

The benefits of domain models for checking the completeness of requirements are known, but have never been evaluated systematically. We focus on requirements written as “shall”-style statements and domain models captured using UML class diagrams. We observe that domain models exhibit near-linear sensitivity to both unspecified (i.e., missing) and under-specified requirements. A fundamental property of external completeness is that it cannot be ascertained in absolute terms. Despite this limitation, one can implement measures for improving (but not guaranteeing) the external completion of requirements. One such measure is domain modeling (Zowghi and Gervasi 2003a; Ferrari et al. 2014). A domain model is an explicit representation of the salient concepts in an application domain. Checking the completeness of NL requirements is particularly challenging, noting that NL requirements specifications may constitute hundreds or thousands of statements. This makes it important to develop a more detailed understanding of mechanisms through which one can identify incompleteness issues in NL requirements. One interesting mechanism to study for this purpose is domain modeling.

The requirements in Fig. 1a have been slightly altered from their original form to facilitate discussion and preserve confidentiality. The requirements document from which this subset was taken is the subject of one Fig. 1 aExamples of shall requirements; bExample domain model represented as a UML class diagram.

An analyst can use a reasonably complete domain model for detecting incompleteness in requirements. For example, the model of Fig. 1 does not convey the constraint stated in REQ1 that the simulations shall be configured “via a web service” We note again that we are arguing under the assumption that the domain model is complete.

In Fig. 1, domain concepts may be referred to several times in the requirements. The higher the level of repetition, the less sensitive the domain model becomes to omissions. Most importantly, we observe that domain models exhibit near-linear sensitivity to both unspecified requirements and requirements that are missing.

domain models are sufficiently sensitive to omissions in NL requirements. The level of sensitivity that domain models show to omissions is more than four 2514 Empirical Software Engineering (2019) 24:2509–2539 times higher when whole requirements are removed.

Despite being promising, our results do not automatically lead to the conclusion that domain models are useful instruments for completeness checking of requirements by analysts. Backward completeness is measured against the body of knowledge established prior to the development of a requirements specification. Forward completeness is, in contrast, measured against the (accumulated) body of knowledge after a requirement specification has been produced. Our mode of using domain models thus coincides with forward checking of NL requirements. Lindland et al. (1994) introduce the notion of feasible completeness, where a conceptual model contains only a subset of the statements in a domain. A conceptual model is feasibly complete with respect to a domain, if any further enhancement of the model is deemed less beneficial than accepting the model as-is. In our case studies, we aim to achieve this completeness for the domain models built. Using NLP, Gigante et al. (2015) extract from a set of requirements and an external source – in their case, higher-level requirements – systematic information in the form of (subject, predicate, object) triplets. They then compare the triplets from the two sources to determine how complete the given set of requirements is. No statistically significant results are obtained for completeness. We examine how a complementary approach, namely domain modeling, contributes to improving requirements completeness. The main components of our study are: (1) constructing feasibly complete domain models, (2) establishing traceability between the domain models and the requirements, and (3) simulating potential omissions in the requirements. The study looked at the usefulness of domain models for completeness checking of requirements. The data collection was aimed at constructing (feasibly complete) domain models, defining potential but realistic omissions from requirements, tracing requirements to domain model elements, and gathering data to argue about the representativeness of the results. In each case study, we randomly selected 35 requirements. We extracted all the atomic noun phrases (NPs) from the sentences in R. Following object-oriented domain modeling guidelines (Larman 2004), we considered each NP as a candidate domain concept. Without revealing R to the domain experts, we had them review the NPs extracted from these requirements. Two researchers (the first two authors) acted as facilitators during modeling. In all three case studies, the experts did a portion of the modeling work offline but collaboratively. The

modeling

activities concentrated on specifying the core domain model elements.

To simulate the omission of requirement segments in a realistic manner, both semantic interdependencies and the significance of the content of segments need to be considered.

The main

criterion to decide whether a segment was omissible was the plausibility of the segment being

overlooked in realistic conditions.

Omissible segments fall into one of the following types: Object, Condition, or Constraint.

Objects

are, in principle, omissible only when several of them are present. Constraints restrict the design

or implementation of the systems engineering process.

3.3 Tracing Requirements to the Domain Model In the last step of data collection, we had the experts in

each case study trace the selected requirements, denoted R , to the respective domain model.

Recall from Section 3.3.1 that each domain model was built around the set of concepts derived from

R .

Fig. 4 shows the union of all trace links originating from a given omissible segment. In our example

of Fig. 4, REQ2 has a condition, Condition 2.1. The term 'simulation' in Condition 2.1 is traceable to

the domain model. This induces a trace link from Condition 2.1 to Simulation.

We present our simulation algorithm in Fig 5. The inputs to the algorithm are: (1) the outcomes of

our data collection procedure, described in Section 3.3, (2) the type of omissions to simulate (T),

and (3) the number of simulation runs (n) Following a randomized process, the algorithm seeds into

requirements progressively larger sets of omission of a given type.

Table 1 provides key statistics about the outcomes of our data collection as per the procedures

discussed in Section 3.3.1. Table 2 provides statistics about the complementary data that we

gathered according to the procedure described in Section 3.4 and with the goal of examining the

representativeness of our case studies. The scatter plot resulting from running the algorithm of

Fig. 5 is the basis for answering RQ1 in Section 4.

Fig. 6 shows the output (scatter plots) for $n=100$ runs of our simulation algorithm (Fig. 5) Each

plot shows, for each case study, the relationship between the number of omissions of a certain type

and the percentage of domain model elements that are no longer supported as the result of the

omissions. The amount of time the researchers spent with the experts for data collection is 8 hours

for each Case A and Case B, and 6 hours for Case C.

In Case C, the domain concepts appear considerably more frequently in the requirements than in Case A

and Case B. Figure 6b, c and d show the sensitivity of the domain models in our case studies to

omissions of conditions, constraints, and objects, respectively.

The level of sensitivity is, on average, 4.4 times higher when requirements are removed in their

entirety than when conditions, constraints and objects are removed. The impact of omitting 10

requirements from Case A is the loss of support for 23.4% of the domain model elements.

Using keyphrases as a surrogate for domain model elements is most practical for predicting

sensitivity to requirement omissions. NPs and VPs are the main meaning-carrying units of requirements statements (Arora et al. 2017). Determining whether a keyphrase is still supported after

a set of omissions is trivial.

The Pearson's correlation coefficient (Warner 2012) for Case A. is 0.97440 ($p < 0.0001$), for Case B.

is. 0.98005 ($p = 0.00001$), and for Case C is 0.96838 ($p > 0.0005$) Figure 9 shows the keyphrase

sensitivity curves for both the requirements subsets and the full documents, organized by case

study.

The main threat to the internal validity of our work is subjectivity in modeling. To minimize

subjectivity about content, we engaged closely with at least two domain experts in each case study.

We believe that other experts, under identical circumstances, would have made similar choices about

content. In measuring sensitivity, we are concerned only with whether domain models contain the

information that is necessary for revealing omissions.

The study is not meant at measuring the overhead associated with investigating such false alarms. The

above overhead appears to be a reasonable price to pay for the genuine requirements incompleteness

issues that one can identify through a domain model.

This article was motivated by the anecdotal observation that domain models are additionally helpful

for detecting incompleteness in requirements. To empirically examine this observation, we conducted

three industrial case studies with subject-matter experts. In each case study, we measured the

incomplete completeness-revealing-power of a domain model by seeding realistic omissions into the

requirements.

Arora C, Sabetzadeh M, Briand L, Zimmer F (2015) Automated checking of conformance to requirements

templates using natural language processing. Ambler S (2004) The object primer: agile model-driven development with UML 2.0, 3rd edn. Cambridge University Press, Cambridge Apache OpenNLP Chunker.

Epa ñna S, Condori-Fernandez N, Gonzalez A, Pastor 'O (2009) Evaluating the completeness and granularity of functional requirements specifications: a controlled experiment. Femmer H, Mager P (2016)

Challenging incompleteness of performance requirements by sentence patterns.

Error during summarization.

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