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An Analysis of Data Sets Used to Train and Validate Cost Prediction Systems

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Abstract

OBJECTIVE - the aim of this investigation is to build up a picture of the nature and type of data sets being used to develop and evaluate different software project effort prediction systems. We believe this to be important since there is a growing body of published work that seeks to assess different prediction approaches. Unfortunately, results – to date – are rather inconsistent so we are interested in the extent to which this might be explained by different data sets.

METHOD - we performed an exhaustive search from 1980 onwards from three software engineering journals for research papers that used project data sets to compare cost prediction systems.

RESULTS - this identified a total of 50 papers that used, one or more times, a total of 74 unique project data sets. We observed that some of the better known and publicly accessible data sets were used repeatedly making them potentially disproportionately influential. Such data sets also tend to be amongst the oldest with potential problems of obsolescence. We also note that only about 70% of all data sets are in the public domain and this can be particularly problematic when the data set description is incomplete or limited. Finally, extracting relevant information from research papers has been time consuming due to different styles of presentation and levels of contextual information.

CONCLUSIONS - we believe there are two lessons to learn. First, the community needs to consider the quality and appropriateness of the data set being utilised; not all data sets are equal. Second, we need to assess the way results are presented in order to facilitate meta-analysis and whether a standard protocol would be appropriate.

1. Introduction

The problem of how to generate useful software cost¹ predictions at an early stage in a project has been the subject

¹Strictly speaking we mean effort prediction since the non-labour costs tend to be ignored in this type of research, however, cost is the more commonly used term.

of a considerable amount of research since the pioneering work of Benington [1] almost 50 years ago. Subsequently researchers such as Kitchenham [8] and Kemerer [5] identified the need for empirical validation of the different, and in many senses competing, prediction systems that were being proposed. This has led to some hundreds of studies that have used different (usually industrially derived), data sets in order to conduct comparative empirical studies of the relative performance of different cost prediction systems. For review articles see [2, 4].

Whilst it is clearly a positive development that cost estimation researchers are active in empirically evaluating prediction systems, this has resulted in a number of new problems. On the whole results have tended to be inconclusive in the sense that study A using data set B finds prediction system X is to be preferred to prediction system Y, whilst study C using data set D finds the reverse. Potential explanations include use of different evaluation procedures and accuracy indicators [7] which can lead to rank reversal problems. Another, probably more significant area lies in the use of different data sets and their influence upon prediction system performance [10]. This is the motivation for this paper. We wish to investigate the nature and type of data sets being used to develop and evaluate different software project effort prediction systems. This could prove useful for future researchers considering how best to evaluate cost prediction systems. It is also a foundation for meta-analysis when researchers seek to systematically combine results from more than one study.

The remainder of this paper is organised as follows. The next section sets out the method of how we identified the research papers for our analysis. We then present our findings both by data set and by research study. We then conclude by considering the implications of these results for future empirical research studies and for those endeavouring to perform meta-analyses.

2. Method

In order to perform the analysis of data sets used to train and validate cost prediction systems, we defined the following

inclusion criteria:

1. the papers were concerned with software cost estimation, and not, for example, size or productivity estimation;
2. the data set(s) were used to evaluate prediction systems (including expert judgement);
3. the data were ‘real’, not simulated;
4. each dataset comprised at least 2 projects (this excluded case studies).

Given the size of the literature we decided to adopt a sampling procedure. We decided to focus upon journals since one would expect more mature and heavily refereed research studies to be published in such outlets. Results from this search identified three journals as those which had most prolifically published relevant papers according to our criteria over the past 25 years. The selected journals were *Information & Software Technology* (IST), the *Journal of Systems & Software* (JSS) and *IEEE Transactions on Software Engineering* (TSE) all of which have featured in other software engineering literature reviews, e.g. Glass and Chen [3]. *Empirical Software Engineering* (ESE) was not included since it is not presently included within the Thomson-ISI Scientific Citation Index.

The search began by using a personal informal bibliographic database², and continued using the Web of Knowledge (wok.mimas.ac.uk/), ScienceDirect (sciencedirect.com), IEEE Explore (ieeexplore.ieee.org) and Google (google.co.uk), using the search terms ‘cost’, ‘estimation’ and ‘effort within the three selected journals.

Details from each paper were catalogued according to information availability within each journal paper. For each paper we identified those data sets that were utilised. And for each data set we collected the following:

- data set name
- version (if any)
- public availability
- contact person (useful for resolving queries concerning the data set)
- start and completion date
- nationality
- number of organisations
- application domain (business sector)

²The database formed part of the Magne Jørgensen’s (Simula Labs, Norway) BEST project.

Group	Count	%
Y	54	73.0
N	6	8.1
?	14	18.9

Table 1. Software Project Cost Data Sets in the Public Domain

- number of projects
- project type (new or enhancement or mixed)
- number of features
- presence of missing values

Additional information was also collected since this pilot is in fact part of a larger study to conduct a meta-analysis of all empirical cost prediction results, however, this is beyond the scope of this paper. We also note that this exercise was far from straightforward and often involved reference to other papers, analysis of the data directly (when available) and discussions with those responsible for collecting the data.

3. Findings

Next we consider our findings, first in terms of the data sets (some of which are used more than once) and then in terms of research study, many of which use more than one data set, i.e. there is a many to many relationship.

3.1 Data Sets

As indicated our search for empirical studies from the three journals identified a total of 74 distinct data sets, though many of them were used more than once. Of these data sets, just over 70% are in the public domain (see Table 1). In some cases, particularly for older data sets, we were unclear whether the data is available. Overall, something over a quarter of data sets used are not easily available which has clear implications for replication and transparency. It is something of a moot point as to whether studies using confidential data should be published since software development organisations are subject to commercial pressures and we do not wish to hinder the flow of data made available for research. One possibility is, of course, the use of sanitisation procedures though this is at the expense of making the research context less precise and the resultant danger that data is used inappropriately.

These data sets varied in age³ from 1979 onwards (see Figure 1). The data sets varied in age from 1979 onwards.

³By age we mean the date of the last completed project as opposed to when the research was actually published.

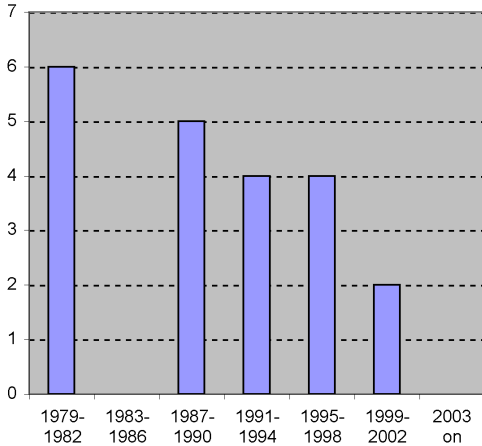


Figure 1. Project Data Sets By Age

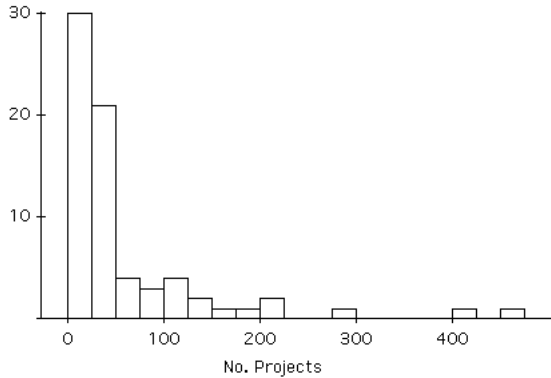


Figure 2. Histogram of Data Set Size (Number of Projects)

Of the 74 data sets, only 21 have exact start and end dates detailed in any study which has used them. Some other studies reported collection dates, often relative to publication. Whilst better than nothing this doesn't give information on when the projects actually completed (which for some data sets can span a considerable period of time). Of course one can also estimate dates by simply assuming the completion date to be prior to the publication date of the paper in which they were used. However, this does not indicate how long prior to publication date the projects were completed.

It is also instructive to observe that the data sets varied considerably in size (the number of cases or projects - see Figure 2) and the richness of information to describe each project (the number of features or variables- see Figure 3).

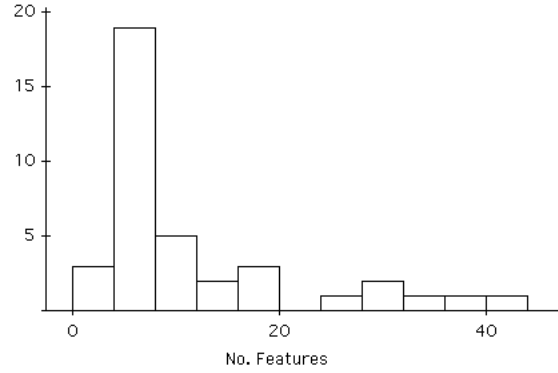


Figure 3. Histogram of Data Set Size (Number of Features)

Group	Count	%
single organisation	37	50.0
multi-organisation	18	24.3
?	19	25.7

Table 2. Single / Multi-Organisation Data Sets

One suspects that the patterns that might be discovered and the prediction systems evolved for a data set of 3 features differs somewhat from a data set of 40+ features. Both histograms indicate a strong tendency towards smaller data sets. As a community, we need to consider what impact this may have upon our results and recommendations to practitioners.

Another area that has been promoting debate recently concerns the use of single or multi-organisation data. For example some large benchmark data sets such as ISBSG contain data from many organisations whereas other data sets contain projects from a single company only. Table 2 indicates that the half of the data sets comprise projects from a single organisation and a disturbing quarter of all data sets fail to make this information clear at all.

Finally, we look at the country of origin of these data sets (see Table 3). It is clear that Europe and North America dominate, however, it is also striking that for almost 20% of the data sets we are not even provided with this what might be regarded as quite basic information.

3.2 Research Studies

The systematic search described in the previous section identified a total of 50 papers that used a total of 74 unique project data sets with some data sets being used repeatedly and some in combination.

Country	Count	%
USA	16	21.6
UK	12	16.2
Other European	11	14.9
Australian / NZ	7	9.5
Japanese	6	8.1
Canadian	4	5.4
Multi-national	4	5.4
?	14	18.9

Table 3. Software Project Cost Data Sets by Country of Origin

Journal	Count	Dates
JSS	19	1981 - 2003
TSE	18	1987 - 2004
IST	13	1994 - 2005
Total	50	

Table 4. Research Studies by Journal and Date

Table 4 shows the distribution of papers between the three journals identified from 1981 to present. The publication trends are shown in 4 and broadly indicate an increase in the number of research papers that use data sets to evaluate cost prediction systems.

Figure 5 shows that the majority of data sets are used only once. This is for two reasons. First our analysis is limited to only three journals so the majority of studies are excluded. Second, and less expectedly is that there are many variants and versions of data sets. Examples are the ISBSG and Finnish data sets that grow over time with new versions

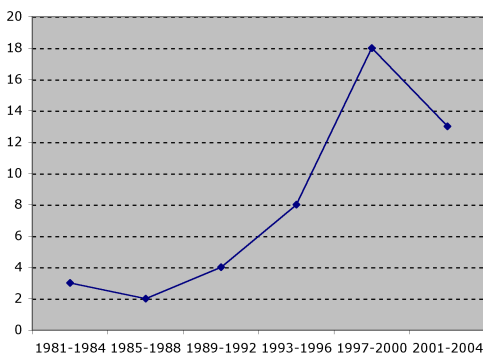


Figure 4. Line Plot of Publications Over Time

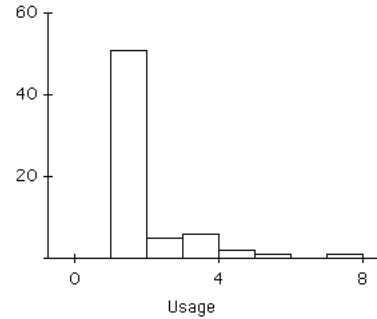


Figure 5. Histogram of Frequency of Data Set Utilisation

being released often on an annual basis. Clearly it is important for researchers to be specific about which version they are using. We also observed on occasions that researchers combined two existing data sets or removed / added a small number of data points. Moreover there is no unambiguous naming convention so it is possible that use of synonyms has caused additional confusion.

We noted that the most heavily data sets (COCOMO, Desharnais, Kemerer and Albrecht and Gaffney) are amongst the oldest data sets dating from the 1970s or 80s. In one sense this is to be expected since these data sets have had the most opportunity for use. However, when conducting meta-analyses or other forms of overall analysis we do need to be somewhat cautious about their age in an industry characterised by rapid change.

4. Discussion

In this study of 50 published empirical studies of cost prediction systems from three software engineering journals we have uncovered some interesting characteristics of data sets that are used to train and evaluate software cost prediction systems.

We observed that some of the better known and publicly accessible data sets were used repeatedly making them potentially disproportionately influential. Such data sets also tend to be amongst the oldest with potential problems of obsolescence. We also note that only about 70% of all data sets are in the public domain and this can be particularly problematic when the data set description is incomplete or limited.

Data sets varied considerably in terms of size, number of features, age, nationality, number of organisations, treatment of missing data and so forth. This means we need to be much more systematic in exploring the relation between data set characteristics and prediction system performance. We also need to avoid using data sets that are no longer rep-

representative of modern software development practices and current data collection opportunities. Since availability of data sets is clearly factor we need to consider making some of the more modern and complex data sets widely available. For this reason initiatives such as the PROMISE [9] are very welcome. Having said this, there is the danger that more complex data sets are more easily misunderstood, so detailed protocols and dialogue with those associated with collection are essential.

In addition, the process of extracting relevant information from research papers has been time consuming due to different styles of presentation and levels of contextual information. Again, we consider initiatives such as the PROMISE [9] helpful.

A possible threat to our findings is the question of how representative are the studies that we have identified? Clearly it would be useful to continue this work in order to construct a more complete picture. Nonetheless we believe we have examined a considerable number of studies over a period of almost 25 years from three international, refereed and archival journals.

Overall we feel our pilot analysis highlights the need to give very careful consideration to three issues. The data sets we use are extremely varied so we need to consider which data sets we use for training and validation, for instance is it appropriate to use an old data set or study mixed (new and enhancement) project types? Second, given this variation, context is important so when publishing data sets it is essential to provide enough contextual information to support meaningful generalisation. Lastly, meta-analyses and systematic reviews [6] will be greatly facilitated by the use of standard protocols.

Acknowledgment

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