



Feature-based defect prediction using Machine Learning methods

Introductory talk

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Introduction & Motivation

- software defects trigger financial loss and reputation damage

Amazon 1p glitch: Software error sees hundreds of items sold for fractions of their value

(independent.co.uk, [1])

Retailers say they could be bankrupted by the fault in software that claims to 'auto-optimize' listings

Software

How one bad algorithm cost traders \$440m

(theregister.co.uk, [2])

A look at the worst software testing day ever

Having 'Null' as a license plate is about as much of a nightmare as you'd expect

The license plate was 'null,' but the tickets were anything but

(theverge.com, [3])

- great interest in tools for detecting faulty code
- development of techniques for default detection and prediction
 - mostly based on methods of machine learning
 - creation of a data set for the training of classifiers
 - data basis: defect-free and faulty historical data
- wide range of learning methods available (Son et al., 2019; Challagulla, Bastani, Yen, & Paul, 2008)
 - Decision Tree based
 - Bayesian methods
 - Regression, k-Nearest-Neighbor, Artificial Neural Networks

- aim of the thesis
 - prediction technique for software defects
 - in consideration of software features
 - based on methods of machine learning
- promising approach
 - defect prediction based on "past" of the software
 - properties of defect-prone features
 - defect susceptibility of features

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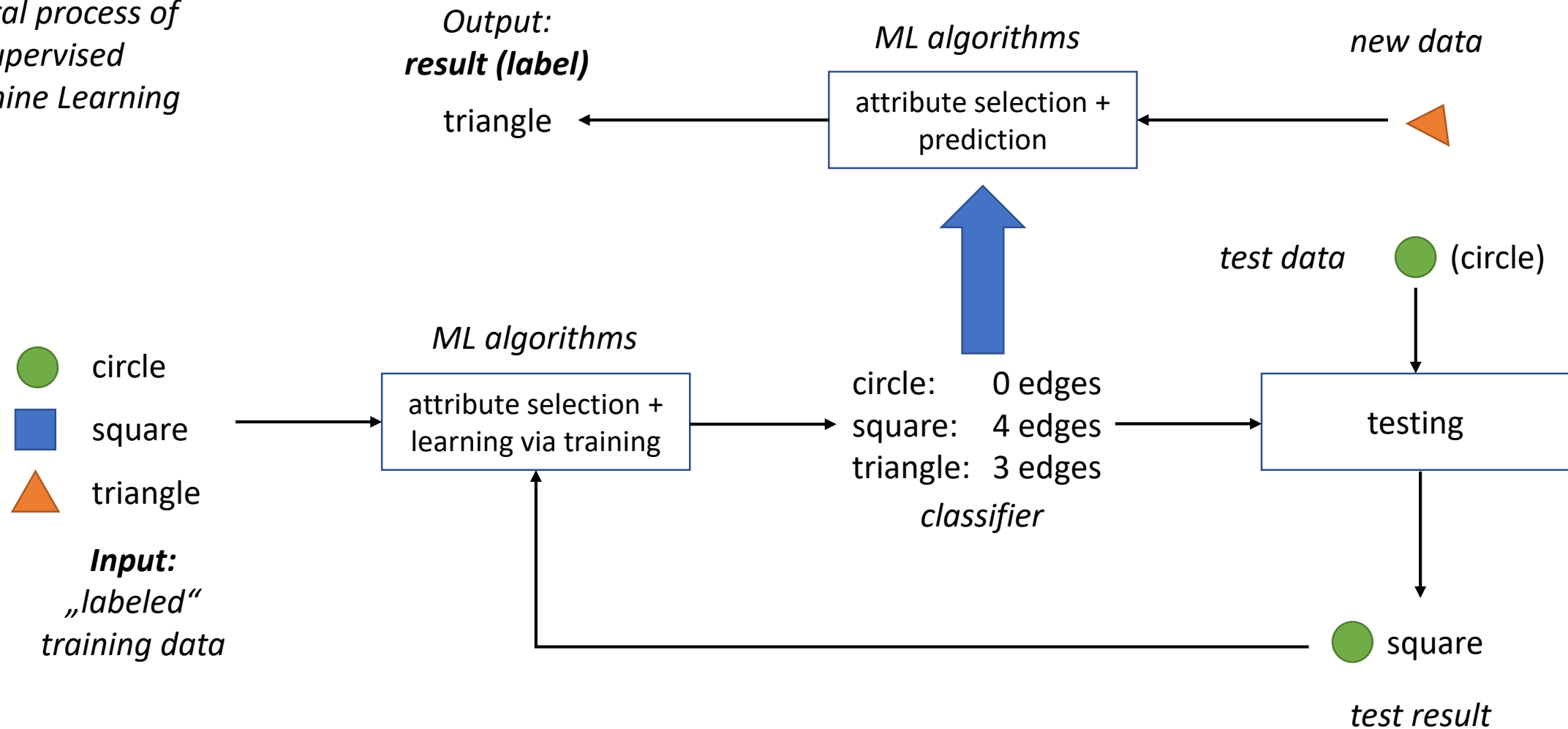
Background

Machine Learning classification

Defect prediction using Machine Learning

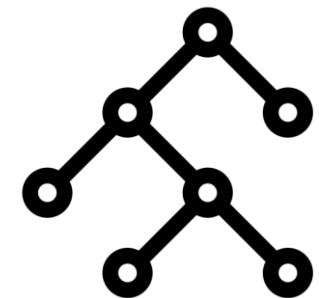
- supervised Machine Learning (Hammouri, Hammad, Alnabhan, & Alsarayrah, 2018)
 - development of a derivation function
 - conclusions from in- and output within a training data set
 - prediction for new input data
 - common algorithms
 - Naïve Bayes
 - Decision Trees
 - Artificial Neural Networks

general process of supervised Machine Learning



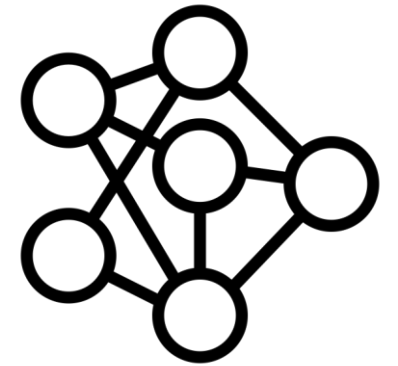
- Naïve Bayes (Hammouri, Hammad, Alnabhan, & Alsarayrah, 2018)
 - probabilistic classifier
 - based on Bayes theorem →
 - independence of attributes
- decision trees (Hammouri, Hammad, Alnabhan, & Alsarayrah, 2018)
 - hierarchical and predicative
 - attributes of the data as branches
 - decisions as leaf nodes

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$



(source of the icon see bibliography)

- Artificial Neural Networks (Hammouri, Hammad, Alnabhan, & Alsarayrah, 2018; Jukes, 2017)
 - inspired by biological neural networks
 - non-linear classifier
 - consisting of quantity of processing units (neurons)
 - parallel execution for the development of expenditures
 - signal transmission through connections
 - calculations based on the sum of the inputs of all neurons



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■ defect prediction using Machine Learning

- Challagulla, V. U. B., Bastani, F. B., Yen, I. L., & Paul, R. A. (2008). **Empirical assessment of machine learning based software defect prediction techniques**. International Journal on Artificial Intelligence Tools, 17(2), 389–400. <https://doi.org/10.1142/S0218213008003947>
- Son, L. H., Pritam, N., Khari, M., Kumar, R., Phuong, P. T. M., & Thong, P. H. (2019). **Empirical study of software defect prediction: A systematic mapping**. Symmetry, 11(2). <https://doi.org/10.3390/sym11020212>

■ feature-based defect prediction using Machine Learning

- Queiroz, R., Berger, T., & Czarnecki, K. (2016). **Towards predicting feature defects in software product lines**. FOSD 2016 - Proceedings of the 7th International Workshop on Feature-Oriented Software Development, Co-Located with SPLASH 2016, 58–62. <https://doi.org/10.1145/3001867.3001874>

feature-based process of supervised machine learning according to Queiroz et. al.

„labeled“ data set based on releases of the tool Busybox			
feature	release	metrics	label
SIGHUP	2.1	12,4,8,9,2	defective
SIGHUP	2.2	14,6,10,6,7	faultless
SIGINT	2.1	5,2,4,6,4	faultless
SIGINT	2.2	6,3,5,10,6	defective
...
SIGQUIT	2.1	8,2,4,3,5	defective
SIGQUIT	2.2	15,5,8,4,8	faultless
...

training data

test data

attribute selection +
learning via training

attributes: process metrics

- COMM
- ADEV
- DDEV
- EXP
- OXP

ML algorithms

NB

Naïve Bayes

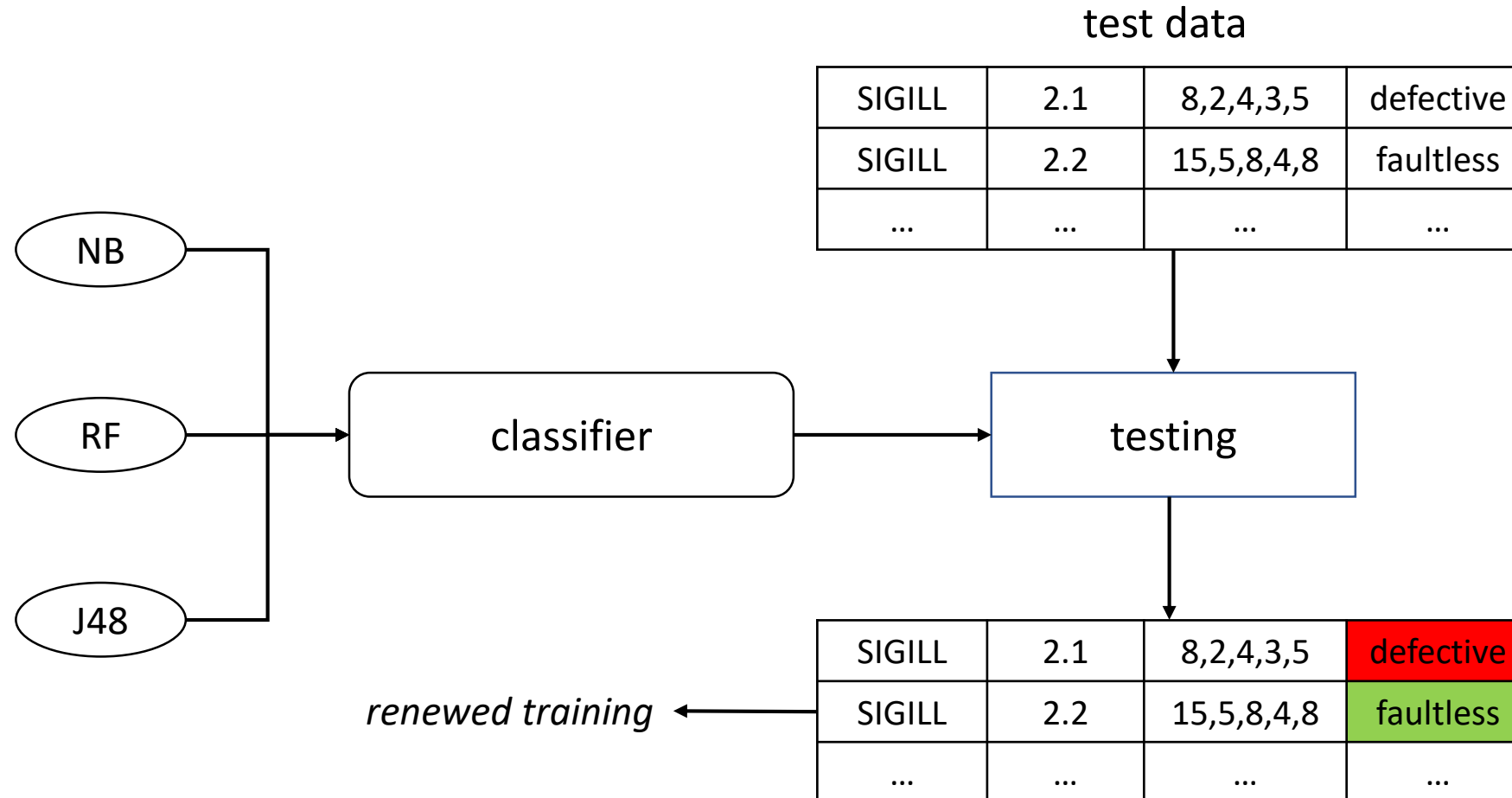
RF

Random Forest

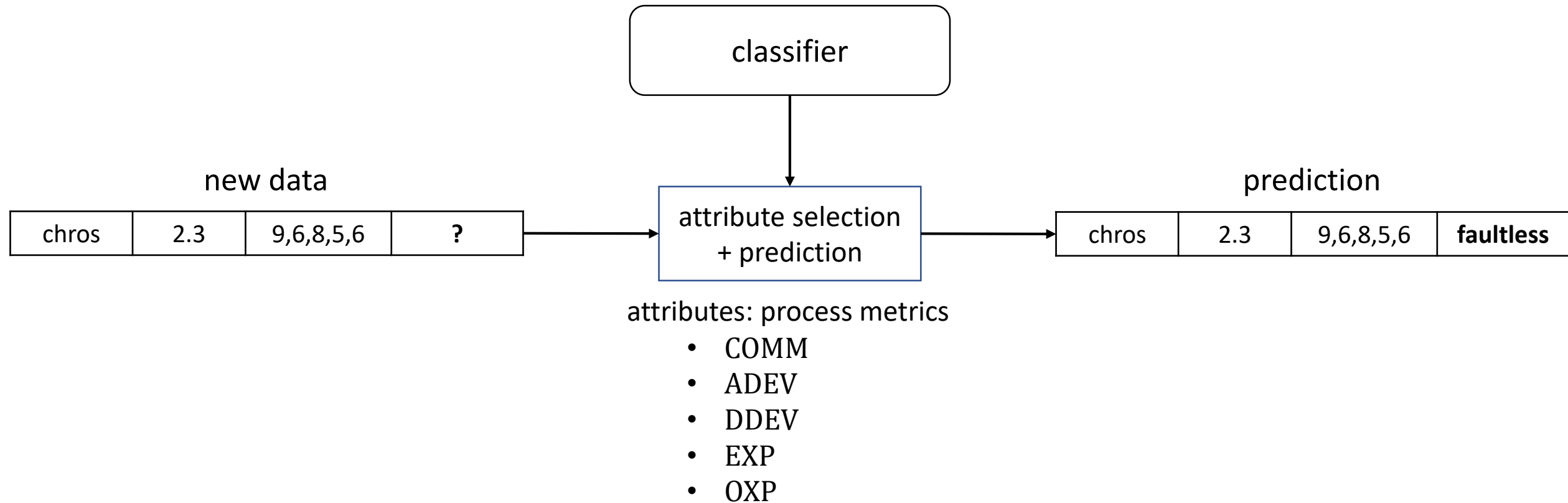
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Decision Tree

feature-based process of supervised machine learning according to Queiroz et. al.



feature-based process of supervised machine learning according to Queiroz et. al.



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Goal and approach

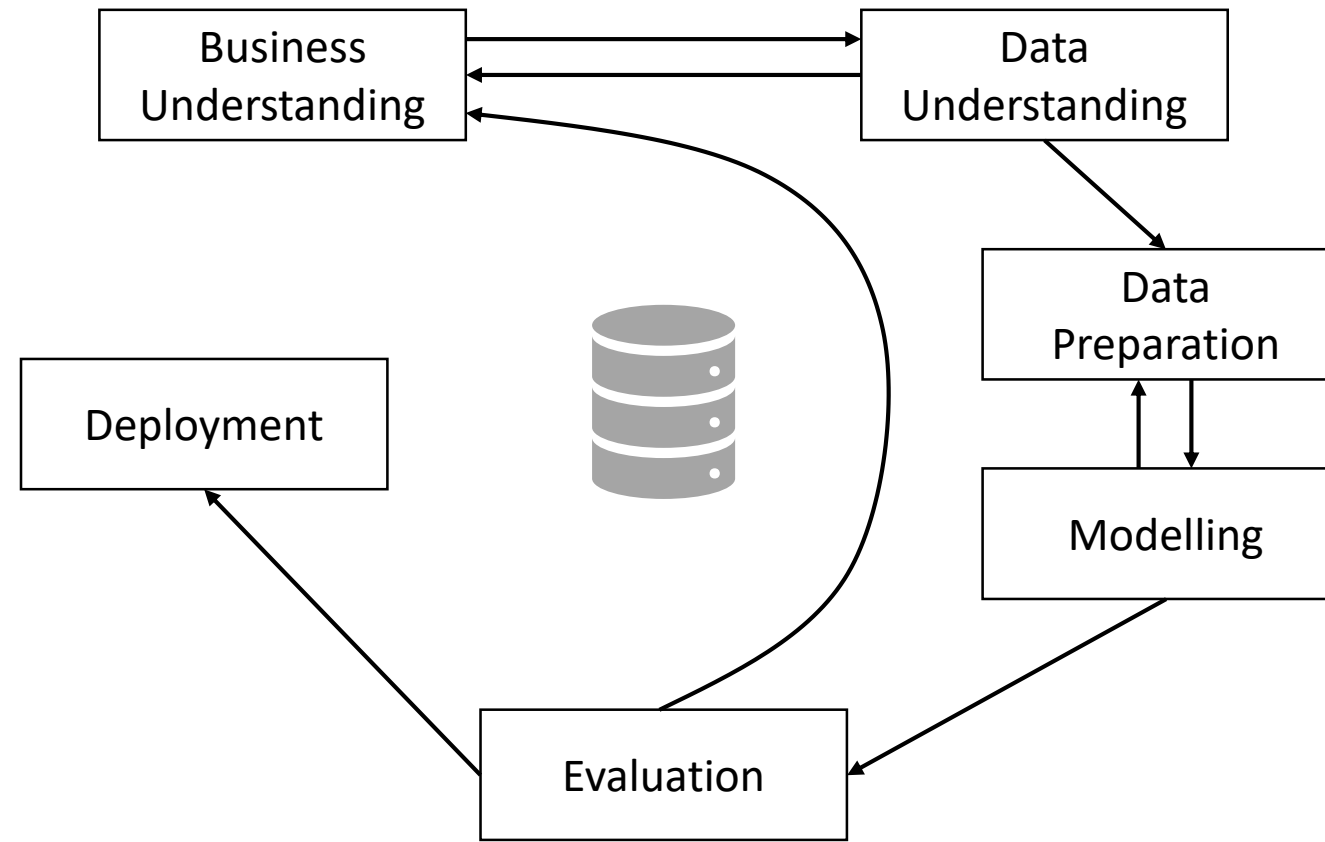
Goal

Methodology

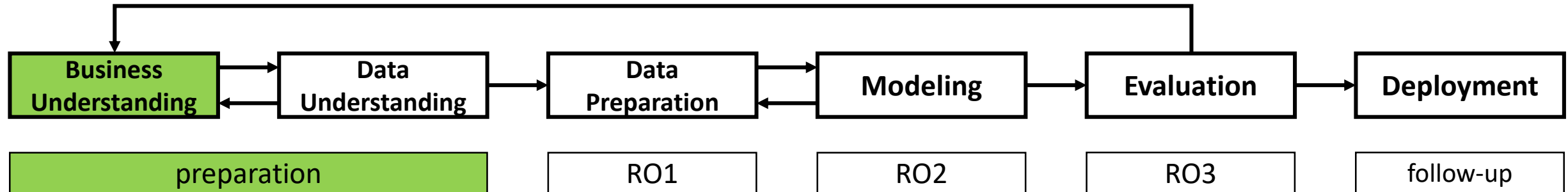
Creation of data set

- overarching goal
 - development of a prediction technique for defects in feature-based software
 - using Machine Learning methods
- data basis: commits of versioning systems (Git)
 - commit: provision of an updated version of a software product
 - faulty and defect-free commits for learning classifiers
- three research objectives
 - creation of data set, training of classifiers, evaluation of classifiers
 - + preparation and follow-up

Cross-Industry Standard Process for Data Mining (CRISP-DM) process modell



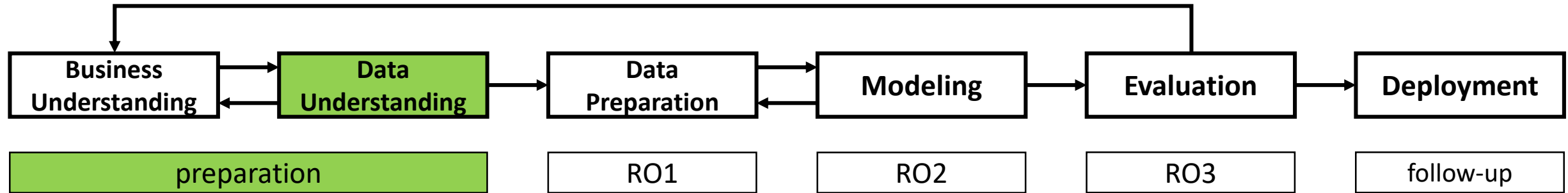
(Chapman et al., 2000)



- Business Understanding (preparation)
 - general familiarization with the topic
 - formulation of research objectives



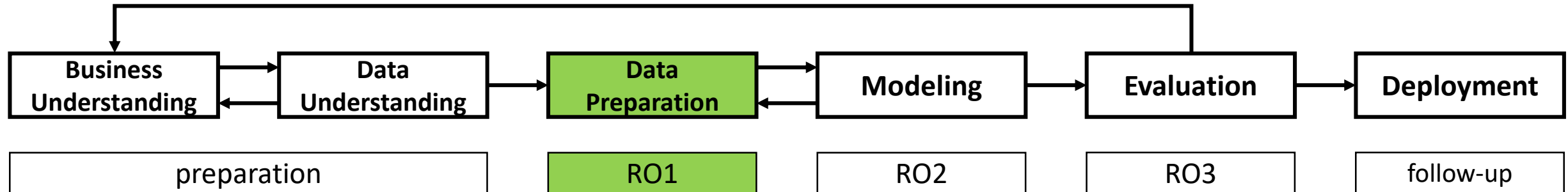
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- Data Understanding (preparation)
 - search + review of relevant data and ready-made data sets
 - search focus: Git repositories



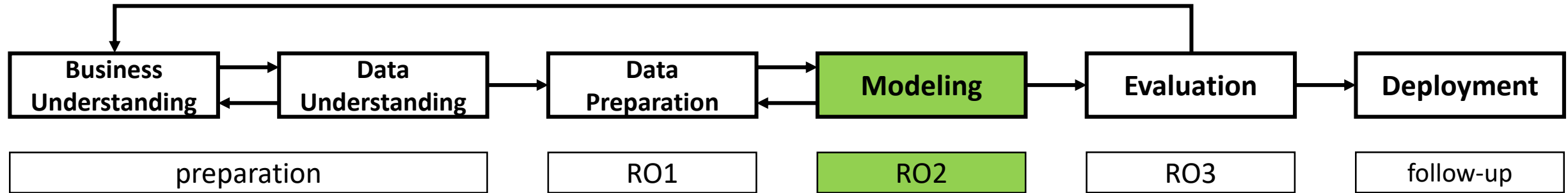
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- Data Preparation (research objective 1)
 - processes for optimizing the data set
 - creation of the final data set



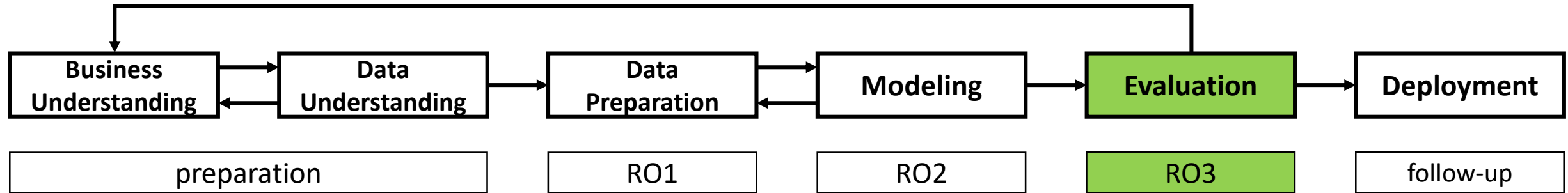
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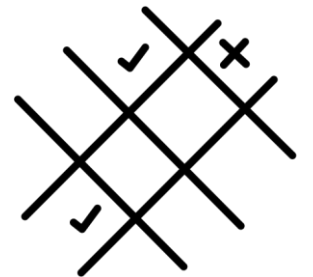
- Modeling (research objective 2)
 - application of the created data set
 - training of Machine Learning algorithms



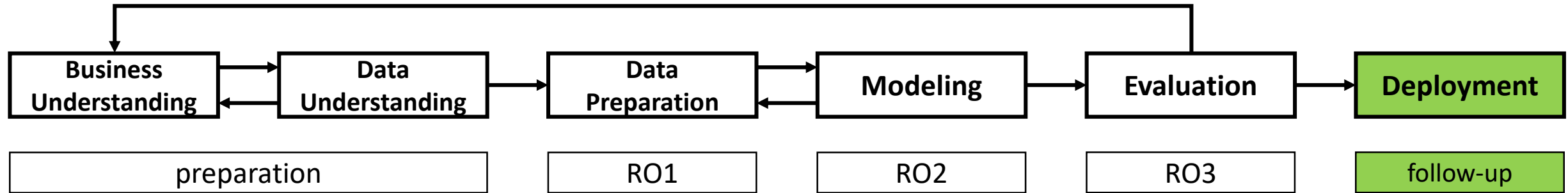
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- Evaluation (research objective 3)
 - evaluation of Machine Learning Algorithms
 - comparison of algorithms



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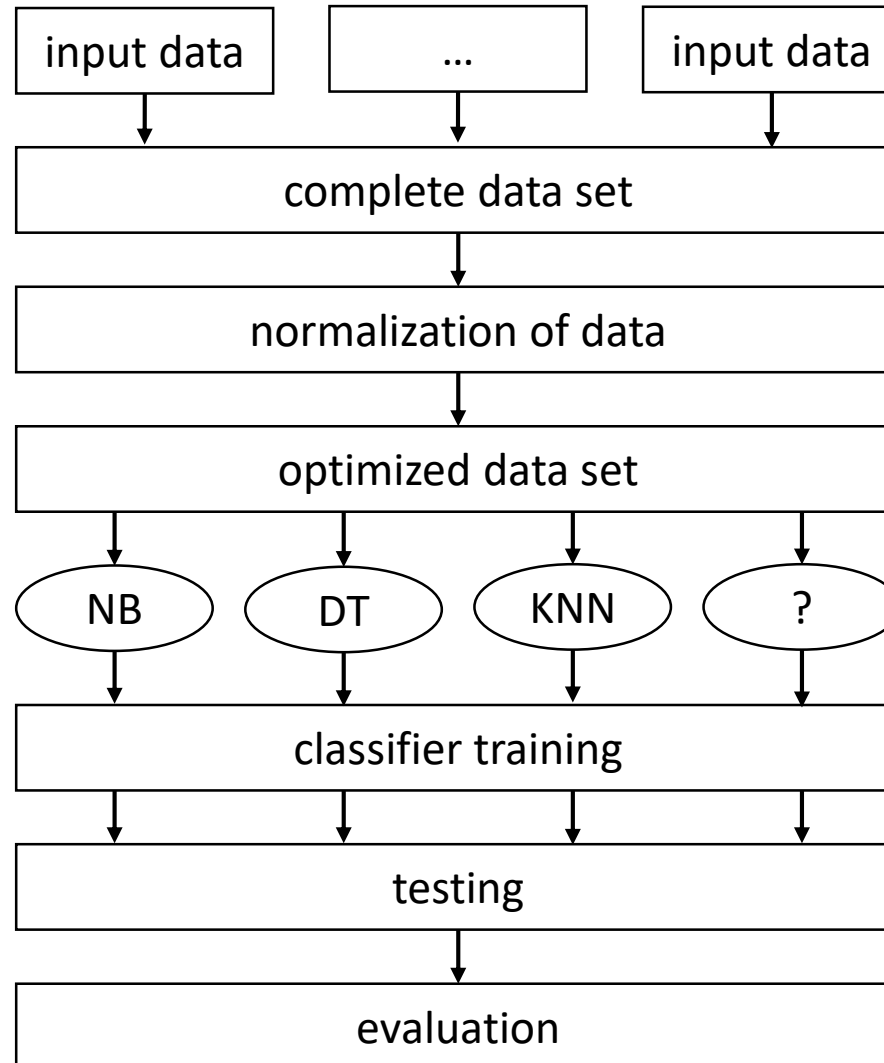


- Deployment (follow-up)
 - preparation of the written elaboration and final presentation
 - holding the colloquium



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*applied machine-learning
method*



commits of feature-based software

consisting of training + test data

Preprocessing, calculation of metrics

metrics as attributes

training of classifiers

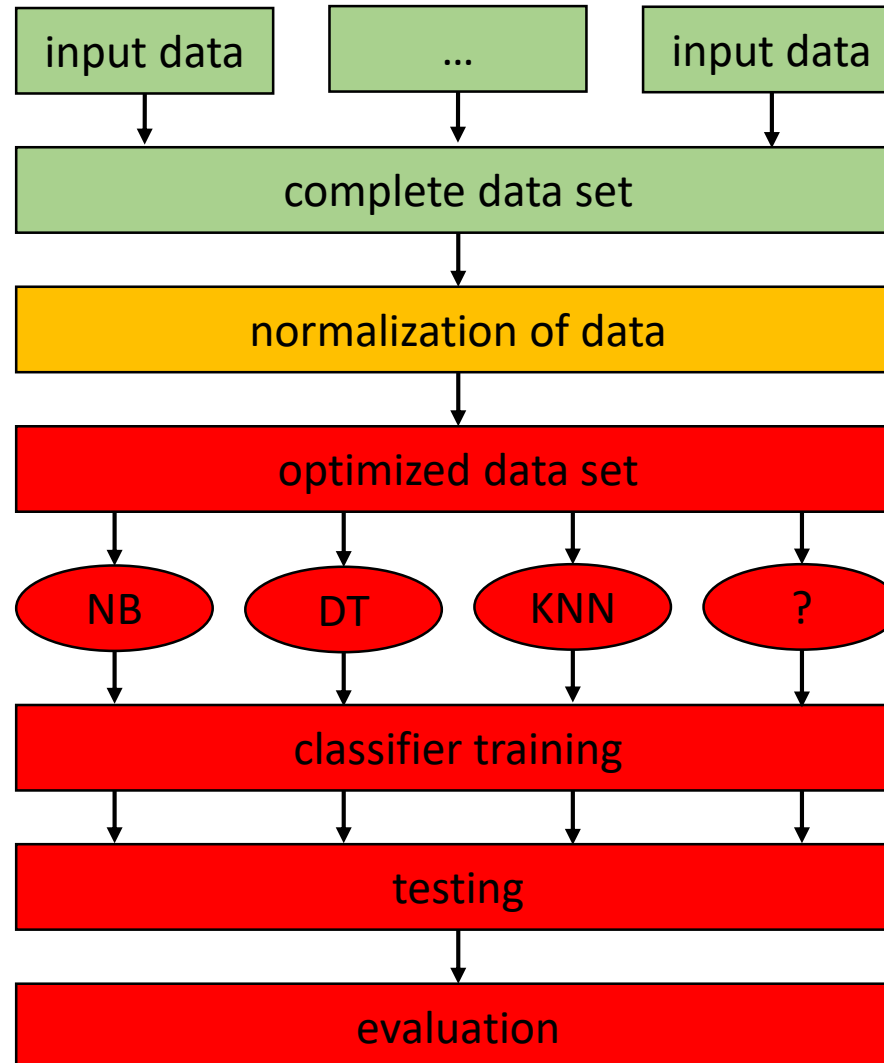
application of test data

Selection of the most performant classifier

(Ceylan, Kutlubay, & Bener, 2006)

Current state

preparation ✓



commits of feature-based software

consisting of training + test data

Preprocessing, calculation of metrics

metrics as attributes

training of classifiers

application of test data

Selection of the most performant classifier

(Ceylan, Kutlubay, & Bener, 2006)

- usage of PyDriller for repository mining
 - Python framework by (Spadini, Aniche, & Bacchelli, 2018)
 - <https://github.com/ishepard/pydriller>
 - easy extraction of commits, developers, diffs and source code (and more)
 - well documented (<https://pydriller.readthedocs.io>)

```
1 for commit in RepositoryMining("link_to_repo").traverse_commits():
2     for m in commit.modifications:
3         print(
4             "Author {}".format(commit.author.name),
5             " modified {}".format(m.filename),
6             " with a change type of {}".format(m.change_type.name),
7             " and the complexity is {}".format(m.complexity)
8         )
```

- historical data of 12 software projects (preprocessor conditionals)
 - feature-based software
 - based on preprocessor conditionals
- selection criterion: previous use in literature (Hunsen et al., 2016; Liebig et al., 2010; Queiroz et al., 2017)
- extracted from Git, GitHub, GitLab and Sourceforge repositories
- divided into commits per release
 - based on tag structure of git repositories

Blender	Busybox	Emacs	Gimp	Gnumeric	Gnuplot
Irssi	Libxml2	Lighttpd	Mpsolve	Parrot	Xfig

	Purpose	Data source	#Releases	#Commits	#Corrective	#Features
Blender	3D modelling tool	GitHub mirror	11	19119	3697	1425
Busybox	UNIX tool package	Git repository	13	4593	1447	204
Emacs	Text editor	GitHub mirror	7	11344	3638	495
Gimp	Photo editor	GitLab repository	14	7295	1226	151
Gnumeric	Spreadsheet	GitLab repository	8	6025	1211	83
Gnuplot	Plotter	GitHub mirror	4	4922	476	531
Irssi	IRC client	GitHub repository	7	367	72	11
Libxml2	XML parser	GitLab repository	10	732	359	150
Lighttpd	Webserver	Git repository	5	2285	1080	316
Mpsolve	Polynomial solver	GitHub repository	8	668	101	28
Parrot	VM	GitHub repository	4	2765	735	78
Xfig	Graphics editor	Sourceforge	7	18	0	135

- data was stored in MySQL database
 - one table for each software project

Column	Description	Column	Description
change_type	Type of change (added, deleted, modified, renamed)	filename	name of changed file
commit_author	responsible developer	lines_added	number of lines added to file
commit_hash	unique identifier of commit	lines_reomved	number of lines removed from file
commit_msg	commit message	name	software name
cycomplexity	cyclomatic complexity of changed file	nloc	lines of code of file
diff	diff of changed file	release_number	associated release number based on tags
feature	features, that were modified in file	status	normal (false) or corrective (true) commit

- next up
 - extract modified features of commits (text mining -> identify #IFDEF) ✓
 - choose relevant metrics
 - COMM ADEV DDEV EXP OXP (from ML process according to Queiroz et. al.)
 - What other metrics that can represent features could be considered?
 - How to calculate metrics based on available data?
 - Which Machine Learning algorithms should be considered?



Thank you for your attention.
Time for questions.

Literature

- Ceylan, E., Kutlubay, F. O., & Bener, A. B. (2006). Software defect identification using machine learning techniques. Proceedings - 32nd Euromicro Conference on Software Engineering and Advanced Applications, SEAA, 240–246. <https://doi.org/10.1109/EUROMICRO.2006.56>
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Literature

- Queiroz, R., Berger, T., & Czarnecki, K. (2016). Towards predicting feature defects in software product lines. FOSD 2016 - Proceedings of the 7th International Workshop on Feature-Oriented Software Development, Co-Located with SPLASH 2016, 58–62. <https://doi.org/10.1145/3001867.3001874>
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- Spadini, D., Aniche, M., & Bacchelli, A. (2018). PyDriller: Python framework for mining software repositories. In Proceedings of the 2018 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering - ESEC/FSE 2018 (pp. 908–911). New York, New York, USA: ACM Press. <https://doi.org/10.1145/3236024.3264598>

Online sources

[1] <https://www.independent.co.uk/news/uk/home-news/amazon-1p-glitch-software-error-sees-hundreds-of-items-sold-for-fractions-of-their-value-9923730.html> (independent.co.uk, 14.12.2014)

[2] https://www.theregister.co.uk/2012/08/03/bad_algorithm_lost_440_million_dollars/ (theregister.co.uk, 03.08.2012)

[3] <https://www.theverge.com/tldr/2019/8/14/20805543/null-license-plate-california-parking-tickets-violations-void-programming-bug> (theverge.com, 14.08.2019)

Icon sources

- Reading by Arafat Uddin from the Noun Project
- Data Analysis by Brennan Novak from the Noun Project
- Data by fizae from the Noun Project
- Machine Learning by Juicy Fish from the Noun Project
- evaluation by Michael Rojas from the Noun Project
- Writing by Kmg Design from the Noun Project