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An Exploratory Analysis of Semantic Network Complexity for Data Modeling Performance

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Abstract

Database modeling performance varies across different constructs. For example, it is usually easier to model a binary relationship than a ternary relationship. Based upon the empirical performance data, ternary relationships are thought to be more complex than binary ones. This paper investigates the relationship between user modeling performance and the complexity of the data model constructs. A complexity estimate is proposed that measures complexity based on three different aspects: component, coordinative and coupling complexity. The aggregation of the three provides the total complexity estimate. Two semantic network variations that users might use are suggested, and their complexity values compared against known user performance. Regression results show reasonable R square values. This analysis suggests that using semantic networks could be a practical way to estimate modeling complexity and user performance. Future research can consider more refined variations of the semantic network, to account for training, experience, and different data models.

Keywords: data modeling, user performance, semantic network

1. Introduction

There has been a steady stream of empirical works on user performance with data models and interfaces. These works have mostly been done through experiments. Recent works show an interest to provide objective estimates that can hopefully predict user performance. For example, Borthick et al. (1997) and Chan (1999) adapted traditional software metrics to apply to database queries. These metrics were tested again user performance data from experiments. Following this general aim of deriving objective estimates, we present another approach for the task of database modeling. Instead of adapting software metrics, we now look towards semantic networks and complexity theory to derive the complexity estimates of modeling constructs.

Data modeling is building an adequate representation of a slice of the real world (Srinivasan and Te'eni, 1995). Different modeling constructs are used to represent different categories of data and their relationships. A representation is the product of complex cognitive activities by the user, involving long term and short term memories and cognitive processing. The analysis presented in this paper concentrates on the construction process of data modeling. Other interesting processes related to data models, such as understanding and recall, are not included.

The subsequent sub-sections gives a brief overview of the entity relationship data model, empirical studies of user data modeling performance, followed by the objective. In Section 2, we discuss the concept of complexity and develop a complexity measure to estimate user data modeling performance. In Section 3 and 4, we develop the semantic network, apply the complexity estimates, and compare with published empirical data on user performance from a number of experiments. Section 5 ends with the concluding statements and recommendations for future research.

1.1 Literature Review: Entity Relationship Model

Chen (1976) proposed the entity relationship (ER) model as a unified view of data. The main components of the ER model are entity types, attributes and relationship types. An entity is a “thing” that can be distinctly identified and a relationship is an association between entities. Entities and relationships have properties that are called attributes. Entities sharing similar attributes are classified into entity types, and relationships among entity types are classified into relationship types. A relationship type can either be one-to-one, one-to-many or many-to-many. In the ER diagram originally proposed by Chen (1976), an entity type was represented by a rectangle, with the entity type name inside the rectangle. A diamond represents a relationship type, with the relationship name inside the diamond, the diamond joined by a single line to each of the entity types participating in the relationship. The lines extending from the diamond are marked with a “1”(one), “N”(many) or “M”(many): to illustrate the different kinds of relationship types.

The ER model has been largely popular in the past two and a half decades. Throughout this period, several enhancements have been proposed to improve the semantic representation and expressive power of the ER model. For example, cardinalities to represent constraints of relationship types were proposed, and composite attributes were suggested.

An Extended Entity-Relationship (EER) model was proposed, adding to the generalization abstraction of Chen’s original model by introducing an IS-A generalization hierarchy. In the a comprehensive and detailed survey on ER model extensions by Saiedian (1997), it is noted that generalization is one of the few important additions to the ER model. Many of the variations are differences reflecting personal preferences, such as ways of drawing diagrams and it may hinder the use of the basic model by causing confusion. The empirical studies referenced in the later sections used the ER model with the addition of generalization, and some studies differ in ER diagrammatic representations.

1.2 Literature Review: Data Modeling Performance

In the past decade, there have been a number of empirical studies on user data modeling performance, using different data models. In Batra at el. (1990), user performance in a data modeling task was measured by its modeling correctness. Batra defined modeling correctness as the degree to which a conceptual model approaches the correct solution, where the correct solution convey the same semantics about the data as the natural language description of the application. This definition was important because it allowed subsequent studies to compare empirically the performance of subjects using different data models to model a given problem description.

Batra also presented the notion of measuring modeling correctness at the level of facets [1]. Prior to this, there was no consistent method of measuring accurate representations of constructs present (e.g. entities, attributes, relationships, etc) in the various data models. Facets were a way of qualifying the constructs of different data models so that they can be evaluated at the same level. A list of commonly occurring facets across different data models were created and these were used as the basis in later empirical studies. The facets identified were: entity, identifier, descriptor, category constructs and the following relationship constructs, unary, binary one-many, binary many-many, ternary one-many-many and ternary many-many-many.

Batra et al. (1990) conducted an experiment whereby subjects were trained in two different data models, EER and Relational. The subjects were given a textual description of a problem description that they had to model using the data models they were taught in. Their modeling performance was graded at the facet level and a comparison was done between the two data models. The results showed that the EER model scored better than the Relational model in all facets except unary relationships.

1.3 Literature Review: Empirical Studies

In other related published papers that followed, similar experiments were conducted to measure user modeling performance of different data models at the facet level. Bock and Ryan (1993) compared the EER and Object Oriented (OO) model. Bock and Ryan (1994), compared the modeling performance of novice and experienced subjects using the EER model. Shoval and Shiran (1997) compared the modeling performance of the EER and OO data model. Liao and Palvia (2000) investigated modeling performance between EER, OO and Relational Model. To provide a better understanding of the different process of each study, we provide a brief overview of the data modeling experiments carried out in each of these studies, including Batra at el. (1990).

Modeling Task
The modeling task given in Bock and Ryan (1993), and also Bock and Ryan (1994) were identical to the textual problem description in Batra et al. (1990). But these two studies used a different ER diagrammatic representation from Batra et al. (1990). The modeling task in Shoval and Shiran (1997) used different textual problem descriptions and also differed in the ER diagrammatic representation used. Liao and Palvia (2000) did not include the textual problem description and ER diagrammatic representation used in their modeling task.

Subjects and Training
42 MIS graduates, who were considered novice database designers participated in the data modeling experiment of Batra at el. (1990). Prior to the data modeling task, these subjects were trained for 45-50 minutes in one of the data models used, Relational or EER model. In Bock and Ryan (1993), 38 MIS students, also considered novice database designers, were trained in one of the data models used, EER or OO model. The instructional period was 8 hours over several days, at the end of which the

[1] Some studies prefer to use the original and more common word “construct”, in place of “facet”. In this paper, “construct” and “facet” for data models have the same meaning.

subjects were given the modeling task. In Bock and Ryan (1994), subjects were divided into two groups. One group consisted of 32 MIS students, who were novices, the other group consisted of 25 professionals who had operational experience in database design. These subjects were trained in EER modeling for a total of 8 hours over a 2 week period and were given the modeling task one week after the instructional period. In Shoval and Shiran (1997), 44 MIS students, considered to be novices, were trained in two data models used in the study, EER and OO model.

The instructional period was 6 hours, and subjects had to complete the modeling task using the two data models they were taught in. In Liao and Palvia (2000), 66 MIS students, considered to be novices, were trained in the EER, OO or Relational model. The instructional period was 75 minutes for the EER and OO model, and 55 minutes for the Relational model, and was given the modeling task one week after.

Grading

These studies followed closely the grading scheme proposed by Batra at el. (1990), with the exception of Liao and Palvia (2000), which did not include details of the grading.

1.4 Objective

Our objective is to propose a simple and intuitive way of estimating modeling task difficulty at the facet level. The complexity estimates can then be tested against these empirical data on user performance to investigate their relationship. Empirical data on user performance in ER modeling are present in each of the studies, all measured at the facet level, which allows for comparison to be made across different studies. In the next section, we will develop our complexity estimate.

2. Complexity

What is complexity? Its definition still eludes many scientists today. The term complexity is highly subjective; what is complex to one observer may be simple to another. For example, many would agree the ordering of a numerical sequence 1, 2, 3, 4, 5, 6, 7, 8, 9 is simple. But the ordering of the sequence 8, 5, 4, 9, 1, 7, 6, 3, 2 seems random and complex. However, those who have observed that the latter sequence is ordered, albeit alphabetically, would not describe it as complex (Corning, 1998).

Presently, there are a number of studies focusing on user performance in the area of database retrieval. Chan et al. (1999) found that three important factors determine user performance during database retrieval using a query language: representation realism, expressive ease, and task complexity. Using empirical data, Borthick et al. (1997) develop complexity measures of database queries and evaluated these measures. Similarly, Chan (1999) employed Lines of Code as a complexity metric to estimate query performance. In the area of database modeling, plenty of empirical data on user modeling performance are available from a number of studies. However, little work has gone into discovering an appropriate complexity metric to estimate user performance in data modeling. Past studies on data modeling appraise user modeling performance at the facet level. This suggests that the proposition of a complexity metric must be tailored to estimate complexity at the level of the facet.

2.1 Complexity Metrics

Data modeling is mostly a cognitive process. On the outset, finding a suitable complexity metric seems to be an uphill task. If we look at the field of large-scale software development, software metrics have been popular in tracing the complexity of the development process. The complexity estimate was then used to gauge the amount of resources that is required. Many different software metrics are available but they have one shared characteristic; they estimate complexity by measuring the different aspects (e.g. module size, parallelism, statement density) of the software development process. This suggests it may be feasible for our complexity metric to be able to measure different aspects of the cognitive process of data modeling. In proposing a software metric for complexity traces in software development, Ebert (1995) took the approach of measuring complexity factors independent of underlying software processes, specification methods, and development environments. This suggest it would be practical for us to put forward a complexity metric that is independent of a particular data model and problem domain specification, that can be applied to estimate the complexity for any data modeling task.

In the field of human behavior studies, Wood (1986) proposed a theoretical model of task defined in terms of three elements; products, acts and information cues. He suggested that in generality, any task could be defined in terms of products, acts and cues. These three elements also serve as building blocks for him to define task complexity along three aspects: component, coordinative and dynamic complexity. Component complexity measures the “number of distinct acts that need to be executed in the performance of a task and the number of distinct information cues that must be processed in the performance of those acts”. Coordinative complexity measures the “form and strength of the relationship between task information cues, acts and products, as well as the sequencing of inputs”. Dynamic complexity measures the changes in the states of the world which have an effect on the relationship between task inputs and task products”. Total task complexity is the aggregation of these three aspects of complexity.

Corning (1998) suggests that complexity often implies the following attributes:

1. A complex phenomenon consists of many parts (or items or units or individuals).
2. There are many relationships/interactions among the parts.
3. The part produce combined effects (synergies) that are not easily predicted and may often be novel, unexpected or even surprising.

This brief discussion of complexity and complexity metrics used in other fields of study presents us with ideas to put forward our own complexity measure for estimating data modeling difficulty in the next sub-section. In particular, our proposed complexity measure incorporates some portion of the theory of task complexity proposed in Wood (1986).

2.2 Proposed Complexity Measure

To explain why user performance varies when modeling different facets of a given data model, the following complexity measure is proposed. Our proposed complexity measure can be used to estimate the complexity of a given data modeling task at the facet level. Data modeling complexity is to be measured along three aspects: component, coordinative and coupling complexity. Total complexity is simply the aggregation of these three types of complexity.

Component Complexity

Component complexity meaures the cognitive effort required to store (in memory) the relevant chunks of information necessary to accomplish modeling of a particular facet. Component complexity is directly proportional to the amount of information needed to successfully model a facet. As the required amount of information increases, component complexity also increases; the user having a harder time coping and keeping track of the larger amount of information.

The empirical study done by Srinivasan and Te'eni (1995) indicated that different abstraction levels were used by subjects during data modeling. As a result, component complexity can be measured along different abstraction levels, depending on the nature of the task at hand. For example, when modeling an entity facet, it is likely that the subject is using a lower level of abstraction, and component complexity might include the attributes of the entity as relevant information necessary to model that facet. Whereas in modeling a binary relationship facet, it is likely the subject is using a higher level of abstraction and the attributes of the two entities would not be regarded as relevant information necessary to model that facet. Component complexity can be reduced by using external aids like paper to jot down ideas, as it reduces the cognitive effort needed in storing information.

Coordinative Complexity

Coordinative complexity measures the cognitive effort required in managing the sequencing of information necessary to perform the modeling task. Coordinative complexity is low when there is little timing or sequencing involved, high when it is necessary to synchronize the timing and sequence to process the different chunks of information. For example, when modeling an entity facet, coordinative complexity is likely to be low since there is little sequencing involved between the relevant chunks of information. In modeling a ternary relationship, coordinative complexity is likely to be higher since certain chunks of information are dependent on others (relationship can only be determine after entities are known), while other chunks of information must be process simultaneously (to determine the type of ternary relationship, we have to process information on all 3 entities). Coordinative complexity can be reduced by referring to explicit instructions on the sequencing steps that needs to be performed to model a facet as less cognitive effort would be required.

Coupling Complexity

Coupling complexity measures the cognitive effort required to form the necessary associations between relevant chunks of information that are related to each another. It is different from component complexity. Thus, a binary relationship is likely to have a lower coupling complexity than a ternary relationship because there are less associations and interactions between the relevant chunks of information.

2.3 Semantic Network

Data modeling process is a cognitive process (Srinivasan and Te'eni, 1995), and it would be useful to utilize existing theories of knowledge representation in the field of cognitive psychology . The semantic network model of memory proposed by Quillian (1969) has been widely applied. A semantic network represents information or concepts as a series of nodes which are connected to one another by links. We will adopt the semantic network as a model of memory for representing the chunks of relevant information during the construction process of modeling each facet. Using the semantic network model, indexes can be computed for the estimating component, coordinative and coupling complexity (3Cs).

2.4 Analysis Approaches

In section 3, a set of semantic networks based on each modeling construct at the general facet level is proposed; corresponding indexes to compute each of the 3Cs are suggested and applied to the semantic networks. The complexity data are compared with the empirical performance data from a number of reported experiments on data modeling. Regression is used to assess the fit between the complexity values and the performance values. In section 4, the set of semantic networks proposed in section 3 are tailored to the particular data model used in the experiments. A smaller set of experiments is used for the regression test. This set of experiments used the same data model problem. Thus each semantic network is the same across the set of experiments. It is likely that a customized network will be a better predictor of performance.

3. General Facet Semantic Network Complexity Analysis

For each facet, a semantic network is develop to indicate how a user may store the facet's information in his memory. The semantic networks for entity, identifier, category, unary relationship (1:1 and 1:M), binary relationship (1:1, 1:M and M:N), and ternary relationship (1:M:N and M:N:O) are shown in Appendix A. For each of the semantic network, complexity estimates are given, based on the component, coordinative and coupling complexity. These are also shown in Appendix A.

Table 1 shows the complexity values and the performance data from various experiments. These data are used for regression studies. The regression results are reported in Table 2. Except for the study by Liao and Palvia (2000), the p-values vary from about 1% to 12%, either significant or close to significant, depending on whether 5% or 10% is adopted for the significance test. The R square values (from 0.352 to 0.882, except for the last study) are reasonable when compared to other studies. For example, Borthick et al. (1997) found R squares ranging from 0.262 to 0.408 for four metrics used to predict user query performance; Chan (1999) reported R square of 0.33 for first order linear regression and 0.81 for quadratic regression for relational queries.

Borthick et al. (1997) and Chan (1999) found that quadratic metrics or regressions can better match user performance. This is also found to be true here. As shown in table 2, most of the R square and p-values improve substantially for the quadratic regressions (i.e. performance = a + b* complexity + c* complexity squared).

	Expe-rience Level	En-tity	Iden-tifier	Cate-gory	U-nary 1 : 1	U-nary 1 : M	Bi-nary 1 : 1	Bi-nary 1 : M	Bi-nary M : N	Bi-nary M:N & attri-bute	Ter-nary 1 : M : N	Ter-nary M : N : O
Complex-ity Estimate	-	1	3	3	12	14	11	12	11	13	17	15
Batra et al. (1990)	Novice	92.3	73.9	76.2	55.2	-	-	84.9	92.9	-	41.3	45.2
Bock et al. (1993)	Expe-rienced	98	96	92	96	-	-	89	100	-	47	79
Bock et al. (1994)	Novice	90.1	78.4	76.6	83.6	-	-	93.0	100.0	-	9.4	10.9
Bock et al. (1994)	Expe-rienced	92.8	86.3	76.0	88.0	-	-	82.0	97.0	-	11.0	9.0
Shoval et al. (1997)	Expe-rienced	99.2	95.5	99.4	88.1	-	94.3	82.6	81.3	-	85.2	94.3
Liao and Palvia (2000)	Novice	-	69.7	-	35.0	45.0	85.0	83.8	74.4	-	-	57.5

Table 1. Complexity estimates based on general facet semantic networks

		Linear Regression		**Quadratic Regression**	
		R square	P value	R square	P value
Batra et al. (1990)	Novice	.430	.078	.604	.098
Bock et al. (1993)	Experienced	.419	.083	.882	.005
Bock et al. (1994)	Novice	.352	.121	.796	.019
Bock et al. (1994)	Experienced	.428	.079	.806	.017
Shoval et al. (1997)	Experienced	.463	.044	.542	.096
Liao and Palvia (2000)	Novice	.095	.501	.234	.587

Table 2. Regression studies based on general facet semantic networks

The exceptionally poor match of complexity with empirical data from Liao and Palvia (2000) suggests that further exploration and analysis should be made. One possible reason for the exception is that the experiment included a substantial time delay from a short training session to modeling execution. This was not present in the other studies. Another possible reason could be the scheme of grading, which was not reported. One suggested approach is to customize the semantic networks based on the actual data modeling problem used in the experiments. This analysis is presented in section 4.

4. Customized Semantic Network Complexity Analysis

It is likely that during data modeling, users will consider the actual entity names, attribute names, relationship names and so on, in addition to the general semantic networks shown in the previous section. Thus, a different set of semantic network is developed that considers the actual data modeling problem used in the experiments. For example, each entity will now have a name, and be linked to each of its named attributes; an entity with 2 attributes will have a component complexity of 3, a coordinative complexity of 1 and a coupling complexity of 2, totaling to a value of 6 for total complexity. Where a modeling problem has more than one entity, the average complexity of all the entities is used. This analysis is limited to 3 experiments that used the same data model problem.

	Experience Level	Entity	Identifier	Category	Unary 1 : 1	Binary 1 : M	Binary M : N	Ternary 1 : M : N	Ternary M : N : O
Complexity Estimate	-	6.75	5.5	5	14	13	13	19	17
Batra et al. (1990)	Novice	92.3	73.9	76.2	55.2	84.9	92.9	41.3	45.2
Bock et al. (1993)	Experienced	98	96	92	96	89	100	47	79
Bock et al. (1994)	Novice	90.1	78.4	76.6	83.6	93.0	100.0	9.4	10.9
Bock et al. (1994)	Experienced	92.8	86.3	76.0	88.0	82.0	97.0	11.0	9.0

Table 3. Complexity estimates based on a customized semantic networks

		Linear Regression		**Quadratic Regression**	
		R square	P value	R square	P value
Batra et al. (1990)	Novice	.431	.077	.723	.040
Bock et al. (1993)	Experienced	.452	.068	.921	.002
Bock et al. (1994)	Novice	.396	.094	.891	.004
Bock et al. (1994)	Experienced	.463	.063	.872	.006

Table 4. Regression studies based on customized semantic networks

The complexity values and experimental performance data are shown in Table 3. Regression studies are shown in Table 4. The results show that customized semantic networks are better matched to the empirical data. For example, the p-values have dropped by half or more for the quadratic regressions. Linear regressions also generally improved, but do not show such substantial improvements as those for the quadratic regressions. The results show that, where possible, semantic networks customized to the modeling problem should be used for better predictions of user performance.

5. Conclusion

This analysis aims to explore how users might use semantic networks to represent data modeling constructs. Comparing the networks' complexity values against known user performance data provides a rough test of the "reality" of these semantic networks. The results indicate reasonable values for R square, when compared with other R square values in related areas. Thus, the proposed semantic networks have some validity, and could indeed to used as rough indicators of performance. The current use and analysis of semantic networks could be an initial step towards better understanding of how users perform data modeling task, as well as better prediction of user performance for various data modeling constructs.

However, the results though reasonable are far from perfect. Much more work can be done. One approach is to use more known empirical data to test various variations in the semantic network. These will allow the identification of a few most plausible variations that can be further tested in specifically designed experiments.

Another exciting future research will be the use of semantic network for explaining performance differences between novice and experienced users. For example, Collins and Loftus (1975), suggested that, with experience, some nodes have more links, and the links are shorter. In the complexity measures proposed in the previous sections, a link has a coupling complexity of 1. This value can be reduced to allow for experience.

Application of semantic networks can also be done for different models, such as relational, entity relationship and object oriented models. This will help to provide an in-depth explanation of the different user performance across data models.

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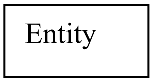
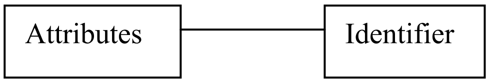
Appendix A – Complexity Measure Applied to Facets

Semantic Network Representation: Entity Facet



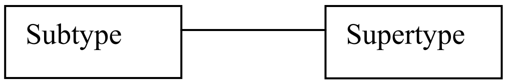
Component Complexity = 1
Coordinative Complexity = 0
Coupling Complexity = 0
Total Complexity = **1**

Semantic Network Representation: Identifier Facet



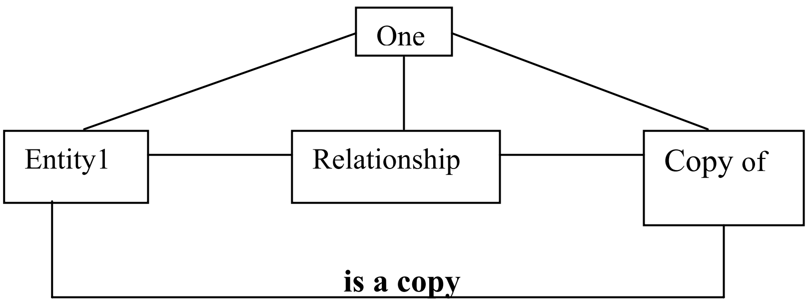
Component Complexity = 2
Coordinative Complexity = 0
Coupling Complexity = 1
Total Complexity = **3**

Semantic Network Representation: Category Facet



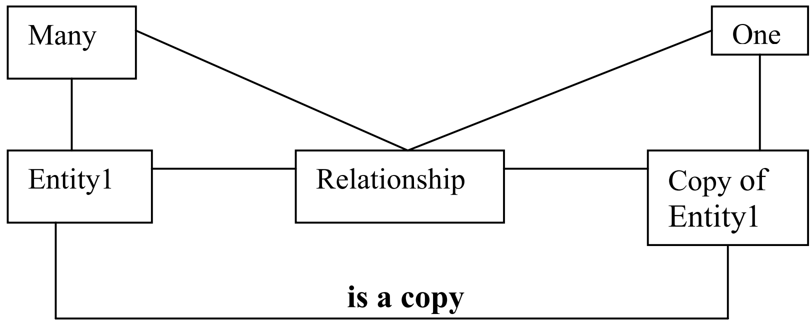
Component Complexity = 2
Coordinative Complexity = 0
Coupling Complexity = 1
Total Complexity = **3**

Semantic Network Representation: Unary 1 : 1 Facet



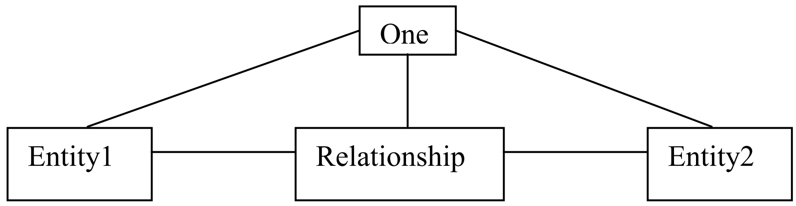
Component Complexity = 4
Coordinative Complexity = 2
Coupling Complexity = 6
Total Complexity = **12**

Semantic Network Representation: Unary 1 : M Facet



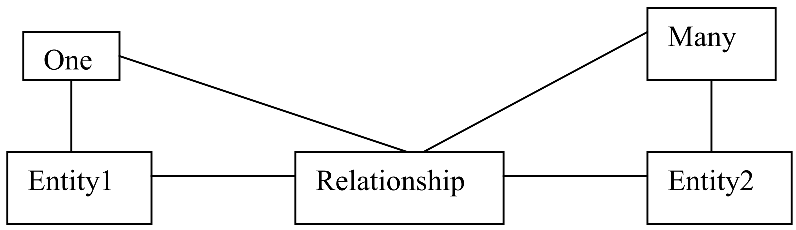
Component Complexity = 5
Coordinative Complexity = 2
Coupling Complexity = 7
Total Complexity = **14**

Semantic Network Representation: Binary 1 : 1 Facet



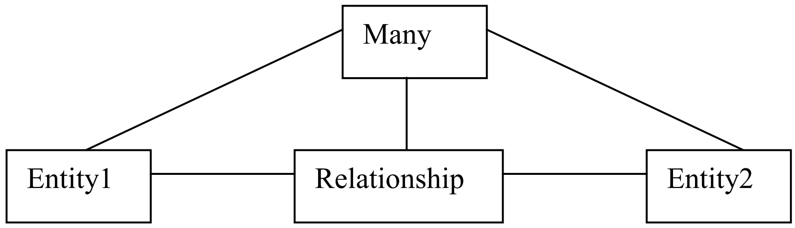
Component Complexity = 4
Coordinative Complexity = 2
Coupling Complexity = 5
Total Complexity = **11**

Semantic Network Representation: Binary 1 : M Facet



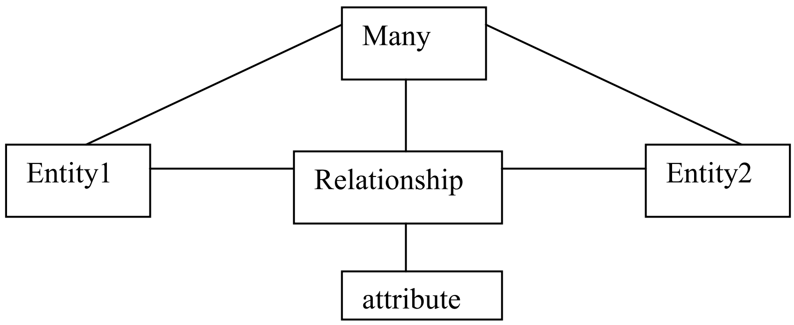
Component Complexity = 5
Coordinative Complexity = 2
Coupling Complexity = 5
Total Complexity = **12**

Semantic Network Representation: Binary M : N Facet



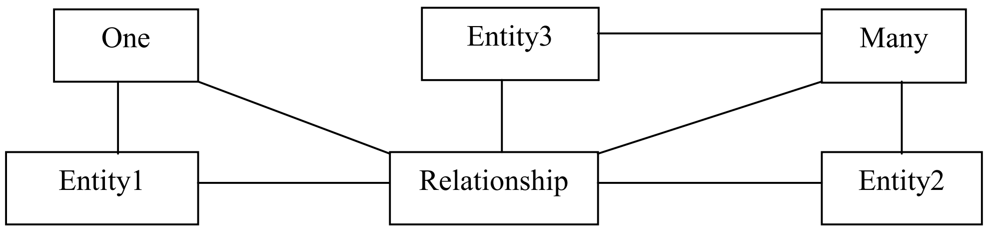
Component Complexity = 4 Coordinative Complexity = 2
Coupling Complexity = 5 Total Complexity = **11**

Semantic Network Representation: Binary M : N Facet with Relationship Attribute



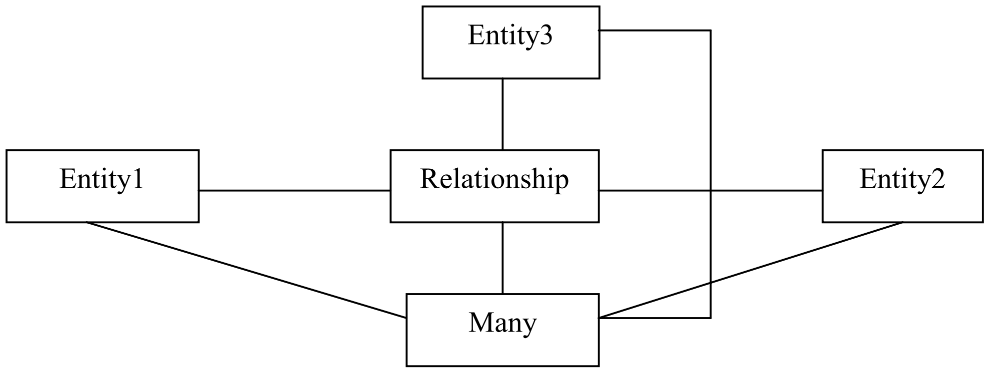
Component Complexity = 5 Coordinative Complexity = 2
Coupling Complexity = 6 Total Complexity = **13**

Semantic Network Representation: Ternary 1 : M : N Facet



Component Complexity = 6 Coordinative Complexity = 3
Coupling Complexity = 8 Total Complexity = **17**

Semantic Network Representation: Ternary M : N : O Facet



Component Complexity = 5
Coupling Complexity = 7

Coordinative Complexity = 3
Total Complexity = **15**