Learning Processes and Consistency in the Quality of Software Development Based on Environmental Influences

by

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Declaration

I, the undersigned, declare that this work has not previously been submitted as an exercise for a degree at this, or any other University, and that unless otherwise stated, is my own work.

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Acknowledgments

Give many thanks and stuff...

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University of Dublin, Trinity College, 2017

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The abstract or summary or whatever...

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Introduction

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Blah, blah, blah!

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Blah, blah, blah!

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Blah, blah, blah!

Chapter 2

The State of the Art

Many researchers are concerned about finding metrics of software quality with the human factor as the most significant part in the development process. Research has also been done in the process of finding and testing factors, influencing the cognitive performance of the developers. In my dissertation I aim to identify metrics how environmental influences can change the progress of improving programming skills of Computer Science students. With the students as a key factor in software engineering, I will analyse the influences in behaviour and performance in a environmnetal and psychological sense. [2] Measuring quality of software projects and gaining information about the progress are valuable information for the software engineers and developers to reflect their performance. The feedback provided feedback helps them identify their weakness to improve their skills or change patterns. [5] [10] Also project managers have a great interest in details about the progress and the products quality to coordinate the schedules and resources. Early knowledge about potential problems can make the difference between the success or failure of a project.

A good programmer nowadays is described as a person who can solve complicated problems by breaking them down in simple problems. The produced code is clean, easy to read and simple. [5] This new approach differs from the early days, when programmers tried to find the shortest and most performant solutions. Code that is written in a

complicated way but which is using as few resources as possible showed how skilled a programmer was. Related to the computing power that rapidly grew and the increasing sizes of software projects with more and more people changed the requirements. In my opinion, it is interesting to get an overview of both aspects to combine the best of both approaches. Therefore the following will summarize information about code metrics and code quality from several decades.

2.1 Software Metrics

Since the late 1960s, when the software engineering was in it ' s beginning, people wanted to measure and produce numbers to characterise code properties. One of the first used metrics where used to measure and evaluate a programmer. Lines of Code (LOC) per month and bugs per thousand lines of code (KLOC) are a very simple but efficient ways for measuring the productivity, which can be used to for comparrision with others. Software metrics is the term that is been used more then 30 years ago up to today. These days some of the most metrics are used to investigate the programmer productivity, the amount of bugs in relation to the amount of code, the initiall number of requierements compared to the requierememts at the current point in the project and the effort it takes to fix faults versus the total time the project reqieres. [8] The metrics have been a great success in the industry. Most of the big software companies and even smaller ones use metrics, though they are barely used in academia. The metrics are created for larger softwares and scopes. Also maintenance and refactoring is not as important in academia as it is in the industry with commercial software. Also, Software metrics in the industry are primarily important for the management rather than for the development process. Industrial software metrics can be used to ensure quality, productivity and even for predictions of the software quality and it ' s reliability. [3] Several researchers investigated and developed approaches to improve the metrics and the results which they are generating. Yue Jiang et. al. from West Virginia University researched methods for improving software quality predictions.

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They used supervised machine learning algorithms with datasets and focused in improving of the information content of the training data in their research. The results at the end showed that the biggest differences in the quality of the predictions are generated by the choice of the right software metrics rather than applying different machine learning algorithm. [4]

2.2 Metrics Measurement and Analysis

PSP - Personal Software Process is a way to gather data about the Software engineering process and analysis of the information. Over the last decades, the University of Hawaii did a lot of research about PSP and they developed different approaches to make students to adopt the PSP. Their first approach was originally described as " A Discipline for Software Engineering " . It required the users to keep records about all the metrics by hand. The massive overhead was a high barrier for the students to adopt and keep on working with the PSP. For the best results they needed to write down every compiler error and they had to track the time they were working on their projects and had to stop it for interruptions. In 1998 the University of Hawaii started the Leap research project to provide a PSP with low overhead for the collection and analysis of the data. This generation of PSP was using automated tools which were asking the user for inputting the data. These tools were also able to display information and analyses to the user. Just a few students adopted the system. The researchers found out that another reason for the reluctant adoption was the constant context switches for the users. Inputting the data during the programming task interrupted and disturbed the ability to focus on the programming tasks. [7] In order to eliminate the adopting barriers, they started the Hackystat project in 2001. Hackystat is an open source framework for automatically gathering all the required metrics by data collection plugins in the development environments of the users. Plugins, that are installed by the in their programming environments automatically collect the data and forward it to a centralized web service. The web service

orders and analyzes the data. If interesting results occur, the webservice sends emails to the developers to inform them about it. The web service also provides a rich visual representation of the data. All the different approaches to provide feedback about the code lead to improvements in the quality and the ability to estimate software projects. [6] The Appalachian State Uiversity in North Carolina described a different approach. Their goal was to decrease the high attrition rate of computer science students and increase the attraction to get a computer science degree in general. The researchers were monitoring the students software development behaviour in order to find good practises for successfully learning programming. For gathering the data of the individual students, they developed a tool called ClockIt. ClockIt allows to, fully automatically, collect the data, analyze it and compare the results with the results from better or more experienced students visually. A web interface provides access to measurements for the student, the course instructor or an administrator. In their results they compared the data of three students out of 75 participants. The students with the best results, an average scoring student and the one with the lowest grade. The comparison showed that the best student also spent the most time on the project, but wrote less code than the average scoring student who spend almost as much time. The worst student spend the least time and submitted the smallest amount of code. There was an interesting correlation between the grade and the compilation errors and the amount of compilations that were made. The best student compiled the code more than double as much as the average student and almost 6 times more than the worst student did. [11]

2.3 Performance Influences in Software Development

The performance of a human in programming arises from their cognitive performance. A lot of different aspects have been investigated by a lot of different reseachers. The human brain needs resources to function well and this resources are provided by the food that the person is eating. The wrong diet can strongly influence the incidences of cognitive

problems as well as a healthy can have positive influence for healthy ageing. Some foods have positive effects on the mental performance containing flavonoids like for example grapes, tea, cocoa and blueberries. Studies on several mammalian species have shown that foods which are rich of flavonoids have beneficial effects on memory and learning with the ability to support neurons and protecting them again stress-induced injury. [13] Other foods can influence the cognitive performance such drinks or food that contains caffeine. Based on the Yerkes-Dodson Law, a higher level of arousal leads to better cognitive performance. As caffeine influences the arousal, Watters, Paul Andrew et. al. [14] found out that the mean for the best cogintive results is an amount of 400 mg caffeine (the amount contained in ca. 5 espresso shots). Researchers from the Brunel University in the UK showed movie clips to invoke different defined moods of the participants before they solved given debugging/coding tests. The results showed improvements in the results after the participants were seeing high arousal video clips. Low arousal clips affected the performance negatively compared to neutral clips. [9] When the mood is influencing the performance of a programmer. Then factor effecting the mood also have an impact in the quality of the written software. Many people believe that for example the weather has a strong influence in the daily mood of a person. Denissen, Jaap JA, et al. [2] found out that the sunshine alone actually has no noteable effect in the mood of the most of the people but they found significant correlations between sunlight, air pressure and precipitation on the tiredness of the participants. A reason for the influence of sunlight could be vitamin D3. The most of it is obtained through exposure to sunlight and it changes the level of serotonin which was found to be partly responsible for the mood of a human.

2.4 Ways to improve performance

Imporving the perfomance in Software Development can be done in a several different ways. One research group from the industry and the North Carolina State University investigated the influence of tooling and work patterns, used for the development [12]. They

developed a tool to automatically recommend more efficinet development tools for programmers. The recommendation system monitored the working patterns of the developer, compares the process with the patterns of other developers and it makes recommendations in case that other developers use a more efficient tool. In order to understand the work patterns, the system needs to gather data from the computer of the developer. Different existing tools like Mylyn Monitor, HackyStat and PROM were used for that purpose. Another approach to improve the development performance is optimizing the work environment. Amabile, Teresa M., et al. [1] are writing about a conceptual model for more creativity in work environment. Five key factors are described. The first two factors are, the encouragement for innovation and creativity as part of the company culture as well as according autonomy or freedom for the employees. Another key describes the adequate availability of resources for a project which might affect people psychologically by the feeling to work on a valuable project. Pressure at work was found out to increase creativity on a balanced level, which is neither to hight or too low. The last key factor in their model is the organizational impediments to creativity which could be caused by internal competitions. A study was designed to investigate two hypotheses: The influence of the model in high-creative projects vs low-creative projects is expected to be much bigger. As well as obstacles scales are lower in high-creative projects compared to low-creative projects for workload with pressure and organizational impediments. Both hypotheses supported by clear results which show that beside the employee's itself, the management can significantly influence the level of creativity and innovation by forming the organization culture. The construction of the teams and definition of the individual roles can have a great impact on the creativity. The human brain needs a fuel to run properly. What we eat is can influence our cognitive abilities a lot. The wrong diet can strongly influence the incidences of cognitive problems as well as healthy food can positively influence for healthy ageing [13]. Some foods demonstrated positive effects on the mental performance containing flavonoids like for example grapes, tea, cocoa and blueberries. Studies on several mammalian species have shown that food that is rich of flavonoids have beneficial

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effects on memory and learning with the ability to support neurons and protecting them again stress-induced injury. Flavonoids also decreases the chances of alzheimer and dementias. Other studies have shown that flavonoid-rich food improves the blood flow and correlates with the growing of new hippocampal cells, which are in the brain region which is important for memory.

Chapter 3

More Content and Stuff

3.1   A section of more Stuff

Blah, blah, blah! Blah, blah, blah! Blah, blah, blah!
Blah, blah, blah! Blah, blah, blah! Blah, blah, blah!

- One

- Two

- Three

3.2   Another section of more Stuff

Blah, blah, blah! Blah, blah, blah! Blah, blah, blah!
Blah, blah, blah! Blah, blah, blah! Blah, blah, blah!

Chapter 4

Design

The design...

Chapter 5

Simulations

The simulations.

Chapter 6

Results

The results.

Chapter 7

Conclusions

And a fancy conclusion...

Appendix A

Abbreviations

Short Term	Expanded Term
DNS	Domain Name System
DHCP	Dynamic Host Configuration Protocol
...	...

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