Dataset Regeneration for Sequential Recommendation

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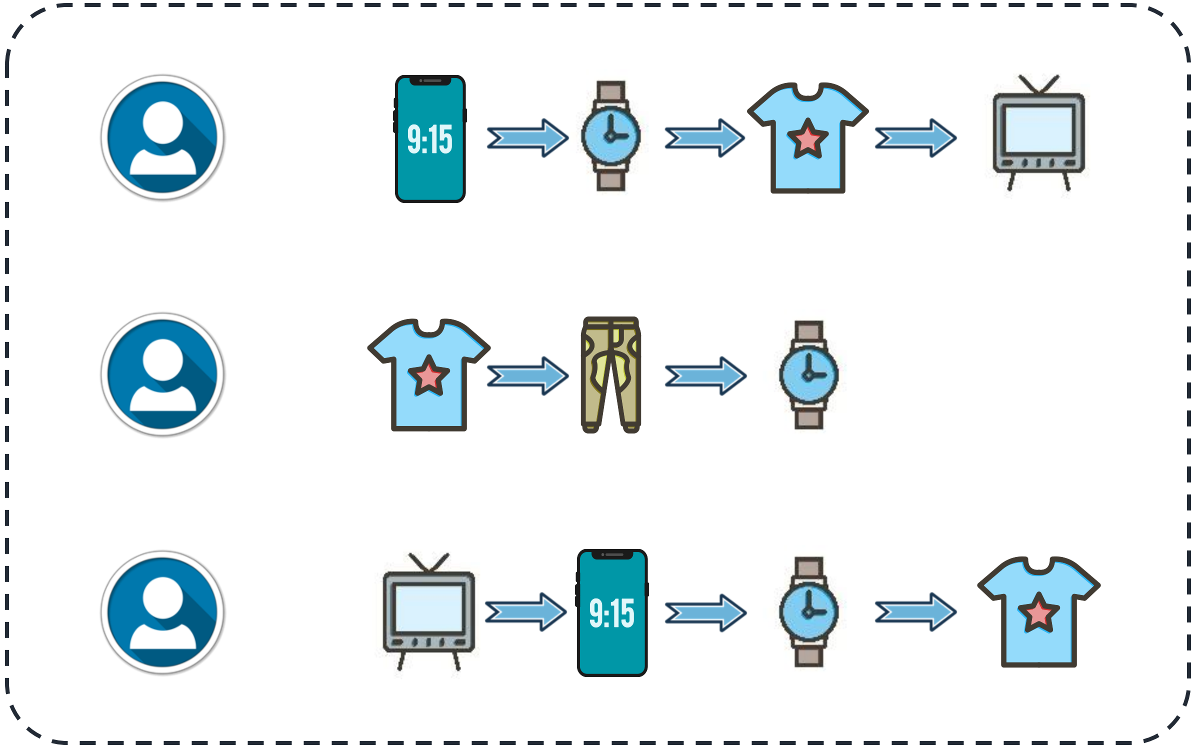
2. Huawei Singapore Research Center

Code: https://github.com/USTC-StarTeam/DR4SR

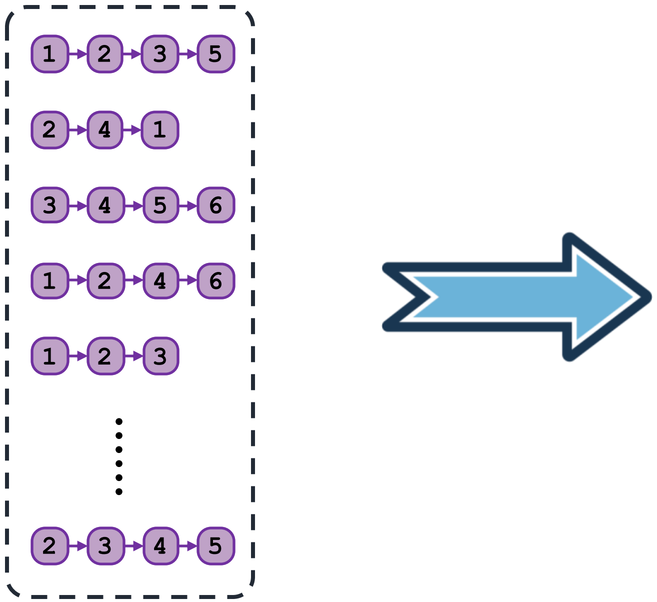
Background

- Users interacted with items provided by recommender systems



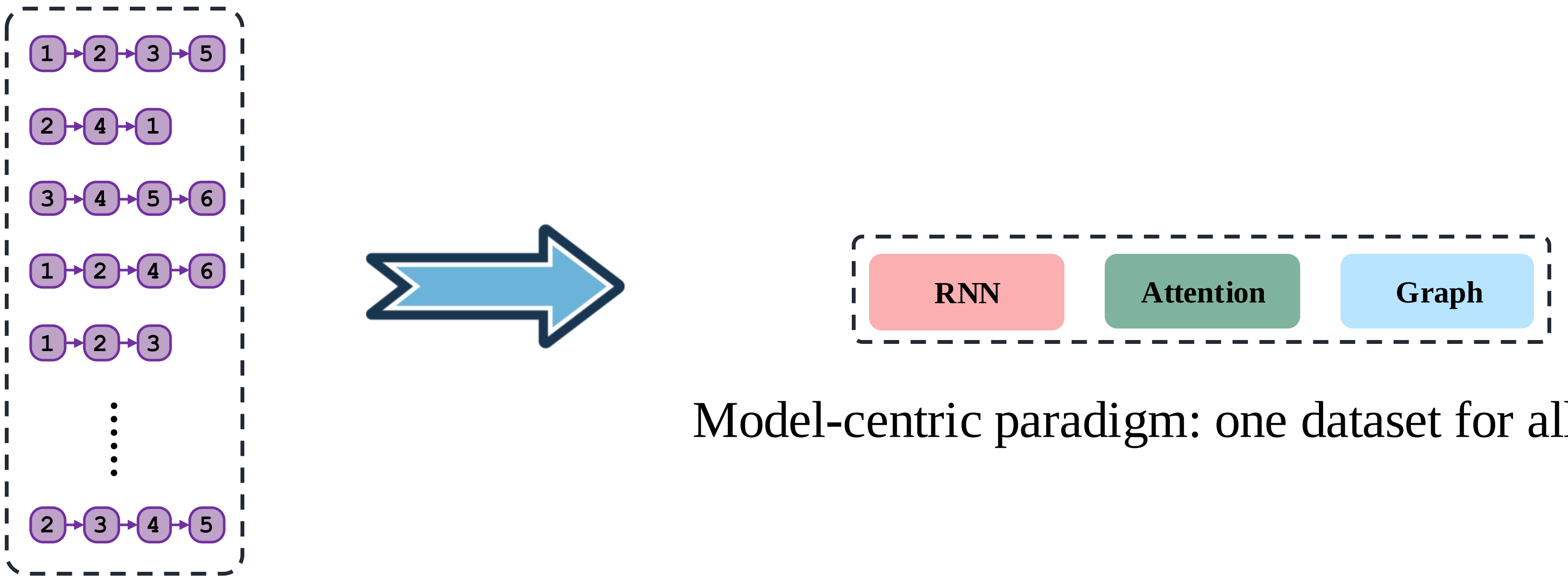
Background

- These behaviors are usually organized in a chronological order



Background

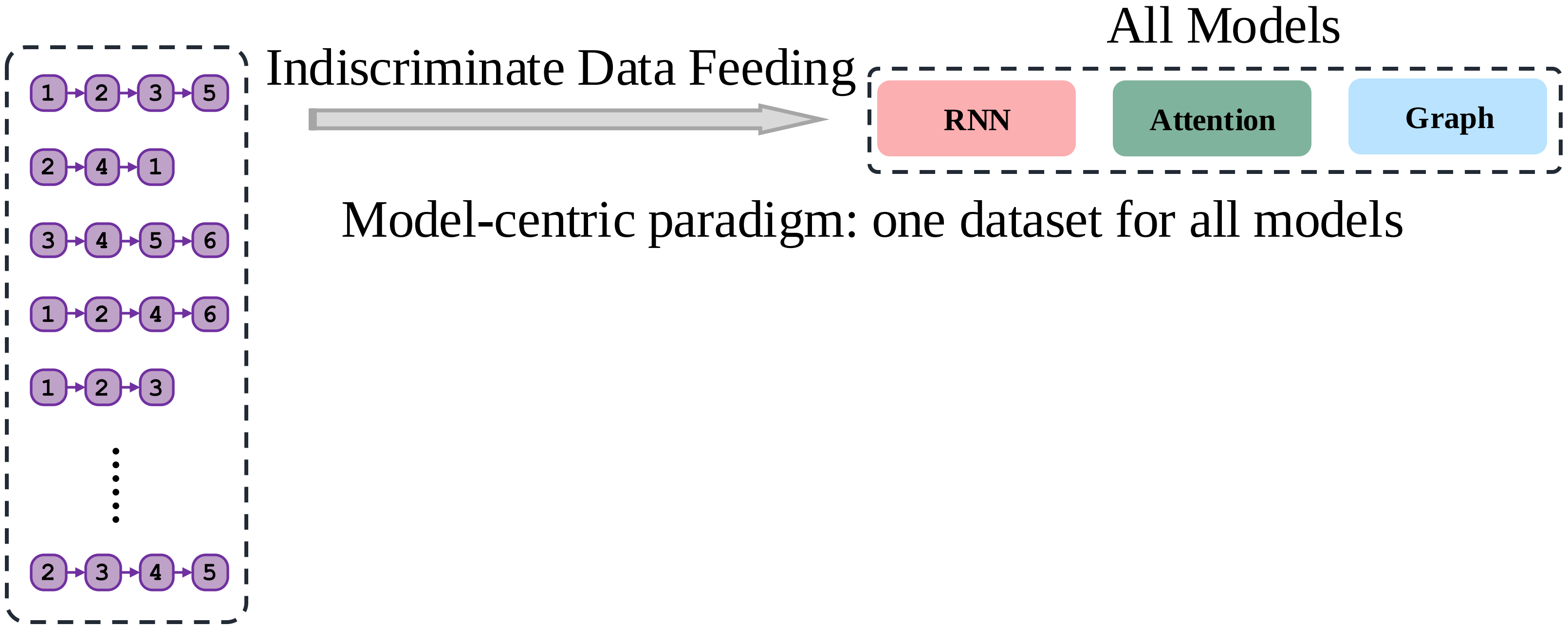
➤ Sequential recommendation in a model-centric paradigm



Model-centric paradigm: one dataset for all models

Background

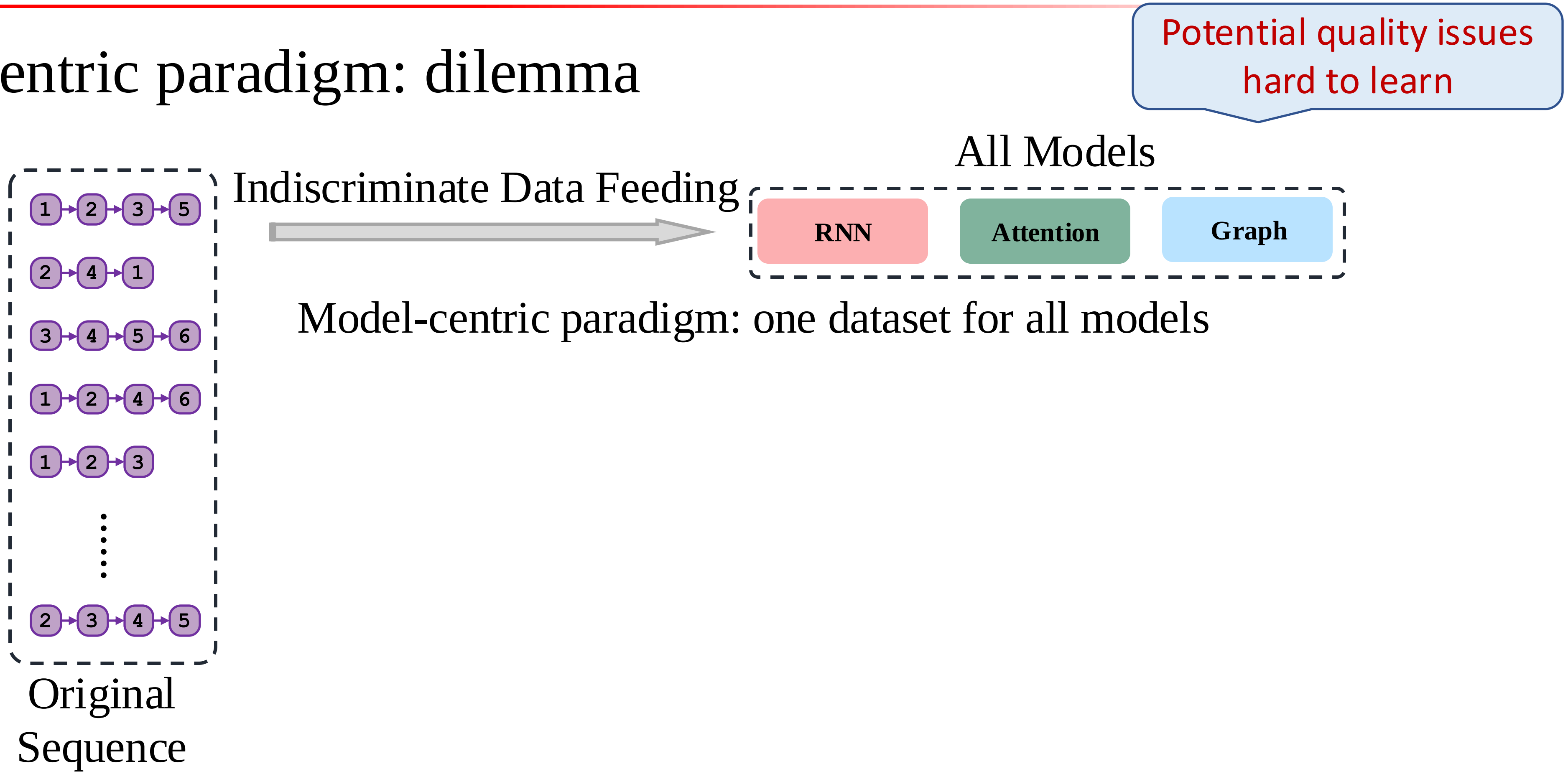
➢ Sequential recommendation in a model-centric paradigm



Model-centric paradigm: one dataset for all models

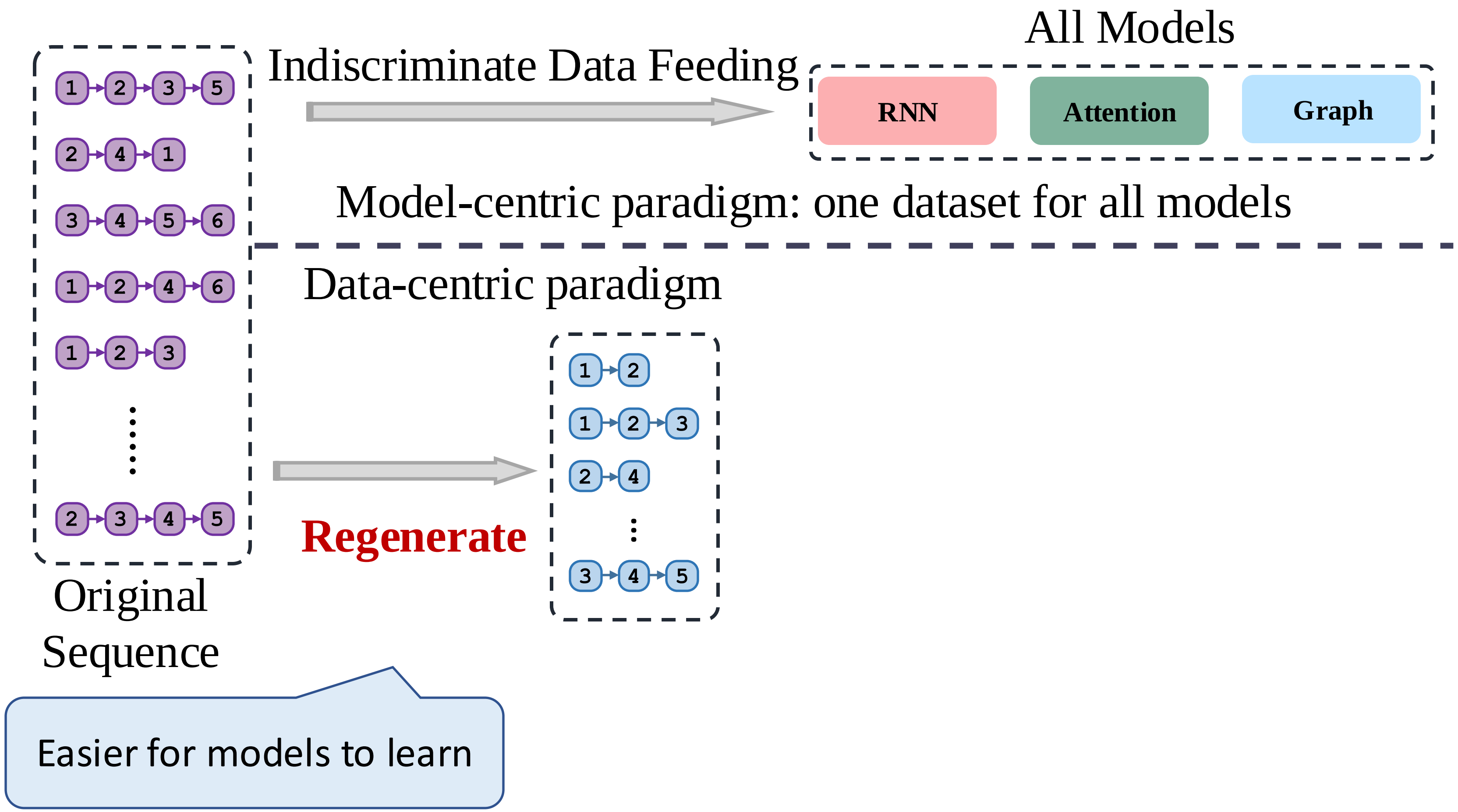
Motivation

- Model-centric paradigm: dilemma

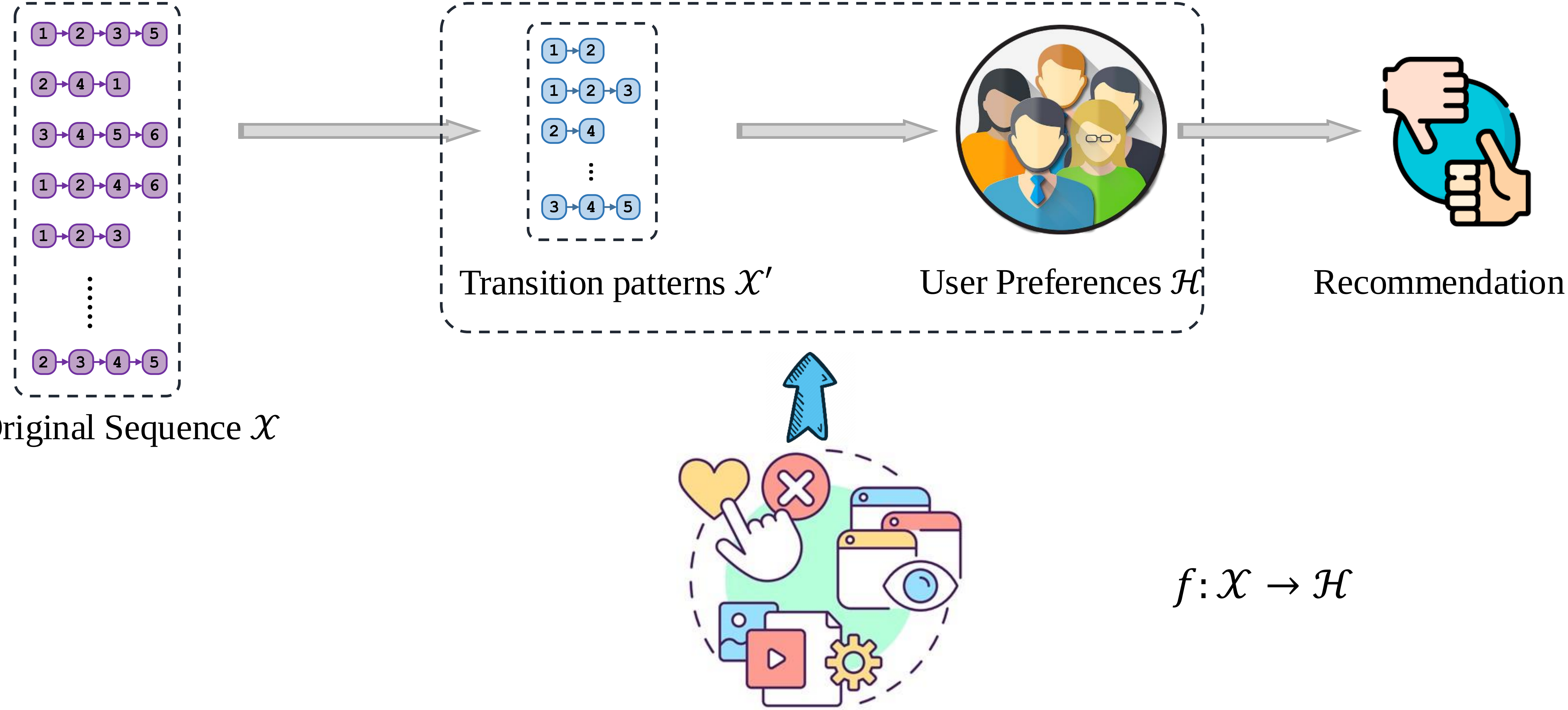


Motivation

➤ Data-centric paradigm: model-agnostic dataset regeneration



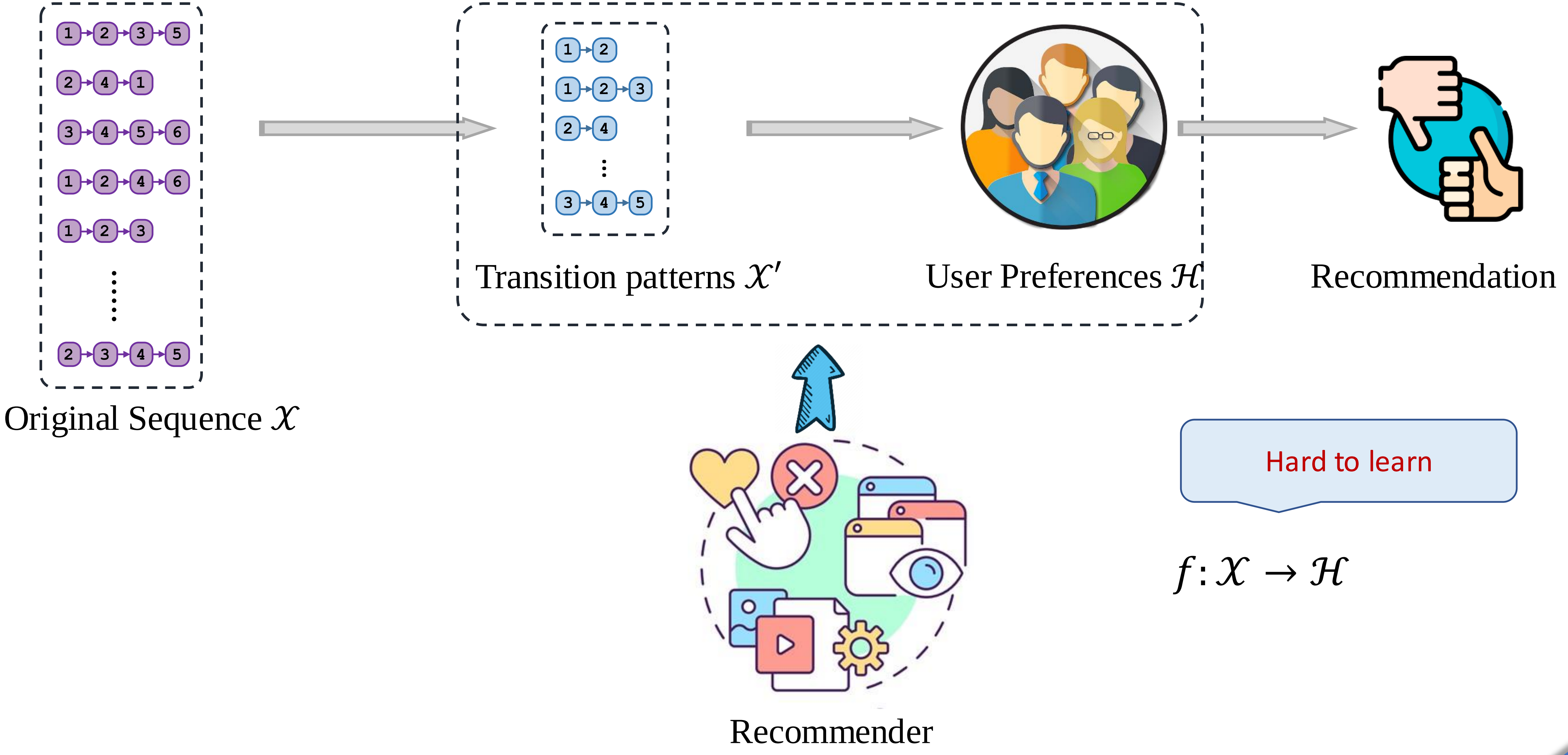
How to regenerate data?



Recommender

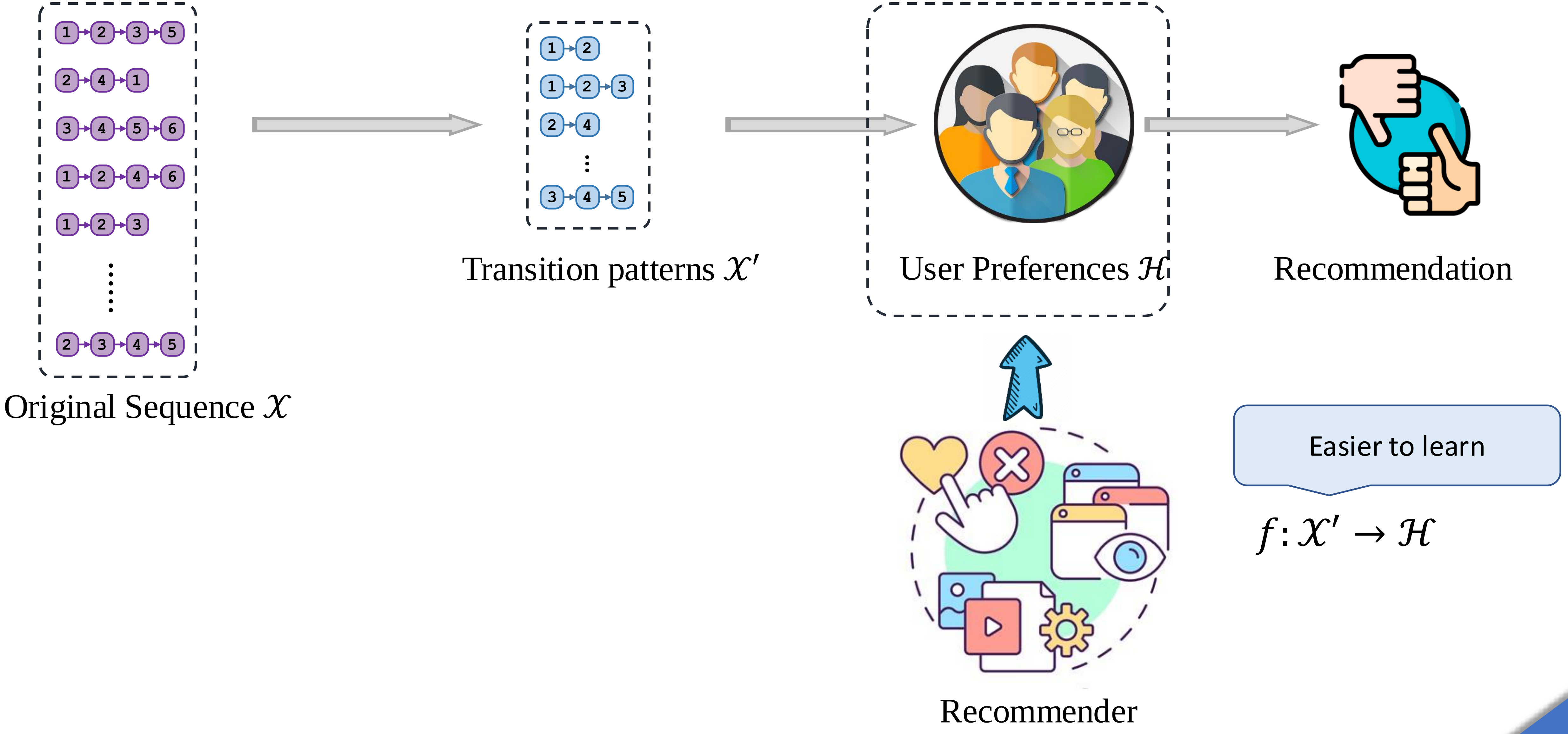
$$f: \mathcal{X} \rightarrow \mathcal{H}$$

Traditional recommenders need to learn a direct mapping from $\mathcal{X}$ to $\mathcal{H}$

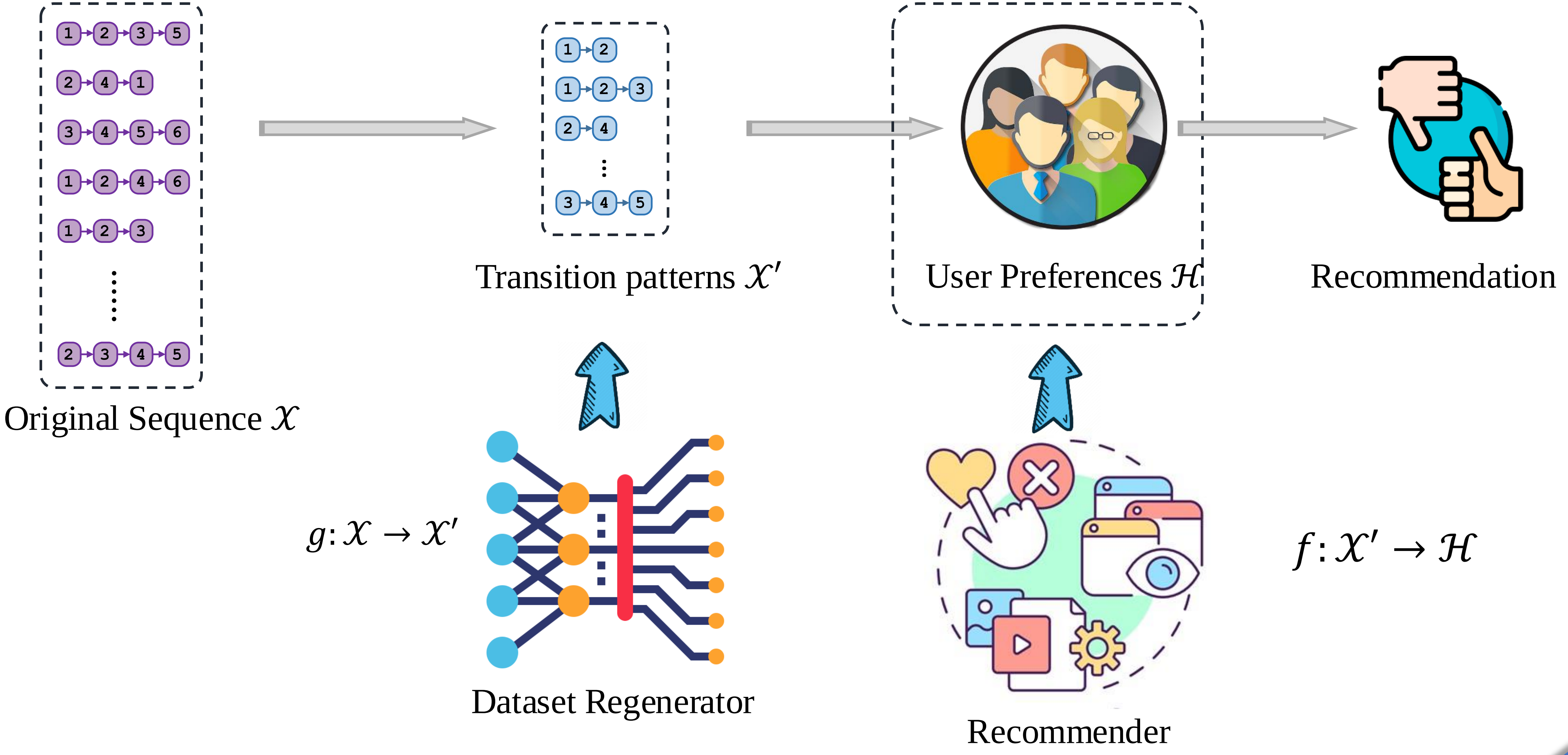


$$f : \mathcal{X} \rightarrow \mathcal{H}$$

It will be easier to learn a recommender that maps $\mathcal{X}'$ to H

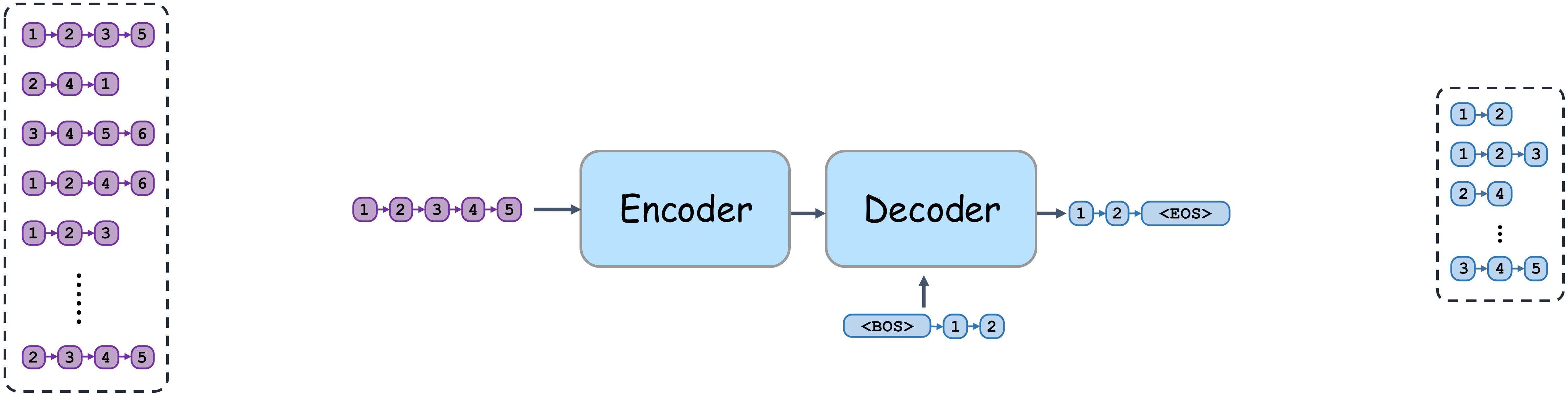


Key idea: learning a dataset explicitly contains item transition patterns

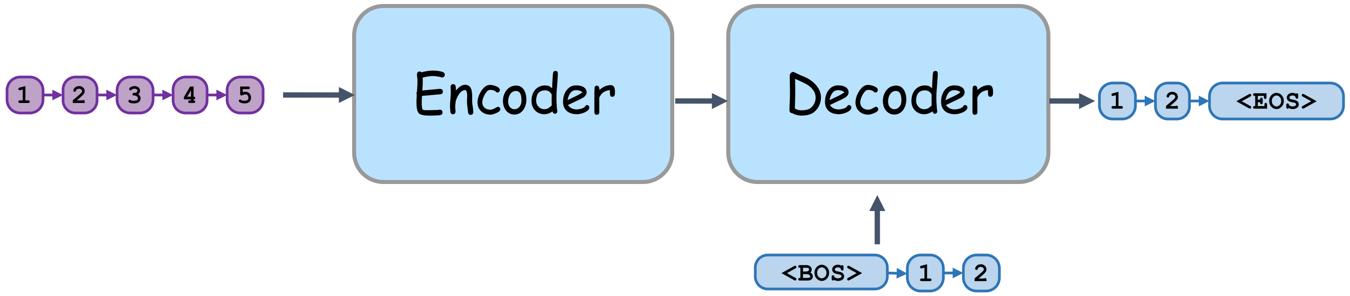


Dataset regeneration is a Seq2Seq

Dataset regeneration with vanilla transformer

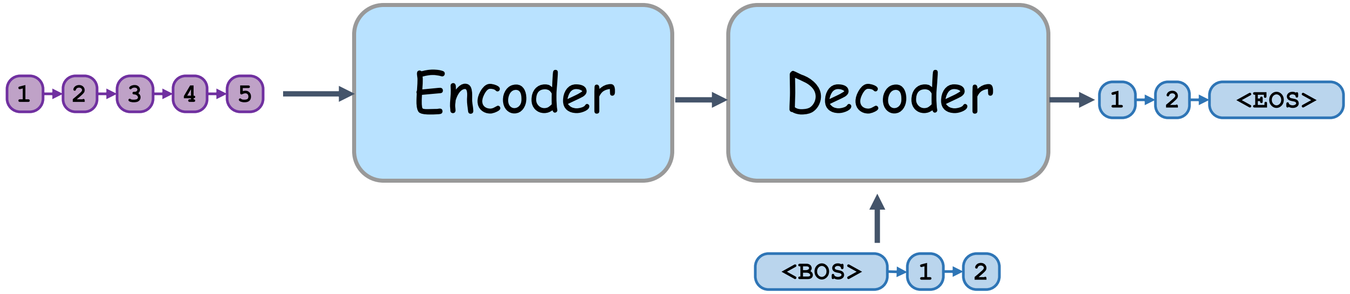


Dilemma: no sequence-pattern pair datasets

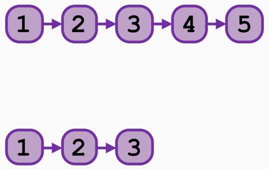


How to train the regenerator without labeled data?

Solution: pre-training dataset with rule-based sequential pattern mining



Pre-training dataset construction with rule-based pattern mining



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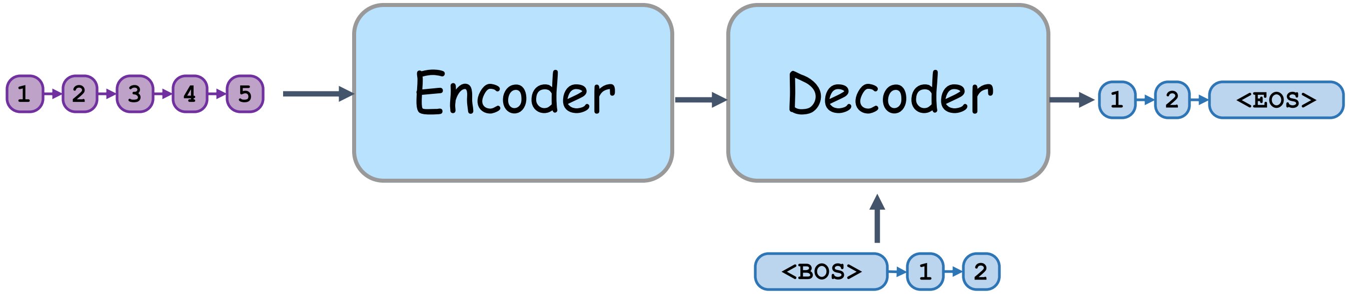

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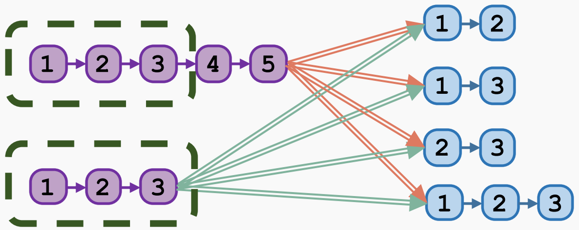
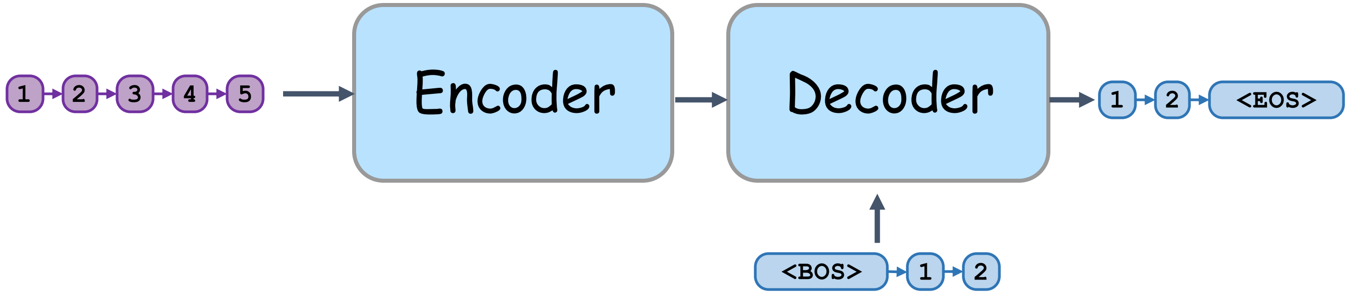
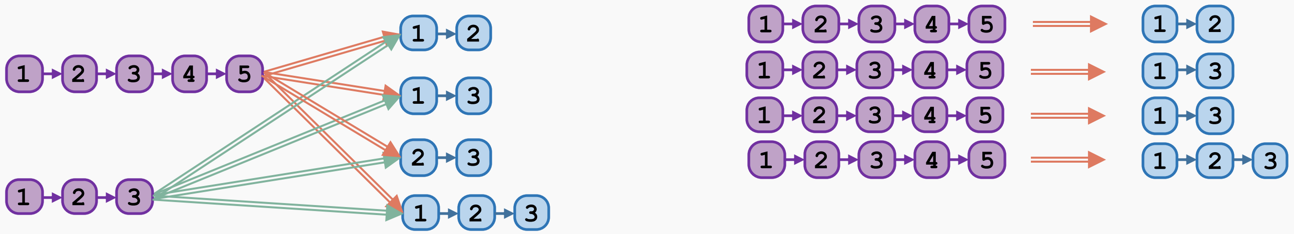


Window size 3 & Min frequency 2

Solution: pre-training dataset with rule-based sequential pattern mining



Pre-training dataset construction with rule-based pattern mining



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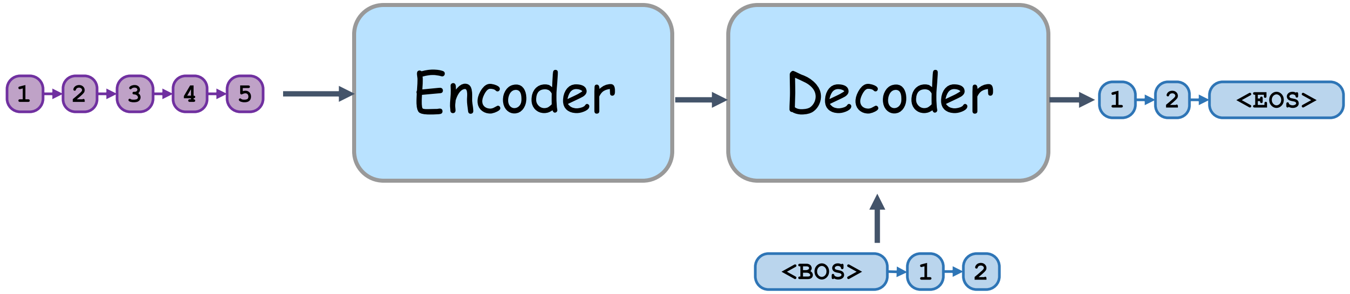
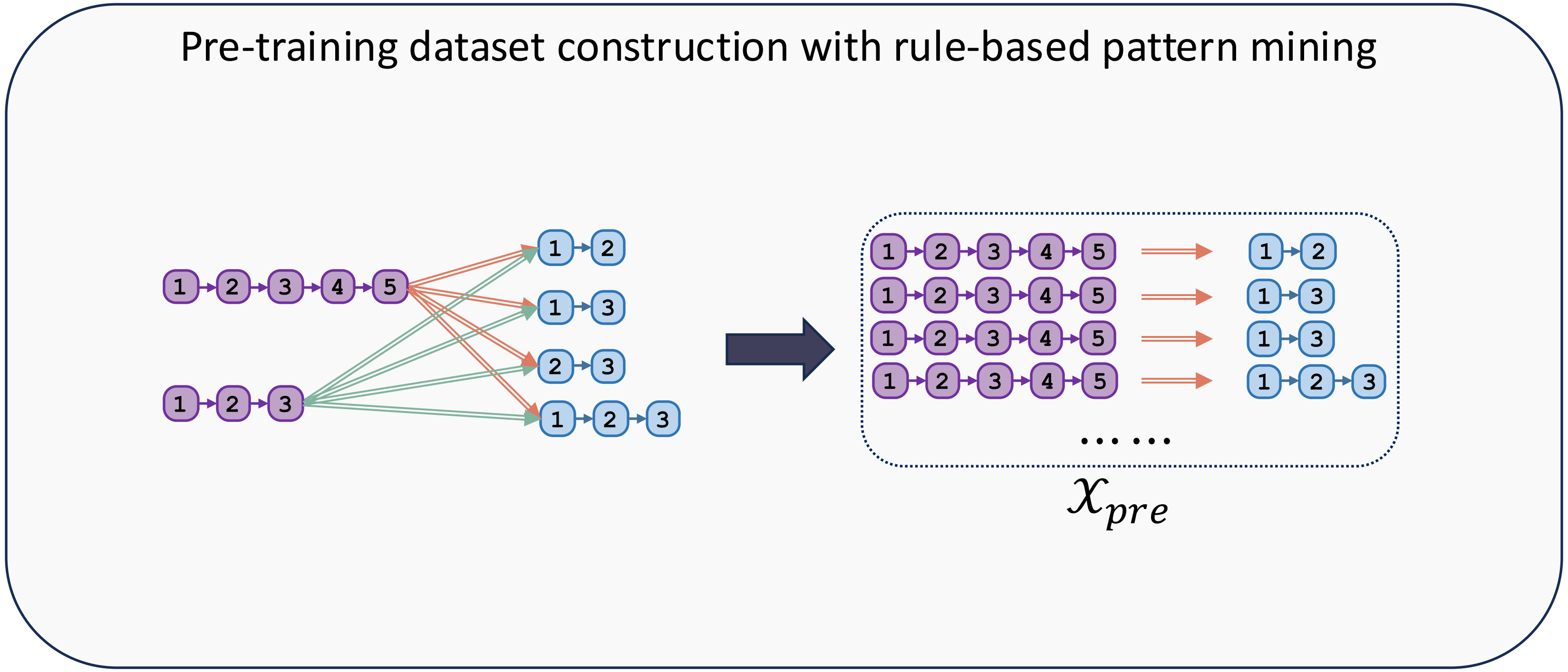
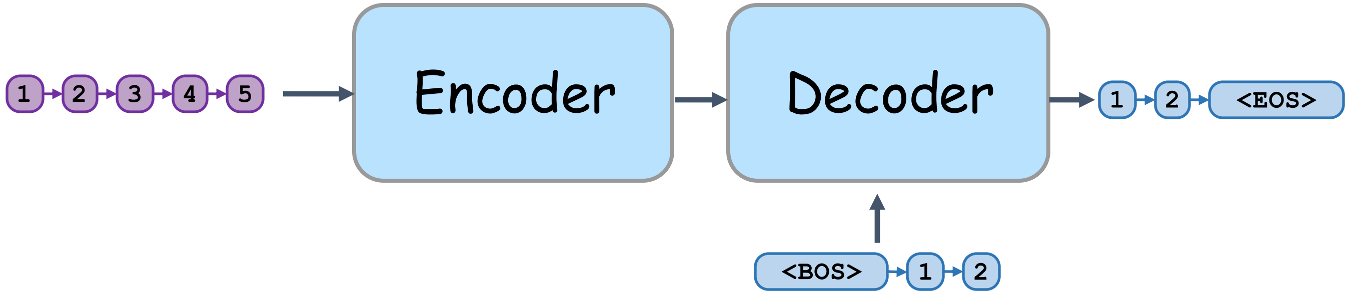
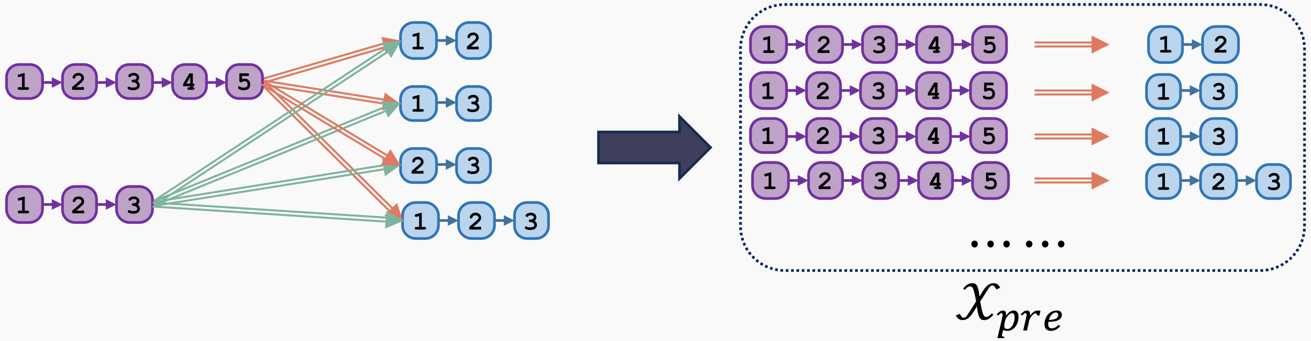




New issue: one-to-many mapping

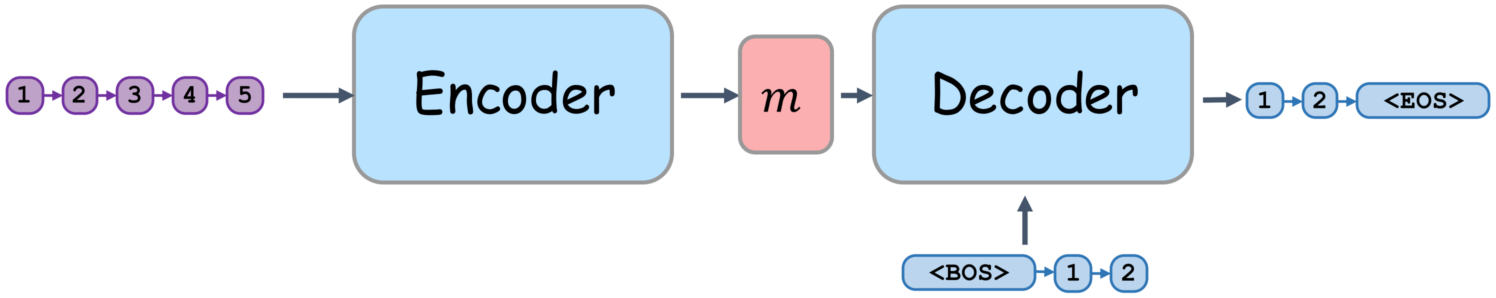


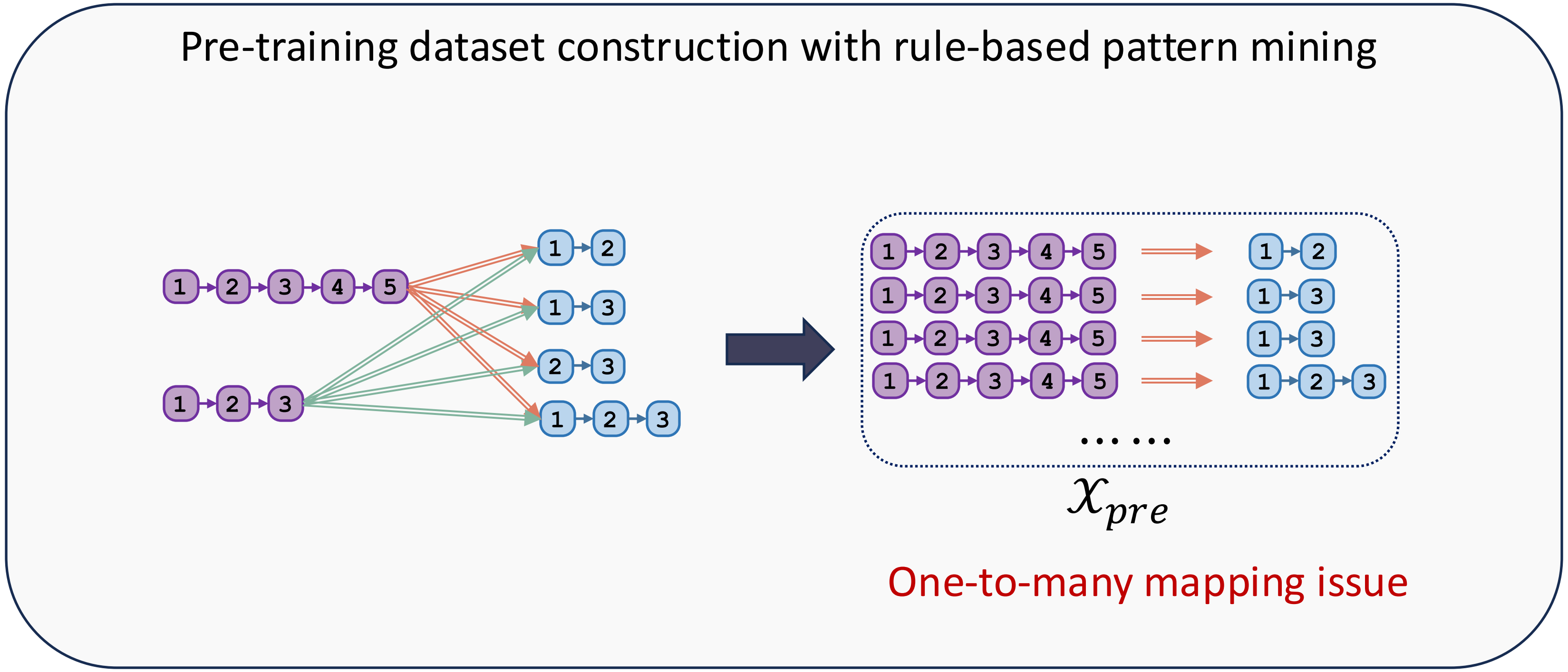
Pre-training dataset construction with rule-based pattern mining



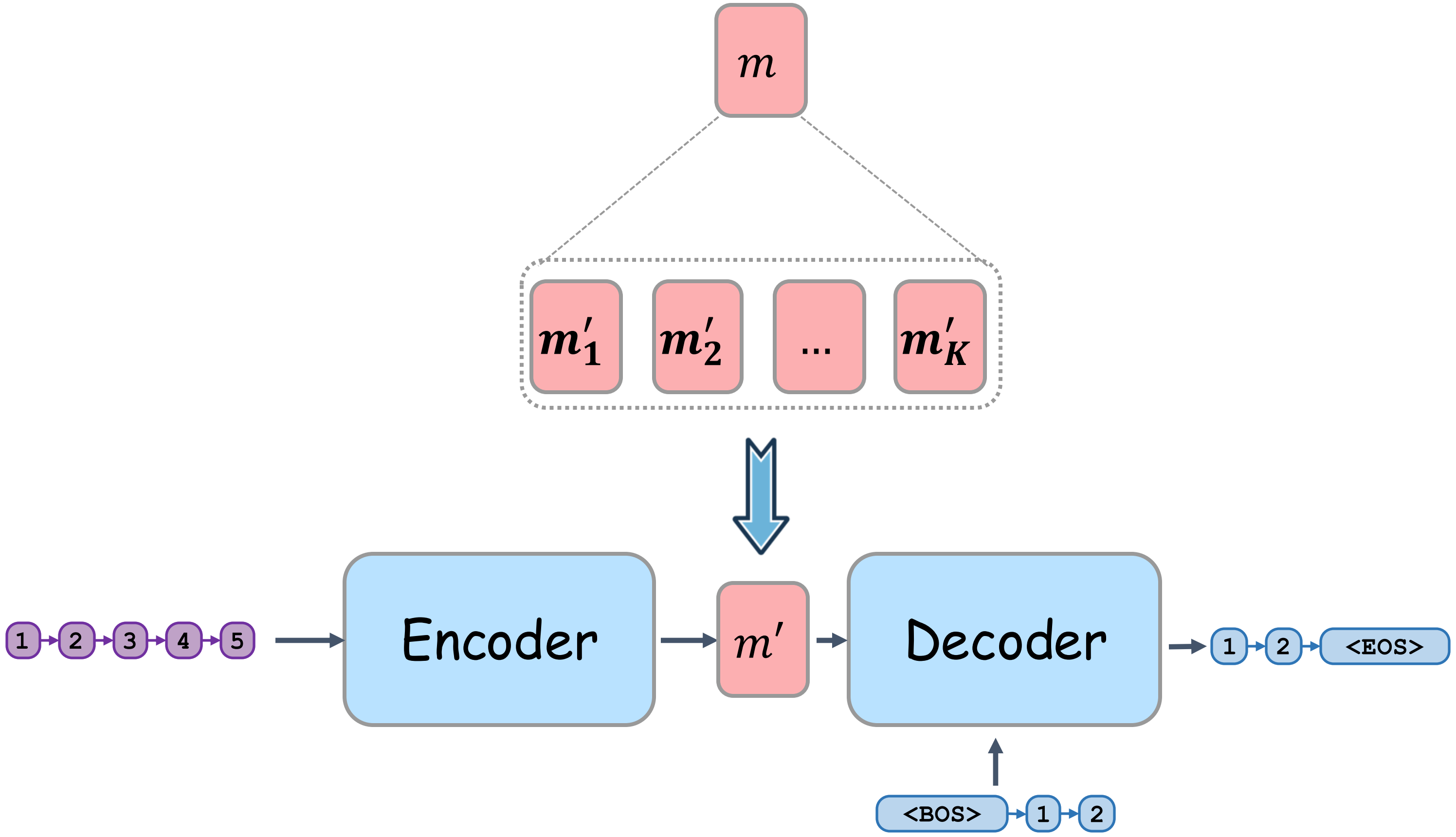
One-to-many mapping issue

The vanilla transformer memory fails to tackle the one-to-many mapping issue





Different memories for different target patterns



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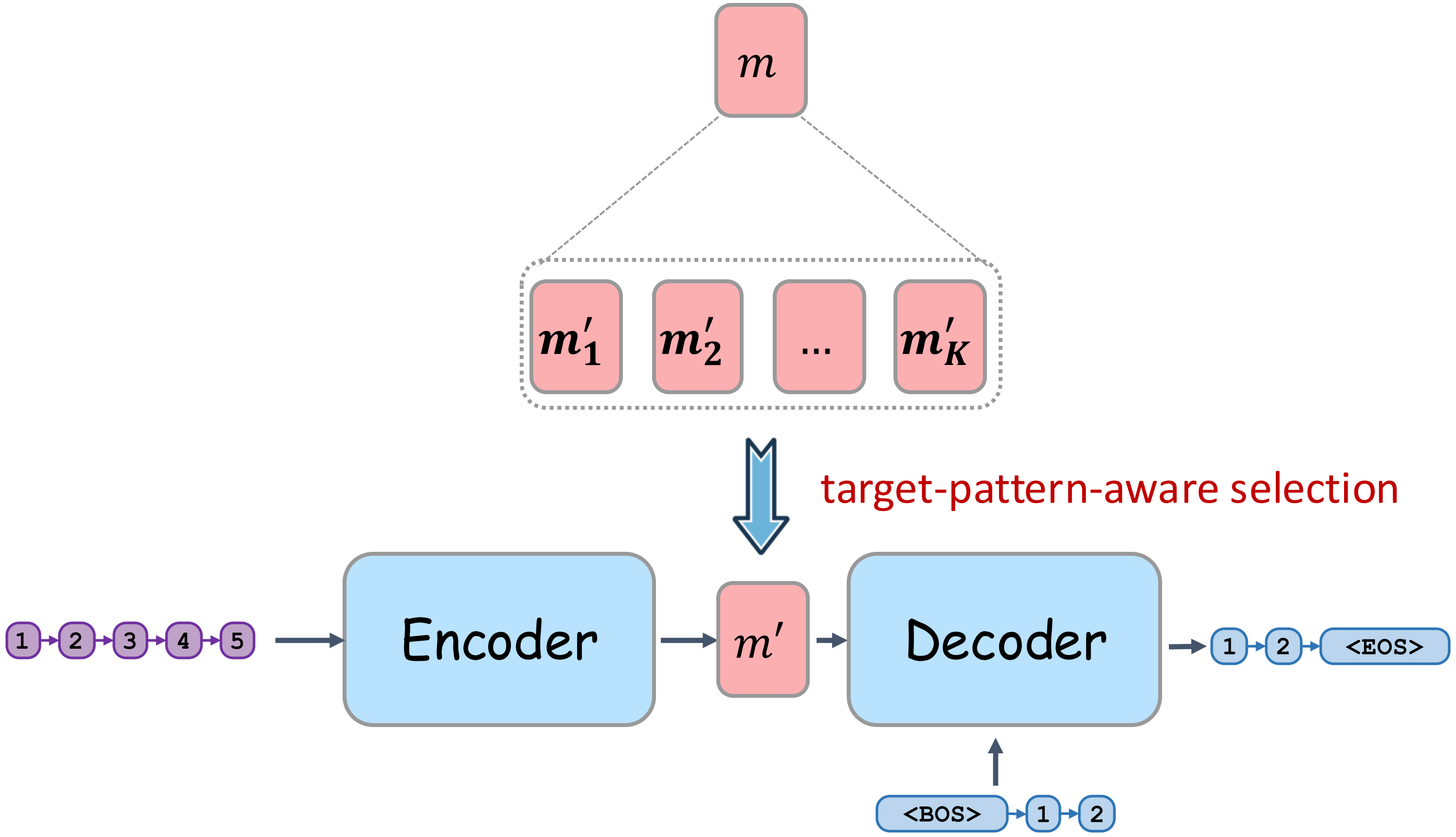
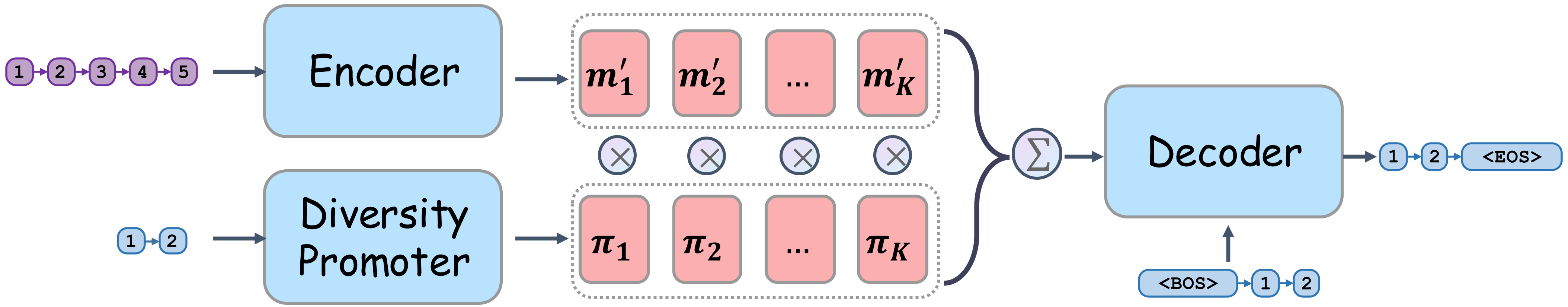
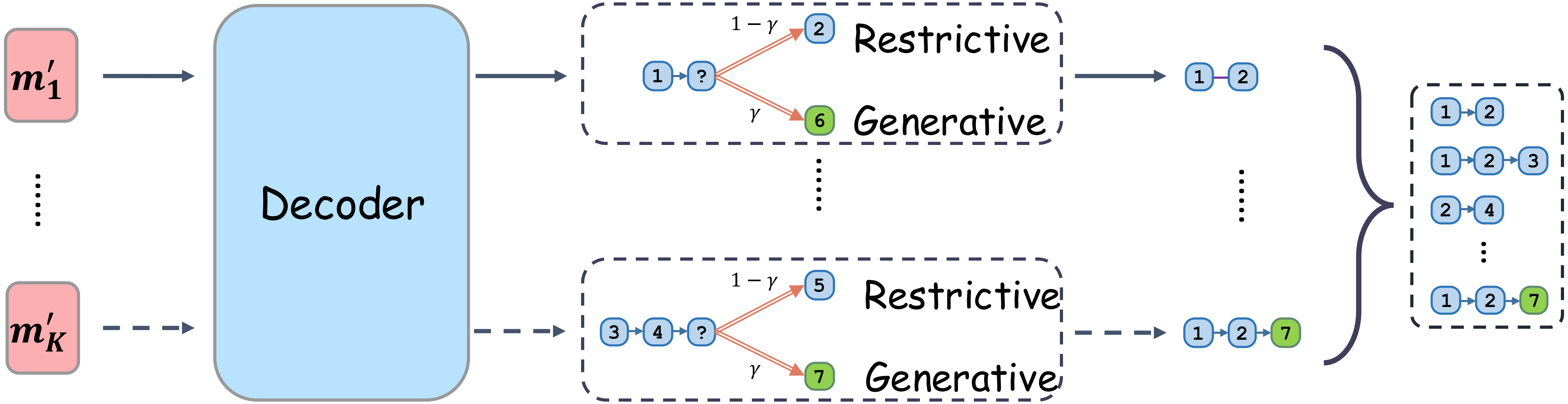


Target-pattern-aware selection with a diversity promoter (a Transformer encoder)



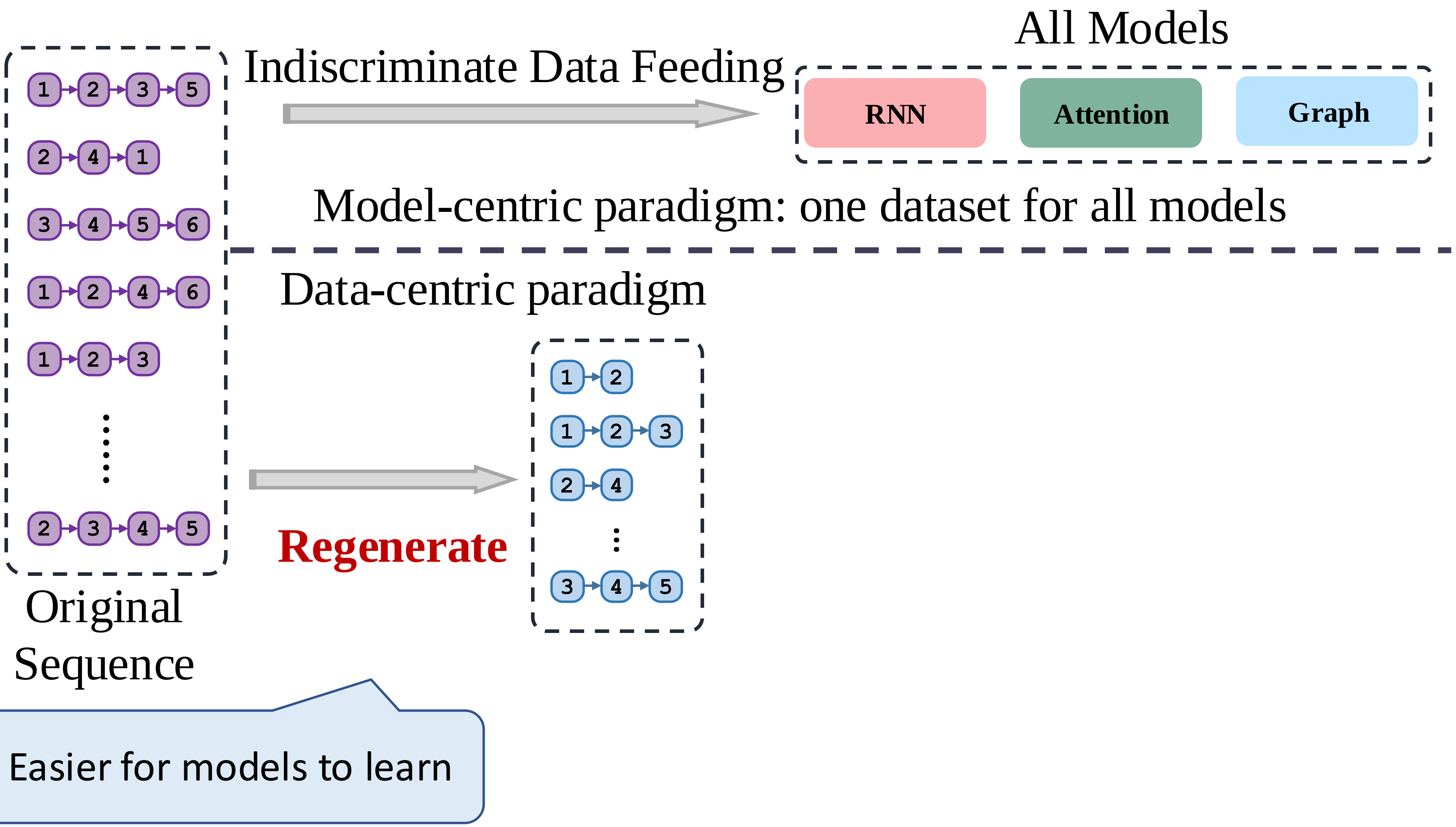
Dataset regeneration with hybrid inference

- Restrictive mode (Exploitation): limited to selecting items in input sequence
- Generative mode (Exploration): no limitation



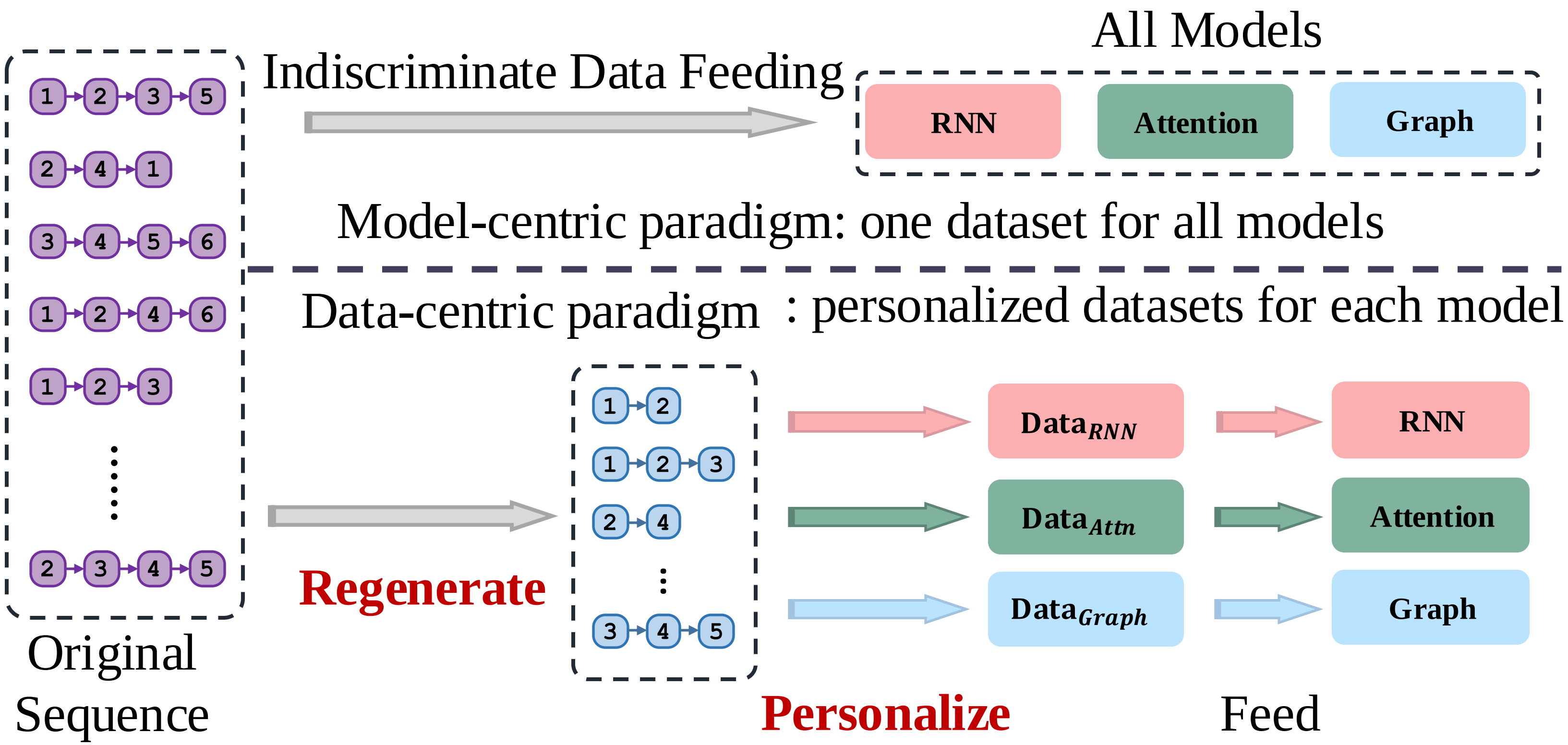
Motivation

➤ Data-centric paradigm: dataset regeneration



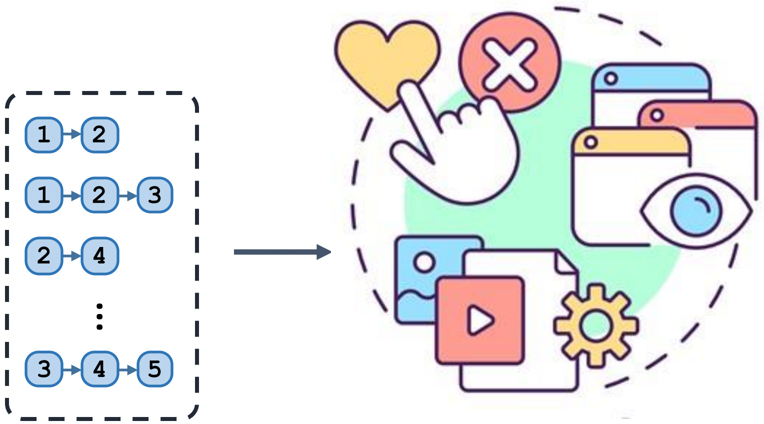
Motivation

- Data-centric paradigm: model-aware dataset regeneration



Personalized datasets for each model

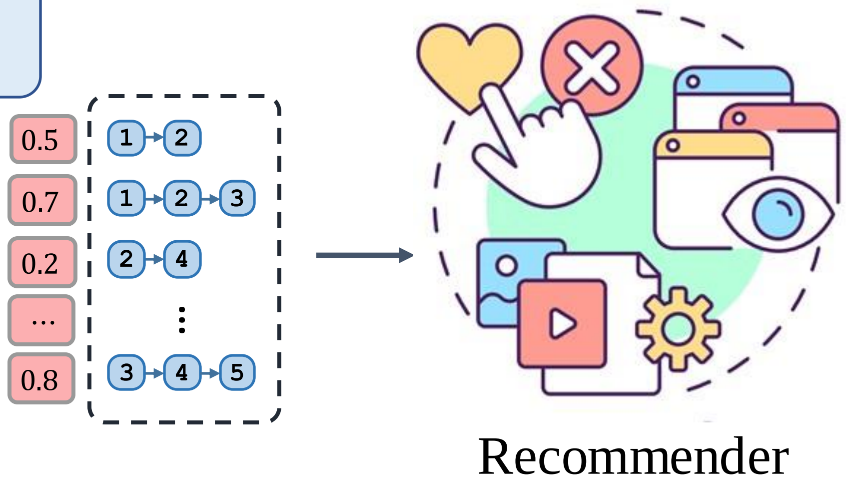
How to personalize data?



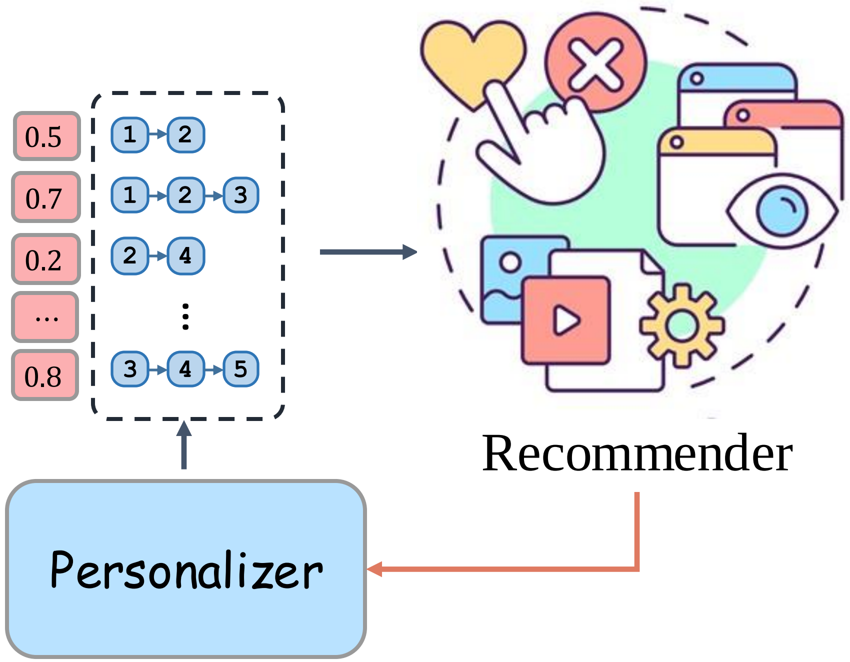
Recommender

Learning coefficients for different patterns

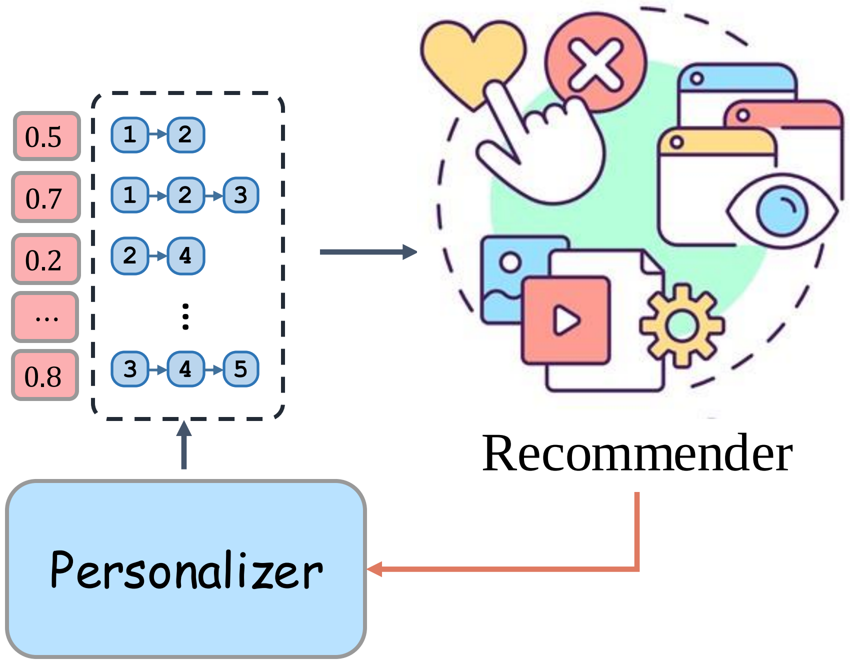
Different models favor different data



Dataset personalization with an MLP-based personalizer



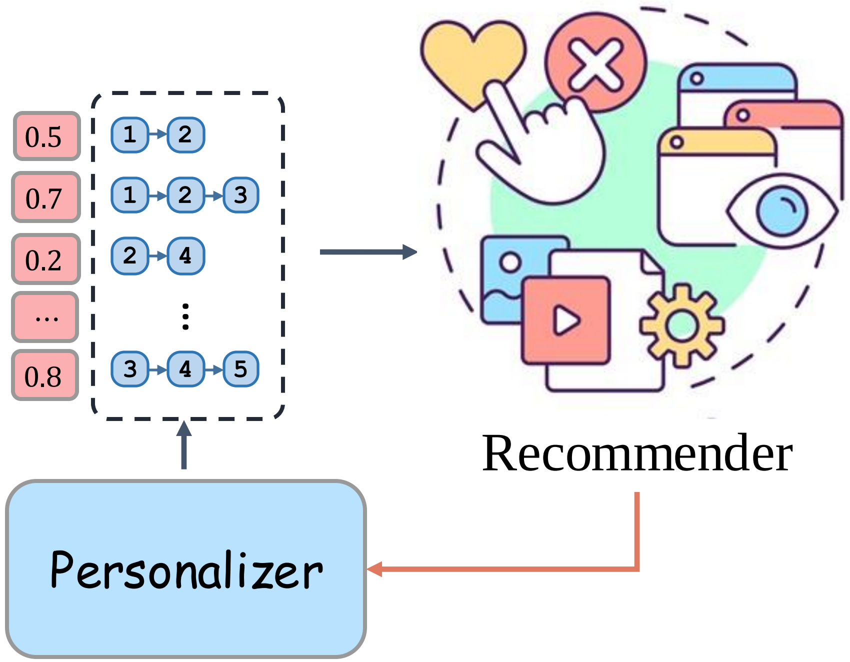
Personalized datasets functions in the training loss



$$\mathcal{L}_{rec-ori} = \sum_{i=1}^{|\mathcal{X}'|} \sum_{t=2}^{|p_i|} \mathcal{L}_{next-item}(i,t) \xrightarrow{\text{weighted}} \mathcal{L}_{rec} = \sum_{i=1}^{|\mathcal{X}'|} \sum_{t=2}^{|p_i|} \boxed{\mathbf{w}_{i,t}} \mathcal{L}_{next-item}(i,t)$$

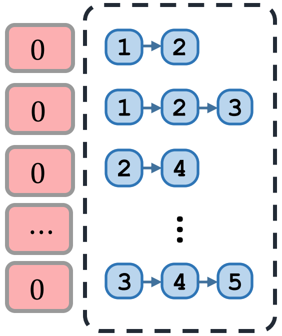
$$w_{i,t} = Gumbel - Softmax\left(g_\phi(h_t^i)\right)_0, where\ g_\phi(h_t^i) \in \mathbb{R}^2$$

Trivial optimization leads to model collapse



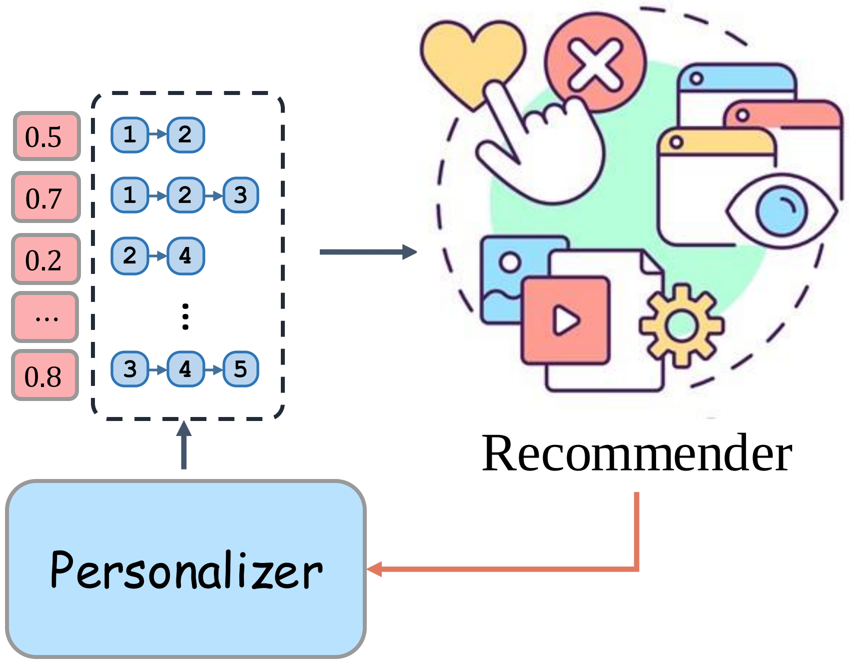
$$\mathcal{L}_{rec} = \sum_{i=1}^{|\mathcal{X}'|} \sum_{t=2}^{|p_i|} \mathbf{w}_{i,t} \mathcal{L}_{next-item}(i,t)$$

Direct optimization



Collapse!

Dataset personalization as a bi-level optimization problem

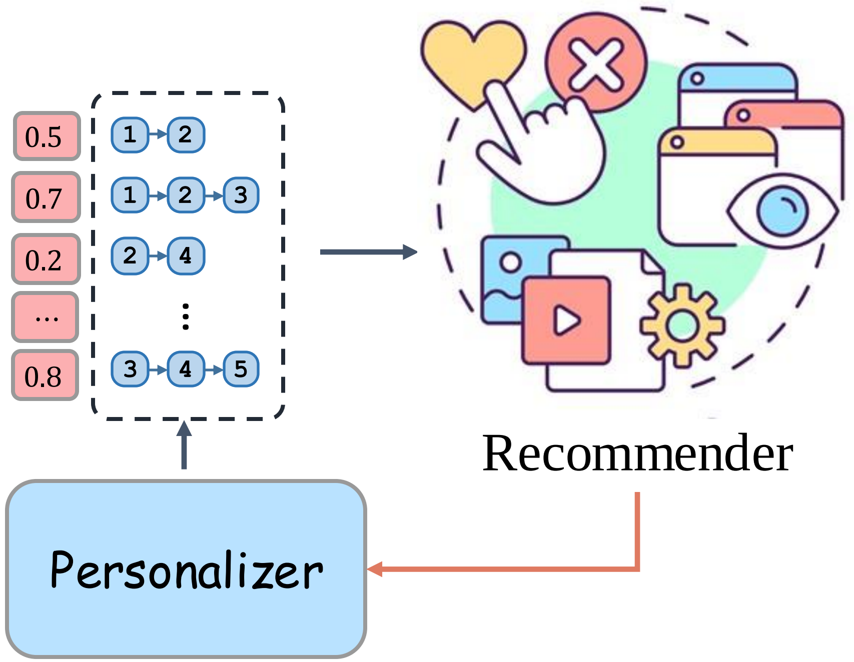


$$\phi^* = \arg\min_{\phi} L_{\text{dev}}(\theta^*(\phi)),$$

$$s.t. \quad \theta^*(\phi) = \arg\min_{\theta} L_{\text{train}}(\theta, \phi)$$

Bi-level optimization problem

Dataset personalization as a bi-level optimization problem



ϕ: Parameters of the personalizer

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θ: Parameters of downstream recommenders

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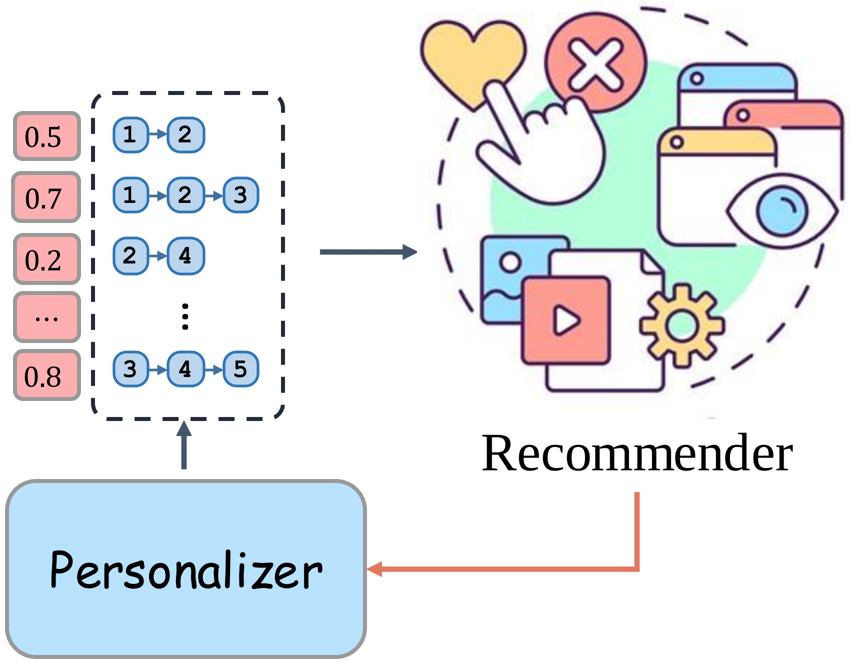

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Dataset personalization as a bi-level optimization problem

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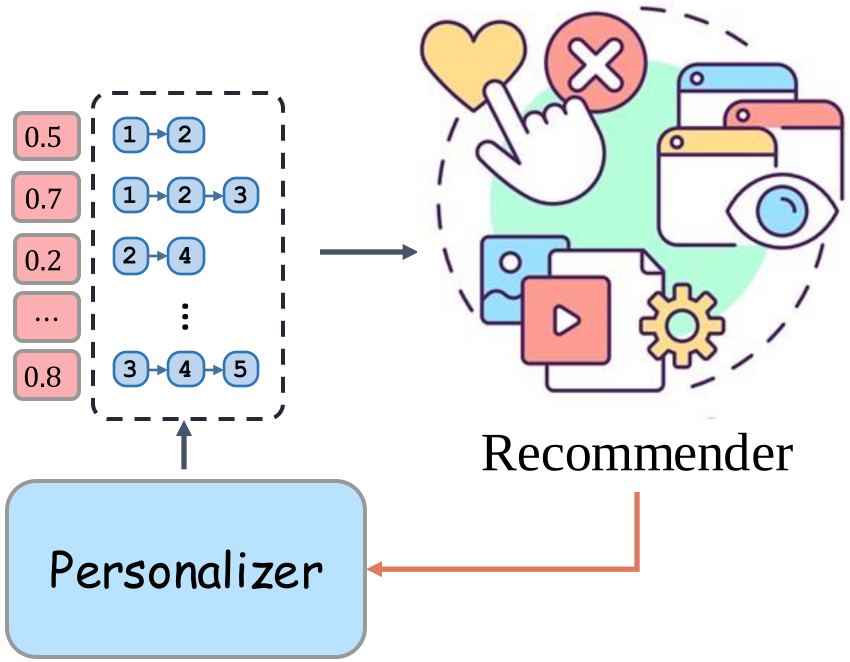

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Lower optimization: Obtain a best recommender given a fixed personalizer

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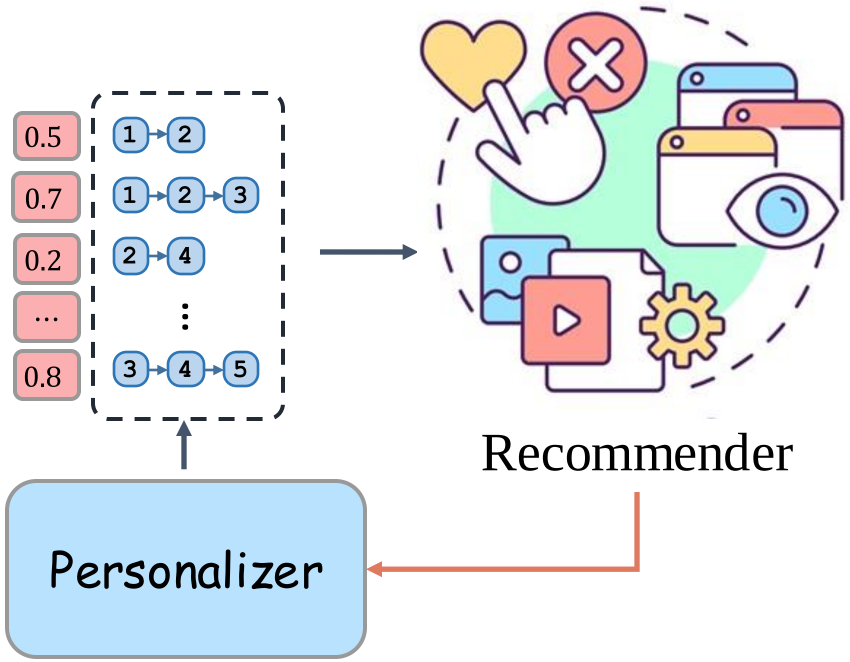

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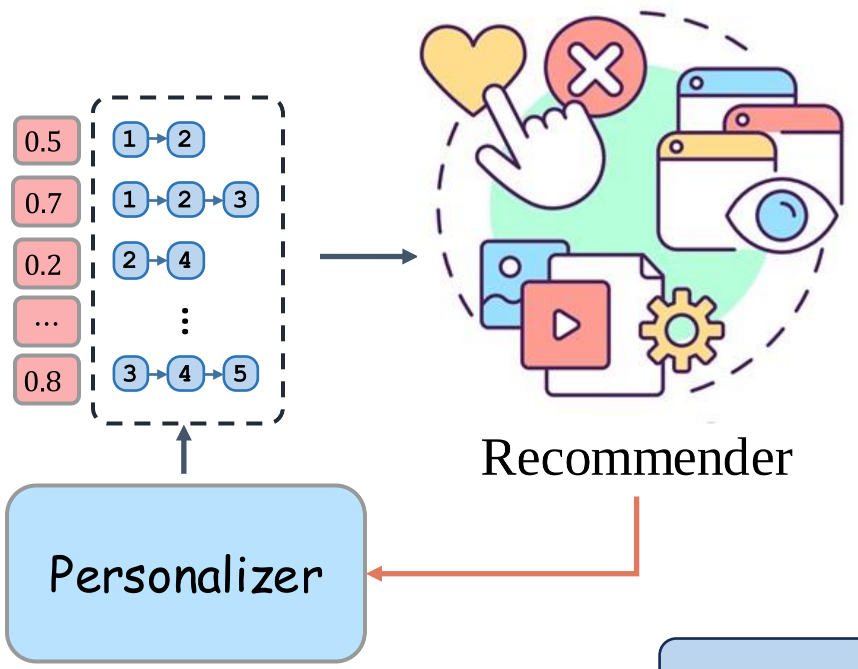

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Lower optimization: Obtain a best recommender given a fixed personalizer

Upper optimization: Validate and update the personalizer

$$\boxed{\phi^* = \arg\min_{\phi} L_{\text{dev}}(\theta^*(\phi)),} \longrightarrow \mathcal{L}_{rec-ori} = \sum_{i=1}^{|\mathcal{X}'|} \sum_{t=2}^{|p_i|} \mathcal{L}_{next-item}(i,t),$$

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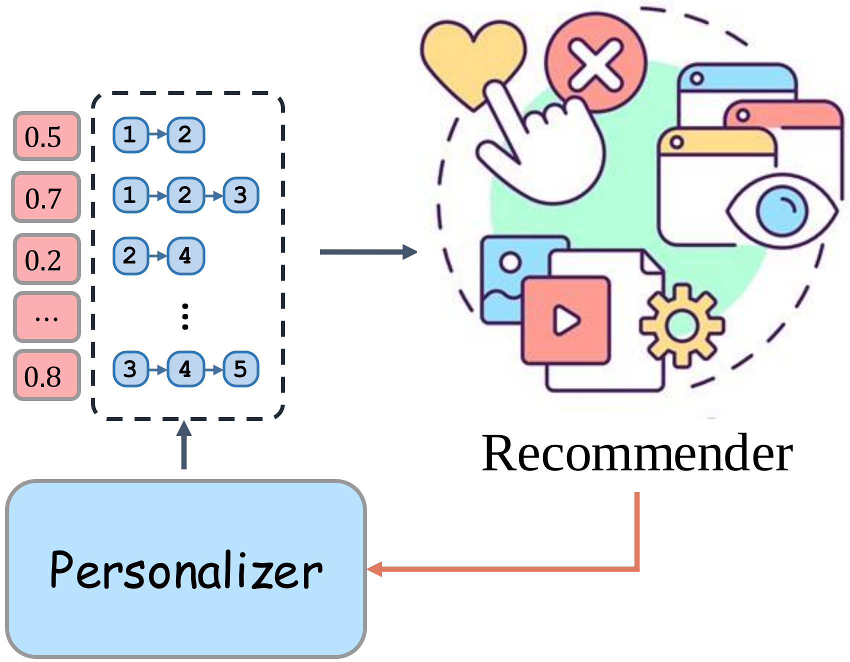

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Prevent Collapse!

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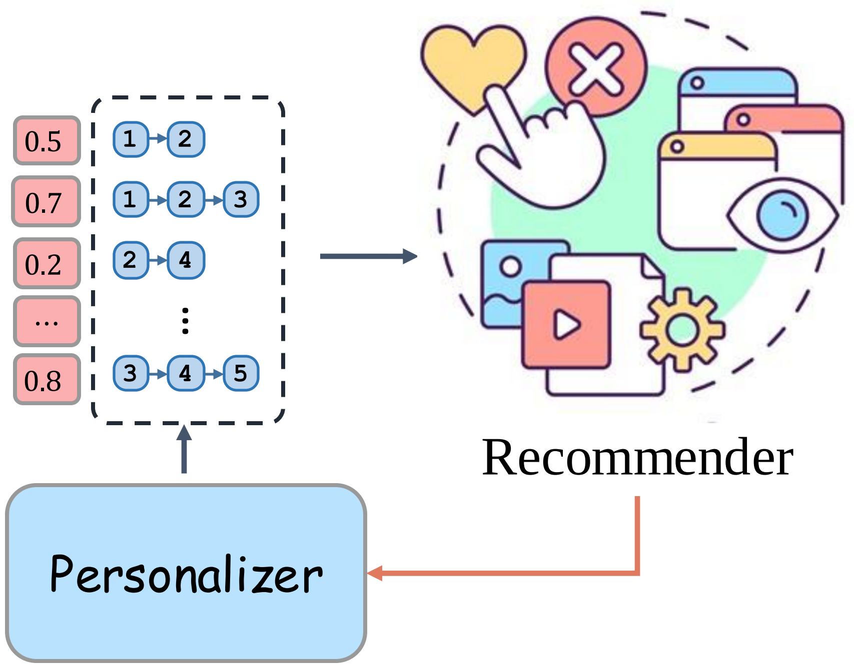

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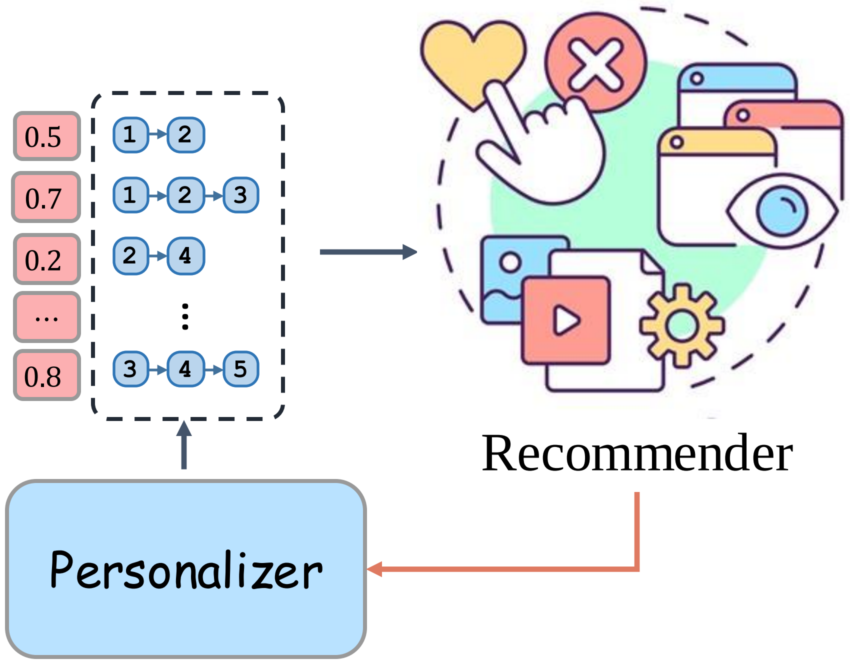
Direct optimization with gradient descent

Dataset personalization as a bi-level optimization problem



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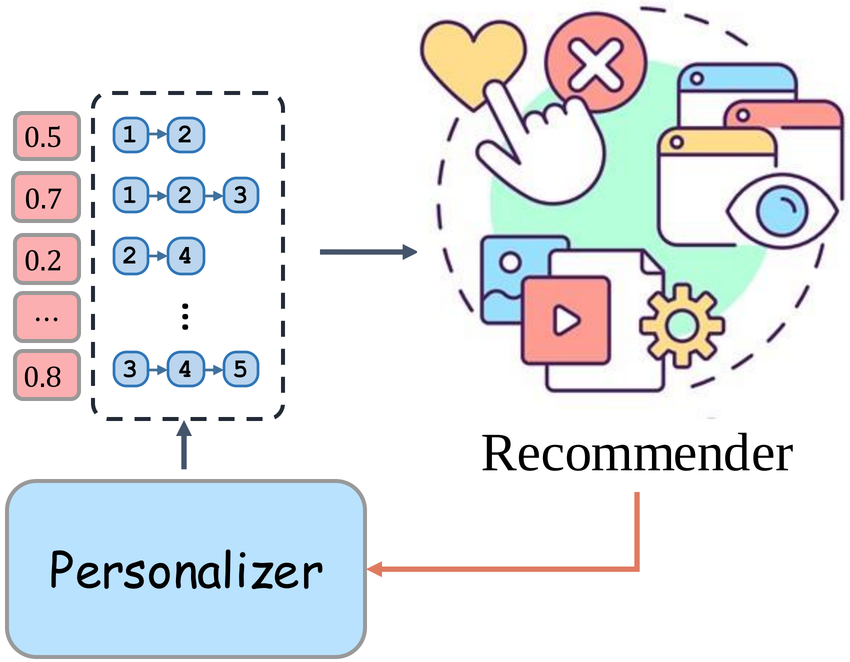
$$s.t. \quad \theta^*(\phi) = \arg\min_{\theta} L_{\text{train}}(\theta, \phi)$$

We need to calculate $\nabla_{\phi} L_{dev}(\theta^*(\phi))$, where $\theta^*(\phi)$ is an implicit function of ϕ

Dataset personalization as a bi-level optimization problem



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Implicit gradient [1,2] for efficient upper optimization

[1] Navon, Aviv, et al. "Auxiliary learning by implicit differentiation." *arXiv preprint arXiv:2007.02693* (2020).
[2] Chen, Hong, et al. "Cross-domain recommendation with behavioral importance perception." Proceedings of the ACM Web Conference 2023.

Overall Evaluation

Table 3: The overall performance. Considering a target model, the best result is bolded while the second-best result is underlined. Superscript * means improvements are statistically significant with $p<0.05$ while ** meaning $p<0.01$.

Dataset	Beauty				Sports				Toys				Yelp			
Metric	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20
∞-AE	0.0478	0.0661	0.0262	0.0308	0.0256	0.0373	0.0144	0.0173	0.0450	0.0593	0.0268	0.0304	0.0252	0.0424	0.0121	0.0162
MELT	0.0577	0.0879	0.0303	0.0379	0.0311	0.0488	0.0163	0.0208	0.0709	0.0987	0.0401	0.0473	0.0293	0.0497	0.0143	0.0195
GRU4Rec	0.0204	0.0382	0.0107	0.0150	0.0160	0.0279	0.0085	0.0115	0.0212	0.0357	0.0099	0.0136	0.0215	0.0364	0.0105	0.0143
DR4SR	0.0252**	0.0448**	0.0128**	0.0177**	0.0208**	0.0341**	0.0102**	0.0135**	0.0252**	0.0418**	0.0124**	0.0165**	0.0235**	0.0403**	0.0114**	0.0156**
Improv	23.5%	17.3%	19.6%	18.0%	30.0%	22.2%	20.0%	17.4%	18.9%	22.4%	25.3%	21.3%	9.30%	10.7%	8.57%	9.09%
DR4SR+	**0.0292****	**0.0473****	**0.0149****	**0.0194****	**0.0223****	**0.0360****	**0.0116****	**0.0151****	**0.0274****	**0.0456****	**0.0134****	**0.0179****	**0.0243****	**0.0415****	**0.0120****	**0.0164****
Improv	43.1%	23.8%	39.3%	29.3%	39.4%	29.0%	36.5%	31.3%	29.2%	27.7%	35.4%	31.6%	13.0%	14.0%	14.3%	14.7%
SASRec	0.0553	0.0847	0.0291	0.0368	0.0297	0.0449	0.0156	0.0194	0.0682	0.0951	0.0381	0.0448	0.0289	0.0488	0.0143	0.0193
DR4SR	0.0595**	0.0906**	0.0317**	0.0395**	0.0330**	0.0512**	0.0174**	0.0220**	0.0762**	0.1049**	0.0432**	0.0504**	0.0304*	0.0512*	0.0151*	0.0202*
Improv	7.59%	6.97%	8.93%	7.34%	11.1%	14.0%	11.5%	13.4%	11.7%	10.3%	13.4%	12.5%	5.19%	4.92%	5.59%	4.66%
DR4SR+	**0.0619****	**0.0919****	**0.0337****	**0.0412****	**0.0349****	**0.0525****	**0.0191****	**0.0235****	**0.0773****	**0.1068****	**0.0453****	**0.0527****	**0.0317****	**0.0523****	**0.0159****	**0.0211****
Improv	11.9%	8.50%	15.8%	12.0%	17.5%	16.9%	22.4%	21.1%	13.3%	12.3%	18.9%	17.6%	9.69%	7.17%	11.2%	9.33%
FMLP	0.0602	0.0934	0.0311	0.0394	0.0323	0.0524	0.0166	0.0217	0.0676	0.0982	0.0377	0.0447	0.0297	0.0495	0.0143	0.0197
DR4SR	0.0635**	0.0993**	0.0332**	0.0421	0.0345	0.0559	0.0177**	0.0230**	0.0717**	0.1061**	0.0400**	0.0486**	0.0316**	0.0524**	0.0158**	0.0210**
Improv	5.48%	6.32%	6.75%	6.85%	6.81%	6.68	6.63%	5.99%	6.07%	8.04%	6.10%	8.72%	6.40%	5.86%	10.5%	6.60%
DR4SR+	**0.0687****	**0.1056****	**0.0357****	**0.0449****	**0.0384****	**0.0597****	**0.0198****	**0.0253****	**0.0788****	**0.1136****	**0.0437****	**0.0524****	**0.0353****	**0.0582****	**0.0171****	**0.0231****
Improv	14.1%	13.1%	14.8%	14.0%	18.9%	13.9%	19.3%	16.6%	16.6%	15.7%	15.9%	17.2%	18.9%	17.6%	19.6%	17.3%
GNN	0.0570	0.0859	0.0311	0.0384	0.0311	0.0476	0.0167	0.0211	0.0697	0.0958	0.0403	0.0469	0.0242	0.0430	0.0118	0.0166
DR4SR	0.0611**	0.0926**	0.0324*	0.0406*	0.0336**	0.0525**	0.0182**	0.0230**	0.0736**	0.1031**	0.0424**	0.0498**	0.0268**	0.0451*	0.0129**	0.0175*
Improv	7.19%	7.80%	4.18%	5.73%	8.04%	10.3%	8.98%	9.00%	5.60%	7.62%	5.21%	6.18%	10.7%	4.88%	9.32%	5.42%
DR4SR+	**0.0637****	**0.0953****	**0.0334****	**0.0414****	**0.0351****	**0.0545****	**0.0189****	**0.0238****	**0.0771****	**0.1082****	**0.0442****	**0.0521****	**0.0272****	**0.0471****	**0.0134****	**0.0184****
Improv	11.8%	10.9%	7.40%	7.81%	12.9%	14.5%	13.2%	12.8%	10.6%	12.9%	9.68%	11.1%	12.4%	9.53%	13.6%	10.8%
CL4SRec	0.0653	0.0947	0.0370	0.0441	0.0381	0.0559	0.0215	0.0259	0.0781	0.1075	0.0456	0.0530	0.0322	0.0535	0.0159	0.0212
DR4SR	0.0732**	0.1016**	0.0423**	0.0495**	0.0401**	0.0600**	0.0227**	0.0274**	0.0821**	0.1113*	0.0481**	0.0551*	0.0344**	0.0561**	0.0174**	0.0229**
Improv	12.1%	7.29%	14.3%	12.2%	5.25%	7.33%	5.58%	5.79%	5.12%	3.53%	5.48%	3.96%	6.83%	4.86%	9.43%	8.02%
DR4SR+	**00756****	**0.1062****	**0.0440****	**0.0517****	**0.0448****	**0.0655****	**0.0247****	**0.0299****	**0.0829****	**0.1140****	**0.0489****	**0.0567****	**0.0363****	**0.0598****	**0.0183****	**0.0241****
Improv	15.8%	1.12%	18.9%	17.2%	17.6%	17.2%	14.8%	15.4%	6.15%	6.05%	7.24%	6.98%	12.7%	11.8%	15.1%	13.7%

Overall Evaluation

Table 3: The overall performance. Considering a target model, the best result is bolded while the second-best result is underlined. Superscript * means improvements are statistically significant with $p<0.05$ while ** meaning $p<0.01$.

Dataset	Beauty				Sports				Toys				Yelp			
Metric	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20
∞-AE	0.0478	0.0661	0.0262	0.0308	0.0256	0.0373	0.0144	0.0173	0.0450	0.0593	0.0268	0.0304	0.0252	0.0424	0.0121	0.0162
MELT	0.0577	0.0879	0.0303	0.0379	0.0311	0.0488	0.0163	0.0208	0.0709	0.0987	0.0401	0.0473	0.0293	0.0497	0.0143	0.0195
GRU4Rec	0.0204	0.0382	0.0107	0.0150	0.0160	0.0279	0.0085	0.0115	0.0212	0.0357	0.0099	0.0136	0.0215	0.0364	0.0105	0.0143
DR4SR	0.0252**	0.0448**	0.0128**	0.0177**	0.0208**	0.0341**	0.0102**	0.0135**	0.0252**	0.0418**	0.0124**	0.0165**	0.0235**	0.0403**	0.0114**	0.0156**
Improv	23.5%	17.3%	19.6%	18.0%	30.0%	22.2%	20.0%	17.4%	18.9%	22.4%	25.3%	21.3%	9.30%	10.7%	8.57%	9.09%
DR4SR+	**0.0292****	**0.0473****	**0.0149****	**0.0194****	**0.0223****	**0.0360****	**0.0116****	**0.0151****	**0.0274****	**0.0456****	**0.0134****	**0.0179****	**0.0243****	**0.0415****	**0.0120****	**0.0164****
Improv	43.1%	23.8%	39.3%	29.3%	39.4%	29.0%	36.5%	31.3%	29.2%	27.7%	35.4%	31.6%	13.0%	14.0%	14.3%	14.7%
SASRec	0.0553	0.0847	0.0291	0.0368	0.0297	0.0449	0.0156	0.0194	0.0682	0.0951	0.0381	0.0448	0.0289	0.0488	0.0143	0.0193
DR4SR	0.0595**	0.0906**	0.0317**	0.0395**	0.0330**	0.0512**	0.0174**	0.0220**	0.0762**	0.1049**	0.0432**	0.0504**	0.0304*	0.0512*	0.0151*	0.0202*
Improv	7.59%	6.97%	8.93%	7.34%	11.1%	14.0%	11.5%	13.4%	11.7%	10.3%	13.4%	12.5%	5.19%	4.92%	5.59%	4.66%
DR4SR+	**0.0619****	**0.0919****	**0.0337****	**0.0412****	**0.0349****	**0.0525****	**0.0191****	**0.0235****	**0.0773****	**0.1068****	**0.0453****	**0.0527****	**0.0317****	**0.0523****	**0.0159****	**0.0211****
Improv	11.9%	8.50%	15.8%	12.0%	17.5%	16.9%	22.4%	21.1%	13.3%	12.3%	18.9%	17.6%	9.69%	7.17%	11.2%	9.33%
FMLP	0.0602	0.0934	0.0311	0.0394	0.0323	0.0524	0.0166	0.0217	0.0676	0.0982	0.0377	0.0447	0.0297	0.0495	0.0143	0.0197
DR4SR	0.0635**	0.0993**	0.0332**	0.0421	0.0345	0.0559	0.0177**	0.0230**	0.0717**	0.1061**	0.0400**	0.0486**	0.0316**	0.0524**	0.0158**	0.0210**
Improv	5.48%	6.32%	6.75%	6.85%	6.81%	6.68	6.63%	5.99%	6.07%	8.04%	6.10%	8.72%	6.40%	5.86%	10.5%	6.60%
DR4SR+	**0.0687****	**0.1056****	**0.0357****	**0.0449****	**0.0384****	**0.0597****	**0.0198****	**0.0253****	**0.0788****	**0.1136****	**0.0437****	**0.0524****	**0.0353****	**0.0582****	**0.0171****	**0.0231****
Improv	14.1%	13.1%	14.8%	14.0%	18.9%	13.9%	19.3%	16.6%	16.6%	15.7%	15.9%	17.2%	18.9%	17.6%	19.6%	17.3%
GNN	0.0570	0.0859	0.0311	0.0384	0.0311	0.0476	0.0167	0.0211	0.0697	0.0958	0.0403	0.0469	0.0242	0.0430	0.0118	0.0166
DR4SR	0.0611**	0.0926**	0.0324*	0.0406*	0.0336**	0.0525**	0.0182**	0.0230**	0.0736**	0.1031**	0.0424**	0.0498**	0.0268**	0.0451*	0.0129**	0.0175*
Improv	7.19%	7.80%	4.18%	5.73%	8.04%	10.3%	8.98%	9.00%	5.60%	7.62%	5.21%	6.18%	10.7%	4.88%	9.32%	5.42%
DR4SR+	**0.0637****	**0.0953****	**0.0334****	**0.0414****	**0.0351****	**0.0545****	**0.0189****	**0.0238****	**0.0771****	**0.1082****	**0.0442****	**0.0521****	**0.0272****	**0.0471****	**0.0134****	**0.0184****
Improv	11.8%	10.9%	7.40%	7.81%	12.9%	14.5%	13.2%	12.8%	10.6%	12.9%	9.68%	11.1%	12.4%	9.53%	13.6%	10.8%
CL4SRec	0.0653	0.0947	0.0370	0.0441	0.0381	0.0559	0.0215	0.0259	0.0781	0.1075	0.0456	0.0530	0.0322	0.0535	0.0159	0.0212
DR4SR	0.0732**	0.1016**	0.0423**	0.0495**	0.0401**	0.0600**	0.0227**	0.0274**	0.0821**	0.1113*	0.0481**	0.0551*	0.0344**	0.0561**	0.0174**	0.0229**
Improv	12.1%	7.29%	14.3%	12.2%	5.25%	7.33%	5.58%	5.79%	5.12%	3.53%	5.48%	3.96%	6.83%	4.86%	9.43%	8.02%
DR4SR+	**00756****	**0.1062****	**0.0440****	**0.0517****	**0.0448****	**0.0655****	**0.0247****	**0.0299****	**0.0829****	**0.1140****	**0.0489****	**0.0567****	**0.0363****	**0.0598****	**0.0183****	**0.0241****
Improv	15.8%	1.12%	18.9%	17.2%	17.6%	17.2%	14.8%	15.4%	6.15%	6.05%	7.24%	6.98%	12.7%	11.8%	15.1%	13.7%

Overall Evaluation

Table 3: The overall performance. Considering a target model, the best result is bolded while the second-best result is underlined. Superscript * means improvements are statistically significant with $p<0.05$ while ** meaning $p<0.01$.

1. DR4SR can regenerate informative and generalizable datasets
2. Different models favor different datasets

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DR4SR	0.0252**	0.0448**	0.0128**	0.0177**	0.0208**	0.0341**	0.0102**	0.0135**	0.0252**	0.0418**	0.0124**	0.0165**	0.0235**	0.0403**	0.0114**	0.0156**
Improv	23.5%	17.3%	19.6%	18.0%	30.0%	22.2%	20.0%	17.4%	18.9%	22.4%	25.3%	21.3%	9.30%	10.7%	8.57%	9.09%
DR4SR+	**0.0292****	**0.0473****	**0.0149****	**0.0194****	**0.0223****	**0.0360****	**0.0116****	**0.0151****	**0.0274****	**0.0456****	**0.0134****	**0.0179****	**0.0243****	**0.0415****	**0.0120****	**0.0164****
Improv	43.1%	23.8%	39.3%	29.3%	39.4%	29.0%	36.5%	31.3%	29.2%	27.7%	35.4%	31.6%	13.0%	14.0%	14.3%	14.7%
SASRec	0.0553	0.0847	0.0291	0.0368	0.0297	0.0449	0.0156	0.0194	0.0682	0.0951	0.0381	0.0448	0.0289	0.0488	0.0143	0.0193
DR4SR	0.0595**	0.0906**	0.0317**	0.0395**	0.0330**	0.0512**	0.0174**	0.0220**	0.0762**	0.1049**	0.0432**	0.0504**	0.0304*	0.0512*	0.0151*	0.0202*
Improv	7.59%	6.97%	8.93%	7.34%	11.1%	14.0%	11.5%	13.4%	11.7%	10.3%	13.4%	12.5%	5.19%	4.92%	5.59%	4.66%
DR4SR+	**0.0619****	**0.0919****	**0.0337****	**0.0412****	**0.0349****	**0.0525****	**0.0191****	**0.0235****	**0.0773****	**0.1068****	**0.0453****	**0.0527****	**0.0317****	**0.0523****	**0.0159****	**0.0211****
Improv	11.9%	8.50%	15.8%	12.0%	17.5%	16.9%	22.4%	21.1%	13.3%	12.3%	18.9%	17.6%	9.69%	7.17%	11.2%	9.33%
FMLP	0.0602	0.0934	0.0311	0.0394	0.0323	0.0524	0.0166	0.0217	0.0676	0.0982	0.0377	0.0447	0.0297	0.0495	0.0143	0.0197
DR4SR	0.0635**	0.0993**	0.0332**	0.0421	0.0345	0.0559	0.0177**	0.0230**	0.0717**	0.1061**	0.0400**	0.0486**	0.0316**	0.0524**	0.0158**	0.0210**
Improv	5.48%	6.32%	6.75%	6.85%	6.81%	6.68	6.63%	5.99%	6.07%	8.04%	6.10%	8.72%	6.40%	5.86%	10.5%	6.60%
DR4SR+	**0.0687****	**0.1056****	**0.0357****	**0.0449****	**0.0384****	**0.0597****	**0.0198****	**0.0253****	**0.0788****	**0.1136****	**0.0437****	**0.0524****	**0.0353****	**0.0582****	**0.0171****	**0.0231****
Improv	14.1%	13.1%	14.8%	14.0%	18.9%	13.9%	19.3%	16.6%	16.6%	15.7%	15.9%	17.2%	18.9%	17.6%	19.6%	17.3%
GNN	0.0570	0.0859	0.0311	0.0384	0.0311	0.0476	0.0167	0.0211	0.0697	0.0958	0.0403	0.0469	0.0242	0.0430	0.0118	0.0166
DR4SR	0.0611**	0.0926**	0.0324*	0.0406*	0.0336**	0.0525**	0.0182**	0.0230**	0.0736**	0.1031**	0.0424**	0.0498**	0.0268**	0.0451*	0.0129**	0.0175*
Improv	7.19%	7.80%	4.18%	5.73%	8.04%	10.3%	8.98%	9.00%	5.60%	7.62%	5.21%	6.18%	10.7%	4.88%	9.32%	5.42%
DR4SR+	**0.0637****	**0.0953****	**0.0334****	**0.0414****	**0.0351****	**0.0545****	**0.0189****	**0.0238****	**0.0771****	**0.1082****	**0.0442****	**0.0521****	**0.0272****	**0.0471****	**0.0134****	**0.0184****
Improv	11.8%	10.9%	7.40%	7.81%	12.9%	14.5%	13.2%	12.8%	10.6%	12.9%	9.68%	11.1%	12.4%	9.53%	13.6%	10.8%
CL4SRec	0.0653	0.0947	0.0370	0.0441	0.0381	0.0559	0.0215	0.0259	0.0781	0.1075	0.0456	0.0530	0.0322	0.0535	0.0159	0.0212
DR4SR	0.0732**	0.1016**	0.0423**	0.0495**	0.0401**	0.0600**	0.0227**	0.0274**	0.0821**	0.1113*	0.0481**	0.0551*	0.0344**	0.0561**	0.0174**	0.0229**
Improv	12.1%	7.29%	14.3%	12.2%	5.25%	7.33%	5.58%	5.79%	5.12%	3.53%	5.48%	3.96%	6.83%	4.86%	9.43%	8.02%
DR4SR+	**00756****	**0.1062****	**0.0440****	**0.0517****	**0.0448****	**0.0655****	**0.0247****	**0.0299****	**0.0829****	**0.1140****	**0.0489****	**0.0567****	**0.0363****	**0.0598****	**0.0183****	**0.0241****
Improv	15.8%	1.12%	18.9%	17.2%	17.6%	17.2%	14.8%	15.4%	6.15%	6.05%	7.24%	6.98%	12.7%	11.8%	15.1%	13.7%

Overall Evaluation

Table 3: The overall performance. Considering a target model, the best result is bolded while the second-best result is underlined. Superscript * means improvements are statistically significant with p<0.05 while ** meaning p<0.01.

1. DR4SR can regenerate informative and generalizable datasets
2. Different models favor different datasets

DR4SR	0.0252**	0.0448**	0.0128**	0.0177**	0.0208**	0.0341**	0.0102**	0.0135**	0.0252**	0.0418**	0.0124**	0.0165**	0.0235**	0.0403**	0.0114**	0.0156**
Improv	23.5%	17.3%	19.6%	18.0%	30.0%	22.2%	20.0%	17.4%	18.9%	22.4%	25.3%	21.3%	9.30%	10.7%	8.57%	9.09%
DR4SR+	**0.0292****	**0.0473****	**0.0149****	**0.0194****	**0.0223****	**0.0360****	**0.0116****	**0.0151****	**0.0274****	**0.0456****	**0.0134****	**0.0179****	**0.0243****	**0.0415****	**0.0120****	**0.0164****
Improv	43.1%	23.8%	39.3%	29.3%	39.4%	29.0%	36.5%	31.3%	29.2%	27.7%	35.4%	31.6%	13.0%	14.0%	14.3%	14.7%
SASRec	0.0553	0.0847	0.0291	0.0368	0.0297	0.0449	0.0156	0.0194	0.0682	0.0951	0.0381	0.0448	0.0289	0.0488	0.0143	0.0193
DR4SR	0.0595**	0.0906**	0.0317**	0.0395**	0.0330**	0.0512**	0.0174**	0.0220**	0.0762**	0.1049**	0.0432**	0.0504**	0.0304*	0.0512*	0.0151*	0.0202*
Improv	7.59%	6.97%	8.93%	7.34%	11.1%	14.0%	11.5%	13.4%	11.7%	10.3%	13.4%	12.5%	5.19%	4.92%	5.59%	4.66%
DR4SR+	**0.0619****	**0.0919****	**0.0337****	**0.0412****	**0.0349****	**0.0525****	**0.0191****	**0.0235****	**0.0773****	**0.1068****	**0.0453****	**0.0527****	**0.0317****	**0.0523****	**0.0159****	**0.0211****
Improv	11.9%	8.50%	15.8%	12.0%	17.5%	16.9%	22.4%	21.1%	13.3%	12.3%	18.9%	17.6%	9.69%	7.17%	11.2%	9.33%
FMLP	0.0602	0.0934	0.0311	0.0394	0.0323	0.0524	0.0166	0.0217	0.0676	0.0982	0.0377	0.0447	0.0297	0.0495	0.0143	0.0197
DR4SR	0.0635**	0.0993**	0.0332**	0.0421	0.0345	0.0559	0.0177**	0.0230**	0.0717**	0.1061**	0.0400**	0.0486**	0.0316**	0.0524**	0.0158**	0.0210**
Improv	5.48%	6.32%	6.75%	6.85%	6.81%	6.68	6.63%	5.99%	6.07%	8.04%	6.10%	8.72%	6.40%	5.86%	10.5%	6.60%
DR4SR+	**0.0687****	**0.1056****	**0.0357****	**0.0449****	**0.0384****	**0.0597****	**0.0198****	**0.0253****	**0.0788****	**0.1136****	**0.0437****	**0.0524****	**0.0353****	**0.0582****	**0.0171****	**0.0231****
Improv	14.1%	13.1%	14.8%	14.0%	18.9%	13.9%	19.3%	16.6%	16.6%	15.7%	15.9%	17.2%	18.9%	17.6%	19.6%	17.3%
GNN	0.0570	0.0859	0.0311	0.0384	0.0311	0.0476	0.0167	0.0211	0.0697	0.0958	0.0403	0.0469	0.0242	0.0430	0.0118	0.0166
DR4SR	0.0611**	0.0926**	0.0324*	0.0406*	0.0336**	0.0525**	0.0182**	0.0230**	0.0736**	0.1031**	0.0424**	0.0498**	0.0268**	0.0451*	0.0129**	0.0175*
Improv	7.19%	7.80%	4.18%	5.73%	8.04%	10.3%	8.98%	9.00%	5.60%	7.62%	5.21%	6.18%	10.7%	4.88%	9.32%	5.42%
DR4SR+	**0.0637****	**0.0953****	**0.0334****	**0.0414****	**0.0351****	**0.0545****	**0.0189****	**0.0238****	**0.0771****	**0.1082****	**0.0442****	**0.0521****	**0.0272****	**0.0471****	**0.0134****	**0.0184****
Improv	11.8%	10.9%	7.40%	7.81%	12.9%	14.5%	13.2%	12.8%	10.6%	12.9%	9.68%	11.1%	12.4%	9.53%	13.6%	10.8%
CL4SRec	0.0653	0.0947	0.0370	0.0441	0.0381	0.0559	0.0215	0.0259	0.0781	0.1075	0.0456	0.0530	0.0322	0.0535	0.0159	0.0212
DR4SR	0.0732**	0.1016**	0.0423**	0.0495**	0.0401**	0.0600**	0.0227**	0.0274**	0.0821**	0.1113*	0.0481**	0.0551*	0.0344**	0.0561**	0.0174**	0.0229**
Improv	12.1%	7.29%	14.3%	12.2%	5.25%	7.33%	5.58%	5.79%	5.12%	3.53%	5.48%	3.96%	6.83%	4.86%	9.43%	8.02%
DR4SR+	**00756****	**0.1062****	**0.0440****	**0.0517****	**0.0448****	**0.0655****	**0.0247****	**0.0299****	**0.0829****	**0.1140****	**0.0489****	**0.0567****	**0.0363****	**0.0598****	**0.0183****	**0.0241****
Improv	15.8%	1.12%	18.9%	17.2%	17.6%	17.2%	14.8%	15.4%	6.15%	6.05%	7.24%	6.98%	12.7%	11.8%	15.1%	13.7%

Overall Evaluation

Table 3: The overall performance. Considering a target model, the best result is bolded while the second-best result is underlined. Superscript * means improvements are statistically significant with $p<0.05$ while ** meaning $p<0.01$.

1. DR4SR can regenerate informative and generalizable datasets
2. Different models favor different datasets
3. Denoising is only part of the problem in developing a better training dataset

Improv	23.5%	17.3%	19.6%	18.0%	30.0%	22.2%	20.0%	17.4%	18.9%	22.4%	25.3%	21.3%	9.30%	10.7%	8.57%	9.09%
DR4SR+	**0.0292****	**0.0473****	**0.0149****	**0.0194****	**0.0223****	**0.0360****	**0.0116****	**0.0151****	**0.0274****	**0.0456****	**0.0134****	**0.0179****	**0.0243****	**0.0415****	**0.0120****	**0.0164****
Improv	43.1%	23.8%	39.3%	29.3%	39.4%	29.0%	36.5%	31.3%	29.2%	27.7%	35.4%	31.6%	13.0%	14.0%	14.3%	14.7%
SASRec	0.0553	0.0847	0.0291	0.0368	0.0297	0.0449	0.0156	0.0194	0.0682	0.0951	0.0381	0.0448	0.0289	0.0488	0.0143	0.0193
DR4SR	0.0595**	0.0906**	0.0317**	0.0395**	0.0330**	0.0512**	0.0174**	0.0220**	0.0762**	0.1049**	0.0432**	0.0504**	0.0304*	0.0512*	0.0151*	0.0202*
Improv	7.59%	6.97%	8.93%	7.34%	11.1%	14.0%	11.5%	13.4%	11.7%	10.3%	13.4%	12.5%	5.19%	4.92%	5.59%	4.66%
DR4SR+	**0.0619****	**0.0919****	**0.0337****	**0.0412****	**0.0349****	**0.0525****	**0.0191****	**0.0235****	**0.0773****	**0.1068****	**0.0453****	**0.0527****	**0.0317****	**0.0523****	**0.0159****	**0.0211****
Improv	11.9%	8.50%	15.8%	12.0%	17.5%	16.9%	22.4%	21.1%	13.3%	12.3%	18.9%	17.6%	9.69%	7.17%	11.2%	9.33%
FMLP	0.0602	0.0934	0.0311	0.0394	0.0323	0.0524	0.0166	0.0217	0.0676	0.0982	0.0377	0.0447	0.0297	0.0495	0.0143	0.0197
DR4SR	0.0635**	0.0993**	0.0332**	0.0421	0.0345	0.0559	0.0177**	0.0230**	0.0717**	0.1061**	0.0400**	0.0486**	0.0316**	0.0524**	0.0158**	0.0210**
Improv	5.48%	6.32%	6.75%	6.85%	6.81%	6.68	6.63%	5.99%	6.07%	8.04%	6.10%	8.72%	6.40%	5.86%	10.5%	6.60%
DR4SR+	**0.0687****	**0.1056****	**0.0357****	**0.0449****	**0.0384****	**0.0597****	**0.0198****	**0.0253****	**0.0788****	**0.1136****	**0.0437****	**0.0524****	**0.0353****	**0.0582****	**0.0171****	**0.0231****
Improv	14.1%	13.1%	14.8%	14.0%	18.9%	13.9%	19.3%	16.6%	16.6%	15.7%	15.9%	17.2%	18.9%	17.6%	19.6%	17.3%
GNN	0.0570	0.0859	0.0311	0.0384	0.0311	0.0476	0.0167	0.0211	0.0697	0.0958	0.0403	0.0469	0.0242	0.0430	0.0118	0.0166
DR4SR	0.0611**	0.0926**	0.0324*	0.0406*	0.0336**	0.0525**	0.0182**	0.0230**	0.0736**	0.1031**	0.0424**	0.0498**	0.0268**	0.0451*	0.0129**	0.0175*
Improv	7.19%	7.80%	4.18%	5.73%	8.04%	10.3%	8.98%	9.00%	5.60%	7.62%	5.21%	6.18%	10.7%	4.88%	9.32%	5.42%
DR4SR+	**0.0637****	**0.0953****	**0.0334****	**0.0414****	**0.0351****	**0.0545****	**0.0189****	**0.0238****	**0.0771****	**0.1082****	**0.0442****	**0.0521****	**0.0272****	**0.0471****	**0.0134****	**0.0184****
Improv	11.8%	10.9%	7.40%	7.81%	12.9%	14.5%	13.2%	12.8%	10.6%	12.9%	9.68%	11.1%	12.4%	9.53%	13.6%	10.8%
CL4SRec	0.0653	0.0947	0.0370	0.0441	0.0381	0.0559	0.0215	0.0259	0.0781	0.1075	0.0456	0.0530	0.0322	0.0535	0.0159	0.0212
DR4SR	0.0732**	0.1016**	0.0423**	0.0495**	0.0401**	0.0600**	0.0227**	0.0274**	0.0821**	0.1113*	0.0481**	0.0551*	0.0344**	0.0561**	0.0174**	0.0229**
Improv	12.1%	7.29%	14.3%	12.2%	5.25%	7.33%	5.58%	5.79%	5.12%	3.53%	5.48%	3.96%	6.83%	4.86%	9.43%	8.02%
DR4SR+	**00756****	**0.1062****	**0.0440****	**0.0517****	**0.0448****	**0.0655****	**0.0247****	**0.0299****	**0.0829****	**0.1140****	**0.0489****	**0.0567****	**0.0363****	**0.0598****	**0.0183****	**0.0241****
Improv	15.8%	1.12%	18.9%	17.2%	17.6%	17.2%	14.8%	15.4%	6.15%	6.05%	7.24%	6.98%	12.7%	11.8%	15.1%	13.7%

Ablation study

Table 4: Abalation study of DR4SR on NDCG@20.

Dataset	Beauty	Sport	Toys	Yelp
SASRec	0.0368	0.0194	0.0448	0.0193
DR4SR+	**0.0412**	**0.0235**	**0.0527**	**0.0211**
(A) -diversity	0.0365	0.0211	0.0470	0.0196
(B) pattern	0.0181	0.0184	0.0407	0.0141
(C) end-to-end	0.0026	0.0029	0.0067	0.0035

- -diversity: replacing the regenerator with a vanilla Transformer
- pattern: regarding the extracted rule-based patterns as regenerated dataset
- end-to-end: directly optimizing the dataset personalizer

Extended experiments: more data forms should be regenerated

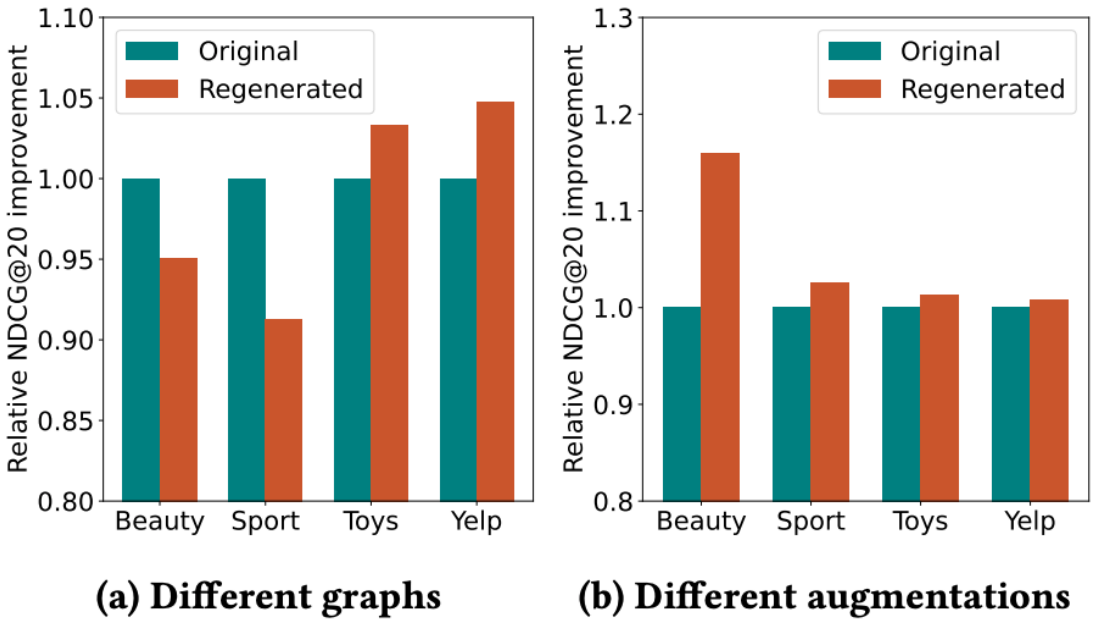

Figure 5: Relative NDCG@20 improvement of graphs and data augmentations on different datasets.

- Which dataset should be used to construct graphs or augmentation data: original one or regenerated one?

Future work

- Delving deeper into dataset regeneration
  - Regenerating more data formats
    - Graph: graph structure learning
    - Data augmentation: learnable data augmentation
    - ……
  - Incorporating more knowledge
    - Introducing semantic information by integrating LLMs
    - Introducing multi-domain information by cross-domain dataset regeneration
    - ……
  - Application
    - Privacy-preserving
    - ……

Dataset Regeneration for Sequential Recommendation

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Code: https://github.com/USTC-StarTeam/DR4SR

THANK YOU

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