

Revisiting the Prepositional-Phrase Attachment Problem Using Explicit Commonsense Knowledge

Yida Xin

yxin@bu.edu

Henry Lieberman

lieber@media.mit.edu

Peter Chin

spchin@cs.bu.edu

Abstract

We revisit the challenging problem of resolving prepositional-phrase (PP) attachment ambiguity. To date, proposed solutions are either *rule-based*, where explicit grammar rules direct how to resolve ambiguities; or *statistical*, where the decision is learned from a corpus of labeled examples (Hamdan and Khan, 2018). We argue that explicit commonsense knowledge bases can provide an essential ingredient for making good attachment decisions. We implemented a module, named PATCH-COMM, that can be used by a variety of conventional parsers, to make attachment decisions. Where the commonsense KB does not provide direct answers, we fall back on a more general system that infers “out-of-knowledge-base” assertions in a manner similar to the way some NLP systems handle out-of-vocabulary words. Our results suggest that the commonsense knowledge-based approach can provide the best of both worlds, integrating rule-based and statistical techniques. As the field is increasingly coming to recognize the importance of explainability in AI, a commonsense approach can enable NLP developers to better understand the behavior of systems, and facilitate natural dialogues with end users.

1 Introduction

Many applications and social scenarios nowadays are eager to see reliable and trustworthy Artificial Intelligence (AI) systems. But, in order to really establish trust, it is not enough to have computers only be able to communicate the end results of their “thought process.” Instead, computers, from the ground up, should be expected to use *explainable* processes to obtain their results, because that makes it easier — and in some cases, possible at all — for people to think about what reasoning processes the computers must have employed to get to those results. An even better solution is to build computers that can actually tell us, in natural language, what their reasoning and thinking processes are.

Today’s neural-network based language models (LM) — such as Transformers and its descendants (Vaswani et al., 2017; Devlin et al., 2018; Liu et al., 2019) — learn implicit knowledge from enormous corpora, but their representations, such as neural network weights, may only make sense to the systems themselves. Work has been done on constructing *post-facto* explanations for opaque inference processes (Petroni et al., 2019; Da and Kasai, 2019; Shwartz et al., 2020), but it is questionable how general the models and explanations really are. They must grapple with a tradeoff between faithfulness to the original process, and understandability by people. On the other hand, if we build a language-understanding system based on explicit commonsense knowledge and inference, from the ground up, reporting the commonsense involved is a good way to provide explanation to users. But it is hard to acquire, explicitly, sufficient knowledge to achieve wide coverage. So knowledge acquisition needs to be automated, which requires the use of Machine Learning mechanisms.

LMs have been proven exceptionally powerful at what they do. Recently, more empirical findings have validated our intuition about these systems: They are great knowledge learners for the domains that they are evaluated in (Sakaguchi et al., 2019; Shwartz et al., 2020). It seems unwarranted not to consider using their great power, just because they are somewhat opaque.

That leads us to the statement of our research agenda: We make language understanding explainable by using explicit commonsense knowledge, and we make the knowledge acquirable by using Machine Learning mechanisms, even if they may be somewhat opaque.

As a first step, we focus on a small but notoriously challenging problem in the realm of language understanding: the prepositional-phrase (PP) attachment problem (Hamdan and Khan, 2018). We also focus on a particular knowledge base and a particular neural-network based architecture for extending the knowledge contained in that knowledge base.

2 Background and Related Work

Hamdan and Khan (Hamdan and Khan, 2018) wrote a comprehensive survey that highlights many historical attempts at the PP attachment problem. Very roughly speaking, there are two approaches: (1) PP attachment can either be treated as a classification/ranking problem where one classifies/ranks the place in the sentence that makes the most sense to associate with the said PP; (2) PP attachment can also be dealt with by writing specific grammars and rules for a parser, where such grammars and rules tell the parser where, by default, the PP is to be attached within the sentence.

In this paper, we work with a rule-based parser that has its own default way of always attaching PPs to the highest *head* in the parse tree. The parser is part of a question-answering system, and that heuristic was deemed to be often appropriate in that application. But recognizing that the default way is not always desirable, we implement a system that makes informed decisions for the parser, so that the parser can consult with our system. And by *informed*, we mean that we have our module querying for knowledge from a knowledge base.

2.1 The START Parser

The parser we work with is the START parser (Katz, 1997). The first reason that we use START is that it is a syntactic parser, whose nested-triples representation allows for additions of semantic knowledge. As an example of how the START parser works, suppose we request START to parse the sentence

“John is playing the guitar with one finger,” (1)

START will output

```
[John      play      guitar]
[play      with      finger]
[finger    has_quantity 1  ]
```

where [John play guitar] and [play with finger] are the results of syntactic knowledge, and [finger has_quantity 1] is semantic knowledge.

The second reason we use the START parser is that it is the parser used by the Genesis story-understanding system (Winston and Holmes, 2018). Our long-term research agenda, which we will articulate in section 4, is to scale up the language-processing capability of existing story-understanding systems like Genesis.

2.2 The ConceptNet Knowledge Base

The knowledge base we use is the ConceptNet commonsense knowledge base (Speer et al., 2017). The first reason that we use ConceptNet is that it is very large: It contains crowdsourced “pure” commonsense knowledge input directly by people, implicit knowledge from behavior in games, and other sources. It is then combined with more “factual” knowledge from WordNet, Wiktionary, and others. See Speer et al. (Speer et al., 2017).

The second reason is that there have been successful attempts at using ConceptNet’s knowledge to reason about out-of-knowledge concepts, using Machine Learning methods (Colon-Hernandez et al., 2019). We would like to take advantage of that research result to give ConceptNet a form of knowledge-acquisition capability, thus advancing our research agenda.

Each piece of knowledge in ConceptNet is represented as an assertion that looks like:

[<relation>, <concept1>, <concept2>]

A concrete example could be:

[/r/HasA/, /c/en/guitar/, /c/en/strings/]

where `HasA` is the relation (`/r/`) that connects the concept (`/c/`) `guitar` to the concept `strings`, and `en` means English. Note that this assertion can only be interpreted as `guitar HasA strings` and not as `strings HasA guitar`.

Since the work on AnalogySpace (Speer et al., 2008), every assertion in ConceptNet now comes with pre-learned numerical weights that indicate its confidence level. In the example here, the assertion `guitar HasA strings` has a weight of 2.83, indicating that ConceptNet is fairly confident that a guitar has strings, provided that 1.0 is the default value that indicates the mere existence of an assertion in ConceptNet.

2.3 Problems with Commonsense Knowledge Bases

Working closely with ConceptNet has helped us think about commonsense knowledge bases — as well as the notion of *commonsense* itself — in much depth.

2.3.1 The Inference Problem

One problem with ConceptNet is what we call the *inference problem*. Here is an illuminating example: The assertion

`[/r/IsA/, /c/en/guitar/, /c/en/string_instrument/]`

exists in ConceptNet, with a weight of 6.32, which is much higher than the previous 2.83. But, querying ConceptNet with just `guitar` (as well as its plural form `guitars`) and `strings` (as well as its singular form `string`), we cannot get to `guitar IsA string_instrument`, because no assertion that connects `string` with `string_instrument` is explicitly given, and ConceptNet alone does not know how to infer an assertion to connect the two concepts.

The inference problem points to an even more fundamental problem with all commonsense knowledge bases: They merely store knowledge as just data, but they do not know the meanings of those data. So, ironically, commonsense knowledge bases lack commonsense.

2.3.2 The Insufficiency Problem

The other problem is the *insufficiency problem*, which says that ConceptNet simply does not have all the knowledge in and about the world. In fact, all knowledge bases and all corpora suffer from the insufficiency problem, to various degrees. To address insufficiency, we utilize the RetroGAN-DRD system, introduced by Colon-Hernandez et al. (Colon-Hernandez et al., 2019), that infers “out-of-knowledge-base” assertions in a manner similar to the way some NLP systems handle out-of-vocabulary words. We will see that, by using RetroGAN-DRD instead of just ConceptNet, we are guaranteed to always get an answer, which ConceptNet alone cannot guarantee. The answers align with our own commonsense and intuition about language, and they inform START’s PP attachment decisions in just that manner.

In addition to RetroGAN-DRD, there are such representative works as ATOMIC/COMET (Sap et al., 2019; Bosselut et al., 2019) in commonsense knowledge base completion and extension. There, the Transformers-based neural networks mechanisms learn both to fill in the gaps of knowledge bases (completion) and to generate and add new knowledge into the knowledge bases (expansion).

Both RetroGAN-DRD (Colon-Hernandez et al., 2019) and COMET (Bosselut et al., 2019) achieve a level of *neural-symbolic integration*. They ensure that a user interacts with their symbolic, understandable information, and that a developer debugs the underlying Machine Learning mechanisms more easily by using the symbolic information as guidance.

3 Implementation Details

We call our system PATCH-COMM, and we will use this name for the remainder of this paper.

3.1 A Simple Case, Using Only ConceptNet

Suppose we request START to parse the sentence:

“John is playing the guitar with one string.” (2)

```

[John      play      guitar]
[play      with      string]
[strings   has_quantity 1  ]

```

Figure 1: START’s output for sentence (2), without using PATCH-COMM.

Then, by default, START alone would output:

Evidently for us, *guitar*, instead of *play*, should be the more sensible attachment for *string*. So clearly, START needs help, and we will explicitly use ConceptNet’s commonsense knowledge to help START to make the more sensible parsing decision.

To do so, we probe START’s partial parsing information. Specifically, START begins and continues parsing just like before, until it reaches a point of ambiguity. But this time, START consults with PATCH-COMM for a parsing decision by sending its latest partial parse to PATCH-COMM:

```

(:ambig-PP
  (PP :prep "with" :det "one" :noun "string")
  :possible-attachments
    ((V :verb "play")
     (NP :det "the" :noun "guitar"))))

```

Figure 2: START’s partial parse for sentence (2).

PATCH-COMM receives it, and takes out the keyword concepts from both the ambiguous prepositional phrase (`:ambig-pp`) and from each of the possible attachments.¹ Namely, PATCH-COMM extracts the concept *string* (and plural *strings*) as well as the concepts *play* and *guitar* (and plural *guitars*).²

We query ConceptNet with a pair of concepts, and ask for the highest-weighted assertion that relates them.³ Specifically, for each extracted concept (as well as its lemmatized or inflected version) from the possible attachments, we pair it up with the extracted concept from the ambiguous PP. In the example here, PATCH-COMM extracts six pairs of concepts, queries ConceptNet with each such pair for a total of six times, and obtains the following information:

Concept Pair	Relation	Weight
(string, play)	—	—
(strings, play)	—	—
(string, guitar)	AtLocation	2.0
(string, guitars)	—	—
(strings, guitar)	HasA	2.8284
(strings, guitars)	—	—

Table 1: ConceptNet’s symbolic knowledge about the ambiguous PP from sentence (2). The concept that appear to the left of a relation is in **blue**, and the concept to the right in **red**.

¹A future work is to try to utilize the other information available in this partial parse, such as the preposition itself. For example, we can treat the querying of ConceptNet for the most sensible relations between keyword concepts as a first loop; and then, we can build a second loop where PATCH-COMM compares the queried relations against the prepositions, and use linguistic information to decide whether, and to what extent, those relations make sense with respect to the prepositions.

²Note that we do not inflect the verb, because in ConceptNet verb concepts are registered in their lemmatized forms.

³We did not implement multi-hop searches between the two concepts. One reason is that, at the commonsense level, it is hard to know what to make of multiple chained-together assertions with potentially wildly different relations, only to try to justify some sort of connection between those two concepts. So we decided to stick with the most straightforward knowledge possible — just the assertions that already exist.

Evidenced by the four empty rows in Table 1, we see that, even after taking into account the singulars and plurals of the nouns, we are still running into the disconnected-knowledge problem (section 2.3.1). Still, to agree with lemmatized nouns in the partial parse, we compress Table 1 into Table 2:

Concept Pair	Relation	Weight
(string, play)	—	—
(string , guitar)	HasA	2.8284

Table 2: ConceptNet’s symbolic knowledge about the ambiguous PP from sentence (2), refined. The concept that appear to the left of a relation is in blue, and the concept to the right in red.

Note that we indeed only preserve the highest-weighted relation overall.

Having obtained the information in Table 2, PATCH-COMM makes the decision, on behalf of START, that the ambiguous PP (ambig-PP “with one string”) is to be attached to the noun phrase (NP “the guitar”) rather than to the verb (V “play”). **Note, crucially, that this decision contradicts START’s default decision.** Our decision is then sent back to START, so that START can continue and complete its parse result:

```
[John      play      guitar]
[guitar    with      string]
[string    has_quantity 1  ]
```

Figure 3: START’s output for sentence (2), using PATCH-COMM querying ConceptNet.

Although the only difference between Figure 3 and Figure 1 is changing the word “play” to the word “guitar” in the second row, it is a big difference.

3.2 A Less Simple Case, Using Only ConceptNet

As a more complex example, suppose we have now:

“John is playing the guitar with one string with one finger.” (3)

What makes sentence (3) more complex is that it has two, instead of one, ambiguous PPs. But just like before, we request START to parse sentence (3). This time, START pauses as soon as it meets the first ambiguity, and sends PATCH-COMM the partial parse:

```
(:ambig-PP
  (PP :prep "with" :det "one" :noun "finger")
  :possible-attachments
  ((V :verb "play")
   (NP :det "the" :noun "guitar")
   (PP :prep "with" :det "one" :noun "string")))
```

Figure 4: START’s 1st partial parse for sentence (3).

And then, just like before, PATCH-COMM extracts concepts, queries ConceptNet with the concepts, and obtains a refined table of information:

Concept Pair	Relation	Weight
(finger, play)	RelatedTo	1.0
(finger, guitar)	—	—
(finger, string)	—	—

Table 3: ConceptNet’s knowledge about the 1st ambiguous PP from sentence (2), refined.

This time with more blank rows in the table, we are also seeing the insufficient-knowledge problem (section 2.3.2) with ConceptNet, in addition to the disconnected-knowledge problem. Recall that a weight of 1.0 is just an indication that an assertion exists in ConceptNet (Speer et al., 2008), so the information we are receiving from ConceptNet in this particular case is pretty weak. But nonetheless, we will still make use of that weak information. PATCH-COMM goes ahead and decides that the ambiguous PP should be attached to the `play`, and sends that decision back to START.

START resumes its parsing process, only to encounter the second ambiguity. So it sends PATCH-COMM its partial parse for a second time:

```
(:ambig-PP
  (PP :prep "with" :det "one" :noun "string")
  :possible-attachments
    ((V :verb "play")
     (NP :det "the" :noun "guitar")))
```

Figure 5: START’s 2nd partial parse for sentence (3).

We notice that this is exactly the same scenario as the one described in section 3.1, so everything proceeds in exactly the same way as if they are for sentence (2). At the end, START completes its parse result:

```
[John      play      guitar]
[play      with      finger]
[guitar    with      string]
[string    has_quantity 1  ]
[finger    has_quantity 1  ]
```

Figure 6: START’s output for sentence (3), using PATCH-COMM querying ConceptNet.

3.3 Using RetroGAN-DRD, A System That Goes Beyond ConceptNet

The final part of our implementation, as promised, addresses ConceptNet’s disconnected-knowledge and insufficient-knowledge problems (section 2.3). The solution we have come up with is incorporating the Deep Relationship Discovery (RetroGAN-DRD) system, a developing system that facilitates common-sense learning and reasoning (Colon-Hernandez et al., 2019).

There are in fact two subsystems: A RetroGAN system, followed by a DRD system. The RetroGAN system utilizes the CycleGAN (Zhu et al., 2017) idea to train a target-domain generator that mimics word vectors that already carry ConceptNet semantics implicitly (Speer and Chin, 2016). Specifically, RetroGAN takes pre-trained fastText (Bojanowski et al., 2017) embeddings in its source domain and retrofitted ConceptNet ensemble (Speer and Chin, 2016) in its target domain, and post-specializes (Vulić et al., 2018) out-of-knowledge, unseen concepts by learning a generalizable mapping from seen fastText concepts and the retrofitted ConceptNet ensemble. The DRD system consists of trained relation-predicting models; each such model corresponds to a ConceptNet relation. Essentially, DRD serves to take a pair of post-specialized concepts from RetroGAN, test it on all the relation models, and output the predicted weights for all the models (i.e., relations).

We query the RetroGAN-DRD system in basically the same way that we query ConceptNet itself: Provide two concepts, and ask for the relation that carries the highest weight.

Taking into account both statistical sensitivity and the fact that RetroGAN-DRD is under development, we took some care to ensure better experimental outcomes. The first thing we did was, for each of the two concepts, we also introduce 5 of its neighbors to make a neighborhood of 6 concepts, represented as a 6×300 tensor. This was done to ensure that “true” concepts are not left out due to possible statistical instability of vectorized knowledge. After drawing two neighborhoods for both concepts, we match up the entire neighborhood of the first concept with that of the second concept, making a total of $6 \times 6 = 36$ pairs. Each such pair then gets fed through the RetroGAN-DRD system, and the system outputs the highest-weighted relation along with the weight. Overall, we get 36 relations and 36 weights.

The second thing we did was that, once all these 36 weights were collected into a list, we treat the highest 3 weights and the lowest 3 weights, along with their corresponding relations, as outliers. We remove these outliers to obtain a remainder of 30 relations and 30 weights, and we compute the following:

$$w^* = \log \left\{ \max_{i=1}^{30} \{ \text{SOFTMAX}(\exp(\vec{w})) \} \right\}$$

where $\vec{w} = [w_1 \ \cdots \ w_{30}]$ is the vector of those 30 weights, and

$$\exp(\vec{w}) = [\exp(w_1) \ \cdots \ \exp(w_{30})].$$

This way, w^* is a statistically less sensitive measure for how the original pair of concepts drawn from the partial parse should relate.

By way of demonstration, when using RetroGAN-DRD on sentences (1) and (2), we have

(1) John is playing the guitar with one finger

Concept Pair	Relation	w^*
(finger, play)	SymbolOf	-3.26578
(finger, guitar)	ObstructedBy	-3.33881

(a) RetroGAN-DRD’s reasoning about the ambiguous PP from sentence (1), refined.

(2) John is playing the guitar with one string

Concept Pair	Relation	w^*
(string, play)	ObstructedBy	-3.38202
(string, guitar)	UsedFor	-3.37002

(b) RetroGAN-DRD’s reasoning about the ambiguous PP from sentence (2), refined.

Table 4: RetroGAN-DRD’s reasoning about ambiguous PPs.

When PATCH-COMM uses the information in Tables 4(a) and 4(b), it will still decide that sentence (1) should have “plays with one finger” and that sentence (2) should have “guitar with one string.” The only difference is that, by using RetroGAN-DRD, we are now able to overcome both the disconnected-knowledge problem and the insufficient-knowledge problem, at least to some extent.

And finally, START’s parse results in this case are:

```
[John      play      guitar]
[play      with      finger]
[string    has_quantity 1   ]
```

Figure 7: START’s output for sentence (1), using PATCH-COMM querying RetroGAN-DRD.

```
[John      play      guitar]
[guitar     with      string]
[string     has_quantity 1   ]
```

Figure 8: START’s output for sentence (2), using PATCH-COMM querying RetroGAN-DRD.

4 Some Results

We evaluated our system on section 23 of Belinkov et al.’s English dataset⁴ (Belinkov et al., 2014). Each data point consists of a *preposition*, its *child*, and a set of candidate *heads* to which the PP, consisted of the preposition and the child, is to be attached.

We only evaluated on the preposition “with” to be consist with our demonstration examples, and we selected only the data points that have at most 3 candidate heads. Overall, there are 17 of them with 2 candidate heads and 31 of them with 3 candidate heads, for a total of 48. The statistics of our results are summarized in the following table:

Baseline	Accuracy	w^* within 0.1	Best
39.2%	45.8%	27.1%	88.7%

Table 5: Our results on a part of the data set developed by Belinkov et al. Baseline accuracy is computed by assigning 50% to the 17 data points with 2 candidates and 33.333% to the 31 data points with 3 candidates. Accuracy is computed as we got 22 correct out of 48. w^* within 0.1 means, among the data points we got wrong, the w^* score for the answer that Patch-Comm picked differs is no more than 0.1 from the ground-truth answer. The last column is the best result from the paper, obtained from evaluations on their entire data set.

These results suggest that the scalability of PATCH-COMM awaits.

5 Discussion and Future Works

This work is an immediate result of our decision to take on the challenge of scaling up the language-processing capacity of story-understanding systems. Scaling-up is important, because all story-understanding systems to date — with Genesis (Winston and Holmes, 2018) being perhaps the most prominent one — can only read and analyze toy stories, but we want them to start reading and analyzing natural-language stories. Scaling-up is a challenge, because natural-language understanding (NLU) is hard.

It soon becomes clear to us that, despite of the seeming bifurcation of *language* and *story* in our setup, both language understanding and story understanding require commonsense knowledge, but perhaps language knowledge and story knowledge should reside on different “levels.” Story knowledge is really *global* information about the story at hand, and what we mean by language knowledge is essentially *local*, sentence-level information. Therefore, we think it makes sense in principle for story knowledge to have the ability to override sentence-level language knowledge. For example, if there is a story context that tells us that John is a three-year-old kid who plays with all kinds of strings all the time, then all of a sudden, it seems all the more likely that John is actually using a piece of string to play the guitar.

We realize that it is actually important to incorporate story-level knowledge, which a story-understanding system already has, to scale up its sentence-level language understanding. Consequently, we have, on our research agenda, the goal of employing global, story-level knowledge to resolve local, sentence-level ambiguities, and to compile the refined local interpretations of all sentences into a global interpretation of the story. In fact, a story-understanding system like Genesis is already able to offer global interpretations for toy stories.

Next up, we want to extend our commonsense knowledge-based approach to other challenging linguistic problems, such as co-reference resolution (a.k.a., pronoun disambiguation). Our hope for co-reference resolution is to go beyond the state-of-the-art benchmarks, such as the series of works on the Winograd Schema Challenge (Levesque et al., 2012; Sakaguchi et al., 2019; Kocijan et al., 2020), and build programs that can resolve more global co-references, like the ones in the following children’s story:

Robbie and Susie were going to Marvin’s birthday party. One of them wanted to buy a kite. “But he already has one,” he said. “He will make you take it back.”

⁴We used the publicly available data set from <https://github.com/boknilev/pp-attachment/tree/master/data/pp-data-english>.

Last but not least, the Holy Grail of NLU is building computer systems that understand discourses. To that effect, story-understanding systems such as the Genesis system are built with the intention of enabling us to gain insights into our own human intelligence, through the lens of story understanding (Winston and Holmes, 2018). We hope to scale up to a point where we will gain a sufficient understanding of our own intelligence by looking at the underlying story-understanding processes that are and will continue to be transparent. And when we understand and can explain ourselves that much better, we will hopefully have raised our own conception of *trust* to a higher level within society.

Acknowledgments

We would like to thank Sue Felshin for sharing with us her valuable experience with and resources of the START natural-understanding system, as well as our in-depth discussions on this project. We would also like to thank Pedro Colón-Hernández for his contributing the RetroGAN-DRD system as well as numerous insights into the problem of computer language understanding.

References

- Yonatan Belinkov, Tao Lei, Regina Barzilay, and Amir Globerson. 2014. Exploring compositional architectures and word vector representations for prepositional phrase attachment. *Transactions of the Association for Computational Linguistics*, 2.
- Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching word vectors with subword information. *Transactions of the Association for Computational Linguistics*, 5:135–146.
- Antoine Bosselut, Hannah Rashkin, Maarten Sap, Chaitanya Malaviya, Asli Çelikyilmaz, and Yejin Choi. 2019. Comet: Commonsense transformers for automatic knowledge graph construction. In *ACL*.
- Pedro Colon-Hernandez, Henry Lieberman, and Catherine Havasi. 2019. Does a dog desire cake?-expanding knowledge base assertions through deep relationship discovery. In *33rd Conference on Neural Information Processing Systems (NeurIPS 2019)*, Vancouver, Canada.
- Jeff Da and Jungo Kasai. 2019. Cracking the contextual commonsense code: Understanding commonsense reasoning aptitude of deep contextual representations. In *Proceedings of the First Workshop on Commonsense Inference in Natural Language Processing*, Hong Kong, China, November. Association for Computational Linguistics.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805 (cs.CL)*.
- Mohammed Hussein Hamdan and Imtiaz Hussain Khan. 2018. An analysis of prepositional-phrase attachment disambiguation. *International Journal of Computational Linguistics Research*, 9(2), June.
- Boris Katz. 1997. Annotating the world wide web using natural language. In *Computer-Assisted Information Searching on Internet*, RIAO '97, page 136–155, Paris, FRA.
- Vid Kocijan, Thomas Lukasiewicz, Ernest Davis, Gary Marcus, and Leora Morgenstern. 2020. A review of winograd schema challenge datasets and approaches. *arXiv preprint arXiv: 2004.13831 (cs.CL)*.
- Hector J. Levesque, Ernest Davis, and Leora Morgenstern. 2012. The winograd schema challenge. In *Proceedings of the Thirteenth International Conference on Principles of Knowledge Representation and Reasoning*, KR'12, page 552–561. AAAI Press.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv: 1907.11692 (cs.CL)*.
- Fabio Petroni, Tim Rocktäschel, Patrick Lewis, Anton Bakhtin, Yuxiang Wu, Alexander H. Miller, and Sebastian Riedel. 2019. Language models as knowledge bases? *ArXiv*, abs/1909.01066.
- Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2019. Winogrande: An adversarial winograd schema challenge at scale. *ArXiv*, abs/1907.10641.

- Maarten Sap, Ronan Le Bras, Emily Allaway, Chandra Bhagavatula, Nicholas Lourie, Hannah Rashkin, Brendan Roof, Noah A. Smith, and Yejin Choi. 2019. Atomic: An atlas of machine commonsense for if-then reasoning. In *AAAI*.
- Vered Shwartz, Peter West, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2020. Unsupervised common-sense question answering with self-talk. *arXiv preprint arXiv: 2004.05483 (cs.CL)*.
- Robert Speer and Joshua Chin. 2016. An ensemble method to produce high-quality word embeddings. *arXiv preprint arXiv:1604.01692*.
- Robert Speer, Catherine Havasi, and Henry Lieberman. 2008. Analogyspace: Reducing the dimensionality of common sense knowledge. In *Proceedings of the 23rd National Conference on Artificial Intelligence - Volume 1*, AAAI’08, page 548–553. AAAI Press.
- Robert Speer, Joshua Chin, and Catherine Havasi. 2017. Conceptnet 5.5: An open multilingual graph of general knowledge. In *Thirty-First AAAI Conference on Artificial Intelligence*.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *arXiv preprint arXiv:1706.03762 (cs.CL)*.
- Ivan Vulić, Goran Glavaš, Nikola Mrkšić, and Anna Korhonen. 2018. Post-specialisation: Retrofitting vectors of words unseen in lexical resources. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 516–527. Association for Computational Linguistics, June.
- Patrick Henry Winston and Dylan Holmes. 2018. The genesis enterprise: Taking artificial intelligence to another level via a computational account of human story understanding. Technical report, MIT DSpace, Computational Models of Human Intelligence Community, CMHI Report Number 1.
- Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A. Efros. 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks. *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 2242–2251.