Multi-stream online transfer learning for software
effort estimation
Minku, Leandro

DOI: 10.1145/3475960.3475988
License: None: All rights reserved

Document Version
Peer reviewed version

Citation for published version (Harvard):

Link to publication on Research at Birmingham portal

Publisher Rights Statement:
This is the Accepted Manuscript version of an article first published in PROMISE 2021: Proceedings of the 17th International Conference on Predictive Models and Data Analytics in Software Engineering, the final Version of Record is available: http://doi.org/10.1145/3475960.3475988

General rights
Unless a licence is specified above, all rights (including copyright and moral rights) in this document are retained by the authors and/or the copyright holders. The express permission of the copyright holder must be obtained for any use of this material other than for purposes permitted by law.

• Users may freely distribute the URL that is used to identify this publication.
• Users may download and/or print one copy of the publication from the University of Birmingham research portal for the purpose of private study or non-commercial research.
• Users may use extracts from the document in line with the concept of 'fair dealing' under the Copyright, Designs and Patents Act 1988 (?)
• Users may not further distribute the material nor use it for the purposes of commercial gain.

Where a licence is displayed above, please note the terms and conditions of the licence govern your use of this document.

When citing, please reference the published version.

Take down policy
While the University of Birmingham exercises care and attention in making items available there are rare occasions when an item has been uploaded in error or has been deemed to be commercially or otherwise sensitive.

If you believe that this is the case for this document, please contact UBIRA@lists.bham.ac.uk providing details and we will remove access to the work immediately and investigate.
Multi-stream Online Transfer Learning for Software Effort Estimation: Supplementary Material

Leandro L. Minku
l1.minku@cs.bham.ac.uk
School of Computer Science, The University of Birmingham
Birmingham, UK

1 SUPPLEMENTARY MATERIAL CONTENT

This file provide larger versions of some figures from the paper [11], and additional information on statistical tests, effect sizes and parameter choices. Specifically, Table 1 presents the effect sizes of the differences in predictive performance of each approach with respect to OATES. Figures 1 and 2 correspond to Figures 1 and 2 from the paper, but with larger size. Figure 3 shows the visualisation of the results of the statistical tests performed to answer RQ3 and relates to Section 6.4 of the paper. The figures are provided from the next page of this report onwards, to enable a higher resolution. Additional information about parameter choices to complement the related work discussed in Section 2 of the paper, OATES’ code is available at [10].

2 ADDITIONAL INFORMATION PARAMETER CHOICE

The parameter values listed below were investigated for each base learning algorithm, leading to 20 different combinations:

- Regression tree: minimum number of examples in a leaf node ∈ {1, 2, 3, 4, 5}, minimum proportion of the data variance at a node for splitting to be performed {10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}}.
- k-Nearest Neighbour: k ∈ {1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20}.
- Linear Regression, including in the log scale: ridge ∈ {0, 0.5, 10^{-1}, 10^{-2}, 10^{-3}, \ldots, 10^{-18}}.

For each dataset, the parameter combination that led to the best median of the n MAE_t measurements for WC P = 1 was selected to be used with all approaches.

The following values were investigated for OATES and Dycom’s parameters: lr ∈ {0.01, 0.05, 0.1, 0.15} and β ∈ {0.3, 0.5, 0.7, 0.9, 1.0}. This also leads to 4 × 5 = 20 combinations. For SL P = 1, 20 different window sizes starting from 10 were investigated. Increments of 1, 2 and 4 were used for the smallest (ISBSG2001 and ISBSGLess), medium (ISBSG2000) and large (ISBSG) datasets. These increments mean that the maximum window size is restricted to \lfloor n/2 \rfloor. Larger window sizes would mean that the SL approach is behaving as WC P = 1 more than half of the time. For SL P = \lfloor n/6 \rfloor, all possible window sizes were used, i.e., {1, \ldots, 5}. Larger window sizes are not applicable because the number of WC training projects for this approach is 6. For each dataset, the parameters and base learners leading to the best median of the n MAE_t measurements were chosen for the analysis.

\[
MAE_t = \frac{1}{\min(n^*, t)} \sum_{i=\max(t-n^*+1,1)}^{t} |\hat{y}_i - y_i|;
\]

\[
M\logAE_t = \frac{1}{\min(n^*, t)} \sum_{i=\max(t-n^*+1,1)}^{t} |\log(\hat{y}_i) - \log(y_i)|,
\]

where \hat{y}_i is the estimation given to the WC project requested to be estimated at time step i, whose true effort is y_i; and t is the current time step.

3 RELATED WORK ON MACHINE LEARNING FOR SOFTWARE EFFORT ESTIMATION

Machine learning for SEE has been studied for many years [2, 4–6, 13, 14, 17]. Existing work has investigated a variety of machine learning algorithms, including linear regression, neural networks, regression trees, k-nearest neighbours, linear programming, etc. As the size of the SEE training sets is typically relatively small, SEE models with too many internal parameters are less likely to perform well [8]. Moreover, the fact that the training sets are heterogeneous makes local learning algorithms such as regression trees, k-nearest neighbours and some cluster-based approaches competitive [1, 7, 9, 12, 14]. Linear regression (potentially applied after log transformations) can also obtain competitive results when the SEE datasets are relatively linear [2, 18]. Ensembles were found to boost the predictive performance of single SEE models [7, 12]. Recently, linear programming has been proposed as a baseline for SEE due to its competitive predictive performance and robustness to different data splits [13]. Some existing work also investigated SEE in the Agile context [3, 15, 16].
Table 1: Effect Size A12 With Respect To OATES’ MAE and MLogAE Across Time Steps

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Dycom</td>
<td>0.52</td>
<td>0.62</td>
<td>0.55</td>
<td>0.57</td>
<td>0.51</td>
</tr>
<tr>
<td>SL P=1</td>
<td>0.56</td>
<td><strong>0.69</strong></td>
<td><strong>0.71</strong></td>
<td>0.56</td>
<td>0.51</td>
</tr>
<tr>
<td>WC P=1</td>
<td>0.63</td>
<td><strong>0.69</strong></td>
<td><strong>0.73</strong></td>
<td>0.64</td>
<td>0.61</td>
</tr>
<tr>
<td>SL P/6</td>
<td><strong>0.74</strong></td>
<td><strong>0.84</strong></td>
<td><strong>0.75</strong></td>
<td><strong>0.77</strong></td>
<td><strong>0.75</strong></td>
</tr>
<tr>
<td>WC P/6</td>
<td><strong>0.91</strong></td>
<td><strong>0.87</strong></td>
<td><strong>0.77</strong></td>
<td><strong>0.79</strong></td>
<td><strong>0.76</strong></td>
</tr>
<tr>
<td>Median</td>
<td><strong>0.66</strong></td>
<td><strong>0.81</strong></td>
<td><strong>0.93</strong></td>
<td><strong>0.78</strong></td>
<td><strong>0.79</strong></td>
</tr>
</tbody>
</table>

Cells with *, ** and *** indicate small, medium and large effect size, respectively. Cells in orange (dark grey) indicate statistically significant difference w.r.t. OATES according to the Nemenyi tests shown in Fig. 1. Positive A12 indicates values in favour of OATES.

ACKNOWLEDGMENTS
This work was supported by EPSRC Grant No. EP/R006660/2.

REFERENCES
Figure 1: Friedman and Nemenyi Tests to Compare Different Approaches in Terms of MAE and MLogAE across time steps. The top ranked approach is shown in red. The dotted horizontal line represents Nemenyi’s critical distance with respect to the mean rank of the top ranked approach. Approaches whose mean rank is above this line are significantly different from the top ranked approach.
Figure 2: MAE and MLogAE Across Time Steps.
Figure 3: Friedman and Nemenyi Tests to Compare OATES with Different Values for $P$ in Terms of MAE and MLogAE across time steps. The top ranked approach is shown in red. The dotted horizontal line represents Nemenyi’s critical distance with respect to the average rank of the top ranked approach. Approaches whose mean rank is above this line are significantly different from the top ranked approach.