Correlation-Sensitive Next-Basket Recommendation

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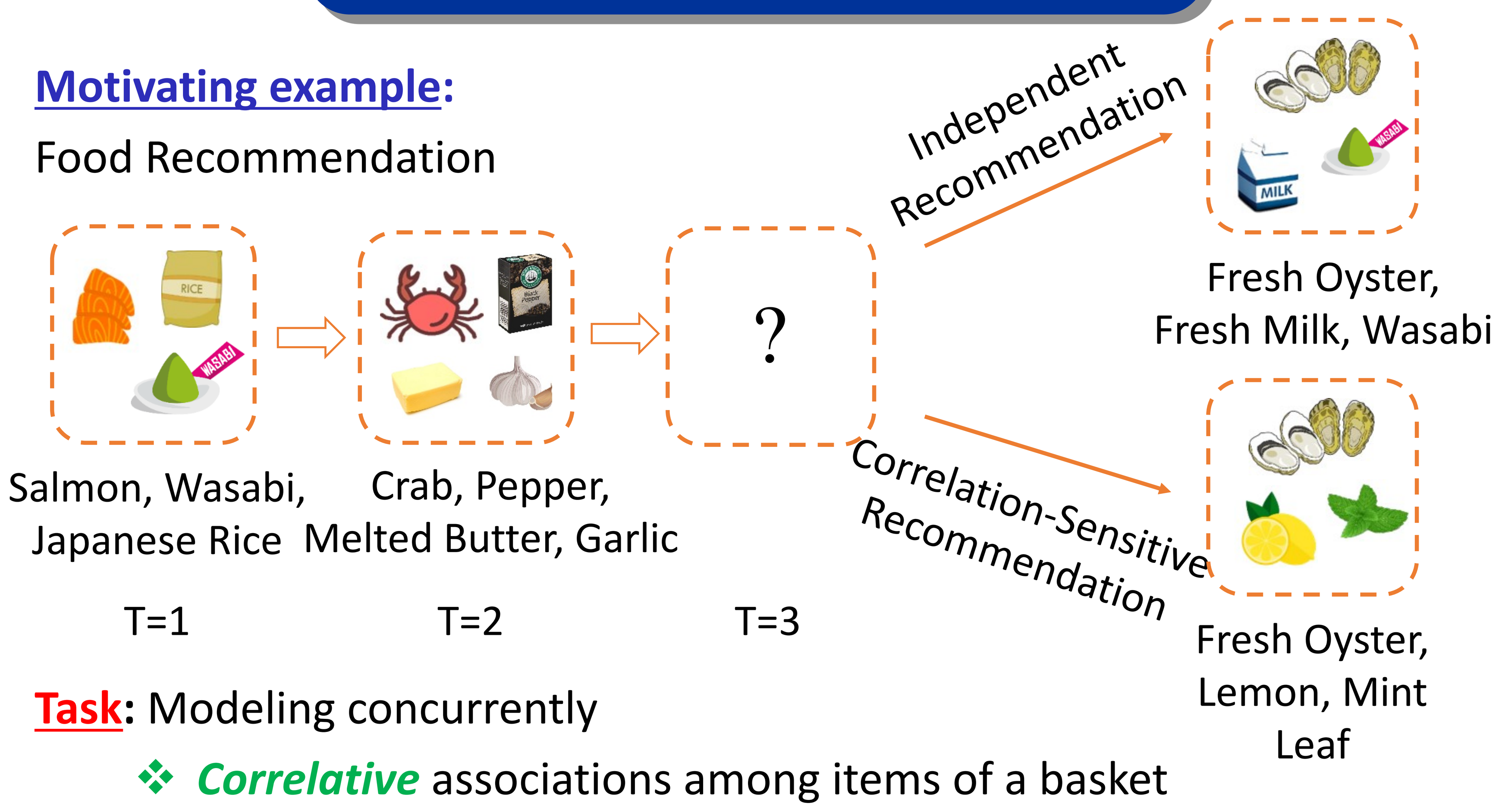
Problem

Motivating example:

Food Recommendation



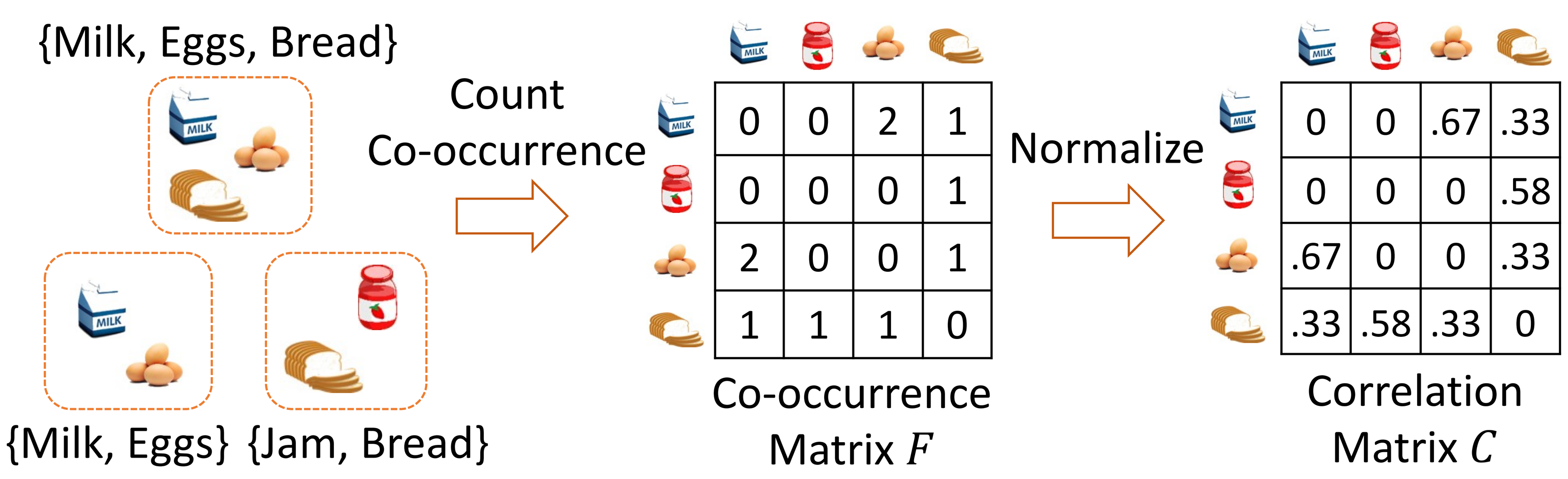
Task: Modeling concurrently

- ***Correlative*** associations among items of a basket
- ***Sequential*** associations across baskets of a sequence

to predict the ***next basket of correlated items***.

Item-Item Correlation Matrix

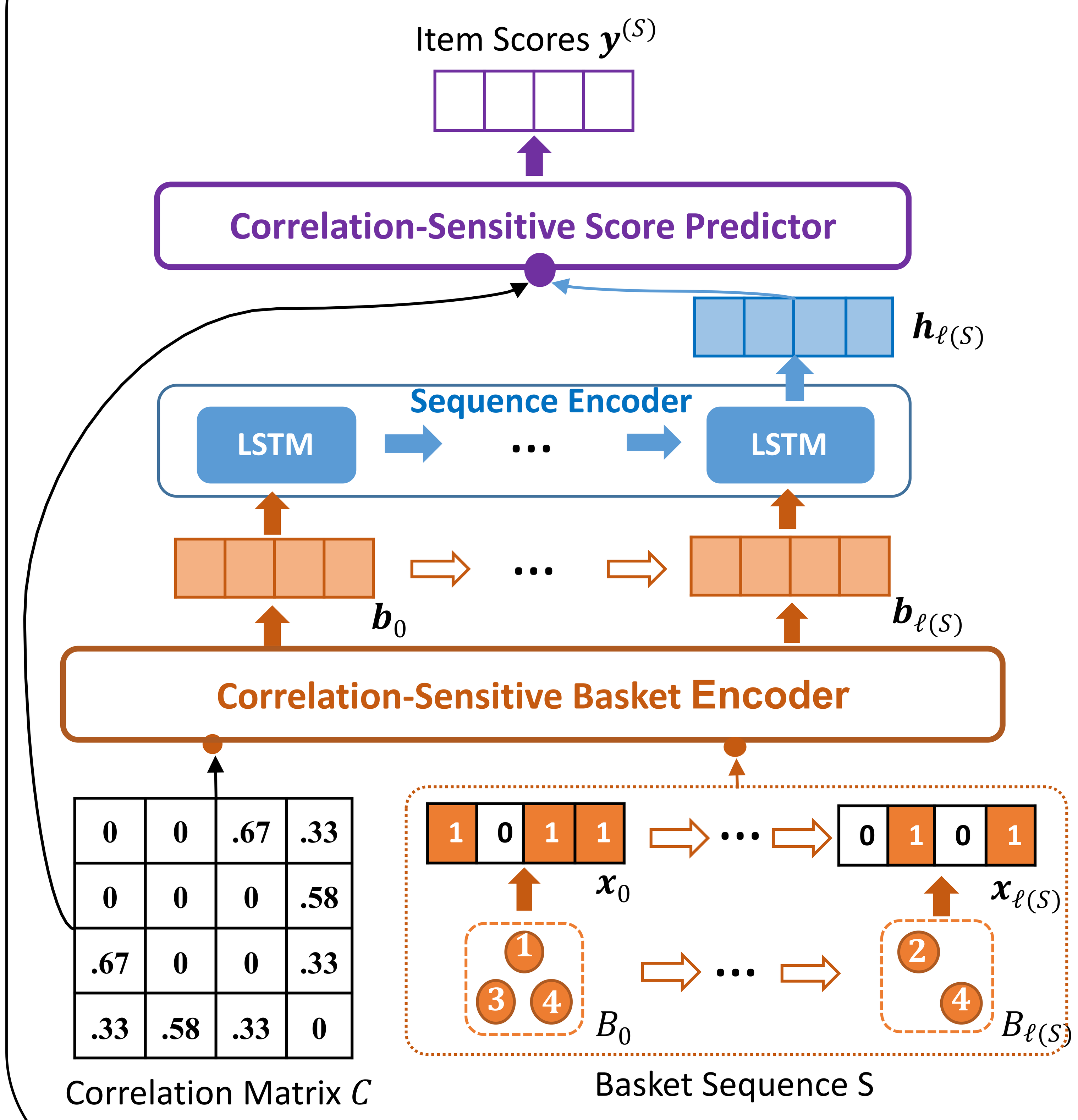
Objective: Leverage correlations between item-item pairs



Properties:

- A pair with **frequent co-occurrence** has a **higher score** than less frequent ones.
- A pair with **exclusive connection** has a **higher score** than non-exclusive ones.

Basket Sequence Correlation Networks (Beacon)



Input: a set of items V; $C \in \mathbb{R}^{|V|\times|V|}$; each basket $B_t \rightarrow \boldsymbol{x}_t \in \{0,1\}^{|V|}$,

#	Module	Operations	Parameters
1	Correlation-Sensitive Basket Encoder	• The immediate representation $\boldsymbol{z}_t \in \mathbb{R}^{\lvert V\rvert}$ of B_t: $\boldsymbol{z}_t = \boldsymbol{x}_t \circ \boldsymbol{\omega} + \mathrm{ReLU}(\boldsymbol{x}_t C - \eta\mathbf{1})$ • The ***L***-dimensional latent representation $\boldsymbol{b}_t \in \mathbb{R}^L$ of B_t: $\boldsymbol{b}_t = \mathrm{ReLU}(\boldsymbol{z}_t\boldsymbol{\Phi} + \boldsymbol{\phi})$	• Item importance $\boldsymbol{\omega} \in \mathbb{R}^{\lvert V\rvert}$ • Noise-cancelling $\eta \in \mathbb{R}^+$ • $\boldsymbol{\Phi} \in \mathbb{R}^{\lvert V\rvert\times L}, \boldsymbol{\phi} \in \mathbb{R}^L$
2	Sequence Encoder	• The ***H***-dimensional recurrent hidden output $\boldsymbol{h}_t \in \mathbb{R}^H$: $\boldsymbol{h}_t = \tanh(\boldsymbol{b}_t\boldsymbol{\Psi} + \boldsymbol{h}_{t-1}\boldsymbol{\Psi}' + \boldsymbol{\psi})$	• $\boldsymbol{\Psi} \in \mathbb{R}^{L\times H}, \boldsymbol{\psi} \in \mathbb{R}^H$ • $\boldsymbol{\Psi}' \in \mathbb{R}^{H\times H}$
3	Correlation-Sensitive Score Predictor	• The sequential signal for next-item adoptions $\boldsymbol{s}^{(S)} \in \mathbb{R}^{\lvert V\rvert}$: $\boldsymbol{s}^{(S)} = \sigma(\boldsymbol{h}_{\ell(S)}\boldsymbol{\Gamma})$ • The correlation-sensitive score $\boldsymbol{y}^{(S)} \in \mathbb{R}^{\lvert V\rvert}$: $\boldsymbol{y}^{(S)} = \alpha(\boldsymbol{s}^{(S)} \circ \boldsymbol{\omega} + \boldsymbol{s}^{(S)}C) + (1-\alpha)\boldsymbol{s}^{(S)}$ $\alpha \in [0,1]$	• $\boldsymbol{\Gamma} \in \mathbb{R}^{H\times\lvert V\rvert}$

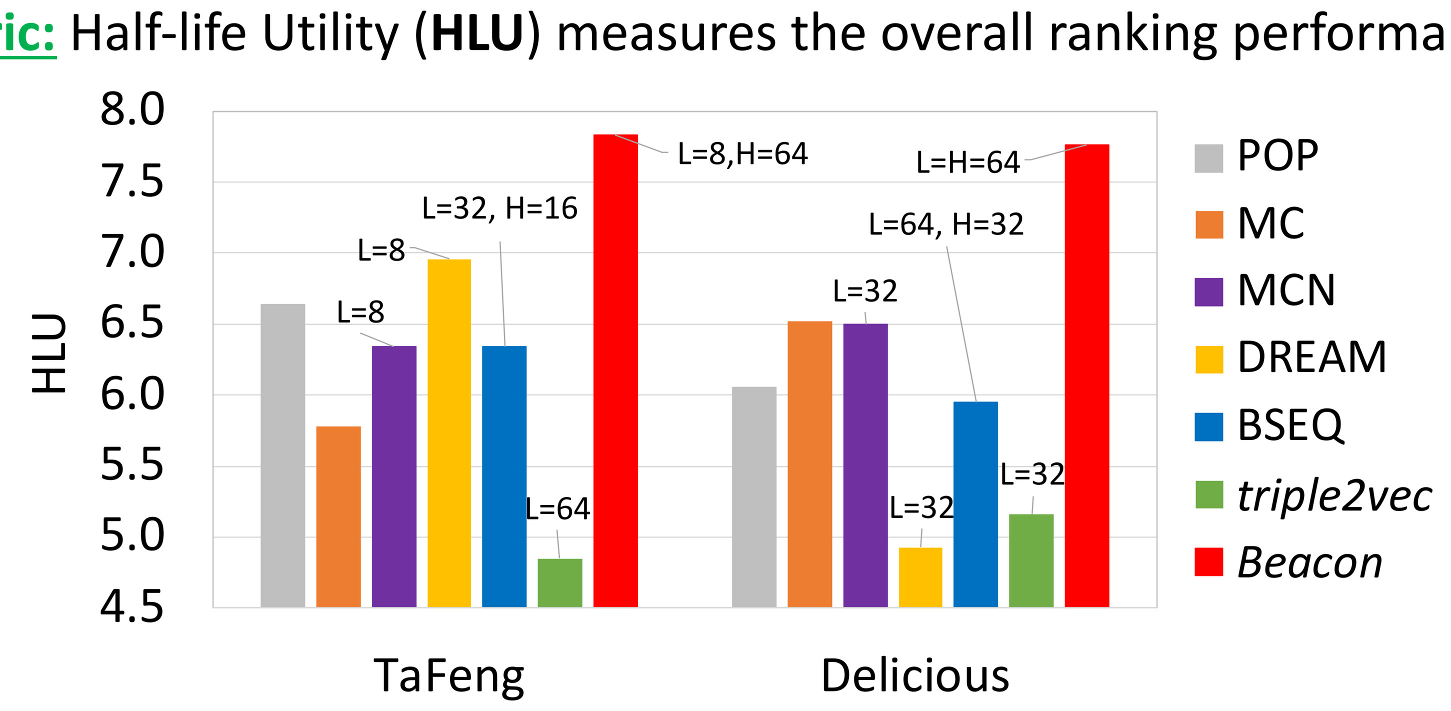
Experiments

Datasets: **TaFeng** (E-commerce); and **Delicious** (Bookmark Tag)

Recommendation: $B_{\text{next}} \leftarrow \{i \mid \mathrm{r}_i^{(S)} \le K\}$, where $\boldsymbol{r}_i^{(S)}$ is the ranking of item i; and $\boldsymbol{r}^{(S)}: \boldsymbol{y}^{(S)} \rightarrow \{1, 2, \dots, N\}$

Methodology: For a given testing basket sequence S, hide last basket B and generate the **next-basket recommendation** given $< S\backslash B >$

Metric: Half-life Utility (**HLU**) measures the overall ranking performance. Higher is better.



Target Bookmark	Delicious Tag Basket Prediction (K=5)		
	Beacon	MC	POP
Manual de jQuery (1)	*web*, design, *programming*, *javascript*, *tools*	digital, sociales, *web*, internet, periodismo	art, *design*, education, video, *tools*
The $300 Million Button (2)	twitter, *ux*, *propinquity*, *critical*, *writing*	*design*, peace, education, *blog*, *tips*	art, *design*, education, video, *tools*

(1) https://desarrolloweb.com/manuales/manual-jquery.html (2) https://articles.uie.com/three_hund_million_button

Conclusion: Experiments on the two datasets show that the modeling of correlation information contributes statistically significant improvements as compared to **traditional basket-sequence models** in terms of top-K recommendations.