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Use and role of artificial intelligence and data science in the automotive industry

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Abstract
The Data science and machine learning area unit the key technologies once it involves the processes and product with automatic learning and improvement to be utilized in the automotive trade of the long run. This text defines the terms “data science” (also stated as “data analytics”) and “machine learning” and the way they're connected. Additionally, it defines the term “optimizing analytics “and illustrates the role of automatic improvement as a key technology together with information analytics. It additionally uses examples to clarify the method that these technologies area unit presently being employed within the automotive trade on the premise of the main sub processes within the automotive price chain (development, procurement; provision, production, marketing, sales and after-sales, connected customer). Since the trade is simply setting out to explore the broad vary of potential uses for these technologies, visionary application examples area unit accustomed illustrate the revolutionary prospects that they provide. Finally, the article demonstrates however these technologies will create the automotive trade a lot of economical and enhance its client focus throughout all its operations and activities, extending from the merchandise and its development method to the shoppers and their affiliation to the merchandise. Now as increasing the work on machines and it is all changing fast and vastly to reach desired output. So, it is necessary to stay with it and stuck with the market flow. Artificial Intelligence is changing the way of working of the entire world. Here we are examining how AI is useful for data science.

Keywords: Technology, data science, analytics, automotive, industry, applications, artificial intelligence, machine learning

Introduction

Data science and machine learning are presently key technologies in our everyday lives, as we tend to are able to see in an exceedingly very multitude of applications, like voice recognition in vehicles and on cell phones, automatic facial and traffic sign recognition, equally as chess and, extra recently, go machine algorithms1 that humans cannot beat (Martin Hofmann1, Florian Neukart 2,3, Thomas Bäck3- Artificial Intelligence and Data Science in the Automotive Industry). The analysis of monumental data volumes supported search, pattern recognition, and learning algorithms provides insights into the behavior of processes, systems, nature, and ultimately people, gap the door to a world of basically new possibilities. In fact, the presently already implementable set up of autonomous driving is sort of a tangible reality for many drivers today with help} of lane keeping help and adaptive management systems inside the vehicle. The Agriculture and the education departments are two elements where the ICT can play the very important role in the development of the country (VD. Jadhav, 2019, IRJET) [3]. The fact that this can be simply the tip of the iceberg, even within the automotive business, becomes promptly apparent once one considers that, at the tip of 2015, Toyota and Tesla's founder, Elon Musk, every declared investments amounting to at least one billion USA greenbacks in computer science research and development nearly at identical time. The trend towards connected, autonomous, and unnaturally intelligent systems that incessantly learn from information and area unit able to create optimum selections is advancing in ways in which area unit simply revolutionary, to not mention essentially important to several industries. This includes the automotive industry, one among the key industries in Germany, in which international aggressiveness are influenced by a brand-new factor in the close to future – particularly the new technical and service offerings that may be supplied with the assistance of knowledge science and machine learning (Martin Hofmann1, Florian Neukart 2,3, Thomas Bäck3- Artificial Intelligence and Data Science in the Automotive Industry). This article provides an summary of the corresponding methods and a few current application examples within the automotive trade. It additionally outlines the potential applications to be expected during this trade terribly shortly. Accordingly, sections a pair of and three begin by addressing the subdomains information of knowledge of information mining (also said as "Big data analytics") and computer science, concisely summarizing the corresponding processes, methods and areas of application and presenting them in context. Section four then provides an summary of current application examples within the automotive trade supported the stages within the industry's value chain –from development to production and provision through to the top client. Based on such Associate in Nursing example, section five describes the vision for future applications victimization three examples: one during which vehicles play the role of autonomous agents that acct with one another in cities, one that covers integrated production improvement, and one that describes firms themselves as autonomous agents. Whether these visions can become a reality during this or any other manner can't be aforementioned with certainty nowadays – however, we will safely predict that the speedy rate of development this space can cause the creation of completely new merchandise, processes and services many of which we will solely imagine nowadays, this can be one amongst the conclusions drawn in section six, beside Associate in regarding the potential future effects of the speedy rate of development during this space.

The Data Mining Process

Gartner uses the term "prescriptive analytics" to explain the highest level of ability to create business choices on the basis of observational analyses. This can be illustrated by the question "what ought to I do?" and prescriptive analytics supplies the specified decision-making support, if someone is still concerned or automation if this can be now not the case. The levels below this, in ascending order in terms of the employment and utility of Artificial Intelligence and knowledge science, area unit outlined as follows: descriptive analytics ("What has happened?"), diagnostics analytics ("Why did it happen?") and prognostics analytics ("What can happen?") see figure below. The last 2 levels area unit supported knowledge science technology, together with knowledge mining and statics, whereas descriptive analytics basically uses ancient business intelligence ideas (data warehouse, OLAP). In this article we tend to look for to interchange the term "Prescriptive analytics" with the term "optimizing analytics". The explanation for this (can be) that a technology can "prescribe" several things, while, in terms of implementation at intervals an organization, the goal is usually to create one thing "better" with reference to target criteria or quality criteria. This improvement is supported by search algorithms, like biological process algorithms in nonlinear cases and operation analysis (OR) methods in abundant rarer-linear cases. It may be supported by application consultants who take the results from the data mining methods and use them to draw conclusion regarding method improvement. One example area unit the decision trees learned from knowledge that application consultants can perceive, reconcile with their own professional information, and then implement in associate degree applicable manner.

Optimizing Analytics	"What am I supposed to do?"	Decision support, multicriterial optimization
Predictive Analytics	"What will happen?"	Modelling
Diagnostic Analytics	"Why did it happen?"	BI, Modelling
Descriptive Analytics	"What happened?"	Business Intelligence

Fig a): The four levels of data analysis usage within a Company

The manual, iterative procedure is also due to the fact that the basic idea behind this approach – as up-to-date as it may be for the majority of applications – is now almost 20 years old and certainly only partially compatible with a big data strategy. The fact is that, in addition to the use of nonlinear modeling methods (in contrast to the usual generalized linear models derived from statistical modeling) and knowledge extraction from data, data mining rests on the fundamental idea that models can be derived from data with the help of algorithms and that this modeling process can run automatically for the most part – because the algorithm "does the work." In applications where a large number of models need to be created, for example for use in making forecasts (e.g., sales forecasts for individual vehicle models and markets based on historical data), automatic modeling plays an important role. The same applies to the use of online data mining, in which, for example, forecast models (e.g., for forecasting product quality) are not only constantly used for a production process, but also adapted (i.e., retrained) continuously whenever individual process aspects change (e.g., when a new raw material batch is used). This type of application requires the technical ability to automatically generate data, and integrate and process it in such a way that data mining algorithms can be applied to it. In addition, automatic modeling and automatic optimization are necessary in order to update models and use them as a basis for generating optimal proposed actions in online applications. These actions can then be communicated to the process expert as a suggestion or – especially in the case of continuous production processes – be used directly to control the respective process. If sensor systems are also integrated directly into the production process – to collect data in real time – this results in a self-learning cyberphysical system 3 that facilitates implementation of the Industry 4.04 vision in the field of production engineering.

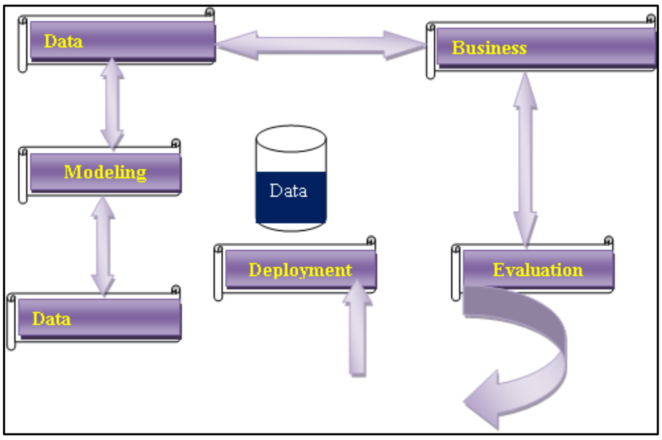

Fig b): Traditional CRISP-DM process optimization step added

8 pillars of artificial intelligence

An early definition of artificial intelligence from the IEEE Neural Networks Council was "the study of how to make computers do things at which, at the moment, people are better."5 Although this still applies, current research is also focused on improving the way that software does things at which computers have always been better, such as analyzing large amounts of data. Data is also the basis for developing artificially intelligent software systems not only to collect information, but also to:

- Learn
- Understand and interpret information
- Behave adaptively
- Plan
- Make inferences
- Solve problems
- Think abstractly
- Understand and interpret ideas and language

Machine learning

At the most general level, machine learning (ML) algorithms can be subdivided into two categories: supervised and supervised, depending on whether or not the respective algorithm requires a target variable to be specified. Supervised learning algorithms Apart from the input variables (predictors), supervised learning algorithms also require the known target values (labels) for a problem. In order to train an ML model to identify traffic signs using cameras, images of traffic signs – preferably with a variety of configurations – are required as input variables. In this case, light conditions, angles, soiling, etc. are compiled as noise or blurring in the data; nonetheless, it must be possible to recognize a traffic sign in rainy conditions with the same accuracy as when the sun is shining. The labels, i.e., the correct designations, for such data are normally assigned manually. This correct set of input variables and their correct classification constitute a training data set. Although we only have one image per training data set in this case, we still speak of multiple input variables, since ML algorithms find relevant features in training data and learn how these features and the class assignment for the classification task indicated in the example are associated. Supervised learning is used primarily to predict numerical values (regression) and for classification purposes (predicting the appropriate class), and the corresponding data is not limited to a specific format – ML algorithms are more than capable of processing images, audio files, videos, numerical data, and text. Classification examples include object recognition (traffic signs, objects in front of a vehicle, etc.), face recognition, credit risk assessment, voice recognition, and customer churn, to name but a few Regression examples include determining continuous numerical values on the basis of multiple (sometimes hundreds or thousands) input variables, such as a self-driving car calculating its ideal speed on the basis of road and ambient conditions, determining a financial indicator such as gross domestic product based on a changing number of input variables (use of arable land, population education levels, industrial production, etc.), and determining potential market shares with the introduction of new models. Each of these problems is highly complex and cannot be represented by simple, linear relationships in simple equations. Or, to put it another way that more accurately represents the enormous challenge involved: the necessary expertise does not even exist. In other words, machine learning is the area of artificial intelligence (AI) that enables computers to learn without being programmed explicitly. Machine learning focuses on developing programs that grow and change by themselves as soon as new data is provided. Accordingly, processes that can be represented in a flowchart are not suitable candidates for machine learning – in contrast, everything that requires dynamic and changing solution strategies and cannot be constrained to static rules is potentially suitable for solution with ML. For example, ML is used when:

- No relevant human expertise exists
- People are unable to express their expertise
- The solution changes over time
- The solution needs to be adapted to specific cases

In contrast to statistics, which follows the approach of making inferences based on samples, computer science is interested in developing efficient algorithms for solving optimization problems, as well as in developing a representation of the model for evaluating inferences. Methods frequently used for optimization in this context include so-called "evolutionary algorithms" (genetic algorithms, evolution strategies), the basic principles of which emulate natural evolution6. These methods are very efficient when applied to complex, nonlinear optimization problems. Even though ML is used in certain data mining applications, and both look for patterns in data, ML and data mining are not the same thing. Instead of extracting data that people can understand, as is the case with data mining, ML methods are used by programs to improve their own understanding of the data provided. Software that implements ML methods recognizes patterns in data and can dynamically adjust the behavior based on them. If, for example, a self-driving car (or the software that interprets the visual signal from the corresponding camera) has been trained to initiate a braking maneuver if a pedestrian appears in front it, this must work with all pedestrians regardless of whether they are short, tall, fat, thin, clothed, coming from the left, coming from the right, etc. In turn, the vehicle must not brake if there is a stationary garbage bin on the side of the road.

Inference and decision-making

This field of research, referred to in the literature as "knowledge representation & reasoning" (KRR), focuses on designing and developing data structures and inference algorithms. Problems solved by making inferences are very often found in applications that require interaction with the physical world (humans, for example), such as generating diagnostics, planning, processing natural languages, answering questions, etc. KRR forms the basis for AI at the human level. Making inferences is the area of KRR in which data-based answers need to be found without human intervention or assistance, and for which data is normally presented in a formal system with distinct and clear semantics. Since 1980, it has been assumed that the data involved is a mixture of simple and complex structures, with the former having a low degree of computational complexity and forming the basis for research involving large databases. The latter are presented in a language with more expressive power, which requires less space for representation, and they correspond to generalizations and fine-grained information.

Data mining and artificial intelligence in the automotive industry

At a high level of abstraction, the value chain in the automotive industry can broadly be described with the following subprocesses:

1. Development
2. Procurement

3. Logistics
4. Production
5. Marketing
6. Sales, after-sales, and retail
7. Connected customer

Each of these areas already features a significant level of complexity, so the following description of data mining and artificial intelligence applications has necessarily been restricted to an overview.

Development

Vehicle development has become a largely virtual process that is now the accepted state of the art for all manufacturers. CAD models and simulations (typically of physical processes, such as mechanics, flow, acoustics, vibration, etc., on the basis of finite element models) are used extensively in all stages of the development process. The subject of optimization (often with the use of evolution strategies31 or genetic algorithms and related methods) is usually less well covered, even though it is precisely here in the development process that it can frequently yield impressive results. Multi-disciplinary optimization, in which multiple development disciplines (such as occupant safety and noise, vibration, and harshness (NVH)) are combined and optimized simultaneously, is still rarely used in many cases due to supposedly excessive computation time requirements. However, precisely this approach offers enormous potential when it comes to agreeing more quickly and efficiently across the departments involved on a common design that is optimal in terms of the requirements of multiple departments. In terms of the analysis and further use of simulation results, data mining is already being used frequently to generate co-called “response surfaces.” In this application, data mining methods (the entire spectrum, ranging from linear models to Gaussian processes, support vector machines, and random forests) are used in order to learn a nonlinear regression model as an approximation of the representation of the input vectors for the simulation based on the relevant (numerical) simulation results32. Since this model needs to have good interpolation characteristics, cross-validation methods that allow the model's prediction quality for new input vectors to be estimated are typically used for training the algorithms. The goal behind this use of supervised learning methods is frequently to replace computation-time-consuming simulations with a fast approximation model that, for example, represents a specific component and can be used in another application. In addition, this allows time consuming adjustment processes to be carried out faster and with greater transparency during development.

Procurement

The procurement process uses a wide variety of data concerning suppliers, purchase prices, discounts, delivery reliability, hourly rates, raw material specifications, and other variables. Consequently, computing KPIs for the purpose of evaluating and ranking suppliers poses no problem whatsoever today. Data mining methods allow the available data to be used, for example, to generate forecasts, to identify important supplier characteristics with the greatest impact on performance criteria, or to predict delivery reliability. In terms of optimizing analytics, the specific parameters that an automotive manufacturer can influence in order to achieve optimum conditions are also important. Overall, the finance business area is a very good field for optimizing analytics, because the available data contains information about the company's main success factors. Continuous monitoring 34 is worth a brief mention as an example, here with reference to controlling. This monitoring is based on finance and controlling data, which is continuously prepared and reported. This data can also be used in the sense of predictive analytics in order to automatically generate forecasts for the upcoming week or month. In terms of optimizing analytics, analyses of the key influencing parameters, together with suggested optimizing actions, can also be added to the aforementioned forecasts. These subject areas are more of a vision than a reality at present, but they do convey an idea of what could be possible in the fields of procurement, finance, and Controlling.

Logistics

In the field of logistics, a distinction can be made between procurement logistics, production logistics, distribution logistics, and spare parts logistics. Procurement logistics considers the process chain extending from the purchasing of goods through to shipment of the material to the receiving warehouse. When it comes to the purchasing of goods, a large amount of historical price information is available for data mining purposes, which can be used to generate price forecasts and, in combination with delivery reliability data, to analyze supplier performance. As for shipment, optimizing analytics can be used to identify and optimize the key cost factors. A similar situation applies to production logistics, which deals with planning, controlling, and monitoring internal transportation, handling, and storage processes. Depending on the granularity of the available data, it is possible to identify bottlenecks, optimize stock levels, and minimize the time required,

Production

Every sub-step of the production process will benefit from the consistent use of data mining. It is therefore essential for all manufacturing process parameters to be continuously recorded and stored. Since the main goal of optimization is usually to improve quality or reduce the incidence of defects, data concerning the defects that occur and the type of defect is required, and it must be possible to clearly assign this data to the process parameters. This approach can be used to achieve significant improvements, particularly in new types of production process – one example being CFRP36. Other potential optimization areas include energy consumption and the throughput of a production process per time unit. Optimizing analytics can be applied both offline and online in this context. When used in offline applications, the analysis identifies variables that have a significant influence on the process. Furthermore, correlations are derived between these influencing variables and their targets (quality, etc.) and, if applicable, actions are also derived from this, which can improve the targets. Frequently, such analyses focus on a specific problem or an urgent issue with the process and can deliver a solution very efficiently – however, they are not geared towards continuous process optimization. Conducting the analyses and interpreting and implementing the results consistently requires manual sub-steps that can be carried out by data scientists or statisticians – usually in consultation with the respective process experts. In the case of online applications, there is a very significant difference in the fact that the procedure is automated, resulting in completely new challenges for data acquisition and integration, data pre-processing, modeling, and optimization. In these applications, even the provision of process and quality data needs to be automated, as this provides integrated data that can be used as a basis for modeling at any time. This is crucial given that modeling always needs to be performed when changes to the process (including drift) are detected. The resulting forecast models are then used automatically for optimization purposes and are capable of, e.g., forecasting the quality and suggesting (or directly implementing) actions for optimizing the relevant target variable (quality in this case) even further. This implementation of optimizing analytics, with automatic modeling and optimization, is technically available, although it is more a vision than a reality for most users today.

Marketing

The focus in marketing is to reach the end customer as efficiently as possible and to convince people either to become customers of the company or to remain customers. The success of marketing activities can be measured in sales figures, whereby it is important to differentiate marketing effects from other effects, such as the general financial situation of customers. Measuring the success of marketing activities can therefore be a complex endeavor, since multivariate influencing factors can be involved. It would also be ideal if optimizing analytics could always be used in marketing, because optimization goals, such as maximizing return business from a marketing activity, maximizing sales figures while minimizing the budget employed, optimizing the marketing mix, and optimizing the order in which things are done, are all vital concerns. Forecast models, such as those for predicting additional sales figures over time as a result of a specific marketing campaign, are only one part of the required data mining results – multi-criteria decision-making support also plays a decisive role in this context. Two excellent examples of the use of data mining in marketing are the issues of churn (customer turnover) and customer loyalty. In a saturated market, the top priority for automakers is to prevent loss of custom, i.e., to plan and implement optimal countermeasures. This requires information that is as individualized as possible concerning the customer, the customer segment to which the customer belongs, the customer's satisfaction and experience with their current vehicle, and data concerning competitors, their models, and prices. Due to the subjectivity of some of this data (e.g., satisfaction surveys, individual satisfaction values), individualized churn predictions and optimal countermeasures (e.g., personalized discounts, refueling or cash rewards, incentives based on additional features) are a complex subject that is always relevant. Since maximum data confidentiality is guaranteed and no personal data is recorded – unless the customer gives their explicit consent in order to receive offers as individually tailored as possible – such analyses and optimizations are only possible at the level of customer segments that represent the characteristics of an anonymous customer subset. Customer loyalty is closely related to this subject, and takes on board the question of how to retain and optimize, i.e., increase the loyalty of existing customers. Likewise, the topic of "upselling," i.e., the idea of offering existing customers a higher-value vehicle as their next one and being successful with this offer, is always associated with this. It is obvious that such issues are complex, as they require information about customer segments, marketing campaigns, and correlated sales successes in order to facilitate analysis. However, this data is mostly not available, difficult to collect systematically, and characterized by varying levels of veracity, i.e., uncertainty in the data.

Sales, after-sales, and retail

The diversity of potential applications and existing applications in this area is significant. Since the "human factor," embodied by the end customer, plays a crucial role within this context, it is not only necessary to take into account objective data such as sales figures, individual price discounts, and dealer campaigns; subjective customer data such as customer satisfaction analyses based on surveys or third-party market studies covering such subjects as brand image, breakdown rates, brand loyalty, and many others may also be required. At the same time, it is often necessary to procure and integrate a variety of data sources, make them accessible for analysis, and finally analyze them correctly in terms of the potential subjectivity of the evaluations37 – a process that currently depends to a large extent on the expertise of the data scientists conducting the analysis. The field of sales itself is closely intermeshed with marketing. After all, the ultimate objective is to measure the success of marketing activities in terms of turnover based on sales figures. A combined analysis of marketing activities (including distribution among individual media, placement frequency, costs of the respective marketing activities, etc.) and sales can be used to optimize market activities in terms of cost and effectiveness, in which case a portfolio-based approach is always used. This means that the optimum selection of a portfolio of marketing activities and their scheduling – and not just focusing on a single marketing activity – is the main priority. Accordingly, the problem here comes from the field of multi-criteria decision-making support, in which decisive breakthroughs have been made in recent years thanks to the use of evolutionary algorithms and new, portfolio-based optimization criteria. However, applications in the automotive industry are still restricted to a very limited scope.

Connected customer

While this term is not yet established as such at present, it does describe a future in which both the customer and their vehicle are fully integrated with state-of-the-art information technology. This aspect is closely linked to marketing and sales issues, such as customer loyalty, personalized user interfaces, vehicle behavior in general, and other visionary aspects (see also section 5). With a connection to the Internet and by using intelligent algorithms, a vehicle can react to spoken commands and search for answers that, for example, can communicate directly with the navigation system and change the destination. Communication between vehicles makes it possible to collect and exchange information on road and traffic conditions, which is much more precise and up-to-date than that which can be obtained via centralized systems. One example is the formation of black ice, which is often very localized and temporary, and which can be detected and communicated in the form of a warning to other vehicles very easily today.

Vision – Vehicles as autonomous, adaptive, and

Social agents & cities as super-agents Research into self-driving cars is here to stay in the automotive industry, and the "mobile living room" is no longer an implausible scenario, but is instead finding a more and more positive response.

Today, the focus of development is on autonomy, and for good reason: In most parts of the world, self-driving cars are not permitted on roads, and if they are, they are not widespread. This means that the vehicle as an agent cannot communicate with all other vehicles, and that vehicles driven by humans adjust their behavior based on the events in their drivers' field of view. Navigation systems offer support by indicating traffic congestion and suggesting alternative routes. However, we now assume that every vehicle is a fully connected agent, with the two primary goals of:

- Contributing to optimizing the flow of traffic
- Preventing accidents

In this scenario, agents communicate with each other and negotiate routes with the goal of minimizing total travel time (obvious parameters being, for example, the route distance, the possible speed, roadwork, etc.). Unforeseeable events are minimized, although not eliminated completely – for example, storm damage would still result in a road being blocked. This type of information would then need to be communicated immediately to all vehicles in the relevant action area, after which a new optimization cycle would be required. Moreover, predictive maintenance minimizes damage to vehicles. Historical data is analyzed and used to predict when a defect would be highly likely to occur, and the vehicle (the software in the vehicle, i.e., the agent) makes a service appointment without requiring any input from the passenger and then drives itself to the repair shop – all made possible with access to the passenger's calendar. In the event of damage making it impossible to continue a journey, this would also be communicated as quickly as possible – either with a "breakdown" broadcast or to a control center, and a self-driving tow truck would be immediately available to provide assistance, ideally followed by a (likewise self-driving) replacement vehicle. In other words, vehicles act:

- Autonomously in the sense that they automatically follow a route to a destination
- Adaptively in the sense that they can react to unforeseen events, such as road closures and breakdowns
- Socially in the sense that they work together to achieve the common goals of optimizing the flow of traffic and preventing accidents (although the actual situation is naturally more complex and many sub goals need to be defined in order for this to be achieved).

If roads become digital as well, i.e., if asphalt roads are replaced with glass and supplemented with OLED technology, dynamic changes to traffic management would also be possible. From a materials engineering perspective, this is feasible:

- The surface structure of glass can be developed in such a way as to be skid resistant, even in the rain.
- Glass can be designed to be so flexible and sturdy that it will not break, even when trucks drive over it.
- The waste heat emitted by displays can be used to heat roads and prevent ice from forming during winter.

In this way, cities themselves can be embedded as agents in the multi-agent environment and help achieve the defined goals.

Conclusion

Artificial intelligence has already found its way into our daily lives, and is no longer solely the subject of science fiction novels. At present, AI is used primarily in the following areas:

- Analytical data processing
- Domains in which qualified decisions need to be made quickly on the basis of a large amount of (often heterogeneous) data
- Monotonous activities that still require constant alertness

In the field of analytical data processing, the next few years will see us transition from exclusive use of decision-support systems to additional use of systems that make decisions on our behalf. Particularly in the field of data analysis, we are currently developing individual analytical solutions for specific problems, although these solutions cannot be used across different contexts – for example, a solution developed to detect anomalies in stock price movements cannot be used to understand the contents of images. This will remain the case in the future, although AI systems will integrate individual interacting components and consequently be able to take care of increasingly complex tasks that are currently reserved exclusively for humans – a clear trend that we can already observe today. A system that not only processes current data regarding stock markets, but that also follows and analyzes the development of political structures based on news texts or videos, extracts sentiments from texts in blogs or social networks, monitors and predicts relevant financial indicators, etc. requires the integration of many different subcomponents – getting these to interact and cooperate is the subject of current research, and new advances in this field are being published every week. In a world where AI systems are able to improve themselves continuously and, for example, manage companies more effectively than humans, what would be left for humans? Time for expanding one's knowledge, improving society, eradicating hunger, eliminating diseases, and spreading our species beyond our own solar system.40 Some theories say that quantum computers are required in order to develop powerful AI systems 41, and only a very careless person would suggest than an effective quantum computer will be available within the next 10 years. Then again, only a careless person would suggest that it will not. Regardless of this, and as history has taught us time and time again with the majority of relevant scientific accomplishments, caution will also have to be exercised when implementing artificial intelligence – systems capable of making an exponentially larger number of decisions in extremely short times as hardware performance improves can achieve many positive things, but they can also be misused.

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