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A Survey of Recent Advances in Commonsense Knowledge Acquisition: Methods and Resources

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Abstract: Imparting human-like commonsense to machines is a long-term goal in the artificial intelligence community. To achieve this goal, constructing large-scale commonsense knowledge resources is an important step. In recent years, due to increasing demand, commonsense knowledge has become a rapidly growing research field, resulting in a surge of new acquisition methods and corresponding resources. These advances have empowered a variety of downstream AI tasks. However, constructing large-scale commonsense knowledge resources remains an ongoing and challenging task. It is still difficult to efficiently collect large-scale, high-quality commonsense knowledge. In this paper, we systematically review recent advances in commonsense knowledge acquisition methods and resources, providing a comprehensive summary of recent research scope, the characteristics of different resources, and unsolved challenges.

Keywords: Commonsense knowledge, knowledge acquisition, knowledge representation and processing, knowledge resource, knowledge engineering.

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1 Introduction

Commonsense has been a longstanding topic in the AI community since the 1950s[1, 2]. The goal of machine commonsense is to create programs that can behave like common people who share commonsense, i.e., knowing the facts that almost everyone knows and having the basic ability to understand and judge, as we expect of common people. Commonsense seems ordinary for humans and does not require expertise[3]. Even a typical little child can possess the ability to utilize commonsense. However, after about sixty years, commonsense remains a critical unsolved problem for AI[4]. Large modern machine learning models like GPT-3 still shows shortcomings in commonsense[5]. It is believed that the progress in machine commonsense will benefit wide range of AI areas, such as text understanding and generation[6–8], computer vision[9], planning and decision-making[10].

Commonsense knowledge is often implicit in human′s everyday life and rarely formally recorded. It is difficult to programmatically store, transfer, and utilize. Therefore, acquisition of commonsense knowledge is regarded as an important part of solving machine commonsense problems, which involves representing commonsense knowledge in machine accessible form and collecting it from humans. In recent years, driven by new acquisition methods and sources, commonsense knowledge resources are rapidly growing, and deeply incorporated with the latest AI systems in natural language processing. Most of recent commonsense projects are based on natural language and loosely structured representation[11, 12], which makes knowledge resources easier to collect and integrate with natural language processing systems. As a result, commonsense knowledge has promoted the performance on various natural language processing (NLP) tasks[13–17]. Also, automatic commonsense knowledge acquisition has widely benefited from recent pretrained language models[18, 19]. The related research not only enriches available commonsense resources but also brings a new window to understand the self-supervised learning results of language models. Despite these advances, there are challenges in knowledge resource construction, which limit the size, diversity and feasibility. A thorough review can inspire better improvement and application of such commonsense knowledge resources.

In this survey, we focus on summarizing recent advances in commonsense knowledge resource construction.

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The outline of this survey is shown in Fig. 1. First, we introduce current research scope of commonsense knowledge, including the definition, characteristics and categories of the commonsense knowledge. All the works we reviewed in this paper are covered by them. Second, we put a brief summary of knowledge representation in existing commonsense knowledge resources, providing an intuitive understanding of the results of commonsense knowledge acquisition. Third, we sort out the acquisition methods of commonsense knowledge and describe the representative projects in detail. Finally, we discuss several upcoming challenges in commonsense knowledge resources construction.

Related surveys. Since commonsense is a longstanding topic, there are surveys and reviews in different eras and different subareas. Reference [20] is a relative early textbook about logic-based formalizations for commonsense knowledge. References [3, 21] are recent surveys about logic-based commonsense reasoning. References [6, 22, 23] review recent commonsense reasoning benchmarks and methods. Different from them, this survey concentrates on recent methods in commonsense knowledge acquisition and corresponding commonsense knowledge resources. In this thread, the most recent survey is [24], which categorizes commonsense knowledge acquisition systems before 2013. Since then, there have been a number of new emerging methods and projects, which are the focus of this paper.

Goals of this paper. The goals of this paper include:

1) Providing the readers with a better understanding of the state of commonsense knowledge acquisition.

2) Summarizing publicly available commonsense knowledge resources in different dimensions, highlighting their respective strengths.

3) Pointing out the main weaknesses and challenges of commonsense knowledge resources construction.

2 What do we know about commonsense knowledge

2.1 Defining commonsense knowledge

Commonsense knowledge is widely possessed by com-

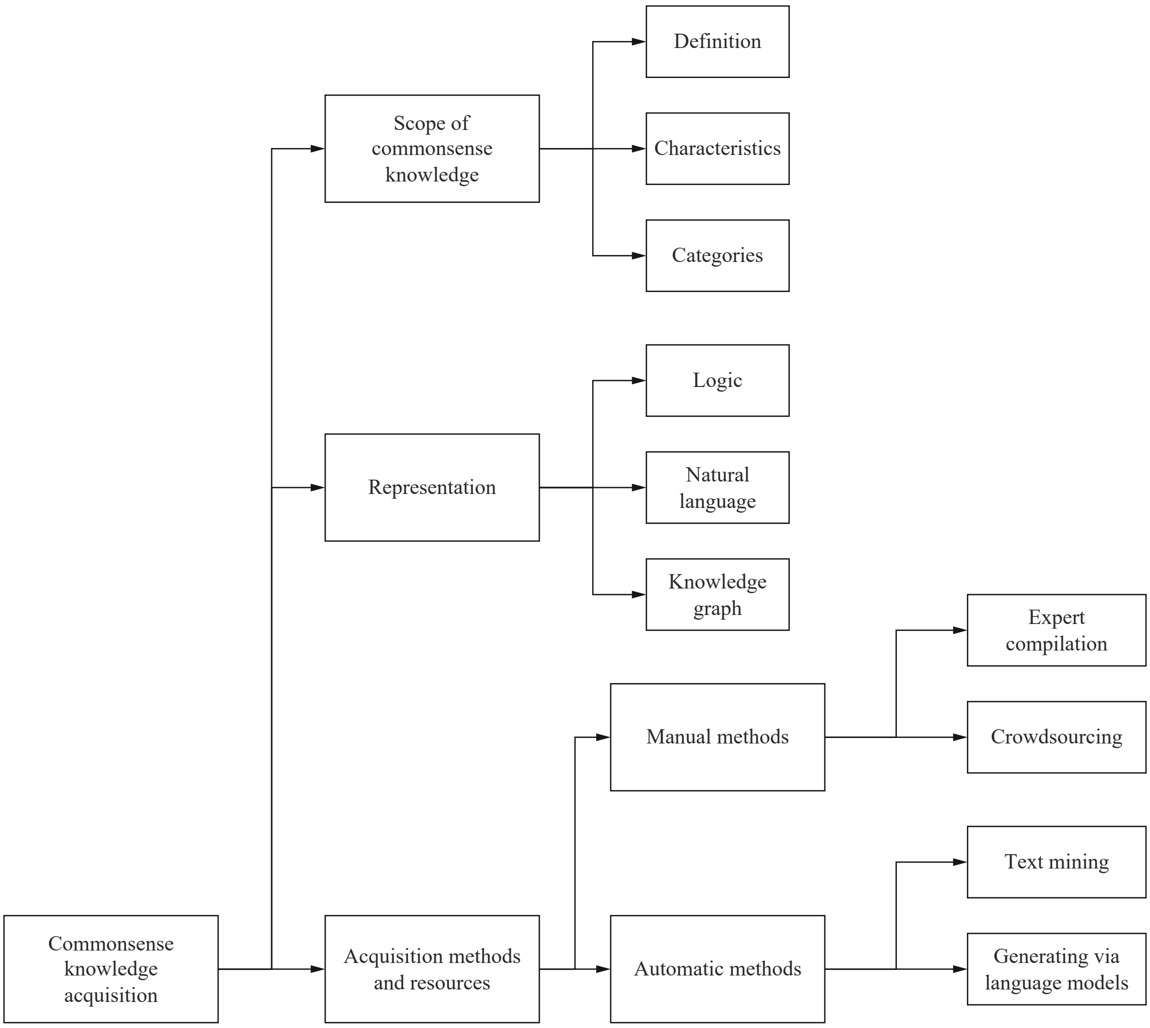

Fig. 1 The overview of this survey

mon people. However, it is rather difficult to systematically and formally define what commonsense knowledge is, and how to build an AI system that masters commonsense knowledge. There are many definitions summarizing commonsense knowledge in different aspects, such as:

"The millions of basic facts and understandings possessed by most people."[25]

"Roughly, what a typical seven-year-old knows about the world."[3]

"Commonsense knowledge includes the basic facts about events (including actions) and their effects, facts about knowledge and how it is obtained, facts about beliefs and desires. It also includes the basic facts about material objects and their properties."[2]

"This unstated background knowledge includes: a general understanding of how the physical world works (i.e., intuitive physics); a basic understanding of human motives and behaviors (i.e., intuitive psychology); and knowledge of the common facts that an average adult possesses."[26]

"Commonsense knowledge differs from encyclopedic knowledge in that it deals with general knowledge rather than the details of specific entities."[27]

However, such definitions still involve many vague concepts like "understanding", "basic" and "intuitive", which are difficult to explain clearly. In general, it is still difficult to draw a systematical definition that exactly clarifies the scope and challenges of commonsense knowledge research. Much of recent work in AI often emphasize the absence of commonsense rather than what commonsense exactly is[28]. In practice, the definitions only provide abstract guidance and roughly depict the boundary of commonsense knowledge. Researchers pay more attention to some known problems rather than give a complete picture.

In this survey, we use a working definition that commonsense knowledge is "everyday knowledge about concepts, events and actions, which is shared by most of people and can be used to draw intuitive physics and social inferences". The definition guides us to focus on the main domains of current commonsense knowledge resources.

2.2 Characteristics

Although it is difficult to systematically and formally define what commonsense knowledge exactly is, people do emphasize some characteristics in AI research practice, which include:

1) Commonality. Commonsense knowledge is often described as widely mastered by common people. Though there is no clear boundary, it is often emphasized that commonsense knowledge is different from expertise. It comes from everyday experience rather than special education.

2) Implicitness. Commonsense knowledge is often described as unspoken background knowledge[29]. People take it for granted, so there is often no need to express it explicitly in use. Therefore, commonsense knowledge is not often directly expressed in corpus, which increases the difficulty of automatically acquiring machine-accessible commonsense knowledge from texts.

3) Generality. In commonsense knowledge research, we care more about the general knowledge about a class of entities or events, rather than specific entities or events. Although "Washington is the first president of the US" is widely-known, such factual knowledge is usually not the focus of research.

4) Wide-range. Commonsense knowledge covers wide range of domains and has large scale in quantity. Therefore, it is difficult to list all commonsense knowledge that people own. Millions of statements in current resources are still far from enough.

5) Default and uncertainty. Unlike factual knowledge, commonsense knowledge is often default assumptions or a set of salient possible cases. Thus, it is defeasible when given a specific context. For example, we assume "birds can fly" by default, but we do know there are exceptions like penguins.

2.3 Category

Another way to trace commonsense knowledge is to divide it in several specific known dimensions or categories. There have been great efforts to organize the scope and taxonomy of commonsense knowledge[30, 31]. However, it is still difficult to exhaust all possible commonsense knowledge categories clearly without dispute. Hence, we mainly focus on the well-explored areas. We propose a coarse-grained category system by summarizing the scope of existing resources. The system mainly highlights the relations or predicates appeared in knowledge statements, which are the main categorization factors in recent commonsense resources.

2.3.1 Intuitive physics

The first part in our category division is about intuitive understanding of physical world, which includes:

1) Time. Temporal relations are important parts of eventuality commonsense knowledge. Many resources capture the time ordering of different events (before/after), or the sub-event relations. For example, it is commonsense that people close the door before starting a car.

2) Location. The common location of things is another well researched category. Most projects capture coarse-grained "located-at/near" relations, such as the books are often in bookstores, libraries and bookcases.

3) Causality. This category includes the general cause and effect relations between events, states and properties. For example, "drinking causes dizziness" (sufficient causes) and "passing exams is the prerequisite of graduating" (contributory causes). Some resources also include the obstacles that hinder some actions or the creation process of some objects, which are related to causalities.

4) Capability. We know the capability of some humans or animals, such as "a teacher can teach a lesson". Also, we know what people can do with a specific thing (the affordance of things), such as "key can be used to open door". Both of these are parts of our commonsense knowledge.

5) Property. Our commonsense knowledge includes wide range of physical properties related to an object, such as material, shape, color, taste, temperature, etc. The examples include "sun is round" and "fire is hot". Also, the quality of creatures has similar expressions, such as "tiger is carnivorous" and "professor is knowledgeable". Further, we also consider components and possessions as property knowledge, such as "human has feet".

2.3.2 Intuitive psychology

From the everyday experience of social interaction, people obtain the intuitive psychology understanding to explain and predict actions and mental status of others. We summarize several categories of commonsense knowledge that are related to intuitive psychology as follows.

1) Desire. With the knowledge about desire, we can infer what others may expect to happen or not, based on their identity and status. For example, "students desire to pass exams" and "starving people desire to have food".

2) Intent. The intent is something we use to explain expected goal behind the certain behaviors of people. It is related to people's desire and belief of causality. For example, we know if someone publishes advertisement, his intent may be to bring better income to his business.

3) Emotion. We also have the intuitive knowledge about how the emotion of people changes in certain situation. For example, we know people can be joyful after participating in a party.

2.3.3 Others

There is other more abstract understanding that is arguable taken as commonsense knowledge. These categories may overlap with other categories to some extent.

1) Taxonomy. People have the knowledge about classification of concepts and their hierarchy, such as "bread is a kind of food". Such knowledge is considered as part of commonsense knowledge, but it is also well studied in linguistic resources and ontology.

2) Language. The basic knowledge about language is sometimes seen as commonsense knowledge. Some commonsense knowledge resources include synonyms, antonyms, and etymology of concepts.

3) Similarity. Different degrees of concept similarity are included in commonsense knowledge resources. Synonyms and antonyms can be seen as strong similarity and distinctness. There are also weaker or general similarity between concepts, such as "wholesome food" and "organic food".

4) Comparison. Some commonsense resources also capture the comparison between objects in some aspects. For example, "elephant is heavier than human" and "airplane is faster than bus".

5) Part-whole. This category of knowledge includes general "is part of" relations between concepts, and can be further specified in different domain, such as the temporal part-whole (sub-event), spatial part-whole (located-in) and the social part-whole (member-of).

3 The representation of commonsense knowledge

In this section, we briefly summarize existing representations of commonsense knowledge. As illustrated in Table 1, there are mainly three kinds of representations for commonsense knowledge: logical formalization, natural language, and knowledge graph.

Table 1 Different representations for commonsense knowledge "birds are feathered"

Representations	Examples
Logic	$\forall_x Bird(x) \Rightarrow Feathered(x)$
Natural language	"Birds are feathered"
Knowledge graph	(Bird, has property, feathered)

3.1 Logical formalization

In the early age of commonsense research, the community preferred to create logical formalization to represent commonsense knowledge and reason about it[20]. In this perspective, commonsense knowledge is clearly encoded as logic statements, such as $\forall_x Bird(x) \Rightarrow Feathered(x)$ in Table 1, and the reasoning is implemented as logic inference. However, decades of efforts show that logic is still unable to formalize wide range of commonsense. And due to the difficulty of compilation, it often requires well-trained experts in knowledge acquisition. These weaknesses make logical formalization not so appealing in recent projects. Nevertheless, logic-based representation still has unique advantage in expressing knowledge exactly and adequately.

3.2 Natural language

Since it is still difficult to create the logical formalization that is competent enough for commonsense knowledge, the community now pay more attention to free-form representations, and especially emphasize the importance of natural language[32]. Just like the examples mentioned in this paper, natural language is the direct way for us humans to express commonsense knowledge, and it is expressive enough to cover wide range of knowledge. The weakness is that natural language is imprecise, variable, and ambiguous, and it is not clear how machine can utilize the commonsense knowledge represented by natural language. However, with the development of natural language processing systems, the weaknesses could be alleviated.

3.3 Knowledge graph

Loosely structured knowledge graph is the mainstream representation in emerging commonsense knowledge projects. In this way, the commonsense knowledge is represented as (head, relation, tail) triples, such as (bird, has property, feathered) in Table 1. The head and tail can be concepts or eventualities expressed in natural language phrases. The relation can be from a predefined set or an open vocabulary. Usually, the triples can be translated into natural language using templates. Therefore, such representation is mostly based on natural language but follows some predefined structure. To make the semantic clear and precise, recent work also try to extend the triple representation with additional aspects and qualifiers, such as the degree of typicality and applicable scope.

4 Manual acquisition methods and resources

In Sections 4.1 and 4.2, we introduce the commonsense acquisition methods and representative projects that rely on human labor. Based on the main contributor, we divide them into expert compilation and crowdsourcing. Manual acquisition of commonsense resources has decades of history. Until recently, most of high-quality commonsense resources still come from manual construction. We will briefly review some classic projects and focus on recent manually constructed resources.

4.1 Expert compilation

4.1.1 Method summary

Expert compilation is an expensive but effective way to construct commonsense knowledge resources. As shown in Fig. 2, a group of experts are responsible to sum up commonsense knowledge in their mind and transform it into machine-accessible format. It is the typical way for early commonsense knowledge projects that adopt logical formalization for representation, which requires well-trained experts to follow the strict compilation specifications. Such resources often have high quality and construction cost. We note some represented projects as follow.

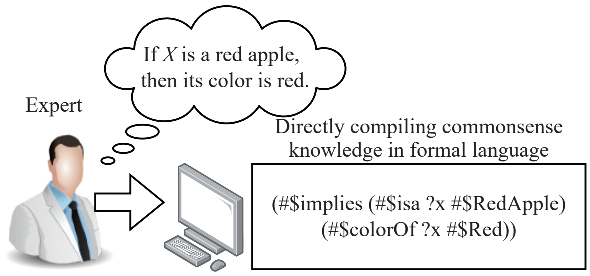

Fig. 2 The typical process of expert compilation

4.1.2 Representative resources

Cyc[33]. Cyc is the most famous expert-compiled commonsense knowledge base. It was started in 1984 by Lenat, and now it is maintained by Cycorp. It is an ambitious high-cost project that aims to manually encode commonsense knowledge of humans from different domains. As shown in Fig. 3, Cyc uses a dedicated representation language, CycL, which is based on first-order logic and has extensions for modal logic and higher-order quantification. Trained experts and volunteers keep contributing commonsense knowledge via CycL and constructing efficient special-purpose inference engines. After decades of development, Cyc has grown to more than 1.5 million concepts and 25 million assertions. Most of the content is not publicly available. There were two public releases of Cyc. OpenCyc is released under the Apache license. It mainly includes the taxonomic knowledge. The latest version (OpenCyc 4.0, released in 2012) contains 239 000 concepts and 2 039 000 facts. ResearchCyc is a release for research purposes but no longer supported after 2019. It contains 500 000 concepts and 5 000 000 facts, which cover more knowledge categories.

Gordon and Hobbs' axioms [30]. Gordon and Hobbs[30] compile a set of axiomatized theories of commonsense knowledge, which aims to capture abstract concepts and relationships across a wide range of commonsense psychology domains. They deliberately focus on the coverage of concepts in the first stage, and then formalize content into logic theories in the second stage. Based on large-scale analysis, they identify the domains involved by commonsense psychology concepts, and codify axiom sets for different domains via first-order logic. In total, they currently create 1 400 axioms organized into 16 background theories and 29 commonsense psychology theories, which involves causality, time, location, goal, emotion and many other domains.

(relationAllExistsCount Dog anatomicalPart Leg 4)	(forall (a e) (if (agentOf a e) (and (agent a)(cause a e))))
Cyc: "Dogs have four legs"	Gordon and Hobbs: "The agent of an event is an agent that causes it"

Fig. 3 The knowledge excerpts from Cyc and Gordon and Hobbs' axioms[30]

4.2 Crowdsourcing

4.2.1 Method summary

The high cost of expert compilation restricts the scale expansion of commonsense resources. As commonsense knowledge is widely mastered by common people, it should be a more efficient way to include common people in the knowledge acquisition rather than only experts. The Internet makes it possible to create large commonsense knowledge resources via crowdsourcing.

A typical process of crowdsourcing is shown in Fig. 4. The experts of a commonsense project design the acquisition guidelines and develop the acquisition program. Following the guidelines, a group of common people participate the project through the Internet and interact with the online acquisition program, which can range from annotation forms to special games with purpose[34]. The collected results are then further processed into target knowledge representations.

However, involving common people in commonsense knowledge acquisition also brings challenges. Logic-based knowledge representations are too difficult for common people. Hence, the crowdsourcing projects mainly collect knowledge represented in natural language or loosely structured knowledge graph. Another challenge is to ensure the quality and coverage of the collected results. Since commonsense knowledge is often open-ended, it is difficult to automatically verify the agreement between workers. To tackle the challenge, researchers come up with various carefully-designed schemes. Recent work usually first collect diverse text materials (e.g., event descriptions or stories) and ask crowdsourcing workers to summarize related commonsense with constraints rather than write assertions freely. Also, some work introduce gamification[35] in commonsense knowledge acquisition to make the collection process more attractive and improve the data quality.

Crowdsourcing has become the dominant way to collect high-quality commonsense knowledge. Most of influential commonsense knowledge projects are collected via crowdsourcing platform. We detail some representative projects as follow.

4.2.2 Representative resources

OMCS[36]**.** Open mind commonsense (OMCS) is an early online project to acquire commonsense knowledge from general public and active from 1999 to 2016. At first, it aimed to gather commonsense knowledge facts represented in natural language, as illustrated in Fig. 5. It presented users with prompt materials (e.g., a story) and asked them to write useful knowledge in free-form natural language. The collected resources could be handed over to information extraction systems to construct more standard representations. The first version of the project gathered 456 195 pieces of commonsense knowledge. After that, the project decided to introduce templates to restrict the user input and use other methods to clarify the entered knowledge. Also, the project designed "games with a purpose"[35] to collect commonsense knowledge in a more entertaining way. In the end, the project has collected millions of English commonsense knowledge facts and extended to several other languages.

ConceptNet[11]**.** ConceptNet is a knowledge graph created from OMCS and becomes its actual successor. As shown in Fig. 5, it focuses on several predefined relations between concepts. The main part of the resource is extracted from OMCS and its sister projects via syntactic patterns and shallow parsing. It also integrates taxonomic and language knowledge from OpenCyc, WordNet and Wiktionary. Currently, ConceptNet has become a large-scale multilingual commonsense knowledge base. Its recent release (ConceptNet 5.7) contains 34 million knowledge tuples about 34 relations.

CSLB[37]**.** The centre for speech, language and the brain (CSLB) concept property norms are a resource about concepts and their normalized features. It is completed by qualified participants online. For a given concept, the participants are asked to choose a relation from a list (including "is", "has", "does", "made of", etc.), and provide features about the concept along the relation, as illustrated in Fig. 5. Then the features are turned into normalized labels to merge different linguistic variants. In the end, the resource contains 22.6 K sen-

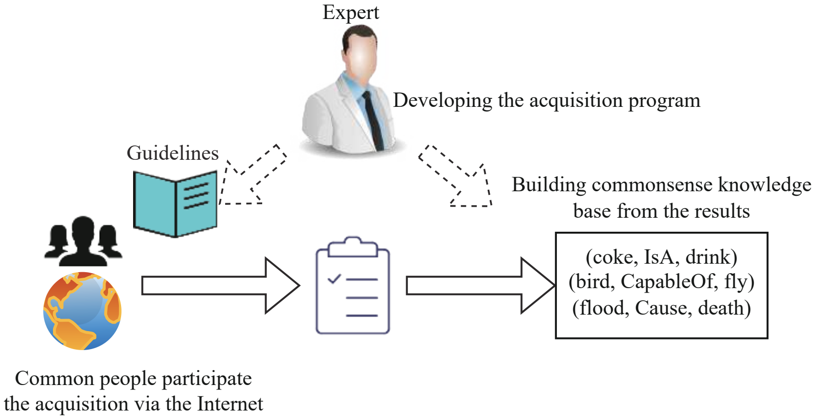

Fig. 4 The typical process of crowdsourcing

tences about 638 concepts.

ATOMIC[12, 38]**.** Atlas of machine commonsense (ATOMIC) is a crowdsourced commonsense knowledge graph about event inferences. The project first collects common events from a variety of corpora and processes them into phrases with person placeholders. Then the online participants are asked to provide commonsense knowledge about the events by answering questions in a form, which are related to a set of predefined commonsense relations. The initial version of ATOMIC contains 880 K knowledge tuples of 9 relations, which is mainly a social commonsense knowledge base about causality, intent and emotion. Its updated version, ATOMIC 2020, integrates a subset of ConceptNet and extends to a comprehensive commonsense knowledge base with 1.33 M knowledge tuples across 23 relations.

ANION[39]**.** Array of commonsense inferences for oppositions and negations (ANION) is a branch project of ATOMIC, dedicated to negated events. It is based on the observations that negated expressions are seldom found in existing commonsense resources, and reasoning systems are in need of the ability to handle negated statements. It first collects different negations for the base events in ATOMIC, considering both explicit or implicit negative cues. Then it crowdsources additional inferences about the negated events based on the relations defined in ATOMIC. The resulting resource contains 627 K knowledge tuples about negated events.

GLUCOSE[40]**.** GLUCOSE is a commonsense knowledge resource dedicated to causality. It identifies 10 causal dimensions to capture different kinds of causes and effects, which cover events, location, possession, and other attributes. The feature of this resource is that each commonsense knowledge statement is grounded in a particular context. To achieve this, the crowdsourcing participants are asked to annotate paired causal explanations for a given sentence in a story. One of them is a specific statement that contains specific people or things appeared in the context, and the other is a general rule that has variables and complies semi-structured templates, as illustrated in Fig. 5. Therefore, the resource has both generalized commonsense knowledge and contextualized inference instances.

5 Automatic acquisition methods and resources

The high-cost of expert compilation limits the growth of commonsense knowledge resources. Although crowdsourcing relaxes the conditions of creating large-scale commonsense knowledge resources, it still relies on extensive human labor. Therefore, most of recent work is looking for automatic acquisition methods for commonsense knowledge. We summarize such methods in three categories: text mining, knowledge graph completion and generating via language models.

5.1 Mining from texts

An appealing idea is to automatically mining commonsense knowledge from texts. The repeated patterns and statistical correlations in a large corpus may contain commonsense knowledge. For example, the expressions of basic physical property of things like "apple is red" could appear many times in the corpus. Unlike mining entity knowledge[41, 42], much more commonsense knowledge may not be expressed directly, yet the co-occurrence text can provide clues for commonsense relationships. We introduce related methods and commonsense resources in this section.

5.1.1 Method summary

As shown in Fig. 6, a typical process of mining commonsense knowledge includes several steps.

First, the source corpora are collected and selected. The type of corpora can alleviate the difficulty of mining commonsense knowledge. For example, search-engine query logs like "why do cats purr" can provide rich clues about capability commonsense[43].

Second, commonsense knowledge candidates are extracted from the corpora via pattern matching or information extraction methods. However, the shallow pattern can only capture limited commonsense knowledge, which typically has simple language structure and are mainly about things rather than events. As discussed before, much commonsense knowledge is rarely expressed explicitly, so automatic mining can often be used in limited knowledge categories. To mine commonsense knowledge

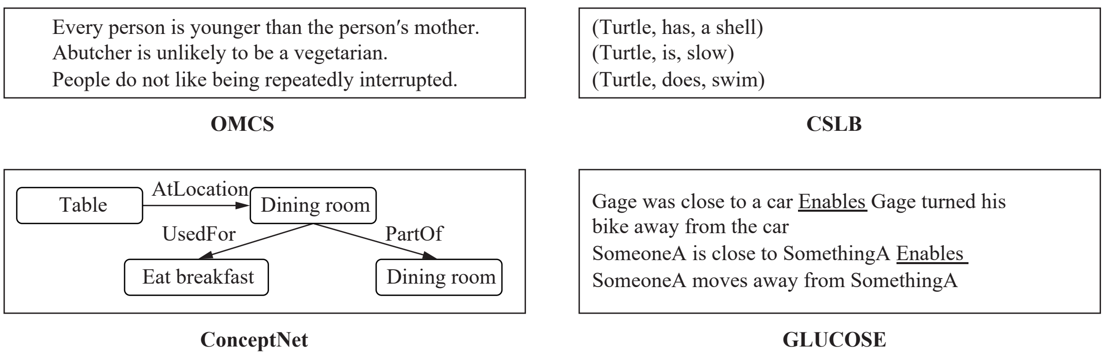

Fig. 5 The knowledge excerpts from OMCS, CSLB, ConceptNet and GLUCOSE

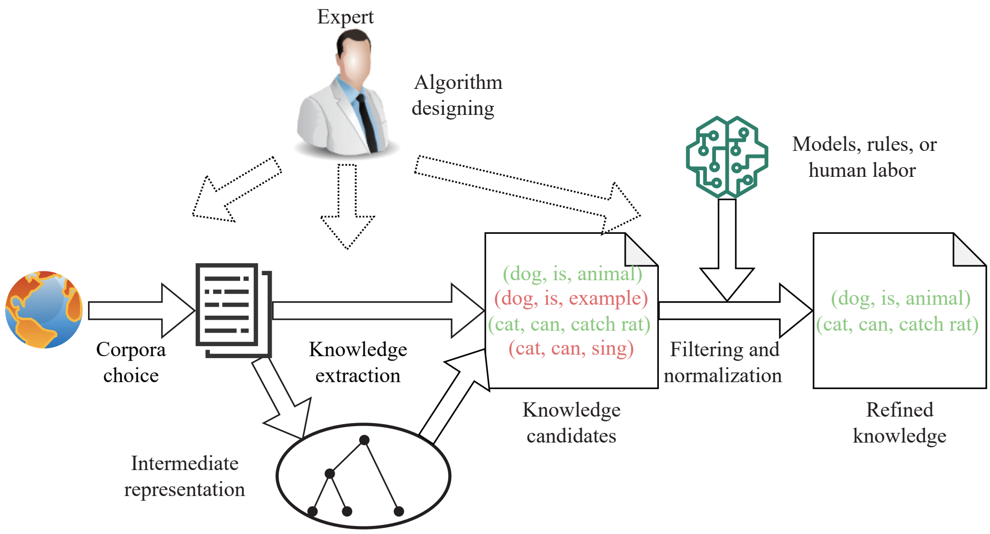

Fig. 6 The typical process of mining commonsense knowledge from text (Colored figures are available in the online version at https://link.springer.com/journal/11633)

with more complex structure, some work first exploit intermediate representations (e.g., dependency graphs) from the corpus and then further mine commonsense knowledge via patterns on the intermediate representations[44, 45].

Third, since large parts of the automatically mined candidates are noisy and redundant, there is usually a post-processing step to remove bad results and normalize the representations[46]. To improve the quality of resources, recent work mainly adopt neural scorer models to refine results, which requires a set of human annotated data[44]. Usually, the annotated data come from manually created resources, which can be inadequate when the mined candidates cover more diverse knowledge domains and categories. Therefore, semi-supervised learning framework has been adopted in knowledge refining[47].

In all of the steps, people mainly design the algorithms and do minimal labeling work. Thus, the cost is comparatively lower and the size of resources is easier to expand. We detail some representative projects in Section 5.1.2.

5.1.2 Representative resources

KNEXT[48, 49]**.** KNEXT is an early project that extracts general possibilistic knowledge from text. The project uses corpora with treebank annotation as source, and applies hand-crafted patterns to automatically extract propositional expressions. The project deliberately distills propositions about generalized concepts and represents them in English sentences, such as “children may live with relatives”. The latest release of KNEXT project contains 73 million generalized propositions. Human evaluation shows about 49%−64% of the propositions are “reasonable general claim”.

WebChild[50, 51]**.** WebChild is a large automatically extracted collection of commonsense knowledge. It uses generic text patterns to extract candidate knowledge assertions from Google N-gram corpus, and implements algorithms based on WordNet to filter out noise and distill commonsense knowledge with fine-grained relations. It mainly covers property, comparison and part-whole commonsense knowledge. In comparison with similar crowdsourcing resources like ConceptNet, WebChild has more detailed relation types such as “has color” and “has shape”, rather than general and ambiguous “has property”. Current version of WebChild contains 2.3 million disambiguated concepts and 18 million commonsense knowledge assertions connected with more than 6 000 relations.

Quasimodo[43]**.** Quasimodo is a resource that distills commonsense properties from non-standard web sources, including search-engine query logs and QA forums. In comparison with WebChild, it focuses more on salient properties that are typically associated with certain concepts, which means not only the knowledge assertions should be generally plausible but also the properties should express important traits and most instances of the concepts should have the properties. To this end, Quasimodo designs automatic scoring for plausibility, typicality, and saliency, respectively, and uses them to rank knowledge candidates. The resulting knowledge base contains 2.3 million assertions for 80 000 concepts.

ASCENTKB[52, 53]**.** ASCENTKB is a project aiming to automatically build a commonsense knowledge graph with better expressiveness. It is based on the observation that knowledge triples in previous work have limited expressiveness, which leads to ambiguous semantics and loss of informative facets. Therefore, ASCENTKB tries to capture the additional semantic facets beyond triple assertions, including the validity qualifiers (e.g., degree, location and temporal) and other informative context (e.g., cause, manner and purpose). Besides, for each concept (e.g., “elephant”), ASCENTKB groups its sub-concepts (e.g., “Asian elephant”) and aspects (e.g., “elephant tusk") to build better concept structures. To achieve these design goals, the project uses documents from web search service as knowledge source, and extracts informative commonsense knowledge assertions via OpenIE, supervised labeling and clustering. The current version of ASCENTKB contains 2 million high-expressiveness assertions about 10 K concepts.

TupleKB[54]**.** TupleKB is a project aiming to extract domain-targeted and high-precision commonsense knowledge tuples from text. It is based on an automatic construction pipeline with limited human supervision. First, it uses a domain vocabulary to specify the target knowledge domain in elementary science, and creates query templates to search appropriate sentences from the larger corpus. Second, it extracts candidate tuples from the narrowed corpus via OpenIE tools, and labels some tuples to train a supervised tuple scorer. Finally, after refining high-precision tuples with the scorer, it introduces a canonical schema induction step to merge equivalent and similar relations into canonical relation. The resulting resource contains 294 K high-precision tuples and has high knowledge recall over the corpus with respect to elementary science.

ASER[55]**.** ASER is a large-scale eventuality knowledge graph. Each node in the graph is an eventuality (events, activities, or states) phrase that has its internal dependency sub-graph. These eventualities are connected via 15 kinds of discourse relations, which captures the preference-like commonsense knowledge between eventualities. Such knowledge is automatically mined from a wide range of web corpora. In the construction, ASER first uses syntactic patterns to extract possible eventualities and then trains a classifier through bootstrapping to identify eventuality relations. The resulting resource contains 194 million eventualities and 64 million edges. Besides direct use, such a huge resource can also be further mapped to traditional commonsense knowledge resources to enrich their content.

TransOMCS[44] **and DISCOS**[45]**.** TransOMCS is an automatically mined knowledge resource that uses ConceptNet-like knowledge representation. Instead of directly mining knowledge from text, it uses ASER as an intermediary. It first matches existing triples of ConceptNet into ASER graph, and then extracts relation patterns based on the matched seeds. These patterns are applied on the whole graph to extract millions of ConceptNet-like commonsense knowledge triples. The complete extracted resource contains 18 million triples while the accuracy is only about 56%. However, with a supervised triple scorer, the accuracy of top-1% triples reaches about 87%, which is close to the quality of crowdsourced commonsense knowledge resources. Similar to TransOMCS, DISCOS is another ASER-based commonsense knowledge resource. It uses hand-crafted rules to align phrases in ATOMIC with nodes in ASER and select candidate edges from the aligned ASER graph. It trains discriminators on the knowledge instances from ATOMIC to determine whether a candidate edge can be transformed to a valid ATOMIC commonsense assertion.

C3KG[56]**.** C3KG is a Chinese commonsense conversation knowledge graph. It extracts event expressions from a Chinese conversation corpus and matches them with a translated version of ATOMIC. Therefore, the nodes in knowledge graph are grounded with their dialogue context in the corpus. To enrich the conversation-specific knowledge, C3KG includes the utterance ordering relationships from the source corpus, and automatically constructs edges between cause, emotions and intent based on the dialogue context. The resulting resource contains 1.3 million triples.

CANDLE[57]**.** CANDLE is a resource dedicated to cultural commonsense knowledge. It focuses on three domains of subjects (geography, religion, occupation) and several cultural facets (food, drinks, clothing, traditions, rituals and behaviors), and extracts related commonsense assertions from English corpus. These assertions are natural language sentences. During the construction pipeline, the sentences are also clustered with concepts appeared in them. Therefore, each commonsense assertion has the metadata of domains, subjects, facets and concepts. In total, CANDLE contains 1.1 million assertions about cultural commonsense knowledge.

GenericsKB[58]**.** GenericsKB is a commonsense knowledge base of generics statements about the members of a category, e.g., "trees remove carbon dioxide from the atmosphere". Unlike other contemporary projects, it uses unstructured natural language sentences rather than knowledge graph or other structured format for knowledge representation. The sentences are extracted from three large text sources, filtered with hand-authored heuristics, and scored with a trained classifier. In total, GenericsKB contains 3.5 million statements, each of which includes metadata about topic, context and confidence score.

5.2 Generating via pretrained language model

5.2.1 Method summary

As discussed before, much commonsense knowledge is rarely expressed explicitly in text. Automatically mining commonsense knowledge from text can be applied in limited knowledge categories, but for some cases (e.g., temporal and causality of events), it requires to design more complex processes. Therefore, people are still looking for alternative solutions.

Pretrained language models (PLM)[59, 60] have profoundly influenced the paradigm of natural language processing[61]. In recent work, PLMs have acted as a novel proxy to acquire commonsense knowledge. These models have seen large-scale corpus during pretraining, and recent work elicit it to generate commonsense knowledge assertions through further adaptation[62]. As shown in Fig. 7, experts provide the PLMs with existed commonsense knowledge assertions to adapt them to generate new ones. The adaptation can finetune the models with massive assertions, or prompt with few-shot examples (in-context learning)[63]. After using the models to generate a number of knowledge candidates, there is also a post-process step to refine the high-quality knowledge.

At first glance, such methods seem similar to automatically mining from texts. But we cannot specify the source of knowledge. In other word, the method distills the knowledge implicitly stored in the model parameters instead of directly extracting from texts. The generated knowledge candidates can also be mixed with a lot of noise and errors like the mined results from texts. Nevertheless, the method alleviates the complexity of extraction pipelines and can be easily applied on various knowledge categories. With the help of trained filtering models, the resulting commonsense knowledge resources can even achieve better quality and coverage than crowdsourced counterparts. These features make generating commonsense knowledge via PLM become an appealing research area.

5.2.2 Representative work

COMET[62]. Commonsense transformer (COMET) is a finetuning framework for generative commonsense knowledge completion. It uses triples from an existing commonsense knowledge graph (e.g., ConceptNet or ATOMIC) to finetune a PLM. The resulting model can generate plausible tail items for any head item with a predefined relation. Therefore, the model can be used to automatically construct a large-scale commonsense knowledge graph or directly act as an out-of-the-box knowledge source in downstream applications. Recent work[64] also create several materialized knowledge resources with millions of assertions based on COMET. Related analyses show the generated knowledge resources have high knowledge recall but lack in typicality and saliency.

ATOMIC-10X[19]. Large PLMs like GPT-3[65] have shown surprising few-shot performance. Such models can adapt to new tasks with a few task-specific examples as prompts. The presence of ATOMIC-10X shows the ability is also applicable to commonsense knowledge generation. ATOMIC-10X is a commonsense knowledge graph covering 7 relation types defined in ATOMIC[12]. In the construction process of ATOMIC-10X, only a few concept phrases and triples are used as seeds to prompt GPT-3 to generate more concepts and triples in similar writing style. This process is different from COMET, which still requires massive existing knowledge triples for training. After generating raw knowledge triples, a supervised triple classifier is used to filter out bad results. The analysis shows ATOMIC-10X surpasses its crowdsourced counterpart (ATOMIC) in quantity, quality and diversity.

CN-AutoMIC[66]. CN-AutoMIC is a Chinese commonsense knowledge graph generated from pretrained language models. Since most commonsense knowledge resources are created from English speakers and corpora, it is necessary to enrich resources in other languages. However, directly translating English corpora may omit the cultural differences. Thus, generating with language models can be an appealing alternative. CN-AutoMIC leverages a construction pipeline similar to ATOMIC-10X[19] but based on a multilingual model MT5. It proposes some tweaks to better acquire massive high-quality results from much noisier raw generation. The evaluation and analysis show the resource has better quality than direct translation and can capture commonsense knowledge specific to Chinese background.

I2D2[67]. To break the dependence on large-scale language models with tens of billions of parameters, the work proposes a framework to fully utilize smaller models (1.5 B) for commonsense knowledge generation. It focuses on free-formed commonsense assertions like GenericsKB[58]. To generate high-quality knowledge via smaller models, it utilizes recent constrained decoding[68] to generate controlled results. The results are filtered with super-

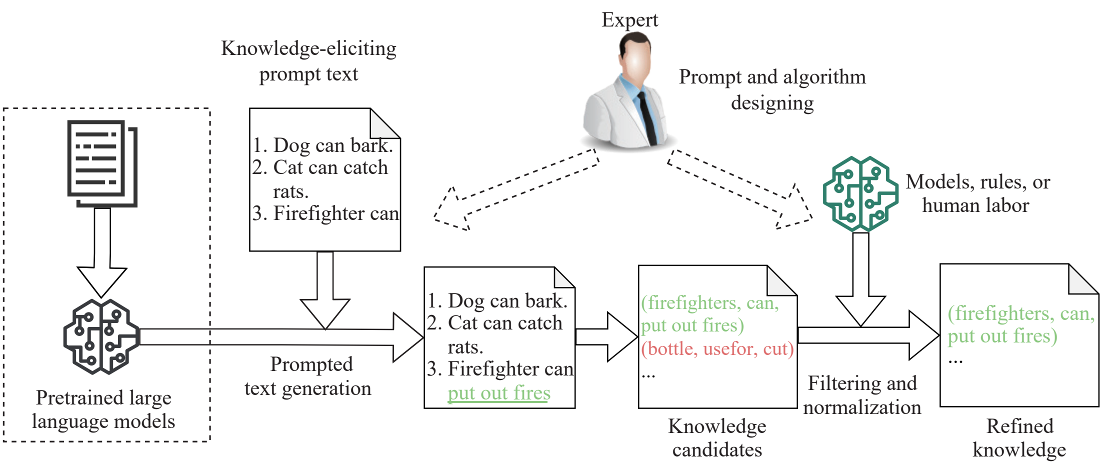

Fig. 7 The typical process of generating commonsense knowledge by prompting pretrained language models (Colored figures are available in the online version at https://link.springer.com/journal/11633)

vised classifiers and then used for further iteratively training the generation model. The work also results in Gen-A-tomic, a commonsense resource with 14 M statements. It has a 1 M high-quality subset, in which 90% of sampled statements are judged as valid. The result shows smaller language models can also be a valid source for commonsense knowledge acquisition.

6 Comparison and analysis

In this section, we will first provide a comparison between different commonsense knowledge resource. Then, based on the summary of knowledge resources, we will provide qualitative summary for the four classes of acquisition methods.

6.1 Dimension

Existing commonsense knowledge resources often differ in representation and scope, and they report evaluation results in different standards. It is difficult to compare them fairly and comprehensively. Therefore, in this section we focus on showing the characteristics and differences of different resources, rather than providing strict evaluation metrics. We summarize the comparison results in Table 2, which includes dimensions as follows.

1) Acquisition method (Acq.). According to the criterion of this survey, this dimension has four values: E=expert compilation, C=crowdsourcing, M=mining from text, G=generating via pretrained language models.

2) Representation format (Rep.). This dimension describes the representation category of the resources. The values include: L=logic, NL=natural language, KG=knowledge graph.

3) Publication year (Pub.). In this dimension, we report when the resources were first published.

4) Size. Although the resources have different struc-

Table 2 The comparison of commonsense knowledge resources (Acq. = acquisition, Rep.= representation, Pub. = publication year, Cov. = coverage)

Resources	Acq.	Rep.	Pub.	Size (year)	Major knowledge category	Evaluation				
						Pre.	Cov.	Sal.	Typ.	Ext.
Cyc	E	L	1984	25.00 million (2019)	Time, location, causality, capability, property, desire, intent, taxonomy, part-whole					√
Gordon and Hobbs	E	L	2017	1 400.00 (2017)	Time, location, causality, capability, property, desire, intent, emotion, similarity, part-whole					
OMCS	C	NL	2000	0.45 million (2002)	Time, location, causality, capability, property, desire, intent, taxonomy, similarity, part-whole	√		√		
ConceptNet	C	KG	2004	34.00 million (2019)	Time, location, causality, capability, property, desire, intent, taxonomy, similarity, part-whole		√			√
CSLB	C	KG	2013	22 600.00 (2013)	Property		√			
ATOMIC	C	KG	2019	1.33 million (2021)	Time, location, causality, capability, property, desire, intent, emotion, part-whole	√	√			√
ANION	C	KG	2021	0.63 million (2021)	Causality, property, desire, intent, emotion		√			√
GLUCOSE	C	KG	2020	0.44 million (2020)	Causality	√	√			√
KNEXT	M	NL	2002	73.00 million (2010)	Location, capability, property, taxonomy, part-whole	√				
WebChild	M	KG	2014	18.00 million (2017)	Time, location, capability, property, emotion, taxonomy, similarity, comparison, part-whole	√	√	√	√	√
Quasimodo	M	KG	2019	2.30 million (2019)	Location, capability, property, similarity, comparison, part-whole	√	√	√	√	√
ASCENTKB	M	KG	2020	2.00 million (2021)	Time, location, causality, capability, property, emotion, similarity, part-whole	√	√	√	√	√
TupleKB	M	KG	2017	0.29 million (2017)	Location, causality, capability, property, desire, taxonomy, part-whole	√	√			
ASER	M	KG	2019	64.00 million (2019)	Time, causality	√	√			√
TransOMCS	M	KG	2020	18.00 million (2020)	Time, location, causality, capability, property, desire, intent, part-whole	√	√			√
C3KG	M	KG	2022	1.28 million (2022)	Time, location, causality, capability, property, desire, intent, emotion, part-whole					√
CANDLE	M	NL	2022	1.10 million (2022)	Time, location, capability, property, desire	√	√	√		
GenericsKB	M	NL	2020	3.50 million (2020)	Location, causality, capability, property	√				√
ATOMIC10X	G	KG	2022	6.50 million (2022)	Time, causality, desire, intent, emotion	√	√			√

tures and representation forms, generally it can be considered that they all have some forms of knowledge statements as basic units, e.g., propositions, declarative sentences, and knowledge triples. We use the count of knowledge statements as the size indicator of different resources.

5) Major knowledge category. We identify the knowledge categories described in Section 2.3 for the resources to provide an overall impression about their focus scope.

6) Evaluation. Most of the resources have the evaluation results of intrinsic evaluation (direct evaluating the samples in the resources) or extrinsic evaluation (evaluating the AI systems enhanced with the resources), but the criteria and implementation may differ greatly and cannot be compared consistently. Therefore, we care more about whether several main dimensions of evaluation have been presented rather than the concrete numerical metrics, and use symbol ✓ to indicate whether a resource has reported a certain dimension in publications. The reported evaluation dimensions include:

i) Precision (Pre.). "Precision" shows the percentage of knowledge that is generally seen as correct or plausible. This metric can also be reported as plausibility or accuracy in some resources. To evaluate the precision, human evaluation is required. 5-point Likert scale[69] and its variants are widely used in such evaluation. The annotators should choose a point from "strongly disagree" to "strongly agree". Some resources normalize the results to positive and negative and report the percentage of positive ones, while some others assign a score to each option and report average scores.

ii) Coverage (Cov.). The coverage indicates how much commonsense knowledge is captured in the resource. Since the complete set of commonsense knowledge is not accessible, some resources instead report the relative knowledge coverage (i.e., recall) against other resources as a proxy. The evaluation is often conducted automatically.

iii) Saliency (Sal.). Saliency indicates the degree that people think a piece of knowledge is easy to associate with a concept on first thought. It reflects a different aspect of knowledge quality from the precision, i.e., how important the knowledge is. Therefore, some resources report the average saliency of sampled knowledge assertions.

iv) Typicality (Typ.). For a piece of knowledge about a concept, it is more typical if it is applicable for most of the instances of the concept. As commonsense knowledge is often not strict truth, the typicality can provide a richer perspective about the knowledge quality. Some resources report the average typicality of sampled knowledge assertions.

v) Extrinsic evaluation (Ext.). Besides intrinsic evaluation (i.e., directly evaluating the knowledge resources themselves), some work also use extrinsic evaluation to test the quality and usability via downstream performance. Specifically, based on the knowledge resources, the evaluation forms may include enhancing a question answering system, or training a knowledge completion model. The performance on these tasks can reflect the quality of the knowledge resource indirectly.

6.2 Results

The comparison results are shown in Table 2. From Table 2, we have the following observations.

The increasing trend. Generally, the emergence of new resources is accelerating after 2019. The total quantity of available resources is rapidly increasing. Most of these resources are created via crowdsourcing or text mining, and they adopt knowledge graphs or natural language as the representation format. This suggests there is a growing interest in improving machine commonsense in recent years. Also, making commonsense knowledge better cooperate with modern natural language models is the focus.

Automatic methods are growing. Although human-edited resources have better quality and cover more knowledge categories, recent resources built via automatic methods are catching up swiftly. Some of them have already reached the same level as human-edited resources in precision with minor human supervision. As automatic methods continue to improve, they have the potential to work better on both quality and quantity, becoming the mainstream way to acquire commonsense knowledge. However, there are still much work to be done, which we will further discuss in Section 7.

Precision and coverage are mainly evaluated. Recent resources tend to report more dimensions of evaluation results. The precision, coverage and extrinsic evaluation are the mainly reported dimensions. However, only a few resources have subtle results about saliency and typicality. As the precision of current resources has reached a relative high level, more attention should be paid on more facets other than precision to holistically evaluate the knowledge quality.

7 Challenges and future work

In previous sections, we have reviewed the significant advancements in recent research on commonsense knowledge. With the contribution of human annotators and the development of automatic knowledge acquisition methods, there have been extensive publicly available resources that cover a range of representations and categories of commonsense knowledge. However, these resources are still inadequate to encompass the full spectrum of human commonsense knowledge, and many acquisition and application issues remain unresolved. At the end of this survey, we provide a summary of several challenging areas that are not well studied.

7.1 Knowledge sources

According to the acquisition methods, most existing commonsense knowledge resources either come from human's contribution, or come from text directly or indirectly. However, due to the implicitness of commonsense knowledge, some may never have been recorded in text, which is more difficult to capture via text-based methods. Therefore, there are also attempts to acquire commonsense knowledge from multi-modal sources.

For example, images are seen as another source of commonsense knowledge. Chen et al.[70] propose a program to automatically discover taxonomy and part-whole commonsense knowledge from the web images based on object detectors and classifiers. Yatskar et al.[71] mine location commonsense knowledge from image-text paired datasets. Yao et al.[72] propose a distant-supervised framework to summarize commonsense relations between objects from bags of images. Liu et al.[73] explore a way to acquire commonsense knowledge through visual question generating and answering. These efforts provide different perspectives to exploit commonsense knowledge hidden in images.

However, static images mainly help to acquire limited categories of commonsense knowledge, such as the location and visual property. Other knowledge categories, such as time and causality, are seldom embedded in static images. Therefore, other modal sources like audio and video may cover richer commonsense knowledge to be excavated. Besides, many believe there are unspoken commonsense knowledge that come from the interaction experience with the world, and machines should reproduce the process to obtain such knowledge. Therefore, making embodied agents directly learn commonsense knowledge through environment is also a promising direction[74].

7.2 Representation

The knowledge representation of commonsense knowledge is also an area that needs long-term development. Although knowledge graph is the dominant representation in recent commonsense resources, its expressiveness is limited. As commonsense knowledge is usually general assumptions and defensible in specific situations, it is important to capture how much a commonsense knowledge assertion holds true, when it should not be used, and what evidence supports it. Also, the free-form expressions in commonsense knowledge graphs can be ambiguous and redundant, which may require further normalization. Although some of the issues have been discussed in earlier work of logic-based representations, it is still unknown how to better meet these demands based on large-scale commonsense knowledge graphs. To enrich the expressiveness, some recent work have explored attaching knowledge assertions with contextual text[40, 75] and detailed facets[53, 76]. Besides, some other work propose abstraction[77] and instantiation[78] based on existed commonsense knowledge assertions. The former aims to induce more generalized assumptions, while the latter tries to find the effective scope and exceptions. These explorations may inspire better representations of commonsense knowledge in the future.

7.3 Evaluation

The evaluation of commonsense knowledge resources still requires improvement and standardization. Currently, human evaluation is often the main method to evaluate the quality of resources, which is subjective and highly dependent on the annotation guidelines. Also, as summarized in Section 6.2, precision is mainly focused in evaluating the knowledge quality. However, a correct or plausible knowledge assertion could be trivial and redundant. It is difficult to represent all the desiderata of commonsense knowledge. More metrics like saliency and typicality should be proposed and applied in evaluation.

7.4 Integrating with large language models

Recent advances of large language models have brought breakthrough performance on various fields. And they have been proven effective on generating intermediate reasoning steps[79] and completing commonsense reasoning tasks[80]. Also, as discussed in Section 5.2, large language models have become a new source to acquire large-scale commonsense knowledge. These new findings demonstrate their emergent commonsense capability. However, recent research also shows the generation of large language models suffer from hallucinations and inconsistency[81]. This raises new questions about how to better integrate external commonsense knowledge resources with large language models.

7.5 Content bias

One of the risks associated with commonsense knowledge resources is content bias. On the one hand, most large-scale commonsense knowledge resources are created by crowdsourcing or text mining, which may have unchecked and biased knowledge sources. Recent work have verified the existence of stereotypes and harmful content in current resources and their downstream models[82]. Further reducing such content remains an important task. On the other hand, commonsense varies across cultures, and commonsense resources that are created in one culture may not be applicable to another culture. However, current commonsense resources are English-centric[83], which may introduce language and culture bias. There have been efforts to enrich non-English commonsense knowledge resources[11, 66], while there is still more work to be done.

8 Conclusions

In this survey, we introduce the recent advances in commonsense knowledge acquisition. We systematically review and categorize the scope of current commonsense knowledge research, the mainstream acquisition methods and representative commonsense knowledge resources. These contents show the quantity and quality of recent commonsense knowledge resources are rapidly improving, based on the increasing research interest and the advances of automatic acquisition methods. Besides, we also summarize several challenging areas that need to be further tackled, including knowledge sources, representation, evaluation, etc. We expect that the review and discussion in this paper could inspire better improvement and application of commonsense knowledge resources.

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Declarations of conflict of interest

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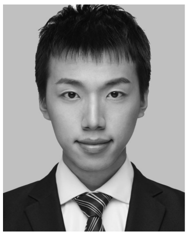

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