Chapter III

How Accurate is an Effort Model?

Abstract

Building effort models or using techniques to obtain a measure of estimated effort does not mean that the effort estimates obtained will be accurate. As such, it is also important and necessary to assess the estimation accuracy of the effort models or techniques under scrutiny. For this, we need to employ a process called cross-validation. Cross-validation means that part of the original data set is used to build an effort model, or is used by an effort estimation technique, leaving the remainder of the data set (data not used in the model-building process) to be used to validate the model or technique. In addition, in parallel with conducting cross-validation, prediction accuracy measures are also obtained. Examples of de facto accuracy measures are the mean magnitude of relative error (MMRE), the median magnitude of relative error (MdMRE), and prediction at 25% (Pred[25]).
Introduction

As previously seen in Chapter II, effort estimation models and techniques aim to provide accurate effort predictions for new projects. In general, these models and techniques use data on past finished projects, which are then employed to obtain effort estimates for new projects. However, providing an effort estimate does not guarantee the estimate will be accurate, that is, close to the actual effort used to develop the new Web project.

To determine how good a model or technique is to estimate effort for new projects, we need to measure its predictive accuracy, which can be calculated using past finished projects for which actual effort is known.

Measuring the predictive accuracy of an effort estimation model \( m \) or technique \( t \) is a four-step process, described below and illustrated in Figure 1.

**Step 1:** Split the original data set into two subsets: validation and training. The validation set represents data on finished projects \( p_n \) to \( p_q \) that will be used to simulate a situation as if these projects were new. Each project \( p_n \) to \( p_q \) will have its effort estimated using the model \( m \) or technique \( t \), and, given that we also know the project’s actual effort, we are in a position to compare its actual effort to the estimated effort obtained using \( m \) or \( t \), and therefore ultimately assess how far off the estimate is from the actual.

**Step 2:** Use the remaining projects (training subset) to build an effort estimation model \( m \). There are estimation techniques that do not build an explicit model (e.g., case-based reasoning). If that is the case, then the training set becomes a database of past projects to be used by the effort technique \( t \) to estimate effort for \( p_n \) to \( p_q \).

**Step 3:** Apply model \( m \) to each project \( p_n \) to \( p_q \), and obtain estimated effort. Once estimated effort is obtained, accuracy statistics for each of these projects \( p_n \) to \( p_q \) can also be calculated. If the technique does not build a model, then this step comprises applying this technique \( t \) to each project \( p_n \) to \( p_q \) to obtain estimated effort, and once estimated effort is obtained, accuracy statistics for each of these projects can be calculated.

**Step 4:** Once estimated effort and accuracy statistics for \( p_n \) to \( p_q \) have been attained, aggregated accuracy statistics can be computed, which provide an overall assessment of the predictive accuracy of model \( m \) or technique \( t \).

It is important to note that the subset of new projects (see Figure 1) comprises data on finished projects, for which actual effort is known. These data are used to simulate a situation where a Web company has a subset of new projects for which
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