Actes de CORIA-TALN 2026
Nantes, France, 29 juin au 3 juillet 2026

A survey of young meaning representation formalisms

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RÉSUMÉ

Étude des formalismes émergents de représentation sémantique

Cet article présente un état de l'art de cinq formalismes récents de représentation sémantique : GKR, UMR, BMR, MR4AP et YARN. L'étude examine les motivations propres à chaque formalisme, les extensions formelles qu'ils proposent, les phénomènes linguistiques qu'ils visent à couvrir et, lorsque disponibles, les corpus et ressources associées. Elle est suivie d'une analyse comparative qui synthétise leurs choix de représentation ainsi que leurs points de convergence et de divergence. Ce travail fournit une base de référence pour analyser les évolutions actuelles de la modélisation sémantique et pour orienter les travaux futurs en analyse sémantique et en traitement automatique des langues.

ABSTRACT

This paper presents a survey of five recent semantic representation frameworks : GKR, UMR, BMR, MR4AP and YARN. The survey examines the motivations behind each formalism, the formal additions they introduce, the linguistic phenomena they target and, when available, the datasets and resources that support them, followed by a comparative analysis that synthesizes their representational choices, annotation assumptions and areas of convergence and divergence. This work provides an initial reference point for understanding current developments in semantic modeling and for guiding future work in semantic parsing and NLP applications.

MOTS-CLÉS : Représentation sémantique, formalismes de représentation du sens, sémantique en graphes, sémantique interlinguistique.

KEYWORDS: Semantic representation, meaning representation frameworks, graph-based semantics, Graphical Knowledge Representation (GKR), Uniform Meaning Representation (UMR), BabelNet Meaning Representation (BMR), Meaning Representation for Application Purposes (MR4AP), laYered meAning RepresentatioN (YARN), semantic parsing, cross-linguistic semantics.

1 Introduction

Meaning (or semantic) representation (MR) can be defined as a representation that reflects the meaning of a text as understood by a language speaker (Abend & Rappoport, 2017). Symbolic meaning representations of natural language text can be traced back to the 1960s (Sadeddine *et al.*, 2024). Earlier work such as Montague Semantics (Montague, 1970a,b, 1973) interpreted natural languages as formal languages. Early 2010s saw the emergence of more abstract and general purpose

Actes des 33ème Conférence sur le Traitement Automatique des Langues Naturelles.
Volume 1 : articles scientifiques originaux, pages 197–220.

MRs such as Abstract Meaning Representation (AMR) (Banarescu *et al.*, 2013) and Universal Conceptual Cognitive Annotation (UCCA) (Abend & Rappoport, 2013). The semantic content of MR schemes includes information related to events ; predicates and arguments ; core and non-core arguments ; semantic roles ; co-reference and anaphora ; temporal relation ; spatial relations ; discourse relations ; logical structure ; inference and entailment (Abend & Rappoport, 2017). Beyond their fundamental role in machine translation and summarization, MRs have found renewed utility in the age of LLMs. By providing a structured layer of interpretability, they enhance downstream tasks such as semantic search and natural language inference. Additionally, the structural rigor of MRs enables sophisticated text manipulation, including style transfer, paraphrase generation, and synthetic augmentation of training sets (Sadeddine *et al.*, 2024). An underlying issue with most MRs is that they tend to be rooted in English. In order to increase their applicability across various languages, some MRs are being developed with the integration of parallel corpora, generalized node labels, and more neutral structural frameworks (Sadeddine *et al.*, 2024). Certain MRs can go beyond sentence-level representation and are able to represent a multi-sentence document in a single MR. Discourse Representation Structure (DRS), the basic units in Discourse Representation Theory (DRT) (Kamp & Reyle, 1993) is an example of such MR. MR parsers also play a crucial role in the production of necessary resources. Modern parsers use sequence-to-sequence architectures, taking texts as input and generating the equivalent graph (Sadeddine *et al.*, 2024). Although SMATCH (Cai & Knight, 2013) has remained the most popular evaluation metric for graph-based MRs, it has many shortcomings (Anchiêta *et al.*, 2019), for example, it gives more weight to the root of the graph than other elements, distorting the analysis. Recent work involves moving away from evaluation metrics by proposing task suites for both AMR (Groschwitz *et al.*, 2023) and DRS (Wang *et al.*, 2021).

In this paper, we study five "**young**" formalisms : Graphical Knowledge Representation (GKR), Uniform Meaning Representation (UMR), BabelNet Meaning Representation (BMR), Meaning Representation for Application Purposes (MR4AP) and Layered Meaning Representation (YARN). Although there already exist several survey papers on older formalisms (Abend & Rappoport, 2017; Giordano & Lopez, 2023; Sadeddine *et al.*, 2024; Pavlova *et al.*, 2023b) only Pavlova (2025) covers these formalisms, and only briefly. However, we try to present each formalism in a much more detailed manner, accompanied by examples for each formalism. Finally, we extend the comparisons found in the existing literature (Sadeddine *et al.*, 2024; Giordano & Lopez, 2023) for the formalisms mentioned above and also present the fine-grained comparison presented in (Pavlova, 2025). Section 2 focuses on the foundational formalisms for the "young" formalisms, which are eventually presented, in chronological order, in the following section 3. Section 4 presents the comparison tables for the five formalisms. Before concluding with section 6, section 5 highlights certain limitations of our work.

2 Background

In this section, the main historical and theoretical formalisms underlying the recent meaning representation frameworks examined in this survey are introduced. More specifically, this section focuses on Abstract Knowledge Representation (AKR), which provides the conceptual basis for Graphical Knowledge Representation (GKR) ; Abstract Meaning Representation (AMR), which serves as a central point of departure for Uniform Meaning Representation (UMR), BabelNet Meaning Representation (BMR) and laYered meAning representatioN (YARN) ; and the Neo-Davidsonian treatment of events, which plays an important role in the event-centered architecture of YARN.

Graphical Knowledge Representation (GKR) is explicitly grounded in the Abstract Knowledge Representation (AKR) framework, originally developed to support precision-focused textual inference within a lexical-functional grammar (LFG) setting (Bobrow *et al.*, 2007). AKR was designed as a formally interpretable semantic representation capable of supporting logical inference, particularly in the context of natural language understanding systems. As explicitly stated in Kalouli & Crouch (2018), GKR inherits its core representational principles from AKR and reformulates them within a graph-based architecture suitable for automatic semantic parsing. AKR represents the meaning of a sentence through a structured decomposition of events, entities, properties, and relations (Bobrow *et al.*, 2007). In this framework, events are treated as discourse referents, and participants are linked to these events through semantically typed roles. This decomposition allows predicate–argument relations to be represented in an explicit and modular way, facilitating compositional interpretation and inference. Rather than encoding meaning as flat predicate structures, AKR organizes semantic content into interconnected units that make the underlying relational structure transparent. A defining characteristic of AKR, emphasized in both the original work and its adaptation within GKR, is the separation between conceptual structure and contextual commitments (Bobrow *et al.*, 2007; Kalouli & Crouch, 2018). The conceptual layer encodes the semantic relations among events and participants, while the contextual layer captures whether these elements are asserted, negated, modalized, presupposed, or embedded under propositional attitudes. This layered distinction enables systematic modeling of scope-related phenomena and supports inference over complex sentences. An example is given in Appendix A.1.

Abstract Meaning Representation (AMR) is introduced here because it constitutes a central point of departure for several of the formalisms examined in this survey. UMR builds directly on AMR's theoretical and representational foundations, BMR reuses and modifies AMR-style graph structures, and YARN adopts AMR as the basis of its layered representation. Abstract Meaning Representation (AMR) was introduced as a semantic formalism aimed at capturing the core meaning of sentences using a rooted, labeled, directed acyclic graph (Banarescu *et al.*, 2013). In AMR, the nodes of the graph correspond to concepts, which may take the form of English lexical items, PropBank framesets (Palmer *et al.*, 2005) that specify predicate senses, or special keywords used to represent abstract categories or semantic functions. Concepts are instantiated in the graph through variables that identify particular events or entities. The labeled edges connecting these nodes express a variety of semantic relations. AMR also provides dedicated relation types for representing lists, quantities, date-entities, and other structured semantic information. AMR applies several normalization conventions to ensure consistent semantic representation across sentences. Syntactic and morphological variants that express the same meaning are mapped to a unified conceptual structure, and pragmatically inferable arguments may be added even when they are not overtly expressed. Coreference is encoded through shared instance labels that link repeated references to the same entity or event. These practices allow AMR to abstract away from the surface form while preserving key semantic information. Efforts to extend its dataset to other genres, modalities, and additional languages are ongoing, supported by shared annotation guidelines and tools made available with the release (Bonn *et al.*, 2024). AMR has been used in several downstream tasks, including machine translation, question answering, semantic search, natural language inference and social reasoning (Sadeddine *et al.*, 2024). More information on AMR resources, parsers, visualization tools and evaluation metrics can be found on the GitHub page AMR-World. AMR objects are mainly [1] represented in two formats : (i) PENMAN format and (ii) graph format. An example is given in Appendix A.2. As shown in the example, AMR omits articles and it does not cover inflectional morphology such as tense and number. Moreover, AMR cannot handle scope phenomena : words like "all" are expressed as predicates. AMR expresses negation with *:polarity* and modals with concepts. For wh-questions, AMR uses the concepts *amr-unknown*.

1. A logic based format is also available in the original paper by Banarescu *et al.* (2013).

Both BMR and AMR are directed acyclic graphs (DAGs). However, they also have structural differences that are further elaborated in the dedicated Subsection 3.3.

Finally, the Neo-Davidsonian treatment of events is relevant because it provides an additional theoretical basis for YARN's event-centered architecture. Although YARN builds on AMR as its base representation, it also relies on the Neo-Davidsonian approach (Parsons, 1970). This approach extends the Davidsonian analysis (Davidson, 1967) of interpreting action verbs as an implicit *event* argument, by introducing thematic roles for events. Examples 2 and 3 show the Davidsonian and the Neo-Davidsonian transformations of the sentence shown in Example 1.

(1) Mary paints a picture in the park.

(2) $\exists e.(\text{paint}\ e\ \text{mary picture}) \wedge (\text{in}\ e\ \text{park})$

(3) $\exists e.(\text{paint}\ e) \wedge (\textbf{agent}\ e\ mary) \wedge (\textbf{theme}\ e\ picture) \wedge (\textbf{location}\ e\ park)$

MR4AP is not derived from any particular foundational MR. For this reason, it is not discussed separately in this background section. However, the motivations behind the creation of MR4AP are presented directly in the dedicated Subsection 3.4.

3 Recent Meaning Representation Formalisms

3.1 GKR : Graphical Knowledge Representation

Graphical Knowledge Representation (GKR) was introduced as a graphical operationalization of Abstract Knowledge Representation (AKR), a framework originally developed for precision-focused textual inference (Bobrow *et al.*, 2007). While AKR provides a formally structured representation of events, entities, and contextual commitments, it was not designed as a graph-based semantic parsing formalism. Its representations are primarily expressed in logical terms and were not intended for direct integration with dependency-based parsing pipelines. As discussed by Kalouli & Crouch (2018), this lack of an explicit graph architecture limits AKR's usability in modern semantic parsing systems, which rely heavily on structured graph outputs aligned with syntactic analyses. GKR was therefore introduced to preserve AKR's layered semantic distinctions while reorganizing them into an explicit multi-layer graph representation. This reformulation enables compatibility with dependency parsing input and facilitates computational manipulation of semantic structures.

In order to address these structural limitations, GKR introduces a set of formal additions that translate AKR's theoretical principles into an explicit, computationally operational graph architecture (Kalouli & Crouch, 2018). Rather than expressing meaning primarily in logical form, GKR organizes semantic information into a system of interconnected graphs aligned with syntactic dependency structure. First, GKR introduces an explicit dependency graph, derived from enhanced Universal Dependencies parses, which serves as the syntactic backbone of the representation. This layer provides the structural input from which semantic graphs are constructed, enabling systematic alignment between syntax and semantics. Second, GKR adds a lexical graph that links surface tokens to their corresponding conceptual nodes. This layer ensures traceability between the textual input and the semantic representation, making the mapping from words to meaning transparent and computationally manageable. Third, GKR formalizes the conceptual graph, which encodes events, entities, and their semantic relations as nodes and labeled edges. While this layer corresponds to AKR's core representational content, GKR explicitly structures it as a directed labeled graph, thereby making its relational architecture computationally explicit. Finally, GKR introduces an explicit contextual graph, that models contextual operators such as negation, modality, and propositional embedding. An example of GKR's layered representation is provided in Appendix A.3. By representing contextual commitments as graph structures rather than purely logical annotations, GKR enables systematic handling of scope and embedding phenomena within the overall architecture.

Kalouli & Crouch (2018) introduce GKR together with a rule-based parsing system that constructs semantic graphs from enhanced Universal Dependencies parses. The parsing procedure operates through deterministic transformation rules that map dependency structures to the corresponding semantic representation. An intrinsic evaluation is then conducted using a subset of the Hewlett–Packard (HP) test suite (Flickinger *et al.*, 1987), a controlled set of syntactic and semantic test sentences. The evaluation focuses on the coverage and correctness of the generated semantic graphs rather than on large-scale corpus-based benchmarking.

GKR has also been applied to natural language inference through Hy-NLI Kalouli *et al.* (2020), where it serves as the semantic representation layer for premise–hypothesis pairs and supports symbolic reasoning beyond semantic parsing.

A key strength of GKR is its formally grounded, multi-layer architecture, which preserves AKR's semantic distinctions while expressing them in an explicit graph structure (Kalouli & Crouch, 2018). The separation of dependency, conceptual, and contextual information enables transparent modeling of event structure and contextual phenomena such as negation and embedding. Its alignment with dependency parsing supports systematic construction from syntactic input. However, GKR has not been accompanied by a large annotated corpus or a widely adopted benchmark. The evaluation presented by Kalouli & Crouch (2018) is conducted on a controlled test suite and primarily demonstrates feasibility rather than large-scale robustness.

3.2 UMR : Uniform Meaning Representation

Although AMR has played a central role in advancing graph-based semantic representation and has provided a valuable foundation for research in semantic parsing, it remains limited in several important respects. As noted in its original specification, AMR does not encode inflectional morphology for tense, aspect, or number, and it omits articles, which results in the loss of grammatical distinctions that are essential for many languages (Banarescu *et al.*, 2013). AMR also lacks a universal quantifier and does not distinguish real, hypothetical, or non-actualized events, which can obscure important semantic contrasts. In addition, AMR relies heavily on English PropBank frames, which means that certain nominal predicates lack appropriate predicate senses, which limits the uniform treatment of related constructions (Banarescu *et al.*, 2013). To overcome these limitations, UMR was introduced as a scalable and learnable cross-linguistic meaning representation that abstracts away from morphosyntactic variation, supports lexical and logical inference, and provides a uniform graph-based framework capable of capturing the grammatical and discourse distinctions required for multilingual and document-level semantic analysis (Gysel *et al.*, 2021).

Building on these objectives, UMR introduces a set of formal additions that extend AMR's representational capacity at both the sentence level and the document level. At the sentence level, UMR refines event semantics through an explicit typology of aspectual classes, distinguishing states, habits, activities, endeavors, and performances. It also provides structured annotation for quantification and scope, which enables the systematic representation of universal, existential, and proportional quantifiers, as well as the interpretation domains over which they range. Importantly, UMR organizes these sentence-level features into a multi-layer architecture that separates conceptual structure, quantification, temporal-aspectual information, and discourse relations, thereby enabling clearer semantic distinctions (Gysel *et al.*, 2021). At the document level, UMR incorporates mechanisms for representing dependencies and relations that extend beyond individual sentences. This includes cross-sentence coreference, which links entities and events throughout the discourse, temporal dependencies that capture ordering and overlap between situations, and modal dependencies that reflect the epistemic and attitudinal perspective of a given conceiver. UMR makes this conceiver-based structure explicit, allowing modality, polarity, and factuality to be represented relative to the individual whose viewpoint anchors the interpretation (Gysel *et al.*, 2021). An example illustrating both the sentence-level graph and the document-level annotation is provided in Appendix A.4.

A UMR corpus has been published that covers six typologically diverse languages : English, Chinese, Arapaho, Navajo, Sanapaná, and Kukama (Bonn *et al.*, 2024). This dataset includes sentence-level graphs, which represent predicate-argument structures, named entities, word senses, aspectuality, and person and number information, and document-level graphs, which represent coreferential, temporal, and modal relations that extend across sentence boundaries (Bonn *et al.*, 2024).

Overall, UMR offers richer semantic detail than AMR by integrating the representation of sentence and document levels, including aspect, quantification, temporal relations, coreference and modal dependencies (Gysel *et al.*, 2021). It is therefore relevant for discourse-aware semantic parsing, although its corpus remains limited in size, annotation is complex, and mature parsers and standardized benchmarks are still lacking.

3.3 BMR : BabelNet Meaning Representation

BabelNet Meaning Representation (BMR) was created as a formalism that fully detaches from syntax and thus stands as a lexical-semantic representation that is able to bring different languages together (Martínez Lorenzo *et al.*, 2022). This MR is based on the two following repositories : BabelNet (Navigli & Ponzetto, 2010) and VerbAtlas (Di Fabio *et al.*, 2019). These two resources link word meanings and predicate-argument structures across languages. Significant work has been done in the past to design a MR that could reduce language-specific constraints and can be used as an interlingual representation. However, they all have some shortcomings. For example, although the semantic relations proposed by Universal Conceptual Cognitive Annotation (UCCA) (Abend & Rappoport, 2013) are not tied to specific languages, UCCA represents concepts as simple lemmas, making it difficult to abstract away from language specific constraints. Similarly, in Parallel Meaning Bank (PMB) (Abzianidze *et al.*, 2017) English sentences are parsed with labels that are automatically projected on non-English translations. But still it cannot be considered as an interlingual representation as it is based on English-specific repositories. Universal Meaning Representation (UMR) (Gysel *et al.*, 2021), on the other hand, enriches AMR by adding language-specific repositories and relations in order to turn the latter into a cross-lingual formalism. Nevertheless, its main focus remains on providing languages with the necessary resources to parse texts, rather than being an interlingual representation.

To build the BMR 1.0 dataset, the mapping performed by Di Fabio *et al.* (2019) was used to link VerbAtlas frames and arguments to PropBank. As the mapping was incomplete, a linguist was assigned the task of mapping between PropBank and VerbAtlas for the missing verbal predicates, while the remaining predicates were adapted to BMR by modifying existing semantic roles and introducing new ones when necessary. Additionally, in BMR the meaning of a multiword expression or idiom is represented with a single node. As a result, BMR abstracts away from language specific lexicon and reduces the graph density. BMR enriches AMR by adding extra grammatical information related to the nodes. Tense for verbal nodes are shown by the semantic role `:timing` where + indicates a future event and − indicates a past event. Similarly, the plurality of the nominal nodes are displayed by assigning the semantic role `:quantity` followed by a +. The notion of aspect is portrayed by adding the semantic role `:ongoing` to verbal nodes where the + mark expresses the imperfective aspect. Finally, BabelNet synsets information is added to the nodes in BMR graphs to make them language-independent. This process of disambiguation of nodes has two advantages : (i) resolving language ambiguity while representing word meaning explicitly, and (ii) interconnecting the same meanings across languages.

In BMR graphs, nodes are represented by triplets in the following format :

$$(id/lemma/Babel\, synset\, id)$$

Edges, by contrast, are represented by semantic relations preceded by a colon. Just like AMR, BMR graphs also consist of inverse relations. Finally, node hierarchy in BMR is represented by means of open and closed round brackets. An example is given in Appendix A.5 for reference.

As an interlingual formalism, BMR does have some constraints. First of all, BabelNet provides information for only the major parts of speech : nouns, verbs, adjectives and adverbs. As a consequence, BMR relies on language-specific lemmas for conjunctions or ambiguous pronouns such as *anyone*. Moreover, BabelNet 5.0 only features a small proportion of the existing languages, making the BMR formalism restricted to those 500 languages. Secondly, BabelNet has no lexicalization of language-specific concepts in other languages. Therefore, these concepts need to be paraphrased in order to be used across languages. Lastly, the word sense disambiguation process used to create the BMR 1.0 dataset cannot disambiguate polysemous words found in BabelNet but not in WordNet. Therefore, 8% of content nodes (i.e., nodes aligned with content words) in BMR are not disambiguated.

3.4 MR4AP : Meaning Representation for Application Purposes

Meaning Representation for Application Purposes (MR4AP) was created with an industrial context where it is crucial to have a formalism that is factual and explicit but also rich in salient linguistic phenomena (Giordano & Lopez, 2023). The remainder of this paragraph discusses some core features of MR4AP. First, MR4AP aims to be factual by making the annotation process strictly unambiguous. Not allowing the option to choose from possible annotation choices ensures that the subjective interpretation of annotators is avoided. Secondly, MR4AP strongly focuses on genericity : it is multilingual in nature, and thus it abstracts away from syntactic dependency. Moreover, the multi-rooted nature of MR4AP solves the problem of inverted arguments found in AMR[2]. In order to make MR4AP's representation as explicit as possible all relations between nodes are named. It uses a subset of VerbNet roles (with some added labels to specify temporal, spatial, discourse and coreference relations) and labels the type of entities to get rid of the need to look for their meanings. MR4AP is similar to UMR as both can be represented at the document and sentence levels. However, in contrast to UMR, these two levels are inseparable in MR4AP and all the discourse relations are present at both levels. Finally, MR4AP is rich in attributes. For instance, there are 7 possible labels for aspectual values (`habitual`, `state`, `process`, `atelic process`, `activity`,

2. AMRs are single rooted directed acyclic graphs (DAG). In order to preserve both these properties, an AMR role can be labeled with `ARG0-of` and its direction can be reversed. Multiple occurrence of such inversions may make an AMR graph multi-rooted and may lead to conception of new cycles within an AMR graph which is supposed to be acyclic.

endeavor and performance); 6 possible labels for modal values (obligation, capacity, suggestion, wish, uncertainty and temporality).

It is impossible to cover all the structural aspects of an MR4AP representation. The annotation guideline is available online at https://github.com/Emvista/MR4AP/blob/main/guidelines/guidelines.md. This paragraph gives a basic overview following the example provided in Appendix A.6. To begin with, MR4AP's graphs are directed graphs, consisting of nodes and relations. Each node can either be : a dynamic event (e.g., eat in "John ate an apple") ; a stative event (e.g., type in "John is a doctor") ; or a feature (aspect, modality, etc.). Nodes can represent (named) entities. Those entities are semantically typed. Nodes are connected by relations. These relations can either be : a thematic role (subset of VerbNet's thematic roles (Schuler, 2005)) ; a discursive, temporal, spatial relation tag (e.g., Condition, TimeMax, Location) ; or a coreference relation (SameAs). Returning to the example, the main event will be the verb finir associated to its English counterpart stop. This event has many feature nodes : Aspect having as value performance ; Polarity having as value positive ; Theme having as value Transfer_mesg which is used for Conférence ; TimeMax having as value 2023-03-23T23:59:04 ; TimeMin having as value 2023-03-23T00:00:00. The node representing Conférence also has its own feature nodes : Aspect having as value process ; Theme having as value 1. To summarize, the graph uses an internal knowledge base for specific event or entity instances (e.g., kb:159279316), the Web Ontology Language (OWL), RDF Syntax and RDF Schema as resources to instantiate the MR4AP formalism represented in the example [3](9).

Currently, there are three MR4AP corpora : (i) MR4AP-tapaco consisting of 100 short French sentences from the **TaPaCo corpus** (Scherrer, 2020) ; (ii) MR4AP-wikinews consisting of 5 manually annotated sentences for each of the randomly selected French Wikinews articles ; (iii) MR4AP-wikipedia consisting of 5 manually annotated sentences for each of the 3 randomly selected French Wikipedia articles. The data of these annotated files were automatically translated into English, Spanish, Italian, and Modern Standard Arabic (MSA) and finally manually annotated. The data is stored as JSON files with three fields : id (the text id), text (the plain text), and rdf [4] (the corresponding RDF representation containing the annotations). MR4APs were annotated using INCEpTION platform (Klie *et al.*, 2018).

Overall, MR4AP presents itself as a robust formalism capable of handling complex phenomena such as event coreference, interrogative sentences, and multiword expressions (MWEs). Nevertheless, for long texts or within multilingual setup the annotation process gets complex and time-consuming. The compatibility towards multilingualism should be studied more by expanding the horizon of language families or by annotating in low-resource setup.

3.5 YARN : laYered meAning RepresentatioN

Based on the ability to encode various semantic phenomena, semantic representation formalisms can be broadly categorized into **logic-based**, such as Montague semantics, Discourse Representation Theory (DRT) etc., and **graph-based**, such as Abstract Meaning Representation (AMR), Universal Conceptual Cognitive Annotation (UCCA) (Pavlova *et al.*, 2024; Pavlova, 2025) etc. Although the former category precedes the latter in terms of encoding power, the latter wins back at ease of readability and interpretability. The main motivation behind introducing YARN is to bridge the gap

3. It should be noted that this instantiation could have been done using any other resource(s). For instance, the original paper (Giordano & Lopez, 2023) uses VerbNet classes to define the main events of an example.

4. The example shown in Appendix A.6 is derived from the field rdf and visualized with the web service RDF Grapher

between these two categories and propose a formalism that can have the best of both worlds. YARN borrows the predicate-argument structure from AMR and builds a layered structure on top of it. Each of these layers encodes a semantic phenomenon and can be "switched off" if needed. This ensures that the overall representation can express various phenomena such as quantification, temporality, modality, negation, among others, all while offering a clean representation.

Following the Neo-Davidsonian approach, YARN puts the events at the center of the representation. YARN proposes different types of nodes and relation types (Pavlova *et al.*, 2023a). An S-node ($s \in S$) represents an entire event, differentiating it from its predicates, which are represented as nodes ($v \in V$). Then, edges are added ($e \in E$) to link the nodes. These edges express the argument role of each predicate and are labeled. YARN mirrors AMR and AMR-based formalisms by borrowing the PropBank based predicates and argument roles. On top of this base, multiple features ($f \in F$) are added to illustrate various semantic phenomena. Each of these features is attached to an S-node. Then, a new type of edge ($l \in L$ for layers) is introduced, connecting a feature to a node. Following that, three new types of edges (belonging to the sets h_{f_E}, h_{f_L} and h_{L_v} respectively) are added : to link a feature$f$ and an edge e; to link a feature$f$ and a layer l; to link a layer l and a node v. Finally, s-nodes are linked via another type of edge ($d \in D$) and a node and an S-node are linked via another type of edge ($c \in C$) and nodes are linked via the ultimate type of edges ($x \in I$). All types of edges are directed except the ultimate type. This leads to the formal definition of YARN which is an 11-tuple where $S =$ state, $V =$ vertex, $E =$ edge, $F =$ feature, $L =$ layer, $h =$ hyperedge, $D =$ discourse, $C =$ clause, $I =$ interpretation (Pavlova, 2025).

$$\langle S, V, F, D, E, C, L, h_{f_E}, h_{f_L}, h_{L_v}, I \rangle$$

It is important to note that the standard YARN format is not a graph. Equivalent graph structures are also proposed where each YARN element is represented as a node in a graph and the edges represent a direct interaction between the objects they connect (Pavlova, 2025). Moreover, each node is also assigned a type to guarantee that no information is lost in the transformation. An example of YARN is shown in Appendix A.7.

A YARN-annotated corpus is available online on GitLab in which YARNs representations are stored in JSON format. This corpus is split into two sub-corpora : PUD 100 and PMB 25, both are available in their standard YARN format and their graph versions. An example of the second sub-corpus is illustrated in Appendix A.7. PUD 100 is a sub-corpus built from the 100 shortest instances of the English version of Parallel Universal Dependencies (PUD) corpus. PMB 25 consists of 102 instances in English taken from the version 4.0.0 of Parallel Meaning Bank (PMB). Both sub-corpora were first annotated with AMR because AMR forms the base of YARN. The annotation procedure involved drawing the YARN representations digitally and then manually annotating their corresponding JSON versions. Finally, a visualization tool was developed to visualize the YARNs.

In terms of limitations, YARN is focused solely on English and thus covers phenomena related to English only. In addition, idiomatic expressions and intricacies of possible world semantics are also not considered in YARN. Another drawback of YARN is its goal to cover as many phenomena as possible without going into the finer distinctions of each phenomenon. This width-centric approach (as opposed to a more depth-centric approach) makes a YARN object more complex. Even a graphical representation of the same can still be cumbersome for machines to process, making its application challenging (Pavlova, 2025).

4 Comparative Analysis

In this section, we present a comparative analysis of the formalisms discussed above. We take inspiration from two previous survey papers : Sadeddine *et al.* (2024) and Giordano & Lopez (2023). The former does not cover any of the five formalisms while the latter covers UMR, BMR and MR4AP. We extend their works for all five formalisms in Tables 1 and 2 respectively.

Several remarks are necessary for Table 1. First, the standard form of YARN is not a graph even though it could be transformed into graphical structures. In terms of composition, YARN was not designed with this feature as one of its underlying principles. When it comes to the node types, as mentioned earlier, MR4AP can be instantiated with any available resource(s) of our choice. GKR, on the other hand, has concepts borrowed from AKR. In terms of semantic roles, they can either be predicate-dependent where the same semantic role can indicate different entities based on the predicate in question. Alternatively, they can be predicate-independent to illustrate more specific and fine-grained semantic roles.

MRF	Subevents	Shape	Compositional	Node type (Flavor)	Edge type
GKR	✓	Graph	✓	Concepts(AKR-style)	predicate-independent
UMR	✓	Graph	-	Synsets(Propbank)	predicate-dependent
BMR	✓	Graph	-	Synsets(BabelNet)	predicate-independent
MR4AP	✓	Graph	✓	resource agnostic	predicate-independent
YARN	✓	not a graph	-	Synsets(Propbank)	predicate-dependent

TABLE 1 – Extended comparison table from Sadeddine *et al.* (2024)

	GKR	UMR	BMR	MR4AP	YARN
Multilingual		✓	✓	✓	
Invariance	✓	✓	✓	✓	✓
Multi-sentence	✓	✓	#	✓	✓
P-A structure	✓	✓	✓	✓	✓
Named relation	✓	#	✓	✓	#
Semantic typing	✓	✓	✓	✓	✓
Anaphora & coreference	✓	✓	✓	✓	✓
Event coreference	✓	✓	✓	✓	✓
Temporal relation	✓	✓	#	✓	✓
Discourse relation		#	#	✓	✓
Modal relation	✓	✓			✓

TABLE 2 – Extended comparison table from Giordano & Lopez (2023)

For Table 2, several features are clarified in the following to make the analysis more comprehensible.

— **Invariance** : It signifies whether semantically equivalent expressions receive the same or highly similar representations despite differences in syntactic configuration.

— **Named relation** : To make a formalism more explicit, all semantic roles must be named. In the absence of this feature, a gloss would be required to understand the opaque semantic roles.

— **Semantic typing** : As with the previous feature, specifying a type for each entity is necessary to make a formalism more explicit.

We omit the final feature **Attribute richness** from the original table because its + based grading lacks clear criteria, making the analysis subjective and unsuitable for our work. Moreover, Partial coverage (#) indicates that a feature is either supported only in certain extensions of the formalism or covered in a limited way.

Finally, a more fine-grained analysis is presented in Appendix B from Pavlova (2025). Although this analysis does not cover BMR, we still believe that our simple analysis serves as a good starting point for digging deeper into the much more complex analysis shown in Table 3.

5 Limitations

This survey provides a detailed comparison of the young semantic frameworks GKR, UMR, BMR, MR4AP and YARN, yet several limitations remain. First, the survey does not cover specialized semantic annotation schemes such as QuantML, discussed by Bunt (2024), since its scope is restricted to quantification phenomena and it is better understood as a complementary semantic module rather than as a full meaning representation framework. Similarly, although UCCA and DRT are mentioned where relevant, they are not developed in the Background section, as the latter is restricted to the foundational formalisms most directly underlying the surveyed representations. Second, the comparison is constrained by the uneven availability of empirical resources in the surveyed formalisms. No publicly available annotated corpora were identified for AKR or GKR, while the BMR corpus is not publicly released. Consequently, the examples used in this survey come either from available corpora or from the original papers, and their differences in language, length and semantic content limit a fully controlled structural comparison. Third, the frameworks differ widely in their objectives, annotation choices, and representational assumptions, which makes it difficult to apply fully uniform comparison criteria in the tables. These limitations make the comparison a preliminary assessment, to be refined as more corpora, parsers and benchmarks become available. Finally, future work could extend the fine-grained comparison presented in Table 3 (Appendix B) by incorporating BMR, which was not included in the original comparative analysis proposed by Pavlova (2025).

6 Conclusion

This survey provided a unified perspective on five young semantic formalisms : GKR, UMR, BMR, MR4AP and YARN. It examined their motivations, their relation to earlier frameworks such as AKR and AMR, the formal extensions they introduce, the linguistic phenomena they cover, and the resources currently available for their study. The comparative analysis shows that these formalisms do not follow a single direction of development, but respond to different representational needs. GKR is mainly relevant for inference-oriented representations grounded in contextual commitments, UMR targets cross-linguistic and document-level semantic annotation, BMR focuses on interlingual lexical-semantic representation through BabelNet synsets, MR4AP is designed for explicit, factual and application-oriented annotation, and YARN aims to combine broad semantic coverage with a layered architecture. To make the comparison more concrete, examples of each formalism are provided in Appendix A, together with brief descriptions of their structural elements. The survey does not aim to identify a single best meaning representation, since such a conclusion would require task-specific implementation and empirical evaluation. As larger corpora, parsers and benchmarks become available, future work will be able to compare these formalisms more systematically and assess their usefulness for semantic parsing, reasoning and downstream NLP applications.

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A Detailed Examples

A.1 AKR

Example (4) is reproduced from the original AKR formulation presented by Bobrow *et al.* (2007). It demonstrates how AKR distinguishes between the subject matter of a sentence (conceptual structure) and the speaker's commitments regarding existence and embedding (contextual structure), with temporal relations represented separately.

(4) Bush claimed that Iraq possessed WMDs.

Conceptual Structure

```
subconcept(claim:37,[claim-1,...,claim-5])
role(Topic,claim:37,claim_cx:37)
role(Agent,claim:37,Bush:1)
subconcept(Bush:1,[person-1])
alias(Bush:1,[Bush])
role(cardinality_restriction,Bush:1,sg)
subconcept(possess:24,[possess-1,possess-3])
role(Destination,possess:24,wmd:34)
role(Agent,possess:24,Iraq:19)
subconcept(Iraq:19,[location-1,location-4])
alias(Iraq:19,[Iraq])
role(cardinality_restriction,Iraq:19,sg)
subconcept(wmd:34,[weapon_of_mass_destruction-1])
role(cardinality_restriction,wmd:34,pl)
```

Contextual Structure

```
context(t)
context(claim_cx:37)
context_relation(t,claim_cx:37,crel(Topic,claim:37))
instantiable(Bush:1,t)
instantiable(Iraq:19,t)
instantiable(claim:37,t)
instantiable(Iraq:19,claim_cx:37)
instantiable(possess:24,claim_cx:37)
instantiable(wmd:34,claim_cx:37)
```

Temporal Structure

```
temporalRel(After,Now,claim:37)
temporalRel(After,claim:37,possess:24)
```

In AKR, indexed labels are used to represent events, entities and discourse referents. For instance, `claim:37` refers to an instance of the concept claim, while `Bush:1`, `Iraq:19` and `wmd:34` refer to entity instances. The predicate `subconcept` links each instance to its conceptual category, whereas `role` specifies semantic relations such as `Agent`, `Topic` and `Destination`. What is particularly important in AKR is the separation between conceptual and contextual structure : the former encodes the predicate-argument content of the sentence, while the latter indicates the contexts in which this content is asserted or embedded. In Example (4), the possession of WMDs is represented inside the context of Bush's claim, rather than as a direct commitment of the speaker.

A.2 AMR

Example (5) taken from the The Little prince corpus 3.0 and it can be visualized at Grew Semantics. The PENMAN format is given below :

(5) Here is a copy of the drawing.

```
(b / be-located-at-91
      :ARG1 (t2 / thing
            :ARG2-of (c / copy-01
                  :ARG1 (p / picture
                        :ARG1-of (d / draw-01))))
      :ARG2 (h / here))
```

The equivalent graphical representation is illustrated in Figure 1.

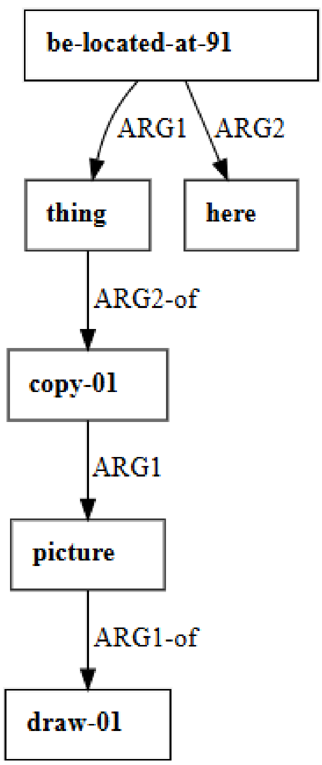

FIGURE 1 – Graph format

In Neo-Davidsonian fashion, in AMR variables are employed for entities, events, properties, and states (Banarescu *et al.*, 2013). "`p / picture`" refers to the instance (called `p`) to the concept picture. AMR heavily uses PropBank frame arguments, such as `:ARG0`, `:ARG1`, `:ARG2` shown above. Inverse relations such as `:ARG1-of` and `:ARG2-of` shown above are also employed, if needed, in order to maintain a rooted structure of the graph. What is interesting is that even for nouns, such as "copy" and "drawing" in this example, AMR strictly sticks to the corresponding verbs' framesets [5]. For example, the frameset "`draw-01`" has three pre-defined slots (`:ARG0` is the artist, `:ARG1` is the art and `:ARG2` is the benefactive). Thus, `p` is expressed as the `:ARG1` of the frameset "`draw-01`", using an inverse relation.

A.3 GKR

Example (6) is reproduced from the original GKR formulation presented by Kalouli & Crouch (2018). Figure 2 shows the layered structure of the representation containing the conceptual graph on the left encodes the predicate–argument structure of the sentence and the contextual graph on the right which captures the existential commitments introduced by the implicative verb *fake*.

(6) The boy faked the illness.

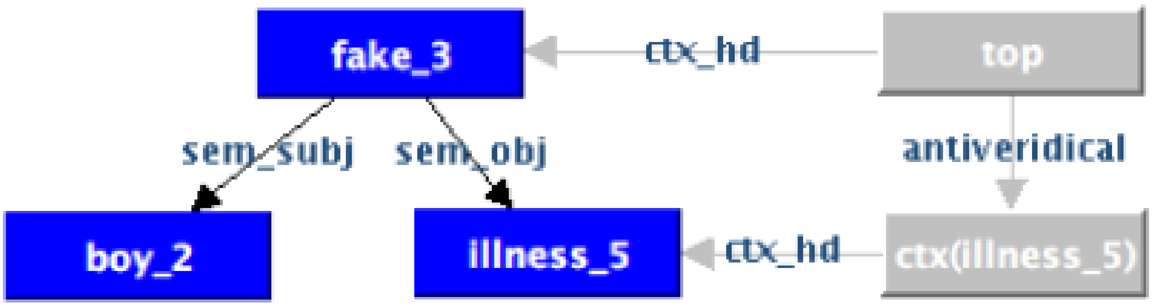

FIGURE 2 – Conceptual and contextual sub-graphs in GKR for *The boy faked the illness*

In this GKR example, the conceptual graph represents the predicate-argument structure of the sentence. The node `fake_3` represents the event expressed by *fake*, while `boy_2` and `illness_5` correspond to its semantic participants. These participants are linked to the event through the relations `sem_subj` and `sem_obj` that indicate the semantic subject and object. The contextual graph, shown on the right, captures the status of the embedded content. The relation antiveridical indicates that the illness is not presented as an actual fact, but as an unreal or non-instantiated situation introduced by the implicative verb *fake*. Thus,the example illustrated how GKR separates the conceptual content of a sentence from its contextual interpretation.

5. The list of PropBank framesets is available online at https://propbank.github.io/v3.4.0/frames/.

A.4 UMR

Example (7) is taken from the UMR 1.0 corpus (Bonn *et al.*, 2023). It demonstrates the multi-layered nature of UMR, comprising a sentence-level semantic graph and a document-level structure.

(7) Naval ships will be used as floating hospitals and command centres for relief and rescue.

Sentence-level graph

```
(S / say-01
    :ARG0 (s11p / person)
    :ARG1 (s11u / use-01
        :ARG0 (s11o / organization)
        :ARG1 (s11s2 / ship
            :mod (s11n / navy))
        :ARG2 (s11a / and
            :op1 (s11h / hospital
                :ARG1-of (s11f / float-01))
            :op2 (s11c / center
                :mod (s11c2 / command-02
                    :aspect process)
                :purpose (s11a2 / and
                    :op1 (s11r / relieve-01
                        :ARG0 s11o
                        :ARG1 (s11p2 / person)
                        :aspect process)
                    :op2 (s11r2 / rescue-01
                        :ARG0 s11o
                        :ARG1 s11p2
                        :aspect process))))
        :aspect process
        :quote s11s)
    :aspect performance)
```

Document-level annotation

```
(S / sentence
    :temporal ((s10s :after s11s)
            (s11s :after s11u)
            (s10h :after s11u)
            (s11u :overlap s11c2)
            (s11u :overlap s11r)
            (s11u :overlap s11r2))
    :modal ((root :modal author)
            (author :full-affirmative s11s)
            (author :full-affirmative s11p)
            (s11p :full-affirmative s11u)
            (s11p :full-affirmative s11c2)
```

```
          (s11p :full-affirmative s11r)
          (s11p :full-affirmative s11r2))
    :coref ((s2t :subset-of s11s)
          (s10p :same-entity s11p)
          (s9t :same-entity s11o)
          (s8p :same-entity s11p2)))
```

Figure 3 presents the sentence-level UMR graph corresponding to Example 7, automatically generated from its PENMAN representation using Graphviz.

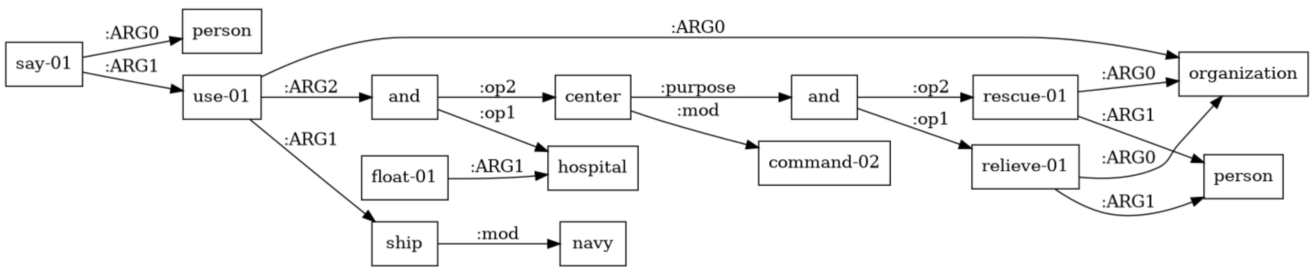

FIGURE 3 – Sentence-level UMR graph for Example 7, generated from its PENMAN representation.

In this UMR example, the sentence level represents the predicate-argument level of the sentence with `use-01` as the main event and `ship`, `hospital` and `center` as the central semantic nodes. UMR also adds semantic features such as `aspect`, as shown by values like `process` and `performance`. The document-level annotation complements this graph by encoding relations that go beyond the sentence itself, including `temporal`, `modal`, and `conference` links. This illustrates how UMR combines sentence-level meaning with document-level semantic dependencies.

A.5 BMR

Example (8) is reproduced from the original BMR formulation presented by Martínez Lorenzo *et al.* (2022).

(8) The students and their parents will take the plane at the last minute.

```
--AMR--

(t/ take-01
   :ARG0 (a / and
      :op1 (p / person
         :ARG0-of (s / study-01))
      :op2 (p2 / person
         :ARG0-of (h / have-rel-role-91
            :ARG1 p
            :ARG2 (p3 / parent))))
   :ARG1 (p4 / plane)
   :time (t2/ minute
      :mod (l / last)))

--BMR--

(t / take / bn:00094732v
   :timing +
   :agent (a / and
      :op1 (s / student / bn:00029806n
         :quantity +)
      :op2 (p / parent / bn:00060643n
         :quantity +
         :related s)
   :theme (p2 / plane / bn:00001697n)
   :timing (t2 / at_the_last_minute
            / bn:00114428r))
```

FIGURE 4 – Figure comparing the AMR and BMR representation of the same sentence

Here, `t` represents the unique identifier of the node represented by the lemma `take` whose Babel synset id is `bn:00094732v`. The additional grammatical feature of the tense is applied to this verbal node by applying `:timing` where + refers to the future tense. This verbal node takes as arguments `:agent`, `:theme` and `:timing`. In the example, the agents are the "students" and their "parents"; the theme is the "plane" and the timing is the prepositional phrase "at the last minute". To show the plurality of the nouns "student" and "parent", the additional feature for number `:quantity` followed by a + mark is added. Lastly, to show that the nominal nodes `student` and `parent` are related, the node id `p` of the latter is equipped with the semantic relation `:related` with the node id `s` of the former.

A.6 MR4AP

Example (9) is a very short French sentence taken from the available MR4AP-tapaco corpus (v0.1). The JSON file containing the example has the following structure. The corresponding RDF graph is shown in Figure 5.

(9) La conférence finira demain.


```
{
    "id": "00006",
    "text": "La conférence finira demain.",
    "rdf": ":mr4ap/kb/100000063 a owl:NamedIndividual,
           :mr4ap/ontology/TimeMax,
           :Httpwwww3org200207owlNamedIndividual;
```

```
  rdfs:label \"2023-03-23T23:59:04.828859856\" .

:mr4ap/ontology/TimeMax a owl:NamedIndividual .

:Httpwwww3org200207owlNamedIndividual a owl:NamedIndividual .

:mr4ap/kb/100000064 a owl:NamedIndividual,
        :mr4ap/ontology/TimeMin,
        :Httpwwww3org200207owlNamedIndividual;
  rdfs:label \"2023-03-23T00:00:00.828859856\" .

:mr4ap/ontology/TimeMin a owl:NamedIndividual .

:mr4ap/kb/159279316 a owl:NamedIndividual,
        :mr4ap/ontology/Event,
        :mr4ap/ontology/Stop;
  :has_theme :mr4ap/kb/1750180486;
  :has_timemax :mr4ap/kb/100000063;
  :has_timemin :mr4ap/kb/100000064;
  :has_aspect \"performance\" ;
  :has_polarity \"Pos\" ;
  rdfs:label \"finira\" .

:mr4ap/kb/1750180486 a owl:NamedIndividual,
        :mr4ap/ontology/Event,
        :mr4ap/ontology/Transfer_mesg,
        :Httpwwww3org200207owlNamedIndividual;
  :has_aspect \"process\" ;
  :has_theme \"1\" ;
  rdfs:label \"Conférence\", \"conférence\" .

:mr4ap/ontology/Event a owl:NamedIndividual .

:mr4ap/ontology/Stop a owl:NamedIndividual .

:mr4ap/ontology/Transfer_mesg a owl:NamedIndividual .
}
```

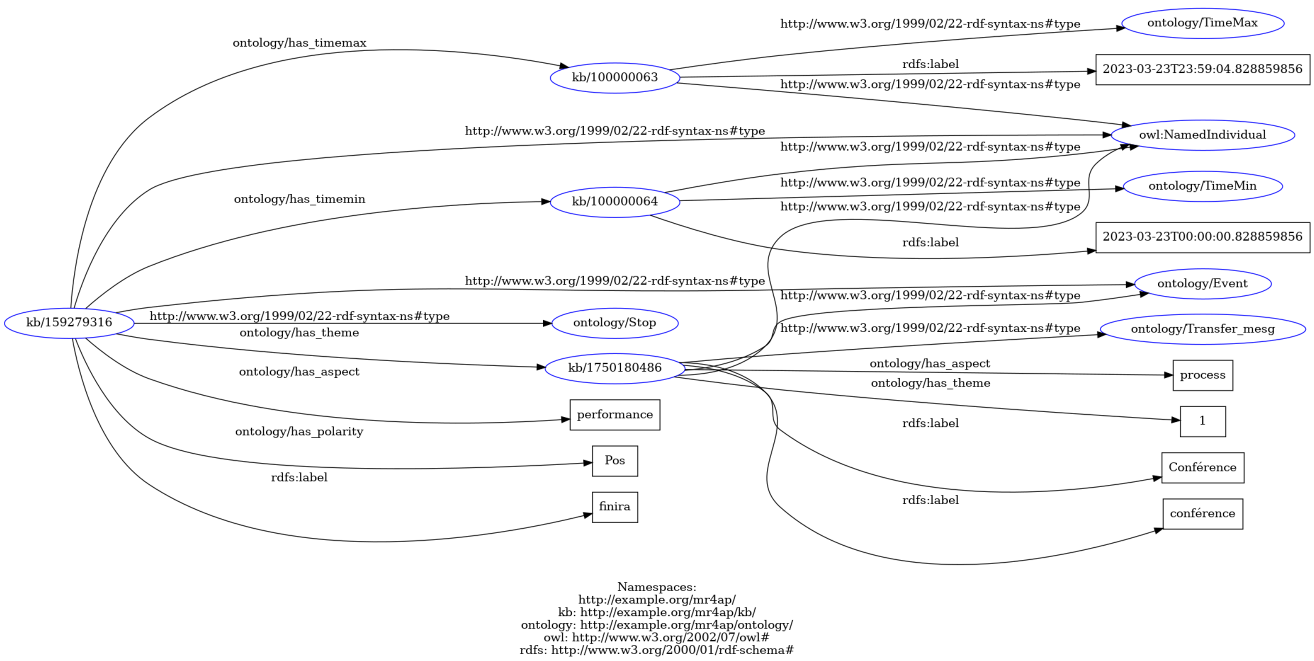

FIGURE 5 – MR4AP RDF graph representation

The structure of this example has been briefly described in Subsection 3.4.

A.7 YARN

The YARN representation of example (10) is shown in Figure 6 and its equivalent graph in Figure 7. From this example, we can have a formal representation as follows :

(10) He isn't running.

$$
\begin{aligned}
S &= \{s_1\} \\
V &= \{run\text{–}02 : run\text{–}02, he : he\} \\
F &= \{temp, aspect, neg\} \\
E &= \{e_1 : (run\text{–}02, ARG0, he)\} \\
L &= \{l_1 : (temp, past, run\text{–}02), \\
&\quad\ l_2 : (aspect, progressive, run\text{–}02), \\
&\quad\ l_3 : (neg, \_, run\text{–}02)\}
\end{aligned}
$$

Here, `s1` represents the entire event. `run-02` and `he` are the two nodes and `ARG0` is the edge that connects these two nodes. Three features named `temp`, `aspect` and `neg` are added to `s1`. They represent three different semantic phenomena : tense, aspect and negation. Finally, three layers `l1`, l2 and l3 are introduced to connect these three features to the node run-02. It is evident that this example does not cover all the nodes and edges of the formal definition. For an all-inclusive example, please refer to pages 67–70 of Pavlova (2025).

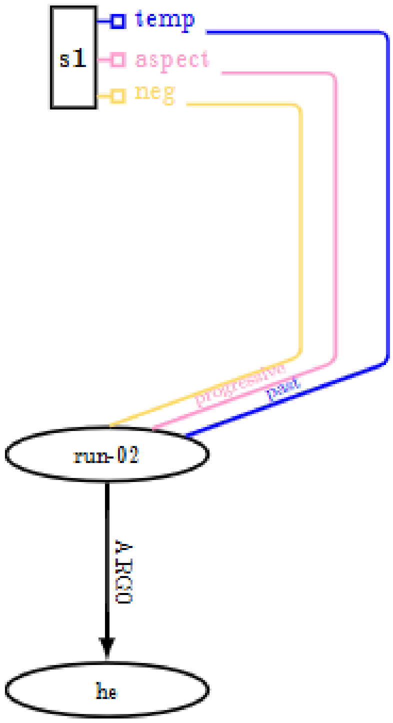

FIGURE 6 – Standard YARN format

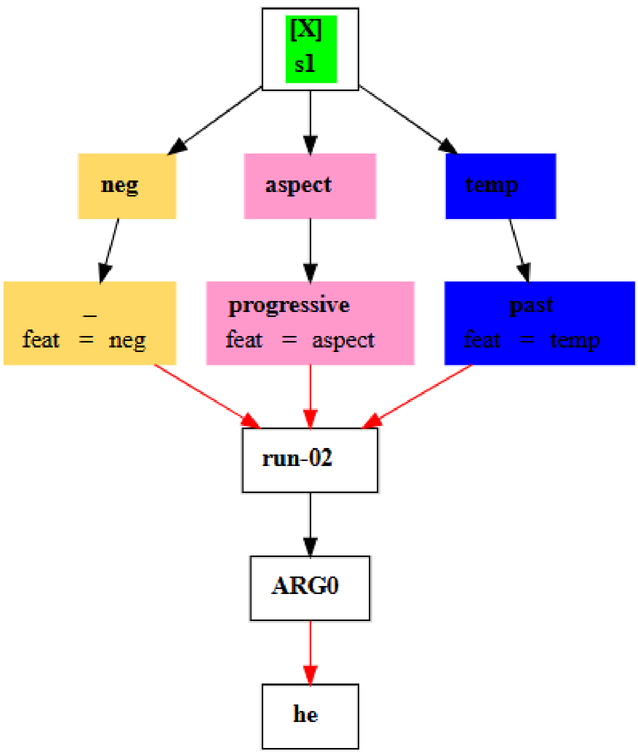

FIGURE 7 – YARN-equivalent graph format

B Continuation of the comparative analysis

	GKR	UMR	MR4AP	YARN
Scalability	✓†	✓†	?	?
Datasets (size)	toy	toy†	medium	medium
Universality	?	✓†	✓	?
Datasets (# lang)	-	-†	5	1
Unicity	✗	✗	✓	✗
Flavor	2	2	2	2
Lexical Resources	✓	✓	✗††	✓
Pred-arg	generic	specific	generic	specific
Temporality	2	2	2	2
Aspect	✓	✓	✓	✓
Spatial	✗	✗	✗	?
Reification	✗	✓	✓	✓
Scope	✓	✓	?	✓
Scope ambiguity	✗	✗	✗	✓
Negation	2	2	2	2
Modality	2	2	1	2
Evidentiality	1	1	1	1
Logical Inference	✓	✓	✗	?
Distributivity	✗	✗	✗	✓
Generation	✓	✓	✓	✓
Analysis	✓	✓	✓	✓
Compositionality	✓	✗	✓	?
SSI	✓	✗	✗	?
Multi-sentence	✓	✗	✓	✓
Questions	0	2	2	2

TABLE 3 – Contracted comparison table from Pavlova (2025)

— ? = possibly, but incomplete or no empirical proof.
— *Temporal*, *Evidentiality* : 1 = only surface, but not grammatical ; 2 = yes ; *Negation*, *Modality* : 1 = encoded, but without scope ; 2 = encoded with scope ; *Questions* : 0 = no special way to encode ; 1 = only wh-questions encoded ; 2 = all types of questions encoded.
— † UMR is designed with scalability and universality in mind, but it is a young formalism and both aspects remain to be verified ; GKR is likewise a young formalism, but the highly automated nature of producing annotations from UD graphs is likely to be an advantage for scaling.
— In flavor 2 formalisms, there are no explicit links defined between graph nodes and surface tokens.
— †† Examples of MR4AP representations usually refer to PropBank or VerbNet predicate senses, but those are only for example purposes.
— ? MR4AP scalability is yet to be verified. Universality : GKR is built for English, but the authors see GKR itself as highly language-independent. MR4AP encodes modality and negation scope, but not quantifier scope.