Narrative-Driven Case Elicitation

Karl Branting1,* Sarah McLeod2

1The MITRE Corporation, McLean, VA, USA
2The MITRE Corporation, Seattle, WA, USA

Abstract
This paper proposes an approach for narrative-driven case elicitation that uses schemas induced from corpora of legal case facts to distinguish relevant from irrelevant utterances and to identify facts that could distinguish between competing hypotheses. This approach to narrative-driven case elicitation builds on recent research in narrative schema induction.

Keywords
case elicitation, narrative schema, law, computational linguistics, machine-learning, human-computer interface

1. Introduction

Law is full of stories, whether these are stories that are told in the courtroom as lawyers try to weave together compelling and competing versions of an event, in the legislative histories that sub tend a body of statutes, or in stories about the origins and acceptance of legal systems [1].

The facts of legal cases are more than mere collections of events. Instead, case facts are narratives that have settings, characters with goals and motives, and events triggered by the characters’ actions. Just as not every set of facts is a story, not every story is legally significant. It is the role of a legal counsel to identify the goals that the client hopes to achieve through a legal process and then to elicit a coherent narrative that is relevant to one or more possible legal remedies that could achieve those goals.

Lay (non-attorney) clients typically have little understanding of what facts are relevant to a possible legal remedy. Accordingly, attorneys must help clients express the facts that are relevant to possible legal remedies and steer clients away from facts irrelevant to those remedies. The legal remedy that appears most likely to achieve client’s goals may change during the interview, requiring a reframing of the relevance of the facts that have been previously expressed and redirecting the elicitation toward the facts relevant to the new remedies.

This paper sets forth an approach to narrative-driven case fact elicitation and situates that approach within a broader architecture for induction and use of legal narratives schemas. The next section provides a background on the role of narrative understanding in providing legal assistance, and recent research in narrative schema induction is reviewed in Section 3. Section 4 presents an algorithm that uses case schemas for narrative-driven case elicitation. Section 5 describes an architecture that incorporates the narrative-driven case elicitation into a framework that includes narrative schema induction. Section 6 sets forth the text processing steps shared by both the schema induction and case elicitation components. Six new corpora for narrative schema induction and case elicitation are described in Section 7, and future steps are proposed in Section 8.

2. The Role of Narrative in Law

Law can be viewed as a framework of rules under which legal arguments often consist of alternative narratives that lead to opposite consequences. Empirical evidence has shown that jurors often decide cases based on which of two competing narratives imposes the highest degree of coherence on the evidence presented at trial [2] [3]. Unsurprisingly, the outcomes of trials often depend on the relative story-telling ability of attorneys and witnesses [4] [5].

In view of the importance of coherent legally relevant narratives to success in litigation, narrative elicitation is widely recognized as a vital legal skill. One study of client interviews revealed the importance of permitting a client ample time to speak, during which the attorney acknowledges the information received and expresses interest but otherwise “refrains from interrupting” except to direct the narrative away from “precarious” legal grounds and toward “possible remedies” “until the client has gone on for long enough to establish the problem at hand” [6]. In general, attorneys try to elicit “the causal and temporal connections that contribute to giving the events contextual meanings . . . with the aim of defining
3. Narrative Schema Induction

A story has been described as “a character-based and descriptive telling of a character’s efforts, over time, to overcome obstacles and achieve a goal” [5]. Early computational studies of narrative were motivated by efforts in cultural anthropology to formalize commonalities among folk stories [11]. Story grammars were an effort to characterize narratives in a rigorous way [12]. However, the brittleness of story grammars eventually led to their almost complete abandonment [13] in favor of “scripts,” stereotypical sequences of events that create expectations and fill in missing details to assist in story understanding [14].

Unlike story grammars, scripts ordinarily lack the hierarchical and recursive structure needed to account for some important properties of stories (e.g., in a picaresque novel or a protective order application there can be a variable number of episodes, and episodes can have sub-episodes). Moreover, both story grammars and scripts initially were entirely manually constructed, which made them unsatisfactory.

However, a series of research advances have made it increasingly feasible to induce “narrative schemas” (i.e., “scripts” in Schank/Abelson terminology) from examples. The seminal work by Chambers and Jurafsky [15] defined “narrative chains” (later termed “narrative schemas” [16]) as “partially ordered set[s] of narrative events that share a common actor.” The most common model for narrative schemas are Markov chain models that assign a probability to an event based on cooccurring (e.g., prior) events. Such models can be used to detect distinguish expected (high probability) events from unexpected (low probability) events and to predict the most likely events at a given point in an event sequence.

The performance of narrative schemas is typically measured by a narrative cloze test, i.e., accuracy in predicting the next or a missing event [16]. Improving narrative cloze performances has been obtained by using stricter constraints on multi-argument consistency [17], topic-specific training sets [18], and alternative language models, e.g., Hidden-Markov [19], Log-Bilinear [20], and Association Rule models [21].

The continuing progress in narrative schema induction techniques suggests that this approach will be an increasingly effective computational story model notwithstanding the limitation that narrative schemas are, as mentioned above, only a partial representation of the elements of story. This is because the aspect of performance that narrative schema induction seeks to optimize, the cloze test, can play a central role in the model of legal case elicitation, as described in the next section.

4. Using Schemas for Case Elicitation

Section 2 described how effective case elicitation requires helping a client articulate the events giving rise to a legal claim in a manner consistent with known legally meaningful narratives, e.g., in the linear fashion required for protective order affidavit. Section 3 described how narrative schemas can be induced from training sets of stories and then used to distinguish expected, unexpected, and missing events. This section describes an approach to narrative-driven case elicitation that uses the predictive capability of narrative schemas derived from prior case facts to guide interactions with a client.

A high-level view of a process for identifying the information that is most relevant to a litigant’s legal goals, in the sense of being the fact that would best discriminate among legally relevant narratives, is set forth in Algorithm 1. The key requirement for the narrative elicitation process is a set of <schema, goal> pairs, (SGs), where each schema is a model capable of evaluating the relative likelihood of a given event sequence, and each goal is a (possibly negated) legal remedy, e.g., a protective order, a child custody order, a finding of employment discrimination, etc. Each schema is induced from a corpus of related case facts for a given area of law using the techniques described in Section 3.1.

1A companion paper to this work describes techniques developing such schemas from representative legal case facts [22].
In Algorithm 1, sgs is a library of SGs, the goal is the objective that the client hopes to achieve through a legal process, the hypothesis is the best matching SG, and the facts consist of the events and relations elicited thus far from the client.

Algorithm 1 Legal narrative elicitation

\begin{verbatim}
sgs ← \{SG\}  
hypothesis ← ∅  
facts ← ∅  
goal ← ask(goal)  
hypothesis ← BestMatch(facts, goal, sgs)  
while match(facts, goal, hypothesis) < threshold do  
    newFact ← ask(getMissing(facts, hypothesis))  
    add(facts, newFact)  
    hypothesis ← BestMatch(facts, goal, sgs)  
end while  
return facts, goal, hypothesis
\end{verbatim}

Algorithm 1 is only a high-level depiction of the actual complex process of case elicitation. The identification of the goal or goals of a client can itself be a complex process requiring mixed-initiative dialogue techniques beyond the scope of this paper. However, there is an extensive body of research on goal-directed dialog (e.g., [23] [24]), and recent work has addressed the specific task of categorizing a legal aid clients’ problems [25].

The function “match(facts, goal, SG)” measures the degree of match between the client’s goal and current facts and the SG. An appropriate baseline function for “match” is the probability of the facts under the schema, or 0.0 if the goals don’t match (i.e., the schema is irrelevant if the goals don’t match, regardless of how well the facts match). The hypothesis is the currently best matching SG ∈ sgs. The function “getMissing(facts, hypothesis)” returns the missing fact or event that, if added to the facts, would most increase the probability of those facts. Performance on this task is equivalent to performance on the narrative cloze test [16], so as advances in narrative schema induction improve performance on cloze, the “getMissing” function should improve as well. The hypothesis is updated after each new fact has been elicited, reflecting the way that an attorney’s assessment of a case may change as more facts are learned.

The process of eliciting additional facts and refining the hypothesis continues until there is no more progress or the match between the hypothesis and the facts and goal exceeds a success threshold. Only at this point are the legal rules for the remedy applied to the case facts. This corresponds to an attorney eliciting the full story from a client before turning to an assessment of the viability of a claim based on that story.

Figure 1 illustrates the initial steps of an elicitation process shown in Algorithm 1. The dialogue manager starts by asking the client’s goal (Step 1). The client replies by stating there was a threat and that the client wishes for help against the threat (Step 2). The dialogue manager uses this goal to instantiate a new case with a goal (Step 3) and the start of an event sequence. The matcher searches for the SG that best matches the goal and initial event sequence of the new case (i.e., the SG whose remedy matches the goal and whose schema maximizes the probability of the case’s fact sequence) and makes that SG the current hypothesis (Step 4).

Figure 2 shows the predictor using the schema of the current hypothesis to predict the most probable missing
fact in the current case (Step 5) and the dialogue manager converting the fact into an appropriate discourse action (Step 6).

A more detailed (although still simplified) visualization of the initial stages in Algorithm 1 is shown in Figure 3. The sequence of events starting with "meeting," "intimate relationship," etc., represents the most probable event sequence under a typical protective order schema. The "case facts" represent a relational representation of a client’s answer to the question, “How did you meet?”

Any practical implementation of Algorithm 1 must ensure a common representation for the schemas and case facts; otherwise, the matching and prediction steps would not be possible. The next section describes an architecture to achieve this common representation.

5. RIM: An Architecture for Schema Induction and Use

A system for narrative schema-based fact elicitation depends on two coordinated capabilities: acquiring narrative schemas from examples; and using those schemas to guide interactions with litigants. Figure 4 sets forth an architecture for providing these two capabilities. This architecture is termed RIM, short for "Relevant, Irrelevant, and Missing," since the key functionality of the system is identifying these three categories of events.

The left side of Figure 4 details an off-line mechanism for inducing schemas from narrative corpora. The right side of Figure 4 depicts the real time component, including the process described in the previous section of using these schemas to distinguish relevant from irrelevant utterances and to identify facts that could distinguish among legal schemas if confirmed or disconfirmed. The
Text Realizer generates questions to determine whether missing events can be confirmed or disconfirmed. Additional events elicited in this manner can distinguish among partially matching narratives or refine the match to the most similar narrative.

The real-time processing depicted on the right side of Figure 4 depends on the existence of a narrative schema for each area of law for which facts are to be elicited. The process of induction of schemata from event sequences, depicted on the left side of Figure 4, is detailed in [22]. However, both the offline and real-time aspects of depend on conversion of raw text into event sequences, as shown as the second and third steps on both sides of Figure 4.

6. Text to Event Sequence Conversion

Offline narrative schema induction and online mixed-initiative case elicitation depend on a shared representation for event sequences.

6.1. Parsing

The first step in converting text to event sequences is to parse each sentence into individual events and, for each event, identify the entities that fill the semantic roles of that event. The next step is analyzing the relationships among events by resolving coreferences and determining the discourse relations among the events. Many alternative approaches could be used to perform these two steps; we use ANAnSI (Advanced Narrative Analytics System Infrastructure) [26], a system that integrates the output of the Stanford Core NLP [27] constituency parser and cTakes [28] into a temporal, causal, and intentional graph represented in Neo4j [29].

Figure 5 shows a portion of the graph for the sentence "During my employment, Respondent placed me on a leave of absence and required me to pass a medical exam in order to return to work" showing temporal and intentional links between pairs of events.

6.2. Graph Linearization

The resulting graph representation for a collection of one or more sentences is then linearized into an event sequence with arguments and semantic roles standardized in the manner proposed in [17] to three alternatives: agent, patient, and other complement. For example, in the event sequence shown in Figure 6, the pronouns "I" and "me" are normalized to "I".

6.3. Lemma Normalization

As discussed below in Section 7, corpora of legal narratives are, in general, many orders of magnitude smaller than the corpora used in previous narrative schema elicitation research, such as the Gigaword corpus. Such small corpora produce sparse transition matrices with little predictive value, e.g., most event pairs in a new (or held out) event sequence will have never been seen before, meaning that there is no frequency data on which to base cloze predictions.

Several normalizations were therefore applied applied
to reduce vocabulary size to improve matching. The most important and general of these was lemma normalization, which consists of clustering events in semantic embedding space$^2$ and replacing each event with the most central member of the cluster in which it occurs. For example, Figure 7 show the results of complete-linkage hierarchical clustering of events in our EEOC corpus (described below) with a minimum cosine threshold of 0.75. For example, both ‘harass’ and ‘threaten’ are replaced by ‘intimidate,’ and ‘ask,’ ‘hear,’ ‘know,’ and ‘let’ are all replaced by ‘tell.’

A second normalization that was particularly useful in the employment domains was to replace each occurrence of a form of "to be" that has as an argument the name of an occupation with the event "be OCCUPATION."$^3$

Lemma normalization shrinks the vocabulary size of the narrative, increasing transition matrix density and therefore reducing the likelihood that event cooccurrences will never have been observed in the training corpus. This reduction in vocabulary size comes at the cost of reducing the specificity of the event representation.

$^2$We used the spaCy large English model, https://spacy.io/models/en.

$^3$We used the list of 1,156 occupations, from “accountant” to “zookeeper” set forth in https://github.com/johnlsheridan/occupations/blob/master/occupations.csv.
Figure 7: Lemma normalization by clustering event types in semantic embedding space.

7. Corpora

A key challenge for narrative schema-based case elicitation is the difficulty of obtaining significant numbers of narrative texts representative of text produced by litigants. In general, such text contains sensitive personal information that precludes sharing in the form of public corpora. Documents filed in legal or administrative bodies are typically public, so statements of facts in petitions, complaints, and other filings can be a source of narrative texts. However, counsel for litigants often draft the statements in facts of court filings, so the text of such statements seldom contains language used by litigants themselves except in the case of self-represented (pro se) litigants, i.e., those who have no attorney to draft their statements in fact. The ideal corpus would consist of statements of fact in pro se litigants’ filings, but such filings are difficult to obtain in bulk.

In this research, we obtained one small corpus of texts by pro se litigants together with five other data sets intended to reflect various characteristics of fact statements:

1. EEOC complaints. The complaints were transcribed from handwritten texts in the field titled “The facts supporting the plaintiff’s claim of discrimination,” in thirty employment discrimination complaints filed in the Northern District of Illinois in 2016. These texts are representative of litigant-generated narrative texts.

2. Multi-LexSum Summaries of Civil Cases. These three hundred sixty four summaries of civil rights lawsuits were created for training and evaluating legal case summarization [30]. The Multi-LexSum text were included to typify procedural histories, a type of narrative required for appeals that court personnel have identified as being challenging for pro se appellants.

3. WIPO cases. The “background facts” of 6,000 decisions by World Intellectual Property Organization in domain name disputes. These fact statements were drafted by the panel deciding the case and are therefore not representative of pro se text. However, the similarity among these fact statements suggests that they could be a benchmark for narrative induction.

4. Board of Veteran Affairs decisions. The “Introduction” section of 1,680 Board of Veterans Appeals (BVA) cases. As with the WIPO cases, these texts are drafted by the judge writing the opinion and are therefore not representative of pro se text but potentially useful as a benchmark for narrative induction.

5. SPOT-HO online housing questions. Two hundred sixty three questions posed to the Suffolk University Law School’s Legal Innovation and Technology (LIT) Lab issue spotting service [31].

6. SPOT-WO online employment questions. Two hundred ninety five employment questions posed to the SPOT site.

The size, type, and authors of each of the corpora are summarized in Table 1.

8. Summary and Discussion

This paper has proposed an approach to narrative-driven case elicitation that builds on recent research in narrative schema induction. This approach uses schemas induced from corpora of legal case facts to distinguish relevant from irrelevant client utterances and to identify facts that could distinguish among competing hypotheses if confirmed or disconfirmed.

Only the offline portion of the RIM model has been implemented in this project, as described in [22]. A working prototype of the narrative elicitation portion of RIM, which is the focus of this paper, would require assembling a library of scheme-goal pairs for a given area of law from a suitable corpus, such as the BVA or WIPO corpora described above. The matching and prediction functions described in Algorithm 1 are basic capabilities of the schemas described in [22], and as mentioned
above there is an extensive literature on the goal-directed mixed-initiative dialogue techniques needed for the dialogue manager. Thus, there are no significant technical obstacles to implementing a prototype.

The narrative-driven case elicitation approach described here is quite unlike the dominant techniques for automated legal assistance, which are overwhelming organized around form-filling [32] or backchaining through logical representations of legal rules [33] (see generally [34]). The narrative-driven approach is intended to change the focus of client interviewing from the structure of the target legal artifacts (completed petitions and legal rules) to the life experiences that give rise to legal claims and to human interactions between client and attorney. While the narrative-driven model proposed here is a drastic simplification of the actual interview process between clients and attorneys, we hope that it will be a first step toward more faithful model and is feasible to implement with current narrative schema induction and dialogue technology.

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References


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Table 1
The size, type, and authors of each corpus of narrative texts.


