Can We Derive General World Knowledge from Texts?

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1. Introduction

We think that there is a largely untapped source of general knowledge in texts, lying at a level beneath the explicit assertional content. This knowledge consists of relationships implied to be possible in the world, or, under certain conditions, implied to be normal or commonplace in the world. For instance, the sentence "*He entered the house through its open door*" suggests that it is possible for a person (or at least a male) to enter a house, that houses have doors, that doors can be open, etc. The goal of the present work is to derive such general world knowledge (initially, from Penn Treebank corpora) in two stages: first, we derive general "possibilistic" propositions from noun phrases and clauses; then we try to derive stronger generalizations, based on the nature and statistical distribution of the possibilistic claims obtained in the first phase.

Our initiative differs from standard knowledge extraction work in both its aims and its methodology. We are attempting to derive a broad range of general relationships from texts, rather than some predetermined specific kinds of facts; and we are using general phrase structure coupled with compositional interpretive rules to obtain general propositional information, rather than employing specialized extraction patterns targeted at specific relationships (e.g., [1, 2, 3, 6, 8, 13, 17]). Our long-range goal is to use the derived knowledge as part of a KB supporting language understanding and commonsense reasoning.

We have reached a stage in our work where we are able to extract large numbers of general propositions from Treebank corpora, and can assess, in a very preliminary and informal way, the prospects for arriving at useful world knowledge by this method, and the limitations of the approach. In the following, we briefly sketch and assess our two-stage technique (with emphasis on the first, implemented stage).

2. Extracting general "possibilistic" propositions

The derivation of possibilistic propositions is based on a mechanism very similar to compositional semantic interpretation. The essential difference is that before combining the meanings of the immediate constituents of a phrase, we *abstract* those meanings, i.e., we simplify and generalize them; this involves stripping modifiers and inessential conjuncts, and generalizing individual terms to types. For example (using English glosses of the logical representations), abstraction of "*a long, dark corridor*" would yield "*a corridor*"; "*a small office at the end of a long dark corridor*" would yield "*an office*"; and "*Mrs. MacReady*" would yield "*a woman*".

The choice of Treebank corpora as a basis for our initial knowledge extraction work is a natural one, since there exist robust, fairly accurate parsers trained on Treebank corpora (e.g., [7, 10, 9]), and these would eventually allow us to bootstrap our approach to very large unannotated corpora. The major challenge was that of providing reasonably reliable interpretive rules, at least for many of the clausal and other phrasal units that we viewed as potential sources of general possibilistic knowledge. In outline, our current algorithms for processing a bracketed (Treebank) sentence operate as follows:

1. Preprocess the input tree (e.g., mark infinitives, passives, temporal noun phrases and prepositional phrases, categorize prepositional phrases, etc.)
2. Apply a set of ordered patterns to the tree recursively; these amount to phrase structure rules allowing for regular expressions (including negation) on the right-hand side
3. For each successfully matched subtree, abstract the interpretations of the essential constituents, and combine the abstracted interpretations in accord with the semantic rule linked to the pattern that matched the subtree
4. In processing the tree recursively, collect interpretations of phrases expected to provide general "possibilistic" propositions
5. Formulate possibilistic propositions from the collected phrasal interpretations, and output these along with simple English verbalizations.

An example of a complete and unedited output for a sentence from the Brown corpus is the following (we do not show the input bracketing, for lack of space):

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(BLANCHE KNEW 0 SOMETHING MUST BE CAUSING STANLEY 'S NEW , STRANGE
 BEHAVIOR BUT SHE NEVER ONCE CONNECTED IT WITH KITTI WALKER .)

OUTPUT (IN ENGLISH, FOLLOWED BY UNDERLYING LOGICAL FORMS):

 A FEMALE-INDIVIDUAL MAY KNOW A PROPOSITION.
 SOMETHING MAY CAUSE A BEHAVIOR.
 A MALE-INDIVIDUAL MAY HAVE A BEHAVIOR.
 A BEHAVIOR CAN BE NEW.
 A BEHAVIOR CAN BE STRANGE.
 A FEMALE-INDIVIDUAL MAY CONNECT A THING-REFERRED-TO WITH A FEMALE-INDIVIDUAL.

((:I (:Q DET FEMALE-INDIVIDUAL) KNOW[V] (:Q DET PROPOS))
 (:I (:F K SOMETHING[N]) CAUSE[V] (:Q THE BEHAVIOR[N]))
 (:I (:Q DET MALE-INDIVIDUAL) HAVE[V] (:Q DET BEHAVIOR[N]))
 (:I (:Q DET BEHAVIOR[N]) NEW[A]) (:I (:Q DET BEHAVIOR[N]) STRANGE[A])
 (:I (:Q DET FEMALE-INDIVIDUAL) CONNECT[V] (:Q DET THING-REFERRED-TO)
  (:P WITH[P] (:Q DET FEMALE-INDIVIDUAL))))
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This output (which is not atypical, quantitatively and qualitatively, for what we obtain for sentences from the Brown corpus or Wall Street Journal corpus) illustrates both the potential of our approach and some of the difficulties still to be overcome. Some of the propositions are arguably general knowledge that any human being is well-aware of, and which could be useful in a general NLU or commonsense reasoning system. (We hope this is somewhat apparent from the English output. Space limitations prevent the discussion of logical form, which is based on episodic logic [18]).

On the other hand, a problem with our extracted propositions is that their content is often unclear or ambiguous, or they are true but arbitrary (e.g., the last of the above extracted propositions certainly seems true enough, but completely arbitrary – not something likely to be useful for language processing or inference). Fortunately, outright falsehoods among the outputs are very rare. We are currently working out a judging scheme that will allow an empirical evaluation of the first-stage output, assessing the coherence, syntactic completeness, nonambiguity, nonarbitrariness, and truth of the output propositions, as determined subjectively by human judges (with sufficient consistency across judges). At the same time, we are considering various methods for improving the output, including use of WordNet [11] for type abstraction, better event-noun identification/classification, use of Treebank-3 information on argument roles, and most importantly, use of a coreference module to guess entity types for pronouns. We are also considering methods of filtering out unwanted output, e.g., discarding propositions as arbitrary if they are derived only once from a large corpus, even after certain abstraction operations.

3. The second stage: Deriving stronger propositions

We have formulated several (as yet unimplemented) methods for strengthening some of the extracted propositions based on the types of symbols comprising them and on the occurrence statistics of related propositions. For example, we frequently extract certain simple variants of the first output proposition above, such as "A MALE-INDIVIDUAL MAY KNOW A PROPOSITION". From such sets of variants we expect to be able to infer that (by and large) *only* people or agencies know propositions. Similarly, preliminary examination of the Brown corpus indicates that we should be able to derive such generalities as (for transitive verb "*carry*"): if x carries y, then if y is a gun, then x is probably a person; if y is a bomb, then x is probably an airplane;[1] if y is a group of people, then x is probably a vehicle; etc. This sort of information is closely related to traditional *selectional preferences* (e.g., [5, 12, 15, 16, 19, 20]), but it is explicitly formulated as propositional knowledge by our methods and hence potentially usable not only for linguistic disambiguation but also for inference. Furthermore, extant methods for extracting selectional preferences from texts tend to "lose the connection" between the arguments of 2- or 3-place predicates (if they attempt to correlate multiple arguments at all). This is because of the myriad argument types that can occur (e.g., carriers found in Brown include persons, vehicles, [business] expansion, books, ants, positions, stories, roads, calculations, etc., and objects carried include [body]weight, passports, the economy, disclaimers, titles, responsibilities, traffic, rigging, etc.)

Our other planned methods of deriving stronger propositions depend on details of the propositions obtained in the first stage. For example, certain propositions involving possessive HAVE[V], such as "A FEMALE-INDIVIDUAL MAY HAVE AN ARM", derived from possessive NPs such as "*her arm*" can be directly and fairly safely strengthened to something like "A FEMALE-INDIVIDUAL GENERALLY HAS AN ARM" under certain conditions, for instance when the thing possessed is a part-type, or (less safely) when there is no possible prior coreferent for it.

4. Concluding remarks

We have described a new method of obtaining general world knowledge from texts that is aimed at a broader range of facts than methods based on specialized extraction patterns, while still not depending on in-depth NLU. As we have indicated, there are some similarities between our derived propositions and the information implicit in selectional preferences. Efforts to extract predicate-argument structure are also related (e.g., Abney's method based on a cascaded finite-state parser [4][2]). However, the attempt to formulate and evaluate the derived information as general propositions about the world is to our knowledge novel.

The quest for general world knowledge also brings to mind CYC [14], but we regard that work as complementary rather than an alternative. Little of the knowledge we are extracting can be found in CYC; and little of the knowledge in CYC is obtainable by our methods. An impediment to merging the two kinds of knowledge, however, is that CYC's invented (and rather heterogeneous) ontology is not easily brought into alignment with linguistically derived knowledge.

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[1] For more extensive or recent texts, x may with some likelihood be a person.

[2] Our experimentation on some Brown corpus sentences suggests that this approach yields very sparse information – for many sentences, no more than a subject-verb relation, because of the parser's very conservative phrase attachment policy.

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