Extending Feature Models with Relative Cardinalities

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RESEARCH REPORT
N° 8843
Janvier 2016
Project-Teams Spirals

ISSN 0249-6399 ISRN INRIA/RR--8843--FR+ENG

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Research Report n° 8843 — Janvier 2016 — 21 pages

Abstract: Feature modeling is widely used to capture and manage commonalities and variabilities in software product lines. Cardinality-based feature models are used when variability applies not only to the selection or exclusion of features but also to the number of times a feature can be included in a product. Feature cardinalities are usually considered to apply in local or global scope. However, through our work in managing variability in cloud computing providers, we have identified cases where these interpretations are insufficient to capture the variability of the cloud environment. In this paper, we redefine cardinality-based feature models to allow multiple relative cardinalities between features and discuss the effects of relative cardinalities on cross-tree constraints. To evaluate our approach we conducted an analysis of relative cardinalities in four cloud computing providers. In addition, we developed tools for reasoning on feature models with relative cardinalities and performed experiments to verify the performance and scalability of the approach. The results from our study indicate that extending feature models with relative cardinalities is feasible and improves variability modeling, especially in the case of cloud environments.

Key-words: Feature Model, Cardinality, Cloud Computing Configuration

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Modèles de caractéristiques augmentés de cardinalités relatives

Résumé : Les modèles de caractéristiques sont largement utilisés dans la représentation et gestion des variabilités dans les lignes de produit logiciel. Cardinalités sont souvent employés quand la variabilité n'applique pas seulement à la selection et exclusion des caractéristiques mais aussi au nombre des fois qu'une caractéristique peut être inclut dans un produit. Les cardinalités des caractéristiques sont usuellement considérées applicables que localement ou globalement. Néanmoins, dans le domaine de l'informatique en nuage on a identifié des situations où ces interpretations sont insuffisantes pour bien décrire la variabilité y trouvé. Dans ce papier, nous redéfinissons les modèles de caractéristiques avec cardinalités pour permettre la description de plusieurs cardinalités relatives entre features et discutons leurs effets dans le système de contraintes des modèles de caractéristiques. Pour évaluer notre approche nous conduisons une analyse des cardinalités relatives dans quatre fournisseurs d'informatique en nuage. En plus, nous avons développé des outils pour le raisonnement automatique sur les lignes de produits décrites par modèles avec cardinalités relatives et avons conduit des expérimentes pour verifier la performance et scalabilité de l'approche.

Mots-clés : modèles des caractéristiques, cardinalités, informatique en nuage

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1 Introduction

Feature modeling is a widely used approach to capture commonalities and variability across software systems that are part of a product line or system family [16]. A feature model is usually depicted as a tree diagram whose nodes represent features that can be selected to build a software product. The tree hierarchy describes a composition relationship between features, while additional constraints refine these relationships.

Several extensions to feature models have been proposed since its inception, usually motivated from pragmatic needs in product line engineering. Among these, feature cardinalities were introduced to deal with scenarios where a feature can be selected multiple times for a given product, each time with a possibly different set of subfeatures [4].

The semantics of cardinalities in feature models and its effects on cross-tree constraints have been thoroughly studied and formalized in different ways [6, 18, 22, 27]. Feature cardinalities are interpreted to apply either locally (in relation to its immediate parent feature) or globally (concerning the whole product configuration). However, through our investigation in managing variability in cloud computing platforms, we found that feature cardinalities may also be related to an ascendant feature that is not the direct parent feature.

To deal with this limitation, we introduce the concept of relative cardinality, which is a generalization of the existing interpretations of feature cardinalities. In this paper we redefine cardinality-based feature models to take into account relative cardinalities, and we analyze the effects on feature model semantics, including cross-tree constraints and cardinality consistency. We then evaluate the use of this extended feature model definition for managing variability in cloud computing platforms as well as the scalability of automatically generating and validating configurations.

In Section 2 we identify the limitations we found in feature cardinalities while designing feature models for cloud computing platforms.Section 3 explains the concept of relative cardinality and discusses how it affects cardinality consistency and cross-tree constraints. Section 4 describes how we implemented relative cardinalities into a tool for automatic analysis and Section 5 evaluates the approach. Finally, we discuss related work in Section 6 and the conclusions in Section 7.

2 Motivation

In the cloud computing paradigm, computing resources are provided as services, usually delivered to customers in the form of *infrastructure*, *platform* or *software* services. Each cloud computing provider offers a different set of services, at different abstraction levels, such as processing power, network communication, virtual machines, containers, software packages, application servers, databases, development and management tools, etc. To choose a provider and to set up the environment to deploy a cloud application, stakeholders need to be aware of the available services and all the constraints between them in order to create a suitable cloud environment configuration.

To support this activity, commonalities and variabilities in the providers' services can be captured as feature models, making it suitable for automatic processing using a software product line approach. This approach has been employed in previous work to support the automatic selection and configuration of a cloud providers [24, 20]. As in cloud computing it is common to have features that can be selected multiple times to be part of a configuration, cardinality-based feature models have been used. However, the feature models used only considered variability and constraints within an application and do not enable to configure multiple applications.

Applications based on a microservices architecture [10] introduce further flexibility into cloud systems. In a microservices architecture, applications are composed of multiple small services that run in independent processes and can be deployed to different execution environments, containers or virtual

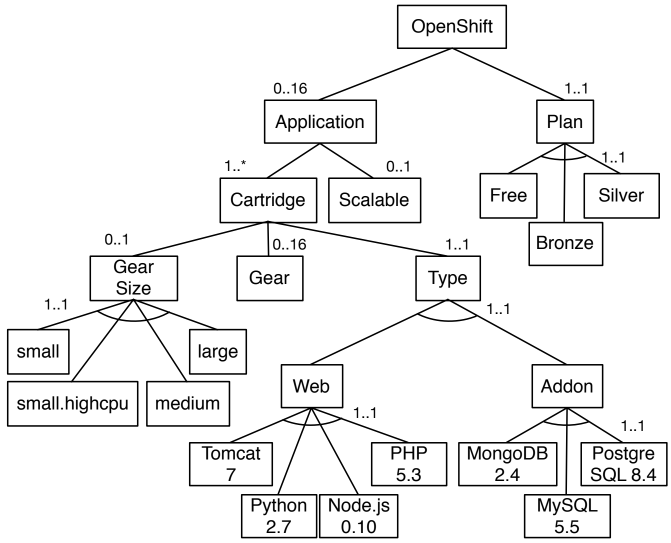


Figure 1: Excerpt from the OpenShift cloud feature model

machines. This architectural style is becoming increasingly popular in cloud computing as services are isolated and can be scaled independently.

However, this also means that variability across applications also needs to be taken into account because deployment of a microservice is usually achieved by deploying multiple cloud applications, where each application represents a service. Subsequently, as we tried to model this variability, we found that existing feature modeling constructs were insufficient to capture all the constraints we identified in cloud providers.

2.1 Motivating example

Figure 1 depicts part of a cardinality-based feature model designed to capture the variability in the `OpenShift` cloud provider using existing constructs. In `OpenShift`, an `Application` is made up of a set of `Cartridge`s, which are software features such as application servers, databases, caching services, management tools etc. `Cartridge`s are run by processing nodes called `Gear`s. For each `Cartridge`, the user can choose a given `Gear Size`, which defines the memory and processing capabilities, and the number of `Gear`s.

`OpenShift` imposes no limits on the number of `Application`s or `Cartridge`s allowed. However, the number of `Gear`s is limited by the user's plan. Considering that the limit for a plan is of 16 `Gear`s, we can have any combination ranging from 1 `Application` with 16 `Gear`s, to 16 `Application`s with 1 `Gear` each. To enable users to describe both of these valid configurations, the feature model is designed in a way that the feature cardinalities of `Application` and `Gear` allow for up to 16 clones. However, though this modeling allows for expressing all possible valid configurations, it does not prevent users from describing invalid ones. For instance, it does not prevent from specifying an application with 16 `Cartridge`s, each one with 16 `Gear`s, thus exceeding the provider limits.

A similar problem can be found when we consider the case of `Web` cartridges. An `Application` can have multiple `Cartridge`s, but the provider requires that exactly one of them have the `Web` feature selected. Nevertheless, the feature model does not provide any information about this restriction and therefore allows the user to configure an `Application` with any number of `Web` cartridges.

This problem occurs because although features `Gear` and `Web` are directly associated to the `Cartridge` feature, the number of allowed instances are respectively associated to the whole product configuration and to `Application` instances. This scenario occurs more often when we have features that consume computing resources, but for which the maximum number of resources is associated to another feature, usually in a higher place in the feature diagram hierarchy.

2.2 Challenges

Providing a way to specify cardinalities in multiple levels would make it possible to better capture the variability found in cloud computing configurations and to increase the expressive power of feature models. Nevertheless, introducing new constructs to feature modeling may affect its semantics.

In this paper we propose to extend feature models in order to better capture the variability found in the cloud computing domain. We then analyze how this extension affects the semantics and the processing of cardinality-based feature models. More specifically, we pursue to deal with the following challenges:

- *Capture multiple relative cardinalities in feature model.* How to extend cardinality-based feature model to consider the mismatch between cardinalities identified in the cloud computing domain. That is, to take into account cardinalities which can be associated to features at different levels of hierarchy.

- *Ensure the consistency between relative cardinalities*. What are the criteria for relative cardinalities to be consistent and how to ensure consistency of a feature model.

- *Update additional constraints to deal with multiple relative cardinalities*. How the introduction of relative cardinalities affect additional constraints and how additional constraints can be changed to take relative cardinalities into account.

3 Relative Feature Cardinalities

Feature cardinalities define the number of instances of a given feature, and their semantics have been previously studied and formalized [6, 18, 27]. Cardinalities are applied either globally or locally. In the first case, all instances of the feature (throughout the entire configuration) are counted, while in the second case, the number of instances are limited by each instance of the parent feature.

Figure 2 shows a feature model with three example configurations that use different interpretations for feature E's cardinality. (a) shows the feature model. In (b) cardinalities are interpreted globally, thus no more instances of E can be added to the configuration (i.e., the limit is 2 in the configuration). In (c) cardinalities are interpreted locally, meaning each instance of D can have 1 or 2 children instances of E.

However, as we have described in the `OpenShfit` example of Figure 1, there are cases where the context of a cardinality is neither global nor local, but relative to some other feature. For such cases we propose relative cardinalities. This can be seen in Figure 2 (d), where the cardinality $1..2$ of E is, for this example, interpreted as relative to feature B. In this case, each instance of B can have 1 or 2 instances of E in its subtree, regardless of the number of instances of D.

3.1 Formalization

We introduce and formalize the concept of *relative cardinality*.

Definition 1. (**Relative cardinality**) The relative cardinality between two features x, y such that x is descendant of y in the corresponding feature diagram is the interval that defines the minimum and maximum number of x instances for each y instance.

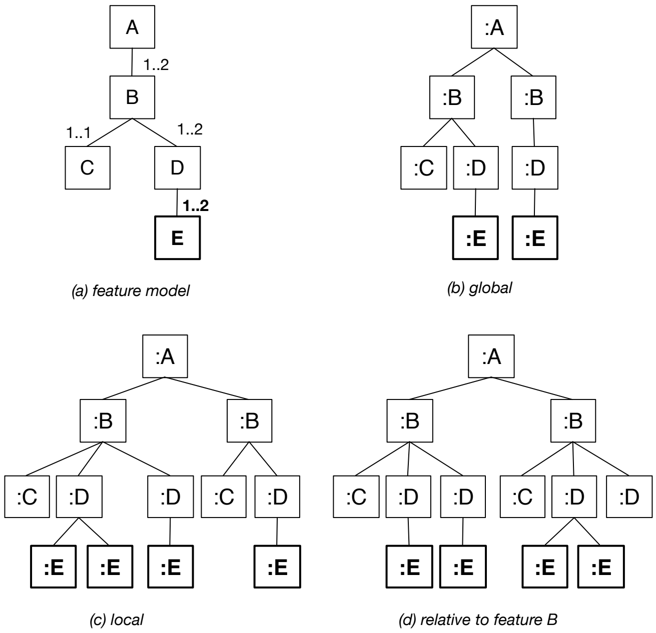


Figure 2: Different interpretations for cardinalities.

Most cardinality-based feature modeling approaches consider that cardinalities apply locally [7, 6, 11, 17, 18, 29]. In this case, the feature diagram hierarchy defines an implicit relative cardinality between any feature and its ancestors. As an example, in Figure 2 (a), if we consider cardinalities apply locally we can infer that the relative cardinality between E and B is $1..4$. Given that each instance of B can have from 1 to 2 instances of D and for each instance of D 1 or 2 instances of E are allowed, the number of E instances for each B instance would be between 1 and 4.

The concept of relative cardinality can be seen as a generalization of the possible interpretations for cardinalities in feature models. In this sense, the cardinality of a feature in relation to the feature model's root is equivalent to its global cardinality. Similarly, the cardinality of a feature in relation to its parent corresponds to its local cardinality.

Although the number of feature instances is in many cases related to the local feature cardinality (i.e., interpreted locally), as shown in the `OpenShift` example (see Figure 1), there are situations in the cloud domain where a local interpretation of cardinalities is insufficient. Although feature cardinalities can be interpreted locally in many cases, as shown in the `OpenShift` example (see Figure 1), there are still many situations in the cloud domain where a local interpretation of cardinalities is insufficient. To deal with this problem, we have extended the existing cardinality-based feature model constructs to consider relative cardinalities as part of their definition. Based on the work done by *Michel et al.* [18], we redefine a feature model as follows:

Definition 2. **(Feature model)** A feature model is a 7-tuple $\mathcal{M} = (\mathcal{F}, G, r, E, \omega, \lambda, \phi)$ such that:

- $\mathcal{F}$ is a non-empty set of features;
- $G \subset \mathcal{F}$ is a possibly empty subset of feature groups;
- $r \in \mathcal{F}$ is the root feature;

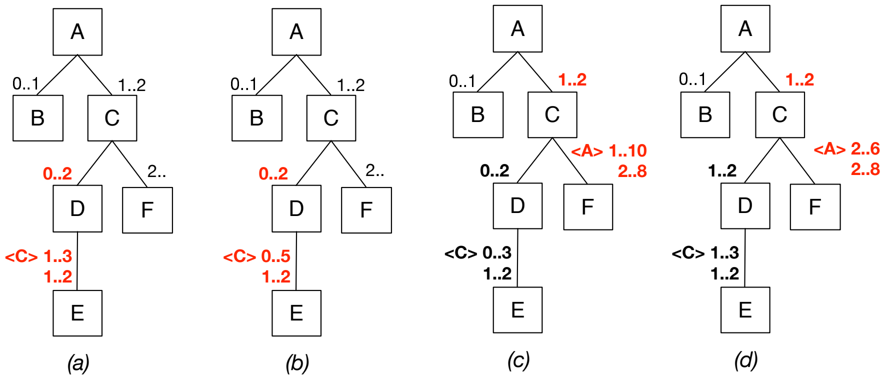


Figure 3: Relative cardinalities consistency

- $E : \mathcal{F} \setminus \{r\} \rightarrow \mathcal{F}$ is a function that represents the *parent-of* relation between features such that its *transitive closure* on $\mathcal{F}$, denoted by E^+, is *irreflexive* and *asymmetric*. These conditions guarantee the tree structure of the feature diagram;

- $\omega : E^+ \rightarrow \mathbb{N} \times \mathbb{N}$ is a function that represents the relative cardinality between two features which are part of the *ancestors-of* relation, denoted by E^+, the *transitive closure* of E on $\mathcal{F}$;

- $\lambda : G \rightarrow \mathbb{N} \times \mathbb{N}$ is a function that represents the group cardinalities of feature groups;

- ϕ is a set of cross-tree constraints (Section 3.3).

The proposed definition updates the cardinality function ω to consider not only a feature but two features which are related in the feature model hierarchy. By doing so, it gives first-class status to relative cardinalities which were only implicit in feature models with local cardinalities. This concept is more general and allows for expressing cardinalities at different levels, including global and local cardinalities.

3.2 Cardinalities consistency

By their nature, relative cardinalities allow defining multiple cardinalities for any given feature, where each cardinality is relative to a different ancestor feature. In order to be valid, these cardinalities need to be consistent among themselves. Cardinality consistency is linked to the notion of *range consistency* [21]. A cardinality is considered range consistent if each value in its range is used in at least one valid product configuration.

In Figure 3 we show some example feature models that were defined with inconsistencies in relative cardinalities. In the given examples, relative cardinalities are described above the feature node using the notation <X> $m..n$, where $m..n$ is its cardinality relative to feature X. When no specifier is given, the cardinality is considered to apply locally and is therefore relative to the feature's direct parent.

In the feature model in Figure 3 (a), feature E has, in addition to its local cardinality $1..2$, a cardinality of $1..3$ relative to its ancestor C. However, this cardinality is inconsistent with the local cardinality $0..2$ of feature D. If an instance of C has no instances of D, it would not be possible to have one instance of E, thus the cardinality $1..3$ between E and C does not hold. In this case there would be no valid products with 0 instances of D, even though the cardinality of D is $0..2$.

In Figure 3 (b), the cardinality of E relative to C allows for up to 5 instances. However, each instance of C allows for a maximum of 2 instances of D, and for each of them a maximum of 2 instances of E, allowing for a total of 4 instances of E for each instance of C. Therefore, the local cardinalities of D and

E are not consistent with the $0..5$ relative cardinality between E and C. Sample fixes for these examples are shown in (c) and (d) where either the relative cardinality between E and C, or local cardinality of D, are updated.

Figure 3 (c) shows another example of inconsistency where the relative cardinality between F and A is $1..10$ but from the local cardinalities of C and F we can infer that we should have at least 2 instances of F in any product. Also, in (d) we have an example where the relative cardinality between F and A has a maximum of 6 instances, which conflicts with the $2..8$ local cardinality of feature F, since no valid products can exist with 7 or 8 instances of F.

When cardinalities are inconsistent the number of allowed instances is ambiguous and are susceptible to diverse interpretations. Moreover, the cardinalities defined in the model do not correctly describe what the actual valid number of feature instances is. Based on the notion of *range consistency* and analysis of the semantic relation between multiple relative cardinalities, we define the criteria for cardinality consistency as below.

Definition 3. **(Cardinality consistency)** Given functions min and max that return the minimum and maximum values for a cardinality range, a feature model $\mathcal{M} = (\mathcal{F}, G, r, E, \omega, \lambda, \phi)$ is consistent concerning its relative cardinalities if $\forall x, y, z \in \mathcal{F} \mid (z, y) \in E^+ \wedge (y, x) \in E^+$ the following conditions hold:

$$min(\omega(z,x)) \geq min(\omega(z,y)) \cdot min(\omega(y,x)) \tag{1}$$

If each x instance has at least $min(\omega(y,x))$ instances of y and each y instance at least $min(\omega(z,y))$ instances of z, then the number of z instances for each x instance is at least $min(\omega(z,y)) \cdot min(\omega(y,x))$.

$$max(\omega(z,x)) \leq max(\omega(z,y)) \cdot max(\omega(y,x)) \tag{2}$$

If each x instance has at most $max(\omega(y,x))$ instances of y and each y has at most $max(\omega(z,y))$ instances of z, then each x instance can have at most $max(\omega(z,y)) \cdot max(\omega(y,x))$ instances of z.

$$min(\omega(z,x)) \leq max(\omega(z,y)) \cdot min(\omega(y,x)) \tag{3}$$

The feature model should enable specifying at least one valid product in which the number of y instances for an x instance is the minimum $min(\omega(y,x))$. In this case, the maximum number of instances of z for each x is $min(y,x) \cdot max(z,y)$. Thus, if $min(\omega(z,x)) \geq max(\omega(z,y)) \cdot min(\omega(y,x))$ there would be no valid products using the lower bound of the cardinality $\omega(y,x)$ and the cardinalities would not be consistent.

$$max(\omega(z,x)) \geq max(\omega(z,y)) \cdot min(\omega(y,x)) \tag{4}$$

Similarly, in at least one product, the number of y instances for each x should be $max(\omega(y,x))$. In this case, the minimum number of instances of z for each x instance is $max(\omega(y,x)) \cdot min(\omega(z,y))$. Thus, if $max(\omega(z,x)) \leq max(\omega(y,x)) \cdot min(\omega(z,y))$ there would be no product with the maximum cardinality $max(\omega(y,x))$.

$$\begin{gathered} min(\omega(z,x)) \leq \\ min(\omega(z,y)) + max(\omega(z,y)) \cdot (max(\omega(y,x)) - 1) \end{gathered} \tag{5}$$

At least one instance of y should have the minimum number of z instances $min(\omega(z,y))$. In this case, if one y instance has this minimum number of z instances, the maximum number of z instances for the x ascendant instance would be reached if all other y instances under the same x had the maximum number of z instances. That said, the maximum number of z instances for this x instance would be $min(\omega(z,y)) + max(\omega(z,y)) \cdot (max(\omega(y,x)) - 1)$. Therefore, if the minimum relative cardinality between z and x was greater than this value, there would be no cases where the lower bound of the cardinality $\omega(z, y)$ would be valid.

$$\begin{gathered} max(\omega(z,y)) \geq \\ max(\omega(z,y)) \; + \; min(\omega(z,y)) \; \cdot \; (min(\omega(y,x)) - 1) \end{gathered} \tag{6}$$

At least one instance of y should have the maximum number of z instances, which is $max(\omega(z, y))$. Also, if at least one y has this maximum number, then the ascendant x instance would have at least $max(\omega(z,y)) \; + \; (min(\omega(y,x)) - 1)$. Therefore, if the maximum bounds of $\omega(z, x)$ is less than this value there would be no valid configuration that uses the maximum cardinality of $max(\omega(z, y))$.

This definition establishes that any three features that are linked in an ancestors-descendant relationship should meet the six identified constraints. Together, these constraints guarantee that for any value in the concerning cardinality ranges, at least one valid product can be defined in which this value is employed. Since these conditions should apply for all possible relative cardinality relationships, it guarantees that the feature model is consistent regarding relative cardinalities.

3.3 Multiple cardinalities and constraints

In cardinality-based feature models, additional constraints such as *implies* and *excludes* need to be adapted to consider the existence of instances of features [18]. To deal with cardinalities in constraints, *Quinton et al.* [22] proposed a *requires* constraint that extends *implies* with cardinalities. A *requires* constraint is defined as in the implication below, where C_{from} and C_{to} are cardinality ranges, F_{from} and F_{to} are features in $\mathcal{F}$, and δ is an optional operation in $\{\emptyset, +, -, *, /\}$.

$$[C_{from}] \; F_{from} \rightarrow \delta[C_{to}] \; F_{to}$$

This definition allows for expressing constraints over the global number of instances of a given feature. For example, a constraint such as $[2, 4] \; G \rightarrow [8, *] \; H$ stipulates that if there are from 2 up to 4 instances of G in a product configuration, the number of instances of H should be greater than 8. A constraint can also include an operation to relate the number of instances of two features. The constraint $G \rightarrow +2 \; H$ states that each G instance requires 2 instances of H, and thus the number of H should be at least twice the number of G. *Requires* constraints have been further extended in [20] to support combining multiple conditions with logical operators *and* ($\wedge$) and *or* ($\vee$).

When we consider multiple relatives cardinalities, additional constraints may need to be defined not only over feature cardinalities but also over their relative ones. In [23], *requires* constraints also allow the definition of the *scope* in which a cardinality range should be evaluated, therefore providing partial support for relative cardinalities. This definition enables to associate a scope feature to each cardinality range in a constraint. However, it does not explain if different scopes can be used in the same constraint nor what their semantics are in this case.

To extend cardinality-based feature model constraints to consider relative cardinalities while allowing for combining multiple conditions, we update existing constraint notations and define their semantics. We first establish the notion of a constraining expression, and based on it, we define the concept of relative cardinality constraints.

Definition 4. **(Constraining expression)** A constraining expression is described by a tuple $\varepsilon = (r, c)$ where

- $r \in \mathbb{N} \times \mathbb{N}$ is a cardinality range;

- $c \in E^+$ is a pair of features part of the child-ancestor relation in the associated feature model.

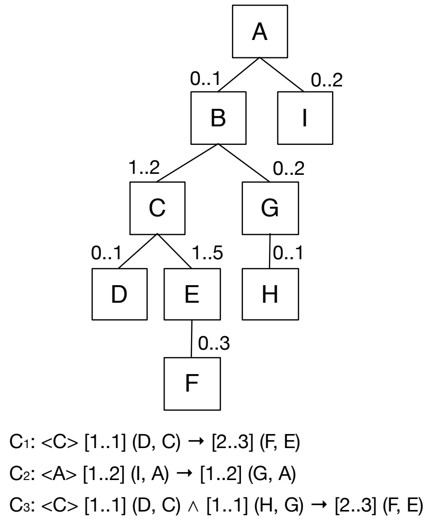


Figure 4: Additional constraints and relative cardinalities

We use the notation $[m..n]$ (x, y) to describe a constraining expression where $r = (m, n)$ and $c = (x, y)$. Such expressions represent a predicate over the number of instances of feature x that are descendant of an instance of y. Therefore constraining expressions represent a condition over a relative cardinality in a feature model.

Definition 5. **(Relative cardinality constraint)** A constraint is defined as an implication between constraining expressions like <*C*> ε_1 δ ... δ $\varepsilon_n \rightarrow \varepsilon_{cons}$ where:

- $C \in \mathcal{F}$ is a feature that defines the context where the constraint will be evaluated;
- $\varepsilon_1 ... \varepsilon_n$ and ε_{cons} are constraining expressions;
- $\delta \in \{\wedge, \vee\}$ is a logical operation.

As an implication, a relative cardinality constraint express that should the composed left hand expressions ε_1 δ ... δ ε_n hold, the right hand ε_{cons} should also hold.

As shown in the above definition, constraining expressions are the base elements for describing a constraint. However, though they express a condition over a relative cardinality, they do not express in which context it should be evaluated. For example, considering the feature model in Figure 4, we can define a constraining expression such as $[5..10]$ (F, C). Does this expression evaluate to true if one instance of C has 5 to 10 instances of F or if all instances of C have 5 to 10 instances of F?

The role of the context feature in the constraint is to remove this ambiguity and specify in which context expressions should be evaluated. Thus, in constraint C_1 (Figure 4), the <C> context indicates that its constraining expressions should be evaluated individually for each instance of C. For instance, the C_1 constraint expresses that *C instances that have exactly one D instance as a child should have 2 or 3 instances of F for each E instance*. Actually, this constraint redefines the local cardinality of F (relative to its parent E) for some set of C instances, those that have exactly one D instance as a child.

Likewise, in C_2 the <A> context indicates that the constraint has to be evaluated globally, for the singleton instance of the root feature A. In this case, C_2 expresses a global implication that should at least one I instance be part of the product configuration then at least one G instance should also be included.

In C_1 and C_2, all constraining expressions deal with features that are under the subtree of the context features <C> and <A> respectively. The semantics of constraint evaluation are simpler as it suffices to consider each instance of C or A individually (and its subtree) and verify if the constraining expressions hold. However, how can we evaluate a constraint such as C_3, which contains combined expressions at different levels of hierarchy, including outside the context feature?

In this case, expressions whose features are not in the subtree of the context feature are evaluated in the context of the lowest common feature. This is the lowest common ancestor, in the feature diagram tree, of all features involved in the constraint; which in the case of C_3 is feature B.

With the described semantics, C_3 expresses that for each c instance of C and b instance of B such that b is an ancestor of c in a configuration tree, we have that if c has exactly one child instance of D, and all instances of G that are children of b have exactly one instance of H, then all instances of F that are children of this same c should have 2 or 3 instances of E.

The proposed constructs enable describing both simple and complex constraints involving relative cardinalities. The introduction of context features along with the semantics described above clarify how constraints can be evaluated even when they involve cardinalities from different levels in the feature diagram tree.

3.4 Contribution summary

In our approach, we tackle the challenges identified in Section 2.2 in the following way:

- To capture cardinality constraints found in cloud computing, we extended the definition of cardinality-based feature models, replacing feature cardinalities by relative cardinalities.
- To ensure consistency between relative cardinalities, we identified a set of constraint conditions to verify range consistency in the presence of multiple relative cardinalities.
- To consider relative cardinalities in cross-tree constraints, we introduced constraining expressions over relative cardinalities and precise semantics for identifying the constraint's context of evaluation.

4 Modeling and automation

This section discusses the tooling support we developed to enable modeling feature models with relative cardinalities, including language support, inference and consistency analysis, and configuration conformance.

4.1 Modeling

To enable the description of feature models with relative cardinalities, we designed a domain specific language based on the definitions given in Section 3.1. Besides the common elements found in feature models, the abstract syntax of the language (see Figure 5) includes the `RelativeCardinality` concept. A relative cardinality contains a cardinality range and is associated to two features (`from` and `to`). In addition, elements `Constraint` and `ConstrainingExpression` allow the definition of relative cardinality constraints as described in Section 3.3.

The proposed language was implemented using the xText framework [3]. An xText grammar was used to define the concrete syntax, while the abstract-syntax was defined using an EMF Ecore metamodel [28]. Additional OCL constraints [19] were used to guarantee that relative cardinalities respect the ascendant-descendant relationship, to avoid repeated definitions of relative cardinalities and to enforce other minor consistency constraints.

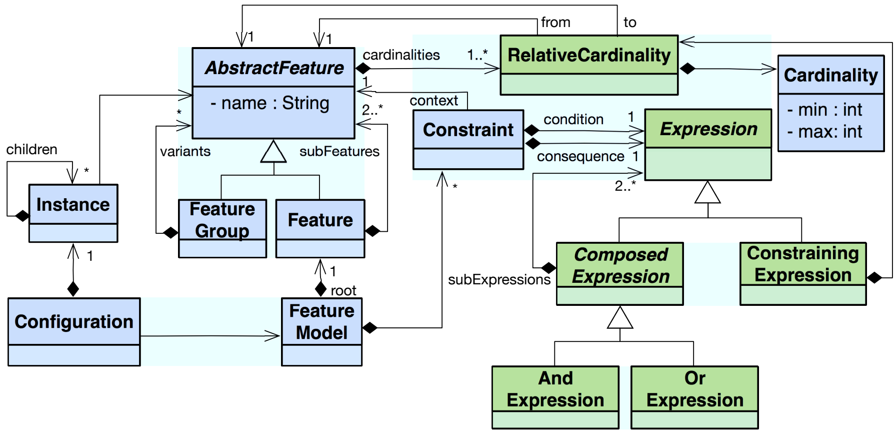


Figure 5: Abstract syntax for feature modeling with relative cardinalities.

4.2 Inference and consistency checking

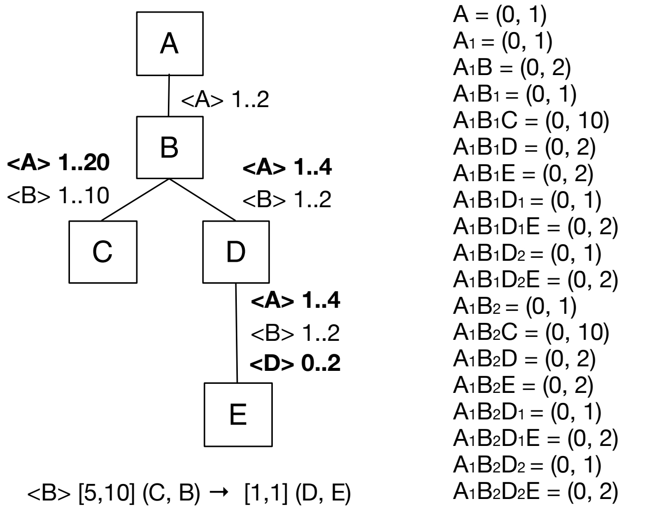
As we can see from the abstract syntax, the language allows the specification of multiple relative cardinalities. However, in most cases, relative cardinalities match exactly with the implicit relative cardinality derived from local cardinalities. In these cases, the product line designer may not want to describe all the relative cardinalities but rather those that are different from the implicit ones, letting the system infer the remaining cardinalities.

To support this requirement the designed language requires to specify only one cardinality for each feature (local or relative) and can automatically infer the remaining relative cardinalities. The inference is achieved by modeling the cardinalities as a constraint satisfaction problem, according to the consistency constraints described in Section 3.2, and finding a solution that maximizes the number of possible configurations. Figure 6 (a) shows an example feature model where cardinalities in bold face were inferred from declared cardinalities. Because the inference process relies on the cardinality consistency constraints, the inferred cardinalities will always be consistent. In addition, if described cardinalities are not consistent the generated constraint problem will not have a solution. Therefore, the cardinality consistency check and inference are executed as a sole process.

4.3 Reasoning on feature models

To automatically verify if a configuration conforms to a feature model, we also translate it into a constraint satisfaction problem and use the Choco Solver[1] [15]. We rely on the translation approach described in [17], extending it to deal with relative cardinalities. The referenced approach considers cardinalities to apply locally, therefore enabling configurations that consider not only the number of feature instances, but also how they are hierarchically organized. For each possible feature instance a boolean variable is created to represent if the instance is part of a configuration and an integer variable is created to represent the number of instances of the feature type in relation to its parent. For example, for each instance of feature B in Figure 6, we create a boolean variable B_i and two integer variables B_iC and B_iD with domains $[0..10]$ and $[0..2]$ that represent the number of instances of C and D for the i-th instance of B. Additional constraints are added to enforce the minimum number of instances for mandatory features, hierarchical dependencies and group feature cardinalities.

[1] http://choco-solver.org/



(a) feature model *(b) CSP variables created*

Figure 6: Feature model evaluation.

To implement the semantics of relative cardinalities, besides creating variables that represent the number of instances of each direct subfeature type, we also create variables to represent the number of descendant features. Still in the example of Figure 6, it means that in addition to the variables B_iC and B_iD, we create a variable B_iE representing the number of instances of E for this given instance of B. Constraints are added to guarantee that B_iE matches with the number of instances of E for each of its D instances. In the given example, we add the constraint $B_iE = B_iD_1E + B_iD_2E$. The variables generated by this process for the feature model in our example are shown in Figure 6 (b). The variable names are prepended by A_1 to express that they represent instances that are under the singleton instance of the root feature A. Instance variables for leaf nodes do not need to be generated as their number is captured by the corresponding feature variable.

To optimize the translation and solving of the constraint problem, variables and constraints for relative cardinalities are only added when they are explicitly declared and do not match the implicit cardinality that is derived from the individual local cardinalities. Also, when validating a configuration against a feature model, we use a generative approach [8] and create variables and constraints according to the configuration size. After generating the variables, those that represent a relative cardinality are used for implementing the additional feature model constraints using simple logic implication constraints. For example, the constraint in the feature model in Figure 6 (a) would generate the following constraint for each i-th instance of B:

$$\text{IF } (B_iC \text{ IN } [5..10]) \text{ THEN } (B_iD_1E = 1 \text{ AND } B_iD_2E = 1).$$

The tools that we developed allow to define feature models with relative cardinalities and configurations of these feature models using a domain specific language. These can then be translated to a constraint satisfaction problem to verify the validity of a configuration or to generate a full configuration from a partial one.

5 Evaluation

To assess the use of relative cardinalities for feature modeling, we analyze their utility in capturing variability in cloud providers as well as the performance and scalability of the automation solutions proposed in the previous section. Besides this, we discuss the limitations of the work and the threats to its validity.

5.1 Usefulness

To evaluate the usefulness of relative cardinalities we captured variability identified from a set of popular cloud providers into feature models with relative cardinalities. Information from cloud providers was obtained from their documentation and through the use of their configuration tools. Table 1 shows the total number of features and constraining expressions for each modeled provider, as well as how many of them employ local and relative cardinalities.

A feature is considered to have a cardinality if its maximum local cardinality is greater than 1, as features whose local cardinality is 1 or 0 are considered as mandatory and optional, respectfully. Features are considered to have a relative cardinality when their cardinalities relative to an ascendant feature do not match the implicit cardinalities derived from intermediary local cardinalities.

A constraint can be composed of many constraining expressions as described in Section 3.3. A constraining expression is considered to employ cardinalities if it constrains a local cardinality whose maximum bound is greater than 1. It is considered to employ relative cardinalities if it applies to a pair of features that are not directly related in the feature model hierarchy.

	Features			Constraining Expressions		
Cloud	Total	card	relCard	Total	card	relCard
`Google`	69	6	3	6	1	5
`Heroku`	45	3	1	0	0	0
`Jelastic`	37	4	5	18	5	13
`OpenShift`	30	3	2	16	1	9

Table 1: Analysis of cloud providers

As seen from the table, in the studied examples, relative cardinalities describe many relationships and constraints that are not covered by previous feature modeling constructs. Though these examples show the use of relative cardinalities are needed for capturing variability in cloud environments, further study is required to determine if they are necessary for modeling variability in other domains.

5.2 Scalability

Adding new constructs to feature modeling may bring additional costs to automated feature model analysis, and eventually render it unfeasible. To identify the effects of relative cardinalities in the performance of feature model analysis, we conducted three experiments with feature models of different sizes. First, we evaluated the performance of checking cardinality consistency. Then we verified the performance of translating feature models to constraint satisfaction problems. Finally, we verified the time for checking if a configuration complies to a feature model.

5.2.1 Experimental setup

To execute the experiments, we randomly generated feature models of different sizes (50, 100, 250, 500, 1000, 2500 features). Feature models were generated to be similar to those found in cloud environments and are based on our experience designing the feature models shown in Table 1. Therefore, features in the first three levels of the hierarchy had a 50% chance of having a local cardinality, while in lower levels this chance would be of 1%. For the features chosen to have cardinalities, a random cardinality was generated with the maximum upper bound of 10 instances. Later, for each generated feature model, we randomly selected half of the features for which local cardinalities were defined and added extra relative cardinalities to them.

For each feature model size, 50 different models were generated and had relative cardinalities added. From this process, we obtained two sets of feature models, one composed of random feature models with local cardinalities, and another composed of the same models augmented with relative cardinalities.

Using the generated feature models we performed experiments to evaluate the scalability of a) the consistency check and inference mechanism; b) the translation to constraint satisfaction problem; and c) the validation of a configuration.

All experiments were run on a MacBook Pro Computer with a 2 GHz Intel Core i7 processor and 8GB of memory. The details of the experiment, including the data obtained from the executions and the source code are available at `http://researchers.lille.inria.fr/~sousa/relativecard/`.

5.2.2 Results

For the first experiment we measured the time to verify the consistency between cardinalities and infer cardinalities that were not described in the model. This includes the time to translate the consistency conditions described in 3.2 into a constraint satisfaction problem and the time to solve the problem.

This experiment was ran only for the set of feature models with relative cardinalities. The average measured time, by number of features of the model, is shown in Table 2.

Features	Average time (ms)	Standard deviation (ms)
50	63.80	17.60
100	220.16	60.79
250	796.82	194.29
500	3,627.55	698.80
1,000	14,923.11	4,438.63
2,500	129,472.05	38,772.75

Table 2: Average time for consistency checking and cardinality inference.

For the second experiment, for both sets of feature models we measured the time to fully translate a model to a constraint satisfaction problem. Figure 7 shows, in a logarithmic scale, the distribution of execution times by the number of features for both sets of feature models.

As many random models were generated for each number of features, we obtained many different translation times for the same number of features. This happens because according to how the hierarchy was generated and where the cardinalities were placed, the number of instances that can be generated by the feature model may vary greatly. Still, as we can see from the chart, translating a feature model with relative cardinalities introduces an overhead into the processing, which in the conducted experiments was on average of 41%.

Despite the overhead added by relative cardinalities in the translation, it is still feasible to use them, and in the worst case found in our experiments it took less than 10 minutes to translate a feature model with 2500 features that can generate configurations with up to 187,770 instances. Feature models from cloud providers have usually far less features, but can still have a large number of possible feature instances.

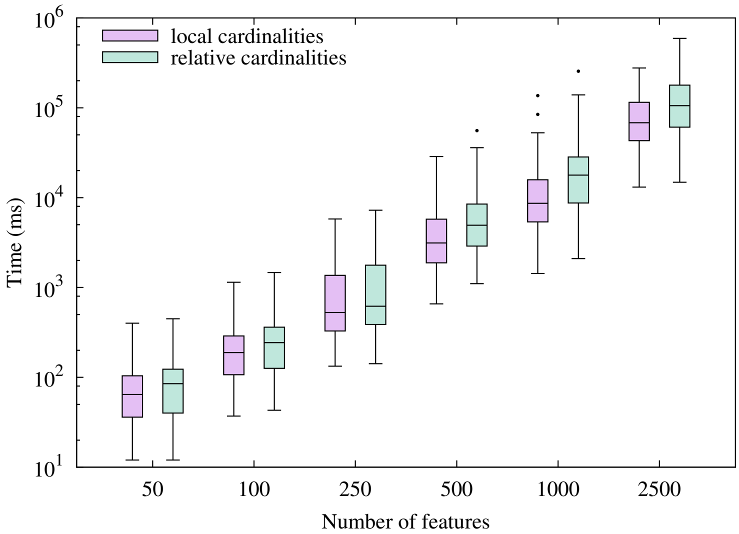


Figure 7: Distribution of time to translate feature model to constraint satisfaction problem

For the last experiment we evaluate the time to check if a configuration conforms to a feature model. Using the translations obtained in the previous experiment we generate valid configurations for feature models in both sets and check their compliance to their respective feature model. Figure 8 shows the time distribution for checking a configuration for feature models with local and relative cardinalities. This time includes the translation of the configuration, together with the conversion of feature model constraints to a constraint satisfaction problem, and the resolution of the problem. From the graph we can see that introducing relative cardinalities did not affect the time to validate a configuration. This may be linked to the fact that configurations for feature models with relative cardinalities tend to be smaller as relative cardinalities usually restrict the number of allowed instances of a feature.

5.3 Threats to validity

The first threat is related to the usefulness of relative cardinalities for variability modeling in feature models. Though we have studied and worked extensively with cloud provider configurations to propose relative cardinalities, we only formally modeled a small number of them for extracting data. Hence, we cannot generalize the importance of relative cardinalities to all cloud providers or to other domains.

A second threat concerns the consistency constraints that have not been formally proven. To mitigate this threat, we created test cases of many consistent and inconsistent scenarios to verify the completeness of the proposed constraints.

Finally, the feature models generated to measure the scalability follow a pattern where cardinalities are mostly concentrated in the upper levels. As the hierarchy of a feature model and placement of cardinalities may greatly influence the size of the translated constraint satisfaction problem, it can also influence the performance of feature model processing negatively. We tried to ensure that the solution is feasible for models similar to those we identified for the cloud domain.

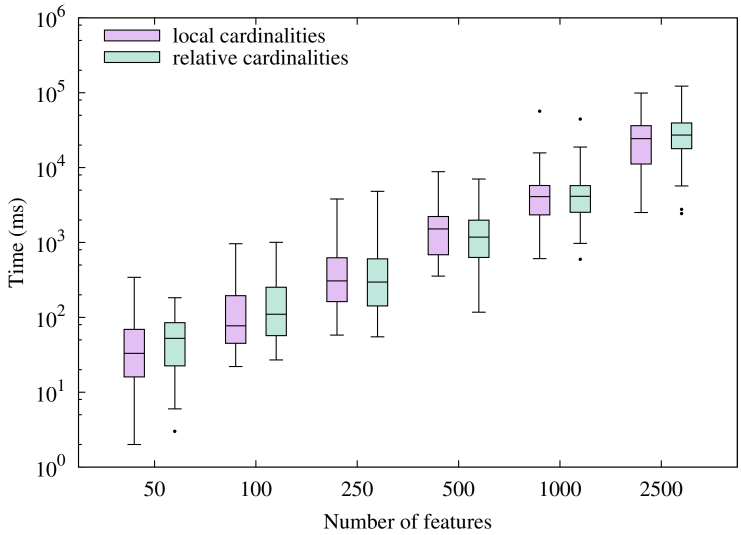


Figure 8: Time to verify compliance of a configuration to a feature model

6 Related Work

The concept of cardinalities has been initially introduced to feature models in [26] as an application of UML multiplicities to feature groups from the original FODA notation [16]. Feature cardinalities were first introduced in [4], motivated by practical application. *Czarnecki et al.* [5] integrated feature model extensions, such as attributes, group and feature cardinalities to formalize the concept of cardinality-based feature models [6]. Our approach relies on this concept as well as other preceding developments in the field of feature models with cardinalities.

In [7], the authors discuss the need to extend additional constraints to deal with cardinality-based feature models, and identify the need for constraints that apply only in a given scope of the feature model. However, the proposed constraints are defined in OCL, which is a general purpose constraint language and whose evaluation may limit the performance of automated analysis of feature models. Similarly, XPath has also been employed as a notation for describing additional constraints in feature models [2]. We consider scopes for not only additional constraints but also for feature cardinalities.

In [18], *Michel et al.* discuss the multiple possible interpretations of group and feature cardinalities and argue for choosing the local interpretation for feature cardinalities. In our work we generalize the concept of the feature cardinality scope enabling users to specify the desired interpretation. The authors also discuss about the effects of cardinalities on additional constraints. They also identify the need for constraints that can capture universal and existential quantification as well as the relationships between feature instances, but do not present any proposal to deal with it.

The requirements concerning constraints identified in [18] are partially achieved by the constraint language proposed by *Quinton et al.* in [22]. Their constraint language allows defining the scope of the cardinalities that are part of a constraint. However, this scope is limited to either global or local and is only considered for additional constraints, which are based on a given condition being met. Our work is based on their approach, but allows for feature cardinalities with different scopes both in the features and in additional constraints.

Feature modeling has been employed to capture variability in cloud environments, but usually in a constrained context. In [9, 25] regular feature models are used to model variability within virtual machine configurations, while in [24] cardinality-based feature models capture variability in cloud providers.

In summary, what distinguishes our proposal from previous work is the possibility of using multiple interpretations of feature cardinalities scope and applying them to both features and additional constraints. At the same time, we consider the use of a specialized feature modeling language instead of employing general purpose constraint languages. Concerning cloud environment modeling, our motivation for using relative cardinalities is to enable capturing all variability in cloud providers, within and across different contexts such as applications, virtual machines, projects, etc.

7 Conclusion

In this paper we introduced the concept of relative cardinalities for feature models. Based on our investigation on managing variability in cloud computing platforms, we identified limitations found in feature cardinalities and the need to extend their interpretation. We proposed a definition of cardinality-based feature models with relative cardinalities, analyzed the issue of consistency between cardinalities, and updated cross-tree constraints to take into account relative cardinalities.

In addition, we proposed a meta-model for describing feature models with relative cardinalities, and a translation process into constraint satisfaction problems for automatic processing. We also demonstrate that relative cardinalities are valuable for modeling variability in cloud computing configurations and that automated reasoning upon them is feasible. We have fully implemented and thoroughly tested our approach. The implementation and our detailed research results can be found in an accompanying site.[2] .

In the future we plan to integrate multiple cloud providers, described using feature models with relative cardinalities, into a multi-product line approach [1, 13]. Our goal is to support the automatic configuration of multi-cloud environments for applications based on microservices architectures. This includes taking into consideration requirements such as scalability, redundancy and location, which will lead to constraints that must be imposed across multiple cloud providers and their respective feature models. Due to the huge number of possible multi-cloud configurations this will lead to, we also intend to evaluate the use of search-based strategies [12] combined with constraints [14] for reasoning on multiple product lines.

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Publisher
Inria
Domaine de Voluceau - Rocquencourt
BP 105 - 78153 Le Chesnay Cedex
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ISSN 0249-6399