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(54) **SLOT FILLING IN SPOKEN LANGUAGE UNDERSTANDING WITH JOINT POINTER AND ATTENTION**

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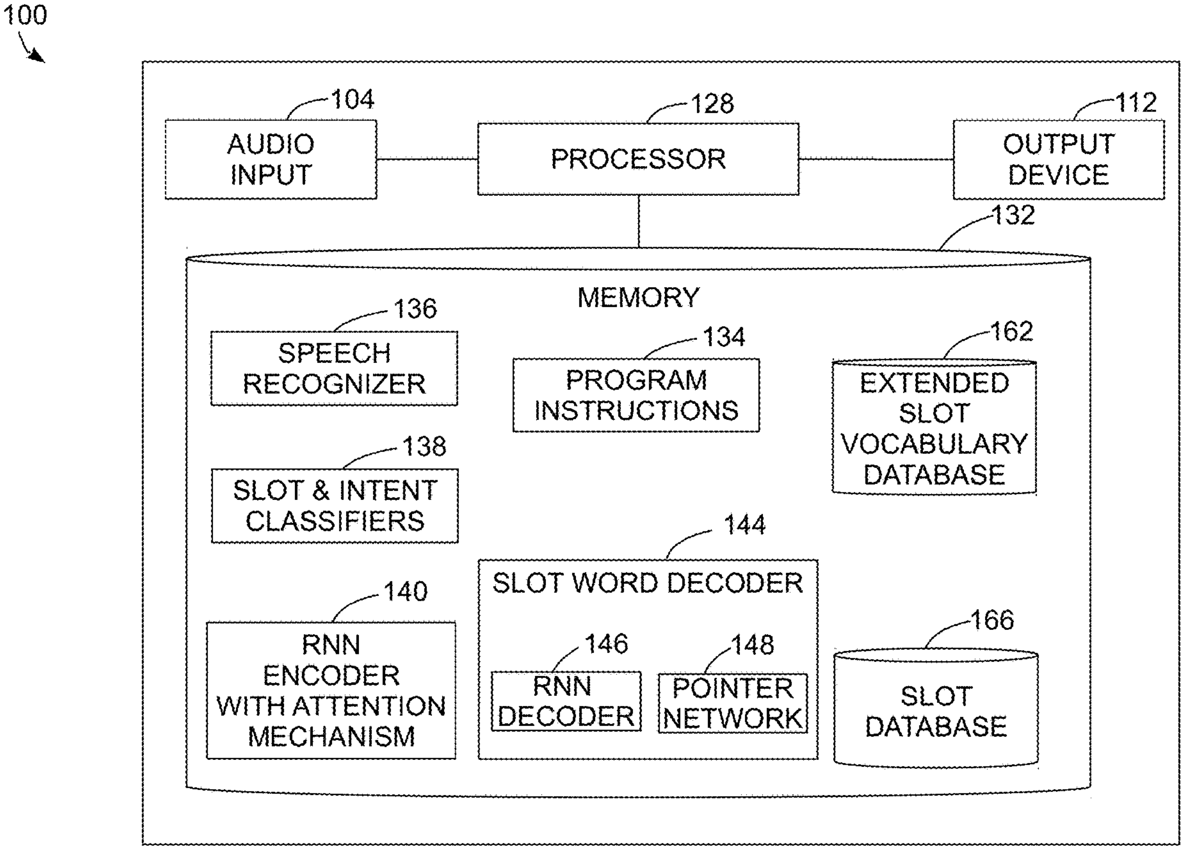
(57) **ABSTRACT**

A method for slot-filling in an automated spoken language understanding (SLU) system includes receiving words in a text phrase, generating an encoded output and attention weights using a recurrent neural network (RNN) encoder with an attention mechanism, generating a first and second probability distributions of slot words in an extended slot vocabulary database using an RNN decoder and a pointer network, respectively, for a time step, generating a combined probability distribution based on the first and second probability distributions, and identifying a slot word corresponding to one word in the extended slot vocabulary database having a highest probability value in the combined probability distribution for the time step.



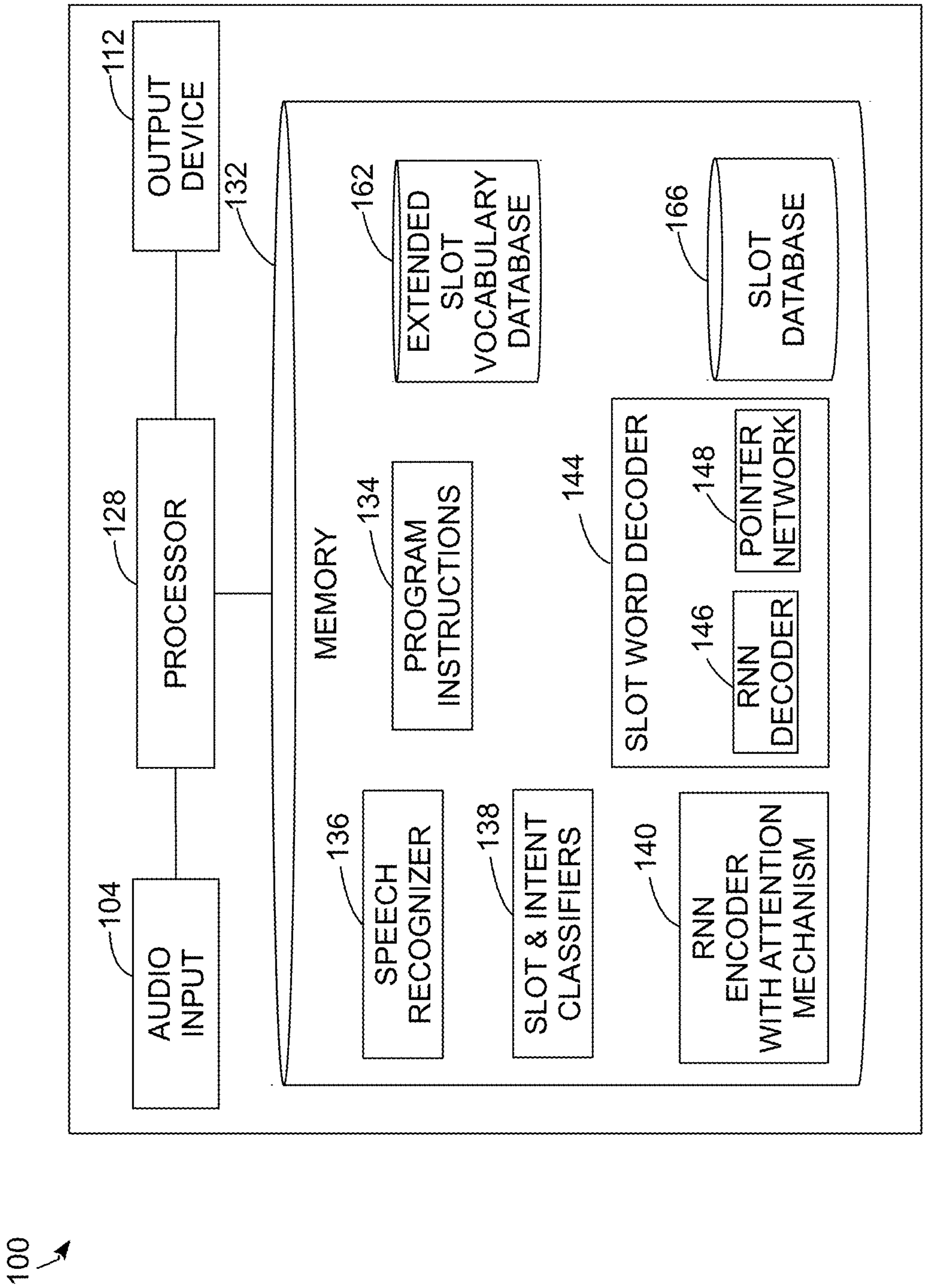

100
AUDIO INPUT
104
PROCESSOR
128
OUTPUT DEVICE
112
132
MEMORY
SPEECH RECOGNIZER
136
SLOT & INTENT CLASSIFIERS
138
RNN ENCODER WITH ATTENTION MECHANISM
140
PROGRAM INSTRUCTIONS
134
SLOT WORD DECODER
144
RNN DECODER
146
POINTER NETWORK
148
EXTENDED SLOT VOCABULARY DATABASE
162
SLOT DATABASE
166

FIG. 1

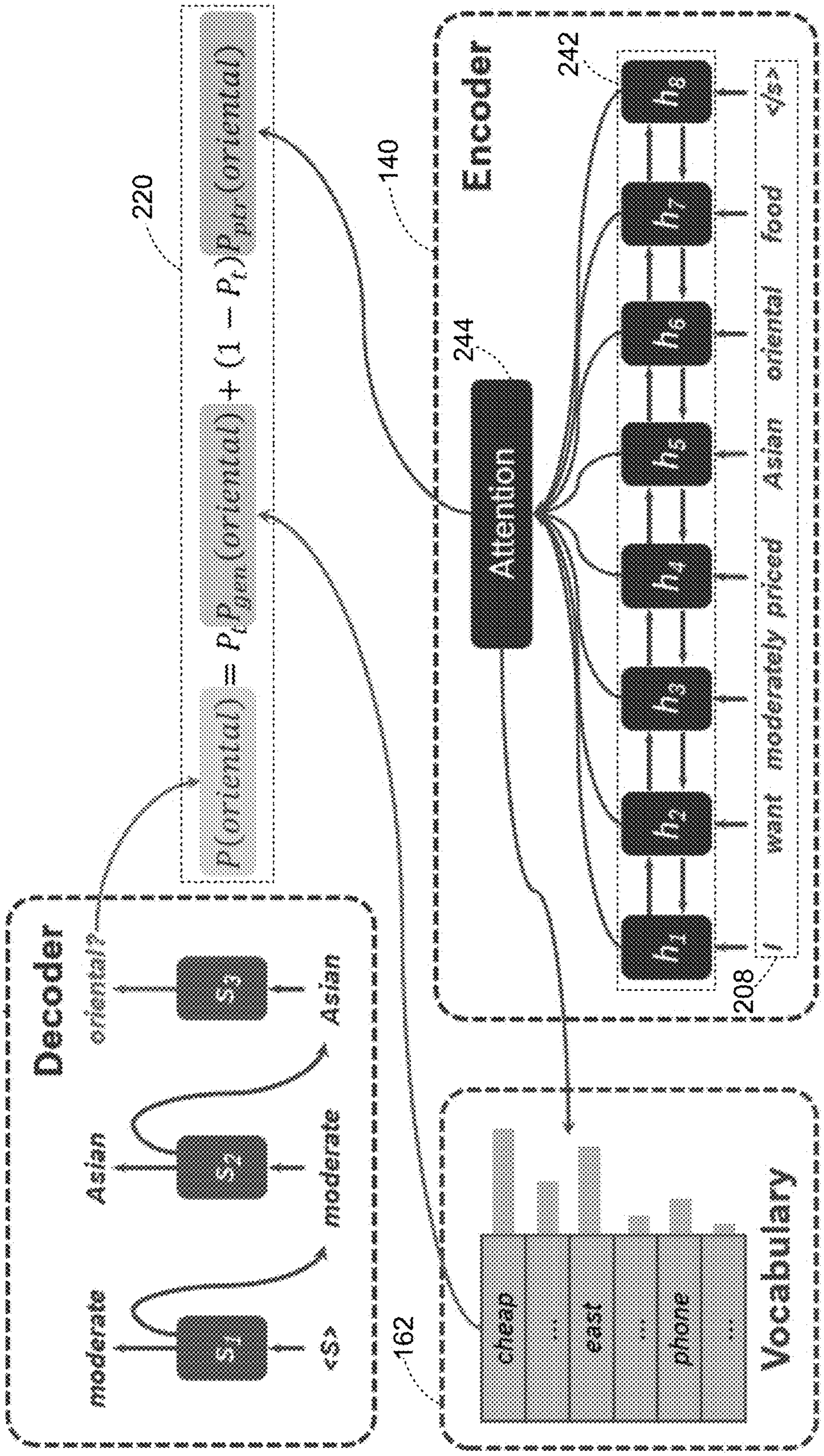

144
Decoder
moderate
Asian
oriental?
s_1
s_2
s_3
<S>
moderate
Asian
220
$P(oriental) = P_t P_{gen}(oriental) + (1 - P_t) P_{ptr}(oriental)$
140
Encoder
244
Attention
242
h_1
h_2
h_3
h_4
h_5
h_6
h_7
h_8
I
want
moderately
priced
Asian
oriental
food
</s>
208
162
Vocabulary
cheap
...
east
...
phone
...

FIG. 2

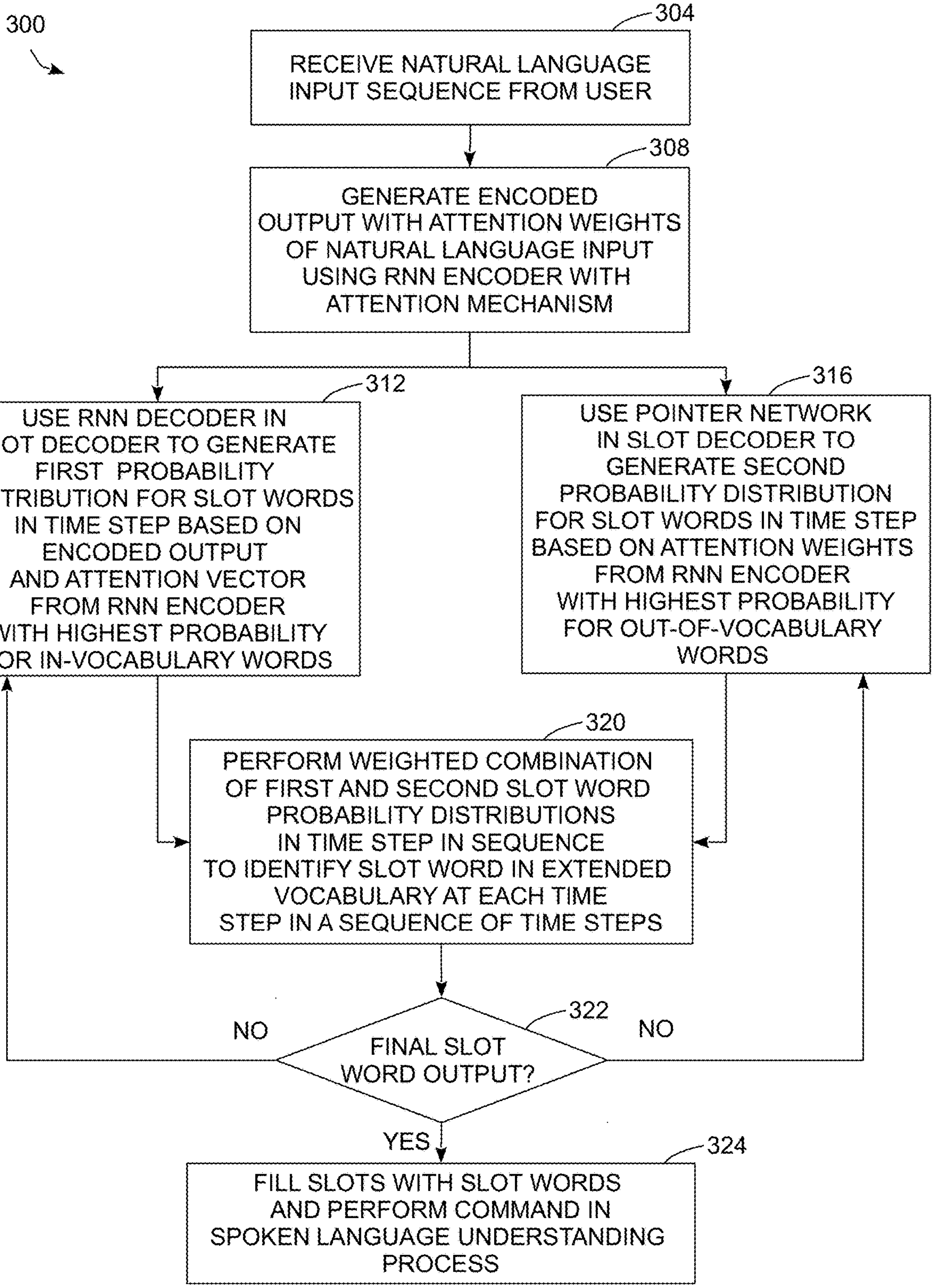

300
304
RECEIVE NATURAL LANGUAGE INPUT SEQUENCE FROM USER
308
GENERATE ENCODED OUTPUT WITH ATTENTION WEIGHTS OF NATURAL LANGUAGE INPUT USING RNN ENCODER WITH ATTENTION MECHANISM
312
USE RNN DECODER IN SLOT DECODER TO GENERATE FIRST PROBABILITY DISTRIBUTION FOR SLOT WORDS IN TIME STEP BASED ON ENCODED OUTPUT AND ATTENTION VECTOR FROM RNN ENCODER WITH HIGHEST PROBABILITY FOR IN-VOCABULARY WORDS
316
USE POINTER NETWORK IN SLOT DECODER TO GENERATE SECOND PROBABILITY DISTRIBUTION FOR SLOT WORDS IN TIME STEP BASED ON ATTENTION WEIGHTS FROM RNN ENCODER WITH HIGHEST PROBABILITY FOR OUT-OF-VOCABULARY WORDS
320
PERFORM WEIGHTED COMBINATION OF FIRST AND SECOND SLOT WORD PROBABILITY DISTRIBUTIONS IN TIME STEP IN SEQUENCE TO IDENTIFY SLOT WORD IN EXTENDED VOCABULARY AT EACH TIME STEP IN A SEQUENCE OF TIME STEPS
322
FINAL SLOT WORD OUTPUT?
NO
NO
YES
324
FILL SLOTS WITH SLOT WORDS AND PERFORM COMMAND IN SPOKEN LANGUAGE UNDERSTANDING PROCESS

FIG. 3

SLOT FILLING IN SPOKEN LANGUAGE UNDERSTANDING WITH JOINT POINTER AND ATTENTION

CLAIM OF PRIORITY

[0001] This application claims the benefit of U.S. Provisional Application No. 62/678,406, which is entitled "Slot Filling in Spoken Language Understanding with Joint Pointer and Attention," and was filed on May 31, 2018, the entire contents of which are expressly incorporated herein by reference.

FIELD

[0002] This disclosure relates generally to the field of automated spoken language understanding and, more specifically, to systems and methods for using joint pointers and attention mechanisms in slot-filling in spoken language understanding system.

BACKGROUND

[0003] Unless otherwise indicated herein, the materials described in this section are not prior art to the claims in this application and are not admitted to the prior art by inclusion in this section.

[0004] Spoken Language Understanding (SLU) systems process language expressed by human speech into a semantic representation understandable by the machines. SLU is the key component of all conversational AI systems. The general tasks of SLU involve intent determination and slot filling from an utterance. The intent determination task can be considered as a semantic utterance classification problem, while the slot filling task can be tackled as a sequence labeling problem of contiguous words. Previous approaches to solving these two related tasks were typically proposed as two separated systems such as Support Vector Machines (SVMs) for intent determination and Conditional Random Fields (CRFs) for slot filling.

[0005] Recent advances in neural networks, especially recurrent neural networks (RNNs), allow joint training model of both intent determination and slot filling. This framework showed advantages over the previous state-of-the-art techniques, and has gained much attention in research community. The success of joint models is contributed by the attention mechanism and the encoder-decoder model. The attention mechanism allows optimized selection of input sequence for decoding for both content and location information.

[0006] In general, an SLU system is deployed as a downstream task of spoken dialogue systems where its inputs are outputs from the front-end Automatic Speech Recognition (ASR) engine. One of the tasks of an SLU system is to assign words that the ASR recognizes in the input speech of a user to slots in a slot-filling operation. As used herein, the term "slot" refers to a machine-understandable data field that is filled with one or more input words in natural language input in the SLU system. For example, one set of spoken language input to a home automation system requests activation of a heater. The input includes multiple slots including a command slot, a slot that indicates the type of device to be activated (e.g. a heater), and another slot includes a setting for the device (e.g. set the temperature to 40° C.). Once assigned to a slot, an automated system uses the input words for each slot to perform additional operations, such as operating components in a home automation system using the example provided above.

[0007] The aforementioned example uses a set of enumerable slots in which there are a well-defined number of valid inputs for each slot in a given system (e.g. well-defined sets of valid commands, automation devices, and valid numeric temperature values), but not all SLU systems can operate with slots that have a well-defined set of enumerable values. Some prior-art SLU systems use machine learning classifiers that are trained using annotated training data to recognize the slots for different words in spoken language input. However, these prior-art SLU systems can have difficulty in performing the slot-filling operation when slots can be filled with words that are not well represented in or entirely absent from the original training data. First, some types of slots may have a large or even unlimited number of possible values, so the classifiers may suffer from the data sparsity problem because the available set of training data is often limited and even large sets of training data cannot classify a large portion of the correct inputs for some types of slots. Another problem is produced by out-of-vocabulary words caused by unknown slot values (e.g., restaurant and street names), which are not practical to predefine in the training data and that are very common in real-world spoken dialogue applications. Consequently, improvements to methods and systems that increase the accuracy of spoken language understanding systems would be beneficial.

SUMMARY

[0008] To address the challenges with the prior-art SLU systems, the embodiments described herein present a neural generative model for slot filling using unaligned dialogue data, specifically for slot value prediction as it has more challenges caused by OOV word. The model uses Seq2Seq learning to predict a sequence of slot values from an utterance. Inspired by the ability of pointer network (Ptr-Net) at addressing OOV problems, we incorporate Ptr-Net into a standard Seq2Seq attentional model to handle OOV slots. The embodiments described herein can predict slot values by either generating one from a fixed vocabulary or selecting a word from the utterance. The final model is a weighted combination of the two operations.

[0009] The embodiments described herein use a neural generative model for slot filling on the data without word-level annotations. The embodiments described herein use a pointer network to handle the OOV problem in slot value prediction, which achieves improved performance over the prior-art without requiring manually-designed rules or features.

[0010] A spoken language understanding (SLU) system receives a command or query in natural language from a user and outputs the intents and slots that are identified in the user input. The SLU system identifies words for slots by using a sequence-to-sequence neural network and a pointer network jointly, in order to specifically handle the out-of-vocabulary problems in many spoken dialogue applications. The system further identifies the user intent and types of slots using convolutional neural networks. The identification of slot values and user intent types can be conducted either in a pipeline or joint framework.

[0011] In one embodiment, a method for operation a spoken language understanding (SLU) system includes receiving, with a processor in the SLU system, a plurality of words in a text phrase, generating, with the processor, an encoded output corresponding to the plurality of words and a plurality of attention weights corresponding to the plurality of words using a recurrent neural network (RNN) encoder with an attention mechanism that receives the plurality of words as inputs to the RNN encoder, generating, with the processor, a first probability distribution corresponding to a plurality of words in an extended slot vocabulary database being a slot word at a time step using an RNN decoder that receives the encoded output from the RNN encoder as input, generating, with the processor, a second probability distribution corresponding to the plurality of words in the input sequence being a slot word at the time step using a pointer network that receives the plurality of attention weights as input, generating, with the processor, a combined probability distribution based on the first probability distribution and the second probability distribution, identifying, with the processor, a slot word corresponding to one word in the extended slot vocabulary database having a highest probability value in the combined probability distribution for the time step, and performing, with the processor, a command using the slot word as a parameter to the command.

[0012] In another embodiment, a system for spoken language understanding (SLU) has been developed. The system includes a input device, an output device, a memory, and a processor operatively connected to the input device, the output device, and the memory. The processor is configured to receive a plurality of words in a text phrase based on an input received with the input device, generate an encoded output corresponding to the plurality of words and a plurality of attention weights corresponding to the plurality of words using a recurrent neural network (RNN) encoder with an attention mechanism stored in the memory that receives the plurality of words as inputs to the RNN encoder, generate a first probability distribution corresponding to a plurality of words in an extended slot vocabulary database stored in the memory being a slot word at a time step using an RNN decoder stored in the memory that receives the encoded output from the RNN encoder as input, generate a second probability distribution corresponding to the plurality of words in the input sequence being a slot word at the time step using a pointer network that receives the plurality of attention weights as input, generate a combined probability distribution based on the first probability distribution and the second probability distribution, identify a slot word corresponding to one word in the extended slot vocabulary database having a highest probability value in the combined probability distribution for the time step, and perform a command using the slot word as a parameter to the command to produce an output with the output device.

BRIEF DESCRIPTION OF THE DRAWINGS

[0013] FIG. **1** is a schematic diagram of one embodiment of an automated spoken language understanding (SLU) system.

[0014] FIG. **2** is a schematic diagram of the embodiment of FIG. **1** while performing a slot-filling operation for a sequence of words in a text phrase.

[0015] FIG. **3** is a block diagram of a process for identifying slot words and using the slot words in an SLU system.

DETAILED DESCRIPTION

[0016] For the purposes of promoting an understanding of the principles of the embodiments disclosed herein, reference is now be made to the drawings and descriptions in the following written specification. No limitation to the scope of the subject matter is intended by the references. This disclosure also includes any alterations and modifications to the illustrated embodiments and includes further applications of the principles of the disclosed embodiments as would normally occur to one skilled in the art to which this disclosure pertains.

[0017] As used herein, the term Recurrent Neural Network (RNN) refers to a type of neural network that receives a series of inputs and generates a series of outputs in which each input to the RNN affects the internal state of the RNN to provide the RNN with a "memory" in which the output of the RNN is affected not only by the present input but on the internal state of the RNN that has been changed based on previously received inputs. Different types of RNNs include neurons that employ a gated recurrent unit (GRU), a long short-term memory (LSTM) unit, or other units that are known to the art in which each "unit" is also referred to as a neuron in an RNN. In an RNN encoder/decoder network, an encoder includes one or more units that receive a sequence of inputs and generate an encoded output, which is typically in the form of a numeric vector or other suitable structure, which includes encoded information about each of the inputs in the sequence. In the embodiments described herein, the sequence of inputs refers to numeric values that map to words in an input sequence. The encoder retains an internal "hidden state" h that is updated for each input in the sequence, which is modeled as a series of time steps t in which the RNN encoder receives an additional input in each time step. The final output of the encoder includes encoded information about all of the inputs that were received in the sequence.

[0018] In the RNN encoder/decoder network, the decoder is another RNN that receives the encoded output vector corresponding to the final hidden state h from the RNN encoder as an input. The RNN decoder emits a sequence of outputs, which in the specific embodiments described herein are probability distributions P_{gen} of different words in a predetermined slot vocabulary, which may include words that are not in the original input, correspond to a slot during a sequence of time steps. Thus, the RNN encoder/decoder network emits a sequence of words that should be applied to slots, and a separate mechanism then uses the joint output of the RNN decoder and the pointer network that is described below to fill in slots with the generated words during an SLU operation. The process also filters words from the plurality of words in a text phrase of the original input sequence that do not correspond to any of the slots. As described above, one drawback of a conventional RNN decoder is that the training process is less effective in identifying out-of-vocabulary (OOV) words that might correspond to slots but that are not well represented in the training data. In the context of this disclosure, OOV means that a word can be identified by an automated speech recognition front-end, but that the word is not directly assignable to an enumerable slot that has a predetermined number of possible inputs that are included in the original training data. By contrast, words that can be assigned to enumerable slots and that are included in the training data are referred to as "in-vocabulary" words.

[0019] The embodiments described herein use both uni-directional and bi-directional RNNs. A uni-directional RNN incorporates one or more neurons to generate a series of outputs based on a series of input values going in one direction in time, which is usually although not exclusively from the earliest input in a sequence to the latest input in a sequence. Some RNNs use multiple layers of neurons although the embodiments described herein can be implemented with a single layer or multiple layers of neurons. A bi-directional RNN includes at least two neurons, such as two instances of the GRU, to generate outputs going both forwards in time and backwards in time. For the embodiments described herein, all of the input data are available prior to using the RNNs so going "backwards" in time simply means that one neuron or set of neurons in the RNN starts from the final value in the input and iterates backwards to the first input value to incorporate hidden state and context information from future values in the sequence instead of previous values in the sequence, which is effectively the configuration of a forward-time RNN that is reversed in time. Another neuron or set of neurons in the RNN generates an output starting from the earliest input in the sequence in a similar manner to the uni-directional GRU. The output of the bi-directional RNN is, for example, a combination of two vectors that are based on the numeric hidden state variable outputs for both the forward and backward direction RNNs to produce an output for each input value in the sequence that is influenced by both previous values and subsequent values in the sequence.

[0020] As described above, in a standard RNN the encoder generates a single output vector that encodes information about all of the inputs in a sequence. As used herein, the term "attention mechanism" refers to an additional process that enables an RNN encoder/decoder to include additional information about the positions of words in the sequence that is not directly encoded into the output vector of the RNN encoder. The attention mechanism generates multiple numeric attention weight values based on a score function of two different hidden states. Examples of score functions include $\mathrm{score}(h_t,\bar{h}_s)=h_t^T W\bar{h}_s$ or $\mathrm{score}(h_t,\bar{h}_s)=v_a^T \tanh(W_1 h_t+W_2\,\bar{h}_s)$ where the term h_t is the vector of a decoder hidden state at the current time step t, $\bar{h}_s$ is the vector of the s-th encoder hidden state in the sequence, and the terms v_a, W, W_1, and W_2 represent numeric weight parameters that are learned during training of the RNN encoder/decoder framework. More generally, the score function calculates the score at decoder time step t based on the correlation between the encoder hidden state and decoder hidden state, thus obtains the focus or "attention" to different words in an input sequence. In one embodiment, the RNN encoder uses an attention mechanism to produce numeric attention weight values a_{ts} based on the scores using the following function:

$$a_{ts}=\frac{e^{(score(h_t,\bar{h}_s))}}{\sum_{s=1}^{S} e^{score(h_t,\bar{h}_s)}}$$

for a total of S source hidden states. The attention mechanism uses the attention weights to generate a context vector c and an attention vector a_t using, for example, the following functions: $c_t=\Sigma_s a_{ts}\bar{h}_s$ and $a_t=f(c_t, h_t)=\tanh(W_c[c_t; h_t])$ where W_c is another weight value. Other embodiments of attention mechanism that employ feed-forward neural networks to determine the attention scores are also known to the art. The RNN decoder can use the output of the attention mechanism in addition to the standard output vector of the RNN encoder to improve the accuracy of generating decoded outputs by using the attention scores that correspond to the sequence of words in the original input to focus on different input words when generating a sequential output.

[0021] As used herein, the term "pointer network" refers to a decoder mechanism that can be used to select an input element in a sequence, such as a word from a sequence of words, in a decoder based on the attention scores that are generated in an RNN encoder. At each decoding step, the pointer network selects a position from the input sequence based on the attention distribution instead of generating a token from the target vocabulary. For example, a pointer network receives an input sequence $X=\{x_1, \ldots, x_T\}$, and generates an output y_t at time step t based on the following function: $P_{ptr}\,(y_t=w|y_1^{t-1}, X)=\Sigma_{i:x_i=w}a_i^t$, where w is an input word, a_i^t is the attention weight of the position i at step t. The value of P_{ptr} is a probability distribution of words, including in-vocabulary and out-of-vocabulary words, that are generated by the pointer network at each decoder time step t where each time step corresponds to one word in the output sequence Y. The embodiments described herein combine the output of the RNN decoder and the output of the pointer network to identify slot words from the input based on an extended vocabulary, where once again the slot words do not necessarily have to be present in the original input. As used herein, the term "extended vocabulary" denotes the union of the slot vocabulary (in-vocabulary words) for enumerable slots that are well-represented in the training data and other words from the input utterances, which further include out-of-vocabulary words.

[0022] FIG. **1** depicts a spoken language understanding (SLU) system **100** that identifies slot words including both in-vocabulary and out-of-vocabulary words for slot-filling operations. The system **100** includes an audio input device **104**, an output device **112**, a processor **128**, and a memory **132**. Examples of hardware embodiments that implement the system **100** include, for example, an in-vehicle information system, personal computer, mobile electronic device such as a smartphone or wearable computing device, and the like. While the system **100** is depicted as a single computing device for illustrative purposes, in some embodiments the system **100** includes a client device that receives input via the an audio input device **104**, generates output via the output device **112**, and transmits recorded audio data or the output of an automated speech recognition system that is implemented in the client to an external server computing system via a data network. The external server computing system then performs additional processing to identify the slots and transmits a final output to the client computing device. In either embodiment, a reference to the operation of a processor, such as the processor **128**, refers interchangeably to the operation of a single processor in a computing device or multiple processors in multiple computing devices that interoperate with each other to implement the functions described herein.

[0023] In the system **100**, the audio input device **104** is, for example, a microphone or a series of microphones that receive spoken input from a human user. The audio input device **104** optionally includes additional circuits including filters, amplifiers, and analog-to-digital converters that produce audio data of a digitized representation of the input speech for additional processing by the processor **128**. While FIG. **1** depicts an audio input device **104**, alternative embodiments use another input device that enables the system **100** to receive a series of words corresponding to human input, such as a keyboard or gesture input device.

[0024] In the system **100**, the output device **112** is, for example, an audio output device or visual display device that produces an output in a dialogue system. The output is based, at least in part, on information provided to the system **100** from the user via the audio input device **104**. As described in more detail below, the system **100** receives speech or text input from a user, encodes the input, and performs a slot-filling operation to assign slots to at least some of the words in the original input. The system **100** processes the slots with particular terms that are understandable in a spoken language understanding framework to produce an output response based on the input from the user. The output device **112** provides an output to the user that mimics a dialogue response expected by the user based on the input from the user, but the system **100** generates the dialogue response in an automated manner.

[0025] In the system **100**, the processor **128** is a digital logic device including, for example, one or more of a microprocessor central processing unit (CPU), microcontroller, digital signal processor (DSP), field programmable gate array (FPGA), graphical processing unit (GPU), application specific integrated circuit (ASIC), or any other suitable digital logic devices that perform the functions and actions of the system **100** that are described herein. In some embodiments, the processor **128** includes acceleration hardware that implements the operations of the RNN encoders and decoders described herein in an efficient manner, although other processing hardware including CPUs and GPUs can implement the RNN encoders and decoders as well. The processor **128** is operatively connected to the audio input device **104**, the output device **112**, and the memory **132**.

[0026] In the system **100**, the memory **132** includes one or more volatile memory devices such as random access memory (RAM) and one or more non-volatile memory devices such as a magnetic or solid state disk. The memory **132** stores programmed instructions **134** and data that implement a speech recognizer **136**, an intent classifier **138**, an RNN encoder **140** that includes an attention mechanism, a slot word decoder **144** that further includes an RNN decoder **146** and a pointer network **148**, an extended slot vocabulary database **162**, and a slot database **166**.

[0027] In the memory **132**, the speech recognizer **136** is a prior-art automated speech recognition (ASR) engine that includes, for example, software and models that convert the audio data that the system **100** receives from the audio input device **104** into a sequence of machine-readable representations of the words in the text phrase. The ARS **136** includes any suitable embodiment of an automated speech recognition system including those using Hidden Markov Models, and various types of neural networks including "deep learning" neural network models. The system **100** uses the speech recognizer **136** to generate a sequence of text words that serve as a basis for the remainder of the spoken language understanding processing that is described herein.

[0028] In the memory **132**, the slot and intent classifiers **138** are neural networks that recognize the slots and intents of the input sequence of text from the user. In one embodiment the slot and intent classifiers **138** are convolutional neural networks (CNN). In another embodiment the intent classifier **138** is an RNN decoder that can receive the output of the RNN encoder **140** and that is jointly trained with the RNN encoder **140**. The term "intent" as known in the art refers to an intended command or query that is recognized by an SLU system based on the input from the user. One example of an intent is a request for a navigation system to identify restaurants based on elements of a user query, where specific elements in the user query provide words that correspond to slots in the query. The slot classifier **138** receives the slot words that the system **100** generates during the process **300** that is described in further detail below, and the process **300** provides words that have a high probability of corresponding to slots in an SLU operation without requiring the slot classifier **138** to process each word of the original input, which in turn improves the accuracy of slot classification. In some embodiments, the slot classifier also receives an intent identifier as an input from the intent classifier in addition to the slot word, which provides context to enable the slot classifier **138** to identify a slot in the slot database **166** for slot words with greater accuracy.

[0029] In the memory **132**, the RNN encoder **140** is an RNN that receives a sequence of numeric values that correspond to words in an input sequence and generates a first encoded representation of the plurality of words as a first vector of hidden state numeric output values h based on the inputs. The processor **128** also implements the RNN encoder **140** using an attention mechanism that produces the attention weights described above. In the embodiment of FIG. **1** the RNN encoder **140** is a bi-directional RNN encoder that is implemented using at least two GRUs although in other embodiments the RNN encoder can be a uni-directional encoder.

[0030] In the memory **132**, the slot word decoder **144** emits a sequence of slot words as output based on words in an input sequence using both the hidden state encoded output and the attention weights from the RNN encoder **140**. The term "slot word" refers to a word in the extended slot vocabulary database **162** that the slot word decoder **144** generates at each time step of a decoding sequence to serve as inputs to the slot classifier **138**. A slot word may be a word that is present in the original input sequence, but the slot word decoder **144** may also emit slot words that are not present in the original input sequence. Additionally, in some situations the slot decoder **144** does not emit words from the original input sequence as slot words.

[0031] The slot decoder **144** includes an RNN decoder **146** and a pointer network **148**. In the embodiment of FIG. **1**, the RNN decoder **146** is a uni-directional decoder that is implemented as an RNN with at least one GRU. The RNN decoder **146** uses the final hidden state of the RNN encoder **140** as input and optionally uses attention vector from the attention mechanism of the RNN encoder **140** to improve the accuracy of output. The RNN decoder **146** emits a series of probability distributions for the most likely in-vocabulary slot words that are contained in the extended slot vocabulary database **162**. In some embodiments, the RNN decoder **146** also uses the output of the attention mechanism of the RNN encoder **140** to enable the RNN decoder **146** to use the attention vector to generate the probability distribution of in-vocabulary slot words. The outputs of the RNN decoder **146** generate probability distributions with potentially non-zero probability values for words that have enumerable in-vocabulary words stored the extended slot vocabulary database **162**, and the output of the RNN decoder **146** may include high probability values for in-vocabulary words that are not present in the original input.

[0032] The pointer network **148** receives the attention weights from the attention mechanism **140** of the RNN encoder **140** as inputs and generates another probability distribution of slots that are assigned to each word in the input sequence. The outputs of the pointer network **148** generate probability distributions with the highest probability values for slot words that are stored as out-of-vocabulary words in the extended slot vocabulary database **162** and that are present in the original input sequence of words, but that are not generally recognized with high accuracy by the RNN decoder **146**. The final output from the slot word decoder **144** is a combination of the outputs of the RNN decoder **146** and the pointer network **148** that provides one or more slot words. The slot word decoder **144** provides an "extended vocabulary" since the slot word decoder **144** generates the slot words using a combined probability distribution for both in-vocabulary and out-of-vocabulary slot words. The system **100** or another automated spoken language system uses slot words to fill one or more slots as part of additional dialogue processing.

[0033] In the memory **132**, the extended slot vocabulary database **162** stores the extended vocabulary of all words and numerical values that includes both in-vocabulary words that can be assigned to enumerable slots and that are well represented during the training process as well as out-of-vocabulary words that can be recognized by the ASR **136** but that are not well represented during the training of the RNN encoder **140** and the slot word decoder **144**. As such, the precise set of words contained in the extended slot vocabulary database **162** depends upon the total corpus of recognized words that the system **100** is configured to process and since the extended slot vocabulary database **162** includes the extended vocabulary, the extended slot vocabulary database **162** includes both "in-vocabulary" words that are well represented in the training of the RNN encoder **140** and RNN decoder **146** as well as "out-of-vocabulary" words that are not well represented during the training process. During operation of the system **100**, the RNN decoder **146** in the slot word decoder **144** uses the hidden state h received from the RNN encoder **140** to identify in-vocabulary words in the extended slot vocabulary database **162** that correspond to slots with the highest probability and the pointer network **148** to identify out-of-vocabulary words that correspond to slots with the highest probability.

[0034] In the memory **132**, the slot database **166** stores a set of predetermined slot labels that correspond to the outputs of the slot classifier **138** when the slot classifier **138** is provided with slot word inputs. The slot database **166** also stores a default NULL value slot that serves as a catch-all identifier for a slot word that does not directly correspond to a specific slot. For example, in one configuration the slot word decoder **144** generates an output sequence of slot words that may correspond to one of the slots in the slot database **166**. The slot classifier **138** receives the words and generates an output with a probability distribution of elements that map to index values of different slots in the slot database **166**. The processor **128** can identify the slot that is assigned to a slot word using the slot database **166**. The system **100** then uses the slot word in conjunction with the slot to perform further processing, such as formulation of a database query with different fields in the database query filled with words that correspond to the slots in the slot database **166**. The exact values of slots in the slot database **166** can vary based on the domain for which the SLU system **100** is trained to provide interaction with a user, and as a non-limiting example one domain is an in-vehicle navigation system that receives requests for various landmarks including restaurants or locations to which a vehicle may travel. The slot database **166** is generated prior to a training process and used in conjunction with the training process of the RNN encoder **140** and the slot word decoder **144** to generate outputs that correspond to the slots in the slot database **166**.

[0035] In one example, the system **100** is configured to perform SLU operations for an in-vehicle navigation system. A predetermined set of training data provides predetermined text phrases and a correspond set of predetermined slots that correspond to words in the text training phrases. The result of the training process is a set of parameters that adjust the GRUs or other neurons in the RNN encoder **140** and the slot word decoder **144** to enable the encoder **140** and decoder **144** to assign slots to words in the input text based on the training data when the RNN encoder **140** with the attention mechanism and the slot word decoder **144** with the RNN decoder **146** and pointer network **148** are used together in the joint model that is described herein. Since the training data are selected to be representative of actual inputs that are expected to be received during operation of the system **100**, the trained RNNs also have a high likelihood of producing accurate outputs when presented with another sequence of input text and in-vocabulary terms that are present in the training data. The pointer network improves the operation of the system **100** in performing slot-filling operations when out-of-vocabulary words are present in the input, and the training process assigns weights to the pointer network. Additionally, the training process uses hyperparameters that are defined prior to commencement of the training process that define various parameters for training the RNN encoder and decoders including hyperparameters that specify a learning rate, minibatch size (used in minibatch gradient descent training processes that are otherwise known to the art), and dropout rate. As known in the art, the GRUs use sigmoid functions that can include a trainable parameter a:

$$\frac{1}{1+e^{-ax}},$$

and the training process assigns values to weights and parameters in the RNN encoder/decoder, attention mechanism, and the pointer network. In the system **100**, the memory **132** stores the parameter data, weights, and other data structures that implement the slot and intent classifiers **138**, RNN encoder **140**, and slot word decoder **144** prior to the inferencing operation of the process **300** that is described in more detail below.

[0036] FIG. **3** depicts a process **300** for operation of a spoken language understanding (SLU) system that processes the output of a speech recognizer to perform a slot-filling operation. The process **300** is also referred to as an inferencing process because the process **200** uses previously trained RNN encoders and decoders along with the attention mechanism and pointer networks in the system **100** to perform slot filling as part of an SLU system. In the description below, a reference to the process **300** performing a function or action refers to the operation of a processor to execute stored program instructions to perform the operation in conjunction with components in an automated spoken language understanding system. For example, the description below includes descriptions of an RNN encoder, attention mechanism, RNN decoder, and a pointer network that refer to operations performed by a processor to execute stored program instructions in conjunction with data structures of the RNN encoders and decoders that are stored in a memory to implement the RNN encoder or decoder. The process **300** is described in conjunction with the embodiments of FIG. **1** and FIG. **2** for illustrative purposes.

[0037] The process **300** begins as the system **100** receives an input sequence including a plurality of words in a text phrase from a human user (block **304**). In the system **100**, the processor **128** uses the automated speech recognizer **136** to generate a sequence of words in the text phrase based on input that is received from the audio input device **104**. In another embodiment, the input may be a free-form text phrase that the user enters with a keyboard or gesture input device. As described above, while the output of the automated speech recognition process can identify a sequence of words in a machine-readable format, the spoken language understanding system requires additional processing to identify words in the extended slot vocabulary database **162** that correspond to slots based on the input sequence.

[0038] The process **300** continues as the system **100** generates an encoded output with attention weights of the natural language using the RNN encoder with attention mechanism **140** (block **308**). The processor **128** uses the trained RNN encoder **140** to generate both the encoded vector output based on a forward-direction and backwards-direction RNN encoder that uses at least two GRUs and the attention mechanism to generate attention weights for each word in the original input sequence of the text phrase. FIG. **2** depicts the operation of the encoder **140** with the bi-directional RNN **242** and the attention mechanism **244** for a sample input sequence of words in a text phrase **208** in more detail.

[0039] During the process **300**, the system **100** uses the RNN decoder **146** in the slot word decoder **144** to generate a first series of probability distribution outputs that identify the most likely word or words that correspond to any slot during each time step in a sequence of time steps (block **312**). The processor **128** uses the encoded output of the final hidden state h from the RNN encoder **140** as the input to the RNN decoder **146**. As described above, the RNN decoder **146** produces outputs that provide probability distribution values for the in-vocabulary words that are stored in the slot vocabulary database **162**, although the RNN decoder **146** generates a sequence of outputs based on the encoded input from the RNN encoder **140** that encodes information about all of the words, both in and out-of-vocabulary, in the input sequence. In some embodiments, the RNN decoder **146** also uses the attention vector from the attention mechanism of the RNN encoder **140** as an input to improve the accuracy of predicting slot words. In some embodiments, the probability output of the RNN decoder **146** is zero at each time step in the output sequence for out-of-vocabulary words while the RNN decoder **146** can produce non-zero probability distribution values for one or more of the in-vocabulary words that are stored in the extended slot vocabulary database **162**.

[0040] During the process **300**, the system **100** also uses the pointer network **148** in the slot word decoder **144** to generate a second series of probability distribution outputs that each predict a probability distribution of potential slot words in the input sequence during a time step based on the attention weights from the attention mechanism of the RNN encoder **140** (block **316**). The processor **128** uses the pointer network **148** to generate the probability distribution for slot values of each word based on the attention weight values for each input word in the sequence and the current time step. FIG. **2** also depicts the operation of the slot word decoder **144** including the pointer network **148** in more detail for the portion of the words in the input sequence **208** including the out-of-vocabulary word "oriental," which is present in the original input sequence **208** and is an out-of-vocabulary word in the example of FIG. **2**. The pointer network **148** produces a probability distribution output for words in the original input sequence, each word of which is also present in the extended slot vocabulary database **162**. The pointer network **148** can produce a probability distribution for both in-vocabulary and out-of-vocabulary slot words that are present in the input sequence, although the system **100** uses the pointer network **148** most heavily for identifying out-of-vocabulary slot words while relying more heavily on the RNN decoder **146** to identify in-vocabulary slot words.

[0041] The process **300** continues as the system **100** uses a weighted combination of the outputs of the RNN decoder **146** and the pointer network **148** to identify a slot word at each time step (block **320**). To combine the outputs, the processor **128** generates a probability distribution over the extended vocabulary based on the following function: $P(w)=p_t P_{gen}(w)+(1-p_t)P_{ptr}(w)$, where w is one word selected from the total set of W words in the extended slot vocabulary database **162**. FIG. **2** depicts this operation applied to the word "oriental" in the sequence **220** of FIG. **2**. In the preceding equation, the term $P_{gen}(w)$ refers to the probability distribution value for the word w that the RNN decoder **146** generates for a given word w and the term $P_{ptr}(w)$ refers to the probability distribution value for the word w that the pointer network **148** generates for the same word w.

[0042] In the weighted combination of the process **300**, the p_t term is a weight value that has a range of $p_t \in [0,1]$ and that is defined as $p_t=\sigma(w_c c_t+w_s s_t+w_d d_t+b)$ where σ is a sigmoid function, d_t is the input to the slot word decoder **144** at time step t, c_t is a context vector of the attention mechanism at time step t, s_t is a hidden state of the RNN decoder **146** at time step t, the terms w_c, w_s, and w_d are each trainable weight values that are part of the pointer network in the slot word decoder **144**, and b represents a bias term, which is a scalar parameter, learned during training together with w_c, w_s, and w_d. The processor **128** generates the weight value p_t and uses the p_t weight value to generate a weighted sum of P_{gen} and $P_{pr\ t}$ to balance the relative contributions of the RNN decoder **146** and the pointer network **148**. More particularly, the p_t value is based on the RNN decoder **146**, and a higher weight value of p_t indicates a that the output of the RNN decoder **146** is favored for in-vocabulary words while a lower value of p_t indicates that the output of the pointer network **148** is favored for out-of-vocabulary words. As described above, the value of p_t changes over a sequence of time steps t to provide varying weight values to the output of the RNN decoder **146** or the pointer network **148**. The processor **128** identifies the slot word for each time step using, for example, the word in the extended slot vocabulary database **162** that has the highest probability value in the combined probability distribution P (W) of all the words W that represents the highest slot word probability of all the words in the extended slot vocabulary database **162** from the combination of both probability distributions from the RNN decoder **146** and the pointer network **148**.

[0043] Referring to FIG. **2**, the equation 220 depicts the weighted sum combination of the outputs of the RNN decoder **146** and the pointer network **148** in the slot word decoder **144** to generate a combined probability distribution with an entry that corresponds to the word "oriental" (P(oriental)). In FIG. **2** the processor **128** assigns a weighted balance to the output P_{ptr} of the pointer network **148** for out-of-vocabulary word "oriental" relative to the output of the RNN decoder **146** using the function p_t at the time step t. In the embodiment of the system **100**, the output of P_{gen} (oriental) from the RNN decoder **146** is zero for the out-of-vocabulary word "oriental", although the probability values for in-vocabulary words are non-zero, and the value of p_t at each time step affects final probability distribution value for the word "oriental" in addition to the output P_{ptr} from the pointer network **148**. The combined result P(w) is included in the probability distribution of slot words that the processor **128** uses to select a slot word for each time step based on the highest probability value in the combined probability distribution. The processor **128** then assigns a slot label from the slot database **166** to one or more slot words with the slot classifier **138**. During the process **300**, the system **100** generates the sequence of slot words based on the combined outputs of the RNN decoder **146** and the pointer network **148** at each time step in the sequence as is described above.

[0044] As described above, the process **300** generates a sequence of slot words over a series of time steps in which both the RNN decoder **146** and the pointer network **148** produce different slot word probability distributions for each time step. The process **300** continues as described above for at least one and potentially more than one time step (block **322**) until reaching the final slot word output at a final time step from either or both of the RNN decoder **146** and the pointer network **148**. After the final slot word output is generated (block **322**), the system **100** uses the slot words as an input to additional SLU processing that is described below. In one embodiment, the slot word decoder **144** stops emitting slot words after either emitting a predetermined end symbol as a slot word (e.g. </s> as depicted in FIG. **2**) or after emitting a predetermined maximum number of slot words, such as ten slot words, without emitting the end symbol.

[0045] Table 1 below depicts some examples of predicted slot words that are generated from sequences of words in text phrase inputs using the slot-filling process **300** and using prior-art processes including a convolutional neural network (CNN) and the Seq2Seq RNN encoder/decoder framework that uses an attention model. As seen below, the process **300** can identify a single slot word or multiple slot words from an input phrase that includes at least one word that corresponds to a slot. The bolded text in each input represents the slot words that should be filled into one or more slots using a slot classifier, where the slots pertain to a characteristic of a restaurant such as the type, location, or price of the restaurant. In the table below, the identified slot words can be present in the original input or may be identified as a word in the extended vocabulary that is not present in the original input.

TABLE 1

Examples of predicted text values for slots		
Input: **Danish** food in the **centre** of town		
System 100	Seq2Seq (prior art)	CNN (prior art)
Danish centre	Spanish centre	Centre
Input: I would like **Singaporean** food		
System 100	Seq2Seq (prior art)	CNN (prior art)
Singaporean	Korean	NULL (not found)
Input: what about **Chiquito**		
System 100	Seq2Seq (prior art)	CNN (prior art)
Chiquito [name of restaurant]	Portuguese	NULL (not found)
Input: an **expensive** restaurant serving **Cantonese** food		
System 100	Seq2Seq (prior art)	CNN (prior art)
Cantonese	Portuguese expensive	expensive

[0046] The process **300** continues as the system **100** performs a command specified in the input phrase from the user using words the identified slots as parameters for execution of the command (block **324**). In some configurations, in addition to identifying the slots for words in the input sequence, the processor **128** uses the intent classifier **138** to identify the intent of the input phrase, and the system **100** performs an operation based on the identified intent using specific slot words and the identified slots as parameters to the operation. Using the input text phrase **208** from FIG. **2** as a non-limiting example, the system **100** identifies the intent as an input request from a user to display restaurants with certain characteristics. The slot word generation process produces probability values at each time step in a sequence of time steps that identify the probability that any word in the extended vocabulary database **162** is a slot word, including both in-vocabulary and out-of-vocabulary words. As described above, the system **100** may generate slot words that are not present in the original input text phrase based on the weighted output of the slot word decoder **144**, and words that are present in the original input text phrase may be omitted from the generated slot words. After generating slot words, the processor **128** uses the slot classifier **138** to identify the particular slot for one or more of the slot words, and the slot classifier **138** does not need to process the original input text, which as described above often includes words that do not correspond to a slot.

[0047] During, the process **300**, the processor **128** uses the slot words that are assigned to specific slots to execute a command such as, for example, a search query to an external database to search for restaurants that meet the criteria of the input and controls the output device **112** to produce an output in response to performing the command that uses the slot words as parameters. In one particular example, the system **100** generates a search query to include particular parameter fields, and each parameter field corresponds to one of the predetermined slots in the slot database **166**. The processor **128** uses the identified slot words from the slot decoder **144** that are assigned to slots using the slot classifier **138** as fields to execute the query. The slot-filling operation enables the system **100** to translate the natural language input from the user into a machine-understandable command, which is a database query in this example, where system **100** identifies the slot words to enable an automated response to the natural language input with improved accuracy.

[0048] The embodiments described herein enable improvements to identifying slot words for slot-filling operations in SLU systems. In particular, the system **100** provides improvements to the combined precision (P) and recall (R) of the slot assignment process that is expressed using the F1 metric. The F1 metric is a weighted average of the precision (P) and recall (R) scores on a predetermined scale, such as a scale of 0.0 (worst) to 100.0 (best), although the F1 metric is also often expressed on a scale of 0.0 to 1.0. Table 2 depicts the results of slot value prediction with varying training size and 00V ratio of a convolutional neural network (CNN), a prior-art RNN encoder/decoder framework with an attention mechanism (Seq2Seq) and the system **100** that performs the process **300**:

TABLE 2

Slot value prediction results with varying training size and OOV ratio

		Training Size			
		5%	10%	15%	20%
		OOV Ratio			
		(16%)	(12%)	(4%)	(2%)
CNN	**P**	91.6	93.0	92.7	93.4
(prior art)	**R**	61.7	62.5	65.8	69.2
	F1	73.7	74.8	77.0	79.5
Seq2Seq	**P**	81.3	83.6	84.1	85.3
w/attention	**R**	69.6	74.7	74.9	76.5
(prior art)	**F1**	75.0	78.9	79.2	80.7
System 100	**P**	86.9	86.4	85.7	85.9
	R	73.2	75.3	77.0	77.4
	F1	**79.5**	**80.5**	**81.1**	**81.4**

[0049] As depicted in Table 2 above, the F1 scores show the highest values for the system **100** over a wide range of training set sizes with different ratios of the input words being considered out-of-vocabulary. The system **100** uses both the RNN encoder/decoder framework and the pointer network to improve the overall results that balance both precision and recall. As shown above, in some instances, the prior-art CNN shows greater precision P but the level of recall R of the prior-art CNN system is substantially lower than the system **100**, and the total F1 scores for the system **100** are higher than either the CNN or Seq2Seq prior-art embodiments. As such, the embodiments described herein including the system **100** and the process **300** each provides improvements to the operation of computers that are used to implement SLU systems.

[0050] It will be appreciated that variants of the above-disclosed and other features and functions, or alternatives thereof, may be desirably combined into many other different systems, applications or methods. Various presently unforeseen or unanticipated alternatives, modifications, variations or improvements may be subsequently made by those skilled in the art that are also intended to be encompassed by the following claims.

What is claimed:

1. A method for operation of a spoken language understanding (SLU) system comprising:

receiving, with a processor in the SLU system, an input sequence including a plurality of words in a text phrase;

generating, with the processor, an encoded output corresponding to the plurality of words and a plurality of attention weights corresponding to the plurality of words using a recurrent neural network (RNN) encoder with an attention mechanism that receives the plurality of words as inputs to the RNN encoder;

generating, with the processor, a first probability distribution corresponding to a plurality of words in an extended slot vocabulary database being a slot word at a time step using an RNN decoder that receives the encoded output from the RNN encoder as input;

generating, with the processor, a second probability distribution corresponding to the plurality of words in the input sequence being a slot word at the time step using a pointer network that receives the plurality of attention weights as input;

generating, with the processor, a combined probability distribution based on the first probability distribution and the second probability distribution;

identifying, with the processor, a slot word corresponding to one word in the extended slot vocabulary database having a highest probability value in the combined probability distribution for the time step; and

performing, with the processor, a command using the slot word as a parameter to the command.

2. The method of claim **1**, the generating of the combined probability distribution further comprising:

generating, with the processor, a weight value based on a state of the RNN decoder; and

generating, with the processor, the combined probability distribution as weighted sum of the first probability distribution and the second probability distribution using the weight value.

3. The method of claim **2** further comprising:

generating, with the processor, the weight value as p_t at the time step t based on the following function $p_t=\sigma(w_c c_t+w_s s_t+w_d d_t+b)$

where c_t is a context vector of the attention mechanism,

s_t is a is a hidden state value of the RNN decoder,

d_t is an input to the RNN decoder,

w_c, w_s, and w_d, are a plurality of trainable weight values,

and b is a bias term.

4. The method of claim **3** further comprising:

generating, with the processor, the combined probability distribution including a probability value P(w) where w is a word in the plurality of words in the extended slot vocabulary database based on the following function:

$$P(w)=p_t P_{gen}(w)+(1-p_t)P_{ptr}(w),$$

where P_{gen} is the first probability distribution, and

P_{ptr} is the second probability distribution.

5. The method of claim **2** wherein the processor generates the weight value to favor the first probability distribution generated by the RNN decoder in response to the first word being an in-vocabulary word and the processor generates the weight value to favor the second probability distribution generated by the pointer network in response to the first word being an out-of-vocabulary word.

6. The method of claim **1** wherein the RNN encoder is a bi-directional RNN encoder.

7. The method of claim **6** wherein the RNN encoder includes at least two gated recurrent units.

8. The method of claim **7** wherein the RNN decoder includes at least one gated recurrent unit.

9. The method of claim **6** wherein the RNN decoder is a uni-directional RNN decoder.

10. The method of claim **1** further comprising:

generating, with the processor, the plurality of words in the text phrase using an automated speech recognition engine based on audio data received using an audio input device.

11. A system for spoken language understanding comprising:

an input device;

an output device;

a memory; and

a processor operatively connected to the input device, the output device, and the memory, the processor being configured to:

receive an input sequence including a plurality of words in a text phrase based on an input received with the input device;

generate an encoded output corresponding to the plurality of words and a plurality of attention weights corresponding to the plurality of words using a recurrent neural network (RNN) encoder with an attention mechanism stored in the memory that receives the plurality of words as inputs to the RNN encoder;

generate a first probability distribution corresponding to a plurality of words in an extended slot vocabulary database stored in the memory being a slot word at a time step using an RNN decoder stored in the memory that receives the encoded output from the RNN encoder as input;

generate a second probability distribution corresponding to the plurality of words in the input sequence being a slot word at the time step using a pointer network that receives the plurality of attention weights as input;

generate a combined probability distribution based on the first probability distribution and the second probability distribution;

identify a slot word corresponding to one word in the extended slot vocabulary database having a highest probability value in the combined probability distribution for the time step; and

perform a command using the slot word as a parameter to the command to produce an output with the output device.

12. The system of claim **11**, the processor being further configured to:

generate a weight value based on a state of the RNN decoder; and

generate the combined probability distribution as weighted sum of the first probability distribution and the second probability distribution using the weight value.

13. The system of claim **12**, the processor being further configured to:

generate the weight value as p_t at the time step t based on the following function $p_t=\sigma(w_c c_t+w_s s_t+w_d d_t+b)$

where c_t is a context vector of the attention mechanism,

s_t is a is a hidden state value of the RNN decoder,

d_t is an input to the RNN decoder,

w_c, w_s, and w_d, are a plurality of trainable weight values,

and b is a bias term.

14. The system of claim **13**, the processor being further configured to:

generate the combined probability distribution including a probability value P(w) where w is a word in the plurality of words in the extended slot vocabulary database based on the following function:

$$P(w)=p_t P_{gen}(w)+(1-p_t)P_{ptr}(w),$$

where P_{gen} is the first probability distribution, and

P_{ptr} is the second probability distribution.

15. The system of claim **12**, the processor being further configured to generate the weight value to favor the first probability distribution generated by the RNN decoder in response to the first word being an in-vocabulary word and the processor generates the weight value to favor the second probability distribution generated by the pointer network in response to the first word being an out-of-vocabulary word.

16. The system of claim **11** wherein the RNN encoder is a bi-directional RNN encoder.

17. The system of claim **16** wherein the RNN encoder includes at least two gated recurrent units.

18. The system of claim **17** wherein the RNN decoder includes at least one gated recurrent unit.

19. The system of claim **16** wherein the RNN decoder is a uni-directional RNN decoder.

20. The system of claim **11**, the input device further comprising:

an audio input device; and

the processor being further configured to generate the plurality of words in the text phrase using an automated speech recognition engine based on audio data received using the audio input device.

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