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(54) **IMPUTATION OF AUTOMATED AGENT DECISION LOGIC**

(71) Applicant: **Scaled Cognition, Inc.**, Amesbury, MA (US)

(72) Inventors: **Dan Klein**, Berkeley, CA (US); **Mathew Gardner**, Irvine, CA (US); **Emmanouil Antonios Platanios**, Fremont, CA (US); **Mitchell Stern**, Berkeley, CA (US); **Adam Pauls**, Berkeley, CA (US)

(73) Assignee: **Scaled Cognition, Inc.**, Amesbury, MA (US)

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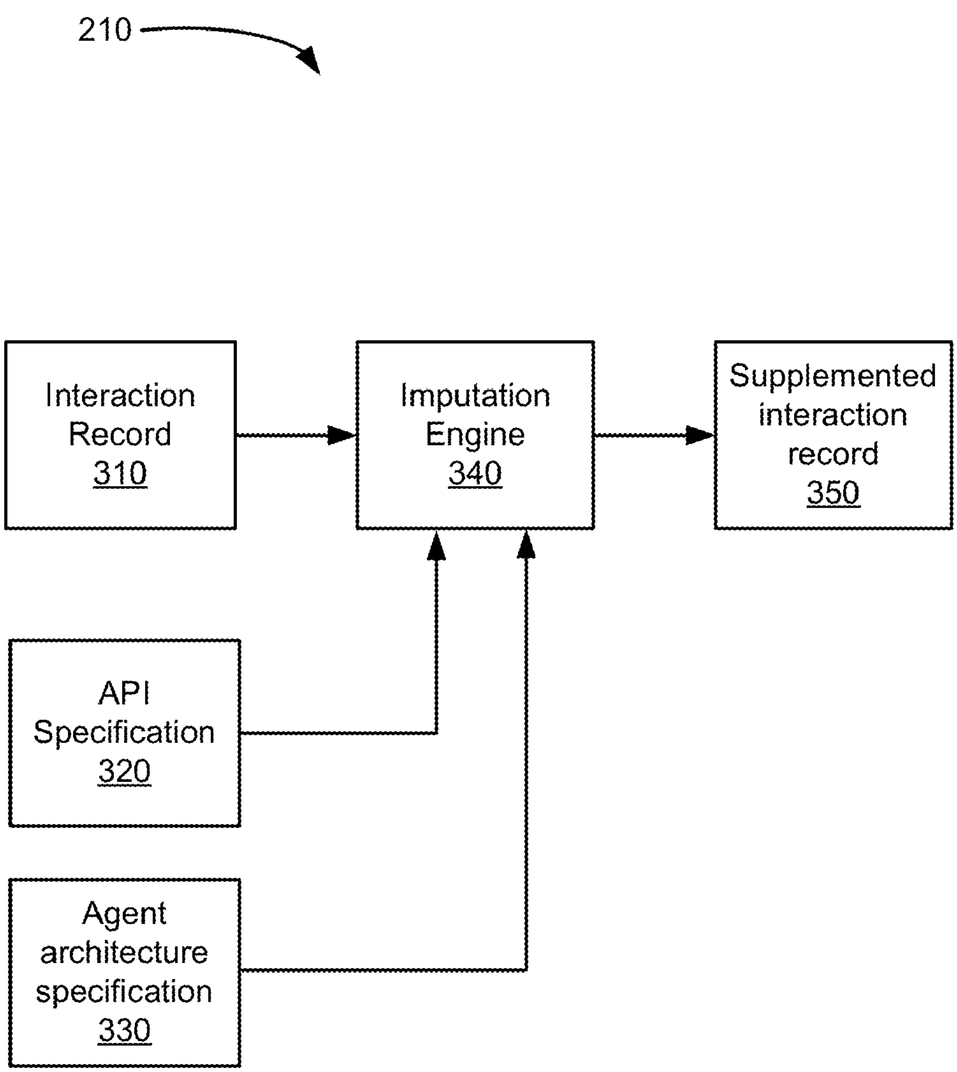
CPC *G06F 9/541* (2013.01)

(57) **ABSTRACT**

A system automatically imputes automated agent decision logic. An interaction record is used with other data to determine an optimal and efficient logical path from a starting point in an interaction record to the end of the interaction record between an automated agent and a client. The logical path can be determined using a process that works backward, from the end point to the starting point, to determine the optimal path. Once complete, the resulting interaction record is supplemented with additional information regarding what states and/or steps were taken in the agent architecture specification to navigate through the interaction record.



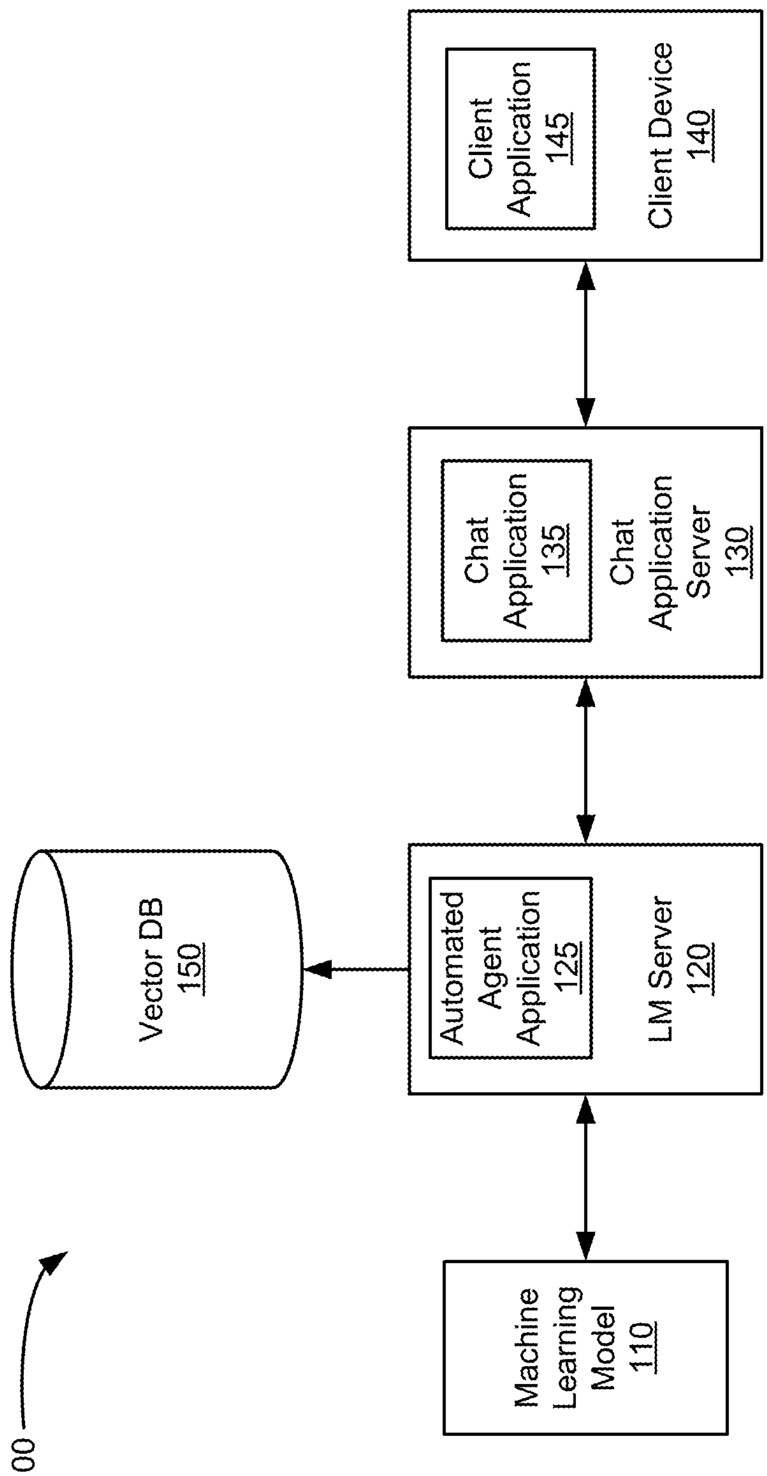

100
Machine Learning Model 110
Vector DB 150
Automated Agent Application 125
LM Server 120
Chat Application 135
Chat Application Server 130
Client Application 145
Client Device 140

FIGURE 1

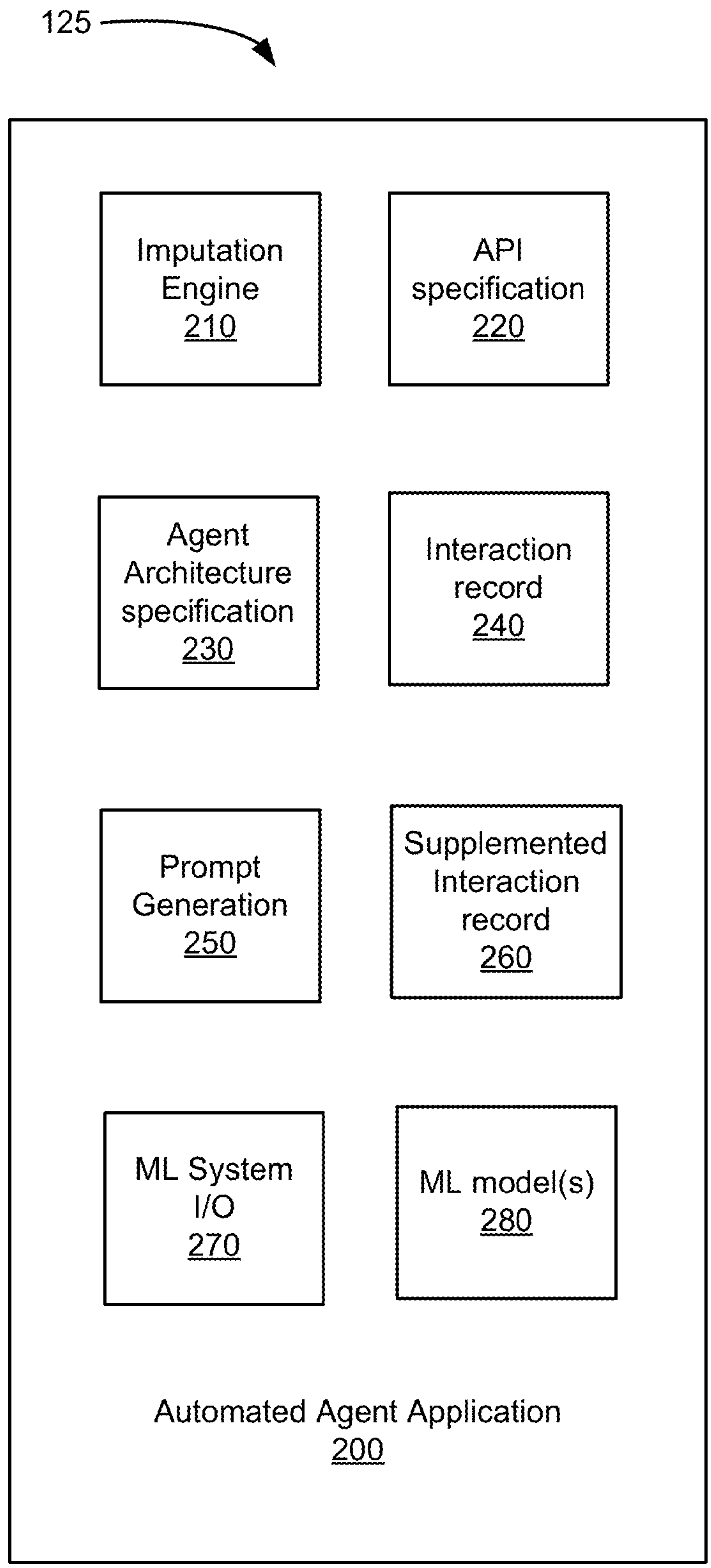

125
Imputation Engine 210
API specification 220
Agent Architecture specification 230
Interaction record 240
Prompt Generation 250
Supplemented Interaction record 260
ML System I/O 270
ML model(s) 280
Automated Agent Application 200

FIGURE 2

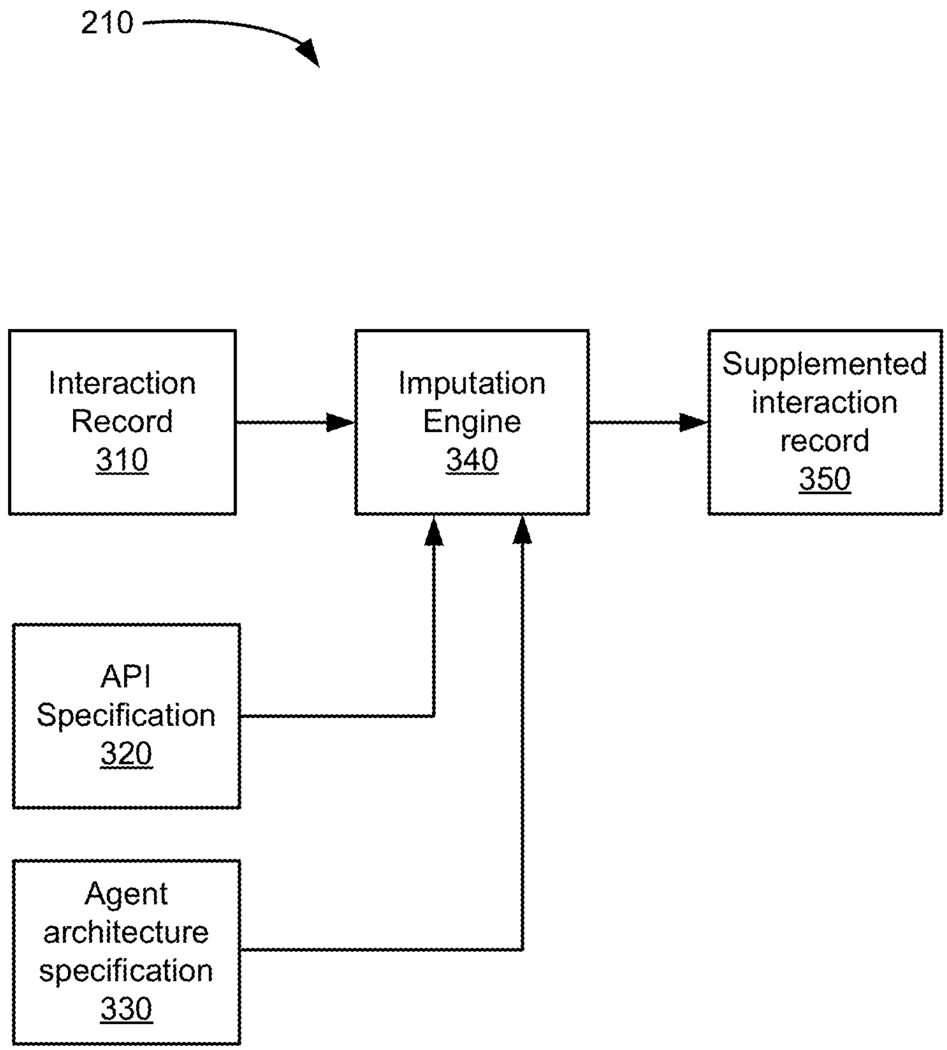

210
Interaction Record 310
Imputation Engine 340
Supplemented interaction record 350
API Specification 320
Agent architecture specification 330

FIGURE 3

310

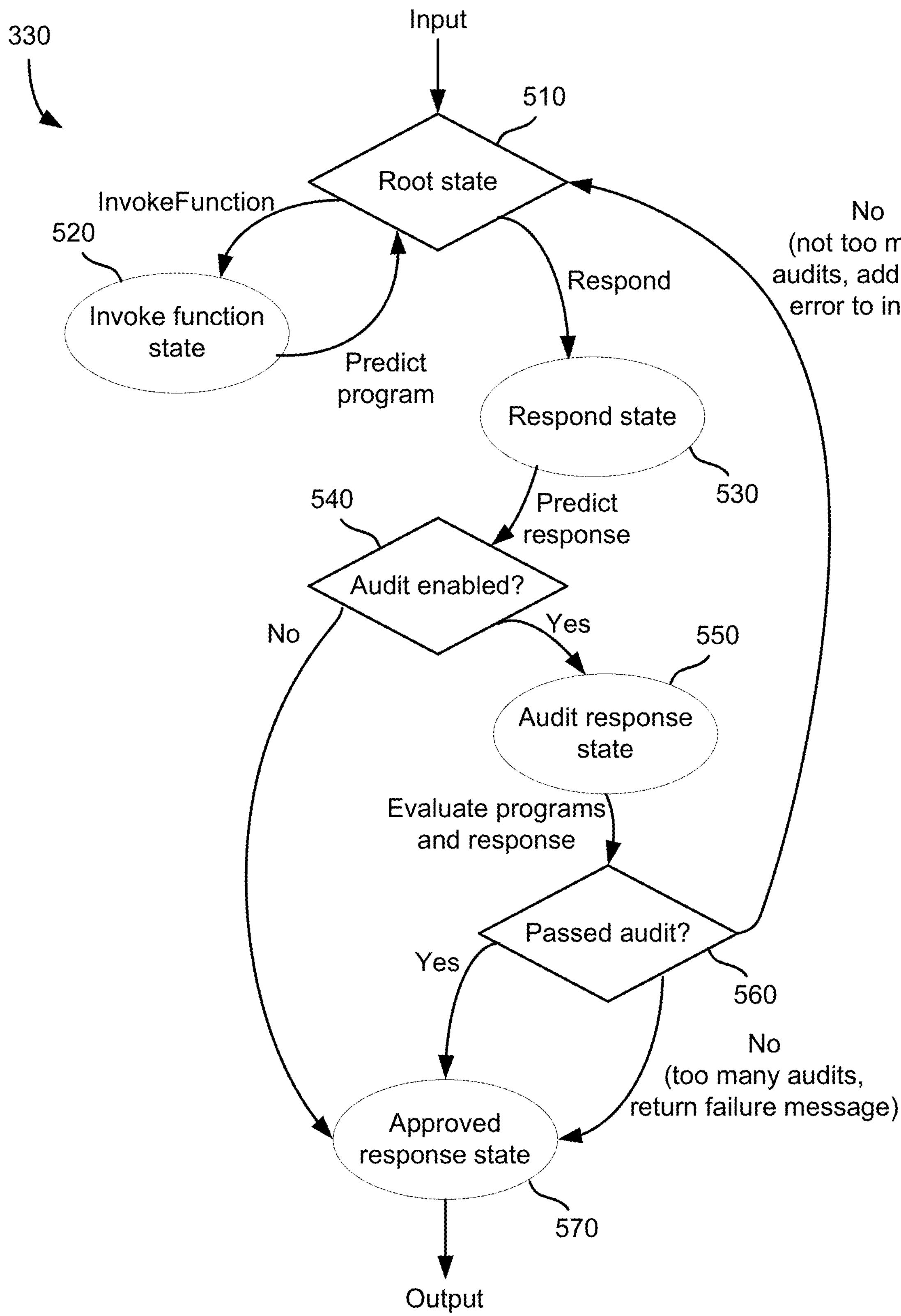
410 CLIENT: Hi, I would like to schedule an appointment.

420 AGENT: I can help you with that. First, I need your name and account number.

430 CLIENT: Sure. I'm Jane Doe, and my account is 11234. I'd like an appointment at 2:00pm on Friday.

440 AGENT: Okay, I've scheduled your appointment for 3:00pm on Friday, November 23.
[invoked program: schedule_appt(11234, "2023-11-24T15:00")]

FIGURE 4



330
Input
510
Root state
InvokeFunction
520
Invoke function state
Predict program
Respond
No (not too many audits, add audit error to input)
Respond state
530
540
Predict response
Audit enabled?
No
Yes
550
Audit response state
Evaluate programs and response
Passed audit?
Yes
560
No (too many audits, return failure message)
Approved response state
570
Output

FIGURE 5

600

[PREDICTED RESPONSE: “Okay, I’ve scheduled your appointment for 3:00pm on Friday, November 23.”’]
[PassedAudit?]
[AGENT:Yes]

440 AGENT: Okay, I’ve scheduled your appointment for 3:00pm on Friday, November 23.
[invoked program: schedule_appt(11234, “2023-11-24T15:00”)]

FIGURE 6

700

[Respond or InvokeFunction?}
[AGENT: Respond]
[PREDICTED RESPONSE: "Okay, I've scheduled your appointment for 3:00pm on Friday, November 23."']
[PassedAudit?]
[AGENT:Yes]

AGENT: Okay, I've scheduled your appointment for 3:00pm on Friday, November 23.
[invoked program: schedule_appt(11234, "2023-11-24T15:00")]

FIGURE 7

800

[Respond or InvokeFunction?]
[AGENT: InvokeFunction]
[PROGRAM: schedule_appt911234, 2023-11-24T15:00")]
[Respond or InvokeFunction?}
[AGENT: Respond]
[PREDICTED RESPONSE: "Okay, I've scheduled your appointment for 3:00pm on Friday, November 23."']
[PassedAudit?]
[AGENT:Yes]

AGENT: Okay, I've scheduled your appointment for 3:00pm on Friday, November 23.
[invoked program: schedule_appt(11234, "2023-11-24T15:00")]

FIGURE 8

900

420 AGENT: I can help you with that. First, I need your name and account number

430 CLIENT: Sure. I'm Jane Doe, and my account is 11234. I'd like an appointment at 2:00pm on Friday.

[Respond or InvokeFunction?]
[AGENT: InvokeFunction]
[PROGRAM: schedule_appt911234, 2023-11-24T15:00")]
[Respond or InvokeFunction?}
[AGENT: Respond]
[PREDICTED RESPONSE: "Okay, I've scheduled your appointment for 3:00pm on Friday, November 23."']
[PassedAudit?]
[AGENT:Yes]

AGENT: Okay, I've scheduled your appointment for 3:00pm on Friday, November 23.
[invoked program: schedule_appt(11234, "2023-11-24T15:00")]

FIGURE 9

1000

[PREDICTED RESPONSE: "I can help you with that. First, I need your name and account number."]
[PassedAudit?]
[AGENT:Yes]

AGENT: I can help you with that. First, I need your name and account number

CLIENT: Sure. I'm Jane Doe, and my account is 11234. I'd like an appointment at 2:00pm on Friday.

[Respond or InvokeFunction?]
[AGENT: InvokeFunction]
[PROGRAM: schedule_appt911234, 2023-11-24T15:00")]
[Respond or InvokeFunction?}
[AGENT: Respond]
[PREDICTED RESPONSE: "Okay, I've scheduled your appointment for 3:00pm on Friday, November 23."']
[PassedAudit?]
[AGENT:Yes]

AGENT: Okay, I've scheduled your appointment for 3:00pm on Friday, November 23.
[invoked program: schedule_appt(11234, "2023-11-24T15:00")]

FIGURE 10

1100

410

CLIENT: Hi, I would like to schedule an appointment.

[Respond or InvovkeFunction?]
[AGENT:Respond[
[PREDICTED RESPONSE: “I can help you with that. First, I need your name and account number.”]
[PassedAudit?]
[AGENT:Yes]

AGENT: I can help you with that. First, I need your name and account number

CLIENT: Sure. I’m Jane Doe, and my account is 11234. I’d like an appointment at 2:00pm on Friday.

[Respond or InvokeFunction?]
[AGENT: InvokeFunction]
[PROGRAM: schedule_appt911234, 2023-11-24T15:00")]
[Respond or InvokeFunction?}
[AGENT: Respond]
[PREDICTED RESPONSE: “Okay, I’ve scheduled your appointment for 3:00pm on Friday, November 23.”’]
[PassedAudit?]
[AGENT:Yes]

AGENT: Okay, I’ve scheduled your appointment for 3:00pm on Friday, November 23.
[invoked program: schedule_appt(11234, “2023-11-24T15:00”)]

FIGURE 11

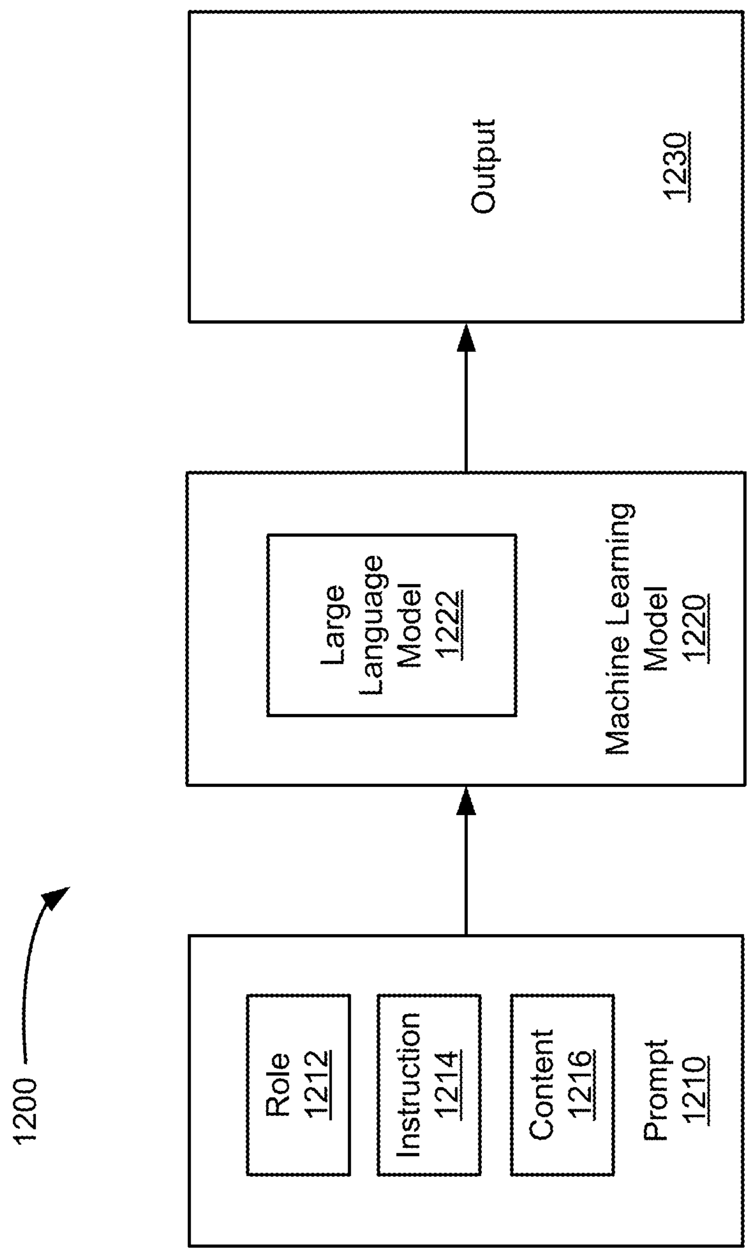

1200
Role
1212
Instruction
1214
Content
1216
Prompt
1210
Large
Language
Model
1222
Machine Learning
Model
1220
Output
1230

FIGURE 12

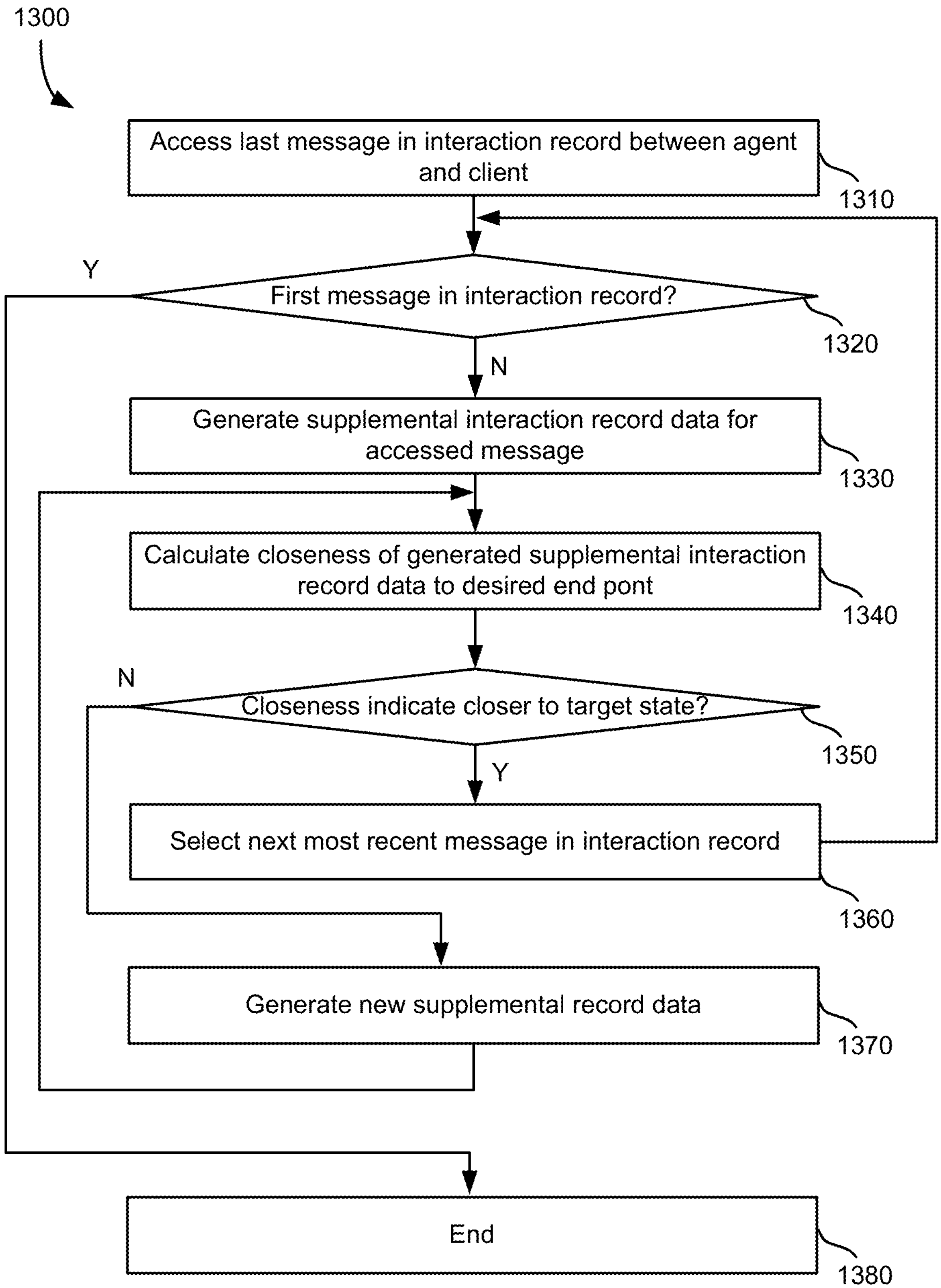

1300
Access last message in interaction record between agent and client
1310
First message in interaction record?
Y
N
1320
Generate supplemental interaction record data for accessed message
1330
Calculate closeness of generated supplemental interaction record data to desired end pont
1340
Closeness indicate closer to target state?
N
Y
1350
Select next most recent message in interaction record
1360
Generate new supplemental record data
1370
End
1380

FIGURE 13

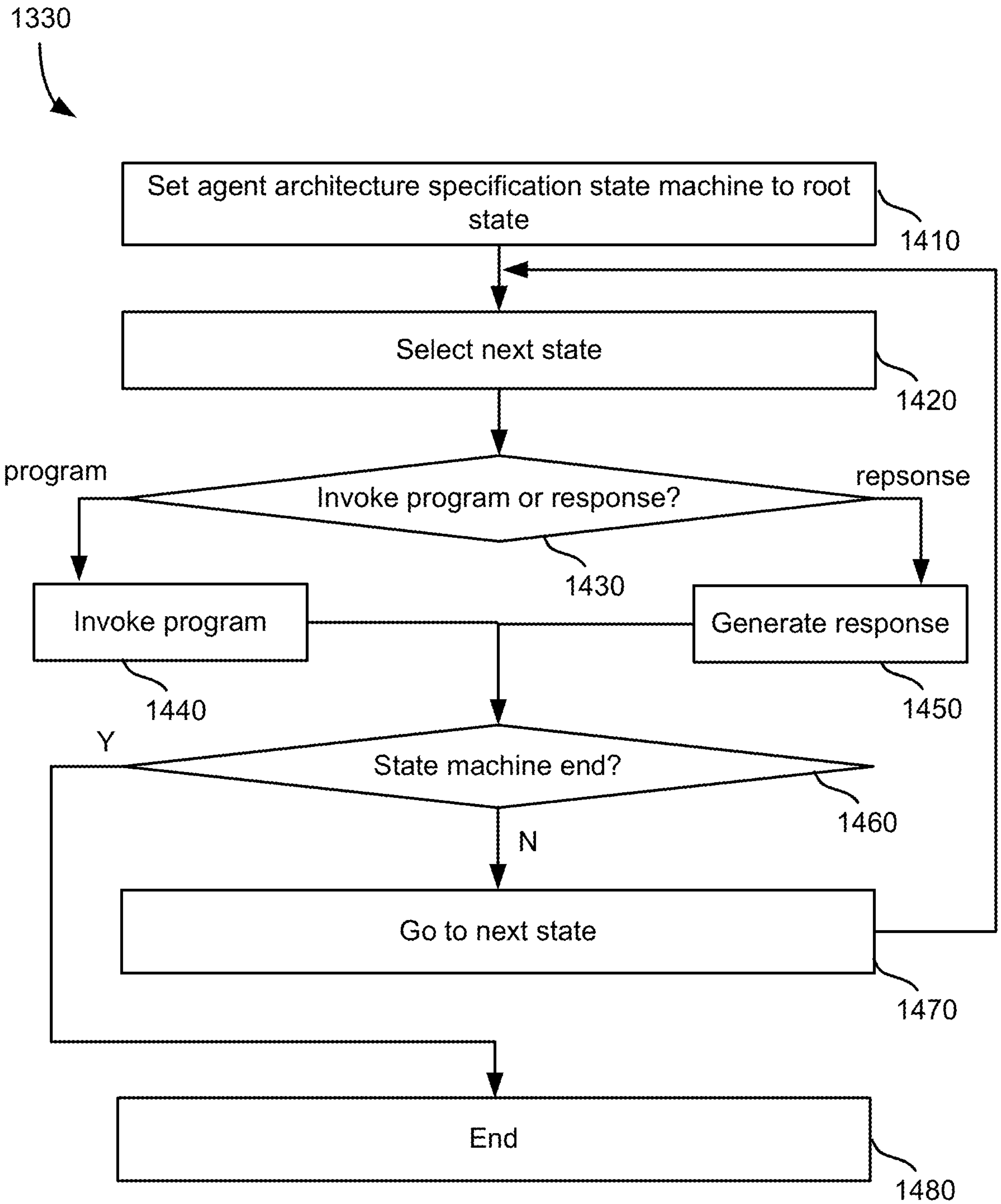

1330
Set agent architecture specification state machine to root state
1410
Select next state
1420
program
Invoke program or response?
repsonse
1430
Invoke program
1440
Generate response
1450
Y
State machine end?
1460
N
Go to next state
1470
End
1480

FIGURE 14

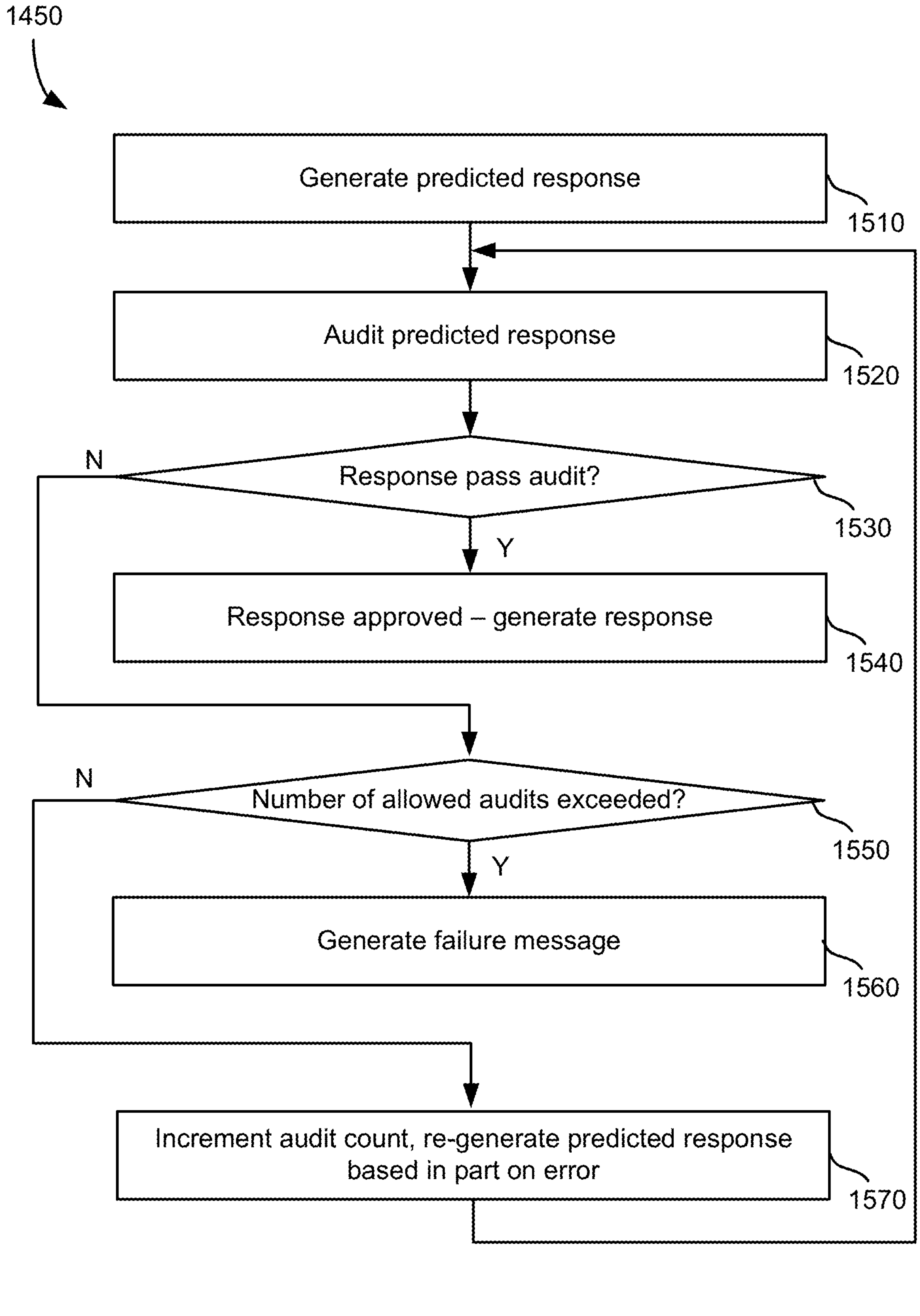

1450
Generate predicted response
1510
Audit predicted response
1520
Response pass audit?
N
Y
1530
Response approved – generate response
1540
Number of allowed audits exceeded?
N
Y
1550
Generate failure message
1560
Increment audit count, re-generate predicted response based in part on error
1570

FIGURE 15

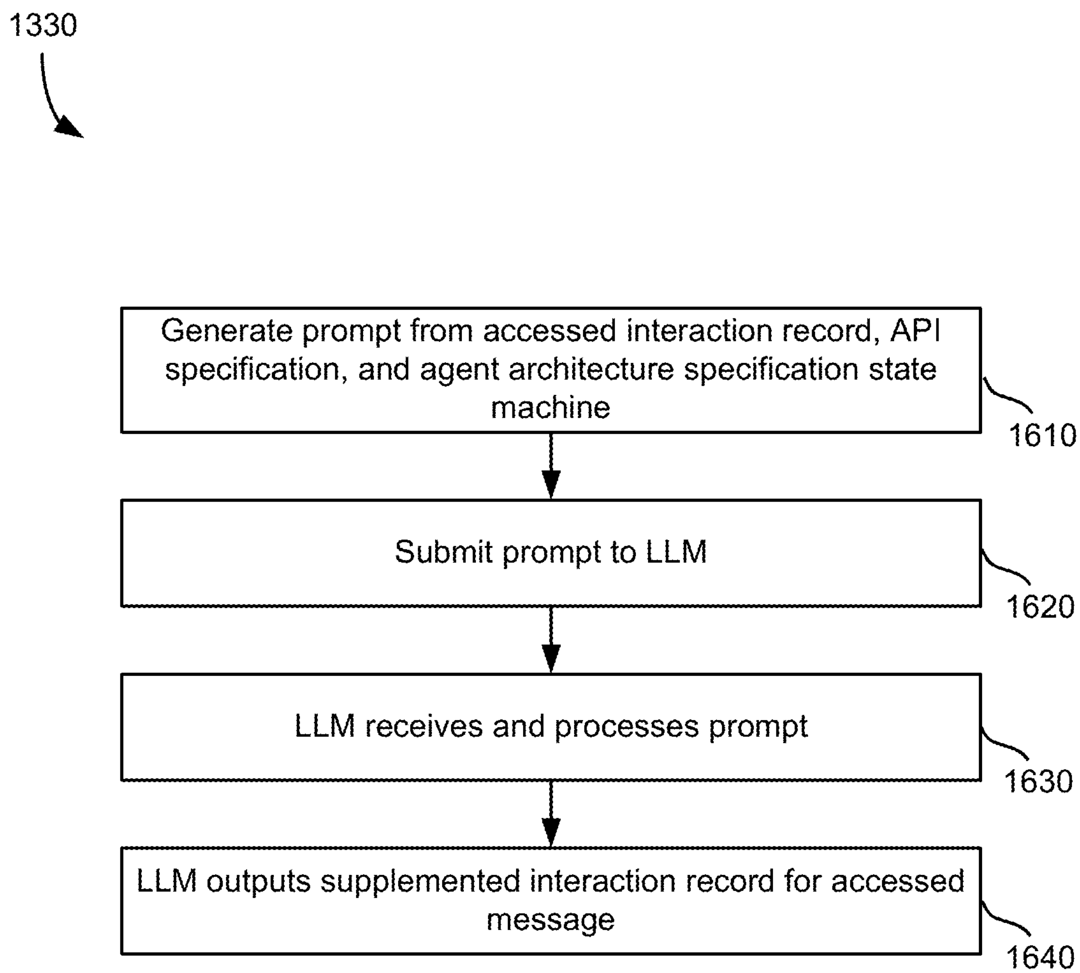

1330
Generate prompt from accessed interaction record, API specification, and agent architecture specification state machine
1610
Submit prompt to LLM
1620
LLM receives and processes prompt
1630
LLM outputs supplemented interaction record for accessed message
1640

FIGURE 16

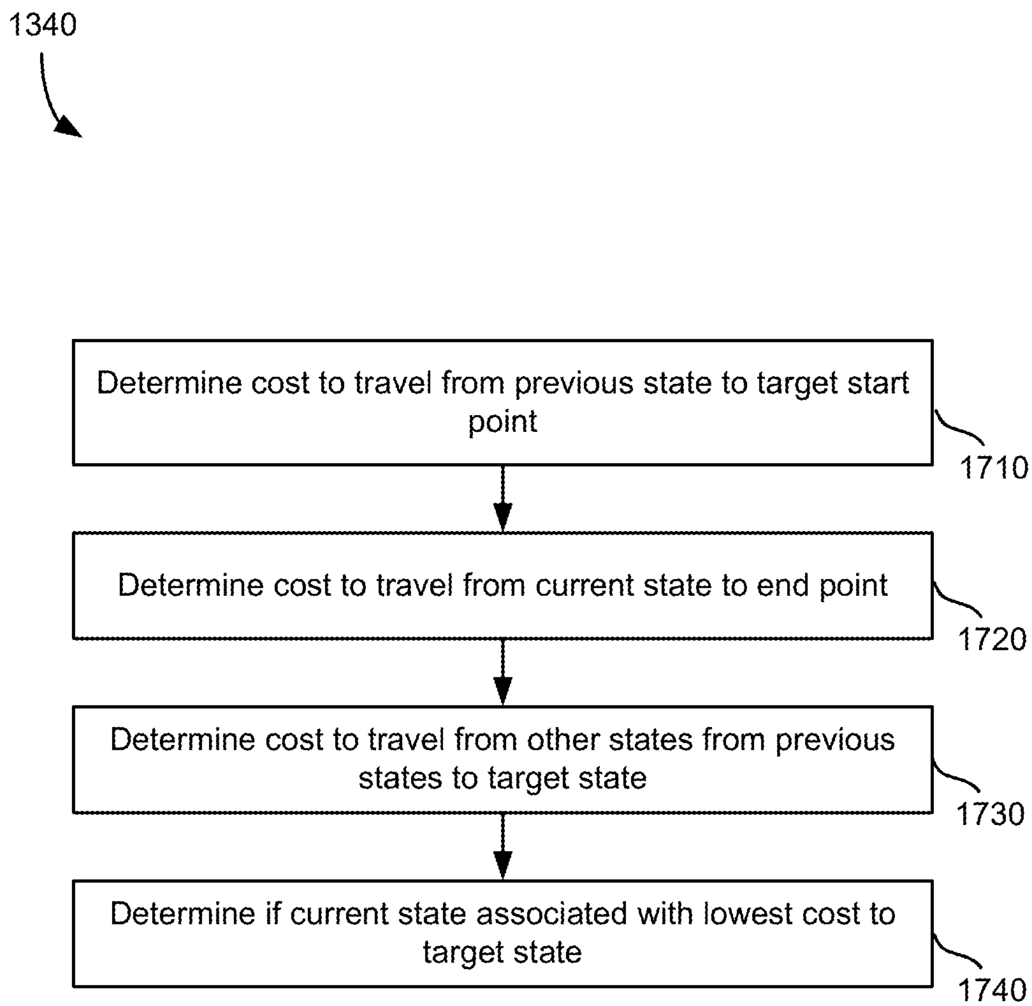

1340
Determine cost to travel from previous state to target start point
1710
Determine cost to travel from current state to end point
1720
Determine cost to travel from other states from previous states to target state
1730
Determine if current state associated with lowest cost to target state
1740

FIGURE 17

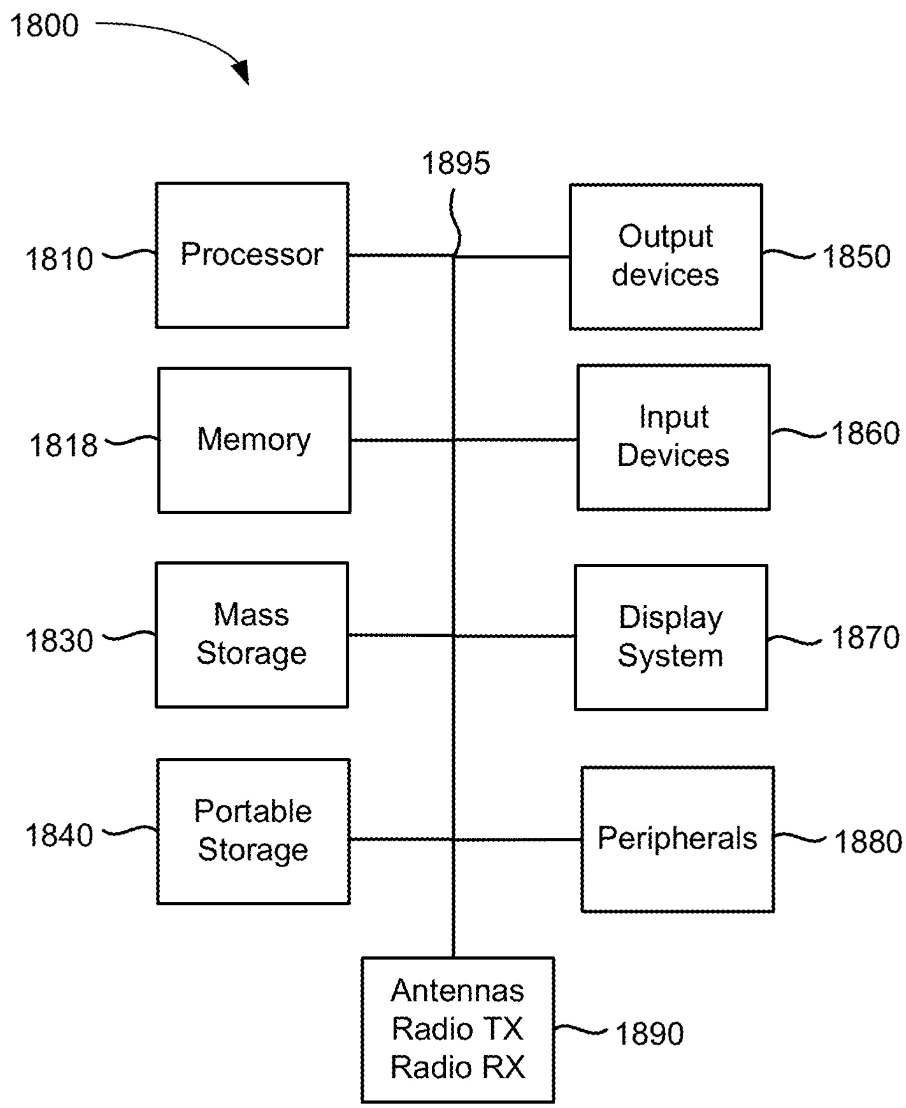

1800
1895
1810
Processor
1818
Memory
1830
Mass Storage
1840
Portable Storage
Output devices
1850
Input Devices
1860
Display System
1870
Peripherals
1880
Antennas
Radio TX
Radio RX
1890

FIGURE 18

IMPUTATION OF AUTOMATED AGENT DECISION LOGIC

CROSS REFERENCE TO RELATED APPLICATIONS

[0001] The present application claims the priority benefit of U.S. provisional patent application 63/551,534, filed on Feb. 9, 2024, titled "Imputation of Automated Agent Decision Logic from Interaction Records," the disclosure of which is incorporated herein by reference.

BACKGROUND

[0002] described, automatically imputes automated agent decision logic. An interaction record is used with other data to determine an optimal and efficient logical path from a starting point in an interaction record to the end of the interaction record between an automated agent and a client. The logical path can be determined using a process that works backward, from the end point to the starting point, to determine the optimal path. Once complete, the resulting interaction record is supplemented with additional information regarding which states and/or steps were taken in the agent architecture specification to navigate through the interaction record.

[0003] The present system accesses an interaction record, an application program interface (API) specification, and an agent architecture specification to supplement an interaction record. The interaction record can include a conversational record of messages exchanged between an automated agent and a client in the past. Hence, the interaction record is associated with an interaction that has already taken place. An API specification is a specification of the programs that can be executed by the automated agent. The agent architecture specification can include logic that the automated agent uses to perform actions as part of the agent functionality. The logic can include a flow chart, state machine, or other decision process through which the optimal path or "golden path" can be imputed.

[0004] In some instances, the present technology performs a method for generating a supplemented interaction record between an automated agent and a client. The method begins with accessing, by an imputation engine on a server, an existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification. The existing interaction record is associated with an interaction between the client and the automated agent that occurred in the past, and includes at least one entry associated with an automated agent. The method continues by determining one or more logical steps performed by an automated agent in determining each entry by the automated agent in the existing interaction record. A supplemented interaction record is generated based on the existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification. The supplemented interaction record includes additional data based on the one or more logical steps performed by the automated agent.

[0005] In some instances, the present technology includes a non-transitory computer readable storage medium having embodied thereon a program, the program being executable by a processor to generate a supplemented interaction record between an automated agent and a client. The method begins with accessing, by an imputation engine on a server, an existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification. The existing interaction record is associated with an interaction between the client and the automated agent that occurred in the past, and includes at least one entry associated with an automated agent. The method continues by determining one or more logical steps performed by an automated agent in determining each entry by the automated agent in the existing interaction record. A supplemented interaction record is generated based on the existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification. The supplemented interaction record includes additional data based on the one or more logical steps performed by the automated agent.

[0006] In some instances, the present technology includes a system having one or more servers, each including memory and a processor. One or more modules are stored in the memory and executed by one or more of the processors to access, by an imputation engine on a server, an existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification, the existing interaction record associated with an interaction between the client and the automated agent that occurred in the past, the existing interaction record including at least one entry associated with an automated agent, determine one or more logical steps performed by an automated agent in determining each entry by the automated agent in the existing interaction record, and generate a supplemented interaction record based on the existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification, the supplemented interaction record including additional data based on the one or more logical steps performed by the automated agent.

BRIEF DESCRIPTION OF FIGURES

[0007] FIG. **1** is a block diagram of a system for imputing automated agent decision logic.

[0008] FIG. **2** is a block diagram of an automated agent application.

[0009] FIG. **3** is a block diagram illustrating the data flow for an imputation engine.

[0010] FIG. **4** illustrates an interaction record between an automated agent and a client.

[0011] FIG. **5** illustrates an agent architecture specification.

[0012] FIGS. **6-11** illustrate supplemented interaction records.

[0013] FIG. **12** is a flow chart illustrating data flow for a large language model.

[0014] FIG. **13** is a method for imputing automated agent decision logic.

[0015] FIG. **14** is a method for generating supplemented interaction record data.

[0016] FIG. **15** is a method for generating a response.

[0017] FIG. **6** is a method for generating supplemented interaction record data using a large language model (LLM).

[0018] FIGS. **17** is a method for calculating closeness of a generated supplemented interaction record data.

[0019] FIG. **18** is a block diagram of a computing environment.

DETAILED DESCRIPTION

[0020] The present technology automatically imputes automated agent decision logic. An interaction record is used with other data to determine an optimal and efficient logical path from a starting point in an interaction record to the end of the interaction record between an automated agent and a client. The logical path can be determined using a process that works backward, from the end point to the starting point, to determine the optimal path. Once complete, the resulting interaction record is supplemented with additional information regarding what states and/or steps were taken in the agent architecture specification to navigate through the interaction record.

[0021] The present system accesses an interaction record, an API specification, and an agent architecture specification to supplement an interaction record. The interaction record can include a conversational record of messages exchanged between an automated agent and a client in the past. Hence, the interaction record is associated with an interaction that has already taken place. An API specification is a specification of the programs that can be executed by the automated agent. The agent architecture specification can include logic that the automated agent uses to perform actions as part of the agent functionality. The logic can include a flow chart, state machine, or other decision process through which the optimal path or "golden path" can be imputed.

[0022] FIG. **1** is a block diagram of a system for imputing automated agent decision logic. System **100** of FIG. **1** includes machine learning model **110**, language model server **120**, chat application server **130**, client device **140**, and vector database **150**. Machine learning model **110** may be implemented locally or remote from language model server **120**. The model **110** may be implemented as one or more machine learning models, large language models, or other learning models.

[0023] Language model server **120** may be implemented as one or more servers or machines over one or more platforms to perform the technology described herein. Language model server **120** may include one or more automated agent application **125**. The automated agent application may generate prompts, communicate with machine learning models, impute interaction records, and perform other functionality as described herein. Automated agent application **125** is discussed in more detail with respect to FIG. **2**.

[0024] Chat application server **130** may host and manage a conversation between an automated agent associated with language model server **120** and a client associated with client device **140**. Server **130** may include a chat application **135**, which can communicate with one or more servers **120** and one or more client devices **140**. Chat application **135** may implement a chat or other electronic interaction, handle communications between servers **120** and device **140**, and perform other functions related to an interaction between an automated agent and a client.

[0025] Client device **140** may include client application **145**. Client device **140** may be used to interact with chat application **135** on behalf of a client which interacts with client application **145**. The client device may be implemented as a mobile device, a computer, work station, a robotic device, and/or another computing device.

[0026] Vector database **150** may communicate with server **120**, server **130**, client device **140**, and machine learning model **110**. In some instances, vector database **150** may store data associated with an interaction record, supplemented interaction record, an API specification, a specification of an agent architecture, machine learning model data, large language model data, including content, requests, and instructions for one or more prompts, and other data for use with the functionality described herein.

[0027] Vector database **150** may be implemented as a data store that stores vector data. In some instances, vector database **135** may be implemented as more than one data store, internal to system **103** and exterior to system **103**. In some instances, a vector database can serve as an LLMs' long-term memory and expand an LLMs' knowledge base. Vector database **135** can store private data or domain-specific information outside the LLM as embeddings. When a user asks a question to an administrative assistant, the system can have the vector database search for the top results most relevant to the received question. Then, the results are combined with the original query to create a prompt that provides a comprehensive context for the LLM to generate more accurate answers. Vector database **150** may include data such as prompt templates, instructions, training data, and other data used by LM application **125** and machine learning model **110**.

[0028] In some instances, the present system may include one or more additional data stores, in place of or in addition to vector database **150**, at which the system stores searchable data such as instructions, private data, domain-specific data, and other data.

[0029] Each of model **110**, servers **120**-**140**, and vector database **150** may communicate over one or more networks. The networks may include one or more the Internet, an intranet, a local area network, a wide area network, a wireless network, Wi-Fi network, cellular network, or any other network over which data may be communicated.

[0030] FIG. **2** is a block diagram of an automated agent application. The block diagram of FIG. **2** provides more detail for application **125** of the system of FIG. **1**. Automated agent application **200** includes imputation engine **210**, API specification **220**, agent architecture specification **230**, interaction record **240** (for an interaction that has taken place previously), prompt generation **250**, supplemented interaction record **260**, machine learning system I/O **270**, and machine learning model(s) **280**.

[0031] Imputation engine **210** determines an optimal or most efficient path using the agent architecture specification from a start point in an interaction record to an end point in the specification record. The imputation engine accesses input of an interaction record **240**, API specification **220**, and agent architecture specification **230**. Based on the accessed input, the imputation engine determines a sequence of steps that form the optimal path between each record end point. The imputation engine **210** creates a supplemented interaction record that includes the interaction record as well as the results of each logical step by the automated agent in creating each response or message in the record by the automated agent. Imputation engine **210** is discussed in more detail with respect to FIG. **3**.

[0032] API specification **220** includes a specification of the programs which are executable by the automated agent. The API specification may include information about the APIs, parameters for executing them, their variables, and other content.

[0033] Agent architecture specification **230** may include logic for processing client requests received through an interaction with a client. In some instances, imputation engine **210** may be implemented as a flowchart, state machine, or other decision process. The Agent architecture specification is used by the imputation engine along with the API specification to determine the most efficient path or "golden path" between an initial entry and a final entry in an interaction record **240** between the automated agent and a client. The most efficient path can be determined from the beginning moving forward or beginning from the last entry in the interaction and moving backwards. Regardless of the direction, each step in the path is determined at least in part using logic contained in the Agent architecture specification.

[0034] Interaction record **240** may include a record of the exchange between an automated agent and a client. The action typically only includes the exchanged messages between the agent and the client, without information about APIs called, programs executed, and other actions taken by the automated agent during an interaction with a client. An example of an interaction record is illustrated in FIG. **4**.

[0035] Supplemented interaction record **260** is generated from an interaction record using an API specification and an agent architecture specification. The supplemented interaction record includes decisions and program results as the automated agent used agent decision logic.

[0036] Prompt generation **250** may generate a prompt for a large language model. The prompt may be generated with request, instructions, and other content. Prompt generation **220** may access the prompt elements, construct the prompt, and provide the prompt to ML system I/O **230** for transmission to a machine learning model.

[0037] Machine learning system I/O **270** may communicate with internal or external machine learning systems. The system may provide input in the form of serial data, streaming data, or a prompt to an external machine learning model, and can receive output from a machine learning model or LLM. The machine learning system I/O module may also communicate with other modules within application **200**.

[0038] Machine learning models **280** may be implemented locally on server **120** or remotely, such as for example as machine learning model **110** in the system of FIG. **1**. Machine learning models **280** may be implemented as a machine learning model, large language model, or other ML system. The machine learning models **240** may be used to predict states within imputation engine **210**, generate supplemented interaction records, and perform other functions.

[0039] Modules illustrated in language model application **200** are exemplary, and could be implemented in additional or fewer modules. Language model application **200** is intended to at least implement functionality described herein. The design of specific modules, objects, programs, and platforms to implement the functionality is not specific and limited by the modules illustrated in FIG. **2**.

[0040] FIG. **3** is a block diagram illustrating the data flow for an imputation engine. An imputation engine **340** can access and/or receive an interaction record **310**, API specification **320**, and an agent architecture specification **330**. The record **310** and specifications **320-330** are used by the imputation engine to generate a supplemented interaction record **350**. The supplemented interaction record may be a statistical model learned from example conversations within the interaction record, and supplemented with information from the API specification and agent architecture specification.

[0041] An example of an interaction record is illustrated in FIG. **4**. The interaction record of FIG. **4** includes 4 entries **410-440** in an interaction between a client and an automated agent. Entries **410** and **430** are initiated by a client and entries **420** and **440** are initiated by an automated agent. The automated agent entries are a response to a previous client entry or message. For each automated agent response, the automated agent progresses through an agent architecture specification, which can be represented as a state machine, flow chart, or other decision process. In response to each client entry or message, the automated agent may determine an action to take, whether it be to predict or generate a response, execute a program, or some other action. A path from the first entry in the interaction record to the last entry in the interaction record is determined based on the agent architecture specification applied in response to each client entry.

[0042] In the interaction record of FIG. **4**, initially, the client indicates they would like to schedule an appointment. The agent receives the message, and, within the interaction, indicates that information is needed to proceed. The information includes the name and account number. The client provides the requested information, and also indicates that the appointment should be at 2 PM on Friday then responds that the appointment has been scheduled. The interaction record three include regarding the actions taken by the automated agent responding to the client.

[0043] The imputation agent determines the optimal path using the agent architecture specification between the first entry and the last entry in the interaction record. The optimal path can be determined as, for example, the path with the fewest state transitions, determined to be the shortest path such that the logical steps taken between the first entry and the last entry are the closest when compared to other paths between the first entry and last entry, the path that requires the fewest computing cycles.

[0044] FIG. **5** illustrates an agent architecture specification. In the implementation of FIG. **5**, the agent architecture specification is expressed as a state machine. The state machine begins at root state **510**. Initially, at root state **510**, a determination is made as to whether the state machine should respond to the client input or invoke a function based on the client input. The decision as to whether to respond or invoke a function can be made by submitting a prompt to a large language model with the input, conversation history (all or part of an interaction record), and other content. In some instances, the automated agent may cycle through an agent architecture specification multiple times in response to receiving a message from a client. The first iteration may execute a program and a second iteration may generate a response.

[0045] If a determination is made to invoke a function, the state machine transitions to invoke function state **520** and the function is invoked. The function may be selected from one or more functions listed in the API specification, and selected by logic within the automated agent or by a machine learning model. The invoked function executes, a result is generated or received, and the state machine transitions back to state **510**.

[0046] If a determination is made at root state **510** to respond to the client, the state machine transitions to respond state **530** where a response is predicted. Predicting a response includes generating a response to the message received from the client in the interaction. After the response is generated, a determination is made as to whether an audit is enabled at state **540**. In some instances, before a response is provided to a client, it may be audited to confirm it is a proper response without any errors.

[0047] If an audit is not enabled, the predicted response is approved at step **570** and provided as output in the interaction between the automated agent in the client. If an audit is enabled, the predicted response is audited at state **550**. The state machine then transitions to step **560** to determine if the predicted response passed the audit. If the response passed the audit, the response is approved and provided as output at state **570**.

[0048] If at state **560** a determination is made that a maximum number of audits has been conducted, the response will not pass the audit, a failure message is generated, and the failure message is provided to the client as the approved message at step **570**. If the response does not pass the audit for reasons other than the number of audits performed, the response and the reasons for failure are sent back to root state **510** if there have not already been a threshold number of audits performed.

[0049] The state machine of FIG. **5** is one example of an agent architecture specification that may be used as decision logic and/or decision process for an automated agent processing a message from a client. In some instances, an automated agent may proceed through a state machine one or more iterations in response to each message received from a client. The state machine of FIG. **5** is intended merely as an example, and other variations of a state machine, with different states in different orders, can be used to process messages received from a client.

[0050] In some instances, an imputation engine builds a supplemented interaction record based on an existing interaction record in a backwards direction, from the last entry in the existing interaction record to the first entry in the interaction record. To build the supplemented interaction record, the imputation engine accesses the existing interaction record, accesses the last entry first, identifies what state in a state machine was the previous state, and executes actions and/or operations associated with the previous state. For each entry or message by an automated agent in the existing interaction record, the supplemented record can be supplemented or modified to indicate the actions associated states previous to the response generation state that resulted in the message from the automated agent.

[0051] FIGS. **6-11** illustrate supplemented interaction records. The interaction record of FIGS. **6-11** illustrate the progressive development of a supplemented interaction record based on the state machine of FIG. **5** and the existing interaction record of FIG. **4**. The development of the supplemented interaction record works backwards from the last entry in the interaction record towards the first entry. The last entry in the record of FIG. **6** is entry **440**, from the automated agent, confirming that the appointment has been scheduled. The entry is generated as a response from the automated agent in response to a previous entry from a client in the interaction record.

[0052] In the state machine of FIG. **5**, a predicted response is audited before it is approved and output to a client. As such, in the partial supplemented interaction record **600** of FIG. **6**, the interaction record is supplemented with data indicating that a predicted response was generated, the predicted response was submitted to an audit, and the automated agent determined that the predicted response passed the audit.

[0053] In the partially supplemented interaction record **700** of FIG. **7**, the imputation agent determines that the automated agent determines, from the root state, whether the automated agent should predict a response or invoke a function. The automated agent determines that a response should be predicted. The response was determined to be entry **440** in the interaction record.

[0054] In the partially supplemented interaction record **800** of FIG. **8**, the imputation agent determines that the automated agent determines, from the root state, whether the automated agent should predict a response or invoke a function. The automated agent determines that a function should be invoked. The function invoked is determined to be a program titled "schedule_appt911234,2023-11-24T1500."

[0055] In the partially supplemented interaction record **900** of FIG. **9**, a client provides a message indicating the client's name and account number, as well as when the client would like the appointment. This is in response to an automated agent communication indicating that the agent can help, but that the agent needs the client's name and account number.

[0056] In the partially supplemented interaction record of FIG. **10**, the automated agent, in order to provide a response to the client indicating that the automated agent needs the name and account number of the client, must generate the response. As such, the partially supplemented interaction record **1000** of FIG. **10** is supplemented by accessing a predicted response, subjecting the response to an audit, and then determining that the response passed the audit.

[0057] In the partially supplemented interaction record of FIG. **11**, to provide a response, the automated agent must first generate a response. As such, the imputation agent determines, from the root state, whether to generate a response or invoke a function. The automated agent determines to generate a response. The automated agent response is generated in response to a client communication **410** indicating the client would like to schedule an appointment.

[0058] FIG. **12** is a flow chart illustrating data flow for a machine learning model. The block diagram of FIG. **4** includes prompt **410**, machine learning model **420**, and output **430**.

[0059] Prompt **410** of FIG. **4** can be provided as input to a machine learning model **420**. A prompt can include information or data such as a role **412**, instructions **414**, and content **416**. The role indicates the authority level at which the automated agent is to assume while working to assist a user. For example, a role can include an entry-level customer service representative, a manager, a director, or some other customer service job with a particular level of permissions and rules that apply to what they can do and cannot do when assisting a customer.

[0060] Instructions **414** can indicate what the machine learning model (e.g., a large language model) is supposed to do with the other content provided in the prompt. For example, the machine learning model instructions may request, via instructions **414**, an LLM to select the most relevant instructions from content **230** to train or guide a customer service representative having a specified role **210**, determine if a predicted response was generated with each instruction followed correctly, determine what function to execute, determine whether or not to transition to a new state within a state machine, and so forth. The instructions can be retrieved or accessed from document **155** of vector database **150**.

[0061] Content **416** may include data and/or information that can help a ML model or LLM generate an output. For an ML model, the content can include a stream of data that is put in a processable format (for example, normalized) for the ML model to read. For an LLM, the content can include a user inquiry, retrieved instructions, policy data, checklist and/or checklist item data, programs and functions executed by a state machine, results of an audit or evaluation, and other content. In some instances, where only a portion of the content or a prompt will fit into an LLM input, the content and/or other portions of the prompt can be provided to an LLM can be submitted in multiple prompts.

[0062] Machine learning model **420** of FIG. **4** provides more detail for machine learning model **110** of FIG. **1**. The ML model **420** may receive one or more inputs and provide an output. In some instances, the ML model may predict an output in the form of whether a policy was followed, whether a particular instruction is relevant, or some other prediction.

[0063] ML model **420** may be implemented by a large language model **422**. A large language model is a machine learning model that uses deep learning algorithms to process and understand language. LLMs can have an encoder, a decoder, or both, and can encode positioning data to their input. In some instances, LLMs can be based on transformers, which have a neural network architecture, and have multiple layers of neural networks. An LLM can have an attention mechanism that allows them to focus selectively on parts of text. LLMs are trained with large amounts of data and can be used for different purposes.

[0064] The transformer model learns context and meaning by tracking relationships in sequential data. LLMs receive text as an input through a prompt and provide a response to one or more instructions. For example, an LLM can receive a prompt as an instruction to analyze data. The prompt can include a context (e.g., a role, such as 'you are an agent'), a bulleted list of itemized instructions, and content to apply the instructions to.

[0065] In some instances, the present technology may use an LLM such as a BERT LLM, Falcon 30B on GitHub, Galactica by Meta, GPT-3 by OpenAI, or other LLM. In some instances, machine learning model **115** may be implemented by one or more other models or neural networks.

[0066] Output **430** is provided by machine learning model **420** in response to processing prompt **410** (e.g., an input). For example, when the prompt includes a request that the machine learning model identify the most relevant instructions from a set of content, the output will include a list of the most relevant instructions. In some instances, when the prompt includes a request that the machine learning model determine if an automated agent properly followed a set of instructions, a policy, or a checklist item during a conversation with a user, the machine learning model may return a confidence score, prediction, or other indication as to whether the instructions were followed correctly by the automated agent.

[0067] FIG. **13** is a method for imputing automated agent decision logic. The imputed automated agent decision logic is the optimal path of logic decisions between the first entry in an interaction record and the last entry in the interaction record.

[0068] A last message in an interaction record between an agent and a client is accessed at step **1310**. A determination is made as to whether the accessed message is the first message in the interaction record at step **1320**. If the accessed message is the first message in the interaction record, then there are no more messages to process and the method ends at step **1380**. If the accessed message is not the first message, supplemented interaction record data is generated for the accessed message at step **1330**.

[0069] Generating a supplemented interaction record data at step **1330** may include going through a state machine or other decision logic to determine what the automated agent did to provide a response, invoke an action or function, or perform some other operation. More details for generating supplemented interaction record data are discussed with respect to the method of FIG. **14**.

[0070] In some instances, generating supplemented interaction record data is performed using one or more machine learning models. A machine learning model may receive input with the message, API specification data, agent architecture specification, a request, and other data to determine how to supplement the interaction record. In some instances, the supplemented interaction record may be generated using a large language model, for example when input is provided as a prompt. More details for generating the supplemented interaction record data by a large language model is discussed with respect to the method of FIG. **16**.

[0071] The closeness of the generated supplemented interaction record data to a desired endpoint is calculated at step **1340**. In some instances, for each step of generating a supplemented interaction record, one or more calculations can be made to determine if the generated supplemented interaction record is getting closer or further away from the desired endpoint. The present system can generate the correct sequence that should have been performed by the automated agent to produce the existing interaction record. The correct sequence can be the most efficient sequence, the shortest sequence, the sequence that uses the fewest resources, and/or the fastest sequence. The correct sequence can be constructed as an ideal path for processing user requests in the interaction with the user, rather than the path actually taken by the automated agent previously or currently.

[0072] Calculating the closeness of a generated supplemented interaction record data to a desired endpoint is discussed in more detail below with respect to the method of FIG. **17**.

[0073] A determination is made as to whether the closeness calculation of step **1340** indicates the path formed by the in-progress supplemented interaction record is getting closer to a target state (e.g., if working backwards, the first entry in the existing interaction record) at step **1350**.

[0074] To determine if the supplemented interaction record path is getting closer to the target state in the interaction record, two or more calculated closeness values can be generated and compared. For example, the closeness of the most recent supplemented state and the previously supplemented state can be compared, the most recent supplemented state and other states that would be a transition (but were not selected to be transitioned to) from the previous supplemented state can be compared, and so forth.

[0075] If the closeness calculation indicates that the supplemented interaction record path is getting closer to a target state, the next most recent message in the interaction record is selected and the method continues to step **1320**. If the closeness indicates it is not getting closer to the target state, a new supplemented record data is generated at step **1370**.

[0076] At step **13470**, the previously generated supplemented interaction data is replaced with replacement supplemented interaction data based on the closeness data. The new (i.e., replacement) supplemented interaction record data can be generated using the previously accessed message and an alternate calculation. In some instances, a different state may be selected, a variable in a function may be changed, a different response may be provided, or some other indication. Selecting new supplemented record data can also include removing the previously generated supplemented interaction record data from the supplemented interaction record. After generating the new supplemented record data, the method returns to step **1340**.

[0077] FIG. **14** is a method for generating supplemented interaction record data. The method of FIG. **14** provides more detail for step **1330** of the method of FIG. **13**. The present system can generate supplemented interaction record data based at least in part on an agent architecture specification, such as the state machine in FIG. **5**. The method of FIG. **14** will illustrate generation of supplemented interaction data based on the FIG. **5** state machine, but other state machines, flow charts, or decision logic can be used.

[0078] An agent architecture specification state machine is set to a root state at step **1410**. The state machine transitions to the next state at step **1420**. A determination is then made as to whether a program should be invoked or a response should be generated at step **1430**.

[0079] If a program should be invoked, the program is invoked at step **1440**. After invoking the program, any result or output from the program is stored, and the method continues to step **1460**. If a response should be generated, the response is generated and provided to a client at step **1450**. In some instances, a response is generated as a predicted response and the predicted response audited to determine if it is acceptable. Generating a response is discussed in more detail with respect to the method of FIG. **15**.

[0080] A determination is made as to whether the state machine ends at step **1460**. If the state machine ends, the method of FIG. **14** ends at step **1480**. If the state machine has not ended, the state machine transitions to the next state at step **1470** and the method returns to step **1420**.

[0081] FIG. **15** is a method for generating a response. The method of FIG. **15** provides more detail for step **1450** of the method of FIG. **14**. A predicted response is generated at step **1510**. The response may be generated based on previous state results, the interaction record, and other data.

[0082] The predicted response is then audited at step **1520**. Auditing the response may include submitting the interaction record, predicted response, and instructions to a LLM to determine if the generated response is acceptable.

[0083] A determination is made as to whether the response passes the audit at step **1530**. If the response passes the audit, the response is approved and may be output in the interaction with a client at step **1540**. If the response does not pass an audit, a determination is made as to whether the number of allowed audits has exceeded at step **1550**. In some instances, for example for latency purposes, the number of audits may be restricted to a certain maximum number, such as three, five, six, ten, or some other number. If the number of audits has been exceeded, a failure message is generated as an approved message at step **1560** and the failure message is output to the client in the interaction. If the number of audits has not been exceeded, the audit count is incremented, the predicted response is regenerated based in part on the error detected in the audit, and the method of FIG. **15** returns to step **1520**.

[0084] FIG. **16** is a method for generating supplemented interaction record data using an LLM. The method of FIG. **16** provides more detail for step **1330** of the method of FIG. **13**, and provides an alternate method for generating a supplemented interaction record. A prompt is generated from an accessed interaction record, API specification, and an agent architecture specification at step **1610**. The prompt is then submitted to a large language model at step **1620**. The large language model receives the input and processes the prompt at step **1630**. A large language model then outputs a supplemented interaction record for the accessed message at step **1640**.

[0085] FIGS. **17** is a method for calculating closeness of generated supplemented interaction record data to a target end point. The method of FIG. **17** provides more detail for step **1340** of the method of FIG. **13**. The closeness from the previous state to the target end state is determined at step **1710**. The cost may be determined as a distance, number of steps or states, and other data. The cost to travel from the current state to the target end state is determined at step **1720**. The cost to travel from other states that could have been transitioned to from the previous state to the target end state is determined at step **1730**. A determination is then made as to whether the current state is the closest state to the target state at step **1740**. Based on determining the closeness from different states to the target state, the automated agent can determine whether the generated path along interaction record is the best path, and in particular the most efficient path, between the endpoint in the starting target point.

[0086] FIG. **18** is a block diagram of a computing environment for implementing the present technology. System **1800** of FIG. **18** may be implemented in the contexts of the likes of machines that implement machine learning model **110**, application server **180**, chat application server **130**, and simulation server **140**. The computing system **1800** of FIG. **18** includes one or more processors **1810** and memory **1820**. Main memory **1820** stores, in part, instructions and data for execution by processor **1810**. Main memory **1820** can store the executable code when in operation. The system **1800** of FIG. **18** further includes a mass storage device **1830**, portable storage medium drive(s) **1840**, output devices **1850**, user input devices **1860**, a graphics display **1870**, and peripheral devices **1880**.

[0087] The components shown in FIG. **18** are depicted as being connected via a single bus **1895**. However, the components may be connected through one or more data transport means. For example, processor unit **1810** and main memory **1820** may be connected via a local microprocessor bus, and the mass storage device **1830**, peripheral device(s) **1880**, portable storage device **1840**, and display system **1870** may be connected via one or more input/output (I/O) buses.

[0088] Mass storage device **1830**, which may be implemented with a magnetic disk drive, an optical disk drive, a flash drive, or other device, is a non-volatile storage device for storing data and instructions for use by processor unit **1810**. Mass storage device **1830** can store the system software for implementing embodiments of the present invention for purposes of loading that software into main memory **1820**.

[0089] Portable storage device **1840** operates in conjunction with a portable non-volatile storage medium, such as a floppy disk, compact disk or Digital video disc, USB drive, memory card or stick, or other portable or removable memory, to input and output data and code to and from the computer system **1800** of FIG. **18**. The system software for implementing embodiments of the present invention may be stored on such a portable medium and input to the computer system **1800** via the portable storage device **1840**.

[0090] Input devices **1860** provide a portion of a user interface. Input devices **1860** may include an alpha-numeric keypad, such as a keyboard, for inputting alpha-numeric and other information, a pointing device such as a mouse, a trackball, stylus, cursor direction keys, microphone, touchscreen, accelerometer, and other input devices. Additionally, the system **1800** as shown in FIG. **18** includes output devices **1850**. Examples of suitable output devices include speakers, printers, network interfaces, and monitors.

[0091] Display system **1870** may include a liquid crystal display (LCD) or other suitable display device. Display system **1870** receives textual and graphical information and processes the information for output to the display device. Display system **1870** may also receive input as a touchscreen.

[0092] Peripherals **1880** may include any type of computer support device to add additional functionality to the computer system. For example, peripheral device(s) **1880** may include a modem or a router, printer, and other device.

[0093] The system of **1800** may also include, in some implementations, antennas, radio transmitters and radio receivers **1890**. The antennas and radios may be implemented in devices such as smart phones, tablets, and other devices that may communicate wirelessly. The one or more antennas may operate at one or more radio frequencies suitable to send and receive data over cellular networks, Wi-Fi networks, commercial device networks such as a Bluetooth device, and other radio frequency networks. The devices may include one or more radio transmitters and receivers for processing signals sent and received using the antennas.

[0094] The components contained in the computer system **1800** of FIG. **18** are those typically found in computer systems that may be suitable for use with embodiments of the present invention and are intended to represent a broad category of such computer components that are well known in the art. Thus, the computer system **1800** of FIG. **18** can be a personal computer, handheld computing device, smart phone, mobile computing device, tablet computer, workstation, server, minicomputer, mainframe computer, or any other computing device. The computer can also include different bus configurations, networked platforms, multiprocessor platforms, etc. The computing device can be used to implement applications, virtual machines, computing nodes, and other computing units in different network computing platforms, including but not limited to AZURE by Microsoft Corporation, Google Cloud Platform (GCP) by Google Inc., AWS by Amazon Inc., IBM Cloud by IBM Inc., and other platforms, in different containers, virtual machines, and other software. Various operating systems can be used including UNIX, LINUX, WINDOWS, MACINTOSH OS, CHROME OS, IOS, ANDROID, as well as languages including Python, PHP, Java, Ruby, .NET, C, C++, Node.JS, SQL, and other suitable languages.

[0095] The foregoing detailed description of the technology herein has been presented for purposes of illustration and description. It is not intended to be exhaustive or to limit the technology to the precise form disclosed. Many modifications and variations are possible in light of the above teaching. The described embodiments were chosen to best explain the principles of the technology and its practical application to thereby enable others skilled in the art to best utilize the technology in various embodiments and with various modifications as are suited to the particular use contemplated. It is intended that the scope of the technology be defined by the claims appended hereto.

1. A method for generating a supplemented interaction record between an automated agent and a client, comprising:

accessing, by an imputation engine on a server, an existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification, the existing interaction record associated with an interaction between the client and the automated agent that occurred in the past, the existing interaction record including at least one entry associated with an automated agent;

determining one or more logical steps associated with a correct sequence that could be performed by an automated agent in determining each entry by the automated agent in the existing interaction record; and

generating a supplemented interaction record based on the existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification, the supplemented interaction record including additional data based on the one or more logical steps performed by the automated agent.

2. The method of claim **1**, wherein the logical steps performed by the automated agent are determined in reverse order from a last entry to a first entry in the existing interaction record.

3. The method of claim **1**, wherein the agent architecture specification includes a state machine.

4. The method of claim **1**, wherein the logical steps include one of generating a response or invoking a function for each entry in the existing interaction record by the automated agent.

5. The method of claim **1**, wherein the supplemented interaction record represents the most efficient logical path from the first entry in the existing interaction record first entry to the last entry in the existing interaction record.

6. The method of claim **1**, wherein a closeness value is determined for a supplemented interaction record that is partially complete, the closeness value determined based on the current supplemented interaction record and the desired end point of the supplemented interaction record.

7. The method of claim **6**, further comprising replacing supplemented interaction data with replacement supplemented interaction data based on the closeness data.

8. A non-transitory computer readable storage medium having embodied thereon a program, the program being executable by a processor to generate a supplemented interaction record between an automated agent and a client, the method comprising:

accessing, by an imputation engine on a server, an existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification, the existing interaction record associated with an interaction between the client and the automated agent that occurred in the past, the existing interaction record including at least one entry associated with an automated agent;

determining one or more logical steps associated with a correct sequence that could be performed by an automated agent in determining each entry by the automated agent in the existing interaction record; and

generating a supplemented interaction record based on the existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification, the supplemented interaction record including additional data based on the one or more logical steps performed by the automated agent.

9. The non-transitory computer readable storage medium of claim **8**, wherein the logical steps performed by the automated agent are determined in reverse order from a last entry to a first entry in the existing interaction record.

10. The non-transitory computer readable storage medium of claim **8**, wherein the agent architecture specification includes a state machine.

11. The non-transitory computer readable storage medium of claim **8**, wherein the logical steps include one of generating a response or invoking a function for each entry in the existing interaction record by the automated agent.

12. The non-transitory computer readable storage medium of claim **8**, wherein the supplemented interaction record represents the most efficient logical path from the first entry in the existing interaction record first entry to the last entry in the existing interaction record.

13. The non-transitory computer readable storage medium of claim **8**, wherein a closeness value is determined for a supplemented interaction record that is partially complete, the closeness value determined based on the current supplemented interaction record and the desired end point of the supplemented interaction record.

14. The non-transitory computer readable storage medium of claim **13**, further comprising replacing supplemented interaction data with replacement supplemented interaction data based on the closeness data.

15. A system for generating a supplemented interaction record between an automated agent and a client, comprising:

one or more servers, wherein each server includes a memory and a processor; and

one or more modules stored in the memory and executed by at least one of the one or more processors to access, by an imputation engine on a server, an existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification, the existing interaction record associated with an interaction between the client and the automated agent that occurred in the past, the existing interaction record including at least one entry associated with an automated agent, determine one or more logical steps associated with a correct sequence that could be performed by an automated agent in determining each entry by the automated agent in the existing interaction record; and, and generate a supplemented interaction record based on the existing interaction record between a client and an automated agent, an API specification, and an agent architecture specification, the supplemented interaction record including additional data based on the one or more logical steps performed by the automated agent.

16. The system of claim **15**, wherein the logical steps performed by the automated agent are determined in reverse order from a last entry to a first entry in the existing interaction record.

17. The system of claim **15**, wherein the agent architecture specification includes a state machine.

18. The system of claim **15**, wherein the logical steps include one of generating a response or invoking a function for each entry in the existing interaction record by the automated agent.

19. The system of claim **15**, wherein the supplemented interaction record represents the most efficient logical path from the first entry in the existing interaction record first entry to the last entry in the existing interaction record.

20. The system of claim **15**, wherein a closeness value is determined for a supplemented interaction record that is partially complete, the closeness value determined based on the current supplemented interaction record and the desired end point of the supplemented interaction record.

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