SMM695

Data Management Systems

Final Group Project

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Group 9

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1. Data cleaning & structuring

The bug data for the Mozilla project was initially cleaned and structured using Python and PostgreSQL. After an initial exploration of the bug dataset, it was observed that there are instances of duplicate information like some assignee information from the "assigned_to_detail" field. Additionally, certain fields contain sub-information that requires cleaning, such as bugs, comments, flags, etc.

To ensure efficient storage, retrieval, and analysis of bug data with consistent integrity, a table called "users" was established. This table contains various personal and contact information such as real names and email addresses. The "users" table accommodates a total of 67,576 user accounts originating from 50,756 distinct users, implying that some individuals possess multiple accounts using various email addresses. To avoid data redundancy and enable efficient storage, the "users" table is designed to store user details only once. Instead of duplicating user information for each bug report, the "reports" table utilizes foreign keys to reference the relevant user details from the "users" table. This approach optimizes the database structure, ensuring consistency and integrity while minimizing data duplication. As a result, bug reports can efficiently link to the corresponding user information through these foreign keys, streamlining the storage and retrieval process while facilitating effective data analysis.

The "report" table is the primary table in the Entity-Relationship Diagram (ERD). It contains essential information about each bug sourced from the datasets. This table houses a comprehensive collection of bug data, encompassing 213,312 bugs contributed by 1,776 users. By consolidating key attributes such as bug ID, summary, status, priority, component, version, target milestone, and additional details into a single cohesive structure, the "reports" table ensures the logical consistency of bug report data. This consolidation not only facilitates better comprehension but also streamlines efficient bug management. For instance, querying the "reports" table directly allows for easy retrieval of bug data with specific statuses or priorities. Furthermore, leveraging the foreign key "assigned_to_id," it becomes effortless to identify users associated with particular bugs. The design choices in the "reports" table enhance data accessibility, accuracy, and relational integrity, making bug analysis and user tracking seamless and effective.

Foreign key constraints play a crucial role in maintaining referential integrity. In the case of four other tables including changes_history, customer_fields, flags, and comments, their foreign key constraints are established to reference the primary key (bug_id) in the reports table.

- The “changes history” table keeps track of the historical modifications made to bug reports. Each entry in this table corresponds to a specific bug report, identified by the “bug_id” foreign key. It stores important details like the timestamp of the change, the user responsible for the modification, the field name that was altered, and the “added” and “removed” values. This information provides valuable insights into how the bug has evolved over time.
- The “customer_fields” table allows for the storage of additional custom fields related to specific bug reports. Each entry in this table is linked to a bug report using the “bug_id” foreign key. It includes the “cf_field_name” to denote the custom field. This table provides flexibility to include user-defined data that might not fit into the standard bug report attributes.
- The “flags” table contains information about various flags associated with bug reports. These flags serve as metadata markers and are linked to the respective bug report through the “bug_id” foreign key. The table holds details such as the type of flag, the “setter” user, the “status” of the flag, and timestamps for “creation_date” and “modification_date.”
- The “comments” table stores the comments and discussions made on specific bug reports. Each comment entry is linked to a bug report using the “bug_id” foreign key. The table includes details such as the “creator” of the comment, the “creation_time” of the comment, the “is_private” status, the “author” of the comment (if different from the creator), the raw text, and the processed “text” of the comment. Additionally, the “count” field keeps track of the total number of comments for a particular bug report, while “tags” allow for additional categorization.

This design ensures that the data contained within these tables correspond to valid bug reports. In addition, utilising these four tables facilitates sorting and organizing various details linked to a unique bug ID. For instance, the “comments” table allows for the storage of numerous discussions, updates, or user interactions pertaining to a bug, and the comments relevant to a bug report can be looked up using the bug_id foreign key. This functionality ensures that crucial context and historical data are preserved for future reference. Similarly, the changes history table documents the modifications made to a bug report over time, capturing essential information such as the modified field, the responsible user, and the old and new values. This capability enables efficient tracking and review of the bug report’s progression.

As the bug data grows over time, the separate tables can handle an increasing number of records efficiently. Additionally, the design accommodates future changes or additions to the data structure, such as introducing new fields or relationships, without requiring major modifications

to the existing schema. This design effectively prevents inconsistencies and inaccurate data associations, ultimately resulting in a more dependable and precise database.

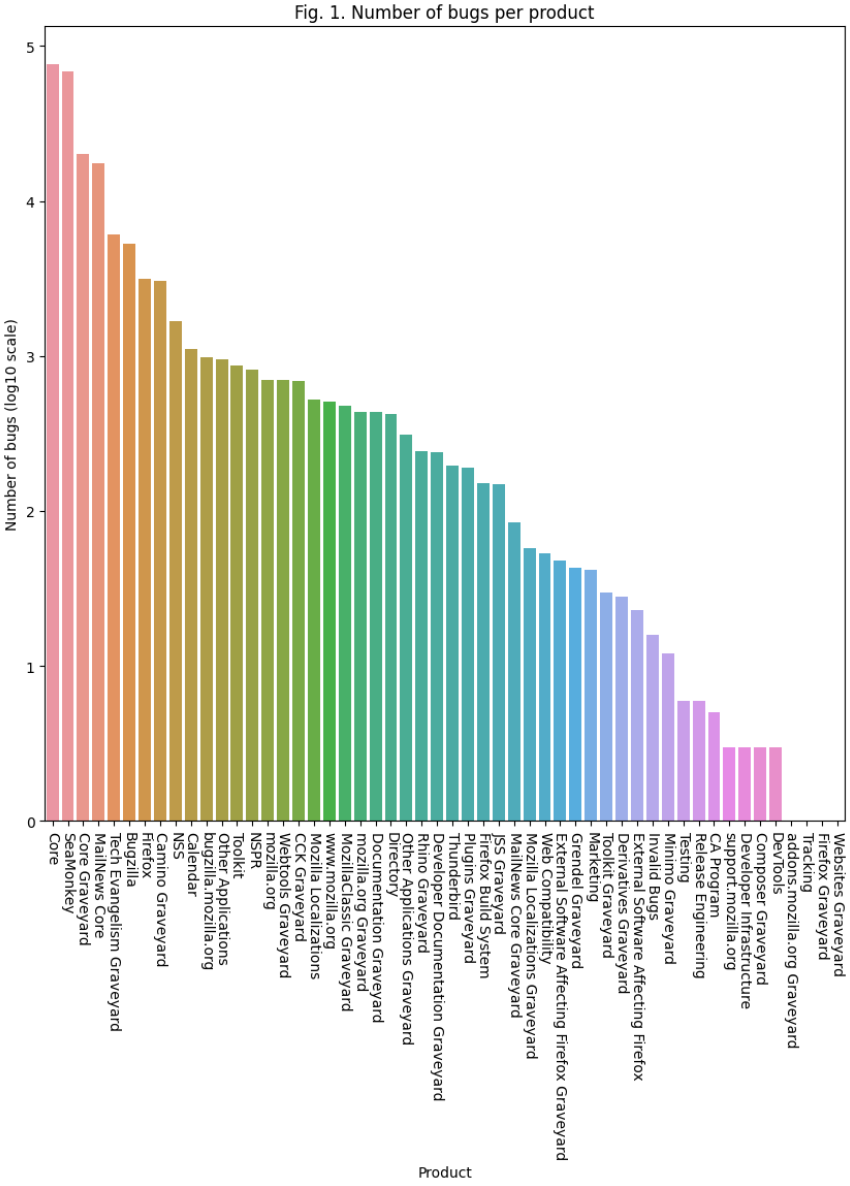
2. Descriptive insights

Using descriptive statistics and visualisation, we aim to analyse Bugzilla bugs to gain insights into its key metrics and enable informed decision-making for bug prioritisation, resource allocation and quality improvement.

2.1 Bug analysis

Total number of bugs at product level – In Fig. 1, we present the total number of bugs associated with each product, to gain insight into relative bug occurrence among various products. The highest number of bugs are for the *Core* followed by *SeaMonkey* product.

Fig. 1. Number of bugs per product

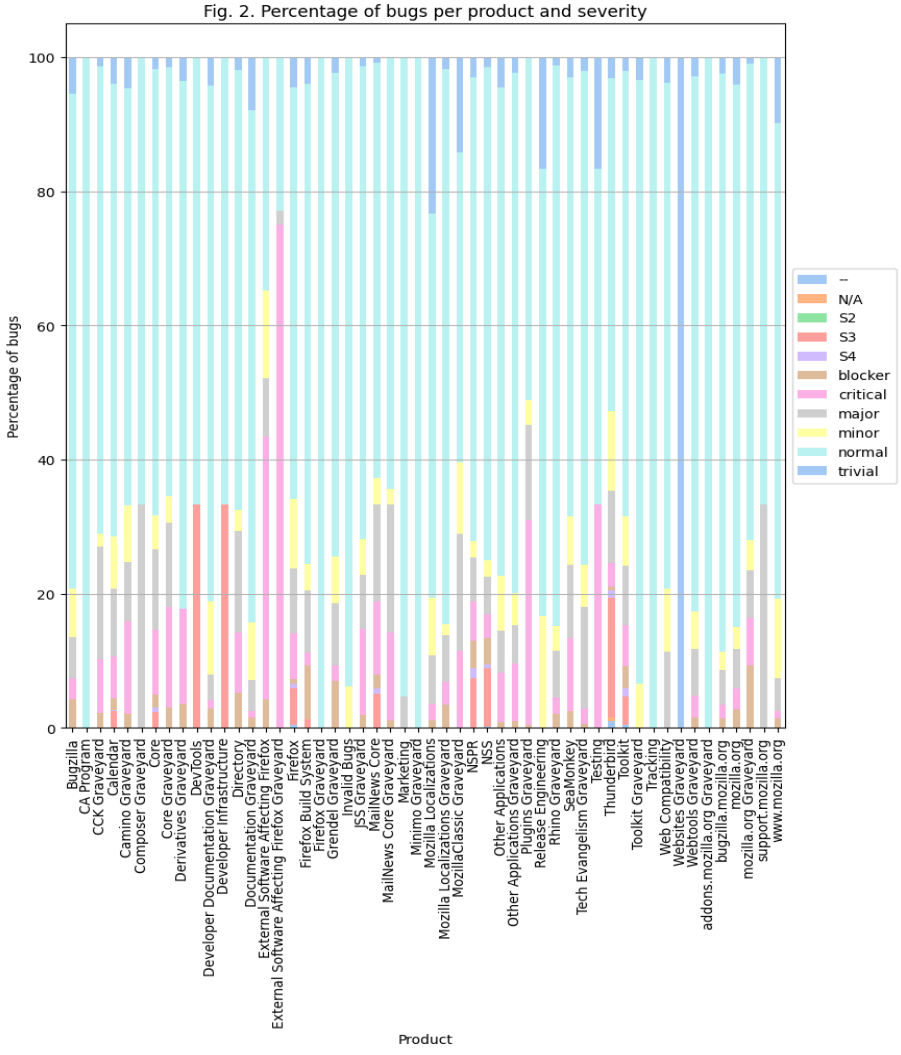


	product text	bug_count bigint
1	Core	76124
2	SeaMonkey	68769
3	Core Graveyard	20022
4	MailNews Core	17573
5	Tech Evangelism Graveyard	6073
6	Bugzilla	5282

Table 1. Top 5 products by bug count

Distribution of bugs by severity per product – We display the percentage distribution of bugs across various products (Fig. 2), with severity levels stacked to provide insights into bug composition within each product. We observe that most of the bugs are of the category *normal*. The product *Websites Graveyard* only has *trivial* bugs, and the product *tracking* only has *normal* bugs. The highest percentage of critical bugs is in the product *External Software Affecting Firefox Graveyard*.

Fig. 2. Percentage of bugs per product and severity

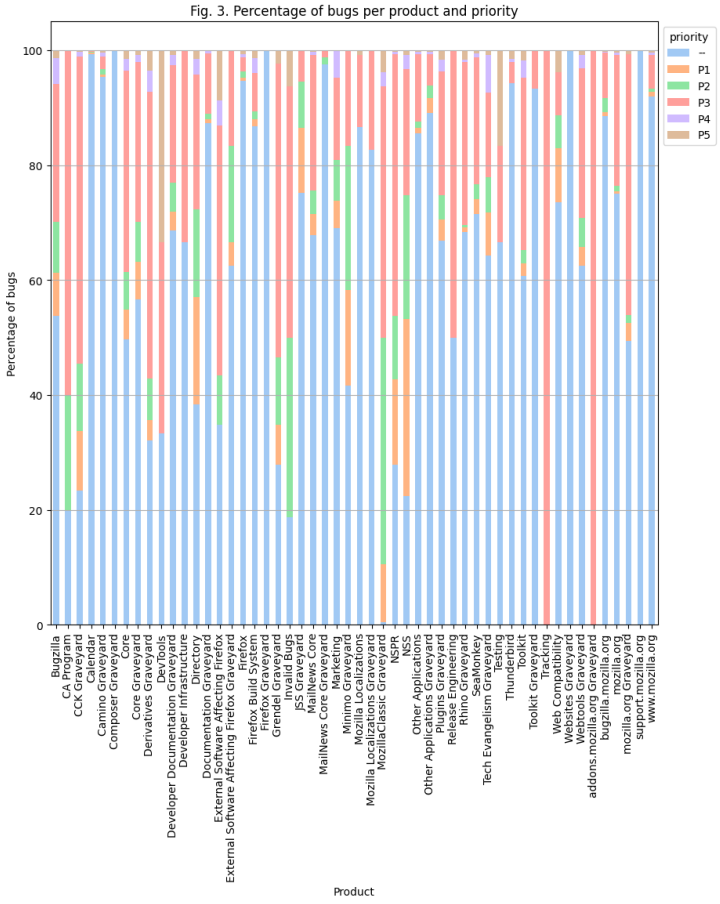


For the product *Core* which has the highest number of bugs, 66% of the bugs are *normal* followed by 12% *major* bugs.

	product text	severity text	bug_count bigint	log_bug_count double precision	percentage numeric
1	Core	normal	50685	4.704879450830577	66.5821554306132100
2	Core	major	9144	3.9611362173872253	12.0119804529451947
3	Core	critical	7388	3.868526886768204	9.7052178025327098
4	Core	minor	3850	3.5854607295085006	5.0575377016446850
5	Core	S3	1749	3.2427898094786767	2.2975671273185855
6	Core	blocker	1399	3.1458177144918276	1.8377909726236141
7	Core	trivial	1303	3.1149444157125847	1.7116809416215648
8	Core	S4	577	2.7611758131557314	0.75797383216856707477
9	Core	--	21	1.3222192947339193	0.02758656928169828175
10	Core	N/A	8	0.9030899869919435	0.01050916925017077400

Table 2. Distribution of bugs per severity level for the product *Core*

Distribution of bugs by priority per product – In a similar way, we visualise the bugs by priority per product in Fig. 3 and observe that most of the bugs are of priority level *P3*.



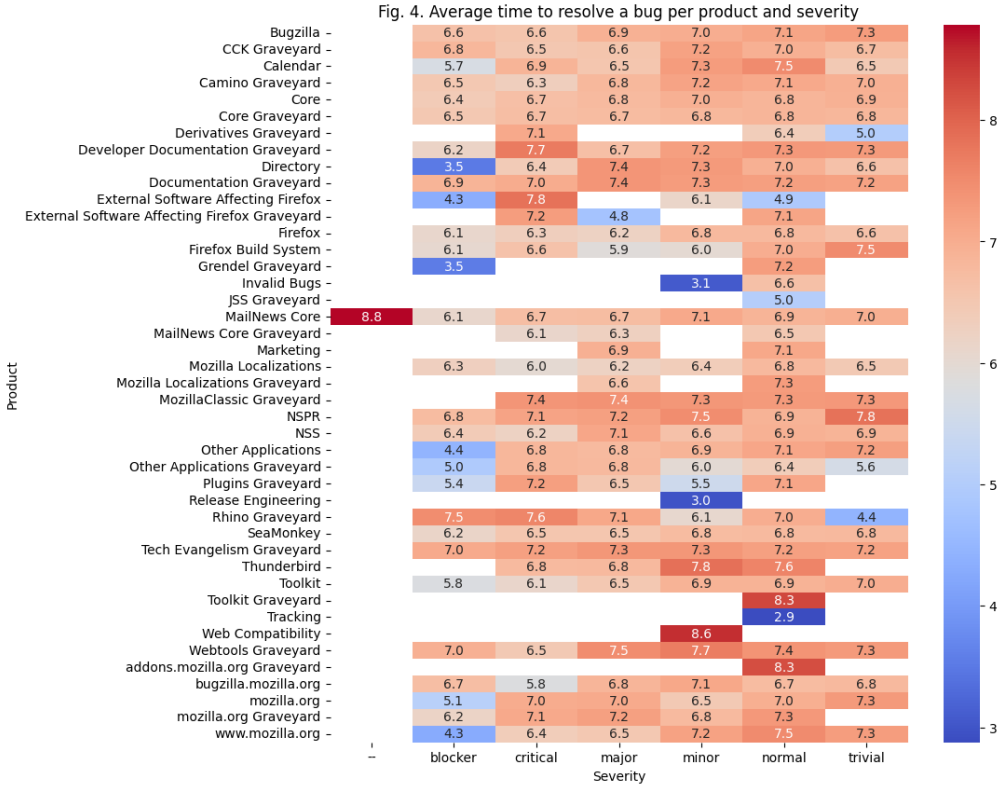
For the product *Core*, 49.76% of the bugs are *in '- -' (no decision)* followed by 34.98% *P3* bugs.

	product text	priority text	bug_count bigint	log_bug_count double precision	percentage numeric
1	Core	--	37880	4.5784099703312355	49.7609163995586149
2	Core	P3	26632	4.425403782148611	34.9850244338185066
3	Core	P2	5041	3.7025166974381505	6.6220902737638590
4	Core	P1	3892	3.5901728315963144	5.1127108402080816
5	Core	P4	1534	3.185825359612962	2.0151332037202459
6	Core	P5	1145	3.0588054866759067	1.5041248489306920

Table 3. Distribution of bugs per priority level for the product *Core*

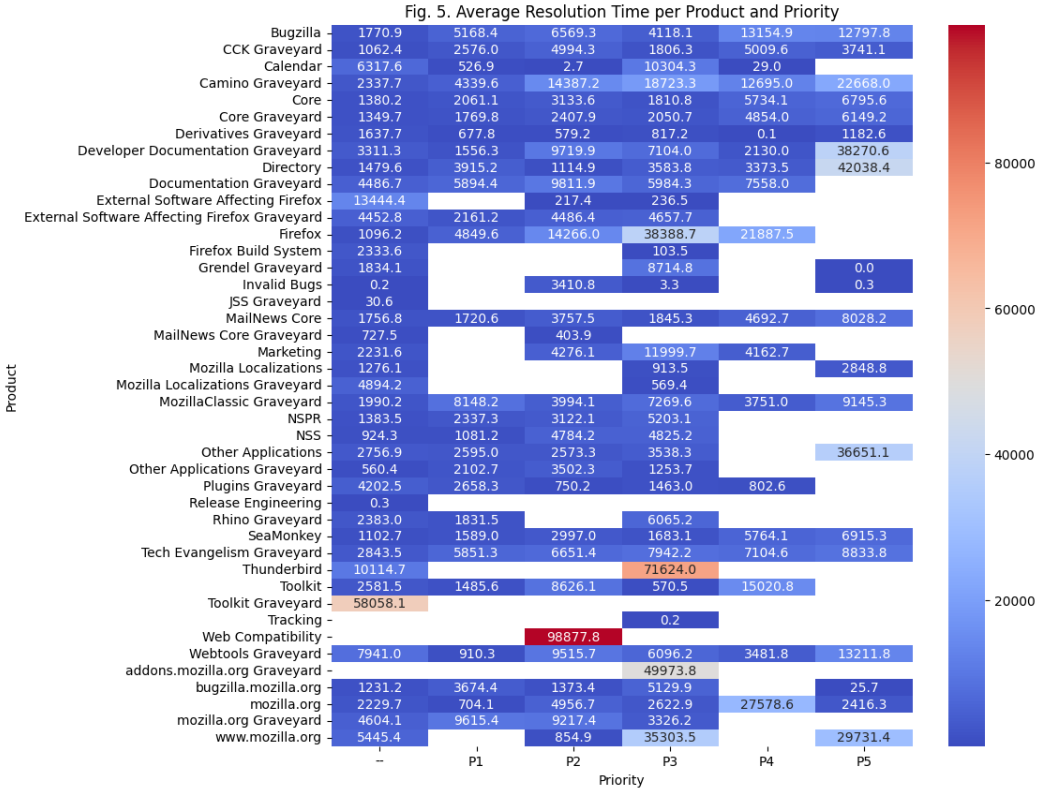
Average time of resolution of bugs per severity level for each product – The heatmap below highlights the variations in resolution times per severity level for products to identify areas of improvement in the resolution process. The dark red shades represent longer resolution times (the highest is for *MailNew Core* – '- - 'severity level (default value for new bugs) while the bluer shades show shorter resolution periods (the lowest is for *Tracking*).

Fig. 4. Average time to resolve a bug per product and severity



Priority and average resolution time – In Fig. 5, a heatmap highlighting the variations in resolution times per priority level for products is shown, to identify areas of improvement in the resolution process. The highest resolution times (darker red) are for *Web compatibility – P2* priority and the lowest (darker blue) is for *Grendel graveyard – P5* priority.

Fig. 5. Average Resolution Time per Product and Priority



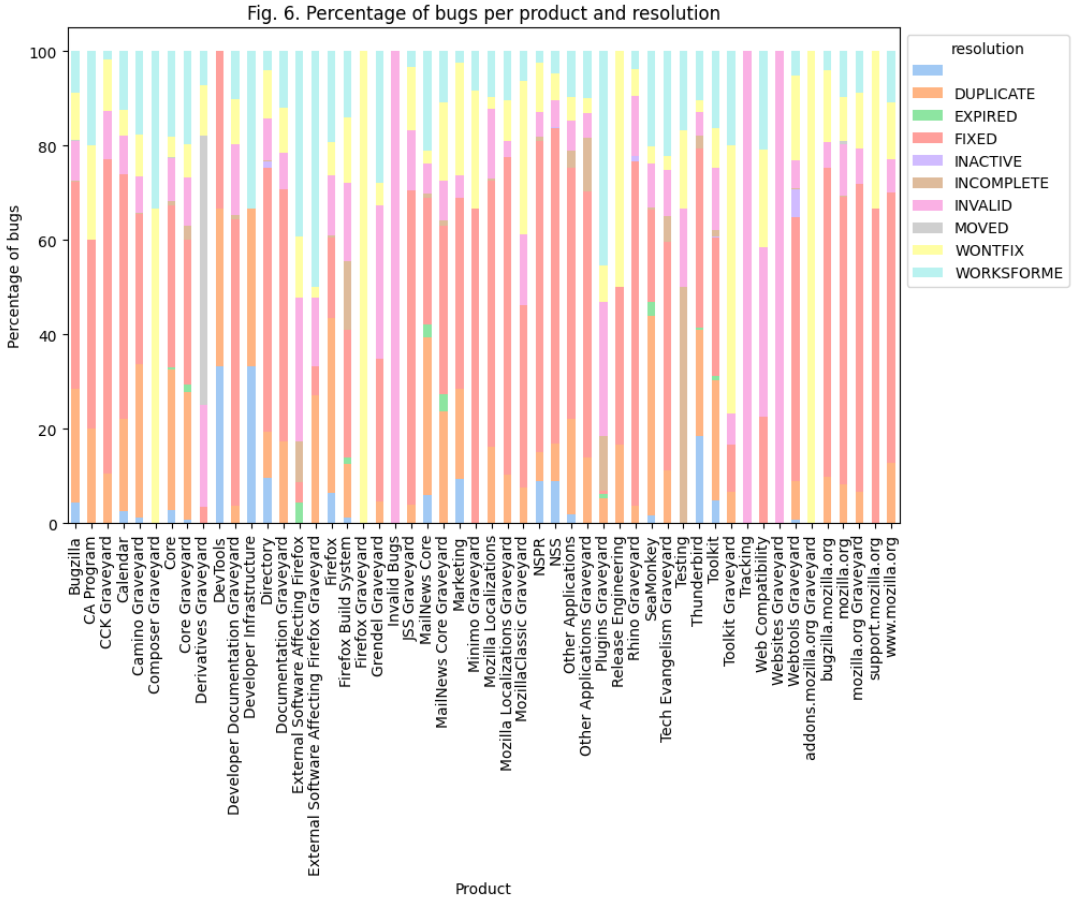
The table below shows the average resolution time in hours for each priority level for the product *Core*. We see that the highest average resolution time is for the *P5* category.

	product text	priority text	avg_res_time_hr numeric
1	Core	--	1380.23471577005846768958
2	Core	P1	2061.12162586246620054142
3	Core	P2	3133.55188338713279234390
4	Core	P3	1810.78927503618155136907
5	Core	P4	5734.12124317891559775831
6	Core	P5	6795.58952697262481674884

Table 4. Resolution times for the product *Core* by priority

Distribution of bugs by resolution per product – Here, we show the percentage of bugs for each resolution status of all products for the bugs that have been resolved (either verified or closed by a QA) to show how being are being resolved. It shows that the resolution status for most of the bugs is Fixed and we see quite a few bugs that are either in the status *Worksforme* or of the status *Wontfix*.

Fig. 6. Percentage of bugs per product and resolution



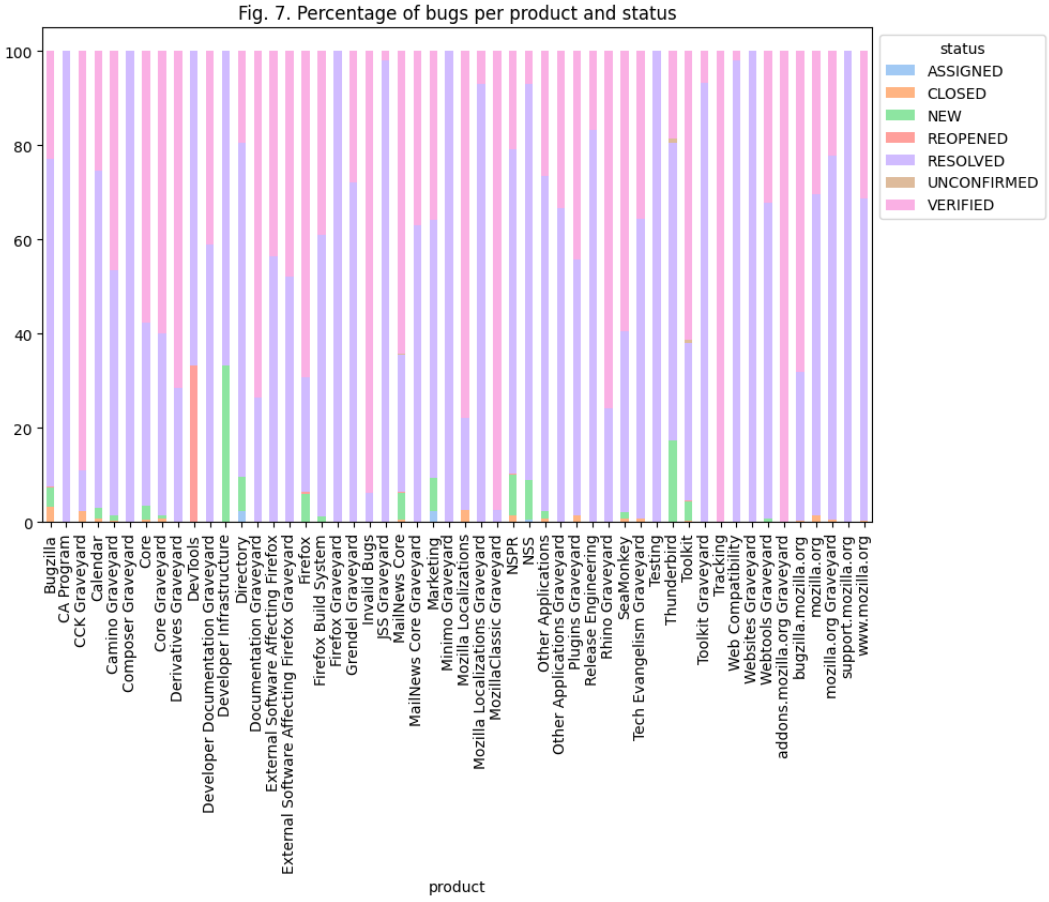
The bug counts for each resolution status level for the product *Core* show that 34% of the bugs have been *Fixed* and an almost equivalent number, 29% of the bugs are *Duplicate* bugs.

	product text	resolution text	bug_count bigint	log_bug_count double precision	percentage numeric
1	Core		2224	3.34713478291002	2.9215490515474752
2	Core	DUPLICATE	22586	4.353839323804543	29.6700120855446377
3	Core	EXPIRED	390	2.591064607026499	0.51232200094582523252
4	Core	FIXED	26007	4.415090257671115	34.1639955861489149
5	Core	INACTIVE	109	2.037426497940624	0.14318743103357679575
6	Core	INCOMPLETE	643	2.808210972924222	0.84467447848247596028
7	Core	INVALID	7031	3.847017097935354	9.2362461247438390
8	Core	MOVED	8	0.9030899869919435	0.01050916925017077400
9	Core	WONTFIX	3437	3.536179532137225	4.5150018391046188
10	Core	WORKSFORME	13689	4.136371723492323	17.9825022331984657

Table 5. Resolution statuses of bugs for the product *Core*

Distribution of bugs by status per product – Below is the visualisation to show the percentage of bugs in each status category to understand the distribution for effective resolution efforts. It shows that most of them are in the status Resolved or Verfied. The higher percentage of *Resolved* but not *Verified* bugs indicates that there are quite a few bugs that are pending QA verification.

Fig. 7. Percentage of bugs per product and status



The bug counts for each status level for the product *Core* also follow a similar trend. 57% of the bugs have been *Verified* by QAs and 38.8% have been resolved which is a good resolution rate.

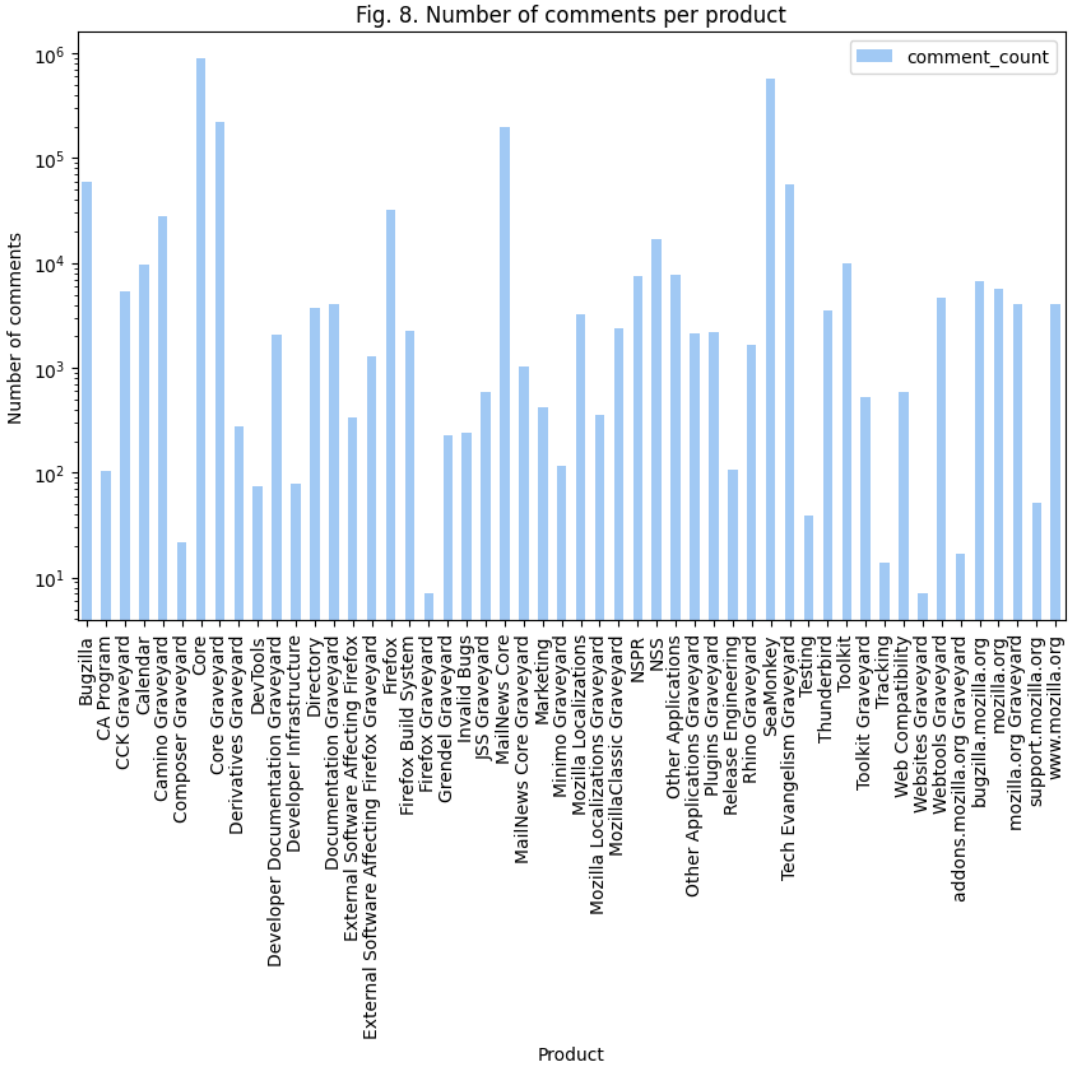
	product text	status text	bug_count bigint	log_bug_count double precision	percentage numeric
1	Core	ASSIGNED	7	0.8450980400142568	0.00919552309389942725
2	Core	CLOSED	498	2.6972293427597176	0.65419578582313068152
3	Core	NEW	2117	3.325720858019412	2.7809889128264411
4	Core	REOPENED	76	1.8808135922807914	0.09983710787662235300
5	Core	RESOLVED	29575	4.470924753299968	38.8510850717250801
6	Core	UNCONFIRMED	24	1.380211241711606	0.03152750775051232200
7	Core	VERIFIED	43827	4.641741743799373	57.5731700909043140

Table 6. Statuses of bugs for the product category *Core*

2.2 Comment analysis

Number of comments per product per bug – We visualise a bar chart to show the number of comments per bug at the product level to help understand the level of engagement around bug discussions within each product.

Fig. 8. Number of comments per product



From Table 7, the majority of them are of the *Core* product.

	product text	bug_id [PK] integer	comment_count bigint
1	Core	18574	772
2	mozilla.org Graveyard	27803	700
3	Core Graveyard	78414	685
4	Core	25537	631
5	Core	76831	450
6	Core	171441	436
7	Core	177175	429
8	MailNews Core	12916	427
9	Core	82534	410
10	Core	915	406

Table 7. Top 10 bugs with the highest number of comments

Comment vs Resolution time – We have plots of resolution time vs. a number of comments vs. severity vs. priority to see if a bug with a higher comment count is taking time to resolve, is of higher severity /priority.

Fig 9(a). Scatter plot matrix of resolution time vs. number of counts vs. severity

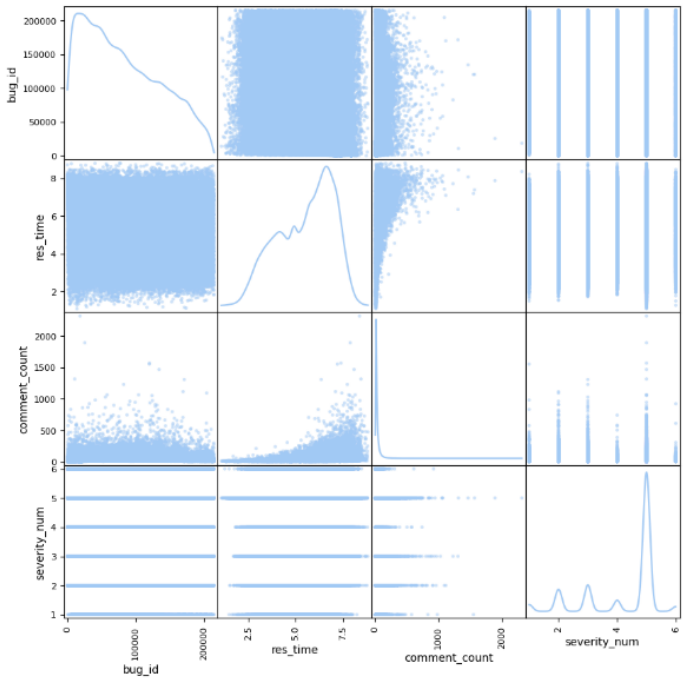
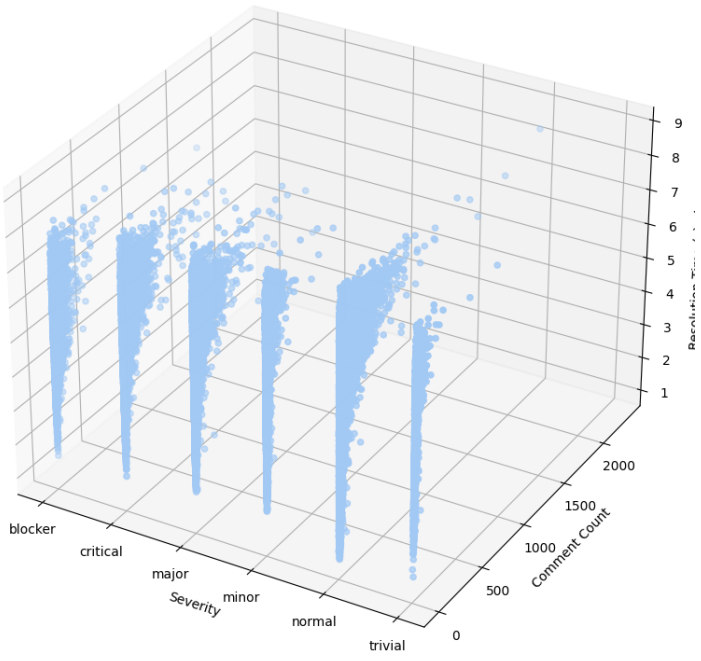


Fig. 9(b). Resolution Time vs. Number of Comments vs. Severity



A general trend that we observe is that for all the bug severity levels, as the number of comments on a bug increases, the average resolution time also increases. However, the

reverse is not true, i.e. a high-resolution time does not necessarily indicate a high comment count.

Count of comments per commenters – Below are the top 10 commenters (nicknames) in Bugzilla which can give insight into individuals actively involved in discussions and contributing to the community.

Commenter	Comment count
Bugzilla	73539
bzbarsky	47187
dbaron	24388
Matti	23993
asa	22602
sspitzer	22275
spam	22033
timeless	20066
leger	18585
Bienvenu	15634

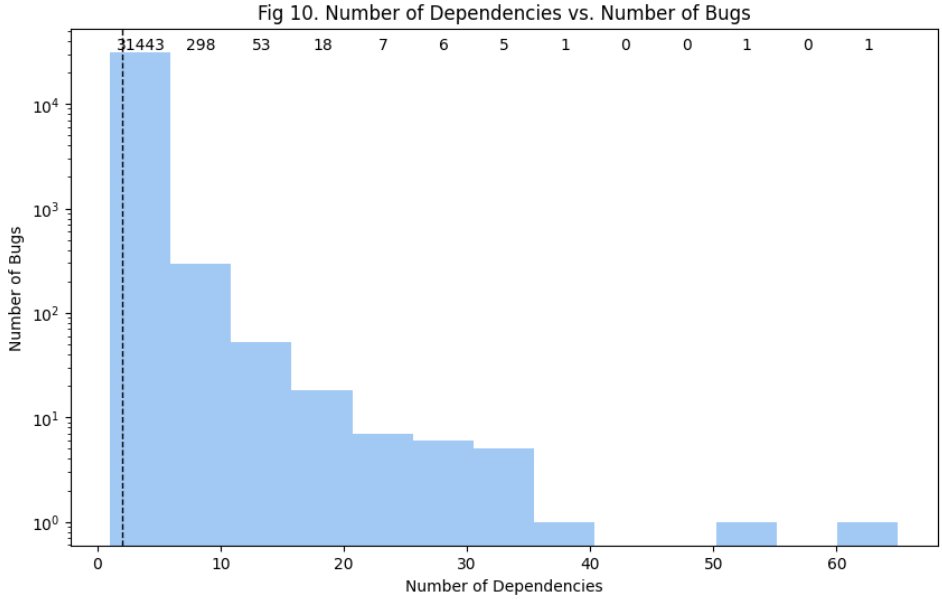
Table 8. Top 10 commenters

Correlation between votes and comment count: This is to see if bugs which have been voted (essential to fix) have a correlation with the comment count (being discussed more or not). A correlation value of **0.4** shows there was not a strong connection.

2.3 Dependency Analysis:

Bug dependencies – Below is the histogram of the number of dependencies for each bug. The vertical line indicates the 90^{th} percentile which tells that most of the bugs have less than or equal to 2 direct dependencies.

Fig 10. Number of Dependencies vs. Number of Bugs

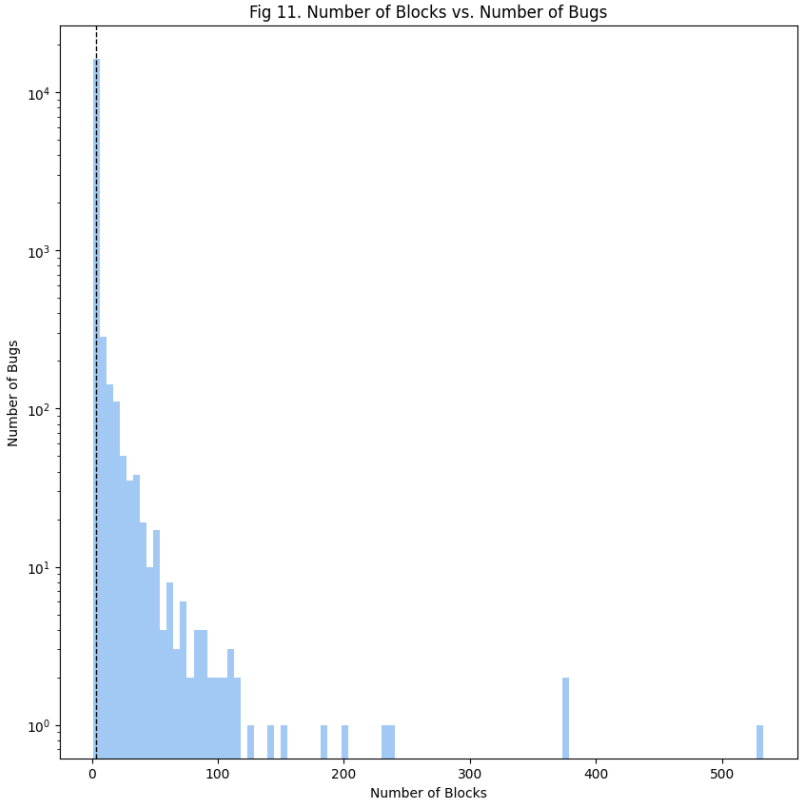


	depends_bugs integer	depends_count bigint
1	75338	65
2	180372	51
3	13374	36
4	34297	35
5	182500	33
6	83774	32
7	103386	32

Table 9. Top 7 bugs which have the highest dependencies

Bug blockage – The histogram of the number of bugs each bug is blocking. The vertical line indicates the 90th percentile which tells that most of the bugs have less than or equal to 3 direct bugs that it blocks.

Fig 11. Number of Blocks vs. Number of Bugs



	blocks_bugs integer	blocks_count bigint
1	104166	533
2	143047	378
3	83989	376
4	11091	238
5	92033	232
6	122274	202
7	7954	187

Table 10. Top 7 bugs which block the most bugs

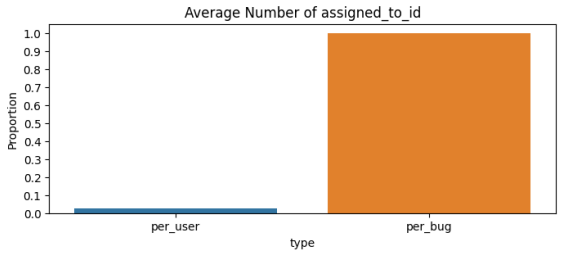
2.4 User Analysis

The user analysis aims to explore relationships between user types and bug categories.

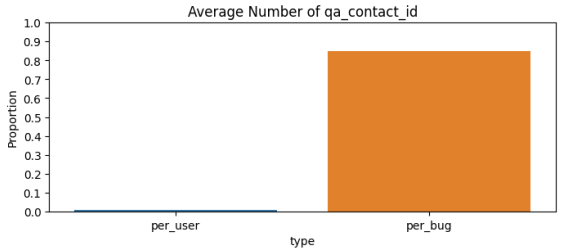
User roles and related bugs – According to the official document from Bugzilla, each bug will only have one developer in charge (defined by "assigned_to_id"), 1 QA (defined by "qa_contact_id") and multiple CC (defined by "cc_id). Each plot in Figure 12 below shows

how the proportions of users tagged as the above roles, and how many bugs have connections to those types of users. According to the first 2 charts, it can be implied that each bug will have one developer in charge and will be 85% likely to have one QA, but the developers in charge are only a minor group of users among the whole population (less than 3%). The last plot indicates that about 70% of users will receive a CC from at least one report and about 68% of bugs would be CC to at least one user.

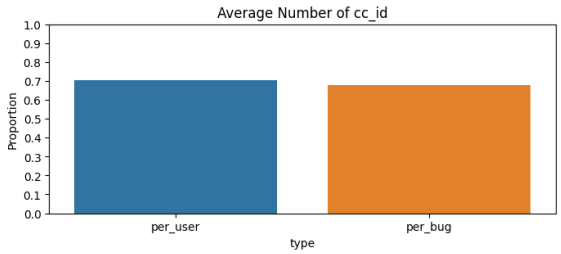
Fig. 12. User roles and bugs



	per_user numeric	per_bug numeric
1	0.026	1.000



	per_user numeric	per_bug numeric
1	0.008	0.848



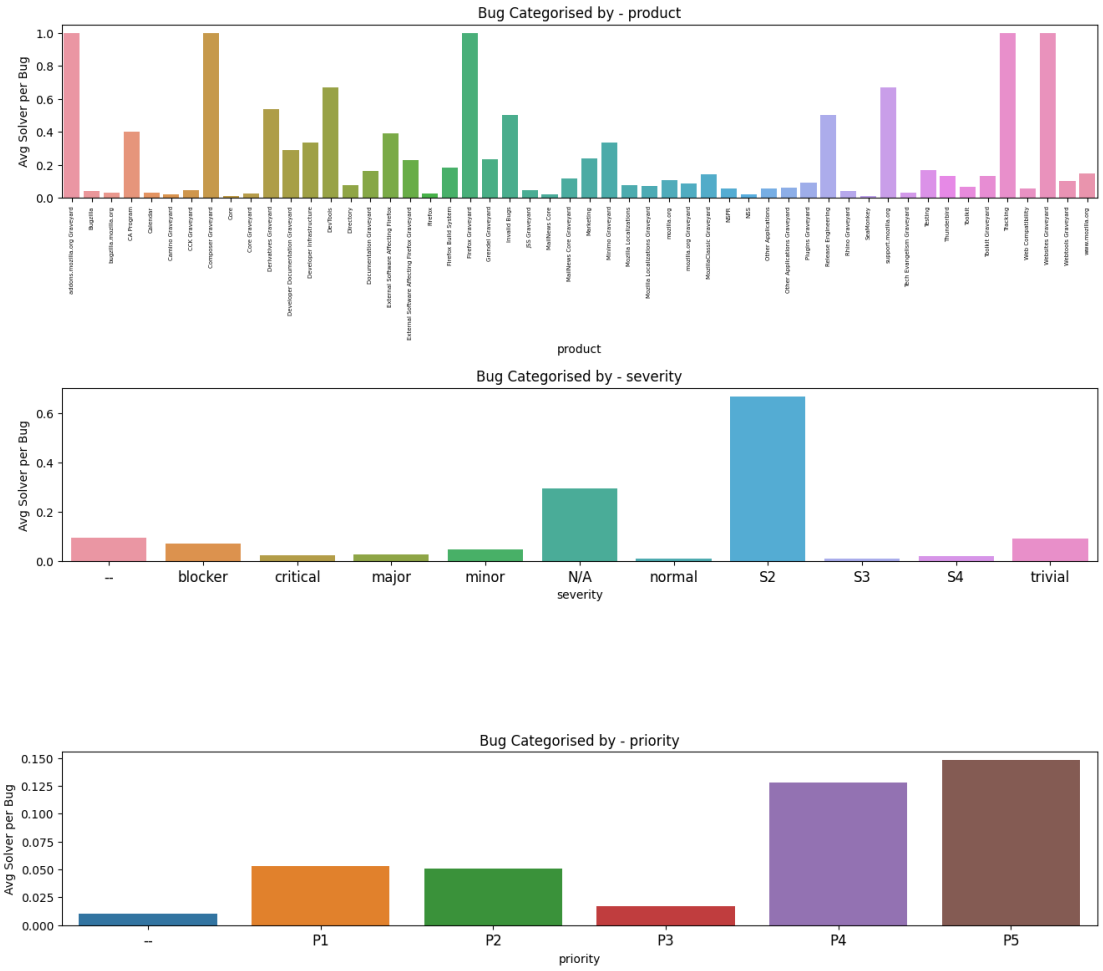
	per_user numeric	per_bug numeric
1	0.705	0.679

The ratio of developer in charge to bugs, by category

The relationship between developer in charge (assignee) and bug is a 1-to-many relationship. In the first chart of Figure 13, a few types of products are solved 1-to-1 by developers, but the average number of developers per product is around 0.246 and the median is 0.113.

In the second graph, two sets of severity scales can be noticed. There are relatively more solvers working on bugs of “S2” and “N/A” within the Firefox severity system, and more “blocker” and “trivial” in the default system. Considering that “S2” and “blocker” are the highest severity level, it can be implied that bugs with higher severity may have developers working on them. In the fourth graph, “P4” and “P5” are the priority levels that have more developers on average working on.

Fig. 13. Average number of solvers per bug by categories



Temporal analysis of status changes (intervals)

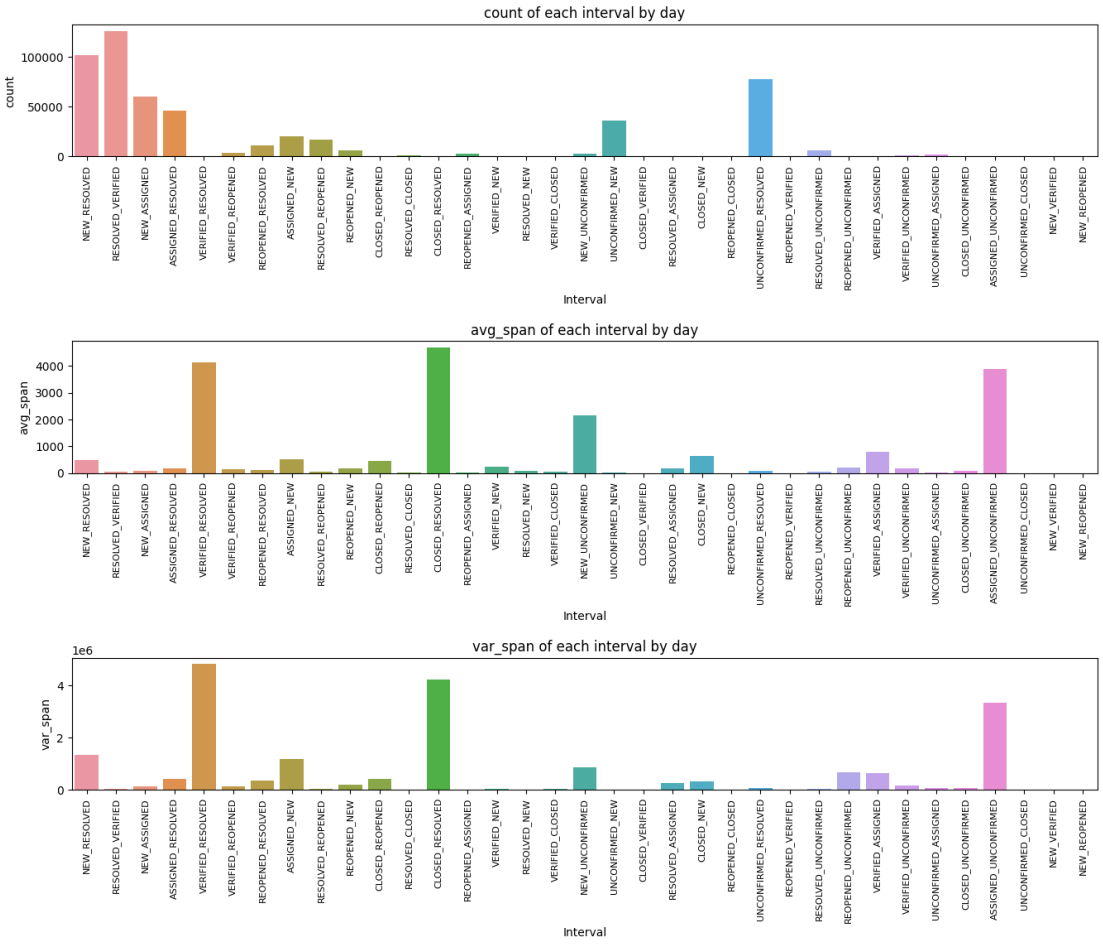
In Figure 14, the first bar chart indicates the count of different intervals. The average interval is around 14,974 days and only those major procedures of solving a bug have higher statistics. The most frequently recorded intervals are "UNCONFIRMED_ RESOLVED", "NEW_RESOLVED" and "RESOLVED_VERIFIED" which indicates that most bugs were resolved directly without going through the resolution process. By contrast, there are around 25 types of intervals that could not be found in the official document which are less frequently recorded. It cannot be inferred if these bugs were recorded by mistake or if they were just not recorded by the official document via this visualisation.

The second graph shows the average span by days of each interval. The average days of all intervals is 566, and the median is 83, which indicates that the data may be influenced by extreme values or outliers and is skewed distributed. According to the graph, "VERIFIED_RESOLVED", "CLOSED_RESOLVED" and "ASSIGNED_UNCONFIRMED" are the extreme interval types, whose average spans are higher than 4,000 days. Comparing the

2nd graph to the 1st graph, all anomaly types only have a few records and are not among the major resolving process according to the official document.

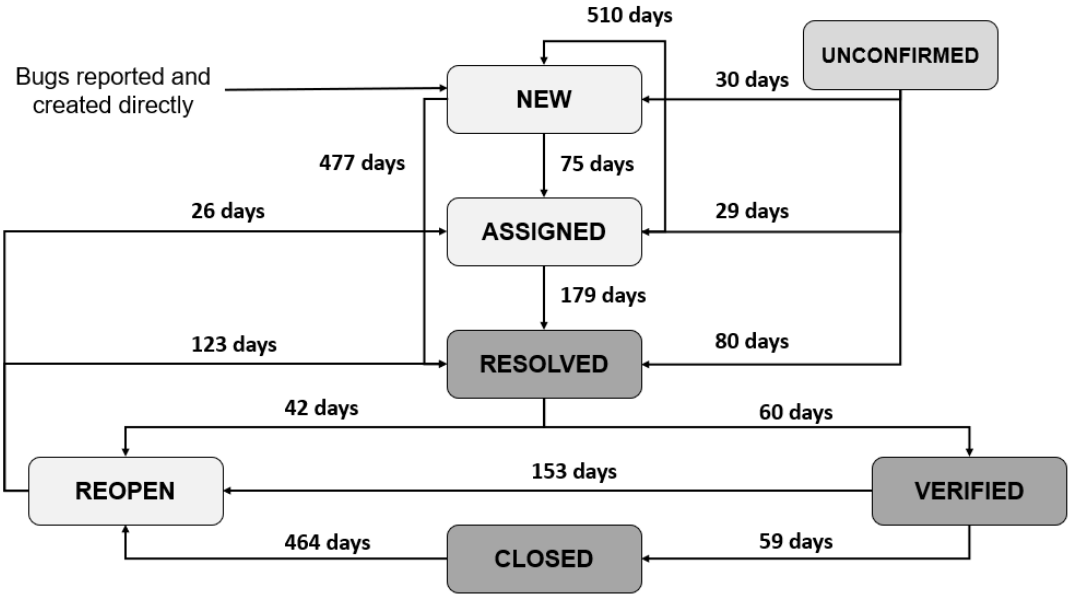
The third graph supports the previous argument, where the intervals that have extremely high variance are those types that have high mean values. The high variance indicates that the mean values of certain types of intervals may be influenced by a few extreme values among a smaller amount of data. The variance of "NEW_RESOLVED" is relatively higher than other common intervals, implying that this process might be diversified and less predictable compared to other common intervals.

Fig. 14. Count, average interval, variance of intervals (days) by status type



The average spans (by day) of the most common statuses are visualised below in the form of a flow chart (Figure 15).

Fig. 15. The average time taken between status changes



3. Network analysis

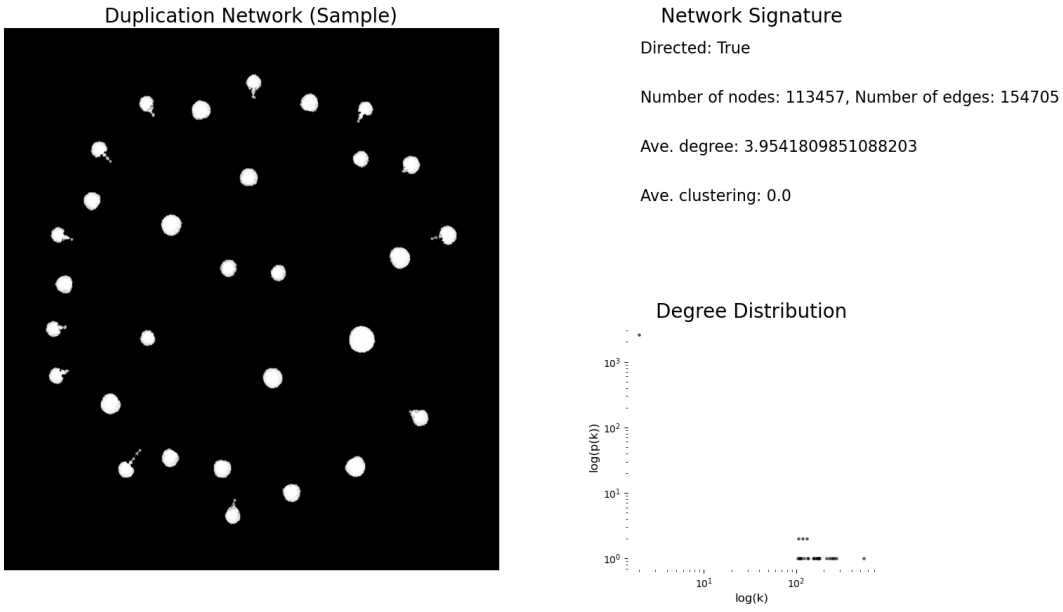
Utilising PySpark, a Python API for Apache Spark, we could efficiently manipulate and run in-depth analysis on the large volumes of data involved. We first established a secure connection to the database using PySpark, which allowed us unreadable access to each table required in the analysis.

Emphasising on the reports table, we ventured into network analysis with PySpark that involved multiple facets:

To begin with, we eliminated duplicated data arising from the 'duplicates' and 'dupe_of' relations. We assembled a visualisation model of the duplicate network. Due to the sheer volume of the network data, we created a function that portrayed a sample area of the network for better comprehensibility.

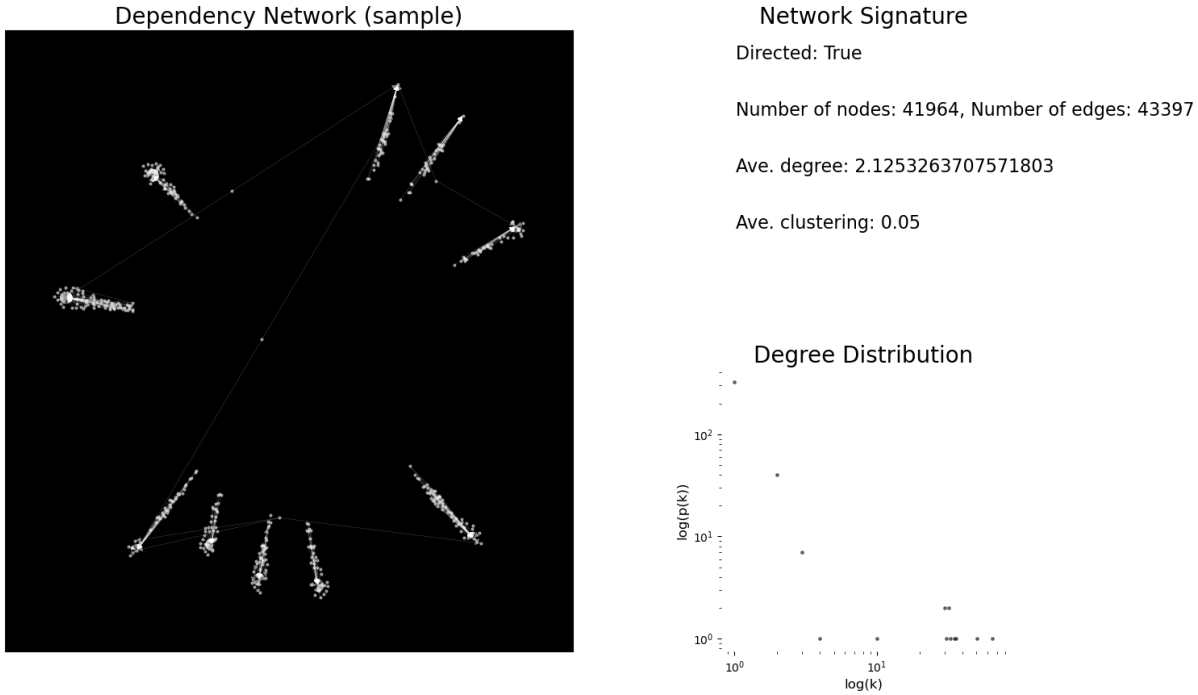
In the network of 113,457 nodes and 154,705 edges, an average degree of roughly 4.0 was observed. Although we detected a power law distribution, the sample size was insufficient to draw any definitive conclusions. The network was not entirely interconnected and showcased many isolated clusters with an apparent core centre. This structure could be attributed to the fact that bugs in software development often replicate each other as developers typically use similar, if not identical, pieces of code across multiple sectors of their project. This duplication, combined with the nature of bugs to be inconsistently dispersed across the software, can lead to isolated clusters with distinct centres, representative of the specific pieces of code where duplication has occurred.

Fig. 16. Duplication network



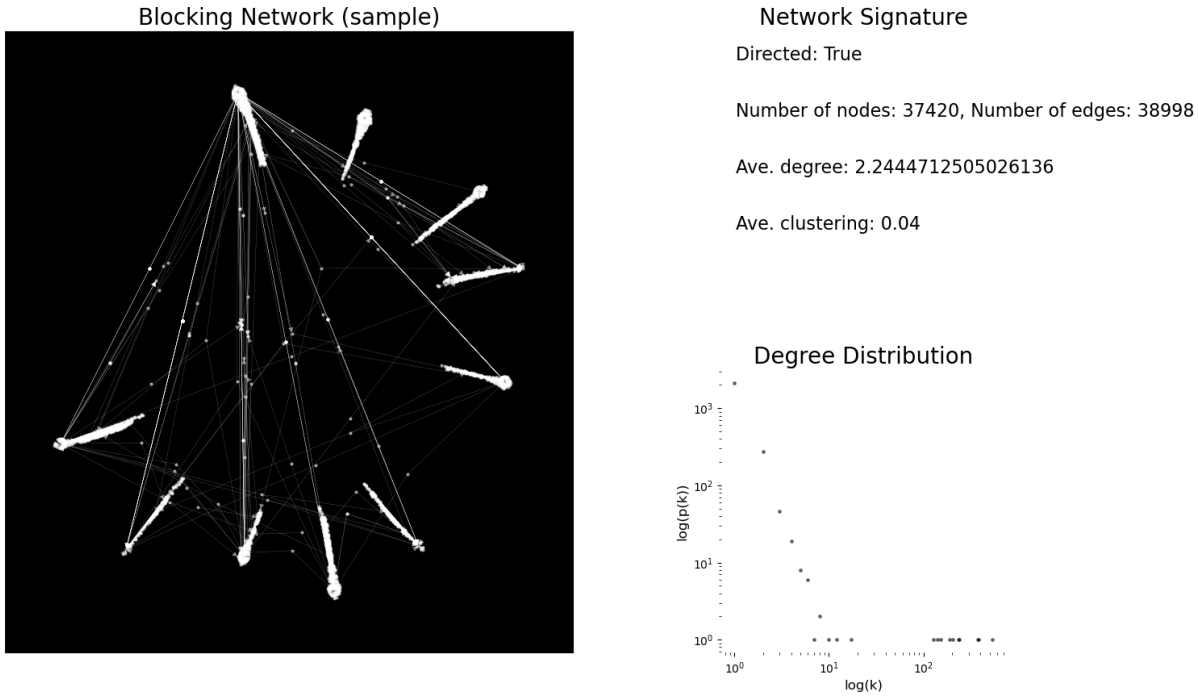
We proceeded to formulate and visualise the dependency network. With 41,964 nodes and 43,397 edges, we again found the network to be disconnected, particularly evident in the chain relations of the isolated clusters. The network had an average degree of 2.1 and a power law distribution. In fact, the average degree of 2.1 and the power law distribution could exemplify that while some bugs hinge on many other bugs, most are independent.

Fig. 17. Dependency network



Next, we constructed a network that represents blockage, which consisted of 37,420 nodes and 38,998 edges. This network was marginally more connected than the dependency network, due to certain bugs blocking multiple others. This network demonstrated an average degree of 2.2 and presented a power law distribution. The marginally greater interconnectedness of this network, as compared to the dependency network, could be due to a phenomenon where one major bug blocks the resolution of many others.

Fig. 18. Blocking network



To provide further insights, we calculated the bug resolution time. By selecting the value of 'cf_last_resolved' from the changes_history table and subtracting the corresponding creation time (from the reports table), we derived the bug resolution time. We then implemented a linear regression model with the centrality measures. Although the R^2 is small, all the positive coefficients suggest that all the relationship will make the resolution time longer.

Moreover, to enhance our understanding of the bug data, we utilised Word2Vec with PySpark to conduct textual analysis. Through simple tokenisation and removal of stopwords, we extracted useful information from the vocabulary. However, a lot of non-vocabulary items were included in the vectors, which necessitated a refined filtering process.

To address this, we removed the specific bug_ids from the Tokenizer leading to a repetition of words similar to 'bug'. To improve these results, we utilised the Spacy tokenizer. It provided better tokenisation due to its extensive linguistic annotations, allowing us to parse formal languages accurately.

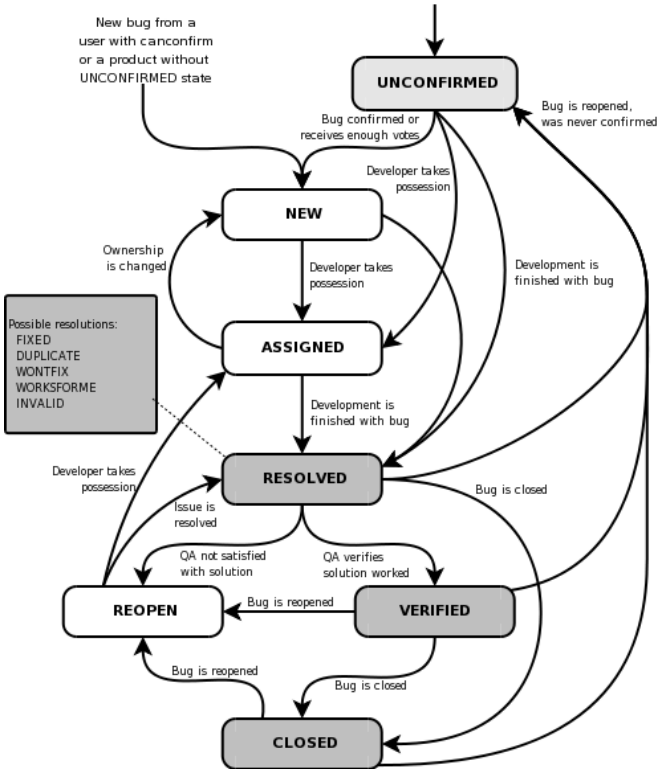
Appendix

Priority	Description
--	No decision
P1	Fix in the current release cycle
P2	Fix in the next release cycle or the following (nightly + 1 or nightly + 2)
P3	Backlog
P4	Do not use. This priority is for the Web Platform Test bot.
P5	Will not fix, but will accept a patch

Appendix 1. Description for Priority levels in bug reports (MozillaWiki, 2022)

Severity	Description
--	Default value for new bugs; bug triagers for components (ie engineers and other core project folks) are expected to update the bug's severity from this value. To avoid them missing new bugs for triage, do not alter this default when filing bugs.
S1	(Catastrophic) Blocks development/testing, may impact more than 25% of users, causes data loss, likely dot release driver, and no workaround available
S2	(Serious) Major functionality/product severely impaired or a high impact issue and a satisfactory workaround does not exist
S3	(Normal) Blocks non-critical functionality and a work around exists
S4	(Small/Trivial) minor significance, cosmetic issues, low or no impact to users
N/A	(Not Applicable) The above definitions do not apply to this bug; this value is reserved for bugs of type Task or Enhancement

Appendix 2. Description for Severity levels in bug reports (MozillaWiki, 2022)



Appendix 3. The life cycle of a Bugzilla bug (Lauhakangas, 2023)

References

Lauhakangas, I. (2023) *QA/bugzilla/fields/status*, *QA/Bugzilla/Fields/Status - The Document Foundation Wiki*. Available at: https://wiki.documentfoundation.org/QA/Bugzilla/Fields/Status (Accessed: 19 July 2023).

MozillaWiki (2022) *BMO/UserGuide/Bugfields*, *BMO/UserGuide/BugFields - MozillaWiki*. Available at: https://wiki.mozilla.org/BMO/UserGuide/BugFields#bug_severity (Accessed: 19 July 2023).