

# KGGEN: EXTRACTING KNOWLEDGE GRAPHS FROM PLAIN TEXT WITH LANGUAGE MODELS

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## ABSTRACT

Recent interest in building foundation models for KGs has highlighted a fundamental challenge: knowledge-graph data is relatively scarce. The best-known KGs are primarily human-labeled, created by pattern-matching, or extracted using early NLP techniques. **While human-generated KGs are in short supply, automatically extracted KGs are of questionable quality.** We present a solution to this data scarcity problem in the form of a text-to-KG generator (KGGen), a package that uses language models to create high-quality graphs from plaintext. Unlike other KG extractors, KGGen clusters related entities to reduce sparsity in extracted KGs. KGGen is available as a Python library (`pip install kg-gen`), making it accessible to everyone. Along with KGGen, we release the first benchmark, **Measure of of Information in Nodes and Edges (MINE)**, that tests an extractor’s ability to produce a useful KG from plain text. We benchmark our new tool against existing extractors and demonstrate far superior performance.

## 1 INTRODUCTION

**Knowledge graph (KG) applications and Graph Retrieval-Augmented Generation (RAG) systems are increasingly bottlenecked by the scarcity and incompleteness of available KGs.** KGs consist of a set of subject-predicate-object triples, and have become a fundamental data structure for information retrieval (Schneider, 1973). Most real-world KGs, including Wikidata (contributors, 2024), DBpedia (Lehmann et al., 2015), and YAGO (Suchanek et al., 2007), are far from complete, with many missing relations between entities (Shenoy et al., 2021). The lack of domain-specific and verified graph data poses a serious challenge for downstream tasks such as KG embeddings, graph RAG, and synthetic graph training data.

Embedding algorithms such as TransE (Bordes et al., 2013) rely on abundant relational data to learn high-quality KG representations. In particular, TransE represents relationships as vector translations between entity embeddings and has demonstrated strong performance in link prediction when trained on large KGs (e.g., 1M entities and 17m training samples). **However, if the KG is sparse or incomplete, embedding models struggle – they cannot learn or infer missing links effectively, degrading performance on knowledge completion and reasoning tasks** (Pujara et al., 2017; Pote, 2024).

Consider retrieval-augmented generation (RAG) with a language model (LM) – this requires a rich external knowledge source to ground its responses. For instance, GraphRAG integrates a KG into the RAG pipeline (Edge et al., 2024). In GraphRAG, a language model (LM) like GPT-4o is used to extract a KG from a text corpus automatically, and this graph is used for retrieval and reasoning. This structured, graph-based augmentation has been shown to improve multi-hop reasoning and synthesis of information across documents (Larson & Truitt, 2024). By traversing relationships in the constructed graph, GraphRAG can “connect the dots” between disparate pieces of information, outperforming baseline RAG that relies only on semantic search over text. **However, GraphRAG’s performance ultimately depends on the quality of the extracted graph** (Zhang et al., 2024). In practice, automatically constructed graphs can be **noisy and incomplete** – some false nodes and edges may

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Code for this project can be found at <https://github.com/stair-lab/kg-gen>

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be introduced and some important ones omitted, which can hinder downstream reasoning (Thakur, 2024).

An emerging line of work that builds on graph-based RAG trains neural networks on KG retrieval. For example, GFM-RAG (Graph Foundation Model for RAG) (Luo et al., 2025) trains a dedicated graph neural network on an extensive collection of KGs, encompassing 60 graphs with over 14 million triples to serve as a foundation model for graph-based retrieval. By learning from diverse KGs, GFM-RAG’s retriever can generalize to unseen graphs and better handle the noise/incompleteness in automatically extracted KGs. **These efforts underscore the importance of having dense, well-connected KGs to feed into RAG systems.**

In this work, we propose KGGGen (Text-to-Knowledge-Graph), **a package that leverages LMs and a clustering algorithm to extract high-quality, dense KGs from text.** KGGGen addresses knowledge scarcity by enabling the automatic construction of KGs from **any textual source rather than being limited to pre-existing databases** like Wikipedia. The package uses an LM-based extractor to read unstructured text and predict subject-predicate-object triples to capture entities and relations. KGGGen then applies an iterative LM-based clustering to refine the raw graph. Inspired by crowd-sourcing strategies for entity resolution (Wang et al., 2012), the clustering stage has an LM examine the set of extracted nodes and edges to identify which ones refer to the same underlying entities or concepts. Variations in tense, plurality, stemming, or capitalization are normalized in this process - e.g., “labors” might be clustered with “labor” and “New York City” with “NYC.” The resulting KG has far less redundancy and is densely interlinked, making it suitable for downstream use.

In addition to KGGGen, we provide the first benchmark to measure text-to-knowledge-graph extraction. Our benchmark feeds 100 Wikipedia-length articles into a KG extractor, then uses RAG to answer questions about the articles. On our benchmark, KGGGen outperforms leading existing text-to-KG extractors by 18%. KGGGen paves the way for a data-rich future when training next-generation KG foundation models and RAG systems.

To summarize our contributions:

1. We introduce KGGGen, an open-source package that uses LMs to extract high-quality KGs from plain text. Our package is available as a Python library.
2. We develop the first-ever benchmark for text-to-KG extractors, allowing for a fair comparison of existing methods.
3. We show that KGGGen outperforms existing extraction methods by 18% on this benchmark, exhibiting its potential to produce functional KGs using LMs.

## 2 EXISTING METHODS

Before describing KGGGen, we explain the two leading existing methods for extracting KGs from plain text, which will serve as a basis for comparison throughout the rest of this paper.

### 2.1 OPENIE

Open Information Extraction (OpenIE) was implemented by Stanford CoreNLP based on Angeli et al. (2015). It first generates a “dependency parse” for each sentence using the Stanford CoreNLP pipeline. A learned classifier then traverses each edge in the dependency parse, deciding whether to create (Yield), continue (Recurse), or stop processing a clause. These decisions split complex sentences into shorter, self-contained clauses. From these clauses, the system produces (*subject*, *relation*, *object*) tuples, each accompanied by a confidence score. Because OpenIE does not require its input text to have a specific structure, OpenIE can handle text in any format.

### 2.2 GRAPH-RAG

Microsoft developed GraphRAG, which integrated graph-based knowledge retrieval with language models (LMs) Larson & Truitt (2024). As a first step, GraphRAG provides functionality for generating KGs from plain text to use as its database. In this process, GraphRAG creates a graph by

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prompting LMs to extract node-entities and relationships between these entities to serve as edges between the nodes. Throughout this extraction, few-shot prompting provides the LM with examples of “good” extractions. GraphRAG aggregates well-connected nodes into “communities” and generates a summary for each community to remove redundancy. The final graph consists of the communities as nodes and sentences summarizing their relationships as edges.

### 3 KGGGen: KGs FROM PLAIN TEXT

Unlike most previous methods of LLM-based KG extraction, we rely on a multi-stage approach involving an LLM (in our case, GPT-4o) to (1) extract entity and relations from each source text, (2) aggregate graphs across sources and (3) iteratively cluster entities and relations. We implement these stages in a modular fashion via a new `kg-gen` Python toolkit consisting of a ‘generate’ module for extraction, an ‘aggregate’ module for source consolidation, and a ‘cluster’ module for dynamic entity resolution. We use the DSPy framework throughout these stages to define signatures that ensure that LLM responses are consistent JSON-formatted outputs. In our case, we use GPT-4o, although the implementation may be used with any model supported by DSPy.

We impose strong constraints on the LLM via prompting to reduce the likelihood of semantically dissimilar duplicate entities. We introduce multiple passes through our extracted edges and relations to cluster similar entities and consolidate the number of edge types. Consolidation and clustering prevent the formation of sparse KGs, which may produce meaningless KG embeddings under standard algorithms such as TransE.

Our extraction method involves several steps, which we outline below. The exact prompts for each step can be found in Appendix A, and the process is illustrated in Figure 1.

#### 3.1 ENTITY AND RELATION EXTRACTION (‘GENERATE’)

The first stage takes unstructured text as input and produces an initial knowledge graph as extracted triples. We invoke the GPT-4o model for each input text through a DSPy signature that instructs the model to output detected entities in a structured format. Then, we invoke a second LLM call through DSPy that instructs the model to output the subject-predicate-object relations, given the set of entities and source text. We find this 2-step approach works better to ensure consistency between entities.

#### 3.2 AGGREGATION (‘AGGREGATE’)

After extracting triples from each source text, we collect all the unique entities and edges across all source graphs and combine them into a single graph. All entities and edges are normalized to be in lowercase letters only. The aggregation step reduces redundancy in the KG. Note that the aggregation step does not require an LLM.

#### 3.3 ENTITY AND EDGE CLUSTERING (‘CLUSTER’)

After extraction and aggregation, we typically have a raw graph containing duplicate or synonymous entities and possibly redundant edges. The clustering stage is a key innovation in our KG extraction methodology that aims to merge nodes and edges representing the same real-world entity or concept. We take an iterative LLM-based approach to clustering, inspired by how a group of humans might gradually agree on consolidating terms. Rather than attempting to solve the entire clustering in one shot (which is intractable for an extensive list of entities), KGGGen performs a sequential series of clustering operations for entities:

1. The entire entities list is passed in context to the LLM, and it attempts to extract a single cluster. An optional cluster-instruction string may be passed to decide how to cluster. The default instructions account for close synonyms and differences in tense and plurality.
2. Validate the single cluster using an LLM-as-a-Judge call with a binary response. If it passes, then add the cluster and remove the cluster entities from the entities list.

3. Assign a label to the cluster that most closely captures the shared meaning of entities in the cluster.
4. Repeat steps 1–3 until  $n$  loops happen without a successful cluster extraction.
5. Remaining entities are checked batch-by-batch, with batch size  $b$ , for whether they should be added to an existing cluster.
6. For each new addition to a cluster, validate the cluster once more using an LLM-as-a-Judge call with a binary response.
7. Repeat steps 5–6 until there are no remaining entities to check.

The same operations are performed on edges, albeit with slightly modified prompts.

The clustering process allows us to create dense KGs that admit meaningful embeddings. To give a real example of the usefulness of our process, in one of our raw KGs, we found the entities “vulnerabilities”, “vulnerable”, and “weaknesses”. Although these are different words, they have similar meanings and should be viewed as equivalent in our KG.

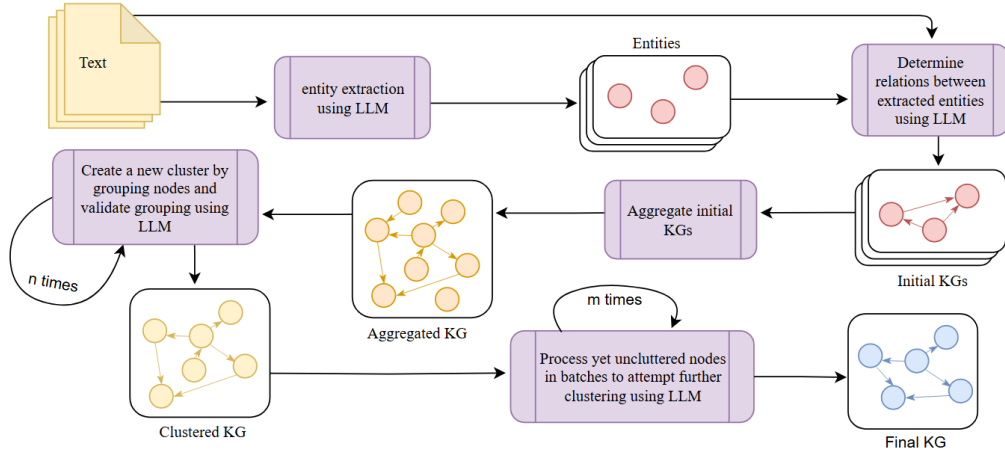


Figure 1: KGGen extraction method

## 4 A BENCHMARK FOR EXTRACTION PERFORMANCE

Although a handful of existing methods attempt to extract KGs from plain text, it is difficult to measure progress in the field due to the lack of existing benchmarks. To remedy this, we produce the Measure of Information in Nodes and Edges (MINE), **the first benchmark that measures a knowledge-graph extractor’s ability to capture and distill a body of text into a KG.**

### 4.1 MINE DESCRIPTION

MINE involves generating KGs for 100 articles, each representing a distinct source of textual data. Each article is approximately 1,000 words long and is generated by an LLM based on a diverse list of 100 topics that range from history and art to science, ethics, and psychology. To evaluate the quality of the generated KGs, we develop a metric to assess how effectively they capture critical information from the articles.

We extract 15 facts—here defined as statements present in the plain text article—from each article by providing an LLM with the article and the extraction prompt found in Appendix C. We manually verify that the 15 facts are accurate and contained in the article. MINE assesses how well a text-to-KG extractor captures the information present in the text by determining whether these 15 facts are captured by the KG generated from the article.

For each article, KGs are generated using the plain-text-to-KG method being benchmarked. The nodes of the resulting KGs are then vectorized using the all-MiniLM-L6-v2 model from SentenceTransformers, enabling us to use cosine similarity to assess semantic closeness between the short sentence information and the nodes in the graph.

For each KG generation method, the KG for each article is queried for each of the 15 facts from that article. We do this by determining the top-k nodes most semantically similar to each fact. Next, we determine all the nodes within two relations of one of the top k-nodes. Finally, we return all these nodes along with their relations as the result of the query. This result is subsequently evaluated using an LLM, provided it is queried for and a specific prompt to produce a binary output: 1 if the fact could be inferred from only the information in the queried nodes and relations, and zero otherwise. The prompt can be found in Appendix C.

The final MINE score of each KG generator on a given article was calculated as the percentage of 1s across all 15 evaluations. This systematic approach objectively compares the methods based on their ability to capture and retrieve information from the articles accurately.

This evaluation process is illustrated in Figure 2.

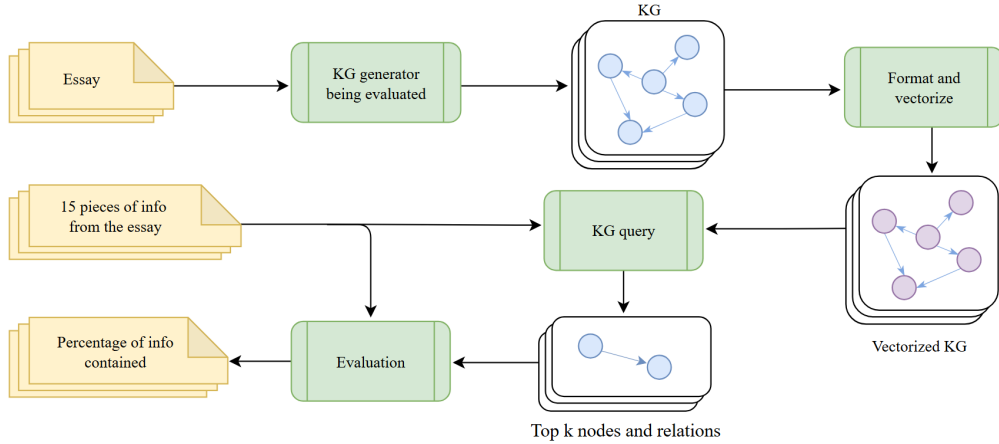


Figure 2: Evaluation process used in MINE

## 5 RESULTS

We use MINE to benchmark KGGen against leading existing methods of plain-text-to-KG extraction: OpenIE Angeli et al. (2015) and GraphRAG Larson & Truitt (2024). After providing this quantitative comparison of extraction fidelity, we present qualitative results demonstrating the advantages of KGGen over past methods.

### 5.1 EVALUATIONS ON MINE

Figure 3 displays accuracies from KGGen, OpenIE, and GraphRAG on MINE. Figure 4 shows an example query from MINE and relevant relations extracted by KGGen, OpenIE, and GraphRAG.

### 5.2 QUALITATIVE RESULTS

As seen in Figure 5b and 5e, GraphRAG often generates a minimal number of nodes and connections for an entire article. **This sparsity results in the omission of critical relationships and information.** For compression, Figure 5a and 5d illustrate sections of the KGs generated by KGGen for the same articles. Figure 5c illustrates one of many issues in OpenIE’s KGs. Firstly, most nodes are unreasonably long, incoherent phrases. **Many of these nodes are redundant copies of one another, adding unnecessary complexity to the graph.** Additionally, as seen in 5f OpenIE frequently produces **generic nodes** such as “it” and “are.” Due to their frequency, these nodes, which contain no

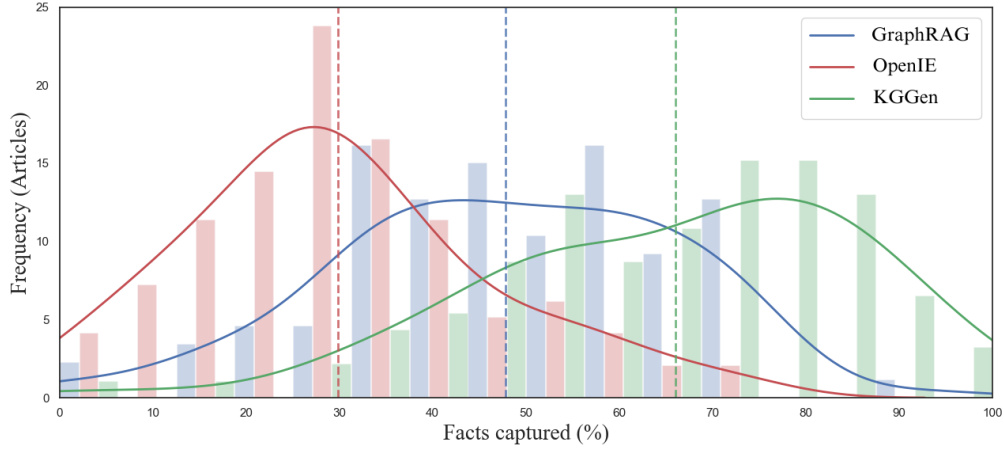


Figure 3: Distribution of MINE scores across 100 articles for GraphRAG, OpenIE, and KGGen. Dotted vertical lines show average performance. KGGen scored 66.07% on average, significantly outperforming GraphRag 47.80% and OpenIE 29.84%.

Fact being queried for: "Decentralization provides users with more control over their funds in cryptocurrencies."		
Extractor	Sample of relevant triples queried from KG	Result
KGGen	(cryptocurrencies, enhance, security) (cryptocurrencies, are, decentralized) (cryptocurrencies, provide control over, funds) (cryptocurrencies, enhance, privacy) (cryptocurrencies, operate on, peer-to-peer network) (cryptocurrencies, revolutionizing, transactions) (blockchain, ensures, transparency)	1
GraphRAG	(CRYPTOCURRENCIES, Cryptocurrencies are having a profound impact on the financial world by introducing new ways of thinking about money and finance, FINANCIAL WORLD) (BLOCKCHAIN, Cryptocurrencies operate using blockchain technology which provides a secure and transparent way to record transactions, CRYPTOCURRENCIES)	0
OpenIE	(cryptocurrencies, allowing transactions to occur between users, without need for intermediaries) (cryptocurrencies, allowing, for transactions to occur directly) (Cryptocurrencies, have taken financial world in, storm) (Blockchain, is, ledger technology) (Blockchain, is distributed, ensures)	0

Figure 4: An example query from the MINE benchmark, along with relevant relations in the KGs extracted by KGGen, GraphRAG, and OpenIE. Note that the relation triples extracted by KGGen contain the fact being queried for, whereas the KGs extracted by GraphRAG and OpenIE do not. The relation types extracted by KGGen are more concise and generalize more easily than those from GraphRAG and OpenIE. The full article that these relations were extracted from can be found in Appendix D.

useful information, often end up as some of the most well-connected nodes in the graph. By contrast, KGGen consistently generates KGs that are dense and coherent, effectively capturing critical relationships and information from the articles.



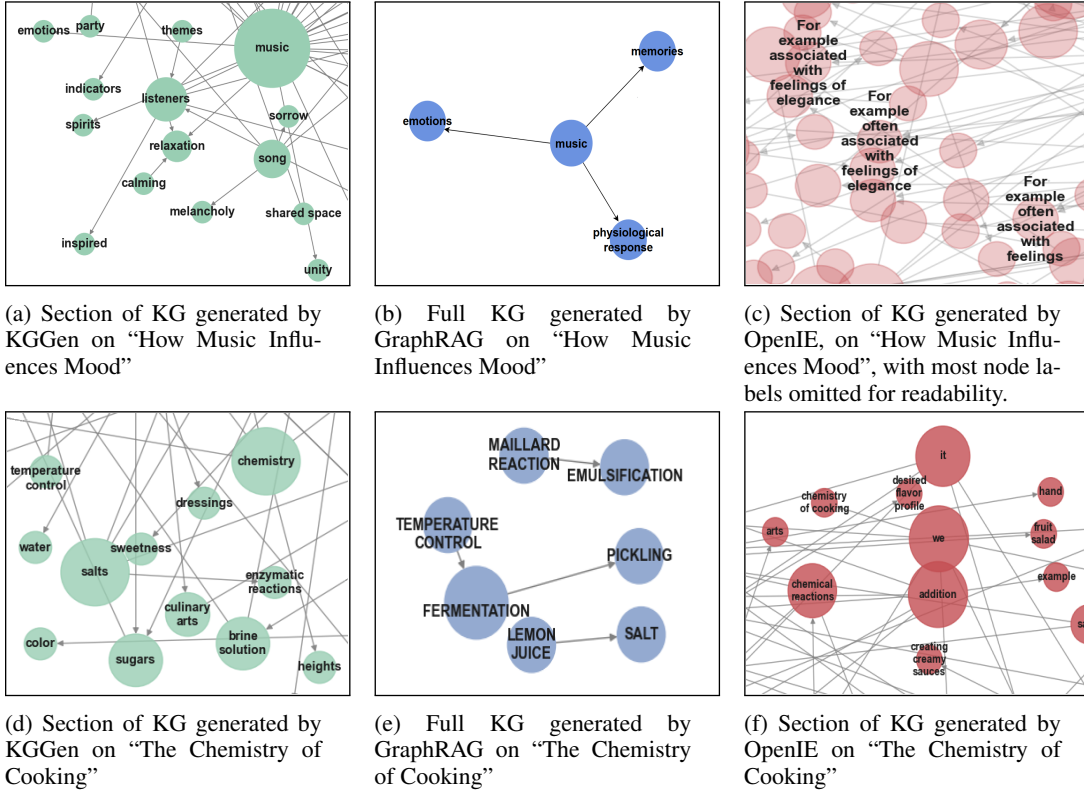


Figure 5: Visual comparison of KGs generated using KGGGen, GraphRAG, and OpenIE. Results show that KGGGen discovers more informative nodes to estimate a richer graph compared to GraphRAG, and collapses synonyms to discover a more informative graph than OpenIE.

## 6 FUTURE WORK

We propose MINE – the first benchmark for KG extraction from plain text. To solve the data-shortage hindering development of graph-based foundation models, we present KGGGen, a plain-text-to-KG extractor that outperforms existing approaches by up to 18% on MINE.

Although KGGGen beats existing methods by significant margins, the graphs still exhibit problems, like **over or under-clustering**. More research into better forms of clustering could improve the quality of our KGs. Additionally, our benchmark, MINE, currently measures performance on relatively **short corpora**, whereas KGs are primarily used to handle massive amounts of information efficiently. Future expansions of our benchmark could focus on larger corpora to better measure the practicality of different extraction techniques.

## 7 RELATED WORK

Interest in automated methods to produce structured text to store ontologies dates back to at least 2001 when large volumes of plain text began to flood the fledgling internet (Maedche & Staab, 2001). KG extraction from unstructured text has seen significant advances through rule-based and LM-powered approaches in the last 15 years. Early work (Suchanek et al., 2007) used hard-coded rules to develop YAGO, a KG extracted from Wikipedia containing over five million facts, and rules-based extraction still has appeal for those producing KGs in multi-modal domains today (Norabid & Fauzi, 2022; Oramas et al., 2015). With the development of modern natural language processing, hard-coded rules generally ceded to more advanced approaches based on neural networks. For instance, OpenIE (Angeli et al., 2015) provides a two-tiered extraction system: first, self-contained clauses are identified by a classifier; then, Angeli et al. run natural logic inference to extract the

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most representative entities and relations from the identified clauses. Stanford KBP (Angeli et al., 2013) presents another seminal early approach to using deep networks for entity extraction.

As early as 2015, some hypothesized that extracting KGs would go hand-in-hand with developing better language models (Domeniconi et al., 2015). More recently, evidence has emerged that transformer-based architectures can identify complex relationships between entities, leading to a wave of transformer-based KG extraction techniques, which range from fully automatic (Qiao et al., 2022; Arsenyan et al., 2023; Zhang & Soh, 2024) to human-assisted (Kommineni et al., 2024). Our contribution to the extraction literature is to build KGs conducive to embedding algorithms such as TransE and TransR (Bordes et al., 2013; Lin et al., 2015). We observed that when one extracts KGs from plaintext, the nodes and relations are often so specific that they are unique. This causes the estimation of embeddings to be under-specified. We develop a method for automatic KG extraction from plain text that clusters similar nodes and edges to prevent this under-specification. This leads to a KG with better connectivity and more functional nodes and edges.

Evaluating the quality of knowledge graphs is important to ensure usefulness and reliability in downstream applications. Early evaluation methods focused primarily on directly assessing aspects such as completeness and connectivity or using rule-based statistical methods, while recent approaches emphasize usability in downstream applications and incorporation of semantic coherence (Xue & Zou, 2023).

In the late 2000s, research focused on assessing the correctness and consistency of KGs. The evaluations relied on expert annotations by selecting random facts from the generated KG and then calculating the accuracy of those facts. (Suchanek et al., 2007) This proved to be laborious and prone to errors. This led to accuracy approximation methods like KGEval (Ojha & Talukdar, 2017) and Two-State Weight Clustering Sampling (TWCS) (Gao et al., 2018), which employed sampling methods with statistical guarantees as well as use less annotation labor. As the KGs became larger and more diverse, particularly with the rise of automated extraction techniques from web data, this generated more pressure on annotators, leading to methods like Monte-Carlo search being used for the interactive annotation of triples (Qi et al., 2022). Furthermore, because accuracy alone did not fully capture the complexity of the knowledge graph, more evaluation metrics like completeness were used to characterize the quality of knowledge graphs. (Issa et al., 2021).

In recent years, the evaluation of knowledge graphs (KGs) has increasingly focused on their role in downstream AI applications, such as augmenting language models (Schneider et al., 2022) and recommendation systems (He et al., 2020). As a result, semantic coherence and usability have become key criteria for assessing the quality of extracted knowledge graphs.

Two notable approaches to KG evaluation are the LP-Measure and the triple trustworthiness measurement (KGTm) model. LP-Measure assesses the quality of a KG through link prediction tasks, eliminating the need for human labor or a gold standard (Zhu et al., 2023). This method evaluates KGs based on their consistency and redundancy by removing a portion of the graph and testing whether the removed triples can be recovered through link prediction tools. Empirical evidence suggests that LP-Measure can effectively distinguish between “good” and “bad” KGs. The KGTm model, on the other hand, evaluates the coherence of triples within a knowledge graph Jia et al. (2019). Based on these evaluation methods, frameworks like Knowledge Graph Evaluation via Downstream Tasks (KGrEaT) and DiffQ (differential testing) emerged. KGrEaT provides a comprehensive assessment of KGs by evaluating their performance on downstream tasks such as classification, clustering, and recommendation (Heist et al., 2023) rather than focusing solely on correctness or completeness. In contrast, DiffQ uses embedding models to evaluate the KG’s quality and assign a DiffQ Score, resulting in improved KG quality assessment. Tan et al. (2024)

This shift towards task-based evaluation underscores the importance of usability and accessibility in KGs. Factors such as expressiveness, context information, and ease of integration into downstream AI applications are now central to evaluating their quality and effectiveness.

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## REFERENCES

- Gabor Angeli, Arun Tejasvi Chaganty, Angel X. Chang, Kevin Scott Reschke, Julie Tibshirani, Jean Wu, Osbert Bastani, Keith Siilats, and Christopher D. Manning. Stanford’s 2013 kbp system. *Theory and Applications of Categories*, 2013. URL <https://api.semanticscholar.org/CorpusID:14273633>.
- Gabor Angeli, Melvin Jose Johnson Premkumar, and Christopher D. Manning. Leveraging linguistic structure for open domain information extraction. In Chengqing Zong and Michael Strube (eds.), *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 344–354, Beijing, China, July 2015. Association for Computational Linguistics. doi: 10.3115/v1/P15-1034. URL <https://aclanthology.org/P15-1034>.
- Vahan Arsenyan, Spartak Bughdaryan, Fadi Shaya, Kent Small, and Davit Shahnazaryan. Large language models for biomedical knowledge graph construction: Information extraction from emr notes. In *Workshop on Biomedical Natural Language Processing*, 2023. URL <https://api.semanticscholar.org/CorpusID:256390090>.
- Antoine Bordes, Nicolas Usunier, Alberto Garcia-Durán, Jason Weston, and Oksana Yakhnenko. Translating embeddings for modeling multi-relational data. In *Proceedings of the 26th International Conference on Neural Information Processing Systems - Volume 2, NIPS’13*, pp. 2787–2795, Red Hook, NY, USA, 2013. Curran Associates Inc.
- Wikidata contributors. Wikidata: A free collaborative knowledge base, 2024. URL <https://www.wikidata.org>.
- Giacomo Domeniconi, Gianluca Moro, Roberto Pasolini, and Claudio Sartori. A study on term weighting for text categorization: A novel supervised variant of tf.idf. 07 2015. doi: 10.5220/0005511900260037.
- Darren Edge, Ha Trinh, Newman Cheng, Joshua Bradley, Alex Chao, Apurva Mody, Steven Truitt, and Jonathan Larson. From local to global: A graph rag approach to query-focused summarization. *arXiv preprint arXiv:2404.16130*, 2024. URL <https://arxiv.org/abs/2404.16130>.
- Junyang Gao, Xian Li, Yifan Ethan Xu, Bunyamin Sisman, Xin Luna Dong, and Jun Yang. Efficient knowledge graph accuracy evaluation. *ACM Transactions on Information Systems*, 36(2): 1–21, 2018. doi: 10.14778/3342263.3342642. URL <https://dl.acm.org/doi/pdf/10.14778/3342263.3342642>. Duke University and Amazon.com.
- Xiangnan He, Kuan Deng, Xiang Wang, Yan Li, YongDong Zhang, and Meng Wang. Lightgcn: Simplifying and powering graph convolution network for recommendation. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR ’20)*, pp. 639–648. ACM, 2020. doi: 10.1145/3397271.3401063. URL <https://doi.org/10.1145/3397271.3401063>.
- Nicolas Heist, Sven Hertling, and Heiko Paulheim. Kgreat: A framework to evaluate knowledge graphs via downstream tasks. In *Proceedings of the 32nd ACM International Conference on Information and Knowledge Management (CIKM ’23)*, pp. 3938–3942. ACM, 2023. doi: 10.1145/3583780.3615241. URL <https://doi.org/10.1145/3583780.3615241>. Published on 21 October 2023.
- Subhi Issa, Onaopepo Adekunle, Fayçal Hamdi, Samira Si-Said Cherfi, Michel Dumontier, and Amrapali Zaveri. Knowledge graph completeness: A systematic literature review. *IEEE Access*, 9:31322–31339, 2021. doi: 10.1109/ACCESS.2021.3056622. URL <https://ieeexplore.ieee.org/document/9344615>.
- Shengbin Jia, Yang Xiang, Xiaojun Chen, Kun Wang, and Shijia. Triple trustworthiness measurement for knowledge graph. In *Proceedings of the World Wide Web Conference (WWW ’19)*, pp. 2865–2871. ACM, May 2019. doi: 10.1145/3308558.3313586. URL <https://doi.org/10.1145/3308558.3313586>.

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- Vamsi Krishna Kommineni, Birgitta König-Ries, and Sheeba Samuel. From human experts to machines: An llm supported approach to ontology and knowledge graph construction. *ArXiv*, abs/2403.08345, 2024. URL <https://api.semanticscholar.org/CorpusID:268379482>.
- Jonathan Larson and Steven Truitt. Graphrag: Unlocking llm discovery on narrative private data. February 2024. URL <https://www.microsoft.com/en-us/research/blog/graphrag-unlocking-llm-discovery-on-narrative-private-data/>.
- Jens Lehmann, Robert Isele, Max Jakob, Anja Jentzsch, Dimitris Kontokostas, Pablo N. Mendes, Sebastian Hellmann, Mohamed Morsey, Patrick van Kleef, Sören Auer, and Christian Bizer. DBpedia – A Large-scale, Multilingual Knowledge Base Extracted from Wikipedia. *Semantic Web Journal*, 6(2):167–195, 2015. doi: 10.3233/SW-140.
- Yankai Lin, Zhiyuan Liu, Maosong Sun, Yang Liu, and Xuan Zhu. Learning entity and relation embeddings for knowledge graph completion. In *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence*, AAAI’15, pp. 2181–2187. AAAI Press, 2015. ISBN 0262511290.
- Lin hao Luo, Zicheng Zhao, Gholamreza Haffari, Dinh Phung, Chen Gong, and Shirui Pan. Gfm-rag: Graph foundation model for retrieval augmented generation, 2025. URL <https://arxiv.org/abs/2502.01113>.
- Alexander Maedche and Steffen Staab. Ontology learning for the semantic web. *IEEE Intelligent Systems*, 16:72–79, 03 2001. doi: 10.1109/5254.920602.
- Idza Aisara Norabid and Fariza Fauzi. Rule-based text extraction for multimodal knowledge graph. *International Journal of Advanced Computer Science and Applications*, 2022. URL <https://api.semanticscholar.org/CorpusID:249304784>.
- Prakhar Ojha and Partha Talukdar. KGEval: Accuracy estimation of automatically constructed knowledge graphs. In Martha Palmer, Rebecca Hwa, and Sebastian Riedel (eds.), *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pp. 1741–1750, Copenhagen, Denmark, September 2017. Association for Computational Linguistics. doi: 10.18653/v1/D17-1183. URL <https://aclanthology.org/D17-1183/>.
- Sergio Oramas, Mohamed Sordo, and Luis Espinosa-Anke. A rule-based approach to extracting relations from music tidbits. In *Proceedings of the 24th International Conference on World Wide Web*, WWW ’15 Companion, pp. 661–666, New York, NY, USA, 2015. Association for Computing Machinery. ISBN 9781450334730. doi: 10.1145/2740908.2741709. URL <https://doi.org/10.1145/2740908.2741709>.
- Manita Pote. Survey on embedding models for knowledge graph and its applications, 2024. URL <https://arxiv.org/abs/2404.09167>.
- Jay Pujara, Eriq Augustine, and Lise Getoor. Sparsity and noise: Where knowledge graph embeddings fall short. In Martha Palmer, Rebecca Hwa, and Sebastian Riedel (eds.), *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pp. 1751–1756, Copenhagen, Denmark, September 2017. Association for Computational Linguistics. doi: 10.18653/v1/D17-1184. URL <https://aclanthology.org/D17-1184/>.
- Yifan Qi, Weiguo Zheng, Liang Hong, and Lei Zou. Evaluating knowledge graph accuracy powered by optimized human-machine collaboration. In *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD ’22)*, pp. 1368–1378. ACM, 2022. doi: 10.1145/3534678.3539233. URL <https://doi.org/10.1145/3534678.3539233>.
- Bin Qiao, Zhiliang Zou, Yurong Huang, Buyue Wang, and Changlong Yu. A joint model for entity and relation extraction based on BERT. *Neural Computing and Applications*, 34(5):3471–3483, 2022. ISSN 1433-3058. doi: 10.1007/s00521-021-05815-z. URL <https://doi.org/10.1007/s00521-021-05815-z>.
- Edward W. Schneider. Course modularization applied: The interface system and its implications for sequence control and data analysis. In *Association for the Development of Instructional Systems (ADIS)*, Chicago, Illinois, April 1973. Presented in April 1972.

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- Phillip Schneider, Tim Schopf, Juraj Vladika, Mikhail Galkin, Elena Simperl, and Florian Matthes. A decade of knowledge graphs in natural language processing: A survey. 11 2022. doi: 10.18653/v1/2022.aacl-main.46.
- Kartik Shenoy, Filip Ilievski, Daniel Garijo, Daniel Schwabe, and Pedro Szekely. A study of the quality of wikidata, 06 2021.
- Fabian M. Suchanek, Gjergji Kasneci, and Gerhard Weikum. Yago: a core of semantic knowledge. In *Proceedings of the 16th International Conference on World Wide Web, WWW '07*, pp. 697–706, New York, NY, USA, 2007. Association for Computing Machinery. ISBN 9781595936547. doi: 10.1145/1242572.1242667. URL <https://doi.org/10.1145/1242572.1242667>.
- Jiajun Tan, Dong Wang, Jingyu Sun, Zixi Liu, Xiaoruo Li, and Yang Feng. Towards assessing the quality of knowledge graphs via differential testing. *Available online, Version of Record*, 2024. URL <https://doi.org/10.1016/j.jss.2024.07.005>. Received 3 October 2023, Revised 15 June 2024, Accepted 26 June 2024, Available online 29 June 2024.
- Harish Thakur. Automatic knowledge graphs: The impossible grail. *Towards AI*, January 2024. URL <https://pub.towardsai.net/automatic-knowledge-graphs-the-impossible-grail-ef71f9c8aad8>.
- Giannan Wang, Tim Kraska, Michael J. Franklin, and Jianhua Feng. Crowder: crowdsourcing entity resolution. *Proc. VLDB Endow.*, 5(11):1483–1494, July 2012. ISSN 2150-8097. doi: 10.14778/2350229.2350263. URL <https://doi.org/10.14778/2350229.2350263>.
- Bingcong Xue and Lei Zou. Knowledge graph quality management: A comprehensive survey. *IEEE Transactions on Knowledge and Data Engineering*, 35(5):4969–4988, May 2023. ISSN 1041-4347. doi: 10.1109/TKDE.2022.3150080. URL <https://doi.org/10.1109/TKDE.2022.3150080>. Published on 10 February 2022.
- Bowen Zhang and Harold Soh. Extract, define, canonicalize: An llm-based framework for knowledge graph construction. In *Conference on Empirical Methods in Natural Language Processing*, 2024. URL <https://api.semanticscholar.org/CorpusID:268987666>.
- Jian Zhang, Wei Liu, Shuo Wang, and Muhan Zhang. Mindful-rag: A study of points of failure in retrieval augmented generation. *arXiv*, March 2024. URL <https://arxiv.org/abs/2407.12216>.
- Ruiqi Zhu, Alan Bundy, Jeff Pan, Kwabena Nuamah, Fangrong Wang, Xue Li, Lei Xu, and Stefano Maureri. Assessing the quality of a knowledge graph via link prediction tasks. In *Proceedings of the 7th International Conference on Natural Language Processing and Information Retrieval (NLP4IR 2023)*, pp. 1–10, Seoul, Republic of Korea, December 2023. ACM. doi: 10.1145/3639233.3639357. URL <https://doi.org/10.1145/3639233.3639357>. School of Informatics, University of Edinburgh, United Kingdom; Huawei Ireland Research Centre, Ireland.

## A PROMPTS FOR KG EXTRACTION

This section provides the exact prompts used to extract KG’s from the text.

The initial KG is extracted using the following two prompts.

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**Prompt for extracting entities:** Extract key entities from the given text. Extracted entities are nouns, verbs, or adjectives, particularly regarding sentiment. This is for an extraction task, please be thorough and accurate to the reference text.

**Prompt for extracting relations:** Extract subject-predicate-object triples from the assistant message. A predicate (1-3 words) defines the relationship between the subject and object. Relationship may be fact or sentiment based on assistant's message. Subject and object are entities. Entities provided are from the assistant message and prior conversation history, though you may not need all of them. This is for an extraction task, please be thorough, accurate, and faithful to the reference text.

After extracting the entities and relations from each unit of text, we begin the clustering process, which is performed using the following prompts.

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**Prompt for clustering entities:**

Find ONE cluster of related entities from this list. A cluster should contain entities that are the same in meaning, with different:

- tenses
- plural forms
- stem forms
- upper/lower cases

Or entities with close semantic meanings.

Return only if you find entities that clearly belong together.

If you can't find a clear cluster, return an empty list.

**Prompt for validating node clusters:**

Verify if these entities belong in the same cluster.

A cluster should contain entities that are the same in meaning, with different:

- tenses
- plural forms
- stem forms
- upper/lower cases

Or entities with close semantic meanings.

Return the entities that you are confident belong together as a single cluster.

If you're not confident, return an empty list.

**Prompt for clustering edges**

Find ONE cluster of closely related predicates from this list.

A cluster should contain predicates that are the same in meaning, with different:

- tenses
- plural forms
- stem forms
- upper/lower cases

Predicates are the relations between subject and object entities. Ensure that the predicates in the same cluster have very close semantic meanings to describe the relation between the same subject and object entities.

Return only if you find predicates that clearly belong together.

If you can't find a clear cluster, return an empty list.

**Prompt for validating cluster edges**

Verify if these predicates belong in the same cluster.

A cluster should contain predicates that are the same in meaning, with different:

- tenses
- plural forms
- stem forms
- upper/lower cases

Predicates are the relations between subject and object entities. Ensure that the predicates in the same cluster have very close semantic meanings to describe the relation between the same subject and object entities.

Return the predicates that you are confident belong together as a single cluster.

If you're not confident, return an empty list.

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## B VALIDATION OF KG EXTRACTION

This section provides the LLM generations used to validate our KG extraction method.

**Prompt for extracting entities:** Extract key entities from the given text. Extracted entities are nouns, verbs, or adjectives, particularly regarding sentiment. This is for an extraction task, please be thorough and accurate to the reference text.

**Prompt for extracting relations:** Extract subject-predicate-object triples from the assistant message. A predicate (1-3 words) defines the relationship between the subject and object. Relationship may be fact or sentiment based on assistant's message. Subject and object are entities. Entities provided are from the assistant message and prior conversation history, though you may not need all of them. This is for an extraction task, please be thorough, accurate, and faithful to the reference text.

## C PROMPTS FOR MINE

This section provides the LLM prompts used by MINE to evaluate KGs.

**Prompt for extracting a fact from article:** Extract 15 basic, single pieces of information from the following text that describe how one object relates to another. Present the pieces of info in short sentences and DO NOT include info not directly present in the text. Your output should be of the form [ "info1", "info2" ,..., "info15" ]. "Make sure the strings are valid Python strings."

**Prompt for evaluating if a fact is contained in the query result:**

ROLE: "You are an evaluator that checks if the correct answer can be deduced from the information in the context.  
TASK: Determine whether the context contains the information stated in the correct answer.  
Respond with "1" if yes, and "0" if no. Do not provide any explanation, just the number.

## D EXAMPLE ARTICLE FROM MINE

This section provides the article that the example fact is from.



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**Title:** The Rise of Cryptocurrencies

**Content:** Cryptocurrencies have taken the financial world by storm in recent years, revolutionizing the way we think about money and transactions. From the creation of Bitcoin in 2009 by an anonymous individual or group known as Satoshi Nakamoto, to the thousands of altcoins that have since emerged, cryptocurrencies have become a significant player in the global economy. One of the key factors contributing to the rise of cryptocurrencies is the decentralized nature of these digital assets. Unlike traditional fiat currencies that are controlled by governments and central banks, cryptocurrencies operate on a peer-to-peer network, allowing for transactions to occur directly between users without the need for intermediaries. This decentralization not only provides users with more control over their funds but also enhances security and privacy. Another driving force behind the popularity of cryptocurrencies is the technology that underpins them { blockchain. Blockchain is a distributed ledger technology that ensures the transparency and immutability of transactions on the network. Each transaction is recorded in a block and linked to the previous block, forming a chain of blocks that cannot be altered once validated by the network. This technology has been instrumental in building trust and confidence in cryptocurrencies, as it eliminates the need for a trusted third party to oversee transactions. The concept of decentralization and blockchain technology has also paved the way for various applications beyond just digital currencies. Smart contracts, for example, are self-executing contracts with the terms of the agreement directly written into code. These contracts automatically enforce and execute themselves when predefined conditions are met, eliminating the need for intermediaries and streamlining processes in various industries. Cryptocurrencies have also gained traction due to their potential for financial inclusion. In many parts of the world, traditional banking services are inaccessible or too costly for a significant portion of the population. Cryptocurrencies offer a way for individuals to access financial services, such as transferring money and making payments, without the need for a traditional bank account. This has the potential to empower individuals in underserved communities and drive economic growth. The volatile nature of cryptocurrencies has attracted both investors seeking high returns and speculators looking to capitalize on price fluctuations. The rapid appreciation of certain cryptocurrencies, such as Bitcoin, has led to a surge in interest from retail and institutional investors alike. While this volatility presents opportunities for profit, it also poses risks, as prices can fluctuate dramatically in a short period. Regulation has been a contentious issue in the cryptocurrency space, with governments and regulatory bodies grappling with how to oversee this emerging asset class.

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Some countries have embraced cryptocurrencies and blockchain technology, recognizing their potential for innovation and economic growth. Others have taken a more cautious approach, citing concerns about money laundering, tax evasion, and consumer protection. Despite the challenges and uncertainties surrounding cryptocurrencies, their rise has been undeniable. As more individuals and businesses adopt digital currencies for transactions and investments, the landscape of finance is evolving rapidly. The future of cryptocurrencies remains uncertain, but their impact on the financial world is already profound. In conclusion, the rise of cryptocurrencies can be attributed to their decentralized nature, blockchain technology, financial inclusion potential, investment opportunities, and regulatory challenges. As these digital assets continue to gain acceptance and adoption, they are reshaping the way we think about money and finance. Whether cryptocurrencies will become mainstream or remain on the fringes of the financial system remains to be seen, but their impact is undeniable and will likely continue to unfold in the years to come.