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Neural Auction: End-to-End Learning of Auction Mechanisms for E-Commerce Advertising

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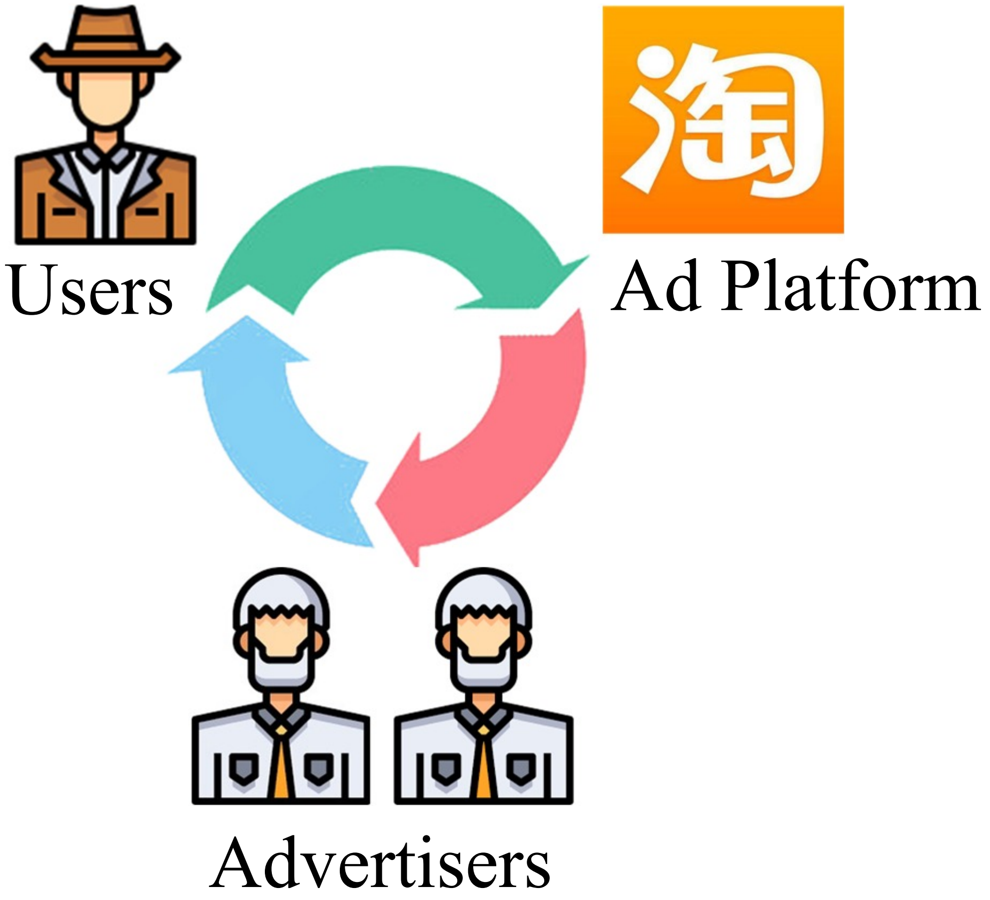
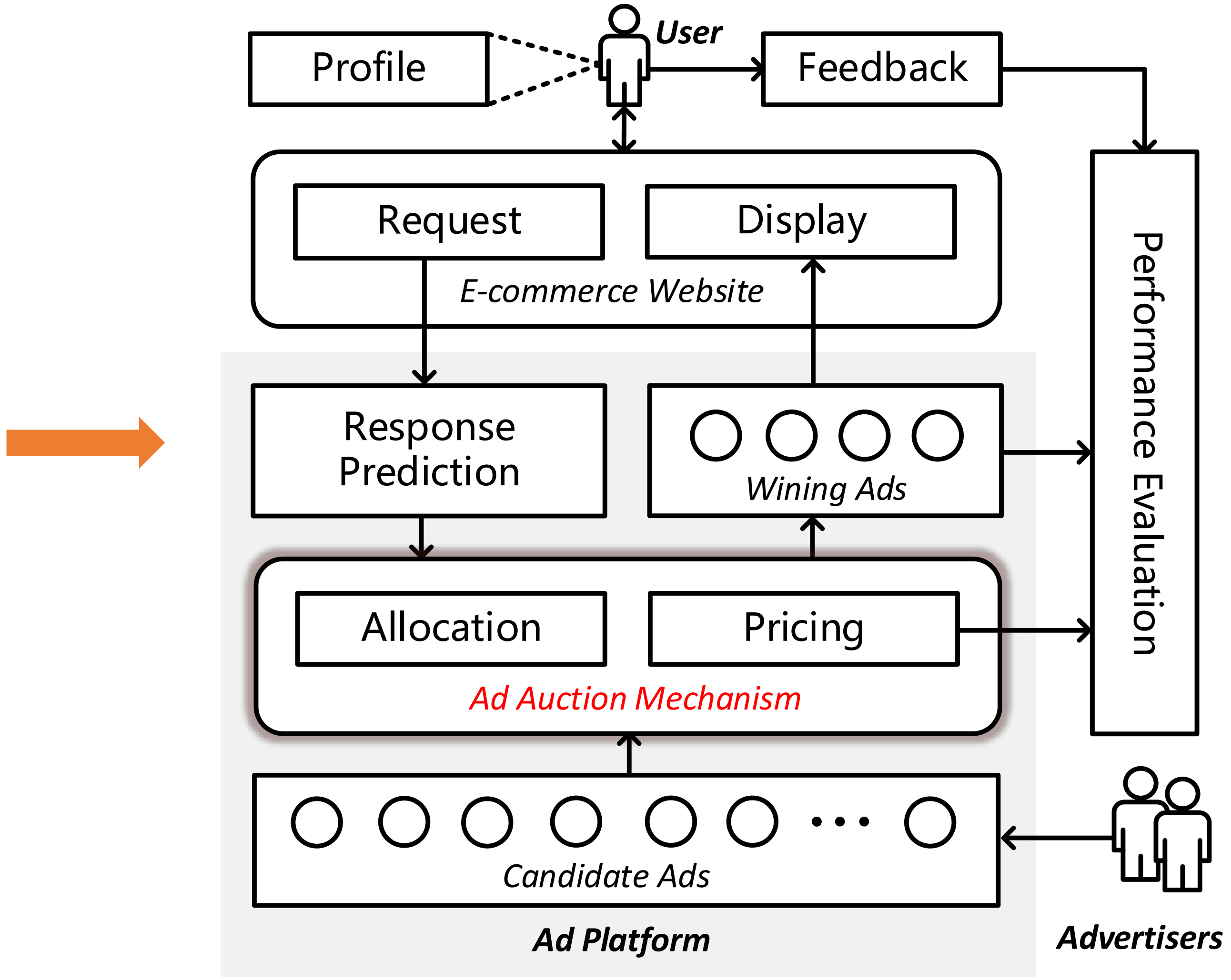
Background

Stakeholders in E-commerce Advertising

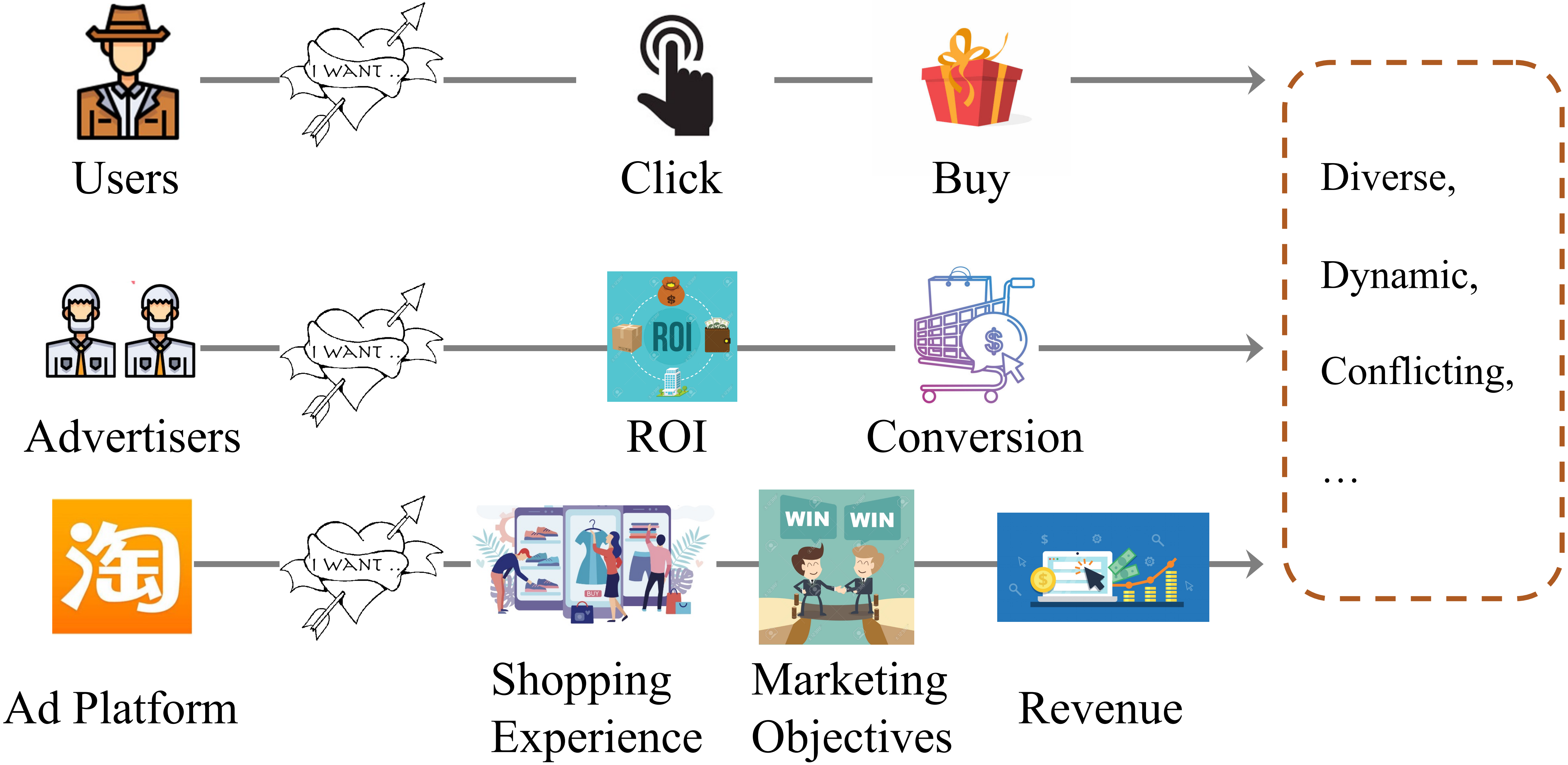


Multiple Stakeholders
in E-commerce Advertising

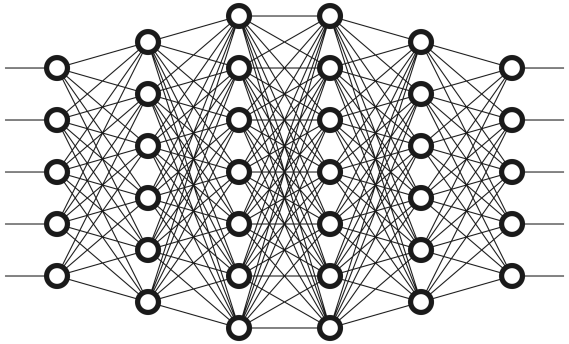


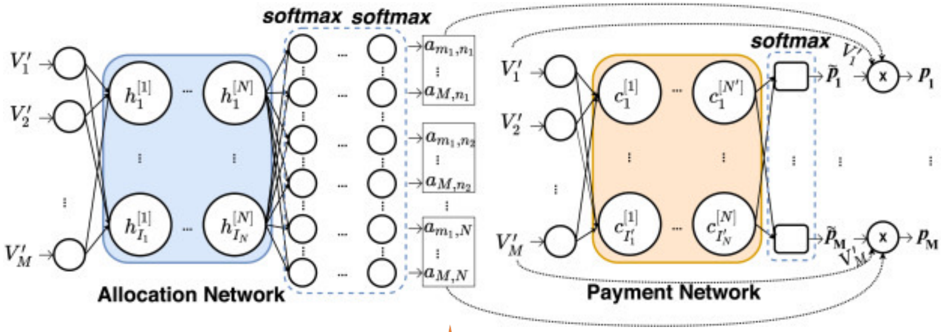
Ad Auction Mechanism

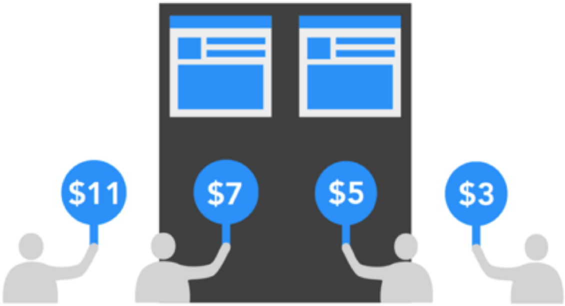
Optimization Objectives



What do we focus on ?







Auction Mechanism

Myerson Auction
Vickrey Auction
Generalized Second-Price Auction
…

Deep Learning

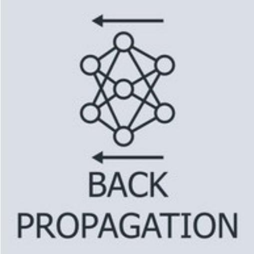
Deep Neural Network

Learning-based Mechanism Design

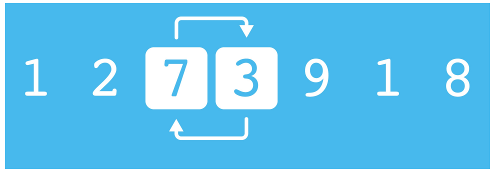
RegretNet [Dütting 19 ICML]
ALGnet [Rahme 21 ICLR]
DeepGSP [Zhang 21 WSDM]
…

Challenges

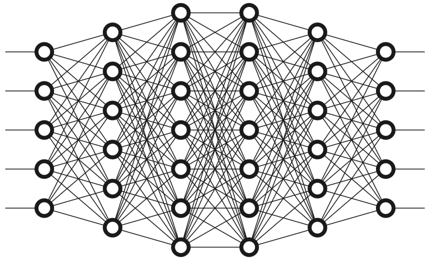
Design Principles



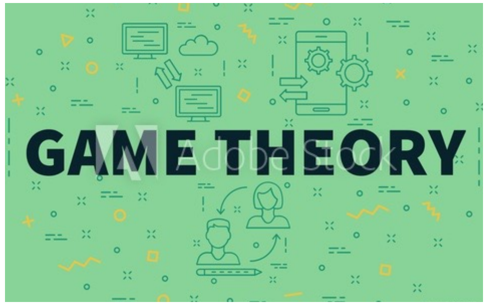
End-to-end Gradient Descent



Discrete Sorting Operation



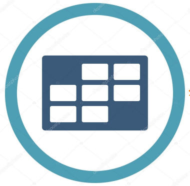
Deep Neural Network



Game Theoretical Properties

Data Efficiency

Advertiser



Data Log

Auction 1

win

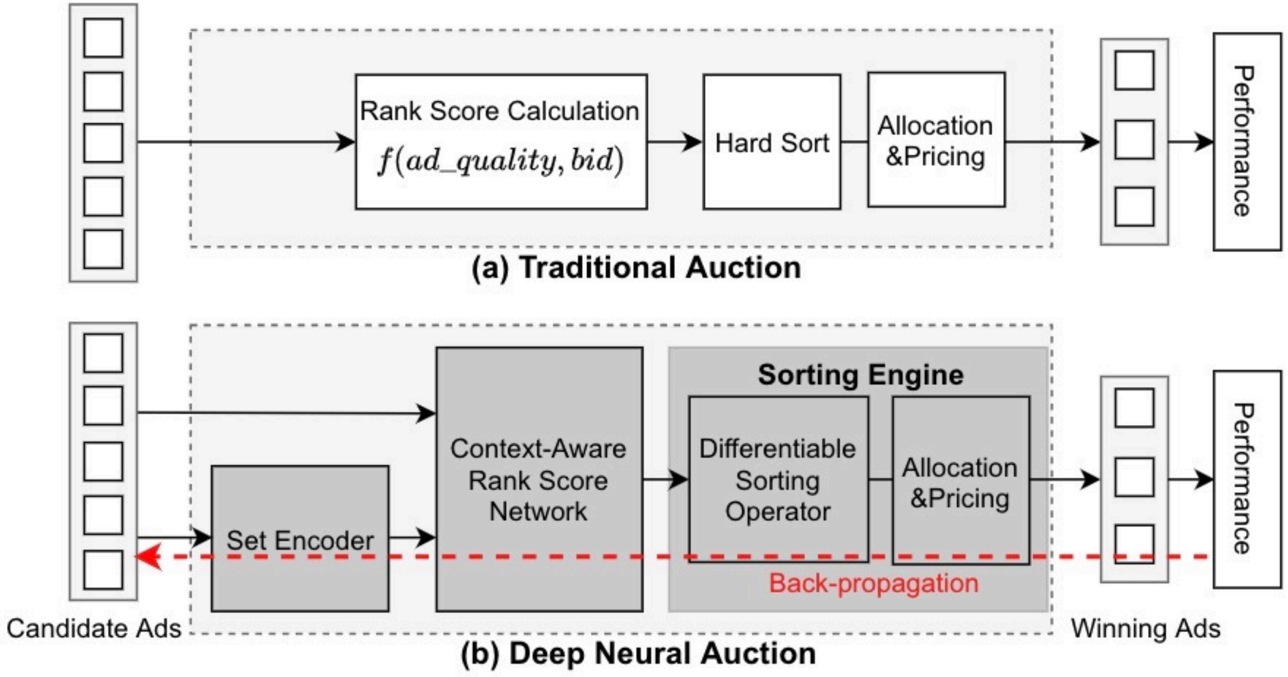
Auction 2

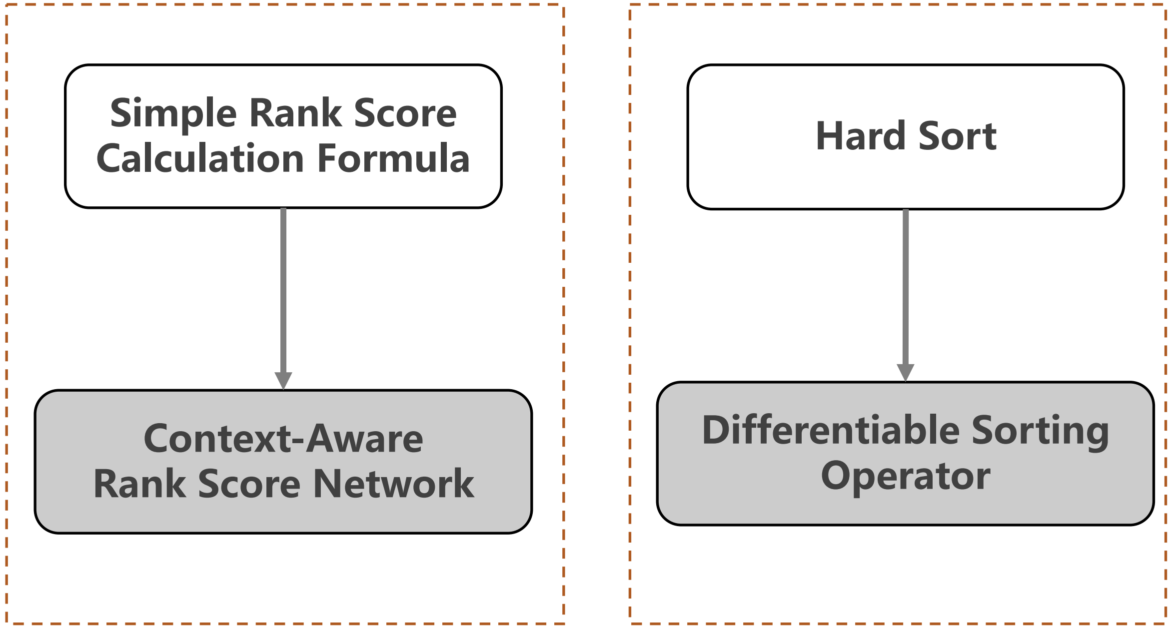
lose

Ambiguity Issue

Our Contribution :

Neural Auction: making full use of the powerful deep learning on designing data-driven auction mechanisms for the industrial e-commerce advertising





Problem Formulation

Formulation:

Multiple performance metrics optimization in the competitive advertising environments

Mechanism: $\mathcal{M}\langle\mathcal{R},\mathcal{P}\rangle$ with allocation $\mathcal{R}$ and pricing $\mathcal{P}$

- $\mathcal{R}$: Select K ads from N candidates
- $\mathcal{P}$: Calculating payment on K wining ads

Goals:

1. Optimizing L performance metrics (RPM, CTR, CVR, GMV, etc.)
2. Desirable mechanism properties: **IC** & **IR**

$$\underset{\mathcal{M}}{\text{maximize}} \quad \mathbb{E}_{\mathbf{b}\sim\mathcal{D}}\left[\sum_{j=1}^{L} w_j \times f_j(\mathbf{b};\mathcal{M})\right]$$

$$\text{s.t.} \quad \textit{Incentive compatibility (IC) constraint,}$$
$$\textit{Individual Rationality (IR) constraint,}$$

Formulation:

- **Second-Price Auctions:**
  - Nice interpretability
  - Easy to deploy in industry
  - The score reflects the degree of ad quality

- **Learning-based Second-Price Auction Framework:**
  - Deep neural network based rank score function: $r_i(b_i)$
  - The training of this non-linear model is under the guideline of optimization objective
- Allocation Scheme $\mathcal{R}$: $r_1(b_1) \geq r_2(b_2) \geq \cdots \geq r_N(b_N)$
- Payment Rule $\mathcal{P}$: $p_i = r_i^{-1}(r_{i+1}(b_{i+1}))$

Economic Properties

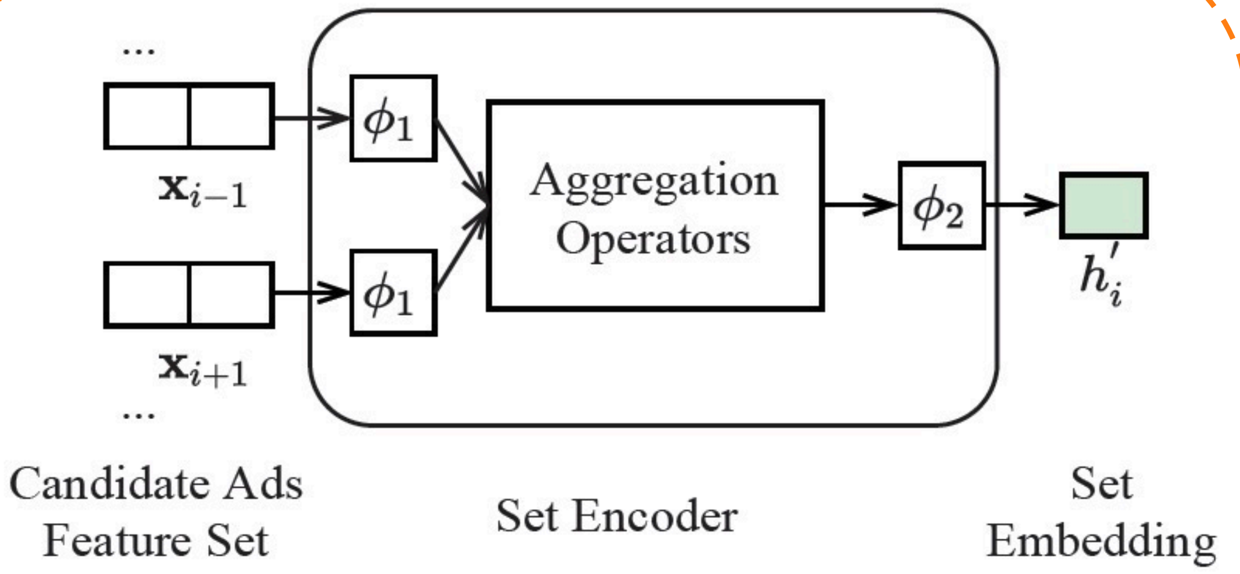
- **Game Theoretical Property of Auction Mechanism**:
  - Incentive Compatibility (**IC**): truthfully report the bid
  - Individual Rationality (**IR**): would not be charged more than their maximum willing-to-pay

- **Value Maximizer**:
  - A value maximizer i optimizes value v_i while keeping payment p_i below her maximum willing-to-pay m_i ; when value is equal, a lower p_i is preferred.
  - "Value maximizer" has been widely adopted in industry, such as Yahoo! and Google.

- **IC & IR conditions for Value Maximizers**:
  - **Monotonicity**: An advertiser would win the same or a higher slot if she reports a higher bid;
  - **Critical price**: The payment for the winning advertiser is the minimum bid that she needs to report to maintain the same slot.

Our Approach: Neural Auction

Neural Auction -- Auction Context Encoding



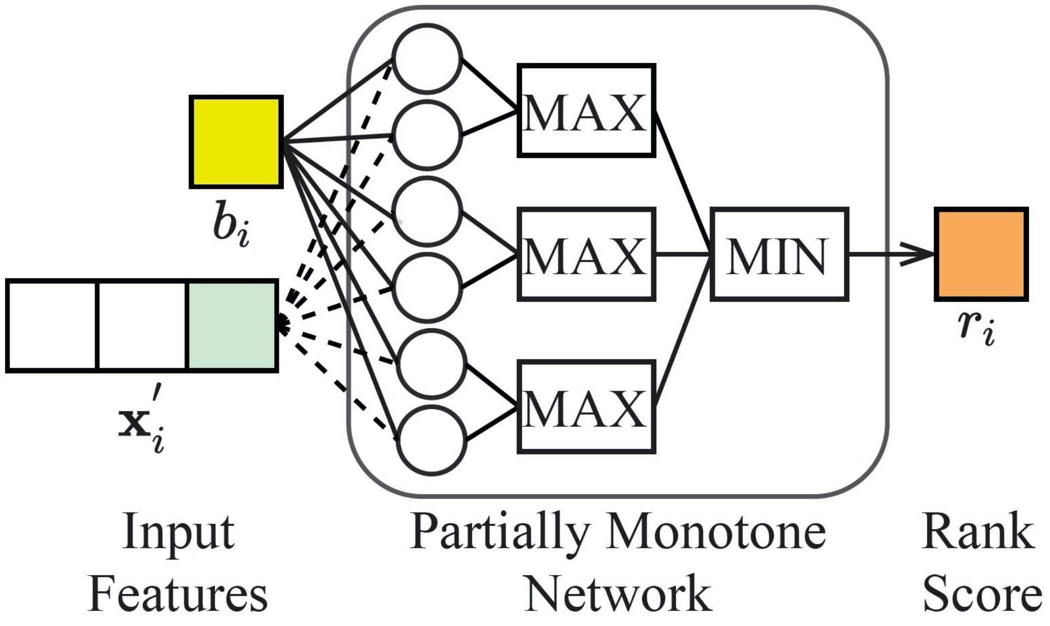
Set Encoder:
Deep Set Architecture

- **Set Encoder:**
  - Automatically extract the feature of the auction context from all the candidate ads via DeepSet [17 Nips].
  - Attached as an augmented feature for each ad to overcome the ambiguity issue.
- **DeepSet Aggregation:**

$$h_i = \sigma(\phi_1(\mathbf{x}_i))$$

$$h_i' = \sigma(\phi_2(\texttt{avgpool}(\mathbf{h}_{-i})))$$

Neural Auction -- Context-Aware Rank Score



Context-Aware Rank Score Function: Partially Monotone MIN-MAX Network

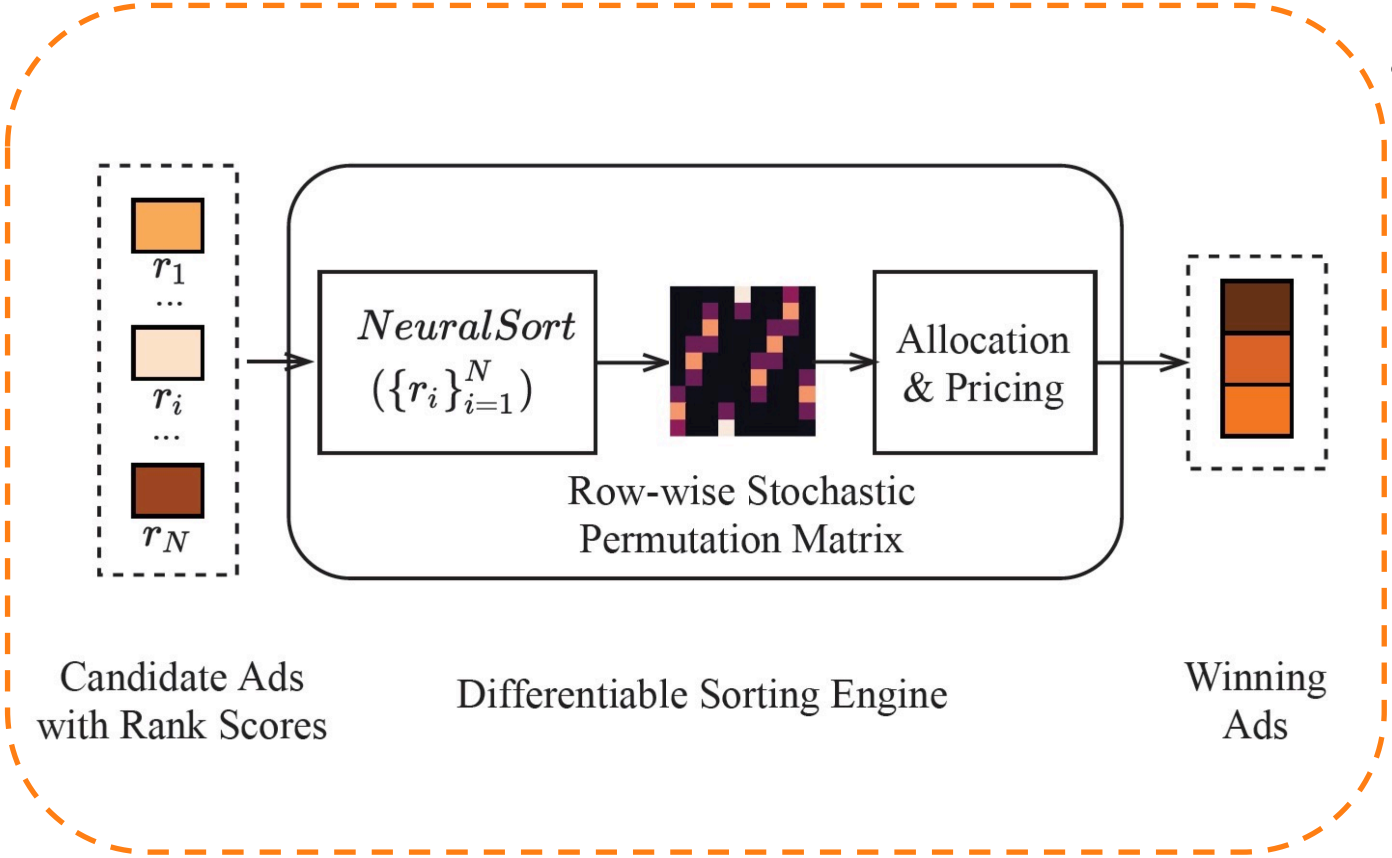
- **Partially Monotone MIN-MAX Network**
  - Strictly non-decreasing on bid
  - The inverse transform can be directly obtained.
- **Rank Score:**

$$r_i = \min_{q \in [Q]} \max_{z \in [Z]} \left(e^{w_{qz}} \times b_i + w'_{qz} \times \mathbf{x}'_i + \alpha_{qz}\right)$$

- **Payment:**

$$p_i = \max_{z \in [Z]} \min_{q \in [Q]} e^{-w_{qz}} \left(r_{i+1} - \alpha_{qz} - w'_{qz} \times \mathbf{x}'_i\right)$$

Neural Auction -- Differentiable Sorting Engine



- **Neural Sort [ICLR19]:**
  - A continuous relaxation to the sorting operator.
  - Enabling gradient-based stochastic optimization over the allocation & pricing results.

$$M_r[k,i] = \begin{cases} 1 & \text{if } i = \texttt{argmax}(c_k), \\ 0 & \text{otherwise}, \end{cases}$$

$$\hat{M}_r[k,:] = \texttt{softmax}\left(\frac{c_k}{\tau}\right),$$

Neural Auction -- Model Training

- **Loss Function:**

$\mathcal{L}_{tgt}$ **: Minimizing the sum of top-K expected negated performance metrics:**

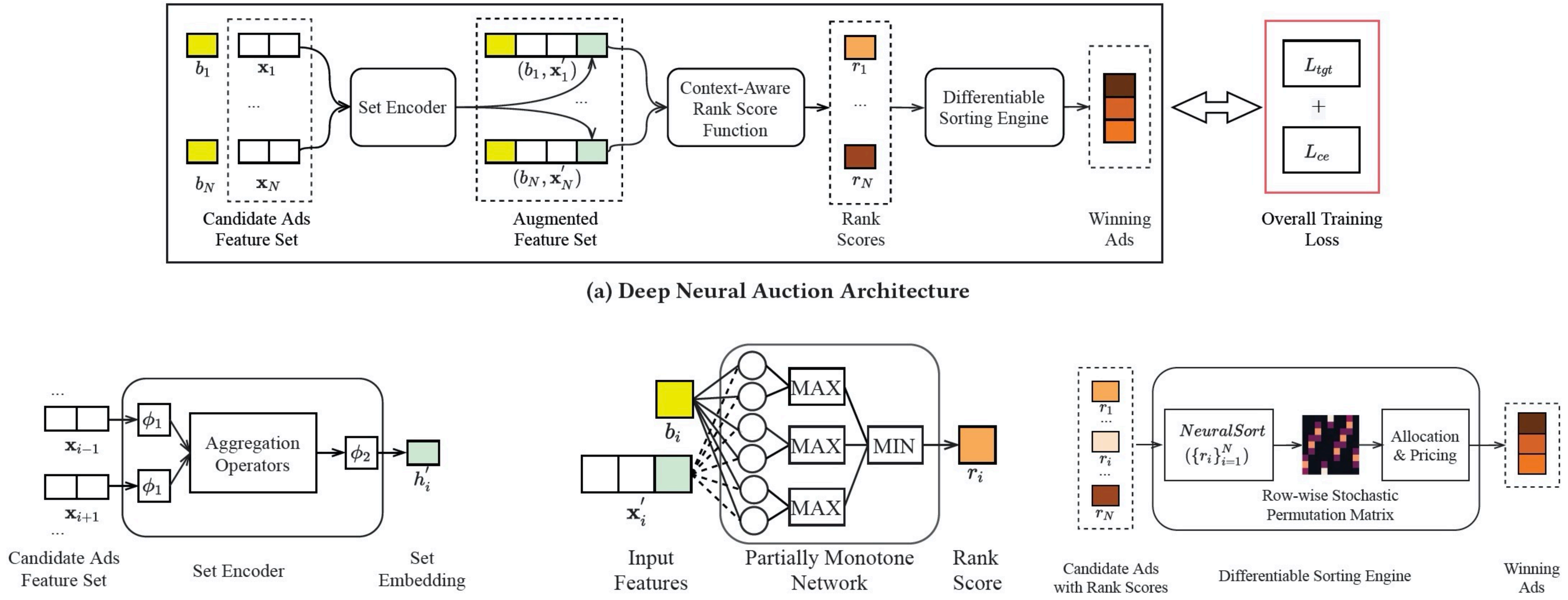
$$\mathcal{L}_{tgt} = -\sum_{i=1}^{K} \boxed{\hat{M}_r}[i,:] \cdot F_{all}$$

$$F_{all} = [\sum_{l=1}^{L} \lambda_l \times f_l^1, \cdots, \sum_{l=1}^{L} \lambda_l \times f_l^N]^T$$

$\mathcal{L}_{ce}$ **: Minimizing the permutation prediction error:**

$$\mathcal{L}_{ce} = -\frac{1}{N} \sum_{k=1}^{N} \sum_{i=1}^{N} \mathbb{1}(M_y[k,i] = 1) \log \hat{M}_r[k,i]$$

Neural Auction -- Overall Framework



(a) Deep Neural Auction Architecture

(b) Set Encoder: Deep Set Architecture

(c) Context-Aware Rank Score Function: Partially Monotone MIN-MAX Network

(d) Differentiable Sorting Engine: NeuralSort Module

Experiments

Offline Experiments

- Data Set: 5870k records logged data from Taobao.
- Baselines: GSP, uGSP, DeepGSP [WSDM 21]
- Performance metrics: RPM, CTR, CVR, GMV
- Intuitive comparisons: $\lambda \times RPM + (1 - \lambda) \times X$

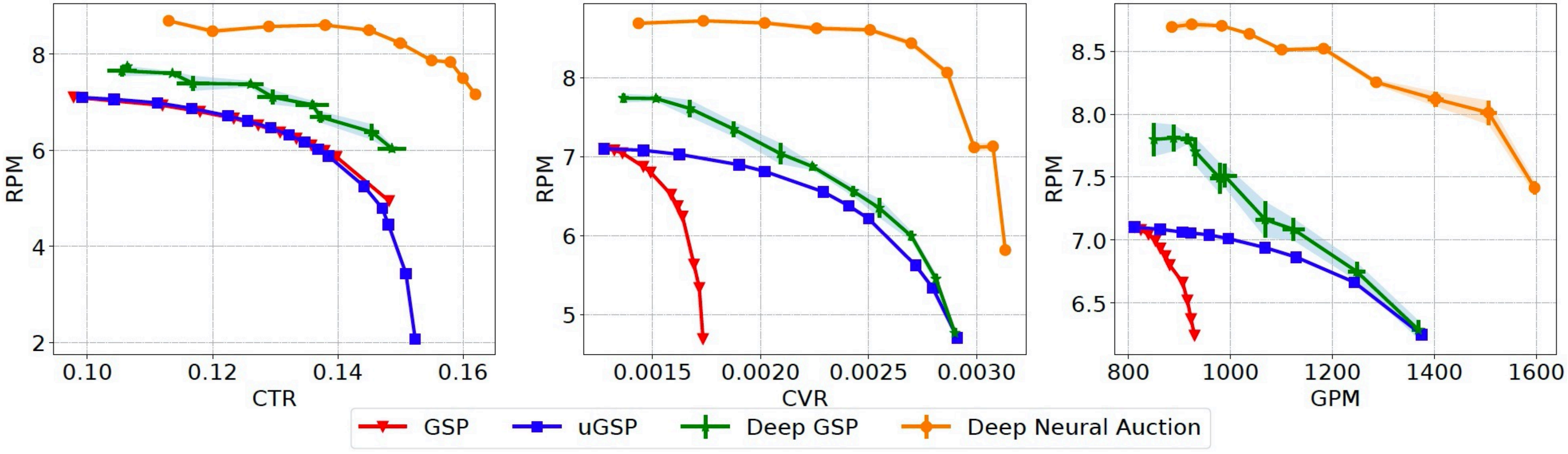


Figure 4: The performance of DNA and other baseline mechanisms in the offline experiments.

Offline Experiments

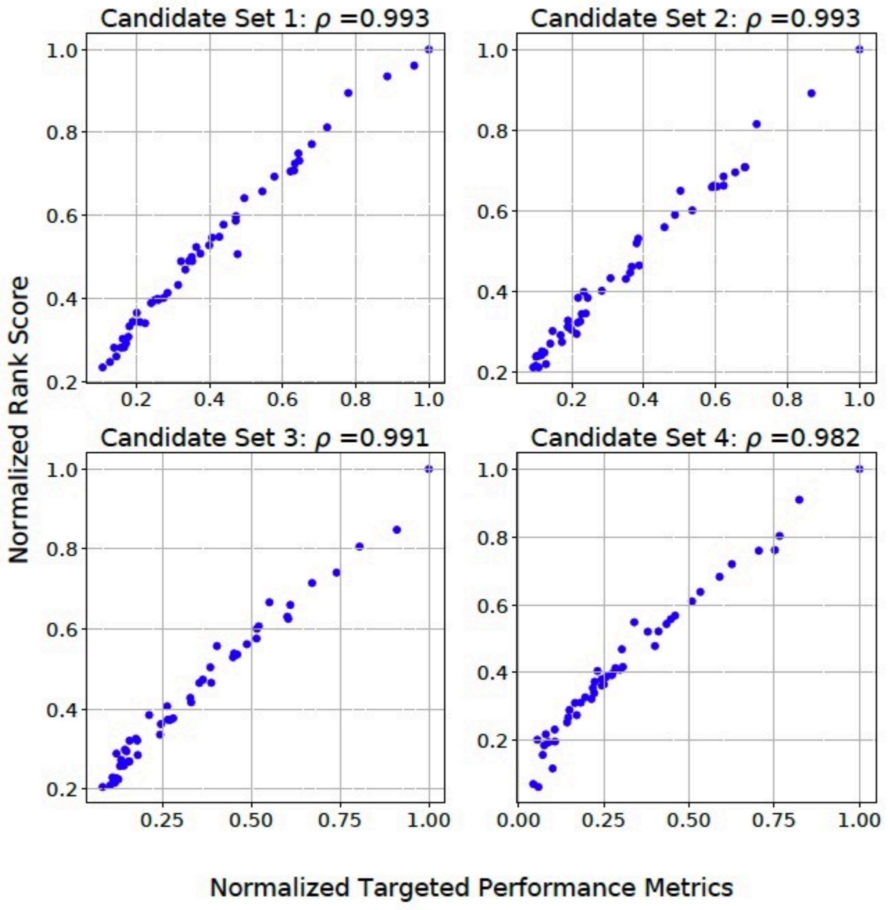


Figure 3: The positive correlations between learned rank scores and the targeted performance metrics. Each blue dot represents an ad in the candidate set.

- **Interpretability:**
  - The strong positive correlation between the learned rank scores and the performance metrics.
  - Implicitly guide advertisers to improve ad quality and then the rank score.

Offline Experiments

- **Data-driven IC Metric for Value Maximizers**
  - Ψ_v: regret on value

$$\Psi_v = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\beta_{k_i}}\max_{b_i'}((\beta_{k_i'} - \beta_{k_i}) \times \mathbb{1}(p_i(b_i') < m_i)),$$

  - Ψ_p: regret on payment

$$\Psi_p = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\beta_{k_i} p_i(b_i)}\max_{b_i'}((\beta_{k_i} p_i(b_i) - \beta_{k_i'} p_i(b_i')) \times \mathbb{1}(k_i' = k_i))$$

Table 1: IC Metric (Ψ) experiments under four tasks with 1000 PV requests randomly selected from the test data. For each bidder, we randomly generate 100 perturbations (ranging from 0.0 to 2.0 times) to her value.

	DNA		uGFP	
	Ψ_v	Ψ_p	Ψ_v	Ψ_p
1.0×RPM	0	**0.042%**	0	13.312%
0.5×RPM+0.5×CTR	0	**0.059%**	0	21.616%
0.5×RPM+0.5×CVR	0	**0.118%**	0	19.280%
0.5×RPM+0.5×GPM	0	**0.028%**	0	16.400%

Online Experiments

- Online A/B tests:
  - 1% of whole production traffic
  - 20210125 - 20210208 (about one billion auctions).

Table 2: Online A/B test compared with uGSP on promoting different performance metrics, keeping the same RPM level.

% Improved	Deep GSP	DNA
CTR	+6.43%	**+11.58%**
CVR	+6.38%	**+31.26%**
GPM	+2.77%	**+16.17%**

Table 3: Online A/B test (nearly two months) compared with GSP on promoting all performance metrics.

	RPM	CTR	CVR	GPM
% Improved	+5.68%	+18.93%	+14.68%	+14.53%

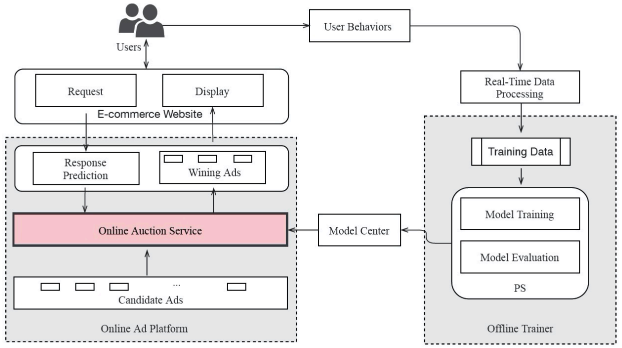
Conclusion

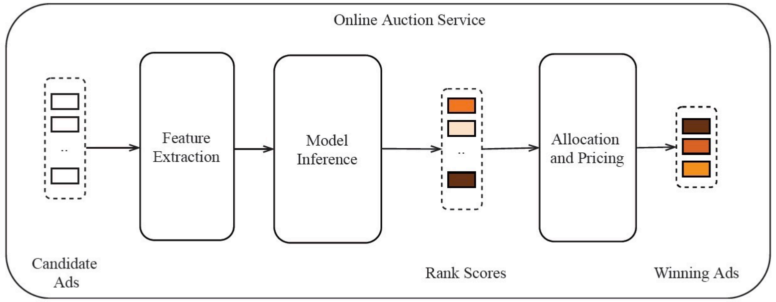
Conclusions

✓We have proposed a **Deep Neural Auction** mechanism, towards learning data efficient and end-to-end auction mechanisms with the guarantee of game theoretical property for e-commerce advertising.

✓Both offline and online experimental results on a real-world e-commerce ad platform validate the effectiveness of the proposed auction mechanism.

Deployment details: https://arxiv.org/abs/2106.03593





We hope the insights and lessons obtained from our industrial deployment would motivate and encourage researchers working on learning-based auction design in both theory and practice.

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