Meta-learning Potential to Assess Uncertainties in Dynamic Risk Management

Elena Stefana

Department of Mechanical and Industrial Engineering, University of Brescia, Brescia, Italy. E-mail: elena.stefana@unibs.it

Nicola Paltrinieri

Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology NTNU, Trondheim, Norway. E-mail: nicola.paltrinieri@ntnu.no

Meta-learning studies how learning systems can increase in efficiency through experience. Its purpose is to understand how learning itself can become flexible according to the tasks or contexts under study. These properties appear particularly interesting in safety field and in Dynamic Risk Management (DRM) process. Indeed, in such a process, the meta-learning strategies can support safety managers in the recommendation of models estimating a particular risk in the presence of various types of uncertainty due to lack of knowledge, omissions, incomplete analysis, and/or simplifying assumptions. The aim of this paper is to provide a narrative review about available meta-learning approaches in DRM process and, particularly, applied for assessing uncertainty in models able to estimate safety risks. No documents are available in the literature that deal with meta-learning approaches for safety topics, for DRM process, or for uncertainty assessment in models for estimating risks. However, the variety of existing studies related to meta-learning principles allows to address the development of a framework applicable in a general DRM process to reduce uncertainty. We discuss some main elements of a novel and preliminary meta-learning framework that should help safety managers to select a subset of models assessing a risk that assures desired uncertainty conditions. Particular emphasis should be given to the identification and definition of relevant meta-attributes, such as data-based, domain-based, uncertainty-based, and sensitivity-based meta-features.

Keywords: Machine learning, learning to learn, model ranking, algorithm selection, epistemic uncertainty, Monte Carlo, model uncertainty, parameter uncertainty, dynamic risk analysis, No-Free-Lunch theorem.

1. Introduction

A recent statement by Vanschoren (2018) well points out the meta-learning concept: "every time we try to learn a certain task, whether successful or not, we gain useful experience that we can leverage to learn new tasks". This is aligned with Biggs' concepts (Biggs 1985) describing meta-learning as being aware of and taking control of one's own learning. According to Vilalta et al. (2004), meta-learning allows achieving the goal of understanding the conditions under which a learning strategy is most appropriate.

In these decades, the attention and interest around the meta-learning topic have been growing, and stimulate scholars to define ever better approaches for solving various real-world problems. Meta-learning ideas and processes also seem to be promising for the improvement of safety issues. Specifically, meta-learning potential can support safety managers to reduce uncertainty and improve decisions in Dynamic Risk Management (DRM) process. DRM is "an approach to risk management that can consider the dynamic evolution of conditions, both internal and external to the system affecting risk assessment" in order to "take into account new risk notions and early warnings and to systematically update the related risks" (Paltrinieri et al. 2014). In this context, safety managers must assess several types of risk in changing working environments. The assessment is based on estimations provided by a multiplicity of mathematical models and associated parameters, whose numerous values may be challenging to handle. These models are characterized by different accuracy degrees, boundary conditions, and assumptions that require continuous comparisons and adaptations to select the best model for a particular scenario. As a consequence, the consideration and analysis of uncertainty should be an important and integral part of exposure assessment (Stefana et al. 2019).

Uncertainty is the lack of knowledge about the true value of a quantity, regarding which of several alternative model representations best describes the system under study, or about which probability distribution functions should represent a quantity of interest (Stefana et al. 2019). For identifying and prioritizing key sources of uncertainty and which inputs are most responsible for the uncertainty in model outputs or variables of interest, uncertainty analysis can be supplemented with sensitivity analysis (de Rocquigny et al. 2008, Stefana et al. 2019).

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This complexity can be effectively and efficiently managed through a meta-learning framework able to identify and predict which is the most suitable model according to the risk and uncertainty sources under investigation. In accordance with das Dôre et al. (2016), meta-learning represents a tool that helps to determine under what conditions a given algorithm is more suitable to be applied instead of others. The adoption of such an approach would guide safety managers lacking risk modeling experience during the risk assessment and management procedures.

For all these reasons, the aim of this paper is to provide a narrative review about available meta-learning approaches in DRM process and, particularly, applied for assessing uncertainty in models able to estimate safety risks. Based on the narrative review results, we identify the potential of meta-learning to assess uncertainty related to the different existing models estimating a specific risk, and propose a novel and preliminary framework for ranking those models according to a multicriteria evaluation measure.

2. Methods

The narrative review conducted for this study allows identifying studies dealing with meta-learning concepts in safety field, in risk management process, and in DRM context. We focus on documents about existing meta-learning approaches that allow the assessment of various uncertainty sources in the DRM process, with particular regard to models involved in risk analysis and estimation phases.

We searched for works in the following electronic databases of scientific publications: ScienceDirect, Scopus, and Web of Science. No limits about language sources or years of publication are imposed. We also carried out an examination of technical documents in specialized or general search engines (e.g., Google Scholar). Additionally, the list of references in each study was checked through a manual examination to identify any additional relevant documents. Several queries were performed and included different combinations of identified keywords: e.g., "meta-learning", "algorithm recommendation", "model ranking", "meta-feature", "safety", "risk assessment", "input uncertainty", "parameter uncertainty", "model uncertainty", "sensitivity analysis", "probabilistic analysis". These keywords are combined in different search strings by using the Boolean operators AND and OR. We rated the relevance of the publications through the reading of the full-text, and critically analyzed all the literature retrieved through our narrative review.

3. Results

The narrative review did not return any documents that tackle meta-learning approaches for safety topics, for DRM process, or for uncertainty assessment in models for estimating risk. On the contrary, the literature offers many studies related to meta-learning principles, applications in various domains, and proposals on architectures. From these results we can take inspiration for the development of a framework applicable to a DRM process to reduce uncertainty. The following sections report the definitions, fundamental concepts, and main elements of a meta-learning system retrieved through the narrative review and useful for our purpose. Due to space constraints, this article only proposes a limited set of interesting references.

3.1 *Meta-learning definitions and algorithm selection problem*

The narrative review points out the existence of several definitions about the meta-learning concept. Table 1 shows an extract of such definitions. The majority of authors agree to refer to meta-learning as "learning to learn" (e.g., Reif et al. 2012, Makmal et al. 2016, Vanschoren 2018) or "learning about learning" (Cohen-Shapira et al. 2019). According to Vilalta and Drissi (2002), Vilalta et al. (2004), and Brazdil et al. (2017), meta-learning differs from base-learning in the scope of the level of adaptation; whereas learning at the base-level is focused on accumulating experience on a specific learning task, learning at the meta-level is concerned with accumulating experience on the performance of multiple applications of a learning system. In accordance with Castiello et al. (2005), whilst the dataset in base-learning is drawn up on the basis of the available data, representing the task tackled by the base-learner, the meta-dataset in meta-learning has to be carefully built up by analyzing the characteristics of each single task and exploiting the accumulated past experience.

Meta-learning constitutes one of the possible and promising approaches for solving the algorithm selection or recommendation problem (Prudêncio and Ludermir 2004, de Souto et al. 2008, Bhatt et al. 2012, Reif et al. 2012, Santos et al. 2012, Filchenkov and Pendryak 2015, Lemke et al. 2015, Cohen-Shapira et al. 2019). It can provide automatic and systematic user guidance on algorithm selection based on the knowledge acquired from the application of a set of algorithms on different problems and extracted from the algorithm learning process (Vilalta et al. 2004, Rossi et al. 2014, Tripathy and Panda 2017).

Table 1. Main meta-learning definitions.

Author(s) (Year)	Definition
Vilalta and Drissi (2002)	The study of how learning systems can increase in efficiency through experience in order to understand how learning itself can become flexible according to the domain or task under study.
Prudêncio and Ludermir (2004)	The automatic process of generating knowledge that relates the performance of machine learning algorithms to the characteristics of the problem.
Vilalta et al. (2004)	The field whose research objective is to understand the interaction between the mechanism of learning and the concrete contexts in which that mechanism is applicable.
de Souto et al. (2008)	The automatic process of generating knowledge that relates the performance of machine learning algorithms to the characteristics of the problem.
Giraud-Carrier (2008)	The understanding of the interaction between the mechanism of learning and the concrete contexts in which that mechanism is applicable.
Brazdil et al. (2009)	The study of the main methods that exploit meta-knowledge to obtain efficient models and solutions by adapting machine learning and the data mining process.
Bhatt et al. (2012)	One of the approaches that acquired knowledge based on the past experience.
Rossi et al. (2014)	The understanding which are the conditions that define whether a learning system is inadequate for a particular task in order to improve its performance in future applications.
Lemke et al. (2015)	An understanding and adaptation of learning itself on a higher level than merely acquiring subject knowledge.
Lemke et al. (2015)	A meta-learning system must include a learning subsystem, which adapts with experience. Experience is gained by exploiting metaknowledge extracted in a previous learning episode on a single dataset, and/or from different domains or problems.
das Dôre et al. (2016)	The study of how learning systems can increase in efficiency through experience in order to understand how learning itself can become flexible according to the domain or task under study.

Table 1 (Continued)

Author(s) (Year)	Definition
Makmal et al. (2016)	A process of acquiring meta-knowledge.
Vanschoren (2018)	The science of systematically observing how different machine learning approaches perform on a wide range of learning tasks, and then learning from this experience, or meta-data, to learn new tasks much faster than otherwise possible.
Vanschoren (2018)	Any type of learning based on prior experience with other tasks.

The aim is to learn the relationship between data and algorithm characteristics and algorithm performance to automatically predict an algorithm or a set of algorithms suitable for a specific problem under study and thus to assist (non-expert) users in the process of algorithm selection, without running every algorithm on the datasets (Brazdil et al. 2003, Prudêncio and Ludermir 2004, de Souto et al. 2008, Smith-Miles 2008, Bhatt et al. 2012, Lemke et al. 2015, Zorrilla and García-Saiz 2015, Tripathy and Panda 2017). In other words, meta-learning permits to learn which problem characteristics contribute to a better performance of one algorithm over others, and to select the most suitable one for a new and/or unseen problem (Ferrari and de Castro 2015). As well highlighted by Santos et al. (2012), the main research questions in this context are: (1) which features of a dataset significantly affect the performance of a learning algorithm, and (2) which algorithms are the most appropriate to solve a given problem.

Rice (1976) was the first scholar providing a framework for algorithm selection problem. The main components and characteristics of this framework are: (1) the problem space constituting by a large and diverse collection of problems, (2) the feature space, (3) the algorithm space that consists of a large and diverse set of algorithms, and (4) the performance measure space, which contains the criteria to measure the performance of a particular algorithm for a particular problem.

Ranking is one of the methods to recommend algorithms, producing their ordered list according to their performance for the dataset of interest (Reif et al. 2014, das Dôre et al. 2016, Tripathy and Panda 2017). Ranking represents a useful and flexible possibility for algorithm selection problem because provides more options compared with selecting only the best algorithm, makes available alternative solutions to users who may wish to incorporate their own expertise or any other criterion into their decision-making process, and offers a next best alternative if the first algorithm seems to be suboptimal (Vilalta et al. 2004, de Souto et al. 2008, Reif et al. 2014, Ferrari and de Castro 2015, Brazdil et al. 2017). Different ranking combination methods are mentioned in the literature: average ranking, score ranking, winner ranking, relative ranking, percentage ranking, and ideal ranking (Ferrari and de Castro 2015, Tripathy and Panda 2017). Soares and Brazdil (2000) also propose a zoomed ranking method. For an overview and details of these methods, readers can refer to Ferrari and de Castro (2015), and Tripathy and Panda (2017).

Strictly related to the algorithm selection problem and ranking option, different authors (e.g., Brazdil et al. 2003, Smith-Miles 2008, Reif et al. 2014, Rossi et al. 2014, Filchenkov and Pendryak 2015, Zorrilla and García-Saiz 2015) emphasize the importance of considering No Free Lunch (NFL) Thereom by Wolpert and Macready (1997). NFL Theorem proves the impossibility to create the universal algorithm for a certain problem, and states that there is no learning scheme that can be uniformly better than all other learning schemes for all problem instances.

3.2 *Elements of a meta-learning system*

Typical meta-learning systems and processes for algorithm selection and ranking are described by Prudêncio and Ludermir (2004), Vilalta et al. (2004), de Souto et al. (2008), Bhatt et al. (2012), Ferrari and de Castro (2015), Brazdil et al. (2017), and Tripathy and Panda (2017).

Prudêncio and Ludermir (2004), and de Souto et al. (2008) also point out the existence of two phases: training and use. Vilalta et al. (2004) speak about acquisition and advisory as the two modes of operation of a meta-learning system. In the acquisition mode, the main goal is to learn about the learning process itself and to create a knowledge base reflecting experience accumulated across different tasks, while during the advisory mode, the meta-knowledge acquired in the exploratory mode is used to configure the learning system in a manner that exploits the characteristics of the new data (Vilalta et al. 2004).

3.2.1 *Meta-features*

Meta-features (or meta-attributes) are features or properties describing the problem, dataset, and data characteristics (Vilalta et al. 2004, de Souto et al. 2008, Bhatt et al. 2012, Reif et al. 2012, 2014, Ferrari and de Castro 2015, Brazdil et al. 2017). For Kalousis and Hilario (2001), they “constitute the attributes of the meta-learning problems”. The meta-features need to be representative and appropriate of the problem domain and of the properties of specific tasks to be solved: a critical component of any meta-learning system regards the identification and extraction of relevant and significant information about the task under analysis and suitable for characterizing a dataset and predicting the performance of the models (Vilalta and Drissi 2002, Vilalta et al. 2004, Castiello et al. 2005, Santos et al. 2012, Reif et al. 2014, Lemke et al. 2015, Zorrilla and García-Saiz 2015). According to Castiello et al. (2005), an adequate set of meta-features should prove to be useful in determining the relative performance of individual learning algorithms, and should not be too difficult to calculate. In the literature (e.g., Vilalta et al. 2004, Castiello et al. 2005, Bhatt et al. 2012, Reif et al. 2012, 2014, Ferrari and de Castro 2015, Filchenkov and Pendryak 2015, Lemke et al. 2015, Zorrilla and García-Saiz 2015, Tripathy and Panda 2017, Cohen-Shapira et al. 2019), several groups of meta-features are proposed:

- simple or general features that are directly derived from the data (e.g., number and type of attributes);
- statistical features describing statistical properties of the data (e.g., variance, kurtosis);
- information theoretic features used for characterizing datasets containing discrete or categorical attributes (e.g., class entropy, noise-signal ratio);
- model-based meta-features, in which a model is induced from the data and the meta-features are based on properties of that model (e.g., the number of leaf nodes of a decision tree);
- landmarkers, which are quick estimates of algorithm performance on a given dataset obtained by running simplified versions of the algorithms or simplified versions of the data.

Bhatt et al. (2012) define the first two categories as genotype, whereas the third as phenotype of the dataset. Additionally, the first three groups derive from direct characterization of the datasets, while the remaining belong to the indirect problem characterization (Bhatt et al. 2012, Ferrari and de Castro 2015, Tripathy and Panda 2017). Zorrilla and García-Saiz (2015) also mention complexity and contextual features, which characterize the apparent complexity of datasets for supervised learning and the dataset domain, respectively.

3.2.2 *Meta-data*

Meta-data contain estimates of the performance of a set of candidate algorithms on the datasets and the meta-features describing their characteristics (Bhatt et al. 2012, Ferrari and de Castro 2015, Brazdil et al. 2017, Cohen-Shapira et al. 2019). Smith-Miles (2008), and Ferrari and de Castro (2015) speak about meta-data or meta-knowledge.

Other authors refer to meta-example. In accordance with Prudêncio and Ludermir (2004), de Souto et al. (2008), and Bhatt et al. (2012), a meta-example stores the meta-features and the performance of a set of candidate algorithms on training datasets and on meta-features. In other words, it is generated by running the candidate algorithms available in the algorithm space on the datasets (Tripathy and Panda 2017).

The success of meta-learning depends on the availability of sufficient number of meta-examples (Tripathy and Panda 2017).

3.2.3 *Meta-learner*

The meta-learner is a learning system that receives as input a set of the meta-examples and acquires knowledge used to predict the algorithm performance for new problems being solved (de Souto et al. 2008, Bhatt et al. 2012). It states conditions over the meta-features to indicate when one base-learner outperforms the others (Prudêncio and Ludermir 2004). The meta-learner produces a meta-model, which matches the values of the meta-features with the most suitable algorithm for each dataset, predicts which tasks are similar, and allows to recommend/rank algorithms for each new dataset on the similar tasks (Vanschoren 2018, Cohen-Shapira et al. 2019). The effectiveness of the meta-learner increases as it accumulates meta-knowledge (Vilalta et al. 2004).

3.2.4 *Algorithm performance*

The performance of an algorithm varies from problem to problem, and from dataset to dataset (Tripathy and Panda 2017). The performance of the candidate algorithms is obtained by directly applying each algorithm to the data and evaluating the obtained result (de Souto et al. 2008). Algorithm performance measures are defined by the type of task (Filchenkov and Pendryak 2015). In the literature (e.g., Brazdil et al. 2003), performance can be assessed by means of a multicriteria evaluation measure that aggregates and combines information concerning some parameters of interest for the candidate algorithms on the selected datasets. Santos et al. (2012) also quote Data Envelopment Analysis.

3.2.5 *Meta-knowledge base*

The meta-knowledge base combines the information derived from the meta-features and the performance evaluation (Vilalta et al. 2004). Tripathy and Panda (2017) refer to a meta-database or metaknowledge base that consists of a number of meta-examples, meta-features, a set of algorithms, and the ranking of the algorithms obtained after applying them on the problems.

4. Discussion

The results retrieved through the narrative review help us to evaluate the use of meta-learning principles in DRM process to assess uncertainty related to the different existing models estimating a specific risk. This evaluation represents the first step for the definition of a novel and preliminary meta-learning framework able to rank a set of comparable candidate models from literature. In other words, the framework provides a ranking of available models based on the uncertainty and sensitivity analysis results, by identifying relationships and correlations between meta-features and uncertainty and sensitivity metrics. The adequacy and suitability of a model depend on the risk to be predicted, on the characteristics of the application, and on uncertainty sources. Based on these desired uncertainty conditions (summarized by the performance measures), the meta-learning system adapts itself for producing an optimized algorithm ranking. The framework should help safety managers to select a model or a subset of models estimating and assessing a risk that assures desired uncertainty conditions (e.g., models producing an output with a small variance, or models optimizing the trade-off between the extent and the dispersion of the output). In this sense, such framework represents a flexible tool because allows safety managers to consider preferences and priorities into the DRM process. Additionally, the dynamic approach is assured by the possibility to continuously introduce new models, evidence, information, and/or lessons learned when they become available.

The focus is on epistemic uncertainty (reducible if additional knowledge, information, and research can be acquired), and on risk analysis and estimation phases. These steps are characterized by both input and model uncertainty, and in which mathematical models have a fundamental role. We refer to “parameter uncertainty” as the imperfect knowledge of the true values of the model parameters, whereas to “model uncertainty” as the awareness that the model is a simplification and imperfect representation of a real system (Stefana et al. 2019). The main elements included in our meta-learning framework are depicted in Figure 1.

The first element of the framework is constituted by datasets. We take inspiration from Santos et al. (2012): a dataset is a collection of data organized in a certain format, containing more than one instance in a specific domain. An instance is a row in a specific dataset describing an observation of a known event in the past in that particular domain (Santos et al. 2012).

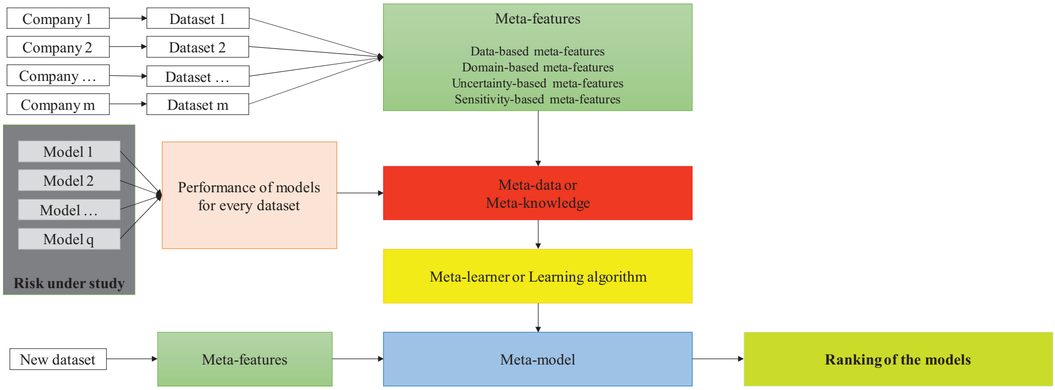

Fig. 1. Main elements of a meta-learning system for ranking models in DRM process under uncertain conditions.

Consequently, we suppose that real-world and comparable datasets are derived from the organizations and regard the outcomes of measurements and/or previous estimates about a particular risk. Particularly, each dataset contains the parameters (or variables) and their related values that are relevant for the risk under investigation. In order to give a complete dataset for the risk assessment, data can be derived from sensors and measuring devices, from literature sources, and/or from equipment designers and suppliers. In addition to these values, other pieces of information can be used, such as types of sensors and sensor placement, the department or process unit where each instance is collected, and the indication of the type of industry. The outcome or dependent variable is represented by the parameter(s) specific for the risk: the knowledge of the outcome variable is required for implementing a strategy of supervised learning (i.e., the training data contain inputs and explicit outputs, and the model can be trained until it produces the correct output for a given input, according to Smith-Miles (2008)). The available datasets are split into training and testing datasets. Training data contain a known output from which the model learns and generalizes, while test data have the goal to test the model prediction.

The identification of meta-features represents a crucial point: the feature space includes a set of meta-features that are informative about the prediction of a ranking of models for estimating a particular risk under uncertain conditions. We propose different categories of meta-features and divide them in the following two sets:

- meta-features for better describing the input datasets and understanding how the input uncertainty (e.g., probability distributions of the input models) affects the model performance: e.g., data-based meta-features for characterizing datasets, and domain-based meta-features for defining the problem under investigation and indicating what the specific source of each dataset is;
- meta-features concerning the outcomes of uncertainty and sensitivity analyses performed for each model considered for that specific risk (obtained by simulating the various models, conducting the uncertainty propagation step, and running common sampling techniques), and useful for understanding how the output uncertainty affects the performance of the candidate models.

The second meta-feature set is specialized for our research topic, and is composed by uncertainty-based and sensitivity-based meta-features. Uncertainty-based meta-features are related to results statistics for the output(s) of interest (e.g., mean, median, mode), percentiles (with a desired level of detail), and some measures about the "dispersion" of the output(s) (e.g., minimum and maximum, standard deviation, variance, skewness, kurtosis). Sensitivity-based meta-features can be: change in output statistics, rank order correlation (based on Spearman rank correlation coefficient), contribution to variance, and sensitivity indices derived from regression-based techniques or from graphical methods.

The large number of meta-features proposed above could require huge resources and computational costs. As a consequence, we can also be interested in carrying out experiments concerning the comparison of the results obtained by the models when different types of meta-features are used. In other words, the understanding of which combination of meta-features enables the best recommendation to be obtained appear particularly interesting.

In addition to meta-feature, another core element of the meta-learning framework is represented by performance measures. A ranking of the candidate models can be generated thanks to a multicriteria evaluation measure: we can evaluate models through a combined metric of measures related to output(s) and its (their) extent (e.g., mean, median, mode) and measures related to the "dispersion" of the results (e.g., standard deviation, variance). As an alternative to producing a single ranking automatically, we can provide two different rankings for a specific dataset: one ranking can be related to the output(s) and its (their) extent, and one concerning the "dispersion" of the results. This can be useful for considering the users' (i.e., safety managers) opinion about the relative importance (in a specific company) of the two performance measures. According to the goal of the safety managers and mainly of the risk assessment, each performance measure assumes proportional importance and thus the meta-learning system can adapt itself to the specific goal, producing an optimized algorithm ranking.

Note that the meta-learning strategies are quite different in these two types of measures. The meta-learning strategy for measures related to output(s) and its (their) extent depends on the models and the specific risk under study. In some cases, safety managers can be interested in adopting a precautionary approach and focusing on the minimal value(s) achieved by the output(s); in other risk assessments, safety managers could be interested in knowing the maximum value(s) of the output(s). On the contrary, the meta-learning strategy for measures related to the "dispersion" of the results can be common and valid for all types of risks and models.

Besides the performance measures about the uncertainty analysis, the meta-learning framework can predict a ranking of candidate models also based on one or more performance measure(s) related to sensitivity analysis. For instance, safety managers could be interested in producing a ranking about the models in terms of the correlation coefficient values of a parameter (input) of interest (chosen by the safety managers themselves). Alternatively, safety managers could be interested in knowing the ranking of algorithms with a certain number of parameters that have a low (defined as a target) correlation coefficient. In this sense, managers could adopt the models whose output uncertainty is scarcely affected by the uncertainty of the inputs.

5. Conclusions

This paper proposes a narrative review about available meta-learning approaches in DRM process and, particularly, applied for assessing uncertainty in models involved in risk analysis and estimation phases. To the best of our knowledge, there are no studies that answer our research question. However, the literature is abundant in general definitions and proposals about meta-learning. The algorithm selection problem constitutes a frequently mentioned application of the "learning to learn" paradigm, where the identification of informative meta-features and performance measures represent the core elements of a meta-learning system. The interest in defining relevant and specialized meta-features is demonstrated by the plethora of studies about the characterization of datasets. All these aspects also constitute the starting point for developing a novel and preliminary framework for ranking models estimating a safety risk in uncertain conditions. The focus is on epistemic uncertainty, and risk analysis and estimation phases. The proposed meta-features permit to describe completely input datasets, understand how the input uncertainty affects the model performance, and comprehend how the output uncertainty affects the performance of the candidate models. Finally, a ranking of the several candidate models is produced through a multicriteria evaluation measure.

The preliminary framework proposed in this paper represents the introductory step of an ongoing and wider research activity about the application of meta-learning ideas for safety management and DRM process.

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