Graph-to-Graph Translations To Augment Abstract Meaning Representation Tense And Aspect

Mollie F. Bakal

University of Michigan

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Advisor: Dr. Steven Abney

Second Reader: Dr. Ezra Keshet

Abstract

Abstract Meaning Representation is a proposed semantic framework to convey meaning. It has potential utility in translation, natural language generation, and understanding. However, it is lacking in a number of ways, including omitting implicit time information which carries meaning. To rectify that, Donatelli et. al. advanced a proposal to add tense and aspect tags to AMR, improving its ability to represent meaning. I have developed a rules-based method to add the roles from that proposal to standard AMR trees, using semantic information encoded in the representation of a dependency tree on the same sentence. Demonstrating that the Donatelli et. al. proposal can be reproduced reliably and that the tags found carry meaning provides evidence of its validity and potential use in future AMR work. This will help represent meaning better, and possibly be a stepping stone towards making AMR a more accurate representation of the English language.

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Literature Review

AMR, or Abstract Meaning Representation, is a semantic representation. Essentially, it is a method of distilling English sentences into a condensed form of their meaning, one suitable for processing using some form of computation (Banarescu et. al., 2013, 178). This form is represented as a graph, with nodes consisting of concepts and edges consisting of relations. In its initial formulation, AMR was explicitly intended for use in translation; its development was funded by a DARPA grant which was intended for language understanding. Given that, it is odd that AMR is explicitly not an interlingua (Banarescu et. al., 2013, 178); some interlingual work has been done, and much of AMR 2.0 was published with side-by-side Chinese and English AMR graphs on translations of the same sentences. Work has been done on modifying AMR for other languages, such as Chinese--in fact, an early paper compares AMR representations for English, Chinese and Czech (Xue et. al, 2014, 1765-1772) and finds them similar. Still, AMR is a semantic representation best designed to work on English. AMR has also been used for natural language understanding in conveying meaning and understanding to robots (Bonial et. al, 2019, 199-210), to search large sets of documents for relevant information (Wang et. al., 2017, 36-43), and answer questions posed in natural language (Mitra & Baral, 2016, n.p.).

```
(w / want-01
  :ARG0 (b / boy)
  :ARG1 (b2 / believe-01
        :ARG0 (g / girl)
        :ARG1 b))
```

Figure 1: a simple AMR graph for a statement which can be represented as “A boy wants the girl to believe him” (Banarescu et. al., 2019)

The AMR standard ties together extant frameworks to indicate meaning. It represents sentences as directed graphs using Penman notation. In this notation, there are variables, which are instantiations of concepts (for example, “(b / boy)” declares “b” as an instantiation of the concept boy). These variables are nodes, which are linked by relations. Nodes may also have attributes, which are traits which are not linked. The entire graph can be expressed as a set of triple relations describing the variables within the graph; epigraphical data encoding a preferred ordering can be included but is not necessary. Relations can be inverted for ease of expression: for example, if “a :role b” is a triple, “b :role-of a” is also allowable. This is useful for AMR; one common evaluation metric for AMR comparison is Smatch, a tool which compares the number of synonymous triples between sentences (Cai & Knight, 2013, 748-752). This notation is very flexible.

AMR fixes and limits the roles which are permitted within a graph (“:time”, “:op”, “:name” …) (Banarescu et. al., 2019), which Penman does not. Some roles are treated more as tags, with simple boolean positive or negative variables, such as “:polarity”. Other roles relate concepts to other concepts: this can include roles like :arg1, which relate a concept and a strictly positional argument (for example, some concepts can take a source as arg1 and a target as arg2; if the sentence does not contain a source but does contain a target, arg2 can be filled without filling arg1).

As AMR is a semantic representation of a statement, it is necessary to have some method of encoding the meaning of words within that statement so that they can be combined into the meaning of the statement as a whole. In the current AMR standard, most concepts are given by OntoNotes predicates (Banarescu et. al., 2019). OntoNotes is so named because it is intended to be an ontology, gathering relations between word senses (Hovy et. al., 2006, 57-60). These sets of senses are hierarchical; the OntoNotes predicates are designed to be usable in a more coarse manner but allow for greater detail, grouping WordNet's many, finely-tuned minor word sense differences by similarity. To develop this, instances of sentences were annotated with proposed word senses, then cross-checked between annotators. The proposed groupings were only permitted if inter-annotator agreement was high, with linguists clarifying and regrouping if accuracy was low (Hovy et. al., 2006, 58). For concepts which are not represented in the OntoNotes data, such as proper names, AMR does allow for treating strings as concepts (Banarescu et. al., 2019). However, this is a second resort--if there is a word sense in OntoNotes, that is preferred. This allows for simplified representation of meaning. An interesting result of the OntoNotes predicates is that in AMR parts of speech are irrelevant. Concepts can be either nouns or verbs, with no distinction between the two; the phrases "the girl destroyed the room" and "the girl's destruction of the room" can and should be represented with the same AMR tree (Banarescu et. al., 2013, 178). This has a number of ramifications on the representation, which will be explored later.

Charniak overview

The Charniak or BLLIP parser is a generative parser (Charniak & Johnson, 2005, 173-180). It maximizes the probability of given labels. It creates a dependency tree, a representation of a given sentence with a tree structure to show the relationship between words in the sentences, and it assigns Penn Treebank labels, a common form of part-of-speech indication (Santorini, 1990, n.p). It is efficient relative to more-complex parsers, returns a parse with fair accuracy, and runs in a reasonable amount of time. For this reason, it is already used in some AMR work; popular AMR parsers such as CAMR (Wang et. al. 2016, 1173-1178) use the dependency tree created by the Charniak parser as a first step towards building an AMR graph.

(S1 (S (NP (DT A) (NN boy)) (VP (VBZ wants) (S (NP (DT the) (NN girl)) (VP (TO to) (VP (VB believe) (NP (PRP him))))))))

```
                  S1
                  |
                  S
     _____________|_______
    |                     VP
    |         ____________|____
    |        |                 S
    |        |         ________|_____
    |        |        |              VP
    |        |        |         _____|_____
    |        |        |        |           VP
    |        |        |        |      _____|___
   NP        |       NP        |     |         NP
 ___|___     |     ___|___     |     |         |
DT      NN  VBZ   DT      NN   TO    VB       PRP
|       |    |    |       |    |     |         |
A      boy wants the     girl  to believe     him
```

Figure 2: The same statement as Figure 1, expressed in dependency form, both parenthetically and as a tree

AMR deficits

A number of proposals have been advanced to modify AMR and to rectify various deficiencies. Some of these have been incorporated into the standard in later revisions, but there are other cases where a proposal has been made but the standard is still lacking.

A major deficit of AMR is its inability to represent scope as used in language. AMR 3.0, the most recent specification, models quantification under the heading of a “mod” concept, which fails to treat scope. For example, the phrase “All the boys” is represented as “(b / boy :mod (a / all))”. Negation is expressed with a single modifier, the relation “:polarity -” (Bos, 2020, 13-20). This can cause semantic confusion; for example, consider the sentences "None of the boys left" and "Not all the boys left". These sentences have different meanings; the second would be understood by any speaker to mean that even though not all the boys left, some did. However, in AMR, the sentences parse to the same graph, Figure 3. This is very bad for AMR's usefulness as a form for natural language processing; if it were to be useful, a method would need to be developed to convert AMR graphs into sentences. However, if the graph in Figure 3 could represent two utterances with very different meanings, such a graph-to-English converter could produce the wrong results.

```
(l / leave-01
   :ARG0 (b / boy
         :mod (a / all
                 :polarity -)))
```

Figure 3 (Banarescu et. al., 2019)

Even though AMR is a semantic representation, it is generalized, which causes issues. For example, the current AMR specification contains a "wiki:" tag, to represent nodes (such as the names of people, or countries) for which a Wikipedia article exists. While this is one method of indicating that more information exists about an object and linking to an external source of that information, this limits parsers to needing an internet connection to query an external source and matching objects in that tree with Wikipedia pages from names alone. This can cause issues when trying to parse domain-specific knowledge; one source (Wang et. al., 2017, 36-43) tried to use AMR to investigate and summarize biomedical data on drug-drug interactions, only to find the pre-trained models lacking in information about the importance of certain terms such as “contraindicated” in a medical context and drug names which are not contained within the general knowledge source of Wikipedia.

Another issue is that AMR is mostly generated by sentence, and cannot use context from the larger document. While the most recent release of AMR has some multi-sentence corpora, this is a fraction of the dataset. Standard AMR representations indicate semantic meaning at the sentence level only and do not link meaning across sentences. (O’Gorman et. al. 2018, pp. 3693-3702). However, persisting context across sentences is crucial in language; singular utterances are typically incomprehensible with no knowledge of the world or the speaker and require context to understand.

The Donatelli et al proposal

One method of augmenting AMR was proposed by Donatelli, et al (2018, pp. 96-108). This proposal modifies how AMR treats time by applying tense and aspect indicators. The current AMR standard specifies time only when explicitly tied to a single specific time mentioned in the sentence. This is indicated in Figure 4, where if the word “yesterday” is not included, no time is shown at all. It also tries to “maximize” time by “pulling out” a time node to represent all children of a conjunction instead of leaving time with each clause, as seen in Figure 5 where the time attribute is the child of the widest-scoped “and” (Banarescu et. al., 2019). This explicit indication of time has value, but there are a number of cases where an implicit use of time is also useful, or time is implied but not used in a verbatim sense. This can include utterances such as “My brother is sick”. In this case, there is no single specific time, so the current AMR standard would not apply any time modifiers to this sentence. However, time can be important--this sentence is different in meaning from “My brother was sick”, or “My brother is sickening”. In the proposed AMR expansion, AMR nodes would be annotated to include implicit times relative to the speaker's present and four AMR roles to indicate aspect (":stable", ":ongoing", ":complete" and ":habitual"); the annotation would primarily apply to verbs from the original sentence, and I will discuss both time and aspect in more detail below.

```
(k / know-01
  :ARG0 (w / we)
  :ARG1 (b / be-located-at-91
        :ARG1 (k2 / knife)
        :ARG2 (d / drawer)
        :polarity -
        :time (y / yesterday)))

(k / know-01
  :ARG0 (w / we)
  :ARG1 (b / be-located-at-91
        :ARG1 (k2 / knife)
        :ARG2 (d / drawer)
        :polarity -
```

Figure 4: AMR representations of "We know the knife was not in the drawer yesterday." and "We know the knife was never in the drawer"

```
(a / and
  :time (d / date-entity
        :weekday (t / tuesday))
  :op1 (a2 / arrive-01
        :ARG1 (b / boy))
  :op2 (l / leave-11
        :ARG0 b))
```

Figure 5: AMR representation of "The boy arrived and left on Tuesday"

The tense system in the Donatelli et. al. proposal is relatively simple. It relates only to the ":time" role, which already existed in AMR. Times can be related to the concept "now" by different roles, such as before now, after now, or up to now, implicitly; this follows from how the event is referred to in the speech act, which is generally indicated by verb tense. This is opposed to the standard AMR system, where time must be explicitly specified in order to be annotated. There are four primary roles relating to a verb's aspect in the Donatelli et. al. proposal. These are ":stable", ":ongoing", ":habitual" and "complete"; below, I will explain what exactly these mean. These do not take concepts as arguments; instead, they act as simple binary flags when present, taking either a "+" or a "-".

When determining aspect, the Donatelli et. al. AMR proposal relies on a differencing of stative and eventive verbs. This definition of aspect is derived from Vendler (1957, pp. 143-160) and his categorization of verbs as states, activities, accomplishments or achievements. In this case, achievements and accomplishments together form the telic verbs which can take a ":complete" role. These are grouped together with activities into the category of eventive verbs. Stative verbs can take the roles of ":stable" and/or ":habitual", while eventive verbs can take ":ongoing", ":complete" and/or ":habitual". In general, determining stativity is a difficult problem; while stativity tends to be constant in a single verb sense, verbs can have both stative senses and non-stative senses which have identical syntax. This can be seen in Figure 6, where the first sentence is stative and the second eventive. This situation is caused by the fact that "lie" takes multiple word senses with the same spelling and verb type.

"The mountain lies to the east" (stative)

"The girl lies to the doctor" (eventive)

Figure 6: Different word senses with different stative/eventive status but the same sentence structure

Stative verbs are classified by stability. “:stable+” verbs are those where the state is long-lasting, while “:stable-“ are shorter, unstable states, generally ongoing states or short point descriptions. The Donatelli et. al. proposal seems to deem these :stable- states to be primarily stative verbs with a continuative tense, as can be seen in Figure 7.

“He used to live in Paris” (“:stable+”)

“He was living in Paris” (“:stable-”)

Figure 7: The difference between “:stable-” and “:stable+” (Donatelli et. al, 2018, p. 99)

Another role which the proposal adds is the “:complete” role. In the Donatelli et al paper, it is described as labeling events which are both telic and realized and which are not ongoing. Telicity is whether or not the verb can be said to have a single goal, and to be complete after that goal is achieved. It is a property of a verb form--some verbs may be telic in one context and atelic in another. It is complicated to determine if an event is telic in English from syntax alone. In English, this property is not syntactically marked, unlike in some languages such as Czech (Filip, 1997, pp. 61-96). Generally, telicity in English is diagnosed by linguists via simple tests, such as whether an action is done “in an hour” or “for an hour”. However, this determination is based on what “sounds right”, and what the meaning entails; it is very difficult to do syntactically. The habitual and ongoing tags are easier to label. Ongoing is defined in the proposal as “the canonical BE + ing” (Donatelli et. al, 2018, pp. 96-108) and as such can be labeled using that criteria--it is a simple way of referring to events which are ongoing at the time the speaker is referring to. Habitual is used by Donatelli et. al. to refer to both eventualities and stative recurring events; these are things which are either done often, with explicit indication, or things which are generic. If a verb is habitual, none of the other tags can apply to it.

One ambiguous syntactic pattern which Donatelli et. al. notes as tricky is the perfective. Semantically, the perfective can mean one of three things: either a state or event occurring continuously, an event for which the speaker wants to emphasize that it had happened, or a very recent event. All of these are annotated differently. The first should be annotated as a continuative event, up to now. The second should be annotated as before now, but with an "mod (e / ever)" role attached to the "before" concept emphasizing that the event has only occurred at the specified time, in all of history. The third should be annotated as before now, but with a "mod (j / just)" role attached to the "before". All of these can be seen below with one subject and verb in Figure 8.

"The Orioles have won Most Likely to Cause an Upset three years running"

"The Orioles have won three World Series championships"

"The Orioles have won!" (Donatelli et. al, 2018, pp. 96-108)

Figure 8: Forms of the perfective with different semantic meaning

Related Work

Other methods of modifying AMR in a graph-to-graph transformation have been proposed. A team modified the Donatelli et. al. AMR proposal for use in robotics (Bonial et. al, 2019, 199-210). This is a very specialized system; it enhances the Donatelli et. al. four-aspect system by allowing for a fifth role of ":completable", to allow for the ability to give commands which a robot can fulfill. This doubly-modified proposal later had a system built to convert standard AMR into the robotics AMR, a graph-to-graph transformation (Abrams et. al, 2020, pp. 459-462). This uses different processes than my proposed AMR conversion. First, a statement is classified into one of five categories--a command, an assertion, a request, a question, or an expression. This is performed using a simple unigram Bayesian classifier, which is machine learning. The system further uses regex to find the root of a command, another Bayesian classifier to determine tense, and treats the AMR graph like a tree to allow for direct extraction of slots from the AMR root to determine aspect. This schema only works on a very limited domain, with embodied robots given simple commands and directions. This does not allow for complex, nested sentences which natural language does allow for.

Other methods have been implemented to modify extant AMR in graph-to-graph transformations. One example is a tool for summarizing text; it takes in an entire text's worth of AMR graphs from individual sentences, and connects and simplifies the concepts to output an AMR graph with a summary of the larger text (Liu et. al., 2015, pp. 1077–1086). This would then allow for text simplification; if an AMR-to-text converter was developed, this would automatically create a simplified summary in text. While a useful procedure, this is exceedingly complex for simpler transformations. This was a neural tool trained using over 350 documents, with an average of 17.5 sentences per document, each with its own AMR graph; this is a lot of information to pre-process so that the neural network can be trained.

Neural networks tend to be very opaque, with few methods of determining if the model is picking up on expected traits. Instead, networks can pick up on a pattern in the data and miss underlying causes of that pattern, pick up on underlying bias, or even interpret random noise as a pattern (Raub, 2018, 529). Neural networks must also be trained on very large quantities of data modeling the expected output, which is difficult and expensive to generate manually. The networks are also very difficult to retrain if initially trained wrong, or if any aspect of the specification changes. One modern AMR generator requires two state-of-the-art GPUs and 19 hours to fully train a classifier on AMR 2.0 (Zhang et. al, 2019, n.p). On the other hand, a rules-based system is very easy to adjust, and can perform almost as well.

Research Question

This paper will focus on one modification of AMR, the proposal by Donatelli et. al. (2018, pp. 96-108). I propose a primarily rules-based method to convert standard AMR to this proposal. A brief overview of my system follows and is visualized in Figure 9. My method takes in an AMR parse, the sentence which it was parsed from, and a pre-parsed tree of the sentence in Penn Treebank form, typically taken from a BLLIP generative parser's interpretation of the sentence. This parser was chosen because a common AMR parser, CAMR, pre-parses sentences using this to create a dependency tree in the Penn treebank format and saves them to a file. Re-using the work already done can be efficient. Some form of preprocessing to form dependencies is necessary; this graph-to-graph transition relies upon finding the tense and aspect of verbs in the original sentence, and some form of classifier is necessary to initially identify which words are verbs so that those can be specified.

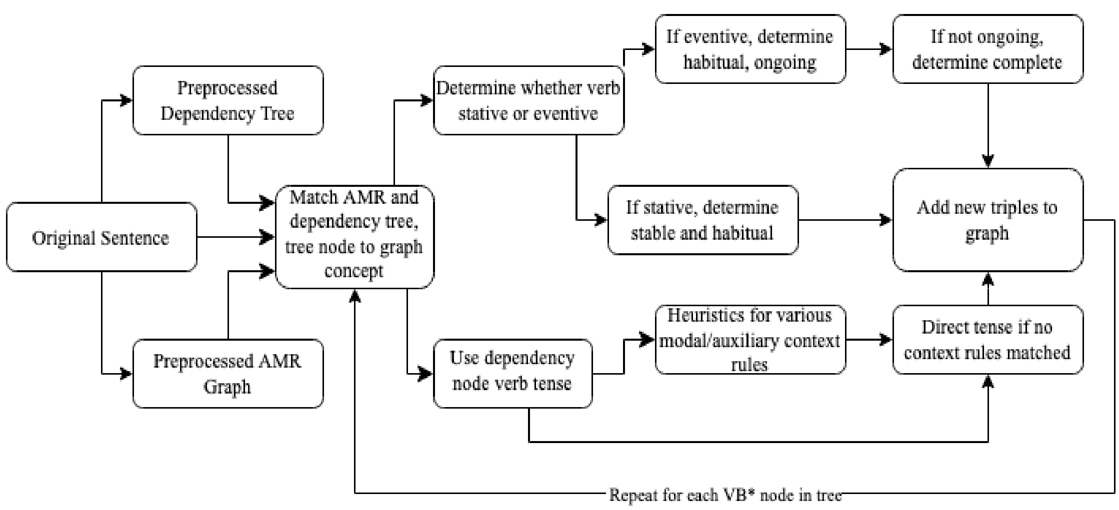

Figure 9: Flowchart of my proposed AMR augmentation method

Generally, AMR graphs are acyclic and can be viewed as trees, and the root of a given tree is the primary verb of the sentence. There are a few niche cases where an AMR graph may legitimately be cyclic; these are few and far-between. Initially, I considered tensing an entire AMR tree by just considering if there was a verb in the original sentence similar to the root of the graph, in essence applying the AMR graph to the Charniak tree. This is the approach used in other graph-to-graph transformations (Abrams et. al, 2020, pp. 459-462). However, this proved to be a poor approach, as different tenses could apply to different clauses of a sentence ("I asked him to the dance yesterday, and I'm going to pick out a dress tomorrow").

Instead, I apply the Charniak dependency tree to the AMR graph. I convert the AMR concepts into simple words by removing the numbered senses (it is rare for the same word with different senses to appear twice in an AMR tree). For each verb in the Charniak tree I search for the closest AMR concept with a string matching algorithm. I then search for the variable associated with this concept. With this matching from Charniak verbs to AMR nodes, I use the information in the Charniak nodes to apply tense and aspect rules, and print out a tree with these augmented nodes included.

My Proposed Implementation of Donatelli Et. Al.

I use both absolute rules and heuristics to determine both aspect and tense. Absolute rules can be used in some clear places; the syntactic past tense nearly always indicates a statement which is intended to indicate semantic past tense. However, this is not the case for other verb tenses; there are cases where semantic tense and syntactic tense are not the same. As AMR is a semantic representation, we try to determine semantic tense. For instance, consider most sentences in the future in English; the general form of such constructions is "will [VERB]" or "going to [VERB]". The verb in this is generally in the syntactic simple present tense, but referring to the future semantically. A function is used to search for constructs with that parent auxiliary clause, so that such sentences can accurately be labeled as future. Another function is used to search for specific words which might indicate the relationship of a statement to the speaker's time within the children of a verb phrase. One kind of this search includes words and phrases such as "yesterday" and "next week", where the statement implies a certain relationship to the present; as such, the entire time phrase can be constructed from these. Another kind of search involves searching for words of specific times for which the relationship to the present time is unknown; for example, "Monday morning" can refer to either a past morning or a future one, but in either case would give a stronger time frame than an implicit "before now" or "after now" alone.

Statitivity is one of the parts of grammatical aspect for which I applied a heuristic. AMR word concepts were derived from OntoNotes, and OntoNotes concepts were converted in part from WordNet concepts. WordNet also released database files, including a text file containing a number of stative verbs; initially, it was hoped that this could be used to determine which OntoNotes predicates corresponded to stative AMR concepts. However, part of the conversion from WordNet to OntoNotes was a reduction of word senses, combining nearly-synonymous ones. As a result, the numbers which indicate senses in WordNet do not align with those in OntoNotes and therefore AMR, and so the list as a whole cannot be used. In addition, the list seems to be overly generous. Some examples seem to be non-stative: consider "The first winter storm broke over New York" (Fellbaum, 2010, pp. 231-243), which describes an event and as such should be eventive. Still, the list has some uses; I extracted a small sample of the words on the list, and use those as stative verbs. I directly check verbs to see if they are on the list. This likely leads to both false positives and false negatives; the former for verbs with stative senses but which are not always stative, and the latter for verbs which are stative but rare enough that I did not encounter them in my training data. After determining if a verb is stative, I have a stability check. If the last three characters of the Charniak word which matches the AMR node end in ING, that indicates a less stable state which gets labeled with ":stable-"; otherwise, stative verbs get labeled with ":stable+".

To approximate the ":complete" tag, I use a heuristic. I consider complete actions to be verbs in simple past tense with some specific argument. The tree node in question must have a right sibling with either an NP node or a PP node with an NP child: the NP node must have a DET child. It cannot be a bare plural, which tends to be a sign of genericity and therefore not referring to a single event. In essence, this ensures that any verb I tag as complete describes a single, definite objective—it is not a generic statement. Consider Figure 10. The sentences are the same, except for the determinant specifying a single object watched. The issue with this is that it undertags. Specifically, it misses instances where a telic verb's argument is a proper name. However, this can be very difficult to analyze, especially when a verb can be interpreted both telically and atelically. Consider Figure 11 as well. These sentences differ only in their objects. Typically, however, when these are uttered, the first would be generally understood as telic and the second as a generic. This is because the first is a short experience and it would make sense to see the entirety at once, while the second is very long, and as such is likely generically referring to watching some part of the show. Without this semantic knowledge, the forms are indistinguishable, and it is possible to construe the latter as telic; consider sentence 3 in figure 11, and how it differs from the atelic sentence 4. To avoid this, we avoid tagging these. Lexical ambiguity between homonyms could also cause overtagging, as seen in Figure 12; unfortunately, this is unavoidable within the constraints of single-sentence AMR parsing, as ambiguity could be resolved elsewhere in a document.

"I watched a show" (telic)

"I watched Netflix" (atelic)

Figure 10: Telic versus non-telic uses of "watched"

"I watched Carmen" (Vendler, 1957, pp. 159) (telic)

"I watched The West Wing" (atelic)

"I watched The West Wing in under two weeks" (telic)

"I watched The West Wing for its entire run" (atelic)

Figure 11: Context changing telicity, even with a verb and object held constant

"I read the New York Times on the train"

Figure 12: Semantic confusion between the homonyms of "read" and "read" distinguishing a generic event from a specific one

As described above, ongoing has a simple canonical definition within eventive verbs: BE + ING. To find this, I determine if a verb ends in ING and has an auxiliary parent. To determine habituality, my proposed system has two tactics. It considers both likely-generic events and clauses with a keyword indicating habituality in them. The former are sentences in simple present tense, with a single plural noun as the subject of the verb, as in Figure 13. This is an indication of a generic statement. The other case for an indication of a habitual statement is explicitly saying so. For this, as well, we check to see if any word indicating a usual habit ("often", "usually", "daily", etc) is present within the children of the verb phrase containing the verb. If a verb is determined to be habitual, none of the other roles are applied.

"Boa constrictors swallow their prey whole"

"I used to make pie daily in the summer" (Donatelli et. al, 2018, pp. 103)

Figure 13: Examples of habitual constructions, both generic and explicit.

To deal with perfective tenses, I am simplifying the Donatelli-suggested three forms of perfect semantics. The form "has [VERB]" and "have [VERB]" can be applied to all three perfective semantics, so to avoid overly-specific errors I annotate that as just a standard before now timing. The "had [VERB]" construct can be used in the extant form ("the team had lost") or in the continuous form ("it had snowed"), but not the just-happened form. This can still be annotated as a plain before-now, as the two cannot be distinguished from this alone. However, the form "have/had/has been [VERB]" can be used in the continuative alone, so that can be annotated as ":time(u / up-to (n / now))".

Results

Aspects of this proposal are difficult to analyze in a quantifiable manner. While the Smatch metric could be used to compare the triples in the produced graphs against the triples of a gold-standard set of graphs, that data would be purely quantitative, which I felt would be inappropriate for the problem. Instead, I decided to show some examples of sentences in extant AMR and their enhancement with this process. The bolded relations and variables are those added by the proposal. All spaces around punctuation are in the original AMR specification, and were present when parsing with the Charniak processor.

```
(s / sit-01
   :ARG1 (i / it)
   :ARG2 (h / high
          :location (h2 / hillside)))
 :time (n / now)
 :stable +
(S1 (S

    (NP (PRP It))

    (VP (VBZ sits)

        (PP (ADVP (RB high))

            (IN on)

            (NP (DT a) (NN hillside))))))
```

Figure 14: “It sits high on a hillside ,”

To begin, this is a simple sentence: it is a single clause, with one verb and an object. For the first example, I have also provided the dependency tree parse for comparison. From this example, we can see the rules applied. As the verb is in simple present tense, the time indicated is now. As “sit” is on my list of stative verbs, the node corresponding to it is tagged with the stable + rule. It does not have any words indicating habituality, and does not seem to be applying to a generic situation; with more context, it could be, but with this short sentence we do not know. No other tags apply. There is clearly useful information conveyed by the new tags, with a difference between “It sat…” “It was sitting”... or other sentences which would be represented by an identical AMR graph.

```
(r / refer-01
   :ARG0 (i / i)
   :ARG1 (p / person
         :quant 200
         :mod (t / this))
   :ARG2 (p2 / person
         :ARG0-of (h2 / have-rel-role-91
                  :ARG1 (h / he)
                  :ARG2 (u / uncle)))
   :manner (c / collective)
   :location (b / below)
   :time (a / after
         :op1 (n / now))
   :ongoing -)
```

Figure 15: “Below I am going to refer to these 200 people collectively as " his uncle . "”.

In this sentence, there is a rule for constructs of the form “going to” immediately preceding a verb (as well as for constructs with a modal, such as “will [verb]” or “would verb”); these generally indicate future tense. The ongoing role is negative; although the “going” is in an ongoing sense, that is just auxiliary to “refer”. The added tense is moderately useful in conveying the author’s speech patterns, but this is a place where it was perhaps not necessary; the sentence could have been expressed as “Below I refer to these 200 people collectively as " his uncle . "” and no meaning would have been lost.

```
(e / email-01
  :ARG0 (p2 / person
        :wiki -
        :name (n / name
                :op1 "Lieutenant"
                :op2 "Uncle"
                :op3 "Allen"))
  :ARG2 (e2 / embassy
        :location (c2 / city
                :wiki "Amman"
                :name (n2 / name
                        :op1 "Amman")))
  :purpose (e3 / explain-01
                :ARG0 p2
                :ARG1 (f / fear-01
                :ARG0 (f2 / family)
                :ARG2 (l2 / life
                        :poss f2)
                :time (b1 / before
                        :op1 (n4 / now))
                :ongoing -)
                :time (n3 / now)
                :ongoing -)
  :time (b / before
        :op1 (n1 / now))
  :ongoing -
  :complete +)
```

Figure 16: “Lieutenant `` Uncle " Allen had emailed the embassy in Amman to explain that the family feared for their lives ;” (sic)

Similar to our first example, the sentence seems to be a shorter clause of a larger sentence. This example displays an example of perfect tense, but an incomplete one; as discussed in Donatelli, perfective tense has three primary causes. The phrase “had emailed” is in the existential perfective, and as a result its time node could be of the form “ :time (b / before :mod (e/ever) :op1 (n1 / now))”. This is also the first example of multiple verbs in the sentence receiving tense and aspect; it can be observed that “feared”, “emailed” and “explain” all receive it. All are not ongoing; “explain” is in the infinitive form, so the “now” time clause is accurate. In general, this sentence is helped by the addition of tense and aspect; surely, having completed emailing an embassy conveys very different information than planning to email the embassy in the future tense.

On a side note, it is also worth noting that this sentence has a number of variables which begin with the same letter. To distinguish them, we add 1 to a number which is appended to the first letter of the concept until we find one not in the pre-existing graph. It is also worth noting that there are multiple instantiations of the same concept in the tree (now and name); this is allowed. These are unrelated within the graph.

```
(a / announce-01
  :ARG0 (c / company
        :wiki "EBay"
        :name (n / name
              :op1 "EBay"))
  :ARG1 (a2 / acquire-01
        :ARG0 c
        :ARG1 (c3 / company
              :wiki "StubHub"
              :name (n2 / name
                    :op1 "StubHub")
              :mod (w / website
                    :purpose (t2 / ticket)))
        :ARG3 (m / monetary-quantity
              :quant 310000000
              :unit (d / dollar
                    :mod (c2 / country
```

```
                    :wiki "United_States"
                    :name (n3 / name
                    :op1 "US"))))
    :time (a1 / after
        :op1 (n1 / now))
    :ongoing -)
 :time (t / today)
 :ongoing -)
```

Figure 17: “EBay Announces Today It will Acquire Ticket Website StubHub for 310 Million US Dollars”

This sentence is an example of the modal future construction, with the verb phrase “will [VERB]” to indicate a future action (in this case, the acquisition). In this case, the “:ongoing-” is not superfluous in its relation to “announce” but does not convey much more information than the extant “ :time (t / today)” role. The “:ongoing-” for the future tense “acquire” does also convey information, even if a progressive future tense is rare. It is possible to conceive of an ongoing future tense sentence (“Next year, I plan on running the marathon”), so it is worth at least expressing that this is not the case.

```
(b / beat-01
 :ARG1 (d / drum
    :consist-of (t / tin)
    :poss (c / child)
    :time (n / now)
    :ongoing -)
 :location (h / head
        :part-of (h2 / he))
 :ARG1-of (h3 / have-degree-91
        :ARG2 (l / loud)
        :ARG3 (m / more
        :mod (e / ever)))
 :time (b1 / before
```

```
        :op1 (n1 / now))
  :ongoing +)
```

Figure 18: “The child 's ' tin drum ' was beating ever louder in his head”

This is an excellent example of a parse which is wrong due to my process. The Charniak parser interprets the word “drum” as a verb, not a noun, and as such applies its rules to that node. There could be some way to mitigate that; perhaps AMR nodes with roles which indicate physical existence (such as “:consist-of”) would indicate that a concept refers to an object, a noun, and not a verb. However, this would not be a placebo; objects do not always have consistency specified, and the Charniak parser labels “drum” as a verb even if “tin” is absent.

The other notable trait of the roles added in this sentence is the previously-unseen ongoing+ relation. This is the past imperfective tense, indicated by the “was” in the form of an “AUX” node which is a sibling of the verb’s parent verb phrase fulfilling the “BE + [verb]ING” form. This is directly useful tense, and it is clear how a different tense and aspect (“had been beating”, “beats”, “would beat”) would convey different information about the unspecified person’s head.

```
(m / multi-sentence
  :snt1 (s / suspect-01
        :ARG1 (a / attack-01
              :ARG1 (y / youth
                    :age (b / between
                    :op1 (t / temporal-quantity
                          :quant 20
                          :unit (y2 / year))
                    :op2 (t2 / temporal-quantity
                          :quant 30
                          :unit (y3 / year))))
              :time (a2 / after
```

```
                    :op1 (l / leave-11
                    :ARG0 y
                    :ARG1 (p / party)))
            :ARG1-of (s2 / serious-02)
            :ongoing -
            :complete -)
        :time (b1 / before
            :op1 (n / now))
        :ongoing -)
    :snt2 (a5 / and
        :op1 (f2 / find-01
            :ARG1 (l2 / lie-07
                :ARG1 (h / he)
                :ARG2 (u2 / unit
                    :ARG1-of (i / include-91
                        :ARG2 (u / unit
                        :part-of (a3 / apartment))))
                :time (n2 / now)
                :stable -)
            :time (b2 / before
                :op1 (n1 / now))
            :ongoing -)
        :op2 (p3 / pronounce-01
            :ARG2 (d / die-01
                :ARG1 h)
            :time (a4 / arrive-01
                :ARG1 h
                :ARG4 (h2 / hospital))
            :ongoing -)))
```

Figure 19: “A youth in his 20s was suspected to have been seriously attacked after he left a party ; he was found lying in one of the apartment units , and was pronounced dead upon arrival at the hospital .”

This is diagrammed in the AMR dataset as a multi-sentence AMR, which is unusual. Presumably, this is treating the semicolon as a splice joining two sentences. In this, we see the “:stable-” tag referring to “lying”, as we are treating “lie” as stative. As none of these verbs are telic (other than leaving the party), it is apparent that although a number have ":ongoing-" as a tag, no completeness tag is necessary on "attacked". As a result, there are two mistakes in this annotation. The first is an issue with irregular verbs; my system does not consider "leave" and "left" similar enough to pair them, and so does not assign any information to this properly ":complete+" left. As a result, the "attack" concept has a larger right subtree than it usually would, and therefore takes a ":complete-" tag when it is not actually telic.

```
(m / mention-01
  :ARG0 (p / piece
        :poss (p2 / person
              :wiki -
              :name (n / name
                    :op1 "Jeff"
                    :op2 "Boucher")))
  :ARG1 (h / have-03
        :ARG0 (v2 / victim
              :ARG1-of (a / abuse-01
                    :manner (s / sexual)))
        :ARG1 (v / voice
              :ARG1-of (r3 / resemble-01
                    :ARG2 (v3 / voice
                          :poss (c / child))))
        :frequency (o / often)
        :ARG1-of (r / resemble-01
              :ARG2 (f / freeze-01
                    :ARG0 (d / develop-02
                          :ARG1 v2))
              :mod (a2 / almost)
              :time (a3 / around
                    :op1 a)))
  :time (n1 / now)
  :habitual +)
```

Figure 20: “Jeff Boucher 's piece mentions how victims of sexual abuse often have childlike voices , almost as if their development was ' frozen ' around the time of their abuse”

This can be seen as an example of the use of the “habitual” tag, with an explicit use of the term “often”. However, it is applied to the wrong verb; it should refer to “have”, not the tree’s root of “mention”. This, like the tin drum sentence, is due to a mistake in pre-processing but in the other direction; under-classifying, not over-classifying. The Charniak parser classifies “had” as an auxiliary verb with label “AUX” -- this typically indicates constructions where “had” is used to establish tense or another grammatical meaning (such as perfective, with “had [VERB]ed”). In this case, the parser is incorrect; “had” should be the verb in the clause, with some “VB*” tag. As the parse is wrong, the AMR converter tries to assign the “often” clause to the verb “mentioned”, as it’s the nearest verb ancestor in the tree.

```
(i / imagine-01
  :ARG0 (i2 / i)
  :ARG1 (j / joke-01
        :mod (f / final))
  :frequency (o / often)
  :time (d / drift-01
        :ARG1 i2
        :destination (s / sigh-02
                        :ARG0 i2
                        :mod (l / last))
        :time (n / now)
        :ongoing -)
  :habitual +)
```

Figure 21: “As I drift toward my last sigh , I often imagine a final joke .”

This is an example of the habitual being assigned correctly with an explicit “often”, in contrast to the last tree. The role may be superfluous with an explicit frequency tag in the graph, though. It is also worth noting that there is no time assigned to “imagine”, as a time node exists in the graph already. The new information contributed by the nodes may help in reproducing the sentence exactly, instead of in a progressive tense, but it is unclear if there is an actual difference in meaning.

```
(r / refer-02
  :ARG0 (o2 / official
        :mod (c / country
              :wiki "United_States"
              :name (n3 / name
                    :op1 "U.S."))
        :location (h / here))
  :ARG1 (p / person
        :ARG1-of (d / displace-01
              :time (b / before
                    :op1 (n1 / now))
              :ongoing -
              :complete -))
  :ARG2 (o3 / organization
        :wiki "United_Nations_High_Commissioner_for_Refugees"
        :name (n4 / name
              :op1 "UNHCR")
        :ARG1-of (c2 / charge-05
              :ARG2 (a / and
                    :op1 (d2 / determine-01
                          :ARG0 o3
                          :ARG1 (s / someone)
                          :ARG3 (t / truth-value
                                :polarity-of (r2 / refugee
                                      :ARG1-of (r3 / real-04)))
                          :time (n6 / now)
                          :ongoing -)
                    :op2 (f / find-01
                          :ARG0 o3
```

```
                    :ARG1 (p2 / place
                        :ARG1-of (s2 / safe-01)
                        :ARG4-of (g / go-02
                            :ARG0 s
                            :time (n8 / now)
                            :ongoing -))
                    :ARG2 s
                    :condition (r5 / refugee
                        :ARG1-of r3
                        :domain s)
                    :time (n7 / now)
                    :ongoing -))
            :time (n2 / now)
            :ongoing -))
    :ARG1-of (r6 / resemble-01
            :ARG2 (p3 / person
            :mod (w2 / world-region
                :wiki "Western_world"
                :name (n5 / name
                    :op1 "West"))
            :ARG0-of (r4 / represent-01)
            :mod (o4 / other)))
    :time (n / now)
    :habitual +)
```

Figure 22: "Like other Western representatives , U.S. officials here refer displaced people to the unhcr , which is charged with determining whether someone is a real refugee , and if so , with finding him a safe place to go ."

This is a long sentence, with a number of clauses. The majority of added roles are correct; the "refer" clause is an example of a non-explicit habitual, with a plural noun performing a singular action indicating genericity. It is worth noting that the sentence in the AMR database does not capitalize the acronym UNHCR, but the label in the AMR graph refers to it correctly; while the Charniak parser classifies it as a single noun, not a proper noun, that does not change the results. The ":ongoing-" and ":time (n/now)" roles are not very helpful for conveying meaning; the entire statement is in a hypothetical generic situation, and so meticulously noting that each concept is occurring at the time frame of the utterance is likely misinformative.

Discussion

It is apparent that at least some semantic information is being preserved with this method. While not all of it is crucial to every sentence which it is in, every role at some point indicated some form of meaning which would be important and which would change the meaning of the statement as a whole if omitted. The ":ongoing-" nodes were the most frequent to not indicate meaning, especially as children of the hypothetical habitual statement in the last sentence.

It is also worth noting that the Donatelli proposal specifically does not treat the concept of "now" as the AMR standard does; it does not try to unify the concept of "now", as shown in Figure 23. As a result, I have followed that precedent and declared a new variable for each use of "now". This is odd semantically; generally, it seems that the proposal treats all time as relative to the speech time, and all the speech in a given utterance is at that utterance's "now". This might be a minor enhancement which could help understanding; in all other AMR terms, different instantiations of the same constant use the same variable (as can be seen in the same figure with the variable "p").

```
(a / and
  :op1 (b / be-located-at-91
        :stable -
        :time (n2 / now)
        :ARG1 (p / person
                :ARG0-of (h / have-rel-role-91
                        :ARG1 (y / you)
                        :ARG2 (b2 / brother)))
        :ARG2 (h2 / hospital))
  :op2 (l / last-01
        :polarity -
        :ongoing -
        :time (a / after
                :op1 (n3 / now))
        :ARG1 p
```

:ARG2 (d / date-entity
:dayperiod (n / night))))

Figure 23: An example from the Donatelli et. al. paper of a statement with distinct variables referring to "now"

While the automated AMR annotation seemed to correctly annotate large parts of the data, there are some clear errors. Most tend to derive from issues with the pre-processing Charniak step. If that is incorrect, the error will cascade, and the corresponding nodes will be wrong in the final tree. If a verb is labelled as not-a-verb, the corresponding concept will not be assigned roles; if a non-verb is labeled as a verb, it will be assigned meaningless roles. While the Charniak parser has a high level of accuracy, at almost 90%, it occasionally misclassifies words; both classifying words into verbs when they should not be and not classifying verbs leads to mistakes.

Another aspect which does lead to mistakes is my use of matching to specific sets of words for irregularity and stativity, and my matching of nodes and concepts by string matching. While necessary, as these traits cannot be extracted solely from syntactic context or semantic OntoNotes concepts, it leads to false positives if a word has multiple word senses and false negatives if a word is not in my list. "Lie" is a verb which is common in both its stative and non-stative forms; assigning it unconditionally to either category guarantees error.

More work could be done to develop this rules-based approach further in the future. Stativity could be narrowed down further to avoid false positives from non-stative word senses; it is possible to inspect the WordNet stative list and compare it to OntoNotes to get a sense for which verbs are stative, and then compare to individual senses of the OntoNotes concepts used in an AMR tree. This was not done, in part because the OntoNotes data was obtained late, and in part because the AMR gold-standard concept senses and OntoNotes sense do not seem to agree; for example, one of the sentences in my results has “lie-07” listed as one of its senses, but OntoNotes 5.0 would likely classify it as lie-verb, group 1, sense 1. It is unclear how to convert one to the other.

Yet another category of mistakes deriving from these heuristics involve stativity and the verb “to be” and its forms, such as “is” or “am”. While some languages distinguish long-lasting, permanent forms of the verb from shorter, unstable forms (consider “ser”/”estar” in Spanish), English does not. Semantic knowledge of what being in a given state would entail would be necessary to classify these directly. In addition, AMR often omits such forms of “be”; nouns and verbs are interchangeable, so an AMR tree for either “I am French” or “I am tired” would be represented as merely the state (French or tired), with the concept “I” as an argument to that sense. As a result, the “be” node simply would not exist in AMR; matching the AMR to such instances of “be” would not be possible, and more work would have to be done to allow for that. The Donatelli et. al. proposal annotates the AMR node corresponding to the state, in that case; that would require a lot of reframing, as my proposal is built around assigning these traits to nodes matching verbs.

The AMR data’s division of sentences is odd. On the one hand, there are cases in the Little Prince Data where a single AMR tree is produced from the following sentence “ It looked like this : I showed my masterpiece to the grown - ups , and asked them whether the drawing frightened them .” The resulting AMR tree is rooted at an “and” conjunction combining all three clauses. In the context of the book, however, this is not just one sentence. There is a paragraph break and an image of a snake after the image; surely, sentences do not often carry between paragraphs. It would make far more sense for the colon to end the first sentence. This may be just an artifact of the book's pre-processing. On the other hand, sometimes AMR sentences seem to be oddly truncated. In the blog data set, one of the sentences is "It sits high on a hillside ," (sic). This seems to be incomplete, and in fact the immediately subsequent sentence is "and the view is so phenomenal that you can imagine your gaze reaching all the way to the Iraqi border , some 200 miles away ." (sic). This would seem to be a single sentence, and it is unclear whether its bisection was intentional or accidental. It is much shorter than other single sentences treated as multi-sentential.

One aspect of this proposal which may be limited by the data set is flexibility of tense. To create this data, I have used the AMR 3.0 dataset downloaded from the Linguistic Data Consortium. This contains a number of different sources for sentences, all parsed into gold-standard AMR trees. I would have generated data from a variety of English sources to demonstrate the flexibility of the parsing rules, but I had a great deal of trouble getting the JAMR and CAMR parsers to work and spent months attempting to port them from Python 2 to Python 3 before the former's end of life. Eventually, I decided to just use the standard AMR dataset and draw training and results data from that.

To determine which rules were necessary and if my preliminary rules worked, I used two subsets of the AMR 3.0; I opted for the Aesop's Fables set at first. I chose this because it was a small set with only training data, no testing or development data. If further work could be done on this in the future, I wanted to leave the large data sets available so that no training would ever be done on testing data. This proved to be a mistake. The Aesop's Fables data are not representative of English sentences; they are all in past tense. In addition, they use antiquated sentence structure (as traditional stories for children do). This did not provide a wide enough base to train my model. Adding the Wikipedia set to determine the accuracy of my rules on different tenses and speech patterns was helpful. The results are all drawn from the Weblog dataset; I had hoped that that would be more typical of common English usage, and it does seem to be.

I also wasted time going down the wrong rabbit holes. I implemented a search function to pattern-match children of a verb phrase which have certain forms (such as "X [days/months/decades] ago" and assign tense based on those patterns (so the "ago" tense would assign that text to the past, or at a time before now). This was superfluous. This kind of explicit time determination is exactly what current AMR excels at; in my testing, I did not find any places where it was actually useful to have. In theory, it is not entirely meritless; for example, it is common to refer to days in both the past week and in the upcoming week by the name of the weekday alone ("I had that horrible test Friday, and I've got another one Tuesday"). Pairing whether the verb is in the past or present tense would provide more semantic information to narrow the referred-to time down to a single day. However, this is not used often enough in the data to justify its inclusion.

One of the potential uses of this rules-based work is a classifier to generate training and testing data for a potential neural network tense and aspect generator. Verifying pre-labeled data can be much faster and easier than generating labeled data from scratch. If this can create training data for other, more-effective and more-accurate classifiers, that would provide a good use for it in the long run.

Conclusion

This work has clearly shown a need for some modification of the time rules in the current AMR standard. All sentences represented had at least one one form of tense and aspect noted implicitly, and for most omitting that tense and aspect would cause a significant difference in meaning. If AMR is to be used as a true semantic representation, it will need to encode this information somehow. The Donatelli et. al. proposal could be used to augment the standard in this manner; the information it makes explicit is useful. While the classifier I developed to implement that proposal is faulty in places, it is fairly accurate at determining and encoding that information. It also has potential for future work in the area: more could be done to improve its accuracy, and it could be used to generate data to train a machine learning classifier.

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