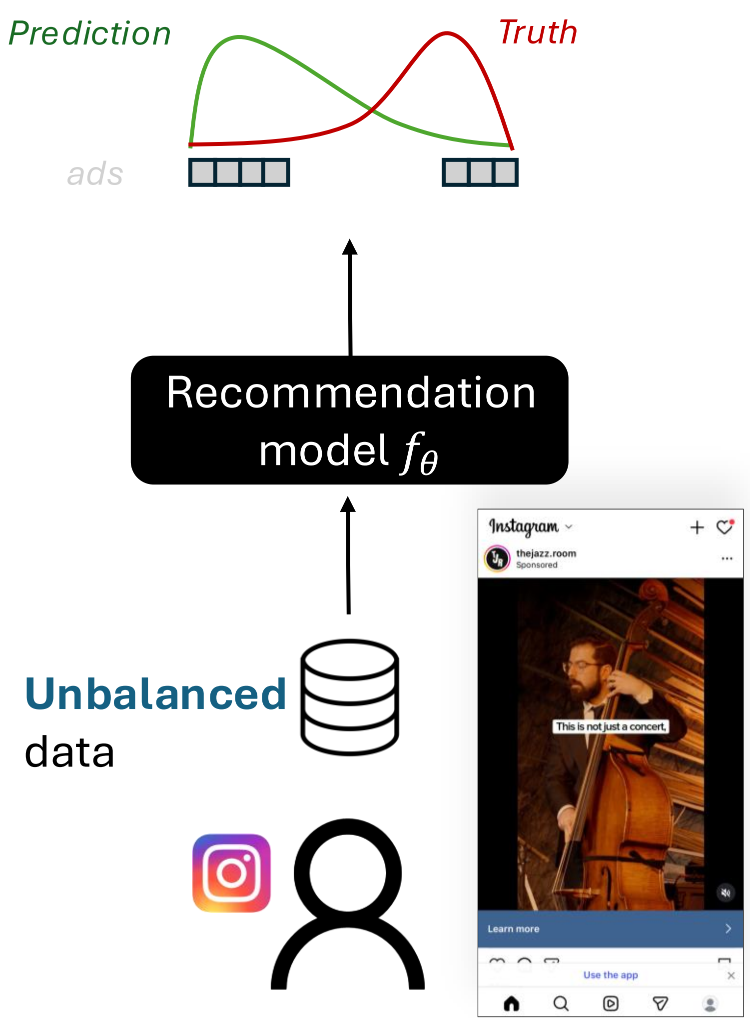
Cross Attention Performs Orthogonal Alignment in Recommendation models

Contents

1. Motivation



Problem: Building **recommendation models** that show advertisement to user.
(If user clicks an ad, that's how company earns money 💰).

Task: We train a model:

$$f_\theta(user_i - ads\ data) \in [0,1]$$

Which represents the probability that $user_i$ clicks on ad_j

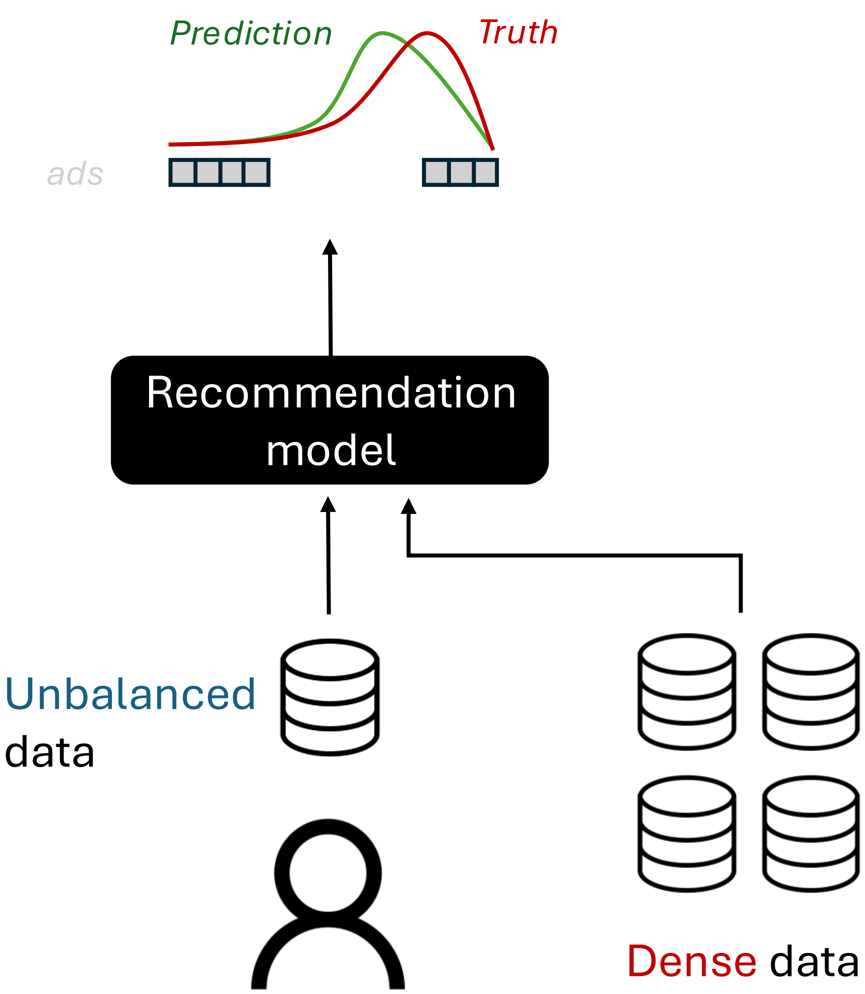
- Times series dataset

$$\boldsymbol{D} = \left\{ \boldsymbol{user_i}, : \left\{ \boldsymbol{time}, \boldsymbol{ad_j}, \{0,1\} \right\} \right\}_{i \in [I], j \in [J]}$$

Challenge: The key challenge was ads-domain data is **Unbalanced**; users rarely click ads.

- Ex: {(14:00, ad-sport, **0**),
  (14:01 ,ad-movie, **0**),
  (14:02 ,ad-movie, **1**),
  ...(14:10, ad-Jazz, **0**)}

1. Motivation



Problem: Building recommendation models that display sponsored posts (ads) to user. *(If user clicks an ad, that's how company earns money💰).*

Challenge: The key challenge was ads-domain data is **Unbalanced;** users rarely click ads.

Cross-Domain Sequential Recommendation(CDSR) : Let's use **dense** data from other domain

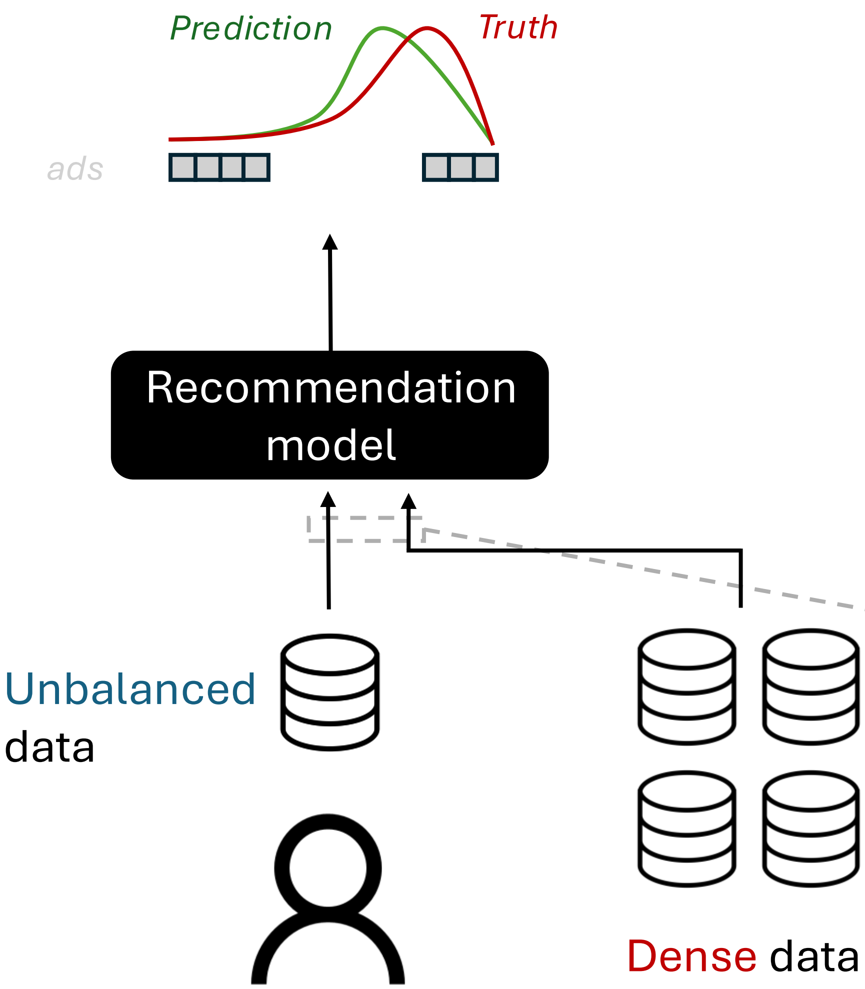
[Source Domain 1] Facebook app – post view duration.

- Ex: {(09/06, post-sport, 30s), (09/06, post-movie, 10s), (09/08, post-Jazz, 300s), … }

[Source Domain 2] Instagram app – post likes.

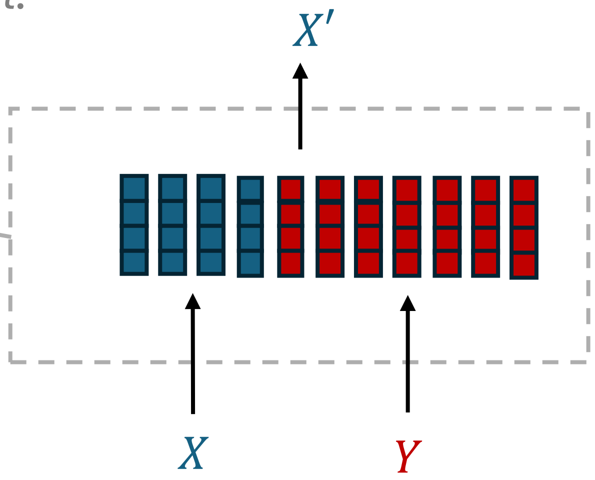
- Ex: {(09/06, post-sport, 1), (09/07, post-Jazz,1), (09/08, post-Jazz, 1), … }

2. Research Question 1



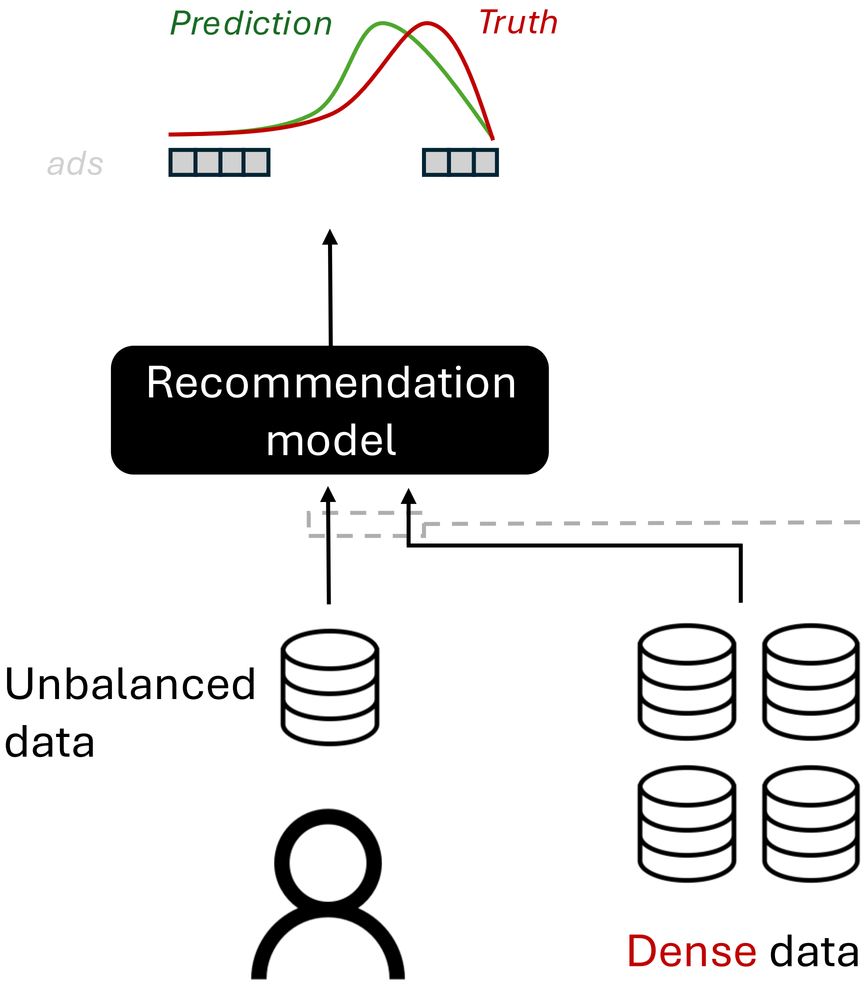
Research Question1: How to fuse those different modality data to improve the performance?

- Naive concatenation: Negative Transfer
  - Domain Noise
  - Preference conflicts: *(ex) user like to "view" video game post for a long time, but do not purchase since user just likes to watch streamer's game broadcast.*



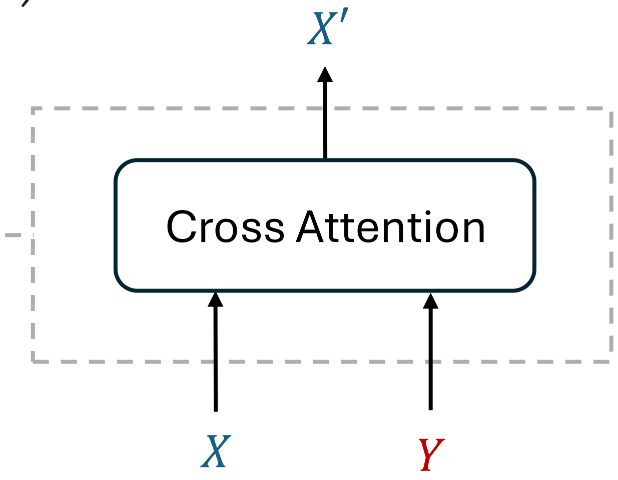
2. Research Question 1

2.1. observation 1



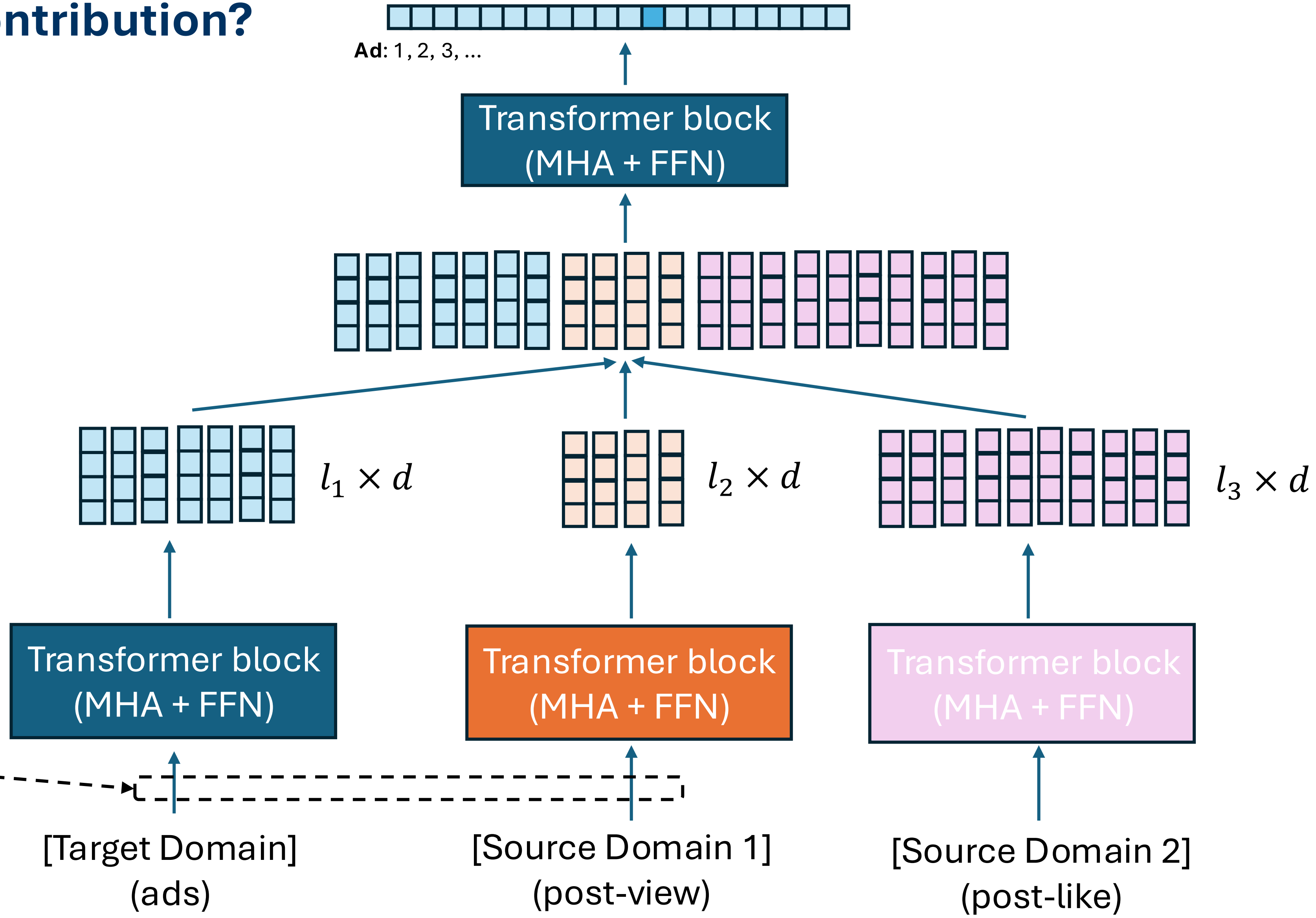
Research Question1: How to fuse those different modality data to improve the performance?

Observation 1: Using Gated Cross Attention at the Early Stage can improve the performance
(First Contribution)



2. Research Question 1

2.2. why contribution?

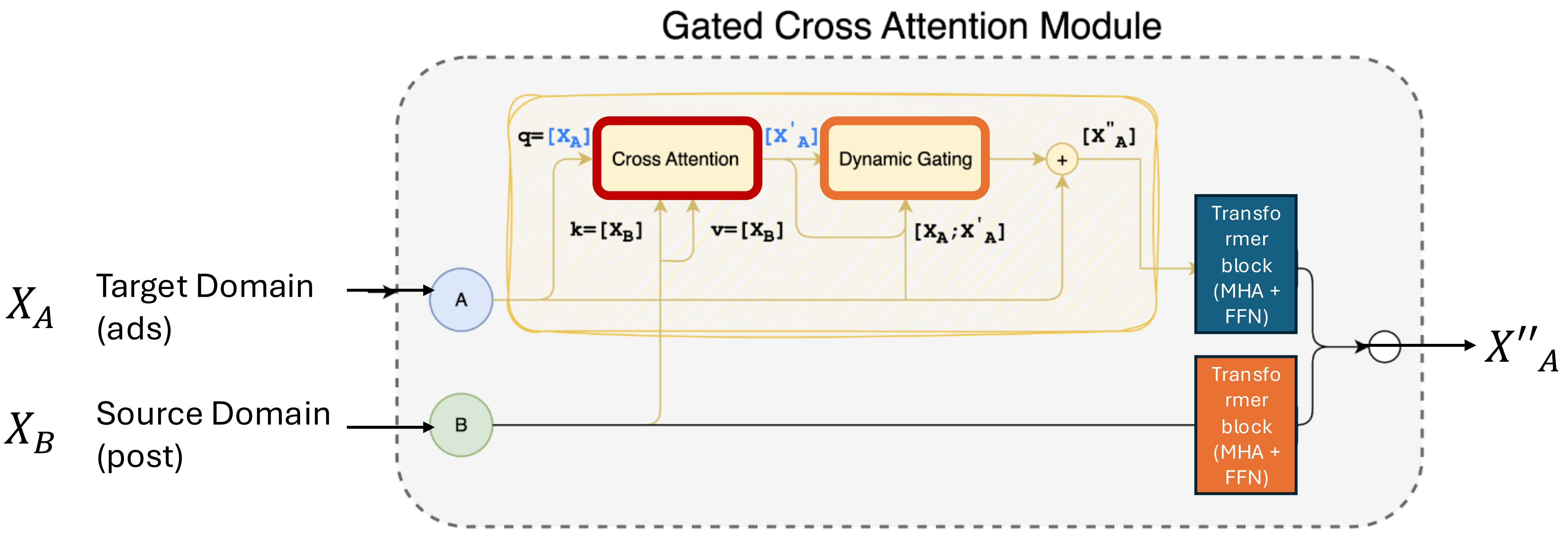


Observation:

Early cross-sequence interactions improve performance

2. Research Question 1

2.3. Gated Cross Attention module



$$X'_A = \mathrm{CrossAttention}(q = X_A,\ k = X_B,\ v = X_B)$$

$$X''_A = X_A + \underbrace{\mathrm{DyanmicGating}([X_A; X'_A])}\odot X'_A$$

Soft update : Feed Forward Network. Gating depends on input.

2. Research Question 1

2.4. Experiment setting

- Baselines : CDSRNP, ABXI, LLM4CDSR
  - On top of baselines, we use Gated Cross Attention (GCA); that is skip connection: $X + \alpha X'$.
- Dataset: Four pairs from Amazon dataset (ex. Beauty-Electronic)

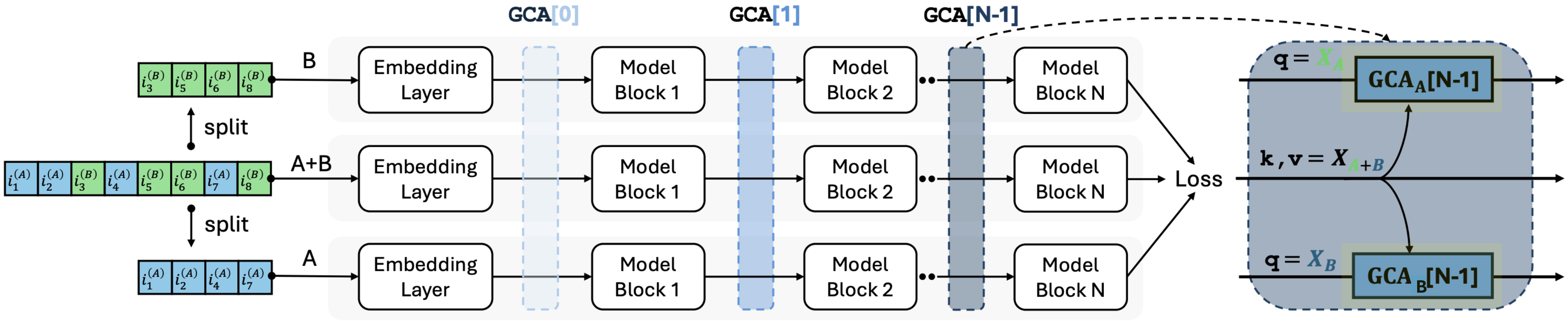


Figure 3 For each baseline model, we insert GCA modules at multiple vertical positions, denoted as $\texttt{GCA}[i]$, where $i = 0$ corresponds to the module closest to the raw data and $i = N$ to the module farthest from the raw data. By design, $\texttt{GCA}[0]$ is always placed immediately after the embedding layer, while $\texttt{GCA}[1], \texttt{GCA}[2], \ldots$ are positioned within intermediate layers of the backbone. Each $\texttt{GCA}[i]$ comprises two parallel gated cross-attention modules, which respectively refine the representations of domains A and B.

2. Research Question 1

2.5. Observation 1

- GCA at the early stage consistently improves performance, but vertical stacking is not scalable.

GCA[0]

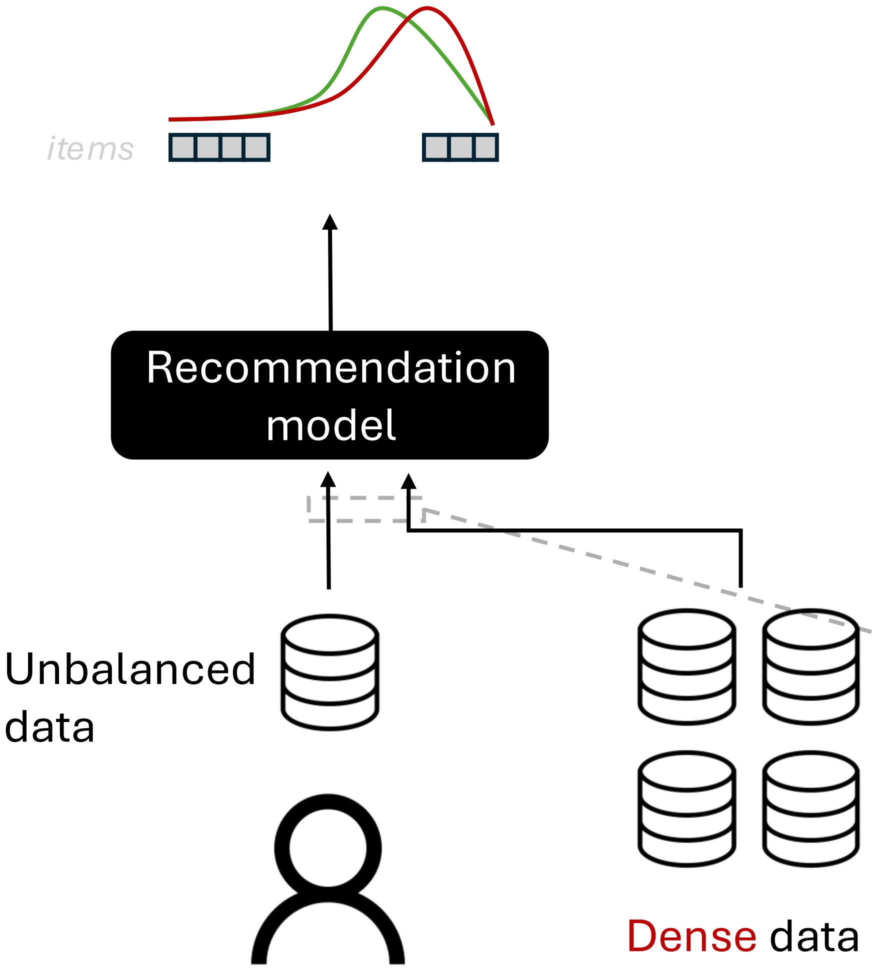
GCA[0,1] or GCA[0,2],..

Model	Dataset (A-B)	$NDCG@1_A$	$NDCG@10_A$	$NDCG@1_B$	$NDCG@10_B$	AUC_A	AUC_B
LLM4CDSR	Cloth-Sport	$0.7157_{\pm 0.0025}$	$0.7821_{\pm 0.0018}$	0.5870 ± 0.0051	0.6493 ± 0.002	0.9216 ± 0.0013	0.8621 ± 0.0054
+ $\texttt{GCA}_{\text{early}}$		0.7283 ± 0.0027	$0.8052_{\pm 0.0014}$	0.5977 ± 0.0054	0.6560 ± 0.0046	0.9364 ± 0.0009	0.8655 ± 0.0038
+ $\texttt{GCA}_{\text{stack}}$		0.7310 ± 0.0012	$0.8056_{\pm 0.0014}$	0.6112 ± 0.0032	0.6638 ± 0.0038	0.9370 ± 0.0010	0.8664 ± 0.0030
LLM4CDSR	Elec-Phone	$0.2101_{\pm 0.0030}$	$0.3512_{\pm 0.0009}$	0.1419 ± 0.0008	0.2608 ± 0.0010	0.7901 ± 0.0008	0.7197 ± 0.0011
+ $\texttt{GCA}_{\text{early}}$		0.2378 ± 0.0011	$0.3815_{\pm 0.0018}$	0.1861 ± 0.0035	0.2845 ± 0.0027	0.7970 ± 0.0018	0.7218 ± 0.0026
+ $\texttt{GCA}_{\text{stack}}$		0.2410 ± 0.0012	$0.3800_{\pm 0.0011}$	0.1994 ± 0.0054	0.3035 ± 0.0049	0.7937 ± 0.0013	0.7252 ± 0.0026
ABXI	Beauty-Elec	$0.0730_{\pm 0.0070}$	$0.1724_{\pm 0.0071}$	0.0548 ± 0.0038	0.1273 ± 0.0028	0.7216 ± 0.0027	0.7123 ± 0.0009
+ $\texttt{GCA}_{\text{early}}$		0.0727 ± 0.0060	$0.1793_{\pm 0.0047}$	0.0544 ± 0.0044	0.1244 ± 0.0025	0.7410 ± 0.0025	0.7169 ± 0.0024
+ $\texttt{GCA}_{\text{stack}}$		0.0733 ± 0.0042	$0.1846_{\pm 0.0057}$	0.0566 ± 0.0052	0.1271 ± 0.0042	0.7354 ± 0.0048	0.6973 ± 0.0051
ABXI	Food-Kitch	$0.0593_{\pm 0.0074}$	$0.1541_{\pm 0.0130}$	0.0416 ± 0.0058	0.1093 ± 0.0113	0.7205 ± 0.0015	0.7180 ± 0.0032
+ $\texttt{GCA}_{\text{early}}$		0.0703 ± 0.0094	$0.1757_{\pm 0.0092}$	0.0548 ± 0.0053	0.1327 ± 0.0072	0.7317 ± 0.0039	0.7150 ± 0.0031
+ $\texttt{GCA}_{\text{stack}}$		0.0882 ± 0.0052	$0.1853_{\pm 0.0013}$	0.0527 ± 0.0020	0.1282 ± 0.0028	0.7148 ± 0.0026	0.6924 ± 0.0009
CDSRNP	Elec-Phone (1M)	0.0499 ± 0.0087	$0.1170_{\pm 0.0079}$	0.0920 ± 0.0050	0.1935 ± 0.0021	-	-
+ $\texttt{GCA}_{\text{early}}$		0.0547 ± 0.0010	0.1209 ± 0.0092	0.0980 ± 0.0010	0.1989 ± 0.0031	-	-
+ $\texttt{GCA}_{\text{stack}}$		0.0531 ± 0.0078	$0.1229_{\pm 0.0125}$	0.0946 ± 0.0022	0.1942 ± 0.0012	-	-

Table 1 NCDG and AUC comparison with the three baselines and adhoc model with GCA. Elec stands for Electronic, and Kitch stands for Kitchen. $\texttt{GCA}_{\text{early}}$ denotes $\texttt{GCA}[0]$ and $\texttt{GCA}_{\text{stack}}$ denotes $\texttt{GCA}[0, i_1, i_2, .., i_N]$ where $i_n > 1, n \in [N]$

3. Research Question 2 (Main)

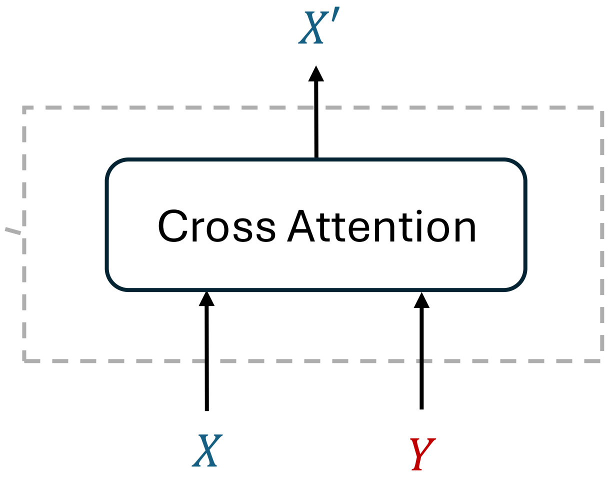
3.1. Research Question 2



So far:
Gated Cross Attention at the early stage can improve performance

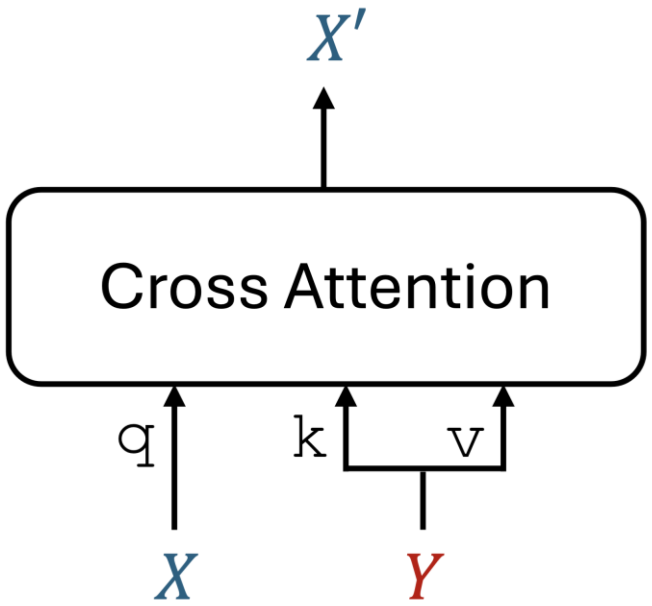
Research Question2:
Why gated cross attention improve the performance?

Observation:
As training goes by, $\cos(X, X')$ goes to zero.



3. Research Question 2 (Main)

3.2. Previous literature: conventional understanding on cross-attention as residual Alignment



Residual Alignment:

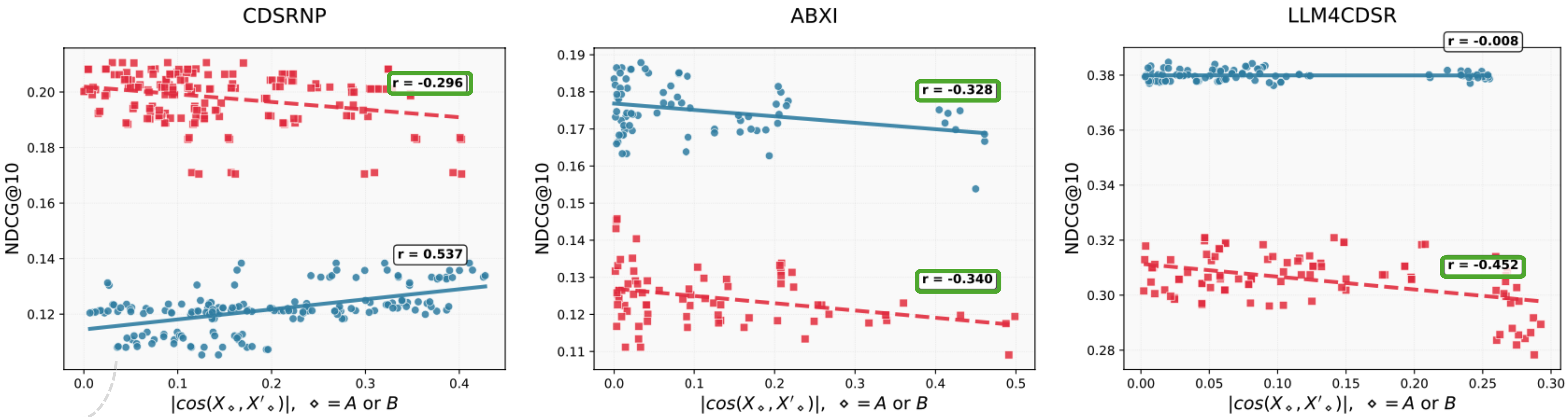
- X' is generated by removing redundant information from X and preserving nonredundant information from X by referring to Y.

  - X : User likes to visit Milan, Italy
  - Y : User bought lots of sports players' uniforms
  - X' : User may likes to buy AC Millan's uniforms

3. Research Question 2 (Main)

3.3. Observation 2 (Supports main message 1)

- We observe negative correlation between $\cos(X, X')$ and model performance regardless of dataset and baseline.

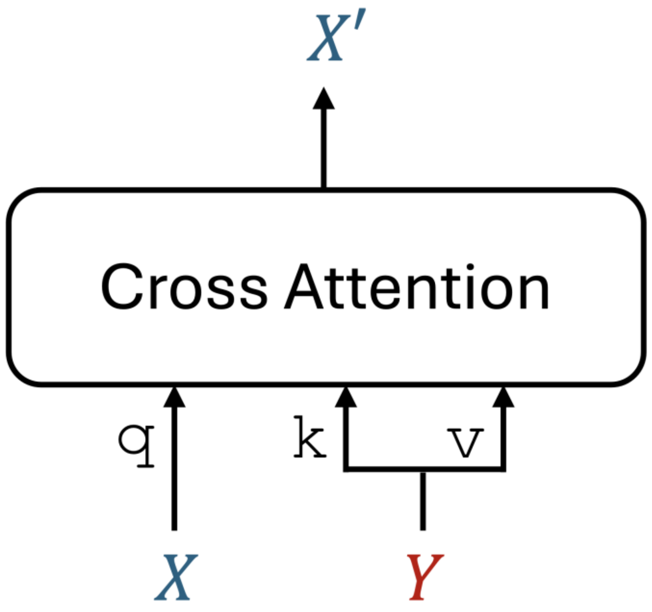


(a) CDSRNP (b) ABXI (c) LLM4CDSR

Vertical Stacking: {GCA[0], GCA[0,1], GCA[0,2],...}
Dataset : {Cloth-sports, Elec-phone, ..}
Hidden dimension: {64, 128, ...}
Num of attention heads: {4, 8, ...}

3. Research Question 2 (Main)

3.4. Main Message 1



Main Message 1

Orthogonal Alignment:

A phenomenon such that as X' and X getting orthogonal, then the model performance increases

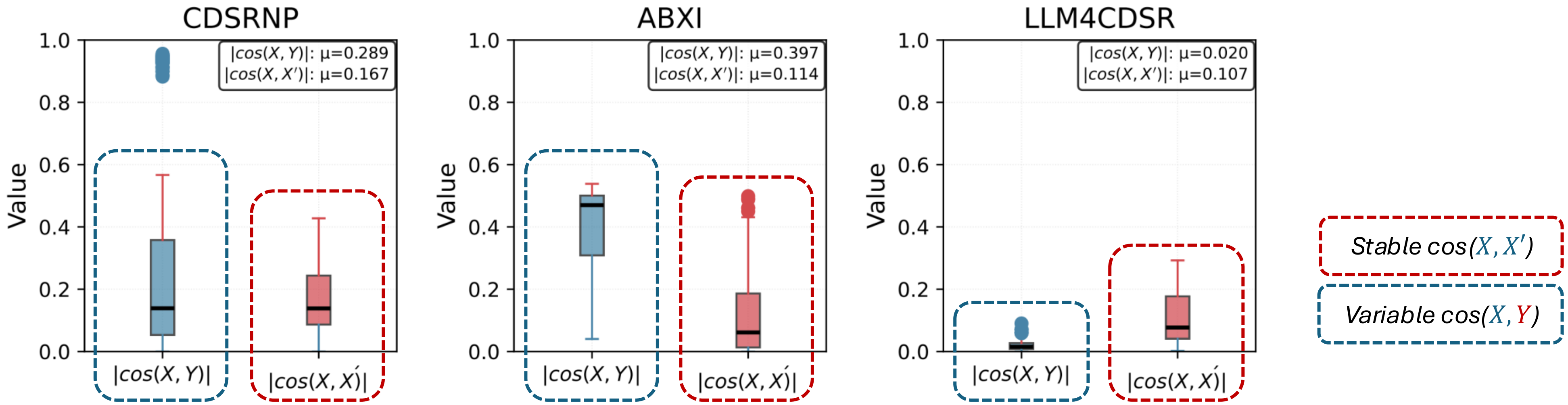
- X' can be trained to contrain information irrelevant to X by referring to Y.

  - X : User likes to visit Milan, Italy
  - Y : User bought lots of sports players' uniforms
  - X' : User may likes to visit Mancherster, England

3. Research Question 2 (Main)

3.5. Observation 3 (Supports main message 1)

- GCA induces orthogonalization independently of how similar X and Y happens to be.

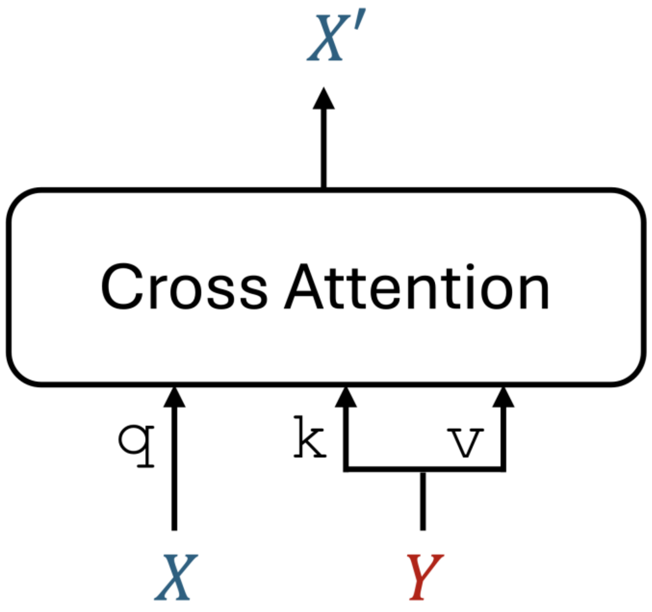


(a) CDSRNP **(b)** ABXI **(c)** LLM4CDSR

Figure 8 Boxplots of cosine similarities $|\cos(X, Y)|$ and $|\cos(X, X')|$. While $|\cos(X, X')|$ remains stable across models (median $\approx\in [0.1, 0.2]$), $|\cos(X, Y)|$ varies substantially depending on the dataset, highlighting that `GCA` induces a consistent degree of orthogonalization regardless of underlying X(query)–Y(key,value) similarity. μ represents a median.

3. Research Question 2 (Main)

3.6. Main Message 2



So far

Orthogonal Alignment:

A phenomenon such that as X' and X getting orthogonal, then the model performance increases

Main Message 2

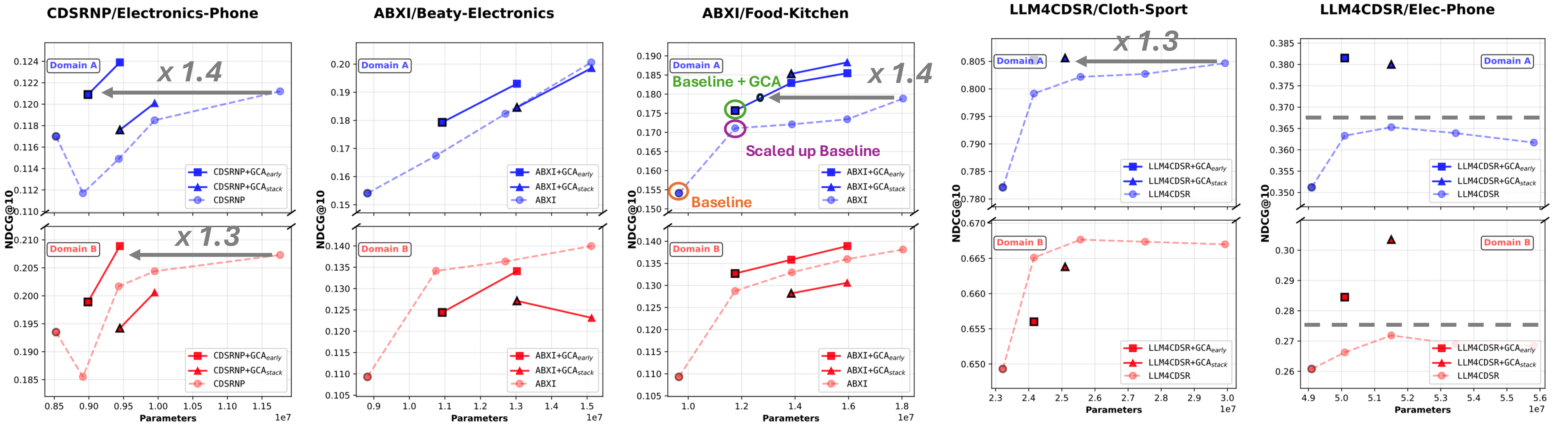
Orthogonal Alignment ***emerges naturally***, since it improves scaling law

- High level : As an perspective of model, feeding $X + \alpha X'$ where $X' \perp X$ is better quality signal than X' as denoised X .

3. Research Question 2 (Main)

3.7. Observation 4 (Supports main message 2)

- Ex: Scaled up Baseline (3M) vs. Baseline (2M) + GCA (1M)
- Orthogonal Alignment provides ~ *x1.4* parameter efficient scaling up.



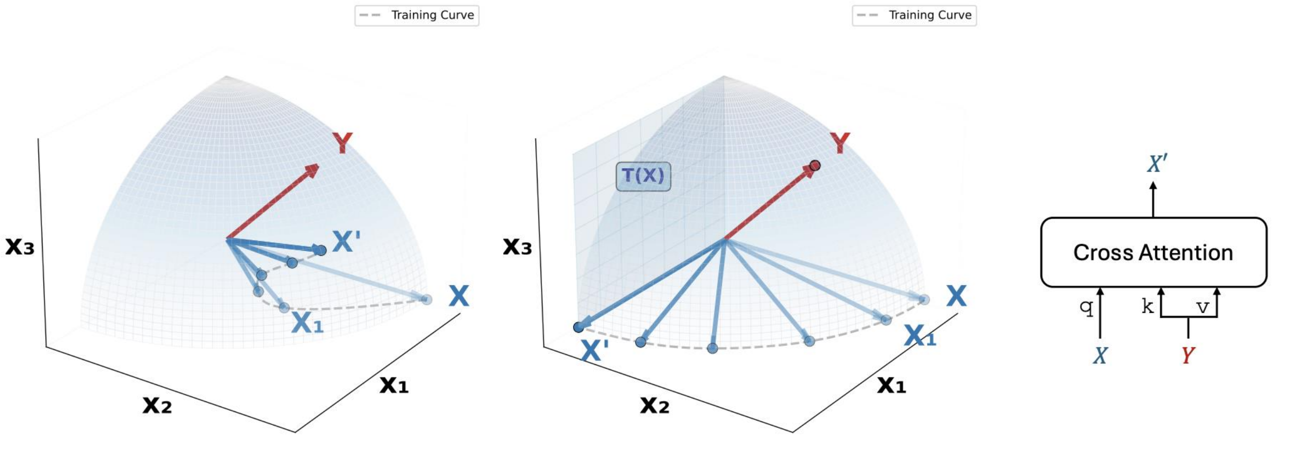
(a) CDSRNP (b) ABXI (Beaty-Elec) (c) ABXI (Food-Kitch) (d) LLM4CDSR (Cloth-Sports) (e) LLM4CDSR (Elec-Phone)

Summary

Motivation: In recommendation models, learning a universal user preference from different modality user behavior data due to some sparse interaction data.

Research Question: Cross-attention is widely used mechanism to fuse different modality data, but it’s inner mechanism is poorly understood.

Main Message:
1. Orthogonal Alignment: If input (X) and output (X’) of cross-attention is getting orthogonal, then performance increases
2. Orthogonal alignment naturally happens since it improves the scaling law.



(a) Residual alignment (b) Orthogonal alignment (c) Cross-attention