

METHOD FOR EVALUATING A USER OF A MARKETPLACE SYSTEM BY A GRAPH MACHINE LEARNING MODEL

TECHNICAL FIELD

[0001] Various aspects of this disclosure relate to methods for evaluating a user of a marketplace system.

BACKGROUND

[0002] Understanding user values is crucial for successful operation of a marketplace system. High-value users typically generate the majority of the system's revenue and thus are of high importance for the operation of the marketplace system. By knowing a user's value, a marketplace system can also recommend the right products or services. Unlike e-commerce or social media platforms where user value is of primary concern, online-to-offline (O2O) businesses, such as ride-hailing and food (or other product) delivery, involve multiple entities. They use both online and offline channels to acquire users and perform transactions. For instance, in a food delivery business, a user ordering food online requires an offline driver to deliver the food to their location. Therefore, the value of the user, the driver, the food merchant, and the delivery address are all critical factors for the success of a food delivery business.

[0003] Accordingly, efficient approaches for evaluating users of a marketplace system which are suitable for online-to-offline (O2O) businesses are desirable.

SUMMARY

[0004] Various embodiments concern a method for evaluating a user of a marketplace system, comprising generating training data elements for a graph machine learning model, wherein each training data element comprises a graph comprising a plurality of user nodes, each user node being associated with a user and a user node feature generated from historical transaction values of the user until a predetermined training date in historical data and the training data element comprises, for the at least one user node, a label generated according to a historical transaction values of the user after the predetermined training date in the historical data, training the graph machine learning model to predict the labels of the training

data elements from the respective graphs of the training data elements, generate, for a user of the marketplace system to be evaluated, a graph comprising a node for the user, wherein the node for the user comprises a user node feature comprising historical transaction values of the user; and predicting a value of the user by processing the graph generated for the user by means of the trained graph machine learning model.

[0005] According to one embodiment, for each training data element and for the user of the marketplace system to be evaluated, the respective graph comprises respective marketplace system nodes, each marketplace system node associated with a respective further marketplace system entity.

[0006] According to one embodiment, the method further comprises predicting a value of one or more of the further marketplace system entities from the predicted value of the user.

[0007] According to one embodiment, at least some of the marketplace system nodes are nodes of various featureless node types and the graph machine learning model comprises a neural network which is trained, in the training of the graph machine learning model, to generate an embedding for each featureless node type which is used as feature of the featureless nodes of the featureless node types in the processing of the graph by the graph machine learning model.

[0008] According to one embodiment, the featureless node types comprise one or more of Internet protocol address nodes, geographical address nodes, user device nodes and network nodes.

[0009] According to one embodiment, for each training data element and for the user of the marketplace system to be evaluated, the respective graph comprises respective edges, wherein each edge represents an interaction between further marketplace entities associated with the nodes connected by the edge, an interaction between a further marketplace entity associated with one of the nodes connected by the edge and a user associated with the other of the nodes connected by the edge or between users associated with the nodes connected by the edge.

[0010] According to one embodiment, each of at least some of the edges represents a respective transaction by a respective user associated with a node to which the edge is connected.

[0011] According to one embodiment, the edge connects the respective user with a respective product or service and represents a purchase of the product or usage of the service, respectively, by the respective user.

[0012] According to one embodiment, the edge has an edge feature determined according to a value of the transaction.

[0013] According to one embodiment, the graph machine learning model is a graph neural network (e.g. a graph convolutional neural network).

[0014] According to one embodiment, the user node feature comprises one or more of an age of an account of the user at the marketplace system, a number of completed transactions by the user within the marketplace system, a total revenue of the marketplace system caused by the user and a total profit of the marketplace system caused by the user.

[0015] According to one embodiment, the marketplace system is an online to offline marketplace system.

[0016] According to one embodiment, each value indicates a worth of the corresponding marketplace system entity for a profit of an operator of the marketplace system.

[0017] According to one embodiment, a computer program element is provided comprising program instructions, which, when executed by one or more processors, cause the one or more processors to perform the method of any one of the embodiments described above.

[0018] According to one embodiment, a computer-readable medium is provided comprising program instructions, which, when executed by one or more processors, cause the one or more processors to perform the method of any one of the embodiments described above.

BRIEF DESCRIPTION OF THE DRAWINGS

[0019] The invention will be better understood with reference to the detailed description when considered in conjunction with the non-limiting examples and the accompanying drawings, in which:

- FIG. 1 shows a communication arrangement of a marketplace system.
- FIG. 2 shows a flow diagram illustrating value prediction according to an embodiment.
- FIG. 3 shows an example of a knowledge graph for entity value prediction.

- FIG. 4 illustrates the functionality of a graph ML model according to an embodiment.
- FIG. 5 illustrates feature and label computation.
- FIG. 6 shows a flow diagram illustrating a method for evaluating a user of a marketplace system.
- FIG. 7 shows a server computer according to an embodiment.

DETAILED DESCRIPTION

[0020] The following detailed description refers to the accompanying drawings that show, by way of illustration, specific details and embodiments in which the disclosure may be practiced. These embodiments are described in sufficient detail to enable those skilled in the art to practice the disclosure. Other embodiments may be utilized and structural, and logical changes may be made without departing from the scope of the disclosure. The various embodiments are not necessarily mutually exclusive, as some embodiments can be combined with one or more other embodiments to form new embodiments.

[0021] Embodiments described in the context of one of the devices or methods are analogously valid for the other devices or methods. Similarly, embodiments described in the context of a device are analogously valid for a vehicle or a method, and vice-versa.

[0022] Features that are described in the context of an embodiment may correspondingly be applicable to the same or similar features in the other embodiments. Features that are described in the context of an embodiment may correspondingly be applicable to the other embodiments, even if not explicitly described in these other embodiments. Furthermore, additions and/or combinations and/or alternatives as described for a feature in the context of an embodiment may correspondingly be applicable to the same or similar feature in the other embodiments.

[0023] In the context of various embodiments, the articles “a”, “an” and “the” as used with regard to a feature or element include a reference to one or more of the features or elements.

[0024] As used herein, the term “and/or” includes any and all combinations of one or more of the associated listed items.

[0025] In the following, embodiments will be described in detail.

[0026] FIG. 1 shows a communication arrangement of a marketplace system, including a smartphone 100 and a server (computer) 106.

[0027] The smartphone 100 has a screen showing the graphical user interface (GUI) of an app for using one or more of various services, such as ordering food or e-hailing, which the smartphone's user has previously installed on his smartphone and has opened (i.e. started) to use the service, e.g. to order food or to book a driver.

[0028] The GUI 101 includes graphical user interface elements 102, 103 helping the user to use the service, e.g. a map of a vicinity of the user's position, food available in the user's vicinity (which the app may determine based on a location service, e.g. a GPS-based location service), a button for placing an order, etc.

[0029] When the user has made a selection for a service, e.g. a selection of a restaurant or an online supermarket and/or a selection of food or groceries to order, the app communicates with a server 106 of the respective service via a radio connection. The server 106 (carrying out a corresponding server program by means of a processor 107) may consult a memory 109 or a data storage 108 having information regarding the service (e.g. prices, availability, estimated time for delivery etc.) The server communicates any data relevant or requested by the user (such as estimated time for delivery) back to the smartphone 100 and the smartphone 100 displays this information on the GUI 101. The user may finally accept a service, e.g. order food. In that case, the server 106 informs the service provider 104, e.g. a restaurant or online supermarket accordingly. The server 106 may also communicate earlier with the service provider 104, e.g. for determining the estimated time for delivery.

[0030] It should be noted while the server 106 is described as a single server, its functionality, e.g. for providing a certain service and advertisement data will in practical application typically be provided by an arrangement (i.e. a server computer system) of multiple server computers (e.g. implementing a cloud service). Accordingly, the functionality described in the following provided by a server (e.g. server 106) may be understood to be provided by an arrangement of servers or server computers.

[0031] The communication arrangement 100 can be seen to realize an online to offline (O2O) marketplace (and thus as an O2O marketplace platform) since they exist online elements like the provision of online information by the server 106 for the smartphone to retrieve from the server 106 as well as offline elements like a driver delivering ordered food. In other words, there are online channels (specifically for transmitting information like for offering food an ordering) and offline channels (here for actual delivery of food).

[0032] Understanding user values is crucial for business success. High-value users typically generate the majority of a company's revenue, so it's important to retain them and optimize their experience. By knowing a user's value, a business can also recommend the right products or services, leading to increased revenue. Unlike e-commerce or social media platforms where user value is of primary concern, online-to-offline (O2O) businesses, such as ride-hailing and food (or other product) delivery, involve multiple entities. They use both online and offline channels to acquire users and perform transactions. For instance, in a food delivery business, a user ordering food online requires an offline driver to deliver the food to their location. Therefore, the value of the user, the driver, the food merchant, and the delivery address are all critical factors for the success of a food delivery business.

[0033] It should be noted that approaches that focus solely on predicting user value (e.g. for social media platforms or online shopping sites where users are the primary entity) are typically not directly applicable to O2O businesses that involve multiple entities since in an O2O context it is important to understand the value of other entities such as drivers, merchants and geolocations. Further, approaches predicting user values based on their historical transactions struggle to provide accurate value predictions before a user has undertaken sufficient activities on the platform, which is known as the cold-start problem.

[0034] Therefore, according to various embodiments, a graph-based method for user value prediction (or user evaluation) is used which is able to provide reliable value predictions even before the user has made any transactions because users are connected to other users on the graph (living in the same residence or connected to the same communication network (e.g. Wifi)) and user values can be inferred based on transactions from these connected users.

[0035] Accordingly, according to various embodiments, a graph-based entity value prediction approach (in particular including a value prediction model) is provided that effectively addresses the aforementioned limitations. The value prediction model is capable of predicting the value of various entities involved in an O2O business, while also providing reliable value predictions for new users.

[0036] FIG. 2 shows a flow diagram 200 illustrating value prediction according to an embodiment.

[0037] The flow is carried out by a data processing device (or system), e.g. server 106.

[0038] The data processing device collects data from various sources such as order, registration, login, device, and card data streams, and leverages the data for graph

construction 201, i.e. to construct a knowledge graph. For each user node on the graph (i.e. a node associated with a user), it computes the (user) node features based on the user's profile and historical transactions. Additionally, for training, it performs label computation 202, i.e. it generates a label for each user node based on its historical value (i.e. the historical value of the user associated with the user node).

[0039] The data processing device performs model training 203 on the knowledge graph and saves the trained model in a model bank 204. During the model serving stage (i.e. for inference 205), the data processing device loads the model parameters of the trained model from the model bank 204 and then runs inference 205 on the new graph, i.e. on the graph constructed for data for which inference is to be performed. The model's prediction results are then passed through post-processing 206 to refine the output. Finally, the resulting entity values are stored in a common storage 207 that can be utilized by various applications 208 (e.g. also running on the data processing device), such as user friction optimization, fraud detection, and more.

[0040] So, according to various embodiments, value prediction is performed on the basis of a knowledge graph that explicitly models various types of entities and their interactions (events) within an O2O business. The set of entities and events collected for the knowledge graph are for example gathered from the following sources (e.g. in response to events triggered by these sources):

- Registration data stream: an event is triggered when a new account is created on the respective platform (e.g. e-hailing site). The data processing device then collects the user ID and the IP address of the user.
- Login data stream: an event is triggered when a user logs into his/her account on the respective platform. The data processing device then collects the user ID and the IP address.
- Order data stream: an event is triggered when a new order is placed. The data processing device then collects user ID, merchant ID, driver ID, and dropoff (i.e. delivery) address.
- Device data stream: an event is triggered when the user of a device starts the app (for using the platform) on the device (e.g. smartphone 100). The data processing device then collects the user ID, IP address, and device ID.

[0041] FIG. 3 shows an example of the constructed knowledge graph 300 for entity value prediction.

[0042] The graph 300 comprises various nodes that represent marketplace system entities such as users and merchants, geographical addresses (i.e. geographical locations), devices (e.g. smartphones using different operating systems), IP addresses, communication networks etc. The edges in the graph represent different types of interactions between these entities, capturing their connections and semantic meanings. For instance, a user (e.g. user #1) may order (e.g. using device#1 and network #1) a dish (e.g. product #1) from a restaurant (e.g. corresponding to a merchant node of the graph, not shown in the example of FIG. 3), which would then be delivered to the geographical living address (delivery location) of the user by a driver (e.g. corresponding to a driver node, not shown in the example of FIG. 3). Such interactions (user orders food, user orders from merchant, driver delivers food, user uses device, user has delivery location, driver delivers to location, device has IP address etc.) are captured by the edges on the graph, providing a comprehensive understanding of the relationships between entities in the O2O business. As shown in the example of FIG. 3, edges may have features. In particular, an edge representing one or more transactions (e.g. a user ordering food) may have the value, revenue or profit (e.g. worth) of/from the transaction(s) as feature (e.g. the cost of the food but alternatively also the profit for the marketplace system operator arising from the order) or a number of transactions as edge feature.

[0043] Thus, the value prediction according to various embodiments not only allows considering users' historical transaction data for value prediction, but, since the knowledge graph 300 encompasses various types of user interactions, also user interactions. For example, users may live in the same residence, share the same WiFi router, or order food from the same merchant, etc. By examining the connections between users on this graph, the data processing device can provide more accurate estimates of user values. Furthermore, the value prediction according to various embodiments allows providing reliable value estimations even before a user has made any transactions. For instance, if a new user registers from a physical location where numerous affluent users have been observed, it is likely that this user will also have a high value. The knowledge graph-based approach according to various embodiments thus goes beyond approaches that use models that solely rely on historical transaction data.

[0044] Given a knowledge graph 300 as shown in Fig 3 and the transactions history from existing users, the task of the model (trained in 203) is to predict the value of different entities on the graph 300. For this, a graph machine learning (ML) model (such as a graph neural network, e.g. a graph convolutional neural network) is used that enables to have reliable value predictions on a user by effectively utilizing information from the user and his/her neighbours on the graph 300. More importantly, the graph ML model is able to provide a decent value prediction even before the user had any transaction on the platform.

[0045] FIG. 4 illustrates the functionality of the graph ML model (i.e. machine learning model for graph processing, e.g. graph convolutional neural network) according to an embodiment.

[0046] The value prediction task (for an entity represented as a node, in particular a user) is handled as a semi-supervised regression problem. The graph ML model takes a heterogeneous knowledge graph 401 with various node and edge types as its input. Historical transactions are encoded into the graph as (user) node features 402.

[0047] The input graph 401 subsequently undergoes multiple convolutional layers 404 (updating the node features, e.g. taking into account types of edges, e.g. an edge representing a WiFi connection and an edge representing a connection to an address are different); with the user value being predicted at a final regression layer (i.e. a node feature is then the predicted value). This method effectively combines the rich information available within the knowledge graph to deliver accurate user value predictions.

[0048] It should be noted that there may be featureless nodes on the graph 401, such as device nodes, IP nodes, and address nodes. Learning a separate node embedding for each of these featureless nodes in a transductive setup causes the number of model parameters to grow rapidly, leading to overfitting. Additionally, operating in a transductive setup requires the model to be retrained whenever a new graph is introduced. Therefore, according to various embodiments, the data processing device has an inductive trainable embeddings module that generates an embedding for each type of featureless node on the graph. This means that for nodes that lack inherent features, such as device or IP address, a machine learning model 403 is used to learn an inductive trainable embedding for them. For instance, an IP address used by a high-value user will have a different learned embedding than one used by a low-value user. The embedding for a featureless node is used as the feature of the featureless node. The node features 402 are concatenated with the features of the featureless

nodes (output by the machine learning model 403, i.e. the trainable embeddings). This concatenation is depicted with a plus sign in FIG. 4.

[0049] This setup keeps the number of model parameters relatively small, as the featureless nodes of the same featureless node type share the same model parameters (of the machine learning model 403). Moreover, the model operates in an inductive setup, which allows running inference on a new graph without retraining the model, offering both improved efficiency and scalability.

[0050] FIG. 5 illustrates feature and label computation.

[0051] The data processing device computes features and labels for users by analyzing their past transactions on the platform. For a given training date 501, the data processing device computes a user's features based on their transactions 502 from X days prior to the training date. Similarly, the data processing device computes a user's label 503 based on the user's transactions 504 from Y days after the training date 501. The values of X and Y are hyperparameters that can be adjusted during the model training process.

[0052] The data processing device computes various domain-specific features for each user node on the graph, such as the user's transaction count, revenue/profit generated, and length of time spent on the platform, among others. An exemplary list of user node features is given in table 1. It should be noted that a user may be represented by an account so a user node may also be seen as account node.

Feature name	Description
Account age	Number of days since the account has been created
Completed transactions	Number of completed transactions from the account in the past X days
Promo transactions	Number of promo related transactions from the account in the past X days
Promo ratio	Percentage of transactions that are promo related in the past X days
GMV (gross merchandise volume)	Total GMV from the account in the past X days

Revenue	Total revenue from the account in the past X days
Profit	Total profit from the account in the past X days

Table 1: Exemplary user node features

[0053] The (graph ML) model is trained on a large-scale graph, e.g. with 200 million nodes and 1.5 billion edges, where 18% of the nodes have labels. Once the model is trained, it is saved into the model bank 204. This means that the values of the model parameters are saved in the model bank. These parameters are for example the weights of the machine learning model 403 (per featureless node type) and the coefficients (i.e. filter weights) for the convolutional layers 404, i.e. for example coefficient vectors of the polynomials of the graph Laplacian and/or weights and biases assigned to the neurons in the respective neural network.

[0054] During the model serving stage, a graph is constructed using the most recent data streams (i.e. from the data for which inference is to be performed), and the trained model from the model bank 204 is used to run an inference on this “new” graph. This generates a value prediction for each user node on the graph.

[0055] Both the training and inference stages are for example run on a CPU instance with a memory size of, e.g., 256 GB, which enables processing large amounts of data efficiently and effectively.

[0056] In the post processing stage, the data processing device derives the value for other entities via heuristics. For example, the value of an address is the average value of all the users that have transacted at this address. An exemplary list of entity value predictions is given in table 2.

Entity type	Description
User	Direct model output
Driver	Summation of the values of the users that have transacted with the driver
Merchant	Summation of the values of the users that have transacted with the merchant

Address	Average of the values of the users that have transacted at the address
Geohash	Average of the values of the users that have transacted at the geohash
Wifi	Average of the values of the users that have connected to the WiFi
Device	Average of the values of the users that have connected to the device
IP address	Average of the values of the users that have registered/logged in via the IP address

Table 2: Exemplary list of entity value predictions

[0057] The entity value predictions can be used for many different purposes, e.g.,

- User friction optimisation: reduce frictions on high value users.
- Fraud detection: discover new fraudulent activities by examining the low value entities.
- Item recommendation: recommending the right items to users based on their value profile.

[0058] The server 106 may store information about interactions between parties, in this example transactions between users like the user of the smartphone 100 and service providers like the service provider 104 in the data storage 108 for analysis. For example, both food order and grocery transactions as well as e-hailing trips (which also can be seen to correspond to a transaction since the passenger pays for the trip) form interactions between customers and merchants (in general service providers including for example also drivers).

[0059] In summary, according to various embodiments, a method is provided as illustrated in FIG. 6.

[0060] FIG. 6 shows a flow diagram illustrating a method for evaluating a user of a marketplace system.

[0061] In 601, training data elements for a graph machine learning model are generated, wherein each training data element comprises (i.e. is generated to comprise) a graph comprising a plurality of user nodes, each user node being associated with a user and a node feature generated from historical transaction values of the user until a predetermined training date in historical data and the training data element comprises, for the at least one user node, a label generated according to a historical transaction values of the user after the predetermined training date in the historical data.

[0062] In 602, the graph machine learning model is trained to predict the labels of the training data elements from the respective graphs of the training data elements.

[0063] In 603, for a user of the marketplace system to be evaluated, a graph is generated comprising a node for the user, wherein the node for the user comprises a node feature comprising historical transaction values of the user.

[0064] In 604, a value of the user is predicted by processing the graph generated for the user by means of the trained graph machine learning model.

[0065] According to various embodiments, in other words, historical data is separated into transactions before a certain date and transaction after a certain date and the ones before the date are used for calculating user node features and the ones after the date labels. So, each user feature can be seen to encode a past value (i.e. worth, e.g. in terms of revenue or profit etc.) of a respective user and the label a training ground truth for a graph machine learning model to predict a future value of the respective user. After training, the graph machine learning model can be used to predict a future value of a user from past transactions (i.e. a past value of the user) only. Even if a user does not have past transactions, the graph ML model can still provide a value prediction for the user based on his/her connected users.

[0066] The method of FIG. 6 is for example carried out by a server computer as illustrated in FIG. 7.

[0067] FIG. 7 shows a server computer 700 according to an embodiment.

[0068] The server computer 700 includes a communication interface 701 (e.g. configured to receive data regarding demand and supply). The server computer 700 further includes a processing unit 702 and a memory 703. The memory 703 may be used by the processing unit 702 to store, for example, data to be processed, such as historical data (i.e. historical transaction information), the various graphs etc.

[0069] The methods described herein may be performed and the various processing or computation units and the devices and computing entities described herein may be implemented by one or more circuits. In an embodiment, a "circuit" may be understood as any kind of a logic implementing entity, which may be hardware, software, firmware, or any combination thereof. Thus, in an embodiment, a "circuit" may be a hard-wired logic circuit or a programmable logic circuit such as a programmable processor, e.g. a microprocessor. A "circuit" may also be software being implemented or executed by a processor, e.g. any kind of computer program, e.g. a computer program using a virtual machine code. Any other kind of implementation of the respective functions which are described herein may also be understood as a "circuit" in accordance with an alternative embodiment.

[0070] While the disclosure has been particularly shown and described with reference to specific embodiments, it should be understood by those skilled in the art that various changes in form and detail may be made therein without departing from the spirit and scope of the invention as defined by the appended claims. The scope of the invention is thus indicated by the appended claims and all changes which come within the meaning and range of equivalency of the claims are therefore intended to be embraced.

CLAIMS

1. A method for evaluating a user of a marketplace system, comprising:
Generating training data elements for a graph machine learning model, wherein each training data element comprises a graph comprising a plurality of user nodes, each user node being associated with a user and a user node feature generated from historical transaction values of the user until a predetermined training date in historical data and the training data element comprises, for the at least one user node, a label generated according to a historical transaction values of the user after the predetermined training date in the historical data;
Training the graph machine learning model to predict the labels of the training data elements from the respective graphs of the training data elements;
Generate, for a user of the marketplace system to be evaluated, a graph comprising a node for the user, wherein the node for the user comprises a user node feature comprising historical transaction values of the user; and
Predicting a value of the user by processing the graph generated for the user by means of the trained graph machine learning model.
2. The method of claim 1, wherein, for each training data element and for the user of the marketplace system to be evaluated, the respective graph comprises respective marketplace system nodes, each marketplace system node associated with a respective further marketplace system entity.
3. The method of claim 2, further comprising predicting a value of one or more of the further marketplace system entities from the predicted value of the user.
4. The method of any one of claims 1 to 3, wherein at least some of the marketplace system nodes are nodes of various featureless node types and the graph machine learning model comprises a neural network which is trained, in the training of the graph machine learning model, to generate an embedding for each featureless node type which is used as feature of the featureless nodes of the featureless node types in the processing of the graph by the graph machine learning model.

5. The method of claim 4, wherein the featureless node types comprise one or more of Internet protocol address nodes, geographical address nodes, user device nodes and network nodes.
6. The method of any one of claims 1 to 5, wherein, for each training data element and for the user of the marketplace system to be evaluated, the respective graph comprises respective edges, wherein each edge represents an interaction between further marketplace entities associated with the nodes connected by the edge, an interaction between a further marketplace entity associated with one of the nodes connected by the edge and a user associated with the other of the nodes connected by the edge or between users associated with the nodes connected by the edge.
7. The method of claim 6, wherein each of at least some of the edges represents a respective transaction by a respective user associated with a node to which the edge is connected.
8. The method of claim 7, wherein the edge connects the respective user with a respective product or service and represents a purchase of the product or usage of the service, respectively, by the respective user.
9. The method of claim 8, wherein the edge has an edge feature determined according to a value of the transaction.
10. The method of any one of claims 1 to 9, wherein the graph machine learning model is a graph convolutional neural network.
11. The method of any one of claims 1 to 10, wherein the user node feature comprises one or more of an age of an account of the user at the marketplace system, a number of completed transactions by the user within the marketplace system, a total revenue of the marketplace system caused by the user and a total profit of the marketplace system caused by the user.

12. The method of any one of claims 1 to 11, wherein the marketplace system is an online to offline marketplace system.
13. The method of any one of claims 1 to 12, wherein each value indicates a worth of the corresponding marketplace system entity for a profit of an operator of the marketplace system.
14. A server computer comprising a radio interface, a memory interface and a processing unit configured to perform the method of any one of claims 1 to 13.
15. A computer program element comprising program instructions, which, when executed by one or more processors, cause the one or more processors to perform the method of any one of claims 1 to 13.
16. A computer-readable medium comprising program instructions, which, when executed by one or more processors, cause the one or more processors to perform the method of any one of claims 1 to 13.