Acquiring Qualitative and Quantitative Knowledge from Verbal Statements and Dialogues in Probabilistic Domains

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Summary

We describe an approach to acquire qualitative and quantitative knowledge from verbal statements and dialogues in complex, probabilistic domains. This work is part of the development of an intelligent environment, MEDICUS (Modelling, explanation, and diagnostic support for complex, uncertain subject matters), that supports modelling and diagnostic reasoning in the domains of environmental medicine and human genetics. The system is designed for professional as well as for further education purposes in these two medical domains. Support for other domains of rapidly changing and uncertain knowledge will be possible as well. In MEDICUS, uncertainty is handled by the Bayesian network approach. Thus *modelling* consists of creating a Bayesian network for the problem at hand. Since MEDICUS is designed for users interested in the domain but not necessarily in mathematical issues, it is possible to state propositions verbally and let the system generate a Bayesian network proposal. This differs from existing reasoning systems based on Bayesian networks, i.e. in medical domains, which contain a built-in knowledge base that may be used but not created or modified by the user. *Diagnostic reasoning and deciding* consists of using the network for stating and testing diagnostic hypotheses, and asking for recommendations.

In this paper we will focus on the modelling component. In order to design a domain model represented as a Bayesian network, it is necessary to specify the qualitative and quantitative information necessary. This is a problem for probability-based as well as for other uncertainty formalisms. We will describe our approaches how to acquire this knowledge from dialogues.

• With respect to *qualitative information*, it is necessary to check whether the dependence and independence relations implied by a Bayesian network correspond to the intentions of the modeller. In MEDICUS, these relations are obtained from diagnostic assertions.

• With respect to *quantitative information*, apriori and conditional distributions have to be obtained in order to be able to use the network for diagnostic reasoning. But even domain experts are usually hesitant to specify numerical relationships. So we argue that in an easily usable system the modeller should be able to state propositions verbally. We are currently developing an approach to assign probabilities to these "fuzzy" relations and concepts.

We will show how to extend these approaches to natural dialogue situations between two or more participants. The purpose of this is to be able to acquire the knowledge from more natural situations, and to model dialogues in probabilistic domains. This is a necessary condition to support them in professional as well as educational contexts.

1. Introduction

Diagnosis and decision making involve reasoning and problem solving tasks that can be quite difficult. This is especially true in medical domains (Barrows & Tamblyn, 1980; Boshuizen & Schmidt, 1992; Elstein et al., 1978; Patel & Groen, 1986) where the knowledge is particularly complex, interrelated, and uncertain. Two examples of such domains are the epidemiology of diseases caused by environmental influences, like pollution, and of human genetic defects. In these domains, clear-cut taxonomies and explanatory models of diseases, or syndromes, have not been developed yet. But these domains are getting increasingly important. This is for example reflected by the fact that currently many further education courses for physicians are established.

The main aim of medical expert systems has been to support diagnostic hypotheses and further diagnostic steps, for example, for differential diagnosis. Some systems also generate therapeutic recommendations. Uncertainty is handled heuristically (i.e. MYCIN, Shortliffe, 1976; CASNET, Weiss et al., 1978; PIP, Szolovits & Pauker, 1978; 1993; INTERNIST, Miller et al., 1982; TRAINER, Reinhardt & Schewe, 1995) or in a probability-based way (i.e., NESTOR, Cooper, 1984; MUNIN, Andreassen et al., 1987; PATHFINDER, Heckerman, 1991). Some systems (e.g. TRAINER) have been developed for education purposes. They enable the user to state diagnostic hypotheses for medical cases and give feedback, or they are able to explain their reasoning (e.g. Clancey, 1983). But they do not allow the user to create new knowledge bases by stating or modifying domain models. Modelling is important for two reasons: Firstly, medical experts would appreciate a tool for summarising and organising assumptions and results of studies. This would help to present information in a compact way as well as in the derivation of research questions. Secondly, within educational contexts the user should have an opportunity not only to practice diagnosis, but also to actively construct models of diseases, their possible causes, and the symptoms associated with them, and to evaluate the consequences of these models.

MEDICUS (Schröder et al., 1996) is a system currently under development. It is designed to enable and assist in the creation of domain models and to support diagnostic reasoning and decision making using the Bayesian network approach, both within professional and educational contexts. In environmental medicine, diagnostic reasoning and deciding does not only refer to diagnosis of a patient's disease, but also to the detection of relevant environmental factors, requiring chemical / technical analyses. Table 1 shows the potential users of MEDICUS.

		context	
		professional	**educational**
appli-cation	**modelling**	epidemiologists	participants of further education courses
	diagnostic reason-ing and deciding	physicians chemical / technical staff	participants of further education courses

Table 1: Tasks, contexts, and potential users of MEDICUS

This paper focuses on the modelling part of MEDICUS. For the creation of a Baysian network domain model, the modeller has to specify a lot of qualitative and quantitative information.

- On the qualitative level, the network implies dependence and independence relations, and it has to be verified that these implications are consistent with the assumptions and intentions of the user. In MEDICUS the user may specify these assumptions by diagnostic assertions.
- On the quantitative level, apriori and conditional distributions are needed for the network. But this information is difficult to obtain. Epidemiological studies often cannot be directly compared because of special conditions, and even domain experts hesitate to specify numerical relationships (Nakao & Axelrod, 1983). Therefore, we enable the modeller to state propositions verbally. We are currently developing an approach to acquire quantitative information from verbal propositions.

We think that it is particularly useful to extend both approaches to natural dialogues between two or more participants. Firstly, in a dialogue the needed information can be acquired in a more natural way. Secondly, modelling dialogues is a prerequisite for supporting tutorial dialogues as well as expert discussions. Thirdly, for diagnostic purposes it seems appropriate to use a model that results from experts' discussions if objective data are not available. Again this requires dialogue modelling.

The next section provides an overview of MEDICUS, including its approaches to acquire the qualitative and quantitative information needed. (A more detailed description can be found in Folckers et al., 1996, and Schröder et al., 1996). Then we will describe how to extend these knowledge acquisition approaches to dialogues. The closing section will state some conclusions.

2. An Overview of MEDICUS

2.1. Design Principles

In order to create a system designed to support problem solving in learning and education contexts, design principles are required that are based on a theory of problem solving and knowledge acquisition. We call our approach an *Intelligent Problem Solving Environment* (IPSE, Möbus, 1995): The learner acquires knowledge by actively *testing hypotheses*. The task of the system is to analyse the hypotheses and to provide help and explanations. The psychological foundation of our IPSE approach is the ISP-DL Theory of knowledge acquisition and problem solving (i.e., Möbus, 1995) which is influenced by van Lehn (1988), Newell (1990), Anderson (1993), and Gollwitzer (1990). Briefly, it states that new knowledge is acquired as a result of problem solving and applying weak heuristics in response to impasses. In contrast, knowledge is optimised if applied successfully. In addition, there are four distinct problem solving phases: deliberating and setting a goal, planning how to reach the goal, executing the plan and evaluating the result. The ISP-DL Theory leads to several design principles for IPSE's (Möbus, 1995). For example, firstly, the theory states that the learner will appreciate help only at an impasse. So the system should not interrupt the learner but offer help on demand. Secondly, feedback and help information should be available any time, aiming at the actual problem solving phase of the learner. Thirdly, the learner should be prevented from trapping into follow-up impasses. Thus help information should refer to the learner's pre-knowledge as much as possible.

MEDICUS is designed according to these criteria. For example, help information is or will always be available on demand. Planning a model is facilitated by a simplified-natural-language model editor that allows the learner to state her or his ideas in an informal way. The evaluation of models is supported qualitatively and quantitatively.

We chose to handle the uncertainty of knowledge by the Bayesian network approach. A Bayesian network (e.g., Neapolitan, 1990; Pearl, 1988) represents a joint probability distribution on a set of propositional variables by a directed acyclic graph. The nodes of the graph represent the variables. The directed arcs represent conditional probabilities (each variable conditioned on its parents in the network). Figure 1 shows a simple Bayesian network. Independencies between variables are represented by omitting arcs, which simplifies the conditional distributions. For example, the variables "benzene" and "flickering" are independent given knowledge about "eye irritations". This means that information whether a patient suffers from flickering is not relevant for the hypothesis that he has been exposed to benzene (and vice versa) if it is already known whether the patient is suffering from eye irritations: p(flickering | eye irritations, benzene) = p(flickering | eye irritations).

This support of qualitative reasoning was an important reason for choosing the Bayesian network approach in MEDICUS. A physician engaged in medical diagnosis proceeds in a highly selective manner (i.e., Elstein et al., 1978). It seems a promising hypothesis that there is correspondence between this selectivity - and human reasoning patterns in general -, and the kinds of (in)dependencies in Bayesian networks (Henrion, 1987; Pearl, 1988).

2.2. The Implementation State

The current implementation state of MEDICUS consists of the following components:

- Components for building domain models:
  - Components for initial model formulation:
    - a graphical model editor for creating Bayesian network graphs
    - a linguistic model editor for creating simplified natural language statements
    - a compiler creating an initial Bayesian network graph in the graphical model editor from a set of sentences stated in the linguistic model editor, and vice versa
  - Components for qualitative model specification and modification:
    - a diagnostic relevance editor for asserting diagnostic relevances
    - a feedback component comparing relevance assertions to the Bayesian network graph, delivering feedback, modification proposals, and explanations
  - Components for quantitative model specification and modification:

- quantification of the Bayesian network graph with apriori and conditional probabilities
- component for assigning probabilities to verbal relational terms stated in the linguistic model editor *(work in progress)*

• A diagnostic support component recommending diagnostic steps concerning history taking, examinations, laboratory tests and environmental tests (taking and analysing for example inroom air samples).

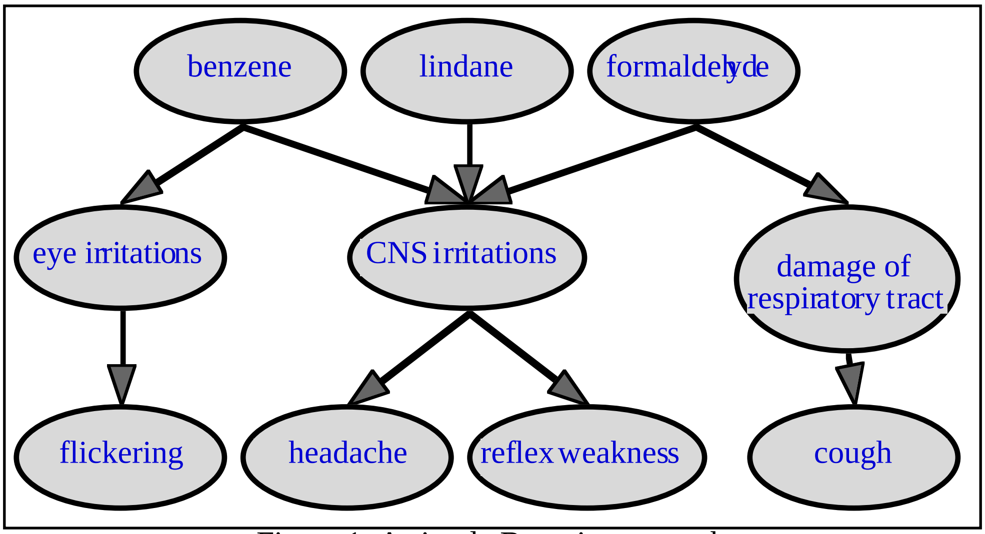


Figure 1: A simple Bayesian network

In the *graphical model editor*, the user may create a graph showing the relationships between variables in the domain of interest (Figure 1).

In order for a computer-based tool to be accepted by a range of different users, it is necessary that the user may state his ideas in an informal way. This can be done in the simplified-natural-language *linguistic model editor*.

Figure 2 shows an example. Each sentence is placed in a sentence field. In order to create sentences, the user may select variable categories, relations, modifier, and logical junctions from a menu, and name them. The relations are classified based on i) probabilistic concepts of causality (Suppes, 1970) organised according to "kind of influence" (positive / negative) and "direction of influence" (forward, backward, or undirected), and ii) has-part / is-a hierarchies. For example, the verb "causes" (sixth sentence in Figure 2) expresses a forward, positive influence between two variables A and B: $t_A \le t_B$, $p(B \mid A) > p(B)$. The user may specify new relations along these dimensions. The sentences created by the learner are checked by a definite clause grammar for syntactical correctness and some semantic restrictions.

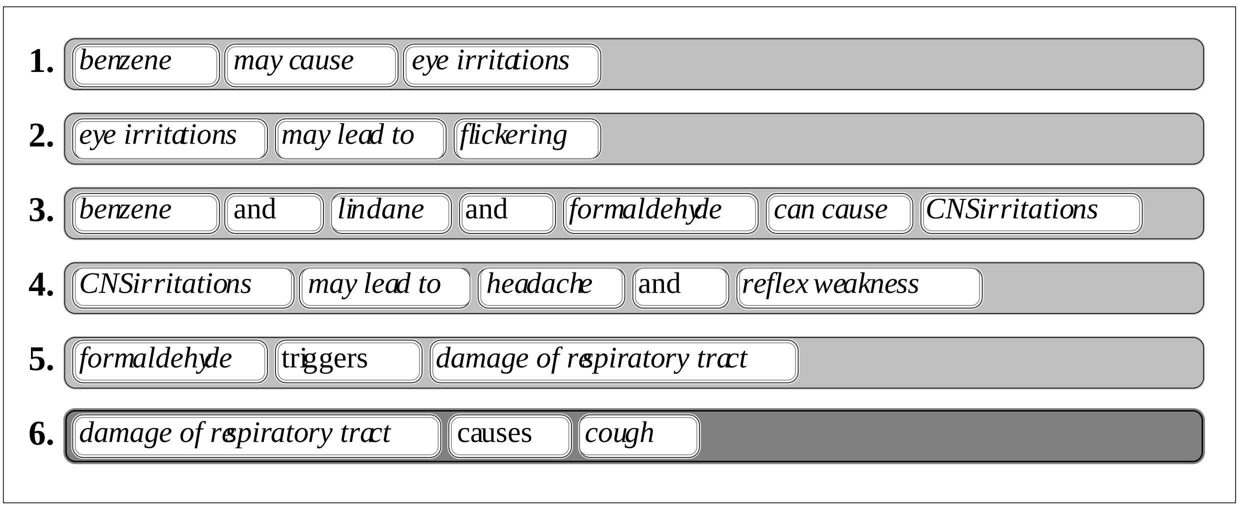


Figure 2: The linguistic model editor

The *compiler* generates an initial graph from the verbal model. For example, the graph in Figure 1 is generated from the set of sentences in Figure 2. Nouns are represented by nodes. The relations between nouns are represented by links whose directions depend on the features of the verb being used in the linguistic model editor (kind and direction of influence). For relations describing undirected relations (like "corresponds to"), a dialogue is evoked: The user is asked to specify the direction, or to specify another variable as the common cause or effect of the variables in question.

After the initial formulation of the model, it has to be analysed and, if necessary, revised on a qualitative level. In particular, it has to be verified that the dependencies and independencies implied by the graph correspond to the knowledge of the modeller. This knowledge has to be acquired by the system in a way that is both comfortable to the modeller and informative for generating independence assertions. Therefore, MEDICUS has a *diagnostic relevance editor*. For a case, the modeller specifies the initial data known, if any. Next, he specifies a diagnostic hypothesis. Thirdly, he specifies what information he would look for next, that is, what information he considers diagnostically relevant to the hypothesis, given the facts already known. Information considered relevant to the hypothesis by the modeller, given the known data, is dependent of the hypothesis, given these data. Information *not* considered relevant is *in*dependent.

The system now checks whether the graph is consistent with the dependencies and independencies specified by the modeller in this way, using the d-separation criterion (Pearl, 1988). If no differences are found, the *feedback component* informs the modeller. If differences are found, a graph is constructed internally from the dependence and independence assertions (Srinivas et al., 1990). This internal graph is compared to the modeller's graph. This may lead to the result that arcs have to be removed from the graph in order to be consistent with the in-/ dependencies, or that arcs have to be added to the graph, or that c) arcs have to be removed and added as well.

On further request, the modeller may ask the system for modification proposals and an explanation of these proposals. The modification proposals stem from the internal graph. The explanation relates the modification proposal to the corresponding assertion made by the user in the diagnostic relevance editor. That is, the proposal to remove an arc is explained by an independence assertion made by the user (the user did not consider the variables connected by the arc relevant to each other). The proposal to add an arc is explained by a corresponding dependence assertion.

When the qualitative structure of the graph is fixed, the modeller may quantify the net with apriori and conditional probabilities, enter evidences, and let the system generate posterior distributions. Like for example in ERGO and HUGIN, evidence propagation is implemented according to the Lauritzen & Spiegelhalter (1988) algorithm.

As noted, as an alternative to entering numerical probabilities, the system will be able to generate the needed conditional probability distributions from verbal relational terms stated in the linguistic model editor. There is literature about the empirical investigation of the semantics of adverb phrases like "probably", "perhaps", "maybe", etc., and modal verb forms like "should", "will", "may", etc. (Kipper & Jameson, 1994; Teigen & Brun, 1995; Wallsten et al., 1986; Wallsten & Budescu, 1995), but this work is not aimed at *relational* terms, like "A may sometimes lead to B", "There is some degree of correspondence between A and B", and the like. We are currently working on this problem. One possibility is to extend the approaches mentioned by acquiring membership functions for relational terms (Schröder et al., 1996). We also consider a different approach that stays within probability theory. Both approaches require empirical judgements concerning the adequacy of verbal relational phrases as descriptions of probability or frequency distributions.

3. Acquiring Qualitative and Quantitative Knowledge from Dialogues

In this section, we describe some extensions of MEDICUS to dialogue situations that are not yet implemented. We think that natural discussions and dialogues are particularly useful for the acquisition of the qualitative and quantitative knowledge necessary for domain modelling with Bayesian networks for several reasons:

• The information can be acquired in a more natural and non-reactive way. This is especially important for users interested in the domain but not in the underlying mathematics of the tool.

• By encouraging or enabling discussions via electronic mail / Internet, it is possible to utilise information from persons at remote locations.

• Any domain of uncertain knowledge is faced with a problem as soon as a domain model is to be utilised for diagnostic purposes: There may be as many models as experts, especially if objective data are not available. By enabling, analysing, and guiding expert dialogues it might be possible to find out the range of opinions and arguments in the domain of discourse, to settle some of the conflicts (for example, spurious conflicts due to different use of terminology), and to structure the discussion in a way that helps to evaluate the different models so that the selection of a particular model is more grounded.

• Modelling dialogues is also a prerequisite for supporting tutorial dialogues. Modelling a dialogue between a tutor and a learner, or between learners, may lead to hypotheses about the learners' knowledge states and about effects of the tutor's utterances on the knowledge state of the learner(s). This can help the tutor to select utterances so that they will achieve desired knowledge changes.

3.1. Qualitative Knowledge

Figure 3 shows how qualitative information about dependencies and independencies may be obtained from a diagnostic dialogue. The verbal utterances (leftmost column) are translated into dependencies (middle column). For example, since expert 1 considers D relevant for C, given no prior information, D and C are not independent given no prior information: $\neg\ I(\{D\},\{\},\{C\})$. The right column shows a parsimonious graph (Srinivas et al., 1990) encoding these dependencies, where A, B, and F are etiology variables (or "causes"), C and E are possible diseases, and H, D and G are symptom variables. Now expert 2 makes an addition that leads to a slightly different graph. But since expert 1 disagrees on that, there are two competing models. In order to find out the reasons for these different opinions and to help settle the conflict if possible, the discussion should continue. This could be stimulated by generating questions where different answers from the two experts are expected. For example, if we ask the experts whether F is important for H, we would expect expert 1 to say "no", because according to his model, $I(\{F\},\{\},\{H\})$, but we would expect expert 2 to say "yes" because according to his model $\neg I(\{F\},\{\},\{H\})$. Examples of other questions are: "Is F important for C if information about H is available?", "Is G important for C if information about H is available?", and so on. If the experts do not settle on one common model but keep their models, these questions can also help to select a model if needed for diagnostic purposes: One would of course select the model with the least inconsistent answers. This kind of dialogue could be extended to groups of experts, or stimulate discussions and explorations within groups of learners.

3.2. Quantitative Knowledge

When the model is fixed on the qualitative level, a quantitative dialogue can be evoked. Figure 4 shows how the effects of "fuzzy" relational utterances of dialogue partners on the domain model of one dialogue partner can be modelled similarly to Kipper (1995). Initially, the learner has no idea about the probabilities, for example, about $p(H+ \mid C+)$. This is represented by a uniform distribution. Now the dialogue partners make utterances concerning the relation between C and H. Distributions for these utterances ($p(E_i \mid p(H+ \mid C+)=x) = ...$) can be obtained empirically using one of the approaches mentioned at the end of section 2. The hypothetical influences of the utterances on the learner's knowledge can then be modelled by computing the probabilities ($p(p(H+ \mid C+)=x) \mid E_i ,E_j, ...$) and calculating their expected value.

In the same way, it would be possible to model the generation of fuzzy relational statements in an experts' discussion, and the impacts of these statements on the models of the other participants. Finally, the effects of all experts' contributions can be used to create a "common" model that can be used for diagnostic purposes and decisions.

4. Conclusions and Further Work

With respect to education and training purposes, one of our long-term goals is to establish MEDICUS as a modelling and diagnostic reasoning tool within university and further education courses. With respect to professional applications, we plan to apply the system as a diagnostic assistant concerning patients with suspected strains of substances such as mercury, lead, benzene, and so on. In both application fields, a tool for analysing, modelling, and supporting dialogues seems promising. For MEDICUS, the approaches presented will lead to the implementation of agents for modelling the knowledge states of the dialogue partners and for participating in and guiding the discussion in expert-expert, tutor-learner and learner-learner dialogues.

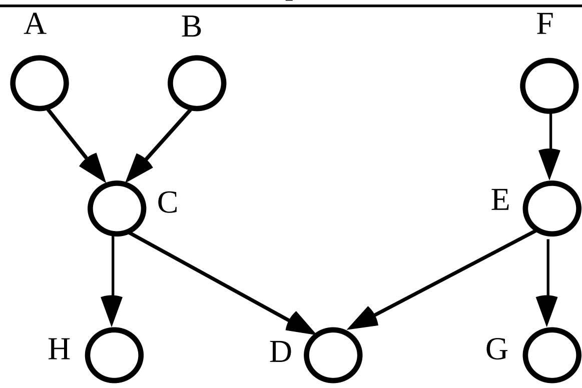
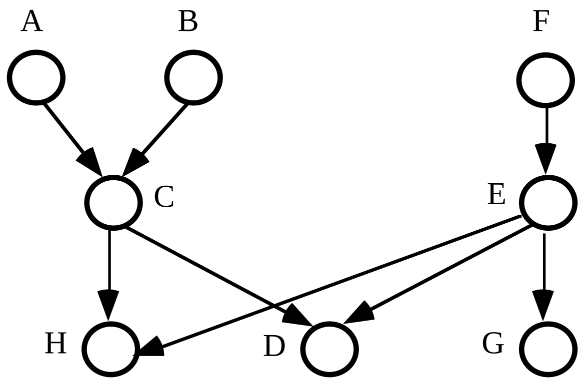
Utterancees	Dependencies	Graphs
Expert 1:		
In order to diagnose C,		
I am looking for symptoms D	¬ I ({D}, {}, {C})	
and H	¬ I ({H}, {}, {C})	
and for possible etiologies A	¬ I ({A}, {}, {C})	
and B.	¬ I ({B}, {}, {C})	
In order to diagnose E,		
I would like to know		
about symptoms D	¬ I ({D}, {}, {E})	
and G.	¬ I ({G}, {}, {E})	
Furthermore, the etiology	¬ I ({F}, {}, {E})	
F is important.		
Expert 2:		
I agree. But in addition		
I think that symptom H	¬ I ({H}, {}, {E})	
is also important for E.		
Expert 1:		
No, I don't think so.		

Figure 3: An example dialogue for the acquisition of qualitative knowledge

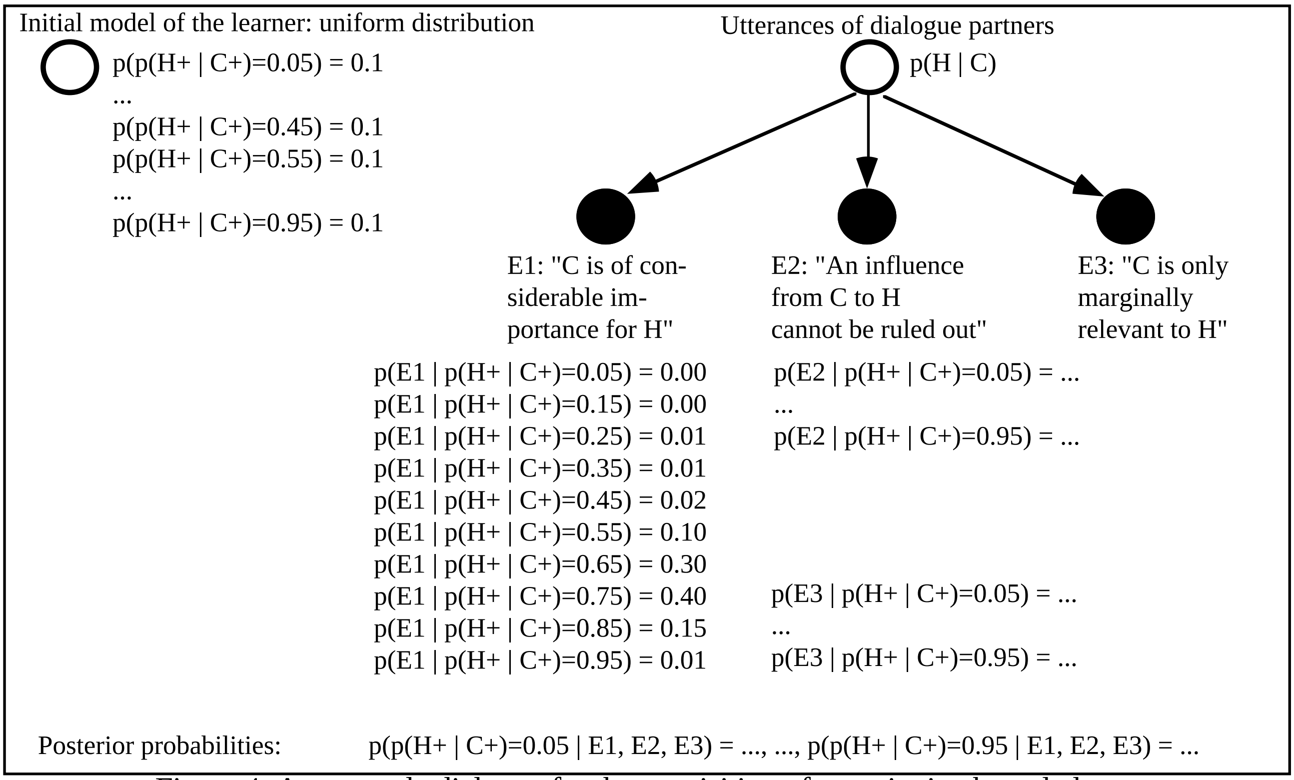


Figure 4: An example dialogue for the acquisition of quantitative knowledge

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