Basket-Sensitive Personalized Item Recommendation

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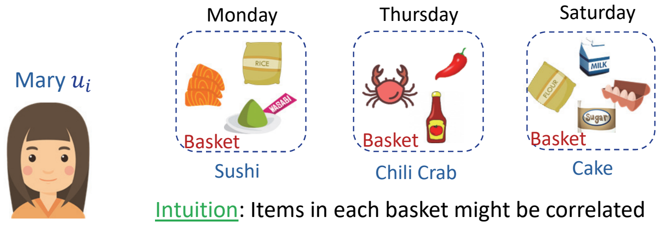
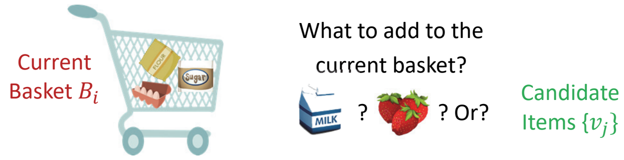
Problem

The notion of basket:



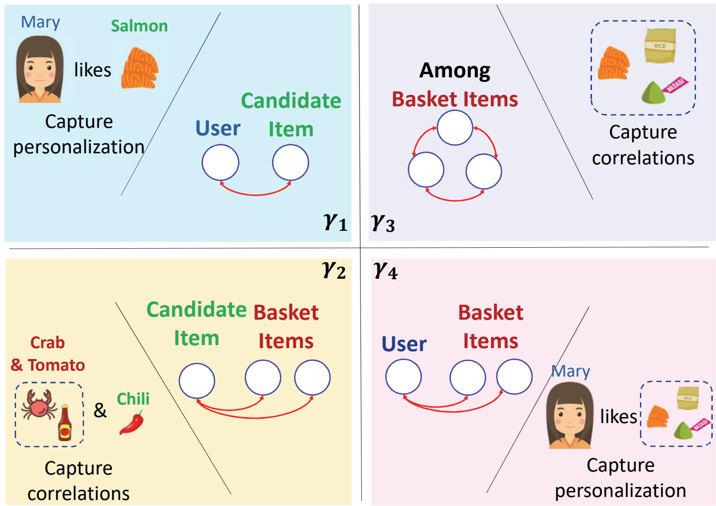
Intuition: Items in each basket might be correlated



Task: Given the current basket, recommend an item for Mary

Solution: Learn a real-valued function from adoptions to rank candidate items: $F(u_i, B_i, v_j; \Theta)$

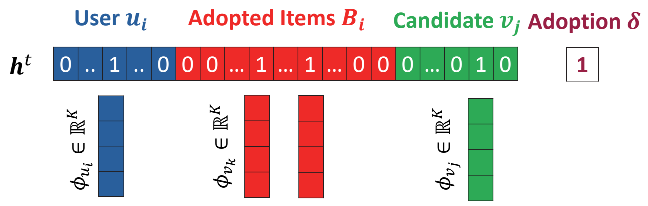
Insight: Association Types



$\gamma_1, \gamma_2, \gamma_3, \gamma_4 \in \{0,1\}$

Approach#1: Basket-Sensitive Factorization Machine (BFM)

Tuple: $t = < u_i, B_i, v_j, \delta > \in T$, N users, M items



Adoption Estimation:

$$\mathcal{F}(\boldsymbol{h}^t;\Theta) = \underbrace{\mu_0 + \sum_{i=1}^{p}\mu_i h_i}_{\text{Global \& Item Bias}}$$

$$+ \underbrace{\gamma_1 \sum_{i=1}^{N}\sum_{j=N+1}^{N+M} h_i h_j (\phi_i^T\phi_j)}_{\text{User \& Candidate Item}} + \underbrace{\gamma_2 \sum_{i=N+1}^{N+M}\sum_{j=M+N+1}^{N+2M} h_i h_j (\phi_i^T\phi_j)}_{\text{Candidate Item \& Basket Items}}$$

$$+ \underbrace{\gamma_3 \sum_{i=N+M+1}^{N+2M}\sum_{j=i+1}^{N+2M} h_i h_j (\phi_i^T\phi_j)}_{\text{Among Basket Items}} + \underbrace{\gamma_4 \sum_{i=1}^{N}\sum_{j=N+M+1}^{N+2M} h_i h_j (\phi_i^T\phi_j)}_{\text{User \& Basket Items}}$$

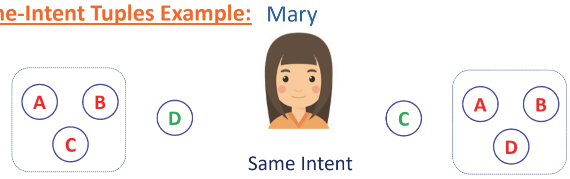
Optimization:

$$OPT\_BFM(T) = \operatorname{argmin}_\Theta \left[\sum_{t\in T} -\ln\left(\sigma(\mathcal{F}(\boldsymbol{h}^t;\Theta)\times t.\delta)\right) + \sum_{\theta\in\Theta}\lambda_\theta \theta^2\right]$$

where $\lambda_\theta \in \mathbb{R}; \sigma(a) = 1/(1+e^{-a})$

Approach#2: Constrained BFM (CBFM)

Same-Intent Tuples Example: Mary



$t_1 = < Mary, \{A, B, C\}, D, 1 >$ ⟷ $t_2 = < Mary, \{A, B, D\}, C, 1 >$

Intuition:

- Same-intent tuples should have similar adoption estimation
- Same-intent pairs may have different degree of correlation.

Constraint: A tuple t and its same-intent tuple $t^m = \operatorname{argmax}_{t' \neq t} \mathcal{F}(\boldsymbol{h}^{t'};\Theta)$

$$\underbrace{PMI(t, t^m)}_{\text{Pointwise Mutual Information}} \times \underbrace{\left(\mathcal{F}(\boldsymbol{h}^t;\Theta) - \mathcal{F}(\boldsymbol{h}^{t^m};\Theta)\right)^2}_{\text{Adoption Estimation Difference}}$$

Optimization:

$$OPT\_CBFM(T) = \operatorname{argmin}_\Theta \Big[\sum_{\theta\in\Theta}\lambda_\theta\theta^2 + \sum_{t\in T}\{-\ln(\sigma(\mathcal{F}(\boldsymbol{h}^t;\Theta)\times t.\delta)) + \underbrace{\alpha/2 \times PMI(t,t^m)\times\left(\mathcal{F}(\boldsymbol{h}^t;\Theta) - \mathcal{F}(\boldsymbol{h}^{t^m};\Theta)\right)^2}_{\text{Constraint}}\}\Big]$$

where $\alpha \in \mathbb{R}$

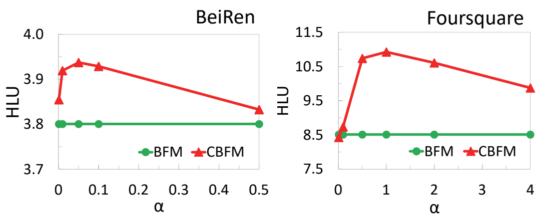
Experiments

Datasets: Grocery Shopping Baskets (**BeiRen**) and Point-of-Interest Check-ins (**Foursquare**).

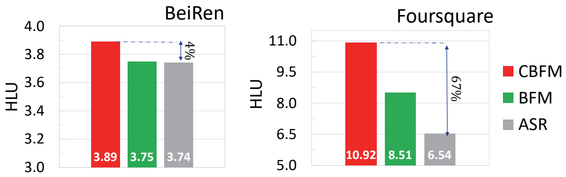
Methodology: For a given testing tuple $t = < u_i, B_i, v_j, \delta >$, hide v_j and generate the **top-K predictions** given v_i and B_i

Metric: Half-life Utility (HLU) measures the probability a user adopts a given item at a specific ranking position.

$$HLU = {}^{1}/_{|T_{test}|} \times C \times \sum_{t\in T_{test}} 2^{(1-r_t)/(\beta-1)}; C = 100, \beta = 5$$



Effect of the constraint controlled by α



Comparison between the basket-sensitive models and the Association-Rules-based model

Conclusion: Experiments on the two datasets show that **Basket-Sensitive Information (BFM) & Constraint (CBFM)** contribute **statistically significant** improvements as compared to the baseline **Association Rules (ASR)** in term of top-K recommendations.