Composing Representations for Processes using Semantic Roles

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1 Introduction

Our vision is targeted acquisition of inference-supporting knowledge that can be used for reasoning tasks such as Question Answering (QA). In particular we focus on knowledge acquisition for standardized test benchmarks such as grade-level science exams [3]. Our prior work on these tasks provide strong motivation for reasoning based approaches [4, 5]. Lexical and syntactic variations render shallow text-derived knowledge ineffective for reasoning, even when using state-of-the-art probabilistic methods [10]. Deeper semantic representations are critical for effective reasoning.

This proposal investigates methods for acquiring knowledge about physical, chemical, and other natural phenomena. The goal is to derive knowledge that allows effective reasoning about scenarios involving these phenomena. We refer to this as process knowledge. Our representation and acquisition methods will be targeted towards the grade science benchmarks but the methodology is general and can be applied to other tasks and domains.

1.1 Motivation

We motivate the need for a semantic-role based representation using two examples from 4^{th} grade science exams. These questions test the ability to recognize a process based on the description of a scenario.

1. *When plants use stored sugar for energy, they go through a process called (A) photosynthesis (B) transpiration (C) respiration (D) perspiration.*

2. *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 first question tests knowledge about biological processes. *Photosynthesis* and *respiration* both involve sugar and energy. Photosynthesis converts light energy to sugar, whereas (cellular) respiration releases energy in the sugar by breaking it down. Not surprisingly these processes are described using similar words, which makes bag-of-words style reasoning unreliable. Understanding the different roles that energy and sugar play in these processes, and knowledge of the main actions involved is key to effective reasoning.

The second question tests knowledge about heat transfer mechanisms. 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 reasoning system that first interprets the input scenario in terms of entities and their semantic roles. In this case, the system would first identify *what is being heated* (the pot), and *what is the purported result* of the heating (the pot handle). Then, it will verify if this interpretation of the actions and the roles match with the expected actions and roles of a conduction process. Specifically the knowledge about conduction should convey that there are two entities that are in direct contact, one of which is being heated or is hot, and the result of conduction is that the other object also becomes *hot*. These bits of information are naturally encoded as semantic roles.

Existing lexical semantic resources and knowledge bases are not well suited for our goals.

On the one hand, existing semantic resources such as FrameNet and PropBank provide different representations of general open-domain actions but do not cover knowledge about scientific processes. 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. On the other hand, automatic knowledge bases built via relation extraction capabilities (e.g., Open IE) scale to arbitrary target concepts but only contain simple binary relations e.g., (Arg1, Rel, Arg2), that do not adequately capture the semantics.

1.2 Proposal

In response, we propose to build a knowledge base about physical, chemical, and biological processes from their textual descriptions. We compose a semantic representation using a combination of pre-determined vocabulary of semantic roles and derive new roles on demand.

We propose to identify roles with respect to a canonical version of the process, rather than based on the actual lexical realization in the sentence. This is similar to frame centric abstraction used by FrameNet. The key difference is that roles are still thematic but are defined with respect to a canonical predicate. Canonicalization during construction reduces reasoning burden by eliminating steps that establish equivalences between effectively equivalent bits of information realized via different predicates.

Handling the variations requires learning from large amounts of training data, which is laborious and requires expert labor. Also mentioned above, existing resources cannot be directly used. FrameNet does not cover the concepts of interest. The need for a canonicalized representation precludes the direct use of existing annotations or tools built for PropBank. Rather than building a role labeler that can work on any sentence, we adopt a simpler approach that works well on a smaller subset of sentences.

The main idea behind the proposal is a targeted acquisition of knowledge from sentences that convey information in expected ways. Leveraging the vastness of the web greatly reduces the need to accurately identify roles in difficult to process sentences. Using a set of manually constructed query patterns we find sentences which convey the roles using expected lexico-syntactic constructs. For instance "<process name> causes <x>" is a simple pattern that can be used to find the *result* role for a process. This strong expectation for how arguments are realized allows us to turn SRL into a simpler task of assessing the confidence on the extraction using features that generalize better across different processes. This allows us to substantially reduces the burden of annotating sentences for each process. Even though PropBank and FrameNet data are not directly usable, the predicate-based roles, and the frame structures provide evidence for composing our target semantic roles. We propose to exploit these features to build a local sentence-level extractor.

Despite the targeted acquisition, local sentence-level extraction alone is not adequate, because not all lexico-syntactic patterns are unambiguous. For example, "evaporates into <x>" extracts steam, a *result*, as well as atmosphere, a *location*.

A second key idea is to perform joint inference over multiple sentences to avoid errors in the local extraction. Because our goal is to acquire knowledge about a process, we turn the variety of expression on the web to our advantage. We build on prior work in Integer Linear Program (ILP) based semi-supervised and unsupervised induction approaches. The ILP attempts to find an assignment of roles that maximizes the sum of extraction confidences, while also minimizing disagreements in labels for similar text spans in similar sentences.

While we start with a set of general purpose roles, *a priori* we don't assume which roles are applicable to each process as this manual assignment is not desirable from a scalability standpoint. Also not all critical information may be covered by the set of roles that hand.

A third contribution includes methods that identify the subset of roles that apply to a process and discover new roles not part of the general vocabulary. As part of the targeted acquisition, we propose an iterative approach with methods to i) assess the coverage of the roles, ii) induce new roles by identifying consistently repeated arguments that don't fit existing roles, and iii) relevance feedback based query pattern generation to expand the knowledge.

The generated knowledge base will be evaluated for intrinsic quality and external utility. For internal evaluations we will perform manual evaluation of the resulting KB. As part of the evaluation, we will also create a large scale curated KB, which relies on correcting the outputs from the system, rather than careful annotation of each sentence. We will also generate a gold standard of the desired roles and role fillers for evaluating coverage. As an external evaluation we will use the knowledge base for answering process recognition questions. All the resources and evaluation test beds will be shared with the research community for further research.

1.3 Prior Work and Contributions

The motivation and direction for this proposal stems directly from our prior work on grade science exams. Our earlier work studied knowledge requirements [5], developed inference-supporting rule knowledge bases [4], and investigated sophisticated state-of-the-art probabilistic reasoning methods for QA [10]. Our ongoing preliminary work investigated the value of a handful of semantic roles in answering process recognition questions and identified the knowledge, representation, and reasoning gaps [15]. This proposal aims to address the central challenges that we've identified through these prior works.

Upon successful completion this project would have made the following contributions:

- Release of a knowledge base covering semantic representations of processes for grade level science.
- Methods for automatically gathering high quality sentences that cover a target set of roles.
- A joint inference method that reconciles roles across different sentences.
- Methods for automatically assessing the applicability, coverage and importance of roles with respect to a target process.

2 Background and Preliminary Work

[**Note to Peter: Please don't read this section yet!**] Much of SRL work has focused on interpreting sentences i.e., identifying roles expressed in a sentence. Our goal is different. We seek to acquire knowledge about processes and represent them in terms of semantic roles. SRL is a challenging structure prediction task which often requires

Prior work either resorted to supervised learning techniques or to semi-supervised approaches However, obtaining training data is often difficult and laborious, especially for complex tasks such as SRL. Several prior approaches have used semi-supervised learning (SSL) approaches to address this issue.

We propose a different approach, where we explicitly find sentences that express the roles of interest and do a joint inference of role labels across all sentences. This allows us greater flexibility in choosing which sentences to use (we can maximize role coverage, diversity of instances etc.). Aligning the various spans within these sentences allows us to do collective labeling (similar in spirit to transduction learning).

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 have been shown to be useful for Open-domain factoid question answering [18, 16], and reading comprehension tasks on process descriptions [1].

2.1 Preliminary Work

As preliminary work, we first analyzed the knowledge requirements for a set of questions 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 [15], we also find that a set of domain specific roles (e.g., Direction, Medium, Physical_Property, Chemical_Property) are also critical. We propose to compose a representation that combines both general and domain specific roles.

Note that these roles are specified based on a canonical view of the process. One of the key challenges in question answering is in overcoming the variability of expression. Labeling with respect to a canonicalized view of the process is a deliberate attempt at addressing the variability problem.

Manually specifying roles for each process is not desirable from a scalability standpoint. Lexical and syntactic cues are indicative of certain roles in sentences. For example a *[process] happens by [event]* pattern suggests the presence of a manner role, and the presence of locative prepositions can indicate location or orientation roles.

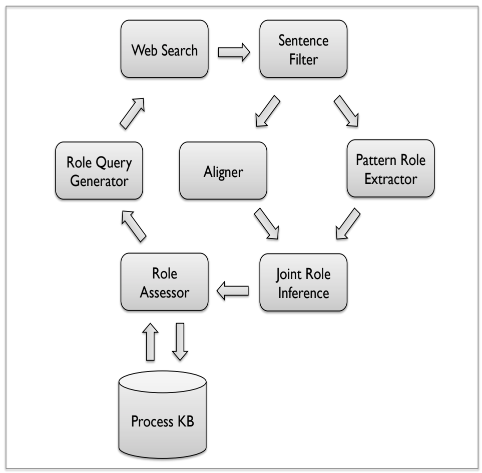

Figure 1: Process KB Acquisition: Proposed Architecture

3 ProcIteRoles: Architecture

ProcIterRoles allows for targeted iterative acquisition and refinement of process roles. The central idea is to collect high quality sentences and roles and iteratively expand the acquisition to include additional sentences and other roles.

Figure 1 shows the architecture of the acquisition process. 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.

4 Sentence Gathering

ProcIterRoles will leverage the vastness of the web to build a targeted collection of sentences that expresses roles of interest. There are two key challenges to address in gathering relevant sentences:

- **Relevance** – We want to find sentences that describe the target process of interest. 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 propose two strategies. First, we target definitional sentences which convey the most salient information. Second, we espouse a feedback strategy that leverages high quality sentences gathered in the earlier phases to guide search in the later stages.

4.1 Querying

We propose to investigate simple but effective query pattern formulation methods. On a related task, our prior work had explored techniques that can find sentences that convey information about different aspects with respect to a topic (e.g., biographical aspects of a person). 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.

4.2 Scoring and Filtering

To account for the challenges in relevance, we seek to build a distributional context model that is seeded with some domain corpus. This model is then refined iteratively to allow for role coverage. Sentences from the web have high variance in quality and relevance.

5 Role Extraction

Many different approaches have been investigated for role labeling. The learning formulations studied range from pipelined classification approaches [9, 2], efficient structured and joint inference [12, 19], to end-to-end deep learning architectures [6]. Many different lexico-syntactic features, such as dependency paths and n-gram contexts, provide weak evidences for determining semantic roles [9]. 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 [7, 11].

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.

5.1 Local Role Extraction

We set up a local (within sentence per role) extraction task. Relying on the patterns alone is problematic. Hand authored patterns, especially specifying the expected 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 [9, 12]. 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 the expectations are met. [**Explain w/ an example**]

5.2 Joint Role Inference

Within sentence joint role inference has been shown to help SRL [17, 12]. Since our objective is to extract knowledge from multiple sentences, we propose to also exploit joint inference of roles across sentences. Local role extraction allows to reliably identify whether the specified role is expressed by the candidate text spans. However, this local classification is often inadequate because some cue patterns are ambiguous. For example, "evaporates into <x>" can match "steam" which is a *result* or "atmosphere" which is a *location*. Relying on the extraction pattern alone is problematic. Therefore, we propose to leverage role predictions on other similar text spans to improve inference.

Formalism

The key premise is that aligned text spans in similar sentences should be assigned same roles. This idea had been successfully used in semi-supervised and unsupervised settings to increase training data for SRL [7, 8, 14]. We adopt it for joint inference over test sentences, similar to the transductive learning approaches [**?**].

We extend an ILP-based formalism which has been shown to successfully model within sentence joint inference for SRL [17]. We add 1) a penalty term to the maximization objective that penalizes assignments that violate smoothness of labeling, 2) constraints that effectively fix labels from the local extractor for certain roles.

As noted earlier, the local extractor scores each text span $t_{i,k}$ from sentence S_k on how likely it is to belong to the role r_j. We 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. Formally, the inference aims to find the best joint assignment to set of indicator variables F that maximizes the following objective function:

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

$$\text{subject to}$$

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

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

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

Sentence and Text Span Alignment

The effectiveness of the joint inference relies on the ability to identify text spans in different sentences that should get the same role. Prior work explored a dependency graph-based approach to align predicate-argument structures in sentences. A linear combination of the overlap in lexical and syntactic structures of the candidate text spans is used to evaluate whether they should get the same roles [7, 8, 13]. This scoring function is used to transfer roles from a labeled sentence to an unlabeled sentence (semi-supervised setting) or to induce roles as clusters of arguments (unsupervised setting).

A key difference in our setting is that 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. Aligning definitional sentences is quite different from aligning definitions with instances or instances with other instances. Instances involve completely different entities which may not align via direct entailment but may align as substitutable siblings. Also, instances often tend to involve other non-essential information with respect to the process, whereas definitions are compact and tend to contain the most salient bits of information. To account for these differences we consider two extensions. Use different sets of weights and different similarity functions to combine the scores based on the types of sentences being aligned.

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

[**Consider changing this to a trained classifier. Use sentence patterns rather than definition or instance sentence distinction.**]

6 Role Aggregation and Assessment

[**To be redone. Emphasize role discovery.**] Inference yields a set of roles that can be reliably identified from the input set of sentences. The knowledge thus gathered is limited by the query patterns that we used to retrieve the sentences in the first place. To expand the knowledge further, we propose an iterative procedure that learns from the inferred roles.

6.1 Aggregation

First, given the current state of the knowledge base and newly inferred roles we devise a simple aggregation procedure that consolidates the roles – resolving any inconsistencies between the different iterations[1].

6.2 Assessment

We inspect the KB to identify roles that apply for a specific process based on the confidences of the inferred roles. Note that we do not make any assumptions a priori about what roles apply to a process. Further not all roles maybe covered by the roles vocabulary. For example, ... We identify regular syntactic signatures that are not classified into existing roles and use them to derive new knowledge.

need to be filled, and pass them on to the sentence gathering components for expansion.

7 Evaluation

Our primary motivation is to compose knowledge that is necessary for grade-level science questions. Therefore 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 KB Evaluation

Our goal is to acquire knowledge about processes along relevant role dimensions. [**To be filled...]**

7.2 Question Answering using Semantic Roles

Testbed Following Clark et al., 2014, we propose to build a large collection of multiple-choice questions at different grade levels. In prior work we leveraged existing collections to select questions. To effectively test the utility of our approach, we propose to create two types of questions in increasing levels of difficultly: 1) Questions that test ability to recognize instances of processes. 2) Questions that require ability to reason about the instance. We will limit the reasoning questions to those that are effectively achieved by following simple axioms defined over the semantic roles. [Example???]

Creating these questions is a difficult task for non-experts. We propose to work with the graduate students in the Department of Education at Stony Brook to collect questions and question templates. Once we have generate question templates that specify what kind of understanding is to be tested, we can scale out the question acquisition process via crowd sourcing.

Method

[1]It is possible to infer new roles with respect to the KB at each iteration, it can introduce many variables in inference and render it inefficient.

We use a simple approach to evaluate the utility of semantic roles for question answering. For the recognition questions we will follow our prior work, where we build a supervised role labeler and use it to parse the question to extract a role based representation. Then for each answer option we match the extracted roles against the roles available in the database.

For reasoning questions, we will utilize the above approach to first recognize the process and identify the roles mentioned in the question. We will utilize hand-written axioms defined over the roles. [Example.?]

8 Development Plan and Timeline

The project will proceed in three phases. In the first phase, we will design the representation and methods for role discovery and acquisition. In the second phase, we will start curating the generated knowledge and build a semantic role labeler for questions. In the third phase we will refine and make necessary adjustments to the pipeline, finish the curation and release the resources. The research plan in calendar years is shown below:

Year 1:

1.
2.
3.

Year 2:

1.
2.
3.

9 Broader Impact

10 Curriculum Development Activities

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.

11 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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