

# Recommending effort estimation methods for software project management<sup>1</sup>

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## Abstract

*Estimating a project's effort or schedule is a crucial task for software project management. However, project leaders are often overwhelmed when selecting an appropriate estimation method to best match the project characteristics and context.*

*Recommender systems (RS) are applications that typically support online users when confronted with large sets of choices. Knowledge-based recommenders are a specific variant of these systems that exploit explicit knowledge models in order to infer matching items based on a set of specific requirements. This paper's contribution lies in its application of knowledge-based recommendation mechanisms to the domain of software project management and presents a recommender for effort estimation methods. An initial evaluation among software professionals showed promising results and disclosed helpful hints for further development.*

## 1. Introduction

In today's competitive software development environment it is of utmost importance to deliver products on time, with the desired quality attributes and at the specified cost. Depending on the specific project, estimation of size, effort and schedule can be done in an iterative way, that is by primarily estimating requirements of the next development step. However, ever increasing competition among software companies often results in fixed-price projects. It is thus important to estimate the effort required, size and schedule of a specific project even in the early stages of software development. Thus accurate estimation methods like, for example, the Function Point method, T-shirt sizing or calibration with project-specific data have gained increasing importance [1], [2]. Notably, this also holds for the development of custom software and integration projects, where functionality is primarily extended or substituted.

Although there is a large amount of literature on software estimation methods [1], [2], there is often no detailed knowledge about when to apply which method. To the best

of our knowledge, no out of the box knowledge base exists that supports the selection and prioritization of adequate techniques depending on a specific project's characteristics. Consequently, there is a need for personalized advice, taking into account the specific project characteristics, the availability and granularity of comparable data and the current state of development.

In particular, the multitude of potential users, the fact that project managers are solely aware of a small number of relevant techniques and the availability of various techniques for diverse project settings suggests that constructing a recommendation application for software estimation techniques would be worthwhile. Furthermore, harnessing a web-based recommendation system may also considerably contribute to the widespread applicability of software estimation techniques in today's mainstream software engineering projects.

Publicly available recommendation applications for software engineering are in the scope of the Austrian Softnet research and innovation program. This paper contributes a knowledge-based recommendation application that allows software project managers to select appropriate methods for effort, size and schedule estimation.

In Section 2 we discuss related work, namely recommendation applications for software engineering, and Section 3 outlines our novel knowledge model for software estimation techniques. Notably, our model takes the cone of uncertainty [2] into account and thus reflects the accuracy of the different estimation methods at various stages of software development. Section 4 presents our pilot application and its user interface. Moreover, we report on a survey about the proposed interaction flow, the results obtained and the underlying hypotheses. Finally, Section 6 concludes our paper.

## 2. Related work

The authors of [1] and [2] present more than 30 estimation methods and their associated properties. It is however hard and time consuming for a user to consider all the methods and then decide which one is best suited for the current project.

To the best of our knowledge no work has been done in trying to implement a recommender system for software estimation techniques. The authors of [3] present a recommender system for project planning. This approach mainly

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Table 1. Project characteristics

Context variable	Description
project type	e.g. <i>new development, maintenance</i> or <i>customization project</i>
development style	<i>iterative</i> or <i>sequential</i> development
project size	<i>small, medium</i> or <i>large</i> depending on development staff
development stage	early or late phases of the development process
stakeholders	audience addressed by the estimate
countable items	defines what can be counted in the current project (e.g. requirements, GUI elements or function points)
available historic data	types of historic data that can be exploited for the current effort estimation task
data granularity	degree of detail of historic data (compare to countable items)

supports project planning by taking previous projects into account. It can be used solely when project-specific data is available from previous projects. Additionally this approach requires information like cost, size and well defined user requirements to be known. In contrast, our technique does not necessitate project specific data, but rather takes project specific data into account if it is available.

Recommendation applications enjoy wide spread used in diverse fields of software engineering. The authors of [4] present a survey of different recommendation tools for software maintenance and development. Based on automatic or manual queries, each tool presented in the survey is capable of recommending what should be done in the upcoming stage of ongoing software development efforts. Other works deal with improvement to developer productivity. The authors of [5] present a recommendation system for identifying the most appropriate functions for implementing a specific software feature. Their approach is based on collaborative filtering algorithms [6]. Moreover the literature reports on successful applications of recommendation systems for detecting software conflicts, as presented in [7], or for focusing software testing on specific modules or components [8].

### 3. Knowledge model for recommendation

Knowledge-based recommender systems exploit a knowledge base that explicitly mediates between user requirements and the characteristics and limitations of different effort estimation methods in order to identify those items that best fulfill them. An overview on knowledge-based recommendation systems can for example be found in [15]. The knowledge base for the RS application presented here was derived by interviews with domain experts and by studying the popular literature on this topic [1], [2]. More concretely, the RS for advising about effort estimation methods elicits the project's context like the development style or the phase the project is currently in via a forms-based dialogue (see Table 1 for the most important domain characteristics). The recommendable items and *effort estimation methods* constitute the product catalog  $I$  containing a finite set of database instances. Items are characterized by a set of properties like the required

level of detail for historical data or their applicability to different project phases. Furthermore, the knowledge-based RS takes a set of constraints, i.e. the knowledge base ( $C$ ) and the specific requirements ( $SRS$ ) describing the project context as input. We employ constraints that are represented as logical implications and consist of a condition (*If* . . .) and a consequent (*then* . . .). In addition, constraints ( $c$ ) possess a weight ( $w_c$ ) that characterizes their relative importance and may be defined as either hard ( $c \in C_{hard}$ ) or soft ( $c \in C_{soft}$ ). The latter means that they can be ignored if no other solution can be found. The specific requirements and the condition parts of constraints are represented by terms utilizing the context variables described in Table 1. Therefore, the function  $app(C, SRS)$  returns all constraints from  $C$  that are applicable in conjunction with  $SRS$ . Consequently, recommended items need only to satisfy the consequent parts of applicable constraints. We denote the consequent part of constraint  $c$  by  $cons(c)$ .

In general, a recommender computes a function  $rec(i, u)$  for a given item  $i$  and an user  $u$  that returns a recommendation score. It expresses the system's belief as to whether the item is of interest for the user. In case the RS's knowledge base consists solely of hard constraints, the assumed utility scores either 1 if an item satisfies all applicable constraints or 0 otherwise. However, in cases where the knowledge base contains soft preference constraints the constraint-based recommendation system is able to compute scores that reflect the sum of weights of fulfilled constraints with respect to the sum of weights of constraints that were *relaxed* in order to include the specific item in the result set. Given product table  $I$ , specific contextual requirements  $SRS_u$  and the relational selection operator  $\delta$  we define that item  $i$  satisfies the conditional constraint  $c$  iff  $i \in \delta_{[cons(c)]}(I)$ . Therefore, our implementation computes recommendation scores as follows:

$$rec(i, u) = \begin{cases} \frac{\sum_{c \in app(C, SRS_u)} i \in \delta_{[cons(c)]}(I) w_c}{\sum_{c \in app(C, SRS_u)} w_c} & : * \\ 0 & : \text{else} \end{cases}$$

$$* \forall c \in app(C_{hard}, SRS_u) i \in \delta_{[cons(c)]}(I)$$

Consequently,  $rec(i, u)$  is the sum of the weights of all constraints that, in conjunction with the specific project context ( $SRS_u$ ), support item  $i$  to be in the result set.  $\sum w_c$  in the denominator normalizes the utility score to the range 0..1. In cases where not all of the hard constraints are able to be fulfilled the score is set to 0. This approach was already proposed in [9] where constraints have been learned from past user interactions. Our computation scheme for recommendations contrasts the knowledge-based relaxation mechanisms presented in Mirzadeh et al. [10] or Jannach [11] who search for query relaxations on the product catalog that determine the result set. While they compute recommendations where each item satisfies the same set of constraints, we rather assign ranks to items based on their individual constraint fulfillments.

The knowledge base consists of around 50 different constraints, some of which are rather obvious like *If the*

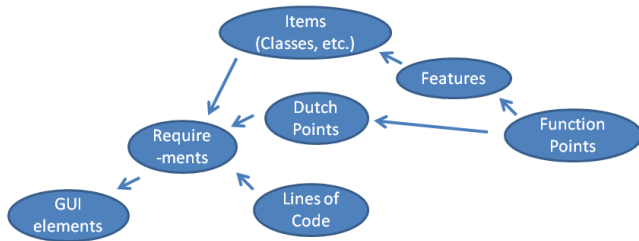


Figure 1. Dependencies among granularity levels of historic data and countable items

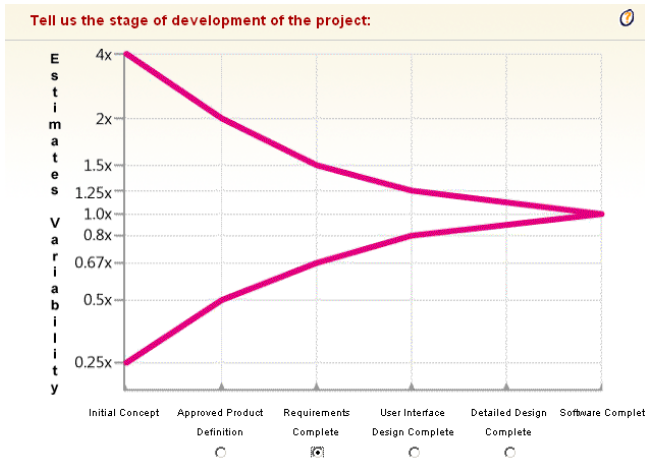


Figure 2. Sample question

project follows development style X then the method should be applicable to development style X. However, matching the historic data requirements of estimation methods with the granularity of the available historic data and the countable items of the current project data is more complex. Figure 1 sketches the assumed dependencies between different classes of countable elements for deriving software estimates. The directed edges indicate an informal containment hierarchy. For instance if one can compute Function Points (FP) then - in principle - Dutch Points (being only a subset of FP elements) or method-level features may also be computed. Therefore, only estimation methods that are applicable to the figuratively *greatest common divisor* or lowest granularity of the available historic data and the countable data in the current project must be selected.

#### 4. Implementation

The implementation is based on a generic recommendation framework [12] that can be instantiated in different application domains. Figure 2 depicts a sample dialogue page that requires the user to specify the current project phase and informs him/her of the variability that can be expected in effort estimation methods at this point. Figure 3 shows parts of the result page of the system, listing the estimation methods that are applicable to the given

The preferred estimation methods are:

Method	Description	Details
T-Shirt Sizing	Used when working with stakeholders. Helps the stakeholders understand the ratio between features and there development costs. Unnecessary functionalities can be eliminated. Wide area of the cone. Each feature/requirement receives two grades, one for its importance and one for its costs. <b>Warning: T-shirt sizing fits only to the current iteration.</b> This method is applicable to an iterative development style. This method is already applicable at the start of the project. The method is applicable to medium-sized projects.	Why?

Figure 3. Results page

project context together with some additional explanations such as under what circumstances the method is applicable or some form of disclaimer like *T-Shirt sizing fits only the current iteration* when proposed in the context of an iterative development process. In addition the application has additional features such as dynamic interaction flow based on user input as well as a type of inconsistency detection for cases where user input seems to be contradictive as presented in [13].

#### 5. Evaluation

To evaluate the initial version of our recommendation application we prepared a questionnaire and asked our industry partners (big companies as well as small and medium-sized enterprises) for their feedback. Primarily project managers, software engineers and IT consultants tested our application and subsequently answered the questionnaire. For this evaluation we hypothesized that potential users are coarsely familiar with software estimation techniques.

Our survey's main intention was to evaluate (1) the practical applicability and usefulness of the system for mainstream software engineering projects, (2) the completeness and comprehensiveness of the proposed methods, (3) the characterization of the project and the project's context, and (4) the traceability of the given recommendations. The seven participants of our survey reported diverse intricacies. In the following we discuss the most notable suggestions for further improvement categorized according to the criteria given above .

- (1) **Practical applicability:** In order to improve the general applicability of the system, our testers reported on various aspects . Rather than identifying a method by merely using its name, our test users encouraged us to provide concrete examples for the individual methods. Some of the testers noted that there is no clear statement w.r.t. to the reliability of the suggested methods. Furthermore, our users suggested the integration of a feature that supports the anonymous evaluation of previous suggestions made by the recommendation application. Most users noticed that our novel recommendation model is able to discriminate between similar methods depending on concrete project scenarios and thus confirmed the adequacy of the model. However, two users complained that the system's decision procedure is not precise enough to be employed for everyday use.
- (2) **Completeness and comprehensiveness:** The majority of test users considered the listed methods as (almost)

complete. Most users stated that they were familiar with two to three methods - primarily with the function point method and expert estimation. The COCOMO and Delphi methods were also known to some.

- (3) **Characterization of project context:** Without exception our test users reported that time for estimation, budgeting and scheduling is required within the development process. Furthermore, the test users pointed out that the recommendation application needs to take into account whether the user involved in custom software development or extensions to existing applications (e.g. add-on development). Some test users requested that the application domain explicitly be asked for.
- (4) **Traceability of recommendations:** The majority of our test users identified this issue as the weakest point of the current version. In this respect our users stated that the system solely lists the applied filters. However - in the opinion of our test users - this does not explain why a proposed method should be applied to a specific project, i.e. the recommendation application comes up with a technical description of the method, but -fails to explain why a specific method is chosen in any straightforward way.

## 6. Discussion and Conclusion

This paper contributed a knowledge-based recommendation application to the domain of selecting appropriate effort estimation methods for software project management. The results of our survey on the pilot system confirmed our assumption that tailoring a recommendation application for project managers and engineers - in contrast to the typical tailoring for sales representatives - requires a very precise formalization of the underlying problem. However, the answers to our questionnaire highlighted that such a recommendation application might be used in practice. This holds particularly for a complex knowledge base as a recommendation system might have genuine value for entering even more detailed facts about the project under consideration.

In addition several technical issues and the need for further clarification of the capabilities of diverse methods (e.g. requesting the application domain directly vs. conveying that the application domain is an input to the method being proposed), traceability must be further improved if the system is to be widely adopted.

In the near future we plan to extend the knowledge base to cover more project details. Besides of this, a user receiving a certain recommendation might be interested in obtaining the necessary information to extend into an accurate method. We plan to address this by incorporating ideas from diagnosis [14] into our recommendation engine.

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