data, as shown in formula (3).

$$A_{TC}^{t}(i,j) = \mathrm{F}\left(\rho_{x_t(i),x_t(j)}\right) \tag{3}$$

[0052] $A_{TC}^{t}(i,j)$ denotes a connection relationship at moment *t* between a base station *i* and a base station *j* that is determined based on traffic. $x_t(i) = \left(x_{t-H+1}(i),\ldots,x_{t-1}(i)\right)$ denotes a collection of traffic of the base station *i* at H moments closest to the moment *t*. $x_t(j) = \left(x_{t-H+1}(j),\ldots,x_{t-1}(j)\right)$ denotes a collection of traffic of the base station *j* at the H moments closest to the moment *t*. $\rho_{x_t(i),x_t(j)}$ denotes a Pearson correlation coefficient between $x_t(i)$ and $x_t(j)$. F is a mapping function, which is used to map $\rho_{x_w(i),x_w(j)}$ to 1 or 0.

[0053] Optionally, in the foregoing several examples, a method for mapping F to a variable is shown in formula (4).

$$\mathrm{F}(z) = \begin{cases} 1, |z| \geq \grave{o} \\ 0, |z| < \grave{o} \end{cases} \tag{4}$$

[0054] z denotes $e^{\left(-\frac{d_{ij}^2}{\sigma^2}\right)}$, $\rho_{x_w(i),x_w(j)}$, or $\rho_{x_t(i),x_t(j)}$. $\grave{o}$ is a hyperparameter, which is used to control a density of a topology view.

[0055] The method for determining a static graph and that for determining a dynamic graph that are applicable to this application are not limited to the examples described above.

[0056] After obtaining the static graphs and the dynamic graphs, the apparatus for performing the method 300 may perform the following steps.

[0057] S320: Generate spatial feature data of the plurality of nodes based on the static graphs and the dynamic graphs.

[0058] For example, the static graphs and the dynamic graphs may be processed by using a graph neural network (graph neural network~~s~~, GCN), and a convolution operation may be performed on the static graph<u>s</u> and the dynamic graphs separately by using a convolution kernel of the GCN to obtain the spatial feature data.

[0059] S330: Obtain time feature data of the plurality of nodes.

[0060] An execution sequence of S320 and S330 is not limited. Observation data of the plurality of nodes in a historical time range may be processed by using a gated recurrent unit (gate recurrent unit, GRU) in a recursive neural network (recursive neural network, RNN) to obtain the

to as a specific time range. In the example in FIG. 5, the specific time range on August 30, 2018 is 6:30 to 9:30 a.m. Similarly, it may be further determined that 6:30 to 9:30 a.m. on August 30, 2018 is the specific time range. In this example, each specific time range may be referred to as T_d.

[0069] For another example, if a period (August 27, 2018 to September 2, 2018) in which the target time range (8:15 to 9:15 a.m.) is located is a second period, a period from August 20, 2018 to August 26, 2018 may be regarded as the first period, and 8:15 to 9:15 a.m. on August 25, 2018 (Saturday) is a time range that corresponds to the target time range and that is in the first period. A time range including this corresponding time range may be referred to as a specific time range. In the example in FIG. 5, a specific time range on August 20, 2018 to August 26, 2018 is 6:30 to 9:30 a.m. on August 25, 2018 (Saturday). Similarly, it may be further determined that 6:30 to 9:30 a.m. on August 11, 2018 (Saturday) is a specific time range. In this example, each specific time range may be referred to as T_w.

[0070] After the specific time range is determined, observation data in the specific time range is the time slice data.

[0071] Similarly, the time slice data may be further determined from traffic data in a historical time range by using a month (month) or a quarter (quarter) as a period.

[0072] In the example shown in FIG. 5, the time slice data further includes traffic data in a time range adjacent to the target time range, and the adjacent time range is, for example, 5:00 to 8:00 a.m. on September 1, 2018 and 8:00 to 11:00 post meridiem (p.m.) on August 30, 2018. In this example, each adjacent time range may be referred to as T_r.

[0073] It should be noted that, the foregoing several examples about the time slice data may be used independently or in combination.

[0074] If traffic data in a historical time range is data obtained at an interval of 15 minutes, each time slice (T_d, T_w, or T_r) in FIG. 5 includes 12 pieces of data. Three pieces of the data in T_d, three pieces of the data in T_w, and four pieces of the data in T_r may be selected as the time slice data. In this case, there are totally 120 pieces of data (equivalent to data in eight hours) in the time slice data. Traffic data in 20 days includes about 1920 pieces of data in total. Compared with original~~the time slice~~ data, performing prediction by using the time slice data can reduce the time required for prediction without affecting the prediction effect.

[0075] After the time feature data and the spatial feature data are obtained, the apparatus for performing the method 300 may perform the following step.

[0076] S340: Obtain a predicted state of a target node in a target time range based on the spatial feature data and the time feature data, where the target node is any node in the plurality of nodes.

[0077] FIG. 6 shows a prediction method according to this application.

[0078] In FIG. 6, X^t denotes data obtained after time slicing processing is performed on base station observation data existing before a moment *t*. X^t is input into a temporal model (temporal model~~ing~~), and time feature data Y^t is output after processing by the temporal model. For example, the temporal model is a GRU.

[0079] Static graphs and dynamic graphs are input into a spatial model (spatial model~~ing~~), and spatial feature data is output after processing by the spatial model. For example, the spatial model is a GCN, and the time feature data includes $\Theta_{*G_i^t}$. $\Theta_{*G_i^t}$ denotes a result of a convolution operation performed on a graph G_i^t by using a convolution kernel Θ of the GCN. G_i^t is one of the dynamic graphs and the static graphs existing before the moment *t*.

[0080] Then, Y^t is input into the spatial model. Based on Y^t and $\Theta_{*G_i^t}$, a result Z_i^t combining a temporal feature and a spatial feature may be obtained, as shown in formula (5).

$$Z_i^t = ReLU\left(\Theta_{*G_i^t}\left(Y^t\right)\right) \tag{5}$$

[0081] $ReLU$ denotes a rectified linear unit (rectified linear unit).

[0082] A final output result Z^t of the spatial model may be obtained by adding up a plurality of Z_i^t, as shown in formula (6).

$$Z^t = \sum_{i=1}^{m} Z_i^t \tag{6}$$

[0083] Then, Z^t may be processed by using a fully connected (fully connected, FC) layer to obtain $\hat{x}_{t+k}$, as shown in formula (7).

$$\hat{x}_{t+k} = Z^t W_f + b_f \tag{7}$$

[0084] W_f is a weight parameter of the FC layer, b_f is an offset parameter of the FC layer, and $\hat{x}_{t+k}$ denotes a predicted state of the target base station at a moment *t+k*.

[0085] It can be learned from the above that, in a process of node state prediction, a dynamic

spatial feature obtained from observation data is used in addition to a time feature and a static spatial feature that are obtained from the observation data. This increases accuracy of node state prediction in a network with a dynamic topological relationship.

[0086] In a training process, co-training may be performed on the temporal model, the spatial model, and the FC layer by minimizing a loss function. An optional loss function is shown in formula (8).

$$L\left(\hat{x}_{t+k}, x_{t+k}\right)=\sum_{t\in T_{train}}\frac{1}{N}\sum_{i=1}^{N}\left(\left(\hat{x}_{t+k}\left(i\right)-x_{t+k}\left(i\right)\right)^2+\alpha\frac{1}{N}\left|\hat{x}_{t+k}\left(i\right)-x_{t+k}\left(i\right)\right|\right) \tag{8}$$

[0087] $L\left(\hat{x}_{t+k}, x_{t+k}\right)$ is the loss function, x_{t+k} is a true state of the target base station at the moment *t+k*, $\left(\hat{x}_{t+k}\left(i\right)-x_{t+k}\left(i\right)\right)^2$ is a mean square error (mean square error, MSE), $\left|\hat{x}_{t+k}\left(i\right)-x_{t+k}\left(i\right)\right|$ is a mean absolute error (mean absolute error, MAE), α is used to balance weights of the MSE and the MA~~E~~D, and N denotes a quantity of nodes.

[0088] The following compares the prediction effect of the method 300 with prediction effects of other methods to describe beneficial effects of this application.

[0089] The methods participating in the comparison include historical average (historical average, HA), Prophet (Prophet), Spatio-Temporal Graph Convolutional Network (spatio-temporal graph convolutional network, STGCN), Attention Spatio -Temporal Graph Convolutional Network (attention spatio-temporal graph convolutional network, ASTGCN) and Diffusion Convolutional Recurrent Neural Network (diffusion convolutional recurrent neural network, DCRNN), and evaluation indicators are a root mean square error (root mean square error, RMSE) and an MAE. Smaller values of the RMSE and the MAE indicate a better predictive capability of a method. Comparison results are shown in Table 1.

Table 1

	15 minutes		30 minutes		45 minutes		1 hour	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
HA	108.9	44.2	108.9	44.2	108.9	44.2	108.9	44.2
Prophet	70.3	42.3	72.2	43.0	73.8	43.7	75.2	44.2
STGCN	52.7±1.0	24.7±0.2	66.8±1.6	30.8±0.4	75.3±2.0	34.7±0.6	82.4±2.5	37.9±0.8
ASTGCN	72.4±2.7	28.5±1.2	74.5±2.7	29.9±1.2	78.1±2.6	32.6±1.2	82.1±2.7	35.2±1.3

topology views is less than a topological relationship change rate of the second-type topology views.

[00102] Optionally, the target network is a communications network, the static graphs are topology views representing a traffic-based topological relationship of the plurality of nodes, and the dynamic graphs are topology views representing a physical-line-based topological relationship of the plurality of nodes.

[00103] For a specific manner in which the apparatus 700 performs the method for predicting a node state and a beneficial effect incurred, refer to related descriptions in the method embodiments.

[00104] FIG. 8 is a schematic structural diagram of a device for predicting a node state according to this application. A dashed line in FIG. 8 indicates that ~~the~~ a unit or the module is optional. A device 800 may be configured to implement the method described in the foregoing method embodiments. The device 800 may be a terminal device, a server, or a chip.

[00105] The device 800 includes one or more processors 801. The one or more processors 801 can support the device 800 in implementing the method in the method embodiments. The processor 801 may be a general-purpose processor or a dedicated processor. For example, the processor 801 may be a central processing unit (central processing unit, CPU). The CPU may be configured to control the device 800, execute a software program, and process data of the software program. The device 800 may further include a communications unit 805, configured to implement input (receiving) and/or output (sending) of signals (such as observation data and prediction results).

[00106] For example, the device 800 may be a chip, and the communications unit 805 may be an input circuit and/or an output circuit of the chip, or the communications unit 805 may be a communications interface of the chip. The chip may be used as a component of a terminal device, a network device, or another electronic device.

[00107] For another example, the device 800 may be a terminal device or a server, and the communications unit 805 may be a transceiver of the terminal device or the server, or the communications unit 805 may be a transceiver circuit of the terminal device or the server.

[00108] The device 800 may include one or more memories 802, which store a program 804. The program 804 may be run by the processor 801 to generate an instruction 803, so that the processor 801 performs the method described in the foregoing method embodiments based on the instruction 803. Optionally, the memory 802 may further store data (for example, observation data). Optionally, the processor 801 may further read the data stored in the memory 802, where the data

CLAIMS

What is claimed is:

1. A method for predicting a node state, comprising:

obtaining static graphs and dynamic graphs of a plurality of nodes in a target network, wherein the static graphs and the dynamic graphs are all topology views;

generating spatial feature data of the plurality of nodes based on the static graphs and the dynamic graphs;

obtaining time feature data of the plurality of nodes; and

obtaining a predicted state of a target node in a target time range based on the spatial feature data and the time feature data, wherein the target node is any node in the plurality of nodes.

2. The method according to claim 1, wherein the obtaining time feature data of the plurality of nodes comprises:

obtaining observation data of the plurality of nodes in a first historical time range, wherein the first historical time range is a time range before the target time range;

slicing the observation data in a time dimension to obtain time slice data, wherein a data amount of the time slice data is less than a data amount of the observation data; and

obtaining the time feature data based on the time slice data.

3. The method according to claim 2, wherein the time slice data comprises:

observation data in a time range that is in the first historical time range and that is adjacent to the target time range.

4. The method according to claim 2 or 3, wherein the time slice data comprises:

observation data in a specific time range in the first historical time range, wherein the specific time range is located in a first period, the target time range is located in a second period, and the specific time range comprises a time range that corresponds to the target time range and that is in the first period.

5. The method according to any one of claims 1 to 4, wherein the obtaining static graphs and dynamic graphs of a plurality of nodes comprises:

obtaining observation data of the plurality of nodes in a second historical time range, wherein the second historical time range is a time range before the target time range; and

constructing the static graphs and the dynamic graphs based on the observation data.

6. The method according to claim 5, wherein the observation data comprises at least one of the following data:

meteorological data, network topology data, traffic data, voice data, signaling data, point of interest POI data, major-event data, ~~and~~ or holiday data.

7. The method according to any one of claims 1 to 6, further comprising:

obtaining a true state of the target node in the target time range; and

training a temporal model and a spatial model based on the true state and the predicted state, wherein the temporal model is used to output the time feature data based on input observation data, and the spatial model is used to output the spatial feature data based on the static graphs and the dynamic graphs that are input.

8. The method according to any one of claims 1 to 7, wherein the static graphs belong to first-type topology views, the dynamic graphs belong to second-type topology views, and a topological relationship change rate of the first-type topology views is less than a topological relationship change rate of the second-type topology views.

9. The method according to any one of claims 1 to 8, wherein the target network is a communications network, the static graphs are topology views representing a traffic-based topological relationship of the plurality of nodes, and the dynamic graphs are topology views representing a physical-line-based topological relationship of the plurality of nodes.

10. An apparatus for predicting a node state, comprising a processing unit configured to:

obtain static graphs and dynamic graphs of a plurality of nodes in a target network, wherein the static graphs and the dynamic graphs are all topology views;

generate spatial feature data of the plurality of nodes based on the static graphs and the dynamic graphs;

obtain time feature data of the plurality of nodes; and

obtain a predicted state of a target node in a target time range based on the spatial feature data and the time feature data, wherein the target node is any node in the plurality of nodes.

11. The apparatus according to claim 10, wherein the apparatus further comprises an input unit, wherein

the input unit is configured to obtain observation data of the plurality of nodes in a first historical time range, wherein the first historical time range is a time range before the target time range;

the processing unit is specifically configured to slice the observation data in a time dimension to obtain time slice data, wherein a data amount of the time slice data is less than a data amount of the observation data; and obtain the time feature data based on the time slice data.

12. The apparatus according to claim 11, wherein the time slice data comprises:

observation data in a time range that is in the first historical time range and that is adjacent to the target time range.

13. The apparatus according to claim 11 or 12, wherein the time slice data comprises:

observation data in a specific time range in the first historical time range, wherein the specific time range is located in a first period, the target time range is located in a second period, and the specific time range comprises a time range that corresponds to the target time range and that is in the first period.

14. The apparatus according to any one of claims 10 to 13, wherein the apparatus further comprises an input unit, wherein

the input unit is configured to obtain observation data of the plurality of nodes in a second historical time range, wherein the second historical time range is a time range before the target time range; and

the processing unit is specifically configured to construct the static graphs and the dynamic graphs based on the observation data.

15. The apparatus according to claim 14, wherein the observation data comprises at least one of the following data:

meteorological data, network topology data, traffic data, voice data, signaling data, point of interest POI data, major-event data, and holiday data.

16. The apparatus according to any one of claims 10 to 15, wherein the processing unit is further configured to:

obtain a true state of the target node in the target time range; and

train a temporal model and a spatial model based on the true state and the predicted state, wherein the temporal model is used to output the time feature data based on input observation data, and the spatial model is used to output the spatial feature data based on the static graphs and the dynamic graphs that are input.

17. The apparatus according to any one of claims 10 to 16, wherein the static graphs belong to first-type topology views, the dynamic graphs belong to second-type topology views, and a

topological relationship change rate of the first-type topology views is less than a topological relationship change rate of the second-type topology views.

18. The apparatus according to any one of claims 10 to 17, wherein the target network is a communications network, the static graphs are topology views representing a traffic-based topological relationship of the plurality of nodes, and the dynamic graphs are topology views representing a physical-line-based topological relationship of the plurality of nodes.

19. A device for predicting a node state, wherein the device comprises a processor and a memory, the memory is configured to store a computer program, and the processor is configured to invoke and run the computer program from the memory, so as to enable the device to perform the method according to any one of claims 1 to 9.

20. A computer readable storage medium, wherein the computer readable storage medium stores a computer program, and when the computer program is executed by a processor, the processor is enabled to perform the method according to any one of claims 1 to 9.