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(54) **CONTEXTUAL LANGUAGE UNDERSTANDING FOR MULTI-TURN LANGUAGE TASKS**

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G06F 17/27 (2006.01)
G10L 15/183 (2013.01)
G06F 17/30 (2006.01)

(52) **U.S. Cl.**
CPC ***G06F 17/2785*** (2013.01); ***G06F 17/279*** (2013.01); ***G06F 17/30976*** (2013.01)

(58) **Field of Classification Search**
CPC G10L 15/18; G10L 15/183; G10L 15/32; G10L 2015/223; G06F 17/27; G06F 17/277; G06F 17/2785
USPC 704/9, 257, 275
See application file for complete search history.

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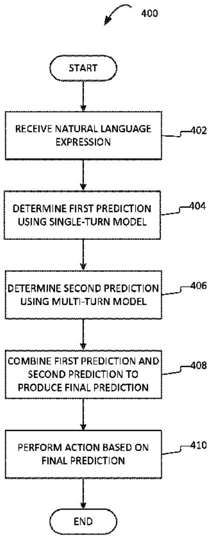
(57) **ABSTRACT**

Methods and systems are provided for contextual language understanding. A natural language expression may be received at a single-turn model and a multi-turn model for determining an intent of a user. For example, the single-turn model may determine a first prediction of at least one of a domain classification, intent classification, and slot type of the natural language expression. The multi-turn model may determine a second prediction of at least one of a domain classification, intent classification, and slot type of the natural language expression. The first prediction and the second prediction may be combined to produce a final prediction relative to the intent of the natural language expression. An action may be performed based on the final prediction of the natural language expression.

20 Claims, 11 Drawing Sheets


400
START
RECEIVE NATURAL LANGUAGE EXPRESSION
402
DETERMINE FIRST PREDICTION USING SINGLE-TURN MODEL
404
DETERMINE SECOND PREDICTION USING MULTI-TURN MODEL
406
COMBINE FIRST PREDICTION AND SECOND PREDICTION TO PRODUCE FINAL PREDICTION
408
PERFORM ACTION BASED ON FINAL PREDICTION
410
END

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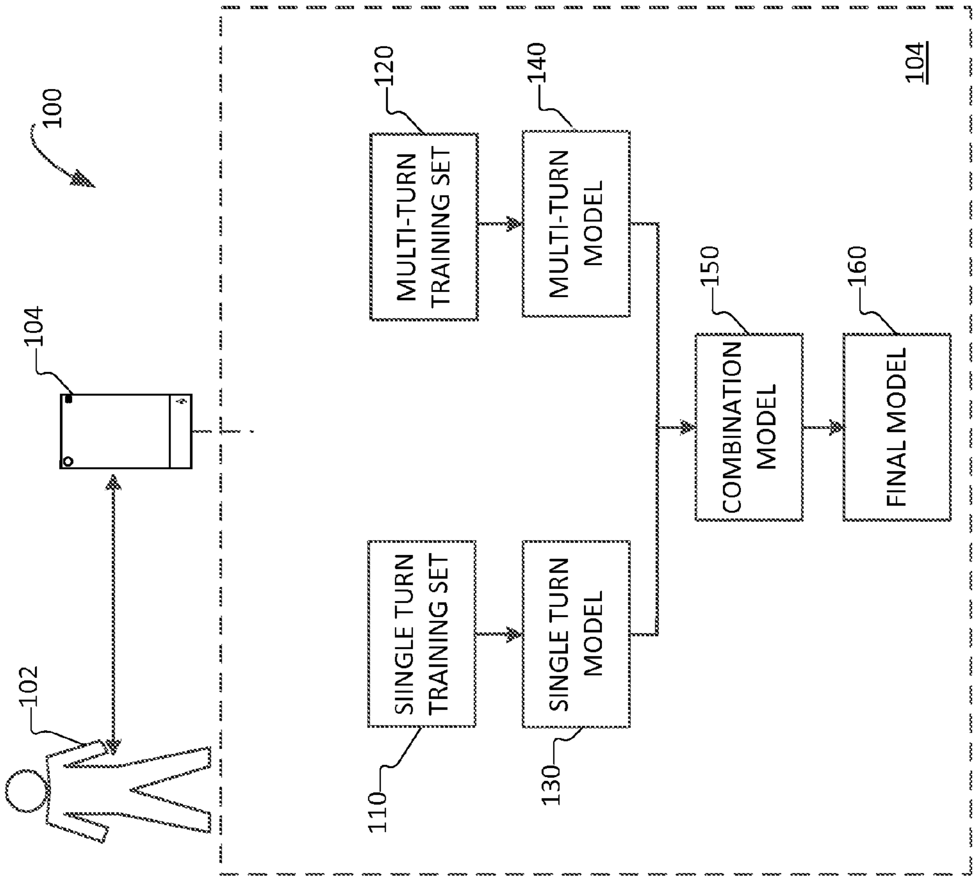
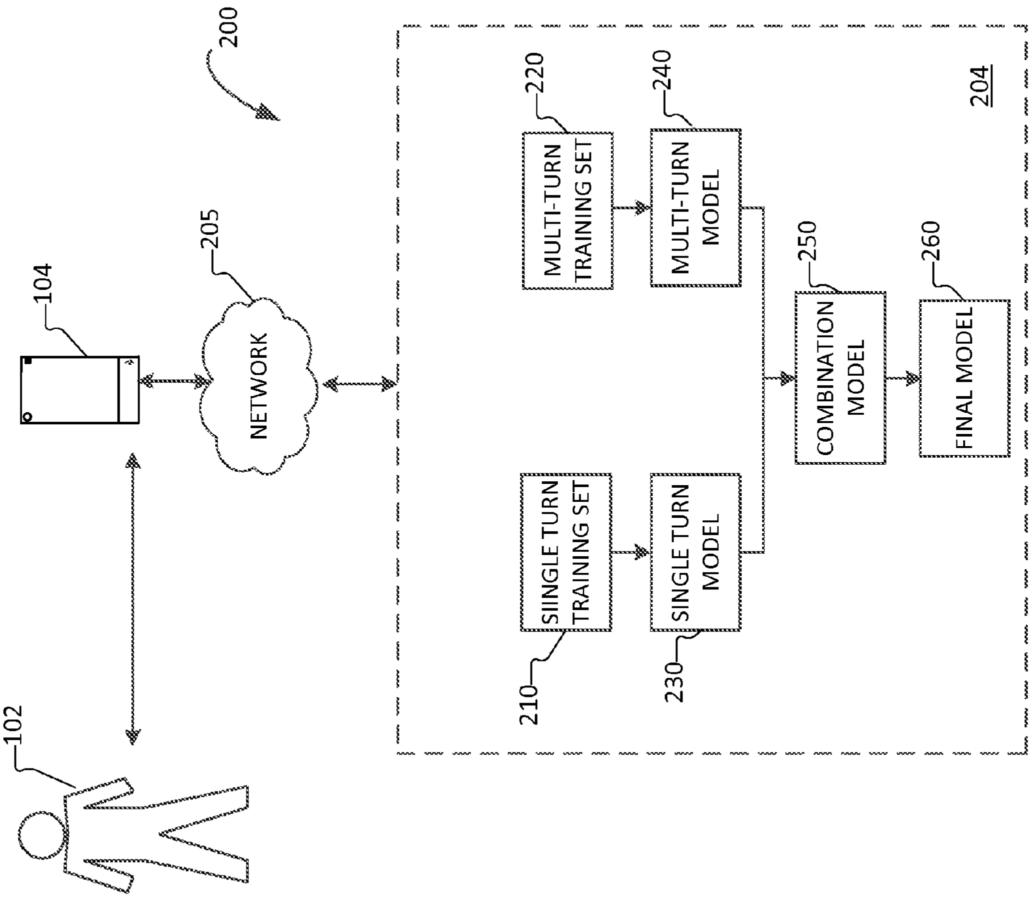

100
104
102
104
120
MULTI-TURN TRAINING SET
140
MULTI-TURN MODEL
110
SIINGLE TURN TRAINING SET
130
SINGLE TURN MODEL
150
COMBINATION MODEL
160
FINAL MODEL

FIG. 1


200
104
205
NETWORK
102
220
MULTI-TURN TRAINING SET
240
MULTI-TURN MODEL
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SIINGLE TURN TRAINING SET
230
SINGLE TURN MODEL
250
COMBINATION MODEL
260
FINAL MODEL
204

FIG. 2

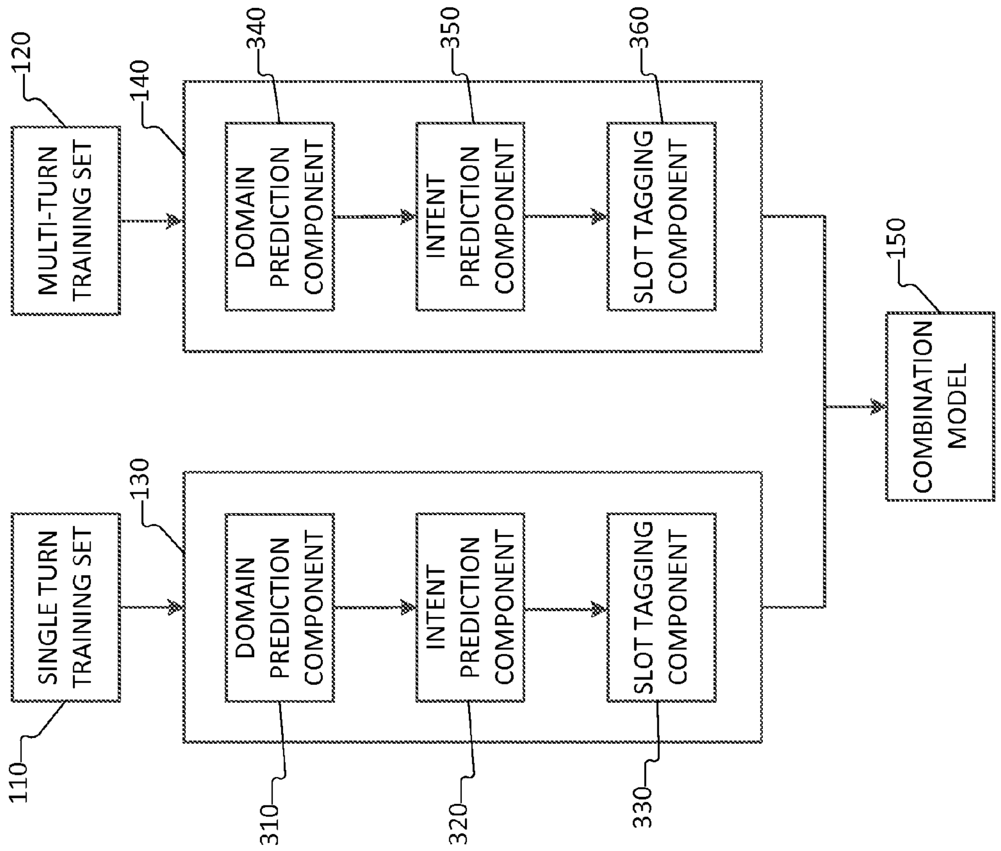

SINGLE TURN TRAINING SET
110
130
DOMAIN PREDICTION COMPONENT
310
INTENT PREDICTION COMPONENT
320
SLOT TAGGING COMPONENT
330
MULTI-TURN TRAINING SET
120
140
DOMAIN PREDICTION COMPONENT
340
INTENT PREDICTION COMPONENT
350
SLOT TAGGING COMPONENT
360
COMBINATION MODEL
150

FIG. 3

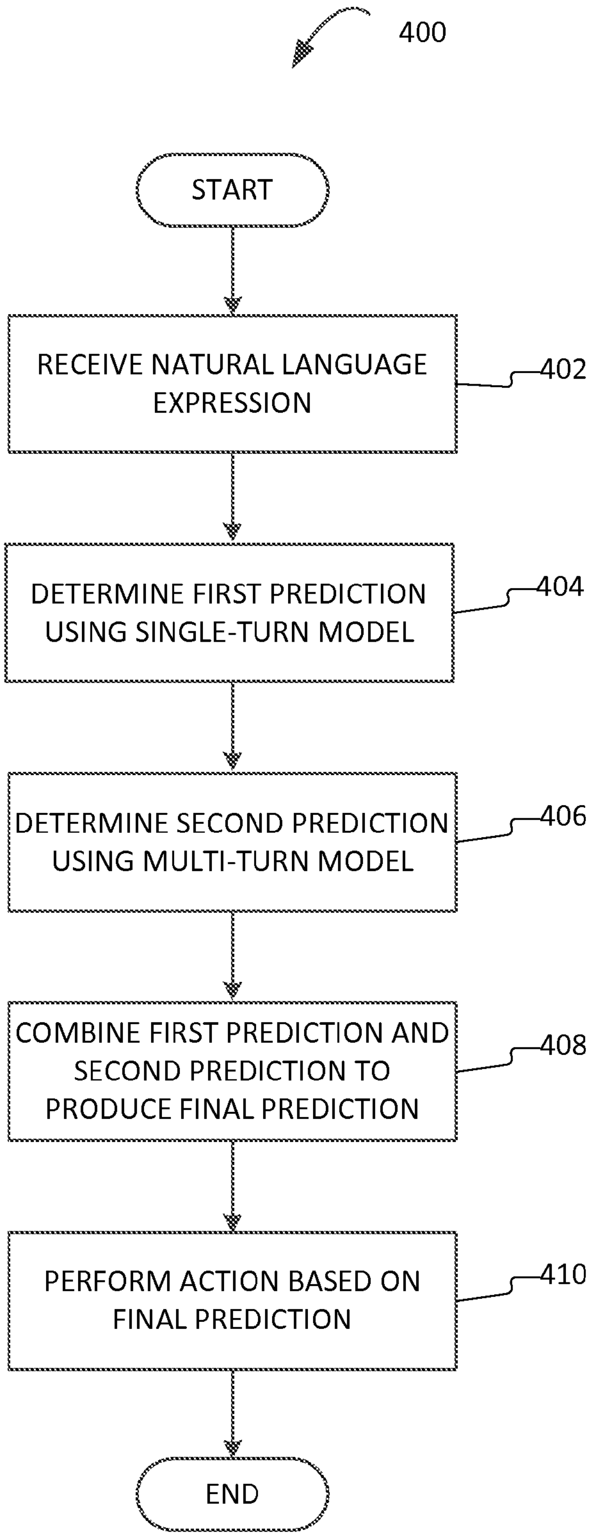

400
START
RECEIVE NATURAL LANGUAGE EXPRESSION
402
DETERMINE FIRST PREDICTION USING SINGLE-TURN MODEL
404
DETERMINE SECOND PREDICTION USING MULTI-TURN MODEL
406
COMBINE FIRST PREDICTION AND SECOND PREDICTION TO PRODUCE FINAL PREDICTION
408
PERFORM ACTION BASED ON FINAL PREDICTION
410
END

FIG. 4

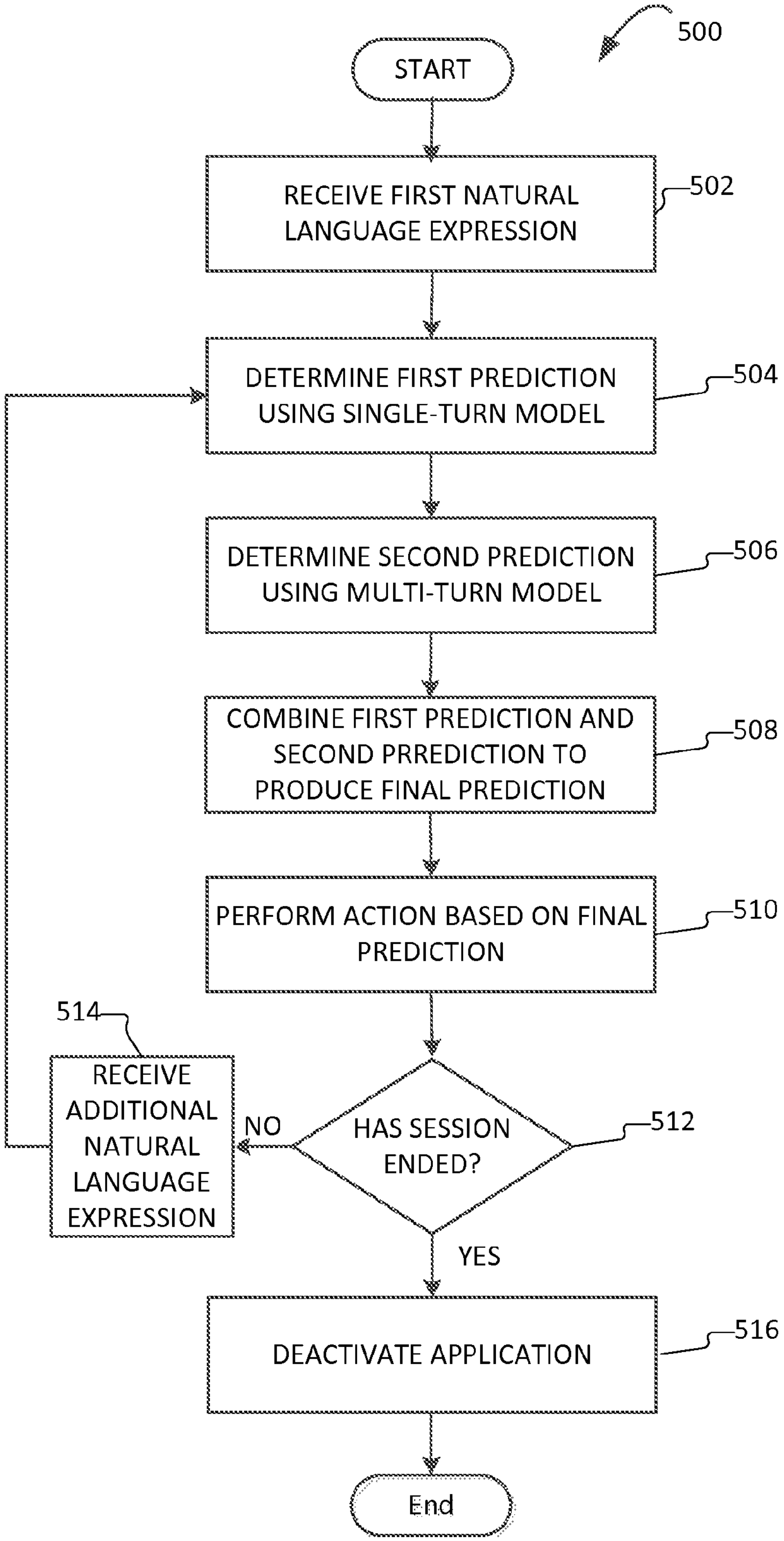

500
START
RECEIVE FIRST NATURAL LANGUAGE EXPRESSION
502
DETERMINE FIRST PREDICTION USING SINGLE-TURN MODEL
504
DETERMINE SECOND PREDICTION USING MULTI-TURN MODEL
506
COMBINE FIRST PREDICTION AND SECOND PRREDICTION TO PRODUCE FINAL PREDICTION
508
PERFORM ACTION BASED ON FINAL PREDICTION
510
514
RECEIVE ADDITIONAL NATURAL LANGUAGE EXPRESSION
NO
HAS SESSION ENDED?
512
YES
DEACTIVATE APPLICATION
516
End

FIG. 5

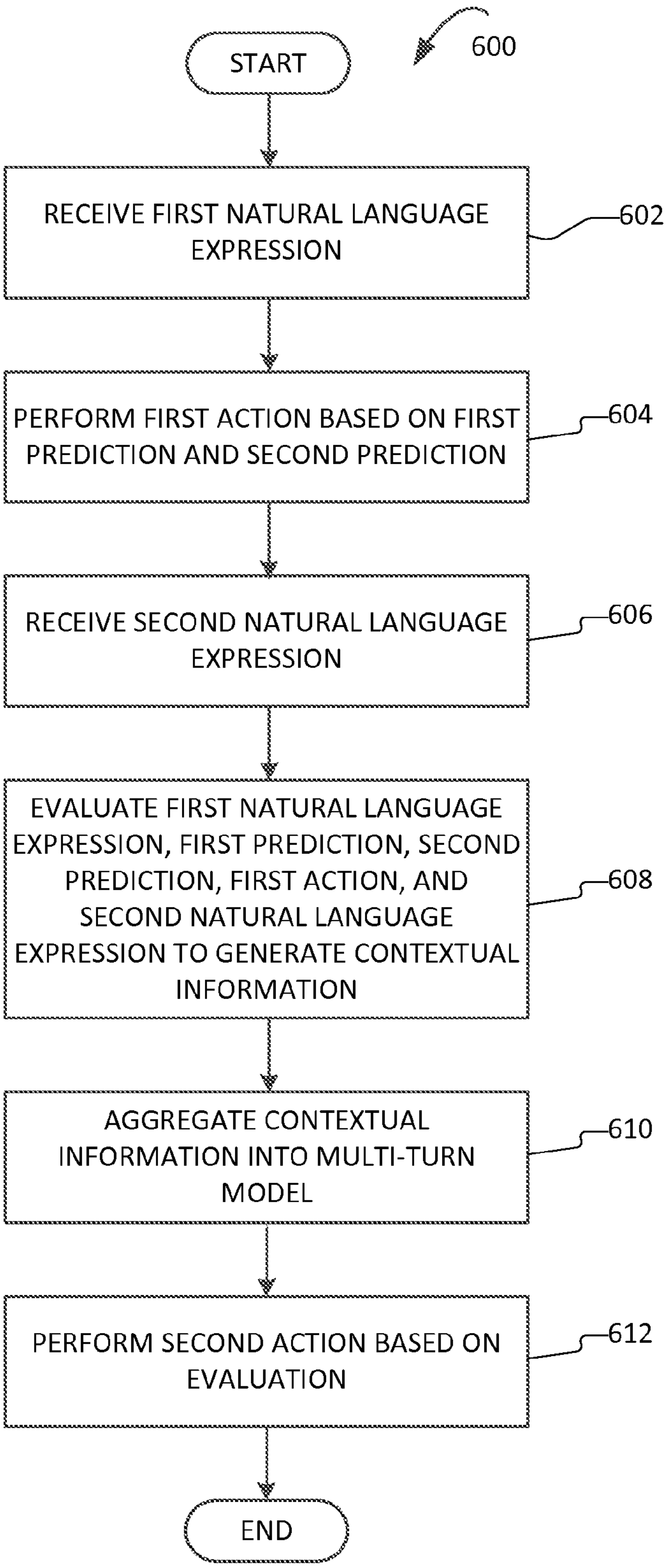

600
START
RECEIVE FIRST NATURAL LANGUAGE EXPRESSION
602
PERFORM FIRST ACTION BASED ON FIRST PREDICTION AND SECOND PREDICTION
604
RECEIVE SECOND NATURAL LANGUAGE EXPRESSION
606
EVALUATE FIRST NATURAL LANGUAGE EXPRESSION, FIRST PREDICTION, SECOND PREDICTION, FIRST ACTION, AND SECOND NATURAL LANGUAGE EXPRESSION TO GENERATE CONTEXTUAL INFORMATION
608
AGGREGATE CONTEXTUAL INFORMATION INTO MULTI-TURN MODEL
610
PERFORM SECOND ACTION BASED ON EVALUATION
612
END

FIG. 6

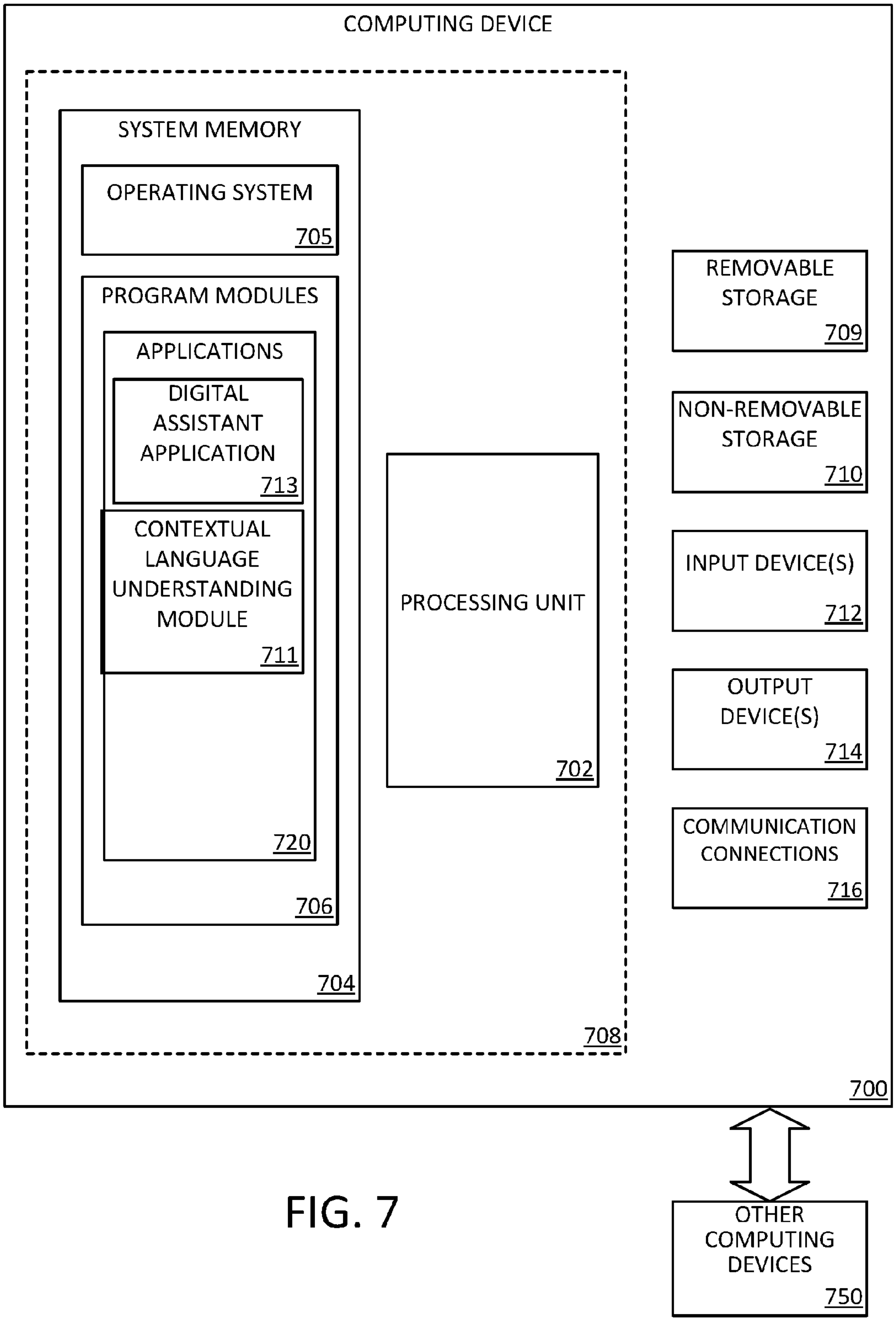
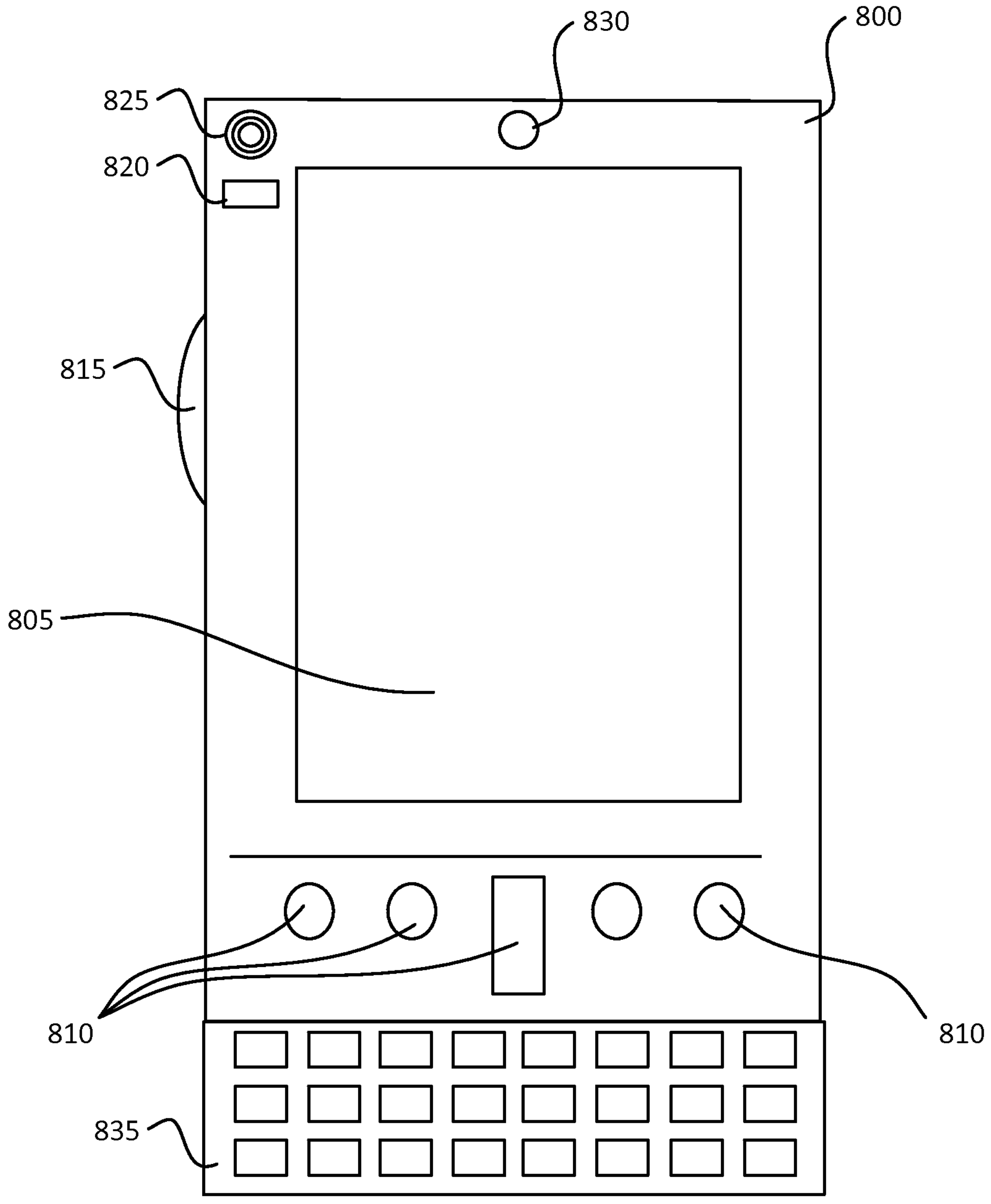

COMPUTING DEVICE
SYSTEM MEMORY
OPERATING SYSTEM
705
PROGRAM MODULES
APPLICATIONS
DIGITAL ASSISTANT APPLICATION
713
CONTEXTUAL LANGUAGE UNDERSTANDING MODULE
711
720
706
704
708
PROCESSING UNIT
702
REMOVABLE STORAGE
709
NON-REMOVABLE STORAGE
710
INPUT DEVICE(S)
712
OUTPUT DEVICE(S)
714
COMMUNICATION CONNECTIONS
716
700
OTHER COMPUTING DEVICES
750

FIG. 7



Mobile Computing Device

FIG. 8A

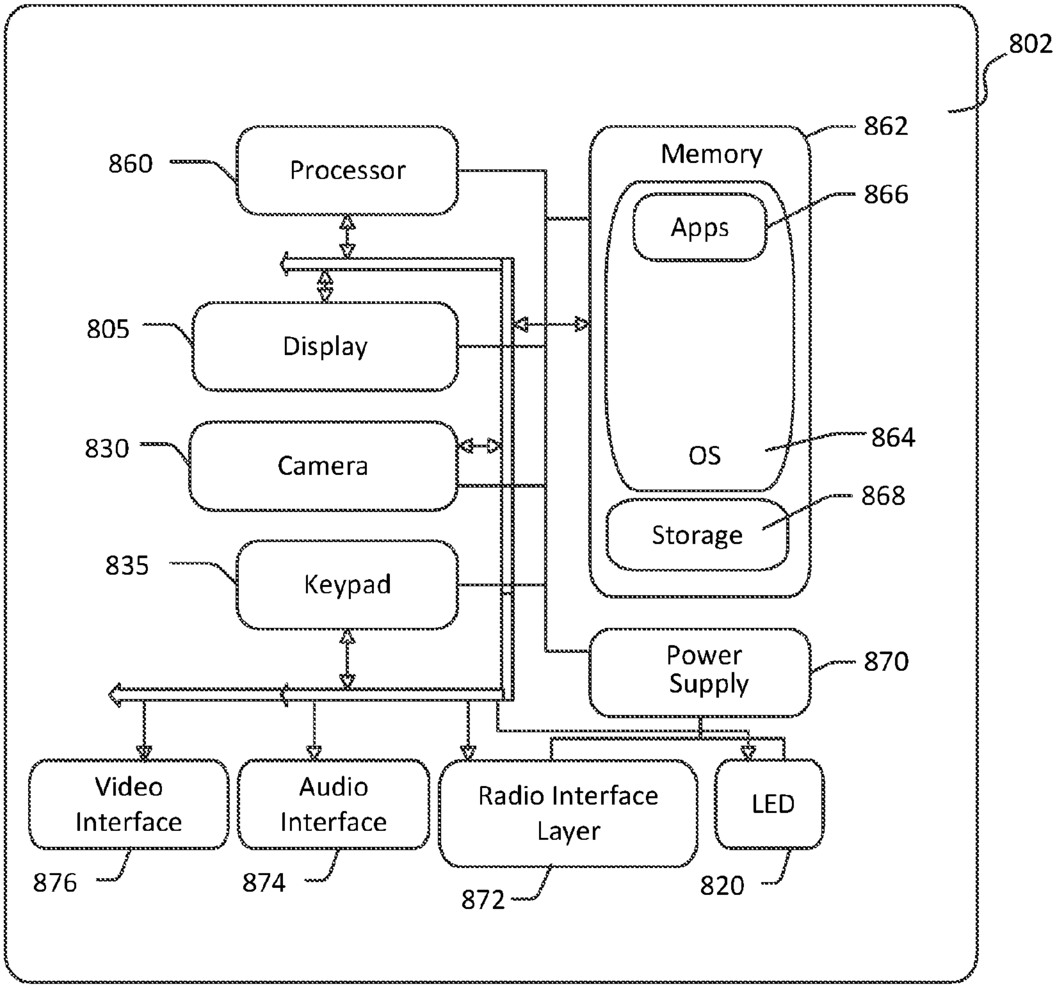

802
Memory
862
Processor
860
Apps
866
805
Display
830
Camera
OS
864
868
Storage
835
Keypad
Power Supply
870
Video Interface
Audio Interface
Radio Interface Layer
LED
876
874
872
820

FIG. 8B

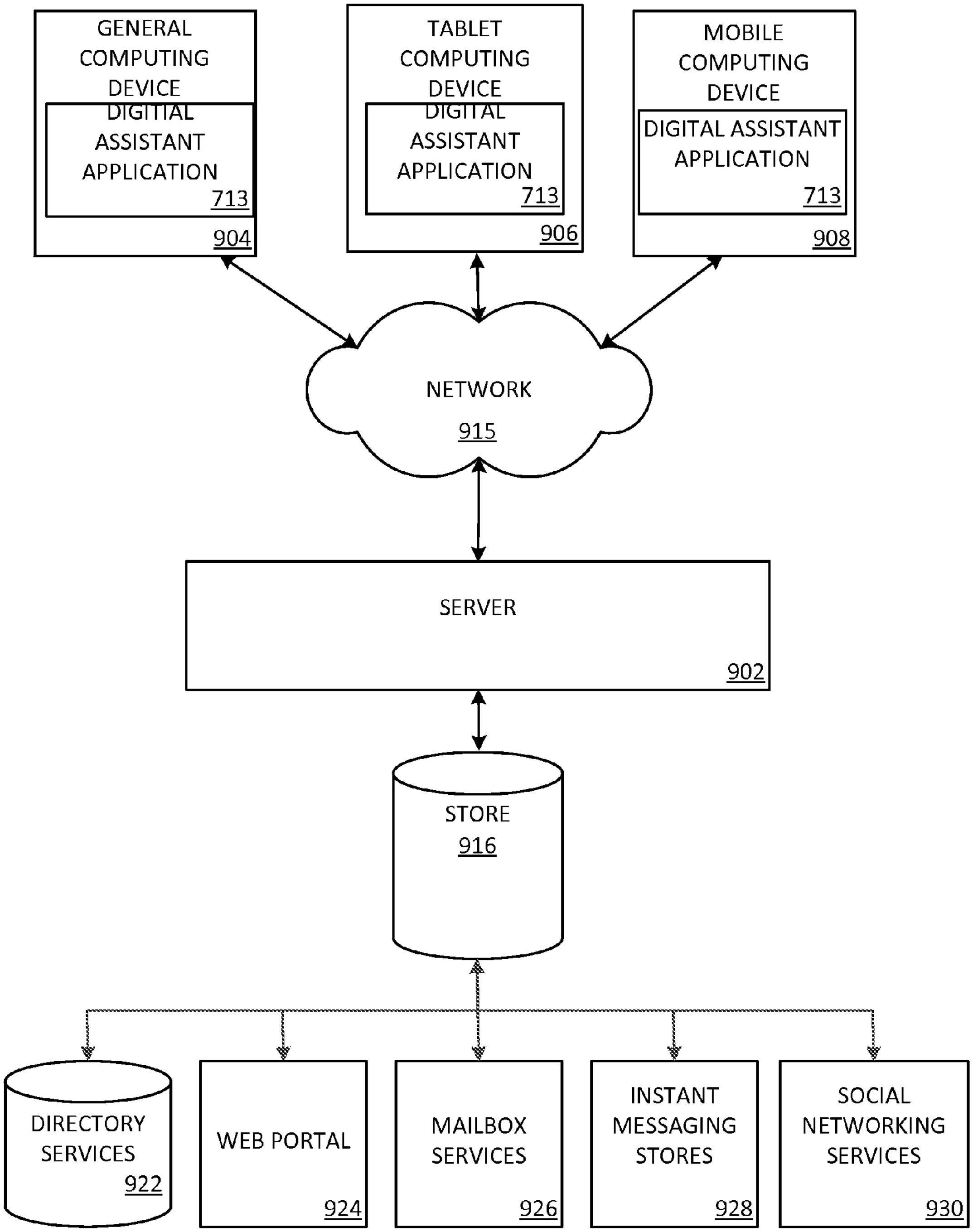

GENERAL COMPUTING DEVICE
DIGITAL ASSISTANT APPLICATION
713
904
TABLET COMPUTING DEVICE
DIGITAL ASSISTANT APPLICATION
713
906
MOBILE COMPUTING DEVICE
DIGITAL ASSISTANT APPLICATION
713
908
NETWORK
915
SERVER
902
STORE
916
DIRECTORY SERVICES
922
WEB PORTAL
924
MAILBOX SERVICES
926
INSTANT MESSAGING STORES
928
SOCIAL NETWORKING SERVICES
930

FIG. 9

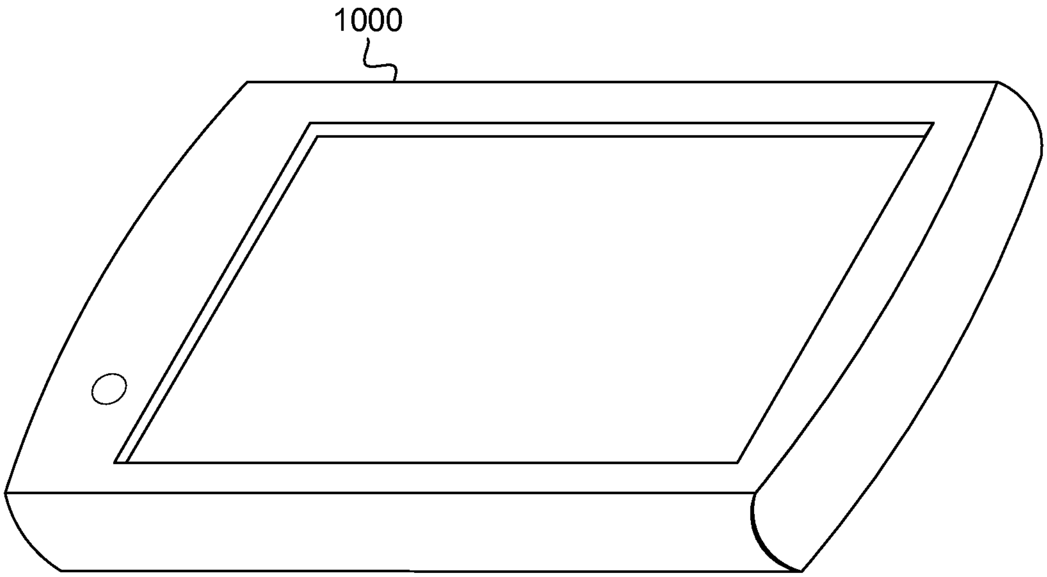


FIG. 10

CONTEXTUAL LANGUAGE UNDERSTANDING FOR MULTI-TURN LANGUAGE TASKS

BACKGROUND

Language understanding applications (e.g., digital assistant applications) require at least some contextual language understanding for interpreting spoken language input. The key to success for language understanding applications is having data. However, at early stages of language understanding system development, data is usually limited, in particular, for multi-turn dialogue scenarios. Due to the lack of data, current commercial language understanding systems have limited support for multi-turn scenarios and tend to rely on deterministic rules. Consequently, as commonly known to the community, rule-based systems do not provide accurate and reliable information in multi-turn scenarios.

It is with respect to these and other general considerations that embodiments have been made. Also, although relatively specific problems have been discussed, it should be understood that the embodiments should not be limited to solving the specific problems identified in the background.

SUMMARY

In summary, the disclosure generally relates to contextual language understanding. More particularly, the disclosure relates to methods and systems for contextual language understanding. For example, a natural language expression may be received at least by a single-turn model and a multi-turn model of a statistical system. The natural language expression may include at least one of words, terms, and phrases. A first prediction of at least one of a domain classification, intent classification, and slot type of the natural language expression may be determined using the single-turn model. A second prediction of at least one of a domain classification, intent classification, and slot type of the natural language expression may be determined using the multi-turn model. The first prediction and the second prediction may be combined to produce a final prediction relative to an intent of the natural language expression. An action may be performed based on the final prediction of the natural language expression.

This summary is provided to introduce a selection of concepts in a simplified form that are further described below in the Detailed Description. This summary is not intended to identify key features or essential features of the claimed subject matter, nor is it intended to be used to limit the scope of the claimed subject matter.

BRIEF DESCRIPTION OF THE DRAWINGS

Non-limiting and non-exhaustive examples are described with reference to the following Figures.

FIG. **1** illustrates an exemplary statistical system implemented at a client computing device for contextual language understanding, according to an example embodiment.

FIG. **2** illustrates an exemplary statistical system implemented at a server computing device for contextual language understanding, according to an example embodiment.

FIG. **3** illustrates an exemplary block diagram of a single-turn model and a multi-turn model for contextual language understanding, according to an example embodiment.

FIG. **4** illustrates an exemplary method for contextual language understanding, according to an example embodiment.

FIG. **5** illustrates an exemplary method for contextual language understanding in a multi-turn scenario, according to an example embodiment.

FIG. **6** illustrates an exemplary method for building a statistical model for contextual language understanding, according to an example embodiment.

FIG. **7** is a block diagram illustrating example physical components of a computing device with which embodiments of the disclosure may be practiced.

FIGS. **8**A and **8**B are simplified block diagrams of a mobile computing device with which embodiments of the present disclosure may be practiced.

FIG. **9** is a simplified block diagram of a distributed computing system in which embodiments of the present disclosure may be practiced.

FIG. **10** illustrates a tablet computing device for executing one or more embodiments of the present disclosure.

DETAILED DESCRIPTION

In the following detailed description, references are made to the accompanying drawings that form a part hereof, and in which are shown by way of illustrations specific embodiments or examples. These aspects may be combined, other aspects may be utilized, and structural changes may be made without departing from the spirit or scope of the present disclosure. Embodiments may be practiced as methods, systems or devices. Accordingly, embodiments may take the form of a hardware implementation, an entirely software implementation or an implementation combining software and hardware aspects. The following detailed description is therefore not to be taken in a limiting sense, and the scope of the present disclosure is defined by the appended claims and their equivalents.

The present disclosure generally relates to using contextual models for contextual language understanding in multi-turn scenarios. Existing techniques for contextual language understanding in multi-turn scenarios rely on deterministic rules and do not provide accurate and reliable information in multi-turn scenarios. For example, pre-determined rules may be written and implemented in current systems based on data (e.g., spoken language inputs) received by the system over time to determine how to respond to spoken language inputs. However, as new spoken language inputs (e.g., queries) are received and new rules are written to handle new queries, the system becomes more complex, and in some cases, may cause already existing rules to be broken. Accordingly, embodiments described herein include contextual models for supporting and/or handling complicated multi-turn scenarios in contextual language understanding. Contextual models may include a combination of statistical machine learning based techniques and rules. In some cases, statistical machine learning based techniques may include techniques such as artificial neural networks, Bayesian classifiers, and/or genetically derived algorithms. Such contextual models enable multi-turn contextual language understanding, and in particular, during early stages of language understanding system development when multi-turn data is limited and single-turn data is more abundant.

Accordingly, a flexible statistical modeling framework for multi-turn scenarios is provided without disrupting an existing single-turn model for language understanding in single-turn scenarios. In one case, single-turn may refer to a scenario where a spoken language input/natural language expression is processed in isolation during a session between a user and a statistical system. In one case, multi-turn may refer to a scenario where more than one spoken language input/natural language expression is processed during a session between a user and a statistical system. In one aspect, a session may include a conversation between a user and application (e.g., a digital assistant application) of a statistical system. The session may start when the application is activated and a user starts speaking and end when the application is de-activated.

With reference to FIG. **1**, one aspect of a statistical system **100** for contextual language understanding is illustrated. In aspects, the statistical system **100** may be implemented on a client computing device **104**. In a basic configuration, the client computing device **104** is a handheld computer having both input elements and output elements. The client computing device **104** may be any suitable computing device for implementing the statistical system **100** for contextual language understanding. For example, the client computing device **104** may be at least one of: a mobile telephone; a smart phone; a tablet; a phablet; a smart watch; a wearable computer; a personal computer; a desktop computer; a laptop computer; and etc. This list is exemplary only and should not be considered as limiting. Any suitable client computing device for implementing the statistical system **100** for contextual language understanding may be utilized.

In aspects, the statistical system **100** may include a single-turn training set **110**, a multi-turn training set **120**, a single-turn model **130**, a multi-turn model **140**, a combination model **150**, and a final model **160**. The various components may be implemented using hardware, software, or a combination of hardware and software. The statistical system **100** may be configured to process natural language expressions. In this regard, the statistical system **100** may facilitate contextual language understanding in multi-turn scenarios. For example, the statistical system **100** may use contextual information for facilitating contextual language understanding in multi-turn scenarios. In aspects, contextual information may include information extracted from each turn in a session. For example, the information extracted may include a domain prediction, an intent prediction, and slot types predicted (e.g., the results) from a previous turn (e.g., a previous natural language expression/request from the current session). In another case, the contextual information may include the response to a previous turn by the statistical system **100**. For example, the response to a previous turn may include how the statistical system **100** responded to the previous request from a user (e.g., what the statistical system output/said to the user), items located on a display of the client computing device **104**, text located on the display of the client computing device **104**, and the like. In another case, the contextual information may include client context. For example, client context may include a contact list on the client computing device **104**, a calendar on the client computing device **104**, GPS information (e.g., a location of the client computing device **104**), the current time (e.g., morning, night, in a meeting, in a workout, driving, etc.), and the like. In another case, the contextual information may include knowledge content. For example, knowledge content may include a knowledge database that maps features from the natural language expression with stored data. As an example, "John Howie" may be mapped to a restaurant in the knowledge database. In yet another case, the contextual information includes any combination of the above-discussed contextual information.

In one example, a natural language expression may include phrases, words, and/or terms in the form of a spoken language input (e.g., a user query and/or request). In another example, a natural language expression may include phrases, words, and/or terms in the form of a textual language input (e.g., a user query and/or request). In this regard, the natural language expression may be ambiguous and/or have missing information. For example, the natural language expression, "how about tomorrow," is ambiguous when analyzed in isolation. In one aspect, a multi-turn scenario is a scenario where more than one spoken language input/natural language expression is processed during a session between a user **102** and the statistical system **100**. In some cases, each natural language expression may be interpreted as a turn during a session. In some cases, a turn may include both the natural language expression and a response/action by the statistical system **100**. That is, a first turn may include both a natural language expression and a response/action by the statistical system **100**. In other aspects, a multi-turn scenario indicates that information from each turn of the session is utilized to make a prediction. In one aspect, a session may include a conversation between a user and application (e.g., a digital assistant application) of the statistical system **100**. The session may start when the application is activated and a user starts speaking and end when the application is de-activated.

In one aspect, the single-turn training set **110** may include data that has been developed over time (e.g., based on an analysis of a large collection of natural language expressions). In one aspect, the data may be user data based on receiving a large collection of natural language expressions from users over time. In other aspects, the data may be data from third party sources such as crowdsourcing and/or service logs of an existing rule-based system, for example. The single-turn training set **110** may be configured to train the single-turn model **130**. For example, the single-turn model **130** may be built by using data from the single-turn training set **110**. In this regard, the single-turn model **130** may include standard spoken language understanding models such as support vector machines, conditional random fields and/or convolutional non-recurrent neural networks for training purposes. One skilled in the art would recognize the basics of the standard language understanding models such as the support vector machines, conditional random fields, and convolutional neural networks. In this regard, the single-turn model **130** may be configured to perform domain and intent prediction (e.g., using the support vector machines) and slot tagging (e.g., using conditional random fields), which will be described in detail below relative to FIG. **3**. In one aspect, the single-turn model **130** is configured to determine predictions for single-turn scenarios. A single-turn scenario may be a scenario where a spoken language input/natural language expression is processed in isolation during a session between a user and the statistical system **100**. A single-turn scenario may indicate that only information from the currently processed natural language expression is utilized to make a prediction.

In one aspect, the multi-turn training set **120** may include data from third party sources such as crowdsourcing and/or service logs of an existing rule-based system, for example. In one case, after developing the multi-turn training set **120** over time (e.g., after an analysis of a large collection of natural language expressions), the multi-turn training set **120** may include user data based on receiving a large collection of natural language expressions from users over time. The multi-turn training set **120** may be configured to train the multi-turn model **140**. For example, the multi-turn model **140** may be built by using the multi-turn training set **120**. In this regard, the multi-turn model **140** may include standard spoken language understanding models such as support vector machines, conditional random fields and/or convolutional recurrent neural networks for training purposes. In this regard, the multi-turn model **140** may be configured to perform domain and intent prediction (e.g., using the support vector machines) and slot tagging (e.g., using conditional random fields), which will be described in detail below relative to FIG. **3**. In one aspect, the multi-turn model **140** is configured to determine predictions for multi-turn scenarios. For example, as discussed above, a multi-turn scenario may be a scenario where more than one spoken language input/natural language expression is processed during a session between a user **102** and the statistical system **100** and/or where information from each turn of the session is utilized to make a prediction.

As discussed above, both the single-turn model **130** and the multi-turn model **140** may determine predictions regarding domain and/or intent of a natural language expression. Both the single-turn model **130** and the multi-turn model **140** may calculate a score for the determined predictions. In one case, the score may be calculated as a dot product between a feature vector and its corresponding weight vector. The score may represent a level of confidence in the determined prediction. For example, the single-turn model **130** may calculate a score of 0.6 for a calendar domain prediction of a natural language expression and the multi-turn model **140** may calculate a score of 0.4 for a calendar domain prediction. That is, in this example, both the single-turn model **130** and the multi-turn model **140** may predict a domain of "calendar" and calculate a different score (e.g., a probability) that the domain is what is predicated, in this case, a calendar domain. In turn, the predictions determined by both the single-turn model **130** and the multi-turn model **140** may be sent to the combination model **150** for processing.

In one aspect, the combination model **150** may be configured to assign weights to each of the single-turn model **130** and the multi-turn model **140** and combine the predictions (e.g., the calculated scores) from the single-turn model **130** and the multi-turn model **140** utilizing the assigned weights to produce a final prediction. In one example, the combination model **150** may use linear interpolation to combine the predictions from the single-turn model **130** and the multi-turn model **140**. The weights may be determined and assigned to the single-turn model **130** and the multi-turn model **140** by measuring the accuracy on a development set of data with different weights. In this regard, the weight that generates the highest accuracy is chosen to be the operating point. In one case, the operating point indicates a level of confidence in the determined predictions of the single-turn model **130** and the multi-turn model **140**. Alternatively, the weight may be learned from a development set of data in an expectation maximization fashion such that the weight is treated as a hidden variable. In some cases, at least one model may be built to determine the weights for the single-turn model **130** and the multi-turn model **140**. The model may be built using the natural language expression and/or contextual information. One skilled in the art would recognize the basics of the linear interpolation technique utilized by the combination model **150** for assigning a weight to each of the single-turn model **130** and the multi-turn model **140** and, in turn, combining the predictions from the single-turn model **130** and the multi-turn model **140**.

In one aspect, the final prediction may be sent to the final model **160**. In this regard, the final model **160** may be configured to receive final predictions from the combination model **150** and perform an action based on the final prediction. For example, an action may include responding to the user's **102** natural language expression. The response may include an answer to the natural language expression based on the final prediction of the ultimate goal of the user **102**. For example, if the natural language expression includes a request for driving directions, the action/answer may include providing driving directions to the user **102** based on the final prediction. In another example, the response may include a question to the user **102**. For example, if the natural language query includes a request to create a meeting, the response may be "for what time." In other cases, the action may include performing a task. For example, the action may include creating a calendar event, sending a text message, setting a reminder, performing a query using a search engine (e.g., Bing, Google, Yahoo), and the like.

FIG. **2** illustrates a statistical system **200** for contextual language understanding according to one or more aspects. In aspects, the statistical system **200** may be implemented on a server computing device **204**. The server computing device **204** may provide data to and from the client computing device **104** through a network **205**. In one aspect, the network **205** is a distributed computing network, such as the internet. In aspects, that statistical system **200** may be implemented on more than one server computing device **204**, such as a plurality of server computing devices **204**. As shown in FIG. **2**, the statistical system **200** may include a single-turn training set **210**, a multi-turn training set **220**, a single-turn model **230**, a multi-turn model **240**, a combination model **250**, and a final model **260**. The statistical system **200** may be configured to process natural language expressions. In this regard, the statistical system **200** may facilitate contextual language understanding in multi-turn scenarios. The single-turn training set **210**, the multi-turn training set **220**, the single-turn model **230**, the multi-turn model **240**, the combination model **250**, and the final model **260** may be configured similar to the single-turn training set **110**, the multi-turn training set **120**, the single-turn model **130**, the multi-turn model **140**, the combination model **150**, and the final model **160** described above relative to FIG. **1**. In this regard, the statistical system **200** may include all the functionality described in the above aspects relative to the statistical system **100** of FIG. **1**.

As discussed above, the server computing device **204** may provide data to and from the client computing device **104** through the network **205**. The data may be communicated over any network suitable to transmit data. In some aspects, the network **205** is a computer network such as the internet. In this regard, the network **205** may include a Local Area Network (LAN), a Wide Area Network (WAN), the Internet, wireless and wired transmission mediums. In this regard, the natural language expression may be received at the client computing device **104** and transmitting over the network **205** for processing by the statistical system **200** at the server computing device **204**. It is appreciated that the statistical system **100/200** components (e.g., to the single-turn training set **110/210**, a multi-turn training set **120/220**, a single-turn model **130/230**, a multi-turn model **140/240**, a combination model **150/250**, and a final model **160/260**) may be located at the client computing device **104**, the server computing device **204**, and/or both the client computing device **104** and the server computing device **204** in any combination. For example, in one aspect, the client computing device **104** may include the single-turn training set **110** and the multi-turn training set **120** and the server computing device **204** may include the single-turn model **230**, the multi-turn model **240**, the combination model **250**, and the final model **260** in one configuration. This is exemplary only and should not be considered as limiting. Any suitable combination of statistical system components at the client computing device **104** and the server computing device **204** for contextual language understanding may be utilized.

FIG. **3** illustrates an exemplary block diagram of a single-turn model **130** and a multi-turn model **140** for contextual language understanding, according to one or more aspects of the present disclosure. As discussed above, both the single-turn model **130** and the multi-turn model **140** may be configured to perform domain and intent prediction (e.g., using the support vector machines) and slot tagging (e.g., using conditional random fields), for example. In this regard, as illustrated in FIG. **3**, the single-turn model **130** may include a domain prediction component **310**, an intent detection component **320**, and a slot tagging component **330**. As discussed above, the domain prediction component **310** may be any standard domain classification component used in language understanding such as support vector machines. In this regard, the domain prediction component **310** may be configured to classify the natural language expression into a supported domain of the single-turn model **130**. Domain may refer to generally known topics such as places, reminder, calendar, weather, communication, and the like.

In one aspect, when the single-turn model **130** receives the natural language expression, the domain prediction component **310** may evaluate the natural language expression in isolation (e.g., the domain prediction component **310** may utilize only the information provided in the natural language expression to classify the natural language expression into a supported domain of the single-turn model **130**). For example, in the natural language expression, “show me driving directions to Portland,” the domain prediction component **310** may extract the feature, “Portland” and classify the natural language expression into the supported domain, “Places,” of the single-turn model **130**. Additionally, the domain prediction component **310** may calculate a score indicative of the probability that the natural language expression, “show me driving directions to Portland,” should in fact be classified into the “Places” domain.

In one aspect, after the domain prediction component **310** classifies the natural language expression into a supported domain of the single-turn model **130**, the intent prediction component **320** may process the natural language expression. As discussed above, the intent prediction component **320** may be any standard intent prediction component used in language understanding such as support vector machines. In this regard, the intent prediction component **320** may be configured to determine intent of the user **102** via the natural language expression. As such, the intent prediction component **320** may process the natural language expression in isolation. For example, in the natural language expression, “show me driving directions to Portland,” the intent prediction component **320** may determine that the intent of the user **102** is an intent classification such as, for example “get_route.” Additionally, the intent prediction component **320** may calculate a score indicative of the probability that the intent of the user **102** via the natural language expression, “show me driving directions to Portland,” is in fact a “get_route” intent classification.

In one aspect, after the domain prediction component **310** classifies the natural language expression into a supported domain of the single-turn model **130** and the intent prediction component **320** determines a prediction for the intent of the user **102**, the slot tagging component **330** may process the natural language expression. As discussed above, the slot tagging component **330** may be any standard slot tagging component used in language understanding such as conditional random fields. In this regard, the slot tagging component **330** may be configured to perform slot detection on the natural language expression. In one case, slot detection may include filling slot types (e.g., slot types supported by the single-turn model **130**) with semantically loaded words from the natural language expression. In one aspect, the slot tagging component **330** may process the natural language expression in isolation. For example, in the natural language expression, “from 2 pm to 4 pm,” the slot tagging component **330** may fill the slot type “start_time” with “2 pm” and the slot type “end_type” with “4 pm.” Additionally, the slot tagging component **330** may calculate a score indicative of the probability that the slot type is in fact correct.

As discussed above, the components of the single-turn model **130** may process the natural language expression in isolation. In this regard, only the currently processed natural language expression is utilized to make predictions and calculate scores. This concept will be demonstrated in the examples described hereafter. In a first example, a first turn of a session may include the natural language expression, “how is the weather tomorrow.” In this example, the domain prediction component **310** may predict the domain classification as “Weather.” A second turn of the same session may include the natural language expression, “how about this weekend.” In a second session, the first turn may include the natural language expression, “what does my schedule look like today.” In this example, the domain prediction component **310** may predict the domain classification as “Calendar.” A second turn of the second session may include the natural language expression, “how about this weekend.” In the first example described above, the single-turn model **130** may not be able to accurately predict the domain classification of the natural language expression, “how about this weekend,” when evaluated in isolation.

In a second example, a first turn of a session may include the natural language expression, “show me driving directions to Portland.” In this example, the domain prediction component **310** may predict the domain classification as “Places,” and the intent prediction component **320** may predict the intent classification of the user as “get_route.” A second turn of the same session may include the natural language expression, “how about Vancouver.” In a second session, the first turn may include the natural language expression, “show me highly rated Chinese restaurants in Seattle.” In this example, the domain prediction component **310** may predict the domain classification as “Places,” and the intent prediction component **320** may predict the intent classification of the user **102** as “find_place.” A second turn of the second session may include the natural language expression, “how about Vancouver.” In the second example described above, the single-turn model **130** may not be able to accurately predict the intent classification of the user via the natural language expression, “how about Vancouver,” when evaluated in isolation.

In a third example, a first turn of a session may include the natural language expression, “create a meeting with Jason.” In this example, the domain prediction component **310** may predict the domain classification as “Calendar,” and the intent prediction component **320** may predict the intent classification of the user **102** as “create_meeting.” A second turn of the same session may include the natural language expression, “from 2 pm to 4 pm.” In a second session, the first turn may include the natural language expression, “postpone the meeting with Jason.” In this example, the domain prediction component **310** may predict the domain classification as “Calendar,” and the intent prediction component **320** may predict the intent classification of the user as “change_meeting.” A second turn of the second session may include the natural language expression, “from 2 pm to

4 pm." In the third example described above, the single-turn model **130** may not be able to accurately identify the slot types of the natural language expression, "from 2 pm to 4 pm," when evaluated in isolation.

As illustrated in the three examples described above, when natural language expressions are evaluated in isolation, errors may be made by any of the domain prediction component **310**, the intent prediction component **320**, and the slot tagging component **330**. Further, errors made earlier in the language understanding processing (e.g., errors made by the domain prediction component **310**) may often lead to incorrect language understanding responses/actions. In this regard, the statistical system **100**/**200** of the present disclosure evaluates the currently processed natural language expression (e.g., utilizing the single-turn model **130**) and both the currently processed natural language expression and contextual information from the currently processed natural language expression (e.g., utilizing the multi-turn model **140**) to reduce the overall error of language understanding systems.

As illustrated in FIG. **3**, the multi-turn model **140** may include a domain prediction component **340**, an intent detection component **350**, and a slot tagging component **360**. The various components may be implemented using hardware, software, or a combination of hardware and software. In some cases, the domain prediction component **350** may include any standard domain classification component used in language understanding such as support vector machines. In other cases, the domain prediction component **340** may include a recurrent convolutional neural network. In this regard, the domain prediction component **340** may be configured to classify the natural language expression into a supported domain of the multi-turn model **140**.

In one aspect, when the multi-turn model **140** receives the natural language expression, the domain prediction component **340** may evaluate the natural language expression using information from the currently processed natural language expression and contextual information from the currently processed natural language expression. As discussed above, contextual information may include information extracted from each turn in a session. For example, the information extracted may include the domain prediction, the intent prediction, and slot types predicted (e.g., the results) from a previous turn (e.g., a previous natural language expression/request from the current session). In another case, the contextual information may include the response to a previous turn by the statistical system **100**. For example, the response to a previous turn may include how the statistical system **100** responded to the previous request from a user (e.g., what the statistical system output/said to the user), items located on a display of the client computing device **104**, text located on the display of the client computing device **104**, and the like. In another case, the contextual information may include client context. For example, client context may include a contact list on the client computing device **104**, a calendar on the client computing device **104**, GPS information (e.g., a location of the client computing device **104**), the current time (e.g., morning, night, in a meeting, in a workout, driving, etc.), and the like. In another case, the contextual information may include knowledge content. For example, knowledge content may include a knowledge database that maps features from the natural language expression with stored data. As an example, "John Howie" may be mapped to a restaurant in the knowledge database. In yet another case, the contextual information includes any combination of the above-discussed contextual information.

Using the same example described above relative to the single-turn model **130**, a first turn of a session may include the natural language expression, "how is the weather tomorrow." In this example, the domain prediction component **340** may predict the domain classification as "Weather." A second turn of the same session may include the natural language expression, "how about this weekend." In this example, the domain prediction component **340** may predict the domain classification as "Weather." For example, the domain prediction component **340** may evaluate the first turn, "how is the weather tomorrow" and the first turn predicted domain classification "Weather," to predict the domain classification of the second turn, "how about this weekend." In this regard, based on the first turn of the same session being a request about the weather and having a "Weather" domain classification, the multi-turn model **340** may predict that the expression "how about this weekend" is related to the first expression "how is the weather tomorrow," and therefore classify the domain as "Weather."

In a second session, the first turn may include the natural language expression, "what does my schedule look like today." In this example, the domain prediction component **310** may predict the domain classification as "Calendar." A second turn of the second session may include the natural language expression, "how about this weekend." In this example, the domain prediction component **340** may predict the domain classification as "Calendar." For example, the domain prediction component **340** may evaluate the first turn, "what does my schedule look like today" and the first turn predicted domain classification "Calendar," to predict the domain classification of the second turn, "how about this weekend." In this regard, based on the first turn of the same session being a request about a schedule and having a "Calendar" domain classification, the multi-turn model **340** may predict that the expression "how about this weekend" is related to the first expression "what does my schedule look like today," and therefore classify the domain as "Calendar."

As illustrated, the multi-turn model **140** uses contextual information from the first turn in the first session to predict that the second turn in the first session, "how about this weekend," is the domain classification "Weather." Additionally, the multi-turn model **140** uses contextual information from the first turn in the second session to predict that the second turn in the second session, "how about this weekend," is the domain classification "Calendar." In this regard, the same natural language expression, "how about this weekend," may be interpreted/predicted differently in different domains by using contextual information extracted from a previous turn in a session.

In aspects, the domain prediction component **340** may calculate a score indicative of the probability that the natural language expression, "how is the weather tomorrow," should in fact be classified into the "Weather" domain and the natural language expression, "how about this weekend," in the first session should in fact be classified into the "Weather" domain. In other aspects, the domain prediction component **340** may calculate a score indicative of the probability that the natural language expression, "what does my schedule look like today," should in fact be classified into the "Calendar" domain and the natural language expression, "how about this weekend," in the second session should in fact be classified into the "Calendar" domain.

In one aspect, after the domain prediction component **340** classifies the natural language expression and/or a plurality of natural language expressions into a supported domain of the multi-turn model **140**, the intent prediction component **350** may process the natural language expression. In one aspect, the intent prediction component **350** may be any standard intent prediction component used in language understanding such as support vector machines. In other aspects, the intent prediction component **350** may include a recurrent convolutional neural network. In this regard, the intent prediction component **350** may be configured to determine intent of the user **102** via the natural language expression. As such, the intent prediction component **350** may process the natural language expression using contextual information.

Using the same example described above relative to the second example of the single-turn model **130**, a first turn of a session may include the natural language expression, "show me driving directions to Portland." In this example, the domain prediction component **340** may predict the domain classification as "Places," and the intent prediction component **350** may predict the intent classification of the user as "get_route." A second turn of the same session may include the natural language expression, "how about Vancouver." In this example, the domain prediction component **340** may predict the domain classification as "Places," and the intent prediction component **350** may predict the intent classification of the user as "get_route." In a second session, the first turn may include the natural language expression, "show me highly rated Chinese restaurants in Seattle." In this example, the domain prediction component **340** may predict the domain classification as "Places," and the intent prediction component **350** may predict the intent classification of the user as "find_place." A second turn of the second session may include the natural language expression, "how about Vancouver." In this example, the domain prediction component **340** may predict the domain classification as "Places," and the intent prediction component **350** may predict the intent classification of the user as "find_place."

As illustrated, the multi-turn model **140** uses contextual information from the first turn in the first session to predict the intent classification of the user **102** from the second turn in the first session, "how about Vancouver," as "get_route." Additionally, the multi-turn model **140** uses contextual information from the first turn in the second session to predict the intent classification of the user **102** from the second turn in the second session, "how about Vancouver," as "find_place." In this regard, the intent for the same natural language expression, "how about Vancouver," may be interpreted/predicted differently within the same domain (e.g., in both sessions the domain was predicted to be "Places") by using contextual information extracted from a previous turn in a session.

Additionally, the intent prediction component **350** may calculate a score indicative of the probability that the intent classification of the user via the natural language expression, "show me driving directions to Portland," is in fact "get_route" and the intent classification of the user via the natural language expression, "how about Vancouver," in the first session is in fact "get_route." In other aspects, the intent prediction component **350** may calculate a score indicative of the probability that the intent classification of the user **102** via the natural language expression, "show me highly rated Chinese restaurants in Seattle," is in fact "find_place" and the intent classification of the user **102** via the natural language expression, "how about Vancouver," in the second session is in fact "find_place."

In one aspect, after the domain prediction component **340** classifies the natural language expression into a supported domain of the multi-turn model **140** and the intent prediction component **350** determines a prediction for the intent of the user **102**, the slot tagging component **360** may process the natural language expression. In one aspect, the slot tagging component **360** may be any standard slot tagging component used in language understanding such as conditional random fields. In other aspects, the slot tagging component **360** may include a recurrent convolutional neural network. In this regard, the slot tagging component **360** may be configured to perform slot detection on the natural language expression. In one case, slot detection may include filling slot types (e.g., slot types supported by the multi-turn model **140**) with semantically loaded words (e.g., semantic words) from the natural language expression. In one aspect, the slot tagging component **360** may process the natural language expression using contextual information, which is described below.

Using the same example described above relative to the third example of the single-turn model **130**, a first turn of a session may include the natural language expression, "create a meeting with Jason." In this example, the domain prediction component **340** may predict the domain classification as "Calendar," and the intent prediction component **350** may predict the intent classification of the user **102** as "create_meeting." A second turn of the same session may include the natural language expression, "from 2 pm to 4 pm." In this example, the domain prediction component **340** may predict the domain classification as "Calendar," and the slot tagging component **360** may predict the slot types as "start_ time=2 pm" and "end_time=4 pm." In a second session, the first turn may include the natural language expression, "postpone the meeting with Jason." In this example, the domain prediction component **340** may predict the domain classification as "Calendar," and the intent prediction component **350** may predict the intent classification of the user **102** as "change_meeting." A second turn of the second session may include the natural language expression, "from 2 pm to 4 pm." In this example, the domain prediction component **340** may predict the domain classification as "Calendar," and the slot tagging component **360** may predict the slot types as "original_start_time=2 pm" and "start_time=4 pm."

As illustrated, the multi-turn model **140** uses contextual information from the first turn in the first session to predict the slot type for the second turn in the first session "from 2 pm to 4 pm" as "start_time=2 pm" and "end_time=4 pm." Additionally, the multi-turn model **140** uses contextual information from the first turn in the second session to predict the slot type for second turn in the second session "from 2 pm to 4 pm" as "original_start_time=2 pm" and "start_time=4 pm." In this regard, the slot types for the same natural language expression, "from 2 pm to 4 pm," may be interpreted/predicted differently within the same domain (e.g., in both sessions the domain was predicted to be "Calendar") by using contextual information extracted from a previous turn in a session. Additionally, the slot tagging component **360** may calculate a score indicative of the probability that the slot types for the second turn in the first session "from 2 pm to 4 pm" is in fact "start_time=2 pm" and "end_time=4 pm." Additionally, the slot tagging component **360** may calculate a score indicative of the probability that the slot types for the second turn in the second session "from 2 pm to 4 pm" is in fact "original_start_t ime=2 pm" and "start_time=4 pm."

In other aspects, as discussed above, the contextual information may include the response/action by the statistical system **100** after processing the natural language expression in addition to information from prior turns of a session. In one example, the first turn of a session may include the natural language expression "send a text message." The response/action by the statistical system **100** after processing the natural language expression (e.g., as described above) may be, "and say what." In this regard, the second turn of the session may include a natural language expression such as, "what will the weather be like tomorrow." The statistical system **100** may use the system response "and say what" in addition to information from the first turn in the session (e.g., predicting the slot type to be "text_message" from the "send a text message" expression) to determine that the ultimate goal and/or intent of the user **102** is to send a text message asking what the weather will be like rather than incorrectly predicting the natural language expression "what will the weather be like tomorrow," to be a weather request for the statistical system **100**.

As discussed above, the components of the multi-turn model **140** may process the natural language expression using contextual information. In this regard, the multi-turn training set **120** may be developed over time and the multi-turn model **140** may be trained over time. For example, as the multi-turn model **140** processes sessions, the contextual information derived and/or learned from each session may be aggregated into the multi-turn training set **120** and ultimately the multi-turn model **140**. In this regard, as discussed above, the multi-turn training set **120** may initially have a smaller data set than the single-turn training set **110** but may develop a larger data set over time. In this regard, in some aspects, the weight assigned to the single-turn model **130** may be greater than the weight assigned to the multi-turn model **140**. In other aspects, the weight assigned to the single-turn model **130** may be 1 and the weight assigned to the multi-turn model **140** may be 0. As such, in this case, the statistical system **100** may process the natural language expression using only the single-turn model **130**. In some cases, as more data is provided and developed for training the multi-turn model **140**, the multi-turn model **140** may be assigned a greater weight than the single-turn model **130**. In some cases, the statistical system **100** may process the natural language expression using only the multi-turn model **140**.

In yet other cases, the statistical system **100** may include a single model for processing the natural language expression. As such, the single model may include the functionality of at least both the single-turn model **130** and the multi-turn model **140**, as described herein. For example, a single model may process the natural language expression and determine predictions for both single-turn scenarios and multi-turn scenarios. In this regard, the single turn model may process a natural language expression both in isolation and using contextual information. As such, the single model may determine a first prediction and a second prediction regarding the intent of a user. In other cases, the single model may determine only a single prediction regarding the intent of a user. In some cases, the single model may include the functionality of the combination model **150** and the final model **160**. It is appreciated that any combination of the components and their corresponding functionality described herein may be implemented in a single model or in multiple models to determine the intent and/or ultimate goal of a user of a digital assistant application, for example.

FIG. **4** illustrates a method for contextual language understanding according to one or more embodiments of the present disclosure. Method **400** begins at operation **402** where a natural language expression is received. For example, the natural language expression may be received by both a single-turn model and a multi-turn model of the statistical system for processing to determine the intent and/or ultimate goal of a user of a digital assistant application, for example. In one example, a natural language expression may include phrases, words, and/or terms in the form of a spoken language input (e.g., a user query and/or request). In this regard, the natural language expression may be ambiguous and/or have missing information. For example, the natural language expression, "how about tomorrow," is ambiguous when analyzed in isolation.

When a natural language expression is received at the statistical system, flow proceeds to operation **404** where a first prediction is determined using the single-turn model. For example, the single-turn model may include standard spoken language understanding models such as support vector machines, conditional random fields and/or convolutional non-recurrent neural networks for training purposes. In this regard, the single-turn model may be configured to perform domain and intent prediction (e.g., using the support vector machines) and slot tagging (e.g., using conditional random fields). In one aspect, the single-turn model is configured to determine predictions for single-turn scenarios. A single-turn scenario may be a scenario where a spoken language input/natural language expression is processed in isolation during a session between a user and the statistical system. A single-turn scenario may provide an indication that only information from the currently processed natural language expression is utilized to make a prediction.

When a natural language expression is received at the statistical system, flow proceeds to operation **406** where a second prediction is determined using the multi-turn model. In this regard, the same natural language expression may be received at both the single-turn model and the multi-turn model for processing. In one example, the multi-turn model may include standard spoken language understanding models such as support vector machines, conditional random fields and/or convolutional recurrent neural networks for training purposes. In this regard, the multi-turn model may be configured to perform domain and intent prediction (e.g., using the support vector machines) and slot tagging (e.g., using conditional random fields). In one aspect, the multi-turn model is configured to determine predictions for multi-turn scenarios. For example, a multi-turn scenario may be a scenario where more than one spoken language input/natural language expression is processed during a session between a user and the statistical system and/or where information from each turn of the session is utilized to make a prediction.

At operation **408**, the first prediction from the single-turn model and the second prediction from the multi-turn model may be combined to produce a final prediction. For example, after the single-turn model and the multi-turn model determine predictions for the natural language expression, the prediction from each model may be sent to a combination model. In one aspect, the combination model may be configured to assign weights to each of the single-turn model and the multi-turn model and combine the predictions (e.g., the calculated scores) from the single-turn model and the multi-turn model utilizing the assigned weights to produce a final prediction. In one example, the combination model may use linear interpolation to combine the predictions from the single-turn model and the multi-turn model. The weights may be determined and assigned to the single-turn model and the multi-turn model by measuring the accuracy on a development set of data with different weights. In this regard, the weight that generates the highest accuracy is chosen to be the operating point. Alternatively, the weight may be learned from a development set of data in an expectation maximization fashion such that the weight is treated as a hidden variable.

When the final prediction is determined, flow proceeds to operation **410** where an action based on the final prediction is performed. In one aspect, the final prediction may be sent to a final model. In this regard, the final model may be configured to receive final predictions from the combination model and perform an action based on the final prediction. For example, an action may include responding to the natural language expression of a user. The response may include an answer to the natural language expression based on the final prediction of the ultimate goal of the user. For example, if the natural language expression includes a request for driving directions, the action/answer may include providing driving directions to the user based on the final prediction. In another example, the action/answer may include initiating an application (e.g., a map application) and providing commands/input to the application. In yet another example, the response may include a question to the user. For example, if the natural language query includes a request to create a meeting, the response may be "for what time." In other cases, the action may include performing a task. For example, the action may include creating a calendar event, sending a text message, setting a reminder, performing a query using a search engine (e.g., Bing), and the like.

FIG. **5** illustrates a method for contextual language understanding in a multi-turn scenario, according to one or more embodiments of the present disclosure. Method **500** begins at operation **502** where a natural language expression is received. For example, the natural language expression may be received by both a single-turn model and a multi-turn model of the statistical system for processing to determine the intent and/or ultimate goal of a user of a digital assistant application, for example. In one example, a natural language expression may include phrases, words, and/or terms in the form of a spoken and/or textual language input (e.g., a user query and/or request). In this regard, the natural language expression may be ambiguous and/or have missing information. For example, the natural language expression, "how about tomorrow," is ambiguous when analyzed in isolation.

When a natural language expression is received at the statistical system, flow proceeds to operation **504** where a first prediction is determined using the single-turn model. For example, the single-turn model may include standard spoken language understanding models such as support vector machines, conditional random fields and/or convolutional non-recurrent neural networks for training purposes. In this regard, the single-turn model may be configured to perform domain and intent prediction (e.g., using the support vector machines) and slot tagging (e.g., using conditional random fields). In one aspect, the single-turn model is configured to determine predictions for single-turn scenarios. A single-turn scenario may be a scenario where a spoken language input/natural language expression is processed in isolation during a session. A single-turn scenario may indicate that only information from the currently processed natural language expression is utilized to make a prediction.

When a natural language expression is received at the statistical system, flow proceeds to operation **506** where a second prediction is determined using the multi-turn model. In this regard, the same natural language expression may be received at both the single-turn model and the multi-turn model for processing. In one example, the multi-turn model may include standard spoken or textual language understanding models such as support vector machines, conditional random fields and/or convolutional recurrent neural networks for training purposes. In this regard, the multi-turn model may be configured to perform domain and intent prediction (e.g., using the support vector machines) and slot tagging (e.g., using conditional random fields). In one aspect, the multi-turn model is configured to determine predictions for multi-turn scenarios. For example, a multi-turn scenario may be a scenario where more than one spoken or textual language input/natural language expression is processed during a session between a user and the statistical system and/or where information from each turn of the session is utilized to make a prediction.

At operation **508**, the first prediction from the single-turn model and the second prediction from the multi-turn model may be combined to produce a final prediction. For example, after the single-turn model and the multi-turn model determine predictions for the natural language expression, the prediction from each model may be sent to a combination model. In one aspect, the combination model may be configured to assign weights to each of the single-turn model and the multi-turn model and combine the predictions (e.g., the calculated scores) from the single-turn model and the multi-turn model utilizing the assigned weights to produce a final prediction. In one example, the combination model may use linear interpolation to combine the predictions from the single-turn model and the multi-turn model. The weights may be determined and assigned to the single-turn model and the multi-turn model by measuring the accuracy on a development set of data with different weights. In this regard, the weight that generates the highest accuracy is chosen to be the operating point. Alternatively, the weight may be learned from a development set of data in an expectation maximization fashion such that the weight is treated as a hidden variable.

When the final prediction is determined, flow proceeds to operation **510** where an action based on the final prediction is performed. In one aspect, the final prediction may be sent to a final model. In this regard, the final model may be configured to receive final predictions from the combination model and perform an action based on the final prediction. For example, an action may include responding to the natural language expression of a user. The response may include an answer to the natural language expression based on the final prediction of the ultimate goal of the user. For example, if the natural language expression includes a request for driving directions, the action/answer may include providing driving directions to the user based on the final prediction. In another example, the response may include a question to the user. For example, if the natural language query includes a request to create a meeting, the response may be "for what time." In other cases, the action may include performing a task. For example, the action may include creating a calendar event, sending a text message, setting a reminder, performing a query using a search engine (e.g., Bing, Google, Yahoo), and the like.

At decision operation **512**, it is determined whether the session between a user and the statistical system has ended. If the session has not ended, flow proceeds to operation **514** where an additional natural language expression is received at the single-turn model and the multi-turn model. The process operations **504**, **506**, **508**, **510**, **512**, and **514** may continue until the session between the user and the statistical system has ended. As such, a plurality of natural language expressions may be processed by the statistical system. In this regard, when an additional natural language expression (e.g., a second turn of the session) is received by the single-turn model and the multi-turn model, the single-turn model may process the additional natural language expression is isolation and the multi-turn model may process the additional natural language expression using contextual information. The predictions and/or calculated scores from each model are then weighted and combined to produce a final prediction. If the session has ended, flow proceeds to operation **516** where an application (e.g., a digital assistant application) of the statistical system is deactivated. For example, the session may be ended.

FIG. **6** illustrates an exemplary method for building a statistical model for contextual language understanding, according to one or more aspects of the present disclosure. Method **600** begins at operation **602** where a first natural language expression is received. For example, the first natural language expression may be received by both a single-turn model and a multi-turn model of the statistical system for processing to determine the intent and/or ultimate goal of a user of a digital assistant application, for example. In one example, a natural language expression may include phrases, words, and/or terms in the form of a spoken or textual language input (e.g., a user query and/or request). In this regard, the natural language expression may be ambiguous and/or have missing information. For example, the natural language expression, "how about tomorrow," is ambiguous when analyzed in isolation.

When the first natural language expression is received, flow proceeds to operation **604** where a first action is performed based on a determined first prediction and a determined second prediction. In one example, an action may include responding to the natural language expression of a user. The response may include an answer to the natural language expression based on a final prediction of the ultimate goal of the user. For example, if the natural language expression includes a request for driving directions, the action/answer may include providing driving directions to the user based on the final prediction. In another example, the response may include a question to the user. For example, if the natural language query includes a request to create a meeting, the response may be "for what time." In other cases, the action may include performing a task. For example, the action may include creating a calendar event, sending a text message, setting a reminder, performing a query using a search engine (e.g., Bing, Google, Yahoo), and the like.

After a first action has been performed, flow proceeds to operation **606** where a second natural language expression is received. For example, the second natural language expression may be received by both a single-turn model and a multi-turn model of the statistical system for processing to determine the intent and/or ultimate goal of a user of a digital assistant application, for example. When the second natural language is received, flow proceeds to operation **608** where the first natural language expression, the first prediction, the second prediction, the first action, and the second natural language expression are evaluated to generate contextual information. For example, domain, intent, and slot type information from the first natural language expression and first and second predictions may be evaluated. In another example, the type of response/action to the first natural language expression based on the first and second predictions may be evaluated. In yet another example, the second natural language expression and the determined predictions for the second natural language expression by the single-turn model and the multi-turn model may be evaluated. In some aspects, any combination of the information described herein may be evaluated to generate contextual information.

When the contextual information is generated based on evaluating the information described herein, flow proceeds to operation **610** where the contextual information is aggregated into the multi-turn model. For example, the multi-turn model may have an initial data set provided by third party sources such as crowdsourcing and/or service logs of an existing rule-based system, for example. As the statistical system processes and evaluates natural language expressions, the statistical system aggregates the data and the generated contextual information from each session into the multi-turn model. In this regard, the multi-turn model may be built over time by processing natural language expressions and generating contextual information that can be built upon and used for processing of future natural language expressions. In turn, the multi-turn model may include a larger data set over time to facilitate a better accuracy rate of determining the intent/goal of a user by the statistical system.

When the contextual information is aggregated, flow proceeds to operation **612** where a second action is performed based on the evaluating operation **608**. For example, a second action may include responding to the natural language expression of a user. The response may include an answer to the natural language expression based on the final prediction of the ultimate goal of the user. For example, if the natural language expression includes a request for driving directions, the action/answer may include providing driving directions to the user based on the final prediction. In another example, the response may include a question to the user. For example, if the natural language query includes a request to create a meeting, the response may be "for what time." In other cases, the action may include performing a task. For example, the action may include creating a calendar event, sending a text message, setting a reminder, performing a query using a search engine (e.g., Bing), and the like.

As described herein, the statistical system of the present disclosure may reduce the overall error rate of language understanding systems. One example of a reduced error rate from using the statistical system described herein is illustrated in the table 1.1 below.

TABLE 1.1

Domain	Error rate of single-turn model	Error rate of combination model
Places	13.05	9.72
Reminder	8.18	7.16
Calendar	14.07	7.65
Weather	9.68	3.34
Communication	7.64	5.87

Table 1.1 shows the error rate reduction for processing 2+ turns of a session. As shown in Table 1.1 a significant improvement in error rate is observed by utilizing the statistical system (e.g., the combination model processing predictions from the single-turn model and the multi-turn model) of the present disclosure. An even more significant improvement is observed for 2+ turn sessions that are ambiguous without contextual information. By utilizing the statistical system of the present disclosure, an improvement in error rate (e.g., an improvement in the accuracy of predicting the intent of a user) may result in a better user experience of the statistical system and/or an application associated with the statistical system (e.g., a digital assistant application). Additionally, a reduction in the error rate may reduce the number of clarifying requests and/or responses the statistical system and/or application has to provide. As such, fewer computations may be required by the client and/or server computing device.

FIGS. **7-10** and the associated descriptions provide a discussion of a variety of operating environments in which aspects of the disclosure may be practiced. However, the devices and systems illustrated and discussed with respect to FIGS. **7-10** are for purposes of example and illustration and are not limiting of a vast number of computing device configurations that may be utilized for practicing embodiments of the disclosure, described herein

FIG. **7** is a block diagram illustrating physical components (e.g., hardware) of a computing device **700** with which aspects of the disclosure may be practiced. The computing device components described below may have computer executable instructions for a digital assistant application **713**, e.g., of a client and/or computer, executable instructions for contextual language understanding module **711**, e.g., of a client, that can be executed to employ the methods **400** through **600** disclosed herein. In a basic configuration, the computing device **700** may include at least one processing unit **702** and a system memory **704**. Depending on the configuration and type of computing device, the system memory **704** may comprise, but is not limited to, volatile storage (e.g., random access memory), non-volatile storage (e.g., read-only memory), flash memory, or any combination of such memories. The system memory **704** may include an operating system **705** and one or more program modules **706** suitable for running software applications **720** such as contextual language understanding applications in regards to FIGS. **1-3** and, in particular, digital assistant application **713** or contextual language understanding module **711**. The operating system **705**, for example, may be suitable for controlling the operation of the computing device **700**. Furthermore, embodiments of the disclosure may be practiced in conjunction with a graphics library, other operating systems, or any other application program and is not limited to any particular application or system. This basic configuration is illustrated in FIG. **7** by those components within a dashed line **708**. The computing device **700** may have additional features or functionality. For example, the computing device **700** may also include additional data storage devices (removable and/or non-removable) such as, for example, magnetic disks, optical disks, or tape. Such additional storage is illustrated in FIG. **7** by a removable storage device **709** and a non-removable storage device **710**.

As stated above, a number of program modules and data files may be stored in the system memory **704**. While executing on the processing unit **702**, the program modules **706** (e.g., contextual language understanding module **711** or digital assistant application **713**) may perform processes including, but not limited to, the aspects, as described herein. Other program modules that may be used in accordance with aspects of the present disclosure, and in particular for contextual language understanding, may include single-turn models, multi-turn models, combination models, final models, and/or computer-aided application programs, etc.

Furthermore, embodiments of the disclosure may be practiced in an electrical circuit comprising discrete electronic elements, packaged or integrated electronic chips containing logic gates, a circuit utilizing a microprocessor, or on a single chip containing electronic elements or microprocessors. For example, embodiments of the disclosure may be practiced via a system-on-a-chip (SOC) where each or many of the components illustrated in FIG. **7** may be integrated onto a single integrated circuit. Such an SOC device may include one or more processing units, graphics units, communications units, system virtualization units and various application functionality all of which are integrated (or "burned") onto the chip substrate as a single integrated circuit. When operating via an SOC, the functionality, described herein, with respect to the capability of client to switch protocols may be operated via application-specific logic integrated with other components of the computing device **700** on the single integrated circuit (chip). Embodiments of the disclosure may also be practiced using other technologies capable of performing logical operations such as, for example, AND, OR, and NOT, including but not limited to mechanical, optical, fluidic, and quantum technologies. In addition, embodiments of the disclosure may be practiced within a general purpose computer or in any other circuits or systems.

The computing device **700** may also have one or more input device(s) **712** such as a keyboard, a mouse, a pen, a sound or voice input device, a touch or swipe input device, etc. The output device(s) **714** such as a display, speakers, a printer, etc. may also be included. The aforementioned devices are examples and others may be used. The computing device **700** may include one or more communication connections **716** allowing communications with other computing devices **718**. Examples of suitable communication connections **716** include, but are not limited to, RF transmitter, receiver, and/or transceiver circuitry; universal serial bus (USB), parallel, and/or serial ports.

The term computer readable media as used herein may include computer storage media. Computer storage media may include volatile and nonvolatile, removable and non-removable media implemented in any method or technology for storage of information, such as computer readable instructions, data structures, or program modules. The system memory **704**, the removable storage device **709**, and the non-removable storage device **710** are all computer storage media examples (e.g., memory storage). Computer storage media may include RAM, ROM, electrically erasable read-only memory (EEPROM), flash memory or other memory technology, CD-ROM, digital versatile disks (DVD) or other optical storage, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, or any other article of manufacture which can be used to store information and which can be accessed by the computing device **700**. Any such computer storage media may be part of the computing device **700**. Computer storage media does not include a carrier wave or other propagated or modulated data signal.

Communication media may be embodied by computer readable instructions, data structures, program modules, or other data in a modulated data signal, such as a carrier wave or other transport mechanism, and includes any information delivery media. The term "modulated data signal" may describe a signal that has one or more characteristics set or changed in such a manner as to encode information in the signal. By way of example, and not limitation, communication media may include wired media such as a wired network or direct-wired connection, and wireless media such as acoustic, radio frequency (RF), infrared, and other wireless media.

FIGS. **8**A and **8**B illustrate a mobile computing device **800**, for example, a mobile telephone, a smart phone, wearable computer (such as a smart watch), a tablet computer, a laptop computer, and the like, with which embodiments of the disclosure may be practiced. In some aspects, the client may be a mobile computing device. With reference to FIG. **8**A, one aspect of a mobile computing device **800** for implementing the aspects is illustrated. In a basic configuration, the mobile computing device **800** is a handheld computer having both input elements and output elements.

The mobile computing device **800** typically includes a display **805** and one or more input buttons **810** that allow the user to enter information into the mobile computing device **800**. The display **805** of the mobile computing device **800** may also function as an input device (e.g., a touch screen display). If included, an optional side input element **815** allows further user input. The side input element **815** may be a rotary switch, a button, or any other type of manual input element. In alternative aspects, mobile computing device **800** may incorporate more or less input elements. For example, the display **805** may not be a touch screen in some embodiments. In yet another alternative embodiment, the mobile computing device **800** is a portable phone system, such as a cellular phone. The mobile computing device **800** may also include an optional keypad **835**. Optional keypad **835** may be a physical keypad or a "soft" keypad generated on the touch screen display. In various embodiments, the output elements include the display **805** for showing a graphical user interface (GUI), a visual indicator **820** (e.g., a light emitting diode), and/or an audio transducer **825** (e.g., a speaker). In some aspects, the mobile computing device **800** incorporates a vibration transducer for providing the user with tactile feedback. In yet another aspect, the mobile computing device **800** incorporates input and/or output ports, such as an audio input (e.g., a microphone jack), an audio output (e.g., a headphone jack), and a video output (e.g., a HDMI port) for sending signals to or receiving signals from an external device.

FIG. **8**B is a block diagram illustrating the architecture of one aspect of a mobile computing device. That is, the mobile computing device **800** can incorporate a system (e.g., an architecture) **802** to implement some aspects. In one embodiment, the system **802** is implemented as a "smart phone" capable of running one or more applications (e.g., browser, e-mail, calendaring, contact managers, messaging clients, games, and media clients/players). In some aspects, the system **802** is integrated as a computing device, such as an integrated personal digital assistant (PDA) and wireless phone.

One or more application programs **866** may be loaded into the memory **862** and run on or in association with the operating system **864**. Examples of the application programs include phone dialer programs, e-mail programs, personal information management (PIM) programs, word processing programs, spreadsheet programs, Internet browser programs, messaging programs, and so forth. The system **802** also includes a non-volatile storage area **868** within the memory **862**. The non-volatile storage area **868** may be used to store persistent information that should not be lost if the system **802** is powered down. The application programs **866** may use and store information in the non-volatile storage area **868**, such as e-mail or other messages used by an e-mail application, and the like. A synchronization application (not shown) also resides on the system **802** and is programmed to interact with a corresponding synchronization application resident on a host computer to keep the information stored in the non-volatile storage area **868** synchronized with corresponding information stored at the host computer. As should be appreciated, other applications may be loaded into the memory **862** and run on the mobile computing device **800**, including the instructions to create a calendar event as described herein (e.g., and/or contextual language understanding module **711**).

The system **802** has a power supply **870**, which may be implemented as one or more batteries. The power supply **870** might further include an external power source, such as an AC adapter or a powered docking cradle that supplements or recharges the batteries.

The system **802** may also include a radio **872** that performs the function of transmitting and receiving radio frequency communications. The radio **872** facilitates wireless connectivity between the system **802** and the "outside world," via a communications carrier or service provider. Transmissions to and from the radio **872** are conducted under control of the operating system **864**. In other words, communications received by the radio **872** may be disseminated to the application programs **866** via the operating system **864**, and vice versa.

The visual indicator **820** may be used to provide visual notifications, and/or an audio interface **874** may be used for producing audible notifications via the audio transducer **825**. In the illustrated embodiment, the visual indicator **820** is a light emitting diode (LED) and the audio transducer **825** is a speaker. These devices may be directly coupled to the power supply **870** so that when activated, they remain on for a duration dictated by the notification mechanism even though the processor **860** and other components might shut down for conserving battery power. The LED may be programmed to remain on indefinitely until the user takes action to indicate the powered-on status of the device. The audio interface **874** is used to provide audible signals to and receive audible signals from the user. For example, in addition to being coupled to the audio transducer **825**, the audio interface **874** may also be coupled to a microphone to receive audible input, such as to facilitate a telephone conversation. In accordance with embodiments of the present disclosure, the microphone may also serve as an audio sensor to facilitate control of notifications, as will be described below. The system **802** may further include a video interface **876** that enables an operation of an on-board camera **830** to record still images, video stream, and the like.

A mobile computing device **800** implementing the system **802** may have additional features or functionality. For example, the mobile computing device **800** may also include additional data storage devices (removable and/or non-removable) such as, magnetic disks, optical disks, or tape. Such additional storage is illustrated in FIG. **8**B by the non-volatile storage area **868**.

Data/information generated or captured by the mobile computing device **800** and stored via the system **802** may be stored locally on the mobile computing device **800**, as described above, or the data may be stored on any number of storage media that may be accessed by the device via the radio **872** or via a wired connection between the mobile computing device **800** and a separate computing device associated with the mobile computing device **800**, for example, a server computer in a distributed computing network, such as the Internet. As should be appreciated such data/information may be accessed via the mobile computing device **800** via the radio **872** or via a distributed computing network. Similarly, such data/information may be readily transferred between computing devices for storage and use according to well-known data/information transfer and storage means, including electronic mail and collaborative data/information sharing systems.

FIG. **9** illustrates one aspect of the architecture of a system for processing data received at a computing system from a remote source, such as a computing device **904**, tablet **906**, or mobile device **908**, as described above. Content displayed at server device **902** may be stored in different communication channels or other storage types. For example, various documents may be stored using a directory service **922**, a web portal **924**, a mailbox service **926**, an instant messaging store **928**, or a social networking site **930**. The digital assistant application **713** may be employed by a client who communicates with server **902**. The server **902** may provide data to and from a client computing device such as a personal computer **904**, a tablet computing device **906** and/or a mobile computing device **908** (e.g., a smart phone) through a network **915**. By way of example, the computer system described above with respect to FIGS. **1-3** may be embodied in a personal computer **904**, a tablet computing device **906** and/or a mobile computing device **908** (e.g., a smart phone). Any of these embodiments of the computing devices may obtain content from the store **916**, in addition to receiving graphical data useable to be either pre-processed at a graphic-originating system, or post-processed at a receiving computing system.

FIG. **10** illustrates an exemplary tablet computing device **1000** that may execute one or more aspects disclosed herein. In addition, the aspects and functionalities described herein may operate over distributed systems (e.g., cloud-based computing systems), where application functionality, memory, data storage and retrieval and various processing functions may be operated remotely from each other over a distributed computing network, such as the Internet or an intranet. User interfaces and information of various types may be displayed via on-board computing device displays or via remote display units associated with one or more computing devices. For example user interfaces and information of various types may be displayed and interacted with on a wall surface onto which user interfaces and information of various types are projected. Interaction with the multitude of computing systems with which embodiments of the invention may be practiced include, keystroke entry, touch screen entry, voice or other audio entry, gesture entry where an associated computing device is equipped with detection (e.g., camera) functionality for capturing and interpreting user gestures for controlling the functionality of the computing device, and the like.

Among other examples, the present disclosure presents systems for contextual language understanding comprising: receiving at least a first natural language expression and a second natural language expression, wherein the first natural language expression and the second natural language expression include at least one of words, terms, and phrases; determining a first prediction of at least one of a domain classification, intent classification, and slot type of the first natural language expression; determining a second prediction of at least one of a domain classification, intent classification, and slot type of the second natural language expression using at least one of the first natural language expression and contextual information; and performing an action based on the second prediction of the second natural language expression. In further examples, the first prediction and the second prediction are determined using a single model. In further examples, the first prediction is determined using a single-turn model, and wherein the second prediction is determined using a multi-turn model. In further examples, the system further comprises combining the first prediction and the second prediction to produce a final prediction relative to an intent of the second natural language expression. In further examples, the first natural language expression and the second natural language expression are at least one of a spoken language input and a textual input. In further examples, determining the first prediction comprises evaluating the first natural language expression is isolation. In further examples, evaluating the first natural language expression in isolation comprises at least: classifying the first natural language expression into a supported domain of the single model; classifying the first natural language expression into a supported intent of the single model; and extracting at least one semantic word from the first natural language expression and filling at least one supported slot type of the turn model with the at least one semantic word. In further examples, evaluating the second natural language expression using contextual information comprises at least: classifying the second natural language expression into a supported domain of the single model using contextual information; classifying the second natural language expression into a supported intent of the single model using contextual information; and extracting at least one semantic word from the second natural language expression and filling at least one supported slot type of the multi-turn model with the at least one semantic word using contextual information. In further examples, the contextual information includes at least one of information extracted from the first received natural language expression, a response to the first received natural language expression, client context, and knowledge content. In further examples, determining a first prediction comprises calculating a first score indicative of a probability of the first prediction being correct. In further examples, determining a second prediction comprises calculating a second score indicative of a probability of the second prediction being correct. In further examples, combining the first prediction and the second prediction to produce a final prediction comprises: assigning a first weight to the single-turn model; assigning a second weight to the multi-turn model; and combining the first score and the second score utilizing the first assigned weight and the second assigned weight.

Further aspects disclosed herein provide an exemplary system comprising: a statistical model for receiving at least a first natural language expression and a second natural language expression during a conversational session, wherein the at least first and second natural language expressions include at least one of words, terms, and phrases; a single-turn model for determining a first prediction of at least one of a domain classification, intent classification, and slot type of each of the at least first and second natural language expressions; a multi-turn model for determining a second prediction of at least one of a domain classification, intent classification, and slot type of each of the at least first and second natural language expressions; a combination model for combining the first prediction and the second prediction of each of the at least first and second natural language expressions to produce a final prediction relative to an intent of at least the second natural language expression; and a final model for performing an action based on the final prediction of at least the second natural language expression. In further examples, performing an action based on the final prediction comprises responding to the second natural language expression. In further examples, responding to the second natural language expression includes an answer to the second natural language expression based on the final prediction of at least the second natural language expression. In further examples, responding to the second natural language expression includes at least one of asking a question and performing a task. In further examples, determining a first prediction for the at least first and second natural language expressions comprises evaluating the first and second natural language expressions in isolation. In further examples, determining a second prediction for the at least first and second natural language expressions comprises evaluating the first and second natural language expressions using contextual information. In further examples, evaluating the second natural language expression using contextual information comprises evaluating a combination of the first natural language expression, the first prediction for the at least first and second natural language expressions, and the second prediction for the first natural language expression.

Additional aspects disclosed herein provide exemplary systems and methods for building a statistical model for contextual language understanding, comprising: receiving a first natural language expression, wherein the first natural language expression includes at least one of words, terms, and phrases; performing a first action based on a first prediction determined by a single-turn model and a second prediction determined by a multi-turn model; receiving a second natural language expression, wherein the second natural language expression includes at least one of words, terms, and phrases; evaluating at least the first natural language expression, the first action, the first prediction, the second prediction, and the second natural language expression to generate contextual information; aggregating the contextual information into the multi-turn model; and performing a second action based on evaluating at least the first natural language expression, the first action, the first prediction, the second prediction, and the second natural language expression.

Aspects of the present disclosure, for example, are described above with reference to block diagrams and/or operational illustrations of methods, systems, and computer program products according to aspects of the disclosure. The functions/acts noted in the blocks may occur out of the order as shown in any flowchart. For example, two blocks shown in succession may in fact be executed substantially concurrently or the blocks may sometimes be executed in the reverse order, depending upon the functionality/acts involved.

The description and illustration of one or more aspects provided in this application are not intended to limit or restrict the scope of the disclosure as claimed in any way. The aspects, examples, and details provided in this application are considered sufficient to convey possession and enable others to make and use the best mode of claimed disclosure. The claimed disclosure should not be construed as being limited to any aspect, example, or detail provided in this application. Regardless of whether shown and described in combination or separately, the various features (both structural and methodological) are intended to be selectively included or omitted to produce an embodiment with a particular set of features. Having been provided with the description and illustration of the present application, one skilled in the art may envision variations, modifications, and alternate aspects falling within the spirit of the broader aspects of the general inventive concept embodied in this application that do not depart from the broader scope of the claimed disclosure.

What is claimed is:

1. A system comprising:

at least one processor; and

a memory encoding computer executable instructions which, when executed by at least one processor, perform a method for contextual language understanding, comprising:

receiving at least a first natural language expression and a second natural language expression, wherein each of the first natural language expression and the second natural language expression include at least one of words, terms, and phrases;

determining, using a single-turn model, a first weighted prediction of at least one of a domain classification, intent classification, and slot type of the first natural language expression;

determining, using a multi-turn model, a second weighted prediction of at least one of a domain classification, intent classification, and slot type of the second natural language expression using at least one of the first natural language expression and contextual information; and

performing an action based on the second weighted prediction of the second natural language expression.

2. The system of claim **1**, further comprising combining the first weighted prediction and the second weighted prediction to produce a final prediction relative to an intent of the second natural language expression.

3. The system of claim **1**, wherein the first natural language expression and the second natural language expression are at least one of a spoken language input and a textual input.

4. The system of claim **1**, wherein determining the first weighted prediction comprises evaluating the first natural language expression in isolation.

5. The system of claim **4**, wherein evaluating the first natural language expression in isolation comprises at least:

classifying the first natural language expression into a supported domain of the single-turn model;

classifying the first natural language expression into a supported intent of the single-turn model; and

extracting at least one semantic word from the first natural language expression and filling at least one supported slot type of the single-turn model with the at least one semantic word.

6. The system of claim **1**, wherein evaluating the second natural language expression using contextual information comprises at least:

classifying the second natural language expression into a supported domain of the single-turn model using contextual information;

classifying the second natural language expression into a supported intent of the single-turn model using contextual information; and

extracting at least one semantic word from the second natural language expression and filling at least one supported slot type of the multi-turn model with the at least one semantic word using contextual information.

7. The system of claim **1**, wherein the contextual information includes at least one of information extracted from the first received natural language expression, a response to the first received natural language expression, client context, and knowledge content.

8. The system of claim **1**, wherein determining the first weighted prediction comprises calculating a first score indicative of a probability of the first weighted prediction being correct.

9. The system of claim **8**, wherein determining the second weighted prediction comprises calculating a second score indicative of a probability of the second weighted prediction being correct.

10. The system of claim **9**, wherein combining the first weighted prediction and the second weighted prediction to produce a final prediction comprises combining the first score and the second score.

11. A system comprising:

a statistical model for receiving at least a first natural language expression and a second natural language expression during a conversational session, wherein each of the first natural language expression and the second natural language expression include at least one of words, terms, and phrases;

a single-turn model for determining a first prediction of at least one of a domain classification, intent classification, and slot type of each of the first natural language expression and the second natural language expression;

a multi-turn model for determining a second prediction of at least one of a domain classification, intent classification, and slot type of each of the first natural language expression and the second natural language expression;

a combination model for combining the first prediction and the second prediction of each of the first natural language expression and the second natural language expression to produce a final prediction relative to an intent of at least the second natural language expression; and

a final model for performing an action based on the final prediction of at least the second natural language expression.

12. The system of claim **11**, wherein performing an action based on the final prediction comprises responding to the second natural language expression.

13. The system of claim **12**, wherein responding to the second natural language expression includes an answer to the second natural language expression based on the final prediction of at least the second natural language expression.

14. The system of claim **12**, wherein responding to the second natural language expression includes at least one of asking a question and performing a task.

15. The system of claim **11**, wherein determining a first prediction for the first natural language expression and the second natural language expression comprises evaluating the first natural language expression and the second natural language expression in isolation.

16. The system of claim **11**, wherein determining a second prediction for the first natural language expression and the second natural language expression comprises evaluating the first natural language expression and the second natural language expression using contextual information.

17. The system of claim **16**, wherein evaluating the second natural language expression using contextual information comprises evaluating a combination of the first natural language expression, the first prediction for the at least first and second natural language expressions, client context, and knowledge content.

18. One or more computer-readable storage media, having computer-executable instructions which, when executed by at least one processor, perform a method for building a statistical model for contextual language understanding, comprising:

receiving a first natural language expression, wherein the first natural language expression includes at least one of words, terms, and phrases;

performing a first action based on a first prediction determined by a single-turn model and a second prediction determined by a multi-turn model;

receiving a second natural language expression, wherein the second natural language expression includes at least one of words, terms, and phrases;

evaluating at least the first natural language expression, the first action, the first prediction, the second prediction, and the second natural language expression to generate contextual information;

aggregating the contextual information into the multi-turn model; and

performing a second action based on evaluating at least the first natural language expression, the first action, the first prediction, the second prediction, and the second natural language expression.

19. The computer-readable storage media of claim **18**, wherein the second action is a response to at least one of the first natural language expression and the second natural language expression.

20. The computer-readable storage media of claim **18**, wherein the first natural language expression and the second natural language expression are at least one of a spoken language input and a textual input.

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