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ARTICLE

Designing a system to extract and interpret timed causal sentences in medical reports

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ABSTRACT
Causal sentences are a main part of the medical explanations, providing the causes of diseases or showing the effects of medical treatments. In medicine, causal association is frequently related to time restrictions. So, some drugs must be taken before or after meals, being ‘after’ and ‘before’ temporary constraints. Thus, we conjecture that medical papers include a lot of time causal sentences. Causality involves a transfer of qualities from the cause to the effect, denoted by a directed arrow. An arrow connecting the node cause with the node effect is a causal graph. Causal graphs are an imagery way to show the causal dependencies that a sentence shows using plain text. In this article, we provide several programs to extract time causal sentences from medical Internet resources and to convert the obtained sentences in their equivalent causal graphs, providing an enlightening image of the relations that a text describes, showing the cause-effect links and the temporary constraints affecting their interpretation.

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Introduction: time and causation

Time plays a leading role in different medical scenarios (Eravnou, 1996). An essential part of medicine is the aetiology or diagnosis based on causes. The causal explanation relates causes and effects and, in medicine, that action is very often linked to temporal constraints. Thus, the diagnosis of a disease is frequently related to the moment in which the symptoms appear. This can be verified in written texts of the medical domain, such as entry forms, e-mails, reports or clinical histories.

Natural language is the means doctors and patients use to express knowledge about diseases. This language includes frequent allusions to temporal aspects and often lacks precision, because the patient is ignorant or he forgets the data about which is questioned. In this vein, Augusto (2005) defended that in the medical field, texts written in natural language are a primordial source of data, showing time restrictions and vague qualifications.

From a computational point of view, natural language is the starting point towards structured languages computable by a machine (Johnson, 2000). Natural language processing (NLP) is the area that aims for this task. While initially the NLP was linked to the formal grammars of Chomsky and the search of parsers, at present includes other areas, such as data mining or information retrieval. Processing time in medical texts describing causal mechanisms is a fertile area that includes at least two tasks: Representation of temporary information and processing of medical causal information.

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The first one historically includes approximations such as the situation calculus, the fluent calculus or the event calculus, and aims to study and formalise the changes in the world due to actions or events that occur one after another. The second one deals with reasoning under temporal constraints and approaches the relationships between temporal entities (points or intervals) for planning, scheduling or NLP. Typical oncoming are those of qualitative constraint representation, representation based on dating schemas or duration-based approach. Allen's interval relationship is a good example of this last taxon.

Medical diagnosis is largely based on causal associations involving time dependence. Frequently, symptoms run overtime making the illness a not static picture but a progressive one. Treatment is also time-dependent. Some drugs must be rigorously scheduled in order to harvest the intended benefits. Medical diagnoses and treatment are collected in textual medical reports and prescriptions. The inspection of them shows some characteristics of the lexicon used regarding the causal relationship based on time.

Time uses a specific lexicon. Temporal sentences frequently include calendar-dating references (year/month/date; seasons, part of the day (morning, evening, etc.)) and conjunctions and prepositions, as by, until, before, since, past, next. Causal phrases as 'secondary to' or 'because of' also denotes temporal causal influence. Frequently, temporal expressions are fuzzy, as shown in the sentences: A little before the admission, few days ago he received a very high dose. Fuzzy time sentences include (i) fuzzy quantifiers (most of, a few (He was bleeding most of the previous days, he was discharged a few days later)), (ii) linguistic hedges (very, rather (He was admitted very early, It was rather sedentary than active)), (iii)temporal adjectives as 'subsequent', 'previous' or adverbs as 'lately', 'afterward'. Some particles as 'occasional', 'abruptly' or 'still' denote also fuzzy time (Zhou & Hripcsak, 2007).

As previously said, time relations can be crisp or fuzzy. Allen (1983) defined an ontology of precise temporal relationships based on three types of relationships: (a) Interval-interval basic relationships, (b) point-point basic relationships and (c) point-interval basic relationships. Fuzzyfication of Allen's ontology can be reached using fuzzy values or fuzzy intervals. A further development of the Allen's approach was provided by Pelavin and Allen (1986), in order to represent planning in temporary rich domains. Fuzzy time was addressed by Dubois and Prade (1989) in the framework of the possibility theory. Ribaric and Basic (1996) aimed t-time Petri Nets as a tool for representing time information in planning and reasoning.

Medical texts frequently include timed and fuzzy causal sentences. In this article, we mine some medical Internet sources in order to check this fact, aiming a contribution to the NLP area, and more specifically to the information retrieval field, proposing several algorithms to recover causal mechanisms affected by temporary restrictions from medical texts, and offer, in addition, in the aim of computational imagery (Glasgow & Papadias, 1992), a representation of the recovered mechanisms in terms of a depicted causal graph with a timeline including vague specifications.

In order to get that objective, the article is structured as follows: In Section 2, we present the Allen time ontology for crisp time relationships and its fuzzyfication. In point 3, the methodology for transforming a causal sentence in a causal graph is presented. In point 4 time annotations to the causal graph are provided. In Section 5, the automatic generation of a summary from it is detailed. In Section 6, we present the main achievements and future work. Finally, we conclude with acknowledgments and references.

Allen's temporal relations and its fuzzyfication

According to Allen (1984), the crisp ontology of time is made from points and intervals. A time point is a single element denoting an instantaneous event. The interval is an ordered pair of time points, being the first point less than the second (in some timescale). The more typical relations are: (i) between time intervals, (ii) time points-time interval and (iii) between time points as can be seen in the following tables that illustrate these relations:

Instants and intervals are taken in the Allen ontology as crisp time items. But causal sentences are frequently stained with fuzzy temporal restrictions. That is especially apparent in medical reports. So, a drug causes a therapeutic effect if it is administrated a little before the meal, being ‘a little’ fuzzy instant, or to lose weight you can not eat protein at night, being ‘at night’ a fuzzy interval, because the night period varies depending on different seasons and cultures. Sentences as those suggest that we should soften the crisp representations of the primitives of the Allen ontology defining a fuzzy time point and a fuzzy interval.

According to Dubois, HadjAli, and Prade (2003), a fuzzy time point p is a point that has no precise situation in a clock. So, he arrived at about 5 o’clock or he is almost 15 years old are examples of fuzzy time points. Fuzzy time points contrasts with crisp time ones, as ‘5 o’clock’. Figure 1 represents both times: The crisp case is depicted by a one-step function, and the fuzzy one by a soft fall function (a triangular function).

A fuzzy time point is modelled by a possibility distribution function, π_p: T `` $\rightarrow$ [0,1]. Then, $\forall$ t $\in$ T, π_p(t) $\in$ [0,1] is the numerical estimation of the possibility that p precisely be t.

If an action concerns more than an instant t, then an interval must be supplied. Dubois et al. described a fuzzy interval as a pair of fuzzy sets] A, B[and [A, B]. The set] A, B[is a set of time points that are more or less certainly between A and B, and the set [A, B] is a set of time points that are possibly between A and B. These proximity measures can be calculated by:

$$\mu_{[A,B]}(t) = sup_{s\leq t\leq s'} min(\pi_A(s), \pi_B(s')) = [A, +\infty) \cap (-\infty, B)$$

$$\mu_{]A,B[}(t) = min(\mu_{]A,+\infty)}(t), \cap (\mu_{(A-\infty B[}(t)) = (-\infty, A)^C \cap [A, +\infty)^C$$

Figure 2 illustrates a case of fuzzy time interval (with no-overlapping distributions) as that corresponding to the sentence, ‘between....about 6’.

Since the beginning of computational intelligence, it was relevant to have models of temporal information and determine their use in logical arguments or causal inferences. In the area of Artificial Intelligence, inferences are usually made with natural language usually involving, especially in the filed of medicine, vague constraints.

In order to retrieve causal mechanisms with temporal restrictions, it seems appropriate to have a relevant model of time, i.e., a model: (a) distinguishing primitive epistemologically fertile elements, (b) capable of mixing with other types of knowledge and (c) cooperating in reasoning tasks. As

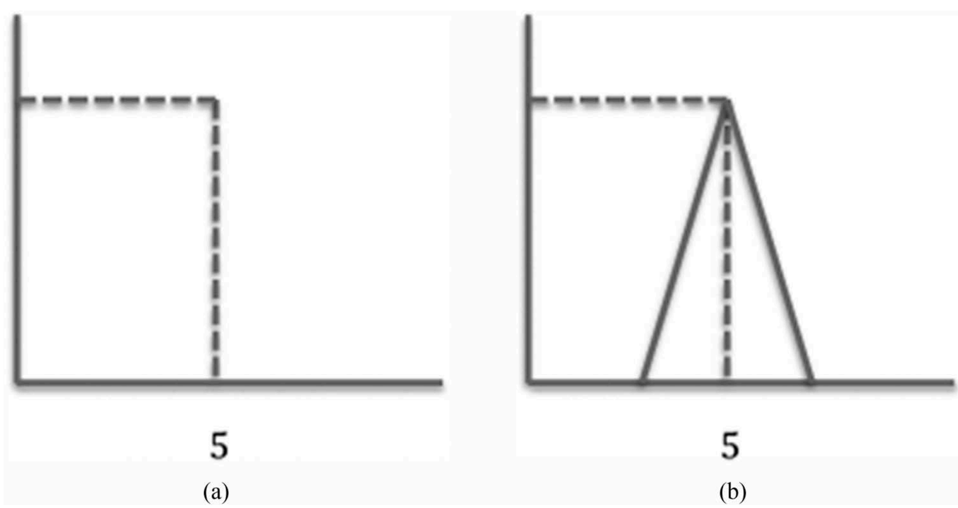

Figure 1. Representation of (a) crisp time ‘five o’clock’, (b) fuzzy time ‘about five’.

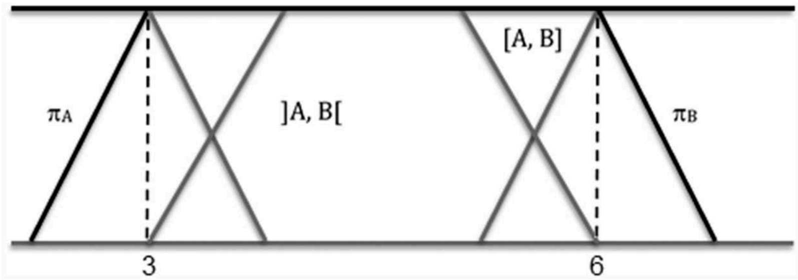

Figure 2. Representation of the fuzzy interval 'between about 3 and about 6'.

time is frequently vague, a model that admits fuzzyfication is convenient. The temporal logic of Allen and its fuzzification by Dubois and Prade provide that tool. It will permit, as you can check in the following sections, its application to the retrieval of temporal causal mechanisms in texts and their illustration by means of causal graphs with a time line.

Mining causal relations

To study the behaviour of conditional and causal sentences in texts, a process able to detect and classify causal sentences in base to certain patterns as seen in Figure 3 was designed. In Puente, Sobrino, Olivas, & Merlo, (2010), we explain deeply the algorithm that creates a four-state automaton, and by means of a morphological and syntactical analyser (*Flex*[1]), it is able to filter causal sentences in texts.

We found that the behaviour of the algorithm was different depending on to the type of analysed text, so we decided to perform and experiment with different text genres, as seen in Table 4. To evaluate the accuracy of the application, we analysed manually some documents belonging to different categories (50 pages per each), and calculate some standard measures like recall R (calculated as the number of correct causal sentences classified by the system divided by the number of causal sentences classified by manual analysis; precision P, calculated as the number of correct causal sentences classified by the program, divided by the total amount of sentences retrieved, and f-measure which is a combination of recall and precision, as the formula F = (2*P*R)/P + R shows, weighting the relative importance of recall and precision.

Structure e2: if + present simple + future simple
Structure e3: if + present simple + may/might
Structure e4: if + present simple + must/should
Structure e6: if + past simple + would + infinitive
Structure e7: if + past simple + might/could
Structure e8: if + past continuous +would + infinitive
Structure e9: if + past perfect +would + infinitive
Structure e10: if + past perfect + would have+ past participle
Structure e11: if + past perfect + might/could have + past participle
Structure e12: if + past perfect + perfect conditional continuous
Structure e13: if + past perfect continuous + perfect conditional
Structure e16: if + past perfect + would + be + gerund
Structure e23: for this reason, as a result
Structure e24: due to, owing to
Structure e26: provided that
Structure e31: have something to do, a lot to do
Structure e34: so that, in order that
Structure e38: although, even though
Structure e43: in case that, in order that
Structure e44: on condition that, supossing that

Figure 3. Set of conditional and causal patterns implemented.

Table 1. Basic temporal relations between intervals.

Relation	Symbol	Inverse	Illustration
A before B	<	>	AAA BBB
A occurs at the same time as B	=	=	AAA BBB
A meets B	m	mr	AAA BBB
A overlaps B	o	or	AAA BBB
A during B	d	dr	AAA BBBBBB
A starts B	s	sr	AAA BBBBB
A finishes B	f	fr	AAA BBBBBBB

Table 2. Relation between time points-time interval.

Relation	Symbol	Inverse	Illustration
tp before B	<	>	■ BBB
tp during B	=	There isn't	BBB■BBB
tp starts B	s	There isn't	■ BBB
tp overlaps B	o	There isn't	■ BBB

Table 3. Relations between time points.

Relation	Symbol	Illustration
p_i occurs at the same time as p_j	=	■ ✷
p_i before p_j	<	■✷
p_i inverse_before p_j(after)	>	✷■

Table 4. Comparison of the extraction and classification results.

Type of text	Total retrieved (Program)	Classified (program)	Classified (manual)	Recall	Precision	F-Measure
Scientific	62	52	80	0,65	0,83,857,097	0,7,323,944
Medicals (Medlars)	11	10	13	0,76923077	0,9090909	0,8333333
Novels	22	12	37	0,32432432	0,5454545	0,4067797
News(Reuters)	14	11	19	0,57894737	0,7857143	0,6666667
Gospel	30	21	42	0,5	0,7	0,5833333

As the previous table shows, the performance of the genres like scientific or medical (0.73 and 0.83, respectively), is much better than the news, novels or Gospel. For this reason, we decided to explore more deeply causality in medicine, a relevant and useful area in the field of science.

Creating a causal graph

Once the knowledge base about a scope (by extracting and classifying its causal and conditional sentences), has been produced, the user has to introduce a question to run another process to select only those sentences related to the proposed input. In Sobrino, Puente, & Olivas, (2014), we created another program, using *Flex, C* programming language and TreeTagger[2] of the University of Stuttgart (Schmid, 1994), to select the main concept from an input query in order to know whether the user is asking for causes or consequences. As source for reliable information, we have selected the Mayo Clinic website using the topic, 'cancer'.[3] For example, if the user asks *What provokes lung cancer?*, the part-of-speech tagger would remark that the nominal clause is *lung cancer* (labelling lung as NN and cancer as NN as well).

Processing this clause with the morphological analyser, the program, that detects the word *provokes* plus the interrogative pronoun *what*, would assume that the user is asking for the cause of lung cancer.

Once the nominal clause has been selected and isolated, another program has been developed to extract those sentences in which these concepts are contained. The searching set is the file created with the conditional and causal sentences. The retrieved set of sentences will serve as the input for the sentence summary process.

Launching the concept 'Lung Cancer' over the previously filtered database, we obtained a set of sentences to be represented into the causal graph related to this concept (Figure 5). A schema of this process is presented in Figure 4.

The retrieved sentences are stored in a database, which is accessed by the graphing process. Once all the phrases have been processed and schematised, the graph algorithm, by tracing the concepts associated to the cause or the consequence, generates then the causal graph shown in Figure 5.

A relationship is labelled by a modifier if the arrow is inside of the modifier cell, otherwise the arrow will be pointing at the border of the node. If the relationship has more than one modifier, the arrow will point to an intermediate node, aiming the arrows to the corresponding modifiers. The intensity of the relationship's arrow (quantifiers) if so, is marked in red, and the type of causal connective in black. As we can see in the graph, there are four nodes with the word *smoking*, or related words, and another four with the words *lung cancer*. The rest of the nodes have been retrieved in the process. So with a graph like this, we could establish new relationships hidden at first sight, for instance between smoking and other nodes. Fuzzy probabilities and fuzzy quantifiers are labelled in the lower side of the arrow.

Causation and time

To introduce time restrictions in the graph, we performed another search with each one of the nodes to select those sentences that had time modifiers. So, we included in our Flex morphological analyser the most common words indicating time, like *after that, time, hour, minute, day, before, now, today, tomorrow, yesterday, always, ever*, etc. From a set of 1214 causal sentences connected to lung cancer, this program obtained 370 involving time markers.

Once isolated, the next step was to identify if the time was associated to the antecedent node or to the consequent. For that we detected the modifier and used the same program as in the previous step were we formulated a question and the system had to know if we were asking for a cause or an effect. Using the Stanford POST, we are able to establish the dependencies of each word of the sentence with the others, knowing if the modifier is affecting to the cause or to the effect. For example, in the sentence 'If, for some reason, surgery is not an option with early stage 1 and 2, treatment is usually radiation therapy', the time constraint works on the cause. In this case, the output of the parser would return the results of Table 5.

So, in this example we can appreciate that the time modifier 'early' is associated to the word stage. Introducing via a *C* program the word or words that compose the node, the program with

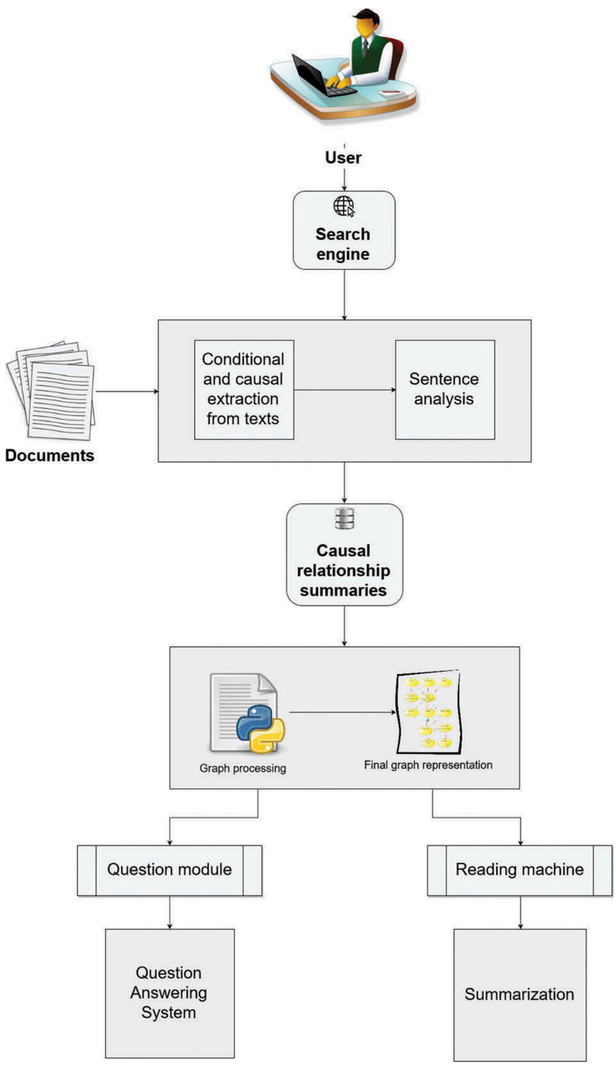

Figure 4. Process to obtain a causal graph from plain text.

this method is able to locate if the modifier is affecting to the antecedent or to the consequence as seen in this program output: '> *Line number: 17,914 If, for some reason, surgery is not an option with early stage 1 and 2, treatment is usually radiation therapy. Modificator found: early, contex: with early stage 1 and Modificador found: usually, contex: is usually radiation therapy*'.

Once the node affected by the time modifier is located the constraint is drown in a time line. Thus, in the sentence 'If you stop smoking before a cancer develops, your damaged lung tissue gradually starts to repair itself.' the cause must happen 'before' the cancer begins to develop. So, the time constraint is associated to the cause and the restriction is stop smoking 'before' if the effect wants to be achieved. Figure 6 illustrates that:

Another type of time modifiers exist: they are fuzzy time constraints, as fuzzy intervals. As previously quoted, fuzzy intervals are represented by fuzzy membership functions, as triangular or trapezoidal ones. For instance, in the sentence '*Some lung cancers are found early by accident as a result of tests for other medical conditions*.' the modifier early points to the effect and denotes a

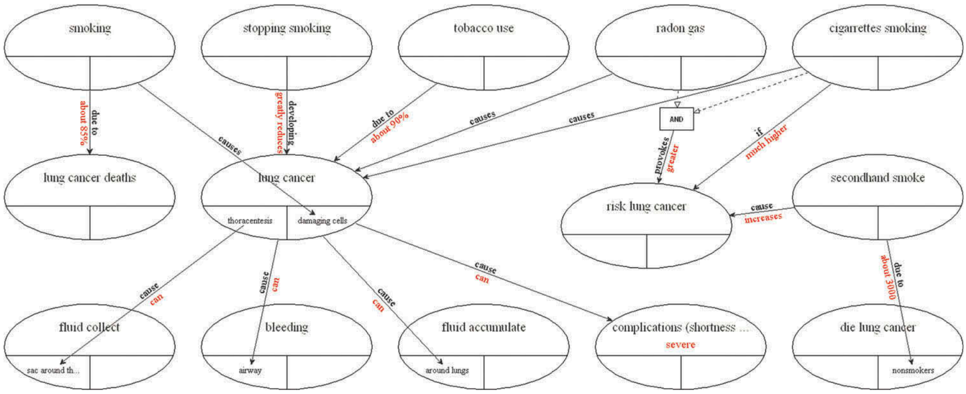

Figure 5. Automatically retrieved causal graph.

Table 5. Output of the Stanford Parser for the sentence 'If, for some reason, surgery is not an option with early stage 1 and 2, treatment is usually radiation therapy'.

Root (ROOT-0, Therapy-23)	Case (Stage-14, with-12)
mark (1–15, If-1)	amod (stage-14, early-13)
case (reason-5, for-3)	nmod (not-9, stage-14)
det (reason-5, some-4)	advcl (therapy-23, 1–15)
nmod (1–15, reason-5)	cc (1–15, and-16)
nsubj (1–15, surgery-7)	conj (1–15, 2–17)
cop (1–15, is-8)	nsubj (therapy-23, treatment-19)
neg (1–15, not-9)	cop (therapy-23, is-20)
det (option-11, an-10)	advmod (therapy-23, usually-21)
nmod:npmod (not-9, option-11)	compound (therapy-23, radiation-22)

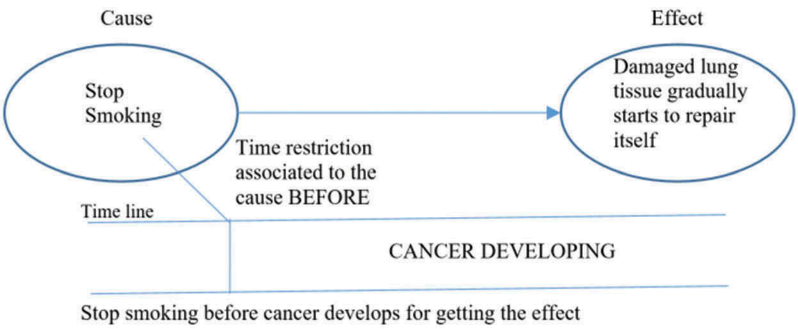

Figure 6. Cause depending on the 'before' crisp time constraint in the time line.

fuzzy time, drown by a decreasing line illustrating that 'early' reaches poor values as it moves away from the beginning, as Figure 7 pictures.

So, with these schemas we analyse each time modifier of the sentence to evaluate which of the classifications is correct. The next step is to modify the original causal graph with this representation of the time. To do so, we performed a new search of causal sentences by means of another *C* program to get all the sentences related to a node with time modifiers. For instance, the sentences related to smoking would be the next: 'If you stop smoking **before** a cancer develops your damaged lung tissue gradually starts to repair itself', 'Although decades have passed since the link between smoking and lung cancers became clear smoking is **still** responsible for most lung

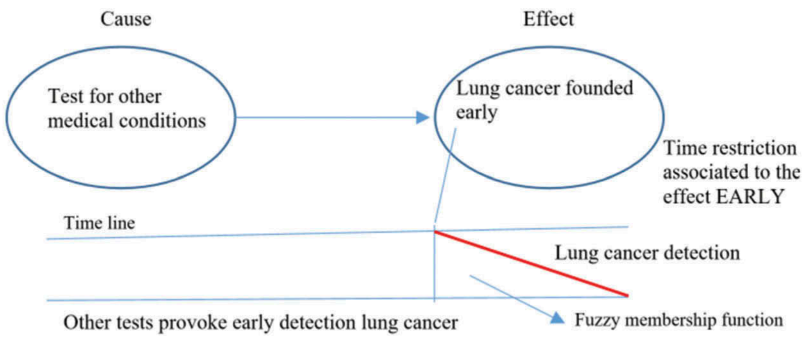

Figure 7. Effect depending on the 'early' fuzzy time constraint in the time line.

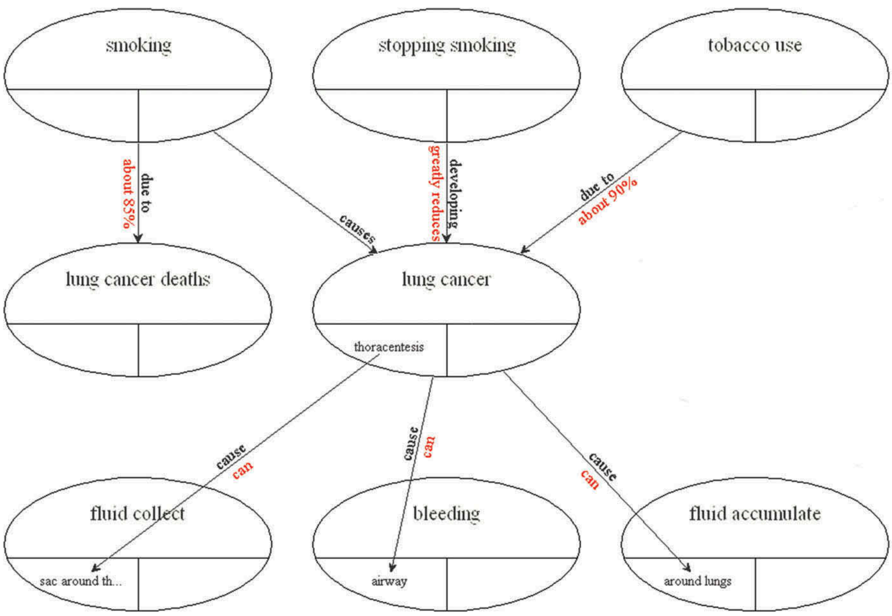

Figure 8. Causal graph obtained with temporal restrictions.

cancer deaths', 'Even if you have already been diagnosed with lung cancer there are **still** benefits to quitting smoking'.

The encountered time modifiers related to smoking are *still* and *before*, but it seems that *before* has a stronger perception than *still*, that is why in the node, will appear the representation of *before* as a time line restriction. To obtain the time related causal graph, we have followed the same process, giving as result the graph presented in Figure 8, where we can observe that some nodes have a temporal representation according with the sentences found related to a concept that had a time restriction. In the case that a node had sentences related with different time modifiers, we have prevailed the representation with the strongest one as in the case described. To complete the graph, we have used the bottom-right space to indicate, if so, the time constraint, or the word/words denoting it.

Practical approach of causality and time

To find applications for theoretical models is not a simple task. In this point, we present an approach about the automatic generation of a summary involving timed causality information from the graph representation depicted in the previous section. Next, we relate, in a shortened way, the main steps involved in that challenge.

The first task is to 'clean' the graph of redundant nodes, i.e., nodes labelled with terms that have linguistic relation of similar meaning, as synonymy, hyperonimy or meronymy. That is the case of 'smoking' and 'tobacco use', for instance. For performing that task, a graph cleaning process reading the graph concepts stored into a database is designed. Its function is to send the concepts to an ontology like Wordnet[4] in order to obtain different similarity degrees for terms that are similar in meaning.

Finding words that are polysemic is another problem to be faced, i.e., words that have multiple meanings each of them belonging to a semantic field. For instance, in a surgery context, 'bleeder' can mean a blood vessel bleeding (Emergency panendoscopy revealed no active bleeder in the visible field, but a lot of fresh blood was gushing from the afferent loop of the jejunum) or a person who suffers haemophilia (A person, such as a haemophiliac or bleeder, who bleeds freely or is subject to frequent haemorrhages). In order to generate a consistent summary or to compose a credible answer to a question, the graph must adequately manage the polysemy of words, choosing the right sense.

To progress in that job, we have gathered all the synsets of every word labelling the nodes of the graph and the text were these concepts appear. A *Java* program is in charge of finding the meaning of these terms as well as the strength of the concepts compared. To calculate its similarity, *wordnet::similarities* is used, providing similarity measures like path length, (Leacock& Chodorow, 1998) or (Wu & Palmer, 1994), among others.

In Figure 9, the output of the cleaning and similarity process is shown. From this output, concepts that are redundant according to their similarity degree are removed preserving

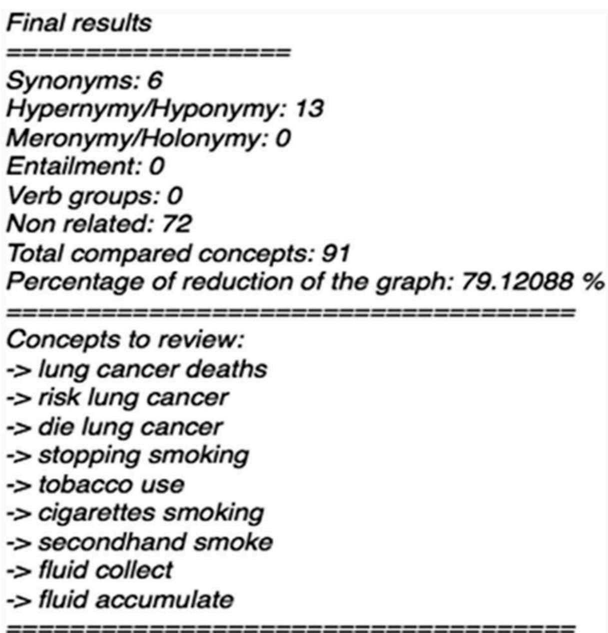

Figure 9. Similarity relations among concepts obtained by the filtering and cleaning process.

temporary factors that could be relevant. In that case, nodes with time restrictions are considered as ‘preferent’, so they remain in the final graph.

As shown in Puente, Olivas, Garrido, & Seisdedos, (2013), this graph can be interpreted as a summary following the process described in Figure 10.

The main difference is that now time is considered. Next, we illustrate how that proposal is materialised through an example. Figure 11 shows a causal process constrained by temporal restrictions. The aimed process detect that the time restriction is associated to the cause, inserting the time particle ‘before (a cancer develops)’ as a temporal prerequisite that the node cause must verify in order to perform its influence on the effect. Note that if that prerequisite is not satisfied, the other causal node, affected by the other time particle ‘still’, targets, without negative restriction, to ‘lung cancer’. That example shows that it is not a trivial task to transform time indicators into text, as their role may be affected by other interacting nodes, a relevant fact to generate significant text.

Conclusions and future work

In this article, we showed the relevance of causal sentences influenced for time constraints in the area of medicine. We approached several programs in order to automatically mine those sentences in medical texts.

Studies on the retrieval of temporary information in medical texts have lied mainly in the extraction of time-date stamps or durations recorded in medical documents. In addition, the problem of detecting textual causal relationships has been a challenge in the field of NLP. But there have been no attempts to extract causal mechanisms (sentences chained by causal relationships) affected by temporal parameters. Our work aims to be a contribution in this area.

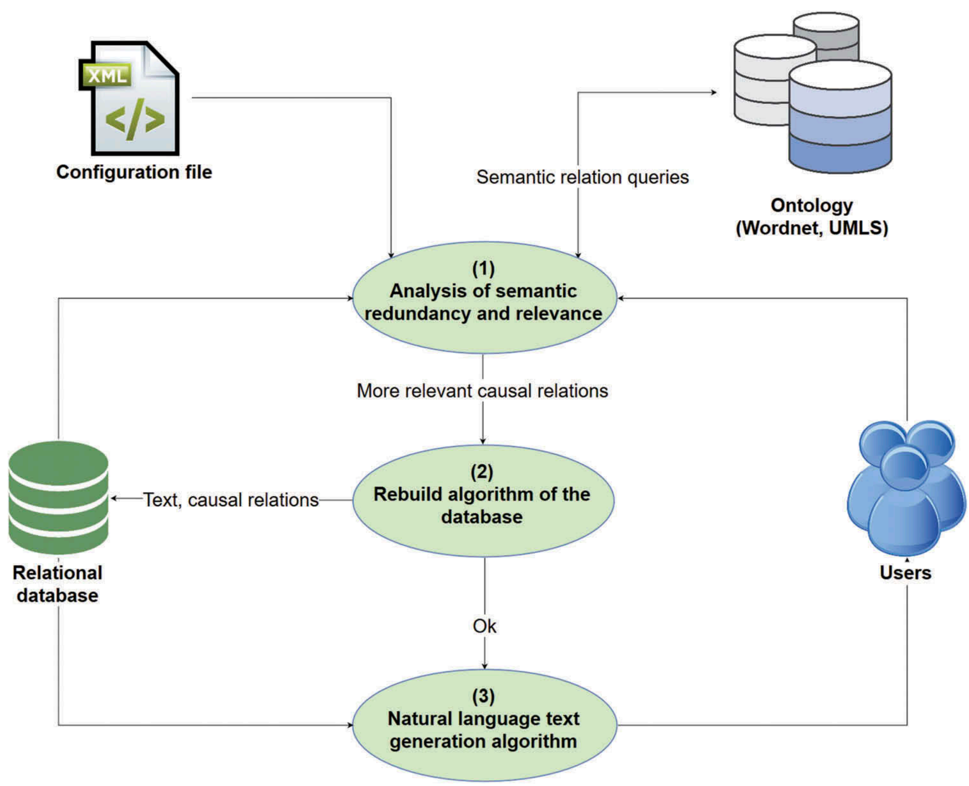

Figure 10. Process to reduce redundancy nodes in a causal graph.

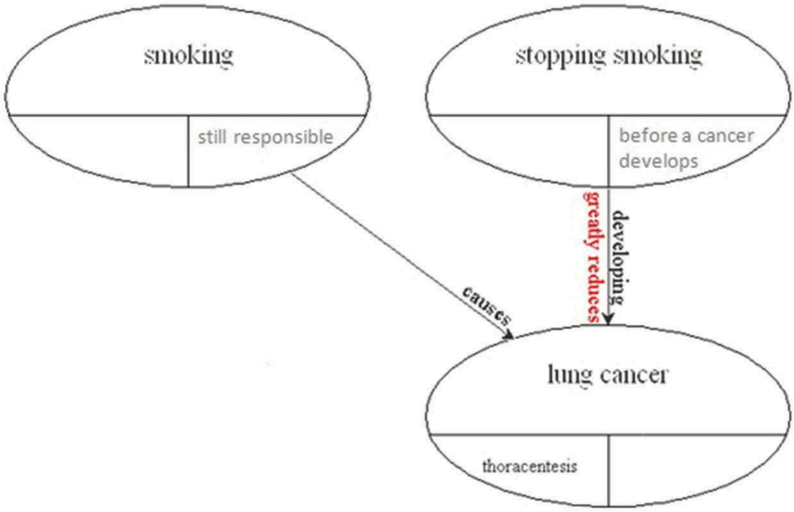

Figure 11. Time causal relationships.

At the same time, computational imagery is a branch of cognitive science that aims to develop useful tools for visual and spatial representation and reasoning, allowing grasping relationships intuitively and doing visual inferences in an easier way than those based on text-analysis. The imagery of causal mechanisms is related to causal graphs. If time is involved in causal mechanisms, the time-line is the tool for representing time-restrictions. Our work aims to contribute to this task by providing algorithms that draw graphs from recovered temporal causal mechanisms, adding a time line illustrating time constraints.

Future work should address the improvement of temporal lexicon classification in order to better tune the restrictions endorsed to the cause or the effect and to represent the temporary constraints in a more compact way, perhaps as part of the causal graph. Another line of work can be to inquire about the role of time in drugs administration. A direct computational application would be the development of apps creating time alerts in base to certain medicines and their time interval of effectiveness.

Notes

1. http://www.gnu.org.
2. http://www.cis.uni-muenchen.de/schmid/tools/TreeTagger/.
3. https://www.mayoclinic.org.
4. https://wordnet.princeton.edu/.

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