Cognitive Computation (2024) 16:3429–3456
https://doi.org/10.1007/s12559-024-10345-6

RESEARCH

PrimeNet: A Framework for Commonsense Knowledge Representation and Reasoning Based on Conceptual Primitives

Qian Liu[1] · Sooji Han[2] · Erik Cambria[3] · Yang Li[4] · Kenneth Kwok[5]

Received: 7 April 2024 / Accepted: 12 August 2024 / Published online: 30 August 2024

Abstract

Commonsense knowledge acquisition and representation is a core topic in artificial intelligence (AI), which is crucial for building more sophisticated and human-like AI systems. However, existing commonsense knowledge bases organize facts in an isolated manner like *bag of facts*, lacking the cognitive-level connections that humans commonly possess. People have the ability to efficiently organize vast amounts of knowledge by linking or generalizing concepts using a limited set of conceptual primitives that serve as the fundamental building blocks of reasoning. These conceptual primitives are basic, foundational elements of thought that humans use to make sense of the world. By combining and recombining these primitives, people can construct complex ideas, solve problems, and understand new concepts. To emulate this cognitive mechanism, we design a new commonsense knowledge base, termed PrimeNet, organized in a three-layer structure: a small core of conceptual primitives (e.g., `FOOD`), a bigger set of concepts that connect to such primitives (e.g., `fruit`), and an even larger layer of entities connecting to the concepts (e.g., `banana`). First, we collect commonsense knowledge and employ a gradual expansion strategy for knowledge integration. After refinement, PrimeNet contains 6 million edges between 2 million nodes, with 34 different types of relations. Then, we design a new conceptualization method by leveraging a probabilistic taxonomy, to build the concept layer of PrimeNet. Finally, we conduct primitive detection to build the primitive layer, where a lexical substitution task is used to identify related concepts, and large language models are employed to generate a rational primitive to label each concept cluster as well as verify the primitive detection process.

Keywords Commonsense acquisition · Knowledge representation and reasoning · Conceptual primitives

Introduction

Commonsense knowledge refers to the information about everyday life that humans are expected to know, such as *painters use pencils* and *animals don't drive cars*. This kind of knowledge is usually taken for granted in human communication and reasoning, even though it may not be explicitly stated [1]. However, machines lack access to this innate commonsense knowledge, which often results in their inferior performance in simple reasoning tasks. As mentioned by Oren Etzioni, commonsense is *"the dark matter"* of AI: it shapes so much of what we do and what we need to do, and yet it's ineffable. To address this limitation, researchers have dedicated significant effort to construct diverse commonsense knowledge bases like Cyc [2], FrameNet [3], ConceptNet [4], TransOMCS [5], ATOMIC [6], CSKG [7], and VoCSK [8]. These knowledge bases are compiled from diverse sources (e.g., encyclopedias, crowdsourcing, and expert annotations), aiming to empower machines with access to commonsense knowledge and enhance the reasoning abilities of AI systems. Despite advancements in existing knowledge bases, the reasoning capabilities of AI systems remain unsatisfactory [9]. One notable limitation is that current knowledge bases often organize facts in a manner resembling a *"millions of facts,"* lacking the cognitive-level connections inherent in human understanding. Humans, on the other hand, exhibit the ability to efficiently organize extensive amounts of knowledge. This capability goes beyond mere accumulation of facts and involves the intricate weaving of cognitive-level connections, enabling a deeper and more nuanced comprehension of the information at hand. We have two observations for human-like knowledge organization.

Firstly, individuals are able to function well in most real-world situations using a much smaller set of *concepts*, as opposed to dealing with an exhaustive list of specific

Extended author information available on the last page of the article

entities. For example, humans generally describe commonsense knowledge like *hammer can be used to drive nails into wood*, as illustrated in Fig. 1. In this example, the more general concepts such as *hammer*, *nail*, and *wood* are used for the description, rather than getting into overly specific terms like *engineering hammer* or *rubber hammer*. From estimates of effective vocabulary, the number of words that people need in order to understand 95% of everyday texts is around 3000 words, and the average size of American freshman college students' vocabulary has been estimated at about 12,000 words [10]. This underscores the human ability to distill extensive information into manageable concepts, facilitating a more streamlined expression and understanding of daily experiences.

Secondly, human cognition relies on a small set of fundamental and innate building blocks called *primitives*. In the *conceptual dependency theory* [11–15], primitives serve as elemental units of information and actions, like `COLOR`, `SHAPE`, `SIZE`, `INCREASE`, and `DECREASE`, and forms the foundation for humans to make generalizations, inferences, and predictions, ultimately facilitating efficient reasoning and understanding in a wide range of real-world situations. For example, we generalize concepts with relevant higher-level primitives. Verb concepts such as *eat*, *slurp*, and *munch* could be related to a primitive `EAT`. Noun concepts like *pasta*, *bread*, and *milk* can be associated with the primitive `FOOD`. Therefore, *eat pasta* or *slurp milk* can be generalized into a primitive-level description, i.e., `EAT FOOD`. Hierarchical concept representations have significant applications in diverse domains, e.g., conceptual metaphor understanding [16, 17] and cognitive analysis [18].

In history, some efforts have been devoted to building knowledge bases more in line with human cognition. For example, VoCSK [8] is designed to exploit concept-level knowledge representation for implicit verb-oriented commonsense knowledge (e.g., *person eats food* instead of *John eats bread*). SenticNet [19] is developed for organizing sentiment knowledge with a core set of primitives. ASER [20] (short for Activities, States, Events, and their Relations) is built to extend the traditional definition of selectional preference to higher-order selectional preference over eventualities. These methods share a common goal of conceptualizing diverse types of commonsense knowledge, mapping them to higher-level cognition, and moving beyond the explicit representation of knowledge as discrete facts. Following this line, we take a further step by constructing a new framework for representing the intricate commonsense knowledge based on conceptual dependency theory.

In this work, we propose a new framework for commonsense knowledge representation and reasoning based on conceptual primitives, named PrimeNet. The data and the code used to develop PrimeNet are available on SenticNet github (https://github.com/senticnet/primenet). Additionally, PrimeNet is also available as an API for verb-noun generalization (https://sentic.net/api/primenet) and as a set of embeddings for aspect-based sentiment analysis available in 80 different languages (https://sentic.net/downloads). The PrimeNet framework consists of three layers, as illustrated in Fig. 2:

- **Primitive**: The primitive layer comprises fundamental and universal elements that act as the building blocks of cognition. These primitives form the foundation upon which the entire knowledge representation is constructed. Examples of basic primitives include `COLOR`, `SHAPE`, `SIZE`, `OBJECT`, `TOOL`, `INCREASE`, `DECREASE`, and others. These primitives are essential for understanding and reasoning about the world.
- **Concept**: The concept layer is commonly used mental representations of categories or classes of objects, ideas, or events that share common features or characteristics. For example, concepts like *hammer* and *nail* fall into this layer. They allow for efficient information organization and grouping based on shared attributes.
- **Entity**: The entity layer represents specific instances or examples of *concepts*. For example, given the concept *hammer*, specific entities include *brick_hammer*, *rubber_hammer*, and *engineer_hammer*. This layer enables a more specific representation of knowledge, capturing individual objects or instances in the real world.

We begin by gathering extensive commonsense knowledge from diverse sources and integrate it to form a raw knowledge graph (Fig. 3). Unlike a simple aggregation of facts, we adopt a gradual expansion approach. Initially, we construct the graph with core concepts and relation types, systematically expanding it by adding more specific entities and incorporating diverse relation types. In the next stage, we establish the conceptual layer of PrimeNet, by assessing the abstractness of all nodes using a new scoring function

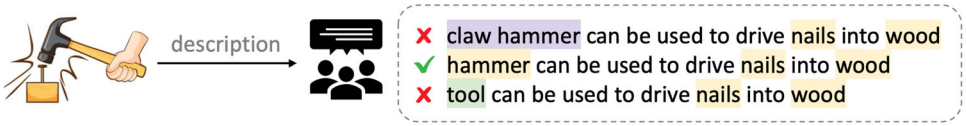


Fig. 1 Example of the description of commonsense knowledge with concepts (e.g., *hammer*, *nail*, and *wood*), instead of specific entities (e.g., *claw_hammer*) or abstract primitives (e.g., `tool`)

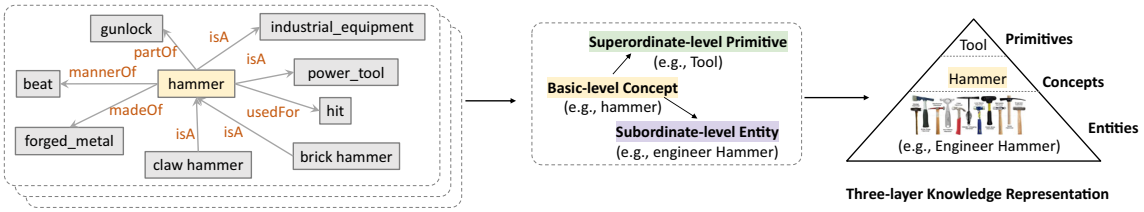


Fig. 2 Illustration of three-layer structure in PrimeNet. Given the factual knowledge, a *concept* layer is generated as the basic level, comprising widely recognized mental representations associated with various categories or classes of objects. Its subordinate layer is termed as *entity* layer, which consists of specific entities, and its superordinate layer is defined as *primitive* level, encapsulating overarching and fundamental primitives

tailored for conceptualization. We leverage the probabilistic taxonomy Probase [21] to identify the abstract concepts, and our scoring method centers around core words rather than the peripheral leaves [8, 22]. Then, we perform primitive detection on the concepts to build the primitive layer of PrimeNet. Formulating a thorough primitive set demands considerable time and effort. To address this, we design a lexical substitution task to discover the set of primitives. This is grounded in the assumption that within a shared context, the associated concepts under a primitive can be seamlessly interchanged, resulting in grammatically accurate sentences upon substitution. To allocate a representative primitive to each concept cluster, we leverage large language models (LLMs) to generate the primitive and employ an LLM-based verifier to validate the assignment of the primitive to concepts.

Moreover, we manually check the primitives, refine the hierarchy structure of the primitives, and generate the explanation of primitives. For example, `DEACTIVATE` is defined as *change the status from on to off*, i.e., `STATE=ON` → `STATE=OFF`. In Table 1, we present several cases of verb primitives used in PrimeNet. This strategy of constructing a primitive layer balances the need for human hand-coding for accuracy with that for crowdsourcing and machine-based knowledge extraction for coverage.

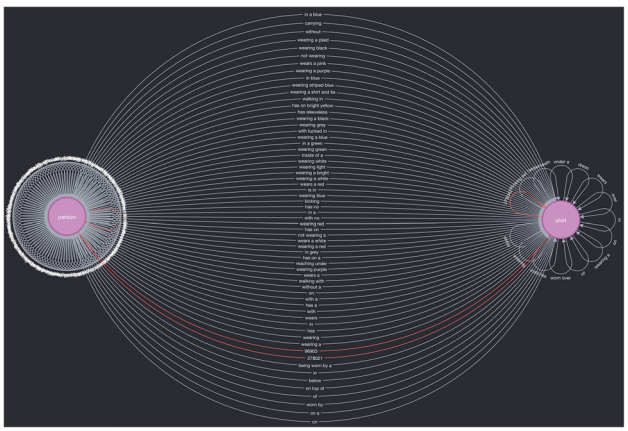


Fig. 3 PrimeNet preliminary knowledge graph. The initial knowledge graph collects all natural language relationships (edges) between concepts (nodes) found in the training data. After several rounds of normalization, the final PrimeNet graph only leverages 34 relationships

The contribution of this work is summarized as follows.

1. **Representation of commonsense knowledge based on conceptual primitives.** We propose a multi-layer commonsense knowledge base based on *conceptual primitives* under the hypothesize that commonsense reasoning could depend on a concise core of concepts. To the best of our knowledge, this is the first work incorporating the idea of conceptual primitives into a general-purpose commonsense knowledge base to provide a generalizable, effective representation of commonsense knowledge for AI tasks.
2. **Construction of a new commonsense knowledge base PrimeNet.** Based on the designed multi-layer structure, we construct a brand new commonsense knowledge base. We first collect commonsense knowledge from various sources and perform knowledge integration to build a knowledge graph.
3. **Conceptualization for PrimeNet.** We design a new scoring method to measure the abstractness of a term for conceptualization, according to the conditional probability and connections to core words. Compared with previous methods, our method centers around core words rather than the peripheral leaves, which is effective in measuring the abstractness of concepts.
4. **Primitive Detection for PrimeNet.** We design a new primitive detection method to build the primitive layer. We employ a lexical substitution task to discover related concepts under the assumption that they share a similar context. For the clusters of related concepts, we leverage LLMs to label their primitives and verify the detection process.

The rest of this paper is organized as follows: Section "Background" introduces conceptual primitive theory and the challenges of building a commonsense knowledge base; Section "Overall Framework" describes the overall framework; Section "Knowledge Graph Construction"

Table 1 Examples of verb primitives in PrimeNet

Input string	Verb primitives	Primitive-level representation and explanation	
Turn off light	Turn off → DEACTIVATE	DEACTIVATE(light)	Light.STATE=ON → light.STATE = OFF
Add salary	Add → INCREASE	INCREASE(salary)	Salary → salary++
Cut budget	Cut → DECREASE	DECREASE(budget)	Budget → budget−−
Drive car	Drive → ACCELERATE	ACCELERATE(car)	INCREASE(car.SPEED):= car.SPEED++
Build house	Build → GENERATE	GENERATE(house)	∄ house → ∃ house
Butcher chickens	Butcher → KILL	KILL(chicken)	TERMINATE(LIFE(chicken))
Revise the manuscript	Revise → FIX	Fix(manuscript)	Manuscript.STATE=BAD → Manuscript.STATE=GOOD
Illuminate the idea	Illuminate → SIMPLIFY	SIMPLIFY(idea)	Idea.STATE=DIFFICULT → Idea.STATE=EASY

Given the input string, we illustrate the detected verb primitives, and its primitive-level representation and explanation. Primitives are marked in green

explains the steps for PrimeNet's initial knowledge graph construction; Section "Concept Detection" illustrates how the concept layer of PrimeNet is built; Section "Primitive Discovery" introduces the primitive detection algorithm for building the primitive layer of PrimeNet; Section "Experiments" reports experiments; Section "Related Works" surveys existing commonsense knowledge bases; Section "Future Directions" discusses future work; finally, Section "Conclusion" provides concluding remarks.

Background

Theory of Conceptual Primitive

In linguistics and cognitive science, *conceptual primitive* commonly refers to a basic, irreducible concept or idea that serves as a foundation for understanding more complex concepts. Conceptual primitives are fundamental elements that are not further defined in terms of other concepts but are instead used to define other, more complex ideas. They are often considered to be the building blocks of thought and language. The exploration of conceptual primitives has a rich history within linguistics. In the 1950s, Chomsky [23] introduced the universal grammar theory, positing innate linguistic structures as foundational conceptual primitives. According to this theory, humans inherently possess the capacity to acquire language, with universal linguistic structures serving as fundamental building blocks shared across all languages. The conceptual dependency theory, put forth by Schank [14], suggested that the basis of natural language is conceptual, forming an interlingual foundation composed of shared concepts and relationships across languages. Jackendoff [11] delved into explanatory semantic representation, asserting the existence of semantic primitives common to all languages, enabling humans to express a diverse range of semantic information. Wierzbicka [15] emphasized that "conceptual primitives and semantic universals are the cornerstones of a semantic theory," asserting that this limited set of primitives can determine interpretations for all lexical and grammatical meanings in natural language. These theories collectively aim to identify a core set of fundamental primitives for language, facilitating the description of lexicalized concepts.

In the realm of cognitive science, theoretical studies on commonsense knowledge representation align with similar insights. Jackendoff et al. [24] highlighted a strong correlation between semantic primitives and cognitive representation. According to Pesina and Solonchak [25], the primitives studied in linguistics form the basis for the formation of a person's conceptual system, which is both unique and universal in many aspects. In this view, language emerges as a central tool for cognitive functions, including conceptualization and categorization. In the development of knowledge representation theories in cognitive science, many have been based on the idea that humans possess a core set of knowledge connecting a vast array of specific knowledge. In the early stages, Minsky [12] studied the framework for knowledge representation and introduced the concept of "frames" as a structured way to organize information about situations or objects. He proposed that humans when encountering new situations, retrieve typical knowledge from their minds. Piaget et al. [26] introduced the term "schema," representing both the category of knowledge and the process of acquiring that knowledge. The knowledge representation based on schema has also been further researched by Rumelhart and Ortony [13], Winograd [27], Bobrow and Norman [28], Johnson [29] and others. Spelke and Kinzler

[30] introduced the core knowledge theory, suggesting that infants are born with "core knowledge systems" supporting basic intuitions about the world. West [31] introduced a data modeling structure divided into primitive and derived concepts, with primitive concepts serving as building blocks for other concepts. These theories collectively underscore that the core primitive set constitutes the fundamental structure of human cognition and provides guidance for knowledge representation.

Challenges

In modern large-scale commonsense knowledge bases, there have been relatively few attempts to build a knowledge base in a way incorporating core primitives based on conceptual dependency theory and linking a vast amount of facts. Cambria et al. [19] has developed a sentiment analysis system based on primitives such as `DECREASE` and `INCREASE` aimed at generalizing sentences into a sort of protolanguage in which it is easier to perform polarity detection, e.g., the sentence "the device's temperature sky rocketed" is first generalized to "`INCREASE`(device.temperature)" and then later transformed into "`device.temperature++`" (Fig. 4). Wachowiak and Gromann [32] proposed to build on large multilingual pre-trained language models and a small dataset of examples from image schema literature to train a supervised classifier that classifies natural language expressions of varying lengths into image schemas. Liu et al. [8] designed conceptualization for verbs and built a knowledge base with conceptual verb-oriented knowledge to represent various instances, e.g., "*John eat apple*" and "*Helen eat bread*" are represented as "`people eat food`."

The primary challenge hindering progress in this field stems from the complexity of constructing a comprehensive set of core primitives to encompass extensive knowledge across diverse domains. On the one hand, managing large-scale factual data makes manual editing and maintenance of a core primitive set impractical. While it is possible to manually craft a small, high-quality core primitive set, this approach becomes intricate when using primitives to interpret other specific concepts, and its coverage of specific knowledge is limited. On the other hand, primitives are not fixed but rather flexible and adaptable. The core primitives are deeply embedded in the human conceptual system, which is both unique and universal in many aspects. The proposed number of semantic primitives varies significantly, ranging from a few units in some studies [15, 24] to several dozens [15] or even hundreds [19] in others. Pesina and Solonchak [25] stated that the main concepts of human society remain relatively stable, but their overall volume changes over time.

Overall Framework

In this section, we first introduce the task definition. Then, we introduce the solution of constructing PrimeNet and the key ideas of each module.

Task Definition

PrimeNet is a hybrid graph $\mathcal{H}$ combining a traditional graph $\mathcal{G}$ where each edge is built among nodes to represent commonsense knowledge in triplets, and a hypergraph $\mathcal{G}^*$ where each edge is built over the nodes to linked their concepts and primitives. For example, in the graph $\mathcal{G}$, its edge is represented as a triplet like (*corgi*, *isA*, *dog*), where *dog* and *corgi* are nodes, and *isA* is a relation type. In the hypergraph $\mathcal{G}^*$, *corgi* is linked to *dog* in the concept layer, and *dog* is linked to `ANIMAL` in the primitive layer. We devise the formal definition of PrimeNet as below.

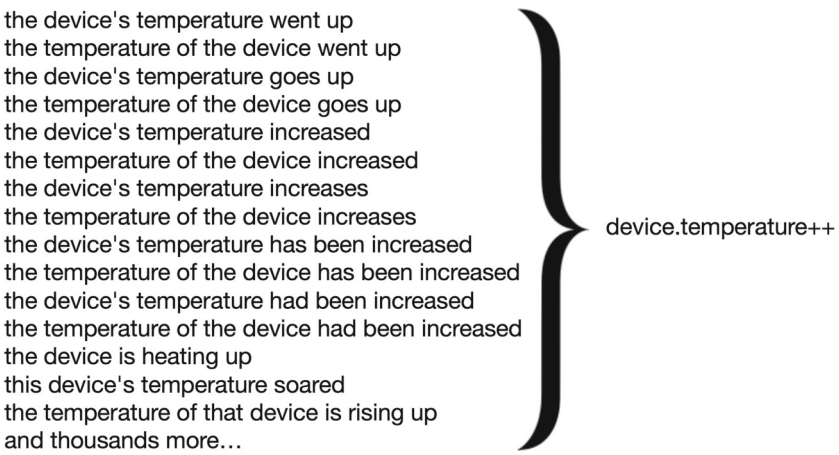


Fig. 4 Example of generalization of sentences into a more abstract, conceptual form

Definition 1 (PrimeNet) PrimeNet is a hybrid graph $\mathcal{H}$ of a knowledge graph $\mathcal{G}$ and a hypergraph $\mathcal{G}^*$. The knowledge graph is denoted as $\mathcal{G} = \{\mathcal{V}, \mathcal{E}, \mathcal{R}\}$ where $\mathcal{V}$ is a node set, $\mathcal{E}$ is an edge set connecting pairs of nodes, and $\mathcal{R}$ is the set of distinct relation types associated with the edges in $\mathcal{E}$. Each node $v \in \mathcal{V}$ is a term. Each edge $e \in \mathcal{E}$ is a triplet (v_i, r, v_j) where v_i and v_j are the connected nodes, and $r \in \mathcal{R}$ is the relation type. The hypergraph is denoted as $\mathcal{G}^* = \{\mathcal{V}, \mathcal{C}, \mathcal{P}, \mathcal{M}\}$, where $\mathcal{V}$ represents the set of entities, $\mathcal{C}$ represents the set of concepts, and $\mathcal{P}$ represents the set of primitives. The hyperedge set $\mathcal{M} = \{\mathcal{M}_{v\to c}, \mathcal{M}_{c\to p}\}$ contains two types of hyperedges. The hyperedge $(v, c) \in \mathcal{M}_{v\to c}$ links the entity $v \in \mathcal{V}$ to its concept $c \in \mathcal{C}$, and the hyperedge $(c, p) \in \mathcal{M}_{c\to p}$ links the concept $c \in \mathcal{C}$ to its primitive $p \in \mathcal{C}$. Overall, we have the PrimeNet $\mathcal{H} = \{\mathcal{V}, \mathcal{E}, \mathcal{R}, \mathcal{C}, \mathcal{P}, \mathcal{M}\}$.

Overall Framework of PrimeNet Construction

The solution of PrimeNet mainly consists of three modules. The first module is to construct the knowledge graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}, \mathcal{R}\}$ to organize the large-scale commonsense knowledge. This knowledge graph is designed to cover a wide range of commonsense knowledge, encompassing specific entities and extensive information. We refer to this graph as the entity layer of PrimeNet. The second module is a conceptualization module, which identifies a small set of concepts $\mathcal{C}$ on top of the set of specific entities $\mathcal{E}$ in $\mathcal{G}$, as well as the hyperedges $\mathcal{M}_{v\to c}$ to link entities to concepts. We consider this concept set and the mapping between concepts and entities as the concept layer of PrimeNet. The third module is a primitive detection module that constructs the core primitive set $\mathcal{P}$ on top of the concept set $\mathcal{C}$ and builds the hyperedges $\mathcal{M}_{c\to p}$ to link concepts to their primitives. This small primitive set and the mapping between primitives and concepts are used as the primitive layer of PrimeNet. In the following, we will provide a more in-depth introduction to each module, along with corresponding examples for illustration.

Module-1: Knowledge Graph Construction

Over the course of many years, a vast reservoir of factual knowledge has accumulated, taking on various forms and originating from diverse sources. In order to systematically organize this wealth of knowledge, we have undertaken the construction of a knowledge graph. Drawing inspiration from the theory of cognitive development put forth by Piaget et al. [26], which posits that human cognitive development occurs in stages, we have adopted a gradual expansion strategy to build our knowledge repository. Rather than merging disparate sources abruptly, our approach is to delicately expand the knowledge base.

The fundamental idea underlying our strategy is that human knowledge acquisition follows a pattern of continuous expansion, rooted in commonly shared and widely accepted information. For instance, individuals typically begin by learning that a "hammer" is a "tool" used for driving "nails," and subsequently delve into more intricate details, such as discerning the differences among various types of hammers like "engineer hammer" and"brick hammer." To emulate this cognitive process, we initially construct a basic graph consisting of widely used concepts and relations as the entity layer of PrimeNet. Subsequently, we systematically enlarge the graph by incorporating a multitude of facts from diverse sources. This method allows for the gradual incorporation of information, mirroring the incremental nature of human knowledge acquisition. We detail this module in Section "Knowledge Graph Construction."

Module-2: Concept Detection

To construct the concept layer over the knowledge graph $\mathcal{G}$, this module focuses on identifying a suitable concept set $\mathcal{C}$ from the node set $\mathcal{V}$ and establishing hyperedges in the set $\mathcal{M}_{v\to c}$ to link entities with their respective concepts. Within PrimeNet, this concept layer encapsulates commonly used mental representations of categories, classes, or ideas that share common features or characteristics. For instance, "hammer" is the concept that represents a category encompassing entities such as "engineering hammer," "brick hammer," and "rubber hammer." Consequently, we initialize the concept set layer using Core WordNet,[1] a compilation of approximately 5000 of the most commonly used words meticulously curated by experts. Then, we design a concept detection method to discover new concepts and expand the concept set, leveraging a large-scale probabilistic taxonomy, i.e., Probase [21], and build the edges to link entities to the detected concepts.

Specifically, Probase encompasses 33.4 million *isA* triples between 2.7 million concepts, automatically extracted from 1.68 billion web pages, with each triplet associated with a frequency score. Our observation underscores that, for a concept, its hyponyms tend to establish robust connections with diverse concepts in a probabilistic taxonomy, whereas a specific entity is more concentrated in its connection to concepts. To capture this regularity, we introduce a novel scoring function designed to identify whether a term qualifies as a concept. In contrast to alternative conceptualization methods, our approach stands out by centering around core words rather than initiating from the leaves of an extensive taxonomy for concept detection. The pre-defined core words enhance diversity and accuracy, distinguishing our strategy as effective in steering clear of misleading information stemming from isolated graphs or incorrect circles within the large-scale taxonomy.

[1] Please find more details from https://wordnet.princeton.edu/. Core WordNet is available in https://wordnetcode.princeton.edu/glosstag.shtml.

Module-3: Primitive Discovery
This module is dedicated to constructing the primitive layer of PrimeNet, involving the establishment of a core primitive set $\mathcal{P}$ and the creation of the hyperedge set $\mathcal{M}_{c\to p}$ to connect concepts with their higher-level primitives. For instance, the primitive `INCREASE` is associated with concepts like *ramp up, go up, broaden, step up, elevate, supplement, redouble, pile up, upward spiral, distend*, and more. The manual definition of the primitive set and linking of primitives to their lower-level concepts is impractical. In our approach, an automated method is designed, utilizing concept clustering and subsequent labeling of their primitives using large language models, followed by error checking to refine both the primitives and concept clusters.

Specifically, it is observed that concepts under the same primitive often share a similar meaning and context. For instance, *elongate* and *stretch* fall under the same primitive `GROW` and share a similar context. Although intuitive, lexical substitution tends to overlook crucial differences between concepts. For example, verbs such as *stretch* and *compress* belong to opposite primitives, `GROW` and `SHRINK` respectively, yet can be identified within similar lexical contexts. To address this issue, we leverage powerful LLMs to filter out incorrect concepts within each cluster, generating a primitive that accurately describes the concept cluster. Manual checks are also employed to ensure the quality of primitives in building the primitive layer. This strategy strikes a balance between human hand-coding for accuracy and crowdsourcing and machine-based knowledge extraction for comprehensive coverage.

Knowledge Graph Construction

In this section, we detail the construction of the knowledge graph ($\mathcal{G}$) of PrimeNet. It mainly contains four stages. First, *commonsense knowledge acquisition* is to collect high-quality knowledge from diverse sources which are created through manually annotated or crowdsourcing. Then, *knowledge integration* is to map the nodes and relations among different sources. Next, the *graph construction* is to organize the knowledge in a graph. Finally, *exploration* is to define functions to leverage the knowledge graph in the downstream tasks. We detail each stage as follows.

Commonsense Knowledge Acquisition

In constructing a commonsense knowledge base, the acquisition of knowledge stands out as a pivotal initial phase. Collecting commonsense knowledge is a challenging task due to its sheer volume, implicit nature, and diverse forms of expression. With decades of human efforts, a wealth of commonsense knowledge has been amassed and stored in various knowledge bases. To ensure quality, in this work, we extract knowledge from expert-crafted databases and crowdsourced repositories, as summarized in Table 2, including:

- Lexical knowledge extracted from WordNet [33], FrameNet [3], and Roget [34].
- Factual knowledge extracted from ConceptNet[2] [4], which is a commonsense knowledge that represents general knowledge and commonsense relationships between concepts.
- Structured information in Wikidata and DBpedia. For DBpedia[3] [35], we extract knowledge from *InfoBoxes* which provide information about a wide variety of topics, e.g., people, places, and organizations, as well as knowledge from *InstanceTypes* which contains instances of 438 types, e.g., book, company, city, and plant.
- Task-specific knowledge, such as inferential knowledge extracted from ATOMIC [6, 36] which is organized as typed "if-then" relations with variables, and visual knowledge extracted from Visual Genome [37].

Knowledge Integration

In commonsense knowledge graph construction, multiple sources can provide complementary knowledge of different types. However, the integration of knowledge from diverse sources is impeded by the varying representation formats. It is noted that many databases provide mappings to other databases, e.g., ConceptNet contains mappings to DBpedia, WordNet, Wikidata, and FrameNet. Yet, these mappings may be incomplete. Recent research endeavors to create high-quality mappings among different knowledge bases, offering a pathway for knowledge integration. For example, CommonSense Knowledge Graph (CSKG) [7] construct mappings across seven knowledge bases (i.e., ATOMIC, ConceptNet, FrameNet, Roget, Visual Genome, Wikidata, and WordNet). We conduct knowledge integration to build a knowledge graph of PrimeNet using these high-quality mappings, as well as lexical-level and semantic-level matching methods. Table 3 summarizes the details of our integration process.

First, we process the individual sources. More specifically, we keep the initial sets of nodes, edges, and relations in ConceptNet and ATOMIC. For other sources, we extract their nodes and edges and convert their relations to the format of relations in ConceptNet, as detailed in Table 3. Then, we conduct mappings between sources for node resolution. On the

[2] We use the ConceptNet version 5.7.0, which is available at https://github.com/commonsense/conceptnet5/wiki/Downloads.

[3] We use the DBpedia version 2022.09.01, which is available at https://www.dbpedia.org/resources/.

Table 2 Sources of commonsense knowledge for building the knowledge graph of PrimeNet

Source	Creation	# R	Size	Example
WordNet	Manual	10	155K words, 176K synsets	(denied, morphy, deny)
FrameNet	Manual	10	1.2K frames, 12K roles, 1.9K edges	(Criminal_process, Subframe, Arrest)
Roget	Manual	2	72k words, 1.4M edges	(explore, Synonym, investigate)
ConceptNet	Crowdsourcing	34	8 M nodes, 21 M edges	(keyboard, part of, computer)
Wikidata	Crowdsourcing	6.7K	75 M objects, 900 M edges	(George Washington, isInstanceOf, human)
DBpedia	Crowdsourcing	53.1K	4.8M nodes, 62 M edges	(Applied_Artificial_Intelligence, discipline, Artificial_intelligence)
ATOMIC	Crowdsourcing	9	300K nodes, 877K edges	(PersonX bakes bread, Before X needed to, buy the ingredients)
Visual Genome	Crowdsourcing	42.4K	3.8M nodes, 2.3M edges, 2.8M attributes	(man, sit on, bench)

Creation denotes the construction methods, *# R* denotes the number of relation types, and *Size* denotes the graph scale

one hand, we leverage mappings released by Ilievski et al. [7][4] to map nodes from different sources. On the other hand, we represent each node using its label and use exact lexical matching to establish the mappings of nodes from different sources. Moreover, we conduct semantic-level matching to identify the same nodes with different labels.

We convert all labels of nodes to embeddings using pre-trained Sentence-BERT [38].[5] Subsequently, we employ the labels of nodes from another source as queries and perform embedding-based semantic search. The cosine similarity metric is employed to measure semantic similarities between two nodes. We establish a link between the query and its top-1 similar node if they share the same representation after lexical tokenization using NLTK.[6]

Graph Construction

Confronted with an extensive dataset of knowledge triplets, creating a graph by incorporating all of them directly is a blunt method. Humans develop core conceptual primitives grounded in the most frequently utilized knowledge. For example, in the realm of *geography*, individuals effortlessly understand fundamental concepts like *country*, *continent*, and *ocean*, forming a foundational understanding without the need to memorize every specific detail, including aspects like the area and visual representation of each country available in DBpedia and Visual Genome, respectively. This insight guides our approach to graph construction through a gradual expansion strategy. We illustrate the construction process in Fig. 5.

Initially, we start from core nodes and relations to construct a new knowledge graph. For core nodes, Core WordNet[7], which contains the most frequently used 5000 words, i.e., 3300 nouns, 1000 verbs, and 700 adjectives. We mainly consider knowledge from WordNet and ConceptNet, with a set of core relations: isA, madeOf, partOf, mannerOf, usedFor, and capableOf. Table 4 details the core relations and their descriptions and examples. We denote this graph as a basic graph, which contains 488,216 nodes and 962,228 edges. Then, we extract instanceOf and isA relations from DBpedia to expand the core graph with more specific nodes. In this step, we employ an embedding-based semantic similarity method using pre-trained Sentence-BERT for mapping. After integration, the graph is expanded to 1.4M nodes and 3 M edges.

Finally, we integrate commonsense knowledge from diverse sources into our graph, ensuring a wide-ranging and diverse coverage. To map nodes from other sources to our graph, we employ the mappings developed by CSKG for integration. Moreover, to merge nodes, we use the embedding-based similarity method to identify nodes with the same meaning, and then use the tokenization-based method for verification. After integration, the nodes in PrimeNet are enriched with different kinds of commonsense knowledge, with 2.04M nodes and 6.03M edges.

Exploration

Then, we design multiple functions for exploring the graph that are capable of:

[4] The project description and mappings are available on https://github.com/usc-isi-i2/cskg. Please refer to o Ilievski et al. [7] for more details on processing individual sources, performing node resolution, and constructing mappings.

[5] Used version: https://huggingface.co/sentence-transformers/all-mpnet-base-v2.

[6] https://www.nltk.org/

[7] https://wordnetcode.princeton.edu/standoff-files/core-wordnet.txt

Table 3 Details of knowledge integration for individual sources and mapping between sources

Step 1. Individual sources	
ConceptNet	Initial nodes and edges are used, and 34 relations are mapped to PrimeNet relations (e.g.,*/r/IsA* is converted to *isA*, */r/UsedFor* is converted to *usedFor*)
ATOMIC	Initial nodes, edges, and 9 relations
WordNet	*Hyponym* and *hypernym* are converted to *isA*, *part holonymy* is converted to *partOf*, *substance meronymy* is converted to *madeOf*
FrameNet*	Four types of nodes are used (i.e., frames, frame elements, lexical units, and semantic types) and 19 relations are mapped to PrimeNet relations (e.g., *is_causative_of* is converted to *cause*)
Roget	Two relations are used, i.e., *synonyms* and *antonyms* are mapped to the PrimeNet relations *synonym* and *antonym*, respectively
Visual Genome*	The image objects are converted to WordNet synsets. The relationships between objects are mapped to the relation *locatedNear*. Object attributes are represented by different relations, conditioned on their part-of-speech, i.e., *capableOf* for verbs and *mayHaveProperty* for adjective attributes
Wikidata*	101K statements in Wikidata-CS subset are used, and the relations are manually mapped to 15 relations
DBpedia	The instance-types subset and infobox-properties subset are used, and *#type* relation is converted to PrimeNet relation *instanceOf*
Step 2. Mapping between sources	
WordNet-WordNet*	Align ConceptNet and Visual Genome using WordNet InterLingual Index (ILI) generating 117,097 mappings
WordNet-Wikidata*	Generate links between WordNet synsets and Wikidata nodes using pre-trained XLNet model for embeddings. Manual validation with 17 students. Keep 57,145 validated edges
FrameNet-ConceptNet*	Link FrameNet lexical units to ConceptNet nodes through Predicate Matrix (3016 edges). Use 200k hand-labeled sentences from FrameNet corpus for additional linking
Lexical matching*	Establish links between nodes in ATOMIC, ConceptNet, and Roget through exact lexical matching of labels
Semantic matching	Establish links between nodes in ConceptNet, Wikidata, and DBpedia through semantic matching of labels

Relation types are in italics. * denotes the processed nodes, edges, or mappings released by Ilievski et al. [7]

- Exploring graph structure of PrimeNet. For example, *nodes* and *edges* functions are designed to generate all concepts and relations in PrimeNet, respectively, and *get_number_of_nodes* and *get_number_of_edges* are designed to count the number of nodes and edges in the knowledge graph.
- Exploring commonsense knowledge for specific concepts. For example, given a concept, *what_is* function is designed to get all its relations, *get_polarity* function is used to get its sentiment polarity, and *find_path* function is designed to find a specific path in PrimeNet given a pair of concepts.
- Integrating new knowledge into PrimeNet. For example, the *add_node* and *add_edge* functions are designed to add new concepts and relations into PrimeNet, and the *add_primenet_new* function is able to incorporate a new knowledge base into PrimeNet.

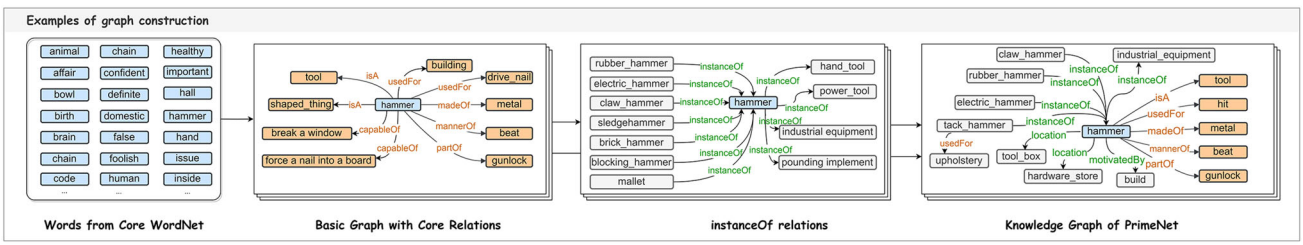


Fig. 5 Illustration of graph construction of PrimeNet. Starting with Core WordNet, we first construct a basic graph with core words and relations from WordNet and ConceptNet. Then, we add instanceOf knowledge from DBpedia and Wikipedia. Next, diverse types of knowledge from other knowledge bases are incorporated into the graph of PrimeNet

Table 4 Core relations of PrimeNet, and their description, example, and mappings to WordNet and ConceptNet

Relations	Description	Example	Mapping to WordNet	Mapping to ConceptNet
isA	A is a specific instance of B	(car, isA, machine)	Hyponym, hypernym	/r/IsA, /r/InstanceOf
madeOf	A is made of B	(car, madeOf, metal)	Meronymy	/r/MadeOf
usedFor	A is used for B; the purpose of A is B	(hammer, usedFor, hit)	–	/r/UsedFor
partOf	A is a part of B	(gunlock, partOf, gun)	Holonymy	/r/PartOf
mannerOf	A is a specific way of B	(screw, mannerOf, revolve)	–	/r/MannerOf
capableOf	Something that A can typically do is B	(bowl, capableOf, hold_water)	–	/r/CapableOf

We detail all the designed functions in Table 5, including their input, output, and description. These functions make it easy to apply PrimeNet in downstream tasks, as well as update PrimeNet with new commonsense knowledge or domain-specific knowledge.

Concept Detection

To create the concept layer of PrimeNet, we conduct concept detection to identify concepts that represent categories or classes of objects, ideas, or events based on shared features

Table 5 Functions designed for exploring PrimeNet

Function	Input	Output	Description
Nodes	–	A list of nodes	Return all nodes in PrimeNet
Edges	–	A list of edges	Return all edges in PrimeNet
get_number_of_nodes	–	An int number	Return the number of nodes in PrimeNet
get_number_of_edges	–	An int number	Return the number of edges in PrimeNet
relation_types	A node	A list of relation types	Return all relation types that the node involved
what_is	A node	A path of the node	Return the first edge of a node
what_can_be	A node	A list of edges	Return all edges of a node
relation_exist	A node and a relation type	True or False	If a relation type exists in the node return True, else False
get_node_with_relation	A node and a relation type	A node	Given a node A and a relation R, return node B if there is an edge (A, R, B)
Explain	A node and a relation type	A chain of this node	Return the chain of a node and a relation type
Generalize	A node	A list of edges	Return the root node of each of its relationships
get_similarity	Two nodes	A float score	Return a score that denotes how similar two nodes are, based on the path similarity computed by SequenceMatcher
get_polarity	A node	Positive or Negative	Return the sentiment polarity of a node
get_path	start_node and end_node	A path	Return a path from the start_node to the end_node.
find_last_nodes	A node	A list of paths	Return all edges where the end_node is the given node
find_all_paths	Start_node and end_node	A list of paths	Return all paths from start_node to end_node
get_node_degree	A node	A number	Return the number of edges which connect with the given node
get_phonetic	A concept	The phonetic information	Return the phonetic information of a concept
add_node	A node	–	Add a node to PrimeNet if it does not exist in PrimeNet
add_edge	An edge	–	Add an edge to PrimeNet
add_primenet_new	A new knowledge graph	–	Add a new knowledge graph to PrimeNet
print_to_file	A knowledge graph	–	Save a knowledge graph to a file

For each function, we introduce its input, output, and description

or characteristics [39]. An intuitive approach is to use the *isA* relation to establish mappings between concepts and entities. For example, *(dog, isA, animal)*, *(cat, isA, animal)*, and *(lion, isA, animal)* indicate that *animal* is a concept, and *dog*, *cat*, and *lion* are entities falling under that concept.

Though simple, in practice, it is sub-optional to identify concepts by checking whether exist entities fall under them. For example, *animal*, *dog*, and *corgi* have specific entities. However, only *animal* and *dog* are widely used as concepts in human daily reasoning, *corgi* are too specific. In this section, we study how to conduct concept detection with appropriate abstractions.

Preliminaries

When considering the conceptualization, it is important to measure the abstractness of a term. For example, *person* is a more abstract concept compared with *student*. Given a graph with *isA* relation, it is observed that abstract terms are usually located at the higher levels in a graph, while the specific terms tend to be positioned at the lower levels Liu et al. [8]. Specifically, the leaf nodes are regarded as the most specific terms, and they are considered as the first level. The level of non-leaf nodes is defined as the length of the longest path from the leaf nodes to itself. Formally, the *level* of a term is defined as follows.

Definition 2 (Level Score) Given a term c, the level score of c is defined as:

$$level(c) = \begin{cases} \max\limits_{c' \in hypo(c)} level(c') + 1, & if \ \ hypo(c) \neq \phi \\ 1, & otherwise \end{cases} \tag{1}$$

where $hypo(c)$ is a set of hyponyms of c, and ϕ denotes an empty set.

The abstract words have higher-level scores and specific terms have smaller-level scores. For example, the level scores of *dog*, *mammal*, and *animal*, are 72, 89, and 362, respectively.

It is also observed that, for an abstract term, its hyponyms are usually positioned at diversified levels, while its hyponyms would be more concentrated for a specific term. Based on it, Liu et al. [8] defined an entropy-based metric for the abstractness measurement. Formally, the entropy score of a term is defined as follows.

Definition 3 (Entropy Score) Given a term c, its entropy score is defined as:

$$entropy(c) = \begin{cases} 0, & \text{if c is a leaf term} \\ -\sum_{i=1}^{l} p_i(c) \cdot \log p_i(c) & otherwise \end{cases} \tag{2}$$

where l is the maximum level, and $p_i(c)$ is the ratio of the number of c's hyponyms at the i-th level to the total number of c's hyponyms.

The entropy of abstract terms is often greater than that of specific terms. For example, the entropy scores of *pupil*, *student*, and *people* are 0.563, 0.927, and 1.790, respectively.

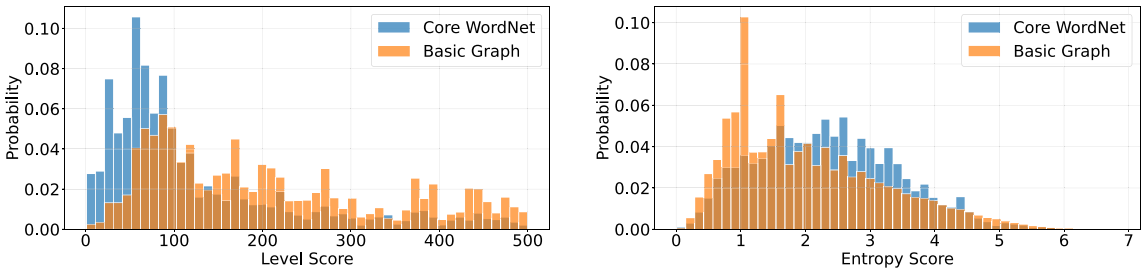
In general, abstract *concepts* and concrete *entities* are differentiated using these abstractness measure methods by manually-defined thresholds [8]. However, these methods are inaccurate and not suitable when applied to complex graphs with large-scale commonsense knowledge. The primary reason is the vast amount of knowledge, inevitably leading to the presence of cycles and isolated subgraphs, significantly reducing the accuracy of the aforementioned methods. Furthermore, some commonly used vocabulary lacks numerous lower-level nodes, e.g., *voice*, *track*, and *driver*, and they have lower scores compared with other words with more hyponyms, e.g., *transport*, *symbol*, and *medicine*. As such, the conceptualization methods which only rely on hierarchical information are not reasonable for such cases.

We perform a probing experiment as illustrated in Fig. 6. We assume that words from Core WordNet are concepts, given their fundamental role in describing the world. For all nodes in Core WordNet and our knowledge graph $\mathcal{G}$ of PrimeNet, we show probability distributions of their level scores and entropy scores. It is observed that a considerable number of words in Core WordNet have level scores below 50, and entropy scores under 1. These words are readily excluded from concept sets, by applying previous methods for conceptualization.

Conceptualization

Previous methods employed a *bottom-up* approach to measure abstractness, where a word's score relies on its hyponym set. Leaves without hyponyms are initiated as the seed set and then inferred for the others. In this work, we initialize the core concepts and then infer other words accordingly.

Specifically, the initial set of concepts, denoted as $\mathcal{C}^0 = \{c_1, c_2, c_3, \cdots\}$, comprises commonly used words from Core WordNet that describe the world in human daily life. In an ideal scenario, the hypernyms of these core words are



(a) Probabilities of Level Scores (b) Probabilities of Entropy Scores

Fig. 6 Illustration of data distribution of Core WordNet and the graph of PrimeNet, considering of the level scores and entropy scores of nodes

expected to be more abstract and should be considered as concepts. However, in a practical scenario, not all of their hypernyms can be unequivocally regarded as concepts due to the intricate interweaving of commonsense knowledge. For instance, relationships such as *(dog, isA, animal)*, *(dog, isA, pet)*, *(pet, isA, animal)*, and *(dog, isA, species)* are all deemed correct and coexist within the knowledge base. Thus, we need a more accurate method to measure the abstractness of hypernyms. It is observed that not all hypernyms have the same weight when working as the concept of a *dog*. This problem has been deeply studied, and a large-scale probabilistic taxonomy, i.e., Probase [21], has been constructed to provide statistical insights of isA relations. It includes "isA" relations for 2.7 million terms, automatically mined from a corpus of 1.68 billion web pages. That is, each triplet *(t, isA, c)* is linked to a frequency score *frec*(t, c), providing frequency information computed through a data-driven method based on the large-scale corpus.

For example, *(dog, isA, animal)* and *(dog, isA, species)* show that both *animal* and *species* are concepts of *dog*, and $freq(dog, animal) > freq(dog, species)$ shows *animal* is a more typical concept for *dog*, compared with *species*. Given a triplet *(t, isA, c)*, it is associated with a frequency score *freq*(t, c) in Probase. The frequency score is an important signal to identify whether this relation is typical or not. Based on this observation, Wang et al. [22] propose a *typicality score*, which is defined based on the frequency information to tell how popular a concept c is as far as an entity t is concerned, and how popular an entity t is as far as a concept c is concerned:

Definition 4 (Typicality Score) Given an term t, the conditional probability $Pr(c|t)$ of a term c is defined as:

$$Pr(c|t) = \frac{freq(t, c)}{\sum_{c_i \in hyper(t)} freq(t, c_i)}, \tag{3}$$

where $hyper(t) = \{c_1, c_2, c_3, \cdots\}$ is the set of hypernyms of t.

Given a concept c, the conditional probability $Pr(t|c)$ of an entity t is defined as:

$$Pr(t|c) = \frac{freq(t, c)}{\sum_{t_i \in hypo(c)} freq(t_i, c)}, \tag{4}$$

where $hypo(c) = \{t_1, t_2, t_3, \cdots\}$ is the set of hyponyms of c.

It is observed that a term tends to be abstract when it is strongly connected with multiple concepts. Continuing the previous example, the term *animal*, *pet*, *species* link to 98, 435, 22 concepts in $\mathcal{C}^0$, respectively. To formalize this regularity, a linking-based metric is designed as follows:

Definition 5 (Conceptual Score) Given a term w and a set of concepts $\mathcal{C}$, the conceptual score of w is defined as:

$$abstract(w) = \sum_{t_i \in hypo(w)} \mathbb{1}(t_i \in \mathcal{C}) * \frac{freq(t_i, w)}{\sum_{o_j \in hyper(t_i)} freq(t_i, o_j)} \tag{5}$$

where $hypo(w) = \{t_1, t_2, \cdots, t_i \cdots\}$ is the set of hyponyms of w, $hyper(t_i) = \{o_1, o_2, \cdots, o_j \cdots\}$ is the set of hypernyms of t_i, and $\mathbb{1}(t_i \in \mathcal{C})$ is set to 1, otherwise 0.

This scoring method is designed to quantify the extent to which a term functions as a universal, abstract link across a diverse array of concepts. Utilizing the initial set $\mathcal{C}^0$, we calculate the abstraction scores of their hypernyms, presenting the top 50 terms in Fig. 7. According to human analysis, all of them are confirmed as conceptual terms. In addition, we present their *level scores* and *entropy scores*, revealing that these metrics fall short in inferring them as abstract terms. For instance, *topic*, *song*, and *adjective* exhibit low-level scores (i.e., 3, 3, and 28), and *author* and *classic* display low entropy scores (i.e., 0.59 and 1.72), excluding them from being identified as concepts.

We employ an iterative approach to augment the concept set by systematically incorporating terms with high abstraction scores. In i-th iteration, we introduce the top-n (e.g.,

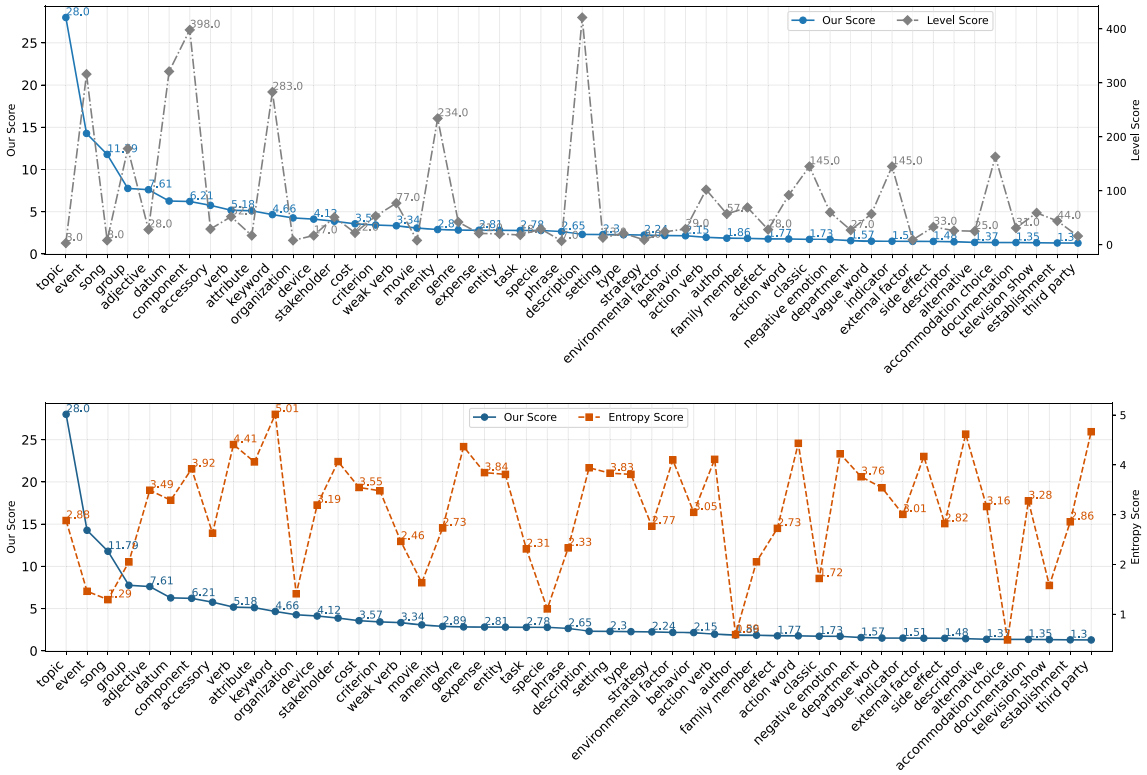


Fig. 7 Examples of top-50 words scored by the designed conceptual score function. We compare their level scores and entropy scores with our conceptual scores

$n = 3$) hypernyms for each concept in $\mathcal{C}^{i-1}$. The constraint imposed is that these hypernyms must surpass a specified threshold T_{abs}. This process results in the construction of an updated concept set, denoted as $\mathcal{C}^i$.

Primitive Discovery

The primitive discovery is to identify the most basic and essential element of the world knowledge, which provides a way to represent and organize knowledge in a structured and meaningful manner [14, 40]. The well-designed primitive set can help to produce more accurate and reusable knowledge bases. However, creating a thorough set of primitives is extremely time-consuming and labor-intensive, hence it is not generally employed in most knowledge bases [11, 12, 14, 19].

In this work, we apply automatically discover a primitive set of commonsense knowledge. The basic idea entails clustering concepts that share similar functions at the cognitive level, then labeling the most representative concept in each cluster as a conceptual primitive. To achieve this goal, initially, we conduct concept clustering to group together related concepts quickly, filtering out those with highly disparate semantic meanings. Subsequently, we conduct a more precise primitive detection process, further refining each cluster to retain only the most consistently coherent concepts at the cognitive level and selecting the most representative concept to serve as the primitive for that specific set of concepts.

Concept Clustering

In this work, the concept clustering is designed to group cognitively related concepts while swiftly eliminating highly unrelated ones, thereby simplifying the following task of accurately conducting primitive detection. To achieve this goal, we employ a lexical substitution task to conduct concept clustering. Specifically, this task is to replace a concept in a sentence with a different concept. If the grammatical structure and overall meaning of the sentence are preserved, these two concepts are considered to have similar meanings. For example, in the sentence "the landlord tried to eject the tenants for not paying rent on time," one could substitute the word "eject" with "dispossess," "remove," "oust," or "evict" without changing the overall meaning of the sentence.

Inspired by Cambria et al. [19], we fine-tune pre-trained language models.[8] for lexical substitution. More specifically,

1. *Training Data.* We extract all the verb-noun and adjective-noun concepts from ConceptNet 5.7 [4] together with a sample sentence for each concept. The collection of concepts is denoted as $\mathcal{E} = \{e_1, e_2, e_3, \cdots, e_n\}$, where each concept $e_i \in \mathcal{E}$ is assigned with a sample sentence s_i. For each concept e_i, we remove it from the sentence s_i and the remaining sentence is denoted as its context c_i. We employ pre-trained language models to represent the concept e_i and its context c_i as fixed-dimensional embeddings, i.e., $\mathbf{e}_i$ and $\mathbf{c}_i$, respectively.
2. *Training Objective.* Then, we fine-tune the pre-trained language model with a lexical substitution task. The assumption is that a relevant lexical substitute should be both semantically similar to the target word and have a similar contextual background. Given a concept e_i, its context c_i is regarded as the positive example. We create negative examples by sampling random concepts, which are denoted as $\mathcal{N}(e_i) = \{e^*_{i,1}, e^*_{i,2}, \cdots, e^*_{i,z}\}$. The training objective function is defined as:

$$O = \sum_{i=1}^{n} (\log(\sigma(\mathbf{e}_i, \mathbf{c}_i)) + \sum_{e^*_{i,j} \in \mathcal{N}(e_i)} \log(\sigma(-\mathbf{e}^*_{i,j}, \mathbf{c}_i))), \tag{6}$$

   where n is the number of training examples, z is the number of negative words for each example, and $\mathbf{e}_i^j$ denotes the representation of a negative concept. After fine-tuning, the representation model is expected to map concepts and context into an embedding space, where concepts that are appropriate for a given context are located close to one another.
3. *Semantic Measure.* We design a semantic measure to find the replacement of the concept in the embedding space. Given a concept e_i and its context c_i, we calculate the cosine distance of all the other concepts, e.g., $w \in \mathcal{E}$ in the embedding space as:

$$Sim(\mathbf{w}, (\mathbf{e}_i, \mathbf{c}_i)) = \cos(\mathbf{w}, \mathbf{e}_i) \cdot \cos(\mathbf{w}, \mathbf{c}_i) \cdot \cos(\mathbf{s}_i, \mathbf{s}_i^w), \tag{7}$$

   where s_i is the original sentence, and s_i^w is a sentence by replacing c_i in s_i with w.

[8] In our experiment, the used pretrained model is *all-mpnet-base-v2* Having undergone pretraining on over 1 billion sentence pairs, this model is capable of mapping input text to a 768-dimensional vector space, ideal for tasks such as clustering or semantic search. Further details can be found at: https://huggingface.co/sentence-transformers/all-mpnet-base-v2.

Using pretrained models, we conduct concept clustering through a fast clustering algorithm[9] developed by SentenceBERT [38]. This algorithm is more efficient than previous hierarchical clustering methods like agglomerative clustering, making it better suited for large-scale, high-dimensional clustering tasks. The clustering process involves two thresholds: the similarity threshold, which determines when two sentences are considered similar, and the min_community_size threshold, specifying the minimum size for a local community. These thresholds allow us to obtain either large, coarse-grained clusters or small, fine-grained ones. In our implementation, based on our experimental observations, we set the similarity threshold to 0.6 and the min_community_size to 10.

Primitive Detection

The primitive detection involves detecting the errors in each cluster and associating a meaningful and generalizable primitive with a cluster of related concepts. For example, the concepts like *ingest*, *slurp*, *munch* are represented by a primitive `EAT`. It is inherent to human nature to try to categorize things, events, and people, finding patterns and forms they have in common.

In this work, we explore the generative ability of large language models (LLMs) for primitive detection. To ensure the accuracy, as illustrated in Fig. 8, we design a detection-verification framework, where the first LLM works as examinee to generate a primitive for the concept cluster, and another LLM works as examiner to check whether the generated primitive is correct. Specifically,

Step-1: Primitive Detection by Examinee LLM The input of examinee (denoted as LLM1) is a cluster of concepts. The designed prompt is *"Please generate a primitive for the following concepts: C.,"* where *C* is a list of concepts in a cluster.

Step-2: Primitive Verification by Examiner LLM The examiner (denoted as LLM2) is to verify whether the primitive generated by LLM1 is correct or not. To setup LLM2, we input the primitive *P* and the related concepts *C* into it, concatenated to the following instructions: *Do you think P is representative for the following concepts: C. Please answer "yes" or "no."*

Step-3: Explainable context by Examiner LLM For the correct primitive and cluster, we ask the LLM2 to generate a sentence as explainable context. With the primitive P and the related concepts *C* into it, concatenated to the following instructions: *Please generate a short sentence to describe the*

[9] More details are available at https://sbert.net/examples/applications/clustering/README.html.

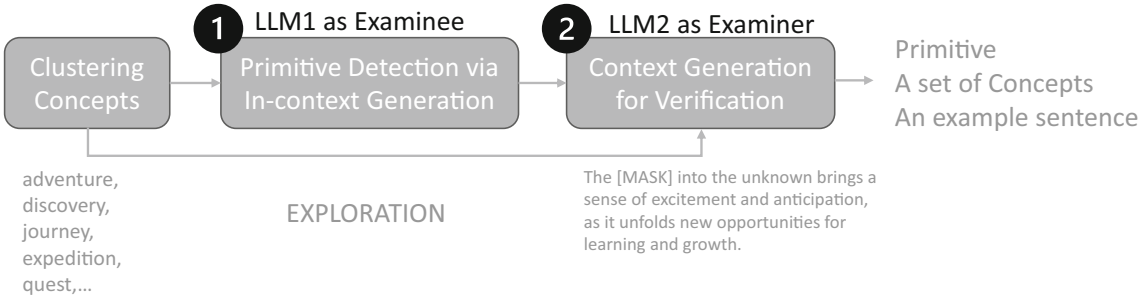


Fig. 8 The overall framework for primitive detection. LLM1 is used as an examinee to generate representative primitive for each concept cluster, and LLM2 is used as an examiner to verify the primitive and its related concepts

primitive P. In this [MASK] can be replaced by the concepts in C.

Experiments

In this section, we compare our PrimeNet with other widely-used knowledge bases in terms of coverage, accuracy, and efficiency. Then, we conduct experiments on semantic similarity and commonsense reasoning to verify the accuracy and efficiency of PrimeNet.

Statistics and Analysis

We first evaluate the coverage and accuracy of commonsense knowledge presented in PrimeNet and other widely used knowledge bases. In Table 6, we summarize the size of different knowledge bases. Then, we conduct a human assessment by utilizing the evaluation method and criteria established by Hwang et al. [36]. Specifically, we randomly select 3000 triplets from PrimeNet and present each triplet in the format of (head_concept, relation, tail_concept). The evaluation involves three annotators who hold Ph.D. degrees in computer science. The annotators use four labels to assess each triplet: (1) *always/often*, indicating the triplet is frequently true; (2) *sometimes/likely*, indicating it is occasionally or probably true; (3) *farfetched/never*, indicating it is false or extremely unlikely; and (4) *invalid*, indicating it is illogical. Triplets labeled as *always/often* or *sometimes/likely* are categorized as *Accept*, while others are categorized as *Reject*.

Table 6 Accuracy (%) assessed by human annotators

Knowledge bases	Size	Accept	Reject	No judgment
TransOMCS	18.5M	41.7	53.4	4.9
ATOMIC	877K	88.5	10.0	1.5
ConceptNet	21 M	88.6	7.5	3.9
PrimeNet	6 M	**92.4**	5.2	2.4

Size denotes the number of triplets in different knowledge bases

To ensure impartial evaluation, annotators are allowed to skip unfamiliar triplets by labeling *No Judgment*. The final results are determined by the majority vote among three annotators.

This experiment assesses PrimeNet's quality and compares it to other commonsense knowledge bases, including:

- **TransOMCS** [5]: This is a knowledge base containing 18.5M triplets that were automatically extracted from syntactic parses of sentences from various web sources, including Wikipedia, Yelp, and Reddit.
- **ATOMIC** [6]: It contains 877K textual descriptions of inferential knowledge. It is organized as typed if-then relations with variables, such as "if X pays Y a compliment, then Y will likely return the compliment."
- **ConceptNet** [4]: This is a large-scale knowledge base that contains relational knowledge collected from resources created by experts, crowdsourcing, and games with a purpose [41].

As shown in Table 6,[10] it is observed that PrimeNet stands out as the highest quality knowledge base with an acceptance rate of 92.4%, showing that PrimeNet is highly reliable and contains commonsense knowledge that is consistent with human understanding. ConceptNet, ATOMIC$^{20}_{20}$, and ATOMIC also demonstrate high quality, with acceptance rates of 88.6%, 91.3%, and 88.5%, respectively. Although TransOMCS has a vast number of triplets (i.e., 18.5M), it has a lower accuracy compared to the other resources, with an acceptance rate of only 41.7%, indicating it may not be as reliable as the other knowledge bases.

Task-1: Semantic Similarity

We evaluate the effectiveness of PrimeNet by examining its impact on improving distributional representations on the word semantic similarity task. Following previous works [4,

[10] Performances of compared knowledge bases are reported by [36], which are evaluated through crowdsourcing on the Amazon Mechanical Turk platform.

36, 42, 43], knowledge bases are used as external knowledge to adjust pre-trained word embeddings. The resulting refined embeddings, molded by insights from various knowledge bases, undergo systematic evaluation in downstream tasks, such as word semantic similarity assessments. Enhanced performance serves as an indicator of the superior quality of knowledge bases in improving distributional representations.

We employ a retrofitting method[11] designed by Faruqui et al. [42] to improve pre-trained word embeddings with different knowledge bases. It is designed to make words that are known to be related in a given knowledge base have similar representations in embedding space. The training objective is to make the new embedding of a word to be both similar to its initial embedding and nearby words in the knowledge base, by minimizing the following objective function:

$$L = \sum_{i=1}^{n} (\alpha_i ||\mathbf{w}_i - \mathbf{w}_i^*||^2 + \sum_{(w_i, w_j) \in \mathcal{R}} \beta_{i,j} ||\mathbf{w}_i - \mathbf{w}_j||^2), \tag{8}$$

where α and β control the relative strengths of associations, $\mathbf{w}_i^*$ is the original embedding of word w_i, and $\mathbf{w}_i$ is its new embedding, $\mathcal{R}$ denotes a set of relations extracted from the knowledge base, and (w_i, w_j) denotes a relation which connects w_i and w_j. We test the retrofitted embeddings with different knowledge bases on two tasks, i.e., semantic similarity and SAT-style analogy.

This task is to measure the degree of similarity between word pairs by calculating the cosine similarities between their embeddings, and then compare the similarities to human judgments. A good method should provide similarities that are strongly correlated with the human judgments evaluated by Spearman correlation coefficient [44]. In our experiment, we conduct experiments on eight widely-used word similarity datasets, including

- **YP-130**: A dataset comprising 130-word pairs with similarity ratings provided by human annotators [45].
- **MenTR-3K**: Consists of 3000-word pairs with similarity judgments collected from human participants [46].
- **RG-65**: Contains 65-word pairs with similarity ratings obtained through human evaluations [47].
- **MTurk-771**: Comprises 771-word pairs with similarity scores obtained through crowdsourcing on Amazon Mechanical Turk [48].
- **SimLex-999**: Includes 999-word pairs with similarity ratings collected from human subjects, aiming to provide a balanced set for evaluating word similarity models [49].
- **SimVerb-3500**: Consists of 3500-verb pairs annotated with similarity judgments by human raters [50].
- **VERB-143**: Contains 143-verb pairs with similarity ratings collected from human annotators [51].
- **WS-353**: Comprises 353-word pairs, including both similarity and relatedness judgments obtained from human raters [52].

Two popular pre-trained word embeddings are used in our experiments, including Word2Vec [53], which is trained on the first 100M of plain text from Wikipedia,[12] and GloVe [54], which are trained on 6 billion words from Wikipedia and English Gigaword[13]. In this task, we compare PrimeNet with FrameNet, WordNet, and ConceptNet, which contain synonyms knowledge.

Table 7 presents the overall performance on different word similarity datasets. PrimeNet demonstrated a significant improvement in retrofitting semantic representations, with an average increase of 6.73%, 5.49%, and 5.31% for Word2Vec (300d), GloVe (50d), and GloVe (300d), respectively. WordNet also achieved notable performance gains, with an average improvement of 4.75%, 3.79%, and 3.98%, benefiting the high-quality synonyms knowledge constructed by experts. While the crowd-sourced ConceptNet only slightly outperformed Word2Vec (300d) and GloVe (50d), and slightly worse than GloVe (300d). The solid performance gain achieved by PrimeNet suggests that it is successful in integrating knowledge from various sources into PrimeNet and creating a robust knowledge base.

Task-2: Neurosymbolic Commonsense Reasoning

Commonsense knowledge is important to natural language understanding through contextual reasoning. An effective method for assessing this understanding is through commonsense question-answering (QA) tasks, wherein the ability to answer questions often hinges on possessing commonsense knowledge [55]. In commonsense QA tasks, pre-trained language models like BERT and RoBERTa have demonstrated their effectiveness in bridging the gap between human and machine performance. Additionally, the incorporation of external knowledge bases has proven crucial for enhancing answer accuracy, providing valuable insights for contextual comprehension and reasoning. Hence, approaches that combine neural pre-trained language models with symbolic knowledge bases, known as *neurosymbolic* methods, have

[11] https://github.com/mfaruqui/retrofitting

[12] We use the Text8Corpus which is available in Gensim: https://github.com/RaRe-Technologies/gensim-data, and the CBOW model for training: https://code.google.com/archive/p/word2vec/

[13] https://nlp.stanford.edu/projects/glove/

Table 7 Overall performance on semantic similarity

Methods	YP-130	MenTR-3K	RG-65	MTurk-771	SimLex-999	SimVerb-3500	VERB-143	WS-353	Average (Δ)
Word2Vec (300d)	0.215	0.600	0.633	0.554	0.287	0.155	0.358	0.705	0.438
+FrameNet	0.334	0.589	0.620	0.571	0.295	0.227	0.321	0.651	0.451 (+1.25%)
+WordNet	0.316	0.620	**0.717**	0.598	0.377	0.237	0.318	0.705	0.486 (+4.75%)
+ConceptNet	**0.386**	0.582	0.577	0.533	0.341	0.229	0.302	0.651	0.450 (+1.16%)
+PrimeNet	0.325	**0.638**	0.680	**0.617**	**0.416**	**0.271**	**0.385**	**0.715**	**0.506 (+6.73%)**
GloVe (50d)	0.377	0.652	0.602	0.554	0.265	0.153	0.250	0.499	0.419
+FrameNet	**0.459**	0.622	0.617	0.568	0.288	0.217	0.240	0.471	0.435 (+1.61%)
+WordNet	0.510	0.649	0.688	0.540	0.342	0.239	0.188	0.500	0.457 (+3.79%)
+ConceptNet	0.427	0.599	0.558	0.493	0.356	0.234	0.236	0.489	0.424 (+0.50%)
+PrimeNet	0.443	**0.674**	**0.707**	**0.597**	**0.376**	**0.236**	**0.273**	0.485	**0.474 (+5.49%)**
GloVe (300d)	0.561	0.737	0.766	0.650	0.371	0.227	0.305	0.605	0.528
+FrameNet	0.589	0.701	0.756	0.639	0.361	0.278	0.274	0.558	0.519 (−0.84%)
+WordNet	**0.610**	0.759	**0.841**	0.679	0.470	0.313	0.256	0.612	0.568 (+3.98%)
+ConceptNet	0.561	0.700	0.747	0.583	0.420	0.288	0.300	0.595	0.524 (−0.34%)
+PrimeNet	0.593	**0.764**	0.818	**0.684**	**0.496**	**0.316**	**0.350**	**0.626**	**0.581 (+5.31%)**

d denotes the dimension of embeddings. The best performance is marked in bold

exhibited significant potential for advancing commonsense reasoning.

Task Setting

Following previous methods [7, 56], we use a neurosymbolic method to evaluate the commonsense QA under a zero-shot setting proposed by Ma et al. [57]. Formally, given a natural language question q and a set of possible answers $\mathcal{A} = \{a_1, a_2, \cdots, a_n\}$, the task is to select the most probable answer a^* from $\mathcal{A}$. The wrong answers in $\mathcal{A}$ are denoted as distractors. The pre-trained language models are used as backbone. RoBERTa-large is used in our experiments. In a zero-shot setting, the model has no access to the training data. The neurosymbolic solution is to transform knowledge from different knowledge bases into an artificial QA set for pre-training. For example, a triplet *(losing weight, usedFor, being healthier)* is generated as *losing weight is for being healthier*, and several distractors are generated by negative sampling. After pre-training, the model are tested on different datasets. We follow the parameter settings in Ma et al. [57]. The experiments are tested for five rounds, and the average accuracy of the predicted answers is used as the metric.

Baselines

We compare the neurosymbolic methods with the following baselines. *Majority* answers each question with the most frequent option in the entire dataset. Self-Talk [58] is an unsupervised method. It generates clarification prompts based on a template prefix, which are leveraged to elicit knowledge from another language model, which is used jointly with the original context and question to score each answer candidate. SMLM [59] is designed to pre-train the LM with three representation learning functions which aim to complete a knowledge triple given two of its elements. To show the upper bound, we report the supervised methods on RoBERTa-large model with access to the training data, as well as the human performance. of this work, we include results of a supervised fine-tuned RoBERTa system and of human evaluation. To facilitate the neurosymbolic method for commonsense reasoning, we compare PrimeNet with ATOMIC, ConceptNet, Wikidata, WordNet, and CSKG. Please refer to Ilievski et al. [60] for more details about QA data generation with different knowledge bases, distractors sampling, and training regimes.

Benchmarks

Following Ma et al. [57], we use five commonsense QA benchmarks for evaluation, including:

- Abductive Natural Language Inference (aNLI) [61] is a binary-classification task, which is to apply abductive reasoning and commonsense to form possible explanations for a given set of observations. Given two observations from narrative contexts, the goal is to pick the most plausible explanatory hypothesis.
- Commonsense Question Answering (CQA) [62] contains 12,247 examples. Each example includes a question and five answer candidates. The questions are sourced from a ConceptNet. Answer candidates are formed by combining ConceptNet nodes with additional distractors gathered through crowdsourcing.
- Physical Interaction Question Answering (PIQA) [63] is a dataset for reasoning about physical commonsense. Each question is associated with two possible solutions. The task is to choose the most appropriate solution, of which exactly one is correct.
- Social Intelligence Question Answering (SIQA) [64] is a dataset for commonsense reasoning about social situations, with 38,000 multiple choice questions. Each example comprises a context, a question, and three answer candidates. The context is derived from ATOMIC, questions are generated based on nine templates corresponding to relations in ATOMIC, and answers are obtained through crowdsourcing.
- WinoGrande (WG) [65] contains 44K problems inspired by pronoun resolution problems in Winograd Schema Challenge (WSG) [60]. Each example includes a context description featuring an emphasized pronoun, with two options provided as possible references.

Performance

The overall performance is shown in Table 8. It is observed that pre-training the language models with external knowledge is effectiveness to improve the performance of commonsense QA task. The main reason is that the external knowledge is important supplementary information for implicit knowledge embedding in pre-trained language models. Our PrimeNet achieved the best performance when RoBERTa is used as backbone, with the average performance gains of 1.74%, 2.88%, 0.82% over ATOMIC, ConceptNet+Wikidata+WordNet, and CSKG, respectively. This experiment indicates that PrimeNet has a good quality in organizing commonsense knowledge.

Case Studies

In our method, we manually checked the detected primitives. This step is conduct by 5 senior Ph.D. students majors in natural language processing. We manually code the explainable of primitives. For example, `INCREASE` is defined as `INCREASE(obj):= obj++`, which is the basic operation that increments the value of an object and provides a foundation for more complex reasoning. It is observed that some primitives have a hierarchical structure. We show examples of primitives in Fig. 9. At *Level-1*, the primitive `GROW` is defined as `GROW(obj) = INCREASE(obj.SIZE):=`

Table 8 Performance of neurosymbolic methods across five commonsense QA tasks in a zero-shot setting

Model	Knowledge base	aNLI	CQA	PIQA	SIQA	WG
Majority	–	50.8	20.9	50.5	33.6	50.4
Self-talk	–	–	32.4	70.2	46.2	54.7
SMLM	–	65.3	38.8	–	48.5	–
RoBERTa-large*	–	85.6	78.5	79.2	76.6	79.3
Human performance	–	91.4	88.9	94.9	86.9	94.1
RoBERTa-large	–	65.5	45.0	67.6	47.3	57.5
	ATOMIC	70.8	64.2	72.1	63.1	59.6
	ConceptNet, Wikidata, WordNet	70.0	67.9	72.0	54.8	59.4
	CSKG	70.5	67.4	72.4	63.2	60.9
	PrimeNet	**71.2**	**68.3**	**72.4**	**64.5**	**62.1**

RoBERTa-large* denotes the performance of RoBERTa-large under a supervised setting

`obj.SIZE++ = obj(l++, h++, w++)`, which is accomplished by using the INCREASE primitive to increment the object's `SIZE` attribute, such as length (l), height (h), and width (w). The *Level-2* primitive `LENGTHEN` is even more specific, adding only length to an object, and it is defined as `LENGTHEN(obj)=INCREASE(obj.SIZE.LENGTH):=obj.SIZE.LENGTH++ = obj(l++, h, w)`.

We have also performed several experiments on affordances by testing how PrimeNet is able to model human-object interactions in different scenarios, e.g., how to identify and use a liquid container, and in different modalities, e.g., speech processing and computer vision (Fig. 10). Finally, we have also carried out preliminary experiments on how PrimeNet can represent and handle different types of domain-specific knowledge, e.g., safety commonsense knowledge (Fig. 11). We intend to provide a more detailed account of these experiments and additional ones in our future work.

Related Works

In this section, we conduct a comprehensive literature review on commonsense knowledge acquisition, including crowdsourcing methods, automatic extraction methods, and approaches centered around extracting implicit knowledge from pre-trained language models. Then, we introduce the conceptual primitives theory, which is a pivotal component in the construction of our commonsense knowledge base.

Commonsense Knowledge Acquisition

Commonsense knowledge is not explicitly defined. It is an inherent understanding of the world that humans possess but machines lack. To narrow the gap between human and machine intelligence, the process of acquiring commonsense knowledge is crucial for improving machine intelligence. There are mainly three major methods to the knowledge

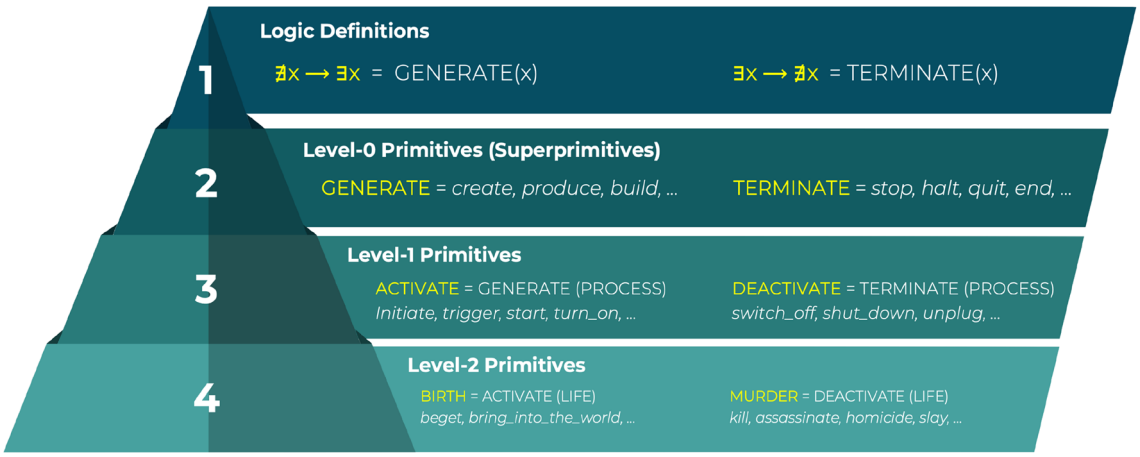


Fig. 9 Examples of the hierarchical structure of primitives in PrimeNet

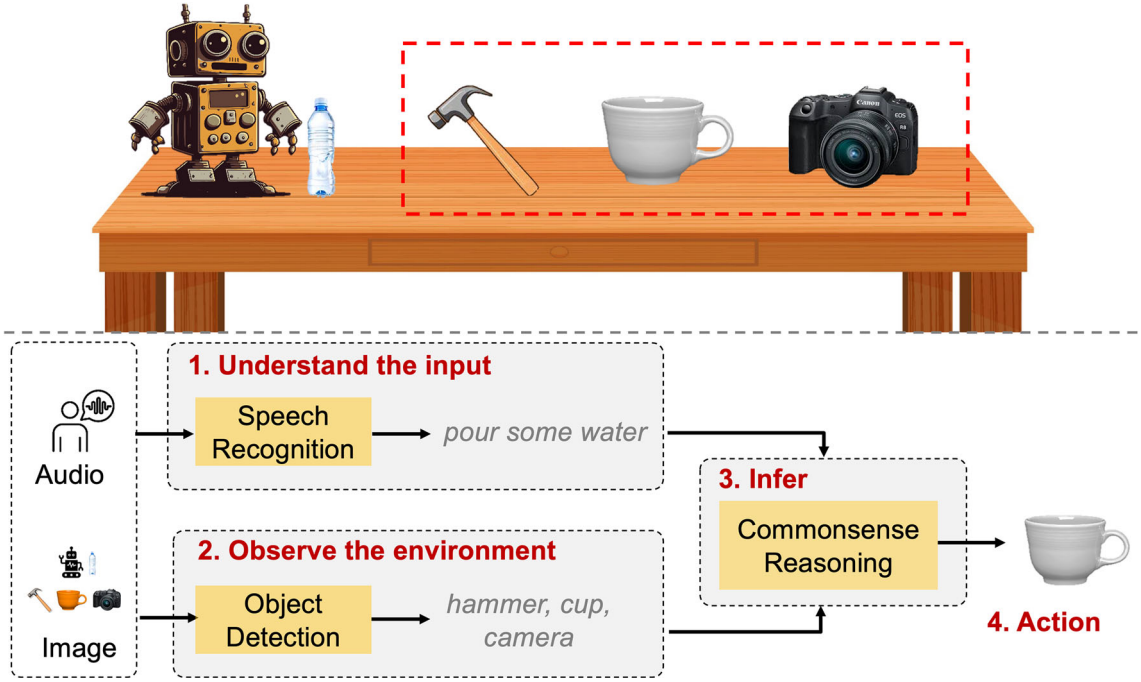


Fig. 10 A sample scenario in which PrimeNet's capabilities of understanding and modeling affordances have been tested

acquisition, i.e., crowdsourcing, automatic extraction, and mining from pre-trained language models.

Crowdsourcing

Crowdsourcing is a useful approach for collecting commonsense knowledge from a diverse group of human contributors, such as human experts [2, 33], web users [66, 67], and participants in human computation games [68, 69]. By tapping into the collective wisdom of individuals, this approach captures intuitions and insights commonly held by people, thus contributing valuable data to the construction of commonsense knowledge bases. The crowdsourcing approach exhibits high adaptability across diverse tasks and domains. By involving a varied group of contributors, it ensures that multiple viewpoints are considered, leading to the creation of a more comprehensive and balanced knowledge pool. The existing knowledge bases built through crowdsourcing typically encompass the following categories of commonsense knowledge.

Factual Knowledge

It represents concrete and specific details about the world, events, people, places, objects, and other observable phenomena, such as "wheel is part of bicycle," "dog is an animal," and "Los Angeles is located in California." In the early 1980s, the Cyc [2] project undertook the task of manually constructing a comprehensive knowledge base using the CycL representation language, encompassing the basic facts and rules about the world. After the efforts of its first decade, the Cyc project expanded to include around 100,000 terms. By the time of its release in 2012, known as OpenCyc 4.0, the knowledge base had undergone substantial growth, encompassing over 2 million facts across 239,000 concepts. In 2002, the DOLCE [70] (Descriptive Ontology for Linguistic and Cognitive Engineering) project was designed to manually collect the ontological categories underlying natural language and human commonsense with disambiguated concepts and relations. Freebase [71] is a collaborative knowledge base by gathering data from various sources, including Wikipedia, the Notable Names Database, and contributions from community users. Google Knowledge Graph [72] is powered in part by Freebase, with an extensive collection of billions of facts about people, places, and things. It is served as a foundation for Google's search results, enabling the search engine to deliver useful and accurate information to users. ConceptNet [4] leverages crowdsourcing contributions from users to acquire commonsense knowledge. It originated from the Open Mind Common Sense [66] and has grown by incorporating data from other crowd-sourced resources, expert-created content, and purposeful games. ConceptNet is a widely used commonsense knowledge base with over 21 million edges and 8 million nodes, covering a diverse range of 36 commonsense relations, such as isA, partOf, usedFor, and capableOf. Moreover, ConceptNet can be linked to other knowledge bases, such as WordNet, Wiktionary, OpenCyc,

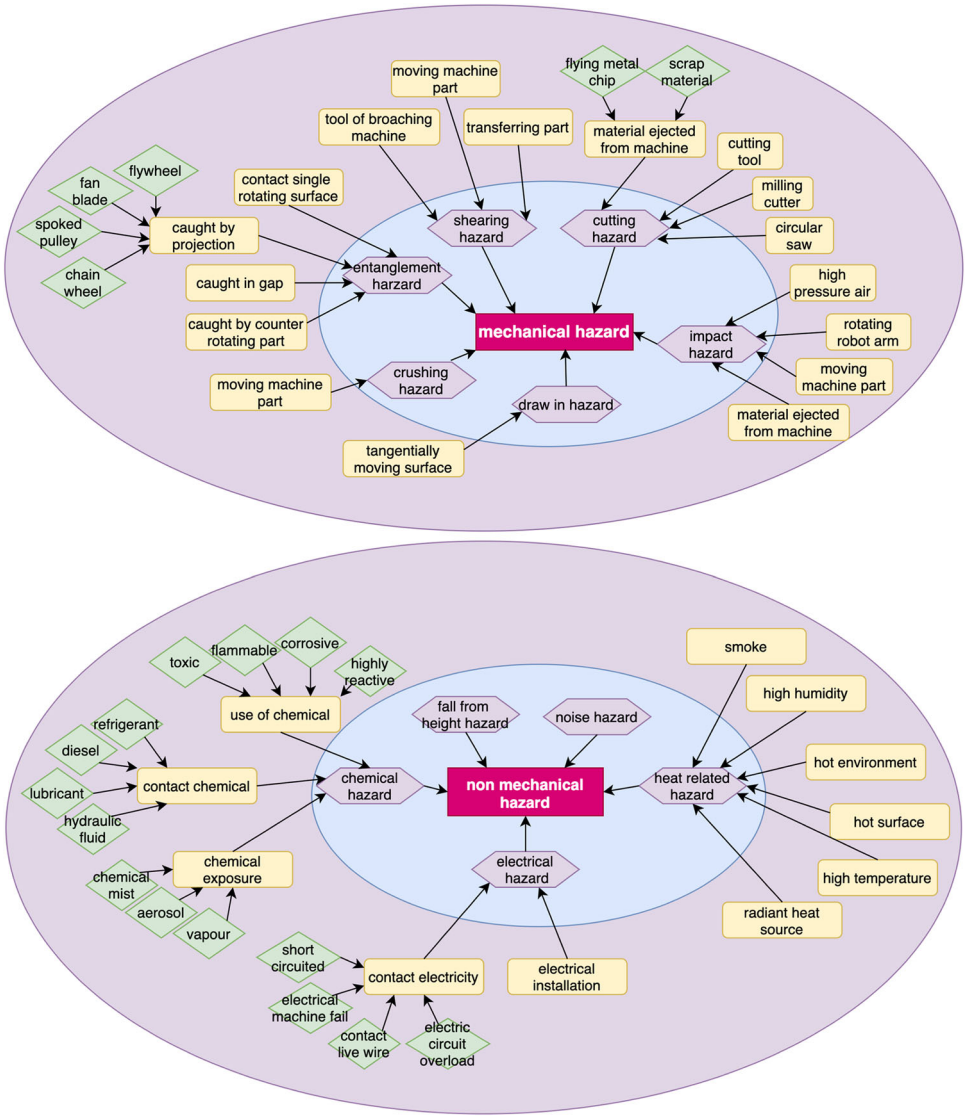


Fig. 11 An example of safety commonsense knowledge in PrimeNet

and DBpedia, and now, it is a multi-lingual knowledge base that can also build connections among 83 languages.

Lexical Knowledge

There are several lexical databases manually created by experts, such as WordNet [33], Roget's Thesaurus [34], FrameNet [3], MetaNet [73], VerbNet [74], and PropBank [75]. Among these lexical knowledge bases, WordNet is a highly popular lexical knowledge base which captures semantic relations between words. Within WordNet, nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. These synsets are interlinked by means of conceptual-semantic and lexical relations. WordNet is now available in over 200 languages, allowing researchers and linguists worldwide to explore the complexities of language and word associations across diverse contexts.

Encyclopedic Knowledge

Encyclopedic knowledge is related to a broad understanding of various subjects and topics. For example, Wikidata [76] is a knowledge graph coupled with Wikipedia, which is a free, open, and multilingual online encyclopedia that is collaboratively edited by volunteers. DBpedia [77] extracts structured information from Wikipedia data and converts it into a machine-readable format for use in the Semantic Web and data mining domains. The encyclopedic knowledge resources offer a wide range of information to help people understand various topics and fields.

Domain Knowledge

More recently, commonsense knowledge bases have been specifically developed to cater to particular tasks, such as dialog systems Young et al. [78]. For example, SenticNet [19] is a sentiment knowledge base which captures the affective

commonsense and emotions expressed in natural language. Visual Genome [37] contains annotations of concepts and their relations found in a collection of images. The image descriptions are manually written by crowd workers, and the concepts are automatically mapped to WordNet senses and further refined by crowd workers. ATOMIC [6] is developed to capture inferential commonsense knowledge, such as cause-and-effect relationships. It is developed by domain experts who contribute and validate information about everyday events and their implied causality. ATOMIC$^{20}_{20}$ [36] is proposed to unify the triples from ConceptNet and ATOMIC, together with some newly developed relations.

Automatic Extraction

Despite commonsense knowledge is not explicitly defined, it has been observed that certain types of commonsense knowledge can be extracted through automatic methods, such as text mining and information extraction. Compared with crowdsourcing, these automatic extraction methods can handle large volumes of data efficiently and at a lower cost, making them valuable tools for efficiently capturing and updating commonsense knowledge from various domains.

Firstly, automatic extraction methods generally acquire commonsense knowledge from large-scale text and web pages. For example, NELL [79] (Never-Ending Language Learning system) is designed to automatically extract structured information from unstructured Web pages. With hundreds of pre-defined categories and relations and 10 to 15 examples of each, NELL extracts knowledge from more than 500 million web pages, resulting in a large knowledge base comprising over 2.8 million instances. WebChild [80] is constructed through automated extraction and disambiguation from Web contents. It utilizes seeds derived from WordNet and pattern matching techniques on large-scale text collections to gather information, including fine-grained relations like "hasShape," "hasTaste," and "evokesEmotion." ASER [20] (activities, states, events, and their relations) is a large-scale eventuality knowledge graph extracted from more than 11-billion-token unstructured textual data. SenticNet [19] is constructed using auto-regressive language models and kernel methods to extract polarity from text in a completely interpretable and explainable manner. Probase [21] is constructed by extracting and organizing knowledge from a vast collection of Web pages and documents. Its subsequent version, named as Microsoft Concept Graph [81], harnesses billions of web pages and search logs to build a huge graph of relations between concepts, and has been proven valuable in enhancing search engines, spell-checkers, recommendation engines, and other AI-driven systems.

Secondly, several methods are used to improve the existing commonsense knowledge bases. The automatic extraction methods can help fill gaps, update outdated information, and supplement missing commonsense knowledge in existing knowledge bases. For example, BabelNet [82] is a multilingual knowledge base which is automatically created by mapping the multilingual encyclopedic knowledge repository (Wikipedia) to the English WordNet based on multilingual concept lexicalizations and machine translations. Dense-ATOMIC [83] is designed to overcome the limitations of ATOMIC in knowledge coverage and multi-hop reasoning, by employing a knowledge graph completion approach to train a relation prediction model and infer missing links within ATOMIC, ensuring high knowledge coverage and facilitating massive multi-hop paths.

Thirdly, some efforts have been made to automatic integrate diverse commonsense knowledge bases, enhancing the overall coverage and richness of the knowledge base. For example, YAGO [84] (Yet Another Great Ontology) is designed to extract commonsense knowledge from Wikipedia, WordNet, WikiData, GeoNames, and other data sources. Bouraoui et al. [85] employed Region Connection Calculus to merge open-domain terminological knowledge. CommonSense Knowledge Graph (CSKG) [7] integrates knowledge bases from seven diverse, disjoint sources such as ConceptNet and WordNet. Based on ASER, Zhang et al. [5] have developed TransOMCS with an algorithm for discovering patterns from the overlap of existing commonsense and linguistic knowledge bases, and a commonsense knowledge ranking model to select the highest-quality extracted knowledge.

Implicit Knowledge in Pre-trained Models

Recent advancements in pre-trained models have demonstrated significant improvements across various tasks, underscoring their robust representation and generalization capabilities. These models, pre-trained on large-scale corpora, have proven adept at encoding diverse forms of knowledge [86, 87]. For example, BERT (Bidirectional Encoder Representations from Transformers) uses a masked language model objective in pre-training, where parts of the input are masked, enabling the model to predict concealed words bidirectionally. This process empowers BERT to capture contextualized representations, comprehensively understanding intricate relationships and meanings in different linguistic contexts. Similarly, GPT [88–90] (Generative Pre-trained Transformer) follows the generative language model paradigm, predicting the next word based on preceding context. With a unidirectional architecture processing text from left to right during training, it acquires knowledge of grammar, facts, reasoning, and even some degree of commonsense.

Currently, there is a trend to mine commonsense knowledge directly from pre-trained language models, leverag-

ing the rich information embedded in these large models. Several works are designed to probe commonsense knowledge directly from large pre-trained models, such as KB-BERT [91], KB-BERTSAGE [92], and PseudoReasoner [93]. These approaches involve fine-tuning pre-trained language models, such as BERT and BART, on commonsense knowledge bases like ATOMIC, ConceptNet, and ASER, with the tasks typically entails providing the head and relation in a commonsense triple as input, with the tail serving as the expected output. COMET [94] (COMmonsEnse Transformers) is designed to leverage GPT to generate rich and diverse commonsense descriptions in natural language. It effectively transforms implicit knowledge from pre-trained models into explicit knowledge within commonsense knowledge graphs, and generates novel knowledge that humans rate as high quality. LAMA [95] (LAnguage Model Analysis) is an unsupervised method to leverage BERT to acquire commonsense knowledge. It also serves as a framework[14] for probing and evaluating the factual knowledge encoded in pre-trained language models [96]. West et al. [97] design a symbolic knowledge distillation to leverage some seeds from ATOMIC as prompts to acquire commonsense knowledge from GPT-3, resulting a large commonsense knowledge graph ATOMIC^{10x} and a compact commonsense model COMET$^{DIS}_{TIL}$. Their work demonstrates the efficacy of collaborative efforts between humans and language models for curating commonsense knowledge graphs and training efficient, high-performing commonsense models.

Commonsense Knowledge Representation

Commonsense knowledge representation plays a vital role in AI, as it entails transforming intricate and valuable human commonsense knowledge into machine-readable formats, and enables the facilitation of complex reasoning tasks. Knowledge representation and reasoning are tightly intertwined, as one of the primary objectives of explicitly representing knowledge is to enable the capacity for reasoning, inference drawing, and asserting new knowledge.

Reflecting the complexities of human cognition, commonsense knowledge is represented through a variety of methodologies. Early techniques, like first-order logic and logic rules, provided structured frameworks for capturing relationships and rules governing the world. These methods encoded knowledge in terms of logical statements and rules, enabling systems to perform deductive reasoning and inference. Beyond logic-based approaches, other methods have emerged to represent commonsense knowledge. For example, semantic networks employ graph structures to depict concepts and their relationships, allowing for intuitive representation and reasoning; frame-based systems organize knowledge into structured frames, capturing attributes, roles, and hierarchies among entities.

More recently, some commonsense knowledge bases have achieved significant success and are widely applied across various AI domains to support different reasoning tasks. Typically, their knowledge representation frameworks adopt a "*millions of facts*" approach. For instance, ConceptNet summarizes millions of facts into a knowledge graph format, where nodes denote entities and edges denote their relationships. Each commonsense knowledge or fact can be represented as a triplet, such as `<dog, isa, animal>`, forming *millions of triplets* within the knowledge base. Similarly, ATOMIC is a commonsense knowledge graph with 1.33 million everyday inferential knowledge tuples about entities and events. It is represented in the form of `IF-THEN` statements, like "if X pays Y a compliment, then Y will likely return the compliment," resulting *millions of if-then statements* within the knowledge base.

While these knowledge representation frameworks have been effectively utilized in many applications, one of main limitations of these knowledge representation frameworks is the lack of a cognitive-level connection. When humans store commonsense knowledge, there are often underlying connections that involve the relevance between concepts, underlying reasoning, contextual information, and so on. However, current knowledge representation methods typically only capture surface-level relationships and lack a deep understanding of cognitive processes and underlying thought mechanisms. Consequently, these frameworks may not fully capture human cognitive levels in complex reasoning tasks, limiting their application and effectiveness in some complex reasoning and inference tasks. Moreover, in implementing commonsense knowledge representation, the absence of cognitive-level connections can lead to challenges in identifying meaningful patterns and relationships within data, resulting in suboptimal performance, limited accuracy, and increased risk of erroneous conclusions. This inefficiency may further lead to resource wastage and ultimately diminish effectiveness in addressing complex reasoning tasks across various AI applications. Additionally, in expanding commonsense knowledge, the lack of cognitive-level connections remains problematic. This deficiency can hinder scalability, organization, and resource utilization, limiting the framework's adaptability to evolving data and challenges.

Conceptual Primitives

Conceptual primitives can be defined as concepts that cannot be defined in terms of other concepts in an integration data model which provides an overview of data, thereby forming foundations for definitions of other concepts [31].

[14] https://github.com/facebookresearch/LAMA

Conceptual primitives have been of practical and theoretical interest to researchers in computer science [12], linguistics [11, 15] and psychology [13]. Such research reports that the decomposition of meanings into lower-level parts is essential for conceptualization.

We apply the idea of conceptual primitives to construct commonsense knowledge by comprising a small core of primitive commonsense concepts and relations, linked to a much more extensive base of factual knowledge instances. Naturally, humans tend to categorize things, events, and people by identifying common patterns and forms, which is the basis of conceptual dependency theory. Thus, commonsense knowledge bases built upon conceptual primitives possess the greater potential to facilitate reasoning tasks. Recently, Cambria et al. [19] constructed SenticNet by generalizing words and multi-word expressions into primitives and super-primitives annotated with emotion labels via pre-trained language models, which achieved better performances on various affective tasks and showed the power of conceptual primitives. Unlike SenticNet, which focuses on sentiment knowledge, we build PrimeNet to cover a broader range of general commonsense knowledge based on conceptual primitives.

Future Directions

PrimeNet is grounded in fundamental conceptual principles that are consistent with human reasoning patterns. It has greater potential than current knowledge bases to enhance AI's reasoning capabilities, particularly in response to the growing demand for more intricate reasoning tasks in the era of large language models. In this section, we discuss several applications where PrimeNet can aid in enhancing AI's reasoning abilities.

Logical Reasoning

Logical reasoning is recognized as central to human cognition and intelligence [98]. It mainly consists of two reasoning types [99], which are deductive reasoning and inductive reasoning. Previously logical reasoning is mostly investigated in the classic AI field and used formal language as knowledge representation. Recently there's a trend of research on deductive reasoning [100] and inductive reasoning [101] that use natural language as knowledge representation, which has various advantages over the previous paradigm of formal language. We argue that PrimeNet could be of essential effect on the research of logical reasoning.

One of the most common types of deductive reasoning is syllogism, which consists of a major and a minor premise and a conclusion. For example, the premises can be "All men are mortal; Socrates is a man," and the conclusion is "Socrates is mortal." Here, PrimeNet can provide the minor premises since it includes a huge amount of taxonomic information. Conversely, PrimeNet is also beneficial to inductive reasoning. One of the most common types of inductive reasoning is inductive generalization, which is about sample-to-population generation. For example, with the observation "Socrates is mortal," inductive reasoning might lead to a conclusion that "All men are mortal." Here, the taxonomic information of PrimeNet can provide important information for an inductive reasoning system to potentially generalize over a larger population.

Implicit Reasoning

Implicit reasoning is a challenging task which does not contain explicitly clues for designing reasoning strategies. For example, *"Did Aristotle use a laptop?"* is an implicit question [102], and it requires to infer the strategy for answering the implicit question, i.e., *temporal comparison*. Recently, AI systems based on pre-trained language models have achieved impressive performance in answering explicit questions, even surpassing human performance in some datasets (e.g., SQuAD [103] and TriviaQA [104]). However, they are failed to answer implicit questions, e.g., the accuracy of answering implicit questions is only 66% [102].

A key property of implicit reasoning is the diverse strategies. Humans cannot pre-define all of the strategies due to the complexity of scenarios. To conduct implicit reasoning, PrimeNet has the potential to build a finite set of strategies at the primitive level, and apply the primitive-based strategies on concepts and entities. For example, the implicit questions, e.g., "Did Aristotle Use a Laptop?," "Did Shakespeare play guitar?," and "Was NATO involved in World War I?," have the same reasoning strategies in the primitive level, e.g., COMPARE(TIME(Entity-1), TIME(Entity-2)). Primitives can be used to conduct implicit reasoning by providing the basic cognitive processes or mental operations that underlie our ability to reason implicitly.

Neurosymbolic Computing

The integration of Symbolism and Connectionism, known as neurosymbolic computing, is widely recognized as a booster for the next generation of AI [105]. Neurosymbolic computing combines neural networks and symbolic reasoning to take advantage of their strengths, such as better interpretability and improved generalization and trustfulness. However, it is bottlenecked by symbolic knowledge acquisition [106].

One way to alleviate this bottleneck is to first transfer specific concepts to primitives, and conduct symbolic computation on the primitives level [19, 107]. In this case, the required symbolic knowledge can be exponentially decreased. Here PrimeNet is of essential effect because the huge taxonomic information in PrimeNet is (mostly) necessary to the process of transformation from concepts to primitives. PrimeNet is capable of linking concepts and entities to a small set of prim-

itives. Hence, it strengthens the neurosymbolic computing system in compositional generalizaition, enabling it to deal with the infinite number of states in the real world [108].

Conclusion

We developed a new commonsense knowledge base, termed PrimeNet, based on conceptual dependency theory. Unlike existing knowledge bases, PrimeNet is constructed based on a small core of conceptual primitives and relations, linked to an extensive set of concepts and entities, which is suited for supporting higher-level inference. Our studies demonstrate that PrimeNet contains high-quality commonsense knowledge that can be used for commonsense reasoning in different downstream tasks thanks to the many intuitive functions developed. In the future, we aim to broaden the scope of commonsense knowledge using generative AI models and will continue to develop additional PrimeNet functions to facilitate commonsense reasoning across a wider range of applications, domains, and languages.

Author Contributions Qian Liu: conceptualization, methodology, software, validation, writing—original draft, visualization. Sooji Han: formal analysis, investigation, writing—original draft. Erik Cambria: conceptualization, methodology, writing—review and editing, supervision, project administration, funding acquisition. Yang Li: software, resources, data curation, writing—review and editing. Kenneth Kwok: investigation, writing—reviewing and editing, funding acquisition.

Funding This research is supported by the Agency for Science, Technology and Research (A*STAR) under its AME Programmatic Funding Scheme (Project #A18A2b0046). The project is also supported by the Ministry of Education, Singapore under its MOE Academic Research Fund Tier 2 (STEM RIE2025 Award MOE-T2EP20123-0005) and by the RIE2025 Industry Alignment Fund - Industry Collaboration Projects (IAF-ICP) (Award I2301E0026), administered by A*STAR, as well as supported by Alibaba Group and NTU Singapore.

Data Availability No datasets were generated or analyzed during the current study.

Declarations

Conflict of Interest The authors declare no competing interests.

References

1. Cambria E, Hussain A, Havasi C, Eckl C. Common sense computing: from the society of mind to digital intuition and beyond. In: Biometric ID management and multimodal communication. Lecture Notes in Computer Science; 2009. vol. 5707, pp. 252–9.
2. Lenat DB. CYC: a large-scale investment in knowledge infrastructure. Commun ACM. 1995;38(11):32–8.
3. Baker CF, Fillmore CJ, Lowe JB. The Berkeley FrameNet project. In: Proceedings of annual meeting of the Association for Computational Linguistics, ACL. 1998. pp. 86–90.
4. Speer R, Chin J, Havasi C. Conceptnet 5.5: an open multilingual graph of general knowledge. In: Proceedings of AAAI conference on artificial intelligence (AAAI). 2017. pp. 4444–51.
5. Zhang H, Khashabi D, Song Y, Roth D. Transomcs: from linguistic graphs to commonsense knowledge. In: Proceedings of the International Joint Conference on Artificial Intelligence, IJCAI. 2020. pp. 4004–10.
6. Sap M, Le Bras R, Allaway E, Bhagavatula C, Lourie N, Rashkin H, Roof B, Smith NA, Choi Y. Atomic: an atlas of machine commonsense for if-then reasoning. In: Proceedings of the AAAI conference on artificial intelligence. 2019. vol. 33, pp. 3027–35.
7. Ilievski F, Szekely PA, Zhang B. CSKG: the commonsense knowledge graph. In: Proceedings of the semantic web - 18th international conference, ESWC. Lecture Notes in Computer Science; 2021. vol. 12731, pp. 680–96.
8. Liu J, Chen T, Wang C, Liang J, Chen L, Xiao Y, Chen Y, Jin K. Vocsk: verb-oriented commonsense knowledge mining with taxonomy-guided induction. Artif Intell. 2022;310: 103744.
9. Cambria E, Mao R, Chen M, Wang Z, Ho S-B. Seven pillars for the future of artificial intelligence. IEEE Intell Syst. 2023;38(6):62–9.
10. Zechmeister EB, Chronis AM, Cull WL, D'Anna CA, Healy NA. Growth of a functionally important lexicon. J Read Behav. 1995;27(2):201–12.
11. Jackendoff R. Toward an explanatory semantic representation. Linguist Inq. 1976;7(1):89–150.
12. Minsky M. A framework for representing knowledge. Cambridge: MIT; 1974.
13. Rumelhart DE, Ortony A. The representation of knowledge in memory. Schooling and the acquisition of knowledge. 1977;99:135.
14. Schank RC. Conceptual dependency: a theory of natural language understanding. Cogn Psychol. 1972;3(4):552–631.
15. Wierzbicka A. Semantics: primes and universals: primes and universals. UK: Oxford University Press; 1996.
16. Ge M, Mao R, Cambria E. Explainable metaphor identification inspired by conceptual metaphor theory. Proc AAAI Conf Artif Intell. 2022;36(10):10681–9.
17. Mao R, Li X, He K, Ge M, Cambria E. MetaPro Online: a computational metaphor processing online system. In: Proceedings of the annual meeting of the association for computational linguistics (Volume 3: System Demonstrations). 2023. pp. 127–35.
18. Mao R, Du K, Ma Y, Zhu L, Cambria E. Discovering the cognition behind language: financial metaphor analysis with MetaPro. In: 2023 IEEE International Conference on Data Mining (ICDM). IEEE; 2023. pp. 1211–16.
19. Cambria E, Zhang X, Mao R, Chen M, Kwok K. SenticNet 8: fusing emotion AI and commonsense AI for interpretable, trustworthy, and explainable affective computing. In: International conference on Human-Computer Interaction (HCII). 2024.
20. Zhang H, Liu X, Pan H, Song Y, Leung CW. ASER: a large-scale eventuality knowledge graph. In: Proceedings of The Web Conference 2020, WWW. 2020. pp. 201–11.
21. Wu W, Li H, Wang H, Zhu KQ. Probase: a probabilistic taxonomy for text understanding. In: Proceedings of the ACM SIGMOD international conference on management of data, SIGMOD. 2012. pp. 481–92.
22. Wang Z, Wang H, Wen J, Xiao Y. An inference approach to basic level of categorization. In: Proceedings of the ACM international Conference on Information and Knowledge Management, CIKM. 2015. pp. 653–62.
23. Chomsky N. Syntactic structures. Berlin, Boston: De Gruyter Mouton; 1957.
24. Jackendoff RS, et al. Semantics and cognition. Cambridge, Massachusetts: The MIT Press; 1983.
25. Pesina S, Solonchak T. Semantic primitives and conceptual focus. Procedia Soc Behav Sci. 2015;192:339–45.

26. Piaget J, Cook M, et al. The origins of intelligence in children, vol. 8. New York: International Universities Press; 1952.
27. Winograd T. Towards a procedural understanding of semantics. Revue internationale de philosophie. 1976;260–303.
28. Bobrow DG, Norman DA. Some principles of memory schemata. In: Representation and understanding. Morgan Kaufmann, San Diego; 1975. pp. 131–49.
29. Johnson M. The body in the mind: the bodily basis of meaning, imagination, and reason. J Aesthetics and Art Criticism. 1989;47(4).
30. Spelke ES, Kinzler KD. Core knowledge. Dev Sci. 2007;10(1):89–96.
31. West M. Developing high quality data models. Morgan Kaufmann Publishers Inc., 340 Pine Street, Sixth FloorSan FranciscoCAUnited States; 2011.
32. Wachowiak L, Gromann D. Systematic analysis of image schemas in natural language through explainable multilingual neural language processing. In: Proceedings of the international conference on computational linguistics, COLING. 2022. pp. 5571–81.
33. Miller GA. Wordnet: a lexical database for english. Commun ACM. 1995;38:39–41.
34. Kipfer BA. Roget's 21st century thesaurus in dictionary form. 3rd ed. New York, NY: Bantam Dell; 2006.
35. Auer S, Bizer C, Kobilarov G, Lehmann J, Cyganiak R, Ives ZG. DBpedia: a nucleus for a web of open data. In: Proceedings of the semantic web, 6th international semantic web conference, 2nd Asian Semantic Web Conference. 2007. vol. 4825, pp. 722–35.
36. Hwang JD, Bhagavatula C, Bras RL, Da J, Sakaguchi K, Bosselut A, Choi Y. Comet-atomic 2020: on symbolic and neural commonsense knowledge graphs. In: Proceedings of the AAAI conference on artificial intelligence. 2020.
37. Krishna R, Zhu Y, Groth O, Johnson J, Hata K, Kravitz J, Chen S, Kalantidis Y, Li L, Shamma DA, Bernstein MS, Fei-Fei L. Visual genome: connecting language and vision using crowdsourced dense image annotations. Int J Comput Vision. 2017;123(1):32–73.
38. Reimers N, Gurevych I. Sentence-bert: sentence embeddings using siamese bert-networks. In: Proceedings of the conference on empirical methods in natural language processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP. 2019. pp. 3980–90.
39. Cambria E, Mao R, Han S, Liu Q. Sentic parser: a graph-based approach to concept extraction for sentiment analysis. In: Proceedings of ICDM workshops. 2022. pp. 413–20.
40. Guarino N. Formal ontology, conceptual analysis and knowledge representation. Int J Hum Comput Stud. 1995;43(5–6):625–40.
41. Von Ahn L. Games with a purpose. Computer. 2006;39(6):92–4.
42. Faruqui M, Dodge J, Jauhar SK, Dyer C, Hovy EH, Smith NA. Retrofitting word vectors to semantic lexicons. In: Proceedings of the conference of the North American chapter of the association for computational linguistics: human language technologies. 2015. pp. 1606–15.
43. Liu Q, Huang H, Zhang G, Gao Y, Xuan J, Lu J. Semantic structure-based word embedding by incorporating concept convergence and word divergence. In: Proceedings of the AAAI conference on artificial intelligence. 2018. pp. 5261–8.
44. Myers JL, Well AD. Research design & statistical analysis. New York: Routledge; 1995.
45. Yang D, Powers DM. Measuring semantic similarity in the taxonomy of WordNet. Australia: Australian Computer Society; 2005.
46. Bruni E, Boleda G, Baroni M, Tran N. Distributional semantics in technicolor. In: Proceedings of the annual meeting of the Association for Computational Linguistics, ACL. 2012. pp. 136–45.
47. Rubenstein H, Goodenough JB. Contextual correlates of synonymy. Commun ACM. 1965;8(10):627–33.
48. Halawi G, Dror G, Gabrilovich E, Koren Y. Large-scale learning of word relatedness with constraints. In: Proceedings of ACM SIGKDD international conference on knowledge discovery and data mining. 2012. pp. 1406–14.
49. Hill F, Reichart R, Korhonen A. Simlex-999: evaluating semantic models with (genuine) similarity estimation. Comput Linguist. 2015;41(4):665–95.
50. Gerz D, Vulic I, Hill F, Reichart R, Korhonen A. Simverb-3500: a large-scale evaluation set of verb similarity. In: Proceedings of the conference on empirical methods in natural language processing, EMNLP. 2016. pp. 2173–82.
51. Baker S, Reichart R, Korhonen A. An unsupervised model for instance level subcategorization acquisition. In: Proceedings of the conference on empirical methods in natural language processing, EMNLP. 2014. pp. 278–89.
52. Finkelstein L, Gabrilovich E, Matias Y, Rivlin E, Solan Z, Wolfman G, Ruppin E. Placing search in context: the concept revisited. In: Proceedings of the international World Wide Web Conference, WWW. 2001. pp. 406–14.
53. Mikolov T, Sutskever I, Chen K, Corrado GS, Dean J. Distributed representations of words and phrases and their compositionality. In: Proceedings of advances in neural information processing systems. 2013. pp. 3111–9.
54. Pennington J, Socher R, Manning CD. Glove: global vectors for word representation. In: Proceedings of the conference on Empirical Methods in Natural Language Processing, EMNLP. 2014. pp. 1532–43.
55. Liu Q, Geng X, Wang Y, Cambria E, Jiang D. Disentangled retrieval and reasoning for implicit question answering. IEEE Trans Neural Netw Learn Syst. 2024;35(6):7804–15.
56. Ilievski F, Oltramari A, Ma K, Zhang B, McGuinness DL, Szekely PA. Dimensions of commonsense knowledge. Knowl-Based Syst. 2021;229:107347.
57. Ma K, Ilievski F, Francis J, Bisk Y, Nyberg E, Oltramari A. Knowledge-driven data construction for zero-shot evaluation in commonsense question answering. In: Proceedings of thirty-fifth AAAI conference on artificial intelligence, AAAI. 2021. pp. 13507–15.
58. Shwartz V, West P, Bras RL, Bhagavatula C, Choi Y. Unsupervised commonsense question answering with self-talk. In: Proceedings of the 2020 conference on Empirical Methods in Natural Language Processing, EMNLP. 2020. pp. 4615–29.
59. Banerjee P, Baral C. Self-supervised knowledge triplet learning for zero-shot question answering. In: Proceedings of the conference on Empirical Methods in Natural Language Processing, EMNLP. 2020. pp. 151–62.
60. Levesque HJ. The winograd schema challenge. In: Logical formalizations of commonsense reasoning, Papers from the 2011 AAAI Spring Symposium, Technical Report SS-11-06. 2011. pp. 1–1.
61. Bhagavatula C, Bras RL, Malaviya C, Sakaguchi K, Holtzman A, Rashkin H, Downey D, Yih W, Choi Y. Abductive commonsense reasoning. In: Proceedings of International Conference on Learning Representations, ICLR. 2020.
62. Talmor A, Herzig J, Lourie N, Berant J. Commonsenseqa: a question answering challenge targeting commonsense knowledge. In: Proceedings of the conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT. 2019. pp. 4149–58.
63. Bisk Y, Zellers R, Bras RL, Gao J, Choi Y. PIQA: reasoning about physical commonsense in natural language. In: Proceedings of the thirty-fourth AAAI conference on Artificial Intelligence, AAAI. 2020. pp. 7432–9.
64. Sap M, Rashkin H, Chen D, Bras RL, Choi Y. Social iqa: commonsense reasoning about social interactions. In: Proceedings of the conference on Empirical Methods in Natural Language Pro-

cessing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP. 2019. pp. 4462–72.
65. Sakaguchi K, Bras RL, Bhagavatula C, Choi Y. Winogrande: an adversarial winograd schema challenge at scale. In: Proceedings of the thirty-fourth AAAI conference on Artificial Intelligence, AAAI. 2020. pp. 8732–40.
66. Singh P, Lin T, Mueller ET, Lim G, Perkins T, Zhu WL. Open mind common sense: knowledge acquisition from the general public. In: On the move to meaningful internet systems. Lecture Notes in Computer Science; 2002. vol. 2519, pp. 1223–37.
67. Chklovski T. Learner: a system for acquiring commonsense knowledge by analogy. In: Gennari JH, Porter BW, Gil Y, editors. Proceedings of the 2nd international conference on knowledge capture (K-CAP 2003). 2003. pp. 4–12.
68. Ahn L, Kedia M, Blum M. Verbosity: a game for collecting common-sense facts. In: Proceedings of the 2006 conference on human factors in computing systems, CHI. 2006. pp. 75–8.
69. Kuo Y, Lee J, Chiang K, Wang R, Shen E, Chan C, Hsu JY. Community-based game design: experiments on social games for commonsense data collection. In: Proceedings of the ACM SIGKDD workshop on human computation. 2009. pp. 15–22.
70. Gangemi A, Guarino N, Masolo C, Oltramari A, Schneider L. Sweetening ontologies with DOLCE. In: Knowledge engineering and knowledge management. Ontologies and the Semantic Web, 13th International Conference, EKAW. Lecture Notes in Computer Science; 2002. vol. 2473, pp. 166–81.
71. Bollacker KD, Evans C, Paritosh PK, Sturge T, Taylor J. Freebase: a collaboratively created graph database for structuring human knowledge. In: Proceedings of the ACM SIGMOD international conference on management of data, SIGMOD. 2008. pp. 1247–50.
72. Singhal A. Official google blog: introducing the knowledge graph: things, not strings. 2012.
73. Dodge E, Hong J, Stickles E. MetaNet: deep semantic automatic metaphor analysis. In: Proceedings of the third workshop on metaphor in NLP. 2015. pp. 40–9.
74. Schuler KK. VerbNet: a broad-coverage, comprehensive verb lexicon. University of Pennsylvania, Philadelphia, PA, United States; 2005.
75. Palmer M, Kingsbury PR, Gildea D. The proposition bank: an annotated corpus of semantic roles. Comput Linguist. 2005;31(1):71–106.
76. Vrandecic D, Krötzsch M. Wikidata: a free collaborative knowledgebase. Commun ACM. 2014;57(10):78–85.
77. Lehmann J, Isele R, Jakob M, Jentzsch A, Kontokostas D, Mendes PN, Hellmann S, Morsey M, Kleef P, Auer S, Bizer C. Dbpedia - a large-scale, multilingual knowledge base extracted from wikipedia. Semantic Web. 2015;6(2):167–95.
78. Young T, Cambria E, Chaturvedi I, Zhou H, Biswas S, Huang M. Augmenting end-to-end dialogue systems with commonsense knowledge. In: Proceedings of the Thirty-Second AAAI conference on artificial intelligence. 2018. pp. 4970–7.
79. Mitchell T, Fredkin E. Never-ending language learning. In: 2014 IEEE International conference on big data (Big Data). 2014. pp. 1–1.
80. Tandon N, Melo G, Suchanek FM, Weikum G. Webchild: harvesting and organizing commonsense knowledge from the web. In: Proceedings of the 7th ACM international conference on web search and data mining, WSDM. 2014. pp. 523–32.
81. Ji L, Wang Y, Shi B, Zhang D, Wang Z, Yan J. Microsoft concept graph: mining semantic concepts for short text understanding. Data Intelligence. 2019;1(3):238–70.
82. Navigli R, Ponzetto SP. Babelnet: the automatic construction, evaluation and application of a wide-coverage multilingual semantic network. Artif Intell. 2012;193:217–50.
83. Shen X, Wu S, Xia R. Dense-atomic: towards densely-connected ATOMIC with high knowledge coverage and massive multi-hop paths. In: Proceedings of the annual meeting of the Association for Computational Linguistics, ACL. 2023. pp. 13292–305.
84. Suchanek FM, Kasneci G, Weikum G. Yago: a core of semantic knowledge. In: Proceedings of the international conference on the World Wide Web, WWW. 2007. pp. 697–706.
85. Bouraoui Z, Konieczny S, Ma T, Schwind N, Varzinczak I. Region-based merging of open-domain terminological knowledge. In: Proceedings of the international conference on principles of knowledge representation and reasoning, KR. 2022. pp. 81–90.
86. AlKhamissi B, Li M, Celikyilmaz A, Diab MT, Ghazvininejad M. A review on language models as knowledge bases. CoRR abs/2204.06031. 2022.
87. Bhargava P, Ng V. Commonsense knowledge reasoning and generation with pre-trained language models: a survey. In: Proceedings of thirty-sixth AAAI conference on Artificial Intelligence, AAAI. 2022. pp. 12317–25.
88. Radford A, Narasimhan K, Salimans T, Sutskever I, et al. Improving language understanding by generative pre-training. Open AI Preprint. 2018.
89. Radford A, Wu J, Child R, Luan D, Amodei D, Sutskever I, et al. Language models are unsupervised multitask learners. OpenAI blog. 2019;1(8):9.
90. Brown TB, Mann B, Ryder N, Subbiah M, Kaplan J, Dhariwal P, Neelakantan A, Shyam P, Sastry G, Askell A, Agarwal S, Herbert-Voss A, Krueger G, Henighan T, Child R, Ramesh A, Ziegler DM, Wu J, Winter C, Hesse C, Chen M, Sigler E, Litwin M, Gray S, Chess B, Clark J, Berner C, McCandlish S, Radford A, Sutskever I, Amodei D. Language models are few-shot learners. In: Proceedings of advances in Neural Information Processing Systems, NeurIPS. 2020.
91. Yao L, Mao C, Luo Y. KG-BERT: BERT for knowledge graph completion. CoRR abs/1909.03193. 2019.
92. Fang T, Wang W, Choi S, Hao S, Zhang H, Song Y, He B. Benchmarking commonsense knowledge base population with an effective evaluation dataset. In: Proceedings of the conference on Empirical Methods in Natural Language Processing, EMNLP. 2021. pp. 8949–64.
93. Fang T, Do QV, Zhang H, Song Y, Wong GY, See S. Pseudoreasoner: leveraging pseudo labels for commonsense knowledge base population. In: Findings of the association for computational linguistics, EMNLP. 2022. pp. 3379–94.
94. Bosselut A, Rashkin H, Sap M, Malaviya C, Celikyilmaz A, Choi Y. COMET: commonsense transformers for automatic knowledge graph construction. In: Proceedings of the 57th conference of the Association for Computational Linguistics, ACL. 2019. pp. 4762–79.
95. Petroni F, Rocktäschel T, Riedel S, Lewis PSH, Bakhtin A, Wu Y, Miller AH. Language models as knowledge bases? In: Proceedings of the conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP. 2019. pp. 2463–73.
96. Petroni F, Lewis PSH, Piktus A, Rocktäschel T, Wu Y, Miller AH, Riedel S. How context affects language models' factual predictions. In: Proceedings of conference on automated knowledge base construction, AKBC0. 2020.
97. West P, Bhagavatula C, Hessel J, Hwang JD, Jiang L, Bras RL, Lu X, Welleck S, Choi Y. Symbolic knowledge distillation: from general language models to commonsense models. In: Proceedings of the conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL. 2022. pp. 4602–25.
98. Goel V, Navarrete G, Noveck IA, Prado J. The reasoning brain: the interplay between cognitive neuroscience and theories of reasoning. Frontiers Media SA. 2017.

99. Salmon MH. Introduction to logic and critical thinking. 1989.
100. Clark P, Tafjord O, Richardson K. Transformers as soft reasoners over language. In: Proceedings of IJCAI. 2020. pp. 3882–90.
101. Yang Z, Dong L, Du X, Cheng H, Cambria E, Liu X, Gao J, Wei F. Language models as inductive reasoners. In: Proceedings of EACL. 2024. pp. 209–225
102. Geva M, Khashabi D, Segal E, Khot T, Roth D, Berant J. Did Aristotle use a laptop? A question answering benchmark with implicit reasoning strategies. Trans Assoc Comput Linguist. 2021;9:346–61.
103. Rajpurkar P, Zhang J, Lopyrev K, Liang P. SQuAD: 100,000+ questions for machine comprehension of text. In: Proceedings of the 2016 conference on empirical methods in natural language processing. 2016. pp. 2383–92.
104. Joshi M, Choi E, Weld D, Zettlemoyer L. TriviaQA: a large scale distantly supervised challenge dataset for reading comprehension. In: Proceedings of the annual meeting of the association for computational linguistics, ACL. 2017. pp. 1601–11.
105. Lake BM, Ullman TD, Tenenbaum JB, Gershman SJ. Building machines that learn and think like people. Behav Brain Sci. 2017;40:253.
106. Musen MA, Lei J. Of brittleness and bottlenecks: challenges in the creation of pattern-recognition and expert-system models. In: Machine intelligence and pattern recognition. 1988. vol. 7, pp. 335–52.
107. Li W, Zhu L, Mao R, Cambria E. SKIER: a symbolic knowledge integrated model for conversational emotion recognition. In: Proceedings of the AAAI conference on artificial intelligence. 2023. pp. 13121–9.
108. Smolensky P, McCoy R, Fernandez R, Goldrick M, Gao J. Neurocompositional computing: from the central paradox of cognition to a new generation of ai systems. AI Mag. 2022;43(3):308–22.

Authors and Affiliations

Qian Liu[1] · Sooji Han[2] · Erik Cambria[3] · Yang Li[4] · Kenneth Kwok[5]

✉ Erik Cambria
cambria@ntu.edu.sg

Qian Liu
liu.qian@auckland.ac.nz

Sooji Han
sooji.han@intapp.com

Yang Li
liyangnpu@nwpu.edu.cn

Kenneth Kwok
kenkwok@ihpc.a-star.edu.sg

[1] School of Computer Science, The University of Auckland, Auckland, New Zealand

[2] Intapp, Berlin, Germany

[3] College of Computing and Data Science, Nanyang Technological University, Singapore, Singapore

[4] School of Automation, Northwestern Polytechnical University, Xi'an, China

[5] Institute of High Performance Computing, A*STAR, Singapore, Singapore