is an automated annotation, and this is often not considered to be fully automated but instead a mix between human and automatic annotation[5].

A few companies have also extended their business models to include professional services where they help customers projects to become more efficient to reduce the number of iterative improvement cycles. Some have even gone upstream in the value chain to help with the data collection. It is still unknown to what extent curation is done by the annotation companies or those who collect and provide the data.

[5]Daniel Langkilde, CTO at Annotell, 29-03-2019.

[6]Per Lundberg, Machine Learning specialist at CEVT, 13-04-2019.

[5]Daniel Langkilde, CTO at Annotell, 29-03-2019.

5.2.3 Tier 1

The tier 1 segment consists of three types of suppliers. Established automotive suppliers that have started to adapt software solutions for ADAS as a complement to their old business models. Spinoffs that have started to focus their core competence on providing complete ADAS solutions were some of the software and hardware is developed in-house. New entrants have taken the approach of becoming the suppliers of the future for software and electronics for AD systems.
Private initiatives by established suppliers are actively shown from the number of investments that have gone into computer vision and machine learning companies. The spinoffs and new entrants have taken more significant focus on an acquisition approach in addition to its investments.

5.2.4 Tier 2

In the tier 2 segment, a significant change can be seen. Traditional tier 2 suppliers who provide hardware components is not found in a large extent focusing on the software development of ADAS/AD. Software has emerged as a part of the tier 2 segment over the last few years. This shift has lead to an increase in new companies which can be seen from the high founding and internally low investment activities. These companies have a similar approach to each other. Focus is on the majority of the steps of computer vision except for annotations[3]. Daniel Langkilde says a tier 2 supplier could choose to do all the development steps for the ADAS/AD solutions by them self. Some of the steps are much more complicated than, and therefore it can be a good idea to outsource these step to become more efficient[5]. The goal is to develop ADAS/AD software that is sold to tier 1 suppliers or directly to OEM[3]. Some of these companies have chosen to integrate horizontally and also become providers of hardware such as sensor and computing chips.

5.2.5 OEM

On the car manufacturer side, there is one company that stands out who has moved its development of ADAS/AD systems to be done internally and focus on developing its car fleet network through private customers. The rest of the OEMs is a more homogenous group where the focus is on developing strategic collaborations, invest and acquire vertically in the value chain. Their focus is more on integrate ADAS/AD solutions in their cars which are then sold to private customers or robo-taxi companies. In order to do this OEMs need to focus on becoming better at understanding what they are buying from suppliers because it is hard to buy something one does not understand[5].

[3]Erik Rosén: Technical Expert - Deep Learning at Zenuity, 11-04-2019.
[5]Daniel Langkilde, CTO at Annotell, 29-03-2019.

5.2.6 Establish Technology Companies

Established technology companies are a group of companies with previous knowledge from working with techniques such as computer vision, machine learning, and advanced computing hardware. They have a strong position in the software and hardware domain and the computer industry but lack knowledge about the automotive industry (Burkacky et al., 2018). Due to the similarities between these companies core competence and the technology used for autonomous cars has the interest of horizontal integration emerged. The approaches were and how they aim to fit in the value chain differs. What they have in common is the focus on hardware and complementary software. In this group, they try to fit in as both tier 1, tier 2 and robo-taxi, some by starting up their divisions that expand horizontally and others by acquiring companies that have established a position in the value chain.

5.2.7 Sensor

Sensor companies do not try to take any unique positions in the market by vertically or horizontally integration. Sensors companies have a strong focus on collaboration and not so much on investing and acquiring activities.

5.2.8 Mobility Solution Companies

Companies in this category span from platform providers for ride-hailing services to software developer retrofitting cars aiming to build robo-taxis. Waymo and Lyft are two companies in the category. Waymo is developing self-driving cars and is looking to provide these at Lyft's platform (Higgins, 2019). Uber is another company that is trying to provide both the app and develop the self-driving technology (Uber, 2019).

These companies focus on developing both hardware and software to enabling level 4-5 cars were a customer can buy a taxi trip from a driverless car. Collaborations with the traditional OEMs is establish where they will handle the production of cars, and the robot-taxi companies develop the AD hardware and software used for these vehicles and also manage the taxi business towards customers.

6
Analysis

In this chapter will the reader be provided with an analysis of the findings of the thesis. The analysis will be divided into four sections were the first section is for the first research question. The second and the third section is analysing the second research question and the fourth section analysing the last research question.

6.1 Computer Vision Value Chain

The process of developing a neural network and refine raw data to valuable training and validation data is illustrated in figure 6.1. The process is initiated by defining a use case that requires a neural network and training data. Data is then collected, curated, and annotated to train a neural network with. As the process of development advances, necessary improvements in preceding steps are increasingly undesirable. An example would be to realize that the annotated data is inaccurate when observing the result of the trained model and would slow down progress as annotations need improvement before proceeding.

Building the algorithms and deep neural networks used in ADAS/AD solutions is sometimes addressed as the problem to solve. However, collecting the right data and processing it requires human consensus that, at first glance, might not get the deserved attention. A massive amount of data is required to train and validate the network with. However, a vast amount of data is not per se valuable. It needs to be the right data and consistently and precisely annotated. Both collecting and annotating the right data is time-consuming and especially annotating data is an expensive task as it requires a lot of manual labour. Therefore, collecting and annotating the right data is vital in the overall process.

A robo-taxi company operating in a suburban area will not need to collect data about highway driving if that is outside the operational design domain. Conversely, an OEM working on a highway pilot solution will not need to gather data about urban driving. Thus, which data to collect is defined by either the OEM or the mobility solution provider aiming for a specific solution or a tier 1 supplier wanting to provide a specific ADAS/AD solution. The collection is often performed by the company developing the ADAS/AD solution since they are the ones' with information about what the solutions are supposed to do when finished. The developer usually has access to the necessary sensors and equipment of collecting data as well. However, the necessary equipment and knowledge about what the solution is intended to do are not enough.

A problem with data collection is the edge cases. Edge cases are situations that a human driver would encounter very few times or maybe never in a lifetime. Thus, it is difficult to collect data about edge cases and eventually train the network with. Hence, having the right equipment with sensors and cars sweeping the roads collecting data is irrelevant if the right data cannot be captured. Simulation becomes an increasingly important piece of the puzzle in order to cope with edge cases. Data about a tricky situation in traffic can in simulation be modified to provide developers with even more challenging cases to train their models with. In addition to training a model on edge cases, the simulation will most likely be an integral part of validation and safety demonstration as it would be impossible to expose the algorithm for every possible solution in real life situations before deployment.

A major challenge when annotating data is to eliminate ambiguities and room for interpretations that eventually could confuse an algorithm controlling a car. Thus, well-defined instructions are critical for annotators. However, humans do not interpret things in the same way. If the people giving the instructions cannot reach consensus on how to interpret things, consistent annotation becomes close to impossible.

An issue with neural networks is the lack of overall knowledge about how they work and which logic they follow. Efforts to understand the behaviours of neural networks and create a standardised framework for inspection and verification could help increase knowledge and support the development of future models.

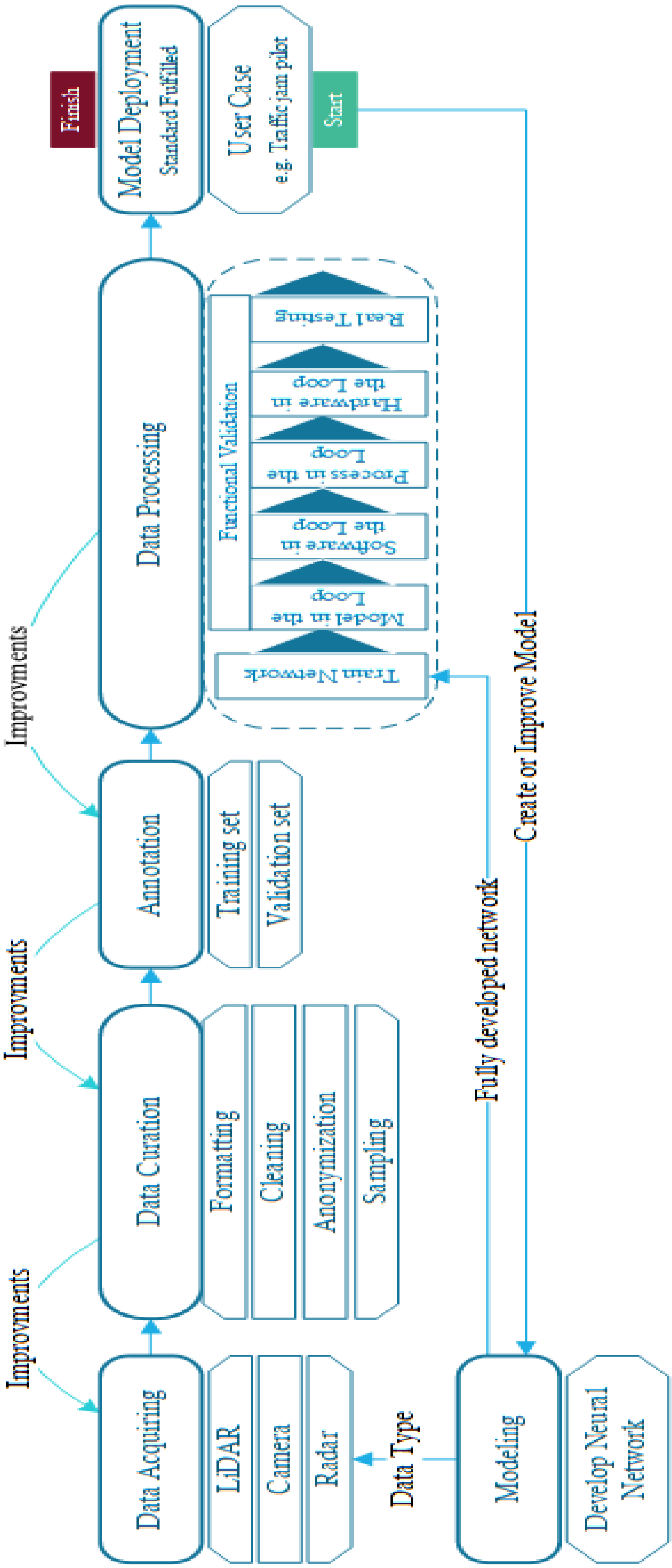

Figure 6.1: Workflow of developing a deep neural network for ADAS/AD.

6.2 Impact on the Automotive Value Chain

To understand the bigger picture of how the value chain has evolved from a traditional linear model to an even more complex ecosystem the computer vision value chain has been combined with a summarized version of the traditional value chains displayed in chapter 2.3. The computer vision value chain is from a software perspective and directly connects to the tier 2 position of the old value chain. Software is often seen as a tier 2 position because it shall be integrated with the tier 1 suppliers hardware. Nonetheless, some tier 2 software developers sell directly to the OEMs. The trend that tier 2 suppliers also sell their products to tier 1 suppliers and OEMs can be seen from the network analysis figure 6.3. One of the important factors to take into account when selling to tier 1 is the compatibility between software and hardware. With the increasing focus on software this becomes a new interaction that affects the value chain both upstream and downstream. The future development of software sets the standard for what hardware is needed to enable the usage of new techniques.

From a tier 1 perspective, the focus is on building both ready to deliver ADAS solutions with OEMs as their focus customer group. There are also some new initiatives were the focus is to develop AD solutions (level 4-5) that can be sold both to OEM and robotaxi companies. The perspective that tier 1 can sell to a customer that is not an OEM is a new one that has emerged from the futuristic ideas of what new types of business models that may occur. This means that it is not clear yet if robo-taxi is a sustainable business idea for the future or if there will be other concepts that tier 1 supplier can also sell their products to. Tier 1 supplier such as Aptiv does even develop their own robot-taxi in collaboration with Lyft which enables them to both take the position as part of a robo-taxi company and a tier 1 supplier. It is uncertain to whom tier 1 suppliers will sell and if they will be active in several parts of the value chain. However, it is clear that the old linear way with OEM as tier 1 only customer will not look the same in the future.

Even if the value chain is changing around OEMs they will hold their dominant position of being car producers. This is because of their long knowledge and no signs of vertical integrations into this domain. OEMs are not expected to become the best att developing ADAS/AD systems. They get involved because they need knowledge in order to become good at buying these solutions. This can be seen in figure 20 that OEM has invested and some have even acquired companies both upstream and downstream in the value chain. The upstream involvements seams to be more to understand what they are buying and that they will have developed ADAS and AD systems that match their products. For those who have gone downstream is seems to be more from an investment opportunity to have a piece of the revenue stream of the futures mobility solution and get closer to the end customer. One of the most obvious changes at this step is that OEMs will no longer only sell to car retailer. Some manufacturers have started to try and cut out the middleman in order to directly sell to end customer. For mobility solutions such as robo-taxi companies has realized that they will not be good at producing cars that is the reason why they have teamed up with OEMs to buy cars from.

There are new types of mobility solution that seems to emerge with this new technology. The most recognized ones within this segment are the robo-taxi companies. These companies focus on managing a fleet of autonomous cars and provide them as a taxi service. They develop most of there technology on their own, and they are only focusing on AD solutions. The software for AD is produced in no small extent entirely because these companies have their core competence within the software. Hardware products such sensors are provided by some of the actors mainly to slim down cost and make the development more efficient. Most robo-taxi companies do not have the intention of producing cars. Their main focus is to transform cars from OEMs to autonomous vehicles which they can use in their business. For the rest of the supply chain is it only some parts of tier 1 and most of the steps for software tier 2 they replace.

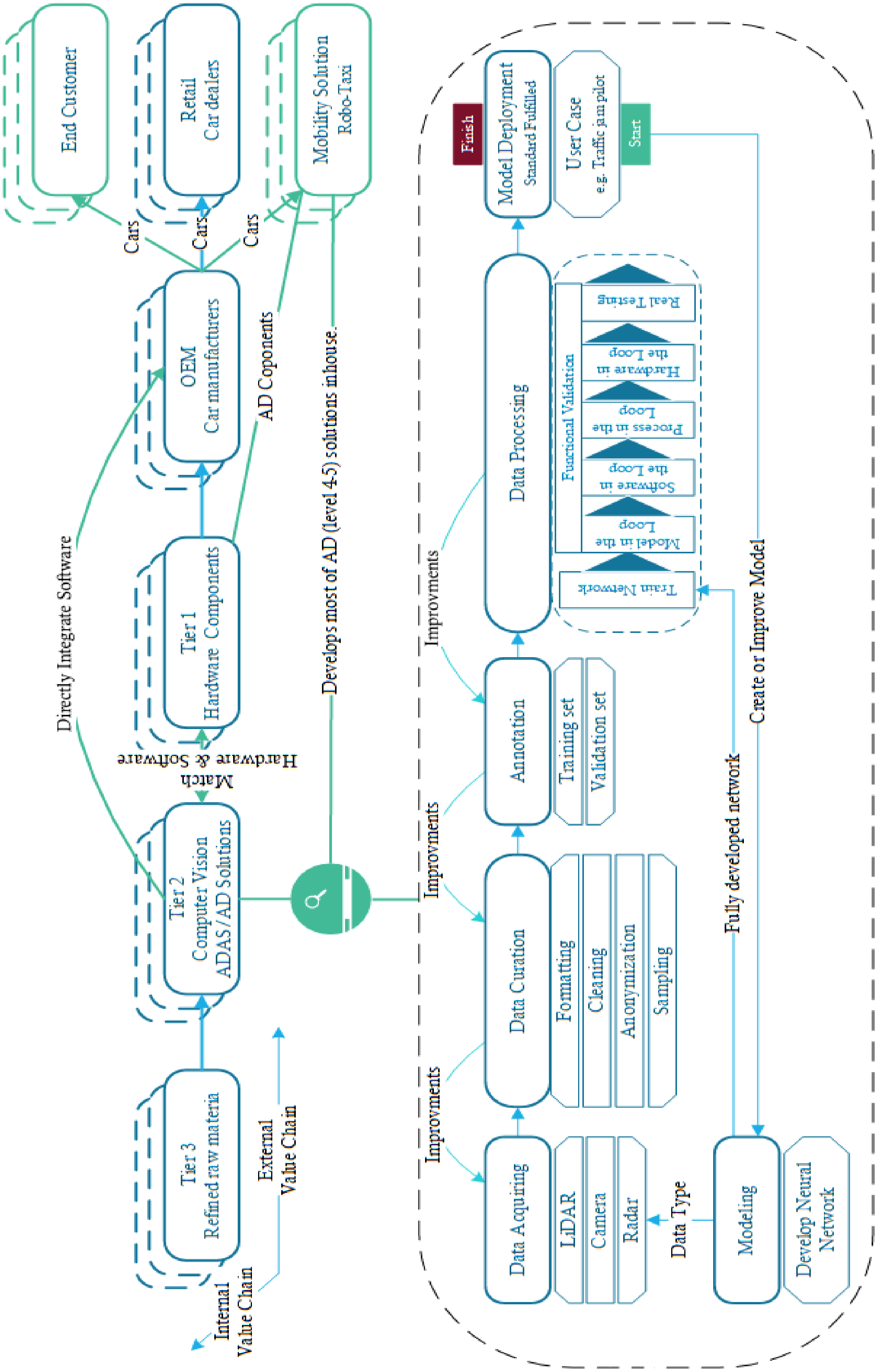

Figure 6.2: Illustration of the whole automotive value chain for ADAS/AD.

6.3 Automotive Business Ecosystem

The network in figure 6.3 is showing the current connections between some of the major players in the development of ADAS/AD. Although each participant's individual ecosystem vary in size, most have a mix between multiple customers, collaborations and investment to drive their development forward. The arrows represent the three categories of connections in a value network, where goods and services are equal to customers, knowledge transfer is equal to collaborations, and intangible benefits are equal to investment and acquisitions. Especially interesting is the amount of collaborations, investments, and acquisition between companies. Collaborations between competitive OEMs strengthen the statement that individual companies do not have what it takes to manage the transition alone. It is also a way of dealing with uncertainty and sharing risk and costs of development. Established tier 1 suppliers, OEMs, and established technology companies have diversified investments in companies from various places in the value chain. Diversification of this sort also shows that companies want to expand to have a small stake independent on who the long-term winner might be. Investments can also be seen as a way to gain short-term wins by fast becoming more credible in the autonomous car industry.

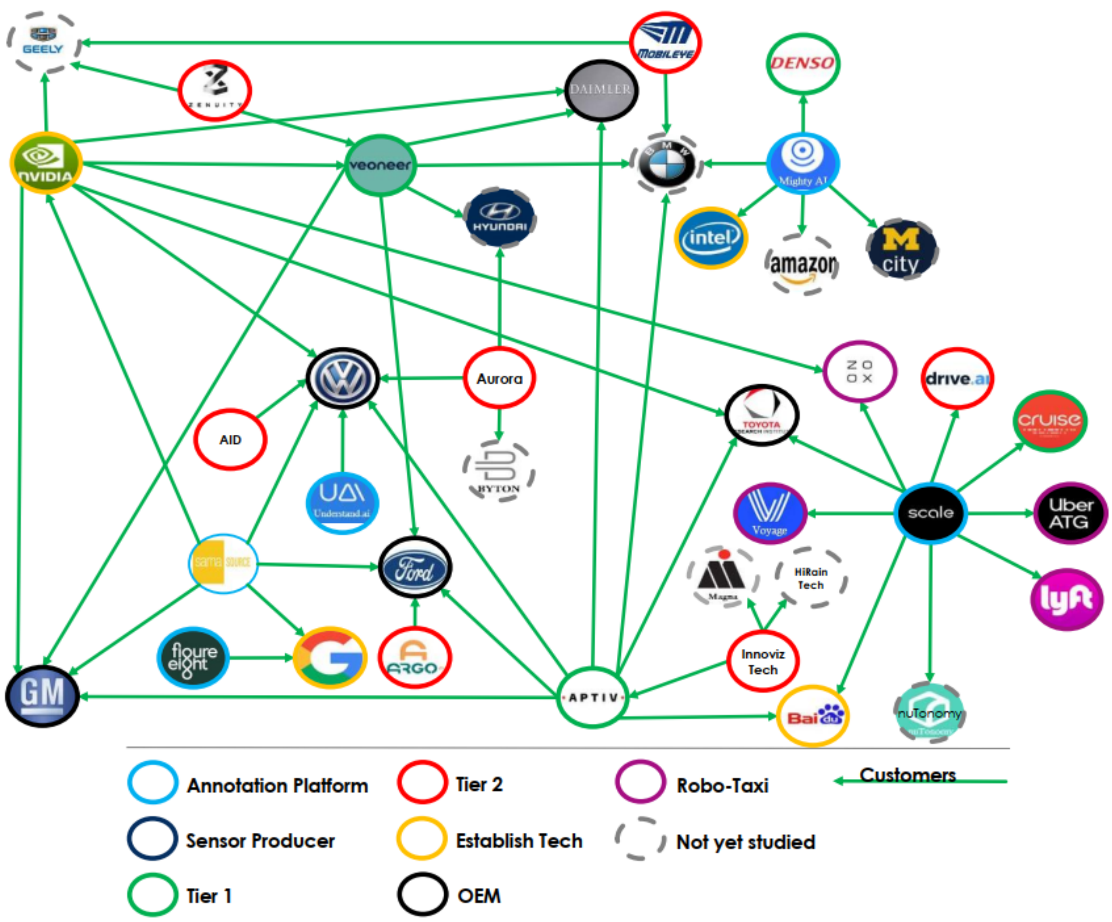

Figure 6.3: ADAS & AD companies customer relations in the Business Ecosystem.

Now when the automotive industry has reached a point where innovation requires more software to create customer value the barriers to enter the traditional ecosystem have become lower. It is due to the shift of what type of expertise that is demanded to drive innovation forward. It has started to move away from the automotive industry expert area towards software where the knowledge much lower. The shift has led to a weakening of the old ecosystem and given access for companies that are experts on software to move horizontally.

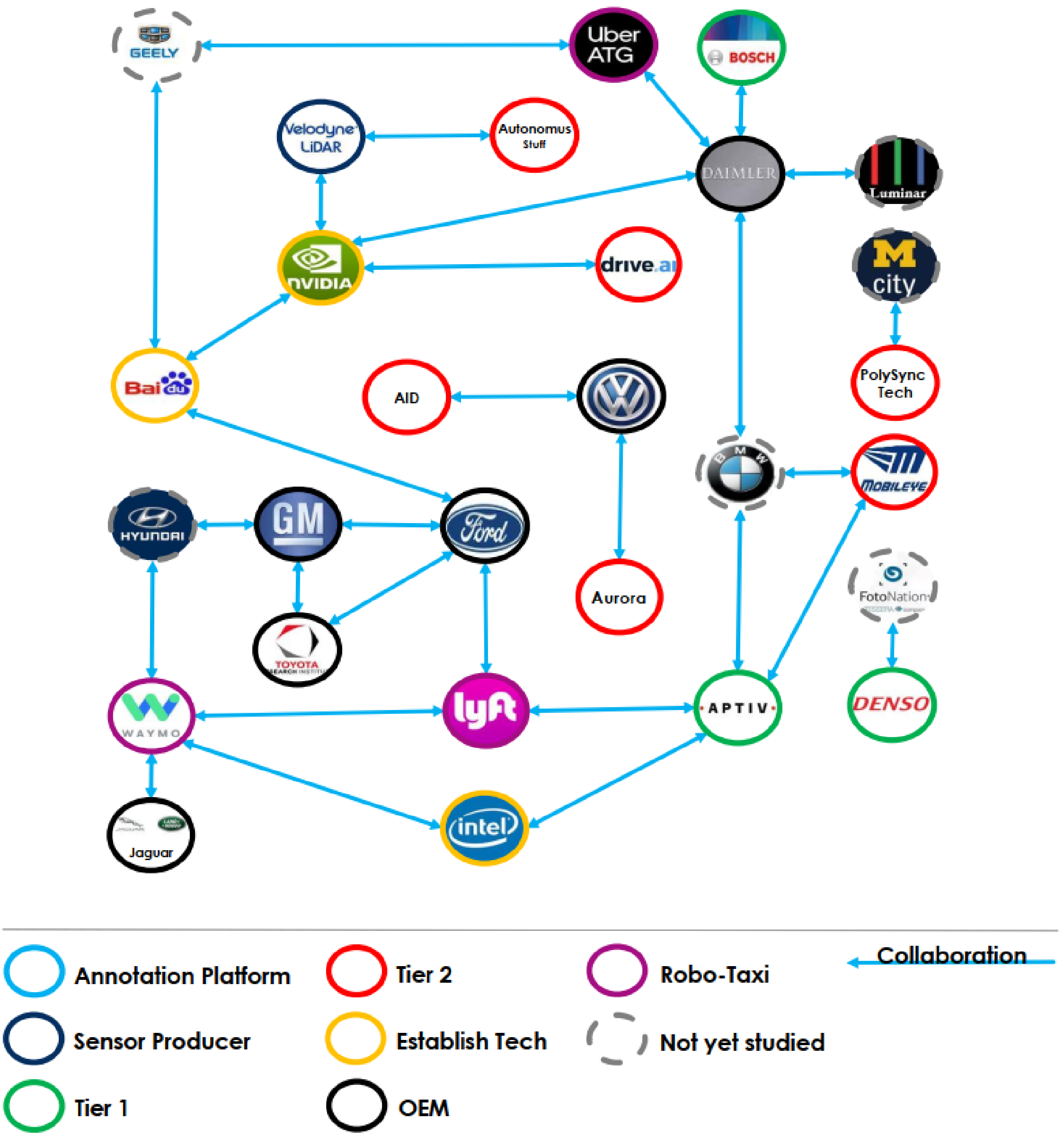

Figure 6.4: ADAS & AD companies collaborations in the Business Ecosystem.

The network displays a higher concentration of collaboration around OEMs. A logical reason for this is that OEMs are the dominant players in the value chain and therefore need to have good connections with their suppliers to improve themselves. However, when analyzing established technology companies and mobility solution companies who are new in this industry, focus on collaboration does not seem as strong.

OEMs collaborates with a diversified mixed of companies all over the value chain when established tech and robo-taxi mostly collaborating with OEMs. One of the reasons OEMs have much more collaborations and investments could be to manage the change from the old ecosystem and still stay relevant. The differences in collaboration could also be a response to the problems of acquiring the right type of competences for AI development. Robo-taxi companies have that knowledge in-house and collaborations is used as a way to be provided with the cars that match their technology. For OEM seems to have a lack of the right knowledge and try to acquire it through collaborations instead.

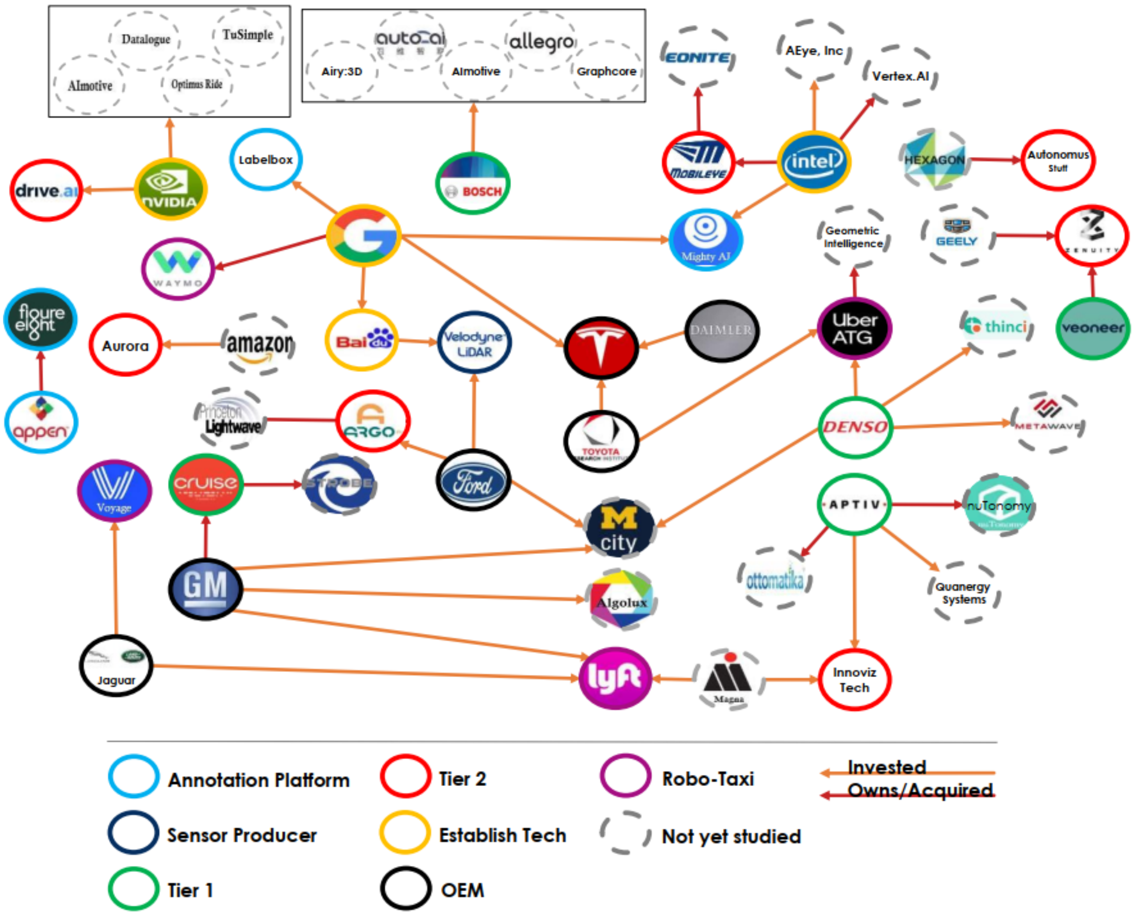

Figure 6.5: ADAS & AD companies investments in the Business Ecosystem.

Vertical integration is occurring to a great extent for tier 1 and OEM trough own initiatives and by acquisitions. OEMs use it as a way to both be relevant with the usage of new technology and strengthen their position for a future that is unclear how it may affect the core business. One of those scenarios can for example in GM's case be that autonomous cars cannibalize on sales.

By investing in mobility companies such as Cruise Automation, GM can keep its position at the end of the value chain and mitigate the effects of declining car sales by selling mobility solutions. For tier 1 suppliers it is also about staying relevant in a technology shift from traditional hardware towards more software. To do so, these companies focus on acquiring the right competence they need to make this transition towards more software focused business to manage the change in flexibility between tier 2 and tier 1 for supplying OEMs as usual.

Horizontal integration can mainly be seen from the non-traditional players, in this case, established technology companies and some of the robo-taxi players like Uber and Lyft. For the established technology companies, players know about working with computer vision however not in the context of automotive. Investing and acquisition play a significant role in the integration where the goal is on getting a ticket into the automotive market. Clear examples here are Intel's acquisition of Mobileye and Alphabet investing and spinning-off Waymo. Robo-taxi companies, such as Uber and Lyft, did not start with the initial idea to become a robo-taxi company, but have been forced on this type of service to be able to keep their positions by meeting future demands. The horizontal integration here is that these companies try to go from being platform providers for taxis to become a robo-taxi company. This transition is supported through investments and collaboration from mainly tier 1 suppliers.

Two companies positioned at the end of the value chain that stands out is Waymo and Tesla. These companies are both involved in the race towards autonomous cars. However, what makes them unique is that they have a rather small amount of connection when it comes to collaboration and investments in comparison to other OEM and mobility solution companies. If Tesla or Waymo would become the winner in this race, even they need to focus on building the ecosystem they want. Tesla and Waymo are also relatively new players on the automotive market, this has given them the opportunity to be more flexible and integrate their long-term strategies when building their ecosystem. Tweaking the strategy is much harder with a well-established ecosystem tailored after an old strategy. In Waymos example, they are owned by Alphabet that is a vast technology conglomerate. One of the explanation to a lower amount of connections to other companies could be that companies as Alphabet are confident that with all their internal resources, they have the power to build an ecosystem mainly depending on companies from the own organization instead of external companies.

6.4 Two Paths Towards Self-driving Cars

As with the general development of autonomous car technology, how firms are going to capitalize on autonomous cars is in many aspects still uncertain. However, two paths towards autonomous cars have been identified. The first one is targeting the consumer market while the second one is aiming for a ride-hailing service with robo-taxis in geo-fenced areas. Both approaches imply a limitation to either the level of automation and/or the operational design domain. The first approach is mostly adopted by OEMs striving to gradually offer more autonomous features to the consumer market until reaching fully autonomous cars. As of today, most OEMs, especially in the premium segment, offer some sort of ADAS whether it be adaptive cruise control, lane keeping assists or something else. However, the step from ADAS to fully autonomous driving is monumental. A common approach is to start by developing features for a strict operational design domain determined, but not limited, by road types, speed ranges, and environmental conditions. Highways are typically easier environments to start with as they, in general, have proper lane markings and are well maintained. The absence of pedestrians and bicyclists make behaviour more predictable on highways as well. Thus, traffic jam assistance that relief the human driver in traffic jams on highways are a common target for OEM since it is limited to a certain road type and speed range. This incremental approach towards self-driving cars will gradually try to expand the operational design domain to include all type of conditions.

The second approach is targeting the consumer service market through ride-hailing services within a geo-fenced area. Companies adopting this approach is targeting autonomous cars directly instead of developing ADAS to existing consumer products. In other words, fully autonomous driving under certain conditions. The difference is that this approach is targeting the consumer market through ride-hailing services without incrementally providing ADAS. Elaborating on their probability of success is outside the scope of this thesis.

7

Conclusion

Autonomous cars are complex products combining expertise from a host of research domains and increasingly so from computer and software engineering. Extensive efforts have been made in terms of research, investment, and acquisitions advancing the technology to a level where companies are pursuing tests on public roads. Nonetheless, autonomous car technology is still surrounded by uncertainties indicated by the absences of common standards in many aspects. One such aspect is the training and validation of algorithms and their reliability in supervised machine learning, which is commonly considered the most successful way to achieve environmental perception for autonomous cars. Data is essential to supervised machine learning algorithms and the development of autonomous cars. However, possessing significant amounts of data will not give companies competitive advantages by definition. In this context, creating value from data is a non-trivial process including acquiring, curating, annotating and processing the data. Both training and testing the model requires sufficiently large datasets of every-day situations and so-called edge-cases. Currently, there is no consensus on what "sufficiently" implies and is left to each developer to determine themselves. Given that a consequence of an error could be fatal, requirements on datasets and models are very high compared to other application areas.

The automotive industry is facing a shifting knowledge-demand. Although mechanical engineering is still a vital part, current technology development requires computer and software engineering to a more significant extent. Acquisitions and collaborations are faster means of getting desired know-how than internal development and reduces cost and risk of development for individual firms. Acquisitions and collaborations have been identified between all levels of suppliers and OEMs and can be seen as a business ecosystem where companies success is dependent on the prosperity of the overall ecosystem. This collaborative approach is practised by many companies in the automotive industry. Nonetheless, it is not the only approach practised as some companies at the forefront of development have extensive in-house development.

How companies will capturing value from ADAS/AD is still uncertain. Currently, two branches have been identified in trying to develop and capitalize on autonomous cars. Traditional OEMs adopts an incremental approach by developing ADAS for consumer products. In a long-term perspective, OEMs are targeting fully autonomous cars while how their business model will look like by then is yet to be revealed. The second approach is companies targeting the raid-hailing market in geo-fenced areas. This approach is in a more direct way trying to realize autonomous cars although still in a limited area initially.

8
Further Research

As computer vision in cars increasingly relies on machine learning and neural networks, data is becoming a crucial asset. Access to a great amount of data and the ability to enhance it is identified as key factors to create value. Further investigating the importance of data and how it can be used as a competitive advantage would be interesting. Many aspects of development are still in an immature phase, flexibility and adaptability are essential as the pace and direction of development could change rapidly.

This thesis has solely focused on the technological perspective of autonomous cars and the ecosystems of companies behind the development. Including regulatory and legislative aspects would further increase knowledge about how development is linked to geographical areas. Comparing different legislative frameworks could highlight external beneficial circumstances of development. Further investigation of beneficial external circumstances including social acceptance and cultural differences could also increase understanding of the demand. Another area of interest would be to study responsibility and the possibility to ensure the safety of software when behaviours of neural networks remain uncertain.

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A

Appendix 1

This chapter provides the reader with the data collected about the companies analysed in the study and creation of the value network. The data is a sample from recognised companies working with computer vision towards autonomous car industry. Every company mentioned in the cells collabs to invested will be taken into account for the network analysis. The reason behind this is that all players do not have a well defines connection to computer vision. Thus also help to reduce the complexity of analysing, especially when there is doubt if they provide additional value for the analysis in answering the research questions. The information from the table is only based on public information and collected from open platforms such as CrunchBase and company home pages. Without the usage of confidential data, there is an increased risk that the data may not be a good represent the reality. For those cells that have the symbol "-" means that no data could be found and for those with "N/A" means that data could be found but were not relevant for thesis.

Table A.1: ADAS & AD company sample

A.1 Annotation Plattforms

Companies	Mighty AI (formerly Spare5)	Appen (figure-eight)	Figure-eight	Samasource	Cmore Automotive	Understand.ai	Labelbox	Scale	Dataloop
Categori	Computer Vision Machine Learning	Crowdsourcing Enterprise Software Social Media	Computer Vision Enterprise Software Machine Learning	Crowdsourcing Enterprise Software Outsourcing	Automotive	Autonomous Vehicles	Computer Vision Enterprise Software Machine Learning	Autonomous Vehicles Developer APIs Image Recognition Machine Learning	Computer Vision Machine Learning SaaS
Computer vision products	Mighty AI delivers training data to companies that build computer vision models for autonomous vehicles	Provide solutions for clients with focus on complex and novel language resource requirements. Also focus on collecting video and picture data and annotate large quantities of data in a short timeframe	Is a Human-in-the-Loop machine learning platform to create customized large scale high-quality training data thru crowdworkers. They supports a wide range of computer vision and natural language processing use cases	Samasource Non-profit org working with crowdworkers performing micro-tasks offers data and content management services to leading enterprise clients.	Selling software tools for acquire, visualize, annotate in 2D and 3D, simulate your high-quality data, Management of the whole project. Consultancy on both strategic and technical matters. define, support and reduce the annotation effort required using automation. Plan and organize all the resources needed in the process.	Provides high-quality training and validation data to enable mobility companies to develop with confidence computer vision. Algorithms is used repetitive tasks and quality check every single image with our in-house multi-level quality assurance team, we are able to quickly and precisely annotate data and thus accelerate the production of training data.	Provides a collaborative training data software to create and manage labeled data for computer vision applications	Helping computer vision teams generate high-quality ground truth data. Our advanced LiDAR, video, and image annotation. APIs include: Sensor Fusion, Semantic Segmentation, 2D Boxes/Polygons, Video, 3D Cuboids, Lines & Splines	Data management and annotation platform streamlines the process of preparing visual data for machine and deep learning. The platform handels data manage, annotations, quality assurance, Train model
Business model	Annotation software (managing, labeling, validating raw data), Team of annotaters thru crowdworkers (spare5), CV algorithms (face anonymization, licenes plate bluring, semi-automated annotation) Consulting Managed services	Annotation, Image and video data collection, Evaluation of data, Transcription,	Training data	Annotationplatfom, Computer vision a Natural langugage processing	Annotation Algorithms for annotations (Image processing Detection and tracking optimization for radar & lidar sensors Feature extraction Classification Mac hine Learning	Annotation Algorithms for annotations (Image processing, Detection and tracking optimization for radar & lidar sensors, Feature extraction, Classification Machin e Learning	Software	Semi automated annotations trough API Quality check	Software
Funding Status	Early Stage Venture	Public	Bought	Grant	-	Seed	Early Stage Venture	Early Stage Venture	Seed
Founding rounds	$27.3M in funding over 3 rounds	-	$58M in funding over 6 rounds	$1.5M in funding over 12 rounds	-	$2.8M in funding over 1	$13.9M in funding over 2 rounds	$22.6M in funding over 3 rounds	-
Customers	Amazon BMW Denso Intel Amazone Mcity Microsoft	Leading Tier 1 suppliers and 6 of the top 10 global OEMs. HQ i Detroit	Google	Google Ford GM Wolkswage Nvidia IBM Continental Microsoft Facebook	-	Wolksvagen	Lytx	Cruise Baidu Lyft Drive.ai zoox Uber Toyota Voyage nuTonomy (now Aptiv)	-
Collabs	IBM	-	-	-	-	Eindhoven University of Technology	-	-	-
Owner	Private	N/A	Appen	Private	-	Private	Private	Private	Private
Investors	Intel Google Ventures Accenture	N/A	-	-	-	N/A	Google	N/A	N/A
Acquiered	N/A	Figure-eight	N/A	N/A	-	N/A	N/A	N/A	N/A
Invested	N/A	N/A	N/A	N/A	-	N/A	N/A	N/A	N/A
References	[1] [2]	[1] [2]	[1] [2]	[1] [2]	[1] [2]	[1] [2]	[1] [2]	[1] [2]	[1] [2]

Table A.2: Collected data from companies, categorised as annotation platforms

[1] *Company website, Retreived 2019-05-21.*
[2] *Crunchbase, Retreived 2019-05-21.*

A.2 Tier 2

Companies	Zenuity	Autonomus intellegent driving	Innoviz Technologies	AutonomouStuff	Aurora	Polysync	Drive.ai	Argo AI	Mobileye
Categori	Autonomous vehicles Software	Autonomous solutions	Autonomous Vehicles	Autonomous Vehicles GPS Sensor Transportation	Automotive, Autonomous Vehicles, Marine Transportation, Transportation	Autonomous Vehicles Robotics	Autonomous Vehicles, Logistics Robotics Software	Autonomous Vehicles Robotics	Automotive
Computer vision products	Software solutions for ADAS and AD	Software solutions for ADAS and AD	Develops technologies for autonomous driving that includes smart 3D sensing, sensor fusion, and accurate mapping and localization.	Provider of autonomy-enabling technologies that specializes in perception sensors, GPS, and computing	Full stack software and hardware that will power the self-driving vehicle industry,	Makers of DriveKit: The vehicle control interface for advanced testing & development	Creating full mobility software solutions for autonomous vehicles using deep learning.	Building self-driving technology to make vehicles safer, more affordable, convenient, and accessible	Developing vision-based advanced driver assistance systems for accident reduction and driver assistance. Both the hardware and software is developed inhouse.
Business model	Develop NN, Train NN, Develop data set, Annotation platform, Curration, Validate, implements the algorithms	Develop NN, Train NN, Develop data set, Annotation platform, Curration, Validate, implements the algorithms	LiDAR Object Identification & Tracking, Sensor Fusion a Mapping & Localization products	Collected data and engineering analysis Simulation environment with a digital clone of vehicle Autonomus software Training on the Autonomus vehicle algorythms HD map a	Software, adas/ad	Pre-built drivers for sensors, Data capture platform for ADAS (Distributed data capture and replay, Data management tools for organizing and re-using data)	Deep learning -	End to end solution	Hardware Software
Funding Status	N/A	-	Late Stage Venture	N/A	Series B	Seed	Early Stage Venture	N/A	Private
Founding rounds	N/A	-	$214M in funding over 4 rounds	N/A	$620M in funding over 2 rounds	$5M in funding over 1 rounds	$77M in funding over 5 rounds	$1B in funding over 1 round	$515M in funding over 3 rounds
Customers	Veoneer Geely Volvo Polestar	Audi	APTIV Magna international Hirain	-	Volkswagen Hyundai Byton	-	-	Ford	Major OEM e.g (Volvo Cars, BMW) Major Tier 1 suppliers
Collabs	-	Wolksvagen Group	-	Velodyne	-	Mcity Texas A&M University	-	Carnegie Mellon University Georgia Institute of Technology	BMW
Owner	Veoneer Volvo	Private	Private	Hexagon	Private	Private	Private	Ford	Intel
Investors	N/A	-	Aptiv Magna international	N/A	Amazon	N/A	Nvidia	N/A	N/A
Acquiered	-	N/A	N/A	N/A	N/A	N/A	N/A	Princeton Lightwave	Eonite Perception
Invested	-	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
References	[1] [2] [7]	[1] [2]	[1] [2]	[1] [2]	[1] [2] [8]	[1] [2]	[1] [2]	[1] [2]	[1] [2] [15]

Table A.3: Collected data from companies, categorised as tier 2 suppliers

[1] *Company website, Retreived 2019-05-21.*
[2] *Crunchbase, Retreived 2019-05-21.*
[4] *Tech crunch (2017), BMW, Intel and Mobileye bring Delphi in on their self-driving platform, 2019-05-21.*
[6] *Business Region Goteborg (2017), Zenuity: "We're our own master", 2019-05-21.*
[7] *Tech crunch (2019), Self-driving car startup Aurora is raising capital at a $2B valuation, 2019-05-21.*

A.3 Tier 1

Companies	Aptiv	Veoneer	Bosch	Denso	Cruse Automation
Categori	Automotive Autonomous Vehicles Electric Vehicle Ride Sharing Software	Manufacturing Sensor	Mobility Solutions Industrial Technology	Electronic automotive supplier	Autonomous Vehicles Robotics Sensor Transportation
Computer vision products	Is a total solution supplier that develops safer, greener, and more connected solutions, which enable the future of mobility	Total solution supplier that produces sensors, control units, software and systems for active safety, autonomous driving, occupant protection and brake control..	Center for Artificial Intelligence focus on research on how Bosch products a.g towards the automation industry can create new value propositions with software solutions.	Is a leading supplier of advanced automotive technology, systems and components for major automakers in vehicles. Is expanding into software-based solutions such as usage of deep neural network.	Cruise Automation is a self-driving car company that develops an autopilot system for existing cars
Business model	Active safety and autonomous drive technology, Infotainment Electrical and wiring products Body control	ADAS solutions	Probabilistic generative models Compressed environment representation optimized for the decision-making Tackle challenges from fusing different sensor outputs into a joint environment perception to defining tasks Creating networks unifying detection and semantic segmentations	Voice Recognition Technology Predict how driving situations Real-time motion plan algorithms Technological validation Simulation on miniature cars	Full solutions from software to electronics
Funding Status	Public	Public	Public	Public	Corporate Round
Founding rounds	-	-	-	-	$3.4B in funding over 5 rounds
Customers	GM VW Ford FCA Daimler Toyota Geely	Daimler Ford GM BMW FCA Hyundai	-	-	-
Collabs	Lyft Intel Mobileye BMW	MIT AgeLab	Daimler	FotoNation	-
Owner	N/A	N/A	N/A	N/A	GM
Investors	N/A	-	N/A	N/A	N/A
Acquiered	nuTonomy Ottomatika	N/A	N/A	N/A	Strobe
Invested	Innoviz Technologies Quanergy Systems	N/A	Graphcore Airy:3D AutoAI Allegro.AI	THINCI Mcity Metawave Uber Advanced Technologies Group	N/A
References	[1] [2] [3] [4] [5]	[1] [2]	[1] [2]	[1] [2]	[1] [2] [3]

Table A.4: Collected data from companies, categorised as tier 1 suppliers

[1] *Company website, Retreived 2019-05-21.*
[2] *Crunchbase, Retreived 2019-05-21.*
[3] *Bloomberg (2018), Retreived from https://www.bloomberg.com/hyperdrive, 2019-05-21.*
[4] *Tech crunch (2017), BMW, Intel and Mobileye bring Delphi in on their self-driving platform, 2019-05-21.*
[5] *Intels website, Retreived 2019-05-21.*

A.4 OEM

Companies	Jaguar/Land Rover	Toyota Research Institute	Daimler	Tesla	Wolksvagen	Volvo Cars	GM	Ford
Categori	Automotive manufacturer	Research Autonomous vehicles	Automotive manufacturer	Automotive manufacturer Autonomous vehicles Electronics		Automotive manufacturer	Automotive manufacturer	Automotive manufacturer
Computer vision products	ADAS/AS as complement solutions for their products	Is an R&D enterprise with an initial focus on artificial intelligence and robotics. Focus on making automobiles safer, more affordable, and more accessible to everyone	ADAS/AS as complement solutions for their products	Develops their technlology inhouse		ADAS/AS as complement solutions for their products	ADAS/AS as complement solutions for their products	plan to be a leader in autonomy, connectivity, mobility, customer experience and analytics
Business model	-	-	-	Do all the development of computervision solutions themself		-	-	-
Funding Status	Private	Public	Public	Public		Private	Public	Public
Founding rounds	-	-	-	$15.1B in funding over 31 rounds		-	-	-
Customers	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Collabs	University of Birmingham Waymo	MIT Stanford GM Ford	Bosch BMW Luminar Nividia	-	Nividia Auorora Intel	Uber Baidu Nvidia	Honda Ford Toyota SoftBank	GM Toyota Lyft
Owner	N/A	N/A	N/A	N/A	N/A	Geely	N/A	N/A
Investors	N/A	N/A	N/A	Toyota Daimler Google	N/A	N/A	N/A	N/A
Acquiered	N/A	N/A	N/A	N/A	N/A	Zenuity	Cruse Automation	N/A
Invested	Lyft Voyage	May Mobility Parallel Domain Blackmore Sensors and analytics Perceptive Automata Apex.AI	Momenta.ai Quanergy ThinCL HERE Starship technologies	N/A	N/A	N/A	Lyft Mcity Algolux	Argo AI Mcity Velodyne
References	[1] [2]	[1] [2] [3] [9]	[1] [2] [3]	[1] [2] [3]	[1] [2] [3]	[1] [2] [3]	[1] [2] [3] [10]	[1] [2] [3] [9]

Table A.5: Collected data from companies, categorised as OEMs

[1] *Company website, Retreived 2019-05-21.*
[2] *Crunchbase, Retreived 2019-05-21.*
[3] *Bloomberg (2018), Retreived from https://www.bloomberg.com/hyperdrive, 2019-05-21.*
[9] *Reuters (2019), GM, Ford and Toyota join to advance self-driving testing, standards, 2019-05-21.*
[10] *Reuters (2018), GM's driverless car bet faces long road ahead, 2019-05-21.*

A.5 Established Tech

Companies	Nvidia	Intel	Google	Baidu
Categori	GPU Hardware Robotics Software Virtualization	Hardware Semiconduct Software	Artificial Intelligence, Enterprise Software Machine Learning Search Engine	Search Engine Social Network
Computer vision products	Creating AI computing platform, Developer Tools and NVIDIA DRIVE™ solution which is a full software solution for autonomous vehicle with features such as OS, Manage computing power, perception, mapping and surroundings visualization.	Trough Mobileye focusing on developing standards and scale up autonomus cars	Trough Waymo focusing on bringing robo-taxi to become a reality	Want to bring autonomus cars to china
Business model	Hardware platform Autonomus vehicle OS Developing tools for e.g DL Simulation Platform Deep neural network training platform	Cameras Autonomus software	Is a well deversifyed technology conglomerat that both specialized in internet-related services and products. Where they have good knowledge in many of those fields connectiong	-
Funding Status	Public	Public	Public	Public
Founding rounds	-	-	-	-
Customers	Audi Mercedes-Benz Toyota Volvo VW Veoneer ZOOX	-	-	-
Collabs	Berkeley Carnegie Mellon University MIT Stanford Baidu Drive.ai Velodyne	Waymo	-	Volvo Ford Nvidia Chery automotive
Owner	N/A	N/A	Alphabet	N/A
Investors	N/A	N/A	-	Google
Acquiered	N/A	Vertex.AI Mobileye	Waymo	
Invested	TuSimple Datalogue AImotive Optimus Ride Drive.ai	Mighty AI AEye, Inc.	-	N/A
References	[1] [2]	[1] [2]	[1] [2]	[1] [2] [3] [8]

Table A.6: Collected data from companies, categorised as Established Tech

[1] *Company website, Retreived 2019-05-21.*
[2] *Crunchbase, Retreived 2019-05-21.*
[3] *Bloomberg (2018), Retreived from https://www.bloomberg.com/hyperdrive, 2019-05-21.*
[8] *Tech crunch (2018), Baidu hits the gas on autonomous vehicles with Volvo and Ford deals, 2019-05-21.*

A.6 Robo-Taxi

Companies	Waymo	Uber Advanced Technologies Group	Lyft	Zoox	Voyage
Categori	Autonomous vehicles Robotics Sensor Transportation	Autonomous vehicles Transportation	Autonomous vehicles Transportation	Autonomous vehicles Robotics Transportation	Autonomous vehicles Transportation
Computer vision products	Focus on the robotaxis business level 4-5 autonomous cars, hence they are not developing ADAS. Also sell their technology to non competitors.	Focus on the robotaxis business level 4-5 autonomous cars	Focus on the robotaxis business level 4-5 autonomous cars. Open platform for other companies to offer autonomous rides trough lyft.	Building autonomous car from scratch, bidirectional etc. Has the approach of Mobility as a service, full stack approach	Delivering on the promise of self-driving cars today
Business model	Sensors Data gathering Manage data and annotations Algorythm development and training	-	Data gathering Manage data Algorythm development and training	-	-
Funding Status	Private	Corporate Round	Public	Early Stage Venture	Early Stage Venture
Founding rounds	-	$1B in funding over 1 round	$4.9B	$790M in funding over 3 rounds	$20.2M in funding, 1 round 2018
Customers	Robotaxi customer Tech customer	Robotaxi customer	Robotaxi customer	-	Housing communities
Collabs	Crysler who provide cars Jaguar Land Rover who provide cars Honda Motor Lyft	Toyota Volov cars Daimler	Aptiv Waymo Ford	-	-
Owner	Google	Uber	N/A	N/A	Private
Investors	N/A	Toyota Denso Softbank	GM Manga International	N/A	Jaguar/Land Rover
Acquiered	N/A	Geometric Intelligence	N/A	N/A	N/A
Invested	Determined AI Halli Labs	N/A	N/A	N/A	N/A
References	[1] [2] [3]	[1] [2] [3]	[1] [2] [3] [11] [12]	[1] [2] [3]	[1] [2] [3]

Table A.7: Collected data from companies, categorised as robo-taxi producers

[1] *Company website, Retreived 2019-05-21.*
[2] *Crunchbase, Retreived 2019-05-21.*
[3] *Bloomberg (2018), Retreived from https://www.bloomberg.com/hyperdrive, 2019-05-21.*
[11] *Tech crunch (2018), Lyft speeds ahead with its autonomous initiatives, 2019-05-21.*
[12] *The Verge (2019), Waymo's self-driving cars are now available on Lyft's app in Phoenix, 2019-05-21.*

A.7 Sensor

Companies	**Velodyne**	**Innosent**
Categori	Machinery Manufacturing Manufacturing Robotics, Sensor	Electronics Manufacturing Software Engineering
Computer vision products	Manufactures sensor products and real-time LiDAR sensors	Developing, producing and marketing radar sensors
Business model	LidaR sensors	Radar
Funding Status	Corporate Round	-
Founding rounds	$150.2M in funding over 2 rounds	-
Customers	-	-
Collabs	-	-
Owner	N/A	Private
Investors	Baidu Ford	N/A
Acquiered	N/A	N/A
Invested	N/A	N/A
References	[1] [2]	[1] [2]

Table A.8: Collected data from companies, categorised as sensor suppliers

[1] *Company website, Retreived 2019-05-21.*
[2] *Crunchbase, Retreived 2019-05-21.*