

NAMED ENTITY RECOGNITION METHOD AND APPARATUS, AND ELECTRONIC DEVICE

TECHNICAL FIELD

[0001] The present disclosure relates to the technical field of computers, and in particular
5 to a named entity recognition method and apparatus, and an electronic device.

BACKGROUND

[0002] In the field of natural language processing, the problem of named entity recognition
in travel review data has attracted much attention. The travel review data generally includes
rich information of entities, such as geographical locations, restaurants, and attractions, and
10 accurately recognizing these entities is critical for the travel industry and information
providers. However, the travel review data is diverse and may be accompanied by random
noise, which makes it difficult for traditional named entity recognition methods to achieve
high-accuracy recognition. In addition, the review data includes a large number of generalized
entities, such as "beach" or "hotel", which are tourism-related entities but do not provide
15 specific information, making them redundant from the perspective of subsequent information
utilization.

[0003] A common method currently is to use bidirectional encoder representation from
transformers (BERT) for text embedding, then use a bidirectional long short-term memory
(LSTM) to extract and summarize contextual information, and finally use a conditional
20 random field (CRF) algorithm to perform named entity recognition. However, a deep learning
model has high requirements for the quantity and the quality of training data, and labeling the
training data requires a lot of labor costs. In addition, in the field of tourism, an efficient and
complete named entity recognition process has not yet been established, and existing methods
fail to effectively differentiate generalized entities from non-generalized entities including
25 actual information, which makes it difficult to use final results directly for subsequent tasks.

SUMMARY

[0004] In view of this, the present disclosure provides a named entity recognition method and apparatus, and an electronic device to help solve the problem in the traditional technologies that the recognized data includes a large number of generalized entities.

5 **[0005]** In a first aspect, some embodiments of the present disclosure provide a named entity recognition method, including:

[0006] Recognizing to-be-recognized data based on a general model to obtain initial prediction data;

10 **[0007]** Recognizing the to-be-recognized data based on a Nth deep learning model to obtain Nth prediction data, where the Nth deep learning model is obtained by training an initial model based on Nth training data, N being a positive integer;

[0008] Determining (N+1)th training data according to the initial prediction data and the Nth prediction data; and

15 **[0009]** Training the initial model based on the (N+1)th training data to obtain a (N+1)th deep learning model, where the (N+1)th deep learning model is configured for entity recognition.

[0010] In some optional embodiments, subsequent to the recognizing the to-be-recognized data based on the general model to obtain the initial prediction data, the method further includes:

20 **[0011]** Determining an initial generalized vocabulary in the initial prediction data in response to a selection operation of a user; and

[0012] Screening the initial prediction data based on the initial generalized vocabulary to obtain 1st training data, where the 1st training data is used to train the initial model to obtain a 1st deep learning model.

25 **[0013]** In some optional embodiments, the determining the (N+1)th training data according to the initial prediction data and the Nth prediction data includes:

[0014] Determining Nth difference data between the initial prediction data and the Nth prediction data;

[0015] Determining a Nth generalized vocabulary in the Nth difference data in response to

a selection operation of a user; and

[0016] Screening the initial prediction data based on the Nth generalized vocabulary to obtain the (N+1)th training data.

[0017] In some optional embodiments, the determining the Nth difference data between the initial prediction data and the Nth prediction data includes:

[0018] Subtracting the Nth prediction data from the initial prediction data to obtain the Nth difference data.

[0019] In some optional embodiments, the number of non-generalized entities included in the (N+1)th training data is greater than the number of non-generalized entities included in the Nth prediction data.

[0020] In some optional embodiments, the number of generalized entities included in the (N+1)th training data is greater than the number of generalized entities included in the Nth training data.

[0021] In some optional embodiments, prior to the recognizing the to-be-recognized data based on the general model to obtain the initial prediction data, the method further includes:

[0022] Acquiring review data;

[0023] Sorting the review data based on user ratings and data lengths; and

[0024] Extracting a preset number of pieces of review data evenly in a sorted order to obtain the to-be-recognized data.

[0025] In a second aspect, some embodiments of the present disclosure provide a named entity recognition apparatus, including:

[0026] A processing module configured to recognize to-be-recognized data based on a general model to obtain initial prediction data;

[0027] The processing module being further configured to recognize the to-be-recognized data based on a Nth deep learning model to obtain Nth prediction data, where the Nth deep learning model is obtained by training an initial model based on Nth training data, N being a positive integer;

[0028] A determination module configured to determine (N+1)th training data according to the initial prediction data and the Nth prediction data; and

[0029] A training module configured to train the initial model based on the (N+1)th training

data to obtain a (N+1)th deep learning model, where the (N+1)th deep learning model is configured for entity recognition.

[0030] In a third aspect, some embodiments of the present disclosure provide an electronic device, including a memory configured to store computer program instructions and a processor configured to execute the program instructions, where when the program instructions are executed by the processor, the electronic device is triggered to perform the method in any one of the embodiments in the first aspect.

[0031] In a fourth aspect, some embodiments of the present disclosure provide a computer-readable storage medium, where the computer-readable storage medium includes a stored program, when the program is run, a device where the computer-readable storage medium is located is controlled to perform the method in any one of the embodiments in the first aspect.

[0032] In a fifth aspect, some embodiments of the present disclosure provide a computer program product, where the computer program product includes executable instructions, when the executable instructions are executed on a computer, the computer is caused to perform the method in any one of the embodiments in the first aspect.

[0033] In the solutions provided by the embodiments of the present disclosure, firstly, to-be-recognized data is recognized based on a general model to obtain initial prediction data, and the to-be-recognized data is recognized based on a Nth deep learning model to obtain Nth prediction data, where the Nth deep learning model is obtained by training an initial model based on Nth training data, and N is a positive integer. Then, (N+1)th training data is determined according to the initial prediction data and the Nth prediction data, and the initial model is trained based on the (N+1)th training data to obtain a (N+1)th deep learning model, where the (N+1)th deep learning model is configured to recognize the to-be-recognized data. In the embodiments of the present disclosure, training data is continuously updated through multiple iterations, after each update, generalized entities included in the training data are reduced, and a training model obtained by training the initial model with these training data may better remove the generalized entities during prediction.

BRIEF DESCRIPTION OF DRAWINGS

[0034] In order to more clearly illustrate the technical solutions in embodiments of the present disclosure, drawings used in the embodiments will be briefly introduced below. It is apparent that the drawings in the following description are only some embodiments of the present disclosure, and other drawings may be obtained by those of ordinary skill in the art from the provided drawings without creative efforts.

[0035] FIG. 1 is a schematic flowchart of a named entity recognition method according to some embodiments of the present disclosure;

[0036] FIG. 2 is a schematic flowchart of another named entity recognition method according to some embodiments of the present disclosure;

[0037] FIG. 3 is a schematic structural diagram of a named entity recognition apparatus according to some embodiments of the present disclosure; and

[0038] FIG. 4 is a schematic structural diagram of an electronic device according to some embodiments of the present disclosure.

DESCRIPTION OF EMBODIMENTS

[0039] In order to better understand the technical solutions of the present disclosure, some embodiments of the present disclosure will be described in detail below with reference to the drawings.

[0040] It should be clear that the described embodiments are only some of rather than all of the embodiments of the present disclosure. Based on the embodiments of the present disclosure, all other embodiments obtained by those of ordinary skill in the art without creative efforts fall within the protection scope of the present disclosure.

[0041] The terms used in the embodiments of the present disclosure are only for the purpose of describing specific embodiments and are not intended to limit the present disclosure. As used in the embodiments of the present disclosure and the appended claims, the singular forms of "a/an", "one", "the" and "said" are intended to include plural forms, unless otherwise clearly specified in the context.

[0042] It should be understood that the term "and/or" used herein describes an association relationship between associated objects and represents that three relationships may exist. For example, A and/or B may represent the following three cases: only A exists, both A and B exist, and only B exists. In addition, the character "/" herein generally indicates an "or" relationship between the associated objects.

[0043] In today's field of natural language processing, named entity recognition on review data on the web may provide people with important information. For example, through recognition on travel review data, geographical locations and tastes of certain hotels may be obtained, or experience of certain attractions may be obtained. Recognizing review data by building a deep learning model is a common recognition method. Common steps include using BERT for text embedding, then using a LSTM to extract and summarize contextual information, and finally using a CRF algorithm to perform named entity recognition. However, the deep learning model has high requirements for the quantity and the quality of training data. For example, in the training data, the number of generalized entities should be minimized as much as possible and the number of non-generalized entities should be maximized. In this way, after the model is trained completely, it may be more inclined to recognize the non-generalized entities and effectively remove the influence of the generalized entities. However, labeling training data requires a lot of labor costs, an efficient and complete named entity recognition process has not yet been established, and existing methods fail to effectively differentiate generalized entities from non-generalized entities including actual information, which makes it difficult to use final results directly for subsequent tasks.

[0044] In order to solve the problem that current named entity recognition includes a large number of generalized entities, which affecting acquisition of important information by a user, some embodiments of the present disclosure provide a named entity recognition method, the number and a proportion of generalized entities in the training data are gradually reduced by updating training data through multiple iterations, which ultimately obtain a more ideal deep learning model.

[0045] The method provided by the embodiments of the present disclosure mainly includes two parts: (1) acquiring and labeling data; and (2) training the deep learning model through multiple iterations.

[0046] In the first part, the user first needs to acquire to-be-recognized data. Taking travel review data as an example, the user may use a web crawler technology to acquire review information of attractions, hotels, restaurants, and other elements in a specific area from major travel websites, and at the same time ratings given by users in reviews are recorded. Then, in the present disclosure, all travel review data is sorted according to two key factors (user ratings and review lengths), and then a preset number of pieces (such as 7,000) of travel review data is evenly extracted from them to obtain the to-be-recognized data. Diversity of the to-be-recognized data may be increased by evenly extracting the travel review data, thereby improving robustness of the deep learning model.

[0047] After acquiring the above to-be-recognized data, the user performs preliminary recognition processing on the to-be-recognized data by using a general large-scale model (e.g., a large language model ChatGPT) to obtain initial prediction data. The user may design a data format for model output as required. For example, the data format may be "Entity Name - Entity Label", and specific data outputted may include: "City A - Location", "Very Fun - Review", "Fried Chicken Set Meal - Food Name", "Photo - Activity", and the like.

[0048] The initial prediction data obtained by the user through using the general large-scale model may include many words like "beach", "hotel", and "park", which are labeled as entities by the general large-scale model but actually lack specific information, and are not useful for downstream tasks. Therefore, in the present disclosure, such words are classified into "generalized entity", while the words such as "Beach A", "Hotel B" and "Park C" including specific information are classified into "non-generalized entity" in the present disclosure.

[0049] In the second part, it is hoped to filter out as many generalized entities as possible through n iterations of training in the present disclosure so that the trained model may recognize and exclude these meaningless entities. Specific steps may be shown in FIG. 1 as follows.

[0050] In step 101, a general large-scale model recognizes to-be-recognized data to obtain initial prediction data.

[0051] In step 102, an initial generalized vocabulary is determined manually.

[0052] In step 103, the initial prediction data is screened based on the initial generalized vocabulary to obtain 1st training data.

[0053] In step 104, an initial model is trained based on the 1st training data to obtain a 1st deep learning model.

[0054] In step 105, the 1st deep learning model recognizes the to-be-recognized data to obtain 1st prediction data.

5 **[0055]** In step 106, the 1st prediction data is subtracted from the initial prediction data to obtain 1st difference data.

[0056] In step 107, a 1st generalized vocabulary is determined manually.

[0057] In step 108, the initial prediction data is screened based on the 1st generalized vocabulary to obtain 2nd training data.

10 **[0058]** In step 109, the initial model is trained based on the 2nd training data to obtain a 2nd deep learning model.

[0059] In step 110, the 2nd deep learning model recognizes the to-be-recognized data to obtain 2nd prediction data.

15 **[0060]** In step 111, a Nth deep learning model recognizes the to-be-recognized data to obtain Nth prediction data.

[0061] In step 112, the Nth prediction data is subtracted from the initial prediction data to obtain Nth difference data.

[0062] In step 113, a Nth generalized vocabulary is determined manually.

20 **[0063]** In step 114, the initial prediction data is screened based on the Nth generalized vocabulary to obtain (N+1)th training data.

[0064] In step 115, the initial model is trained based on the (N+1)th training data to obtain a (N+1)th deep learning model.

25 **[0065]** In the step 101, the initial prediction data recognized by the general large-scale model generally includes a large number of generalized entities, and the user manually screens the initial prediction data to determine the initial generalized vocabulary. The initial generalized vocabulary includes common high-frequency generalized entities. The user filters the initial prediction data based on the initial generalized vocabulary to obtain the 1st training data. Specifically, generalized entities that exist in both the initial generalized vocabulary and the initial prediction data are deleted from the initial prediction data. After being filtered by
30 the initial generalized vocabulary, the number of generalized entities included in the 1st

training data is much less than the number of generalized entities included in the initial prediction data.

[0066] The initial model is trained based on the 1st training data to obtain the 1st deep learning model. After model is trained completely, the 1st deep learning model recognizes the to-be-recognized data to obtain the 1st prediction data. Due to preference of the deep learning model (the training process is more inclined to mine named entities with a higher proportion), the number of generalized entities in the 1st prediction data is less than the number of generalized entities in the 1st training data. The above process is the steps included in the 1st iteration.

[0067] The 2nd iteration starts from step 105, in which the 1st prediction data is first subtracted from the initial prediction data to obtain the 1st difference data. For example, if the initial prediction data is $A = \{(ent_1, l_1), (ent_3, l_1), (ent_5, l_2), (ent_4, l_3)\}$ and the 1st prediction data is $B = \{(ent_1, l_1), (ent_2, l_1), (ent_5, l_2)\}$, then $A - B = \{(ent_3, l_1), (ent_4, l_3)\}$. The number of non-generalized entities in the initial prediction data is similar to the number of non-generalized entities in the 1st prediction data, while the number of generalized entities in the 1st prediction data is much less than the number of generalized entities in the initial prediction data. After subtraction, most of the 1st difference data is generalized entities, and a little is non-generalized entities.

[0068] Then, the user determines the 1st generalized vocabulary manually. Specifically, the 1st generalized vocabulary may be determined based on the generalized entities in the 1st difference data. The 2nd training data may be obtained by screening the initial prediction data based on the 1st generalized vocabulary. Since the number of generalized entities included in the 1st generalized vocabulary is greater than the number of generalized entities included in the initial generalized vocabulary, the number of generalized entities in the 2nd training data is less than the number of generalized entities in the 1st training data. The 2nd deep learning model may be obtained by training the initial model based on the 2nd training data. The 2nd deep learning model has higher predictive capability than the 1st deep learning model due to higher quality (fewer generalized entities) of the 2nd training data. The 2nd iteration has been completed till step 109.

[0069] The steps performed in subsequent iterations are similar to those in the 2nd iteration.

The 3rd iteration starts from step 110, and the Nth iteration starts from step 111 in which the Nth deep learning model recognizes the to-be-recognized data to obtain the Nth prediction data. The Nth prediction data is subtracted from the initial prediction data to obtain the Nth difference data. The user determines the Nth generalized vocabulary based on generalized entities in the Nth difference data. The number of generalized entities in the Nth generalized vocabulary is greater than the number of generalized entities in a (N-1)th generalized vocabulary. The (N+1)th training data may be obtained by screening the initial prediction data based on the Nth generalized vocabulary. The (N+1)th deep learning model may be obtained by training the initial model based on the (N+1)th training data. With each iteration, the quality of the training data continues to improve, and the capability of the deep learning model generated based on the training data also improves. The capability of the (N+1)th deep learning model meets expectations and may be used for entity recognition on other review data.

[0070] The above iteration process will be further described below with specific embodiments. Specific data in the iterations may be shown in Table 1:

Number of iteration	Data name	Non-generalized entity	Generalized entity
1st iteration	Initial prediction data	500	300
	Initial generalized vocabulary	0	150 (high-frequency generalized entity)
	1st training data	500	150
2nd iteration	1st prediction data	450	50
	1st difference data	50	250
	1st generalized vocabulary	0	250
	2nd training data	500	50

3rd iteration	2nd prediction data	480	20
	2nd difference data	20	280
	2nd generalized vocabulary	0	280
	3rd training data	500	20

Table 1

[0071] In the 1st iteration, after the general large-scale model recognizes the to-be-recognized data, initial prediction data is obtained, which includes 500 non-generalized entities and 300 generalized entities. The user manually selects 150 high-frequency generalized entities from the 300 generalized entities to generate the initial generalized vocabulary. The high-frequency generalized entities appear more frequently, and it takes less time for the user to determine the initial generalized vocabulary. The initial prediction data is filtered based on the initial generalized vocabulary to obtain the 1st training data. The above 150 high-frequency generalized entities are deleted from the 1st training data. The 1st deep learning model may be obtained by training an initial model with the 1st training data. Compared with the general large-scale model, the 1st deep learning model may better remove the generalized entities when performing named entity recognition.

[0072] In the 2nd iteration, after the 1st deep learning model predicts the to-be-recognized data, the 1st prediction data is obtained, which includes 450 non-generalized entities and 50 generalized entities. Since the training process of the deep learning model is more inclined to mine non-generalized entities with a higher proportion, the number of generalized entities in the 1st prediction data may be greater than the number of generalized entities in the 1st training data. The number of the non-generalized entities in the 1st prediction data is reduced from 500 to 450. In order to eliminate this effect, the 1st prediction data may be subtracted from the initial prediction data to obtain the 1st difference data. The 1st difference data includes 50 non-generalized entities and 250 generalized entities. The user takes less time manually to filter the non-generalized entities in the 1st difference data to generate the 1st

generalized vocabulary. The 1st generalized vocabulary includes only 250 generalized entities. The 2nd training data may be obtained by screening the initial prediction data based on the 1st generalized vocabulary. The 2nd training data includes 500 non-generalized entities and 50 generalized entities. Compared with the 1st prediction data, the number of the non-generalized entities in the 2nd training data returns to 500, which may be used to train the initial model to obtain the 2nd deep learning model.

[0073] In the 3rd iteration, the 2nd deep learning model after training recognizes the to-be-recognized data to obtain the 2nd prediction data. Compared with the 1st prediction data, the 2nd prediction data includes more non-generalized entities and fewer generalized entities.

The 2nd prediction data is subtracted from the initial prediction data to obtain the 2nd difference data. The user manually deletes 20 non-generalized entities from the 2nd difference data to obtain the 2nd generalized vocabulary. The 3rd training data may be obtained by filtering the initial prediction data based on the 2nd generalized vocabulary. Compared with the 2nd training data, the 3rd training data includes the same number of non-generalized entities and a smaller number of generalized entities.

[0074] In each subsequent iteration, the number of generalized entities in the training data may continue to decrease, and the deep learning model after training may be more inclined to output non-generalized entities when recognizing other review data, providing the user with more valuable information.

[0075] In some embodiments, the user re-collects review data and performs entity recognition in the following three manners respectively: (1) performing recognition by using only the general large-scale model; (2) training a deep learning model by using the initial prediction data outputted by the general large-scale model, and then using the deep learning model for recognition; and (3) performing recognition by using the named entity recognition method provided by the embodiments of the present disclosure that is, using a deep learning model generated after multiple iterations to perform recognition.

[0076] Comparisons between recognition results and correct results in the first manner are shown in Table 2, comparisons between recognition results and the correct results in the second manner are shown in Table 3, and comparisons between recognition results and the correct results in the third manner are shown in Table 4:

Label of entity	Number of entity	Precision rate	Recall rate	F1 score
All labels	1110	0.39	0.48	0.43
[Attraction]	805	0.40	0.55	0.48
[Restaurant]	40	0.42	0.85	0.57
[Food]	51	0.49	0.74	0.59
[Activity]	214	0.17	0.54	0.26

Table 2

Label of entity	Number of entity	Precision rate	Recall rate	F1 score
All labels	1154	0.43	0.66	0.52
[Attraction]	853	0.49	0.84	0.62
[Restaurant]	45	0.40	0.90	0.55
[Food]	55	0.49	0.79	0.61
[Activity]	201	0.20	0.58	0.30

Table 3

Label of entity	Number of entity	Precision rate	Recall rate	F1 score
All labels	952	0.62	0.78	0.69
[Attraction]	682	0.74	0.84	0.78
[Restaurant]	25	0.68	0.81	0.74
[Food]	48	0.54	0.76	0.63
[Activity]	197	0.20	0.56	0.30

Table 4

[0077] As may be seen from the above tables, performing recognition by using only the general large-scale model produces the worst results, with the lowest precision rate, recall rate, and F1 score; training a deep learning model by using the initial prediction data outputted by the general large-scale model and then using the deep learning model for recognition produces better results, with increased precision rate, recall rate, and F1 score; and performing recognition by using the named entity recognition method provided by the embodiments of the present disclosure, which is a deep learning model generated after multiple iterations, produces the best recognition results, with significantly increased precision rate, recall rate,

and F1 score. Where $F1=2 \text{ (precision rate} \times \text{recall rate)} / (\text{precision rate} + \text{recall rate})$.

[0078] FIG. 2 is a schematic flowchart of another named entity recognition method according to some embodiments of the present disclosure. The method may be applied to an electronic device. As shown in FIG. 2, the method may include the following steps.

5 **[0079]** In step 201, to-be-recognized data is recognized based on a general model to obtain initial prediction data.

[0080] In step 202, the to-be-recognized data is recognized based on a Nth deep learning model to obtain Nth prediction data.

10 **[0081]** In step 203, (N+1)th training data is determined according to the initial prediction data and the Nth prediction data.

[0082] In step 204, the initial model is trained based on the (N+1)th training data to obtain a (N+1)th deep learning model.

[0083] Specific details between the steps may refer to the description in FIG. 1 above. Based on the above process, after the electronic device finally trains the initial model based on the (N+1)th training data, the (N+1)th deep learning model may be obtained. The (N+1)th deep learning model may be configured to perform named entity recognition on other text data, whose output results may include fewer generalized entities and most non-generalized entities, so that the user may be provided with valuable information.

20 **[0084]** FIG. 3 is a schematic structural diagram of a named entity recognition apparatus according to some embodiments of the present disclosure. The apparatus may be deployed in an electronic device. As shown in FIG. 3, the apparatus may include a processing module 310, a determination module 320, and a training module 330.

[0085] The processing module 310 is configured to recognize to-be-recognized data based on a general model to obtain initial prediction data.

25 **[0086]** The processing module 310 is further configured to recognize the to-be-recognized data based on a Nth deep learning model to obtain Nth prediction data.

[0087] The determination module 320 determines (N+1)th training data according to the initial prediction data and the Nth prediction data.

30 **[0088]** The training module 330 trains an initial model based on the (N+1)th training data to obtain a (N+1)th deep learning model.

[0089] A specific process may refer to the description in the above method flowchart.

[0090] Corresponding to the above embodiments, the present disclosure further provides an electronic device. FIG. 4 is a schematic structural diagram of an electronic device according to some embodiments of the present disclosure. The electronic device 400 may include a processor 401, a memory 402, and a communication unit 403. These components perform communication by using one or more buses. Those skilled in the art may understand that a structure of the electronic device shown in the figure imposes no limitation on the embodiments of the present disclosure, which may be a bus structure or a star structure and may include more or fewer components than those illustrated, or combine some components, or arrange the components in a different manner.

[0091] The communication unit 403 is configured to establish a communication channel so that the electronic device may communicate with other devices to receive user data from the other devices or send user data to the other devices.

[0092] The processor 401 is a control center of the electronic device, is connected to all parts of the entire electronic device by using various interfaces and lines, and performs various functions of the electronic device and/or processes data by running or executing software programs, instructions, and/or modules stored in the memory 402 and invoking data stored in the memory. The processor may include an integrated circuit (IC), for example, may include a singly-encapsulated IC or may include a plurality of connected encapsulated ICs with a same function or different functions. For example, the processor 401 may include only a central processing unit (CPU). In some embodiments of the present disclosure, the CPU may be a single computing core, or may include a plurality of computing cores.

[0093] The memory 402 is configured to store execution instructions of the memory 401. The memory 402 may be implemented by any type of volatile or non-volatile storage device or a combination thereof, such as a static random access memory (SRAM), an electrically erasable programmable read-only memory (EEPROM), an erasable programmable read-only memory (EPROM), a programmable read-only memory (PROM), a read-only memory (ROM), a magnetic memory, a flash memory, a magnetic disk, or an optical disc.

[0094] When the execution instructions in the memory 402 are executed by the processor 401, the electronic device 400 is enabled to perform some or all of the steps in the

embodiments shown in FIG. 1.

[0095] In specific implementation, the present disclosure further provides a computer storage medium. The computer storage medium may store programs. When executed, the program may include some or all of the steps in each embodiment of the named entity recognition method provided in the present disclosure. The storage medium may be a magnetic disk, an optical disc, a read-only memory (ROM), a random access memory (RAM), or the like.

[0096] In specific implementation, the present disclosure further provides a computer program product. The computer program product includes executable instructions. When the executable instructions are executed on a computer, the computer is caused to perform some or all of the steps in each embodiment of the named entity recognition method provided in the present disclosure.

[0097] Some embodiments of the present disclosure further provide a non-transitory computer-readable storage medium. The non-transitory computer-readable storage medium stores computer instructions. The computer instructions cause the computer to perform the named entity recognition method provided in some embodiments of the present disclosure.

[0098] The non-transitory computer-readable storage medium may be any combination of one or more computer-readable media. The computer-readable medium may be a computer-readable signal medium or a computer-readable storage medium. The computer-readable storage medium may be, for example, but not limited to, a system, apparatus or device of an electrical, magnetic, optical, electromagnetic, infrared or semiconductor type, or any combination thereof. More specific examples (non-exhaustive list) of the computer-readable storage medium include an electrical connection of one or more wires, a portable computer disk, a hard disk, a RAM, a ROM, an EPROM, a flash memory, an optical fiber, a portable compact disc read-only memory (CD-ROM), an optical storage device, a magnetic storage device, or any appropriate combination thereof. Herein, the computer-readable storage medium may be any tangible medium including or storing a program. The program may be used by or in combination with an instruction execution system, apparatus or device.

[0099] The computer-readable signal medium may include a data signal propagating in a baseband or as part of a carrier, which carries computer-readable program codes. Such data

signal may be propagated in many forms, which include, but are not limited to, an electromagnetic signal, an optical signal, or any appropriate combination thereof. The computer-readable signal medium may alternatively be any computer-readable medium other than the computer-readable storage medium. The computer-readable medium may send,
5 propagate, or transmit programs used by or in combination with an instruction execution system, apparatus or device.

[00100] The program codes included in the computer-readable medium may be transmitted over any appropriate medium, which includes, but is not limited to, wireless, wire, optic cable, radio frequency (RF), and any appropriate combination thereof.

10 **[00101]** Those skilled in the art may clearly understand that the technology in the embodiments of the present disclosure may be implemented by means of software plus a necessary general hardware platform. Based on such understanding, the technical solutions in the embodiments of the present disclosure essentially, or the part contributing to the prior art may be embodied in a form of a software product. The computer software product may be
15 stored in a storage medium, such as a ROM/RAM, a magnetic disk, or an optical disc, and includes several instructions to cause a computer device (which may be a personal computer, a server, a network device, or the like) to perform the methods described in various embodiments or part of the embodiments of the present disclosure.

20 **[00102]** Same and similar parts among the embodiments in this specification may be referred to one another. In particular, the apparatus embodiments and the terminal embodiments are basically similar to the method embodiments, so the description thereof is relatively simple. Related parts may be obtained with reference to the description in the method embodiments.

CLAIMS

What is claimed is:

1. A named entity recognition method, comprising:

recognizing to-be-recognized data based on a general model to obtain initial prediction data;

recognizing the to-be-recognized data based on a Nth deep learning model to obtain Nth prediction data, the Nth deep learning model being obtained by training an initial model based on Nth training data, N being a positive integer;

determining (N+1)th training data according to the initial prediction data and the Nth prediction data; and

training the initial model based on the (N+1)th training data to obtain a (N+1)th deep learning model, the (N+1)th deep learning model being configured for entity recognition.

2. The method according to claim 1, wherein subsequent to the recognizing the to-be-recognized data based on the general model to obtain initial prediction data, the method further comprises:

determining an initial generalized vocabulary in the initial prediction data in response to a selection operation of a user; and

screening the initial prediction data based on the initial generalized vocabulary to obtain 1st training data, wherein the 1st training data is used to train the initial model to obtain a 1st deep learning model.

3. The method according to claim 1, wherein the determining the (N+1)th training data according to the initial prediction data and the Nth prediction data comprises:

determining Nth difference data between the initial prediction data and the Nth prediction data;

determining a Nth generalized vocabulary in the Nth difference data in response to a selection operation of a user; and

screening the initial prediction data based on the Nth generalized vocabulary to obtain the (N+1)th training data.

4. The method according to claim 3, wherein the determining the Nth difference data between the initial prediction data and the Nth prediction data comprises:

subtracting the Nth prediction data from the initial prediction data to obtain the Nth difference data.

5. The method according to any one of claims 1 to 3, wherein the number of non-generalized entities comprised in the (N+1)th training data is greater than the number of non-generalized entities comprised in the Nth prediction data.

6. The method according to any one of claims 1 to 3, wherein the number of generalized entities comprised in the (N+1)th training data is greater than the number of generalized entities comprised in the Nth training data.

7. The method according to claim 1, wherein prior to the recognizing the to-be-recognized data based on the general model to obtain the initial prediction data, the method further comprises:

acquiring review data;

sorting the review data based on user ratings and data lengths; and

extracting a preset number of pieces of review data evenly in a sorted order to obtain the to-be-recognized data.

8. A named entity recognition apparatus, comprising:

a processing module configured to recognize to-be-recognized data based on a general model to obtain initial prediction data;

the processing module being further configured to recognize the to-be-recognized data based on a Nth deep learning model to obtain Nth prediction data, the Nth deep learning model being obtained by training an initial model based on Nth training data, N being a positive integer;

a determination module configured to determine (N+1)th training data according to the initial prediction data and the Nth prediction data; and

a training module configured to train the initial model based on the (N+1)th training data to obtain a (N+1)th deep learning model, the (N+1)th deep learning model being configured for entity recognition.

9. An electronic device, comprising a memory configured to store computer program

instructions and a processor configured to execute the program instructions, wherein when the program instructions are executed by the processor, the electronic device is caused to perform the method according to any one of claims 1 to 7.

10. A computer-readable storage medium, wherein the computer-readable storage medium comprises a stored program, wherein when the program is run, a device where the computer-readable storage medium is located is controlled to perform the method according to any one of claims 1 to 7.