



Acquiring and modeling abstract commonsense knowledge via conceptualization

Mutian He, Tianqing Fang, Weiqi Wang, Yangqiu Song*

The Hong Kong University of Science and Technology, Hong Kong SAR, China

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ABSTRACT

Conceptualization, or viewing entities and situations as instances of abstract concepts in mind and making inferences based on that, is a vital component in human intelligence for commonsense reasoning. Despite recent progress in artificial intelligence to acquire and model commonsense attributed to neural language models and commonsense knowledge graphs (CKGs), conceptualization is yet to be introduced thoroughly, making current approaches ineffective to cover knowledge about countless diverse entities and situations in the real world. To address the problem, we thoroughly study the role of conceptualization in commonsense reasoning, and formulate a framework to replicate human conceptual induction by acquiring abstract knowledge about events regarding abstract concepts, as well as higher-level triples or inferences upon them. We then apply the framework to ATOMIC, a large-scale human-annotated CKG, aided by the taxonomy Probase. We annotate a dataset on the validity of contextualized conceptualizations from ATOMIC on both event and triple levels, develop a series of heuristic rules based on linguistic features, and train a set of neural models to generate and verify abstract knowledge. Based on these components, a pipeline to acquire abstract knowledge is built. A large abstract CKG upon ATOMIC is then induced, ready to be instantiated to infer about unseen entities or situations. Finally, we empirically show the benefits of augmenting CKGs with abstract knowledge in downstream tasks like commonsense inference and zero-shot commonsense QA.

1. Introduction

Commonsense knowledge like “people want to eat when feeling hungry,” as a critical component for artificial intelligence, has regained focus among researchers and obtained substantial progress in recent few years. This is particularly signified by commonsense knowledge graphs (CKGs), the predominant form to represent commonsense. Recent large-scale text-based CKGs collect and solidify the implicit knowledge into triples $\langle h, r, t \rangle$, with the textual head node h and tail node t connected by a relation (i.e., edge) r . ATOMIC [1] is a typical example, which contains amounts of human-annotated triples for head events and their causes or consequences in loosely-formed texts, such as $\langle h: \text{PersonX is hungry}, r: \text{xWant (then PersonX wants)}, t: \text{to have lunch} \rangle$. With a large amount of commonsense knowledge consolidated into CKGs as in Table 1, ATOMIC-like CKGs [1–5] have been widely utilized in a broad range of downstream scenarios, including dialog systems [6–8], narrative understanding [9,10], script learning [11,12], and question answering (QA) [13–16].

* Corresponding author.

E-mail addresses: mhear@connect.ust.hk (M. He), tfangaa@cse.ust.hk (T. Fang), wwangbw@cse.ust.hk (W. Wang), yqsong@cse.ust.hk (Y. Song).

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Table 1

Statistics of recent ATOMIC-like textual event-centric large-scale CKGs. Considering Probable concepts of at least ten occurrences, Appeared Probable Concept is calculated by the proportion of concepts directly mentioned in heads by word matching, and Average Distinct Concept is the average number of distinct concepts per head.

	ATOMIC [1]	ATOMIC-2020 [17]	DISCOS [5]
#Head events	24.3 K	44.0 K	1,103.0 K
#Triple	793.3 K	1,246.6 K	3,235.9 K
Average Degree	32.6	28.4	2.9
Appeared Probable Concept	0.34%	0.76%	8.00%
Average Distinct Concept	0.093	0.114	0.048

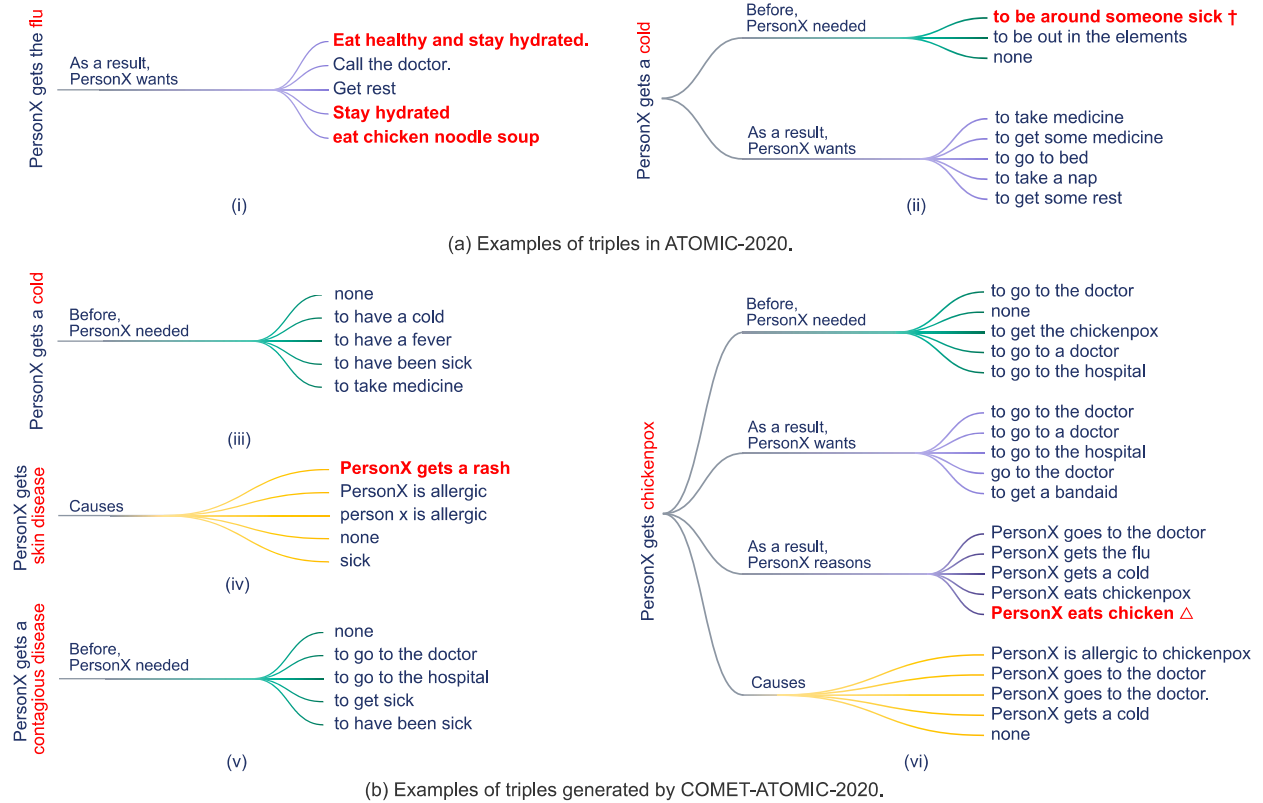


Fig. 1. Examples of triples from ATOMIC-2020 and COMET-ATOMIC-2020 from their online demo (available at <https://mosaickg.apps.allenai.org/home>), indicating the insufficient coverage and lack of generalization: Reasonable consequences in (i) applicable to many diseases are not covered in (ii). A root cause of (ii) is covered (†), but COMET fails to predict that for other *contagious diseases* in (iii), (vi), and (v) when we directly query about that abstract concept. It also gives a common consequence of *skin diseases* (iv), but not in its instance *chickenpox* (vi), and reflects superficial textual links instead (△).

Despite the success of current CKGs, conceptualization, a key ingredient in human intelligence and commonsense remains *terra incognita*. There is an infinite number of entities and situations in the real world, including vast objects, persons, events, states, and actions. Even with the extremely large scale as in Table 1, finite CKGs may never cover all the events involving inexhaustible entities and situations, let alone the relations or triples between them. For example, as shown in Fig. 1 (i), $\langle \text{PersonX gets the flu}, \text{xWant}, \text{get hydrated} \rangle$ is covered by ATOMIC-2020 [17], an extension of ATOMIC combined with ConceptNet [18]. But this tail is not found for the head *PersonX gets a cold* (ii), although the concepts of *flu* and *cold* are closely related as similar respiratory infections, making the tail valid for both of them. Moreover, in this finite CKG, we won't be able to find all such heads like *PersonX gets pneumonia*, *PersonX gets chickenpox*, *PersonX gets a bad flu*, etc. Using Probbase, a large-scale taxonomy of concepts for entities and situations [19], we inspect the proportion appearing in ATOMIC as well DISCOS, which is automatically generated and hence much larger. Despite the large scale, most concepts covered by Probbase are never mentioned in the head events as indicated by *Appeared Probable Concept*, not to say potential triples or inferences about them. It is similar in ATOMIC-2020 even though it explicitly incorporates ConceptNet for more knowledge about physical entities. Furthermore, as shown by the low *Average Distinct Concepts* per node, directly expanding the scale of CKGs would not be cost-effective to cover various entities and situations.

Alternatively, commonsense models like COMET [20] and COMET-ATOMIC-2020 [17] claim to bypass this challenge by employing the text-form nodes. Fine-tuned on ATOMIC from recent pretrained language models (PTLMs) like GPT2 [21] or BART [22], they are able to draw inferences by generating possible tails given arbitrary ATOMIC-like textual events. However, neural language models (LM) follow the principle of **induction on word co-occurrence** like the co-appearance of pox and their causes in texts. It is doubtful if COMET can truly go beyond superficial textual clues, as exemplified in Fig. 1 (vi) † linking the cause of chickenpox to chicken. In fact, there is evidence that such LMs suffer from limited generalization to broader scenarios [23,24]. Specifically, as a *contagious disease*, a critical precondition to *get a cold* is to *be around someone sick*. But even this triple is covered by ATOMIC-2020 as in (vi) △, COMET could only generate some over-general or even meaningless causes of *get a cold* as in (iii), not to mention the causes of relevant events like *gets a contagious disease* (v) or *chickenpox* (vi). Admittedly, COMET shows some generalization to unseen entities and situations, such as associate *chickenpox* with *bandaid*. But in (vi) many critical inferences like *need to be around patients*, *get a rash*, etc. are missing. Furthermore, it is impossible for COMET to infer about knowledge beyond training, such as *PersonX gets COVID-19*, not to mention the prohibitive computation costs and data requirements of such large models.

Instead, humans rely on **conceptualization**. *Concepts are the glue that holds our mental world together* [25]. We capture the commonsense in this world through conceptualization, e.g., through summarizing what we learn from each particular past experience of seeing each movie, and linking them to the abstract concept of “seeing a movie” in our mind, so that we can realize what to do in its future new instances. Without concepts in mind, one may not know that a new apple is edible, no matter how many apples the person has eaten. Without concepts in mind, one may not know how to buy tickets whenever seeing a new movie, even if the person has done it before. Intelligence without concepts, either human or artificial, would be lost in a mess of isolated facts on disconnected instances, unable to understand the world as a whole. For people not knowing chickenpox, when told that it is an instance of *contagious disease* or *skin disease*, they may easily draw the critical inferences mentioned above. This is from knowledge about the abstract concepts of contagious disease and skin disease, i.e. **abstract knowledge** [26]. Such abstract knowledge cannot be directly experienced, but indirectly induced from experiences on their instances like flu, measles, etc. This **conceptual induction** [27] process leverages inherent taxonomic relations between concepts instead of mere word co-occurrence. This is not limited to objects: Knowing that getting chickenpox is a painful experience, people can easily infer that others will feel sorry for that just like other painful experiences. People understand and reason about events, actions, and states in a similar conceptual way.

Such conceptual induction, though desirable for AI, is never easy to replicate on machines. First, due to the inherent flexibility of language, even for simple texts used in ATOMIC, it can be difficult to identify the actual entity or situation referred to, e.g. to decide that *hot dog* is not a dog, *a cup of tea* refers to *tea* not *cup*, and the action *give a speech* is more than *giving* something. Second, an instance is possibly related to multiple concepts, depending on the context and what we intend to induce about: A tomato could be vegetable in the kitchen but a fruit in a biology class; A dog can run since it is an animal, but it is furry since it is a mammal. Third, we need to draw inferences about abstract concepts. Chickenpox causes rashes, and flu causes coughs. In both cases, a patient sees a doctor since both are *diseases*, but an unspecified *disease* doesn’t typically cause rashes or coughs. More, it suffers from reporting bias [37] in that we talk about instances much more often than concepts. LMs trained on textual data may struggle with knowledge of more abstract concepts even if it’s obvious for humans, as shown by the “contagious disease” example in Fig. 1 (v).

Although there are sporadic works of conceptualization for acquiring and modeling commonsense, they are based on early symbolic approaches [28] or focused on specific and restricted scenarios such as conceptualization of arguments of each event [4,29] without considering the higher-level conceptualization of events and their relations. In contrast, we intend to thoroughly chart this area by formulating and implementing the whole process of conceptual induction in modern commonsense reasoning: We acquire **abstract knowledge** in the form of **abstract events** and **abstract triples**, which are summarized from existing **situational CKGs** through **conceptualization**, using a combination of taxonomy, linguistic rules, and neural models. The abstract knowledge can then be utilized to handle unseen entities and situations in the future. Table 2 summarises the terms we use to discuss the process, to be further elaborated later.

We leverage PTLMs for their strong language understanding capability, which is critical to capturing the contextualized meaning of words in a sentence to decide the appropriate conceptualization. They are fine-tuned on a large dataset of valid and invalid conceptualizations we annotate on 92 K entities and situations (eventualities) in head events, as well as 81 K abstract triples upon them. In this way, the models are not merely induced from language but also aware of conceptual relations. Through this pipeline, we induce a conceptualized version of ATOMIC, **Abstract ATOMIC**, covering 70 K abstract events and 2.9M abstract triples. We further show that directly incorporating Abstract ATOMIC is already helpful in downstream tasks such as COMET-like inference and zero-shot commonsense QA. To summarize, our contributions are:

1. We formulate the task and framework of machine conceptual induction and abstract knowledge acquisition.
2. We annotate a large-scale dataset for valid and invalid conceptualization on both event and triple level.
3. We develop a series of neural models and sophisticated heuristic rules to carry out the steps in the pipeline of abstract knowledge acquisition.
4. We induce a sizable set of abstract knowledge from ATOMIC using our pipeline.
5. We investigate the value of abstract knowledge in commonsense modeling and reasoning tasks.

As shown in Fig. 2, the paper is organized as follows: Section 2 discusses the background of commonsense knowledge, its representation and modeling, and the cognitive process of conceptualization. Section 3 formulates the three-stage abstract knowledge acquisition task for conceptual induction. Section 4 elaborates on the exact methods to implement each stage. Section 5 explains the data collection process. Section 6 builds the neural models in each stage using the data, which are then applied to harvest

Table 2

Explanation of several important terms we use in this paper, based on the terminology of ASER [4] and Probase [19].

Term	Explanation
Entity	A person, organization, object, phenomenon, etc., mentioned in language, usually as a noun or nominal phrase, such as “cold” in “PersonX gets a cold.”
Eventuality	A state, action, or event mentioned in language ¹ , usually as a sentence or clause, such as “PersonX gets a cold,” and “he enjoys himself” in “PersonX says he enjoys himself.”
Concept	An abstract concept in our mind, in this paper represented by nodes in a taxonomy like Probase. We consider every entity or eventuality as an instance of a concept.
Abstract Event	A textual event containing a bracket-enclosed concept like “PersonX gets [disease],” representing a <i>class</i> of its <i>instance events</i> , like “PersonX gets flu,” “PersonX gets a cold,” etc.
Abstract Triple	A triple with an abstract head event, representing an inference on the head, typically shared in a class of events, such as $\langle h: \text{PersonX gets [disease]}, r: \text{xWant}, t: \text{see a doctor} \rangle$.
Situational Knowledge	Knowledge represented in current event-centric CKGs (situational CKGs) on concrete and specific events and their inferences.
Abstract Knowledge	Knowledge summarized from situational knowledge regarding concepts, which is generalizable to the instances, represented in abstract events and triples.
Event/Triple	The process or action to build an abstract event/triple based on the a textual event/triple from the situational knowledge. This is by
Conceptualization	conceptualizing an entity/eventuality mentioned in the text into a concept and then replacing it with that concept.

¹ *Eventuality* [30], used interchangeably with *situation* [31], is a linguistic term denoting various types of predicates abovementioned in the general sense. We keep the ATOMIC terminology to call heads as *events*, though it is linguistically imprecise.

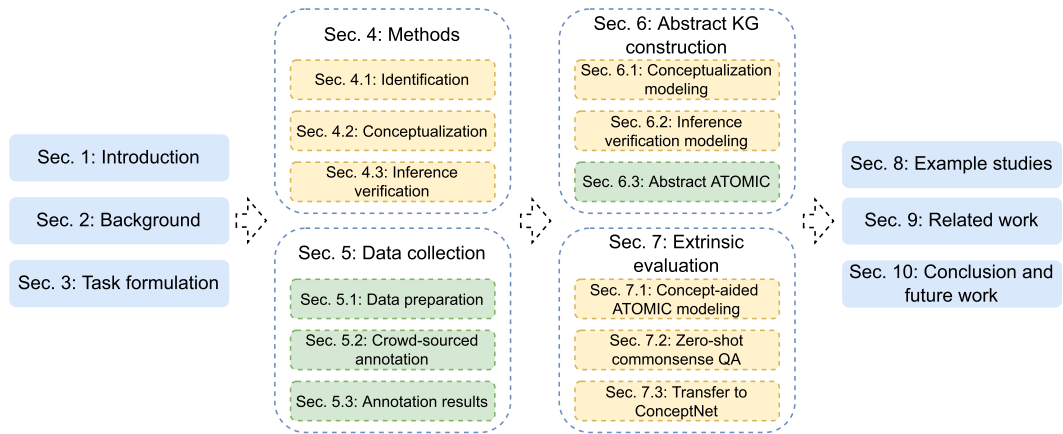


Fig. 2. Paper roadmap. Parts focused on empirical methods are marked in yellow, and those on data processing in green. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

an abstract CKG from ATOMIC. Section 7 evaluates the abstract CKG in downstream tasks. Section 8 studies examples from the data. Section 9 reviews related previous works. Section 10 concludes the paper. All data and codes are publicly released at <https://github.com/HKUST-KnowComp/atomic-conceptualization>.

2. Background

In this section, we introduce the important background of this study, including the characteristics of commonsense knowledge, relevant CKGs and taxonomies, the role of PTLMs for commonsense, previous research on human conceptualization, as well as their implications for our design choices.

2.1. Commonsense knowledge

Commonsense knowledge, like *a person will pay the bill after buying groceries* and *a person is larger than a dog*, is a set of “millions of basic facts and understanding possessed by most people” [32]. Even though such commonsense can be understood by most sixth-grade pupils, its AI replication proves elusive. Particularly, compared to general or factual knowledge like *Paris is in France*, there are three unique challenges:

1. **Scale and Variety:** Commonsense knowledge covers not only knowledge about enormous entities in this world themselves, but also diverse eventualities involving them in our lives, with an exceptionally long tail [33] that modern CKGs struggle to cover, as mentioned in Section 1.
2. **Defeasibility:** Unlike definite facts from factual knowledge that is always true, each piece of commonsense knowledge is known as a *factoid* [34] that is only **plausible** or **typically true** according to human intuition before logical reasoning [35]. They can

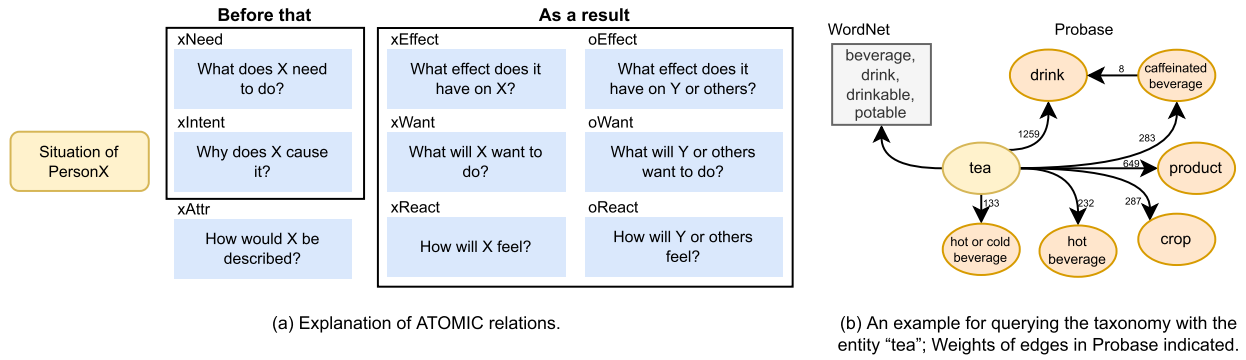


Fig. 3. Explanations and examples for knowledge graphs used in our methods.

be false under specific circumstances or even conflict with each other. For example, it is possible to find a dog that is larger than a person, and when a person gets an invitation, either accepting it or rejecting it is totally plausible.

3. **Implicitity:** People tend not to explain the knowledge that is held by all parties in a conversation [36]. For example, people may say, “There is a fire, so someone calls firefighters,” without explaining the firefighters’ job. Therefore, usual, trivial, or certain knowledge is rarely stated in human language. Due to this phenomenon of **reporting bias** [37], induction only from human language, even with strong neural models, will fail to fully capture commonsense in humans’ minds [38].

2.2. Commonsense knowledge graphs

Below we introduce ATOMIC, the CKG we choose to perform conceptual induction upon, as well as the source of taxonomic knowledge we use, both holding a number of advantages, making them for our goal.

Current CKG: the ATOMIC approach Knowledge graph (KG) is the primary form of machine knowledge representation. A KG, denoted as $\mathcal{G} = \{\mathcal{V}, \mathcal{E}, \mathcal{R}\}$, is a graph consisting of a set of nodes \mathcal{V} , and a set of edges or triples $\mathcal{E} = \{(h, r, t) \mid h, t \in \mathcal{V}, r \in \mathcal{R}\}$. Typically, nodes in a KG represent things of interest, while edges, typed with a relatively small and pre-specified set \mathcal{R} , denote the relation between the head h and tail t . KGs for factual knowledge like DBpedia [39] typically contain facts about real-world entities as heads and tails, like $\langle h: \text{Paris}, r: \text{AtLocation}, t: \text{France} \rangle$, while earlier commonsense knowledge bases (KBs) like Cyc [40] and [41] consolidate commonsense into LISP-style logical assertions for formal logic reasoning.

However, as mentioned above, human commonsense is after all not logical. In the recent interest in commonsense within the NLP community, event-centric or situational CKGs gain more popularity, which typically represent nodes in rather free-form texts. Nodes in the earlier ConceptNet are mostly entities, with only a small set of verbal nodes in phrases like “eat food” and “go to a gift shop” [18], while ATOMIC is the very first large-scale event-centric textual CKG [1]. As shown in Fig. 3 (a), ATOMIC covers head events regarding everyday situations of an unspecified PersonX, which are then linked to tails with a rich set of nine predefined relations of various subjective and objective causes and consequences of the event. The head events are harvested from various corpora by selecting common verbs and their arguments. Subjects of the event are normalized to PersonX, and other mentioned persons as PersonY and PersonZ. Events with diverse and infrequent arguments are conflated using wildcards like “PersonX eats _”. Then crowd-sourced workers are asked to compose possible tails of each relation, so that reporting bias is alleviated.

The ATOMIC paradigm relies on humans to annotate commonsense that is *plausible*, which is subjective and intuitive. Different from formal logic, it better aligns with the unique characteristic of commonsense knowledge and addresses the challenges above, as thoroughly discussed in [35]. Moreover, textual representations can be easily incorporated into neural models with strong semantic understanding capabilities, to be applied to various downstream scenarios. All these factors support our choice to focus on ATOMIC.

Taxonomy As a specific type of KG, a taxonomy represents **taxonomic knowledge** with nodes being a set of concepts \mathcal{C} , connected by the *is-a* or hypernym-hyponym edges, which is essential to our study. A widely used taxonomy is WordNet [42], which organizes senses of English words into 117 K *synsets* designated by linguistic experts, and builds a tree-like hierarchy of *is-a* relations between the synsets. Although it enjoys the finest quality, a hierarchy is too strict in reality (to be discussed in Section 2.4), the taxonomy has limited coverage, and they are often too coarse-grained to differentiate specific concepts.

Therefore, we mainly use Probase [19] as our source for taxonomic knowledge. Harvested from the Web corpora, Probase contains 2.7M nodes as *concepts*, linked by 4.5M *is-a* or concept-instance pairs. As shown in Fig. 3 (b), concepts in Probase are not represented in manually disambiguated senses, but more variable and fine-grained multi-word terms in natural language, e.g. *caffeinated beverage*. The *is-a* edges are not black-and-white assertions but backed by the number of evidence from text corpora. Furthermore, Probase is not a strict tree-like hierarchy but a complex network, which is even not acyclic. A concept can be viewed as the instance of (i.e. conceptualized to) more abstract super-concepts in multiple ways due to the complexity of word meanings and usages, which is more realistic and better imitates human cognition. In this way, larger-scale, more fine-grained, and more realistic taxonomic knowledge is introduced.

2.3. Language models for commonsense knowledge

Significant progress has been made in NLP thanks to recent PTLMs from BERT [43] to GPT series [44,21,45], which contains rich commonsense knowledge learned from training corpora [46–48]. Hence they have greatly pushed forward the state-of-the-art on multiple commonsense tasks like COPA and WSC after fine-tuning [49]. Also, as mentioned in Section 1, rich textual knowledge from pretraining has been successfully leveraged to make commonsense inferences from textual events following the COMET path of fine-tuning generative PTLMs on ATOMIC-style triples [17,20]. Given these successes, PTLMs shall play an essential role in our attempt of conceptual induction on text-form commonsense.

Nevertheless, generations from such fine-tuned models lack diversity and novelty, often semantically close to each other or training samples, and not well generalized to unseen entities and eventualities [23,24,50,51]. More, there is evidence that PTLMs miss certain important aspects of commonsense [47,52–54], often become too vague and over-generalized [55], fail on negations [56,57], and suffer from reporting bias [38,58]. Particularly relevant, PTLMs are found ineffective in capturing conceptual relations between entities as well as knowledge about them [59,60]. All the weaknesses highlight that PTLMs are not silver bullets, and we must meticulously design the fine-tuning tasks and dataset to make the best out of PTLMs for our goal.

2.4. Human conceptualization

As mentioned above, we infer knowledge of new and unseen entities and eventualities as instances of abstract concepts by **conceptual induction** using analogy with knowledge in our mind [61]. From this point of view, unlike LMs chained in the cave of texts, the Platonic forms or ideas are in our minds that transcend from instances in the mundane world. This whole paper is inspired by this process. Particularly, we make our key decision choices based on the following theories and observations on our mind and cognition:

Flexibility, complexity, and context dependency Among the theories of concepts, we are particularly inspired by the knowledge theory, that we learn about a concept in integration with related knowledge [62], which, as for AI, could be factoids or triples involving the concept in CKGs. This contradicts the classical or definitional theory that concepts are characterized by strict definitions and form a hierarchy [63], as reflected by the idea of WordNet. Humans will disagree on borderline cases for conceptualization, and the task of deciding on proper conceptualization can be effortful [25]. Also, the conceptualization of an entity or eventuality can be diverse and context-dependent, sometimes due to a shift of perspectives. For example, to conceptualize a whale as a mammal is useful for inferring physiological features but not ecological ones [64]. Another aspect of variety comes from different levels of abstractness in the hierarchy. Humans recognize concepts in a non-strict hierarchy with *is-a* relation in a mixed manner. The hierarchy might be partially pre-built in our minds [65] just like the taxonomies available, but further inferred on the fly according to the context [64]. Importantly, humans do not adopt strict conceptual induction either [64]: we recognize that birds can fly, even if penguins and ostriches can't. It is also noteworthy that we follow a broad definition of concepts including not only entities but also eventualities, since human cognition may process eventualities in a similar hierarchical way, as formulated in the K-line theory [65].

Basic-level concepts Concepts in a chain of *is-a* relations are not equal. There are *basic-level concepts* (BLCs) of intermediate abstractness which humans tend to use to refer to instances [66]. For example, when seeing a large black bulldog, people more often shout "There is a dog" not "There is a large black bulldog" or "There is an animal." BLCs lead to an additional aspect of reporting bias, which we term **concept bias**, that even for human-annotated sentences as in ATOMIC, instances are more often represented by the words for BLCs. Nevertheless, finding BLCs is already a challenging task. More importantly, non-BLCs are also useful: Subordinate concepts carry more specific information about the particular target entity or eventuality of reasoning, while the more abstract superordinates have broader coverage [64]. For example, when inferring the health impact of drinking Dr. Pepper, it is reasonable to conceptualize it as the impact of drinking [sugary beverage], certainly a non-BLC, and infer that it will lead to weight gain, based on possible known impacts from drinking soda, Frappuccino, etc.

Word meaning We are particularly inspired by referential semantics [67], which posits that the meaning of language is what it refers to in a (possibly) real world. When I narrate "I get a cold," "I" refers to a specific person, and "cold" a specific phenomenon of disease happens to me at a certain time point. We are also inspired by event semantics [68] that a clause refers to an event, an existence that takes place in the world at a certain time. Hence the whole sentence refers to a specific event of "I" getting a "cold" in the real world. In this way, nouns or clauses in language can be viewed as references to specific instances of entities or eventualities in the real world, yet to be conceptualized into the abstract existence in our mind.

2.5. Implications

The findings above reveal the complexity of human conceptualization, similar to human commonsense. There are earlier methods for formal logical conceptual reasoning on a strict hierarchy like First-orderized Cyc [28], theories on abstraction like [69], and default inheritance reasoning [70, §3.1]. While following the spirit of ATOMIC, we believe that conceptualization should be based on annotated text-form plausible situations, contextualized neural LMs, and flexible *is-a graphs* like Probase, upon both entities and eventualities. Also, both BLCs and non-BLCs, as represented by the rich fine-grained concepts in Probase, should be taken into account. We also believe that we shall view the existing ATOMIC triples as textual descriptions of plausible situations, and process the more abstract knowledge after conceptualization in a distinct way.

3. Task formulation

In this section, we introduce the conceptual induction framework by first specifying the goal of collecting a distinct set of abstract knowledge, and then elaborating on the complexity of event and triple conceptualization. In the end, we propose our pipeline for machine conceptual induction to meet our demands.

3.1. Situational vs abstract knowledge

Limitation of situational knowledge An early attempt to introduce conceptualization to CKGs [71] pointed out that then CKGs extracted from text corpora are primarily restricted to those directly existing in the world. Following this perspective and the discussion in Section 2.5, we consider current **situational CKGs** as an excerpt of the world that picks numerous textual descriptions of actual possible situations plus their causes and consequences, ATOMIC being an example with heads extracted from corpora. For instance, an ATOMIC triple about “a person gets a cat, then the person will buy cat food” can be viewed as a textual description of a real situation and the consequent action possibly happen to an actual person and actual cat. The validity of an event or triple is tacitly defined as the plausibility of the situation in real life according to the annotator. The more plausible is a situation in the real world, the more valid is the corresponding event or triple in the CKG. That is to say, $p(\text{triple}) \propto p(\text{situation})$, p representing the validity or plausibility.

They do reflect plenty of commonsense knowledge generalizable to broader scenarios, since the events are often prototypical and in lack of more specific modifiers. ATOMIC goes one step further by normalizing persons and sometimes objects. Hence, humans can implicitly understand the inferences from the head event “PersonX gets a cat” as general knowledge about a class of various events like “Alice gets a black cat.” However, it is elusive for the machine to determine to what extent will an ATOMIC event or triple generalize, say, whether the “cat food” inference applies to, e.g., “My neighbor adopts a ragdoll” or “The vet gets a sick cat to treat”, given the tails of that head event in a situational CKG like ATOMIC. Without explicitly inducing a distinct set of abstract knowledge, generalization to different entities and eventualities can be reduced to be circuitous, superficial, or oversimplified, as exemplified in Section 1.

Abstract knowledge In contrast, we pursue **abstract knowledge** explicitly *above* the realm of **situational knowledge**. We also represent it by textual events and triples, but characterized by the concept within. For example, an abstract event can be “PersonX drinks [tea],” with a concept “[tea]” indicated by the brackets. Instead of representing an event on its own, it represents a *class* of instance events, such as “PersonX drinks a cup of tea,” “PersonX drinks black tea with milk,” “PersonX drinks earl grey,” or just “PersonX drinks tea,” which can be all *possibly* found in ATOMIC. Similarly, an abstract triple given an abstract event represents a class of triples, or inferences on a class of instance events, e.g., $\langle h: \text{PersonX drinks [tea]}, r: \text{xNeed}, t: \text{boil water} \rangle$, which reflects the precondition on the class of events mentioned above.

More formally, an **abstract CKG** to represent abstract knowledge is defined as $\mathcal{G}_a = \{\mathcal{V}, \mathcal{T}, \mathcal{C}, \mathcal{V}_a, \mathcal{E}_a, \mathcal{R}\}$. In addition to the vertices \mathcal{V} and relations \mathcal{R} as in Section 2.2 in standard CKGs, there is a set of templates \mathcal{T} . Each template $t \in \mathcal{T}$ is a string with a slot in it, like “PersonX drinks _.” We then leverage a predefined textual concept set \mathcal{C} , e.g. the Probase one. After that, we can create a set of abstract vertices \mathcal{V}_a by pairing some $t \in \mathcal{T}$ with some $c \in \mathcal{C}$ like [tea] to form a $v_a = (t, c)^1$: “PersonX drinks [tea].”

Although both heads and tails in ATOMIC can be conceptualized, we discover that tails in ATOMIC are less complete as sentences and much more noisier to parse and analyze for conceptualization. To reach better quality for our abstract knowledge, we limit the abstract vertices to head events. That is to say, \mathcal{V}_a is a set of abstract head events, while the set of tails is kept as-is. In this way, the abstract triples are formed as $\mathcal{E}_a = \{(h, r, t) \mid h \in \mathcal{V}_a, t \in \mathcal{V}, r \in \mathcal{R}\}$.

Validity of abstract knowledge Following this definition, the validity of an abstract event or triple is determined by the plausibility of the class of instances behind it. More formally, for an abstract event $v = (t, c)$, considering the instance c , $p(v)$ depends on $p((t, i) \mid \text{isA}(i, c))$. Similarly, $p(\langle h, r, t \rangle, h = (t, c))$ depends on $p(\langle h', r, t \rangle)$ in which $h' = (t, i)$ and $\text{isA}(i, c)$. We consider an abstract event or triple as valid, if its instances are **typically** plausible, following the spirit discussed in Section 2.5 to reflect human cognition. We don’t need to (and are also unable to) examine all the instances of a mentioned concept to decide if a sentence makes sense. After all, we accept that birds can fly, and that we need to boil water before drinking tea, even though we are clearly aware of the existence of penguins and bottled tea.

Notably, under this criterion, an abstract event can be valid even if it is weird or counter-intuitive when viewed as a natural sentence or ordinary situational knowledge found in the original ATOMIC. The reason is that the abstract event represents a class of events, and the concept in the event can be rather fine-grained and distinct from BLCs we typically use in our language. Examples include “PersonX drinks [natural beverage],” “[relaxing event]” (if we conceptualize the whole event), “PersonX spends [time interval] reading,” and “PersonX is [technical job],” etc., which are valid based on their instances, not themselves.

¹ A template is similar to a logical sentence with a free variable, which could be assigned as a concept c . However, as free-form text, it is elusive to further analyze the meaning of t and its interaction with c in a formalized way beyond simply pairing them up as (t, c) or possibly $t(c)$. Hence we choose to follow the ATOMIC paradigm and focus on a non-formal NLP perspective.

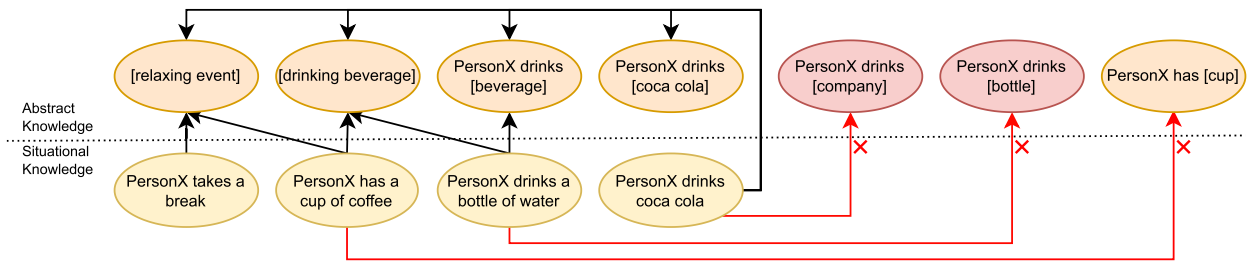


Fig. 4. Examples of events in situational and abstract knowledge, linked by the edges of *event conceptualization*. Invalid abstract events of “PersonX drinks [company]” and “PersonX drinks [bottle]” are marked red; invalid edges like the one between “PersonX has [cup]” and “PersonX has a cup of coffee” are marked red with a cross.

3.2. Levels of conceptualization

Now that the target is specified, the next issue is how to acquire the desired abstract knowledge. Similar to humans, we induce possible abstract knowledge upon instances we encounter, which can be found in situational CKGs in the form of events/triples. For this induction, we carry out three levels of conceptualization, upon 1) each entity/eventuality (as an instance of a concept); 2) each event (as an instance of an abstract event); and 3) each triple (as an instance of an abstract triple), as elaborated below:

Entity/eventuality conceptualization Within each textual ATOMIC event, we may identify some entities and eventualities as **conceptualization candidates**. Specifically, each ATOMIC event as a whole is also an eventuality. We consider all of them as instances of some concepts $c \in C$. For example, within the event “PersonX drinks coca cola,” the candidates we may find include the object “coca cola” and the whole event itself.² Then, by 1) finding the concepts within C that match the candidate; and 2) utilizing known taxonomic relation between concepts, we can determine which concept the candidate is an instance of. For example, the object of the specific “coca cola” is an instance of (i.e. conceptualized to) the concepts “[coca cola],” “[beverage],” “[sugary beverage],” “[phosphate containing beverage],” etc., while the whole event can be conceptualized to “[drinking beverage],” “[relaxing event],” “[action],” etc. In this case, the unspecified PersonX is implicitly considered as the semantic agent or initiator of the eventuality.

As discussed in Section 2.4, we want to consider possible concepts with diverse granularity and perspectives to best reflect the flexibility of human conceptualization. To capture such great flexibility in a practical way, we choose to combine the nodes in WordNet and Probase as our concept set C and use their set of is-a relations, so that we can achieve the best inclusiveness.

Event conceptualization By replacing each conceptualization candidate in the text with a concept, abstract events can be formed. Fig. 4 exemplifies this **event conceptualization** process, forming a bipartite graph between the abstract events and the original ATOMIC ones with many-to-many edges, as:

- An entity or eventuality can be conceptualized with different levels of abstractness, such as “PersonX drinks coca cola” as “[drinking coca cola],” “[drinking beverage],” or “[action].”
- An entity or eventuality can be conceptualized in different perspectives, such as “coca cola” as “[sugary beverage],” “[phosphate containing beverage],” or “[iced drink],” not in a strict hierarchical taxonomy.
- An event can be conceptualized into various abstract events of different template by conceptualizing different entities or eventualities appeared in it.
- Different events can be conceptualized into the same abstract event.

Notably, conceptualization of a candidate in an event doesn’t automatically grant a valid event conceptualization, unless it falls under the class represented by the formed abstract event, as shown in Fig. 4:

- Coca Cola is a [company], but “PersonX drinks [company]” derived from “PersonX drinks Coca Cola” doesn’t make sense.
- “PersonX has [cup]” is a valid abstract event representing a class of events like “PersonX has a cup,” “PersonX has a beautiful tea cup,” etc., but not really “PersonX has a cup of coffee.”

In both cases, the candidate entity doesn’t really refer to an instance of the corresponding concept: “PersonX *has*” here means “PersonX *drinks*,” and what PersonX actually drinks is the beverage, not the company or the cup. Therefore, we require that an abstract event can only represent the instance events that, the corresponding entity/eventuality is indeed an instance of the concept under the context, and hence the instance event being semantically covered by the abstract one. To the extreme, “PersonX drinks [company]” is considered invalid as it may not represent any actual event. This criterion mimics how we actually conceptualize in a contextualized way, but nevertheless adds to the complexity of the problem and demands semantic understanding of the event to determine if an event conceptualization is valid.

² Since ATOMIC is already generalized across unspecified persons, we leave “PersonX” untouched.

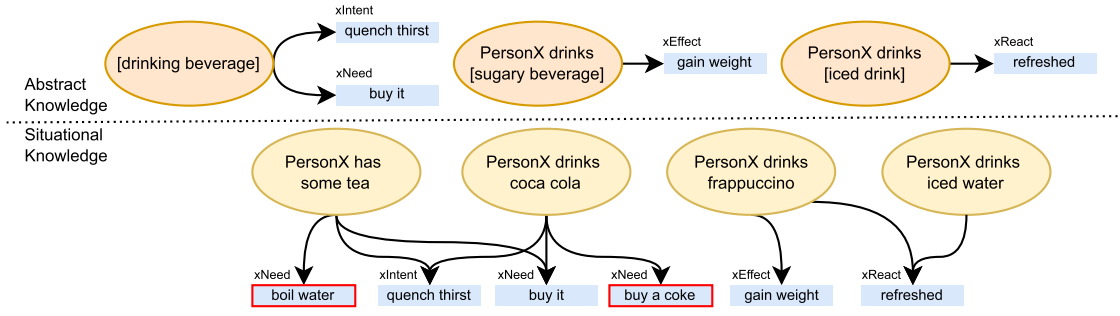


Fig. 5. Examples of triples in situational knowledge, as well as triples in abstract knowledge inferred from them. Inferences like “xNeed: boil water” that are not suitable for the corresponding abstract event are marked in red.

Overview of conceptual induction from ATOMIC in 4 stages

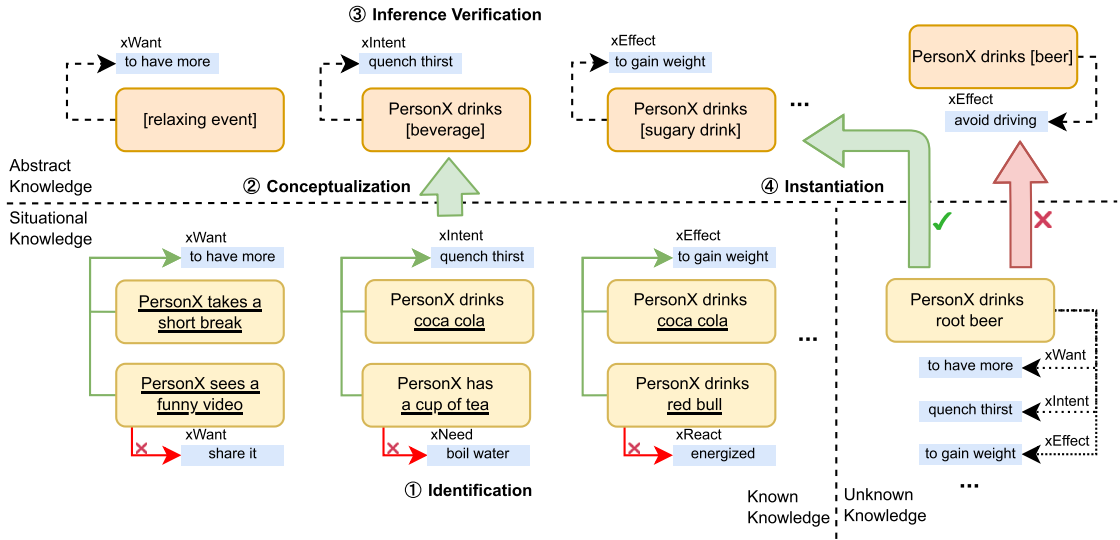


Fig. 6. An overview of our 4-stage formulation of conceptual induction using examples. By identifying candidates (underlined) in the events and conceptualizing them into concepts (e.g. “coca cola” and “a cup of tea” into “[beverage]”), abstract events are built. Next, inferences typically held on the instance events are collected as abstract triples, otherwise indicated in red lines with crosses. The whole procedure mimics how we learn abstract knowledge from instances. When a new event like “PersonX drinks root beer” comes, we can conceptualize it into abstract events by reusing stage 1&2, while incorrect conceptualizations like “PersonX drinks [beer]” are excluded. We can then make inferences of this event using corresponding abstract triples.

Triple conceptualization Using the triples of the instance events, we then find the inferences that are typically plausible for this class of events to form or induce abstract triples, as exemplified in Fig. 5: the abstract triple $\langle h: [\text{drinking beverage}], r: \text{xNeed}, t: \text{buy it} \rangle$ can be induced from the same inference upon instance events “PersonX has some tea” and “PersonX drinks coca cola.” Note that this is an incomplete induction: Although this inference is also valid for “PersonX drinks Frappuccino,” the original CKG may fail to cover that. On the other hand, some inferences on the instance event like “xNeed: boil water,” are not typically held for the abstract event and will not be included as abstract triples.

3.3. Summary

Given the discussions above, we imitate human conceptual induction in four stages as shown in Fig. 6:

1. Identification: Given an original event, identify the entities or eventualities as candidates of conceptualization, as indicated by underlined words.
2. Conceptualization: Given an identified candidate in an event, correctly conceptualize it into some concepts in C to form abstract events.
3. Inference Verification: Considering all the inferences on instance events of each abstract event, determine which of them are typically held, so as to form the abstract triples correctly.
4. Instantiation: When encountering any new event, conceptualize it into abstract events, so that we can leverage the corresponding abstract triples to make inferences about it.

Implementation of abstract knowledge acquisition for building Abstract ATOMIC

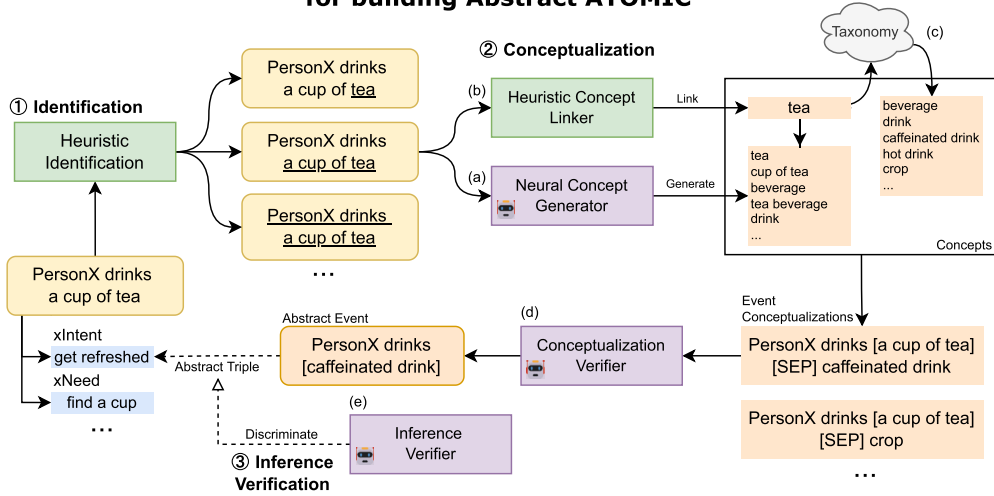


Fig. 7. Our implementation of acquiring abstract knowledge from ATOMIC, demonstrated by an example. We first identify entities/eventualities by heuristic rules. Then the identified candidates go through two pathways: (a) A transformer-based *neural concept generator* to predict possible conceptualizations, and (b) heuristic rules to link to concepts in C , to be further directly conceptualized using *is-a* relations in the taxonomy (c). Next, we form the event conceptualizations and use a similar *conceptualization verifier* (d) to determine their validity, forming abstract events. Finally, possible abstract triples are collected from instance triples and verified by an *inference verifier* (e).

For stage four, when queried about a new event presumed to be valid, finding its abstract events is identical to the first two stages. As the abstract triples or inferences are typically valid among the instance events including the queried one, we may assume that they are quite plausible to be held to the queried one, or at least valuable for further inspection. Therefore, the task to replicate conceptual induction highlights the first three stages to acquire a comprehensive set of abstract knowledge in the form of abstract events and triples, ready to be instantiated whenever unknown events are encountered.

4. Methods

Below we present how we implement each step in abstract knowledge acquisition, as outlined in Fig. 7.

4.1. Identification

First, we need to correctly identify conceptualization candidates from words or phrases in a text-form event. However, simply matching the words leads to errors due to word inflection and ignorance of boundaries between syntactic constituents. For example, in “She gives her pet food,” “pet food” can be incorrectly identified as a separate entity. Instead, we first parse the event with spaCy [72], and then work on the dependency tree to inspect each subtree (i.e. **constituent**) to decide if it is a possible nominal candidate (entity) or predicative candidate (eventuality) according to linguistic features of the head (root) word, including the surface form, lemma, coarse or fine-grained part-of-speech (POS), and dependency tag (DEP).

Unfortunately, both the original data and the predicted linguistic features contain errors, making it imprecise to rely on a single type of feature. Hence we curate a set of error-tolerant rules for identification. We iteratively test and improve them on the ATOMIC data, aimed at collecting most of the valid candidates while avoiding errors, to make the results useful for future conceptual induction with our best effort.

To be more specific, a constituent is considered an entity/nominal candidate if:

- Its DEP indicates a nominal subject (*nsubj*), object (*obj*, *dobj*), or nominal attribute (*attr*); or,
- It has nominal POS (like *NOUN*, *PROPN*, *PRON*) or it is a gerund, and it has potentially nominal DEP (such as complement).

A constituent is considered an eventuality/predicative candidate if:

- Its DEP indicates a predicate or clause, like *ROOT* (for a whole event), *acl*, *advcl*, *relcl*, etc.; or,
- It has predicative POS (like *VERB* and *ADJ*), and potentially predicative DEP (such as complement).

In addition, for conjuncts connected by conjunctions (e.g. “coffee and tea”), if one of them is identified as a nominal or predicative candidate, others will be included as the same type of candidate. It is possible for a constituent to be marked as both nominal and predicative, like gerunds, which is by design so that we can find the most accurate conceptualizations in the next stage. A constituent

Table 3

Methods to determine the linked concept(s) under various cases in the heuristic pathway, plus examples of the results, target candidates underlined. The algorithm is often recursive that performs linking based on the linking results of some sub-constituent/subtree(s). WordNet linkings are limited to nodes with matched POS depending on whether it is a nominal or predicative candidate. Different inflections of the resultant concept are all included to be inspected later.

Type	Example	Concepts	Method
Word	PersonX finds <u>some cats</u>	cat	Directly use the headword, possibly lemmatized
Compound/ Phrase	PersonX sees <u>many stray cats</u>	stray cat	Collect compounds or phrases in nominal candidates by word matching in the constituent, subject to inflections
Predicate (Verb)	PersonX <u>drinks coffee</u> PersonX says he enjoys <u>himself</u>	drinking enjoyment	Directly use the gerund of the verb Check WordNet and NOMBANK for the noun form of the verb
Predicate (Adj.)	PersonX is <u>happy</u>	happiness	Same as above, for a copula with adjective complement
Conjunction	PersonX sees <u>doctors and nurses</u>	doctor, nurse	Use concepts from both conjuncts
Nominal Candidate with Classifiers	PersonX has a <u>cup of tea</u> PersonX sees a <u>group of people</u>	tea group, people	Directly return results from the accompanied argument, if the head and the preposition form a transparent construction according to NOMBANK If an argument is connected to another one by “of” but not a transparent construction, both the head and accompanied argument are used.
Verb Phrase	<u>PersonX drinks coffee</u>	drinking coffee	Combine the verb with its arguments
Phrasal Verb	<u>PersonX gets up late</u>	get up	Check WordNet for combination of the verb and one or two particle in the text
Light Verb	<u>PersonX gives a speech</u> <u>PersonX goes shopping</u>	giving, speech shopping	For light verbs like <i>give, take, have</i> , etc., the predicand can be the actual concept Directly use results from the predicand when it is a gerund
Aux./Raising-to- subject	<u>PersonX seems to be happy</u>	happiness	Directly use results from the predicand for verbs like <i>seem, appear, used</i> , etc.
Catenative Verb	<u>PersonX wants to leave</u>	want, leave	Use both the head (superordinate verb) and results from its complement
Adj. + Infinitive	<u>PersonX is likely to leave</u>	leave	Directly use results from the infinitive for a copula + adjectives like <i>likely, going, about, able</i> , etc. as complement

with DEP like *cc, advmod, prep*, etc. doesn’t correspond to an entity or eventuality, hence it is deemed not a candidate. After that, a set of candidates is collected, represented as a set of subtrees, to be verified in the next stage.

4.2. Conceptualization

We then conceptualize candidate entities/ eventualities using the concept set C . This also verifies the previous stage, as we consider those fail to match any concept in C as invalid, or at least not usable. As mentioned in Section 3.2, we first need to match a candidate to known concepts, termed **concept linking**.

This is nevertheless a non-trivial task: In both ATOMIC events and natural language, entities/ eventualities can be modified in diverse ways. The corresponding fine-grained concept may be absent in the taxonomy, which renders it impossible for further use by *is-a* relations. For example, when conceptualizing the object in “PersonX has a lovely small siamese cat,” we surely need to ignore the determiner, but still “[lovely small siamese cat]” is certainly not in WordNet or Probase. Instead, only “[siamese cat]” can be found in Probase. Hence we define the concept linking task as finding the concept(s) from C that describe or cover the candidate in the most precise way. When linking an eventuality, PersonX will be implicitly considered as the semantic agent of the concept, e.g. [having pet]. In this way, we try to find the most precise, low-level, or informative concepts for the mentioned entity/ eventuality, with the most potential for further conceptualization into more abstract concepts.

However, this remains a challenging goal due to the variability of language. The actual concept that a constituent refers to may not match the headword or even any word within it, but depends on its meaning as a whole. For example, the constituent may involve light verbs (e.g. “take a shower”), transparent constructions [73] (e.g. “a cup of tea,” “the city of New York”), or require deeper semantic understanding (e.g. “[cohabitation]” for “PersonX lives with her boyfriend”).

Utilizing known *is-a* relations is also elusive if we try to further conceptualize the linked concept. Homonymy like “bank” as river bank or savings bank causes some ambiguity, but more serious issues come from polysemy like “coca cola” as the beverage or the company, as in Fig. 4. It may even go beyond lexical ambiguity and require commonsense to handle. For the same real-world referent, conceptualization can be different due to the context. For example, as for “drink [coca cola] after eating spicy salsa,” “[coca cola]” can be conceptualized into “[iced drink],” but in “coca cola gains you weight” it is no longer the case.

Therefore, the complexity of conceptualization surpasses the capacity of mere heuristic rules and requires a more complicated pipeline: We first develop heuristic linking rules to propose possible concepts. Upon these results, we leverage *is-a* relations to obtain some more abstract ones. Another route is to train a neural concept generator to directly predict the concepts of the candidate. In all the three cases, the results can be imprecise. Hence we follow the principle similar to the identification stage, considering them as ways to produce good candidates with best efforts, to be later verified by a neural model, as elaborated below.

4.2.1. Heuristic approach

Heuristic concept linking In addition to simply using the headword of each candidate constituent, we also consider a number of syntactic and semantic phenomena in the constituent, and develop a recursive algorithm trying to extract the actual and precise concept based on the parsed (sub-)tree, as listed in Table 3.

Handling predicative candidates is especially challenging, as Probase is relatively in lack of verbal nodes compared to WordNet. We nevertheless attempt to find and use the nominal form of predicative candidates by combining WordNet and NOMBANK [73] so as to link the candidate to Probase with richer taxonomic knowledge. More semantic nuances like negations and modalities are left to be handled by later verification. Additional explanations of more complicated cases are available in Appendix A.

Further conceptualization Given text-form linked concepts as the most precise and low-level conceptualization of the entity/eventuality, we further try to identify more abstract ones using the taxonomy. Regarding WordNet where nodes are not raw text but disambiguated synsets, we first feed the event to pretrained GlossBERT [74] (PersonX/Y/Z replaced by actual names) to determine the synset, and then pick its hypernyms. As for Probase nodes, we pick the ten best conceptualizations ordered by mutual information, which provides relatively high-quality and relevant results. Over-general or meta concepts like “word,” “noun,” “concept,” etc. are excluded.

4.2.2. Neural approach

In addition to heuristics, we use neural models fine-tuned on human-annotated data to be elaborated in Section 5. Based on PTLMs, those models are better at capturing the semantic meaning under the context for conceptualization. We carefully design the dataset aided by taxonomic knowledge, so that the models don't merely learn to induce by word co-occurrence in natural language, but also implicitly reflect taxonomic knowledge with reduced reporting bias, concept bias in particular. Nevertheless, neural LMs suffer from diversity and novelty issues, and the heuristic approach leverages more diverse knowledge explicitly from the taxonomy, much larger than our dataset. Therefore, both approaches are deemed essential.

To be more specific, we use a paired event conceptualization dataset $S_a = \{(x, y)\}$, each sample formed by an event conceptualization x and its binary label y , where each $x = (h, c)$ contains a head event h with the candidate identified, plus a concept c . The dataset is split into *trn/dev/tst* subsets according to the original ATOMIC partition, in which the head events in different subsets are ensured to be dissimilar.

Concept generation We first use a GPT2-based LM to generate possible concepts for the candidate in a way similar to COMET: Each positive sample $((h_i, c_i), y_i)$ where $y_i = 1$ is formed as a sequence of tokens $t_i = \text{Concat}[p_i, [\text{GEN}], c_i, [\text{EOS}]]$, with the head h_i represented in a prompt p_i . The standard causal LM loss on c_i is used: Suppose h_i plus [GEN] correspond to first m tokens in t_i with total n tokens, the loss is

$$L = - \sum_{t_i} \sum_{j=m+1}^n \log P(t_{i,j} | t_{i,<j}). \quad (1)$$

Conceptualization verification Finally, we combine the possible event conceptualizations from all the three sources, and feed them into a neural model as an ultimate gatekeeper to filter out those not matching the context, as exemplified in Fig. 7. As a text classification task, we fine-tune RoBERTa [75] to predict the valid probability $D_a(x_i)$ from the first hidden vector, using binary cross-entropy loss given the label y_i :

$$L = - \sum_{(x_i, y_i)} (y_i \log(D_a(x_i)) + (1 - y_i) \log(1 - D_a(x_i))). \quad (2)$$

4.3. Inference verification

Based on the abstract events we produce by the verified event conceptualizations, we can now inspect all the triples of their instance events as possible abstract events. By training a neural discriminator just like the conceptualization verifier on the validity of abstract triples, a model similar to the scorer in standard KG link prediction, the valid inferences on the abstract events (i.e. abstract triples) are determined.

5. Data collection

To build the neural models and to collect conceptualization data for future research, we annotate a large-scale dataset on the validity of conceptualizations on events and triples based on existing events and triples from ATOMIC, aided by Probase, expected to evade concept bias without sacrificing flexibility.

5.1. Data preparation

Before all else, we have to first clean, filter and parse the ATOMIC data to eliminate errors in the data that will hinder following conceptualization. This is by fixing errors, parsing the sentences, and dropping those with unresolved errors, leaving 23.6 K out of 24.3 K ATOMIC events for further processing.

The next step is to pick events and entities/eventualities suitable for annotation. First, we skip all events with wildcard objects (“_”), as they are over-generalized and prevent us from leveraging more taxonomic knowledge. All following data processing and experiments are performed on this filtered ATOMIC event subset of 18.9 K events. Then, we identify and skip 3.0 K events that are

PersonX finds a stray cat

Report Incomplete Set Phrase Report Error

What concept does "a stray cat" describe?

☒ stray cat "PersonX finds (the/that) stray cat" describes "PersonX finds (a stray cat)"

Add stray cat

The highlight part can also be: stray_cat

Reload Step 2?

Which ones are plausible abstractions for the given concept in the context?

stray cat

☐ predator ☒ wild animal

☐ specie ☒ free living animal

☐ pest ☒ animal

☐ animal problem ☒ free-living animal

☐ mammalian nest predator ☒ critter

☒ cat

Add cat

Submit

(a) An example for round one annotation interface.

PersonX finds a stray cat

Do the sentences below cover the meaning above?

PersonX finds stray cat ☒ Yes ☐ No

PersonX finds animal ☒ Yes ☐ No

PersonX finds animal problem ☐ Yes ☒ No

PersonX finds free living animal ☒ Yes ☐ No

PersonX finds critter ☒ Yes ☐ No

PersonX finds free-living animal ☒ Yes ☐ No

PersonX finds mammalian nest predator ☐ Yes ☒ No

PersonX finds predator ☐ Yes ☒ No

PersonX finds wild animal ☒ Yes ☐ No

PersonX finds feline ☒ Yes ☐ No

PersonX finds specie ☐ Yes ☒ No

PersonX finds mammalian ☐ Yes ☒ No

Feel free to add these determiners before the substitution to make it valid: the, a, PersonX's, some, the event of, the action of, at (the state of), with (the attribute of), ...

Submit

(b) An example for round two annotation interface.

I heard that PersonX gets hit by a car

Do the sentences below cover the meaning above?

I heard about (the/PersonX's) accident ☒ Yes ☐ No

I heard about (the/PersonX's) emergency ☒ Yes ☐ No

I heard about (the/PersonX's) traffic incident ☒ Yes ☐ No

I heard about (the/PersonX's) offense ☐ Yes ☒ No

I heard about (the/PersonX's) serious violation ☐ Yes ☒ No

I heard about (the/PersonX's) traffic offense ☐ Yes ☒ No

I heard about (the/PersonX's) emergency situation ☒ Yes ☐ No

I heard about (the/PersonX's) unexpected event ☒ Yes ☐ No

I heard about (the/PersonX's) car accident ☒ Yes ☐ No

I heard about (the/PersonX's) event ☒ Yes ☐ No

I heard about (the/PersonX's) injury ☒ Yes ☐ No

I heard about (the/PersonX's) traumatic event ☒ Yes ☐ No

Feel free to add these determiners before the substitution to make it valid: the, a, PersonX's, some, the event of, the action of, at (the state of), with (the attribute of), ...

Submit

(c) An example for round two annotation interface, for conceptualization of a whole event.

Question 1

If PersonX asks PersonY [marriage], after that/as result, the Effect on PersonX is: personX puts a ring on personY's finger.

How likely is this sentence going to happen? (Invalid if it does not make sense to you)

☐ Always / Usually

☐ Typical: Often / Probable

☐ Atypical: Farfetched / Never

☐ Invalid: Can't understand the meaning

(d) An example for a question in round three annotation interface.

Fig. 8. Screenshots for the web interface in the annotation process with three rounds.

idiomatic. This is because Wiktionary idioms are among the sources of events in ATOMIC, while set phrases like idioms do not follow the principle of compositionality, hence conceptualization of a particular part of an idiom is usually meaningless. Next, among the rest 15.9 K events, we identify 31.1 K entities and eventualities as conceptualization candidates using the rules above. This set of *ATOMIC conceptualization candidates* is used as the source of Abstract ATOMIC to be discussed in Section 6.3. In the end, we try to de-duplicate the candidates by removing and merging those too similar, so as to reduce costs, improve efficiency, and introduce more diversity and representativeness in the annotation. From the 18.7 K candidates in 12.0 K events after de-duplication, 10,000 of them are randomly picked for annotation of their event conceptualization, identified from 8,045 original ATOMIC events. More details for data preparation are available in Appendix B.1.

5.2. Crowd-sourced annotation

We recruit human workers on Amazon Mechanical Turk for annotation. However, even with human intelligence, the task can be difficult, as discussed in Section 2.4, and requires careful design, thorough guidance, stringent criteria, and annotators' painstaking work to obtain acceptable quality. We introduce the three-round annotation procedure below, while more details are available in Appendix B.2.

5.2.1. Entity/eventuality-level annotation

Concept linking annotation We ask the worker to annotate all the three level of conceptualization, starting from the entity/eventuality level upon all the 10,000 candidates, based on an interactive website as the annotation interface shown in Fig. 8. Given an event with the target candidate (entity/eventuality) highlighted, we first ask the worker to *type in* some concepts that *best describe* the entity as in (a). This parallels the concept linking step. The worker can only submit a concept available in Probase, checked by the back-end instantly during typing. We find that workers are able to give precise or even creative responses like "PersonX surfs the web"³ as "internet surfing," "PersonX tells PersonY's boss" as "sharing information," and "PersonX has always wanted to go to" as "long-

³ The underlined part of an event indicates the target conceptualization candidate.

Table 4

Statistics for the event/triple conceptualization annotation: the number of questions with agreement (i.e. not indecisive), the positive rate among agreed questions, and the agreement rate between annotators and with our manual check.

	Event	Triple
Total Questions	131,004	90,207
Questions with Agreement	92,235	81,197
Positives	40,833	65,900
Positive Rate	44.27%	81.16%
Inter-annotator Agreement	71.4%	73.0%
Manual Inspection Agreement	87.0%	86.5%

term goal” or “dream vacation”, though distinct from the expression in the sentence. Therefore the free typing approach to finding candidate concepts allows the worker to utilize their commonsense to produce rather flexible and high-quality results.

In case an erroneous or not understandable event escapes the filtering in Section 5.1, workers should click “Report Error.” While in addition to idioms, set phrases like “go to bed” do not follow compositionality as well, making conceptualization meaningless (e.g. if we conceptualize it to “furniture” and consider other instances like “go to chair”). Hence they should also report when the target is part of a set phrase.

Further conceptualization In the second step, the top ten Probase conceptualizations of each typed concept will appear below the typing section in the webpage, as in Fig. 8 (a). The worker is asked to select the appropriate ones that *cover* the meaning of the typed concept in the context. This allows the worker to consider various possible conceptualizations from the taxonomy that are often not as intuitive as BLCs, and hence alleviates concept bias mentioned in Section 2.4. The worker may still type their own answers, which will then be appended to the list for that concept for future workers to choose from.

5.2.2. Event-level conceptualization

A second-round annotation is carried out with the goal of verifying the first-round results explicitly at the event level for better quality. Among the 10,000 candidates, those not reported as *error* or *set phrase component* by any annotator are used to construct event conceptualizations to be verified, leaving 8,748 targets from 7,196 different ATOMIC events. For each target, we then build possible abstract events using all the concepts annotated for it in both steps of Round 1. As shown in Fig. 8 (b), we ask the worker to decide if each of the abstract events covers the meaning of the original one, i.e. if the event conceptualization is valid. Additional textual hints are given on the page when the target is a whole event as in (c).

5.2.3. Triple-level conceptualization

Next, we collect possible abstract triples to annotate their validity. Specifically, we sample a subset of conceptualization candidates in a DEP-balanced way. For each corresponding head event, we include all the instance triples paired with all the derived abstract events, so as to completely depict the inferences on all the conceptualizations of an instance. We reuse the pipeline to annotate ATOMIC-like triples in [76,77] with an interface like Fig. 8 (d), except that we instruct the workers to consider the validity of an abstract triple based on its instances as defined in Section 3.1.

5.2.4. Quality assurance

In all the three rounds, we go through a rigid process to recruit and educate workers. Only workers from English-speaking countries with good past records are included. Carefully written instructions along with more than 30 examples are provided for workers in each round that cover various cases in the annotation corresponding to those in Table 3. We also curate multiple sophisticated qualification tests, and inject random tests during the first 100 responses of each worker. Besides such gate-keeping during recruitment, quality assurance measures are also carried out during the whole annotation process: From time to time, we carefully monitor all the workers’ responses, randomly select them for manual inspection, send the workers explanations when errors are found, and listen to workers’ suggestions to improve the instructions and the interface. Error-prone workers are warned and then disqualified, and their annotations are discarded.

In all three rounds, each question is annotated by five valid workers. In Round 2, an event conceptualization is determined valid if it gets ≥ 4 out of 5 votes, and invalid if it gets ≤ 1 vote. In Round 3, we count a positive vote if the worker responds Always/Usually or Typical, otherwise negative. With a higher possibility for the candidates to be correct, we set the valid and invalid bar to ≥ 4 and ≤ 2 votes instead. All annotations with the number of votes in-between are deemed *indecisive* and discarded.

5.3. Annotation results

Statistics of the annotation are given in Table 4. As for events, we retrieve 40,833 positive conceptualizations upon 7,019 ATOMIC events towards 8,545 different Probase concepts, forming 18,964 different positive abstract events. Hence each abstract event is conceptualized from 2.15 candidates on average.

Table 5

Accuracy (%) of different conceptualization verifiers, including the *Supervised Discriminator* trained on our annotated dataset, *NS* trained by negative sampling, and using perplexity from a *Generator* as a scorer.

Accuracy	<i>dev</i>	<i>tst</i>
Supervised Discriminator	83.9	85.0
NS	78.4	78.8
Generator - Supervised	76.9	77.6
- GPT2 Zero-shot	55.1	58.5

Table 6

BLEU score (%) of our concept generator trained on our annotated dataset, cf. zero-shot GPT2 generations.

	BLEU-1		BLEU-2	
	<i>dev</i>	<i>tst</i>	<i>dev</i>	<i>tst</i>
Supervised Generator	65.1	68.0	61.1	56.5
GPT2 Zero-shot	25.0	20.4	4.8	2.6

Based on the positive abstract events, a total of 1,149,118 possible abstract triples are collected. Hence we have to limit the annotation to a small subset, randomly selected as mentioned above. In this way, 90,207 triples on 2,756 abstract events are annotated, based upon 708 entities or eventualities in 689 ATOMIC events. A total of 65,900 abstract triples are determined positive.

With a large-scale dataset collected, we then look at its quality and compute the inter-annotator agreement rate, both $>70\%$. Furthermore, we manually inspect 200 random samples with decisive answers from each stage, and find $>85\%$ agreement rates with the majority vote. Besides, with a majority of triples being valid, we compute the annotation precision to identify negative samples compared to our manual inspection, which gives 70.45%. All these results indicate that the annotation is consistent with acceptable quality.

A considerable amount of event and triple level candidates (46% and 19%, respectively) are annotated as negative. However, the candidate events in round 2 are proposed by annotators in round 1, and candidate triples in round 3 are valid inferences at least for some instance event. Therefore they are all reasonable in some sense, and can be all considered as hard negatives. The amount of such negative samples indicates the challenge of conceptualization on both levels that can not be handled by superficial induction, which highlights their value for model training. It is also noteworthy that there is an imbalance between the DEP of the annotated candidates. More details are available in Appendix B.3.

6. Abstract KG construction

With data annotated in Section 5, we are now able to train the models described in Section 4.2.2. Under a supervised learning setting, models are fine-tuned from PTLMs with textual prompts. Their performances are evaluated against multiple baselines. Then we apply the three-stage abstract knowledge acquisition approach discussed in Section 4 to ATOMIC, and harvest a large-scale abstract CKG, namely **Abstract ATOMIC**. More details of the experiments, including the prompts we use, are available in Appendix C.

6.1. Conceptualization modeling

Using the annotated event conceptualization validity dataset S_a , we can simply train the conceptualization verifier as a RoBERTa-based text classifier. While from the subset of positive samples S_a^+ , we can train the GPT2-based neural concept generator. The models are then evaluated on the *dev* and *tst* subset of S_a , measured by accuracy or BLEU-2 score for the two types of models, respectively. In addition, we report BLEU-1 for the generator since the reference concept often contains one word only.

In contrast, we build several baselines that do not (fully) rely on our annotated data:

1. Negative sampling (NS): As commonly used in KG completion, we build a discriminator only based on the positive subset S_a^+ . For each sample in S_a^+ where $(x_i = (h_i, c_i), y_i = 0)$, we uniform-randomly sample five $c'_{i,k}$ from all concepts C^+ appeared in S_a^+ to build five pseudo-negative samples, forming

$$S_a^- = \{(h_i, c'_{i,k}), y_i = 0 \mid (h_i, c_i) \in S_a^+, 1 \leq k \leq 5\}. \quad (3)$$

Then the discriminator is trained upon $S = S_a^+ \cup S_a^-$ similarly with binary cross-entropy loss.

2. Supervised generator: We also use the supervised generator as a discriminator by using the negated perplexity given each sample as its score, with the classification threshold tuned on *dev* set.

3. GPT2 Zero-shot: We directly feed the sample with a prompt into the pretrained GPT2 generator in a zero-shot way as a generator, or a discriminator using the perplexity score as well.

As shown in Table 5 and Table 6, both the Supervised Discriminator and Supervised Generator reach satisfying results, and both zero-shot models fail to produce high-quality predictions, highlighting the difficulty of our task and the necessity of our annotated

Table 7

AUC of models discriminating the validity of abstract triples: Supervised models trained on our annotated dataset, NS models trained by negative sampling, and one scorer based on a COMET-like generator directly trained on ATOMIC. Training data are possibly augmented by ATOMIC triples.

AUC	<i>dev</i>	<i>tst</i>
Supervised	0.72	0.74
Supervised + ATOMIC	0.73	0.76
NS - ATOMIC	0.62	0.65
- Annotated	0.67	0.67
- Annotated + ATOMIC	0.63	0.65
Generator (ATOMIC)	0.49	0.50

Table 8

The number of abstract events, event conceptualizations, and triples built upon ATOMIC, with different scores given by the corresponding verifier. Those included in the Abstract ATOMIC are underlined, indicating the large scale of Abstract ATOMIC. Abstract events are counted according to their corresponding event conceptualization with the highest score.

	0.7~0.8	0.8~0.9	≥ 0.9
Event Conceptualization (by Neural Concept Generator)	10.3 K	17.7 K	171.1 K
Event Conceptualization (by Heuristic Concept Linker)	8.3 K	11.5 K	81.3 K
Event Conceptualization (Total)	16.7 K	<u>26.2 K</u>	<u>203.0 K</u>
Different Abstract Event	4.3 K	<u>7.0 K</u>	<u>63.0 K</u>
Abstract Triple	542.2 K	937.2 K	<u>2,947.9 K</u>

data. Particularly, the supervised discriminator significantly outperforms the baselines, indicating the necessity of a validity dataset with negative samples annotated.

6.2. Inference verification modeling

We then train and evaluate models on the set of annotated abstract triples $S_t = \{(h_i, r_i, t_i)\}$ for inference verification, again adapted from RoBERTa, and report results with the measure of Area Under Curve (AUC) due to imbalanced data. While we also consider several baselines and alternative methods:

1. +ATOMIC: Since the abstract triples are often similar to ATOMIC triples, and the size of ATOMIC is much larger, we attempt to mix the cleaned ATOMIC data S_A created in Section 5.1 into training. We select a subset S_A^* based on randomly sampled heads in S_A with the same number of heads with S_t , forming a 1:1-mixed data $S_{mix} = S_t \cup S_A^*$.

2. Negative Sampling (NS): We train the model in a similar negative sampling manner, possibly combined with +ATOMIC, performing NS upon the ATOMIC samples S_A^* , positive samples in the annotated data S_t^+ , or a mix of $S_{mix}^+ = S_t^+ \cup S_A^*$. We form four negative samples with randomly sampled tails in S_A^+ , S_t^+ , or S_{mix}^+ per each positive one to match the ground truth proportion.

3. Generator (ATOMIC): we directly use a COMET-like generator for classification in the same way above, which is fine-tuned from GPT2-medium on ATOMIC and reaches a good 30.3 BLEU-2 score on S_A .

For models trained purely on ATOMIC data, concept indicators (brackets) are removed during evaluation.

As in Table 7, the supervised models significantly outperform all the models that do not (fully) rely on our annotated data, while +ATOMIC brings slight improvements. The ATOMIC generator is almost ineffective. All the results above indicate that PTLMs themselves have limited capabilities on the task and our annotated dataset is crucial, which is also consistent with observations from concurrent works evaluating conceptual knowledge of PTLMs [59,60].

6.3. Abstract ATOMIC

With the whole pipeline built and models available, we are now able to build a conceptualized version of ATOMIC for abstract knowledge that can be derived from ATOMIC under the framework in Fig. 7.

On all the 31.1 K entities or eventualities identified in ATOMIC after filtering as mentioned in Section 5.1, we apply the heuristic concept linker and the neural concept generator (with a 10-beam search), with outputs evaluated by the supervised discriminator. Event conceptualizations with scores no less than 0.8 are considered valid. We then run the supervised inference verifier for the possible abstract triples from the derived abstract events. Triples with scores no less than 0.9 are picked as valid, forming our **Abstract ATOMIC** that could be used for future conceptual induction. Similarly, Abstract ATOMIC is partitioned into *trn/dev/tst*, used in the following experiments, according to the split of the instance ATOMIC events.

Statistics of the Abstract ATOMIC are given in Table 8, regarding the number of events (from rules or models) and triples, whose scores fall in different ranges. The underlined numbers indicate the part that is considered valid and included into Abstract ATOMIC. As demonstrated, an extensive abstract CKG with total 70.0 K abstract events, 229.2 K event conceptualizations, and 2.95M abstract triples is induced.

Table 9

Manually-inspected validity for event conceptualizations and abstract triples built upon ATOMIC, in different verifier score ranges. Those included in the Abstract ATOMIC are underlined, indicating a satisfying quality of Abstract ATOMIC.

	0.7~0.8	0.8~0.9	≥ 0.9
Event Conceptualization (by Neural Concept Generator)	0.64	<u>0.72</u>	<u>0.88</u>
Event Conceptualization (by Heuristic Concept Linker)	0.67	<u>0.74</u>	<u>0.90</u>
Abstract Triple	0.41	0.55	<u>0.71</u>

Table 10

Performance (BLEU-2 score, %) for COMET-like modeling on an ATOMIC subset, possibly with the human-annotated or automatically-derived abstract triples injected, and possibly then fine-tuned on the target ATOMIC subset.

BLEU-2	GPT2-base		GPT2-medium	
	<i>dev</i>	<i>tst</i>	<i>dev</i>	<i>tst</i>
Baseline	17.4	17.7	19.8	19.6
+Conceptualization (human)	19.1	19.2	21.0	22.4
+Fine-tune	20.7	20.6	23.0	23.5
+Conceptualization (auto)	19.3	19.1	19.7	20.0
+Fine-tune	19.5	19.3	20.9	21.0
+Conceptualization (both)	18.7	18.5	21.0	21.6
+Fine-tune	19.0	19.0	22.4	22.9

As for the quality of this automatically-derived abstract CKG, from each score range of event conceptualizations and abstract triples, we manually inspect 100 random samples. As shown in Table 9, the validity is satisfying, though it indicates that the modeling of conceptualization remains rather challenging. It also explains why we have to pick a high threshold (0.8 or 0.9) for an acceptable (> 0.7) quality.

By comparing the total number of event conceptualizations with the number from the two routes in Table 8, we can find that both routes have their own contribution with only 22.9% overlap. More, we notice that the heuristic linker gives broader and more diverse candidates, as the large-scale taxonomy is explicitly leveraged. But it also brings more errors, which makes the discriminator crucial. While the LM generator produces a smaller number of conceptualizations that are more coherent to the semantic context and more likely to be valid. All these findings justify our dual-route design. See Appendix D for more details.

7. Extrinsic evaluation

7.1. Concept-aided ATOMIC modeling

We now intend to explore the possible use of abstract knowledge for commonsense modeling. It is intuitive that since abstract knowledge provides a more general view, it may help inference on commonsense knowledge, particularly when there is limited knowledge known.

Therefore, we attempt to inject abstract knowledge as a kind of data augmentation to COMET-like training. Given 65,900 human-annotated (*human*) abstract triples linked to 688 ATOMIC instance events, we pick a subset of ATOMIC and the automatically-derived (*auto*) Abstract ATOMIC corresponding to the same set of events. Then we perform COMET-like causal LM training on the ATOMIC subset, possibly mixed with the *trn* split of the *human* and/or *auto* abstract samples.

Since the abstract data contain more triples, the ATOMIC data is upsampled with a 1:2 ratio. In addition, the model can be fine-tuned on the ATOMIC subset we use after the mixed training. Experiments are carried out on both GPT2-base and GPT2-medium. We then evaluate on the whole ATOMIC dataset.

As reported in Table 10, all models injected with abstract knowledge can significantly outperform the baseline trained merely on the original non-abstract ATOMIC, while further fine-tuning will lead to varied improvements. Therefore, abstract knowledge, either annotated or automatically derived, may implicitly help the modeling of situational commonsense, even without any explicit instantiation.

7.2. Zero-shot commonsense QA

In addition to modeling the base CKG, we also try to explore the impact of conceptualization on the *zero-shot commonsense QA* task [15,89] to show the improvements abstract knowledge can bring to commonsense reasoning. This task assesses the model's ability to reason on unseen situations in a generalizable manner without any training on the target data [90]. For this goal, current state-of-the-art methods [16,55,91,92] leverage synthetic QA pairs transformed from CKG triples, where the head and relation are turned into a question using templates, and the tail serves as the answer. While distractors can be generated by sampling unrelated triples with the same relation, upon which PTLMs are fine-tuned using marginal ranking (MR) loss to create a general commonsense QA model, to be evaluated on various target benchmarks [14].

Table 11

Zero-shot evaluation results (Accuracy %) on five commonsense QA benchmarks. -L stands for the *-large* model, ATM_{10X} for $ATOMIC_{10X}$ [88], and Abs.ATM for Abstract ATOMIC (i.e. our approach). \uparrow stands for the accuracy gains by comparing models trained on Abstract ATOMIC against ATOMIC only. The best performances are bold-faced.

Model	KG	a-NLI [78]	CSQA [79]	PIQA [80]	SIQA [81]	WG [82]	Avg.
Majority label	-	50.8	20.9	50.5	33.6	50.4	41.2
GPT2-L [21]	-	56.5	41.4	68.9	44.6	53.2	52.9
RoBERTa-L [75]	-	65.5	45.0	67.6	47.3	57.5	56.6
DeBERTa-v3-L [83]	-	59.9	25.4	44.8	47.8	50.3	45.6
Self-talk [15]	-	-	32.4	70.2	46.2	54.7	-
COMET-DynGen [84]	ATOMIC	-	-	-	50.1	-	-
SMLM [85]	*	65.3	38.8	-	48.5	-	-
MICO [86]	ATOMIC	-	44.2	-	56.0	-	-
STL-Adapter [16]	ATOMIC	71.3	66.5	71.1	64.4	60.3	66.7
BUCA [87]	ATOMIC	-	60.3	-	61.4	-	-
RoBERTa-L + MR 340M	ATM_{10X}	70.8	59.4	72.1	58.5	58.3	63.8
	ATOMIC	70.8	64.2	72.1	63.1	59.2	65.9
	Abs.ATM	71.4 _{10.6}	65.8 _{11.6}	72.9 _{10.8}	65.5 _{12.4}	59.7 _{10.5}	67.1 _{11.2}
DeBERTa-v3-L + MR 435M	ATM_{10X}	75.1	71.6	79.0	59.7	71.7	71.4
	ATOMIC	76.0	67.0	78.0	62.1	76.0	71.8
	Abs.ATM	78.2 _{12.2}	68.1 _{11.1}	78.2 _{10.2}	63.5 _{11.4}	78.3 _{12.3}	73.2 _{11.4}
Large Language Models							
GPT-3.5 (text-davinci-003)	-	61.8	68.9	67.8	68.0	60.7	65.4
ChatGPT (gpt-3.5-turbo)	-	69.3	74.5	75.1	69.5	62.8	70.2
Supervised Learning & Human Performance							
RoBERTa-L (Supervised)	-	85.6	78.5	79.2	76.6	79.3	79.8
Human Performance	-	91.4	88.9	94.9	86.9	94.1	91.2

To investigate the effects of introducing abstract commonsense knowledge, we keep such QA synthesis protocol and model training process unchanged, and ablatively study the role of abstract knowledge. Specifically, we use ATOMIC as the base CKG, and Abstract ATOMIC as its top-on expansion for abstract knowledge. As for Abstract ATOMIC, we utilize both the human-annotated and the automatically generated data. Those abstract triples are synthesized into QA pairs in combination with the original situational ATOMIC triples to train the QA model, marked by **Abs.ATM**.

We report results of various existing baselines, including vanilla PTLMs such as RoBERTa and DeBERTa [83] as well as previous works on the task including Self-talk [15], STL-Adapter [16], etc., evaluated on multiple benchmarks including a-NLI [78], CSQA [79], etc., as listed in Table 11. We then compare the results obtained by MR [14] on ATOMIC and the much larger $ATOMIC_{10X}$ [88] against those obtained on Abstract ATOMIC to study the role of introducing abstract knowledge. As for methods that consolidate multiple CKGs, only ATOMIC is used as the knowledge source for fair comparison. We also report the zero-shot performance of GPT3.5 [93] and ChatGPT as two more competitive baselines [55].

As reported in Table 11, among the baselines the best performance is achieved by DeBERTa-v3-Large trained with the MR approach [14] on ATOMIC and $ATOMIC_{10X}$, followed by ChatGPT. The $ATOMIC_{10X}$ -based models fail to surpass the ATOMIC-based ones, suggesting the limitations of distilled commonsense knowledge from PTLMs in $ATOMIC_{10X}$. While our top-performing system, which is based on DeBERTa-v3-large with Abstract ATOMIC, outperforms all the baselines significantly, improving performance by an average of 1.4%, compared to the best baseline (the same model with ATOMIC). It also champions two challenging benchmarks and outperforms ChatGPT by an average of 3%. These results underscore the effectiveness of using abstract commonsense knowledge to benefit downstream QA tasks.

7.3. Transfer to ConceptNet

With a variety of formats for knowledge representation in different CKGs, it is valuable to verify if our constructed pipeline can be applied to other CKGs beyond ATOMIC, such as ConceptNet [18]. Therefore, we examine our GPT2-based concept generator obtained in Section 6.1. We randomly sample 100 event-like nodes from ConceptNet and prompt our model to generate plausible conceptualizations for each of them. To ensure consistency with the textual styles used in ATOMIC, we pre-processed the events using natural language templates as described by [76]. Then, we employ the skills of three postgraduate students well-versed in commonsense reasoning to carry out expert assessments on the generated conceptualizations and determine the proportion of plausible ones. The findings indicate that 76% of them are accurate, highlighting the value of generative models trained on Abstract ATOMIC annotations in comprehending and conceptualizing alternative form of knowledge in other CKGs like ConceptNet.

8. Example studies

In this section, we investigate some examples of the annotated and automatically derived data for event conceptualizations and abstract triples.

Table 12

Examples of positive and negative annotations on event conceptualization, target entities/eventualities underlined.

Event	Positive Annotation	Negative Annotation
PersonX gives <u>birth to children</u>	life event, giving birth, happy event	life skill, common procedure, routine medical procedure
PersonX wraps <u>PersonY's arms</u>	cuddling, hold, type of intimacy, embrace, holding, bodily contact	bind, physical barrier, protection, technique, cover
PersonX buys <u>a new iphone</u>	new iphone, product, iphone, smart phone, mobile technology, device	essential technology, item
PersonX takes PersonY <u>to the pound</u>	pound, animal housing facility, multi animal facility, animal shelter	non profit, currency, organization, unit, imperial unit
PersonX has trouble <u>paying PersonX's bills</u>	pay, payment, paying bill, expense	transaction, task, simple task, handle, routine task, service

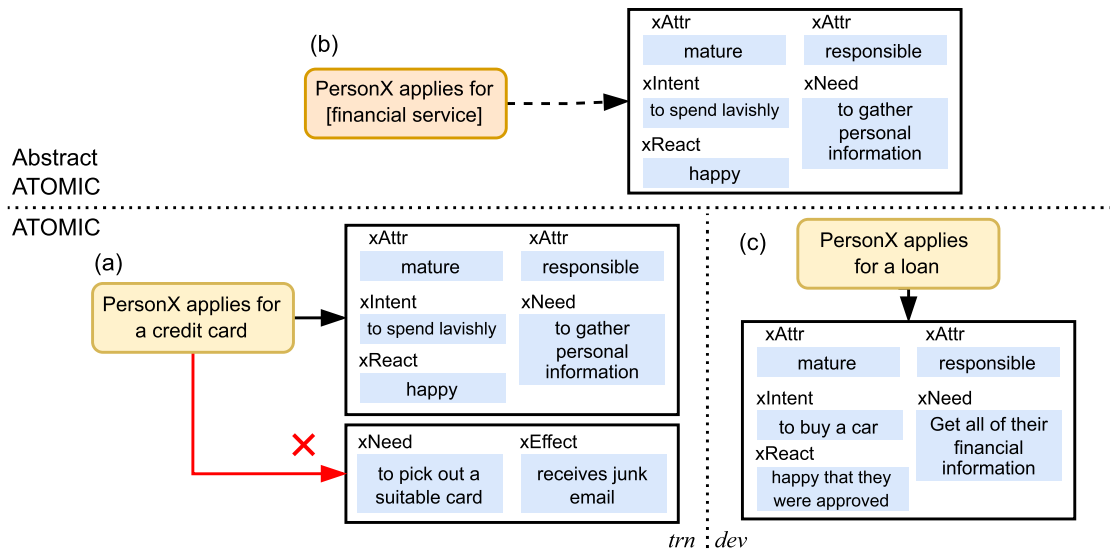


Fig. 9. An example of conceptual induction on the original ATOMIC based on Abstract ATOMIC. From an event and its triples from the ATOMIC *trn* split, the generalized abstract event and its inferences are built using our pipeline. Inferences deemed not typically held for the abstract event according to our inference verifier are excluded, marked in the red edge with a cross. Then the abstract triples could be instantiated to reason about an unseen event in the *dev* split.

Event conceptualization Examples of annotated event conceptualization are given in Table 12. We can find that the results are acceptable on various types of entities and eventualities, although not perfect (consider “mobile technology” and “item” for the “a new iphone” example).

Examples of event conceptualizations in Abstract ATOMIC are given in Table 13, some covered in the annotated data. We can find that the methods generalize to unseen entities and eventualities of various types, and the rule-based and neural routes complement each other, often both giving adequate results. Sometimes the rule-based ones can be more diverse and fine-grained, as in the “water bill” and “get a cold” case. By leveraging WordNet for word sense disambiguation and nominalization, rule-based results are improved, like the “bad day at work” case where the verb “have” is linked to the sense of experience. However, in some cases, heuristics give results of lower quality that are inadequate or incomplete, particularly in non-object cases (like in the “wrap” case) and those requiring contexts (like in the “bad day at work” case). Fortunately, those incorrect results are mostly ruled out by the verifier, which features its necessity as a final gatekeeper. The generator produces fair examples in most cases, although there are still generations that seemingly simply come from textual relevance, as in the results like “domestic pet” in the “pound” case.

Abstract triples Examples from both the annotated abstract triples and Abstract ATOMIC are given in Table 14. As a more challenging task, more errors are found. Nevertheless, many tails that hold only in specific instances are correctly excluded. For example, as for “PersonX calls [health professional],” tails regarding specific disciplines of health care (like those on “vet” and “dentist,” e.g. “xIntent: to clean their teeth”) should not be included. According to our manual inspection, among 31 tails collected from the instances and deemed negative, 22.6% fall in this category of over-specific ones. While among 115 tails classified as positive, there is a lower rate of 14.8%. Similarly, for the more general “PersonX calls [professional]” case, many of the health-related tails are identified and excluded.

Conceptual induction An example of conceptual induction is illustrated in Fig. 9. The event “PersonX applies for a credit card” can be found in the original ATOMIC as in (a). Using our pipeline, an abstract event “PersonX applies for [financial service]” is built in

Table 13

Examples of event conceptualizations in Abstract ATOMIC. Positive event conceptualizations according to the discriminator are marked in bold, and target conceptualization candidates are underlined.

Event	Linked Concepts	Heuristic-based Conceptualizations	Generated Conceptualizations
<u>PersonX gives birth to children</u>	giving birth, birth, gift	occasion, birth, life change, life event, happy event , gift, business courtesy, routine medical procedure, biological process	creation, birth, event, life event, life cycle event, life changing event
<u>PersonX wraps PersonY's arms</u>	wrapping	wrapping , surgical and endovascular procedure, technique	close contact, physical touch, physical contact, action , close
<u>PersonX buys a new iphone</u>	iphone, new iphone	ios device, smart phone, mobile device, device, iphone, apple device, product , product release, wishlist item, revolutionary product	smart phone, phone, product, iphone, electronic device, device, mobile device
<u>PersonX takes PersonY to the pound</u>	pound	pound, animal management facility , unit, measurement, poet, currency	animal shelter, animal facility, business, public facility , domestic pet, domestic animal, farm facility, place
<u>PersonX has trouble paying PersonX's bills</u>	pay, payment, payroll	expense related aspect, financial activity, payment, expense , banking service, financial service, longstanding issue, cost	paying bill, payment , transaction, pay, paying bills
<u>PersonX pays PersonX's water bill</u>	bill, water bill	bill, expense, basic household expense, user charge, utility bill, water bill , document, documentary evidence	bill, expense, water bill , calculation, transaction
<u>PersonX gets a cold</u>	contracting, cold	cold, common illness, illness, infection, minor ailment, respiratory infection, upper respiratory infection, viral infection , abiotic stress, contracting, work arrangement	cold, condition, sickness , injury, unexpected event
<u>PersonX has a bad day at work</u>	experience	experience , criterion, meeting specific requirement, personal characteristic, personal factor, qualification, variable	difficulty, negative event, problem, unpleasant experience , stress, unpleasant day

Table 14

Examples of positive and negative abstract triples in the annotated data (the first row) and the automatically derived Abstract ATOMIC (following rows). The *Instances* column shows examples of the original ATOMIC events that are the instances of the abstract event, indicated by the corresponding instances for the bracket-enclosed concept.

Abstract Event	Instances	Relation	Positive Tails	Negative Tails
PersonX buys [item]	a new chair, a new shirt, skateboard, etc.	xNeed xAttr xEffect	to go to the store, to open his wallet, to go to the clothing store decisive, stylish, excited, rich gets receipt, get a coupon, style changes	to pick out a new shirt athletic, utilitarian, carefree person x takes skate board home
PersonX calls [health professional]	the doctor, the dentist, the vet, PersonX's doctor, PersonX's dentist	xWant xIntent xNeed	set an appointment, to ask what they should do, to ask for device, to get a filling, to ask the doctor a question, to tell the doctor their problems to schedule an appointment, to help pet, to be healthy, to feel better dial the number, find the number, look up things online, to pick up the phone, to want them to get better, to research medical care in the area	to take their pet there, to ask a question to know about their pet, to clean their teeth, to be informed to have a sick animal, to get PersonX's doctor's phone number, to grab a phone
PersonX calls [professional]	the doctor, plumber, exterminator, cable guy, locksmith, etc.	oWant xIntent xEffect	set an appointment, to unclog the pipe, give an estimate a service, to make an appointment, be healthy, to watch tv a voice mail plays, admits in hospital, gets advice, waits for their appointment	catches rodents, to get paid, to make a new key to change a lock, to clean their teeth, to be informed, to fix some plumbing PersonX has to pay a bill for the repairman, is checked by the doctor, ask a question
[homecoming]	PersonX makes it home safely, PersonX comes back, PersonX comes to PersonY's house, etc.	oWant xIntent xReact	to greet PersonX, to hug him, to help him relax, to eat out, to invite PersonX inside see their family, to get home, to sleep, see their family, to attend some competition cozy, happy, nostalgic, relaxed	To greet X, to go eat, to have dinner, to talk to PersonX have a break from learning, to attend the wedding, to be with someone drink, ready to eat, sleepy

Abstract ATOMIC, along with its inferences in (b). Some of the credit-card-specific inferences marked by red edges in (a) are excluded by the verifier, so that abstract triples in (b) are mostly valid in the general sense. There is also an event "PersonX applies for a loan" in the *dev* set as in (c), which is a new and unseen one under the ATOMIC split. It could be conceptualized to the event as well through our pipeline. Therefore the abstract triples can be instantiated to the (c) event to create inferences like "xAttr: responsible,"

“xNeed: to gather personal information,” etc. Its ground truth ATOMIC inferences are given in (c), and we can find that our inferences through the conceptual induction pipeline are identical or relevant to them.

9. Related work

9.1. Commonsense knowledge acquisition

As an indispensable component of AI, there has been plenty of work studying commonsense knowledge, for which the primary step is to acquire the knowledge. Below introduce the approaches for commonsense acquisition, which can be broadly classified into four types. We then discuss our choice to base our research upon the event-centric textual CKG, ATOMIC, by comparing it with other types of knowledge.

Human annotation Human annotation has been a critical part of collecting commonsense starting from early pioneer works, possibly as logical formulae in Cyc [40,94] or textual assertions in OMCS [95], which is later utilized as a core part of the renowned ConceptNet [32,18] focused on entity-centric knowledge. There are also attempts to annotate event-centric/situational knowledge, with focuses on social commonsense [96,2]), dialog [97,98], and narratives [3], as well as ATOMIC [1] and ATOMIC-2020 [17] with a range of dimensions of if-then reasoning on events. Despite their high quality, such CKGs suffer from limited scale and coverage over various entities and eventualities, as well as potential human bias [99] possibly including concept bias. These drawbacks stand among our major motivations to introduce conceptualization.

Information extraction To scale up the size of CKGs, automatic extraction from large corpora based on dedicated schema and templates comes out as an alternative solution [34,100,101]. On top of them, ASER [4,102] proposes a unique paradigm to retrieve a large-scale CKG for eventualities as linguistic graphs of predicates and their arguments linked by various discourse relations. However, without human supervision, such methods suffer from much lower quality and larger noise despite much their larger scale. Moreover, they are particularly exposed to reporting bias, including concept bias. Hence such CKGs alone may not be ideal for our goal to acquire high-quality knowledge covering various entities and eventualities.

Generating from language models With knowledge from enormous pretraining data internalized into PTLMs, a pile of works is conducted to mine knowledge from them [46–48,103], which engenders a line of research to directly use PTLMs as commonsense KB, even as a source of knowledge to train COMET [88], possibly through various prompt discovery methods [104–106]. Furthermore, they are directly applicable to commonsense reasoning tasks [107]. However, as mentioned in Section 2.3, LMs merely based on induction from word co-occurrence may not generalise well to diverse entities and eventualities, while we explicitly incorporate taxonomy and annotated conceptual knowledge to tackle the problem.

Extending from existing knowledge graphs A number of efforts have been made to complete or extend existing CKGs by commonsense reasoning and modeling, and our conceptual induction approach can be also viewed as one of them. Early works are mostly focused on logical reasoning [33], while link prediction or densification of factual KGs based on structural information using negative sampling is a well-studied task [108]. As for CKGs, with the importance of semantic information in text-form nodes, NLP methods become essential [109,110]. More recently, there are many attempts to combine semantic and structural information [111–116], which might be valuable for conceptualization as well. Nevertheless, we focus on text-based approaches and left it for future work.

In addition to the densification approach that only brings new edges, there are also generative models to predict new tail nodes given text-form events [117], which leads to COMET [20]. The successive work is further focused on directly using the model COMET-ATOMIC-2020 as a neural KB for commonsense inference from an event [17]. We follow a similar approach to view the extension of existing CKGs as an NLP task, with PTLMs as a key component. However, we leverage taxonomies instead of mere PTLMs to directly create more abstract events and make higher-level inferences upon them, and such abstract knowledge is essentially distinct from the original lower-level situational knowledge.

Another approach is CKG population, like TransOMCS [118] and DISCOS [5,76], which extends CKGs by transferring from external knowledge [119], e.g. from the larger and noisier extracted CKGs to smaller human-annotated ones. Attempts like CSKG further try to combine existing CKGs altogether [120,121], which have been shown promising for downstream tasks [14]. They are also close to our approach to extend existing CKGs with other KGs, but we are specifically motivated by human conceptualization and thus focused on utilizing external taxonomic knowledge.

Comparison with other types of knowledge We follow ATOMIC to study the **event-centric commonsense** represented by rather free-form texts in an intuition-based approach. As mentioned in Section 2.2, this is distinct from Cyc-like **symbolic reasoning** [40,41], **factual knowledge** defined in traditional KBs like DBPedia [39], Freebase [122], and YAGO [123], as well as **entity-centric commonsense** like ConceptNet [32,95,100,124]. It is also different from **script knowledge** [125,126], which represents “a standardized sequence of events that describes some stereotypical human activity” [127]. Although both centered on events, script knowledge focuses on the *sequence* of events that leads to a potential script, while ATOMIC-like CKGs are *graphs* defined by pairwise relations, which highlight diverse possibilities of outbound edges for an event. Also, script knowledge is focused on temporal relations between events, whereas ATOMIC covers a broad range of dimensions including intentions, prerequisites, attributes of the agent, etc. Although there are efforts to distill pairwise relations among events from script chains, such as temporal event relation extraction

[128] and script knowledge graph construction [129], the focus is restricted to the temporal ordering of events without considering broader and more fine-grained commonsense inferences.

As discussed in Section 2.2, the choice of the ATOMIC approach is backed by multiple theoretical advantages. While from practical aspects, ATOMIC enjoys relatively high quality compared to many other automatically extracted event-centric CKGs, hence desirable as the foundation for dataset annotation and CKG extension with optimal quality. Furthermore, being event-centric and represented in texts, ATOMIC knowledge can be flexibly applied or transformed to suit various commonsense-related tasks over natural texts. For example, fine-tuning a QA model on ATOMIC leads to more robust performance on multiple commonsense QA benchmarks [14,16], and training COMET on ATOMIC results in more resilient and diverse commonsense inference generation compared to ConceptNet [17]. ATOMIC has also demonstrated its usefulness in other commonsense-related tasks such as empathy dialog generation [8] and story generation [130]. Such superior downstream performance further justifies our choice to use ATOMIC.

9.2. Conceptualization

Conceptualization, as a significant component of human intelligence [25], has been investigated before under various contexts, including NLP, commonsense knowledge, as well as symbolic reasoning. Also, concept linking is necessary for the conceptualization from text. Below introduce these previous works.

Conceptualization on natural language Our work is based on conceptualization upon entities and eventualities represented by natural texts, which has been investigated in multiple previous works. Taxonomies like WordNet [42] and Probase [19] collect *is-a* relations between words, and hence provide context-free conceptualization on entity-level semantics, which is essential for more complicated scenarios like our case. Based on that, an early line of work is particularly interested in conceptualizing verb arguments into WordNet nodes of appropriate abstractness (namely BLCs) to model selectional preference by co-occurrence statistics [131–133], using various heuristics or statistic models [134–137]. While they are all based on the strict WordNet hierarchy, and do not match our goal to cover a broader set of non-BLC concepts.

Similar to our choice as discussed in Section 2.2, the more flexible non-hierarchical Probase with more fine-grained concepts and informative *is-a* edges has been leveraged to conceptualize verb arguments [138,139], conceptualize entities in short texts like search queries, or further represent the meaning of the query by concepts [140–142]. In addition to all these context-free cases, contextualized conceptualization, as emphasized in our framework, is also carried out by leveraging the topic [143] and relations between entities and verbs/attributes [144] as well as other entities [145] within the text.

All methods above are based on heuristics, statistics, or at most traditional machine learning techniques. While recently, [146] leverages neural models to classify entities in texts towards Probase concepts. Nevertheless, all those works are substantially different from ours as they are 1) not aimed at capturing commonsense knowledge; 2) not covering the general sense of conceptualization upon all eventualities but restricted to nominal entities; and 3) not based on modern PTLMs with sophisticated semantic understanding for contextualized conceptualization. While very recently, there are attempts to examine PTLMs' conceptual abilities [59,60], which discover that current PTLMs have limited capabilities in memorizing *is-a* relations, understanding properties of concepts, and particularly, performing conceptualization within the context, even after fine-tuning on labeled data. This supports our choice to combine PTLMs, taxonomy, and annotated data in the whole pipeline so that we could reach satisfying results.

Conceptualization for commonsense knowledge Unsurprisingly, conceptualization has been applied to commonsense knowledge as well, such as works to summarize abstract knowledge from KNEXT using WordNet [71], and to instantiate arguments to induce more specific triples [147], which are most similar to our work, though both before the emergence of current neural NLP techniques and flexible event-centric CKGs. Other explorations include matching concepts in software specifications to identify ambiguities [148], and to harvest relations between nominal BLCs based on patterns upon texts [149].

More recently, VoCSK induces plausible eventualities by summarizing arguments of verb phrases to BLCs by the minimum description length using Probase [150,151]. Similarly, [29] measures the consistency of neural models given texts with arguments in different abstractness and attempts to improve consistency and to leverage BLCs for scoring eventualities. Hence they are different from our work, which considers all types of entities and eventualities towards concepts of varied abstractness, including non-BLCs. While GenericsKB directly extracts and annotates statements or generics that apply to all instances of certain central concepts, similar to abstract events in our framework, but more focused on common factual knowledge instead of commonsense [152]. [153] instead directly prompts and controls PTLMs to generate generic statements about a set of concepts. Both of them are limited to generics that may naturally appear in language and thus suffer from reporting bias, while the abstract events that are more general but less linguistically natural are covered in our approach. [154] defines instantiations and exceptions (part of them being invalid instances in our words) of generics in logical forms. Their approach is similar to our framework but in a different direction that identifies concepts from 653 known textual generics by parsing, replacing the concepts with instantiations (instead of conceptualizations in our framework), and then scoring the candidate instantiations and exceptions based on PTLMs. Focused on the instantiations and exceptions of known generics, the method is unlikely to cover the broad range of situations in the world.

More importantly, the works above are all limited to conceptualization within an event, without touching high-level conceptualization upon non-nominal concepts, such as clauses and the whole event, as well as the even higher-level relations between those abstract events (i.e., abstract triples). ASER 2.0 makes a significant step forward to include abstract triples based on Probase statistics, but is still limited to the conceptualization of arguments within eventualities [4]. Several recent works cover conceptual relations

between eventualities: ELG harvests *is-a* relations between whole non-abstract eventualities [155], [156] attempts to identify entailment relations between ASER eventualities, and FolkScope utilizes conceptualization to extract the abstract intention behind various event types common in online shopping experiences [157]. All these methods above reflect some aspects of the conceptualization approach presented in this paper, but none of them systematically analyze and implement the whole human conceptual induction process.

Machine reasoning through concepts Instead of approaches mentioned above centered around natural language, reasoning based on concepts and taxonomic relations has been heavily discussed in the early symbolic methods for AI, particularly on commonsense reasoning. For example, [69] defines abstraction on formal systems for theorem proving, [70] introduces inheritance and default inheritance of attributes of entities based on description logics [158], while [28] represents ResearchCyc into first-order logic with quantifiers. Particularly relevant, inheritance reasoning is a type of non-monotonic reasoning to draw conclusions about the properties of objects based on their inheritance relationships [159–161] through methods like shortest path reasoning [162] and most path reasoning [163]. They focus on determining incorrect reasoning paths of exceptions, for example, the exception of “penguins don’t fly” versus the general default inheritance of “birds can fly” [154]. Instead, we focus on the inverse process of conceptualizing an instance.

Nevertheless, as discussed in Section 2.5, due to the complexity and defeasibility of the real world and human cognition of this world, it is elusive to represent all such commonsense knowledge in formalized forms for symbolic reasoning, and this is the same for such formalized reasoning approaches. This is also supported by the recent researches that already apply our approach for commonsense modeling and reasoning on automatically constructing new training data based on our Abstract ATOMIC using one-hop conceptualization inference, such as in few-shot COMET [164] and zero-shot commonsense QA [55].

Concept linking Concept linking is a non-trivial task, and previous attempts of conceptualization on texts are mostly based on word matching, possibly with additional heuristics [13]. There are also works restricted to a limited set of strict ontologies using heuristic or statistic methods [165,166]. For the more general case on ConceptNet, heuristics have been developed on word chunks [167] and linguistic features on the dependency tree [168,169]. As for concept linking to Probase, there are methods to use the longest covering concept [141] or statistic scoring [145], and YAGO or DBpedia entities have been used as intermediate proxies [170]. Besides, ComFact [171] annotates data on relevant retrieved facts based on sentence embedding similarities, while they focus on fact instead of concept linking on dialog systems. Different from previous methods, our work reaches better and more generalized concept linking by a set of sophisticated rules covering both nominal and verbal candidates, combined with strong generative and discriminative models.

The task is also related to ultra-fine entity typing [172], which can be achieved by various methods such as leveraging box embeddings [173], weak supervision from PTLMs [174], and label reasoning [175]. But instead of typing a nominal entity into free-form phrases, our goal is to link the nominal or verbal candidates to pre-defined textual concepts, so that we can leverage known taxonomic knowledge for conceptual induction.

10. Conclusion and future work

In this paper, we formulate the task of conceptual induction on commonsense knowledge graphs (CKGs) and design a pipeline to replicate the human conceptual induction, so that we can apply known knowledge to unseen entities and eventualities. A large-scale dataset for the validity of conceptualizations of entities and eventualities is annotated. Upon that, neural models are trained as part of the pipeline. Combined with heuristic rules, we create a large abstract CKG, and demonstrate its application in downstream tasks.

Considering the limitations of our work, future work will be focused on three aspects:

1. To improve the quality of the data, the pipeline, and the inferred abstract knowledge. As a crowd-sourced dataset, our annotated data inevitably contain errors, and the difficulty of our task amplifies this situation. Hence it is important to further clarify the annotation criterion and clean the data accordingly. As for our pipeline, recently, large language models have been introduced to commonsense reasoning, along with various parameter-efficient training methods. Improvements in the neural model and fine-tuning strategy, as well as better formalization, might be incorporated to capture abstract knowledge with higher quality.

2. To depict more detailed aspects in commonsense modeling and conceptualization, as various more sophisticated cases of conceptualization are yet to be explored. For example, modality, negations, and other modifiers in the context make subtle differences in the concept and inferences, while in our work, they are either ignored or conceptualized as a whole without more finer-grained analysis, such as inspecting the relationship between a concept and its negation. Also, groups of concepts with certain logical or quantifying relationships (e.g. “doctor and nurse,” “a cup of tea”) are common in our language but not precisely handled in our implementation. The case is similar for event groups. An example is that one will eat only if there is food *and* the person is hungry. Furthermore, more in-depth analysis of the inferences, such as probabilities for the consequences and exceptions among instances (like “penguins can’t fly”) will be desirable.

3. To apply the method in more scenarios, as the value and potential applications of our method are not fully explored in this paper. The framework can be applied to other CKGs, for example, to perform conceptualization and to form the abstract version of discourse-based commonsense knowledge as in ASER. Also, since abstract knowledge is shown to be helpful for commonsense modeling, efforts can be made to develop better methods to utilize the knowledge. For example, abstract knowledge collected through our pipeline might be directly applicable to commonsense reasoning tasks, possibly through instantiations.

CRediT authorship contribution statement

Mutian He: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Tianqing Fang:** Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing, Validation. **Weiqli Wang:** Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing, Validation. **Yangqiu Song:** Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Link for the data and code is provided in the article.

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Appendix A. Concept linking rules

As shown in Table 3 above, in addition to the simple case when we can directly match the headword with some concept, we also consider various other phenomena. Additional explanations are provided below.

Headword concepts The simplest case is when the headword itself directly corresponds to the concept. For each nominal headword, we try to match possible concepts with both of its original and lemmatized forms (using spaCy), possibly prepended/appended by the modifiers before or after it within the constituent according to the DEP tag. Regarding predicative candidates, in addition to finding the nominal form by WordNet or NOMBANK (more specifically, NOMLEX-PLUS), we also search for the adjuncts and arguments by DEP tag after it within the constituent, so that we can identify phrasal verbs in WordNet or verb phrases by combining with the argument.

Non-headword concepts The headword of the constituent may not represent the actual concept. For nominal candidates, transparent nouns like classifiers (e.g. “a cup of tea”), which take the semantic property of their argument, are thoroughly discussed by NOMBANK [176]. In such cases, the head noun is more like an optional modifier to its argument, hence we directly conceptualize the argument without considering the head noun. While there are also words that are not strictly transparent (e.g. “a group of people”) and not covered in NOMBANK, in which case we include both the head noun itself and the argument, as both of them make sense as the conceptualization of the constituent, and the combination of them, though more precise, may not appear in the taxonomy. After all, they can still be filtered out in later stages if found not suitable in the end. As for predicative candidates, we follow the same idea when handling light verbs and catenative verbs (e.g. “take a shower” and “want to go”) by including both of them for further conceptualization. While in the more certain cases like auxiliary verbs (e.g. “used to swim”) or raising-to-subject verbs (e.g. “appears to be happy”) that are similar to transparent construction with limited semantic impact, we conceptualize the predicand directly. For certain verbs (e.g. “go shopping”) and adjectives (e.g. “be able to speak English”) with rather light semantic meaning comparable to auxiliary/modal verbs, we follow this protocol as well.

Conjunction A special case is a conjunction like “doctors and nurses,” which is unlikely to be present in the taxonomy. However, the inferences on the event are often both valid when applied to the two abstract events based on either side: after PersonX “sees doctors and nurses,” “sees [doctor],” or “sees [nurse],” in all the three cases PersonX will get treated. Therefore, in this work, to enrich abstract knowledge for further use, we link the constituent to both “[doctor]” and “[nurse]” based on its two conjuncts, though the constituent is not precisely their instances.

Appendix B. Data collection

B.1. Data preparation

Regarding the foremost step of data cleaning, we first attempt to fix a number of language errors in ATOMIC events, including incomplete sentences, errors in verb forms, misuse of inflections, inconsistency of tense and aspect, missing verbs and marks, etc. We curate a set of rules to fix them and to change some expressions (such as replacing PersonX/Y/Z with person names and underlines

to proper-noun-like names, and fixing missing determiners and possession case marks) so that the sentences can be more accurately parsed. Total 5.4 K events are changed in this cleaning process. Then we parse the sentences and restore the replaced words. Next, we remove events with obviously impossible dependency trees. We find that they indicate unresolved grammatical errors. Finally, we remove all duplicate events after the cleaning.

Regarding the filtering of idioms, we match the events with the sources like entries crawled from the English Wiktionary labeled as idioms, which is supposed to be the original source of those idioms in ATOMIC. Later, when identifying the entities/eventualities, we exclude cases like PersonX/Y/Z and pronouns which have limited value for conceptualization, save transparent ones like “all of the people.” As for the de-duplication process, similar sentences and clauses such as those with only differences in a set of minor modifiers (e.g. determiners) are merged. Also, for better entity diversity, a candidate is skipped if it is linked to a non-verbal WordNet synset with a probability above 0.75 from GlossBERT and the synset has been included for more than five times. When considering the instance triples, all “none” tails are excluded.

B.2. Crowd-sourced annotation

Annotation platform During the crowd-sourced annotation, we leverage the Mechanical Turk platform to recruit the workers, run qualifications, and collect the results. In addition to the HTML templates provided by the website, we also leverage the functionality of *external questions* to host the question by ourselves, which allows flexible interaction with the back-end such as matching the typed concept with Probase instantly, so as to optimize the experience and productivity of the workers.

Annotation targets As reflected by the scale of Abstract ATOMIC, we can induce an extremely large number of possible abstract triples from ATOMIC, hence we are bound to annotate a very tiny subset of them. Therefore, for better representativeness, instead of sampling a set of largely unrelated triples to annotate, we choose to sample a subset of identified conceptualization candidates (entities or eventualities) in the original ATOMIC events. For each selected candidate, we include abstract triples upon all its corresponding conceptualizations. In this way, all the possible positive and negative samples based on each selected candidate (which contrast with each other) can be completely depicted. Furthermore, due to the imbalance of the types of candidates regarding their DEP, to be illustrated below, abstract events on candidates with less-presented DEP tags are up-sampled by exponential balance to give more diversity. The number of selected candidates of each DEP $N_i \propto p_i^{0.8}$, in which p_i is the proportion of candidates with each DEP among all DEP tags.

Quality assurance We carry out multiple quality assurance measures. Regarding worker recruitment, we only consider experienced workers with above 95% past acceptance rate on at least 1,000 tasks. We then provide carefully written instructions for workers that cover various cases in the annotation corresponding to those in Table 3, along with more than 30 examples for each round. In this way, the workers may understand the goal to find correct event conceptualizations and to determine the validity of abstract triples according to our defeasible and intuition-based criterion upon their instances. For the first two rounds, tests with confirmed answers are randomly added to the first 100 responses of each worker to probe the workers’ correctness. Additionally, for the second and the third rounds that require more accurate answers, workers need to pass qualification tests beforehand to prove their understanding of our requirements. As for the second round, two tests are used. The first practice test allows the worker to take it multiple times, and the worker could pass it only if all of the 13 yes-or-no questions are correctly answered, so that the workers are well-trained on the requirements. The second one, which requires a score of 13 out of 15, serves as a real gatekeeper that the worker may take only once a day. As for the third round, we conduct a qualification test as well, with a bar of 9 out of 10. All test questions are carefully curated to represent typical but challenging cases in the annotation.

B.3. Annotation statistics

Some additional statistics are given in Fig. B.10, which highlights the distribution of candidates with different DEP tags. As shown in (a), 24,622 (60.3%) entities or eventualities as conceptualization candidates have the *ROOT* DEP tag corresponding to the whole sentence. This is intuitive because each ATOMIC event itself can be conceptualized as a whole, but it does not necessarily contain other candidates. Following *ROOT*, other common DEP tags are *dobj* and *pobj* for nominal objects. There is a tail of other less common DEP tags, such as complement and clauses, many of them representing verbal concepts inside an event. This imbalance of DEP is the reason for us to implement the DEP-balanced sampling for picking the samples for triple-level annotation. To construct a diverse and complete dataset, all these types are included. As shown in (b) and (c), though not completely balanced in positive rate, candidates of each type of DEP produce a number of different event conceptualizations and abstract triples deemed positive. Numbers of abstract triples of each relation are imbalanced, which is due to the imbalance in the original ATOMIC, but added by the discrepancy of positive rates, ranging from 77.8% to 90.0%, as in (d).

Appendix C. Empirical experiments

C.1. Model configuration

In all the experiments, the model configurations are decided empirically. In a series of pilot experiments, we attempt to use alternative text templates, such as different usage of special concept tokens and different prompts, but no meaningful improvements are found. The case is similar to alternative hyper-parameters.

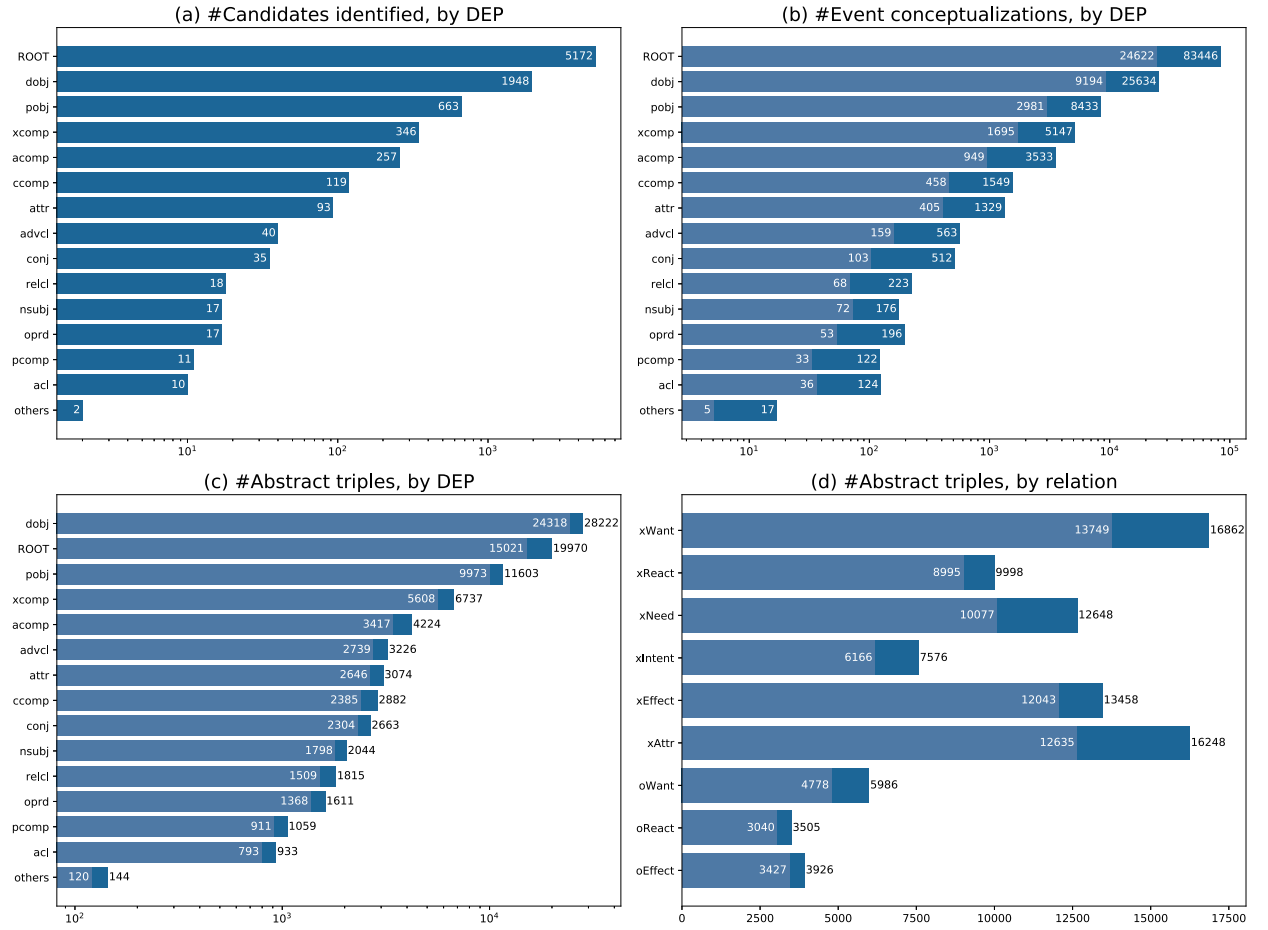


Fig. B.10. Statistics of data used in and from annotation, when split by DEP tags and relations. Positive samples are shown in the lighter-colored sub-bars. Due to the large range, the first three sub-figures are in log scale.

Table C.15

Textual prompt for the relations used in the template for inference verifier.

Relation	Prompt
xNeed	Before that PersonX needs:
xIntent	PersonX's intention is:
xAttr	PersonX will be described as:
xEff	Effects on PersonX will be:
xWant	After that PersonX wants:
xReact	After that PersonX feels:
oEff	Effects on others will be:
oWant	After that others want:
oReact	After that others feel:

The conceptualization verifier is derived from RoBERTa-base under the common fine-tuning setting, with batch size 64 and learning rate $2e-5$ to match our computational resources, and so is the conceptualization generator, from GPT2-base with batch size 32 and learning rate $1e-5$.

The models are trained using the *trn* subset of the dataset and validated on the *dev* subset. Regarding the abstract event dataset, the partition of each abstract event is decided by the ATOMIC partition of its instance ATOMIC event. When there are many, we follow the event that appears the earliest in ATOMIC. The partition of each abstract triple follows the partition of the head abstract event.

The discriminator or verifier is measured by accuracy with the classification threshold tuned on *dev* set, while the generator is measured by BLEU-2 scores from the best output of a 10-beam search. The model with the best performance on *dev* subset across different training steps is used to report the result on the *tst* subset.

C.2. Model prompts

As mentioned above, we formulate the samples into textual inputs to the NLP model by textual templates/prompts chosen through pilot experiments, as demonstrated by the examples below.

As for the conceptualization verifier on event conceptualization, we concatenate the event (with the candidate indicated) and the concept, separated by the [SEP] token. For example, when conceptualizing “PersonX drinks a cup of coffee” into “beverage”, the whole prompt will be:

```
[CLS] PersonX drinks [a cup of coffee] [SEP] beverage
[SEP]
```

As for the neural concept generator, the model is expected to generate the tokens after the [GEN] token, similar to COMET. For the example above, the whole prompt will be:

```
PersonX drinks <c> a cup of coffee </c> . <c> a cup of
coffee </c> is an instance of [GEN] beverage [EOS]
```

As for zero-shot conceptualization verifiers like GPT2 without any fine-tuning, we replace the PersonX/Y/Z with persons' names and try to feed the input with a prompt more similar to natural language. For the example above, the whole prompt will be:

```
Anderson drinks “a cup of coffee.” “a cup of coffee” is an
instance of beverage [EOS]
```

As for the inference verifier, we use a template similar to the conceptualization verifier, but with the relations indicated using prompts given in Table C.15. For example, for $\langle h: \text{PersonX drinks [coffee]}, r: \text{xReact}, t: \text{refreshed} \rangle$, the whole prompt will be:

```
PersonX drinks [coffee] [SEP] After that PersonX feels:
refreshed [EOS]
```

While regarding the Generator (ATOMIC) model trained in a COMET-like way for discriminating abstract triples, we also adopt the COMET template with a separate token per relation. For the example above, the whole prompt will be:

```
PersonX drinks coffee [EOS] [GEN] [xReact] refreshed [EOS]
```

Appendix D. Abstract ATOMIC statistics

More statistics of Abstract ATOMIC are demonstrated in Fig. D.11. Discussions in Section 6.3 are supported by (b): Heuristic rules (orange bar) produce a large number of potential event conceptualizations, but the acceptance rate is relatively low. While the generator (blue bar), as a PTLT, produces fewer samples but fits better with the context. This highlights the crucial role of the PTLT-based verifier to filter out the event conceptualizations unsuitable in the context. In addition, Abstract ATOMIC has an imbalance similar to the annotated data as shown in Fig. B.10 regarding DEP tags and relations, due to the limitation of the base dataset ATOMIC, but still it reaches a good coverage of various DEP tags (i.e., types of entities and eventualities) and relations.

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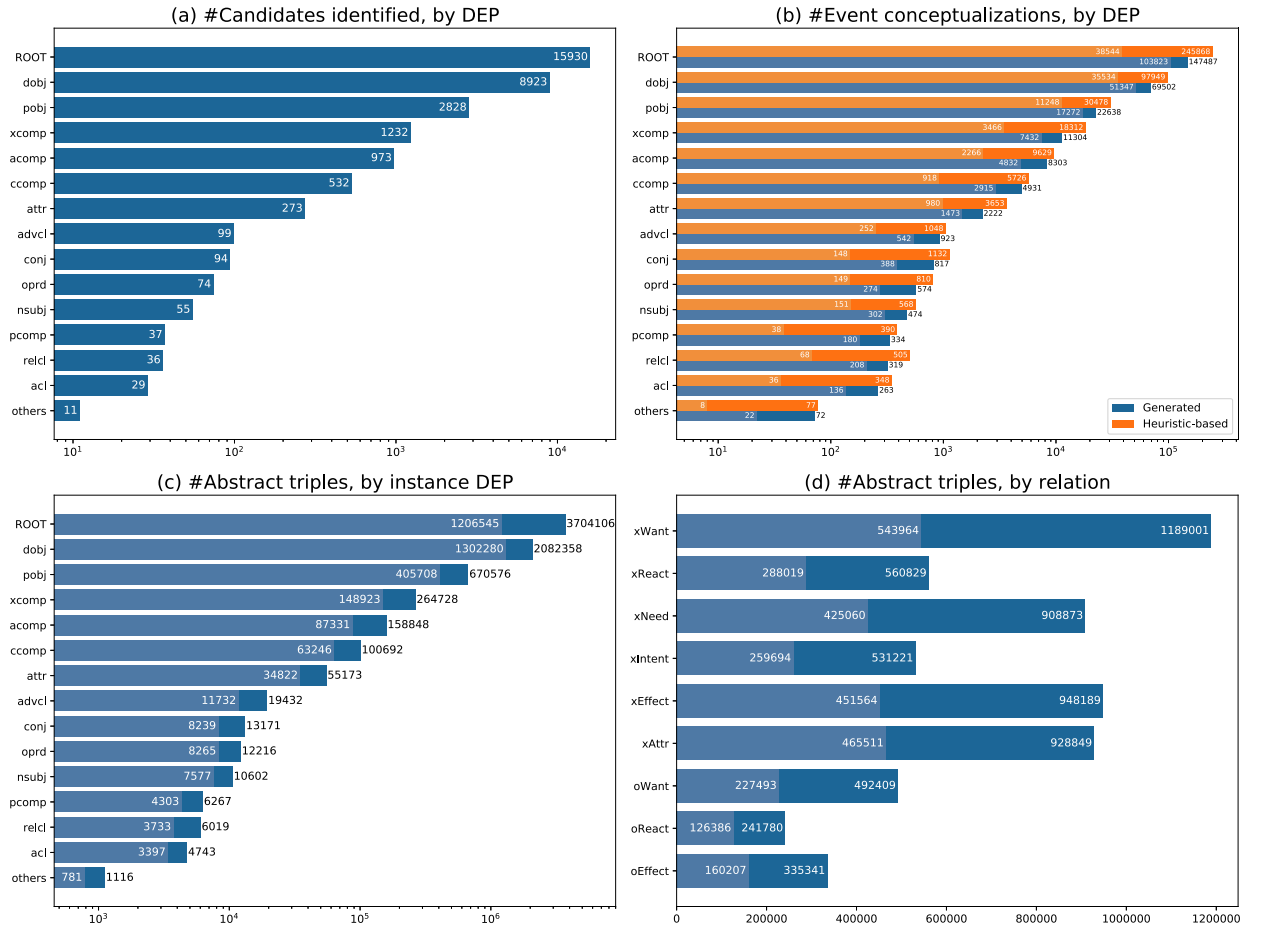


Fig. D.11. Statistics of data used in and from Abstract ATOMIC, when split by DEP tags and relations. Positive samples are shown in the lighter-colored sub-bars. Due to the large range, the first three sub-figures are in log scale.

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