Motivating example: Food Recommendation

\[
\begin{align*}
\text{Salmon, Wasabi, Japanese Rice} & \quad \text{Motivating as compared to} \quad \text{Conclusion:} \\
\text{Crab, Pepper, Melted Butter, Garlic} & \quad \text{Metric:} \\
\text{Fresh Oyster, Fresh Milk, Wasabi} & \quad \text{Methodology:} \\
\text{Fresh Oyster, Lemon, Mint Leaf} & \quad \text{Correlation Matrix}
\end{align*}
\]

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.

Objective: Leverage correlations between item-item pairs

\[
\begin{align*}
\text{Metric:} & \quad \text{Count Co-occurrence} \\
\text{Methodology:} & \quad \text{Correlation Matrix} F \\
\text{Properties:} & \quad \text{A pair with frequent co-occurrence has a higher score than less frequent ones.} \\
& \quad \text{A pair with exclusive connection has a higher score than non-exclusive ones.}
\end{align*}
\]

Input: a set of items \(V; C \in \mathbb{R}^{|V| \times |V|}\); each basket \(B_t \rightarrow x_t \in \{0, 1\}^{|V|}\).

<table>
<thead>
<tr>
<th>Module</th>
<th>Operations</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The immediate representation (z_t \in \mathbb{R}^{</td>
<td>V</td>
</tr>
<tr>
<td></td>
<td>The (L)-dimensional latent representation (b_t \in \mathbb{R}^L) of (B_t): (b_t = \text{ReLU}(z_t \Phi + \phi))</td>
<td>Noise-cancelling (\eta \in \mathbb{R}^+)</td>
</tr>
<tr>
<td></td>
<td>The (H)-dimensional recurrent hidden output (h_t \in \mathbb{R}^H): (h_t = \tanh(b_t \Psi + h_{t-1} \Psi^\top + \psi))</td>
<td>(\Phi \in \mathbb{R}^{</td>
</tr>
<tr>
<td>2</td>
<td>The sequential signal for next-item adoptions (s^{(S)} \in \mathbb{R}^{</td>
<td>V</td>
</tr>
<tr>
<td></td>
<td>The correlation-sensitive score (y^{(S)} \in \mathbb{R}^{</td>
<td>V</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

Recommendation: \(B_{\text{next}} \leftarrow ([r_i^{(S)} \leq K])\), where \(r_i^{(S)}\) is the ranking of item \(i\); and \(r^{(S)}: y^{(S)} \rightarrow \{1, 2, ..., N\}\)

Methodology: For a given testing basket sequence \(S\), hide last basket \(B\) and generate the next-basket recommendation given \(S \setminus B\)

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

Experiments

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.