USING TRACEABILITY IN MODEL-TO-MODEL TRANSFORMATION TO QUANTIFY CONFIDENCE BASED ON PREVIOUS HISTORY.

by

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Abstract

A widely used method when generating code for the purposes of transitioning systems, security, the automotive industry and other mission critical scenarios is model-to-model transformation. Traceability is a mechanism for relating the source model elements and the destination elements. It is used to identify how the latter came from the former as well as indicating when and in what order. In these application domains, traceability is a very useful tool for debugging, validating and performance tuning of model transformations. Recent advances in big data technologies have made it possible to produce a history of these executions. In this thesis, we present a method on how we can use such historical data that quantifies the confidence a user has on a newly proposed transformation. For a given trace of execution, considering historical traces that are either well tested, or performed correctly over time, we introduce a measure of confidence for the new trace. This metric is made to compliment that of traditional verification and validation. For example, our metric will aid in deciding whether to deploy automatically generated code when there is not enough time or resources for thorough verification and validation. We shall evaluate our framework by providing a transformation that transitions a relational database into that of a NoSQL database, specifically Apache HBase. This transformation involves changing the nature of the data that is mapped, such that a loss in integrity occurs in the event of its failure.

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CHAPTER 1

INTRODUCTION

It is common to use model-to-model (M2M) transformation to bridge the semantic gap between a user and a developer. The skill sets between the two can vary from equal to entirely different. In software, often the latter is closer to the truth. Users do not always know how to implement, at least efficiently, their needs; whereas developers are not always capable of knowing what a user wants precisely. This difference in skill set appears in many industries including the automotive, telecommunication, medical and other embedded industries in need of the efficient deployment of mission critical code.

M2M transformations are black-box processes and therefore produce no accountability for the resultant model. They are potentially multi-layered processes: text-to-model (T2M, parsing), M2M and then model-to-text (M2T, code generation), this adds more complexities to what is being done to produce the result. How do we provide confidence in what the process is doing? Traceability is a mechanism to open this black-box and allows us to see what is going on. Unlike most white-box approaches, which rely on static analysis, formal verification and quality test case generation, traceability provides runtime information specific for

each instance. Our research attempts to provide a method for quantifying the amount of trust we have in the transformation by looking at previous runtime execution information. The underlying idea uses the information about previous traces that involve the same rule set, a typical and recurring scenario in many instances of M2M transformation. If a particular combination of rules worked well in a previous transformation, we might intuitively think that it may work better than an unseen combination. To inspire confidence in an M2M transformation, we often verify or validate the process. Verification determines whether the product satisfies the the conditions imposed, whilst validation determines whether the product satisfies the specified requirements. The former usually relates to formal verifcation that guarantees the correctness of the product. The latter is contractual between the specification and the product's outputs. We adopt an entirely different approach that can be used to compliment the above methods. Instead, we adapt a theory of how we as humans recognise features of visual stimuli to recognise objects: feature analysis. The more experience with a feature increases our confidence that something is what we expect. No different to us looking for a green lock on a browser, so we recognise the fact that a site is secure. Or that two wheels usually dictates we are observing a bicycle of some form.

In model driven development (MDD) the use of a domain specific language (DSL) enables a user to define problems in their terms or business logic. DSLs remove the unnecessary complexities of mapping a user's requirement into a developer's software. For example, the Structured Query Language (SQL) is a DSL that bridges the gap between a user of a database and the database engine itself. This language enables the user to interact with some database engines that are SQL compliant, ignoring the intricacies of individual engines and only concentrating on the user's

view of the data. Allowing database administrators, or those that wish to query databases, to access the data they require. Using a DSL attempts to remove the majority of basic errors of understanding between the two parties. By their nature, these pieces of software are modular as to allow different permutations of devices that can work in tandem or allow for alternative devices with the same functionality to be used or upgraded. As we have already mentioned, SQL can communicate with multiple engines, each of those engines may optimise those queries differently to suit their internal representations of data. We have the same source, but its interpretation into an executable model is different.

The core motivation for our research was from a computer security perspective. Here we described a forensic virtual machine (FVM), a small virtual machine (VM) that uses introspection to detect symptoms of malicious behaviour in other VMs (Harrison et al. 2012; Shaw et al. 2014). Attempting to detect malware from outside of the OS that contains it allows us to circumvent many techniques used by writers to hide their software, for instance disabling the anti-virus and intercepting and modifying API calls. These symptoms may not mean anything on their own. However, combinations of them can prove to be evidence of a piece of malware. Introspection is used to read and interpret a raw byte stream as there is no operating system API available to the developer. It involves generating low-level C code from a yet unpublished declarative DSL or Cyber Observable eXpressions (CybOX), a Mitre product (The MITRE Corporation 2017a). The latter is an eXtended Markup Language (XML) instance to describe cyber observables that include the types of objects we would be investigating. We, however, concentrated our efforts on detecting key material (Saxon, Bordbar, and Harrison 2015a,b). When completing this function, the FVM uses shared resources primarily served for

a VM host's clients, for example, CPU and memory so any mistakes can be costly. It is important to know that any automatically generated code is suitable and safe for use in production before deployment. A typical case of our system would be the discovery of a zero-day vulnerability; we need to produce code to monitor and find its prevalence in an FVM's corpus of client VMs quickly. Often there is little time to validate or verify the FVM code in such scenarios. Unfortunately, the FVMs we had developed had no common ground and little variability. The only variable available to us was the RSA key length, so our attempt to gain confidence was an equality check due to how specialised our RSA detecting FVMs were. Rather than developing more FVMs, we chose to transform another, more general domain: a relational database to a non-relational database.

We present a systematic framework to use the historical data, about the execution of traces, so that the experts can make informed decisions based on existing evidence within the confines of the time available to them. Our approach stores M2M transformation traces, extracts their execution information and compares it to previous transactions using sub-graph isomorphism and a complexity measure for weighing. Subgraph isomorphism is used to determine which components of the new trace have been seen before in respect of past executions. Considerations must be made upon the complexities of each rule, as an invocation only acknowledges its execution. We then use McCabe's cyclomatic complexity as a coefficient to counter-act rule prominence on its workload. The metric is used to determine the number of execution pathways within a function. We assume that the more pathways that are available, there is a higher probability of traversing an incorrect path. Therefore we must be more cautious of the function's output. For instance, in the event of a conditional branch, the condition may not be specific enough

allowing more or fewer executions of its block. Alternatively, when iterating an array, a bounds error may occur when not handling indices properly. For the result of a transformation to be deployed: our method uses these traits to provide a quantifiable measure of confidence based on the previous history. In the event of transformation fringes, i.e. segments previously unseen, we are then able to focus validation efforts.

The process need not start with parsing or a T2M transformation. We have transformed a live relational database into a non-relational database, specifically Apache HBase (Saxon, Bordbar, and Akehurst 2015). Here we are transforming the shape of the data. Rather than keeping its normalised state such that it retains its integrity and reduces duplicate data, we denormalise the data to increase redundancy and read speeds. The tool Kettle uses the Extract, Transform, Load methodology to migrate data in an automated fashion (Casters, Bouman, and Dongen 2010). Due to the lack of driver support for databases, Kettle provided a configurable system to migrate data from one source to another, which involves changing its structure, as well as the ability to integrate data from multiple source types. This work sparked more frameworks and methodologies for the transformation of relational into non-relational data (Ma, Yang, and Abraham 2016).

This thesis is structured as follows; we shall introduce our aims and some key points related to our contribution in Section 1.1, then we provide background and preliminary information in Chapter 2. This is then followed by three contribution chapters: *1)* the introduction of a new meta-model for traceability (Chapter 3), *2)* the introduction of assurability in M2M transformation (Chapter 4), and *3)* a case study that bringing the two together (Chapter 5). Finally, we discuss our

findings and conclude in Chapter 6.

1.1 Objectives and Contributions of Thesis

Our objective is to design, implement and evaluate a system that can use previous executions of M2M transformations as a basis to drive development in time critical settings. The ability to make a risk assessment based on experience allows us to focus efforts on lesser known artefacts to aid in the decision of mitigating those risks or accepting them. A crucial component is the weighing mechanism that can alter the effects of what we have seen before. This approach removes induced biases from coverage alone as we are no longer treating each node within an execution path as equal. As well as mapping experience onto new inputs, we can skew those values using a configurable weighing function, providing semantic information upon the rules invoked. Another significant capability of our work is the introduction of a new meta-model for traceability. This new structure allows us to evade side-effects caused in imperative or hybrid transformation languages. If transformation languages have side-effects or any global state, then the ordering of the process is dependent the input and that state. Our meta-model captures the order of rule invocations to be able to recreate the state if necessary and also be able to prevent the largest side-effect available in M2M transformation: orphans, objects created outside of the engine.

This thesis makes the following contributions:

- A new meta-model that describes the graph-like structure of an M2M transformation retaining invocation information allowing accurate debugging for

engines with a global state.

- A generalised algorithm to implement this within multiple transformation engines.

- Two approaches to capturing *orphaned* objects created by imperative code blocks that have no trace information; so it is impossible to know what or why they were created.

- A quantitative evaluation of capturing this information in a well-used transformation engine, Epsilon Transformation Language (ETL) (Kolovos, Paige, and Polack 2008), as well as our own, The Simple Transformer (SiTra) (Akehurst et al. 2006).

- A workflow that enables users to make informed decisions to either focus validation efforts or accept the risk of a new M2M transformation based on experience.

- The formalisation of an execution trace and a method to persist it. This graph and the identifying features of model elements allows for the recognition of chains of M2M transformations.

- A tool set, in Python, that can persist, analyse and provide feedback on new transformation traces in respect to previous executions.

CHAPTER 2

BACKGROUND

2.1 Model Driven Architecture

Model-driven architecture (MDA) is a methodology that puts models at the forefront of development. At its core, it defines a Platform-Independent Model (PIM) of an application's business functionality and its behaviour (*MDA Specifications*). A PIM defines an application's state and how it can be interacted with or mutated. A Platform-Specific Model (PSM) is a transformation of a PIM. The PSM is a specific version of a PIM allowing for different underlying implementations of the same functionality. For example, changing the volume setting on a computer changes the output from its speakers. However, laptops come with various makes of volume controls. Modelling the core behaviour allows us to swap devices without changing the interaction in the main program.

The transformation of a PIM to a PSM requires a meta-model. Unlike compilers that deal with the concrete models, transformers deal with meta-models that describe the concrete. Meta-modelling languages define the abstract idea of a

component and its behaviour. In the case of a volume control, we have a current value that defines its state, i.e. the current level. There are also four main methods of interacting with such a device: increment, decrement and mute and unmute. The state and the behaviour define the meta-model of the control, whilst providing an Application Programming Interface (API) to interact with it. These abstractions allow us to write more modular code and provide generality to our transformation rules. MDA provides the MOF standard to define this behaviour (Object Management Group, Inc. 2016b), others exist such as ECORE from the Eclipse Modelling Framework (Steinberg et al. 2008) and Kermeta (Falleri, Huchard, and Nebut 2006).

2.2 Model Transformation

The previous section described what model driven architecture is, how it is used and how the use of meta-modelling can define it. Model transformation is a fundamental component of MDA. It forms a general mechanism to convert a concrete model into another using their respective abstract models. There are three variations: *1)* text-to-model (T2M), *2)* model-to-model (M2M) (Object Management Group, Inc. 2016a) and *3)* model-to-text (M2T) (Object Management Group, Inc. 2008). Conceptually all of these are M2M transformations; however, the first is often linked specifically to parsers and the latter to code generation. The fact of the matter is that often a combination of these is used. Deserializing texts into an abstract model, iteratively changing that model and then serialising it. These processes can be chained to form more complex transformations. Take for example the transformation of a domain specific language (DSL) to a general purpose language

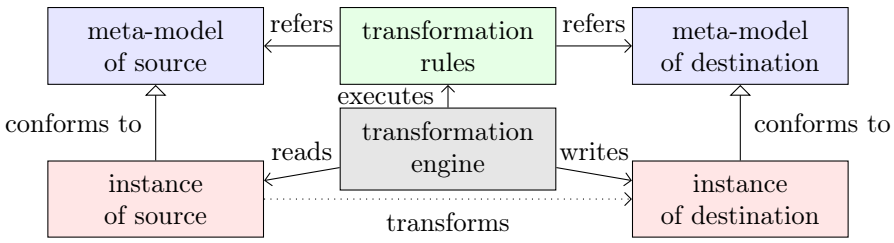


Figure 2.1: An Overview of M2M Transformation

(GPL) and then into bytecode. This section introduces rule-based transformation and the three types of M2M transformation.

2.2.1 Rule-Based Model Transformation

In this section, we shall concentrate on rule-based model transformation. A model transformation often consists of rules mapping the source model to the destination, via their respective meta-models. If a rule applies to the input object, it is then applied to create the output. In the event of parsing, or T2M, the input is a string input to be parsed. Backus-Naur Form defines the syntax of the source and provides the basis for the transformation parsing rules. For model-to-text or code-generation, a templating language transforms the input into a textual output. The output comes from interpreting the model and for each template that accepts it producing the string element for it. These rules are recursive, not unlike regular M2M transformation, allowing more complex interpretation of input.

For the purpose of this thesis, we shall concentrate on rule-based M2M transformation. This layer, conceptually, includes the other two forms. Figure 2.1 shows the overall structure of an M2M transformation (Czarnecki and Helsen 2006). It consists of three components: *1)* a source and target meta-model, *2)* an input

mode that conforms to the source meta-model, and *3)* a selection of rules that map the two meta-models. Applying a rule to an appropriate source will generate an instance of the target meta-model.

In a very general sense a transformation rule is a function, $r(s) \rightarrow t \iff$ r applies to s. It is often shown as $L \rightarrow R$ in graph rewriting. Where L is the pattern to match or the left-hand side, and R is the replacement graph or the right-hand side. Other engines, however, use a guard. r will apply to s if this guard is true. A transformer schedules the application of rules, while the rules do the transformation itself. The Simple Transformer (SiTra) is a selection of Java interfaces that define the requirements of a transformer and its rules (Akehurst et al. 2006). A rule consists of three phases: *1)* a guard, to determine the applicability of the rule to the given input; *2)* an initializer, to create the necessary target objects; and *3)* a binding method, to set attributes and relationships on and between the newly created target objects.

2.2.2 Model-to-Model Transformation

A common use of an M2M transformation is the conversion of one representation of data into another. This process can be for many reasons. One valuable reason of this transformation is to provide interoperability between applications and organisations. For instance, several businesses may model the same data differently, implying several meta-models, for varying reasons. This library of meta-models might be due to non-disclosure agreements, the protection of intellectual property, not knowing of others working on the same problem at the time of development, or application optimisations.

Often standards are produced to improve interoperability between organisations, which provide a general model that can aid in sharing data (Clinical Data Interchange Standards Consortium 2013; SAE International 2013). Enterprise service buses (ESBs) are a form of communication that facilitates communication between applications in a service orientated architecture (Chappell 2004). Rather than rewriting existing code bases, or removing application specific optimisations, ESBs have the ability to transform inputs and pass them on. This approach allows a company to share its data with other organisations using two transformations. The first to transform their data into the standard model and another to reverse this into their model. Thus sharing their data but not their internal structures and processes. For example, the Clinical Data Interchange Standards Consortium (CDISC) provide XML schemas to standardise data that relate to clinical trials. This standardisation allows vendors to share data with governmental clinical bodies, like the Food and Drug Association (FDA), the Pharmaceuticals and Medical Devices Agency (PDMA), and other research organisations to aid in collaboration.

Another use of M2M transformation is optimisation and the removal of performance anti-patterns. Khan and El-Attar (2016) describes an approach that used M2M transformation to detect and refactor instances of the Unified Modeling Language (UML) with the aim to remove anti-patterns from use cases. For example, actors with identical names are a source of confusion within the same use case model. Their names should be unique to be able to distinguish their responsibilities, the same applies to the associations between actors. This trait is deemed to be an anti-pattern as it broadens the scope from a system view to include external processes. General optimisations are usually completed by compilers to generate bytecode. An example of an optimisation is loop-invariant code motion, also known

as hoisting or scalar promotion (Srivastava 1999). Loop-invariant code motion detects code that remains constant before and after a loop and moves it outside of the block. Compilers apply this optimisation to increase the application's runtime performance by computing the detected expressions once opposed to during each iteration.

As well as in place transformations, M2M transformation is also applicable to complete conversions of data representations. In our work, we transform an input model of a relational database into a non-relational database, specifically Apache HBase (Saxon, Bordbar, and Akehurst 2015). An extension of this is part of this thesis and explained in detail in Chapter 5.

Additionally we have looked at generating forensic virtual machines (FVMs) (Harrison et al. 2012; Saxon, Bordbar, and Harrison 2015a; Shaw et al. 2014) using a DSL to define symptoms of malicious behaviour. These small VMs use very complex C code to interact with a raw byte stream. They do not have the added benefits of an operating system's API as they live outside of the host they are introspecting. The traversal of a volatile memory space is fraught with dangers. For example, an address change within the target VM could cause the FVM to move into invalid memory space. To avoid errors, we want to define what is a symptom in the domain of malware and generate this C code. The key difference between this transformation is the shift from what we are looking for and then how we are going to look for it. We are currently looking at transforming Cyber Observable eXpression (CybOX) a Mitre XML markup for describing observables within a working OS into C code (The MITRE Corporation 2017a). CybOX is an XML schema for the specification, capture, characterization and communication of events in an operational domain. It is part of a larger framework of XML schemas used

to convey information regarding cyber security issues. For instance, the Structured Threat Information Expression (STIX) schema uses CybOX to describe malware as a whole with additional information so it can be stored and analysed in a consistent manner (The MITRE Corporation 2017b). CybOX comes with a comprehensive library of observables including processes, files, email messages, network traffic and Windows registry keys.

2.2.3 Text-to-Model Transformation

T2M transformers are parsers for streams of serialised data, and upon completion, it provides a deserialized model for processing. These streams of data can come from many locations but are often domain specific languages (DSLs). DSLs are languages that attempt to bridge the semantic gap between a developer, or application, and a user. This mechanism allows a user to write in a manner that is more natural to them and their business logic. A prime example of this is that of Structured Query Language (SQL). SQL is a standard language to allow developers to interact with database engines to maintain a relational dataset. Another example is a GPL. A GPL bridges the gap between its user and the generated machine code. In both cases, the user would be a software engineer or developer and the target's audience is to be interpreted by an application. However, a T2M transformation can aid in the communication between developers and users too. By providing users with a specification DSL (this could be graphical), developers can interpret the deserialised model to complete the actual tasks. The previous section introduced CybOX, an XML markup for specifying cyber observables. This markup needs to be parsed as XML initially prior to being understood by an application in a more native form.

This process makes an assumption that the user knows what they want to do but don't know the all of the essential details to complete the task itself. The first part of this process involves parsing the source code, or script, into a model that can be interpreted by a compiler. This model is often the abstract syntax tree (AST) that represents the language in question. It is a basic model that simply represents the expression and its location within the source. An AST allows a compiler to further transform or interpret the input in a manner it understands to complete its task, to generate bytecode for example. Generally speaking, all compilers are formed of a T2M transformation, allowing them to parse source code before mutating it and finally serialising it.

Other examples include JAXB for the serialisation and de-serialisation of JSON and XML (Kawaguchi, Vajjhala, and Fialli 2009). XML and JSON are common formats used throughout the Internet to communicate data. These technologies are often used on the web to create asynchronous web applications. Asynchronous web applications use these data formats to update their page content without sending the raw HTML/CSS to do so. Instead, they optimise their efforts only to send raw data or HTML snippets and allow the client to take care of presenting it. This approach reduces the CPU utilisation on the server side, as it does not have to prepare the full webpage, and provides an exchange that can be used by third party vendors.

2.2.4 Model-to-Text Transformation

Model-to-text (M2T) transformation relates to the serialisation of a model into some form of linearized text representation (Object Management Group, Inc. 2008).

Allowing a user to generate various text artefacts such as code, specifications, reports and for basic data storage. These are created using a templating system such that a $f(x) \rightarrow String$ where x is a model element. We have already introduced an example of M2T: JAXB (Kawaguchi, Vajjhala, and Fialli 2009). JAXB allows its users to not only read XML and JSON but write it to files. Using Java annotations on classes, or some XML bindings, it can generate the textual form required for transmission. The result of which aids in the transfer of data between systems or a format easily used for storage. JAXB comes with the application XJC. XJC transforms an XML Schemas into Plain Old Java Objects for use within an application. Opposed to making the developer interpret the raw XML or JSON, they can then traverse an object orientated model based on an XML Schema.

Another example of this is an Object Relational Mapper (ORM) for example JPA and Hibernate Goncalves 2013; *Hibernate ORM*. An ORM will generate SQL from an internal representation of a query. This automatic generation allows interaction with an SQL-compliant server without any SQL code being written, depending on the ORM. Instead of directly interfacing with the engine, one can instead programmatically write queries using a query builder in the native language of the application. This API bridges the semantic gap between the developer and the database engine itself, while simultaneously allowing the developer to interact with a plethora of engines.

2.3 Software Assurance

In the previous section, we spoke about MDA and model transformation in all its forms. However, once we have completed a transformation how can we use it? We

need to have the assurance that it works in a manner fitting for what it is meant to do. This section describes software assurance and links it to MDA and M2M transformation through validation.

Assurance provides *the grounds for justified confidence that a claim has been or will be achieved* ("IEEE Trial-Use Standard–Adoption of ISO/IEC TR 15026-1:2010 Systems and Software Engineering–Systems and Software Assurance–Part 1: Concepts and Vocabulary" 2011). The main use is within Quality Assurance (QA). QA is the *planned and systematic pattern of all actions necessary to provide adequate confidence that the item or product conforms to established technical requirements* ("Systems and software engineering – Vocabulary" 2010). This trait comes from being able to connect the requirements, design, implementation and validation processes together within the software development life-cycle. This *assures* the overall development process of a final product.

The most important aspect of the life-cycle, to stakeholders', is that the product functions as required. Thus the connection to requirements and tests is invaluable, proving that they have what they needed. The level of this QA is quite high, and it does not regard the individual components, tools and languages used in a system. The overall process may or may not acknowledge them; they are a means to an end. Therefore the functionality of the components are not assured themselves, thus must be revalidated on reuse.

2.3.1 Software Specific Definitions

In the realm of software, assurability is related to the software lifecycle and how it affects the final product. The definition provided by the National Aeronautics and

Space Administration (NASA) is a direct derivative of that specified by ISO-24765 (NASA 2005; "Systems and software engineering – Vocabulary" 2010). The main alterations are to relate directly to software, processes and products, and that they need to conform not only to requirements but standards and procedures too.

The National Information Glossary, the United States Department of Defence (DoD) and SAFECode best practices all have a concept of confidence and assurability within their standards (*National Information Assurance (IA) Glossary*; Komaroff and Baldwin 2005; SAFECode 2008). By showing that the final product does as intended and that the process of creating it is free of, and does not introduce, vulnerabilities increases this confidence. As the method of creating software can be several layers deep, T2M $\rightarrow$ M2M $\rightarrow \ldots \rightarrow$ M2T $\rightarrow$ T2M $\rightarrow \ldots$, the probability of introducing vulnerabilities increases.

The Object Management Group, Inc. provides a very vague definition (Object Management Group, Inc. 2005). It simply states that the process provides *justifiable trustworthiness in meeting established business and security objectives*. This statement is still comparable to the definition from the "Systems and software engineering – Vocabulary" (2010). They mention increasing the level of justifiable trustworthiness to meet business needs, i.e. function as intended, and security requirements, i.e. the introduction of vulnerabilities.

Thus assurability in software processes increases the confidence in the final product by:

1. showing that the process does as it is meant to; and

2. confirming that it does not introduce and is free of vulnerabilities.

In M2M transformation, black-box and white-box testing provide assurances that

the resultant model is "correct" given certain conditions. The next two sections discuss these two types of validation.

2.3.2 Black-box Testing

M2M transformations are considered primarily to be black-box operations. Black-boxes are processes that have no concept of what happens to an input to generate the output. There are no execution paths between the two. More often than not, a function is a black-box process. Since an M2M transformation is a *simple* function, it is considered to be a type of black-box as there are no associations between the source and destination model elements. Thus validation requires the comparison between the origin and target models.

Validation within M2M Transformations

Validation in M2M transformation requires a selection of Oracle functions. These methods provide assurances that the target model is correct concerning the source model. Many take into account only the input and output models; these black box methods say what the target model should *look like*. There are six such oracles as defined by Mottu, Baudry, and Le Traon (2008).

1. *Reference model transformation* is an oracle that repeats the transformation and compares it to an expected output model.

2. An *inverse transformation* attempts to get the same input model from a target when provided an inverse function.

3. *Expected model output* compares the actual output with an *expected* model.

4. A *generic contract* is defined using constraints linking both sides of the transformation, such that the target and the test model satisfy some rule.

5. An *Object Constraint Language (OCL) assertion* does not consider the input model and instead checks to see if the output satifies a constraint.

6. Finally *model snippets* verify to see if the target model contains some model fragments.

These oracles primarily concentrate on model-comparison, contracts and pattern matching.

2.3.3 Opening the Black-Box (White-box Testing)

White-boxes consider more than the inputs and outputs; they consider the internal processes needed to produce the result as well as model constraints. This process involves the static analysis of a function's dependency graph to determine related operations. Then test models that conform to the source meta-model are deduced using a combination of their dependency graph and other user-defined constraints by using SAT- or CSP- based solvers. These user-defined constraints could include UML's association multiplicity (n..m), bounds checking, string formats and other semantic properties for the model in question. For example, the minimum hourly rate of an employee must be above the minimum wage for the country they are employed.

DSLs used for M2M transformation make the creation of dependency graphs easier as the prototype of the rule contains all of the output model elements up-front. However, side-effects within a language can make it possible to generate

more model elements making the dependency graph incomplete. Take for example a rule whereby the binding phase creates an object and binds it to the resultant object. The program that extracts the dependency graph needs to look at more than the prototype of the transformation. It will need to traverse the execution of that phase to capture any new object types it may come across. Thus hybrid and imperative languages could report incorrect dependency graphs, which could have undesired effects. The dependency graph and user constraints may generate an incomplete suite of tests.

Traceability

Traceability, in the general sense, is a technique to link two or more components of the development process together such that one can trace forward, or backward, from any given point within the process ("Systems and software engineering – Vocabulary" 2010). The primary use of this in software is requirements traceability (Winkler and Pilgrim 2010). It allows a user, or business owner, to trace a requirement through specification, development, validation, deployment and any iterations of each. For example, before signing off on deploying new software, we might want to be shown the steps in validating a particular requirement. Often using matrices, we can trace a requirement to particular tests via the development lifecycle to see if a reasonable amount of testing was carried out.

M2M transformation can also use this method but at a much higher level of abstraction. Traceability, in this case, provides the associations between the source model and the destination, and by what means the target model came to exist. This feature allows us to see the internal execution of a transformation at runtime,

which in turn enables us to view what source model elements caused the existence of particular target model elements. Although useful, it is often too fine-grained for tracing requirements, unless it is interpreted in some manner befitting its audience. Requirements traceability need not know how it is done, it only needs to know that it has been. Each trace link represents the invocation of a rule upon a source or a set of sources to generate a destination model. Given a set of rules R and a set of sources S, an invcocation can be defined as:

$$(r, s) \rightarrow t \text{ where } t = r(s), r \in R, s \subseteq S \iff r \text{ applies to } s$$

Engines query their trace for each input to find out if there is an existing association to return the previously instantiated objects unless the rule is lazy and requires new objects for each invocation (Jouault et al. 2008). Since the invocation contains all of the information, often a cache is used to assist the process:

$$(r, s) \rightarrow i \text{ where } i = (r, s, t), t = r(s), r \in R, s \subseteq S \iff r \text{ applies to } s$$

More often than not we want the same result back given the same input and rule. This internal representation prevents repeated calls of the same transformation upon the same source by using the two as a unique identifier for the invocation. However, using this format we are unable to generate a dependency graph to generate test cases. We have a list of invocations with no dependency information, if they are indeed available at all.

Availability of Trace Data The availability of a transformation trace differs from engine to engine. Often these associations are private to the engine and are unavailable to the developer or user for persistence or analysis. The Atlas Transformation Language (ATL) (Jouault et al. 2008) and Operational Query/View/Transform (QVT-O) (Object Management Group, Inc. 2016a) for example use the transformation trace to track what it creates and is part of its scheduler, however, does not expose these structures via an API or any other means. These are called internal traces (Jouault 2005). The opposite, as implemented in the SiTra (Akehurst et al. 2006) and the Epsilon Transformation Language (ETL) (Kolovos, Paige, and Polack 2008), provide access to these internal structures for persistence and future analysis. These are *external* traces. The lack of external traces causes M2M transformations to be black-box processes, such that we do not know what occurs within.

By High Order Transformation Jouault (2005) uses a high order transformation (HOT) to provide traceability to all engines, including those that only use their trace internally. The HOT modifies the transformation rules themselves. This modification adds additional output objects, which conform to a trace meta-model, and binds them together using an imperative block. The substitution of this new rule with the original provides an additional output model, that of a transformation trace. This approach applies to all languages in that a transformation of the base AST would allow the addition of these trace elements and their automatic binding.

Verbosity The verbosity of the trace, up to now, is usually in the form of a linear list of invocations. These invocations contain information about what rule transformed which source objects into what target objects. The linearity of this list provides information regarding the order of instantiation. This trait is only true for single-threaded transformers, which is currently standard practice. Schedulers do not know what can and cannot be parallelized due to the lack of a dependency graph. The ETL engine used this form of a trace, as do many others, it is implemented by iterating all available rules and finding matching inputs. It then instantiates the target model elements and stores it all as an invocation. The engine iterates this list of invocations to bind all of the target objects.

Uses of Traceability

Traceability is part of the software lifecycle, not just MDA and model transformation. It instead, in the general sense, connects each part of development together. Traces are used to link the requirements of a product to the component that provides it. Often they follow all phases through specification, development and validation. The ability to show that a requirement is fulfilled by n specification points and are validated using m tests illustrates the lifecycle of the process.

However, the result is the same: how does the final element come to exist. This process can be applied to many fields but is prominent in M2M transformation as it is a black box. This section describes how traceability is used in MDA to show its prominence in the field.

Kessentini, Sahraoui, and Boukadoum (2011) uses a linear trace defined by Falleri, Huchard, and Nebut (2006) to provide a risk assessment based on previous

good examples. The core of this method is the use of traceability for comparison. Base transformation examples are encoded and compared to generate detectors of *risky* transformations. These detectors are applied to new transformations for analysis and reporting to the user to focus validation efforts. The comparison of clean traces uses a method based on a dynamic programming algorithm used in bioinformatics to locate similar regions between two sequences of Deoxyribonucleic Acid (DNA), Ribonucleic Acid (RNA) or proteins: the Needleman-Wunsch algorithm (Carrillo and Lipman 1988).(Carrillo and Lipman 1988).

Incremental M2M Transformation Model transformations are time consuming processes. The size of the input model or the complexity of the transformation itself increases the time of the mapping. The naive way to consider changes to a source model is to re-execute the process on the amended model. However, *incremental transformation* is a current research field to overcome these performance issues (Kusel et al. 2013). Incremental transformation engines concentrate on only reapplying rules when the source objects that concern them change. Varró et al. (2016) discusses four patterns for this process. *No incrementality*, the simple mechanism we have mentioned. *Dirty incrementality*, where model elements are tagged as dirty when changed, and therefore rules that concern them are re-executed. *Incrementality by Traceability* takes the trace of an initial transformation and then when re-applied, detects untraceable elements and transforms only those objects. *Reactive incrementality* closely relates to the observer pattern. They look for changes in the source model to trigger the applicable transformation rules.

2.4 Pattern Recognition

At this point, we have introduced MDA and the application of traceability within M2M transformation, a key element within MDA. Traceability comes in many forms with differing levels of detail dependent on the requirements of the engine. In the event of a big transformation, we will need to reduce the effects traceability has to increase the throughput of the process itself. However, smaller input models allow us to retain more associations with the target model. This process is, of course, assuming that the transformation trace is available to the user at all.

The next step is to learn from previous experience. To do this, we look at how we as humans recognise objects. For example, assuming we have no previous knowledge, and we were provided with a stool. To begin with, we would break it down into its components and learn its use. We might note that it has four legs and a flat surface for sitting on. Then we would store this information. If after this we were then provided with a chair, we would recognise the flat surface and the four legs. However, we would have a new component the back of the chair. We would then have to investigate what this was to learn its purpose and in turn remember it in a knowledge base. Humans, however, do not just remember good stimuli but the bad too. So if the chair had a spike, then they would remember this to avoid it!

In this section, we shall look at how we as humans recognise objects to know quality transformations based on their transformation trace.

An essential requirement of our work, once we have a transformation trace, is the comparison of trace elements such that we "recognise" sub-components of our new trace in respect to the older model transformations. Berry (2014)

describes mechanisms that we use in computer science to mimic our understanding of recognising objects. Specifically, there are four approaches of interest: *template matching*, *prototype matching*, *feature analysis* and *recognition by components*.

2.4.1 Template Matching

Template matching is a normalised cross-correlation between a known and a new image to classify. These known images create a long term memory, or knowledge base, of elements that have been seen before to represent the processes' experience and learning. A direct comparison between the new input and each of the templates provides a match. This type of comparison has a drawback as they need to be identical, preventing the recognition of variations unless those too are within the knowledge base.

2.4.2 Prototype Matching

Prototype matching extends template matching by using a prototype that defines the characteristics of the object in question. For instance, the concept of a vehicle with two wheels and a chain is a prototype for a bicycle or a motorcycle. We can extend this prototype to include an engine to represent the latter of the two. Unlike template matching, this method allows for variations between input models and those in the knowledge base. This method provides us with a probable match within a hierarchy of prototypes.

2.4.3 Feature Analysis

This approach contains four main components: detection, pattern dissection, comparison and recognition. In essence, sensory information is broken down and compared with known features, partial or otherwise for a match. The process generalises the input information and breaks it down into components. For example, if we were received visual information that contained a dog, we might break it down into a body, four legs, a head and a tail. We would then look into our knowledge base looking for "things" with these traits. Naturally, using only these traits there are a plethora of false-positives, in fact, most four legged invertebrates with tails!

This approach closely mimics the model-snippets Oracle when validating M2M transformations, as discussed in Section 2.3.2. Model-snippets involves breaking down the resultant model of an M2M transformation and comparing sub-models to known models. If all sub-models are present, then the test case is deemed successful.

Detection and Dissection To summarise, the first component looks at receiving and dissecting relevant information from an input. We have already mentioned how we as humans can use feature analysis to look for a dog from visual stimuli. This process can differ between domains and look for different traits. If we were to attempt to recognise components within a scanned image, we'd use pixel intensities as our "visual sensory" information. Then we'd dissect the input to find lines, arcs and other interesting vectors. Another example is in facial recognition. We would attempt to detect dominant, or cardinal points, related to facial fiducial points, the eyes, chin, cheeks, mouth, etc. (Wang et al. 2017).

Comparison and Recognition The next step is to find a match given a set of features. This process involves comparing the input features to those of instances that we have seen previously. Continuing our detection and dissection of vectors, we could recognise components from various diagrams. In circuitry, if for example, we had the knowledge that a lamp is a circle with two perpendicular lines crossing inside, we can compare permutations of features to see if we can recognise this configuration regarding the input. Likewise, the knowledge that two parallel lines where one is shorter and bolder than the other can aid in distinguishing a cell. We can use similar heuristics to find components within chemical diagrams given the previous experience. Two parallel lines where one is shorter than the other could denote a double bond. Characters indicate the location of atoms and their types. The lack of a character at a junction of two bonds suggests an implicit carbon atom.

In the case of facial recognition, we would have spatial information of the five traits discussed above for each face in the knowledge base, as well as the original photo. Comparing the input to each object could aid in identifying people. This type of comparison would not be as clean cut as others.

2.4.4 Recognition by Components

Recognition-by-components specialises feature detection but rather than looking at labelled features; we instead look at three-dimensional geometric shapes called Geons. Thus the features are not labelled in the sense of a body; we might say an ellipsoid instead. Geons better describe and can be more telling on what we are viewing. A feature detector is then used to find these primitives. For example,

rectangles, squares and circles in two-dimensional space, but also cuboids, cubes and spheres in three-dimensional space. A match comes from comparing the combination and orientation of these geometric shapes with images found within a knowledge base. Using the example of a dog, the geons of a dog's head and that of a cat's head can distinguish the two animals whereas a "head" like object cannot.

The theory by Biederman (1987), suggests that there are fewer than 36 geons, which, in combination, make up the objects seen in life. For instance, we might decompose a cup into two cylindrical-components. The first makes up the main body and the second for the handle. However, these two components would also be present in many other objects. A bucket, for example, may also be composed of the same cylindrical-components only the configuration would differ such that the handle would be on the flat end of the body opposed to being attached to the side.

Using our dog example, geons are not labelled in the sense of a body; we might say an ellipsoid instead. Geons better describe and can be more telling on what we are viewing. The geons of a dog's head and that of a cat's head can distinguish the two animals whereas a "head" cannot.

2.5 Chapter Summary

In this chapter, we have discussed the state-of-the-art in M2M transformation. We then introduced software assurance: the general mechanisms that are used to increase confidence in software processes, presenting traceability as the core effort to provide confidence in M2M transformation. We embellish on how it is applied, black- and white-box approaches, and its usage, incremental transformation, formal verification and validation. After this, we then spoke about the inspiration of this

work, pattern recognition. Looking at some theories of how we as humans recognise items in the real world, making comparisons to our oracles in M2M transformation a core element that is used in our work.

CHAPTER 3

DESIGN OF NEW TRACEABILITY MECHANISM

To learn from a transformation's history, we need to be able to see what is happening within the engine to form the basis of our comparison. To do this, we must consider the tasks that are completed to transform a source to its destination and provide us with a representation that we can analyse. Traceability is commonly used to open the black box of model-to-model (M2M) transformation. It is a technique for keeping track of rule invocations (Object Management Group, Inc. 2016a). It has been used in many applications and has been discussed at length as an essential requirement ("Advanced Traceability for ATL"; Briand et al. 2014; Fritzsche et al. 2008; Paige et al. 2010; Vara et al. 2014; Willink and Matragkas 2014). For a survey of traceability see "Survey of Traceability Approaches in Model-Driven Engineering" (Galvao and Goknil 2007).

There are however two levels of traceability: *a) internal*; and *b) external* as defined by (Jouault 2005). Internal traceability provides the transformation engine with information regarding what it is doing and often is not available after the completion of the process. The engine uses this trace to track what rule and

source combinations caused the creation of what outputs. ATLAS Transformation Language (ATL) (Jouault et al. 2008), Xtend (Eclipse Foundation 2014) and Eclipse's implementation of Operational Query/View/Transform (QVT-O) follow this mechanism. An external trace differs from an internal as it is accessible to the user after completion. This accessibility enables its users to persist or use the trace for further analysis. The Simple Transformer (SiTra) and the Epsilon Transformation Language (ETL) provide a linear trace of what rules and inputs have created what outputs.

This section concentrates on the looking into what current external traceability provides us and considers challenges that are present in current implementations when considering full accountability. We pay particular attention to the structure of the trace, i.e. the standard linear trace that loses information regarding the graph-like execution of the transformation. We also provide implementation details for SiTra, showing how we overcame the drawbacks discovered. To demonstrate the generality of our approach we then provide information as to how to migrate our approach for use with ETL, this shows our efforts can provide a full transformation trace in a plethora of engines.

3.1 Challenges of Tracing in Model Transformation

M2M transformation is often a black box process. It is identified as such because the engine does not provide associations between the source model and the destination model. Transformation engines such as ETL (Kolovos, Paige, and Polack 2008) and ATL (Jouault et al. 2008) require the meta-models of the source, destination

and a set of transformation rules as input. Then the engine, behind the scenes, automatically executes the rules and converts an input model to generate the destination model. Even during validation, all existing research focuses on correctness of rules, while treating the transformation engine as a black-box that is assumed to execute correctly. One exception to this "black-box" routine is the process of *tracing* (Aizenbud-Reshef et al. 2006; Ebner and Kaindl 2002; Object Management Group, Inc. 2016a). Traceability can be supported in transformation engines and gives access to the associations between source and destination models established by an engine's execution (Object Management Group, Inc. 2016a). To the best of our knowledge the first tracing mechanism, within non-graph based transformation engines, was implemented and used by UML2Alloy (Shah, Anastasakis, and Bordbar 2010) through SiTra (Akehurst et al. 2006). UML2Alloy produces Alloy models from a Unified Modeling Language (UML) class diagram and Object Constraint Language (OCL) statements via a transformation. The trace implemented within SiTra was used to convert a counter example, produced by Alloy, back to UML.

To demonstrate the issues we have in current traceability: suppose we have a set of rules, $R = \{r_0, r_1, \ldots, r_i\}$ and a set of source objects S: we can define a transformation trace as a sequence of tuples containing a set of sources and the rule that was applied to them, as shown in Equation (3.1). This form of a trace is one-dimensional and loses information regarding what is occurring within a transformation. An execution of rules upon a source input model is a graph of rule invocations, i.e. rules will require the result of other rules, while others may need the product of a previously invoked rule. The linear trace loses these relationships.

```
1 class AtoC extends Rule<Attribute, Column> {
2   private static Integer sequence = 0;
3   public void setProperties(Column target, Attribute source,
4       Transformer tx) {
5     target.setName(source.getName());
6     target.setOrder(AtoC.sequence++);
7   }
8 }
```

Figure 3.1: A SiTra transformation rule with a global state.

$$T = \langle (r_i, s_i) \mid s_i \subseteq S, r_i \in R, i = \{0, 1, \ldots, |T| - 1\} \iff r \text{ applies to } s \rangle \quad (3.1)$$

In this section, we discuss some of the shortfalls from current external traceability: specifically the loss of information that comes from only having linear data. We look at the relationships between invocations and what they imply about the relationships between the rules themselves. Finally, we look at orphans: objects that are not traced by the engine as the engine does not instantiate them. Instead, the hybrid/imperative language behind it does.

3.1.1 Ordering of Rule Execution

For the maintenance and debugging of an M2M transformation, the developers need to be able to recreate the conditions and the process itself. This ability is of particular importance when using a language, or engine, that can cause side-effects. Side-effects are changes in a program which occur as a by-product of the evaluation of an expression, a rule invocation (M. et al. 2001). A global state in hybrid or imperative languages can cause this particular side-effect. Figure 3.1 is an example

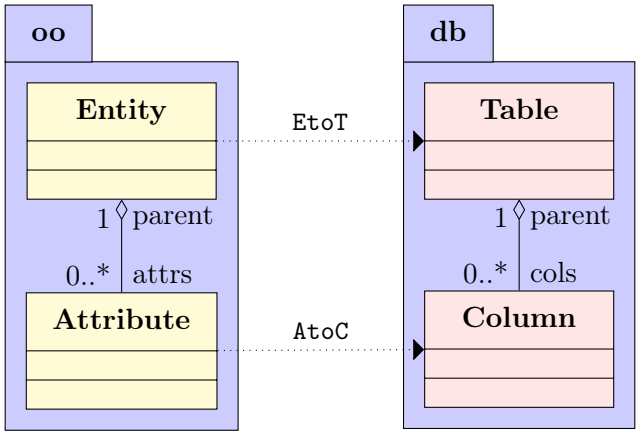


Figure 3.2: A sample of rule dependencies.

of side effects within a rule for SiTra. It shows a static integer that is used to provide some form of ordering upon the columns that it creates (see line 6). Here we can see that the value of the column's order attribute is dependent on the order of the rule's invocation.

It is reasonable to assume that given a list of attributes, that their order of application might differ. This variation could be a side-effect of the following.

1. The low-level implementation of collections used, i.e. whether it is an ordered array or not, or the type of iterator used.

2. The input model element that was used to initiate the transformation.

3. The source model itself. If read from an eXtended Markup Language (XML) file, for example, the process of parsing is dependent on the implementation of the XML library. Given a schema it is possible that a complex type was defined as a sequence, implying order, if not there may be no guarantees.

4. How the engine is scheduled.

To illustrate and expand on these issues we shall introduce a simple transformation between an Entity and Attribute to a Table and Column, as depicted in Figure 3.2. The UML shows two meta-models, both containing a bi-directional one-to-many relationship. This commonality creates a simple one-to-one transformation.

Collections

An Entity has an association with a collection of Attributes. The overall transformation requires the rule EtoT to transform the attributes during its binding phase to generate the columns and assign their parent to the resultant Table object. Iterators may not return objects from a collection in the same order they were inserted. A HashSet in Java, for example, provides no guarantees as to the iteration order of the set. Thus a second execution may result in a different order of elements. For example, given an ordered list one might obtain a trace that resembles: $T = \langle(\text{EtoT}, e), (\text{AtoC}, a_0), (\text{AtoC}, a_1), (\text{AtoC}, a_2)\rangle$. Another platform, however, might provide $T = \langle(\text{EtoT}, e), (\text{AtoC}, a_2), (\text{AtoC}, a_0), (\text{AtoC}, a_1)\rangle$. The generated model may or may not be structurally correct, but is certainly not semantically the same, as the attributes are no longer in their original order. Given the rule in Figure 3.1: all attributes in the second transformation would have different order values when compared to the first run, due to the evident global state.

Starting Point

The starting point of a transformation can also change the result structurally, or semantically if there is a global context. Take again, an entity with three attributes,

if we were to start the transformation with an entity our trace would look like:

$$T = \langle(\text{EtoT}, e), (\text{AtoC}, a_0), (\text{AtoC}, a_1), (\text{AtoC}, a_2)\rangle$$

Whereas if we chose to start with the second attribute, a1, we would have:

$$T = \langle(\text{AtoC}, a_1), (\text{EtoT}, e), (\text{AtoC}, a_0), (\text{AtoC}, a_2)\rangle$$

This effect is more apparent, given the same rule from Figure 3.1, a_0 and a_1 would have different values for their order attribute.

Transformation Input

The output can also be dependent on how the source model is read, or generated, as it could reorder collections. For instance, if an XML Schema Definition (XSD) incorrectly defined a *sequence* as an *all*, i.e. with no order, the developer is reliant on the parser to interpret the input deterministically. This schematic issue may become problematic when changing parsers, or even if the current parser is updated. Another example is when building a model from a database. If a data query does not specify an order, the database's natural ordering will be used, which can differ between database engines and their versions. The effects of either of these can produce similar results to that of the previous points.

Transformation Engine

The engine's scheduler can have effects that may combine the all of the above. There are four main categories within rule scheduling in use within M2M transformation:

a) Formed; *b)* Rule Selection; *c)* Rule Iteration; and *d)* Phasing (Czarnecki and Helsen 2006). Due to the focus of the languages we have investigated, we primarily look at explicit internal scheduling, non-deterministic Rule Selection when no rule is specified and phasing. Explicit internal scheduling is where the developer decides what rule should be applied when transforming an element from within a transformation rule. If no rule is specified, then the engine determines what it should do. This decision is often to fall back onto Rule Selection. Favouring the first transformation rule that applies to the source. This selection may not be deterministic as it depends on how the engine stores the available rules it can run. Another mechanism is that of phasing, the separation of work into jobs. In M2M transformations there are two key phases: the creation of the target elements, instantiation; and the setting of attributes, binding. Other exist, for example, ETL has *pre-* and *post*-phases to complete jobs before and after the transformation has completed.

It is essential to capture the correspondence between the source and destination elements as a part of tracing. We propose the extension of existing trace mechanisms, such that they retain the ordering of rule invocations. This additional information would enable developers to study the transformation to recreate the transformation at any point for analysis.

3.1.2 Invocation and Rule Dependencies

In the previous section, we discussed four main contributing factors regarding the relationships between the individual invocations of rules within an M2M transformation. We paid particular attention to the ordering, which is important

when dealing with a global state. In this section, we look into what these invocations suggest about the rules themselves and their execution. Consider the example in Figure 3.2, which involves two dependent rules, *EtoT* and *AtoC*. *EtoT* would call *AtoC* on all of the source's attributes, and *AtoC* would call *EtoT* to set the attribute's parent. Here we can see the dependencies between invocations, i.e. the invocation of *EtoT* upon an entity, e, will invoke *AtoC* upon every attribute that e has. To demonstrate this more precisely we shall consider the scheduling of ETL, which consists of two phases. The first involves the creation of target model elements for all permutations of the source model when an applicable rule exists. For instance, if we had an entity with five attributes, *EtoT* would instantiate a single table once, and *AtoC* would instantiate a single column five times. This phase is known as the instantiation phase. The second involves setting the relationships between the newly generated model elements and any applicable primitive types. This phase is known as the binding phase and is usually the main body of the rule in question. The procedure for SiTra however differs slightly. SiTra applies rules on demand, i.e. the initialization phase is only completed when a transformation requires it. To maintain this information, we redefine a trace as:

$$T = \langle (r_i, s_i, T'_i) \mid r_i \in R, s_i \subseteq S, T'_i \subseteq T, i = \{0, 1, \ldots, |T|-1\} \iff r_i \text{ applies to } s_i \rangle \tag{3.2}$$

Where T'_i is a subset of trace elements that the current invocation call. Using our example of one entity e, with three attributes $a_{\{0,1,2\}}$. If the transformation started with e, our t_0 would equate to $(EtoT, e, \{t1, t2, t3\})$ such that $t1, t2, t3$ subsequently transforms the attributes. Thus any rule that requests the result of another implies a dependency between the results of the transformation, i.e. the

target model elements. Many engines that use this type of scheduler will imply the same. The relationships between the rules themselves are also derived here. The binding phase will request the transformation of other source elements. In this case, *EtoT* would request the transformed model elements of its source's attributes, as would *AtoC* request the mapped object of its source's parent. More formally we start by defining a function type that returns the type of rule used within by an execution trace element, i.e. $type : T \rightarrow R$. From here we can define the set of transformation rule dependencies as per Equation (3.3). Continuing with our example, we would receive a set equal to $\{(EtoT, AtoC), (AtoC, EtoT)\}$.

$$\mathrm{R_d}(T) = \{(\mathrm{type}(t_i), \mathrm{type}(t_j)) \mid t_j \in T'_i, t_i \in T, t_j \in T\} \tag{3.3}$$

Repeated Rule Invocation

We have discussed the nesting of rule invocations, but a transformation is not a simple tree structure, as we have previously mentioned it is a graph. Frequently transformation rules may be called upon more than once on the same input. However, this process should return the same output. The result is found in the engine's trace, preventing a repeat of its execution. That is, rather than transform it again; we instead return the previously processed objects. However, this implies not just a dependency between the rules themselves but between rule invocations, or the applications of it. If *EtoT* invokes *AtoC* upon its columns and *AtoC* then recalls the transformation of *EtoT* to set the attribute's table, then it will *hit* the cache, implying the results are also dependent on each other. An issue may arise when this rule causes side effects. Without an external trace, to show us when these

```
1 if (c.‘extends‘.isDefined()) {
2   var fk : new DB!ForeignKey;
3   var childFkCol : new DB!Column;
4   ...
```

Figure 3.3: Example of ETL using the `new` keyword.

targets were initially bound, we do not know what invoked this transformation.

3.1.3 Orphans Objects

In previous sections, we have discussed the incomplete structure that the linear trace has, i.e. the links between different rule invocations and the relationships between the rules themselves that are implied by those invocations. In this section, we discuss another phenomenon known as orphans. Orphan objects are untracked objects, created during a transformation. This behaviour can often happen in hybrid and imperative languages that allow the developer/user to instantiate objects of their own, for instance, using the `new` keyword. This behaviour is available within ETL and SiTra. Hence orphans are not accounted for within the trace, i.e. if one were to attempt to find what caused its very existence, there would be no link, internally or otherwise.

To illustrate this, consider the well-known example of mapping object-orientated models to a relational database. The example we shall use is the OO2DB by Epsilon[1]. The rule `Class2Table` has a conditional statement to determine whether it requires a foreign key to reference a parent table (see Figure 3.3). The use of Java's native allocation, opposed to that of the engine, prevents the `Column` and `ForeignKey`

[1] `https://www.eclipse.org/epsilon/examples/index.php?example=org.eclipse.epsilon.examples.oo2db`

```
@abstract
rule AbstractClass2Table
  transform c: OO!Class
  to t: DB!Table, pk: DB!Column {
  ... }
```

(a) A sample for an abstract rule.

```
rule Class2Table
  transform c: OO!Class
  to t: DB!Table, pk: DB!Column
  extends AbstractClass2Table {
  guard:
    not c.‘extends‘.isDefined()
  ... }
```

(b) Class to Table with no parent.

```
rule Class2ExtendedTable
  transform c: OO!Class
  to t: DB!Table, pk: DB!Column, fkCol: DB!Column,
    fk: DB!ForeignKey
  extends AbstractClass2Table {
  guard: c.‘extends‘.isDefined()
  ... }
```

(c) Class to Table, where the Class has a parent.

Figure 3.4: Using inheritance to avoid the `new` keyword in ETL.

from being tracked by the transformer.

Of course, in the above example, the ETL code can be refactored to avoid using this keyword by using the language's ability to implement inheritance between rules. A transformation to allow this would involve three rules (as shown in Figure 3.4).

1. An abstract, rule that contained the core mapping of a class into a table Figure 3.4a.

2. A concrete definition of this rule, for classes that do not extend other classes Figure 3.4b.

3. Another concrete definition, for classes that do extend other classes. This extension would include new objects that relate to the foreign key Figure 3.4c.

```
class Class2Table {
  Table t = new Table();
  Column pkCol = new Column();
  PrimaryKey pk = new PrimaryKey();
}
```

(a) A *tuple* for a composite destination.

```
class Class2ExtendedTable
    extends Class2Table {
  Column fkCol = new Column();
  ForeignKey fk = new ForeignKey();
}
```

(b) An extended *tuple* for a composite destination.

Figure 3.5: Using inheritance to allow for multiple outputs in SiTra.

In the case of SiTra, due to the restrictions placed upon in Java, the definition of a rule must only have one input and one output, i.e. `Rule<Input, Output>`. Two possible solutions for this are the use of tuples or other objects that represent a tuple. For example, the output for the former could involve a `Triple<Table, Column, ForeignKey>` for our current example. However type erasure would prevent type safety with these elements, the extension also becomes an issue. Maintenance of such an approach would be cumbersome as tuples would have positional accessors rather than named and inheritance may become difficult to understand. The latter approach would be to create an object that contains all elements that are required, as shown in Figure 3.5. This method would allow the engine to name the output attributes and provide maintainable inheritance between outputs. The implementation of this is out of the scope of this section; however, Appendix A.1.2 demonstrates the necessary steps to allow SiTra to enable inheritance in rule definitions extensively.

In either case, the solutions we provide here do not stop the developer from using the `new` keyword and can increase the complexity of the rules themselves for developers with less experience. It is not possible to remove the new keyword entirely. As a result, there is a clear scope in modifying the execution engines

within the transformations frameworks to take good care of orphans.

This section has concentrated on the issues that arise in M2M transformations with regards to traceability. We have focused on the loss of data when considering a trace, post-mortem, as well as the ability to create objects out of the engine's scope. The next section introduces our implementation of an updated SiTra that contains a new meta-model to hold this additional information and a dynamic proxy to capture orphan objects. Following this, we show the generality of our approach by adding the same functionality to another engine, ETL. This adaptation confirms that our method can be incorporated into other engines that provide an external trace.

3.2 The Simple Transformer

SiTra is an imperative, Java, implementation of an M2M transformation (Akehurst et al. 2006). It provides two interfaces that can be used to create a transformation engine and the rules for it. The bundle comes with an engine as standard. Seyyed M. A. Shah et al. amended this to add traceability (Shah, Anastasakis, and Bordbar 2010). However this, like others, has all of the problems we have discussed in the previous section regarding traceability. We now discuss the changes we have made to SiTra to solve these issues. This solution comes in two parts: *a)* a new meta-model for transformation's trace; and *b)* a dynamic proxy. The former allows us to store the relationships between rule invocations, while the latter provides us with the ability to intercept setters and getters to collate objects that have not been instantiated by the transformation engine itself.

```
1  public class EtoT implements Rule<Entity, Table> {
2    public void setProperties(Table table, Entity source,
3        Transformer tx) {
4      for(Attribute attr: source.getAttrs()) {
5        Column col = tx.transform(attr);
6        table.getCols().add(col);
7      } ... } ... }
8
9  public class AtoC implements Rule<Attribute, Column> {
10   public void setProperties(Column target, Attribute source,
11       Transformer transformer) {
12     Table parent = transformer.transform(source.getParent());
13     target.setParent(parent);
14     ...  } ...  }
```

Figure 3.6: An example of an inter-rule dependency.

3.2.1 Capturing Rule and Transformation Dependencies

We have already discussed the initialisation and binding phases within M2M transformation engines. In SiTra the initialisation phase is synonymous to the `build` method, and binding is the `setProperties` method; however the scheduling differs from more declarative engines as they are called explicitly rather than phased. For instance, if EtoT were to iterate through a collection of attributes to generate columns then each of them would be transformed on demand. If one were to call a transformation, which was dependent on itself, its destination objects need to be available to the lower stack frames. The conversion of an Attribute, from an object orientated (OO) model, to a Column, from a relational database view, would require access to the newly transformed Table to set its owner. Without this, we would have an infinite loop. We illustrate this inter-rule dependency with our EtoT and AtoC rules shown in Figure 3.6. Both rules call upon each other to set references.

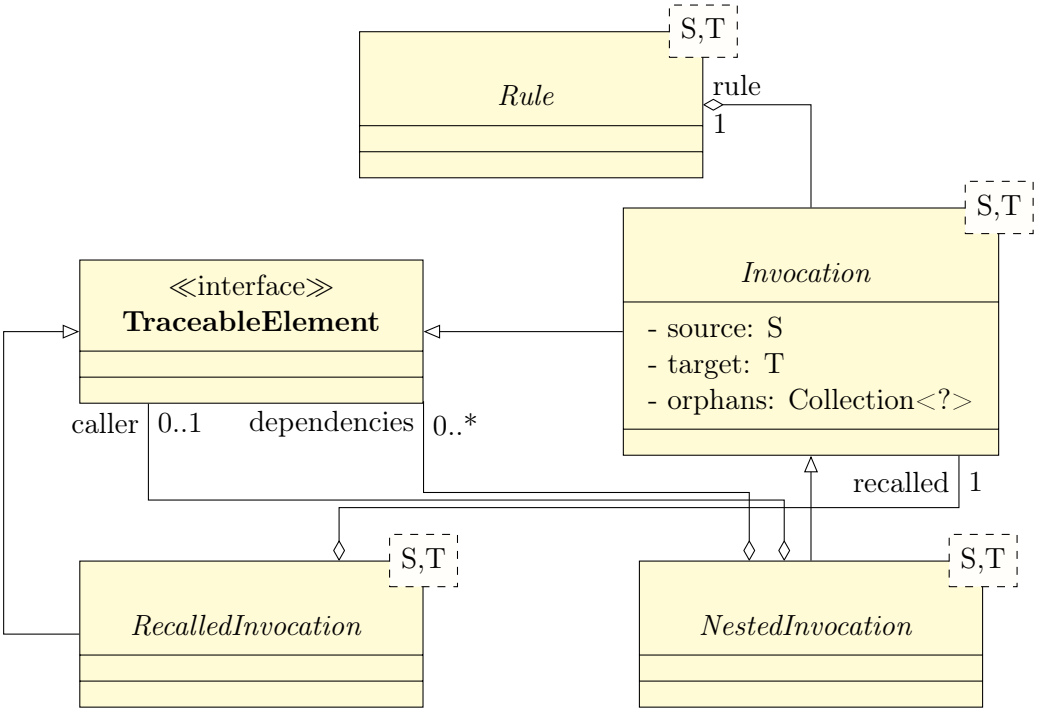


Figure 3.7: A new meta-model for a traceable model transformation.

While exploring this, we also found that SiTra would only transform a source object once. SiTra uses a cache as not to repeat a transformation more than once. This cache uses the source object as the key ($s \to r(s)$). The map $(r, s) \to r(s)$ uses both the input and the rule as the key; this allowed us to request any transformation of a particular source given a rule with ease. A similar behaviour was found in ETL as well. Using the `equivalent()` method or `::=` operator seemed to return the first item within the trace. It is possible to transform a source object using multiple rules, however, if the user requires the results from a rule defined later in the transformation script, they need to specify which.

The largest issue we have found within transformation traces is the verbosity of the trace itself. The tracking structure does not represent what happens during execution. The current state-of-the-art provides a chronological list of rules; we

never get to see the dependencies between those and invocations of them. ETL uses an equivalent structure as SiTra's ITrace interface (Shah, Anastasakis, and Bordbar 2010), inferred from the QVT standard (Object Management Group, Inc. 2016a). In which is contained the map as described above. This tuple does not take into consideration the nested nature of a transformation, and only concerns the instantiation phase on the first run. It may also be important to see what calls the `build` method and which have the object returned from the cache. Figure 3.7 shows the new transformation trace within SiTra. Here we have introduced new trace elements to aid in retaining structural information. `Invocation` is the equivalent of the previous `ITrace`; it contains the source, target and the rule responsible for the transformation. This object alone can provide the current state-of-the-art in traceability within rule-based engines. We have introduced two more types of traceable elements within SiTra: *a)* `NestedInvocation`; and *b)* `RecalledInvocation`. These provide more detail to the actual internals of the transformation. The former provides the same information as the standard, however, contains two more elements: *a)* the calling transformation trace element (if applicable); and *b)* the trace elements generated because of the current transformation. The latter is an indicator that the current execution required the results of a previously transformed set of sources. To maintain this list, and to reduce the effect on performance by traversing it, we amended the internal cache once more: $(r, s) \rightarrow (r(s), t)$ such that $t \in T$. Using this latest implementation, we can now see that a source element, s, and a rule, r, returns the target object $r(s)$ and is referenced by the `TraceableElement` t. This map can be further simplified as the traceable element includes $r(s)$: $(r, s) \rightarrow t$.

Algorithm 1 demonstrates the execution of transforming an object within SiTra.

This process is a general algorithm allowing it to be used within a plethora of other transformation engines to retain structural information about its internal workings. The two phases, instantiation and binding, can be found at Line 12 and Line 20 respectively. Before either of these, we check the cache to see if the transformation has been completed already (lines 5-9). A cache hit is indicative of a recalled invocation. Likewise, lines 14-18 is where the first attempt of transforming a given set of sources by a rule and therefore is where they must be instantiated and then bound. In both cases, they depend on an execution stack to determine what invocation is dependent on another. The stack is pushed (Line 19) and popped (Line 21), before and after the binding phase (Line 20) as this method can induce recursion. The recursion of transformations will increase and decrease the size of the stack; however, the top will always be the invocation that is directly related to the current.

Our meta-model provides solutions to retain the order of execution of transformation rules and the ability to recreate the transformation. This is provided by the nested nature of our meta-model as it explains what rules are completed and what invoked them. The capability to find the actual binding phase, opposed to a recollection, is provided by the new recalled invocation type. Allowing the user to recreate the situation at the time of creation. This recalled invocation aids in providing a graph of rule dependencies.

3.2.2 A Dynamic Proxy to Catch Orphans

We have now described the new meta-model for traceability within M2M transformations. The amendment we have developed can include the full execution path

Algorithm 1 The scheduler that is provided with SiTra, which maintains the graph structure of M2M transformations.

Require: A transformation rule, $r \in R$.
Require: A set of sources, $s \subseteq S$.
Require: A first-in-last-out stack representing the execution stack of the transformation.
Require: A cache of invocations defined by $(r, s) \rightarrow t$

```
1:  function TRANSFORM(r, s)
2:      if r does not apply to s then return null
3:      end if
4:      if s has already been instantiated by r then
5:          if the execution stack is not empty then
6:              Record a recall of (r, s) and add it as a dependency of the top of the
    execution stack.
7:          else
8:              Record a recall of (r, s).
9:          end if
10:         return the previously instantiated target objects.
11:     else
12:         Instantiate target objects, t.
13:         Put t into the cache with a key of (r, s).
14:         if the execution stack is not empty then
15:             Record an invocation of (r, s) and add it as a dependency of the top
    of the execution stack.
16:         else
17:             Record an invocation.
18:         end if
19:         Push the invocation onto the execution stack.
20:         Bind t and s using r in respect to this transformation.
21:         Pop the execution stack.
22:         return t
23:     end if
24: end function
```

that the engine completes to generate its result. In this section, we describe how we gather orphan objects in a general way such that other engines might implement them. Orphans are objects that are created by the rules directly rather than delegating the work to the transformation engine. These orphans are not tracked by the trace as they are unknown to the engine. The process of transforming an input model involves invoking mutator methods to change the state of the destination object. The main body of a rule takes care of setting references between objects and their attributes. It is also the location where the `new` keyword is available. In a well-formed transformation rule, these mutators would receive primitives based on the source or objects already created by the engine. However, in the case of a rule that is susceptible to creating orphans, mutators would receive newly allocated objects. To catch these orphans, we need to intercept all mutators to check to see if the additional objects are within the trace. For example, when adding a foreign key to a child table, we need to intercept the list of constraints.

For each transformation of a source s using a rule r, we get a set of destination objects $r(s) \rightarrow D$. To intercept we instead return a set of proxies such that $D = \{Proxy(d) \mid d \in D\}$. These proxies maintain the functionality of the original destination object, however, the mutators are modified. For each mutator, we check to see if the input argument is inside of the trace, and if not we add it the current invocation. After this, we delegate to the actual mutator method to change the state of the object in question. To ensure traces are added for all orphans, as well as grandchildren of the target, instead of passing the real parameter we pass a proxy of it. This process allows the recursion of the orphan tracking.

There are two types of call to intercept: mutator and accessors methods. We define a mutator method as one that has no return type, one parameter and begins

with the string "set". Intercepting this call allows us to catch objects that change the state of the object in question. We define accessor methods as one that has no parameters and begins with the string "get". What we do here differs based on the return type. If the accessor returns a plain old Java object (POJO), we return a proxy of that object, if it is not already one, as to be able to capture its mutators. In the event of a `Collection`, we proxy the collection and intercept their accessors and mutators, for example, `put`, `add` and `addAll`. This proxy allows us to recursively capture elements added or removed from a list, while also enabling us to proxy its contents as well.

Our approach here is not without its drawbacks. For example, if one were to create an orphaned list and add orphaned objects to it before adding it to the target model. The list's items would not be known to the engine's trace. An orphaned object is, in essence, a POJO. So the addition of objects to an orphaned list is not captured. This same behaviour will occur with an orphaned object with an orphaned state. An object's mutator methods are not intercepted to capture its state changes. To solve this, we can traverse the value passed into a proxied mutator. This traversal may have a relatively significant impact on the transformation itself, as it would require reflection. Reflection would allow the transformer to find object accessors at runtime and traverse the new object until it finds a null value or a previously proxied object. These terminators would prevent an infinite loop in what could be a recursive structure. It would be beneficial to implement this for complete coverage, however, for our experiments, it is possible to avoid this by placing the object into the target model before modifying it.

Figure 3.8 contains a code snippet that illustrates this drawback. Here we create a ForeignKey and a reference Column for the transformation of an Entity that

```
1  public ExEtoT extends EtoT {
2    public void setProperties(Table target, Entity entity,
3        Transformer tx) {
4        // setup primary keys, columns, etc.
5        super.setProperties(target, entity, tx);
6
7        // get referenced table
8        Table references = tx.transform(source.getExtended());
9        Column primaryKey = references.getPrimaryKey();
10
11       // create and setup foreign key
12       ForeignKey foreignKey = new ForeignKey();
13       Column column = new Column();
14       column.setName(references.getName() + "_" + target.getName());
15       foreignKey.setReference(primaryKey);
16       foreignKey.setColumn(column);
17
18       target.getConstraints().add(foreignKey);
19   }
20 }
```

Figure 3.8: An example of when a dynamic proxy will not capture nested orphans due to performing operations upon POJOs directly and not calling for a proxy.

extends another, implying a one-to-many relationship. The foreign key's attributes are then set using its mutators. Then the new column is used to reference the primary key of the parent table. Finally, the constraint is added to the target table to model the relationship. Before line 18, we deal directly with the POJOs themselves. The act of calling getConstraints() on line 18 returns a proxy of the underlying collection and therefore recognises that the trace has no record of foreign key and retains it within the trace. However, the column does not appear in the trace. This outcome is due to the capturing algorithm not going further into the foreign key object. Orphans to the trace have no context attached to themselves to say why or where they were needed. If the trace contained the column object, we would be able to determine the reason for its existence. Without knowing about its existence, it is programmatically difficult to note that the column does not appear in the target table's column list.

3.3 Epsilon Transformation Language

In the previous section, we discussed the application of our new meta-model within SiTra, as well as a method to capture orphan objects that have not been instantiated by the transformation engine. This section shows the applicability of our meta-model in other engines as we provide an instance of it that is compliant with ETL. It is composed of two steps: *a)* an amended transformation strategy that creates our transformation trace and *b)* an execution listener that listens for the use of the new keyword.

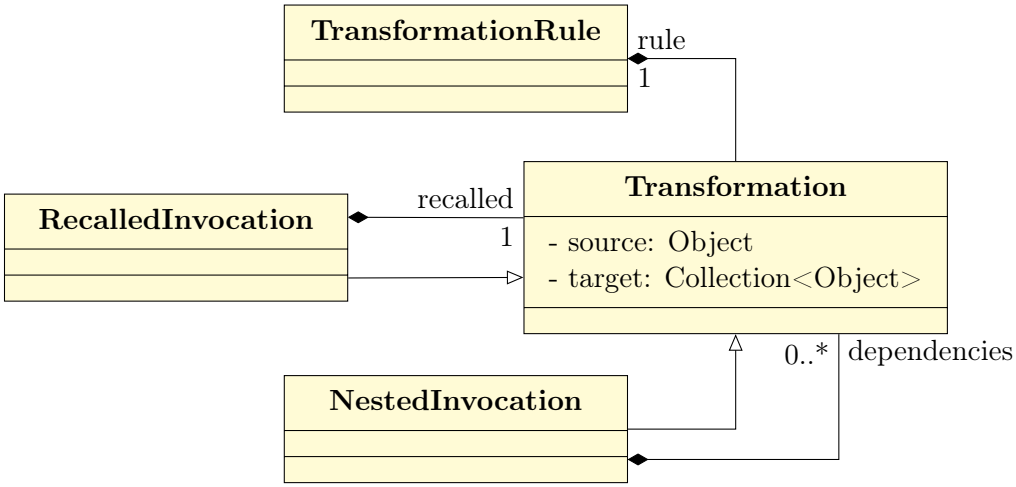


Figure 3.9: An amended meta-model for a traceable model transformation in ETL.

3.3.1 Transformation Strategy

This section describes what steps are required to use our new, adapted, meta-model within ETL. At the core of traceability within ETL, there is a *transformation strategy*. The strategy determines and schedules the execution of transformation rules. As packaged, ETL comes with two strategies: *1)* the *default strategy* transforms sources on demand; while *2)* the *fast strategy* instantiates the targets first and then binds them afterwards. The latter is intended to allow the Java Virtual Machine (JVM) to allocate all the required memory upfront, reducing the amount movement within memory to a minimum. Memory allocation is more intensive than the majority of binding phases as they primarily use setters and getters.

Before creating our strategy, we needed to generate a model for our transformation trace. We could not simply use our meta-model directly due to the lack of abstraction provided for traceability within ETL. Figure 3.9 shows the meta-model that was used to retain the information we needed. The reader should note that

all trace elements have source and target attributes, including the definition for recalled invocations, because of the reason we have just discussed. However, it is also important to notice that it is unnecessary to retain a separate list of orphans, as shown in Figure 3.7. Instead, we can simply add it to the list of targets when we detect them (as explained in Section 3.3.2).

Another minor change had to be applied to the `TransformationTrace` as it hard-coded the type of traceable element that it used opposed to allowing us to set the transformation trace within the context of ETL. This model is used to hold and to expose ETL's trace. The trace itself is a simple POJO, thus to persist it one must interpret it programmatically or use the `post` phase of the transformation within the ETL script. This process will require a meta-model that represents the trace for persistence. We concentrate on keeping this information within the engine for use within an application rather than storing it into a file, so persistence using the post phase is out of the scope of this section.

Now we have an implementation of our trace; we could focus our efforts on the strategy required for retaining and using this information. Our strategy extends that of the fast strategy provided by ETL. By default, this maintains a linear trace of the instantiation phase, i.e. creates an invocation for each possible rule execution. This linear trace contains our new NestedTransformation, which enables us to add our links between each element. To collect the links between dependent executions, we introduce a stack. This approach is not unlike our approach in SiTra. By keeping this stack, we can see that newer elements are dependent on those below them. By interpreting the phase of execution, we can ascertain whether a rule has initially *invoked* or *recalled*.

```
class OrphanCapture implements IExecutionListener {
  public void finishedExecuting(AST ast, Object result,
      IEolContext context) {
    if(NewInstanceExpression.class.isInstance(ast)) {
      // are we being called in an ETL context?
      if(IEtlContext.class.isInstance(context)) {
        IEtlContext etlContext = IEtlContext.class.cast(context);
        // add 'result' to trace, via IEtlContext's trace strategy.
      } } } }
```

Figure 3.10: The concept of an execution listener to capture orphans.

3.3.2 Orphans and the Execution Listener

The general nature of the Epsilon framework allows it to work with multiple inputs and output types. Thus the framework contains abstraction layers to handle each of the possible model's types and the functionalities within, including traversal. This particular feature is important as it allows the user to transform POJOs, which do not necessarily have a mechanism to traverse all of an object's children, unlike ECORE whose modelling framework provides this natively, via a tree iterator. To enable the capture of orphans for all of these types, we must use the framework itself, making the approach applicable to a plethora of outputs.

To collect orphans, we use an *execution listener*. This functionality stems from ETL's parent language: the Epsilon Object Language (EOL). It provides the ability to intercept an EOL program's execution based upon its executable model elements. The execution of model elements causes the triggering of all listeners. To capture the `new` keyword we need only intercept instances of `NewInstanceExpression`. Upon triggering, our listener receives the newly allocated orphan. This process allows us to store the new value in the trace via the strategy we discussed in the previous section. Figure 3.10 partially illustrates this. The strategy exposes the

execution trace such that we can access the top most transformation invocation. When triggered, the new objects belong to the rule currently being invoked.

Unlike Section 3.2.2 whereby dynamic proxies are used and therefore can lose information if not used correctly, this approach catches *all* orphans created within the binding phase. Including those that may not be present in the final target model, this may occur when using temporary variables. Our listener enables this behaviour by waiting on the execution of the `new` keyword rather than setters and getters of POJOs. This approach has the effect of potentially gathering too much information opposed to not enough. For example, the use of temporary variables would incur additional orphans. These may not be relevant for the final model, however, are nevertheless allocated outside of the engine. If this becomes an issue, e.g. memory consumption or storage, then we can either:

1. Ensure the orphan is for an outbound model. Here we would determine whether the orphan object belongs to an output model being generated by the transformer.

2. Check to see if each orphan is within the output model on completion of its binding phase. As above, but post-invocation.

3. Complete a post-mortem pruning upon the trace such that it no longer contains objects not found in any of the output models. This process would require the traversal of the trace to find all objects that are not part of an output model.

3.4 Chapter Summary

To provide confidence, we need to gain full accountability for the transformation of a source into its destination model. The overall process is a black-box, and this limits this property. Traceability is used to retain the associations between source and target; however, the current state of the art does not provide full accountability. Current transformation traces only account for the order source elements and rules are matched. This method does not take into consideration the transformer's susceptibility to side-effects. Having global state within the binding phase causes these side-effects, moreover, tracing the order of rule invocations is more significant than that of matching. The latter is merely a scheduling issue for the engine.

In this chapter, we have explained these challenges and discussed our solutions for them. A vital component of this is a new meta-model that can hold these associations. The links between invocations provide us with a trace that now considers the binding phase opposed to the matching. This data structure affords us with full accountability of each invocation of a rule and gives us the ability to use the information to add context to rules that cause side-effects.

As an example of a side effect, we introduced a common practice when using hybrid or imperative transformation languages: orphan objects, the creation of objects outside of the instantiation phase. This trace, along with a stack trace, allowed us to capture orphans unbeknown to the engine. To demonstrate this, we explained a mechanism that would capture these objects via a dynamic proxy for SiTra. The proxy would intercept setters of instantiated objects to store references to new values unknown to the engine. It would also intercept getters as to allow recursive checking of setters called upon objects further down the object tree. A

small modification to the meta-model allows us to implement our transformation trace into ETL showing generality to our approach and that it can be incorporated into another mature transformation engine. This alteration was required not because the model would not work, but instead due to the lack of an interface for a transformation trace in ETL. Additionally, a more streamlined orphan capture method was available to us via ETL's executable abstract syntax tree. Opposed to intercepting calls to getters and setters, one can catch calls to the `new` keyword directly. A listener would receive this object, and the transformer can then save it as we already know it is an orphan.

CHAPTER 4

EFFICACY IN MODEL-TO-MODEL TRANSFORMATION

In Chapter 3 we have discussed the issues that arise in the verbosity of a transformation trace, paying close attention to the loss of information. This loss includes the actual execution of a rule and the unaccounted objects that are not in the trace (see Section 3.1). We then solved these by implementing a meta-model that could capture the internal execution and a set of object proxies to capture orphans for use with the Simple Transformer (SiTra) in Section 3.2. To show the generality of our approach amongst other engines, we implemented an adapted meta-model and an execution listener to capture orphans for the Epsilon Transformation Language (ETL) in Section 3.3. This process allows us to have a complete overview of what is occurring within a transformation.

With this completed transformation trace we can retain it, when available post-mortem, to provide a knowledge base of past executions. A newly transformed target would produce a new trace comparable to this data set to find traits and features that we have encountered before. We assume that if we saw some part of the new trace before then, we are more likely to trust its result when compared

to that of an unknown segment. This decision process generates a heat map over the full transformation showing areas that users are less inclined to trust. This information can be used to focus validation resources, i.e. to resolve the cold spots, or be used to decide what to do next: whether we accept the risks, or attempt to mitigate it.

The following four sections discuss our approach to quantify confidence within a model-to-model (M2M) transformation. Section 4.1 explains that to maintain a knowledge base, we need to be able to store previous executions for comparison. To do this, we formalise our execution graph and store it in an appropriate database. Secondly, we look at how prominent a graph is on another, with the assumption that if we have seen a segment before we are more confident in its use in Section 4.2. Up to now, prominence considers all rules equally. However, this is almost never the case as some are more complex than others. Section 4.3 then introduces a weighing mechanism to remove prominence bias. Finally, we combine prominence and complexity to generate a value to show the confidence that we have in a new transformation in respect to previous executions in Section 4.4.

4.1 Persistence of Trace Data

To be able to learn from previous experience, in the case of M2M transformations, we need to be able to store previous instances of trace data. We have discussed in Chapter 3 a new meta-model to encompass trace data within M2M transformations. This data, or at least part of it, requires persisting to a data store for analysis. The trace we have modelled is an execution graph of what has occurred within the engine after a transformation has taken place.

To store an execution graph, we must first formalise it for storage. To generalise our meta-model we define an execution graph as a labelled multi-digraph defined by a 7-tuple:

$$G = (\Sigma_V, \Sigma_E, V, E, \iota, \ell_V, \ell_E)$$

Where V is a finite set of vertices, which represent unique invocations of a rule upon a set of sources, $V = T$; $E \subseteq V \times V$ is a set of directed edges such that (v_1, v_2) implies that $v1$ called $v2$ and not vice versa. The incidence function, $\iota(e)$, returns a tuple of vertices that concern an edge. Σ_V is the finite label set for vertices and represent the rules within the transformation; ℓ_V is the mapping of a vertex and its label, i.e. $\ell_V(v) := r \iff (r, s) = v$. Σ_E and ℓ_E are for labelling edges, such that:

$$\ell_E(e) := \begin{cases} \text{invoked} & i < j, (v_i, v_j) = \iota(e) \\ \text{recalled} & \text{otherwise} \end{cases}$$

An invocation, as shown in Figure 2.1, involves three key elements: *a)* a set of sources; *b)* a rule that is applied; and *c)* a set of target objects, generated by applying the rule to the set of sources. These three items form the identifying features of an invocation and are the vertices of our graph. However, these elements themselves could be incorporated into our physical graph as shown in Figure 4.1. Here we use the same example found in Section 3.1 to show two invocations. t_0 is a trace element transforming an entity *input*, *using* the transformation rule `EtoT` and *output*ting a table. Subsequently, t_0 *invoked* t_1, which used `AtoC` to transform an attribute within the entity that then *recalled* t_0's result. This recollection implies that `EtoC` and `AtoC` call upon each other. Naturally, we now have three more vertices and edges for each invocation. The decision to keep this information is

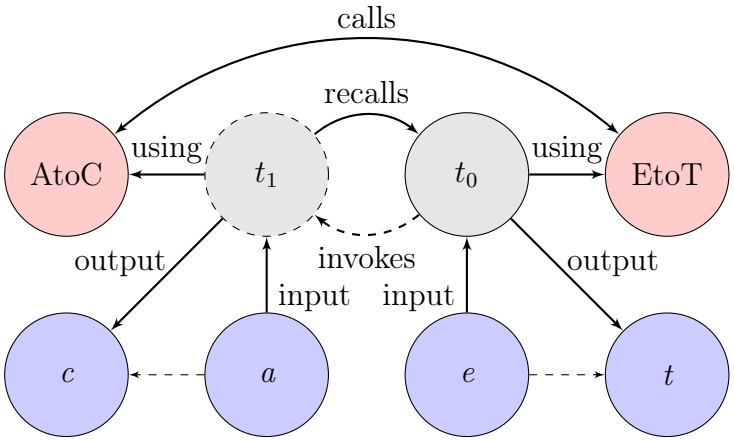


Figure 4.1: A view of two dependent rule invocations.

dependent on the available resources. It might be more prudent to keep object identifiers within each vertex to save on space.

There are an ever-increasing number of engines that could be used to store large amounts of data, and to be able to query them; however, we felt using a graph database would be more suitable. A graph database would be able to keep the structure as is and be able to visualise them natively. A relational database would be an enormous index table, and other key-value databases would be cumbersome and inappropriate for our data as our knowledge base grew.

Initial thoughts were to use GraphML, an XML markup language, for storing graph data in a collection of files. Despite being useful for prototyping, this would not scale in a production environment. This approach would require a vast quantity of disk space and would be inefficient for querying due to the amount of I/O needed for comparison. With this a file structure would have to be maintained, this in effect would become a hierarchical database. Neo4j is currently the most prominent graph database engine in use today[1]. Engineered such that it can store and query

[1]Statistics found at: `http://db-engines.com/en/ranking_trend/graph+dbms`.

vast amounts of graph data.

4.1.1 SiTra in Python and Neo4j

To aid in prototyping for the case studies, we rewrote SiTra as a Python library[1]. This change was due to its toolset for domain specific language development, generating code, graph library support (specifically isomorphism) and its compact form. However, due to the language's duck typing, or lack of type safety, a transformation rule must explicitly check the type of its input. The kind of input is often the main criterion of a rule, for example, `EtoT` must have an entity passed into it. This check is a form of *guard*, often implicit in type safe transformation engines. Another fundamental difference between SiTra.py and its Java equivalent is that of orphan capture. We can intercept Python's "magic" methods opposed to looking for traits that we deem look like setters and getters, i.e. does the function start with "set" or "get".

Upon completion of a transformation, a post-transformation method converts the resultant trace into a graph using *networkx*. networkx is a Python library used for graph creation, modification and analysis. This conversion required each *invocation* to have a vertex and relationships to be generated based on their heritage, parent and dependent invocations. A *recall*ed invocation creates an edge between the two vertices that represent the caller and the original invocation it is recalling. This graph was then used to generate Cypher, the query language used in Neo4j, for node creation within a database instance. The snippet below is an instance of Cypher, which creates the graph shown in Figure 4.2a on Page 68 (explained in

[1]SiTra.py is available at: `http://github.com/sacko87/sitra.py`.

Section 4.2). Parentheses denote a vertex, and square brackets denote a relationship between two vertices.

```
CREATE (n1:EtoT { timestamp: timestamp() }),
       (n2:AtoC { timestamp: timestamp() }),
       (n1)-[:INVOKED { timestamp: timestamp() }]->(n2),
       (n2)-[:RECALLED { timestamp: timestamp() }]->(n1);
```

Opposed to using a post-transformation method, an extension to SiTra could be made to build the graph natively. Having the graph integrated into SiTra would increase performance with regards to memory and CPU usage as there would be no post-processing, which creates another representation of the trace. Rather than maintaining the meta-model described in Chapter 3; one can manage the trace using networkx directly. A second option would be to integrate SiTra with Neo4j. However, this option would induce a significant amount of I/O between the application and the database. The above snippet would become four instructions rather than a batch operation. As the scale of the transformation increases, there needs to be more interaction with the Neo4j instance. It would be beneficial to use a networkx integration and interpret that into a batch operation into Neo4j. In either case, an abstraction is necessary to allow any traceability implementation to be employed.

4.2 Prominence of Historical Data

With the trace data stored in technology that can store significant amounts of data, we need to now look at how we are to use this to induce *confidence* within

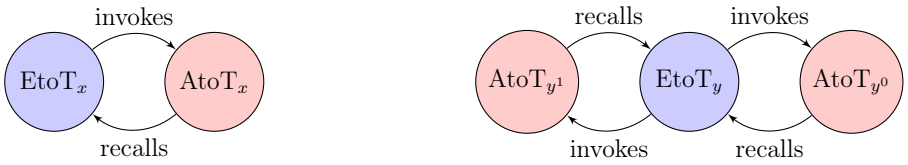
M2M transformation. As mentioned in Section 4.1, the data is stored within a graph database as this is the data's natural form. We make the assumption that the prominence of a rule on a graph is related to the number of times it appears within our historic dataset. So we are essentially forming a heat map that overlays the entire execution path so we can find hot and cold areas, where the red areas are well used and blue not so. This representation allows us to focus efforts on other complimentary tasks, like verification and validation. Cold spots can be used to prioritise resources, i.e. it is indicative of less usage, and therefore one might want to test those invocations. However, if that particular rule is frequently used elsewhere in the trace, one might accept this risk and deploy the resultant model.

Suppose we choose a previous execution h from a set of historic data, $H = \{h_0, h_1, \ldots, h_n\}$, and a new graph G: there are a set of sub-graphs within G that are isomorphic to h. This algorithm is sub-graph isomorphism (Ullmann 1976). We denote this as a function:

$$\forall h \in H, \text{matches}_G(h) := \{G_i \mid G_i \subseteq G, G_i \simeq h\}$$

For example, Figure 4.2 contains two traces of execution from the classic object orientated model to the relational database. They involve two rules: *1) EtoT*, which transforms an entity to a table; and *2) AtoC*, which maps an attribute to a column. They both depend on each other as shown by the relationships between the invocations. `EtoT` invokes `AtoC` and `AtoC` recalls the result of `EtoT` to maintain heritage. Using Figure 4.2b as our new graph and Figure 4.2a as our historic, we can clearly see that our historic appears twice.

A critical issue with sub-graph isomorphism is that it is NP-Complete. This



(a) Transformation of a class with a single attribute.

(b) Transformation of a class with two attributes.

Figure 4.2: Trace execution graph for a simple M2M transformation.

trait means that the solution can be verified quickly, in polynomial time. However initially, there is no known method can efficiently find the solution. There are few methods for finding these sub-graphs due to the nature of the process. We chose VF2 as it had a better time/spatial complexity than the others, and our graphs can become cumbersome for larger transformations. networkx provides VF2 natively as part of its comparison framework.

To overcome the detrimental effect of this we use graph labelling. Each node within our graph represents an invocation, i.e. a 2-tuple of the sources that were involved and the transformation rule that transformed them. To distinguish the type of node, we label them with the name of the rule. Graph comparison becomes more efficient as the number of each kind of tag discounts many historical traces automatically. Using our previous example, we can see that both graphs in Figure 4.2 have two rules, and therefore labels: *a)* `EtoT`; and *b)* `AtoC`. If we were to check for subgraphs of Figure 4.2a g, which are isomorphic to Figure 4.2b g', we could easily discount this as $g' > g$. Likewise, assuming two instances of Figure 4.2a, g and g' respectively, where g' uses `ExToT` rather than `EtoT`, the number of labels are not comparable so they cannot be isomorphic. Of course this is a trivial example; however the larger the graph, the more important these checks are.

We assume the importance of an individual invocation is related to the number of times it appears in isomorphic matches found within the historical data set. To calculate prominence of a given rule, we need to know how many times it is used in a graph, so we define a function:

$$\forall l \in \Sigma_V, \text{coverage}_G(l) = \frac{|\{v \mid \ell_V(v) = l\}|}{|V|}$$

This function returns a ratio representing the number of times a label appears in a graph. The input could be vastly larger when compared to the sub-graph found in our historic dataset. We take the ratio of the two values to weigh the importance to prevent coverage biases, as shown below:

$$\forall h \in H, v \in V, \sum_{G_i \in \text{matches}_G(h)} \frac{\text{coverage}_{G_i}(v)}{\text{coverage}_G(v)}$$

To stop the subtle effect of that sum, which would affect results by depreciating lower, but still well-tested values, we take the ln of that value. Additionally, we add one to the sum to ensure we are calculating the ln of numbers above one to get positive values, as shown in Equation (4.1).

$$\forall h \in H, v \in V, \text{prominence}_G(v, h) = \ln\left(1 + \sum_{G_i \in \text{matches}_G(h)} \frac{\text{coverage}_{G_i}(v)}{\text{coverage}_G(v)}\right) \tag{4.1}$$

Table 4.1 lists values of prominence when applying our method to each vertex of Figure 4.2b on the discovered sub-graph, Figure 4.2a. For the vertex EtoT_y the

v	Equation (4.1)
EtoT_y	$\ln\left(1+2\frac{\frac{1}{2}}{\frac{1}{3}}\right) \approx 1.38629$
AtoC_{y^n}	$\ln\left(1+1\frac{\frac{1}{2}}{\frac{2}{3}}\right) \approx 0.55962$

Table 4.1: Vertex prominence of Figure 4.2b in respect to Figure 4.2a.

coverage is $\frac{\frac{1}{2}}{\frac{1}{3}}$ this is due to the rule being present half of the time in the sub-graph and only a third of the time in the larger graph. However, the vertex itself appears in both isomorphic matches thus is doubled. Whereas both AtoC_{y^i} only appears once in each subgraph found to be isomorphic; however is two-thirds of the larger graph.

4.3 Complexity of Transformation Artefacts

In the formulation presented in the previous section (Section 4.2) we do not consider the complexity of each invocation. Our *overview* of execution, i.e. a transformation trace, does not equate to work completed by each rule. We only consider that a sequence of events has occurred. Each event, however, may have more complexity than another. Here we are not discussing computational complexity, i.e. time and memory consumption, but that each rule has some distinct features that can be used to weigh it. In the case of `AtoC`, we might surmise that the rule only sets the name and type of a column element; whereas `EtoT` has to iterate through attributes to transform them, impose constraints, keys and indices. One can argue that the task carried out by these two have different levels of complexity, so is it right that the values for $EtoT_y$ outweighs $AtoCy^i$ (see Table 4.1) by so much and will continue

to do so when it appears so many times?

$$\forall h \in H, v \in V, \text{confidence}_G(v, h) = \text{prominence}_G(v, H) \times W_{\ell_V}(v) \tag{4.2}$$

Equation (4.2) shows an amendment of Equation (4.1), which takes into account a complexity value for a label, in our case a rule. This modification provides us with a weighing mechanism to stop values becoming disproportionately large. A key decision here is to determine what we are looking at; this will influence the measure of complexity we use. Below we explain two types of complexity. The method presented here is not dependent the complexity metric. The key decision is what are we trying to analyse? Are we analysing the transformation itself, the generated code, or both?

Rule Complexity

The main components of an M2M transformation are the rules that can be utilised by the transformer. Thus the complexity is directly related to the work that these do in changing the representation of one model to another. The guard and bind phases contain the bulk of a rule's complexity in M2M transformation for languages like the ATLAS Transformation Language (ATL) and ETL or in the case of SiTra the `check` and `set_properties` methods (Akehurst et al. 2006). These are the functions that decide whether the rule is relevant and takes care of the setting of attributes and relationships. The initialisation phase has a negligible impact due to its pure nature of creating objects. The complexity of the checking phase is required as it may attempt to transform more or fewer objects than it should.

This problem has two sides. On the one hand, it might generate an incomplete final model as it discounts input model elements for transformation. On the other, however, it would not only cause an increase in resources, but it may also cause runtime errors due to incomplete value checking. These additional objects are of particular importance when using a duck-typed language. If a rule identifies an attribute as an entity, a `TypeError` would occur when looking for its constraints as attributes do not have them. The effects are the same with regards to the binding phase, as code becomes more complex there is a higher probability of mistakes happening.

Complexity comes from many places when considering transformation rules. For instance, we can attempt to calculate the complex nature of the code itself. McCabe (1976) introduces cyclomatic complexity: an algorithm to analyse the execution graph of a program. It is a quantitative measure of linearly independent paths through the source code of an application. This value was an attempt to reduce the complexity of modules. If the value was above ten, then the module should be broken down further or a reason provided as to why it was an accepted risk. Here we can assume the more independent paths there are, the higher the risk of error. Particularly when we consider conditional branches, if the condition were to be incorrect undefined behaviour could occur. With this in mind, we would want to be more cautious of functions with higher complexity values as there is more of a potential for error. Assume $M_0, M_1, \ldots, M_k$ represents the complexity of rules $r_0, r_1, \ldots, r_k$ respectively. We consider the relative complexity of a rule $\frac{M_{\ell_V(v)}}{\sum_{i \in \Sigma_V} M_i}$. We use $1 - \frac{M_{\ell_V(v)}}{\sum_{i \in \Sigma_V} M_i}$ as a coefficient for prominence function to reduce the confidence in more complex rules. We want for higher ratio to have smaller confidence, as a rule, is more complex. Formally we define W_{ℓ_V} as:

$$W_{\ell_V}(v) = 1 - \frac{M_{\ell_V(v)}}{\sum_{i \in \Sigma_V} M_i} \tag{4.3}$$

Another metric could be the number of test cases that have been carried out for a given rule. It is only natural for developers to generate more test cases for larger and more complex modules. Therefore it is reasonable to assume that the more tests that are available to the model are indicative of the complexity of the rule. This assumption also relates directly to the users as validation provides *confidence* that a product will do as it is expected. In the case of `EtoT` and `AtoC`, if `EtoT` had 200 test cases and `AtoC` had ten then we might accept a higher score for our example. Unlike McCabe's cyclomatic complexity, we want a higher ratio to have a higher value. Here we assume that $M_0, M_1, \ldots, M_k$ represent the number of tests available to rules $r_0, r_1, \ldots, r_k$ respectively. However this time we do not negate the fraction as follows:

$$W_{\ell_V}(v) = \frac{M_{\ell_V(v)}}{\sum_{i \in \Sigma_V} M_i}$$

Deferred Complexity

Often M2M transformations result in a model that will be used to generate code. For example, the result of our object-orientated view to a relational might be used to generate SQL to create the database or to create data access objects for querying. Another, more general, example might be the generation of an imperative language from a declarative, i.e. the translation of business logic into code that will complete the tasks required.

Other options include annotating templates to inform what its output will

		Probability		
		High	Moderate	Low
Severity	High	2	1	1
	Moderate	3	2	1
	Low	3	3	2

(a) Risk Class of a task given the probability of its failure and severity if it were to occur.

		Detectability		
		High	Moderate	Low
Class	1	2	1	1
	2	3	2	1
	3	3	3	2

(b) Risk Priority given the Risk Class and how detectable a failure would be.

Table 4.2: GAMP5 matrices to determine the Risk Priority of a task.

eventually be used to do. For instance, *will this generated code write to memory? Will this modify any existing data?* Alternatively, *will this interact with mission critical devices, like a heart monitor?* In these instances, we need to know what is present in the output. Here we can look at the structural or semantic meanings of the outputted code.

A key issue with this type of metric is how one would quantify it. One approach would be to use Risk Priority Numbers (RPN) to form the basis of the weighing mechanism. Risk prioritisation is from Failure Mode, Effects and Criticality Analysis (FMECA) and involves looking at the probability of failure, the severity of its effects if it were to happen, and how detectable the failure would be (Handbook 1982). Let us say we had code that was being generated to interact with a heart monitor. The probability of failure might be slim as we are using an API to acquire data from sensors. However, its severity might be high as if it incorrectly reported the value, we do not know the real status of the patient. It could also be difficult to detect if there is no practitioner available to verify it at the time so this might be deemed very complex. RPN, in the case of FMECA, uses one to ten as possible values

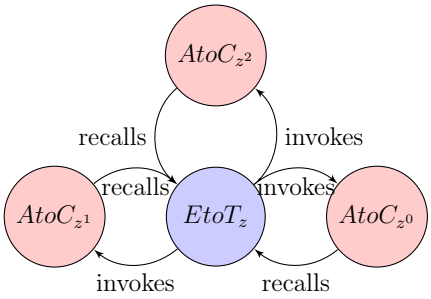


Figure 4.3: Transformation of a class with three attributes.

and simply multiplies them together to get a risk priority of the item in question. We can use risk priority using the weighing equation as shown in Equation (4.3). This data can be applied to rules and templates using annotations. RPN is also well used in clinical trials and is a vital part of Good Automated Manufacturing Practice (GAMP5) (GAMP 2008). However, in clinical trials, the value comes from a set of matrices as shown in Table 4.2. Given the probability of a failure in a task and the severity of that failure, if it were to occur, a Risk Class is generated. Using this Risk Class and how detectable the failure is would produce a Risk Priority.

4.4 Complexity and Prominence Combined

Figure 4.3 shows one more example that involves a single entity with three attributes. To show the sudden increase when purely using prominence, we have calculated Equation (4.1) against Figure 4.2a and Figure 4.2b, seen in Table 4.3. Here we can see, despite that $EtoT_z$ is more complex, it is considered to have twice the coverage thus we must involve complexity as a weighing mechanism.

Using our running example of transforming an object orientated representation to a relational: the transformation of a set of attributes to columns can be quite

v	Equation (4.1)
$EtoT_z$	$\ln\left(1+3\frac{\frac{1}{2}}{\frac{1}{4}}+6\frac{\frac{1}{3}}{\frac{1}{4}}\right)\approx 2.70805$
$AtoC_{z^n}$	$\ln\left(1+1\frac{\frac{1}{2}}{\frac{3}{4}}+2\frac{\frac{2}{3}}{\frac{3}{4}}\right)\approx 1.65292$

Table 4.3: Prominence of Figure 4.2a and Figure 4.2b in terms of Figure 4.3 to show sudden increase of our *heat* value.

trivial; whereas converting an entity to a table requires iterating the attributes, creating constraints and indices, and transforming related tables so it might reference them. For the purpose of showing our metric in this section, we shall involve test based complexity. Here we are assuming that the number of tests that pertain to a rule is an indicator of how complex it is. This indication is often true as there must be enough tests to have complete code coverage; however, this does not mean all execution paths have been tested as this becomes infeasible very quickly. Each conditional branch doubles the number of independent paths as of its location.

Figure 4.4 shows the confidence we have for a transformation of Figure 4.3 in regards to the ratio of tests in respect to `EtoT`. As above, we involve two historic traces: *a)* an entity with one attribute (see Figure 4.2a); and *b)* an entity with two attributes (see Figure 4.2b). This graph can be used to determine how much confidence we want in any either component. For example, say we want the same confidence in both rules then we need only around 40% of the total tests to be applied to `EtoT`. This is due to that trace element appearing in every isomorphic match. However, if we know that `EtoT` has some additional complexities, then we can find the ratio that suits the needs of the day. For instance, if a bug were to be found in `EtoT` we might add more experiments for it, thus moving it to have 60% of tests, it would in effect reduce the confidence in `AtoC`; however we would have

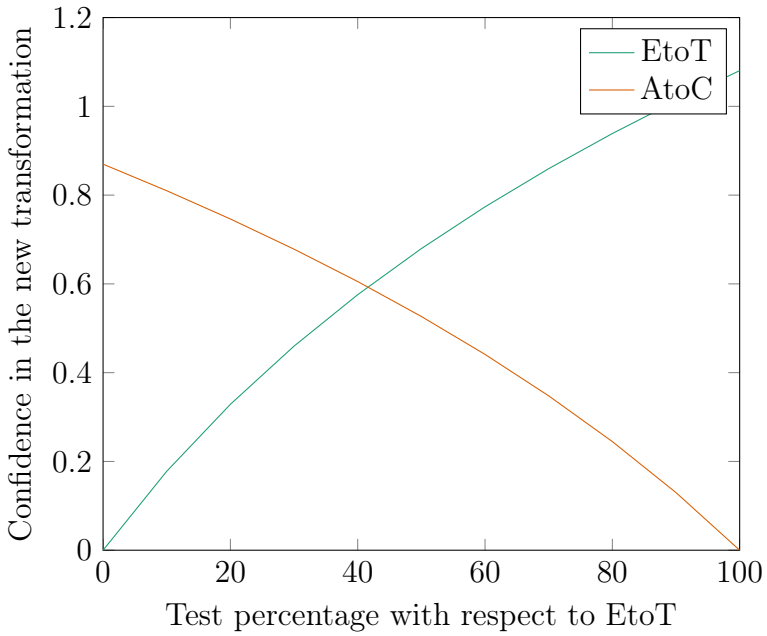


Figure 4.4: The confidence we have in a transformation of an entity with three attributes in respect to the ratio of tests in relation to *EtoT*. This is in consideration of a history of two previous transformations: one with one attribute the other with two.

accepted this when we decided to produce more test data.

4.5 Chapter Summary

In Chapter 3 we introduced a meta-model and algorithm for containing full accountability within model transformation. This is a necessity for having confidence within a transformation process. How can one be assured that we have witnessed a sequence of events before when we do not have the full view of what has gone on? This chapter has built upon additional trace information and turned it into a knowledge base for learning and performance analysis.

We have formalised our trace to make it possible to store it within a graph-based database. Retaining this representation keeps it in its natural form and presents us with other opportunities for debugging and optimisation, as well as for our use: providing confidence. For example, the execution graph can help developers to find bottlenecks in their transformation to focus performance analysis to specific rules. Parallelisation is possible where there are no recursive dependencies or loopbacks. Further parallelisation, over different hosts, is available to connected graphs. This information can aid in increasing the speed of M2M transformation.

For our work, however, we use it to gain assurance in a process. Acknowledging our assumption that the more times we have seen something work before, the more confident we are that it will work again opposed to a yet unseen operation. We formalise a ratio of how necessary a rule is in respect to its transformation and its use in another, more recent, one. This data provides us with the prominence of that rule's use in a historical trace concerning a new trace. A drawback of this trait is that it introduces a bias into our value: it assumes that each invocation is

equal, which is not true. The result of that transformation can be used to generate code that interacts with critical services or sensors. The transformation itself could be involved when considering the code that is written to complete the task. To avoid such biases, we include a weighing mechanism and explain a few examples. We concentrate on cyclomatic complexity, the number if linearly accessible paths through an execution graph. Our assumption here is that the higher the value, there would be a higher chance of traversing the incorrect branch. Combining these affords us a value to quantify our confidence within a process, concerning other historical processes.

CHAPTER 5

EVALUATION BY CASE STUDY

Chapters 3 and 4 both introduce methods to increase our confidence in model transformation. The former looks at what is happening in the process of transforming a source into a destination model, capturing the essence of this mapping using traceability. It finds and attempts to resolve issues with the current state of the art to improve accountability during the generation of the target model. This property is required to provide assurance when using imperative or hybrid transformation engines as these can cause side-effects that may become problematic. The latter looks at using this information to determine a *value* for confidence: how confident we are that a particular invocation is going to succeed when compared to others. Our process includes the persistence of trace data into a database and using this as a basis for learning. We can then have more assurance of a new trace input that can be at least somewhat composed of historical traces, than that of one that cannot.

The key to this is our Java and Python implementations of the Simple Transformer (SiTra) that both enforce our meta-model to capture the links lost in the traditional linear trace model as well as a dynamic proxy to capture objects not

instantiated by the engine, called orphans. We then adapted this to the Epsilon Transformation Language (ETL) to show its generality to other engines. Persistence into a Neo4j database allows us to retain execution graphs for analysis.

This chapter demonstrates our method with the use of a case study. It attempts to shows that we can feasibly acquire full accountability for use in production systems. The extra processing required to capture data regarding order and a particularly common side-effect will have some form of impact upon the transformation itself. If it is too great, then the benefits do not outweigh the costs. To do this, we need a non-trivial transformation that can be scaled in size to see the lasting effects of obtaining this data.

Section 5.1 introduces a non-trivial transformation of a relational database into that of a NoSQL database, specifically Apache HBase. This case study attempts to transform a relational database into a view more representative of the questions one might ask when querying the data. For example if one were to get all patients registered to a hospital, the relational database would have to look at two tables: *a)* The hospital table to find the hospital's key; and *b)* The patient table to find the patients that are assigned to it. This query would be completed using a JOIN which can become cumbersome for large datasets. Regarding a non-relational database, the hospital would be an entity that would contain all of its patients, reducing the query time and the necessary computation. Likewise in the event of the reverse, a patient would be an independent entity containing a copy of the hospital. Data duplication implies that non-relational databases accept a loss of integrity to increase horizontal scalability.

After showing the feasibility of live capture, we attempt to explain that it can be persisted and used for performance analysis, specifically looking at parallelisation.

Focusing on what and why parts are candidates for concurrent processing. Then using models that iteratively increase in size, explain how we can use the past to learn using our transformation of the relational into the non-relational.

5.1 Relational to Apache HBase

A relational database is a data store that favours integrity over redundancy. This trait is enforced by normalisation, i.e. splitting information into multiple tables and linking them using *keys*. Normalisation removes the need for data duplication, which prevents inconsistencies when reading. However, to query data in a useful way, tables must be *joined* on their keys. This process can be expensive depending on the size of the dataset. These databases can be generalised, such that a single meta-model can be used to model the core structure of many engines in use. Naturally these can be extended for engine specific functionalities, like Oracle and PostgreSQL's inheritance; however, we are concentrating on raw, tabular data, so these are out of scope for use in our case study. The Structured Query Language (SQL) provides us with an abstraction of what structure and the data look like within a relational table.

The opposing approach, denormalisation, favours redundancy and fast reads over integrity. The duplication of data means writing requires more time to propagate throughout the database, which in turn can allow data inconsistencies upon reporting. However, the effect allows developers to reduce the number or queries by having relevant information in one location on a per query basis. Many non-relational NoSQL databases apply this function. Apache HBase is such a database engine (The Apache Foundation 2016). Apache HBase is an open source,

non-relational database, and is currently the second most popular of its kind and fifteenth most popular databases engine in general[1]. This popularity is what drove us to transform a general relational database into this engine.

In this section we discuss the transformation of a relational database into Apache HBase and apply our methods within this transformation.

5.1.1 Meta-Models of the Source and Destination

As described in Figure 2.1 we need an input and target meta-model to describe instances of the relational and Apache HBase to write rules to map them (Czarnecki and Helsen 2006). In this section, we shall introduce both meta-models that involve the structure and the data of each model. The transformation will allow us to migrate a database and its data rather than just propose its structure. Adding more complexity to the conversion, as it will need to manually traverse tables to follow foreign keys to get related rows. Not only this, until Apache HBase has data its form is a collection of tables and column families. There is no standard way to transform a relational database to a non-relational, so transforming the content would allow us to see what it might look like in an automated fashion. The relational organises data into tables and columns in a manner that reduces data redundancy and increases integrity (normalisation) (Sanders and Shin 2001). Apache HBase, and indeed many other NoSQL databases do the opposite, and they instead optimise reading data by duplicating it. These approaches vary substantially so a transformation between the two would be complex enough to test our approach.

[1]http://db-engines.com/en/ranking (visited on Jan 2017)

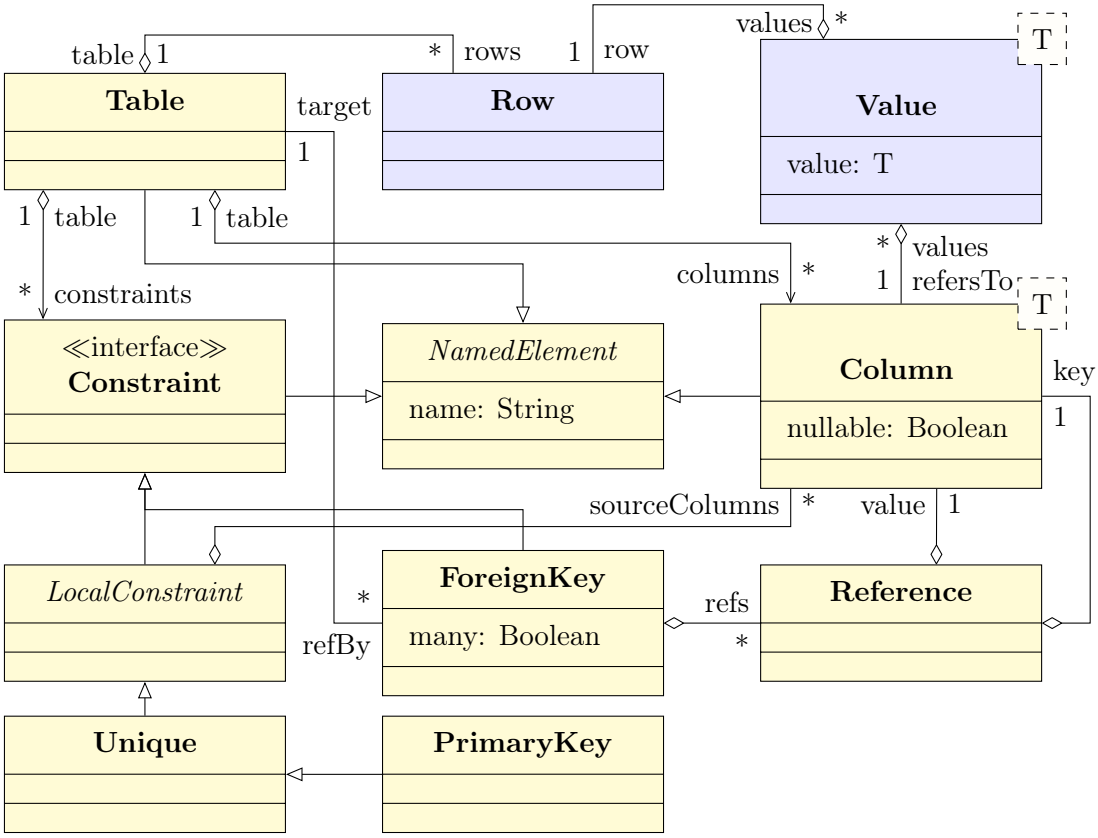


Figure 5.1: The meta-model of a relational database.

Meta-Model of a Relational Database

SQL engines back standard relational databases: for example MySQL, PostgreSQL and Oracle. The main artefacts used within these engines are tables, columns, rows, constraints and values. Figure 5.1 illustrates the meta-model of a general-purpose relational database. The database itself is a collection of tables. The tables contain rows of values that are relevant to the table's purpose; these values conform to a set of column definitions. These definitions determine what type a value must be and other attributes to describe the nature of the data. Specifically, they are used to define the structure of the data within the table and provide type safety.

A table's constraints specify rules for the data within a table. We concentrate on three of the most common constraints in SQL.

1. The unique constraint prevents duplicate values in one or more columns.
2. The primary key constraint defines a key that is used to identify a single row; this implies that the column is also unique.
3. The foreign key constraint allows one or more columns to reference a table's primary key.

The latter two are the basis of providing one-to-many and many-to-one relationships. Although many-to-many relationships exist conceptually, in practice, they involve an additional table, a lookup table, and two one-to-many relationships.

We include values in our meta-model to allow us to map not just the structure, which would be trivial, but the data itself. This additional task generates a set of complex transformation rules that must denormalize data for Apache HBase. Without this, we would simply be generating a succession of column families for each table.

Meta-Model of Apache HBase

Apache HBase is an open-source, distributed, versioned, non-relational database based upon Google's Bigtable (Chang et al. 2008). Its aim is to host large tables, i.e. billions of rows by millions of columns. Figure 5.2 illustrates its meta-model, the destination of our transformation. Here we can see that the structure is much simpler than that of a relational database, as shown in Figure 5.1. This simplicity comes from the basic key/value style of Apache HBase. A namespace, opposed to

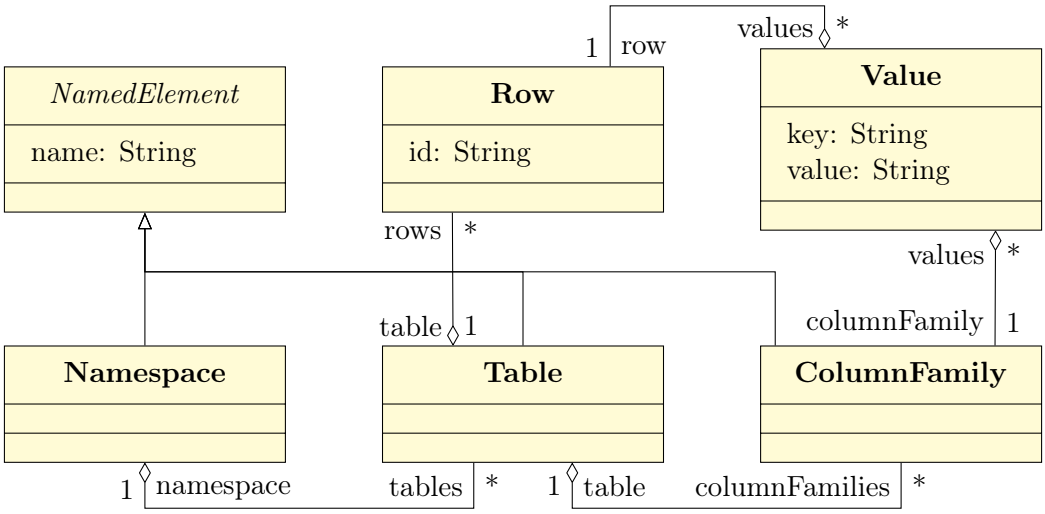


Figure 5.2: The meta-model of a Apache HBase.

a database, is a grouping of tables which each contain column families defining the general structure of the data within. Column families are a conceptual grouping of columns that have no definition. Users add data into the "buckets" on demand. For example, if a column family called `patients` existed, one could write values to `patients:id` and `patients:name` with no information regarding the column qualifiers. Each table indexes a set of rows based on their ID. These IDs allow the engine to spread the data amongst the data cluster to share resources where needed. Finally, we include values: Apache HBase only supports textual or byte data natively. To store other types, one must encode them or know the type upfront to cast them within the application calling upon it. In either case, they directly relate to a row and a column family. Our representation's Value takes the key/value literally and contains the value it represents and the column qualifier, or key that identifies it.

This meta-model allows us to realise the structure and the data of Apache HBase. Since NoSQL databases do not have schemas, we needed a meta-model

that includes its data. The main structures act like buckets for textual or binary data. Therefore to properly transform a database we need to access the data within the relational tables to create a viable destination model.

5.2 Relationship Considerations

Relational databases normalise data to reduce duplication with a goal to increase integrity. This feature eliminates redundancy and anomalies caused by inserting, updating or deleting data. Information is spread over tables and referenced by row keys to provide these assurances Integrity, however, induces performance issues as querying the databases will no doubt require joining these tables together, or using multiple queries. Both can be expensive operations, especially since datasets increase.

NoSQL databases take a different approach and favour data duplication to provide faster reads; this additional redundancy makes for a more horizontally scalable database engine. Therefore these databases have no concept of relationships, i.e. many-to-one, one-to-one and many-to-many. This duplication can create anomalies as data needs to be written in more locations and therefore can be out-of-date when reported. Often this denormalisation will look at the questions that are asked by the user. For example: *What users are assigned to a project?* Or *What projects is a user assigned to?* This bidirectional question would imply two tables, a projects table and a users tables. The projects table would duplicate all of the user's data within it, so only one read would be necessary. The reverse would be the same; the user would have project information within its table. To illustrate the data anomalies consider updating the user, one would first modify

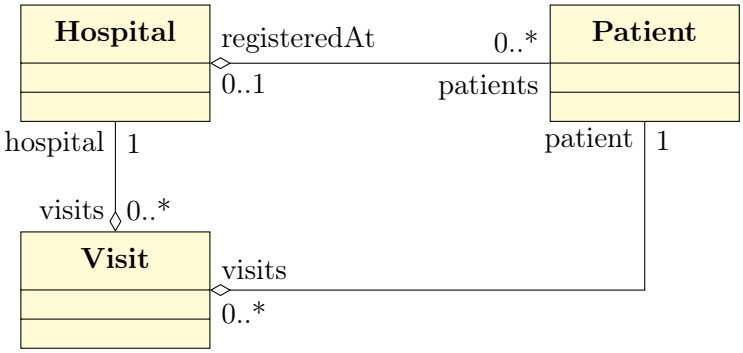


Figure 5.3: A small UML example showing the relationship between a hospital and its patients.

the user's row in the user table and then find all of the projects that contain him and update those.

Our case study attempts to transform a relational database into Apache HBase automatically. However, we do not have any concept of these questions during the transformation, so we make some considerations when mapping a table's relationships. To do this, we introduce a small example that encompasses the more complex relationships. Figure 5.3 illustrates a database about the relationship between a hospital and its patients. For example, a patient can be registered to a hospital (many-to-one), a hospital can have many patients (one-to-many), and a patient can make many visits to a hospital (many-to-many). The next sections explain our design decisions when transforming these links into a representation whereby they do not exist.

5.2.1 One-to-Many and Many-to-One Relationships

A relation between *hospitals* and *patients* could be considered *one-to-many*; a hospital will have many registered patients; however, the patient may only register

at one hospital. This relationship is illustrated using the Unified Modeling Language (UML) in Figure 5.3. In an SQL database, both would have their table, and a reference would be present within the patient table to say which hospital a patient is registered. For NoSQL databases, however, the queries are more related to the questions that are asked to query it. In this case it the questions would be: *1) what patients are registered at a hospital*; and *2) what hospital is a patient registered at?* The optional relationship shows that they are independent, i.e. regarding an SQL database the reference could be `NULL`. Independence implies that each would have a table even in NoSQL. Traditionally one might query the hospital and get its identifier and then traverse each row within the patient table to find instances where the patient references that hospital ID. This process is what a `JOIN` would do in an SQL setting, but the developers are expected to do this themselves. In a distributed NoSQL database, the latency of multiple queries can be quite substantial as the engine needs to determine on which nodes the data resides.

The common approach is to duplicate the data in both tables. For instance, the hospital table would contain the patients *and* their data opposed to their identifiers such that the question *what patients are registered at a hospital?* requires only one query. In the event of the second question, the patient could include a copy of the hospital's data so when a patient is queried we know where they are registered. In both cases, information can be accessed using one query. The main drawback of this approach is that data now needs to be updated in many areas of the database. However, this is often the case for NoSQL databases.

Table 5.1 shows example data that conforms to the many-to-one relationship between hospitals and patients, as defined in Figure 5.3. We can see there are two hospitals and four patients. Three of those patients are registered at hospitals (using

hospital_id	hospital_name
1	County Hospital
2	Cheadle Hospital

(a) Example *hospital* data.

patient_id	hospital_id	patient_name
1	1	Carol Edmunds
2	1	Alexandra Church
3	2	Peter Turner
4		Robert Lewis

(b) Example *patient* data.

Table 5.1: Example data related to bidirectional the one-to-many relationship concerning hospitals and patients.

a foreign key). The fourth, however, is not (illustrated by the `NULL` value). This row shows that the relationship is an optional one. Thus there is no dependency upon the hospital and that a patient can be independent. In UML this would be an aggregation rather than a composite relationship.

A Non-Relational Many-to-One

A many-to-one relationship is simply the characteristic of an entity being referenced by more than one of another. In the case of our example, shown in Figure 5.3: *a)* there are many patients registered to a single hospital; and *b)* there are many visits involving a single patient and the hospital they visited. So how does one transform this into a non-relational database? As we have previously discussed, a naive approach would be to map the relational table into a document. However, in this case, the developer would have to join the data based on each row's identifier manually. This process increases the complexity of the application and is expensive, regarding latency, in a distributed database. Thus not taking advantage of the redundancy ethos of NoSQL databases.

The more non-relational approach would be to duplicate the related data: nesting it within the root element itself. To show this we use the relationship

between the patient and hospital, i.e. many patients *can* be registered to one hospital. Table 5.2 illustrates how the data could be laid out in an Apache HBase table. Each value is a tuple consisting of the row identifier, the column and a timestamp. Thus we have null values. Physically those `NULL`s do not exist in HBase. Apache HBase uses column families to denote a conceptual grouping of columns, so our HBase table would have two column families for the patient table, per row: *1)* a column family, to hold the core attributes of the patient; and *2)* a column family, to hold the attributes of the hospital. In both cases, qualifiers are used to identify attributes. Each hospital value would be accessible using `registered_at:id` and `registered_at:name`, where `registered_at` is the column family while `id` and `name` are qualifiers. This column family is a bucket for all of the hospital's data via the registered at relationahip.

A Non-Relational One-to-Many

The previous section discussed the many-to-one relationship between relational tables and introduced the mechanism to be used to implement it within a key-value setting. This section shall discuss a possible implementation of a one-to-many relationship. This relationship is simply the reverse of the many-to-one. Opposed to discussing the relationship on the patient we now look from the perspective of the hospital. Asking for the list of patients that registered with a particular hospital, rather than for the hospital a patient registered.

A relationship that is at the *one* end of a relationship can be considered fairly trivial to maintain, i.e. a column family to place that entities data inside. However, there is no list structure within Apache HBase to allow us to have multiple elements.

Row Key	t	Column Family *(patient)*	Column Family *(registrated_at)*
1	t1	`patient:id` = 1	
1	t2	`patient:name` = "Carol Edmunds"	
1	t3		`registrated_at:id` = 1
1	t4		`registrated_at:name` = "County Hospital"
2	t5	`patient:id` = 2	
2	t6	`patient:name` = "Alexandra Church"	
2	t7		`registrated_at:id` = 1
2	t8		`registrated_at:name` = "County Hospital"
3	t9	`patient:id`=3	
3	t10	`patient:name` = "Peter Turner"	
3	t11		`registrated_at:id` = 2
3	t12		`registrated_at:name` = "Cheadle Hospital"
4	t13	`patient:id` = 4	
4	t14	`patient:name` = "Robert Lewis"	

Table 5.2: The conceptual mapping of a many-to-one relationship in a key/value database.

Instead, we look at creating a column family for each entity and use the qualifier as our identifier. Table 5.3 shows how we write this relationship in the hospital table. Firstly we have a column family that reflects the core data of a hospital, and once again its ID is used as a row identifier. Then for each column in the patient table, we create a column family, i.e. `patient.id` and `patient.name`. To distinguish each row, we use the column qualifier, for example, `patient.name:1` denotes the patient name whose ID is 1. Likewise `patient.id:3` denotes the patient ID whose ID is 3.

To query this data we can use a combination of column family filter and a qualifier filters. For example to access all columns that relate to patient data within this hospital, one might filter by `patient.*`, this can be reduced by only selecting some areas. The use of qualifier filters could be used to select certain patients using IDs. For singular queries, one might argue that it would be better to access the patient directly and access the hospital via the many-to-one relationship we discussed in the previous section. More complex filters are available to acquire ranges, in the event of time series data; however, this is out of the scope of our research and does not look into this.

5.3 Transformation Rules

We have so far introduced our meta-models that represent the two domains we are transforming and mentioned the considerations that needed to be made to take relational data and generate denormalised data successfully. In this section, we shall discuss what is needed to occur in each transformation. We have three main topics to transform: *1) prime tables* or tables that are independent of others;

Row Key	t	Column Family *(hospital)*	Column Family *(patients.id)*	Column Family *(patients.name)*
1	t1	`hospital:id` = 1		
1	t2	`hospital:name` = "County Hospital"		
1	t3		`patient.id:1` = 1	
1	t4			`patient.name:1` = "Carol Edmunds"
1	t5		`patient.id:2` = 2	
1	t6			`patient.name:2` = "Alexandra Church"
2	t7	`hospital:id` = 2		
2	t8	`hospital:name` = "Cheadle Hospital"		
2	t9		`patient.id:3` = 3	
2	t10			`patient.name:3` = "Peter Turner"

Table 5.3: The conceptual mapping of a one-to-many relationship in a key/value database.

2) any-to-one table relationships that end with a single item; and *3) one-to-many table* relationships that conclude with the many side of the relationship.

Our example in Figure 5.3 contains a many-to-many relationship between the hospital and patient entities via the visit table; however, a visit is complex many-to-many as its presence is indicative of additional attributes. Thus it is interpreted as a prime table with two bidirectional one-to-many relationships. Our transformation treats non-complex many-to-many relationships, i.e. simple lookup tables, and the complex equally. An extension of our work could allow the removal of the index table and traverse the indices to denormalise the data. Automating this is not a trivial undertaking as we need a method to identify this data.

5.3.1 The Database

A relational database is simply a collection of tables; this conceptual grouping is synonymous with the Apache HBase namespace, a collection of HBase tables. This view is a key starting point for a transformation such that we might transform an entire database of tables. A rule to complete this is a simple one, create a namespace, set its name based on the input and then transform the relational database's contents.

5.3.2 Prime Tables

Table Transformation

For the purpose of this case study, we refer to tables with no or optional foreign keys as prime tables. These are candidates for Apache HBase tables. If no foreign key references the table, there is no dependency upon the entity in question. For example the hospital references a set of patients; however a patient is independent of the hospital, i.e. the registered status is optional. In the case of the visit table, a visit requires a hospital, but the reverse is not true. The hospital table itself has no dependencies it only has dependents.

For a given prime table we need an HBase table and a column family. This family is necessary to contain the columns of a relational table. Since we are using SiTra in Python, we can generate multiple output objects and as such will use this approach for this rule: $f(\text{RelationalTable}) \rightarrow (\text{HBaseTable}, \text{HBaseColumnFamily})$. This process, however, creates two orphans, as the trace knows about the tuple but not its contents. We would receive no result if one were to complete a reverse

lookup on either the HBase table or column family. Here we depend on the proxy we have implemented to intercept these objects when they are bound together. However as explained in Section 3.2.2 we need to do this at the beginning of the binding phase so we might capture subsequent orphans.

Following the transformation of the table's basic features, we must then transform its rows and foreign key constraints. These mappings would be completed automatically given a scheduled engine. However, SiTra is explicitly scheduled and needs to transform each as such.

Data Transformation

We now have a transformation that will generate a table and a column family for the table's data. Next, we concentrate on the data itself. There are two directions for this, iterate each row or each column. The final effect of this is to transform each value. Due to how data is indexed we chose to transform each row individually. The rule itself returns a new Apache HBase row for each relational row it finds. The binding phase is a simple one: *1)* setup the structural elements, i.e. assign it to the table; *2)* formulate a row key, using the primary key of the relational table; and *3)* iterate each value to transform the data. The row key is the identifier for a row within the prime table and is used to distribute the data amongst the cluster. It involves the primary key's value(s). For the purpose of our experiments, we do not consider composite keys as we feel that they would need further configuration as to determine their value. If we had a two column composite key, how should it be used? It would be sensible to use both, however in which order. Once more we ask the question, what are we querying? This issue makes it hard to automate, if

indeed necessary.

Given an Apache HBase row, we now need to iterate the values within the relational row converting them into Apache HBase values. Since we are transforming prime tables, the mapping of their values is a simple one. This process involves setting up the components of an individual value and setting its attributes such that it retains its data, a reference to the right row and a reference to the default column family generated in Section 5.3.2. Since all data in Apache HBase can be a string or an array of bytes: all values would be treated as strings for the purpose of testing. In a real setting, one might attempt to serialise them correctly. For example, an array of four bytes could be used to keep a 32-bit integer inside, whereas when using a character array, each power of ten adds a byte to represent its ASCII representation.

5.3.3 Relationships

We have now transformed the basic elements of a relational table; we now need to discuss the logic on how we transform relationships. These become more complex as we need to transform a foreign key about a table: either its target or owning table. Since there is only one object regarding the relationship, we need a composite input, i.e. the owning table with the foreign key and the target table with the foreign key. Other, more declarative, languages like Operational Query/View/Transform (QVT-O) and the ATLAS Transformation Langauge (ATL) have a scheduler that can do such operations. SiTra, both Python and Java, is unable to do this implicitly. To explicitly do this we need to create a composite of elements to transform and transform that instead. In the case of Java, one might use the approach found

in Section 3.1.3. However, in Python, we can generate tuples on demand and transform them without creating specific containers.

Any-to-One Relationships

Any-to-one transformations include both many-to-one and one-to-one relationships. Specifically looking at the *one* side, i.e. the current element can only be referenced by one related item. As explained in Section 5.2.1: all values within this can be placed into a single column family, using the column name as the qualifier for the value itself. In the case of Table 5.2, we have `id` and `name` as the qualifiers within the column family `registered_at`. A column family is used to represent a bucket for the data of each of these relationships.

To transform data however we need to map a relational row in respect of a table and a foreign key. The table determines the direction of the transformation and where the results should be bound. If the table is the foreign key's target we need to look at the referencing table, if the table is the owning table then we need to look locally. Our transformation rule introduces many orphans as we iterate each value within the row in question and map them manually rather than delegating to another rule. Not unlike the foreign key and foreign key column in the OO2DB example as explained in Section 3.1.3; however, our new objects come from a controlled and yet variable loop. This part of our transformation was a design decision to enable us to verify orphan capture.

One-to-Many Relationships

The concept of this transformation is explained in Section 5.2.1 and illustrates that we need a column family for each column of the child table. For instance, the hospital table would need a column family for each patient column to emulate a nested table. The transformation would require the rule to instantiate a list of column families for binding. This phase will initially create a list of orphans. The engine itself knows that the transformation of a relationship produces a list, but it does not recurse into the list to gather its contents. However, the list passed into the binding phase is a proxy. Therefore any accessors used to retrieve column families would automatically add them into the transformation trace.

Transforming the data is not unlike that of any-to-one relationships however the column has its container identified by the row's primary key. Table 5.3 has column families for each patient column, and the patient's ID identifies every patient "row" as the column family's qualifier.

5.4 Benchmarking Traceability for SiTra

In this section, we shall discuss the overhead of our latest meta-model upon a model-to-model (M2M) transformation. We have already introduced our new tracing mechanism and explained how we capture orphan objects in Section 3.2. Our method was implemented primarily in Java; however, due to our usage of Python for the efficacy of a transformation, we shall focus on our Python framework. This piece of software consists of four engines: *1)* one that has no tracking; *2)* one with a linear trace; *3)* one that retains the interconnectivity of the transformation,

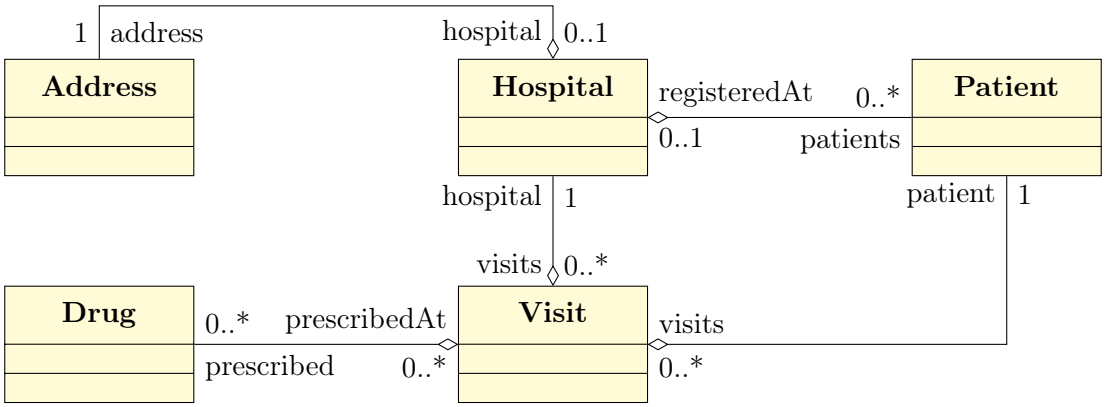


Figure 5.4: A meta-model containing all types of relationships available to relational databases, providing full coverage of the transformation.

and *4)* another like 3) but captures orphan objects. The first provides us with a base value, i.e. the time to transform the source to the destination with minimal overhead. The second allows us to determine the overhead induced by introducing the current state of the art in traceability with rule-based transformations. The third provides us with our new trace meta-model to retain the execution graph. The last engine does the above as well as retaining orphans; this is the heavyweight of the four as it involves proxying objects, which in turn queries the trace to verify if an object is an orphan.

Our performance metric is the time it takes for a transformation to take place, indicative of the additional complexities that our approach introduces. To do this, we needed an input model that we could transform. We created a database that has all of the traits we have defined in Section 5.3. Once we extended our original model to include more relationships (as shown in Figure 5.4), we created varying sizes of the input model. Each instance had a different number of rows per table, so we see the increase in time as our model gets larger and larger. The model size will increase proportionally to the number of rows, so this is a candidate axis for

analysis. We used the `perf` Python module to measure the time it took to run a succession of transformations. This module runs a function so many times that it reduces the effects of random factors, such as address space layout randomisation, and enough to get a uniform distribution. Finally, it provides a median time and the standard deviation of the sample set.

Table 5.4 contains the results of our benchmark tests for the first three types of transformation engine. As we are testing the performance of our transformation trace, we are using the SimpleTraceableTransformer as the base reading. This engine represents the current state of the art within rule-based M2M transformation engines. The `SimpleTransformer` is there to indicate the resource gain that would be in effect if one were to remove traceability. The `SimpleNestedTraceableTransformer` is present to show the extension made to retain the graph-like nature of a transformation trace.

Generally speaking there is a decrease of up to 7% when traceability is turned off. In the case of zero rows, there is an increase of ~14%. However, the transformation itself completes in microseconds rather than seconds. This degree of accuracy means the result is more susceptible to background interference from other processes and I/O latencies would be a more prominent within small transformations as there is less work for the transformation to complete. This metric is simply to show the additional effort in providing the current state of the art of traceability within M2M transformation.

Figure 5.5 portrays these results in graphical form. Here we can see that the increase in work is linear as the input model increases in size. As we retain more information, i.e. the real internal structure we might incur a performance hit of up to 10%; however on average incurring a 6% increase in throughput. The increase in

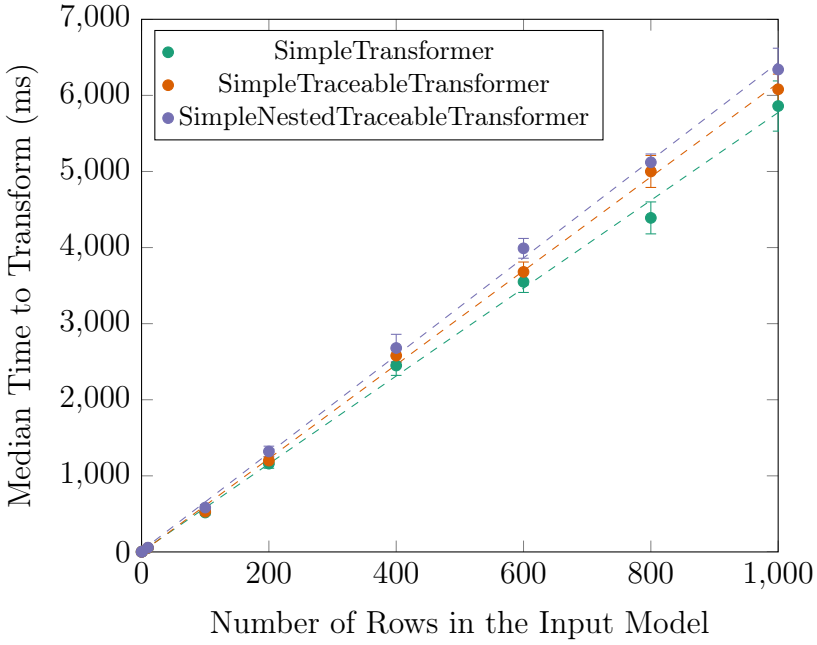


Figure 5.5: Graphical representation of Table 5.4 to show the linear impact upon performance when capturing the nested nature of an M2M transformation.

workload is manageable when we consider that in the case of a database instance with 1000 rows per table the transformation is mapping 55651 source objects into 138169 destination objects. Our benchmarking completed this in ~6.3s, an increase of ~0.3s upon our baseline.

We then completed benchmarking using our fourth transformation engine. This engine allowed us to trace orphan objects. In all of our tests, every orphan has a link to the source model and rule that was used to generate it. Table 5.5 and Figure 5.6 shows the performance of our process when capturing orphans. They illustrate that tracking orphans using proxies have a much larger impact upon M2M transformation. For instance, with the time it takes to transform a scenario containing 20 rows with orphan capturing, it would be possible to transform an instance with $\tilde{1}200$ rows without. This difference in performance is due to the

	Transformer	Time (ms)		Overhead
		Median	Std. Dev.	Increase (%)
0	SimpleTransformer	0.591	0.043	-14.0988
	SimpleTraceableTransformer	0.688	0.034	0
	SimpleNestedTraceableTransformer	0.722	0.033	4.9419
1	SimpleTransformer	5.66	0.31	-6.2914
	SimpleTraceableTransformer	6.04	0.50	0
	SimpleNestedTraceableTransformer	6.29	0.31	4.1391
10	SimpleTransformer	52.2	4.4	-1.5094
	SimpleTraceableTransformer	53.0	1.6	0
	SimpleNestedTraceableTransformer	56.4	2.0	6.4151
100	SimpleTransformer	518	33	-2.0794
	SimpleTraceableTransformer	529	18	0
	SimpleNestedTraceableTransformer	583	38	10.2079
200	SimpleTransformer	1160	60	-3.3333
	SimpleTraceableTransformer	1200	50	0
	SimpleNestedTraceableTransformer	1320	70	10.0000
400	SimpleTransformer	2450	130	-5.0388
	SimpleTraceableTransformer	2580	90	0
	SimpleNestedTraceableTransformer	2680	180	3.8760
600	SimpleTransformer	3550	140	-3.5326
	SimpleTraceableTransformer	3680	130	0
	SimpleNestedTraceableTransformer	3990	130	8.4239
800	SimpleTransformer	4390	210	-12.2
	SimpleTraceableTransformer	5000	210	0
	SimpleNestedTraceableTransformer	5120	110	2.4
1000	SimpleTransformer	5860	330	-3.6184
	SimpleTraceableTransformer	6080	200	0
	SimpleNestedTraceableTransformer	6340	280	4.2763

Table 5.4: Benchmark results of three of SiTra's engines.

	Time (ms)	
	Median	Std. Dev.
0	3.54	0.31
1	42.7	3.3
10	1960	110
20	7990	330
40	31700	1900
60	66800	3000
80	108000	4000
100	189000	5000

Table 5.5: Benchmark results of orphan capture.

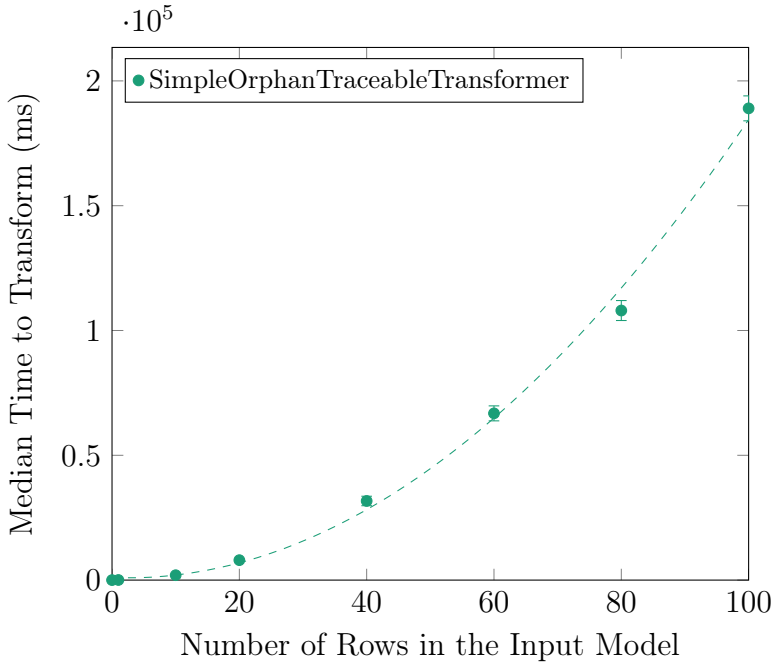


Figure 5.6: Graphical representation of Table 5.5 to show the exponential impact upon performance when capturing orphaned objects during an M2M transformation.

creation and processing overheads of object proxies to intercept accessors and mutators. In the event of the call of a mutator method, the transformation engine looks for the new object inside of its trace. If it is not available, the object is an orphan and therefore kept. The object is then being proxied itself to allow recursion. Accessors, however, return proxies for objects to allow any setters and getters on the acquired object to be captured. A map could be used to optimise this process. However, there are two considerations:

1. A cache is often implemented using a map, which creates a hash based on the key object. Thus a means of determining object equality must be provided to the destination model. `hashCode` is used to determine which *bucket* an object will go into, while `equals` determine whether two objects are logically similar. Without this implementation often the object's memory address is used for equality; however this value can be reused by other objects as and when objects are swapped out and back in again. This behaviour is true for Java and Python at the time of writing, for larger transformations this cannot work as memory will be swapped and therefore there is a chance of reuse.

2. The cache itself can also become significant. Mapping a POJO to its proxy to save on time creating a new one. In a worst case scenario, we need twice the number of objects in the destination as each object needs a proxy. Potentially inducing more memory movement and using up resources available to the transformation itself.

The cost of using a cache to save on the instantiation time of proxies weighs against the resources that are available. In the case of no cache, we would decrease the transformation's throughput, as for each item we return a new proxy, potentially

many proxies per destination object. However, when we introduce a cache we would, up to a point, increase throughput but at the same time reduce the number of resources available to the transformation itself.

This data has changed our approach to using the *SimpleOrphanTraceableTransformer* as a general purpose transformation engine and instead it is to be used to detect orphans during development. This method will help developers to find orphans and refactor their rules such that they do no create them. Following this they then can fall back onto the *SimpleNestedTraceableTransformer* to retain the structure of the overall transformation, knowing that all objects are accounted for.

Our case study has provided us with the concept of orphan leakage. These come from two locations: *1)* the instantiation phase, where one might return an array of objects, and *2)* the previously discussed binding phase.

Orphan leakage occurs in the binding phase of an M2M transformation. Not unlike real memory leaks, these are potentially out of control and are unstable. For instance if one were to allocate some memory to a pointer and forget to free it, the leak itself has limited effects; however if one were to reuse that address, in a loop for example, and continue to allocate memory, it could have crippling consequences for the process. This issue applies to the accountability of destination objects within the trace of an M2M transformation. Our case study implements this leak by generating some value objects for each row in a loop. Apache Values are orphans until a proxy detects them. We expected that our proxies will catch these orphans. If one used this system to detect them during development, it would allow the developer to refactor their rules such that they are at built during instantiation. Thus one may fall back upon a faster engine, removing the need for proxies.

The instantiation phase produces a containment of new objects when returning

a collection. The engine can traverse these containments automatically as they should be a one-dimensional array of presently unrelated objects. This collection is iterable, and therefore the list can be traversed and its objects tracked before the binding phase. These orphans are stable, and despite the possibility of returning a dynamic number of elements (using generators), can all be captured before and then passed into the `set_properties` method.

It is possible to rewrite the transformation of the relational to non-relational such that it creates no orphans. These changes are minor modifications, and simply involve the building a list of HBase values in the instantiation phase opposed to lazily creating them. We calculate the number of values up front, and their indices within the array can be used to identify them. Our transformation *zips* them with the appropriate columns, to make related tuples of relational columns and their Apache HBase value counterparts. The actual change adds 18 lines of code and deletes 9.

5.5 Benchmarking Traceability for ETL

To show the applicability of our meta-model within other engines: we have implemented the same transformation, as per Section 5.4 for ETL. ETL is a declarative language used for defining M2M transformations. However, its execution uses an executable Abstract Syntax Tree (AST). An ETL module will parse a given script and interpret its instructions. ETL is an extension of the Epsilon Object Language (EOL) and various other libraries that allow the framework to accept a plethora of meta-model and model types. It also provides abstract layers to enable different model providers the ability to use Epsilon's toolset. We show that our

slight extension to ELT allows us to complete the same transformation, retain the structure and capture orphans with relatively minor performance decreases. In all cases, the additional workload was linear, unlike SiTra's use of proxies which was exponential.

The bundled version of ETL provides an external linear trace without orphan tracking. That is a trace that does not maintain invocation or rule dependency information. It is used by the engine to schedule the transformation. ETL's transformation strategy matches all sources and rules before any binding. This phase is completed by iterating through each rule and finding all permutations of individual input model elements. When it finds a match, it generates an *invocation*, and the target objects instantiated. Once all rules are processed, and matching sources found, the engine iterates through each of them and binds them. This way, no rule invokes another, the scheduler itself invokes them. However, rules do depend on other rules, i.e. they can rely on the result of other invocations. Whether the engine scheduled it, or whether another invocation catalysed it. We build upon this version of ETL to provide the same mechanics used in SiTra to retain the invocation graph, by using a simple stack to track the *current* transformation and the new meta-model mentioned in Figure 3.7.

ETL is also open to orphans, as shown in Section 3.1.3. EOL is what provides the `new` keyword to its developers and is what causes this side effect. The nature of ETL's execution allows us to intercept all elements of the language's AST. It does this via an execution listener with pre- and post- methods. In the event of a new object, the newly allocated instance is passed into the handler and then added to the current invocation's target elements. This approach bypasses checks required by SiTra. We know that at the time of execution it is new and therefore has no

association to the source model. There is a possibility that this object may never see the final model. However, it existed for a time during the transformation. At the time of execution we cannot know whether it is a temporary variable or not, so we err on the side of caution by retaining it.

During this investigation, we wrote a transformation rule that created many column families and another that created many values to validate our orphan capture. These numbers were variable, so a simple refactoring, as described in Figure 3.4, would not suffice. Instead, we might rethink the transformation such that one transforms the individual components, i.e. the `Column` or `Value` objects. To keep the same type of conversion as used for SiTra, we used an EOL Sequence and populated it within the binding phase. This method is another kind of producer for orphans.

The conversion of our transformation we have for the Python version of SiTra is not a simple one. The current transformation strategy of ETL only handles individual inputs. To emulate multiple source objects, we must wrap them within another object. For instance, the mapping of a foreign key into a NoSQL setting is bidirectional. Thus we transform in respect to the table that owns the foreign key its and the target table. In Python we transformed $(forignKey, owner)$ and $(foreignKey, target)$. This is an interim transformation. To have the same effect, we create an interim transformation to generate wrapper objects. This approach is necessary for all engines that do not support multiple inputs, like ETL and the Java implementation of SiTra. We show the transformation for ETL in Appendix A.2, and for completeness, show an example of how to do this with SiTra in Appendix A.1, specifically Appendix A.1.1. Once we have these wrappers, we can then run the core transformation, which recognises them to complete the overall process.

The python version of SiTra does not suffer from this drawback as there is: *a)* a primitive tuple type that can be used to wrap objects; and *b)* no automatic scheduler, all transformations are on demand, so tuples are built ad-hoc within the binding phase. This different strategy removes the need for an interim model transformation that would be otherwise necessary for ETL and the Java version of SiTra.

Naturally, as shown with SiTra, the capture of this additional information has a cost. Retaining this information will inevitably require more resources, CPU and memory, slowing the overall transformation. To show their effects within ETL, we ran benchmarks upon the same transformation for 0, 1, 10, 100, 200, 400 and 600 rows of data per table using the same scenario as illustrated in Figure 5.4. Table 5.6 show the results of this.

The original engine already has a much larger overhead than that of SiTra. An increase of ~258% when compared with its rival SimpleTraceableTransformer upon a model with 200 rows of data. Two factors that contribute to this are: *1)* the executable DSL, which requires parsing from a file before execution; and *2)* the overhead of abstraction within the Epsilon framework itself. The former needs I/O and this can be a great and yet variable source of latency. The latter, however, means the framework itself adds overhead to the transformation. Epsilon is a library of languages and tools that share components and are built upon others to handle many combinations of model types and meta-modelling types. These mechanisms provide modularity to ETL where SiTra does not.

On average, retaining the full execution graph costs an extra 26.51% in processing time, when compared to the generation of a linear trace that ETL creates by default. This performance cost is due to retaining and managing a stack trace consisting of

	Transformer	Time (ms)		Overhead
		Median	Std. Dev.	Increase (%)
0	ETL with a linear trace	6.229825	0.612452	0
	ETL with a nested trace	8.514919	0.573941	36.679907
	ETL with orphan capture	8.556511	0.81482	37.347534
1	ETL with a linear trace	19.902245	1.826349	0
	ETL with a nested trace	24.263144	2.186637	21.911593
	ETL with orphan capture	26.21286	2.08612	31.708056
10	ETL with a linear trace	133.756232	10.212291	0
	ETL with a nested trace	162.768136	4.38434	21.690133
	ETL with orphan capture	193.802431	9.967215	44.892263
100	ETL with a linear trace	1326.779902	60.447172	0
	ETL with a nested trace	1770.572461	108.372241	33.448845
	ETL with orphan capture	1872.282795	21.471793	41.114799
200	ETL with a linear trace	3098.549138	185.59442	0
	ETL with a nested trace	3721.827262	31.727956	20.115160
	ETL with orphan capture	3993.323147	40.129216	28.877193
400	ETL with a linear trace	7619.275643	431.847744	0
	ETL with a nested trace	9153.195927	303.909982	20.132101
	ETL with orphan capture	9149.502545	61.406627	20.083627
600	ETL with a linear trace	12976.374704	1255.039679	0
	ETL with a nested trace	17071.978681	107.142481	31.562005
	ETL with orphan capture	17740.626044	114.793355	36.714810

Table 5.6: Benchmark results of three of the ETL traceability methods.

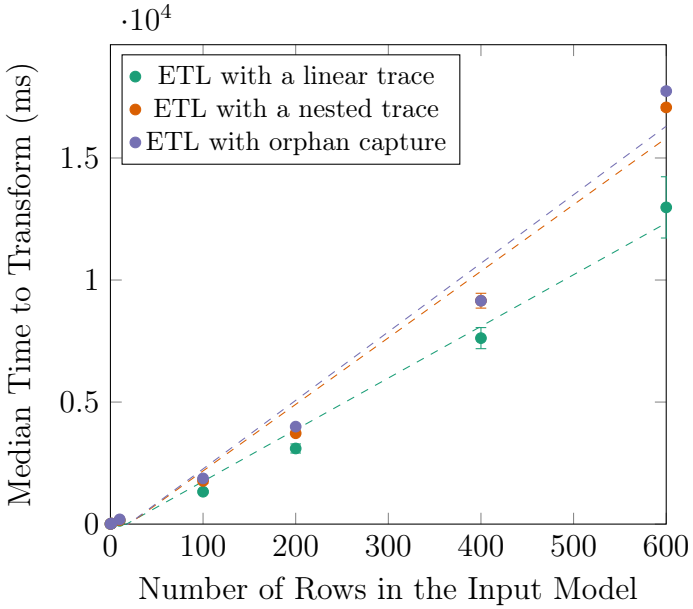


Figure 5.7: Graphical representation of ETL's three transformation strategies to show the linear impact upon performance when capturing the execution graph and a transformation's orphans.

rule invocations, as well as the AST's execution stack trace.

The inclusion of orphans increases this on average another 6.36%. However, unlike SiTra, the cost is linear. We can see in Figure 5.7 that the performance increase when retaining orphan information is proportional to the number of orphans introduced. This is due to the executable AST in use within ETL, which removes the need to intercept mutators and accessors. Thus when `new` is executed, we can *blindly* retain the object and insert in into the current invocation's target list. This is an improvement on SiTra as this becomes a manageable impact upon the overall transformation and therefore if possible outside of development; instead, its use extends to production.

5.6 Persisting the Trace for Analysis

In the previous section, we discussed the performance costs imposed when retaining a trace with increased verbosity. Detailing the effects of creating the execution graph within a transformation and the impacts of capturing orphans when using dynamic proxies during the process. Due to the impact imposed by capturing orphans, we stated that the method is still useful for detecting their creation. This application would be primarily for development to ensure that there are associations for all destination model elements. Then the previous engines can be used for production transformation systems. To show the generality of this, we recreated the case study for ETL and demonstrated the linear performance cost of the executable AST over object proxies. The two engines now provide a meta-model that contains what is happening within an M2M transformation. In this section, we shall insert these graphs into a Neo4j database for analysis.

We have already defined what an execution graph is in regards to an M2M transformation in Section 4.1 and defined the basic elements of Neo4j using CYPHER, Neo4j's query language, in Section 4.1.1. Using Python's `networkx` and `neo4j` modules we can convert our trace into a real graph and then persist it into Neo4j. This process is a simple traversal of the trace to access all invocations and their dependencies. The type of invocation labels the relationships between each of the graph nodes that represent th invocations of rules.

Figure 5.8 illustrates the transformation of our hospital scenario containing a single row in each table. It is stored within a Neo4j instance and contains the invocation information and their relationships to one another, as well as the rules used. Initially the graph looks very complicated; however, it can be used to optimise

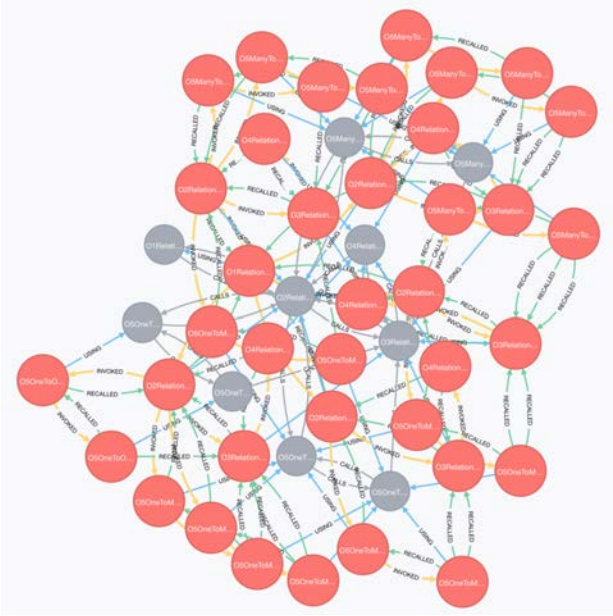


Figure 5.8: The execution graph of our scenario with a single row defined in Figure 5.4 stored within Neo4j. Showing the invocations and their relationships to each other and the rules that were used.

the transformation itself, given a capable engine. Opposed to looking at the whole graph we can separate it into two graphs: *1)* an invocation graph; or *2)* a rule dependency graph.

Invocation Graph

With our execution graphs stored within a graph database, we can use it to see what is happening within an M2M transformation. If for example, we see clusters of invocations that do not depend on each other, we might look at parallelising them onto many machines, or cores, if possible. This process is assuming that the source model is immutable, and as a general rule, this is usually the case for common transformations. Issues may only occur when using in-place transformations. These occur due to the modification of associations while traversing the model. Using

a copy of the input model avoids this problem, and provides a stable destination model. This problem mimics a concurrent modification exception in Java, but rather than amending a list; we are iterating an entire object tree where references may change. For this part, we shall only consider the use of non-in-place M2M transformations.

To parallelize any transformation is a difficult task for two reasons: *1)* parallel code is hard to write, and *2)* knowing what portions of code are eligible for parallelisation. The former is particularly important in interpreted languages as the most popular use a Global Interpreter Lock (GIL) (Beazley 2010). This lock prevents interpreters from sharing code that is not thread-safe with other threads. To complete this task, often new processes are created such that each process has their own GIL. Compiled languages, however, do not necessarily suffer from this trait, and allow executors to be shared and used by their threads.

Naturally adding threading code to M2M transformation rules may be considered a cross-cutting concern, an issue for Aspect Orientated Programming (AOP). On the one hand we want the business logic of our transformation to be obvious; however, on the other, we wish to optimise our transformation for speed. Being able to transform multiple tables at once reduces the overall time quite substantially. The question as to where to implement threading is an important one. If implemented within the rule: it is up to the developer to know the possible outcomes of what rules depend on each other. If implemented within the engine: it must be scheduled, but how can the engine know? In SiTra the obvious choice would be to parallelize those transformed using the `transformAll` method. Its use implies that the sources within the list are independent. Our transformation uses this method to transform each table within the database. The denormalization of data means they do not

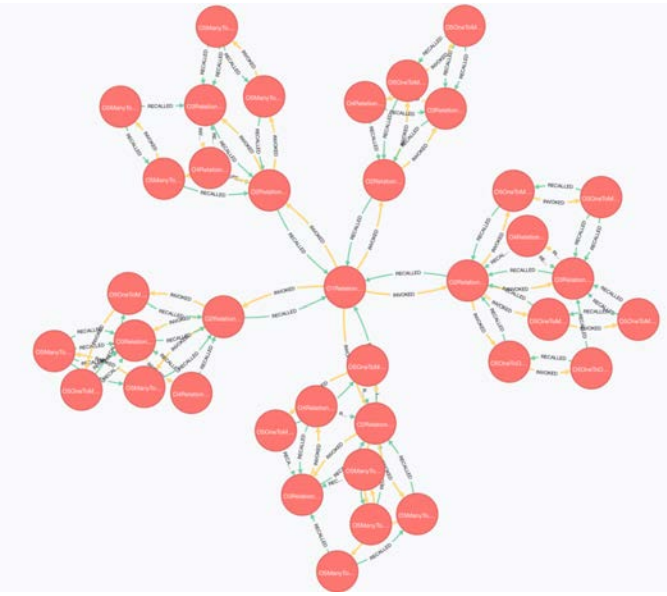


Figure 5.9: The invocation subgraph of Figure 5.8.

need to reference other tables.

The execution graph implies what is shown in Figure 4.1, i.e. the labelled directional graph defined in Section 4.1. Figure 5.9 illustrates the invocation subgraph of Figure 5.8. Removing the rule nodes we have a clearer view of what is occurring within the transformer with regards its execution. We can see what invocations others require. For instance, we know that the rule for transforming a relational database to an Apache HBase namespace is the root of the transformation and although the reverse is also possible, no other rule depends directly upon the namespace. However, this type of relationship is a perfect candidate for parallelization. Transforming a single table is a time-consuming task, even more so when transforming a sequence of them. This optimisation allows us to transform an instance with 100 rows of data using the `SimpleNestedTraceableTransformer` in 255 milliseconds rather than 588 milliseconds, a reduction of ~56% and only requires a small change to the code. The use of parallelisation has its costs, for instance

transforming a single row takes 23 milliseconds opposed to 6.29 milliseconds. The developer must know the limitations of the transformation to balance performance changes. These costs come from setting up new worker processes or threads.

The performance increase of this one optimisation shows the effects of multi-processing, or multi-threading, upon M2M transformations. The main question is what implements the parallelisation. As we have previously mentioned, this process is not relevant to the transformation. It is not part of the business logic of how to transform a source into a destination model. This knowledge implies that the engine takes care of scheduling these. How does the engine know what can and cannot be parallelised? It must have the ability to detect candidate rules for parallelization. Historical data allows the transformer to determine links between determine links between rules and derive possible parallelization techniques.

Another feature of the invocation graph is that we can see when invocations call upon others repeatedly, for instance when used within a loop. Whilst running our case study, we found our transformation of a foreign key was repeatedly calling for the conversion of the related row for each new value. The row was required to bind the Apache HBase value to it. This flaw meant for each value, the transformer was being asked to return the same value, which involves cache lookups and queries to other internal structures. Since the function is not constant, compilers will not and cannot optimise this. Moving this transformation to the outside of the loop prevents these unnecessary lookups and increases the overall performance of the entire transformation. Initially this may not have a large impact on small input models; however when a larger model is transformed: performance is paramount.

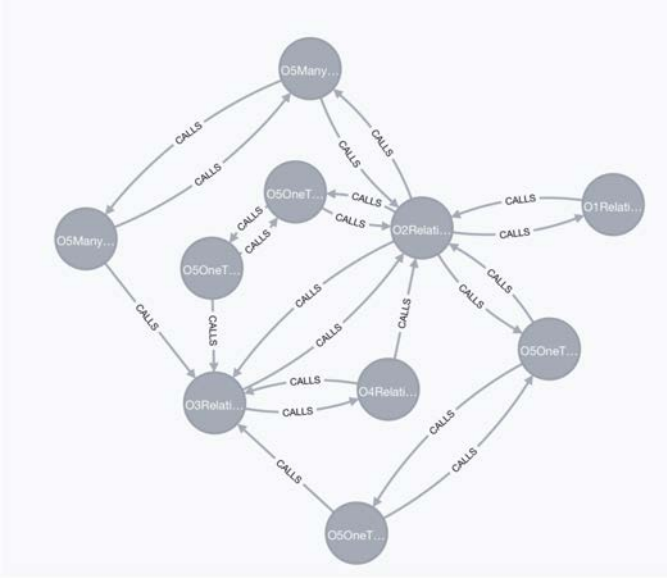


Figure 5.10: The rule dependency subgraph of Figure 5.8. Showing the abstract view invocations within an M2M transformation.

Rule Dependencies

The invocation graph provides plenty of information regarding what happens within transformations. We can view how invocations are related to each other, and what causes them to occur. They show independent paths of execution enabling developers to see potential candidates for parallelization to expedite a transformation. Another view of the invocation graph is the rule dependency graph. Figure 5.10 shows the rule dependency graph of our case study with one row per table, allowing for full coverage of our transformation. We can see that much of the transformation revolves around the rules that transform a table and that of the conversion of a row. This behaviour is due to the assignment of a column family and a row, from a specific table, for each value. Effort could be made here to optimise these rules as they are potential bottlenecks for larger datasets.

Our Python transformation does not use a modelling or powerful transformation

strategy, so it generates a heavily connected graph. To get a deterministic model, no matter where in the model we start the conversion, we need to bind both sides of a UML relationship. When using SiTra with plain old python objects (POPyO), the conversion of the database must transform and add all of the tables into the namespace's list. The engine would not transform any tables if it were not for this explicit call. Likewise, the transformation of a relational table into an Apache HBase table requires the mapping of the relational table's parent database to set the HBase table's namespace. Again, this explicit transformation will map the database into a namespace if it has not already done so.

This approach applies to all transformation engines; however, it is possible to forgo this when using a modelling framework as it will automatically modify the attributes that represent the reverse of the relationship. Naturally, this makes the transformation less general, and dependent on a modelling framework. OO2DB, an example by Epsilon that we have previously looked at, applies this method. When transforming a class into a table, it does not transform all of its columns. Instead, it is up to the transformation of the column itself to set its parent. The use of ECORE will automatically add it to the opposing side of the relationship. This approach changes the dependency graph of the transformation. The mapping of tables is dependent upon the conversion of a database; however, the reverse is no longer true. The namespace no longer invokes, or recalls, the results of the mapping of tables.

Another use of this graph is that it can show connected components. Connected components in graph theory are subgraphs that are in isolation within a larger graph. These are candidates for transformation upon different threads or even machines due to their independence from the rest of the process.

5.7 Confidence within Model Transformation

In previous sections, we have benchmarked the effects of implementing our new meta-model in two different M2M transformation engines, SiTra and the ETL. This new meta-model allowed us to retain the full execution of a transformation, and to capture objects instantiated within the binding phase. These mechanisms provide full accountability as to why and how each object within the destination model came to exist. This graph can be used to identify components for optimisation, parallelisation and general debugging. For every transformation we make, we gain more experience in the form of traces. These traces depicted the internal workings of the engine and abstract from the source and result. This abstraction allows us to discard the resultant models and focus on the events that occurred. These invocation events can simply dictate that a type was transformed into another type via a pathway. We persisted this information into a Neo4j instance, a graph database, storing these traces for later analysis.

In this section, we use these previous graphs as a knowledge base to provide some confidence in future transformations, by *learning* from experience. We use a form of feature analysis to find traces that we have once seen before. Feature analysis is a theory about how we as humans recognise certain patterns and shapes. The theory dictates that our minds break down sensory information into features and a comparison between that and what we have experienced previously evaluates to whether we recognise the scene or not (see Section 2.4.3). We have explained in Section 4.4 that there are two main components used to complete this task: *1)* graph comparison: to determine how relevant previous trace executions are concerning a new instance; and *2)* a weighing mechanism based on the activities of

the result or the transformation to prevent prominence bias. The first represents our recognition process of what we have seen before while the latter gives us more information about how important individual features are.

Historic Prominence. If our knowledge base contains any applicable trace instances, i.e. executions that are isomorphic or subgraph isomorphic to the new input: how important are they in respect to the latest execution. Historical prominence provides us with this information. These graphs come in varying sizes and from different rule sets, so it stands to reason that only those that are of equal size or less can be recognised. In the event of graph equality, the previous transformation executed in the same manner as the latest, if that previous execution was successful, then this is more relevant than a subgraph. However, in the event of a smaller feature, a sub-graph, its prominence is lower. When we find subgraphs, we are extracting features from the input. These characteristics cannot be larger than the overall graph. If the feature is a negligible part of the transformation, then it is of little importance for recognition. However, if we come across an execution that closely resembles the input, then it has a higher value. If we were to have many subgraphs that overlap, this increases the prominence of an invocation not in the new transformation trace.

Labelling aids in reducing the workload for the NP-Complete task of sub-graph isomorphism by reducing the possible permutations of vertices. We do not need to look at graphs or sub-graphs that have rules that are not present in the new input, as these cannot be isomorphic. Formally, we look for a historical entry h within new graph G where there exists $g \subseteq G$ such that $g \simeq h$. For g to be isomorphic to

h, and therefore sub-graph isomorphic to G, the label set of the candidate graph must equal that of g and also be a subset of the whole graph. If $\Sigma_{V_h} \setminus \Sigma_{V_G} \neq \emptyset$ then h cannot be a subgraph of G as $\Sigma_{V_h} \simeq \Sigma_{V_g} \subseteq \Sigma_{V_G}$.

When found, these sub-graphs can be overlayed, creating a *map* of the transformation. In effect creating a heat-map of rule invocations, i.e. nodes with a higher frequency. If this were to be inverted, then we would see cold spots concerning the input. These areas are parts of the execution graph that we have less experience with in respect to the rest. This experience relates to the confidence we have with them, so we are less sure about the consequences of the result and thus less confident in the final product. Looking at these allows us to focus efforts to mitigate or accept the risks that are involved with these segments.

Weighing Mechanism. The prominence of previous transformation traces only informs us that a sequence of events, invocation of transformation rules, has occurred before. These invocations have done some work to generate the resultant model. This task could be from: *a)* the transformation logic itself, or *b)* deferred task. The first involves the rule specification and its logic, the rationale behind the mapping of an object into another. This information can be measured by the amount of validation it has had, or a complexity metric, like McCabe (1976). The second would be similar to the first; however, it would focus on what was next in the process specifically the use of the resultant model. For example, if the resultant model was going to be used to generate code, i.e. there was a subsequent model-to-text process, what does that code do? Does it interface with anything of critical importance? Consider that the result of the transformation has some

interaction with a heart monitor, an infusion machine, a railway signalling system, or the life support systems on the Hubble Space Telescope. If the generated code were incomplete or incorrect: the use of the software could put lives at risk. Including these risks into our metric prevents the bias of prominence, and rather than treating all invocations as equal, we instead weigh down our level of confidence. This approach is not too dissimilar to our interactions with technology. Take a car, for example; we are more cautious with the response of the accelerator than the volume control of its radio.

5.7.1 Applying our Metric on a Small Transformation

Our full case study involves the transformation of a relational database to that of a non-relational database, specifically Apache HBase. The transformation itself is defined in Section 5.3 and consists of several rules that map the source to the destination including the structure and data of relational representation of data. We have benchmarked the collation of a more verbose trace in Section 5.4 and Section 5.5. Here we shall introduce the weighing mechanism used within our algorithm, specifically McCabe's cyclomatic complexity.

McCabe as a Complexity Metric

McCabe's algorithm is used to determine the number of linearly independent pathways within a graph, specifically within an execution graph. The core idea behind this is to limit the complexity of modules within a code base. A higher value is indicative of higher complexity, and therefore the module comes under scrutiny as to why it is so complicated rather than breaking it down into smaller functions.

If it is above ten, then the function should be broken down further to improve maintainability and reduce the surface area for mistakes. It is defined as follows: $M = E - N + 2P$, where E and N are the number of edges and nodes, respectively, in an execution graph, and P is the number of connected components. In a single routine: P is 1 and therefore the equation is often seen as $M = E - N + 2$. We used the Python library `mccabe` to calculate the cyclomatic complexity of the individual rules that form the overall transformation from the relational to the non-relational.

The core complexities of a rule is that of the guard and binding phases, the `check` and `set_properties` methods respectively. If the guard was incorrect, then it is reasonable to assume that the output of the transformation would also be incorrect. For instance, if the rule said it was applicable to a source object when it was not, it would tell the engine to execute the instantiation and binding phases. Often this would stop the transformation engine looking for other rules later in its internal list. Another side-effect of this is that the transformation of this source may generate more or fewer output objects of varying types. If another rule depended on the results of this particular invocation, runtime errors would occur. In the event of executing the binding phase, the source model may not have the correct structure or information to run without error, structurally or semantically. Both of these methods are important with regards to the complexity of a transformation rule. To combine them, we simply add the two values together.

Figure 5.11 lists the transformation rules, available to the engine, to map a relational database to an Apache HBase namespace and their complexity values. We have also provided a shortened identifier, in the form of r_i, for use during the remainder of this section. Note the different levels of work involved for each rule. Rules r_2 and r_3 have very low complexity within their method bodies. Both

Rule Identifier	Rule Name	Cyclomatic Complexity
r_0	O1RelationalDatabaseToHBaseNamespace	4
r_1	O2RelationalTableToHBaseTable	7
r_2	O3RelationalRowToHBaseRow	2
r_3	O4RelationalValueToHBaseValue	2
r_4	O5ManyToOne	4
r_5	O5ManyToOneRow	7
r_6	O5OneToMany	5
r_7	O5OneToManyRow	5
r_8	O5OneToOne	4
r_9	O5OneToOneRow	7

Figure 5.11: This table contains the cyclomatic complexity of the rules required to transform the relational into Apache HBase. Each has an identifier r_i, its name (implying its use) and its McCabe value.

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methods have a value of one due to the simple nature of setting attributes or returning a simple boolean expression. Due to the use of duck typing in Python, the rule r_9 has a substantially higher value. The `check` method for this rule requires a tuple for input, a foreign key and two tables. The expansion is necessary so that the individual components can be accessed and a decision made based on them. Three things could go wrong here:

1. The interpreter is unable to expand the input as it is not a tuple.

2. The tuple may have a different number of elements and again cannot be expanded into the number of parts expected.

3. The objects within the tuple may be of the incorrect type and may cause runtime errors later in the procedure.

These errors are captured within an umbrella try ... catch, which causes additional

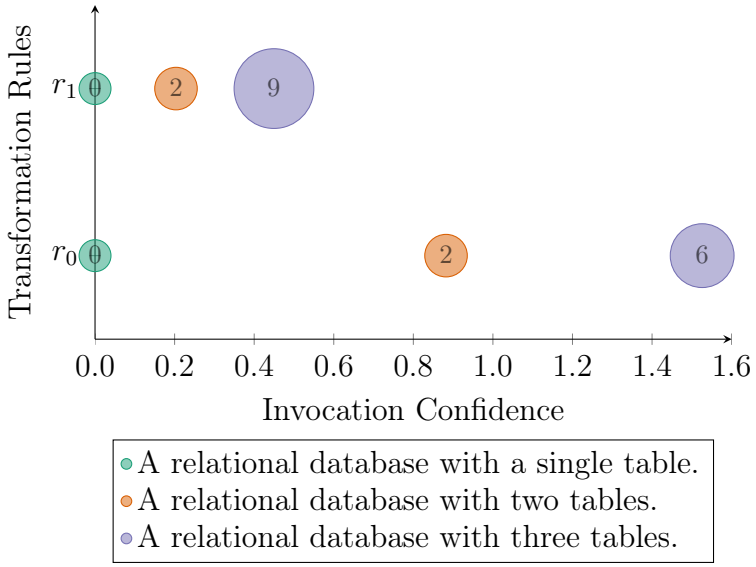


Figure 5.12: The confidence increase as we increase the knowledge base of a database with one, two and three tables. It is weighted by McCabe's cyclomatic complexity as defined in Figure 5.11.

branches in the execution path, which in effect increases the McCabe value. This practice is common in our case study as many transform tuples. Another example of high complexity is r_1. r_1 does not use tuples and therefore doesn't have the same reasons as to why there is more complexity. The guard must look for *prime tables*, which involves nested conditionals and loops. Whilst the binding phase iterates through the tables constraints and the tables that reference it.

Confidence in Transforming the Relational into the Non-Relational

We can form a subset of our transformation such that the invocation graphs are not unlike our example in Section 4.1. The invocation graphs Figures 4.2 and 4.3, on Pages 68 and 75 respectively, can all be generated using our case study. Rather than using an entity with varying numbers of attributes we can use a relational database with different numbers of tables. To show our increase in confidence,

we will initially describe our method using this, smaller, example using McCabe's weighing mechanism and the values in in Figure 5.11.

Figure 5.12 illustrates the progression of our metric against the rules they apply to as the historical data set increases in size. Specifically, we use Figures 4.2a, 4.2b and 4.3 to enhance our knowledge base incrementally and view our confidence in their output. This bubble graph represents the distinct confidence values we have for invocations in a new transformation concerning past transformations. The size of each bubble is indicative of the number of instances of that value, however for clarity, and due to the necessary limitations on the size of a bubble, the number of instances appears within each point. The further to the right we move in the graph the more confidence we have in that group of invocations that the bubble represents.

No experience. Initially, we have no previous experience. There are no models within our knowledge base and therefore no previous experience regarding transforming the relational into the non-relational. Assume we transform a single relational table into a single HBase table and a Column Family, which creates a trace as per Figure 4.2a, we have nothing to compare. Thus we must complete a form of validation on the resultant model before we deploy it to the next step. Whether into another model transformation or possibly code generation. Our graph illustrates this with the zero values for both rules. Assuming this is successful, we deploy the resultant object and retain the trace within our dataset.

A Knowledgebase Containing a Database with a Single Table. We now have one item within the knowledge base to use as our history. Given a database with two tables, as per Figure 4.2b, and a knowledge base containing Figure 4.2a, we can see two sub-graphs are isomorphic matches. r_0 appears twice in two separate graphs and r_1 once for each table. Since the confidence value will be the same for both instances of r_1, we can group them. The number two within each bubble illustrates this; there are two cases of this with a particular value. r_1 has a much lower confidence value as now the complexity of transforming columns and constraints is taken into account. Despite having no columns or constraints, the rule has this capability; therefore, the cyclomatic complexity still exists. Prominence alone creates a disparity of 59.6% between the two rules; the complexity increases this to 76.9%. Since we have only seen each of these twice we would consider more validation and then if applicable, add this to our knowledge base.

Database with a single table and another with two tables. We now have a knowledge base containing two traces. If we were to receive a new transformation of a database with three tables: creating a trace as per Figure 4.3 on Page 75. Six symmetric subgraphs are related to the first two: three against Figure 4.2a and three against Figure 4.2b. When we consider symmetry in our process, we only allow a subgraph to be considered once for a given set of vertices. For example, assume the isomorphism between the new instance and Figure 4.2b. Specifically the mapping of $EtoT_y \rightarrow EtoT_z, AtoC_{y^0} \rightarrow AtoC_{z^0}, AtoC_{y^1} \rightarrow AtoC_{z^1}$. We can see that the mappings of y^0 and y^1 are interchangeable. We disregard this in a symmetric case. Once again r_0 is in all instances as it is the root of all

transformations. Additionally, all invocations of table require the result of it to maintain the heritage between tables and their database. r_1, on the other hand, has nine matches. Due to the underlying nature of the isomorphic graphs, all invocations have the same value of confidence so we can group them. The weight of r_1 continues to weigh down the original value of prominence.

5.7.2 Introducing New Features with an Increasing Knowledge Base

The previous section discussed a small example showing the increase in confidence as the knowledge base grew. However, the transformation traces were especially small and unrealistic. Often an M2M transformation will consider a larger input, in our case a few tables with varying columns and amounts of data. Using the same incremental style, we enrol the full transformation of a relational database into an Apache HBase namespace. Firstly we shall transform, separate tables with different numbers of columns and rows, and then we shall include new rules that resolve foreign key constraints.

Figure 5.13 illustrates the first phase of building confidence using separate and unrelated tables. Here we can see the progression of trust in an M2M transformation as the input size increases in various ways. Our knowledge base increases in size as we continue to transform more input models and accept their result. Subsequent models develop in structural complexity, i.e. we use more relational features, which in turn increases the number of rule types that are utilised by the engine. Initially, when we have one table and one column there is no experience to speak of, our confidence is zero. We then introduce rows of data into it and increment the

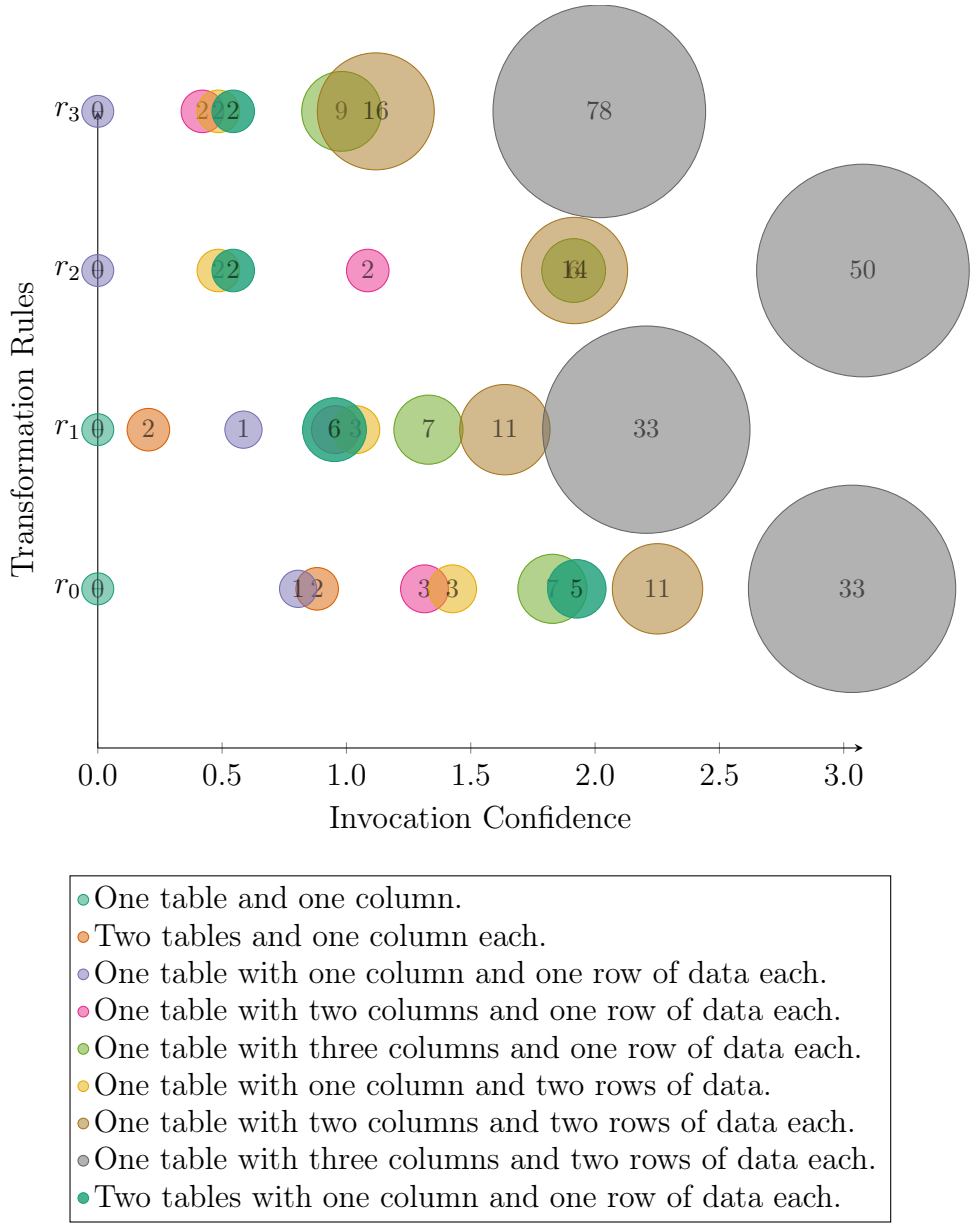


Figure 5.13: The progression of confidence in future input models as the knowledge base increases in size.

number of columns. The general trend of confidence is that the more times a node appears in historical traces, the more confident we are. So we expect our trust in a transformation to increase as we recognise more and more features of it.

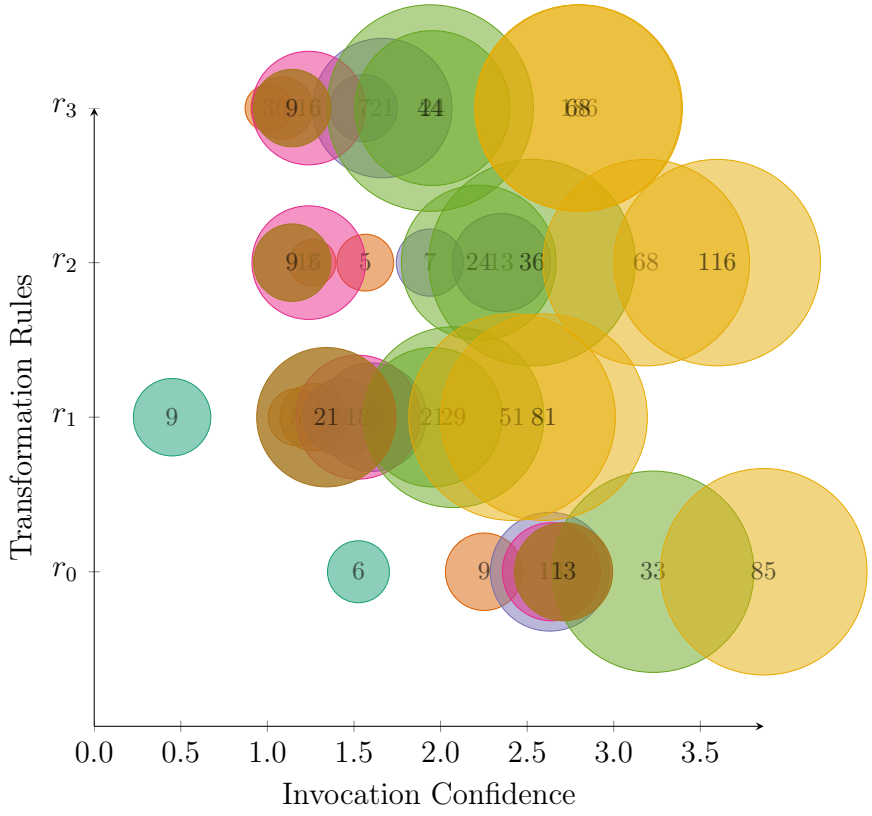
Our test data was designed to increase linearly, such that our confidence would rise as experience increases. However, this is not always the case. This graph also shows a drop in trust when considering another dimension, the number of columns. The test case of *two tables with one column and one row of data each only* matches with the first three input models. Anything with more than one row or column is not comparable due to the historical trace having more vertices labelled as r_2 and/or r_3:

$$\{v \mid v \in V(h), l = \ell_{V_h}(v) = r_i\} \setminus \{v \mid v \in V(g), l = \ell_{V_g}(v) = r_i\} \neq \emptyset \text{ for } i \in \{2, 3\}$$

Here we remark that there is a drop in confidence as we cannot reconcile much of the graph in question.

Continuing this process, Figure 5.14 shows more transformations given the previous data sets. In this instance, we transform models that related to more of our knowledge base. Specifically, we introduce more inputs that contain two tables and then create a new three table model. This incremental approach increases the applicable historical traces that relate to the three table. We see that there is a general increase in our confidence value as we see more and more matches in the past set. However, there is a sudden decrease when we reach the last as there are only five historic graphs that are relevant for analysis due to the reduction of rows in each table.

Another key difference to note that there are more values per rule for a given



- Three tables and one column each.
- Two tables with one and two columns respectively and one row of data each.
- Two tables with one and three columns respectively and one row of data each.
- Two tables with one column and two rows of data each.
- Two tables with one and two columns respectively and two rows of data each.
- Two tables with one and three columns respectively and two rows of data each.
- Three tables with one column and one row of data each.

Figure 5.14: Further progression of confidence, given Figure 5.13 as an initial knowledge base.

transformation. This trait occurs by the introduction of a variable number of columns within tables. So far the input models have been symmetrical, and therefore the confidence we have in invocations that use a particular rule has been equal across the graph. We now have invocations of the same rule with multiple confidence values. This result is due to the coverage of previous traces. For instance, when looking at *two tables with one and two columns respecively*, we can only have instances with one column apply to the first, while the opposing side can match with those with one and two causing us to have a higher confidence in the second table as more matches apply. Consider a knowledge base consisting of two traces that have transformed the individual tables separately, i.e. a table with one column, h_0, and another with two, h_1. Assuming that our new execution trace is composed of them both $g = h_0 \cup h_1$: since $h_0 \subset h_1$, all matches that relate to h_1 will contain matches of h_0 too. Once more, since h_1 is larger than h_0, the reverse is not true and results in different confidence values for those nodes.

These effects happen when we introduce brand new rules, i.e. new behaviour. Figure 5.15 uses the same knowledge base as our previous examples; however this time we introduce a one-to-many relationship between the two tables. We are yet to have seen, test or investigate the results of this transformation. Thus we have four zero points. This value is indicative of having no previous knowledge of a subgraph that is smaller than the input graph invoking such a rule. These rules, r_4, r_5, r_6 and r_7, all relate to the de-normalisation of either side of a one-to-many rule. The graph then shows what happens if we see the same graph as an input, now it has theoretically been tested and added to the database of historical traces. You'll notice that we now have an instance of each of those four rule types, allowing us to determine whether we should continue or not. Since we only have one instance,

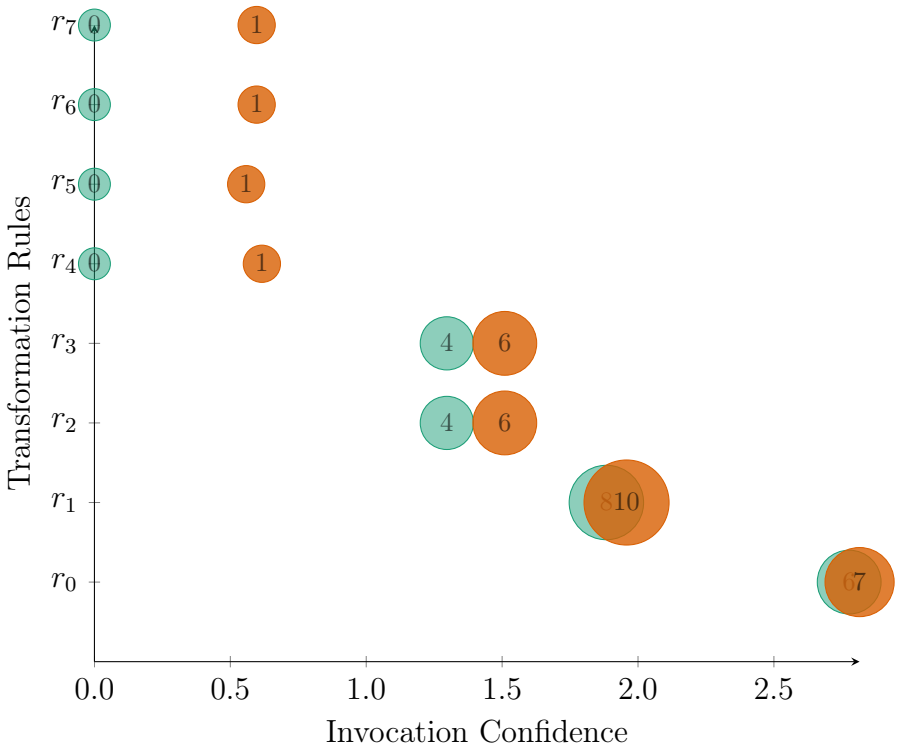


Figure 5.15: Using Figure 5.14 as a knowledge base, this shows the confidence we have in a new transformation containing two tables with a column and a row each; however these two tables are related via a previously unseen one-to-many relationship.

it would be more prudent to generate and test a succession of input models that include this trait. In turn increasing the number of cases within the knowledge base that become a subgraph of the input, thus improving their prominence and confidence.

5.8 Chapter Summary

In showing benchmarks for both our meta-model and our new algorithm in SiTra and ETL (see Sections 5.4 and 5.5), we have shown that collecting data regarding the execution of a transformation is feasible within production environments. Therefore the accountability of a transformation has been increased with minimal effects upon performance. However, when capturing orphans ETL is the only engine of the two that was able to complete this task acceptably. The effects to performance when considering SiTra is exponential. This time increase is due to the generation of proxies that recursively intercept new objects assigned to the target tree. Generally speaking, processes such as this should be side-effect free. So we argue that while this component is not of any use within a production environment, it is possible to use it during development, to avoid the generation of orphans in the first place. This approach would allow the user the efficiency of a simple Java-based engine while training developers to evade making these kinds of rules.

Following this, we placed these traces into Neo4j, a graph-based database (see Section 5.6). Here we formalised the transformation trace to define what nodes and vertices would mean. We then show that we can use this graph for more than confidence. The whole graph contains essential subgraphs that are vital for optimisation of transformations. For instance, an invocation graph minus the rule nodes

can unravel a graph into subgraphs that are not backwards dependent: these are candidates for parallelisation. Another example, it makes sense that an invocation should only call upon another once and if this is not true there is an issue with the calling rule. An instance of this appears in our transformation; we attempted to transform an element within a loop. The input of this transformation did not change, so the engine had to complete the same job (checking for applicable rules, finding the result if it had been transformed before, transform it if not, and return it). Moving this call outside of loop reduced the engine's workload. Additionally, the rule dependency graph can potentially detect connected components. The independent graphs are indicative of independent transformations, which can be cut down and potentially completed on other hardware.

Finally, we demonstrated the acquisition of confidence using our newly created knowledge base (see Section 5.7). This process entailed running our case study using our Python version of SiTra to transform instances of a relational database that gradually increase in size and feature set, for instance, variations of singular and multiple tables and columns, and table relationships. By phasing the process, we were able to use smaller and less feature-rich samples to provide a knowledge base that provides confidence in a new, more feature rich sample. We illustrated this in a bubble graph where each bubble represents a distinct confidence value, and its size represents the number of instances that value appears in the graph. The larger the number of instances of a given value demonstrates the importance of the overall graph of that particular type of invocation. If we had a low confidence value and many of them, we would have noticeably low assurance in that group of invocations for that transformation.

5.8.1 Testing Environment

A MacBook Pro 15" (Late 2013) with a 2.3GHz i7 and 16GB of RAM sequentially executed our benchmark experiments. The machine was left alone until completion or until it was deemed too infeasible to wait for the result. The latter was particularly important when we consider the exponential effects of capturing orphans with SiTra.

5.8.2 Validity of Experiments

Decision to use SiTra and ETL

We limited our evaluation to using SiTra and ETL due to the availability of the trace in rule-based M2M transformation engines. As we have discussed in Section 2.3.3, there are two types of trace: internal and external, and only the latter makes the associations available to post-mortem processes. The ATLAS Transformation Language (ATL) (Jouault et al. 2008) and Operational Query/View/Transform (QVT-O) (Object Management Group, Inc. 2016a) both use an internal trace. It is questionably possible to access the trace from QVT-O; however, it uses an API that has restricted access. This access requirement informs us that it is meant to be for internal use only, and therefore we did not want to tamper with it, as we were unsure as to how it would affect the engine's internals. Additionally, our previous work heavily involved SiTra, so implementation and porting to Python was a relatively simple task. We also had some support from the ETL community that allowed us to know how ETL worked and how we might inject our trace meta-model safely. Even with these two engines, we have shown some generality

for those wishing to implement our algorithm into their engines.

We attempted to use Xtend (Eclipse Foundation 2014), however, this was simply a declarative Java language with inbuilt templating. Thus, Xtend has no natural transformation engine or scheduler. The development of this is out of the scope of our work and would have virtually recreated SiTra, as that is what we know! The only additional feature would have been the ability to use polymorphic dispatch. This functionality allows a specific method for each sub-class without the need of a visitor pattern or multiple rules: a feature unavailable in Java. The benefits of this are minute when we consider that the guard will become more complicated as to allow for all instances where it is applicable. One would have to determine what was better for the process: inheritance or the visitor pattern. We believed, based on the fact we were using object orientation, inheritance was a better choice, which in turn just recreated SiTra.

Comparion between SiTra and ETL

The biggest factor threatening the validity of our comparison between the results of SiTra and ETL was the way in which ETL executes. Due to the executable abstract syntax tree, we were unable to reuse the result of parsing an ETL script. The effect of this was that for each iteration, we needed to read the ETL script and clean up each time. This interaction with I/O can be variably affected by other system processes that we attempted to minimise, power saving, system updates, etc. Rules for SiTra, on the other hand, were purely written in its native programming language: Python or Java. Thus rules were present for subsequent transformations, and no more I/O was involved as they were already in memory. To make the

comparison valid, we used a new instance of the SiTra transformer as to start afresh for each transformation. Creating the new instances would involve reinitialising the rules used, the caches and traces. Using a specialised `ClassLoader` in the event of Java, or using `reload` to reload the Python module containing the rules, would induce a certain level of I/O variability to the process. At this point, we felt that altering how the JVM or the Python interpreter loaded and unloaded class and modules would again introduce more variability, so we chose to continue without this.

CHAPTER 6

SUMMARY, DISCUSSION AND CONCLUSION

6.1 Summary

We presented an approach to quantify confidence in a model-to-model (M2M) transformation based upon previous executions, specifically combining the validation Oracle, model-snippets, and a theory of how humans recognise objects. We investigated issues within the current state-of-the-art in rule based M2M transformation. This research uncovered some problems that, for full assurance, needed to be fixed to provide full accountability of all resultant objects. We introduced a general algorithm to resolve these issues and demonstrated these in two transformation engines, the Simple Transformer (SiTra) and the Epsilon Transformation Language (ETL). From the point of full coverage, we were then able to store traces into a database to form a knowledge base of what we have *seen* before. Basing our comparison on the execution itself opposed to the resultant model allowed us to look for features within a path and provide information based on coverage. We generate a heat map over a new trace to view components that we have experienced

before, inverting this gives us information about items that we have no or less experience. This process, however, was biased as it treated every invocation of a rule as equal, which is not true. Our method then incorporated a mechanism to weigh down, or even up, the value of a node based on the complexity of the rule itself and its place in the transformation.

Our work has made the following contributions:

- An investigation into traceability within M2M transformation and the identification of elements that prevent full accountability, namely orphans and the use of an inappropriate structure.
- The design of a general algorithm to maintain a full trace to provide accountability.
- A full implementation of SiTra that addresses these issues and a quantitative analysis of its drawbacks with regards to performance.
- To demonstrate the independence of our approach, we have written an extension of ETL that also maintains a full trace and quantitatively analysed its performance.
- A qualitative analysis of how one might learn from previous experience regarding M2M transformation.
- A toolset that enables a trace to be persisted into a knowledge base and later analysed for comparison to new transformations to aid in the quick deployment of resultant models based on previous experience.

6.2 Discussion

The primary contributions of this thesis are the introduction of a new meta-model for traceability within M2M transformation (see Figure 3.7) and a general algorithm for collecting information about the execution of a transformation (see Algorithm 1). We introduced mechanisms to collect objects that were not created by the engine (see Sections 3.2.2 and 3.3.2). Then with the complete transformation trace, we were able to develop a metric to determine how much of a transformation we recognise from previous experience (see Chapter 4).

Our algorithm and meta-model provides an implementation independent approach to be used in many M2M transformation engines that have problems with side-effects and the lack of information within their own trace system. These come in the form of imperative or hybrid languages that are not specific to transformation and allow global state, such as Operational Query/View/Transform (QVT-O), SiTra and ETL (Saxon, Bordbar, and Akehurst 2015). With this meta-model, rule dependencies can be derived, assuming full code coverage, enabling the possibilty of incremental transformations. This dependency information allows us to see what transformed a source and then what that transformation called, enabling the engine to re-transform any subsequent rules. Once the rule dependency structure is known, it is also possible to parallelise rule types depending their interactions. This time we must assume that the source model is fixed and is not going to change during the transformation itself.

Naturally, we can store more than just the invocation information. We can actually store the source and target information too. This enables us to view chains of transformations, i.e. the result of one going into another. When using ETL, the

context is only relevant to one transformation, which in turn is assigned to a script. We had issues when testing the performance of our approach as we were unable to reuse transformers so our tests included the I/O required to open and close the the ETL scripts themselves. However, if this is true, it means a context cannot be related to another and therefore relationships between them must be derived. The ATLAS Transformation Language (ATL) also requires a re-initialise before continuing with another transformation. However, our implemenation of SiTra allows us to change the rule set and then transform again using the same context and therefore retain the entire transformation. This ability enables us to store the source and target models, whilst at the same time automatically connecting the links between chained transformations.

The additonal work load in collecting this information is, for SiTra, on average 6% with a worst case of upto 10%. However, transforming 55k objects into 138k objects took around 6.3s opposed to 6s (see Section 5.4). In the greater scheme of transformation this performance hit is manageable for most transformations. However, when we include the orphans it increases exponentially. We shall explain more on this in the next section. Whereas our addition to ETL increases the overall throughput by 26.51%. Consider that the use of this framework decreases the performance by around 258% when compared to SiTra before retaining any more information than a linear trace. The inclusion of ophans is an important point though, it rises linearly and is only an extra 6.36% on average (see Section 5.5). It is up to the developer whether, they need to be nearer the processor or whether they can accept higher thoughputs for the convenience a framework like Epsilon suppies.

The previous work allows us to have complete accountability within M2M

transformation. Without this we would not necessarily know what caused an invocation of a rule to begin with, or how the transformer completed its task. Additionally, the target model may contain elements that cannot be reversed back to the source; an object with an existential crisis, with no reason to be. Now we can see the entire transformation we can compare it to previous invocations to learn from past experience. Our system can quantify how much of a execution graph it has seen before by overlaying the old over the new creating a heat map of a transformation, taking into account the differences in size of the historic to the new (see Section 4.3). It does this by associating information to each node within the latest execution path from each historial path. To avoid bias we have provided a mechanism to weight up or down a rule invocation (see Section 4.4). Validating this by using McCabe's cyclomatic complexity, showing that not all rule invocations are equal (see Section 5.7.1). This is a general function pointer, taking in a rule and returning its weight and is customisable for different algorithms.

6.2.1 Weaknesses

A fundamental issue with our approach is that sub-graph isomorphism is NP-Complete (or more specifically, it is NP-Complete when there are no labels or when repeated labels are present). That is the solution is difficult to discover, however, once found is easy to verify. This trait is proven by the clique problem and the Hamiltonian cycle problem (Cook 1971; Karp 1972). This obstacle results in an exponential amount of work finding matches, per historical trace. Our framework currently doesn't do anything to reduce this. Due to the way our graphs are stored, in Neo4j, labels are indexed within the database engine. It would be more prudent

to narrow down the number of candidate graphs before passing them over the network. We have already discussed in Section 5.7 that we need only involve graphs that are less than or equal to the size of the new graph G, use a subset of the rules that were used and have no more instances of those rules than those in G. More formally, where we have a new trace $G = \langle V, E, \ell_V, \ell_E, \iota \rangle$ and a historical trace $h = \langle V', E', \ell'_V, \ell'_E, \iota' \rangle$, we only require it for comparison if $|V_G| \geq |V_h|$, $\ell'_V \setminus \ell_V = \emptyset$ and $\forall l \in \ell'_V, |\{v \mid v \in V, \ell_V(v) = l\}| \geq |\{v \mid v \in V', \ell'_V(v) = l\}|$ for all historical traces in the system. This reduction could substantially reduce the number of candidates delivered from the database engine preventing unnecessary comparisons and network traffic.

Additionally, performance increases may be achievable using other sub-graph isomorphism techniques. Bonnici et al. (2013) introduced a method that creates a search tree, not unlike VF2, however, reorders the search tree based on fast and straightforward heuristics to prune options earlier in the proceedings. The process reorders the search tree such that nodes with the most-constraints fail-first (Bonnici and Giugno 2017). Using the fail-first principle stops the traversal earlier, opposed to the general brute force or look-ahead methods. We were unable to test this approach as there was no viable method to use it within our framework. To allow this, we would need to implement this method in Java or Python to work with our current toolset. However, performance increases in subgraph-isomorphism may be negligible within small transformations, as shown by Carletti, Foggia, and Vento (2013).

Another key area of weakness is that of orphan capture, as described in Section 3.2.2. The approach for our engine, SiTra, increases exponentially as the input increases. The effects are manageable for smaller transformations; however, the

more invocations that occur time will become an issue. This problem comes from intercepting all accessor and mutator methods to proxy the inputs and outputs to capture what we have not seen before. We are increasing the workload for simple getter and setters quite substantially. The engine needs to know whether the input of a setter came from any previous rule invocations as well as the orphans created by them. By this point, the trace could be massive. A way we could get around this is to, once we have found an orphan is to keep a mapping of it to the invocation that created it, but where do we stop caching? The more we cache, the more memory the engine needs. Despite ETL having longer response times, they are at least linear when capturing orphans. The executable abstract syntax tree that ETL uses captures the *new* keyword and only needs to retain the object. This is because the object is an orphan at this point, the engine did not create it, and therefore can blindly be preserved. A framework specific version of SiTra would be able to use meta-modelling observer patterns. For example, if one were to use EMF we could use the notification adapters that it implements to track setters to find orphans. It would also enable us to traverse with ease into new objects via their tree iterable.

Our approach also only looks at *good* trace elements. That is the knowledge base contains transformation traces that are deemed to have been successful in deployment. It does not include times where they did not work. An extension of our framework could include the ability to use anti-trace patterns. A way of negating the cumulative effect of the transformation trace. This consequence would occur when a trace has not completed its task correctly. However, for this to work rules would have to be versioned as it would be unrealistic to expect brand new transformation rules for every bug discovered. An inclusion of a version number

in the graph labelling would enable the engine to distinguish the variety of rules. An argument against this is the increase in graphs within the knowledge base, increasing the number of candidate graphs to analyse.

Another drawback is that it does not take into account rule maintenance or the fact that software progresses. The way we label our rules is using its name, it would be more prudent to add a version string to it. This addition would automatically ignore all previous traces that include older versions for comparison as the label would differ. Therefore pruning the potential list of traces that apply to the new transformation. A further idea may include the ability to specify a range of possible versions for comparison. However, the matching technique would become more complicated due to the additional pruning code required. Additionally, as software progresses rapidly, traces may become irrelevant and numerous quite quickly. A consideration to evade this would be to have a sliding window of traces that makes traces obsolete after a period. How much time may depend on the frequency of transformations and the development of the rules required and thus would be dependent upon the domain in question.

Our work was only evaluated using one simulated domain, the transformation of a relational database into a non-relational database, specifically Apache HBase. However, this transformation had all of the hallmarks that we have defined in Section 3.1 and since the move to *big data* is becoming prominent, we felt that this was a good demonstration of both capturing trace data and making sure that the data is in good shape afterwards. A continuation of this work should revisit our assumptions about transforming relationships and possibly create a library to enable others to migrate their data to test our framework in a real setting. Additionally, other domains should be investigated. In our view the future of our

work could be extended in a few ways:

- Investigation of new matching techniques — this may include new heuristics to reduce the number of graphs to check or other ways to compare the graphs.
- The use within other domains — initial efforts were on transforming a DSL to describe the symptomatic behaviour of malware into C code to find them; however, the transformation albeit not simple in regards to the binding phase, it was regarding the invocation of the transformation. It was also very orphan intensive, which started our research into that area.
- Investigate anti-trace patterns — currently we know what worked well, but if something ceased to work: what should we do next?
- How to interact with this information — currently we have a bubble graph to show the values about the rules in question. Depending on the size of the transformation, a navigable graph might be better placed to allow us to see exactly where the cold spots are.
- Parsing and code generation — we have the information for many levels of M2M transformations, however in the event of text-to-model, we have no knowledge of what part of the AST caused the source to exist. Likewise, with model-to-text, what source becomes part of the final AST?
- Handle evolving transformation rules and software systems — our process currently uses all historic traces and does not take into account rule versioning. Naturally as software progresses legacy traces should be pruned, and as rules are modified previous versions should be deprecated.

6.3 Conclusion

Verification and validation are common methods to make sure that something works as intended, however, sometimes these mechanisms are time-consuming and can be too complex to be feasible. We have looked into using traceability to provide information to focus validation efforts or to give developers the ability to mitigate risk based on previously deployed instances. Systems like this could be used to expedite the development process when needed, for instance, when migrating large amounts of data or generating low-level, mission critical code. We hope that we have introduced work and ideas to provide a base for future development.

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APPENDIX A

APPENDICES

A.1 Multiple Inputs and Outputs for SiTra

At the core of the Simple Transformer (SiTra) is the definition of a rule. A rule is a simple mapping of a single type to another, `Rule<S, T>`. The use of generics, however, makes the transformation of composite objects difficult. Specifically, in the type safe world of Java. Here we shall demonstrate a method to solve this issue using a wrapper for composite sources.

A.1.1 Inputs

To have multiple inputs we need to generate wrappers for transformation. To do this, we perform another interim mapping. Figure A.1 illustrates such a transformation. Continuing with our case study example, the mapping of a relational database to an Apache HBase database (see Section 5.1), we need to view foreign keys bidirectionally. This process is necessary for the denormalization of data. Firstly we define some wrapper classes: `Relationship`, `FromOne`, `FromMany`, `ToOne` and

`ToMany`. These objects wrap the applicable tables with the foreign key for expansion into their Apache HBase tables. The `From*` variety of relationship relates to the target table. The `To*` variety of relationship relate to the table that owns the foreign key, or the table that refers to the target. A transformation of a `ToOne` relationship would build a column family within the target Apache HBase table. A conversion of a `ToMany` would involve creating column families for all fields of the owning table to emulate a sub-table within the target instance. Next, we define a transformation rule for one-to-many relationships in Figure A.1. This rule simply creates an pair of relationships, in essence creating two stable orphans. This method, however, allows the engine to iterate the collection before the binding phase to detect these orphans. Alternatively, the engine will proxy the entry and intercept its accessors.

A.1.2 Outputs

Many alternative transformation engines allow the user to return a collection of objects. This feature is often available in transformation specific languages opposed to general purpose languages. In the case of our Java version of SiTra we are only able to return one object, `T` (defined in `Rule<S, T>`). To evade this drawback, we can wrap output objects. Not unlike how we created wrappers for inputs. However, our outputs contain constant values.

Figure A.2 illustrates the transformation of an entity to a table, comparable to that explained in Section 3.1.3. Here we have four classes: two output wrappers and two transformation rules that use them. The first two are wrappers containing only the objects required for each output. We need only a table, a primary key and

```
1  public abstract class Relationship {
2      public final ForeignKey foreignKey;
3
4      public Relationship(ForeignKey foreignKey) {
5          this.foreignKey = foreignKey;
6      }
7  }
8
9  public class FromOne extends Relationship { /* ... */ }
10 public class FromMany extends Relationship { /* ... */ }
11 public class ToOne  extends Relationship { /* ... */ }
12 public class ToMany  extends Relationship { /* ... */ }
13
14 public class DenormaliseOneToManyRelationship extends
15     Rule<ForeignKey, List<Relationship>> {
16   @Override
17   public boolean check(ForeignKey source) {
18     return source.isMany() /* && ... */;
19   }
20
21   @Override
22   public List<Relationship> build(ForeignKey source,
23       Transformer tx) {
24     return new AbstractMap.SimpleEntry<>(new FromOne(source), new ToMany(source));
25   }
26 }
27
```

Figure A.1: An interim transformation to handle multiple input objects.

a column for a basic transformation. However, the transformation itself changes if the input entity extends another. If this is the case, a foreign key and a referring column are required to create the relationship between the table and its target. We then have two rules. This first defines the transformation of a Java Class into the base model of our output. The latter extends the former but builds the extended wrapper. This class calls upon the binding phase of the parent rule (on line 41) and then continues with its specific binding.

```
1  public class EtoTOut {
2    public final Table table = new Table();
3    public final PrimaryKey primaryKey = new PrimaryKey();
4    public final Column primaryKeyColumn = new Column();
5  }
6
7  public class ExEtoTOut extends EtoTOut {
8    public final ForeignKey foreignKey = new ForeignKey();
9    public final Column foreignKeyColumn = new Column();
10 }
11
12 public EtoT extends extends Rule<Class<?>, EtoTOut> {
13   @Override
14   public boolean check(Class<?> source) {
15     return source.getSuperclass().equals(Object.class);
16   }
17
18   @Override
19   public EtoTOut build(Class<?> source, Transformer transformer) {
20     return new EtoTOut();
21   }
22
23   public void setProperties(EtoTOut target, Class<?> source, Transformer tx) {
24     /* bind attributes */
25   }
26 }
27
28 public ExEtoT extends EtoT {
29   @Override
30   public boolean check(Class<?> source) {
31     return !source.getSuperclass().equals(Object.class);
32   }
33
34   @Override
35   public ExEtoTOut build(Class<?> source, Transformer transformer) {
36     return new ExEtoTOut();
37   }
38
39   public void setProperties(ExEtoTOut target, Class<?> source, Transformer tx) {
40     /* to bind attributes */
41     super.setProperties(target, source, tx);
42     /* then the bind foreign key */
43   }
44 }
```

Figure A.2: An example of how to produce multiple outputs in SiTra.

A.2 Multiple Inputs for ETL

Like SiTra, the Epsilon Transformation Language (ETL) is also unable to accept multiple inputs. The domain specific language does not account for this and therefore is currently unable be written in such a way. The engine itself is also unable to accept more than one object as a source object. This behaviour is due to the underlying implementation only taking a single source object. Thus the language and the engine would need modification to enable multiple inputs in ETL.

However, like SiTra, it is possible to resolve this using an interim transformation. Our case study in Section Section 5.5 uses this approach. Figure A.3 shows one of these transformations. The transformation here is a more primitive form of Appendix A.1.1; however, it does not imply which side the transformation is on. The `To*` and `From*` forms implicitly indicate whether it the transformation is with the referred table or the referencing table. Instead, we explicitly define the table in which the wrapper relates. For our purpose, we assume all relationships are bidirectional and therefore two wrappers are created for each relationship. The transformation of such a wrapper involves an additional guard within the rule as to verify that the table given is the referrer or the referring table. Opposed to a simple type check that forms the core operation of ETL's scheduling process.

```
rule TableAndForeignKey
    transform foreignKey: Rel!relational::ForeignKey
    to left: Interim!rel2hbase::TableAndForeignKey,
    right: Interim!rel2hbase::TableAndForeignKey {
    left.table = foreignKey.table;
    left.foreignKey = foreignKey;

    right.table = foreignKey.target;
    right.foreignKey = foreignKey;
}
```

Figure A.3: A simple transformation that generates wrappers to transform combinations of items using ETL.