Beyond Learning from Next item: Sequential Recommender System via Personalized Interest Sustainability

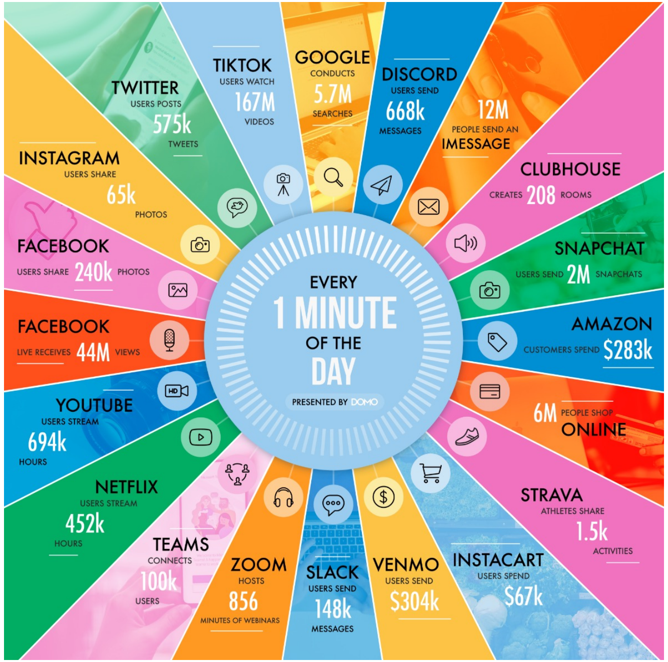
Dongmin Hyun, Chanyoung Park, Junsu Cho, Hwanjo Yu

POSTECH KAIST

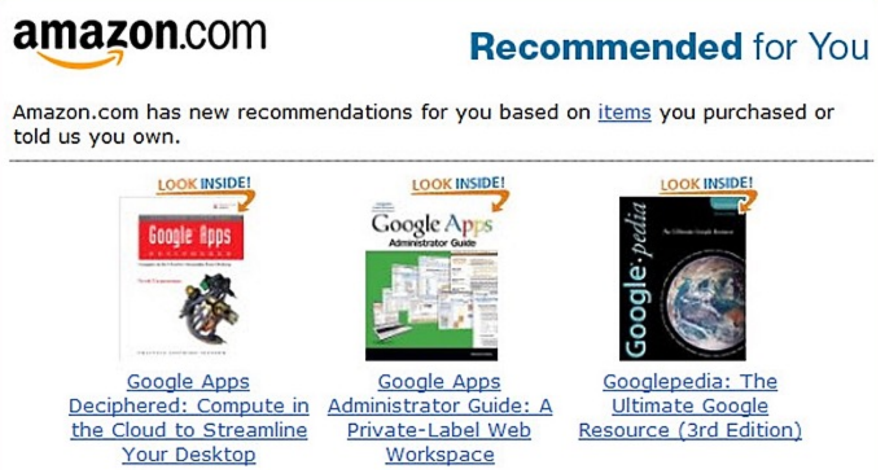
Recommender System

The system is an information filtering system dealing with information overload.

- **Amazon**: an estimated 30% of page views from product recommendations



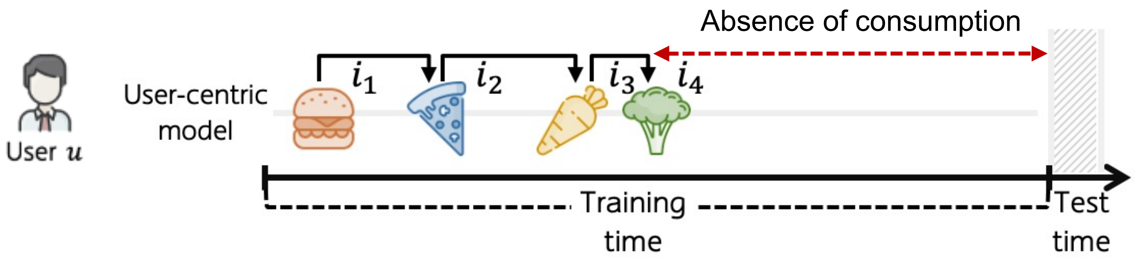
[Infographic 'Data Never Sleeps 9.0 by Domo Company]



User-centric sequential recommender systems

They predict the next items to capture the sequential dynamics of consumed items.

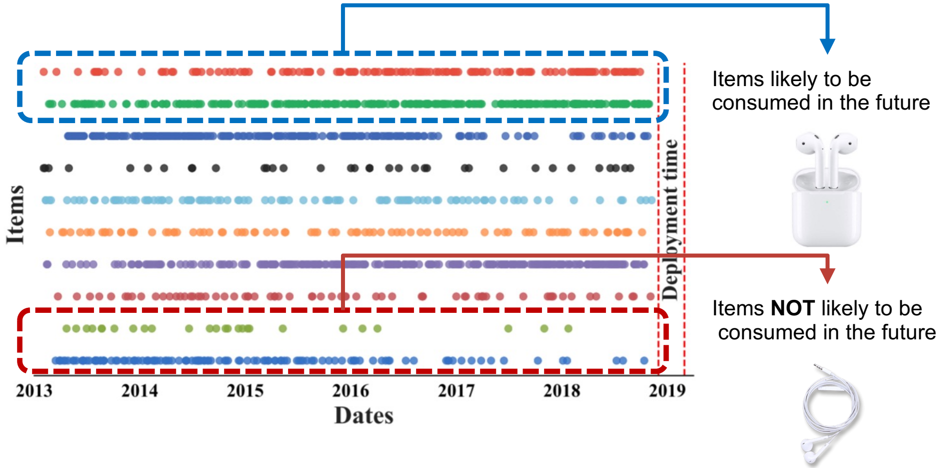
- ☺ The sequential dynamics enable the models to track personalized interest drift.
- ☹ The models do not explicitly consider the time at which recommendation is performed.
  - ❑ E.g., a user who consumed up to *2019* represents the user's interest only up to *2019*.
  - ❑ It is inaccurate to recommend in *2022* (future) due to the prolonged absence of consumption.



Item-centric sequential recommender systems (1/2)

Recent research studies users' global interest drift in items.

- It predicts whether each item will be consumed in a recent period of training data.
  - ❑ More recent interest can be captured than user-centric models based on next item prediction.
- **Interest sustainability**: how much users' global interest in items will sustain in the future.



Hyun, Dongmin, et al. "Interest Sustainability-Aware Recommender System." *2020 IEEE International Conference on Data Mining (ICDM)*. IEEE, 2020.

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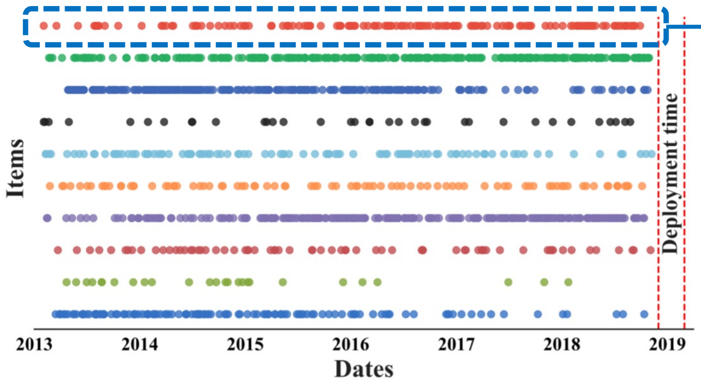

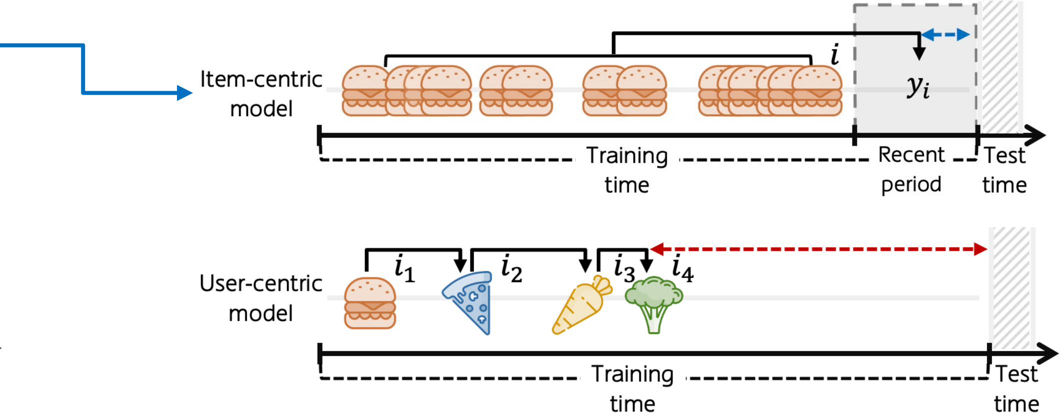

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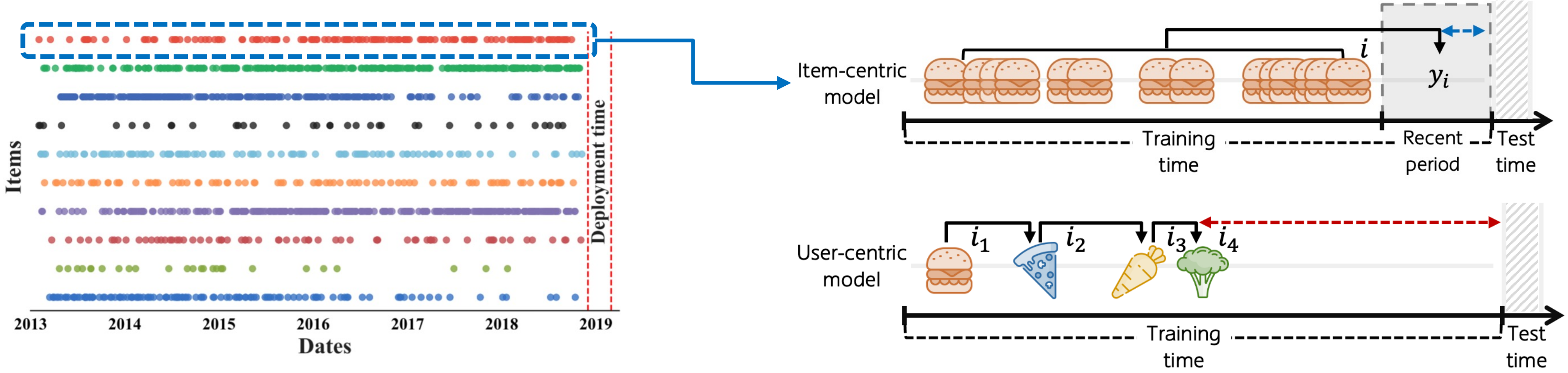
Item-centric sequential recommender systems (2/2)

Recent research studies users' global interest drift in items.

- ☺ The models can explicitly consider the time at which recommendation is performed.
- ☹ They neglect each user's preference.
  - ❑ E.g., the same interest sustainability score of an item for different users



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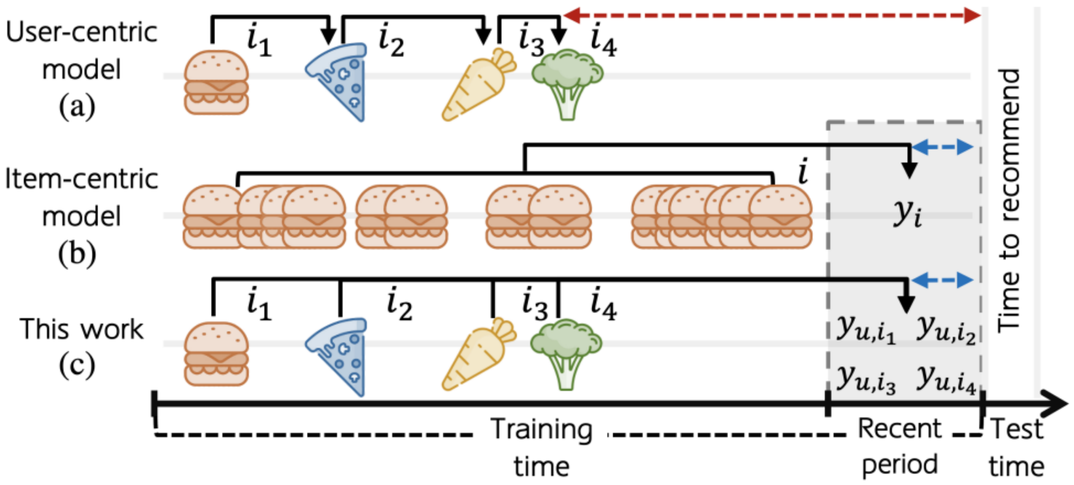
Proposed model & conceptual comparison

We propose a sequential model capturing the benefits of both user- and item-centric models.

- User-centric model (a): personalized interest drift (but no interest sustainability)
- Item-centric model (b): Interest sustainability of items (no personalization)

➢ **Proposed model** (c): personalized interest sustainability

- ❑ It predicts which items each user will consume in the recent period of the training time.



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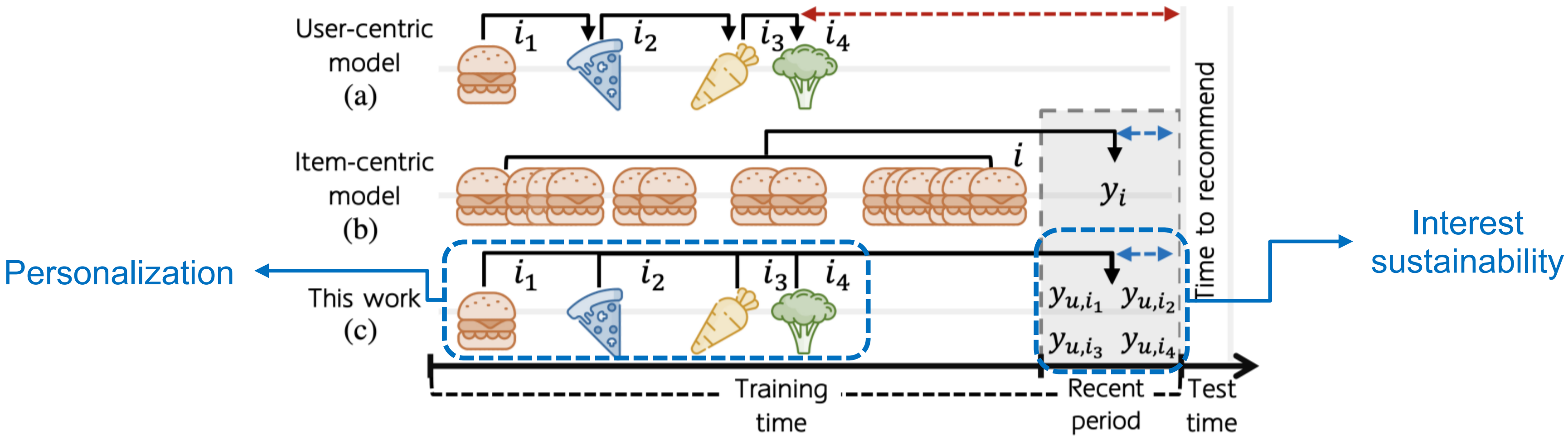


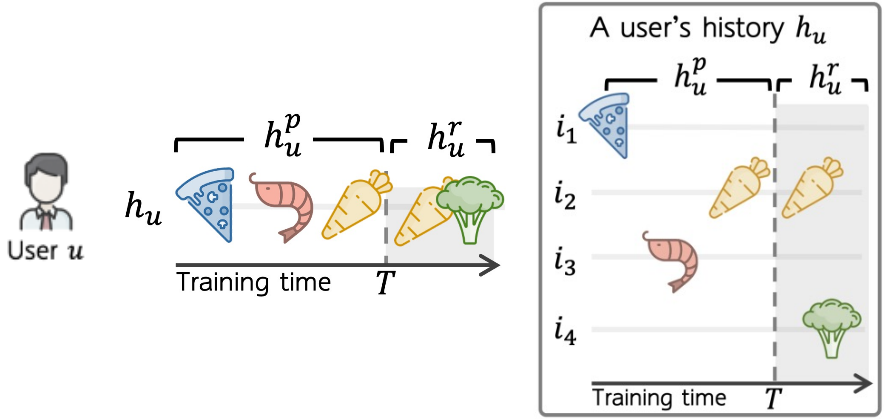
Personalized interest sustainability prediction

It requires predicting whether a user consumed items in a recent period: $\hat{y}_{u,i} = f_S(\mathbf{b}_{u,i})$

The past part h_u^p for defining **features** of items (Consumption frequency bins: $\mathbf{b}_{u,i} \in \mathbb{R}^N$)

The recent part h_u^r for defining **labels** of items (Consumed or not: $y_{u,i} = \mathbb{1}[i \in h_u^r]$)

After training, we predict users' interest beyond the training time by expanding the frequency bins up to the whole training time.



(a) Data split

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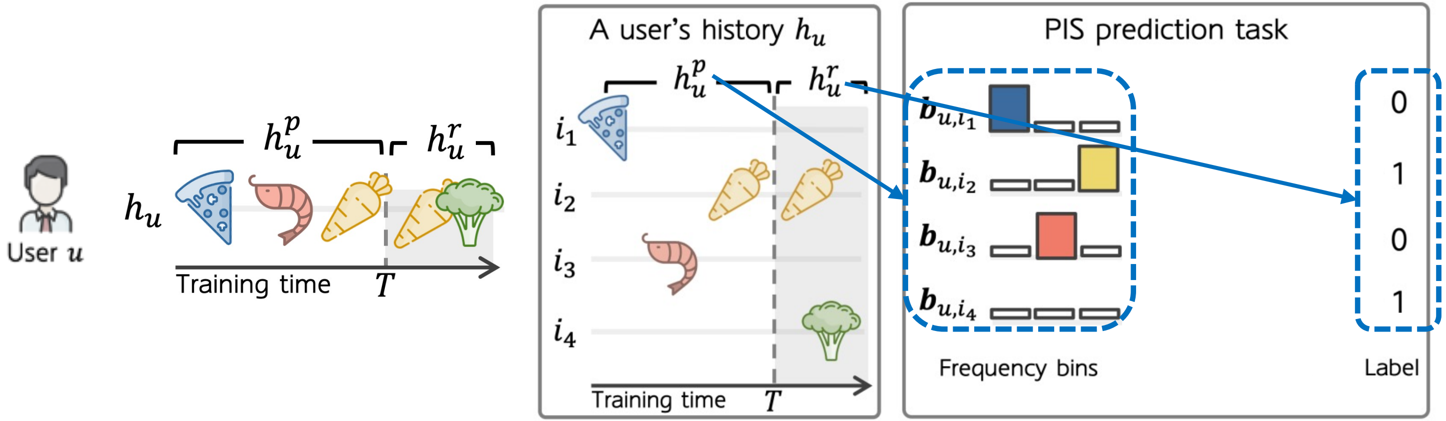

(a) Data split (b) Model training

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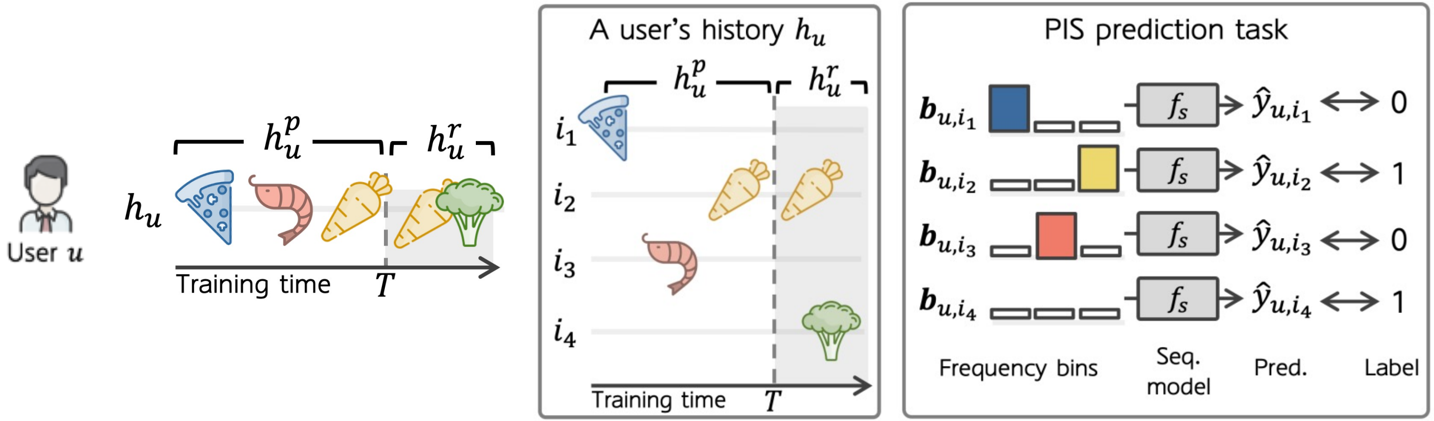

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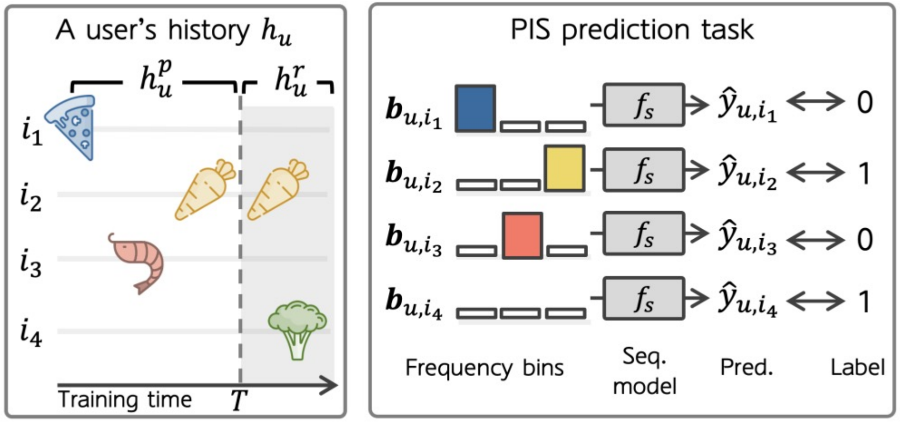
This task is feasible to solve based on the temporal consumption patterns (freq. bins).



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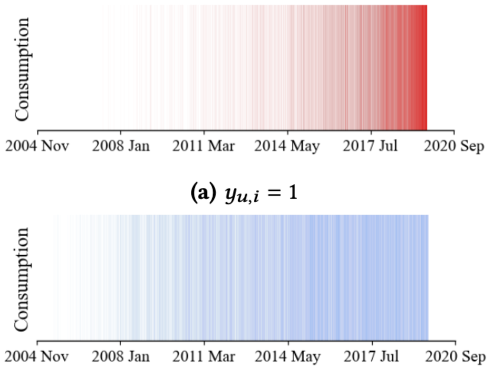

(a) $y_{u,i} = 1$

(b) $y_{u,i} = 0$

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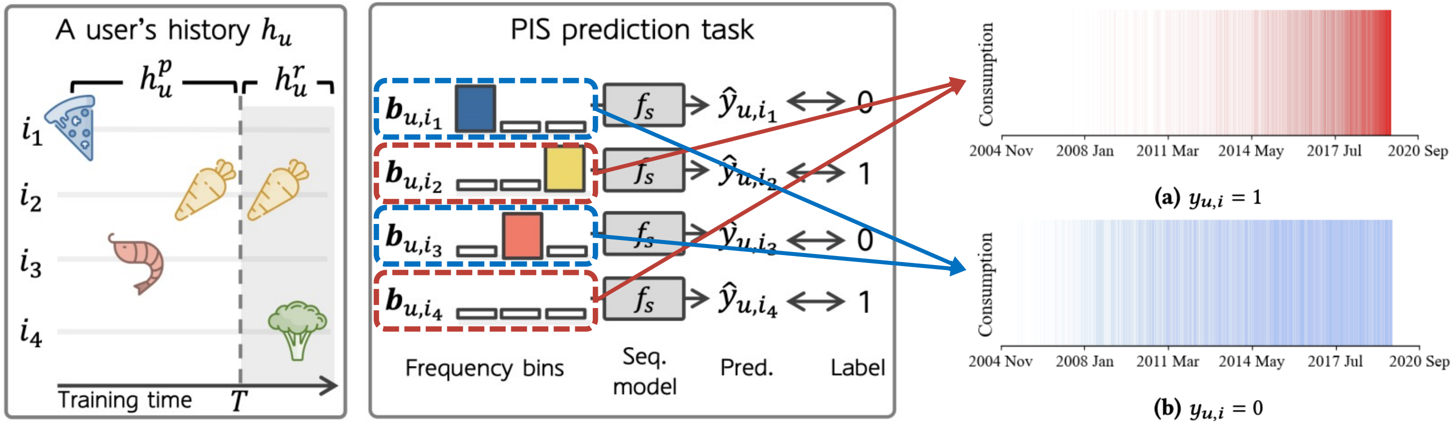


(a) Data split

(b) Model training

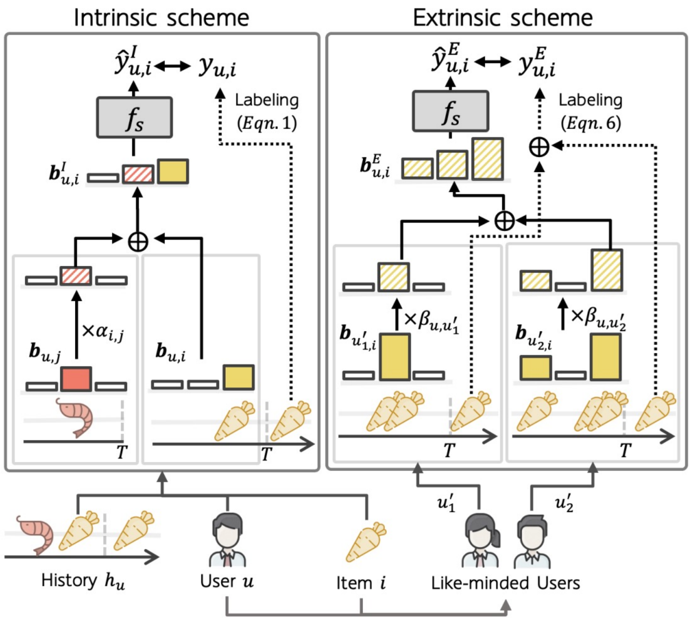
Data Sparsity & Solutions

The proposed task is challenging due to the data sparsity.

Most users have insufficient consumption history per item.

In Yelp data, users have 2.6 interactions per item on average.

- Intrinsic supplementation scheme
  - augments each user's consumption history for an item **based on other items consumed by the user**.
- Extrinsic supplementation scheme
  - supplements a user's consumption history **by referring to other like-minded users' consumption history**.



Intrinsic Supplementation Scheme

It augments each user's consumption history for an item based on other items consumed by the user.

A user's interest in an item (espresso) is assumed to sustain if the user recently consumes a similar item (cappuccino).

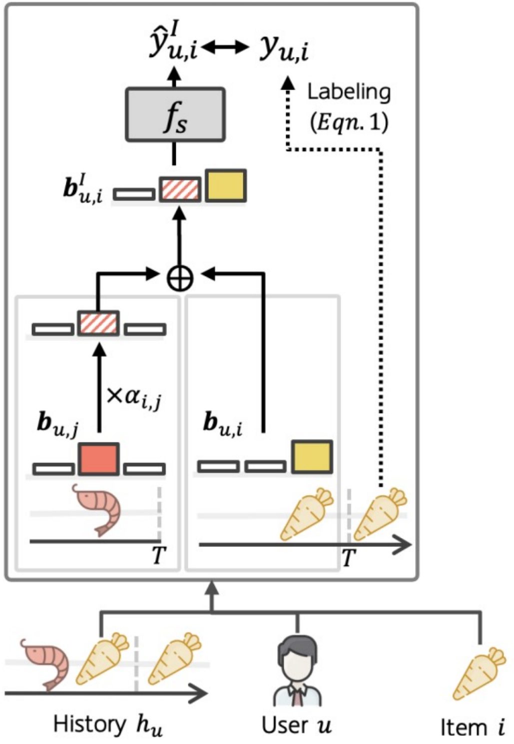
Feature augmentation

$$\left\{ \begin{aligned} \mathbf{b}^{I}_{u,i} &= \mathbf{b}_{u,i} + \sum_{j \in h^{p}_{u} \setminus \{i\}} \alpha_{i,j} \cdot \mathbf{b}_{u,j} \\ \alpha_{i,j} &= \mathtt{sim}(\mathbf{v}_i, \mathbf{v}_j) \end{aligned} \right.$$

$$\mathcal{L}_I = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \sum_{i \in h_u} (y_{u,i} - \hat{y}^{I}_{u,i})^2)$$

$$\hat{y}^{I}_{u,i} = f_s(\mathbf{b}^{I}_{u,i} + \mathbf{e}_{u,i})$$

Intrinsic scheme



Extrinsic Supplementation Scheme

The goal is to infer a target user's interest in items through the like-minded users' interest in the items.

It supplements the consumption history of each user (vegan) by referring to the history of other like-minded users (other vegans).

Feature augmentation

$$\mathbf{b}^{E}_{u,i} = \sum_{\mathbf{b}_{u',i} \in B_{u,i}} \beta_{u,u'} \cdot \mathbf{b}_{u',i}$$

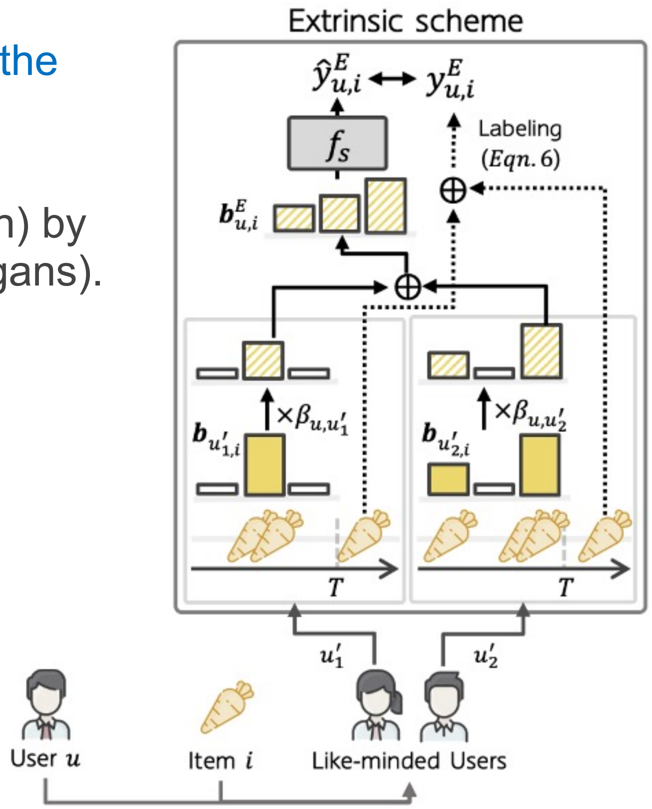
$$B_{u,i} = \{\mathbf{b}_{u',i} || u' \in \mathcal{U} \setminus \{u\},\ i \in h^{p}_{u'},\}$$

$$\beta_{u,u'} = \mathtt{sim}(\mathbf{u}_u, \mathbf{u}_{u'})$$

Labeling

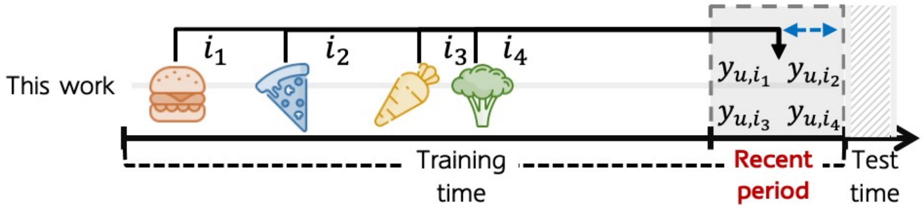
$$y^{E}_{u,i} = \mathbb{1}[\sum_{u'} \beta_{u,u'} \cdot y_{u',i} \geq 1]$$

$$\mathcal{L}_E = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \sum_{i \in h_u} (y^{E}_{u,i} - \hat{y}^{E}_{u,i})^2)$$



Model Training

The label $y_{u,i}$ can be noisy because a user can still prefer an item even though the user does not consume the item in the recent period.



To complement the label noise, we train our model along with conventional preference learning, which utilizes ground-truth labels (consumed items).

$$\mathcal{L}_F = \lambda\{\mu\mathcal{L}_I + (1-\mu)\mathcal{L}_E\} + (1-\lambda)\mathcal{L}_P$$

BPR, CML, …

Recommendation score at the inference time.

$$r_{u,i} = \lambda\{\mu\hat{y}^I_{u,i} + (1-\mu)\hat{y}^E_{u,i}\} + (1-\lambda)\hat{y}^P_{u,i}$$

Experimental Settings

- Datasets
  - Amazon, Yelp, and Google data

Data	# users ($|\mathcal{U}|$)	# items ($|\mathcal{I}|$)	# data ($|\mathcal{D}|$)	Int./ user	Int./ item	Time span
Cell phones	8,192	47,671	118,323	14.44	2.48	2000.10-2014.05
Digital music	6,062	65,094	127,484	21.03	1.96	1998.05-2014.05
Tools	8,971	61,271	150,780	16.81	2.46	1999.11-2014.05
Grocery	8,215	54,452	168,933	20.56	3.10	2000.08-2014.05
Toys	12,636	99,051	230,473	18.24	2.33	1999.10-2014.05
Health	14,149	68,810	252,356	17.84	3.67	2000.12-2014.05
Sports	16,959	99,927	276,214	16.29	2.76	2000.07-2014.05
Clothing	35,824	315,818	578,135	16.14	1.83	2000.11-2014.05
CDs	40,339	330,179	1,278,176	31.69	3.87	1997.11-2014.05
Yelp	18,284	83,871	384,330	21.02	4.58	2004.10-2020.11
Google	125,341	1,552,812	3,066,438	24.46	1.97	1990.12-2014.01

- Ranking metrics
  - Hit ratio and normalized discounted cumulative gain (nDCG)

Recommendation Accuracy

PERIS outperforms baseline models including general, user-centric, and item-centric sequential models.

An item-centric sequential model shows better performance than user-centric models thanks to the interest sustainability.

Recent general models reach the performance of sequential models without considering sequence signals.

Setting		General RS				User-centric Sequential RS					I-SRS	Proposed RS		
Dataset	Metric	BPR	CML	SML	SimX	SSR	TSSR	Caser	HGN	LSAN	CRIS	PERIS	Δ_G	Δ_S
Cell Phones	H@5	48.17	48.91	50.85	52.89	45.79	50.15	43.78	51.95	54.21	56.07	**63.68**	20.4%	13.6%
	H@10	59.61	60.68	63.57	63.84	59.32	63.31	56.73	63.63	65.55	68.38	**76.28**	19.5%	11.6%
	N@5	35.34	36.50	38.02	39.57	32.44	36.36	32.28	39.63	40.79	43.19	**48.74**	23.2%	12.9%
	N@10	39.06	40.32	42.16	43.09	36.84	40.62	36.46	43.42	44.47	47.20	**52.84**	22.6%	11.9%
Digital Music	H@5	35.21	34.49	38.46	37.22	24.10	25.00	25.56	25.38	34.83	27.78	**47.31**	23.0%	35.8%
	H@10	44.53	44.49	50.21	46.54	31.97	36.37	36.28	34.53	44.79	37.78	**58.50**	16.5%	30.6%
	N@5	25.71	25.30	28.32	27.98	16.53	16.99	18.56	18.64	25.46	19.38	**35.31**	24.7%	38.7%
	N@10	28.73	28.53	32.12	30.98	19.06	20.52	22.05	21.58	28.70	22.62	**38.93**	21.2%	35.6%
Tools	H@5	36.55	36.53	37.78	39.83	34.79	32.96	30.70	34.92	37.95	35.61	**43.64**	9.6%	15.0%
	H@10	48.89	47.86	50.50	52.69	48.03	47.45	44.95	47.45	48.93	49.77	**57.15**	8.5%	14.8%
	N@5	25.67	25.80	26.39	28.13	23.48	22.65	20.66	24.35	26.40	24.19	**31.35**	11.4%	18.8%
	N@10	29.66	29.46	30.50	32.30	27.78	27.31	25.27	28.41	29.94	28.75	**35.73**	10.6%	19.3%
Grocery	H@5	46.85	46.27	47.61	46.78	45.36	46.12	43.46	45.24	46.27	49.50	**51.86**	8.9%	4.8%
	H@10	56.93	56.64	58.32	57.98	57.10	57.19	55.36	56.28	57.26	60.60	**62.91**	7.9%	3.8%
	N@5	33.91	33.91	34.86	34.99	33.98	34.00	30.03	34.41	34.33	37.13	**40.55**	15.9%	9.2%
	N@10	37.17	37.27	38.32	38.61	37.78	37.56	33.88	37.98	37.88	40.73	**44.13**	14.3%	8.3%
Toys	H@5	45.87	45.89	46.84	48.53	34.22	35.11	35.87	42.41	48.73	49.54	**53.21**	9.6%	7.4%
	H@10	57.08	57.28	58.73	61.74	48.73	52.02	48.61	55.28	61.46	62.63	**66.61**	7.9%	6.4%
	N@5	33.99	33.67	34.91	35.46	22.62	23.70	25.37	31.28	36.18	36.68	**39.64**	11.8%	8.1%
	N@10	37.61	37.35	38.75	39.75	26.97	29.11	29.50	35.42	40.31	40.92	**43.99**	10.7%	7.5%
Health	H@5	46.43	47.97	49.07	51.18	43.50	44.92	46.06	49.03	50.31	52.43	**53.99**	5.5%	3.0%
	H@10	60.20	60.35	61.57	62.78	57.93	58.60	56.20	59.99	61.84	64.92	**66.38**	5.7%	2.2%
	N@5	32.71	34.55	35.09	37.68	31.72	32.23	34.42	37.72	37.64	38.77	**42.48**	12.7%	9.6%
	N@10	37.17	38.55	39.14	41.43	36.37	36.67	37.70	41.24	41.38	42.82	**46.48**	12.2%	8.5%
Sports	H@5	47.90	48.73	49.18	50.85	39.59	39.81	40.78	46.82	48.89	49.81	**54.30**	6.8%	9.0%
	H@10	58.53	60.23	60.66	64.12	52.38	54.35	53.38	59.07	60.39	61.38	**66.82**	4.2%	8.9%
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Clothing	H@5	39.26	40.01	36.83	46.95	40.17	43.51	39.88	38.78	38.99	45.36	**50.48**	7.5%	11.3%
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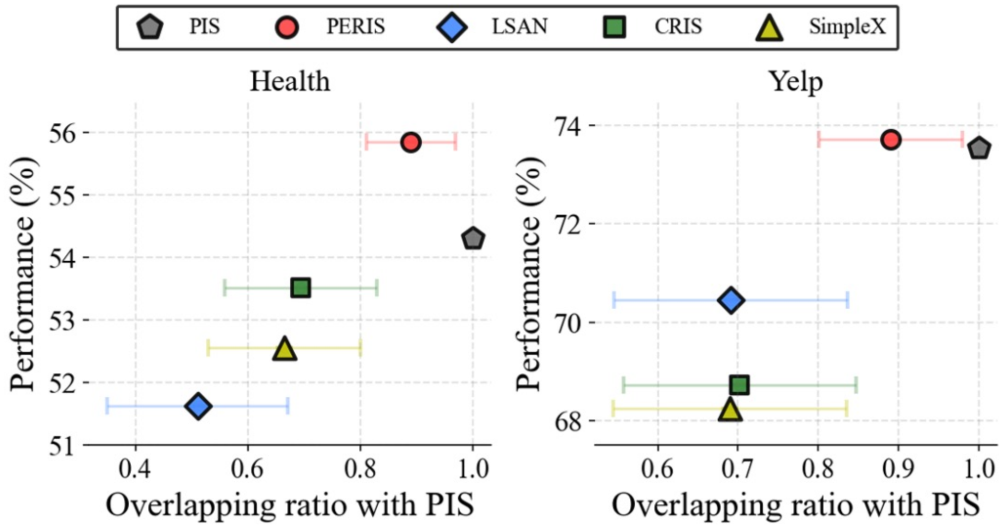
	H@10	75.53	74.83	75.57	71.28	50.29	53.68	67.87	68.44	73.56	73.90	**76.25**	0.9%	3.2%
	N@5	47.57	47.40	48.51	45.30	26.19	30.32	43.18	44.15	46.51	49.37	**51.45**	6.1%	4.2%
	N@10	51.65	51.51	52.63	49.12	30.07	34.12	46.98	47.87	50.64	52.88	**55.06**	4.6%	4.1%
Yelp	H@5	66.13	63.60	65.21	65.21	43.41	46.36	62.38	64.34	68.79	66.09	**73.93**	11.8%	7.5%
	H@10	84.53	82.74	82.42	84.11	61.75	63.75	78.21	80.02	85.63	84.38	**87.29**	3.3%	1.9%
	N@5	47.66	45.98	47.19	46.50	28.59	31.93	45.20	46.60	50.59	46.90	**55.06**	15.5%	8.8%
	N@10	53.66	52.20	52.78	52.65	34.55	37.58	50.37	51.73	56.06	52.84	**59.45**	10.8%	6.0%
Google	H@5	60.38	74.40	75.83	73.01	33.09	37.76	42.63	67.31	60.46	74.01	**81.01**	6.8%	9.5%
	H@10	68.69	81.08	82.54	78.62	44.54	48.01	53.97	73.83	72.76	81.94	**86.83**	5.2%	6.0%
	N@5	49.43	63.27	64.67	61.49	23.23	28.03	31.30	57.65	46.83	61.88	**70.33**	8.8%	13.7%
	N@10	52.12	65.44	66.85	63.33	26.93	31.35	34.97	59.76	50.81	64.47	**72.23**	8.0%	12.0%

Personalized Interest Sustainability in Baseline Models

Baseline models that learn users' future interests cannot fully capture the PIS.

Depending solely on the PIS score can result in inaccurate recommendations.



$$r_{u,i} = \boxed{\boxed{\lambda\{\mu\hat{y}^{I}_{u,i} + (1-\mu)\hat{y}^{E}_{u,i}\}} + (1-\lambda)\hat{y}^{P}_{u,i}}$$

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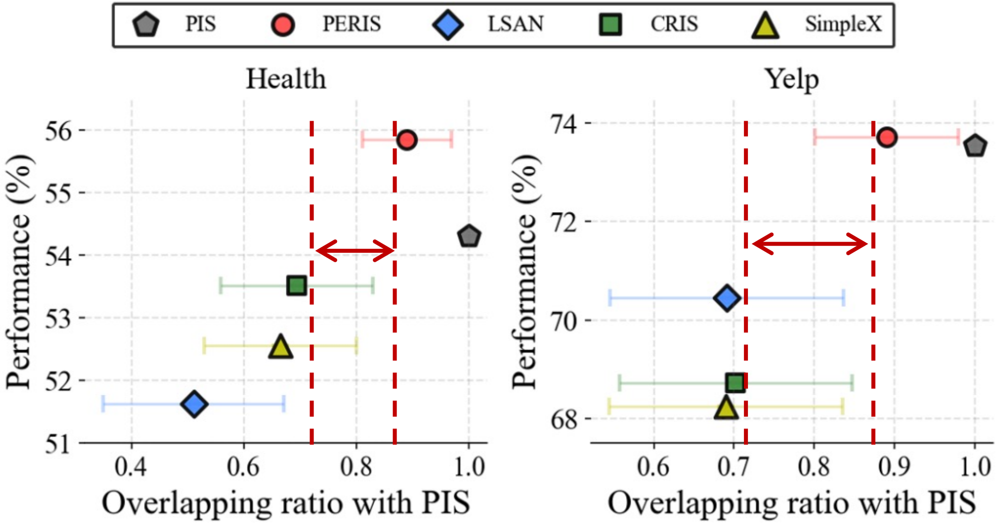
Baseline models that learn users' future interests cannot fully capture the PIS.

Depending solely on the PIS score can result in inaccurate recommendations.

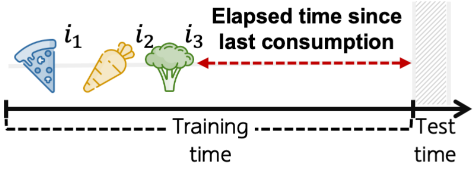


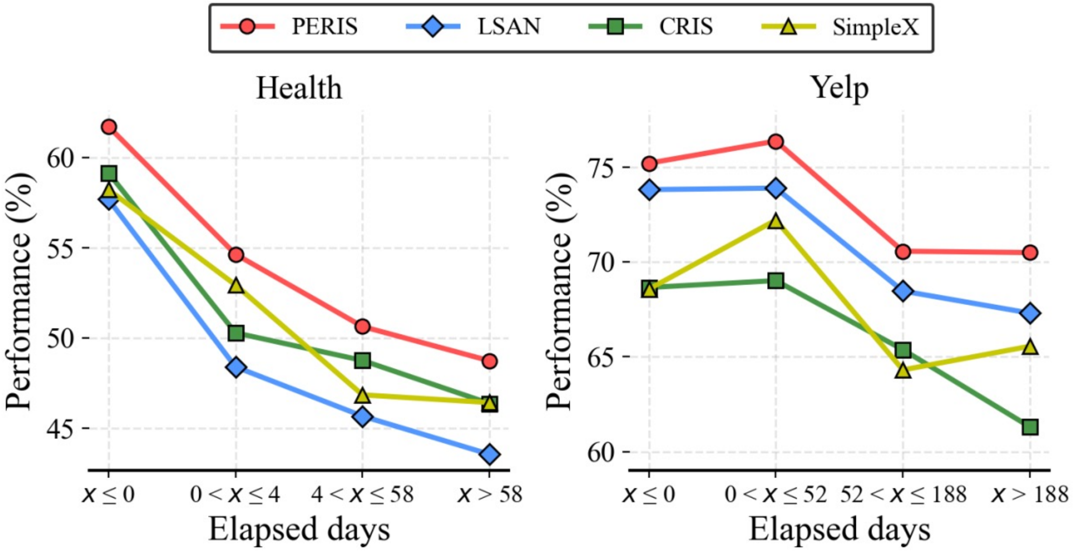
$$r_{u,i} = \boxed{\boxed{\lambda\{\mu\hat{y}^{I}_{u,i} + (1-\mu)\hat{y}^{E}_{u,i}\}} + (1-\lambda)\hat{y}^{P}_{u,i}}$$

Elapsed Time Since Users' Last Consumption

The performance of the models is generally degraded when the elapsed time since their last consumption becomes long.

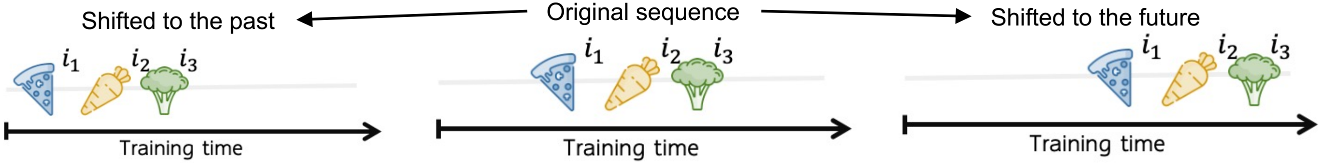
PIS is beneficial to infer users' interest even though they have a long elapsed time since their last consumption.



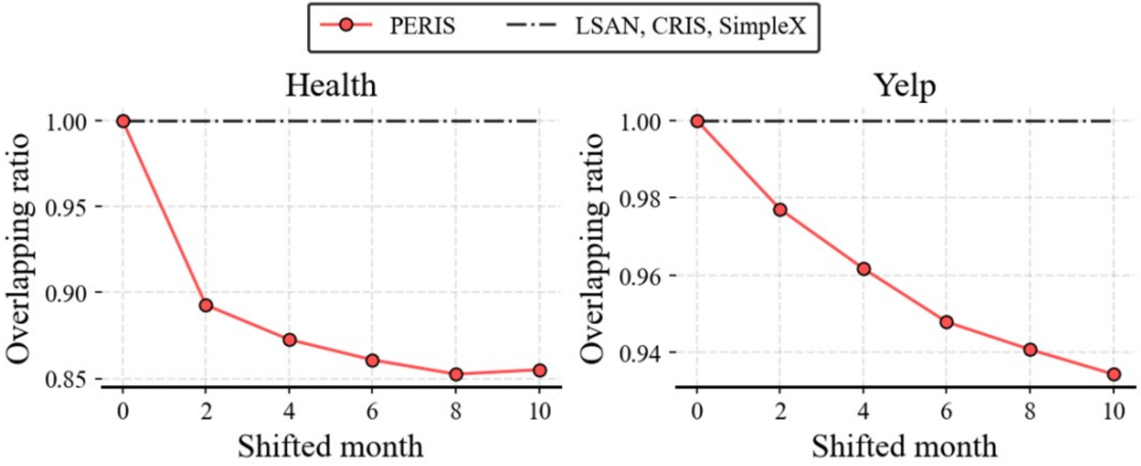


Sensitivity to Shifted Consumption History

We shift users' item sequences by month from its start time to the relative past or future.



PERIS is sensitive to the temporal change of sequences, which supports the superior performance of PERIS.



Ablation Study on Supplementation Schemes

The vanilla PIS prediction task (PIS) suffers from the sparsity of users' consumption history.

The intrinsic ($Int.$) and extrinsic ($Ext.$) supplementation schemes are vital to successfully perform the PIS prediction task.

Components			Tools		Toys		Yelp	
Int.	Ext.	PIS	H@10	N@10	H@10	N@10	H@10	N@10
✓	✓	✓	**60.34**	**39.16**	**71.73**	**51.36**	**89.85**	**59.53**
✗	✓	✓	59.39	38.24	69.55	49.57	87.79	58.94
✓	✗	✓	46.60	25.03	64.62	44.12	86.77	53.96
✗	✗	✓	46.41	24.95	64.25	43.15	88.10	54.10
✗	✗	✗	52.01	31.96	65.92	46.23	85.15	53.87

Conclusion

- **New training objective** for sequential RSs instead of next item prediction.
- Simple yet effective **supplementation schemes** for the proposed prediction task.
- **Superior performance** compared to 10 baseline models on 11 real-world datasets.
- **More personalized recommendation** thanks to the personalized interest sustainability.

Source code: https://github.com/dmhyun/peris

Contact information: dm.hyun@postech.ac.kr