Predicting the Perceived Modularity of MOF-based Metamodels

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Abstract: As model-driven engineering (MDE) gets applied for the development of larger systems, the quality assurance of model-driven artifacts becomes more important. Here, metamodels are particularly important as many other artifacts depend on them. However, existing metrics have been rarely validated for metamodels or, even more, evaluation results disproved a correlation between these existing metrics and perceived metamodel modularity. In this paper, we present a new entropy-based metric to capture the perception of metamodel modularity and evaluate the metric in multiple case studies. In the case studies, we correlate the metric results of 32 metamodels across three different domains with 164 responses of a quality assessment questionnaire for which we collected responses in two empirical experiments. The results show significant and strong correlations in all three domains between the metric results and the perceived metamodel modularity.

1 INTRODUCTION

Metamodels are a central artifact of model-driven engineering (Schmidt, 2006) as many other artifacts depend on them. If a metamodel contains design flaws, then presumably all other artifacts have to compensate for them (Di Ruscio et al., 2012). It is therefore very important to detect such design flaws as early as possible to avoid unnecessary development efforts in dependent artifacts.

In the Neurorobotics-platform developed in the scope of the *Human Brain Project* (HBP), these dependent artifacts include not only editors, but also an entire simulation platform where the connection between robots and neural networks is described in models (Hinkel et al., 2015; Hinkel et al., 2016a). As the HBP is designed for a total duration of ten years, it is likely that the metamodel will degrade unless extra effort is spent for its refactorings (Lehman, 1974; Lehman et al., 1997). For such refactorings, we aim to measure their success and potentially automate them.

In object-oriented programming, several approaches exist to detect design flaws, which can be categorized into patterns and metrics. Patterns are commonly used, for example to describe and detect code smells. If a pattern can be found in the code, there is a high defect probability and the smell may be avoidable through better design. On the other hand, metrics have been established to monitor the complexity of object-oriented design not captured by smells, such as the depth of inheritance or lines of code.

Many metamodels nowadays are specified in implementations of the Meta Object Facility (MOF, (Object Management Group (OMG), 2015)), especially in the EMOF specification of this standard and its implementation Ecore.

In prior work (Hinkel et al., 2016b), we have identified modularity as a quality attribute of Ecore metamodels that has a significant influence on the perception of metamodel quality, among correctness and completeness. While the latter are hard to measure, metrics exist to measure modularity in object-oriented design.

Metamodels essentially describe type systems just as UML class diagrams do. In fact, the differences between usual class diagrams and formal metamodels lies mostly in the degree of formalization and how the resulting models are used. Whereas UML models of object-oriented design are often used only for documentation or to generate code skeletons, metamodels are usually used for a multitude of artifacts such as editors, analyses and transformations. Like class diagrams, metamodels can be structured in packages to enforce modules, which makes it appealing to apply class diagram modularity metrics onto metamodels.

Given the similarity of metamodels to object-oriented design, we have tried to adapt metrics

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for object-oriented design such as the metrics from Sarkar (Sarkar et al., 2008). We validated these metrics against human perception of metamodel modularity: In absence of an accepted metric for metamodel modularity, we analyzed to what degree metamodels with a higher metric score are perceived as more modular. The rationale here is that if we find a metric that has a very strong correlation with perceived modularity, then this metric can be used to automate and objectify the assessment of metamodels.

However, the results for the metrics by Sarkar (Hinkel and Strittmatter, 2017) were discouraging because the metric values did *not* correlate with perceived metamodel modularity. In particular, we could statistically disprove even a slight positive correlation between metric values and perceived modularity in some cases.

If it is not the quality in terms of the Sarkar metrics, this raises the question how modelers perceive the modularity of a metamodel. To answer this, we concentrated more on the characteristics that are easier to perceive, tried to bundle these characteristics in a metric and evaluated the metric in three case studies. In particular, we aim to quantitatively measure how classes are distributed to packages, rather than answering the question whether this distribution is reasonable.

In the paper, we propose a metric to measure to which degree classes are contained in different packages and validate the correlation of this metric to the perceived metamodel modularity in two experiments and three domains. We further apply the metric to different versions of existing metamodels in the domain of software architecture description to check whether the ranges of metric values obtained in the experiments match the metric values of realistic metamodels.

The remainder of this paper is structured as follows: Section 2 explains our new metric to measure to what degree a metamodel is modular. Section 3 presents the setup of the empirical experiments that we use to validate this metric. Section 4 presents the results from these experiments. Section 5 discusses threats to validity of the results. Section 6 applies our proposed metric to existing metamodels. Finally, Section 7 discusses related work before Section 8 concludes the paper.

2 THE DEGREE OF MODULARIZATION

The goal of the proposed metric is to measure the degree to which a metamodel employs a package structure. From a good package structure, we expect to know the purpose of a class to a certain degree only based on the package that contains the class.

Assuming that each class has a unique purpose, this can be encoded into the question, how much information we have about a class based only on its package.

The answer can be given using an entropy, borrowed from stochastics. The entropy $H[X]$ of a discretely distributed random variable X with probability mass function P is given by:

$$H[X] = -\sum_{i=1}^{n} P(x_i)\log_b P(x_i) = E[I[X]].$$

Here, b denotes the base of the used logarithm. The term $-\log_b P(x_i)$ is also called the *information* of x_i, expressing informally how special the occurence of x_i is. The entropy is a lower bound on encodings, i.e., the value of X cannot be described with less than $H[X]$ b-ary numbers. The entropy is 0 if and only if there is only one event x_i that always happens ($P(x_i) = 1$). However, the entropy of a random variable can be arbitrarily high, depending on how many events there are.

Mapping entropies to metamodel metrics, our events are that a class is encapsulated in a given package, i.e., x_i means that a randomly chosen class is contained in package p_i. Thus,

$$P(x_i) = \frac{|\mathcal{C}(p_i)|}{|\mathcal{C}|}$$

where $\mathcal{C}(p)$ denotes the classes in package p and $\mathcal{C}$ denotes the set of all classes.

The entropy of the package pointer is 0 if and only if all classes reside in the same package. The more classes are scattered among packages, the higher is the entropy. It can even be shown that for a fixed number of packages, the entropy is highest if the classes are distributed evenly across the packages.

At the same time, the entropy also takes the total number of classes into account, much better than just an average number of classes per package. In particular, creating some packages with few classes does not help to improve the metric as long as there are still huge packages left that encapsulate a significant part of the classes.

However, we still have the problem that the entropy can get arbitrarily high and the developer does not necessarily have an idea what value is sufficient. In the spirit of Sarkar et al. (Sarkar et al., 2008), we would like to obtain a metric with fixed bounds. Therefore, we scale the entropy with the maximum entropy that can be achieved with the given number of classes. This maximum entropy is given if each class is encapsulated in its own package. The entropy in this case is exactly $log_b|\mathcal{C}|$, where again $\mathcal{C}$ is the set of classes.

A further advantage of this approach is that the base *b* cancels out, such that we do not even have to analyze its effects when calculating the metric.

Hence, the degree of modularization (*DM*) is defined as follows (we suppressed the base *b* because its value does not matter):

$$DM = -\frac{1}{\log|\mathcal{C}|}\sum_{p\in\mathcal{P}}\frac{|C(p)|}{|\mathcal{C}|}\log\frac{|C(p)|}{|\mathcal{C}|}.$$

For any metamodel, the values of this metric must range between 0 and 1. The value is 0 if and only if all classes reside in a single package. The value is 1 if and only if all classes reside in their own packages. Because the metric divides by the logarithmic number of all classes, the *DM* metric formula is only well-defined for any metamodel that contains at least two classes. Metamodels with fewer classes are assigned a *DM*-metric of 1.

To get a better understanding of the values that the *DM*-metric assigns to metamodels, consider a metamodel with a^k classes for some $a \in \mathbb{N}_{>1}$ and some $k \in \mathbb{N}$. Let the classes be evenly distributed across a^i packages for some $m \in \mathbb{N}$ with $m \leq k$. This means, each package contains a^{k-m} classes. In this case, we have that $P(x_i) = a^{-m}$ for each package. Thus, we arrive at

$$DM = -\frac{1}{k\log a}\sum_{i=1}^{a^m} a^{-m}(-m)\log a = \frac{m}{k}.$$

Thus, if the metamodel with n classes contains roughly $\sqrt{n}$ packages with evenly distributed packages, this gives a DM value of $\frac{1}{2}$. If the classes are not evenly distributed across the packages, the DM value is lower.

In most cases, it is not useful to encapsulate every class into its own package. Therefore, the value range of this metric has to be taken into account carefully. Furthermore, the metric does not tell us anything about whether the purpose of the classes in a package can easily be generalized, i.e., whether it makes sense to group these classes in a package. However, the metric may provide hints whether the package structure should be refined.

3 EXPERIMENT SETUP

To validate the correlation of the *DM* metric to perceived metamodel modularity, we first used the data collected from a previous controlled experiment on metamodel quality perception (Hinkel et al., 2016b). In this experiment, participants were asked to manually assess the quality of metamodels created by peers. The material – domain descriptions, assessments and created metamodels – are publicly available online[1]. Due to space limitations, we therefore only replicate a very short description of the experiment.

The 24 participants created metamodels for two domains. Each domain was described in a text and the participants were asked to design a metamodel according to it. The participants consisted of professional researchers as well as students from a practical course on MDE. They were randomly assigned to the domains, ensuring a balance between the domains. Each participant was asked to assess the quality of several metamodels using a questionnaire. We collected 89 responses, equally distributed among the domains.

The first domain regards user interfaces of mobile applications. Participants were asked to create a metamodel that would be able to capture designs of the user interface of mobile applications so that these user interface descriptions could later be used platform-independently. The participants created the metamodel according to a domain description in natural language from scratch. We refer to creating the metamodel of this mobile applications domain as the *Mobiles* scenario.

The second domain was business process modeling. Here, the participants were given a truncated metamodel of the Business Process Modeling Language and Notation (BPMN) (The Object Management Group, 2011) where the packages containing conversations and collaborations had been removed. The task for the participants was to reproduce the missing part of the metamodel according to a textual description of the requirements for the collaborations and conversations. We refer to this evolution task as the *BPMN* scenario in the remainder of this paper.

To confirm the results in yet another domain, we also apply the metric to student solutions to a modeling task that had to be done in several editions of a practical course on model-driven engineering. In this task, students had to create a metamodel based on a textual domain description and were allowed to work in pairs. Over the three years, we have collected 19 metamodels. In the controlled setting, we collected 75 responses evaluating the quality of these metamodels.

The meta-modeling task was creating a metamodel for component-based software architectures, inspired by the Palladio Component Model (Becker

[1] https://sdqweb.ipd.kit.edu/wiki/Metamodel_Quality

et al., 2009). However, in contrast to PCM that also models the resource demands of service calls, the domain description only contained modeling entities to describe component types, the architecture of a component-based system through instances of these components and the description of a deployment. Unlike the original PCM with more than 200 classes, the resulting metamodels had between 21 and 45 classes. We refer to this task as the *CBSE* scenario in the remainder of this paper.

We asked the students of the most recent year to manually assess the quality of these metamodels, randomly assigning students to metamodels. The manual assessment was done in a controlled setting and after the students submitted their own metamodel. We made sure that nobody assessed their own metamodel by rolling new assignments until this constraint was met. However, students were allowed to discuss the metamodels with peers assigned to review the same metamodels. Like in the previous experiments, we used a six-level Likert scale to encode the degree of modularity from very bad (-5) to very good (5).

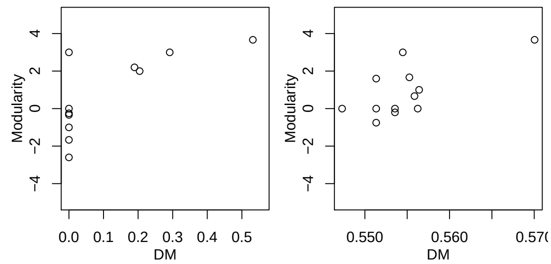
To ease the comparison between this third domain and the other ones, we have used the same questionnaire to collect the metamodel quality assessments as we used in the original experiment (Hinkel et al., 2016b).

We correlated the metric results with the manual modularity assessments and applied a t-test to test and reject the null-hypothesis that the metric values are uncorrelated with perceived metamodel modularity. Additionally, we also use the available data to depict the correlations of *DM* to other quality attributes. The statistical tests assume a normal distribution. To reason whether this assumption is reasonable, we plot the sample distributions against the theoretical quantiles of a normal distribution. If the quantiles are in a line, the normal distribution assumption is justified.

4 RESULTS

We correlated the manual quality assessments with the metric results for the metamodels created by the experiment participants. The discussion of the results is split into three sections, one for each of the scenarios and a fourth for discussion.

We have plotted the results for the first two scenarios in Figure 1. Both graphs show a correlation between the metric results and the perceived modularity, though the metric values were generally higher in the BPMN scenario. This is due to the fact that the participants only evaluated the user extension from other participants, while the remaining metamodel showed



(a) Mobiles scenario (b) BPMN scenario

Figure 1: Metric results for Degree of Modularization *DM* in Mobiles and BPMN scenario.

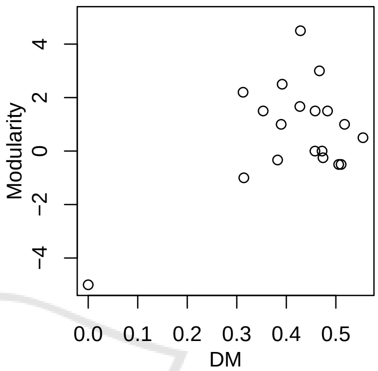


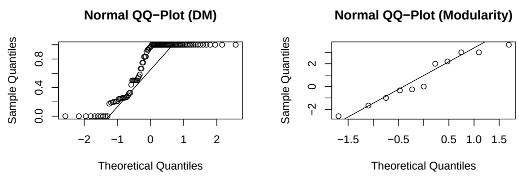
Figure 2: Results for the *DM* metric in the CBSE scenario.

already a good modularization.

Further, we plotted the results for CBSE against the perceived modularity in Figure 2.

4.1 Mobiles

The assumption of a normal distribution is reasonable for the modularity as the quantiles appear on a line in Figure 3b. The QQ-plot for the *DM* metric appears as a step-function (cf. Figure 3a), because many metamodels only received a *DM*-value of 0, as they did not use any package structure. Therefore, correlations in this scenario may not be as reliable as in the other scenarios.



(a) *DM*-metric (b) Modularity

Figure 3: Normal QQ-Plots in the Mobiles scenario.

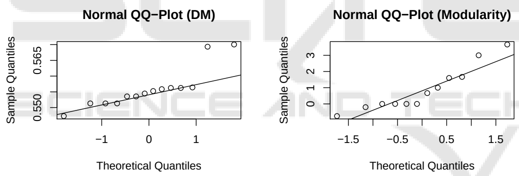
The results correlating the metric results against manually assessed metamodel quality perceptions are depicted in Table 1. To get a quicker overview, we have printed strong correlations ($|\rho| > 0.5$) in bold.

In this domain, many of the resulting metamodels consisted of a single package that constantly were evaluated with a *DM* of 0. The modularity of these metamodels is perceived rather differently. We can see metamodels assessed as having a *bad* (-3) modularity and ones that have a *good* modularity (+3), where the latter case is rather an exception (cf. Figure 1a). However, all of the metamodels that employ a package structure all have a *good* modularity, which in the end results in quite a good correlation coefficient of $\rho = 0.74$.

As we have 14 different metamodels, the t-Test leads to a *p*-value of 0.0012. Therefore, we can reject the null-hypothesis that the values of *DM* are uncorrelated with perceived metamodel modularity in this scenario at 99% confidence.

4.2 BPMN

In the BPMN scenario, the quantiles of the *DM* metric are more in a line, with the exception of two metamodels that have received the highest modularities, see Figure 4a. In the QQ-plot of the modularity, the points are also roughly on a line (cf. Figure 4b).



(a) *DM*-metric (b) Modularity

Figure 4: Normal QQ-Plots in the BPMN scenario.

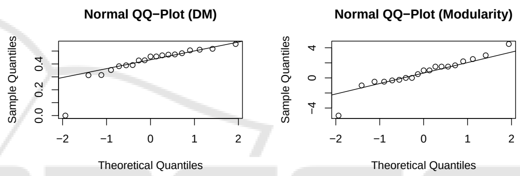
The correlations we observed are depicted in Table 2. Despite the participants had only evaluated the manual extensions, the metric results were taken from the complete metamodels, also taking into account the larger part of the metamodel that had not been changed. While this means that the metric values are not comparable across scenarios, it does not have an influence on correlations within the scenario. Furthermore, we do think that this better represents an evolution scenario which is more common than creating a metamodel from scratch.

In the BPMN scenario, we also observe a strong correlation of *DM* values to perceived modularity with a correlation coefficient of 0.68. As the entire metamodel was measured and already the existing metamodel employed a detailed package structure, there are no metamodels with a *DM* value of 0. Further, the metric values are much closer together, since the majority of the metamodel is still the same. However, we can see in Figure 1 that the metamodel with the highest *DM*-metric, also has the best perceived modularity.

As we again have 14 different metamodels, this leads to a *p*-value of 0.0063 in the t-Test. Thus, we can again reject the hypothesis that the values of *DM* are uncorrelated with perceived metamodel modularity at the 99% confidence level.

4.3 CBSE

In the CBSE scenario, the quantiles of the *DM*-metric and for modularity are well on a line, see Figures 5a and 5b. The only exception is the metamodel that only used a single package and therefore was perceived as least modular. However, the remaining data quantiles fit very well on a line, which is why we rely on this scenario most.



(a) *DM*-metric (b) Modularity

Figure 5: Normal QQ-Plots in the CBSE scenario.

The observed correlations for *DM* in the CBSE scenario are depicted in Table 3. Again, we can see a strong correlation of *DM* to modularity, while the correlation to any of the other quality attributes is not significant. For modularity, the t-Test to reject the hypothesis that *DM* is uncorrelated with perceived modularity can be rejected with a *p*-value of 0.011, so we can be sure at least at a 95% confidence level.

This correlation is due to the fact that solutions that did not divide their classes into packages were perceived to have a very bad modularity. On the other hand, we can see that metamodels that did divide their classes into packages received quite different scores in the perceived modularity, though they have a similar *DM* score.

4.4 Estimated Influence

To reason on the influence of the *DM* metric, we fitted a linear regression model. We chose linear regression because the scatter plots in Figures 1 and 2 indicate this kind of connection. Because the evaluation of the perceived quality was only assessed for the user extension in the *BPMN* scenario, we only took the

Table 1: Correlations of metric results to quality attribute assessments in the Mobiles scenario. Strong correlations ($|\rho| > 0.5$) are printed in bold.

	Quality	**Complexity**	**Understandability**	**Conciseness**	**Modularity**	**Consistency**	**Completeness**	**Correctness**	**Changability**	**Instance Creation**	**Transformation**
DM	0.18	-0.08	0.28	0.17	**0.74**	0.19	0.04	0.03	**0.56**	0.24	**0.57**

Table 2: Correlations of metric results to quality attribute assessments in the BPMN scenario. Strong correlations ($|\rho| > 0.5$) are printed in bold.

	Quality	**Complexity**	**Understandability**	**Conciseness**	**Modularity**	**Consistency**	**Completeness**	**Correctness**	**Changability**	**Instance Creation**	**Transformation**
DM	0.29	0.26	0.21	0.41	**0.68**	0.32	0.41	0.35	0.49	0.10	-0.05

Table 3: Correlations of metric results to quality attribute assessments in the CBSE scenario. Strong correlations ($|\rho| > 0.5$) are printed in bold.

	Quality	**Complexity**	**Understandability**	**Conciseness**	**Modularity**	**Consistency**	**Completeness**	**Correctness**	**Changability**	**Instance Creation**	**Transformation**
DM	0.26	-0.30	0.21	-0.25	**0.52**	0.19	0.26	0.08	0.21	0.17	0.12

observations from the other two case studies into account.

We fitted the following linear model:

$$Modularity \sim a \cdot DM + b.$$

The results for this linear regression model are depicted in Table 4.

For this linear model, 3 responses had to be ignored due to missing values. The linear model is significant at the 95% confidence level with a p-value of 0.0218. According to the linear regression model, the *DM* metric has an estimated influence of $0.56 \cdot 4.04 = 2.25$, which is more than one Likert-level but on the other hand not much more than that.

On the contrary, the metamodel with the worst average score of modularity has an assessment of -5 while the metamodel with the best score has an average modularity of 4.5, making up a total range of 9.5. Very roughly, the *DM* metric only measures about one fourth of the perceived modularity. The residuals range from -4.48 to 3.52. Thus, the linear model also suggests that there are other factors to consider and that the *DM* metric alone is not a very well predictor of perceived modularity, though with 95% confidence a better predictor than no predictor.

To get a better understanding of the influence of other factors, as a first approach, we have taken the scenario as another indicator of modularity. Thus, we assume that there is a characteristic of the modeling scenario that also has an influence to the perceived modularity, though we do not know it. This also balances the difference in the assessments: While the assessment of metamodels in the *Mobiles* domain was conducted by a mixed group of students and professionals, the assessment in the *CBSE* domain was done only by students.

$$Modularity \sim a \cdot DM + b \cdot Scenario + c.$$

For this, we encoded the scenario with a 0 for the *Mobiles* scenario and a 1 for the *CBSE* scenario. The

Table 4: Results of fitting a Linear Regression Model for $Modularity \sim a \cdot DM + b$.

	Estimate	Std. Error	t-Value	p-value	
Intercept (b)	-0.52	0.61	-0.85	0.40	
DM (a)	4.04	1.66	2.43	0.0218	*

Table 5: Results of fitting a Linear Regression Model for $Modularity \sim a \cdot DM + b \cdot Scenario + c$.

	Estimate	Std. Error	t-Value	p-value	
Intercept (c)	-0.23	0.54	-0.43	0.67	
DM (a)	8.70	2.14	4.07	$3.71 \cdot 10^{-4}$	***
Scenario (b)	-2.69	0.90	-2.99	$5.83 \cdot 10^{-3}$	**

resulting test results are shown in Table 5.

The linear model is significant with an F-statistic of 8.272 on 2 and 27 degrees of freedom and a resulting p-value of $1.58 \cdot 10^{-3}$. We face minimum residuals of -2.37 and maximum residuals of 3.69 such that we have to assume that there are other influence factors.

From the influence factors considered, the results indicate a very strong influence of the *DM* metric. In particular, the linear model suggests that a difference of 0.23 in the *DM* metric is equivalent to one of the Likert levels that we used to encode the perceived modularity.

On the other hand, the *DM* metric only ranged from 0 to 0.56 in the questionnaires taken into consideration. This explains a span of the perceived modularity of $0.56 \cdot 8.70 = 4.84$ meanwhile the actual span is 9.5. Therefore, it is not only the package structure that was assessed by the study participants but roughly half of the modularity assessment can be predicted using the *DM* metric and the scenario indicator.

4.5 Discussion

Due to the fact that participants of the experiment had to evaluate the entire metamodel in the Mobiles and CBSE scenario but only a small part of it in the BPMN scenario, we performed our correlation analysis for each scenario separately. The findings may thus be depending on the domain. In this section, we try to overcome this problem by discussing how the results from all scenarios fit together.

The *DM* metric showed a very strong and significant correlation with modularity in both scenarios, unlike previous experiments with adapted versions of the Sarkar metrics (Hinkel and Strittmatter, 2017). However, the metric *DM* alone is not sufficient. We can see for example in both sides of Figure 1 that there is still a quite different perception of modularity among equally modularized metamodels (in terms of *DM*). Furthermore, when thinking about auto-tuning, the *DM* metric can be easily optimized for by isolating every class into its own package.

The fact that the results for *DM* were so good in comparison to *IC* (inheritance-based coupling) and *AC* (association-based coupling) in earlier work (Hinkel and Strittmatter, 2017) may result from the degree of modularization being very easy to perceive. In the corner cases (when *DM* is very high over low), one can directly see that a metamodel employs a module structure or not. On the contrary, the couplings measured by e.g. *IC* and *AC* are more subtle. For example, the Palladio Component Model (Becker et al., 2009) contains multiple cycles of inheritance couplings between packages that remained undetected for a long time, though the model was actively developed. These are problems that the *DM* metric simply cannot detect, as it does not take inheritance or references into account.

The results from the influence of this metric to the overall modularity match this observation: While the analysis indicates that the influence of *DM* is significant when predicting the modularity, we also see that *DM* is not enough and has to be combined with other metrics for an accurate prediction of perceived modularity.

Thus, we see a high potential in combining our newly introduced *DM* metric with the coupling metrics *IC* and *AC* introduced in earlier work (Hinkel and Strittmatter, 2017). How exactly these metrics should be combined will be subject of further research. Our sample size is too low to make a good recommendation. For *AC*, we propose, supported by the data, that better results can be achieved by restricting the associations under review to containments and container references or opposite references. However, for this decision, our study did not consist of sufficiently many data points so that we must also shift this open question to future work.

5 THREATS TO VALIDITY

The internal threats to validity described in the original experiment description (Hinkel et al., 2016b) also apply to the Mobiles and BPMN scenarios when using the collected data to validate metamodel metrics. We do not repeat them here due to space limitations. As we are performing post-mortem analysis, we can exclude any subject effect.

In the CBSE scenario metamodels were not created in a controlled environment, but uncontrolled as a homework assignment. However, we think this is a more realistic case and after all, the CBSE domain was also slightly more complex than the Mobiles and BPMN domain. However, we can also exclude a subject effect as the students did not know the *DM*-metric when assessing the metamodels.

We are correlating the metrics results with perceived modularity in order to utilize the wisdom of our study participants. However, metrics are most valuable if they find the subtle flaws that humans do not perceive in order to raise awareness that there might be something wrong. Furthermore, the experience of our experiment participants, especially the students, may be insufficient.

From a statistics point of view, the assumption of a normal distribution is often a difficult one. The perceived modularity we are working with is a mean perception of a few experiment participants: To keep the effort of study participants reasonable, every participant only reviewed between one and two metamodels in each the *Mobiles* and *BPMN* domain or seven metamodels in the *CBSE* domain. Therefore, the modularity perception is not necessarily normally distributed. Although we briefly discussed the assumption of a normal distribution for each scenario, one may want to have more evidence or a stricter compliance to a normal distribution.

The conclusions on correlations are only valid in the range of metric values that we have observed. In particular, we do not know whether a *DM* value greater than approximately 0.6 would improve the modularity further. In fact, we doubt that. Especially the corner case of $DM = 1$, a metamodel where each class is separated in its own package, is not a sign of good modularization. Therefore, we check the values of *DM* for realistic metamodels in the following section.

Lastly, correlation does not imply causality and thus, we do not know whether the metric is of any value, if modelers are forced to meet a certain threshold.

6 APPLICATION TO EXISTING METAMODELS

We applied the *DM*-metric on different versions of metamodels for software systems. We automatically obtained versions of these metamodels from online repositories and performed measurement series for representative versions in order to have a better overview of the measurement results. The inspected metamodels are:

- *Knowledge Discovery Metamodel (KDM)* (Pérez-Castillo et al., 2011): an OMG standard for the modernization of legacy systems. We obtained four versions of this metamodel from the MoDisco plugin (Bruneliere et al., 2010) for the Eclipse Modeling Framework (EMF).
- *Palladio Component Model (PCM)* (Reussner et al., 2016): a metamodel for performance and reliability predictions of component-based architectures with the Palladio Simulator. We selected seven representative versions from all 97 versions between 2007 and 2012.
- *Descartes Metamodel (DMM)* (Kounev et al., 2010): a metamodel for self-aware runtime management of component systems inspired by PCM. We inspected one version.
- *SOFA 2* (Bureš et al., 2006): a metamodel for hierarchically composed, dynamic component architectures and behaviour specifications. We obtained six versions.
- *Kevoree* (Fouquet et al., 2014): a metamodel for the design and implementation of distributed reconfigurable systems with component architecture. We selected seven revisions.

For each metamodel, the measurements of the different versions are plotted in their chronological order. For the PCM, the number of classifiers more than doubled, while the others remained constant in size. This is also due to the fact that the versions span over five years for the PCM and over much shorter periods of time for all other metamodels.

The graph for the *DM* metric clearly shows the lack of any package structure in the Kevoree and SOFA 2 metamodels. The other metamodels have roughly similar *DM* values. For PCM and Descartes, this is reasonable since Descartes was inspired by PCM, though adjusted to model the runtime of component-based systems. The KDM metamodel has a slightly lower *DM* value, simply because the 300 classes are distributed only to 12 packages.

In the evolution of PCM, we can also see that the degree of modularization has roughly stayed the same

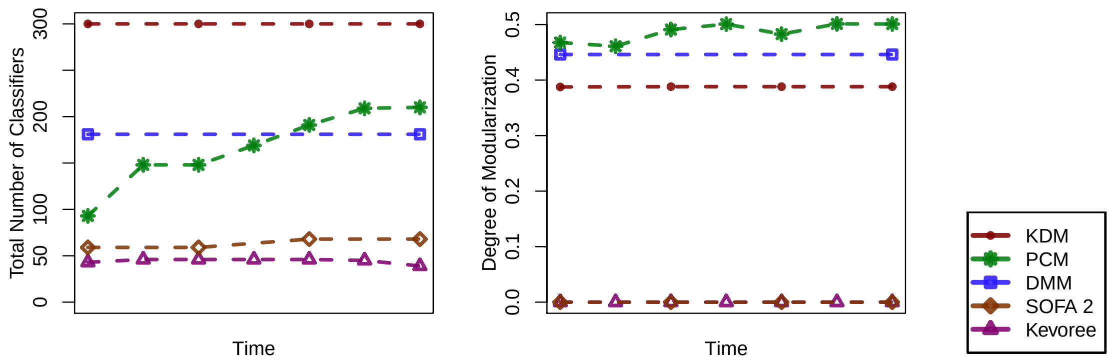


Figure 6: Size metrics results for different versions of component-based metamodels.

during a long evolution process. Therefore, we think that the observed *DM*-values of up to 0.5 are realistic.

7 RELATED WORK

Our paper on the usage of Sarkar metrics to evaluate the modularity of metamodels presents an alternative approach to obtain a quantitative quality assessment of metamodels (Hinkel and Strittmatter, 2017). However, the results were not as good as the *DM* metric based on the same experiment data.

Related work in the context of metamodel quality consists mostly of adoptions of metrics for UML class diagrams and object-oriented design. However, to the best of our knowledge, the characterization of metamodel quality has not yet been approached through the perception of modeling experts.

Bertoa et al. (Bertoa and Vallecillo, 2010) present a rich collection of quality attributes for metamodels. However, as it is not the scope of their work, they do not give any information how to quantify the attributes.

Ma et al. (Ma et al., 2013) present a quality model for metamodels. By transferring metrics from object-oriented models and weighting them, they provide composite metrics to quantify quality properties. They calculate these metrics for several versions of the UML metamodel. However, they do not provide a correlation between their metrics and quality.

López et al. propose a tool and language to check for properties of metamodels (López-Fernández et al., 2014). In their paper, they also provide a catalog of negative properties, categorized in design flaws, best practices, naming conventions and metrics. They check for breaches of fixed thresholds for some metrics, but both their catalog and also these thresholds stem from conventions and experience and are not empirically validated.

Vépa et al. present a repository for metamodels, models, and transformations (Vépa et al., 2006). The authors apply metrics that were originally designed for class diagrams onto the metamodels of the repository. They give a rationale on how to relate some of the metrics to metamodel quality. However, no validation is given.

Williams et al. applied a variety of size metrics onto a big collection of metamodels (Williams et al., 2013). However, they did not draw any conclusions with regards to quality.

Di Rocco et al. also applied metrics onto a large set of metamodels (Di Rocco et al., 2014). Besides size metrics, they also feature the number of isolated metaclasses and the number of concrete immediately featureless metaclasses. Further, they searched for correlations of the metrics among each other. E.g., they found that the number of metaclasses with super class is positively correlated with the number of metaclasses without features. Based on the characteristics they draw conclusions about general characteristics of metamodels. However, to the best of our knowledge, they did not correlate the metric results to any quality attributes.

Gomez et al. propose an approach which aims at evaluating the correctness and expressiveness of a metamodel (Gómez et al., 2012). A metamodel is considered correct, if it only allows valid instances. Expressiveness is the degree to which it is able to express the instances it is supposed to. Their approach automatically generates a (preferably small) set of instances to evaluate these two criteria.

Garcia et al. developed a set of domain-specific metamodel quality metrics for multi-agent systems modeling languages (García-Magariño et al., 2009). They propose three metrics: availability, specificity and expressiveness. These metrics take domain knowledge into account, e.g., the "number of necessary concepts" or the "number of model elements necessary for modelling the system of the problem domain".

Leitner et al. propose complexity metrics for domain models of the software product line field as well as feature models (Leitner et al., 2012). However, domain models are not as constrained by their metamodels as it is the case with feature models. The authors argue, that the complexity of both, feature and domain models, influences the overall quality of the model, but especially usability and maintainability. They show the applicability of their metrics, but do not validate the influence between the metrics and quality.

Vanderfeesten et al. investigated quality and designed metrics for business process models (Vanderfeesten et al., 2007). Some of them can be applied to metamodels or even graphs in general. The metrics are validated by assessing the relation between metric results and error occurrences and manual quality assessments (Mendling and Neumann, 2007; Mendling et al., 2007; Sánchez-González et al., 2010; Vanderfeesten et al., 2008). For example, their separability metric measures the amount of nodes which are the only connection between two cohesive clusters of nodes. They find, that size, separability and structuredness are good indicators for errors, as they influence models complexity and thus understandability. However, it is subject of further research to investigate how these metrics can be adapted to metamodels.

8 CONCLUSION AND OUTLOOK

The proposed metric *DM* based on entropies of the package structure strongly correlates with perceived metamodel modularity, at least in the domains we have analyzed. This is good, because this insight helps to understand how modelers perceive the quality of metamodels. It is also a bad signal, because apparently, at least the participants of our experiments did not care about more subtle factors that influence modularity, such as coupling. We suspect that this is caused by the tooling, which puts focus on where classes are placed in the package structure and what kind of features they have, but puts no emphasis on where relations point to with regard to the package structure.

To obtain a meaningful quantitative analysis on the quality of modularization for a given metamodel, the *DM*-metric therefore has to be combined. In particular, the results from fitting linear regression models suggest that the *DM* metric makes up very roughly a quarter of what is taken into consideration for the perception of modularity.

The combination of this new metric *DM* with slightly altered versions of the inheritance-based and association-based coupling indices *IC* and *AC* we presented earlier (Hinkel and Strittmatter, 2017) is promising as these metrics may compensate each others weaknesses. Both of these metrics favor different extremes such that metamodels with a good modularization may be detected, if both metrics are balanced.

Based on these results, we are hoping to confirm our results in larger applications. If this can be done successfully, we are striving to integrate the automated evaluation of metamodels into the metamodel design process and into automated refactorings of metamodels to improve the modularization.

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REFERENCES

Becker, S., Koziolek, H., and Reussner, R. (2009). The Palladio component model for model-driven performance prediction. *Journal of Systems and Software*, 82:3–22.

Bertoa, M. F. and Vallecillo, A. (2010). Quality attributes for software metamodels. In *Proceedings of the 13th TOOLS Workshop on Quantitative Approaches in Object-Oriented Software Engineering (QAOOSE 2010)*.

Bruneliere, H., Cabot, J., Jouault, F., and Madiot, F. (2010). Modisco: a generic and extensible framework for model driven reverse engineering. In *Proceedings of the IEEE/ACM international conference on Automated software engineering*, ASE '10, pages 173–174, New York, NY, USA. ACM.

Bureš, T., Hnetynka, P., and Plášil, F. (2006). Sofa 2.0: Balancing advanced features in a hierarchical component model. In *Proceedings of the fourth International Conference on Software Engineering Research, Management and Applications*, pages 40–48. IEEE.

Di Rocco, J., Di Ruscio, D., Iovino, L., and Pierantonio, A. (2014). Mining metrics for understanding metamodel characteristics. In *Proceedings of the 6th International Workshop on Modeling in Software Engineering*, MiSE 2014, pages 55–60, New York, NY, USA. ACM.

Di Ruscio, D., Iovino, L., and Pierantonio, A. (2012). Evolutionary togetherness: how to manage coupled evolution in metamodeling ecosystems. In *International Conference on Graph Transformation*, pages 20–37. Springer.

Fouquet, F., Nain, G., Morin, B., Daubert, E., Barais, O., Plouzeau, N., and Jézéquel, J.-M. (2014). Kevoree Modeling Framework (KMF): Efficient modeling techniques for runtime use. Technical report, SnT-University of Luxembourg.

García-Magariño, I., Gómez-Sanz, J., and Fuentes-Fernández, R. (2009). An evaluation framework for mas modeling languages based on metamodel metrics. *Agent-Oriented Software Engineering IX*, pages 101–115.

Gómez, J. J. C., Baudry, B., and Sahraoui, H. (2012). Searching the boundaries of a modeling space to test metamodels. *Software Testing, Verification, and Validation, 2008 International Conference on*, 0:131–140.

Hinkel, G., Groenda, H., Krach, S., Vannucci, L., Denninger, O., Cauli, N., Ulbrich, S., Roennau, A., Falotico, E., Gewaltig, M.-O., Knoll, A., Dillmann, R., Laschi, C., and Reussner, R. (2016a). A Framework for Coupled Simulations of Robots and Spiking Neuronal Networks. *Journal of Intelligent & Robotics Systems*.

Hinkel, G., Groenda, H., Vannucci, L., Denninger, O., Cauli, N., and Ulbrich, S. (2015). A Domain-Specific Language (DSL) for Integrating Neuronal Networks in Robot Control. In *2015 Joint MORSE/VAO Workshop on Model-Driven Robot Software Engineering and View-based Software-Engineering*.

Hinkel, G., Kramer, M., Burger, E., Strittmatter, M., and Happe, L. (2016b). An Empirical Study on the Perception of Metamodel Quality. In *Proceedings of the 4th International Conference on Model-driven Engineering and Software Development (MODELSWARD)*. Scitepress.

Hinkel, G. and Strittmatter, M. (2017). On Using Sarkar Metrics to Evaluate the Modularity of Metamodels. In *Proceedings of the 5th International Conference on Model-Driven Engineering and Software Development*.

Kounev, S., Brosig, F., Huber, N., and Reussner, R. (2010). Towards self-aware performance and resource management in modern service-oriented systems. In *Proceedings of the IEEE International Conference on Services Computing (SCC)*, pages 621–624. IEEE.

Lehman, M., Ramil, J., Wernick, P., Perry, D., and Turski, W. (1997). Metrics and laws of software evolution-the nineties view. In *Software Metrics Symposium, 1997. Proceedings., Fourth International*, pages 20–32.

Lehman, M. M. (1974). *Programs, cities, students: Limits to growth? (Inaugural lecture - Imperial College of Science and Technology ; 1974)*. Imperial College of Science and Technology, University of London.

Leitner, A., Weiß, R., and Kreiner, C. (2012). Analyzing the complexity of domain model representations. In *Proceedings of the 19th International Conference and Workshops on Engineering of Computer Based Systems (ECBS)*, pages 242–248.

López-Fernández, J. J., Guerra, E., and de Lara, J. (2014). Assessing the quality of meta-models. In *Proceedings of the 11th Workshop on Model Driven Engineering, Verification and Validation (MoDeVVa)*, page 3.

Ma, Z., He, X., and Liu, C. (2013). Assessing the quality of metamodels. *Frontiers of Computer Science*, 7(4):558–570.

Mendling, J. and Neumann, G. (2007). Error metrics for business process models. In *Proceedings of the 19th International Conference on Advanced Information Systems Engineering*, pages 53–56.

Mendling, J., Neumann, G., and Van Der Aalst, W. (2007). Understanding the occurrence of errors in process models based on metrics. In *On the Move to Meaningful Internet Systems 2007: CoopIS, DOA, ODBASE, GADA, and IS*, pages 113–130. Springer.

Object Management Group (OMG) (2015). MOF 2.5 Core Specification (formal/2015-06-05).

Pérez-Castillo, R., De Guzman, I., and Piattini, M. (2011). Knowledge discovery metamodel-iso/iec 19506: A standard to modernize legacy systems. *Computer Standards & Interfaces*, 33(6):519–532.

Reussner, R. H., Becker, S., Happe, J., Heinrich, R., Koziolek, A., Koziolek, H., Kramer, M., and Krogmann, K. (2016). *Modeling and Simulating Software Architectures – The Palladio Approach*. MIT Press, Cambridge, MA.

Sánchez-González, L., García, F., Mendling, J., Ruiz, F., and Piattini, M. (2010). Prediction of business process model quality based on structural metrics. In *Conceptual Modeling–ER 2010*, pages 458–463. Springer.

Sarkar, S., Kak, A. C., and Rama, G. M. (2008). Metrics for measuring the quality of modularization of large-scale object-oriented software. *Software Engineering, IEEE Transactions on*, 34(5):700–720.

Schmidt, D. C. (2006). Model-driven engineering. *IEEE Computer*, 39(2):25.

The Object Management Group (2011). Business process model and notation 2.0. http://www.bpmn.org/.

Vanderfeesten, I., Cardoso, J., Mendling, J., Reijers, H. A., and van der Aalst, W. (2007). Quality metrics for business process models. *BPM and Workflow handbook*, 144.

Vanderfeesten, I., Reijers, H. A., Mendling, J., van der Aalst, W. M., and Cardoso, J. (2008). On a quest for good process models: the cross-connectivity metric. In *Advanced Information Systems Engineering*, pages 480–494. Springer.

Vépa, E., Bézivin, J., Brunelière, H., and Jouault, F. (2006). Measuring model repositories. In *Proceedings of the 1st Workshop on Model Size Metrics*.

Williams, J. R., Zolotas, A., Matragkas, N. D., Rose, L. M., Kolovos, D. S., Paige, R. F., and Polack, F. A. (2013). What do metamodels really look like? In *Proceedings of the first international Workshop on Experiences and Empirical Studies in Software Modelling (EESSMod)*, pages 55–60.