Assessing Developer Beliefs: A Reply to “Perceptions, Expectations, and Challenges in Defect Prediction”

Shrikanth N.C., IEEE Member and Tim Menzies, IEEE Fellow

Abstract—It can be insightful to extend qualitative studies with a secondary quantitative analysis (where the former suggests insightful questions that the latter can answer). Documenting developer beliefs should be the start, not the end, of Software Engineering research. Once prevalent beliefs are found, they should be checked against real-world data. For example, this paper finds several notable discrepancies between empirical evidence and the developer beliefs documented in Wan et al.’s recent TSE paper “Perceptions, expectations, and challenges in defect prediction”. By reporting these discrepancies we can stop developers (a) wasting time on inconsequential matters or (b) ignoring important effects.

For the future, we would encourage more “extension studies” of prior qualitative results with quantitative empirical evidence.

Index Terms—defects, beliefs, empirical software engineering

I. INTRODUCTION

Just because software developers say they believe in “X”, that does not necessarily mean that “X” is true. Jørgensen & Gruschke [7] note that software engineering seldom uses lessons from past projects to improve their future reasoning (to the detriment of new projects). Passos et al. [11] note that developers often assume that lessons learned from a few past projects are general to all future projects [11]. Devanbu et al. record opinions about software development from 564 Microsoft software developers from around the world [5]. They comment that programmer beliefs can (a) vary with each project; and (b) may not necessarily correspond with actual evidence in their current projects.

Accordingly, we think it is important to evaluate developer beliefs reported in (e.g.) Wan et al.’s recent TSE paper “Perceptions, expectations, and challenges in defect prediction” [13]. That study collected 395 responses from practitioners to document developer beliefs about willingness to adopt technologies, challenges, defect prediction metrics, etc. Some of those beliefs about defect prediction can be tested empirically via correlations to project data:

- In Table I the % agree columns shows a strength number that is larger when more developers believe something (in this table seven beliefs are based on prediction metrics, while B4 is based on prioritization strategies).
- Figure 1 shows correlation between the beliefs in Table I and data from 46 projects.

Note that the beliefs do not correspond with the empirical evidence. For example, B6 has the highest correlation in the data but it ranked bottom half in Table I. Also, B3 has the lowest correlations in our data yet it is ranked in the top half of Table I. Other issues are discussed later in III.

Shrikanth N.C. Tim Menzies. Computer Science, NC State, USA. Email: snaraya7@ncsu.edu and timm@ieee.org

| # | Belief | % Agree |
|---|---|---|
| B1 | Files changed by more developers are more buggy. | 64 |
| B2 | A file with more added lines is more bug-prone | 61 |
| B3 | Recently created files tend to be buggy | 52 |
| B4 | A file with more Lines of Code (LOC) | 48 |
| B5 | Files with more bugs are more bug-prone | 48 |
| B6 | A file with more commits is more bug-prone | 46 |
| B7 | A file with more removed lines is more bug-prone | 35 |
| B8 | Files with fewer lines contributed by their owners (who contribute most changes) are more bug-prone | 30 |

TABLE I: Developer beliefs, sorted by percent of developers who endorsed that belief. From Wan et al. [13].

Before going any further, we stress that while we doubt some of the answers offered by Wan et al., we do not doubt the value of the questions they ask. Software analytics research needs to mature to the point where it can offer a set of N conjectures (that can be quickly tested) about what might reduce software project quality. The analysis of Wan et al. is an important step towards that goal.

The other point to stress about Wan et al. is that it is an exemplary model of how to do large scale qualitative Software Engineering (SE) research. That said, that paper did not empirically assess the beliefs it documented. As shown by the following, such an assessment can be an insightful quantitative extension to an initial qualitative study. In the future, we would encourage more such dual qualitative-quantitative studies where the former suggests insightful questions that the latter can explore. For other examples of this dual approach, see [4], [10].

The rest of this paper discusses how we tested the Wan et al. results and what was learned in the process.
II. Method

To test the beliefs in Table I, we used a corpus from a recent ESEM'18 paper [12] (and that sample was drawn from projects labelled “most suited (popular and active)” in Github). From this, we randomly selected 50 projects in accordance with development language popularity [3] (so the projects under consideration were developed in C, C++, Java, JavaScript, PHP, Python, Ruby, Shell, and HTML-CSS).

Initially, we targeted 50 projects since that was all we could reasonably present in a short TSE paper. After some data quirks, that resulted in the 46 projects of Table II. This sample contains data modified in the period 2005 to 2019 by 13,821 developers in 592,094 file entries. These modifications were made to 145,715 active branch commits (in all, 21,760,416 line insertions and 14,992,194 line deletions).

The kinds of files we found in each project were very varied. Let that variation complicated the analysis, we divided the files into several, non-overlapping, categories:

- Source code files ending in .c, .cpp, .java etc;
- Test cases files whose file/path names include “test”;
- Configuration files whose names end in .yml, .pom, .etc.
- Commits were labelled “bug fixing” if they contained any derivatives of the following stemmed words like bug, fix, issue, error, correct, proper, deprecate, broke, optimize, patch, solve, slow, obsolete, vulnerab, debug, perf, memory, minor, wart, better, complex, break, investigat, compile, defect, inconsist, crash, problem or resolv in their commit message. We found a minimum of 13% and an average of 30% bug(defect) fixing commits among the 46 projects we use in this study.

We say a file’s defect proneness “D” is the number of times it was changed(committed) for the purpose of fixing a defect.

The correlation between D and project attributes was checked using the Pearson’s correlation ρ = cov(X,Y) / σxσy between two samples X, Y (with means π and ν), as estimated using

\[ \rho = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}(y_i - \bar{y})^2} \]

Our study then used advice from [2, 6, 8, 9], as follows:

- For B1: More developers, we correlated D to the number of unique developers who made non-zero changes (line insertions or deletions) to a file. For B2: Added lines, we correlated D to the number of lines added to a file during commit.

For B3: Recently Created, the premise here is that newly created files quickly introduce new defects [9]. To test this, we correlated creation time (larger value ⇒ recent) of a file’s “AGE” [8] with the time interval between created time and the time of first defect fixing commit.

For B4: LOC we correlated D to a file’s lines of code (additions + deletions throughout its commit history).

For B5: More Bug Fixes, Similar to the approach in [6], we split a file’s commit history into two equal halves after sorted by time in ascending order. We then reported the correlation between the number of defect fixes in the first half with the number of defect fixes in the second half.

For B6: More Commits, we correlated D to the number of commits for a file. For B7: Removed Lines, the concern is that deleting too many lines in a file could make it defect prone. To test this, we correlated D and the number of lines deleted in a file during a commit.

For B8: Ownership, we used Bird et al. [2]’s idea of major and minor contribution. For each file, we correlated D to % of developers who wrote < 5% of lines.

III. Results

The first row of Figure I shows that three beliefs B6,B1,B4 are supported by the data (as witnessed by their high median correlations). The B1 finding (that more developers leads to more bugs) is definitely consistent with the Table II results. However, this high support for B6 (that more commits means more bugs) is somewhat at odds with Table I since, in that table, developers endorse B6 less than half the time. The clear message from B1 and B6 is that the more we have to tinker with code, the more bugs will be found. It is a question for future work if such tinkering is necessitated by the presence of bugs or whether or not that tinkering causes the bugs.

As to B4 (that large files have more bugs), this result is somewhat equivocal. The larger range of p in the results mean that there will be several projects where larger files do not have no more bugs. So we say that B4 has somewhat weaker support in the data than B1 and B6.

| github.com/ | *Language | Commits | github.com/ | *Language | Commits | github.com/ | *Language | Commits |
|------------|-----------|---------|------------|-----------|---------|------------|-----------|---------|
| activeadmin/activeadmin | Ru CSS | 6373 | karm/reitre | Ru Ht | 996 | resque/resque | Ru Js | 2487 |
| activeemmerchant/active_emmerchant | Ru Ht | 4482 | iar/mackup | Python | 1914 | restsharp/RestSharp | CSS Ht | 1613 |
| awscookbooks-works-cookbooks | Ru Erb | 2047 | hussichert-logstash | Ru | 790 | res-simulation/gazebos_ro_pyhgs | C++ Python | 1398 |
| django-branch | Python Ht | 2179 | Luminati/PHPCVGitLab | PHP Ht | 1973 | logjobs/logs | Ru Ht | 2109 |
| bundler/bundler | Ru Ht | 11724 | makel/mait | Ru | 1901 | scripture/javascript | Java | 954 |
| cakePHP/phinx | PHP CSS | 2304 | teilehain/sidekiq | Ru Js | 3866 | Sendlane/monolog | PHP | 2119 |
| codeception/codeception | PHP Ht | 6028 | python/lombok | Ru | 1385 | strick/rsqladmin | Js Ru | 4487 |
| django-tastypie/django-tastypie | Python Ht | 1335 | oonco/co-services | Python C | 12982 | spottybug/bug | Python Js | 3751 |
| dookerepm/gem/dooker | Ru Erb | 1798 | pennser/django-allauth | Python Ht | 2058 | swanson/stringer | Ru | 934 |
| drapergem/drapers | Ru Ht | 1165 | pentadis/data-access | Java Js | 2757 | tramacapb/capybara | Ru | 3756 |
| encoded/javascript-ossframework | Python Ht | 8329 | platformio/simple_form | Ru | 20601 | cloudfilth/bourbon | CSS Ht | 1439 |
| emberhub/emberhub | Ru Ht | 2813 | propellor/Propelli | PHP Ht | 4287 | threshold/generic | Rb Ht | 2026 |
| exerciseexerciser.io | Ru | 6911 | puppetlabs/beaker | Ru Shell | 5127 | wlasnianenjak/pipiMesh | Python Ht | 1600 |
| greptool/petcat | PHP Python | 3004 | puppetlabs/puppetlabs-nginx | Ru | 3224 | shinjiruru/ckeditor | Java Ht | 2480 |
|ジュンギオーバーマーク | C C++ | 3800 | gets/react-reacts | Js Ru | 1880 | Ze-FCommissions/ZFUser | PHP SQL | 887 |

TABLE II: 46 Projects developed in various programming languages and of varying sizes (commits). We present the top 2 programming languages dominated by quantity in Language column (if applicable). *Language Ht = HTML , Js = JavaScript, Ru = Ruby and Erb = Embedded Ruby. This data is available on-line at [github.com/ai-se/defect_perceptions](https://github.com/ai-se/defect_perceptions).
At the other end of the scale, our results offer little support for B3 (that recently changed files tend to be buggy); B5 (that files with more fixed bugs are more bug-prone); and B7 (that files with more lines removed is more bug prone). All these beliefs show poor correlations to empirical data, especially B3 (whose correlations are often found near $\rho = 0$). The B5 and B7 results are consistent with Wan et al.’s developer beliefs (who did not rate this belief highly in Table I). However, the B3 results are a discrepancy since developers in Table I agreed with this belief at least half the time.

As to other beliefs, these exhibit many correlations below accepted thresholds for “strong” correlation [4]. Hence we cannot support B2 (that a file with more added lines is more bug-prone) or B8 (that prevalence of changes by file owners decreases bugs). The B8 results are consistent with Table I. However, the B2 results are a discrepancy since it is ranked higher in Table I.

IV. Threats to Validity

Any data mining project is prone to sample bias where the conclusions are distorted by the data used to make the conclusions. To mitigate that problem, we have explored a large sample of projects. Also, all our data is online so that other researchers can check for data distortions (see large sample of projects. Also, all our data is on-line so conclusions. To mitigate that problem, we have explored a large sample of projects. Also, all our data is online so that other researchers can check for data distortions (see github.com/ai-se/defect_perceptions).

Another kind of sampling bias is “cherry picking” which beliefs to explore and which to ignore. This paper only explores 8 of the 33 beliefs documented by Wan et al. We found that some of the modeling decisions about how to map data into Table I required extensive, possibly even arcane, explanations. Accordingly, we elected to use just the Table I beliefs since these could be easily mapped into data via simple correlation. We assert that we finalized the list of beliefs in Table I before checking for correlations. That is, we did not maliciously “cherry pick” just a set of beliefs that have some discrepancies with empirical data.

This work required several modeling decisions in order to map the available data into Table I. For example:

- For belief B3: Recently Created, it is possible that a file may be involved in fixing defects multiple times in its lifetime, especially older files. In such cases we consider the interval between the two most recent defect fixes.
- We do not analyze static files (such as image, text etc) since we think it safe to assume that these are not used in fixing software bugs.
- A very small number of files ($\leq 5\%$), had no reported defects (especially for the configuration files). These files were grouped into the little set of Figure I since such files offer no support for any belief.
- To make our conclusions, we had to decide what was a high correlation. Using advice from the literature [11], we used $\rho > 0.7$. We acknowledge that the decision is debatable.
- Etc.

These decisions introduce a threat to validity (i.e. if those modeling decisions were wrong, then so are our conclusions). In order to mitigate that problem, where possible, we took advice from recent research papers [2], [6], [8], [9].

Finally, Wan et al. did not explore language-specific stratifications of the data. Since we are comparing our results to theirs, we also did not check the effect of programming languages on the beliefs of Table I (but that might be an insightful extension for future work).

V. Conclusion

At the start of a software analytics project, it is important to focus software analytics on questions of interest to the client. Therefore, it is very important to document developer beliefs, as done by Wan et al.

That being said, once project data becomes available, it is just as important to update the focus in accordance with the observed effects.

Going forward, this work prompts us to explore better tool support for belief revision in software analytics. There must be some way to politely, yet convincingly, encourage developers to update their beliefs when evidence demands it. In this way, we can stop developers wasting time on inconsequential matters (e.g. B2-B3), or ignoring important effects (e.g. B6).

References

[1] A. Asuero, A. Sayago, and A. Gonzalez. The correlation coefficient: An overview. Critical reviews in analytical chemistry, 36(1):41–59, 2006.
[2] C. Bird, N. Nagappan, B. Murphy, H. Gall, and P. Devanbu. Don’t touch my code!: Examining the effects of ownership on software quality. In Proceedings of the 19th ACM SIGSOFT Symposium and the 13th European Conference on Foundations of Software Engineering, ESEC/FSE ’11, pages 4–14, New York, NY, USA, 2011. ACM.
[3] S. Cass and P. Bulusu. IEEE Spectrum interactive: The top programming languages 2018. https://spectrum.ieee.org/static/interactive-the-top-programming-languages-2018. Accessed: 2019-03-18.
[4] D. Chen, K. Stolee, and T. Menzies. Replication can improve prior results: A github study of pull request acceptance. In ICPC’19, 2019.
[5] P. Devanbu, T. Zimmermann, and C. Bird. Belief & evidence in empirical software engineering. In Proceedings of the 38th International Conference on Software Engineering, pages 108–119. ACM, 2016.
[6] T. L. Graves, A. F. Karr, J. S. Marron, and H. Siy. Predicting fault incidence using software change history. IEEE Transactions on Software Engineering, 26(7):653–661, July 2000.
[7] M. Jørgensen and T. M. Grusckhe. The impact of lessons-learned sessions on effort estimation and uncertainty assessments. Software Engineering, IEEE Transactions on, 35(3):368 –383, May-June 2009.
[8] Y. Kamei, E. Shihab, B. Adams, A. E. Hassan, A. Mockus, A. Sinha, and N. Uabayashi. A large-scale empirical study of just-in-time quality assurance. IEEE Transactions on Software Engineering, 39(6):757–773, June 2013.
[9] S. Kim, T. Zimmermann, E. J. Whitehead Jr., and A. Zeller. Predicting faults from cached history. In 29th International Conference on Software Engineering (ICSE’07), pages 489–498, May 2007.
[10] T. Menzies and J. S. D. Stefano. More success and failure factors in software reuse. IEEE Trans. Software Eng., 29(5):474–477, 2003.
[11] C. Passos, A. P. Braun, D. S. Cruzes, and M. Mendonca. Analyzing the impact of beliefs in software project practices. In ESEM ’11, 2011.
[12] N. Walkinshaw and L. Minku. Are 20% of files responsible for 80% of defects? In Proceedings of the 12th ACM/IEEE International Symposium on Empirical Software Engineering and Measurement, ESEM ’18, pages 2:1–2:10, New York, NY, USA, 2018. ACM.
[13] Z. Wan, X. Xia, A. E. Hassan, D. Lo, J. Yin, and X. Yang. Perceptions, expectations, and challenges in defect prediction. IEEE Transactions on Software Engineering, pages 1–1, 2018.