ABSTRACT

The exponential growth of volume, variety and velocity of data is raising the need for investigations of automated or semi-automated ways to extract useful patterns from the data. It requires deep expert knowledge and extensive computational resources to find the most appropriate mapping of learning methods for a given problem. It becomes a challenge in the presence of numerous configurations of learning algorithms on massive amounts of data. So there is a need for an intelligent recommendation engine that can advise what is the best learning algorithm for a dataset. The techniques that are commonly used by experts are based on a trial and error approach evaluating and comparing a number of possible solutions against each other, using their prior experience on a specific domain, etc. The trial and error approach combined with the expert’s prior knowledge, though computationally and time expensive, have been often shown to work for stationary problems where the processing is usually performed off-line. However, this approach would not normally be feasible to apply to non-stationary problems where streams of data are continuously arriving. Furthermore, in a non-stationary environment, the manual analysis of data and testing of various methods whenever there is a change in the underlying data distribution would be very difficult or simply infeasible. In that scenario and within an on-line predictive system, there are several tasks where Meta-learning can be used to effectively facilitate best recommendations including 1) pre-processing steps, 2) learning algorithms or their combination, 3) adaptivity mechanisms and their parameters, 4) recurring concept extraction, and 5) concept drift detection. However, while conceptually very attractive and promising, the Meta-learning leads to several challenges with the appropriate representation of the problem at a meta-level being one of the key ones.

The goal of this review and our research is, therefore, to investigate Meta-learning in general and the associated challenges in the context of automating the building, deployment and adaptation of multi-level and multi-component predictive system that evolves over time.

Keywords  Adaptive Mechanisms · Domain Adaption · Meta-features · Meta-knowledge · Meta-learning · Transfer Learning

1 Introduction

One of the major challenges in Machine Learning (ML) is to predict when one algorithm is more appropriate than another to solve a learning problem [1]. Traditionally, estimating the performance of algorithms has involved an intensive trial-and-error process which often demands massive execution time and memory together with the advice of experts that are not always easy to acquire [2]. Meta-level Learning (MLL) has been identified as a potential solution to this problem [3]. It uses examples from various domains to produce a model, known as a Meta-learner, which is responsible for associating the characteristics of a problem with the most appropriate candidate algorithms found to have worked best on previously solved similar problems. The knowledge which is used by a Meta-learner is acquired
While there has been a lot of interest in MLL approaches and significant progress has been made, there are a number of outstanding issues that will be explained and some of which will be addressed. The main challenge of this work is research on MLL strategies and approaches in the context of adaptive multi-level, multi-component predictive systems. This problem leads to several research challenges and questions which are discussed in detail in Section 3.

Extracting MFs from a dataset plays a vital role in the MLL task. Several MF generation approaches are available to extract a variety of information from previously solved problems. The most commonly used approaches are descriptive (or simple), statistical, information-theoretic, landmarking and model-based. The Descriptive, Statistical and Information-Theoretic (DSIT) features are easy to extract from the dataset as compared to the other approaches. Most of them have been proposed in the same period of time and are often used together in most of the studies. These approaches are used to assess the similarity of a new dataset to previously analysed datasets. Landmarking is the most recent approach that tries to relate the performance of candidate algorithms to the performance obtained by simpler and computationally more efficient learners. The Model-based approach attempts to capture the characteristics of a problem from the structural shape and size of a model induced from the dataset. The decision tree models are mostly used in this approach, where properties are extracted from the tree, such as tree depth, shape, nodes per feature, etc.

The MF extraction approaches listed above are used in several implementations of decision-support systems for algorithm selection. One of the initial studies to address the practice of MLL was the Machine Learning Toolbox (MLT) project by[13]. The project was a kind of expert system for algorithm selection which gathered user inputs through a set of questions about the data, the domain and user preferences. Although its knowledge-base was built through expert-driven knowledge engineering rather than via MLL, it still stood out as the first automatic tool that systematically relates application domain and dataset characteristics. In the same period, [14] contributed with statistical and information-theoretic measures based approach for classification tasks, known as Statistical and Logical learning (StatLog). A large number of MFs were used in StatLog together with a broad class of candidate models for the algorithm selection task. The project produced a thorough empirical analysis of various classifiers and learning models using different performance measures. StatLog was followed by various other implementations with some refinement in MF set, input datasets, Base-level Learning (BLL) and MLL algorithms. An EU funded research project Meta-Learning Assistant (METAL) had a key objective to facilitate a selection of the best-suited classification algorithm for a data-mining task. [15] METAL introduced new relevant MFs and ranked various classifiers using statistical and information-theoretic approaches. A ranking mechanism was also proposed by exploiting the ratio of accuracy and training time. An agent-based architecture for distributed Data Mining, Meta-learning Architecture (METALA) was proposed in [16]. Its aim was the automatic selection of an algorithm that performs best from a pool of available algorithms by automatically carrying out experiments with each learner and task to induce a Meta-model for algorithm selection. The Intelligent Discovery Assistant (IDA) provided a knowledge discovery ontology that defined the existing techniques and their properties. IDA used three algorithmic steps of the knowledge discovery process, which included: 1) pre-processing, 2) data modelling, and 3) post-processing. It generated all valid processes and then a heuristic ranker could be applied to compute user-specified goals which were initially gathered as input. Later, [18] research focused on extending IDA approach by leveraging the interaction between ontology to extract deep knowledge and case-based reasoning for MLL. One of the recent contributions to MLL practice was made by [19] under Pattern Recognition Engineering (PaREn) project. A Landmarking operator was one of the outcomes of this project which was later embedded in RapidMiner. These systems are described in more detail in Section 2.5.
1.1 The review context and the INFER project summary

The research described in this report is closely related to and was conducted within the framework of the recently completed INFER project. INFER stands for Computational Intelligence Platform for Evolving and Robust Predictive Systems and was a project funded by the European Commission within the Marie Curie Industry-Academia Partnerships & Pathways (IAPP) programme with a runtime from July 2010 until June 2014.

INFER project’s research programme and partnership focused on pervasively adaptive software systems for the development of an open, modular software platform for predictive modelling applicable in different industries and a next generation of adaptive soft sensors for on-line prediction, monitoring and control in the process industry.

The main project goals were achieved by pursuing the following objectives within three overlapping research and partnership programme areas:

1. Computational Intelligence – Objective 1: Research and development of advanced mechanisms for adaptation, increased robustness and complexity management of highly flexible, multi-component, multi-level evolving predictive systems.
2. Software Engineering – Objective 2: Development of professionally coded INFER software platform for robust predictive systems building and intelligent data analysis.
3. Process Industry/Control Engineering – Objective 3: Development of self-adapting and monitoring soft sensors for the process industry.

When the project was starting in 2010, there were several freely accessible general-purpose data mining and intelligent data analysis software packages and libraries on the market which could be used to develop predictive models, but one of their main drawbacks was that advanced knowledge of how to select and configure available algorithms was required. A number of commercial data mining/predictive modelling software packages were also available. These tools attempted to automate some steps of the modelling process (e.g., data pre-processing, handling of missing values or even model complexity selection) thus reducing the required expertise of the user. Most of them were however either front-ends for a single data mining/machine learning technique or they were specialised tools designed specifically for use by a single industry. All these tools had one thing in common – generated models were static and the lack of full adaptability implied the need for their periodic manual tuning or redesign.

The main innovation of the INFER project was therefore the creation and investigation of a novel type of environment in which the ‘fittest’ predictive model for whatever purpose would emerge – either autonomously or by user high-level goal-related assistance and feedback. In this environment, the development of predictive systems would be supported by a variety of automation mechanisms, which would take away as much of the model development burden from the user as possible. Once applied, the predictive system should be able to exploit any available feedback for its performance monitoring and adaptation.

There were (and still are) a lot of fundamental research questions related to the automation of data-driven predictive models building, ensuring their robust behaviour and development of integrated adaptive/learning algorithms and approaches working on different time scales from real-time adaptation to life long learning and optimisation. All of these questions provided the main thrust of advanced research conducted in the project and resulted in contributions to a large number (over 70) of high impact publications in top journals and international conferences. While all of the papers can be accessed via the project website (http://www.infer.eu) some of the key ones related to this review are listed below for easy access and reference. We split the publications using a set of distinct areas of interest and investigation and combine both the older ones which led to the conception of the project in the first place and some which resulted from running the project. These are: i. complex adaptive systems and architectures ([20, 21, 22, 23]); ii. classifier and predictor ensembles ([24, 25, 26, 27, 28, 29, 30, 31]); iii. multi-level and multi-component predictors ([24, 32, 33, 34, 35, 36, 37, 38]); iv. meta-learning ([39, 40, 41, 42, 43, 44, 45, 46]); v. learning and adaptation in changing environments ([41, 42, 43, 44, 45, 46]); vi. representative data sampling and predictive model evaluation ([47, 48, 49]); vii. adaptive soft sensors ([50, 51, 52, 53, 54, 55, 56, 57, 42, 58]) and viii. other application areas ([59, 60, 61, 62]).

A variety of application areas and contexts have been used to illustrate the performance of developed models and/or to understand the mechanisms governing their behaviour. One of the key applications considered and tackled was that of adaptive soft sensors needed in the process industry.

The INFER software platform, developed with the creation of highly flexible, multi-component, multi-level evolving predictive systems in mind, supports parallel training, validation and execution of multiple predictive models, with each of them potentially being in a different state. Moreover, various optimization tasks can also be run in the background, 

\[\text{http://infer.eu/}\]
taking advantage of idle computational resources. The predictive models running within the INFER platform are inherently adaptive. This means that they constantly evolve towards more optimal solutions as new data arrives. The importance of this feature stems from the fact, that real data is seldom stationary – it often undergoes various changes, which affect the relationships between inputs and outputs, rendering fixed predictive models unusable. A distinguishing feature of the INFER software is an intelligent automation of the predictive model building process, allowing non-experts to create well-performing and robust predictive systems with minimal effort. At the same time, the system offers full flexibility for the expert users in terms of the choice, parameterisation and operation of the predictive methods as well as efficient integration of domain knowledge. While there is still a substantial development effort required before a viable commercial software product could be delivered the strong foundations have been created and it is our intention to build on them in the future.

More information on the INFER project and its outcomes can be found following the link in the footnote.

The rest of the report is structured as follows. The next chapter covers the existing research in MLL area, including some important components of an MLL system. Those components include 1. the sources of existing and ways of automatic generation of datasets, 2. Meta-feature generation and selection using various approaches, and 3. base-level learning algorithms performance measures, such as accuracy, execution time, etc. This is followed by sections discussing existing Meta-learning systems in the context of their applicability to the supervised and unsupervised algorithms. The last section of Section 2 illustrates the adaptive mechanism aspect in detail. Based on the conclusions and recommendations extracted from the literature review, Section 3 describes the research challenges of this work in the context of multi-component and multi-level adaptive systems. And finally, the summary is provided in Section 4.

2 Existing Research

A lot of research has been conducted on automating ML algorithm selection in the last three decades. The focus of many of those studies is on various components of MLL. Because of our particular interest in MLL, the scope of this literature review is confined to areas that are directly related to the MLL research. The high-level overview of the components which are discussed in this chapter is shown in Figure 1. The first section is discussing ways of gathering real-world datasets and techniques to create synthetic datasets which are known as EoD. These EoD are used to generate MFs and associated performance measures which are discussed in Sections 2.2 and 2.3 respectively. MF are combined with performance measures to build MK dataset which becomes the input of MLL. The last section illustrates adaptive mechanisms in the context of MLL which are an important aspect of our research focus.

![Figure 1: Scope of existing research review](http://infer.eu/)

2.1 Repository of Datasets

A repository of datasets representing various problems is one of the key components of the entire MLL system. As [9] states, there is no lack of experiments being done, but the datasets and information obtained often remain in the people’s heads and labs. This section explores the sources of real-world datasets that are used in the existing studies to build MK database. However, real-world datasets are usually hard to obtain but artificially generated datasets would be
a possible solution to this problem. In the following subsections, studies that are dealing with the real-world data, those which elaborate the techniques to generate artificial datasets, and published resources are discussed.

2.1.1 Real-world Datasets

The real-world datasets can be difficult to find and gather in the desired format. An effort has been made to extract useful sources of data from various studies. Table 1 presents datasets that are used in different researches for MLL purpose. Most of them are gathered from UCI Machine Learning Repository (UCI) [63].

Table 1: Real-world datasets used in various studies

| Research Work | Datasets | Sources | Dataset Filters |
|---------------|----------|---------|-----------------|
| [14]          | 12       | Satellite image, Hand written digits, Karhunen-Loeve digits, Vehicle silhouettes, Segment data, Credit risk, Belgian data, Shuttle control, Diabetes, Heart disease, German credit, Head injury | - |
| [65]          | 80       | UCI and DaimlerChrysler | - |
| [66]          | 19       | Satellite image, Hand written digits, Karhunen-Loeve digits, Vehicle silhouettes, Segment data, Credit risk, Belgian data, Shuttle control, Diabetes, Heart disease, German credit, Head injury and 7 other datasets used in StatLog project | Three datasets of StatLog having cost information involved in misclassification |
| [15]          | 58       | METAL project datasets | - |
| [67]          | 45       | UCI and DaimlerChrysler | 38 datasets with no missing values |
| [17]          | 15       | METAL project datasets | Dataset with more than 1000 instances |
| [68]          | 65       | UCI and METAL project datasets | - |
| [69]          | 53       | UCI and DaimlerChrysler | 38 datasets with no missing values |
| [18]          | 23       | UCI and METAL project datasets | Datasets with more than 100 instances |
| [12]          | 47       | UCI | - |
| [70]          | 78       | UCI | - |
| [71]          | I: 99 Time-series Data Library and II: M3 competition | I: Stationary data and II: Yearly data |
| [72]          | 50       | WEKA project | On average datasets contain 4,392 instances and 14 features |
| [73]          | 46 and 5 Time Series Data-mining Archive and Time Series Data Library | - |
| [22]          | 3        | Thermal oxidiser, Industry drier, and Catalyst activation datasets of process industry | On-line prediction datasets |

http://datamarket.com/data/list/?q=provider:tsdl
http://forecasters.org/resources/time-series-data/m3-competition
Machine Learning Group at University of Waikato http://www.cs.waikato.ac.nz/ml/weka
http://www.cs.ucr.edu/~eamonn/time_series_data
http://datamarket.com/data/list/?q=provider:tsdl
NN3 consisting of 111 TSS monthly business with 52-126 observations and NN4 daily cash machine withdrawals with 735 observations in each series NN5 including some missing values

Datasets with more than 100 instances 

Leukemia, Heart, Wisconsin, Spam, and Ionosphere are real-world datasets gathered from UCI and two synthetic datasets parity and monks

Travel Time Prediction (TTP) consists of 24,975 instances and Electricity Demand Prediction (EDP) consists of 27,888 instances

 wrote a concise handbook that covers the most useful sources of publicly available datasets. A lot of new sources of free and publicly available data that have emerged over the last few years are discussed. Apart from discussing data-sources, methods to get datasets in bulk from those sources are also discussed in detail. Table 2 presents most of the sources from the author’s book.

| Source                      | Description                                                                                                                                                                                                 | Datasets | Industry                                   |
|-----------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|--------------------------------------------|
| AnalcatData                 | Datasets that are used by Jeffrey S. Simonoff in his book *Analyzing Categorical Data*, published in July 2003                                                                                                  | 83       | Cross-industry                             |
| Amazon Web Services         | A centralized repository of public datasets                                                                                                                                                                  | -        | Astronomy, Biology, Chemistry, Climate, Economics, Geographic and Mathematics |
| Bioassay data               | Virtual screening of bioassay (active/inactive compounds) data by Amanda Schierz                                                                                                                                 | 21       | Life Sciences                              |
| Canada Open Data            | Canadian government and geospatial data                                                                                                                                                                        | -        | Government & Geospatial                    |
| Datacatalogs data.gov.uk   | List of the most comprehensive open data catalogs                                                                                                                                                            | -        | Government and Public Sector               |
| data.london.gov.uk          | Data of UK central government departments, other public sector bodies and local authorities                                                                                                                   | 9616     | Government and Public sector               |
| Data.gov/Education          | Educational high-value datasets                                                                                                                                                                             | 563      | Cross-industry                             |
| ELENA                       | Non-stationary streaming data of flight arrival and departure details for all the commercial flights within the USA                                                                                           | 70,897   |Aviation                                    |
| KDD Cup                     | Annual Data Mining and Knowledge Discovery competition datasets                                                                                                                                              | 13 features and 116 million instances | cross-industry                             |
| Open Data Census US Census Bureau | Assesses the state of open data around the world                                                                                                                                                           | -        | Government and Public sector               |
| OpenData from Socrata       | Freely available datasets                                                                                                                                                                                     | 10,000   | Business, Education, Government, Social and Entertainment |
| Open Source Sports UCI      | Many sports databases, including Baseball, Football, Basketball and Hockey                                                                                                                                 | 199      | Physical Sciences, Computer Science & Engineering, Social Sciences, Business and Game |
| Yahoo Sandbox datasets      | Language, graph, ratings, advertising and marketing, competition, computing systems and image datasets                                                                                                      | -        | Cross-industry                             |

8 Neural Network forecasting competition
2.1.2 Synthetic Datasets

MFs are used as predictors in an MLL system. Typically, many MFs are extracted from a dataset, thereby leading to a high-dimensional sparsely populated feature space which has always been a challenge for learning algorithms. Hence, to overcome this problem sufficient number of datasets are required which may not be possible only from the repositories of the real-world datasets as they can be hard to obtain. So, artificially generated datasets might help in solving this issue. [77] work on systematic artificial data generation is considered as one of the initial efforts in this regard. [78] used 320 artificially generated boolean datasets with 5 to 12 features in each one. These artificial datasets were benchmarked on 16 UCI and DaimlerChrysler real-world datasets. Similarly [11] generated 222 datasets, each containing 20 numeric and nominal features having 1K to 10K instances classified between 2 to 5 classes. Additionally, 18 real-world UCI problems were used to evaluate the proposed approach. [79] proposed a method to generate a large number of datasets by transforming the existing datasets, known as datasetoids. An artificial dataset was generated against each symbolic attribute of a given dataset, obtained by switching the selected attribute with the target variable. This method was used on 64 datasets gathered from the UCI repository and it generated a total of 983 datasetoids. At the end potential anomalies related to the artificial datasets were also discussed as well as their proposed solutions were presented. Those identified anomalies were: 1) the new target variable having missing values, 2) the target variable being very skewed, and/or 3) the corresponding target variable being completely unrelated to the remaining features. One very simple solution proposed for these problems was to simply discard the datasetoids which showed any of the above mentioned properties. This method produced promising results, therefore enabling the generation of new datasets that could solve the scarce datasets problems. [73] used both synthetic and real-world Time Series (TS) from diverse domains for MLL based forecasting method selection study. The details of real-world datasets are given in Table 1 while remaining synthetic datasets were generated using statistical simulation to facilitate the detailed analysis of forecasting association with data characteristics. A total of 264 artificial datasets were generated to exhibit a number of different characteristics including, for instance, perfect and strong trend, perfect seasonality, or certain type and level of noise. The data was transformed into a sample of 1000 instances for each of the original TSs while it was unchanged for the number of data-points smaller than 1000. [80] generated 160 artificial datasets to obtain a wide range of cluster structures. There were two methods used to generate datasets: 1) a standard cluster model using Gaussian multivariate normal distributions, and 2) Ellipsoid cluster generator. There were three parameters selected for both techniques including i) the number of clusters which were the same for both cases (2, 4, 8, 16), ii) dimensions (2, 20 for Gaussian, and 50, 100 for Ellipsoid), and iii) the size of each cluster for both techniques were the same (uniformity in [10, 100] for 2 and 4 clusters case and [5, 50] for 8 and 16 clusters case). For each of the 8 combinations of cluster number and dimension, 10 different instances were generated, giving 80 datasets in each method. [7] used two artificially generated datasets out of a total of seven whereas the remaining five were the real-world problems. One artificially generated dataset had binary features, named as Parity, whereas the other one with nominal features was known as Monks. These support features are computed using Quality of Projected Clusters (QPC) projection. [81] presented a novel data generator approach for numerical features and classification datasets that could be used as input datasets for MLL which represented an entirely different approach from [79]. The proposed system was able to generate datasets using genetic programming with customized parameters. In the proposed setting MLL could be supported in two different ways: 1) the MFs space could be filled in a more controlled way and the discovered “empty areas” could be populated rather than generating random datasets, and 2) thoroughly investigating MFs based on their descriptive power which could be useful for certain MLL problems and generating datasets with MFs allowed more controlled experiments that might lead to a significant utilization of particular MFs. Since the dataset was generating multiple MFs therefore this task was treated as a multi-objective optimization problem. The proposed system was able to incorporate a variable set of arbitrary MFs. The user was able to build a custom set of MFs simply by providing the functions that compute the MFs.

2.1.3 Datasets from Published Research

Another source of EoD are the published ML studies. As ML has been one of the most active research areas in the last few decades where several experiments have been conducted, these experiments become a very useful way of gathering EoD representing various domains. The additional benefit that usually comes with most of the datasets used in existing ML benchmarking and experimental studies is the relative ranking and predictive performance data for the evaluated ML algorithms. It is of particular interest as the ML algorithms performance data is used and needed as a target variable.
in the context of an MLL system. It is very time, memory and processor consuming task to compute performance measures for the massively large number of datasets and numerous configurations of learning algorithms.

Usually, presumably due to space limitations on publications, researches publish only the final results with minimal details. However, in the context of MLL, relying on such minimal information leads to several problems, for example, in most of the instances researches only report the best algorithm, usually report limited number and detail of experimentations, mostly skip detailed configurations of the algorithms, etc. [82] introduced a novel platform for ML research known as OpenML. ML researchers can share datasets, algorithms, their configurations, and experiment setups on this platform which other researchers can use to compare results. OpenML framework is one of the possible solutions for most of the mentioned concerns which resolves two key challenges of MLL systems: i) gathering a large number of datasets from different domains, and ii) performances of the tested ML algorithms on these datasets.

2.1.4 Discussion and Summary

An MLL system relies on a good training dataset to build a reliable and well-performing predictive model. Similarly, at the Meta-level, the MK dataset is used as a training-set of MLL and the quality of this MK dataset is dependent on sufficient number and quality of EoD from different domains. These EoD are used to generate MFs which act as predictors and the estimated predictive performance evaluated ML algorithms for these EoD are used as the target variable in the MK dataset. However, gathering a sufficient number of real-world datasets is quite difficult. The real-world datasets which are used in various studies for experimentations are listed in Table 1. Most of the studies gathered datasets from the UCI with different filtering options and the remaining few studies gathered datasets from different data-mining competitions. In most cases, the number of EoD that are used to build [MK] has been very low. However, as identified and shown in Table 2 there are various sources from which a relatively large (and quickly growing) number of real-world datasets representing different domains could be beneficially used in the future though they have not been used so far.

Some MLL researches resolved the problem of the number and quality of available datasets by building their MK datasets using artificially generated EoD. They have adopted two different approaches to generate these synthetic datasets: 1) by transforming real-world datasets; and 2) by utilizing statistical and genetic programming approaches. [78], [79], [73] proposed different feature transformation approaches to generate different combinations of datasets from the limited number of real-world datasets. The statistical and genetic programming approaches were proposed by [80] and [7] for MLL systems. In some of the approaches, statistical functions with a threshold (or cut-off) values are used to generate data while others used optimization techniques. [81] proposed an intelligent technique which does not generate random data, but fill the MFs in a more controlled way by discovering and populating the empty areas within the real-world datasets.

Combining all the proposed approaches iteratively could offer a potential solution to the dataset scarcity; i.e., initially gathering the existing available real-world problems, then transforming those datasets by generating several others and finally applying various other techniques to generate artificial datasets independently (see Figure 2). Although this solution could be useful if the purpose would be only gathering a large number of EoD in the context of the MLL research the predictive performance data for numerous learning algorithms and their configurations are needed and not normally readily available. Considering all three necessary components of an MLL system, gathering datasets from published experimental evaluations and benchmarking of ML algorithms would seem to be more attractive, however, there are a lot of challenges with such data related to reporting only the best learning algorithms, publishing limited information of experimentations, availability of datasets used in the research, lack of detailed configurations of evaluated learning algorithms, etc. OpenML platform has attempted to address most of these issues focusing on the consistency and completeness of the gathered information but as it is in a preliminary stage of development it currently lacks a sufficiently large number of problems from different domains and sufficiently robust and comprehensive number of ML algorithms tested for each of the datasets to be very useful in its current form.

2.2 Meta-features Generation and Selection

One of the primary applications of MLL is to recommend the best learning algorithm or to rank various ML algorithms for a new problem without the need for executing and evaluating these learning algorithms on the problem at hand. The role of such systems is to identify previously solved similar problems, and with the assumption that the previously found best algorithms will also work best on the new problem, make appropriate recommendations. As directly comparing large and complex datasets is normally infeasible, the similarity between different problems/datasets is carried out using a number of so called MFs offering a simplified representation of the problems/datasets. There are three most commonly used MF generation approaches which allow to induce a mapping between the characteristics of a problem and the best performing learning algorithms for the problem. These approaches are discussed in the following sections.
2.2.1 Descriptive, Statistical and Information-Theoretic Approach

The DSIT approach is the simplest and the most commonly used MF generation approach that extracts a number of DSIT-based MF values directly from a dataset representing an ML problem. The DSIT-based MFs and the related MLL approaches primarily based on such MFs are reviewed below.

[5] proposed Variable-bias Management System (VBMS) that was one of the earliest efforts towards data characterization. Only two descriptive MFs, namely: the number of training instances and the number of features, were used to select the best among three symbolic learning algorithms. Later [77] enhanced the existing system by adding useful MFs of complexity based on shape, size and structure. StatLog project by [14] further extended VBMS MFs by considering a larger number of dataset characteristics. A problem was described in the context of its descriptive and statistical properties. Several characteristics of a problem spanning from simple (descriptive) to more complex (statistical) ones were generated and later used by various studies. These characteristics were used to investigate why certain algorithms perform better on a particular problem as well as to produce a thorough empirical analysis of the learning algorithms.

[66] initially used most of the datasets and MFs that were used in StatLog project which were later on enhanced with information-theoretic MFs. Furthermore, three new descriptive features were added by transforming the existing MFs, for example in the form of ratios. These MFs were used to rank several classification algorithms with considerably better performance as compared to the previous studies. It was also claimed that the classification error and execution-time are important response variables to choose a suitable classification algorithm for a problem.

In the same year [65] proposed an extensive list of DSIT-based MFs of a problem under the name of Dataset Characterization Tool (DCT). The authors distinguished three categories of dataset characteristics, namely simple, statistical and information-theory based measures. The descriptive MFs have been used to extract general characteristics of the dataset, whereas statistical characteristics were mainly extracted from numeric attributes, while information-theoretic based measures from nominal attributes. A Case-based Reasoning (CBR) approach to select the most suitable algorithm for a given problem was also proposed.

[83] presented a novel approach of generating informative MFs by simply averaging overall attributes of the source datasets. They proposed a two-fold approach. In the first fold DSIT-based MFs are generated using the previously introduced traditional approach. The second fold is used to describe the differences over datasets that are not accessible using the typically used mean of MFs that have been computed in the first fold. This approach preserves more information on such MFs while producing a feature vector with a fixed size. An additional level of MFs selection is proposed to automatically select the most useful MFs out of the initially generated ones. All MFs that are used in the above studies are shown in Figure 3.

2.2.2 Landmarking Approach

Another technique of MF generation is Landmarking which characterizes a dataset using the performance of a set of simple learners. Its main goal is to identify areas in the input space where each of the simple learners can be regarded as an expert [8].

The basic idea behind Landmarking is to use the estimated performance of a learning algorithm on a given task for discovering additional information about its nature. A landmark learner or landmarker is defined as the learning
were constructed for the experiments from the UCI datasets (see Table 1) which contained up to 25% missing values. Following these conditions, RapidMiner provided the landmarkers shown in Figure 3 and the target landmarker has to be simple and require minimum execution (processing) time; and 2) it has to be simpler than the other approaches as part of an open-source RapidMiner data-mining tool. As mentioned repeatedly in the above studies, landmarkers presented an overview of a landmarking operator and its evaluation. This landmarking operator was developed not significantly different from previous meta-learning studies.

Error rates for ten different classification algorithms from the METAL project were determined for different subsets of the 45 datasets, with more than 1000 instances, mostly gathered from the UCI [63] and the DaimlerChrysler repositories. These datasets have been ranked by the Nearest-Neighbour method, the authors varied the value of \( k \) from 1 to 25. In comparison with other studies reported in the literature, the sample-based relative landmarking approach showed improvements in the algorithm ranking task as compared with the traditional DCT measures.

One of the earliest studies on Landmarking was conducted by [78]. This approach is claimed to be simpler, more intuitive and effective than the DSIT measures. A set of 7 landmarkers were trained on 10 different sets of equal size. Each dataset was then described by a vector of MFS (see Landmarkers branch of Figure 3), which are the error rates of the 7 landmarkers, and labelled by the target learners (see Table 3) which produce the highest accuracy. Several experiments have been performed to compare the landmarking approach with DSIT. In the first experiment Landmarking was compared with 6 information-theoretic DCT features of [65] (see information-theoretic MFS section of Figure 3). In most of the cases this experiment landmarking outperformed the DSIT based approach. In another experiment, the ability of landmarking to describe a problem and discriminate between two areas of expertise are highlighted. In most of the cases C5.0 Adaptive Boosting (C5.0 boost) [84] landmarked based performed best. The last experiment benchmarked 16 real-world datasets from the UCI [63] and the DaimlerChrysler where again the landmarking approach resulted in the best overall performance.

[11] also evaluated a landmarking approach while comparing it with the DSIT MFS generation approach - DCT. They performed three types of experiments, namely: 1) Artificial rule list and sets generation, 2) Selecting learning models, and 3) Comparing the landmarking with the information-theoretic approach. These experiments were almost the same as performed by [78], and the target learners (see Table 3) were the same as used in METAL project. In the first experiment the set of 6 landmarkers consisted of a Linear Discriminant Analysis (LDA) Naive Bayes and C5.0 Decision Tree (C5.0 tree) learners, while the base-learners performance relative to each other was predicted using C5.0 boost, LDA and Rule Learner (Ripper). In addition to 3 landmarkers, 5 descriptive MFS (shown in the descriptive approach in Figure 3) have also been extracted from 216 datasets. The Ripper was found to be the top performer in this experiment. For selecting the best learning model experiment, the authors tried to investigate the capability of landmarking in deciding whether a learner involving multiple learning algorithms performs better than the other candidate algorithms. Here only C4.5 Decision Tree algorithm (C4.5) was used as a Meta-learner trained with 222 artificial boolean datasets and tested with 18 UCI problems [63]. Even though the landmarking accuracy was higher it did not have a significant effect on the overall performance of a system whose ultimate goal is to accurately select the best learning model. In the last experiment, the landmarking approach was compared with the DSIT and also the combination of both approaches. 320 artificially generated binary datasets were produced where the combined approach performed best for all 10 Meta-learners followed by the landmarking with a significant difference as compared to DCT approach.

[67] sample-based landmarkers used estimates of the performance of algorithms on a small sample of the data and then had been used as the predictors of the performance of those algorithms on the entire dataset. Additionally, a relative landmarker addressed the inability of the earlier landmarker to assess the relative performance of algorithms. This sampling-based relative landmarking approach was later compared with the DSIT DCT MFS as done by most of the landmarking studies. The ten algorithms, listed in Table 3 were used on 45 datasets, with more than 1000 instances, mostly gathered from the UCI [63] and the DaimlerChrysler repositories. These datasets have been ranked by the Nearest-Neighbour using Adjusted Ratio of Ratios (ARK) measure. To observe the performance of the ranking method, the authors varied the value of \( k \) from 1 to 25. In comparison with other studies reported in the literature, the sample-based relative landmarking approach showed improvements in the algorithm ranking task as compared with the traditional DCT measures.

[70] proposed a new approach for assessing the quality of case bases constructed using landmarking and DCT based MFS. The meta-learner was based on a case-base reasoning approach using the quality assessed cases. Tasks were described by their similarity, consistency, incoherency, uniqueness and minimality. A brief overview of the necessary requirements for the implementation of the case-based properties has also been provided in their study. A comprehensive experimentation was performed to compare variants of DCT DSIT approach, landmarking and their combinations. MFS were constructed for the experiments from the UCI datasets (see Table 1) which contained up to 25% missing values. Error rates for ten different classification algorithms from the METAL project were determined for different subsets of data characteristics mentioned in Table 3 and restricted to three Base-learners that are shown in Figure 3. The empirical results show the proposed approach in combination with DSIT and landmarking approaches as a promising one though not significantly different from previous meta-learning studies.

[74] presented an overview of a landmarking operator and its evaluation. This landmarking operator was developed as part of an open-source RapidMiner data-mining tool. As mentioned repeatedly in the above studies, landmarkers selection is a critical process and the two basic criteria to select a landmarker were suggested in this study to be: 1) a landmarker has to be simple and require minimum execution (processing) time; and 2) it has to be simpler than the target learner(s). Following these conditions, RapidMiner provided the landmarkers shown in Figure 3 and the target...
algorithms, for which the accuracy was predicted (see Table 3). For the evaluation of these landmarkers, 90 datasets from the UCI [63] and other sources were collected with at least 100 samples in each. By following the existing studies, the landmarking operator has been compared with the DSIT MFs of StatLog [14] and DCT [65], where landmarking resulted in 5.1-8.3% overall performance improvement in all cases.

Table 3: Target Learners used in various studies

| Target Learners                        | [73], [11], [67], [70], [85], [74] |
|----------------------------------------|-------------------------------------|
| C5.0 tree                              | ✓                                   |
| C5.0 Rule Induction (C5.0 rules)       | ✓                                   |
| C5.0 boost                             | ✓                                   |
| Naive Bayes classifier (NB)            | ✓                                   |
| Instance-based Learning (IBL)          | ✓                                   |
| Multi-layer Perceptron (MLP)           | ✓                                   |
| Radial-basis Function (RBF)            | ✓                                   |
| LDA                                    | ✓                                   |
| Ripper                                 | ✓                                   |
| Linear Discriminant Trees (Ltree)      | ✓                                   |
| k-Nearest Neighbour (k-NN)             | ✓                                   |
| Random Forests (RF)                    | ✓                                   |
| One Rule Learner (OneR)                | ✓                                   |
| Support Vector Machines (SVM)          | ✓                                   |
| Total Target Learners                  | 10                                  |

2.2.3 Model-based Approach

Model-based MF generation is another effort towards task characterization in MLL domain. In this approach, the dataset is represented in a data structure that can incorporate the complexity and performance of the induced hypothesis. Later the representation can serve as a basis to explain the reasons behind the performance of the learning algorithm [4]. Several research works utilizing the Model-based approach are discussed below.

[10] study was an initial effort towards a model-based approach. The authors proposed to capture the information directly from the induced decision trees for characterizing the learning complexity. Figure 3 lists the 10 descriptors computed from induced decision trees. Using these MFs a task representation and algorithm to store and compare two different tree structures has been explained in detail with examples. The authors also elaborated on the motivation of using the induced decision trees directly rather than the predefined properties used in decision tree-based MFs that made explicit properties implicit in the tree structure. Finally, higher-order MLL approach was generalized by proposing data structures to characterize other algorithms. A tree-like structure was used for Decision Trees (DT) in this work, sets were proposed for rule sets and graphs for Neural Networks (NNs).

[12] effort was towards improving the dataset characterization by capturing the structural shape and size of the decision tree induced from the dataset. For that purpose 15 features were proposed, known as DecT and shown in Figure 3 which do not overlap with [10]. These measures were used to rank 10 learning algorithms in various experiments. In the first experiment, DecT [65] DSIT MFs and 5 landmarkers (Worst Nodes Learner, Average Nodes Learner, NB, and LDA) were compared with DecT. The results proved the performance enhancement of the proposed approach. In another experiment, DecT measures were compared with the same DCT measures and landmarkers to rank the learning algorithms based on the accuracy and time where again DecT performed better. The last experiment was performed to select MFs by reducing the number of features to 25, 15 and 8 respectively. The k-Nearest Neighbour algorithm, with various values of k between 1 to 40, was used to select k datasets for ranking the performance of learning algorithms. The results suggested that the proposed feature selection did not significantly influence the performance of either DecT or even DCT. Overall, DecT outperformed the other approaches.

Neuro-cognitive inspired mechanism was proposed by [7] to analyse learning-based transformations that generate useful hidden features for MLL. The types of transformations include restricted random projections, optimization using projection pursuit methods, similarity and general kernel-based features, conditionally defined features, and features derived from partial successes of various learning algorithms. The binary features were extracted from DT and rule-based algorithms, continuous features were discovered by projection pursuit, linear SVM and simple projections. NB was used to calculate posterior probabilities along these lines while k-NN and kernel methods were used to find similarity-based features. The proposed approach also evaluated and illustrated Multi-dimensional Scaling (MDS)
mappings and Principal Component Analysis (PCA), Independent Component Analysis (ICA), QPC, SVM projections in the original, one-, and two-dimensional space. Various real-world and synthetic datasets (details can be found in Table 1) were used for visualization and to analyse the kind of structures they create. The classification accuracies for each dataset were predicted using five classifiers including NB, k-NN, Separability Split Value Tree (SSV), Linear and Gaussian kernel SVM in the original, one- and two-dimensional spaces. The results showed an overall significant improvement almost in all five algorithms as compared to the existing approach also proposed by the authors.

Figure 3: Meta-features used in various studies

9 Tabular representation of the visualization can be seen in Appendix A
2.2.4 Discussion and Summary

There are three common MF generation approaches proposed in the reviewed publications for MLL: 1) DSIT, 2) Landmarking, and 3) Model-based. The DSIT MFs approach was introduced at the early stage of MLL development where [5] proposed two descriptive features for VBMS. Later on [77] added more descriptive features to the original list. The statistical MFs were introduced by [14], and [66] proposed information-theoretic features combined with some existing descriptives to represent a problem at a Meta-level. Finally, [65] proposed an extensive list of DSIT MFs known as DCT. The DCT measures became a benchmarked approach to represent a problem using the DSIT approach. These measures were later used in several studies for experimentation, e.g. [15], [85], etc., and compared with other MF approaches.

Landmarking and Model-based approaches are more recent ones and have been outperforming the DSIT in almost all the comparative studies. The earliest study on landmarking was conducted by [78] where the approach was claimed to be simpler, more intuitive and efficient than DSIT. The proposed approach was compared with and outperformed information-theoretic measures of DCT with a significant difference. Though one common deficiency that is observed in several MLL studies is the use of a smaller number of EoD for experimentations which raised a question on the significance of the reported results. [11] used a different set of landmarkers but the same target learners as [78]. This work can be considered to offer improvements to the previous one in two aspects: 1) a huge number of synthetic datasets were used, and 2) some descriptive MFs were combined with the landmarkers. This approach was also compared with DCT features where landmarking showed significant improvement in the results. Similarly [67], [70] and [74] used different sets of target learners, landmarkers, number of dataset examples, and compared their approaches with a different set of DSIT measures. All of them reported improved results of the landmarking approach over the DSIT approach.

[10] approach to characterizing the learning complexity by directly inducing MFs from the model is the earliest work towards model-based approach. In this work, 10 descriptors (MFs) were computed from the induced decision trees which can be seen in Figure 3. [12] effort was towards improving this characterization by focusing on the structural shape and size of the decision tree induced from the datasets. The other dimension of this work was to compare the proposed model-based approach with DCT, DSIT and landmarking measures. Various experimentations were performed with variations of MFs and landmarkers where the model-based approach consistently performed better. A problem with these Meta-level problem representations is that they can not easily accommodate non-stationary environments. Most of the effort has been dedicated to the stationary environment, even though some recent studies are addressing MFs for a dynamically changing environment, i.e. [75], but these are not mature enough to represent the entire domain. Although [75] used traditional MF that are used to characterize stationary data, only those MFs were computed that characterize individual variables. Moreover, there are separate features computed for training and selection windows. Their reliability is highly dependant on the number and quality of examples, thus the larger the number of examples in a window, the potentially higher the reliability of the problem representation at the Meta-level. However, in a rapidly changing environment, there is often a very limited number of examples between consecutive concept changes. Hence there is an unaddressed need for novel MFs and approaches that can cope with small data samples.

From the above studies, it can be observed that combining significant MFs from different feature generation approaches might be useful as shown in Figure 4.

Figure 4: Combining Significant Meta-features from various approaches
2.3 Base-level Learning

In the context of MLL, BLL algorithms are used to build predictive models on input datasets and for MLL purposes are used to compute a set of performance measures, i.e., accuracy, execution-time, etc. These performance measures are combined with their respective MFs in the MK database. A Meta-learner uses these performances as a target variable. The remaining sections discuss several studies concerned with the roles and characteristics of individual and combined BLL algorithms utilised within the MLL context.

[69] proposed an MLL based approach to rank candidate algorithms where k-NN was used to identify the datasets that were most similar to the query dataset. The pool of candidate algorithms contained an ensemble method, namely C5.0 boost, which performed well for 19 out of 53 datasets in the presence of 9 other algorithms. The performance of ensemble methods was ranked with individual learning algorithms. In general, several kinds of research used C5.0 boost ensemble method with other individual algorithms and found it to be the top-performing method.

The applicability of MLL on a TS task was demonstrated by [39]. Several individuals and a combination of forecasting algorithms were used to investigate which model works best in which situation. In the experiments 5 forecasting combination methods were used including 1) simple average where all available forecasts are averaged, 2) simple average with trimming which do not take the worst-performing 20% models into account, 3) variance-based method where weights for a linear combination of forecasts are determined using past forecasting performance, 4) out-performance method which determines weights based on the number of times a method performed best in the past, and 5) variance-based pooling which first groups past forecast performance into 2-3 clusters and then takes their average to obtain the final forecast. The results of these experiments showed that the forecast combination methods perform better than individual models which are listed in Table 4. Further discussion of this work can be found in Chapter 2.5.

[86] proposed a new MLL based ensemble scheme for one-class problems know as TUPSO. The TUPSO combined one-class Base-classifiers via a Meta-classifier to produce a single prediction. The BLL component generates predictions of classifiers that are used to extract aggregated MFs as well as one-class accuracy and f-score estimates. The one-class performance evaluator computed each Base-classifier on only positively labelled instances using 4 algorithms including 1) global density estimation, 2) peer group analysis, 3) SVM, and 4) attribute distribution function approximation (ADIFA) on 53 distinct datasets (details can be seen in Table 1). There are 15 aggregated MFs computed from the predictions of Base-classifiers that are clustered into four groups: 1) summation-based (votes, predictions, weighted predictions, power and log of weighted predictions), 2) variance-based (votes, predictions, and weighted), 3) histogram-based, and 4) representation-length. In an empirical evaluation an ensemble method, Fixed-rule, produced worse classification accuracy when compared to MLL based ensembles - TUPSO.

Table 4: Base-level learning strategies used in different studies

| Research Work | Sampling Strategy | Base-learners | Performance Measure |
|---------------|-------------------|---------------|---------------------|
| [14] 9-fold Cross Validation (CV) for datasets with less than 2500 instances | k-NN, RBF, Density Estimation, Classification and Regression Trees (CART), Inductive CART (INDCART), Back-propagation, NewL, C4.5, C2 Induction Algorithm (C2I), Quadratic Classifier (Quadra), Cal5, AC, Smooth Multiple Additive Regression Technique (SMART), Logistic Regression, Fisher’s Linear Discriminant (LDA), IBk, Causal Structure for Inductive Learning (CASTLE), NB, LDA, Ripper, Ltree | - Misclassification error, Run-time speed |
| [78] stratified 10-fold CV | NB, MLP, RBF, C5.0 tree, C5.0 rules, C5.0 boost, IBL | - |
| [11] 10-fold CV | NB, MLP, RBF, C5.0 tree, C5.0 rules, C5.0 boost, IBL | Mean Absolute Error (MAE) |
| [67] - | NB, MLP, RBF, C5.0 tree, C5.0 rules, C5.0 boost, IBL | Mean Squared Error (MSE), Run-time speed |
| [12] 10-fold CV | C5.0 tree, C5.0 rules, C5.0 boost, Ltree, LDA, NB, IBL | MSE and Spearman’s Rank Correlation Coefficient (SRCC) |
| [68] 10-fold CV | C5.0 tree, C5.0 rules, C5.0 boost, Ltree, Ripper, NB, k-NN, LDA | |
| [70] 10-fold CV | NB, MLP, RBF, C5.0 tree, C5.0 rules, C5.0 boost, IBL | |
10-fold CV
I: Train and test and II: train, test and validate
10-fold CV
80% training and 20% testing partition
10-fold CV
Training and testing
Training and testing

2.4 Discussion and Summary

The MK database usually consists of MFs and performance measures (target) of different learning algorithms which are predicted accuracies for EoD. These predictive values are computed, in the context of MLL, through BLL. The predictive accuracies of learning algorithms are used as a basis for identifying the best algorithm from the pool of methods, their ranking, and/or a combination. Another level of complexity is introduced by the different parametrizations of the algorithms which were overlooked by several studies where only default configurations were considered. Furthermore, most of them selected only the best algorithm from the pool to minimize the representation complexity of MK dataset, therefore very few of them stored information about the ranking and relative performance of evaluated BLLs. Table 4 shows different learning strategies, Base-learners and performance measures that various MLL studies used at the Base-level. It can be observed that the 10-fold cross-validation strategy, MAE accuracy measure and few learning algorithms have become a norm to use at the Base-level. The same Base-level learning strategies are used in some MLL studies for TS with different ARIMA and exponential smoothing algorithms. Another common deficiency that can be observed from various studies is related to the granularity of information that is being stored in MK database.

Table 5 summarises and groups the reviewed studies according to the four dominant performance measures which were used as the target variable for an MLL system.

| Performance Measure(s)       | Description                                                                                           | Research Work |
|------------------------------|--------------------------------------------------------------------------------------------------------|---------------|
| Best learning algorithm      | The performance measure only contains of the classification accuracy of best learning algorithm for each single dataset | [89], [13], [14], [10] |
| Ranking of learning algorithms | To predict a ranked list of learning algorithms in a pool which are sorted based on a performance measure, e.g. classification accuracy, run-time, etc. | [13], [69], [90] |
| Quantitative Prediction      | To directly predict the performance of the target learning algorithm in an appropriate unit, i.e., by training separate regression model for each target algorithm | [92], [66], [20], [23], [91] |
| Predicting Parameters        | The MLL target variable could be one parameter value or a set of values                                   | [94], [95], [22], [39] |

10 hidden nodes = 1, 2, 3, 8, 16, 32
2.5 Meta-learning

The Meta-learning (MLL) systems provide a means for making informed decisions in relation to which algorithms are likely to perform best/well for a given problem. This section presents the history of the most promising decision-support systems for algorithm selection, followed by a review of the applicability of MLL to the supervised and unsupervised learning algorithms.

### 2.5.1 Existing Systems

Based on the reviewed literature, can be considered as the earliest effort towards developing MLL systems where a system named Shift To A Better Bias (STABB) was proposed. It was a demonstration that a learner’s bias could be adjusted dynamically. Later this work became an initial point of reference and was enhanced in several studies. One of them was Variable-bias Management System (VBMS) by , where a relatively simple MLL system was proposed. VBMS selected the best among three symbolic learning algorithms as a function of only two dataset characteristics, namely, the number of training instances and the number of features. As mentioned in one of the previous sections, this was then further improved in.

Machine Learning Toolbox (MLT) project by was one of the initial attempts to address the applications of MLL. MLT produced a toolbox consisting of 10 symbolic learning algorithms for classification. The part of MLT project that assists with the algorithm selection is known as a Consultant. The Consultant was based on a stand-alone expert system that maintained a knowledge-base that considered the experiences acquired from the evaluation of learning algorithms. Considerable insight into many important ML issues was gained which had been translated into rules that formed the basis of Consultant-2. Consultant-2 was also an expert system for algorithm selection that gathered user inputs through a set of questions about the data, the domain and user preferences. Based on the user response relevant rules led to either additional questions or, eventually, a classification algorithm recommendation. Although its knowledge base had been built through an expert-driven knowledge engineering rather than via MLL it still stands out as the first automatic tool that systematically related application domain and dataset characteristics to the most suitable classification algorithms. Additionally, Consultant-3 provided advice and help on the combination of learning algorithms. It is also able to perform self-experimentation to determine the effectiveness of an algorithm on a learning problem.

In Statistical and Logical learning (StatLog) project presented the results of comprehensive experiments on classification algorithms. The project was an extension of VBMS by considering a larger number of MFs together with a broad class of candidate models for algorithm selection. It aimed to compare several symbolic learning algorithms on twelve large real-world classification tasks. Some MLL algorithms were used for model selection tasks where statistical measures, e.g., skewness, kurtosis and covariance, that produced higher accuracy were reported. Additionally, a thorough empirical analysis of 16 classifiers on 12 large real-world datasets and learning models using accuracy and execution time measures of performance were produced. There is no single algorithm that performed best in the experimentation phase. Symbolic algorithms resulted in the best performance for datasets with extreme distributions, i.e., where distribution was far from normal (i.e., specifically with skew > 1 and kurtosis > 7), and the worst in the scenarios where the datasets were evenly distributed. In contrast, the Nearest Neighbour algorithm was found to be accurate for datasets containing evenly distributed in terms of scale and importance of the features.

The Meta-Learning Assistant (METAL) project was developed to facilitate the selection of the best-suited classification algorithm for a data-mining task. It guides the user in two ways: 1) in discovering new and relevant MFs and 2) in a selection or ranking of classifiers using an MLL process. The main deliverable of this project was the Data Mining Advisor (DMA) a Web-based MLL system for the automatic selection of classification learning algorithms. The DMA returned a list of ten algorithms that were ranked according to how well they met the stated goals in terms of accuracy and training time. It implemented ranking mechanisms by exploiting the ratio of accuracy and training time. The choice of an algorithm ranking, rather than selecting the best-in-class, was motivated by a desire to give as much information as possible and as a consequence, a number of algorithms could be subsequently executed on the dataset.

The Meta-learning Architecture (METALA) developed by was an agent-based architecture for distributed Data Mining supported by MLL. The system supported an arbitrary number of algorithms and tasks, and automatically selected an algorithm that appeared best from the pool of available algorithms. Like in the case of DMA each task was characterized by features relevant to its usage, including the type of input data it required, the type of model it induced, and how well it handled noise. It had been designed to automatically carry out experiments with each learner and task, and induce a Meta-model for an algorithm selection. As new tasks and learning algorithms were added to the system, corresponding experiments were performed and the Meta-model was updated.
The Intelligent Discovery Assistant (IDA) provided a Knowledge Discovery (KD) ontology that defined the existing techniques and their properties [17]. It supported three algorithmic steps of the KD process, including preprocessing, data modelling and post-processing. The approach used in this system was the systematic enumeration of valid data-mining processes so that potentially fruitful options were not overlooked, and effective ranking of these valid processes based on user-defined preferences e.g., prediction accuracy, execution speed, etc. IDA systematically searched for an operation whose pre-conditions have been met and whose indicators were consistent with the user-defined preferences. Similarly, its post-conditions searched for an operation and the process terminated once the goal had been reached. Once all valid KD processes had been generated, a heuristic ranker was applied to return user-specified goals. [18] research had focused on extending the IDA approach by leveraging the interaction between ontologies to extract deep knowledge and case-based reasoning for MLL. The system also used procedural information in the form of rules fired by an expert system. The case-base was built around 53 features to describe cases and the ontology came from human experts.

[19] developed a landmarking operator in RapidMiner as part of PaREN project, which was an open-source system for data mining. This operator extracted landmarking features from a given dataset by applying seven fast computable classifiers on it (shown in Figure 3).

Table 6: Existing Meta-learning Systems

| Research Work | Title | Approach | Contributions | Limitations |
|---------------|-------|----------|---------------|-------------|
| [89] STABB    | Statistical | Initial effort towards MLL | Limited to altering only one kind of learner’s bias with fixed order of choices |
| [5] VBMS      | Descriptive | Biases are dynamically located and adjusted according to problem characteristics and prior experience | VBMS is a relatively simple MLL system that learns to select the best among three symbolic learning algorithms as a function of only two dataset characteristics |
| [77] DSIT     | Empirical Learning as a Function of Concept Character | Complex MFs based on shape, size and concentration, and artificial data generation is used | These complex MFs are expensive to compute |
| [13] MLT      | Rule-based | An expert system for algorithm selection by gathering user input through questions and trigger relevant rules while the knowledge-base was built through expert-driven knowledge engineering | Its knowledge base was built through expert-driven knowledge engineering rather than MLL |
| [14] StatLog  | Statistical | A thorough empirical analysis of learning algorithms and models is produced by comparing several symbolic learning algorithms on twelve real-world classification tasks | For a given dataset, algorithms were characterized only as applicable or non-applicable, i.e., they do not provide a way to rank the algorithms; furthermore, that characterization was based on a simple comparison of accuracies regardless of any statistical significance test |
| [15, 85] METAL-DMA | DSIT and Landmarking | Discovers new and relevant MFs and algorithm ranking in terms of accuracy and execution time | The outcome of the prediction model is only the best classifier for the new dataset. It does not support multi-operator workflows |
| [16] METAL-A | Model-based | Agent-based architecture for distributed data-mining, automatically carry out experiments and induce a Meta-model for algorithm selection, it provides architectural mechanisms necessary to scale the DMA | DMA MFs are used to represent a problem, no contribution to introduce new features |
| IDA | Model-based | Its goal is to rank pre-processing, modelling and post-processing steps that are both valid and consistent with the user-defined preferences | The data should be already pre-processed considerably by the user for IDA to model it and evaluating the resulting models |
|------|-------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| IDA  - An Ontology-based Approach | Model-based | Extending IDA approach by leveraging the interaction between ontology for deep knowledge and Case-Based Reasoning for MLL | The case-based is built on fixed 53 features and the system is still in the early stages of implementation |
| PaREn | Landmarking | A Landmarking operator for MLL developed in RapidMiner | Very limited EoD (from UCI) are used to build MK |
| e-Laboratory for Interdisciplinary Collaborative Research (e-LICO) | Model-based | An e-Laboratory for interdisciplinary collaborative research in data-mining and data-intensive science | Meta-learning component is using RapidMiner’s landmarking system which is built on only 90 UCI datasets |

**e-LICO** was a project for data-mining and data-intensive science [96]. This project comprised of three layers: 1) e-Science, 2) Application, and 3) Data-mining. The e-Science and data-mining layers formed a generic environment that was adapted to different scientific domains by customizing the application layer. The architecture of e-LICO project was shown in Figure 5.

![The e-LICO Architecture](image)

**Figure 5: e-LICO project architecture**

The e-Science layer was built on an open-source e-science infrastructure that supported content creation through collaboration at multiple scales in dynamic virtual communities. The Taverna [11] open-source data-mining and predictive analysis solution (RapidAnalytics) and RapidMiner [19] components had been used to design and enact data-analysis workflows. The system also provided a variety of general-purpose and application-specific services and a broad tool-kit in designing and sharing such workflows with data-miners all over the word using myExperiment portal. The IDA [17] exposed MLL capabilities by automatically creating processes tailored for the specification of input data and a modelling task. The RapidMiner’s DMA component helped to design processes by recommending operators that fitted well with the existing operators in a process. The data-mining layer provided comprehensive multimedia data-mining tools that were augmented with pre-processing and learning algorithms developed specifically to meet challenges of...
data-intensive, knowledge-rich sciences. The knowledge-driven data-mining assistant relied on a data-mining ontology and knowledge-base to propose ranked workflows for a given task. The application layer initially came as an empty shell that had to be built by the domain user from different components of the system. At the application layer, e-LICO was showcased in two application domains: 1) a systems biology, and 2) a video recommendation task.

### 2.5.2 Regression and Classification Problems

This section covers various aspects of MLL that are used for regression and classification tasks in different systems. It addressed a novel approach of predictive clustering trees to rank classification algorithms using dataset properties. The approach was to illustrate ML algorithms ranking where the relative performance of the algorithms had to be predicted from a given dataset's MFs. For that purpose, the performance of eight Base-level algorithms, mentioned in Table 4, has been measured on 65 classification tasks gathered from the UCI repository and the METAL project. Furthermore, DSIT dataset characteristics from StatLog and DCT were combined to create an MK dataset consisting of 33 MFs. The properties of individual attributes were aggregated using average, minimum or maximum functions. The landmarking approach was used in this study with 7 simple and fast learners, shown in Figure 5, to investigate the ranking task performance. The proposed dataset characterization approach with clustering tree outperformed with a significant margin the DCT and the histogram approach which used a trained aggregation of DCT properties.

[8] presented four approaches to MLL consisting of learning from Base-learners; 1) Stacked generalization, 2) Boosting, 3) Landmarking, and 4) Meta-decision trees. The information collected from the performance of BLL algorithms were incorporated into the MLL process. Stacked generalization was considered a form of MLL where each set of Base-learners was trained on a dataset and the original feature representation was then extended with the predictions of the Base-learners. These predictions were received by successive layers as inputs and the output was passed on to the next layer. A single (Meta-)learner at the topmost layer computed the final prediction. Boosting was another approach that was considered as a form of MLL. It generated a set of Base-learners by generating variants of the training set using sampling with replacement technique under a weighted distribution. This distribution is modified for every new variant by assigning more weights to the incorrectly classified examples using the most recent hypothesis. Boosting took the predictions of each hypothesis over the original training set to progressively improve the classification of those examples for which the last hypothesis failed.

In the last proposed approach, the Base-learners consisted of a combination of several inductive models induced from Meta-decision trees. A decision tree was built where each internal node represented a MF that predicted a class probability for a given example by a set of models whereas the leaf nodes corresponded to a predictive model. Given a new example, the Meta-decision tree selected the most suitable model to predict the target value. [97] used the same approach for MLL discussed in this section.

An instance-based learning algorithm, k-NN, was used to identify the datasets that were most similar to the one at hand by [69]. The candidate Base-learning algorithms were not ranked but selected based on a multi-criteria aggregated measure that took accuracy and time into account. The proposed methodology had been evaluated using various experiments and analysis at the Base- and Meta-level learning. The Meta-data used in this study was obtained from METAL project which contained estimates of accuracy and time for 10 algorithms (listed in Table 4) on 53 datasets, using 10-fold CV. The k-NN algorithm was used at the Meta-level to select the best candidate algorithm for a new dataset. For two values of the number of neighbours, 1 and 5, the k-NN showed a significant improvement in the results, particularly with k=1, as compared to the trial-and-error approach.

Two MLL approaches were investigated to select models for TS forecasting by [71] in different case studies. In the first case study, a single BLL algorithm was used to select models to forecast stationary TS. The base-level and meta-level learning algorithms and configurations are given in Table 4 and Table 7 for both case studies while details of datasets and MFs are listed in Table 1 and Figure 3 respectively. In another case study, a more recent and sophisticated approach - NOEMON [22] was used to rank three models of the M3-Competition. In both case studies, the experiments revealed significant results by taking into account the quality of algorithm selection and forecasting algorithm performance aspects of the selected models.

Active MLL method, in combination with Uncertainty Sampling and outlier detection, had been proposed by [72] to support the selection of informative and anomaly-free Meta-examples for MLL. Some experiments were performed in a case study where MLP was used to predict the accuracies of 50 regression problems at the Base-level learning (the details can be seen in Table 1) and k-NN at the Meta-level. The MFs used in the case study consisted of 10 simple and statistical measures which can be seen in Figure 5. The results of the experiments revealed that the proposed approach was significantly better than the previous work on Active MLL. Also, the Uncertainty Sampling method increased the performance when the outliers were eliminated from the MK which affected 5% of the data.

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12\( k = 1, 3, 5, 7, 9 \) and 11 nearest neighbours
An empirical study on rule induction based forecasting method selection for univariate TS was conducted by [73]. The study defined as building a high-level global knowledge of the models which were incrementally grown by applying meta-level learning. At the base-level, SVM with different kernel functions (listed in Table 7) were applied (shown in Figure 3). Furthermore, the C4.5 decision tree learning technique was used to generate quantitative rules of regression and classification algorithms. It extracted features of input examples from available datasets and associated them with the performance of the candidate algorithms in clustering that data to construct MK database. The MK database was used as an input dataset for the Meta-level learning and generated a Meta-model which was used in the zoomed ranking method and on its combination. This study concluded that the ranking-based combination of forecasting methods outperformed the individual methods in all experiments.

The Meta-level Learning module of [22] architecture was responsible for high-level learning, control and decision making. Meta-level was the most complex and least diverse top layer of the architecture. In this study, a Meta-learner was defined as building a high-level global knowledge of the models which were incrementally grown by applying the evolving architecture to various tasks. The main goal of Meta-level layer was to optimise the predictions in terms of the global performance function which was achieved by 1) controlling the population at lower levels to cover unexplored parts of the input space, 2) looking for relations between algorithm configurations of the paths and the achieved performance, and 3) adapting the combinations in order to reflect the current state of the data. In general, this layer was used to learn the dependency between the pool of learning algorithms and the performance at various levels. Several experiments had been performed using three real-world datasets from the process industry where adaptive and static techniques were compared. The automated data pre-processing and model selection took a lot of the model development effort away from the user.

An empirical study on rule induction based forecasting method selection for univariate TS was conducted by [73]. The study aimed to identify characteristics of a univariate TS and evaluated the performance of four popular forecasting methods (listed in Table 4) using a large collection of datasets listed in Table 1. These two components are integrated into an MLL framework which automatically discovers the relations between forecasting methods and data characteristics (shown in Figure 3). Furthermore, the C4.5 decision tree learning technique was used to generate quantitative rules of MFs and categorical rules were constructed using an unsupervised clustering approach.

[39] investigated applicability of MLL for TS prediction and identified an extensive set of MFs that were used to describe the nature of TS. The feature pool consisted of general statistical, frequency spectrum, autocorrelation, and behaviour of forecasting methods (diversity) measures (see Figure 1). These measures were extracted for two sets of datasets from popular TS competitions, see Table 1 for details, and the target was to predict the next 18 observations for NN3 and 56 for NN5. Using these datasets empirical experiments had been performed that had provided the basis for further MLL analysis. An extensive list of simple (seasonal), complex (ARIMA), structural and computational intelligence (Feed-Forward NN), and forecast combination methods were used for experimentation which can be seen in Table 2. From the pool of individual algorithms, NN and MA performed quite well for NN3 series while for NN5 the SMAPE in general, was quite high where a combination method variance-based pooling outperformed all the individual and combination algorithms. At the end three experiments were performed to explore MFs using decision trees, comparing various MLL approaches (details are given in Table 7), and simulating NN5 on zoomed ranking method and on its combination. This study concluded that the ranking-based combination of forecasting methods outperformed the individual methods in all experiments.

### 2.5.3 Clustering

This section discusses the use of MLL in the context of unsupervised learning.

[99] presented a novel framework that applied an MLL approach to clustering algorithms, which was one of the initial efforts towards unsupervised algorithms. The proposed architecture was very similar to the MLL approach used to rank regression and classification algorithms. It extracted features of input examples from available datasets and associated them with the performance of the candidate algorithms in clustering that data to construct MK database. The MK database was used as an input dataset for the Meta-level learning and generated a Meta-model which was used in the selection or ranking of the candidate algorithms at a test mode. Some implementation issues were also addressed which

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\[k=1\]

\[\text{Neural Network forecasting competition, http://www.neural-forecasting-competition.com}\]
Various studies investigated the applicability of MLL for TS problems including [71], [73], and [39]. Apart from the existing software systems and tools, there have been several studies where MLL was used specifically to solve data-mining and data-intensive problems. This project used MLL for algorithm recommendation by landmarking based algorithm recommendation system is available as part of the RapidMiner, a commonly used software. The landmarking based algorithm recommendation system is available as part of the RapidMiner, a commonly used operator in the software. One of the most recent and large-scale projects related to MLL was e-LICO, the purpose of which was to solve data-mining and data-intensive problems. This project used MLL for algorithm recommendation by leveraging the existing systems, i.e., IDA and RapidMiner’s DMA component proposed by [17]. Limitations of those systems are discussed in Table 6.

Apart from the existing software systems and tools, there have been several studies where MLL was used specifically for regression, forecasting, classification or clustering tasks. Several MF-based problem representations have been proposed for the regression and classification tasks. Most of the comparisons in those studies focused on different MF approaches, selection of candidate algorithms, and different sets of Meta-Learners. The problem representation using DSIT features has received the most attention, with landmarking and model-based approaches frequently compared with DCT features and outperforming the DSIT approach in all reported studies with a significant difference. Not much effort has been dedicated to the model-based approach in the last few years as the landmarking with additional DSIT features have been considered as an overall better approach. The landmarking has also been proposed to solve problems other than algorithm recommendations, e.g., [22] used a landmarking approach for a recurrent concept extraction. Various studies investigated the applicability of MLL for TS problems including [71], [73], and [39]. [39] proposed descriptive and statistical features to represent a TS task to rank various seasonal and ARIMA models. Later on [39] used an extensive list of MF covering statistical, frequency spectrum, autocorrelation, and diversity measures for a TS prediction task. The pool of TS algorithms contained seasonal, ARIMA, structure and computational intelligence, and forecasting combination methods. The features used in this study to represent TS task at the Meta-level were better as compared to the previous studies.

There have been a few studies that applied the MLL to clustering algorithms. Effort was the initial step in investigating the knowledge representation for unsupervised problems. Landmarking was used to rank several unsupervised candidate algorithms, as listed in Table 7 combined with eight descriptive and statistical MFs which were used to represent unsupervised problems at the Meta-level. Most of them were the same as used in the number of regression and classification problem representations. [80] employed framework by enhancing the list of landmarks and proposed two different MF representations of an unsupervised task. One of the MFs list consisted of features proposed by [99]. The results showed an improvement of the proposed approach over the default base-line, but no significant difference was observed between the two different representations of the unsupervised problems. Finally, the authors had also highlighted the selection of MFs in the context of unsupervised MLL as an important issue that could be subjected to further analysis.

### 2.5.4 Discussion and Summary

There have been several MLL systems developed since the beginning of this area. Almost all the systems are developed for algorithm recommendations for the classification and regression tasks. Three main MF generation approaches were used in these systems which are listed in Table 6 where DSIT approach is found to be the most widely used. The methodology was evaluated using 160 artificially generated datasets, whose details are discussed in Section 2.1. Both Meta-learners were applied to the two sets of MFs separately and then compared with the default ranking method. The rankings predicted by the SVR and MLP methods were found to be significantly higher correlated than the default ranking. However, there was no significant difference between the correlation values of MLP and SVR methods for both Meta-datasets. Finally, the authors had also highlighted the selection of MFs as an important issue that could be subjected to further analysis.
could be subjected to further analysis. All the existing MLL studies discussed in this section have only considered and were applied within stationary environments. Additionally, these systems have the same issue which was discussed in the previous sections that the MK dataset did not have a sufficient number of Meta-examples (MEs).

| Research Work | Learning Strategy | Meta-learners | Performance |
|----------------|-------------------|---------------|-------------|
| [66]           | DSIT approach     | Disc, QDisc, LoGID, k-NN, Back-propagation, Learning Vector Quantization (LVQ), Kohonen, RBF, INDCART, C4.5 | Disc algorithm ranked as top performing algorithm |
| [65]           | Numeric, Symbolic and Mixed features characterization | NB, MLP, RBF, CN2, Iterative Dichotomiser, LID, MC4, T2, Winnow, Oblique Classifier, {OCL, OneR, Ripper, IBL, C5.0 tree, Naive Bayes/Decision-Tree (NB1)}, Lazy Decision Trees (LazyDT), Parallel Exemplar-Based Learning System (PEBLS) | Numeric and mixed features characterization performed better |
| [78]           | Landmarking approach compared with Information-Theoretic characterization | NB, k-NN, Elite-Nearest Neighbour (e-NN), Decision Nodes Learner (Decision Nodes), Worst Nodes Learner, Randomly Chosen Nodes Learner (Randomly Chosen Nodes), LDA | Landmarking C5.0 rules approach outperformed Information-Theoretic |
| [11]           | Landmarking approach compared with DSIT characterization | C5.0 tree, Ripper, Ltree | Landmarking C5.0 boost performed better than others |
| [12]           | Model-based approach compared with Landmarking and DSIT characterization | k-NN | Model-based approach outperformed the remaining two |
| [71]           | Descriptive and Statistical approach | I: Simple ES and Time-delay NN and II: RW, Holt’s linear ES (HL), Auto-regressive (AR), NOEMON | The proposed approach outperformed the default ranking |
| [69]           | Landmarking approach to rank unsupervised learning algorithms | Single Linkage (SL), Complete Linkage (CL), Average Linkage (AL), k-Means (k-M), Mixture Models (M), Spectral Clustering (SP), Shared Nearest Neighbours (SNN) | Normalized MSE and CORR between predicted and target values |
| [87]           | Descriptive and Statistical approach | SVM with linear, quadratic, and RBF (γ=0.1, 0.05, 0.01) functions | The proposed approach outperformed the default ranking |
| [81]           | Landmarking approach to rank unsupervised learning algorithms | SL, C4.5, AL, k-M, M, SNN, Farthest First (FF), DB-Scan (DBS), X-Means (XM) | The proposed approach showed superiority over simple model selection approaches |
| [73]           | Statistical approach on TS | ES, ARIMA, RW, NN | Landmarking approach (kNN) outperformed others |
| [39]           | Statistical approach on TS | NN, DT, SVM, Zoomed ranking (best method and combination) | MetaStream outperformed default and ensemble approaches |
| [74]           | Landmarking approach compared with Descriptive, DSIT characterization | NB, k-NN, MLP, OneR, RF | MetaStream outperformed default and ensemble approaches |
| [88]           | DSIT               | RF | |
| [75]           | DSIT               | RF, NB, k-NN | |

\[15\] 0-4
\[16\] k=1
2.6 Adaptive Mechanisms

The ML and heuristic search algorithms require tuning of their parameters for a good performance. It can be achieved through off-line sensitivity analysis by testing different parameters to determine their best value in a stationary environment [100]. However, the optimal set of values for the parameters keep changing over time in non-stationary environments because of the change in the underlying data distribution where off-line sensitivity analysis becomes ineffective. In a dynamically changing environment domain, MLL mechanism is considered to be one of the most effective techniques to learn the optimal set of parameters [100]. The rest of this section discusses various techniques of acquiring and exploiting MK in non-stationary environments, that have been proposed in the context of the existing predictive systems.

One of the earliest efforts employing an MLL based approach to achieve adaptivity in a non-stationary environment was presented by [101]. MLL was applied in time-varying environments for the purpose of selecting the most appropriate learning algorithm. For a traditional two-level learning model different types of attributes were defined at the Base- and Meta-level. The predictive attributes were used to induce models at the Base-level on raw examples from datasets if there existed a significant correlation between the predictors and the observed class distribution. On the other hand, contextual attributes were employed to identify the current concept associated with the data and systematic changes in their values which indicated a concept drift. These attributes were identified using an MLL approach which was proposed in [101]. This allowed a learning algorithm to select the examples that had the same context as the training data and newly arrived examples. These conceptual clues helped in adapting the systems faster by filtering the historical instances used for training that had the same context as the newly arrived instances. The proposed technique was evaluated by comparing two operational systems at the Meta-level that differed in the underlying learning algorithm as well as their way of processing contextual information including METAL(B) that used a Bayesian classifier and METAL(IB) that was based on instance-based learning. The instance-based learner was used in four variants which included: 1) context-relevant instance selection; 2) instance weighting; 3) feature weighting; and 4) combination of instance and feature weighting. The general conclusion of numerous experiments that were performed using real-world and synthetic datasets was that MLL produced quite a significant improvement over the existing approaches for changing environments. Additionally, from the results, it could be observed that the METAL(B) approach proved to be effective in domains (datasets) with high noise rates and several irrelevant attributes whereas the instance-based approach showed higher accuracy for the remaining domains.

[102] proposed an MLL framework for automatically selecting the most promising algorithm and its parametrization at each step in time where the data was arriving in batches. For each batch a set of MFs (as listed in Table 9) were extracted directly from the raw data which was used in the BLL to create a Meta-example. A number of Meta-examples were used to induce a Meta-learner whenever a new batch became available, which in turn, helped in predicting the best learning algorithm and the best set of instances at a given time point. The MFs used in this work were more relevant to the problem under analysis. Furthermore, this work also investigated the aspects used to speed-up the algorithm selection process using the proposed MLL approach without losing the gained reduction in the error rate. The proposed drifting concept approaches, i.e., adaptive time window and batch selection strategy, were evaluated by comparing them with three non-adaptive mechanisms: 1) full memory, 2) no memory, and 3) fixed-size window. The experiments were performed using two real-world problems: 1) information filtering of unstructured business news data, and 2) predicting the business cycle from the economics domain. For the business news dataset, both adaptive techniques outperformed trivial non-adaptive approaches. Two evaluations were performed for the business cycle dataset where the data was split into 5 and 15 equally sized batches where the fixed size window approach performed slightly better than the adaptive techniques.

[100] proposed an MLL mechanism to learn the optimal parameters while the learning algorithm was trying to learn its target concept in a non-stationary environment. MLL was used to tune a temperature (τ) parameter of the Softmax Reinforcement Learning (RL) algorithm using a Boltzmann distribution. Moreover, the time-weighted method had been used where the action value estimates were the sample average of prior rewards. The Softmax algorithm became a random search for a higher τ value, whereas for a low value it approached a greedy search. The effectiveness of the proposed MLL algorithm was evaluated by dynamically learning the optimal value of τ using two case studies: 1) k-Armed bandit - the classic RL problem, and 2) bidding strategy - stylized e-procurement problem. In the k-Armed bandit problem the variable k was defined as actions available to an agent and each action returned a reward from a different distribution. In this work (k=10) actions (1,...,10) were available to an agent where each action returned a reward using Normal distribution. The effectiveness of MLL in a non-stationary environment was tested by rotating the reward distributions among the 10 actions. The algorithm was tested with three different temperature parameter values of 5, 50 and 500 for both stationary and dynamic environments. For the stationary environment, the performance of τ=5 approached the best action with a maximum average reward. As the environment became more and more dynamic these rewards kept falling. In contrast, the performance of the MLL algorithm returned better rewards in both environments as well as responded faster to the changes in the environment. The bidding problem was analysed as...
a 2 player symmetric game (2 homogeneous sellers) with \( n \) actions, where \( n \) was the variable cost (price) range split into equally sized bands. One of the sellers was modelled using the Softmax \( \text{RL} \) algorithm while the other one was supposed to be using different learning algorithms, i.e., \( \epsilon \)-greedy - a genetic algorithm proposed by [103]. The same three values of \( \tau \) were used for both stationary and dynamic environments, where the stationary environment produced the best result for the lowest value of temperature. However, no single value of temperature did best in the dynamic environment, while \( \text{MLL} \) algorithm approached the best reward for both environments. Furthermore, it was observed from the experiments that the best value of \( \tau \) was achieved from \( \text{MLL} \) approach in all the scenarios.

[22] architecture supports life-long learning by providing several adaptation mechanisms across computational path level (preprocessing methods followed by individual base-level algorithms), path combination level (a combination of base-level algorithms) and a Meta-level hierarchical structure. There were four adaptation loops defined across various levels of hierarchy including the self-adaptation capability of the computational and combination layer, whereas the remaining two loops connected the Meta-layer to the lower layers. These feedback loops helped the proposed architecture to keep the validity of the models in changing environments. It could be achieved by switching particular modules to the incremental mode. The computational path level adaptation loop consisted of the predictions feedback which were compared to the actual (target) values. Whereas at the path combination level the combinations were represented in the same way as in the computational path, which was a benefit of this representation that and meant that similar adaptation mechanisms could be applied at different levels. In the case of weighted combinations, the contribution of particular computation paths was dynamically changed to the final prediction by modifying the weights. A Meta-level adaptation influenced the dynamic behaviour of the entire architecture. At this level, the performance measures were gathered from all levels of the architecture together with the global performance. It allowed us to analyse the performance achieved across various levels and also to estimate the influence of the changes at different states of the model. Several experiments demonstrated that the variety of adaptation mechanisms applied at different levels may have a significant effect on the performance of the models. One of the key contributions of the proposed architecture was the opening of a large space for future research that could focus on the interaction between different techniques, dynamic behaviour, implementation of novel adaptation techniques and meta-level methods.

A comprehensive framework, design problems, the taxonomy of adaptive learning, and different areas of learning under concept drift were presented by [104]. The proposed framework was used to analyse the problem of the training set formation where two areas, i.e., 1) incremental learning; and 2) causes of concept drift were discussed. The incremental learning explained the difference between concept drift and periodic seasonality with examples while the causes of concept drift were elaborated on using Bayesian decision theory, where three causes were highlighted that might change over time. There were four design sub-problems and techniques addressed within the framework that needed to be solved: 1) future assumptions about source and target instances; 2) structural change types or configuration patterns of data over time; 3) identified four key learner adaptivity areas, and 4) model selection which was further categorized into two different groups. The taxonomy of concept drift learners was categorized as an evolving learner where four methods were proposed and the methods that determined how the models or instances were to be changed at a given time were grouped separately under a triggering concept. In the end, three major research areas were outlined: 1) time context; 2) transfer learning by gaining knowledge from a similar type of past problems; and 3) models that have properties of adaptation incorporated into learners. Also, several dimensions that are relevant to the applications implementing concept drift were defined. Figure 6 presents all the key areas and available solutions of learning under concept drift.

An \( \text{MLL} \) approach for periodic and automatic algorithm selection for time-changing data, named Meta-Stream, was presented by [88]. A Meta-classifier was periodically applied to predict the best learning algorithm for a new unlabelled chunk of data. General DSIT \( \text{MFs} \) of the Travel Time Prediction (TTP) problem were extracted from the historical and new data (see Figure 3) and mapped together with their predictive performance computed from different models to induce the Meta-classifier. Experiments were performed to compare the performance of the MetaStream to the default trial-and-error approach for both static and dynamically updating strategies at the Meta- and Base-levels. Moreover, the Base-level MetaStream and Default results were compared with the dynamic Ensemble approach. The learning strategy adopted at the Base-level can be seen in Table 4, also the training window (\( \omega \)) of 1000 instances with a step size (\( \lambda \)) of 1 was used at this level. The Meta-level learning strategy was presented in Table 7. The \( \text{MFs} \) labelled as tie were investigated separately by keeping and discarding them from the training and test sets. The empirical results showed that the MetaStream outperformed the baseline and ensemble approaches with a significant margin in most of the cases for both stationary and dynamic environments. In general, the two pairs of algorithms, e.g., \( \text{RF-CART and SVM-CART} \) were found to be the best algorithms for TTP problem. Finally, the authors also realized that the \( \text{MFs} \) should be related to the non-stationary data problem rather than characteristics that were extracted for the traditional MLL problems.

[75] extended their original work [88] in two main directions: 1) instead of selecting only a single algorithm, a combination of multiple regressors could be selected when the average of the predictions performed better than the individual; and 2) more comprehensive experimental evaluation was performed by adding another real-world problem - Electricity Demand Prediction (EDP) (see Table 1). Furthermore, the list of \( \text{MFs} \) extracted from the data was also
enhanced in this work, as listed in Table 8. The characteristics were extracted separately from the training and evaluation windows because the training window had target information available from where supervised characteristics could be extracted, i.e., information about the relationship between the predictive and target variables. The pool of Base- and Meta-level algorithms with their configurations are listed in Table 4 and Table 7 respectively. The experimental results showed that for the TTP dataset the pair of regressors, regardless of the presence of the tie resolution strategy, outperformed the default and ensemble-based approaches. However, in the case of EDP, the MetaStream clearly outperformed the default but was worse than the ensemble which could lead to a conclusion that the observations made for pairs of regressors were also valid for multi-regressors. Moreover, a slightly higher error rate was recorded for the RF Meta-learner of the MetaStream than the default but was lower than the ensemble approach for the TTP dataset, whereas for the EDP dataset the MetaStream outperformed the default but was worse than the ensemble. These results showed that the MetaStream was able to select the best algorithm more accurately than the baseline trial-and-error and ensemble-based approaches in a time-changing environment.
Table 8: Meta-features used in MetaStream to characterize the data

| Meta-features                                      | Training window | Selection window |
|----------------------------------------------------|-----------------|------------------|
| Average, Variance, Minimum, Maximum and Median of continuous features | ✓               | ✓                |
| Average, Variance, Minimum, Maximum and Median of the target          |                 |                  |
| Correlation between numeric features                  | -               | ✓                |
| Correlation of numeric attributes to the target        | ✓               |                  |
| Possibility of existence of outliers in numeric features | -               | ✓                |
| Possibility of existence of outliers in the target     |                  |                  |
| Dispersion gain                                       | ✓               |                  |
| Skewness of numeric features                         |                  | ✓                |
| Kurtosis of numeric features                         |                  |                  |

2.6.1 Discussion and Summary

This section covered the adaptability mechanisms of a number of existing systems using MLL approaches. In these studies, the main focus was put on the applicability of MLL particularly in the context of non-stationary environments. MLL can be beneficial in such a case by minimizing the processing time that is consumed to periodically train the model, extracting recurring concepts, automatically detecting concept drift and estimating dynamic adaptive window size, which in turn can generate accurate predictions in dynamic environments. However, applying MLL to support an adaptive mechanism is a recent and emerging area. As a result, most of the research works use the same MFs for a time-varying environment as for the stationary environments. If MLL is introduced in a system then the overall performance of such a system becomes dependent on an appropriate representation of the problem at the Meta-level in the form of extracted, informative MFs. The drawback of using a set of MFs which are usually used in a stationary environment is that the entire target dataset should be available at once when MLL is applied to find the best algorithm for that dataset. This is not normally the case for streaming data and the unavailability of target variables makes the calculation of some useful MFs impossible.

[101]'s work on applying MLL for non-stationary environments is considered to be the earliest effort. It addressed two key areas in the context of dynamic environments: 1) dynamic tracking of changes; and 2) extraction of recurring concepts. The problem representation in [101] was quite general as very few predictive and contextual MFs were extracted. However, neither of the two proposed MLL approaches performed better than the default for several domains. [102] used different BLL algorithms which were automatically selected at the Meta-level. Additionally, the Meta-level approach for adaptive time window and recurring concept extraction for the target concept was part of the research. The research was one of the initial efforts to represent an adaptivity problem with the relevant MFs rather than using general features that were usually productive for the stationary environment. Although these features (as listed in Table 9) were not sufficiently expressive to represent a non-stationary environment at the Meta-level, they were still better than general features (used to represent stationary problems) as evidenced by the experiments which showed a significant improvement.

[100] proposed a reinforcement learning approach to address the automatic algorithm recommendation problem using MLL in a non-stationary environment. The focus of the research was to find the optimal value of the Softmax algorithm's parameter $\tau$ where it would recommend the best algorithm for the target concept at the Meta-level. The same deficiency was observed in this work that the non-stationary problem representation was not addressed in sufficient detail and focus was only on the algorithm recommendation using MFs which were proposed for static data. [22] proposed a life-long learning architecture that provided several adaptation mechanisms across a pool of candidate learning algorithms and their combinations. The dynamic behavior of the entire architecture was analysed at the Meta-level where the global performances as well as information from both pools could be analysed to estimate the influence of the changes at different levels of the model. The decrease in the prediction ability of a local model below a certain level was considered as a new concept which led to building a new receptive field. The landmarking approach was quite simple and effective to detect concept drift, and based on that, periodically train a new local predictor. The effectiveness of MLL for the two mentioned areas was supported by improved results recorded from two case-studies.

[88] approach was quite similar to [102] where periodic algorithm selection for a time-changing data was proposed. Similarly to various other studies, the authors computed the DSIT MFs. Even though the Meta-level approach performed better than the Base-level, there was no comparison shown with the other MLL systems from where it could be concluded that even the general representation of the problem could work for a non-stationary environment. The problem representation using general MFs was a drawback of this effort which was subsequently attempted to rectify in [75]. The authors computed separate MFs for historical and incoming data. As the target variable was not available
in the incoming data the unsupervised features were computed for the data available in the evaluation window. The performance of the proposed approach was better than the BLL and worse than an ensemble-based approach but despite this, it was considered to be a good effort towards representing a time-varying problem at the Meta-level. In almost all the studies that are discussed in this section MLL outperformed the BLL methods. However, a common drawback has been observed in the problem representation area at the Meta-level for time-varying data. Most of the work used general MFs whereas only some tried to focus on this area by proposing some features for the non-stationary data.

Table 9: Adaptive mechanisms used in previous studies

| Research Work | Adapty mechanisms addressed | Meta-features/Parameters |
|---------------|-----------------------------|--------------------------|
| [101]         | Recurring concept extraction | window size=100 and significance level=0.01 |
| [102]         | Recurring concept extraction, adaptive time window, periodic algorithm selection | No. of batches used for training at the previous batch No. of non-interrupted most recent training batches Most successful learner on the previous batch Most successful learner overall on all batches seen so far |
| [22]          | Concept drift detection and Periodic algorithm selection | Landmarking |
| [83]          | Periodic algorithm selection | ML: \(\omega=1000, \lambda=1, \eta=0\) MLL: \(\omega=300, \gamma=25, \lambda=1, \eta=0\) |
| [75]          | Periodic algorithm selection (with more relevant representation of the non-stationary problem) | ML: \(\omega=1000, \lambda=1, \eta=2\) TTP dataset: ML: \(\omega=300, \gamma=24, \lambda=1, \eta=0\) MLL: \(\omega=672, \lambda=336, \eta=0\) EDP dataset: ML: \(\omega=300, \gamma=25, \lambda=1, \eta=0\) MLL: \(\omega=300, \gamma=25, \lambda=1, \eta=0\) |

3 Research Challenges

The goal of MLL is to analyse and recommend the best methods and techniques for a problem on the basis of previously solved problems and without or with minimal intervention of human experts [7]. The existing approach of analysing the problem and selecting the best learning algorithm is to apply a wide range of algorithms, with many possible parametrizations, on a problem simultaneously and then select an algorithm from a ranked list based on performance estimates like accuracy, execution-time, etc. Also choosing the best algorithm for a specific problem in an ever increasing number of models and their almost infinite configurations is a challenging task. Even with sophisticated and parallel learning algorithms, the computational power in terms of the execution-time, memory, and the overall human effort are still one of the biggest limitations. Every task leads to new challenges and demands dedicated effort for detailed analysis and modelling.

The main theme of this work is research on MLL strategies and approaches in the context of adaptive multi-level, multi-component predictive systems for time-varying environments. In these systems, there are multiple areas where MLL can be used to efficiently recommend the most appropriate methods and techniques. Therefore three areas of evolving predictive systems dealing with streaming data have been identified where the applicability of MLL can be an effective and efficient approach. These are listed below:

1. Pre-processing Steps Recommendation: MLL can be applied to find the most appropriate combination of pre-processing steps for MK dataset. As MLL is proposed for four different areas within a system which means in case a concept drift is detected a maximum of four MK datasets, which will be representing different problems, will require pre-processing. The applicability of MLL on changing environment requires dynamically growing MK dataset where a fixed set of pre-processing methods and techniques can be ineffective. Alternatively, trying various pre-processing methods and techniques to find the best combination for the current concept will make the entire system ineffective. Instead of spending time on testing various methods on every concept drift detection MLL helps to instantly and optimally recommend the best pre-processing steps for the current concept.

2. Algorithm Recommendation: Finding the optimal algorithm for a dataset is a traditional application of MLL [Giraud-Carrier, 2008]. Automatic discovery of optimal algorithm can be beneficial for both stationary and particularly non-stationary environments where it can help in minimizing the processing time which is usually spent on the rigorous testing of various
learning algorithms with their different parametrizations. MLL can recommend the optimal learning algorithm and parametrization instantly.

3. Recurring Concepts Extraction:
In a non-stationary environment, the underlying distribution of the incoming data keeps changing which makes the most recent historical data ineffective to retraining the model for the batch of data available in the evaluation window. Using MLL the historical batches (concepts) of data can be extracted from MK dataset which can be used as effective data for training of the current concept. This process can be named as Reverse Knowledge Extraction where MFs of the current concept can be used to extract the MEs of relevant concepts from MK datasets. These MEs will ultimately lead to extract the model that can be the best representation of the current concept. This model can be retrained to incorporate a new concept in the existing model.

4. Dynamic Concept Drifting and Adaptivity Mechanism Parameters:
The most process and memory-intensive task in the system is model training which has to be performed on the identification of every new concept. In an adaptive mechanism retraining of model is usually triggered by a change detection process where intelligent triggering can maximize the overall system efficiency. MLL can help to automatically detect the concept drift and trigger the algorithm retraining process instantly. For instance, the MFs of incoming data can be computed as well as cumulated on the arrival of every batch and simultaneously compared with the set of MEs from MK dataset, whose learning algorithm (used as target variable in MK) is used to score the current batches of data. The concept drift is detected at Meta-level if the ME of the current concept does not match with the cluster of MEs whose learning algorithm is currently selected.

Using the same technique the dynamic adaptive mechanism parameters problem within the non-stationary environment can also be addressed. The static parameters of adaptive mechanism, i.e., training window size, evaluation window size, step size, and delay, would be ineffective for the dynamic environments where the underlying distribution of incoming data keeps changing. A MK dataset can be gathered containing the various parameters of the adaptive mechanism as MFs and mapped with the algorithm or combination that is performing the best for those parameters. Based on the currently selected algorithm the appropriate set of parameters can be extracted from the MK dataset. This task is can be named as Reverse Meta-level Learning.

The first potential area where MLL can be leveraged to find the most appropriate combination of pre-processing steps is already under investigation within the INFER project. So this area is excluded from the scope of this research. The applicability of MLL on the remaining three proposed areas leads to several research questions which are listed below.

1. Gathering examples of datasets for building Meta-knowledge database
   i. The time-changing environments require dynamic MK databases which must be updated with the MFs of different batches of data having different distribution. A dynamic MK database keeps on growing with the ME of new concepts. Apart from the dynamically growing database, which will be empty in the initial phase of the system and will gradually build-up, is there need of static MK database, atleast for this phase, which is usually used by traditional MLL systems?
   ii. In absence of static MK database, MLL would be ineffective specifically in the initial phase of the system until a sufficient amount of concept drifts are identified. At Meta-level this impact would greatly effect because one ME in MK dataset will be extracted from one concept drift which might consist of several batches of data. What could be the alternative of static MK database so that the system can leverage from MLL process even in the initial stage of the system?
   iii. The static MK database could be a potential solution of the above challenge, but it raises another research challenge that what sources and techniques will be used to gather examples of datasets, e.g., is it possible to find enough real-world problems to extract sufficient MEs for MK database or synthetic data will be used to produce more MEs?
   iv. If real-world datasets, which are quite rare and hard to find, would be insufficient then generating synthetic data could be a potential solution. In that case what type of techniques will be used to generate examples of synthetic datasets or else by transforming the existing MEs which are generated by real-world datasets, the MK database will be enhanced?

2. Base-level learning to compute performance measures for Meta-examples
   i. Base-level Learning is used to build predictive models using examples of datasets to compute a comprehensive set of performance measures. What type of strategy will be used to select the best learning algorithm and its parametrization, i.e., selection, ranking, combination?
   ii. To what level of granularity the learning algorithm parametrization would be sufficient enough for an effective MLL process, e.g., how to deal with continuous parameters, numerous parameters for a learner?
iii. What performance measures will be used to rank different algorithms for a dataset, i.e., accuracy, run-time speed?

3. Feature generation and selection to represent a problem at Meta-level
   i. Would the traditional MF generation approach be the better representation of the three different problems where MLL would be able to outperform Base-learning?
   ii. From the traditional MF generation approaches what techniques can be used to represent the problem of the mentioned areas?
   iii. The traditional MF generation approaches, which are only specialized for algorithm recommendation task, would be adequate to represent three new areas of the system or based on the complexity of a problem a new problem representation would be required?
   iv. Within a MF generation approach what set of MFs could be significant to better represent a problem? What statistical methods would be used to dynamically select significant MFs for a batch of data?
   v. In a non-stationary environment, the target variable would not be available at the time of algorithm selection at Meta-level. It will restrict computing a few important MFs e.g., the correlation between target and predictors. What would be the approach of selecting a significant set of MFs in the absence of a target variable?
   vi. In a later stage, when the target variable becomes available then how MLD database will be updated, i.e., retraining with new MFs where the target variable will be involved?

4. Representation and storage of dynamically growing complex Meta-Knowledge database
   i. A single MK database consisting of numerous MFs would be productive to represent all three areas or separate MK databases, specialized to solve a specific problem, would be gathered at different levels and at different times?
   ii. What level of granularity would be required for the better representation of a problem? For instance, the target variable of the MEs would be only the best learning algorithm, all the available algorithms with their rankings, algorithm parametrization.
   iii. What type of performance measures will be stored in MK database for three different areas, e.g., accuracy, run-time speed? For instance, the run-time speed measure might be useful particularly for a non-stationary environment which helps to identify accurate as well as an efficient learning algorithm.

5. Meta-level Learning
   i. What type of different learning strategies and algorithms would be used at Meta-level to efficiently search the best algorithm from MK database?
   ii. If MLL process recommends an entirely new algorithm for a new concept then what would be the impact of replacing the current algorithm instantly?
   iii. Replacing the algorithm for a concept will enhance the overall performance of the system in all the cases or is there a possibility that replacing algorithms may disturb the accuracy of the system?
   iv. MLL is proposed for three most important areas within the system, would it be effective enough to rely a lot on Meta-level learning?

4 Summary

This literature review and identification of key research challenges have been focused on the detailed study of existing MLL concepts and systems for both stationary and non-stationary environments. We are particularly interested in fully automating the process of building, deployment and maintenance of potentially complex multi-component, multi-level evolving predictive systems operating in continuously changing environments, as described in some of our previous publications and those resulting from the INFER project.

The review of the existing research has been structured into the coverage of five key components of an MLL system: (i) Available real and synthetic datasets for modelling at the Meta-level; (ii) Meta-features generation and selection approaches; (iii) Base-level learners as an input to the Meta-learning; (iv) Meta-learning; (v) Meta-learning based adaptive mechanisms for non-stationary environments.

There are various methods to gather EoD discussed though all of them have some limitations. Similarly, several Meta-feature generation techniques are reviewed from previous work though the majority of them have been introduced in the context of and are suitable for a stationary MLL system. Hence the applicability and effectiveness of such Meta-features for non-stationary environments remain an open research question. A consistently and systematically evaluated performance of base-models on EoDs forms a critical part of a reliable input data (i.e. label or target variable)
for the MLL. Collecting such performance data is the most time and processor-intensive task especially if numerous configurations and parametrisations of base-learners are to be adequately taken into account. Such a reliable collection of previously solved problems with thorough benchmarking of base-learners suitable for MLL does not currently exist and remains an open challenge.

A number of previously proposed MLL systems have been discussed in detail which included the application of MLL to both supervised and unsupervised learning problems. The development and evolution of the MLL field in the last three decades has been discussed and various systems have been compared with the previous ones. However, there are very few systems that have been targeted towards and can deal with non-stationary problems which are our main areas of interest. It is only in the last five years that non-stationary MLL have been receiving some interest. The primary focus has been on the problem representation of streaming data at the Meta-level.

There are multiple roles for Meta-learning in the scope of the INFER project and the developed automated and autonomous predictive modelling system and approaches working in continuously changing environments which we are intending to explore in our continuing research in this area.
### A Meta-features

#### Table 10: Meta-features used in various studies

| Meta-Features       | 5 | 12 | 20 | 31 | 77 | 105 | 110 |
|---------------------|---|----|----|----|----|-----|-----|
| **Descriptive Meta-features** |   |    |    |    |    |     |     |
| Number of Classes (k) |   |    |    |    |    |     |     |
| Frequency of most common class |   |    |    |    |    |     |     |
| Number of Features (p) |   |    |    |    |    |     |     |
| Number of Training instances (r) |   |    |    |    |    |     |     |
| Number of Test instances (t) |   |    |    |    |    |     |     |
| Number of Binary Features (b) |   |    |    |    |    |     |     |
| Number of Numeric features (n) |   |    |    |    |    |     |     |
| Number of Nominal features (s) |   |    |    |    |    |     |     |
| Proportion of binary features (b/p) |   |    |    |    |    |     |     |
| Proportion of nominal features (s/p) |   |    |    |    |    |     |     |
| Span of nominal values |   |    |    |    |    |     |     |
| Average of nominal values |   |    |    |    |    |     |     |
| Training instances to features ratio |   |    |    |    |    |     |     |
| **Statistical Meta-features** |   |    |    |    |    |     |     |
| Relative probability of missing values |   |    |    |    |    |     |     |
| Instances with missing values |   |    |    |    |    |     |     |
| Proportion of features with outliers |   |    |    |    |    |     |     |
| Mean Skewness (SKEW) |   |    |    |    |    |     |     |
| Mean Kurtosis (KURT) |   |    |    |    |    |     |     |
| Variance |   |    |    |    |    |     |     |
| Minimum |   |    |    |    |    |     |     |
| Maximum |   |    |    |    |    |     |     |
| Median |   |    |    |    |    |     |     |
| Correlation between predictor and target |   |    |    |    |    |     |     |
| Standard Deviation (StdDev) of the class distribution |   |    |    |    |    |     |     |
| Homogeneity of Covariances (S/D Ratio) |   |    |    |    |    |     |     |
| Orthogonality (MNSQ) |   |    |    |    |    |     |     |
| Proportion of largest Eigenvalue |   |    |    |    |    |     |     |
| Default Accuracy coefficient of variation (COEF-VAR) |   |    |    |    |    |     |     |
| Absolute value of the SKEW and KURT coefficients |   |    |    |    |    |     |     |
| Mean absolute values of first 5 auto-correlations (Mean-CORR) |   |    |    |    |    |     |     |
| Test of significant auto-correlations (TAC) |   |    |    |    |    |     |     |
| Significance of the 1, 2, and 3 Auto-correlation (TAC-1,2,3) |   |    |    |    |    |     |     |
| Test of Turning Points for randomness |   |    |    |    |    |     |     |
| First coefficient of auto-correlation (AC1) |   |    |    |    |    |     |     |
| Type |   |    |    |    |    |     |     |
| Trend |   |    |    |    |    |     |     |
| Turning point |   |    |    |    |    |     |     |
| Durbin-Watson statistic of regression residual |   |    |    |    |    |     |     |
| Step changes |   |    |    |    |    |     |     |
| Predictability measure |   |    |    |    |    |     |     |
| Non-linearity measure |   |    |    |    |    |     |     |
| Largest Lyapunov exponent |   |    |    |    |    |     |     |
| Largest power spectrum frequencies |   |    |    |    |    |     |     |
| Maximum value of power spectrum |   |    |    |    |    |     |     |
| Number of peaks > 60% |   |    |    |    |    |     |     |
| Auto-correlations at lags 1 and 2 |   |    |    |    |    |     |     |
| Partial auto-correlations at lags 1 and 2 |   |    |    |    |    |     |     |
| Seasonality Measure |   |    |    |    |    |     |     |
| Mean SMAPE |   |    |    |    |    |     |     |
| Mean absolute deviation of SMAPE |   |    |    |    |    |     |     |
| Mean absolute correlation coefficient |   |    |    |    |    |     |     |
| StdDev of correlation coefficient |   |    |    |    |    |     |     |
| Methods in top performing cluster |   |    |    |    |    |     |     |
| Distance to top performing cluster to second best |   |    |    |    |    |     |     |

17 only these two features are used in [5], they are also part of [77]
18 Log
19 of the series
20 of the de-trended series
21 of the series / StdDev of the de-trended series
22 ratio
| Feature                                                                 | k = 1 | k = 3 |
|------------------------------------------------------------------------|-------|-------|
| Min of CORR between predictors and target                              | ✔     | ✔     |
| Max of CORR between predictors and target                              | ✔     | ✔     |
| Mean of CORR between predictors and target                             | ✔     | ✔     |
| StdDev of absolute value of CORR between predictors and target         | ✔     | ✔     |
| Min of CORR between pairs of predictors                                | ✔     | ✔     |
| Max of CORR between pairs of predictors                                 | ✔     | ✔     |
| Mean of CORR between pairs of predictors                                | ✔     | ✔     |
| StdDev of absolute value of CORR between pairs of predictors           | ✔     | ✔     |
| Information Theoretic Meta-features                                    |       |       |
| Entropy of Classes (HC)                                               | ✔     | ✔     |
| Entropy of nominal features                                            | ✔     | ✔     |
| Joint Entropy of Classes (HCX)                                         | ✔     | ✔     |
| Average Mutual Information between Class and Nominal Features (MCX)   | ✔     | ✔     |
| Class Entropy to Mutual Information ratio                              | ✔     | ✔     |
| Noise to Signal Ratio (NoiseRatio)                                     | ✔     | ✔     |
| Dispersion Gain                                                         | ✔     | ✔     |
| Decision Nodes                                                         |       |       |
| Worst No. of Leaves (Worst Nodes)                                      | ✔     | ✔     |
| Homogeneity of Leaves Nodes                                            | ✔     | ✔     |
| Landmarkers                                                            |       |       |
| Nodes per attribute                                                    | ✔     | ✔     |
| Nodes per instance                                                     | ✔     | ✔     |
| Average leaf co-occurrence                                            | ✔     | ✔     |
| Average gain-ratio difference                                          | ✔     | ✔     |
| Maximum depth                                                          | ✔     | ✔     |
| No. of repeated nodes                                                  | ✔     | ✔     |
| Shape                                                                  | ✔     | ✔     |
| Homogeneity                                                             | ✔     | ✔     |
| Imbalance                                                              | ✔     | ✔     |
| Internal symmetry                                                       | ✔     | ✔     |
| No. of Nodes in each level - width                                     | ✔     | ✔     |
| No. of levels - Height                                                 | ✔     | ✔     |
| No. of nodes in the tree                                               | ✔     | ✔     |
| No. of leaves in the tree                                              | ✔     | ✔     |
| Maximum no. of nodes at one level                                      | ✔     | ✔     |
| Nodes per attribute                                                    | ✔     | ✔     |
| Parameters                                                             | ✔     | ✔     |
| No. of repeated nodes                                                  | ✔     | ✔     |
| Shape                                                                  | ✔     | ✔     |
| Homogeneity                                                             | ✔     | ✔     |
| Imbalance                                                              | ✔     | ✔     |
| Internal symmetry                                                       | ✔     | ✔     |
| No. of Nodes in each level - width                                     | ✔     | ✔     |
| No. of levels - Height                                                 | ✔     | ✔     |
| No. of nodes in the tree                                               | ✔     | ✔     |
| No. of leaves in the tree                                              | ✔     | ✔     |
| Maximum no. of nodes at one level                                      | ✔     | ✔     |
| Mean of the no. of nodes                                               | ✔     | ✔     |
| Nodes per attribute                                                    | ✔     | ✔     |
| Parameters                                                             | ✔     | ✔     |
| No. of repeated nodes                                                  | ✔     | ✔     |
| Shape                                                                  | ✔     | ✔     |
| Homogeneity                                                             | ✔     | ✔     |
| Imbalance                                                              | ✔     | ✔     |
| Internal symmetry                                                       | ✔     | ✔     |
| No. of Nodes in each level - width                                     | ✔     | ✔     |
| No. of levels - Height                                                 | ✔     | ✔     |
| No. of nodes in the tree                                               | ✔     | ✔     |
| No. of leaves in the tree                                              | ✔     | ✔     |
| Maximum no. of nodes at one level                                      | ✔     | ✔     |
| Mean of the no. of nodes                                               | ✔     | ✔     |
| Standard deviation of the no. of nodes                                  | ✔     | ✔     |
| Standard deviation of the length of the longest branch                 | ✔     | ✔     |
| Standard deviation of the mean of the branch length                    | ✔     | ✔     |
| Standard deviation of the minimum occurrence of Features               | ✔     | ✔     |
| Standard deviation of the maximum occurrence of Features               | ✔     | ✔     |
| Standard deviation of the mean of the occurrences of Features          | ✔     | ✔     |
| Weight sum of dataset                                                  | ✔     | ✔     |
| Minimum weight sum of dataset                                          | ✔     | ✔     |
| Average weight sum of dataset                                          | ✔     | ✔     |
| Standard deviation of the weight sum of dataset                         | ✔     | ✔     |
| No. neighbours for dataset                                             | ✔     | ✔     |
| Minimum No. neighbours for dataset                                     | ✔     | ✔     |
| Maximum No. neighbours for dataset                                     | ✔     | ✔     |
| Average No. neighbours for dataset                                     | ✔     | ✔     |
| Standard deviation of the no. of neighbours for dataset                | ✔     | ✔     |
| PCA skewness                                                           | ✔     | ✔     |
| PCA kurtosis                                                           | ✔     | ✔     |
| Total Meta-features                                                    | 9     | 13    | 19    | 25    | 10    | 14    | 8     | 7     | 15    | 3     | 7     | 11    | 10    | 9     | 23    | 7     | 10    | 22    |

23. of raw and trend/seasonally adjusted
24. of raw and trend/seasonally adjusted
25. k = 3 used only in [115]
26. k = 1
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