Abstract
Modeling the temporal information in the medical record is an important area of research. This paper describes an extension of TimeText, a temporal reasoning system designed to represent, extract, and reason about temporal information in clinical text, to include the use of fuzzy temporal constraints. The addition of fuzzy temporal constraints increases TimeText’s ability to handle uncertainty in temporal relations. We use a three-state, staircase possibility distribution function in conjunction with earlier methods of finding solutions to fuzzy temporal constraint networks. We perform analysis to determine the complexity of using this staircase in conjunction with finding solutions to fuzzy temporal constraint satisfaction problems and show that these solutions can be efficiently computed in $O(n^3)$.

Introduction
Temporal information is an important aspect of the medical record [1–3]. The ability to perform automated reasoning on temporal data has the potential to enhance our ability to do clinical decision support and to support knowledge discovery from the medical record. Because of this, the development of automated methods to extract temporal information out of the medical record is an important area of research.

In the electronic medical record (EMR), this temporal information exists in both the structured data as well as in the free text narrative reports written by clinicians. In the narrative reports, there is frequently uncertainty or “fuzziness” regarding the accuracy of temporal statements. Many statements in the medical record are also explicitly vague or uncertain. Examples of such statements typically contain phrases such as “about three days ago” or “between three to four weeks ago.” In addition, there is also a need to combine evidence of when an event may have actually taken place. There are situations where in narrative reports the same event is referred to multiple times, but with contradictory temporal statements.

In this paper, we will describe an approach to efficiently computing on fuzzy temporal constraint networks in the medical context. We will show that computations on fuzzy temporal constraint networks can be performed efficiently and discuss the implications of this result.

Methods
We previously developed a systematic temporal reasoning methodology and system called TimeText for handling temporal information in electronic clinical reports, with the aim of improving biomedical information applications such as information retrieval, medical errors detection, and syndromic surveillance [4–6]. TimeText contains four components, a temporal constraint structure tagger, the MedLEE natural language processor (NLP) [7, 8], a knowledge based system to extract implicit temporal knowledge, and a simple temporal constraint satisfaction problem solver.

This simple temporal constraint problem (STP) engine is based on Dechter’s simple temporal constraint satisfaction (TCS) problem framework [9]. In this TCS problem framework, a time window is placed around uncertain statements. This time window defines the range of possible temporal distances between two time points. One drawback of this framework is that it assumes all possible values in the temporal constraint have an equal probability of occurring. Using a uniform distribution on the time window either loses information or provokes temporal contradictions. For example, an event said to have occurred three weeks ago may possibly have occurred zero to ten or more weeks ago, where the highest likelihood is around three weeks. Creating a uniform time window from zero to ten weeks ago loses much of the information that the event is most likely three weeks ago. Picking a narrow one, say from two to four weeks, misses the less likely possibility of it occurring further away, which may then lead to a temporal contradiction. If instead, it can be represented that the area around three weeks is most likely, but a wider range is possible but less likely, then the information can be preserved without provoking contradictions.

The uniform distribution was originally chosen in part because of its feasibility. A bounded continuous uniform distribution that models temporal distances between events can be used to find all times that an event can occur and all possible relationships between two events. The solution can be calculated by applying Floyd-Warshall’s all-pairs-shortest-path algorithm to the distance graph [10]. The complexity
of computing a solution using this algorithm can be shown to be $O(n^3)$.

In an extension of Dechter’s simple temporal constraint satisfaction problem framework, Vila and Godo describe an approach they term possibilistic temporal logic for performing fuzzy temporal reasoning [11]. They modeled each fuzzy temporal statement, using a constraint structure they refer to as a possibility distribution. This possibility distribution associates a degree of possibility to any temporal distance between a pair of time points.

Vila and Godo extended a set of basic binary operations that are used in computing simple temporal constraint problems to these fuzzy temporal constraints. They restricted their domain of possibility distribution functions to be those that are unimodal. With this restriction, these operations had certain properties that allowed for a tractable computation of a fuzzy temporal constraint network solution. One of these key properties is the fact that the intersection or composition of two unimodal distribution functions results in another unimodal distribution function. An example fuzzy temporal constraint network can be seen in Figure 1. In the example, we see temporal events centered around 3 hours, 2 hours, and 1 hour ago. However, one question Vila and Godo’s work did not specifically address was the complexity of computing a solution.

![Figure 1: Example temporal network with fuzzy unimodal possibility distribution functions.](image)

Based on Vila and Godo’s results, we approached fuzzy temporal reasoning with possibility distribution functions that had three levels of possibility. These possibilities were not possible, low possibility, and high possibility. The high possibility region is defined to be the bounded continuous uniform distribution in which the statement is most likely to correspond with the temporal statement. The low possibility region is defined to be the temporal deviation that is outside of the high possibility region, but is still considered possible. A possibility distribution function of this type results in a staircase function as seen in Figure 2.

![Figure 2: Unimodal staircase possibility distribution.](image)

This type of possibility distribution function is still unimodal and therefore still has the same properties as those determined by Vila and Godo.

Results and Discussion

Figure 3 shows an example of composing two possibility distribution functions. In the example, there are possibility distribution functions $\pi$ and $\pi'$. With staircase possibility distribution functions, Vila and Godo’s composition function reduces to the addition of each of the temporal distances. Assume that $\pi$ represents a temporal constraint statement that states an event occurred centered around 4 time units ago. $\pi$ also shows a high possibility region between 3 and 5 time units and a low possibility region between 1 and 7 time units. Let’s assume that $\pi'$ similarly represents a temporal constraint statement centering an event around 6 time units before $\pi$, with a high possibility region between 5 and 7 time units, and a low possibility region between 3 and 9 units. The composition of these two statements, $\pi \circ \pi'$, is a possibility distribution function centered around 10 time units ago, with a high possibility region between 8 and 12 units and a low possibility region between 4 and 16 units.

Figure 4 shows three examples of the intersection of two possibility functions. The intersection operator is simply the minimal possibility of the overlap of two possibility functions. In example A, $\pi$ and $\pi'$ overlap in both the high and low possibility sections. When $\pi$ and $\pi'$ are intersected, one sees that the low and high possibility regions are reduced. In example B, $\pi$ and $\pi'$ overlap only in the low possibility section. This occurs, the resulting intersection is only a possibility function where only a low possibility region exists. In Example C, there are two possibility distribution functions, $\pi$ and $\pi'$, where $\pi'$ is completely covered by $\pi$. When the minimum of these two possibility distribution functions is taken, all that remains is the distribution function, $\pi'$.

From the possibility distribution function composition and intersection examples, one can see that with unimodal staircase functions, the results of these two operations results in a unimodal staircase function. In most cases, the intersection of two possibility distribution functions results in a staircase function. In the
case where the high possibility regions contradict each other, all that remains is a low possibility region.

Because Vila and Godo’s composition function reduces simply to the independent sum of each of the corresponding temporal distances and because the intersection is simply the minimum, the staircase distributions can be decomposed into a pair of independent STPs. That is, the start and end points of any high area is always the result of the start and end points of other high areas, and the start and end points of any low area is always the result of the start and end points of other low areas (where “low area” here actually refers to the union of the low and high areas).

Figure 5 illustrates the decomposition. One STP contains only the high possibility areas, and the other STP contains the union of the low and high possibility areas. The all-pairs-shortest-path algorithm is run on each STP independently. The final staircase network is assembled by using the second (union) STP to create the low areas and then using the first (high) STP to create the high areas, where the high areas override the low areas.

If a temporal contradiction occurs in the second (union) STP, then there is no solution to the temporal network: the constraints are inconsistent. If, however, a contradiction occurs only in the first (high) STP, then all the high areas disappear and the staircase result reduces to a simple temporal problem with uniform possibilities and wide ranges (i.e., it is as if one started with only the low areas).

These results have important implications. Existing algorithms to calculate temporal relationships for STPs can be used for fuzzy networks that employ staircase distributions. This includes speedup optimizations for sparse networks [12]. The running time is \(2n^3\), which reduces to a complexity of \(O(n^3)\). More than three levels can be used, and the complexity will remain the same other than a constant.

In Figure 6, we show an example clinical narrative in which we can apply fuzzy temporal reasoning. In this example, consider the case where evidence from the clinical record showed that a patient began to cough one week prior to admission. Three days after the cough began, the patient had a fever. Three days after the fever began, the patient was admitted. When reading these temporal statements, a human will make a number of assumptions about the accuracy of these statements.

Because supposedly the cough began one week before admission and the patient subsequently had a
fever and was admitted to the hospital, the documented times do not completely agree, based on simple transitive closure. (A to B, and B to C, should add up to the distance between A to C.) One such possibility is that the cough did not actually occur 7 days before admission, but closer to 6 days before admission. In addition, perhaps the statements concerning the duration of time between the cough and the fever and the fever and the admission were closer to 3.5 days.

The STP engine can also handle these types of assumptions through the inclusion of a window around the temporal statements. However, using too narrow a window will result in a contradiction. Using too wide a window will diminish the utility of the conclusions one can make from the output. As shown in Figure 7, running the above example through the STP algorithm gives the following high possibility solution: cough began between 5.4 and 6.6 days before admission and the fever began between 2.7 and 3.3 days before admission. Similarly, it can be shown that the fever began between 2.7 and 3.3 days after the cough. For the low possibility solution for this example, cough likely began between 4.5 and 7.5 days before admission and fever likely began between 2.25 and 3.75 days before admission.

By using the fuzzy staircase probability distribution approach we have described, one can widen the intervals as necessary, recompute the STP and maintain polynomial complexity. This allows one to answer queries on temporal distances with different levels of fuzziness. We have modified TimeText to produce two levels of possibility, with the high possibility areas being narrower than TimeText’s old windows and the low possibility areas being wider than TimeText’s old windows. We set the window sizes according to the results of our recent study [13], which measured the degree of uncertainly of temporal assertions. We use a width of two and five standard deviations to either side of the temporal statement for the high and low possibility regions respectively. A width of two standard deviations should cover approximately 95.45% of all statements and five standard deviations should cover approximately 99.99994% of all statements.

For example, one use of this fuzzy temporal constraint network is in pharmacovigilance. To assert causality, that a medication caused a side effect rather than that a symptom prompted the prescription of the medication, temporal ordering of symptoms and medication orders is necessary. Symptoms tend to be asserted in narrative text rather than in structured data, so temporal narrative processing is important. Without a fuzzy representation of the temporal information, it is necessary to set wide uncertainty ranges to prevent a contradiction. Unfortunately, wide uncertainty windows result in the medication and symptom overlapping, masking the causality. By employing a fuzzy representation, narrow high possibility windows can be used to preserve the true ordering of events, while wider low possibility windows avoid contradictions that prevent drawing any conclusions from the network of temporal constraints.
Conclusion
We have shown that one can find a solution to fuzzy temporal constraint satisfaction problems when using staircase possibility distribution functions by decomposing the problem into a separate STP for each possibility level. The calculation has a complexity of $O(n^3)$ and can be computed using standard all-pairs-shortest-path STP algorithms. The use of a fuzzy function allows one to both specify fairly narrow high-possibility windows around temporal assertions while still allowing for the lower possibility of greater deviations.

Acknowledgments
This work was funded by National Library of Medicine (NLM) “Discovering and applying knowledge in clinical databases” (R01 LM06910).

References