Deep Situation-aware Interaction Network for Click-Through Rate Prediction

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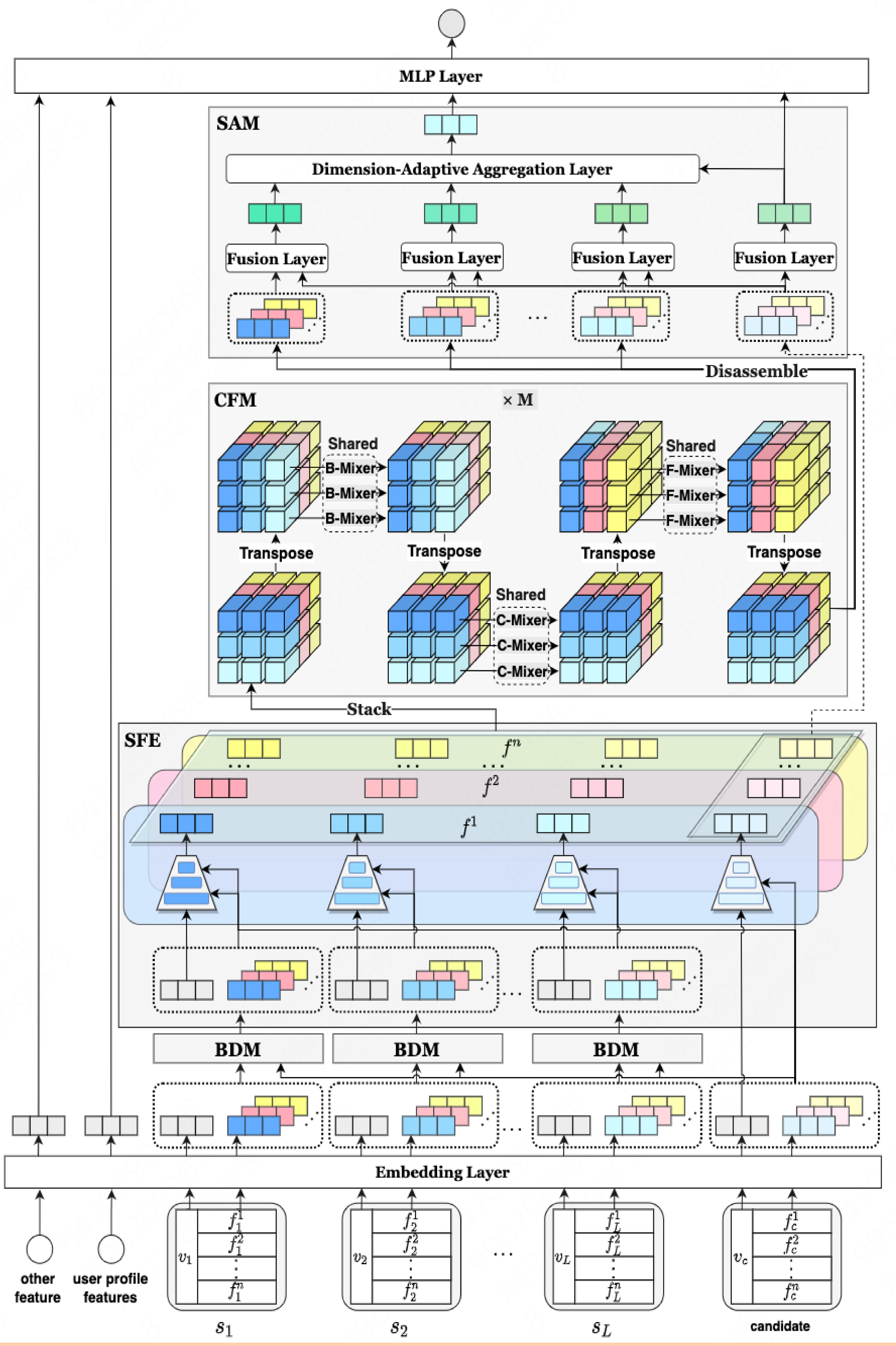
Motivation

- **Background:** User behavior sequence modeling plays a significant role in Click-Through Rate (CTR) prediction. Except for the interacted items, user behaviors contain rich interaction information, which has not yet been fully exploited.
- **Challenge**: Given a user behavior and the corresponding situational features (i.e., behavior-related side information), how do we generate high-quality embeddings for these situational features and the behavior, if taking into consideration multiple internal correlations, including but not limited to the correlations between different situational features of the same behavior?

DSAIN (Deep Situation-Aware Interaction Network)



- **Behavior Denoising Module (BDM)**
  - Identify the noise in behavior sequences
  - Utilize the reparameterization trick to reduce noise interference
- **Situational Feature Encoder (SFE)**
  - Combine commonalities and differences in situational features of the same type into representations
  - Parameterize embeddings of situational features to learn the approximated interaction between item ID and some situational feature
- **Correlation Fusion Module (CFM)**
  - Devise a light-weighted scheme for modeling tri-directional correlations
  - Capture cross-behavior, cross-situational feature, and cross-channel correlations
- **Situation Aggregation Module (SAM)**
  - Generate embeddings for historical behaviors and the target behavior by aggregating situational features
  - Devise a dimension-adaptive unit to adjust contributions of historical behavior representations at the dimension level

Experimental Results

Overall Performance Comparison

Dataset	Metric	Group I			Group II		Group III			DSAIN
		DIN	DIEN	CAN	DMT	FeedRec	CARCA	Trans2D	DIF-SR	
Taobao	AUC	0.6223	0.6241	0.6276	0.6268	0.6312	0.6289	0.6303	<u>0.6330</u>	**0.6452**
	Logloss	0.2622	0.2618	0.2607	0.2611	0.2592	0.2603	0.2599	<u>0.2588</u>	**0.2571**
Eleme	AUC	0.6368	0.6420	0.6450	0.6435	0.6477	0.6455	0.6464	<u>0.6502</u>	**0.6634**
	Logloss	0.1245	0.1198	0.1157	0.1173	0.1143	0.1152	0.1149	<u>0.1135</u>	**0.1116**
Meituan	AUC	0.6577	0.6612	0.6645	0.6635	0.6715	0.6683	0.6709	<u>0.6740</u>	**0.6823**
	Logloss	0.1922	0.1884	0.1855	0.1861	0.1819	0.1842	0.1825	<u>0.1799</u>	**0.1763**

- DSAIN consistently outperforms all baselines and achieves state-of-the-art performance on all datasets (two public datasets: Taobao and Eleme; one industrial dataset: Meituan)

Performance of variants with different CFMs

	$DSAIN_1^‡$	$DSAIN_2^‡$	$DSAIN_3^‡$	$DSAIN_4^‡$	$DSAIN_5^‡$	$DSAIN_6^‡$	$DSAIN_7^‡$	DSAIN
behavior-mixer	✓			✓	✓		✓	✓
channel-mixer		✓		✓		✓	✓	✓
feature-mixer			✓		✓	✓	✓	✓
GELU	✓	✓	✓	✓	✓	✓		✓
AUC	0.6805	0.6779	0.6793	0.6798	0.6812	0.6770	0.6806	**0.6823**
Logloss	0.1765	0.1767	0.1767	0.1766	0.1764	0.1769	0.1765	**0.1763**

- DSAIN achieves the best performance by jointly leveraging three mixers, thus coherently capturing the tri-directional correlations, i.e., cross-behavior, cross-channel, and cross-feature correlations

Online A/B Test

- In the Meituan food delivery platform, for seven days beginning on December 6, 2022
- DSAIN increases the CTR by 2.70%, the CPM by 2.62%, and the GMV by 2.16%