

CLAIMS

What is claimed is:

1. A recommendation model training method, comprising:

obtaining a first recommendation model, wherein a model parameter of the first
5 recommendation model is obtained through training based on n first training samples, the first training sample comprises information about a first user, information about a first recommended object, and a sample label of the first training sample, the sample label of the first training sample is used to indicate whether the first user performs an operation action on the first recommended object, and n is an integer greater than 1;

10 determining an impact function value of each first training sample with respect to a verification loss of m second training samples in the first recommendation model, wherein the second training sample comprises information about a second user, information about a second recommended object, and a sample label of the second training sample, the sample label of the second training sample is used to indicate whether the second user performs an operation action
15 on the second recommended object, and m is an integer greater than 1;

determining, based on the impact function value of each first training sample with respect to the verification loss of the m second training samples in the first recommendation model, a weight corresponding to each first training sample; and

20 training the first recommendation model based on the n first training samples and the weights corresponding to the n first training samples, to obtain a target recommendation model.

2. The method according to claim 1, wherein

the weight corresponding to each first training sample has a negative correlation with the impact function value of each first training sample with respect to the verification loss of the m second training samples.

25 3. The method according to claim 1 or 2, wherein an impact function value of each first training sample with respect to a prediction loss of the m second training samples in the first recommendation model satisfies the following formula:

$$\phi(z_i) = \sum_j \phi(z_i, z_j) = -[\sum_j \nabla_{\theta} l(z_j, \hat{\theta})]^T H_{\hat{\theta}}^{-1} \nabla_{\theta} l(z_i, \hat{\theta}), \text{ wherein}$$

30 z_i represents a i^{th} first training sample, $\phi(z_i)$ represents an impact function value of the i^{th} first training sample with respect to the prediction loss of the m second training samples in the first

recommendation model, z_j represents the j^{th} second training sample, $\phi(z_i, z_j)$ represents an impact function value of the i^{th} first training sample with respect to a verification loss of the j^{th} second training sample in the first recommendation model, $\nabla_{\theta} l(z_j, \hat{\theta})$ represents a gradient of z_i on the first recommendation model $\hat{\theta}$, $\sum_j \nabla_{\theta} l(z_j, \hat{\theta})$ represents a sum of gradients of the m second training samples in the first recommendation model $\hat{\theta}$, and $H_{\hat{\theta}}^{-1}$ represents an inverse matrix of a Hessian matrix of all first training samples.

4. The method according to claim 3, wherein the determining, based on the impact function value of each first training sample with respect to the verification loss of the m second training samples in the first recommendation model, a weight corresponding to each first training sample comprises: the weight corresponding to each first training sample satisfies the following formula:

$$\pi_i = \frac{1}{1 + e^{\frac{\alpha \phi(z_i)}{\max(\{\phi(z_i)\}) - \min(\{\phi(z_i)\})}}, \text{ wherein}$$

π_i represents a weight corresponding to the i^{th} first training sample, α represents a weight adjustment coefficient, and $\{\phi(z_i)\}$ represents a set of impact function values of the n first training samples with respect to the verification loss of the m second training samples in the first recommendation model.

5. The method according to any one of claims 1 to 4, wherein the m second training samples are obtained when there is a same probability that candidate recommended objects in a candidate recommended object set are presented, and the second recommended object is a candidate recommended object in the candidate recommended object set.

6. The method according to claim 5, wherein that the m second training samples are obtained when there is a same probability that candidate recommended objects in a candidate recommended object set are presented comprises:

the m second training samples are obtained when the candidate recommended objects in the candidate recommended object set are randomly presented to the second user; or

the m second training samples are obtained when the second user searches for the second recommended object.

7. The method according to any one of claims 1 to 5, wherein the m second training samples belong to data in a source domain, and the n first training samples belong to data in a target domain.

8. A recommendation method, comprising:

obtaining information about a target user and information about a candidate recommended object; and

inputting the information about the target user and the information about the candidate recommended object into a recommendation model, to predict a probability that the target user performs an operation action on the candidate recommended object, wherein

a model parameter of the recommendation model is obtained by training a first recommendation model based on n first training samples and weights corresponding to the n first training samples, the first recommendation model is obtained through training based on the n first training samples, a weight corresponding to each first training sample is determined based on an impact function value of each first training sample with respect to a verification loss of m second training samples in the first recommendation model, the first training sample comprises information about a first user, information about a first recommended object, and a sample label of the first training sample, the sample label of the first training sample is used to indicate whether the first user performs an operation action on the first recommended object, n is an integer greater than 1, the second training sample comprises information about a second user, information about a second recommended object, and a sample label of the second training sample, the sample label of the second training sample is used to indicate whether the second user performs an operation action on the second recommended object, and m is an integer greater than 1.

9. The method according to claim 8, wherein that a weight corresponding to each first training sample is determined based on an impact function value of each first training sample with respect to a verification loss of m second training samples in the first recommendation model comprises:

the weight corresponding to each first training sample has a negative correlation with the impact function value of each first training sample with respect to the verification loss of the m second training samples in the first recommendation model.

10. The method according to claim 8 or 9, wherein the impact function value of each first training sample with respect to the verification loss of the m second training samples in the first recommendation model satisfies the following formula:

$$\phi(z_i) = \sum_j \phi(z_i, z_j) = -[\sum_j \nabla_{\theta} l(z_j, \hat{\theta})]^T H_{\hat{\theta}}^{-1} \nabla_{\theta} l(z_i, \hat{\theta}), \text{ wherein}$$

z_i represents the i^{th} first training sample, $\phi(z_i)$ represents an impact function value of the

i^{th} first training sample with respect to a prediction loss of the m second training samples in the first recommendation model, z_j represents the j^{th} second training sample, $\phi(z_i, z_j)$ represents an impact function value of the i^{th} first training sample with respect to a verification loss of the j^{th} second training sample in the first recommendation model, $\nabla_{\theta} l(z_j, \hat{\theta})$ represents a gradient of z_j on the first recommendation model $\hat{\theta}$, $\sum_j \nabla_{\theta} l(z_j, \hat{\theta})$ represents a sum of gradients of the m second training samples in the first recommendation model $\hat{\theta}$, and $H_{\hat{\theta}}^{-1}$ represents an inverse matrix of a Hessian matrix of all first training samples.

11. The method according to claim 10, wherein that a weight corresponding to each first training sample is determined based on an impact function value of each first training sample with respect to a verification loss of m second training samples in the first recommendation model comprises: the weight corresponding to each first training sample satisfies the following formula:

$$\pi_i = \frac{1}{1 + e^{\frac{\alpha \phi(z_i)}{\max(\{\phi(z_i)\}) - \min(\{\phi(z_i)\})}}}, \text{ wherein}$$

π_i represents a weight corresponding to the i^{th} first training sample, α represents a weight adjustment coefficient, and $\{\phi(z_i)\}$ represents a set of impact function values of the n first training samples with respect to the verification loss of the m second training samples in the first recommendation model.

12. The method according to any one of claims 8 to 11, wherein the m second training samples are obtained when there is a same probability that candidate recommended objects in a candidate recommended object set are presented, and the second recommended object is a candidate recommended object in the candidate recommended object set.

13. The method according to claim 12, wherein that the m second training samples are obtained when there is a same probability that candidate recommended objects in a candidate recommended object set are presented comprises:

the m second training samples are obtained when the candidate recommended objects in the candidate recommended object set are randomly presented to the second user; or

the m second training samples are obtained when the second user searches for the second recommended object.

14. The method according to any one of claims 8 to 13, wherein the m second training samples

belong to data in a source domain, and the n first training samples belong to data in a target domain.

15. A recommendation model training apparatus, comprising:

an obtaining unit, configured to obtain a first recommendation model, wherein a model parameter of the first recommendation model is obtained through training based on n first training samples, the first training sample comprises information about a first user, information about a first recommended object, and a sample label of the first training sample, the sample label of the first training sample is used to indicate whether the first user performs an operation action on the first recommended object, and n is an integer greater than 1; and

a processing unit, configured to:

determine an impact function value of each first training sample with respect to a verification loss of m second training samples in the first recommendation model, wherein the second training sample comprises information about a second user, information about a second recommended object, and a sample label of the second training sample, the sample label of the second training sample is used to indicate whether the second user performs an operation action on the second recommended object, and m is an integer greater than 1;

determine, based on the impact function value of each first training sample with respect to the verification loss of the m second training samples in the first recommendation model, a weight corresponding to each first training sample; and

train the first recommendation model based on the n first training samples and the weights corresponding to the n first training samples, to obtain a target recommendation model.

16. The training apparatus according to claim 15, wherein the determining, based on the impact function value of each first training sample with respect to the verification loss of the m second training samples in the first recommendation model, a weight corresponding to each first training sample comprises:

the weight corresponding to each first training sample has a negative correlation with the impact function value of each first training sample with respect to the verification loss of the m second training samples.

17. The training apparatus according to claim 15 or 16, wherein an impact function value of each first training sample with respect to a prediction loss of the m second training samples in the first recommendation model satisfies the following formula:

$$\phi(z_i) = \sum_j \phi(z_i, z_j) = -[\sum_j \nabla_{\theta} l(z_j, \hat{\theta})]^T H_{\hat{\theta}}^{-1} \nabla_{\theta} l(z_i, \hat{\theta}), \text{ wherein}$$

z_i represents the i^{th} first training sample, $\phi(z_i)$ represents an impact function value of the i^{th} first training sample with respect to the prediction loss of the m second training samples in the first recommendation model, z_j represents the j^{th} second training sample, $\phi(z_i, z_j)$ represents an impact function value of the i^{th} first training sample with respect to a verification loss of the j^{th} second training sample in the first recommendation model, $\nabla_{\theta} l(z_j, \hat{\theta})$ represents a gradient of z_j on the first recommendation model $\hat{\theta}$, $\sum_j \nabla_{\theta} l(z_j, \hat{\theta})$ represents a sum of gradients of the m second training samples in the first recommendation model $\hat{\theta}$, and $H_{\hat{\theta}}^{-1}$ represents an inverse matrix of a Hessian matrix of all first training samples.

18. The training apparatus according to claim 17, wherein the processing unit is specifically configured to:

the weight corresponding to each first training sample satisfies the following formula:

$$\pi_i = \frac{1}{1 + e^{\frac{\alpha \phi(z_i)}{\max(\{\phi(z_i)\}) - \min(\{\phi(z_i)\})}}, \text{ wherein}$$

π_i represents a weight corresponding to the i^{th} first training sample, α represents a weight adjustment coefficient, and $\{\phi(z_i)\}$ represents a set of impact function values of the n first training samples with respect to the verification loss of the m second training samples in the first recommendation model.

19. The training apparatus according to any one of claims 15 to 18, wherein the m second training samples are obtained when there is a same probability that candidate recommended objects in a candidate recommended object set are presented, and the second recommended object is a candidate recommended object in the candidate recommended object set.

20. The training apparatus according to claim 19, wherein that the m second training samples are obtained when there is a same probability that candidate recommended objects in a candidate recommended object set are presented comprises:

the m second training samples are obtained when the candidate recommended objects in the candidate recommended object set are randomly presented to the second user; or

the m second training samples are obtained when the second user searches for the second

recommended object.

21. The training apparatus according to any one of claims 15 to 20, wherein the m second training samples belong to data in a source domain, and the n first training samples belong to data in a target domain.

5 22. A recommendation apparatus, comprising:

an obtaining unit, configured to obtain information about a target user and information about a candidate recommended object; and

a processing unit, configured to input the information about the target user and the information about the candidate recommended object into a recommendation model, to predict a probability that the target user performs an operation action on the candidate recommended object, wherein

a model parameter of the recommendation model is obtained by training a first recommendation model based on n first training samples and weights corresponding to the n first training samples, the first recommendation model is obtained through training based on the n first training samples, a weight corresponding to each first training sample is determined based on an impact function value of each first training sample with respect to a verification loss of m second training samples in the first recommendation model, the first training sample comprises information about a first user, information about a first recommended object, and a sample label of the first training sample, the sample label of the first training sample is used to indicate whether the first user performs an operation action on the first recommended object, n is an integer greater than 1, the second training sample comprises information about a second user, information about a second recommended object, and a sample label of the second training sample, the sample label of the second training sample is used to indicate whether the second user performs an operation action on the second recommended object, and m is an integer greater than 1.

25 23. The recommendation apparatus according to claim 22, wherein that a weight corresponding to each first training sample is determined based on an impact function value of each first training sample with respect to a verification loss of m second training samples in the first recommendation model comprises:

the weight corresponding to each first training sample has a negative correlation with the impact function value of each first training sample with respect to the verification loss of the m second training samples in the first recommendation model.

24. The recommendation apparatus according to claim 22 or 23, wherein the impact function value of each first training sample with respect to the verification loss of the m second training samples in the first recommendation model satisfies the following formula:

$$\phi(z_i) = \sum_j \phi(z_i, z_j) = -[\sum_j \nabla_{\theta} l(z_j, \hat{\theta})]^T H_{\hat{\theta}}^{-1} \nabla_{\theta} l(z_i, \hat{\theta}), \text{ wherein}$$

5 z_i represents the i^{th} first training sample, $\phi(z_i)$ represents an impact function value of the i^{th} first training sample with respect to a prediction loss of the m second training samples in the first recommendation model, z_j represents the j^{th} second training sample, $\phi(z_i, z_j)$ represents an impact function value of the i^{th} first training sample with respect to a verification loss of the j^{th} second training sample in the first recommendation model, $\nabla_{\theta} l(z_j, \hat{\theta})$ represents a gradient of z_j on the first recommendation model $\hat{\theta}$, $\sum_j \nabla_{\theta} l(z_j, \hat{\theta})$ represents a sum of gradients of the m second training samples in the first recommendation model $\hat{\theta}$, and $H_{\hat{\theta}}^{-1}$ represents an inverse matrix of a Hessian matrix of all first training samples.

25. The recommendation apparatus according to claim 24, wherein that a weight corresponding to each first training sample is determined based on an impact function value of each first training sample with respect to a verification loss of m second training samples in the first recommendation model comprises: the weight corresponding to each first training sample satisfies the following formula:

$$\pi_i = \frac{1}{1 + e^{\frac{\alpha \phi(z_i)}{\max(\{\phi(z_i)\}) - \min(\{\phi(z_i)\})}}, \text{ wherein}$$

15 π_i represents a weight corresponding to the i^{th} first training sample, α represents a weight adjustment coefficient, and $\{\phi(z_i)\}$ represents a set of impact function values of the n first training samples with respect to the verification loss of the m second training samples in the first recommendation model.

26. The recommendation apparatus according to any one of claims 22 to 25, wherein the m second training samples are obtained when there is a same probability that candidate recommended objects in a candidate recommended object set are presented, and the second recommended object is a candidate recommended object in the candidate recommended object set.

27. The recommendation apparatus according to claim 26, wherein that the m second training

samples are obtained when there is a same probability that candidate recommended objects in a candidate recommended object set are presented comprises:

the m second training samples are obtained when the candidate recommended objects in the candidate recommended object set are randomly presented to the second user; or

5 the m second training samples are obtained when the second user searches for the second recommended object.

28. The recommendation apparatus according to any one of claims 22 to 27, wherein the m second training samples belong to data in a source domain, and the n first training samples belong to data in a target domain.

10 29. A recommendation model training apparatus, comprising at least one processor and a memory, wherein the at least one processor is coupled to the memory, and is configured to read and execute instructions in the memory, to perform the training method according to any one of claims 1 to 7.

15 30. A recommendation apparatus, comprising at least one processor and a memory, wherein the at least one processor is coupled to the memory, and is configured to read and execute instructions in the memory, to perform the recommendation method according to any one of claims 8 to 14.

20 31. A computer-readable medium, wherein the computer-readable medium stores computer program code, and when the computer program code runs on a computer, the computer is enabled to perform the method according to any one of claims 1 to 7, or claims 8 to 14.