

Research Statement

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My research focuses on the computational foundations of *intelligent behavior*, through the lens of *natural language*. Towards this end, I am interested in developing both *theories* and *systems*, using unified methodologies. My goal, in the long run, is to understand and develop capabilities for *natural language understanding*. In the short term, I am motivated by near-term applications in natural language processing (NLP), empowered by machinery like *deep learning* and *information extraction*.

The challenges span a range of fields – from foundational questions in *learning*, *knowledge-representation*, and *reasoning* to experimental paradigms and large-scale system development — and draw on methods from machine learning, theoretical computer science and statistics (Figure 1). AI, and particularly natural language processing, have been strongly influenced recently by the success of deep learning in a range of tasks. My work builds on these machine learning advances and focuses on reasoning with learned models and scaling learned models into plausible supervision scenarios.

During my Ph.D. studies I have focused on addressing a number of interrelated research questions:

- (A) Can systems understand and *reason* about complex natural language questions? (for example, queries that require chaining multiple pieces of information, including external knowledge)?
- (B) Can systems acquire the bulk of knowledge from raw and *freely-available data*, and use it to behave robustly when presented with new, previously unseen, situations?
- (C) Today, we access information uniformly through search engines (e.g., Google). Can systems equipped with better natural language understanding help us better *understand* and *organize* various *perspectives* expressed about claims made in the text?

The following sections represent parts of my past and ongoing explorations in response to the questions above, followed by possible directions along which I feel confident to expand my research.

(A) Reasoning with respect to Natural Language Queries

The fundamental language *understanding* problems such as Question Answering (QA) and Textual Entailment have received significant attention, especially recently, thanks to the advances in NLP and Machine Learning. Unfortunately, research has shown that many existing

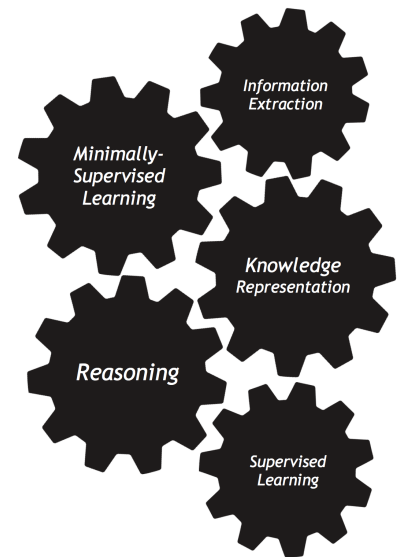


Figure 1: The different aspects of my research and their interdependence. The whole system would not work if any of the elements were malfunctioning.

systems possess a very shallow understanding of text [Kaushik and Lipton, 2018]. One of the common ways to show such limitations is by exposing their brittleness to small changes (Figure 2).

A major theme of my research is motivated by addressing the limitations of existing systems and building alternate paradigms.

Question Answering on science exams. One of my projects is concerned with solving elementary school science exams. Such standardized tests have been suggested as grand challenges for AI [Clark and Etzioni, 2016], as they involve a wide variety of nontrivial inference and knowledge use that goes beyond factoid retrieval.

In our proposed system, TableILP,¹ we treat question answering as a subgraph selection problem over semi-structured knowledge base (e.g., tables of information; see Figure 3). Most importantly, this formulation allows multiple, semi-formally expressed facts to be combined to answer questions, a capability outside the scope of Information Retrieval or even deep-learning-based QA systems. Empirically, we observed that the system achieved competitive results for this task, significantly boosting the performance when combined with unstructured methods (e.g., retrieval techniques).

Our effort has had multiple impacts since publication. Our work has inspired others to build systems based on our design and to improve the state of the art in other domains; e.g., [Khot et al., 2017]. In addition, the system has been incorporated into Allen Institute’s reading-comprehension project² and was shown to give a significant boost to their performance [Clark et al., 2016]. Even after two years, the system was shown to be among the best systems on a challenging reading comprehension task [Clark et al., 2018].

I would like to highlight a few recent threads I have pursued, building upon the aforementioned project:

- *Reasoning over raw text.*³ We extend our abductive reasoning system to consume raw text as input knowledge. This is the first system to successfully use a wide range of semantic abstractions to perform a high-level NLP task like Question Answering.
- *A challenge dataset for reasoning.*⁴ To motivate the community to work on more challenging forms of natural language comprehension, we propose a dataset that requires reasoning over multiple sentences.
- *Formalizing limitations of multi-step reasoning.*⁵ We developed a theoretical formalism to investigate fundamental limitation pertaining to multi-step reasoning in the context of natural language problems.

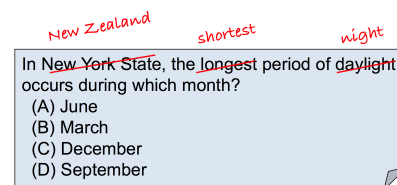


Figure 2: A system answering the original question for the “right” reason should be robust with respect to small changes to the query.

¹ D. Khashabi, T. Khot, A. Sabharwal, P. Clark, O. Etzioni, and D. Roth. Question answering via integer programming over semi-structured knowledge. In *IJ-CAI*, 2016

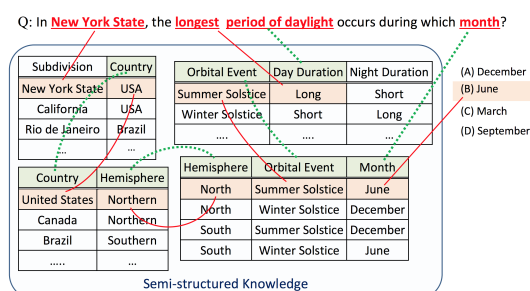


Figure 3: Depiction of reasoning process done by TableILP for the example provided in Figure 2. The system searches for the best support graph (chains of reasoning) connecting the question to an answer, in this case *June*.

² <https://allenai.org/aristo/>

³ D. Khashabi, T. Khot, A. Sabharwal, and D. Roth. Question answering as global reasoning over semantic abstractions. In *AAAI*, 2018b

⁴ D. Khashabi, S. Chaturvedi, M. Roth, S. Upadhyay, and D. Roth. Looking beyond the surface: A challenge set for reading comprehension over multiple sentences. In *NAACL*, 2018a

⁵ D. Khashabi, E. Sadeqi Azer, T. Khot, A. Sabharwal, and D. Roth. On the capabilities and limitations of reasoning for natural language understanding, under review

(B) Harnessing “Hints” from Freely-Available Information

The recent high-profile success of AI in NLP is primarily owed to *supervised learning*, where there is direct annotation for the target task. Despite the success, there are critical issues associated with this methodology that limit the progress; to name a few, supervised approaches (a) are costly in terms of resources; (b) are limited to a fixed set of classes, once trained; (c) are not robust enough to withstand domain change.

The goal of this research direction is to go beyond these barriers, by creating useful representations from freely available data (free-form text, Wikipedia links, Freebase, etc.) And thus to create “cheap” supervision for interesting tasks. Below I provide two examples to highlight how this idea was used to improve NLP tasks and make them more robust.

Profiling concepts and entities. One of the hardest aspects of language is being able to map shallow surface information to its actual meaning. The *Seattle Seahawks* and *Seattle, WA*, are different entities, even though they may sometimes appear identically in text.

One of my early projects was focused on creating *profiling systems* that provide insights into concepts and entities.⁶ The profiling component provides a new way of representing, aggregating, and supporting the use of knowledge about concepts and entities in NLP. By examining the profiles of related concepts, one can discover interesting patterns (e.g., strong similarity of all the *sports teams* to each other; Figure 4). We have used concept profiling in a variety of applications to significantly improve the performance of the existing systems (e.g., “hard” Winograd Schema-like pronoun resolution⁷).

Entity typing, without costly supervision. Entity typing refers to the task of identifying the semantic type of a given entity mention. The problem has been studied predominantly in a supervised learning fashion, mostly with task-specific annotations (for coarse types) and sometimes with distant supervision (for fine types). In a recent work we propose a *zero-shot* entity typing approach that requires *no annotated data* and can flexibly identify newly defined types (Figure 5). Our approach exploits the idea that a semantic type can be *defined*, e.g., by some representative members of each type, and this insight can be transformed into an algorithmic approach that makes use of recent pre-training deep-learning methods to develop a no-supervision (zero-shot) and open domain (new types can be added on the fly) typing system. Our research has shown significant gains over other zero-shot systems, as well as better generalization across domains compared to other existing supervised systems.⁸

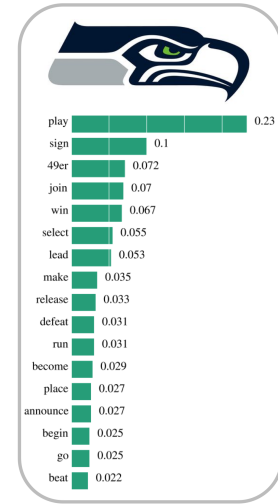


Figure 4: The sub-profile of “Seattle Seahawks”; a profile reveals much information about the nature of the concept.

⁶ Z. Fei, D. Khashabi, H. Peng, H. Wu, and D. Roth. Illinois-Profiler: knowledge schemas at scale. *Workshop on Cognitive Knowledge Acquisition and Applications (Cognitum)*, 2015

⁷ H. Peng, D. Khashabi, and D. Roth. Solving hard coreference problems. In *NAACL*, 2015

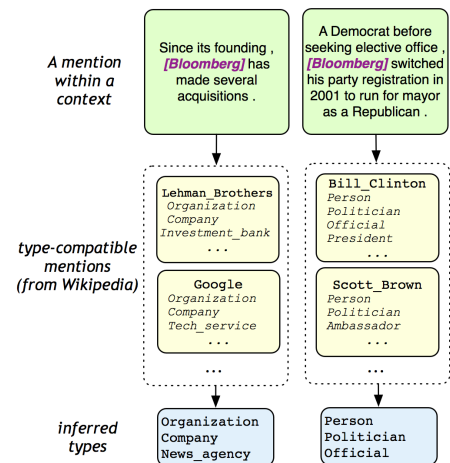


Figure 5: Our entity-typing system maps a given mention to its *type-compatible* entities in Wikipedia, using which it infers a collection of types.

⁸ B. Zhou, D. Khashabi, C-T. Tsai, and D. Roth. Zero-shot open entity typing as type-compatible grounding. In *EMNLP*, 2018

(C) Helping Individuals Navigate through [Mis]Information

One of the biggest challenges facing us in the age of data is the problem of *mass information distortion*. Societies are increasing in diversity, bringing together people with different backgrounds and perspectives about contentious questions. On the other hand, we are exposed to an increasing amount of content (news, social media, ads, etc) in our daily lives, and a significant portion of them distort the truth (whether intentionally or unintentionally) by showing only part of the picture. This is further exacerbated by personalized social media algorithms which tend to deliver content that corroborate our existing beliefs and encourage the formation of “bubbles” of like-minded people. This is the focus of one of my current projects.

Helping individuals see issues from different perspectives. In a recent project, we are building systems that encourage an inclusive and holistic view of many challenging issues. Take the following controversial question: “can animals have lawful rights?” There might not be a simple answer to this question, as there are many different aspects to address.

Our goal in this project is to explore better ways to organize ideas and perspectives. We would like to help individuals see the other sides of the aisle, by organizing different aspects of the problems. In our first step, we focus on the goal of defining the key underlying NLP challenges and developing a dataset that will drive the community to work on this task.⁹ In the task, a search system is expected to discover all the relevant perspectives (supporting or undermining), followed by extracting all the pieces of evidence that substantiate each perspective (Figure 6). We are hoping that this line of research will encourage movement towards better organization of ideas and will create a broader societal impact in the near future.

Future Research Directions

For future work, I would like to build upon the past directions and augment them with new ideas. In addition, I would like to add new angles to my current work, as I briefly explain below:

- *Principled decision-making, robustness guarantees, and explainability:* One of the missing components in the modern AI technologies (especially *deep learning*) is the lack of high-level understanding and explainability. Many systems seem to work fine in narrow domains, but we don’t exactly understand the extent of their abilities and the regions of their brittleness. I believe that in the coming decade, with the increasing push for *robustness guarantees* and *explainability*

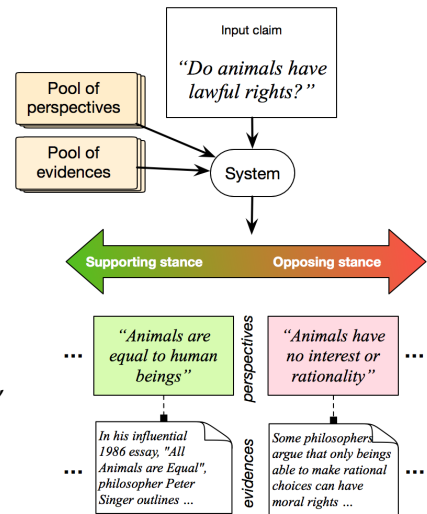


Figure 6: Given a *claim*, the system is expected to discover different *perspectives* that are substantiated with *evidence* and their *stance* with respect to the claim.

⁹S. Chen, D. Khashabi, W. Yin, C. Callison-Burch, and D. Roth. See things from a different angle: Formalizing diverse perspectives about queries, under review

of decisions, there will be a growing need for principled solutions addressing big AI problems. Of course, the interplay between *reasoning* and *representation* will play a key role in this direction.

- *Textual common-sense*: The easiest problems for humans are usually the hardest for computers. Such problems often go unmentioned, due to their triviality (for humans). For instance, humans trivially know the many differences between “going to college” and “going to the movies” (e.g., duration, prerequisites, etc). Our current technologies so far don’t have any responses to such problems.

Common-sense knowledge/reasoning is therefore essential for language comprehension. As we transition towards harder problems in AI, I hypothesize that mining common-sense knowledge will be a major highlight of coming years. I am planning to work both on common-sense knowledge acquisition, and on reasoning methods that will allow principled use of this knowledge in AI systems.

- *Theory to support empirical intuition*: While my research is driven by empirical work, I do believe in the importance of theory and the supporting intuition it can bring. Theoretical contributions could result in general formalisms and explain the extent and limitations of our empirical understanding.

In the past, I have explored a few ideas with this theme. For instance, in [Quanrud and Khashabi \[2015\]](#)¹⁰ we explore the adverse effects of delays in optimization problems, a setting that is widely used in practice, but not fully understood.

I would like to continue this thread and guide my empirically-driven work with theoretical understanding.

Finally, I would like to highlight the importance of *building and releasing tools* that could benefit the research community. NLP research is driven with applications, and a big chunk of my work was spent on building systems. Just to name one, our library CogComp-NLP¹¹, a suite of NLP annotators, has successfully been used in a few industrial projects and is being broadly used by the community. In the future, I would like to maintain the weight on building useful systems with the goal of making real impact on the field.

¹⁰ K. Quanrud and D. Khashabi. Online learning with adversarial delays. In *NIPS*, 2015

¹¹ D. Khashabi et al. CogCompNLP: your Swiss army knife for nlp. In *LREC*, 2018

References

- S. Chen, D. Khashabi, W. Yin, C. Callison-Burch, and D. Roth. See things from a different angle: Formalizing diverse perspectives about queries, under review.
- P. Clark and O. Etzioni. My computer is an honor student - but how intelligent is it? standardized tests as a measure of AI. *AI Magazine*, 2016.

- P. Clark, O. Etzioni, D. Khashabi, T. Khot, A. Sabharwal, O. Tafjord, and P. Turney. Combining retrieval, statistics, and inference to answer elementary science questions. 2016.
- P. Clark, I. Cowhey, O. Etzioni, T. Khot, A. Sabharwal, C. Schoenick, and O. Tafjord. Think you have solved question answering? try ARC, the AI2 reasoning challenge. In *AAAI*, 2018.
- Z. Fei, D. Khashabi, H. Peng, H. Wu, and D. Roth. Illinois-Profiler: knowledge schemas at scale. *Workshop on Cognitive Knowledge Acquisition and Applications (Cognitum)*, 2015.
- D. Kaushik and Z. C. Lipton. How much reading does reading comprehension require? a critical investigation of popular benchmarks. In *EMNLP*, 2018.
- D. Khashabi, T. Khot, A. Sabharwal, P. Clark, O. Etzioni, and D. Roth. Question answering via integer programming over semi-structured knowledge. In *IJCAI*, 2016.
- D. Khashabi, S. Chaturvedi, M. Roth, S. Upadhyay, and D. Roth. Looking beyond the surface: A challenge set for reading comprehension over multiple sentences. In *NAACL*, 2018a.
- D. Khashabi, T. Khot, A. Sabharwal, and D. Roth. Question answering as global reasoning over semantic abstractions. In *AAAI*, 2018b.
- D. Khashabi, E. Sadeqi Azer, T. Khot, A. Sabharwal, and D. Roth. On the capabilities and limitations of reasoning for natural language understanding, under review.
- D. Khashabi et al. CogCompNLP: your Swiss army knife for nlp. In *LREC*, 2018.
- T. Khot, A. Sabharwal, and P. Clark. Answering complex questions using open information extraction. *ACL*, 2017.
- H. Peng, D. Khashabi, and D. Roth. Solving hard coreference problems. In *NAACL*, 2015.
- K. Quanrud and D. Khashabi. Online learning with adversarial delays. In *NIPS*, 2015.
- B. Zhou, D. Khashabi, C-T. Tsai, and D. Roth. Zero-shot open entity typing as type-compatible grounding. In *EMNLP*, 2018.