Engineering AI Systems: A Research Agenda

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Abstract

Deploying machine-, and in particular deep-learning, (ML/DL) solutions in industry-strength, production quality contexts proves to challenging. This requires a structured engineering approach to constructing and evolving systems that contain ML/DL components. In this paper, we provide a conceptualization of the typical evolution patterns that companies experience when employing ML/DL well as a framework for integrating ML/DL components in systems consisting of multiple types of components. In addition, we provide an overview of the engineering challenges surrounding AI/ML/DL solutions and, based on that, we provide a research agenda and overview of open items that need to be addressed by the research community at large.

Introduction

Over the last decade, the prominence of artificial intelligence (AI) and specifically machine- and deep-learning (ML/DL) solutions has grown exponentially [1,3]. Because of the big data era, more data is available than ever and can be used for training ML/DL solutions. In parallel, progress in high-performance parallel hardware such as GPUs and FPGAs allows for training solutions of scales unfathomable even a decade ago. These two concurrent technology developments are at the heart of the rapid adoption of ML/DL solutions in industry.

The hype around AI has resulted in virtually every company having some form of AI initiative, or host of AI initiatives, ongoing and the number of experiments and prototypes in industry is phenomenal. Unfortunately, our research [2, 5, 6] shows that the transition from prototype to industry-strength, production-quality deployment of ML/DL models proves to be challenging for many companies. In particular, the engineering challenges surrounding this prove to be significant, even if many data scientists and companies fail to recognize these.
The purpose and contribution of this paper is threefold. First, we provide a conceptualization of the typical evolution patterns that companies experience as well as a framework for integrating ML/DL components in systems consisting of multiple types of components. Second, we provide an overview of the engineering challenges surrounding ML/DL solutions. Third, we provide a research agenda and overview of open items that need to be addressed by the research community at large.

The remainder of the paper is organized as follows. In the next section, we provide a brief overview of the empirical basis for the concepts, challenges and research agenda that we present in this paper. The next section introduces the HoliDev model as well as the AI adoption evolution model. Subsequently, we provide an overview of the engineering challenges that we have identified in our research so far. The next section is concerned with the AI engineering research agenda that we have defined based on the identified challenges and our assessment of available solutions. Finally, we conclude the paper.

**Empirical Basis**

In the context of Software Center\(^1\), we work with more than a dozen large, international embedded systems companies, including Ericsson, Tetra Pak, Siemens, Bosch, Volvo Cars, Boeing and several others around, among others, the adoption of ML/DL. In addition, we frequently have the opportunity to study and collaborate with companies outside of Software Center that operate as SaaS, online companies that operate in a variety of business domains.

Due to the limited length of the article, we are not able to provide a full overview of these companies nor the research methods that we employed in our various research activities. For this, we refer the reader to our papers, some of which are available in the reference list as well as to the Software Center website. However, the work presented in this paper is based on data collected from well over 20 companies from around the world, though with a focus on the software-intensive embedded systems industry in Europe and the Nordic countries.

**Conceptualizing AI Engineering**

Engineering AI systems is often portrayed as the creation of a ML/DL model, deploying it and moving on. In practice, however, the ML/DL model is only a small part of the overall system and significant additional functionality is required to ensure that the ML/DL model can operate in a reliable and predictable fashion with proper engineering of data pipelines, monitoring and logging, etc. [3,7].

In development of complex systems, AI development is only a fraction of the entire system development. Further, system and software architecture are usually far more complex than

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particular ML/DL solutions; he ML/DL models are not necessarily the central focus of the system, but generally are just one of several or many components in the system. To capture these aspects of AI engineering we defined the Holistic DevOps (HoliDev) model [4]. As shown in the figure below, a typical system contains components developed in three different ways. First, traditional requirements driven development will remain as there are features, such as regulatory, commodity and competitor parity features that can and should be built based on a specification. Second, increasingly many companies adopt outcome or data-driven development. In this case, development teams receive a target to improve specific KPIs or measurable factors of a system, such as conversion rate in e-commerce systems, and then use experimentation, e.g. A/B testing, to drive improvement of the desired outcome. Finally, companies use AI-driven development when large data sets are available, there is a clear success metric and there is a combinatorial explosion of alternatives that makes it difficult for humans to formulate algorithms to solve the problem well.

The challenge is that the results of each of the aforementioned types of development end up in the same system and are subject to monitoring of their behaviour as well as continuous deployment. In industrial deployments that we have studied, also AI models are constantly improved, retrained and redeployed.

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**Figure 1**: The HoliDev Model

In a transformation to AI-driven development, companies, over time, tend to develop more skills, capabilities and needs in the ML/DL space and consequently they evolve through several stages. In the AI Evolution model shown in figure 2 we illustrate how companies, based on our research [5, 6], develop over time.
• **Experimentation and prototyping:** In this stage, teams in the company are using available data sets to explore the possibilities of employing AI solutions. This stage is purely exploratory and the results are not deployed in a production environment. Consequently, AI engineering challenges are not present in this stage.

• **Non-critical deployment:** In this stage, a ML/DL model is deployed as part of a product or system in a non-critical capacity, meaning that if the model fails to perform, the overall product or system is still functional and delivers value to customers.

• **Critical deployment:** Once the confidence in the ML/DL models increases, key decision makers become sufficiently comfortable with deploying these models in a critical context, meaning that the product or system fails if the ML/DL model does not perform correctly.

• **Cascading deployment:** With the increasing use of ML/DL models, the next step is to start to use the output of one model as the input for the next model in the chain. In this case, monitoring and ensuring correct functioning of the system becomes more difficult as the issues may be emergent, rather than directly associated with a specific ML/DL model.

• **Autonomous ML/DL components:** In the final stage, ML/DL models monitor their own behaviour, automatically initiate retraining and are able to flag when the model observes that, despite retraining using the latest data, it does not provide acceptable accuracy.

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**Figure 2:** The AI adoption evolution model

Each step requires increased activities of “AI engineering” - a set of methods and tools that originated from software engineering in a system life cycle, and procedures, technologies and tools from data science and AI. While the first step, which is today state of the practice, typically covers end-to-end ML development cycle (data acquisition, feature engineering, training and evaluation, and deployment), the next steps require partially the existing approaches from software engineering (e.g. system testing), and partially completely new methods that will need to become an integrated part of software and AI engineering (e.g. continuous training, or version management of code and data).
AI Engineering: A Research Agenda

The subject of AI and the notion of engineering for building AI systems is a multi-faceted and complex problem. Consequently, few, if any, models exist that seek to create a structure and conceptualization of the problem space. Here we provide a structured view on the challenge of AI engineering and to provide a research agenda.

In the figure below, we provide a model that is organized in three concentric circles. The most inner circle is concerned with the basic Data science and AI activities. The second circle is concerned with the basic AI engineering activities that any organization using ML/DL models has to consider as part of their work. The outer circles are concerned with advanced Domain specific AI engineering activities that companies in specific domains or addressing specific challenges will have to contend with. In the remainder of this section, we discuss each of these in more detail.

Figure 3: Conceptualization of AI engineering
AI/data science

As the activities in this scope are the regular AI/data science activities, we will discuss these only briefly:

- **Assemble data sets**: The first activity in virtually any ML/DL project is to assemble the data sets that can be used for training and evaluation and to evaluate these in order to understand the relevant features in the data, the statistical distribution, the quality of the data in terms of missing or erroneous values, etc.
- **Create & evolve ML/DL model**: After analysing the data sets, the next step is to experiment with different ML algorithms or DL models and to select the most promising one for further development. Once the model has been selected and developed, over time it may become necessary to evolve the model.
- **Train & evaluate**: Once the model has been developed, the next step is to train the model using a subset of the data and to evaluate it using a validation subset of the data.

The process as described above has many additional aspects and is typically conducted in an iterative manner. As the focus of this paper is on AI engineering and not the specific data science aspects, we do not discuss these aspects in more detail.

AI Engineering

Building and deploying successful ML/DL components and systems requires more than data science alone. There are several other activities required that are concerned with engineering activities. We distinguish between generic AI engineering activities that are required for virtually any system using ML/DL and domain specific AI engineering activities that are required for more specific situations. In this section we focus on the first category and discuss the activities in a lifecycle order including development, deployment and evolution. It is important to realize that also ML/DL models, in most cases that we have studied, are subject to the same DevOps activities as the other software in systems, meaning that models evolve, are retrained and deployed on continuous basis.

The activities in basic AI engineering include the following:

- **Manage multiple models**: The first concern that often surfaces in teams working on ML/DL models is that it is difficult to keep track of all the models that are being considered during the development phase. We discussed parts of this challenge in [2].
- **Reuse of pre-developed models**: Most companies prefer to employ models developed by others or that have been developed earlier inside the company. However, reuse of existing ML/DL models is not trivial as the separation between the generic and specific parts of the model are not always easy to separate, in particular when the run-time context is different from that used in training phase.
- **Integration of models & components**: As we discussed when presenting the HoliDev model shown in figure 1, ML/DL models need to be integrated with the remainder of the
system containing regular software components. However, it is not always trivial to connect the data-driven ML/DL models with the computation-driven software components. Also traditional testing and evaluation of the models must be integrated, that combine software methods with data-science evaluation methods.

- **Deployment**: Deployment of a ML/DL model in an operational system requires integration with the other parts of the system that are traditional software components. Depending on the criticality of the ML/DL model for the overall performance of the system, the validation activities need to be more elaborate and strict. Deployment of MD/DL models may require substantial change in the overall architecture of the system.

- **Set up data pipelines**: As ML/DL models are heavily data dependent, the data pipelines needed for feeding the models as well as the data generated by the models need to be set up. This can be particularly challenging when different types of data and different sources of data are used; in addition to questions of availability, accuracy, synchronisation and normalisation, huge problems related to security and privacy appear.

- **Monitoring & logging**: Once the model is deployed and used in operation, it is important to monitor its performance and to log events specific to the performance of the model. As ML/DL models tend to lack on the explainability front, the monitoring and logging is required to build confidence in the accuracy of the models and to detect situations where the performance of a model starts to deteriorate. Also a more tight integration between run-time and development environment is required; data from logging and monitoring should be utilized in continuous training of ML/DL models.

- **A/B testing of models**: During evolution, the improved model is deployed for operation. However, experience shows that models that perform better in training do not necessarily perform better in operations too. Consequently, we need solutions, often variants of A/B testing, to ensure that the new model also performs better in deployment.

- **Storage and computing infrastructure**: Although many assume that all ML/DL deployments operate in the cloud, our interaction with industry shows that many companies build up internal storage and computing infrastructure because of legal constraints, cost or quality attributes. Developing these infrastructures, for example for the development of autonomous driving solutions, is a major engineering and research challenge. This can also lead to changes in the development organisation. Typically collection and storing of data is organized centrally on the enterprise level, while development of AI solution is distributed over several development teams.

- **Design methods and processes**: There are surprisingly few design methods, processes and approaches available for the development of ML/DL models. Experienced data scientists do not need these, but with the rapidly growing need for AI engineers, many less experienced data scientists and software engineers are asked to build these models. These professionals would very much benefit from more methodological and process support. Integration of end-to-end data lifecycle with software lifecycle is inevitable for a successful development AI-based systems.

- **Automated labelling**: Finally, as the data sets that we started with are limited sources for training and validation, we ideally want to collect the data sets for training evolving
models during operation in deployment. Although it is easy to collect the input data, the labels used in supervised learning are often much harder to add. Consequently, we need solutions for, preferably, automated labelling of data so that we have a constant stream of recent data for training and validation purposes during evolution.

- **Data quality management:** As data pipelines tend to be less robust than software pipelines, it is important to provide solutions for the management of data quality. This can be concerned with simple checks for data being in range or even being present or more advanced checks to ensure that the average for a window of data stays constant over time or that the statistical distribution of the data remains similar.

**Domain Specific AI Engineering**

Although the recent emergence of ML/DL models in industry started in the online SaaS world, this has been rapidly followed by increasing interest in the software-intensive embedded systems industry. The main difference with cloud-based deployments is that the ML/DL models are deployed in embedded systems out in the field such as base stations, cars, radars, sensors and the like. In this section, we present the unique research topics for three application domains in which ML/DL technologies are being deployed, i.e. software-intensive embedded systems, safety-critical systems, and autonomously improving systems. Our research shows that each domain brings with it a set of unique activities and research challenges associated with AI engineering topics. Below we discuss the key for the three domains indicated in figure 3.

**Cyber physical systems**

Cyber physical systems are often organized around three computing platforms, i.e. the edge device where the data for ML/DL is collected, an on-premise server of some kind and the infrastructure in the cloud. Each of these platforms has its own characteristics in terms of real-time performance, security and privacy, computational and storage resources, communications cost, etc.

The consequence of this is that data management, training, validation and inference associated with ML/DL models has a tendency to become federated as it happens over these three computing platforms as most capabilities that customers care about will cross-cut all three platforms. This leads to a set of unique research challenges for this domain that we discuss below.

- **Federated/distributed model creation:** Due to the presence of multiple computing platforms, the architect or data scientist needs to distribute the ML/DL model over these computing platforms, resulting in a federated model. This is an open research area related to the system and data lifecycles, performance, availability, security, computation, etc.
- **Federated/distributed storage of data:** Parallel to the model, the data used for training and inference needs to be managed in a distributed and federated fashion. Local
storage on device instances minimizes communication cost, but tends to increase the bill-of-materials for each device and these architectural drivers need to be managed. Further, different sources of data and its heterogeneity, have an impact on development lifecycle.

- **Transfer learning**: Especially for companies that have thousands or millions of devices deployed in the field, the challenge is the balancing between centralized and decentralized learning. The most promising approach is to distributed centrally trained models and to allow each individual device to apply its local learnings to the centrally trained model using transfer learning approaches.

- **Mass-customization of models**: As some embedded systems companies have many instances of their products in the field, the ML/DL models deployed in these instances should, ideally adjust their behaviour to the specifics of the users using the instance, i.e. mass-customization. However, there are few solutions available for combining both continuous deployment of centrally trained models with the customization of each product instance.

- **Deploy on heterogeneous hardware**: Finally, because of both cost and computational efficiency, embedded systems often use dedicated hardware solutions such as ASICs and FPGAs. Additionally MD/DL models require huge amount of parallel computation, both during training and implementation, realised in GPUs. These execution platforms use different development environments, programming languages, and execution paradigms. In many cases embedded systems have strong constraints on computational and storage resources, as well as limitations on power consumption. Deploying ML/DL models on these types of hardware frequently requires engineering effort from the team as there are no generic solutions available.

**Safety-critical systems**

A special class of cyber physical systems are safety-critical systems, i.e. those systems whose failure or malfunction may result in significant bodily, environmental or financial harm. The community struggles with balancing two forces. On the one hand, we seek to avoid harm by taking conservative approaches and introducing new technologies only after careful evaluation. On the other hand, the slow introduction of new technologies may easily cause harm in that the new technologies can help avoid safety issues that were not possible to avoid with conventional technologies only.

One of these new technologies is, of course, ML/DL. In the automotive industry, among others, the use of ML/DL allows for advanced driver support functions as well as fully autonomous driving. The open challenge is establishing the safety of these systems. In our research, we have identified three research topics specific for safety-critical AI-based systems.

- **Validation of safety-critical systems**: The basic enabler for deployment of ML/DL models in safety critical systems is the validation of these systems. Validation concerns
both the correct behaviour in situations where application should act, but we also need to show that the system will not engage in situations where it is not necessary or even dangerous to do so. Validation of safety-critical systems starts from requirements of justifiable prediction and of deterministic system behavior, while ML/DL solutions are based on statistical models, so in principle non-deterministic behavior. In practice, the ML/DL models can be more accurate and reliable, but justification of these models requires new approaches, methods, and standards in the validation process.

- **Explainable models:** As it is impossible to test a system to safety, the community often uses various approaches to certify systems. This is performed by assessors who need to understand the functionality of the system. This requires that ML/DL models are explainable, which today is unsolvable or at least a non-trivial problem for most models.
- **Reproducibility:** For a variety of factors, an ML/DL model may end up looking different when it is given a different seed, order of training data, infrastructure it is deployed on, etc. Especially for safety critical systems, it is critical that we can reproduce the model in a predictable manner, independent of the aforementioned factors.

**Autonomously improving systems**

There is an emerging category of systems that uses ML/DL models with the intent of continuously improving the performance of the system autonomously. In practice, there are humans involved in the improvement of the system, but the system employs mechanisms for experimentation and improvement that do not require human involvement.

The primary way for systems to achieve this is through the use of ML/DL models that analyse the data, train using it and then provide interference. This requires forms of automated experimentation where the system itself generates alternatives and, for example, deploys these alternatives in A/B testing or similar contexts and measures the impact of these changes. There are two challenges that need to be addressed for autonomously improving systems:

- **Data generation for machine learning:** Traditional ML/DL model development requires data scientists to spend significant amounts of time to convert available data sets that often are intended for human consumption into data sets that are usable for machine learning. In autonomously improving systems, the data that is generated by the system needs to be machine interpretable without any human help. What is required to accomplish this, though, is an open research question.
- **Automated experimentation:** Although the notion of automated experimentation is conceptually easy to understand, actually realizing systems that can operate in this fashion is largely an open research challenge where little work is available.

**Other domain specific systems**

We described the domain specific research challenges for building ML/DL systems for specific types of systems. There of course are other domains that likely have specific research
challenges as well. These challenges might be the same as for non-AI-based systems, but new methods must be developed to meet these challenges (for example, develop new methods to ensure system reliability, availability, security, reusability, or other non-functional properties). However, in many cases, by deployment of ML/DL solutions, new challenges, previously non-relevant or non-existing, have emerged (for example, quality of data, real-time data access, enormous increase in efforts in the development life cycle, severe challenges in combination of security, functionality and privacy, etc.)

Conclusion

Artificial intelligence, and specifically machine- and deep-learning, has, over the last decade, proven to have the potential to deliver enormous value to industry and society. This has resulted in most companies experimenting and prototyping with a host of AI initiatives. Unfortunately, our research [2, 5, 6] show that the transition from prototype to industry-strength, production-quality deployment of ML/DL models proves to be challenging for many companies. The engineering challenges surrounding this prove to be significant [7], even if many data scientists and companies fail to recognize these.

In this paper, we provide a conceptualization of the typical evolution patterns that companies experience when adopting ML/DL as well as a framework for integrating ML/DL components in systems consisting of multiple types of components. In addition, we provide an overview of the engineering challenges surrounding ML/DL solutions and, through this, present a research agenda and overview of open items that need to be addressed by the research community at large. We present the research challenges for general AI engineering as well as for three domains that have specific challenges that require attention.

ML/DL has the potential to deliver enormous value for industry and society at large. For us to capture this value, however, we need to be able to engineer solutions that deliver production-quality deployments. This requires research to address the challenges that we present in this paper and in future work, we aim to address several of these research challenges in our research and collaboration with industry. In particular, collaboration with industry in real industrial settings is crucial - since ML/DL methods build upon empirical methods and directly depend on the amount and types of data, building prototypes without using real data lead to results that are not only inrelevant but basically useless. On the other hand, it is about technology starting to be used in large scale and in all possible contexts. For this reason, industrial development is not enough. For this reason, we are actively organizing events in the Nordics and at international conferences to create awareness for the identified challenges and to encourage other researchers to join us.
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Highlights.
AI engineering is different. It is not enough to use the standard methods from Software Engineering. Neither Data Science/Engineering is sufficient to solve the increasing problems in the development of AI-based systems. Many new challenges, if not addressed in a systematic way, jeopardize the use of AI based systems, potentially causing a new “AI winter”, despite the huge expectations, due to the inability of companies to cope with the new requirements. The current problem for industry is a combination of a lack of new methods and expertise in managing the novel demands driven by AI engineering. There are however fundamental challenges to be addressed. Integration of data and code is an antipattern in Software Engineering - for ML/DL it is a principle. Formal proof and analysis of source code is one of the basic principles in Software Engineering. ML/DL is based on data and trial/error attempts. For this reason it is not enough to solve the current practical industrial problems related to deployment of new technology, to increase of competence and reorganisations. Laboratory-based or theoretical research is useless without real data and real contexts in which the systems are performed. For this reason, extensive cooperation between industry and academia is needed.