

Wie schreibe ich mein Guided Research?

Und vor allem: Warum sollte ich?

Dr. Elmar Juergens, Roman Haas

In enger Abstimmung mit Dr. Angelika Reiser

2000 - 2006



2006 - heute



2009 - heute

Grundlage: www.thesisguide.org

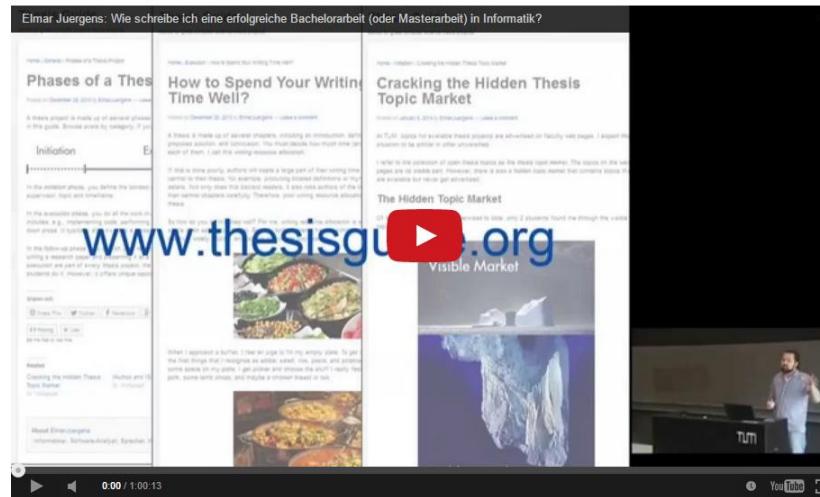
- Folien
- Video
- Detaillierte Essays
- FAQ

Preface

My thesis project was the most rewarding experience of my computer science studies. Unfortunately, many students suffer theirs as frustrating, tedious and with few opportunities for personal growth.

In this guide, I want to share the pitfalls and best practices from supervising 30+ thesis projects in computer science at TUM. I hope that it helps you write a great thesis and grow in the process. [Start reading here](#).

Below is a video of a presentation in November 2014 (in German).



Presentation on Master's Thesis (English): 12.6., 18 Uhr, Interims 2

Vortrag Bachelorarbeit (Deutsch): 3.7., 18 Uhr, HS2

Agenda

1. Motivation
2. Anbahnung
3. Durchführung

Guided Research

- Eigene Forschungsarbeit & Vortrag
- Läuft genau ein Semester
- Erstreckt sich möglicherweise in die Semesterferien

Fakultät für Informatik
Technische Universität München

Startseite

Die Fakultät +

Für Studieninteressierte +

Für Studierende -

Bachelor Studiengänge +

Master Studiengänge -

Informatik -

Studienplan +

Wahlmodule +

Überfachliche Grundlagen

Interdisziplinäres Projekt +

Forschungsarbeit unter Anleitung

Abschlussarbeit

Prüfungsordnung +

Startseite › Für Studierende › Master Studiengänge › Informatik › Forschungsarbeit unter Anleitung

Forschungsarbeit unter Anleitung

Die Forschungsarbeit ist Teil der Profilbildung *Forschung*. Hier wird erbracht. Es wird empfohlen mit dem Betreuer zu klären, welche Vorbereiten können. Der Student kann hier die Vorlesungen ansehen.

Inhaltliche Beschreibung

siehe Modulkatalog ↗

Ablauf

- Anmeldung in der ersten Vorlesungswoche jedes Semesters
- Zu erbringende Leistungen:
 - erfolgreiche Durchführung der Arbeit
 - regelmäßige Durchführung der Kontakttermine
 - Präsentation der Ergebnisse durch einen Vortrag (an einer Tagung)
 - Abgabe eines knappen wissenschaftlichen Ergebnisberichts
- Spätestens zu Beginn des folgenden Semesters: Die Abschlussarbeit muss bis zur ersten Vorlesungswoche des Folgesemesters beim Betreuer abgegeben werden.

<https://www.in.tum.de/de/fuer-studierende/master-studiengaenge/informatik/forschungsarbeit-unter-anleitung/>

Formalitäten

- Informatik, Data Engineering&Analytics
Wirtschaftsinformatik, Informatik: Games Engineering,
Biomedical Computing
- Anmeldung in 1. Vorlesungswoche
- Abgabe Ende Semester
- Nicht verlängerbar
- Man muss schon im Master eingeschrieben sein
- Keine Anerkennung aus dem Ausland (man kann aber mit TUM-Betreuer auch im Ausland schreiben)

Guided Research

- Freiwillig
- 10 ECTS (aber nicht weniger Arbeit)
- Konferenzvortrag oft deutlich nach Abgabe
- ca. 40/Semester

Bachelorarbeit

- Verpflichtend
- 15 ECTS
- Mit Abgabe & Vortrag abgeschlossen
- ca. 200/Semester?

2011 - 2017



2017 - heute



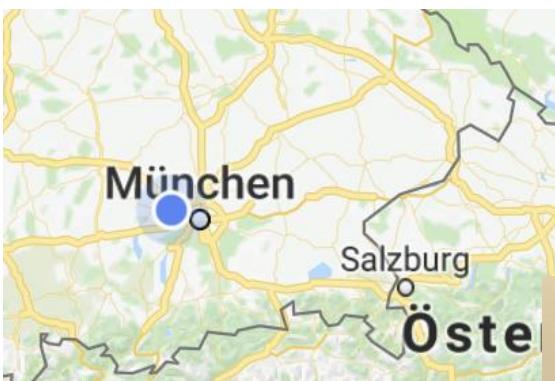
2014: BA

2015: GR

2016-2017: MA

Learning to Rank Extract Method Refactoring Suggestions for Long Methods

- Gegeben: Eine Menge von Refactoring-Vorschlägen für lange Methoden
- Gesucht: Ordnung der Vorschläge
- Ansatz: Machine Learning



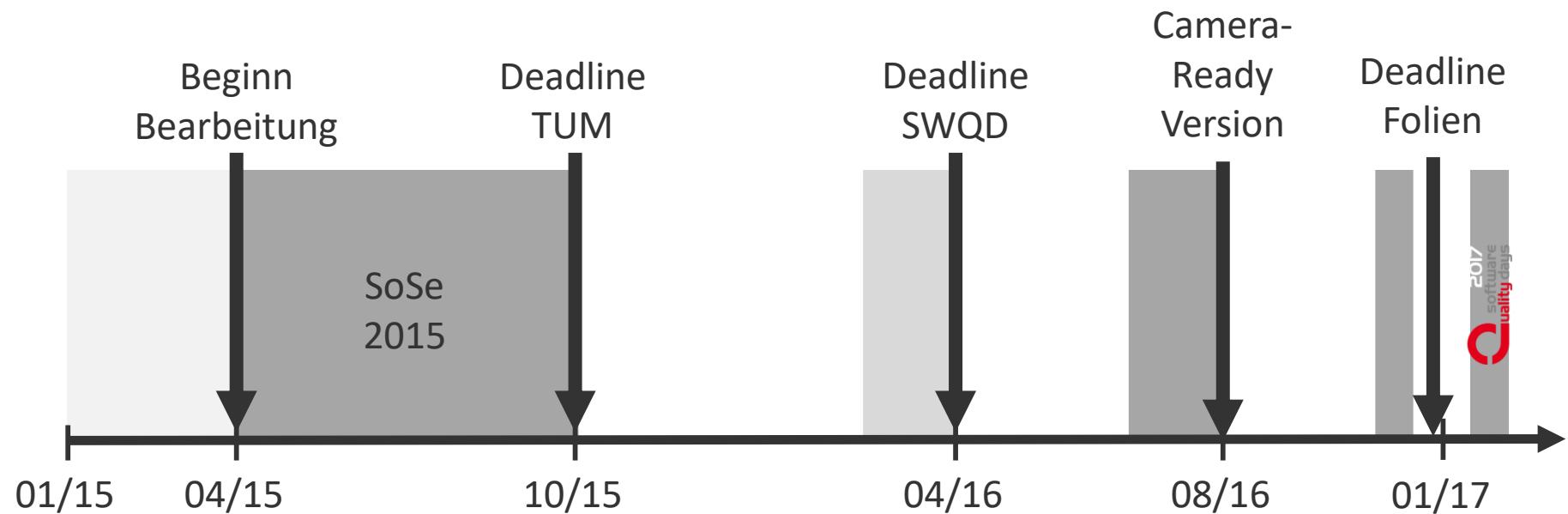
Track A	Track B	Track C	Scientific-Track	Solution Provider Forum I	Solution Provider Forum II

Exhibition area / Kaffeepause & Networking im Ausstellungsbereich



14:05				
14:25				
14:35	Kontinuierliche Architektonal analyse (Software Quality Lab, Linz) Deutsch , Einsteiger	Strukturierte Tests bei defizitärer Dokumentation - Wie man zwei Fliegen mit einer Klappe schlägt (SRC Security Research & Consulting GmbH, Bonn, DE) Deutsch , Fortgeschritten	Continuous Delivery - Feel your Quality - Every Day (Automic Software GmbH (CA Technologies), Wien, AT) (Automic Software GmbH, Wien, AT) Englisch , Fortgeschritten	A portfolio of internal quality metrics for software architects (University of Gothenburg, Gothenburg, SE) Englisch , Fortgeschritten
14:55				
				Zertifizierung Quality Engineer für das Internet der Dinge (ISQI GmbH, Potsdam, DE) Englisch , Experte

Zeitlicher Überblick



Delta zu Alternativen im Masterstudium

- Mehr Freiheiten
 - Themenrichtung
 - Eigene Forschung mit abgestimmter Methodik
 - Eigenes Tempo und eigener Zeitplan
- Höhere Anforderungen an Selbstorganisation
- Mehr Möglichkeiten für persönliches Wachstum

Persönliches Fazit

- GR war über das gesamte Masterstudium auf meinem „mentalnen Stack“
- GR hat mich aus meiner Komfortzone geholt
- Ich habe richtige Forschung betrieben
- Ich habe die Forschungscommunity kennengelernt
- Ich würde das GR nochmal machen

Finanzierung

Zu deckende Kosten: 1k€ bis 5k€

- Anreise und Übernachtung
- Konferenzgebühr

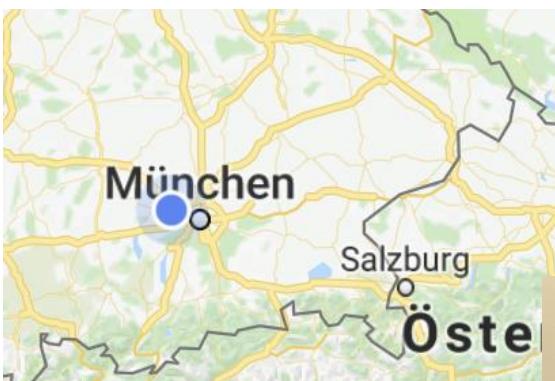
Finanzierungsquellen (oft Mischfinanzierung)

- Reisekostenzuschuss der Fakultät
- Lehrstühle
- DAAD Stipendien
- CQSE

Entscheidungsprozesse dauern oft lange -> Früh kümmern

Agenda

1. Motivation
2. Anbahnung
3. Durchführung



Track A	Track B	Track C	Scientific-Track	Solution Provider Forum I	Solution Provider Forum II

Exhibition area / Kaffeepause & Networking im Ausstellungsbereich



14:05				
14:25				
14:35	Kontinuierliche Architektonal analyse (Software Quality Lab, Linz) Deutsch , Einsteiger	Strukturierte Tests bei defizitärer Dokumentation - Wie man zwei Fliegen mit einer Klappe schlägt (SRC Security Research & Consulting GmbH, Bonn, DE) Deutsch , Fortgeschritten	Continuous Delivery - Feel your Quality - Every Day (Automic Software GmbH (CA Technologies), Wien, AT) (Automic Software GmbH, Wien, AT) Englisch , Fortgeschritten	A portfolio of internal quality metrics for software architects (University of Gothenburg, Gothenburg, SE) Englisch , Fortgeschritten
14:55				
				Zertifizierung Quality Engineer für das Internet der Dinge (ISQI GmbH, Potsdam, DE) Englisch , Experte

Einreichungen

Auswahlverfahren

Agenda



Hackordnung



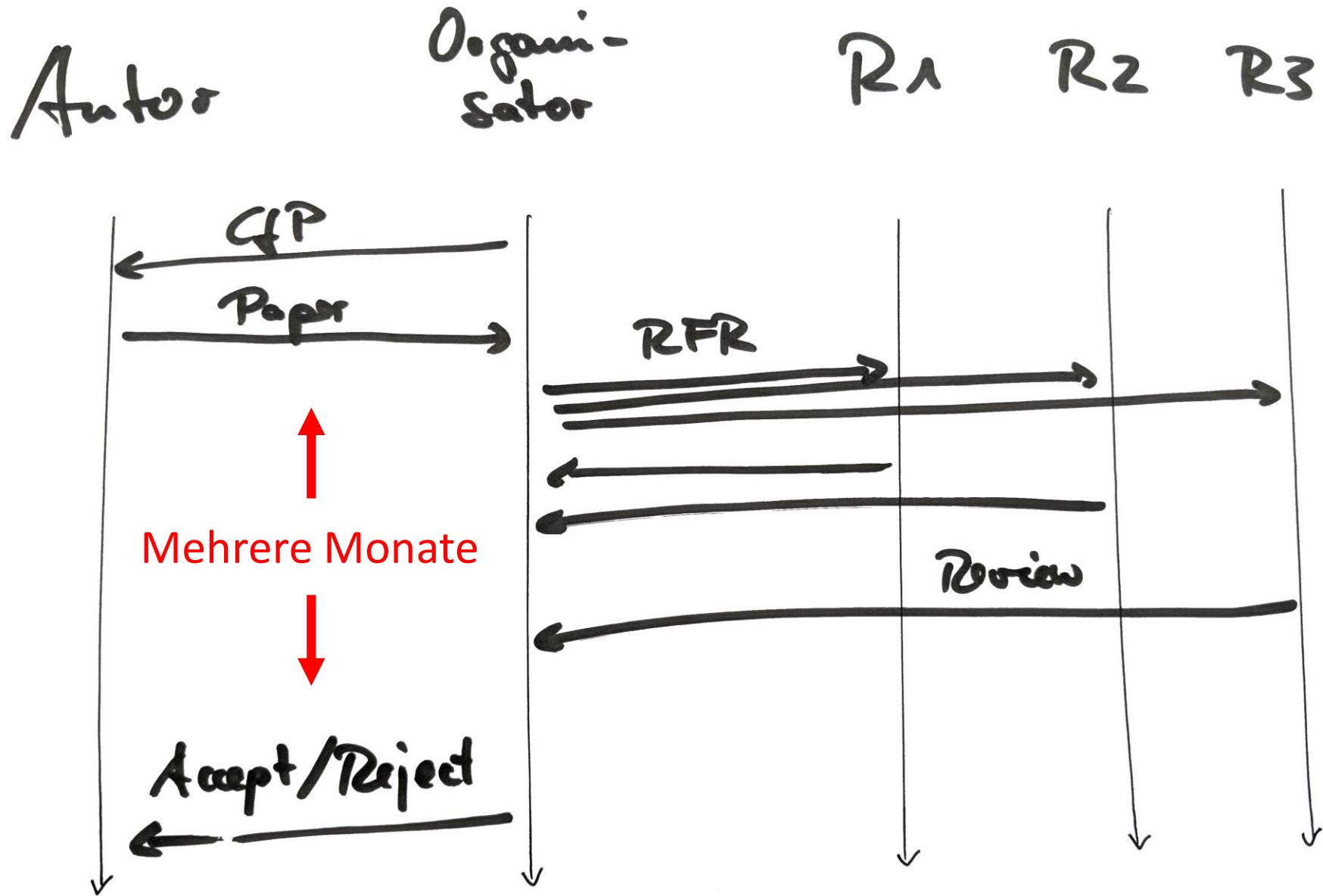
Acronym	Full Name	Date
CHASE	11th International Workshop on Cooperative and Human Aspects of Software Engineering	27-May
CSI-SE	5th International Workshop on Crowd Sourcing in Software Engineering	27-May
MET	International Workshop on Metamorphic Testing	27-May

RAISE	SoHeal	MiSE	GE	SQUADE	SE4COG	SER&IP	SE4Science
SEAD	WETSEB	SEHS	RoSE	AST	FairWare	SESoS	RET
SEsCPS	GREENS	CESI	SEFAIAS	SBST	RCoSE	GI	SEEM

Ziel: Einreichung auf Workshops

Konferenz
10%-25%

Workshop
40%-60%



Call for Papers

12th International Workshop on Software Clones (IWSC 2018)

Co-located with [the 25th IEEE International Conference on Software Analysis, Evolution, and Reengineering \(SANER 2018\)](#)

March 20, 2018, Campobasso, Italy

Software clones are often a result of copying and pasting as an act of ad-hoc reuse by programmers, and can occur at many levels, from simple statement sequences to blocks, models, requirements or architectures today.

IWSC series of events has provided IWSC aims to bring researchers in particular, we expect the in-depth about IWSC 2018 are here on this

TOPICS OF INTEREST:

Topics of interest include but not

- Use cases for clones and clone detection
- Experiences with clones and clone detection
- Types and nature of clones
- Causes and effects of clones
- Techniques and algorithms for clone detection
- Clone and clone pattern visualization
- Tools and systems for detection
- Applications of clone detection
- System architecture and clones
- Effect of clones to system
- Clone analysis in families of systems
- Measures of code similarity
- Economic and trade-off models
- Evaluation and benchmark
- Licensing and plagiarism issues
- Clone-aware software design
- Refactoring through cloning
- Higher-level clones in modular systems
- Clone evolution and variation
- Role of clones in software engineering

PAPERS SOUGHT:

Each paper will be reviewed by at least three members of the program committee following a full double-blind process. Authors must adhere to SANER's double blind guidelines - <http://saner.unimol.it/restrack>. The following types of papers are sought:

- Full papers (7 pages maximum)
- Position papers (2 pages maximum)
- Tool demonstration papers (4 pages maximum)

SUBMISSION:

Papers must conform to the [IEEE proceedings paper format guidelines](#). If the paper is accepted, at least one author must attend the workshop and present the paper. Accepted papers will be published in the [IEEE Xplore Digital Library](#) along with the SANER proceedings.

All submissions must be in PDF and must be submitted online by the deadline via the IWSC 2018 EasyChair conference management system.

[Submit your papers here >>> EasyChair <<](#)

IMPORTANT DATES:

- Abstract submission deadline: January 19, 2018 AoE
- Paper submission deadline: January 26, 2018 AoE
- Notifications: February 16, 2018
- Camera Ready deadline: ** February 22, 2018 **
- Workshop day: March 20 2018

GENERAL CHAIR:

TBD

PROGRAM CO-CHAIRS:

- [Ying \(Jenny\) Zou](#) (ying.zou@queensu.ca), Queen's University, Canada
- [Matthew Stephan](#) (stephamd@miamioh.edu), Miami University, USA

STEERING COMMITTEE:

- [James R. Cordy](#), Queen's University, Canada
- [Katsuro Inoue](#), Osaka University, Japan
- [Rainer Koschke](#), University of Bremen, Germany

Call for Papers

12th International Workshop on Software Clones (IWSC 2018)

Co-located with [the 25th IEEE International Conference on Software Analysis, Evolution, and Reengineering \(SANER 2018\)](#)

March 20, 2018, Campobasso, Italy

Software clones are often a result of copying and pasting as an act of ad-hoc reuse by programmers, and can occur at many levels, from simple statement sequences to blocks, models, requirements or architectures today.

IWSC series of events has provided IWSC aims to bring researchers in particular, we expect the in-depth about IWSC 2018 are here on this

TOPICS OF INTEREST:

Topics of interest include but not

- Use cases for clones and clone detection
- Experiences with clones and clone detection
- Types and nature of clones
- Causes and effects of clones
- Techniques and algorithms for clone detection
- Clone and clone pattern visualization
- Tools and systems for detection
- Applications of clone detection
- System architecture and clones
- Effect of clones to system
- Clone analysis in families of systems
- Measures of code similarity
- Economic and trade-off models
- Evaluation and benchmark
- Licensing and plagiarism issues
- Clone-aware software design
- Refactoring through cloning
- Higher-level clones in modular systems
- Clone evolution and variations
- Role of clones in software engineering

PAPERS SOUGHT:

Each paper will be reviewed by at least three members of the program committee following a full double-blind process. Authors must adhere to SANER's double blind guidelines - <http://saner.unimol.it/restrack>. The following types of papers are sought:

- Full papers (7 pages maximum)
- Position papers (2 pages maximum)
- Tool demonstration papers (4 pages maximum)

SUBMISSION:

Papers must conform to the [IEEE proceedings paper format guidelines](#). If the paper is accepted, at least one author must attend the workshop and present the paper. Accepted papers will be published in the [IEEE Xplore Digital Library](#) along with the SANER proceedings.

All submissions must be in PDF and must be submitted online by the deadline via the IWSC 2018 EasyChair conference management system.

[Submit your papers here >>> EasyChair <<](#)

IMPORTANT DATES:

- Abstract submission deadline: January 19, 2018 AoE
- Paper submission deadline: January 26, 2018 AoE
- Notifications: February 16, 2018
- Camera Ready deadline: ** February 22, 2018 **
- Workshop day: March 20 2018

GENERAL CHAIR:

TBD

PROGRAM CO-CHAIRS:

- [Ying \(Jenny\) Zou](#) (ying.zou@queensu.ca), Queen's University, Canada
- [Matthew Stephan](#) (stephamd@miamioh.edu), Miami University, USA

STEERING COMMITTEE:

- [James R. Cordy](#), Queen's University, Canada
- [Katsuro Inoue](#), Osaka University, Japan
- [Rainer Koschke](#), University of Bremen, Germany

Call for Papers

12th International Works
Co-located with the 25th IEEE In
March 20, 2018, Campobasso, It

Software clones are often a result of
statement sequences to blocks,
models, requirements or architec
today.

IWSC series of events has provi
IWSC aims to bring researchers
particular, we expect the in-depth
about IWSC 2018 are here on thi

TOPICS OF INTEREST:

Topics of interest include but not

- Use cases for clones and c
- Experiences with clones ar
- Types and nature of clones
- Causes and effects of clon
- Techniques and algorithms
- Clone and clone pattern vis
- Tools and systems for dete
- Applications of clone detec
- System architecture and cl
- Effect of clones to system
- Clone analysis in families o
- Measures of code similarity
- Economic and trade-off mo
- Evaluation and benchmark
- Licensing and plagiarism is
- Clone-aware software desi
- Refactoring through clone
- Higher level clones in mod
- Clone evolution and variati
- Role of clones in software

PAPERS SOUGHT:

Each paper will be reviewed by at lea
double blind guidelines - <http://saneru>

- Full papers (7 pages maximum)
- Position papers (2 pages maxim
- Tool demonstration papers (4 p

Program Committee

Name	Institution	Country
Toshihiro Kamiya	Shimane University	Japan
Daqing Hou	Clarkson University	USA
Tien Nguyen	University of Texas at Dallas	USA
Nils Göde	CQSE GmbH	Germany
Jens Krinke	University College London	UK
Otavio Lemos	ICT-UNIFESP	Brazil
Manishankar Mondal	University of Saskatchewan	Canada
Ravindra Naik	Tata Consultancy Services	India
Robert Tairas	Vanderbilt University	USA
Minhaz Zibran	University of New Orleans	USA
Eunjong Choi	Nara Institute of Science and Technology	Japan
Michael Godfrey	University of Waterloo	Canada
Yoshiki Higo	Osaka University	Japan
Foutse Khomh	Ecole Polytechnique de Montréal	Canada
Nicholas A. Kraft	ABB Corporate Research	USA
Chanchal Roy	University of Saskatchewan	Canada
Hitesh Sajnani	Microsoft	USA
Suresh Thummalapenta	Microsoft	USA
Xioyin Wang	University of Texas at San Antonio	USA
Norihiro Yoshida	Nagoya University	Japan

Anforderungen an Thema

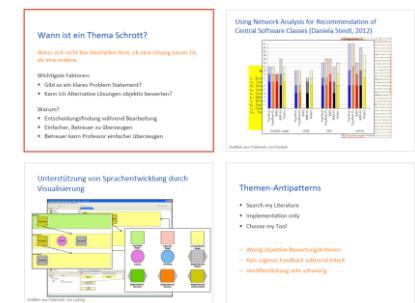
- Gibt es ein klares Problem Statement?
- Kann ich Alternative Lösungen objektiv bewerten?

Warum?

- Entscheidungsfindung während Bearbeitung
- Einfacher, Betreuer zu überzeugen
- Einfacher, PC zu überzeugen

Noch wichtiger für GR, als für BA oder MA.

Mehr Infos: www.thesisguide.org



Anforderungen an Betreuer

- Veröffentlichungserfahrung notwendig
- Idealerweise auf geplantem Workshop
- Quellen: scholar.google.com, DBLP, persönlich Webseite.



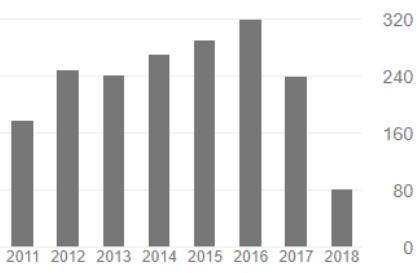
Elmar Juergens 

FOLGEN

CQSE GmbH
Bestätigte E-Mail-Adresse bei cqse.eu - [Startseite](#)
Software Qualität

TITEL	ZITIERT VON	JAHR
Do code clones matter? E Juergens, F Deissenboeck, B Hummel, S Wagner Software Engineering, 2009. ICSE 2009. IEEE 31st International Conference on ...	375	2009
COPE-automating coupled evolution of metamodels and models M Hermannsdoerfer, S Benz, E Juergens European Conference on Object-Oriented Programming, 52-76	198	2009
Clone detection in automotive model-based development F Deissenboeck, B Hummel, E Jürgens, B Schätz, S Wagner, JF Girard, ... Proceedings of the 30th international conference on Software engineering ...	172	2008

Zitiert von	Alle	Seit 2013
Zitate	2140	1441
h-index	21	20
i10-index	34	26

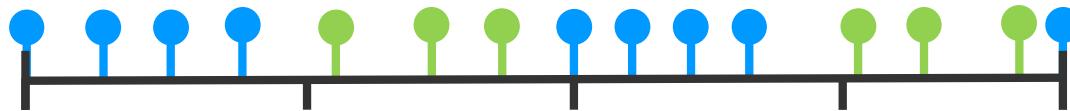


Jahr	Zitate
2011	160
2012	240
2013	240
2014	320
2015	320
2016	320
2017	240
2018	80

Agenda

1. Motivation
2. Anbahnung
3. Durchführung

Sicht eines BA/MA-Betreuers



- ⌚ Regelmäßiges Treffen
- ⌚ Treffen nach Bedarf

1	Izattino P. Oliveira and Renata Souza	Stories for New Products: A Research on the Use of Storytelling in Requirements Identification in Software Engineering
2	Hans Jochen Scholl, William Menten-Weil and Timothy S. Carlson	Artifact Evaluation with TEDSRate
3	Celal Ziftci and Jim Reardon	Who Broke the Build? Automatically Identifying Changes That Induce Test Failures In Continuous Integration at Google Scale
4	Uma Viswanath and Ramya Shyama Palakodati	Measuring Leanness in a lean software organization: A model to gauge the lean implementation using the 3 dimensional approaches of Process, Product, and People
5	Sofia Modesto and Miguel Mira Da Silva	Gamification to Increase Scrum Adoption
6	Guillermo Rodriguez, Alvaro Soria and Marcelo Campo	A Case-based Reasoning Approach to Reuse Quality-driven Design Alternatives in Service-Oriented Architectures
7	Andrea Arcuri	Back After 5 Years In Industry As Software Engineer / Tester: We Need Usable Automated Test Generation
8	Christof Ebert and Michael Weyrich	Architecture Evolution for the Internet of Things
9	Andrew Ko	A Three-Year Participant Observation of Software Startup Software Evolution
10	Torvald Mårtensson, Par Hammarström and Jan Bosch	Continuous Integration Is Not About Build Systems
11	Junjie Wang, Qiang Cui, Song Wang and Qing Wang	Domain Adaptation for Test Report Classification in Crowdsourced Testing
12	Fernando Pindori, Jose Luis Barros Justo and Raymundo Forradellas	Aspect-Oriented Business Process Modeling Approaches: An assessment of AOP4ST
13	Paul L. Li, Andrew J. Ko and Andrew Begel	Expert Non-Software-Engineers's Perspectives on Why Software Engineering Teams Succeed or Fail
15	Balbir Barn, Souvik Barat, Tony Clark and Vinay Kulkarni	Reviewing the Software Engineering Nexus of Current Research, Practice, and Future Prospects
16	Saad Mubeen, Mikael Sjödin, Harold Lawson, John Lundback, Mattias Gålinander and Kurt-Lennart Lundbäck	Provisioning of Predictable Embedded Software in the Vehicle Industry: The Rubus Approach
17	Christopher Theisen, Brendan Murphy, Kim Herzog and Laurie Williams	Risk-Based Attack Surface Approximation: How Much Data is Enough?
18	Daniel Russo, Paolo Clancarini, Tommaso Falasconi and Massimo Tomasi	Software Quality Concerns in the Italian Bank Sector: the Emergence of a Meta-Quality Dimension
19	Akond Rahman, Asif Partho, David Meder and Laurie Williams	Which Factors Influence Practitioners' Usage of Build Automation Tools?
20	Culyun Gao, Yichuan Man, Hui Xu, Jieming Zhu, Yangfan Zhou and Micheal R. Lyu	Assist Developers in Mobile Advertising via User Reviews and Case Studies
21	Zhitao Hou, Hongyu Zhang, Haidong Zhang and Dongmei Zhang	MetroEyes: A Visual Analytics System for Exploring Multi-Dimensional Data
22	S M Sohan, Craig Anslow and Frank Maurer	Automated Example Oriented REST API Documentation at Cisco
23	Terese Besker, Antonio Martini and Jan Bosch	Time to Pay Up - Technical Debt From a Software Quality Perspective
24	Dale Blue, Orna Raz, Rachel Tzoref-Brill, Paul Wojciek and Marcel Zalmanovici	Novel applications of combinatorial testing in validating software design
25	Jingzheng Wu, Shen Liu, Shouling Ji, Mutian Yang, Yanjun Wu, Yongji Wang and Tianyue Luo	Exception Beyond Exception: Crashing Android System by Trapping in "uncaughtException"
26	Charles Weir, Awais Rashid and James Noble	Dialectical Security: Challenging the Developers of Mobile and IoT Software
27	Samuel Marks and Andrew White	Code-generation driven development
28	Daniel Izquierdo-Cortazar, Nelson Sekitoleko, Jesus M. Gonzalez-Barahona and Lars Kurth	Using Metrics to Track Code Review Performance: the Xen Case
29	Zakariya Dehlawi and Andrew J. Ko	Predicting the Diffusion of Software Security Activities
30	Marcos Kalinowski, Pablo Curty, Alinne Paes, Alexandre Ferreira, Rodrigo Spinola, Daniel Méndez Fernández, Michael Felderer and Stefan Wagner	Supporting Defect Causal Analysis in Practice with Cross-Company Data on Causes of Requirements Engineering Problems
31	Steven D. Fraser and Dennis Manci	"No Silver Bullet" Revisited: Panel Session
32	Trishank Kuppusamy, Vladimir Diaz and Justin Cappos	Mercury: Bandwidth-Effective Prevention of Rollback Attacks Against Community Repositories
33	Mojdeh Golaghi, Alexander Pretschner, Dominik Fisch and Roman Nagy	Reducing Failure Analysis Time: An Industrial Evaluation
34	Atif Memon, Zebao Gao, Bao Nguyen, Sanjeev Dhanda, Eric Nickell, Rob Siemborski and John Micco	Taming Google-Scale Continuous Testing
35	Arun Kalyanasundaram, Judith Bishop and James Herbsleb	Industrial Open Source Project Decisions, Best Practices and Community Engagement: A Case Study at Microsoft
36	Bargav Jayaraman, Anurag Dwarkanathan, Breno D. Cruz and Collin McMillan	A Deep Learning approach for the Multi-lingual identification of Vagueness
37	Jingzheng Wu, Sizhe Zhao, Shouling Ji, Mutian Yang, Tianyue Luo, Yanjun Wu and Yongji Wang	MAD-API: Detection, Correction and Explanation of API Misuses in Android Applications
38	Remo Eckert, Sathyai Key Meyer and Matthias Stuermer	Capability Maturity Model of Inner Source Implementation
39	Khaled Alnawasreh, Patrizio Pelliccione, Zhenxiao Hao, Mårten Rånge and Antonia Bertolini	Online Robustness Testing of Distributed Embedded Systems: an Industrial Approach
40	Yulai Zhou, Patrizio Pelliccione, Johan Haraldsson and Majfuij Islam	Improving Robustness of AUTOSAR Software Components with Design by Contract: A study within Volvo AB
41	Henrik Edholm, Mikaela Lidström, Jan-Philipp Steghöfer and Håkan Burden	Crunch Time: The Reasons and Effects of Unpaid Overtime in the Games Industry
42	Jacob Krüger, Andy Kenner, Christopher Kruczek and Thomas Leich	Modularizing Conditional Compilation: An Automatic Minimal-Invasive Approach
43	Katja Kevic, Brendan Murphy, Laurie Williams and Jennifer Beckmann	Characterizing Experimentation in Continuous Deployment: a Case Study on Bing
44	Jakub Misek and Filip Zavoral	Binding semantic tree of dynamic languages to static language constructs
45	Ivana Crnkovic and Anna Börjesson Sandberg	Meeting Industry – Academia Research Collaboration Challenges with agile methodologies
46	Eero Laukkaniemi, Maria Paasivaara, Juha Iktonen, Casper Lassenius and Teemu Arvonnen	Towards Continuous Delivery by Reducing the Feature Freeze Period: A Case Study
47	Pete Rotella, Cody Peebles and Mark-David McLaughlin	Prioritizing Security Bug Fixes: A Novel Text Analytics Approach
48	Mohamad Kassab, Jooyoung Lee, Manuel Mazzara, Giancarlo Succi and Rasul Tumyrkin	Software Quality – Traditional vs. Agile: an Empirical Investigation
49	Kumar Abhinav, Alpana Dubey, Sakshi Jain, Gurdeep Virdi, Alex Kass and Manish Mehta	CrowdAdvisor: A Framework for Worker Assessment in Crowdsourcing
50	Lingfang Bao, Zhengchang Xing, Xin Xia, David Lo and Shaping Li	Who Will Leave the Company? A Large-Scale Industry Study of Developer Turnover by Mining Monthly Work Report
51	Padmalatha Nista and Kesav Vilthal Nori	Towards A Software Product Quality Taxonomy to Elicit Quality Requirements
52	Christoph Seidl, Thorsten Berger, Christoph Elsner and Klaus-Benedikt Schulzis	Challenges and Solutions for Opening Small and Medium-Scale Industrial Software Platforms
53	Jayati Deshmukh, Anurva K M, Sanjay Podder, Shubhashis Sengupta and Neville Dubash	A Deep Learning Approach for Accurate Duplicate Bug Detection
54	Aysen Tosun, Ozgur Turkoglu, Dogan Razan, Hamza Yusuf Aydemir and Arda Gureller	Predicting defects using test execution logs in an industrial setting
55	Raffaele Cirillo, Alexander Richter and Gerhard Schwabe	When Prototyping Meets Storytelling: Practices and Malpractices in Innovating Software Firms
56	Rebekka Wöhrle, Patrizio Pelliccione, Eric Knauß and Mats Larsson	Agility in Automotive: Continuous Engineering of Systems Engineering Artifacts
57	Yingxia Wei, Rui Wang and Yu Jiang	From Off-line Towards Real-time : A Runtime Verification Approach for Robot Systems
58	Kee-Choon Kwon, Jang-Soo Lee and Eunkyoung Jee	Application of Safety Case for Digital Reactor Protection System in Nuclear Power Plants
59	Ulrik Eklund and Christian Berger	Scaling Agile Development in Mechatronic Organizations - A Comparative Case Study
60	Jürgen Cito, Fábio Oliveira, Philipp Leitner, Priya Nagpurkar and Harald Gall	Context-Based Analytics - Establishing Explicit Links between Runtime Traces and Source Code
61	Francesco Sorrentino	Elastic Partitioning: A Tool for Testing Scalable Distributed Systems
62	Hennie Huijgens, Leandro Minku, Chris Lokaan and Arie van Deursen	Effort versus Cost in Software Development: A Comparison of Two Industrial Data Sets
63	Ma. Laura Calusco, Emiliano Reynares, Néstor Revinos, Juan Echagüe, Santiago Sosa and Agustín Martinez	Ontology-Driven Information Systems at the Oil & Gas Domain: An Experience Report
64	Simon Harrer, Matthias Geiger, Vincenzo Ferme, Cesare Pautasso, Jörg Lenhard, Mariagianna Skouradaki and Frank Leymann	Lessons Learned in Evaluating Workflow Management Systems -- "What you Expect and What you Get"
65	Helena Holmström Olsson and Jan Bosch	So Much Data; So Little Value A multi-case study on improving the impact of data-driven development practices
66	Franz Zierl and Lutz Prechelt	Pair Programming Feasibility Critically Depends on Task Difficulty
67	Abram Hindle and Curtis Onuczko	Stopping Duplicate Bug Reports before they start with Continuous Querying for Bug Reports
68	Denae Ford, Thomas Zimmermann, Christian Bird and Nachiappan Nagappan	Personas in Practice: Adapting Knowledge Worker Actions to Software Engineers

1	Izautino P. Oliveira and Renata Souza	Stories for New Products: A Research on the Use of Storytelling in Requirements Identification in Software Engineering	1	Sep 03, 04:18
2	Hans Jochen Scholl, William Merten-Well and Timothy S. Carlson	Artifact Evaluation with TEDRate	1	Sep 19, 21:10
3	Celal Ziftci and Jim Reardon	Who Broke the Build? Automatically Identifying Changes That Induce Test Failures In Continuous Integration at Google Scale	1	Sep 27, 20:32
4	Uma Viswanath and Ramya Shyama Palakodati	Measuring Leanness in a lean software organization: A model to gauge the lean implementation using the 3 dimensional approaches of Process, Product, and People	1	Oct 05, 04:09
5	Sofia Modesto and Miguel Mira Da Silva	Gamification to Increase Scrum Adoption	1	Oct 14, 15:51
6	Guillermo Rodriguez, Alvaro Soriano and Marcelo Campo	A Case-based Reasoning Approach to Reuse Quality-driven Design Alternatives in Service-Oriented Architectures	1	Oct 14, 19:08
7	Andrea Arouri	Back After 5 Years In Industry As Software Engineer / Tester: We Need Usable Automated Test Generation	1	Oct 15, 16:58
8	Christof Ebert and Michael Weyrich	Architecture Evolution for the Internet of Things	1	Oct 16, 05:59
9	Andrew Ko	A Three-Year Participant Observation of Software Startup Software Evolution	1	Oct 17, 22:08
10	Torvald Mårtensson, Pär Hammarström and Jan Bosch	Continuous Integration Is Not About Build Systems	1	Oct 19, 19:43
11	Junjie Wang, Qiang Cui, Song Wang and Qing Wang	Domain Adaptation for Test Report Classification in Crowdsourced Testing	1	Oct 20, 08:09
12	Fernando Pinciroli, Jose Luis Barros Justo and Raymundo Forradellas	Aspect-Oriented Business Process Modeling Approaches: An assessment of AOP4ST	1	Oct 20, 13:32
13	Paul L. Li, Andrew J. Ko and Andrew Begel	Expert Non-Software-Engineer's Perspectives on Why Software Engineering Teams Succeed or Fail	1	Oct 20, 16:10
14	Balbir Barn, Souvik Barat, Tony Clark and Vinay Kulkarni	Reviewing the Software Engineering Nexus of Current Research, Practice, and Future Prospects	1	Oct 21, 14:00
15	Saad Muheen, Mikael Stjörd, Harold Lawson, John Lundback, Mattias Gålinander and Kurt-Lennart Lundback	Provisioning of Predictable Embedded Software in the Vehicle Industry: The Rubus Approach	1	Oct 22, 19:47
16	Christopher Thelen, Brendan Murphy, Kim Herzog and Laurie Williams	Risk-Based Attack Surface Approximation: How Much Data is Enough?	1	Oct 23, 03:16
17	Daniel Russo, Paolo Ciancarini, Tommaso Falasconi and Massimo Tomasi	Software Quality Concerns in the Italian Bank Sector: the Emergence of a Meta-Quality Dimension	1	Oct 23, 19:51
18	Akond Rahaman, Asif Partha, David Neder and Laurie Williams	Which Factors Influence Practitioners' Usage of Build Automation Tools?	1	Oct 24, 00:43
19	Culyun Gao, Yichuan Man, Hui Xu, Jieming Zhu, Yangfan Zhou and Micheal R. Lyu	Assist Developers in Mobile Advertising via User Reviews and Case Studies	1	Oct 24, 17:49
20	Zhihao Hou, Hongyu Zhang, Haidong Zhang and Dongmei Zhang	MetroEyes: A Visual Analytics System for Exploring Multi-Dimensional Data	1	Oct 25, 00:49
21	S.M.Soham, Craig Anslow and Frank Maure	Automated Example Oriented REST API Documentation at Cisco	1	Oct 25, 05:34
22	Teresse Beseker, Antonio Martini and Jan Bosch	Time to Pay Up - Technical Debt From a Software Quality Perspective	1	Oct 25, 08:53
23	Dale Blue, Orna Raz, Rachel Tzoref-Brill, Paul Wojciech and Marcel Zalmanovici	Novel applications of combinatorial testing in validating software design	1	Oct 25, 12:40
24	Jingzheng Wu, Shen Liu, Shouling Ji, Mutan Yang, Yanjun Wu, Yongji Wang and Tianyue Luo	Exception Beyond Exception: Crashing Android System by Trapping in "uncaughtException"	1	Oct 25, 14:28
25	Charles Weir, Awaiss Rashid and James Noble	Dialectical Security: Challenging the Developers of Mobile and IoT Software	1	Oct 25, 16:38
26	Samuel Marks and Andrew White	Code-generation driven development	1	Oct 25, 18:35
27	Daniel Izquierdo-Cortazar, Nelson Sekitoleko, Jesus M. Gonzalez-Barahona and Lars Kurth	Using Metrics to Track Code Review Performance: the Xen Case	1	Oct 25, 18:45
28	Zakariya Dehlawi and Andrew J. Ko	Predicting the Diffusion of Software Security Activities	1	Oct 25, 19:02
29	Marcos Kallinowski, Pablo Curvy, Alme Paes, Alexandre Ferreira, Rodrigo Spinola, Daniel Méndez Fernández, Michael Felderer and Stefan Wagner	Supporting Defect Causal Analysis in Practice with Cross-Company Data on Causes of Requirements Engineering Problems	1	Oct 25, 20:07
30	Steven D. Fraser and Dennis Mancl	"No Silver Bullet" Revisited: Panel Session	1	Oct 25, 20:14
31	Trishank Kuppusamy, Vladimir Diaz and Justin Capos	Mercury: Bandwidth-Effective Prevention of Rollback Attacks Against Community Repositories	1	Oct 25, 20:52
32	Mojdeh Golagha, Alexander Pitschner, Dominik Fleisch and Roman Nagy	Reducing Failure Analysis Time: An Industrial Evaluation	1	Oct 25, 21:41
33	Atif Memon, Zebao Gao, Bao Nguyen, Sanjeev Dhanda, Eric Nickell, Rob Sliemorski and John Micco	Taming Google-Scale Continuous Testing	1	Oct 25, 23:03
34	Arun Kalyanasundaram, Judith Bishop and James Herbsleb	Industrial Open Source Project Decisions, Best Practices and Community Engagement: A Case Study at Microsoft	1	Oct 26, 01:40
35	Bargav Jayaraman, Anurag Dwarkanath, Breno D. Cruz and Collin McMillan	A Deep Learning approach for the Multi-lingual identification of Vagueness	1	Oct 26, 02:19
36	Jingzheng Wu, Sizhe Zhao, Shouling Ji, Mutan Yang, Tianyue Luo, Yanjun Wu and Yongji Wang	MAD-API: Detection, Correction and Explanation of API Misuses in Android Applications	1	Oct 26, 03:13
37	Remo Eckert, Sathyu Kay Meyer and Matthias Stuermer	Capability Maturity Model of Inner Source Implementation	1	Oct 26, 05:17
38	Khaled Alnawasreh, Patrizio Pelliccione, Chenxiao Hao, Mårten Rånge and Antonia Bertolini	Online Robustness Testing of Distributed Embedded Systems: an Industrial Approach	1	Oct 26, 06:56
39	Yulai Zhou, Patrizio Pelliccione, Jahan Haraldsson and Mafjuul Islam	Improving Robustness of AUTOSAR Software Components with Design by Contract: A study within Volvo AB	1	Oct 26, 07:03
40	Henrik Edholm, Mikaela Lidstrom, Jan-Philip Steghofer and Håkan Burden	Crunch Time: The Reasons and Effects of Unpaid Overtime in the Games Industry	1	Oct 26, 07:26
41	Jacob Krüger, Andy Kenner, Christopher Krucke and Thomas Leich	Modularizing Conditional Compilation: An Automatic Minimal-Invasive Approach	1	Oct 26, 07:42
42	Katja Kevic, Brendan Murphy, Laurie Williams and Jennifer Lai	Success factors, challenges and lessons learned: An empirical study of software projects in the public sector	1	Oct 26, 20:34
43	Jakub Misek and Filip Zavoral	A Framework for Continuous Testing of RESTful Web Services	1	Oct 26, 20:39
44	Ivana Crnkovic and Anna Borjesson Sandberg	Paving the Roadway for Safety of Automated Vehicles: An Empirical Study on Testing Challenges	1	Oct 26, 20:44
45	Eero Laukkonen, Maria Paasharva, Juha Ikonen, Casper Laike	An scalable and adaptable maturity model for product development teams	1	Oct 26, 20:49
46	Pete Rotella, Cody Peebles and Mark-David McLaughlin	Continuous Prototyping: Unified Application Delivery from Early Design to Code	1	Oct 26, 20:59
47	Lukas Alperowitz, Andrea Marie Weintraud, Stefan Christoph Kofler and Bernd Bruegge	Towards Converging Agile to Human Centered Design: an action research study	1	Oct 26, 21:17
48	Mohamad Kasab, Jooyoung Lee, Martin Mazzara, Gianluca Arditò, María Teresa Baldassarre, Danilo Calvano and Rosa Lanziotti	Prediction of Software Modul Growth in Practice	1	Oct 26, 21:46
49	Kumar Abhinav, Alpana Dubey, Sakshi Jain, Gurdeep Virdi, Jan Schröder, Christian Berger, Alessia Kusari, Harril Prejean, Mohammad Ali, Miroslaw Starow and Thomas Herpel	What Types of Build Failures Stop Continuous Delivery? An Empirical Study at ING NL	1	Oct 26, 21:48
50	Lingfeng Bao, Changxing Xie, Xia Lin, David Lo and Shahai Almog	Specifying Uncertainty in Use Case Models in Industrial Settings	1	Oct 26, 21:57
51	Padmalatha Nitala and Kesav Vithal Nori	AN ADAPTIVE PROCESS FRAMEWORK FOR ARCHITECTING REAL-TIME BIG DATA SYSTEMS	1	Oct 26, 22:00
52	Christoph Seidl, Thorsten Berger, Christoper Elsner and Klaus Laike	Continuous Delivery in the Automotive Ecosystem: Transparency Trade-offs in Software Value-Chains	1	Oct 26, 22:01
53	Jayati Deshmukh, Anverrra K M, Sanjay Podder, Shubham Bhattacharya	Leveraging Crowdsourcing For Team Elasticity: An Empirical Evaluation at TopCoder	1	Oct 26, 22:41
54	Aysen Tosun, Ozgur Turkoglu, Dogan Razan, Haniza Yusuf and Ayse Yilmaz	Analytics-Driven Load Testing: An Industrial Experience Report on Load Testing of Large-Scale Systems	1	Oct 26, 23:31
55	Raffaele Cirillo, Alexander Richter and Gerhard Schwabe	An Industrial Evaluation of Unit Test Generation: Finding Real Faults in a Financial Application	1	Oct 27, 00:13
56	Rebekka Wohlrab, Patrizio Pelliccione, Eric Knauss and Matz Blaauw	A Lightweight Verification Framework for Regular Expressions	1	Oct 27, 00:13
57	Yingxia Wu, Ruil Wang and Yu Jiang	Practices and Perceptions of UML Use in Open Source Projects	1	Oct 27, 00:32
58	Kee-Choon Kwon, Jang-Soo Lee and Eunkyoung Jee	Collabora: a collaborative architecture for evaluating individuals participation during the development of activities	1	Oct 27, 00:46
59	Ulrik Eklund and Christian Berger	Daily Meetings in Agile Teams: A multiple case study	1	Oct 27, 02:30
60	Jürgen Cito, Fábio Oliveira, Philipp Leitner, Priya Nagprakar	SFCI: A Tool for Security Focused Continuous Integration	1	Oct 27, 02:31
61	Francesco Sorrentino	Focused Certification of an Industrial Compilation and Static Verification Toolchain	1	Oct 27, 03:17
62	Hennie Huijgens, Leandro Minku, Chris Lokan and Arië van Deursen	An Empirical Study of Search-Based Task Scheduling in Global Software Development	1	Oct 27, 03:52
63	Ma Laura Calisico, Emilioino Revhares, Néstor Reynoso, J. Rosales	Pair Programming: An Experience Report	1	Oct 27, 04:32
64	Simon Harmer, Matthias Geiger, Vincenzo Ferme, Cesare Farina and Michael Lanza	Patterns of Identity and Interaction in an Evolving Agile Workplace	1	Oct 27, 04:37
65	Helena Holmstrom Olson and Jan Bosch	A Lightweight Model-Driven Design Environment for the Engineering Practice of Train Controller	1	Oct 27, 05:44
66	Franz Zierl and Lutz Prechelt	How do Female and Male Software Professionals Work with Others? Insights from the Trenches	1	Oct 27, 05:50
67	Abram Hindle and Curtis Onuszko	On Developing Linear Quadratic Performance Controllers for Cloud Applications	1	Oct 27, 06:21
68	Denae Ford, Thomas Zimmermann, Christian Bird and Nachiketa Chitnis	A Characteristic Study of Parameterized Unit Tests in .NET Open Source Projects	1	Oct 27, 07:29
69	Shreya Kumar and Charles Wallace	Automated Test Input Generation for Android: Towards Getting There in an Industrial Case	1	Oct 27, 07:58
70	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	Systematic Spreadsheet Construction Processes	1	Oct 27, 09:54
71	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	Agile Cultural Challenges in Europe and Asia: Insights from Practitioners	1	Oct 27, 09:55
72	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	Using Iaas or Not?	1	Oct 27, 10:15
73	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	Zero-Downtime SQL Database Schema Evolution for Continuous Deployment	1	Oct 27, 10:39
74	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	Transferring Code-Clone Detection and Analysis to Practice	1	Oct 27, 10:41
75	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	Six Key Metrics for Understanding Flow and Impediments in Software Engineering	1	Oct 27, 10:50
76	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	What Factors Affect Spreadsheet Performance? An Analysis of 4 Datasets	1	Oct 27, 11:04
77	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	Collaborative Identification of Code Smells: A Multi-case Study	1	Oct 27, 11:13
78	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	Group Behavior Aggregator for Realtime Simulation of Cyberspace Situation Awareness	1	Oct 27, 12:02
79	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	Exploiting ontologies for harnessing, aligning and integrating software design requirements and implementation issues: The PoolParty Case Study	1	Oct 28, 03:41
80	Yiannis Lampropoulos, Siwei Wang, Ming Guo and Ming Tang	Predicting Defect Resolution Time using Cosine Similarity	1	Oct 31, 15:24



Reviews of Submissions Assigned to Me

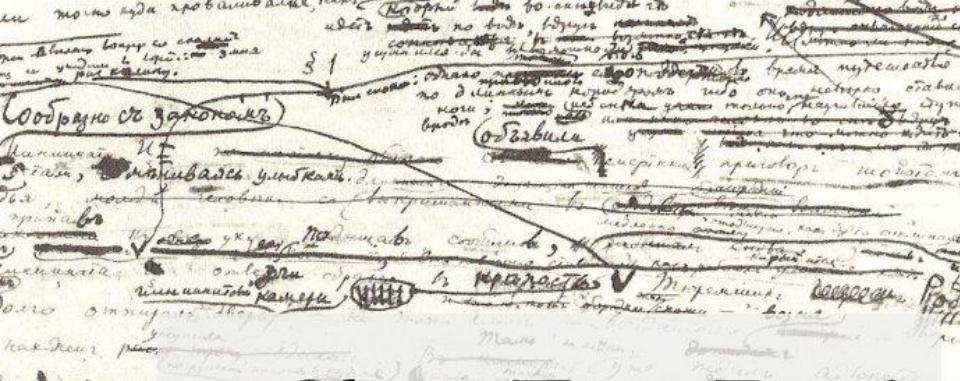
Review submission or updates have now been disabled. Please contact chairs if you believe they should be enabled.

#	Submission	Details	Paper	Show reviews	Contact subreviewer
2	Hans Jochen Scholl, William Menten-Weil and Timothy S. Carlson. <i>Artifact Evaluation with TEDRate</i>				
35	Arun Kalyanasundaram, Judith Bishop and James Herbsleb. <i>Industrial Open Source Project Decisions, Best Practices and Community Engagement: A Case Study at Microsoft</i>				
95	Cornel Barna, Marin Litoiu, Marios Fokaefs, Mark Shtern and Joe Wigglesworth. <i>On Developing Linear Quadratic Performance Controllers for Cloud Applications</i>				
102	Yingnong Dang, Dongmei Zhang, Song Ge, Ray Huang, Chengyun Chu and Tao Xie. <i>Transferring Code-Clone Detection and Analysis to Practice</i>				

Reviews and Comments			
PC member: Reviewer: Time: Overall Evaluation: Potential Impact to Industry: Real World Focus: Reviewer's confidence:	Guenther Ruhe Didar Al Alam <didar522@gmail.com> Nov 27, 23:35 2: (accept - I support acceptance) 4: (High - Work impacting industry) 4: (Excellent - 100% real world focus) 5: (expert)	Confidential remarks for the program committee: Good topic, but weak presentation.	+ treat above findings in (5) - change presentation to have three parts, namely (1) study set and best practices to be used in other companies, e.g. how to I
Review:	1. This paper presents multiple case study making and best practices for open source projects. 2. Points for the paper: <ul style="list-style-type: none">Context of the paper and purpose of itOf strong interest for (large) organizationsWell organized background study. Aut explained and the whole paper is structuredComparison of projects from two different divisions regarding generalizing results across projectsThe paper revealed findings related to firm to open source projects. The paper finds and practices are supported Points against the paper: <ul style="list-style-type: none">Overall, the paper would benefit from more detailsArchival data from GitHub is mentionedThe abstract should present a summary of the paperDecision points and trade-off decisions are mentionedFor projects with multiple repositories discuss under "Threats to validity" how it seems, the data is collected from GitHub over time as well.For some findings, some of the examples present the percentage of projects following themEach section consists of a set of findings hard to identify the key message. Read itIn section iv-c, the authors discussed pros and cons of both approaches.In section iv authors discussed decision conditions.Authors identified a number of metricsMeasures like download counts, number of commits are identified when the data is filtered based on popularity. Or should we consider themSome of the best practices are applicable. This information should be added for each findingKey findings and messages of the paper are summarized or visualized. It is goodo DEE is first user reader does not know what DEE stands for. It was first defined one section latero Justifications for not recording interview is not clear. Recording has its positive arguments as well 4. Suggested improvements: <ul style="list-style-type: none">Improve messaging by highlighting specific findingsProvide more concrete dataAddress issues listed under 3. Potentially interesting paper if some more details and concrete numbers and findings would be synthesized from all the writing.	PC member: Guenther Ruhe Reviewer: Didar Al Alam <didar522@gmail.com> Time: Dec 28, 17:11 Comment: Thanks, Natalia Comment 2	
Review:	PC member: Reviewer: Time: Overall Evaluation: Potential Impact to Industry: Real World Focus: Reviewer's confidence:	Elmar Jurgens Dec 22, 10:02 -2: (reject - I support rejection) 2: (Low - Not expected much impact) 3: (Good - Enough real world focus) 4: (high)	PC member: Guenther Ruhe Yes, they do. My former concerns already have been that the paper does not offer too much on tangible take-ways from an industrial perspective. I agree with the related comment made by Reviewer 3. The main reason I scored 2 was the attractive TOPIC and the good presentation. Comment: I modified my evaluation. Thanks, Guenther Time: Dec 28, 19:17
Review:	Confidential remarks for the program committee: To me, this is a research track paper, not a SEIP paper. For the most part, something. For me as a practitioner, the paper lacks a specific problem or solution.	PC member: Guenther Ruhe Reviewer: Didar Al Alam <didar522@gmail.com> Time: Dec 28, 19:18 Overall Evaluation: -1: (weak reject - reject, but could accept) Potential Impact to Industry: 3: (Enough - Work could impact industry) Real World Focus: 3: (Good - Enough real world focus) Reviewer's confidence: 5: (expert)	Review 1
Review:	Comments: The paper presents a study based on interviews and data extracted from research division and from a product division at Microsoft. Most of the data is from the research division. The paper deals too much with what is easy to measure, not what is important. My main concern with the paper is the lack of a strong problem statement. The paper does not clearly define the problem or the goal of the study. The community in terms of success of external engagement and later on introduce a new feature. The paper does a good job at iterating different motives for open-sourcing code, which is good. However, the reader will not understand the specific goal such as a general measurement as DEE has different dimensions and measure behaviors differently, depending on project life cycle phase or release cycle. In a nutshell, the paper deals too much with what is easy to measure, not what is important. Points in favor: <ul style="list-style-type: none">Our community would benefit from a better understanding of the factors that influence open-source development.Direct developer involvement Points against: <ul style="list-style-type: none">Most of the projects are from the research division. As the paper states, the research division is the primary source of projects. For the in practice track, this is not a good fit to me.There is very little information that I as a practitioner who faces these challenges can use.The introduction reads too much like a related work / survey and too little like a research paper. Minor points: <ul style="list-style-type: none">On page 1, the acronym DEE is used before it is defined on page 2. This is a common mistake in academic papers.In page 2, the paper states that the projects were "carefully selected". This is a common mistake in academic papers.It is unclear to me why the fact that "project owners [that] are more concerned about the quality of their code than the popularity of their project" is a concern for this study. If they are "more" concerned, they are probably not represented in the sample.Why would a deeper knowledge of user demographics help developers? This is a common mistake in academic papers.On p5, "external contributions" explicitly contain contributions that "no number of commits authored by external developers" and thus probably refers to contributions from external contributors. Further points: I was personally very excited to start reading this paper, since the title indicates that the majority of the paper is about the research, not the product division.	PC member: Guenther Ruhe Reviewer: Didar Al Alam <didar522@gmail.com> Time: Dec 28, 19:18 Overall Evaluation: -1: (weak reject - reject, but could accept) Potential Impact to Industry: 3: (Enough - Work could impact industry) Real World Focus: 3: (Good - Enough real world focus) Reviewer's confidence: 5: (expert)	
Review:	Comments: To me, this is a research track paper, not a SEIP paper. For the most part, something. For me as a practitioner, the paper lacks a specific problem or solution.	Review	
Review:	Comments: We are starting the discussion phase.	1. This paper presents multiple case studies at Microsoft. It examines the challenges of open sourcing industrial projects. The authors analyzed decision making and best practices for open sourcing projects. They also compare challenges and practices from projects under different divisions.	
Review:	Comments: Guenther, since you are the one with a different view here, could you please tell us whether they modify your view?	2. Points for the paper: <ul style="list-style-type: none">Context of the paper and purpose of the study are well explained.Of strong interest for (large) organizations following hybrid closed and open source development.Well organized background study. Authors identified existing gaps in literature and mapped with contributions of the paper. Goal of the study is well explained and the whole paper is structured around the goals.Comparison of projects from two different divisions. It helps to understand the commonalities and differences between divisions. It also makes reader aware of generalizing results across projects.The paper revealed findings related to assessing DEE in industrial OSS projects. Extracted best practices will provide a road map for any industrial software firm to open source projects. The paper does not provide decision support, but helps to understand the decision process.Findings and practices are supported by example projects, interview statements.	
Review:	Comments: Thanks, Natalia Time: Dec 28, 17:11	Points against the paper: <ul style="list-style-type: none">Overall, the paper would benefit from some higher degree of specificity. For example, when talking about trade-offs, what are the dimensions of it?Archival data from GitHub is mentioned in the abstract. Wish there would be more details on that process and the data.The abstract should present a summary of findings. Reader does not have any clue of actual findings until they reach the end of the introduction.Decision points and trade-off decisions are mentioned several times in the paper. However, the decision scenario is not made explicit. What are the decision alternatives? Utility function(s)? Who makes the decision? Based on what?For projects with multiple repositories, authors considered only one (to "avoid complications"). This looks like a strong simplification. The author should discuss under "Threats to validity" how this decision impacts the study.It seems, the data is collected from GitHub over time. Why forks, stars and watchers are considered as static data instead of temporal. These values change over time as well.For some findings, some of the examples presented show completely different behavior. Along with reporting these behaviors, authors should also present the percentage of projects following them.Each section consists of a set of findings or practices. Authors should list the key findings in each section. With all the examples, stories and discussion, it is hard to identify the key message. Reader may get lost and miss important information easily.In section iv-c, the authors discussed converting industrial projects to OSS being done early vs. late. For a fair comparison, authors should discuss pros and cons of both approaches.In section iv authors discussed decision making under different conditions. It would be good to suggest a certain option that works better under specific conditions.Authors identified a number of metrics (from practice) for DEE calculation. Any recommendation on their application?Measures like download counts, number of page views in GitHub, and number of logins give an estimate of the user activity. However, size of the user base is identified when the data is filtered based on IP (Internet Protocol) addresses and other unique identifiers. Author should explain, how DEE calculations will get affected in case of considering one vs. the other.To measure popularity of a project, a number of metrics are presented. How all these metrics will come together to calculate an overall value of the popularity. Or should we consider them independently?Some of the best practices are applicable for both industrial and non-industrial OSS projects. Some are only applicable to industrial open source projects. This information should be added for each practice.Key findings and messages of the paper should be summarized or visualized. The study is comprehensive. A large list of findings is presented with discussion, example and practices. It is hard for the reader to keep track of the content or identify all the findings and their applicability.Minor:<ul style="list-style-type: none">o DEE is first user reader does not know what DEE stands for. It was first defined one section later.o Justifications for not recording interview is not clear. Recording has its positive arguments as well.	
Review:	Comments: Thanks, Guenther Time: Dec 28, 19:17	4. Suggested improvements: <ul style="list-style-type: none">Improve messaging by highlighting some concrete and operational findings.Provide more concrete dataAddress issues listed under 3.	
Review:	Confidential remarks for the program committee: The authors present a case study a promising benefits from open source. (trade-offs and best practices).	Potentially interesting paper if some more details and concrete numbers and findings would be synthesized from all the writing.	
Review:	Comments: 2) Points for the paper <ul style="list-style-type: none">The paper is relevant as it presents findings from industrial projects.The research approach using interviews is valid.Many observations are discussed in detail. 3) Points against the paper <ul style="list-style-type: none">While the paper is strong in digging into the research, it lacks a clear conclusion.Topics such as security etc. are treated more superficially.I also find it interesting to read that Microsoft and IBM are mentioned.	PC member: Guenther Ruhe Reviewer: Didar Al Alam <didar522@gmail.com> Time: Dec 28, 19:18 Overall Evaluation: -1: (weak reject - reject, but could accept) Potential Impact to Industry: 3: (Enough - Work could impact industry) Real World Focus: 3: (Good - Enough real world focus) Reviewer's confidence: 5: (expert)	
Review:	Comments: Thanks, Guenther Time: Dec 28, 19:17	PC member: Guenther Ruhe Yes, they do. My former concerns already have been that the paper does not offer too much on tangible take-ways from an industrial perspective. I agree with the related comment made by Reviewer 3. The main reason I scored 2 was the attractive TOPIC and the good presentation. Comment: I modified my evaluation.	
Review:	Comments: Thanks, Guenther Time: Dec 28, 19:17	PC member: Guenther Ruhe Ok. We reject this paper then.	
Review:	Comments: Thanks, Natalia	Comment 3	

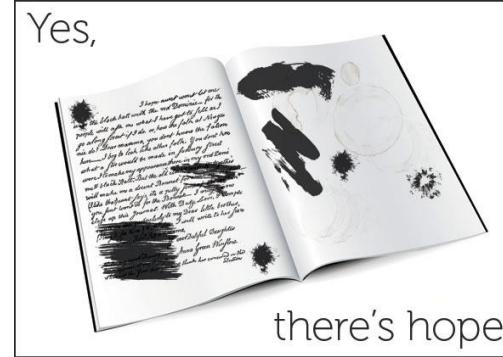
Für den Reviewer schreiben

- Problem-Statement und Contribution herausarbeiten
- Etablierte Gliederung verwenden:
<https://thesisguide.org/2014/10/13/thesis-architecture/>
- Text einfach lesbar machen. Das ist hart und anstrengend.
Aber planbar und erlernbar, keine Talentfrage.



SHITTY
FIRST
DRAFTS

Shitty First Drafts



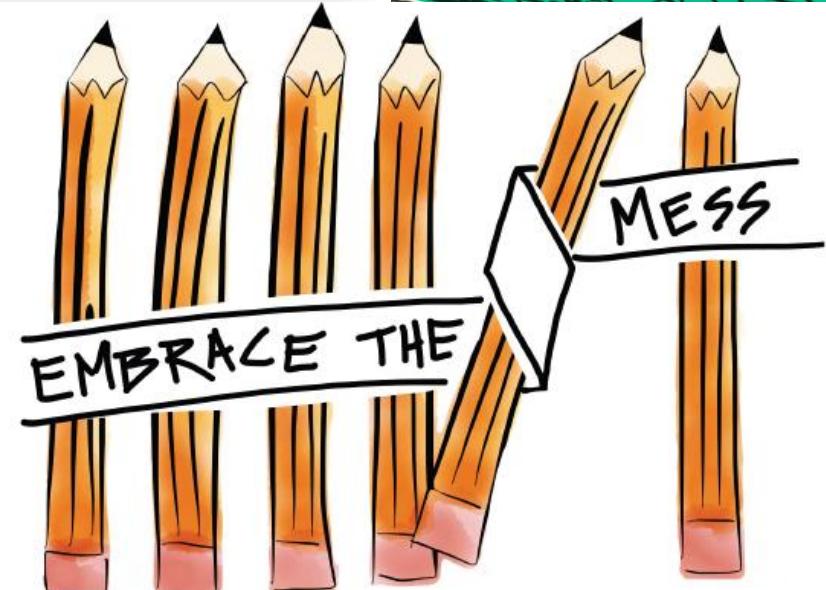
Yes,

there's hope.

THE FIRST
DRAFT
OF ANYTHING
IS SHIT.

Ernest Hemingway

First drafts
don't have to be
perfect.
They just have to
be written.



Was mir am meisten bringt

- Schreibzeit blocken
- Outline zuerst
- Schreiben und verbessern voneinander trennen
- Kompletten Absatz schreiben, bevor ich irgendwas verbessere
- Text „abkühlen lassen“ und dann *nochmal* Korrekturlesen.
Bei mir am besten mind. 1 Tag später.
- Es gibt nicht die eine „richtige“ Art zu schreiben, die für alle gleich gut funktioniert.

Scott Berkun: Essay-Schreiben im Zeitraffer

The screenshot shows a Microsoft Word document window titled "How to write an essay - Microsoft Word". The document contains the following content:

How to write an essay

- Montaigne and blogging
- The stupid way they teach (but neglect that most essays suck)
- Finding ideas and starting
- Getting Stuck
- Reading and revising
- Knowing when you are done

People forget writing is comprised of three things: words, sentences and paragraphs. If you know a few words, you can make a sentence. If you write a few sentences you can make a paragraph. Keep it simple and filling pages gets easy. It's when you make writing more complex that problems arise. The first lesson then is to string words together. One, two, four, ten. There is always time to make it more complex later.

There is no answer to how to start. Make an outline if you like. I often do. It's true all writing begins with ideas, but we forget ideas are like whispers in our minds all the time, and we can hear them if we have the quiet courage to listen. I keep a notebook with me at all times and that's one source for writing I use. In conversations with friends, watching TV, or waiting for the bus, I put down little ideas.

All writing begins with ideas, and that's where I generally start. I get an idea from a conversation, or a book, or while daydreaming and write it down. When I write it down I sometimes find there are several sub ideas underneath the first one that are interesting or explain the first point I started with, so I write those down as well. Sometimes this goes on for 30 seconds, other times for 5 minutes. I may come back a week later and flesh one of these sets of notes out, but more often I abandon them. I have books and books of abandoned lists of ideas for things in various stages of incubation. It's a good habit to have as a writer – lots of half-baked little things lurking around. When you're bored or stuck, it's an inventory of things partially done, and that's a gift to the future me who might just need a little boost to start from next time.

From, I take that list of ideas or points and put it in the beginning of a blank screen. That's my outline. I don't want it too detailed, and I don't want it too vague. Short sentences that have a clear point of view and divide the world, however nicely into two piles, are good sentences. They're personalized grenades, loaded with both venom and nutrients designed for my particular mind.

Youtube: <http://youtu.be/BNDEDWwZyKM>

English Writing Center

- Kostenlose 45-minütige Einzelsessions mit englischsprachigen Muttersprachlern
- Beratung zum Schreiben englischsprachiger Texte
 - GR, Abschlussarbeit, Hausaufgabe, Lebenslauf etc.
 - auch wenn der Text noch nicht fertig ist

www.tum.de/writing-center

Professioneller Lektor

When I approach a buffet I feel an urge to fill my empty plate

How to Spend Your Writing Time Well?

Every A thesis comprises is made up of several chapters, such as including an introduction, definitions, related work, proposed solution, and conclusion. You must decide how much time (and pages) to spend on each of them. I call this *writing resource allocation*.

If this step is done poorly, authors will waste a large part of their writing time on chapters that are not central to their thesis; for example, producing bloated definitions or a myriad of irrelevant technical details or other waste. Not only does this distract readers, it also inevitably robs authors of the time they need to write their central chapters carefully. Therefore, pPoor writing resource allocation is thus an effective recipe to write for a bad thesis.

So hHow to do you do it this step well? For me, writing resource allocation is a lot like allocating plate space when eating at a large buffet. For bBoth problems have, there is a similar solution strategy that is intuitive, widely applied, and reliable to produce poor results.

To get quick results, I put pasta, and Ppotatoes. I get more pickypickier fPpork, some Llamb about to leave with a full Ibe a fool to leave it out! I ice for the Sscallops and everybodyanyone that not

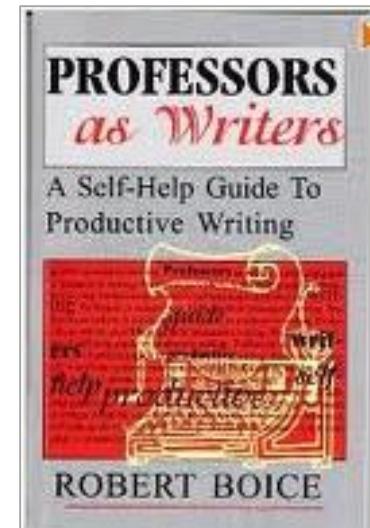
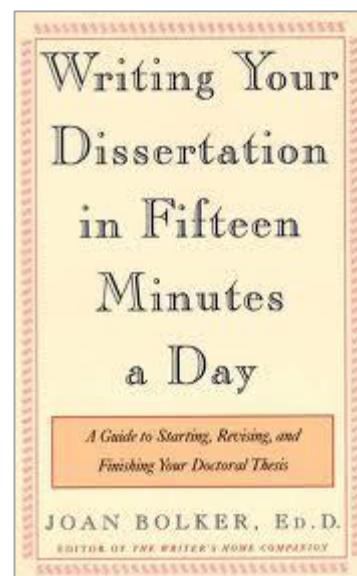
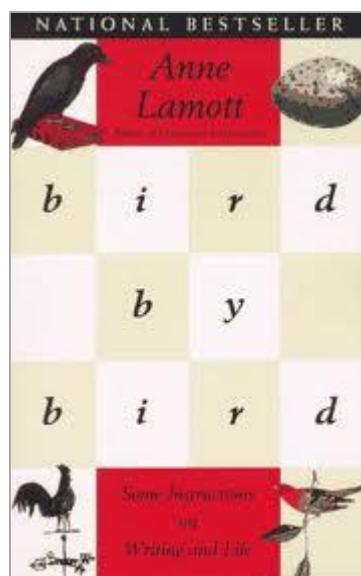
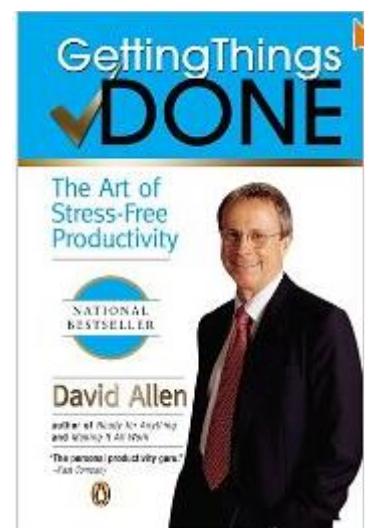
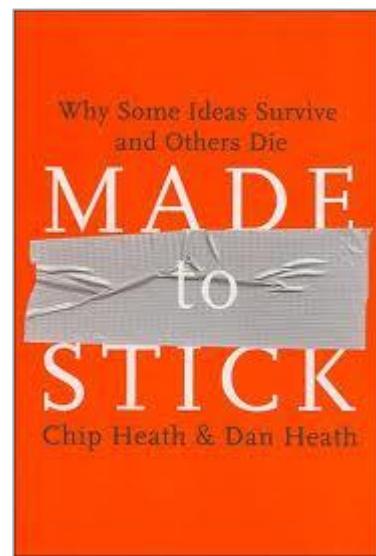
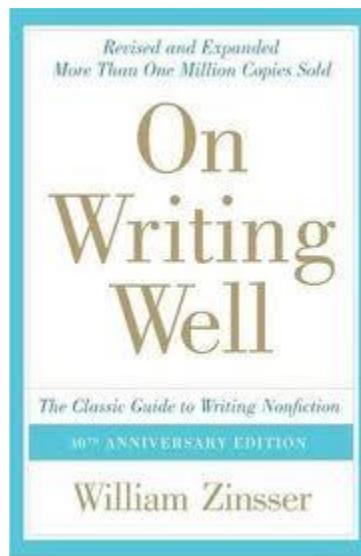
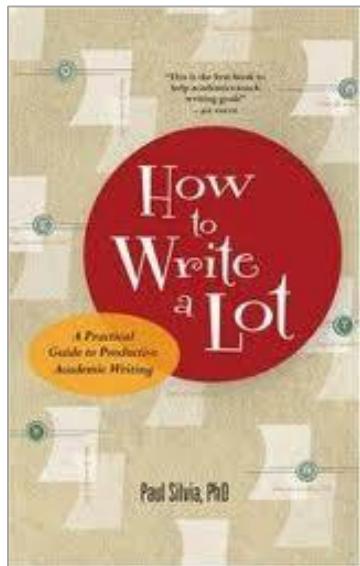
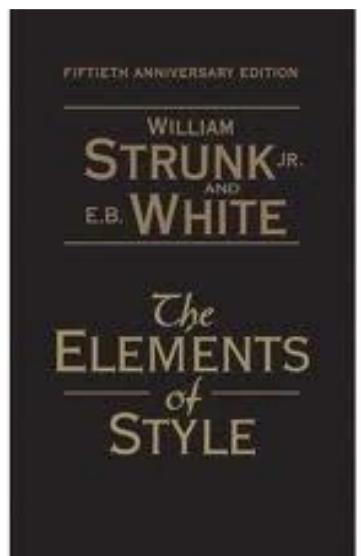
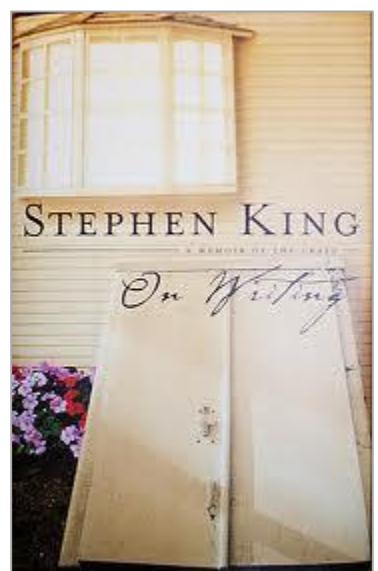
reedy allocation strategy.
yellow:

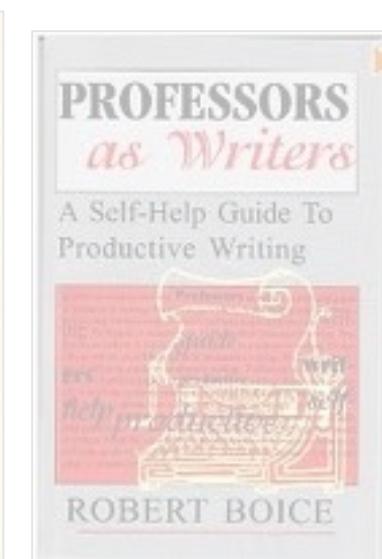
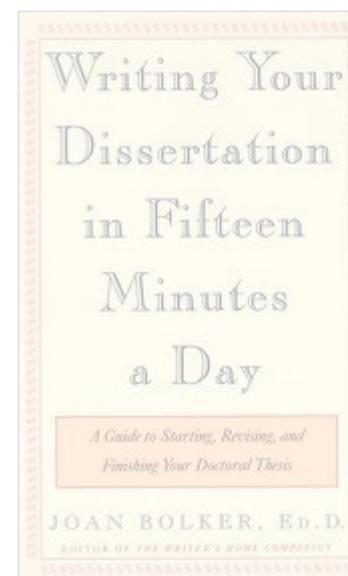
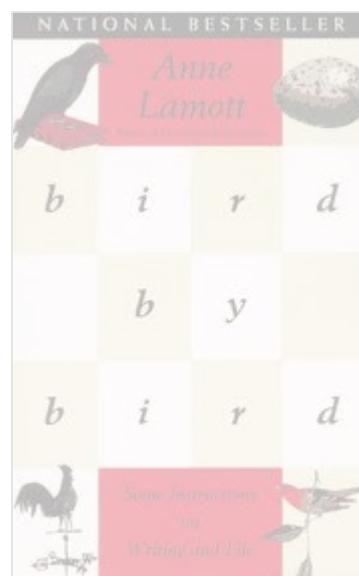
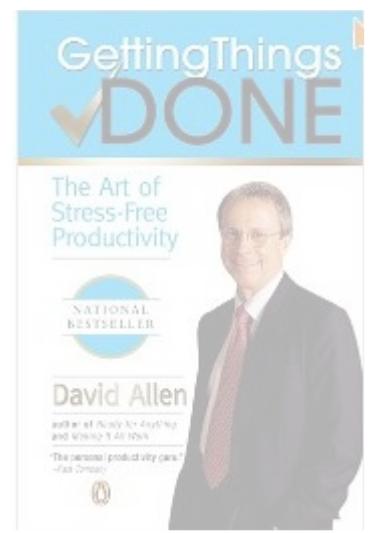
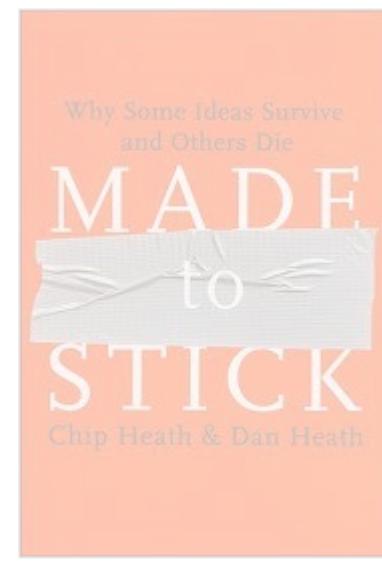
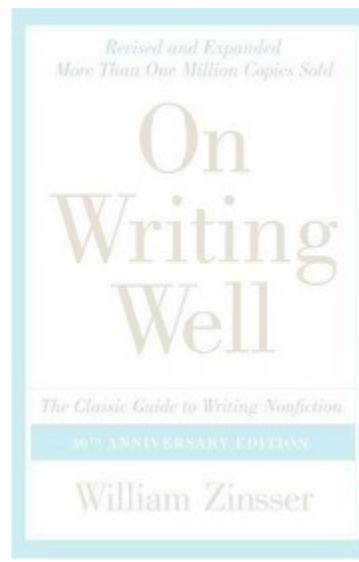
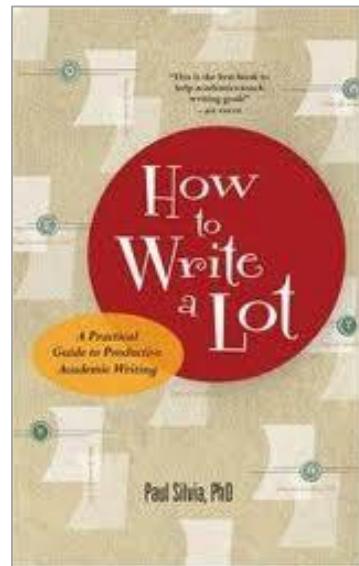
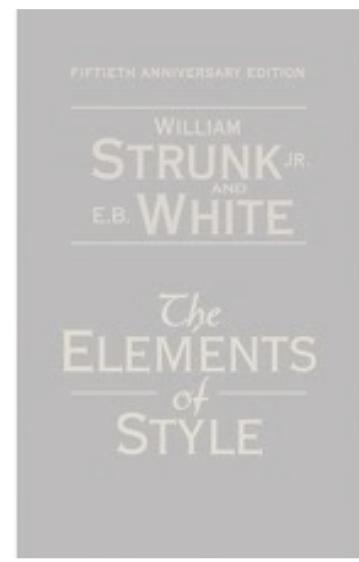
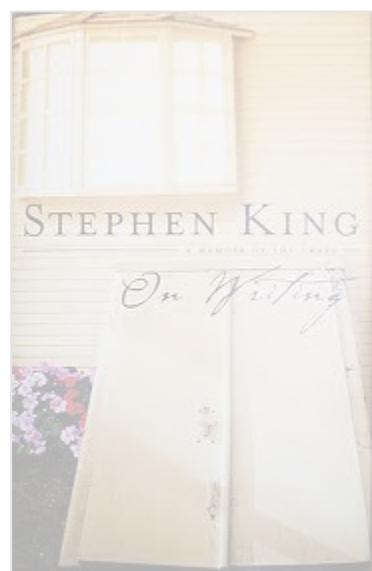
pty pages. To get quick s is often the introduction tions. Its It can be gin adding three pages just heard a course about, ay. So it should be in the

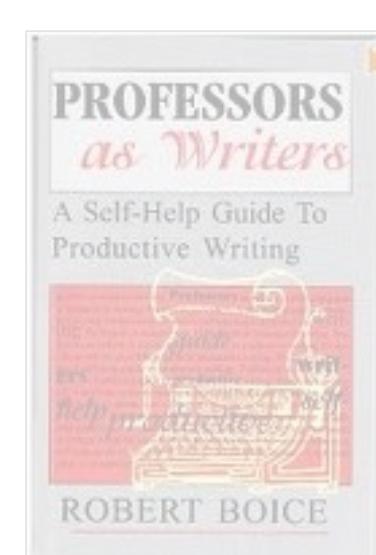
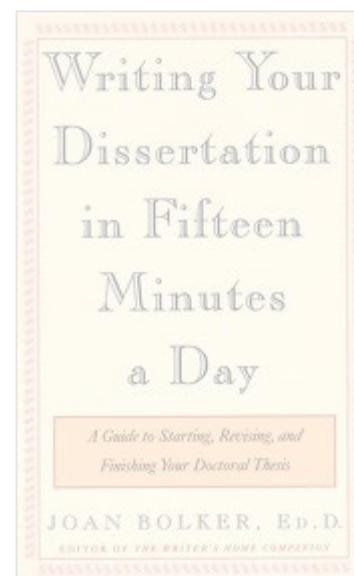
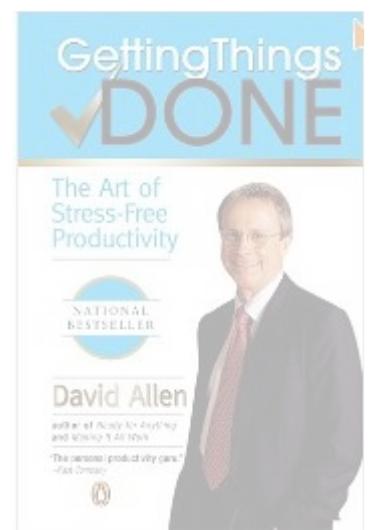
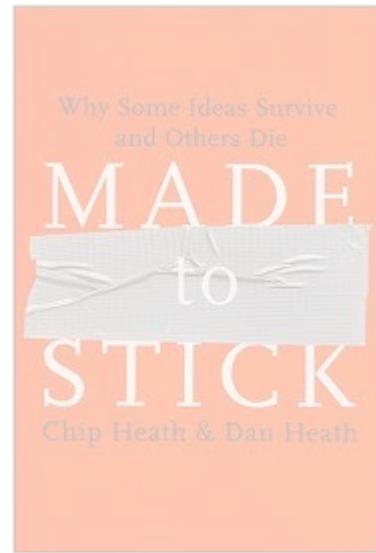
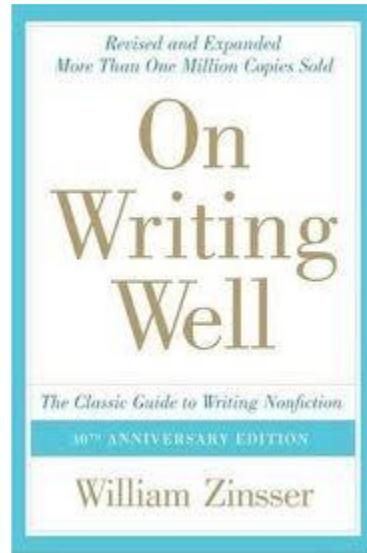
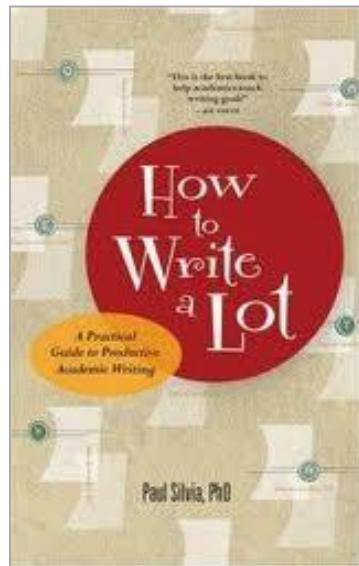
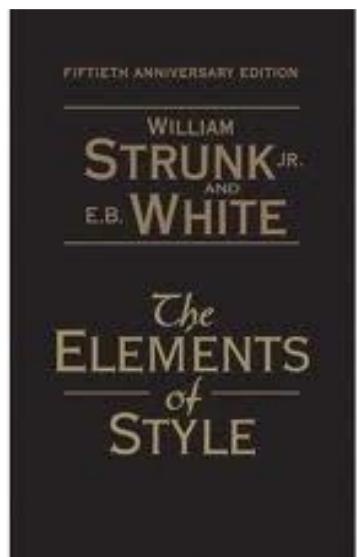
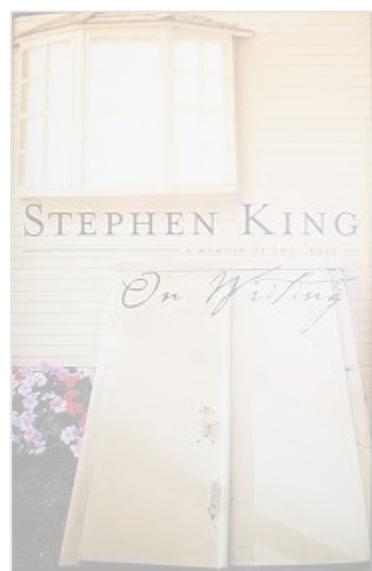
dy strategy when it comes to the important chapters. You are hard pressed for time when you When it comes time to write the contribution and evaluation, or whichever chapters matter most, you find yourself pressed for time. To make things worse, the really interesting ideas often come only after you have been immersed into a topic for a while; that is, - This is at the end of your writing time. Just as like with for the really tasting tastiest buffet items, there is no space left. They end up are either being left out, or they

James Morrison
jmedits@gmail.com

comes to the important chapters. You are hard pressed for time when you When it comes time to write the contribution and evaluation, or whichever chapters matter most, you find yourself pressed for time. To make things worse, the really interesting ideas often come only after you have been immersed into a topic for a while; that is, - This is at the end of your writing time. Just as like with for the really tasting tastiest buffet items, there is no space left. They end up are either being left out, or they







Learning to Rank Extract Method Refactoring Suggestions for Long Methods

Roman Haas¹ and Benjamin Hummel²

¹ Technical University of Munich, Lichtenbergstr. 8, Garching, Germany
² CQSE GmbH, Lichtenbergstr. 8, Garching, Germany
 hummel@tum.de

Summary. Extract method refactoring is a common way to shorten long methods and to increase readability. It improves code readability, reduces complexity, and is one of the most frequently used refactorings. Nevertheless, sometimes developers refrain from applying it because identifying an appropriate set of statements that can be converted into a new method is error-prone and time-consuming. In this paper, we propose a learning approach to automatically derive extract method refactoring suggestions for long Java methods.

Our approach uses a learning-to-rank system to identify suitable candidates for an extract method refactoring that could be suggested to developers. Even though the evaluation has shown that the suggestions are useful for a large set of Java methods, there is still room for improvement. In this paper, we present research on the single scoring features, and their importance for the ranking capability. In addition, we evaluate the ranking capability of the suggested scoring function, and derive a better and less complex one using learning to rank system.

Key words: Learning to Rank, Refactoring Suggestion, Extract Method Refactoring, Long Method

1.1 Introduction

A long method is a bad smell in software systems [2], and makes code harder to read, understand and test. A straight-forward way of shortening long methods is to extract parts of them into a new method. This procedure is called “extract method refactoring”, and is the most often used refactoring in practice [28].

The process of extracting a method can be partially automated by using tools like JBoss Seam Refactor [29] or SonarQube [30]. However, in our Java code base, we found that a set of extractable statements into a new method, however, developers still need to find this set of statements by themselves, which takes

ment development time. It requires code readability, reduces complexity, and is one of the most frequently used refactorings. Nevertheless, sometimes developers refrain from applying it because identifying an appropriate set of statements that can be converted into a new method is error-prone and time-consuming. In this paper, we propose a learning approach to automatically derive extract method refactoring suggestions for long Java methods, that can be used by developers.

Problem statement. The scoring function is an essential part of our approach to derive extract method refactoring suggestions for long methods. It is designed to rank the quality of suggestions, and also to rank methods. The pairwise approach learns by comparing two training objects [8]. The pairwise approach learns by comparing two training objects and their given ranks (“ground truth”), whereas in our case the pairwise approach learns from the list of all given ranking suggestions for a long method. This is important because the pairwise approach approaches usually perform better than the pointwise approach. Therefore, we do not rely on a pointwise approach but use pairwise and listwise learning to rank.

Contribution. We do further research on the scoring function of our approach to derive extract method refactoring suggestions for long Java methods. We use learning to rank techniques in order to learn which features of the scoring function are relevant, to get meaningful refactoring suggestions, and to keep the scoring function as simple as possible. In addition, we evaluate the ranking capability of the suggested scoring function, and its performance with the new scoring function that we learned. For the machine learning setting, we use 177 training and testing data sets that we obtained from 13 well-known open source systems by manually making five to nine randomly selected Java code snippets.

In this paper, we show how we derived better extract method refactoring suggestions than in our previous work using learning to rank tools.

1.2 Fundamentals

We use learning to rank techniques to obtain a scoring function that is able to rank extract method refactoring candidates, and use normalized discounted cumulative gain (NDCG) metric to evaluate the ranking performance. In this section, we explain the techniques, tools and metrics that we use in this paper.

into the code. Therefore, in the pruning step of our approach, we usually iterate over candidates that need more than three input parameters, thus avoiding the long parameter list⁴ mentioned by Fowler [2]. We avoid learning that too many input parameters are bad, we considered only candidates that had less than four input parameters.

We ranked the selected candidates manually with respect to complexity reduction and readability improvement. The higher the ranking was a developer’s preference for the refactoring suggestion.

Some of the randomly selected methods were not suitable for an extract method refactoring. That was most commonly the case when the code would not benefit from the extract method, but from other refactorings. In addition, for some methods, the learned scoring function was not able to find any length measurement, using each of the length measurements one at a time. We continued with the feature set until only one feature was left.

To answer RQ1, we used the learning to rank tools SVM-rank and ListMLE to perform a 10-fold cross validation on our training and test data set of 177 long methods, and a total of 1,185 refactoring candidates. We illustrate the stability of the single coefficients by using box plots that show how the coefficients are distributed over the ten iterations of the 10-fold cross validation.

To answer RQ2, we simplified the learned scoring function by omitting features, where the selection criterion for the omitted features is preservation of the top 10% of the learned coefficients. Our analysis showed that we contained six different measures of length. For the sake of simplicity, we would like to have only one measure of length in our scoring function. To find out which measure best fits in with our training set, we re-ran the validation procedure with the removed feature. For the SVM-rank, the coefficients of ListMLE are much more stable compared with SVM-rank. SVM-rank shows coefficients with a big variance between the single iterations of the training process; that is, despite the heavy overlapping of the training sets, the learned coefficients will only a car and hardly be generalized.

1.4.3 Results

The following paragraphs answer the research questions.

RQ1: What are the results of the learning tools?

Figures 1-2 and 1-3 show the results of the 10-fold cross validation for ListMLE and for SVM-rank, respectively. For each single feature, i , there is a box plot of the corresponding coefficient, c_i .



Fig. 1-2: Learning Result From ListMLE With All Features



Fig. 1-3: Learning Result From SVM-rank With All Features

RQ2: How stable are the learned scoring functions?

Table 1-2 shows the average, minimum and maximum coefficients of variation (CV) for the learned coefficients for ListMLE and for SVM-rank. Small CVs indicate that in relative terms the results from the single runs in the 10-cross fold procedure did not vary a lot, whereas big CVs indicate big differences between the learned coefficients. As the learned single feature from ListMLE are more stable than the ones from SVM-rank, the coefficients of ListMLE are much more stable compared with SVM-rank. SVM-rank shows coefficients with a big variance between the single iterations of the training process; that is, despite the heavy overlapping of the training sets, the learned coefficients will only a car and hardly be generalized.

RQ3: Can the scoring function be simplified?

For practical reasons, it is useful to have a scoring function with a small number of features. Adding features for a real-world scoring function, the coefficients of the learned scoring function should not vary a lot during the 10-fold cross evaluation procedure.

RQ4: How does the learned scoring function compare with our manually determined one?

In our previous work, we derived a scoring function by manual experiments. Now we can use our learning data set to evaluate the learned scoring function of the previously defined scoring function, and to compare it with the learned one.

⁴ On http://is.gd/haas12r_smc_data.xls we provide our rankings and the corresponding code bases from which we generated the refactoring candidates.

Learning to rank refers to machine learning techniques for training the model in a ranking task [4]. There are several learning to rank approaches for training the model. The pairwise learning to rank approaches, where the pairwise and the listwise approach perform better than common pointwise regression approaches [8]. The pairwise approach learns by comparing two training objects and their given ranks (“ground truth”), whereas in our case the pairwise approach learns from the list of all given ranking suggestions for a long method. C₀, with refactoring candidates, C , suppose that x_i is the ranking list on C , and y_i the set of manually determined grades, then, the DCG at position k is defined as $DCG(k) = \sum_{j=1}^{min(k,|C|)} G(j)/D(x_j)$, where $G(j)$ is the grade of the j -th candidate, and $D(x_j)$ is a decreasing function of the position of refactoring candidate x_j in x_i . We set $G(j) = 2^{j-1}$ and $D(x_j) = \frac{1}{log(1+x_j)}$. To normalize the DCG, and to make it comparable with results of other long methods, we divide this DCG by the DCG of a perfect ranking. The NDCG of a candidate x is the ratio of a candidate’s ranking will always be in $[0, 1]$, where the NDCG of 1 can only be obtained by perfect rankings. In our evaluation, we consider the NDCG value of the last position so that all ranks are taken into account. See Haas [6] for further details.

which is described in more detail by Jarvenpaa and Karwanen [9], and measures the goodness of the reading list (obtained by the application of the scoring function). Mistakes in the top-most ranks have a bigger impact on the DCG measure. This is useful and important to us because we will not suggest all possible refactoring candidates, but only the top-most ones. We set $D(x_j)$ to give a long method, m , with refactoring candidates, C , suppose that x_i is the ranking list on C , and y_i the set of manually determined grades, then, the DCG at position k is defined as $DCG(k) = \sum_{j=1}^{min(k,|C|)} G(j)/D(x_j)$, where $G(j)$ is the grade of the j -th candidate, and $D(x_j)$ is a decreasing function of the position of refactoring candidate x_j in x_i . We set $G(j) = 2^{j-1}$ and $D(x_j) = \frac{1}{log(1+x_j)}$. To normalize the DCG, and to make it comparable with results of other long methods, we divide this DCG by the DCG of a perfect ranking. The NDCG of 1 can only be obtained by perfect rankings. In our evaluation, we consider the NDCG value of the last position so that all ranks are taken into account. See Haas [6] for further details.

1.3 Approach

We discuss our approach to improve the scoring function in order to find the best suggestions for extract method refactoring.

1.3.1 Extract Method Refactoring Candidates

In our previous work [6] we presented an approach to derive extract method refactoring suggestions automatically for long methods. The main steps are defining and extracting the statements from the code, and ranking the candidates according to the candidate list.

In the following, a *refactoring candidate* is a sequence of statements that can be extracted from a method into a new method. The *remodifier* is a method that contains the statements of the refactoring candidate. The suggested refactoring will help to improve the readability of the code and reduce its complexity, because these are main reasons for developers to follow the code refactoring.

We derived refactoring candidates from the control and data flow graph of a Java program with 10 with 10 sets, that is, we split our learning data into sets of (nearly) equal size. We performed 10 iterations using these sets, where nine of the sets were considered to be training data and one set was used as test data.

Test data is used to evaluate the ranking performance of the learned scoring function by comparing the grade of a refactoring candidate determined by the learned scoring function with its grade given by the developer. We use NDCG metric to compare different scoring functions and their performances.

1.2.2 Training and Testing

The learning process consists of two steps: training and testing. We applied cross-validation [10] with 10 sets, that is, we split our learning data into 10 sets of (nearly) equal size.

We use learning to rank techniques to obtain a scoring function that is able to rank extract method refactoring candidates, and use normalized discounted cumulative gain (NDCG) metric to evaluate the ranking performance. In this section, we explain the techniques, tools and metrics that we use in this paper.

1.2.3 Evaluation

In this section, we present and evaluate the results from the learning procedure.

1.4.1 Research Questions

The following paragraphs answer the research questions.

RQ1: What are the results of the learning tools?

Figures 1-2 and 1-3 show the results of the 10-fold cross validation for ListMLE and for SVM-rank, respectively. For each single feature, i , there is a box plot of the corresponding coefficient, c_i .

On the ranking performance and removed it in the next iteration. A scoring function that only considered the number of input parameters and length and nesting area still had an average NDCG of 0.885.

RQ2: How does the learned scoring function compare with our manually determined one?

The scoring function that we presented in [6] achieved a NDCG of 0.891, which is better than the best scoring function learned in this evaluation.

1.4.4 Discussion

Our results show that, in the initial run of the learning to rank tools, features indicating a reduction of complexity are much more relevant for the ranking, and therefore have a comparatively high impact. Furthermore, the length of ListMLE is higher on our data set than the length of SVM-rank. For SVM-rank there is a big variance in the learned coefficients, which might also be due to the fact that the learned scoring function is not very good.

The results for RQ3 show that it is possible to achieve a great simplification without big reductions in the ranking performance. The biggest influences on the ranking performance were the reduction of the number of statements, the reduction of nesting areas (but complexity indicators).

1.5 Threats to Validity

Learning from data sources that are either too similar or too small means that there is a chance that no generalization of the results is possible. We used our data to evaluate to learn a scoring function that can rank extract method refactoring suggestions for 13 Java open source systems from various domains, and of different size. We consider a method to be “long” if it has more than 40 LOC. From this project we randomly selected 13 Java open source systems and evaluated the learned scoring function for valid refactoring candidates, where the number of candidates depended on the method length.

Mondal et al. [16] rank clones for refactoring using mining techniques. Their idea is to find clones in a code base and to rank them together by similarity. They also proposed a learning method, and filtered out those that were not appropriate for the learned method. We followed the same idea, but we did not use any mining technique. Instead, we used a learning method to find the most relevant features, and then we used a learning method to rank the refactoring candidates.

We also considered the threat that there is no generalization of the learned scoring function to other Java code bases. We used learning to rank techniques to learn a scoring function that is capable of ranking extract method refactoring candidates from other Java code bases.

We were able to find several scoring functions that had only a handful of features and a better ranking performance than our scoring function from previous work. Obviously, the learning tools were not able to find optimal refactoring suggestions for the features for the learned scoring function.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We also considered the threat that the learned scoring function is not able to rank extract method refactoring suggestions for long methods. We used a learning to rank technique to learn a scoring function that had only a few features and a better ranking performance than our scoring function from previous work.

We

Vortrag Vorbereiten

The image is a collage of four photographs illustrating the process of preparing a presentation:

- Top Left:** A sequence of four small diagrams showing a collection of yellow sticky notes being organized into a grid, then into a single column, and finally into a single row.
- Top Right:** A wall covered in numerous yellow sticky notes with handwritten text and drawings, next to a black trash can containing discarded notes.
- Bottom Left:** A large wall covered in many yellow sticky notes, with several larger rectangular sticky notes overlaid, suggesting a storyboard or outline.
- Bottom Right:** A screenshot of a blog post titled "How to Draft Your Presentation" from "thesisguide.org". The post includes a summary of the process, a link to the full article (<http://thesisguide.org/2015/03/04/how-to-draft-your-presentation/>), and a small version of the "grid-to-single-row" diagram.

[https://thesisguide.org/2015/03/04/how-to-draft-your-presentation/](http://thesisguide.org/2015/03/04/how-to-draft-your-presentation/)

Vortragsplanung: Delta BA/MA

- Probevortrag vor Betreuer
- Vortrag auf Englisch üben
- Einstiegssätze aufschreiben und auswendig lernen.
- Backup Folien für mögliche Fragen

Forschungsarbeiten @ CQSE

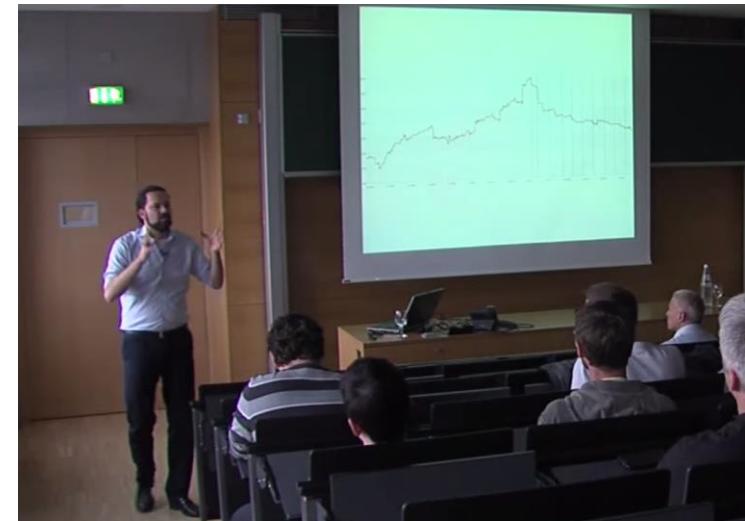
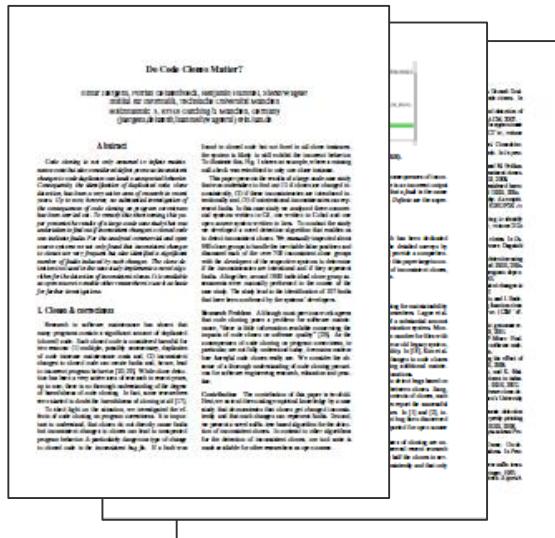
- Mi., 27.06., 17 Uhr im Gate
- Agenda: Ablauf einer Forschungsarbeit @ CQSE
 - Analyse-Implementierung
 - Studie
 - Betreuung
 - Pitch aktueller Themen
- Hinterher Pizza und Bier ☺



Anmeldung: <https://forschungsarbeiten-cqse.eventbrite.de>

Fazit

Willst Du selbst Forschen und die Forschungscommunity kennenlernen? Dann mach ein Guided Research.



Danke!

Bei Interesse einfach bei uns melden:

juergens@cqse.eu

haas@cqse.eu

Am 26.6. um 17 Uhr: Forschungsarbeiten @ CQSE

Mehr Infos: www.thesisguide.org