Making Sense to Modelers
Presenting UML Class Model Differences in Prose

Harald Störrle
Department of Informatics and Mathematical Modeling, Technical University of Denmark,
Richard Petersens Plads, 2800 Lyngby, Denmark

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Abstract: Understanding the difference between two models, such as different versions of a design, can be difficult. It is a commonly held belief in the model differencing community that the best way of presenting a model difference is by using graph or tree-based visualizations. We disagree and present an alternative approach where sets of low-level model differences are abstracted into high-level model differences that lend themselves to being presented textually. This format is informed by an explorative survey to elicit the change descriptions modelers use themselves. Our approach is validated by a controlled experiment that tests three alternatives to presenting model differences. Our findings support our claim that the approach presented here is superior to EMF Compare.

1 INTRODUCTION

Motivation. In model based and model driven development, code is increasingly being replaced by models. Thus, model version control becomes a critical development activity for all but the smallest modeling projects. (Kuhn et al., 2012) provide empirical evidence to this claim. Consequently, version control operators for models have attracted great attention over the last years. For instance, there are two ongoing workshop series on this issue, "Model Evolution" (ME) and "Comparison and Versioning of Software Models" (CVSM). The on-line bibliography "Comparison and Versioning of Software Models" (see (CVSM Bibliography, 2012)) records well over 400 publications in the area in the last 20 years, more than 250 of which have been published in the last five years. However, only less than ten out of these 250 publications consider the presentation of differences, even though the best difference computation is little use if the modeler cannot make sense of the change report.

Apparently, it is a commonly held belief in the model differencing community that the best way of presenting a model difference is by graph or tree-based visualizations, while text-based difference reports are considered inferior. For instance, Ohst et al. maintain that "*the concept of [side-by-side presentation] works well with textual documents, [...but] does not work well with graphical documents such as state charts, class diagrams, etc.[...].*" (cf. (Ohst et al., 2003, p. 230)). Schipper at al. believe "*that there is a real need for a visual comparison*" (cf. (Schipper et al., 2009, p. 335)). Wenzel even claims that "*The textual presentation [of differences] [...] is very difficult, or even impossible, to be read by human readers*" (cf. (Wenzel, 2008, p. 41)).

Approach. We disagree with this opinion. It is certainly true that high-accuracy difference computations leads to very large numbers of low-level differences, and simply dumping these to the user is not very helpful: modelers are overwhelmed by the amount of information they are confronted with. There is, however, no reason, why we cannot try and find a more abstract textual difference representation that is equally accurate but less detailed, and thus easier to understand for modelers.

Also, it is well known that conformance between questions and answers increases task performance and reduces cognitive load. We therefore propose presenting model differences in the same terminology and with the same aggregation size that modelers use to describe changes in their models. This way, we hypothesize, will modelers find it more easy to understand model difference presented to them. In other words: a model difference will make more sense to a modeler if it is presented in the right terms. We ex-

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plore this idea, formalize its notions, implement them, and present empirical evidence comparing it to existing approaches.

Contribution. In this paper we propose an approach to compute model differences with maximum accuracy, automatically derive high-level explanations from them to reduce the level of detail, and present these high-level differences in user-friendly textual way. Our approach to version control of models looks at models as knowledge bases providing an abstract view into some application domain. We present a tool implementation of our approach and briefly evaluate its performance.

We report on two empirical studies discovering the model change terminology and granularity used by modelers, and exploring and comparing ways to present model differences. We find considerable evidence in support of our hypothesis. The ideas reported in this paper have evolved through a series of papers (see (Störrle, 2007b; Störrle, 2007a; Störrle, 2012)).

2 DIFFERENCE ALGORITHM

In the context of model comparison for version control, we typically want to compare two models that are subsequent versions of the same model. Thus, we can typically assume that (1) the two models have been created using the same tool, and (2) they have a large degree of overlap. This means, that both models use the same kind of internal identifiers for model elements, and that most of the model elements have the same identifiers in both versions. Thus, there is no need to align models, and matching between their elements becomes trivial. These assumptions are clearly not applicable in other, related areas, such as general comparison of models, or model clone detection (see e.g., (Störrle, 2011a)). Note that EMF Compare (see www.eclipse.org/emf/compare) has a wider focus and includes an explicit matching phase before computing model differences, although only identifier and hash-based matching seem to be currently available.

Mathematically speaking, we interpret a model as a finite function from model element identifiers to model element bodies, which are in turn finite functions from slot names to values, which of course may be (sets of) model element identifiers. We define the following domains.

$\mathcal{I}$ Identifiers are globally unique elements.

$\mathcal{S}$ Slot names are identifiers that are unique in a given model element, in meta-model based languages like UML they correspond to meta-attributes.

$\mathcal{V}$ Slot values may be of arbitrary type, including basic and complex data types, and references to (sets of) model elements.

$\mathcal{B} : \mathcal{P}(\mathcal{S} \to \mathcal{V})$ Model element bodies are maps from slot names to slot values.

$\mathcal{M} : \mathcal{P}(\mathcal{I} \to \mathcal{B})$ Models are maps from model element identifiers to model element bodies.

We use the notation $dom(f)$ to denote the domain of a function, and $f \downarrow_X$ to denote the restriction of f to the sub-domain $X \subseteq dom(f)$. For example, if $f : A \to B$, then $dom(f) = A$ and $f \downarrow_X = \{\langle x, f(x)\rangle \,|\, x \in X, X \subseteq A\}$. The operator $/$ denotes set difference, i.e., $X/Y = \{x \,|\, x \in X \wedge x \notin Y\}$.

The domain definitions and notations introduced above allow us to formulate the difference computation as basic set-operations. Let P and P' be two versions of a model, then the following definitions are obvious.

$$\begin{array}{lll}
\text{Unchanged} & U = & P \cap P' \\
\text{Added} & A = & P' \downarrow_{dom(P')/dom(P)} \\
\text{Deleted} & D = & P \downarrow_{dom(P)/dom(P')} \\
\text{Changed} & C = & P'/(U \cup A)
\end{array}$$

In order to compute the detailed changes of the changed elements, similar definitions apply. For every changed model element $c \in C$ with identifier i, we define the following sets for the slots of C.

$$\begin{array}{lll}
\text{unchanged} & c_u = & P(i) \cap P'(i) \\
\text{added} & c_a = & P'(i) \downarrow_{dom(P'(i))} \\
\text{deleted} & c_d = & P(i) \downarrow_{dom(P'(i))} /c_u \\
\text{changed} & c_c = & P'(i)/(c_u \cup c_a)
\end{array}$$

Clearly, all of these sets can be computed trivially and efficiently. Observe that the result of applying these operators are not necessarily consistent models. For instance, if model P contains only a class A, and model P' contains also a class B and an association between A and B, then $P' \downarrow_{dom(P')/dom(P)}$ (the set of added elements) contains class B and the association, but not class A, that is, the association contains a slot pointing to A, i.e., a dead link.

Algorithm 1 : Compute difference between two models *OLD* and *NEW*.

```
function DIFF($OLD, NEW$)
    compute sets $A$, $D$, and $C$ as defined
    for all $c \in C$ compute $c_a$, $c_c$, and $c_d$
    tag elements with their change type
    return $A \cup D \cup \bigcup_{c \in C}(c_a \cup c_c \cup c_d)$
end function
```

Consider the example in Fig. 1. It shows two subsequent versions of a class model in the insurance domain. Obviously, this is only a small toy example with a modest number of straightforward changes, finding

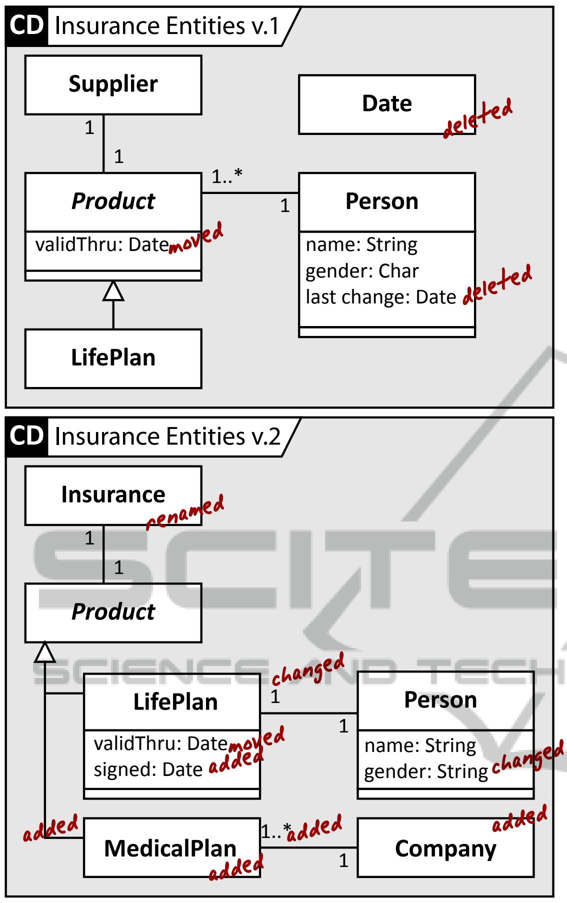


Figure 1: Running example for versioning models: original version (top); and subsequent version (bottom), with changes annotated in red.

all of them can be difficult. But even a complete and explicit list of the changes may be difficult to read if the number of changes grows too large. Even in the small example from Fig. 1, there are 36 changes between the two models, making this change report difficult to understand.

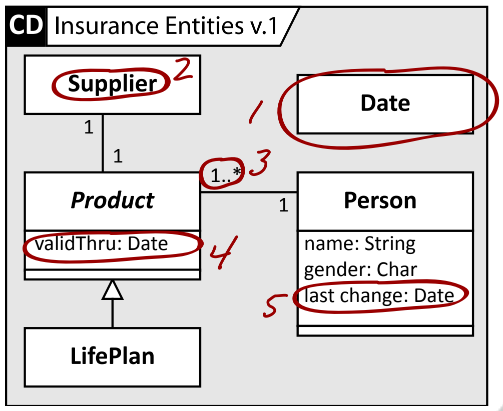
However, we have observed patterns in these low-level change reports: usually, groups of changes occur together as the effect of a single modeling action. Reconstructing these high-level changes from the low level observations will improve the understanding of model changes. This is the topic of the next section.

3 EXPLORING MODELERS' DIFFERENCE PERCEPTION

In order to learn what concepts and abstractions modelers find helpful when talking and reasoning about model differences, we explored modelers' perception of model differences through a qualitative study. We created three pairs of sample UML class diagrams that contained between 8 and 12 changes each. All kinds and sizes of changes were covered at least twice. We highlighted all changes by circling their effect in the diagrams in red and numbering them randomly. Fig. 2 (left) shows an example. Next we presented these model pairs to 4 graduate students and asked them to describe the highlighted model changes in their own words. We asked them to write down their change descriptions, referring to the numbers associated to the changes in the diagrams. We also asked them to speak out loud what they were thinking in the process and audio-recorded their utterances.

We found that there were three dimensions of variation in the ways study participants described model differences. Firstly, there were variations in the grammar and vocabulary, particularly the choice of verbs. For instance, subjects might use “remove” instead of “delete”, and “change” instead of “update”. Similarly, subjects might use either present tense or past tense, or even a mix of both when describing changes. Since both of these variations appeared without any perceivable pattern, we hypothesize that the variables grammar and vocabulary are of little importance to model change description. Mostly, subjects used the passive voice rather than the active voice or imperative. For instance, the change marked 1 in Fig. 2 would be described as “Class 'Date' was deleted” rather than “Delete Class 'Date' ”. We attribute this to the fact that it was not clear to the study participants who had actually done the changes, so there was no obvious grammatical subject to use in the change descriptions.

Secondly, some changes were described in a generic way while others were described in a more specific way. For instance, the change marked (2) in Fig. 2 would always be described as a 'renaming' rather than a change or update of the meta-attribute 'name'. In some cases, both types of change descriptions could be observed. For instance, change (3) would often be described as a decrease in 'Products' associated to 'Persons', but sometimes subjects might also describe it as “change the multiplicity of the association from 1..* to 1'. Similarly, changes to the meta attribute 'isAbstract' would usually be described as 'making abstract' or 'making concrete' of a class. There were yet other occasions, however, where no specific description applied, and subjects would use a variant of the generic description schema, i.e., we would observe a change description like “The type of feature 'gender' was changed from 'Char' to 'String' ”. Generally speaking, most subjects preferred 'special case descriptions' over the generic description pattern most of the time. Assuming that



	Task	Change Description
A	*You are looking at two versions of a class model retrieved from a version control systems. Describe the changes made in the second version!*	(1) Class 'Date' was deleted. (2) Class 'Supplier' was renamed to 'Insurance'. (3) The number of 'Products' associated with a 'Person' was reduced from 'one or more' to 'one'.
B	*You are looking at two alternative versions of a class model. Describe the differences between these two versions!*	(1) V.1 has a class 'Date' while v.2 does not. (2) Class 'Supplier' in v.1 is called 'Insurance' in v.2. (3) In v.2, a 'Person' is associated to only one 'Product', while in v.1 there may be one or more.

Figure 2: Exploration of change descriptions by modelers: model markup (left); change description as a function of task description (right).

the subjects always tried to describe the changes in the most accurate way they could, we concluded that these changes were considered strictly different by the subjects, and should be described in specific terms rather than generic terms. However, there were some changes that were described in rather different ways by different subjects. For instance, changing generalizations between classes, was described as 'let x inherit from y rather than z' by one subject, while another subject described it as 'replace z by y as generalization of x'. We attribute this variation to different degrees of UML-sophistication in the subjects, which might mean that there should be different ways of describing the same change in different situations and to different audiences.

Thirdly, we observed that the wording of the task description had great influence on the change descriptions produced by the subjects, as this description would hint at an application scenario which lead subjects to use different constructions matching the imagined scenario. Consider the variants of task descriptions and resulting change descriptions as shown in Fig. 2 (right). These two scenarios describe models as (A) subsequent or (B) alternative versions, i.e., as dependent or independent of each other. In the former case, descriptions typically used past tense and passive voice, using activity verbs like “add” or “delete” to describes changes. In the latter case, change descriptions typically contrasted two states using the present tense of state-describing verbs, especially 'be' or 'have'.

4 DIFF INTERPRETATION

Abstraction Rules. The overall idea is to provide rules to explain sets of changes in a more abstract way. For instance, if a class C is deleted, its transitive parts and attached associations are also deleted. So, computing the difference results in a large number of detail changes that might confuse the modeler. This set of detail changes can often be replaced by a single modeler-level explanation, e.g., something like 'deleted C and parts (cascading)'. Also, some changes are more important than others, and some may be reported summarily. For instance, changing the name of a class is often more important than changing its visibility. So we defined the following rules for abstracting low-level changes, based on observations on change protocols of difference computations of a set of modeling case studies (see (Störrle, 2011a) for more details on these case studies).

Rename. Replacing a change *“update attribute 'name' of class 'Supplier' to 'Insurance' ”* into *“rename 'Supplier' to 'Insurance'* obviously does not reduce the number of changes, but makes it easier to understand the change.

Move. Moving an element from one container to another changes the list of contained elements of both containers, so a pair of low-level changes can be accounted for with a single high-level change, and the operation “move” is easier to make sense of than a pair of addition and deletion, in particular if these are not presented together.

Delete. Deleting an element also deletes its parts, removes a link to it from the part-list of its container, and any references from other elements to it. Typically model elements have several parts, which might again have parts so that deleting a single element may cascade a number of times, and a substantial number low-level changes can be abstracted this way.

Add. Similarly, adding an element again also changes the part-list of its container, often adds parts, and possibly references from other elements to it. Furthermore, similar additions could be grouped, such as when adding several properties to a class: a single change can summarize such a change set.

Associate/Dissociate. Adding or removing an association between some elements amounts to adding or removing the element itself, its (transitive) parts and properties, and references to these parts. For instance, an association is a connection between properties of the associated elements, and it is them who own the properties rather than the association.

Re-associate. Exchanging one participant of an association by another replaces a pair of overlapping associate and dissociate-changes.

Tool Specific. Some changes refer to tool specific elements such as extension elements, internal libraries and so on. These should be suppressed in a high-level view.

Implementing these rules must satisfy two major design goals. Firstly, the number of the reported changes should be substantially reduced and their understandability increased (**Goal 1:** reduce number of changes). Secondly, it should be easy to inspect a high-level change and find out what low-level changes it actually accounts for, so that both the results and the procedure are transparent (**Goal 2:** account for abstractions). Thirdly, the rules should be independent of each other such that it is easy to add or change them (**Goal 3:** Independence).

Difference Abstraction Algorithm. In a first attempt, we tried to provide a set of explanation rules that would consume the computed changes of a model difference. This way, each high-level change could be made to contain the low-level changes it accounts for which would satisfy the design goals 1 (change reduction) and 2 (accountability). Such an algorithm works fine when considering only renaming, moving, and additions/deletions of classes, properties, and similar entities.

However, there are many cases where the same low-level change can be explained by different explanations. For instance, consider the following three high-level changes possible to deduce from our above rules.

- adding class 'Company',
- associating class 'Company' to class 'MedicalPlan', and
- re-associating another class with 'Company'

All of these high-level changes would account for the low-level changes *"add anonymous property"* and *"update ownedMember of 'Company'"*. Of course, creating a high-level change report should explain as many low-level changes as possible, and so each rule is "greedy". This would imply that each rule must have a great number of case distinctions that encode deep knowledge about all other rules and what low-level changes may or may not have already been accounted for by another rule. Clearly, this contradicts the third design goal (independence of rules). So, the first design of simply consuming low-level changes is inadequate.

Instead we chose a different approach. If a high-level explanation E is found to account for a set of changes $C = \{c_1, \ldots, c_n\}$, then the elements of C are marked as accounted for, and linked to their high-level explanation E, while E is being added to the list of computed changes. Clearly, this approach allows to satisfy design goals 2 (accountability) and 3 (independence), but not 1 (reduce number of changes), since the number of changes steadily increases. However, the number of changes not accounted for *does* decrease, and so a slight variant of design goal 1 is indeed satisfied. This solution has the added benefit that there may now also be rules to abstract from previous abstractions (e.g., rule "Re-associate").

Since the number of low- and high-level changes never reaches zero and we cannot know in advance how far their number may be reduced, we use a fixed-point algorithm to implement this solution. In other words, the rules are applied until the set of changes does not change any further, which includes both the overall size of the set and the number of accounted-for changes. Conflicts between different explanation rules need to be resolved by the programmer at design-time; different orderings might result in different interpretations. The final algorithm is shown as Algorithm 2. Clearly, the algorithm terminates, if there is at least one explanation for each change. We achieve this by adding the default explanation, where a change is explained by itself. This rule applies only as a fall-back, i.e., if no other explanation applies earlier.

As an added benefit, this approach is independent of the ordering in which rules for interpreting low-level changes are applied. While the ordering of model changes has no influence on the interpretation, some sequences of operations are currently not detected. For instance, deleting an element and creating another element that is equal up to identity in another place might be understood as a movement by a user, but will not be recognized as such by the tool.

Algorithm 2: Interpret difference D between two models OLD and NEW.

```
function EXPLAIN($DIFF$)
    pick some $d \in DIFF$ marked as 'fresh'
    if there is an explanation $E$ for change $d$ then
        find largest $D \subseteq DIFF$ explained by $E$
        add $E$ to $DIFF$
        link $D$ to $E$ for tracing
        mark $E$ as 'fresh' in $DIFF$
        mark all $D$ as 'stale' in $DIFF$
    end if
    return $DIFF$
end function

function INTERPRET($DIFF$)
    mark all $D \in DIFF$ as 'fresh'
    $DIFF' \leftarrow DIFF$
    repeat
        $DIFF \leftarrow DIFF'$
        $DIFF' \leftarrow explain(DIFF)$
    until $DIFF = DIFF'$
    remove all 'stale' elements in $DIFF'$
    return $DIFF'$
end function
```

5 IMPLEMENTATION

As in previous work on other model management operations (see (Störrle, 2011b; Störrle, 2011a)), we equate domain models with domain knowledge bases and represent models as collections of Prolog facts. Therefore, we have implemented our algorithm in Prolog, too. There is a straightforward reversible mapping between more conventional model formats such as XMI and our Prolog representation.

Modelers can choose between different formats for model difference, including low and high levels of abstraction, and tabular or textual presentations. Modelers are also offered statistics about the model size, number of changes, and change rate.

Change Description Size. Using the running example from Fig. 1, we may obtain difference reports from EMF Compare, the low-level output from our approach, and our high level output, presented in tabular and textual format. In the remainder, we will refer to these as treatments (1), (2), (3A) and (3B), respectively.

Observe that the table and the prose text contain identical information; they just present them in different formats. Clearly, EMF Compare uses by far the most screen real estate to present changes, which will be detrimental in maintaining an overview over large differences. Also, the difference presentation of EMF Compare is much more verbose without offering more information, while at the same time demanding heavy interaction by the modeler inspecting the differences when unfolding the difference tree. This will likely increase the effort of the modeler in trying to understand a model difference.

A quantitative comparison of the number of changes is shown in Fig. 3. It is obvious that the number of high-level changes is lower than the number of changes reported by EMF Compare, which in turn is markedly smaller than the number of low-level changes (36 vs. 15). Observe, however, that the difference in numbers of changes reported by EMF Compare and the low-level changes is almost entirely explained by changes to the container attributes ("ownedMember" et al.), and EMF Compare does not report most of these changes.[1] Simply dropping this type of information from the low-level change report will result in almost identical numbers as compared to EMF Compare. The number of high-level changes, on the other hand, is notably smaller than the number of changes reported by EMF Compare (10 vs. 15). What is more important, however, is the way the changes are presented in our approach, which we will show to be much more understandable in Section 6.

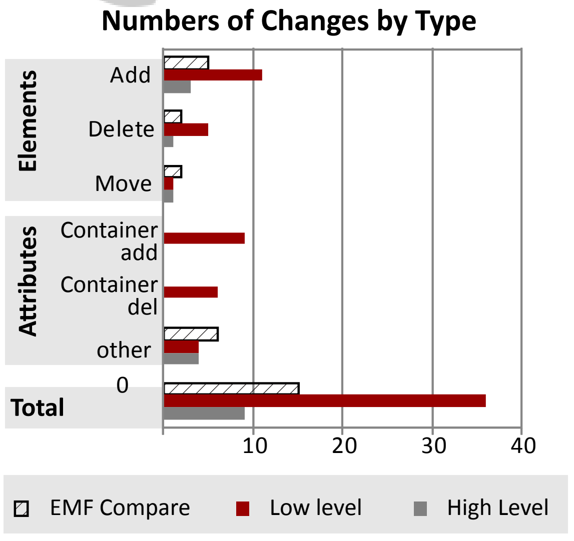


Figure 3: Computational Performance.

Computational Performance. Contrary to common prejudice, using a high-level language like Prolog does not necessarily sacrifice run time for devel-

[1] The exception being the order of the entries in one such container attribute, which, conversely, our approach does not consider.

opment time. In fact, we have consistently observed that our approach outperforms conventional Eclipse-based tools, often by an order of magnitude or more. In order to test this in the present setting, we have timed a series of sample runs of our tool on a laptop computer with an Intel Core i5-2520M, 2.5 GHz, 8GB RAM under Windows 7. Fig. 4 summarizes our findings. It seems that both model size and change size have an impact on execution time. The sample models range approximately from 1,000 to 2,000 model elements, which makes them non-trivial, though not extremely large. The response times are well below a second, that is, our approach is practically viable. A direct comparison to EMF Compare would require instrumentation of the EMF Compare source code, and is thus beyond our reach. Timing a user is inadequate, as EMF Compare requires interactions during the differencing procedure. Discounting for these, EMF Compare needs between 1 and 4 seconds for the same models, i.e., it is considerably slower than our approach.

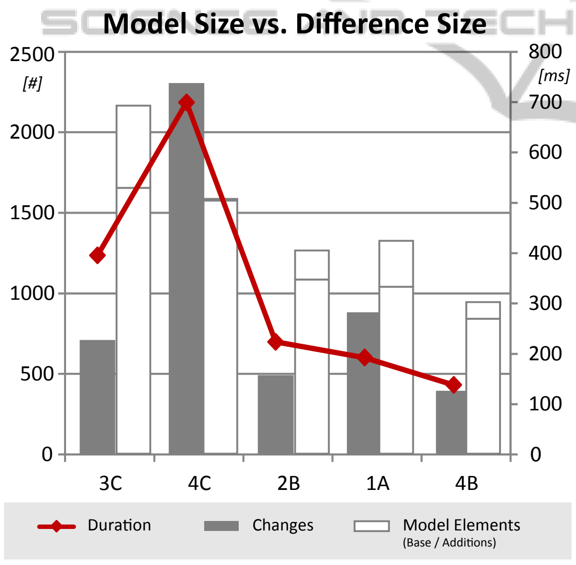


Figure 4: Relating model and difference size with run time: the gray bars indicate the number of changes, the white bars represent the sizes of two model versions by number of model elements. The different case studies are plotted left to right.

6 EVALUATION

Study Design, Materials, and Participants. We validated our approach using a controlled experiment. We prepared two pairs of diagrams with differences, based on the models shown in Section 3. We removed the change markup and created the difference descriptions for each pair with EMF Compare and both our own high level change descriptions, respectively. We created a set of questionnaire sheets that display a pair of models together with one of the difference presentations and the instruction to check the difference description for correctness wrt. the diagrams shown. We then combined two of these sheets into one questionnaire, permuting the sequence of the presentation formats in different questionnaires.

We presented these questionnaires to 25 graduate and undergraduate students; 17 of them returned a questionnaire. All participants had an IT-related university degree or were studying to obtain one. We asked the subjects to validate the correctness of the change presentations at their own pace. The tasks were assigned randomly. A number of data points were unusable because participants did not complete all tasks or misunderstood tasks. Completion ranged from 36% to 93% (average at 63%) depending on treatments and measure.

Observations. We recorded the following three variables:

- the number of errors (including both false negatives and false positives);
- cognitive load (assessed subjectively through two independent questions), recorded on a 5-point Likert scale and later normalized to the interval from 0 to 10;
- and the time used by the participants.

The observations are summarized in Table 1, a visualization is shown in Fig. 5. As the data clearly show, subjects make two to three times as many errors when using EMF Compare as compared to when using one of the other difference descriptions, although they spend approx. 50% more time on the task. At the same time, subjects report the highest subjective difficulty and lowest confidence when using EMF Compare. Interestingly, there is no large difference in both objective measures (errors and time) for treatments (3A) and (3B), while substantial differences in favor of treatment (3B) can be observed in subjective assessments.

Inferences. We have tested hypothesis of the form $\mathbf{H_i}$ "There are no differences wrt. x in modeler performance for the three difference presentation formats", where x is number of errors, difficulty, confidence, and duration. As the distributions are strongly skewed, we used the Wilcoxon test. Despite the small number of replies in some categories, there are some significant results as shown in Table 2. We calculate

Table 1: Observations in our experiment: Confidence and Difficulty are normalized to a scale 0..10, time is in seconds; Treatments are EMF Compare (1), Table (3A), and Prose (3B).

TREATMENT	(1) $\mu(\sigma)$	(3A) $\mu(\sigma)$	(3B) $\mu(\sigma)$
ERRORS	4.2 (2.0)	1.2 (0.7)	1.8 (1.6)
CONFIDENCE	4.0 (1.8)	3.8 (1.0)	5.3 (1.8)
DIFFICULTY	6.3 (1.3)	5.8 (1.5)	4.5 (1.5)
TIME	947 (348)	640 (56)	636 (390)

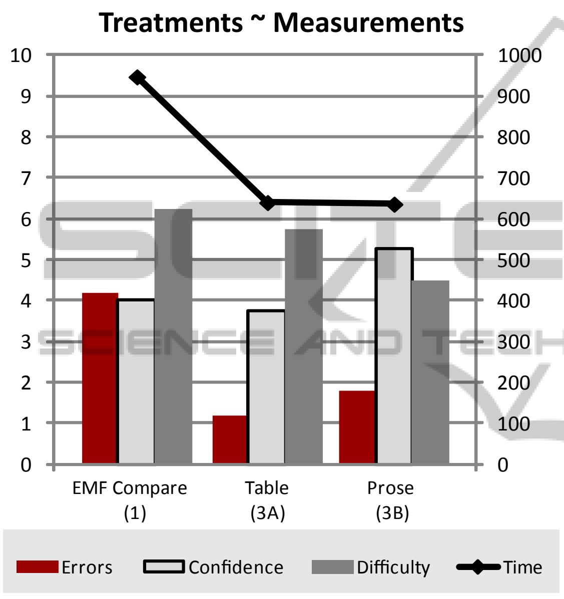


Figure 5: Observations of the controlled experiment.

the effect size as Cohen's *d* for the significant results and find large effect sizes.

Overall, we conclude that treatment (1) – using EMF Compare to represent model differences – is significantly inferior to both novel methods presented in this paper. The data are not as clear when distinguishing between treatments (3A) and (3B), though. Follow-up interviews revealed, that some subjects were confused by the sequence in which the differences were presented. In particular, treatment (3A) accidentally presented changes in a more intuitive way than treatment (3B). As one subject put it: "*The table is better...I don't have to jump around*". Similarly, the prose presentation can be improved by providing more context to a given change. One participant commented that "*locating the elements [in the diagram] takes too much time*". We conclude that there is room for improvement that would likely impact on the findings reported here.

Threats to Validity. There are several potential threats to validity. We eliminated bias through the experimenter by assigning the tasks randomly, providing only written instructions, and asked the subjects to fill in and return the questionnaires anonymously. We eliminated bias through learning effects by presenting all task permutations roughly the same number of times; any learning effects are canceled out this way.

Table 2: Results of testing hypotheses "There is no difference in modeler performance for the change presentations of EMF Compare vs. our approach" for different measurements, with p-value of a one-tailed Wilcoxon test and Cohen's *d*, showing large effect size.

MEASURE / TREATMENTS		p	d
ERRORS	1 vs. 3A	0.009 (**)	2.002
	1 vs. 3B	0.016 (*)	0.755
DIFFICULTY	1 vs. 3A	0.308	
	1 vs. 3B	0.019 (*)	1.282
CONFIDENCE	1 vs. 3A	0.567	
	1 vs. 3B	0.943	
TIME	1 vs. 3A	0.124	
	1 vs. 3B	0.102	

Bias through unrepresentative population sample is controlled by a relatively large sample size ($n = 25$) and by using three disjoint, relatively different populations. All of the subjects are representative in the sense that they are comparable to junior software developers in the industry in terms of their expertise. Observe that cultural bias can safely be excluded since the participants came from more than 15 different (western) countries. Likewise, using class diagrams might be criticized as not representative for all of UML. Indeed, collateral observations lead us to believe that different types of model might require very different types of descriptions. However, class models are by far the most commonly used of all UML diagrams, as Dobing and Parsons have repeatedly shown (see e.g., (Dobing and Parsons, 2006)).

Another potential source of bias is the measurement procedure, in particular wrt. cognitive load measures. We have taken two different measurements that can be understood as aspects of cognitive load (cf. (Paas et al., 2003)). Both of these measurements show the same effect, though to varying degrees. Using subjective assessments rather than objective measures such as skin conductivity or pupillary dilatation is justified by the high correlation between subjective and objective assessments of cognitive load (cf. (Gopher and Braune, 1984)). Finally, the task formulation could bias the outcome. However, the task was presented in mostly visual form with no reference to difference formats, with only very generic and brief textual instructions.

7 RELATED WORK

There are mainly two approaches to presenting model differences, both of which are primarily visual. On the one hand, model differences may be visualized by color-highlighting different change states in the diagrams used for presenting the model (see e.g. (Girschick, 2006)). While initially quite appealing, this approach has some severe limitations. First, using colors to differentiate element status is limited by the number of colors humans effectively (i.e.: pre-attentively) distinguish in a diagram. Long-standing research in psychophysics informs us that this limit is at five different colors (Bertin, 1981). Second, the relatively wide-spread occurrence color vision deficiencies limits the effectiveness of this approach (up to 10% of the western male popultion have partial or total color blindness). Third, only those changes can easily be represented by color highlighting that affect elements presented in some diagram. Changes to the model structure, say, or removal of hidden model elements (which is frequently the case for model clones) have to be presented in different ways. Finally, even those model changes that are presented in a diagram might be difficult to present when they affect more than one diagram. For instance, consider the changes done to a model as part of the rework assignment after a model review: this is likely to be spread out all over the model and over several diagrams of different types.

On the other hand, model differences may be visualized by side-by-side presentations of containment trees of models, possibly enhanced by color coding or connecting lines for movements (see e.g. the treatment in EMF Compare). This way, some of the limitations inherent in the first approach are avoided: issue relating to color vision are less important or can be neglected altogether. Also, all changes can be displayed uniformly, whether the elements affected are presented in a set of diagrams, a single diagram, or no diagram at all. However, this approach does not offer a satisfactory solution for large change sets: if a model difference results in a large number of low level changes, modelers can easily be overloaded by the amount of information, resulting in confusion and errors.

8 SUMMARY & RESULTS

In order to overcome problems with existing model differencing approaches, we propose a new approach to difference computation and presentation in this paper. The difference computation and presentation we propose here has been developed in a series of papers (see (Störrle, 2007b; Störrle, 2007a; Störrle, 2012)). The current paper contributes numerous small improvements such as a better formalization of the domains and algorithms, implementation, and performance evaluation. The main contribution, however, are the qualitative study to explore modelers' understanding of changes, and the controlled experiment to validate our approach.

These studies provide strong evidence to support our hypothesis that a textual model difference presentation can be as effective or even more effective than the model difference presentation provided by EMF Compare. Follow-up interviews reveal, that there is further potential for improving the difference presentations. We expect these to yield even clearer results when testing.

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