A Novel Benchmark for Decision-Making in Uncertain and Competitive Games

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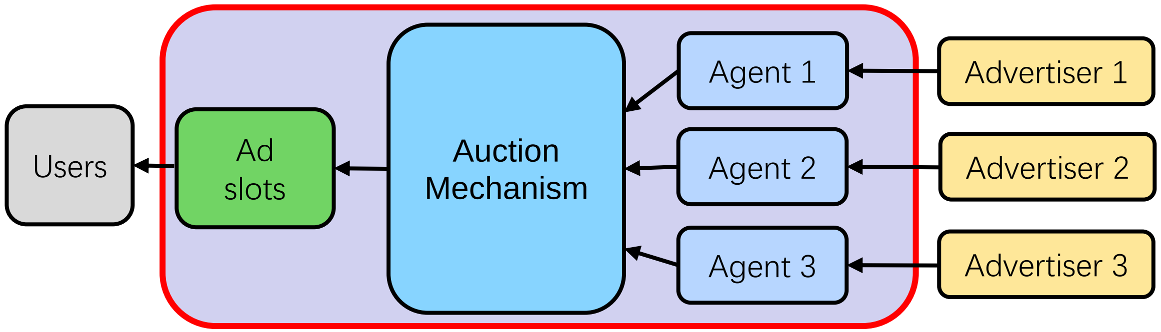
Outline

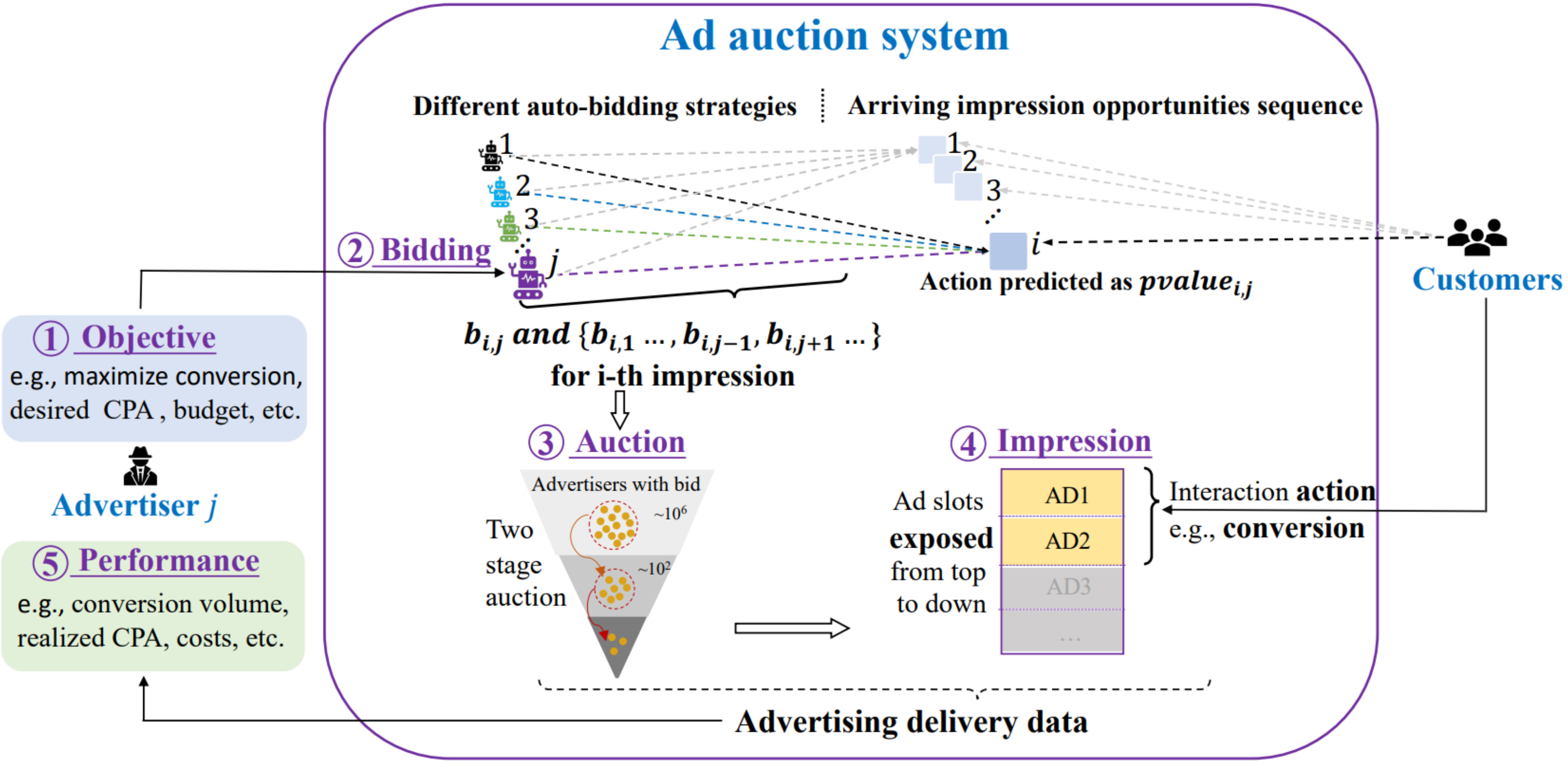
- **Background**
- **Problem formulation and method**
- **Experiments**

Online advertising and auto-bidding

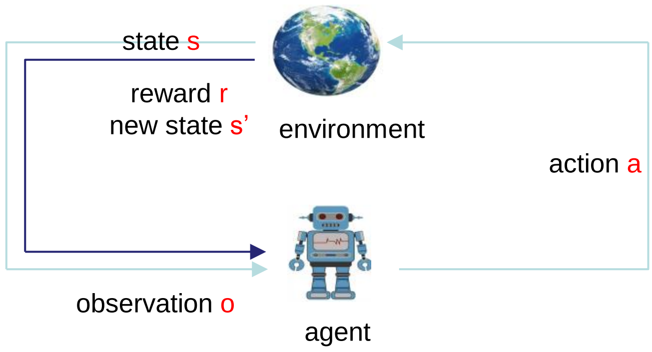


The platform connects advertisers with potential users through automated bidding technology.

The process of auto-bidding



Problem Formulation



- **The MDP of the auto-bidding problem**
  - **State:** $s = (b, f, v)$
    - **Budget:** $b = (b_1, b_2, \cdots, b_n)$
    - **Feature:** $f = (f_1, f_2, \cdots, f_m)$
    - **Value:** $v = \{v_i^j\} \in R^{n \times m}$
  - **Action: bid rate** $a_i = \alpha_i$
    - $bid_i = (\alpha_i v_i^1, \alpha_i v_i^2, \cdots, \alpha_i v_i^m)$
  - **Reward: Given** $bid = (bid_1, bid_2, \cdots, bid_n)$ **and the auction mechanism, auction result** $x_i = (x_i^1, \cdots, x_i^m)$**, reward** $r_i(s, a) = \sum_j x_i^j v_i^j$
  - **Transition:**
    - **Given cost** c^j**, new budget** $\hat{b}_i = b_i - \sum_j x_i^j c^j$
    - **New feature** $\hat{f}$ **and value** $\hat{v}$
    - $\hat{s} = (\hat{b}, \hat{f}, \hat{v})$

Problem Formulation: tasks

- **BCB：auto-bidding under budget constraint, basic task**

$$\max \sum_{t=1}^{T} \left\langle \boldsymbol{x}_i^t, \boldsymbol{v}_i^t \right\rangle$$
$$\text{s. t.} \sum_{t=1}^{T} \left\langle \boldsymbol{x}_i^t, \boldsymbol{c}^t \right\rangle \leq b_i,$$

  - $\boldsymbol{r_i(s_t, a_t) =< x_i^t, v_i^t >}$

- **CSB：with CPA constraint，advanced task**

$$\mathrm{cpa}_i = \frac{\sum_{t=1}^{T} \left\langle \boldsymbol{x}_i^t, \boldsymbol{c}^t \right\rangle}{\sum_{t=1}^{T} \left\langle \boldsymbol{x}_i^t, \boldsymbol{v}_i^t \right\rangle}$$

$$\max \sum_{t=1}^{T} \left\langle \boldsymbol{x}_i^t, \boldsymbol{v}_i^t \right\rangle$$
$$\text{s. t.} \sum_{t=1}^{T} \left\langle \boldsymbol{x}_i^t, \boldsymbol{c}^t \right\rangle \leq b_i$$
$$\mathrm{cpa}_i \leq d_i.$$

$$p(\mathrm{cpa}_i; d_i) = \min \left\{ \left(\frac{d_i}{\mathrm{cpa}_i} \right)^{\beta}, 1 \right\}$$
$$r_i^{\mathrm{CSB}} = p(\mathrm{cpa}_i; d_i) \sum_{t=1}^{T} \left\langle \boldsymbol{x}_i^t, \boldsymbol{v}_i^t \right\rangle$$

Problem Formulation：data

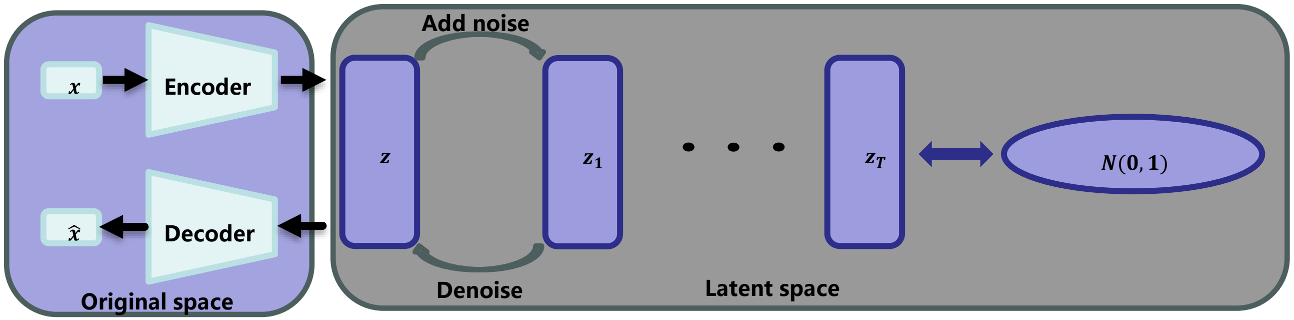
- **Feature f:**
  - **Personal information**
  - **Consumption behavior information**
- **Value v：a higher value means a higher probability of clicking or consumption**
  - **CTR：Click Through Rate**
  - **CVR：Conversion Rate**
  - $v = CTR * CVR$
- **Category informantion and time information：**
  - **Two discrete values for simplicity**

Challenges and objectives

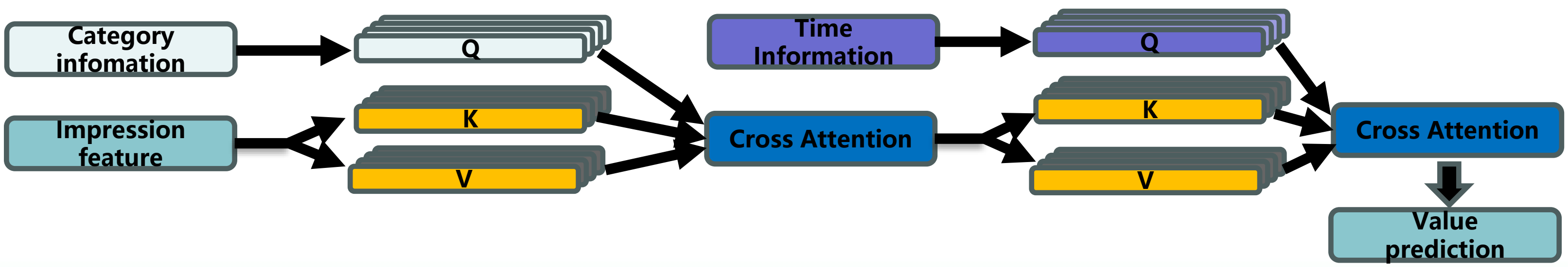
- **Critical issues:**
  - **How to ensure the simulation environment reflects the characteristics of real-world problems ?**
    - **Trust the capability of generative model**
  - **How to prove it?**
    - **Experimental design**
- **the characteristics of real-world problems**
  - **Value of impression opportunities varies with time and category**

Method

- **The structure of the impression generative model**
  - **Feature generation：Latent Diffusion Model**



  - **Value prediction：cross-attention for information fusion**



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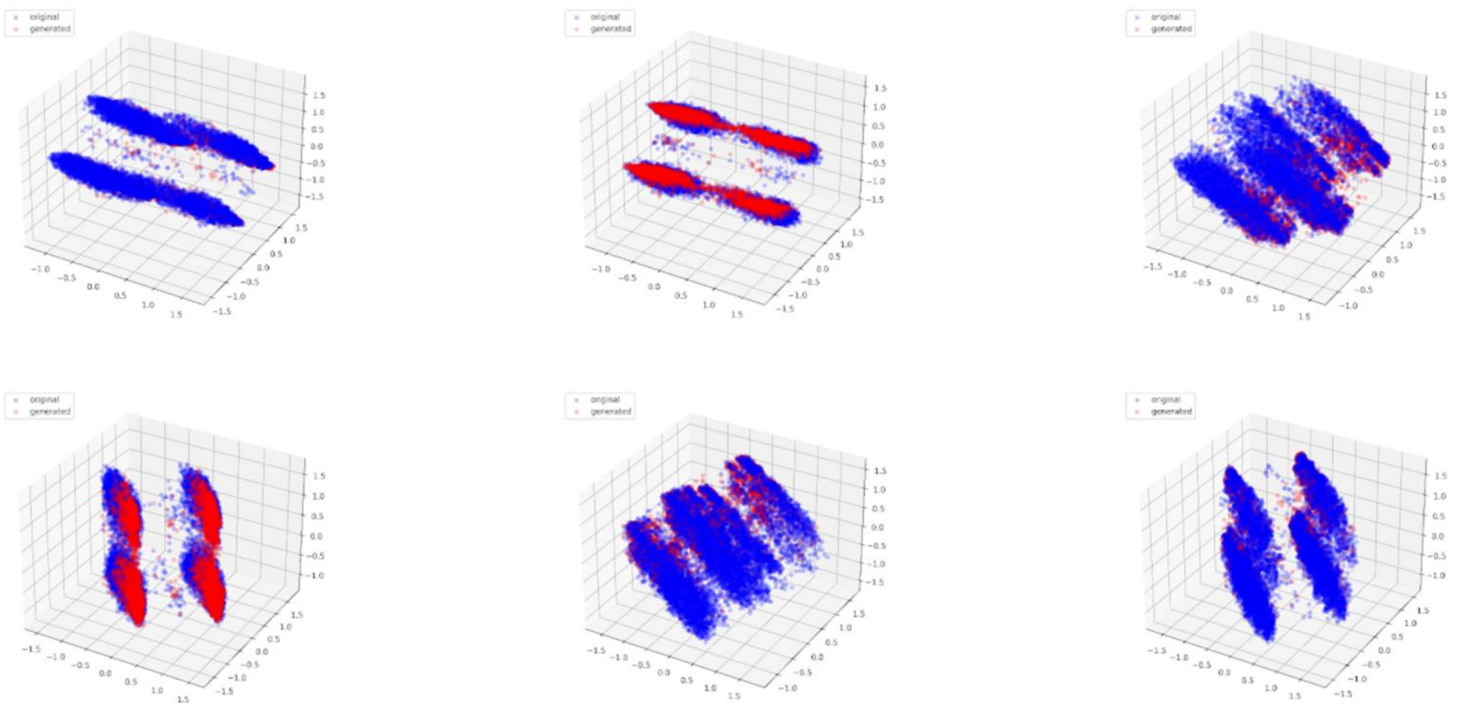
Experiments

- **Empirical results：visualization**
  - **3D-PCA visualization of impression feature**



Experiments

- **Empirical results: distribution of feature value**

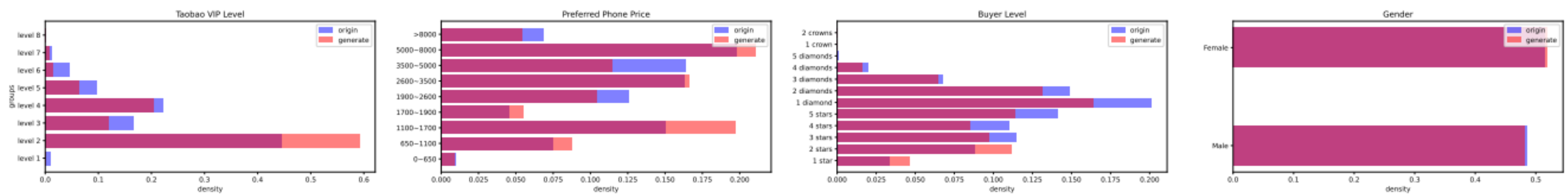


Figure 6: The distribution of identity information including the Taobao VIP level, the preferred phone price, the buyer level, and the gender in 100K generated data and 100K real-world data.

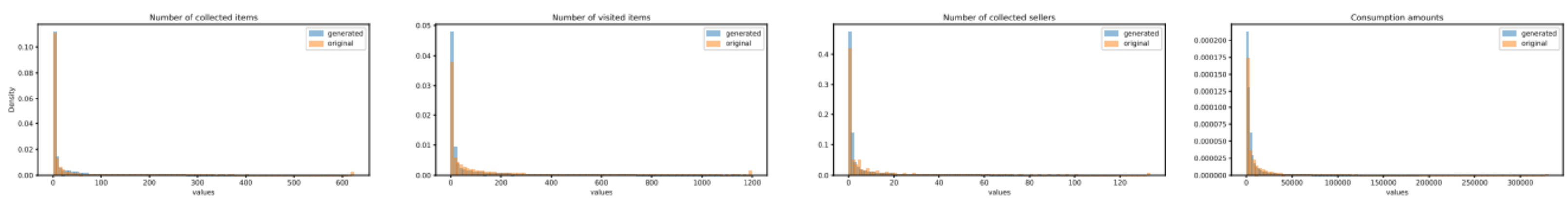
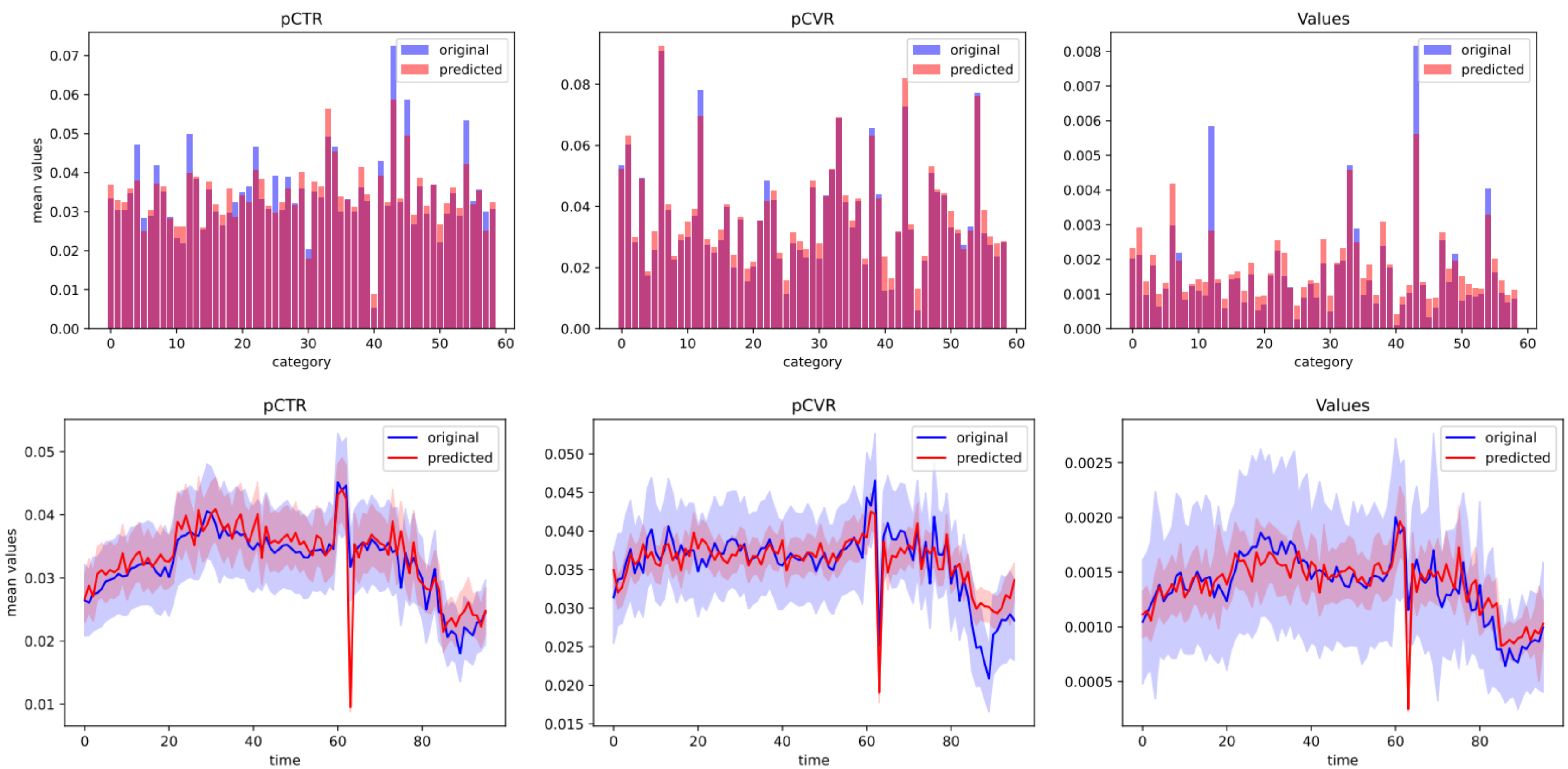


Figure 7: The distribution of consumption behavior information including the number of collected items, the number of visited items, the number of collected sellers, and the consumption amounts in 100K generated data and 100K real-world data.

Experiments

- **Empirical results： reflects the characteristics of real-world problems**



Thank you for listening