Addressing the Barriers to Interlingual Rule-based Machine Translation with a Concept Specification and Abstraction Semantic Representation

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ABSTRACT

Interlingual machine translation offers the prospect of better preservation of meaning and requires fewer language/translation models than big data-based machine translation approaches. However, it lacks popularity primarily because of the extensive training and labour required to define the language rules. To address this, we present a semantic representation that 1) treats all bits of meaning as individual concepts that 2) refine or further specify one another to build a network that relates entities in space and time. Also, the representation can 3) encapsulate propositions and thereby define concepts in terms of other concepts supporting the abstraction of underlying linguistic and ontological details. The proposed natural language generation, parsing, and translation strategies are also amenable to probabilistic modeling and thus to learning directly from example data.

I. INTRODUCTION

There are a large number of minority languages in the world. Although many of these are in danger of extinction [1], there are thousands of viable non-mainstream languages representing many tens of millions of people’s native tongue. While statistical machine learning and deep learning have been a boon to improving the quality of machine translation between the most common languages on the Internet, these approaches do not work well without the necessary substantial bilingual corpus, something often lacking for minority languages. Also, in recent years several startups have focused on natural language generation (NLG), turning data into readable narratives. Unfortunately, these are restricted to only a few key languages. Having a means of rapidly adding new languages to the list could provide a competitive edge in this space. Other natural language applications such as information retrieval, sentiment analysis, and question answering that involve a form of semantic analysis would stand to benefit from the use of an interlingua to extend cross-linguistically.

Interlingual machine translation approaches substitute the need of large bilingual corpus for encoded expert knowledge – someone formally describes how to express a specific language in terms of the interlingua (a carefully designed intermediate or “hub” language). If designed well, the interlingua will be capable of representing the breadth of meaning across languages. Translation between any two languages (including minority languages), then, would require only that they be defined in terms of the interlingua. Translation proceeds by first translating from the source language into the interlingua and then from the interlingua into the target language. Besides potentially better preservation of meaning through translation, the key feature of using an interlingua is that it only requires one translation model per supported language. In contrast, modern statistical machine learning approaches technically need a bilingual corpus for each translation pair, although they sometimes use one or more intermediate languages such as English that are not designed as an interlingua to find a path with enough bilingual corpus to generate reasonable results. In spite of its potential benefits, interlingual machine translation is not the engine behind commonly used translation products.

Historically, interlingual machine translation systems have been rule-based machine translation systems. Such systems use a long list of rules to take source language text and generate target language text. One key advantage of rule-based machine translation over statistical or neural machine translation is that there is no upper limit to the translation quality, since appropriate rules can model even anomalous or rarely used language that big data approaches would gloss over. In practice, rule-based machine translation can be practical for adjusting translations for similar dialects, but is very challenging otherwise. The trouble is that crossing the morphosyntactic and semantic domains of two disparate languages is very complicated and rule interactions can become unwieldy. In addition, “Whatever the power of representation of a (meta) language is, there exist some linguistic phenomena requiring exceptional processing...” [2]. The greatest barrier, however, appears to be the large amount of skilled human effort required to build the language rules.

At the heart of solving these rule-based machine translation challenges, we believe, is a user-friendly and statistically tractable semantic representation. As will be discussed in Section VI, existing related representations are capable of translation and/or NLG, but they require the manual building of new language models and the encoding of content in terms of their interlingua, which requires substantial human training, time, and effort. Also, because of their complexity, it is doubtful that serious data-driven statistical models could be effectively employed to help develop new language models.
Thus we propose a new semantic representation for rule-based machine translation with the following goals:

- provide the simplest, most accessible way to represent and model meaning (for humans and computers) and leave room for users to easily tailor the representation as required
- have a natural affinity for natural language generation (realisation), parsing, and statistical tractability
- span the representation of meaning from the individual concept to high-level discourse relations
- be expressive enough to encode all aspects of meaning expressed in the surface text of any language
- prove consistent, unambiguous, and canonical:
  - given a sentence with no inherent ambiguity, there should be exactly one semantic representation that is also unambiguous
  - different sentences should share the same semantic representation when they share exactly the same underlying concepts, which are related to one another in the same way.

The rest of this paper is organized as follows. Section II introduces the semantic representation with rationale for the principle features of the approach. Using numerous examples, Section III provides guidelines for how to represent a variety of linguistic phenomena in terms of the approach. Sections IV and V describe general strategies for transduction and translation and section VI relates three thematic role-based representations, which are among the most similar semantic representations to the present approach, each employing an interlingua as well.

II. AN EXAMPLE-BASED INTRODUCTION

To achieve the above-named goals, our semantic representation is defined by several key principles:

- separation: all divisible elements of meaning in a sentence are expressed as individual concepts
- specification: concepts further specify or narrow the meaning of other concepts to form networks of meaning that relate entities to one another
- encapsulation: individual conceptual networks can be encapsulated and treated as a single concept.

Our representation takes the form of a tree. Figure 1 provides two examples. In them, each node is a concept and each arrow points from a concept being further specified to the concept providing the additional detail. Although rare, it can have more than one root, and will often have many leaf nodes, which usually specify/narrow only one concept, but sometimes specify more than one. The trees can generally be written into a single line of text that we refer to here as tree-line notation, which provides an easy mode of data entry. Let’s illustrate the three key principles of our approach with these two network formats using a running narrative example.

“Anne was quiet.”  \( (1) \)

Anne > quiet > \{past\}  \( (2) \)

In a semantic representation, it is important to have a consistent way of relating concepts for network building and usage. Specification provides a natural, intuitive rule by which to relate concepts. An important feature of Universal Conceptual Cognitive Annotation \( [3] \) is that it requires less training of annotators than do other approaches, involving only a dozen semantic relations to learn for constructing graphs. We aim to simplify this further by embedding the relationships entirely in graph the structure using specification. When uncertain about the arrangement between two concepts, the question, “Which concept specifies or narrows the meaning of the other,” can help clarify. In our first example, the attribute concept “quiet” further describes or specifies the entity (noun) concept “Anne”, and “quiet” is further specified as a “\{past\}” tense attribute. Note that a convention we use is to surround a concept in “{}” when it has no natural stem of its own in the language being modeled but rather affects the expression of others (e.g., tense, plurality, tone, etc.). For example, we view tense as an attribute specifier or a verb specifier rather than as a distinct verb (see Section III-B on tense and copula for more details).

“Reluctantly, Anne approached the stern teacher.” \( (3) \)

approach > \{past\}, \{subject\} > Anne, \{object\}  \( (4) \)

\( (teacher > stern) > the, reluctantly \)

The entity “teacher” is described as being “stern”, the determiner “the” specifies a certain stern teacher, and the adverb “reluctantly” describes how the “approach” was made. Event concepts in propositions will tend to form the roots of trees and entities the branches. Adjectives, adverbs, and determiners often make up the leaves.

In this event proposition, the \{subject\} and \{object\} concepts are needed to specify which person takes which role. To keep the representation simple, \{subject\} and \{object\} are represented as concepts rather than as a separate class of “relations” \( [4], [5], [6] \) or function “slots” \( [7] \). This approach is also in contrast with those that attempt to represent a proposition in a vectorized format, also known as sentence embeddings. To maintain a constant length vector in such an approach, either there must be regions of the vector devoted to each possible role or else strongly similar concepts with
different roles (e.g., “Anne” and the “teacher”) must mingle (e.g., [8]) and risk confusion.

Implicitly, a semantic representation should strip away syntactic or morphological features, leaving the meaning behind. To achieve this, every bit of meaning encoded by syntax or inflectional morphology is converted into a separate concept. In our example, the verb “approached” is decomposed into its constituent stem “approach” and tense “{past}” elements. The benefit is a common basis for simpler transfer to other languages, which, for example, may not express tense by inflecting the verb. Indeed, handling details of morphology is often left out of a semantic representation. This has less effect in English, but in languages where subject and/or object can be bounded morphemes (e.g., Orizaba Aztec [9]) it will be more important. Implied concepts are also included in our approach by appropriately inserting in the network the implied concept and specifying it with the { implied} concept (see Table I for examples). Also in the present approach, all elements of meaning are expressed as concepts only. In contrast, first-order logic, for example, employs various classes to embody elements of meaning including terms, predicates, functions, and quantifiers. This can lead to awkwardness and language expressability difficulties (e.g., quantifiers cannot be functionalized [10]). Using a single meaning element class avoids the complication of crossing the boundaries between classes of meaning. Symbols of logic rendered as concepts along with their conceptual arguments can still be identified and used for conducting inferences in this approach as needed.

Using square brackets in the tree-line notation enables the single concept “approach” to be specified by a list of concepts. Specification by multiple concepts has no formal ordering, no required set of specifying concept arguments, and technically no limit to the number or variety of concepts that may be included. In contrast to some approaches (e.g., FrameNet [11]), this means that users of a language model need not know or look up any particulars (e.g., functional arguments, class, etc.) of any given concept before invoking it, except perhaps for differentiating between homographs (two or more concepts with the same spelling).

The ability to encapsulate and treat a proposition as a new concept is powerful, achieving several important functions. In the previous example, it allowed us to build up a more descriptive entity before refining it further. It would allow distinguishing between the “stern teacher” in the narrative and possibly a different teacher in the vicinity. It provides a way of ordering of operations, in support of unambiguity. In the noun phrase, “all silk clothing”, it allows us to encode “all [past] silk clothing” and “all [pastcont.] silk clothing” differently. This is also a feature of Combinatory Categorial Grammar [12] where the semantic relationships have an explicit order of operations or nested groupings based on the order in which combinatory rules are applied.

“The teacher softened, however, because

Anne was crying.” (5)

(soften > [{past}, {subject} > teacher > the]) >

because > (cry > [{pastcont}, {subject} > Anne})

Here, encapsulation has a different function, where two propositions enclosed by parentheses are related via the “because” concept, capturing the cause and effect nature between two separate propositions. Encapsulation can lead to even higher, discourse-level organization of meaning, which might prove helpful in applications like text summarization. The word “however” in the current example could be related back to the teacher’s sternness in a similar fashion.

All encapsulations discussed so far only temporarily house a small network of concepts. But if a particular network of concepts were used frequently enough, it would seem worthwhile to label it and refer to it thereafter by name. Defining concepts in terms of other concepts is an important feature of our approach. For example, if we wanted to define Anne as an imaginative girl, we could represent this as,

Anne = girl > imaginative,

where girl = human > [young, female], which tells us that ultimately Anne is human. This capability provides a convenient basis for abstraction of underlying linguistic and ontological details. Suppose we were to define forks, fly swatters, and staplers as “instruments” with associated specifications. Then, when grammar treats instruments in a certain way, these objects would be treated similarly without having to tag them with each use, as is done in other representations. Later, suppose you chose to define a pitchfork in terms of a fork. It would then automatically inherit its status as an instrument. Another benefit of this abstraction is that after all the definitions are in place, users and algorithms that know nothing about the language definitions/rules will have the same benefits and will not have had to learn to label instruments.

In relation to the gamut of semantic representations [10], [13], the present representation falls somewhere between sentence diagramming and a semantic network having logical form. In sentence diagramming (e.g., Reed-Kellogg [14]), all of the words of the sentence must be used and be fit into the framework. Our approach naturally leans toward the use of all underlying concepts in the sentence, even the most minute, but does not force all words to be included, since some words serve only syntactic purposes and do not add to the meaning (e.g., John called the dog vs. The dog was called by John). Logical form semantic networks like Abstract Meaning Representation [15] drop pronouns and instead link their actions to the entities they reference, building a graph of logical interactions between entities. While our approach is not averse to the use of additional processing to produce similarly abstract networks, it natively maintains all of the underlying concepts in the surface structure, including pronouns, articles, tense etc. to provide the most direct and complete interpretation of the surface structure’s meaning. This will help preserve the same meaning in translation to another language, with as little disturbance to the original content as possible.

III. GUIDELINES FOR USE

In the previous section, examples were provided to explain the primary mechanisms of the representation. Here, we pro-
pose ways of using our approach to interpret the meaning of certain types of concepts and surface structures, with examples provided in Table 1 matching the discussion in the following subsections. Although our examples are kept short for clarity, sentences of any length can be represented. Our goal is to adhere to natural intuitions about how concepts are related, even when this not straightforward, and to generate similar representations for sentences with similar meaning even when the syntax is different.

A. Straightforward Concept Specification

Many standard aspects of language can be represented simply as one concept specifying or narrowing the meaning of another. Adjectives and adverbs, for instance, describe how an event was performed or specify an attribute of an entity. Tense narrows the details of an event or an attribute concept by specifying timing. Determiners further specify the instance of the concept they refer to. Prepositions and prepositional phrases further specify where in space or time an entity is or an event takes place. Emphasis via bold font, italics, exclamation marks, etc. adds to meaning and can also be tracked as a specifying, stemless concept. Such emphasis sometimes serves to identify which concept(s) should be further specified by others. Intensive pronouns add emphasis in a different way but are represented in the same way. Numbers are simply a further specification of an entity, as is plurality. Logic concepts and modals are also simple specifications on concepts. Naturally, we consider questions to be substantially different from affirmative statements or commands. This is certainly true for how people respond, but in terms of representing their meaning, our approach employs another simple specification by applying the \{?\} concept to the unknown concept. In true-or-false questions it is usually applied to an entire proposition, but could also be applied to a particular concept within if an appropriate emphasis were applied. Wh- questions involve specifying the appropriate concept with the wh- and the question concept. The notion of concepts further specifying one another is a powerful one that unifies the representation of a large number of disparate linguistic phenomena.

B. Tense, Copula, and Reification

So far, we have shown tense being used to further specify events and even the attributes of entities. Events are naturally specified by tense, expressing roughly when the action occurs. When applied to entities, tense specifies the timing of another specifying concept. This steps into the realm of copula, where in English the verb “to be” (often expressed by “is” and “was”) is not treated as an event but rather as a means of expressing the tense or timing of an attribute specifying a concept. By convention, tense concepts in our representation are always surrounded with “\{\}” and make up a large portion of the stemless concepts. As an aside, the linguist has the freedom to adjust these stemless concepts to suit their purposes. For example, it would make sense to abbreviate the most commonly used of these to make data entry more efficient. Also some languages will need a different set of them (e.g., different tenses). We will look at how to represent most semi-copulas or linking verbs in our later discussion of event concepts. However the concepts “seem” and “appear” behave somewhat differently, like a modal. Existential clauses sometimes do and sometimes do not behave as a copula. In the sentence, “There is a God,” the standard interpretation is, “A God exists.” However, in the sentence, “There are boys in the yard,” the interpretation is not that “boys exist ... in the yard”, but that an instance or reification of “boys” has the prepositional attribute of being “in the yard”.

Reification is the process of making real or creating an instance of a concept. For example, when we talk of “a dress” we are not describing the concept “dress” but a particular one. Most of the time, entities referred to in text are reified. When beneficial, one way to represent reified concepts is to have that concept specify a stemless reification concept (e.g., “\{re\} > dress > a”). For clarity, and because in a computerized implementation copies or instances of the concepts will be used in the semantic networks, we do not normally include this. Technically it should not be contained in the underlying definition of concepts since those are not reifications. It comes in hand, though, when two or more reified entities refer back to the same underlying entity. Consider the example, “Fred is the plumber.” Both “Fred” and “the plumber” are separately reified entities, but the copula used here tells us that they refer to the same entity and could be represented as “\{re\} > [Fred, plumber > the] > \{present\}”.

C. Specialized Entities or Nouns

Named entities, as well as pronouns can be specified in the same way as other entities. Named entities such as “Canada” or “South America” could possibly be reified by definition since there is only one real-world instance of them. A different, but common, way of specifying a noun is with reference to a previous event. For example, “The dog that ate the peanut butter barked happily.” In this sentence, the dog appears as the subject of two events. One of the propositions specifies which dog is being talked about in the yard,” the interpretation is not that “boys exist ... in the yard”, but that an instance or reification of “boys” has the prepositional attribute of being “in the yard”.

In our conception, the barking dog is further specified as the subject of another proposition. In tree-line notation, we make the connection through an encapsulation boundary (“\)” with the prefix “\>>>”). Also, when we want to designate one of the encapsulated concepts to be further specified by a concept on the outside, we would add the prefix “<<\>>>”. In some cases this is useful, as in, “She loved the cat that caught the rat that found the cheese.” Some definitions can make use of this mechanism as well. We can represent, “Mary is a beautiful singer,” as Mary > ((singer > beautiful) > a) >
Table I

Examples of how a variety of different aspects of language behave in this semantic representation.

| Type                  | Example Sentence | Free-line Notation |
|-----------------------|------------------|--------------------|
| Adjectives            | The dress is green. | (dress > [the] > green > [present]) |
| Adverbs               | Quickly, he ran home. | run > [past], [subject] > he, home, quick |
| Determiners           | John lifted a rock. | lift > [past], [subject] > John, [object] > rock > [a] |
| Prepositions          | The ball is under the table. | (ball > the) > (under > table > the) > [present] |
| Emphasis              | Holy cow! | holy cow > {present} |
| Intensive pronouns    | He himself bought the car. | buy > [past], [subject] > he > [emphasis], [object] > car > [the] |
| Numbers               | John will order two hamburgers. | order > [future], [subject] > John, [object] > hamburger > two |
| Plurality             | Mary will pick up the eggs. | pick up > [{future}, [subject] > Mary, [object] > egg > [plural]) > [the] |
| Logic concepts        | All silk clothing is comfortable | (clothing > [silk] > all) > comfortable > [present] |
| Intensive pronouns    | She can go. | (go > [present], [subject] > she) |
| Numbers               | John’s dog is hungry. | dog > [hungry] > [object] > hungry > [past] |
| Plurality             | John will order two hamburgers. | order > [future], [subject] > John, [object] > hamburger > two |
| Possessives           | Who created the world? | who > [create] > [present] |
| Noun phrase           | The dog that ate the | the > [dog] > subject > eat > [past] |
| Participles           | The trembling bird flew away. | fly > [past], away, [subject] > (tremble > [object]) > [present] |
| Gerunds               | Swimming is fun. | swim > [present], [subject] > fun > [present] |
| Multi-Object Verbs    | John traded Mary his marble for her ribbon. | trade > [past], [subject] > John, [object] > Mary, [object] > marble > his, [object] > ribbon > her |
| Linking Verbs         | That chicken tastes good. | (chicken > that) > (taste > good) > [present] |
| Verbs Followed by Infinitives | I want to go home. | want > [present], [subject] > I, [object] > (go) > [subject] > I > [past] |
| Ergative verbs        | The sun melted the ice. | melt > [past], [subject] > ice > [the] |
| The ice melted.       | melt > [past], [object] > ice > [the] |
| Possessives           | John’s dog is hungry. | dog > [hungry] > [subject] > hungry > [past] |
| Voice/Topicalization  | The truck was driven by John. | drive > [past], [subject] > John, [object] > (truck > the, [topic]) |
| Prepositional phrase  | John fell through the rotting floor. | fall > [past], [subject] > John, through > |
| Simile and Degree     | She ran like a scared rabbit | run > [subject] > (like > [scared rabbit]) > [the] |
| Cause and Effect      | If John confesses then Bill will be angry. | (Bill > angry > [future]) > if > (confess > [present], [subject] > John) |
| Contrast              | She hid but I found her. | (hide > [past], [subject] > she) |
| Groups                | I like her but she doesn’t like me. | like > [subject] > I, [object] < [she] > (like > [subject] > she, [object] > I, [not]) |
| Nonsense              | Colourless green ideas sleep furiously | (idea > [plural]) > green > colourless, furious |
D. Specialized Events or Verbs

Most of the events we have dealt with so far have at most one object. However, some events have more than one object. For example, the verb “to trade” has four roles that must be identified: subject, object, object 2, and an indirect object. In such circumstances the linguist can create new stemless concepts like the {subject} and {object} to denote these roles in the semantic representations. Our approach does not employ thematic roles as concepts except when there are two or more entities (e.g., John and Mary) that could sensibly fill any of two or more roles (e.g., the {subject} and {object} roles).

There are some categories of verbs that do not behave like standard events. Linking verbs (e.g., tastes, feels, looks) appear in place of the copula “to be” in English and reflect the state of the entity they specify rather than indicate an event between entities. One challenge to natural language parsing of surface text into our representation may be to identify when these linking verbs behave in this way rather than as a standard relation (e.g., John felt good vs. John felt the silk). There is a group of verbs that are often followed by infinitives (e.g., I want to go home. She tried to tell you). These can be seen as an event with an {object} that is itself an encapsulated proposition. Ergative verbs are such that when you drop the subject (making them intransitive), the object behaves like the subject (e.g., The sun melted the ice vs. The ice melted (intransitive form)). Note that by adding a copula, the intransitive form’s object behaves as an object again (i.e., The ice was melted). Light verbs such as make, take, give, do, etc., are treated in the same way as normal verbs. If it is the desire of the linguist to simplify the meaning structure by removing them, this can be done. However, in principle, our approach allows users to stick as closely as possible to the surface text, only dropping words that do not add to meaning at all. To reiterate, our representation allows the linguist to use the provided conventions for how to handle the different types of syntactic phenomena or to adjust them as they wish. Consistency within a language model, however, will be valuable for natural language generation and parsing.

Possessives can be represented in terms of the verb “to have”. The possessor becomes the subject and the thing possessed is specified by the {object} of “to have”. In “John’s dog is hungry”, we get the representation, “(dog > (have > {[<subject>, >>{object}]) > John) > hungry > {present})”. If beforehand we define “{have} = (have > {[<subject>, >>{object}])”, the representation is reduced to “(dog > {have} > John) > hungry > {present})”. As an aside, we can use the same approach to define the composition of entities (e.g., bird = organism > {have} > [wing > two, feather > {plural}]). It is tempting to just use the {have} concept without bothering to define it, but if this were our policy regarding definitions, we might miss out on the use of data examples that inform generation and parsing according to the underlying structure within the definition.

Voice and topicalization make certain concepts in a sentence the focus. This could be simply noted using a {topic} stemless concept to specify the focal entity. In a multi-proposition sentence, an entire proposition as well as an entity within it may need such a marker.

E. Multiple Propositions and Beyond

Many sentences contain two or more propositions, connecting to one another by different means. Some prepositional phrases behave in this way and use a preposition or connecting word (e.g., “after”, “when”), which may then be specified by a proposition. Similes and other comparisons by degree also behave in this way, but their connection is between the quality applied to each of the propositions. Cause and effect-related concepts (e.g., because, since, if...then) usually connect two propositions, one being the cause and one being the effect. Contrasts also connect two propositions and specify them in the same way. Some, like “however”, tend to have a clear orientation like cause and effect. Others have a very similar meaning regardless of which proposition specifies the other. It could be argued that there is always an orientation since the order in the surface structure emphasizes one proposition
over the other. If there is no difference in meaning, it would be more canonical to represent them as a group. Conjunctions like “and” and “or” group together two or more concepts or propositions and are represented as, “and > [proposition 1, proposition 2, ..., proposition n]”. The reader may wonder how this example using “and” differs from merely specifying a concept by a collection of propositions (or concepts). The latter applies all of the propositions or concepts at the same time (e.g., The feathers were green-blue-yellow) whereas the former distinguishes each from the others (The feathers were green, blue, and yellow.)

Our representation can also be used to organize the meaning of propositions between multiple sentences. Sometimes, the connection is made explicitly by a word such as in the “however” example of Section II. In other cases, it may be less obvious. Again, certain propositions will specify further details or explain aspects of another proposition and the connections in the network can be made accordingly. A common discourse-level connector is sequence. For example, “She was frightened. She ran.” In this example the first sentence leads the way to the actions in the second. This could be represented as, (frighten > [{past}, {subject} > she]) > {seq} > (run > [{past}, {subject} > she]). Unless made explicit by concepts in the sentences themselves, these discourse-level connections tend to be implied or inferred and thus will not normally be part of a first pass of converting surface text into a semantic representation.

F. Tips for Building the Representation of Surface Text

We have provided guidelines for a wide variety of situations, but not all. When trying to identify the semantic network for a sentence, consider the following tips:

- Start by building the subnetworks of all the parts you know: connecting events and entities, specifying nouns with adjectives and determiners, etc.
- Try reordering the words and phrases using the same concepts as much as possible. This helps to identify how concepts are specifying one another.
- Remember that not all words have a concept behind them. Some just help make the grammar work.
- Conversely, some concepts are implied and missing from the sentence. Try making them explicit in your sentence to see if this clarifies conceptual relationships.
- A single concept may be expressed as two or more words together (e.g., “pick up” as in “Mary will pick up the eggs.”). Try removing or changing one of the words to see if the meaning is maintained or lost. If lost, it may be a multi-word concept, and sometimes these words may not be adjacent in a phrase (e.g., either... or)

IV. NATURAL LANGUAGE GENERATION (REALISATION) AND PARSING

While our representation stands on its own as a way of understanding meaning, adding the ability to generate surface text from it and to some degree parse surface text makes it much more practical. The following covers activities within the same language or set of concepts. We will briefly examine translation between sets of concepts in Section V. Please note that we provide only the briefest of treatments here, the details of which would fill a subsequent paper.

So far, we have introduced our representation and how to define concepts in terms of other concepts. We now introduce the notion of “rules”, which relate a semantic network (or subnetwork) to the ordering of its constituent concepts in surface text. Before we get started, however, we will say that whenever a semantic network is composed of a single concept alone, it is realised as the text of its label. For example, the concept labeled trust will be generated as ‘trust’.

Our simplest type of rule includes ordered concepts and surface text,

\[
\text{trust} > \{\text{past}\} \iff [\text{trust}, '+ed']
\]

Here, we see that to express the past tense of the verb “trust”, the rule tells us that the trust concept will be followed by “+ed” in the surface text. And, since we know how to express the trust concept alone, we can substitute it in to get [‘trust’,'+ed’] or “trusted”. Note that without the “+” in “+ed”, we would have added a space to get “trust ed”. It’s also possible to use the same approach for prefixes (e.g., ‘un+’, ‘wanted’ = ‘unwanted’) and to “remove” letters (e.g., ‘berry’, ‘-y’, ‘+ies’ = ‘berries’). Although this simple example of generation (“trusted”) is morphological in nature, the same mechanism is used to generate syntax as well. Consider the more complex rule,

\[
\text{trust} > \{\text{past}\}, \{\text{subject}\} > \text{he}, \{\text{object}\} > \text{John} \\
\iff [\text{he}, \text{trust} > \{\text{past}\}, \text{John}]
\]

This rule defines a subject-verb-object concept ordering commonly used by English propositions. Using the total set of rules, we get the following sequence that generates surface text from a meaning representation.

\[
\text{trust} > \{\text{past}\}, \{\text{subject}\} > \text{he}, \{\text{object}\} > \text{John} \\
[\text{he}, \text{trust} > \{\text{past}\}, \text{John}] \\
[\text{'he', 'trust', ' +ed', 'John'}] \\
[\text{'he', 'trusted', 'John'}]
\]

Since it is not practical to make rules for every combination of possible concepts, we will use similarity between concepts to decide on-the-fly the likelihood of each rule being appropriate for use. We can use our representation to build a lexicon and in it define,

\[
\text{trust} = \{\text{verb}\}
\]

\[
\text{jump} = \{\text{verb}\}
\]

Then, if given the semantic representation

\[
\text{jump} > \{\text{past}\},
\]

we can use the fact that both the trust and jump concepts are verbs and apply the “trust”-associated rules in an analogous way,

\[
\begin{align*}
\text{\{jump\}} & > \{\text{past}\} \\
\text{\{jump\}}, \{^{\prime} + ed\} \\
\{\text{jump}^{\prime}\}, \{^{\prime} + ed\} \\
\{\text{jumped}\}
\end{align*}
\] (15)

Similarity between two concepts or subnetworks will be based on more than just concept definition. The algorithm will compare the subnetwork shapes and may use an ontology such as Wordnet [16] to involve synonomy and hyperonomy between concepts. Another possibility is, with sufficient examples, to build up a concept-to-vector representation like Word2vec [17] and use those concept vector values as a similarity metric.

Parsing is generation in reverse. From the surface text, we first seek an ordered set of concepts that when realised produces the full string. Using the same rules, but in the reverse direction, we iteratively build subnetworks and networks of subnetworks that eventually become a single, complete semantic representation. However, it is not expected to be as robust as generation since, like any parser, word sense disambiguation and implicit concepts are involved.

To make life easier for the linguist, we also propose to auto-generate rules from semantic representation-surface text pairs. That way, when the linguist encounters an error in generation/parsing, they only have to provide the correct semantic representation for the surface text instead of understanding how rules are defined. Rule generation is done by parsing the surface text using existing rules. The rule for our earlier example of “trusted” could have been auto-generated knowing only that trust \(<=\) “trust” (QED). A more advanced approach to free the linguist even further might be to use a bilingual corpus and a mature source language model to generate the corpus’ interlingual representation and then deduce from surface text the lexicon and the synthesis and transfer rules. Such an approach is the end-goal of this research, making interlingual translation a practical reality.

With the rules we have provided in our examples, there was only one surface structure or “hypothesis” that could be generated. As we add more rules and invoke the similarity metric, we will have multiple overlapping rules for transforming networks into surface structures. When this happens, we duplicate the current hypotheses to separate the use of the overlapping rules. Using the most similar rules we can generate a variety of possible surface structures, which we can rank according to a similarity score derived from the rule similarities, a priori probabilities, sentence length, or other metrics. For semantic networks with multiple valid surface texts, the valid surface texts will have the highest rankings. Ranking by similarity is important so that in the event of an error, the linguist’s provision of a correct semantic representation plus rule or surface structure (for auto-generation of the rule) will correct the error in the top-ranked generations/parses.

Ultimately, our generation and parsing strategy is designed to be simple to use, both for the linguist and the software developer needing a realisation tool. There is no need here to fatigue linguists with complicated rule-interactions. No need to distinguish between morphological and syntactical decisions. No need to burden developers with identifying the concept interaction case roles. By providing a single tree-structure, the system will generate a surface text string.

Status of Development: Initial development and testing of generation and parsing of the examples in Section III has been successfully completed. Translation is still pending. The most challenging issues in generation were computing the similarity between two semantic networks and making that process sufficiently fast. In parsing, handling concepts not in the lexicon and making these and their candidate stems equally weighted was also difficult. Word-sense disambiguation by syntactical role naturally emerges from this approach as does named entity recognition to some degree. Presently, development of a full English language model is underway as well as refinement of the generation and parsing functionality.

V. Translation between Sets of Concepts or Languages

While Section IV provides a system for converting between surface text and a semantic representation, this section describes the process of translating between two sets of concepts, as would be used to define two different languages.

The process simply involves the replacement of concepts and subnetworks in the source language semantic network with concepts and subnetworks from the target language. These will be referred to as “transfer rules”. Transfer rules need not only be between the two languages. Transfer rules within a language can be used to adjust the mode of expression and may make translation into the target language easier or clearer.

As in the building of surface text from semantic representations, the process is iterative and bifurcates with each new applicable transfer rule. Although this sounds similar to the generation algorithm, there is a difference. Here, the source language semantic representation will be traversed and rules matched over the entire network, much like a convolution computes a “match” at every interval between two signals. In generation, the matches are instead rooted solely at the “head” concepts rather than at any node across the semantic network.

To make the translation paradigm complete, an interlingual lexicon is proposed with the following features:

- concepts may be contributed from any language, but any that can be expressed in English will be used. It is a global language in use by a large proportion of linguists (i.e., potential users). Concepts from other languages will have English glosses supplied.
- a base set of interlingual concepts will be identified representing primitive concepts likely to be common across languages. If a language has transfer rules from it to all base interlingual concepts, it will assure that the intended meaning will be communicated, or at least all aspects that are present in the target language.
- higher-level concepts can be added to the interlingua, but must be provided with explications in terms of the base concepts.
A language does not need to specify transfer rules for all base concepts before using the interlingua. Provided that all of the concepts in the source semantic network that need translating have their associated transfer rules, the translation can proceed. Entities having more than one reference will have their references (including pronouns) connected through the reification \{re\} concept. Pronouns will not be dropped in case we want to translate them directly.

VI. RELATED WORK

A wide variety of semantic representations exist, for a wide range of applications. Here we discuss only a few in detail—those that are designed for language translation. All three approaches we look at here are thematic-role-based representations. According to Schubert [10], these “...may prove to be of significant value in machine translation (since intuitively roles involved in a given sentence should be fairly invariant across languages).”

A. Thematic-role-based Approaches

The Translator’s Assistant [4, 5] (TTA), begun in 2005, is, “... a multilingual natural language generator based on linguistic universals, typologies, and primitives”. Focusing on providing an interface suited to linguists, the purpose is to provide draft translations that will allow human translators to complete translations more efficiently. In this system, manual effort is required to generate the desired interlingual representation of a source text and to build up the natural language generation rules for new languages. Then, authors that want to translate their works will encode them once and generate them in the available languages. Allman [5] indicates that translators’ speeds increased four-fold with the use of this approach. Work on this approach continues, although mostly among the originators.

The Universal Networking Language [6] or UNL is a language-independent knowledge base representation introduced by the United Nations University in 1996. Later a separate organization was formed to support its development. Primarily UNL serves as an interlingua into which information can be transmitted and later generated into multiple languages. Substantial work has gone into the development of web tools for authoring UNL representations and adding to the grammars and lexicons of a variety of languages. There are also tools for target language realisation, but their official “text-to-text” initiative for automated translation has not yet been released. A few parsers called “deconverters” and multiple realisers called “deconverters” have been developed by various parties for transduction between specific languages and UNL. From searching the main technical website [18], it seems like little work on this approach has occurred since 2015, although a few papers have been published since then that use UNL.

KANT [7], which is derived from “Knowledge-based, Accurate Natural-language Translation” was introduced in 1989 at the Center for Machine Translation at Carnegie Mellon University. It was used to translate technical English into French, German, and Spanish. Translators would write their technical English into a specialized editor that would help them constrain their expressions to those that could be correctly translated by the system. The technical English would be automatically interpreted into a standardized interlingua, which was finally used to generate text in the target language. In essence, this system could actually translate English text into several other languages automatically. Although still available, development was discontinued in the early 2000’s.

B. The Semantic Representations

The semantic representations of these approaches are similar in some ways and quite different in others. UNL provides a summary of the types of features contained within a Thematic-role-based semantic representation. Figure 5 captures the main elements called “Words”, “Attributes”, and “Relations”. Words are simply concepts. Attributes are set of concepts that provide additional information (e.g., tense, gender, manner, lexical category, etc.). There are more than 300 officially defined attributes falling into 33 categories and subcategories. Relations describe the way in which two Words interact. Relations, sometimes referred to as case roles, are directed and can take any of the 40 predefined values in UNL. Like our approach, UNL also has a mechanism for encapsulating subgraphs within a Word, allowing for high-level Relations. TTA defines their semantic representation a little differently. Concepts fall into one of seven categories, most notable of which are the Object (i.e., noun), Event (i.e., verb), and Relations (i.e., case role) concepts. Object concepts have 6 “features” each (e.g., polarity, proximity, number). Each feature is set to one of a number of mutually exclusive values that have been predefined according to the feature type. Events have four features a piece (time, aspect, mood, and polarity), which similarly have many possible predefined settings. There are nine predefined Relations that can be used to relate Objects and Events. Propositions are attributed with a further 15 different features (e.g., type, discourse genre, speaker), each having their own set of values. In total, there are more than 250 possible feature values that are used in this approach.

KANT represents concepts as “frames” that are somewhat like functions with “slots” or function arguments. Frames represent objects, events, and properties, each having a certain number of slots. The slot values can be limited to certain classes of concepts, according to the associated ontology. This helps it to do a better job of disambiguation during parsing, by finding the concept sense with constrained slots that are most suited to the other parsed inputs. In the case of an Event frame (i.e., a verb), the “agent” (subject) and “theme” (object) are key case roles that are to be filled. A sentence can take the form of of an instantiated event frame that specifies the values of its necessary slots and can add additional features such as necessity, mood, and voice. The expressiveness of the KANT system is limited to its vocabulary and use of technical English, in spite of being a multi-lingual translation system.

In summary, all three approaches invoke a complex set of features that must be learned by prospective users when performing generation or when building grammars for additional languages. This makes the learning curve steep, setting up a barrier to entry. UNL offers free online training to achieve
several certifications to help mitigate this. In all approaches, the building of language rules is almost entirely manual, complicated, and very time-consuming. In contrast, the current representation is designed to be simpler such that users should be able to learn it relatively quickly. Further development is also planned to enable users to fix mistakes in parsing and generation by providing the correct surface text/meaning representation pair. In this way they will not even have to learn how to create rules.

The existing approaches interpret or label features of a sentence with technical linguistic or ontological terms, whereas the current approach allows these to be abstracted away and presents commonly understood concepts on the surface. This makes the semantic representation much more readable to the layman and therefore more accessible, especially if the terms are in a different language than the one being worked in. Also in our approach, by forcing every bit of meaning to become a concept and avoiding traditional case roles, a user or automated system does not have to decide whether the bit of meaning should take the form of a case role, a concept, or a property. There is less interpretation required overall for human and machine alike. In total, these benefits will make all aspects of language building more efficient, even when done manually.

As an aside, our representation at first glance may look like a simple parse of a sentence, but it is not. It is different in the following ways:

- it is not forced to include all words in the sentence and label them. This approach does not need to know what class of word each is or list its part of speech.
- it lightly abstracts away from the surface text itself such that it is possible for multiple sentences with different parses to have the same semantic representation.
- it can separate and express stemless concepts which are not expressed by a particular word (e.g., {?}. {topic})
- it is intended to be able to identify and include clearly implied concepts

C. Generation

KANT generates surface text in the target language by first finding target concepts to match each of the interlingual concepts, and then forms a target language “f-structure” or describes it in terms of suitable grammatical elements present in the target language. Finally, the concepts are inflected and ordered according to the target language rules. Generation rules are akin to functions. Embedded in a rule is a set of concept qualities that are compared against a to-be-generated interlingual representation. If there is a match, the rule is applied, grammatically organizing parts of the proposition (the f-structure).

UNL uses a complex system of rules to generate target text. There are different types of “transformation rules” (T-rules) that transform networks into simpler networks, networks into trees, trees into lists of concepts, and lists into surface text. The various rules describe the kinds of functional transformations that their associated structures can undergo (e.g., add, replace, or delete concepts, etc.). The target language-specific rules are defined in terms of these T-rules. The target language generation rules are ordered giving earlier rules priority in generation. The rules are applied recursively, that is, repeatedly on the resulting outputs, until they no longer apply, and then move onto the next T-rule in the grammar. The definition of a T-rule is lengthy, though we will not go into detail here.

Like KANT, TTA uses a two-stage approach to generating text. The semantic representation is converted to a target-language structure using the “transfer grammar” and ultimately into target-language text using a “synthesizing grammar”. It is no easy task to convert from one collection of concepts to another because while there will be many direct concept matches between two languages (or an interlingua and target language), differences in culture will mean the absence of certain concepts and linguistic features in one of the languages. TTA’s transfer grammar employs a sequence of nine different kinds of transfer rules. Of these, the most complicated would appear to those that require some form of deduction or
knowledge of the wider context. Necessary features in the target language that are not present in the source language seem particularly challenging. In the case of honorifics, the relationship between speakers in a dialog must be determined from the context. Although not discussed here because TTA does not parse, pronouns must have their referent identified for proper translation into languages that do not use pronouns, or that use pronouns differently. Also, when the target language requires the explication of a concept in other terms, and that concept occurs frequently in a short span, repeated explication can make the translation unnatural and misleading. TTA solves this problem by providing the explication the first time the concept is used and then a referring concept (behaving like a pronoun) thereafter. According to Allman, the building of a language’s transfer grammar is more time-consuming than building the synthesizing grammar. In TTA’s synthesizing grammar, there are eight types of rules. These include spellout rules, clitic rules, phrase structure rules, and more. Of these, the most complicated would seem to be the choice of when to use pronouns and when not to use them. At any rate, it would seem that keeping track of which reified entity each pronoun or referring concept points to will be necessary for accurate translations.

A question worth asking is, “Why aren’t any of these approaches thriving?” Perhaps it is because there is 1) limited application, 2) the learning curve is too steep, and 3) the manual effort required is more than the perceived benefit. Users are willing to trial approaches that are simple to use and quick to get useful results. In contrast, approaches that require a lot of manual effort and skill training and still require manual editing afterward are less appealing. Our approach aims to lessen the impact of these factors. Modern statistical techniques require the raw text of bilingual corpora to train translation models. It would seem that enabling our approach to derive rules from data would be another step in the right direction. Our approach also supports: 1) the use of an interlingua, 2) a means of correcting translation, parsing, and generation errors, and 3) a framework for implementing solutions to contextually-dependent translations. These features are not offered by statistical machine translation in general.

Our approach is not without its challenges, however. To name a few:

- learning the list of stemless concepts. Although we try to minimize the learning curve associated with this approach, there will be a number of stemless concepts to define and/or learn.
- representing certain syntactical phenomena (e.g., relative clause) can be complicated. As in the {have} concept example, it would be possible to define some of these to make them easier to grasp and use.
- language design variability. Because we put so much “power” in the hands of the linguist to shape the grammar, lexicon, and indeed the semantic representation itself, variability will occur. This will be greatest when the user is dealing directly with semantic networks in the target language and least when dealing with a common interlingua, to which all target language definitions would ultimately interface.

VII. Conclusion

Developing a semantic representation that is versatile yet comprehensive is a challenging task, especially for the purpose of language translation which requires both. The present semantic representation seeks to do this by providing a minimalist structure based on specification, breaking down meaning at the morpheme level, and employing encapsulation which serves to assert canonicity, support high-level connections between propositions, and define concepts hierarchically. It is a departure from standard thematic-role-based representations that have been designed with language translation in mind. It is more accessible to linguists and software developers because it largely strips away case roles and abstracts away many underlying linguistic and ontological details. It also naturally allows for data-driven methods to be built on top of it. Since the existing thematic-role representations seem to be losing attention to statistical and neural machine translation approaches, such novel qualities will be necessary to enable interlingual processing to become practical. Much work remains but, if successful, such an approach has the potential to enable a greater the coverage of the world’s languages for automated or semi-automated translation and other useful NLP tasks.

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