Mutual Information Learning for CTR Prediction (Supplementary Material)

1 PROOF OF THE INFORMATION FEATURE SELECTION EMBEDDING LAYER

THEOREM 1.1. Under the CTRLID assumption of orders k_1 and k_2 , the high-order conditional mutual information is equivalent to:

$$I(X_m; L|S) = \frac{1}{\binom{2}{k_1}\binom{|S|}{k_2}} \sum_{\substack{L_{k_1}^i \in L_{k_1} \ S_{k_2}^j \in S_{k_2}}} \sum_{\substack{I(X_m; L_{k_1}^i | S_{k_2}^j) + \sum_{l_t \in L - L_{k_1}^i} I(X_m; l_t | L_{k_1}^i, S_{k_2}^j)}$$
(1)

Proof. First, we have the CTRLID assumption:

$$p(L|X_{m},S) = \prod_{\substack{L_{k_{1}}^{i} \in L_{k_{1}} S_{k_{2}}^{j} \in S_{k_{2}}}} \left[p(L_{k_{1}}^{i}|X_{m}, S_{k_{2}}^{j}) \right]$$

$$= \prod_{\substack{l_{t} \in L - L_{k_{1}}^{i} \\ L_{k_{1}} \in L_{k_{1}} S_{k_{2}}^{j} \in S_{k_{2}}}} \left[p(L_{k_{1}}^{i}|X_{m}, S_{k_{2}}^{j}) \right]$$

$$= \prod_{\substack{L_{k_{1}}^{i} \in L_{k_{1}} S_{k_{2}}^{j} \in S_{k_{2}}}} \left[p(L_{k_{1}}^{i}|X_{m}, S_{k_{2}}^{j}) \right]$$

$$= \prod_{\substack{L_{t} \in L - L_{t}^{i} \\ L_{t} \in L_{t} = L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i}) \right]$$

$$= \prod_{\substack{L_{t} \in L_{t} \in L_{t}^{i} \\ L_{t} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t} \in L_{t}^{i} \\ L_{t} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \\ L_{t} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \\ L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \\ L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \\ L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \\ L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \\ L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \\ L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \\ L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{j}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \\ L_{t}^{i} \in L_{t}^{i}}}} p(l_{t}|X_{m}, S_{k_{2}}^{i}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{i}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, S_{k_{2}}^{i}, L_{k_{1}}^{i})$$

$$= \prod_{\substack{L_{t} \in L_{t}^{i} \in L_{t}^{i} \in L_{t}^{i}}} p(l_{t}|X_{m}, L_{t}^{i})$$

$$= \prod_{\substack$$

Now, we can express the mutual information as follows:

$$I(X_m; L|S) = \frac{1}{\binom{2}{k_1}\binom{|S|}{k_2}} \sum_{\substack{L_{k_1}^i \in L_{k_1} \\ S_{k_2}^j \in S_{k_2}}} \sum_{H(l_t|X_m, S_{k_2}^j) + \sum_{l_t \in L - L_i^{k_1}} H(l_t|X_m, L_{k_1}^i, S_{k_2}^j)}$$
(5)

According to the definition of conditional mutual information in Formula 5 we have:

$$H(L_{\mathbf{k}_{1}}^{i}|X_{m},S_{\mathbf{k}_{2}}^{j})=H(L_{\mathbf{k}_{1}}^{i}|S_{\mathbf{k}_{2}}^{j})-I(X_{m};L_{\mathbf{k}_{1}}^{i}|S_{\mathbf{k}_{2}}^{j}) \tag{6}$$

$$H(l_t|X_m, L_{k_1}^i, S_{k_2}^j) = H(l_t|L_{k_1}^i, S_{k_2}^j) - I(X_m; l_t|L_{k_1}^i, S_{k_2}^j)$$
(7)

Let $\theta_1 = H(L_{\mathbf{k}_1}^i | S_{\mathbf{k}_2}^j)$ and $\theta_2 = H(l_t | L_{\mathbf{k}_1}^i, S_{\mathbf{k}_2}^j)$, which are two constants. Thus,

$$I(X_{m};L|S) = H(L|S) - H(L|X_{m},S)$$

$$= H(L|S) - \frac{1}{\binom{2}{k_{1}}\binom{|S|}{k_{2}}} \sum_{L_{k_{1}}^{i} \in L_{k_{1}}} \sum_{S_{k_{2}}^{i} \in S_{k_{2}}} \left\{ H(L_{k_{1}}^{i}|X_{m}, S_{k_{2}}^{j}) + \sum_{l_{t} \in L - L_{k_{1}}^{i}} H(l_{t}|X_{m}, L_{k_{1}}^{i}, S_{k_{2}}^{j}) \right\}$$
(8)
$$= H(L|S) - \frac{1}{\binom{2}{k_{1}}\binom{|S|}{k_{2}}} \sum_{L_{k_{1}}^{i} \in L_{k_{1}}} \sum_{S_{k_{2}}^{j} \in S_{k_{2}}} \left\{ \theta_{1} - I(X_{m}; L_{k_{1}}^{i}|S_{k_{2}}^{j}) + \sum_{l_{t} \in L - L_{k_{1}}^{i}} (\theta_{2} - I(X_{m}; l_{t}|L_{k_{1}}^{i}, S_{k_{2}}^{j})) \right\}$$
(9)
$$= \frac{1}{\binom{2}{k_{1}}\binom{|S|}{k_{2}}} \sum_{L_{k_{1}}^{i} \in L_{k_{1}}} \sum_{S_{k_{2}}^{j} \in S_{k_{2}}} \left\{ I(X_{m}; L_{k_{1}}^{i}|S_{k_{2}}^{j}) + \sum_{l_{t} \in L - L_{k_{1}}^{i}} I(X_{m}; l_{t}|L_{k_{1}}^{i}, S_{k_{2}}^{j}) \right\}$$

$$+ H(L|S) - \theta_{1} - \theta_{2}$$
(10)
$$\propto \frac{1}{\binom{2}{k_{1}}\binom{|S|}{k_{2}}} \sum_{L_{k_{1}}^{i} \in L_{k_{1}}} \sum_{S_{k_{2}}^{j} \in S_{k_{2}}} \left\{ I(X_{m}; L_{k_{1}}^{i}|S_{k_{2}}^{j}) + \sum_{l_{t} \in L - L_{k_{1}}^{i}} I(X_{m}; l_{t}|L_{k_{1}}^{i}, S_{k_{2}}^{j}) \right\}$$
(11)

where $\theta_1 - \theta_2$ is a constant.

THEOREM 1.2. Under the CCTRFD assumption of orders k_1 and k_2 , the high-order conditional mutual information is equivalent to:

$$I(X_m; L|S) = \frac{1}{\binom{2}{k_1}\binom{|S|}{k_2}} \sum_{\substack{L_{k_1}^i \in L_{k_1} \\ k_2}} \sum_{S_{k_2}^j \in S_{k_2}} \{I(X_m; L_{k_1}^i, S_{k_2}^j)\}$$
(12)
$$-\frac{1}{\binom{|S|}{k_2}} \sum_{S_{k_2}^j \in S_{k_2}} I(X_m; S_{k_2}^j)$$
(13)

Proof. According to the definition, we have:

$$p(X_m|L,S) = \prod_{L_{k_1}^i \in L_{k_1}} \prod_{S_{k_2}^j \in S_{k_2}} \left[p(X_m|L_{k_1}^i, S_{k_2}^j) \right]^{\frac{1}{\binom{2}{k_1} \cdot \binom{|S|}{k_2}}}$$
(14)

$$p(X_m|S) = \prod_{S_{k_2}^j \in S_{k_2}} [p(X_m|S_{k_2}^j)]^{\frac{1}{\binom{|S|}{k_2}}}$$
 (15)

$$H(X_m|S) = \frac{1}{\binom{|S|}{k_2}} \sum_{S_{k_0}^j \in S_{k_2}} \{ H(X_m|S_{k_2}^j) \}$$
 (16)

$$H(X_m|L,S) = \frac{1}{\binom{2}{k_1}\binom{|S|}{k_2}} \sum_{L_{k_1}^i \in L_{k_1}} \sum_{S_{k_2}^j \in S_{k_2}} \{H(X_m|L_{k_1}^i, S_{k_2}^j)\}$$
(17)

$$\begin{split} I(X_m;L|S) &= H(X_m|S) - H(X_m|L,S) \\ &= \frac{1}{\binom{|S|}{k_2}} \sum_{S_{k_2}^j \in S_{k_2}} \{H(X_m|S_{k_2}^j)\} \\ &- \frac{1}{\binom{2}{k_1}\binom{|S|}{k_2}} \sum_{L_{k_1}^i \in L_{k_1}} \sum_{S_{k_2}^j \in S_{k_2}} \{H(X_m|L_{k_1}^i, S_{k_2}^j)\} \\ &= \frac{1}{|S|_{k_2}} \sum_{S_{k_2}^j \in S_{k_2}} \{H(X_m) - I(X_m; S_{k_2}^j)\} \\ &- \frac{1}{\binom{2}{k_1}\binom{|S|}{k_2}} \sum_{L_{k_1}^i \in L_{k_1}} \sum_{S_{k_2}^j \in S_{k_2}} \{H(X_m) - I(X_m; L_{k_1}^i, S_{k_2})^j\} \\ &= H(X_m) - \frac{1}{\binom{|S|}{k_2}} \sum_{S_{k_2}^j \in S_{k_2}} \{I(X_m; S_{k_2}^j)\} - H(X_m) \\ &+ \frac{1}{\binom{2}{k_1}\binom{|S|}{k_2}} \sum_{L_{k_1}^i \in L_{k_1}} \sum_{S_{k_2}^j \in S_{k_2}} \{I(X_m; L_{k_1}^i, S_{k_2}^j)\} \\ &= \frac{1}{\binom{2}{k_1}\binom{|S|}{k_2}} \sum_{L_{k_1}^i \in L_{k_1}} \sum_{S_{k_2}^j \in S_{k_2}} \{I(X_m; L_{k_1}^i, S_{k_2}^j)\} \\ &- \frac{1}{\binom{|S|}{k_2}} \sum_{S_{k_1}^j \in S_{k_2}} \{I(X_m; S_{k_2}^j)\} \end{split}$$

COROLLARY 1

Under the CCTRFD assumption of order k_1 and k_2 , the high-order conditional mutual information is equivalent to:

$$I(X_m; L|S) = \frac{1}{\binom{2}{k_1} \cdot \binom{|S|}{k_2}} \sum_{\substack{L_{k_1}^i \in L_{k_1} \ S_{k_2}^j \in S_{k_2}}} \{I(X_m; L_{k_1}^i | S_{k_2}^j)\}$$
 (18)

Proof. According to the definition of joint mutual information, we obtain:

$$I(X_m; L_{k_1}^i, S_{k_2}^j) = I(X_m; S_{k_2}^j) + I(X_m; L_{k_1}^i | S_{k_2}^j)$$
 (19)

Then.

$$I(X_m; L|S) = \frac{1}{\binom{2}{k_1} \cdot \binom{|S|}{k_2}} \sum_{\substack{L_{k_1}^i \in L_{k_1} \\ S_{k_2}^j \in S_{k_2}}} \{I(X_m; L_{k_1}^i | S_{k_2}^j)\}$$
 (20)

When $k_1 = 1$, $k_2 = 1$:

$$I(X_m; L|S) = \frac{1}{2 \cdot |S|} \sum_{l_i \in L} \sum_{X_j \in S} \{ I(X_m; l_i | X_j) \}$$
 (21)

COROLLARY 2

Under the CCTRFD assumption of order k_1 and k_2 , the high-order conditional mutual information is equivalent to:

$$I(X_m; L|S) = \frac{1}{\binom{2}{k_1}} \sum_{\substack{L_{k_1}^i \in L_{k_1}}} I(X_m; L_{k_1}^i) + \frac{1}{\binom{2}{k_1} \cdot \binom{|S|}{k_2}} \sum_{\substack{L_i^{k_1} \in L_{k_1} \\ L_i^j \in L_{k_1}}} \sum_{S_j^{k_2} \in S_{k_2}} \{I(X_m; S_{k_2}^j)\}$$
(22)

Proof. According to the definition of joint mutual information, we obtain:

$$I(X_m; L_{k_1}^i, S_{k_2}^j) = I(X_m; L_{k_1}^i) + I(X_m; S_{k_2}^j | L_{k_1}^i)$$
 (23)

Then

$$I(X_m; L|S) = \frac{1}{\binom{2}{k_1}} \sum_{\substack{L_{k_1}^i \in L_{k_1}}} I(X_m; L_{k_1}^i)$$

$$+ \frac{1}{\binom{2}{k_1} \cdot \binom{|S|}{k_2}} \sum_{\substack{L_{k_1}^i \in L_{k_1}}} \sum_{S_{k_2}^j \in S_{k_2}} \{I(X_m; S_{k_2}^j | L_{k_1}^i)\}$$

$$- \frac{1}{\binom{|S|}{k_2}} \sum_{\substack{S_{i_2}^k \in S_{k_2}}} \{I(X_m; S_{k_2}^j)\}$$

$$(24)$$

When $k_1 = 1$, $k_2 = 1$:

$$\begin{split} I(X_m;L|S) &= \frac{1}{2} \sum_{l_i \in L} I(X_m;li) + \frac{1}{2 \cdot |S|} \sum_{l_i \in L} \sum_{X_j \in S} \{I(X_m;X_j|l_i)\} \\ &- \frac{1}{|S|} \sum_{X_i \in S} \{I(X_m;X_j)\} \end{split}$$

REFERENCES