A Survey of Commonsense Knowledge Organization, Structuring and Categorization

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Abstract

Commonsense knowledge (CK) in artificial intelligence (AI), is an expanding field of research. Because CK is intrinsically implicit, current data-driven machine learning models are still far from competent compared to humans in commonsense reasoning tasks. To minimize the gap between machine learning models with the goal of artificial general intelligence (AGI), researchers propose to collect such CK from human and text corpus for commonsense augmentation. Over the years there have been many ways that commonsense knowledge (in AI) has been implemented. However, there has not been a systematic review conducted on how CK can be organized, structured and categorized. The aim of this paper is to do a literature survey on how existing knowledge sources organize, structure and categorize within the general frameworks of CK. The organization can decide the design schema of a knowledge graph (KG), the structuring decides the format and the categorization decides what dimensions and criteria a KG employs.

1 Introduction

Commonsense knowledge (CK) is information that can generally be assumed to be possessed by most people, and, according to the Gricean maxims [19], it is typically omitted in written/oral communication. As an example, say you were told "Jenny walked through the rain into the library across the street." with no additional context. For human beings, it is implicitly understood that *Jenny got wet*. Why? Because we know that *walking through the rain makes you wet*. Although this statement might seem obvious for humans, it is not obvious for a machine. That is, unless the machine is explicitly told so.

Because of the implicitness of CK, it is difficult to put into automated systems [38]. Our understanding of CK is very ambiguous, and reviewing how existing literature comprehends CK in AI opens up room for further research. In particular, surveying how CK could be organized, structured, and categorized can provide meaningful insights into the current state of CK research. Currently, there are many different commonsense knowledge graphs (CSKGs) available, each with their own task(s) falling within their own dimension(s) [23], and design schema [21]. The survey conducted in this paper, will focus be on the example resources for **representative public commonsense sources**. Particularly, on the sources of CK within the CSKG [26], WikiData [54], VerbNet [48] and ImageNet [26].

The main question to answer is: **How can commonsense knowledge be organized, structured, and categorized?** The division is as follows:

- **How can commonsense knowledge be organized?**

  This refers to the design schema or ontology of CK. In particular, this section goes over the Winograd schema [32] and the Semantic Web [55]. Because this is a broad question, it is not the main focus and many topics will not be covered. However, a brief introduction is given, as well as suggestions to access more information regarding the ontologies.

- **How can commonsense knowledge be structured?**

  The structure of CK means what kind of format CK is stored in, and what impact such a structure has on the KG. In particular, it identifies what kind of tasks the different representative public commonsense sources can do based on their format. The advantages and disadvantages of these KG formats are highlighted. The format that is used for the CSKG [26] is also discussed [22].

- **How can commonsense knowledge be categorized?**

  Aims to answer the question of how existing work builds up a taxonomy of CK. Meaning, the different methods and dimensions of categorizing knowledge sources, but also the criteria employed when doing so. The categorization of KG research gives an overview of how far along this field has come. This aids researchers when trying to consolidate different sources of KGs.

The goal of this literature survey is to highlight and give an overview of the way CK is organized, structured, and categorized in AI. This will give further insight into the ever-expanding field of CK research.

This paper begins by introducing the methodology, including how resources were gathered, organized and what strategy was employed to answer the research question. Then the contributions of this paper and research in the field of CSKGs are discussed, followed by sections breaking down each one of the sub-questions. Other interesting CSKGs and their utilization are highlighted, after which shortcomings and challenges of KGs are discussed. After a brief note regarding responsible research, the survey comes to a conclusion and potential future work is explored.

2 Methodology

This section describes how resources such as research papers, articles, journals, books, conference papers, etc., were gathered. It further discusses the general organization and other tools used to write this paper. Lastly, a description is given of how the sub-questions are addressed.

2.1 Gathering Knowledge

At the start of the project, two anchor papers were provided: [26] and [23]. There was also a video playlist with topics relating to CSKG [63]. Going through the references within those anchor papers really helped in giving an idea of what has been researched. Searching through Scopus, Web of Science and Google Scholar resulted in more useful research papers. A list of the Scopus search queries is given in the appendix. Sometimes, there was no access to an article or journal. The TU Delft library provided help in those instances. I also took matters into my own hand, by finding other means of obtaining a paper (such as emailing the authors).

2.2 Organizing Resources

To organize all resources (such as research papers, links, documents, notes etc.) a Notion database [1] was used. This was convenient, as it allowed for easy tagging, organizing, and sharing. It also allowed for creating filtered views, for example: to see all the resources tagged with "Structured". Using tools such as *Citation Machine* [2] and *Cite this for me* [3] allowed for easy BibTex citation generation. An online table generator was used to make LaTeXtables [4].

2.3 The General Procedure

In general, the best strategy was to answer each sub-question one-by-one, without completely ignoring the other sub-questions. It just meant that the primary focus was on one of the sub-questions at a time. The first two weeks were spent gathering knowledge. The remainder of the weeks were (as evenly as possible) divided between answering each sub-question. Everything is cited properly as it is written. Finally, clustering papers that are similar in one aspect or another made the writing process for each sub-question go smoothly.

3 Contributions

The contribution of this paper is a literature survey on CSKGs to highlight the way it is structured, categorized and organized. To do this, first the historical research is examined. This motivates the current-day research and the general contents of this paper.

3.1 Historical Analysis

As mentioned in section 2, the anchor papers were the first step. The search started by looking for articles and more literature on the internet. For example, searching through Scopus yielded an overview of the general research done relating to the research question, as seen in Figure 1.

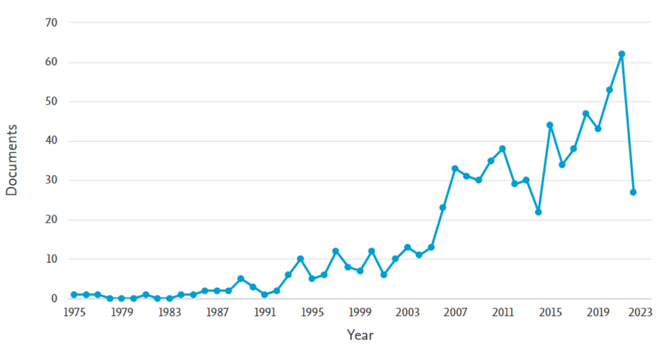

Figure 1: Documents per year of the general research done in the Computer Science field relating to how CK can be organized, structured and categorized. Query: *TITLE-ABS-KEY (((commonsense AND knowledge) OR (common AND sense AND knowledge) OR cskg) AND (structure* OR dimension* OR organiz* OR categor*)) AND (LIMIT-TO (SUBJAREA , "COMP"))*

[1]https://www.notion.so/

[2]https://www.citationmachine.net

[3]https://www.citethisforme.com/

[4]https://www.tablesgenerator.com/#

According to Figure 1, most CSKG research started taking place in the 90's, peaking in recent years. This motivates the reason to survey how CSKGs can be organized, structured and categorized, since it promotes further research of CK. CSKGs can be used to reason in downstream tasks and improve the efficiency or accuracy for concepts such as broad and social commonsense reasoning [23].

3.2 Current Research

While scoping out the field of KGs, it became clear that there are many types, each with their own variants and implementations of CSKGs [23] [26] [36] [10]. The main focus of this paper will be on the general representative public commonsense sources, as seen in [26]. Relevant literature has been collected and organized to give a comprehensive review of CSKGs.

The KGs discussed are:

1. ConceptNet [50]
2. Web Child [53]
3. ATOMIC [46]
4. WikiData [54]
5. WikiData-CS [25]
6. WordNet [39]
7. Roget [28]
8. VerbNet [48]
9. FrameNet [2]
10. Visual Genome [30]
11. ImageNet [12]

Table 1 contains an overview of these CSKGs. These graphs have their own methods of consolidation and principals [24] [26].

There are also different ways each CSKG organizes, structures and categorizes their content. The upcoming sections will delve into details regarding all of this. Section 7 discusses other interesting implementations of KGs. For general information on knowledge graphs (their organization, structuring and much more), refer to [21].

4 The Organization of Commonsense Knowledge

This question refers to the ontology or the design schema of CK. In this context, an ontology is "a concrete, formal representation of what terms mean within the scope in which they are used (e.g., a given domain)" [20]. Classes and their logical connections such as subsumption and disjointness refer to their *ontology* or *schema* [59]. There are many different types of schemas for KGs [21]. AS far back as the 1980s, CK was being organized to comprehend natural language and solve problems [45]. In this section, only the *Winograd schema* and the *Semantic Web* will be discussed. Additional references will be given at the end of the section.

4.1 Winograd Schema

A Winograd schema [32] is a pair of sentences that differ only in one or two words (see Figure 2) and that contain a referential ambiguity that is resolved in opposite directions in the two sentences. It is an alternative to the Turing Test. A comprehensive categorization to answer the Winograd Schema Challenge (WSC) is presented in WinoWhy [65].

Source	Included in CSKG?	Describes	Size	External Mappings
ConceptNet	✓	everyday objects, actions, states, relations (multilingual)	36 relations, 8M nodes, 21M edges	WordNet, DBpedia, OpenCyc, Wiktionary
Web Child		everyday objects, actions, states, relations	4 relation groups, 2M nodes, 18M edges	WordNet
ATOMIC	✓	event pre/postconditions	9 relations, 300k nodes, 877k edges	ConceptNet, Cyc
WikiData		instances, concepts, relations (general-domain knowledge graph)	1.2k relations, 75M various objects, 900M edges	various
WikiData CS	✓	a commonsense subgraph of Wikidata	71243 nodes, 101771 edges, 44 edge types, 50 relations	ConceptNet, WordNet, Roget
WordNet	✓	words, concepts, manual relations	10 relations, 155k words, 176k synsets	
Roget	✓	words, relations manual	2 relations, 72k words, 1.4M edges	
VerbNet		verbs, relations	273 top classes, 23 roles, 5.3k senses	FrameNet, WordNet
FrameNet	✓	frames, roles, relations	1.9k edges, 1.2k frames, 12k roles, 13k lexical units	
Visual Genome	✓	image objects, relations, tributes	42k relations, 3.8M nodes, 2.3M edges, 2.8M attributes	WordNet
ImageNet		image objects	14M images, 22k synsets	WordNet

Table 1: Survey of existing sources of commonsense knowledge, adapted from Table 1 of [26, p. 3], and extended with [25].

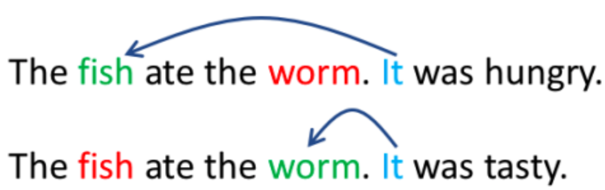

Figure 2: A pair of questions in WSC that only differ by the final word, which changes the context. Taken from [65, p. 1].

A *Pronoun Coreference Resolution* (PCR) is the task of resolving pronominal expressions to all mentions they refer to [64]. Given a PCR question, and the correct answer from the original WSC data, WinoWhy attempts to solve this question using commonsense reasoning. WinoWhy uses language representation models to select the plausible reasons for answering WSC questions. Refer to [29], where other WSC approaches and datasets are reviewed.

4.2 The Semantic Web

The Semantic Web is an extension of the World Wide Web, with the aim to make the internet more machine-readable [55]. It is possible to map between ontologies on the semantic web using GLUE, which is ”a system that employs machine learning techniques to find such mappings. Given two ontologies, for each concept in one ontology GLUE finds the most similar concept in the other ontology” [13, p. 1]. GLUE has incorporated CK and domain constraints when learning to match ontologies on the Semantic Web [13] [14].

4.3 Other Ontologies Usages

Refer to [49] for more information on using the Semantic Web to solve Winograd Schemas. CK and ontology (together with text mining) is also useful to automatically identify and manage implicit requirements [15]. Organizing opinions and sentiments extracted from the Web using AffectiveSpace can aid in performing emotive reasoning [8]. To find out more on building topic-specific ontologies, refer to [6] where it is described how to approach building topic ontologies for specific commonsense topics.

5 The Structuring of Commonsense Knowledge

The structure of CK refers to the format in which it can be stored. CSKGs can be stored in many different types of formats. Depending on this structure, a KG can be transformed, created, enhanced, or analyzed in different ways. Firstly, the different formats of the representative public commonsense sources will be discussed. These are the formats seen in Ta-

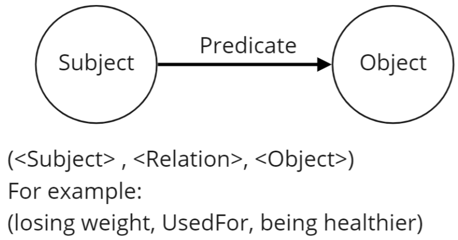

Figure 3: A (semantic) triple represented by the SPO format.

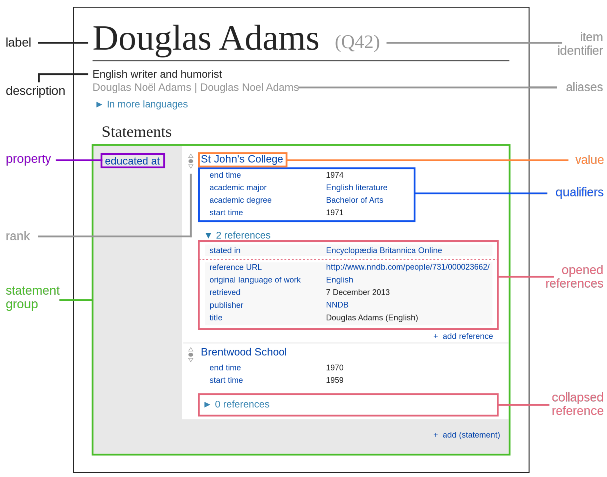

Figure 4: Overview of a WikiData statement.

ble 2. The CSKG also has its own format it is structured in called the Knowledge Graph ToolKit (KGTK) format [26] [22]. The reasoning behind choosing such a format will be discussed.

5.1 The Different Formats to Structure Commonsense Knowledge

Triples are a format to store data used by ConceptNet [50] [35], WebChild [53] [52] and ATOMIC [46]. In this context, RDF (Resource Description Framework) triples, semantic triples, or SPO (Subject, Predicate, Object) triples are used interchangeably [31]. A format like triples allows knowledge to be represented in a way that is both machine- and human readable, as can be seen in Figure 3. The *ConceptNet* KG connects terms (word and phrases of natural language) with assertions (labeled weighted edges) [50]. It has a triple that is structured as *(start node, relation label, end node)*. *WebChild* triples connect nouns with adjectives through fine-grained relations, similarly to the SPO format. Meanwhile, *ATOMIC* triples are represented as *(event, relation, event)*.

Linked statements are used by *WikiData* [54] [61]. The data model used is machine-readable. Statements consist of a property-value pairs about items, as seen in Figure 4. Linked data refers to publishing structured data in order to interlink it. This in turn means that data contributed by volunteers can be linked to other datasets, sources and knowledge bases.

A **tabular** format of data is used by WikiData-CS [25] and VerbNet [48] [41]. *Wikidata-CS*, (not to be confused with WikiData [54]) is an extracted subset of WikiData which uses the KGTK tabular format *(an edge file, a node file, and a qualifiers file)* to integrate with the CSKG [25]. It consists of around 101000 statements that have been manually mapped to 15 ConceptNet relations. *VerbNet* represents a shallow, disconnected hierarchy of verb behaviour [41]. This ranges from groups of verb classes that share similar semantics to the tree structure of the verb classes themselves.

Linked synsets such as *WordNet* are interlinked by means of lexical and conceptual-semantic relations [39]. Synsets are unordered sets of synonyms. Words with several different meanings are represented in many well defined synsets, and thus each form-meaning pair in WordNet is distinctive. *ImageNet* also consists of linked synsets, but by means of images [12]. It utilizes the hierarchical structure given by WordNet [39]. The synsets here are interlinked by several types of relations.

Roget is a **thesaurus** that can easily be transformed into graphs, lattices or a hypertree view depending on the task at hand and which visualization works best [28].

Frame elements (FEs) are the basic unit of analysis in the semantic frame, which are a type of event or state and the participants and "props" associated with it [3]. FEs are used by *FrameNet* [2]. The FrameNet database uses lexical units (LUs) and processes them in order to attach a frame to the database [18]. In [1] additional details regarding the structure of the FrameNet database is given.

Scene graphs are data structures that arrange the logical and spatial objects in a scene and the relationships between these objects [9]. *Visual Genome* uses scene graphs for these images, which can be visualized in many different ways [30]. Each image has exactly one scene graph, with 40 to 50 region graphs (with an average of 42) built from objects. Thus if a description contains no objects, then it has no region graphs to be associated with.

5.2 The Reasoning for the Knowledge Graph Toolkit

The Knowledge Graph Toolkit (KGTK) is a file format that represents KGs as hypergraphs [22]. Using tab-separated and a column-based text format, it can describe any attributed, labeled or unlabeled hypergraph. Hypergraphs store facts about the world in the form of relations among any number of entities [17]. The function of KGTK is to help with operations

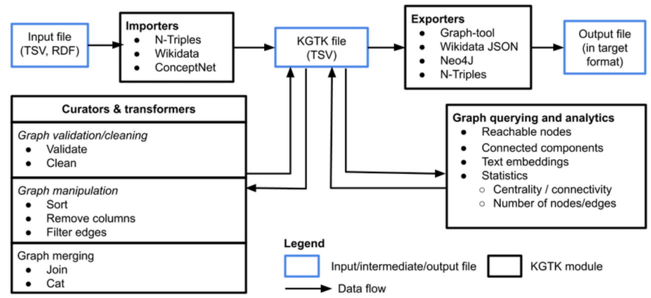

Figure 5: Overview of the different capabilities of KGTK [22, p. 6].

Source	Category	Dimensions	Format
ConceptNet	Commonsense KGs	1-10, 12, 13	Triples
WebChild	Commonsense KGs	2, 4-6, 8, 10-13	Triples
ATOMIC	Commonsense KGs	9, 10, 12	Triples
WikiData	Common KGs	1-8, 10, 12, 13	Linked statements
WikiData CS	Commonsense KGs	1-8, 10, 12, 13 *	Tabular
WordNet	Lexical resources	1-5	Linked synsets
Roget	Lexical resources	2, 3	Thesaurus
VerbNet	Lexical resources		Tabular
FrameNet	Lexical resources	1-4, 8, 10, 12, 13	Frame elements
Visual Genome	Visual sources		Scene graphs
ImageNet	Visual sources		Linked synsets

Table 2: Overview of commonsense knowledge sources, the format in which they are stored and their corresponding relations, adapted from Table 1, Table 2 and Table 4 of [23, p. 3,5,9]. The numbers in the "Dimensions" column corresponds to the dimensions described in section 6. The '*' indicates that WikiData-CS uses 3 principals to extract commonsense knowledge and thus wont have all the same things in its dimensions (e.g. named entities like /r/IsA relation) as its WikiData superset.

such as manipulating, curating, and analyzing the contents of KGs, in which each statement may have multiple qualifiers [22]. Figure 5 demonstrates the features and general workings of KGTK. Additionally, in [21] a selection of different graph-structured data models are presented.

The advantage of supporting many common formats for importing and exporting is that it allows for data to be generalized and easily consolidated. As a real-world example, during the 2020 COVID pandemic a lot of data was being generated and published by many sources [57]. These efforts used KGs to have easy access to all information regarding the virus, which brought up some complications [22]. KGTK was designed to address these challenges.

The disadvantage of this format is knowledge granularity, sparsity, and different creation methods. These challenges are discussed in section 8.

6 The Categorization of Commonsense Knowledge

This section reviews how existing work builds up a *taxonomy* of CK, also known as *semantic networks* [11]. Each knowledge source has a different set of criteria or relations on which it is categorized. All KGs fall under a general taxonomy [27]. Additionally, CK sources also fall within some dimensions [23]. The way a KG is categorized can determine its use, strengths and (potential) weaknesses.

6.1 The Dimensions of CK Sources

According to [23] there are **13 dimensions** in which CK sources can be grouped into:

1. lexical
2. similarity
3. distinctness
4. taxonomic
5. part-whole
6. spatial
7. creation
8. utility
9. desire/goal
10. quality
11. comparative
12. temporal
13. relational-other

Table 2 gives an overview of each knowledge dimension and the corresponding category, relations, and format they take on. Because some of these sources have not been (manually) mapped to any relationships they are lacking dimensions. For example, there was an instance where 2 authors tried to perform mappings for WikiData-CS, but sometimes annotators disagreed on the relationship mappings [25]. This indicated that there is a lack of the same precise relation, forcing the annotators to opt for a more generic relation after a joint discussion. The WikiData-CS lacks certain relations within its dimensions (such as /r/IsA) due to the principals applied. This challenge of modeling relations is briefly discussed in section 8. Thus, *defining* a taxonomy for each of these knowledge sources is beyond the scope of this paper, as that is its own topic and would require its own attention.

The coverage of each source varies with respect to their dimension(s) [23]. Some sources within the CSKG such as WikiData-CS, ConceptNet and FrameNet cover a wide variety of dimensions. Whereas others, such as Roget or ATOMIC focus on specific dimensions. This narrow focus usually corresponds with the sources having more depth for the few dimensions they cover, with the set of edges being much larger. Having a broad set of dimensions to cover also means that there is a limited amount of edges in comparison, and varying focus.

6.2 The Criteria for Categorization

In Table 1 the external mappings for each of the knowledge sources are given. WikiData has various external identifiers [60]. Some of these mappings might be incomplete. Regardless, they provide an opening for consolidation of CK [26]. Generally, there are 5 principals that can be followed for the consolidation of sources into a CSKG [26]:

- P1. Embrace heterogeneity of nodes
- P2. Reuse edge types across resources
- P3. Leverage external links
- P4. Generate high-quality probabilistic links
- P5. Enable access to labels

This approach can also be adapted to strive for a certain set of principals, depending on the KG that is being built (such as in [25]). Even when performing knowledge elicitation, knowledge can be categorized in different dimensions depending on the aim [4]. A *generative knowledge* triple can be *postive* $(+ < concept, relation, input >)$ or *negative* $(- < concept, relation, input >)$. *Discriminative knowledge* quadruples are positively represented $(+ < concept\#1, concept\#2, relation, input >)$. To discriminate between the 2 concepts, the relation and its associated input are only applied to concept#1 but not to concept#2. Categorizing knowledge properly like this enables quality control (to a certain extent), diverse knowledge extraction and post-processing the resulting knowledge.

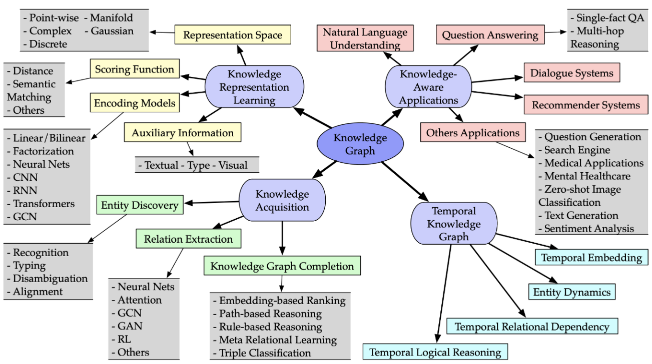

Figure 6: Categorization of KG research [27].

The research on KGs has been categorized in 4 ways, namely, *Knowledge Representation Learning* (KRL), *Temporal Knowledge Graphs*, *Knowledge Acquisition* and *Knowledge-aware Applications* [27]. Each of these build up their own taxonomy and cover different areas, as seen in Figure 6. With only textual information, KRL can accomplish different tasks by being further categorized in *Closed-world* and *Open-world* assumption models [56]. CK falls falls into the *Knowledge-aware Applications* category, as it can facilitate language understanding and also generation [66].

There are different techniques to categorizing commonsense reasoning [11]. The 3 main approaches are *knowledge-based*, *crowd-sourcing* and *web-mining*. In Figure 7 these approaches and what they entail are shown in an overview. The knowledge-based approach can be divided into mathematical formulations, informal taxonomy (as opposed to the mathematical one), but also target large-scale knowledge collection.

7 Other Applications of (Commonsense) Knowledge Graphs

There are many different use cases for KGs in general, as seen in Figure 6. Although there are many interesting applications of CSKGs, they can be pretty niche, not widely accessible, or used in a private domain. Because of that, the focus of this paper was not on such (commonsense) KGs. The KGs that have mostly been discussed in this paper are *Open knowledge graphs* [21]. There are also *Enterprise knowledge graphs* which can be used for web search, finance, social networks, commerce, and other industries. Although there are

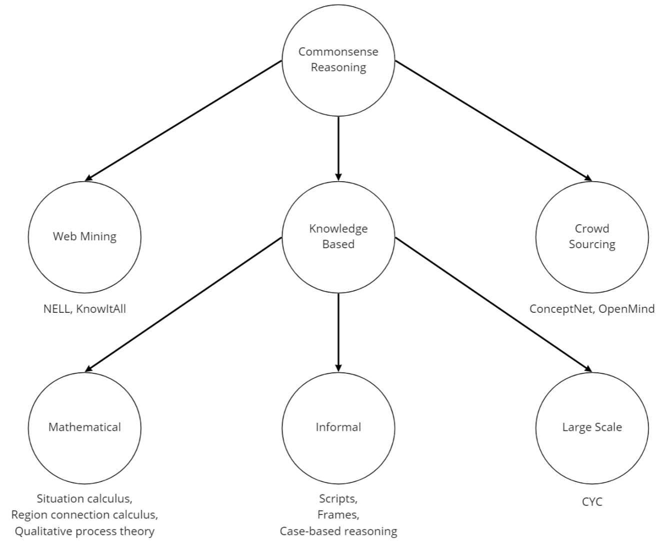

Figure 7: Taxonomy of approaches to commonsense reasoning [11].

many applications for CK integration, only two examples will be given to highlight these possibilities.

7.1 AliCoCo2

One such example is AliCoCo2, the latest version of the first CSKG in e-commerce [36]. In Figure 8 an overview can be seen of AliCoCo2. Implementing CK into the KG benefited various downstream e-commerce tasks such as query rewriting, item representation and search relevance. The goal is to allow machines to have the ability of commonsense reasoning in industrial scenarios, which experimental results indicate with positive feedback. Integrating mapping relations from AliCoCo2 improved Gross Merchandise Volume (GMV) by 0.6%. Whereas, any online improvement larger than 0.5% is considered meaningful. Search relevance using knowledge representation learning and existing systems resulted in 2.03% improvements. Recommendation tasks Hit Rate (HR) also had improvements, with a maximum of 8.81%.

7.2 Decision Support Systems

Another interesting example of incorporating CK into an enterprise task, is that of Financial Decision Support Systems (FDSS) [10]. FDSS are made to improve decision making by integrating expert system (ES) models to automatically process market information with the available knowledge [67]. The cutting-edge techniques of textual news analysis, such as text mining and natural language processing (NLP), were not enough [62]. This is because understanding the news at a linguistic level alone often led to semantic meanings being overlooked [10]. And thus, CK was used to develop a system that automatically analyzes the high-frequency market reactions. Empirical results show promise for CK integration within the securities market and FDSS.

8 Discussing Shortcomings and Challenges

Although consolidating different sources of CK into a KG has benefits, there are also challenges that arise [24].

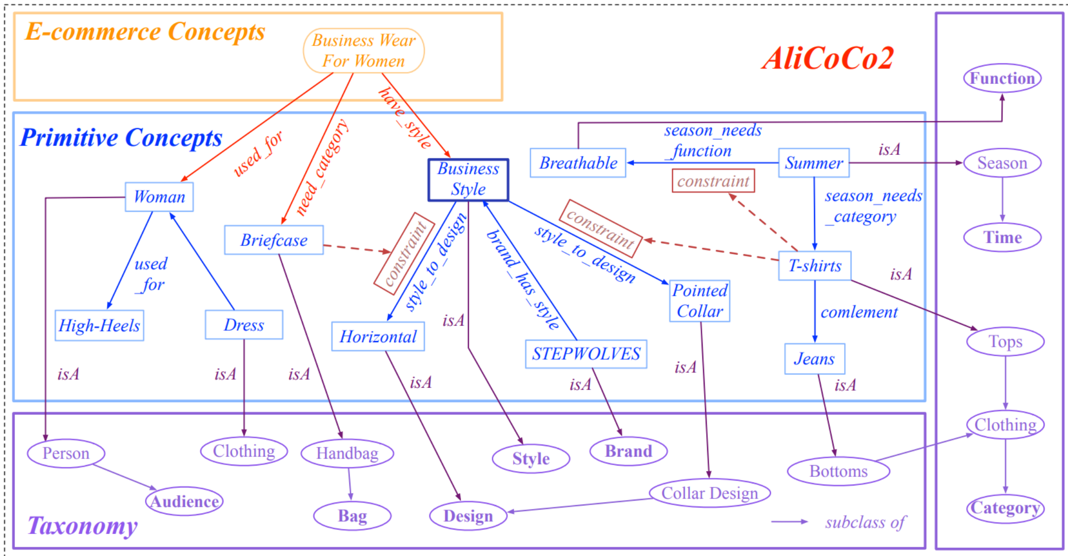

Figure 8: Overview of AliCoCo2, which mainly focuses on describing e-commerce commonsense knowledge taken from [36].

Firstly, KGs are known to suffer from sparsity [58] [33]. The sources in CSKG have **sparse overlap and mappings** due to having different versions or target (lemma or synset), the sources being disjoint, and establishing (identity) connections being particularly difficult [24]. These gaps are difficult to bridge because they are a modeling and integration challenge. The scale and sparsity of CSKGs are due to these graphs consisting of nodes that are represented by *non-canonicalized*, *free-form* text [37].

Secondly, **modeling relations** between different magnitudes of sources is a challenge [24]. In Table 1 it is clear that sources such as ConceptNet [50] and WordNet [39] have very few relations in comparison to other sources such as WikiData [54] or Visual Genome [30]. When trying to consolidate these sources there is an inherent decision making process that needs to take place.

The next challenge comes in the form of **knowledge granularity** [24]. This entails the granularity of relations that are being used to model data. Table 2 shows the formats the different sources model their data (nodes) as. Even though e.g., triples may be able to fit some sources of knowledge, a more open format that could represent the entire spectrum of granularity would be ideal. There is quite a lot of variance in the way nodes are being created, represented and in their actual size.

Which brings up the next challenge, **different creation methods and quality** [24]. Automatically extracted sources can be very efficient, but also contain a lot more noise. The manual way of creating knowledge sources, such as crowdsourcing can also go wrong or be useless if not properly vetted. There is already research being done on improving and enriching CSKGs using language models (LMs) [42]. Using knowledge contained in LMs, the strength of the edges in a KG are updated to better represent relations between concepts.

Natural language (NL) nodes often contain **imprecise descriptions** [24]. This introduces undesired ambiguity. Ideally the various phrasings that share concepts would be consolidated, allowing easy and efficient access to these concepts based on their NL labels or aliases. Because of how huge and diverse KGs can be, *contextualization* (pinpointing a set of KG facts which are relevant or needed to answer a question), is not easy [16] [58].

Some **commonsense reasoning tasks** still show shortcomings [47] [43] [40]. This is why a method to assess how well a KG can identify, align and integrate gaps of reasoning for a task is quite useful. KG-to-task match uses three phases to accomplish this for three (diverse) KGs [5]. Additionally, incorporating KG information into CK reasoning models is already actively being researched [40] [51] [7] [34].

Knowledge base (KB) **coverage** is another major challenge. Even though it is a concern, there is evidence that points to the coverage of KBs improving with little signs of slowing down [44]. In particular, there are signs that the KB coverage is improving for at least one of the KGs discussed here, WikiData [54].

9 Responsible Research

The literature survey conducted in this paper has been performed without funding, a hidden agenda or conflict of (personal) interest. Thus, the topics presented and discussed have been done in a way that is the most fair and unbiased possible. It is all on existing work done in this field. As there were no experiments conducted, there are no biased results of that kind. This also means that since the work is unrelated to humans directly, there are no such ethical or privacy concerns. Research papers and other resources were collected from the internet, many of which do conduct experiments.

Although there is a possibility of results being tweaked in the favor of the adequate party, the integrity of the authors shall be trusted. Each of these collected articles were funded by their own or an external set of institutions. Some of these papers are quite recent, don't have many citations, or both. The datasets gathered and built by these other studies might have biases, privacy involvement or ethical concerns of their own. They may also contain bias towards certain cultural or regional differences. These points might present some bias on a per-paper basis, but there was nothing noticeable for this paper. The procedures applied for this literature survey are easily reproducible, as seen in section 2, which is the Methodology section.

10 Future Work

In the future, the challenges presented in section 8 must be addressed to further advance the field of CK with the goal of AGI. Consolidation efforts have already tried addressing some of these issues, but there are still some obstacles to overcome [24]. Even though CK in AI may have its shortcomings, this survey showed that there are still many real-life applications and advantages to incorporating CK into a system. For example, there is already more research being done on incorporating KG information into CK reasoning models [40] [51] [7] [34]. CK has helped many downstream AI tasks, and has even been used in enterprise applications with success [36] [10]. LMs are already being used to improve CSKGs [42]. There are also signs that KB coverage is improving for some sources [44], but more research must be done on the other sources of CK and their coverage.

11 Conclusion

Research in the many ways to organize, structure and categorize commonsense knowledge (CK) in artificial intelligence (AI) has been on the rise since the 90's. Thus a systematic review of how CK can be organized, structured and categorized provides insights into the current state of CK research. This survey was conducted with the focus on representative public commonsense sources, such as those found in the commonsense knowledge graph (CSKG). Each of these sources have different sizes, descriptions and mappings. **Organizing** CK refers to the ontology or design schema of CK. The way CK is organized can give a direction for the schema a KG uses. Even though there are many ways to do this, only the Winograd Schema and Semantic Web were discussed. There are other usages for CK ontologies, such as automatically identifying and managing implicit requirements, organizing opinions and sentiments extracted from the web, aiding in emotive reasoning and building topic-specific ontologies for CK topics. The format in which CK is stored is called its **structure**. Depending on this structure, a knowledge graph (KG) can be transformed, created, enhanced, or analyzed in different ways. However, when consolidating these different knowledge sources the Knowledge Graph Toolkit (KGTK) format is used. The KGTK format represents KGs as hypergraphs. **Categorization** of CK reviews how existing work builds up a taxonomy of CK. There are 13 dimensions in which CK is grouped into, and 5 general principals to consolidate sources into the CSKG. KG research itself is categorized in 4 ways. Categorizing CK into dimensions shows the coverage of each knowledge source. It also shows the criteria on making different dimensions, as they might have different principals or techniques. CK is also used in enterprise applications such as e-commerce or financial decision-making. Consolidating sources of CK has many challenges, along with shortcomings on CK reasoning tasks and knowledge base coverage. Even with these challenges, there is great utility in CSKGs with CK finding applications in AI and the CK field still being researched.

A Search Queries

Description	Query
Getting information on all 3 topics of commonsense knowledge graphs	((commonsense AND knowledge) OR (common AND sense AND knowledge) OR cskg) AND (structure* OR dimension* OR organiz* OR categor*)
Getting information on all 3 topics of commonsense as well as any knowledge graphs	((commonsense AND knowledge AND graph*) OR (common AND sense AND knowledge AND graph*) OR cskg OR (knowledge AND graph*)) AND (structure* OR dimension* OR organiz* OR categor*)
Researching into the visual sources within the categorization part	((commonsense AND knowledge AND graph*) OR (common AND sense AND knowledge AND graph*) OR cskg OR (knowledge AND graph*)) AND (dimension* OR categor*) AND (image* OR visual* OR ImageNet OR genome)
General research into the categorization part	((commonsense AND knowledge AND graph*) OR (common AND sense AND knowledge AND graph*) OR cskg OR (knowledge AND graph*)) AND (dimension* OR categor* OR taxo*)
General research into the structured part	((commonsense AND knowledge AND graph*) OR (common AND sense AND knowledge AND graph*) OR cskg OR (knowledge AND graph*)) AND (structure* OR format*)
General research into the organized part	((commonsense AND knowledge AND graph*) OR (common AND sense AND knowledge AND graph*) OR cskg OR (knowledge AND graph*)) AND (organiz* OR ontolog* OR design AND schema)
General statistics on what commonsense knowledge research has been done in the field of computer science	((commonsense AND knowledge) OR (common AND sense AND knowledge) OR cskg) AND (structure* OR dimension* OR organiz* OR categor*) AND (LIMIT-TO (SUBJAREA , ”COMP”))

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