IMKG: The Internet Meme Knowledge Graph

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Abstract. Internet Memes (IMs) are creative media that combine text and vision modalities that people use to describe their situation by reusing an existing, familiar situation. Prior work on IMs has focused on analyzing their spread over time or high-level classification tasks like hate speech detection, while a principled analysis of their stratified semantics is missing. Hypothesizing that Semantic Web technologies are appropriate to help us bridge this gap, we build the first *Internet Meme Knowledge Graph (IMKG)*: an explicit representation with 2 million edges that capture the semantics encoded in the text, vision, and metadata of thousands of media frames and their adaptations as memes. IMKG is designed to fulfil seven requirements derived from the inherent characteristics of IMs. IMKG is based on a comprehensive semantic model, it is populated with data from representative IM sources, and enriched with entities extracted from text and vision connected through background knowledge from Wikidata. IMKG integrates its knowledge both in RDF and as a labelled property graph. We provide insights into the structure of IMKG, analyze its central concepts, and measure the effect of knowledge enrichment from different information modalities. We demonstrate its ability to support novel use cases, like querying for IMs that are based on films, and we provide insights into the signal captured by the structure and the content of its nodes. As a novel publicly available resource, IMKG opens the possibility for further work to study the semantics of IMs, develop novel reasoning tasks, and improve its quality.

Keywords: internet memes · knowledge graphs · content enrichment

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Fig. 1. Dissection of an Internet Meme.

1 Introduction

Internet Memes (IMs) can be defined as "a piece of culture, typically a joke, which gains influence through online transmission" [6]. An IM is based on a medium, typically an image representing a well-understood reference to a prototypical situation within a certain community [32]. IMs have become very popular in today's Internet era where the real and the virtual are getting closer and closer, and almost any person, event, and idea have a Web counterpart. According to a recent survey by Facebook, 75% of people between 13 and 36 share Internet Memes (IMs), and 30% do it daily.[1] Thus, IMs easily traverse the Web, originating from niche platforms with low-moderation strategies and then migrating to mainstream social media [32]. During their migration, IMs change to gain the peculiar cultural fingerprint of each community until they become less relevant.

As potential vectors for misinformation [21] and political propaganda [25], but also as a novel digital medium for expressing complex and relatable ideas [5], IMs have been of interest to cognitive linguistics [5], psychology [13], and neuroscience [23]. Recent computer science research on IMs focuses on analyzing their spread (i.e., "virality") [18,22,31] or their relation to hate speech in fringe communities [10,14,15]. However, to our knowledge, no prior work has attempted to dissect the IM semantics at scale.

This paper is built on the premise that Knowledge Graphs (KGs) and their interlinking within the Semantic Web can adequately capture the semantics of IMs. We design and construct the first Internet Meme Knowledge Graph (IMKG), which explicitly represents the semantics encoded in the text, vision, and metadata of IMs. Based on the well-motivated characteristics of IMs from the literature, we derive a set of seven requirements that an IMKG should fulfil. We design a data model that aligns the notions of a media frame (i.e., the original scene that inspires the meme), the meme itself, and the underlying template that can be used to generate additional memes. We populate our KG with IM information scraped from a variety of popular IM sources: a meme encyclopedia, an IM generation website, and an open KG. We enrich the data by object detection from the meme image, entity extraction from the meme caption and

[1] https://www.facebook.com/notes/10158928003998415, accessed 17/12/2022.

background description, and Wikidata knowledge for adding background knowledge about the extracted entities and existing memes. We complete the IMKG construction by integrating the sources into a cohesive graph that is publicly available as RDF and a labelled property graph (LPG). Our analytics of IMKG shows that its data is centred around popular memes and slang terms, that the different modalities provide complementary information, and that it can support novel use cases like obtaining IMs that are based on films or meme matching by similarity. In summary, the paper makes the following contributions, described in detail in the indicated sections:

1. We study and motivate the need to study Internet Memes, pointing to their unique properties of multimodality, succinctness, relatability, and fluidity (Sect. 2). We formalize these properties into seven requirements for a comprehensive KG of IMs (Sect. 3).
2. We construct IMKG: the first Internet Meme Knowledge Graph that satisfies these requirements. The creation of IMKG consists of four main steps: KG modelling, data collection, knowledge enrichment, and knowledge integration (Sect. 4).
3. We provide insights into the structure of IMKG, analyze its central concepts, and measure the effect of knowledge enrichment from different information modalities. We demonstrate its ability to support novel use cases, like querying for IMs that are based on films, and we provide insights into the signal captured by the structure and the content of its nodes (Sect. 5).

2 Background

Origin of Internet Memes. The idea of IMs stems from Richard Dawkins' notion of biological memes, coined as a "*unit of cultural transmission, or a unit of imitation*" [7]. Dawkins draws an analogy between memes and genes, describing both as self-replicating entities: like genes, memes are transmitted between individuals, yet through imitation rather than duplication. Thus, memes propagate themselves through people and, then, through time. As a recent actualization of the meme phenomenon, IMs are concepts, customs, and habits, i.e., the building blocks of culture and society. According to Davison [6], a key defining aspect of IMs is *online transmission*, which requires IMs to be encoded into an internet-viable medium (visual, sound, text, or multimodal), and shared online. In the rest of the paper, we use "meme" and "Internet Meme" as synonyms.

Sources of IMs. On the Web, millions of minds work in tune to create, manipulate, adapt, and share IMs. The spread is extremely fast due to the hyper-connected nature of Web communities. Therefore, large **social media platforms**, such as Reddit, 4chan, and Twitter, are the natural habitat for IMs. An essential aspect of IMs' virality is their accessibility to the general public: anybody is a content creator on the Web. Meme **generators**, e.g., ImgFlip, are essential as they provide blank IMs templates for users to caption without

Table 1. Summary of Internet Meme Sources.

	Example	Open	Data Quality	Virality	Lore	Usage
Generators	ImgFlip	partially	medium	partially	no	yes
Encyclopedias	KYM	yes	high	yes	yes	partially
Large KGs	Wikidata	yes	high	no	partially	no
Social Media	reddit,twitter	partially	low	yes	no	yes

requiring editing skills. Central resources for IM knowledge are IM **encyclopedias:** non-academic efforts that collect and catalog IMs. A popular example is KnowYourMeme[2], which serves as a reference source for memes, analogous to how Wikipedia is the reference source for general world knowledge. Encyclopedias like KnowYourMeme provide essential background information about memes. They strive to explain their underlying lore and identify the IM origins, variations, usage, and, sometimes even interpretations of their meaning. Like Wikipedia, IM encyclopedias are collaborative, i.e., volunteers provide the information as unstructured and semi-structured text.

The popularity of IMs has reached a level that knowledge graphs like Wikidata [34], DBpedia [2], and Freebase [3] provide a wealth of background knowledge about IMs and their described concepts. As such, these sources promise to provide implicit knowledge not provided in IMs or their metadata. Among the listed sources, Wikidata has been found to have the highest quality [9], owing to its crowd-sourcing approach, semantic validation mechanisms, and active contributor pool. Wikidata has nearly 1.5 billion statements about nearly 100 million entities, including reliable links to thousands of other sources, including KnowYourMeme.

Table 1 summarises the characteristics of different IM sources. As apparent in this table, open and high-quality information about IMs is available in IM encyclopedias and large KGs, while the information type varies across sources. For instance, Lore is described in encyclopedias, and usage information is found in generators in social media. In this work, we focus on aggregating knowledge from generators, encyclopedias, and large KGs. We leave social media sources for future work, as these platforms are often restricted in their access and provide limited hints to IM interpretation.

Prior Work on IMs. IMs have been a prerogative subject of cognitive linguistics studies [5], although their relevance is noticeable also in psychology [13], neuroscience [23], and online communication studies [25]. Most prior works on IMs in AI have focused on understanding their virality and spread on social media over time [18,22,31]. Another popular direction has been detecting forms of hate speech in memes. The Hateful Memes Challenge and Dataset [14] is a competition and open-source dataset with over 10 thousand examples. The goal is to leverage vision and language understanding to identify memes that employ hate

[2] https://knowyourmeme.com/.

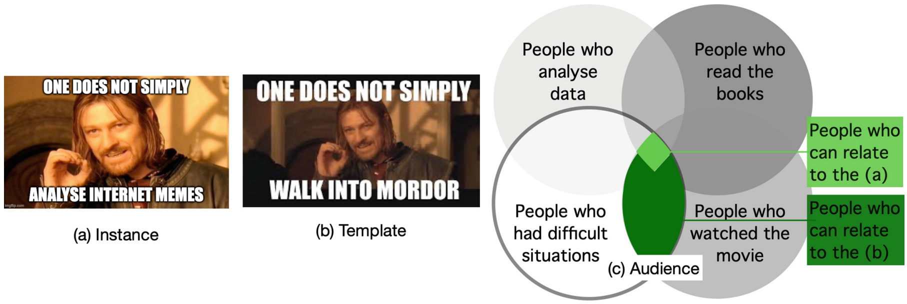

Fig. 2. Examples of multimodality and relatability explained.

speech. Kirk et al. [15] compare memes in this challenge to memes in the 'wild', observing that extracting captions is an open challenge and that open-world memes are more diverse than traditional memes. The Multimedia Automatic Misogyny Identification (MAMI) [10] challenge asks systems to identify misogynous IMs based on text and images in the input memes. MAMI has two subtasks: binary categorization of memes as misogynous or not misogynous, and finer categorization of types of misogyny as a stereotype, shaming, objectification, or violence. Methods for these challenges typically employ Transformer-based models that incorporate vision and language, like ViLBERT [20], UNITER [4], and CLIP [26]. Case-based reasoning methods that reason over instances or IM prototypes have been developed, providing explanations and visualizing them in a user-friendly interface [32]. Most similar to ours is the work by Sheratt [30] on organizing memes into genealogy with the goal to build a comprehensive knowledge base in the future. To our knowledge, no prior work has produced a KG to capture the stratified semantics of IMs provided explicitly in text or vision or implicitly through references to assumed background knowledge.

3 Problem Statement

Challenges. Prior works on memes are limited for two main reasons: 1) the multifaceted nature of IMs unveils a number of hard challenges for AI that make the automated analysis of IMs an open problem; 2) they limit their data work to few, exclusive yet limited datasets, a common pitfall for AI work [29]. A highly-curated and evolving Knowledge Graph of Internet Memes can address both issues. We identify four key challenges that concern the construction of a comprehensive KG about Internet Memes:

C1: IMs are **multimodal**, they come in different formats, generally visuals and text, but also gifs and sounds. At present, the integration of text and vision is a challenging problem for AI, relating to challenges of representation, information fusion, and reasoning [17]. IMs are constructed by overlaying a natural language

Fig. 3. Examples of Variations.

caption over a visual medium, e.g., an image [5,36]. A meme overlays information over a visual medium, i.e., an image or video, with a natural language caption. Figure 2 a) and b) clarify the multimodality showing the template and an example of the IM "One does not simply walk into Mordor", which consists of a frame from Peter Jackson's 2002 movie adaptation depicting Sean Bean. The interplay between the visual and the textual information enables for a creative expression of ideas, be it humour or political commentary, and relies heavily on background knowledge [32].

C2: IMs are **succinct**, i.e., they convey complex messages with simple language. The IM succinctness owes to the stratified semantics that includes the original media frame, the template, a meme adaptation, and the background knowledge that constitutes the IMs' lore. Figure 1 shows such a stratification for the running example, illustrated with a reference frame *Difficulty in Action*. Namely, one can reuse the Lord of the Rings frame that symbolizes a futile undertaking [5] to express their perspective that analyzing memes is more difficult than expected. According to [19], memes should be considered as examples of multimodal similes, not multimodal metaphors, since the source and the target domain are not blended, but continue to be available as dissimilar, yet corresponding, domains.

C3: IMs are **relatable**, i.e., they are recognizable by the members of a certain community. Figure 2 c) exemplifies the community associated to the IM "One does not simply walk into Mordor" as we used in our example "One does not simply analyse internet memes". The target audience of our IM is clearly who normally analyse data, which are used to difficult tasks. Nonetheless, the IM results are clearer to those that have read the book and/or watched the movie. The IM relatability seems to alternate the sentiment of the referred situation, i.e., they trigger a sense of sympathy in the viewer, especially those who understand the lore. Thus, IMs can be powerful tools for social good, such as traumatic confessions and coping mechanisms [1], but also vehicles for political propaganda [25] and hate speech [14]. Relatability is often supported by a humorous and lightweight tone, however, IMs are not intrinsically funny. Indeed, Fig. 2 does not pass a positive message, yet the expected reaction from a target viewer is positive similar to "misery loves company".

C4: IMs are **fluid**, i.e., they are subject to variations and alterations. In one study by Meta, 121,605 different variants of one particular meme were posted across 1.14 million status updates. Figure 3 shows a few variations of the IM

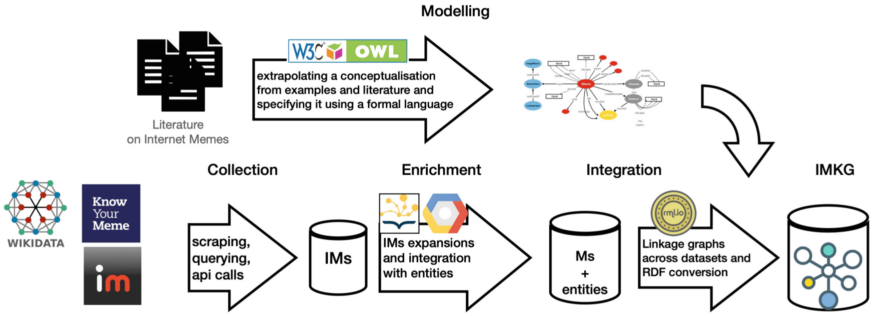

Fig. 4. IMKG Construction Pipeline

"One does not simply walk into Mordor". Such variations include, but are not limited to, (i) image and text to include community-specific slang; (ii) visual changes that further contextualise the caption; (iii) image redoing that extends the lore (e.g., setting from Dr Who), and (iv) image revision that crossover with extra source (e.g., Disney's logo).
It is important to distinguish, at the modelling level, between variations that are within the utilisation pattern of the IMs (e.g., captioning) and those that imply a change in the semantics, e.g., an extension of the meme lore or a change of sentiment. A deep understanding of the IM dynamics over time and across platforms is essential to grasping their semantics.

Notably, these four IM characteristics are tightly connected. Fluidity combines with relatability making IMs attractive for spreading across online communities. Relatability can impact multimodality because some communities are more present on social media networks with more video content than images.

Requirements. We transform these challenges into requirements for the construction and maintenance of an IMKG. Addressing *multimodality* requires constructing a KG that reliably captures both textual and visual information during its data collection and content provision. In other words, IMKG must collect information about *multiple modalities* (R1), and make that information *available* as appropriate (R2). To address the aspect of *succinctness*, IMKG must design a process that clearly dissects the IM stratification (R3). It also must provide the means for *exploring and interpreting* the various semantic layers (R4). To support *relatability*, the IMKG representation must represent links between communities that generate IMs (R5). To facilitate *fluidity*, it must record links to and between the original IM sources (R6). Moreover, fluidity requires that the IMKG incorporates *variations* of a given meme by recording the original media frame, its adaptations, and the common template (R7).

4 Construction of the Internet Meme Knowledge Graph

The construction of IMKG consists of four steps, as shown in Fig. 4. Namely, we start by designing a KG model that can capture the semantics of Internet

Memes, reflecting their multimodality, intended succinctness, relatability, and fluidity. We collect data from representative sources of internet memes, combining encyclopedias, meme generation sites, and open large KGs. We enrich the collected information based on textual processing, visual processing, and background knowledge. Finally, we integrate the extracted information following the developed model by using a schema mapping language and publish IMKG in RDF and LPG format.

Step 1: Data Modelling. We design an integrated conceptual model that can express key properties of IMs following data integration principles [16]. We scope the coverage of our IMKG to **Image macros**, common and representative subgenre of Internet Memes consisting of: (i) A background image that is chosen such that it is immediately recognizable by the intended audience and provides them context (ii) Superimposed text as a caption, whose position is fixed, and that contains the IMs message. The caption in an Image macro may take the form of a catchphrase or a snowclone (i.e., a phrasal template that can be recognized in multiple variants) and contain additional contextual information.

Figure 5 shows the conceptual model of IMKG. At the heart of IMKG's model lies the class `Media Frame`, which is defined as follows.

Definition 1. *A Media Frame is a multimedia object used to represent a "memeable" situation, i.e., one that is familiar to the creator and a broader community.*

For instance, the quote "One does not simply walk into Mordor" is a Media Frame that comes directly from the movie Lord of the Rings. Media Frames are instances of specific subclasses of Image macro, such as `kym:Catchphrase`, thus allowing the organization of IMs into a hierarchy. Media Frames are described in terms of their origin, spread, about, label, and year, and have connections to other media frames that are similar (`rdf:seeAlso`) or broader (`skos:broader`). Media Frames may refer to entities in their tags, about sections, or images.

Media frames can be adapted numerous times by a `Meme`. A Meme is, therefore, a notable example and an instance of a Media Frame. A Meme inherits the about section, tags, and image, but it builds on top of them by adding a new

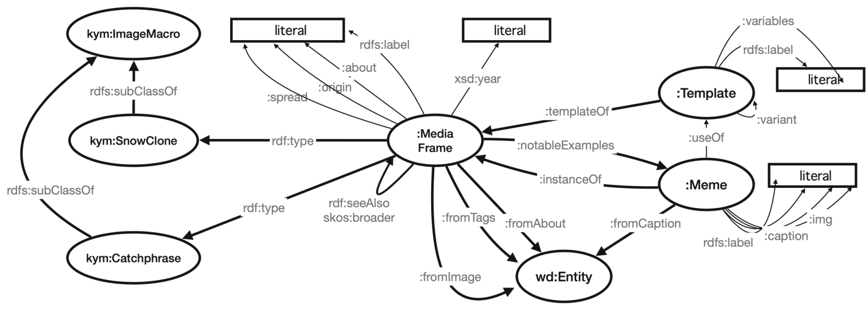

Fig. 5. Data Model of IMKG.

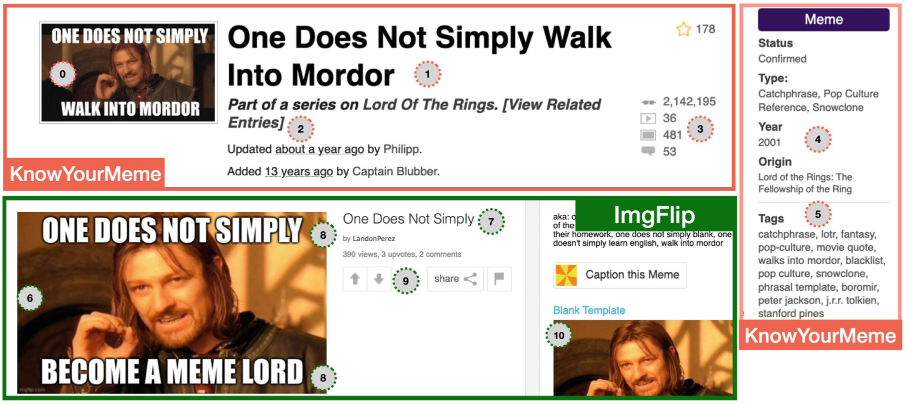

Fig. 6. Snippet of information on KYM (red box) and ImgFlip (green box). (Color figure online)

caption. The entities associated with a Meme are those present in the caption. For a Meme, we also store its textual label, caption, and image URI as strings.

To complete our model, we introduce the notion of `Template`, defined as:

Definition 2. *Templates are multimedia structures for a given Media Frame, typically consisting of an image and a placeholder for caption text.*

For a Media Frame to be used, IM generators publish a captionable blank image to generate a Meme. In ImgFlip, the template base structure is set but modifiable, e.g., the On Does Not Simply[3] template starts with two text boxes. In IMKG, we associate a template with two literals: its label and the default number of captions (variable). While a given Meme is generated by exactly one Template, multiple Templates can be associated with a given Media Frame. Indeed, Templates are user-proposed and can be duplicated or adapted over time, i.e., a Template can be a variant of another Template, e.g., One Does Not Simply Spiderman.[4]

Step 2: Data Collection. We bootstrap the construction of IMKG starting from open large KGs like Wikidata and expanding onto IM generators (ImgFlip) and encyclopedias (KnowYourMeme). We prioritize these sources over social media platforms since these platforms seldom provide meaningful information alongside the IMs.

Wikidata is an open knowledge graph maintained by the Wikimedia foundation. It includes the item Internet Memes (`Q2927074`), with a conceptualisation that is sufficiently similar to ours, i.e., *concept that spreads from person to person via the Internet*. At the time of writing, Wikidata includes 556 instances of such classes, characterised by *977* unique properties, including both object properties

[3] https://imgflip.com/meme/One-Does-Not-Simply.
[4] https://imgflip.com/memetemplate/20502958/one-does-not-simply-Spider-Man.

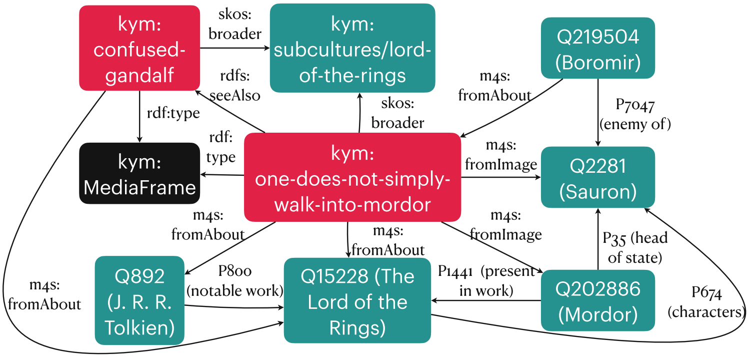

Fig. 7. Enrichment example for *kym:one-does-not-simply-walk-into-mordor*.

(that connect a given IM to other entities) and datatype properties. We denote the initial Wikidata IMs as *seeds* in the IMKG.

KnowYourMeme (KYM) is a well-known collaborative encyclopedia with information about IMs and people and events relevant to IM understanding. KYM provides the largest and most structured catalogue of internet memes and their lore, origin, and meaning. As KYM lacks an API or a similar method for programmatically querying this data, we crawl the entire KYM website, starting from a particular IM page and following the links to other pages describing related memes. The scraping focuses on collecting the following information: media frame (note 0 in Fig. 6), meme label (1), links to broader ("Part of a series on" section) and related ("View Related Entries") memes (2), popularity statistics (3), an infobox containing information about status, type, year, and origin of the meme (4), and the set of tags (5). Not shown in this figure, we also obtain the paragraphs describing a meme's about, origin, and spread. We scrape KYM by using Selenium, which takes two days.

ImgFlip is one of the most popular sites for meme generation, allowing users to quickly personalize one of the available meme templates using a custom caption. Moreover, registered users can vote and comment on the quality of the instantiated memes. ImgFlip organizes memes around templates, a blank version of the IM to be captioned. Users can also propose templates that others can adopt. Multiple Templates may be derived from any original Template, and many Memes may be created based on each of those Templates. For each Meme from ImgFlip, we recorded the media (6), title, author, views, and comment counts (7), the captioning text (8), upvotes (9), and the Template ID (10), which can be used to reconstruct the template URI.

Step 3: Data Enrichment. We perform three different types of enrichment: 1) textual, by extracting and linking entities from media frame descriptions and meme captions; 2) visual, by extracting entities from IM images by object detection; and 3) knowledge-based, by iteratively enriching information about memes and their entities with existing KGs.

We perform **textual enrichment** using DBpedia Spotlight [24]. Specifically, we extract entities from the paragraphs scraped from KYM, i.e., about, origin, and spread, and from the textual captions from ImgFlip. We filter out entities with confidence below 0.5. We map the resulting entities and entity types from DBpedia to Wikidata entities via the site links mapping file to maintain the usage of Wikidata as a central background resource. We also convert KYM tags to Wikidata entities following the same method.

We perform **visual enrichment** using the Google Vision API.[5] Given the cost of the service, we limit the extraction of objects to only the Media Frame image. The vision extraction tool detects objects and links them to Freebase. We map these entities to Wikidata by using the identifier property *P646*.

We perform two forms of **knowledge enrichment** using Wikidata. First, we obtain all information directly associated with the seed memes in Wikidata, i.e., we collect statements whose subject is one of the 556 seed memes. Second, we extract all Wikidata statements connecting two nodes (entities or memes) from the former enrichment steps. We use the Knowledge Graph Toolkit [12] to extract background knowledge about the meme seeds and entities from Wikidata.

An example snippet of an enriched graph for the media frame *kym:one-does-not-simply-walk-into-mordor* is shown in Fig. 7. The figure shows that this enrichment includes key entities such as Lord of the Rings, J.R.R. Tolkien, Mordor, Sauron, and Boromir, extracted from images or the about section in KnowYourMeme. The entities are tightly connected based on numerous Wikidata links, indicating for instance that Mordor is present in the work Lord of the Rings, created by Tolkien, that Boromir is the enemy of Sauron, and that Sauron is a character in Lord of the Rings. The figure also shows the effect of the data modelling, which allows us to connect similar media frames based on their broader subculture or explicit "rdfs:seeAlso" links in KnowYourMeme.

Step 4: Data Integration. We glue together the various datasets by deriving links across their entities. We obtain links between 276 memes in Wikidata and KYM via the property *P6760*. On the other hand, the KYM/ImgFlip linkage requires multiple steps. We first extract all direct ImgFlip links mentioned within our KYM crawled data and manually select the most reliable connections. Next, we perform a string match between memes titles in both datasets. We discovered about 60 matches above a safety threshold of 85% similarity. Finally, for the 276 seeds IMs identified above, we manually map the Templates (from ImgFlip) with the corresponding Media Frame (from KYM). Notably, given the user-based nature of ImgFlip templates, such a relationship is one-to-many, i.e., a given Media Frame has many templates, while a template is assigned to one and only one Media Frame, e.g., *One does not simply Spiderman*.[4]

Since the data comes in different formats (e.g., crawled data is in JSON, Wikidata in the KGTK TSV format [12]), we include a **data conversion** step with RML [8], a mapping language for KG construction. To sustain FAIR data management [35], we choose RDF as the data model of choice and N-Triples as the data format. We implement a parallel conversion pipeline from various

[5] https://cloud.google.com/vision.

Table 2. Overall statistics of IMKG and its constituent sources. I2K stands for the collection of links between ImgFlip templates and KYM memes.

source	#nodes	#edges	#rels	degree	#frames	#memes	#templates
KYM	167,662	914,941	18	10.91	12,585	12,585	0
ImgFlip	4,698,912	15,129,606	10	6.44	0	1,326,032	1,765
I2K	343	244	1	1.42	96	0	241
WD subset	85,917	504,781	805	11.75	242	242	0
IMKG	**4,850,636**	**16,549,810**	**836**	**6.82**	**12,585**	**1,338,617**	**2,006**

sources for scalability. For maintainability, we made an extensive effort to ensure the definition of identifiers: whenever possible, we reuse those from Wikidata, ImgFlip, and KYM. Notably, we avoid the use of blank nodes. Besides RDF, we also provide a property graph version of IMKG for scalable analytics.

5 Analysis

This section provides insights into the extent of knowledge covered in IMKG. We start by describing general graph statistics and indicators of centrality. We next explain how IMKG can support novel use cases. We then show how IMKG can facilitate hybrid applications based on both structural and content similarity.

Overall Statistics. Table 2 shows IMKG's general statistics. IMKG has 4.8M nodes described with 16.5M edges. Over a quarter of its nodes are memes, most of which come from ImgFlip. IMKG also has around two thousand templates, i.e., it has on average 2593 IMs per unique template and over twelve thousand frames that are linked to its memes. Most of the edges in IMKG, as can be expected, come from ImgFlip, whereas KnowYourMeme and Wikidata both contribute with hundreds of thousands of edges. The frames in IMKG come from KYM, the memes from practically all sources, and the templates primarily from ImgFlip. As such, IMKG is more than a sum of its parts, as it integrates knowledge in a compatible form.

The three most common relations in IMKG are `fromCaption`, `template`, and `image_url`. In total, IMKG has over 800 relations, most of which come from the enrichment with Wikidata. In terms of centrality, the Wikidata node for IM (*Q2927074*) has the largest PageRank values, followed by the Wikidata nodes Q978 (meme), Q336 (science), Q30 (United States), and Q11862829 (academic discipline). These statistics show that the Wikidata information that enriches the graph plays a key role in connecting the memes via background links.

Effect of Enrichment. In total, over 20% of IMKG consists of edges that connect memes to entities extracted from images or text, and over 3% (505k) of IMKG's edges come from the enrichment with background knowledge from Wikidata. Most of our entities come from captions (3,344,941), followed by 388,579 entities extracted from images, and 47,455 from the textual description. Table 3

Table 3. Most common entities extracted from each enrichment source: captions, images, and text description. "Org." stands for "Organization".

m4s:fromCaption	m4s:fromImage	m4s:fromAbout
Internet meme	font	image macro
meme	image	4chan
information technology	Internet meme	Internet meme
bling-bling	Know Your Meme	catchphrase
Batman	meme	YouTube
CAN bus	art	parody
human brain	happiness	Japanese
Hotline Bling	gesture	Tumblr
Kermit the Frog	illustration	meme
National Org. for Women	fictional character	United States of America

Table 4. Use-cases enabled by IMKG: for each, we show the KGTK query's match clause, the three matches of the results and the number of results in brackets.

Use case	Match query	Results
IMs that depict Sponge Bob	(h)-[:'m4s:fromImage']→(:Q83279), (h)-[:'rdf:type']→(:'kym:Meme')'	kym:are-you-feeling-it-now-mr-krabs, kym:big-meaty-claws, kym:bold-and-brash,... (130)
Most meme-able person	(h)-[]→(person), (h)-[:'rdf:type']→(:'kym:Meme'), (person)-[:P31]→(:Q5)	Q22686 (Donald Trump), Q18738659 (Kyle Craven), Q15935 (Kanye West)
IMs based on films	(h)-[:'m4s:fromAbout']→(t), (t)-[:P31]→(:Q11424)	kym:hitlers-downfall-parodies→Q152857 (Downfall), kym:cat-transcendence → Q1534001 (The Prophecy),... (51)
Sex or gender distribution	()-[]→(person), (person)-[:P21]→(gender)	male: 10,333, female: 2,865, transgender female: 20,...

provides the top 10 most common entities extracted from each source. We observe that some more general entities are found in practically every modality (Internet meme, meme). Meanwhile, others are idiosyncratic to certain sources: for instance, bling-bling (Q44359) and Kermit the Frog (Q1107971) are dominantly extracted from meme captions, happiness (Q8) and art (Q735) from images, and Japanese language (Q5287) and USA (Q30) from textual descriptions. Notably, the most common Wikidata relations are P31 (instance-of) with 59K occurrences, P136 (genre) with 34K occurrences, and P106 (occupation) with 28K occurrences.

Illustrative Use Cases. We describe four novel use cases that are handled with simple queries over IMKG. These four use cases ask for IMs that depict Sponge Bob, for the most meme-able persons in IMKG, for Media Frames based on film scenes, and for sex or gender distribution of the people in IMKG (Table 4). We

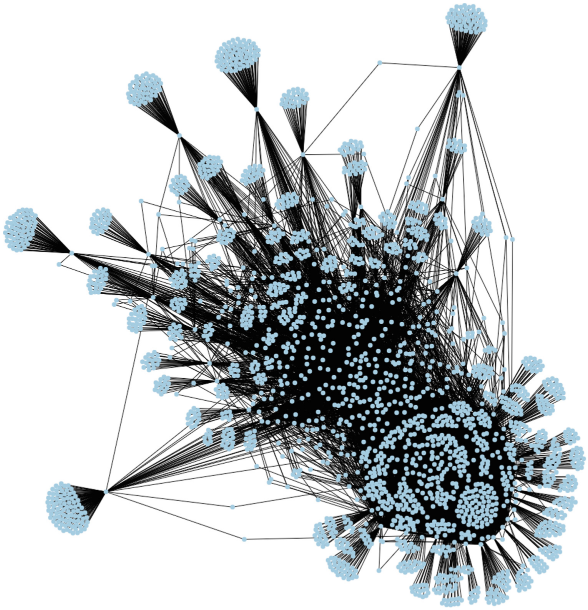

Fig. 8. Connections for media frames with the entity Sponge Bob Square Pants.

observe that there are 130 media frames that depict Sponge Bob in their image. We show a graph of these media frames with their one-hop information in Fig. 8. Curiously, the most meme-able people are a controversial modern-day politician (Donald Trump), a viral fictional character (Kyle Craven), and a controversial celebrity figure (Kanye West). While these entities are intuitively popular in memes, IMKG enables us to single them out statistically for the first time. Further, we learn that 413 of our media frames are based on films - for instance, the frame *kym:hitlers-downfall-parodies* is based on the 2004 film Downfall, while the frame *kym:cat-transcendence* on the 1995 film called The Prophecy. We find that over three-quarters of the people in IMKG are male, three times fewer are female, and dozens of people are trans women, intersex, or non-binary. While these use cases demonstrate a wide range of queries that can be asked about Internet memes for the first time, all of them are facilitated by the property of IMKG to harmonize data across sources (generators, encyclopedia, large open KGs), and to extract and enrich this data with entities and their relations from Wikidata.

Alignment Between Content and Structure. Our IMKG combines information encoded in its structure with information stored in its literals. As shown in Fig. 5, IMKG includes a number of literal properties, some of which are typically filled with long paragraphs of text. While we extract entities from these paragraphs, there is more information embedded in the text that can be naturally encoded with language models. We showcase the benefit of the hybrid informa-

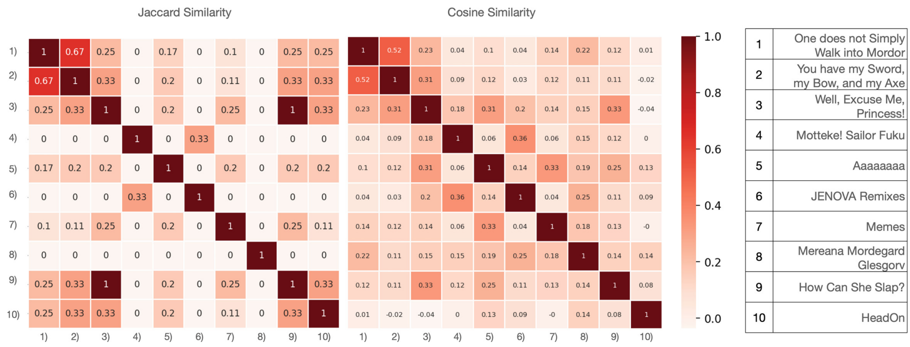

Fig. 9. Similarity heatmap of IM types vs Jaccard (left)/Cosine (right) of 'about'.

tion stored in IMKG here, by measuring the alignment between the IM types and the meme 'about' sections. We measure type similarity between two memes based on the Jaccard overlap between their types, and we measure the similarity of their 'about' sections based on cosine similarity over their SentenceBERT [27] embeddings. As apparent by the similar colour patterns in Fig. 9, memes that are considered more similar by SentenceBERT typically belong to similar types. Such an example is the meme 'One Does Not Simply Walk Into Mordor', of the types kym:snowclone, kym:catchphrase, and kym:pop-culture-reference, which is judged to be similar to the meme 'You Have My Sword, and My Bow, and My Axe', belonging to the types kym:snowclone and kym:catchphrase.

6 Conclusion and Outlook

This paper described the creation of the first Internet Meme Knowledge Graph. Starting from the meme characteristics of multimodality, reliability, succinctness, and fluidity, we defined seven requirements for a comprehensive IMKG. We created IMKG in four steps: data modelling, data collection, enrichment, and integration. The resulting IMKG consisted of over 2 million edges describing over 600K nodes collected from a popular meme encyclopedia (KnowYourMeme), a generation website (ImgFlip), and an open KG (Wikidata). Our analysis showed the importance of the extracted entities from images, captions, and text descriptions, and demonstrated how these entities can facilitate novel use cases such as obtaining all IMs based on films. To make IMKG knowledge was shown to be possible by a combination of IMKG with language model embeddings.

The current IMKG demonstrated the potential of our approach and the significance of aggregating the meme semantics following Semantic Web principles. We see two main directions for future work on IMKG. First, we propose to improve the coverage of IMKG as follows: (i) multimodality by studying videos in addition to images (ii) relatability by connecting user profiles to their meme comprehension based on crowdsourcing (iii) succinctness by incorporating frames from FrameNet [11] (iv) fluidity by further studying the similarity of the memes to other memes and to the original media frame.

Second, we propose that IMKG should be incorporated into methods for downstream reasoning tasks. IMKG may improve the accuracy and explainability of neuro-symbolic methods for IM, like hate speech detection and classification [14,32]. IMKG can facilitate the creation of novel reasoning tasks, such as Internet Meme QA. Third, we plan recurrent releases of the KGs, following emerging principles from the graph data management community to handle scalability in terms of volume [28] and velocity [33].

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