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Introduction of an industrial transfer learning use case systematization for machine tools

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Abstract

Traditional intelligent systems such as fault detection are mainly developed for isolated use on single machines and are mostly trained individually. A cross-machine knowledge transfer of intelligent systems holds an immense potential and can reduce implementation effort of intelligent systems. To enable a structured analysis of real-world transfer problems, an industry-relevant, far-reaching systematization of typical machine tool use cases is developed. This provides the overview over different typical use case classes from the industrial use case perspective. Based on the derived transfer criteria of each use case class, a conceptual approach of concrete transfer methods is proposed.

Keywords: Transfer learning; industrial transfer learning; knowledge transfer; transfer learning systemization; machine tools

1. Introduction

In industrial systems, it is often not just individual machines that are monitored, but larger machine parks. Intelligent systems, such as fault detection models [1], are often trained and applied separately for individual machines. Since these machine fleets often contain closely related machine units, there is a great need for transferability and generalization of intelligent industrial systems. In many practice cases the hardware, software, machine state or operational conditions vary within fleets which typically leads to different data spaces and distributions between different machine units [2]. Thus, models trained on the training data of the original machine will likely fail to perform sufficiently well on other machines of the fleet. Even if the machines are performing the same task under the same conditions [3], these models must either be trained from scratch with new data or at least must be re-trained and tuned to perform well on the target machine [4]. Collecting sufficient training data and training the models is one of the key cost drivers of machine learning projects [5]. For large scale applications such separate repetitive training processes for the same task on identical or similar machines are highly inefficient, while labelled data of the target machine can be expensive or even impossible to acquire [6].

Previous research on transfer learning approaches targeting knowledge transfer, has made strong progress in recent years but mainly focuses on theoretical descriptions of mathematical models [7]. However, widespread application of transfer learning between beams in industry has not yet occurred. In particular, the lack of an industry-relevant, far-reaching systematization of typical use cases, hinders a structured discussion and analysis of underlying real-world transfer problems and thus can build a bridge to finding solutions in the area of transfer learning.

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The goal of this work is to introduce an industrial perspective on transfer learning use cases by introducing a transfer use case systematization using the example of gantry kinematics / machine tools. Typically occurring transfer use cases should thus be systematically and intuitively subdivisible in order to serve as a basis for further analyses of the data implications. By this, a bridge between industrial and mathematical transfer perspective is to be created.

2. Related work

Leveraging existing learned knowledge for related settings or domains is a widely known problem in the industry. In the last two decades several transfer related branches of research emerged under different terminologies such as context-sensitive learning, incremental/cumulative learning, inductive transfer, knowledge consolidation, knowledge generalization, knowledge-based inductive bias, knowledge transfer, learning to learn, lifelong learning, meta-learning and multitask learning [8, 9].

Transfer learning as a subgroup of machine learning recently attracted significant interest in literature. These approaches aim to transfer the knowledge from one or more previous tasks to a target task based on mathematical methods [8]. Transfer learning problems are commonly categorized either solution-based with regards to the transfer strategy or problem-based with regards to feature and label availability or with regards to the similarity of source and target input feature spaces [8, 9].

Typical transfer learning applications include for example text and natural language processing [10, 11], computer vision and image processing [12, 13], healthcare [14, 15], forensic applications [16], automated planning [17], WiFi localization [18], software defect prediction [19], classification for computer aided design (CAD) [20], production [21] and human activity recognition [22].

While research in transfer learning indicates a great potential in mathematical transfer methods, it has not yet reached the industrial practice of machine tool applications on a wide scale [23]. As different use cases arise as motivation and application for transfer approaches, [23] propose a high-level differentiation of base transfer use cases to reflect the industrial transfer motivation: Cross-phase, cross-state, cross-entity and cross-domain transfer, while cross-state and cross-entity transfer can be grouped as cross-environment transfer. [24] differentiates three different types of industrial transfer and generalization use cases: The transfer from one operational condition to another, the transfer from a single system to a whole fleet and the transfer from synthetic simulation models to real physical systems. While the basic idea of systemizing industrial transfer use cases raised first interest, the literature does not allow for a practical and intuitive differentiation of transfer use cases between different machine tool scenarios as well as a derivation of typical implications concerning potential transfer solution methods.

3. Transfer use case systematization and implications for transfer approaches

To allow for a structured differentiation about industrial transfer use cases on machine tools a clear differentiation of transfer dimensions is required. These dimensions are meant to characterize the similarity or difference between the source and target machine. This goes beyond the purely technical description of the machine, as would be possible, for example, on the basis of the mechatronics concept with its subareas of mechanics, electronics and information technology [25]. A complete machine system context description of machine tools is described by the semantic models for fleet ontology proposed by [26] and [27]. Building on this terminology for characterizing machine fleets, the machine system context scope can be defined by the following three context dimensions: The technical context, the usage context, and the environmental and operational context. The terminology and denotation of the three contextual dimensions is further congruent with the fleet characterization of [28]. A high-level use case systematization for transfer problems in the machine tools domain can be described as follows. While technical context can include the most basic case of a machine transfer between related machine tools, the fleet transfer can be distinguished as a large-scale variation including additional characteristics as for example knowledge integration. Synthetic transfer is a special case of the technical dimension, where knowledge is transferred from simulations and virtual machine models to a physical machine unit. The usage context transfer dimension describes transfer problems in which a transfer is justified on the basis of different machine missions or tasks. Finally, the transfer dimension of environmental and operational conditions includes transfer situations in which a transfer is justified due to different environmental or operational conditions such as degradation state or machine wear. Hybrid forms of the transfer dimensions can occur in many use cases. As a result, it is now possible to differentiate and delineate the difference dimensions between machines, enabling clear structured differentiation of problem settings and further in-depth systemizations. Figure 1 illustrates the three context dimensions as well as the described transfer type characterization.

Since in industrial applications there are no exactly identical source and target systems, e.g. due to manufacturing tolerances alone, this usually leads to changed data situations which has negative influence on the performance of industrial systems [2] [29]. Furthermore, the data availability for the source and target machines is often limited. Since the knowledge of a trained model of the source machine is to be transferred, consequently, access to labelled source machine data can be considered as given. On the other hand, as motivated, labelled data are typically not available for the target machine, since the generation and the labelling of data is costly and often not even possible [6]. In contrast, unlabelled data of the target machine can usually be generated in a short time without great effort, for example by means of test or even reference runs widely used in the industry [30].

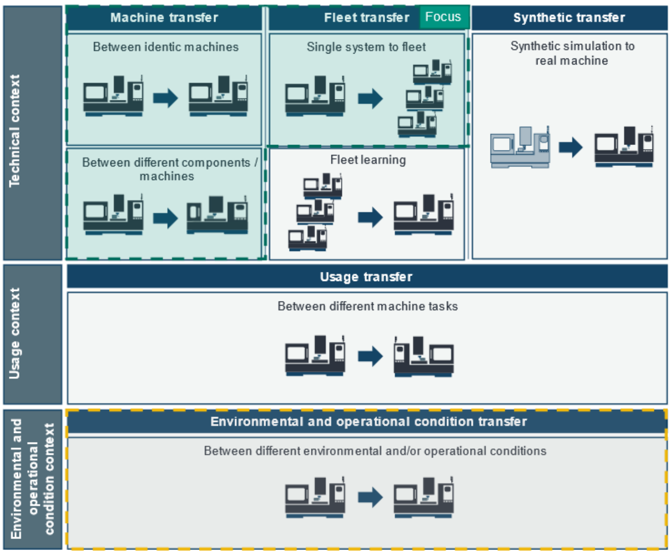

Fig. 1 Systematization of transfer dimensions based on the technical context, usage context and environmental and operational condition transfer

As motivated, focus of this work is on the transfer between technically different but related machines while the influence of the technical similarity of the machines is primarily considered. The usage context and most environmental and operating conditions can be controlled and kept constant and are therefore considered secondary, while the authors emphasise that in some applications non-controllable environmental and operational influences such as degradation development need to be considered as additional influences on transfer scenarios. Figure 1 illustrates the transfer focus of the introduced problem setting based on the described transfer dimension terminology.

4. Introduction of a machine tool transfer use case systematization

The differentiation according to different transfer contexts now allows a differentiation of dimensions which characterize the differences between machine tools. However, this is not yet sufficient for a sufficiently complete discussion and differentiation as well as a deeper transfer analysis of different concrete use cases. In particular, the question to what extent two machines differ in the technical context entails very far-reaching implications and is not yet sufficiently defined to derive further conclusions for the transfer of intelligent systems. This is particularly important in order to generate a general understanding of the problem among the various actors involved and to be able to clearly distinguish which concrete transfer situation and which typical implications are present in the respective case.

Therefore, a systematization is necessary that divides practice-relevant use cases into classes based on the degree of technical differences and thus allows a comprehensible gradation of the transfer problem. The breath of the systematization of the motivated cross-machine transfer use cases is intended to range from the basic extreme case of transfers between identical machines to an extreme case of different machines. However, for the feasibility of a successful transfer project, a certain degree of relatedness between the machines must be assumed. In addition, the systematization should allow a distinction with regard to the process functionality of the machines, i.e., the ability to functionally execute the same machine tasks.

4.1. Terminology and criteria for a transfer use case systematization

To further differentiate different transfer use case scenarios in the technical context dimension it is necessary to introduce a practical technical description of the similarity of machines. The technical characterization of a unit on machine level or component level can basically be caried out by classifying the exact equipment series type and its related properties [27]. For the differentiation on the introduced abstraction levels, a similarity terminology is required to compare different units. [31] suggest considering systems as identical when the systems consist of the same critical equipment, [27] propose to use three qualitative similarity terms to differentiate units: Identical, similar and heterogeneous. Identical equipment (machine level or component level) is defined by the identical series type, whereby the technical properties of the machines must implicitly be theoretically identical. Machines or components are considered to be different with regards to the technical context if they deviate mechanically, software-wise, electrically/electronically, or in any other mechatronics discipline. The advantage of the described concepts is that the terminology used is generally known and that industry practitioners are able to handle it in practice due to its intuitiveness.

4.2. Transfer use case systematization for machine tools

Based on the described differentiation dimensions and the terminology, a series of qualitative interviews with representative industry experts was conducted to collect data of typical industry transfer use cases on machine tools, their commonalities and relevance. Through a subsequent clustering of the evaluated data and further interviews, a categorization of five cross-machine transfer use case classes (short: transfer class) for application machines could be derived, covering the range from technically identical machines to different but functionally related machines based on a differentiation at machine and component level.

Transfer class 1 denotes the base transfer case of a replication between machines. This means that the underlying transfer application is here to be transferred between two technically identical machines with identical components. Since this transfer class covers theoretically identical machines, the machine process functionality is also identical between the machines. Based on industry experts, this class is the most common and relevant transfer case, which occurs, for example, when machine manufacturers equip not customized identical units with fault detection applications, which needs to be transferred from a trained source machine to technically identical target machines. Transfer class 2 describes, like the class 1, a replication however with the difference that one or more underlying components are different, which do not have an influence on the machine process functionality. This means

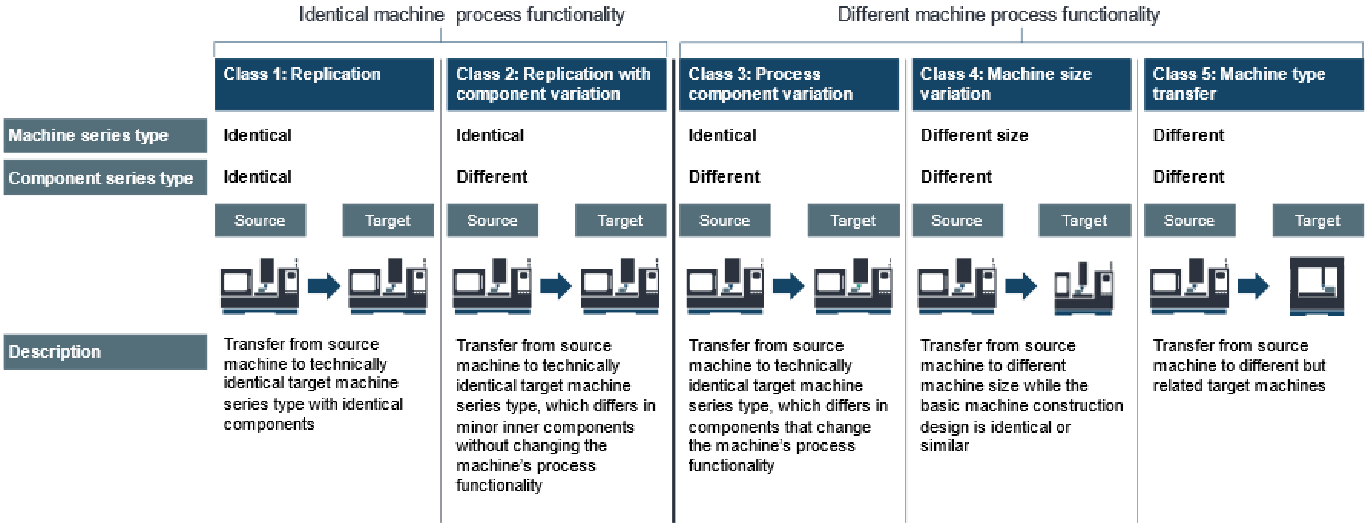

Fig. 2 Transfer use case class systematization based on the differentiation on machine and component series type

that this replication with component variation is less restrictive than transfer class 1 but does not allow the machines to perform differently. This transfer class is particularly relevant because machine manufacturers may have to change components within a machine series type. Opposed to transfer class 2, class 3 describes a transfer between machines with identical machine series types, while variation occurs on component level, which changes the machine process functionality. The differentiation from transfer class 2 is based on the fact that the component difference between source and target machine has an influence on the observable behaviour or the functionality of the machine. This leads to the fact that although the underlying machine series type is identical, the machine has a different machine process functionality. Transfer class 4 describes the transfer case between two related machines of different size or scale, while the basic construction design of the machine is identical or similar. Finally, transfer class 5 concludes the systematization of the cross-machine transfer cases and represents the extreme case of the largest possible deviation between two machines considered in this systemization. Beside different underlying components series types, also a variation of the machine series type is present. The latter goes beyond size scaling and allows a complete variation of the machine type with the only restriction that the latter must be functionally related. This ensures the transfer potential. Consequently, the machine process functionality is considered to be different. Figure 2 illustrates the five described transfer use case classes for machine tools.

5. Technical differences between machines and derivation of data implications

Based on the systematization of machine tool transfer use cases the question arises which typical implications at the technical level can be expected and thereby which transfer approaches are applicable. The main goal hereby is to describe typical changes between source and target machines on a technical level to derive potential data differences between the source and target machines. Due to the high industry relevance and the comparatively simple comprehensibility of the transfer problem of the transfer use case class 1: Replication, the derivation of implications is described below with a focus on this use case class.

5.1. Derivation of typical technical differences for transfer use cases

By methodically creating cause-and-effect diagrams, which elaborate possible factors influencing the technical differences between the source and target machine for each transfer use case class, implications on the data situation can be derived. This technique is based on Ishikawa diagrams which were introduced by [32] and adapted for appropriate influencing factors to reflect the technical context relevant for this work. The implications on the underlying data of the source and target machine need to be structured along different criteria and dimensions to appropriately describe the data. For this, in the first step an intuitive technical description of the data is chosen, which covers the structure of the data, the data behavior, the local instance, data noise, and data labels, in order to capture a complete data picture.

For the example of transfer use case class 1: Replication, the main causes for a difference between source and target machine can be reduced to causes of the machine realization and non-controllable environmental and operational conditions. This follows directly from the definition of the use case class, which includes use cases where the basic machine and component series types are identical. The machine realization includes all influences connected to the production, assembly, control and calibration of the machines. Those factors can typically cause differences in the data of a source and target machine. In a naive technical description, this would result in a deviation of the local data instances, for example a shift of the time series data on the X- or Y-axis.

5.2. Derivation of data implications for transfer use cases

Subsequently, this intuitive technical description can be translated into a mathematical data description, which is used in the most common transfer learning literature. Thereby the technical practitioner perspective and the mathematical

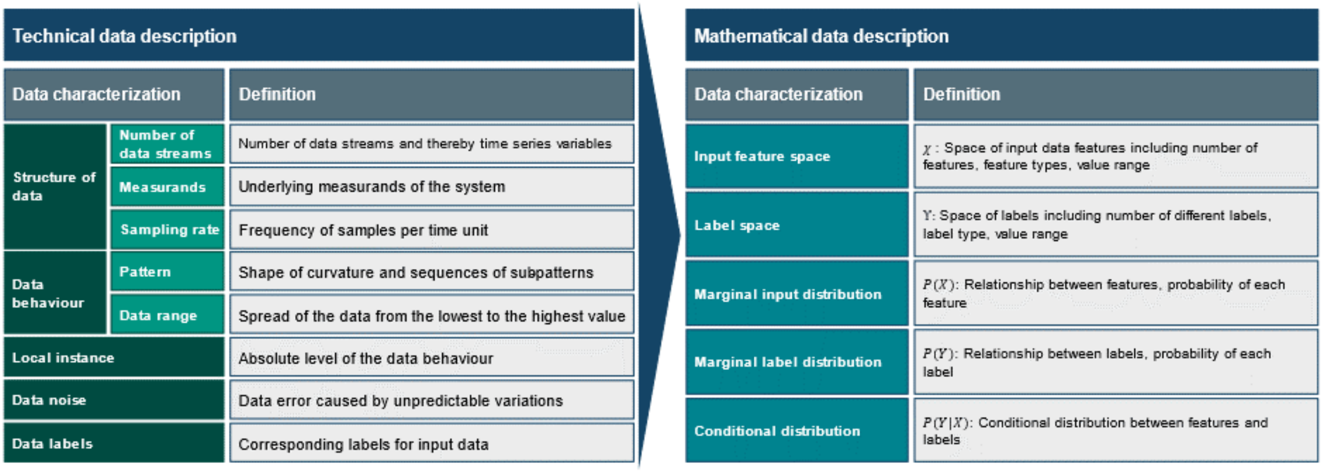

Fig. 3 Derivation of data implications based on technical cause-effect diagrams of machine tools

perspective are connected following generally known mathematical terminology as shown in Figure 3.

While the output space ϒ includes all possible labels, the input feature space χ is the space of all existing feature vectors. For a given input feature vector X or label vector Y, P(X) resp. P(Y) denotes the marginal probability of one specific outcome in the presence of all possible outcomes of the other random variable. A domain D is defined by two components, the feature space χ and a corresponding marginal probability distribution P(X). For a given domain D, a task T is defined by two components: A label space ϒ, and a decision function f, where f learns the relationship from the sample vector and label pairs {x_i, y_i}. For a given X and Y, P(X|Y) denotes the conditional probability of one specific outcome for the random variable X, given a outcome for random variable Y. The terminology definitions are based on the research surveys from [8] and [9].

In the exemplary case of transfer use case class 1: Replication, this potential difference in the local data instance can cause different marginal input distributions. For example, a Y-axis offset of the respective time series will result in a shifted input distribution, while the other mathematical data characterization categories are not influenced.

Since this work focuses on the group of use cases characterized by transfer between machine tools with the same task, it follows from the definition of the task T that the label space γ as well as the conditional probability distribution P(Y|X) between source and target problem can be assumed to be identical. Basically, two groups of use case can be identified: Transfer class 1 and 2 are characterized by a difference of the marginal input distribution, which is due to the difference of the local instance of the basic data behaviour. Transfer class 3, 4 and 5, on the other hand, have additionally different feature spaces in the source and target domains due to possible changes in the data structure and the data behaviour influenced by this. This can be caused by many factors, for example additional data streams that occur due to a process component variation which then leads to different features increasing the input feature space χ_T. Since the domain D by definition consists of the feature space χ and the corresponding marginal distribution of the features P(X), this means that D_S≠D_T applies for all five transfer classes. Table 1 summarizes the derived typical data implications of the different machine tool transfer use case classes. The identified differences between source and target problem setting shown in Table 1 now allow a specification of the transfer learning need by the actual expected mathematical description differences. As intended, this provides the basis for the necessary understanding of the problem at the data and model level and identifies the starting point for possible solutions. The latter must aim at resolving the difference of the feature spaces or, depending on the transfer class, also the difference of marginal distributions for the case of this work.

Table 1. Mathematical description of data differences in the transfer problem setting between source and target problem

	Class 1	Class 2	Class 3	Class 4	Class 5
Input feature space	Identical	Identical	Different	Different	Different
Label space	Identical	Identical	Identical	Identical	Identical
Marginal Input distribution	Different	Different	Different	Different	Different
Marginal label distribution	Identical	Identical	Identical	Identical	Identical
Conditional distribution	Identical	Identical	Identical	Identical	Identical

5.3. Industry relevance and practicability

The application of the systematization was validated during an in-depth collaboration with two representative German machine tool manufacturers. As producer of different related machines, the initial motivation is the rollout of intelligent systems such as fault detection [33] to identic machine tools which can be also described as a transfer between exactly identical machines. Based on the description of the underlying problem situation the machine tool manufacturers were able to select the present category characteristics on machine and component level. By applying the introduced use case systematization, it was then possible to clearly identify the underlying transfer use case class 1: Replication and thereby establish a common understanding of the problem situation for all parties. The later revealed that a precise description and terminology helped to reduce the complexity of the present use case. Further, the derived typical data implications of the transfer use case class served as starting point to precise and delimit the solution space for applicable transfer approaches and thereby facilitated the implementation of transfer learning.

6. Conclusions

The goal of this article was to establish an industrial perspective on knowledge transfer use cases on machine tools and thereby facilitate the application of state-of-the-art transfer learning approaches. Therefore, a novel transfer use case systematization for machine tools was introduced for the first time based on widely known machine fleet terminology. Thereby, typically occurring transfer use cases can be clearly differentiated and allow for a structured discussion about different problem settings and to serve as a basis for further analyses of the data implications. Subsequently, implications on the data situation of the source and target machine were derived and systematized based on the technical differences of the machines. By this, a bridge between industrial and mathematical transfer perspective was established allowing for the derivation of clear criteria on potential transfer learning approaches. Further, the industrial relevance and practicability of the introduced machine tool transfer use case systemization was illustrated.

Integrating the presented use case systemization into a coherent user assistance system can enable industrial users to find concrete transfer learning approaches for the respective transfer setting. Furthermore, extending the motivated problem focus to further applications beyond machine tools can add significant value.

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