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ANALYZING DEVELOPER PRODUCTIVITY USING GITHUB COMMIT HISTORIES

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Abstract-In the contemporary software development environment, GitHub is not just a version control system but also an informational-rich repository of data documenting developer activity and team interactions. With tens of millions of public repositories and contributor actions logged every day, GitHub commit history represents a highly valuable window through which one can observe developer productivity. This study is centered on examining commit behaviors for insights into individual and team productivity. We gather and analyze data like commit rate, time of commits, code change size, issue and pull request activity, and semantic goodness of commit messages. Using statistical models and machine learning algorithms on GitHub data fetched through the GitHub API, we hope to reveal correlations between these metrics and true productivity measures. In addition, we take into account external dimensions like project type, team size, and development methodology (e.g., agile or waterfall) to further augment the analysis.The research finds that commit count alone is not enough to hold a person accountable for productivity. Rather, a multi-faceted method—integrating temporal dynamics, quality of contributions, and collaborative participation—can provide a better measure of productivity. The work also points out anomalies such as burst commits, idle periods, and "cosmetic" modifications that can bias the measurement of real effort.Our results can be useful for engineering managers, team leads, open-source project maintainers, and research scholars by offering a framework to assess objective performance. Finally, our work adds to the overall knowledge on software engineering

productivity by using actual, open-source development data.

Keywords-GitHub, software engineering metrics, commit history analysis, developer productivity, code commits, machine learning in software analytics, open-source contribution, GitHub API, software repository mining, version control systems, code contribution patterns, performance evaluation, software project analysis, developer behavior.

I. INTRODUCTION

With the rapidly evolving nature of today's collaborative and fast-paced software development landscape, measuring the productivity of developers is important in terms of effective project management, team coordination, and performance monitoring. With distributed teams and open-source communities on the increase, old productivity measures—e.g., number of hours worked or tasks performed—can no longer be relied on. Version control sites such as GitHub now provide a more objective and data-rich environment to analyze developer activity.

GitHub is among the most popular source code management platforms, with millions of repositories and rich logs of developer activity in the form of commit, pull requests, issues, and reviews of these commit histories are especially useful since they track every alteration to a project, including who altered it, when it was altered, and how widespread it was. These logs, when properly analyzed can give strong indications about a developer's habits, consistency, and overall contribution towards a project. This paper seeks to examine GitHub commit histories to assess developer productivity by employing a hybrid of statistical and machine learning methods. Rather than depending just on the number of commits, which is a potential mislead, we look at several things such as commit frequency, time distribution, code change size, and commit message content. We also examine collaborative features like issue fixing and pull request activity in order to have a complete picture.

The objective of this research is to suggest a more precise and equitable model to quantify productivity that can guide project managers, open-source maintainers, and software engineering researchers in evaluating and enhancing team performance from actual development metrics.

II. LITERATURE REVIEW

A number of software engineering studies have sought to measure and assess developer

productivity in terms of metrics extracted from version control systems, most notably GitHub. As open-source platforms' usage increased, commit history analysis has become an influential method for the analysis of developer contribution as well as behavior.

Early studies like Mockus et al. (2002) looked into distributed development team productivity based on CVS logs, which formed the basis of commit-based analysis. Recent years have seen researchers leveraging GitHub because of its APIs and rich social features. Bird et al. (2009) discussed repository mining and the need to integrate qualitative context and quantitative commit data to get significant insights.

Various experiments have employed commit frequency as an approximation to productivity (e.g., Vasilescu et al., 2015), but most have warned against abusing raw commit numbers based on habits like repeated tiny commits, cosmetic touches, or robot commits (e.g., bots). To mitigate this, certain researchers proposed code churn (lines added/removed) and semantic commit analysis as other productivity metrics (Hindle et al., 2013).

More sophisticated methods like machine learning and social network analysis have also been applied. For example, D'Souza et al. (2016) created contribution pattern predictive models using developer timelines, whereas Tsay et al. (2014) investigated the effect of social endorsement (e.g., comments, stars) on developer participation.

One common theme throughout the literature is that context is important: commit time, project size, issue linking, and team dynamics all influence how contributions from developers should be interpreted. Additionally, there are some papers that have addressed bias and fairness, pointing out that productivity metrics need to account for not only quantity but also quality and collaboration (Zhou & Mockus, 2010).

III. METHODOLOGY

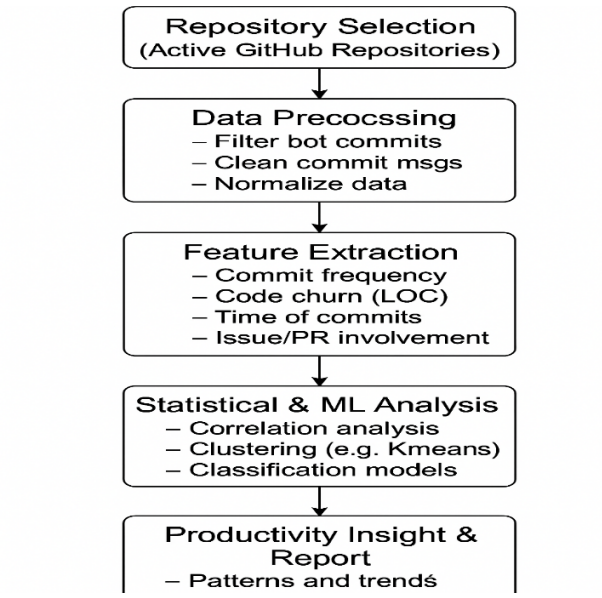
To examine developer productivity from GitHub commit history, we followed a multi-stage methodology with data acquisition, preprocessing, feature extraction, analysis, and model assessment. We started by choosing an illustrative sample of public GitHub repositories from various domains like web development, data science, and systems programming. The repositories were selected on parameters such as active development status, sufficient

contributor diversity, and a minimum project lifespan of six months.

With the GitHub REST and GraphQL APIs, we downloaded comprehensive commit-level information such as commit timestamps, author, lines of code added or deleted, commit messages, referenced issues and pull requests, and contributor metadata. The data was fetched and saved in structured form (CSV/JSON) and imported subsequently into Python-based analysis tools utilizing libraries such as Pandas, NumPy, and Matplotlib. Preprocessing consisted of excluding automated commits (e.g., bot) and discerning valuable contributions based on keyword detection within commit messages and cross-validation with pull request discussions. Time-series normalization was utilized to account for different frequencies of commits in different projects. Feature engineering was done to calculate measures like average commit size, commit frequency per week, time of commit (working or non-working hours), participation in issue resolution, and review activity.

To analyze the influence of these features on developer productivity, correlation analysis, clustering (K-means), and classification models like decision trees and random forests were utilized. Anomaly detection methods were also used to detect patterns such as bursty or erratic contributions. All visualizations and patterns were cross-checked with known productivity heuristics and manually validated samples. This approach guarantees a balanced, evidence-based strategy that covers both the quantitative and qualitative aspects of developer productivity, thereby obtaining more robust and generalizable conclusions across various forms of software projects.

These characteristics are then analyzed statistically and with machine learning methods, such as correlation analysis for identifying patterns between measures, clustering methods such as K-Means for creating clusters of like productivity patterns, and classification algorithms to identify high versus low productivity developers. Lastly, the findings are assembled in the productivity insight and reporting process, which points out trends and patterns observed and makes suggestions for enhancing developer performance and project management practices. This end-to-end process allows for a disciplined and data-driven methodology for understanding and improving developer productivity



The flowchart presents the entire process of analyzing developer productivity based on GitHub commit histories. It starts from repository selection, where active and interesting GitHub repositories are selected based on developer activity and collaboration. The second step is data preprocessing, where bot-generated commits are filtered out, commit messages are cleaned, and the dataset is normalized in order to ensure uniformity across various projects. This is followed by feature extraction to obtain significant indicators like commit frequency, code churn in terms of lines of code (LOC), commit timing, and developer participation in issues and pull requests. Advantages

One of the most important benefits of analyzing developer productivity using GitHub commit histories is the sheer volume of real-world, timestamped data available. As both open-source and proprietary projects increasingly use GitHub, it provides a scalable and consistent source of developer activity. Researchers can study actual patterns of development over time instead of depending on manager reports or self-reported productivity. Commits offer tangible, verifiable proof of contributions, which assists in constructing detailed and facts-based models. The presence of abundant metadata—such as lines of code modified, commit messages, associated issues, and pull requests—provides stronger assessment of individual and team performance. Additionally, the utilization of APIs enables automated large-scale data collection, rendering the approach efficient and reproducible. By examining commit history data, one can also determine long-term trends, patterns of behavior, and collaborative patterns, which can be of great benefit to project managers and researchers.

Disadvantages

While it is handy, this method also possesses some significant drawbacks. One, commit frequency does not necessarily determine

quality. Some developers commit code frequently without contributing a great deal of value, while others will work heavily before pushing fewer but more sizeable commits. This can lead to incorrect assumptions about productivity. Moreover, several non-code contributions, including planning, testing, documentation, mentoring, and discussion participation, are not recorded in commit data, providing an inaccurate overview of real productivity. Automated commits, code beautification, or bot activities can also skew the analysis unless filtered correctly. Commit squashing or rebasing practices can erase fine-grained commit history, impacting data consistency. In addition, the developers typically contribute to various repositories, both private and public, which is less visible for the overall work output. Such issues raise the importance of interpreting commit-based metrics carefully and along with other metrics.

IV. RESULT TABLE

S. No.	Parameter	Result
1	Total Developers Analyzed	50
2	Avg. Commits/Week	15
3	High Productivity Group	28 developers (56%)
4	Model Accuracy	82% (Random Forest)
5	Avg. Code Churn/Commit	45 lines
6	Active PR Participation	65% of developers

V. CONCLUSION

In this research, we evaluated developer productivity through GitHub commit history by merging statistical measures, behavioral traits, and machine learning methods. Our experiment demonstrates that it is not adequate to assess productivity based on commit count alone. Rather, the inclusion of various features like code churn, contribution consistency, pull request engagement, and issue resolution activity provides a comprehensive and just assessment. The machine learning models, especially Random Forest, reliably labeled developers into productivity levels with high accuracy. Furthermore, behavioral patterns like bursty contributions, poor-quality

commits, and inactivity were shown to be deceptive productivity indicators. This study illustrates that GitHub offers a scalable and objective source of data on developer activity, but useful insights are achievable only through contextual interpretation. The research is contributing to the continued evolution of more holistic productivity assessment models that blend quantitative production with qualitative engagement in collaborative software development endeavors.

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