Smooth-AUC: Smoothing the Path Towards Rank-based CTR Prediction (short paper)

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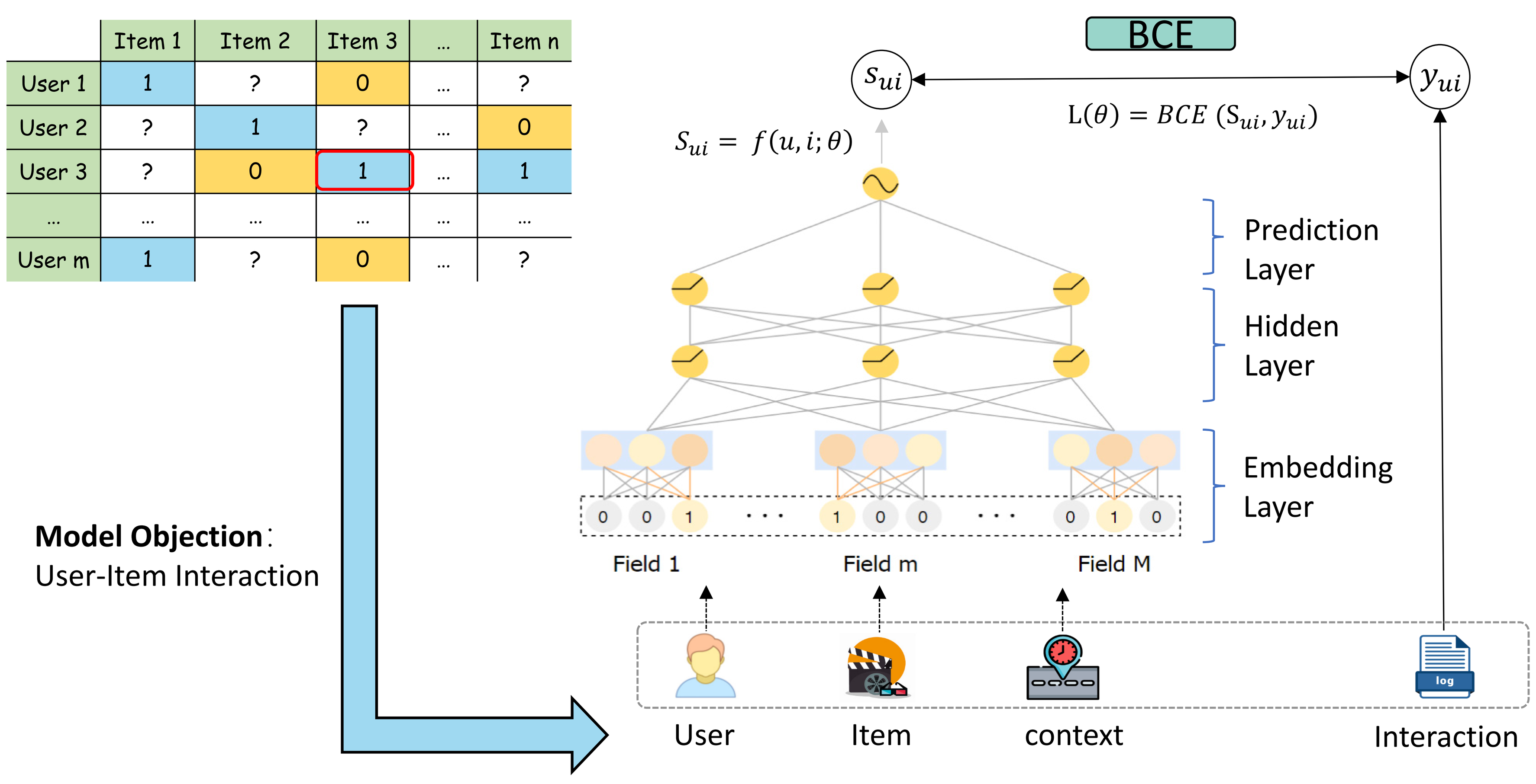
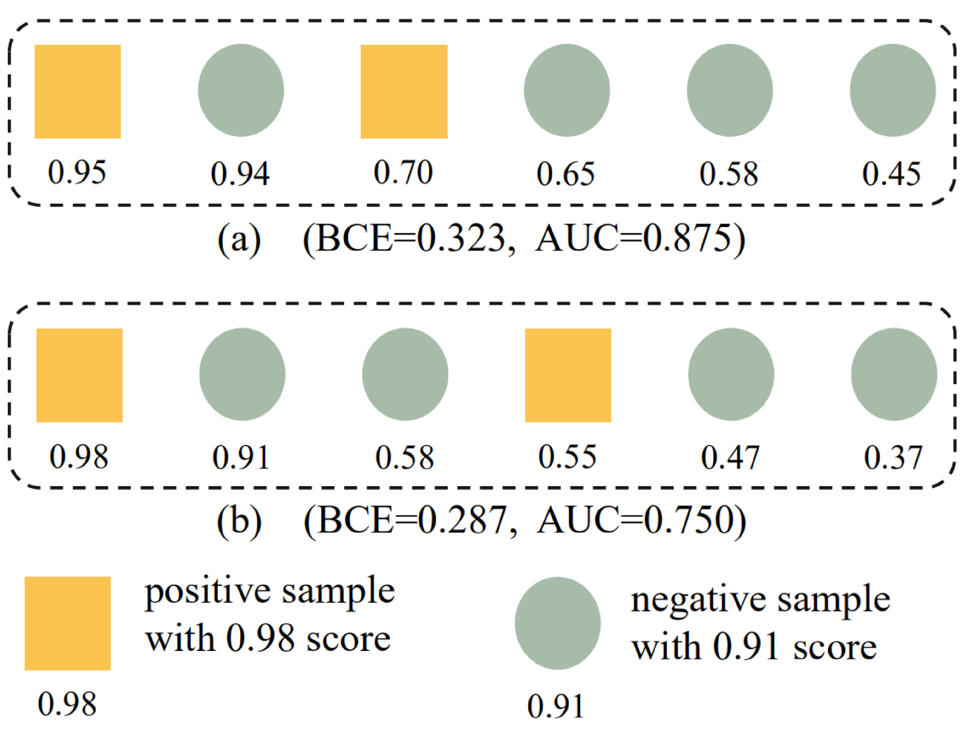
Click-Through Rate Estimation



- ➢Click-through rate (CTR) prediction is a crucial task in many recommendation applications.
- ➢For Most existing DNNs-based CTR models, BCE is the common loss, AUC is the common metric.

Measuring CTR Estimation Performance



- ➢The is an inconsistency between BCE loss and AUC.
- ➢Our Goal – Optimize a smoothed version of the AUC Metric.

$$L_{BCE} = s_{ui}log(y_{ui}) - (1 - s_{ui})log(1 - y_{ui})$$

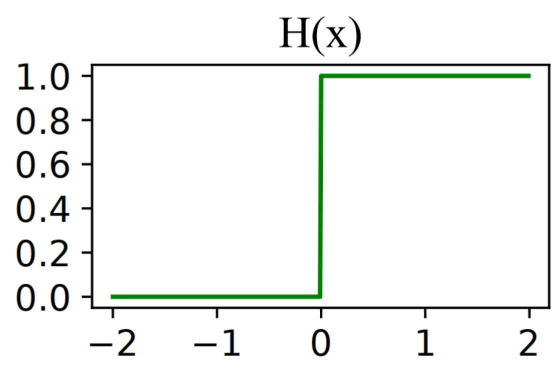
$$AUC(u) = \frac{\sum_{i\in P_u}\sum_{j\in N_u}\mathbb{I}(s_{ui} > s_{uj})}{|Pu| \times |N_u|}$$

s_{ui} and y_{ui}: the preference score and ground truth by user u on item i.
P_u and N_u: the positive and negative items.

Smoothing the Area Under the ROC Curve

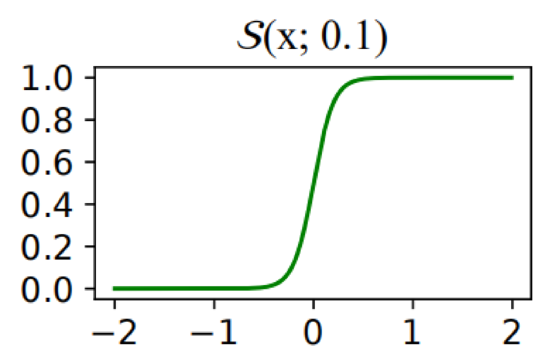
- ➢AUC loss includes a non-differentiable Heaviside function.

$$\mathcal{L}_{AUC} \propto H(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases}$$

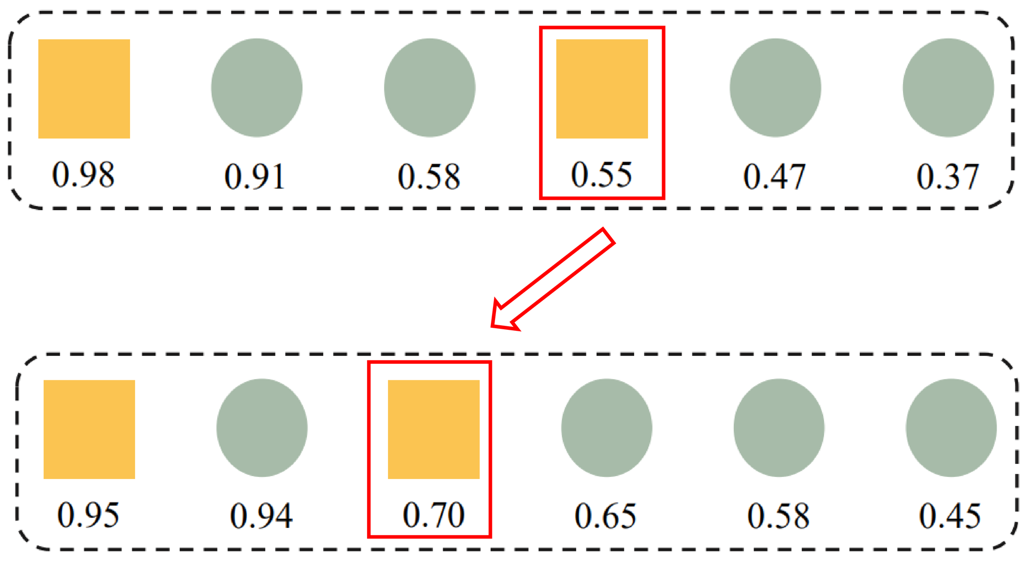


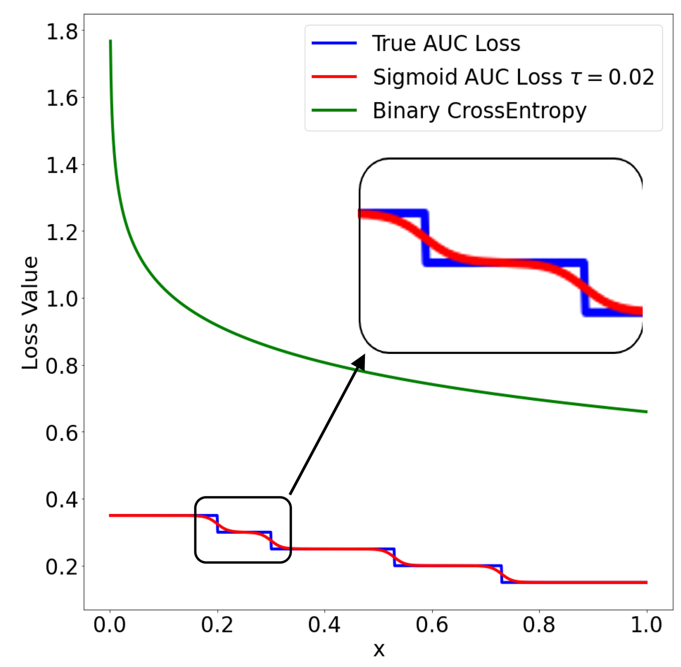
- ➢We replace the Heaviside function by a sigmoid function $\mathcal{S}(x;\tau)$

$$\mathcal{L}_{SAUC} \propto \mathcal{S}(x;\tau) = \frac{1}{1 + e^{-\frac{x}{\tau}}}$$



Smoothing-AUC





- ➢Smooth-AUC optimizes a ranking metric

$$L_{SAUC} = -\frac{1}{|U|}\sum_{u=1}^{|U|}\left[\frac{1}{|Pu| \times |Nu|}\sum_{i=1}^{|Pu|}\sum_{j=1}^{|Nu|}\mathcal{S}(D_{uij};\tau)\right]$$

- ➢Compared with BCE loss, Smooth-AUC loss is closer to true AUC loss
- ➢Smooth-AUC is a plug-and-play objective that can be utilized by any DNNs-based CTR model

Experiments

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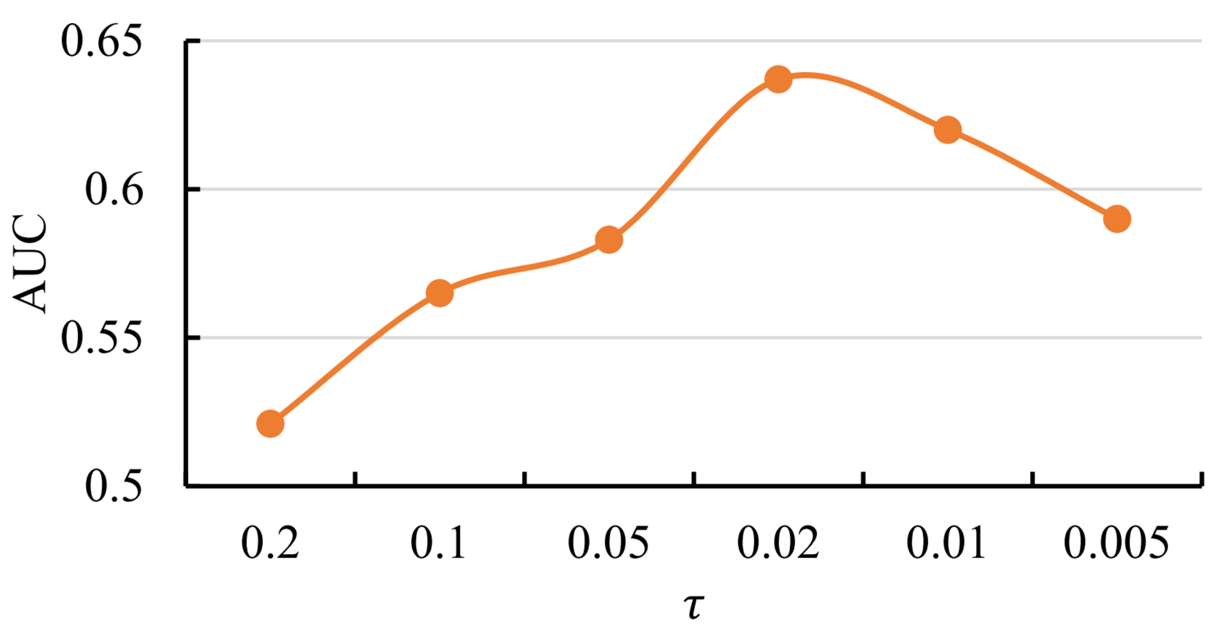
	AUC	MRR	P@10	AUC	MRR	P@10
DeepFM	0.861(+3.60%)	0.248(+36.69%)	0.539(+27.83%)	0.600(+6.17%)	0.076(+42.11%)	0.166 (+14.46%)
DeepFM-BPROPT	0.887(+0.56%)	0.304(+11.51%)	0.623(+10.59%)	0.626(+1.76%)	0.089(+21.35%)	0.177(+7.34%)
* DeepFM-SAUC	**0.892**	**0.339**	**0.689**	**0.637**	**0.108**	**0.190**
FiBiNET	0.875(+1.60%)	0.262(+32.44%)	0.585(+18.12%)	0.621(+2.58%)	0.087(+12.64%)	0.183(+4.92%)
FiBiNET-BPROPT	0.880(+1.02%)	0.316(+9.81%)	0.625(+10.56%)	0.631(+0.95%)	0.093(+5.38%)	0.187(+2.67%)
* FiBiNET-SAUC	**0.889**	**0.347**	**0.691**	**0.637**	**0.098**	**0.192**
ONN	0.877(+1.60%)	0.264(+32.95%)	0.583(+18.35%)	0.621(+2.25%)	0.091(+13.19%)	0.188(+5.85%)
ONN-BPROPT	0.886(+0.56%)	0.334(+5.09%)	0.645(+6.98%)	0.632(+0.47%)	0.095(+8.42%)	0.195(+2.05%)
* ONN-SAUC	**0.891**	**0.351**	**0.690**	**0.635**	**0.103**	**0.199**

* our method

- ➢BPROPT & SAUC> BCE: attributed to the benefit of considering relative order between positive items and negative items.
- ➢SAUC > BPROPT: SAUC not only considers the relative order of item pairs, but also optimizes the metric used for evaluation.
- ➢parameter-sensitive: it would be crucial to keep a trade-off between AUC approximation and an enough non-zero interval.



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