PROGRAMMING, RESEARCH AND... COFFEE? AN ANALYSIS OF WORKPLACE ACTIVITIES BY COMPUTING INTERNS

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INTRODUCTION

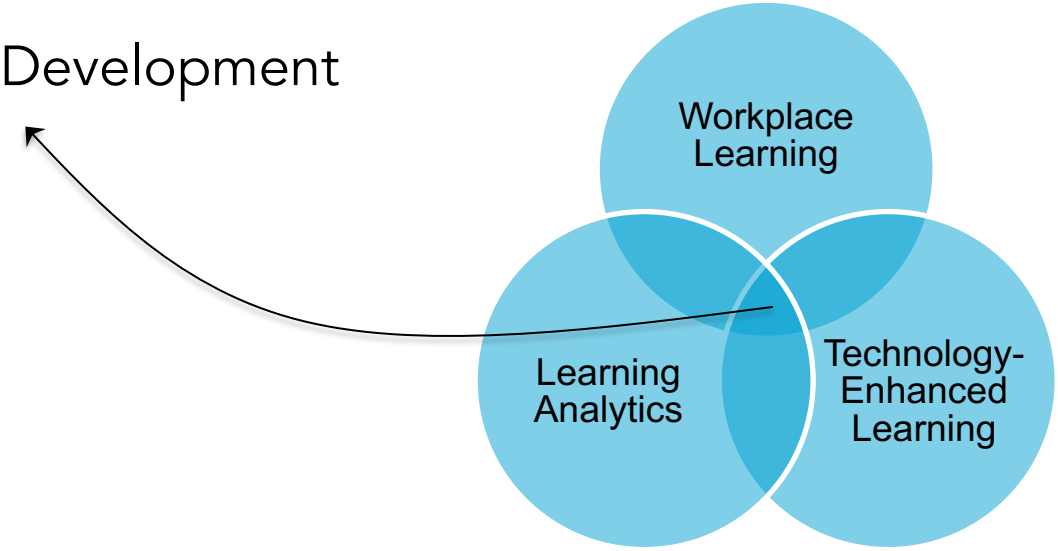
- Skills gap: industry demands vs. learning outcomes [EC16][EPRS17][HM09][WP10]

- Workplace learning in computing curricula [T13][Z+16]
  - Transfer from university to practice
  - Authentic tasks
  - Recent technologies

- However: lack of insight in workplace activities
  - Distance between coach and student
  - No cohort-based overviews

THEORETICAL BACKGROUND

- **WPL:** Workplace Learning
  [N+08]
- **TE(W)L**: Technology-Enhanced (Workplace) Learning
  [SK06][S+12][KP14][vdSZ17]
- **(WP)LA**: (Workplace) Learning Analytics
  [RC+17][vdS18]
- Data-driven Curriculum Development
  [SK10][D14][M14][TR16]



RESEARCH QUESTIONS

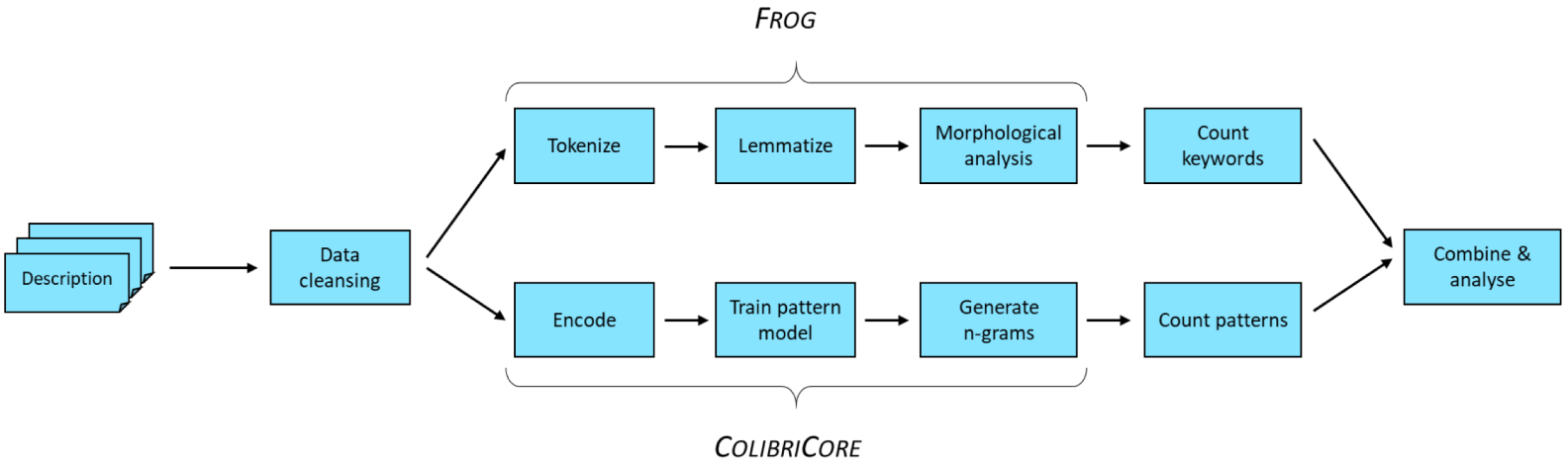
When students in higher professional computing education perform an internship in industry:

1. Which activities do they perform most?
2. Which activities do they find most difficult?
3. Which technologies do they use most?

METHODOLOGY

- Provide application to interns
- Opt-in to justify working days (alternative offline)
- Collect all registered activities

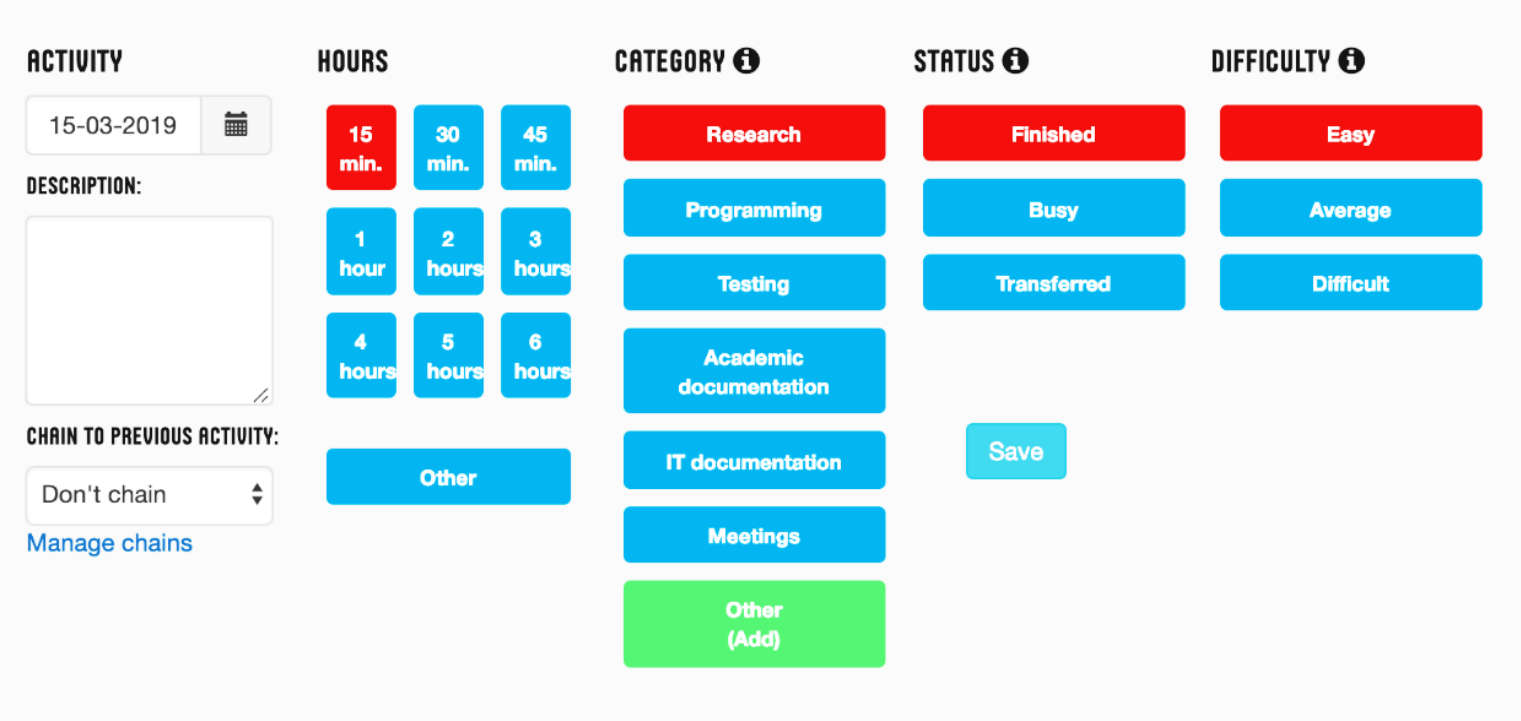
- Analyze both statistically (RQ1&2) and textually (RQ3)



APPLICATION

- Open-source TEWL-application [vdSZ17]

- Supports learning process with
  - Learning analytics
  - Automated feedback



DATA COLLECTION

- Fall Semester 2018
- 100-day internships

	#students
Internship	183
Registered for app	81
Registered >=1 day	68
Registered >=20 days	54
Male	49
Female	5

- Three computing Bachelor programs:
  - Business Informatics (BI)
  - Software Engineering (SE)
  - IT Systems & Networks (SN)

RESULTS: DESCRIPTIVE STATS

Cohort	#students	#activities		total duration in hours		#days		#activities per day		duration of a single activity in hours	
		μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
BI	12	195	118.0	752.8	156.00	94.6	19.53	2.1	1.09	4.9	2.18
SE	29	204	93.5	735.6	161.08	92.5	19.40	2.2	0.90	4.0	1.23
SN	13	150	88.8	635.1	278.51	79.8	36.10	1.9	0.64	4.8	1.67
Total	54	189	100.9	715.2	200.24	89.9	25.18	2.1	0.90	4.4	1.64

RESULTS: CATEGORIES

Default Categories

All cohorts

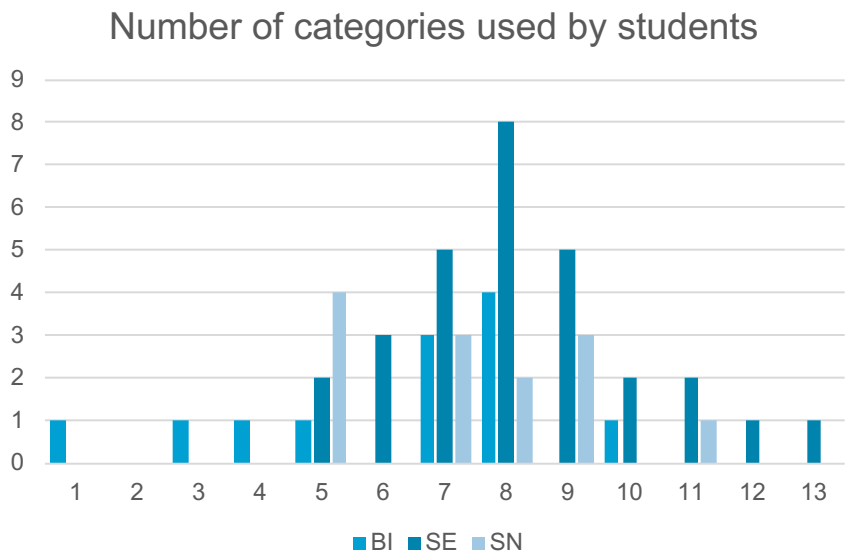
- Academic Documentation
- IT Documentation
- Meeting
- Research
- Testing

BI & SN

- Implementation / Configuration

SE

- Programming



User-generated categories (coded)

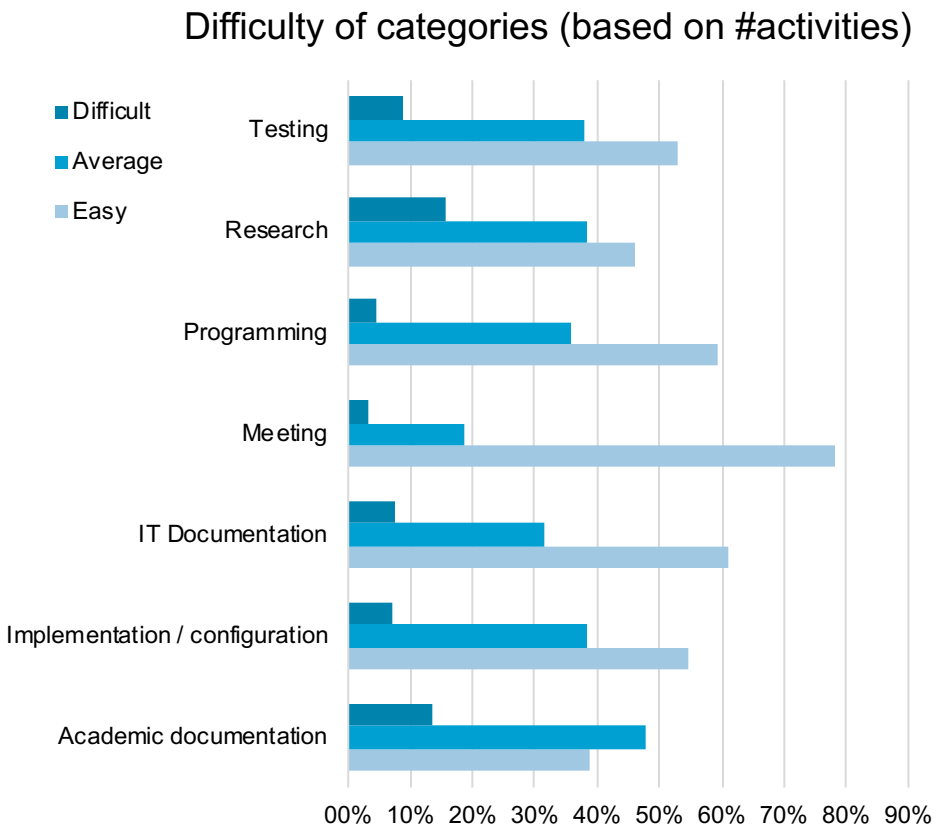
Category class	#students
'Other'	16
Illness, Breaks, Outside of work, Absent	11
'Container category'	5
Introduction	13
Training / course	10
Demo / presentation	9
Preparation	8
Setting up	6

RESULTS: MOST OCCURING CATEGORIES

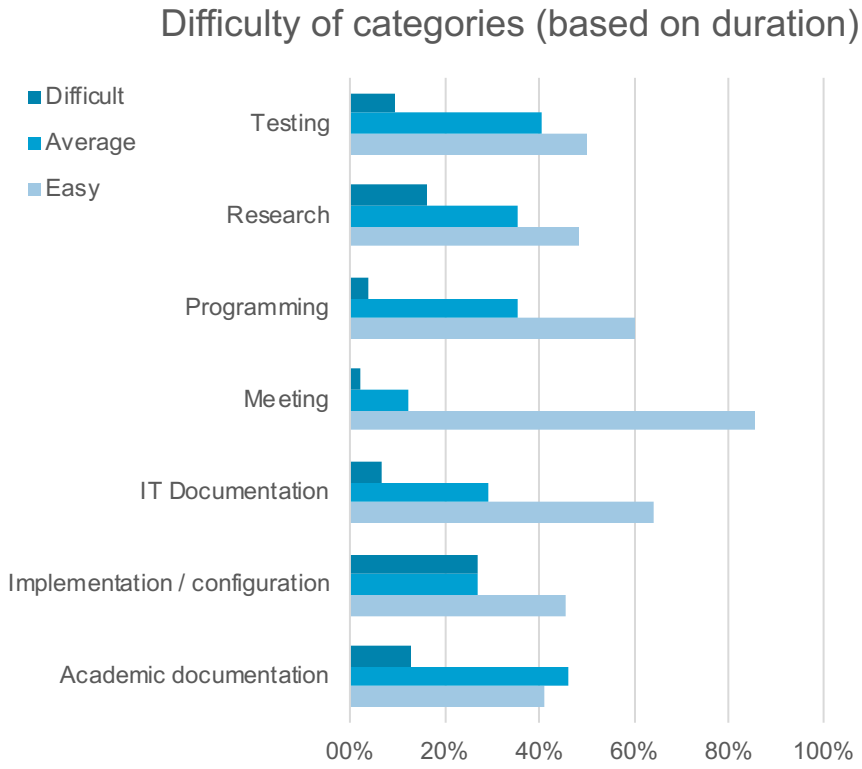
Category class	BI	SE	SN	Overall
Programming		44,7%		25,7%
Academic documentation	29,1%	16,4%	32,3%	22,4%
Research	27,5%	13,6%	21,1%	18,2%
IT Documentation	13,2%	13,6%	12,6%	13,3%
Implementation/ configuration	8,1%		19,1%	5,7%
Meeting	5,7%	4,2%	4,4%	4,6%
Container category	8,4%	0,2%	4,3%	2,8%
Testing	1,1%	2,7%	2,3%	2,2%
Other	1,1%	0,5%	0,8%	0,7%
Introduction	1,7%	0,3%	0,6%	0,7%
Illness	0,3%	0,5%	0,9%	0,6%
Planning		0,8%		0,5%
Preparation	0,2%	0,5%	0,3%	0,4%
Proof of concept	1,6%			0,4%
Training / course / personal development	0,3%	0,4%	0,0%	0,3%
Demo / presentation	0,8%	0,1%	0,1%	0,3%

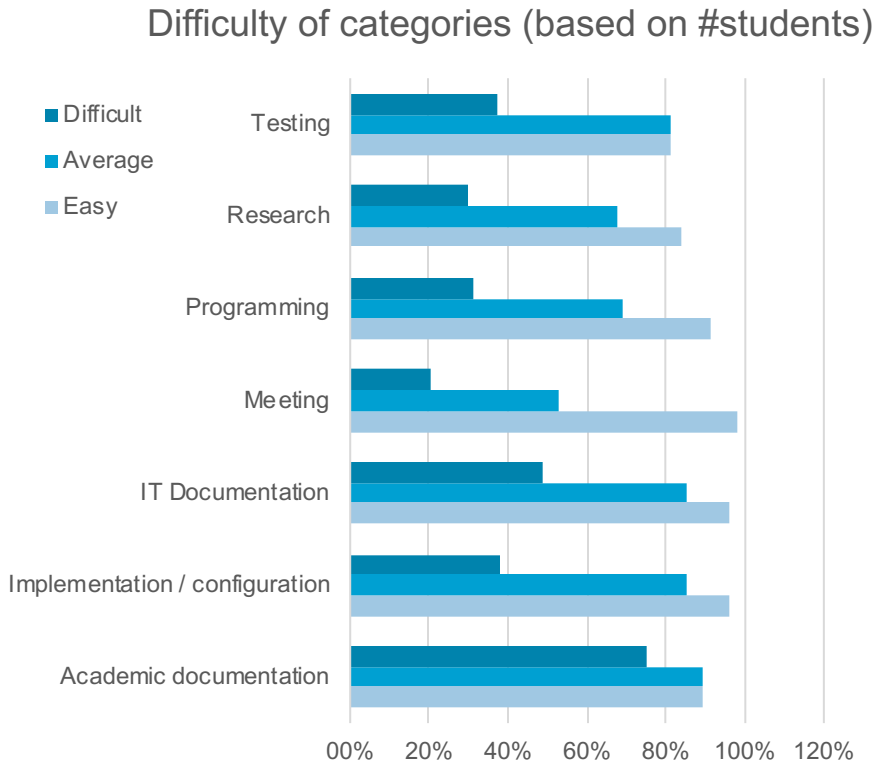
RESULTS: DIFFICULTY OF ACTIVITIES #1

Difficulty	Activities	Percentage	Duration
Easy	6,101	59.8%	20,419h
Average	3,394	33.2%	14,906h
Difficult	714	7.0%	3298h
Total	10,209	100%	38,623h



RESULTS: DIFFICULTY OF ACTIVITIES #2





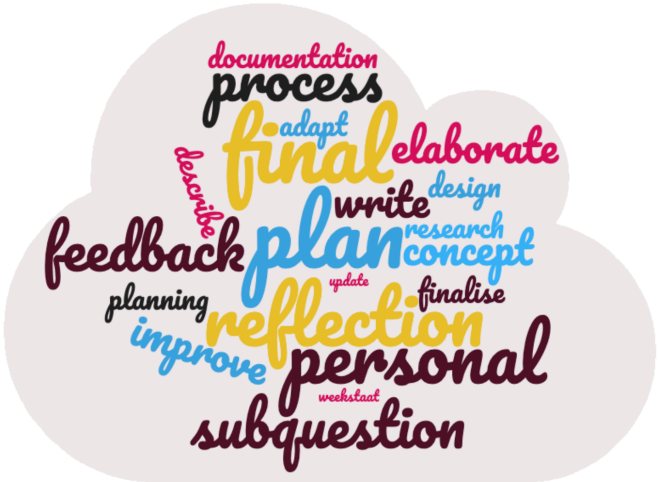
RESULTS: STUDENTS' PERCEPTIONS #1

Meeting

Research

Testing

Academic documentation



RESULTS: STUDENTS' PERCEPTIONS #2

Implementation / configuration

IT Documentation

Programming

RESULTS: TECHNOLOGIES

Software Engineering

(n=29)

Technology	Count	#students
API	134	14
Database	88	14
REST*	38	12
Git*	27	12
Angular	57	10
Jira	113	9
CSS	39	9
HTTP*	18	8
Azure	39	7
JSON	29	7
Jenkins	21	6
JavaScript	12	6
ASP	10	5
Docker	5	5
Windows	16	4
SQL	8	4
Kubernetes	6	4
iOS	5	4
Xamarin	47	3

IT Systems & Networks

(n=13)

Technology	Count	#students
Network	50	11
Server	55	7
Router	16	6
Cluster	17	4
Windows	15	4
Cisco	8	4
Firewall	5	4
VM	11	3
Elasticsearch	9	3
Office	7	3
Exchange	31	2
Docker	21	2
Kubernetes	17	2
VPN	12	2
Azure	7	2

CONCLUSIONS

- Cohort-level analysis of workplace learning in higher computing education is feasible
- Programming, (academic) documentation and research most ocurring categories
- Categories added by students:
  introduction, preparation, training, demo/presentation
- Most difficult: research, academic documentation and implementation /configuration
- Testing, research, meetings, and academic documentation are congruous with labels
- Technology usage in line with our expectations
- Results can be used for expectation management towards new interns

DISCUSSION

- Data quality
  - User-generated
  - Lazy users
  - Self-selection bias

- Future work
  - Larger N
  - Other educational domains
  - Other workplace data (e.g. logs)
  - Detect trends over time
  - Use text analysis for category ‘Other’

QUESTIONS?

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