**Cover Page**

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**Introduction**

First, we must ask the question of why we want to measure software engineering. Steve McConnell (Construx Software, 2016) (see also <https://www.getclockwise.com/blog/measure-productivity-development>) gives a number of reasons why firms would want to measure the productivity of their engineers, including, to track their progress over time, to recognise the top engineers and, to help develop benchmarks and standards.

**Software Productivity**

<https://ifs.host.cs.st-andrews.ac.uk/Books/SE9/Web/Planning/productivity.html>

<https://medium.com/@infopulseglobal_9037/top-10-software-development-metrics-to-measure-productivity-bcc9051c4615>

Two types of metrics

* Size-related metrics
* Function-related metrics

Productivity metrics should be

* Consistent
* Auditable
* Available
* Repeatable

**Measuring Engineering Activity**

The first section of this report will look to explore *how* you can measure software engineering. The question at hand is not whether software engineering is measurable but rather what data is available to help measure engineering activity and whether the metrics being used are useful and fair. Although there are standards around software measurement, most notably the ISO Standard 15939 (International Organization for Standardization, 2017), there is no one definitive way to measure engineering productivity and this section aims to discuss some notable metrics and their strengths and weaknesses.

**Source Lines of Code**

A basic metric used to measure an engineer’s output is to count the number of lines code they write. There are several ways to measure source lines of code (SLOC). For example, do we measure the number of actual lines in the source file (physical SLOC), or should we consider each statement to be a line of code (logical SLOC). In general, the latter is used, and comments are generally excluded with only functional code being measured. A common criticism is that greater SLOC does not necessarily correspond to increased efficiency or skill, and often when we refactor code, we look to reduce the amount of code. Two engineers can implement the same functionality but the number of SLOC could vary by a factor of ten (Construx Software, 2016). Additionally, depending on the language and coding conventions used the SLOC differs.

**Commits & Pull Requests**

Like SLOC, the number of commits and pull requests are an easy measurement to extract. The argument for measuring commits is that engineers are encouraged to make small and frequent commits, increasing transparency and incremental delivery. At its most basic, those who commit more should be rewarded, and vice versa. However, commits tell you nothing about value. Engineer A could be working on a challenging problem, making no commits for a week while they work out a solution, whereas Engineer B may be tasked with cleaning up comments in the code base making multiple commits a day? Who is adding more value to the product?

Measuring pull requests (PRs) follows similar logic, with common criticisms being that it doesn’t factor in the size or the effort of the work and may encourage small and unnecessary PRs. However, PRs can be useful to measure team performance. For example, by measuring the pull request lead time you can get an idea of how long it takes for a PR to get merged/closed leading to better estimates. Additionally, PR discussions can be measured giving you an idea of how your team collaborates.

**Functions Point**

Whereas SLOC measures engineering activity from a code point of view, function points (FPs) attempt to measure engineering activity through the functionality offered to users and is “code agnostic”. This metric does not measure an individual engineer’s productivity but rather is used to quantify the functionality offered by an engineering project. Function Point Analysis (FPA) involves measuring the functional requirements in terms of *transactions* a user can perform with the software and the *data* that can be stored/accessed by the software. Calculating FPs involves identifying, classifying, and weighting each transaction or data type[[1]](#footnote-1). FPs are useful for quantifying an engineer’s contribution to a business and are also not language specific so allow for more consistent comparison across the board. However, they are complicated to calculate, and many managers view them as more effort than they’re worth (Alvater, 2017).

**Code Churn**

As mentioned, quantity is not always a good metric for code quality. One measurement used to help evaluate the quality of engineering work is called code churn. Code churn is when someone rewrites their own code within a short period of its first release (usually within three weeks). It is usually measured in lines of code or a percentage. Although, it’s normal for an engineer to make changes to their previous work as they go, high levels of code churn or unexpected fluctuations can signal to a manager that the engineer may be struggling. Like all metrics, the context needs to be considered, and what is interpreted as a worrying level of code churn on one project may be normal for another.

Chart

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Figure 1: An example of "normal" fluctuation of code churn throughout a project's lifecycle. Note that the percentages of healthy code churn will vary from project to project and it is up to the manager to decide what is normal and how to interpret the levels. (Source: Pluralsight)

Some examples of what could cause a worrying level of code churn include, an engineer’s lack of experience, or poor communication between stakeholders and ambiguous requirements.

For example, Engineer A may commit 100 lines of code and Engineer B may commit 30. By measuring code churn it is revealed that Engineer A committed 40 lines of code in week one, decided that they wanted to take a different approach and rewrote that code with 30 lines in week two, and then in week three decided to rewrite everything with 30 lines of different code. Although they may have committed 100 lines over the three weeks, Engineer A churned 100% of their code with none of their original code from weeks one or two adding any value to the project.

**Agile Process Metrics – Team Velocity & Sprint Burndown**

The next two metrics, team velocity and sprint burndown, are specific to measuring engineering activity when Agile methods are being used.

Velocity measures the amount of work done by a team within a specific time, usually per sprint. It is usually measured in story points or hours. The benefits of this metric include more accurate delivery estimates, insight into whether the team is blocked by anything, and being able to quantify changes to results due to process changes (Infopulse, 2019).

Sprint burndown helps visualise a team’s progress throughout a sprint. This is a useful way of measuring engineering activity as it allows you to visualise whether you are consistently finishing the work for the sprint early, or if you often miss sprint goals. This can then inform how the next sprint is planned so that the engineering is completed more efficiently.

**Chart, line chart

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Figure 2: A sample burndown chart that plots a team's progress throughout a sprint. (Source: Wikipedia)

**Problems with Measuring Engineering Activity**

As previously touched on, measuring engineering activity is not straightforward. The metrics themselves may be easy to measure but interpreting them in a useful and fair is complex. Abi Noda, previous Senior Product Manager at GitHub, gave an interesting talk[[2]](#footnote-2) around this topic at GitHub Universe 2019 titled “The elusive quest to measure developer productivity” (Noda, 2019). Noda discusses what he calls the “Flawed Five”, five measurements commonly used to measure software engineering. However, according to him they don’t work, and all share the common characteristic of trying to measure output and productivity. The “Flawed Five” are:

1. Commits
2. Lines of Code
3. Pull Request Count
4. Velocity Points
5. “Impact”

The downfalls of the first three have been discussed above and velocity points is similar to team velocity discussed under Agile process metrics. Impact is an abstract concept that is essentially lines of code but also considers how many files were touched, and how much new code was written.

So, what are the overarching problems faced when measuring engineering activity? First, managers tend to collect and analyse data that is easily accessible, not necessarily metrics that measure value creation. There is an Albert Einstein quotation that summarises this flaw, “Not everything that can be counted… counts”. This leads into the second point, many of these metrics can be gamed, and therefore end up incentivising bad behaviours. For example, Noda describes the behaviour changes he noticed when average code review turnaround time was used as a metric for productivity. The obvious change was that the quality of reviews fell as people tried to finish as many code reviews as possible. Additionally, code reviews were no longer being put up on Fridays as the software used to measure productivity did not take into account that people didn’t work weekends. Another common criticism is that by taking these measurements it often disincentivises engineers to be creative or to take on more complex problems. For example, if your productivity is being measured by the number of pull requests, you will lean towards making smaller and safer pull requests.

Graphical user interface, text, application, email

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Figure 3: A screenshot from Twitter that touches on the problem with measuring an individual's "productivity". (Source: Allen Holub, Twitter)

Finally, the very crux of this problem is that it is very hard to define what “productivity” is, and it is context specific. Many simplify productivity down to output, but as we’ve already seen, for example with lines of code, more is not always better. We have also seen that if we only look at output, engineers will game it, and this often leads to a decline in quality. I would take the view that software engineering needs to be viewed as an art, and not like a factory assembly line where you can easily measure what you are producing.

We have now heard the criticisms, so what is the solution? There is no perfect one-size-fits-all solutions and as mentioned, I believe engineering should be viewed as an art. Therefore, it takes a good lead to define and interpret what it means to be productive, not a standalone metric. However, we can’t scrap these measurements altogether. Noda suggests what we should measure processes over outputs. Some metrics that measure processes include, code review turnaround time, pull request size, work in progress, and time to open. Additionally, we should measure against targets as opposed to absolutes. No two teams work the same, even within the same organisation, so each team needs to define their own goals. Finally, Noda advises against using individual metrics, as experience tells us that any benefits they may introduce are never enough to counteract the disadvantages. However, this raises the question, if we shouldn’t measure individuals how do you identify the strongest and weakest members, especially as there is evidence that on average the strongest engineer is 20 times more productive than the weakest (Construx Software, 2016)?

**Development Analysis Platforms**

In the first section of this report, we looked at *what* we could measure. This section aims to explore *how* we can measure it in terms of the platforms and services available to gather and process this data efficiently.

**Pluralsight Flow**

Flow, originally called GitPrime and acquired by Pluralsight in 2019, is a platform used to help measure software engineering productivity. It works by taking data available from Git such as pull requests, commits and tickets to provide metrics to engineers and managers about their software development process. Flow calculates a huge number of metrics[[3]](#footnote-3) covering a wide range of the development process, from metrics about the codebase to metrics about a team’s collaboration. To keep this concise I will only touch on some sample example metrics, but this is in no way exhaustive.

Flow provides a “code fundamentals” dashboard which concisely visualises a number of individual and team metrics. Managers can use this as a starting point for discussion during one-on-ones. One sample use case is using the impact measurement to gauge how long it takes for a new hire to create value for an organisation.

Graphical user interface

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Figure 4: A sample of Flow's "code fundamentals" dashboard. Key metrics such as commits per day and impact are visualised. (Source: Pluralsight)

Another sample dashboard offered by Flow is the “project timeline”. This visualises a team’s total output and allows you to see how much time is spent writing new code versus altering legacy code.

Chart, histogram

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Figure 5: A sample of Flow's "project timeline" view. The total impact on a code base over a specified period is visualised. (Source: Pluralsight)

Other products similar to Pluralsight Flow which I don’t have space to discuss include Waydev[[4]](#footnote-4), LinearB[[5]](#footnote-5), and Jellyfish[[6]](#footnote-6).

**SonarQube**

SonarQube is another platform used to help measure software engineering activity. Unlike Pluralsight Flow which leans towards measuring developer productivity, SonarQube is an open source platform used to help measure code quality and security. Their products range from a free community edition to paid editions for developers and enterprises. It is used to analyse code and detect bugs, code smells, as well as security vulnerabilities. It also compiles reports about the code in regards to a number of issues such as adherence to coding standards, code coverage and testing, code complexity, and commenting. Unlike Pluralsight Flow which retrieves data from Git, SonarQube performs static analysis of code and can be integrated with things like Maven and Gradle, or integrated with IDEs like Visual Studio and IntelliJ.

Graphical user interface, application, website

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Figure 6: A sample landing page in SonarQube which shows the results of the FindBugs plugin which analyses Java code for bugs. (Source: Wikipedia)

**Jira**

Jira is a product developed by Atlassian and is one of the industry leaders when it comes to product management in software development. At a high level Jira can be used for planning and tracking software and by Agile teams to maintain scrum and kanban boards. As Jira is commonly used to organise workloads into sprints, it can easily extract data from its platform to calculate sprint/epic burndown, velocity, and control charts, to name a few examples (Radigan, n.d).

As sprint burndown and velocity were covered previously in this report, as an example I will focus on control charts. Control charts visualise the time for an issue to move from “in progess” to “done”. This data is extracted from the data Jira has from the team’s scrum or kanban board. In this way, it doesn’t extract data from an external source like Git, but simply visualises what is already available on Jira so the lead/manager can interpret it.

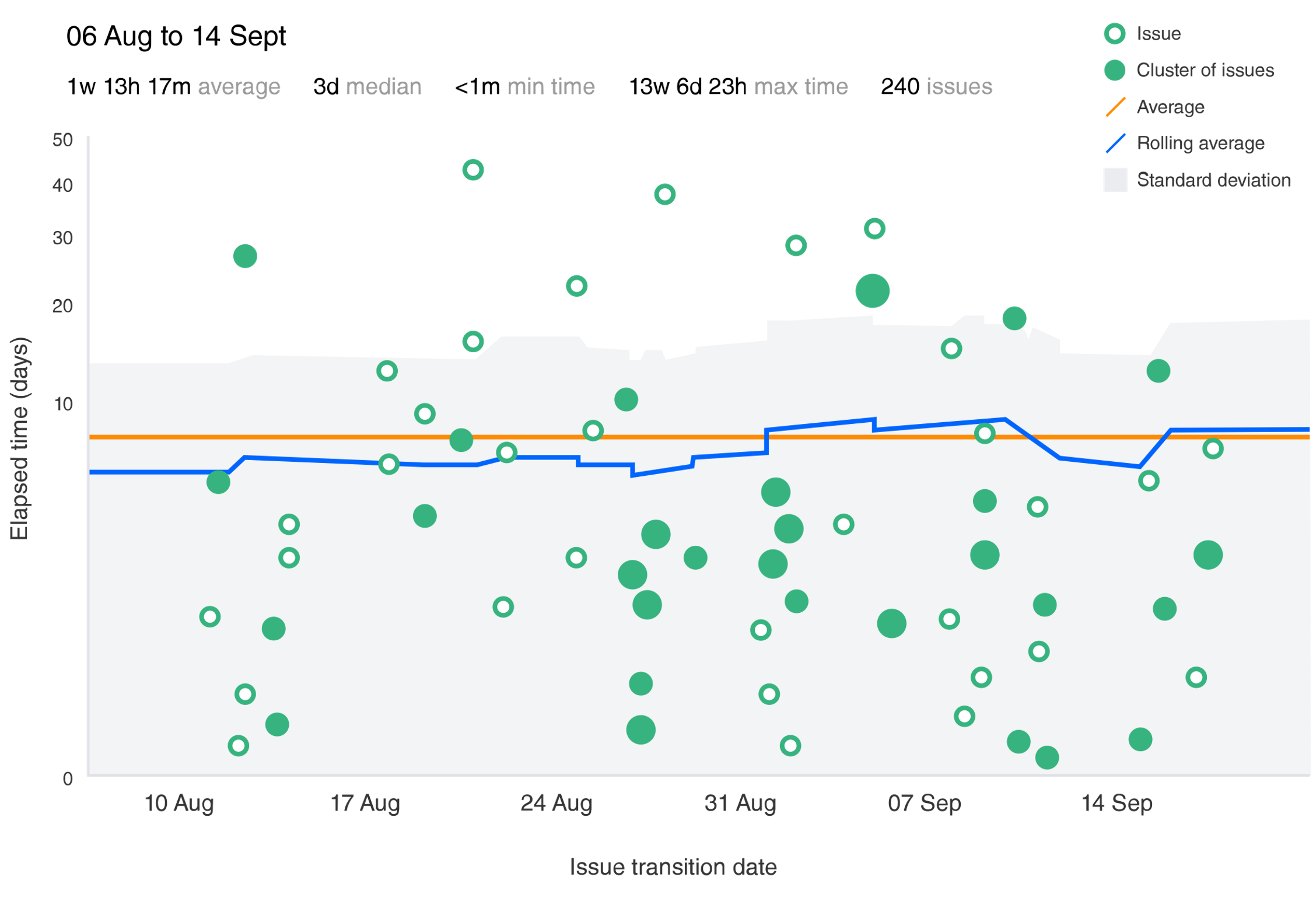
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Figure 7: A sample control chart produced by Jira. (Source: Atlassian Agile Coach)

**Algorithmic Approaches**

Judging developers by using easily attainable metrics, like the number of commits they make, is clearly not enough to give a comprehensive overview of their performance. As illustrated by looking at the platforms above, to make more interesting analyses, sophisticated algorithms and AI is often used. This section will discuss some algorithms used to measure different aspects of the software development process and then discuss some of the shortcomings of these approaches.

**Software Complexity – Cyclomatic Complexity**

Unlike metrics such as the number of commits, quantifying a piece of software’s complexity is not as simple as querying a data set, and there is not one objective value. Not to be confused with complicated, which suggests something is hard to understand, complex refers to the number of interactions between different parts of a system. A common measure of software complexity is McCabe’s cyclomatic complexity metric. Cyclomatic complexity is defined as “the number of linearly independent paths” in a piece of code (GeeksforGeeks, 2021). The Control flow graph of the program is used to compute the complexity. Each node in the graph represents and indivisible group of commands, and there is a directed edge between two nodes is the second command can be executed directly after the first. For example, if the code contains one if-statement, the cyclomatic complexity is 2 because there are two possible paths, true or false. Figure 8 shows an example code snippet and how that is translated into a control flow graph.

Diagram

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Figure 8: An example code snippet and its corresponding control flow graph. (Source: GeeksforGeeks)

The equation used to calculate cyclomatic complexity (CYC) is , where E is the number of edges in the graph, N is the number of nodes in the graph, and P is the number of connected components. So for the above example the complexity would be .

Again, like all other metrics discussed, cyclomatic complexity does not offer an objective metric to judge an engineer on. For example, the complexity of an engineer’s commit will depend on the task they were assigned in the first place, and so context must always be taken into account to avoid unfair comparisons.

**Developer Productivity**

As touched on previously, it is not easy to quantify productivity as it is largely contextual. Products like Pluralsight Flow attempt to do this through various metrics but the exact details of such algorithms are not public and involve complex AI. In this section, I will discuss some more simplistic algorithms used to quantify a developer’s productivity (Chatterjee, n.d). In the past, often the following equation was used to measure productivity: , where ESLOC is the effective/equivalent source lines of code, and PM is person months. When all code committed is new it is simple to calculate the SLOC (explained at the start of this report), however, if old code is modified other factors need to be taken into account. For example, how much time the developer spent understanding the legacy code to make their changes and if there was poor documentation the developer would need to spend time reverse engineering the code. With factors such as these taken into consideration, an adaptation adjustment factor (AAF) is calculated using . is the percentage of reused software that needed redesigning/reverse engineering, is the percentage of software code that needed to be modified/recoded, and is the percentage of reused software that requires regression testing. Using the AAF, we now have , where S is the number of new, modified, and reused lines of code respectively. However, how this final productivity figure is interpreted is down to the team itself, as a good figure for one team could be terrible for another. For context, Chatterjee writes that a team at Borland were producing 1000 lines/week, whereas a Microsoft Windows team were producing 1000 lines/year. The company Quantitative Software Management (QSM) collects SLOC figures from a range of products across different industries as well provides performance benchmark tables to clients. Additionally, SonarQube, one of the platforms mentioned previously has a built in feature that calculates SLOC automatically.

**Shortcomings**

Again, no method is free of its shortcomings. A manager can calculate all the metrics they want, or view AI generated reports but at the end of their day these are ultimately tools used to help sway their judgement and make their lives easier. These algorithms alone should never be left to make the decisions themselves as we have not gotten to a stage where human judgement can be replaced. One could also argue that a lot of machine learning algorithms smooth out the noise and present an averaged out picture, however, at times those intricacies not caught by the system are crucial. On the other hand, one could argue that managers and leaders themselves often present many biases, consciously and subconsciously, and by using AI and these algorithms to calculate a variety of performance metrics it can help engineers be viewed on a more level playing field. More discussion on whether we should be measuring software development in these ways will be in the final section.

**Ethics**

We’ve discussed at length how software engineers are being measured, and the strengths and weaknesses of various metrics. Now it is time to ask whether we should be taking these measurements in the first place and the ethics behind using this data to evaluate performance.

**Effect on the Individual**

Most firms employ these metrics and AI models to get the most of their employees, however, what effect does this have on the individual? We have already discussed that when individuals know they are being monitored they will change their behaviour, this is also known as the Hawthorne effect. The metrics we choose determine how an employee behaves, and oftentimes gaming these metrics leads to an individual changing their workflow, for the worse. This can become a dilemma when it comes to employees choosing between keeping their job and “playing the game”, or taking on more creative and difficult projects that don’t measure well against certain metrics. Is it fair to expect all members of a team to be compared against the same metrics? In my opinion, I think when used in moderation and to compliment a manager’s judgement it can be useful. But I have issue in the fact that by increasing the influence of these metrics on an individual’s job, it is almost whittling down each position to a certain “ideal” and that individual quirks and personalities begin to get ignored and discouraged.

On the other hand, one could argue that through using these data driven metrics it could actually make the work force a fairer place. It’s no secret that many managers have their own internal biases, and oftentimes look to hire or promote those who are like them. By employing metrics based on hard data, we could reduce these biases and have an objective footing to measure employees against (this is assuming the metrics used are fair and accurate, which will be covered in the next section). AI used on data collected on an individual’s development process could also help inform what projects individuals would be most suited for.

However, what about when it comes down to firing or promoting someone over some figure these algorithms generate? We need to remember that the use of these could impact someone’s entire livelihood. This is not a space to be experimenting and playing around with. Is it fair for someone who is tasked with “quick fixes” to be measured against someone working on a larger project? Again, I think there is a healthy middle ground to be met in this situation. These measurements should all take context into account and not replace a manager’s judgement or be solely used to justify the firing or hiring of someone. In my opinion, these metrics are good to ensure an individual is within certain boundaries. For example, if someone’s number of commits fall in either of the two extreme tail points of the normal distribution it’s a good indicator to the manager to investigate their performance. But, for the people who lie in the middle I don’t think you should be comparing these people down to the figure.

**Accuracy**

A huge issue when it comes to the ethics of using these algorithms and AI systems to measure people is their accuracy. In my opinion, as long as the algorithms are proven to be inaccurate or biased, they are unethical to use to evaluate an individual. Machine learning systems are only as good as the datasets they are trained on, rubbish in, rubbish out. One example of this is the gender biases in AI algorithms. The reality is that we don’t have as much sample data on women, especially in software engineering, as men. A famous example of this is the Amazon AI recruiting tool. The system itself was trained by looking at the CVs submitted to Amazon in the last decade, and most of these were those of men. Therefore, when used to automate the recruitment process, it favoured male applicants as the traits seen in their CVs were mirrored in the dataset the system was trained to view as good. In short, machine learning does not eradicate our human biases and often reflects them, and historical and social inequalities (Manyika, Silberg and Presten, 2019). Judging human behaviour is a subtle art and often the use of AI removes the intricacies associated with each individual. Products that produce an AI generated “productivity score” don’t reflect these and end up reducing everyone down to the same ideal. If an AI learns how to measure employee behaviour from a predominantly male sample, which is almost always the case when it comes to software development, females may be branded as less competent because they approach their job differently, but not less effectively. It is worth noting here that I am using gender as a basis for bias, but the same holds true for other minorities.

**Use at a Team Level**

In my opinion, when it comes to using AI at an individual level and using this to make decisions, it largely becomes ethically questionable. However, I think it becomes more reasonable when you look at using AI to measure performance at a team or organisational level, without singling out individual people. For one, it is less of a privacy issue as you are not analysing data attributed to one individual, and additionally you are not having as much of an impact on someone’s life. It is not reasonable to say we should never use these metrics, as we have always measured performance in one form or another and you would not know what was happening if you didn’t. The difference now is the scale of data we have to be manipulated. Using AI to predict development patterns across a team can lead to better success predicters and estimates for stakeholders. You can also process the data a lot more accurately when you are looking at something less abstract such as output (rather than productivity).

**Going Further than Software Development**

Up until this point we have talked about metrics related to the software development process, however, a huge shift is being seen at the moment across industries when it comes to using AI to measure employee productivity. In my opinion, it is these products that are of most concern ethically. The onset of the Covid-19 pandemic catalysed the shift to remote working, and a side effect of this was an increase in surveillance software. One example is Hubstaff which records an employees’ keyboard and mouse use, as well as the websites they visit. Another product is Time Doctor which takes it to the next level by taking videos of an employee’s screen, as well as having permission to take a picture through their webcam every 10 minutes to check if they are still at their desk. From an ethical standpoint, I am completely against this as I view it as a complete invasion of privacy as well as a practice that ultimately undermines trust between employers and employees. My stand point is, if you can get the tasks you are assigned done on time it should not matter how you spend your day. Additionally, the knowledge that you are being monitored will change the way you work, and cause unnecessary anxiety.

Enaible is another such product and is an “AI that dynamically learns how you work, unlocking the fullest potential of your work, inspiring like no other in the world” (Enaible, n.d). It learns an individual’s workflow, for example by learning what triggers them (emails, calls, etc.) and how long they spend on tasks. It then generates a productivity score, which is supposedly agnostic, meaning it can be used to compare employees across an organisation regardless of their job. To me this is a huge issue as employers will be tempted to compare all employees with this same score, despite each employee serving a different purpose, and undoubtedly creating value in different ways. This is also an issue for those who don’t do repetitive work, and again going back to treating software engineering as an art, how can boil down their work to a productivity score when their work is ever changing and contextual. My biggest ethical issue with is product is that they also have an algorithm that recommends how employees can improve. My fear with this is that employers will start seeing this as a call to optimise everything, including their workforce, leading to many losing their jobs. This shift towards optimising every process seems to be leading the way towards forgetting about employee well-being, focusing on what they output rather than the processes that get them there.

**A Framework for Ethics of Data and AI**

To finish, I would like to introduce a framework proposed by Josh Bersin in which he describes “Four Dimensions of Trust” (Bersin, 2019). First, it asks whether the data and algorithms being used are fair. Does it accurately reflect the individual/team you are assessing and is it taking biases into account? Secondly, is looks at whether the data systems and algorithms are safe. Are people’s privacy being respected and is their data secure?

**Chart

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Figure 9: A framework for ethics of data and AI. (Source: joshbersin.com)

**Conclusion**

<https://blog.pragmaticengineer.com/can-you-measure-developer-productivity/>

<https://www.gitclear.com/measuring_developer_productivity_a_comprehensive_guide_for_the_data_driven> - see can developer productivity really be measured

**References**

Altvater, A., 2017. *What Are Software Metrics and How Can You Track Them?*. [online] Stackify. Available at: <https://stackify.com/track-software-metrics/> [Accessed 27 December 2021].

Bersin, J., 2019. *People Analytics and AI in the Workplace: Four Dimensions of Trust*. [online] joshbersin.com. Available at: <https://joshbersin.com/2019/05/the-ethics-of-ai-and-people-analytics-four-dimensions-of-trust/> [Accessed 30 December 2021].

Construx Software, 2016. *Measuring Software Development Productivity | Steve McConnell*. [video] Available at: <https://www.youtube.com/watch?v=x4IboMnTdSA> [Accessed 27 December 2021].

Chatterjee, D., n.d. Measuring Software Team Productivity. *Sutardja Center for Entrepreneurship & Technology, Berkeley Engineering*, pp.5-9.

Enaible n.d. [online] Available at: <https://enaible.io/> [Accessed 30 December 2021].

GeeksforGeeks, 2021. *Cyclomatic Complexity*. [online] Available at: <https://www.geeksforgeeks.org/cyclomatic-complexity/> [Accessed 28 December 2021].

Heaven, W., 2020. *This startup is using AI to give workers a “productivity score”*. [online] MIT Technology Review. Available at: <https://www.technologyreview.com/2020/06/04/1002671/startup-ai-workers-productivity-score-bias-machine-learning-business-covid/> [Accessed 30 December 2021].

Infopulse, 2019. *Top 10 Software Development Metrics to Measure Productivity*. [online] Medium. Available at: <https://medium.com/@infopulseglobal\_9037/top-10-software-development-metrics-to-measure-productivity-bcc9051c4615> [Accessed 27 December 2021].

International Organization for Standardization, 2017. *ISO/IEC/IEEE 15939:2017 Systems and software engineering — Measurement process*. [online] Available at: <https://www.iso.org/standard/71197.html> [Accessed 27 December 2021].

Pluralsight. n.d. *Introduction to Code Churn: Causes & Fixes*. [online] Available at: <https://www.pluralsight.com/blog/tutorials/code-churn> [Accessed 27 December 2021].

Manyika, J., Silberg, J. and Presten, B., 2019. *What Do We Do About the Biases in AI?*. [online] Harvard Business Review. Available at: <https://hbr.org/2019/10/what-do-we-do-about-the-biases-in-ai> [Accessed 30 December 2021].

Noda, A., 2019. *The elusive quest to measure developer productivity - GitHub Universe 2019*. [video] Available at: <https://www.youtube.com/watch?v=cRJZldsHS3c> [Accessed 27 December 2021].

Pluralsight.com. n.d. *Pluralsight Flow*. [online] Available at: <https://www.pluralsight.com/product/flow> [Accessed 28 December 2021].

Radigan, D., n.d. *Five agile metrics you won't hate | Atlassian*. [online] Atlassian. Available at: <https://www.atlassian.com/agile/project-management/metrics> [Accessed 28 December 2021].

Reisenwitz, C., 2021. *How to Measure Productivity in Software Engineering*. [online] Clockwise Blog. Available at: <https://www.getclockwise.com/blog/measure-productivity-development> [Accessed 27 December 2021].

Sonarqube.org. n.d. *SonarQube*. [online] Available at: <https://www.sonarqube.org/> [Accessed 28 December 2021].

Total Metrics. 2021. *What are Function Points?*. [online] Available at: <https://www.totalmetrics.com/function-point-resources/what-are-function-points> [Accessed 27 December 2021].

1. For more detail on how to identify, classify and weight each functional component and carry out an analysis see the Total Metrics article from the reference section. [↑](#footnote-ref-1)
2. If interested, the talk itself can be viewed at <https://www.youtube.com/watch?v=cRJZldsHS3c> [↑](#footnote-ref-2)
3. A list of all the common metrics and what and why they are measured can be found here: <https://help.pluralsight.com/help/metrics> [↑](#footnote-ref-3)
4. See <https://waydev.co/> [↑](#footnote-ref-4)
5. See <https://linearb.io/> [↑](#footnote-ref-5)
6. See <https://jellyfish.co/> [↑](#footnote-ref-6)