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Measuring Software Ticket Quality using Quantitative Data Analysis

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ABSTRACT

Issue tracking systems have become the defacto standard for tracking work items in software projects - they guide engineers towards better planning and managing their progress throughout complex projects. However, there are few studies that investigate what makes for a high quality ticket. This can lead to multiple issues in a company, such as increased communication friction between developers and end users filing bug reports, as well as increased overall costs due to waste of development effort. In this research paper, we present our findings after investigating a large number of variables surrounding software tickets. Our results show that the presence and type of attachments, comments complexity, summary and description complexity, presence of stack traces, presence of steps to reproduce, grammar correctness scores, as well as sentiment can significantly influence the quality of the ticket. We supply one of the largest dataset statistically analysed in this particular field, as well as state-of-the-art sentiment and grammar correctness analyses.

1. INTRODUCTION

In the past decade software projects have inherently become more complex and they now require an increasing number of developers on the team. Studies such as the one conducted by Herbsleb [12] show how software engineering teams have transitioned from small, collocated to globally distributed teams. One reason elicited in the paper is the increasing popularity of communication tools, such as Slack or Google Hangouts. Due to this, developers have created issue tracking systems as means of planning, managing and tracking work products in the form of *software tickets* or *issues*.

There are multiple platforms for providing such issue tracking systems, among which the most popular are Jira and Bugzilla. For both platforms, the tickets are split into two main categories: feature requests (i.e. feature to be implemented into the system) and bug reports (i.e. issue encountered by an end user or discovered by a developer in the codebase). Regardless of the type of ticket, they possess various information that can be filled in by the reporter (i.e. person who created the ticket; can be both an end user or a developer in the team), providing the developers a detailed view of what is requested or what went wrong.

Even though tickets provide such comprehensive data regarding a specific task, evidence shows that fixing bugs is one of the most common and time consuming tasks performed by developers [18]. One of the reasons for this is the communication friction between developers and end users [16] as developers might need clarification regarding what information the users have provided (e.g. cannot reproduce the bug, screenshot is unclear). Another main reason for this waste of effort on solving tickets, according to Just et al. [15] and Zimmermann et al. [30], is the generally poor design of issue tracking systems. This can lead to various issues, including increased costs for the company, wasted development effort, decreased customer satisfaction and overall poor performance.

Therefore, there is a need in the community to find the answer to what makes for a high quality software ticket that would improve the overall performance of the development team and, inherently, the company. Considering the many fields of a ticket, there are numerous elements that could influence its quality, such as the presence of stack traces.

In this research paper, we present and discuss our findings after running a quantitative data analysis on over 300,000 tickets taken from more than 38 open source projects. To this aim, we implemented a Go application with multiple commands (i.e. store, analyze, plot, statistics) that can automatically fetch any number of tickets from a Jira instance, analyze them, generate plots and run statistical tests.

For the analysis we investigate several variables in correlation with *Time-To-Close*, which we define as the *indicator of quality*. More specifically, an inverse relationship was assigned between the two: as *Time-To-Close* increases, the quality decreases. *Time-To-Close* represents the period of time between the creation and the closing of a ticket; more specifically, the creation of the ticket is marked when the status of the ticket is set to *Open* and the closing of a ticket is considered when the ticket status is set to *Closed* (or some similar status, such as *Fixed*, *Resolved*). *Time-To-Close* is our dependent variable, and as independent variables (i.e. variables controlled in order to test the effects on the dependent variable) we set a number of ticket fields.

In order to provide answers to what factors influence quality in a software ticket, we investigated the following seven research questions in this paper (Section 5):

- does the presence of attachments and their type (e.g. code snippet, screenshot) influence the *Time-To-Close* for a ticket?
- does the presence of stack traces reduce *Time-To-Close*?
- does the presence of steps to reproduce reduce the *Time-To-Close*?
- is there a relationship between the number of words in comments and *Time-To-Close*?

- does the total number of words in summary and description have an impact on *Time-To-Close*?
- does the number of grammar errors in summary, description and comments have an effect on *Time-To-Close*?
- does a positive or negative ticket influence its *Time-To-Close*?

This study brings several contributions to the research community:

- an innovative tool was built for the purpose of this project, providing efficient data collection and analysis of tickets;
- it is one of the few studies in the field that performs a quantitative analysis rather than a qualitative one;
- it is one of the very few research projects that investigates such a large number of tickets (over 300,000) extracted from 38 different projects;
- it is, to our knowledge, the first study to conduct sentiment and grammar correctness analyses on software tickets.

The rest of the paper is structured as follows. In Section 2 we iterate over state-of-the art studies in the field and then continue with Section 3 where we discuss how the ticket data set was collected and analysed. We continue with describing the data set (Section 4) where we provide insights into various aspects of the data (e.g. size of database, number of tickets with attachments) and then discuss correlations between the variables (Section 5). Finally, we provide future research directions in Section 6 and present our conclusions in Section 7.

2. RELATED WORK

In this section we will present some of the state-of-the art studies in the issue/ticket quality field. More specifically, we will look at research papers that investigated what makes for a high quality ticket, how one can extract structured/unstructured data from tickets (e.g. stack traces), ticket duplication and its positive and negative outcomes, quality of modern issue tracking systems as well as automating the process of summarizing tickets or the optimal assignee.

The study of Bettenburg et al. [2] showed what makes for a high quality bug report through qualitative analysis. After conducting interviews with over 450 developers, Bettenburg et al. concluded that one of the main factors behind a quality ticket is grammar correctness in summary and description. Another aspect which was flagged as helpful by the interviewees was the presence of stack traces and steps to reproduce in tickets. A further contribution brought by the authors to the community is the creation of a tool called Cuezilla which is able to automatically predict the quality of a bug report with an accuracy of around 40%.

Another research paper that strenghtens the argument that readability is a quality factor in software tickets is the one presented by Hooimeijer et al. [13]. They conducted their analysis on over 25,000 bug reports from the Mozilla project, investigating readability, daily load, submitter reputation, the whole changelog histories and severity. They conclude that not only readability in the textual fields of a ticket influences the *Time-To-Close*, but also that the presence of attachments and the number of comments have a clear lowering effect on the duration of triaging. On the other hand, the patch count and other similar fields did not provide significant value to the quality of tickets.

However, there are other types of information typically included in software tickets which might prove beneficial for developers and subsequently improve the ticket quality. One such type is stack traces - Schroter et al. [23] analyse how quickly tickets are closed depending on whether they have stack traces included in their fields (e.g. description) or not. They collected their data from the Eclipse project using the InfoZilla tool proposed by Bettenburg et al. [4]. Then, they linked the stack traces to changes in source code by mining the Eclipse version controlled repository. The results showed that around 60% of the bugs that contained stack traces in their reports were fixed in one of the methods in the frame. Moreover, more than 40% of the tickets having stack traces got fixed in the first stack frame.

Software tickets can have duplicates, usually meaning that the most important fields, such as summary or description, describe the same feature request or bug report. Even though one might believe that they cannot bring any value to a software project, the work of Bettenburg et al. [3] shows the contrary. The authors collected large amounts of data from the Eclipse open source project and ran various kinds of textual and statistical analysis on the data to find answers. After the results were computed, they concluded that usually bug duplicates contain information that is not present in the master report (i.e. the original report that was filed). The developers also specified that they have often found value in these duplicate bug reports and that they can even aid automated triaging techniques.

Another study that investigates duplicate bug reports is the work conducted by Prifti et al. [21]. The authors first collected 75,000 bug reports from Bugzilla for the Firefox project. Then, they created a tool for detecting bug report duplicates with an accuracy of 53%. However, due to prior findings showing both that duplicate reports can improve the quality [3] but also decrease it [7], this study tries to achieve a middle ground - before the reporter can file the bug in the system, the duplicate detection tool previously described runs and checks whether there are any duplicates. If there are, the user is presented with the possibility of simply adding extra information, if suitable, to one of the duplicates found. This is indeed a novel approach that can bring great benefits to the software engineering community and the authors state that they wish to pursue future work on this idea.

Bettenburg et al. [5] present in their work an application called infoZilla. This tool can parse bug reports and correctly extract stack traces, patches and source code. When evaluated on over 150,000 bug reports, it proved to have a very high rate of over 97% accuracy. We applied some of the techniques shown in the study and successfully managed to retrieve stack traces as well with a great accuracy.

The first information to be filled in by end users or developers on any issue tracking system is the summary field, which holds a small description, usually between 5 and 30 words, of the request or bug being reported. In the study conducted by Rastkar et al. [22], the authors investigated whether tickets could be summarized automatically and ef-

ficiently. What that implies is that developers would no longer be required to look at tickets on the whole, comprising of a large number of fields, but rather at a simple summary of a couple of lines encapsulating the whole information. The authors selected the Mozilla, Eclipse, GNOME and KDE open source projects and they asked volunteering university students to annotate the tickets in the issue tracking systems. More specifically, they wrote a summary of maximum 250 words using both technical and non-technical terms, depending on their expertise. In parallel, Machine Learning algorithms were also employed to parse these summaries and learn how to efficiently create automated summaries for new bug reports. After both methods had been run, software developers were asked to rate these auto-generated summaries against the original ones; the conclusion was that existing conversation-based extractive summary generators used for software tickets produce the best results.

The work of Just et al. [15] examines a rather different aspect of quality in tickets - they are investigating the quality of the underlying issue tracking systems instead. After running a survey on 175 developers from Eclipse, Apache and Mozilla, the authors applied a card sort in order to organize the comments into hierarchies to identify common patterns. Their findings can be summarized in the following top seven suggestions: create differentiation between bug report difficulty levels between novices and experiences reporters, encourage users to input as much information as possible, add ability to merge tickets when needed, recognise and reward valuable bug reporters, integrate reputation into user profiles to mark experienced reporters and ensure the ability to expressively search through tickets.

Having discussed about various factors that can influence the quality in software tickets, we also need to take into account how can we apply this knowledge to solving the issue of poor design in issue tracking systems and how the ticket creation process could be improved. The study conducted by Lamkanfi et al. [17] looks at this aspect and shows how issue tracking systems could be extended in order to automatically generate the severity of a ticket (e.g. assign story points to a Jira issue). The authors conducted their research on the Mozilla, GNOME and Eclipse and projects and split their approach into four steps: extract and organize tickets, pre-process tickets (i.e. tokenization, stop word removal and stemming), train the classifier on two datasets of tickets - 70% training and 30% evaluation and apply the trained classifier on the evaluation set. The conclusions they drew from running the evaluation process were rather interesting: terms such as segfault, deadlock, crash, hand or memory typically indicate a severe bug, when analyzing the textual description they found that using simple one line summaries resulted in less false positives and increased precision levels, the classifier needs a large number of tickets in order to predict correctly, depending on how well a software project is modularised and, lastly, one can use a predictor per module rather than a universal one.

Another overall aspect of software tickets and issue tracking systems that could be improved through determining the quality factors for tickets is automatically assigning a bug report or a feature request to the most suitable developer (or team of developers). Anvik et al. [1] propose a Machine Learning technique that could automatically assign a bug report to the developer with the most expertise in that specific area. Firstly, the algorithm takes as input various types of information from tickets: textual description and summary, operating system used when the bug occurred, developer who owns the source code, which developers have lighter workloads at that point in time etc. After the tool was evaluated, the authors concluded that it can be used in production as it provides a high rate of accuracy when assigning the developers, but it needs more data so that the model is trained properly.

3. BUILDING THE DATA SET

The first step towards building the data set was to create a tool that was able to execute all the necessary commands: fetching the tickets from any Jira instance, storing them into some form of database, analyze the variables of interest, automatically plot the correlations between them and run statistical analysis on the data. After careful consideration, we decided that Go was the best way to go for various reasons:

- it is designed with simplicity in mind, thus making it easy for others who might join the project to read and understand the codebase; this would prove useful for developing the tool further;
- it is a compiled, statically typed language that produces cross-platform executables when building the application; this is helpful for our research as we can use any machine or cluster of computers regardless of the operating system running on them and collect even larger number of tickets than what we have collected so far;
- it is designed with concurrency in mind, thus it helps reduce times of execution and computing power considerably; in our case, it helps by allowing access to goroutines, very lightweight threads that can scale even up to millions; we use this powerful concept while fetching tickets from Jira or storing in the database - at one point, there were more than 30,000 goroutines running at the same time.

Throughout the entire application, we applied the UNIX philosophy of creating small applications that do one thing, but do it well. Therefore, we implemented clean and simple packages where we used the standard library as much as possible so that potential contributors coming to the project would find it easy to start working directly on the code. Also, we designed the tool with extensibility in mind, so that other database providers (e.g. CockroachDB) or issue tracking systems (e.g. Bugzilla) could be easily implemented - this was achieved using the elegant Go interfaces and the idea of composition.

We split our tool into four main commands: *store*, *analyse*, *plot* and *stats*. By following the flow shown in Figure 1 and completing the whole application cycle, a database of analysed tickets is produced, as well as plots and statistics for investigating correlations, saved on the filesystem.

In the following three subsections we describe how we designed and implemented the commands mentioned above.

3.1 Fetch and Store

This is the first command implemented in our tool - it is desgined to fetch, from any valid Jira URL, any number of tickets and then store everything inside an instance

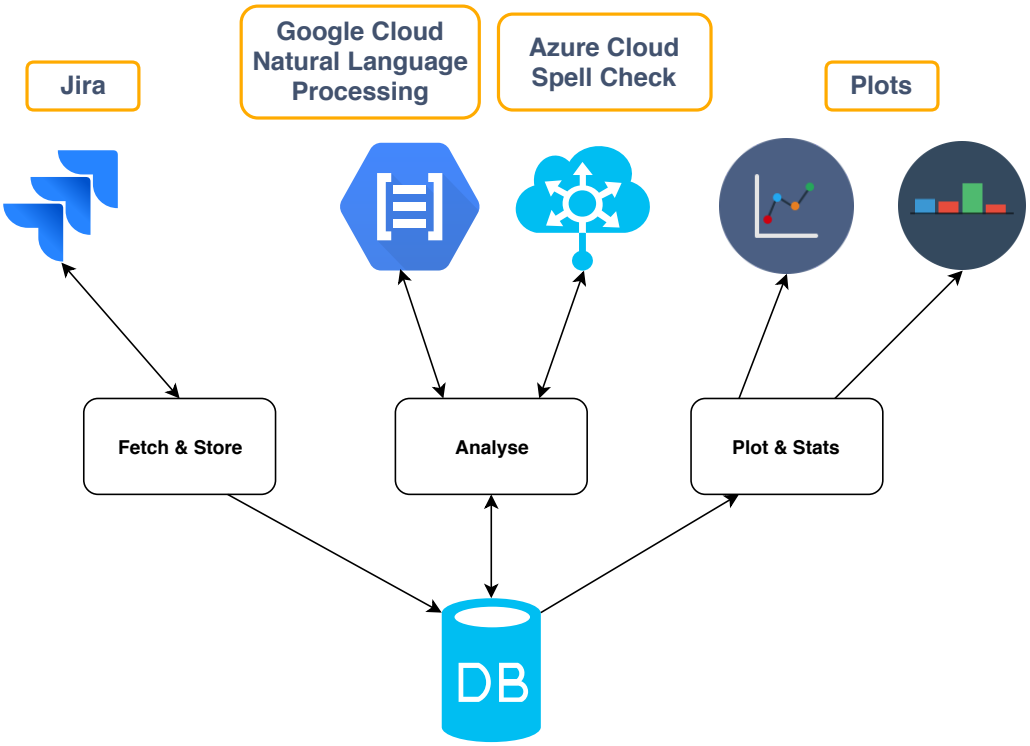

Figure 1: Application flow of the Go tool.

of BoltDB [14], a key-value pair database. The whole process is parallelized with the possibility of scaling even up to hundreds of goroutines (i.e. lightweight threads) running concurrently.

The decision of choosing Bolt in favor of well tested, more traditional databases such as Postgres or MySQL came naturally when we noticed that we did not need to query the database often, but rather get the whole array of tickets and manipulate them. Moreover, a MongoDB or Postgres DB would have required a running server.

The goroutines interact with the Jira Server REST API. The goroutines exploit the pagination facility in the API, which means slicing the whole set of tickets into multiple smaller arrays to improve performance and reduce the load on the server. We also specified to Jira exactly what set of issue fields to return and, as responses were retrieved from the instance, they were stored into our Bolt DB instance.

The way we chose to store them was to set the issue key (i.e. unique identifier that differentiates a ticket from all others across all projects inside a Jira instance) as the key of the pair and the value is the JSON representation of the ticket. This storage method, in conjunction with the simplicity of Bolt, helped us reduce the size of the database significantly. For small databases, using RDBMSs (e.g. Postgres, MySQL, Oracle) is not performance critical, but when the data set is large such as in our study, bottlenecks might start affecting the progress of the project. This is mainly due to the structure in which Jira returns the tickets; for example, all issues have comments as a field, consisting of an array of structs with body, author, created time etc. Then, each comment has a changelog history attached to it, having in turn multiple changelog groups and also each group can have multiple changelog items. Therefore, this long pipeline became a serious bottleneck for us once we reached a certain number of tickets because we had relations between all these tables, compared to Bolt which does not link any key-value pair to another. Another major point when we decided to proceed with Bolt was that we did not need to query the data at all as processing was too complex to convert the logic into an SQL query.

3.2 Analyse

Once the Bolt DB instance is completely populated with all the tickets we were interested in, the analyze command first fetches all the issues in the database. The next step is to filter out the tickets based on the following criteria:

- tickets are *High Priority* - the ticket status marked as either Blocker, Critical, Major or High;
- tickets are closed with a maximum *Time-To-Close* value of 27,000 hours (roughly 3 years) (we added the higher bound as well in order to eliminate outliers retrieved by Jira);
- remove outliers for all categories - some fields had extreme values for a small number of tickets (e.g. one ticket had over 270,000 comments) introduced by the team behind the project and we needed to exclude them so that the analysis produced correct results (they were removed as they were skewing the results due to erroneous completion of fields).

Then, the analysis routine runs in parallel the *seven types of analysis* for answering the research questions outlied in

Section 1, each in its own separate goroutine in order to speed up the process:

- *attachments* - checks whether attachments influence *Time-To-Close* and also look at what types of attachments (e.g. screenshots, archive, code snippets) influence *Time-To-Close* the most;
- *steps to reproduce* - performs a complex regex to detect steps to reproduce and then checks whether their presence influence the *Time-To-Close* of a ticket; the regular expression was adapted after the general guidelines elicited by Bettenburg et al. [4] on how to extract structured data, including enumerations (of which steps to reproduce are a subset);
- *stack traces* - runs complex regex for detecting exception stack traces in either summary, description or comments and verifies whether their presence influence Time-To-Close for the ticket; this analysis only inspects projects written in Java as it is the most popular proponent built-in of stack traces;
- *comments complexity* - loops through all comments and counts all words; then, the tool verifies whether the number of words in comments has an impact on the Time-To-Close for the ticket;
- *fields complexity* - same analysis as comments complexity, but only for summary and description wordiness;
- *grammar correctness* - it uses Azure Cloud Bing Spell Check API to perform analysis on summary, description and comments; after concatenating everything and making it compatible with the API allowed formats, the tool receives back in the JSON payload not only the number of flagged tokens (i.e. grammar errors), but also their types (e.g. unknown token, misspell);
- *sentiment* - uses Google Cloud Platform's Natural Language Processing API to retrieve the sentiment score for summary, description and comments; it first concatenates everything and makes it conform to Google's API and then sends the request, receiving a score from -1 to 1 inclusive (-1 means most negative, 1 means most positive);

We needed to be extra cautious when working with Google Cloud Platform and Bing Spell Check APIs, especially regarding rate limiting. Google's NLP APIs have a maximum rate of 10 requests per second, while Microsoft APIs have a maximum rate of 100 requests per second, thus we needed to conform to their guidelines and restrict our application not to send more than allowed, otherwise our IP addresses could have been blacklisted. The number of free trial credits was limited, therefore we calculated in advance how many requests we had available and computed scores only for those tickets.

The application first checks Bolt for tickets and gets either all of them in memory (easier to parse, but heavy on resource utilization) or slices them into smaller arrays to get processed afterwards (harder to parse as it eventually requires re-creation of the whole array of tickets before inserting back into the database, but it is much lighter on computing power). After having the tickets available, we start looping through them and perform all analysis types mentioned above. Once a value is computed (e.g. grammar correctness score), it gets set in its corresponding field in the ticket struct and is subsequently stored back in the database. We chose this approach because we do not want to run the analysis every time we want to plot correlations between variables, but rather have the data already available there. Moreover, for analysis depending on third party services such as the Google Cloud Platform Natural Processing Language API, we would incur costs; thus having everything saved in the database and running the analysis only if the value had not been already computed allowed us to investigate the tickets without exceeding the free trial credits.

3.3 Plots and Statistical Tests

Next, we created two extra commands for automatically generating plots (i.e. scatter plots and bar charts) and running statistical tests on the collected data.

For plotting the data, we first connect again to the Bolt database instance and then filter out only the issues that have the variable *Time-To-Close* set (i.e. tickets marked as closed when they were fetched from the Jira instance; even though we passed a filter for not fetching tickets still marked as Open, there was a small number erronously retrieved by Jira). In order to compute correct results, we run the same checks on issues as the ones listed in the analyse command (e.g. plot only tickets of high priority). Afterwards, we save either scatter plots or bar charts to disk presenting relationships between all the variables we tested.

In terms of technology used for plotting the data, we used a library called go-chart [8] created by Will Charczuk. It is an extensible library with a focus on extensibility - it does not provide the end user a large number of default options, but rather let him/her extend their graphs as much as it is needed (e.g. add specific labels for axes, plot a secondary Y axis).

Also, in order to validate our findings, the statistics command fetches all the data from the database and runs two types of tests: Welch's T Test [28] for analysing categorical data (e.g. has/does not have attachments) and Spearman's rank correlation coefficient [26] for investigating continuous data (e.g. grammar correctness score based on number of grammatical mistakes). For computing Spearman R Tests we made use of a simple statistics library created by Damian Gryski called onlinestats [11], while for Welch T Tests we created our own custom types and functions.

They have both been created with extensibility in mind. Also, before we ran both statistical tests and the plotting command, we tested them thoroughly and checked whether the libraries compute stable and robust results.

4. CHARACTERISING THE DATA SET

The data that we collected is stored, as previously mentioned, in a Bolt database instance which is around 6 GB in size. All tickets are stored as key-value pairs, where the key is the ticket's unique ID (e.g. KAFKA-100) and the value is the JSON encoded representation of the ticket. The tickets stored have the following fields available for investigation:

- attachments - files or images attached to tickets;
- summary - short description of the ticket;

- description - more detailed information regarding what is requested or what bug was encountered;
- time estimate - estimated number of hours to complete the task (set by triagers or developers);
- time spent - time period between opening the ticket and a specific point in time;
- created timestamp;
- issue status - jira specific statuses, including Open, Closed, Awaiting Review, Patch Submitted;
- due date - optional deadline for when the ticket should get closed;
- comments - discussion around the ticket conducted by developers, end users, triagers;
- priority - it can range from low priority (minor) to critical/blocker;
- issue type - specific Jira field that specifies whether the ticket is either a bug, a feature request or a general task.

Another component of issues that we stored and proved to be crucial in our analysis is changelog histories together with their corresponding items. They represent the whole history of a ticket and can show status transitions, story points modifications, summary/description editing etc. What made them useful for our study was that we needed to see when tickets were marked closed and, as Jira does not provide this in a separate field, we looped through the changelog history items and saved when the transition to Closed or a similar status was made.

There are other fields that can be configured inside Jira, including custom fields, but we did not collect them as they would not have been relevant for the analysis. However, in addition to the fields we saved, we also stored grammar correctness scores, sentiment scores, whether they have steps to reproduce, if stack traces are present and number of words in comments, summary and description. Even though all of them, apart from grammar and sentiment scores, can be computed locally, we store them because of performance issues due to the very large size of the database.

In total, we have collected 303,138 tickets spanned across 38 projects from the Apache Software Foundation: Impala, Eagle, Groovy, Lucene, Hadoop, Kafka, Apache Infrastructure project, Tika, Solr, ActiveMQ, ZooKeeper, Velocity, Tez, Storm, Stratos, CouchDB, Cassandra, Beam, Aurora, Bigtop, Camel, CarbonData, Cloudstack, Flex, Flink, Ignite, HBase, Mesos, Ambari, Cordova, Avalon, Atlas, Cactus, Flume, Felix, Geode, Ivy and Phoenix. These projects are using a large varieties of programming languages, ranging from Java, C, Go to Python and Ruby [10]. Moreover, in terms of contributors, the projects we selected range from small teams of people such as Tika to large numbers of developers spread across the globe, such as Kafka. We came to this final number and range of tickets and projects due to the following reasons:

- the study needed as much diversity as possible in order to correctly analyse and validate the data;
- these are the most important, up-to-date and contributed to Apache projects by the open source world;
- Apache is one of the few companies/foundations that use Jira exclusively for their projects and it is public (they do provide a Bugzilla alternative, but it is rarely updated compared to Jira).

More specifically, we computed the following numbers for the tickets we collected:

- out of the 303,138 tickets, 236,383 tickets were closed (i.e. marked Closed, Resolved, Done or Completed) by the time we fetched them from the Jira instance;
- 287,120 tickets are of high priority (i.e. marked as Blocker, Critical, Major or High);
- 201,786 tickets have all our requirements for running the analysis: were closed by the time we fetched the data, are of high priority and are not *wrong* values retrieved from Jira (i.e. outliers);
- 103,397 tickets have attachments which we split in the following categories:
  - 4,082 have code attachments (e.g. Go, Java, Python);
  - 7,171 have image attachments (e.g. png, jpg/jpeg, gif);
  - 164 have video attachments (e.g. mkv, avi, mp4);
  - 13,990 have text attachments (e.g. txt, md, doc(x));
  - 918 have config attachments (e.g. json, xml, yml);
  - 2,491 have archive attachments (e.g. zip, tar.gz, rar, 7z);
  - 280 have spreadsheet attachments (e.g. csv, xlsx);
  - 80,015 have other attachments (i.e. any file extension not pre-defined by us in one of the above categories).
- 270,907 tickets have comments;
- 39,988 tickets have steps to reproduce (i.e. sequence of steps specified by the bug reporter that would reproduce a certain bug); we applied the general guidelines described by Bettenburg et al. [4] on how to extract structured data (including steps to reproduce) from tickets in order to create a regular expression for capturing them;
- 1,942 tickets have Java stack traces - we applied the technique described by Bettenburg et al. [4] for extracting structured data from bug reports;
- 133,689 tickets have grammar correctness scores (i.e. number of grammar mistakes inside summary, description and comments) - they were computed using Microsoft Azure Bing Spell Check API which is one of the best grammar checking tool in the industry;
- 157,047 tickets have sentiment scores (i.e. positive/negative sentiment on a scale from -1 to 1 drawn from summary, description and comments) - they were calculated using Google Cloud Platform Natural Language Processing APIs.

All these numbers are also stored inside the database in a different bucket for easier access in the future. Moreover, the statistical tests that were run on the tickets are saved as well in the database.

5. CORRELATIONS

In this section we present our results to the research questions we set to answer. We computed charts for all independent variables using either scatter plots for continuous variables (e.g. number of comments/ *Time-To-Close*) or bar charts for categorical variables (e.g. presence of attachments/ *Time-To-Close*). We also computed statistical analysis for all variables to test their significance and rank correlation coefficient and we will present each of them in their corresponding subsection.

The answers to our research questions are all statistically significant and they can be summarised as follows:

- having attachments reduces *Time-To-Close* of a ticket;
- having steps to reproduce reduces *Time-To-Close* of a ticket;
- having stack traces reduces *Time-To-Close* of a ticket;
- more grammar errors increase *Time-To-Close* values;
- lower sentiment scores result in increased *Time-To-Close* values;
- verbose comments result in increased *Time-To-Close* values;
- verbose summary and description increase *Time-To-Close* values.

For every type of analysis, we also discuss possible reasons why certain correlations occured. Furthermore, for all of them we give possible solutions that could be implemented in order to maximise the ticket quality as cost-effective and efficient as possible.

5.1 Attachments

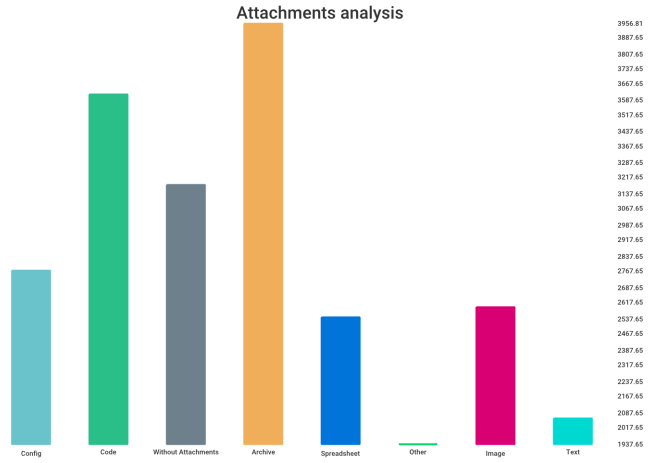

Figure 2: Attachments analysis.

Attachments are, as mentioned previously, files attached to software tickets that can take any form - from code snippets written in Java to tar archives. We analysed all tickets that were both of high priority and were closed by the time we had collected the data. Then we split all these tickets into two main categories: with attachments and without attachments. Furthermore, the tickets that were marked as having attachments were split into the categories specified in Section 4. In total, we looked at 201,786 tickets, among which 98,311 had attachments and 103,475 without any attachments.

Using the plot package in our Go tool, we automatically generated the bar chart shown in Figure 2. As it can be seen, various types of attachments produce completely different *times-to-close*. For tickets with archive we can see the longest *Time-To-Close* mean while tickets with text attachments are at the other end of the spectrum. The smallest mean is for other attachments, which is represented by any file that does not have an extension specified in one of the other categories.

We assume that image attachments are screenshots attached to the ticket in order to help developers see and subsequently reproduce the bug. Thus, we can clearly see that the difference between the means of *Time-To-Close* for tickets without attachments and tickets with screenshots is significantly in favor of the latter. This can indicate that developers indeed find screenshots helpful in solving the ticket faster.

Another insightful result is the fact that having text, config and spreadsheet attachments significantly reduces the *Time-To-Close* for the ticket. For example, when a config file is present, it might contain several environment variables that would help developers recreate the bug quicker. Similarly, a markdown file might have logging output which potentially directs engineers towards fixing the issue faster.

On the other hand, having no attachments does not necessarily mean that the ticket will get closed after a longer period of time. As it can be seen in the figure, the mean *Time-To-Close* value for tickets without attachments is somewhat neutral in the entire data set.

However, we need to take into consideration tickets that have code attachments which are a *threat to validity*. When a snippet of code is attached, it might result in more complex tickets due to developers spending more time on understanding what is going on and reasoning about the attached code. Also, engineers might need to run or test the code attached which can again increase the Time-To-Close.

A Welch T Test was computed to test the difference between tickets with attachments and those without attachments. The analysis revealed significant difference with $p < 0.01$ with an average of 1380.551 hours for tickets with attachments and an average of 3180.882 hours for tickets without attachments.

Thus, our analysis shows that having attachments in most formats, ranging from markdown files to PNG screenshots and snippets of code, can help developers solve the tickets faster. We believe that a solution to maximising the value of a ticket through attachments lies in issue tracking systems making it explicit to the reporters that uploading a screenshot or a code snippet could help reduce the *Time-To-Close* for the ticket.

5.2 Steps to Reproduce

Steps to reproduce are a means of specifying to the developers what actions they need to undergo in order to re-

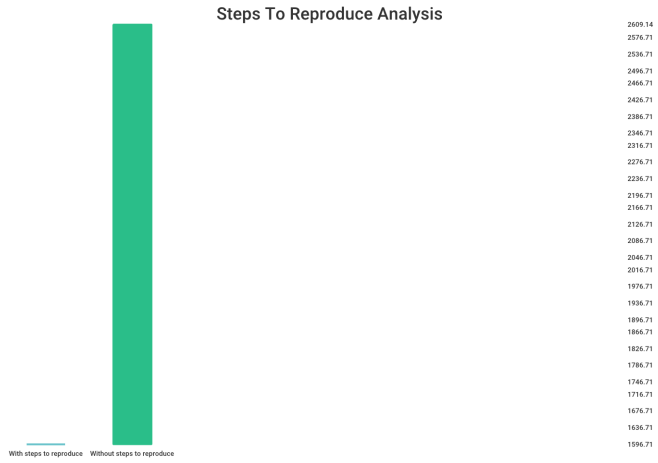

Figure 3: Steps to reproduce analysis.

produce a certain bug. They can take various forms, but as Jira uses a wiki style markdown format for their description and comments fields, they can be inserted as a bullet point list which can be easily extracted with a regular expression.

Figure 3 shows the bar chart representing all closed, high priority tickets with or without steps to reproduce in either the description field or in any of the comments. We looked in total at 201,786 tickets among which 39,988 tickets had steps to reproduce and 161,798 did not.

As it is shown in the figure, having steps to reproduce significantly reduces the *Time-To-Close* for the ticket. Even though the data collected does not have many tickets with steps to reproduce (39,988 compared to the total number of 201,786 tickets), it is still a valuable finding which shows that steps to reproduce are indeed a quality factor for software tickets.

What we can infer from this result is that steps to reproduce reduce the communication friction between the reporters and the developers - in the case of a bug which is harder to reproduce (e.g. maybe the bug occurs only on Linux and the developer is running MacOS, but the reporter did not specify his/her operating system in the ticket), the developer might need to contact the reporter either directly or through commenting on the issue. This consequently implies a waiting time until the reporter comes back on the issue tracking system or sees the notification that he/she received a new message, which subsequently causes the ticket to remain open for a longer period of time.

A Welch T Test was computed to test the difference between tickets with steps to reproduce and those without steps to reproduce. The analysis revealed significant difference with $p < 0.01$ with an average of 1596.714 hours for tickets with steps to reproduce and an average of 2609.142 hours for tickets without steps to reproduce.

Thus, the answer to our research question is that the presence of steps to reproduce in tickets has a positive influence on the *Time-To-Close*. One solution that we propose for maximising their benefit is that issue tracking systems require steps to reproduce, or at least indicate on the ticket creation form, that adding them would aid developers fix the bug faster. Moreover, issue tracking systems could also automatically add a new system field (like summary or description) for any project created and the project maintainers or administrators could make them mandatory for when a ticket is created by reporters.

5.3 Stack Traces

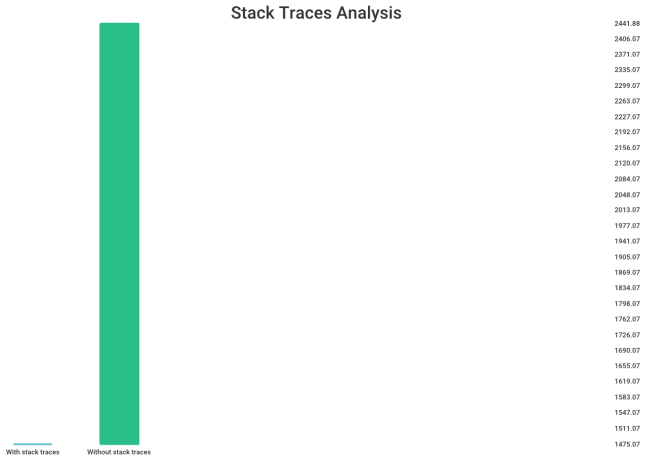

Figure 4: Stack traces analysis.

Stack traces are active stack frames at a certain point in time while the program is executing. Many programming languages provide stack traces through their standard libraries, but the most popular proponents are Java and C#. As Java is the main programming language used throughout the Apache Software Foundation projects (231 projects [10]), many of the projects we collected (22) are also written in Java, thus we had a considerable chunk of data to analyze.

For this analysis, we only looked at tickets of high priority, closed and the project they correspond is written in Java. We then ran a complex regular expression derived from the works of Bettenburg et al. [5] and Moreno et al. [20] and collected all the tickets that have stack traces. In the end, we got a total number of 1,942 tickets that had at least an exception stack trace attached in either summary, description or any of the comments.

As shown in Figure 4, we can see that the presence of exception stack traces can reduce the *Time-To-Close* of a ticket in orders of magnitude. This could imply that stack traces help developers working on the project localise the code that is running exceptions

We computed a Welch T Test to test the difference between tickets with stack traces and tickets that do not have stack traces. The analysis revealed significant difference with $p < 0.01$ with an average of 1475.074 hours for tickets with stack traces and an average of 2441.877 hours for tickets without them.

5.4 Comments

The comment field is comprised of a textual body, a corresponding author, its time of creation and any updates that were performed on it throughout its lifecycle. They provide a space for developers and end users to discuss anything re-

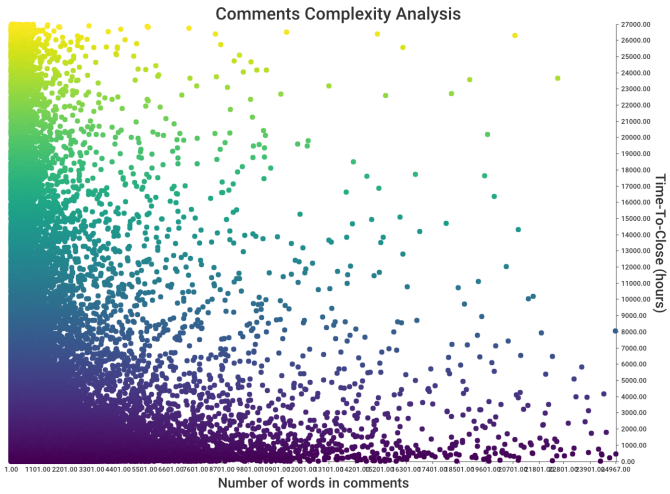

Figure 5: Comments complexity analysis.

lated to the ticket they belong to. Any popular issue tracking system, such as Jira, does not enforce any limit on any component of a comment, thus the number of words for a single comment can range from only 5 to well over 1,000.

We concatenated all comments into a single large string in order to be analysed for total number of words. This step was performed at the end of each ticket's lifecycle. We ran our comments analysis on 201,786 tickets among which 113,344 had comments and 88,442 did not have any comments. What we calculated as number of words inside comments is all the words inside all comments corresponding to a ticket summed up.

In Figure 5 we illustrate the relationship between the total number of words in comments per ticket and the corresponding *Time-To-Close*. We can observe in the scatter plot that most tickets tend to have up to around 3,200 words in total. However, there are tickets that have a total number of words as high as around 25,000.

From the figure we cannot clearly deduce whether increased number of words in comments influence the Time-To-Close positively or negatively. Actually, we can assume at first sight that there is a descending trend implying more words produce smaller Time-To-Close values. However, the bulk of values plotted are in the range of 1 to 1,600 total comment words per ticket (76,633 tickets) and in this slice of tickets, the trend is descending. We did not generate the plot containing solely these values because there would still be 36,711 tickets left out. Therefore, the curve is skewed to the right, although the bulk of tickets that dictate the trend, are on the left side.

A correlational analysis run on all 201,786 tickets, however, releaved a weak positive relationship with $r = 0.271$ and $p < 0.01$. This implies a statistically significant finding - as the number of comments increases, the *Time-To-Close* value of the ticket also increases.

Even though this might be surprising at first, we need to analyse the possible context where such large number of words in comments occur. What if the bug was so difficult to reproduce that the developers needed to ask more than one user how they experienced the issue in the tool? Another case might be that even though the comments start by discussing fixing or implementing a feature, the developers and end users might engage in new conversations about the product in general or other features that they might want to see implemented. Also, what if comments are a means of communication for developers in the team? There are studies, such as the one conducted by Lotufo et al. [19], that show the importance of comments in software tickets in relation to communication activities surrounding the project. Another possible explanation for having increased number of comments increase the *Time-To-Close* value and, thus, decrease quality, is that having many comments or very verbose comments can lead to more difficult information extraction. On the other hand, if there was a light discussion, the developers would be able to quickly analyse all the comments and collect whatever is necessary to resolve the ticket.

One possible solution that we propose to this manifested trend is to have the ability to limit the number of comments per ticket. As to our knowledge, one cannot do this in neither Jira nor Bugzilla. However, if it were possible, we believe that this might help developers find the information they need quicker. But what happens if the threshold is reached and there is still a need for clarifying certain aspects? We believe that having a button redirecting anyone still interesting in commenting on the ticket to a messaging tool, such as Slack, would be beneficial for the project overall. Thus, if they were redirected to Slack, a small tool could automatically be run that created a new channel specifically for that ticket with the name set to the unique ticket key (e.g. LUCENE-2901). We believe that such a solution could aid both developers in completing tasks quicker but also end users to feel more involved and valuable to the project.

5.5 Summary and Description

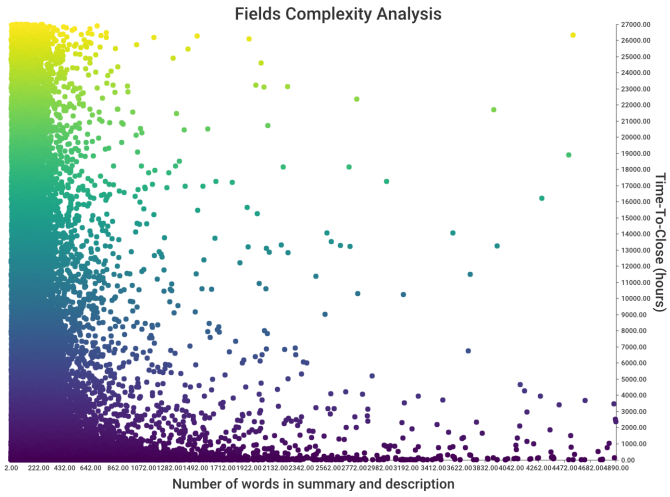

Figure 6: Summary and Description Complexity Analysis.

Summary and description are the two most important and most frequently completed fields in a ticket on any issue tracking system. Even though summary is required on any issue tracking system, description might be omitted if the reporter does not feel the need of adding any extra detail other than what is in the summary. However, as bug reports are usually complex, there is a very small percentage

of descriptions not filled in by the reporters. They do not typically have any word limits, thus the reporter can add as much information as they see fit.

Figure 6 shows the scatter plot for the sum of numbers of words in summary and description, as well as the Time-To-Close for the ticket. We have analysed a total number of 238,286 tickets, as they all have both summaries and descriptions. We concatenated the summary and description for every ticket at the end of the ticket lifecycle.

The figure shows a very similar correlation to the one for comments complexity - graphically, it seems that as the number of words in summary and description increases, the Time-To-Close will decrease. This is true for the majority of the tickets which are in the range of 2 to 290 words, but as in the case of comments complexity analysis, we did not generate the plot only for those as we would have left 61,322 tickets out (out of a total of 201,786 tickets analysed).

However, a correlational analysis run on all 201,786 tickets revealed a weak positive relationship with $r = 0.178$ and $p < 0.01$. This implies both that our results are statistically significant and also that as the number of words in summary and description increases, the Time-To-Close increases, thus the quality of the ticket decreases.

This is not a surprise - as previously mentioned, summary and description are the core components of any ticket. As summary is described by Jira, it should represent a short textual description of the bug or the feature request. However, we have identified tickets having summaries with even more than 200 words. This is not optimal and might obfuscate the essential reason of filing that ticket from triagers and developers working on the project. One of the findings Zimmermann et al. [29] present in their study is that a good, succint summary can significantly reduce the effort invested by the developers.

Description, on the other hand, even though it is made to be a more detailed summary of the report, it should still be within some reasonable parameters. During our analysis process, we identified more than 50 tickets having descriptions with more than 4,000 words. Even though they included various types of information, including steps to reprodce, we believe that the reason why Jira and the other popular issue tracking systems created so many fields for bug reports is that the information that could all be put in description should be split across these fields:

- if there are stack traces or steps to reproduce, as we mentioned above, there should be specific fields created exclusively for them;
- if the end user is an experienced one and has reported numerous bugs or feature requests for the project, they might also be able to provide an estimate for the difficulty of the task; however, that should be stored in the Jira system field called Story Points;
- the user might also want to provide excerpts of code or previous discussions with other end users/developers; however, they should not upload it inside the description field, but rather create a text attachment (e.g. markdown document) and attach it separately so that they keep the description clean and easy to follow.

A solution for this issue could be a setting to cap the total number of words allowed for summary and description. Even though this is possible with Jira, the process of configuring it is not trivial, thus many administrators do not perform this step. An even better approach would be to have a tool automatically generating word limits based on, for example, the experience of the reporter - if he/she has significant knowledge regarding the project, they should be allowed to include lengthier summaries or descriptions mainly because they are more inclined to know that without a very good reason, following this approach is not the most optimal way.

Another simple and straightforward solution can be the simple addition of hints below or above the text boxes for summary and description where administrators can write succint messages adivising reporters to not write verbose paragraphs unless they really have a very good reason to do so.

5.6 Grammar Correctness

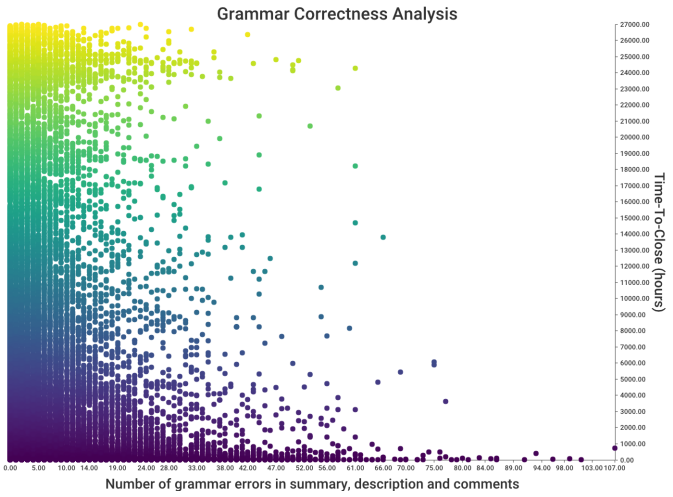

Figure 7: Grammar correctness score analysis.

By calling Microsoft Azure's Bing Spell Check API, one of the best grammar analysis APIs in the industry, we managed to calculate the total number of grammar errors in summary, description and comments for a total number of 133,689 tickets. As shown in a number of studies, the number of spelling errors can influence the quality of a ticket. However, in the work conducted by Schugerl et al. [24], the authors found that spelling errors can be found in both high and low quality tickets, thus should not be considered as a reliable factor for determining the Time-To-Close for a ticket. In the rest of this section we will demonstrate the contrary - tickets with more grammar errors (spelling errors are just a subset of the types of errors we are investigating) imply lower quality tickets (i.e. increased *Time-To-Close*).

This analysis type is called grammar correctness rather than spelling scores because the range of errors returned by Bing Spell Check API are of many types, some of which are:

- spelling errors; however, they go much further than a simple character mistyped - for example, if one would type Micrsft, it would automatically flag it as a grammar error because it also takes into account a large database of words not in standard dictionaries, but also popular words in the tech world (e.g. company names) or jargon language (e.g. dab dance);

- contextual errors - e.g. I ate a book today; even though this is not a misspell, the API will return *book* as a grammar error due to the fact that it is used in the wrong context;
- it can detect the wrong usage of a verb tense in a specific context;
- it can flag wrong conjugations of verbs.

After concatenating the strings for all comments, summary and description, we ran our analysis and then plotted the data which is depicted in Figure 7. A correlational analysis revealed a weak positive relationship with $r = 0.134$ and $p < 0.01$. Thus, our results are statistically significant, implying that having more grammar errors in a ticket will increase the Time-To-Close for a ticket and, thus, decrease the quality.

This is expectable as having a text difficult to grasp and understand makes it harder to reason about what needs to be done in order to fix a ticket. As it can be seen in the graph, most tickets are concentrated in the range of 0 to 40 grammar errors per ticket. Having 40 grammar errors in a ticket is quite a large number, considering the fact that many tickets don't have comments at all and summary and description are not large in general.

However, we can not change this through automation like the solutions we presented in the previous analysis types. We cannot call, for example, the Bing Spell Check API every couple of seconds on the text the user is inputting in the ticket as the costs would become unbearable very rapidly. Thus, what can be done to fix this? It is, after all, in the human nature to make mistakes, and mistyping is no exception. If we, for example, have some hint or a rule in the code of conduct for the project stating that everything should be 100% gramatically correct, many reporters with a different language than English as their primary one would feel unwelcome and they might not get involved in the project anymore.

The solution we are proposing implies a local, lightweight spell checker that is run automatically as the user types. This tool would not make any external calls, so there would be no costs and the load on the server would also be lower. There are already local applications that can be used for performing such real-time analysis on the text, one of them being LibreOffice's built-in spell checker.

5.7 Sentiment Scores

Sentiment analysis is a technique of employing Machine Learning algorithms in order to infer a sentiment score from textual information. These algorithms need to be trained on very large data sets in order to produce valid results. Moreover, we would have also needed an already annotated data set, which means a number of strings where we compute the score by hand given a mathematical formula we define. Even though there are open source libraries that can help with creating and employing the algorithms, such as TensorFlow, we would still have needed tickets where we defined what is meant by positive/negative tickets, as well as manually computing the scores for a large range of them. Therefore, we ended using a third party API - Google Cloud Platform Natural Language Processing, considered the best such service at the moment. This API returns a score between -1 (most negative) and +1 (most positive) for any text encoded in the HTTP request.

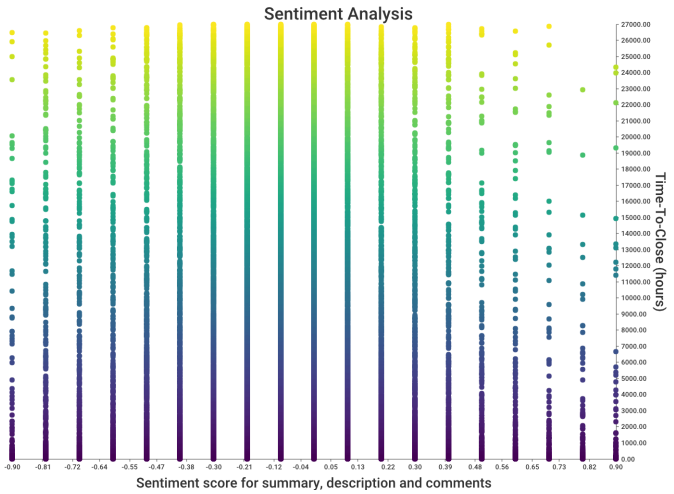

Figure 8: Sentiment score analysis.

After we concatenated summaries, descriptions and all the comments for every ticket, we sent our requests to Google and we plotted the data shown in Figure 8. A correlational analysis revealed a weak negative relationship with $r = -0.114$, $p < 0.01$. Therefore, we obtained statistically significant results implying that as the sentiment decreases (i.e. becomes more negative), the Time-To-Close increases, thus decreasing the quality of a ticket.

We can see in Figure 8 that neutral scores (i.e. between -0.42 and 0.42) correspond to rather average *Times-To-Close*, as was expected.

However, as the sentiment decreases, we can clearly observe that the *Time-To-Close* increases significantly. This might signify that once the discussion becomes "heated", the developers might lose interest in solving the task anymore. Also, rude language might be a driver for increased *Times-To-Close*: the engineer might become rude or impolite, which can make the interlocutor feel unwelcome and start to lose interest in helping the project anymore.

On the other side of the spectrum, having a more positive score leads to reduced *Time-To-Close* values for tickets. Calefato et al. [6] conducted a study where they show that a positive sentiment has the biggest impact on the quality of an answer on Stack Overflow, one of the most popular websites related to programming in general. This implies that when developers and triagers treat their reporters respectfully and offer support whenever possible, the users will feel more welcomed and willing to help report other bugs in the future as well. We also have scores of over 0.9, meaning that the actors participating in the discussion (or the reported summary/description) might compliment each other for doing a great job.

We strongly believe that having a positive sentiment score for tickets is beneficial for everyone: the company behind the projects sees increased overall performance and productivity, developers feel better working in the team or on that specific tool and reporters will be more willing to contribute in the future with other tickets.

A solution for pushing towards this ideal scenario would be expensive for the company, but the most efficient - have a sentiment analysis tool running in the background as the

user is typing in any text box. If they reach a certain low threshold and it is believed that they are becoming rude or unpolite, there could be a warning/pop-up on the screen advising them against submitting the comment and encouraging them to be polite, engaging and friendly. One other solution is a much more cost-effective one, but less efficient - the issue tracking system administrators could include a section in the code of conduct for the project stating that promoting a positive environment will help everyone. This way, people revolving around the project might be more inclined to be friendly.

6. FUTURE WORK

The first extension to the Go tool we created would be to add support for Bugzilla. We already achieved this when we were first prototyping the application, but we decided to proceed exclusively with Jira mainly because the APIs proved to be more reliable and also versatile in terms of what data could be collected. Another reason was that we were time restricted, thus we wanted to have first a well tested and stable solution for Jira and only after add support for other issue tracking systems. However, we already prepared for other potential systems by adding interfaces for tickets and REST clients, making Bugzilla, Manuscript, YouTrack or any other issue tracking system straightforward to add to the application.

One other improvement to the application could be adding more robust support for statistical analysis. At the moment, our tool uses our own custom types and functions for generating Welch T Test and Spearman R Test results, and even if it produces the expected p and r *coefficient* values, end users of the application might want to analyse even more possible correlations. As the Go community lacks native libraries to perform statistical tests, the users of our tool might miss the simplicity of running such tests in R. A solution can be to integrate Senseye's Roger library [25] inside the stats package, which basically allows any Go application to communicate with R via TCP.

There is also room for future work in terms of the data collected. Even though the database we collected is large, there are never too many tickets to analyse. Thus, the store command of the tool could be run against other Jira instances apart from Apache's and collect tickets from other projects, thus improving the diversity and the total number of tickets to be analysed. As we did not have access to any cluster or virtual machines in the cloud, we ran all our analyses on local machines (laptops) and it could still take well over two hours to complete with over 10 GB of RAM and 70% CPU in usage.

Furthermore, the project could greatly benefit from having access to closed source repositories in addition to the open source ones. Most closed source projects have much more structured planning, tracking and management activities - as Crowston et al. [9] present in their study, open source projects lack organized coordination which, in the context of our study, means that people do not invest much effort into properly creating tickets in issue tracking systems, triaging efficiently, planning the work and tracking it. On the other hand, closed source projects follow more strict guidelines: standard working hours (would make tracking and linking the source code changes to tickets easier), adding story points (i.e. adding estimated difficulty or time to complete) and properly planning tickets before work starts on the task, tickets properly distributed to developers based on availability and expertise etc. These benefits of closed source projects would prove helpful for our analysis.

Another aspect that could be improved is allocating a budget for Google Cloud Platform credits. This would be required for running the Natural Language Processing APIs on large amounts of data. We used the credits provided in the free trial but quickly ran out completely after only 160,000 tickets. Also, credits on Microsoft Azure would prove useful as their Spell Check API is the most efficient at the moment.

A major future work candidate is availability of a technique to calculate the difficulty of a ticket based on the information inside it. Unfortunately, at the moment, the research community has not come up with such an approach. Vijayakumar et al. [27] proposed a method of predicting how much effort is required for fixing a bug, but after running it on our data, it did not prove successful. After such a technique becomes available, we could incorporate it inside our tool and group the tickets compared in all analysis types based on their difficulty in order to have better results.

We wish that our final deliverable would be either a *goodness* metric, describing the quality of a ticket based on the information inside, or a recommender tool that could automatically create high quality tickets. This requires intensive work over a longer period of time, but we believe that with the findings presented in this study together with other state-of-the-art research in the field, it is possible to implement it.

7. CONCLUSIONS

Software tickets are a vital part of every software project's lifecycle. Even though there might be other means of planning, managing and tracking work for a software team, issue tracking systems are deployed in virtually any company that provides a computer application or service.

Deriving a quality score only from textual information and other non-structured data such as images is not trivial. However, in this study we managed to create an application that can automatically fetch and store tickets from any Jira instance, analyse them and compute statistical tests and graphs.

We managed to answer all seven research questions and find factors that can positively or negatively affect the *Time-To-Close* value of a ticket. All of our results are statistically significant and we can summarise them as follows:

- the presence of steps to reproduce reduces the *Time-To-Close* for a ticket;
- the presence of stack traces reduces the *Time-To-Close* for a ticket;
- the presence of attachments reduces the *Time-To-Close* for a ticket - more specifically tickets with screenshots, config files or text files help tickets get closed quicker than those without attachments;
- higher numbers of grammar errors imply increased *Time-To-Close* values;
- higher sentiment scores imply reduced *Time-To-Close* values for a ticket;
- higher numbers of words in comments imply increased *Time-To-Close* values for a ticket;

- higher number of words in description and summary increase the *Time-To-Close* values for tickets.

We intend to continue work on the project and implement the points we have listed in Section 6. We believe that by open sourcing the application and making the data publicly available, we can provide a valuable starting point for other studies investigating this particular field of software engineering.

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