# Robust, Generalizable and Minimally Supervised Knowledge Acquisition from Human Language

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## 1 Introduction and Background

My research focuses on promoting the advancement of intelligent computational systems with better acquisition and awareness of world knowledge, which leads to more efficient information exchange between the system, people and the environment. My goal, in the long term, is to leverage minimal supervision to allow machines confidently understand the relations of concepts, entities and events in human language, as well as the interactions of objects in nature (such as molecules and biomolecules). In the near term, I am motivated by the objective of developing robust machine learning methods for information extraction and knowledge acquisition, and extending their use in various tasks for natural language processing, knowledge base construction, and various cross-domain and interdisciplinary research.

The challenges span over a range of fields, from the fundamental questions in the acquisition, representation and inference of knowledge, to systematic paradigms for scalable data management, mining and retrieval. In this decade, AI systems in various application domains are empowered by representation learning technologies for automatically discovering and acquiring relations, patterns and properties of objects from large-scale data. In particular, such technologies involve relational embedding, language modeling and constrained learning. My work seeks to trigger the advancement of these technologies, with focus on knowledge acquisition from data in different modalities, and in scenarios with or without plausible supervision signals. My investigation in these research directions has led to over 60 published papers in leading AI, NLP, ML and data science venues, and have broadly benefited real-world applications in various computational and interdisciplinary areas. The

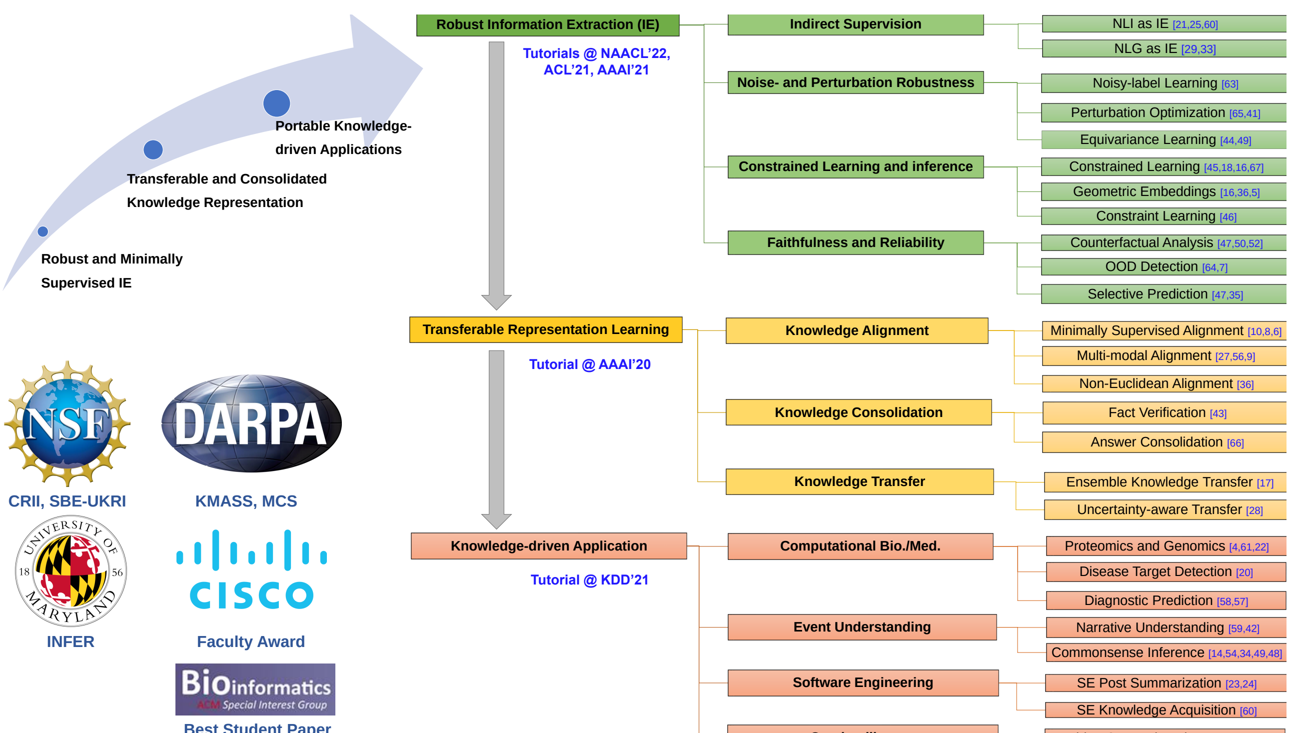


Figure 1: A roadmap of my research on robust, generalizable and minimally supervised knowledge acquisition.

following of this statement presents parts of my investigation into these directions along a research roadmap (Fig. 1), followed by some exciting future directions that I am planning to explore.

**Robust and Minimally Supervised Knowledge Extraction** Structural knowledge representations, such as knowledge graphs (KGs), are integral to intelligent systems in nearly all domains. Despite their importance, existing efforts for acquiring structural knowledge representation are generally conducted manually. This leads to the cost of tens of millions of dollars to produce just one mid-scale commodity KG in the general domain, and could cost significantly more in scientific domains like biology and medicine. To alleviate the costly efforts and provide reliable systems for automatically acquiring knowledge, my research has focused on *robust* and *minimally supervised* learning and inference technologies for knowledge extraction from natural language text. Specifically, my research systematically leads to transformative advancement in the following four dimensions.

*(1) Indirect supervision.* Learning to extract structural knowledge has largely relied on *direct supervision* from structurally annotated corpora that are similarly expensive as a structural knowledge representation itself [32]. I instead study a novel direction of *indirect supervision*, leading to robust and generalizable knowledge extraction models without sole reliance on task-specific annotations. In particular, my study has produced principled approaches for reformulating and transferring supervision signals from natural language inference (NLI) [25], summarization [29] and linguistic pattern matching [33]. This reformulation allows rich (indirect) supervision signals to be transferred from well-developed learning resources and models for signal-providing tasks that align well with knowledge extraction. It also emancipates knowledge extraction from the limitation of fixed label sets, allowing new types of knowledge that are unseen in training to be inferred. In this context, I have also explored with semantic representation of tasks and labels [21, 13] to further reduce the need of direct task supervision. This systematic study of indirectly supervised learning has led to SOTA performance on a large number of benchmarks for relation extraction, named entity recognition, ultra-fine entity typing, event extraction and event process typing. Specifically, for all those tasks, my systems have demonstrated excellence in extremely few-shot [29, 21, 5] or zero-shot performances [25] that were close to those that perviously offered by full-shot, directly supervised models.

*(2) Noise- and perturbation-robustness.* In addition to insufficiency of annotated data, the cost and difficulty of structural annotation often lead to significant training noise. In the same context, real-world application scenarios often expose the model with way larger and more diverse data, for which the inference of model needs to frequently handle perturbations and out-of-distribution (OOD) exceptions. My study accordingly enhance the robustness of the model from two perspective. Towards robust training, my study developed a co-regularized knowledge distillation approach that can proactively identifying noisy training instances and preventing the discriminative model from fitting the noise [63]. This leads to significant improvement in both noise-robustness and computational efficiency over previous ensemble-based denoising and noise-filtering methods. In this context, my study also proposed sharpness-aware minimization with dynamic reweighting ($\delta$-SAM [65]) to further enhance the model robustness using adversarial perturbation training, as well as self-supervised cross-lingual perturbation training [41]. On the other hand, to enhance the robustness in inference, I have studied margin-based contrastive learning methods [64, 7] that led to near-perfect unsupervised OOD detection performance, helping the model selectively identify cases where no extraction should be made. I also developed structure-aware equivariance learning techniques [44, 49] to allow data-to-text generation models to generate consistent representation for structural priors where semantic-invariant perturbations are free to be introduced. Those technologies systematically improves the reliability of knowledge extraction systems in real-world scenarios where training and inference phases are abundant with noise, perturbations and exceptions.

*(3) Logically constrained learning and inference.* Extracts are not standalone and can possess complex logical dependencies. A robust knowledge extraction system needs to ensure that the extracts are self-contained, and free of inconsistency and redundancy. My work accordingly suggests solutions to this problem with novel constrained learning and inference approaches. Specifically, I have studied joint constrained learning approaches for enforcing logical consistency in relation extraction tasks [45], probabilistic constrained learning with $t$-norm based optimization [18], logically constrained learning for linear relational embeddings [11] and probablistic

box embeddings [16]. Considering that logical constraints may be costly to define and hard to articulate, my recent study also proposed the approach to learn linear inequalities for automatically capturing logical constraints from data [46].

*(4) Faithfulness.* Current knowledge extraction models are mainly developed on large pre-trained language models and are short of training annotations in general. In this situation, my study has discovered that pre-training knowledge, distribution biases or existing annotation artifacts could often cause models to unfaithfully extract what is described in a given context, but instead to "guess" with a context-irrelevant extract using prediction shortcuts [50, 52]. Faithfulness, while being an under-explored research area, is undoubtedly a premise of reliable information extraction. In this context, my study has so far delivered several pilot studies to mitigate prediction shortcuts in entity-centric and event-centric information extraction with counterfactual analysis [50, 47], and counterfactual data augmentation [52]. On the other hand, to ensure that models make selective decisions on exception cases where nothing should be extracted, we contribute with selective prediction techniques based on high-order metric learning [28, 35] and Dirichlet parameterization [47].

Contributions in this line of research has been systematically summarized in my tutorial at NAACL 2022 [3], and has led to the support from a Cisco Faculty Research Award, the DARPA KMASS and the DARPA MCS programs.

**Transferable Representation Learning for Structural Knowledge.** Structural representation learning is the requisite for incorporating symbolic knowledge into deep learning models. A key contribution I have made to this field is on the *transferability* of such representations. Different domains or sources of data, or even different languages, often provide *interchangeable* and *complementary* knowledge. Hence, it is particularly important to develop a universal representation learning method that captures the association of knowledge across multiple data sources with minimal supervision, and support with credible knowledge transfer across different domains. I started this line of research with the first embedding framework that bridges multiple language-specific KGs [10, 15], by performing semi-supervised alignment of multiple relational embedding models. To more precisely capture the knowledge association with minimal supervision, I have extensively extended the alignment learning process based on iterative co-training [8], multi-view representation [9, 56], incidental supervision from free text [6], unsupervised visual pivoting [27] and coarse-to-fine entity linking [19]. I have also contributed with relational embedding techniques that are robust against scarcity and structural heterogeneity of data, particularly based on box embeddings [16], concept contextualization [37] and attentive neighborhood aggregation [38]. Particularly, for highly complex structures of knowledge representation, I have investigated on new paradigms in non-linear embedding spaces [36, 30, 5]. For knowledge transfer from multiple sources of (inconsistent) learning resources, my work addresses the problem of inducing trustworthy inference results with ensemble knowledge transfer [17]. In this context, my study also contribute with answer consolidation [66] and multi-modal fact verification [43] that seeks to resolve the redundancy and inconsistency of local extracts for global knowledge representation.

This line of research has received a wide recognition by the community for its importance, and has received over a thousand citations in the past four years. A wide spectrum of applications have also been benefited from the techniques proposed in my papers and follow-up works. The advancement in this research topic has been featured in my tutorial at AAAI-2020 [2] and our recent survey paper [39], and has been recognized with an NSF CRII Award in 2021.

**Portable Knowledge-driven Applications** The robust knowledge extraction and knowledge transfer technologies allow efficient and broad utility of the knowledge in computational research. This allows my study to further contribute to various narrative understanding [59, 42] and commonsense reasoning tasks [54, 14, 34, 33, 49, 48] that are at the core of current NLP research. My recent study also extends the utility of robust information extraction [60] and summarization techniques [23, 24] for knowledge acquisition and dissemination from online programming tutorials and discussions, aiming at helping software developers make more informed decisions and supporting the development of knowledge-based tools. Besides, I also accumulated good practice of transferring the above two lines of technologies to tackle important tasks in computational biology and medicine, including protein-protein interaction prediction [4], proteomic mutation effect estimation [61], circular RNA detection [22], disease target identification [20], and clinical diagnostic prediction [57, 58]. In addition, a recent thread of my research also interfaces language modeling with geographical data [26], aiming at benefiting automated machine comprehension and dissemination of digital map information. I am excited about the broad utility of knowledge acquired from my fundamental research on information extraction and knowledge transfer, and will continue the investigation on solving important problems in various areas.

## 2 Research Agenda: Directions for Future Work

My future research will continue to focus on helping machines efficiently and reliably acquire general-domain and expert knowledge from natural language text with minimal supervision, and leverage transferable representations to solve problems in various domains and interdisciplinary areas. Particularly, I intend to extend my investigation in the following directions.

**Event-Centric Natural Language Processing.** Human languages evolve to communicate about events happening in the real world. Therefore, understanding events plays a critical role in natural language understanding. A key challenge to this mission lies in the fact that events are not just simple, standalone predicates. Rather, they are often described at different granularities, temporally form event processes, and are always directed by specific central goals. Understanding events requires the understanding of how events are connected, form procedural or membership structures, and recognizing typical properties of events (e.g., space, time, salience, essentiality, implicitness, preconditions, consequences, etc.). Our prior studies have investigated on inferring the logical constraints [45, 46], analogical properties [54], evolution patterns [67], salience [59] and membership relations [14] of events. Yet, more fundamental challenges persist. Particularly, unlike entities, events have their internal structures, such that ensuring consistent information extraction for internal components and external relations of events remain as an unresolved problem. Besides, machine comprehension of causal relations, conditions and consequences requires unrealized human-like cognitive understanding. As events may evolve and be described in different ways among documents, inferring the relations of events across documents, consolidating unique and consistent global knowledge representation from highly diverse cross-document event descriptions represents a daunting challenge to event-centric information extraction. Moreover, reasoning about events challenges commonsense reasoning agents with often implicitness of event mentions, event arguments and event properties (e.g., essentiality [55], preconditions [33], and spatial attributes). My recent tutorials at ACL 2021 [12] and AAAI 2021 [13] have systematically summarized the current (pre-mature) status of event-centric NLP, and positioned the emerging fundamental research challenges, including the above, that will be at the core of my future research. In this context, I also plan to study the use of event knowledge to improve the coherence of narrative (e.g., our prior study [59]) and dialogue systems, enhance the factuality of summarization systems, as well as realize clinical event understanding to tackle important but expensive clinical diagnostic tasks [58, 57].

**Harnessing Massive Language Models.** Massive language models (also known as foundation models) such as GPT-3 and PaLM have excelled in many NLP tasks with their strong ability of distilling knowledge from Web-scale pre-training corpora, and raised opportunities in research directions such as in-context learning. Despite the progress, there are two critical issues with NLP solutions based on massive language models. First, massive language models still fall short of supporting with reasoning, including logical, quantitative and cognitive reasoning. Our recent study on machine comprehension of medical reports and tabular data has found that massive language models still fail to correctly infer the relations between time intervals, and do not meaningfully support numeracy. Our study also found that GPT-3 fails at cognitive understanding tasks, for example, by offering an AUC of 63% for inferring the essentiality of events [55], whereas humans can achieve around 87%. Second, after costing tens of millions of dollar to be trained, massive language models have to remain fixed within their year-long life cycles, causing them to be inadaptive to vastly streaming new information about the ever-changing world. My future research will tackle these issues in two directions. First, I will develop various mid-scale language models where dedicated kernel functions or neural symbolic modules are incorporated into the Transformer architectures, seeking to realize diverse types of reasoning processes. These models will form mixture-of-experts (MoE) or hero-gang structures together with the massive language model, providing complementary reasoning abilities. Second, towards adaptation to changing information, I will mainly investigate on two methodologies. Specifically, I will continue our study on parameter-efficient adaptation [53] to allow plug-in of memory modules about new knowledge into the MoE structure, for which added information in the memory modules may come from both new data and human-in-the-loop. Moreover, I will leverage our robust information extraction technologies to timely capture new information from the Web, and realize retrieval-augmentation of massive language models at inference.

**Generalizing Indirect Supervision for Scalable NLP.** My prior studies have demonstrated the success of indirect supervision from NLI and NLG tasks to enhance information extraction within the scope of single documents [25, 21, 29]. I will further extend this line of study in three directions. First, to allow more enriched knowledge extraction, it is essential to enable the extraction process across documents. As cross-document extraction tasks, such as cross-document co-reference resolution and cross-document relation extraction suffer more severely from insufficient training data than their single-document counterparts, my study will focus on (i) multi-hop dense retrieval approaches [51] for discovering evidence that supports cross-document relations, and (ii) indirect supervision from multi-document tasks, such as multi-document summarization and sentence fusion. Second, beyond the use of any existing source tasks for supervision signals, I will also design linguistic pattern mining and generative data augmentation methods that can automatically find or generate large-scale weak supervision data (a preliminary study has been conducted for preconditioned commonsense inference [33]). In the same context, I will further study methods that proactively select and filter task-specific weak supervision data following my prior studies on unsupervised denoising [63, 65]. Last, to understand the learnability of different sources of indirect supervision, we will study methods to quantify the contribution from each source task to the target task objectives, as well as parameter-level affinity measurement that helps select the substructures of the models for optimized cross-task signal transfer.

**Equivarience in NLP** As an important an important but largely under-explored component of robust NLP systems, both the language understanding and generation processes need to handle equivariance properties in data. For example, the narrative structure of an article can be reorganized, while still presenting the same content. In constrained NLG tasks with structural priors (e.g. structured data-to-text generation), the structure of the prior can also be modified while presenting semantically equivalent content. However, existing sequential modeling of languages cause downstream information extraction and NLG systems to be brittle to content-neutral transformations of input data. Our pilot study realizes equivarience learning by incorporating structured masking and transformation-invariant position encoding mechanisms in pre-trained Transformer models for data-to-text [44] and scene-to-text [49] generation tasks. Following this direction, I will investigate on principled approaches to address three research questions: (i) How to capture implicit but semantically equivalent structures (e.g., narrative structures) of natural language text, and accordingly generate equivariant language representations; (ii) How to disentangle semantic and syntactic representation in large language models; (iii) How to composite information from multiple components of text (e.g., sentences, paragraphs, or documents) while ensuring the equivarience to positional and frequential perturbations.

**Cross-domain and Interdisciplinary Research.** I always believe that a useful technology should address problems in several related research areas rather than a single one. Therefore, beyond core NLP tasks, my research has also contributed to computational biology [4, 61, 22], medical informatics [58, 57, 20], geo-intelligence [26] and social media analysis [40, 1]. Particularly, I have been interested in AI technologies for common good that could contribute to fairness [62], healthcare [58, 57] and education [31]. Given the previous success in transfering technologies to different areas, I am enthusiastic about developing open-source libraries and software, and facilitating collaborations with people outside my areas. I am excited about any opportunities to apply my expertise in NLP and representation learning to solve important problems in other areas and disciplines.

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