

GEOSPATIAL TRANSPORTATION DATA PROCESSING METHOD, APPARATUS, AND ELECTRONIC DEVICE

[0001] This application claims priority to a Chinese Patent Application No.
5 202410414256.0, filed with the Chinese Patent Office on April 7, 2024, entitled “Geospatial
Transportation Data Processing Method, Apparatus, and Electronic Device”, the entire
contents of which are incorporated herein by reference.

TECHNICAL FIELD

[0002] The present disclosure relates to the field of computer technology, and more
10 particularly, to a geospatial transportation data processing method, an apparatus, and an
electronic device.

BACKGROUND

[0003] In a geospatial transportation application scenario, downstream tasks such as
navigation, arrival time estimation, and route determination all need to process information
15 such as a geospatial location, road network data, etc. For example, in an instant delivery
scenario, a navigation distance may be used to determine business district division, generate
a delivery range of a business. And based on the navigation distance, an arrival time and a
delivery fee may be computed, and scheduling and sharing is conducted. In order to improve
the performance of downstream tasks, various algorithm models are often used in the related
20 art, and these independent algorithm models have insufficient accuracy and are difficult to
unify in effect, which also causes waste of resources.

SUMMARY

[0004] In view of this, embodiments of the present disclosure provide a geospatial
transportation data processing method, an apparatus, and an electronic device, to implement
25 the processing of multiple downstream tasks by multimodal training a geospatial
transportation data processing model, and unify the representation of the location features
and the path features in the geospatial transportation data through the location encoding

model, the road segment encoding model, and the geospatial transportation data processing model, thereby improving the effect and performance of multiple downstream tasks, and increasing the resource utilization rate.

5 [0005] According to a first aspect, an embodiment of the present disclosure provides a geospatial transportation data processing method, including:

[0006] acquiring a location-path pair dataset including a plurality of pairs of location information and path information having a correspondence;

10 [0007] performing corresponding feature encoding on the location-path pair dataset based on a pre-trained location encoding model and a pre-trained road segment encoding model, respectively, to obtain location feature information and path feature information of a plurality of location-path pairs; and

[0008] performing multimodal training based on the location feature information and the path feature information of the plurality of location-path pairs to obtain a geospatial transportation data processing model.

15 [0009] According to a second aspect, an embodiment of the present disclosure provides a geospatial transportation data processing method, including:

[0010] acquiring target task information including location information and/or path information;

20 [0011] inputting the target task information into a pre-trained geospatial transportation data processing architecture for processing to obtain a corresponding task result;

[0012] where the geospatial transportation data processing architecture includes a location encoding model, a road segment encoding model, and a geospatial transportation data processing model, the location encoding model is configured to perform feature encoding on location information, the road segment encoding model is configured to perform feature encoding on route information, the geospatial transportation data processing model is obtained by performing multimodal training based on a location-path pair dataset, the location encoding model and the road segment encoding model, and the location-path pair dataset includes a plurality of pairs of location information and path information having a

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correspondence.

[0013] According to a third aspect, an embodiment of the present disclosure provides a geospatial transportation data processing apparatus, including:

5 **[0014]** a dataset acquisition unit, configured to acquire a location-path pair dataset including a plurality of pairs of location information and path information having a correspondence;

[0015] a feature encoding unit, configured to perform corresponding feature encoding on the location-path pair dataset based on a pre-trained location encoding model and a pre-trained road segment encoding model, respectively, to obtain location feature information and path feature information of a plurality of location-path pairs; and
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[0016] a training unit, configured to perform multimodal training based on the location feature information and the path feature information of the plurality of location-path pairs to obtain a geospatial transportation data processing model.

15 **[0017]** According to a fourth aspect, an embodiment of the present disclosure provides a geospatial transportation data processing apparatus, including:

[0018] an information acquisition unit, configured to acquire target task information including location information and/or path information;

[0019] a processing unit, configured to input the target task information into a pre-trained geospatial transportation data processing architecture for processing to obtain a corresponding task result;
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[0020] where the geospatial transportation data processing architecture includes a location encoding model, a road segment encoding model, and a geospatial transportation data processing model, the location encoding model is configured to perform feature encoding on location information, the road segment encoding model is configured to perform feature encoding on route information, the geospatial transportation data processing model is obtained by performing multimodal training based on a location-path pair dataset, the location encoding model and the road segment encoding model, and the location-path pair dataset includes a plurality of pairs of location information and path information having a
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correspondence.

[0021] According to a fifth aspect, an embodiment of the present disclosure provides an electronic device, including a memory and one or more processors, where the memory is configured to store one or more computer program instructions, and the one or more
5 computer program instructions are executed by the one or more processors to implement the method of the first aspect or the second aspect of the embodiments of the present disclosure.

[0022] According to a sixth aspect, an embodiment of the present disclosure provides a computer-readable storage medium, where the computer-readable storage medium stores therein a computer program that, when executed by one or more processors, implements the
10 method of the first aspect or the second aspect of the embodiments of the present disclosure.

[0023] According to a seventh aspect, an embodiment of the present disclosure provides a computer program product that, when run on a computer, causes the computer to perform the method according to the first aspect or the second aspect of the embodiments of the present disclosure.

[0024] In the embodiments, a location-path pair dataset including a plurality of pairs of location information and path information having a correspondence is acquired, corresponding feature encoding is performed on the location-path pair dataset based on a pre-trained location encoding model and a pre-trained road segment encoding model, respectively, to obtain location feature information and path feature information of a
15 plurality of location-path pairs, and multimodal training is performed based on the location feature information and the path feature information of the plurality of location-path pairs, to obtain a geospatial transportation data processing model. Therefore, in the embodiments, the processing of multiple downstream tasks can be implemented by multimodal training of a geospatial transportation data processing model, and the representation of the location
20 features and the path features in the geospatial transportation data can be unified through the location encoding model, the road segment encoding model, and the geospatial transportation data processing model, thereby improving the effect and performance of multiple downstream tasks, and increasing the resource utilization rate.
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BRIEF DESCRIPTION OF DRAWINGS

[0025] The above and other objects, features, and advantages of the present application will become more apparent from the following description of embodiments of the present application with reference to the accompanying drawings, in the drawings:

5 [0026] FIG. 1 is a diagram of a geospatial transportation data processing architecture according to an embodiment of the present disclosure;

[0027] FIG. 2 is a flowchart of a method for training a location encoding model according to an embodiment of the present disclosure;

[0028] FIG. 3 is a diagram of a process for determining a feature information sequence of location objects according to an embodiment of the present disclosure;

10 [0029] FIG. 4 is a flowchart of a method for fine-tuning a location encoding model according to an embodiment of the present disclosure;

[0030] FIG. 5 is a flowchart of a method for training a road segment encoding model according to an embodiment of the present disclosure;

15 [0031] FIG. 6 is a flow diagram of a process for training a road segment encoding model according to an embodiment of the present disclosure;

[0032] FIG. 7 is a flowchart of a geospatial transportation data processing method according to an embodiment of the present disclosure;

[0033] FIG. 8 is a flow diagram of a process for training a geospatial transportation data processing model according to an embodiment of the present disclosure;

20 [0034] FIG. 9 is a flowchart of a method for fine-tuning a geospatial transportation data processing model according to an embodiment of the present disclosure;

[0035] FIG. 10 is a flow diagram of a process for fine-tuning a geospatial transportation data processing model according to an embodiment of the present disclosure;

25 [0036] FIG. 11 is a flowchart of another geospatial transportation data processing method according to an embodiment of the present disclosure;

[0037] FIG. 12 is a diagram of a geospatial transportation data processing apparatus according to an embodiment of the present disclosure;

[0038] FIG. 13 is a diagram of another geospatial transportation data processing apparatus according to an embodiment of the present disclosure;

5 [0039] FIG. 14 is a diagram of an electronic device according to an embodiment of the present disclosure.

DETAILED DESCRIPTION

[0040] The present disclosure is described below with reference to embodiments, but the disclosure is not limited to these embodiments. In the following detailed description of the present application, some specific details are described in detail. It will be apparent to those skilled in the art that the present disclosure may be practiced without these specific details. In order to avoid obscuring the essence of the present disclosure, well-known methods, processes, flows, elements and circuits are not described in detail. In addition, it should be understood by those of ordinary skill in the art that the drawings are provided for illustrative purposes only and are not necessarily drawn to scale. Unless the context clearly requires otherwise, the words “include,” “comprise” etc., in the entire application document should be interpreted as inclusive rather than exclusive or exhaustive; that is to say, “include but not limited to”. In the description of the present disclosure, it should be understood that the terms “first,” “second,” etc., are used for descriptive purposes only and cannot be understood as indicating or implying relative importance. In addition, in the descriptions of the present disclosure, unless otherwise specified, “a plurality of” means two or more. All solutions described in this specification and the embodiments thereof that involve the processing of personal information will be carried out only where a lawful basis exists (e.g., after obtaining the consent of the individual concerned and, where applicable, the public, or where such processing is necessary for the performance of a contract) and will be limited to the scope prescribed or agreed upon. If a user refuses to allow the processing of personal information that is not necessary for the basic functions, the user’s ability to use those basic functions will not be affected.

[0041] FIG. 1 is a diagram of a geospatial transportation data processing architecture

according to an embodiment of the present disclosure. In the present embodiment of the present disclosure, the location encoding model, the road segment encoding model, and the geospatial transportation data processing model may be trained by using various types of geospatial transportation information in a specific geospatial transportation application scenario, such that the unified feature representation of various types of information in geospatial transportation can be implemented by using the location encoding model, the road segment encoding model, and the geospatial transportation data processing model, i.e., the various types of geospatial transportation information are encoded into a unified feature space, to implement various types of downstream transportation tasks (e.g., downstream tasks such as route planning, distance estimation, and arrival time estimation), and improve the effects and performance of the various downstream transportation tasks. At the same time, in the data processing architecture of the present embodiment, each model is not an independent algorithm, and compared to the related art in which various independent algorithm models are adopted to respectively improve downstream transportation tasks, the waste of resources is reduced and resource utilization rate is increased.

[0042] Specifically, as illustrated in FIG. 1, in the present embodiment of the present disclosure, various types of geospatial transportation information (e.g., location data, road and route data, AOI and POI data) may be encoded into a unified feature space by using a pre-trained location encoding model, a road segment encoding model, and a geospatial transportation data processing model, to process downstream transportation tasks.

[0043] In an embodiment, in the present embodiment of the present disclosure, supervised fine-tuning may be performed on the pre-trained model based on historical downstream task data of various downstream traffic tasks, thereby further improving task processing effects of the various downstream traffic tasks, and reducing task training costs.

[0044] In some embodiments, for example, in the instant delivery field, the location data may include a static user location and a business location, or may include a dynamic delivery resource location and status. The road and route data may include attribute information (e.g., designation, status, lane attributes, etc.) on the road, historically adopted route data, etc. An area of interest (AOI) represents a geospatial area (e.g., a business circle area, an industrial park area, etc.) with a certain range or boundary on a map, a point of interest (POI) represents a location (e.g., a store or a bus stop) having a point entity. It should be understood that

specific content of the foregoing various types of data may be the corresponding geospatial transportation data obtained according to different application scenarios, and the embodiments of the present disclosure are not limited to the field of instant delivery; other fields, such as ride-hailing, express delivery, and other geospatial transportation-related application fields, can all adopt the geospatial transportation data processing architecture described in embodiments of the present disclosure.

[0045] In an embodiment, the location encoding model is obtained by pre-training based on a location dataset, and may encode geospatial locations into corresponding feature vectors. In some embodiments, the location encoding model of the present embodiment can adopt absolute position encoding, relative position encoding, or position masking encoding. Further, the location encoding model may adopt the Transformer original location encoding, learnable location encoding, encoding based on a convolutional neural network, models introducing relative position encoding such as Transformer-XL, recursive location encoding, periodic location encoding, or dynamic location encoding as the base model for model training.

[0046] In another optional implementation, the location encoding model in the present embodiment implements model pre-training based on geospatial contrastive learning.

[0047] FIG. 2 is a flowchart of a method for training a location encoding model according to an embodiment of the present disclosure. In some embodiments, as illustrated in FIG. 2, the method for training a location encoding model in the present embodiment includes the steps described below.

[0048] At step S110: a location dataset is acquired.

[0049] In an embodiment, the location dataset may include information about any location in the corresponding area. Further, the location information in the location dataset may be determined based on a location related to a corresponding application field. For example, in an instant delivery application scenario, the location dataset is determined based on a business location, a delivery resource stay location (e.g., a location whose stay frequency is greater than a frequency threshold or whose stay duration is greater than a time threshold), and/or other locations (e.g., a temporary storage cabinet location). For another example, in

an online ride-hailing application scenario, the location dataset is determined based on pickup and drop-off points within each area, origin and destination points where the task volume exceeds the task volume threshold, and/or vehicle stay positions.

5 [0050] In an embodiment, the location in the location dataset may be determined based on information such as a location and a trajectory in a historical task, or may be determined based on location information in a road network, which is not limited in the present embodiment.

10 [0051] At step S120: a feature information sequence of a location object in the location dataset is acquired. The feature information sequence is determined based on geospatial information objects within a predetermined range of the location object

15 [0052] In some embodiments, the geospatial information object may include an AOI, a POI, and/or a road network object within a predetermined range of the corresponding location object. The road network object is used to represent an object representing a road segment or a road segment combination in the road network, which may include a path object, a road object, a road segment object, etc. In some embodiments, the present embodiment does not limit the division manner of the predetermined range and the range size, which may be set according to specific application scenarios. For example, in the present embodiment, a circle may be drawn with a location object as the center and the predetermined distance as the radius to determine the predetermined range, or, a polygonal shape may be drawn with the location object as the center to determine the predetermined range.

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[0053] In the present embodiment, the feature information sequence of the location object is obtained by acquiring feature information of geospatial information objects of the location object within a predetermined distance range, and sorting feature information of geospatial information objects based on a predetermined condition. In some embodiments, the predetermined condition includes distance proximity of the respective geospatial information objects relative to a corresponding location object. For example, geospatial information objects g1, g2, and g3 exist within a predetermined distance range of the location object P1, and the feature information of the geospatial information objects g1, g2, and g3 is f1, f2, and f3, respectively. Distances from the geospatial information objects g1,

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g_2 , and g_3 to location object P_1 are d_1 , d_2 , and d_3 , respectively, and if $d_2 > d_3 > d_1$, the feature information sequence of the location object P_1 is $\{f_1, f_3, f_2\}$.

[0054] In other optional implementations, the category of the geospatial information objects and their distance proximity relative to the location object may be used as the predetermined condition. Specifically, the geospatial information objects may be classified, the geospatial information objects in the same category are sorted according to distance proximity, and each category of geospatial information objects is sorted based on a predetermined category order to obtain a corresponding feature information sequence. For example, the categories of geospatial information objects within the predetermined distance range of the location object P_1' include C_1 and C_2 , where the geospatial information objects g_1' and g_2' within the predetermined distance range of the location object P_1' belong to the category C_1 , and the geospatial information objects g_3 and g_4' belong to the category C_2 . The feature information of the geospatial information objects g_1' , g_2' , g_3' and g_4' is f_1' , f_2' , f_3' and f_4' , respectively. The geospatial information objects g_1' , g_2' , g_3' , and g_4' have distances d_1' , d_2' , d_3' , and d_4' from the location object P_1' , respectively. If $d_2' > d_1'$, and $d_3' > d_4'$, and the predetermined category sequence is $\{C_1, C_2\}$, the feature information sequence of the location object P_1' is $\{f_1', f_2', f_4', f_3'\}$. It should be understood that other predetermined conditions for sorting may also be applied to the present embodiment, which is not limited in the present embodiment.

[0055] Further, in an embodiment, the feature information of a geospatial information object includes one or a combination of: an object identifier, an object shape, an object location, a relationship with a location object, or location information relative to the location object. The object shape may include a shape corresponding to a contour of the geospatial information object, e.g., a contour of an AOI. In some embodiments, the object shape may be characterized by maximum coordinate values of the geospatial information object in multiple directions, or by coordinate values of multiple vertices, which is not limited in the present embodiment. The object location may be a latitude and longitude representation of the geospatial information object. The location relationship with the location object may be an inclusive or non-inclusive relationship. If the location object is inside the geospatial information object, it is an inclusive relationship, or if the location object is outside the geospatial information object, it is non-inclusive relationship. Further In some embodiments,

the location of the geospatial information object may be represented by longitude and latitude of a center point of the geospatial information object. In some embodiments, the center point of the geospatial information object may be the center point of the inscribed image or the circumscribed image of the geospatial information object, which is not limited in the present embodiment.

[0056] In an embodiment, the feature information is obtained by encoding the information of the geospatial information object in a predetermined manner. For example, the feature information of the geospatial information object may be encoded by using an encoding manner such as label encoding, one-hot encoding, ordinal encoding, binary encoding, counting encoding, and/or hash encoding, etc., which is not limited in the present embodiment.

[0057] In an embodiment, when the information of the geospatial information object is encoded, a predetermined masking method may be used to mask some features in the original information, so as to hide, obscure, or desensitize a feature region or feature in the corresponding geospatial space data. In some embodiments, a geospatial information masking manner may be used, e.g., pixelation, perturbation, aggregation, location shift, geometric deformation, or empty area filling, etc., which is not limited in the present embodiment. Further, in the present embodiment, random content masking may be performed on the original information of the geospatial information object according to a certain proportion, e.g., the original information is replaced with a mask. In other implementations, the location of the masked content may be selected first, and then the selected location is partially replaced with a mask, partially randomly replaced with other content, and the remaining location content remains unchanged. It should be understood that the present embodiment does not limit the specific masking operation, as long as it can adapt to the corresponding application field.

[0058] FIG. 3 is a diagram of a process for determining a feature information sequence of location objects according to an embodiment of the present disclosure. As illustrated in FIG. 3, for a location object P, within a predetermined distance range of the location object P, geospatial information objects O1, O2, O3, and O4 exist. The geospatial information objects O1 and O2 are AOI objects, the geospatial information object O3 is a POI object, and the geospatial information object O4 is a road network object. Further, information of the

geospatial information objects O1, O2, O3 and O4 is obtained and encoded to obtain corresponding feature information f_{01} , f_{02} , f_{03} and f_{04} . The feature information f_{01} , f_{02} , f_{03} and f_{04} respectively include the corresponding features f1-f5. In some embodiments, the feature f1 represents an object identification feature, f2 represents an object shape feature, f3 represents an object location feature, f4 represents a relationship feature between a corresponding geospatial location object and the location object P, and f5 represents a location feature relative to the location object P. The feature f3 corresponding to the geospatial information object O2 and the features f3 and f5 corresponding to the geospatial information object O4 are masked to ensure data privacy. Therefore, in the present embodiment, the feature information sequence $F = \{f_{01}, f_{02}, f_{03}, f_{04}\}$ of the location object P may be obtained.

[0059] At step S130: training is performed based on the feature information sequences to obtain the location encoding model.

[0060] In an embodiment, according to the feature information sequences of the respective geospatial objects, the location encoding model GeoEncoder is obtained by pre-training using a geospatial contrastive learning method. Geographic contrastive learning (GCL) is an unsupervised training method that learns a feature representation of data by comparing similarities or differences between different data samples (e.g., different location objects in the present embodiment). In the present embodiment of the present disclosure, a spatial relationship and attribute information in geospatial data are used to learn a representation of a geospatial feature by using a contrastive learning method, to implement tasks such as automatic geospatial information extraction, classification, and recognition.

[0061] In some embodiments, parameter adjustment may be performed on the location encoding model in the present embodiment by learning corresponding loss function through geospatial contrastive learning. In some embodiments, the corresponding loss function may be determined by the difference between the prediction results of similarity or difference between different location objects and the true labels. It should be understood that a specific loss function is not limited in the present embodiment. Therefore, in the present embodiment, the feature information of each location object is adjusted based on the similarity and/or difference of the location object, to accurately return (obtain) the feature information of the respective location objects.

[0062] In another implementation, the location encoding model may be trained in a pre-training manner combining a geospatial information masking manner and a geospatial contrastive learning method.

5 [0063] In the present embodiment, parameter adjustment may be performed on the location encoding model based on the geospatial information masking loss and the geospatial contrastive learning loss to obtain the location encoding model.

[0064] Further, because using the geospatial information masking may cause a loss of the geospatial information to a certain extent, in the present embodiment, the performance loss caused by the data loss may be compensated by using the geospatial information masking
10 loss, or whether to perform the masking operation on the data is determined by balancing the performance difference before and after the data masking, to further improve the accuracy of the location encoding model.

[0065] In an embodiment, an unsupervised training manner is used for the location encoding model obtained through pre-training, and in the present embodiment, supervised training
15 may be performed on the pre-trained location encoding model by using a small volume of training data, to fine-tune the pre-trained location encoding model, thereby further improving accuracy of the location encoding model.

[0066] FIG. 4 is a flowchart of a method for fine-tuning a location encoding model according to an embodiment of the present disclosure. In some embodiments, as illustrated
20 in FIG. 4, in the present embodiment, fine-tuning is performed on the unsupervised pre-trained location encoding model through the method steps described below.

[0067] At step S140: a location map-matching pair dataset is acquired. The location map-matching pair dataset includes a plurality of pairs of location feature information and map-matching information having a correspondence. Map-matching means capturing or
25 identifying the corresponding road or road segment based on the corresponding location. In some embodiments, the road or road segment corresponding to the location may include a road or road segment on which the location is located, and/or an available road or road segment corresponding to route planning corresponding to the location.

[0068] In an embodiment, e.g., in an application scenario with an origin point and a destination point, the location feature in the location map-matching pair includes an origin point feature and a destination point feature, and the corresponding map-matching information includes origin point map-matching mark information and destination point map-matching mark information. It should be understood that the location map-matching pair in the present embodiment is not limited to the origin point and the destination point, and other locations where the map-matching operation needs to be performed may also be applied to the present embodiment.

[0069] At step S150: supervised training is performed on a pre-trained location encoding model based on the location map-matching pair dataset to obtain the final location encoding model.

[0070] In the present embodiment, a plurality of pairs of location features and map-matching information having a correspondence in the location map-matching pair dataset may be input into the pre-trained location encoding model for processing, to obtain corresponding location feature information and road segment feature information, a model loss is determined based on a similarity between the location feature information and the road segment feature information having the correspondence, and the location encoding model is adjusted based on the loss until performance required by the model is met.

[0071] For example, in the application scenario with origin point and destination point, the origin point location information, destination point location information, origin point map-matching information, and destination point map-matching information are input into the position encoding model for processing, to obtain the origin point feature information, the destination point feature information and the road segment feature information corresponding to the map-matching. The model loss is determined by computing the similarity between the origin and destination point feature information and the road segment feature information corresponding to the map-matching. The position encoding model is adjusted based on the loss until the position encoding model meets the required performance of the model.

[0072] In the present embodiment of the present disclosure, unsupervised pre-training of the location encoding model is implemented through geospatial contrastive learning, and the

location encoding is fine-tuned through supervised training, such that not only the encoding model performs feature encoding on location information more accurately, but also performs ranking and scoring recalled roads in a map-matching task, thereby further reducing model complexity and a computation amount of different tasks.

- 5 **[0073]** In an embodiment, the road segment encoding model is obtained by training based on a path sequence dataset, and may encode information of a road segment into a corresponding feature vector. The information of the road segment may include a road segment identifier, a road segment type, lane types of the road segment, and auxiliary information (e.g., speed limit information and construction information).
- 10 **[0074]** FIG. 5 is a flowchart of a method for training a road segment encoding model according to an embodiment of the present disclosure. As illustrated in FIG. 5, the method for training a road segment encoding model according to an embodiment of the present disclosure includes the steps described below.

- 15 **[0075]** At step S210: a path sequence dataset is acquired. The path sequence dataset includes a plurality of path sequences, where each of the path sequences includes at least one road segment. Each path sequence may include information of one or more corresponding road segments.

- 20 **[0076]** In an embodiment, the feature information is obtained by encoding the information of the road segment in a predetermined manner. For example, the road segment information may be encoded by using an encoding manner such as label encoding, one-hot encoding, ordinal encoding, binary encoding, counting encoding, and/or hash encoding, etc., which is not limited in the present embodiment.

- 25 **[0077]** In an embodiment, when the information of the road segment is encoded, a predetermined masking method may be used to mask a part of features in the original information, so as to hide, obscure, or desensitize a feature region or feature in the corresponding geospatial space data. In some embodiments, a geospatial information masking manner may be used, e.g., pixelation, perturbation, aggregation, location shift, geometric deformation, or empty area filling, etc., which is not limited in the present embodiment. Further, in the present embodiment, random content masking may be

performed on the original information of the road segment information object according to a certain proportion, e.g., the original information is replaced with a mask. In other implementations, the location of the masked content may be selected first, and then the selected location is partially replaced with a mask, partially randomly replaced with other content, and the remaining location content remains unchanged. It should be understood that the present embodiment does not limit the specific masking operation, as long as it can adapt to the corresponding application field.

[0078] At step S220: pre-training is performed based on the path sequence dataset by using a masked training method to obtain the road segment encoding model.

[0079] In the present embodiment of the present disclosure, the masked training method is used to mask some road segments in the input path sequence, to predict a masked road segment based on a road segment in an unmasked path sequence. Therefore, the road segment encoding model in the present embodiment of the present disclosure can fully learn information about road segments and information about adjacent road segments, thereby improving a generalization capability and robustness.

[0080] In an embodiment, in the present embodiment of the present disclosure, dense embedding is performed on the feature information of the sparse path sequence, to obtain a corresponding hidden representation, to obtain an output result, then compute a corresponding loss based on the output result, and adjust parameters of the road segment encoding model based on the loss, to obtain the trained road segment encoding model.

[0081] In an implementation, because different path sequences may have the same or similar road segments, in the present embodiment of the present disclosure, sample sampling is performed by using a sampling softmax classifier, to obtain a part of training samples in all categories through sampling, to compute a loss, such that a computation amount of each training iteration can be reduced while a capability of distinguishing between different categories is ensured.

[0082] FIG. 6 is a flow diagram of a process for training a road segment encoding model according to an embodiment of the present disclosure. As illustrated in FIG. 6, in the present embodiment, after feature encoding is performed on the road segments in each path sequence,

corresponding sparse features are obtained, the sparse features are input into a dense embedding layer to compress the high-dimensional sparse features into dense data, so as to improve model performance and reduce computational complexity, and corresponding features or information are extracted from the dense data to obtain a representation of a hidden space (Hidden Representation), and then the feature representation of the hidden space is converted to obtain an output result (Output Matrix), and a loss corresponding to a training period is computed based on the output result and a predetermined loss function, so as to adjust parameters of the road segment encoding model based on the loss to obtain a road segment encoding model meeting predetermined performance.

[0083] In some embodiments, as illustrated in FIG. 6, because different path sequences may have the same or similar road segments, in the present embodiment of the present disclosure, sample sampling is performed by using a sampling softmax classifier, to obtain a part of training samples in all categories through sampling, to compute a loss, such that a computation amount of each training iteration can be reduced while a capability of distinguishing between different categories is ensured.

[0084] In the present embodiment, the geospatial transportation data processing model processes the information in the location-path pair dataset based on the location encoding model and the road segment encoding model, and performs multimodal training based on the processed result. Multimodal training can simultaneously process and understand multiple different types of data or “modalities”, such as different types of geospatial transportation data, and during the training process, the internal connections and information consistency between different modalities can be captured and fused, thereby better understanding and expressing geospatial transportation information.

[0085] FIG. 7 is a flowchart of a geospatial transportation data processing method according to an embodiment of the present disclosure. Specifically, as illustrated in FIG. 7, the geospatial transportation data processing method according to the embodiment of the present application includes the steps described below.

[0086] At step S310: a location-path pair dataset is acquired. The location-path pair dataset includes a plurality of pairs of location information and path information having a correspondence.

[0087] In an embodiment, the location-path pair dataset may be an OD-path sequence pair dataset. In other words, the location-path pair dataset may include a plurality of pairs of origin points and destination points and corresponding path sequences. In some embodiments, the location-path pair dataset may be constructed by origin point and destination point in the historical tasks and corresponding actual routes. It should be understood that the location-path pair dataset of the present embodiment may be constructed based on a corresponding application scenario, e.g., in the field of instant delivery, the origin point and destination point may include a rider location, a business location, or a business location and a user location, and the path sequence may be a route traveled by a delivery resource.

[0088] At step S320: corresponding feature encoding is performed on the location-path pair dataset based on a pre-trained location encoding model and a pre-trained road segment encoding model, respectively, to obtain location feature information and path feature information of a plurality of location-path pairs.

[0089] In the present embodiment, feature encoding is performed on the location information in the location-path pair dataset, by using the location encoding model trained through the foregoing training process, to obtain location feature information. In some embodiments, the location feature information may include the origin point location features and the destination point location features.

[0090] Feature encoding is performed on the path sequence in the location-path pair dataset, by using the road segment encoding model trained through the foregoing training process, to obtain path feature information. The path feature information includes feature information of each road segment in the corresponding path sequence.

[0091] At step S330: multimodal training is performed based on the location feature information and the path feature information of the plurality of location-path pairs to obtain a geospatial transportation data processing model.

[0092] In an embodiment, pre-training is performed based on the location feature information and the path feature information of the respective location-path pairs after

feature alignment and by using multimodal geospatial information masking and location-path matching to obtain the geospatial transportation data processing model.

[0093] In the present embodiment, multimodal geospatial information masking may enable a plurality of different types of geospatial transportation information data to be processed and analyzed by using a specific masking technology. Therefore, the geospatial transportation data processing model in the present embodiment of the present disclosure may extract and highlight geospatial data features required by a corresponding downstream task, such that other types of downstream traffic tasks can be processed, thereby ensuring accuracy of various downstream traffic tasks.

[0094] Further, the location path matching method (MATCH) is a method for implementing cross-modal information integration and transfer. In some embodiments, the location path matching method of the present embodiment may enable the model to dynamically assign weights according to correlations between different modalities through an attention mechanism, thereby focusing on key areas or features in data of different modalities.

[0095] In some embodiments, spatial alignment, fusion, and conversion of features of different modalities may be implemented by constructing a multi-modal interaction layer, to capture fine-grained information related to geospatial transportation data of different modalities.

[0096] Specifically, in the present embodiment of the present disclosure, feature information of a plurality of modalities is aligned by using a multimodal interaction layer, i.e., feature alignment is performed on location feature information and path feature information of location-path pairs, to implement unified representation of a plurality of types of geospatial transportation information in the same feature space. In some embodiments, the multimodal interaction layer may be designed through attention mechanism, element-level intersection, gating mechanism, cross-mode pooling, deeply separable convolution, joint embedding space, or bilinear pooling/transformation. In the present embodiment of the present disclosure, the multimodal interaction layer may be designed in a corresponding design manner based on a specific application scenario, which is not limited in the present embodiment.

[0097] In some embodiments, transportation data streams from a plurality of modalities may be simultaneously processed and optimized through joint training, such that the road segment encoding model can understand and associate different types of input data as a whole.

- 5 [0098] In some embodiments, matching targets (e.g., using origin and destination points and routes as matching targets, etc.) or loss functions may be set via cross-modal matching, enabling the geospatial transportation data processing model to establish effective mapping relationships between multiple modalities.

[0099] FIG. 8 is a flow diagram of a process for training a geospatial transportation data processing model according to an embodiment of the present disclosure. In some
10 embodiments, as illustrated in FIG. 8, in a training process of the geospatial transportation data processing model in the present embodiment of the present disclosure, a location-path pair dataset D is first obtained, and a plurality of training samples (i.e., a plurality of location data pairs) are acquired from the location-path pair dataset D. The location data pair includes
15 an origin location o_l , a destination location d_l , and a path sequence path.

[0100] Further, the origin location o_l and the destination location d_l are input into the pre-trained location encoding model 81 to obtain the location feature information OD including the origin point feature information and the destination point feature information, and the path sequence *path* is input into the pre-trained road segment encoding model 82 to obtain
20 the link path feature information.

[0101] In the present embodiment, the acquired OD location feature information and link path feature information are input into the geospatial transportation data processing model 83 to be trained, an output of the geospatial transportation data processing model 83 is obtained through a multi-layer neural network architecture (e.g., including a neural network
25 layer for implementing a multimodal interaction layer), and parameters of the geospatial transportation data processing model 83 are adjusted based on the output, the MATCH loss, and the multimodal mask loss, until a model meeting performance of the application scenario is obtained. In some embodiments, a final loss may be obtained by using a weighted sum of the MATCH loss and the multimodal mask loss, and parameter adjustment is performed
30 based on the final loss. It should be understood that the present embodiment does not limit

the computation method of the final loss, and it may be determined by direct summation, etc.

[0102] In an embodiment, parameters of the location encoding model and the road segment encoding model may be maintained in the training period of the geospatial transportation data processing model 83, or the location encoding model and the road segment encoding model may be further fine-tuned in the training period of the geospatial transportation data processing model 83, to further improve the accuracy of the geospatial transportation data processing architecture. A specific parameter adjustment manner is not limited in the present embodiment of the present disclosure.

[0103] In some embodiments, the multi-layer neural network architecture of the geospatial transportation data processing model 83 includes a multi-head attention mechanism layer (Multi-Head Attention) 831, an addition and normalization layer (Add & Norm) 832, a feedforward layer (Feed-Forward) 833, and an addition and normalization layer (Add & Norm) 834.

[0104] The multi-head attention mechanism layer 831 can capture different subspace features of data, enhancing the ability of the model to understand and learn complex dependencies, and can perform parallel processing, which can effectively improve the computing efficiency. Further, in the present embodiment, a corresponding multimodal interaction layer may be designed based on the multi-head attention mechanism layer 831, to implement spatial alignment of multimodal features. An addition and normalization layer (Add & Norm) 832 and an addition and normalization layer (Add & Norm) 834 are arranged after the multi-head attention mechanism layer 831 and the feedforward layer 833 for improving stability and efficiency during model training. The feedforward layer 833 may process the geospatial transportation data through linear transformation and an activation function, and output a final feedforward result. It should be understood that the multi-layer neural network architecture of the geospatial transportation data processing model 83 in the present embodiment is merely exemplary, and other network architectures applicable to the embodiments of the present disclosure, e.g., a plurality of feedforward layers, may be applied to the present embodiment, which is not limited in the present embodiment.

[0105] In an embodiment, unsupervised training may be further performed on the model in the pre-training phase by using the training data (i.e., the foregoing location-path pair dataset) through transfer learning, and fine adjustment is performed on a specific downstream task, such that the geospatial transportation data processing model can transfer knowledge learned from one modality to another modality.

[0106] FIG. 9 is a flowchart of a method for fine-tuning a geospatial transportation data processing model according to an embodiment of the present disclosure. In some embodiments, as illustrated in FIG. 9, the method for fine-tuning a geospatial transportation data processing model in the present embodiment includes the steps described below.

[0107] At step S340, a specific-task dataset corresponding to each of at least one specific task is acquired.

[0108] At step S350: supervised training is performed on parameters of the geospatial transportation data processing model based on the at least one specific-task dataset to obtain a final geospatial transportation data processing model.

[0109] In an embodiment, taking an instant delivery application scenario as an example, the at least one specific task includes a distance task. The specific-task dataset includes a plurality of pairs of location information and distance information having a correspondence. In some embodiments, an origin and destination point-distance dataset is constructed through historical data from the historical delivery tasks. Further, in the present embodiment, a corresponding dataset is constructed by using historical delivery tasks that meet a predetermined condition. The predetermined condition may be a condition such as timely delivery, which is not limited in the present embodiment.

[0110] In an embodiment, the distance task may be a delivery distance task, a business delivery range task based on a delivery distance, etc.

[0111] In some embodiments, the geospatial transportation data processing model is fine-tuned by regressing the difference between the predicted distance corresponding to the origin and destination points (i.e., the output of the geospatial transportation data processing model) and the true distance, until the discrepancy between the predicted distance output by the

geographic transportation data processing model and the true distance meets the performance requirements of the specific application scenario.

5 [0112] In another implementation, the at least one specific task includes a time determination task. The specific-task dataset includes a plurality of pairs of location information and time information having a correspondence.

[0113] In some embodiments, a dataset of origin and destination point-arrival times is constructed through the historical data from the historical delivery tasks. In some embodiments, a corresponding dataset is constructed by using historical delivery tasks that meet a predetermined condition. The predetermined condition may include a condition such as timely delivery, which is not limited in the present embodiment.

15 [0114] In some embodiments, the geospatial transportation data processing model is fine-tuned by regressing the difference between the predicted arrival time corresponding to the origin and destination points (i.e., the output of the geospatial transportation data processing model) and the true arrival time, until the discrepancy between the predicted arrival time output by the geographic transportation data processing model and the true arrival time meets the performance requirements of the specific application scenario.

[0115] In another implementation, the at least one specific task includes a route scoring task. The specific-task dataset includes a plurality of pairs of location information and route information having a correspondence.

20 [0116] In some embodiments, a dataset of the origin and destination point-delivery route is constructed through historical data from the historical delivery tasks. In some embodiments, a corresponding dataset is constructed by using historical delivery tasks that meet a predetermined condition. The predetermined condition may include a condition such as timely delivery, which is not limited in the present embodiment.

25 [0117] In some embodiments, the geospatial transportation data processing model is fine-tuned by regressing the matching degrees between the origin and destination points and their corresponding routes, until the error between the routes determined by these matching degrees (between the origin and destination points and their corresponding routes) output by

the geographic transportation data processing model and the actual routes meets the performance requirements of the specific application scenario

[0118] In another optional implementation, the at least one specific task includes a road label mining task. The specific-task dataset includes a plurality of pairs of route information and label information having a correspondence.

[0119] In some embodiments, a dataset of the route and the road label may be constructed by the route of the historical delivery task and the road label corresponding to the route. Further, a corresponding dataset is constructed by using historical delivery tasks that meet a predetermined condition. The predetermined condition may include a condition such as timely delivery, which is not limited in the present embodiment.

[0120] In some embodiments, the geospatial transportation data processing model is fine-tuned through a classification task based on the discrepancy between the road label categories output by the model and the actual road label categories, until the error between the road label categories output by the geographic transportation data processing model and the actual road label categories meets the performance requirements of the specific application scenario.

[0121] It should be understood that different geospatial transportation application scenarios correspond to different specific tasks, the present embodiment is merely described by using an instant delivery task as an example, and a specific task in another application scenario may also be fine-tuned based on transfer learning to adapt to a corresponding specific task.

[0122] FIG. 10 is a flow diagram of a process for fine-tuning a geospatial transportation data processing model according to an embodiment of the present disclosure. As illustrated in FIG. 10, in the fine-tuning process of the geospatial transportation data processing model, a specific-task dataset of a specific task is acquired, an origin point o₁ and a destination point d₁ in the specific-task dataset are input into the location encoding model 101, to obtain the origin and destination point location feature information, route data in the specific-task dataset is input into the road segment encoding model 102 to obtain corresponding route feature information, the origin and destination point location feature information and the route feature information are input into the geospatial transportation data processing model

103 for processing, to obtain an output state h_o corresponding to the origin point, an output state h_d corresponding to the destination point, a route output state h_{path} and a road segment output state h_{link} . Further, in the present embodiment, the output states h_o , h_d , the route output state h_{path} and/or the road segment output state h_{link} are decoded to
5 obtain the output result of the corresponding specific task, and the corresponding loss is computed based on the actual data in the specific-task dataset, such as the loss *DIS Loss* corresponding to the distance task, the loss *ETA Loss* corresponding to the time determination task, the loss *LABEL Loss* corresponding to the road label mining task, etc., so as to adjust the parameters of the geospatial transportation data processing model 103
10 based on the corresponding loss to obtain the fine-tuned geospatial transportation data processing model 103.

[0123] In an embodiment, a method of the embodiment of the present disclosure further includes: inputting the target task information into a pre-trained geospatial transportation data processing architecture for processing to obtain a corresponding task result. The target
15 task information includes location information and/or route information. The task result includes one or a combination of the following: distance information, time prediction information, route information, and road label information that correspond to the target task. The geospatial transportation data processing architecture includes a location encoding model, a road segment encoding model, and a geospatial transportation data processing
20 model. It should be understood that the target task may be any specific task involved in the model fine-tuning process, which may be determined based on the corresponding geospatial transportation application scenario. In the embodiments of the present disclosure, a location-path pair dataset including a plurality of pairs of location information and path information having a correspondence is acquired, corresponding feature encoding is performed on the
25 location-path pair dataset according to a pre-trained location encoding model and road segment encoding model, location feature information and path feature information of the plurality of location-path pairs are acquired, and multimodal training is performed based on the location feature information and the path feature information of the respective location-path pairs to obtain a geospatial transportation data processing model. Therefore, in the
30 embodiment, the processing of multiple downstream tasks can be implemented by multimodal training a geospatial transportation data processing model, and unify the representation of the location features and the path features in the geospatial transportation

data through the location encoding model, the road segment encoding model, and the geospatial transportation data processing model, thereby improving the effect and performance of multiple downstream tasks, and increasing the resource utilization rate.

[0124] FIG. 11 is a flowchart of another geospatial transportation data processing method according to an embodiment of the present disclosure. As illustrated in FIG. 11, the geospatial transportation data processing method in the present embodiment of the present disclosure includes the steps described below.

[0125] At step S410: target task information is acquired. The target task information includes location information and/or path information.

[0126] At step S420: the target task information is input into a pre-trained geospatial transportation data processing architecture for processing to obtain a corresponding task result.

[0127] The geospatial transportation data processing architecture includes a location encoding model, a road segment encoding model, and a geospatial transportation data processing model, the location encoding model is configured to perform feature encoding on location information, the road segment encoding model is configured to perform feature encoding on route information, the geospatial transportation data processing model is obtained by performing multimodal training on a dataset, the location encoding model, and the road segment encoding model based on a location path, and the location-path pair dataset includes a plurality of pairs of location information and path information having a correspondence.

[0128] It should be understood that pre-training and fine-tuning of the location encoding model, the road segment encoding model, and the geospatial transportation data processing model in the foregoing geospatial transportation data processing architecture are similar to those in the foregoing embodiments, which is not described herein again.

[0129] In the present embodiment of the present disclosure, the target task information is processed by using the transportation data framework including the location encoding model, the road segment encoding model, and the geospatial transportation data processing model in the architecture, to obtain the corresponding task processing result. Therefore, in the

embodiment, the processing of multiple downstream tasks can be implemented by multimodal training a geospatial transportation data processing model, and unify the representation of the location features and the path features in the geospatial transportation data through the location encoding model, the road segment encoding model, and the geospatial transportation data processing model, thereby improving the effect and performance of multiple downstream tasks, and increasing the resource utilization rate.

[0130] FIG. 12 is a diagram of a geospatial transportation data processing apparatus according to an embodiment of the present disclosure. As illustrated in FIG. 12, the geospatial transportation data processing apparatus 12 in the present embodiment of the present disclosure includes a dataset acquisition unit 121, a feature encoding unit 122, and a training unit 123.

[0131] The dataset acquiring unit 121 is configured to acquire a location-path pair dataset, the location-path pair dataset including a plurality of pairs of location information and path information having a correspondence. The feature encoding unit 122 is configured to perform corresponding feature encoding on the location-path pair dataset based on a pre-trained location encoding model and a pre-trained road segment encoding model, respectively, to obtain location feature information and path feature information of a plurality of location-path pairs, The training unit 123 is configured to perform multimodal training based on the location feature information and the path feature information of the plurality of location-path pairs to obtain a geospatial transportation data processing model.

[0132] In an embodiment, the training unit 123 is further configured to perform pre-training based on the location feature information and the path feature information of the plurality of location-path pairs after feature alignment and by using multimodal geospatial information masking and location-path matching to obtain the geospatial transportation data processing model.

[0133] In an embodiment, the geospatial transportation data processing apparatus 12 further includes a supervised training unit configured to acquire a specific-task dataset corresponding to each of at least one specific task, and perform supervised training on parameters of the geospatial transportation data processing model based on the at least one specific-task dataset.

[0134] In an embodiment, the at least one specific task includes a distance task, and the specific-task dataset includes a plurality of pairs of location information and distance information having a correspondence.

5 [0135] In an embodiment, the at least one specific task includes a time determination task, and the specific-task dataset includes a plurality of pairs of location information and time information having a correspondence.

[0136] In an embodiment, the at least one specific task includes a route scoring task, and the specific-task dataset includes a plurality of pairs of location information and route information having a correspondence.

10 [0137] In an embodiment, the at least one specific task includes a road label mining task, and the specific-task dataset includes a plurality of pairs of route information and label information having a correspondence.

[0138] In an embodiment, the geospatial transportation data processing apparatus 12 further includes a location encoding model training unit configured to: obtain a location dataset;
15 acquire a feature information sequence of a location object in the location dataset, where the feature information sequence is determined based on geospatial information objects within a predetermined range of the location object; and perform training based on the feature information sequences to obtain the location encoding model.

[0139] In an embodiment, the location encoding model training unit is further configured to:
20 acquire feature information of geospatial information objects of the location object within a predetermined distance range, and sort each feature information of the geospatial information objects based on a predetermined condition to obtain the feature information sequence of the location object.

[0140] In an embodiment, the predetermined condition includes the distance proximity of
25 the respective geospatial information objects relative to a corresponding location object.

[0141] In an embodiment, the feature information of a geospatial information object includes one or a combination of: an object identifier, an object shape, an object location, a relationship with a location object, or location information relative to the location object.

[0142] In an embodiment, the geospatial information object includes an AOI object, a POI object, and/or a road network object within a predetermined range of the corresponding task object.

5 [0143] In an embodiment, the location encoding model training unit is further configured to: according to the feature information sequences of the respective geospatial objects, pre-train by using a geospatial contrastive learning method to obtain the location encoding model.

[0144] In an embodiment, the location encoding model training unit is further configured to: acquire a location map-matching pair dataset, where the location map-matching pair dataset includes a plurality of pairs of location feature information and map-matching information
10 having a correspondence; and perform supervised training on the pre-trained location encoding model according to the location map-matching pair dataset to obtain the location encoding model.

[0145] In an embodiment, the geospatial transportation data processing apparatus 12 further includes a road segment encoding model training unit configured to: acquire a path sequence
15 dataset including a plurality of path sequences, where each of the path sequences includes at least one road segment; and obtain the road segment encoding model through pre-training based on the path sequence dataset by using a masked training method.

[0146] In an embodiment, the geospatial transportation data processing apparatus 12 further includes a task processing unit configured to: input target task information into a geospatial
20 transportation data processing architecture for processing, to obtain a corresponding task result, where the target task information includes location information and/or path information, and the task result includes one or a combination of the following: distance information, time prediction information, route information, and road label information that correspond to the target task; where the geospatial transportation data processing
25 architecture includes a location encoding model, a road segment encoding model, and a geospatial transportation data processing model.

[0147] In the embodiments of the present disclosure, a location-path pair dataset including a plurality of pairs of location information and path information having a correspondence is acquired, corresponding feature encoding is performed on the location-path pair dataset by

using a pre-trained location encoding model and road segment encoding model, to obtain location feature information and path feature information of the plurality of location-path pairs, and multimodal training is performed according to the location feature information and the path feature information of each location-path pair to obtain a geospatial transportation data processing model. Therefore, in the embodiment, the processing of multiple downstream tasks can be implemented by multimodal training a geospatial transportation data processing model, and unify the representation of the location features and the path features in the geospatial transportation data through the location encoding model, the road segment encoding model, and the geospatial transportation data processing model, thereby improving the effect and performance of multiple downstream tasks, and increasing the resource utilization rate.

[0148] FIG. 13 is a diagram of another geospatial transportation data processing apparatus according to an embodiment of the present disclosure. As illustrated in FIG. 13, the geospatial transportation data processing apparatus 13 in the present embodiment of the disclosure includes an information acquisition unit 131 and a processing unit 132.

[0149] The information obtaining unit 131 is configured to acquire target task information including location information and/or path information. The processing unit 132 is configured to input the target task information into a pre-trained geospatial transportation data processing architecture for processing to obtain a corresponding task result. The geospatial transportation data processing architecture includes a location encoding model, a road segment encoding model, and a geospatial transportation data processing model, the location encoding model is configured to perform feature encoding on location information, the road segment encoding model is configured to perform feature encoding on route information, the geospatial transportation data processing model is obtained by performing multimodal training on a dataset, the location encoding model, and the road segment encoding model based on a location path, and the location-path pair dataset includes a plurality of pairs of location information and path information having a correspondence.

[0150] In the present embodiment of the present disclosure, the target task information is processed by using the transportation data framework including the location encoding model, the road segment encoding model, and the geospatial transportation data processing model in the architecture, to obtain the corresponding task processing result. Therefore, in the

embodiment, the processing of multiple downstream tasks can be implemented by multimodal training a geospatial transportation data processing model, and unify the representation of the location features and the path features in the geospatial transportation data through the location encoding model, the road segment encoding model, and the geospatial transportation data processing model, thereby improving the effect and performance of multiple downstream tasks, and increasing the resource utilization rate.

[0151] FIG. 14 is a diagram of an electronic device according to an embodiment of the present disclosure. In the present embodiment, the electronic device 14 includes a server, a terminal, etc. As illustrated in FIG. 14, the electronic device 14 includes at least one processor 141; a memory 142 communicatively connected to the at least one processor 141; and a communication component 143 communicatively connected to the geospatial transportation data processing apparatus, and the communication component 143 receives and transmits data under the control of the at least one processor 141; where the memory 142 stores instructions executable by the at least one processor 141, and the instructions are executed by the at least one processor 141 to implement the above geospatial transportation data processing method. Specifically, the electronic device includes one or more processors 141 and a memory 142, and one processor 141 is used as an example in FIG. 14. The processor 141 and the memory 142 may be connected by using a bus or in another manner, and connection by using a bus is used as an example in FIG. 14. As a non-volatile computer-readable storage medium, the memory 142 may be configured to store non-volatile software programs, non-volatile computer-executable programs and modules. The processor 141 executes various functional applications and data processing (i.e., implementing the above method for processing geospatial transportation data) of the device by running the non-volatile software programs, instructions and modules stored in the memory 142. The memory 142 may include a program storage area and a data storage area, where the program storage area may store an operating system and an application program required by at least one function; and the data storage area may store a list of options. In addition, the memory 142 may include a high-speed random access memory, and may further include a non-volatile memory, e.g., at least one magnetic disk storage device, a flash memory device, or another non-volatile solid-state storage device. In some embodiments, the memory 142 may optionally include memories remotely disposed relative to the processor 141, and these remote memories may be connected to an external device through a network. Examples of

such networks include, but are not limited to, the Internet, intranets, local area networks, mobile communication networks, or combinations thereof. The one or more modules are stored in the memory 142, and when executed by the one or more processors 141, perform the geospatial transportation data processing method in any one of the foregoing method
5 embodiments. For technical details not described in detail in the present embodiment, refer to the method provided in the embodiments of the present disclosure.

[0152] In the embodiments of the present disclosure, a location-path pair dataset including a plurality of pairs of location information and path information having a correspondence is acquired, corresponding feature encoding is performed on the location-path pair dataset by
10 using a pre-trained location encoding model and road segment encoding model, to obtain location feature information and path feature information of the plurality of location-path pairs, and multimodal training is performed according to the location feature information and the path feature information of each location-path pair to obtain a geospatial transportation data processing model. Therefore, the embodiment can implement the
15 processing of multiple downstream tasks by multimodal training a geospatial transportation data processing model, and unify the representation of the location features and the path features in the geospatial transportation data through the location encoding model, the road segment encoding model, and the geospatial transportation data processing model, thereby improving the effect and performance of multiple downstream tasks, and increasing the
20 resource utilization rate.

[0153] Another embodiment of the present disclosure relates to a non-volatile storage medium, configured to store a computer-readable program, where the computer-readable program is used by a computer to perform some or all of the foregoing method embodiments. That is, those skilled in the art can understand that all or part of the steps in the method of
25 the above embodiments can be completed by instructing related hardware through a program, and the program is stored in a storage medium and includes several instructions to cause a device (which may be a single-chip microcomputer, a chip, etc.) or a processor to perform all or part of the steps of the method of each embodiment of the present application. The foregoing storage medium includes: any medium that can store program code, such as a
30 USB flash drive, a removable hard disk, a read-only memory (ROM), a random access memory (RAM), a magnetic disk, or an optical disc.

[0154] The above are some embodiments of the present application and are not intended to limit the present application, and for those skilled in the art, the present application may have various modifications and changes. Any modification, equivalent replacement, improvement, etc., made within the spirit and principle of the present disclosure shall fall
5 within the protection scope of the present disclosure.

CLAIMS

1. A geospatial transportation data processing method, comprising:
acquiring a location-path pair dataset comprising a plurality of pairs of location
5 information and path information having a correspondence;
performing corresponding feature encoding on the location-path pair dataset based
on a pre-trained location encoding model and a pre-trained road segment encoding model,
respectively, to obtain location feature information and path feature information of a
plurality of location-path pairs; and
10 performing multimodal training based on the location feature information and the
path feature information of the plurality of location-path pairs to obtain a geospatial
transportation data processing model.
2. The method according to claim 1, wherein performing multimodal training based on
15 the location feature information and the path feature information of the plurality of location-
path pairs to obtain the geospatial transportation data processing model comprises:
based on the location feature information and the path feature information of the
plurality of location-path pairs after feature alignment, performing pre-training by using
multimodal geospatial information masking and location-path matching to obtain the
20 geospatial transportation data processing model.
3. The method according to claim 1, further comprising:
acquiring a specific-task dataset corresponding to each of at least one specific task;
and
25 performing supervised training on parameters of the geospatial transportation data
processing model based on the at least one specific-task dataset.
4. The method according to claim 3, wherein the at least one specific task comprises a
distance task, and the specific-task dataset comprises a plurality of pairs of location
30 information and distance information having a correspondence.
5. The method according to claim 3, wherein the at least one specific task comprises a

time determination task, and the specific-task dataset comprises a plurality of pairs of location information and time information having a correspondence.

6. The method according to claim 3, wherein the at least one specific task comprises a route scoring task, and the specific-task dataset comprises a plurality of pairs of location information and route information having a correspondence.

7. The method according to claim 3, wherein the at least one specific task comprises a road label mining task, and the specific-task dataset comprises a plurality of pairs of route information and label information having a correspondence.

8. The method according to claim 1, wherein a training step of the location encoding model comprises:

acquiring a location dataset;

acquiring a feature information sequence of a location object in the location dataset, wherein the feature information sequence is determined based on geospatial information objects within a predetermined range of the location object; and

performing training based on feature information sequences to obtain the location encoding model.

9. The method according to claim 8, wherein acquiring the feature information sequence of the location object in the location dataset comprises:

acquiring feature information of geospatial information objects of the location object within a predetermined distance range; and

sorting feature information of the geospatial information objects based on a predetermined condition to obtain the feature information sequence of the location object.

10. The method according to claim 9, wherein the predetermined condition comprises distance proximity of the geospatial information objects relative to the corresponding location object.

11. The method according to claim 9, wherein the feature information of the geospatial

information object comprises one or a combination of: an object identifier, an object shape, an object location, a relationship with the location object, or location information relative to the location object.

5 12. The method according to claim 8, wherein the geospatial information objects comprise an AOI object, a POI object, and/or a road network object within a predetermined range of a corresponding task object.

13. The method according to claim 8, wherein performing training based on the feature
10 information sequences to obtain the location encoding model comprises:

performing pre-training based on the feature information sequences by using a geospatial contrastive learning method to obtain the location encoding model.

14. The method according to claim 13, wherein performing training based on the feature
15 information sequences to obtain the location encoding model further comprises:

acquiring a location map-matching pair dataset, wherein the location map-matching pair dataset comprises a plurality of pairs of a location feature and map-matching information having a correspondence; and

performing supervised training on a pre-trained location encoding model based on
20 the location map-matching pair dataset to obtain the location encoding model.

15. The method according to claim 1, wherein a training step of the road segment encoding model comprises:

acquiring a path sequence dataset comprising a plurality of path sequences, wherein
25 each of the path sequences comprises at least one road segment; and

performing pre-training based on the path sequence dataset by using a masked training method to obtain the road segment encoding model.

16. The method according to claim 1, further comprising:

30 inputting target task information into a geospatial transportation data architecture for processing, to obtain a corresponding task result, wherein the target task information comprises location information and/or path information, and the task result comprises one

or a combination of: distance information, time prediction information, route information, or road label information that correspond to the target task; and

the geospatial transportation data architecture comprises a location encoding model, a road segment encoding model, and a geospatial transportation data processing model.

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17. A geospatial transportation data processing method, comprising:

acquiring target task information comprising location information and/or path information; and

inputting the target task information into a pre-trained geospatial transportation data processing architecture for processing to obtain a corresponding task result;

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wherein the geospatial transportation data processing architecture comprises a location encoding model, a road segment encoding model, and a geospatial transportation data processing model, wherein the location encoding model is configured to perform feature encoding on location information, the road segment encoding model is configured to perform feature encoding on route information, the geospatial transportation data processing model is obtained by performing multimodal training based on a location-path pair dataset, the location encoding model and the road segment encoding model, and the location-path pair dataset comprises a plurality of pairs of location information and path information having a correspondence.

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18. A geospatial transportation data processing apparatus, comprising:

a dataset acquisition unit configured to acquire a location-path pair dataset comprising a plurality of pairs of location information and path information having a correspondence;

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a feature encoding unit configured to perform corresponding feature encoding on the location-path pair dataset based on a pre-trained location encoding model and a pre-trained road segment encoding model, respectively, to obtain location feature information and path feature information of a plurality of location-path pairs; and

a training unit configured to perform multimodal training based on the location feature information and the path feature information of the plurality of location-path pairs to obtain a geospatial transportation data processing model.

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19. A geospatial transportation data processing apparatus, comprising:
an information acquisition unit configured to acquire target task information comprising location information and/or path information;

a processing unit configured to input the target task information into a pre-trained
5 geospatial transportation data processing architecture for processing to obtain a corresponding task result;

wherein the geospatial transportation data processing architecture comprises a location encoding model, a road segment encoding model, and a geospatial transportation data processing model, wherein the location encoding model is configured to perform
10 feature encoding on location information, the road segment encoding model is configured to perform feature encoding on route information, the geospatial transportation data processing model is obtained by performing multimodal training based on a location-path pair dataset, the location encoding model and the road segment encoding model, and the location-path pair dataset comprises a plurality of pairs of location information and path
15 information having a correspondence.

20. An electronic device, comprising a memory and one or more processors, wherein the memory is configured to store one or more computer program instructions, and the one or more computer program instructions are executed by the one or more processors to
20 implement the method according to any one of claims 1-17.

21. A computer-readable storage medium, wherein the computer-readable storage medium stores therein a computer program that, when executed by one or more processors, implements the method according to any one of claims 1-17.

22. A computer program product that, when run on a computer, causes the computer to perform the method according to any one of claims 1-17.