

WHAT IS CLAIMED IS:

- 1 1. A computer-implemented method comprising performing, by a
2 processing computer:
3 receiving an access request to access a resource by a user device, the
4 access request including a resource provider identifier and a user identifier of a
5 plurality of user identifiers respectively associated with a plurality of user devices;
6 retrieving, from an embedding table, a user embedding associated with
7 the user identifier and comprising a plurality of dimensions, each dimension of the
8 plurality of dimensions associated with a context of the user identifier appearing in
9 previous access requests within temporal proximity to other access requests from a
10 subset of other user devices among the plurality of user devices, wherein the user
11 embedding provides a multidimensional data point indicating a similarity of the user
12 device to the subset of other user devices;
13 inputting the user embedding into a first machine learning model of the
14 processing computer that is trained using the embedding table; and
15 determining, by the first machine learning model, an access score for
16 determining whether to authorize the user device to access the resource, the access
17 score corresponding to a level of authenticity of authorizing the user device to
18 access the resource.
- 1 2. The computer-implemented method of claim 1, wherein the user
2 identifier is associated with a user account number of a user of the user device.
- 1 3. The computer-implemented method of claim 1, wherein the user
2 embedding is one of a plurality of user embeddings within the embedding table, the
3 multidimensional data point corresponding to a vector, each value of the vector
4 associated with a dimension of the plurality of dimensions.
- 1 4. The computer-implemented method of claim 3, wherein the
2 similarity of the user device to the subset of other user devices is determined based
3 at least in part on comparing each value within respectively associated vectors.
- 1 5. The computer-implemented method of claim 1, wherein the first
2 machine learning model comprises a neural network that is trained based at least in

3 part on utilizing a value corresponding to a dimension of the user embedding as
4 input to determine a weight of a node of the neural network.

1 6. The computer-implemented method of claim 1, further
2 comprising:
3 transmitting to an authorization computer an authorization request
4 message including the access score;
5 receiving an authorization response message including an
6 authorization response, the authorization response based at least in part on the
7 access score; and
8 transmitting the authorization response to an access device associated
9 with a resource provider, the authorization response used to determine whether to
10 authorize the user device to access the resource.

1 7. The computer-implemented method of claim 1, further
2 comprising:
3 receiving training data comprising a second plurality of user identifiers
4 that are respectively associated with the subset of other user devices, each user
5 identifier of the second plurality selected to be included in the training data based at
6 least in part on appearing in at least one of the previous access requests with the
7 resource provider identifier;
8 inputting the training data into a second machine learning model of the
9 processing computer;
10 generating, by the second machine learning model, the embedding
11 table based at least in part on the training data; and
12 training the first machine learning model using the training data and the
13 embedding table, wherein an authenticity of the previous access requests is known.

1 8. The computer-implemented method of claim 7, wherein the
2 second machine learning model is trained based at least in part on minimizing a loss
3 function that is configured to determine a difference between a ground truth user
4 identifier and a predicted user identifier.

1 9. The computer-implemented method of claim 1, wherein the first
2 machine learning model is further trained to generate the access score based at

3 least in part on a resource provider embedding corresponding to the resource
4 provider identifier.

1 10. The computer-implemented method of claim 1, further
2 comprising performing:
3 subsequent to generating the user embedding, receiving a second
4 access request to access a second resource by the user device, the second access
5 request including a second resource provider identifier and the user identifier of the
6 plurality of user identifiers respectively associated with the plurality of user devices;
7 retrieving, from a second embedding table, a second user embedding
8 associated with the user identifier and comprising a second plurality of dimensions,
9 each dimension of the second plurality of dimensions associated with a second
10 context of the user identifier appearing in previous access requests within temporal
11 proximity to other access requests from a second subset of other user devices
12 among the plurality of user devices, wherein the second user embedding provides a
13 second multidimensional data point indicating a second similarity of the user device
14 to the second subset of other user devices;
15 inputting the second user embedding into a transformation model of the
16 processing computer that is trained based at least in part on the second embedding
17 table and the embedding table;
18 determining, by the transformation model, a transformed user
19 embedding;
20 inputting the transformed user embedding into the first machine
21 learning model of the processing computer; and
22 determining, by the first machine learning model, a second access
23 score for determining whether to authorize the user device to access the second
24 resource.

1 11. The computer-implemented method of claim 10, wherein the first
2 machine learning model that receives as input the transformed user embedding is
3 trained based at least in part on the embedding table that was generated prior to the
4 second embedding table.

1 12. The computer-implemented method of claim 10, wherein the
2 transformation model comprises a third neural network, and generating the third
3 neural network corresponds to generating a mapping between the user embedding
4 and the second user embedding based at least in part on minimizing a loss function.

1 13. The computer-implemented method of claim 1, further
2 comprising:
3 subsequent to generating the embedding table, generating, by a
4 second machine learning model of the processing computer, a second embedding
5 table comprising a second user embedding, the second user embedding associated
6 with the user identifier and comprising a second plurality of dimensions, each
7 dimension of the second plurality of dimensions associated with a second context of
8 the user identifier appearing in previous access requests within temporal proximity to
9 other access requests from a second subset of other user devices among the
10 plurality of user devices, wherein the second user embedding provides a second
11 multidimensional data point indicating a second similarity of the user device to the
12 second subset of other user devices; and
13 generating, based at least in part on the embedding table and the
14 second embedding table, a transformation model that is trained to determine a
15 mapping between a first embedding of the embedding table and a second
16 embedding of the second embedding table.

1 14. The computer-implemented method of claim 13, wherein a
2 neural network of the transformation model is a non-linear model.

1 15. The computer-implemented method of claim 13, wherein the first
2 embedding corresponds to a first vector, each value of the first vector associated
3 with a respective dimension of the plurality of dimensions, and the second
4 embedding corresponds to a second vector, each value of the second vector
5 associated with a respective dimension of a second plurality of dimensions.

1 16. The computer-implemented method of claim 15, wherein the
2 plurality of dimensions and the second plurality of dimensions correspond to different
3 contextual spaces.

1 17. The computer-implemented method of claim 15, wherein a
2 neural network of the transformation model is trained based at least in part on
3 minimizing a loss function that is configured to determine a mean squared error
4 (MSE) between the first vector and the second vector or determine a cosine distance
5 between the first vector and the second vector.

6 18. The computer-implemented method of claim 17, further
7 comprising:
8 determining an accuracy of the transformation model based at least in
9 part on determining a K-nearest neighbor utilizing the determined cosine distance.

1 19. The computer-implemented method of claim 18, wherein the first
2 machine learning model or the second machine learning model is re-trained upon the
3 determined accuracy matching a predetermined threshold value.

1 20. The computer-implemented method of claim 13, wherein a
2 neural network of the transformation model is a linear model.

1 21. The computer-implemented method of claim 13, wherein a
2 plurality of sets of training data are used to train the second machine learning model,
3 each set of training data associated with a different resource provider.

1 22. A processing computer comprising: a processor; and a
2 computer readable medium, the computer readable medium comprising code,
3 executable by the processor, for implemented a method according to any of the
4 claims 1-21.