A Model-Agnostic Framework for Recommendation via Interest-aware Item Embeddings

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Introduction and Problem Formulation

Goal: To enhance recommendation model performance via capturing user interests within the learned item representations, while maintaining generalisability without requiring extensive architectural alterations or the introduction of supplementary data.

Constructs and Problem Settings:

- Item identifier as i, and the set of user interactive behaviour sequences, encompassing clicked or viewed items by user u as $\mathbb{S}_u$
- User's basic profile information as u_p, Candidate item identification as i_t
- Feature function capturing candidate item characteristics based on item information (i_t) and associated information (r_t) from the recommendation system, as $f(i_t, r_t)$
- The user interest vector has a dimension denoted by h, and K represents the number of dimensions in the user vector.
- i_u^1 signifies one of the multiple interest vectors of the user, while $\mathcal{I}$ represents the collection of these interest vectors.

Modelling User Interests: We leverage off-the-shelf Capsule network as an auxiliary task to model user interests, below are the key components:

$$\textbf{User Interests: } \mathcal{I}_u = f(\mathbb{S}_u, u_p) \mid \mathcal{I} = (\mathrm{i}_u^1, \mathrm{i}_u^2, \dots, \mathrm{i}_u^K) \in \mathbb{R}^{h \times K}$$

$$\textbf{Candidate Item Embeddings: } c_t = f(i_t, r_t) \mid c_t \in \mathbb{R}^h$$

$$\textbf{Relationship Score: } \mathcal{R}_{\text{score}}(\mathcal{I}_u, c_t) = c_t^T \mathrm{i}_u^K$$

A scoring mechanism $\mathcal{R}_{\text{score}}$ to quantitatively assess the relationship between a candidate item and the user's interests.

Contributions: A framework for acquiring interest-oriented item representations through the utilisation of the user Interest-aware Capsule network (IaCN), provided

- the proposed framework is model-agnostic and operates as an auxiliary task, facilitating the simultaneous learning of item representations.
- our approach that combines a joint learning method and hyperparameter optimisation within the IaCN framework. Through extensive experimentation on benchmark datasets, our results demonstrate significant improvements across various existing recommendation models.

Methodology

Item Representation: Utilised dynamic routing mechanism for Behavior-to-Interest routing [2], employing capsules to learn multi-interest representations based on user profiles and interactive behaviour sequences.

- **Capsule's Input (s_j):**

$$s_j = \sum_{i,j} a_{ij} \hat{x}_{j|i} = \sum a_{ij} W_{ij} x_j, a_{ij} = \frac{\exp(b_{ij})}{\sum_k \exp(b_{ik})}$$

$$\text{where, output: } \mathrm{i}_j = \|s_j\|^2 / (1 + \|s_j\|^2)(s_j / \|s_j\|)$$

- **Relationship between User's Interest and the Item:**

$$b_{ij} = u_j^T M c_i \mid i \in I^c \forall \{0, 1, \dots, n\}, j \in \{0, 1, \dots, K\}$$

- **Item Embeddings:** $\mathbb{E} = \mathbb{E}_{\text{original}} \oplus \mathbb{E}_{\text{auxiliary}}$
- **Overall Loss Function:**

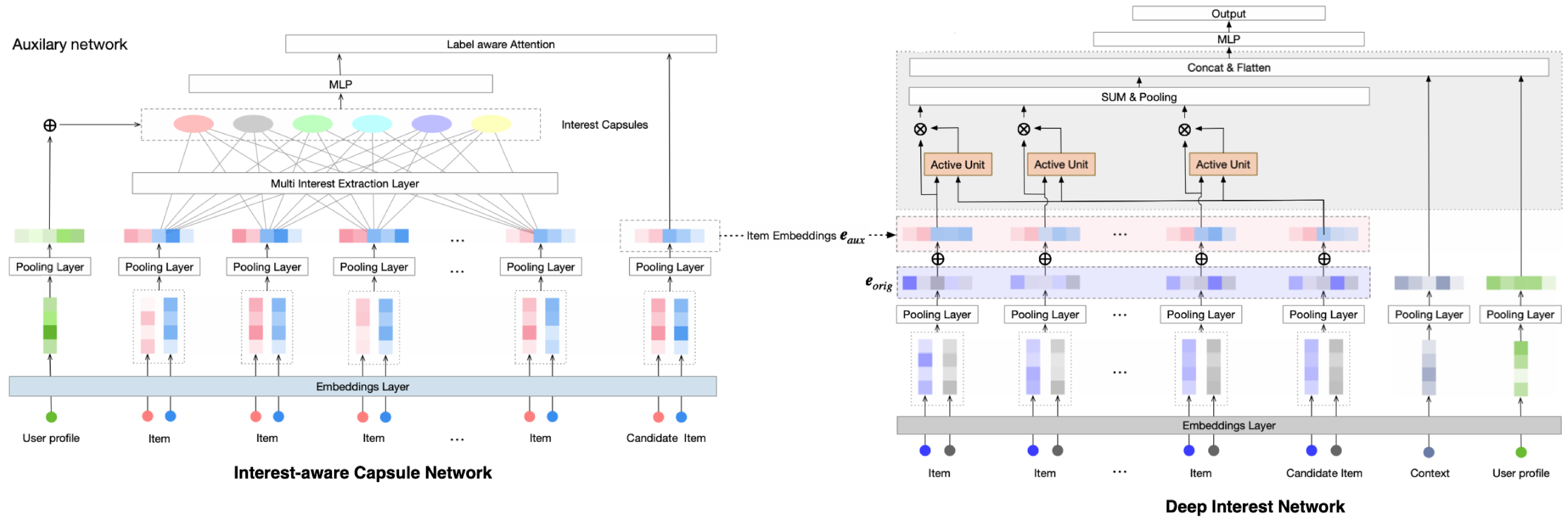
$$\mathcal{L} = \mathcal{L}_{\text{DIN}} + \lambda \mathcal{L}_{\text{IaCN}} \text{where, } \mathcal{L}_{\text{IaCN}} = \sum_{u,i} \log P(c_i \mid \mathrm{i}_u), \mathcal{L}_{\text{DIN}} \text{ follows [1]}$$

- **Gradient of Auxiliary Model:**

$$g^e_{\text{auxiliary}} = (1 - \delta) g^e_{\text{auxiliary\_auxiliary}} + \delta g^e_{\text{auxiliary\_main}} \mid \delta \in [0, 1]$$

Model & Experiments

Interest-aware Capsule Network (IaCN) Framework



Results

Table 1. Performance of individual models on the Amazon datasets. And, the analysis of hyperparameter δ for DIEN with the auxiliary network (IaCN) on Amazon books dataset.

Model \ Dataset	Books		Electronics	
	AUC	SD	AUC	SD
DIN [19]	0.7970	0.0010	0.7569	0.0009
DIN [19]+IaCN	0.8002	0.0009	0.7606	0.0013
Wide and Deep [1]	0.7860	0.0013	0.7461	0.0015
Wide and Deep [1]+IaCN	0.7928	0.0009	0.7502	0.0010
DIEN [18]	0.8534	0.0018	0.7706	0.0021
DIEN [18]+IaCN	0.8633	0.0019	0.7723	0.0002

DIEN [18]+IaCN			
δ	AUC	δ	AUC
0.1	$0.862_{\pm 0.0018}$	0.6	$0.861_{\pm 0.0014}$
0.2	$0.864_{\pm 0.0019}$	0.7	$0.862_{\pm 0.0010}$
0.3	$0.864_{\pm 0.0005}$	0.8	$0.862_{\pm 0.0018}$
0.4	$0.864_{\pm 0.0013}$	0.9	$0.862_{\pm 0.0012}$
0.5	$0.861_{\pm 0.0012}$	1.0	$0.860_{\pm 0.0022}$

Table 2. Performance with different user interactive behaviour sequences length l on Amazon books

Model	10	20	50
DIEN [18]	$0.854_{\pm 0.0016}$	$0.853_{\pm 0.0018}$	$0.850_{\pm 0.0022}$
DIEN [18]+IaCN	$0.857_{\pm 0.0018}$	$0.863_{\pm 0.0019}$	$0.861_{\pm 0.0014}$

Conclusion:

- Introduced a novel framework that directly learns interest-oriented item representations through a user interest-aware capsule network.
- Integration of the user interest-aware capsule network as an auxiliary component to facilitate joint learning of item-based and interest-based item representations.
- Demonstrated notable improvements in click-through rate (CTR) prediction performance on Amazon product reviews data for longer sequences of viewed items and a broader spectrum of user interests.

References:

[1] Zhou, G., Zhu, X., Song, C., Fan, Y., Zhu, H., Ma, X., ... & Gai, K. (2018, July). Deep interest network for click-through rate prediction. In Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining (pp. 1059-1068).

[2] Li, C., Liu, Z., Wu, M., Xu, Y., Zhao, H., Huang, P., ... & Lee, D. L. (2019, November). Multi-interest network with dynamic routing for recommendation at Tmall. In Proceedings of the 28th ACM international conference on information and knowledge management (pp. 2615-2623).