FACTORS AFFECTING CLASSIFICATION ALGORITHMS RECOMMENDATION: A SURVEY

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ABSTRACT

A lot of classification algorithms are available in the area of data mining for solving the same kind of problem with a little guidance for recommending the most appropriate algorithm to use which gives best results for the dataset at hand. As a way of optimizing the chances of recommending the most appropriate classification algorithm for a dataset, this paper focuses on the different factors considered by data miners and researchers in different studies when selecting the classification algorithms that will yield desired knowledge for the dataset at hand. The paper divided the factors affecting classification algorithms recommendation into business and technical factors. The technical factors proposed are measurable and can be exploited by recommendation software tools.

KEYWORDS

Classification, Algorithm selection, Factors, Meta-learning, Landmarking

1. INTRODUCTION

There is a lot of raw data stored in business organizations databases, and with the progressively competitive markets and computers capabilities, businesses find themselves faced with the massive amount of data stored and the need to identify patterns, correlations, and predictive information that business experts may miss. Data mining is the field that helps business experts make better decisions based on the discovered patterns and relationships in the data available.
One key data mining task is classification, where it addresses the problem of assigning the unit of analysis of a dataset to target classes to help in more accurate predictions. There are different categories of classification algorithms. But, any classification algorithm needs one or more fields to be used as predictors, and a target field to predict.

To stay on track in a data mining project, a standard methodology or a list of best practices has to be followed. Efforts were made to use a standard data mining methodology that will guide the implementation of different data mining tasks, [1]. The most popular methodologies followed by researchers are CRISP-DM: Cross-industry standard process for data mining and SEMMA: Sample, Explore, Modify, Model, and Assess. CRISP-DM was founded by the European Strategic Program on Research in Information Technology, while SEMMA was developed by SAS Institute. Both of these methodologies have well-defined phases for modelling the data by an algorithm and evaluating the model after being created. Also, the first methodology; KDD: Knowledge Discovery in Database was adopted for years by data scientists. During modelling, there are several algorithms that could be used to perform the same data mining task and still produce different results. For example, to address a classification problem, one may choose from many algorithms, neural nets, where it has a lot of variants and considered as a black box model, another option is C5.0 and CHAID, which are considered as decision tree algorithms, last but not

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least, one can choose to use a statistical model with all its assumptions about the data. Given the findings, the tested models are ranked according to criteria such as model accuracy or time complexity. Later on, models with high quality are evaluated according to how the data mining results achieve the business goals.

In Table. 1, all the phases of the three methodologies mentioned are presented. None of these methodologies defined explicitly a phase for assessing the dataset in hand along with the algorithms available to select the most appropriate algorithm for addressing a data mining task before modelling. This introduces the challenge of selecting the most appropriate algorithm for a data mining task depending on evaluation criteria. For example, classification task, some algorithms provide highly accurate results, but interpretability could have higher priority than accuracy, in this case, other algorithms should be considered.

Table 1. Data mining methodologies phases

Knowledge Discovery in Database - KDD	**Sample, Explore, Modify, Model, and Assess - SEMMA**	**Cross-industry standard process for data mining - CRISP-DM**
Pre KDD	-	Business Understanding
Selection	Sample	Data Understanding
Pro processing	Explore	
Transformation	Modify	Data Preparation
Data Mining	Model	Modelling
Interpretation/Evaluation	Assessment	Evaluation
Post KDD	-	Deployment

As per the no-free-lunch theorem [3], it is not expected to identify a single algorithm that performs best on all datasets. Rather, researchers have aimed to study and evaluate the factors considered when selecting an appropriate data mining algorithms and offer guidelines to non-experts as well as researchers. The algorithm selection problem was described by Rice, [2], and multiple systems have been developed since. These systems perform algorithm selection based on different factors. Depending on these factors one or more algorithms are selected as most appropriate for the dataset at hand. The system's selection is justified by evaluating the performance of the selected algorithm(s) compared to the other algorithms depending on some criteria, like accuracy.

Most of the approaches followed by researchers to determine these factors relied on the concept of meta-learning. Where data characteristics were calculated and grouped into simple or general measurements, information theoretic measurements and discriminant analysis measurements. In these studies, the predictors were the data characteristics and the target was the algorithm the performs best on these data. Other researchers combined algorithms characteristics along with data characteristics to find out the most appropriate algorithms.

Land marking is another source of dataset characterization. Land marking concept is to exploit the information obtained on samples of the dataset. The accuracy results from these dataset samples act as the characteristics of the dataset and are referred to as sub-sampling landmarks. These characteristics are then used to guide in the selection of an appropriate classification algorithm for the dataset of interest [4].

This paper provides a survey of the different factors considered by researchers and business experts when selecting the most appropriate algorithm for the data at hand. This survey groups different factors into categories, and shows the importance of each category depending on the related studies.

2. RELATED WORK

In this section, some of the work and studies were done which are related to the problem of selecting the most appropriate classification algorithm for a particular dataset were briefly covered.

As known, each classification algorithm has its own advantages, disadvantages and assumptions, also known that each dataset has its own characteristics, which doesn't always satisfy the assumptions of a classification algorithm.

One approach to tackle the problem of selecting the most appropriate classification algorithm for a dataset is to follow brute force approach; apply all available classification algorithms on the dataset at hand and select the classification algorithm that provides the most suitable results (depending on the evaluation criteria). Following the brute force approach would waste a lot of resources. As a result, researchers study the factors that affect the selection of the appropriate classification algorithm for a dataset and produce tools to recommend the most appropriate classification algorithm for a dataset.

Several studies have proposed the factors and proposed different techniques for dataset characterization to tackle the problem.

[7] proposed a conceptual map of the common knowledge models techniques and intelligent data mining techniques recommender tool based on some dataset characteristics. There was no study carried out to show on which basis were these dataset characteristics used.

In [8], based on the characteristics of datasets and the performance of classification algorithms, mapping between the datasets and the benchmark performance of different classifiers is carried out. K-similar datasets are returned and then ranking of classification algorithms is done so that a classification algorithm is recommended for the dataset at hand.

A subset of the dataset meta-features/characteristics was used without a mention of why this specific subset was favoured over the rest of available meta-features.

Statlog [10], considered different meta-features in the study and some non-technical factors affecting the classification algorithm selection problem as well. New dataset characteristics extraction approaches like model-based and land marking weren't considered.

Although in [18] exhaustive study has been carried out to evaluate the meta-features all together, other non-technical factors weren't discussed.

[19] proposed Algorithm Selection Tool (AST) based on Case-Based Reasoning. Data Characterization Tool (DCT) developed by Guido Lindner and Robert Engels was used to computes data characteristics. All the dataset characteristics extracted were used as is. No study of the impact of different factors on the selection process was carried out.

[35] carried out a survey for meta-learning with land marking. The current studies and work related to Land marking in meta-learning were reviewed and presented. The survey didn't consider the other approaches used in meta-learning.

After reviewing the papers in the literature, the following limitations were found. None of the papers considered all the meta-features as well as the business/non-technical factors. The work was done to produce a classification algorithm recommendation tool used only a subset of the dataset meta-features. It was never mentioned explicitly on what basis was this subset selected.

3. FACTORS CATEGORIZATION

This section provides a categorization of the factors considered when selecting the appropriate classification algorithm as reported in the literature. The goal is simply to summarize and present current views.

The literature on classification algorithms and factors affecting the selection of the appropriate algorithm for the dataset at hand was conducted to give insights into how the data miners select an algorithm to use in classification tasks. The authors mentioned the factors used, others mentioned the relevant importance of these factors according to the conducted studies. The analysis of these factors allowed the induction of a categorization tree of factors that can be taken into account when selecting the most appropriate classification algorithm for a dataset.

After defining the data mining task, it's time to select the most appropriate algorithm for this task. This paper considers the classification task, and the factors affecting the choice of classification algorithms. Although many factors are common with other data mining tasks, the focus of this paper is the factors affecting algorithm selection for the classification task. There are several factors that can be considered when selecting an appropriate classification algorithm. Figure 1 shows a categorization of these factors, where each factor is described in details in upcoming sections.

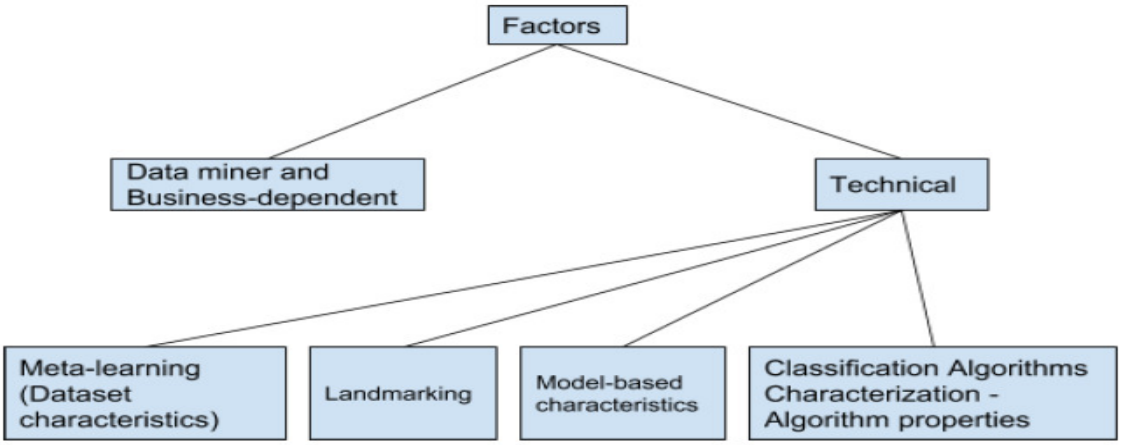

Figure 1. Factors categorization

Table 2. Categorization of factors affecting classification algorithms recommendation

Data miner and Business-dependent Factors	Data miner's proficiency in the business domain	
	Familiarity with an algorithm	
	Algorithm's ease of use and comprehensibility of the results	
Technical Factors	Dataset-dependent	Meta-learning
		Land marking
		Model-based meta-data
	Algorithm-dependent	Characterization of Classification Algorithms

4. DATA MINER AND BUSINESS-DEPENDENT FACTORS

These factors are not technical. These are the factors that depend on the business needs and the data miner experience in the business area of interest where classification is applied, e.g. banking industry.

4.1. Data miner's proficiency in the business domain

The proficiency in the business domain, along with familiarity with the business data and systems, play a critical role in the process of choosing the most appropriate algorithm that can achieve the business objectives. One of the main tasks in a data mining project is translating the business objectives into specific data mining goals. Thus, it requires proficiency in the business domain, so that there is awareness with the challenges that could arise ahead in the data mining process.

4.2. Familiarity with an algorithm

The expertise of data miner is very valuable. Choosing an algorithm that will solve the classification task is often challenging and needs a lot of research to be done in addition to studying the datasets metadata as well as the algorithm characteristics. Prior experience with a certain algorithm may influence the data miner's decision as it could make him/her biased towards the algorithm he/she is familiar with.

Data miners may embrace the algorithms they are conversant with though there is a possibility that the selected algorithms may not be the most appropriate for the task to be performed [5].

4.3. Algorithm's ease of use and comprehensibility of the results

There are two subjective evaluation criteria for a classification algorithm: the comprehensibility of the results and the ease-of-use of the algorithm to non-experienced data mining users [10]. An algorithm is considered as easy to use if it can be implemented quickly, relatively based on data miners experience with using the algorithm. Moreover, with regard to the algorithm configuration

parameter, finding out the best setting has high computational cost, so an easy to use algorithm is the one with good defaults or the one that requires fine tuning [10, 26].

The comprehensibility of the algorithm's results is also another very important factor. Some algorithms can produce more comprehensible results. Depending on the business, an algorithm result must be explained. For example, if-else rules are often considered more understandable than a neural network. Neural networks are generally viewed as powerful algorithms especially for classification tasks, but the interpretation of the results of the mathematical model that is used behind the scenes is difficult to comprehend than the other types of models [22, 50, 53]. In this case, the business context is the first decider in the choice of the algorithm. A business organization like a bank might disagree to use such an algorithm and could prefer decision trees over neural networks, despite the higher accuracy of neural networks. This is because decision trees result in a rule set that can be revisited and easily interpreted by decision makers in the business, but for neural networks, there are no universally accepted guidelines for its use or its complexity. [17, 45].

So, based on the interpretability of the algorithm results, data miners may select an algorithm that is close enough to result in the required classification results. [5, 31].

5. TECHNICAL FACTORS

There are different techniques for tackling the algorithm selection problem. Researchers depend on different technical factors to build an automated system that tackles the problem. These factors are directly related to the dataset characteristics or the classification algorithm parameters or characteristics.

5.1. Meta-learning

The most appropriate algorithm for modelling a particular dataset depends crucially on the metadata of that dataset [10]. Many studies were carried out considering classification algorithms performance with respect to datasets metadata [22, 31, 56]. The fact that dataset metadata and implementation details may influence the accuracy of an algorithm cannot be denied [22]. All dataset metadata examined so far during the implementation of classification recommendation systems were found to affect the success of classification algorithms rate significantly [5, 10].

Meta-learning exploits the datasets' characteristics. Different metadata are presented in meta-learning. These features are divided into several categories [18]. Researchers used meta-learning along with historical performance results of classification algorithms to select the most appropriate algorithm on the current dataset. The term meta-learning stems from the fact that the system tries to learn the function that maps metadata to classification algorithm performance estimates [15]. It is used to gain insight into the algorithm's behaviour with datasets with certain meta-characteristics. Meta-learning might significantly reduce the development time of a classification task by decreasing the required level of expertise for selecting a suitable classification algorithm for a given dataset [18]. and functional use of meta-learning is building a system that maps an input space consisting of datasets to an output model space consisting of classification algorithms [16]. Different evaluation criteria could be used to evaluate the systems built; mostly accuracy, computational complexity, robustness, scalability, integration, comprehensibility, stability, and interestingness [22]. Several approaches have been developed in this area and it was reported that, regardless of the approach used by the system to select the most appropriate algorithm, the selected algorithm, has high chances of good performance [26].

Meta-learning is not used only to tackle the algorithm selection problem, for example, the authors in [29] tried to resolve the main issue in Knowledge data discovery process, which is the support of data pre-processing. As any difference in the pre-processing techniques followed can affect the classification algorithm's accuracy or speed [22]. The system gives advice for Pre-processing based on datasets metadata extracted by DCT; Data characterization Tool. The research results showed interesting and helpful pre-processing can be defined that is based on the several test statistics that are calculated. The dataset metadata was used to give an indication of the complexity of the dataset. Other metadata measures indicated the dispersion of values the dataset variables can have.

Although a lot of attention was paid to data pre-processing importance, it can't replace the importance of classification algorithm selection problem. It was reported that the classification algorithm selection process is very important despite the data pre-processing [22]. The nature of dataset determines the most appropriate classification algorithm for it.

Depending on studies of meta-learning, multiple systems have been developed. By using meta-learning, classification algorithms can be accurately recommended as per the given data [8, 22]. Many different metadata have been proposed in the literature. This meta-data is obtained from different concepts, thus can be assorted into three main groups: simple, statistical, and information-theoretic [18]. The central idea is that high-quality metadata provide information to differentiate the performance of a set of classification algorithms [16].

There are different approaches to address the algorithm selection problem. Ofttimes, the selection method is not compared with the other methods [26]. Systems considered so far involved; 1- Case-based reasoning systems, the system has the ability to reason its selection by keeping track of how a problem is solved [25], along with knowledge about past problems. [19] is a case-based reasoning system supporting classification algorithm selection. 2- Classification or regression: algorithm selection task is a classification task that can be solved using a classification or regression algorithm to predict the most appropriate classification algorithm, using a dataset of historical datasets metadata along with classification algorithms portfolios.

For non-experts, it is recommended to use case-based reasoning systems for the algorithm selection problem,[26] due to its simplicity. Case-based reasoning algorithms achieve high performance in the algorithm selection task, with respect to the number of historical datasets considered.

Besides manual meta-feature selection, there is work on automatic feature selection for meta-learning [18]. Sometimes reducing the set of metadata increases the performance of a meta-learning system [32].

There is a need to develop an adaptive system which will be smart enough to select the most appropriate classification algorithm [8]. In [25] different approaches to exploit meta-learning to select the appropriate algorithm were discussed. [25] discussed a perspective view on how to exploit metadata and build a dynamic learner, that improve their bias dynamically through experience by piling up meta-knowledge. The interesting approach Dynamic-bias selection was discussed. Dynamic-bias is about considering using different subsets of metadata in the dataset meta-learning studies. Since the algorithm selection task is itself a classification task, so different feature selection approaches studies could be applied to metadata as well. In this case, the dataset used is a dataset of metadata about historical datasets, where each dataset is represented in one row, as an example/instance and each attribute represents a metadata measure.

[27] proposed a factor analysis for datasets with a large number of attributes so that the independence among the factors is ensured and the importance level can be measured and new factors can be discovered. Using the method proposed In this study, relevant datasets metadata can be selected based on necessary and sufficient conditions of significance and completeness.
Not only meta-learning that could affect the choice of an algorithm, recent experiments suggested that parameter tuning may affect the classification algorithm accuracy notably [8], but not all of the studies considered parameter tuning. On the same hand, some data pre-processing attempts can affect on the accuracy for some classification algorithms [22]. Keep in mind that the choice of an appropriate feature selection method depends on various dataset metadata; data types, data size and noise [28].

5.1.1. Dataset metadata: Simple, Statistical, Information theoretical

Simple metadata or general data characteristics are measurements which can be simply calculated i.e. extracted for the whole dataset i.e. obtained directly from the data [8]. Statistical metadata is mainly discriminant analysis and other measurements, which can only be computed on numerical attributes. Statistical metadata depicts the statistical properties of the data, e.g. kurtosis. Information theoretical, are metadata which can only be computed on categorical attributes. Although statistical metadata is originally developed for numerical attributes while information theoretical for numerical, both metadata types can be converted to each other, by discretization [18]. A collection of dataset metadata used in different studies is presented in Appendix B.

Statlog project [10], is a comparative study of different classification algorithms. The project tried to depict datasets as a meta-learning step towards creating if-then-else rules that identify under what circumstances which classification algorithm is feasible [6]. These results can be exploited to build models that specify when each algorithm is feasible. The results are strong hardcoded rules or guidelines to guide the algorithm selection process. The metadata considered by Statlog were simple and statistical. Statlog compared the performance of 23 algorithms from symbolic learning, statistics, and neural networks on 21 datasets for the classification task. In StatLog, most of the algorithms had a tuning parameter that was set to its default value, when feasible. Datasets were pre-processed, and the algorithms were evaluated based on the number of criteria. Three of the evaluation criteria were objectively measurable: accuracy, misclassification cost, and the time taken to produce results the other two were subjective: the comprehensibility of the results and the ease-of-use of the algorithm to users with relatively little or no experience. As concluded by Statlog, different learning methods are suitable for different problems. The guiding rules concluded by Statlog listed at [10], they were all dependent on the dataset metadata. The ruleset can be turned into a system of if-else and recommend an algorithm for a dataset accordingly.
The Data characteristics tool (DCT), is implemented in a software environment (Clementine) [9]. The DCT is widely used for calculating the three dataset metadata groups about a given data set. In [8], algorithm selection is proposed for classification tasks, by mapping the metadata of datasets extracted by DCT and the performance of classification algorithms. Then for a new dataset, metadata are again extracted using DCT and K-similar datasets are returned. Then ranking of classification algorithms is performed based on performance, and classification algorithm recommended for the problem at hand is based on the highest rank. The study was based on 11 simple metadata, 2 statistical and information theoretical. Results were generated using nine different classification algorithms on thirty-eight benchmark datasets from the UCI repository. The proposed approach used a K-nearest neighbour algorithm for suggesting the most appropriate algorithm. The experimentation showed that predicted accuracies for classification algorithms are matching with the actual accuracies for more than 90% of the benchmark datasets used. It was concluded that the number of attributes, the number of instances, number of classes, maximum probability of class and class entropy are the main metadata which affects the accuracy of the classification algorithm and the automatic selection process of it.

Another large-scale project that utilizes meta-learning is METAL [11]. METAL's main objective was enhancing the use of data mining tools and specifically to expand savings in the experimentation time [16]. The METAL project [13] focused on finding new and significant data characteristics. It used metadata of the datasets along with the classification algorithms to learn how they can be combined. The project resulted in the Data Mining Advisor (DMA) [12]. DMA is a web-enabled solution that supports users in algorithm selection by automatically selecting the most appropriate classification algorithms. It was developed as an implementation of a meta-learning approach. DMA provides recommendations for classification algorithms in the form of rankings. A list ordered from best to worst is produced. The list is sorted in consonance with a weighted combination of parameters as accuracy and time taken in training [16]. DMA uses the DCT and a k-Nearest Neighbor algorithm to rank ten target classifiers. The DMA presented two different evaluation approaches for the ranking of the classification algorithms; first technique makes use of the ratio of accuracy and training time and the other ranking technique is based on the concept of data envelopment analysis [14].

[18] performed an exhaustive evaluation of the three dataset metadata categories along with other factors for meta-learning using regression. The research was based on 54 datasets from the UCI machine learning repository and from StatLib. It was concluded that utilizing the dataset metadata for algorithm selection performs better than the baseline. [18] utilized the Pearson product-moment correlation coefficients, to automatically select highly correlated metadata from the metadata groups for the set of target classification algorithms. It was shown that the automatic feature selection selects the most useful metadata. This is one recent research area, utilizing automatic features selection techniques to select the most significant metadata measures.

DM assistant tool [7] and Algorithm Selection Tool, AST [19] use a case-based reasoning approach to support classification algorithm selection. AST benefits from data characteristics extracted by DCT and considered application restrictions for the algorithm selection process. AST gives the user recommendation which algorithm should be applied, along with an explanation for the recommendation in the form of past experiences available in the case base. A new algorithm can be added to the case base of AST easily without testing on all historical datasets. [19] considered the use of all of the three dataset metadata categories in building AST. The metadata was used to compute the most similar cases. All the classification algorithms of the case base were tested with their default parameters values, no fine tuning for the parameters. Also, AST had no preferences in the metadata extracted by DCT, they were all used with equal importance. The results were evaluated, overall the accuracy of ACT for the most appropriate algorithm of the first similar case is applicable in 79%. For datasets with only numerical attributes or with numerical and categorical attributes, the rate is over 85%. While datasets with only categorical attributes are less than 68%. This is an indicator that the metadata for the categorical attributes are still insufficient and those additional measurements are required. Fine tuning for the categorical attributes or selecting the most relevant ones could enhance the accuracy of AST for datasets with only categorical attributes. Some of the dataset metadata may be irrelevant, others may not be adequately represented, while some important ones may be missing [24].

DM assistant offers the users the most appropriate data mining techniques for the problem of interest. The system automatically extracts the most relevant metadata from a given dataset to find the most similar cases. Some of the metadata extracted by DM assistant are the number of classes, the entropy of the classes and the percent of the class mode category [7]. There were no specific details of the metadata extracted and used to measure the distance with historical datasets to find the most relevant.

In [21] the complexity of each dataset was measured by considering its metadata. The three metadata categories; simple, statistical, and information theoretic were considered for each dataset. A total of 21 metadata measures were calculated. Most of the metadata measures

described in [23]. The overall accuracy of the system in predicting the most appropriate classification algorithm is 77%. This makes confidence in the metadata measures used by [21] good enough to be used in other studies. [21] trained a neural network to predict a classification algorithm performance. Dataset metadata are fed as input to the neural network, and the output is a ranked list of techniques predicting their likely performance on the dataset. To model the classification algorithms performance, 57 datasets were used from the UCI machine learning repository, a total of 21 metadata measures that describe the characteristics of the data were calculated. And six classification algorithms were modelled.

The goal of [20] was to assist users in the process of selecting an appropriate classification algorithm without testing the huge array of classification algorithms available. [20] aimed to determine the dataset metadata that lends themselves to superior modelling by certain classification algorithms by introducing a rule-based classification approach (C5.0) for classification algorithm selection. Most of the generated rules are generated with a high confidence rating. The metadata of the datasets used in this study described in [21]. The metadata of each dataset was extracted and quantitatively measured, it was combined along with the empirical evaluation of classification algorithms performance, to generate the rules. The rules generated for all eight classification algorithms based on the classification performance of 100 datasets.

[24] presented a meta-learning approach to boost the process of selecting an appropriate classification algorithm. It used the k-Nearest Neighbor algorithm to detect the datasets that are closest to the dataset of interest. The research studied the importance of a relatively small set of dataset metadata, but it is believed that this small set of metadata provide information about properties that affect algorithm performance. Performance of the candidate classification algorithms on the datasets was used to recommend the most appropriate algorithm to the user in the form of ranking. The algorithm's performance is evaluated using a multicriteria evaluation measure that considers the accuracy and the training time. Results show, most of the metadata used were useful to select classification algorithms on the basis of accuracy. To avoid bias, the author recommended using feature selection methods at the meta-level to select the appropriate metadata for a given multicriteria setting. A visual analysis of the set of metadata was performed aiming to identify the measures that appear to provide less useful information. The visual analysis was done by analyzing the correlation between the values of a specific meta-attribute and each algorithm's performance. The research metadata used were simple, statistical and information-theoretical, described in details by [23].

[22] used metadata that represents a set of characteristics that affect the classification algorithms' performance. Regression models developed in this study that offer hints to data miners about the classification algorithm expected accuracy and speed based on dataset metadata. Moreover [22] studied the correlations between dataset metadata and accuracy and it was found that all these metadata can affect the classification algorithm performance, i.e. make a significant difference in the classification algorithms success rate. Criteria used in the classifiers evaluation are mostly accuracy, computational complexity, robustness, scalability, integration, comprehensibility, stability, and interestingness. Ten datasets collected from the UCI Machine Learning Repository were used to run the 14 classification algorithms. Datasets were preprocessed and all numeric attributes in the datasets were converted to categorical attributes by binning them into intervals within ±1 standard deviation and saved as new attributes. The results showed that some of the classification algorithms studied cannot handle continuous variables and dense dimensionality. Moreover [22] claimed that the metadata: the high number of variables and the high number of instances increase the classification task difficulty and impact the algorithm classification power. In summary, all dataset metadata were found to affect the success rate significantly.

[30] exploited DCT to extract metadata from datasets. The three metadata categories were considered. [30] proposed a Zoomed ranking technique. In the zooming phase, the k-Nearest Neighbor algorithm is employed with a distance function based on a set of dataset metadata to identify datasets from previously processed datasets, that are similar to the one at hand. These datasets performance information is expected to be relevant for the dataset at hand. In ranking phase, the adjusted ratio of ratios ranking method is used. The ranking is on the basis of the performance information (accuracy and total execution time) of the candidate algorithms on the datasets selected in zooming phase. [30] made no investigation on the metadata used, whether they are relevant or not. And, no investigation was made to determine if different weights should be assigned to them in the distance function. Metadata measures were chosen because they are provided by DCT and were used before for the same purpose. Although no statistical support, it was claimed that zooming improves the quality of the rankings generated, which gives an indication that the metadata used in the study is good enough to be used in other studies.

Although all of the studies discussed here made heavy use of metadata of datasets, and showed the different techniques necessary to build effective meta-learning systems, it is emphasized the importance of studying alternative meta-features in the characterization of datasets [16].

There are a lot of studies for the metadata extracted from the datasets. This unleashes two research questions, 1- should different dataset metadata be considered? 2- How good are the available feature selection techniques in selecting significant metadata.

5.2. Landmarking

Landmarking is a new and promising approach to extract metadata [35], that utilizes simple and fast computable classification algorithms [18]. Land marking attempts to determine the position of a specific dataset in the space of all available historical datasets by directly measuring the performance of some simple and significant classification algorithms themselves [25, 34, 35]. One idea of land marking is about characterizing datasets by classification algorithms themselves. Land marking features can be seen as dataset characteristics, where these characteristics represent the performance of some fast, simplified versions of classification algorithms on this dataset [15, 24]. These simplified versions of the algorithms are called landmarks [37]. This means that landmarks are estimates to the performance of the full version of the algorithms for a given dataset. There are some conditions that have to be satisfied when choosing a landmark, described in [37]. Based on some classification algorithm evaluation criteria, one algorithm is the winner over another for the dataset at hand.

Another idea of landmarking is to exploit information obtained on samples of datasets and the full version of the algorithm. Accuracy results on these samples serve to characterise the datasets and are referred to as sub-sampling landmarks. This information is subsequently used to select the most appropriate classification algorithm [16].

Experiments showed that landmarking selects with a mild and rational level of success, the best performing algorithm from a set of classification algorithms [34]. Experiments show that landmarking approach compares favourably with other meta-learning approaches [38]. It was reported that landmarking-features are well suited for meta-learning [37]. The landmarking features are acceptable and can be used to build systems for selecting the most appropriate classification algorithm for a dataset. Using landmarking features for predicting the most appropriate classification algorithm - out of pair and out of all available classification algorithms - has been evaluated by different researchers [18].

Although many research studies were done in the area of landmarking there are still many open challenges in this area that need additional experiments and research.

5.3. Model-based Metadata

Model-based metadata is a decision tree model -without pruning- different properties, created from the dataset [18,35]. Examples of decision tree model properties are number of leaves, number of nodes, nodes per attribute, nodes per sample and leaf correlation [35]. The hypothesis is that the decision tree model induced from datasets owns the characteristics that are highly dependent upon the dataset. There is a number of important connections between dataset characteristics and induced trees, the properties of the induced tree model are mapped to data characteristics in [39].

In this approach, instead of using classification algorithms' performances to describe datasets, as in landmarking, or metadata measures of datasets, as in the traditional approach algorithm's hypotheses were used [39].

5.4. Characterization of Classification Algorithms

There are many classification algorithms available in the literature, all of them need one or more predictors or attributes to portion the data, and a target to predict. Because classification algorithms have different characteristics, this allowed grouping them according to their characteristics, many studies were conducted to compare the classification algorithms in terms of performance; Accuracy, Complexity, and Training Time [22, 31, 43, 45, 47, 56]. Studies also revealed how feature selection could improve the classification ability of classification algorithms [28, 44]. Studies considered combination/ensemble of the models of several algorithms as it usually has a positive effect on the overall quality of predictions, in terms of accuracy, generalisability and/or lower misclassification costs [42, 44, 53] For instance, random forest, is ensemble algorithm, and it is known as one of the accurate classification algorithms [43].

Although algorithms within the same group, share many characteristics like how new instances are scored, differ in the other characteristics. Each group has its strengths and weaknesses [10, 42, 43]. The classification algorithms were mainly grouped into 3 different groups [10, 31]; symbolic algorithms (Trees and rules), statistical algorithms and neural networks. A brief description of categories of classification algorithms is presented in Appendix A.

5.4.1. Predictors fields and target field(s) types

Some classification algorithms can be used with categorical and continuous predictors while others can be used with categorical only [41]. Also, some algorithms are more appropriate than others when it comes to the predicted field, or the target, as some are able to classify only categorical targets. Neural networks, for example, can handle any predictor and target. So, this is a decision making factor, in the process of algorithm selection problem.

5.4.2. How are missing data handled

Missing values are a common occurrence in datasets, and handing these missing values needs a strategy to be followed. As a missing value can have different meanings in the dataset. Classification algorithms treat missing values differently. Some algorithms cannot process missing values in the dataset whereas others can. Commonly, algorithms ignore the missing values, or discard any raw in the dataset containing missing values, or substitute the missing values with the mean if the attribute is continuous, or deduce missing values from existing values.

Handling these missed values is a very important subtask in data preprocessing phase [10, 31, 41, 55]. That is one reason, why the ratio of missing values is always importantly considered as a significant statistical metadata measure of the dataset and considered in many pieces of research [19, 20, 21, 24, 30, 37].

Algorithms handle missing data differently, ways of handling missing attribute described in [54]. Some algorithms just ignore it, others consider it as a new value of the attribute, another handling procedure is to replace them with the most frequent value or the mean [10, 43, 54].

5.4.3. Model Assumptions

A potential problem with different algorithms is that each has one or more assumption [52]. One assumption is the normality assumption [10, 29, 52]. Other examples of model assumptions are the sample size for neural networks [10, 17, 52]. Linearity between dependent and independent variables and the multivariate normal distribution of the independent variable is other assumptions by different classification algorithms groups [10, 52]. The performance of a classification algorithm compared to other candidates depends on the dataset characteristics and how well these characteristics comply with the assumptions made by the classification algorithm [18].

6. CONCLUSIONS

The study of different factors considered when selecting the most appropriate classification algorithm for a dataset showed that the resulted model is sensitive to changes in data characteristics and classification algorithm characteristics. Considering the proposed factors helps data miners recommend an appropriate classification algorithm and build classification algorithms recommendation systems. Generally, more than one factor should be considered to recommend the most appropriate classification algorithm for a dataset.

It was shown that different classification algorithm recommendation systems considered meta-learning, where metadata of the dataset is extracted and studied so that the recommendation system can use the extracted metadata to select the most appropriate algorithm [8, 9, 11, 12, 22]. It was also shown that these metadata can be categorized into simple, statistical and information theoretic [18].

Due to the importance of the stage of selecting the most appropriate classification algorithm in data mining - as it defines the type of results that will be produced, which will later influence the subsequent decisions- different paths were considered to facilitate the classification algorithm recommendation process. It was shown here, landmarking and model-based metadata.

Landmarking exploits simple and fast computable classification algorithms to determine the position of a specific dataset in the space of all available historical datasets by directly measuring the performance of some simple and significant classification algorithms themselves. On the other hand, the model-based metadata utilizes decision tree model -without pruning- different properties. The hypothesis is that the decision tree model induced from datasets owns the characteristics that are highly dependent upon the dataset.

Experiments showed that landmarking approach compares favourably with other meta-learning approaches, but there are many open challenges for further research in the area of landmarking and model-based metadata.

It was also emphasized the characteristics of classification algorithms that can be measured and used as factors to recommend the most appropriate classification algorithm for a dataset.
The main conclusion is that: there is no single factor or group of factors that can be used alone to recommend a classification algorithm for a dataset. Although most of the studies for studying these factors depends crucially on metadata of the datasets. It was shown that there are other paths that can be considered as well in recommending a classification algorithm for a dataset.
In future work, the factors used to recommend the most appropriate classification algorithm for the dataset at hand have to be refined. The main point is to prioritize the metadata extracted for meta-learning, according to their significance.

APPENDIX A: CLASSIFICATION ALGORITHMS CATEGORIES

A.1. Symbolic algorithms

They produce a set of rules that divide the inputs into smaller decisions in relation to the target. Algorithms that produce a tree belong to this group as trees can be turned into a set of rules easily. Symbolic algorithms are very easy to implement, interpret, and represent a good compromise between simplicity and complexity [40, 43, 46]. A lot of studies carried out to describe, review and compare these algorithms [10, 31, 41, 42, 45]. It was reported that symbolic algorithms are a good choice for maximizing classification accuracy if the dataset metadata shows that the data has extreme distribution [10, 45]. On the other hand, they become poor choices if misclassification cost should be minimized, or the dataset has equally important numerical attributes [10]. Studies were also conducted to compare among available symbolic algorithms and evaluate its performance, in terms of the tree size and complexity and training time, for instance [31].

A.2. Statistical algorithms

The resulted model of a statistical algorithm is expressed by an equation, and statistical tests can lead field selection in the model. Statistical algorithms assume certain distributions in the data, which makes them more harder than symbolic algorithms but still less difficult than neural networks. Because using statistics science with data allows analysis and interpretation of the data, there are many classification algorithms based on statistics and tremendous quantities of research for statistical algorithms [51].

A.3. Neural networks

Neural networks consider the human brain as their modelling tool [22]. Neural networks are used to perform nonlinear statistical modelling, as they have the ability to detect complex nonlinear relationships between dependent and independent attributes in the data [50]. There are multiple training algorithms for neural networks that have been studied and presented, showing how they work [17, 25, 48, 49] They don’t produce rules or equations.

Lately, a lot of emphases has been placed on neural networks, because of it powerfulness in prediction [44, 47, 50]. The accuracy of neural network classifications was found to be significantly influenced by the size of the training set, discriminating variables and the nature of the testing set used [17, 50]. Although its reported robustness, high adaptability and accuracy, neural networks algorithms require large machine resources [10]. Also, neural networks are prone to overfitting. With overfitting, the error on the training set is driven to a very small value, thus the model won’t be able to generalize well to new data [5].

APPENDIX B: COLLECTION OF DATASET METADATA USED IN DIFFERENT STUDIES

Simple meta-features: number of samples, number of classes, number of attributes, number of nominal attributes, number of numerical attributes, the ratio of nominal attributes, the ratio of numerical attributes, dimensionality (number of attributes divided by the number of samples).
Statistical meta-features: kurtosis, skewness, canonical discriminant correlation (cancor1), first normalized eigenvalues of the canonical discriminant matrix (fract1), absolute correlation.
Information-theoretic meta-features: normalized class entropy, normalized attribute entropy, joint entropy, mutual information, noise-signal-ratio, the equivalent number of attributes.

REFERENCES

[1] Shafique, Umair & Qaiser, Haseeb. (2014). A Comparative Study of Data Mining Process Models (KDD, CRISP-DM and SEMMA). International Journal of Innovation and Scientific Research. 12. 2351-8014.
[2] Rice, J. R. (1976). The algorithm selection problem. Advances in Computers. 15. 65–118.
[3] Wolpert, David & Macready, William G. (1997). No free lunch theorems for optimization. IEEE Transac. Evolutionary Computation. 1. 67-82.
[4] Soares, C. & Petrak, J. & Brazdil, P. (2001) Sampling-Based Relative Landmarks: Systematically Test-Driving Algorithms before Choosing. In: Brazdil P., Jorge A. (eds) Progress in Artificial Intelligence. EPIA 2001. Lecture Notes in Computer Science. 2258.
[5] Chikohora, Teressa. (2014). A Study Of The Factors Considered When Choosing An Appropriate Data Mining Algorithm. International Journal of Soft Computing and Engineering. 4. 42-45.
[6] Michie, D. & Spiegelhalter, D.J. & Taylor, C.C. (1994). Machine Learning, Neural and Statistical Classification, Ellis Horwood, New York.
[7] Gibert, Karina & Sànchez-Marrè, Miquel & Codina, Víctor. (2018). Choosing the Right Data Mining Technique: Classification of Methods and Intelligent Recommendation.
[8] N. Pise & P. Kulkarni. (2016). Algorithm selection for classification problems. SAI Computing Conference (SAI). 203-211.
[9] Peng, Yonghong & Flach, Peter & Soares, Carlos & Brazdil, Pavel. (2002). Improved Dataset Characterisation for Meta-learning. Discovery Science Lecture Notes in Computer Science. 2534. 141-152.
[10] King, R. D. & Feng, C. & Sutherland, A. (1995). StatLog: comparison of classification algorithms on large real-world problems. Applied Artificial Intelligence. 9. 289-333.
[11] Esprit project Metal. (1999-2002). A Meta-Learning Assistant for Providing User Support in Machine Learning and Data Mining. Http://www.ofai.at/research/impml/metal/.
[12] Giraud-Carrier, C. (2005). The data mining advisor: meta-learning at the service of practitioners. Machine Learning and Applications. 4. 7.
[13] Giraud-Carrier, Christophe. (2008). Meta-learning tutorial. Technical report, Brigham Young University.
[14] Paterson, Iain & Keller, Jorg. (2000). Evaluation of Machine-Learning Algorithm Ranking Advisors.
[15] Leite, R. & Brazdil, P. & Vanschoren, J. (2012). Selecting Classification Algorithms with Active Testing. Machine Learning and Data Mining in Pattern Recognition. 7376. 117-131.
[16] Vilalta, Ricardo & Giraud-Carrier, Christophe & Brazdil, Pavel & Soares, Carlos. (2004). Using Meta-Learning to Support Data Mining. International Journal of Computer Science & Applications. 1.
[17] Foody, G. M. & Arora, M. K. (1997). An evaluation of some factors affecting the accuracy of classification by an artificial neural network. International Journal of Remote Sensing. 18. 799-810.
[18] Reif, M. & Shafait, F. & Goldstein, M. & Breuel, T.M.& Dengel, A. (2012). Automatic classifier selection for non-experts. Pattern Analysis and Applications. 17. 83-96.
[19] Lindner, Guido & Ag, Daimlerchrysler & Studer, Rudi. (1999). AST: Support for algorithm selection with a CBR approach. Lecture Notes in Computer Science. 1704.
[20] Ali, Shawkat & Smith-Miles, Kate. (2006). On learning algorithm selection for classification. Applied Soft Computing. 6. 119-138.

[21] Smith, K.A. & Woo, F. & Ciesielski, V. & Ibrahim, R. (2001). Modelling the relationship between problem characteristics and data mining algorithm performance using neural networks. Smart Engineering System Design: Neural Networks, Fuzzy Logic, Evolutionary Programming, Data Mining, and Complex Systems. 11. 357–362.

[22] Dogan, N. & Tanrikulu, Z. (2013). A comparative analysis of classification algorithms in data mining for accuracy, speed and robustness. Information Technology Management. 14. 105-124.

[23] Henery, R. J. Methods for Comparison. Machine Learning, Neural and Statistical Classification, Ellis Horwood Limited, Chapter 7, 1994.

[24] Brazdil, P.B.& Soares, C. & da Costa. (2003). Ranking Learning Algorithms: Using IBL and Meta-Learning on Accuracy and Time Results. J.P. Machine Learning. 50. 251-277.

[25] Vilalta, R. & Drissi, Y. (2002). A Perspective View and Survey of Meta-Learning. Artificial Intelligence Review. 18. 77-95.

[26] Kotthoff, Lars & Gent, Ian P. & Miguel, Ian. (2012). An Evaluation of Machine Learning in Algorithm Selection for Search Problems. AI Communications - The Symposium on Combinatorial Search. 25. 257-270.

[27] WANG, HSlAO-FAN & KUO, CHINC-YI. (2004). Factor Analysis in Data Mining. Computers and Mathematics with Applications. 48. 1765-1778.

[28] Dash, M. & Liu, H. (1997). Feature Selection for Classification. Intelligent Data Analysis. 1. 131-156.

[29] Engels, Robert & Theusinger, Christiane. (1998). Using a Data Metric for Preprocessing Advice for Data Mining Applications. European Conference on Artificial Intelligence. 430-434.

[30] Soares C. & Brazdil P.B. (2000). Zoomed Ranking: Selection of Classification Algorithms Based on Relevant Performance Information. Principles of Data Mining and Knowledge Discovery. 1910.

[31] Lim, TS. & Loh, WY. & Shih, YS. (2000). A Comparison of Prediction Accuracy, Complexity, and Training Time of Thirty-Three Old and New Classification Algorithms. Machine Learning. 40. 203-228.

[32] Todorovski, L. & Brazdil, P. & Soares, C. (2000). Report on the experiments with feature selection in meta-level learning. Data Mining, Decision Support, Meta-Learning and ILP. 27–39.

[33] Kalousis, A. & Hilario, M. (2001). Feature selection for meta-learning. Advances in Knowledge Discovery and Data Mining. 2035. 222–233.

[34] Pfahringer, Bernhard & Bensusan, Hilan & Giraud-Carrier, Christophe. (2000). Meta-learning by Landmarking Various Learning Algorithms. International Conference on Machine Learning. 7. 743-750.

[35] Balte, A., & Pise, N.N. (2014). Meta-Learning With Landmarking: A Survey. International Journal of Computer Applications. 105. 47-51.

[37] Daniel Abdelmessih, Sarah & Shafait, Faisal & Reif, Matthias & Goldstein, Markus. (2010). Landmarking for Meta-Learning using RapidMiner. RapidMiner Community Meeting and Conference.

[38] Bensusan H., Giraud-Carrier C. (2000). Discovering Task Neighbourhoods through Landmark Learning Performances. Principles of Data Mining and Knowledge Discovery. 1910. 325-330.

[39] Bensusan, Hilan & Giraud-Carrier, Christophe & J. Kennedy, Claire. (2000). A Higher-order Approach to Meta-learning. Meta-Learning: Building Automatic Advice Strategies for Model Selection and Method Combination. 109-117.

[40] Podgorelec, Vili & Kokol, Peter & Stiglic, Bruno & Rozman, Ivan. (2002). Decision Trees: An Overview and Their Use in Medicine. Journal of medical systems. 26. 445-63.

[41] M. AlMana, Amal & Aksoy, Mehmet. (2014). An Overview of Inductive Learning Algorithms. International Journal of Computer Applications. 88. 20-28.

[42] Behera, Rabi & Das, Kajaree. (2017). A Survey on Machine Learning: Concept, Algorithms and Applications. International Journal of Innovative Research in Computer and Communication Engineering. 2. 1301-1309.

[43] Ponmani, S. & Samuel, Roxanna & VidhuPriya, P. (2017). Classification Algorithms in Data Mining – A Survey. International Journal of Advanced Research in Computer Engineering & Technology. 6.

[44] Aggarwal C.C., Zhai C. (2012). A Survey of Text Classification Algorithms. Mining Text Data. 163-222.

[45] Bhuvana, I. & Yamini, C. (2015). Survey on Classification Algorithms for Data Mining:(Comparison and Evaluation). Journal of Advance Research in Science and Engineering. 4. 124-134.

[46] Mathur, Robin & Rathee, Anju. (2013). Survey on Decision Tree classification algorithms for the Evaluation of Student Performance.

[47] Abd AL-Nabi, Delveen Luqman & Ahmed, Shereen Shukri. (2013). Survey on Classification Algorithms for Data Mining:(Comparison and Evaluation). Computer Engineering and Intelligent Systems. 4. 18-24.
[48] Schmidhuber, Juergen. (2014). Deep Learning in Neural Networks: An Overview. Neural Networks. 61.
[49] Kotsiantis, Sotiris. (2007). Supervised Machine Learning: A Review of Classification Techniques. Informatica (Ljubljana). 31.
[50] Tu, Jack V. (1996). Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. Journal of Clinical Epidemiology. 49. 1225-1231.
[51] Bousquet O., Boucheron S., Lugosi G. (2004). Introduction to Statistical Learning Theory. Advanced Lectures on Machine Learning. 3176. 169-207.
[52] Kiang, Melody Y. (2003). A comparative assessment of classification methods. Decision Support Systems. 35. 441-454.
[53] Gama, João & Brazdil, Pavel. (2000). Characterization of Classification Algorithms.
[54] P. Nancy & R. Geetha Ramani. (2011). A Comparison on Performance of Data Mining Algorithms in Classification of Social Network Data. International Journal of Computer Applications. 32. 47-54.
[55] Soroush Rohanizadeh, Seyyed & Moghadam, M. (2018). A Proposed Data Mining Methodology and its Application to Industrial Procedures.
[56] Brazdil P. & Gama J. & Henery B. (1994). Characterizing the applicability of classification algorithms using meta-level learning. Machine Learning. 784. 83-102.

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