MASSIVE Multilingual Abstract Meaning Representation: A Dataset and Baselines for Hallucination Detection

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Abstract

Abstract Meaning Representation (AMR) is a semantic formalism that captures the core meaning of an utterance. There has been substantial work developing AMR corpora in English and more recently across languages, though the limited size of existing datasets and the cost of collecting more annotations are prohibitive. With both engineering and scientific questions in mind, we introduce MASSIVE-AMR, a dataset with more than 84,000 *manually annotated* items, currently the largest and most diverse of its kind: AMR graphs for 1,685 information-seeking utterances mapped to 50+ typologically diverse languages. We first describe how we constructed our resource and detail many of its unique characteristics before reporting on experiments using large language models for multilingual AMR and SPARQL parsing as well as experiments utilizing AMRs for hallucination detection in the context of knowledge base question answering, with results shedding light on persistent issues using LLMs for structured generation.

1 Introduction

Knowledge base question answering (KBQA) has a long history in natural language processing, with the task of retrieving an answer from a knowledge base (KB) such as Wikidata or DBPedia (Lehmann et al., 2015) integral to many large-scale question answering systems (Kapanipathi et al., 2021). In KBQA, a natural language question is converted into a structured query language such as SPARQL, an executable semantic parse. However, data to train models is expensive, few multilingual resources are available, and performance is limited for long-tail queries when generative models are prone to hallucinate relations, a problem compounded by arbitrary variability in form-meaning mappings across languages (Croft, 2002).

Most notably, research in multilingual KBQA is hindered by lack of data (Usbeck et al., 2018; Cui et al., 2022; Perevalov et al., 2022). To address this, we create a dataset 20 times larger and with 5-6 times more languages than currently available (Table 1) selecting 1685 QA utterances with existing manual translations from the MASSIVE corpus (FitzGerald et al., 2022) and manually compose Abstract Meaning Representation (AMR) for each (Banarescu et al., 2013), amounting to 84,000 gold text-to-graph annotations, a significant boon to AMR and KBQA research.

	AMR3.0	**QALD9-AMR**	**MASSIVE-AMR**
# of languages	1	9+	52
# utterances (utt)	59K	508	1685
# utts-to-graphs	59K	5K	84K
mean tokens/utt	15.9	EN: 7.5	EN: 8.2
AMR nodes	EN	EN	EN+local

Table 1: Existing AMR corpora compared with our dataset, MASSIVE-AMR. QALD9-AMR and MASSIVE-AMR target multilingual QA utterances.

Graphs with localized entities (Table 2) and the long-tail utterances in MASSIVE-AMR (Appendix A.2) increase the complexity of our multilingual dataset (Section 3). To explore the utility of our resource, we examine how to leverage AMRs to gauge a model's confidence in SPARQL query generation (Section 4), reporting on multilingual structured generation and SPARQL relation hallucination detection using large language models (LLMs) (Section 5).

Our research contributions thus include: (1) creation of the largest-scale multilingual AMR question corpus to date; (2) evaluation of LLMs on generation of SPARQL and AMRs structures across languages; and (3) design, development, and evaluation of generative models leveraging AMRs for SPARQL relation hallucination detection. We will publicly release the MASSIVE-AMR training and validation data upon publication[1].

[1]Sample prompts, code, and data: https://github.com/anon-thistle-palms/anon-massive-amr

	Utterance	AMR
MASSIVE-AMR	when was obama born	(b / bear-02 :ARG1 (o / “obama") :time (u / unknown))
	quand est né sarkozy	(b / bear-02 :ARG1 (s / “sarkozy") :time (u / unknown))
	+50 langs.	+50 local AMRs
QALD9-AMR	Who developed Skype? Qui a développé Skype?	(d / develop-02 :ARG0 (u / unknown) :ARG1 (s / “Skype"))
	+7-8 langs.	Same AMR, all languages

Table 2: Compared with existing multilingual AMR datasets, MASSIVE-AMR has local entities (English ‘obama’, French ‘sarkozy’) and covers >5x more languages. AMRs simplified to fit table.

2 Related Work

We present related work in QA, Knowledge base question answering (KBQA), the AMR formalism, AMRs for KBQA, hallucination detection, and multilingual QA resources.

2.1 Question Answering

Question answering (QA) is the task of retrieving or predicting an answer to a natural language query given document(s), a list of answers, knowledge triples, or with a generative model. QA encompasses research in Information Retrieval (Lewis et al., 2020), Machine Reading Comprehension (MRC) (Das et al., 2018), and Open-Domain Question Answering (Lewis et al., 2021; Zhang et al., 2023). Research targeting model confidence for calibration of QA systems (Jiang et al., 2021; Kadavath et al., 2022) has aims similar to our own.

2.2 KBQA

Knowledge base question answering (KBQA) is the task of retrieving answers from a knowledge base given a question. The challenges in retrieving textual information are fundamentally different from the primary challenge of KBQA: generating semantically accurate KB queries.

Various approaches to KBQA have been proposed over the decades, including converting queries to logical forms, semantic parses, and decomposing complex questions (Zelle and Mooney, 1996; Zettlemoyer and Collins, 2005; Talmor and Berant, 2018). Scalable KBQA systems utilize structured representations (SPARQL) to query a KB (e.g., DBPedia[2]), a collection of triples of form <subject, rel_j, object>, with rel_j a semantic relation from ontology $\mathcal{R}$ (of various sizes, e.g., $|\mathcal{R}_{\text{DBPedia}}| > 2500$). Baselines for SPARQL generation are available (Banerjee et al., 2022), with a central challenge being how to identify generated queries not covered by a given $\mathcal{R}$, cases where models tend to hallucinate relations.

In the age of large language models, querying manually-curated knowledge bases provides numerous advantages such as: (1) factuality guarantees, (2) the ability to update information in real time, and (3) risk mitigation for users, reducing exposure to sensitive or toxic content. With these motivations in mind, we turn our attention to AMRs.

2.3 Abstract Meaning Representation

Abstract Meaning Representation (AMR) (Banarescu et al., 2013) is a linguistic formalism that represents the meaning of utterances as directed, mostly acyclic graphs. Graph nodes denote key concepts associated with an utterance, primarily event and event participant semantics. Nodes in turn are connected by labeled edges for event-event, event-entity, and entity-entity relations.

Early AMR research targeted parsing, with the JAMR parser (Flanigan et al., 2014) paving the way for state-of-the-art models based on transitions (Drozdov et al., 2022), seq2seq approaches (Bevilacqua et al., 2021), and ensemble distillation (Lee et al., 2022). In lieu of such heavily engineered approaches, we target generative models with in-context learning and fine-tuning following recent work in this area (Ettinger et al., 2023).

The original AMR reference-based metric is Smatch (Cai and Knight, 2013), a measure of overlapping triples, which has led to the newly optimized Smatch++ (Opitz, 2023) and S2match (Opitz et al., 2020) which uses embeddings to match concepts within triples. Wein and Schneider (2022) released multilingual AMR metrics such as XS2match using LaBSE embeddings (Feng et al., 2022) for cross-lingual AMR evaluation.

2.4 AMR for KBQA

Using symbolic representations for QA is well studied in NLP (Niu et al., 2023; Wang et al., 2023). A mapping of AMR nodes to SPARQL concepts and variables is shown to improve KBQA systems (Kapanipathi et al., 2021), and sequence-to-sequence

[2] https://www.dbpedia.org/

models learn to apply these rules selectively for improved generalization (Bornea et al., 2022).

2.5 Hallucination detection

Hallucinations, the inclusion of flawed or incongruous assertions in synthetic text, represent a persistent problem with LLMs (Ji et al., 2023). Much research in hallucination detection targets the *text-to-text* paradigm, for example checking factuality of summarized texts (Gabriel et al., 2021) or proposing mitigation strategies to make synthetic text attributable (Aksitov et al., 2023; Rashkin et al., 2023). In contrast, we examine *text-to-graph* systems that generate executable semantic parses, experimenting with AMRs to detect *easy* and *hard* cases of hallucination, ranking generations of dual representation types in a joint space as we will detail in Section 4.

2.6 Multilingual QA resources

For research in multilingual dialogue systems, MASSIVE (FitzGerald et al., 2022) is a collection of 20K utterances with manual translations into 50+ typologically diverse languages[3]. For our dataset, we select all QA utterances from MASSIVE and add AMR annotations (see Section 3).

The multilingual QA resource most similar to ours is QALD9-AMR (Lee et al., 2022) which has English-only AMRs and SPARQL mapped to questions in nine languages (Usbeck et al., 2018). In comparison, our resource has mostly English AMRs with local entities like in Table 2[4].

AMRs were not designed to function across languages (Banarescu et al., 2013), and while language has a measurable effect on AMR structure (Wein et al., 2022), efforts have been made to effectively represent the meaning of non-English sentences in AMRs (Xue et al., 2014; Hajič et al., 2014). In typology, a Uniform Meaning Representation (Van Gysel et al., 2021) better accounts for formal and semantic differences across languages, and work tying multilingual resources to a common formalism is ongoing (Navigli et al., 2022).

3 Data: Corpus Creation

To create a corpus of multilingual AMR graphs, we started with an existing dataset of QA utterances, tailored AMR 3.0 guidelines to our use case, trained a team of professional annotators to create AMRs for English utterances, and then made automatic mappings to multilingual utterances using existing entity mention spans, a process which from start to finish took three months. In this section, we report details about the data we started with, guidelines, and annotation agreement scores.

Acquiring scaleable multilingual data. We target a variety of QA utterances and thus select 1685 English examples from MASSIVE (FitzGerald et al., 2022) including entity annotations like in the multilingual examples in Table 3.

Lang.	Example utterance
en-US	what is the population of [place: new york]
sl-SL	koliko prebivalcev ima [place: ljubljana]
it-IT	qual è la popolazione di [place: roma]
sq-AL	cila është popullësia e [place: tiranës]
cy-GB	beth yw poblogaeth [place: efrog newydd]
af-ZA	wat is die bevolking van [place: kaapstad]
is-IS	hver er íbúafjöldi [place: reykjavíkur]
az-AZ	[place: sumqayıtın] halisi n qdrdir

Table 3: MASSIVE examples for the population of local cities, with entity annotations in brackets.

Long-tail QA. Many utterances in MASSIVE are described as long-tail, that is, associated with low user feedback in interactions with a digital assistant. In some cases, it is clear what increases friction (an incomplete utterance, or a speech-to-text error). Examining translations of English utterances provides insight (Appendix A.2).

Entity localization. In comparable datasets (Cui et al., 2022; Perevalov et al., 2022), entities are shared across languages (e.g., English *Where did Abraham Lincoln die?* corresponds to German *Wo starb Abraham Lincoln?*). To address challenges of large-scale QA systems, MASSIVE entities are local, e.g. German questions target German entities (*wo starb otto von bismarck*[5]).

AMR datasets differ in composition: AMR 3.0 (Banarescu et al., 2013) is based on news and other written discourse and consists of relatively few factoid or information-seeking questions (less than 10%). In contrast, MASSIVE-AMR includes requests about currency conversions, quantities, comparative and superlatives, and simple arithmetic. For more details about how the corpora compare, see Appendix A, Table 11.

Annotation principles: Canonical forms. In keeping with original AMR guidelines[6], an AMR

[3] 52 languages in v1.1

[4] Also, unlike QALD9-AMR, MASSIVE-AMR has no ground truth SPARQL.

[5] In MASSIVE, all utterances are uncased.

[6] https://github.com/amrisi/amr-guidelines/

captures meaning, not form. We hence prefer canonical forms for utterances like currency conversion and arithmetic: e.g., 'how much is the euro versus the dollar' and 'what is the euro worth compared to the dollar' map to similar graphs. Likewise, arithmetic questions are associated with top node 'equal-01' even without token 'equal' present ('how much is two plus two' and 'sum of two and two' treated like 'what does two and two equal').

Question-imperative continuum. It proved difficult to reach agreement for annotations of question versus imperative forms. In English, 'could you tell me the price of google', 'what is the price of google', and 'tell me the price of google' share the same meaning. However, treating the imperative (e.g., an embedded question 'tell me what the price is') as a question is out-of-line with AMR 3.0. The guideline we adopt is to preserve imperative form and treat polite questions (e.g., English 'could you tell me the price') the same as the base question forms (e.g., 'what is the price').

Annotation agreement scores. 4-5 trained annotators created AMRs for 1685 utterances, examining differences in batches of 200 weekly, with inter-annotator agreement ranging from 78-82% Smatch, comparable to reported agreement for AMR experts (Banarescu et al., 2013). We note that MASSIVE-AMR consists of many similar questions and simple utterances, with on average 50% less length compared to AMR 3.0 (Table 1). We select the single best AMR in candidate sets and manually retrofit to increase consistency.

For non-English entities, we replace AMR node labels using MASSIVE annotations. We note that not all utterances have annotations, and that a lack of entity alignments adds noise since often word order matters (e.g., currency conversion). To improve data quality, we manually curate validation and test sets (25% of total).

4 SPARQL hallucination detection

Scaleable QA systems often utilize structured representations (e.g., SPARQL) for knowledge base retrieval, pairing a natural language utterance with an executable semantic query. The SPARQL in the Wikidata or DBPedia case is straightforward: we get a question in, the system produces an answer out. However, in practice we simply need a system capable of judging if a given answer is correct, which using generative methods we study as *hallucination detection*.

Hallucinations. A problem in open-domain question-answering regards *hallucinations*, cases when effectively the target Ontology (in our case, DBPedia) does not have valid symbols for a given input question. For example, if the relation 'crimeRate' does not exist, a SPARQL generation model will stumble on a question like 'What is the crime rate in LA?' by generating a query with a non-existing relation, which we can verify with a set membership check. A harder case to detect is when the model predicts a relation for an utterance that is ambiguous, e.g., 'Who created Iron Man' may refer to its fictional (Tony Stark) or non-fictional (Stan Lee) creator. We would like to design and test methods for the detection of such hallucinations using LLMs.

An advantage of AMR is that its ontology is open: i.e. if a given concept is missing, we can practically lemmatize the English. Or more often, AMR tends to be more granular, and more complex meanings (that in an Ontology might be collapsed into a single symbol) are split into several constituents (i.e. 'crimeRate' might be a single symbol in an Ontology, but it is instead split into constituents by AMR). Hence, hallucinations are much less of a problem in AMR.

We hypothesize that if we train a single semantic parser to generate both SPARQL and AMRs, simply mixing the training data (i.e. for multi-task learning), and generate multiple parse candidates in a target `N`-best, the inclusion of AMRs will allow us to detect SPARQL hallucinations. That is to say, a high confidence AMR and lower confidence SPARQL serve as a signal that a given utterance is not covered by an ontology, as in Table 4.

We examine dual subtasks of SPARQL hallucination detection: (1) How accurate are models at the **easy** task of checking *set membership*, in our case, verifying generated relations are in a given relation set:

$$r_{pred} \overset{?}{\in} \mathcal{R}_{given}$$

and, (2) How good are models at flagging ambiguous queries (e.g., 'Who created Iron Man?'), the task of **hard** hallucination detection, detailed more in the next section.

5 Experiments

To gain insight into our hypothesis that AMRs can help detect hallucinations in generated SPARQL queries, we first report on experiments in semantic

Utterance	Rank #1	Rank #2	Prediction

Who created Iron Man?	SELECT DISTINCT ?uri
	WHERE {
	res:Iron_Man **dbo:creator** ?uri
	}
		(c / create-01
		:ARG0 (u / unknown)
		:ARG1 (i / Iron_Man))
			SPARQL query likely OK

Who created Iron Man?	(c / create-01
	:ARG0 (u / unknown)
	:ARG1 (i / Iron_Man))
		SELECT DISTINCT ?uri
		WHERE {
		res:Iron_Man **dbo:author** ?uri
		}
			Utterance is likely ambiguous
			creator vs. author
			'Hard' to detect

Crime rate in NYC?	(c / crime-02
	:location (n / NYC)
	:frequency (r / rate-entity-91
	:ARG1 (u / unknown)))
		SELECT ?crimeRate
		WHERE {
		res:NYC **dbo:crimeRate** ?crimeRate .
		}
			Relation does not exist
			Hallucination: crimeRate
			'Easy' to detect

Table 4: A joint AMR-SPARQL generation model helps detect potentially imprecise semantic relations (relations in **bold**) by leveraging a N-best list of candidates of mixed representation types. For 'Who created Iron Man?', when the relation **creator** exists and is precise (top), the model ranks its SPARQL query higher than an AMR. Or, (middle) the AMR ranks higher when the utterance is likely ambiguous (predicates associated with multiple relations). Models also generate non-existent relations (bottom), detected via ranking or a look-up operation.

representation generation, a first-of-its-kind in a diverse multilingual setting. Next, we experimentally confirm models do indeed hallucinate relations, before moving on to our target task of hallucination detection. We compare in-context learning and fine-tuned LLMs, training and evaluating on an existing corpus of questions with gold AMRs and SPARQL (QALD9) and sampled MASSIVE-AMR. We are guided by the following **research questions**:

1. How good are LLMs at generating AMRs and SPARQL queries across languages?
2. How prevalent are SPARQL relation hallucinations with generative models?
3. How good are models at detecting hallucinated SPARQL relations?
4. Can we use a joint AMR-SPARQL model to do better relation hallucination detection?

The standard approach to study the coverage of a set of relations is use all the data associated with a relation set $\mathcal{R}$ to train semantic parser $SP_{\mathcal{R}}$; we then remove all examples that contain relation r_j and train $SP_{\{\mathcal{R}-r_j\}}$, measuring how well the model does for queries likely to require r_j.

An advantage of training a joint AMR-SPARQL model from scratch is having complete control over the input relations; a disadvantage is that, in the case we use a LLM, we have no knowledge about what relations the model may have seen in pre-training. For our early experiments, we use LLMs trained on 1000s of examples without hard constraints on allowed relations[7].

We define *hallucination detection* as the ability of an LLM to verify generated relations are members of a predefined set. We consider cases of *hard hallucination detection*, when a model generates a relation that is inexact, a case which occurs when the needed relation for a query is not covered by a given $\mathcal{R}$. For experiments, we compare in-context learning with fine-tuned LLMs.

5.1 In-context learning

For in-context learning, we use GPT models (OpenAI, 2023) with prompts of length <2400 tokens (see Appendix C) composed employing strategies we describe in this section.

Strategy #1: Constrain and verify relations. We give a list of allowed SPARQL relations and which the model uses to verify each predicted relation. We include eight (8) examples of joint AMR-SPARQL predictions in multiple languages[8].

Strategy #2: Simulate missing relations. To control for relations (Table 5), we count DBPedia relations in QALD9-AMR training data, select the 140 more frequent relations[9], and set aside 1+ relations for utterances in prompt where the model should prefer AMR over SPARQL, ensuring examples abide by constraints.

To test our *hard hallucination detection* hypothesis, we determine DBPedia relations to control for by manually grouping similar relations (e.g., 'creator,' 'writer,' and 'developer' are similar; Ta-

[7]This could be done in decoding, setting logits of all non-relation tokens to `-inf` after a colon, an unambiguous signal of a SPARQL relation.

[8]In our experiments, English and Spanish

[9]Observed >1 times, about 50% of data

Relations	Subset descriptions
All observed	$\mathcal{R}_{\text{obs}}$
In-context	$\mathcal{R}_{\text{context}} \subset \mathcal{R}_{\text{obs}}$
Subsets similar	$\{\mathcal{R}_1^{\text{sim}}, \ldots, \mathcal{R}_j^{\text{sim}}\}$, $\mathcal{R}_i^{\text{sim}} \subset \mathcal{R}_{\text{obs}}$
Controlled	$r_{\text{cntl}} \in \mathcal{R}_i^{\text{sim}}, \notin \mathcal{R}_{\text{context}}$
Ground truth	$\{r_m, .., r_{\text{cntl}}, .., r_n\} \subset \mathcal{R}_{\text{obs}}$

Table 5: To test how well a generation model adheres to following instructions for allowed relations, we leave similar relations out as a control.

ble 5, row 3) and select questions associated with any of these relations. We compare predictions allowing all relations versus the allowed list less the controlled relation (Table 5, row 4).

Strategy #3: Simulate ranking. We would like the model to rank without access to ground truth confidence scores, so we assign random confidence scores using a Dirichlet distribution (K=3), dropping the minimum value[10]. SPARQL with only allowed relations rank higher than AMRs.

Strategy #4: In-context examples of hallucination detection. Prompts (Appendix C) include cases of easy and hard hallucination detection, and we direct the model to AMRs ranked higher[11].

5.2 Additional controls

We include results with an oracle, in which we direct the model's attention to the disallowed relation, providing an upper bound on achievable performance and giving insight into analysis. For consistency across datasets, we normalize all utterances (lower case, no punctuation).

5.3 Fine-tuning

We fine-tune a joint AMR-SPARQL model using various publicly available LLMs: a knowledge distilled variant of GPT-2-XL (West et al., 2022) and LLaMA-13B (Touvron et al., 2023); for model details, see Appendix B. For challenging test data, we use same-sized samples (900) from QALD9 and MASSIVE-AMR of the same languages[12].

5.4 Evaluation guidelines

For AMR generation, we report Smatch (Cai and Knight, 2013), and for SPARQL we check query executability[13] and verify if answers exist in DBPedia. We do not evaluate answer factuality, as our objective is to measure model confidence in semantic parse correctness, not the model's knowledge of the contents of a given KB[14].

For hard hallucination detection experiments using in-context learning, we employ quantitative and qualitative means of analysis. For perturbed examples (i.e., generate a query for a question with a known disallowed relation), a predicted ranking is good if the model: (1) ranks the AMR higher, (2) ranks the SPARQL higher and simultaneously verifies the relation is not allowed, or (3) generates a valid alternative SPARQL[15]. For easy hallucination detection, we measure query executability and stratify results by dataset.

For fine-tuned joint AMR-SPARQL, with a diverse beam search (n=5) we examine top-ranked generated sequences, majority N-best, and transition scores for first tokens[16]. Our hypothesis is models will prefer SPARQL over AMR for QALD9 and vice versa for MASSIVE-AMR, since all QALD9 is matched with ground truth SPARQL.

For evaluation, models output a queryable object (JSON) with three key-value pairs (generated query, list of relations in query, and relation verification; see Appendix C), with very few structural errors observed (<1% in our studies).

5.5 Results

We present results on in-context learning for generation of AMR (Table 6) and SPARQL (Table 7) across languages, report on SPARQL hallucinations (Table 8), and then present results of fine-tuned joint AMR-SPARQL (Table 10).

5.6 Analysis and discussion

For **AMR generation** (Research question 1), results (Table 6, examples and error analysis in Appendix D) show that state-of-the-art AMR systems still outperform in-context learning with margins between 10-20%, a display of the strengths of engineered modular systems, data augmentation, and AMR post-processing. Comparing few-shot models, GPT-4 outperforms GPT-3.5 by a margin of 10-13% F1, with performance on QALD9 14-17% F1 higher than MASSIVE-AMR, evidence of the challenge of the latter. Models perform 5-12% F1 higher for MASSIVE- compared to more diverse

[10] The minimum value represents the probability density of bottom predictions in latent N-best ranking

[11] The prompt reads: "Rank AMRs higher when predicted SPARQL is likely wrong, like in exs 5 and 8."

[12] English, Spanish, German, French, Russian

[13] Using Python SPARQLWrapper

[14] KBs change over time, many local entities do not have a DBPedia entry, etc.

[15] We check executability and evaluate manually

[16] Either 'AMR' or 'SPARQL' or first sub-token therein

	Model	Data	F1 ↑
Few-shot/EN	gpt-3.5	MASSIVE-EN	$0.43_{\pm0.20}$
		QALD9-EN	$0.57_{\pm0.17}$
	gpt-4	MASSIVE-EN	$0.53_{\pm0.21}$
		QALD9-EN	$0.70_{\pm0.16}$
Few-shot/non-EN	gpt-3.5	MASSIVE+	$0.33_{\pm0.22}$
		MASSIVE-	$0.42_{\pm0.20}$
		QALD9	$0.44_{\pm0.20}$
	gpt-4	MASSIVE+	$0.46_{\pm0.21}$
		MASSIVE-	$0.49_{\pm0.20}$
		QALD9	$0.58_{\pm0.22}$
SOTA	Struct-BART	QALD9-EN	0.90
		AMR 3.0	0.84

Table 6: AMR generation results, with F1 by model, dataset, and language subset, with in-context learning (top two sections) and SOTA (Lee et al., 2022). Overall, in-context scores are low.

	Data	Exec. ↑	Returns ↑
gpt-3.5	MASSIVE+	0.93	0.32
	MASSIVE-	0.94	0.41
	QALD9	0.97	0.53
gpt-4	MASSIVE+	0.94	0.34
	MASSIVE-	0.99	0.50
	QALD9	1.00	0.52

Table 7: Few-shot SPARQL generation results across datasets and models. We report executability and how many return existing records.

	Data	Perturb	#Utts	Halluc. ↓	Detects ↑
gpt-3.5	MASSIVE+	No	38	0.21	0.0
		Yes	62	**0.71**	0.04
	MASSIVE-	No	38	0.16	0.0
		Yes	62	**0.59**	0.0
	QALD9	No	110	0.22	0.09
		Yes	110	**0.84**	0.0
gpt-4	MASSIVE+	No	34	0.06	0.50
		Yes	66	**0.48**	0.09
	MASSIVE-	No	36	0.0	n/a
		Yes	64	**0.54**	0.14
	QALD9	No	50	0.04	0.0
		Yes	50	**0.46**	0.08

Table 8: Rates of SPARQL hallucination and hallucination detection with a SPARQL-only model. When we perturb a relation, hallucination is high; in all settings, detection rates (gray) are consistently poor.

MASSIVE+ (see Appendix A.3), the first reported AMR results we are aware of for many languages.

SPARQL generation. Results of SPARQL generation with in-context learning (Table 7, examples in Appendix E) provide evidence that LLMs perform well in a few-shot setting, exceeding 90% F1 across datasets and languages. However, as LLMs are not trained on up-to-date data, no more than 52% of queries for QALD9 and 32% of MASSIVE-AMR return existing DBPedia records. Models display good performance for MASSIVE+, where AMR performance was observed to decrease, evidence that LLMs contain more knowledge about SPARQL over AMR structures.

SPARQL relation hallucination rates (Research question 2). In Table 8, we examine two questions: (1) do models hallucinate SPARQL relations when we remove some relations from an allowed list? and (2) can models also detect these hallucinations? We observe that models do hallucinate relations and yet fail at detection consistently. Specifically, we find that under normal, non-perturbed conditions across languages (odd rows of Table 8), GPT-3.5 exhibits hallucination rates between 16-22%, which GPT-4 reduces to 0-6%. As expected, when we perturb (disallow) a relation likely to be needed in the query (even rows), hallucination rates increase considerably: for GPT-3.5 between 40-60% and for GPT-4 between 42-54%.

Hallucination detection, non-joint model. With 2-shot SPARQL query generation, models show poor rates of hallucination detection, with GPT-4 detecting no more than 14% of all hallucinations. In a vast majority of cases (86-100%, gray column, Table 8), models are deceptive, incorrectly verifying disallowed relations (Ex. 2 in Appendix E), providing us with justification to see if we can do better with a joint model.

Hallucination detection, in-context joint model (Research question 3). GPT-4 with an oracle for held-out relations shows better hallucination detection, demonstrating (1) more accurate semantic relation confirmation (i.e. greater honesty when the model ignores instructions), and (2) ranking AMRs higher more often for ambiguous utterances.

Considering cases of potentially ambiguous utterances (*hard hallucination detection*), GPT-4 mostly abides by constraints (e.g., generating 'author' instead of 'creator' for 'who created iron man'). However, it is difficult to assess correctness as much depends on the target KB and if an utterance is unambiguous. Overall, GPT-4 employs dual hallucination detection strategies well: for 1 in 5 hallucinations, ranking AMRs higher, and, for 3 of 5, generating queries with disallowed relations that it accurate verifies as non-existent.

Hallucination detection, fine-tuned joint model (Research question 4). In contrast to an oracle, results of fine-tuned joint models are inconclu-

Model	Oracle	#Perturb	Halluc. ↓	Detects ↑
gpt-3.5	no	60/120	0.58	0.07
gpt-4	no	60/120	0.39	0.17
gpt-4	yes	150/240	0.31	0.76

Table 9: Results of joint AMR-SPARQL detection with in-context learning (8-shot, GPTs), targeting 140 SPARQL relations and 8 languages. Hallucination occurs in at least 1 in 3 cases, and hallucination detection is low except with an oracle (last row).

	Langs.	Data	Top1	Top5	Token1
gpt2-distill	EN	QALD9	0.50 ×	0.68 ✓	0.83 ✓
		MASSIVE-AMR	0.58	0.62	0.80
	Non-EN	QALD9	0.53 ×	0.55 ×	0.74 ✓
		MASSIVE-AMR	0.54	0.54	0.70
LLaMa	EN	QALD9	0.82 ✓	0.95 ×	0.90 ~
		MASSIVE-AMR	0.76	0.95	0.88
	Non-EN	QALD9	0.78 ×	0.95 ×	0.82 ×
		MASSIVE-AMR	0.88	0.98	0.95

Table 10: Fine-tuning results for two models, with test sets of on English (EN) and non-English data. Features of N-best generation (top-1, top-5 majority, and token-1 transition score) help estimate confidence in SPARQL vs AMR. For the hypothesis that models generate rank-1 SPARQL for QALD9 over MASSIVE-AMR, (✓) indicate evidence in support. Overall, inconclusive.

sive (Table 10). With GPT-2-XL$_{\text{distill}}$, preference between SPARQL vs AMR is mostly 50-50, with variation only with the first token transition score metric. Fine-tuned LLaMa, in contrast, shows bias towards SPARQL under every condition (between 75-95%), and only in one setting (top-1 prediction) favoring SPARQL consistently for QALD9. Qualitative analysis reveals LLaMa prefers AMR for incomplete utterances such as 'describe' and 'calculate this', and it often misclassifies currency conversion utterances as having valid SPARQL[17]

With fine-tuned models (Table 10), we examine an N-best space from multiple perspectives (top-1 prediction, majority, transition scores). We speculate that the proportion of AMRs versus SPARQL in fine-tuning likely has an effect: in our experiments, we include more AMRs than SPARQL (Appendix B), suggesting a study with more varied proportions may be warranted. Also, we used limited amounts of fine-tuning data (less than 6k examples), which we can increase in future work.

Overall, in-context learning for hallucination detection is quite challenging. With an oracle (Table 9), GPT-4 misreports 24% of cases of disallowed relations. Without an oracle, the rate of 'deception' exceeds 80%, which proved challenging to overcome despite multiple prompt variations, which included promised rewards for sticking to allowed relations, veiled (and unveiled) threats, repeated warnings, and legalese which bound the model to abide by restrictions, tactics the models consistently disregarded, leaving plenty of space for improvement in future work.

[17] In principle, currency conversion values could be stored in a KB, but in practice KBs are not updated in real-time.

6 Conclusion

We present MASSIVE-AMR, to date the largest and most diverse dataset of multilingual questions paired with abstract meaning representation (AMR) graphs. We tell a short story about where the data is from, and detail the process of dataset creation and curation from start to finish.

To examine the utility of our dataset in controlled studies using large language models, we first consider the task of **structure generation**, showing results for both AMR and SPARQL structures across languages. Overall, performance for AMR generation with in-context learning is low compared with state-of-the-art methods; still, qualitative assessment of generated structures reveals many coherent, correct graphs despite low similarity with a ground truth. In comparison, SPARQL generation performance is high across languages, at least in small studies using the QALD-9 dataset.

One of motivations for creating MASSIVE-AMR was to test the utility of AMRs for knowledge base question answering, specifically asking if AMRs can help **detect incongruous SPARQL queries**. To this end, we confirm that models do indeed hallucinate semantic relations, and 'easy' hallucination detection, asking the model to verify relations are allowed, is actually quite hard, even for GPT-4. Further, 'hard' hallucination detection, the identification of utterances that are likely ambiguous, is indeed hard, with a joint AMR-SPARQL model only helping to detect 1 in 5 cases.

We hope our dataset will support research in multilingual QA and other downstream applications, as well as research into the use of meaning representations for model interpretability, using linguistic structure as an inductive bias in model training, as well as studies in construction grammar and language typology.

7 Ethical considerations

Informed Consent: We ensured that all individuals providing annotations were fully informed about the purpose of the annotation task, how their data will be used, and what rights they have in relation to their data.

Fair Compensation: We ensured that individuals providing annotations were fairly compensated for their time and effort. For this project, professional annotators were compensated at least $30/hour, working between 20-80 hours each for the duration of data collection.

Transparency: We were transparent about the purpose and scope of the annotation task, as well as the potential benefits of the project, helping to build trust with individuals providing annotations and ensuring that they understood the significance of their contributions. We intend that through these practices data annotation efforts are overall more effective, resulting in a higher quality resource.

Environmental impact: We considered the environmental impact of the research, including the energy consumption of computing resources used. With GPT-4 inference, we limited input to 100s of examples to reduce costs. In-house fine-tuning was done using parameter efficient fine-tuning methods, allowing all experiments to be done on 1-2 NVIDIA Quadro RTX 8000 GPUs in <24 hours per run.

8 Limitations

1. Our work involved research into multilingual SPARQL and AMR parsing; though our dataset includes 52 languages, we report results on no more than 10-12 of these. Many of the languages we included are Indo-European, with only a few exceptions (Korean, Japanese, Amharic, Vietnamese).

2. No experiments in joint AMR-SPARQL parsing involved hypotheses about performance across languages, though some evidence of performance shifts has been observed.

3. Fine-tuning models was done with less than 6k AMRs and 3-4k SPARQL training examples. Test data was limited to 100s examples per language in order to allow for multiple iterations and explore hyperparameter settings. Increasing the sizes of training and test sets is left for future work.

4. Testing was limited to four large language models in this work (GPT-2-XL$_{distill}$, GPT-3.5, GPT-4, LLaMa). LLaMa does include multilingual data in training (Touvron et al., 2023), particularly languages using Latin and Cyrillic scripts. We did not test models explicitly trained for multilingual purposes and for other scripts, leaving such work for the future.

5. The MASSIVE-AMR dataset matches multilingual utterances to unique AMR graphs, making it the largest such dataset to date. However, unlike QALD9-AMR (Lee et al., 2022), MASSIVE-AMR does not include gold SPARQL queries. We emphasize that the use case we explore in this paper is only one of many possible, and we hope future research explores beyond this single application.

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10 Appendices

A Characterizing Massive-AMR

A.1 AMR top nodes across datasets

AMR 3.0	#	QALD9-AMR	#	MASSIVE-AMR	#
and	7k	give-01	76	rate-01	105
say-01	3k	have-03	50	define-01	103
contrast-01	3k	have-degree	27	tell-01	94
multi-sentence	1.7k	have-org-role	21	have-quant	87
possible-01	1.7k	be-located-at	15	equal-01	86
cause-01	1.6k	die-01	14	price-01	70
state-01	1.5k	write-01	14	describe-01	66
have-concession	944	bear-02	13	be-located-at	64
think-01	901	marry-01	13	person	58
person	705	show-01	12	mean-01	50
have-03	618	locate-01	10	have-degree	50
have-condition	605	have-rel-role	10	bear-02	46
date-entity	538	person	9	have-org-role	32
know-01	451	name-01	9	show-01	21
have-degree	440	list-01	8	find-01	21

Table 11: 15 most frequent top AMR nodes in AMR 3.0, QALD9-AMR and MASSIVE-AMR, with counts for a single language (English).

A.2 Describing the MASSIVE long tail

We note long-tail characteristics of utterances in MASSIVE (FitzGerald et al., 2022).

- Outliers in terms of utterance length: some 1-2 tokens, others quite long (40+ tokens)
- Ambiguous referents (‘chase’ in ‘is chase doing good’ could be a bank, person, or activity)
- Incomplete arithmetic (‘tell me what equals two three’)
- Less frequent expressions (‘who is the better half of obama’)
- Incomplete questions (‘synonym for word’, ‘is equal to’, ‘research someone’)

A.3 QALD-9, MASSIVE-, MASSIVE+

	Language	# speakers	# Wiki pgs
QALD9/MASSIVE-	English	1.5b	58.7m
	French	320m	12.6m
	Russian	258m	7.7m
	German	76.5m	7.8m
	Italian	66m	7.7m
	Lithuanian	2.8m	0.5m
MASSIVE+	Vietnamese	85.2m	19.4m
	Japanese	125m	4.0m
	Korean	81.7m	3.1m
	Hungarian	8.2m	1.5m
	Urdu	91.5m	1.0m
	Amharic	31m	15k
	Azeri	24m	195k
	Finnish	5.1m	1.4m

Table 12: Indo-European languages in QALD-9 and MASSIVE- (top) and a more diverse sample MASSIVE+ (bottom); Based on https://meta.wikimedia.org/wiki/List_of_Wikipedias.

B Model details

	Element	Detail
Fine-tuning	Train set (QALD9/MASSIVE-AMR)	6000/2000
	Train set (SPARQL/AMR)	3000/5000
	Train set (langs)	1300 exs for 6 langs.
	Test set (QALD9/MASSIVE-AMR)	700/500
	Test set (langs)	200 exs for 6 langs.
	Block size (GPT-2/LlaMa)	512/2048
	Number epochs	8-16
	Learning rate	$3e^{-5}$
	Optimizer	AdamW
Inference	Number beams	20
	Number beam groups	10
	Diversity penalty	1.0
	Minimum length	8
	Maximum length	256

Table 13: Finetuning with GPT-2-XL$_{distill}$ & LlaMa.

Element	Detail
Number in-context exs.	8-12
Number tokens in prompt	2400
In-context langs.	English, Spanish
Test set (QALD9/MASSIVE-AMR)	150/150
Test set (langs)	20-40 exs for 10 langs.
Temperature	1.0

Table 14: In-context learning with GPT-3.5/4.

C Example prompts

C.1 SPARQL generation (Research question 1b)

```
{["messages": [
    {
        "role": "system",
        "content": "You are SPARQL-Predictor-GPT, a language model that predicts one SPARQL query for a given question."
    },
    {
        "role": "system",
        "content": "This is important! All relations in the predicted SPARQL query must be in
                the allowed_relation_list: ['abbreviation', 'accessioneudate', ... 'leadername']."
    },
    {
        "role": "system",
        "content": "Make a list of all the relations in the predicted SPARQL query.
                Verify that all relations are in allowed_relation_list,
                reporting True or False for each relation."
    },
    {
        "role": "system",
        "content": "Return the prediction in JSON form:
                {'sparql_query': str, 'relations': list(), 'verification': list()}"
    },
    {
        "role": "user",
        "content": "where did abraham lincoln die"
    },
    {
        "role": "assistant",
        "content": "{'sparql_query': 'PREFIX dbo: <http://dbpedia.org/ontology/>
                                    PREFIX res: <http://dbpedia.org/resource/>
                                    SELECT DISTINCT ?uri WHERE
                                    { res:Abraham_Lincoln dbo:deathPlace ?uri. }',
                    'relations': ['deathplace'],
                    'verification': [True] }"
    },
    {
        "role": "user",
        "content": "give me all cosmonauts."
    }
],
"gold_sparql": "SELECT DISTINCT ?uri WHERE
                { ?uri a <http://dbpedia.org/ontology/Astronaut>
                { ?uri <http://dbpedia.org/ontology/nationality> <http://dbpedia.org/resource/Russia> }
                UNION
                { ?uri <http://dbpedia.org/ontology/nationality> <http://dbpedia.org/resource/Soviet_Union> } }",
"perturbed": 1,
"rel_excluded": "nationality",
"question": "give me all cosmonauts.",
"completion": "{'sparql_query': 'PREFIX dbo: <http://dbpedia.org/ontology/>
                                PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
                                SELECT DISTINCT ?cosmonaut WHERE
                                { ?cosmonaut rdf:type dbo:Astronaut. }',
                'relations': ['type'],
                'verification': [True] }",
"label": "qald9",
"hallucination": 0,
"hallucination-detection": 0,
"sparql_executable": 1,
"sparql_result": 1,
"sparql_malformed": 0}
```

Figure 1: Example prompt for SPARQL generation with completion and associated features. Our controlled setting for hallucination detection is then reduced to verifying all relations in a generated query are in the given list, verification the model outputs along with the generated sparql_query. For considerations of space, we show only 3 (of 140) relations given as the allowed_relation_list (second system message in prompt).

D AMR generation examples (GPT-4, 8-shot learning) and error analysis

Ex. 1 (QALD9, Spanish): cuánto pesa el satélite más ligero de júpiter (English: ‘how much does jupiter’s lightest moon weigh’)

```
Reference

(h2 / heavy
   :quant (a / amr-unknown)
   :domain (m / moon
      :ARG1-of (h / have-degree-91
         :ARG2 (l / light-06
            :ARG1 m)
         :ARG3 (m2 / most)
         :ARG5 (m3 / moon
            :poss (p / planet
               :name (n / name
                  :op1 "Jupiter"))))))
```

```
Generated

(p / pesar-01
   :ARG1 (s / satellite
      :degree (m / more
         :quant (l / light))
      :location-of (j / planet
         :name (n / name
            :op1 "Júpiter"))))

F1: 0.3
Error: missing amr-unknown; non-English frame
```

Ex. 2 (QALD9, French): combien de théories albert einstein a-t-il produit (English: ‘how many theories did albert einstein come up with’)

```
Reference

(c / come-up-11
   :ARG0 (p / person
      :name (n / name
         :op1 "Albert"
         :op2 "Einstein"))
   :ARG1 (t / theory
      :quant (a / amr-unknown)))
```

```
Generated

(p / produce-01
   :ARG0 (p2 / person
      :name (n / name
         :op1 "Albert"
         :op2 "Einstein"))
   :ARG1 (t / theory
      :quant (c / count-01
         :op1 (a / amr-unknown))))

F1: 0.77
Diff: English come-up-11 vs French produce-01
Note: Better metric needed for semantic similarity
```

Ex. 3 (Massive, English): what is the worlds record for the longest head of hair

```
Reference

(h / have-degree-91
    :ARG1 (h2 / hair
        :part-of (h3 / head)
        :mod (a / amr-unknown))
    :ARG2 (l / long-03
        :ARG1 h2)
    :ARG3 (m / most)
    :ARG5 (w2 / world)
    :ARG1-of (r / record-01))
```

```
Generated

(r / record-01
    :mod (w / world)
    :topic (l / long-02
        :degree (m / most)
        :ARG1 (h / hair-01
            :part-of (p / person))
        :duration (a / amr-unknown)))

F1: 0.38
Error: invents hair-01
Semantics of amr-unknown as 'duration'
Good: 'longest head of hair' = 'longest hair'
```

Errors in AMR generation include:

- Lack of AMR token for questions ‘amr-unknown’ (33/100 examples, see Ex. 1); We note 6 of 8 examples in the prompt model this (2 of 8 are imperatives);
- 3/100 generations filtered by Smatch (missing parenthesis or nodes with duplicate variable name);
- Frequent errors with AMR -91 frames (Exs. 1 & 3), e.g., rate-entity-91, have-degree-91;
- 21 of 100 examples have F1<0.5 (Ex. 3); of these, 5 are QALD9 and 16 are MASSIVE-AMR
- Arithmetic problems are correct but do not follow canonical form, though we note there are no math examples in prompts; this suggests more than one reference graph would be helpful for evaluation.

E Results of SPARQL generation

```
Example 1: Massive- (Italian), Perturbed=False, Hallucination=False, Detection=False, Difficult=False

Question: quanti anni ha giorgia (English: `how old is giorgia`)

Completion: {'generated_sparql_query':
    'PREFIX dbo: <http://dbpedia.org/ontology/>
     PREFIX res: <http://dbpedia.org/resource/>
     SELECT (YEAR(NOW()) - YEAR(?birthDate)) AS ?age WHERE
        { res:Giorgia dbo:birthdate ?birthDate. }',
    'relations': ['birthdate'],
    'verification': [True]}

-------

Example 2: Massive+ (Hungarian), Perturbed=True, Hallucination=True, Detection=False, Difficult=False

Relation excluded: ['birthdate']

Question: milyen id s t th vera (English: `how old is toth vera`)

Completion: {'generated_sparql_query':
    'PREFIX dbo: <http://dbpedia.org/ontology/>
     PREFIX res: <http://dbpedia.org/resource/>
     SELECT (YEAR(NOW()) - YEAR(?birthdate)) WHERE
        { res:T th_Vera dbo:birthDate ?birthdate. }',
    'relations': ['birthDate'],
    'verification': [True]}

-------

Example 3: Massive+ (Japanese), Perturbed=True, Hallucination=True, Detection=True, Difficult=False

Relation excluded: ['birthdate']

Question:                                     (English: `how old is atsuro watabe`)

Completion: {'generated_sparql_query':
    'PREFIX dbo: <http://dbpedia.org/ontology/>
     PREFIX res: <http://dbpedia.org/resource/>
     SELECT DISTINCT ?date WHERE
        { res:Atsuro_Watabe dbo:birthDate ?date. }',
    'relations': ['birthDate'],
    'verification': [False]}

-------

Example 4: Massive- (English), Perturbed=True, Hallucination=??, Detection=False, Difficult=True

Relation excluded: ['creator']

Question: who created the comic captain america?

{'generated_sparql_query':
    'PREFIX dbo: <http://dbpedia.org/ontology/>
    PREFIX res: <http://dbpedia.org/resource/>
    SELECT DISTINCT ?uri WHERE
        { res:Captain_America dbo:foundedby ?uri. }',
    'relations': ['foundedby'],
    'verification': [True]}
```

Figure 2: Examples of SPARQL generation using GPT-3.5 showing hallucinations and hallucination detection.