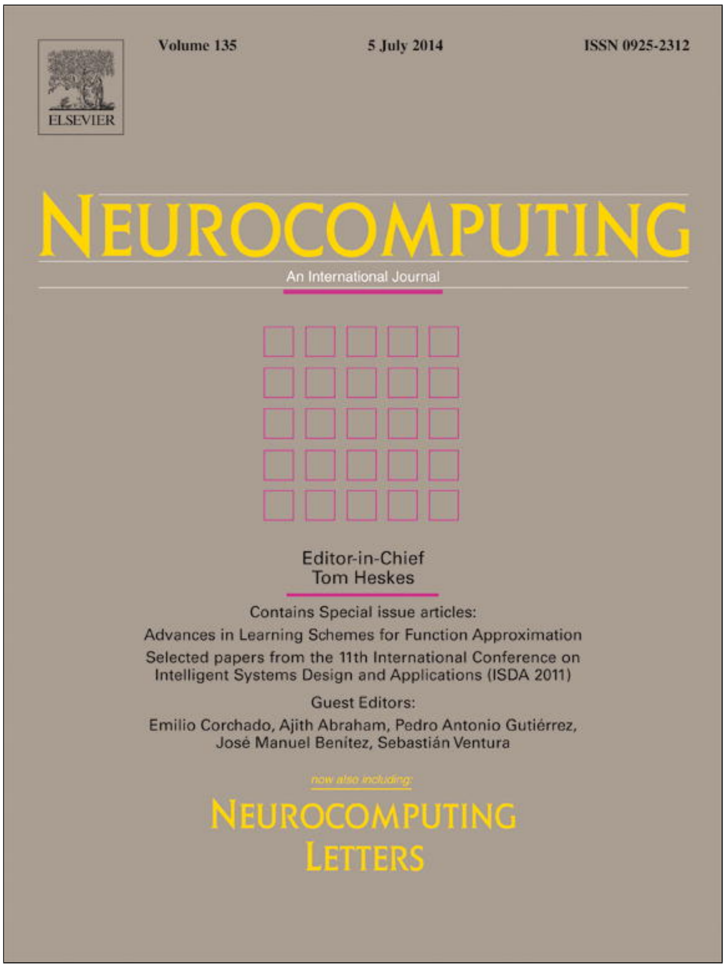
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# Extracting answers from causal mechanisms in a medical document

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The aim of this paper is to approach causal questions in medical documents eventually recovered from a search engine. Causal questions *par excellence* are *what*, *how* and *why*-questions. The 'pyramid of questions' shows this. At the top, why-questions are the prototype of causal questions. Usually why-questions are related to scientific explanations. Although cover law explanation is characteristically of physical sciences, it is less common in biological or medical knowledge. In medicine, laws applied to all cases are rare. It seems that doctors express their knowledge using mechanisms instead of natural laws. In this paper we will approach causal questions with the aim of: (1) answering what-questions as identifying the cause of an effect; (2) answering how-questions as selecting an appropriate part of a mechanism that relates pairs of cause-effect (3) answering why-questions as identifying central causes in the mechanism which answer how-questions. To automatically get answers to why-questions, we hypothesize that the deepest knowledge associated to them can be obtained from the central nodes of the graph that schematizes the mechanism. Our contribution is concerned with medical question answering systems, even though our approach does not address how to retrieve medical documents as a primary answer to a question, but how to extract relevant causal answers from a given document previously extracted by using a search engine. Thus, our paper deals with the automatic detection and extraction of causal relations from medical documents.



## 1. Introduction

Causality is an ancient topic that came from Aristotle [1,2], who distinguished between four types of causes:

- Material cause, involving the physical matter of which something is made; that is, the mass of which it consists.
- Formal cause, focusing on the way that a thing is intended and planned to be.
- Efficient cause, quoted as 'the primary source of the change'; the prior movement or the source energy that triggers the final effect.
- Final cause, as the end, goal or aim that a process leads to. The final cause is the teleology (from greek *telos*) that something is supposed to serve.

The Aristotelian view of causality traditionally offered a frame for providing answers to causal questions, as *what-q* or *why-q*.

In effect, Aristotle's typology serves to answer *what* and *for-what* questions. For example, in the presence of a statue, we can ask for the following queries, which belong to the types of cases aforementioned:

- 'What is it made from?' It is made of metal (material cause);
- 'What is its form?' A man in a praying attitude (formal cause);
- 'What produced it?' The sculptor (efficient cause);
- 'For what purpose?' To pay tribute to a virtuous person (final cause).

But Aristotle's typology enables to answer why-questions as well. Efficient causes seem to be the more appropriate for this task. In this paper we will follow this view.

Aristotle's efficient cause is intended as a way of performing explanations. Explanations are usually related to why-questions. A typical – although not academic – way to provide an explanation is to distinguish the components involved in a process identifying the first cause or impulse. In the aforementioned example, the sculptor is who acted in the first place.

More in depth, and referring to a medical context, we can argue that the efficient cause of a diagnosis it is not a doctor, but his

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medical knowledge. As we previously said, Aristotle pointed out that efficient causes are the primary source of change. The transmission of such changes in a causal network is known as a mechanism. So, efficient causes are related to mechanisms. In this paper we deal with the analysis of *what*, *how* and *why*-questions focusing on efficient causes and mechanisms.

The following pyramid arranges interrogative particles depending on the potential complexity of their answers [3] (Fig. 1).

Ascending in the pyramid means the use of causal interrogatives, demanding complex answers instead of *yes, no* replies to questions, stimulating reflective and deepening thinking. At the top, why-questions ask for some kind of explanation.

Medical research provides mechanisms for explaining diseases, leading to new ideas about how the disease can be treated both for therapeutic and theoretic purposes. A disease explanation is better understood showing a causal mechanism, describing the interrelations among multiple factors involved in its origin and development. F. ex., the U.S National Institute of Health concluded that there is a correlation between bacterial infection and ulcers or, more specifically, a causal influence between infection with Helicobacter Pylori and the duodenal ulcer. But note that correlation is not the same as causation. Correlation can provide evidence for causes in terms of probabilistic contrast; that is, in terms of how much probable is an effect (e) with a cause (c) than without it (c). Cheng baptized that difference as the 'causal power of *c*' [4]. But whereas the probability with which *c* produces (when *c* is present or is absent), is an observable frequency, the causal power is a theoretical entity, like electrons induced from observations of traces. May be that *e* is due to alternative causes to *c*. Therefore, the causal power of *c* over *e* is better interpreted as a dispositional property of some entities to provoke, in the long run, other entities; i.e., the propensity – not probability – of *c* causing *e*. But propensity is a dispositional and imprecise concept.

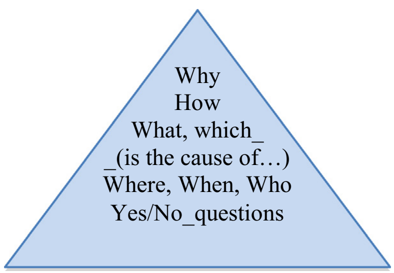


**Fig. 1.** Pyramid of questions' complexity.

In Medicine, diseases like schizophrenia, bulimia, or anorexia, frequently show fuzzy causal boundaries, as they present similar symptoms. Thus, causes frequently are complex and vague. That is, in medicine we should shift from the classic scientific paradigm of 'theory' to the more evasive of 'mechanism'. Causes are not single, but complex [5] and are not crisp, but imprecise [6].

This paper will approach how to reach answers to causal questions from mechanisms: (1) what-questions as identifying the cause of a mechanism; (2) how-questions as selecting the appropriate parts of a mechanism and (3) why-questions as extracting and summarizing highlighted paths in the answer of how-questions. Answers to why-questions match scientific explanations in a negative and a positive note: (−) as previously said, scientific explanations in medicine are based on mechanisms instead of natural laws; (+) scientific explanations are generally concerned with deepening or centrality, providing explanations as detailed as possible.

Medical question answering systems (MQ-AS) aim to provide the users with direct answers to the posed questions; instead of furnishing them with a large amount of relevant potentially documents. For seeking direct answers, MQ-AS need to go beyond the surface-level analysis of texts, providing lexical-syntactic and semantic resources, as well as reasoning capabilities, providing inference mechanisms to obtain more adequate answers. Traditional MQ-AS accept questions as inputs; those questions trigger a search engine providing relevant documents and, finally, the system operates over those documents in order to reach the direct answer to the question. In our approach, the step 2 is omitted. We act directly over a document previously recovered.

Although most MQ-AS have exploited syntactic or semantic resources, few approaches have scanned the utility of inference mechanisms. Our approach uses syntactic and semantic resources to perform an inference-based one, as aims to extract causal semantic relations from inferential mechanisms. Our approach is in the vein of the Girju's work about how to automatically detect and extract causal relations from texts [7].

Thus, our contribution is organized as follows: in section I we analyze the mechanism to provide an answer to what-questions. In Section 2 we will focus on the answer to how-questions. In Section 3 why-questions are addressed. Finally, a section of conclusions and references close this work.

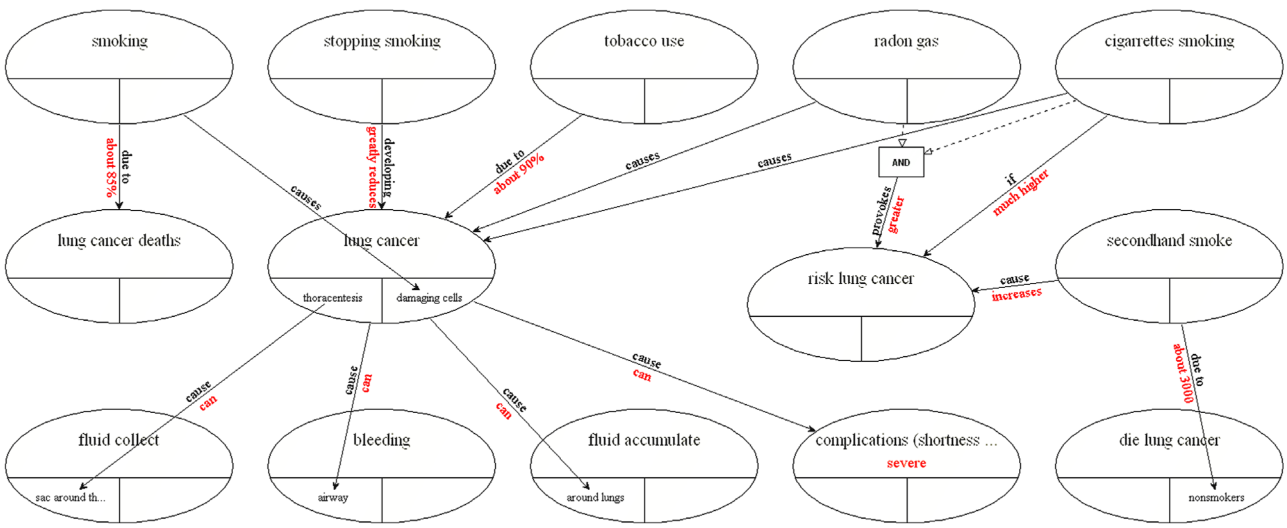


**Fig. 2.** Causal graph of the question 'What causes lung cancer?'

## 2. Answering what questions

In [8] we described a procedure to automatically display a causal graph from medical knowledge included in several medical documents.

Sentences from medical texts frequently show causality as imperfect or approximate in nature. This feature comes from the linguistic hedges or fuzzy quantifiers included in these sentences. A Flex and C program was designed to analyze causal phrases denoted by words like ‘cause’, ‘effect’ or their synonyms, highlighting vague words that qualify the causal nodes or the links between them. Another C program receives as input a set of tags from the previous parser and generates a template with a starting node (cause), a causal relation (denoted by lexical words), possibly qualified by fuzzy quantifiers, and a final node (effect), possibly modified by a linguistic hedge showing its intensity. Finally, a Java program automates this task.

Fig. 2 graphically shows this template.

Once the graph is performed, it is stored in a database attending to the following structure.

Causal information stored in terms of nodes and relationships among them will be useful in the task of finding answers to what-questions. Next we briefly summarize the overall process (Fig. 3).

- Locate the sought concept within the database and point to the records where it is contained.
- If the user is asking for causes, locate the records of the ‘relationship’ table with the sought concept as effect, and retrieve the cause_concept information from the ‘Concept’ table (like location, specification and intensity attributes, if exist).
- If the user is asking for effects, locate the records of the ‘relationship’ table with the sought concept as cause_concept, and retrieve the effect_concept information (with all the attributes) from the ‘Concept’ table.
- Compose each part of the answer ‘translating’ the information into these obtained records, linking the records obtained by the ‘and’ connective and processing the information contained like modifiers and quantifiers.
- When composing the answer, evaluate the type of causal connector to make a correct reading of the causal relationship,

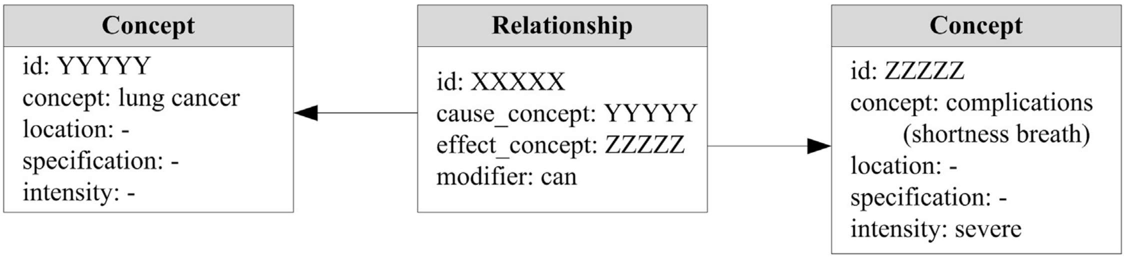


**Fig. 3.** Causal database structure.

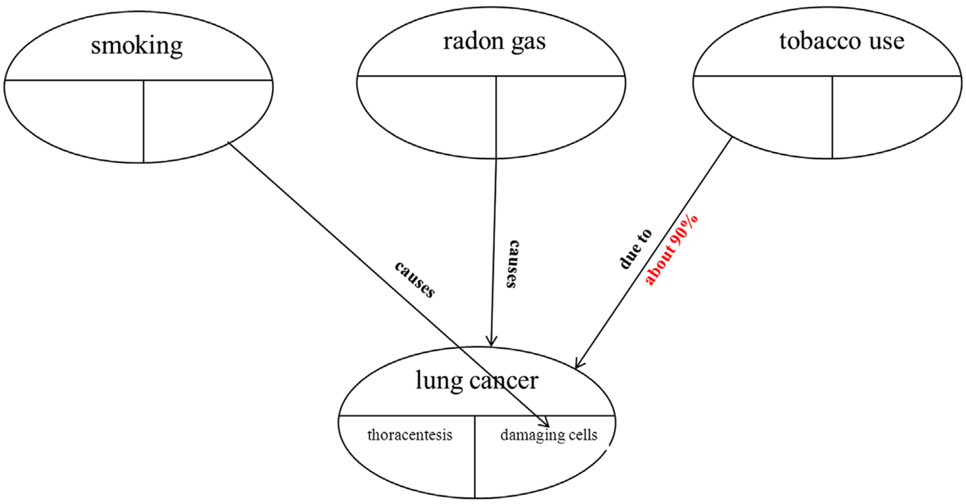


**Fig. 4.** Graph example to answer What causes lung cancer?.

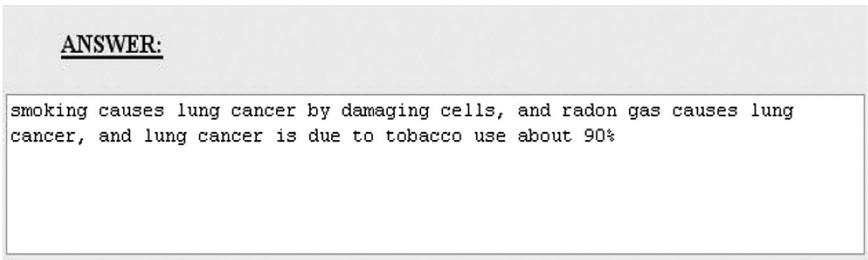


**Fig. 5.** Automatic answer to the question What causes lung cancer?

and place the relationship modifier (if it exists) in the right place attending to the type of causal connector. For example, if the causal link is 'cause' in Fig. 4 you can say that *smoking* 'cause' *lung cancer*; but if the causal connector is 'due to', the reading is upside down and you cannot say that *tobacco use is due to lung cancer*, but *lung cancer is due to smoking.*

Graphically, what this algorithm achieves is to mimic a causal graph without drawing it, tracking the links contained in the database. For example, if the user asks *What causes lung cancer*? The following graph is deployed:

To compose an answer, we just have to gather the nodes and relationships pointing at the lung cancer node, e.g., in this case, *smoking*, *radon gas* and *tobacco* use.

The algorithm with this information performs the answer displayed in Fig. 5. A simple interface, using Php and HTML languages, translates de graph to text:

## 3. Answering how questions

To address *how*-questions, the first step it to locate the causal paths connecting the concepts involved in the question. How-questions usually involve two concepts in the same question, the concept 'cause' and the concept 'effect'. Thus, if we ask *How X causes Y*?, the objective is to find the causal path connecting *X* (as head of this path) to *Y*. Once the 'cause' concept has been located in the database (it will appear in the Relationship table as *cause_concept*), a recursive algorithm finds the possible paths connecting the concept cause with the concept effect. The main steps of it are the following:

- Look for the sought cause concept and store it as head of all causal paths.
- Locate all the effect nodes linked to this cause concept and create one different path per node (the head node of all of these paths will be the sought cause node).
- If the sought effect node is among the effect nodes, stop the recursive procedure and proceed to evaluate the different paths connecting the node cause with the node effect. On the contrary, repeat this step as many times as indicated (the number of paths can be high if this point is not controlled, so we have established a depth of eight nodes as maximum connecting the sought node cause with the sought node effect. This number of nodes or levels can be modified).
- Once all the possible paths have been located, establish some criteria to order them on the basis of their relevance.
- Translate the information included in the three more relevant paths into a suitable answer (using the same procedure as in *what* questions).

In the example presented in Fig. 6, the question *How smoking causes death*? has been performed. That question displayed the following causal graph as a result.

The graph example shows several causal paths connecting the nodes *smoking* and *death*. Thus, it seems convenient to establish some criterion to classify them. Kosko's max–min approach to fuzzy cognitive maps serves to this purpose [9]. Inspired by Kosko, we calculate the indirect effect and total effect from the node *smoking* to the node *death* establishing a partially ordered set including all the quantifiers labeling the graph. The lowest of these values is *eventually* and the highest, *provokes*. Between them, all the rest in the order that the set *P* shows: *P*={eventually < can < about 85% < 90% < provokes < =causes}.

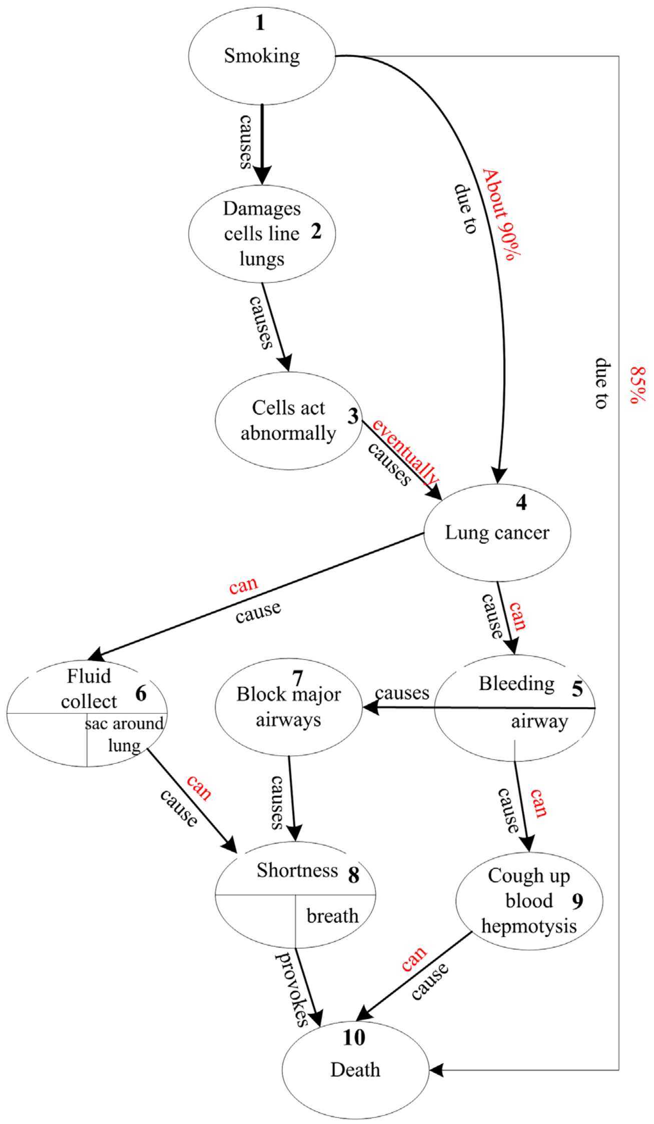


**Fig. 6.** Graph to answer the question *How smoking causes death*?

In this example there are five possible paths linking *smoking* and *death*, so the indirect effect of each path is (the number denotes the node):

- $I\{n_1,n_2,n_3,n_4,n_6,n_7,n_9\}$=min{causes, causes, eventually, can, can, provokes}=eventually.
- $I\{n_1,n_2,n_3,n_4,n_5,n_8,n_9\}$=min{causes, causes, eventually, can, can, can}=eventually
- $I\{n_1,n_4,n_6,n_7,n_9\}$=min{about 90%, can, can, provokes}=can.
- $I\{n_1,n_4,n_5,n_8,n_9\}$=min{about 90%, can, can, can}=can.
- $I\{n_1,n_9\}$=min{85%}=85%.

The total effect that the *smoking* node has upon the *death* node is the maximum of all the indirect effects; that is, the strongest of all the weakest links.

Thus, the answers to the question *How smoking causes death*? would be:

## 4. Answering why questions

In [10], Bechtel and Abrahamsen said that: 'biologists explain *why* by explaining *how*'. Following this quotation, our hypothesis is that to answer a *why*-q is not the same, but it is contained in the answer to a *how*-question.

As we previously remarked, *why*-questions are frequently related to cover law explanations. Nevertheless, cover law explanations provide only a partial frame to obtain answers to *why*-questions in a medical domain, because in this field it is not frequent to get general laws that always hold [11]. In medicine, mechanisms are more common than natural laws. Despite this, some characteristics of explanations are profitable to provide answers to *why*-questions: science, through cover law explanations, is impelled to get at the ultimate causes of phenomena [12]. In this vein, answers to *why*-questions should pursue the deepest or proximate cause.

An explanation is a kind of logical relation between the *explanans* and the *explanandum* [1]. In *why*-questions, the assertive part of the query can be chosen as the *explanadum* and, as a capital part of the *explanans*, we can select the prior cause, from which all the explicative process is triggered. In most cases, nevertheless, to invoke only to the primary cause is quite limited. Other information should join the prior cause in the explanation. A reasonable candidate will be the information included in the relevant nodes of the graph. Our hypothesis is that nodes with high centrality values would be the relevant ones in this task. Depending on whether the answer is for people with expertise in medicine (in the example at hand) or without it, we can select one or more central nodes to conduct the causal relation between the prior cause and the final effect (in fact, the assertive part of the question).

In order to advance in this task, we represent a mechanism by a graph and we follow the widely shared conjecture that the higher is the centrality of a node in the graph, the greater is its relevance [6]. Next, here is some notation concerning centrality measures in a graph.

A graph $G=(V, E)$ consists of a finite set $V$ of vertices and a finite set $E \subseteq V \times V$ of edges. An edge connects two vertices $u$ and $v$. The vertices $u$ and $v$ are said to be *incident* with the edge $e$ and *adjacent* to each other. Centrality is a function $C$ which maps every vertex $v$ (of a given graph G) to a value $C(v) \in \Re$. A vertex $u$ is more important than another vertex $v$ if $C(u) > C(v)$. Vertices have different relevance. Centrality measures provide a calculus to perform it. In the sequel, we will exemplify some centrality measures for the following graph, which schematizes the mechanism showed in Fig. 6.

More specifically, and regarding to this graph, we will calculate the out degree centrality, closeness, betweenness and *eigenvector* centrality for several nodes.

– *Out degree centrality*: the degree $d(v)$ of a vertex is the number of its incident edges. For standardization, divide each score by $n-1$ ($n$, number of nodes). In directed graphs, edges have a direction associated. Accordingly, there are two different types of degree centrality: in-degree centrality; that is, the number of edges pointing to a node, and out-degree centrality; i.e., the number of edges pointing out from a node. Next, we show the out-degree values for the above graph:

*Out-degree centrality*

| Node | Score | Standard Score |
|---|---|---|
| 1 | 3 | 3/8 |
| 2 | 2 | 1/8 |
| 3 | 2 | 1/8 |
| 4 | 2 | 2/8=1/4 |
| 5 | 2 | 1/8 |
| 6 | 2 | 1/8 |
| 7 | 2 | 1/8 |
| 8 | 2 | 1/8 |
| 9 | 2 | 1/8 |

– *Closeness*: in contrast with centrality, closeness uses not only the maximum distance between the vertex of reference and all the other vertices, but the sum of the distances of this vertex and all the other vertices.

*Closeness*

| Node | Score | Standard score |
|---|---|---|
| 1 | 1/30 | 8/23 |
| 2 | 1/23 | 8/23 |
| 3 | 1/18 | 8/18 |
| 4 | 1/15 | 8/15 |

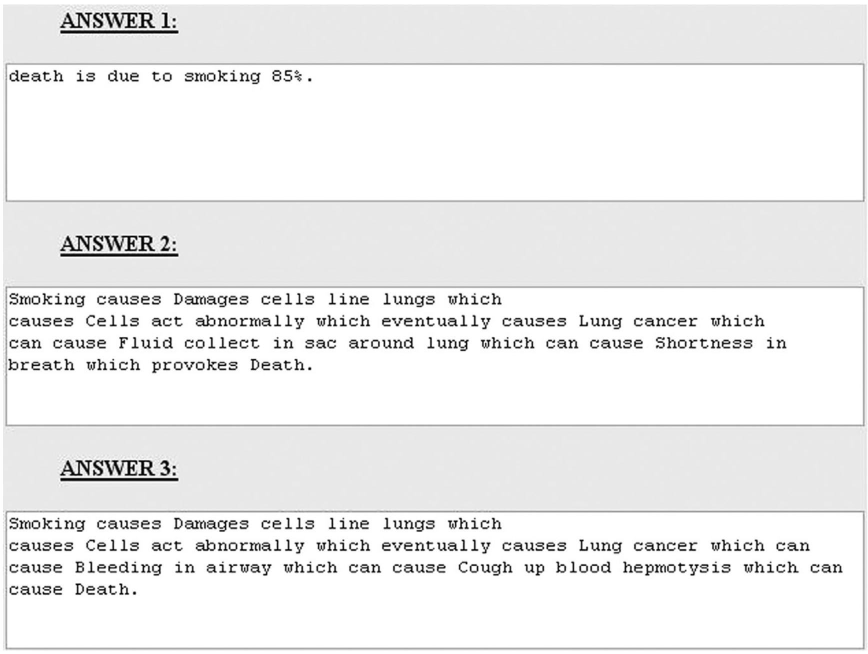


**Fig. 7.** Automatic answer to the question *How smoking causes death*?

| | | |
|---|---|---|
| 5 | 1/18 | 8/18 |
| 6 | 1/18 | 8/18 |
| 7 | 1/19 | 8/19 |
| 8 | 1/19 | 8/19 |
| 9 | 1/24 | 8/24 |

– In order to calculate the closeness centrality we need to calculate the inverted score after we count the total number of steps to a node. For standardization, divide a score by $n-1$ ($n$, number of nodes) and then take the inverse.
– *Betweenness*: is defined as the share of times that a node $i$ needs a node $k$ (whose centrality is being measured) in order to reach a node $j$ via the shortest path. Put bluntly, this measure basically counts the number of geodesic paths (the shortest path between two nodes) that pass through a node $k$. To calculate the betweenness centrality, we take every pair of the network and count how many times a node can interrupt the geodesic distance between the two nodes of the pair. For standardization, the denominator is $(n-1)(n-2)/2$.
For example, the betweenness centrality for the node 4 will be
Betweenness centrality(4)=fraction_paths_broken

(1, 2)=0+(2, 3)=0+(3, 4)=1+(4, 5)=1+
+ (1, 3)=0+(2, 4)=1+(3, 5)=1+(4, 6)=1+
+ (1, 4)=1+ (2, 5)=1+(3, 6)=1+(4, 7)=1+
+ (1, 5)=1+ (2, 6)=1+(3, 7)=1+(4, 8)=1+
+ (1, 6)=1+ (2, 7)=1+(3, 8)=1+(4, 9)=2/2=1+
+ (1, 7)=1+ (2, 8)=1+ (3, 9)=2/2=1+
+ (1, 8)=1+ (2, 9)=2/2=1+(1, 9)=0+
+ (5, 8)=0+(6, 7)=0+ (7, 9)=0+(8, 9)=0
+ (5, 9)=0+(6, 9)=0+
N=0+0+1+1+1+1+1+0+0+1+1+1+1+1+1+1-
+1+1+1+1+1+1+1+1+1+1+1+1+1+0+0+0+0-
+0+0=21/32=0,656
Operating a similar calculus for the node 5, the result is
=0+0+0+1+0+0+1+0+0+0+1+0+0+1+0.5-
+0+1+0+0+1+0.5+1+0+0+1+0.5+1+1+0-
+0+0+0=11.5/32=0.334 significantly lower than the previous one, as expected.

– *Out Eigenvector centrality*: it is based on the assumption that the value of a single vertex depends on the values of the neighboring vertices and not only on the position of a vertex within the graph. The moral is that the popularity of a node depends also on its proximity to other nodes highly connected. *Mathematica*® software shows the following out-eigenvector centrality measure for the graph of our example:

*Out-eigen vector centrality*

| Node | Score |
|---|---|
| 1 | 0.999991 |
| 2 | 0.004339 |
| 3 | $8.16933 \times 10^{-8}$ |
| 4 | $3.27441 \times 10^{-15}$ |
| 5 | 0,0000188273 |
| 6 | $1.77148 \times 10^{-10}$ |
| 7 | $1.77326 \times 10^{-10}$ |
| 8 | $7.68872 \times 10^{-13}$ |
| 9 | $7.69543 \times 10^{-13}$ |

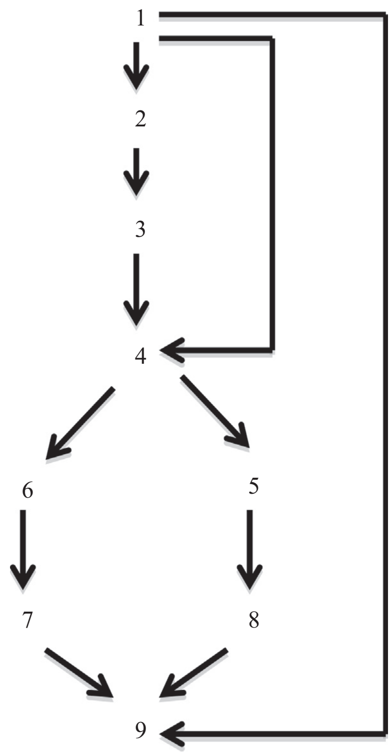


**Fig. 8.** Base graph.

In the previous example we note that node 1 has a higher degree than node 4, but node 4 has a higher score in closeness and betweenness that node 1. As suggested by Obietat et al. in [14], we think that it is convenient to combine the degree, betweenness and closeness centrality measures in order to reach a consensus centrality measure. Combination is needed because the degree measure only takes into account direct connections, ignoring the importance of indirect links. If we adopt the arithmetical mean as the consensus measure, we can see – regarding to our example – that node 1 has a consensus measure: 0.375 (degree)+0.348 (closeness)+0.25 (betweenness)/3=0.324 and node 4: 0.25+0.533+0.656/3=0.480. Thus, node 4 is the node with a highest centrality measure in the graph.

*Table for Betweenness*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 1 | – | 1–2 | 1–2–3 | 1–4 | 1–4–5 | 1–4–6 | 1–4–7 | 1–4–5–8 | 1–9 |
| 2 | – | – | 2–3 | 2–3–4 | 2–3–4–5 | 2–3–4–6 | 2–3–4–6–7 | 2–3–4–5–8 | 2–3–4–6–7–9 2–3–4–5–8–9 |
| 3 | – | – | – | 3–4 | 3–4–5 | 3–4–6 | 3–4–6–7 | 3–4–5–8 | 3–4–6–7–9 3–4–5–8–9 |
| 4 | – | – | – | – | 4-5 | 4–6 | 4–6–7 | 4–5–8 | 4–6–7–9 4–5–8–9 |
| 5 | – | – | – | – | – | – | – | 5–8 | 5–8–9 |
| 6 | – | – | – | – | – | – | – | 6–8 | 6–7–9 |

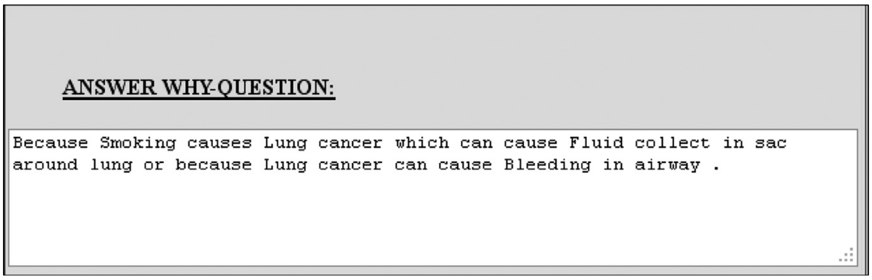


**Fig. 9.** Automatic answer to the question *Why smoking causes death*?

Therefore, the content of node 4 complements the prior cause in the *why*-question explanation. This would be enough to answer to a lay audience. But if people involved in the inquiry are specialized, other than centrality nodes should provide technical information. Eigenvector centrality permits to select nodes not only because they are central, but because they are highly connected to central nodes. In our example, nodes with high eigenvalue score are: $1>2>5>3>6$. Perhaps we need to perform a selection in this set. Node 1 is out as it is the prior cause. Nodes 2 and 3 are before node 4, the central node par excellence. Thus, nodes 2 and 3 are explanans of node 4, as node 4 is part of the explanans elicited by the *why*-q; thus, general information contained in nodes 2 and 3 is ruled out. Only nodes 5 and 6 remain.

That is, if we take the graph of Fig. 6 and launch it against the query *Why John died*? Some answers arise. The graph has a main node or prior cause that directly or indirectly connects with the effect. So, a tentative answer could be to locate the root node and say: *Because John was a smoker*. But, as previously said, why-questions are concerned – if accessible – with deepening in knowledge. Thus, other nodes should be explored. Our hypothesis is that central nodes in the mechanism include relevant content. In the quoted graph, the central node is node 4. But we can tune perhaps a little more the answer. A *why*-question can be made by a skilled or a non-skilled, interrogator. If the questioner is not specialized, the causal link between the prior cause and the central node is perhaps enough to arrange the answer. As in the previous example, *Because John was a smoker*, *causing lung cancer.* But if the questioner is specialized, more specific knowledge is needed. Eingenvector centrality values detect nodes connected with a few neighbors of high importance. If the node with the highest centrality value is node 4, the nodes with more eingencentrality are 1, 2, 5, 3 and 6. Node 1 is ruled out by the root cause. Nodes 2 and 3 do not include specific content, as they are before node 4, the central node. Thus, nodes 5 and 6 are the candidates to express specific explanations about why lung cancer causes death. Thus, the answer for a specialized questioner will be the following causal chain: *Because John was a smoker*, *provoking lung cancer*, *that leads to fluid collect or bleeding* (*leads to* synonym of *causing*, included in the final answer in order to make it more stylish from a linguistic point of view).

In order to provide an automatic answer of a *why*-question, we have partially modified the algorithm used to respond how-questions. Remember that his procedure selected all the possible paths linking the node cause with the node effect. Each one of these paths would be a cluster of nodes to summarize. So, the steps to answer (and summarize) a *why*-question are the following:

- Locate the main cause node (head of the diagram), and the effect node.
- Calculate the centrality measure of each node (but the cause and effect nodes).
- Select the node with the highest centrality value.
- Select those nodes with the highest eingencentrality value related to the node with the highest centrality value.
- Reject those nodes selected in the previous step which number is lower than the node with the highest centrality value.
- Order the nodes to compose an appropriate answer.
- Compose an answer summarizing the retrieved nodes.

In the graph showed in Fig. 6, the algorithm would locate nodes 1 and 9 as cause and effect nodes. The node with the highest centrality value would be node 4, so the eingencentrality values will be calculated in base to this node. As a result four more nodes are obtained in this order, 2, 5, 3 and 6, but nodes 2 and 3 are rejected because they are lower than 4. On the other hand, nodes 5 and 6 will be included in the new answer, as well as the causal paths that link these nodes with the effect node.

The next step is to order the nodes to compose an answer. So, with all these nodes, the final answer would be the composition of nodes 1, 9, 4, 5, 6, and the causal paths derived from nodes 5 and 6 as seen in the following figure: Figs. 7–9.

## 5. Conclusion

As Hirschman and Gaizauskas point out in [13], the Q/A processing consists of three main processing phases: question processing, document processing and answer phase. Our approach skips the second step and focuses only in the first and third ones.

Our aim was to approach how to get answers to causal questions from mechanisms reflecting medical knowledge. In the pyramid of causal questions, what-q, how-q and – at the top – why-questions have been analyzed and preprocessed using templates. Solutions to get answers for each one of them are provided.

These solutions are dependent of the field selected – medical knowledge – and even of the furnished example. We are aware that other domains or examples request for a broader approach. Therefore, a challenge for future work will be to generalize our method to larger domains and to extend analysis of the graph considering several types of causal networks: serial, converging and diverging connections, focusing on the specific properties identifying each one.

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