Are All Classes Created Equal? Increasing Precision of Conceptual Modeling Grammars

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Recent decade has seen a dramatic change in the information systems landscape that alters the ways we design and interact with information technologies, including such developments as the rise of business analytics, user-generated content, and NoSQL databases, to name just a few. These changes challenge conceptual modeling research to offer innovative solutions tailored to these environments. Conceptual models typically represent classes (categories, kinds) of objects rather than concrete specific objects, making the class construct a critical medium for capturing domain semantics. While representation of classes may differ between grammars, a common design assumption is what we term different semantics same syntax (D3S). Under D3S, all classes are depicted using the same syntactic symbols. Following recent findings in psychology, we introduce a novel assumption semantics-contingent syntax (SCS) whereby syntactic representations of classes in conceptual models may differ based on their semantic meaning. We propose a core SCS design principle and five guidelines pertinent for conceptual modeling. We believe SCS carries profound implications for theory and practice of conceptual modeling as it seeks to better support modern information environments.

CCS Concepts: • **Information systems → Data management systems**; • **Software and its engineering → Software notations and tools**; *Unified Modeling Language (UML)*; • **Theory of computation →** *Program semantics*;

Additional Key Words and Phrases: Conceptual modeling, database design

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1 INTRODUCTION

Symbolic representations are the bases of information systems (IS) (Kent 1978; Wand and Weber 1993; Rey 1986). The symbolic nature of IS is particularly exemplified by conceptual modeling – a phase of IS development that specifies the kinds of objects to be represented in the IS using a variety of symbols put together following predetermined rules (conceptual modeling grammars) (Mylopoulos 1998; Krogstie et al. 1995; Wand and Weber 2002; Gemino and Wand 2003).

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As human society begins to depend on IS for its basic functions, the precision with which symbolic representations reflect reality has become a major issue (Floridi 2010; Lukyanenko 2016). Indeed, historically, progress in symbolic precision precipitated major milestones, such as the development of literary tradition and the spread of monotheistic religions (Levinson 1998). Improvements in the ability to represent phenomena drives progress in science (Hoyningen-Huene 2013).

We hope to motivate conceptual modeling research to increase the precision with which modern conceptual modeling grammars are developed. The need to make grammars more precise is timely. The last decade has seen a dramatic change in the IS landscape that alters the ways we design and interact with IS (Jabbari Sabegh et al. 2017; Recker 2015; Storey and Song 2017; Storey et al. 2015). Some of these changes are the:

— rise of "big data" and the corresponding question whether conceptual models can be leveraged to structure and visualize massive datasets (Chen et al. 2012; Rai 2016; Storey and Song 2017; Wixom et al. 2014);
— explosive growth in machine learning, natural language processing, data mining, and business analytics and the corresponding question of whether conceptual models can be used to support various activities involved (Endicott et al. 2017; Maté et al. 2017; Pick et al. 2017);
— dramatic shifts in the logical (database) technologies, including the spread of NoSQL databases that challenge traditional assumptions about conceptual modeling (Kaur and Rani 2013; Hills 2016; Storey and Song 2017);
— rise in social media, user-generated content, and crowdsourcing, which tend to be significantly more open and appear to require greater flexibility than afforded by traditional conceptual models (Lukyanenko et al. 2017; Turetken and Olfman 2013);
— ubiquitous, mobile, and wearable computing that invite new challenges of modeling that takes advantage of human mobility and powerful new sensors, while addressing small interface constraints (Krogstie et al. 2003; Lukyanenko and Parsons 2013a; Michael and Mayr 2013; Pick et al. 2017; Storey and Song 2017).

Researchers and practitioners have argued that traditional conceptual modeling is limited in the face of new challenges, and call for the development of new types of conceptual models more capable of supporting modern information environments (Chen 2006; Hills 2016; Liddle and Embley 2007; Lukyanenko et al. 2015; Recker 2015; Storey and Song 2017).

These developments occur amidst recent advances in cognitive psychology that suggests classes (or categories)—a fundamental construct of conceptual modeling grammars—are more multifaceted than commonly understood by existing conceptual modeling research. It is reasonable to posit that a more nuanced usage of classes in conceptual modeling can prove more effective at supporting emerging information environments.

While the representation of classes may differ between grammars, a common design assumption of modern conceptual modeling is what we call "different semantics same syntax" (D3S). Under this assumption, all classes are depicted using the same syntactic symbols, effectively suggesting that all classes are equal from the point of view of domain semantics.

Following recent findings in cognitive psychology and the dramatic changes to the IS landscape, we introduce a novel design assumption—semantics-contingent syntax (SCS) whereby syntactic representations of classes in conceptual models may differ based on their semantic meaning. We posit a core design principle and propose specific design guidelines for conceptual modeling grammars to adhere to SCS. By offering a nuanced approach for using classes in conceptual modeling, we hope to improve the precision of the representational function of modern IS.

2 BACKGROUND: TRADITIONAL UNDERSTANDING OF THE CLASS CONSTRUCT

Conceptual models are created to represent objects of interest to users of IS (Roy et al. 2015). Conceptual models typically represent classes of objects rather than concrete specific individual objects, thus classes (sometimes referred to as entity types, kinds, categories, or concepts) are central constructs in most conceptual modeling grammars (Smith and Smith 1977; Mylopoulos 1998; Borgida et al. 2009; Olivé 2007; Chen 1976; Fettke 2009).[1]

Since 1970s, over a hundred different conceptual modeling grammars have been proposed, tested, and adopted in practice. In many such grammars, classes are represented explicitly. These are typically models of "substance and form" (Burton-Jones and Weber 2014) (sometimes also referred to as "conceptual data models")—modeling "things" in the world and their properties organized into classes. These include such popular modeling techniques as the Entity Relationship Model (ERM) and Unified Modeling Language (UML) (when used to model application domain, rather than systems architecture) (Chen 1976; Dobing and Parsons 2006; Fettke 2009; Jacobson et al. 1999). In other types of conceptual modeling grammars such as those that emphasize "possibility and change" (also known as "process models") (see, e.g., Arazy and Woo 2002; Burton-Jones and Weber 2014; Recker et al. 2011; Taghavi and Woo 2017; Samuel et al. 2015) classes of business activity and goals are modeled implicitly. For example, in business process modeling notation (BPMN), swimlanes may depict a type of participant in a process, effectively forming a class (Wahl and Sindre 2006; Soffer and Wand 2005).

While representation of classes may differ between grammars, a common feature of most conceptual modeling grammars is showing classes that may represent very different types of objects using the same syntax. Thus, the syntax of a rectangle would be used to model such seemingly different domain objects as "human" and "chair". According to the prevailing conceptualization of the class construct, classes representing different objects share the same syntax; we term this assumption as *different semantics same syntax* (D3S).

To illustrate the meaning of the D3S assumption, consider a simple scenario of a university domain depicting typical entity types for this context, such as professor, class, student as well as the context in which the interaction among these entity types occurs (e.g., facilities, parking). Under D3S, all classes are depicted using the same syntactic symbol (e.g., box in ERM, see, Figure 1) despite these classes potentially representing very different kinds of entities in the domain (e.g., natural kinds, social entities, artificial entities, see below). Effectively, Figure 1 suggests that professors, classes, students, and parking permits have the same ontological status. As syntax imposes constraints on the kinds of semantics that analysts are able to express, treating these different entity types as syntactically equivalent results in uniform treatment and interpretation of the semantic content of these entity types, which may or may not be desirable.

The same problem could also be found in modeling grammars that do not have an explicit class construct. For example, although BPMN distinguishes between participants of the process and artifacts, BPMN modelers could use the same rectangular swimlane syntax to model "customer" as well as "customer service department" thus not distinguishing through syntax between physical and social classes (White and Miers 2008).

Despite having a wide diversity of conceptual modeling approaches over the past forty years, the D3S assumption is widely held. Yet this position appears to be somewhat contrary to the

[1]In this work, we use the terms (e.g., classes, attributes) based on the domain of discourse. Conceptual modeling research typically uses terms such as (1) classes, sets, or entity types; (2) objects, members, entities, or instances; and (3) attributes or properties to denote what psychology commonly refers to as (1) concepts, categories, or kinds; (2) objects, individuals, or members; and (3) features, characteristics, attributes or properties, respectively.

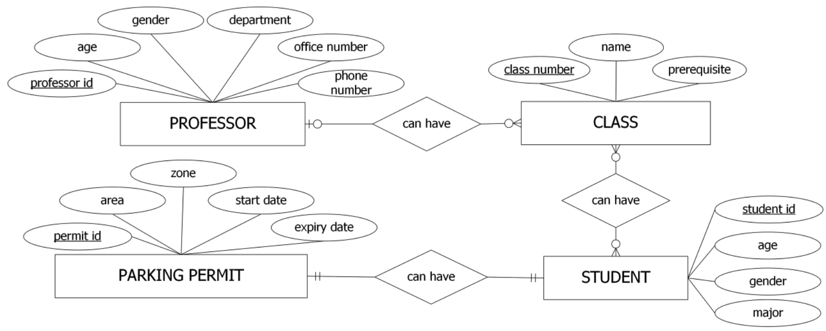

Fig. 1. ER diagram from Rainer et al. (2013)
Note: Attributes are added to the original diagram in Rainer et al. (2013).

growing body of research in cognitive psychology. Cognitive psychology—a major reference discipline for conceptual modeling (Lukyanenko et al. 2014a; Wand et al. 1995)—has increasingly examined differences in how concepts are mentally represented and processed, and implies fundamental differences among concepts in IS (i.e., classes in conceptual modeling) (Medin 1998; Medin et al. 2000).

We also find awareness of this issue in conceptual modeling work. As examples, Parsons and Wand's notions of class vs. category (2008a, 2008b) as well as March and Allen's (2012, 2014, 2015), Bergholtz and Eriksson's (2015), and Lukyanenko et al.'s (2015) distinction between social and material objects could be used to support an argument about encouraging syntactic differences between semantically different classes in conceptual modeling scripts. These arguments further motivate our efforts.

In this article, we consider an alternative possibility: syntax contingent on the semantics to be conveyed by the class—*semantics-contingent syntax (SCS)* assumption. To develop this possibility, we next survey cognitive psychology research.

3 THEORETICAL FOUNDATIONS IN COGNITIVE PSYCHOLOGY

The idea that representation of concepts differs due to their fundamentally different nature began to emerge in cognitive psychology in 1970s. Prior to 1970s the dominant theory was a *classical theory* that treated concepts as sets of necessary and sufficient conditions that definitively determined whether a particular object was a member of the class. The assumptions for forming and representing classes under the classical view did not distinguish classes based on their semantics and therefore upheld the D3S assumption.

In 1970s, the pioneering work of Eleanor Rosch developed a *prototype theory* of concepts (Rosch 1975, 1978, 1999; Rosch et al. 1976). This model viewed concepts as sets of typical attributes not fully sufficient to establish class membership. The view advocated family resemblance as a principal for representing classes and determining class membership of an object (Rosch and Mervis 1975; Wittgenstein 1953). Family resemblance allowed for *feature centrality* showing that some features could be more important than others in determining class membership (e.g., *has feathers* can be more important than *has round head* for determining something is a bird), and also suggested some attributes may have different weights (a consequence of feature centrality). Thus, for example, the attribute *has feathers* might be more salient than the attribute *has two legs* for a class of bird. This also implied that some attributes may be optional (e.g., *has round head* for bird) when depicting classes.

Following the prototype theory of concepts, other theories emerged also motivated by the many shortcomings of the classical theory. The *exemplar theory* of concepts proposed that concepts are represented as sets of exemplars or specific objects, each potentially different from one another. The theory posits that when people first encounter objects, they store them uncategorized as a constellation of attributes (termed "exemplars") (Wills and Pothos 2012; Nosofsky 1986). Later, when another object is experienced, it is compared to stored exemplars to determine similarity, and if deemed sufficiently similar, the two objects are associated together forming a class (Nosofsky 1986; Pothos 2007). Yet, the similarity between two exemplars is not required to be exact, thus two objects, while members of the same class, retain their unique, non-sharable features (attributes) in human memory (Barsalou et al. 1998).

Finally, the *theory theory* of concepts suggested that in addition to the representation mechanisms explored by the classical, prototyping and exemplar theories, individuals utilize their broader knowledge network and background of the world in forming and representing concepts (Murphy 2004; Murphy and Medin 1985). This view moved beyond the traditional assumption that in forming classes only the "internal structure" of the class (i.e., members' attributes) is considered. For example, theory theory suggests that an avid bird watcher might have a different representation of the concept 'bird' because of their richer and more nuanced background knowledge about the world, including facts that trees can accommodate nests, the largest predators live on land, and flight is an energy-intensive process. All these background presuppositions impact how one could reason and think about which features (attributes) are key for a concept and how these attributes are related to each other. Thus, an avid bird watcher might consider the attributes *lays eggs, has wings*, and *needs constant nutrition* as more central to the concept bird due to their in-depth knowledge. This does not necessarily have to apply only to experts in a domain, but humans do this as they look to connect their varying knowledge bases. Importantly, given the influence of background knowledge on how classes are formed, it may be important to explicitly model the background knowledge together with the classes.

Cognitive psychology research shows that conceptual representations may differ not only between major models of classification, but also *within* models. In addition to proposing the prototype theory of concepts, Rosch et al. (1976) argued that when considering different levels of a hierarchical taxonomy (e.g., animal—bird—common tern), one level particularly stands out. This level was coined the *basic level* (Berlin et al. 1973; Rosch 1973). Basic level tends to be a taxonomic middle (e.g., "bird" as opposed to "animal" or "common tern") and cognitively privileged in many ways. Basic level tends to be the first/entry level that people think about when they encounter that type of object. People tend to name significantly more attributes of the basic level compared to other levels. Basic also happens to be the highest level at which objects can be mentally visualized. Members of basic level (i.e., subordinate categories) tend to be quite similar (e.g., birds look very much the same), however neighboring basic-level categories are quite dissimilar from each other (e.g., fish versus bird). Basic-level words tend to be the most frequent ones used in ordinary discourse and also one of the first words learned by children. Basic-level effects have been demonstrated for both natural and artificial domains. The special status of basic-level categories potentially suggests that it may be important to designate classes as basic or non-basic (a point considered in the next section).

The disillusionment of psychologists with the classical model of concepts (Murphy 2004) led to numerous studies that suggested further distinctions in processing and representing concepts. Among this is the work by Barsalou (1983) on ad hoc categories. Barsalou noted that some categories are not stable the same way many artificial and natural categories are, but instead they are constructed to fit a particular scenario or situation. For example, one could construct the category "things to be taken out of a burning house" which would include children, pets, and material valuables. Importantly, members of these categories fail to share many features and are bound together by a common objective or goal. This also means that drawing inferences about members of this category beyond this goal is quite problematic. Thus, it appears that an important function of classification—inferential utility (Parsons 1996; Parsons and Wand 2008b)—is weakly available when dealing with these categories beyond their objective or goal for being categorized together.

An important consequence of the emergence of the alternative views of classes is the fact that in the process of exploring these views and contrasting them with the classical theories, psychologists begin to explore whether a particular model is more germane to a particular set of phenomena or particular domain (Murphy 2004). For example, the classical theory of concepts appears to be well positioned at representing certain artificial phenomena and artificial rules. A poster child example in the classical theory is a concept of a triangle that can be effectively defined using necessary and sufficient features. In contrast, advocates of the exemplar and prototype theories tended to explore its advantages for natural concepts, such as birds, plants, and geographic or celestial objects; it appears their structure is more aligned with the family resemblance notion. Despite decades of debate, a common consensus is that no single theory of psychology is adequate at fully capturing concepts (Barsalou 2008; Gentner and Kurtz 2005; Medin 1998; Murphy 2004; Ross and Murphy 1999; Smith and Medin 1981; Smith 2005). It is now widely held that different ways of representing concepts may be more effective and appropriate, depending on what is being represented.

Reflecting on these developments in psychology, Medin et al. (2000) argue that while one could not definitively claim that different concepts (classes) exist, the "sensitivity to kinds of concepts is quite an effective research strategy" (Medin et al. 2000:138). We pursue this strategy in the next section and propose a core design principle and design guidelines for conceptual modeling consistent with the semantics contingent syntax assumption rooted in modern psychology.

4 GUIDELINES FOR USING THE SEMANTICS CONTINGENT SYNTAX IN MODELING

Given that conceptual modeling research widely recognizes cognitive psychology as a major reference discipline, the modern position among cognitive psychologists can be regarded as offering a strong endorsement for the use of the semantics-contingent syntax assumption in conceptual modeling. We propose the following core SCS design principle for conceptual modeling: *When classes in a conceptual model exhibit different structure or behavior, select the syntax consistent with the semantics of each class.* We now discuss specific manifestations of this core design principle in conceptual modeling as follows from cognitive psychology reviewed in the previous section.

Optional Attributes. Conceptual modeling research previously proscribed the use of optional properties on ontological grounds (Gemino and Wand 2005; Bodart and Weber 1996; Bodart et al. 2001; Burton-Jones et al. 2013; Saghafi and Wand 2014). Recent arguments in psychology suggest that some classes can be represented more faithfully using prototypes, which implies conceptual modeling grammars should be amended by including attribute optionality when dealing with unique salient attributes, which are not part of the general class definition (attribute salience is discussed in Guideline 2). We thus recommend:

Guideline 1 (Optional Attributes). When members of a class are expected to have unique salient attributes, which are not part of the general class definition, model those unique relevant attributes as optional.

Each grammar may have its own syntax for depicting optional attributes. For example, an attribute may be underlined with a dashed line, italicized, or preceded with "opt". Thus, in a biological monitoring database, a class *bird* may have *can fly* as an optional attribute; ostriches, kiwis, and penguins would not have this attribute.

Attribute Salience. Unlike optional attributes, attribute salience or centrality has not been extensively considered in conceptual modeling research. Psychology, however, indicates that humans routinely conceptualize essential, particularly noticeable or important properties of classes to remember or convey the gist or essence of their members. Attribute salience can also vary depending on context and intended purposes and can be elicited from users by asking which attributes are more important (Tversky 1977; Ross and Murphy 1999). Attribute salience can be depicted by attaching weights (e.g., 0.5) to indicate the attributes' salience for a given application, as commonly done in applied psychology (Tversky 1977; Lovett et al. 2009). We propose accordingly:

Guideline 2 *(Attribute Salience).* When some attributes are more essential for a class in a given domain, indicate their salience (e.g., by using attribute weights).

To illustrate, when modeling credit card services analysts may choose to indicate *card limit, credit score* and *income required* as more central attributes of a class "credit card", whereas other attributes, such as *card design*, and *loyalty program*, as mandatory, but not so salient. The centrality of these attributes may be important to specify to communicate special legal, business process, or customer service requirements.

Typical Members. According to prototype and exemplar theories, some classes are best thought in terms of exemplar or prototypical members. Most commonly, these are natural classes—classes of phenomena in physical world (which typically exhibit large natural variability of features among members) or new natural and social classes with very few known members (Murphy 2004; Nosofsky 2011). We propose the following guideline:

Guideline 3 *(Typical Members).* When classes exhibit substantial natural variation of attributes that is important to preserve, or when dealing with classes that have not been fully established, represent these classes using "typical" or "exemplar" members.

To illustrate Guideline 3, return to the case of students and professors from Figure 1. Both students and professors are natural classes representing physical individuals. There is considerable variation in possible valid attributes of both classes, so analysts may choose to represent them by showing a "typical" student or professor (using, for example, ORM, UML Object Diagram, or ER Set Diagram notations) (Elmasri and Navathe 2009; Jacobson et al. 1999; Balsters and Halpin 2008) or some future grammar more capable of showing typical objects. This may be advantageous if the storage technology is flexible (e.g., a value-pair NoSQL database) and permits storing attributes for professors and students which may not be anticipated at the time of the design.

This guideline also applies to social classes (or classes that represent human institutions and social categories) (Searle 1995; Bergholtz and Eriksson 2015; March and Allen 2014). Thus, when modeling a future "academic conference" with no known instances (e.g., when a new conference is being established), analysts may choose to model this social class using a typical example of such conference (using the same syntax as for typical students and professors) to explicitly permit for variation and change of features once more conferences are held and the institutional norms become more established.

Guideline 3 implies a considerable reconceptualization in conceptual modeling research of the traditionally assumed relationship between the syntax of classes and the syntax for depicting individuals. It contrasts with both traditional and emerging approaches that proposed novel conceptual modeling grammars, including those based on representing individuals, rather than classes (Heath and Bizer 2011; Lukyanenko et al. 2017), but yet retained the D3S assumption.

Basic Level Classes. Psychology research claims that among classes, one level is particularly privileged—basic level—and thus it may be important to denote basic level classes (consistent with its special status in human cognition). There are potentially numerous implications of the basic level categories for conceptual modeling (McGinnes 2011; Castellanos et al. 2016). For example, the fact that basic-level categories are frequently the entry-level, suggests that they can be a source of various biases with both positive and negative consequences for conceptual modeling. For example, analysts and users working with a conceptual model may be able to understand basic level classes easier than other ones. When data collection is organized around basic level classes (as opposed to more specific ones), the accuracy and quantity of information provided may be higher (Lukyanenko et al. 2014a, 2014b). Considering these effects, it may be important to have a special designation in a conceptual model to indicate basic-level classes:

Guideline 4 *(Basic-level).* Analysts should identify basic-level classes in a model and denote them to communicate their privileged status among classes.

Naturally, effective use of the basic level in a conceptual model would presuppose a working knowledge of the procedures to identify it by analysts. Research in conceptual modeling recently began to consider the steps to determine which classes in a model are basic (Castellanos et al. 2016). While analysts can already refer to this work, this is a relatively recent topic in conceptual modeling and more research is needed to understand the basic level better in the context of information systems and communicate the value of this special class to practitioners.

Ad hoc Classes. Research in psychology argues that some classes are less stable and are created for a fleeting task at hand. Termed "ad hoc categories" in psychology (Barsalou 1983), these may describe objects joined together for a limited period of time. For example, humans routinely form such ad hoc classes as "objects to take on vacation," "items permitted on the midterm exam," or "topics to discuss during tomorrow's meeting." An important characteristic of all these classes is that they typically contain completely dissimilar members (e.g., sun screen and travel maps). Given that their members are so different in their properties, drawing inferences about the members of these classes is usually impractical (beyond the organizing principle that puts these objects into the same class). For example, knowing that one item to take on a vacation is a passport, does not allow one to infer properties of other items, such as, sun screen or credit card (beyond the organizing property of being useful for the vacation). The lack of inference carries implications for how these classes are used, thus warranting identifying ad hoc classes in conceptual models:

Guideline 5 *(Ad-hoc Classes).* Analysts should identify ad hoc classes—classes created temporarily for the task at hand that have highly dissimilar members.

We suggest noting ad-hoc classes with dotted lines of the box around the class, instead of a solid line. We believe this is apt with the potential temporary nature of the class that may vanish later. Ad-hoc classes carry several implications for conceptual modeling research. Traditionally, conceptual modeling research has cautioned analysts when creating and using classes that do not permit inferences (Parsons and Wand 1997). For this reason, Parsons and Wand (2008a, 2008b) drew a distinction between a "class" and "category". A class mapped to something that exists in the world, manifested by the fact that having observed some properties, more properties can be inferred. For example, having identified an object as a bird (based on observable features), people can make additional inferences about unobservable properties such as *has heart, lays eggs, builds nests.* In contrast, ad-hoc categories lack the ability to infer additional properties from those needed to identify an object as a member of the category.

While the distinction between classes and categories remains important for the identification of natural classes in conceptual models, Guideline 5 provides an additional rationale for using classes with weak inferences—the ability to capture objects needed for an ad-hoc task. Ad hoc classes can play an important role in building a conceptual model over an existing set of data sources for analysis (a common task in the age of big data). For example, analysts may analyze a "big data set" looking to find patterns for a particular purpose (Storey and Song 2017; Frisendal 2016).

Table 1. Guidelines based on the Core SCS Design Principle for Conceptual Modeling

Guideline Name	Guideline Description
G1: Optional Attributes	When members of a class are expected to have unique salient attributes, which are not part of the general class definition, model those unique relevant attributes as optional.
G2: Attribute Salience	When some attributes are more essential for a class in a given domain, indicate their salience (e.g., by using attribute weights).
G3: Typical Members	When classes exhibit substantial natural variation of attributes that is important to preserve, or when dealing with classes that have not been fully established, represent these classes using "typical" or "exemplar" members.
G4: Basic Level	Analysts should identify basic level classes in a model and denote them to communicate their privileged status among classes.
G5: Ad-hoc classes	Analysts should identify ad hoc classes—classes created temporarily for the task at hand that have highly dissimilar members.

This may result in "temporarily" treating some objects or instances as equivalent. For example, banks, lawmakers, municipalities, lenders, and mortgage brokers could result in an ad-hoc class of "institutions involved in the 2008 financial crisis". Knowing that this is an ad hoc category may also guide the decision to select a NoSQL database (to store extreme variation in the attributes of the instances).

A summary of our guidelines can be seen in Table 1. Next, we turn to implications of the proposed guidelines for theory and practice of conceptual modeling, database design, and information systems development.

5 OUTLOOK FOR FUTURE

Currently, no existing grammars support all the proposed guidelines as research remains generally unaware of the semantics contingent syntax assumption, thus effectively treating all classes equally.

The fact that modern grammars treat all classes similarly results *in construct incompleteness* (Moody 2009; Wand and Weber 1993; Fettke and Loos 2003), as grammars lack the facility to represent a variety of different classes that cognitive psychology research suggests may exist. Further, as modern grammars tend to reserve a single construct for potentially different (according to cognitive psychology) classes (e.g., established vs. new ones), this produces *construct overload*—whereby potentially different real-world semantics are represented using the same syntax. Construct incompleteness and construct overload may engender difficulty in creating conceptual modeling scripts, using grammars for domain understanding and IS development, and may ultimately result in poor information quality of data stored in IS (Wand and Wang 1996; Moody 2009; Saghafi and Wand 2014; Wand and Weber 1993; Lukyanenko et al. 2016a; Jabbari Sabegh et al. 2017). We call on future studies to rethink the prevailing D3S assumption and consider our proposed SCS alternative.

The SCS assumption, manifested through the core design principle and five guidelines, promises to shed new light on a number of ongoing debates in conceptual modeling research. To illustrate, consider a recent debate in the conceptual modeling community on the distinction between material and social classes. Recent conceptual modeling research, drawing on ontology rather than cognitive psychology, is beginning to distinguish between social and material categories. Social categories (e.g., corporation, conference) may *precede* the existence of instances of objects (i.e., top-down), whereas material categories emerge after observing perceived similarities among objects in the world (bottom-up) (Bergholtz and Eriksson 2015; Lukyanenko et al. 2015; March and Allen 2012, 2014, 2015). This distinction for instance may be important in developing and evaluating conceptual modeling grammars. For example, grammars such as ERM and UML appear to promote "inherent classification" (Parsons and Wand 2000), an assumption that stipulates instances must belong to existing classes, whereas emerging instance-based grammars advocate a precedence of instances over classes (Lukyanenko et al. 2015; Lukyanenko and Parsons 2013b; Parsons and Wand 2000). Thus far, both positions have been considered to be diametrically opposing each other. Our work (see Guideline 3) suggests that an important new distinction may be between established social classes and new social classes, rather than between social classes and material ones. We suggest that for new (social, material) classes, as all attributes have not been fully defined, representation using typical members may be more appropriate (and more consistent with cognitive psychology). In contrast, established social classes (e.g., long-standing institutions and social categories, such as traditional marriage or gender), can be treated in a similar fashion as material classes in that their attributes are well understood.

The potential existence of different kinds of concepts carries important implications for empirical studies in conceptual modeling. Therefore, considering the differences between concepts may be important for a more nuanced understanding of empirical findings in conceptual modeling. For example, failure to support a hypothesis about the advantages of instance-based conceptual modeling grammars may be due to the nature of concepts used in the study (e.g., social, top-down concepts as opposed to potentially more faithful to the approach bottom-up, material and natural concepts) which all appear the same under D3S. Similarly, the presence of basic level categories along with non-basic level classes in a conceptual modeling diagram may bias participants, which may inadvertently confound the results. Thus, it is important to consider the potential diversity among classes (i.e., SCS) when developing and evaluating conceptual modeling grammars, methods and approaches.

The SCS carries profound implications for database design too. Above, we already suggested that some of the classes presuppose a NoSQL rather than a relational environment; Guidelines 1 and 3 suggests adopting a flexible storage schema capable of representing diverse instances. In future work, we hope to explore additional implications of SCS for data/information storage and processing. This area of work continues to grow in importance as the landscape of storage technologies rapidly evolves and researchers have noted the absence of guidance from conceptual modeling to bridge the gap between domain semantics and novel kinds of database objects (Kaur and Rani 2013; Hills 2016). We hope our work can contribute here.

To illustrate the value of a more precise modeling for other aspects of IS development, consider its potential implications for information quality—accuracy, completeness, and timeliness of data in databases (Burton-Jones and Volkoff 2017; Batini and Scannapieca 2006). Both optional attributes and attribute salience can be used for subsequent data quality control and assurance. For example, knowing that a certain attribute is optional may be used to design appropriate data input restrictions. Likewise, once developers know that a certain attribute is essential for the class, its input validation routines may be engineered to be particularly stringent. We can also predict that systems which are based on basic level classes (Guideline 4) may be easier to use for non-expert users; this also suggests a promising new connection between conceptual modeling and participatory design and usability research (Lukyanenko et al. 2016b) which can be explored in future studies.

We should also caution that incorporating SCS assumptions into conceptual modeling may have negative consequences on the understandability of conceptual modeling diagrams. While the improvement in precision of a conceptual model encompassing SCS would be a welcome addition to a modeling grammar, divergent ways of representing classes *may* impede understandability due to the decreased parsimony of the grammar. At the same time, SCS may offer an opportunity to rethink the way conceptual modeling scripts are being created. Online software tools are popular for developing conceptual models. The new affordances of this software can potentially be used to mitigate the increased complexity (e.g., by utilizing rich graphics, offering dynamic zoom, putting different constructs on layers that can be turned on and off, etc.). We call for research on innovative software tools capable of reducing visual complexity (Moody 2009) of conceptual modeling grammars.

We also encourage researchers to extend our design principles by considering application-specific (Lukyanenko and Parsons 2013a) needs or by making further theoretical refinements (e.g., by synthesizing arguments from philosophy and other theoretical perspectives, see Clarke et al. (2016)). For example, a potential extension to Guideline 3 is to measure and show the extent of variation of the attributes within a class—for example, by indicating via syntax that there exists a "long tail" of attributes of students that are rare and not shared among many students (e.g., "is a Rhodes scholar". "Secondary citizenship", a host of medical, ergonomic preferences) (see, e.g., Lukyanenko and Parsons (2013b) and Dewan and Ramaprasad (2012)). Clearly, if attribute variation is extremely high, it may be impractical to list every single one as this may increase diagram complexity and result in lower ability to comprehend and use the diagram (Batra 2007; Cooper and Podgorny 1976; Gemino and Wand 2005); at the same time, research has shown that information variation is an important consideration when making decisions (Tremblay et al. 2012). With this work, we motivate future research on ways to represent highly variable attributes while keeping the diagrams clear and simple.

Future research should seek to develop a unified framework for understanding the diversity and consequences of different representations of classes. Our work contributes to this effort by catalyzing the discussion and reviewing relevant research in cognitive psychology. Future research should also consider arguments from other major reference disciplines of conceptual modeling such as philosophy where the differences between classes (kinds, categories, universals, concepts) have also been debated (Mattessich 2013; Piccinini and Scott 2006; Smith 2004; Smith and Mark 2003; Weiskopf 2009). Considering arguments from philosophy (e.g., ontology) is further important as it can shed more light on the nature of classes, and may possibly introduce additional considerations into the SCS assumption. We hope our initial effort can be used as a starting point for a more methodical analysis of the diverse classification landscape.

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