A Survey of Meaning Representations – From Theory to Practical Utility

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Abstract

Symbolic meaning representations of natural language text have been studied since at least the 1960s. With the availability of large annotated corpora, and more powerful machine learning tools, the field has recently seen several new developments. In this survey, we study today's most prominent Meaning Representation Frameworks. We shed light on their theoretical properties, as well as on their practical research environment, i.e., on datasets, parsers, applications, and future challenges.

1 Introduction

Being able to represent the semantic structure of a text has been an important research goal since the early days of NLP. Early works developed natural language interfaces for specific databases. They transformed raw text into an executable language, using formalisms such as SQL, first-order logic or lambda-calculus (Mooney, 1996; Wong and Mooney, 2006; Mooney, 2007). Another avenue of research, which is the focus of this work, has developed general-purpose, non-executable Meaning Representations (MRs), inspired by formal grammars. These often take the form of human-readable graphs. Figure 1 shows an example.

Such MRs are used to improve the accuracy of NLP systems in tasks such as summarization or machine translation (Gao and Vogel, 2011; Liu et al., 2015; Mohamed and Oussalah, 2019; Liao et al., 2018; Song et al., 2019; Ribeiro et al., 2022). In the age of large language models (LLMs), they also get leveraged for their interpretability, e.g., to enhance semantic search (Bonial et al., 2020; Cai et al., 2022; Opitz and Frank, 2022b) or natural language inference (Opitz et al., 2023b). They are also used to generate paraphrases (Cai et al., 2021), augment training data (Shou et al., 2022), or to do style-transfer (Jangra et al., 2022; Shi et al., 2023).

In this survey, we provide a structured overview of current Meaning Representation Frameworks. Several other surveys have discussed MRs before us. However, they are either focused on linguistic theory (Abend and Rappoport, 2017; Pavlova et al., 2023) and thus tend to neglect applications, parsers, and resources, or they focus on the practical application only (Verrev, 2023). Our survey aims to strike a middle ground: It presents both the different formalisms and their applications, resources, and parsers. This balance allows us to describe a bigger picture of the field and outline open challenges. Our survey thus aims to be a handy reference for anyone who wishes to choose, understand, build, or use a Meaning Representation.

In Section 2 we introduce the main concepts and properties of MRs. Section 3 tackles Shallow MRs, and Section 4 Deep MRs. Finally, Section 5 discusses open challenges in the domain.

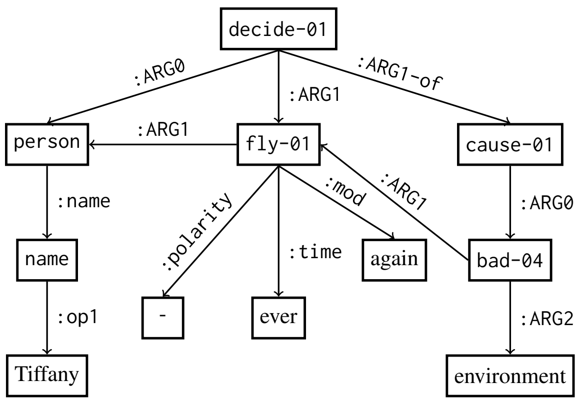

Figure 1: AMR graph for the sentence "Tiffany decided that she would never fly again, because it is bad for the environment".

2 Meaning Representations

Given a text in natural language, MR parsing is the task of producing a symbolic representation of its meaning, as it is understood by a language speaker (Abend and Rappoport, 2017). Different Meaning Representation Frameworks (MRFs)

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MRF	Subevents	Shape	Compositional	Node type (Flavor)	Edge type
SR	-	Tree	-	Text spans (1)	Numbered
RST	-	Tree	✓	Text spans (1)	Theory-oriented
UDS	-	Tree	✓	Text spans (1)	Numbered & theory-oriented
SD	✓	Graph	-	Augmented Text Spans (0)	Numbered
EDS	✓	Graph	-	Augmented Text Spans (1)	Numbered
UCCA	✓	Tree	✓	Text spans (1)	Theory-oriented
AMR	✓	Graph	-	Synsets (Propbank) (2)	Predicate-dependent
DRS	✓	Graph	✓	Synsets (WordNet) (2)	Predicate-independent

Table 1: Properties of the Meaning Representation Frameworks that we survey. The middle line separates shallow and deep formalisms.

have been developed. In this survey, we are interested in graph-like MRFs with their corpora and parsers. We focus on **Semantic Roles (SR)**, **Rhetorical Structure Theory (RST)**, **Universal Decompositional Semantics (UDS)**, **Semantic Dependencies (SD)**, **Elementary Discourse Structures (EDS)**, **Universal Conceptual Cognitive Annotation (UCCA)**, **Abstract Meaning Representation (AMR)**, and **Discourse Representation Structure (DRS)**. We will focus on English sentences, and discuss the aspects of multi-sentence and multi-lingual support where relevant.

MRFs are often inspired by a Neo-Davidsonian semantics, and see *events* as the main elements of sentences. The *predicate* of an event defines the type of the event, and is most often a verb (`decide-01` or `fly-01` in Figure 1). The *arguments* of the event are the entities that participate in the event ("Tiffany" in the example), or the circumstances of the event, such as its place or manner (a negative polarity "-", in our example). The *semantic role* of an argument specifies the role that the participant plays in the event. In our example, the semantic role of *Tiffany* in the `decide-01` event is the subject/agent (`ARG0` in AMR jargon).

Based on this, the semantic information in a sentence can be decomposed into three levels: The level in the middle describes events. The sub-event level decomposes the arguments of events into smaller components – up to words and possibly even sub-words. In our example, "bad for the environment" is modeled by the link from `bad-4` to `environment` with the semantic role `ARG2`. The supra-event level links events to other events. This is done using *discourse relations*. In our example, the `cause-01` node connects `decide-01` and `bad-04`, meaning that the decision was taken *because* flying is bad for the environment. Discourse relations can even link events across sentences.

Different MRFs vary these general ideas along several axes, which we show in Table 1. First, not all MRFs can represent sub-events (Column 2 in Table 1). We call a MRF *deep* if it can represent sub-events, and *shallow* otherwise. Second, MRFs construct either trees (where each node has at most one parent) or full-fledged graphs (Column 3). Our example in Figure 1 is not a tree: `fly-01` and `person` have two different parents, because they play two different roles. Third, some MRFs are *compositional* (Column 4), which means that they contain nodes that compose the meaning of other nodes. Our example in Figure 1 is not compositional: every node contains the same level of information. However, we can imagine creating a node that represents the fact that the `fly-01` event is negated. This would then be a compositional node. The difference between compositional and non-compositional MRFs is thus similar to the difference between dependency and constituency trees in syntactic parsing.

MRFs can further be distinguished by how abstract their node labels are (Column 5): Nodes can be labeled with a span from the text, but they can also be augmented with extra information such as a POS tag. Some representations go as far as using abstractions such as synsets from predefined vocabularies, to help reduce (or even eliminate) lexical ambiguity, and make events invariant to surface form. In the case of compositional MRFs, this property applies to leaf nodes. The node type can be completed with the Flavor hierarchy proposed by Oepen et al. (2019). This hierarchy differentiates MRFs based on anchoring, i.e. on the explicit correspondence between nodes and the input sentence. Flavor 0 means that each node injectively corresponds to one word; Flavor 1 relaxes the anchoring constraints, allowing a node to correspond to a whole span, and the same span to correspond to several nodes; and Flavor 2 marks the absence of explicit links between the nodes and the text.

Finally, the MRFs differ in their edge type (Column 6): Some MRFs use roles that depend on a specific linguistic theory, like `elaboration` (discourse theory) or `scene` (cognitive science). These schemes can describe only a limited array of relations, and do not distinguish the agents and patients of events. Other representations are more specific and use numbered semantic roles (`A0`, `A1`, ...). In these schemes, `A0` and `A1` usually correspond to Dowty's Proto-Agent and Proto-Patient (Dowty, 1991), respectively. These proto-roles are defined by their features: Typical agent features are *awareness, movement*, and *volition*, while typical patient features are *change of state*, *being stationary*, etc. The other semantic roles (`A2`, `A3`, ...) usually do not have such a predefined meaning. Again other MRFs are more specific, and use predicate-independent semantic roles that distinguish finer roles such as `Agent` and `Patient`. Finally, some MRFs make the meaning of the role dependent on the predicate: in Figure 1, `ARG0` means "pilot, agentive entity capable of flight" for `fly-01`, while it means "decider" for `decide-01`. These MRFs thus describe their arguments very specifically.

3 Shallow Meaning Representation Frameworks

3.1 Semantic Roles

A prominent Shallow Meaning Representation Framework is the Semantic Roles framework (SR, Gildea and Jurafsky, 2000). Given an input sentence and a predicate, its purpose is to determine the arguments of the predicate and their semantic roles – a task known as Semantic Role Labeling (SRL). SRL focuses on event-level relations, which means that its predicates are verbs. There are (at least) three different implementations of semantic roles. The most popular one is *PropBank SRL*, where semantic roles are split into core and non-core roles according to PropBank (Palmer et al., 2005). The non-core roles are also called modifiers, and they always have the same meaning: `ARGM-CAU` indicates cause, `ARGM-LOC` indicates location, etc. The meaning of core roles ($\texttt{ARG}_{2...n}$) depends on the predicate. However, `ARG0` and `ARG1` usually correspond to Dowty's Proto-Agent and Proto-Patient (Dowty, 1991). Other paradigms exist: *FrameNet SRL* generalizes descriptions across similar verbs (e.g., say, speak) as well as similar nouns and other words (e.g., speech), based on FrameNet (Baker et al., 1998). *Semantic Proto-Role Labeling* (SPRL) aims at directly approximating Dowty's Proto-Roles with features such as movement, awareness, etc (Dowty, 1991).

Figure 2 shows a merger of three parsings for our example (in PropBank-SRL style), for the predicates "decided", "fly", and "is". Since an SRL graph consists of only one predicate node and its arguments, the graph is a dependency tree, with text spans as nodes.

SRL is a rather light annotation, and it is used to enhance LLMs (Zhang et al., 2020b), e.g., for downstream tasks such as Fact Checking (Zhong et al., 2020), Question Answering (Pillai et al., 2018), and Summarization (Mohamed and Oussalah, 2019; Zhang and Bansal, 2021).

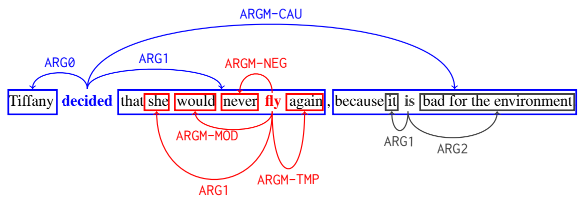

Figure 2: Semantic Role Labeling of our example sentence in span-graph style. Each color corresponds to a predicate (bold) and its arguments (solid)

Resources. PropBank-SRL has been the focus of several shared tasks, which produced datasets that are used to this day. CoNLL 2005 (Carreras and Màrquez, 2004, 2005) introduced span-based SRL, while CoNLL 2008 (Surdeanu et al., 2008) and 2009 (Hajič et al., 2009) introduced dependency-based SRL (which labels only the syntactic heads of the arguments). These works are based on the expert annotations of the WSJ section of the Penn Treebank (in English) from Propbank. The resulting training sets consist of 40,000 sentences each. Other datasets provide FrameNet SRL (Burchardt and Pennacchiotti, 2008; Das and Smith, 2011; Hartmann et al., 2017) and SPRL annotations (Reisinger et al., 2015; White et al., 2016).

Parsing. Regardless of the flavor of SRL, many approaches for parsing (or labeling) are heavily reliant on syntactic features (Pradhan et al., 2005; Punyakanok et al., 2008; Li et al., 2018; Fei et al., 2021). The progress in Neural Networks has allowed systems to become more syntax-agnostic (Zhou and Xu, 2015; He et al., 2017; Tan et al., 2018; Rudinger et al., 2018; Arora et al., 2022; Spaulding et al., 2023), so much that recent approaches extract not just the arguments, but also the predicates themselves (Cai et al., 2018; He et al., 2018; Zhang et al., 2022). This is particularly appealing, as it allows to directly transform a text into a MR.

3.2 Rhetorical Structure Theory

Rhetorical Structure Theory (RST, Mann and Thompson, 1988) takes interest in discourse relations. It sees the text as a sequence of *Elementary Discourse Units (EDUs)*, which roughly correspond to events, and seeks to identify the relations between these units, such as `Condition`, `Contrast`, `Cause`, `Result`, or `Elaboration`. RST models a text as a tree, in which discourse relations are recursively applied to connect discourse units. Leaf nodes are EDUs (text spans), while inner nodes are unlabeled compositional nodes. Figure 3 shows the RST MR of our example sentence. The EDUs coincide with the spans delimited by predicates and arguments in the SRL graph. Each discourse relation links a *satellite* (supporting information) to a *nucleus* (central information). In our example, the nucleus of the `Reason` relation is the fact that Tiffany decided to never fly again, and the satellite is the reason for that decision. The repertoire of discourse relations depends on the dataset.

Discourse relations can cross sentence boundaries, which means that one rhetorical structure can represent a multi-sentence document. RST has been used for Summarization (Xu et al., 2020) and Question Answering (Ouyang et al., 2021), and even for Argument Mining (Peldszus and Stede, 2013; Mitrović et al., 2017; Chakrabarty et al., 2019).

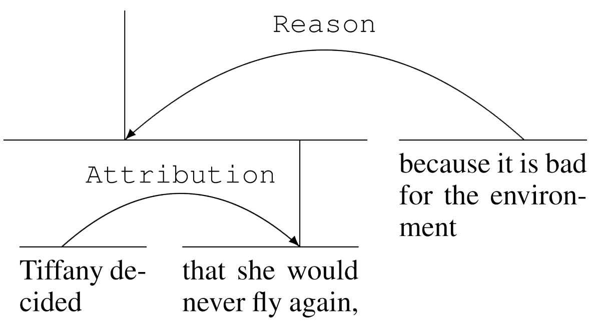

Figure 3: RST-DT style annotation for our example.

Resources. The main dataset for RST is RST-DT (Carlson et al., 2001), which defines 78 discourse relations, divided into 16 classes. The dataset contains 385 documents from the Wall Street Journal corpus, which have been annotated with around 20,000 EDUs by expert linguists on the basis of an extensive annotation manual.

Parsing is usually performed in two steps: EDU Segmentation and Tree Building. Wang et al. (2018) achieves a near-perfect performance on segmentation using a Bi-LSTM-CRF based model. First approaches for Tree Building (Soricut and Marcu, 2003; Hernault et al., 2010) used handcrafted features. Ji and Eisenstein (2014) introduced the first RST-DT neural parser, followed by bottom-up parsers (Li et al., 2016; Braud et al., 2017; Wang et al., 2017; Yu et al., 2018), and more recently top-down ones (Lin et al., 2019; Zhang et al., 2020a; Kobayashi et al., 2020). Though they have different approaches, Nguyen et al. (2021) and Koto et al. (2021) are the current best-performing systems for this task.

3.3 Universal Decompositional Semantics

Universal Decompositional Semantics (UDS) is a multi-layer semantic annotation scheme, which means that it allows annotating the same sentence on different dimensions. These dimensions include factuality and time for predicates, and genericity and word sense for arguments. UDS builds a semantic compositional tree, where the leaf nodes are the words of the sentence (or special tokens) and inner nodes represent larger semantic units. The graph structure is based on PredPatt (White et al., 2016), a pattern-based framework for predicate-argument extraction that operates on (syntactic) Universal Dependencies (UD, de Marneffe et al., 2021). It focuses on event-level relations, which means that the extracted structure is close to that of merged SRL graphs. UDS uses Dowty's Proto Roles decomposition, which, as mentioned above, describe features of event participants and how they are affected by the event (*movement*, *volition*, *change of state*, and so on).

Resources. The UDS dataset can be accessed through the Decomp Toolkit (White et al., 2020). The original annotations include proto-roles (Reisinger et al., 2015), word sense, and factuality. Around 10,000 arguments were annotated with proto-roles, using answers of Mechanical Turk workers to simple questions about the arguments. The framework was enriched with annotations on time (Vashishtha et al., 2019), and generalizing statements (Govindarajan et al., 2019), and also some discourse relations (Gantt et al., 2022).

Parsing. UDS Parsing is a fairly unexplored task. Zhang et al. (2018) performs cross-lingual UDS parsing with a pipeline approach performing graph transduction, coreference resolution and semantic proto-role labeling. Stengel-Eskin et al. (2020) proposes an end-to-end parser with an encoder-decoder structure, while Stengel-Eskin et al. (2021) parses UD and UDS jointly.

4 Deep Meaning Representation Frameworks

Deep Meaning Representation Frameworks go further than shallow ones by representing relations at all levels of the text, in particular at the sub-event level. They aim to model the meaning of the text exhaustively, representing as many phenomena as possible (negations, comparisons, modifiers, time, cause, etc.).

4.1 Semantic Dependencies

Semantic Dependencies (SD) is a family of MR frameworks that are used in the SemEval 2014 & 2015 challenges (Oepen et al., 2014, 2015). Their aim is to go further than syntactic dependency parsing, and to represent the semantic structure of a sentence – a process called Semantic Dependency Parsing (SDP). Four main frameworks have been proposed, derived from independent annotation schemes with different formalisms: DM (DELPH-IN MRS-Derived Bi-Lexical Dependencies, Flickinger et al., 2012), PAS (Enju Predicate-Argument Structures, Miyao, 2006), PSD (Prague Semantic Dependencies, Hajič et al., 2012), and CCD (Combinatory Categorial Grammar Dependencies, Hockenmaier and Steedman, 2007).

All frameworks see the semantic structure as a dependency (non-compositional) graph with Flavor 0 (every node corresponds to exactly one word in the sentence). In contrast to syntactic dependency trees, the modeling of semantic dependencies requires a graph, as nodes can have several incoming edges (a phenomenon called *re-entrancy*) if a word is the argument of several predicates, as well as none if they are semantically vacuous. A node is a word that can be augmented with its lemma, POS-tag or framework-specific identifier. The exact vocabulary of semantic roles, as well as the way the graph models different phenomena, varies across frameworks. Most of them use unspecific semantic roles (`ARG1`, `ARG2`, `ARG3`, ...). Nevertheless, similar to SRL, `ARG1` and `ARG2` usually correspond to Dowty's Proto-Agent and Proto-Patient.

Still, SD has the advantage to be easily understandable by human readers. Figure 4 shows DM annotations for our example sentence. The event decomposition goes all the way to the token level: the adjective phrase "bad for the environment" is seen as an object of interest, with "for" being a predicate, with the arguments "bad" and "environment".

Resources. Oepen et al. (2016) proposes a corpus with annotations for all four frameworks, with close to 37,000 English sentences from the WSJ corpus, which were obtained through expert annotation. The dataset also provides a corpus of annotations in ohter languages: Chinese for PAS, and Czech for PSD. Other corpora are formalism-specific: DeepBank for DM (Flickinger et al., 2012), the Enju Treebank for PAS (Miyao, 2006), the Prague Czech-English Dependency Treebank for PAS (Hajič et al., 2012), CCGBank for CCD (Hockenmaier and Steedman, 2007).

Parsing. Most parsing approaches for SDP are inspired by syntactic dependency parsing (Dozat and Manning, 2018; Fernández-González and Gómez-Rodríguez, 2020). The best results across the different SDP variants are achieved by a multi-task system (Wang et al., 2021b).

Variations. English Resource Grammar (ERG), of which DM is a reduction, produces MRs in the Minimal Recursion Semantics (Copestake et al., 2005). These structures are particularly expressive and can model scope, but they are also complex to read and exploit. Elementary Discourse Structures (EDS, Oepen and Lønning, 2006) try to reduce this complexity by making the graph non-compositional. The main difference between EDS and DM is that EDS are Flavor 1 graphs, which has more abstract node labels: in addition to POS tags and identifiers, nodes can be labeled with properties, such as time or number.

4.2 Universal Conceptual Cognitive Annotation

The Universal Conceptual Cognitive Annotation (UCCA, Abend and Rappoport, 2013) is a semantic annotation scheme aiming to be "universal", i.e., it aims to be resistant to syntactic variation within and across languages. An UCCA Representation takes the form of a compositional tree whose leaf nodes are the words of the sentence, and intermediate

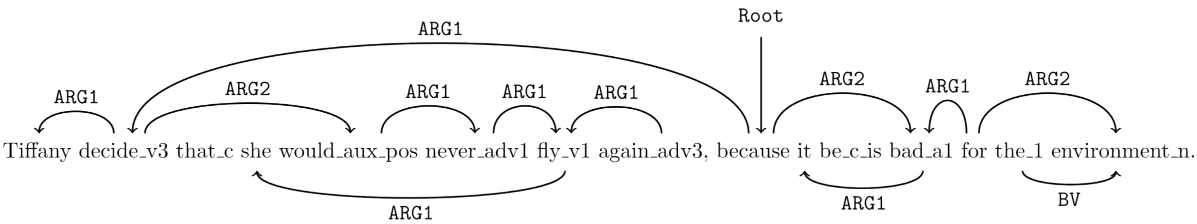

Figure 4: A Semantic Dependency Parse in DM-style for our running example.

nodes, called `units`, are unlabeled. UCCA identifies 3 levels of semantic information. On the central level, scene units correspond to events. They are linked to a predicate, to its core arguments by a generic label `participant`, as well as to non-core arguments using several other labels (see Figure 5). On the lower level, *sub-scene units* help specify the participants of a scene. Finally, *superparallel units* can link two scenes with generic `parallel scene` edges, and possibly a cue word indicating the type of discourse relation with a `linker` edge. At any level, *functional units* can represent phenomena such as prepositions, articles, or expletive pronouns. UCCA can annotate several sentences in a single graph.

There are very few semantic roles in UCCA, which makes the annotation task more accessible to non-experts and portable to other languages. Semantic roles have a generic interpretability, but it can be hard to exploit them directly: for instance, the `participant` role doesn't make a difference between what would be labeled as `ARG0` (Agent) and `ARG1` (Patient) in other frameworks. UCCA is multi-layered, which makes it possible to add extensions to the representation, for instance to annotate co-reference links, more specific semantic roles, or more abstract node types. UCCA is cross-lingual, and as such found applications in Machine Translation (Slobodkin et al., 2022; Birch et al., 2016), but also in Text Simplification (Sulem et al., 2018a,b).

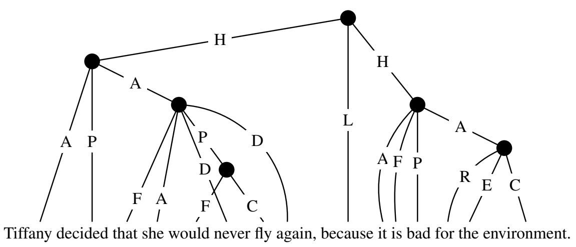

Figure 5: UCCA graph for our example. H: Parallel Scene, L: Linker, P: Process, A: Participant, D: Adverbial, F: Function C: Center, E: Elaborator, R: Relator.

Resources. UCCA comes with a large expert-annotated multilingual corpus (Abend and Rappoport, 2013). Its English version annotates a total of 1350 passages (more than 200,000 tokens). This includes not only elements from Wikipedia, the Web- and Penn Treebanks, but also from the literature (e.g. *The Little Prince*).

Parsing. The first proposed parser for UCCA (Hershcovich et al., 2017) was transition-based. Other methods exploit constituency parsers (Jiang et al., 2019; Bölücü and Can, 2021). Nowadays, the best parsers are sequence-to-sequence models (Ozaki et al., 2020; Samuel and Straka, 2020).

4.3 Abstract Meaning Representation

Abstract Meaning Representation (AMR, Banarescu et al., 2013) aims at further abstracting away from syntax, even mapping named entities to Wikipedia. AMR has no explicit alignments between nodes and the text. The representation itself takes the form of a rooted, acyclic, directed dependency graph, where each node is labeled with a *concept*, and represents an instance of this concept. The root of an AMR is used for modeling the focus, or main event, of a text. Figure 1 shows the AMR graph for our running example.

AMR has an abstract node type: a node can be labeled with PropBank frames (for events and entities), unambiguous English words, or special frames (e.g. for dates, modalities, negations, comparisons, or family relationships). Semantic roles are either PropBank roles, which have accessible predicate-specific interpretation, or manually-crafted ones (e.g. `:name`, `:location`, `:cause`, `:concession`, `:month`, `:poss`, `degree`...).

Many AMR roles can be reified and used as concepts, thus allowing the focus to be on the relation itself. AMR also makes use of re-entrancy: in our example, Tiffany appears only once as a node, and is linked to both `decide-01` and `fly-01`. AMR also represents explicit quantities and temporal relations. This makes AMR graphs nearly unambiguous. However, the lack of explicit scope can still lead to ambiguity: in our example, it is unclear whether what is bad for the environment is the fact of flying or the fact that Tiffany will never fly again – which is the opposite of the meaning of the sentence.

Of all MRFs, AMR has probably garnered the most attention in recent years. It has been used in tasks such as Machine Translation (Song et al., 2019), Question Answering (Kapanipathi et al., 2021; Lim et al., 2020; Xu et al., 2021), Toxic Content Detection (Elbasani and Kim, 2022), Semantic Search and Natural Language Inference (Opitz and Frank, 2022b; Opitz et al., 2023b), and Social Reasoning (Chanin and Hunter, 2023).

Resources. The most important AMR corpus is the AMR Annotation Release (Banarescu et al., 2013). It was constructed fully manually by trained annotators, and contains about 60,000 English AMR graphs in its latest (3.0) version, including multi-sentence graphs (O'Gorman et al., 2018). AMR graphs are often linearized in the 'Penman' form (Kasper, 1989), which is easy to read, and allows processing with neural models in a sequence-to-sequence manner (the Penman form uses a depth-first traversal and can, in principle, linearize any directed rooted graph).

Parsing. Many AMR parsers have been proposed through the years, graph-based (Flanigan et al., 2014; Werling et al., 2015; Cai and Lam, 2020), transition-based (Wang et al., 2015; Vilares and Gómez-Rodríguez, 2018; Lee et al., 2020), or seq-2-seq (Barzdins and Gosko, 2016; Peng et al., 2018; Bevilacqua et al., 2021), possibly leveraging adapters to better incorporate graph topology (Vasylenko et al., 2023). Most systems of the 2020s leverage large pre-trained language models and achieve strong performance on AMR 3.0.

Extensions. AMR has been extended to model tense and aspect (Donatelli et al., 2018), as well as scope (Pustejovsky et al., 2019), and larger documents (Naseem et al., 2022). The BabelNet Meaning Representation (Navigli et al., 2022) aims at making it multilingual by using BabelNet synsets for concepts (Navigli et al., 2021) and semantic roles from VerbAtlas (Di Fabio et al., 2019). Perhaps even more ambitious, the Universal Meaning Representation (UMR, Van Gysel et al., 2021) aims at compensating all main shortcomings of AMR, adding aspect and scope, integrating document-level annotations with coreference, temporal and modal relations between sentences, and making the representation language-agnostic.

4.4 Discourse Representation Structure

Discourse Representation Structure (DRS) is the fruit of Discourse Representation Theory (DRT, Kamp, 1981; Kamp and Reyle, 1993) and provides a meaning representation that fully integrates with first order logic. We focus here on the characteristics of the DRS format used in the Parallel Meaning Bank (PMB, Abzianidze et al., 2017), based on Segmented Discourse Representation Theory (Asher and Lascarides, 2003), which augments DRT with discourse relations. A Discourse Representation Structure (DRS) is not a graph, but a recursive structure of nested boxes. Figure 6 shows the representation of our example sentence.

As in AMR, elements are represented by a Wordnet synset (Miller, 1995), accompanied by an identifier. Wordnet has a very wide coverage of English, which means that most words can be mapped to such Wordnet synsets. Semantic roles are taken from VerbNet (Kipper et al., 2000), augmented by hand-crafted roles (e.g. `Quantity`, `Name`, `Owner`, `Time`). These roles are generic, and no predicate-specific interpretation is available.

Usually, a simple box represents an event (similar to an EDU). Discourse relations are represented similarly to semantic roles, but with boxes as arguments. This means that DRS is compositional, and naturally equipped for multi-sentence representation. Modal logic operators can also be applied to boxes (negation, possibility, and necessity), which allows for a precise scoping of these operators: in the example, "she will never fly again" is represented as the negation of the box expressing that Tiffany flies at some point in the future.

Even though there may be no ideal way to transform a DRS into a graph (Abzianidze et al., 2020), we can see concepts as nodes, and semantic roles as labels of the edges between these nodes. Boxes would be another type of nodes, with discourse relations linking them. The most recent development of DRS, the Sequence Notation (Bos, 2023), proposes a similar graph equivalent. With this view, DRS are compositional graphs, where high-level nodes represent scope.

Resources. DRS annotations are hard to produce even for experts, which makes constructing large corpora difficult. The Groningen Meaning Bank

(GMB, Basile et al., 2012) was the first DRS corpus, followed by the Parallel Meaning Bank (PMB, Abzianidze et al., 2017). These banks were built using an automatic pipeline using the rule-based parser Boxer (Bos, 2008). The PMB tries to make DRS language-neutral by associating English documents with translations to one or several languages. The latest release contains almost 10,000 "gold", i.e., human-checked, English documents.

Parsing. Several DRS parsers are available, exploiting transition-based parsing (Evang, 2019), DAG Grammars (Fancellu et al., 2019) or POS-tags and dependency graphs (van Noord, 2019). Modern parsers use LLMs (van Noord et al., 2018, 2020) and generally outperform older ones.

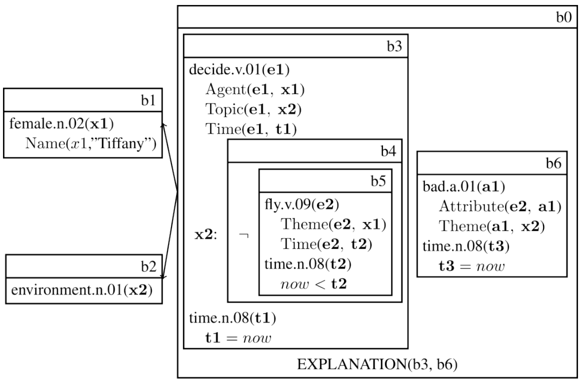

Figure 6: DRS for our running example

5 Current Research Trends

Synthesizing insights from our overview of MRFs, we see research trends in three main areas for Deep MRFs: MRF design, MR parsing, and MR applications.

5.1 Trends in MRF design

MRs seem to lend themselves to multi-linguality, since they represent semantic concepts such as *agent*, *patient*, *instrument*, and *cause* that appear to be universal. However, these concepts, and more generally their structure, are still based on English semantics. Only UCCA, built on Basic Linguistic Theory (Dixon, 2009), is natively fully language independent. To make them more language-agnostic, some MRFs are being equipped with parallel corpora, node labels, and even more neutral structure (Abzianidze et al., 2020; Navigli et al., 2022; Giordano and Lopez, 2023; Van Gysel et al., 2021).

Multi-sentence representation is also a topic of research. Compositional MRFs are naturally well-equipped for this, to the point that RST and DRS are already able to represent multi-sentence document in one MR. Several AMR extensions (Naseem et al., 2022; Van Gysel et al., 2021) also work in this direction.

Another trend is to make MRFs more expressive. This happens along three axes: One axis extends existing MRFs (as illustrated by AMR extensions for tense or scope modeling, see above); another axis uses multi-layer annotation schemes (as exemplified by UCCA or UDS); and yet another one employs more complex structures (as DRS does).

However, there is a trade-off between expressivity and simplicity of a MRF. The simpler an MRF is, the easier it is to generate training data sets. In fact, several works aim at reducing the annotation load: some aim at crowd-sourcing MRs (e.g., by re-formulating annotation tasks into simple questions White et al., 2016); others improve annotation tools (e.g., with a CodePilot machine-in-the-loop Cai et al., 2023); and again others create new, simpler MRFs, based on AMR (Feng et al., 2023) or DRS (Bos, 2023).

It is interesting to note that most works on AMR focus on increasing expressivity, while works on DRS tend to focus on improving simplicity. This might indicate hat the right balance lies somewhere between the two.

5.2 Trends in MR Parsing

Parsing. For humans, producing an MR is an arduous task, particularly for abstract frameworks: a trained annotator needs about 10 minutes to annotate a sentence in AMR (Banarescu et al., 2013). Therefore, much research has been dedicated to building automatic parsing systems, with many ideas shared between frameworks in Deep Meaning Representations Parsing, as highlighted by the SemEval shared tasks (Oepen et al., 2019, 2020). Traditional approaches to Neural MR Parsing usually fall into two main categories: graph-prediction, which try to identify nodes and the best edge assignment, and transition-based parsers, which build the graph iteratively with a restrained set of actions and a stack-buffer structure. Graph-prediction seems particularly suited for SDP, as the nodes are the input tokens bearing strong relations to syntactic dependency parsing (Almeida and Martins, 2015; Dozat and Manning, 2018). However, when integrated into a pipeline that performs concepts identification and afterwards relations prediction, it straightforwardly extends to AMR (Flanigan et al., 2014; Werling et al., 2015; Lyu and Titov,

2018) or EDS (Cao et al., 2021; Chen et al., 2019). Transition-based parsers seem suited to predict abstract structures, and were used for building UCCA parsers (Hershcovich et al., 2017; Jiang et al., 2019; Bölücü and Can, 2021), DRS parsers (Evang, 2019; Fancellu et al., 2019) and AMR parsers (Wang et al., 2015; Vilares and Gómez-Rodríguez, 2018). Most parsers now use sequence-to-sequence architectures (Ozaki et al., 2020; Samuel and Straka, 2020; van Noord et al., 2018, 2020; Bevilacqua et al., 2021; Zhou et al., 2021). These models take text as input, and output the linearized graph. However, there is a wide variety of learning strategies: graph pre-training (Bai et al., 2022; Wang et al., 2023), instruction fine-tuning (Lee et al., 2023), graph information distillation (Vasylenko et al., 2023), or even prompting (Ettinger et al., 2023). Other approaches mix deep learning with classical ideas, using the representations of language models in transition-based parsing (Astudillo et al., 2020; Zhou et al., 2021), graph-prediction parsing (Lyu and Titov, 2018), or ensembling (Hoang et al., 2021; Lorenzo et al., 2023).

Evaluation. The evaluation of graph-based MRs is 'classically' addressed through metrics such as SMATCH (Cai and Knight, 2013; Opitz, 2023) that measure the structural similarity of the output graph to a reference graph. Three main issues have been observed in SMATCH: First, the procedure it is inefficient, because computing graph isomorphism is NP complete. Different heuristics have been developed to remedy this problem, based on graph traversals (Song and Gildea, 2019; Liu et al., 2020) or SMATCH distillation (Opitz et al., 2023a). The second issue is that SMATCH evaluations consider only the graph structure, and fail to see, e.g., that a node `cat` is similar to a node `kitten` or a sub-graph `cat :mod young`. Different neural networks and graph algorithms are developed to remedy this issue (Opitz et al., 2020, 2021; Shou and Lin, 2023). Finally, SMATCH struggles to discriminate between strong parsers (Opitz and Frank, 2022a). Finer semantic graph measures are thus being developed, using neural networks or graph algorithms (Opitz et al., 2020, 2021; Shou and Lin, 2023; Kachwala et al., 2024). As an alternative approach to metric evaluation, MRF-specific 'challenge sets' are proposed for AMR (Groschwitz et al., 2023) and DRS (Wang et al., 2021a), to test parsers across a suite of tasks, e.g., difficult 'Winograd' pronouns (Levesque et al., 2012), or tense.

5.3 Trends in MR Application

We may wonder what is the place of MRFs in a domain dominated by always better-performing large language models (LLMs). However, different from LLMs, MRs make all facets of the meaning of a text explicit, which can provide **accuracy**, **control**, **robustness**, and **explainability** to any NLP pipeline. And indeed, these assets have been leveraged in several ways, also in combination with LLMs.

A 'classic' strategy is to use the MR as *supporting information*, which is exploited in a neural architecture. For this, MRs can be fed into sequence encoders as linearized strings (Ouyang et al., 2021; Xu et al., 2020), or into graph neural networks that exploit structure (Song et al., 2019; Xu et al., 2021; Lim et al., 2020; Ribeiro et al., 2022). Other works use discourse-level information to perform scene-aware attention (Slobodkin et al., 2022), or combine sentence and MR embeddings to refine representations (Cai et al., 2022).

Another strategy is to *exploit the graphs directly in symbolic or neuro-symbolic pipelines*, so as to control the results or explain them. Some works leverage MRs for improved paraphrasing (Cai et al., 2021; Huang et al., 2023) and style transfer (Jangra et al., 2022), neutralizing 'translationese' in translation references (Wein and Schneider, 2024), or link prediction (Yang et al., 2023). Other approaches apply MR-to-text generation after manipulating or splitting MR subgraphs, e.g., for data augmentation (Shou et al., 2022) or text simplification (Sulem et al., 2018b). Graph metrics are used to assist textual inference between pairs of sentences (Bonial et al., 2020; Opitz et al., 2023b). Other works use MRs for symbolic reasoning (Kapanipathi et al., 2021; Chanin and Hunter, 2023).

Yet another strategy is to *indirectly exploit* MRs: Opitz and Frank (2022b) partition text embeddings into interpretable linguistic features by binding distances between embedding parts to distances between MR-subgraphs that elicit, e.g., polarity, or semantic roles. A technical advantage of this is that a parser is not required at inference.

MRFs are thus being combined fruitfully with LLMs, contributing interpretability, useful intermediate representations, and a bridge towards formal logic.

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6 Limitations

Our survey is limited to graph-like meaning representations. While these are indeed the most popular meaning representations these days, there are others that could be discussed in this survey. Raymond Mooney's ground-breaking works (Mooney, 1996; Wong and Mooney, 2006; Mooney, 2007), e.g., or L. Zettlemoyer's work on CCG parsing (Kwiatkowski et al., 2011; Wang et al., 2014; Dasigi et al., 2019), aim at building MRs from a corpus for a target application. The compactness of this survey also prevents us from going more into detail for the parsing techniques. While we do discuss current methods and future trends, parsing itself could merit a survey. The majority of applications presented in Section 5 stem from AMR. This is simply because AMR is the most popular MRF, with very well-performing parsers. However, this does not mean that the other MRFs are less useful. They each have their unique properties that predispose them to different applications.

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