BabelNet Meaning Representation:
A Fully Semantic Formalism to Overcome Language Barriers

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Abstract

Conceptual representations of meaning have long been the general focus of Artificial Intelligence (AI) towards the fundamental goal of machine understanding, with innumerable efforts made in Knowledge Representation, Speech and Natural Language Processing, Computer Vision, *inter alia*. Even today, at the core of Natural Language Understanding lies the task of Semantic Parsing, the objective of which is to convert natural sentences into machine-readable representations. Through this paper, we aim to revamp the historical dream of AI, by putting forward a novel, all-embracing, *fully* semantic meaning representation, that goes beyond the many existing formalisms. Indeed, we tackle their key limits by fully abstracting text into meaning and introducing language-independent concepts and semantic relations, in order to obtain an *interlingual representation*. Our proposal aims to overcome the language barrier, and connect not only texts across languages, but also images, videos, speech and sound, and logical formulas, across many fields of AI.

Introduction

Enabling a machine to automatically process and interpret text and then communicate a response verbally is one of the key goals of Natural Language Processing (NLP) and a long-standing dream of AI (Turing 1950). However, although thanks to the emergence of large language models (Devlin et al. 2019) significant advances can be today observed for language comprehension tasks, it has been pointed out that machines do not learn meaning from form alone (Bender and Koller 2020; Bender et al. 2021). Indeed, in order to perform Natural Language Understanding (NLU), i.e., to enable computers to make sense of language and comprehend text, we need to transform text in any language into an explicit *semantic representation* (Navigli 2018), a popular task called semantic parsing. The representations produced by a semantic parsing system can then act as an interface between humans and machines, thanks to their being human-intelligible (in contrast to latent vector representations) and at the same time also ready to be further processed automatically. Different language formalisms – based on diverse linguistic theories – have been proposed over the years, namely, Discourse
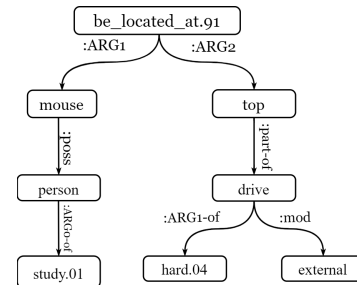
Figure 1: The AMR graph for the English text *"The student's mouse is on top of the external hard drive"*.

Representation Theory (Kamp and Reyle 1993, DRT), Elementary Dependency Structures (Oepen and Lønning 2006, EDS), Prague Tectogrammatical Graphs (Hajič et al. 2012, PTG), Universal Conceptual Cognitive Annotation (Abend and Rappoport 2013, UCCA), Abstract Meaning Representation (Banarescu et al. 2013, AMR), Universal Decompositional Semantics (White et al. 2016, UDS) and, more recently, an extension of AMR called Universal Meaning Representation (Gysel et al. 2021, UMR). In fact, AMR has become one of the most popular formalisms for encoding text into semantic structures (Bevilacqua, Blloshmi, and Navigli 2021), and it has several promising applications in Machine Translation (Song et al. 2019), Text Summarization (Hardy and Vlachos 2018; Liao, Lebanoff, and Liu 2018), Human-Robot Interaction (Bonial et al. 2020a), Information Extraction (Rao et al. 2017) and Question Answering (Lim et al. 2020; Bonial et al. 2020b; Kapanipathi et al. 2021), to name just a few. We focus here on AMR and discuss other formalisms below, in the Related Work section.

AMR is modeled as a labeled graph where nodes are concepts and edges are semantic relations between them. An example of an AMR graph is shown in Fig. 1. Even though AMR was designed for English sentence representation and is not an interlingua (Banarescu et al. 2013), a lot of research has been done on adapting this formalism for other languages, due to the rich amount of information it encodes (Xue et al. 2014; Damonte and Cohen 2018; Zhu, Li, and Chiticariu 2019; Gysel et al. 2021). Nevertheless, there are several challenges that prevent AMR from being a *fully* semantic formalism, making it inadequate to act as an interlin-

gua. First, AMR draws its concepts from the English lexicon (e.g., *mouse, top, drive, external* in Fig. 1), and the PropBank verbal framesets (Palmer, Gildea, and Kingsbury 2005) (e.g., *study.01, hard.04*), from which it also takes the core predicate argument roles (e.g., `:ARG1`, `:ARG2`). Unfortunately, PropBank is based on the English language, and even where similar predicate inventories in other languages exist, they rely on language-specific rules and theories. Moreover, the usage of a lexicon means that AMR cannot be fully semantic, since words are not only ambiguous but also language-specific. Finally, the encoding guidelines for additional relations and concepts within AMR make it difficult to transfer this formalism cross-lingually.

BabelNet Meaning Representation

We put forward the idea that, to get closer to solving the puzzle of NLU – which we insist should not revolve mainly around the English language – we need a *fully* semantic language-independent representation. Such a representation would be useful i) at a practical modeling level, since it would provide a unified representation for text in all languages instead of multiple language-specific ones, and, ii) at the wider application level, e.g., as the long-sought interlingual representation in Machine Translation (Richens 1958). Importantly, a language-independent meaning representation would also abstract away from the communication medium and could be used i) to represent not only the content of text, but also images, videos, speech, sound, etc., and ii) to connect pieces of information of different modalities, thereby enhancing the intelligibility and interpretability of AI systems. In this paper we argue that, given the recent availability of large multilingual resources, this longstanding dream can now be realized and we propose the BabelNet Meaning Representation (BMR).

BMR Ingredients

To achieve the goal of a language-independent representation we rely on two main lexical-semantic inventories:

1. The BabelNet inventory of concepts to use as *fully semantic nodes* of the graph representations. BabelNet (Navigli and Ponzetto 2010; Navigli et al. 2021) is a multilingual encyclopedic dictionary and semantic network that organizes word meanings into multilingual synsets, i.e., sets of synonymous lexicalizations in 500 languages. It integrates heterogeneous sources of knowledge such as Wikipedia and WordNet (Miller 1994), which makes it attractive for large-scale applications and tasks across domains and languages.[1]

2. VerbAtlas (Di Fabio, Conia, and Navigli 2019) to obtain *cross-lingual* verbal frames for the predicate nodes, and *cross-frame* argument roles to be used as semantic relations in the graph. VerbAtlas is a hand-crafted lexical-semantic inventory of predicates and argument

structures, organized into frames which cluster verbal concepts[2] into semantically-coherent frames and cross-frame human-readable relations (e.g., AGENT, LOCATION, BENEFICIARY, etc.), as opposed to PropBank used in AMR, which is language-specific and defines enumerative roles (e.g., ARG0, ARG1, etc.).

From AMR to BMR

BMR has a similar structure to that of AMR, in that it is modeled as a directed labeled graph, where concepts are connected by semantic relations. However, BMR brings language independence in three steps, which we describe hereafter.

Concepts. We replace lexical, language-specific symbols (i.e., words) with *fully semantic symbols* (i.e., concepts) as nodes of the graph representation. To do this, we replace AMR verbal predicates, which are based on the English PropBank (or other language-specific inventories), with language-independent VerbAtlas frames. For all other nodes, instead of using words as is done in AMR, we use BabelNet synsets as nodes in BMR graphs. This can be achieved by leveraging state-of-the-art multilingual Word Sense Disambiguation (WSD) systems which, given an input text, associate WordNet and BabelNet synsets with its content words. Thanks to recent neural architectures, today this step can be carried out with performances in the range of 80-85% in many languages (Pasini, Raganato, and Navigli 2021; Bevilacqua et al. 2021). In a similar manner, named entity nodes can be associated with synsets thanks to the high-accuracy Entity Linking systems (De Cao et al. 2021).

Semantic relations. As a result of replacing AMR predicates with VerbAtlas frames, as explained in the first step, we can straightforwardly move from resource- and language-specific lexical-semantic relations to *cross-frame* and *language-independent semantic relations*.

Multiword and idiomatic expressions. In AMR, multiword and idiomatic expressions (e.g. *bus driver* or *miss the boat*, respectively) are typically represented compositionally. However, this hampers language independence in that different languages will have different subgraphs. Therefore, we replace such subgraphs with *simpler, non-compositional meaning representations* from BabelNet whenever these are available, or compose their underlying meaning otherwise.

The above three steps are aimed at obtaining a truly semantic representation, where nodes are fully symbolic concepts bound to a multilingual knowledge base, and edges are semantic relations that hold true across languages. Here we do not have room to discuss further aspects like temporal information and plurality, which are taken into account by UMR (see Related Work section). We just note that nothing prevents these notions from being incorporated into BMR as well.

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[1]We are aware of the limitations of BabelNet regarding the supported languages, which does not allow full language independence. However, it is the largest multilingual semantic resource to date, hence we consider it a good starting point towards our goal.

[2]Although VerbAtlas is built starting from the English WordNet, its frames include multilingual synsets from BabelNet due to inter-resource mapping, and are therefore language-independent.
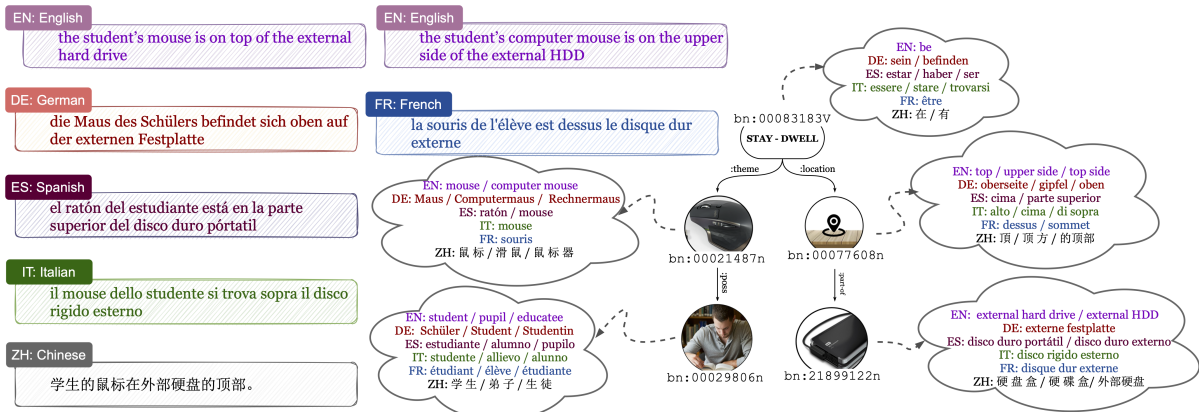
Figure 2: Equivalent sentences in different languages (left) and their BMR graph (right) with multiple possible lexicalizations. STAY-DWELL is the VerbAtlas frame that includes the verb *to be*, while bn:[...] denotes a synset identifier in BabelNet.
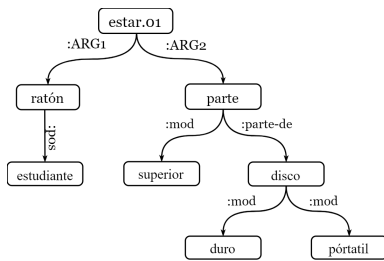

Figure 3: The AMR graph for the Spanish text *"El ratón del estudiante está en la parte superior del disco duro pórtatil"*.

Creating a training corpus. Given an input text, existing semantic parsers produce a representation in AMR or another formalism. Such systems typically employ Transformer-based models (Bevilacqua, Blloshmi, and Navigli 2021; Procopio, Tripodi, and Navigli 2021), which require large training sets. To make the BMR idea realistic, we put forward a procedure for creating a similar dataset for BMR. We can start from the biggest AMR dataset[3] comprising 59,255 English sentences from different sources annotated with their respective AMR graphs.[4] We then propose applying the above three-step procedure for moving from AMR to BMR automatically to all the graphs of an existing AMR bank. Some technical details include:

1. Identifying the node(s) associated with a disambiguated word or multiword, which can be addressed by making use of the AMR word-to-node alignments (Flanigan et al. 2014) to propagate synsets into the graph.

2. The integration of VerbAtlas frames into AMR can be obtained by replacing PropBank framesets with their corresponding VerbAtlas frames by exploiting the mappings made available by Di Fabio, Conia, and Navigli (2019).

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[3] AMR 3.0: https://catalog.ldc.upenn.edu/LDC2020T02

[4] While BMR might seemingly be more difficult to learn than an AMR graph, thus requiring more training data, we leave this assumption to be investigated by future empirical studies.

BMR by Example

Here we illustrate, using the example in Fig. 2, how BMR compares to AMR in representing sentences with a fully-semantic language-independent structure.

Concepts. Consider the AMR graph in Fig. 1. While a human can easily choose *computer device* as the most likely meaning of *mouse* in this graph – due to the co-occurrence with *external hard drive* – using an ambiguous word in the graph leaves open the less likely possibility that an *animal* is on the drive. Since BMR uses synsets as nodes, instead, this is no longer an issue: in the BMR graph, *mouse* is explicitly represented as a *computer device* and, even more importantly, it is represented with the same synset in any language. Similarly, the explicit semantics of the other nodes in BMR is maintained across languages, as shown in Fig. 2.

Semantic relations. As mentioned earlier, the semantic relations which connect parts of an AMR graph are provided by the English PropBank. There have been several attempts to annotate non-English sentences with structures similar to AMR using language-specific PropBank-like ontologies, such as AncoraNet in Spanish (Aparicio, Taulé, and Martí 2008) and Chinese PropBank (Xue and Palmer 2009). An example of the Spanish translation for the example in Fig. 1 is shown in Fig. 3.[5] In addition to the inherent differences in concept nodes due mainly to different lexicons of the two languages, we also observe two main differences due to the usage of different predicate inventories: i) some frames included in one are not found in the other, e.g., *hard.04* versus *duro*, *be-located-at.91* versus *estar.c1*, ii) semantic relations are differently expressed or no longer apply due to the missing frames, e.g., ARG1-of versus :mod for the nodes *hard.04* and *duro*, respectively. Moreover, PropBank-like arguments are both predicate-specific and language-specific, leading to different representations across languages. These differences are overcome by BMR which represents the

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[5] We notice that no predefined rules exist on how to apply AMR in Spanish, we therefore try to achieve a structure that is comparable to that of English AMR in Fig. 1.

Spanish sentence using the same graph as its parallel translations in other languages (see Fig. 2).

Multiword and idiomatic expressions. Idioms and multiword expressions are poorly represented in AMR, which assumes their meaning can be broken down literally according to their constituents, e.g., *external hard drive* in Fig. 1 represented with three nodes. In BMR instead, thanks to BabelNet's coverage of multiword expressions, we can assign a single node to the whole term (see Fig. 2). Most importantly, the same synset is defined semantically across different languages. The situation is even worse when we consider idioms (e.g. *miss the boat*), where a representation would not be produced in terms of its components, as its overall meaning is *not deducible* from those of the individual words.

Miscellanea. AMR maximizes the usage of PropBank frames, whenever possible, ignoring the morphological category of words. In Fig. 1, a *student* is represented as *a person who studies*. First, this is not entirely equivalent semantically, as not every person who studies is a student. In addition, these language-specific rules do not apply across languages. In contrast, BMR uses BabelNet synsets to abstract all translations as shown in Fig. 2, reducing graph complexity and being equally applicable across languages.

Related Work

While most of the formalisms focus on English, more recently various attempts have been made towards formally representing non-English text. Abend and Rappoport (2013) proposed UCCA as a cross-lingual annotation which connects words in a sentence using semantic relations that are not language-specific. However, UCCA does not represent the meaning of individual words explicitly and the semantic relations are highly coarse-grained, thus it is not suitable as a fully-semantic language-independent representation. PTG (Hajič et al. 2012) is another formalism that enriches syntactic structures with the core predicate-argument relations of a sentence. Similarly to AMR, it relies on PropBank-like inventories to represent sentences, thus it is inapplicable when such an inventory does not exist. More recently, Abzianidze et al. (2017, PMB) proposed a parallel meaning bank based on the DRT formalism, i.e., a formal logic meaning representation which includes syntactic and semantic annotations of text. PMB obtains non-English sentence representations by automatically projecting through English using word alignments. Its dependency on English, however, means its representation cannot be truly language-independent. Regarding AMR instead, several works attempted to adjust it for cross-lingual applicability. Xue et al. (2014) analyzed the suitability of AMR as an interlingua by annotating non-English sentences with language-specific inventories, while others (Damonte and Cohen 2018; Blloshmi, Tripodi, and Navigli 2020) projected English-centric AMR as a representation for parallel sentences in multiple languages. These works pointed out the limitations of AMR as an interlingua. Recently, Zhu, Li, and Chiticariu (2019) and Gysel et al. (2021) worked at the formalism level; the former suggested simplifying AMR so as to express only predicate roles and linguistic relations in a sentence, in order to be able to apply

it across languages. In marked contrast, the latter designed UMR, an extension of AMR which i) adds aspect and scope, ii) includes document-level temporal and modal dependencies, and iii) adapts AMR to a cross-lingual formalism allowing language-specific distinctions with extra relations. Nevertheless, none of these enhancements put forward an *interlingual* representation. Indeed, this is the goal of BMR, which fully abstracts away from form by using concepts and semantic relations that are shared cross-lingually.

Scope of BMR

We believe that BMR has the potential to unify the data and knowledge processed in many key areas of AI, including:

Machine Translation (MT). An immediate example is that of interlingual MT (Richens 1958), which casts the task into two subsequent parts: parsing text into an interlingua, and generating text from it. The key advantage brought by BMR is to drop the current requirement of bilingual corpora which particularly affects low-resource languages.

Question Answering (QA). Intermediate symbolic representations can be a useful means in QA for achieving better question comprehension and then retrieval of facts from a knowledge base, which in their turn further enable an interpretable, cross-lingual form of QA (Kapanipathi et al. 2021).

Dialogue. Humans wish to speak to computers, e.g., digital assistants, using the same language with which they speak to each other. Indeed, an interlingua – which decouples comprehension from generation – would ease the path for human-computer interaction in any language, as the intent of a user could be encoded in a language-independent, but human-readable form.

Vision, Speech, and More. Besides language, humans interact through information from diverse channels, including visual, audial, and haptic feedback. Thanks to its full abstraction to concepts, BMR aspires to achieving universality in representing all these channels of information, and enabling interconnections across modalities, preparing the ground towards e.g., multimodal conversational AI, a direction of growing interest (Yu 2020).

Knowledge Representation. Semantic representations, and especially an *interlingua*, are at the core of the theoretical foundations of the knowledge representation problem (Davis, Shrobe, and Szolovits 1993). The grounding of BMR in a large semantic network of interconnected knowledge sources allows the elements of logical formulas to be linked to explicit concepts which explain their meaning and how such meanings are related, thus opening an important direction towards Explainable AI (Lecue 2020).

Conclusions

We have presented BMR, a new formalism for a language-independent representation of meaning. We hope that, once implemented, it will provide the expected benefits and prove its potential as a universal representation, not only in NLP tasks, but also in several other areas of AI.

Acknowledgments

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