Towards Interpretation Strategies for Multimodal Instructional Analogies

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Abstract

People often use instructional analogies to introduce new concepts or explanations. Examples of these analogies can be found in instructional science texts and guides for in-service teachers. Building software that can understand instructional analogies has two potential benefits. First, it would enable an individual to convey new or existing qualitative concepts to a machine using analogies, thereby allowing them to explain ideas that may be cumbersome to describe otherwise. Second, a computational model of interpreting multimodal instructional analogies can be used as the basis of intelligent educational software, given that the use of analogies to teach science is a common and recommended practice for teachers. In this paper, we describe work in progress on techniques using qualitative spatial representations for interpreting analogies that are composed of simplified English text and sketches, illustrated by a running example.

Introduction

A common strategy for conveying new information is to provide it in contrast to something more familiar. In an educational setting, this is achieved through the use of instructional analogies, which are comparisons between something familiar and something unfamiliar with the intent of building up knowledge about the unfamiliar thing. Instructional analogies are common tools for explanation in science textbooks and in-class activities. As a result, several guidelines and best practices have been developed for teachers so that they can use analogies effectively (Zeitoun 1984, Harrison & Coll 2007, Glynn 2008, Holyoak & Richland 2014). Psychological evidence suggests that analogies can be beneficial for students because they enable students to make inferences that persist into novel situations (i.e. far transfer) (Loewenstein et al. 1999, Gentner et al. 2009, Gadgil et al. 2012). For teachers (or any individual explaining something), analogies can be useful for providing explanations for things that cannot readily be observed (e.g. atomic structure). This is especially true for analogies that are presented through visual representations. For example, electrical currents are often taught by analogy to water, using pictures or physical models. By comparing electricity to water, students can draw on their everyday experiences with fluids to conceive of electrical currents *flowing* from one place to another, even though they cannot literally see it happening. For novices, this qualitative knowledge is very flexible and can be used to solve problems and explain new phenomena.

Given the importance of analogies in explanation, there are two benefits of building software that can understand them. First, the ability to interpret instructional analogies opens up the range of data that may be used for knowledge capture. For example, much of the foundation for scientific and engineering domains rests on qualitative, conceptual models based on everyday experience. Acquiring such models via natural interaction (including the use of multimodal analogies) can help provide the knowledge endowment needed for conceptual and qualitative problem solving. The other potential benefit is in education. A model of instructional analogy understanding can potentially be used as the basis of intelligent tutoring systems that help students understand new topics in terms of more familiar ones. Such tutoring systems have been proposed and implemented (Murray et al. 1990, Clement 1993, Lulis et al. 2004), but none have approached the problem of instructional analogy understanding from a domain general and multimodal perspective.

Related Work

Analogical reasoning has been used for learning and problem solving in many domains (e.g. computer programming (Burstein 1985) and planning (Carbonell 1983)). In addition to within-domain reasoning, cross-domain analogies between observed behaviors (Falkenhainer 1990) and worked solutions (Klenk & Forbus 2013) have been used to transfer information to novel problems. Cross-domain analogies between conceptual domains have been used to repair knowledge and generate explanations (Friedman et al. 2012). Analogical reasoning has also been used to align and merge multimodal information, i.e. text and sketches (Lockwood & Forbus 2009), which we build on below.

This work focuses on instructional analogies, rather than information transfer between prior worked solutions and novel problems. The goal of these analogies is to build up qualitative conceptual knowledge that can be used for future reasoning or question answering. Our goal is to build on previous work on cross-domain instructional analogies and multimodal integration to interpret analogies using automatic, multimodal semantic interpretation of texts with sketches.

Background

Our approach for interpreting multimodal instructional analogies makes use of existing models of analogical reasoning, natural language understanding, and sketch understanding, and is built on the companions cognitive architecture. We briefly summarize them here.

Structure Mapping

Structure mapping is a theory of analogy and similarity that is based on the idea that people prefer comparisons that have shared relational structure as opposed to shallow or superficial comparisons (Gentner 1983). In this work, we use the Structure Mapping Engine (SME) (Falkenhainer et al. 1989), which is a computational model of analogy based on structure-mapping theory. SME takes two structured, relational descriptions, called a base and a target, as input. SME constructs a mapping between the base and the target, consisting of *correspondences*, which indicate how entities and expressions align to each other, and *candidate inferences*, which are things that are true in one description and hypothesized to be true in the other. SME is able to model a wide range of comparisons and has been used for spatial problem solving (Lovett et al. 2009), sketch-based educational software (Yin et al. 2010), and category learning (McLure et al. 2015). SME provides optional *match constraints* that operate as advice, which are automatically computed by systems using it to encode task demands. *Partition constraints* require that items of the same type correspond to each other (e.g. apples to apples and oranges to oranges). These are useful for literal matches where types or surface attributes matter. *Required correspondences* are constraints on individual items (e.g. apple1 must correspond to apple2). These are useful in situations where correspondences are given explicitly, as is often the case in instructional analogies. Partition constraints and required correspondences are used in our interpretation of instructional analogies.

Explanation Agent NLU

The Explanation Agent Natural Language Understanding system (EANLU) (Tomai & Forbus 2009) automatically produces semantic representations for simplified natural language text. EANLU takes a pragmatic approach to natural language understanding. Semantic interpretation of text is made tractable by using sentences with simplified syntax. In other words, the goal is not have complete coverage of natural language inputs, but rather to have very broad coverage of the knowledge that can be expressed to the system using simple sentences.

EANLU uses three sources of knowledge that guide the interpretation process. First, abduction over *narrative functions* (McFate et al. 2014) provides a means to resolve ambiguities via task-relevant information. Second, *analogical word sense disambiguation* (Barbella & Forbus 2013) uses analogies between the current and prior syntactic and semantic analyses to suggest how to resolve ambiguities. Third, a simple set of heuristics is invoked for remaining ambiguities. These heuristics can be extended, and we describe one such extension below. The semantic representations are taken from ResearchCyc[1] and an implementation of Discourse Representation Theory (Kamp & Reyle 1993) is used to build sentence and discourse representations. EANLU supports identifying analogical dialogue acts (Barbella & Forbus 2011).

For multimodal instructional analogies, we use EANLU to automatically build semantic representations of the text portion of the analogy.

CogSketch

CogSketch is a domain-independent sketch understanding system (Forbus et al. 2011). The basic building blocks of a sketch are called *glyphs*. To draw a glyph, the user draws ink using a mouse or stylus and tells the software when the glyph is done. This means that ink is manually segmented into conceptually coherent collections of ink. Ink editing tools allow the user to merge and re-segment ink as they draw. Grouping tools also allow the user to group conceptual items together (e.g. two wheels and a frame can be grouped together to represent a bicycle). The user also provides conceptual labels for glyphs so that the software has an accurate model of the user's intent. This approach has two main advantages over recognition of raw ink. The first is that it avoids segmentation and recognition errors because the user explicitly tells the software how to group ink and what they want the ink to represent. The second is that this draw-and-label interface is amenable to educational settings because students are required to label sketches and explicitly provide their (possibly incorrect)

[1] http://www.cyc.com/

Base	Target	Example Inference
City	Cell	Mitochondria provide energy
Earth	Cell	DNA fragments have many codons
Battery	ATP	ATP can be reused

Table 1: Three analogies used to teach novices about the cell. Each analogy is intended to lead to many inferences, but key examples are shown here for illustration.

interpretation of what they have drawn. Also, ink recognition without labeling would not work across multiple domains, since the mapping from shapes to concepts is many to many. It is especially problematic when a new domain is being introduced, since training recognizers requires many examples.

CogSketch automatically generates qualitative spatial representations for what is drawn in a sketch. Topological relations (e.g. intersection, containment) and positional relations (e.g. above, right of) are automatically computed between adjacent glyphs. Spatial relations between non-adjacent glyphs can be computed on-demand. The conceptual labels provided by the user are also used by CogSketch so that spatial and conceptual information exist in the same reasoning environment.

For interpreting the visual portion of instructional analogies, we create sketches using CogSketch. The spatial and conceptual representations generated by CogSketch are then used for further reasoning.

Companion Cognitive Systems

The Companion Cognitive Architecture (Forbus et al. 2009) is based on the idea that intelligent systems are social organisms that collaborate with others and learn over extended periods of time (e.g. from experience). In a Companion, analogy is a central reasoning mechanism. Each Companion is capable of using multiple modes of interaction. It has a natural language interface that is built upon EANLU and a sketching interface that uses CogSketch. We use the Companion cognitive architecture to model the interpretation of multimodal instructional analogies.

Approach

The interpretation process takes as input a sketch of the base and target and a text passage describing the analogy. It produces a model of the target concept, based on the analogy. There are three major challenges in this task. The first is how to interpret the text and visual representations in a way that is coherent and sensitive to the instructional analogy. Each modality provides unique information that should be shared, requiring that the sketch and text must be aligned and merged into a more general description. The second challenge is determining how to extract information about two separate domains from one source of input. The instructional analogy requires the comparison of a base domain and a target domain, yet information about each description is not necessarily packaged separately. Instructional analogies used in textbooks often interleave information about the different descriptions. If new information is being introduced, the reader cannot be expected to have a full vocabulary of the target domain, and must therefore use linguistic cues or visual information to make sense of it. The third challenge is how to construct the instructional analogy itself. This involves adhering to the constraints implied by the description of the analogy, e.g. that particular things correspond.

We explored methods for addressing these challenges with respect to three classic analogies that are used to teach novices about cell parts and function (Table 1), adapted from a teaching guide for instructors (Harrison & Coll 2007). In the following sections, we describe the inputs to our system and our current interpretation strategies.

Sketch and Text Interpretation

The Companion takes as input a text file with a simplified natural language description of the analogy and a CogSketch sketch file with a drawing of the base and the target of the analogy. The input to EANLU is as seen in Figure 1. The input to CogSketch is the ink seen in Figure 2, along with the conceptual information entered by the user and the spatial relations automatically computed by CogSketch. The conceptual information includes labels for each individual glyph (e.g. that a glyph depicts a cell nucleus or a wind power plant) and labels for each grouped glyph (e.g. that all the cell parts grouped together make up a cell).

Semantic Interpretation of Text

The text portion of the analogy is processed using the existing approaches in EANLU. Natural language is inherently ambiguous. Words have multiple senses and sentences have possible parses. Each of these alternatives is formally represented as a *choice set* (Forbus & de Kleer 1993), and a semantic interpretation of a text is a logically consistent selection of choices from each choice set. There can be subtle dependencies between them, e.g. a parsing choice might require a particular part of speech for one of the words in the phrase, and the choice of verb meaning can constrain what participates in its roles. Once EANLU has generated choice sets, the Companion automatically constructs interpretations by using two heuristics. The first

A cell is like a city. The city government controls the city. The nucleus controls all the cell's activities. A power station provides electricity. A mitochondrion is like the power station. Construction companies build houses. The ribosomes make proteins. Roads, cars, buses and trucks provide transportation. The endoplasmic reticulum transports materials. The city government changes direction after elections and is very adaptable. The nucleus always controls the cell.

Figure 1: Text representation for the analogy: a cell is like a city.

heuristic gives preference to semantic choices that involve things mentioned in the sketch. For example, the word "cell" may be interpreted as being an instance of one of three *collections* (i.e. concepts): an animal cell, a battery cell, or a prison cell. The Companion chooses the animal cell interpretation because there is a glyph labeled animal cell in the sketch. That is, because there is an instance of animal cell in the sketch, the interpretation that the entity mentioned in the text is also an instance of the animal cell collection is preferred. The second heuristic gives preference to choices that lead to the greatest information gain. That is, if two interpretations have equal preference, but one of the interpretations involves more facts than the other, then the one with more facts will be preferred.

After an initial semantic interpretation is constructed, analogical dialogue acts (Barbella & Forbus 2011) are found via abduction to make hypotheses about what entities belong in the base and target and detect any explicit statements about how entities should correspond. Six different types of dialogue acts are detected by EANLU: (1) introduce a comparison, (2) extend the base or target, (3) introduce a correspondence, (4) block a correspondence, (5) introduce a candidate inference, and (6) block a candidate inference. Using the text in Figure 1 as an example, the first sentence captures a dialogue act that introduces a comparison, where the cell is the target and the city is the base. The second sentence extends the base (by providing additional information about the city). The rest of the sentences provide additional information about the base and target and introduce a specific correspondence (the power station and mitochondrion).

Sketch and Text Alignment

At a very general level, the sketch and text both describe the same thing. However, there is conceptual information in the text that does not exist in the sketch and spatial information in the sketch that does not exist in the text. It is therefore necessary to merge sketch and text representations in a way that preserves meaning across the two representations.

Following Lockwood & Forbus (2009), we use SME to align sketch and text information and impose constraints on the matching process to reflect the literal nature of the mapping. However, we go beyond that work in several

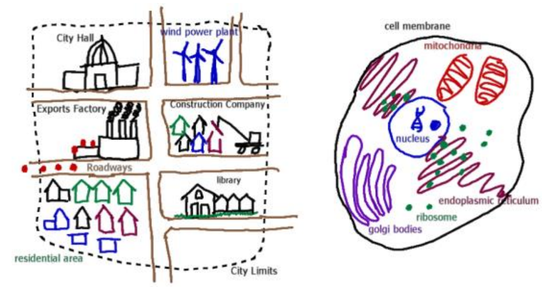

Figure 2: Sketch representation for the analogy: a cell is like a city.

ways. First, they used semi-automatic interpretation of the text, i.e. when there were ambiguities that the system could not resolve, those ambiguities were presented to the trainer to select the appropriate choice. By contrast, we use a combination of cues from the sketch, analogical dialogue acts, and heuristics to interpret text automatically. Second, our system automatically generates partition constraints (described above) to help align the sketch and the text. For example, since there is a cell nucleus in both the sketch and text, a partition constraint on that concept ensures that the nucleus introduced in the text aligns with the nucleus introduced in the sketch.

When the collections in both sketch and text are identical, this method works well. But this is not always the case. For instance, a text may refer to a power station, while the sketch may refer to something more specific or more general, like a wind power plant. In such cases, the system relies on relational information to make the appropriate matches. There are two reasons why collections might be different across modalities. First, they can use subordinate/superordinate concepts, e.g. power station versus wind power plant above. This condition is partially addressed by *generic event interpretation,* described below. The second reason is that one modality may describe a concept in general terms by using a plural form to denote a set of instances, while another modality may only refer to an instance. To address this, we introduce object groups in both modalities so that, for example, a concept that represents a group (e.g. "houses") can match to a set of similar entities (e.g. house1, house2, house3).

Potentially there are multiple instances of the same concept in both the sketch and the text that should remain distinct. For example, if our analogy distinguished between ribosomes that float freely in cytoplasm and ribosomes that are bound to the endoplasmic reticulum, then the sketch and text could be aligned in different ways. We have not yet observed this issue, but additional conceptual or spatial information would be needed to arrive at the correct sketch-text alignment in such cases.

The alignment between the sketch and text is used to create a *generalization*, where items that correspond to each other in a mapping are merged together to create a coherent representation that integrates both modalities.

Generic Event Interpretation

Generic event interpretation is an elaboration technique that enables structural matches between entities that do not belong to identical collections. It assumes that descriptions of functions and events are generic statements about collections as a whole. For language understanding in general, detecting generic statements is a hard problem. However, in an instructional context, it is often reasonable to assume that most statements are generic assertions. For each event or function that is detected in the text modality, we detect the main participants of the event and assume that participation in the event type is a property of all entities of the same type. For instance, the statement "Construction companies build houses" is interpreted as a property of all construction companies. These general properties are then projected onto the visual modality, to speculate about events, roles, and entities in the sketch that are not explicitly drawn. The event structure in both modalities can then be used to support matches between entities that may not have other relations or attributes in common. For example, the statement about power stations providing electricity tells us that power stations, in general, provide electricity. By projecting this information to the sketch, we can speculate about wind power plants also providing electricity because wind power plants are a subset of power stations. This shared structure is used as support to put wind power plants and power stations into correspondence, despite their non-identical collection membership (Figure 3). In addition to encouraging accurate matches, generic event interpretation provides the type of general facts that are often needed to answer questions about a domain.

Base and Target Extraction

Once a multimodal description of the analogy is created (e.g. multimodal facts about the cell and the city) the base and target must be extracted so that the analogy can be constructed. We use information gained from analogical dialogue act detection, event interpretation, and glyph grouping to extract base and target information. Analogical dialogue acts indicate that the city is part of the base domain and the cell is part of the target domain. This suggests that items in the sketch that are grouped with the city are part of the base domain and that items in the sketch that are grouped with the cell are part of the target domain. This step is important for capturing the relationships between entities that are from the same domain but not mentioned in the same sentence. From these seed entities, we detect events that they participate in, and include those in the description as well. This approach is not complete, but it will capture entities that are directly related to seed base and target entities via text-based or visual relations.

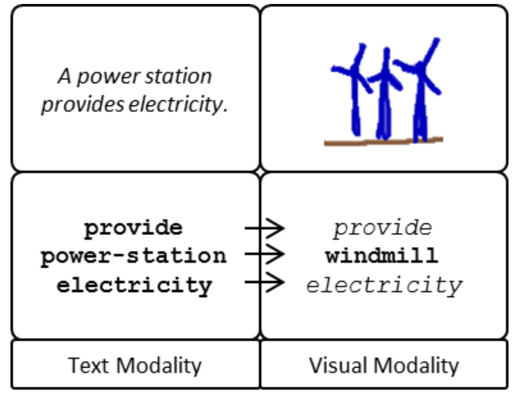

Figure 3: An illustration of how generic event interpretation suggests a correspondence between power stations and wind power plants. Italicized items in the middle right cell are speculative items that are not explicitly drawn in the sketch.

Instructional Analogy Interpretation

Once the base and target have been extracted, the instructional analogical mapping can be constructed. Unlike the text-sketch alignment technique described above, this is a cross-domain analogy. Match constraints that require instances of the same collection to correspond to each other are too literal. We have observed, however, that events are a special case. Instructional analogies are often intended to convey the importance of functional relationships, which are often conveyed in terms of events. In our cell-city analogy, the important functions are described as controlling, providing, and making. By requiring that events and their primary participants correspond to each other, we encourage mappings that are more likely to transfer functional information between domains.

Biology Analogies

We applied our interpretation strategies to three analogies adapted from (Harrison & Coll 2007): a cell is like a city, a cell is like the earth, and ATP is like a battery. For each analogy, we used the approach described above to interpret and merge sketch and text representations and to build the analogical mapping. Table 2 shows the number of facts that were used for each analogy at each stage of interpretation before constructing the mapping. The total numbers of facts for the text and sketch descriptions include only information that is conveyed in their respective modalities. Because sketch and text representations are interpreted independently at the beginning, the total number of facts

	ATP / Battery	Cell / City	Cell / Earth
Text	82	106	56
Sketch	48	169	120
Combined	114	213	160
Base	27	97	74
Target	31	84	19

Table 2: Total number of facts for each analogy at each stage of interpretation. Combined facts are those that are found from merging sketch and text representations.

for each modality is different. The process of merging sketch and text representations is not just a union of the facts in each modality since entities are merged together based on how well they align with each other. Since some information is redundant, the total number of combined facts is less than the sum of sketch and text facts. Lastly, the totals for base and target descriptions illustrate that some of the facts in the combined description don't make it into either the base or target descriptions, highlighting one of the challenges to automatic case extraction. Table 3 summarizes the size of each mapping along with the accuracy of correspondences and candidate inferences. As the totals for correspondences indicate, the three analogies varied in size. The cell/city analogy was the most detailed, yielding the most number of correspondences and candidate inferences. The analogies also varied in their capacity for generating inferences. The accuracy of those inferences is noticeably lower than that of the correspondences because candidate inferences represent hypotheses about what might be true in the target domain. Some of those hypotheses are expected to be false. It is also possible for important inferences to be overlooked. For example, while our interpretation of the ATP/Battery analogy finds that ATP is *used* it currently fails to capture the notion that ATP can be *reused*.

To illustrate the interpretation and matching process in greater detail, we walk through one analogy in the next section.

	Correspondences (% correct)	Candidate Inferences (% correct)
ATP/Battery	15 (67%)	12 (25%)
Cell/City	50 (80%)	49 (39%)
Cell/Earth	10 (60%)	44 (11%)

Table 3: Summary of correspondences and candidate inferences for each analogy.

Example: A Cell is like a City

Table 4 shows the entity correspondences in our cell-city analogy. Correspondences are guided by linguistic cues, conceptual information, and spatial information. The correspondence between the cell (Gen-Cell) and the city (Gen-City) is required by the analogical dialogue act in the first sentence of the text (for a detailed description on detection of analogical dialogue acts, please see Barbella & Forbus, 2011). Other entities, like the cell nucleus and city government, correspond to each other because of their participation in similar events (i.e. they control the cell and city respectively). In contrast, the city limits and cell membrane correspond to each other based on qualitative spatial information alone, since neither one is mentioned in the text description.

This mapping has a few inaccurate matches as well. One of the house entities and the library (a distractor in the sketch) correspond to another mitochondrion instance and the full set of mitochondria. In this case, irrelevant spatial information negatively influences the match. These unexpected correspondences are supported by the entities' spatial relationship (i.e. containment) to the city limits and cell membrane.

This analogy has over 40 candidate inferences, many having to do with spatial information and conceptual attributes. For instance, one inference suggests that the mitochondrion is a wind power plant. This comes from their correspondence but is of course not literally true. However, that correspondence also supports a reasonable inference, which states that there is an energy providing event that is performed by the mitochondrion. This information,

Base Item	Target Item
`city-limits`	`membrane`
`Gen-CityGovernment`	`Gen-CellNucleus`
`Gen-Roadway`	`Gen-EndoplasmicReticulum`
`Gen-SetOfTypeFn-House-Modern`	`Gen-SetOfTypeFn-ProteinMoleculeType`
`factory`	`golgi-bodies`
`Gen-City`	`Gen-Cell`
`group-of-election`	`Gen-SetOfTypeFn-Action`
`Gen-WindPowerPlant`	`Gen-Mitochondrion`
`house-3`	`mitochondrion2`
`library`	`Gen-SetOfTypeFn-Mitochondrion`
`Gen-ConstructionCompany`	`Gen-Ribosome`

Table 4: Entity correspondences in cell-city analogy. Prefix "Gen-" indicates entities that have been merged between text and sketch representations.

while not explicitly stated in the text, is useful for understanding the functional role of the mitochondria. Another inference suggests that the cell membrane is a border. While not literally true, an elaboration of the city domain may lead to a better understanding of the cell membrane's function.

Discussion & Future Work

By examining commonly used analogies for teaching about cell structure and function, we have identified an initial set of strategies for interpreting multimodal instructional analogies. First, we use information from both modalities to guide the semantic interpretation of the texts. Where there are multiple possible interpretations, the contents of the sketches are used as a heuristic for resolving ambiguities. Second, we developed generic event interpretation, which we use to elaborate on the functional properties of the things mentioned in the texts and to speculate about functional properties of things in the sketches. By interpreting events as generic statements, we are able to infer type level properties that are often needed to answer questions about a domain. Third, we use information from both modalities (dialogue acts and event structure found in the text as well as conceptual groupings found in the sketch) to automatically extract information about the base and target domain.

Our approach uses analogical reasoning in two ways. The first is for aligning sketch and text representations and merging them into an integrated interpretation. The second is for creating a cross-domain instructional analogy that can be used for building a new target domain. The degree to which conceptual information constrains these analogies depends on the purpose of the analogy. In aligning and merging, literal matches are enforced. For the cross-domain instructional analogy, events and role relations drive the mapping to support correspondences and inferences that highlight functional relationships.

A major challenge to address is how to evaluate candidate inferences. Inferences have varying degrees of structural support, but the utility of that support depends on the quality of the original representations. As seen in our cell-city analogy, many inferences are not useful for developing accurate target knowledge. On the one hand, correspondences like the one between cell activities and city elections might not lead to useful inferences. On the other, conceiving of a membrane as a border, which follows from the membrane corresponding to city limits, seems potentially useful if base domain knowledge were recruited and generalized appropriately. A related issue arises when candidate inferences introduce new entities. These new entities are called *analogy skolems* and they represent things in the base domain that do not exist (but are suggested to exist) in the target domain. For example, one of the inferences from the city cell analogy is that the mitochondrion does *something like* making electricity available. The energy providing event doesn't explicitly exist in the target domain but it is suggested by the analogy. Since there is nothing in the mapping that corresponds to providing electricity, a skolem is created. To solve this issue, the presence of skolems in inferences may be used as triggers for rerepresentation, where alternative mappings are explored so that a target item can be found as a potential match. If no potential matches can be found, more general terms for the skolem could be explored to see if there is some parent concept that can be relevant to both the base and target domain. In this case, a more general concept than electricity is needed in the target domain to support the existence of a biological energy production event. In most cases, it seems that evaluating candidate inferences (and any skolems they introduce) requires a great deal of common sense knowledge. An important next step will involve exploring domain-general strategies for filtering candidate inferences.

To concretely evaluate the knowledge that can be captured through multimodal instructional analogies, we are expanding the current approach to cover a set of twelve recommended biology analogies from an instructional guide for teachers (Harrison & Coll 2007). As of this writing, we have interpreted three out of twelve. We are also developing question answering strategies so that the target knowledge from these analogies may be used to answer questions on standardized assessments[2,3]. We do not expect that instructional analogies will be able to cover the full range of questions asked on those assessments. But, we do expect that they will provide a broad set of qualitative knowledge that, when paired with question answering heuristics, can model the type of qualitative knowledge that novices often use to solve novel problems.

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[3] http://www.doe.mass.edu/mcas/

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