

KIREPRO1PE

Compression of Programs and the Similarity Distance

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Supervisor: Mircea Lungu <mlun@itu.dk> Lines of code changed (LoCC) is one of the most widely used distance metrics in the software industry, but it suffers from several key drawbacks that can mislead when analyzing developer effort and project activity. In this paper, we explore the shortcomings of LoCC and propose an alternative metric: Difference in Compression Distance (ΔCD), derived from Normalized Compression Distance (NCD). Formally, $CD(x, y) = |C(x \cup y)| - |C(x)|$, $\Delta CD(x) = CD(x - 1) - CD(x)$ where $|C(\cdot)|$ denotes the compressed size of the concatenated commit buffer. The results suggest that ΔCD provides a more nuanced and robust measure of software evolution, to be used as a complementary metric to proven metrics like LoCC, while being aware of the biases in the metric.

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They took away the old timbers from time to time, and put new and sound ones in their places, so that the vessel became a standing illustration for the philosophers in the mooted question of growth, some declaring that it remained the same, others that it was not the same vessel.

— Plutarch, Life of Theseus 23.1

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1. Introduction

Software engineering has consistently explored metrics to measure and compare the complexity and evolution of software systems. Being able to quantify the impact of code changes in software systems is central to understanding software evolution, team productivity, and system complexity. There are many ways to quantify the impact of code changes. Among these, *Lines of code changed* (LoCC) [1] is one of the most widely used distance metrics in the software industry [2]. It is often used as a measure of software complexity, maintainability, and productivity.

While LoCC is simple to compute and interpret, it suffers from several key limitations (ambiguous definition, rename-detection pitfalls, automation-driven spikes, no survivorship bias) that can mislead when analyzing developer effort and project activity. In this paper, we will explore the shortcomings of LoCC and propose an alternative metric: Difference in Compression Distance (ΔCD). By measuring the compressibility of changes between software revisions, ΔCD offers a novel perspective on software evolution, addressing many of the shortcomings inherent in LoCC.

1.1. Research Questions

This paper investigates three research questions:

- RQ1: To what degree is the ΔCD of a commit correlated with LoCC?
- RQ2: To what extent is ΔCD able to discriminate between commit types?
- RQ3: What are the limitations of ΔCD in quantifying the contributions of developers?

1.2. Contributions & Paper Organization

We make the following contributions:

- We identify and characterize key limitations of LoCC as a proxy for developer effort and system evolution.
- We define Compression Distance (CD), a distance metric based on lossless compression, and derive its per-commit Difference in Compression Distance (ΔCD) as a complementary metric to LoCC.
- We implement ΔCD computation as API endpoints in the Git Truck analysis tool, leveraging ZStandard with a 2 MB search window by default.
- We empirically evaluate ΔCD on two projects (Git Truck and Commitizen), answering RQ1-RQ3 and demonstrating ΔCD 's advantages in quantifying complexity and discriminating commit types.
- We discuss the practical biases and limitations of ΔCD , offering guidelines for its adoption in research and industry.

The remainder of the paper is organized as follows. Section 2 reviews LoCC and its limitations. Section 3 presents our proposed ΔCD metric and its theoretical foundation. Section 4 details the methodology: data collection, metric computation, commit classification, and statistical analysis. Section 5 reports results for RQ1-RQ3. Section 6 discusses implications, practical considerations, and limitations. Finally, Section 7 concludes and outlines directions for future work.

2. Background

2.1. Information distance and Similarity Distance Metrics in Software Engineering

In the field of information theory, the concept of *information distance* is used to quantify the similarity between two objects [3]. This is done by measuring the amount of information needed to transform one object into another using a mathematical function F . The most common way to measure this distance is by using a *distance metric*, which is a function that quantifies the difference between two objects.

While such a function F only exists in theory, we can still approximate the information distance between two objects using various practical techniques such as diffing and compression algorithms, as we will explore in this paper.

2.1.1. LoCC as a measure of information distance

Since many projects utilize version control systems, such as Git [4], for keeping track of changes, we can track LoCC over time using diffing algorithms. The LoCC metric is typically defined as the number of lines added and removed in a commit. This provides a measure of the information distance between revisions of a software system. Git includes this functionality by default using the numstat argument. [5]. This is a commonly used technique used to detect activity in software systems over time [6]. It can be used to assess team velocity, developer productivity and more. These metrics can be automatically obtained via version control systems using tools like Git Truck[7]. LoCC is a useful metric for quantifying contributions or regions of interest in software systems over time and tools like Git Truck have shown the effectiveness of LoCC in the analysis of software evolution [8], [9].

2.1.2. Limitations of LoCC

There are however multiple limitations when relying on LoCC as a sole metric of productivity.

2.1.2.1. Ambiguous LoCC definitions

Firstly, the term itself is ambiguous and subjective to the formatting of the code. One could say that line breaks are just an arbitrary formatting character. In reality, the program could have been written in a single line of code.

See the following ambiguous examples in Listing 1. A few questions arise: should these snippets be counted as three separate lines of code or collapsed into a single line? In terms of actual work, a developer who writes either version is equally productive, yet if we simply count physical lines changed, the author of the first listing would be credited with three times the contribution of the second. This discrepancy shows how formatting alone can skew LoCC-based distance measures, as trivial style differences inflate the perceived distance between revisions and undermine the metric's reliability.

<code>if (foo) { bar(); }</code>	<code>if (foo) { bar(); }</code>	<code>if (foo) bar();</code>
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Listing 1: Three semantically equivalent code snippets with different physical line counts

2.1.2.2. Rename-detection pitfalls

The LoCC metric can be distorted also by file renames, which may artificially inflate contribution counts, since renaming a file requires little effort but appears as significant line changes. Git supports rename detection using a similarity threshold¹, comparing deleted and added files to identify likely renames, utilized by tools such as Git Truck. While Git doesn't exclude renames by default, this tracking can be used to filter them out manually. However, rename detection is inherently ambiguous – at what point should we stop treating a change as a rename and instead count it as having deleted the old file and added a new one?²

The issue is further exacerbated when developers squash commits, potentially losing rename information. Ultimately, it's a trade-off between inflating the impact of trivial renames and missing substantial, legitimate contributions.

2.1.2.3. Automation-driven LoCC spikes

Another case where the LoCC metric falls short is when performing automated actions that affect a vast amount of files and leads to spikes in line changes. Examples of this include running formatting and linting scripts or automated lock file updates when installing packages, all of which can lead to astronomical amounts of line changes. These kinds of changes do not directly reflect genuine development effort, but they still result in high LoCC values from which one often draws this conclusion. As an illustrative example, see Figure 1 for a visualization from the tool Git Truck showing accumulated line changes per file. Notice how the file "package-lock.json" is dominating the rest of the files, due to it being an auto generated file that is modified automatically by package managers in the JavaScript ecosystem. This is an example of line changes that should be disregarded.

¹<https://git-scm.com/docs/git-log#Documentation/git-log.txt-code-Mlntngtcode> ^o

²https://en.wikipedia.org/wiki/Ship_of_Theseus ^o

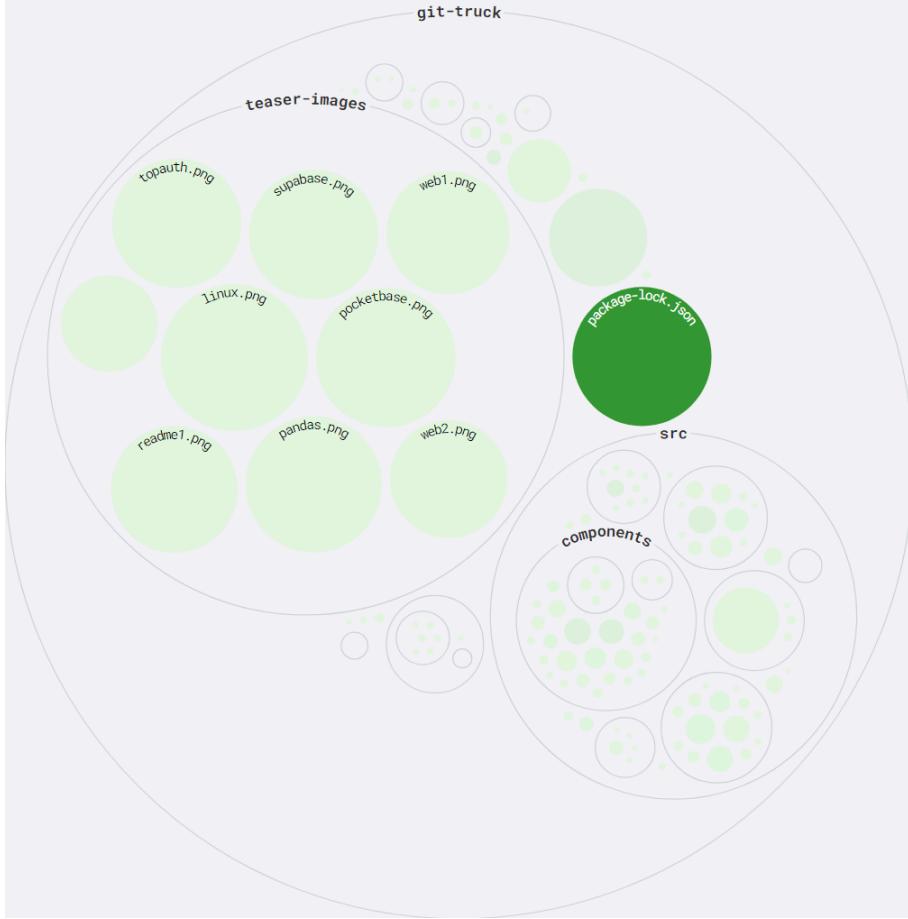


Figure 1: Screenshot of Git Truck [10] visualizing accumulated line changes per file. More vibrant colors indicate larger amounts of LoCC

If the developers practice good Git hygiene (such as keeping commits small and focused, not using squash merging, and writing descriptive commit or conventional commit messages³), you can perform filtering to focus on for example commits fixing bugs, refactoring or implementing features, but in reality, not all teams conform to these practices.

This shows why this metric cannot stand alone as a measure of productivity. This may cause the results to be misinterpreted, overstating the activity levels of certain developers or areas of the system.

2.1.2.4. Lack of survivorship bias

Another problem with the LoCC metric is that it does *not* include survivorship bias. This means that if a developer made a lot of changes to a file in the past, but then later removed all of them, they would still be credited for all of those changes, even though they are not present in the current version of the file. This is a problem when trying to analyze the history of a project and understand how it has evolved over time. Tools like Git Truck track LoCC through the entire history of a project by default, weighing ancient changes as much as recent changes. In the development of Git Truck, this was attempted to be mitigated by looking at blame information⁴ instead and only considering how the files that are still present in the system as of today have changed through time. However, this technique is still prone to the

³Some projects conform to conventional commit messages using tools like Commitizen [11]

⁴<https://github.com/git-truck/git-truck/commit/12582272b5854d6bf23706b292f3519750023fdd>

errors introduced by the problem stated in Section 2.1.2.2. Another attempt to solve this was the introduction of the time range slider⁵, which led the user being able to select a duration of time to analyze and ignore past changes in analysis.

⁵<https://github.com/git-truck/git-truck/pull/731> °

3. Approach

To mitigate the limitations of LoCC, we use the metric ΔCD to quantify the impact of contributions in version-controlled software systems.

3.1. Normalized Compression Distance

Normalized Compression Distance (NCD) [12] is a effective way of measuring the similarity between two compressible objects, using lossless compression algorithms. It is a way of approximating the Normalized Information Distance and has widespread uses, such as clustering analysis [13].

According to [14], NCD is an effective distance measurement, as long as it is used properly, which can be achieved if you understand how compression algorithms work. Most compression algorithms use a sliding window of context from which to compare new data to old data, in order to limit memory consumption. If the size of this window is too small, matches might not be found and the data might not compress as well. Since we are using the compression to quantify the similarity, it is crucial that we use a compression algorithm with support for a window size that exceeds the size of the data that we want to compare. In fact, if we compare two version of an object to determine how it has changed over time, we need a window size twice the size of the largest version of the object, in order to not overlook shared patterns.

However, nobody has used NCD based distance metrics in version control system analysis. The hypothesis of this project is that NCD-derived metrics could function as a complement to the more well-known LoCC metric, and be resilient to the problems that LoCC suffers from.

In the rest of this chapter, we will show how to build this metric by trying to tackle the limitations imposed by LoCC.

3.2. Mitigating the problem of ambiguous definitions of LoCC and rename-detection pitfalls

To mitigate the ambiguity of LoCC described in Section 2.1.2.1, we can instead consider the change in the number of bytes as a quantifier of developer activity. However, this means we can no longer rely on line-based diffing algorithms, akin to those used in Git [15] and must use an alternative method to measure the distance between revisions. We can mitigate the problem with ambiguity and renames by concatenating all the files existing in each commit into a single file buffer. We will refer to this as the concatenated commit buffer, CCB.

We can compute the change in the size in bytes before and after the commit, which gives us the byte distance, $\Delta(x)$. See Equation 1 for the formal definition.

$$\Delta(x) = |x| - |x - 1| \quad (1)$$

$\Delta(x)$ is the distance in bytes between this and the previous commit, $|x|$ is the size of the given commit buffer and $|x - 1|$ is the size of the previous commit buffer.

However, this method does not address the problem with automatic actions overstating developer impact. This leads us to defining ΔCD instead in the following chapter.

3.3. Mitigating the problem of automation-driven LoCC spikes and lack of survivorship bias

Instead of measuring the static distance in bytes before and after the commit, we can instead try to measure the compression of the changes we added. Using a lossless compression algorithm, we compress the concatenation of the given commit buffer x with the newest revision of the project y and compare this value with the one for the previous commit $x - 1$. The hypothesis being that this would make it such that large repetitive actions would have a lower impact, since they would compress better than smaller, but more complex changes. This assumes that the changes added in a commit will compress better in the presence of similar code. This requires the compression algorithm to have search window larger than double the size of the project files we intend to analyze, as explored in [14].

We define the Compression Distance CD as a measure of how much a given concatenated commit buffer compresses with the baseline commit buffer, see Equation 2.

$$CD(x, y) = |C(x \cup y)| - |C(x)| \quad (2)$$

$CD(\cdot)$ is the compression distance between x and y , x and y are the given concatenated commit buffer that we wish to compare and $C(\cdot)$ is a lossless compression algorithm.

Unlike NCD which is bounded, this metric is unbounded and depends on the absolute sizes of the compressed buffers. This is acceptable for our use case, as we are comparing commits within the same project, and the magnitude of the CD reflects the impact of each commit.

Now we can define the impact of the commit, the ΔCD metric, compared to the previous commit buffer. See Equation 3 for the formal definition.

$$\Delta CD(x) = CD(x - 1) - CD(x) \quad (3)$$

Note that if the CD of $x - 1$ has decreased after applying commit x , it means that we have gotten closer to the final revision. This is a bit unintuitive, as it is the opposite of Euclidian distances, but this is due to the fact that we are going backwards throughout the history of the project, which means distances are inverted. A positive ΔCD indicates that we moved closer to the final revision, while a negative ΔCD means we moved away from the project.

This method introduces intentional survivorship bias by compressing each commit buffer in the presence of the final commit buffer. As a result, changes that are more similar to the final version compress better and are valued more highly. This helps tell a story about how the codebase evolved toward its current state and which commits were most influential in getting there. For some purposes, this bias is acceptable—as long as it’s acknowledged. For instance, a detour that was later discarded will show a negative ΔCD , indicating it moved the project away from the final state, though it may still have been a valuable exploration. See Figure 2 for a diagram illustrating how some commits increase the distance from the final version.

$|\Delta CD|$ for the last 100 commits to github.com/zeeguu/api

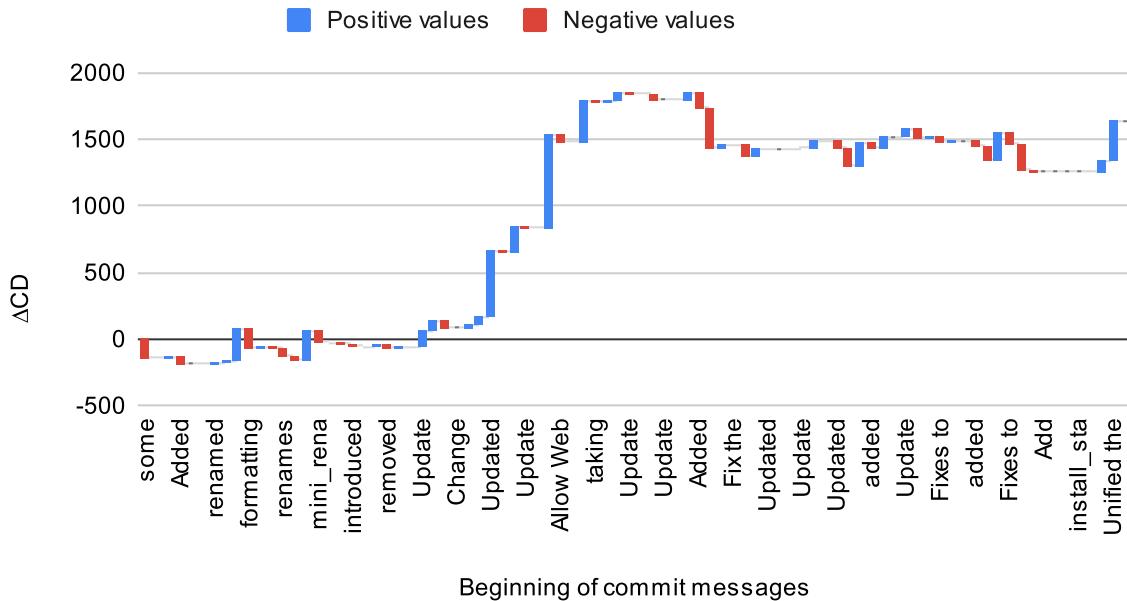


Figure 2: Waterfall diagram showing ΔCD for the latest 100 commits in the repository github.com/zeeguu/api°

If we don't want the survivorship bias and intend to value these types of detours better, we can use the magnitude of the distance instead, which then gives us the impact of the commit, no matter if it moved the project closer or further from the project.

To mitigate these problems, we can use an alternative approach where we concatenate the entire state of the repository, which makes the analysis resistant to renames, as we don't care about file names, we only care about the bytes contained in the commit. However, in this case, we can no longer rely on diffing the concatenated string. We need to use another approach to derive the information distance from before and after a commit.

4. Methodology

4.1. Data collection

During this project, the analysis tools were implemented as API endpoints exposed in the Git Truck project [16]. This was done due to the foundation for performing git analysis were already readily available in Git Truck project, which sped up the development of the tools.

We used these endpoints to collect and visualize data about different repositories to draw conclusions about the ΔCD metric.

4.1.1. Repository Selection

For the analysis of this project, two differently sized projects were chosen. Git Truck was chosen, as we were familiar with its history and knew that an attempt was made to conform to good practices of making git commits, such as using the imperative mood etc., which made categorizing the commits simpler. Commitizen was chosen as well, due to its nature of conforming to the use of Conventional Commits [17], which automatically could be categorized.

The different versions of Git Truck where chosen due to the known time periods on which the project was worked on by a previously known set of contributors.

From Table 1, all the chosen repositories lie below the maximum of 1MB for level 3 zstd compression (see Section 4.2.2 for more details).

REPOSITORY@REVISION	COMMITS	HASH	BUFFER SIZE
Git Truck@ncd [10]	1,356	bf46e09	0.365 MB
Git Truck@v2.0.4 [10]	1,260	d385ace	0.318 MB
Git Truck@v1.13.0 [10]	1,242	71ae30d	0.259 MB
Commitizen@master [11]	1,977	e177141	0.771 MB

Table 1: Git repositories and revisions that were chosen for this project and some of their properties

4.1.2. File Inclusion/Exclusion

Certain file extensions were included/excluded, to focus the results on code files.

In general, file extensions commonly associated with code were included, while binary files like images, videos, and audio files as well as miscellaneous files were excluded [18].

If any extensions were found that were neither included nor excluded, an automatic warning was reported in the console, in order to consider whether it should be included or excluded.

4.1.3. API Data retrieval

The tool is able to go through a specified range of the history of a git repository and compute metrics for each commit.

The current version of the tool is as of writing not published yet and has to be run manually by cloning the source code.

Queries can be performed using query parameters like so: Among other metrics, the endpoint is able to compute the Δ CD in relation to the baseline commit, the newest commit at the given revision in the repository.

- Repository can be specified using the `repo=<folder>` parameter⁶
- Baseline branch or revision is specified with the `branch=<revision>` parameter.
- Amount of commits to analyze is specified using the `count = N|Infinity` parameter, going backwards from branch⁷

To generate the data for this project, the following queries were used:

REPOSITORY	BRANCH	COUNT
git-truck	ncd	Infinity
git-truck	v2.0.4	Infinity
git-truck	v1.13.0	Infinity
commitizen	master	Infinity

Table 2: Parameters used to gather the analysis data

This produces a CSV output that can be processed in a data processing tool. During this project, Google Sheets was used for this purpose. Useful information and progress updates is reported in the console.

4.2. Metric Computation

In this section, the steps to compute Δ CD for each commit are described. The process is divided into the following sections:

4.2.1. Concatenated Commit Buffer (CCB) Construction

A concatenated commit buffer (CCB) was constructed for every commit, reading all the file contents into a single buffer. The contents of the files were obtained by calling the `git cat-file <blob hash>` command and reading the standard output of the command into buffers. For each commit buffer, a second buffer was created by concatenating with the newest revision buffer, in order to create the components needed for Equation 2.

4.2.2. Compression Setup

Each CCB was compressed using ZStandard (zstd) [19]. The ZStandard compression algorithm (zstd) [20], has a window log of 21 [19] for its default 3 level compression, making the window size $2^{21} = 2\text{MB}$. This makes zstd suitable for this task, as long as you are aware of the limit and remember to adjust it as needed. As mentioned in Section 4.1.1, it was ensured that the repositories used were smaller than half of this size⁸, to ensure that the sliding search window of the compression algorithm was able to take the entire commit buffer into account.

⁶The repo parameter refers to a specific git repository folder located relative to where the tools was downloaded.

⁷Passing Infinity as count makes the tool go through all the commits in the given repository.

⁸Due to compressing the newest commit buffer with each commit, meaning that a window size of at least 2x the baseline buffer was needed, assuming that no commit buffer is larger than the final buffer

4.2.3. Calculating Δ CD

The Δ CD for each commit is computed by subtracting the CD for the previous commit from the CD for the current commit, as shown in Equation 3.

4.3. Commit Classification

Using keyword searching, it was possible to categorize the many of the commits automatically. For the Commitizen repository, all the commits were automatically categorized due to the nature of conforming to Conventional Commits. The following keywords for categorizing the commits were used:

- For Commitizen, the standard keywords from Conventional Commits were used: **Test, Fix, Feat, Refactor, Style and Docs.**
- For Git Truck, these keywords were used: **Bump, Refactor, Fix, Feature.**

4.4. Statistical Analysis

It was evaluated whether per-commit Δ CD aligns with traditional complexity measured by LoCC. For each repository, a log-log scatter plot with regression trend-lines was created. From the trend-lines, the coefficient of determination was computed, R^2 , between Δ CD and LoCC across all commits.

5. Results

In this section, we will explore whether we have answered the research questions presented in Section 1.1, provided here for convenience:

- RQ1: To what degree is the ΔCD of a commit correlated with LoCC?
- RQ2: To what extent is ΔCD able to discriminate between commit types?
- RQ3: What are the limitations of ΔCD in quantifying the contributions of developers?

Before presenting our findings, we state our hypotheses for each research question.

- H1: For RQ1, we expect a positive correlation between per-commit ΔCD and LoCC, but not a perfect one, since we hope that the compression captures semantic similarity beyond trivial line counting.
- H2: RQ2, we expect ΔCD to be able to discriminate between certain commit types.
- H3: For RQ3, we expect the cumulative ΔCD to differ from cumulative LoCC, due to the nature of the survivorship bias built into the ΔCD metric.

The data used to answer these questions is published in Google Sheets [21], [22].

5.1. RQ1: LoCC vs. ΔCD Correlation

To answer RQ1, the newest version of each repository is explored to see how the ΔCD metric correlates with LoCC. The branch worked on the latest for Git Truck is the NCD branch and for Commitizen it is the master branch.

We use linear regression on ΔCD and LoCC values throughout the histories of the two repositories. We then determine the coefficient of determination r^2 for both linear and power regression, to investigate whether the two metrics are correlated.

5.1.1. Correlation Results

From Table 3, it seems that for Git Truck, there exists a slight linear correlation between LoCC and ΔCD , however for Commitizen, a power regression produces a better correlation.

PROJECT	REVISION	R^2 , LINEAR	R^2 , POWER
Git Truck	ncd	0.825	0.494
Commitizen	master	0.297	0.506

Table 3: Correlation between LoCC and ΔCD

From this, we accept H1, as we observe a partial correlation, but not a perfect one as expected.

5.2. RQ2: Discrimination Across Commit Types

5.2.1. ΔCD Distributions by Category

For this experiment, the Commitizen repository will be considered. If each category of commits are plotted as series on a log-log scatter-plot, some interesting patterns can be seen. See Figure 3.

ΔCD vs LoCC for commitizen-tools/commitizen (github)

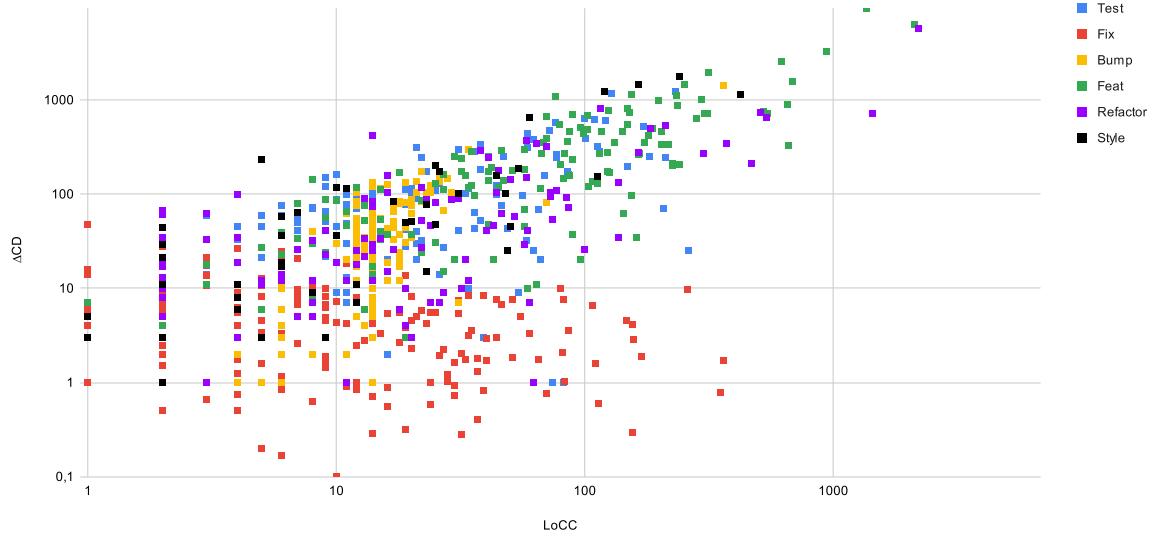


Figure 3: Log-log scatter-plot of commits in the Commitizen repository, with automatically categorized commits

From the plot, it can be seen that bug fix commits specifically has a tendency to have a lower ΔCD metric. It can also be seen that version bumps vary much less in impact compared to the other categories. Feature commits generally have a larger LoCC than other commits, and might contain more novel code that compress less, compared to bug fixes.

From this, we accept H2, as we can clearly see patterns that partly discriminate between commit types.

5.3. RQ3: Developer Contribution Analysis

For this experiment, we will look at the Git Truck repository across two time periods and see whether survivorship bias plays a role in ΔCD .

The byte distance, LoCC and ΔCD are accumulated for each developer throughout the two time periods.

We then aggregate each metric for each contributor throughout the history of the repository.

For context, Git Truck was initially developed by a group of four developers. Later, the project was continuously contributed to several developers, and even later Thomas contributed to the project during his master thesis.

We will compare the project before and after the master thesis by Thomas.

5.3.1. Author-Level Aggregates

To assess how CD shifts our view of who “moves the most code” compared to traditional LoCC, we compute cumulative ΔCD and cumulative LoCC per author at two key snapshots: before Thomas’ master’s-thesis work (v1.13.0) and afterwards (v2.0.4). See Figure 4 for a diagram visualizing the differences.

AUTHOR	ΔCD	LoCC	AUTHOR	ΔCD	LoCC
Jonas	66.285%	65.807%	Jonas	46.412%	58.445%
Thomas	21.744%	14.571%	Thomas	46.377%	24.550%
Emil	5.958%	11.958%	Dawid	3.224%	1.946%
Dawid	4.847%	2.245%	Emil	3.120%	10.364%
Mircea	0.681%	0.467%	Mircea	0.549%	0.405%
Kristoffer	0.443%	4.946%	Kristoffer	0.329%	4.287%
Anders	0.041%	0.004%	Anders	-0.012%	0.004%

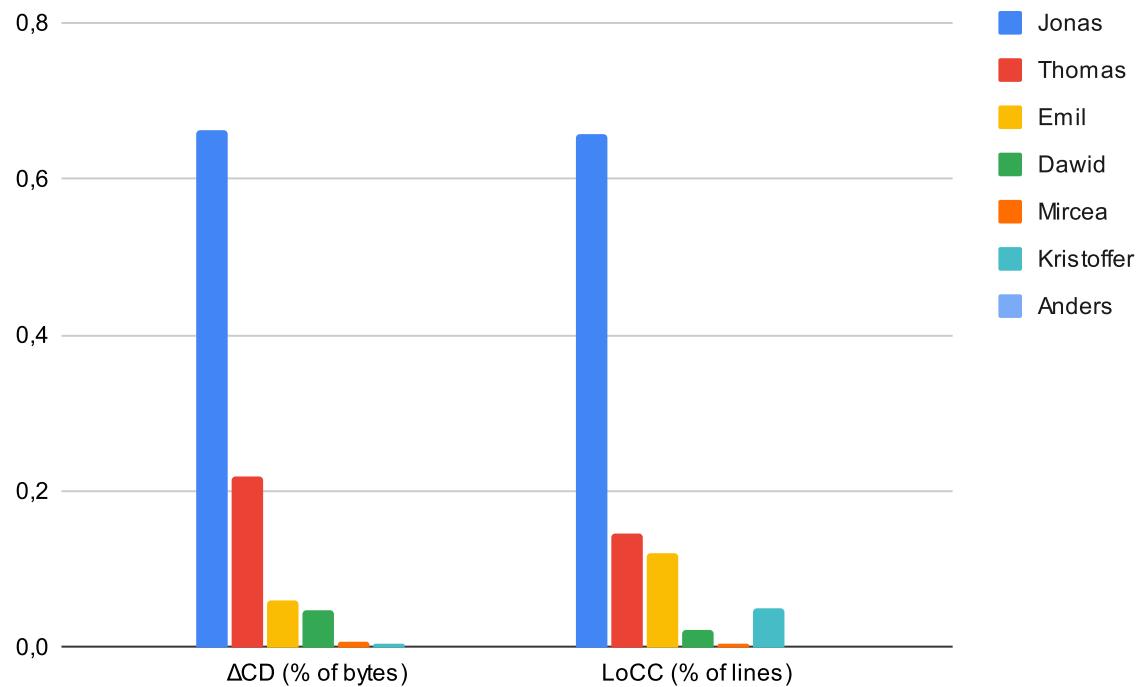
Table 4: Cumulative LoCC and ΔCD

Left: Before Thomas' master thesis (v1.13.0), Right: after (v2.0.4)

See Figure 4 for the distribution over cumulative byte distance, LoCC and ΔCD over the two time periods. The top charts show the author distribution before the thesis project by Thomas and the bottom charts show the author distribution after.

See Figure 5 for how the cumulative distribution has changed over time.

Cumulative Δ CD vs. LoCC, before thesis



Cumulative Δ CD vs. LoCC, after thesis

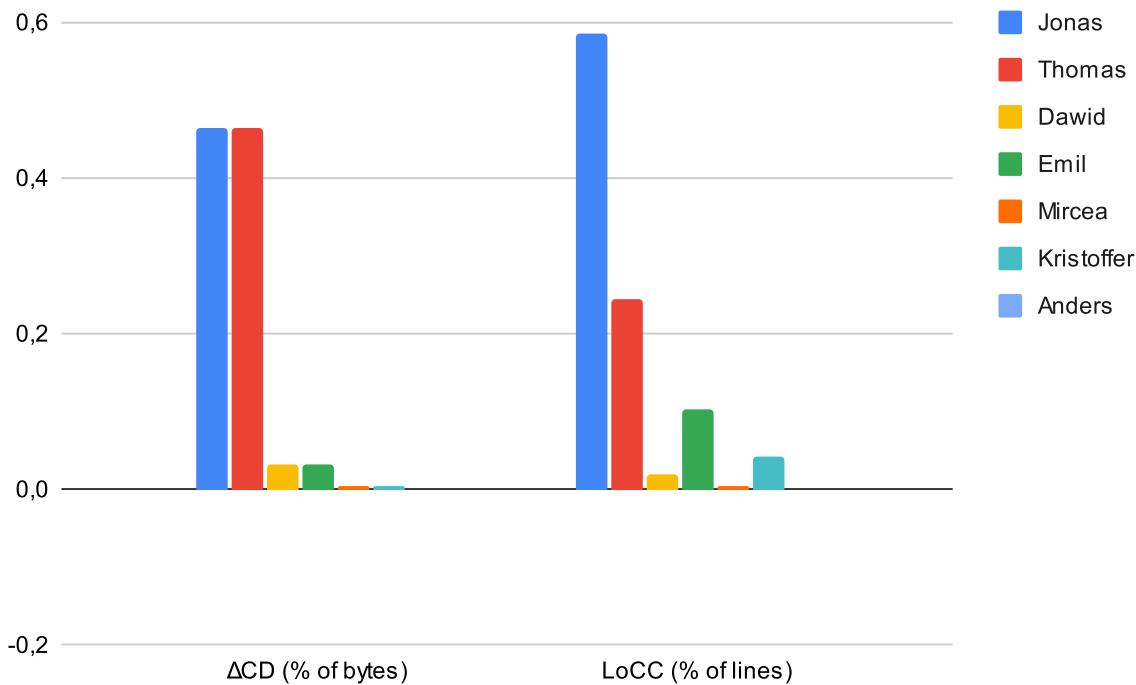


Figure 4: Bar charts of the cumulative author distribution before (top) and after (bottom) the thesis project by Thomas

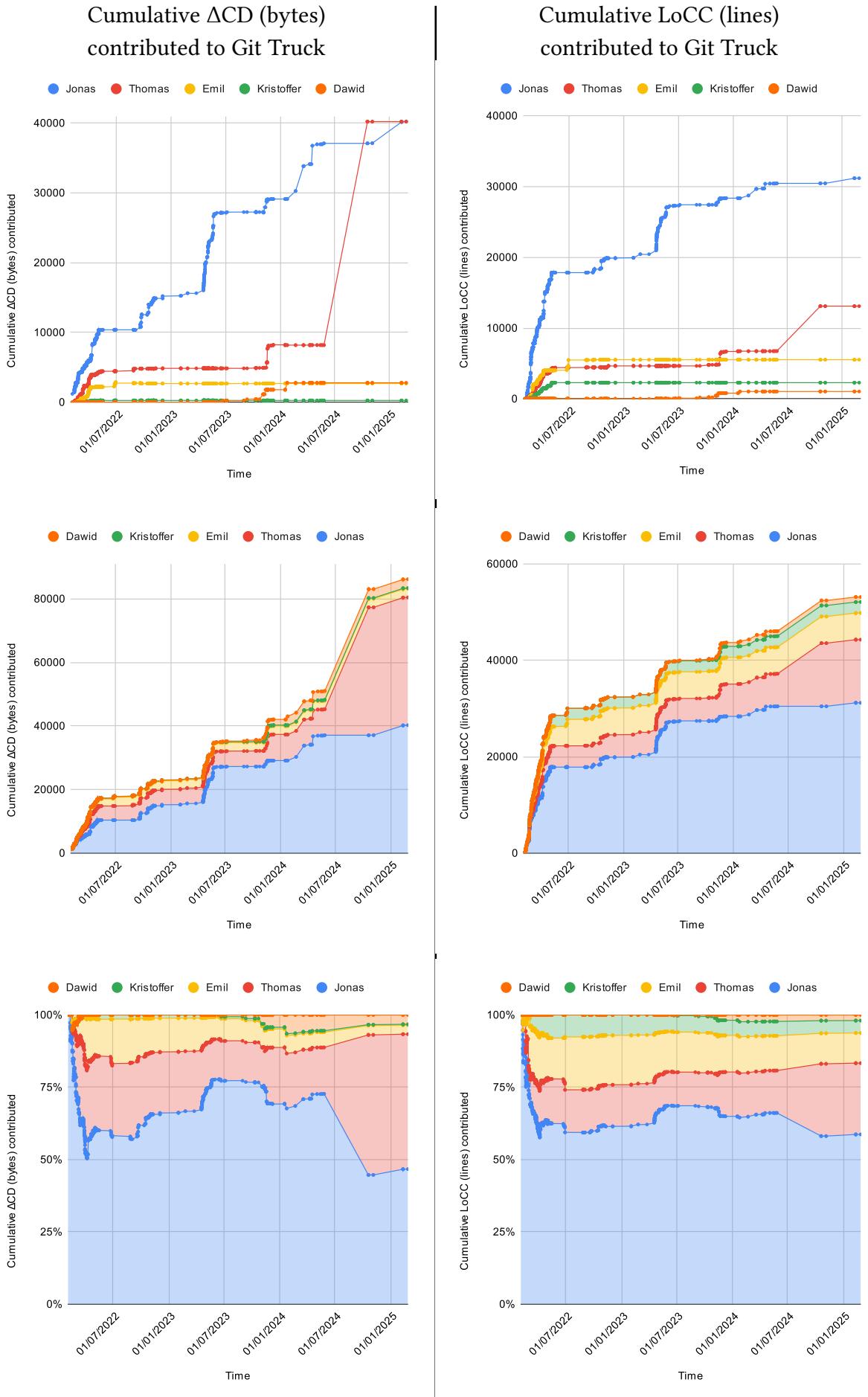


Figure 5: Cumulative author distribution over time to Git Truck.

Overlap (top), stacked (middle) stacked 100% (bottom)

5.3.2. Observations

Before Thomas worked intensively on the Git Truck project, his contribution distributions measured in LoCC and Δ CD were fairly close in value, however, after writing his thesis, Thomas' share of accumulated Δ CD equalized with that of Jonas.

This is also clear to see on the area time series charts in Figure 5. We can see that using the Δ CD metric, Thomas is able to surpass Jonas in the author distribution. We can also clearly see when Thomas merged his master thesis into the repository and that the merge technique was squashing all of the commits into one, hence the big spike upwards and long period of few commits. This clearly illustrates the information that is lost when developers choose squash merging over regular merges or rebase merging strategies. This is a limitation that neither LoCC, Δ CD or any other metric can preserve, unless the commits are recovered by rebasing them back into the branch.

Another interesting observation from Table 4 is that Mircea's cumulative Δ CD is larger than his share of LoCC. This is most likely due to him contributing by adding a Dockerfile and CI workflows, that are a small part of the project and therefore his changes compress less.

From this, we accept H3, as we observed that the survivorship bias is indeed included in the metric.

6. Discussion

6.1. Interpretation of RQ1 Findings

In Section 5.1, observations showed that there was no clear correlation between LoCC and ΔCD , which indicates that the two metrics measure different things and have their own purpose.

6.2. Interpretation of RQ2 Findings

In Section 5.2, observations showed that certain types of commits contribute more information to the codebase than others. This is intuitive, as introducing a novel feature typically adds more unique content than modifying existing code for bug fixes or version bumps.

6.3. Interpretation of RQ3 Findings

There are several hypotheses for the differences observed in Section 5.3. Since Thomas changed a lot of the codebase during his thesis work, the survivorship bias of the metric favors his recent changes, when judging the history of the project. Another part of the explanation might be that his thesis entailed adding a database to Git Truck, contributing a lot of SQL code to an already TypeScript dominated project, which might also explain the large spike in the ΔCD attribution to Thomas. The hypothesis being that contributing SQL code to the codebase will compress worse than contributing TypeScript code.

This demonstrates the built in survivorship bias that the metric includes and illustrate how you need to be aware of this when using the metric for judging work. For judging work done in group projects, one should select time ranges that correspond to the period of work during the project.

If the author distribution is measured based on cumulative ΔCD contributions, survivorship bias is built into the metric, which tells more about who contributed the most to get the system in its current state.

6.4. Practical Implications

This study has shown that if implemented with caution for compression window sizes and built in bias, a metric like the compression distance has its place in the arsenal of metrics used in analyzing software evolution. It's a viable supplement to existing metrics and might especially be useful for assessing student projects, as long as detours in the project are also noticed.

6.5. Considerations for End users

While measuring automatic velocity is a good idea, it is not the only thing to consider. For a user facing project, it is important to also consider the user experience and the impact of changes on the end users. Some small bug fix might have a small impact on the code, but a large impact on the end user.

6.6. Limitations

There are however some limitations to this approach, that makes it less desirable compared to alternatives, depending on the needs.

6.6.1. Performance

With its current implementation, compressed distance is much slower to compute than traditional metrics like LoCC built in to Git Truck. For example, analyzing the entire history of Commitizen in Git Truck was measured to take 1.55 ± 0.07 seconds, while it takes 374.28 ± 5.41 seconds for the proposed tool in its current state, making it a ≈ 250 times slower metric in this scenario.

6.6.2. Scalability

For very large repositories, it becomes unfeasible to calculate the compression distance for the entire project at once, as it requires a lot of memory and processing power. This is due to the fact that the compression algorithm needs to keep track of the entire state of the repository in memory. The limited window size [14] leading to distorted distance measurements, especially in worst case when comparing identical objects exceeding these size constraints. This means that we are back to just measuring something similar to the byte distance.

6.6.3. Biases

The built in survivorship bias is included with this metric for better or for worse. Alternative algorithms were tested during the project, but did not show promise and were abandoned early on.

7. Conclusion

In this project, we set out to quantify software evolution via a novel compression Distance (CD) metric, complementing the existing LoCC measure. Below we recap our key contributions before outlining directions for future research.

7.1. Summary of Key Contributions

We defined the Compression Distance (CD) metric as an information-distance complement to LoCC (Equation 2). We implemented CD computation in the Git Truck API using ZStandard with a 2 MB search window. Empirical evaluation on Git Truck and Commitizen (RQ1-RQ3) showed that CD more finely quantifies code complexity and distinguishes commit types. Finally, we discussed CD's biases and provided adoption guidelines.

7.2. Future Work

There are many directions to take this project further, including exploring usability, scalability, performance and bias elimination.

7.2.1. Usability

Incorporating the tool into Git Truck would make it so others could experiment with the data as well. It would also be interesting to see how this data could be incorporated and presented into the visualizations of Git Truck. It could work as an extension of the author distribution already found in Git Truck, that is currently based on LoCC.

7.3. Scalability

Attempting to run the tool on a large repository, like the source code for Linux [23] yields a maxBuffer exceeded error:

```
RangeError: stdout maxBuffer length exceeded
    at Socket.onChildStdout (node:child_process:481:14)
    at Socket.emit (node:events:507:28)
    at addChunk (node:internal/streams/readable:559:12)
    at readableAddChunkPushByteMode (node:internal/streams/readable:510:3)
    at Socket.Readable.push (node:internal/streams/readable:390:5)
    at Pipe.onStreamRead (node:internal/stream_base_commons:189:23) {
      code: 'ERR_CHILD_PROCESS_STDIO_MAXBUFFER',
      cmd: 'git ls-tree -r HEAD'
```

This shows that future work could be done to investigate whether this metric could scale to very large repositories.

7.4. Performance

Future work could be done to investigate methods of speeding up the computational process. The process might be parallelizable and could utilize using shared memory with dynamic garbage collection, to reduce the memory overhead of the analysis. The current approach caches file buffers, but leaves garbage collection to the runtime.

7.5. Bias elimination

Attempting to design an algorithmic formula for avoiding the survivorship bias included in the metric might be an interesting project to undertake, if the bias is deemed undesirable to the use case.

7.6. Acknowledgments

The git analysis pipeline powering Git Truck was used as a foundation for developing the analysis tool.

I would like to thank Christian Gram Kalhauge <chrg@dtu.dk> for proposing the idea for this project and for his valuable external supervision and guidance.

```
while (workingOnThisProject) {  
    Jonas.becameAFather();  
}
```

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