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REGULAR PAPER

The next evolution of MDE: a seamless integration of machine learning into domain modeling

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Abstract Machine learning algorithms are designed to resolve unknown behaviors by extracting commonalities over massive datasets. Unfortunately, learning such global behaviors can be inaccurate and slow for systems composed of heterogeneous elements, which behave very differently, for instance as it is the case for cyber-physical systems and Internet of Things applications. Instead, to make smart decisions, such systems have to continuously refine the behavior on a per-element basis and compose these small learning units together. However, combining and composing learned behaviors from different elements is challenging and requires domain knowledge. Therefore, there is a need to structure and combine the learned behaviors and domain knowledge together in a flexible way. In this paper we propose to weave machine learning into domain modeling. More specifically, we suggest to decompose machine learning into reusable, chainable, and independently computable small learning units, which we refer to as microlearning units. These microlearning units are modeled together with and at the same level as the domain data. We show, based on a smart grid case study, that our approach can be significantly more accurate than learning a global behavior, while the performance is fast enough to be used for live learning.

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1 Introduction

In order to meet future needs, software systems need to become increasingly intelligent. A prominent example is cyber-physical systems (CPSs) and Internet of Things (IoT) applications, where smart objects are able to autonomously react to a wide range of different situations, in order to minimize human intervention [34]. Advances in software, embedded systems, sensors, and networking technologies have led to a new generation of systems with highly integrated computational and physical capabilities, which nowadays are playing an important role in controlling critical infrastructures, like the power grid. Such systems face many predictable situations for which behavior can be already defined at design time of the system. In order to react to critical overload situations, for example, the maximum allowed load for customers can be restricted. This is called *known domain knowledge*. In addition, intelligent systems have to face events that are unpredictable at design time. For instance, the electric consumption of a house depends on the number of persons living there, their activities, weather conditions, used devices, and so forth. Although such behavior is unpredictable at design time, it is identifiable and a hypothesis about it can be already formulated and solved later by observing past situations, once data become available. Sutcliffe et al. [43] suggest to call this *known unknown*.

To make smart decisions, intelligent systems have to continuously refine behavior that is known at design time with what can be learned only from live data to solve known unknowns.

1.1 Coarse-grained versus fine-grained learning

We distinguish two different learning granularities, coarse-grained and fine-grained. Coarse-grained learning means extracting commonalities over massive datasets in order to resolve unknown behaviors.

Fine-grained learning, on the other hand, means instead of searching for commonalities over the whole dataset, to apply learning algorithms only on specific elements of the dataset. To decide which parts of the dataset should be taken into consideration for which learning algorithm usually requires domain knowledge, e.g., structured in form of domain models.

Nonetheless, nowadays the most common usage of machine learning algorithms is to resolve unknown behaviors by extracting commonalities over massive datasets. Peter Norvig describes machine learning and artificial intelligence as "*getting a computer to do the right thing when you don't know what that might be*" [37]. Learning algorithms can infer behavioral models based on past situations, which represent the learned common behavior. However, in cases where datasets are composed of independent and heterogeneous entities, which behave very differently, finding one coarse-grained common behavior can be difficult or even inappropriate. This applies particularly for the domain of CPSs and IoT. For example, considering the electrical grid, the consumption of a factory follows a very different pattern than the consumption of an apartment. Searching for a coarse-grained, common behavior across all of these entities (the whole or at least large parts of the dataset) is not helpful. Coarse-grained learning alone, which is based on the "*law of large numbers*," can be inaccurate for systems which are composed of heterogeneous elements which behave very differently. In addition, in case of data changes, the whole learning process needs to be fully recomputed, which often requires a lot of time.

Instead, following a *divide-and-conquer* strategy, learning on finer granularities can be considerably more efficient for such problems [13,48]. This principle is, for example, also used in text sentiment [29], where a segmentation by the domain of words can help to reduce complexity. Similarly, multigranular representations [49] have been applied to solve hierarchical or microarray-based [11] learning problems. Aggregating small learning units [39] has also been successfully used to build probabilistic prediction models [8]. In accordance with the pedagogical concept [27], we refer to small fine-grained learning units as "*microlearning*." We believe that microlearning is appropriate to solve the various known unknown behavioral models in systems which are composed of heterogeneous elements which behave very diverse and can be significantly more accurate than coarse-grained learning approaches.

1.2 Modeling ML versus domain modeling with ML

Applying microlearning on systems, such as the electric grid, can potentially lead to many fine-grained learning units. Furthermore, they must be synchronized and composed to express more complex behavioral models. Therefore, an appropriate structure to model learning units and their relationships to domain knowledge is required. Frameworks like TensorFlow [1], GraphLab [32], or Infer.NET [4] also divide machine learning tasks into reusable pieces, structured with a model. They propose a higher-level abstraction to model the learning flow itself by structuring various reusable and generic learning subtasks. These approaches focus solely on modeling the learning flow without any relation to the domain model. As a consequence, domain data and its structure are expressed in different models than learning tasks, using different languages and tools, and lead to a separation of domain data, knowledge, known unknowns, and associated learning methods. This requires a complex mapping between learning units and domain data. A similar conclusion has been drawn by Vierhauser et al. [44] for monitoring system of systems.

To address this complexity, in this paper we propose to weave micromachine learning seamlessly into data modeling. Specifically, our approach aims at:

– Decomposing and structuring complex learning tasks with reusable, chainable, and independently computable microlearning units to achieve a higher accuracy compared to coarse-grained learning.
– Seamlessly integrating behavioral models which are known at design time, behavioral models that need to be learned at runtime, and domain models in a single model expressed with one modeling language using the same modeling concepts.
– Automating the mapping between the mathematical representation expected by a specific machine learning algorithm and the domain representation [4] and independently updating microlearning units to be fast enough to be used for live learning.

We take advantage of the modeled relationships between domain data and behavioral models (learned or known at design time), which implicitly define a fine-grained mapping of learning units and domain data. This is a natural extension of basic model-driven engineering approaches.

We implemented and integrated our approach into the open-source framework GreyCat.[1] GreyCat is an extension and the successor of the Kevoree modeling framework KMF [14].[2] Like EMF [5], KMF is a modeling framework and code generation toolset for building object-oriented

[1] http://greycat.ai/.

[2] http://modeling.kevoree.org/.

applications based on structured data models. It has been specifically designed for the requirements of CPSs and IoT.

1.3 Motivating case study

Let us consider a concrete use case. We are working together with Creos Luxembourg, the main electrical grid operator in Luxembourg, on a smart grid project. A major challenge in this project is to monitor and profile various data, e.g., consumption data, in order to be able to detect anomalies and predict potential problems, like electric overload, before they actually happen. The important smart grid entities for the context of this paper are *smart meters* and *concentrators*. Smart meters are installed at customers houses and continuously measure electric consumption and regularly report these values to concentrators, where the data are processed. To which concentrator a meter sends its data depends on various conditions, e.g., distance or signal strength, and changes frequently over time [19].

For various tasks, like electric load prediction or detection of suspicious consumption values, customers' consumption data need to be profiled independently and in real time. This is challenging due to performance requirements but also mainly due to the large number of profiles, which need to be synchronized for every new value. To model such scenarios, we need to express a relation from a machine learning profiler to the consumption of a customer. Since the connections from smart meters to concentrators vary over time, a concentrator profiler depends on the profiles of the currently connected meters. Coarse-grained, in this context, means profiling on the concentrator level, while fine-grained means profiling on a smart meter level and then combining the profiles of the smart meters connected to one concentrator together. Profiling on a concentrator level is often needed to evaluate the electric load situation for a specific geographical region of the grid, and many operational decisions are based on this. One coarse-grained profiler at the concentrator level will not take real-time connection changes and their implications in predicting the electric load into account. Coarse-grained profiling alone can be very inaccurate in such cases.

Another example where microlearning and composing complex learning from smaller units can be significantly more accurate than coarse-grained learning are recommender systems. In such systems, coarse-grained learning is to recommend to the users of the same category or user groups, the same products. Fine-grained learning creates one microlearning unit per user and/or per product. Again, using only coarse-grained profiles for customers and products can be very inaccurate, or generic. In case of recommender systems, microlearning can be even combined with coarse-grained learning by using the coarse-grained learning in cases where the user's fine-grained learning does not have enough information to recommend accurately.

The bottom line is that microlearning units and combining them to larger learning tasks are especially useful for systems which are composed of multiple independent entities which behave very differently. CPSs and IoT systems are domains where these characteristics apply specifically.

We evaluate our approach on a concrete smart grid case study and show that:

- Micromachine learning for such scenarios can be more accurate than coarse-grained learning.
- The performance is fast enough to be used for live learning.

1.4 Remainder of this paper

The remainder of this paper is as follows. Section 2 introduces the necessary background. Section 3 presents our model-based micromachine learning approach. We discuss the metamodel definition used in our approach and present a modeling language to seamlessly model machine learning and domain data. In Sect. 4 we evaluate our approach on a smart grid case study, followed by a discussion in Sect. 5. The related work is discussed in Sect. 6. A conclusion and future work is presented in Sect. 7.

2 Background

In this section we introduce modeling and metamodeling techniques and present an overview of machine learning and metalearning techniques.

2.1 Modeling techniques

Modeling is a fundamental process in software engineering. Over time different formalisms to model and reason about systems have been developed and used for different purposes [2,24,41]. For example, entity-relationship models [7] are a general modeling concept for describing entities and the relationships between them. They are widely used to model schemas of relational databases. Ontologies, RDF [30], and OWL [45] are other modeling approaches, which are mainly used in the domain of the Semantic Web. Model-driven engineering (MDE) [28] is probably one of the best known modeling techniques. As an extension of MDE, an emerging paradigm called models@run.time [36] proposes to use models both at design and runtime to support reasoning processes, mainly for CPSs. Most of these approaches have in common that they describe a domain using a set of concepts (classes, types, elements), attributes (or properties), and the relations between them.

Closely related to modeling is the concept of **metamodeling**. A metamodel is an abstraction of the model itself. It defines the properties of the model. A model conforms to its metamodel, comparable to how a program conforms to the grammar of the language it is written in. The meta object facility (MOF) [33] proposed by the object management group (OMG) is a popular language for defining metamodels. Specifying formal metainformation helps to make data machine understandable.

To clarify the used terminology, Fig. 1 shows the relations between a metamodel, model, and object graphs.

First, the domain is modeled using a metamodel, defined in languages like EMF, UML, or other graphical or textual domain specific languages. Then, one or several transformation or generation steps transform the metamodel into the actual model, usually implemented in an object-oriented programming language like Java, Scala, or C++. This model is then used in the implementation of an application. During runtime it can be interpreted as an object graph. In this paper we use the terms runtime model and object graph synonymously. To refer to a metamodel we use the terms metamodel or domain model.

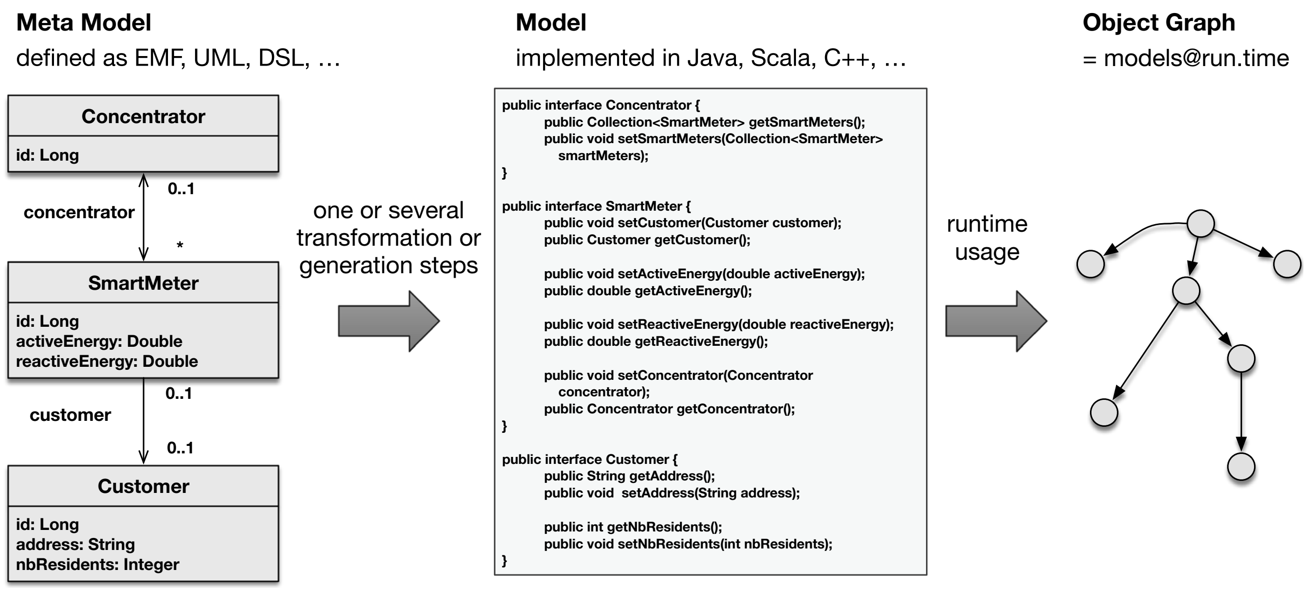
During runtime, application data are usually never static but evolve over time. Nonetheless, for many tasks, like machine learning, it is usually not enough to analyze only the latest data. Different approaches to represent and traverse temporal data have been suggested, e.g., [18,42]. Regardless of the concrete implementation (in the implementation of our framework we follow the approach presented in [20,21]), for this paper we assume that our object graphs evolve over time and that we can access historical data.

2.2 Machine learning techniques

Machine learning (ML) is an evolution of pattern recognition and computational learning theory in artificial intelligence. It explores the construction and study of algorithms that can learn from and make predictions on data. It uses algorithms operating by building a mathematical model from example inputs to make data-driven predictions or decisions, rather than strictly static program instructions [46]. The essence of ML is to create compact mathematical models that represent abstract domain notions of profiles, tastes, correlations, and patterns that (1) *fit well* the current observations of the domain and (2) are able to *extrapolate well* to new observations [35].

Several categorizations of ML techniques are possible. We can divide these techniques according to the nature of the used learning: In *supervised learning* data have predefined and well-known fields to serve as expected output of the learning process, while in *unsupervised learning* input data are not labeled and does not have a known field defined as output. ML algorithms try to deduce structures present in the input data to find hidden patterns. Many ML algorithms require some parameters (called *hyper-parameters*) to configure the learning process itself. In some situations, these parameters can also be learned or adapted according to the specific business domain. Thus, they are called *metalearning parameters* and the process of learning such parameters is called **metalearning**. For the rest of the paper we will refer to such parameters simply as *parameters*.

Another categorization of ML techniques is according to the frequency of learning: In *online learning*, for every new observation of input/output, the learning algorithm is executed and its state is updated incrementally with each new



```
public interface Concentrator {
        public Collection<SmartMeter> getSmartMeters();
        public void setSmartMeters(Collection<SmartMeter>
           smartMeters);
}

public interface SmartMeter {
        public void setCustomer(Customer customer);
        public Customer getCustomer();

        public void setActiveEnergy(double activeEnergy);
        public double getActiveEnergy();

        public void setReactiveEnergy(double reactiveEnergy);
        public double getReactiveEnergy();

        public void setConcentrator(Concentrator
           concentrator);
        public Concentrator getConcentrator();
}

public interface Customer {
        public String getAddress();
        public void  setAddress(String address);

        public int getNbResidents();
        public void setNbResidents(int nbResidents);
}
```

Fig. 1 Relations between a metamodel, model, and object graphs

observation. This is also known as live, incremental, or on-the-fly ML. We speak of *offline learning* or *batch learning* when a whole dataset or several observations are sent in "one shot" to the learning algorithm. The learning technique is trained using a small batch or a subset of observations similar to the requested input. This type offers a case-based or context-based reasoning because the learning is tailored for the requested input.

Finally, a ML module can be composed by combining several ML submodules. This is usually called *ensemble methods*. It is often used to create a strong ML model from multiple weaker ML models that are independently trained. The results of the weaker models can be combined in many ways (voting, averaging, linear combination) to improve the overall learning. *Random forests* are a powerful example of these techniques, where the global ML module is composed of several decision trees, each trained on a subset of data and features. *Neural networks* are another example, where the global network is composed by several neurons, and each can be seen as an independent learning unit.

A generic modeling framework for ML should be flexible enough to model any of these ML types. This principle served as a guideline for the development of our framework.

3 Weaving microlearning and domain modeling

In this section we first discuss the objectives of our approach. Then we present the metamodel definition (meta–meta model) which we use for the implementation of our approach and detail what exactly microlearning units are. Next, we present the syntax and semantic of our modeling language and show concrete examples of its usage. This section ends with presenting important implementation details.

3.1 Objective: domain modeling with ML

In order to weave micro-ML into domain modeling we need to extend modeling languages to model learned attributes and relations and "default" ones seamlessly together. It requires modeling languages to allow to specify in a fine-grained way *what* should be learned, *how* (algorithm, parameters) something should be learned, and *from what* (attributes, relations, learned attributes, learned relations) something should be learned. To be appropriate for live learning, these fine-grained learning units need to be independently computable and updateable.

We use a meta–meta model to define this weaving. A meta–meta model specifies the concepts which can be expressed in a concrete metamodel, i.e., it specifies what can be expressed in metamodels conforming to it. This allows domain modes to express learning problems. Based on this, we can define a concrete modeling language providing the necessary constructs to weave ML into domain modeling.

3.2 Meta–meta model

We first specify the metamodel definition (meta–meta model) underlying our approach. This definition, shown in Fig. 2, is inspired by MOF/EMOF and extended with concepts to express machine learning directly in the domain modeling language. Section 3.4 describes the modeling language we built around this meta–meta model and defines the syntax and formal semantic of the language.

Elements related to ML are depicted in the figure in light gray. We focus on these elements since other parts comply with standard metamodel definitions, like EMOF or MOF. As can be seen in the figure, we define metamodels consisting of an arbitrary number of metaclasses and enums. Metaclasses in turn have an arbitrary number of properties. Properties are attributes, relations, or what we call "*specified properties*." Specified properties are either "*learned properties*" or "*derived properties*." Learned properties are relations or attributes which will be learned by a specific machine learning algorithm. A concrete learning algorithm can be specified with the "*specification*" "*using*." Parameters for the learning algorithm can be defined with the specification "*parameter*." The "*feature*" specification allows to access properties from other metaclasses or enums.

Derived properties are similar to learned properties; however, derived properties do not have a state associated, i.e., they do not need to be trained but simply compute a value. The value of a derived attribute is calculated from the values of attributes of other metaclasses, whereas the value of a learned attribute depends on a state and past executions, i.e., on learning. As we will see in Sect. 3.6, this is reflected by the fact that for derived properties we only generate so-called "*infer*" methods, whereas for learned properties we generate "*learn*" and "*infer*" methods.

3.3 Microlearning units

The core elements of our approach are microlearning units. As explained in Sect. 1 we use the term "microlearning unit" to refer to small fine-grained learning units. These units are designed to decompose and structure complex learning tasks with reusable, chainable, and independently computable elements. Figure 3 illustrates a concrete example of a microlearning unit and set it into relation to the meta and instance levels. In the top left of the figure we see the definition of a `SmartMeter` metaclass. Besides two attributes, `activeEnergy` and `reactiveEnergy`, one derived property named `aboveThreshold` and one learned property, which we named `powerProbabilities`, are defined. As will be detailed in Sect. 3.6, specifying the learned

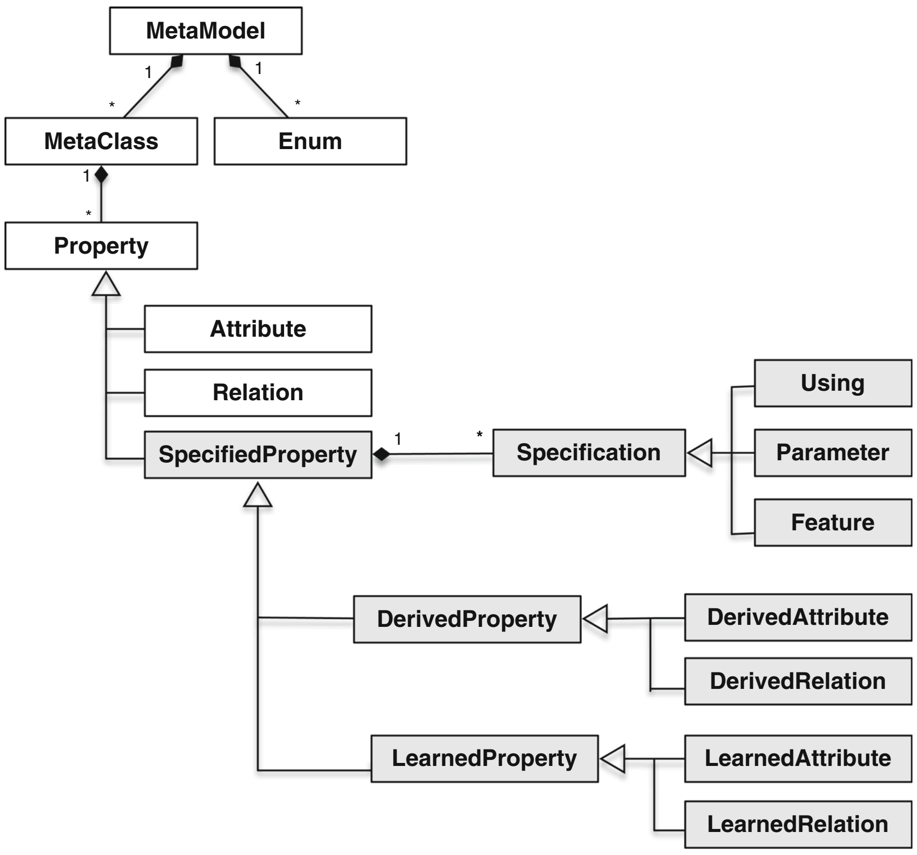


Fig. 2 Meta–meta model

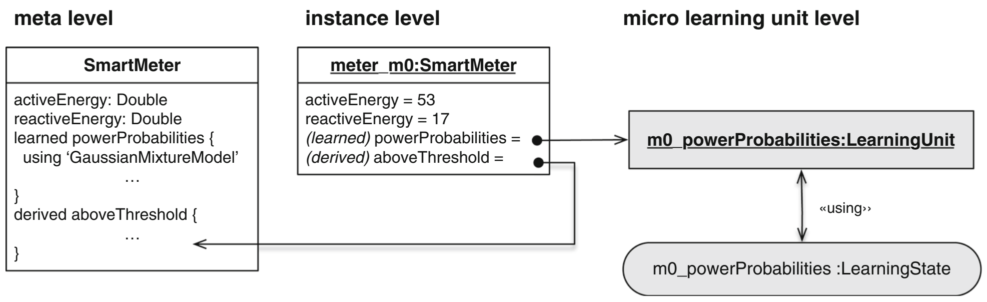

meta level
instance level
micro learning unit level
SmartMeter
activeEnergy: Double
reactiveEnergy: Double
learned powerProbabilities {
using 'GaussianMixtureModel'
...
}
derived aboveThreshold {
...
}
meter_m0:SmartMeter
activeEnergy = 53
reactiveEnergy = 17
(learned) powerProbabilities =
(derived) aboveThreshold =
m0_powerProbabilities:LearningUnit
«using»
m0_powerProbabilities :LearningState

Fig. 3 Schematic representation of a microlearning unit

property `powerProbabilities` results in automatically generating the necessary code for the mapping between the internal representation of a machine learning algorithm and domain models. The machine learning algorithm will be "weaved" inside the metamodel instances, in this case of `SmartMeter` instances. As illustrated, the microlearning unit is an instance of a learning algorithm, contained in an object and related to a state. It is also related to the instance of the `SmartMeter` class, or more specifically to the learned attribute. In fact, every instance of a `SmartMeter` class has its own (automatically generated) instance of a microlearning unit.

As can be seen in the figure, ML (via learned properties) can be seamlessly integrated and mixed with domain modeling. Section 3.4 presents our proposed modeling language and details how this can be defined within the concrete syntax of this language. The resultant ability to seamlessly define relationships from learned properties to domain properties and to other learned properties—and vice versa from domain properties to learned properties—enables composition, reusability, and independent computability/updates of microlearning units. An additional advantage of independent microlearning units is that they can be computed in a distributed way. Basically, every learning unit can be computed on a separate machine. Such distribution strategy relies on a shared model state, as for example presented in [22]. The computation can then be triggered in a bulk-synchronous parallel (BSP) way [15] over this shared state.

Our approach is built in a way that the same learning models can be used in several tasks without the need to duplicate it. For example, in the smart metering domain, the electricity consumption profile of a user can be used to: predict the electrical load, classify users according to their profile, or to detect suspicious consumption behavior. The possibility to compose microlearning units allows a segregation of learning concerns. In case an application requires a combination of different ML techniques, it is not necessary to mash traditional algorithms for each step together. Instead, independent microlearning units can be composed in a divide-and-conquer manner to solve more complex learning problems. This is shown in more detail in Sect. 3.5. In addition, the learning algorithm itself is encapsulated and the mapping between the domain model and the data representation expected by the respective learning algorithm is automatically generated. In this way, the learning algorithm can be easily changed without the need to change the interface for the domain application.

The possibility to derive attributes from others, allows to create richer models. In fact, *ensemble methods* in the ML domain, derive stronger ML models from weaker ML models by combining the results of the smaller units. In our framework, we enable ensemble methods from several learned attributes (learnt through different weaker ML models) by creating a derived attributed that combines their results.

The smart meter profiler is a representative example for microlearning. The profiler works on a specific smart meter instance, instead of profiling, lets say, all smart meters. In addition, this learning unit can be reused and composed. For example, a concentrator profiler can be defined as an aggregation of all smart meter profilers of the smart meters connected to the concentrator. By defining microlearning units in a metamodel, the relationships between domain classes and microlearning units are explicitly defined and can be used to infer for which changes a microlearning unit needs to be recomputed.

Even though our approach promotes microlearning, there are nonetheless scenarios where it is helpful to also learn coarse-grained behavior, e.g., the consumption profile of all customers. Therefore, we allow to specify a scope for learned properties. The default scope is called `local` and means that the learning unit operates on an per instance level. For coarse-grained learning we offer a `global` scope, which means that the learning unit operates on a per class level, i.e., on all instances of the specified class.

3.4 Modeling language

In this section we introduce our modeling language to enable a seamless definition of domain data, its structure, and associated learning units. The following definitions intend to avoid ambiguities and to formally specify the capabilities and limits of our proposed language. The language is inspired by the state of the art in metamodeling languages (e.g., UML [38], SysML [16], EMF Ecore [5]). The semantic of the language follows the one of UML class diagrams extended by the concept of microlearning units. Many modeling languages, like UML, are graphical. Advantages of graphical modeling languages are usually a flatter learning curve and better readability compared to textual modeling languages. On the other hand, textual modeling languages are often faster to work with, especially for experts. Also, editors and programming environments are easier to develop and less resource hungry for textual languages. A recent study of Ottensooser et al. [40] showed that complex processes and dependencies are more efficient to express in a textual syntax than a graphical one. For these reasons we decided to first implement a textual modeling language. For future work we plan to propose an additional graphical modeling language.

In the following we first present the syntax and grammar of the language followed by a definition of its semantic. The purpose of this formalization is to clearly detail the capabilities and limits of our proposed language, i.e., to formally define what can be expressed with it. Then, we illustrate by means of the concrete smart grid use case how this language can be used to express different combinations of machine learning and domain modeling.

3.4.1 Syntax

The syntax of our textual modeling language is inspired by Emfatic [9] and is an extension of the language defined in [14]. Listing 1 shows its formal grammar. The parts in bold show the language extensions.

Listing 1 Grammar of our modeling language

```
metaModel ::= (class | enum)*
enum ::= 'enum' ID '{' ID (',' ID)* '}'
class ::= 'class' ID parent? '{' property* '}'
property ::= annot* ( 'att' | 'rel' ) ID : ID spec?
parent ::= 'extends' ID (',' ID)*
annot ::= ( 'learned' | 'derived' | 'global' )
spec ::= '{' (feature | using | param )* '}'
param ::= 'with' ID ( STRING | NUMBER )
feature ::= 'from' STRING
using ::= 'using' STRING
```

This grammar basically reflects the classic structure of object-oriented programs. Multiplicities of relationships (indicated by the keyword `rel`) are by default unbounded, i.e., too many. Explicit multiplicities can be defined using the `with` clause, e.g., `with maxBound *` or `with minBounds 1`. Metamodels are specified as a list of metaclasses (and enums). `Classes`, `Enums` and their `Properties` are defined similar to Emfatic. To distinguish static, learned, and derived properties, we introduce annotations for attribute and relation definitions. In addition to this, a specification block can optionally refine the behavior expected from the corresponding property. A specification can contain statements to declare the algorithm to use, feature extraction functions, and metaparameters to configure the used algorithms. Feature extraction statements are using string literals where a OCL-like notation is used to navigate to reachable properties.

3.4.2 Semantic

Our modeling language follows the formal descriptive semantic and axioms of UML class diagrams, as defined in [50]. We first present the necessary formalism of UML class diagrams and then extend this formalism to include axioms for weaving learned and derived properties into our language. The semantic is defined with respect to the syntax of our language, defined in Sect. 3.4.1.

Definition 1 Let $\{C_1, C_2, \ldots, C_n\}$ be the set of concrete metaclasses in the metamodel, we have $\forall x\ (C_1(x) \vee C_2(x) \vee \cdots \vee C_n(x))$ is an axiom

In this definition we state that any object x should be at least (inheritance) an instance of one of the metaclasses defined in the metamodel. Additionally, given an object x all metaclasses verifying $C(x)$ should be linked by a relationship of inheritance following classical UML semantics and as defined in [50]. This inheritance model is not described here for sake of simplicity and to keep the emphasis on learning aspects. In the syntax of our language, the definition of a metaclass starts either with the keyword `class` or `enum`.

Definition 2 For each meta-attribute att of type T in C, we have: $\forall x, y\ C(x) \wedge (att(x, y) \rightarrow T(y))$ is an axiom

In the second definition, we are stating that if x is an instance of a metaclass C, which has a certain meta-attribute att of type T, the value y of this meta-attribute should always be of type T. Attributes are defined using the keyword `att` in the syntax of our proposed language.

Definition 3 For each relationship rel from metaclass C_1 to another metaclass C_2, we have:
$\forall x, y\ (C_1(x) \wedge rel(x, y)) \rightarrow C_2(y)$ is an axiom

In this definition, if a metaclass C_1 has a relationship rel to a metaclass C_2, and x is an instance of C_1, having a relation rel to y, this implies that y should be an instance of C_2. In the syntax of our proposed language, relationships are defined using the keyword `rel`.

Definition 4 For each relationship rel from metaclass C_1 to C_2, if '$e_1..e_2$' is its multiplicity value, we have:
$\forall x\ C_1(x) \rightarrow (e_1 \leq ||y|rel(x, y)|| \leq e_2)$ is an axiom.

Similarly, for each meta-attribute att in C_1, if '$e_1..e_2$' is its multiplicity value, we have:
$\forall x\ C_1(x) \rightarrow (e_1 \leq ||y|att(C_1, x) = y|| \leq e_2)$ is an axiom

In Definition 4, we state that an attribute or a relationship can have minimum and maximum bounds defined in the metamodel, and any instance of the metaclass should have its attributes and relationships respecting these bounds.

Following the same approach, we extend the classical UML definition of metaclass, by adding two new kinds of properties: learned and derived attributes and relations. In particular, a metalearned attribute $learnedatt$, in a metaclass C, is a typed attribute of a type T that represents a known unknown in the business domain. It is learned using a machine learning hypothesis. This hypothesis can be created from a parameterized ML algorithm, its parameters, a set of features extracted from the business domain, and a past learned state that represents the best fitted model of the learning algorithm to domain data. A metaderived attribute $derivedatt$, is very similar to the $learnedatt$ with the only difference that the deriving algorithm does not depend on a past state but only on extracted features. In other terms, a metaderived attribute, has a type T, a set of extracted features, a deriving parameterized algorithm and its parameters. The same definition applies for learned and derived relations that behave in the same manner than attributes with only a different result type (e.g., collection of nodes as output). In the syntax of our proposed language, derived/learned attributes and relationships are defined with the keywords `derived att`, `derived rel`, `learned att`, and `learned rel`.

A step called **feature selection** in the metamodeling of C_x is required in order to specify the dependencies needed in order to learn $learnedatt$ or derive $derivedatt$. The feature selection can be done only over meta-attributes reachable within the host metaclass C_x. We define this reachability function by the following:

Definition 5 $reach : (metaClass \times metaAtt) \mapsto boolean$
$reach(C_x, a) = att(C_x, a) \vee learnedatt(C_x, a) \vee derivedatt(C_x, a)$
$\vee(\exists C_y | rel(C_x, C_y) \wedge reach(C_y, a))$

In this definition, a meta-attribute a is considered as reachable from a metaclass C_x, either if it is a meta-attribute, metalearned attribute, or metaderived attribute within the metaclass C_x itself, or if C_x has a relationship to another class C_y, which contains a or it can be reachable from there, using recursively another relationship.

Definition 6 Let F be the set of features to extract in order to learn $learnedatt$ in a metaclass C, we have:
$\forall f \in F, (f! = learnedatt) \wedge reach(C, f)$ is an axiom.
Similarly, in order to derive $derivedatt$, we have:
$\forall f \in F, (f! = derivedatt) \wedge reach(C, f)$ is an axiom.

In other words, a metalearned or derived attribute can extract their features from the meta-attributes defined within the metaclass C (except itself to avoid circular reasoning) or reachable from its relationships in a recursive way.

Definition 7 To summarize, a metalearned attribute $learnedatt$ has a type T, a set of feature extractions F, a parameterized learning algorithm $alg_{p_1,\ldots,p_n}$, a set of parameters $p_1, \ldots, p_n$, and an learned state LS.
Moreover, we have: $\forall x, y\ C(x) \wedge (learnedatt(x, y) \rightarrow T(y))$
$\wedge\ y = alg_{p_1,\ldots,p_n}(eval(F), LS)$ is an axiom.
Similarly, a metaderived attribute $derivedatt$ has a type T, a set of feature extractions F, a parameterized learning algorithm $alg_{p_1,\ldots,p_n}$, a set of parameters $p_1, \ldots, p_n$.
We have: $\forall x, y\ C(x) \wedge (derivedatt(x, y) \rightarrow T(y))$
$\wedge\ y = alg_{p_1,\ldots,p_n}(eval(F))$ is an axiom

In Definition 7, we present that the metalearned or derived attribute is typed in the same manner of classical meta-attributes (Definition 2), and the type has to be always respected. By extension, learned and derived relations follow strictly the same definition than learned and derived attributes and therefore will not be repeated here. Moreover, the learned attribute is calculated by executing the parameterized learning algorithm over the extracted features and the learned state. For the derived attribute, it is calculated by executing the parameterized deriving algorithm over only the extracted features. Both learned and derived properties are considered as specified properties, because they require some specifications (features, parameters, algorithm), in order to be calculated. This is depicted in our meta–meta model in Fig. 2. Finally, at an instance level, an object state is composed by the state of its classical attributes, relationships, and the states of each of its learned attributes.

As our model has a temporal dimension, every meta-attribute has a time dimension, and by extension, the learned state has as well a temporal dimension. All meta-attributes, relationships, states, and parameters are replaced by their temporal representation (For example: $att \mapsto att(t)$). For feature extraction, it is possible to extract the same attributes but coming from different points in time as long as the attributes are reachable.

3.5 Model learning patterns

Similarly to how modeling methodologies have led to design patterns to solve common problems, in this subsection we describe patterns to weave machine learning into models. We describe how our language can be used on the concrete smart grid use case with different combinations of machine learning and domain modeling. The section starts with a simple domain model, then explains different combinations of domain data and learning, and ends with a more complex example on how different learnings can be composed.

3.5.1 Weaving learned attributes into domain classes

Let's start with a simple example. Listing 2 shows the definition of a class `SmartMeter`. It contains two attributes `activeEnergy` and `reactiveEnergy` and a relation to a `customer`. These are the typical domain attributes defining a `SmartMeter` class.

In this class we define a learned attribute `anomaly` that automatically detects abnormal behavior, based on profiling active and reactive energy. To do so, we specify to use a Gaussian anomaly detection algorithm as learning algorithm. Based on this definition, the code generator of GreyCat generates the `SmartMeter` domain class—including features like persistence—and weaves the necessary machine learning code into it. A template of the underlying Gaussian mixture model algorithm is implemented in GreyCat and used by the generator to weave the machine learning code into the domain class. In this example, the attribute `anomaly` can be seamlessly accessed from all `SmartMeter` instances. In fact, the attribute can be used similar to "normal" ones (i.e., not learned ones), however instead of the default getter and setter methods, the generated API offers a `train` and an `infer` method. This example shows how learned attributes can be seamlessly woven into domain classes.

Listing 2 Meta model of a smart meter with anomaly detection

```
class SmartMeter {
  att activeEnergy: Double
  att reactiveEnergy: Double
  rel customer: Customer
  learned att anomaly: Boolean {
   from"activeEnergy"
   from "reactiveEnergy"
   using "GaussianAnomalyDetection"
  }
}
```

3.5.2 Defining a learning scope for coarse-grained learning in domain models

Listing 3 shows an example of a power classification problem. In this listing, first an enumeration `Consumption Type` with three categories of consumption types (low, medium and high) is defined. Then, we extend the class `SmartMeter` to add a global `classify` attribute which classifies users according to their consumption behaviors. It learns from `activeEnergy`, `reactiveEnergy`, and `nbResidents`.

This example shows coarse-grained learning, where all instances of a domain class contribute to one learning unit. It demonstrates that attribute extractions cannot only happen at the level of attributes of the current instance but also to any reachable attribute from the relation of the current instance. In this example, the attribute `nbResidents`, which is the number of residents within the household of each customer, is extracted from a concrete `Customer` instance of a concrete `SmartMeter` instance. Moreover, it shows how to specify the machine learning hyper-parameters (here the learning rate and regularization rate) within the learned attribute using the keyword `with`. With this definition, GreyCat generates, besides the enum `ConsumptionType`, a domain class `SmartMeter`. As in the previous example, the machine learning code for the linear classification is directly woven into the generated domain class. Again, a template of a linear classification algorithm is integrated in GreyCat and used by the generator to generate the concrete code.

Listing 3 Meta model of a power classifier

```
enum ConsumptionType { LOW, MEDIUM, HIGH }
class SmartMeter{
  [...]
  global learned att classify: ConsumptionType {
    from "customer.nbResidents"
    from "activeEnergy"
    from "reactiveEnergy"
    with learningRate 0.001
    with regularizationRate 0.003
    using "LinearClassifier"
  }
}
```

3.5.3 Modeling relations between learning units and domain classes

Listing 4 shows the metaclass of a `SmartMeterProfiler`. In a first step we define that such profilers have relationships to `SmartMeter` instances and vice versa. Then, we extract several attributes from this relationship. For instance, we get the hour of the day (with a GreyCat built-in function `Hour(date)`), the active and reactive energy and calculate the square value. Attribute extractions can be any mathematical operations over the attributes that are reachable from the relationships defined within the class. In this example, the profiler learns the probabilities of the different power consumptions, hourly based, using a Gaussian mixture model algorithm [23]. For this scenario, GreyCat generates the domain classes `SmartMeter` and `SmartMeterProfiler`. The machine learning code, based on a template implementation of a Gaussian mixture model algorithm, is injected into the generated code. The `SmartMeterProfiler` is generated as a regular domain class (with a learned attribute).

Listing 4 Meta model of a smart meter profiler

```
class SmartMeterProfiler {
  rel smartMeter: SmartMeter
  learned att powerProbabilities: Double[] {
   from "Hour (smartMeter.time)"
   from "smartMeter.activeEnergy^2"
   from "smartMeter.reactiveEnergy^2"
   using "GaussianMixtureModel"
  }
}

class SmartMeter {
  [...]
  rel profile: SmartMeterProfiler
}
```

3.5.4 Decomposing complex learning tasks into several microlearning units

For the last example, we show how to use domain information to derive an advanced profiler at the concentrator level using the fine-grained profilers at the smart meters. First, we define a class `Concentrator` that contains relations to the connected smart meters. Then, we define a `Concentrator Profiler` with a relation to an `Concentrator` and vice versa. Inside this profiler, we derive an attribute `powerProbabilities` using the keyword `derived` and using an `aggregation` function that combines the probabilities from the fine-grained profiles. This example shows how fine-grained machine learning units can be combined to larger ML units. Similar to the previous examples, GreyCat generates, based on this definition, two domain classes: `Concentrator` and `Concent ratorProfiler`.

Listing 5 Meta model of a concentrator and its profiler

```
class Concentrator {
  rel connectedSmartMeters: SmartMeter
  rel profile:ConcentratorProfiler
}

class ConcentratorProfiler {
  rel concentrator: Concentrator
  derived att powerProbabilities: Double[] {
   from concentrator.connectedSmartMeters.profile
   using "aggregation"
  }
}
```

3.5.5 Coarse-grained learning

As discussed, our approach also allows coarse-grained learning. The following example shows how coarse-grained learning can be expressed with our proposed language. A class `ConcentratorProfiler` is used to profile the consumption values of all connected smart meters using a `GaussianMixtureModel` algorithm. This example is similar to the previous one but instead of aggregating the fine-grained learned profiles of the individual smart meters (fine-grained learning), in this example we directly profile the consumption values of the smart meters connected to a concentrator in a coarse-grained manner.

Listing 6 Meta model of a coarse-grained consumption profiler

```
class Concentrator {
  rel connectedSmartMeters: SmartMeter
  rel profile:ConcentratorProfiler
}

class ConcentratorProfiler {
  rel concentrator: Concentrator
  learned att powerProbabilities: Double[] {
   from "Hour(concentrator.connectedSmartMeters.time)"
   from "concentrator.connectedSmartMeters.activeEnergy^2"
   from "concentrator.connectedSmartMeters.reactiveEnergy^2"
   using "GaussianMixtureModel"
  }
}
```

3.6 Framework implementation details

Our approach is implemented as a full modeling environment integrated into IntelliJ IDE.[3] The development process with our framework follows default MDE approaches, starting with a metamodel definition. The complete *LL* grammar of our extended modeling language is available as open-source.[4] Therefore, our framework contains a code generator based on Apache Velocity[5] to generate APIs for object-oriented languages. Currently, our generator targets Java and TypeScript.

The generated classes can be compared to what is generated by frameworks like EMF. In the following, we focus on the ML extensions. According to what is defined in the metamodel, our code generator "weaves" the concrete machine learning algorithms into the generated classes and also generates the necessary code to map from a domain representation (domain objects and types) to the internal mathematical representation expected by the learning algorithm (double arrays, matrices, etc.) and vice versa. Various machine learning algorithms can be integrated in our framework. Currently, we implemented the following algorithms:

- *Regression* Live linear regression
- *Classification* Live decision trees, Naive Bayesian models, Gaussian Bayesian models
- *Clustering* KNN,StreamKM++
- *Profiling* Gaussian Mixture Models (Simple and Multinomial)

For every derived property our generator adds an `infer` method to the generated class, which contains the code to compute the property according to its metamodel definition. Similar, for every learned property our generator adds an `infer` to read the state of the learning unit and a `train` method to trigger the injected learning algorithm.

Since our framework targets CPSs and IoT applications it has a strong focus on performance. Thus, we do not rely on in-memory models but instead on a specialized graph storage. This has been developed to handle the high volatility of learning unit states.

Since relationships between domain classes and microlearning units are explicitly defined, they can be used during runtime to infer for which changes a microlearning unit needs to be recomputed. This is realized using change listeners and an asynchronous message bus. As a result, our framework supports fully independent updates of learning units. Leveraging the underlying shared graph storage model this can even be done in a distributed manner.

4 Evaluation

In this section we evaluate our approach based on two key performance indicators: (1) Can micromachine learning be more accurate than coarse-grained learning and (2) is the performance of using micromachine learning fast enough to be used for live learning.

4.1 Setup

We evaluate our approach on the smart grid use case introduced in Sect. 1. We implemented a prediction engine for customers' consumption behavior using our modeling framework. This engine predicts the consumption behavior based on live measurements coming from smart meters. We implemented this evaluation twice, once with a classical coarse-grained approach and another time with our microlearning-based approach. The goal is to demonstrate

[3] https://www.jetbrains.com/idea/.

[4] https://github.com/kevoree-modeling/dsl.

[5] http://velocity.apache.org/.

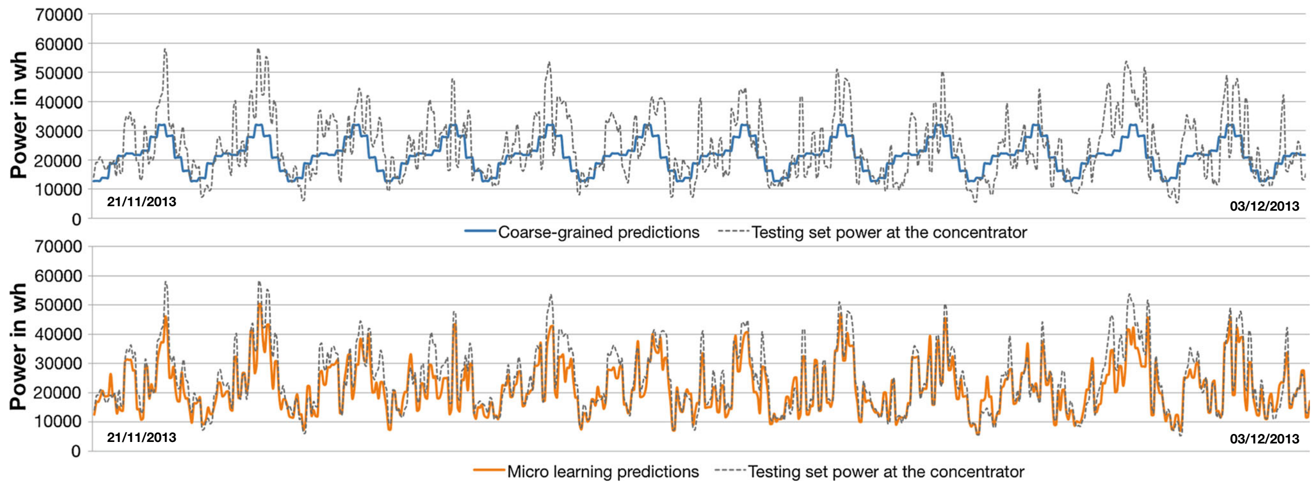


Fig. 4 Coarse-grained profiling (*top*) versus microlearning profiling (*bottom*)

that our microlearning-based approach can be more accurate while remaining fast enough to be used for live learning.

For our evaluation we consider 2 concentrators and 300 smart meters. We use publicly available smart meter data from households in London.[6] The reason why we use publicly available data instead of data from our industrial partner Creos is that these data are confidential what would prohibit to publish these data for reproducibility. Our evaluation is based on 7,131,766 power records, from where we use 6,389,194 records for training and 742,572 records for testing. The used training period is 15/08/2012 to 21/11/2013 and the testing period from 21/11/2013 to 08/01/2014.

For the first evaluation, we use a coarse-grained profiler on the concentrators. All smart meters send their data regularly to concentrators where the sum of all connected smart meters is profiled. In a second evaluation we use our microlearning-based approach and use one individual profiler for every smart meter and define an additional profiler for every concentrator, which learn from the individual profilers of the connected smart meters. As learning algorithm we use in both cases Gaussian mixture models, with 12 components, profiling the consumption over a 24 h period, resulting in 2-h resolution ($24/12 = 2$). We train the profilers for both cases during the training period, then we use them in the testing period to estimate/predict the power consumptions for this period.

We simulate regular reconfigurations of the electric grid, i.e., we change the connections from smart meters to concentrators. This scenario is inspired by the characteristics of a typical real-world smart grid topology, as described in [19]. Every hour we randomly change the connections from smart meters to concentrators. At any given point in time, each concentrator has between 50 and 200 connected meters.

We performed all evaluations on an Intel Core i7 2620M CPU with 16 GB of RAM and Java version 1.8.0_73. All evaluations are available at GitHub.[7]

We use the traditional holdout method, where the dataset is separated into a training set and a testing set, instead of a k-fold cross-validation method. When it comes to time-series, the seasonal effect can introduce a bias when splitting the dataset in equivalent sets, required by the k-fold cross-validation method [12]. Moreover, in our evaluation we want to demonstrate the accuracy of modeling with microlearning units rather than evaluating the efficiency of the ML algorithm itself.

4.2 Accuracy

First, we compare the coarse-grained profiling to the microlearning approach to predict the power consumption over the testing set. Figure 4 shows the results of this evaluation. In both plots, the blue curve represents the testing dataset, i.e., the real power consumption that has to be predicted.

The coarse-grained profiler is not affected by the topology changes. In fact, the profiler at the concentrator level has learned an average consumption that is always replayed without considering the connected smart meters. This explains the periodic, repetitive aspect of the prediction curve.

In contrary, the microlearning approach defines a profiler on the concentrator as a composition of the profilers of all connected smart meters, as shown in the metamodel in Listing 6. In case the topology changes, e.g., a smart meter disconnects, the concentrator profiler (composed of

[6] http://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households.

[7] https://github.com/kevoree-modeling/experiments.

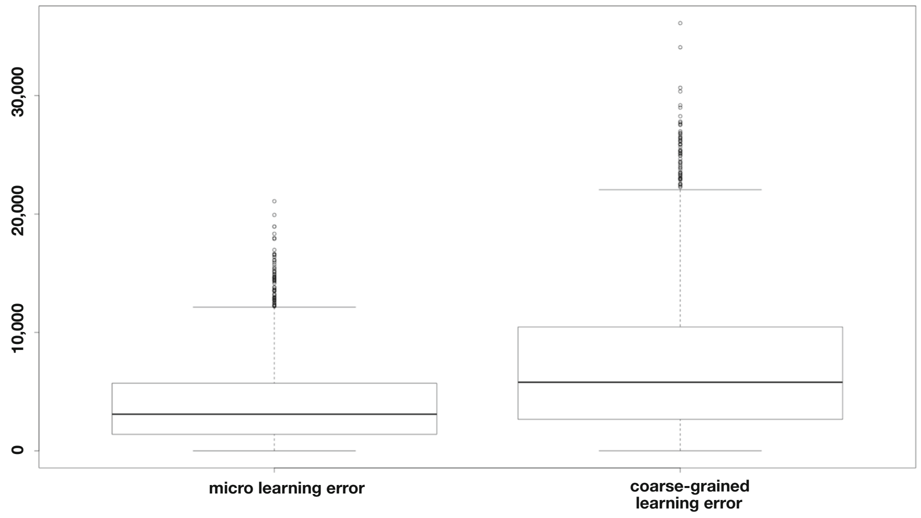


Fig. 5 Average prediction error and confidence intervals (in Watt per hours, Wh)

several smart meter profilers) will no longer rely on the profiler of the disconnected smart meter. As depicted in Fig. 4, for the micromachine learning profiling, the plotted curve is significantly closer to the curve of the real testing set than the coarse-grained learning. Although, both uses the same profiling algorithm: a Gaussian mixture model. For readability reasons we only display the first 12 days of predictions. Prediction curves in case of microlearning are very close (even hard to distinguish) to the real testing set.

We plot the histogram of the prediction errors for both, coarse-grained and microlearning in Fig. 6. It shows the distribution of the prediction error of both cases. Overall, microlearning leads to an average error of 3770 Wh, while coarse-grained learning leads to an average error of 6854 Wh. In other words, the error between the prediction and real measurement is divided by two. Knowing that the average power consumption overall the testing set is 24,702 Wh, we deduce that the microlearning profiling has an accuracy of 85%, while coarse-grained learning has an accuracy of 72%. The accuracy is calculated by $(1 - \text{avgError}/\text{avgPower})$. Figure 5 depicts the average prediction error and associated confidence interval for both methods: fine-grained and coarse-grained. We can observe that the confidence intervals are around 12 kWh for the fine-gained method and, respectively, 21 kWh for the coarse-grained approach. Based on these results, we can conclude that microlearning can be significantly more accurate than coarse-grained learning.

A noticeable result is that the same algorithm can lead to a better accuracy when used at a smaller level and combined with the domain knowledge. Therefore, we argue that this decision is very important and motivate by itself the reason why we focus this contribution on offering modeling abstractions for this purpose.

4.3 Performance

In terms of performance, Table 1 shows the time needed in seconds to load the data, versus the time needed to perform the live profiling for different numbers of users and power records. For instance, for 5000 users and their 150 million power records, it takes 1927 s to load and parse the whole dataset from disk (around 32 min, knowing that the dataset is around 11 GB large). However, only 564 s are spent for profiling (less than 10 min).

Another observation that can be deduced from Table 1 is that both loading and training time are linear with the number of records loaded ($O(n)$ complexity). A considerable performance increase can be achieved by distributing and parallelizing the computation, especially using microlearning where every profile can be computed independently. We decided to present results without the usage of a distributed storage backend (e.g., HBase[8]). This would pollute computation times due to networking and caching effects. However, our results allow to meet the performance requirements of case studies like the smart grid. Indeed, during these evaluations our modeling framework ingest more than 60,000 values per seconds on a single computer. This is comparable to data processing frameworks like Hadoop [6]. Moreover, fine-grained machine learning units can be computed independently and can therefore be easily processed in parallel. In fact, every learning unit can naturally be computed in an own process.

4.4 General applicability of the presented approach and modeling language

In this section, we show the general applicability of our approach and how it can be applied to different domains.

[8] https://hbase.apache.org/.

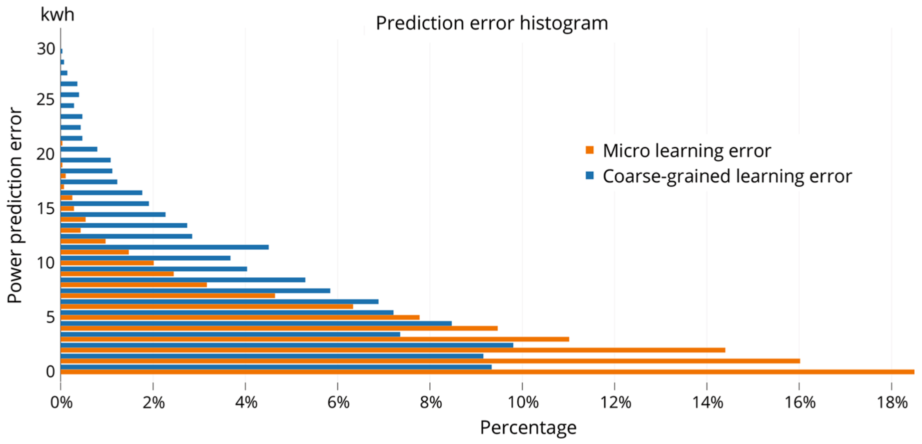


Fig. 6 Power prediction error histograms

Table 1 Loading time and profiling time in seconds

Number of users	Number of records	Loading data time in s	Profiling time in s
10	283,115	4.28	1.36
50	1,763,332	21.94	7.20
100	3,652,549	44.80	14.44
500	17,637,808	213.80	67.12
1000	33,367,665	414.82	128.53
5000	149,505,358	1927.21	564.61

Scalability test over 5000 users and 150 millions power records

Therefore, we discuss examples from different domains and show how they can be modeled using our approach and proposed modeling language. This shows the benefits of a seamless integration of machine learning into domain modeling.

Let us take recommender systems as a first additional example outside the smart grid domain. In recommender systems, the goal is to monitor prior actions of users in order to recommend potential future actions. Applied to sales, for instance, this can be translated into potential next items to sell or next movies to watch. Different types of recommender systems exist [25]. Some recommender systems cluster users to similar behaviors and thus recommend the items to buy according to what other users of the same behavior group already bought. These system are known as *user-user* recommender systems [25]. Other recommender systems cluster items according to their similarities or complementarity and thus suggest to a user to buy the items that are usually bought together. These systems are known as *item-item* recommender systems [25]. Other systems ask users about their preferences and from these preferences they recommend the most suitable products. These systems are known as *user-item* recommender [25].

With our proposed modeling language and approach, we can integrate these 3 types within the same model, thus allowing system designers to change from one type of recommendation system to another—or even have all 3 types of recommendations at the same time, at a minimum cost (by learning the profiles once, and reusing many times). For instance, instead of going to a coarse-grained recommender system by grouping users or items together, we can go to a more fine-grained approach, by attaching a profile to every user and to every product. These profiles represent an abstract mathematical notion of taste in a N-dimensional space in which we can quickly compare users or items together. Moreover, these profiles can be updated in live after every purchase. Then, in order to achieve a user-user recommender system, we can create a derived clustering algorithm that compares and groups users with similar profiles together. The same can be done for the item-item recommender systems by clustering the products with the same profiles together. A user-item recommender system can be achieved by a derived algorithm that fast search for products that match a user profile with an item profile. This way, we manage to separate the different concepts in different layers that are reusable. Moreover, we can reuse business knowledge in machine learning (for instance by not recommending past items already bought if the learning algorithm has access to the historical purchases of the users), and vice versa, by taking business decisions based on machine learning results (recommending new product to sell). Listing 7 shows an example metamodel of such a recommender system.

Listing 7 Meta model of a recommender system

```
enum Category { ELECTRONIC, BOOKS, MUSIC, MOVIES, ... }
class Index{
  rel users: User
  rel products: Product
}

class User {
  att userId: Long
  att name: String
  [...]
  rel purchasedProducts: Product
  rel profile: UserProfiler with maxBound 1
}
class Product {
  att productId: Long
  rel category: Category with minBound 1 with maxBound 1
  att price: Double
  [...]
  rel purchasedBy: Customer

  rel profile : ProductProfiler with maxBound 1
}
class UserProfiler {
  rel user: User
  learned rel userProfile: TasteProfile {
    from"user.purchasedProducts"
    using "IncrementalSVD"
  }
}
class ProductProfiler {
  rel product: Product
  learned rel productProfile: TasteProfile {
    from "product.category"
    from "product.price"
    using "IncrementalSVD"
  }
}
class TasteProfile {
  att svdVector: double[]
}

class UserUserRecommender {
  rel index: Index
  derived rel similarUsers: User {
    from index.users.profile
    using "ClusteringAlg"
  }
}
class ItemItemRecommender {
  rel index: Index
  derived rel similarItems: Item {
    from index.items.profile
    using "ClusteringAlg"
  }
}
class UserItemRecommender {
  rel index: Index
  rel currentUser: User
  derived rel directRecommender: Item{
    from currentUser.profile
    from index.items.profile
    using "SimilarityAlg"
  }
}
```

A second example is the domain of transportation systems. The goal is to optimize the public transportation by suggesting to people different transportation alternatives. Again, in this domain, machine learning can be modeled by fine-grained profilers and recommender systems can be built on top of these profilers. For instance, in [47] the authors create profiles for each of the following:

– price of taxi fare per distance unit according to the hour of the day
– traffic on different road segments
– parking place availabilities

Each of these profiles can be modeled as a completely independent, fine-grained, and reusable learning unit in our modeling language. A recommender system can calculate the recommendation by deriving the information from these different learning units. Moreover, the advantage of our framework is that the business domain knowledge is at the same level as the learned knowledge. For instance, a learning unit can depend directly on the bus or train schedules, if they are known in advance. Listing 8 shows an example metamodel of how such transportation recommender system could be modeled in our proposed approach.

Listing 8 Meta model of a transportation recommender system

```
enum Transportation {CAR, TAXI, BUS, TRAIN, BICYCLE, WALKING}

class Index {
    rel users: User
    rel taxis: Taxi}//end of class
class User {
    att userId: Long
    att name: String
    att GPSLongitude: double
    att GPSLatitude: double
    rel preferredTransportationMeans: Transportation
    rel userProfile: PositionProfiler}//end of class
class Taxi {
    att taxiId: Long
    att name: String
    att GPSLongitude: double
    att GPSLatitude: double
    att pricePerKm: double
    rel taxiProfile: PositionProfiler}//end of class
class PositionProfiler {
    rel user: User
    learned att userProfile: double[] {
        from "user.GPSLongitude"
        from "user.GPSLatitude"
        using "GaussianMixtureModel"}}//end of class
class TaxisPriceProfilers {
    rel index: Index
    derived att averageTaxiPrice: double {
        from index.taxis.pricePerKm
        using "Averaging"}}//end of class
```

```
class RoadSegment {
    att roadId: Long
    att gpsLongituteStart: double
    att gpsLongituteEnd: double
    att gpsLatitudeStart: double
    att gpsLatitudeEnd: double
    att currentTraffic: int
    learned att roadTrafficProfile: double[] {
        from "currentTraffic"
        using "GaussianMixtureModel"}}//end of class
class Parking {
    att parkingId: Long
    att parkingName: String
    att currentEmptyPlaces: int
    learned att emptyPlaceProfile: double[] {
        from "currentEmptyPlaces"
        using "GaussianMixtureModel"}}//end of class
class BusLine {
    att busLineId: Long
    att busLineName: String
    att busSchedule: double[]}//end of class
class TrainLine {
    att trainLineId: Long
    att trainLineName: String
    att trainSchedule: double[]}//end of class
class Map {
    rel roads: RoadSegment
    rel busLines: BusLine
    rel trainLines: TrainLine
    rel parkings: Parking}//end of class
class TransportationRecommender {
    rel user: User
    rel taxiPriceProfiler: TaxisPriceProfilers
    rel map: Map
    derived att recommendation: Transportation {
        from user.userProfile
        from taxiPriceProfiler.averageTaxiPrice
        from map.roads.roadTrafficProfile
        from map.trainLines.trainSchedule
        from map.busLines.busSchedule
        from map.parkings.emptyPlaceProfile
        using "customTransportationAlgorithm"}}//end of class
```

4.5 Threats to validity

We decided to evaluate our approach on an end-to-end real-world case study. Despite that we showed the usefulness of the approach for other domains, one threat to validity remains that the evaluation case study might be especially appropriate for the presented solution. Additional case studies need to be considered to better estimate the general applicability of the presented approach. Nonetheless, the evaluated case study is representative for the domains targeted by our approach. Another threat to validity might be the sampling rate of the smart meter measurements of the used case study, which could affect the error rate, e.g., missing peaks due to averaging intervals. However, the used sampling rate is already comparatively low with respect to the used dataset. Therefore, this risk is rather low.

5 Discussion

Weaving machine learning into domain modeling opens up interesting possibilities in the intersection of metalearning and metamodeling. Metalearning is about learning the parameters of the learning class itself and adapting these parameters to the specific business domain where the learning is applied to. The following points are considered as typical metalearning problems:

- Changing the inference algorithm.
- Adding or removing more input attributes.
- Modifying the math expression of an attribute.
- Changing learning parameters (for ex. learning rate).
- Chaining or composing several learning units.

Such changes can be introduced during the execution of the system, reflecting a new domain knowledge that have to be injected. Therefore, considering that we model learning parameters, this makes it necessary to enable metaclass changes at runtime. This feature is enabled in our modeling framework. However, changing learning algorithms or parameters can occur more often than classical metamodel changes. This opens up the reflection on new research directions about frequent metamodel updates.

We developed our modeling framework for microlearning. Nonetheless, as discussed, we support fine-grained but also coarse-grained learning. However, our framework—and approach—is clearly designed for microlearning and is therefore mainly useful for systems which are composed of several elements which behave differently. Examples for such systems are CPSs, IoT, and recommender systems. For systems dealing mainly with large datasets of “flat data,” i.e., unstructured data without complex relationships between, our model-based microlearning approach is less beneficial. Instead, our approach is mostly beneficial for systems dealing with complex structured and highly interconnected domain data which have to continuously refine behavioral models that are known at design time with what can be learned only from live data to solve known unknowns. A current restriction of our approach is that it considers only known unknowns, i.e., it is necessary to know what is unknown and what can be learned. Moreover, our approach focuses on live learning scenarios where only small learning units, which individually are fast to recompute, have to be updated. While this is especially useful in cases where only few microlearning units i.e., only parts of the model need to be updated, it is less beneficial for cases where the whole model needs to be recomputed. In such cases, batch learning methods can be more efficient.

6 Related work

TensorFlow [1] is an interface for expressing machine learning algorithms and an execution engine to execute these on a wide range of devices from phones to large clusters. A TensorFlow computation is represented as a directed graph. Nodes in the graph represent mathematical operations, called *ops*, while the edges represent multidimensional data arrays, called *tensors*. An op takes zero or more tensors, performs computations, and produces zero or more tensors. Two phases are distinguished in TensorFlow. A construction phase where the graph is assembled and an execution phase which uses a session to execute ops in the graph. TensorFlow is used within Google for a wide variety of projects, both for research and for use in Google's products. Similar to our approach, TensorFlow allows to model ML at a higher level of abstraction. However, unlike in our approach ML is expressed in its own model aside from the domain model and not connected to it. TensorFlow is adapted for image and video recognition, whereas our approach is adapted for learning from frequently changing domain data.

GraphLab [32] goes in a similar direction than TensorFlow. Low et al.propose an approach for designing and implementing efficient and provably correct parallel ML algorithms. They suggest to use a data graph abstraction to encode the computational structure as well as the data dependencies of the problem. Vertices in this model correspond to functions which receive information on inbound edges and output results to outbound edges. Data are exchanged along edges between vertices. GraphLab aims at finding a balance between low-level and high-level abstractions. In contrary to low-level abstractions GraphLab manages synchronization, data races, and deadlocks and maintains data consistency. On the other side, unlike high-level abstractions GraphLab allows to express complex computational dependencies using the data graph abstraction. In Low et al. [31] present a distributed implementation of the GraphLab abstraction. Like TensorFlow, GraphLab is an interface for expressing ML algorithms and an execution engine. While there are similarities, like the idea that ML algorithms should be expressed with a higher-level abstraction, our approach focuses on weaving ML algorithms into domain modeling. This allows to use results from learning algorithms in the same manner than other domain data.

In [4] Bishop proposes a model-based approach for ML. He introduces a modeling language for specifying ML problems and the corresponding ML code is then generated automatically from this model. As a motivation Bishop states the possibility to create highly tailored models for specific scenarios, as well as for rapid prototyping and comparison of a range of alternative models. With *Infer.NET* he presents a framework for running Bayesian inference in graphical models. Similar to Bishop we propose to express ML problems in terms of a modeling language and automate the mapping of a domain problem to the specific representation needed by a concrete ML algorithm. While Bishop suggests to specify ML problems in separate models with a dedicated modeling language, our approach extends domain modeling languages with the capability to specify ML problems together with domain models using the same modeling language. This allows to decompose learning into many small learning units which can be seamlessly used together with domain data.

Domingos et al. [10] propose an approach for incremental learning methods based on Hoeffding bounds. They suggest to build decision trees on top of this concept and show that these can be learned in constant memory and time per example, while being very close to the trees of conventional batch learners. With massive online analysis (MOA) [3] Bifet et al. present an implementation and a plugin for WEKA [17] based on Hoeffding trees. Our contribution is a methodology to weave micro-ML into data modeling to support applications which need online analysis of massive data streams.

Hido et al. [26] present a computational framework for online and distributed ML. There key concept is to share only models rather than data between distributed servers. They propose an analytics platform, called Jubatus, which aims at achieving high throughput for online training and prediction. Jubatus focuses on real-time big data analytics for rapid decisions and actions. It supports a large number of ML algorithms, e.g., classification, regression, and nearest neighbor. Jubatus only shares local models, which are smaller than datasets. These models are gradually merged. Jubatus, like our approach, allows independent and incremental computations. However, Jubatus does not aim at combining domain modeling and ML, neither does it allow to decompose a complex learning task into small independent units, which can be composed.

7 Conclusion and future work

Coarse-grained learned behavioral models do not meet the emerging need for combining and composing learnt behaviors at a fine-grained level, for instance for CPSs and IoT systems, which are composed of several elements which are diverse in live behaviors. In this paper we proposed an approach to seamlessly integrate micromachine learning units into domain modeling, expressed in a single type of model, based on one modeling language. This allows to automate the mapping between the mathematical representation expected by a specific machine learning algorithm and the domain representation. We showed that by decomposing and structuring complex learning tasks with reusable, chainable, and independently computable microlearning units the accuracy compared to coarse-grained learning can be significantly improved. We demonstrated that the ability to independently compute and update microlearning units makes this approach fast enough to be used for live learning. Besides simplifying the usage (flatter learning curve), a graphical language can be more intuitive for many users, especially for nondevelopers. We are also working on integrating additional machine learning algorithms in our framework to make it applicable for a broader range of problems. For example, for stream clustering, we are planning to include and experiment with algorithms like cluStream, clusTree, DenStream, D-Stream, and CobWeb. In addition, we are experimenting with adding GPU support for the computation of ML algorithms to our framework to investigate the advantages and disadvantages of it for different use cases.

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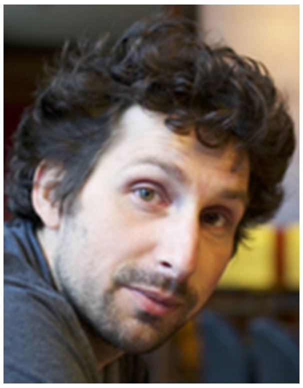

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