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MEASURING TRIGGERING-INTERACTION COMPLEXITY ON ACTIVE DATABASES†

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Abstract — Distinct software metrics have been proposed for programs. By contrast, metrics for databases have been neglected on the grounds that databases were mere plain files that do not affect considerably information systems maintainability. However, later enhancements on database systems have considerable increase the complexity of the elements kept within the database realm. Such complexity makes metrics a valuable tool to understand, monitor, control, predict and improve software development and maintenance database projects. Triggers are a case in point. Several reports warned about the difficulties to cope with large sets of triggers. Based on the difficulty to ascertain the causes that make a given rule to be triggered, this paper proposes three different metrics for measuring trigger complexity, namely, the triggering potential, the number of anchors and the distance of a trigger. These measures are characterised above the level of the ordinal scale using the measurement theory. Validation of the proposed metrics has been conducted through a set of empirical experiments.

Key words: Triggers, Metrics, Databases

1. INTRODUCTION

Software engineers have been proposing large quantities of metrics for software products, processes and resources [4, 3, 8, 5, 15]. However, most of the metrics focus on program characteristics, disregarding databases [22]. Several works address data model comparison [2, 20, 10] but there is shortage of proposals for ascertaining schemata complexity. Some recent proposals have been published for conceptual schemata [14, 16], but no insights are given for conventional databases, excepting normalization theory.

This disregard could be explained as databases used to be just "simple files/tables" with minor contributions to the complexity of the overall system. However, this is no longer the case. New applications have fuelled the enhancement of database management systems (DBMSs) with new data types, triggers, generalisations, complex objects and stored procedures. Metrics for schemata complexity can be most useful for choosing among design alternatives or giving designers limit values for certain characteristics (analogously to value 10 for McCabe complexity of programs).

This paper focuses on active DBMSs, that is, DBMSs that allow the definition and management of triggers. This mechanism enables the DBMSs to respond automatically to events associated with the issue of a command from the data manipulation language. This mechanism is currently available in a large number of commercial products (Oracle, Sybase, DB2, SQL-Server, Interbase), and triggers are reckoned to be useful for a large number of applications [24]. Despite its usefulness, early reports show some disappointment: *"we find projects where a few hundred rules represent a real maintenance problem. This is a problem that really scares off users"* [12]. Similar disquieting was pointed out at the closing panel at the RIDE-ADS workshop dedicated to Active Database Systems [23].

†Recommended by Nicole Bidoit

As these reports suggest, the lack of maintainability is a main obstacle for active systems to become widely used. Maintainability is contributed by three factors: understandability, modifiability and testability, which in turn are influenced by complexity† [13].

This paper addresses the complexity of large sets of triggers by means of three measures: the triggering potential, the number of anchors and the distance of a trigger. These measures are characterised using the measurement theory, particularly the formal framework proposed by Zuse [25].

The rest of the paper is organised as follows. Section 2 briefly introduces those aspects of active DBMSs significant for this work. Section 3 presents the different complexity measures proposed. We give a brief introduction to the Zuse's framework in Section 4, which is used to characterise the proposed metrics in Section 5. Section 6 presents the experiments performed in order to empirically validate the metrics. Conclusions and future work are given at the end of the paper.

2. CHARACTERIZATION OF ACTIVE DATABASES

Active DBMSs are able to react to significant events. These systems provide a way to describe events and their associated reactions (i.e. the knowledge model) as well as the runtime strategy to process and combine this active behaviour (i.e. the execution model).

A common approach to the knowledge model uses the event-condition-action rules paradigm (hereafter ECA rules or just rules) where ECA rules are described through an event that indicates the happening to which the rule may be able to respond, a condition that examines the context in which the event has taken place, and an action which describes the task to be carried out by the rule if the relevant event has ocurred and the condition has been satisfied. The event part can be a primitive event (e.g. a database operation) or a composite event, i.e. a combination of primitive or composite events using a range of operators that constitute the event algebra (e.g. conjunction, disjunction, sequence, etc.). For the purpose of this paper, the *cardinality* of the rule event corresponds to the number of primitive events that are (either direct or indirectly) referred to in the event part of the rule, regardless of the composite operator used.

The execution model specifies how a set of rules is treated at run-time. Among other aspects, this model includes *the coupling mode* that determines when the condition (action) is evaluated (executed) relative to the triggering (evaluation) of the event (condition). In this paper, only the *immediate coupling mode* is considered where the condition (action) is evaluated (executed) immediately after the event (condition). The question of what happens when events occur during the execution of the rules action is addressed by *the cycle policy.* This paper considers a *recursive model* where events risen during action execution are immediately taken into account. This causes the suspension of the current rules action, so that any rules monitoring these events can be processed at the earliest opportunity. Further information on active DBMSs can be found in [17, 24].

Early reports on the use of active systems point out the feeling of lack of control experimented by users. The implicit binding among rules and the insidious ways in which they interact, make difficult not only to foresee but even to ascertain which were the causes that make a rule to be fired. Unlike traditional programming languages, where sequential control is specified both explicitly and statically by the programmer, ECA rules are fired dynamically by the system based on the previous flow of events. This flow of events describes the circumstances that make the rule to be triggered off. It reflects the context that explains why the rule is considered for execution. The problem is that these causing events could not have happened at once, or even in quick succession, but are temporally distributed.

Indeed, the audience at the RIDE-ADS94 closing panel [23], described ECA-rule applications with more than 7 rules or more than 5 layers of rule triggering as unfeasable. It is worth noticing that the obstacle identified during this workshop was not the unavailability of appropriate mechanisms, but the complexity of the already commercial systems.

†Henderson-Sellers distinguishes three types of complexity: computational, psychological and representational, and for psychological complexity he considers three components: problem complexity, human cognitive factors and product complexity [16]. This paper is about product complexity.

3. MEASURES FOR ACTIVE DATABASE COMPLEXITY

Design product metrics can be sub-divided into intra-module and inter-module metrics [11]. Likewise, rule complexity can be characterised as *intra-rule complexity* where the rule in isolation is measured, and *inter-rule complexity* where the implicit interaction among rules is measure. Experience in building active systems suggests that what affects the sense of lack of control felt by the user is the degree of interactions rather than the number or complexity of the rules themselves. More concretely, two aspects are felt to be specially significant in the interaction of rules:

- The width of the argumentation, which reflects the intuition that the larger is the flow of event occurrences that conforms the rules circumstance, the more difficult will be to understand these rules. Of course, rules being fired by composite events are potentially more intricate that those with a single event. However, what our experience shows up is that a factor that complicates things even more occurs whenever the very same event type that participates in the rules event can be produced in distinct places. This means that the rules circumstance can raise in different contexts. As a result, the user has a tougher job at ascertaining which of the potential circumstances (i.e. event occurrences) makes the rule to be triggered.
- The depth of the argumentation, that is, the intricacy of the line of reasoning that connects the rule with the context where its circumstance has been produced. The depth and number of threads required to encompass the rules circumstance certainly affects its complexity (i.e. difficulty of understanding what is happening).

These intuitions were corroborated at the RIDE-ADS forum, where *"the term broad and shallow was coined to describe applications that may have a large number of rules, but the rules do not interact very much. It was felt that these applications are already quite manageable. However, it was felt that deep applications, where rules have significant interactions, are very difficult to develop and manage, even with very small number of rules"* [23]. The insight is, that the relevant aspect is the degree of interaction rather than the number of rules. Therefore, interaction complexity will be our main concern.

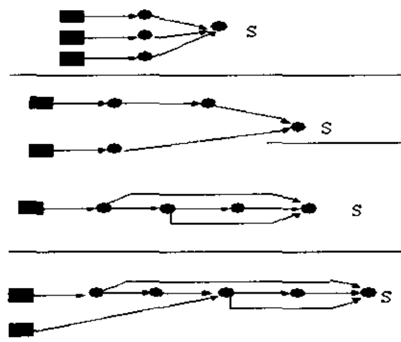
When measuring rules circumstance, we can make use of the notion of a triggering graph as defined in [1]. A triggering graph is a pair $< S, L >$ where S represents the set of ECA rules, and L is a set of directed arcs where an arc is drawn from Si to Sj if Si's action causes the happening of an event occurrence that participates in Sj's events.

This notion of triggering graph is slightly modified for our purposes in two aspects. First, arcs are weighted by the number of potential event occurrences produced by the triggering rule (i.e. Si) that could affect the triggered rule (i.e. Sj's event). Second, nodes S are extended with the set of transactions T. A transaction is an atomic set of (database) actions where any of these actions could correspond to an event triggering one or more rules. Therefore, T nodes will have outgoing links but never incoming links, as we assume that a transaction can never be fired from within a rules action or another transaction.

An example of an extended triggering graph is shown in Figure 1, where *T0* can produce three significant events for *S4*, and one for *S1*. The figure also illustrates the fact that *S4*'s events can arise from *T0*, *S2* and *S3* which potentially produce 3, 1 and 2 significant events, respectively.

The intuitive notions identified previously (i.e. the width and depth of the argumentation) can now find correspondence as triggering graph measures, namely:

- *NA, the minimum number of anchors* required to encompass the whole set of potential causes of Si. An anchor is a transaction node of the triggering graph which has a link (either direct or transitively) with at least one cause of Si. Anchors always correspond to transaction nodes: as an anchor represents the ultimate cause of the triggering, this has to be sought outside the rules themselves. Even if a rule triggers itself, you still need some action that triggers the rule for the very first time. The intuition is that each of these anchors represents a line of reasoning to be followed to understand the rules circumstance. The bigger is the number of anchors, the higher is the number of processes the designer has to follow to understand the context in which the rule is triggered.



TP	NA	D
3	3	2
2	2	3
3	1	4
3	2	5

Fig. 1: Measuring Different Triggering Graphs

- *D, the distance.* This measure corresponds to the length of the longest path that connects Si with any of its anchors. The intuition is that this measure reflects the intricacy of the line of reasoning as the number of inferences which are required to connect the ultimate cause with its effect (i.e. the triggering of Si).

- *TP, the triggering potential.* Given a triggering graph $< S, L >$, and a node of the graph, rule Si, the number of causes of Si, is the sum of weights of the incoming arcs arriving to Si. The triggering potential for a rule R is the quotient between the number of potential causes of Si, and Si's event cardinality. This measure attempts to reflect the width of Si's circumstance by giving an indication of the potential different circumstances which can make Si to be triggered.

Figure 1 illustrates the previous measures for distinct triggering graphs where the event cardinality for rule S is 1, and the weight of arcs is 1. In the next sections, we will characterise these measures by using the Zuse's framework.

4. AN INTRODUCTION TO ZUSE'S MEASUREMENT FRAMEWORK

Proposing metrics could be quite straightforward. The challenge is for the measures to adhere to the science of measurement to be valid and accepted [7]. Several frameworks for measure characterisation have been recently proposed. In this paper, we will follow the Zuse's formal framework [25] in order to describe the properties of the metrics defined in the previous section. This framework is based on an extension of the classical measurement theory, which provides a sound basis for measure validation and classification (i.e. measurement scales).

Zuse describes measurement as *"a detour, necessary because humans mostly are not able to make clear and objective decisions or judgments"*. Measurement is more than producing numbers, it is the combination of empirical entities with numerical entities. In Figure 2 the measurement process is shown. This process starts with the real world, which contains the objects that should be measured. Properties of these objects are then abstracted away using numbers so empirical relations between objects, such as *"higher than"* or *"equally high or higher"* than can be formally assessed. Such approach allows to overcome the intelligence barrier which impedes to reduce information out of the real world. With the aid of mathematics and statistics the empirical objects and relationships are mapped into proper numerical objects and relationships. This way an homomorphism, that is, a mapping between empirical and numerical information, is established. The mapping is then established between two systems: the Empirical Relational System and the Numerical Relational System. An Empirical Relational System is a triple:

$$A = (A, \bullet \geq, o)$$

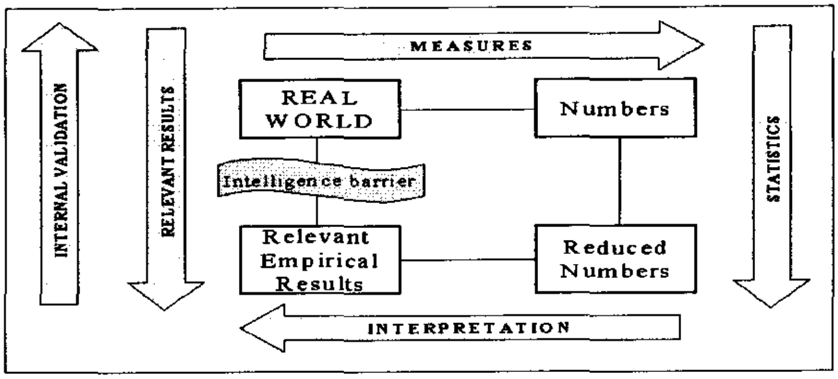


Fig. 2: Measurement Process as Presented by Zuse

where A is a non-empty set of objects, $\bullet \geq$ is an empirical relation on A, and o is a closed binary (concatenation) operation on A. For instance, these empirical relations can stand for "higher than" or "equally high or higher than".

As remarked in [25], the concatenation operation *(o)* can be contra-intuitive in the area of software engineering. However, it provides a means to build up complex measurement structures, giving a more precise interpretation of numbers. A concatenation operation should follow:

$A1\ o\ A2 \in A, \forall\ A1,\ A2 \in A$

$f(A1,\ A2){:}\ A\ x\ A \rightarrow A$ where function f is a combination rules such that $u(A1\ o\ A2) = f(u(A1),\ u(A2))$

As for a Numerical Relational System can be defined as a triplet

$$B = (\Re, >=, +)$$

where $\Re$ are the real numbers, $>=$ a relation on $\Re$, and $+$ a closed binary operation on $\Re$. Finally, a measure is a mapping $u : A \rightarrow \Re$ such that:

$$a \bullet \geq b \Leftrightarrow u(a) > = u(b); \forall\ a,\ b \in A$$

Once the mapping is established, mathematics and statistics can be used to process the information (e.g. obtaining means or variances).

Measurement theory gives also conditions for the translation of numerical statements back to empirical statements. In order to check whether the measure satisfies the user needs, Zuse proposes an internal validation, based on the comparison between the empirical interpretation of numbers and the empirical statements in the real world. On this framework, Zuse defines a set of axioms for measures which gives rise to distinct structures. Table 1 presents the most important ones.

There exist five scale types (see Table 2), namely (in hierarchical order): nominal, ordinal, interval, ratio and absolute. Each scale type is defined by admissible transformations. Software measurement starts with the ordinal scale.

Measures may be classified in a scale type, depending on whether they assume an extensive structure or not. When a measure accomplishes this structure, it also accomplishes the independence conditions and can be used on the ratio scale levels

In the next paragraph we adapt this framework to active databases, verifying the fulfilment of each axiom in regard of the three metrics proposed in Section 3.

MODIFIED EXTENSIVE STRUCTURE	INDEPENDENCE CONDITIONS	MODIFIED RELATION OF BELIEF
Axiom1: (A, • >=) (weak order) **Axiom2**: A1 o A2 • >= A1 (positivity) **Axiom3:** A1 o (A2 o A3) ≈ (A1 o A2) o A3 (weak associativity) **Axiom4**: A1 o A2 ≈ A2 o A1 (weak commutativity) **Axiom5**: A1 • >= A2 ⇒ A1 o A • >= A2 o A (weak monotonicity) **Axiom6**: If A3 • > A4 then for any A1, A2, then there exists a natural number n, such that A1 o nA3 • >A2 o nA4 (Archimedean axiom)	**C1**: A1 ≈ A2 ⇒ A1 o A ≈ A2 o A and A1 ≈ A2 ⇒ A o A1 ≈ A o A2 **C2**: A1 ≈ A2 ⇔ A1 o A ≈ A2 o A and A1 ≈ A2 ⇔A o A1 ≈ A o A2 **C3**: A1 • >= A2 ⇒ A1 o A • >= A2 o A, and A1 • >= A2 ⇒ A o A1 • >= A o A2 **C4**: A1 • >= A2 ⇔ A1 o A • >= A2 o A, and A1 • >= A2 ⇔A o A1 • >= A o A2	**MRB1**: ∀ A, B ∈ ℑ: A • >= B or B • >= A (completeness) **MRB2**: ∀ A, B, C ∈ ℑ: A • >= B and B • >= C ⇒ A • >= C (transitivity) **MRB3**: ∀ A ⊇ B ⇒ A • >= B (dominance axiom) **MRB4**: ∀ (A ⊃ B, A ∩ C = ϕ) ⇒ (A • >= B ⇒ A U C • > B U C) (partial monotonicity) **MRB5**: ∀ A ∈ ℑ: A • >= 0 (positivity)
As we know, binary relation • >= is called weak order if it is transitive and complete: A1 • >= A2, and A2 • >= A3 ⇒ A1 • >= A3 A1 • >= A2 or A2 • >= A1	Where A1 ≈ A2 if and only if A1 • >= A2 and A2 • >= A1, and A1 • > A2 if and only if A1 • >= A2 and not (A2 • >= A1).	

Table 1: Zuse's Formal Framework Properties

Name of scale type	Admissible transformation g
Nominal scale	Any one-to-one
Ordianle scale	g:strictly increasing monotonic function
Interval scale	$g(x) = ax+b,\ a>0$
Ration scale	$g(x) = ax,\ a>0$
Absolute scale	$g(x) = x$

Table 2: Scale Types and Their Transformation

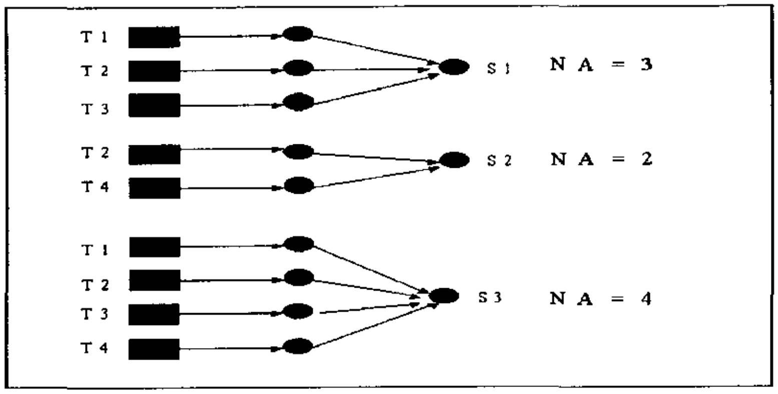


Fig. 3: NA as a Non-Additive Homomorphism

5. CHARACTERIZATION OF ACTIVE DATABASE COMPLEXITY METRICS

For ECA rules, the Empirical Relational System, $A = (S, \bullet \geq, o)$ could be defined as follows:

1. S is a non-empty set of rules;
2. $\bullet \geq$ is the empirical relation *"more or equally complex than"* on S;
3. o is a closed binary (concatenation) operation on S such that concatenation of rules *S1(E1, C1, A1)* and *S2(E2, C2, A2)* produces a rule *S3*, where:
   (a) event *E3* is obtained as *E1 OR E2* ;
   (b) condition *C3* is obtained as *(C1 AND e1) OR (C2 AND e2)* where *ei* is a Boolean variable where true (false) indicates the occurrence (absence) of the Ei event†;
   (c) action *A3* can be defined as: *IF e1 THEN A1, IF e2 THEN A2.*

Section 3 introduced a set of intuitive measures for rule sets. Next subsections characterise the intuitive measures introduced in Section 3 within the Zuse's structures. The outcome is that the proposed measures do not represent an extensive structure, but can be characterised above the ordinal scale by fulfilling some of the properties of modified relations of belief.

5.1. Measure 1: Minimum Number of Anchors Required to Encompass the Whole Set of Potential Causes of a Rule (NA)

The NA measure is a mapping, NA: S $\rightarrow \Re$ such that:

$$Si \bullet \geq Sj \Leftrightarrow NA(Si) >= NA(Sj);\ \forall\ Si,\ Sj \in S$$

Concatenation o is defined as follows:

$$NA\ (Si\ o\ Sj) = NA\ (Si) + NA(Sj) - NA(Si \bigcap Sj)$$

where $NA\ (Si \bigcap Sj)$ is the number of anchors which are common to (belong to the intersection of) *Si* and *Sj*. From this definition, it can be drawn that NA is a non additive homomorphism as $NA\ (Si\ o\ Sj) \neq NA\ (Si) + NA\ (Sj)$. For example, in Figure 3, $NA(S1) = 3$, $NA(S2) = 2$, and $NA(S3) = 4$, if we consider $S3 = S1\ o\ S2$.

†This boolean variables are available in some systems. For instance, Oracle provides three such variables (i.e. inserting, deleting, updating) to ascertain the event type that make the trigger to be fired.

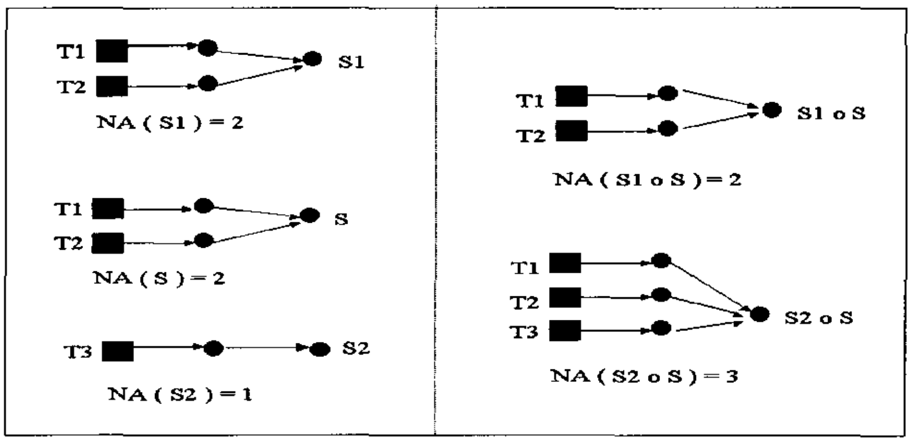


Fig. 4: NA Does not Fulfil Axiom 5

Is NA a modified extensive structure? NO

1. Axiom1: *(S, • ≥)* (weak order). YES
2. Axiom2: *S1 o S2 • ≥S1* (positivity). YES
3. Axiom3: *S1 o (S2 o S3)* ≈ *(S1 o S2) o S3* (weak associativity). YES
4. Axiom4: *S1 o S2* ≈*S2 o S1* (weak commutativity). YES
5. Axiom5: *S1 • ≥ S2 ⇒ S1 o S • ≥ S2 o S* (weak monotonicity). NO. As we can see in Figure 4, *S1* has a value for the metric which is higher than the value for *S2*, but after the concatenation operation of both with *S*, the value for *S1 o S* is lower than the value for *S2 o S*. 10.
6. Axiom6: *S1 o S3 o S3 ... •> S2 o S4 o S4 o S4 ..., S3 • >S4* (Archimedean axiom). NO. NA is idempotent as Si o Si = Si, so there is no way the Archimedean axiom can be fulfilled.

Is NA an independence condition structure? NO

1. C1: *S1 ≈ S2 ⇒ S1 o S ≈ S2 o S* and *S1 ≈ S2 ⇒ S o S1 ≈ S o S2*. NO. The metric does not accomplish the axiom of weak monotonicity, so that it cannot accomplish the independence condition 1.
2. C2: *S1 ≈ S2 ⇔ S1 o S ≈ S2 o S* and *S1 ≈ S2 ⇔S o S1 ≈ S o S2*. NO
3. C3: *S1 • ≥ S2 ⇒ S1 o S • ≥ S2 o S*, and *S1 • ≥ S2 ⇒ S o S1 • ≥ S o S2*. NO
4. C4: *S1 • ≥ S2 ⇔ S1 o S • ≥ S2 o S*, and*S1 • ≥ S2 ⇔ S o S1 • ≥S o S2*. NO

Is NA a modified relation of belief structure? NO

1. MRB1: ∀ *S, R ∈ ℑ: S • ≥ R or R • ≥ S* (completeness). YES
2. MRB2: ∀ *S, R ∈ ℑ: S • ≥ R* and *R • ≥ C ⇒ S • ≥ C* (transitivity). YES
3. MRB3: ∀ *S ⊇ R ⇒ S • ≥ R* (dominance axiom). YES on the assumption that a trigger *S1(E1, C1, A1) ⊇ S2(E2, C2, A2)* if all the simple events that compose *E2* are present in *E1*, and analogously for the terms of condition *C2* and instruction of action *A2*.
4. MRB4: ∀ *(S ⊃ R, S ⋂ C = ϕ) ⇒ (S • ≥ R ⇒ S ⋃ C • ≥ R ⋃ C)* (partial monotonicity). NO because although a trigger *S1 ⊃ S2* and *S1 ⋂ S3 = ϕ* , the anchors of *S1* can be the same of *S3*, but different of *S2* and so *NA(S1 ⋃ S3)* can be lower than *NA(S2 ⋃ S3)*.
5. MRB5: ∀ *S∈ ℑ: S • ≥ 0* (positivity). YES since a trigger must have an anchor.

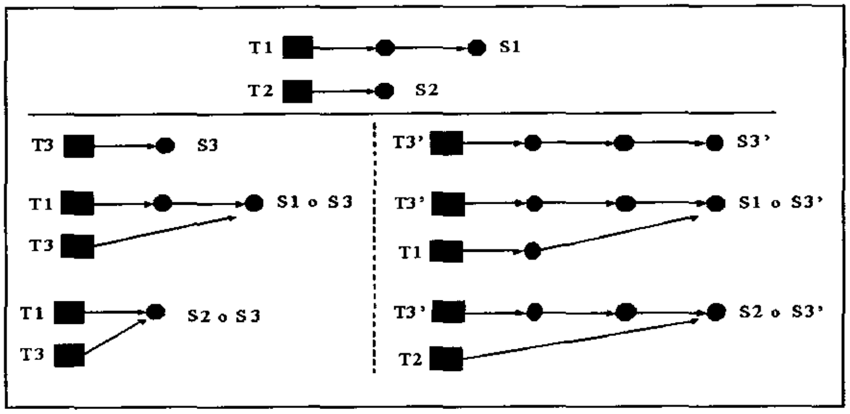


Fig. 5: D Fulfils Axiom 5

5.2. *Measure 2: Length of the Longest Path that Connects a Rule with Any of Its Anchors (D)*

The distance D is a mapping: $S \rightarrow \Re$ such that

$$Si \bullet \geq Sj \Leftrightarrow D(Si) >= D(Sj) \ \forall \ Si, Sj \in S$$

Concatenation o is defined as follows:

$$D\ (Si\ o\ Sj) = MAX\ (D(Si), D(Sj))$$

Is D a "modified extensive" structure? NO

1. Axiom1: $(S, \bullet \geq)$ (weak order). YES
2. Axiom2: $S1\ o\ S2 \bullet \geq S1$ (positivity). YES
3. Axiom3: $S1\ o\ (S2\ o\ S3) \approx (S1\ o\ S2)\ o\ S3$ (weak associativity). YES
4. Axiom4: $S1\ o\ S2 \approx S2\ o\ S1$ (weak commutativity). YES
5. Axiom5: $S1 \bullet \geq S2$? $S1\ o\ S \bullet \geq S2\ o\ S$ (weak monotonicity). YES. As an example, consider Figure 5. If *S3* is "shorter than or as long as" *S1* or *S2*, the relationship between *S1* and *S2* will remain the same. If *S3* is longer, the concatenation of *S3* with *S1* or *S2* will be the same length as *S3*. So, weak monotonicity is fulfilled.
6. Axiom6: $S1\ o\ S3\ o\ S3 \ldots \bullet > S2\ o\ S4\ o\ S4\ o\ S4 \ldots$, $S3 \bullet > S4$ (Archimedean axiom). NO. D is idempotent as $Si\ o\ Si = Si$, so there is no way the Archimedean axiom can be fulfilled.

Is D an "independence condition" structure? NO

1. C1: $S1 \approx S2 \Rightarrow S1\ o\ S \approx S2\ o\ S$ and $S1 \approx S2 \Rightarrow S\ o\ S1 \approx S\ o\ S2$. YES
2. C2: $S1 \approx S2 \Leftrightarrow S1\ o\ S \approx S2\ o\ S$ and $S1 \approx S2 \Leftrightarrow S\ o\ S1 \approx S\ o\ S2$. NO, as illustrated in Figure 6.
3. C3: $S1 \bullet \geq S2 \Rightarrow S1\ o\ S \bullet \geq S2\ o\ S$, and $S1 \bullet \geq S2 \Rightarrow S\ o\ S1 \bullet \geq S\ o\ S2$. YES
4. C4: $S1 \bullet \geq S2 \Leftrightarrow S1\ o\ S \bullet \geq S2\ o\ S$, and $S1 \bullet \geq S2 \Leftrightarrow S\ o\ S1 \bullet \geq S\ o\ S2$. NO, because $D(S1\ o\ S)$ can be greater than or equal to $D(S2\ o\ S)$, but $D(S1)$ can be lower than $D(S2)$ if S is longer than $S1$ and $S2$.

Is D a "modified relation of belief" structure? NO

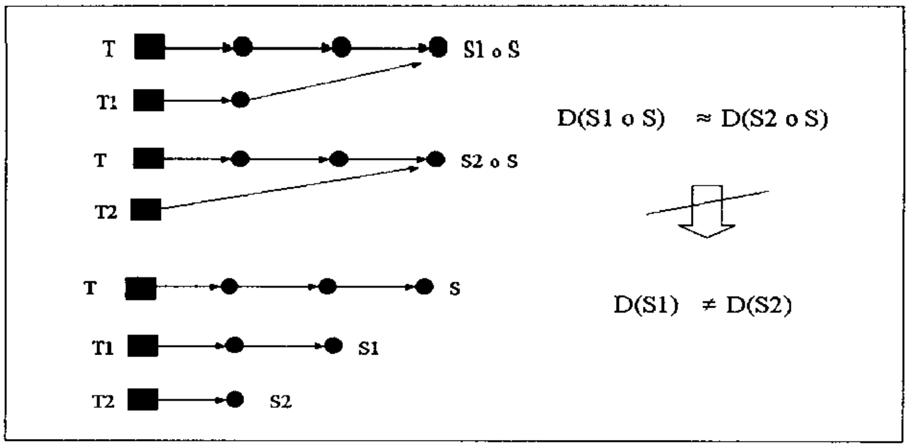


Fig. 6: D Does not Fulfil Condition 2

1. MRB1: $\forall$ *S, R* $\in \Im$: $S \bullet \geq R$ or $R \bullet \geq S$ (completeness). YES
2. MRB2: $\forall$ *S, R, C* $\in \Im$: $S \bullet \geq R$ and $R \bullet \geq C \Rightarrow S \bullet \geq C$ (transitivity). YES
3. MRB3: $\forall\, S \supseteq R \Rightarrow S \bullet \geq R$ (dominance axiom). YES
4. MRB4: $\forall$ $(S \supset R, S \bigcap C = \phi) \Rightarrow (S \bullet \geq R \Rightarrow S \bigcup C \bullet > R \bigcup C)$ (partial monotonicity). NO. Let *S1* be a trigger containing another trigger, *S2* (thus, *S1* $\bullet$ >*S2*). If these triggers are combined with a third one, *S*, the result as far as the distance is concerned can be just the same, if the distance of *S* is greater than the distance of both *S1* and *S2.*
5. MRB5: $\forall$ S $\in \Im$: $S \bullet \geq 0$ (positivity). YES since a trigger must have a minimum distance of 1.

In summary, we can characterised *D* as a measure above the level of the ordinal scale, but unfulfilling the extensive structure.

5.3. Measure 3: Triggering Potential (TP)

The *TP* measure is a mapping: *TP:* $S \rightarrow \Re$ such that:

$$Si \bullet \geq Sj \Leftrightarrow TP(Si) \geq TP(Sj)\ \forall\ Si, Sj \in S$$

TP is not additive related.
As *TP* is defined as:

$$TP(S) = \frac{causE(S)}{cardE(S)}$$

Concatenation *o* is defined as follows:

$$TP(SioSj) = \frac{causE(Si)+causE(Sj)}{cardE(Si)+cardE(Sj)-cardE(Si\bigcap Sj)}$$

Is TP a modified extensive structure? NO

1. Axiom1: $(S, \bullet \geq)$ (weak order). YES
2. Axiom2: *S1 o S2* $\bullet \geq$ *S1* (positivity). NO. We can have a rule S with a numerator for the rule lesser than the denominator $TP(S2) = \frac{1}{2}$, then after the concatenation with a rule *S1* such $TP(S1) = \frac{2}{2} = 1$, we will obtain a value lesser for the concatenation $TF(S1oS2) = \frac{2+1}{2+2} = 0.75$ than the value of *TP(S1)*.

3. Axiom3: *S1 o (S2 o S3)* $\approx$ *(S1 o S2) o S3* (weak associativity). YES

4. Axiom4: *S1 o S2* $\approx$ *S2 o S1* (weak commutativity). YES

5. Axiom5: *S1* $\bullet \geq$ *S2* $\Rightarrow$ *S1 o S* $\bullet \geq$ *S2 o S* (weak monotonicity). NO. Let *S1*, *S2* and *S* be three triggers with $TP(S1) = \frac{2}{2}$, $TP(S2) = \frac{1}{1}$, and $TP(S) = \frac{1}{2}$, respectively, with $E1 \bigcap E2 = \phi$ and $cardE(S \bigcap S2) = 1$. Once *S* is concatenated with *S1* and *S2*, the *TP* value will be *TP(S1 o S)=0,75* and *TP(S2 o S)=1*.

6. Axiom6: *S1 o S3 o S3 ...* $\bullet >$ *S2 o S4 o S4 o S4, ...S3* $\bullet >$*S4* (Archimedean axiom). The metric is not idempotent then, it is necessary to test the Archimedean axiom. This axiom is not accomplished because we can have, for example, that $TP(S3) = \frac{1}{1}$, $TP(S4) = \frac{1}{2}$, $TP(S1) = \frac{1}{1}$, $TP(S2) = \frac{1}{1}$, $cardE(S1 \bigcap S2) = 0$ and $cardE(S2 \bigcap S4) = 1$. In this case, $TP(S3) > TP(S4)$ but $TP(S1oS2) = \frac{1+n*1}{1+n*1} = \frac{n+1}{n+1}$ and $TP(S2oS4) = \frac{1+1*n}{1+2*(n-1)*n} = \frac{n+1}{n+1}$, so $TP(S1oS3) = TP(S2oS4)$.

Is TP an independence condition structure? NO. Since the metric does not accomplish axiom 5 in the modified extensive structure, it cannot accomplish the independence conditions.

1. C1: *S1* $\approx$ *S2* $\Rightarrow$ *S1 o S* $\approx$ *S2 o S* and *S1* $\approx$ *S2* $\Rightarrow$ *S o S1* $\approx$ *S o S2*. NO

2. C2: *S1* $\approx$ *S2* $\Rightarrow$ *S1 o S* $\approx$ *S2 o S* and *S1* $\approx$ *S2* $\Leftrightarrow$ *S o S1* $\approx$ *S o S2*NO

3. C3: *S1* $\bullet \geq$ *S2* $\Rightarrow$ *S1 o S* $\bullet \geq$ *S2 o S* and *S1* $\bullet \geq$ *S2* $\Rightarrow$ *S o S1* $\bullet \geq$ *S o S2*. NO

4. C4: *S1* $\bullet \geq$ *S2* $\Leftrightarrow$ *S1 o S* $\bullet \geq$ *S2 o S* and *S1* $\bullet \geq$ *S2* $\Leftrightarrow$ *S o S1* $\bullet \geq$ *S o S2*. NO

Is TP a modified relation of belief structure? NO

1. MRB1: $\forall$ *S, R* $\in \Im$: *S* $\bullet \geq$ *R* or *R* $\bullet \geq$ *S* (completeness). YES

2. MRB2: $\forall$ *S, R, T* $\in \Im$: *S* $\bullet \geq$ *R* and *R* $\bullet \geq$ *T* $\Rightarrow$ *S* $\bullet \geq$ *T* (transitivity). YES

3. MRB3: $\forall$ *S* $\supseteq$ *R* $\Rightarrow$ *S* $\bullet \geq$ *R* (dominance axiom). NO. Since the numerator of *TP* could be the same for two triggers *S1* and *S2* (*S1* containing *S2*) but the denominator of *S1* could be greater, then the value of the metric for *S1* could be lesser than the value of the metric for *S2*.

4. MRB4: $\forall$ *(S* $\supset$ *R, S* $\bigcap$ *T* $= \phi) \Rightarrow$ *(S* $\bullet \geq$ *R* $\Rightarrow$ *S* $\bigcup$ *T* $\bullet >$ *R* $\bigcup$ *T)* (partial monotonicity). NO. Similar to MRB3.

5. MRB5: $\forall$ *S* $\in \Im$: *S* $\bullet \geq$ *0* (positivity). YES. Both numerator and denominator of *TP* are greater then zero.

In summary, we can characterise *TP* as a measure above the level of the ordinal scale, but which does not fulfil the extensive structure. Table 3 summarises the properties fulfilled by the three metrics following Zuse's framework.

6. EMPIRICAL VALIDATION

Metrics must not only fulfil sound theoretical principles, but also prove that they are practical. This section presents the experiments led to determine the effects of two factors, the distance (D) and the triggering potential (TP) on active database schema understandability.

Since understandability is the aspect to be assessed, we should consider how this aspect is influenced by two parameters: how the reasoning is carried out, and the user experience. As for the former, rules can be seen as cause-and-effect links where two questions can be posed: what effects can a rule produce (forward reasoning) or how a given effect can be produced (backward reasoning). Forward reasoning begins with an operation (event) and determines its effects in the database. This process is more common during trigger definition. By contrast, backward reasoning

Axioms	Number of anchors	Distance	Triggering Potential
Axiom 1	yes	yes	yes
Axiom 2	yes	yes	no
Axiom 3	yes	yes	yes
Axiom 4	yes	yes	yes
Axiom 5	no	yes	no
Axiom 6	no	no	no
Ind. Cond. 1	no	yes	no
Ind. Cond. 2	no	no	no
Ind. Cond. 3	no	yes	no
Ind. Cond. 4	no	no	no
MRB 1	yes	yes	yes
MRB 2	yes	yes	yes
MRB 3	yes	yes	no
MRB 4	no	no	no
MRB 5	yes	yes	yes

Table 3: Characterisation of Rule's Circumstance Measures

begins with a database state and strives to ascertain the causing operation. This process is more common during trigger maintenance. As for the second aspect, the user experience, two user profiles have been considered: students and practitioners. Both aspects results in a total amount of four experiments.

These experiments are prepared using the following steps: listing of the hypotheses; description of the subjects; description of the material conforming the experiment; design guidelines; and finally, checking the results against the initial hypotheses [18].

6.1. *Initial Hypotheses*

- Null Hypothesis: Different values of metrics do not affect the comprehension of the database schema.

- Alternative Hypothesis 1: The value of the D metric affects the comprehension of the database schema.

- Alternative Hypothesis 2: The value of the TP metric affects the comprehension of the database schema.

- Alternative Hypothesis 3: The combination of the D and TP metrics affects the comprehension of the database schema.

6.2. *Subjects*

Two user profiles are considered: students and database practitioners. As for the students, the participants were final-year (undergraduate) Computer Science students at the University of the Basque Country, who were enrolled in a one-semester advanced database course. The students were already familiar with relational database, and some laboratories had already been conducted on the definition of triggers. The students were unaware of the experiment, till the very same day of its conclusion. Forty-five students participated but only thirty-five were finally processed†.

As for the practitioners, two different small and medium Spanish consultant companies were involved whose personnel had an average experience of four years on working with relational databases and use triggers sparsely. Eighteen persons were involved, but finally only twelve gave correct answers.

†As this is a time-based measure of correct answers, subjects with incorrect results were discarded.

		Factor TP	
		LOW	HIGH
Factor D	LOW	(1,1)	(1,3)
	HIGH	(3,1)	(3,3)

Table 4: Crossed Design for the Experiment

6.3. *Experimental Materials*

Three documents were prepared, namely,

1. a document with a relational database schema together with the corresponding entity/relationship diagram, and an extension (set of tuples) for each of the four tables (see Appendix A).
2. the "forward-reasoning" document with four tests (see Appendix A). Each test has a set of triggers, and the subject (either a student or a practitioner) were asked about the final database state reached once a given operation is produced. Some triggers could cascade.
3. the "backward-reasoning" document with four tests. Each test has a set of triggers, and the subject were asked to ascertain of the operations which cause a given database state (see Appendix A). Some triggers could cascade.

A handout was given to each person, and the time spent in each test was recorded. Only correctly answered tests were included in the statistics. A preliminary experiment was led with a different and smaller set of students to improve the final version.

6.4. *Experimental Design*

The experiment attempts to measure two factors: the distance (D) and the triggering potential (TP). We have a factorial model, since all the values a factor can take are combined with all values of the other factor. This way, observations can be represented in a two-entry chart. As we have a constant number of observations in each experimental cell (number of students who answered correctly), the model is balanced. A crossing design as the one described above produces the matrix shown in table 4 where each value of the matrix is a pair (TP,D).

6.4.1. *Independent Variables*

The independent variables are the distance and the triggering potential. Each one of these independent variables has two levels, 1 and 3.

6.4.2. *Dependent Variables*

In our experiments, the dependent variable is time. Since the aspect to be measured is understandability, we decided to give our subjects as much time as they needed to finish the tests. This way, only those tests that had been correctly answered would be taken as valid, and thus, our study would focus on the different amounts of time needed for the completion of the tests of the experiments.

The spent time dedicated to each question was annotated by the student in the questionaire.

6.4.3. *Controlled Variables*

We have tried to minimise variability among participants choosing students from the same degree. As for practitioners, finding a substantial amount of professionals with the same background and experience is really challenging; so, a margin of three years was defined between the youngest and the most experienced practitioners. Effects of irrelevant variables were minimised by making the same trials for all the subjects.

Variation Source	Q_i	Degrees of freedom	F-Ratio
D	285.71	1	37.1
TP	16.457	1	2.13
Interaction	0.714	1	0.0927
Error	1048.4	136	
TOTAL	1351.286	139	

Table 5: Results of the F-Statistic for the Forward Experiment (Students)

Variation Source	Q_i	Degrees of freedom	F-Ratio
D	1031.429	1	104
TP	475.457	1	48.1
Interaction	247.11	1	25
Error	1344.171	136	
TOTAL	3098.17	139	

Table 6: Results of the F-Statistic for the Backward Experiment (Students)

6.4.4. Procedure

Experiments were made consecutively during an hour and a half session. Subjects assume responsibility for annotating the starting and the ending hour in each test. Although the two experiments (i.e. backward and forward) were made in the same order by all subjects (first the forward one and after the backward one), the tests within each experiment were arranged in different order. Only valid answers were considered.

6.5. Experimental Results for the Students

There are three major items to consider when choosing the analysis techniques: the nature of the data collected, the motivation for performing the experiment, and the type of experimental design used [18].

As already indicated, a factorial model have been used where interactions between the two factors (D and TP) must be proved. The F statistic has been chosen [19].

Tables 5 and 6 show the results for the F-statistic for the forward experiment the backward experiment, respectively. In these tables, the first column represents the dependent variables, the second column the variability[†], the third column indicates the degrees of freedom whereas the forth one records the results obtained for the experiment. Besides, the interaction, the error and the total are also shown.

The power of a statistical test lies on three different aspects: the error margin, α , the size of the effect being investigated, and the number of subjects. Since the effect size and the number of subjects are constants, increasing α is the only option for increasing the power of the test applied. Instead of the most common value α=0,05 (95% level of confidence), we choose a value α=0,1 (90% level of confidence). This way, we look for the statistic value in tables where the numerator is 1 (in the three cases, D, TP and interaction, we have a degree of freedom), and the denominator is 136 (degree of freedom of the error), seeing that the value is $F_{1,136}=2.71$.

On these grounds, some observations can be drawn for the forward and backward experiment. For the former:

- Alternative Hypothesis 1: *"The value of the D metric affects the comprehension of the database schema"*. Since $37.1 > F_{1,136}$, D affects the results of the experiment. So, alternative hypothesis 1 is valid because the value of the D metric affects the results obtained.

[†]Among both rows and columns of the interaction as well as for each experimental plot, which is not due neither to the factors we are analysing here nor to their interaction.

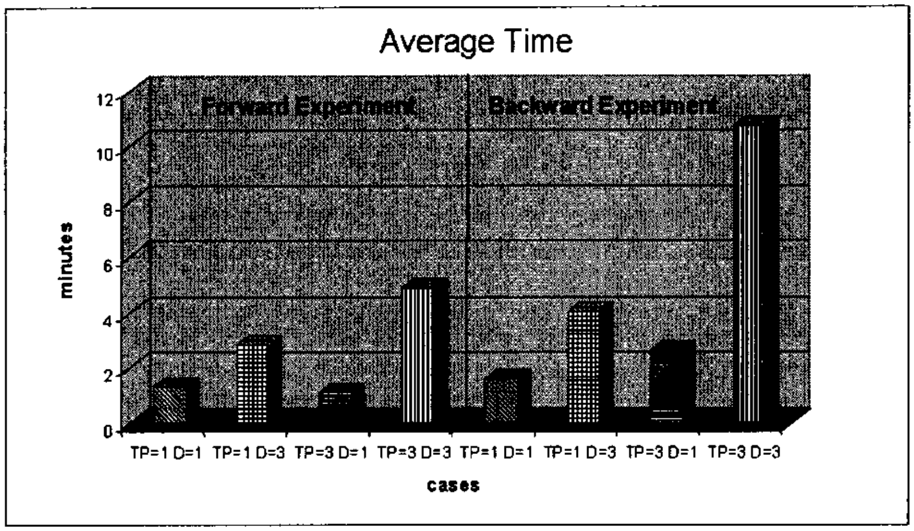


Fig. 7: Average Time in the Execution of the Tests in Both Experiments (Students)

- Alternative Hypothesis 2: *"The value of the TP metric affects the comprehension of the database schema"*. Since 2.13 < $F_{1,136}$, TP does not affect the results of the experiment. So, alternative hypothesis 2 is invalid because the value of the TP metric does not affect the results obtained.

- Alternative Hypothesis 3: *"The combination of the D and TP metrics values affect the comprehension of the database schema"*. Since 0.0927< $F_{1,136}$, the interaction of the metrics does not affect the results of the experiment. So, alternative hypothesis 3 is invalid because the combination of the values of the D and the TP metrics does not affect the results obtained.

Summing up, the triggering potential is a more solid indicator of understandability, and the distance is no relevant by itself. The distance cannot modulate the effect of the triggering potential.

Following [21], D can be classified as a dominant metric whereas TP is a redundant metric. However, due to the low margin between the value obtained from the experiment and the value found in the tables for the TP metric, a new experiment might be convenient. This experiment will take more differentiated values so that the impact of TP on rule understandability could be better assessed.

As for the backward experiment:

- Alternative Hypothesis 1: *"The value of the D metric affects the comprehension of the database schema"*. Since 104> $F_{1,136}$, D affects the results of the experiment. So, alternative hypothesis 1 is valid because the value of the D metric affects the results obtained.

- Alternative Hypothesis 2: *"The value of the TP metric affects the comprehension of the database schema"*. Since 48.1> $F_{1,136}$ TP affects the results of the experiment. Hence, alternative hypothesis 2 is valid because the value of the TP metric affects the results obtained.

- Alternative Hypothesis 3: *"The combination of the D and TP metrics values affect the comprehension of the database schema"*. Since 25> $F_{1,136}$, the interaction of the metrics affects the results of the experiment. Thus, alternative hypothesis 3 is valid because the combination of the values of the D and the TP metrics affects the results obtained.

We can conclude that both metrics are solid indicators of rule understandability. Therefore, D and TP can be classified as a dominant metrics. Figure 7 shows the average time per test in both experiments.

Variation Source	Q_i	Degrees of Freedom	F-Ratio
D	85.33	1	42.1
TP	14.08	1	6.95
Interaction	0.083	1	0.04
Error	89.16	44	
TOTAL	188.66	47	

Table 7: Results of the F-Statistic for the Forward Experiment (Practitioners)

Variation Source	Q_i	Degrees of Freedom	F-Ratio
D	123.52	1	24.5
TP	63.02	1	12.5
Interaction	28.52	1	5.6
Error	89.16	44	
TOTAL	436.4	47	

Table 8: Results of the F-Statistic for the Backward Experiment (Practitioners)

6.6. *Experimental Results for the Practitioners*

Tables 7 and 8 show the results for the forward and backward experiment, respectively. Comparing these tables with $F_{1,44}$ (2.84) the following conclusions can be drawn. As for the forward experiment:

- Alternative Hypothesis 1: *"The value of the D metric affects the comprehension of the database schema"*. Since 42.1>2.84, D affects the results of the experiment. So, alternative hypothesis 1 is valid because the value of the D metric affects the results obtained.
- Alternative Hypothesis 2: *"The value of the TP metric affects the comprehension of the database schema"*. Since 6.95>2.84, TP affects the results of the experiment. So, alternative hypothesis 2 is valid because the value of the TP metric affects the results obtained.
- Alternative Hypothesis 3: *"The combination of the D and TP metrics values affect the comprehension of the database schema"*. Since 0.04<2.84, the interaction of the metrics does not affect the results of the experiment. Hence, alternative hypothesis 3 is invalid since the combination of D and TP does not show any effect on the results. In other words, D does not depend on TP, and vice versa.

To conclude, both the triggering potential and the distance are solid indicators of understandability in a forward-reasoning context. Moreover, and as a consequence of the unfulfilment of the third hypothesis, we can ensure that the metrics are influential by themselves, independently of their value. Following Schneidewind [21], D and TP can be classified as dominant metrics. Finally, the second forward experiment does not corroborate the no-influence of TP which were obtained in the first forward experiment with the students. This stems from the fact that the distance obtained in the controlled experiments between the table value and the empirical value was not significant enough.

As for the backward experiment:

- Alternative Hypothesis 1: *"The value of the D metric affects the comprehension of the database schema"*. Since 24.5>2.71, D affects the results of the experiment. As a result, alternative hypothesis 1 is valid because the value of the D metric affects the results obtained.
- Alternative Hypothesis 2: *"The value of the TP metric affects the comprehension of the database schema"*. Since 12.5>2.71, TP affects the results of the experiment. Therefore, alternative hypothesis 2 is valid because the value of the TP metric affects the results obtained.

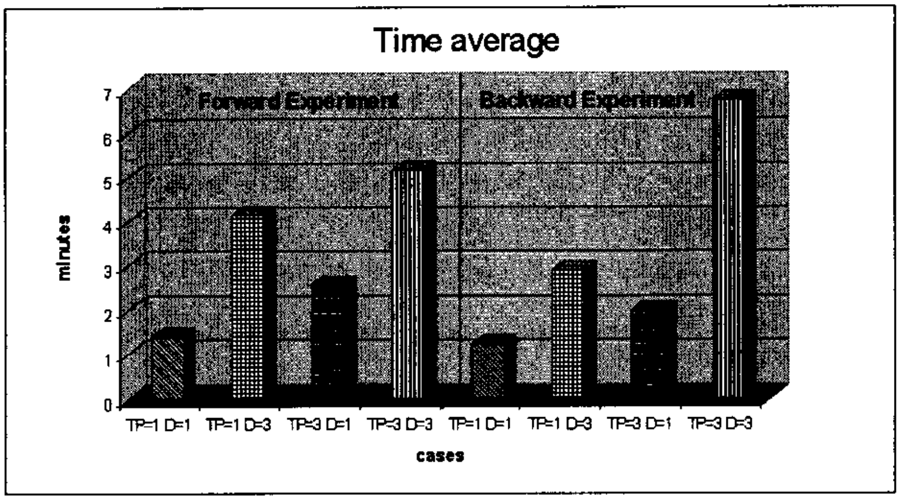


Fig. 8: Average Time in the Execution of the Tests in Both Experiments (Practitioners)

- Alternative Hypothesis 3: *"The combination of the D and TP metrics values affect the comprehension of the database schema"*. Since 5.6>2.71, the interaction of the metrics affects the results of the experiment. So, alternative hypothesis 3 is valid.

These results corroborate that D and TP are solid indicators of understandability. Figure 8 shows the average time per test in both experiments.

7. CONCLUSIONS AND FUTURE WORKS

Software measurement is widely recognised as an effective means to understand, monitor, control, predict and improve software development and maintenance projects. Databases are not an exception. This paper addresses metrics for active databases. Metrics can be used to flag outlying rules for special attention, and in so doing, allowing for a more precise debugging and maintenance where attention is drawn to a fraction of the rules rather than the whole rule set.

Three triggering measures are proposed to assess the deviousness of the rules circumstance: the triggering potential, the number of anchors and the distance. These metrics are developed and characterised in accordance to a set of sound measurement principles. Similar to the difficulties faced by Zuse with object-oriented measures, the concatenation operation of rules is more complicated than classic measures. These measures do not assume an extensive structure, but can be characterised above the ordinal scale by fulfilling some of the properties of modified relations of belief.

Some experiments were conducted which provide reasonable certitude about the usefulness of the distance and the triggering potential as indicators of active database schemata understandability. More experiments are required to corroborate these conclusions and to assess the validity of NA as an understandability indicator. We are conscious, however, that controlled experiments have problems (such as the large number of variables that causes differences, dealing with low level issues, microcosm of reality and small set of variables and so on) and limits (do not scale up, conducted in training situations, made in vitro and face a variety of threats of validity). Things being so, it is convenient to run multiple studies, mixing controlled experiments and case studies. For these reasons, a deeper empirical evaluation is under way in collaboration with industrial and public organisations in real situations.

We are also adapting our framework to the standard recently proposed by the SQL committee [9]. In this way, we envisage a more precise guide to the metrics usage and the development of a tool for automatic metrics collection. Metrics for active databases are also being complemented with others metrics for object-relational databases [6].

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REFERENCES

[1] A. Aiken, J.M. Hellerstein, and J. Widom. Static analysis techniqies for predicting the behaviour of active database rules. *ACM Transactions on Databases*, **20**(1):3–41 (1995).

[2] D. Batra, J.A. Hoffer, and R.P. Bostrom. A comparison of user performance between the relational and the extended entity/relationship models in the discovery phase of database design. *Communications of the ACM*, **33**(2):126–139 (1990).

[3] P. Bourque and V. Cote. An experiment in software sizing with structured analysis metrics. *Journal of Systems & Software*, **15**:159–172 (1991).

[4] L. Briand, C. Bunse, J. Daly, and C. Differing. An experimental comparison of the maintainability of object-oriented and structured design documents. In M.J. Harrold and G. Vissagid, editors, *Proceedings of the International Conference on Software Maintenance*, pp. 130–138 (1997).

[5] L.C. Briand, S. Morasca, and V.R. Basili. Property-based software engineering measurement. *IEEE Transactions on Software Engineering*, **22**(1):68–85 (1996).

[6] C. Calero, M. Piattini, F. Ruiz, and M. Polo. Validation of metrics for object-relational database. In *International Workshop on Quantitative Approaches in Object-Oriented Software Engineering*, Lisbon, Portugal, p, 332, Springer Verlag (1999).

[7] N. Fenton. Sofware measurement: a necessary scientific basis. *IEEE Transactions on Software Engineering*, **20**(3):199–206 (1994).

[8] N. Fenton and S.L. Pfleeger. *Software Metrics: A Rigurous Approach (2nd. edition)*. Chapman & Hall, London (1997).

[9] ISO/IEC 9075:1999. Information Technology - Database Languages - SQL - part 2: Foundation. (1999).

[10] Y.G. Kim and S.T. March. Comparing data modeling formalisms. *Communications of the ACM*, bf 38(6):103–115 (1995).

[11] B.A. Kitchenham and S.J. Linkman. Design metrics in practice. *Information and Sofware Technology*, **32**(4):304–310 (1990).

[12] A.M. Kotz. Active database functionality in a real-world banking environment. In *Dagstuhl Seminar on Active DBMS*, Germany (1994).

[13] H.F. Li and W.K. Chen. An empirical study of software metrics. *IEEE Trans. on Software Engineering*, **13**(6):679–708 (1987).

[14] S.G. MacDonell, M.J. Shepperd, and P.J. Sallis. Metrics for database systems: An empirical study. In *Proceedings of the Fourth International Software Metrics Symposium (Metrics'97)*, pp. 99–107, IEEE Computer Society (1997).

[15] A. Melton A, editor. *Software Measurement.* Thomson Computer Press, London, 1996.

[16] D.L. Moody. Metrics for evaluating the quality of entity relationship models. In *Proceedings of the Seventeenth International Conference on Conceptual Modelling (ER'98)*, Singapore, pp. 211–225, Springer-Verlag (1998).

[17] N. Paton and Diaz O. Active database systems. *ACM Computer Surveys*, **31**(1):63–103 (1999).

[18] S.L. Pfleeger. Experimental design and analysis in software engineering. *Annals of Software Engineering*, **1**(1):219–253 (1995).

[19] V.K. Rohatgi. *An introduction to probability theory and mathematical statistics.* Wiley Series in Probability and Mathematical Statistics (1976).

[20] M. Rossi and S. Brinkkemper. Complexity metrics for systems development methods and techniques. *Journal of Information Systems*, **2**(1):209–227 (1996).

[21] N.F. Schneidewind. Software metrics for quality control. In *Proceedings of the Fourth International Software Metrics. Symposium (Metrics'97)*, pp. 127–136, IEEE Computer Society (1997).

[22] H.M. Sneed and O. Foshag. Measuring legacy database structures. In Peeters Coombes and Van Huysduynen, editors, *Proceedings of the European Software Measurement Conference (FESMA)*, pp. 199–211 (1998).

[23] J. Widom. Research issues in active database systems: Report from closing panel at ride-ads' 94. In *SIGMOD RECORD*, **23**(3):41–43 (1994).

[24] J. Widom and S. Ceri, editors. *Active Database Systems.* Morgan Kaufmann (1996).

[25] H.A. Zuse. *A Framework of Software Measurement.* Walter de Gruyter, Berlin (1998).

APPENDIX A

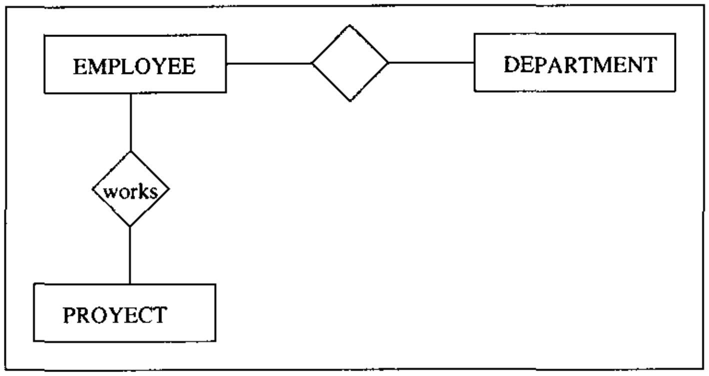

Fig. 9: Database Schema

Table **Employee**						Table **Works**	
IdEmp	**Name**	**Salary**	**Manager**	**NDept**		**NProj**	**NEmp**
12456	Pepe Cacabelos	2200000	58862	120		1000	12456
23458	Juan Lopez	1400000	45544	130		1000	30215
98735	Maria Madrid	2600000	45544	140		1004	45544
15975	Lara Velasco	2200000	58862	120		1003	01587
56874	Miguel Tardon	1400000	12559	120		1010	15975
30215	Angel Molina	1800000	12559	160		1009	45879
01587	Esteban Martin	1400000	45544	140		1009	91659
45782	Ana Marquez	1700000	12559	130		1008	56874
45879	Laura Garcia	1800000	58862	170		1007	98735
45544	Martin Pascual	4000000	58862	140		1000	45782
99912	Paco Perez	2500000	89531	100		1002	99912

Table **Project**					Table **Department**		
NProj	**Name**	**Budget**	**Manager**		**NDept**	**Name**	**Budget**
1000	Mariposa	341234	01587		100	Publicidad	4134
1001	Elefante	41324	45544		110	Marketing	34124
1002	Mamut	32412	45544		120	Economia	52345
1003	Sardina	413412	58862		130	RRHH	563
1004	Perro	43434	12559		140	Informatica	6536
1005	Lobo	3143	12599		150	Juridico	3456
1006	Hormiga	76747	45782		160	Investigacion	4674
1007	Gato	45764	91345		170	Comunicaciones	879
1008	Coyote	78009	67912		180	Produccion	647
1009	Gallina	780790	89531		190	Compras	3124
1010	Tigre	7800	04010		200	Exterior	6356

Fig. 10: Table Extensions

Question/Answer Paper of the Forward Experiment
Parameters: D=1, TP=1

STARTING HOUR (hour:minute)→

- Rules:

  ON delete to Employee

  IF true

  DO delete to Works where Employee.NEmp = Works.NEmp

- When the next trigger is produced:

  DELETE to Employee where NEmp='01587'

which row key(s) are deleted in each table?

Employee	Department	Project	Works

ENDING HOUR (hour:minute) →

Fig. 11: Tests for the Forward Experiment

Question/Answer Paper of the Backward Experiment
Parameters: D=1, TP=1

STARTING HOUR (hour:minute)→

- Rules:

  ON delete to Department

  IF true

  DO delete to Employee where Employee.NDep = Department.NDep

- If the next rows have been deleted:

Employee	Department	Project	Works
12456	120		
15975			
56874			

What operations have been executed?

ENDING HOUR (hour:minute) →

Fig. 12: Tests for the Backward Experiment