Feature Defect Prediction

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ABSTRACT

Software errors are a major nuisance in software development and can lead not only to damage of reputation but also to considerable financial losses for companies. For this reason, numerous techniques for detecting and predicting errors have been developed over the past decade, which are largely based on machine learning methods. The usual approach of these techniques is to predict errors at file level. For some years now, however, the popularity of feature-based software development has been increasing - a paradigm that relies on function increments of a software system (features) and thus ensures a wide variability of the software product. A common implementation technique for features is based on annotations with preprocessor instructions, such as #IFDEF and #IFNDEF, whose code is spread over several files of the software's source code ("code scattering"). A bug in such a feature code can have far-reaching consequences for the functionality of the entire software. If a part of the feature code contains errors, the entire function of the feature becomes faulty and may lead to the failure of the entire functionality of the software (features are "cross-cutting"). This problem is the subject of this thesis. A prediction technique for faulty features is developed, which is based on methods of machine learning. The evaluation of eight classifiers, each based on an individual classification algorithm, shows that the feature-based data set created for this thesis allows an accuracy of up to 84% for the prediction of faulty or error-free features. It is also shown how the feature orientation aspect was incorporated into the creation of the dataset and what results were achieved compared to the traditional file-based methodology. This comparison showed that the additional inclusion of the feature aspect in the file-based defect prediction has no significant influence on the prediction results.

1 INTRODUCTION

Software errors are a significant trigger for financial damage and damage to the reputation of companies. Such errors range from minor bugs to serious security vulnerabilities. For this reason, there is a great deal of interest in warning a developer when they release updated software code that may contain one or more bugs. To this end, researchers and software developers have developed various techniques for error detection and error prediction over the past decade, which are largely based on methods and techniques of Machine

Learning [3]. These techniques usually use historical data of defective and defect-free changes to software systems in combination with a carefully compiled set of attributes (usually called features[1]) to train a given classifier [1, 6]. This can then be used to make an accurate prediction of whether a new change to a piece of software is defective or clean. The choice of algorithms for classification is large. Studies show that, out of the pool of available algorithms, both tree-based (e.g. J48, CART or Random Forest) and Bayesian algorithms (e.g. Naïve Bayes (NB), Bernoulli-NB or multinomial NB) are the most widely used [16]. Alternative algorithms include regression, k-nearest-neighbors or artificial neural networks [3]. It should be noted, however, that there is no consensus on the best available algorithm, since each algorithm has different strengths and weaknesses for specific use cases. The goal of this work is to develop such a prediction technique for software errors based on software features. These features describe increments of the functionality of a software system. The software systems developed in this way are called software product lines and consist of a set of similar software products. They are characterized by having a common set of features and a common code base [18]. By having different features along the software products, a wide variability within a product line can be achieved. In the development of the prediction technique, the implementation of features is performed by means of preprocessor instructions, such as #IFDEF and #IFNDEF (also called preprocessor directives). This approach [11], which has so far only been considered once in a case study, is promising for several reasons:

(1) Since a given feature might be historically more or less error-prone, a change that updates the feature may be more or less eror-prone as well.
(2) Features more or less likely to be error-prone might have certain characteristics that can be harnessed for defect predictoin.
(3) Code that contains a lot of feature-specific code (specifically, the so-called feature interactions) might be more error-prone than others.

The above-mentioned goal of the work consists of several sub-goals. Among them is the creation of a dataset including the feature aspect. This dataset in turn serves to train a representative selection of classifiers with a subsequent comparative evaluation of these. In addition, the feature-based data set is compared with a classical file-based data set, the development of which was taken from a scientific paper [9].

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[1]To avoid ambiguous and misleading use of the feature term, the term "attribute" will be used throughout this paper to describe the characteristics of data.

2 BACKGROUND / RELATED WORK

3 METHODOLOGY

3.1 Creation of Dataset

The data set forms the basis for the training of the machine learning classifiers and is created specifically for this work based on commits from 12 feature-based software projects. The software projects are selected on the basis of previous use in scientific literature [7, 8, 11, 12]. The software projects used for this thesis are listed in Table 1 together with their purpose and data sources.

Table 1: Used software projects

Project	Purpose	Data source
Blender	3D modelling tool	GitHub mirror
Busybox	UNIX toolkit	Git repository
Emacs	text editor	GitHub mirror
GIMP	graphics editor	GitLab repository
Gnumeric	spreadsheet	GitLab repository
gnuplot	plotting tool	GitHub mirror
Irssi	IRC client	GitHub repository
libxml2	XML parser	GitLab repository
lighttpd	web server	Git repository
MPSolve	polynom solver	GitHub repository
Parrot	virtual machine	GitHub repository
Vim	text editor	GitHub repository

To get the commit data of the software projects the Python library PyDriller[2] was used [17]. This allows easy data extraction from Git repositories to obtain commits, commit messages, developers, diffs, and more (called "metadata" in the following). The URLs to the Git repositories of the software projects were used as input for the specially created Python scripts for receiving the commit metadata. Furthermore, the metadata was divided into commits per release. This was made possible by specifying release tags in the PyDriller code, based on the tag structure of Git repositories. For each modified file within a commit and a release, the following metadata was retrieved using PyDriller:

- commit hash (unique identifier of a commit)
- commit author
- commit message
- filename
- lines of code
- cyclomatic complexity
- number of added lines
- number of removed lines
- diff (changeset)

The data obtained in this way was stored in a MySQL database after retrieval. For each software project, a separate table was created in which, in addition to the metadata above, the name of the software project and the release numbers associated with the commits were stored. Each modified file of a commit receives one row

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²https://github.com/ishepard/pydriller

of the database tables. The further construction of the data set is divided into several phases of data processing and optimization.

The first phase consists of extracting the features involved in a modified file. This was done by using a Python script to identify the preprocessor statements #IFDEF and #IFNDEF in the diffs of the modified files, and then saving the string following the directives as a feature until the end of the line of code. The identification was done using regular expressions. The features identified per file are stored in an additional column in the respective MySQL tables. In case a feature is identified after the #IFNDEF directive, the feature is stored with a preceding "not". It will be saved as a separate feature, along with its non-negated form. Combinations of features are stored in their identified form. If no feature could be identified, "none" is saved accordingly.

This way of identification has some obstacles. In some C programming paradigms, it is common to include header files in the source code using preprocessor directives, so that they appear to be features. However, these "header features", as they will be referred to later, should be ignored as they do not create variability throughout the source code. In general, these header features are identifiable by their naming in the form of an appended _h_ to the feature name, such as featurename_h_. This appended part allows the header features to be identified and filtered out using regular expressions. It is also possible that "wrong" features can be identified. Examples of this can come from #IFDEFs used in comments. Such false features were removed in a manual review of the identified features and replaced with "none".

The next phase of processing consists of identifying corrective commits. A common method used for this, and one used in this paper, is to analyze commit messages for the presence of certain keywords [19]. The keywords are "bug," "bugs," "bugfix," "error," "fail," "fix," "fixed," and "fixes. The analysis was carried out by means of a Python script using simple methods of Natural Language Processing (NLP). Identification was limited to the first line of each commit message. The results were stored in another column of the MySQL tables (true = corrective, false = not corrective).

The search for corrective commits is followed by an analysis for commits that introduced bugs. A PyDriller implementation of the SZZ algorithm according to Sliwerski, Zimmermann and Zeller was used [15, 17]. This algorithm allows to find commits that introduce bugs in locally stored software repositories [2]. It requires that the corrective commits have already been identified, as they serve as the algorithm's input [2].

An overview of the number of corrective and bug-introducing commits and the number of features identified per software project is given in Table 2.

Here!

3.2 Selection of Metrics

As already mentioned, attributes are used to train the machine learning classifiers. In this scenario, so-called metrics are used as attributes. Metrics are numerical values that quantify properties of a software project. In this case, the metrics are divided into the usual categories code metrics and process metrics and each is calculated using the existing raw data of the main tables [13]. Code metrics are used to measure properties of source code, such as "size" or

Table 2: Number of corrective and bug-introducing commits and number of identified features

Project	#corrective	#bug-introducing	#features
Blender	7.760	3.776	1.400
Busybox	1.236	802	628
Emacs	4.269	2.532	718
GIMP	1.380	854	204
Gnumeric	1.498	1.191	637
gnuplot	854	1.215	558
Irssi	52	22	9
libxml2	324	88	200
lighttpd	1.078	929	230
MPSolve	151	211	54
Parrot	3.109	3.072	397
Vim	371	696	1.158

complexity [13]. Process metrics are used to measure properties that can be discussed using metadata from software repositories [13]. Examples include the number of changes made to a particular file or the number of active developers on a project. For this work, eleven feature-based metrics were calculated, divided into seven process and four code metrics. Five of the process metrics were taken from scientific papers [11, 13]. The other six metrics were calculated based on the commit metadata obtained from PyDriller. A list of the eleven metrics and their descriptions can be found in Table 3. The individual metrics were calculated either directly using SQL queries or combined using SQL queries and calculations by a Python script.

In view of the evaluation of the feature-based dataset that follows in the next section, two additional datasets were created to make the impact of the feature-based metrics on the classifiers' predictions comparable. Both further data sets follow a classical file-based approach as it is common in machine learning based error detection and are based on the methodology developed by Moser et al. [9]. The 17 process metrics of this scientific work were also adopted and are listed in Table 4. A visualization to distinguish the three data sets is shown in Figure 1.

The figure shows the ways of creating the feature-based dataset (path A - G) and the file-based data sets according to [9].These are divided into the "simple" file-based dataset (paths A, B, H, I) and the extended file-based dataset (combination of both paths). The creation of the feature-based dataset has already been explained in detail up to this section. More information about finalizing the datasets will follow as this section progresses.

The creation of the file-based datasets is also based on the raw data of the software project commits obtained with PyDriller and the modified files (A + B) extracted from them. Thus no further processing of the raw data is necessary. They then serve as a basis for the calculation of the 17 metrics (H) according to [9]. To calculate the time-based metrics AAGE and WAGE, the raw data or the commits listed in the raw data had to be supplemented with their publication date. This was also done with PyDriller. The date of the first commit of a release was chosen as the starting point for calculating the past weeks.

The feature-based and the "simple" file-based dataset (G + I) consist of the calculated feature- (F) and file-related (H) metrics and the labels of the target class. The values of the metrics are calculated for the data of each software project. The resulting tables contain as columns the values of the eleven or 17 metrics and the label (target class) "defective" or "clean" and as rows the features or files aggregated by release. This means that if a feature or file has been edited multiple times in a release (i.e. it is edited in multiple commits), the average value of the respective metrics within the release is calculated and stored. The procedure for determining the label is performed for each change to a feature or file using the following pattern:

bug-introducing	+	corrective	=	defective
bug-introducing	+	not corrective	=	defective
not bug-introducing	+	corrective	=	clean
not bug-introducing	+	not corrective	=	clean

The information on the status of a feature is based on the files on which it is based. If a feature or a file has been edited several times within a release, the label is determined according to the following rules:

- in the case of features, it is checked whether the feature was marked as "defective" at least once within the release. If this is the case, it is assumed that the feature is broken in the release in question. If this is not the case, the feature is assumed to be clean.
- in the case of files, the last commit of the files in that release is checked. If the file is marked "clean" there, it is assumed to be error-free. If it is marked as "defective", it is assumed that it is defective in this release.

The individual tables created in this way are then concatenated into a common table, resulting in a comprehensive listing of metrics including the associated labels. This list specifies the characteristics a feature or file must have in order to be classified as "defective" or "clean" and serves as a training basis for classifiers for future predictions.

A special feature is the second file-based data set created for the comparison within the evaluation (J). It is based on the "simple" file-based dataset (I) with the metrics from [9], but additionally includes the eleven metrics of the feature-based dataset (G) from Table 3. For this purpose, the values of the feature-based metrics were mapped or transferred at file level. This means that for each file of a release referenced in the file-based dataset, it was analyzed which features were mentioned in the respective file. From these features, the corresponding metrics of the feature-based dataset were determined and the average value was calculated and entered into the entered dataset. If no features were mentioned in a file, the value 0 is stored for the feature-based metrics. As mentioned at the beginning of this section, this way the feature-based dataset can be compared with a classical file-based dataset, because the conditions for the comparison have been created. A direct comparison between the different datasets is not practical for the reasons mentioned above.

Some supplementary key figures for the datasets are listed in Table 5. The row "unique" indicates how many unique rows are

Table 3: Overview of used metrics

	Metric	Description	Source
Process metrics	Number of commits	Number of commits associated with the feature/file in a release.	[11]
	Number of active developers	Number of developers who have edited (changed, deleted or added) the feature / file within a release	[11]
	Number of distinct developers	Cumulative number of developers who have edited (changed, deleted or added) the feature / file within a release	[11]
	Experience of all develepoers	geometric mean of the experience of all developers who have edited (changed, deleted or added) the feature / file within a release.~ Experience is defined as the sum of the changed, deleted or added lines in the commits associated with the feature / file.	[11]
	Experience of the most involved developers	Experience of the developer who has edited (changed, deleted or added) the feature / file most often within a release. Experience is defined as the sum of changed, deleted, or added lines in the commits associated with the feature/file.	[11]
	Degree of modifications	Number of edits (change, removal, extension) of the feature / file within a release.	*
	Scope of modifications	Number of edited features / files within a release (feature or file overlapping value). Idea: The more features / files have been edited in a release, the more error-prone they seem to be.	*
Code metrics	Lines of code	Average number of lines of code of the files associated with the feature / ~file within a release.	*
	Cyclomatic Complexity	Average cyclomatic complexity of the files associated with the feature / file within a release.	*
	Number of added lines	Average number of lines of code added to the files associated with the feature / file within a release.	*
	Number of removed lines	Average number of lines of code deleted from the files associated with the feature / from the file within a release	*
These values were calculated based on the metadata obtained with PyDriller. Feature-level metrics were calculated based on the metadata of the underlying files.			
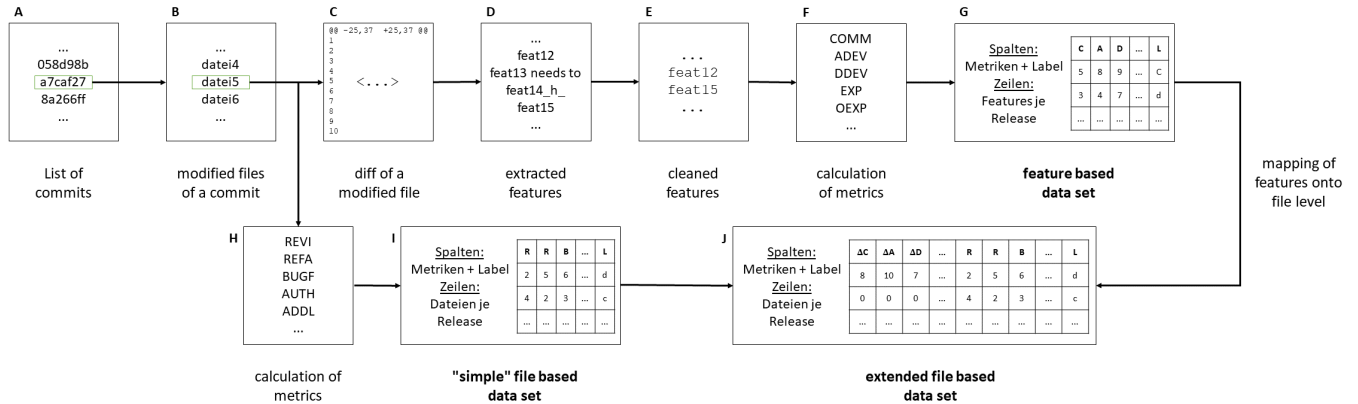
Figure 1: Visualization to distinguish the three data sets

contained in the datasets. The datasets created in the manner described above can now be used to train the classifiers. This process will be explained in the next section.

3.3 Selection of Classifiers

Although programming with the Python programming language was often used to create the data sets, the choice of a machine learning tool was not the library scikit-learn [10], but an independent solution. The WEKA-Workbench[3] is used as a machine learning tool. This tool proved to be suitable for the underlying task by numerous citations in scientific papers (among others in [6, 11, 14]). The WEKA-Workbench (WEKA as acronym for **W**aikato **E**nvironment for **K**nowledge **A**nalysis) was developed at the University of Waikato in New Zealand and offers a large collection of machine learning algorithms and preprocessing tools for use

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[3]https://www.cs.waikato.ac.nz/ml/weka/

Table 4: Process metrics according to [9]

Metric	Description
REVISIONS	Number of revisions of a file.
REFACTORINGS	Number of times a file has been refactored.
BUGFIXES	Number of times a file was involved in bug-fixing.
AUTHORS	Number of distinct authors that checked a file into the repository.
LOC_ADDED	Sum over all revisions of the lines of code added to a file.
MAX_LOC_ADDED	Maximum number of lines of code added for all revisions.
AVE_LOC_ADDED	Average lines of code added per revision.
LOC_DELETED	Sum over all revisions of the lines of code deleted from a file.
MAX_LOC_DELETED	Maximum number of lines of code deleted for all revisions.
AVE_LOC_DELETED	Average lines of code deleted per revision.
CODECHURN	Sum of (added lines of code − deleted lines of code) over all revisions.
MAX_CODECHURN	Maximum CODECHURN for all revisions.
AVE_CODECHURN	Average CODECHURN per revision.
MAX_CHANGESET	Maximum number of files committed together to the repository.
AVE_CHANGESET	Average number of files committed together to the repository.
AGE	Age of a file in weeks (counting backwards from a specific release).
WEIGHTED_AGE	$WeightedAge = \frac{\sum_{i=1}^{N} Age(i) * LOC\_ADDED(i)}{\sum_{i=1}^{N} LOC\_ADDED(i)}$

Table 5: Key figures of the data sets

	feature-based data set	"simple" file-based data set	"extended" file-based data set
#attributes	11 + label	17 + label	28 + label
#data records	14.059	76.986	76.986
thereof defective	2.735	1.899	1.899
thereof clean	11.324	75.087	75.087
thereof unique	8.447	52.564	52.783

within a graphical user interface [5]. There are also interfaces for the Java programming language [5]. An overview of the selected classification algorithms can be found in Table 6. This also includes the abbreviations of the classifiers that will be used in the following.

All classification algorithms presented above are already integrated in the WEKA tool. It receives as input the final data sets in a proprietary file format. The 13 calculated metrics form the attributes, whereas the target class is represented by the labels "defective" and "clean".

The training process of the classifiers took place within the graphical user interface of WEKA. Before the training, the split ratios for the division of the data sets into training data and test data were determined. It was determined individually for each of the software projects used and is based on the number of releases available in each case. However, care was always taken to approximate the commonly used split ratios of 80:20 and 75:25 as well as 70:30. The training data ranges from 67% to 80% of the data records of the data sets. The earlier releases were assigned to the training data. The training data contains the data records of the later releases. An overview of the division into training and test data per software project is shown in Figure 2. The resulting split ratios for the entire data sets are: 69:31 (feature-based data set) and 71:29 ("simple" and extended file-based data set).

The training of the classifiers in WEKA was carried out for each classification algorithm with the respective standard settings. Only for the algorithms NN and RF further configurations were made. For the RF-algorithm a number of instances of 200 was defined. This means that 200 decision trees are processed simultaneously in parallel. For the NN algorithm a hidden layer structure of $(13,13,13$ was chosen. This means that the artificial neural network has three hidden layer layers of 13 hidden layer neurons each. This allows

them to process the large number of attributes more efficiently. Furthermore, no validation data was generated, since it is not intended to perform attribute selection or to adjust further classifier settings.

An analysis of the training process also showed that the file-based data sets are highly unbalanced with regard to the target class. With a value of about 97% there are far more entries that are assigned to the label "clean". Balancedness, i.e. a balanced ratio (50:50 is not mandatory in the binary case) within the target classes, is however a prerequisite for the correct training of most classifiers. Ignoring this problem can lead to a misleading accuracy (hit accuracy of the classifier), because most data sets are correctly assigned to the overrepresented class. To solve this problem, the SMOTE algorithm was applied to the file-based datasets [4]. The algorithm, whose acronym stands for **S**ynthetic **M**inority **O**ver-sampling **Te**chnique, performs an oversampling of the underrepresented class [4]. Using next-neighbor calculations based on the Euclidean distance between the attribute values of each dataset's datasets, new synthetic datasets are added (oversampling) so that the number of datasets of the relevant class increases [4]. In this case, the percentage of synthetic records generated is 2000, so for each existing record of the underrepresented class, 20 additional synthetic records are generated. Thus, the percentage of records labeled "defective" was increased to about 41%. At the same time the number of records grew by about 60%. The algorithm was only applied to the training data [4] . An application to the test data is not foreseen, so that the "ground truth" is not distorted or falsified. As a result, the metrics of the file-based datasets also changed. These are shown in Table 7.

The results obtained using the test data, which reflect the performance of the individual classifiers, are presented in the following chapter as part of the evaluation.

4 EVALUATION

5 DISCUSSION

6 CONCLUSION

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Table 6: Selection of classification algorithms

Algorithm	Abbreviation
J48 Decision Trees	J48
k-Nearest-Neighbors	KNN
Logistic Regression	LR
Naïve Bayes	NB
Artificial Neural Networks	NN
Random Forest	RF
Stochastic Gradient Descent	SGD
Support Vector Machines	SVM

Table 7: Key figures of the data sets

	"simple" data set		extended data set	
	before	**after**	**before**	**after**
#attributes	17 + label	17 + label	28 + label	28 + label
#data records	76.986	111.706	76.986	112.706
thereof defective	1.899	37.619	1.899	37.619
thereof clean	75.087	75.087	75.087	75.087
thereof unique	52.564	86.155	52.783	86.381
overall split ratio	71:29	81:19	71:29	81:19

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(a) Blender
split ratio: 73:27

(b) Busybox
split ratio: 71:29

(c) Emacs
split ratio: 71:29

(d) GIMP
split ratio: 71:29

(e) Gnumeric
split ratio: 75:25

(f) gnuplot
split ratio: 80:20

(g) Irssi
split ratio: 71:29

(h) libxml2
split ratio: 80:20

(i) lighttpd
split ratio: 67:33

(j) MPSolve
split ratio: 75:25

(k) Parrot
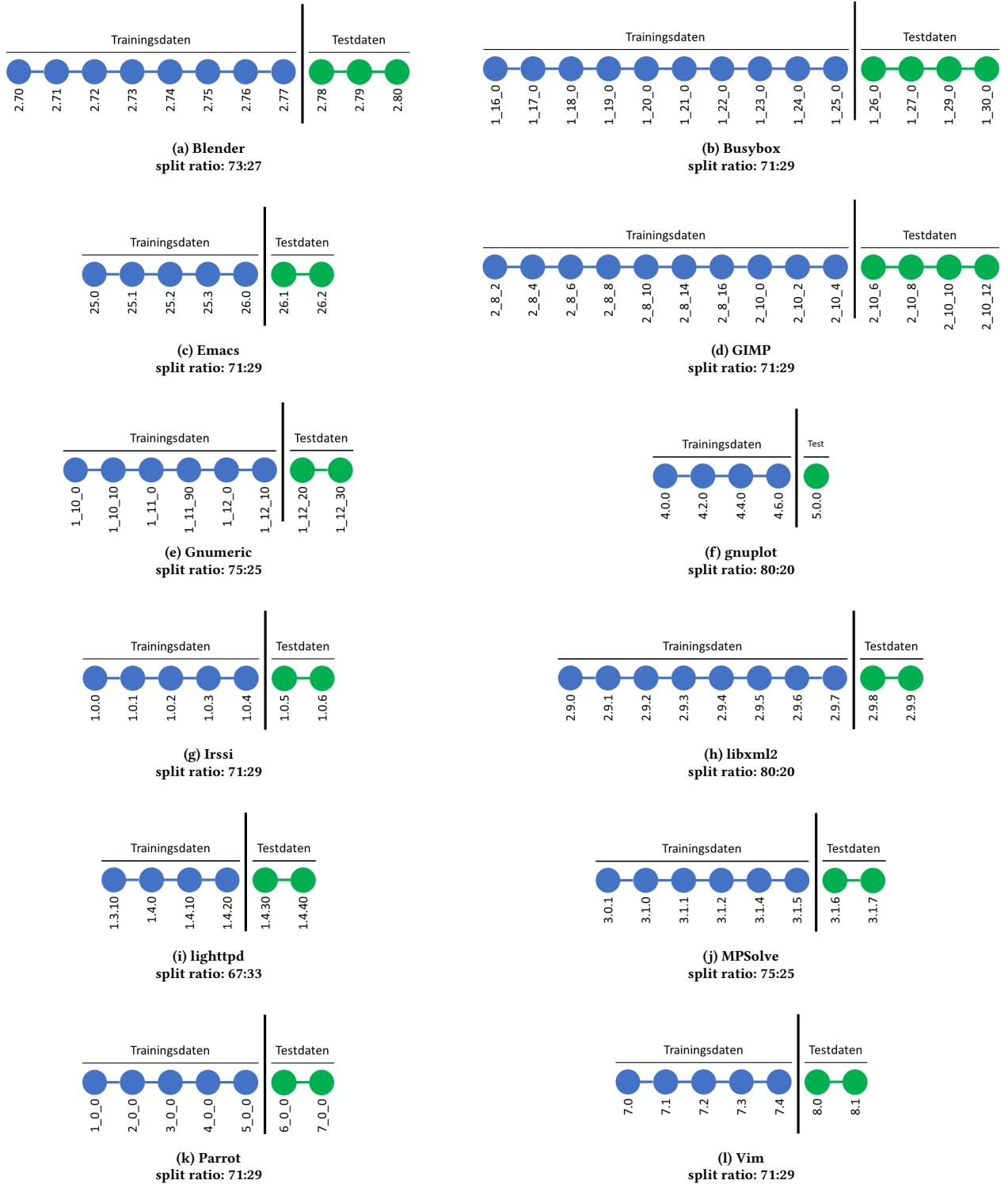**split ratio: 71:29**

(l) Vim
split ratio: 71:29

Figure 2: Overview of the division into training and test data