Correction of “A Comparative Study to Benchmark Cross-project Defect Prediction Approaches”

Steffen Herbold, Alexander Trautsch, Jens Grabowski

Abstract—Unfortunately, the article “A Comparative Study to Benchmark Cross-project Defect Prediction Approaches” has a problem in the statistical analysis which was pointed out almost immediately after the pre-print of the article appeared online. While the problem does not negate the contribution of the the article and all key findings remain the same, it does alter some rankings of approaches used in the study. Within this correction, we will explain the problem, how we resolved it, and present the updated results.

Index Terms—cross-project defect prediction, benchmark, comparison, replication, correction

1 INTRODUCTION

Unfortunately, the article “A Comparative Study to Benchmark Cross-project Defect Prediction Approaches” [1] has a problem in the statistical analysis performed to rank Cross-Project Defect Prediction (CPDP) approaches. Prof. Yuming Zhou from Nanjing University pointed out an inconsistency in Table 8 of the the article. He noted that in some cases the rankscores are worse even if the mean values for performance metrics are better. While this is possible in theory, with the Friedman test [2] with post-hoc Nemenyi test [3], such inconsistencies are unlikely. Therefore, we immediately proceeded to check our results. These checks revealed that the inconsistencies are due to a problem with our statistical analysis for the Research Question 1 (RQ1) “Which CPDP approaches perform best in terms of F-measure, G-measure, AUC, and MCC?”. None of the raw results of the benchmark, nor any of the other research questions are affected by the problem.

We will describe the problem and how we solved in in Section 2. Then, we will show the updated results regarding RQ1 and discuss the changes in Section 3. Afterwards, we analyze the reasons for the changes in Section 4 to determine if all changes due to the correction are plausible and the correction resolves the inconsistencies reported by Y. Zhou. In Section 5 we describe how we updated our replication kit as part of this correction. Finally, we will conclude in Section 6. Please note, that we assume that readers have read to the original article and are familiar with the terminology used. We do not re-introduce any of the terminology in this correction.

2 PROBLEM WITH THE NEMENYI TEST IMPLEMENTATION

On July 15th 2017, Y. Zhou informed us that he found an inconsistency between the results of CV-NET and CamargoCruz09-DT for the RELINK data for the performance metric AUC. He noted that the mean value for CV-NET was higher than for CamargoCruz09-DT, but the rankscore was lower. He went to the raw data provided as part of the replication kit [4] and confirmed that the mean values were correct, and the AUC for CV-NET was higher for all three products of the RELINK data. Based on this observation, we re-checked our statistical analysis of the results. We found the problem in our implementation of the Nemenyi post-hoc test.

2.1 Summary of the Friedman and Nemenyi tests

To understand the problem, we briefly recap how the Friedman test with post-hoc Nemenyi test works. The Friedman test determines if there are stastical significant differences between populations. This is done using pair-wise comparisons between the rankings of populations. If the Friedman test determines significant differences, the Nemenyi post-hoc test compares the populations to each other to determine the statistically significantly different ones. The analysis with the Nemenyi test is based on two parameters: the Critical Distance (CD) and the average ranks of the populations in the pair-wise comparisons between all populations on each data set. Following the description by Demšar [5], CD is defined as

$$CD = q_α \sqrt{\frac{k(k+1)}{6N}}$$  (1)
2.2 z-values instead of Ranks

Now that the concepts of the statistical tests are introduced, we can discuss the actual problem in our implementation. We used the `posthoc.friedman.nemenyi.test` function of the PMCMR package [7] to implement the test. As part of the return values, the function returns a matrix called `PSTAT`. Without checking directly in the source code, we assumed these were the average ranks for each population, based on the documentation of the package. However, these are actually the absolute z-values multiplied with \( \sqrt{2} \), i.e.,

\[
z' = \frac{|R_i - R_j|}{\sqrt{\frac{k(k+1)}{6N}}} \cdot \sqrt{2}.
\]

Thus, when we compared ranks, we did not actually compare the average ranks, but the mean z'-values. This led to a wrong determination of ranks, which explain the inconsistencies found by Y. Zhou.

1. For simplicity, we refer to the studentized range distribution as \( q_{tukey}(\alpha, N, \text{inf}) \), following the name of the related method in R.

2. Both implementations of the test do not return the raw pair-wise comparisons and can, therefore, not be used directly.

2.3 The solution

To resolve the problem, we adopted the code from the PMCMR package that determines the average ranks. We cross-checked our code with another implementation of the Nemenyi test [8], to ensure that the new code solves the problem. We then used the mean averages from that code, instead of the z-values that were returned from the PMCMR package. As a result, the Nemenyi-test became much more sensitive, because the scale of the average ranks is different than the scale of the z-values. Let us consider the scales for our experiments with the JURECZKO data. Here, we have \( N = 62 \) data sets and \( k = 135 \) populations, i.e., CPDP approach and classifier combinations. The best possible average rank is 135 (always wins), the worst possible is 1 (always loses). Thus, the average ranks are on a scale from 1 to 135. In comparison, the highest possible z'-value is

\[
z = \frac{135 - 1}{\sqrt{\frac{135 \cdot 136}{6 \cdot 62}}} \cdot \sqrt{2} \approx 26.97,
\]
i.e., the scale is just from 0 (no difference in average ranks) and 26.97. Thus, the scale of the z'-values has only about a fifth of the range the scale of the average ranks has. Basically, with z'-values, 135 populations are fit into the scale 0 to 26.97, with rankings in the scale 1 to 135. This means that the average distance between approaches is 0.2 with z'-values and 1 in case of average ranks. Considering that we have a \( CD \approx 1.26 \) for \( \alpha = 0.95 \) in this example, this makes a huge difference. With z'-values, it is unlikely that two subsequently ranked approaches to have a distance greater than CD, because \( CD \) was more than 6.3 times higher than average distance expected on the scale. This changes if the real scale with ranks is used. If you have 135 cases with an average distance of 1, it is quite likely that a few of these distances will be greater than 1.26, i.e., the CD.

We discuss this change in scales in this detail, because it requires a small change in the ranking of approaches based on the Nemenyi test. Before, we considered three distinct ranks for the calculation of the rankscore to achieve non-overlapping ranks:

- The populations that are within the CD of the best average ranking population (top rank 1).
- The populations that are within the CD of the worst average ranking population (bottom rank 3).
- The populations that are neither (middle rank 2).

This was the only way to deal with the small differences that resulted from using the z'-values. However, this approach breaks on the larger scale, because the distances now become larger, meaning fewer results are within the CD from the best/worst ranking. For example, for the JURECZKO data and

\[
q_{tukey}(\alpha, \sqrt{2}) \text{ distribution with infinite degrees of freedom divided by } \sqrt{2}, \text{ } \alpha \text{ the significance level, } k \text{ the number of populations compared and } N \text{ the number of data sets.}
\]
the performance metric AUC, only two approaches would be on the first rank, i.e., only one approach is within the CD of the best approach. Similarly, only six approaches would be on the third rank, i.e., only five approaches are within the CD of the worst approach. This would leave us with 127 approaches on the middle rank. This ranking would be too coarse, and not show actual differences between approaches anymore. To deal with this larger scale of ranks, we use a simple and more fine-grained grouping strategy to create the ranks. We sort all approaches by their average ranking. Each time that the difference between two subsequently ranked approaches is larger than the CD, we increase the rank. Because the rank is only increased if the difference is larger than the CD, we ensure that each group only contains approaches that are statistically significantly different from the other groups. Afterwards, we calculate the normalized rankscore as before. Algorithm 1 formalizes this strategy. This change in ranking increases the sensitivity of the test and makes the results more fine-grained in comparison to our original ranking procedure.

Algorithm 1 Ranking algorithm.

1: Input: Sorted mean ranks \( R_i \) such that \( \forall i, j \in \{1, \ldots, N\} : i < j, R_i \geq R_j \)
2: Output: rankscore\(_i\) for all ranks.
3: \( rank_{tmp1} = 1 \)
4: \( current\_rank \leftarrow 0 \)
5: for \( i=2, \ldots, N \) do
6: \( \triangleright \) If difference is larger than CD increase rank
7: if \( R_{i-1} - R_i > CD \) then
8: \( current\_rank \leftarrow current\_rank + 1 \)
9: end if
10: \( rank_{tmp} \leftarrow current\_rank \)
11: end for
12: \( rank_{max} \leftarrow current\_rank \)
13: \( \triangleright \) Determine rankscores
14: for \( i=1, \ldots, N \) do
15: \( \text{rankscore}_i \leftarrow 1 - \frac{rank_{tmp}}{rank_{max}} \)
16: end for

3 RESULTS

We now show the corrected results for RQ1. We will directly compare the changes in the results with the originally published results. Figure 1 shows the mean rankscore averaged over the four performance metrics F-Measure, G-Measure, AUC, and MCC and the five data sets JURECZKO, MDP, AEEEM, NETGENE, and RELINK. Table 2 shows detailed results including the mean values and rankscores for each performance metrics and each data set. Figure 2 is the correction of Figure 3 and Table 2 the correction of Table 8 from the original publication. Table 2 and Figure 2 only report the results for the best classifier for each approach. In case these changed between the original results and our correction, you will not find the exact same rows. For example, for CamargoCruz09, we reported DT as best classifier in the original analysis, and now NB. This is because with the problem in the statistical analysis DT was ranked best for CamargoCruz09, but in the corrected version NB performs better. The reasons for these, and other changes are explained in Section 4.

The most important finding remains the same: the approach CamargoCruz09 still provides the best-ranking classification model with a mean rankscore of 0.917 for CamargoCruz09-NB. However, the rankscore is not a perfect 1.0 anymore. We attribute this to the more sensitive ranking due to the correction of the Nemenyi test. The differences to the next-ranking approaches are still rather small, though the group of approaches that is within 10% of the best ranking approach now only consists of CV-RF, Amasaki15, Peters15, and Ma12. The bottom of the ranking is nearly unaffected by the changes as well. The last seven ranked approaches are still the same. Additionally, our findings regarding the comparison of using ALL data, versus transfer learning approaches has not changed: ALL is still in the upper mid-field of approaches. With the corrected and more fine-grained ranking, only six of the cross-project approaches actually outperform this baseline, whereas seventeen are actually worse.

With respect to CV versus CPDP, we still observe that CPDP can outperform CV in case multiple performance criteria are considered because CV-RF is outperformed by CamargoCruz09-NB. Thus, we still note that this is possible, but far less conclusively than before, where CV was actually only in the mid-field of the approaches and not a close second.

Due to these small overall small differences, we change our answer to RQ1 slightly:
For FILTERJURECZKO and SELECTEDJURECKO, we show the difference in the mean values to JURECZKO.

| Method            | AUC F-measure G-measure MCC AUC F-measure G-measure MCC AUC F-measure G-measure MCC |
|-------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| ALL-NB            | 0.72 (1)                        | 0.28 (0.6)                     | 0.35 (0.48)                     | 0.2 (0.53)                     |
| Amasaki15-NB      | 0.73 (1)                        | 0.77 (1)                       | 0.47 (0.95)                     | 0.62 (0.88)                    |
| CamargoCruz09-NB  | 0.71 (1)                        | 0.77 (1)                       | 0.47 (0.95)                     | 0.62 (0.88)                    |
| Kawata15-NB       | 0.28 (0.6)                      | 0.34 (0.43)                    | 0.2 (0.53)                      | 0.19 (0.87)                    |
| Koshgoftaar08-NB  | 0.63 (0.56)                     | 0.39 (0.85)                    | 0.5 (0.71)                      | 0.26 (0.76)                    |
| Panichella14-CODEP-BN | 0.63 (0.56)                   | 0.39 (0.75)                    | 0.51 (0.71)                     | 0.25 (0.65)                    |
| Peters12-NB       | 0.69 (0.61)                     | 0.32 (0.56)                    | 0.45 (0.65)                     | 0.24 (0.56)                    |
| Trivial-FIX       | 0.5 (0.02)                      | 0.31 (0.35)                    | 0.00 (0)                        | 0.00 (0.02)                    |
| Turhan09-NB       | 0.72 (0.7)                      | 0.4 (0.87)                     | 0.62 (0.98)                     | 0.28 (0.72)                    |
| ZHe13-RF          | 0.64 (0.44)                     | 0.38 (0.44)                    | 0.58 (0.82)                     | 0.36 (0.72)                    |
| Zimmermann06-NB   | 0.71 (1)                        | 0.34 (0.9)                     | 0.5 (0.91)                      | 0.22 (0.81)                    |

**TABLE 1**

Mean results over all products with rankscores in brackets. Bold-faced values are top-ranking for the metric on the data set. For FILTERJURECZKO and SELECTEDJURECKO, we show the difference in the mean values to JURECZKO.
The changes two the replication kit are two-fold. We updated the replication kit archived at Zenodo [9]. The changes two the replication kit are two-fold.

- We corrected the problem with the statistical analysis in the generate_results.R script.
- We updated the provided CD diagrams due to the changes in the Nemenyi test.

The changes can be reviewed in detail in the commit to the GitHub archive of the replication kit [3].

6 CONCLUSION

A problem with the implementation of the Nemenyi post-hoc test led to incorrect results being published in our benchmark paper on cross-project defect prediction. The mistake only affected research question RQ1, the other three research questions were not affected. Within this correction paper, we explained the problem in the statistical test, how this problem affected our results, presented the corrected, and explained the changes that occurred. The major findings regarding RQ1 are not changed, including the best performing approach, the result that the naive baseline of using all data outperforms most proposed transfer learning approaches, as well as that cross-validation can be outperformed by CPDP. Thus, the contributions of the article are still valid. Still, the correction leads to differences in the rankings which are properly corrected and discussed here. We apologize for this mistake and hope that this timely correction mitigates the potential negative impact the wrong results may have.

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