

BAYESIAN NETWORK-BASED QUESTION-ANSWERING APPARATUS, METHOD AND STORAGE MEDIUM

This application claims priority for Chinese Patent Application submitted to the National
5 Intellectual Property Administration, PRC on October 13, 2017, Application No. 201710955002.X,
and titled “Bayesian Network-based Question-answering Apparatus and Method, and Storage
medium”, with all its contents hereby incorporated by reference.

TECHNICAL FIELD

This application relates to the technical field of man-machine interaction, in particular to a
10 Bayesian network-based question-answering apparatus and method, and a computer readable storage
medium.

BACKGROUND

Man-machine interaction is a science studying the interactive relationship between systems and
users, wherein the systems may be various machines or computerized systems and software. By
15 means of man-machine interaction, various artificial intelligence systems can be fulfilled, such as
intelligent customer service systems and voice control systems. As a typical application of
man-machine interaction, intelligent question-answering systems are able to automatically answer
questions put forth by users. However, existing intelligent question-answering systems obtain
answers by retrieving texts or knowledge bases and typically do not possess a deep inference
20 capacity.

SUMMARY

The main objective of this application is to fulfill a deep inference capacity during an intelligent
question-answering process by providing a Bayesian network-based question-answering apparatus
and method, and a computer readable storage medium.

25 In order to fulfill the above objective, this application provides a Bayesian network-based
question-answering apparatus. The Bayesian network-based question-answering apparatus
comprises a memory and a processor, wherein a Bayesian network-based question-answering

program is stored in the memory and is executed by the processor the implement the following steps:

Parameter extraction: receiving and parsing a question input by a user by means of a client, so as to recognize in the question a target parameter representing user intent and an attribute parameter associated with the target parameter;

5 Inference: inputting the target parameter and the attribute parameter into a pre-trained Bayesian network model, and using a directed acyclic graph and a conditional probability table set of the Bayesian network model to infer a value of the target parameter; and

Answer generation: returning the value of the target parameter inferred by the Bayesian network model to the user.

10 In addition, in order to fulfill the above objective, this application further provides a Bayesian network-based question-answering method. The Bayesian network-based question-answering method comprises the following steps:

Parameter extraction: receiving and parsing a question input by a user by means of a client, so as to recognize in the question a target parameter representing user intent and an attribute parameter
15 associated with the target parameter;

Inference: inputting the target parameter and the attribute parameter into a pre-trained Bayesian network model, and using a directed acyclic graph and a conditional probability table set of the Bayesian network model to infer a value of the target parameter; and

20 Answer generation: returning the value of the target parameter inferred by the Bayesian network model to the user.

In addition, in order to fulfill the above objective, this application further provides a computer readable storage medium. A Bayesian network-based question-answering program is stored in the computer readable storage medium and is executed by a processor to implement the steps of the Bayesian network-based question-answering method.

25 Compared with the prior art, the Bayesian network-based question-answering apparatus and method, and the computer readable storage medium provided by this application can perform causal inference of a question input by a user by means of a Bayesian network model and can answer the question put forth by the user on the basis of an inferred result. User demands are appreciated by the

way of a natural dialogue, thus improving user interaction experience.

BRIEF DESCRIPTION OF DRAWINGS

FIG. 1 is a schematic diagram of a preferred embodiment of a Bayesian network-based question-answering apparatus of this application;

5 FIG. 2 is a module diagram of a Bayesian network-based question-answering program in FIG. 1;

FIG. 2a is an undirected acyclic graph of a Bayesian network model;

FIG. 2b is a directed acyclic graph of the Bayesian network model;

FIG. 2c is a schematic diagram of a probability table set of the Bayesian network model;

10 FIG. 3 is a flow diagram of a preferred embodiment of a Bayesian network-based question-answering method of this application;

FIG. 4 is a specific flow diagram of the Bayesian network model involved in the Bayesian network-based question-answering method of this application.

15 The realization of the objectives of this application and the functional characteristics and advantages of this application are further described below with reference to the accompanying drawings.

DESCRIPTION OF EMBODIMENTS

It should be understood that the embodiments in the following description are only used for explaining this application, and are not intended to limit this application.

20 This application provides a Bayesian network-based question-answering apparatus 1. Please refer to FIG. 1 which is a schematic diagram of a preferred embodiment of the Bayesian network-based question-answering apparatus 1 of this application.

In this embodiment, the Bayesian network-based question-answering apparatus 1 is an electronic device with an operation function such as a smartphone, a tablet computer, an e-book reader, or a portable computer.

25 The Bayesian network-based question-answering apparatus 1 comprises memory 11, a processor 12, a display 13, a communication bus 14, and a network interface 15. The apparatus acquires service data from a service database by Internet.

The memory 11 comprises an internal memory and at least one readable storage medium. The

internal memory provides a cache for the operation of a mobile terminal. The readable storage medium is a nonvolatile storage medium such as a flash memory, a hard disk, a multimedia card, or a card memory. In certain embodiments, the readable storage medium is an internal memory unit of the Bayesian network-based question-answering apparatus 1, such as a hard disk of the Bayesian network-based question-answering apparatus 1. In certain other embodiments, the readable storage medium is an external memory device of the Bayesian network-based question-answering apparatus 1, such as a plug-in type hard disk, a smart media card (SMC), a secure digital card (SD), or a flash card on the Bayesian network-based question-answering apparatus 1.

In this embodiment, the readable storage medium of the memory 11 is typically used for storing applications and history service data of the Bayesian network-based question-answering apparatus 1, such as a Bayesian network-based question-answering program 10 and history default data of customers. The memory 11 is also used for temporarily storing output data or to-be-output data.

In certain embodiments, the processor 12 is a central processing unit (CPU), a microprocessor, or other data processing chips, and is used for executing program codes or processing data stored in the memory 11. For example, the processor 12 executes the Bayesian network-based question-answering program 10 to implement any one of the steps of an under-mentioned Bayesian network-based question-answering method.

In certain embodiments, the display 13 is an LED display, a liquid crystal display, a touch liquid crystal display, or an organic light-emitting diode (OLED) touch display. The display 13 is used for displaying a processing result of the Bayesian network-based question-answering apparatus and a visual user interface.

The communication bus 14 is used for realizing a communication connection between these modules.

The network interface 15 is connected to a server to carry out data communication with the server.

Preferably, the Bayesian network-based question-answering apparatus 1 further comprises a user interface, wherein the user interface is a standard wired interface or a standard wireless interface. Optionally, the user interface comprises an input unit such as a keyboard, a voice input device such as

a microphone or other devices with a voice recognition function, and a voice output device such as a loudspeaker or an earphone.

Preferably, when the Bayesian network-based question-answering apparatus 1 is a mobile electronic device such as a mobile phone, the Bayesian network-based question-answering apparatus 1 further comprises at least one sensor such as light sensors, motion sensors, or other sensors. Particularly, the light sensors include an ambient light sensor and a proximity sensor, wherein the ambient light sensor is able to adjust the brightness of the display according to the brightness of ambient light, and the proximity sensor is able to turn off the display and/or backlight when the mobile phone moves close to the ear. As one of the motion sensors, a gravity acceleration sensor is able to detect the accelerations in all directions (namely in the three axis directions), is able to detect the magnitude and direction of the gravity in a static state, and is used for recognizing attitude applications (such as horizontal and vertical screen switching, related games, magnetometer attitude calibration) of the mobile terminal and realizing vibrating recognition of related functions (such as pedometers and knocking). The mobile phone may also be equipped with fingerprint sensor, a pressure sensor, an iris sensor, a molecule sensor, a gyroscope, a barometer, a hygrometer, thermometer, and other sensors such as infrared sensors, and unnecessary details will not be given anymore herein.

The Bayesian network-based question-answering device 1 shown in FIG. 1 is provided with the modules 11-14 and is based on the Bayesian network-based question-answering program 10. However, it should be understood that the Bayesian network-based question-answering device 1 does not definitely comprise all the modules shown in the figure and may alternatively comprise more or less modules.

FIG. 2 is a module diagram of a preferred embodiment of the Bayesian network-based question-answering program 10 in FIG. 1.

In this embodiment, the Bayesian network-based question-answering program 10 is divided into a parameter extraction module 110, an inference module 120, and an answer generation module 130, wherein the parameter extraction module 110, the inference module 120, and the answer generation module 130 are stored in the memory 11 and are executed by one or more processors 12 to complete

this application. The module referred to in this application is a series of computer program instruction segments capable of fulfilling a specific function. Operations and functions to be fulfilled by the parameter extraction module 110, the inference module 120, and the answer generation module 130 are particularly introduced below.

5 The parameter extraction module 110 is used for receiving and parsing a question input by a user by means of a client, so as to recognize in the question a target parameter representing user intent and an attribute parameter associated with the target parameter.

10 As for a given text, the parameter extraction module 110 parses the specific text into a parameter in a standard format, and the parameter extraction module 110 typically comprises a rule template unit 111 and a probability judgment unit 112.

15 The rule template unit 111 is configured mainly by means of a regular expression and a specific syntactic structure, wherein the regular expression is used for extracting parameters, and the specific syntactic structure is used for mapping the extracted parameters into a standard format. The regular expression and the preset syntactic structure are adopted, wherein the regular expression extracts parameters from a character string in a natural language question input by the user and parses the extracted parameters into a preset syntactic structure to be output. The regular expression is a logic formula for operating the character string by means of a regular character string formed by certain pre-defined specific characters and combinations of these specific characters, and the regular character string expresses a filtering logic of the character string. For example, a rule template for
20 “age” is as follows:

 #“age”

 {:dim:age_g

 :integer true

 :value(get {“age”“null”}

25 (:text %1))}

 “<age>”

 [(dim:number)#“age”]

 {:dim:age_g

```

:value (if (<= (:value %1) 25) 0
(if (and (>= (:value %1) 26) (<= (:value %1) 30)) 1
(if (and (>= (:value %1) 31) (<= (:value %1) 35)) 2
(if (and (>= (:value %1) 36) (<= (:value %1) 40)) 3
5 (if (and (>= (:value %1) 41) (<= (:value %1) 45)) 4 5))))))}

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That is, ages of customers are piecewise assigned, wherein the ages under 25 are assigned with 0, the ages from 25 to 30 are assigned with 1, the ages from 31 to 35 are assigned with 2, and the like.

Similarly, educations of the customers are also assigned to be classified, wherein the education from primary school to middle school is assigned with 0, the high-school education is assigned with 1,
10 the undergraduate education is assigned with 2, the postgraduate education is assigned with 3, and the like.

Similarly, incomes of the customers are also assigned, wherein the annual income under 50,000 yuan is assigned with 0, the annual income from 50,000 yuan to 100,000 yuan is assigned with 1, the annual income from 100,000 yuan to 200,000 yuan is assigned with 2, and the annual income over
15 200,000 yuan is assigned with 3.

The probability judgment unit 112 performs training by means of samples and a corresponding classification model to calculate the probability of multiple potential results of a text and to select and parse a result which most represents the user intent. A data structure that most conforms to the user intent is screened out from all data structures of the natural language question by means of a machine
20 learning model. For instance, the machine learning model is a Naive Bayesian classification model which is obtained by performing training on the basis of a large quantity of natural language questions and data structure training corpora. For instance, in the case where the user inputs the question “How much is the monthly mortgage payment if a personal car loan of 100,000 yuan is borrowed from XXXX bank”, the user intent is “interest calculation”, and the rule template unit 111
25 extracts the parameters “XXXX bank”, “personal car loan”, “monthly”, and “100,000 yuan”. The following data structures may be generated:

```

Data structure 1: (!fb:property.context.LoanAmountRange (argmax (number 1) (number 10)
(and (fb:type.loan.loanN fb:loanN.gerengouchedaikuan 1) (fb:type.loan.company

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fb:company.XXXX)) (reverse (lambda x (!fb:rank.entity.rank (var x))))))

Data structure 2: (!fb:property.context.MonthFeeRate (!fb:property.context.LoanAmountRange
fb:company.XXXX))

Data structure 3: fb:company.XXXX

5 Data structure 4: (* (!fb:attribute.attribute.MonthFeeRateD
(!fb:property.context.MonthFeeRate (and (and (fb:type.loan.loanN fb:loanN.gerengouchedaikuan 1)
(fb:type.loan.company fb:company.XXXX)) (fb:property.context.LoanAmountRange
(fb:attribute.attribute.MaxLoanAmountRange (>= (number 100000)))))))(number 100000))

10 After the four data structures are input to the Naive Bayesian classification model, the
probability judgment unit 112 selects the data structure that most represent the user intent from the
four data structures.

15 Furthermore, the parameter extraction module 110 is also used for converting the extracted
target parameter and the attribute parameter into parameters in a standard format. For instance, as for
the question “What is the overdue rate of postgraduates with an annual income of 300,000”, standard
mapping of parameters is as follows: annual income-recent_income-300,000 yuan-3,
education-education-postgraduate-3, and repayment-debt-overdue-1. Then, the question is parsed as
follows:

20 [{:end 13,
 :start 11,
 :value {:value 3},
 :body “postgraduate” ·
 :dim :education}
 [end 18,
 :start 16,
25 :value {:value 1},
 :body “overdue” ·
 :dim:debt}
 {:end 9,

```
:start 0,  
:value { :value 3 },  
:body "annual income 300000" ,  
:dim :recent_income}]
```

5 The inference module 120 is used for inputting the target parameter and the attribute parameter into a pre-trained Bayesian network model and using a directed acyclic graph and a conditional probability table set of the Bayesian network model to infer a value of the target parameter.

Bayesian network-based inference is performed to calculate the probability of values of certain other nodes by means of a structure and a conditional probability table of a Bayesian network, after
10 node attribute values are given. A message passing algorithm is adopted for accurate inference particularly in such a manner: a processor is configured for each node, and each processor performs calculation by means of a probability passed from the adjacent node and a conditional probability stored in the processor to obtain a posteriori probability of its own, and then passes a calculation result to the adjacent node.

15 For instance, in the case of a question "What is the overdue rate of customers with an annual income of 300,000 yuan", customer attributes in the question only include: annual income-recent_income-300,000 yuan-3 and repayment-debt-overdue-1. According to the directed acyclic graph and the conditional probability table, when the annual income of the customers is certain, the probability of overdue repayment of the customers can be inferred according to the
20 educations of the customers, that is, different educations have an influence on the probability of overdue repayment of the customers.

The answer generation module 130 is used for returning the value of the target parameter inferred by the Bayesian network model to the user.

After the user inputs the question into the Bayesian network model, the value of the target
25 parameter is as follows:

```
key:income=3,education=3;debt=1;value:0.01935
```

For the sake of a more visual result, the answer generation module 130 converts the output target parameter in the standard data format into a text and returns the result in the text format to the user as

an answer. The result obtained by conversion of the value of the target parameter is as follows:

The overdue rate of postgraduates with an annual income of 300,000 yuan is 1.935%.

The Bayesian network-based question-answering system is able to appreciate user demands by the way of a natural dialogue and performs deep inference according to a question put forth by a user, thus improving man-machine interaction experience.

In addition, this application further provides a Bayesian network-based question-answering method. Please refer to FIG. 3 which is a flow diagram of a preferred embodiment of the Bayesian network-based question-answering method of this application. The method can be performed by a device which is implemented by software and/or hardware.

In this embodiment, the Bayesian network-based question-answering method comprises:

S10: a question input by a user by means of a client is received and parsed, so as to recognize in the question a target parameter representing user intent and an attribute parameter associated with the target parameter.

A specific given text is parsed into a parameter in a standard format, and a rule template and a probability judgment are typically involved in this step.

The rule template is configured mainly by means of a regular expression and a specific syntactic structure, wherein the regular expression is used for extracting parameters, and the specific syntactic structure is used for mapping the extracted parameters into a standard format. The regular expression and the preset syntactic structure are adopted, wherein the regular expression extracts parameters from a character string in a natural language question input by the user and parses the extracted parameters into a preset syntactic structure to be output. The regular expression is a logic formula for operating the character string by means of a regular character string formed by certain pre-defined specific characters and combinations of these specific characters, and the regular character string expresses a filtering logic of the character string. For example, a rule template for "age" is as follows:

#"age"

{:dim:age_g integer true

:value (get {"age""null"})

(:text %1))}

“<age>”

[(dim :number) #“age”]

{:dim :age_g

:value (if (<= (:value %1) 25) 0

5 (if (and (>= (:value %1) 26) (<= (:value %1) 30)) 1

(if (and (>= (:value %1) 31) (<= (:value %1) 35)) 2

(if (and (>= (:value %1) 36) (<= (:value %1) 40)) 3

(if (and (>= (:value %1) 41) (<= (:value %1) 45)) 4 5))))))}

10 That is, ages of customers are piecewise assigned, wherein the ages under 25 are assigned with 0, the ages from 25 to 30 are assigned with 1, the ages from 31 to 35 are assigned with 2, and the like.

Similarly, educations of the customers are also assigned to be classified, wherein the education from primary school to middle school is assigned with 0, the high-school education is assigned with 1, the undergraduate education is assigned with 2, the postgraduate education is assigned with 3, and the like.

15 Similarly, incomes of the customers are also assigned, wherein the annual income under 50,000 yuan is assigned with 0, the annual income from 50,000 yuan to 100,000 yuan is assigned with 1, the annual income from 100,000 yuan to 200,000 yuan is assigned with 2, and the annual income over 200,000 yuan is assigned with 3.

20 The probability judgment mainly refers to training performed by means of samples and a corresponding classification model to calculate the probability of multiple potential results of a text and to select and parse a result which most represents the user intent. A data structure that most conforms to the user intent is screened out from all data structures of the natural language question by means of a machine learning model. For instance, the machine learning model is a Naive Bayesian classification model which is obtained by performing training on the basis of a large quantity of

25 natural language questions and data structure training corpora. For instance, in the case where the user inputs the question “How much is the monthly mortgage payment if a personal car loan of 100,000 yuan is borrowed from XXXX bank”, the user intent is “interest calculation”, and the rule template unit 111 extracts the parameters “XXXX bank”, “personal car loan”, “monthly”, and

“100,000 yuan”. The following data structures may be generated:

Data structure 1: (!fb:property.context.LoanAmountRange (argmax (number 1) (number 10) (and (fb:type.loan.loanN fb:loanN.gerengouchedaikuan 1) (fb:type.loan.company fb:company.XXXX)) (reverse (lambda x (!fb:rank.entity.rank (var x))))))

5 Data structure 2: (!fb:property.context.MonthFeeRate (!fb:property.context.LoanAmountRange fb:company.XXXX))

Data structure 3: fb:company.XXXX

Data structure 4: (* (!fb:attribute.attribute.MonthFeeRateD (!fb:property.context.MonthFeeRate (and (and (fb:type.loan.loanN fb:loanN.gerengouchedaikuan 1) (fb:type.loan.company fb:company.XXXX)) (fb:property.context.LoanAmountRange (fb:attribute.attribute.MaxLoanAmountRange (>= (number 100000))))))) (number 100000))

10

After the four data structures are input to the Naive Bayesian classification model, the probability judgment unit 112 selects the data structure that most represent the user intent from the four data structures.

15 Furthermore, S10 comprises: the extracted target parameter and the attribute parameter into parameters are converted into in a standard format. For instance, as for the question “What is the overdue rate of postgraduates with an annual income of 300,000”, standard mapping of parameters is as follows: annual income-recent_income-300,000 yuan-3, education-education-postgraduate-3, and repayment-debt-overdue-1. Then, the question is parsed as follows:

20 [{:end 13,
:start 11,
:value {:value 3},
:body “postgraduate” ·
:dim :education}
25 {:end 18,
:start 16,
:value {:value 1},
:body “overdue” ·

```
:dim:debt}  
{:end 9,  
:start 0,  
:value {:value 3},  
5 :body "annual income 300000" ,  
:dim :recent_income}]
```

S20: the target parameter and the attribute parameter are input into a pre-trained Bayesian network model, and a directed acyclic graph and a conditional probability table set of the Bayesian network model are used to infer a value of the target parameter.

10 Bayesian network-based inference is performed to calculate the probability of values of certain other nodes by means of a structure and a conditional probability table of a Bayesian network, after node attribute values are given.

A message passing algorithm is adopted for accurate inference particularly in such a manner: a processor is configured for each node, and each processor performs calculation by means of a probability passed from the adjacent node and a conditional probability stored in the processor to
15 obtain a posteriori probability of its own, and then passes a calculation result to the adjacent node.

For instance, in the case of a question "What is the overdue rate of customers with an annual income of 300,000 yuan", customer attributes in the question only include: annual income-recent_income-300,000 yuan-3 and repayment-debt-overdue-1. According to the directed acyclic graph and
20 the conditional probability table, when the annual income of the customers is certain, the probability of overdue repayment of the customers can be inferred according to the educations of the customers, that is, different educations have an influence on the probability of overdue repayment of the customers.

S30: the value of the target parameter inferred by the Bayesian network model is returned to the
25 user.

After the user inputs the question into the Bayesian network model, the value of the target parameter is as follows:

```
key:income=3,education=3;debt=1;value:0.01935
```

For the sake of a more visual result, the output target parameter in the standard data format is converted into a text, and the result in the text format is returned to the user as an answer. The result obtained by conversion of the value of the target parameter is as follows:

The overdue rate of postgraduate students with an annual income of 300,000 yuan is 1.935%.

5 The Bayesian network-based question-answering method is able to appreciate user demands by the way of a natural dialogue and performs deep inference according to a question put forth by a user, thus improving man-machine interaction experience.

On the basis of the first embodiment of the Bayesian network-based question-answering method, a second embodiment of the Bayesian network-based question-answering method is provided. As
10 shown in FIG. 4, in this embodiment, the Bayesian network model in FIG. 3 is constructed particularly through the following steps:

S01: an attribute associated with a default customer is extracted from each piece of history default data of history service data, and conditional mutual information among all the attributes is calculated;

15 S02: the conditional mutual information of the attributes is sorted in a descending order, attribute pairs with high conditional mutual information values are selected to serve as nodes, a maximum weight span tree is constructed under the principle of no loop generation until n nodes are obtained, and (n-1) edges are selected to form an undirected acyclic graph;

S03: a root node of each node in the undirected acyclic graph is determined, and the undirected
20 acyclic graph is converted into the directed acyclic graph with the direction from the root nodes to child nodes as a direction between the nodes; and

S04: a conditional probability of a random variable represented by each node in the directed acyclic graph is calculated according to the history service data to obtain the conditional probability table set of the Bayesian network model.

25 For the purpose of determining a topological relation between the random variables to form the directed acyclic graph (DAG), a Bayesian network is constructed in such a manner: nodes of the Bayesian network are determined first, and then the structure of the Bayesian network is learnt by means of a large quantity of training data. A tree augmented Naive Bays (TAN) algorithm is used for

structure learning.

Training of the Bayesian network, namely parameter learning, is performed mainly for the purpose of determining the conditional probability table, namely the conditional dependency among the random variables. Parameter learning mainly includes parameter learning of complete data and parameter learning of incomplete data, wherein complete data means that each example have complete observation data, namely both education data and income data; and incomplete data means that certain examples have data missing or observation anomalies, for instance, certain people have education data, and other people do not have education data while having income data. Generally, the data in these cases are incomplete. A maximum likelihood estimation method is adopted for parameter learning of the complete observation data, and an expectation-maximization (EM) algorithm is adopted for parameter learning of the incomplete data.

The conditional probability of the random variable represented by each node in the DAG is calculated according to the history service data to obtain the conditional probability table set of the Bayesian network model.

In this embodiment, the Bayesian network comprises a DAG and a probability table set, as shown in FIG. 2c and FIG. 2d.

In FIG. 2c, three nodes in the DAG represent three random variables, and a directed edge represent the conditional dependency among the random variables.

In other embodiments, the random variable represented by each node is a directly-observed variable or a hidden variable, wherein the hidden variable is a variable that cannot be directly and accurately observed and can be evaluated through other methods such as the level of intelligence.

In FIG. 2d, each element in the conditional probability table corresponds to one node in the DAG, and the joint conditional probability of each node with respect to all pre-drive nodes of this node is stored:

$$P\left(O = T/E = 0, I = 0\right) = \frac{P(O = T, E = 0, I = 0)}{P(O = T)}$$

Wherein, E refers to the education of the default customer, I refers to the annual income, P refers to the probability, T refers to overdue repayment, and F refers to normal repayment.

For example, attributes associated with the default customer, such as the age, education, annual income, gender, nationality, work experience, asset (having a car or a house or not), having insurance or not, and marital status, are extracted from the history default data of a financial service institution, and the conditional mutual information among different attributes is calculated.

5 A class variable attribute is added to TAN, the association between the attributes needs to be recalculated under the condition where a classification attribute is determined, different class attribute values reflect different attribute associations, and the calculation formula is as follows:

$$I(X, Y|C) = \sum_{c \in C} P(c) \sum_{y \in Y} \sum_{x \in X} P(x, y|c) \log \left(\frac{P(x, y|c)}{P(x|C)P(y|c)} \right)$$

10 Wherein, $P(x, y|c)$ refers to joint distribution of two random variables x and y , $P(x|c)$ and $P(y|c)$ respectively refer to marginal distribution of a random variable X and marginal distribution of a random variable Y , C refers to the class variable, X and Y respectively refer to attribute variables associated with the default customer, and $I(X, Y|C)$ refers to conditional mutual information between the attributes X and Y .

15 If the conditional manual information between the attributes is: a value of the mutual information between the education and the annual income (0.8)>a value of the mutual information between the annual income and the overdue repayment (0.7)>a value of the mutual information between the age and the annual income (0.4)>a value of the mutual information between the gender and the overdue payment (0.2), the attribute pairs with high mutual information values are
20 sequentially selected to serve as nodes.

Furthermore, S02 comprises: a mutual information threshold is preset to serve as a criterion for determining the number of attribute pairs or edges to be reserved. The attributes are selected with the mutual information values from high to low, so that edges with high dependency associations are reserved. Suppose the preset mutual information threshold is 0.5, attribute pairs with the mutual
25 information values greater than 0.5 are selected to serve as nodes, that is, the education, annual income and overdue repayment are used as the nodes to form the undirected acyclic graph shown in FIG. 2a.

The “overdue repayment” node, the “education” node, and the “annual income” node are connected to form the directed acyclic graph show in FIG. 2b.

According to the Bayesian network-based question-answering method of this application, the Bayesian network model is constructed, so that the method is able to appreciate user demands by the way of a natural dialogue and performs deep inference according to a question put forth by a user, thus improving man-machine interaction experience.

In addition, this application further provides a computer readable storage medium, wherein a Bayesian network-based question-answering program is stored in the computer readable storage medium and is executed by a processor to implement the following operations:

Parameter extraction: receiving and parsing a question input by a user by means of a client, so as to recognize in the question a target parameter representing user intent and an attribute parameter associated with the target parameter;

Inference: inputting the target parameter and the attribute parameter into a pre-trained Bayesian network model, and using a directed acyclic graph and a conditional probability table set of the Bayesian network model to infer a value of the target parameter; and

Answer generation: returning the value of the target parameter inferred by the Bayesian network model to the user.

The specific implementation of the computer readable medium of this application is approximately the same as that of the Bayesian network-based question-answering method and thus will not be detailed anymore herein.

It should be noted that in this description, the term “comprise” or “include”, or any other variants thereof is intended to refer to non-exclusive inclusion, and on this basis, a process, method, article or system including a series of elements not only includes these elements listed, but also includes other elements not clearly listed, or includes intrinsic elements of the process, method, article or system. Unless otherwise specifically limited, an element defined by the statement “comprise a/an...” is not exclusive of other identical elements in the process, method, article or system comprising this element.

The serial number of the embodiments of this application is used for the purpose of description

only, and does not indicate the priority of these embodiments. Those skilled in the art would clearly appreciate that the above embodiments of the method can be implemented by means of software and an indispensable universal hardware platform or by means of hardware, and in most cases, the former implementation is preferred. On the basis of such appreciation, the technical solution of the invention
5 or the parts making a contribution to the prior art can be essentially reflected in the form of a computer software product, which is stored in the above-mentioned storage medium (such as ROM/RAM, disk, or CD) and includes a plurality of instructions used for instructing a terminal device (such as a mobile phone, a computer, a server, an air-conditioner, or a network device) to implement the method in the embodiments of this application.

10 The aforesaid embodiments are only preferred ones of this application, and are not intended to limit the patent scope of this application. All equivalent structure or process transformations made on the basis of the contents in the specification and accompanying drawings of this application, or direct or indirect applications to other related technical fields should also fall within the protection scope of this application.

CLAIMS

1. A Bayesian network-based question-answering apparatus, comprising a memory and a processor, wherein a Bayesian network-based question-answering program is stored in the memory and is executed by the processor to implement the following steps:

5 parameter extraction: receiving and parsing a question input by a user by means of a client, so as to recognize in the question a target parameter representing user intent and an attribute parameter associated with the target parameter;

inference: inputting the target parameter and the attribute parameter into a pre-trained Bayesian network model, and using a directed acyclic graph and a conditional probability table set of the Bayesian network model to infer a value of the target parameter; and

10 answer generation: returning the value of the target parameter inferred by the Bayesian network model to the user.

2. The Bayesian network-based question-answering apparatus according to Claim 1, wherein the Bayesian network model is constructed particularly through the following steps:

15 extracting an attribute associated with a default customer from each piece of history default data of history service data, and calculating conditional mutual information among all the attributes;

sorting the conditional mutual information of the attributes in a descending order, selecting attribute pairs with high conditional mutual information values to serve as nodes, constructing a maximum weight span tree under the principle of no loop generation until n nodes are obtained, and

20 selecting (n-1) edges to form an undirected acyclic graph;

determining a root node of each node in the undirected acyclic graph, and converting the undirected acyclic graph into the directed acyclic graph with a direction from the root nodes to child nodes as a direction between the nodes; and

calculating a conditional probability of a random variable represented by each node in the directed acyclic graph according to the history service data to obtain the conditional probability table set of the Bayesian network model.

3. The Bayesian network-based question-answering apparatus according to Claim 2, wherein

the conditional mutual information between the attributes is calculated according to the following formula:

$$I(X, Y|C) = \sum_{c \in C} P(c) \sum_{y \in Y} \sum_{x \in X} P(x, y|c) \log \left(\frac{P(x, y|c)}{P(x|C)P(y|c)} \right)$$

wherein, $P(x, y|c)$ refers to joint distribution of two random variables x and y , $P(x|c)$ and $P(y|c)$ respectively refer to marginal distribution of a random variable X and marginal distribution of a random variable Y , C refers to a class variable, X and Y respectively refer to attribute variables associated with the default customer, and $I(X, Y|C)$ refers to the conditional mutual information between the attributes X and Y .

4. The Bayesian network-based question-answering apparatus according to Claim 1, wherein the step of parameter extraction comprises:

converting the extracted target parameter and attribute parameter into parameters in a standard format.

5. The Bayesian network-based question-answering apparatus according to Claim 2, wherein the step of parameter extraction comprises:

converting the extracted target parameter and attribute parameter into parameters in a standard format.

6. The Bayesian network-based question-answering apparatus according to Claim 3, wherein the step of parameter extraction comprises:

converting the extracted target parameter and attribute parameter into parameters in a standard format.

7. The Bayesian network-based question-answering apparatus according to any one of Claims 1-6, wherein the step of answer generation comprises:

converting the value of the target parameter inferred by the Bayesian network model into a text, and returning a result in a text format to the user as an answer.

8. A Bayesian network-based question-answering method, comprising the following steps:
parameter extraction: receiving and parsing a question input by a user by means of a client, so as to recognize in the question a target parameter representing user intent and an attribute parameter

associated with the target parameter;

inference: inputting the target parameter and the attribute parameter into a pre-trained Bayesian network model, and using a directed acyclic graph and a conditional probability table set of the Bayesian network model to infer a value of the target parameter; and

5 answer generation: returning the value of the target parameter inferred by the Bayesian network model to the user.

9. The Bayesian network-based question-answering method, wherein the Bayesian network model is constructed particularly through the following steps:

10 extracting an attribute associated with a default customer from each piece of history default data of history service data, and calculating conditional mutual information among all the attributes;

 sorting the conditional mutual information of the attributes in a descending order, selecting attribute pairs with high conditional mutual information values to serve as nodes, constructing a maximum weight span tree under the principle of no loop generation until n nodes are obtained, and selecting (n-1) edges to form an undirected acyclic graph;

15 determining a root node of each node in the undirected acyclic graph, and converting the undirected acyclic graph into the directed acyclic graph with a direction from the root nodes to child nodes as a direction between the nodes; and

20 calculating a conditional probability of a random variable represented by each node in the directed acyclic graph according to the history service data to obtain the conditional probability table set of the Bayesian network model.

10. The Bayesian network-based question-answering method according to Claim 9, wherein the conditional mutual information between the attributes is calculated according to the following formula:

$$I(X, Y|C) = \sum_{c \in C} P(c) \sum_{y \in Y} \sum_{x \in X} P(x, y|c) \log \left(\frac{P(x, y|c)}{P(x|C)P(y|c)} \right)$$

25 wherein, P(x, y|c) refers to joint distribution of two random variables x and y, P(x|c) and P(y|c) respectively refer to marginal distribution of a random variable X and marginal distribution of a random variable Y, C refers to a class variable, X and Y respectively refer to attribute variables

associated with the default customer, and $I(X, Y|C)$ refers to the conditional mutual information between the attributes X and Y .

11. The Bayesian network-based question-answering method according to Claim 8, wherein the step of parameter extraction comprises:

5 converting the extracted target parameter and attribute parameter into parameters in a standard format.

12. The Bayesian network-based question-answering method according to Claim 9, wherein the step of parameter extraction comprises:

10 converting the extracted target parameter and attribute parameter into parameters in a standard format.

13. The Bayesian network-based question-answering method according to Claim 10, wherein the step of parameter extraction comprises:

 converting the extracted target parameter and attribute parameter into parameters in a standard format.

15 14. The Bayesian network-based question-answering method according to any one of Claims 8-13, wherein the step of answer generation comprises:

 converting the value of the target parameter inferred by the Bayesian network model into a text, and returning a result in a text format to the user as an answer.

20 15. A computer readable storage medium, having a Bayesian network-based question-answering program stored therein, wherein the Bayesian network-based question-answering program is executed by a processor to implement the following steps:

 parameter extraction: receiving and parsing a question input by a user by means of a client, so as to recognize in the question a target parameter representing user intent and an attribute parameter associated with the target parameter;

25 inference: inputting the target parameter and the attribute parameter into a pre-trained Bayesian network model, and using a directed acyclic graph and a conditional probability table set of the Bayesian network model to infer a value of the target parameter; and

 answer generation: returning the value of the target parameter inferred by the Bayesian network

model to the user.

16. The computer readable storage medium according to Claim 15, wherein the Bayesian network model is constructed particularly through the following steps:

extracting an attribute associated with a default customer from each piece of history default data
5 of history service data, and calculating conditional mutual information among all the attributes;

sorting the conditional mutual information of the attributes in a descending order, selecting
attribute pairs with high conditional mutual information values to serve as nodes, constructing a
maximum weight span tree under the principle of no loop generation until n nodes are obtained, and
selecting (n-1) edges to form an undirected acyclic graph;

10 determining a root node of each node in the undirected acyclic graph, and converting the
undirected acyclic graph into the directed acyclic graph with a direction from the root nodes to child
nodes as a direction between the nodes; and

calculating a conditional probability of a random variable represented by each node in the
directed acyclic graph according to the history service data to obtain the conditional probability table
15 set of the Bayesian network model.

17. The computer readable storage medium according to Claim 16, wherein the conditional
mutual information between the attributes is calculated according to the following formula:

$$I(X, Y|C) = \sum_{c \in C} P(c) \sum_{y \in Y} \sum_{x \in X} P(x, y|c) \log \left(\frac{P(x, y|c)}{P(x|C)P(y|c)} \right)$$

wherein, $P(x, y|c)$ refers to joint distribution of two random variables x and y, $P(x|c)$ and $P(y|c)$
20 respectively refer to marginal distribution of a random variable X and marginal distribution of a
random variable Y, C refers to a class variable, X and Y respectively refer to attribute variables
associated with the default customer, and $I(X, Y|C)$ refers to the conditional mutual information
between the attributes X and Y.

18. The computer readable storage medium according to Claim 15, wherein the step of
25 parameter extraction comprises:

converting the extracted target parameter and attribute parameter into parameters in a standard
format.

19. The computer readable storage medium according to Claim 16 or 17, wherein the step of parameter extraction comprises:

converting the extracted target parameter and attribute parameter into parameters in a standard format.

5 20. The computer readable storage medium according to Claim 19, wherein the step of answer generation comprises:

converting the value of the target parameter inferred by the Bayesian network model into a text, and returning a result in a text format to the user as an answer.