Multi-Dimensional Process Analysis of Software Development Projects

Thanh Nguyen[1], Saimir Bala[1][a] and Jan Mendling[1,2][b]
[1]*Humboldt Universität zu Berlin, Department of Computer Science, Unter den Linden 6, 10099 Berlin, Germany*
[2]*Weizenbaum Institute, Research Group: Security and Transparency in Processes, Hardenbergstraße 32, 10623 Berlin, Germany*
{firstname.lastname}@hu-berlin.de

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Abstract: Software processes are complex as they involve multiple actors and data which interplay with one another over time. Process science is the discipline that studies processes. Works in this area are already using multi-dimensional analyses approaches to provide new insights in business processes that go beyond the discovery of control flow via process mining. In this paper, we investigate the applicability of multi-dimensional process analysis. More specifically, we extract data from GitHub open-source repositories that was generated during software development, and evaluate diverse software development metrics. Our results help to explain performance issues by revealing multiple contributing factors, such a side-work, that hinder the progress completing a development task. With this work, we pave the way for multi-dimensional process analysis on software development data.

1 INTRODUCTION

Software development is a complex process that generates vast amounts of data. The increasing volume and complexity of data produced during software development has led to the need for innovative techniques to extract meaningful insights. Multi-dimensional process analysis (Fahland, 2022) is a new paradigm for analyzing and extracting insights from business processes. This approach shifts the focus away from the notion of cases in a process. Instead, it takes into account all the relations between all actors in the process that are found in trace data. By looking into their relations, it is possible to understand and explain various issues that occur as a consequence of the actors' interplay.

The many dimensions of software development can be seen by developers in a software development process as layers that provide information about the data as a whole such as: entities, actors, events, time, social networks, workload, etc. Analyzing and understanding these dimensions of data is crucial for improving the quality and efficiency of software development. However, the vast amounts of data generated during software development make it challenging to extract meaningful insights manually. Hence, the need for new automated techniques to analyze and extract insights from software development datasets has arisen. As software development needs analysis techniques to help the managers understand how various issues manifest, multi-dimensional process analysis presents a unique opportunity for new ways of investigation.

In this work, we adapt multi-dimensional process analysis techniques to software development. We apply the method to construct an a so-called event-knowledge graph. On top of that, we provide various insights into patterns and compute Key Performance Indicators (KPIs). We applied our approach to real-world repositories and gained insights that are informative to managers. As such, we provide information about issue resolution times, identifying bottlenecks, developers focus shift, code complexity, recurring issues, file/commit dependency analysis and issue escalation analysis. With these we underscore potential areas that require increased management attention.

The remainder of the paper is structured as follows. Section 2 describes the setting of software development and formulates our research questions. Section 3 outlines our method to apply multi-dimensional process analysis to software data. Section 4 presents various metrics computed on top of a GitHub repository. Section 5 discusses the results against our research questions. Section 6 concludes the paper.

[a] https://orcid.org/0000-0001-7179-1901
[b] https://orcid.org/0000-0002-7260-524X

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2 BACKGROUND

2.1 Related Work

This paper focuses on the use of data for quantitative analysis. In this realm, we distinguish two streams of works: *i)* data mining works; and *ii)* process analysis.

In the data-mining related-works stream fall those works which use data mining techniques to compute quantitative analysis (e.g., KPIs) about the software. In this context, the focus is to learn how users relate to the artifacts in the repositories (Oliva et al., 2011), or at analyzing the evolution of changes over time (Zimmermann et al., 2005). To achieve that, these techniques are based on identifying and process events (Zimmermann and Weißgerber, 2004) from the software repository data and abstracting them onto higher-level activities (Oliva et al., 2011). The goal is to measure aspects of software such as the type of work (i.e., what kind of files are being worked on) (Vasilescu et al., 2014), the type of resources (Agrawal et al., 2016) or measure KPIs (Rastogi et al., 2013). All these works provide valuable insights into the software development efforts done in the project, but focus on low-level indicators or relations.

The second stream includes *process analysis* related works. Works in this area aim at understanding how things in software development unfold over time. For that they take into account various elements (Vavpotic et al., 2022) of the software development. There are approaches to transform software development data in process-mining compatible event-logs (Kindler et al., 2006; Poncin et al., 2011). There are also approaches that enable process analytics of fine-grained events from evolving artifacts (Beheshti et al., 2013). More complex approaches use repository data to analyse well-known processes. The work from (Marques et al., 2018) uses process mining (van der Aalst, 2016) to analyze bug resolution processes, while (Bala et al., 2015; Bala et al., 2017; Jooken et al., 2019) use version data to analyse commits, and gather insights respectively about the project timeline, hidden dependencies and *de-facto* teams.

Most of the techniques in the process mining stream require the input data to have well-defined attributes (i.e., an event log with defined case, activity, and timestamp). These works cannot be readily applied to data from software development (Tsoury et al., 2018). As well, they only focus on discovering and analyzing predefined relations, by fixing the notion of case and following its traces in the data. However, the notions of case and activity of a process, especially in software data, are in practice loosely defined (Bala et al., 2018).

2.2 Multi-Dimensional Process Analysis

In recent years, process mining approaches are moving toward multi-dimensional analysis. Indeed, concepts like object-centric process mining (van der Aalst, 2019) and standards like OCEL (Ghahfarokhi et al., 2021) are increasingly gaining interest. Thus, the tendency is to use as much information as possible. One way to holistically capture the information contained in the event logs is through the use of so-called *event knowledge graphs* (Khayatbashi et al., 2023) and store them in graph databases (Esser and Fahland, 2021).

Multi-dimensional process analysis serves to deepen our understanding of the software development process by amalgamating data from various sources. These sources may encompass software development tools such as compilers and debuggers, version control systems like Git, bug trackers like Jira, and code repositories like GitHub. By synergistically analyzing the data from these diverse sources, we can unravel patterns, trends, and anomalies that might be unnoticeable when each source is scrutinized in isolation.

Software development is characterized by the execution of the software process (e.g., one or more sprints) and the production of multiple entities. For example, in one git commit there may be information regarding different entities involved in a singular execution context, such as a specific software development task, commit, which developer is responsible for what or bug fix issue, all contributing towards the ultimate goal of multi-dimensional process analysis.

To analyze the inter-dependencies among the various elements involved in the software development process, we rely on the notion of *event graph*. This provides the basis for visualizing and interpreting the connections between entities, events, and their attributes. Therefore, systems like graph-databases provide the starting point for building multi-dimensional process mining on data extracted from software repositories.

2.3 Research Question

In the light of the challenges faced by traditional approaches and the opportunities arising by multi-dimensional process analysis, we derive the following research question. **RQ:** *How can we exploit multi-dimensional process analysis to analyze software development traces in a repository?*

In the following, we describe the development of an artifact (i.e., an approach) – following a Design Science Research (Wieringa, 2014) methodology – that serves the purpose of applying a process mining solution to a new domain (i.e., software development).

3 APPROACH

We devise a four-steps approach. These steps consist in pre-processing the repository data to extract event, building a knowledge-graph from these events, analysing them via multiple queries, and presenting the results to the end user. Next, we present the goals of our approach following the Goal-Question-Metric (GQM) paradigm from (Basili et al., 1994). Then, we describe each step of our approach.

3.1 Goals and Metrics

We define the following three main goals and related questions.

- **GQ1.** *Goal 1*: analyze the development of individual modules, especially those showing signs of delay, to identify potentially problematic areas. For instance, if `developerA` discontinues work on `moduleA`, understanding the reasons behind such disruptions is crucial to address underlying workflow or project management issues and provide timely solutions. *Question 1*: What are the reasons behind discontinued work?
- **GQ2.** *Goal 2*: comprehend the impacts of shifting developer attention or "side-tracking", thus addressing and mitigating impacts on overall productivity. *Question 2:* How to trace task transitions and discern whether such shifts arise from urgent issues or mismanaged priorities?
- **GQ3.** *Goal 3*: inform long-term planning and resource allocation, especially for specialized knowledge areas. *Question 3*: How to investigate code complexity and recurrent issues in files that necessitate frequent developer attention?

The following five *metrics* are identified to gauge progress towards our goals-questions. As metrics can be used to address more than one question, we provide a their description separately and map them to the relative goal-question (GQ). *Module/Task Progress* (Paasivaara and Lassenius, 2003) measures the completion rate of tasks or modules, focusing on indicators like "task completion time" (GQ1). *Developer Activity* (Shin et al., 2011) assesses a developer's activity on a project by evaluating the number and frequency of commits (GQ1). *Code Churn* (Shin et al., 2011) examines the amount of code rewritten or revised, indicating issues with code complexity or quality (GQ1, GQ3). *Issue Tracking* (Meneely et al., 2010) metrics (e.g.,"Number of Open Issues") signal potential problems within the software (GQ1, GQ3). *Task Switching* (Benbunan-Fich et al., 2011) records instances of developers switching tasks, aiding in identifying its frequency and impact (GQ1, GQ2, GQ3).

3.2 Data Preprocessing

We focused on feature selection from the GitHub API to shape our event knowledge graph, choosing parameters that reflect various dimensions of the development process. Thus, we fetch the datasets from the software repository (e.g., GitHub) and select the most relevant dimensions for our purpose. We include *commit data*, *issue event data*, *pull requests* and *branch data*.

When extracting commit data we include fields like SHA, committer, author's name, commit message, verification status, commit parents, merge status, URL, stats, files involved, author-login, repos, URL, organizations URL, and branch name. These parameters are chosen to visualize the essence, trajectory, and workflow of the software development process based on file modifications over time after each commit.

When extracting issue event data, we include data about both open and closed issues from the chosen repository, and their correlated events. We fetch information about the issue, event type, commit-id, event-creator, state, and a timestamp indicating whether the issue was closed and when.

When extracting the data of pull requests we include the pull-request number, title, state (closed, open or all), user who made the PR, creation time of the PR, merge time (if merged), and the merge commit's SHA code. With these parameters, we can get a better understanding of what transpires when a developer decides to merge a pull request from one branch into another and how commits are being handled for both the merging branches. We can also compare the data of two states: what data are being generated when users open a pull request versus what data are being recorded after it gets closed.

Finally, when extracting the branch data, we include the branch name for the purpose of better navigation the data from commits and subsequently from pull requests. To fetch the data in a systematic manner, we wrote a Python script and used it together with the requests library. These data served as the foundation for our event knowledge graph and were critical in reflecting the intertwined relationships among different software development events and activities.

3.3 Building an Event Knowledge Graph

In the following, we describe the steps to convert the acquired data from the repository into the event knowledge graph. In order to do so, we rely on Neo4j[1] graph

[1] https://neo4j.com

database and its Cypher query language.

3.3.1 Creating Nodes

The first phase consists of loading event data extracted from the repository during the pre-processing step and stored into CSV files. That is, for each of the four datasets *commit data*, *issue event data*, *pull requests* and *branch data*, we have a corresponding .csv file. With these we create the primary nodes of the knowledge graph. Each type of node represents a unique entity in the software development process.

We used a Cypher query[2] to create entities from the *commits* dataset (i.e., `commit.csv` file). From this dataset we can create the following nodes: `Commit`, `Author`, and `File`. Each `Commit` node is associated with an `Author` node representing the individual who made the commit and several `File` nodes representing the files that were altered in the commit. The `Commit` nodes include properties such as `commit_id`, `message`, `URL`, `stats`, `date`, and `merge`, which provide detailed information about each commit while `Author` nodes contain information or each individual. Nodes for `File` help to show the state of each file after a modification has been done by a commit.

Queries for creating entities from the issue, events and pull requests nodes are similar. For commits we create `Author` nodes and for issue events we create `Users` nodes to distinguish the different type of GitHub's users. `Author` are the GitHub users or developers that are actively involve in the process of the development process. `Users` are the people from the open community that contributed to the issue through activities such as comment or reference.

3.3.2 Creating Relationships

Next we describe how we create the relationships.

Branches, Authors, Files and Commits. In this step, relationships `:COMMITTED` (between an `Author` and a `Commit`) and `:BELONGS_TO` (between a `Commit` and a `Branch`) are formed and each commit is linked to the files (`File`) it modifies through the `:MODIFIES` relationship. These are established by connecting the `Author` node who `:COMMITTED` to the `Commit` node and linking each `Commit` to the `Branch` node it belongs to. This will relatively show which commit belongs to which branch and eventually who worked on a specific branch or file.

[2]All the queries can be found in our GitHub repository https://anonymous.4open.science/r/Multi-Dimensional-Process-Analysis-on-Software-Data-F33F/

Directly Follows Relation for Commits. This relationship, represented as `:DF`, connects two commit nodes that directly follow one another in time, regardless of the branch they belong to. This is similar to the commit history displayed on GitHub but not limited to a specific branch. The `:DF` relationship makes it possible to trace the chronological sequence of commits across all branches.

Directly Follows Relation of Commits-Modification. This relationship, symbolized as `:DF_M`, connects two commit nodes that directly follow each other only if they have modified the same file. Like `:DF`, this relationship also tracks the sequence of commits, but it narrows down the scope to those modifying the same file. This allows a detailed view of how individual files evolve over time. It also helps at detecting patterns to highlight developers who stop working on the file.

The relationships `:DF` and `:DF_M` enrich the structure of the event knowledge graph by adding a time dimension. Queries for creating `Issue`, `Event` and `PullRequest` relationships can be found in our GitHub repository.

3.4 Performing the Analysis

We leverage graph databases to extract the following Key Performance Indicators (KPIs).

3.4.1 Basic Key Performance Indicators

Code Churn Analysis. Code churn (Munson and Elbaum, 1998) is the measure of lines of code added and removed from a file over time. The code churn can be calculated using the formula $\text{Code Churn} = \text{Lines Added} + \text{Lines Deleted}$. We compute this for all the developers. This also allows to rank the developers by contribution (e.g., by sorting the respective churn value in decreasing order).

Ratio of Closed and Open Issues. This metric provides insight into the project's issue management efficiency and effectiveness (Meneely et al., 2010). Assesses the project's issue management efficiency and effectiveness and indicates well-managed projects and areas for improvement in the development process.

We compute this metric as $\text{Ratio (State)} = \frac{\text{Issues (State)}}{\text{Total Issues}}$, where the input parameter $State$ can take the values $Open$ or $Close$ to indicate respectively opened or closed issues.

Cycle Time. This is a performance-related software development metric, representing the time taken to implement, test, and correct a piece of work from the moment work begins until it's ready for delivery (Agrawal and Chari, 2007). It measures the time taken from beginning work to delivery, providing a more granular view of the development process.

The *cycle time* in software development can be calculated using the formula Cycle Time = Completion Date − Start Date. We do this for all the issues. We are also able to compute the cycle time of each user that has worked on a given issue. With this, we allow for identifying patterns or anomalies in cycle times associated with specific users, providing a more granular view of the development process.

3.4.2 KPIs for Process Analysis

Next, we provide some metrics for process analysis. We focus on, i) issue resolution time, ii) collaboration, iii) file/commit dependency, and iv) issue escalation.

Issue Resolution Time Analysis. With this metric we analyze how long it takes to resolve different types of issues. Specifically, we look into two aspects: the individual issues that take the longest to resolve, and the users who, on average, take longer to complete issues. Utilizing a Cypher query we can perform the analysis by extracting information of issues or users with the longest cycle time with simple queries. More specifically, this is computed as the cycle time of each user that is associated to an issue. That is, it computes the amount of time elapsed between the first and last events of that user on the issue.

Collaboration Analysis. Analyzing collaboration (Biazzini and Baudry, 2014) between team members reveals patterns in how team members interact on issues and files. For example, we can identify which team members often work on the same issues or files.

We compute this as two KPIs regarding respectively the issues and the files that were collaboratively worked on. We consider all the *collaborative* events from two users `u1`, `u2` that were recorded within the same issue. We apply the same logic for what concerns the commonly modified files. We return the number of shared issues as the collaboration value. Same holds for the shared files.

File/Commit Dependency Analysis. This metric helps to identify relationships between different parts of the codebase (Bala et al., 2017). For instance, it makes it possible to identify files that are frequently modified together, revealing areas of the codebase that are tightly coupled and may benefit from refactoring to improve modularity. We compute this KPI by considering the set of shared commits among the various files. Files that appear together in more commits have a higher dependency with one another.

Issue Escalation Analysis. Analyzing issue escalation (Keil, 1995) helps to identify patterns in issue evolution over time. We identify issues that undergo a larger number of events and consider them potentially problematic as they may require more management attention. To do so, we navigate the event knowledge graph and collect all the issues along with their related events, sorted in decreasing order.

3.4.3 Extracting a Process Model

To extract a process model we use the computed `:DF` (directly-follows) relationships from between event nodes correlated to the same entity node. We repeat this for all the processes or dimension we want to investigate. Then, we classify the event nodes to event classes and retrieve a multi-entity directly-follows graphs (DFGs) through aggregation. Ultimately, through this approach we can obtain a process model that represents multi-entity DFGs.

We applied the techniques from (Esser and Fahland, 2021; Fahland, 2022). Hence, we could aggregate the graph nodes to class nodes. Then we constructed filtered directly-follows relationships and retrieved a *proclet* model (van der Aalst et al., 2001) that provides one distinct behavioral model per entity. We aggregate the event class nodes for branch and commits nodes, after analyzing the resulting graph.

Next, we raise the level of abstraction. We adapt the query for DFG discovery to aggregate `:DF` relationships between classes. To obtain the *proclet* model, we proceed by adding synchronized edges between event classes of the same activity in different entity types.

Finally, we simplify the resulting proclet model by raising again the level of abstraction. We create a higher-level class node for branch (that could be considered as an 'Activity' in a process) corresponding to how the event nodes and class nodes were constructed.

This concludes the steps required to perform the analysis of the software development process. The evaluation of the results can then be carried out by a domain expert (e.g., a manager or a senior software developer) who can then use the extracted KPIs and models to gather insights into the status of the project.

4 RESULTS

We tested our approach on the GitHub repository of Microsoft Visual Studio Code[3] (`vscode`).

[3]https://github.com/microsoft/vscode

Table 1: Top 10 Users with the Longest Average Cycle Times.

User	Hours	Minutes
aeschli	23	44
bhavyaus	23	11
Danielmelody	23	11
weinand	23	11
dtroberts	18	56
christian-bromann	18	44
JacksonKearl	18	34
jzyrobert	18	34
joelday	18	34
AmitPr	18	34

KPIs and Process Analysis Queries. Table 1 reports the values of the issue resolution time analysis KPI in the `vscode` repository. On top, it is we can observe the user who spent more time on average on resolving issues. All the Cypher queries and analyses to achieve these results can be found in our GitHub repository.

Process Model. We derived a process model after filtering the entire database to focus on the progression of a specific file over time. For the purpose of demonstration we picked the file `quickInput.ts`. Using a Cypher query, we connect, label by category and display the events that happened on the file on the different dimensions. The resulting model can be seen in Figure 1a.

In this model, we used branches to represent 6 process activities, focusing mainly on the progression of `File` nodes, the associated `Commits` and their `Authors`. Additionally, `Issue` nodes are also involved in the process where they got raised to signify that a file needed to be worked on and areas that need attention. Here we could also see the cycle time of each resolved issue as well as the users that were involved in helping to solve the issue.

In Figure 1a we can also observe that in Activity T3 and T4, there are some commits that belong to different branches, a deeper investigation revealed these as revert commits from T4, occurring post-merge of the T3 working branch into the main branch, signaling an issue necessitating further work on the file. The author that was responsible for this action is highlighted in the Figure, and we can observe that he continued to work on the process in the next Activity T5 as well before pausing for a significant time period until there was an issue that require the process to be merged into the main branch. In Activity t6 we can also see that there were another few direct changes by 2 other authors before finishing the workflow for this file.

Further insights were sought on why the author from T4 and T5 paused before merging their work into the main branch. By filtering the workflow for this specific author during that timeframe, we can delve into the cause of this “sidetracking” and visualize their work progression during this period.

Table 2: Total churn of developer TJL in a certain time period. File path prefixes are left out.

File	Total Churn (lines)	Most Churning Dev
.../mainThreadAuthentication.ts	105	TJL
.../authenticationService.ts	105	TJL
.../vscode.d.ts	105	TJL
.../extHostAuthentication.ts	105	TJL
.../authentication.ts	105	TJL
.../vscode.proposed.getSessions.d.ts	105	TJL
.../extHost.protocol.ts	105	TJL
.../githubServer.ts	44	TJL
.../github.ts	44	TJL
.../quickInput.ts	10	TJL

Figure 1b reveals the author worked on another branch during the hiatus. The graph depicts the states of the file in question (yellow nodes) and the other files the author worked on during that period (brown nodes). The multi-dimensional process analysis enabled us to identify the sidetracking issue and explain it by the help of another dimension with one simple query.

After utilizing the metric *code churn*, and filtering the time and the name of the author in question, we obtained a comprehensive list of what the author was working on or “side-tracking” during that time period in a relational form of data. This is shown is Table 2.

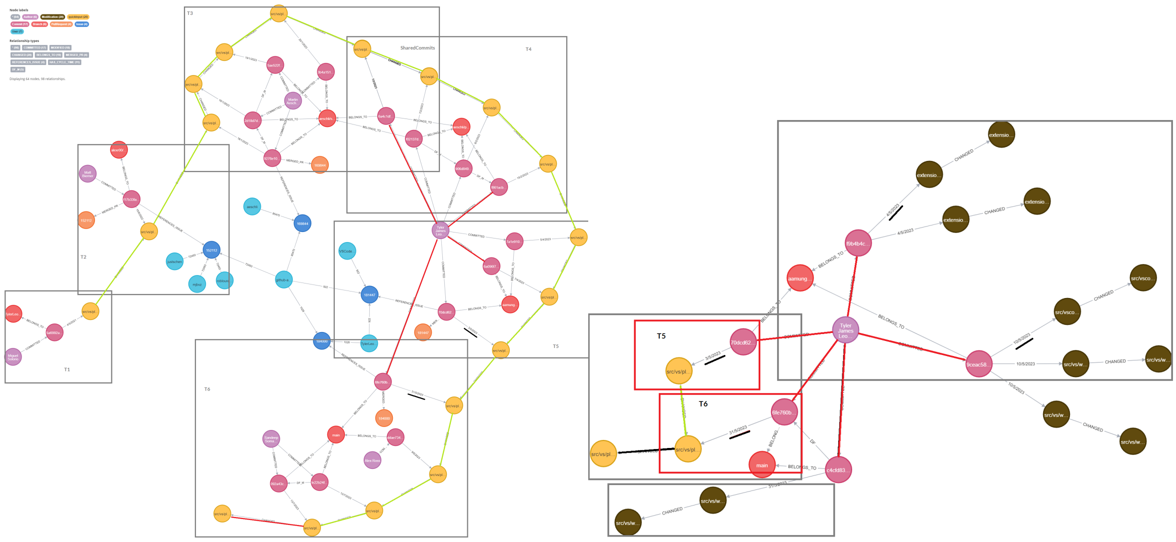
The relational database results can be exported in formats like .csv or .json. This allows for subsequent data loading into tools such as Python Library or NumPy, facilitating further analyses and visualizations by creating charts or statistics.

5 DISCUSSION

The work presented in this paper is driven by the research question: *How can we exploit multi-dimensional process analysis to analyze software development traces in a repository?*. To answer this question we used multi-dimensional process mining.

We found that multidimensional process mining is applicable and useful to analyze software repositories. This is inline with previous work from (Poncin et al., 2011) who applied traditional process mining. This work overcomes issues of applying traditional process mining such the project-orientation of development processes (Bala et al., 2015) and the non existence of clear case and activities (Bala et al., 2018).

Key findings of this paper are that i) multi-



(a) The process of developing file `quickInput.ts`. (b) Author side-tracking problem.

Figure 1: The process of developing file `quickInput.ts`.

dimensional process mining is suitable for analysing software repository data; and ii) it is possible to obtain a comprehensive view of the overall process that happens behind software development. The first point (i) is shown by the queries presented in the first part Section 3. Another evidence of the suitability of this approach for software development analysis is the fact that various KPIs can be reproduced by means of Cypher queries. The second point is evident by the analysis of Figure 1a. In this picture, it is possible to observe not only the sequence of commit activities performed by one user to a file, but also other activities that influenced the user behavior. This, for instance, enables the explanation of why certain files took longer to be developed. In this case, we see that the reasons are that more developers were involved (purple nodes) and that some developers also worked on other files before continuing to contribute on the file `quickInput.ts`.

Compared to previous studies that focus on extracting a process workflow from their repositories, we argue that this study is a first attempt on gathering a multi-perspective view. Well-known approaches such as (Kindler et al., 2006; Poncin et al., 2011) only tackle one dimension (i.e., they force the notion of a process case). Existing process mining approaches that output DFGs tend to make this assumption. Instead, our approach can show information beyond the discussed KPIs. For example, we can to observe in Figure 1a that certain users (like Tyler) contribute to more commits than others – suggesting that these maybe senior users – or that certain issues are more complex to solve because they are related to busy users or they simply require more work.

6 CONCLUSION

This paper explored the possibility of implementing multi-dimensional process analysis on software development data. In particular, we could i) show how multi-dimensional process analysis can be applied to software repository data, ii) compute basic KPIs to analyze the performance, and iii) perform process analysis by means of event-knowledge graphs. We applied this approach to real-world data from GitHub and could observe its utility in uncovering reasons for underperformance, such as author side-tracking.

In future work, we aim to extract further details from process repositories in order to increase the amount of relationships stored in the event knowledge graph. We plan to investigate how the personal workflow of software developers affects the overall process.

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