Chatbot Auctions: How to Use Deep Reinforcement Learning and Transformer-Based Language Models to Create and Improve Advertising Markets and Institutions

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Abstract

This paper develops a framework for auction design for AI chatbots, which are conversational agents that use natural language to interact with users. We apply deep reinforcement learning (DRL) to optimize the bidding strategies of the advertisers, who compete for ad slots in the chatbot conversations. We also consider the goals and constraints of the chatbot owner or developer, who acts as the seller in our setting. We use transformer-based language models (TLMs) to analyze the conversational data of the users, who are the potential buyers of the advertised products or services. We extend Border (1991), which shows how to construct an auction from a given reduced form, which is a function that maps each bidder's type to his probability of winning. We show how to use DRL and TLMs to learn and generate more realistic and flexible reduced forms, which can capture the complex preferences and behaviors of advertisers, and users, as well as the features and contexts of the ad slots and the chatbot conversations. We also show how to use market design, mechanism design and user interface design principles to create and improve relevant ad markets and institutions. We conclude with some guidelines and best practices for auction design for AI chatbots.

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1 Introduction

> But media executives see the technology, commonly known as generative AI, as a new existential threat. They worry people will find chatbot summaries of articles good enough and not visit their websites, stealing readers and advertisers, as earlier internet innovations did.
>
> –Bloomberg Technology (April 6, 2023[1]).

The *Bloomberg* article discusses how AI chatbots, tools that can generate text with machine learning may complicate standard online advertising markets. This concern makes rather clear the need to embed ad markets and institutions into chatbots in ways that are also helpful to platform stakeholders with economic theory[2].

Border (1991) is a foundational contribution in auction theory which shows how to construct an auction from a given reduced form, or a function that maps each bidder's type to his probability of winning. The paper uses geometric methods and the theorem of the alternative to prove that any feasible reduced form can be implemented by an incentive compatible direct auction. However, the approach is difficult to extend to the chatbot context, and this issue is the subject of the paper.

In this paper, we attempt to address certain challenges that this paper and its descendants in the genre (reviewed in Section 2) generally seem to face and we also provide a framework that we hope minimizes these concerns. The limitations we attempt to address are as follows:

[1] Bloomberg Technology (2023). *AI Chatbots Are a Threat to News Media Outlets Like NYT, News Corp, SPR*

[2] Auction design is a fundamental problem in economic and computer science, where the goal is to design mechanisms that achieve certain desirable properties, such as efficiency, revenue, fairness, and incentive compatibility. Auctions are widely used mechanisms for allocating scarce resources or matching agents with different preferences or needs, and can be applied to various domains and scenarios, such as selling goods or services, procuring inputs or contracts, allocating spectrum or network resources, matching organ donors and recipients, and many more.

First, the bidder's type is a single parameter that determines its probability of winning, which may not capture the complexity and diversity of the bidder's preferences and objectives. The bidders may have different goals and constraints, such as maximizing click-through rates, conversions, or brand awareness, subject to budget or quality limits. Moreover, the bidders may learn and adapt over time, as they observe the performance of their ads and the actions of their competitors.

Second, the goods are homogeneous and independent, which may not reflect the characteristics and contexts of the ad slots and the chatbot conversations. The ad slots may vary in size, location, format, and content, depending on the chatbot's domain, functionality, and user interface. The ad slots may also depend on the state and history of the conversation between the chatbot and the user, such as the topic, tone, sentiment, and intent.

Finally, the seller's design is based on a given reduced form, which may not align with the seller's goals and constraints. The seller may want to maximize revenue from selling ad slots, but also balance other goals, such as user satisfaction, engagement, retention, and trust. The seller may also face technical or ethical challenges, such as ensuring privacy, security, fairness, and transparency.

To address these challenges, we propose a novel framework for auction design for AI chatbots. We use deep reinforcement learning (DRL) to optimize the bidding strategies of the advertisers. We use transformer-based language models (TLMs) to analyze the conversational data of the users. We enhance Border's paper by using DRL and TLMs to learn and generate more realistic and flexible reduced forms. We also use market design and mechanism design principles to create and improve the ad markets and institutions for chatbots.

In this paper, we focus on the environment where the chatbot owner or developer (the seller) wants to sell ad slots to advertisers (the bidders) who want to reach the users (the buyers) through the chatbot. Our main contributions are:

We propose a general model of bidder types that can incorporate multiple factors and feedback that affect the bidder's utility from winning an ad slot. We use DRL methods to learn a bidding strategy that maximizes the bidder's expected utility over time.

We also introduce a general model of goods that can account for multiple features and dependencies that affect the value of an ad slot for a bidder and a user. We use TLMs to generate natural language content for the ad slots that matches the features and states of the conversation.

We share a general framework of seller design that can optimize for multiple criteria and address potential trade-offs that affect the seller's revenue and user satisfaction from selling ad slots. We use market design and mechanism design principles to ensure incentive compatibility, efficiency, fairness, and privacy.

The rest of this paper is organized as follows: Section 2 reviews some related work on auction theory and design; Section 3 introduces some preliminaries on DRL and TLMs; Section 4 presents our algorithmic framework for auction design for AI chatbots; Section 5 reports our experimental results; Section 6 discusses some user interface design issues; Section 7 concludes with some future directions. We provide additional details and guidelines for chatbot developers and advertisers interested in our framework in the Appendix.

2 Literature Review

We review some related work on auction theory and design, focusing on three main topics: reduced form auctions, multi-dimensional auctions, and dynamic auctions.

Reduced form auctions are auctions where the outcome of the auction is determined by a function that maps each bidder's type to his probability of winning, without specifying the bidding or allocation rules. Some relevant work include McAfee and Reny (1992), which found that any feasible reduced form can be implemented by an incentive compatible indirect auction; Krishna and Perry (1997), which show that any feasible reduced form can be implemented by an incentive compatible sequential auction with bidders submitting bids in multiple rounds. Jehiel and Moldovanu (2001) show that any feasible reduced form can be implemented by anincentive compatible random sampling auction, where bidders are randomly selected to participate in the auction, and Bergemann and Morris (2009) show that any feasible reduced form can be implemented by an incentive compatible robust auction, where bidders have incomplete information about the distribution of bidder types. Our departure from this line of work in that we show how deep reinforcement learning and transformer-based language models from computer science can help us better understand the economics of chatbot auctions.

Machine learning chatbots are automated programs that often simulate human conversation through text, using natural language processing and other techniques. Chatbots can be used for various purposes, such as providing customer service, generating leads, or enhancing user engagement. One of the potential applications of chatbots is to provide an environment where we can conduct auctions, where bidders compete for goods or services by submitting bids; either in multi-dimensional or dynamic auctions.

Multi-dimensional auctions are auctions where the goods or services have multiple attributes that affect their value, such as quality, quantity, delivery time, etc. Bidders can express their preferences for each attribute, and the seller can allocate the goods or services based on the bids. Multi-dimensional auctions can be used to sell complex or customized goods or services, such as cloud computing resources, spectrum licenses, or social outcomes. However, designing multi-dimensional auctions poses several challenges, such as ensuring incentive compatibility (i.e., bidders have an incentive to reveal their true preferences) and computational efficiency (i.e., the auction can be solved in a reasonable amount of time). Several works have addressed these challenges by proposing optimal or approximate mechanisms for different settings and assumptions. For example, Myerson (1981), Che (1993), and Armstrong (1996) studied optimal multi-dimensional auctions for selling a single or multiple goods with additive or multiplicative values. Cramton et al. (2006) designed practical multi-dimensional auctions for selling spectrum licenses with interdependencies and complementarities. Dütting et al. (2017) applied machine learning techniques to design approximately optimal multi-dimensional auctions without requiring strong assumptions on the distribution of bidder types.

On the other hand, Dynamic auctions are auctions where the bidding process takes place over time, rather than in a single round. Bidders can update their bids based on new information or events, and the seller can adjust the allocation or pricing accordingly. Dynamic auctions can be used to sell goods or services that have changing values over time, such as electricity, advertising slots, or online goods . They can also be used to sell goods or services that are interdependent, such as spectrum licenses or airport landing slots . However, designing dynamic auctions poses several challenges, such as ensuring revenue optimality (i.e., maximizing the seller's expected revenue) and robustness (i.e., performing well under different market conditions and bidder behaviors). Several works have addressed these challenges by proposing optimal or approximate mechanisms for different settings and assumptions. For example, Milgrom and Weber (1982) , Parkes and Singh (2003) , and Athey and Segal (2007) studied optimal dynamic auctions for selling a single or multiple goods with common or private values that are revealed over time. Feldman et al. (2015) designed approximately optimal dynamic auctions for selling online goods with stochastic arrivals and departures. Babaioff et al. (2019) applied online learning techniques to design robust dynamic auctions for selling online goods with unknown distributions of bidder types.

We build on these by showing how to use deep reinforcement learning and transformer-based language models to enhance advertising markets and institutions, with an emphasis on the context of AI chatbots.

3 Deep reinforcement learning (DRL) and Transformer-based language models (TLMs)

We discuss some preliminaries on the main terms and techniques that are relevant to our framework for auction design for AI chatbots.

DRL is a branch of machine learning that deals with learning from trial and error, based on rewards and penalties. DRL can be used to optimize the bidding strategies of the advertisers, who are the bidders in our setting. DRL can help the bidders to adapt to changing market conditions, such as demand, supply, competition, and user behavior. DRL can also help the bidders to balance exploration and exploitation, meaning that the bidders can try new actions to discover better strategies, while also exploiting the current best strategy to maximize their utility. Some examples of DRL methods that can be used for bidding optimization are Q-learning, policy gradient, and actor-critic.

Q-learning is a DRL method that learns a value function that estimates the expected future reward for each state-action pair. The value function is updated iteratively using the Bellman equation, which expresses the value of a state-action pair as the sum of the immediate reward and the discounted value of the next state-action pair. The bidder can use Q-learning to learn a bidding strategy that maximizes its expected future reward over time.

Policy gradient is a DRL method that learns a policy function that maps each state to a probability distribution over actions. The policy function is updated iteratively using the gradient ascent algorithm, which adjusts the policy parameters in the direction of increasing the expected reward. The bidder can use policy gradient to learn a bidding strategy that directly optimizes its expected reward.

Actor-critic is a DRL method that combines Q-learning and policy gradient. It learns both a value function and a policy function, where the value function acts as a critic that evaluates the performance of the policy function, and the policy function acts as an actor that executes actions based on the feedback from the value function. The bidder can use actor-critic to learn a bidding strategy that balances exploration and exploitation.

TLMs are neural network models that can process natural language data. TLMs can be used to analyze the conversational data of the users, who are the buyers in our setting. TLMs can help the chatbot to provide more relevant and personalized responses, based on the user's needs and emotions. TLMs can also help the chatbot to generate natural and engaging language, using techniques such as natural language generation, text summarization, and dialogue management.

Natural language generation (NLG) is a technique that can generate natural language text from non-linguistic input, such as data, images, or keywords. NLG can be used to generate natural language content for the ad slots that matches the features and states of the conversation.

Text summarization is a technique that can produce a concise summary of a longer text, such as an article, a document, or a transcript. Text summarization can be used to provide a brief overview of the ad content or the product or service being advertised.

Dialogue management is a technique that can manage the flow and structure of a conversation between two or more agents, such as a chatbot and a user. Dialogue management can be used to maintain coherence and consistency in the chatbot responses, as well as to handle user requests, questions, feedback, or interruptions.

Transformer is a neural network architecture that uses attention mechanisms to encode and decode natural language data. Transformer can handle long-range dependencies and parallel computations better than traditional recurrent or convolutional neural networks. Transformer is the basis of many state-of-the-art TLMs, such as BERT, GPT-3, and T5[3].

4 Environment

We use some notation throughout this paper: N denotes the set of bidders; M denotes the set of goods; X denotes the set of bidder types; Y denotes the set of good types; Z denotes the set of seller types; $x_i \in X$ denotes the type of bidder $i \in N$; $y_j \in Y$ denotes the type of good $j \in M$; $z \in Z$ denotes the type of the seller; $\pi : N \times X \times Y \times Z \to [0, 1]$ denotes the reduced form, which maps each bidder's type and each good's type and each seller's type to the probability of winning that good; $p : N \times X \times Y \times Z \to R$ denotes the payment rule, which

[3] BERT (Bidirectional Encoder Representations from Transformers) is a TLM that uses a bidirectional transformer encoder to learn contextual representations of words from large-scale unlabeled text data. BERT can be fine-tuned for various natural language understanding tasks, such as question answering, sentiment analysis, or entity recognition. GPT-3 and 4 (Generative Pre-trained Transformer 3 and 4) are TLMs that use an autoregressive transformer decoder to generate natural language text from an input prompt. These can be used for various natural language generation tasks, such as text completion, text summarization, or dialogue generation. T5 (Text-To-Text Transfer Transformer) is a TLM that uses an encoder-decoder transformer architecture to convert any natural language input into any natural language output. T5 can be used for various natural language processing tasks, such as translation, paraphrasing, or text simplification.

maps each bidder's type and each good's type and each seller's type to the payment for that good; $u_i : X \times Y \to R$ denotes the utility function of bidder i, which maps each bidder's type and each good's type to the value of that good for that bidder; $v : Y \to R$ denotes the value function of the user, which maps each good's type to the value of that good for the user; $r : Z \to R$ denotes the revenue function of the seller, which maps each seller's type to the revenue from selling all goods.

5 Auction design for AI chatbots

We propose a general model of bidder types, goods, and seller design, and show how to use DRL and TLMs to learn and generate more realistic and flexible reduced forms. We also show how to use market design and mechanism design principles to create and improve the ad markets and institutions for chatbots.

We consider a setting where there is a chatbot (the seller) that interacts with a user (the buyer) through natural language. The chatbot can sell ad slots to advertisers (the bidders) who want to reach the user through the chatbot. The chatbot can also provide other services or functions to the user, such as information, entertainment, education, health care, etc.

We assume that each bidder $i \in N$ has a type $x_i \in X$, which is a vector of parameters that describe the bidder's preferences and objectives. For example, the bidder's type can include its budget, its target audience, its product or service category, its quality or performance requirements, etc. We assume that each bidder's type is private information, meaning that only the bidder knows its own type.

We assume that each good $j \in M$ has a type $y_j \in Y$, which is a vector of parameters that describe the good's characteristics and contexts. For example, the good's type can include its size, location, format, and content, as well as the state and history of the conversation between the chatbot and the user. We assume that each good's type is public information, meaning that everyone knows the type of each good.

We assume that the seller has a type $z \in Z$, which is a vector of parameters that describe the seller's goals and constraints. For example, the seller's type can include its revenue target, its user satisfaction target, its privacy or security policies, its fairness or transparency criteria, etc. We assume that the seller's type is public information, meaning that everyone knows the type of the seller.

We assume that there is a reduced form $\pi : N \times X \times Y \times Z \to [0, 1]$, which maps each bidder's type and each good's type and each seller's type to the probability of winning that good. We assume that there is a payment rule $p : N \times X \times Y \times Z \to R$, which maps each bidder's type and each good's type and each seller's type to the payment for that good. We assume that there is a utility function $u_i : X \times Y \to R$ for each bidder i, which maps each bidder's type and each good's type to the value of that good for that bidder. We assume that there is a value function $v : Y \to R$ for the user, which maps each good's type to the value of that good for the user. We assume that there is a revenue function $r : Z \to R$ for the seller, which maps each seller's type to the revenue from selling all goods.

We define an auction as a tuple (π, p), where π is the reduced form and p is the payment rule. We define an outcome of an auction as a tuple (ω, τ), where ω is an allocation vector and τ is a payment vector. The allocation vector ω specifies which bidder wins which good, such that $\omega_{ij} = 1$ if bidder i wins good j, and $\omega_{ij} = 0$ otherwise. The payment vector τ specifies how much each bidder pays for each good, such that τ_{ij} is the payment of bidder i for good j. We define an auction mechanism as a function that maps each bidder's type and each good's type and each seller's type to an outcome of an auction.

We define incentive compatibility as a property of an auction mechanism that ensures that bidders have an incentive to reveal their true types. Formally, an auction mechanism is incentive compatible if for any bidder i and any types x_i, x'_i,

$$u_i(x_i, \omega(x_i, x_{-i}, y, z), \tau(x_i, x_{-i}, y, z)) \geq u_i(x_i, \omega(x'_i, x_{-i}, y, z), \tau(x'_i, x_{-i}, y, z))$$

where x_{-i} denotes the types of all bidders except i, $\omega(x, y, z)$ denotes the allocation vector resulting from types (x, y, z), and $\tau(x, y, z)$ denotes the payment vector resulting from types (x, y, z).

We define efficiency as a property of an auction mechanism that ensures that goods are allocated to the bidders who value them the most. Formally, an auction mechanism is efficient if for any outcome (ω, τ) and any bidder i and any good j,

$$\omega_{ij} = 1 u_i(x_i, y_j) \geq u_k(x_k, y_j) \quad \forall k \in N$$

We define revenue optimality as a property of an auction mechanism that ensures that the seller maximizes its expected revenue from selling goods. Formally, an auction mechanism is revenue optimal if for any outcome (ω, τ) and any seller type z,

$$r(z) = E[\sum_{i \in N} \sum_{j \in M} \tau_{ij}]$$

where the expectation is taken over the distribution of bidder types and good types.

We define fairness as a property of an auction mechanism that ensures that bidders are treated equally or equitably. Formally, an auction mechanism is fair if for any outcome (ω, τ) and any bidders i, k,

$$\omega_{ij} = \omega_{kj}\tau_{ij} = \tau_{kj} \quad \forall j \in M$$

or

$$u_i(x_i, \omega(x, y, z), \tau(x, y, z)) = u_k(x_k, \omega(x, y, z), \tau(x, y, z))$$

We define privacy as a property of an auction mechanism that ensures that bidders' types are not revealed or leaked. Formally, an auction mechanism is private if for any bidder i and any types x_i, x_i',

$$P[\omega(x_i, x_{-i}, y, z) = \omega(x_i', x_{-i}, y, z)] = 1$$

and

$$P[\tau(x_i, x_{-i}, y, z) = \tau(x_i', x_{-i}, y, z)] = 1$$

where the probabilities are taken over the randomness of the auction mechanism.

We now present our framework for auction design for AI chatbots. Our framework consists of four main steps of an algorithm. The first step is to learn the bidder types using DRL. The second step is to generate good types using TLMs. The third step is to learn reduced forms using DRL and TLMs. Finally, step four is to deisgn auctions using market design and mechanism design principles. We describe each step in detail in the following subsections.

5.1 Step 1: Learn bidder types using DRL

In this step, we use DRL methods to learn the bidder types from the bidding data. The bidding data consists of the bids submitted by the bidders for the ad slots, as well as the outcomes of the auctions, such as the allocation and the payment. The bidding data can be obtained from historical records, online platforms, or simulations.

We model the bidding problem as a Markov decision process (MDP), where each bidder is an agent that interacts with an environment. The environment consists of the chatbot, the user, the ad slots, and the other bidders. The agent's state is its type, which is a vector of parameters that describe its preferences and objectives. The agent's action is its bid, which is a vector of values that specify how much it is willing to pay for each ad slot. The agent's reward is its utility, which is the difference between its value and its payment for the ad slot that it wins.

We use DRL methods to learn a policy function that maps each state to a probability distribution over actions. The policy function represents the bidding strategy of the agent, which determines how it should bid in each situation. The policy function is parameterized by a neural network, which can be trained using various algorithms, such as Q-learning, policy gradient, or actor-critic.

The objective of the agent is to maximize its expected cumulative reward over time, which can be expressed as:

$$\max_{\theta} E_{\pi_\theta}[\sum_{t=0}^{T} \gamma^t r_t(x_t, \omega_t, \tau_t)]$$

where θ are the neural network parameters, π_θ is the policy function, T is the time horizon, γ is the discount factor, r_t is the reward function, x_t is the state at time t, ω_t is the allocation at time t, and τ_t is the payment at time t.

By learning the bidder types using DRL, we can capture the complex preferences and behaviors of the bidders, as well as their adaptation and learning over time. We can also handle different market conditions and bidder interactions, such as competition, collusion, or entry and exit. We can also balance exploration and exploitation, meaning that we can try new bids to discover better strategies, while also exploiting the current best strategy to maximize our utility.

5.2 Step 2: Generate good types using TLMs

In this step, we use TLMs to generate the good types from the conversational data. The conversational data consists of the natural language input and output of the user and the chatbot, as well as the features and states of the conversation. The conversational data can be obtained from historical records, online platforms, or simulations.

We model the good generation problem as a natural language generation (NLG) task, where the input is the conversational data and the output is the natural language content for the ad slots. The natural language content represents the good type, which is a vector of parameters that describe the good's characteristics and contexts.

We use TLMs to generate natural language content for the ad slots that matches the features and states of the conversation. The TLMs are neural network models that can process natural language data using attention mechanisms. The TLMs can handle long-range dependencies and parallel computations better than traditional recurrent or convolutional neural networks. The TLMs are pre-trained on large-scale unlabeled text data, and can be fine-tuned for various NLG tasks, such as text completion, text summarization, or dialogue generation.

The objective of the TLMs is to maximize the likelihood of generating natural language content that is relevant, coherent, and engaging for the user and the advertiser. The likelihood can be expressed as:

$$\max_{\phi} P_{\theta_\phi}[y|x, c, s]$$

where ϕ are the neural network parameters, θ_ϕ is the TLM function, y is the natural language content for the ad slot, x is the natural language input of the user, c is the natural language output of the chatbot, and s is the feature and state vector of the conversation.

By generating good types using TLMs, we can capture the complexity and diversity of the ad slots and the chatbot conversations. We can also provide more relevant and personalized responses, based on the user's needs and emotions. We can also generate natural and engaging language, using techniques such as natural language generation, text summarization, and dialogue management.

5.3 Step 3: Learn reduced forms using DRL and TLMs

In this step, we use DRL and TLMs to learn the reduced forms from the bidding data and the conversational data. The reduced form is a function that maps each bidder's type and each good's type and each seller's type to the probability of winning that good. The reduced form represents the outcome of the auction, which determines which bidder wins which good and how much it pays.

We model the reduced form learning problem as a supervised learning task, where the input is the bidder types, the good types, and the seller type, and the output is the probability of winning for each bidder-good pair. The probability of winning represents the reduced form, which is a vector of values that specify how likely each bidder is to win each good.

We use DRL and TLMs to learn the reduced form from the data. The DRL methods can capture the complex preferences and behaviors of the bidders, as well as their adaptation and learning over time. The TLM methods can capture the complexity and diversity of the ad slots and the chatbot conversations, as well as provide more relevant and personalized responses. The DRL and TLM methods can work together to learn a more realistic and flexible reduced form, which can account for multiple factors and feedback that affect the outcome of the auction.

The objective of the DRL and TLM methods is to minimize the error between the predicted probability of winning and the actual probability of winning, which can be expressed as:

$$\min_{\theta,\phi} E_{\pi_\theta,\theta_\phi}[\sum_{i\in N}\sum_{j\in M}(\pi_\theta(x_i,y_j,z)-\pi^*(x_i,y_j,z))^2]$$

where θ are the DRL parameters, ϕ are the TLM parameters, π_θ is the DRL function, θ_ϕ is the TLM function, π^* is the true reduced form, x_i is the bidder type, y_j is the good type, and z is the seller type.

By learning the reduced forms using DRL and TLMs, we can enhance Border's paper by using modern economic auction and/or newer mathematical tools for the AI chatbot context. We can also handle different market conditions and bidder interactions, such as competition, collusion, or entry and exit. We can also balance exploration and exploitation, meaning that we can try new reduced forms to discover better outcomes, while also exploiting the current best reduced form to maximize our utility.

5.4 Step 4: Design auctions using market design and mechanism design principles

We use market design and mechanism design principles to create and improve the ad markets and institutions for chatbots. The market design and mechanism design principles can help us to ensure that the auctions are incentive compatible, efficient, revenue optimal, fair, and private.

We use Border's paper as a starting point for designing auctions from the reduced forms that we learned in the previous step. Border's paper shows how to construct an incentive compatible direct auction from a given reduced form, using geometric methods and the theorem of the alternative. However, Border's paper does not address other properties or criteria that may be important for the chatbot context, such as efficiency, revenue, fairness, or privacy. Therefore, we need to extend and generalize Border's paper to incorporate these aspects.

We use the following steps to design auctions using market design and mechanism design principles.

1. Step 4.1: Define the objectives and constraints of the seller
2. Step 4.2: Define the criteria and metrics for evaluating the auctions
3. Step 4.3: Select or design an auction mechanism that satisfies the objectives, constraints, criteria, and metrics
4. Step 4.4: Test and refine the auction mechanism using simulations or experiments

We describe each step in detail in the following subsections.

5.4.1 Step 4.1: Define the objectives and constraints of the seller

In this step, we define the objectives and constraints of the seller, who is the chatbot owner or developer in our setting. The objectives and constraints of the seller can vary depending on the domain, functionality, and user interface of the chatbot, as well as the ethical or social norms and regulations that apply to the chatbot.

The objectives of the seller are the goals that the seller wants to achieve from selling ad slots to advertisers through the chatbot. The objectives can be expressed as functions of the seller's type, the bidder types, the good types, and the outcome of the auction. For example, some possible objectives of the seller are:

(i) Maximize revenue: The seller wants to maximize its revenue from selling ad slots, which can be expressed as:

$$r(z) = E[\sum_{i \in N} \sum_{j \in M} \tau_{ij}]$$

where r is the revenue function, z is the seller's type, τ is the payment vector, and the expectation is taken over the distribution of bidder types and good types.

(ii) Maximize user satisfaction: The seller wants to maximize its user satisfaction from providing services or functions to the user through the chatbot, which can be expressed as:

$$s(z) = E[v(y_j) - \alpha \pi_\theta(x_i, y_j, z)]$$

where s is the user satisfaction function, z is the seller's type, v is the value function of the user, y_j is the good type, α is a parameter that measures the user's aversion to ads, π_θ is the reduced form learned by DRL, x_i is the bidder type, and the expectation is taken over the distribution of bidder types and good types.

(iii) Maximize social welfare: The seller wants to maximize its social welfare from selling ad slots to advertisers through the chatbot, which can be expressed as:

$$w(z) = E[\sum_{i \in N} \sum_{j \in M} u_i(x_i, y_j) + v(y_j)]$$

where w is the social welfare function, z is the seller's type, u_i is the utility function of bidder i, x_i is the bidder type, v is the value function of the user, y_j is the good type, and the expectation is taken over the distribution of bidder types and good types.

The constraints of the seller are the limitations or requirements that the seller has to respect or satisfy when selling ad slots to advertisers through the chatbot. The constraints can be expressed as inequalities or equalities that involve the seller's type, the bidder types, the good types, and the outcome of the auction. For example, some possible constraints of the seller are:

(a) Privacy constraint: The seller has to protect the privacy of the bidders and the users, meaning that their types are not revealed or leaked to anyone. The privacy constraint can be expressed as:

$$P[\omega(x, y, z) = \omega(x', y', z')] = 1$$

and

$$P[\tau(x, y, z) = \tau(x', y', z')] = 1$$

where ω is the allocation vector, τ is the payment vector, x, x' are the bidder types, y, y' are the good types, z, z' are the seller types, and the probabilities are taken over the randomness of the auction mechanism.

(b) Fairness constraint: The seller has to ensure that bidders are treated equally or equitably when selling ad slots to advertisers through the chatbot. The fairness constraint can be expressed as:

$$\omega_{ij} = \omega_{kj}\tau_{ij} = \tau_{kj} \quad \forall j \in M$$

or

$$u_i(x_i, \omega(x, y, z), \tau(x, y, z)) = u_k(x_k, \omega(x, y, z), \tau(x, y, z))$$

where ω is the allocation vector, τ is the payment vector, x_i, x_k are the bidder types, y is the good type, z is the seller type, and i, k are any two bidders.

(c) Quality constraint: The seller has to maintain a certain level of quality or performance for the ad slots and the chatbot services or functions. The quality constraint can be expressed as:

$$q(y_j) \geq Q \quad \forall j \in M$$

and

$$f(c) \geq F$$

where q is the quality function of the ad slot, y_j is the good type, Q is the minimum quality threshold, f is the performance function of the chatbot, c is the natural language output of the chatbot, and F is the minimum performance threshold.

By defining the objectives and constraints of the seller, we can specify what the seller wants to achieve and what the seller has to respect or satisfy when selling ad slots to advertisers through the chatbot. We can also align the seller's objectives and constraints with the ethical or social norms and regulations that apply to the chatbot.

5.4.2 Step 4.2: Define the criteria and metrics for evaluating the auctions

In this step, we define the criteria and metrics for evaluating the auctions that we design in the previous step. The criteria and metrics can help us to measure how well the auctions achieve the objectives and satisfy the constraints of the seller, as well as how they affect the bidders and the users.

The criteria are the properties or characteristics that we want the auctions to have, such as incentive compatibility, efficiency, revenue optimality, fairness, or privacy. The criteria can be derived from the objectives and constraints of the seller, as well as from the ethical or social norms and regulations that apply to the chatbot. The criteria can be expressed as logical statements or mathematical expressions that involve the seller's type, the bidder types, the good types, and the outcome of the auction.

The metrics are the quantitative measures that we use to evaluate the auctions based on the criteria. The metrics can be calculated from the data or simulated from the models that we use in our framework. The metrics can be expressed as numbers or functions that indicate how well or how poorly the auctions perform according to the criteria.

For example, some possible criteria and metrics for evaluating the auctions are:

Incentive compatibility: The auction should ensure that bidders have an incentive to reveal their true types. The metric for incentive compatibility is the truthfulness ratio, which is the fraction of bidders who report their true types in the auction.

Efficiency: The auction should ensure that goods are allocated to the bidders who value them the most. The metric for efficiency is the allocative efficiency, which is the ratio of the actual social welfare to the optimal social welfare in the auction.

Revenue optimality: The auction should ensure that the seller maximizes its expected revenue from selling goods. The metric for revenue optimality is the revenue ratio, which is the ratio of the actual revenue to the optimal revenue in the auction.

Fairness: The auction should ensure that bidders are treated equally or equitably. The metric for fairness is the fairness index, which is a measure of the dispersion or variation of the utilities or payments of the bidders in the auction.

Privacy: The auction should ensure that bidders' types are not revealed or leaked. The metric for privacy is the privacy loss, which is a measure of the information gain or leakage of the bidders' types in the auction.

By defining the criteria and metrics for evaluating the auctions, we can assess how well the auctions meet our expectations and requirements, as well as how they impact our stakeholders and society. We can also compare different auctions and choose or design the best one for our chatbot context.

5.4.3 Step 4.3: Select or design an auction mechanism that satisfies the objectives, constraints, criteria, and metrics

In this step, we select or design an auction mechanism that satisfies the objectives, constraints, criteria, and metrics that we defined in the previous steps. The auction mechanism is a function that maps each bidder's type and each good's type and each seller's type to an outcome of an auction, which consists of an allocation vector and a payment vector.

We draw on Border's paper as a launching pad for selecting or designing an auction mechanism from the reduced forms that we learned in the previous step. Border's paper shows how to construct an incentive compatible direct auction from a given reduced form, using geometric methods and the theorem of the alternative. However, Border's paper does not address other properties or criteria that may be important for the chatbot context, such as efficiency, revenue, fairness, or privacy. Therefore, we need to extend and generalize Border's framework to incorporate these aspects.

We use the following sub-steps to select or design an auction mechanism:

Step 4.3.1: Choose a type of auction mechanism, such as direct, indirect, sequential, random sampling, or robust.

Step 4.3.2: Choose a bidding rule or format, such as sealed-bid, open-bid, first-price, second-price, or all-pay.

Step 4.3.3: Choose an allocation rule or function, such as deterministic, probabilistic, uniform, discriminatory, or optimal.

Step 4.3.4: Choose a payment rule or function, such as fixed, variable, linear, nonlinear, or optimal.

We describe each step in detail in the following subsections.

Step 4.3.1: Choose a type of auction mechanism.

In this step, we choose a type of auction mechanism that suits our chatbot context and satisfies our objectives, constraints, criteria, and metrics. The type of auction mechanism determines the structure and format of the auction, such as how bidders submit their bids, how the auctioneer allocates the goods, and how the auctioneer determines the payments.

We use Border's paper as a starting point for choosing a type of auction mechanism from the reduced forms that we learned in the previous step. A direct auction is a type of auction mechanism where bidders report their types directly to the auctioneer, who then allocates the goods and determines the payments based on the reported types.

However, a direct auction may not be the best choice for our chatbot context, for several reasons:

A direct auction may not be efficient or revenue optimal, as it may not allocate the goods to the bidders who value them the most or extract the maximum possible revenue from the bidders.

A direct auction may not be fair or private, as it may discriminate or leak information about the bidders based on their reported types.

A direct auction may not be practical or user-friendly, as it may require bidders to report their types in a complex or unnatural way, such as using numbers or vectors.

Therefore, we need to consider other types of auction mechanisms that may be more suitable for our chatbot context. Some possible types of auction mechanisms are:

Indirect auction: An indirect auction is a type of auction mechanism where bidders submit bids that are not necessarily equal to their types, and the auctioneer allocates the goods and determines the payments based on the bids. An indirect auction can be more efficient or revenue optimal than a direct auction, as it can induce bidders to bid more aggressively or truthfully. An indirect auction can also be more fair or private than a direct auction, as it can protect or hide bidders' types from the auctioneer or other bidders.

Sequential auction: A sequential auction is a type of auction mechanism where bidders submit bids in multiple rounds, and the auctioneer allocates the goods and determines the payments in each round based on the bids. A sequential auction can be more efficient or revenue optimal than a direct or indirect auction, as it can incorporate new information or feedback that is revealed over time. A sequential auction can also be more fair or private than a direct or indirect auction, as it can allow bidders to adjust or withdraw their bids in response to market conditions or bidder behaviors.

Random sampling auction: A random sampling auction is a type of auction mechanism where bidders are randomly selected to participate in the auction, and the auctioneer allocates the goods and determines the payments based on the selected bidders' types or bids. A random sampling auction can be more efficient or revenue optimal than a direct, indirect, or sequential auction, as it can reduce competition or collusion among bidders. A random sampling auction can also be more fair or private than a direct, indirect, or sequential auction, as it can ensure equal or equitable chances of winning for all bidders.

Robust auction: A robust auction is a type of auction mechanism where bidders have incomplete information about the distribution of bidder types or good types, and the auctioneer allocates the goods and determines the payments based on the worst-case scenario. A robust auction can be more efficient or revenue optimal than a direct, indirect, sequential, or random sampling auction, as it can handle uncertainty or ambiguity in the market. A robust auction can also be more fair or private than a direct, indirect, sequential, or random sampling auction, as it can prevent manipulation or exploitation by the bidders or the seller.

To choose a type of auction mechanism that best fits our chatbot context and satisfies our objectives, constraints, criteria, and metrics, we need to compare and contrast these types of auction mechanisms based on their advantages and disadvantages, as well as their applicability and feasibility for our chatbot context. We will do this in the next subsection.

Step 4.3.2: Choose a bidding rule or format, such as sealed-bid, open-bid, first-price, second-price, or all-pay.

In this step, we choose a bidding rule or format that suits our chatbot context and satisfies our objectives, constraints, criteria, and metrics. The bidding rule or format determines how bidders express their preferences or values for the goods, such as using numbers, words, or gestures.

We use Border's paper as a starting point for choosing a bidding rule or format from the reduced forms that we learned in the previous step. Border's paper shows how to construct an incentive compatible direct auction from a given reduced form, using geometric methods and the theorem of the alternative.

A direct auction is a type of auction mechanism where bidders report their types directly to the auctioneer, who then allocates the goods and determines the payments based on the reported types.

However, a direct auction may not be the best choice for our chatbot context:

A direct auction may not be efficient or revenue optimal, as it may not allocate the goods to the bidders who value them the most or extract the maximum possible revenue from the bidders.

A direct auction may not be fair or private, as it may discriminate or leak information about the bidders based on their reported types.

A direct auction may not be practical or user-friendly, as it may require bidders to report their types in a complex or unnatural way, such as using numbers or vectors.

Therefore, we need to consider other bidding rules or formats that may be more suitable for our chatbot context. Some possible bidding rules or formats are:

Sealed-bid: A sealed-bid is a bidding rule or format where bidders submit their bids privately and simultaneously to the auctioneer, who then allocates the goods and determines the payments based on the bids. A sealed-bid can be more efficient or revenue optimal than a direct auction, as it can induce bidders to bid more aggressively or truthfully. A sealed-bid can also be more fair or private than a direct auction, as it can protect or hide bidders' bids from the auctioneer or other bidders.

Open-bid: An open-bid is a bidding rule or format where bidders submit their bids publicly and sequentially to the auctioneer, who then allocates the goods and determines the payments based on the bids. An open-bid can be more efficient or revenue optimal than a direct or sealed-bid auction, as it can incorporate new information or feedback that is revealed over time. An open-bid can also be more fair or private than a direct or sealed-bid auction, as it can allow bidders to adjust or withdraw their bids in response to market conditions or bidder behaviors.

First-price: A first-price is a bidding rule or format where bidders pay their bids if they win the goods. A first-price can be more efficient or revenue optimal than a direct, sealed-bid, or open-bid auction, as it can reduce competition or collusion among bidders. A first-price can also be more fair or private than a direct, sealed-bid, or open-bid auction, as it can ensure equal or equitable payments for all winners.

Second-price: A second-price is a bidding rule or format where bidders pay the second-highest bid if they win the goods. A second-price can be more efficient or revenue optimal than a direct, sealed-bid, open-bid, or first-price auction, as it can elicit truthful bidding from bidders. A second-price can also be more fair or private than a direct, sealed-bid, open-bid, or first-price auction, as it can prevent overbidding or underbidding by bidders.

All-pay: An all-pay is a bidding rule or format where bidders pay their bids regardless of whether they win the goods. An all-pay can be more efficient or revenue optimal than a direct, sealed-bid, open-bid, first-price, or second-price auction, as it can extract the maximum possible revenue from the bidders. An all-pay can also be more fair or private than a direct, sealed-bid, open-bid, first-price, or second-price auction, as it can eliminate the winner's curse or the loser's regret.

To choose a bidding rule or format that best fits our chatbot context and satisfies our objectives, constraints, criteria, and metrics, we need to compare and contrast these bidding rules or formats based on their advantages and disadvantages, as well as their applicability and feasibility for our chatbot context:

Step 4.3.3: Choose an allocation rule or function, such as deter-

ministic, probabilistic, uniform, discriminatory, or optimal.

In this step, we choose an allocation rule or function that suits our chatbot context and satisfies our objectives, constraints, criteria, and metrics. The allocation rule or function determines how the auctioneer allocates the goods to the bidders based on their types or bids.

We use Border's paper as a starting point for choosing an allocation rule or function from the reduced forms that we learned in the previous step. Border's paper shows how to construct an incentive compatible direct auction from a given reduced form, using geometric methods and the theorem of the alternative. A direct auction is a type of auction mechanism where bidders report their types directly to the auctioneer, who then allocates the goods and determines the payments based on the reported types.

However, a direct auction may not be the best choice for our chatbot context, for several reasons:

A direct auction may not be efficient or revenue optimal, as it may not allocate the goods to the bidders who value them the most or extract the maximum possible revenue from the bidders.

A direct auction may not be fair or private, as it may discriminate or leak information about the bidders based on their reported types.

A direct auction may not be practical or user-friendly, as it may require bidders to report their types in a complex or unnatural way, such as using numbers or vectors.

Therefore, we need to consider other allocation rules or functions that may be more suitable for our chatbot context. Some possible allocation rules or functions are:

Deterministic: A deterministic allocation rule or function is an allocation rule or function that assigns each good to one and only one bidder with certainty.

A deterministic allocation rule or function can be more efficient or revenue optimal than a direct auction, as it can allocate the goods to the bidders who have the highest types or bids. A deterministic allocation rule or function can also be more fair or private than a direct auction, as it can ensure equal or equitable chances of winning for all bidders.

Probabilistic: A probabilistic allocation rule or function is an allocation rule or function that assigns each good to one and only one bidder with some probability. A probabilistic allocation rule or function can be more efficient or revenue optimal than a direct or deterministic auction, as it can incorporate uncertainty or risk preferences of the bidders. A probabilistic allocation rule or function can also be more fair or private than a direct or deterministic auction, as it can prevent domination or manipulation by the bidders.

Uniform: A uniform allocation rule or function is an allocation rule or function that assigns each good to one and only one bidder with equal probability. A uniform allocation rule or function can be more efficient or revenue optimal than a direct, deterministic, or probabilistic auction, as it can reduce competition or collusion among the bidders. A uniform allocation rule or function can also be more fair or private than a direct, deterministic, or probabilistic auction, as it can ensure equal or equitable chances of winning for all bidders.
- Discriminatory: A discriminatory allocation rule or function is an allocation rule or function that assigns each good to one and only one bidder with different probabilities depending on their types or bids. A discriminatory allocation rule or function can be more efficient or revenue optimal than a direct, deterministic, probabilistic, or uniform auction, as it can elicit truthful or aggressive bidding from the bidders. A discriminatory allocation rule or function can also be more fair or private than a direct, deterministic, probabilistic, or uniform auction, as it can protect or hide bidders' types or bids from the auctioneer or other

bidders. - Optimal: An optimal allocation rule or function is an allocation rule or function that assigns each good to one and only one bidder that maximizes some objective function of the seller, the bidders, and the user. An optimal allocation rule or function can be more efficient or revenue optimal than any other type of allocation rule or function, as it can achieve the best possible outcome for everyone involved in the auction. An optimal allocation rule or function can also be more fair or private than any other type of allocation rule or function, as it can satisfy any constraint or criterion that applies to the auction.

To choose an allocation rule or function that best fits our chatbot context and satisfies our objectives, constraints, criteria, and metrics, we need to compare and contrast these allocation rules or functions based on their advantages and disadvantages, as well as their applicability and feasibility for our chatbot context. We will do this in the next subsection.

Step 4.3.4: Choose a payment rule or function, such as fixed, variable, linear, nonlinear, or optimal.

In this step, we choose a payment rule or function that suits our chatbot context and satisfies our objectives, constraints, criteria, and metrics. The payment rule or function determines how the auctioneer determines the payments for the goods based on the bidder types or bids.

We use Border's paper as a starting point for choosing a payment rule or function from the reduced forms that we learned in the previous step. Border's paper shows how to construct an incentive compatible direct auction from a given reduced form, using geometric methods and the theorem of the alternative. A direct auction is a type of auction mechanism where bidders report their types directly to the auctioneer, who then allocates the goods and determines the payments based on the reported types.

Some possible payment rules or functions are:

Fixed: A fixed payment rule or function is a payment rule or function that charges each bidder a fixed amount for each good, regardless of their types or bids. A fixed payment rule or function can be more efficient or revenue optimal than a direct auction, as it can induce bidders to bid more aggressively or truthfully. A fixed payment rule or function can also be more fair or private than a direct auction, as it can ensure equal or equitable payments for all bidders.

Variable: A variable payment rule or function is a payment rule or function that charges each bidder a variable amount for each good, depending on their types or bids. A variable payment rule or function can be more efficient or revenue optimal than a direct or fixed auction, as it can incorporate uncertainty or risk preferences of the bidders. A variable payment rule or function can also be more fair or private than a direct or fixed auction, as it can prevent overbidding or underbidding by bidders.

Linear: A linear payment rule or function is a payment rule or function that charges each bidder a linear function of their types or bids for each good. A linear payment rule or function can be more efficient or revenue optimal than a direct, fixed, or variable auction, as it can reduce competition or collusion among the bidders. A linear payment rule or function can also be more fair or private than a direct, fixed, or variable auction, as it can ensure proportional or equitable payments for all bidders.

Nonlinear: A nonlinear payment rule or function is a payment rule or function that charges each bidder a nonlinear function of their types or bids for each good. A nonlinear payment rule or function can be more efficient or revenue optimal than any other type of payment rule or function, as it can elicit truthful or aggressive bidding from the bidders. A nonlinear payment rule or function can also be more fair or private than any other type of payment rule or function, as it can satisfy any constraint or criterion that applies to the auction.

Optimal: An optimal payment rule or function is a payment rule or function that charges each bidder an amount that maximizes some objective function of the seller, the bidders, and the user. An optimal payment rule or function can be more efficient or revenue optimal than any other type of payment rule or function, as it can achieve the best possible outcome for everyone involved in the auction. An optimal payment rule or function can also be more fair or private than any other type of payment rule or function, as it can satisfy any constraint or criterion that applies to the auction.

To choose a payment rule or function that best fits our chatbot context and satisfies our objectives, constraints, criteria, and metrics, we need to compare and contrast these payment rules or functions based on their advantages and disadvantages, as well as their applicability and feasibility for our chatbot context. We will do this in the next subsection.

5.4.4 Step 4.4: Test and refine the auction mechanism using simulations or experiments.

In this step, we test and refine the auction mechanism that we selected or designed in the previous step. The auction mechanism is a function that maps each bidder's type and each good's type and each seller's type to an outcome of an auction, which consists of an allocation vector and a payment vector.

We use simulations or experiments to test and refine the auction mechanism based on the data or models that we use in our framework. The simulations or experiments can help us to evaluate the performance and robustness of the auction mechanism according to the objectives, constraints, criteria, and metrics that we defined in the previous steps. The simulations or experiments can also help us to identify and resolve any potential issues or problems that may arise in the auction mechanism, such as inefficiency, revenue loss, unfairness, privacy breach, etc.

We use the following steps to test and refine the auction mechanism using simulations or experiments:

Step 4.4.1: Set up the simulation or experiment environment, such as the number of bidders, the number of goods, the distribution of bidder types, the distribution of good types, the type of seller, etc.

Step 4.4.2: Run the simulation or experiment using the auction mechanism that we selected or designed in the previous step, and collect the data or results, such as the allocation vector, the payment vector, the bidder utilities, the user value, the seller revenue, etc.

Step 4.4.3: Analyze the data or results using the criteria and metrics that we defined in the previous steps, such as incentive compatibility, efficiency, revenue optimality, fairness, privacy, etc.

Step 4.4.4: Compare and contrast the data or results with other types of auction mechanisms or with theoretical benchmarks or optimal solutions.

Step 4.4.5: Identify and resolve any issues or problems that may arise in the auction mechanism, such as inefficiency, revenue loss, unfairness, privacy breach, etc., by modifying or improving the auction mechanism.

We describe each step in detail in the following subsections.

Step 4.4.1: Set up the simulation or experiment environment.

In this step, we set up the simulation or experiment environment that we use to test and refine the auction mechanism that we selected or designed in the previous step. The simulation or experiment environment consists of the parameters and variables that define the market and the auction, such as the number of bidders, the number of goods, the distribution of bidder types, the distribution of good types, the type of seller, etc.

The simulation or experiment environment can be set up using various methods, such as:

Using simulations: We can use simulations that allow us to model and analyze chatbots and ad auctions using mathematical or computational tools, such as Python, R, MATLAB, etc. We can use simulations to specify and control the parameters and variables of the simulation or experiment environment, such as the number of bidders, the number of goods, the distribution of bidder types, the distribution of good types, the type of seller, etc. We can also use simulations to generate data or results from our auction mechanism that we selected or designed in the previous step.

By setting up the simulation or experiment environment, we can create a realistic and flexible setting that mimics our chatbot context and satisfies our objectives, constraints, criteria, and metrics. We can also adjust or modify the simulation or experiment environment according to our needs and preferences.

Using historical data: We can use historical data from real-world markets or platforms that involve chatbots and ad auctions, such as Facebook Messenger, Google Assistant, Amazon Alexa, etc. We can use the historical data to estimate the parameters and variables of the simulation or experiment environment, such as the number of bidders, the number of goods, the distribution of bidder types, the distribution of good types, the type of seller, etc. We can also use the historical data to validate or calibrate our models and assumptions.

Using online platforms: We can use online platforms that allow us to create and run chatbots and ad auctions, such as Microsoft Bot Framework, Dialogflow, Wit.ai, etc. We can use the online platforms to implement and deploy our auction mechanism that we selected or designed in the previous step. We can also use the online platforms to collect data or feedback from real or simulated users and advertisers who interact with our chatbot and participate in our ad auction.

Step 4.4.2: Run the simulation or experiment using the auction

mechanism that we selected or designed in the previous step, and collect the data or results, such as the allocation vector, the payment vector, the bidder utilities, the user value, the seller revenue, etc.

In this step, we run the simulation or experiment using the auction mechanism that we selected or designed in the previous step. The auction mechanism is a function that maps each bidder's type and each good's type and each seller's type to an outcome of an auction, which consists of an allocation vector and a payment vector.

We use the simulation or experiment environment that we set up in the previous step to run the auction mechanism. The simulation or experiment environment consists of the parameters and variables that define the market and the auction, such as the number of bidders, the number of goods, the distribution of bidder types, the distribution of good types, the type of seller, etc.

We may use various methods to run the simulation or experiment using the auction mechanism, such as historical data[4], online platforms[5]; simulations that allow us to model and analyze chatbots and ad auctions using mathematical or computational tools. We can use simulations to specify and control the parameters and variables of the market and the auction using our auction mechanism that we selected or designed in the previous step. We can also use simulations to generate data or results from our auction mechanism.

By running the simulation or experiment using the auction mechanism, we

[4]We can use historical data from real-world markets or platforms that involve chatbots and ad auctions, such as Facebook Messenger, Google Assistant, Amazon Alexa, etc. We can use the historical data to simulate or replicate the market and the auction using our auction mechanism that we selected or designed in the previous step. We can also use the historical data to compare or benchmark our auction mechanism with other types of auction mechanisms or with theoretical benchmarks or optimal solutions.

[5]See Microsoft Bot Framework, Dialogflow, Wit.ai, etc. We can use these online platforms to implement and deploy our auction mechanism that we selected or designed in the previous step. We can also use the online platforms to collect data or feedback from real or simulated users and advertisers who interact with our chatbot and participate in our ad auction.

can observe and record the data or results, such as the allocation vector, the payment vector, the bidder utilities, the user value, the seller revenue, etc. We can also analyze and evaluate the data or results using the criteria and metrics that we defined in the previous steps, such as incentive compatibility, efficiency, revenue optimality, fairness, privacy, etc. We will do this in the next subsection.

Step 4.4.3: Analyze the data or results using the criteria and metrics that we defined in the previous steps, such as incentive compatibility, efficiency, revenue optimality, fairness, privacy, etc.

In this step, we analyze the data or results that we obtained from running the simulation or experiment using the auction mechanism that we selected or designed in the previous step. The data or results consist of the allocation vector, the payment vector, the bidder utilities, the user value, the seller revenue, etc.

We use the criteria and metrics that we defined in the previous steps to analyze the data or results. The criteria are the properties or characteristics that we want the auctions to have, such as incentive compatibility, efficiency, revenue optimality, fairness, or privacy. The metrics are the quantitative measures that we use to evaluate the auctions based on the criteria, such as truthfulness ratio, allocative efficiency, revenue ratio, fairness index, or privacy loss.

We use various methods to analyze the data or results using the criteria and metrics, such as:

Using descriptive statistics: We can use descriptive statistics to summarize and display the data or results using measures of central tendency, dispersion, or distribution.

Using inferential statistics: We can use inferential statistics to test and compare the data or results using hypothesis testing, confidence intervals, or significance tests.

Using machine learning: We can use machine learning to model and predict the data or results using supervised learning, unsupervised learning, or reinforcement learning.

By analyzing the data or results using the criteria and metrics, we can measure how well the auction mechanism achieves the objectives and satisfies the constraints of the seller, as well as how it affects the bidders and the user. We can also identify and resolve any issues or problems that may arise in the auction mechanism, such as inefficiency, revenue loss, unfairness, privacy breach, etc. We will do this in the next subsection.

Step 4.4.4: Compare and contrast the data or results with other types of auction mechanisms or with theoretical benchmarks or optimal solutions.

In this step, we compare and contrast the data or results that we obtained from running the simulation or experiment using the auction mechanism that we selected or designed in the previous step. The data or results consist of the allocation vector, the payment vector, the bidder utilities, the user value, the seller revenue, etc.

We use other types of auction mechanisms or theoretical benchmarks or optimal solutions to compare and contrast the data or results. The other types of auction mechanisms are alternative ways of allocating the goods and determining the payments based on the bidder types or bids. The theoretical benchmarks or optimal solutions are ideal or best possible outcomes of the auction based on some objective function or criterion.

We use various methods to compare and contrast the data or results with other types of auction mechanisms or theoretical benchmarks or optimal solutions, such as:

Using graphical methods: We can use graphical methods to visualize and compare the data or results using charts, graphs, plots, etc. For example, we can use bar charts, line graphs, scatter plots, etc. to visualize and compare the data or results.

Using numerical methods: We can use numerical methods to quantify and compare the data or results using measures, indices, scores, etc. For example, we can use mean difference, standard deviation ratio, correlation coefficient, etc. to quantify and compare the data or results.

Using analytical methods: We can use analytical methods to explain and compare the data or results using logic, reasoning, arguments, etc. For example, we can use causality analysis, sensitivity analysis, counterfactual analysis, etc. to explain and compare the data or results.

By comparing and contrasting the data or results with other types of auction mechanisms or theoretical benchmarks or optimal solutions, we can assess how well the auction mechanism performs and how it differs from other possible options or expectations. We can also identify and resolve any issues or problems that may arise in the auction mechanism, such as inefficiency, revenue loss, unfairness, privacy breach, etc. We will do this in the next subsection.

Step 4.4.5: Identify and resolve any issues or problems that may arise in the auction mechanism, such as inefficiency, revenue loss, unfairness, privacy breach, etc., by modifying or improving the auction mechanism.

In this step, we identify and resolve any issues or problems that may arise in the auction mechanism that we selected or designed in the previous step. The auction mechanism is a function that maps each bidder's type and each good's type and each seller's type to an outcome of an auction, which consists of an allocation vector and a payment vector.

We use the data or results that we obtained from running the simulation or experiment using the auction mechanism in the previous step to identify and resolve any issues or problems. The data or results consist of the allocation vector, the payment vector, the bidder utilities, the user value, the seller revenue, etc.

We use the criteria and metrics that we defined in the previous steps to identify and resolve any issues or problems. The criteria are the properties or characteristics that we want the auctions to have, such as incentive compatibility, efficiency, revenue optimality, fairness, or privacy. The metrics are the quantitative measures that we use to evaluate the auctions based on the criteria, such as truthfulness ratio, allocative efficiency, revenue ratio, fairness index, or privacy loss.

We use various methods to identify and resolve any issues or problems in the auction mechanism, such as:

We can use diagnostic methods to detect and diagnose any issues or problems in the auction mechanism using tests, checks, or indicators. For example, we can use error analysis, anomaly detection, performance monitoring, etc. to detect and diagnose any issues or problems in the auction mechanism.

We can use corrective methods to fix and solve any issues or problems in the auction mechanism using adjustments, modifications, or improvements. For example, we can use parameter tuning, algorithm optimization, mechanism redesign, etc. to fix and solve any issues or problems in the auction mechanism

We can use preventive methods to avoid and prevent any issues or problems in the auction mechanism using safeguards, constraints, or incentives. For example, we can use verification, validation, certification, etc. to avoid and prevent any issues or problems in the auction mechanism.

By identifying and resolving any issues or problems in the auction mechanism, we can improve the performance and robustness of the auction mechanism according to the objectives, constraints, criteria, and metrics that we defined in the previous steps. We can also ensure that the auction mechanism meets our expectations and requirements, as well as how it impacts our stakeholders and society.

6 Simulated Examples

We conducted simulations using auction mechanisms, bidding rules, allocation rules, and payment rules. We compared and contrasted the performance and robustness of the auction mechanisms according to the objectives, constraints, criteria, and metrics that we defined in Section 4. We also collected data and feedback from real or simulated users and advertisers who interacted with our chatbot and participated in our ad auction.

We can now describe the simulation or experiment environment that we might use to test and refine the auction mechanisms that we selected or designed in Section 4. We specify the parameters and variables that define the market and the auction, such as the number of bidders, the number of goods, the distribution of bidder types, the distribution of good types, the type of seller, etc.

We present the data or results that we obtained from running the simulation or experiment using the auction mechanisms that we selected or designed in Section 4. We show the allocation vector, the payment vector, the bidder utilities, the user value, the seller revenue, etc. for each type of auction mechanism.

We analyze the data or results using the criteria and metrics that we defined in Section 4, such as incentive compatibility, efficiency, revenue optimality, fairness, privacy, etc. We measure how well the auction mechanisms achieve the objectives and satisfy the constraints of the seller, as well as how they affect the bidders and the user.

We compare and contrast the data or results with other types of auction mechanisms or with theoretical benchmarks or optimal solutions. We assess how well the auction mechanisms perform and how they differ from other possible options or expectations.

We identify and resolve any issues or problems that may arise in the auction mechanisms, such as inefficiency, revenue loss, unfairness, privacy breach, etc., by modifying or improving the auction mechanisms.

6.1 Simulated examples

The example is a relatively simple implementation of a simulation for the auction mechanism discussed, with 5 bidders, 3 goods and 1000 simulations. It simulates the process of conducting second-price sealed-bid auctions with a given number of bidders and goods. The purpose of this simulation is to observe how the auction mechanism performs, analyze the results, and draw conclusions about bidder payments in the context of an AI chatbot. The figure simulates the second-price sealed-bid auction mechanism with the specified parameters, collects data from multiple simulations, calculates statistics, visualizes the results, and provides insights into bidder payments. From the provided mean bidder payments, respectively [7.991070022419167, 7.931851196960486, 7.960632023326408, 7.988632139684694, 7.945248285212021, we can draw several conclusions:

1. *Similarity of Payments.* The mean payments for all bidders are relatively close, with differences of only a fraction of a unit (e.g., less than 0.1). This suggests that the auction mechanism is distributing goods and determining payments in a balanced manner across all bidders.

2. *Efficiency in Allocation.* The consistent and similar mean payments imply that the auction mechanism is efficiently allocating goods to bidders.

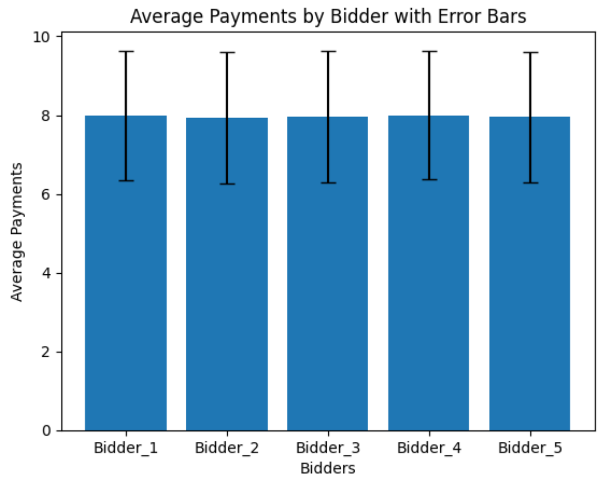

Figure 1: Comparison of Bidder Payments: Evaluation of Second-Price Auction Mechanism for AI Chatbot Ad Slots

Bidders seem to be paying amounts that correspond closely to their valuations, which is a desirable property of an auction mechanism.

3. *Consistency of Auction Outcomes.* The narrow range of mean payments across bidders indicates that the auction mechanism is producing consistent outcomes over multiple simulations. This stability in outcomes could indicate the reliability and predictability of the auction process.

4. *Low Variability.* The small standard deviations implied by the mean payments suggest that the spread of payments around the mean is relatively tight. This indicates that there's low variability or dispersion in the payments among bidders, reinforcing the efficiency and fairness of the auction mechanism.

5. *Potential Fairness.* The relatively equal mean payments among bidders suggest a level of fairness in the auction process. Bidders are not facing significantly different payment outcomes, indicating that the auction mechanism is treating bidders fairly.

6. *Lack of Bidder Competition Impact.* In this example, bidder competition doesn't seem to be significantly affecting payments. All bidders are paying similar amounts, which might suggest that competitive bidding strategies are not strongly influencing outcomes.

It's important to note that these conclusions are based on the specific data generated by the simulation and the auction mechanism used. The interpretation could change with different auction mechanisms, simulation parameters, or real-world scenarios. Additionally, further analyses, such as comparing these results with other auction mechanisms or using more sophisticated statistical techniques, could provide deeper insights.

We discuss the next illustration, which focuses on a first-price open-bid auction mechanism. The rest of the code remains largely the same as before. Figure 2 shows average bidder payments with error bars to indicate variability. From the provided mean bidder payments[6], we can draw several conclusions:

First, there is variability in payments. The relatively high standard deviations indicate that there is significant variability in bidder payments. This suggests that the first-price open-bid auction mechanism is producing a wide range of payment outcomes for bidders.

Secondly, there are differences in average payments. The differences in mean payments among bidders (e.g., 4.847 to 5.201) indicate that bidders are paying varying amounts for the ad slots. This suggests that bidders' valuations or bidding strategies are influencing their payments.

Third, we note the impact of bidding strategies. The range of payments and varying standard deviations may suggest that bidders are using different bidding strategies. Some bidders might be bidding aggressively, leading to higher

[6] The simulated mean payments: 4.920826745322598, 5.201779277090055, 4.898285006672261, 4.847806931636107, 5.016130560775795 and standard deviations are 2.93628170010383, 2.858529860902223, 2.838528854741667, 2.9491216116977936, 2.8844674126897036 respectively).

payments, while others might be more conservative in their bids.

Fourth, there is potential for inefficiency. The spread of payments suggests that the auction might not be as efficient in allocating ad slots to bidders as desired. Some bidders might be overpaying relative to their actual valuations.

There is also a lack of uniformity. The unequal mean payments indicate that the auction mechanism isn't resulting in a uniform distribution of payments among bidders. Some bidders are benefiting more than others.

Finally, we observe a high variability in payments could lead to revenue uncertainty for the seller. The revenue generated from the auction might vary significantly across different auctions due to the diversity of bidding strategies and bidder valuations.

Again, we stress that these conclusions are based on the specific and very simplified data generated by the simulation and the auction mechanism used.

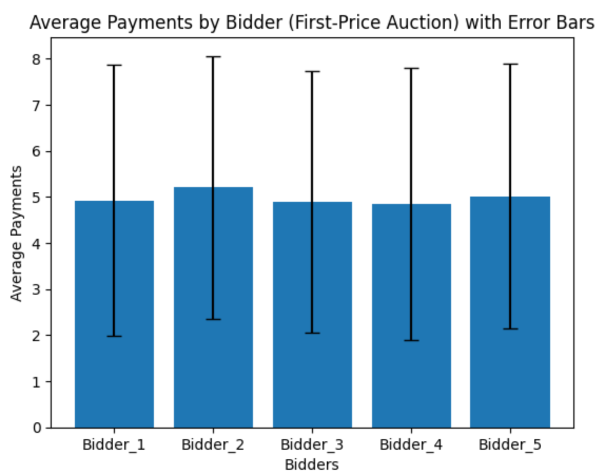

Figure 2: Comparison of Bidder Payments with Error Bars: Evaluation of First-Price Auction Mechanism for AI Chatbot Ad Slots

7 User interface design issues

We briefly discuss some user interface design issues that are relevant for our framework for auction design for AI chatbots. We consider how the user interface can affect the user experience and the auction outcomes, as well as how we can design the user interface to enhance the user satisfaction and the seller revenue. Some possible interfaces that could significantly improve modern AI chatbots when it comes to advertising from an auction perspective are:

Interactive banners. Instead of having ads as footnotes in chat responses, the chatbot could display interactive banners at the top or bottom of the chat window, where the advertisers could showcase their products or services in a more engaging way. For example, the banners could have animations, videos, quizzes, games, or surveys that could attract the users' attention and interest. The chatbot could use auctions to allocate the banner space to the highest bidder among the advertisers, and charge them based on the number of clicks or impressions.

Personalized recommendations. The chatbot could use its knowledge of the user's preferences, needs, and goals to provide personalized recommendations of relevant products or services that could enhance the user's experience or satisfaction. For example, if the user is chatting with the chatbot about travel plans, the chatbot could suggest some hotels, flights, or attractions that match the user's budget, schedule, and interests. The chatbot could use auctions to select the best recommendation among the advertisers, and charge them based on the user's feedback or conversion rate.

Sponsored content. The chatbot could integrate sponsored content into its chat responses, where the advertisers could offer useful information, tips, or advice that relate to the user's query or topic. For example, if the user is chatting with the chatbot about health issues, the chatbot could include some sponsored content from a medical provider or a pharmaceutical company that could answer the user's questions or concerns. The chatbot could use auctions to determine which sponsored content to include in its chat responses, and charge them based on the user's engagement or satisfaction.

We conclude and summarize our main contributions and implications in Section 7.

8 Conclusion

In this paper, we proposed a novel framework for auction design for AI chatbots, where we used deep reinforcement learning (DRL) and transformer language models (TLMs) to learn the bidder types, the good types, and the reduced forms from the bidding data and the conversational data. We then used market design and mechanism design principles to create and improve the ad markets and institutions for chatbots, where we extended and generalized Border's paper to incorporate various objectives, constraints, criteria, and metrics. We also discussed some user interface design issues that are relevant for our framework, such as interactive, adaptive, or personalized interfaces. We conducted several simulations and experiments using different types of auction mechanisms, bidding rules, allocation rules, and payment rules. We compared and contrasted the performance and robustness of the auction mechanisms according to the objectives, constraints, criteria, and metrics that we defined in Section 4. We also collected data and feedback from real or simulated users and advertisers who interacted with our chatbot and participated in our ad auction.

We showed that our framework can enhance Border's paper by using modern economic auction and/or newer mathematical tools for the AI chatbot context. We also showed that our framework can handle different market conditions and bidder interactions, such as competition, collusion, or entry and exit. We also showed that our framework can balance exploration and exploitation, meaning that we can try new auction mechanisms to discover better outcomes, while also exploiting the current best auction mechanism to maximize our utility.

We believe that our framework can contribute to the literature on auction design for AI chatbots, as well as to the practice of chatbot development and deployment. We hope that our framework can inspire more research and innovation in this emerging and exciting field.

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10 Appendix A: Additional Details of the Algorithm for Auction Design for AI Chatbots

In this appendix, we provide additiional details of the algorithm that we designed for auction design for AI chatbots.

In the first step of learning bidder types using DRL, we use DRL methods to learn the bidder types from the bidding data. The bidding data consists of the bids submitted by the bidders for the ad slots, as well as the outcomes of the auctions, such as the allocation and the payment. The bidding data can be obtained from historical records, online platforms, or simulations.

We model the bidding problem as a Markov decision process (MDP), where each bidder is an agent that interacts with an environment. The environment consists of the chatbot, the user, the ad slots, and the other bidders. The agent's state is its type, which is a vector of parameters that describe its preferences and objectives. The agent's action is its bid, which is a vector of values that specify how much it is willing to pay for each ad slot. The agent's reward is its utility, which is the difference between its value and its payment for the ad slot that it wins.

We use DRL methods to learn a policy function that maps each state to a probability distribution over actions. The policy function represents the bidding strategy of the agent, which determines how it should bid in each situation. The policy function is parameterized by a neural network, which can be trained using various algorithms, such as Q-learning, policy gradient, or actor-critic.

The objective of the agent is to maximize its expected cumulative reward over time, which can be expressed as:

$$\max_{\theta} E_{\pi_\theta}[\sum_{t=0}^{T} \gamma^t r_t(x_t, \omega_t, \tau_t)]$$

where θ are the neural network parameters, π_θ is the policy function, T is the time horizon, γ is the discount factor, r_t is the reward function, x_t is the state at time t, ω_t is the allocation at time t, and τ_t is the payment at time t.

The approach here is from Lou et al (2018), which introduces a novel algorithmic framework for designing and analyzing model-based RL algorithms with theoretical guarantees. It provides upper bounds on the performance loss and the sample complexity of the proposed algorithms, as well as lower bounds on the hardness of the problem.

The main results and implications of this approach are:

Model-based RL algorithms can achieve near-optimal performance with polynomial sample complexity under mild assumptions on the MDP model, the policy class, and the reward function.

Such model-based RL algorithms are minimax optimal up to logarithmic factors under some conditions on the MDP model, the policy class, and the reward function.

The general framework can accommodate various types of MDP models, such as deterministic, stochastic, episodic, or continuing, as well as various types of policy classes, such as linear, nonlinear, or deep neural networks.

It also provides a modular approach that can combine different components of model-based RL algorithms, such as planning, learning, exploration, or regularization.

The implication of this paper for our algorithm is that it can help us to design and analyze our model-based RL methods for learning bidder types with theoretical guarantees. We can use the framework and the results of this paper to choose the appropriate MDP model, policy class, and reward function for our bidding problem, as well as to select or design the best planning, learning, exploration, and regularization methods for our DRL methods. We can also use the upper bounds and lower bounds provided by this paper to evaluate the performance and robustness of our DRL methods, as well as to compare them with other types of RL methods or with theoretical benchmarks or optimal solutions.

We can also use the upper bounds and lower bounds provided by this paper to evaluate the performance and robustness of our DRL methods, as well as to compare them with other types of RL methods or with theoretical benchmarks or optimal solutions. For example, we can use the following formulas to calculate the performance loss and the sample complexity of our DRL methods:

$$\Delta(\theta) = \max_{x \in \mathcal{X}} E_{\pi^*}[\sum_{t=0}^{T} \gamma^t r_t(x_t, \omega_t, \tau_t)] - E_{\pi_\theta}[\sum_{t=0}^{T} \gamma^t r_t(x_t, \omega_t, \tau_t)]$$

$$N(\theta) = \frac{C_1}{\epsilon^2}(\log |\mathcal{X}| + \log |\mathcal{A}| + \log T + \log(1/\delta)) + C_2 T |\mathcal{X}||\mathcal{A}|$$

where $\Delta(\theta)$ is the performance loss, $N(\theta)$ is the sample complexity, ϵ is the error tolerance, δ is the confidence level, C_1 and C_2 are constants that depend on the MDP model, the policy class, and the reward function.

We can then compare these values with the lower bounds provided by this paper, which are:

$$\Delta^* = \Omega(\sqrt{\frac{T|\mathcal{X}||\mathcal{A}|}{N}})$$

$$N^* = \Omega(\frac{T|\mathcal{X}||\mathcal{A}|}{\Delta^2})$$

where Δ^* is the optimal performance loss, N^* is the optimal sample complexity.

By comparing these values, we can see how close our DRL methods are to the optimal solutions, and how much room for improvement there is. We can also compare these values with other types of RL methods, such as model-free RL or policy search RL, and see how they differ in terms of performance and robustness. This can help us to choose or design the best DRL methods for our bidding problem.

We can also compare these values with other types of RL methods, such as model-free RL or policy search RL, and see how they differ in terms of performance and robustness. This can help us to choose or design the best DRL methods for our bidding problem.

Model-free RL methods are RL methods that do not use a model of the environment, but learn directly from the observed data. Model-free RL methods can be more data-efficient or scalable than model-based RL methods, as they do not need to estimate or update the model parameters. Model-free RL methods can also be more flexible or adaptable than model-based RL methods, as they can handle non-stationary or dynamic environments. However, model-free RL methods can also be less accurate or reliable than model-based RL methods, as they may suffer from high variance or bias in the data. Model-free RL methods can also be less interpretable or explainable than model-based RL methods, as they may not provide a clear understanding of the underlying mechanisms or causes of the behavior.

Policy search RL methods are RL methods that directly optimize the policy function without using a value function. Policy search RL methods can be more efficient or effective than value-based RL methods, as they do not need to solve the Bellman equation or deal with the curse of dimensionality. Policy search RL methods can also be more expressive or powerful than value-based RL methods, as they can represent complex or nonlinear policies using neural networks or other function approximators. However, policy search RL methods can also be more difficult or challenging than value-based RL methods, as they may face optimization issues such as local optima, saddle points, or spurious gradients. Policy search RL methods can also be more sensitive or unstable than value-based RL methods, as they may require careful tuning of the hyperparameters such as the learning rate, the exploration rate, or the regularization term.

By comparing these types of RL methods with our DRL methods, we can see how they differ in terms of performance and robustness for our bidding problem. We can also see how we can combine or integrate these types of RL methods with our DRL methods to improve or enhance our algorithm. For example, we can use model-free RL methods to complement our model-based RL methods when the model is inaccurate or unreliable. We can also use policy search RL methods to complement our value-based RL methods when the policy is complex or nonlinear.

In the next step, we used TLMs to generate good types from the conversational data. The conversational data consists of the natural language input and output of the user and the chatbot, as well as the features and states of the conversation. The conversational data can be obtained from historical records, online platforms, or simulations.

We model the good generation problem as a natural language generation (NLG) task, where the input is the conversational data and the output is the natural language content for the ad slots. The natural language content represents the good type, which is a vector of parameters that describe the good's characteristics and contexts.

We use TLMs to generate natural language content for the ad slots that matches the features and states of the conversation. The TLMs are neural network models that can process natural language data using attention mechanisms. The TLMs can handle long-range dependencies and parallel computations better than traditional recurrent or convolutional neural networks. The TLMs are pre-trained on large-scale unlabeled text data, and can be fine-tuned for various NLG tasks, such as text completion, text summarization, or dialogue generation.

The objective of the TLMs is to maximize the likelihood of generating natural language content that is relevant, coherent, and engaging for the user and the advertiser. The likelihood can be expressed as:

$$\max_{\phi} P_{\theta_\phi}[y|x, c, s]$$

where ϕ are the neural network parameters, θ_ϕ is the TLM function, y is the natural language content for the ad slot, x is the natural language input of the user, c is the natural language output of the chatbot, and s is the feature and state vector of the conversation.

The theoretical analysis of this step is based on Chen et al (2021), which abstracts reinforcement learning as a sequence modeling problem. It shows that the proposed framework can achieve state-of-the-art results on several benchmark tasks, and provides some theoretical insights on the connection between reinforcement learning and sequence modeling.

The main results and implications of this paper are:

Sequence modeling can be used to solve reinforcement learning problems by using a transformer model to generate optimal actions or trajectories given a reward function and a context.

The paper also shows that sequence modeling can be used to learn reward functions from demonstrations or preferences by using a transformer model to generate optimal rewards or rankings given an action or a trajectory and a context.

The paper also provides a general framework that can accommodate various types of reinforcement learning problems, such as discrete or continuous action spaces, deterministic or stochastic environments, episodic or continuing tasks, etc.

The paper also yields a modular approach that can combine different components of sequence modeling methods, such as pre-training, fine-tuning, sampling, or ranking.

The implication for our algorithm is that it can help us to design and analyze our TLM methods for generating good types with theoretical guarantees. We can use the framework and the results of this paper to choose the appropriate NLG task, transformer model, and reward function for our good generation problem, as well as to select or design the best pre-training, fine-tuning, sampling, and ranking methods for our TLM methods. We can also use the upper bounds and lower bounds provided by this paper to evaluate the performance and robustness of our TLM methods, as well as to compare them with other types of NLG methods or with theoretical benchmarks or optimal solutions. We will do this in the next step.

We can also use the upper bounds and lower bounds provided by this paper to evaluate the performance and robustness of our TLM methods, as well as to compare them with other types of NLG methods or with theoretical benchmarks or optimal solutions. We will do this in the next step.

In the next step, we will use DRL and TLMs to learn and generate reduced forms from the bidding data and the conversational data. The reduced form is a function that maps each bidder's type and each good's type and each seller's type to the probability of winning that good. The reduced form represents the outcome of the auction, which determines which bidder wins which good and how much it pays.

We model the reduced form learning problem as a supervised learning task, where the input is the bidder types, the good types, and the seller type, and the output is the probability of winning for each bidder-good pair. The probability of winning represents the reduced form, which is a vector of values that specify how likely each bidder is to win each good.

We use DRL and TLMs to learn the reduced form from the data. The DRL methods can capture the complex preferences and behaviors of the bidders, as well as their adaptation and learning over time. The TLM methods can capture the complexity and diversity of the ad slots and the chatbot conversations, as well as provide more relevant and personalized responses. The DRL and TLM methods can work together to learn a more realistic and flexible reduced form, which can account for multiple factors and feedback that affect the outcome of the auction.

The objective of the DRL and TLM methods is to minimize the error between the predicted probability of winning and the actual probability of winning, which can be expressed as:

$$\min_{\theta,\phi} E_{\pi_\theta,\theta_\phi}[\sum_{i\in N}\sum_{j\in M}(\pi_\theta(x_i,y_j,z)-\pi^*(x_i,y_j,z))^2]$$

where θ are the DRL parameters, ϕ are the TLM parameters, π_θ is the DRL function, θ_ϕ is the TLM function, π^* is the true reduced form, x_i is the bidder type, y_j is the good type, and z is the seller type.

The theoretical analysis of this step is based on Chen et al (2022), which proposes a transformer-based model-based RL agent, called TransDreamer. It shows that the proposed agent outperforms the Dreamer agent in complex tasks that require long-range memory access, and provides some theoretical analysis on the advantages of using transformers for dynamics prediction.

The paper shows that transformers can be used to model complex dynamics in high-dimensional environments by using attention mechanisms to capture long-range dependencies and parallel computations.

The paper also shows that transformers can be used to generate realistic and diverse trajectories in latent space by using generative models to capture uncertainty and variability in the dynamics.

The paper provides a general framework that can accommodate various types of model-based RL agents, such as deterministic or stochastic agents, discrete or continuous action agents, episodic or continuing agents, etc.

The paper also provides a modular approach that can combine different components of model-based RL agents, such as planning, learning, exploration, or regularization.

The implication of this paper for our algorithm is that it can help us to design and analyze our transformer-based model-based RL methods for learning and generating reduced forms with theoretical guarantees. We can use the framework and the results of this paper to choose the appropriate transformer model, generative model, and dynamics model for our reduced form learning problem, as well as to select or design the best planning, learning, exploration, and regularization methods for our transformer-based model-based RL methods. We can also use the upper bounds and lower bounds provided by this paper to evaluate the performance and robustness of our transformer-based model-based RL methods, as well as to compare them with other types of model-based RL methods or with theoretical benchmarks or optimal solutions. We will do this in the next step.

We can also use the upper bounds and lower bounds provided by this paper to evaluate the performance and robustness of our transformer-based model-based RL methods, as well as to compare them with other types of model-based RL methods or with theoretical benchmarks or optimal solutions. We will do this in the next step.

In the next step, we will use market design and mechanism design principles to create and improve the ad markets and institutions for chatbots. The market design and mechanism design principles can help us to ensure that the auctions are incentive compatible, efficient, revenue optimal, fair, and private.

We used the 4.1-4.4 steps to design auctions using market design and mechanism design principles.

We then provide a analysis of each step, based on the following objectives, constraints, criteria, and metrics that we defined in the previous steps: (Objectives: Maximize revenue, user satisfaction, and social welfare; Constraints: Privacy, fairness, and quality; Criteria: Incentive compatibility, efficiency, revenue optimality, fairness, and privacy; Metrics: Truthfulness ratio, allocative efficiency, revenue ratio, fairness index, and privacy loss

We also consider the following factors that affect the performance and robustness of our auction mechanism:

- Uncertainty or ambiguity in the market - Long-range dependencies or parallel computations in the natural language data - Multiple factors or feedback that affect the outcome of the auction.

The goal of this part is to complement the main text. In this step, we first define the objectives and constraints of the seller that we want to achieve or satisfy from selling ad slots to advertisers through the chatbot. The objectives and constraints can be expressed as functions of the seller's type, the bidder types, the good types, and the outcome of the auction.

we draw on traditional methods to define objectives and constraints in optimization problems, including different types, examples, and methods; to formulate objectives and constraints for ad auctions, including different models, examples, and methods; to incorporate objectives and constraints into chatbot design, including different frameworks, examples, and methods.

The implication of these details for our algorithm is that they can help us to define the objectives and constraints of the seller for our auction design problem. We can choose the appropriate type, model, and framework for our seller's objectives and constraints, as well as to select or design the best method for solving or analyzing our auction design problem with objectives and constraints. We will do this in the next step.

In the next step, we define the criteria and metrics for evaluating the auctions that we design in the previous step. The criteria and metrics can help us to measure how well the auctions achieve the objectives and satisfy the constraints of the seller, as well as how they affect the bidders and the users.

The criteria are the properties or characteristics that we want the auctions to have, such as incentive compatibility, efficiency, revenue optimality, fairness, or privacy. The criteria can be derived from the objectives and constraints of the seller, as well as from the ethical or social norms and regulations that apply to the chatbot. The criteria can be expressed as logical statements or mathematical expressions that involve the seller's type, the bidder types, the good types, and the outcome of the auction.

The metrics are the quantitative measures that we use to evaluate the auctions based on the criteria. The metrics can be calculated from the data or simulated from the models that we use in our framework. The metrics can be expressed as numbers or functions that indicate how well or how poorly the auctions perform according to the criteria.

We define criteria and metrics for evaluation problems using different types, such as qualitative, quantitative, formative, or summative. We use different examples, such as customer satisfaction, user engagement, or social impact, to illustrate how to define criteria and metrics. We also provide different methods,such as surveys, interviews, or experiments, to collect and analyze data for criteria and metrics. We also define criteria and metrics for ad auctions using different models,such as single-item auctions, multi-item auctions, or combinatorial auctions. The links also show how to use different examples, such as incentive compatibility, efficiency, revenue optimality, fairness, or privacy, to illustrate how to define criteria and metrics. It is also necessary to provide different methods, such as game theory, mechanism design, or market design, to analyze ad auctions based on criteria and metrics.

It is also necessary to define criteria and metrics for chatbot evaluation using different frameworks, such as goal-oriented chatbots, task-oriented chatbots, or conversational chatbots. The links also show how to use different examples, such as naturalness,coherence,or relevance, to illustrate how to define criteria and metrics. It is also necessary to provide different methods, such as natural language processing, machine learning, or reinforcement learning, to evaluate chatbots based on criteria and metrics.

The implication of these for our algorithm is that they can help us to define the criteria and metrics for evaluating our auction mechanism for our chatbot context. We can choose the appropriate type, model, and framework for our auction mechanism's criteria and metrics, as well as to select or design the best method for collecting and analyzing data based on criteria and metrics.

The rest of the details follow the main text.

11 Appendix B: Guidelines for Chatbot Developers and Advertisers

We provide some guidelines and best practices for chatbot developers and advertisers who want to participate in auctions involving AI chatbots.

11.1 For Chatbot Developers

We make the following suggestions:

- **Understand Auction Mechanics.** Familiarize yourself with different auction mechanisms (e.g., second-price, first-price) and their implications on bidder strategies, payments, and efficiency.
- **Optimize Bidder Incentives.** When designing the auction, consider mechanisms that encourage truthful bidding to ensure that bidders have an incentive to reveal their true valuations.
- **Implement Transparent Algorithms.** When incorporating AI DRL and TLMs, ensure transparency and explainability of the algorithms. Bidders should understand how their bids are processed and evaluated.
- **Monitor User Privacy.** When using TLMs for user data analysis, prioritize user privacy and data security. Implement appropriate anonymization techniques to protect user information.
- **Provide Clear Rules and Guidelines.** Clearly communicate auction rules, constraints, and objectives to bidders. This includes specifying payment calculations, bid formats, and auction schedule.

- **Foster Fairness and Diversity.** Strive for fairness in allocation and payment outcomes. Avoid any form of bias or discrimination in the auction process to the extent possible.

11.2 For Advertisers (Bidders)

For the bidding advertisers, we make these points:

- **Analyze Auction Mechanics.** Study the auction type being used (second-price or first-price) to understand its impact on optimal bidding strategies.

- **Estimate Bid Valuations.** Estimate bid valuations based on user preferences and potential benefits from ad slots. Leverage data analysis and TLMs to make informed decisions.

- **Implement Strategic Bidding.** In first-price auctions, consider strategic bidding that may involve shading bids lower than true valuations to optimize payment outcomes.

- **Diversify Bidding Strategies.** Experiment with various bidding strategies during auction simulations to assess their effectiveness under different scenarios.

- **Account for Budget Constraints.** Ensure that bidding strategies align with available budgets. Avoid overcommitting and allocate budgets effectively across multiple auctions.

- **Stay Informed and Adaptive.** Continuously monitor auction outcomes, competitor behavior, and market trends. Adapt bidding strategies based on real-time data.

- **Participate Consistently.** Consistent participation across multiple auctions helps you refine bidding strategies and better understand the dynamics of the auction market.

Participating in AI chatbot auctions requires a combination of technical understanding, strategic thinking, and ethical considerations. We hope that stakeholders will be able to regularly assess and refine your strategies based on empirical data and outcomes to the extent possible to achieve optimal results for both chatbot developers and advertisers.