CRII:III: Composing Process Knowledge using Semantic Roles

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Contents

1 Introduction

AI systems have achieved impressive success with answering factual questions (e.g., "When was Bill Clinton born?"), using information from large-scale text or database resources [4, 12, 7, 32, 19]. To scale more challenging problems that go beyond factual answer retrieval [33, 9, 5], AI systems will need the ability to reason about the world. In particular they need knowledge of generalities and how it applies to the specific situations. Despite significant advances in AI, acquiring general knowledge and using it to reason effectively remains a huge challenge.

We propose to investigate this challenge in the context of learning and reasoning about *processes*. Knowledge about processes is a fundamental to part of our understanding of the world and it is essential to make predictions and answer questions about specific scenarios involving them. Our goal is to develop solutions to construct a large repository of simple process knowledge automatically, and demonstrate its use to answer process questions that go beyond fact lookup.

1.1 Motivation

We motivate the need for process knowledge using an example from an actual 4th grade science exam.

> **A pot is heated on a stove. What causes the metal handle of the pot to become hot?**
> (A) conduction (B) convection (C) radiation (D) combustion.

The question tests the ability to recognize a specific scenario involving a heat transfer process. To establish that conduction is the cause, a reasoning system must establish that there is some heat transfer happening through *direct contact*. We envision a system that first interprets the scenario and apply its knowledge about the heating process and the conduction process. In this case, the system needs to first identify *what is being heated* (the pot), and *what is the purported result* of the heating (the pot handle becoming hot). Then, knowledge about *heating* should allow it to conclude that the thing being heated (the pot) will become hot. Knowledge about *conduction* should suggest that anything *in direct contact* with a hot object (the pot handle) should also become hot. Combining these bits the system can verify that the described scenario indeed matches the conduction process. Replicating this type of reasoning requires knowledge about conduction and heating in a suitable computational representation.

At a high level the main bits of required knowledge are: what is undergoing the process, what is the result, what is the main action etc. These bits of information are naturally encoded as semantic roles. PropBank [21] and FrameNet [1] are two of the highly successful efforts which provide this kind of semantic role based knowledge. They have spurred tremendous advances in automatic semantic role labeling and their applications [17, 39, 13, 34]. While these resources provide exhaustive coverage for modeling general open-domain actions, they only provide partial coverage on processes in the science domain. FrameNet, for instance, does not have entries for nearly half of the processes described in 4th grade science exams. The coverage is likely worse for higher grade levels with deeper knowledge domains.

In response we propose to investigate methods to automatically construct a large repository of simple knowledge about processes. Specifically, we will make three main contributions:

- A method for **automatic extraction of process knowledge** that combines extraction and joint inference.
- A framework for **iterative knowledge expansion**, which allows the system to discover new roles involved in a process and expand the process representation to accommodate them.

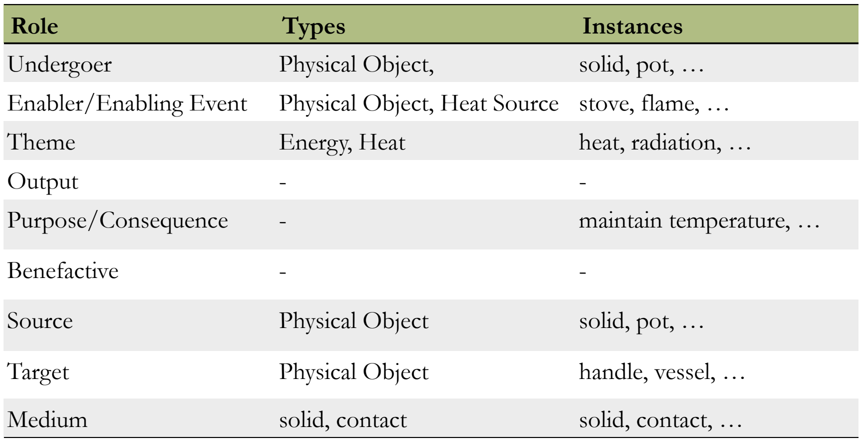
- The first comprehensive, large-scale **knowledge base of processes**, describing the roles and changes involved in that process.

To provide a concrete test-bed for development and evaluation purposes, we will initially develop this in the domain of elementary science, and evaluate it using unedited science exam questions about processes. We expect the resource to be useful to other researchers working in the areas of natural language processing, text processing, and question answering.

2 Proposal Synopsis

Our primary motivation is to design a representation that effectively supports reasoning while also being amenable for automatic extraction. We target a simple[1] form of knowledge that captures information about the entities involved and their semantic roles within the process.

We turn to the inferential needs of the target application to guide our choices. Our preliminary work in this domain suggests a mix of **pre-specified semantic roles** that apply to many processes, and a set of **automatically induced roles** that are process specific [27]. We also find that we need both **definitional** – describing the key classes of entities and types of actions involved – and **instance level** knowledge about specific scenarios in which the processes occur – providing details on the specific entities and actions.



Role	Types	Instances
Undergoer	Physical Object,	solid, pot, …
Enabler/Enabling Event	Physical Object, Heat Source	stove, flame, …
Theme	Energy, Heat	heat, radiation, …
Output	-	-
Purpose/Consequence	-	maintain temperature, …
Benefactive	-	-
Source	Physical Object	solid, pot, …
Target	Physical Object	handle, vessel, …
Medium	solid, contact	solid, contact, …

Figure 1: An example entry for the process *thermal conduction*.

Figure 1 shows an example for the envisioned knowledge. The table includes a set of pre-specified general purpose roles such as *Undergoer*, *Enabler* and also a process specific role *Medium* that is automatically derived from inspecting sentences that describe the process. In addition to the *instance* role fillers, it also includes *definitional* type information which encodes class level information where possible.

Research Questions

There are many research challenges in automatically extracting this knowledge from text.

- SRL systems typically rely on large amounts of training data in order to generalize over sparse features. How can we leverage the abundance of information on the web to reduce the need for large training data?
- A priori it is not clear how to identify which set of sentences are likely to contain relevant information. How to gather sentences that convey the necessary knowledge?

[1] Process knowledge is typically complex with sub-events, and temporal dependencies. They are beyond the scope of this investigation.

- How do we account for process specific roles?

Our investigation aims to answer these questions.

2.1 Automatic Extraction of Process Knowledge

General semantic role labeling task is challenging because of the lexical and syntactic variations in role realizations. Handling the variations requires learning from large amounts of training data, which is laborious and requires expert labor.

Our key premise is that to gather role knowledge we don't need a semantic role labeler that works well on all sentences. We are interested in role acquisition and not role interpretation. We exploit the abundance and variety of information available on the web to target extraction from sentences that convey the same information in expected (easy to extract) constructs and use joint inference to further improve performance. Our approach includes:

- **Targeted Pattern-based Extraction** – We build a simple pattern-based local role extractor augmented with a classifier. Using a set of manually constructed query patterns we search the web to find sentences and extract role fillers. A simple classifier then assesses if the extraction is valid. Unlike traditional SRL tasks, here we have a strong expectation of the type of role and where the filler is likely to be located. This expectation allows us to design simple structural features that generalize better across different roles and processes, thereby reducing need for large amounts of training data.
- **Joint Inference Across Sentences** – We propose a joint inference model that operates over multiple sentences to avoid errors in the local extraction. Despite the targeted acquisition, local sentence-level extraction alone is not adequate, because not all patterns are unambiguous. For example, "evaporates into <x>" extracts steam, a *result*, as well as atmosphere, a *location*. Redundancy and variety of expression on the web can help us: If the *atmosphere* were in fact a *result* then we might expect to see other sentences where it is expressed as a result with unambiguous patterns. We propose a joint inference formulation that favors roles minimizing disagreements in labels for similar text spans in similar sentences.

2.2 Iterative Knowledge Expansion

Determining the best set of knowledge bearing sentences *a priori* is extremely difficult. The quality and scope of the extracted knowledge is effectively determined by the set of sentences retrieved by the query patterns. The query patterns may have limited coverage in some cases especially for roles that were not part of the pre-specified vocabulary. We propose an iterative expansion of the knowledge to improve coverage of existing roles, and to discover new roles. An inspection of the gathered knowledge can provide valuable guidance in expanding and refining the knowledge. We propose to investigate methods to 1) assess the coverage of the roles, 2) induce new roles by identifying consistently repeated arguments that don't fit existing roles, 3) bootstrap extractors and query patterns using relevance feedback techniques, 4) refine the knowledge by organizing the knowledge in clusters of scenarios/instances.

2.3 Knowledge Base of Processes

Our target domain is grade level science. Based on initial analysis we estimate to generate about entries for around 2000 processes encompassing simple physical, chemical, biological, and other natural processes in this domain. As part of the proposed work, we propose to curate a subset of this knowledge base. Recent work has shown an effective question-based mechanism for acquiring semantic role labels via crowd sourcing [18]. To foster further research, we will release the knowledge base, and open source the code, and host web services that will allow dynamic construction of knowledge for new unseen processes. We anticipate this knowledge base will also be useful for QA in the science domain, for communities interested in AI systems, and to the semantic role labeling community at large.

The proposed methods will be evaluated for intrinsic quality and external utility. For internal evaluations we will perform manual evaluation of the resulting KB. As an external evaluation we will use the knowledge base for answering process recognition questions.

The remainder of this proposal provides details on these three main contributions.

3 Background and Prior Work

Much progress has been made on question answering involving simple facts [4, 12, 7, 32]. This is in large part due to the availability of large scale curated relational knowledge bases such as Freebase, coupled with significant advances in automatic relation extraction [28, 8, 38]. Similar advances in large scale inference-supporting knowledge is vital for making significant progress in reasoning-based QA tasks.

Recently introduced tasks such as *MCTest* reading comprehension challenge [33], grade-level science exams [9], and process comprehension tasks [5] serve as excellent benchmarks for developing reasoning-based question answering systems. These tasks test the ability of the systems to interpret and reason about scenarios and situations.

PI's prior work on knowledge requirements analysis for grade-level science exams shows the need for deep inference supporting knowledge [11, 10]. Also PI's recent work on reasoning shows that even with advanced state-of-the-art reasoning techniques, shallow text-derived knowledge is ineffective due to lexical and syntactic variations in language [20]. Scalable acquisition of deeper semantic knowledge is essential for effective reasoning in these tasks.

In this work, we target extraction of semantic knowledge about physical, chemical, and other natural phenomena. The goal is to derive knowledge that allows effective reasoning about scenarios involving these phenomena. Our central premise is that the entities involved in a process and the roles they play provide a powerful representation for reasoning and QA. Similar representations are shown to be useful for Open-domain factoid question answering [35, 30], and comprehension questions on process descriptions [5].

As preliminary work, we first analyzed the knowledge requirements for a set of questions from fourth grade science exams targeting around 150 processes. While a small collection of general purpose roles (e.g., Undergoer, Result, Enabler, Trigger) capture the key semantic elements for a majority of the processes [27], we also find that a set of domain specific roles (e.g., Direction, Medium) are also critical. We propose to compose a representation that combines both general and domain specific roles.

4 System Architecture

Figure 2 shows our envisioned architecture. The main idea is to collect high quality sentences and roles and iteratively expand the acquisition to include additional sentences and other roles.

Using simple query patterns we search for sentences that express roles with highly regular lexical cues. A sentence filter addresses sense issues and to remove malformed sentences. The filtered sentences are then processed through a pattern-based extractor that identifies and scores the candidate roles. In parallel, the sentences are also aligned to identify lexical units that should play similar semantic roles in the sentences. A joint inference module then provides a collective label assignment for all the sentences. The extracted roles are then assessed in conjunction with the existing roles. The assessor determines which roles should be added to the KB and also determines which roles need further additions. New query patterns are created for the roles that need addition and whole procedure is repeated again.

In the subsequent sections, we describe each component in greater detail.

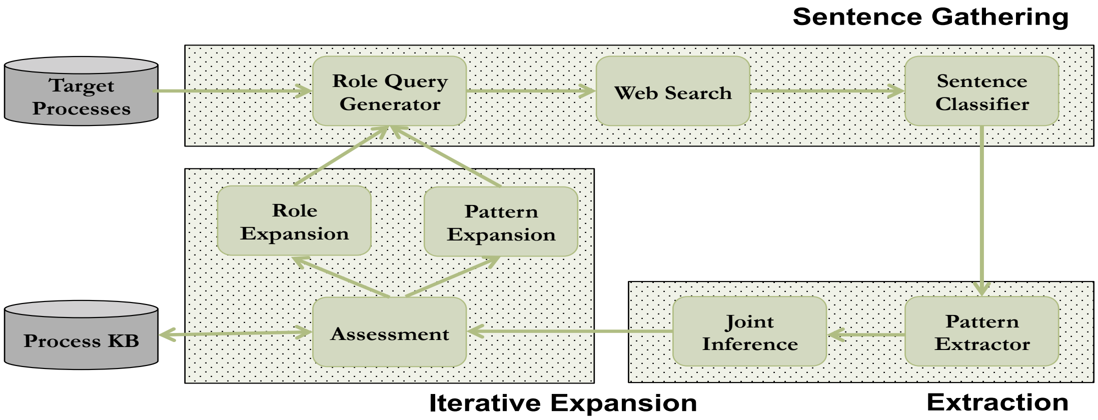


Figure 2: System Architecture

5 Automatic Extraction of Process Knowledge

5.1 Sentence Gathering

We will leverage the vastness of the web to build a targeted collection of sentences that expresses roles of interest. Ability to locate many information bearing sentences is critical to the success of our approach. We anticipate two main challenges in gathering relevant sentences:

- **Relevance** – The vastness of the web also means that there is information on nearly any possible interpretation of the words used to describe the process. For instance if we are interested in the process *crop fertilization*, we might also find information on *fertilization* in the reproductive sense, or in other metaphorical uses such as *cross fertilization of ideas*. Also, the target sense may not be a dominant sense on the web. Constructing effective keyword queries is therefore critical for finding relevant information.
- **Role Coverage** – We want to find sentences that cover all applicable roles that convey the desired information via simple expected constructions. Some roles are often expressed via highly regular lexico-syntactic constructions. On the other hand, roles such as x can be expressed in many different ways. Again with the vastness of the web, constructing effective role patterns is critical for finding useful sentences.

To address these challenges we espouse a feedback strategy: High quality sentences gathered in earlier phases can guide search in later stages. We find that definitional sentences can be found reliably using simple lexical patterns and they convey the most salient information. Therefore, we first target definitional sentences, and in subsequent iterations, we use them as a guide for finding additional sentences involving other roles.

5.1.1 Role Query Generator

We propose to investigate simple but effective query pattern formulation methods. Our preliminary work shows that simple lexical templates e.g., "<process name> is the process by which" can yield high quality *definitional* sentences about processes. We use additional lexical templates for roles with regular lexicon-syntactic constructions e.g., "<process name> causes" is an effective pattern to find sentences that express the *result* roles of processes. The key challenge is to figure out querying patterns for roles with diverse lexical realizations. We propose adopting the standard bootstrapping approach used in relation extraction techniques to borrow functional patterns that introduce roles in other processes. Bootstrapping is known to introduce noise and topic drift issues. However, our approach doesn't entirely rely on the patterns alone.

Rather we propose strong scoring and filtering mechanisms that can remove noise introduced via bootstrapping.

5.1.2 Sentence Classifier

Sentences from the web have high variance in quality and relevance. To account for the challenges in relevance, we build a classifier that is trained to identify malformed sentences. We adopt a sentence classifier that we built in our prior work for identifying biographical sentences from the web [2]. The classifier will use morphologic (capitalization, special characters etc.), and n-gram language model features to prune low quality sentences. In addition we extend this classifier to also use a distributional context model built from a target domain corpus (e.g. 4th grade science book). The relevance of the sentence and its surrounding context is evaluated against this context model for filtering out out-of-domain senses and usages. This context model allows us to guard against topic drift issues that could arise in subsequent bootstrap iterations.

5.2 Extraction

Many different approaches have been investigated for role labeling. The learning formulations studied range from pipelined classification approaches [17, 6], efficient structured and joint inference [23, 40], to end-to-end deep learning architectures [14]. Many different lexico-syntactic features, such as dependency paths and n-gram contexts, provide weak evidences for determining semantic roles [17]. Because these path-based and n-gram features are sparse, these supervised techniques require large amounts of training data. Semi-supervised and unsupervised approaches have been proposed as a means to address the training data problem [15, 22].

The focus of these approaches have been to build a SRL system that can identify the roles mentioned in a sentence. Our requirement is subtly different. We need to build a mechanism for acquiring the typical role fillers for a given process. First, we formulate a simpler local classification task that avoids the need for learning over role and predicate specific patterns. Starting with sentences that are likely to contain a specific role and a candidate text span from the sentence, we pose a classification task to determine if the candidate is indeed expressing role of interest. Then, we pose a joint inference task over multiple sentences, which allows us to use role decisions on similar text spans to influence each other.

5.2.1 Pattern-based Extraction

We set up a local – within sentence and per role – extraction task. Relying on the patterns alone is problematic. Hand authored patterns, especially with specified syntactic structure of the argument is quite limiting. Instead we generate many possible arguments that match a range of weakly indicative argument patterns and train a classifier.

The inputs are a sentence S, the role R for which it was retrieved, and the role pattern X_R that it matches, and a set of candidate spans C. The task is to predict if for each span if it is expressing the role of interest.

We adopt the standard SRL features such as clause, dependency path features, and n-gram context features [17, 23]. We explore two types of extensions that are specific to our setting:

- Different from a standard SRL setting, we seek identification of roles with respect to a canonical realization of the process. One can view this task as finding a mapping from predicate-specific semantic role to the process-specific role. To this end, we use an SRL system trained on PropBank data to identify predicate level semantic roles and use those as features to derive this mapping. Similarly, the frames that are evoked by the predicates in the sentence also provide important signals. For example, knowing that there is a conversion frame in a sentence increases the possibility of finding a result of a change of state of process like evaporation.

- Also we have strong expectations on *how* the argument is realized because the sentence is retrieved via a specific query pattern. This allows us to encode features that test if these expectations are met.

5.2.2 Joint Role Inference

Local role extraction allows us to reliably identify whether the specified role is expressed by the candidate text spans. However, this local classification can suffer because some cue patterns are ambiguous. For example, "evaporates into <x>" can match "steam" which is a *result* or "atmosphere" which is a *location*. If the *atmosphere* were in fact a *result*, we hope to leverage information from other sentences where it is expressed via less asmbiguous patterns. Therefore, we propose to leverage role predictions on other similar text spans to improve inference.

Effectively, our proposal is to combine ideas from two threads of prior work: Semi-supervised and unsupervised SRL have exploited labels on similar text spans to account for sparse training data [15, 16, 25]. Joint modeling techniques have leveraged structural and linguistic constraints to improve within sentence role labeling [31, 23, 36]. We will investigate methods that allow us to effectively incorporate this in joint inference.

Modeling Example ILP-based formalisms have been successfully used for joint inference for SRL [31, 23, 36]. Joint inference across sentences can be cast as the task of finding role label assignments that *minimize label disagreements across sentences for similar text spans*, while also respecting *within sentence structural and linguistic constraints on roles* [31]. We sketch an example instantiation of this idea as an ILP:

Let $\rho(t_{ik}, r_j)$ indicate the local extractor scores for text span $t_{i,k}$ from sentence S_k on how likely it is to belong to the role r_j. Use indicator variables to denote role assignment. z_{ijk} represents if the text span t_{ik} in sentence S_k is assigned the role r_j. Find the best joint assignment to set of indicator variables $\mathcal{F}$ that maximizes the sum of extractor scores with penalties for assignments that violate smoothness of labeling. Use constraints or parameterizations that effectively fix labels from the local extractor for certain roles. Formally, the inference aims to find the best joint assignment to set of indicator variables $\mathcal{F}$ that maximizes the following objective function:

$$\arg\max_{\mathbf{z}} \sum_{i,j,k} z_{ijk} \cdot \rho(t_{ik}, r_j) \cdot \lambda_j - \beta \left\{ \sum_{i,k,l,m} \sigma(t_{ik}, t_{lm}) \left(\sum_{c \in |R|} |z_{ick} - z_{lcm}| \right) \right\}$$

subject to

$$\forall z_{ick} \in \mathbf{z}, \sum_{c=1}^{|R|} z_{ick} \leq 1 \text{[A span gets only one role.]}$$

$$\forall S_k \forall c \in |R|, \sum_{t_{ik} \in S_k} z_{ick} \leq 1 \text{[Roles are not repeated.]}$$

$$\cdots\text{[Other within sentence constraints.]}$$

Alignment

One of the key challenges in joint inference is to identify text spans in different sentences that should get the same role. Aligning text spans in web retrieved sentences poses many challenges. There are different sub-groups of sentences with different alignment characteristics. *Definition* sentences describe the process in terms of classes of entities and *instance* sentences which involve specific entities. Instances involve completely different entities which may not align via direct entailment but may align as substitutable siblings. Also, instances may include intervening unrelated information, whereas definitions are compact and tend to contain the most salient bits of information.

Our work will investigate methods that addresses these challenges using various information sources. We propose to train a feature-based classifier that combines many indicative features including source query patterns that were used to retrieve the sentences, textual entailment scores of the spans [37], alignment scores of the words within the spans [41], as well as use paraphrastic scores from resources such as PPDB [29].

To more explicitly account for alignments from different sentence types, we also consider parameterizations that allow different sets of weights and similarity functions based on the types of sentences being aligned. For example, a predicate-argument alignment function used in prior work [15, 16, 24], can be parameterized with the types of sentences (u, v) of the candidate spans as below:

$$\sigma(t_{ik}, t_{lm}, u, v) = \alpha_{uv} \cdot lexsim_{uv}(t_{ik}, t_{lm}) + (1 - \alpha_{uv}) \cdot synsim_{uv}(t_{ik}, t_{lm})$$

6 Iterative Knowledge Expansion

We envision an iterative procedure. In each iteration, we first find sentences that match all query patterns for all the roles. Inference yields a set of role fillers that can be reliably identified from this combined input set of sentences. However, the yield of role fillers is limited by the set of roles and the query patterns used. To expand the knowledge further, we propose an iterative procedure that learns from the inferred roles to find new query patterns.

6.1 Role Assessor

The iterative process poses a potential challenge in consolidating the new role fillers with the existing knowledge. Role fillers from the current iteration may be inconsistent with roles obtained from previous iterations. We build a role assessor that explores two approaches: 1) A pipelined winner-takes-all approach that compares the normalized inference scores from each iteration to determine a winner. The inference for the losing iteration is repeated again. 2) A more integrated approach that uses previously determined labels as strong priors (or constraints) during joint inference, thereby eliminating the need for repeated inferences. The key distinction between the methods is the trade-off in the number of variables and constraints in each iteration versus the number of iterations that are needed.

6.2 Pattern Expansion

We propose to combine bootstrapping techniques from information extraction with relevance modeling techniques from information retrieval. For each role, we identify the role fillers that were inferred with the highest confidence and use them to locate new query patterns. We will inspect the sentences that are already retrieved and also issue new queries to find additional sentences. We will extract the most compact lexico-syntactic dependency patterns involving the fillers and use them as candidate patterns. To avoid noise compounding and topic drift, we propose to evaluate the candidates based on the relevance of their sentence contexts to the process as a whole as well as to other sentences expressing the role. We propose to borrow ideas from our prior work on sentence relevance models [2] and standard relevance modeling techniques from IR [26].

6.3 Role Expansion

At each iteration we will also inspect if there are any new roles that need to be added to the role set. For many processes there are specific important roles that do not fit any of the general roles. Some examples:

- *Phototropism* is the mechanism by which plants grow towards a light source. The notion of a target *light source* and the *direction* or *orientation* of the growth are critical for distinguishing positive and negative phototropism. However, neither notion fits with any of the existing roles.

- *Heat transfer* processes such as radiation have notion of a *medium*, which is critical for distinguishing between instances such as convection and radiation Again medium doesn't fit with any existing roles.

We propose to investigate methods for identifying candidates for new role fillers and methods to score the candidates. Our intuition is that information about how candidates are related to currently identified roles is helpful in scoring possible candidates. As part of our preliminary work, we find that most of these process specific new roles tend to be realized via prepositional, noun-noun, or other noun modifier relations that attach to one of the existing roles.

Candidate Identification We use two sources for identifying candidates. First, we obtain candidates from the local extraction pipeline that were assigned low scores by the inference and then we extend it with candidates from a separate PropBank style argument identification pipeline [24]. Second, we also inspect role fillers for existing roles that can be broken up into fine-grained roles. For example, "towards a light source" can be further split into two roles one relating to the "direction" of the growth and the other relating to the goal "light source".

Scoring Having identified candidates we iterate through the pipeline to find additional sentences that contain these candidates and the core roles or predicates for the process. Following prior role induction work, we extract a context signature for each candidate and cluster the candidates that are realized with similar contexts. The key contribution here is that we extend the signature with semantic contexts that include information about the currently identified roles.

7 Knowledge Base of Processes

We propose to generate process knowledge for the target domain of grade-level science ranging from levels four through twelve. Using the domain texts, glossaries, and exam questions, we will manually identify the processes of interest. We anticipate to build a list of around 2000 processes. We propose both an intrinsic evaluation that measures the accuracy of the extracted roles, and an external evaluation where we assess the utility of the roles in question answering.

7.1 Intrinsic Evaluation

Our goal is to acquire knowledge about processes along relevant role dimensions. Following our prior work on schema evaluation [3], we propose a crowdsourcing approach for evaluating the generated knowledge. We will devise an evaluation methodology that assesses the precision and recall of relevant information about the process.

7.2 External Evaluation

We propose to closely collaborate with the Allen Institute for Artificial Intelligence (AI2) for evaluating the knowledge[2] for use in reasoning-based questions in grade-level science exams. As part of preliminary work we have built a question answering system that leverages semantic roles to recognize process questions [27]. We will extend this approach to work with the substantially larger knowledge base of semantic roles generated by this work.

We propose to work with AI2 to leverage their large collections of question banks. We will also work with them to author new questions if need be. Creating these questions is a difficult task for non-experts without careful guidance. We will also work with the graduate students aiming for teaching professions to collect questions and question templates to identify the kinds of understanding that needs to be tested. We can then scale out the question acquisition process via crowd sourcing.

[2] Please see attached letter of support.

8 Development Plan and Timeline

The project will proceed in four stages. 1) Representation design 2) Extraction methods 3) Expansion methods 4) Curation and release. The developed components will be evaluated and improved continually. The research plan in calendar years is shown below:
Year 1:

1. Inferential needs gathering and representation design.
2. Implement sentence gathering.
3. Extraction and joint inference methods.
4. Intrinsic evaluation of the knowledge base.

Year 2:

1. Investigate methods for improving joint inference and iterative expansion.
2. Expansion of the KB to all target concepts and evaluation of the resulting knowledge base and
3. Curation and release of knowledge base. Open source release of the software and web service.

9 Broader Impacts of the Proposed Activities

Knowledge about processes is fundamental to our understanding of the world and vital for AI systems that interact with the world and with humans. Computational representations of scientific knowledge has tremendous applications in improving access to critical information, as well as in accelerating discovery and research processes. Moreover AI systems are increasingly adopted for use in many types of decision making in critical areas such as technology, science, and medicine. Knowledge based reasoning is crucial for building systems that have the ability to explain their decisions or predictions. Such systems require an understanding how to represent knowledge in a form that lends itself to computational reasoning for complex tasks.

9.1 Curriculum Development Activities

The PI teaches grad-level Introduction to Natural Language Processing, and Advanced Topics in Computational Linguistics. With advent of big data ecosystem understanding and extracting knowledge is becoming increasingly relevant in industry. I plan to teach a course centered around the core concepts of knowledge representation, and scalable extraction techniques for knowledge. This course is relevant for both Masters and PhD students. Most NLP-based technology companies and technology companies with a large web presence have a need for extracting and organizing knowledge from their user engagement data. This course will provide a basic overview of a distributed information extraction pipeline, persistence, and building applications that rely on the extracted data.

9.2 Community Outreach

There is an increased enthusiasm for advanced placement computer science courses in the high schools in local communities. The proposed project deals with computational representations of scientific processes discussed in grade level sciences. This provides an unique opportunity to introduce computer science concepts using an application domain that they are familiar with. The familiarity and the far reaching impact possibilities provide an excellent platform to attract the attention of high school students. The PI plans to offer introductory technical lectures, and project opportunities to engage high school students in the context of the proposed project.

10 Prior NSF Support

Dr. Niranjan Balasubramanian has broad expertise in information extraction, esp. in large scale knowledge generation and its application to complex NLP tasks but has not received prior support from NSF.

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