

Episodic Ologs : Category Theoretic Knowledge Representation Based on Episodic Logic with Coherence Based Knowledge Acquisition

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Abstract

We propose a semantic representation/knowledge representation (SR/KR) based on Spivak and Kent's ologs and Schubert's Episodic Logic with attention to issues of bias in knowledge acquisition. Ologs are a category theoretic approach to SR/KR where concepts are objects and conceptual relations are morphisms, Episodic Logic is a SR/KR with a Montague style logical form, oriented towards deep natural language understanding (NLU) vis-à-vis attention to semantic expressivity and reasoning/inference. One of the main challenges in NLU is how to populate an NLU system with sufficient data to make natural derivations of meaning and inferences about the meaning in general or in some situation. Part of the challenge of acquiring knowledge for an NLU system is the discrepancy between reality and its descriptions in text (reporting bias). We will sketch how ologs could be extended to incorporate the semantic features of Episodic Logic and how the formalization of instance data present in ologs could be used to establish a notion of knowledge coherence which could mitigate issues of reporting bias.

1 Introduction

Schubert (2015) argues that a SR/KR oriented towards comprehensive NLU suitable for reasoning needs to capture the full spectrum of different kinds of semantic content and do so in a form suited to inference. In the same work the author argues that Episodic Logic is especially competitive in both of these regards compared to other SR/KRs. An additional issue discussed in the same paper is the knowledge acquisition bottleneck, where acquiring sufficient contextual and general knowledge to guide deep NLU and inference is difficult to accomplish. What's more, textual sources of knowledge

aiming to be factual often differ from reality in ways that are difficult to discern without sufficient background knowledge, whether via benign issues of implication and emphasis of content or non-factuality and bias proper, a circular dependency in the problem barring exhaustive hand-authoring of verifiable knowledge. We will sketch how a category theoretic approach to SR/KR, in particular Spivak and Kent's ologs (Spivak and Kent, 2012), can provide a unified foundation for the expressive and potentially the inferential features of Episodic Logic, an approach to issues of consistency and factuality in knowledge acquisition, as a means of grounding and coordinating multiple modular SR/KRs, and in general, an approach to SR/KR and knowledge acquisition which models some of the core mechanisms are used in semantic representation of data and knowledge acquisition at the human level.

2 Background

2.1 Overview of Category-Theoretic Terminology

Category theory, is a theory of mathematical structure and structural relationships. Roughly speaking, a *category* is a collection of *objects* of concern, and *morphisms* or *arrows*, describing relationships between objects in the category that satisfy certain basic properties, namely, every object has a morphism connecting it to itself, and morphisms between objects compose transitively, i.e. given for a morphism f from an object A to an object B , and another morphism g from objects B to C , written:

$$f : A \rightarrow B$$

$$g : B \rightarrow C$$

there is always another morphism:

$$g \circ f : A \rightarrow C$$

¹I am using ACL style guidelines and citation format.

100 There are also *functors*, roughly, ways of relating a
 101 category \mathcal{C} to another other category \mathcal{D} , and *natural*
 102 *transformations*, ways of relating two functors
 103 connecting the same categories, e.g. $F, G : \mathcal{C} \rightarrow \mathcal{D}$.
 104 There are many additional structures and concepts
 105 that category theory captures in addition to these
 106 (see appendix A for relevant definitions), all of
 107 which have in common category theory's relational
 108 emphasis and its resulting potential for abstraction.
 109 This emphasis is less apparent and requires work
 110 to recover in logic and type theory and their vari-
 111 ants and extensions which ground most SR/KRs,
 112 although these category theoretic ideas *can* be recovered
 113 in logic and type theory. As we will see, this relational
 114 focus of category theory has potential for developing a flexible SR/KR which can
 115 better reflect human organization and coordination
 116 of knowledge, in addition to providing a better set-
 117 ting for a SR/KR to fulfill Schubert's requirements.

120 2.2 Ologs

121 Spivak and Kent's ologs and Patterson's relational
 122 ologs both describe a category theoretic approach
 123 to SR/KR, where objects stand in for concepts and
 124 morphisms stand in for relations between concepts,
 125 and functors are used to model instances or real-
 126 izations of concepts or relations between concepts.
 127 Relational ologs are oriented towards modeling De-
 128 scription Logic, which is decidable, unlike first
 129 order logic, at the expense of being less expressive
 130 than first order logic (Patterson, 2017), and have
 131 the further advantage of examination due to the
 132 beginnings of a computer implementation ². Ologs
 133 are also designed with the possibility of being eas-
 134 ily converted into databases, which has a possible
 135 advantange over other SR/KRs in terms of efficient
 136 retrieval of information. On the other hand there
 137 seem to be no fully formed advancements in auto-
 138 mated inference for ologs, although there published
 139 efforts towards automated inference in category
 140 theory (Kozen et al., 2006). Given the maturity and
 141 uniqueness of ologs as a category theoretic SR/KR,
 142 these will be our starting point for developing a
 143 category theoretic SR/KR with Schubert's require-
 144 ments in mind, in particular, to recover as many of
 145 the expressive devices available in Episodic Logic
 146 in an olog based SR/KR.

²<https://github.com/AlgebraicJulia/Catlab.jl>

3 Episodic Logic

150 Episodic Logic is a Montague-style logical form
 151 based SR/KR with relative strength in semantic
 152 expressivity and inferetiability in comparison to
 153 other SR/KRs, making it better comparatively bet-
 154 ter suited for deep NLU (Schubert, 2015). Episodic
 155 Logic allows for generalized quantifiers, lambda ab-
 156 straction, reification and modification of sentences
 157 and predicates, intensional predicates, unreliable
 158 generalizations, and explicit situational variables
 159 (Schubert and Hwang, 2000). Episodic Logic with
 160 its inference engine EPILOG provide a way to cap-
 161 ture a relatively comprehensive range of semantic
 162 phenomena compared to other SR/KRs, in a way
 163 which affords inference about semantic data at a
 164 comparable efficiency with automated inference en-
 165 gines for first order logic (Schubert, 2015). It also
 166 has an associated knowledge base KNEXT which
 167 is capable of parsing sentences into factoids, gener-
 168 alizing them (through a process called quantifica-
 169 tional sharpening), and making certain judgements
 170 about whether a generalized factoid is redundant or
 171 inconsistent with anything established in the knowl-
 172 edge base.

4 Category Theory and Modeling Conceptual Understanding

174 Human knowledge acquisition makes heavy use
 175 of comparison and analogy. Finding differences
 176 and commonalities between currently understood
 177 concepts, situations, or data in general, and a new
 178 instance of the same kind of data can help to under-
 179 stand the new data in a systematic way (Brown and
 180 Porter, 2006). This can be extended to cases where
 181 the known and new data might have some over-
 182 lap, in which case the burden of labor for acquir-
 183 ing the new knowledge depends on where the new
 184 data differs from known data, e.g. if one already
 185 knows how to print a document from a device, then
 186 learning how to print the document double sided
 187 is mostly an issue of remembering how to select a
 188 relevant option during the rest of a process which
 189 is already known. Category theory and its focus on
 190 structure, relationships between structures, and ab-
 191 straction over structure provide a convenient setting
 192 for formalizing certain formal notions of analogy
 193 and comparison (Brown and Porter, 2006), which
 194 adds further credence to the case that a category the-
 195 oretic SR/KR can be used to better model human
 196 level knowledge acquisition. Navarrete and Dart-
 197 nelli (2017) further develops this idea in a way that

situates category theoretic treatments of different kinds of analogy explicitly within human learning and cognition, developing concrete models of different kinds of analogy that could be used in an SR/KR. Phillips and Wilson (2010) even asserts that category theory as a means of modeling relationships between structures or representations, and relationships between such relationships etc., can be used to model core aspects of higher-cognition in general. All of these support the potential for such a category theoretic SR/KR's ability to better model human-level reasoning and knowledge acquisition.

5 Category Theory in Knowledge Acquisition

Gordon and Durme (2013) explain how reporting bias can effect development of a SR/KR and its knowledge base during knowledge acquisition. Reporting bias is a collection of phenomena in language data, namely, how what is described in text can fail to be factual depending on genre and other context, and how the lexical and world knowledge humans use to discern whether textual material can be possibly considered factual, is something that generally is not represented in text. This poses a problem for knowledge acquisition in that there is not just the issue of how to formally judge newly presented information against some set of ground truths, but acquiring these ground truths cannot be automatic by and large, e.g. there is no sufficiently comprehensive set of textual material from which an SR/KR could be populated in order to make sufficiently educated judgements. Healy and Caudell (2004) develop the idea of a category of concepts, i.e. the objects are concepts and the morphisms are conceptual relations, which can encode a hierarchy of concepts via considering the notions of sub-concept or super-concept relations as concept morphisms. They further develop considerations of different realizations (or instance data) among the same representation of diagram (structure of objects and morphisms) in the concept category. In the case of the Healy and Caudell (2004), neural networks are the representational context where concept structures are realized. The authors treat neural networks categorically like concepts, and incorporate functors from the concept category to the neural network category. From here, the authors develop a notion of *knowledge coherence* across the different realizations of a concept at a particular

level using natural transformations (a structured relationship between two functors which map in the same direction between the same categories).

This formalization of conceptual hierarchy and conceptual relations and the way it can be used to develop an idea of knowledge coherence seems like it could be the beginning of a way to address reporting bias during knowledge acquisition. When some new information data is extracted, it can be evaluated at least based on coherency with previously seen information, a more general version of the comparison done during knowledge acquisition in KNEXT. A layered approach could also be taken along with conceptual hierarchy to model realizations of concepts at different levels of certainty. However, it is not clear in what senses or under what circumstances these ideas would be tractable to fully formalize, implement, or compute.

For the alterations relevant to knowledge acquisition, using analogy to enhance assimilation of new knowledge as discussed by Navarrete and Dartnell (2017) is another avenue of investigation, and in particular using the notion of knowledge coherence from Healy and Caudell (2004) to assess whether some new data is consistent with the existing data instances and/or the related concepts in general, as a means to address reporting bias encountered in knowledge acquisition. Another direction to explore is how to utilize the notion of instance data in ologs to create a multi-tiered understanding of some collection of concepts, which can be further used with the notion of knowledge coherence to model levels of certainty about how a concept can be realized.

6 Recovering the Expressive Devices of Episodic Logic In Ologs

Most of the semantic features of Episodic Logic can be recovered in in a set theoretic context, thus are amenable to being recovered in cartesian closed categories (CCC) (MacLane and Moerdijk, 1992). A CCC:

- Has a **terminal** object (every object in the category has a unique morphism to this object).
- Any two objects X, Y in a CCC have:
 - A **product** object $X \times Y$ (the categorical generalization of set-theoretic product).
 - An **exponential** object Y^X (roughly, the collection of morphisms from X to Y can be seen as an object in the category)

Generalized Quantifiers Classical quantifiers can be accounted for in elementary topoi (a kind of CCC). The existential and universal quantifiers are formalized respectively as left and right **adjoints** of a functor between powersets (Goldblatt, 2006). As a result, quantifiers in general seem to be definable in any category theoretic context where one can define a notion of powersets and subsets for objects in the category in the same way that these notions are available in the category of sets. This is also the case for non-classical quantifiers (Hedges and Sadrzadeh, 2019), except further notions of set membership and cardinality need to be recovered for quantifiers like *some* or *most*, presumably through something like subobject classifiers. In all cases this would need to take place on the instance data/realization level of ologs given these set theoretic notions (especially the powerset functor) would not be able to be guaranteed at the concept level.

λ -abstraction Lambda abstractions can be modeled via exponential objects provided the category in question has an exponential object for every pair of objects, e.g. where $g : X$ and $\phi(g) : Y$, the term $\lambda g.\phi(g) : Y^X$. This seems possible to guarantee at the conceptual level, since “the collection of conceptual relations from concept A to concept B” itself can be considered a concept.

Sentence and Predicate Modification Adverbial modifiers would likely be represented by an object in the category describing the state of the subject of the modified predicate, connecting both the subject and the predicate (in category theoretic terms the morphism from the subject to the predicate *factors through* the morphism from the subject to the modifier). Non-adverbial modifiers like tense would ideally have to take on some kind of similar relational interpretation, whether in the same olog to some other diagram of objects, or to another olog encoding some previous or future point in time. This has issues depending on the level of granularity required, and while there are category theoretic approaches to describing time, this is an open area of research and it’s unclear whether such approaches (Kato, 2017) are technically feasible or necessary to implement given their complexity.

Sentence and Predicate Reification Reification of sentences and predicates are broadly, cases of mention instead of use, e.g. *Carmen put in new lighting.* is a use of the sentence whereas *Carmine*

said Carmen put in new lighting. involves the mention of the sentence, thus reification in EL involves reference of propositional content by other propositional content or object. The first impulse in this case is to first describe the reified content as some diagram and the entity referring to the content as a *limit* of the diagram, and find some way to have the morphisms of the limit (the morphisms modeling the reference of the entity to the content) reflect the nature of reference, which on one level seems as if it would be an issue of labeling morphisms as is typically done in ologs, but on the other hand there is a difference in interpretation of reified content which would need to also be reflected, since for instance, *Carmen put in new lighting.* and *Carmen didn’t put in new lighting.* cannot both be true, but *Carmine said Carmen put in new lighting.* and *Charlotte said Carmen didn’t put in new lighting.* can both be true as their truth values do not depend on the reified content. In this sense of relating content in the form of diagram or otherwise to some other object or diagram that requires a difference in interpretation, capturing this is similar to capturing intentional predicates or sentential modifiers.

Intentional Predicates Similar considerations for reified content and sentential modification would likely have to be made for intensional predicates (having to do with an agent believing, wanting) in terms of interpretation and how to encode the relationship between the agent and different kinds of themes, such as objects versus propositional content, e.g. *Claire believed the paper* vs *Claire believed that the paper’s reasoning was correct if poorly presented.* Ultimately an agent in an olog would be represented by an object and the agent-specific predicate would be a labeled morphism or a collection of labeled morphisms from the agent to some other object or diagram describing a situation (again the notion of a *limit* of a diagram). As with reification and sentential modification this could also potentially involve a functor into another olog to model the difference in interpreting the content versus interpreting the agent’s relationship to the content.

Non-Logical Generalization Non-logical/defeasible generalizations would likely be heavily dependent on context and thus, where not hand-authored, would likely benefit from the idea of knowledge coherence used in knowledge acquisition. In the case of hand-authoring they

would be encoded into domain specific ologs.

Situational Variables Casual and situational relationships can be encoded in general or domain specific ologs at the conceptual level, and where necessary can be realized in instance data, where they would be susceptible in principle to the same reasoning tools at the conceptual level.

7 Experiments and Future Work

7.1 Implementation

EPILOG, the inference engine for Episodic Logic, and KNEXT a knowledge base utilizing Episodic Logic are both written in Lisp. In general functional programming seems to be a setting amenable to implementation of logical or semantic structures, in particular Haskell lends itself to this (van Eijck and Unger, 2010) along with implementation of category theoretic formalisms (Milewski, 2018). Tentatively we can say an implementation of Episodic ologs will use Haskell to implement these category theoretic formalisms which capture the expressive devices of Episodic Logic in a way informed by the way EPILOG and KNEXT handle these in the context of Lisp. A complete implementation of Episodic Ologs would require an implementation of ologs, implementation of the additional structures needed to capture the semantic features of EL within ologs, an implementation of some form of automated inference in order to make it competitive with other SR/KRs oriented towards deep NLU, and at least an attempt at implementing tests of knowledge coherence towards negotiating issues of reporting bias.

7.1.1 A Knowledge Base: Ologs and Databases

Any valid olog by design admits a database schema and any instance data or realization of that olog can be seen as a database state fitting that schema (Spivak and Kent, 2012). This potentially affords the possibility of a knowledge base that can make use of more standard and efficient database tools. Haskell has libraries for interfacing with database engines which support SQL (HDBC, HSQL), but finding a way to do this in a way that is formally acceptable with the rest of the implementation (set theoretic and category theoretic reasoning about instance data) might take a significant amount of effort compared to the rest of the project.

7.2 Knowledge Acquisition Experiments

In terms of eventual experimentation that compares this approach with other SR/KRs, some implementation of this SR/KR in a given language and especially the methods to detect reporting bias (via knowledge coherence as natural transformations over functors of instance data) would be necessary. There would need to be an investigation into whether other SR/KRs attempt this classification, and then development of some kind of annotated corpus of data of varying degrees of factuality, and evaluating our system (along with the others if applicable) on whether (comparatively) this approach actually has the potential for efficacy in determining the reliability and admissibility of new data. The other issue which this experiment is that it depends on having knowledge base utilizing this SR/KR populated sufficient basic data to make these judgements, thus there would initially have to be significantly rich hand-authored ologs in order to have a basis for judgement of incoming textual data. From these experiments (or the failure to implement them) possibilities of where using probabilistic methods, such as involving machine learning, could aid in the overall process, likely using probabilistic methods and olog where efficiency and verifiability, respectively, are needed.

7.3 Further Formalization and Automated Inference

As discussed before, category theoretic techniques seem to hold the potential for abstracting over different SR/KRs or at least their ontologies and functioning as a foundation to integrate them. If something like this can be done with the implementation, where at the base is something more general like a basic olog structure and additional expressive and descriptive features for different ontologies can be captured in additional modular layers. Additionally, one way in which this olog-based approach to SR/KR is lacking compared to Episodic Logic, there have been efforts to integrate category theory into automated theorem proving environments like Coq, for instance (Gross et al., 2014) and ³, even though we have found no efforts which have been specific to ologs besides some plans for future research discussed in Patterson (2017). One possible avenue for automated inference given an implementation of ologs in Haskell, is that there are successful tools for using Coq to verify Haskell pro-

³<https://github.com/jwiegley/category-theory>

grams (Breitner et al., 2018). However this would likely incur not insignificant organizational and computational complexity in the implementation.

7.4 Scope and Timeline

Given the structural complexity of the different tasks, minus issues of getting certain libraries to interact with each other as intended, it seems most feasible to first make a naïve implementation of ologs in Haskell which can coordinate with a particular database engine, followed by implementation of the different semantic features of Episodic Logic, followed by implementation of automated inference, followed by implementation of knowledge acquisition and notions of knowledge coherence.

7.5 Weaknesses

There are many weaknesses to this proposal. All of the challenges in creating an implementation described, assuming they can be overcome even in a straightforward way, would require a significant number of person-hours, anything that could be built in the span of a semester, even with multiple people, would in all likelihood be very brittle and difficult to meaningfully test. For comparison, Episodic Logic and its corresponding software suite have been in development since the late 90s, and while impressive, they still have noticeable shortcomings. Finally, while the abbreviation “SR/KR” has been used throughout this paper to suggest that semantic representation and knowledge representation are interchangeable in a number of critical ways, ologs were designed for the task of knowledge representation, encoding meaning in a fixed, general, and conceptual way. Tasks oriented towards NLU, require dealing with information which is not knowledge, information that is less certain and potentially more subtle and granular, and working with it in ways that involve dynamically making assumptions, and in general using defeasible reasoning. If a category-theoretic SR/KR is to be used for NLU, it must capture these different levels of certainty and ambiguity, neither ologs nor any of the other category theoretic proposals we have encountered seem really adequate to capture this without significant alteration.

8 Conclusion

We have developed a case for using a category theoretic approach to SR/KR along with integrating features suited to deep NLU, and sketched how this

might take place. We gave some background description of basic category theoretic concepts and ologs, a sketch of how to recover each of the expressive features of Episodic Logic in a category theoretic context, an explanation of how category theory can be used to mitigate issues of reporting bias in knowledge acquisition, how category theoretic ideas have a possible advantage in modeling knowledge acquisition and conceptual understanding in a way more concomitant with NLU. We discussed a general approach to implementing these ologs with the expressive devices of Episodic Logic and additional functionality the implementation would need for practical use. Given the advantages we’ve seen of using category theoretic techniques to coordinate different expressive devices, along with the features which could potentially be used to mitigate issues of knowledge acquisition, enriching ologs with these capabilities and the expressive devices of Episodic Logic seems to be a worthwhile avenue of exploration. Even if the only purpose it serves is to further articulate the weaknesses described in the previous subsection, and thereby develop a more informed understanding of what would be needed in the design of category-theoretic SR/KRs for NLU, or of SR/KRs for NLU in general.

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A.3 Diagrams

Intuitively, a diagram is a graph, depicting a category or a particular part of a category about which we are curious¹. For instance consider the following objects in **Set**: $\mathbb{N}, \mathbb{Z}, \mathbb{R}, \mathbb{C}$. Also the following morphisms in **Set**, the inclusion maps: $i_1 : \mathbb{N} \rightarrow \mathbb{Z}$, $i_2 : \mathbb{N} \rightarrow \mathbb{R}$, $i_3 : \mathbb{Z} \rightarrow \mathbb{C}$, and $i_4 : \mathbb{R} \rightarrow \mathbb{C}$. Given these, a diagram in **Set** could be:

$$\begin{array}{ccc} \mathbb{N} & \xrightarrow{i_2} & \mathbb{R} \\ i_1 \downarrow & & \downarrow i_4 \\ \mathbb{Z} & \xrightarrow{i_3} & \mathbb{C} \end{array}$$

A diagram, however leaves all the *nonessential* details for the reader to fill in. Because given the earlier objects and morphisms, with the category's axioms of identity and composition, the complete version of the earlier diagram is:

$$\begin{array}{ccccc} & 1_{\mathbb{N}} & & 1_{\mathbb{R}} & \\ & \curvearrowleft & & \curvearrowright & \\ \mathbb{N} & \xrightarrow{i_2} & \mathbb{R} & & \\ & \searrow i_1 & \swarrow i_4 & & \\ & \mathbb{Z} & \xrightarrow{i_3} & \mathbb{C} & \\ & \curvearrowleft & & \curvearrowright & \\ & 1_{\mathbb{Z}} & & 1_{\mathbb{C}} & \end{array}$$

We say a diagram *commutes* if all directed paths in the diagram lead to the same result by composition. For instance our earlier diagram commutes:

$$\begin{array}{ccc} \mathbb{N} & \xrightarrow{i_2} & \mathbb{R} \\ i_1 \downarrow & & \downarrow i_4 \\ \mathbb{Z} & \xrightarrow{i_3} & \mathbb{C} \end{array}$$

since:

$$i_3 \circ i_1 = i_4 \circ i_2$$

A.4 Products and Exponential Objects

Products For a category \mathcal{C} , and X_1, X_2 in $Obj(\mathcal{C})$, a **product** of X_1 and X_2 is an object of

¹The formal definition is more complicated but equivalent.

\mathcal{C} usually written as $X_1 \times X_2$ with a pair of morphisms, called *canonical projections*:

$$\pi_1 : X_1 \times X_2 \rightarrow X_1$$

$$\pi_2 : X_1 \times X_2 \rightarrow X_2$$

such that, for every Y in $Obj(\mathcal{C})$, every f_1 in $Hom_{\mathcal{C}}(Y, X_1)$, and every f_2 in $Hom_{\mathcal{C}}(Y, X_2)$, there is a unique morphism $f : Y \rightarrow X_1 \times X_2$ such that:

$$\begin{array}{ccccc} & & Y & & \\ & f_1 \nearrow & \downarrow f & \searrow f_2 & \\ X_1 & \xleftarrow{\pi_1} & X_1 \times X_2 & \xrightarrow{\pi_2} & X_2 \end{array}$$

commutes.

Exponential Objects Where \mathcal{C} is a category, Z and Y objects of \mathcal{C} , and \mathcal{C} has all binary products with Y . An exponential object consists of an object

$$Z^Y$$

and a morphism

$$\text{eval} : (Z^Y \times Y) \rightarrow Z$$

such that for any object X and morphism

$$g : X \times Y \rightarrow Z$$

there is a unique morphism $\lambda g : X \rightarrow Z^Y$ such that the following diagram commutes.

$$\begin{array}{ccc} X & & X \times Y \\ \downarrow & & \downarrow \\ \lambda g \downarrow & & \lambda g \times 1_Y \downarrow \\ Z^Y & & Z^Y \times Y \\ & & \xrightarrow{\text{eval}} Z \end{array}$$

The notation Z^Y for the collection of morphisms from Y to Z might seem backwards at first, but there is an analogy here with integer exponents. For example, the number of total functions from a set of three elements to a set of two elements is eight, in notation, $2^3 = 8$.

1. An **initial object** **False** in a category \mathcal{C} , is an object, where, for each object X in $Obj(\mathcal{C})$ there is a unique morphism from **False** to X .
2. A **terminal object** **True** in a category \mathcal{C} , is an object, where, for each object X in $Obj(\mathcal{C})$ there is a unique morphism from X to **True**.

800 A.5 Functors and Natural Transformations

801 **Functors** Given categories \mathcal{C} and \mathcal{D} a **functor**
802 $F : \mathcal{C} \rightarrow \mathcal{D}$ is a mapping between categories with
803 the following characteristics:

- 804 1. For every X in $Obj(\mathcal{C})$, there is an associated
805 object $F(X)$ in $Obj(\mathcal{D})$
- 806 2. For every $f : X \rightarrow Y$ in $Hom(\mathcal{C})$, there is an
807 associated morphism $F(f) : F(X) \rightarrow F(Y)$
808 in $Hom(\mathcal{D})$ such that the following hold:
809
- 810 (a) F preserves identity morphisms, i.e. for
811 any X in $Obj(\mathcal{C})$:

$$812 F(1_X) = 1_{F(X)}$$

- 813 (b) F preserves composition of morphisms,
814 i.e. for any $f : X \rightarrow Y$ and $g : Y \rightarrow Z$
815 in $Hom(\mathcal{C})$:

$$816 F(g \circ f) = F(g) \circ F(f)$$

817 **Natural Transformations** Given functors

$$818 F : \mathcal{C} \rightarrow \mathcal{D}$$

$$819 G : \mathcal{C} \rightarrow \mathcal{D}$$

820 a **natural transformation**, $\eta : F \rightarrow G$ consists of,
821 for every X in $Obj(\mathcal{C})$, a **component map**:

$$822 \eta_X : F(X) \rightarrow G(X)$$

823 such that for every f in $\mathcal{C}[X, Y]$ the following dia-
824 gram commutes:

$$825 \begin{array}{ccc} F(X) & \xrightarrow{\eta_X} & G(X) \\ F(f) \downarrow & & \downarrow G(f) \\ F(Y) & \xrightarrow{\eta_Y} & G(Y) \end{array}$$

826 B Supplemental Material

827 C Category Theory as a Meta-SR/KR

828 A SR/KR generally constitutes an ontology and a
829 logic (Sowa, 2000), and just as knowledge can be
830 domain specific, so can SR/KRs, in which case the
831 ontology and logic respectively concern the objects
832 of the domain and their interactions, relations, and
833 operations. Human level knowledge and reasoning
834 however involves not only knowledge in multiple

835 dependent and independent domains, but the abil-
836 ity to coordinate knowledge and reasoning among
837 different domains, often in real time. Institutions
838 are category theoretic treatment of the notion of a
839 “logical system” which can provide the ability to
840 range over multiple theories and manage ontolo-
841 gies, (Kent, 2018), (Schorlemmer and Kalfoglou,
842 2008) which enables multiple kinds of problem
843 solving and domains of reasoning. However this
844 meta approach isn’t limited to institutions

845 Integrating multiple ontologies and their corre-
846 sponding logics is also necessary for an SR/KR
847 which hopes to capture multiple domains of knowl-
848 edge since, while different objects, structures, or
849 patterns of reasoning might be meaningful in their
850 respective domains, their combination is not nec-
851 essarily meaningful given a reasonably compre-
852 hensive ontology, and for this reason, an idea or
853 treatment of meaning, within SR/KRs, depends funda-
854 mentally on some interpretation (Sarbo, 2013).
855 Similarly, category theory can be used to merge
856 ontologies (Hitzler et al., 2005), though how this
857 approach handles the different reasoning method-
858 ologies accompanying different ontologies, and
859 whether this approach is advantageous for our goals
860 in SR/KR over the aforementioned approaches, is
861 something to investigate. Patterson (2017), cites
862 that further work in coordinating different ontolo-
863 gies in a categorical SR/KR could potentially be
864 accomplished using doctrines or sketches, both
865 category theoretic models of the idea of a “the-
866 ory” in logic (a formal language used to axiomatize
867 some collection of one or more formal systems or
868 models.)